Información General

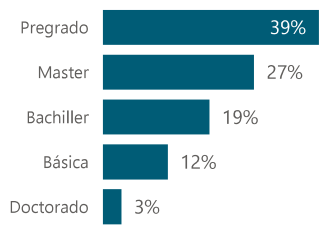
Pregrado
Nivel Educativo Promedio

$65 mil
Salario Mensual Promedio

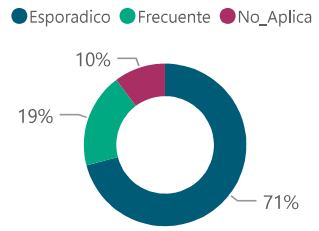
9
Distancia Casa-Trabajo Prom. KM

2
Promedio Años para Promoción

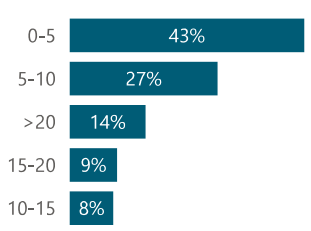
Nivel Educativo



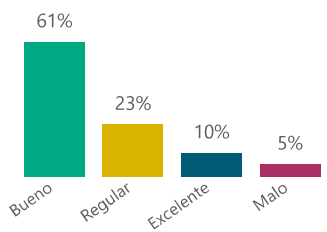
Viaje de Negocios



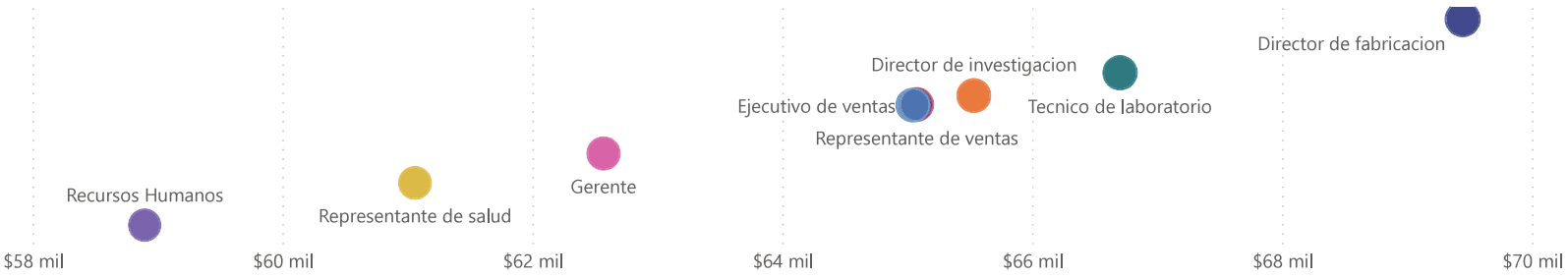
Distancia al Trabajo en KM



Balance Vida Laboral/Personal



Salario Mensual por Cargo



Desercion
- No
- Si

Area
- Investigacion & Desarrollo
- Recursos Humanos
- Ventas

Nivel Educativo
- Básica
- Bachiller
- Pregrado
- Master
- Doctorado

Rol
- Cientifico investigador
- Director de fabricacion
- Director de investigacion
- Ejecutivo de ventas
- Gerente
- Recursos Humanos
- Representante de salud
- Representante de ventas
- Tecnico de laboratorio

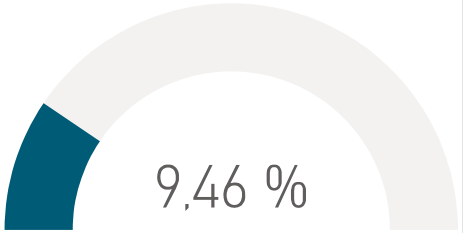
Indicadores de Desempeño

25
Promedio Anual de Ausencias

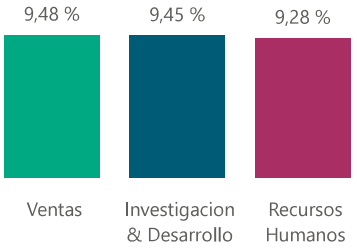
7
Prom. Años en la compañía

11
Promedio Años de Experiencia

Promedio de Ausentismo

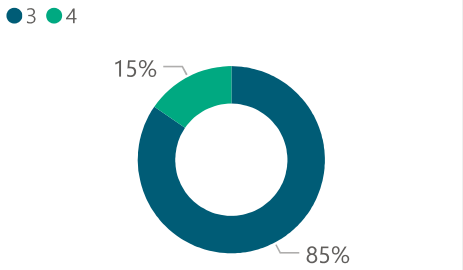


Ausentismo por Área

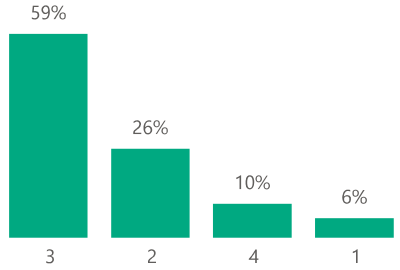


Promedio Horas Laborales

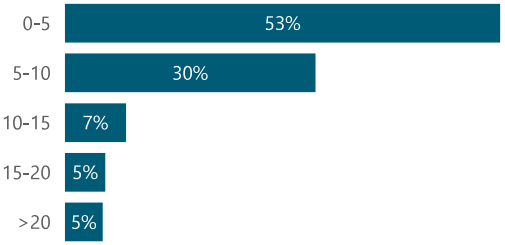
Desempeño



Compromiso del Empleado



Años en la Compañía



Desercion
No
Si

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Recursos Humanos
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Representante de ventas
Tecnico de laboratorio

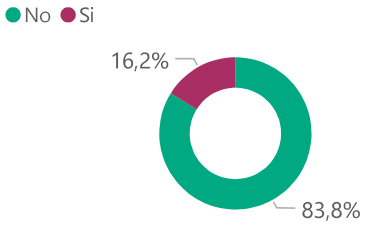
Reporte de Deserción

4.300	695
Total Empleados	Retiros

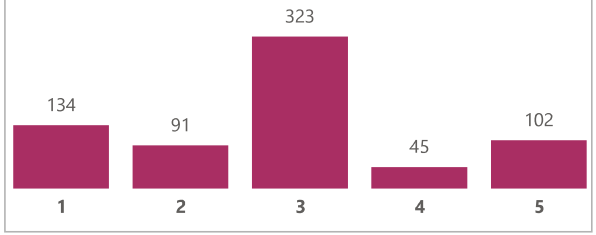
Retiros por Género

34	5
Edad Promedio Retirados	Prom. de Antigüedad Ret.

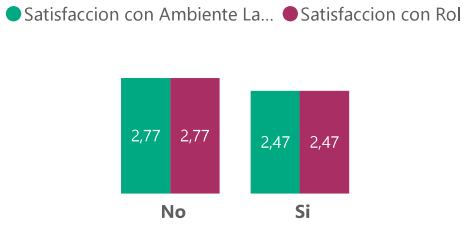
Deserción General



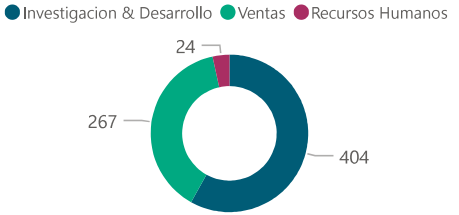
Retiros por nivel de cargo



Promedio encuestas segun Deserción

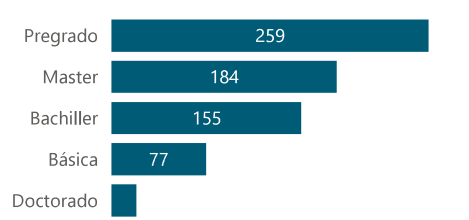


Deserción por Área



Deserción por Cargo

Deserción por Nivel Educativo



Genero
- Femenino
- Masculino

Area
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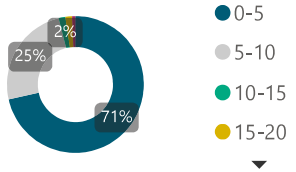
Alerta de Deserción

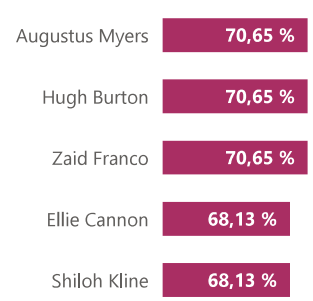
3.605	36,43 %	256
Total Emp. Activos	Riesgo Desercion Promedio	Empleados en Alerta

Riesgo de Retiro Promedio por Area

Alertas por Antiguedad (Años)



Top 5 Empleados en Riesgo



Alertas por Area

Nombre	Rol	Area	Antiguedad	Educación	Horas Prom/Dia	Distancia Casa Km	Satisfacción Laboral	Balance Laboral/Personal	Probabilidad Retiro
Aaden Bautista	Tecnico de laboratorio	Investigaci...	1	Pregrado	11	10	3	1	46,5 %
Aaliyah Christensen	Ejecutivo de ventas	Ventas	9	Bachiller	6	5	2	4	31,6 %
Aaliyah Higgins	Tecnico de laboratorio	Investigaci...	1	Bachiller	6	24	3	3	32,2 %
Abagail Barber	Ejecutivo de ventas	Ventas	8	Bachiller	6	3	3	4	18,5 %
Abbey Carr	Ejecutivo de ventas	Ventas	4	Master	6	8	3	3	32,5 %
Abbie West	Ejecutivo de ventas	Ventas	26	Bachiller	7	25	2	2	35,2 %
Abbigail Mendez	Representante de salud	Ventas	6	Pregrado	8	28	2	2	33,7 %
Abbigail Wilkerson	Ejecutivo de ventas	Ventas	7	Bachiller	11	10	1	3	47,0 %
Abby Andrews	Representante de ventas	Ventas	2	Pregrado	8	1	1	3	49,6 %
Abby Bolton	Representante de ventas	Ventas	1	Bachiller	7	9	1	2	46,6 %
Total			**7**		**8**	**9**	**3**	**3**	**36,4 %**

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- Representante de ventas
- Tecnico de laboratorio

Modelamiento - Probabilidad de Deserción Candidatos

Preparación inicial

In [1]:
```
#Librerias numericas y graficos
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

#Graficos
import plotly as py
import plotly.graph_objs as go

#Manejo de fechas
import datetime as dt

#Para Regresion Logistica
from sklearn.linear_model import LogisticRegression

#Modelos de Arboles
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier

#Medidas
from sklearn import metrics
from sklearn import model_selection
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score

#Split X - y en conjuntos training y testing
from sklearn.model_selection import train_test_split

#Mostrar todas las columnas de frame
pd.set_option('display.max_columns', None)

#Asignar el formato de los decimales
np.set_printoptions(formatter={'float': lambda x: "{0:0.10f}".format(x)})
```

```
#Para datos desbalanceados
from pylab import rcParams

from imblearn.under_sampling import NearMiss
from imblearn.over_sampling import RandomOverSampler
from imblearn.combine import SMOTETomek
from imblearn.ensemble import BalancedBaggingClassifier
from imblearn.over_sampling import SMOTE
from imblearn.over_sampling import ADASYN

from collections import Counter
```

In [2]:
```
#Carga de datos
ruta = r'C:\Users\Jaime Andres Molina\Documents\Maestria\Proyecto Empresarial\Fuentes\01_Fuentes\all_attrition_modeling.csv'
#CSV
df = pd.read_csv (ruta, sep = ';')
```

In [3]:
```
#Tipos de datos
df.dtypes
```

Out[3]:

```
ID_empleado                   int64
Edad                          int64
Desercion                    object
Frecuencia_viaje             object
Area                         object
Distancia_Casa                int64
Nivel_Educativo               int64
Campo_Educativo              object
Recuento_Empleado             int64
Genero                       object
Nivel_Rol                     int64
Rol                          object
Estado_Civil                 object
Salario_Mensual             float64
Companias                     int64
Mayor18                      object
Porcentaje_Aumento_Salarial   int64
Horario                       int64
Nivel_Opcion_Acciones         int64
Anos_Trabajados               int64
Entrenamientos                int64
Antiguedad                    int64
Anos_Ultima_Promocion         int64
Anos_Lider_Actual             int64
Satisfaccion_Entorno          int64
Satisfaccion_Laboral          int64
Balance_VidaTrabajo           int64
CompromisoTrabajo             int64
Rendimiento                   int64
Prom_Horas                  float64
Porcentaje_Ausentismo       float64
Ausentismo                    int64
dtype: object
```

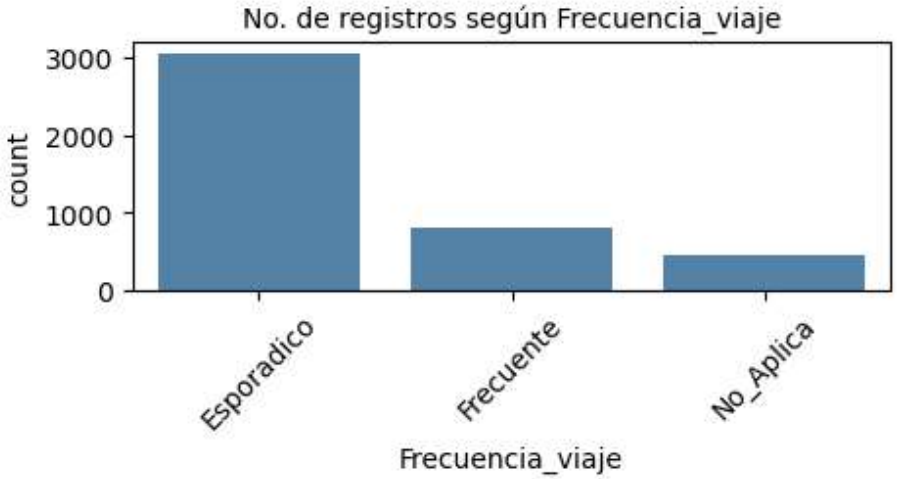
In [4]:

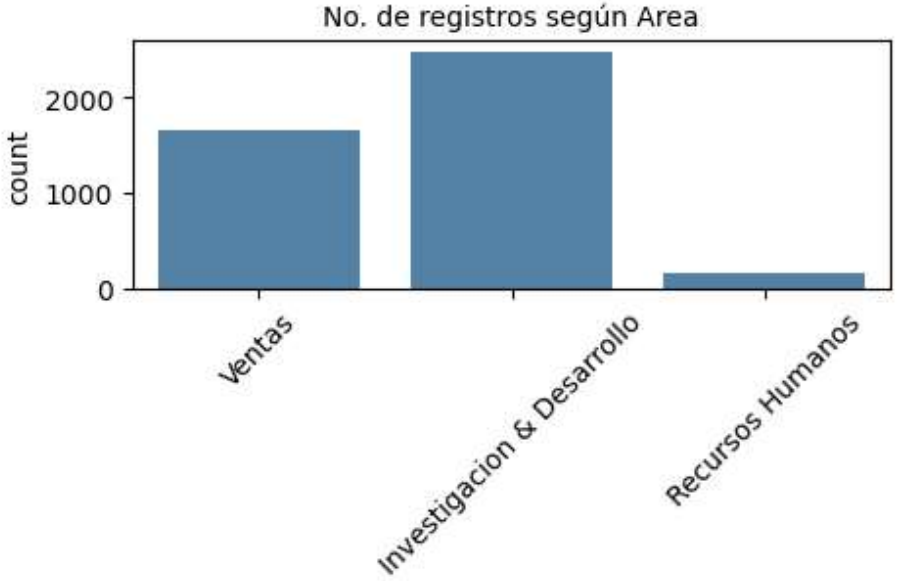
```
# Valores nulos por columna en porcentaje
df.isnull().sum()/df.shape[0]*100
```

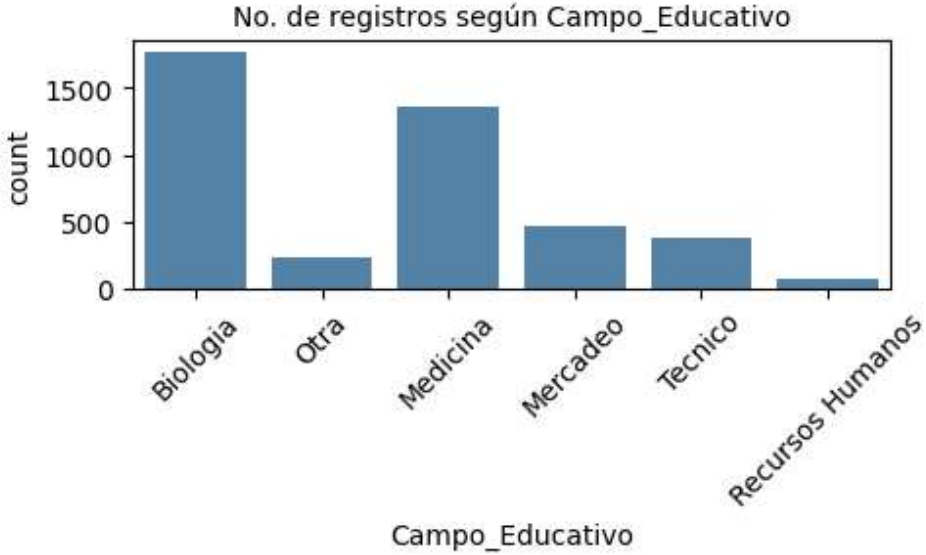
Out[4]:
```
ID_empleado                 0.0
Edad                        0.0
Desercion                   0.0
Frecuencia_viaje            0.0
Area                        0.0
Distancia_Casa              0.0
Nivel_Educativo             0.0
Campo_Educativo             0.0
Recuento_Empleado           0.0
Genero                      0.0
Nivel_Rol                   0.0
Rol                         0.0
Estado_Civil                0.0
Salario_Mensual             0.0
Companias                   0.0
Mayor18                     0.0
Porcentaje_Aumento_Salarial 0.0
Horario                     0.0
Nivel_Opcion_Acciones       0.0
Anos_Trabajados             0.0
Entrenamientos              0.0
Antiguedad                  0.0
Anos_Ultima_Promocion       0.0
Anos_Lider_Actual           0.0
Satisfaccion_Entorno        0.0
Satisfaccion_Laboral        0.0
Balance_VidaTrabajo         0.0
CompromisoTrabajo           0.0
Rendimiento                 0.0
Prom_Horas                  0.0
Porcentaje_Ausentismo       0.0
Ausentismo                  0.0
dtype: float64
```

In [5]:
```
#Histograma campos categoricos varias cajas
features=['Desercion', 'Frecuencia_viaje', 'Area','Campo_Educativo', 'Genero', 'Rol','Estado_Civil','Mayor18']
fig=plt.subplots(figsize=(11,14))
for i, j in enumerate(features):
    plt.subplot(4, 2, i+1)
    plt.subplots_adjust(hspace = 1.5)
    sns.countplot(x=j,data = df, color='steelblue')
    plt.xticks(rotation=45)
    plt.title("No. de registros según "+j, fontdict={'size': 10})
```

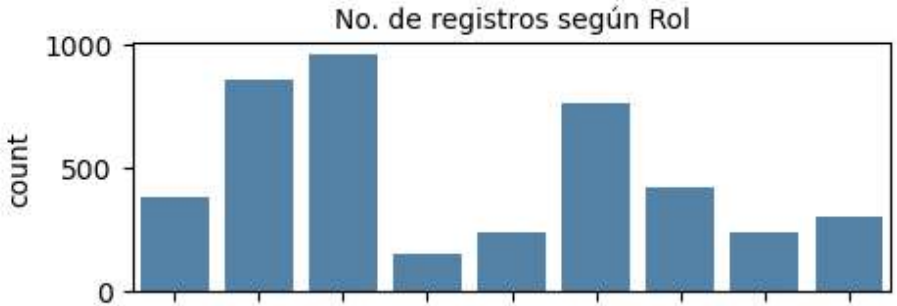

No. de registros según Desercion
count
3000
2000
1000
0
No
Si
Desercion

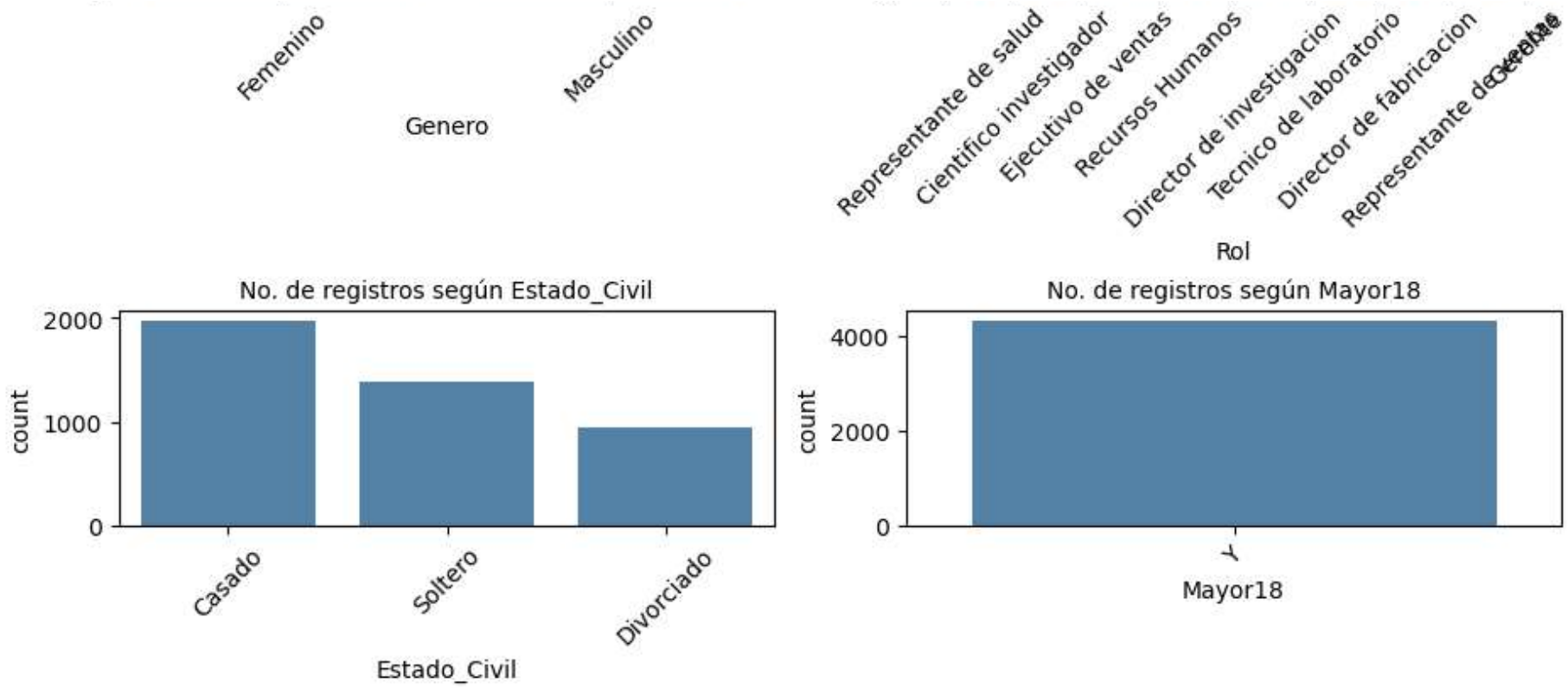

No. de registros según Frecuencia_viaje
count
3000
2000
1000
0
Esporadico
Frecuente
No_Aplica
Frecuencia_viaje


No. de registros según Area
count
2000
1000
0
Ventas
Investigacion & Desarrollo
Recursos Humanos
Area

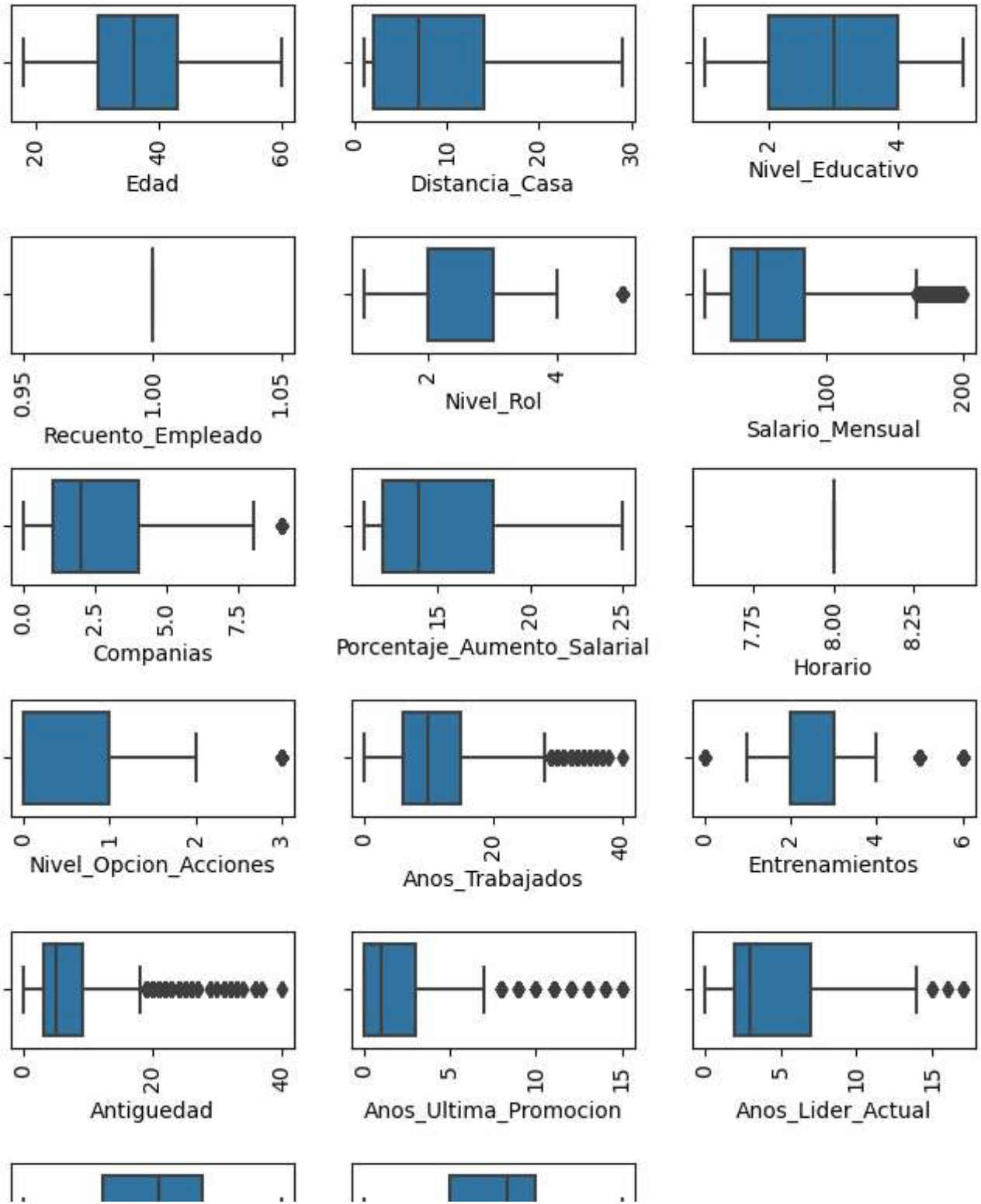

No. de registros según Campo_Educativo
count
1500
1000
500
0
Biologia
Otra
Medicina
Mercadeo
Tecnico
Recursos Humanos
Campo_Educativo

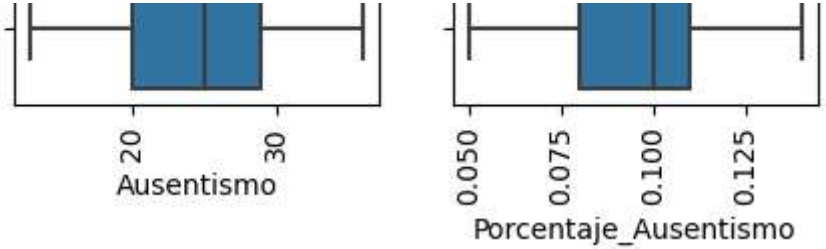

No. de registros según Genero
count
2000
1000
0


No. de registros según Rol
count
1000
500
0



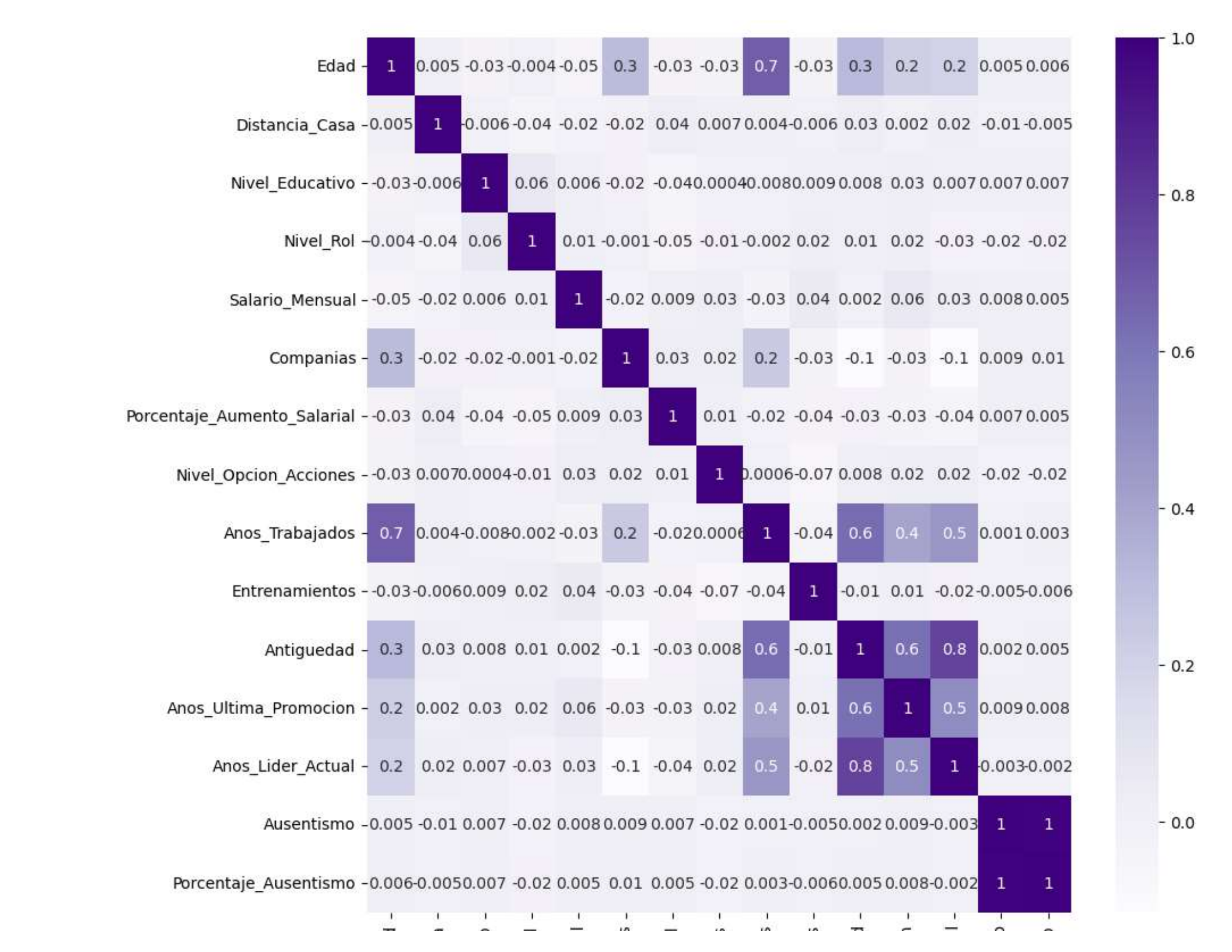
In [6]:
```
#Boxplots con seaborn multiples cajas
features=['Edad', 'Distancia_Casa', 'Nivel_Educativo', 'Recuento_Empleado', 'Nivel_Rol', 'Salario_Mensual',
       'Companias', 'Porcentaje_Aumento_Salarial', 'Horario', 'Nivel_Opcion_Acciones', 'Anos_Trabajados',
       'Entrenamientos', 'Antiguedad', 'Anos_Ultima_Promocion', 'Anos_Lider_Actual','Ausentismo',
        'Porcentaje_Ausentismo']
fig=plt.subplots(figsize=(8,30))
for i, j in enumerate(features):
    plt.subplot(16, 3, i+1)
    plt.subplots_adjust(hspace = 1.0)
    sns.boxplot(x=df[j])
    plt.xticks(rotation=90)
```

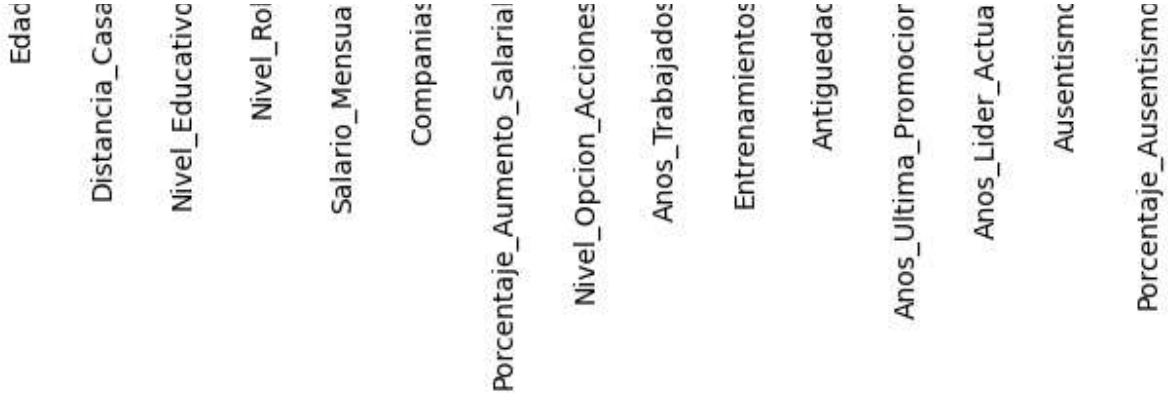

Edad
Distancia_Casa
Nivel_Educativo
Recuento_Empleado
Nivel_Rol
Salario_Mensual
Companias
Porcentaje_Aumento_Salarial
Horario
Nivel_Opcion_Acciones
Anos_Trabajados
Entrenamientos
Antiguedad
Anos_Ultima_Promocion
Anos_Lider_Actual



In [7]:
```
#Grafico de correlacion
corr_features=['Edad', 'Distancia_Casa', 'Nivel_Educativo', 'Nivel_Rol', 'Salario_Mensual',
               'Companias', 'Porcentaje_Aumento_Salarial', 'Nivel_Opcion_Acciones', 'Anos_Trabajados',
               'Entrenamientos', 'Antiguedad', 'Anos_Ultima_Promocion', 'Anos_Lider_Actual','Ausentismo',
               'Porcentaje_Ausentismo']

corr = df[corr_features].corr()
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(corr,
            xticklabels=corr.columns.values,
            yticklabels=corr.columns.values,
            #cmap=sns.diverging_palette(220, 10, as_cmap=True),
            annot=True, cmap="Purples", fmt = '.1g')
```

Out[7]:
```
<AxesSubplot:>
```


Edad 1 0.005 -0.03 -0.004 -0.05 0.3 -0.03 -0.03 0.7 -0.03 0.3 0.2 0.2 0.005 0.006
Distancia_Casa -0.005 1 -0.006 -0.04 -0.02 -0.02 0.04 0.007 0.004 -0.006 0.03 0.002 0.02 -0.01 -0.005
Nivel_Educativo -0.03 -0.006 1 0.06 0.006 -0.02 -0.04 0.0004 0.008 0.009 0.008 0.03 0.007 0.007 0.007
Nivel_Rol -0.004 -0.04 0.06 1 0.01 -0.001 -0.05 -0.01 -0.002 0.02 0.01 0.02 -0.03 -0.02 -0.02
Salario_Mensual -0.05 -0.02 0.006 0.01 1 -0.02 0.009 0.03 -0.03 0.04 0.002 0.06 0.03 0.008 0.005
Companias 0.3 -0.02 -0.02 -0.001 -0.02 1 0.03 0.02 0.2 -0.03 -0.1 -0.03 -0.1 0.009 0.01
Porcentaje_Aumento_Salarial -0.03 0.04 -0.04 -0.05 0.009 0.03 1 0.01 -0.02 -0.04 -0.03 -0.03 -0.04 0.007 0.005
Nivel_Opcion_Acciones -0.03 0.007 0.0004 -0.01 0.03 0.02 0.01 1 0.0006 -0.07 0.008 0.02 0.02 -0.02 -0.02
Anos_Trabajados 0.7 0.004 -0.008 -0.002 -0.03 0.2 -0.02 0.0006 1 -0.04 0.6 0.4 0.5 0.001 0.003
Entrenamientos -0.03 -0.006 0.009 0.02 0.04 -0.03 -0.04 -0.07 -0.04 1 -0.01 0.01 -0.02 -0.005 -0.006
Antiguedad 0.3 0.03 0.008 0.01 0.002 -0.1 -0.03 0.008 0.6 -0.01 1 0.6 0.8 0.002 0.005
Anos_Ultima_Promocion 0.2 0.002 0.03 0.02 0.06 -0.03 -0.03 0.02 0.4 0.01 0.6 1 0.5 0.009 0.008
Anos_Lider_Actual 0.2 0.02 0.007 -0.03 0.03 -0.1 -0.04 0.02 0.5 -0.02 0.8 0.5 1 -0.003 -0.002
Ausentismo -0.005 -0.01 0.007 -0.02 0.008 0.009 0.007 -0.02 0.001 -0.005 0.002 0.009 -0.003 1 1
Porcentaje_Ausentismo -0.006 -0.005 0.007 -0.02 0.005 0.01 0.005 -0.02 0.003 -0.006 0.005 0.008 -0.002 1 1
1.0
0.8
0.6
0.4
0.2
0.0



In [8]:
```
#Quitar columnas por nombre
cols_del = ['ID_empleado','Mayor18','Recuento_Empleado','Horario','Genero','Anos_Lider_Actual','Ausentismo',
            'Frecuencia_viaje','Porcentaje_Aumento_Salarial','Nivel_Opcion_Acciones','Entrenamientos','Antiguedad',
            'Anos_Ultima_Promocion','Satisfaccion_Entorno','Satisfaccion_Laboral','Balance_VidaTrabajo',
            'CompromisoTrabajo','Rendimiento','Prom_Horas','Porcentaje_Ausentismo']
df_in = df.loc[:, [name for name in df.columns if name not in cols_del]]
```

In [9]:
```
df_in.head()
```

Out[9]:

	Edad	Desercion	Area	Distancia_Casa	Nivel_Educativo	Campo_Educativo	Nivel_Rol	Rol	Estado_Civil	Salario_Mensual	Companias	A
0	51	No	Ventas	6	2	Biologia	2	Representante de salud	Casado	131.16	1	
1	31	Si	Investigacion & Desarrollo	10	1	Biologia	3	Cientifico investigador	Soltero	41.89	0	
2	32	No	Ventas	17	4	Otra	3	Ejecutivo de ventas	Casado	193.28	1	
3	38	No	Recursos Humanos	2	5	Biologia	3	Recursos Humanos	Casado	83.21	3	
4	32	No	Ventas	10	1	Medicina	3	Ejecutivo de ventas	Soltero	23.42	4	

In [10]:
```
#Dummificar variables seleccionadas
df_in= pd.get_dummies(df_in, columns=['Desercion', 'Area','Campo_Educativo', 'Rol', 'Estado_Civil'])
df_in.head()
```

Out[10]:

	Edad	Distancia_Casa	Nivel_Educativo	Nivel_Rol	Salario_Mensual	Companias	Anos_Trabajados	Desercion_No	Desercion_Si	Area_Investigacion & Desarrollo	Area_R H
0	51	6	2	2	131.16	1	1	1	0	0	
1	31	10	1	3	41.89	0	6	0	1	1	
2	32	17	4	3	193.28	1	5	1	0	0	
3	38	2	5	3	83.21	3	13	1	0	0	
4	32	10	1	3	23.42	4	9	1	0	0	

In [11]:
```
#Quitar columnas redundantes
cols_del_in = ['Desercion_No']
df_in = df_in.loc[:, [name for name in df_in.columns if name not in cols_del_in]]
```

Entrenamiento de Modelos

In [12]:
```
#Hay desbalanceo de clases en la variable objetivo
print(df_in.shape)
print(pd.value_counts(df_in['Desercion_Si'], sort = True))
```

```
(4300, 29)
0    3605
1     695
Name: Desercion_Si, dtype: int64
```

In [13]:
```
#Resultados con modelo normal sin estrategia de desbalance para tener punto de comparacion

#Definimos nuestras etiquetas y features
y = df_in['Desercion_Si']
X = df_in.drop('Desercion_Si', axis=1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=16)
```

In [14]:
```
#Modelo de Regresion Logistica
logreg_model = LogisticRegression(C=1.0,penalty='l2',random_state=1,max_iter=10000)
logreg_model.fit(X_train, y_train)
```

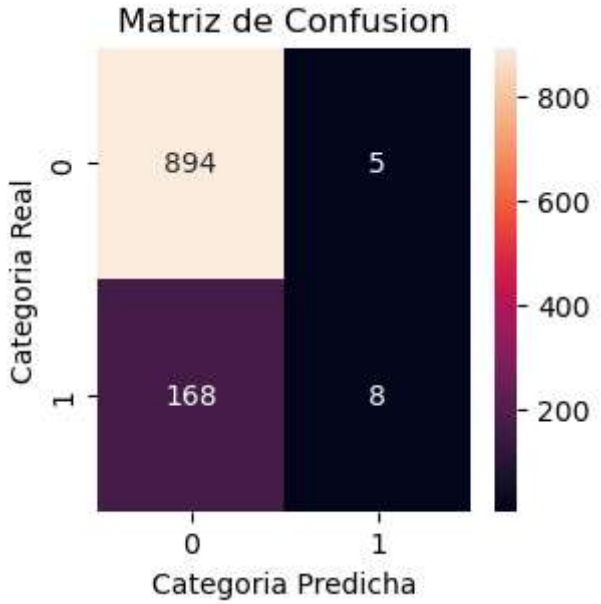
Out[14]:
```
LogisticRegression(max_iter=10000, random_state=1)
```

In [15]:
```
#Definimos funcion para mostrar los resultados
def mostrar_resultados(y_test, pred_y):
```

```
    conf_matrix = confusion_matrix(y_test, pred_y)
    plt.figure(figsize=(3, 3))
    sns.heatmap(conf_matrix, annot=True, fmt="d");
    plt.title("Matriz de Confusion")
    plt.ylabel('Categoria Real')
    plt.xlabel('Categoria Predicha')
    plt.show()
    print (classification_report(y_test, pred_y))
```

In [16]:
```
#Definimos funcion para medidas de comparación
def metricas_comparacion(y_test, pred_test, y_train, pred_train):
    #Accuracy
    accuracy_comparacion = metrics.accuracy_score(y_test, pred_test)
    print("Accuracy: ",accuracy_comparacion)

    #AUC test
    fpr, tpr, _ = metrics.roc_curve(y_test,  pred_test)
    auc_test = metrics.roc_auc_score(y_test, pred_test)
    print("AUC test: ",auc_test)

    #AUC train
    fpr_train, tpr_train, _train = metrics.roc_curve(y_train,  pred_train)
    auc_train = metrics.roc_auc_score(y_train, pred_train)
    print("AUC train: ",auc_train)

    #Delta AUC
    print("Delta AUC (overfitting): ",abs(auc_test-auc_train))
```

In [17]:
```
#Resultados de prediccion
pred_y = logreg_model.predict(X_test)
mostrar_resultados(y_test, pred_y)
#Recall de attrition de 18% a mejorar, activos en 98%
```



	precision	recall	f1-score	support
0	0.84	0.99	0.91	899
1	0.62	0.05	0.08	176
accuracy			0.84	1075
macro avg	0.73	0.52	0.50	1075
weighted avg	0.80	0.84	0.78	1075

Aplicando SMOTE sobre la base (oversampling)

In [18]:
```
sm = SMOTE(sampling_strategy='auto', k_neighbors=5, random_state=1)
X_sm, y_sm = sm.fit_resample(X, y)
```

In [19]:
```
#Nuevos registros por categoria
print(y_sm.shape)
y_sm.value_counts()
```

Out[19]:
```
(7210,)
0    3605
1    3605
Name: Desercion_Si, dtype: int64
```

In [20]:
```
#Dividir la base en train y test de SMOTE
X_train_sm, X_test_sm, y_train_sm, y_test_sm = train_test_split(X_sm, y_sm, test_size=0.25, random_state=28)
```

Aplicando ADASYN sobre la base (oversampling)

In [21]:
```
ada = ADASYN(sampling_strategy='auto', n_neighbors=5, random_state=1)
X_ada, y_ada = ada.fit_resample(X, y)
```

In [22]:
```
#Nuevos registros por categoria
print(y_ada.shape)
y_ada.value_counts()
```

Out[22]:
```
(7045,)
0    3605
1    3440
Name: Desercion_Si, dtype: int64
```

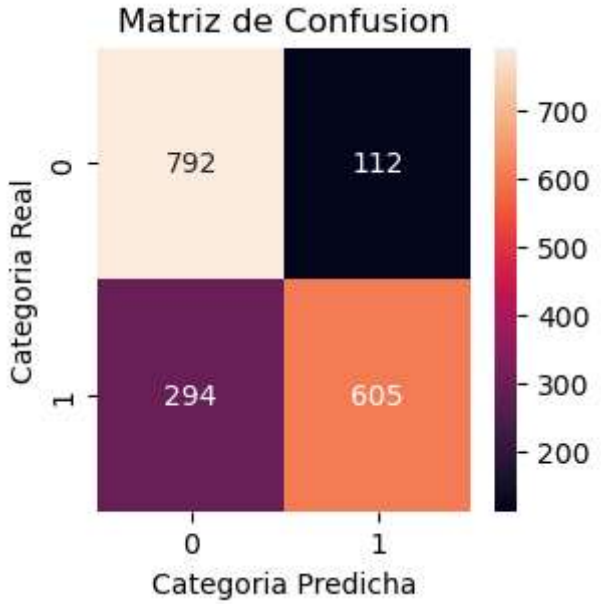
In [23]:
```
#Dividir la base en train y test de ADASYN
X_train_ada, X_test_ada, y_train_ada, y_test_ada = train_test_split(X_ada, y_ada, test_size=0.25, random_state=28)
```

Entrenamiento SMOTE Logistic Regression

In [24]:
```
#Modelo de Regresion Logistica SMOTE
logreg_model_sm = LogisticRegression(C=1.0,penalty='l2',random_state=1,max_iter=10000)
logreg_model_sm.fit(X_train_sm, y_train_sm)
```

Out[24]:
```
LogisticRegression(max_iter=10000, random_state=1)
```

In [25]:
```
#Prediccion sobre el test
pred_y_log_sm = logreg_model_sm.predict(X_test_sm)
mostrar_resultados(y_test_sm, pred_y_log_sm)
#Recall de attrition de 67%, activos en 88%

#Prediccion sobre el train
pred_y_log_sm_train = logreg_model_sm.predict(X_train_sm)
```



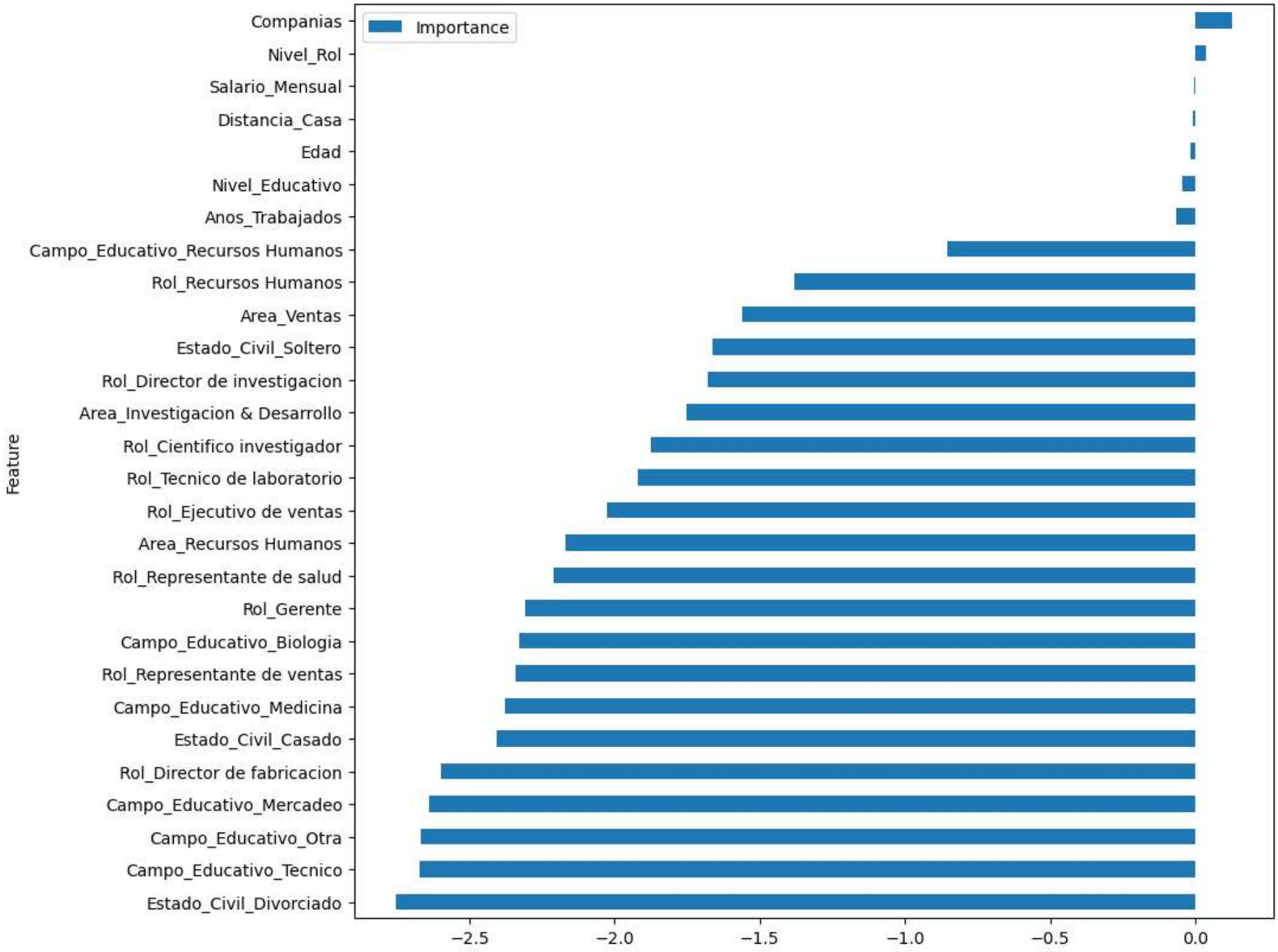
	precision	recall	f1-score	support
0	0.73	0.88	0.80	904
1	0.84	0.67	0.75	899
accuracy			0.77	1803
macro avg	0.79	0.77	0.77	1803
weighted avg	0.79	0.77	0.77	1803

In [26]:
```
metricas_comparacion(y_test_sm, pred_y_log_sm, y_train_sm, pred_y_log_sm_train)
```

```
Accuracy:  0.7748197448696617
AUC test:  0.774538080659927
AUC train:  0.7813070109261221
Delta AUC (overfitting):  0.006768930266195072
```

In [27]:
```
#Importancia de las variables
coefficients_log_sm = logreg_model_sm.coef_[0]

ft_importance_log_sm = pd.DataFrame({'Feature': X_sm.columns, 'Importance': coefficients_log_sm})
ft_importance_log_sm = ft_importance_log_sm.sort_values('Importance', ascending=True)
ft_importance_log_sm.plot(x='Feature', y='Importance', kind='barh', figsize=(10, 10))
```

Out[27]:
```
<AxesSubplot:ylabel='Feature'>
```



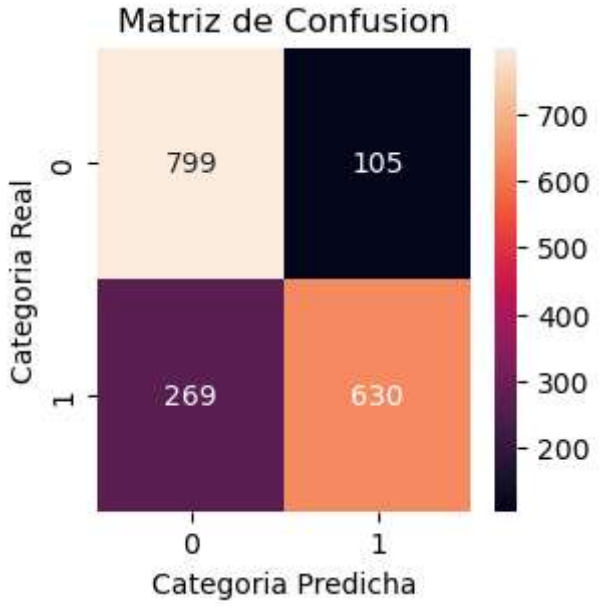
In [28]:
```
#Modelo de Regresion Logistica SMOTE (solo importantes)

#Quitar columnas con menos importancia
```

```
cols_del_imp = ['Nivel_Rol','Salario_Mensual','Distancia_Casa','Edad','Nivel_Educativo']

X_train_sm_imp = X_train_sm.loc[:, [name for name in X_train_sm.columns if name not in cols_del_imp]]
X_test_sm_imp = X_test_sm.loc[:, [name for name in X_test_sm.columns if name not in cols_del_imp]]
```

In [29]:
```
#Entrenar de nuevo
logreg_model_sm_imp = LogisticRegression(C=1.0,penalty='l2',random_state=1,max_iter=10000)
logreg_model_sm_imp.fit(X_train_sm_imp, y_train_sm)
```

Out[29]:
```
LogisticRegression(max_iter=10000, random_state=1)
```

In [30]:
```
#Prediccion sobre el test
pred_y_log_sm_imp = logreg_model_sm_imp.predict(X_test_sm_imp)
mostrar_resultados(y_test_sm, pred_y_log_sm_imp)
#Recall de attrition de 70%, activos en 88%

#Prediccion sobre el train
pred_y_log_sm_train_imp = logreg_model_sm_imp.predict(X_train_sm_imp)
```



```
              precision    recall  f1-score   support

           0       0.75      0.88      0.81       904
           1       0.86      0.70      0.77       899

    accuracy                           0.79      1803
   macro avg       0.80      0.79      0.79      1803
weighted avg       0.80      0.79      0.79      1803
```

In [31]:
```
metricas_comparacion(y_test_sm, pred_y_log_sm_imp, y_train_sm, pred_y_log_sm_train_imp)
```

```
Accuracy:  0.7925679423183583
AUC test:  0.79231410022936
AUC train:  0.7875896885252047
Delta AUC (overfitting):  0.0047244117041552736
```

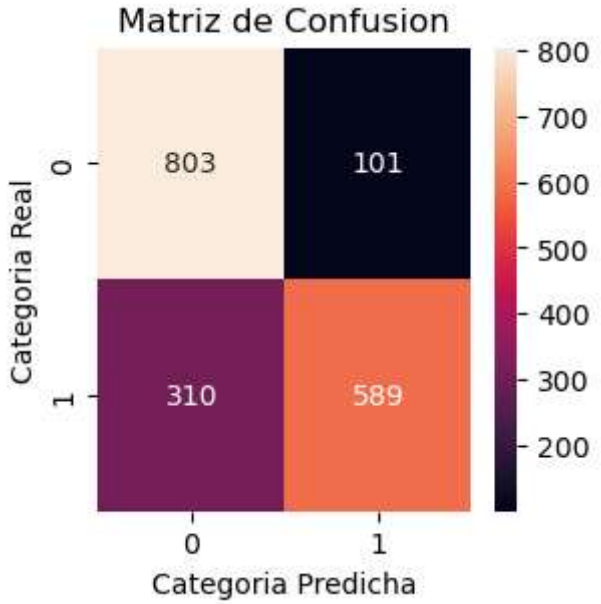
In [39]:
```
#Importancia de las variables
#coefficients_log_sm_imp = logreg_model_sm_imp.coef_[0]

#ft_importance_log_sm_imp = pd.DataFrame({'Feature': X_train_sm_imp.columns, 'Importance': coefficients_log_sm_imp})
#ft_importance_log_sm_imp = ft_importance_log_sm_imp.sort_values('Importance', ascending=True)
#ft_importance_log_sm_imp.plot(x='Feature', y='Importance', kind='barh', figsize=(10, 10))
```

Entrenamiento SMOTE Decision Tree

In [32]:
```
#Arbol de Decision individual SMOTE
dectree_model_sm = DecisionTreeClassifier(max_depth= 5, random_state = 1)
dectree_model_sm.fit(X_train_sm,y_train_sm)
```

Out[32]:
```
DecisionTreeClassifier(max_depth=5, random_state=1)
```

In [33]:
```
#Prediccion sobre el test
pred_y_dectree_sm = dectree_model_sm.predict(X_test_sm)
mostrar_resultados(y_test_sm, pred_y_dectree_sm)
#Recall de attrition de 66%, activos en 89%

#Prediccion sobre el train
pred_y_dectree_sm_train = dectree_model_sm.predict(X_train_sm)
```



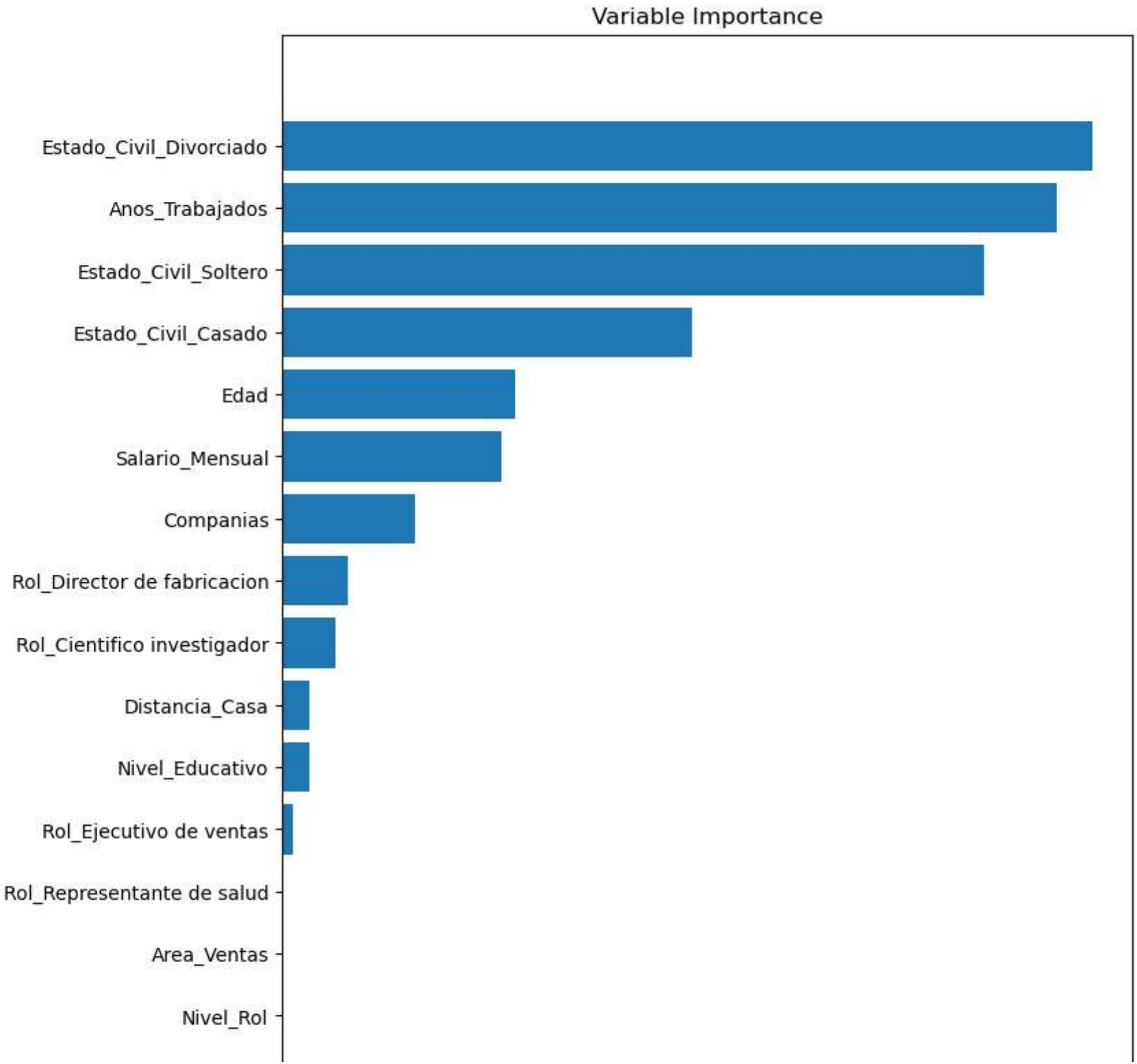
	precision	recall	f1-score	support
0	0.72	0.89	0.80	904
1	0.85	0.66	0.74	899
accuracy			0.77	1803
macro avg	0.79	0.77	0.77	1803
weighted avg	0.79	0.77	0.77	1803

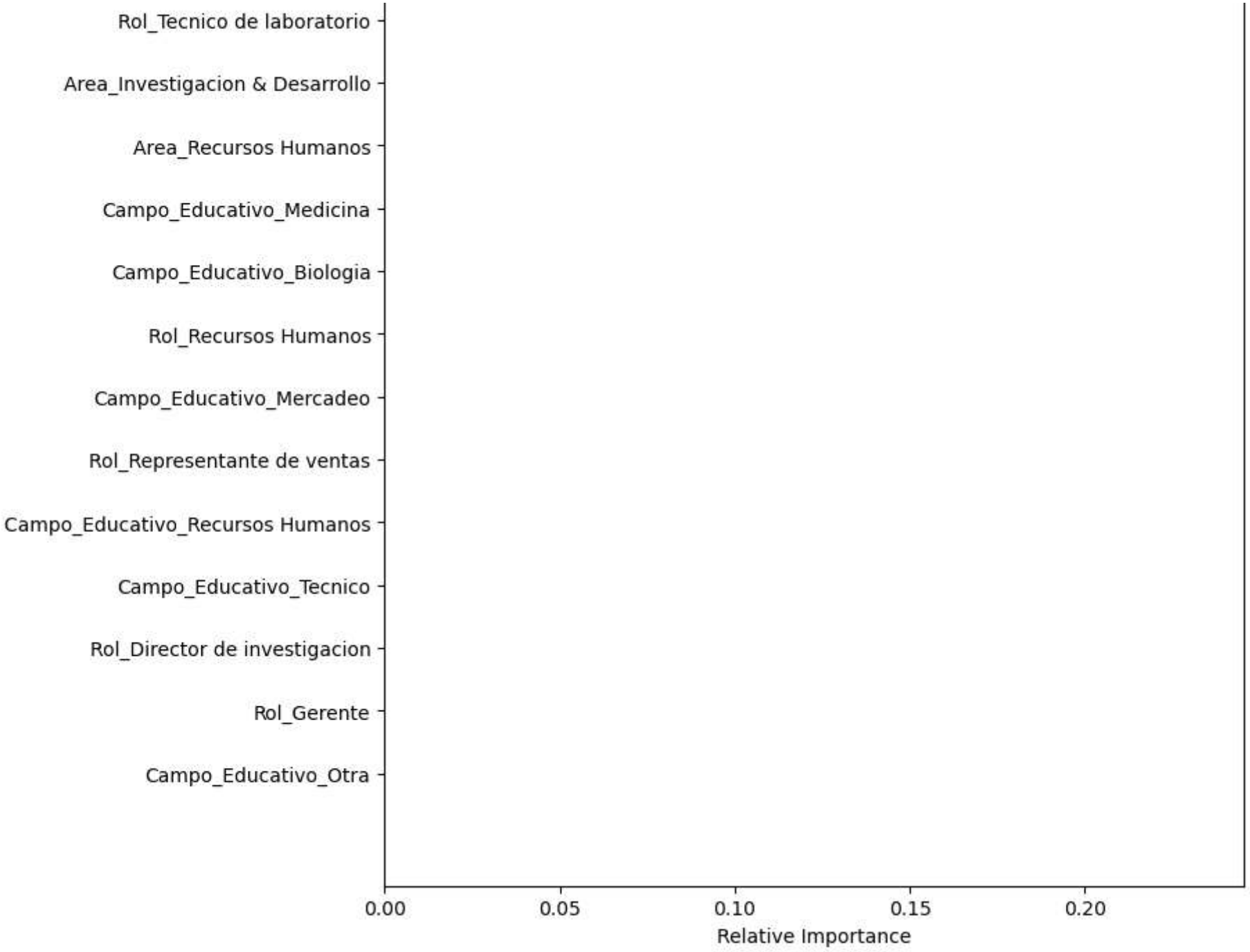
In [34]:
```
metricas_comparacion(y_test_sm, pred_y_dectree_sm, y_train_sm, pred_y_dectree_sm_train)
```

```
Accuracy:  0.7720465890183028
AUC test:  0.7717233750381447
AUC train:  0.7626369117348067
Delta AUC (overfitting):  0.009086463303337955
```

In [35]:
```
feature_importance = dectree_model_sm.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                             #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5

plt.figure(figsize=(8, 18))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_sm.keys()[sorted_idx])
plt.xlabel('Relative Importance')
```

```
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Estado_Civil_Divorciado
Anos_Trabajados
Estado_Civil_Soltero
Estado_Civil_Casado
Edad
Salario_Mensual
Companias
Rol_Director de fabricacion
Rol_Cientifico investigador
Distancia_Casa
Nivel_Educativo
Rol_Ejecutivo de ventas
Rol_Representante de salud
Area_Ventas
Nivel_Rol



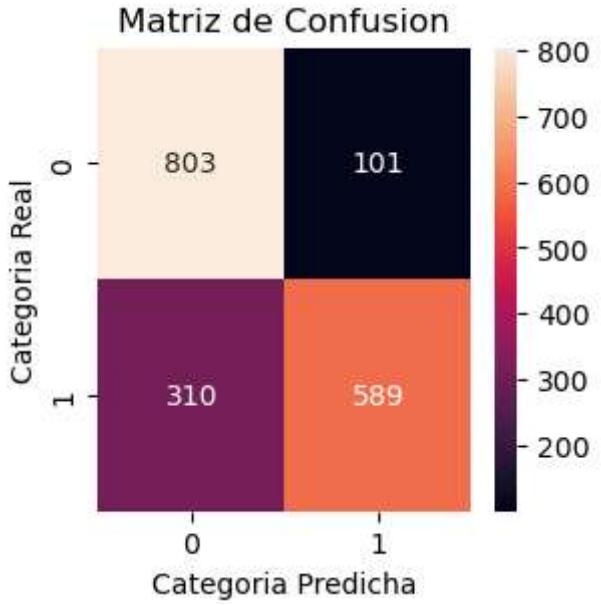
In [36]:
```
#Modelo de Decision Tree SMOTE (solo importantes)

#Quitar columnas con menos importancia
```

```
cols_del_imp = ['Rol_Representante de salud','Area_Ventas','Nivel_Rol','Rol_Tecnico de laboratorio',
                'Area_Investigacion & Desarrollo','Area_Recursos Humanos','Campo_Educativo_Medicina',
                'Campo_Educativo_Biologia','Rol_Recursos Humanos','Campo_Educativo_Mercadeo','Rol_Representante de ventas',
                'Campo_Educativo_Recursos Humanos','Campo_Educativo_Tecnico','Rol_Director de investigacion',
                'Rol_Gerente','Campo_Educativo_Otra']

X_train_sm_imp = X_train_sm.loc[:, [name for name in X_train_sm.columns if name not in cols_del_imp]]
X_test_sm_imp = X_test_sm.loc[:, [name for name in X_test_sm.columns if name not in cols_del_imp]]
```

In [37]:
```
#Entrenar de nuevo Arbol de Decision individual SMOTE
dectree_model_sm_imp = DecisionTreeClassifier(max_depth= 5, random_state = 1)
dectree_model_sm_imp.fit(X_train_sm_imp,y_train_sm)
```

Out[37]:
```
DecisionTreeClassifier(max_depth=5, random_state=1)
```

In [38]:
```
#Prediccion sobre el test
pred_y_dectree_sm_imp = dectree_model_sm_imp.predict(X_test_sm_imp)
mostrar_resultados(y_test_sm, pred_y_dectree_sm_imp)
#Recall de attrition de 66%, activos en 89%

#Prediccion sobre el train
pred_y_dectree_sm_train_imp = dectree_model_sm_imp.predict(X_train_sm_imp)
```



	precision	recall	f1-score	support
0	0.72	0.89	0.80	904
1	0.85	0.66	0.74	899
accuracy			0.77	1803
macro avg	0.79	0.77	0.77	1803
weighted avg	0.79	0.77	0.77	1803

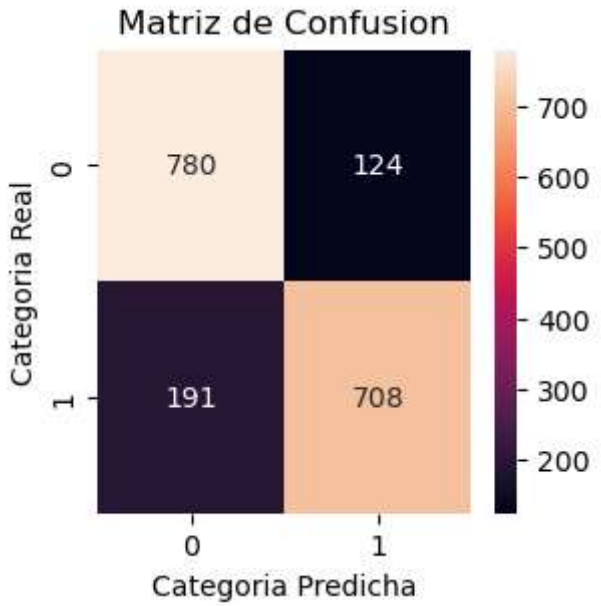
In [39]:
```
metricas_comparacion(y_test_sm, pred_y_dectree_sm_imp, y_train_sm, pred_y_dectree_sm_train_imp)
```

```
Accuracy:  0.7720465890183028
AUC test:  0.7717233750381447
AUC train:  0.7626369117348067
Delta AUC (overfitting):  0.009086463303337955
```

Entrenamiento SMOTE Random Forest

In [40]:
```
#Random Forest con SMOTE
rf_model_sm =RandomForestClassifier(max_depth=5,random_state=1, class_weight = 'balanced')
rf_model_sm.fit(X_train_sm,y_train_sm)

#Prediccion sobre test
y_pred_rf_sm = rf_model_sm.predict(X_test_sm)
```

In [41]:
```
mostrar_resultados(y_test_sm, y_pred_rf_sm)
#Attrition 79%, Activos 86%
```



	precision	recall	f1-score	support
0	0.80	0.86	0.83	904
1	0.85	0.79	0.82	899
accuracy			0.83	1803
macro avg	0.83	0.83	0.83	1803
weighted avg	0.83	0.83	0.83	1803

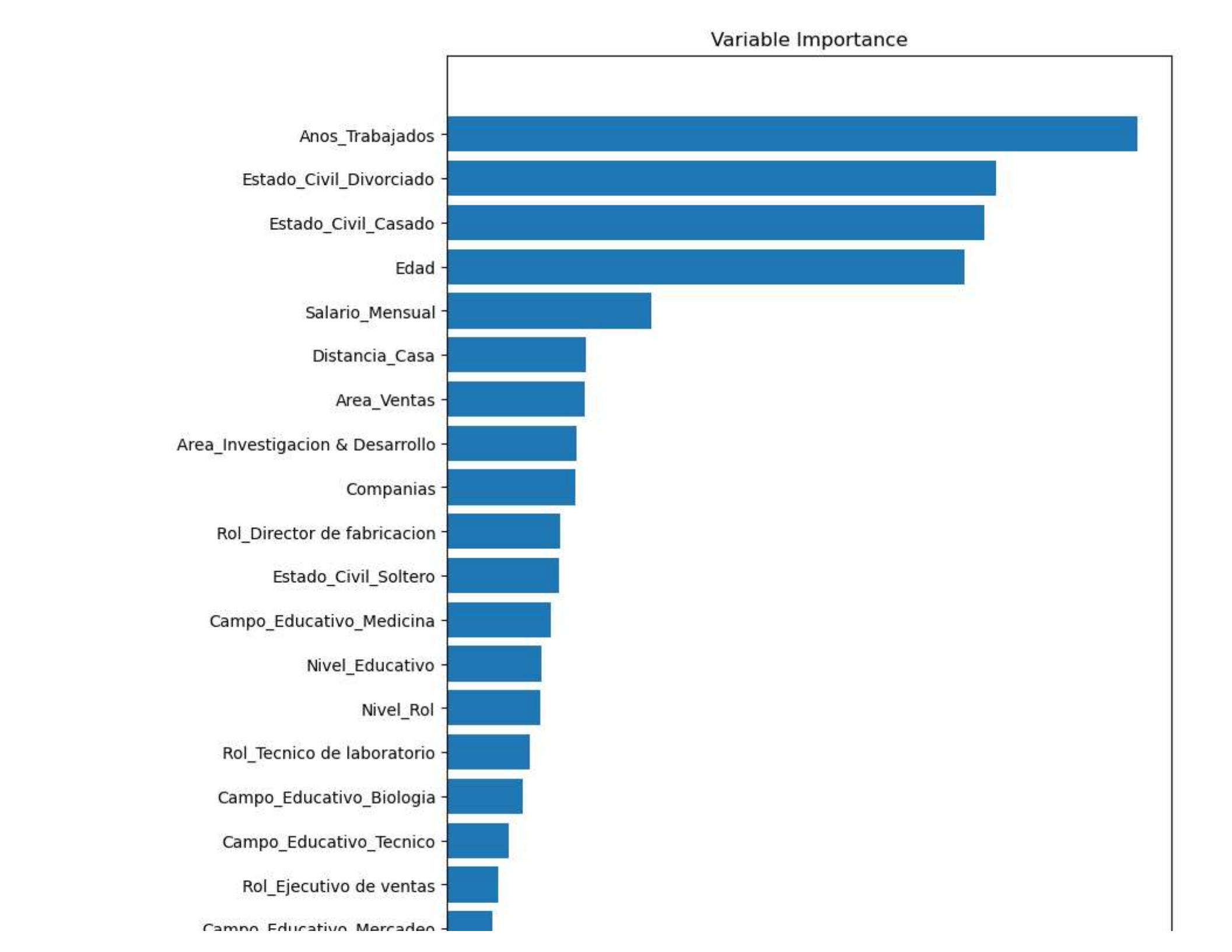
In [42]:
```
#Prediccion sobre el train
y_pred_rf_sm_train = rf_model_sm.predict(X_train_sm)
```

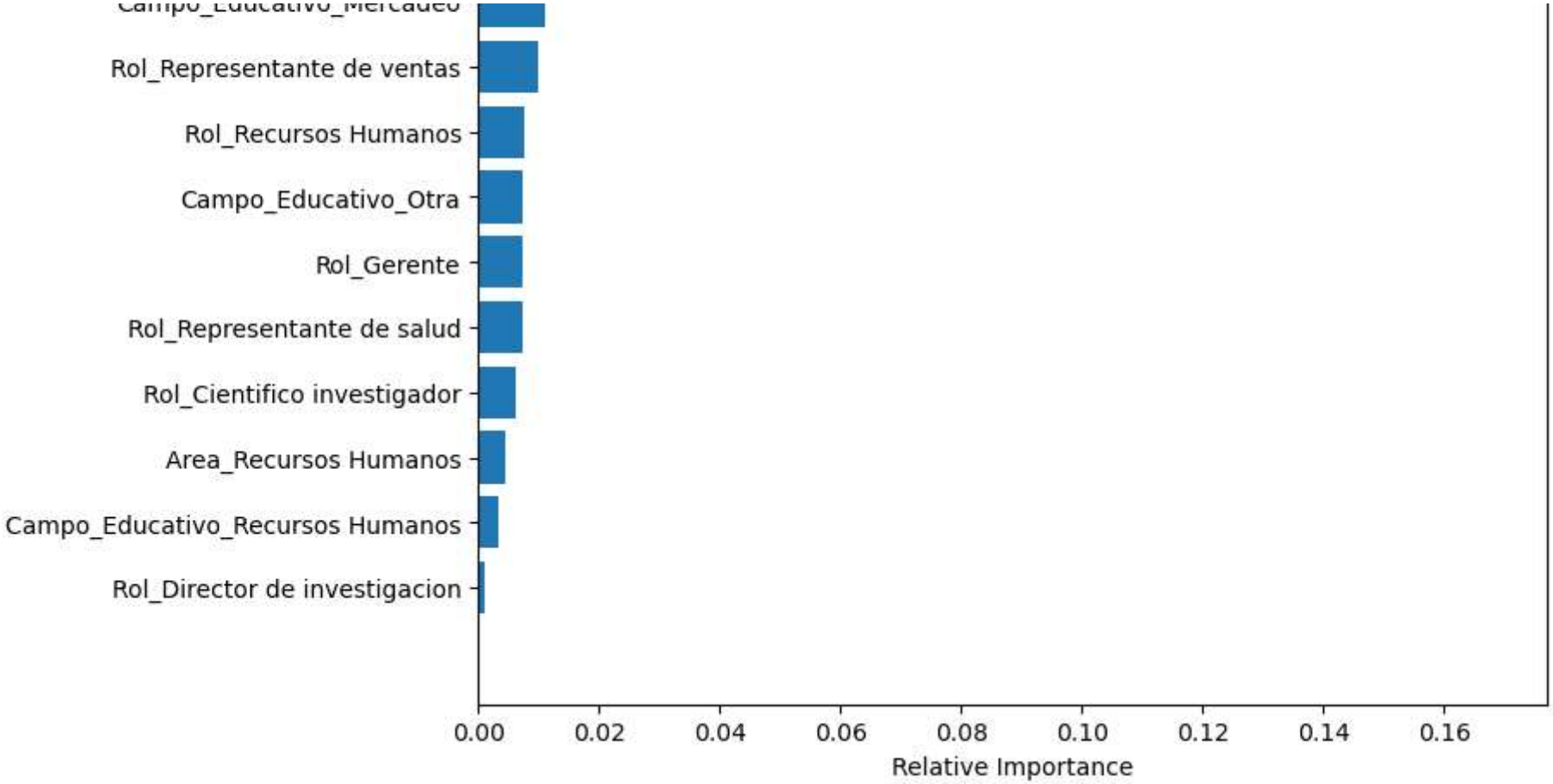
In [43]:
```
metricas_comparacion(y_test_sm, y_pred_rf_sm, y_train_sm, y_pred_rf_sm_train)
```

```
Accuracy:  0.8252911813643927
AUC test:  0.82518678571077
AUC train:  0.8173086368876545
Delta AUC (overfitting):  0.007878148823115438
```

In [44]:
```
#Importancia variables
feature_importance = rf_model_sm.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                              #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5
```

```
plt.figure(figsize=(8, 15))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_ada.keys()[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Anos_Trabajados
Estado_Civil_Divorciado
Estado_Civil_Casado
Edad
Salario_Mensual
Distancia_Casa
Area_Ventas
Area_Investigacion & Desarrollo
Companias
Rol_Director de fabricacion
Estado_Civil_Soltero
Campo_Educativo_Medicina
Nivel_Educativo
Nivel_Rol
Rol_Tecnico de laboratorio
Campo_Educativo_Biologia
Campo_Educativo_Tecnico
Rol_Ejecutivo de ventas

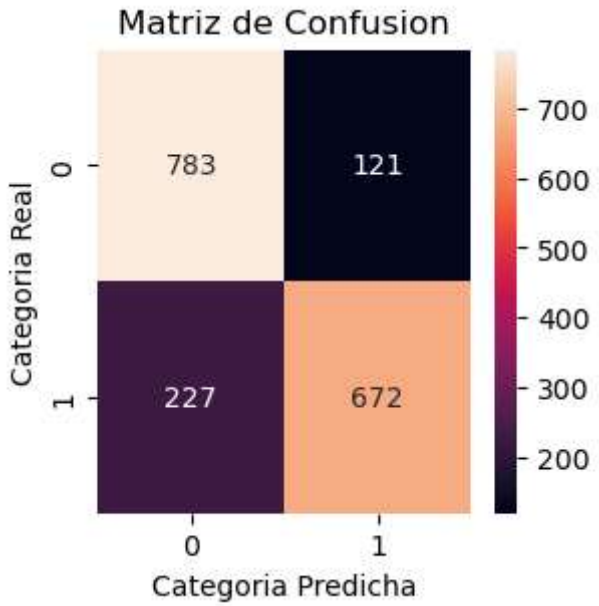


In [45]:
```
#Modelo de Random Forecast SMOTE (solo importantes)
# Segun la grafica las varaibles de rol, campo educativo, compromiso trabajo, nivel de acciones,
# rendimiento no son importantes, se deja frecuencia de viaje frecuente porque las demas estan arriba
# se quitan todos los roles y areas para ser consistentes

#Quitar columnas con menos importancia
cols_del_imp = ['Rol_Ejecutivo de ventas','Campo_Educativo_Mercadeo','Rol_Representante de ventas','Rol_Recursos_Humanos',
                'Campo_Educativo_Otra','Rol_Gerente','Rol_Representante de salud','Rol_Cientifico investigador',
                'Area_Recursos Humanos','Campo_Educativo_Recursos Humanos','Rol_Director de investigacion']

X_train_sm_imp = X_train_sm.loc[:, [name for name in X_train_sm.columns if name not in cols_del_imp]]
X_test_sm_imp = X_test_sm.loc[:, [name for name in X_test_sm.columns if name not in cols_del_imp]]
```

In [46]:
```
#Entrenar modelo de nuevo
rf_model_sm_imp =RandomForestClassifier(max_depth=5,random_state=1, class_weight = 'balanced')
rf_model_sm_imp.fit(X_train_sm_imp,y_train_sm)
```

```
#Prediccion sobre test
y_pred_rf_sm_imp = rf_model_sm_imp.predict(X_test_sm_imp)
```

In [47]:
```
mostrar_resultados(y_test_sm, y_pred_rf_sm_imp)
#Attrition 75%, Activos 87%
```



	precision	recall	f1-score	support
0	0.78	0.87	0.82	904
1	0.85	0.75	0.79	899
accuracy			0.81	1803
macro avg	0.81	0.81	0.81	1803
weighted avg	0.81	0.81	0.81	1803

In [48]:
```
#Prediccion sobre el train
y_pred_rf_sm_train_imp = rf_model_sm_imp.predict(X_train_sm_imp)
```

In [49]:
```
metricas_comparacion(y_test_sm, y_pred_rf_sm_imp, y_train_sm, y_pred_rf_sm_train_imp)
```

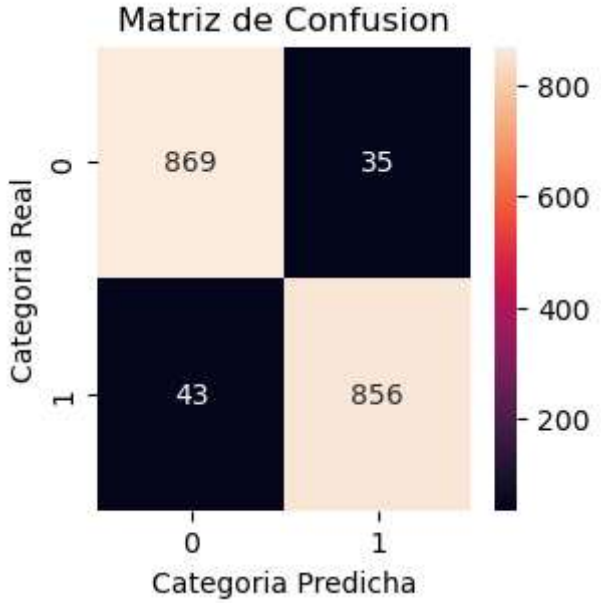
```
Accuracy:  0.8069883527454242
AUC test:  0.8068238308051227
AUC train:  0.8071545864729961
Delta AUC (overfitting):  0.00033075566787343913
```

Entrenamiento SMOTE Gradient Boosting

In [50]:
```
#Gradient Boosting individual
gbm_model_sm = GradientBoostingClassifier(max_depth = 5,max_features = 'auto',random_state = 1)
gbm_model_sm.fit(X_train_sm,y_train_sm)
```

Out[50]:
```
GradientBoostingClassifier(max_depth=5, max_features='auto', random_state=1)
```

In [51]:
```
#Prediccion sobre el test
pred_y_gbm_sm = gbm_model_sm.predict(X_test_sm)
mostrar_resultados(y_test_sm, pred_y_gbm_sm)
#Recall de attrition de 95%, activos en 96%

#Prediccion sobre el train
pred_y_gbm_sm_train = gbm_model_sm.predict(X_train_sm)
```

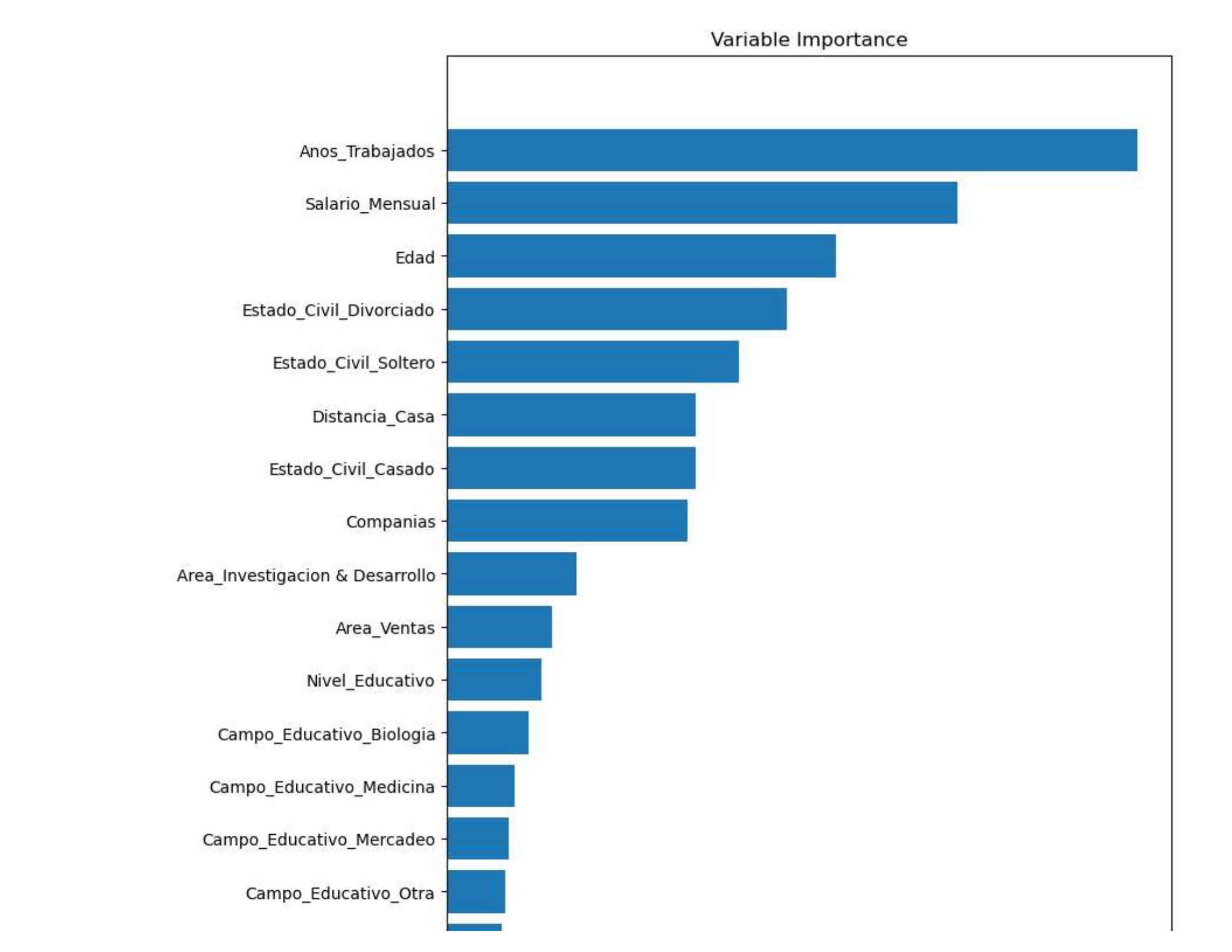


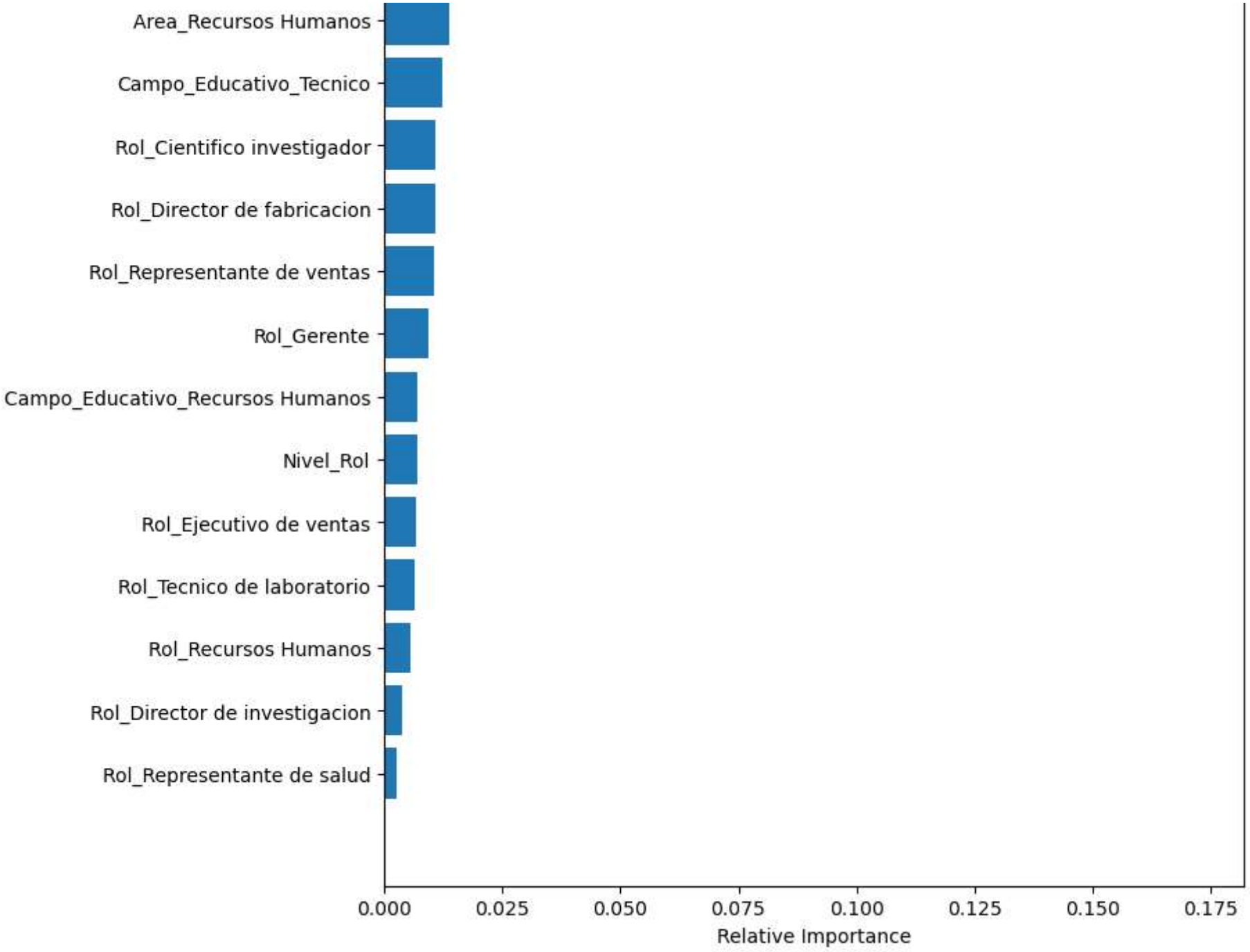
	precision	recall	f1-score	support
0	0.95	0.96	0.96	904
1	0.96	0.95	0.96	899
accuracy			0.96	1803
macro avg	0.96	0.96	0.96	1803
weighted avg	0.96	0.96	0.96	1803

In [52]:
```
metricas_comparacion(y_test_sm, pred_y_gbm_sm, y_train_sm, pred_y_gbm_sm_train)
```

```
Accuracy:  0.956738768718802
AUC test:  0.9567261312963272
AUC train:  0.9763338042656453
Delta AUC (overfitting):  0.01960767296931809
```

In [53]:
```
feature_importance = gbm_model_sm.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                              #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5

plt.figure(figsize=(8, 18))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_sm.keys()[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Anos_Trabajados
Salario_Mensual
Edad
Estado_Civil_Divorciado
Estado_Civil_Soltero
Distancia_Casa
Estado_Civil_Casado
Companias
Area_Investigacion & Desarrollo
Area_Ventas
Nivel_Educativo
Campo_Educativo_Biologia
Campo_Educativo_Medicina
Campo_Educativo_Mercadeo
Campo_Educativo_Otra



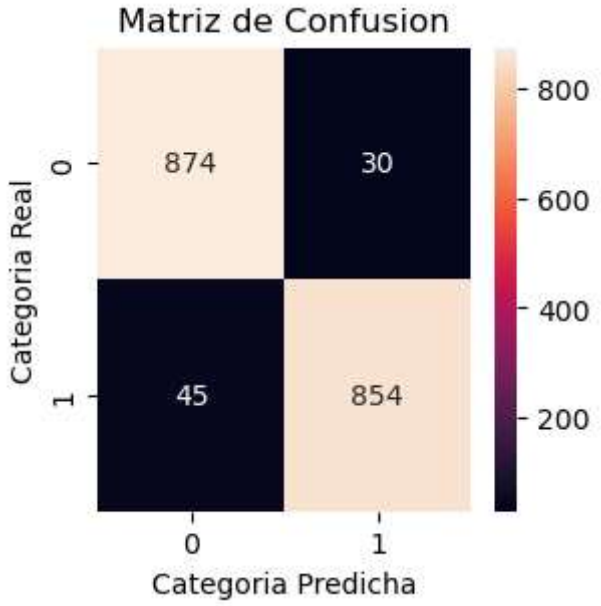
In [54]:
```
#Modelo de Gradient Boosting SMOTE (solo importantes)

#Quitar columnas con menos importancia
```

```
cols_del_imp = ['Area_Recursos_Humanos','Campo_Educativo_Tecnico','Rol_Cientifico investigador',
                'Rol_Director de fabricacion','Rol_Representante de ventas','Rol_Gerente',
                'Campo_Educativo_Recursos Humanos','Nivel_Rol','Rol_Ejecutivo de ventas','Rol_Tecnico de laboratorio',
                'Rol_Recursos Humanos','Rol_Director de investigacion','Rol_Representante de salud']

X_train_sm_imp = X_train_sm.loc[:, [name for name in X_train_sm.columns if name not in cols_del_imp]]
X_test_sm_imp = X_test_sm.loc[:, [name for name in X_test_sm.columns if name not in cols_del_imp]]
```

In [55]:
```
#Entrenar de nuevo
gbm_model_sm_imp = GradientBoostingClassifier(max_depth = 5,max_features = 'auto',random_state = 1)
gbm_model_sm_imp.fit(X_train_sm_imp,y_train_sm)
```

Out[55]:
```
GradientBoostingClassifier(max_depth=5, max_features='auto', random_state=1)
```

In [56]:
```
#Prediccion sobre el test
pred_y_gbm_sm_imp = gbm_model_sm_imp.predict(X_test_sm_imp)
mostrar_resultados(y_test_sm, pred_y_gbm_sm_imp)
#Recall de attrition de 95%, activos en 97%

#Prediccion sobre el train
pred_y_gbm_sm_train_imp = gbm_model_sm_imp.predict(X_train_sm_imp)
```



```
              precision    recall  f1-score   support

           0       0.95      0.97      0.96       904
           1       0.97      0.95      0.96       899

    accuracy                           0.96      1803
   macro avg       0.96      0.96      0.96      1803
weighted avg       0.96      0.96      0.96      1803
```

In [57]:
```
metricas_comparacion(y_test_sm, pred_y_gbm_sm_imp, y_train_sm, pred_y_gbm_sm_train_imp)
```

```
Accuracy:  0.9584026622296173
AUC test:  0.9583792709697108
AUC train:  0.9829880833054905
Delta AUC (overfitting):  0.024608812335779717
```

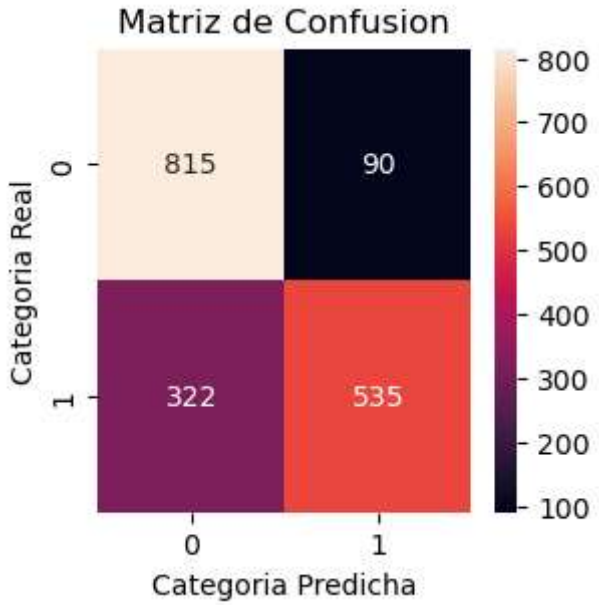
In [62]:
```
#feature_importance = gbm_model_sm_imp.feature_importances_
##Importancia relativa a la importancia maxima
#feature_importance = 100.0 * (feature_importance / 100)
#                             #feature_importance.max())
#sorted_idx = np.argsort(feature_importance)
#pos = np.arange(sorted_idx.shape[0]) + .5
#
#plt.figure(figsize=(8, 18))
#plt.barh(pos, feature_importance[sorted_idx], align='center')
#plt.yticks(pos, X_train_sm_imp.keys()[sorted_idx])
#plt.xlabel('Relative Importance')
#plt.title('Variable Importance')
#plt.show()
```

Entrenamiento ADASYN Logistic Regression

In [59]:
```
#Modelo de Regresion Logistica ADASYN
logreg_model_ada = LogisticRegression(C=1.0,penalty='l2',random_state=1,max_iter=10000)
logreg_model_ada.fit(X_train_ada, y_train_ada)
```

Out[59]:
```
LogisticRegression(max_iter=10000, random_state=1)
```

In [60]:
```
#Prediccion sobre el test
pred_y_log_ada = logreg_model_ada.predict(X_test_ada)
mostrar_resultados(y_test_ada, pred_y_log_ada)
#Recall de attrition de 62%, activos en 90%

#Prediccion sobre el train
pred_y_log_ada_train = logreg_model_ada.predict(X_train_ada)
```



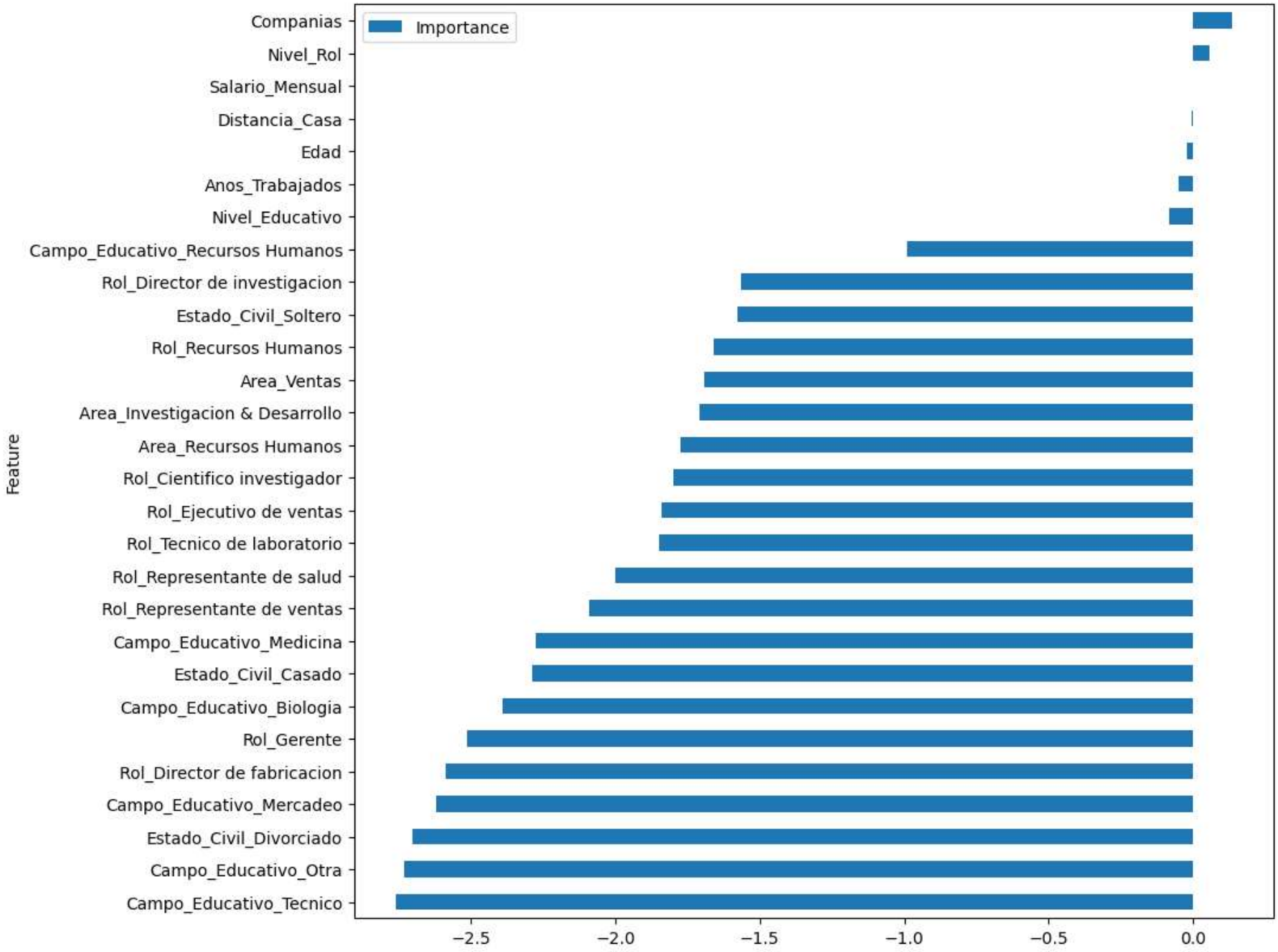
	precision	recall	f1-score	support
0	0.72	0.90	0.80	905
1	0.86	0.62	0.72	857
accuracy			0.77	1762
macro avg	0.79	0.76	0.76	1762
weighted avg	0.78	0.77	0.76	1762

In [61]:
```
metricas_comparacion(y_test_ada, pred_y_log_ada, y_train_ada, pred_y_log_ada_train)
```

```
Accuracy:  0.7661748013620885
AUC test:  0.7624115989865714
AUC train:  0.7754723190089046
Delta AUC (overfitting):  0.013060720022333161
```

In [62]:
```
#Importancia de las variables
coefficients_log_ada = logreg_model_ada.coef_[0]

ft_importance_log_ada = pd.DataFrame({'Feature': X_ada.columns, 'Importance': coefficients_log_ada})
ft_importance_log_ada = ft_importance_log_ada.sort_values('Importance', ascending=True)
ft_importance_log_ada.plot(x='Feature', y='Importance', kind='barh', figsize=(10, 10))
```

Out[62]:
```
<AxesSubplot:ylabel='Feature'>
```



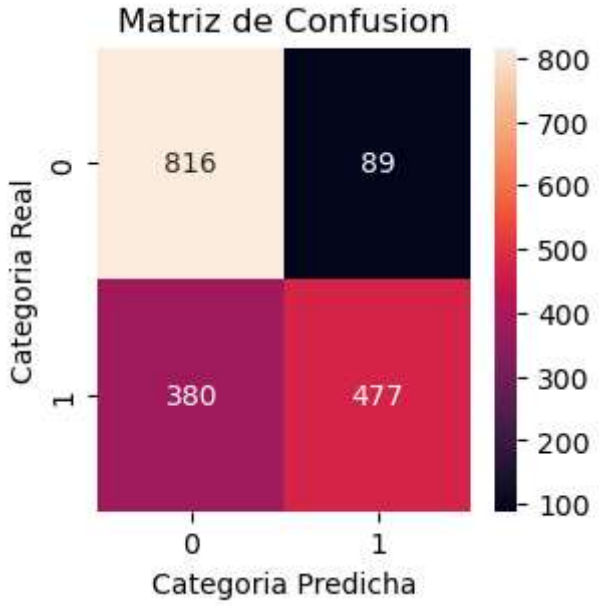
In [63]:
```
#Modelo de Regresion Logistica ADASYN (solo importantes)

#Quitar columnas con menos importancia
```

```
cols_del_imp =  ['Nivel_Rol','Salario_Mensual','Distancia_Casa','Edad','Anos_Trabajados']

X_train_ada_imp = X_train_ada.loc[:, [name for name in X_train_ada.columns if name not in cols_del_imp]]
X_test_ada_imp = X_test_ada.loc[:, [name for name in X_test_ada.columns if name not in cols_del_imp]]
```

In [64]:
```
#Entrenar de nuevo
logreg_model_ada_imp = LogisticRegression(C=1.0,penalty='l2',random_state=1,max_iter=10000)
logreg_model_ada_imp.fit(X_train_ada_imp, y_train_ada)
```

Out[64]:
```
LogisticRegression(max_iter=10000, random_state=1)
```

In [65]:
```
#Prediccion sobre el test
pred_y_log_ada_imp = logreg_model_ada_imp.predict(X_test_ada_imp)
mostrar_resultados(y_test_ada, pred_y_log_ada_imp)
#Recall de attrition de 56%, activos en 90%

#Prediccion sobre el train
pred_y_log_ada_train_imp = logreg_model_ada_imp.predict(X_train_ada_imp)
```



```
              precision    recall  f1-score   support

           0       0.68      0.90      0.78       905
           1       0.84      0.56      0.67       857

    accuracy                           0.73      1762
   macro avg       0.76      0.73      0.72      1762
weighted avg       0.76      0.73      0.73      1762
```

In [66]:
```
metricas_comparacion(y_test_ada, pred_y_log_ada_imp, y_train_ada, pred_y_log_ada_train_imp)
```

```
Accuracy:  0.7338251986379115
AUC test:  0.7291251120122231
AUC train:  0.7578500451671183
Delta AUC (overfitting):  0.028724933154895216
```

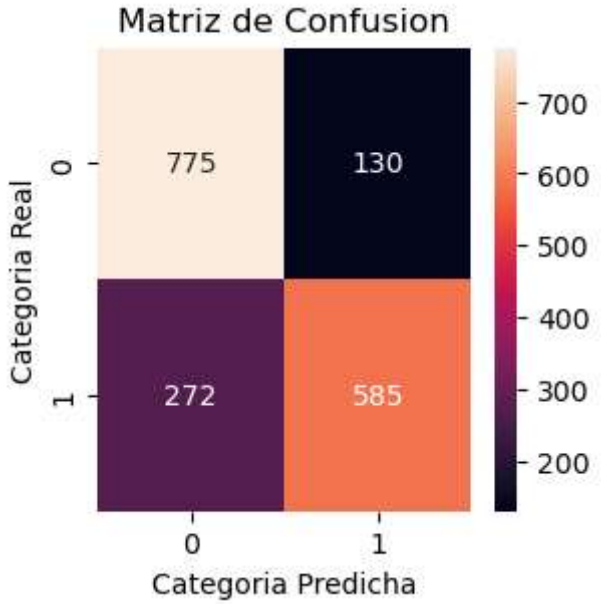
In [39]:
```
#Importancia de las variables
#coefficients_log_ada_imp = logreg_model_ada_imp.coef_[0]

#ft_importance_log_ada_imp = pd.DataFrame({'Feature': X_train_ada_imp.columns, 'Importance': coefficients_log_ada_imp})
#ft_importance_log_ada_imp = ft_importance_log_ada_imp.sort_values('Importance', ascending=True)
#ft_importance_log_ada_imp.plot(x='Feature', y='Importance', kind='barh', figsize=(10, 10))
```

Entrenamiento ADASYN Decision Tree

In [67]:
```
#Arbol de Decision individual ADASYN
dectree_model_ada = DecisionTreeClassifier(max_depth= 5, random_state = 1)
dectree_model_ada.fit(X_train_ada,y_train_ada)
```

Out[67]:
```
DecisionTreeClassifier(max_depth=5, random_state=1)
```

In [68]:
```
#Prediccion sobre el test
pred_y_dectree_ada = dectree_model_ada.predict(X_test_ada)
mostrar_resultados(y_test_ada, pred_y_dectree_ada)
#Recall de attrition de 68%, activos en 86%

#Prediccion sobre el train
pred_y_dectree_ada_train = dectree_model_ada.predict(X_train_ada)
```



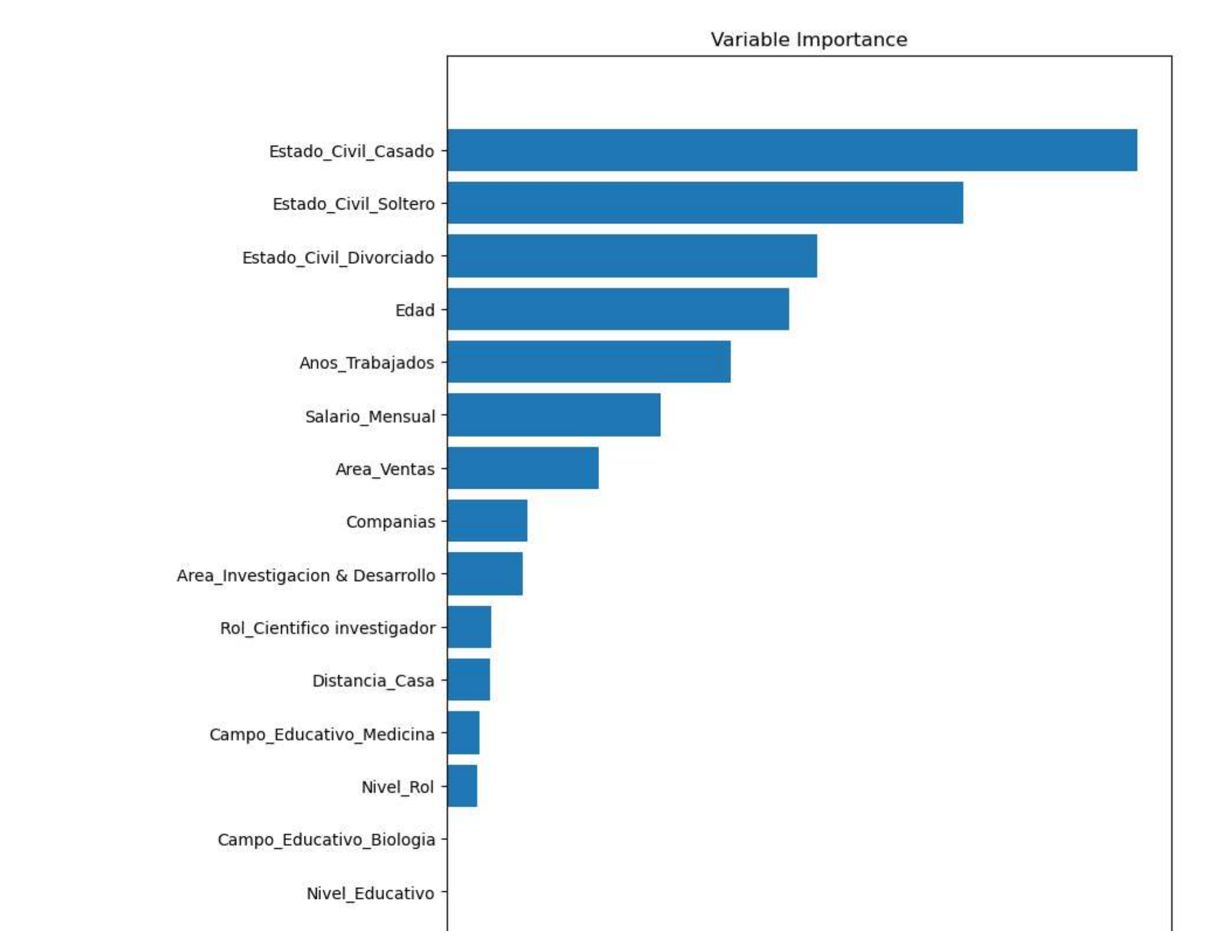
	precision	recall	f1-score	support
0	0.74	0.86	0.79	905
1	0.82	0.68	0.74	857
accuracy			0.77	1762
macro avg	0.78	0.77	0.77	1762
weighted avg	0.78	0.77	0.77	1762

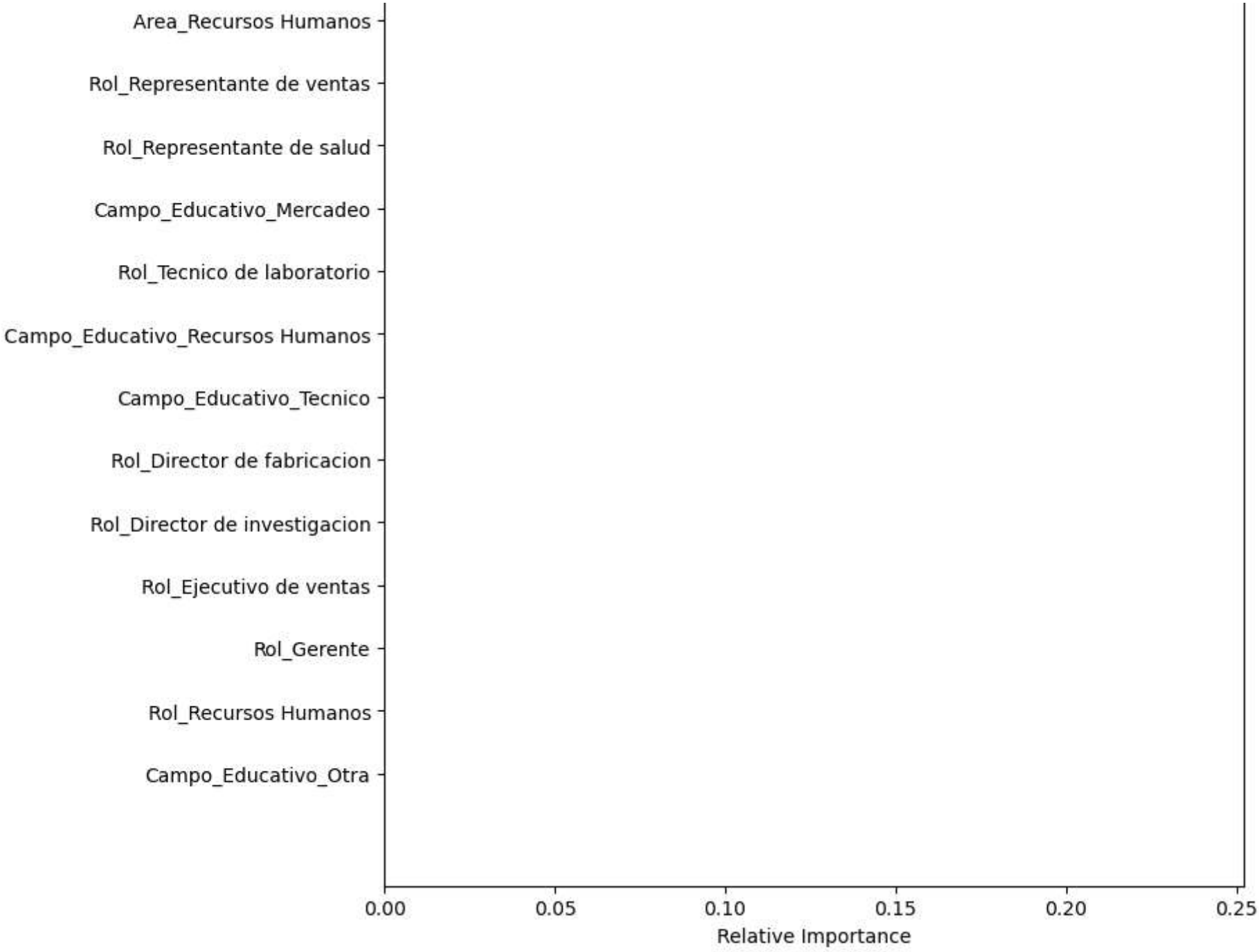
In [69]:
```
metricas_comparacion(y_test_ada, pred_y_dectree_ada, y_train_ada, pred_y_dectree_ada_train)
```

```
Accuracy:  0.771850170261067
AUC test:  0.7694836800608572
AUC train:  0.7671441476319525
Delta AUC (overfitting):  0.0023395324289047226
```

In [70]:
```
#Hallar variables importantes
feature_importance = dectree_model_ada.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                              #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5

plt.figure(figsize=(8, 18))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_sm.keys()[sorted_idx])
```

```
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Estado_Civil_Casado
Estado_Civil_Soltero
Estado_Civil_Divorciado
Edad
Anos_Trabajados
Salario_Mensual
Area_Ventas
Companias
Area_Investigacion & Desarrollo
Rol_Cientifico investigador
Distancia_Casa
Campo_Educativo_Medicina
Nivel_Rol
Campo_Educativo_Biologia
Nivel_Educativo



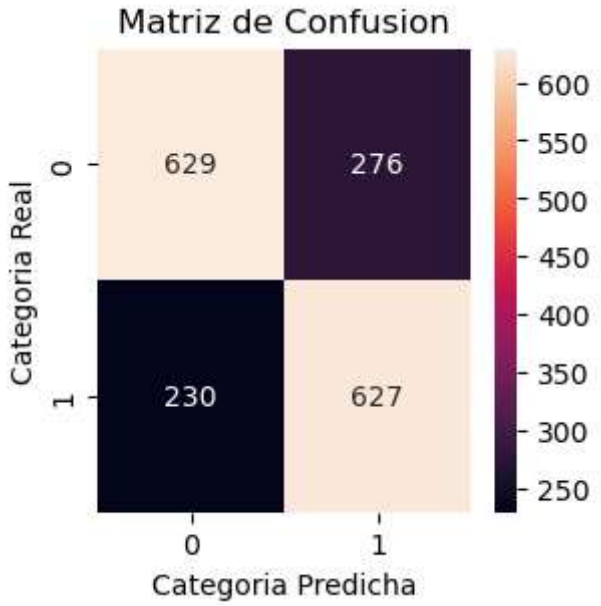
In [71]:
```
#Modelo de Decision Tree ADAYSIN(solo importantes)

#Quitar columnas con menos importancia
```

```
cols_del_imp = ['Campo_Educativo_Biologia','Nivel_Educativo','Area_Recursos Humanos','Rol_Representante de ventas',
                'Rol_Representante de salud','Campo_Educativo_Mercadeo','Rol_Tecnico de laboratorio',
                'Campo_Educativo_Recursos Humanos','Campo_Educativo Tecnico','Rol_Director de fabricacion',
                'Rol_Director de investigacion','Rol_Ejecutivo de ventas','Rol_Gerente','Rol_Recursos Humanos',
                'Campo_Educativo_Otra']

X_train_sm_imp = X_train_sm.loc[:, [name for name in X_train_sm.columns if name not in cols_del_imp]]
X_test_sm_imp = X_test_sm.loc[:, [name for name in X_test_sm.columns if name not in cols_del_imp]]
```

In [72]:
```
#Arbol de Decision individual ADASYN con variables importantes
dectree_model_ada_imp = DecisionTreeClassifier(max_depth= 5, random_state = 1)
dectree_model_ada_imp.fit(X_train_ada_imp,y_train_ada)
```

Out[72]:
```
DecisionTreeClassifier(max_depth=5, random_state=1)
```

In [73]:
```
#Prediccion sobre el test
pred_y_dectree_ada_imp = dectree_model_ada_imp.predict(X_test_ada_imp)
mostrar_resultados(y_test_ada, pred_y_dectree_ada_imp)
#Recall de attrition de 73%, activos en 70%

#Prediccion sobre el train
pred_y_dectree_ada_train_imp = dectree_model_ada_imp.predict(X_train_ada_imp)
```



```
              precision    recall  f1-score   support

           0       0.73      0.70      0.71       905
           1       0.69      0.73      0.71       857

    accuracy                           0.71      1762
   macro avg       0.71      0.71      0.71      1762
weighted avg       0.71      0.71      0.71      1762
```

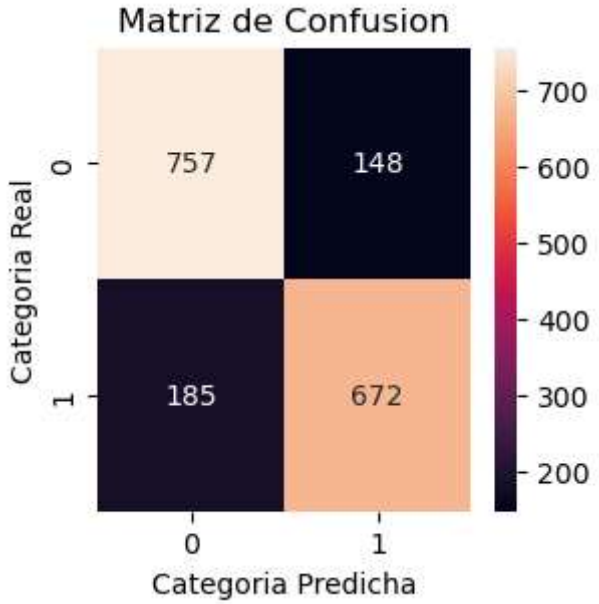
In [74]:
```
metricas_comparacion(y_test_ada, pred_y_dectree_ada_imp, y_train_ada, pred_y_dectree_ada_train_imp)
```

```
Accuracy:  0.7128263337116912
AUC test:  0.7133247806494453
AUC train:  0.7310878823073945
Delta AUC (overfitting):  0.017763101657949254
```

Entrenamiento ADASYN Random Forest

In [75]:
```
#Random Forest con ADASYN
rf_model_ada =RandomForestClassifier(max_depth=5,random_state=1, class_weight = 'balanced')
rf_model_ada.fit(X_train_ada,y_train_ada)

#Prediccion sobre test
y_pred_rf_ada = rf_model_ada.predict(X_test_ada)
```

In [76]:
```
mostrar_resultados(y_test_ada, y_pred_rf_ada)
#Attrition 78%, Activos 84%
```



	precision	recall	f1-score	support
0	0.80	0.84	0.82	905
1	0.82	0.78	0.80	857
accuracy			0.81	1762
macro avg	0.81	0.81	0.81	1762
weighted avg	0.81	0.81	0.81	1762

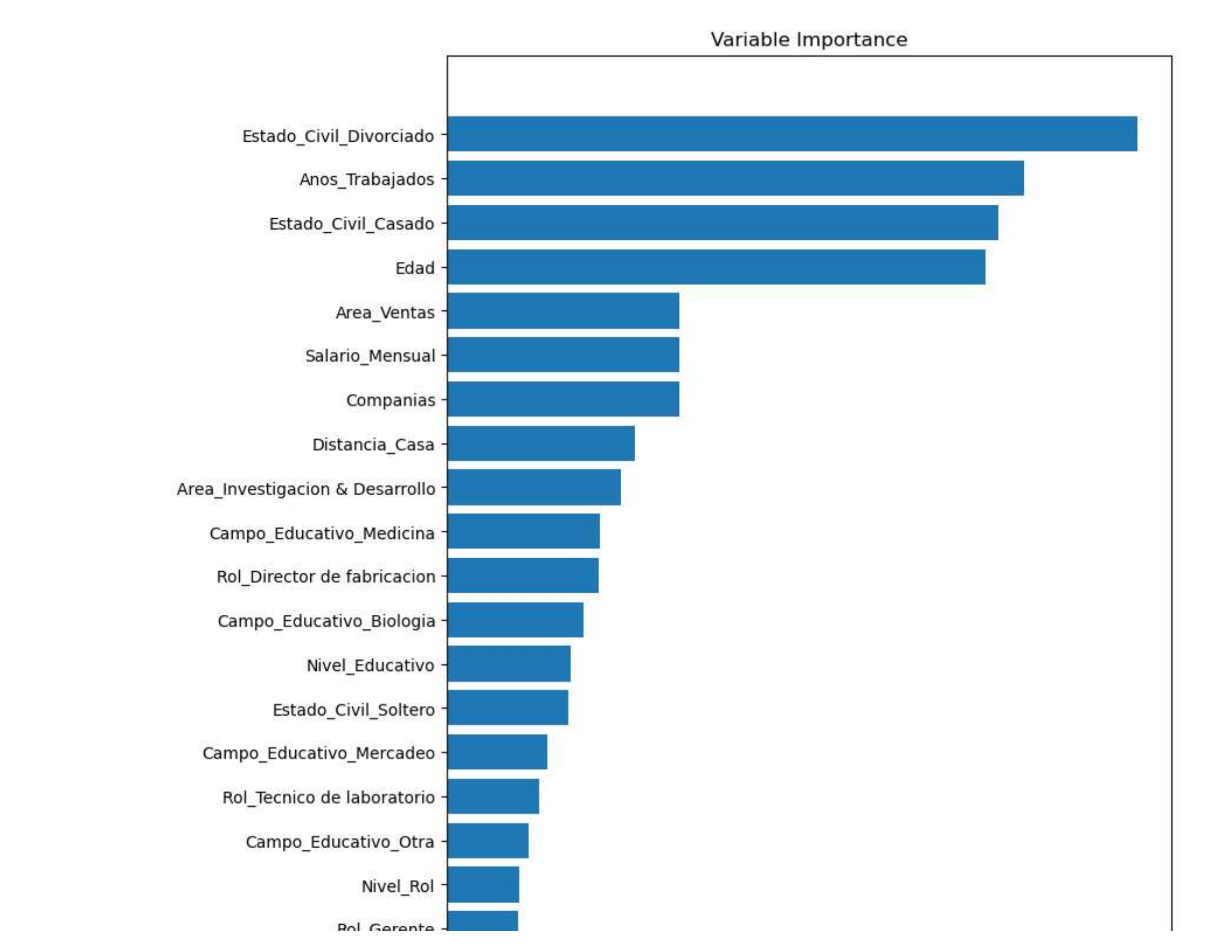
In [77]:
```
#Prediccion sobre el train
y_pred_rf_ada_train = rf_model_ada.predict(X_train_ada)
```

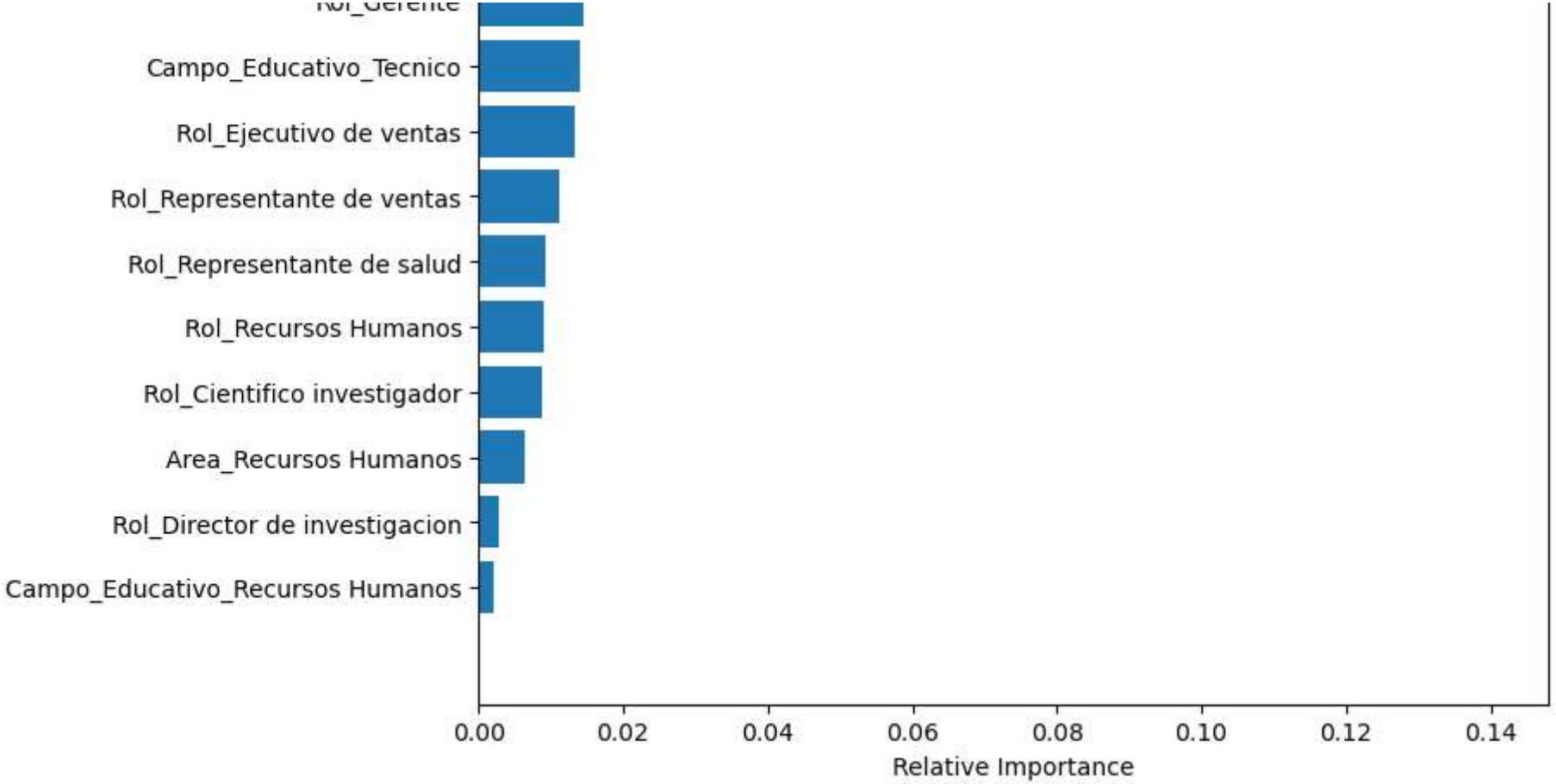
In [78]:
```
metricas_comparacion(y_test_ada, y_pred_rf_ada, y_train_ada, y_pred_rf_ada_train)
```

```
Accuracy:  0.8110102156640182
AUC test:  0.8102973884229324
AUC train:  0.8255194218608853
Delta AUC (overfitting):  0.01522203343795292
```

In [79]:
```
#Importancia variables
feature_importance = rf_model_ada.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                              #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5
```

```
plt.figure(figsize=(8, 15))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_ada.keys()[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```

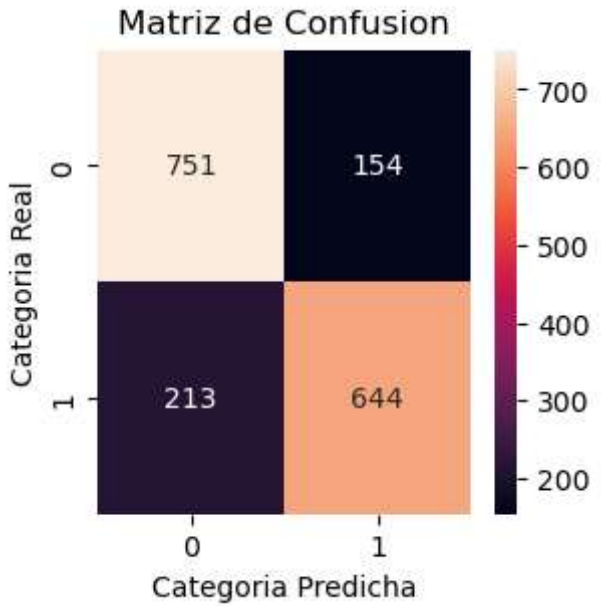

Variable Importance
Estado_Civil_Divorciado
Anos_Trabajados
Estado_Civil_Casado
Edad
Area_Ventas
Salario_Mensual
Companias
Distancia_Casa
Area_Investigacion & Desarrollo
Campo_Educativo_Medicina
Rol_Director de fabricacion
Campo_Educativo_Biologia
Nivel_Educativo
Estado_Civil_Soltero
Campo_Educativo_Mercadeo
Rol_Tecnico de laboratorio
Campo_Educativo_Otra
Nivel_Rol
Rol_Gerente



In [80]:
```
#Modelo de Random Forecast ADASYN (solo importantes)

#Quitar columnas con menos importancia
cols_del_imp= ['Nivel_Rol','Rol_Gerente','Campo_Educativo_Tecnico','Rol_Ejecutivo de ventas','Rol_Representante de ventas',
               'Rol_Representante de salud','Rol_Recursos Humanos','Rol_Cientifico investigador',
               'Area_Recursos Humanos','Rol_Director de investigacion','Campo_Educativo_Recursos Humanos']

X_train_ada_imp = X_train_ada.loc[:, [name for name in X_train_ada.columns if name not in cols_del_imp]]
X_test_ada_imp = X_test_ada.loc[:, [name for name in X_test_ada.columns if name not in cols_del_imp]]
```

In [81]:
```
#Entrenar el modelo de nuevo con variables importantes
#Random Forest individual
rf_model_ada_imp =RandomForestClassifier(max_depth=5,random_state=1, class_weight = 'balanced')
rf_model_ada_imp.fit(X_train_ada_imp,y_train_ada)

#Prediccion sobre test
y_pred_rf_ada_imp = rf_model_ada_imp.predict(X_test_ada_imp)
```

In [82]:
```
mostrar_resultados(y_test_ada, y_pred_rf_ada_imp)
#Attrition 75%, Activos 83%
```



	precision	recall	f1-score	support
0	0.78	0.83	0.80	905
1	0.81	0.75	0.78	857
accuracy			0.79	1762
macro avg	0.79	0.79	0.79	1762
weighted avg	0.79	0.79	0.79	1762

In [83]:
```
metricas_comparacion(y_test_ada, y_pred_rf_ada_imp, y_train_ada, y_pred_rf_ada_train)
```

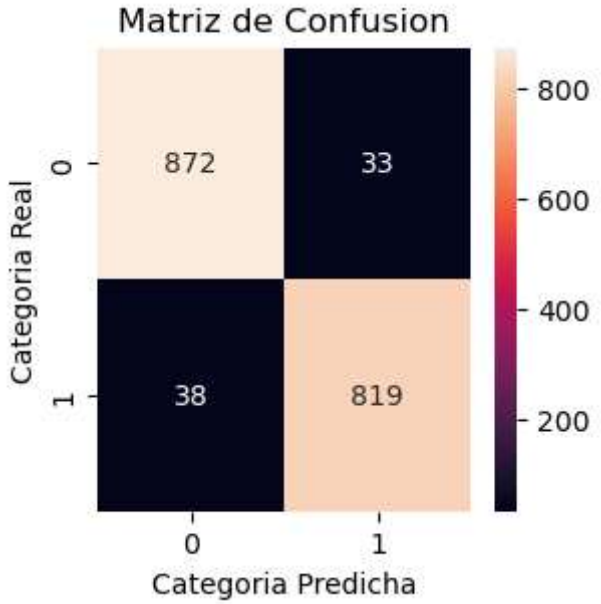
```
Accuracy:  0.7917139614074915
AUC test:  0.7906464152865257
AUC train:  0.8255194218608853
Delta AUC (overfitting):  0.034873006574359655
```

Entrenamiento ADASYN Gradient Boosting

In [84]:
```
#Gradient Boosting individual
gbm_model_ada = GradientBoostingClassifier(max_depth = 5,max_features = 'auto',random_state = 1)
gbm_model_ada.fit(X_train_ada,y_train_ada)
```

Out[84]:
```
GradientBoostingClassifier(max_depth=5, max_features='auto', random_state=1)
```

In [85]:
```
#Prediccion sobre el test
pred_y_gbm_ada = gbm_model_ada.predict(X_test_ada)
mostrar_resultados(y_test_ada, pred_y_gbm_ada)
#Recall de attrition de 96%, activos en 96%

#Prediccion sobre el train
pred_y_gbm_ada_train = gbm_model_ada.predict(X_train_ada)
```



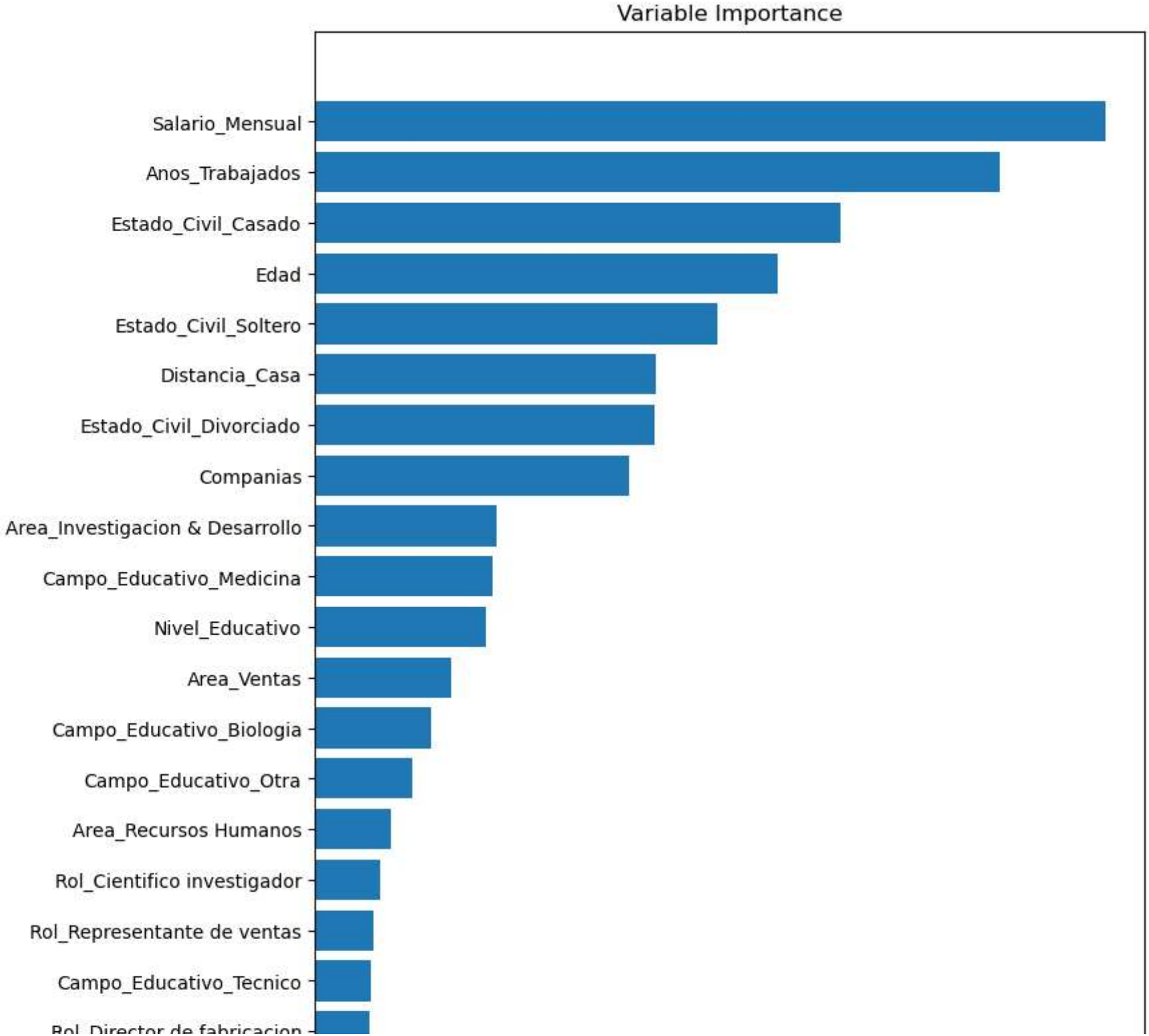
	precision	recall	f1-score	support
0	0.96	0.96	0.96	905
1	0.96	0.96	0.96	857
accuracy			0.96	1762
macro avg	0.96	0.96	0.96	1762
weighted avg	0.96	0.96	0.96	1762

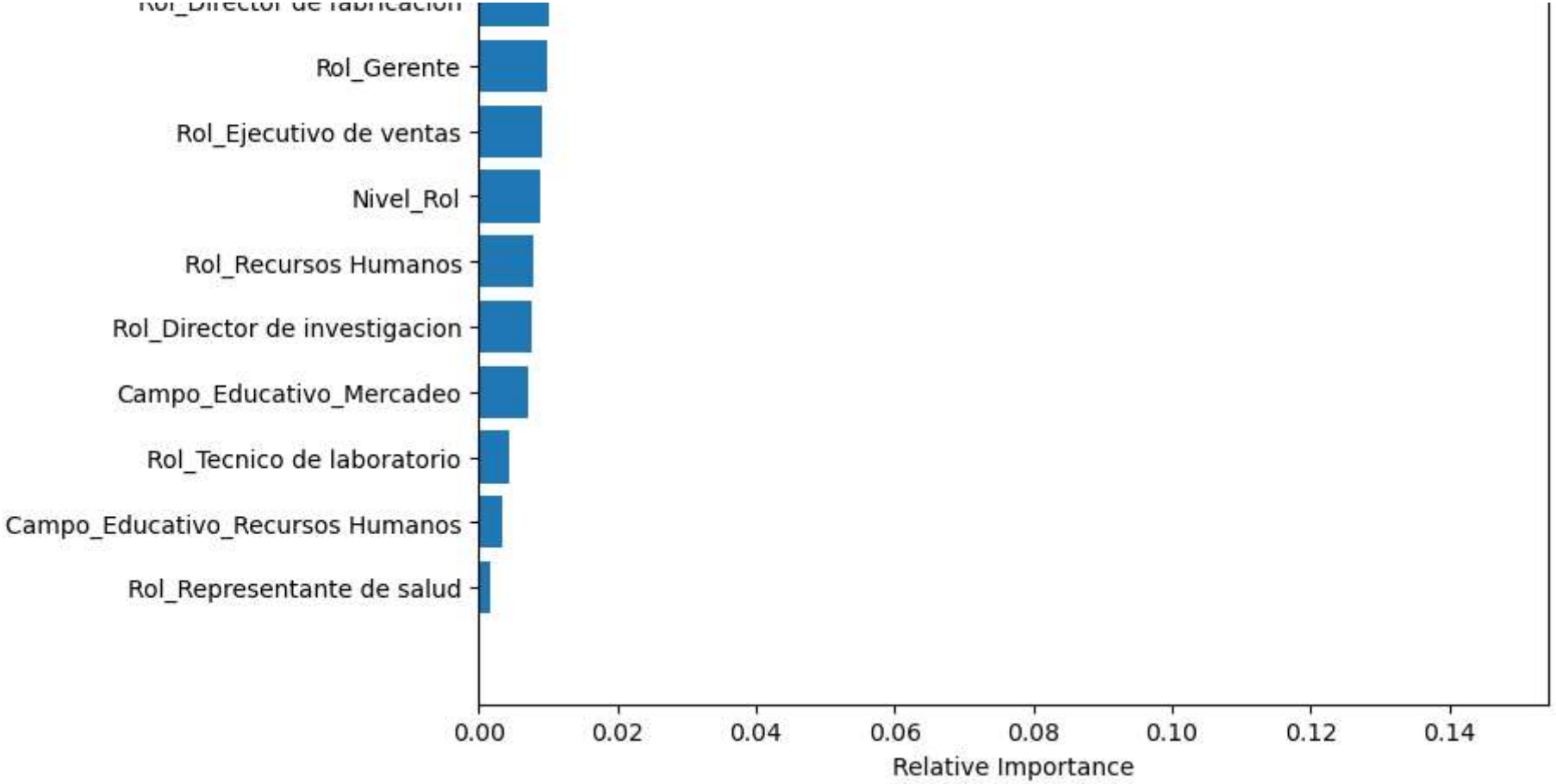
In [86]:
```
metricas_comparacion(y_test_ada, pred_y_gbm_ada, y_train_ada, pred_y_gbm_ada_train)
```

```
Accuracy:  0.9597048808172531
AUC test:  0.9595975940741506
AUC train:  0.9843276551813137
Delta AUC (overfitting):  0.024730061107163137
```

In [87]:

```
feature_importance = gbm_model_ada.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                             #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5

plt.figure(figsize=(8, 15))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_ada.keys()[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Salario_Mensual
Anos_Trabajados
Estado_Civil_Casado
Edad
Estado_Civil_Soltero
Distancia_Casa
Estado_Civil_Divorciado
Companias
Area_Investigacion & Desarrollo
Campo_Educativo_Medicina
Nivel_Educativo
Area_Ventas
Campo_Educativo_Biologia
Campo_Educativo_Otra
Area_Recursos Humanos
Rol_Cientifico investigador
Rol_Representante de ventas
Campo_Educativo_Tecnico
Rol_Director de fabricacion

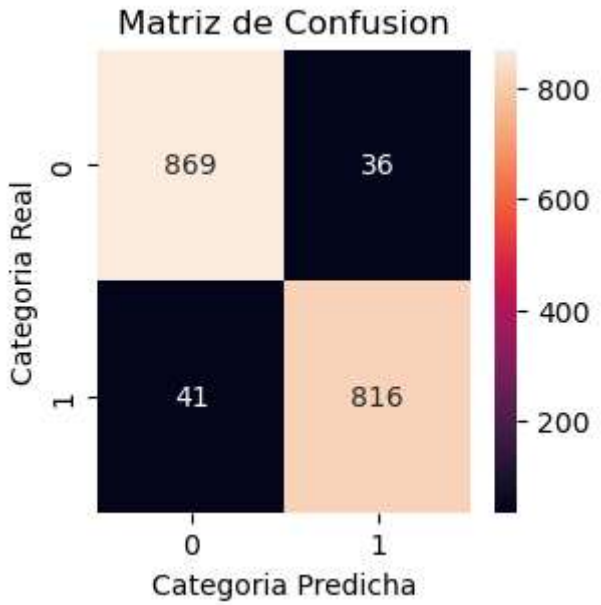


In [88]:
```
#Modelo de Gradient Boosting ADASYN (solo importantes)

#Quitar columnas con menos importancia
cols_del_imp = ['Area_Recursos Humanos','Rol_Cientifico investigador','Rol_Representante de ventas',
                'Campo_Educativo_Tecnico','Rol_Director de fabricacion','Rol_Gerente','Rol_Ejecutivo de ventas',
                'Nivel_Rol','Rol_Recursos Humanos','Rol_Director de investigacion','Campo_Educativo_Mercadeo',
                'Rol_Tecnico de laboratorio','Campo_Educativo_Recursos Humanos','Rol_Representante de salud']

X_train_ada_imp = X_train_ada.loc[:, [name for name in X_train_ada.columns if name not in cols_del_imp]]
X_test_ada_imp = X_test_ada.loc[:, [name for name in X_test_ada.columns if name not in cols_del_imp]]
```

In [89]:
```
#Entrenar de nuevo
gbm_model_ada_imp = GradientBoostingClassifier(max_depth = 5,max_features = 'auto',random_state = 1)
gbm_model_ada_imp.fit(X_train_ada_imp,y_train_ada)
```

Out[89]:
```
GradientBoostingClassifier(max_depth=5, max_features='auto', random_state=1)
```

In [90]:
```
#Prediccion sobre el test
pred_y_gbm_ada_imp = gbm_model_ada_imp.predict(X_test_ada_imp)
mostrar_resultados(y_test_ada, pred_y_gbm_ada_imp)
#Recall de attrition de 95%, activos en 96%

#Prediccion sobre el train
pred_y_gbm_ada_train_imp = gbm_model_ada_imp.predict(X_train_ada_imp)
```



	precision	recall	f1-score	support
0	0.95	0.96	0.96	905
1	0.96	0.95	0.95	857
accuracy			0.96	1762
macro avg	0.96	0.96	0.96	1762
weighted avg	0.96	0.96	0.96	1762

In [91]:
```
metricas_comparacion(y_test_ada, pred_y_gbm_ada_imp, y_train_ada, pred_y_gbm_ada_train_imp)
```

```
Accuracy:  0.9562996594778661
AUC test:  0.9561898437953287
AUC train:  0.9822402890695573
Delta AUC (overfitting):  0.026050445274228617
```

In [62]:
```
#feature_importance = gbm_model_ada_imp.feature_importances_
##Importancia relativa a la importancia maxima
#feature_importance = 100.0 * (feature_importance / 100)
```

```
#                               #feature_importance.max())
#sorted_idx = np.argsort(feature_importance)
#pos = np.arange(sorted_idx.shape[0]) + .5
#
#plt.figure(figsize=(8, 18))
#plt.barh(pos, feature_importance[sorted_idx], align='center')
#plt.yticks(pos, X_train_ada_imp.keys()[sorted_idx])
#plt.xlabel('Relative Importance')
#plt.title('Variable Importance')
#plt.show()
```

In [93]:
```
X_train.columns
```

Out[93]:
```
Index(['Edad', 'Distancia_Casa', 'Nivel_Educativo', 'Nivel_Rol',
       'Salario_Mensual', 'Companias', 'Anos_Trabajados',
       'Area_Investigacion & Desarrollo', 'Area_Recursos Humanos',
       'Area_Ventas', 'Campo_Educativo_Biologia', 'Campo_Educativo_Medicina',
       'Campo_Educativo_Mercadeo', 'Campo_Educativo_Otra',
       'Campo_Educativo_Recursos Humanos', 'Campo_Educativo_Tecnico',
       'Rol_Cientifico investigador', 'Rol_Director de fabricacion',
       'Rol_Director de investigacion', 'Rol_Ejecutivo de ventas',
       'Rol_Gerente', 'Rol_Recursos Humanos', 'Rol_Representante de salud',
       'Rol_Representante de ventas', 'Rol_Tecnico de laboratorio',
       'Estado_Civil_Casado', 'Estado_Civil_Divorciado',
       'Estado_Civil_Soltero'],
      dtype='object')
```

Búsqueda de mejor semilla sobre modelo elegido: Random Forest (ADASYN) con todas las variables

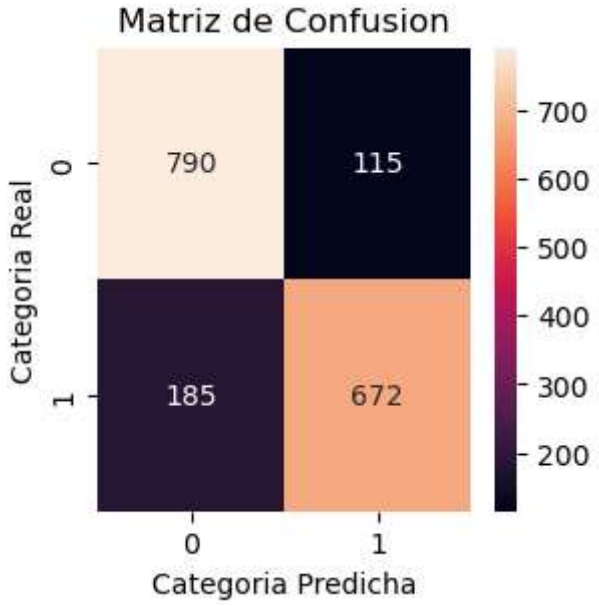
In [96]:
```
#Almacenamiento inicial de semilla y AUC
mejor_seed = 4455
mejor_auc = 0.8285294

#Iterador sobre semillas y predicciones
for i in range(2001,5001):
    #Random Forest individual
    rf_model_ada =RandomForestClassifier(max_depth=5,random_state=i, class_weight = 'balanced')
    rf_model_ada.fit(X_train_ada,y_train_ada)
    #Prediccion sobre test
    y_pred_rf_ada = rf_model_ada.predict(X_test_ada)
    #AUC test
    fpr, tpr, _ = metrics.roc_curve(y_test_ada,  y_pred_rf_ada)
    auc_test = metrics.roc_auc_score(y_test_ada, y_pred_rf_ada)
    if auc_test > mejor_auc:
        mejor_seed = i
```

```
        mejor_auc = auc_test

#Imprimir mejores resultados
print("Mejor Seed: ",mejor_seed)
print("Mejor AUC test: ",mejor_auc)

#corriendo hasta 5001
```

```
Mejor Seed:  4455
Mejor AUC test:  0.8285294326218274
```

In [97]:

```
#Resultados Random Forest ADASYN con semilla ganadora
rf_model_ada =RandomForestClassifier(max_depth=5,random_state=4455, class_weight = 'balanced')
rf_model_ada.fit(X_train_ada,y_train_ada)

#Prediccion sobre test
y_pred_rf_ada = rf_model_ada.predict(X_test_ada)

mostrar_resultados(y_test_ada, y_pred_rf_ada)
```



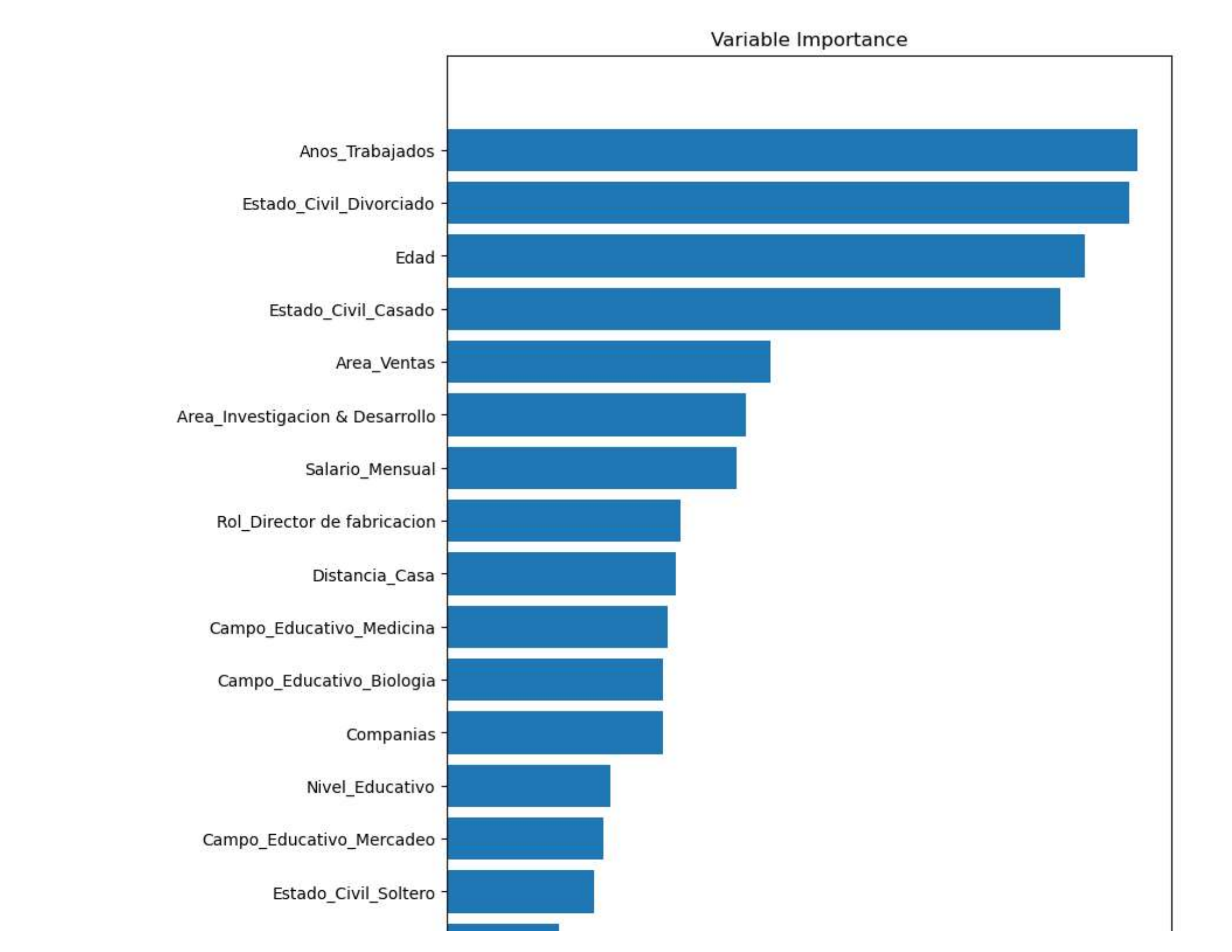
```
              precision    recall  f1-score   support

           0       0.81      0.87      0.84       905
           1       0.85      0.78      0.82       857

    accuracy                           0.83      1762
   macro avg       0.83      0.83      0.83      1762
weighted avg       0.83      0.83      0.83      1762
```

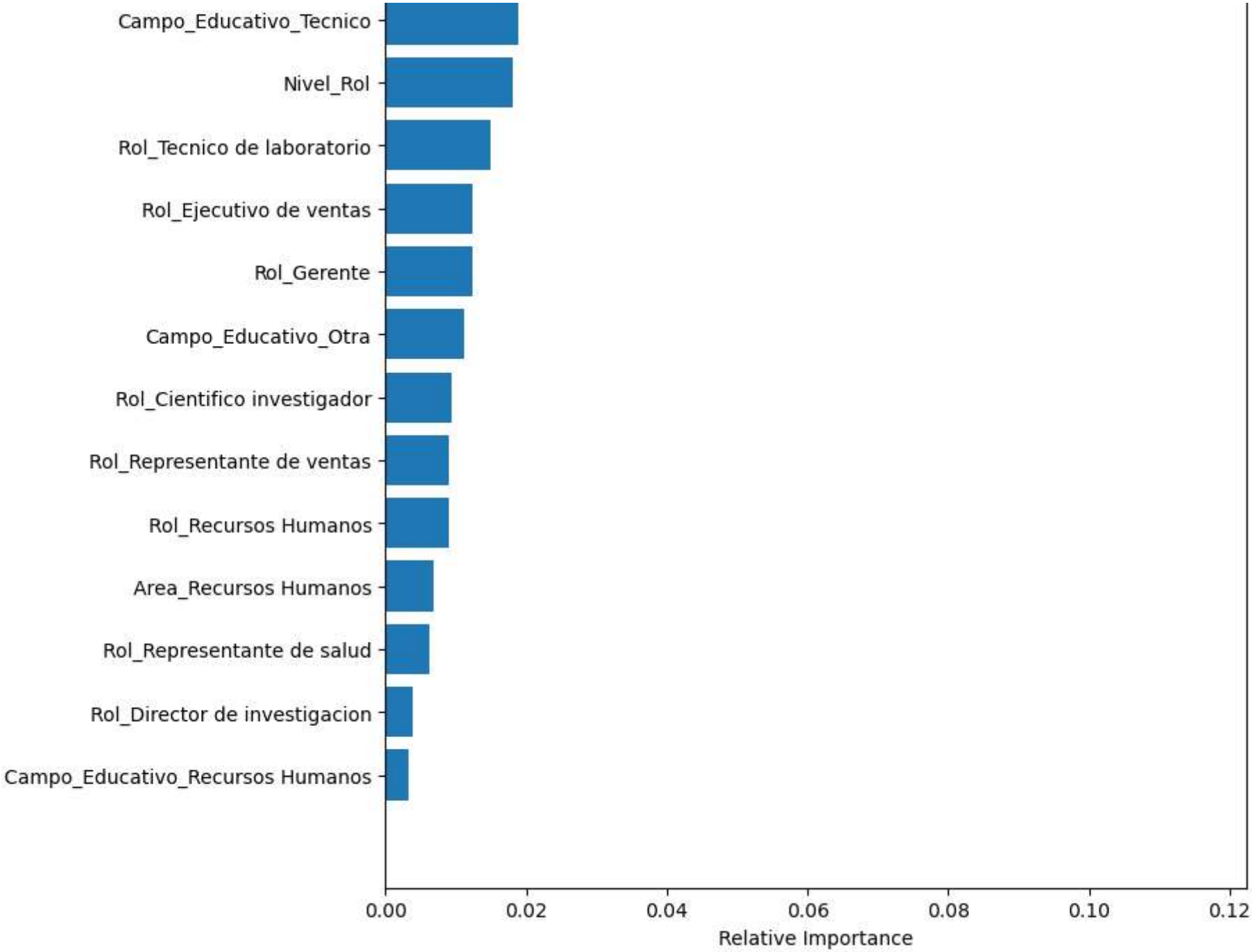
In [98]:
```
#Prediccion sobre el train
pred_y_rf_ada_train = rf_model_ada.predict(X_train_ada)
```

In [99]:
```
metricas_comparacion(y_test_ada, y_pred_rf_ada, y_train_ada, pred_y_rf_ada_train)
```

```
Accuracy:  0.8297389330306469
AUC test:  0.8285294326218274
AUC train:  0.8378429474770939
Delta AUC (overfitting):  0.009313514855266436
```

In [101…
```
#Hallar variables importantes
feature_importance = rf_model_ada.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                              #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5

plt.figure(figsize=(8, 18))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_ada.keys()[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Anos_Trabajados
Estado_Civil_Divorciado
Edad
Estado_Civil_Casado
Area_Ventas
Area_Investigacion & Desarrollo
Salario_Mensual
Rol_Director de fabricacion
Distancia_Casa
Campo_Educativo_Medicina
Campo_Educativo_Biologia
Companias
Nivel_Educativo
Campo_Educativo_Mercadeo
Estado_Civil_Soltero


Campo_Educativo_Tecnico
Nivel_Rol
Rol_Tecnico de laboratorio
Rol_Ejecutivo de ventas
Rol_Gerente
Campo_Educativo_Otra
Rol_Cientifico investigador
Rol_Representante de ventas
Rol_Recursos Humanos
Area_Recursos Humanos
Rol_Representante de salud
Rol_Director de investigacion
Campo_Educativo_Recursos Humanos
0.00
0.02
0.04
0.06
0.08
0.10
0.12
Relative Importance

Modelamiento - Probabilidad de Deserción empleados activos

Preparación inicial

In [1]:
```
#Librerias numericas y graficos
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

#Graficos
import plotly as py
import plotly.graph_objs as go

#Manejo de fechas
import datetime as dt

#Para Regresion Logistica
from sklearn.linear_model import LogisticRegression

#Modelos de Arboles
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier

#Medidas
from sklearn import metrics
from sklearn import model_selection
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score

#Split X - y en conjuntos training y testing
from sklearn.model_selection import train_test_split

#Mostrar todas las columnas de frame
pd.set_option('display.max_columns', None)

#Asignar el formato de los decimales
np.set_printoptions(formatter={'float': lambda x: "{0:0.10f}".format(x)})
```

```
#Para datos desbalanceados
from pylab import rcParams

from imblearn.under_sampling import NearMiss
from imblearn.over_sampling import RandomOverSampler
from imblearn.combine import SMOTETomek
from imblearn.ensemble import BalancedBaggingClassifier
from imblearn.over_sampling import SMOTE
from imblearn.over_sampling import ADASYN

from collections import Counter
```

In [2]:
```
#Carga de datos
ruta = r'C:\Users\Jaime Andres Molina\Documents\Maestria\Proyecto Empresarial\Fuentes\01_Fuentes\all_attrition_modeling.csv'
#CSV
df = pd.read_csv (ruta, sep = ';')
```

In [3]:
```
#Tipos de datos
df.dtypes
```

Out[3]:

```
ID_empleado                   int64
Edad                          int64
Desercion                    object
Frecuencia_viaje             object
Area                         object
Distancia_Casa                int64
Nivel_Educativo               int64
Campo_Educativo              object
Recuento_Empleado             int64
Genero                       object
Nivel_Rol                     int64
Rol                          object
Estado_Civil                 object
Salario_Mensual             float64
Companias                     int64
Mayor18                      object
Porcentaje_Aumento_Salarial   int64
Horario                       int64
Nivel_Opcion_Acciones         int64
Anos_Trabajados               int64
Entrenamientos                int64
Antiguedad                    int64
Anos_Ultima_Promocion         int64
Anos_Lider_Actual             int64
Satisfaccion_Entorno          int64
Satisfaccion_Laboral          int64
Balance_VidaTrabajo           int64
CompromisoTrabajo             int64
Rendimiento                   int64
Prom_Horas                  float64
Porcentaje_Ausentismo       float64
Ausentismo                    int64
dtype: object
```

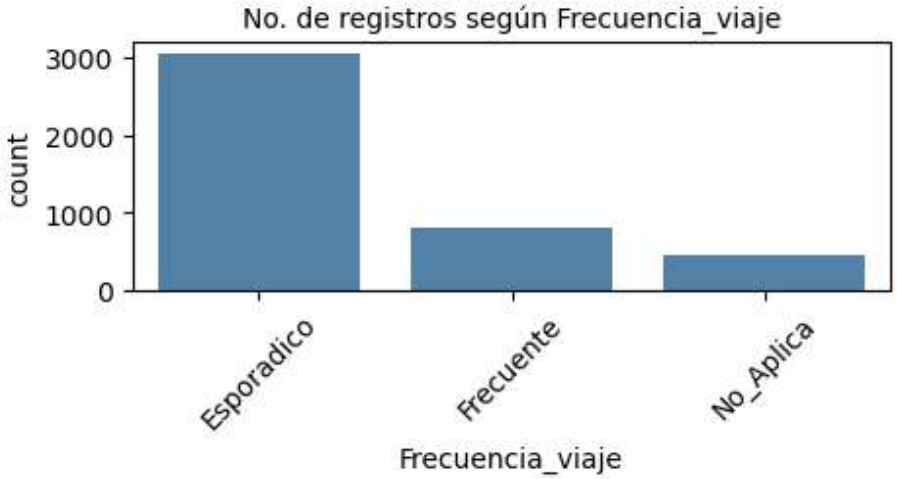
In [4]:

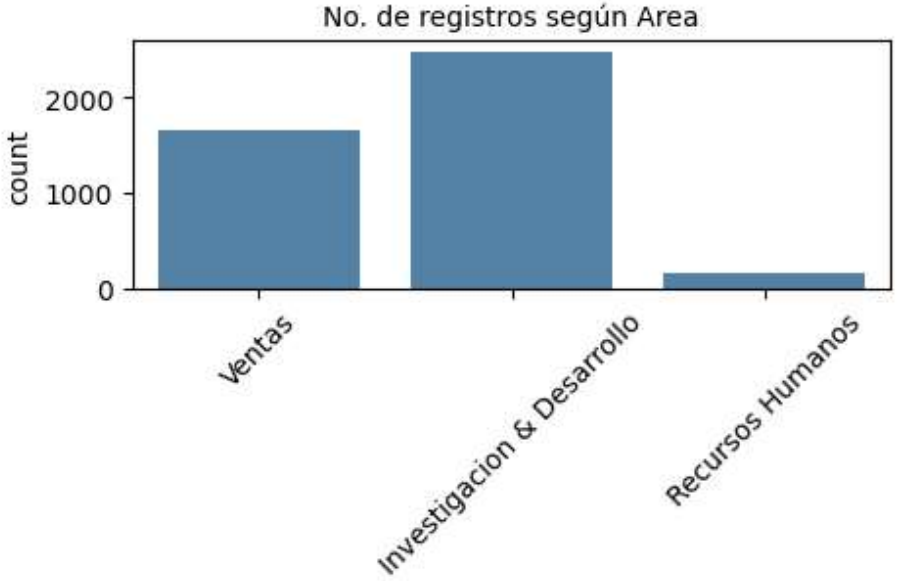
```
# Valores nulos por columna en porcentaje
df.isnull().sum()/df.shape[0]*100
```

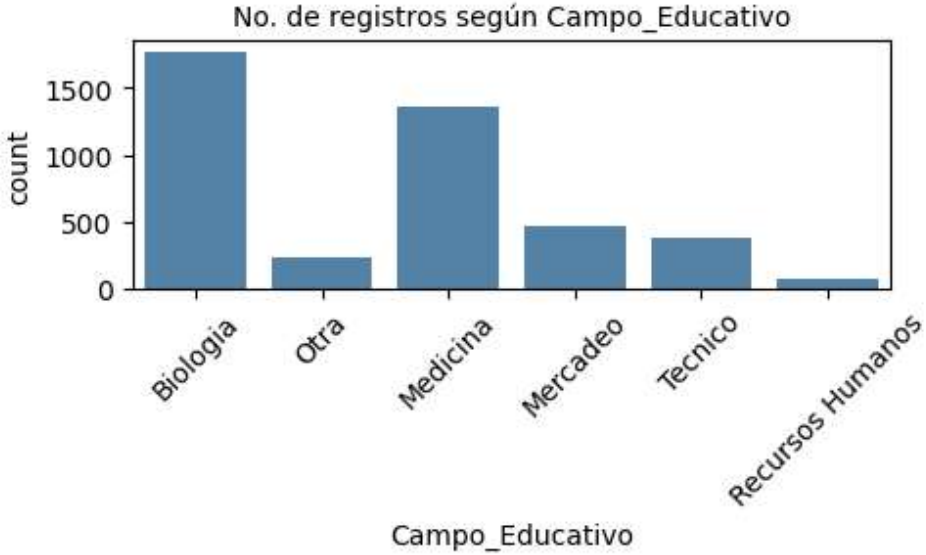
Out[4]:
```
ID_empleado                 0.0
Edad                        0.0
Desercion                   0.0
Frecuencia_viaje            0.0
Area                        0.0
Distancia_Casa              0.0
Nivel_Educativo             0.0
Campo_Educativo             0.0
Recuento_Empleado           0.0
Genero                      0.0
Nivel_Rol                   0.0
Rol                         0.0
Estado_Civil                0.0
Salario_Mensual             0.0
Companias                   0.0
Mayor18                     0.0
Porcentaje_Aumento_Salarial 0.0
Horario                     0.0
Nivel_Opcion_Acciones       0.0
Anos_Trabajados             0.0
Entrenamientos              0.0
Antiguedad                  0.0
Anos_Ultima_Promocion       0.0
Anos_Lider_Actual           0.0
Satisfaccion_Entorno        0.0
Satisfaccion_Laboral        0.0
Balance_VidaTrabajo         0.0
CompromisoTrabajo           0.0
Rendimiento                 0.0
Prom_Horas                  0.0
Porcentaje_Ausentismo       0.0
Ausentismo                  0.0
dtype: float64
```

In [5]:
```
#Histograma campos categoricos varias cajas
features=['Desercion', 'Frecuencia_viaje', 'Area','Campo_Educativo', 'Genero', 'Rol','Estado_Civil','Mayor18']
fig=plt.subplots(figsize=(11,14))
for i, j in enumerate(features):
    plt.subplot(4, 2, i+1)
    plt.subplots_adjust(hspace = 1.5)
    sns.countplot(x=j,data = df, color='steelblue')
    plt.xticks(rotation=45)
    plt.title("No. de registros según "+j, fontdict={'size': 10})
```

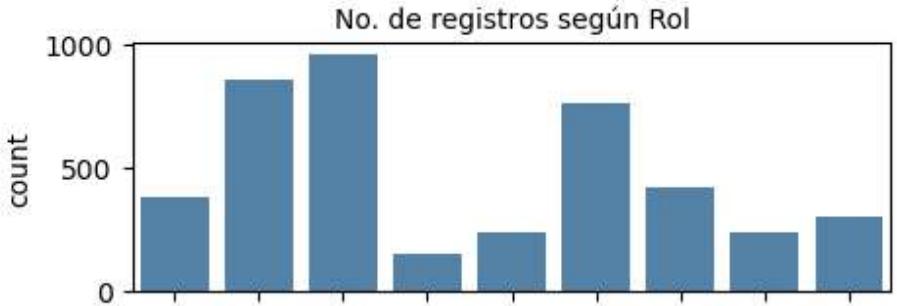

No. de registros según Desercion
count
3000
2000
1000
0
No
Si
Desercion

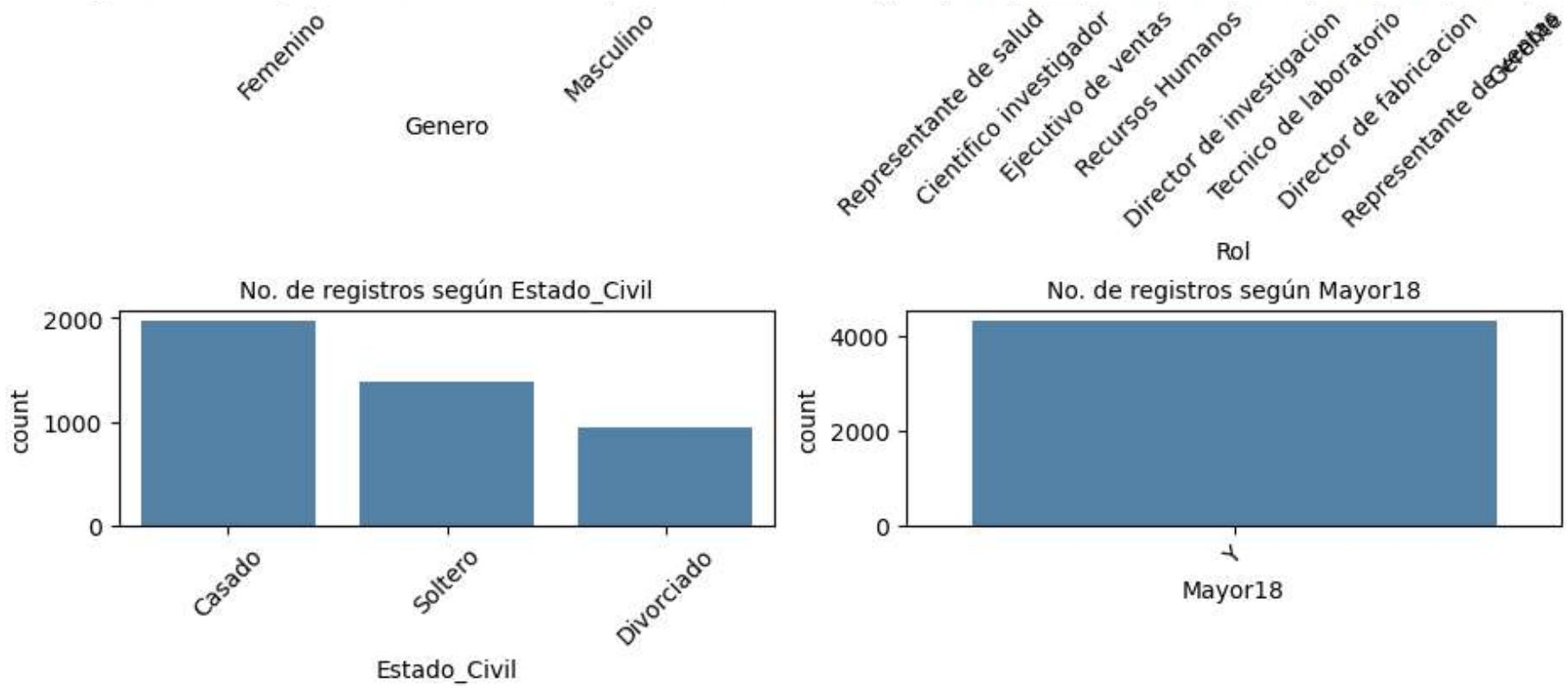

No. de registros según Frecuencia_viaje
count
3000
2000
1000
0
Esporadico
Frecuente
No_Aplica
Frecuencia_viaje


No. de registros según Area
count
2000
1000
0
Ventas
Investigacion & Desarrollo
Recursos Humanos
Area

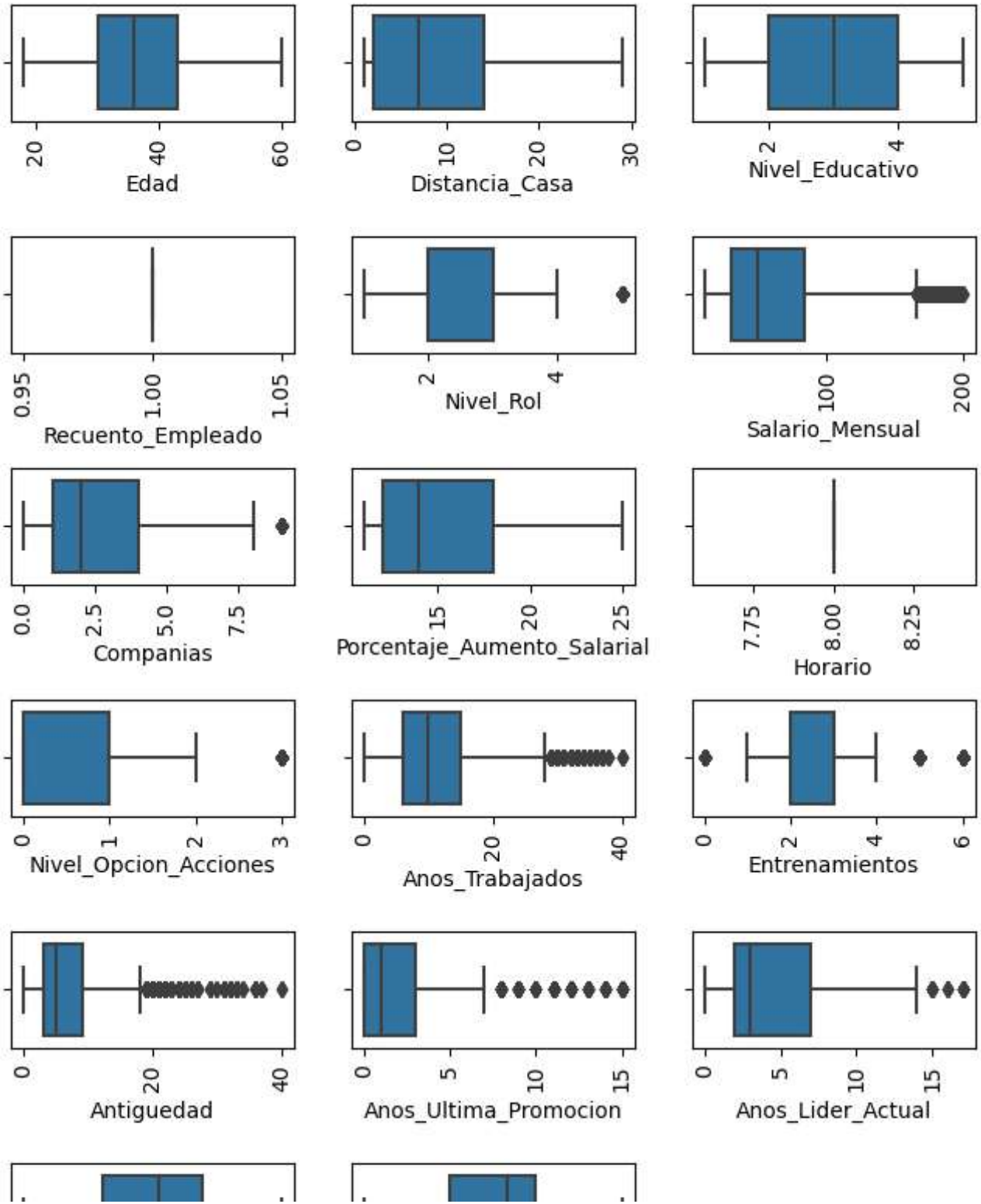

No. de registros según Campo_Educativo
count
1500
1000
500
0
Biologia
Otra
Medicina
Mercadeo
Tecnico
Recursos Humanos
Campo_Educativo

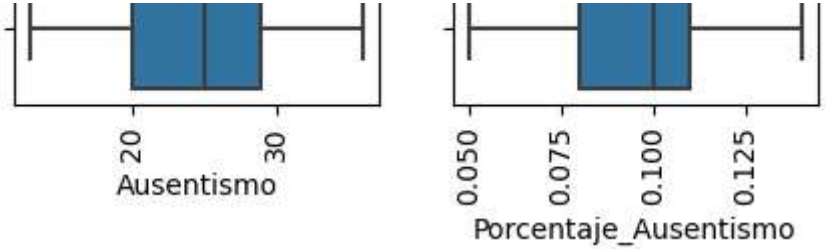

No. de registros según Genero
count
2000
1000
0


No. de registros según Rol
count
1000
500
0



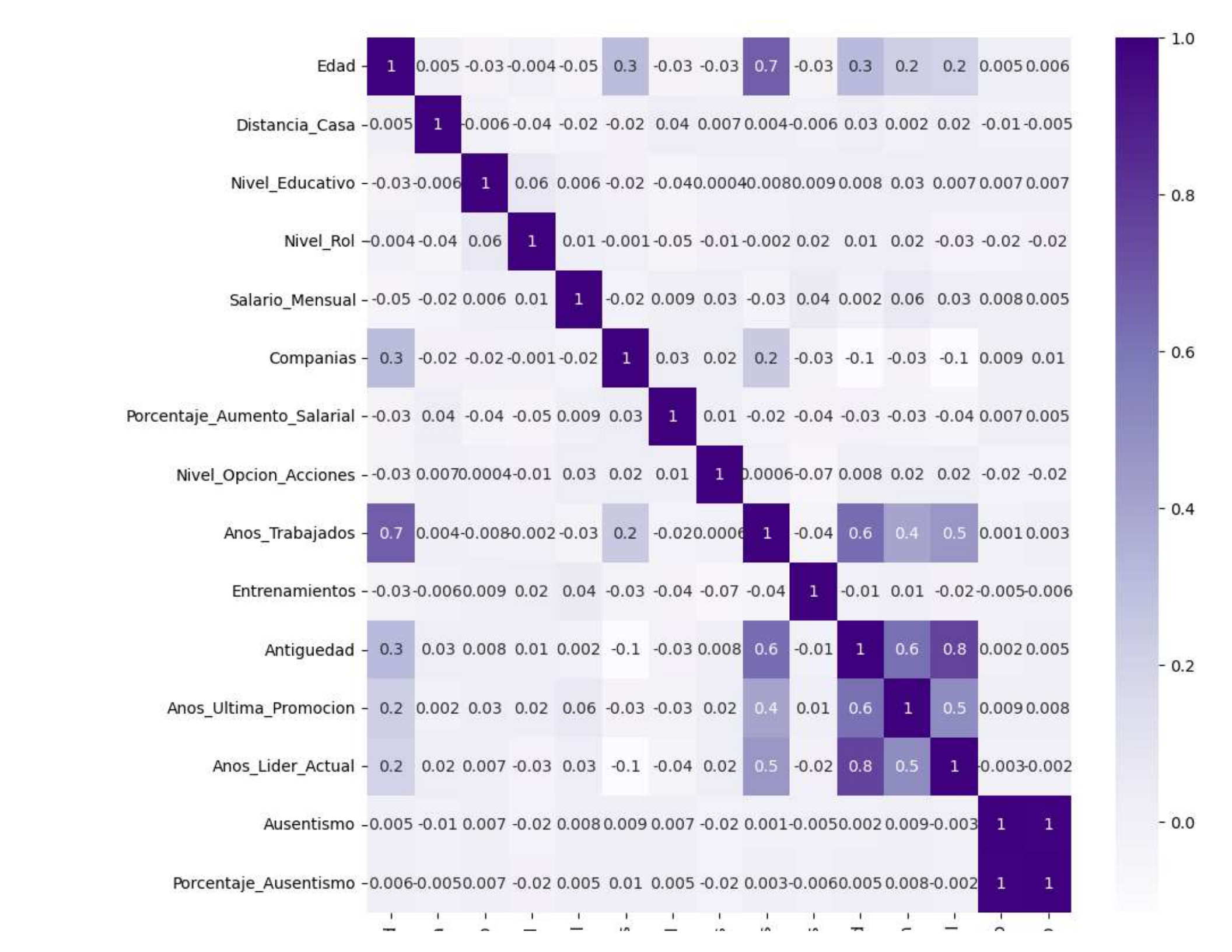
In [6]:
```
#Boxplots con seaborn multiples cajas
features=['Edad', 'Distancia_Casa', 'Nivel_Educativo', 'Recuento_Empleado', 'Nivel_Rol', 'Salario_Mensual',
       'Companias', 'Porcentaje_Aumento_Salarial', 'Horario', 'Nivel_Opcion_Acciones', 'Anos_Trabajados',
       'Entrenamientos', 'Antiguedad', 'Anos_Ultima_Promocion', 'Anos_Lider_Actual','Ausentismo',
        'Porcentaje_Ausentismo']
fig=plt.subplots(figsize=(8,30))
for i, j in enumerate(features):
    plt.subplot(16, 3, i+1)
    plt.subplots_adjust(hspace = 1.0)
    sns.boxplot(x=df[j])
    plt.xticks(rotation=90)
```


Edad
Distancia_Casa
Nivel_Educativo
Recuento_Empleado
Nivel_Rol
Salario_Mensual
Companias
Porcentaje_Aumento_Salarial
Horario
Nivel_Opcion_Acciones
Anos_Trabajados
Entrenamientos
Antiguedad
Anos_Ultima_Promocion
Anos_Lider_Actual



In [7]:
```
#Grafico de correlacion
corr_features=['Edad', 'Distancia_Casa', 'Nivel_Educativo', 'Nivel_Rol', 'Salario_Mensual',
               'Companias', 'Porcentaje_Aumento_Salarial', 'Nivel_Opcion_Acciones', 'Anos_Trabajados',
               'Entrenamientos', 'Antiguedad', 'Anos_Ultima_Promocion', 'Anos_Lider_Actual','Ausentismo',
               'Porcentaje_Ausentismo']

corr = df[corr_features].corr()
fig, ax = plt.subplots(figsize=(10,10))
sns.heatmap(corr,
            xticklabels=corr.columns.values,
            yticklabels=corr.columns.values,
            #cmap=sns.diverging_palette(220, 10, as_cmap=True),
            annot=True, cmap="Purples", fmt = '.1g')
```

Out[7]:
```
<AxesSubplot:>
```


Edad 1 0.005 -0.03 -0.004 -0.05 0.3 -0.03 -0.03 0.7 -0.03 0.3 0.2 0.2 0.005 0.006
Distancia_Casa -0.005 1 -0.006 -0.04 -0.02 -0.02 0.04 0.007 0.004 -0.006 0.03 0.002 0.02 -0.01 -0.005
Nivel_Educativo -0.03 -0.006 1 0.06 0.006 -0.02 -0.04 0.0004 0.008 0.009 0.008 0.03 0.007 0.007 0.007
Nivel_Rol -0.004 -0.04 0.06 1 0.01 -0.001 -0.05 -0.01 -0.002 0.02 0.01 0.02 -0.03 -0.02 -0.02
Salario_Mensual -0.05 -0.02 0.006 0.01 1 -0.02 0.009 0.03 -0.03 0.04 0.002 0.06 0.03 0.008 0.005
Companias 0.3 -0.02 -0.02 -0.001 -0.02 1 0.03 0.02 0.2 -0.03 -0.1 -0.03 -0.1 0.009 0.01
Porcentaje_Aumento_Salarial -0.03 0.04 -0.04 -0.05 0.009 0.03 1 0.01 -0.02 -0.04 -0.03 -0.03 -0.04 0.007 0.005
Nivel_Opcion_Acciones -0.03 0.007 0.0004 -0.01 0.03 0.02 0.01 1 0.0006 -0.07 0.008 0.02 0.02 -0.02 -0.02
Anos_Trabajados 0.7 0.004 -0.008 -0.002 -0.03 0.2 -0.02 0.0006 1 -0.04 0.6 0.4 0.5 0.001 0.003
Entrenamientos -0.03 -0.006 0.009 0.02 0.04 -0.03 -0.04 -0.07 -0.04 1 -0.01 0.01 -0.02 -0.005 -0.006
Antiguedad 0.3 0.03 0.008 0.01 0.002 -0.1 -0.03 0.008 0.6 -0.01 1 0.6 0.8 0.002 0.005
Anos_Ultima_Promocion 0.2 0.002 0.03 0.02 0.06 -0.03 -0.03 0.02 0.4 0.01 0.6 1 0.5 0.009 0.008
Anos_Lider_Actual 0.2 0.02 0.007 -0.03 0.03 -0.1 -0.04 0.02 0.5 -0.02 0.8 0.5 1 -0.003 -0.002
Ausentismo -0.005 -0.01 0.007 -0.02 0.008 0.009 0.007 -0.02 0.001 -0.005 0.002 0.009 -0.003 1 1
Porcentaje_Ausentismo -0.006 -0.005 0.007 -0.02 0.005 0.01 0.005 -0.02 0.003 -0.006 0.005 0.008 -0.002 1 1
1.0
0.8
0.6
0.4
0.2
0.0

Edad
Distancia_Casa
Nivel_Educativo
Nivel_Rol
Salario_Mensua
Companias
Porcentaje_Aumento_Salarial
Nivel_Opcion_Acciones
Anos_Trabajados
Entrenamientos
Antiguedad
Anos_Ultima_Promocion
Anos_Lider_Actua
Ausentismo
Porcentaje_Ausentismo

In [8]:
```
#Quitar columnas por nombre
cols_del = ['ID_empleado','Mayor18','Recuento_Empleado','Horario','Genero','Anos_Lider_Actual','Ausentismo']
df_in = df.loc[:, [name for name in df.columns if name not in cols_del]]
```

In [9]:
```
df_in.head()
```

Out[9]:

	Edad	Desercion	Frecuencia_viaje	Area	Distancia_Casa	Nivel_Educativo	Campo_Educativo	Nivel_Rol	Rol	Estado_Civil	Salario_Mensu
0	51	No	Esporadico	Ventas	6	2	Biologia	2	Representante de salud	Casado	131.
1	31	Si	Frecuente	Investigacion & Desarrollo	10	1	Biologia	3	Cientifico investigador	Soltero	41.
2	32	No	Frecuente	Ventas	17	4	Otra	3	Ejecutivo de ventas	Casado	193.
3	38	No	No_Aplica	Recursos Humanos	2	5	Biologia	3	Recursos Humanos	Casado	83.
4	32	No	Esporadico	Ventas	10	1	Medicina	3	Ejecutivo de ventas	Soltero	23.

In [10]:
```
#Dummificar variables seleccionadas
df_in= pd.get_dummies(df_in, columns=['Desercion', 'Frecuencia_viaje', 'Area','Campo_Educativo',
                                      'Rol', 'Estado_Civil'])
df_in.head()
```

Out[10]:

	Edad	Distancia_Casa	Nivel_Educativo	Nivel_Rol	Salario_Mensual	Companias	Porcentaje_Aumento_Salarial	Nivel_Opcion_Acciones	Anos_Trabajados	Er
0	51	6	2	2	131.16	1	11	0	1	
1	31	10	1	3	41.89	0	23	1	6	
2	32	17	4	3	193.28	1	15	3	5	
3	38	2	5	3	83.21	3	11	3	13	
4	32	10	1	3	23.42	4	12	2	9	

In [11]:
```
#Quitar columnas redundantes
cols_del_in = ['Desercion_No']
df_in = df_in.loc[:, [name for name in df_in.columns if name not in cols_del_in]]
```

Entrenamiento de Modelos

In [12]:
```
#Hay desbalanceo de clases en la variable objetivo
print(df_in.shape)
print(pd.value_counts(df_in['Desercion_Si'], sort = True))
```

```
(4300, 44)
0    3605
1     695
Name: Desercion_Si, dtype: int64
```

In [13]:
```
#Resultados con modelo normal sin estrategia de desbalance para tener punto de comparacion

#Definimos nuestras etiquetas y features
y = df_in['Desercion_Si']
X = df_in.drop('Desercion_Si', axis=1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=16)
```

In [97]:
```
#Modelo de Regresion Logistica
logreg_model = LogisticRegression(C=1.0,penalty='l2',random_state=1,max_iter=10000)
logreg_model.fit(X_train, y_train)
```

Out[97]:
```
LogisticRegression(max_iter=10000, random_state=1)
```

In [14]:
```
#Definimos funcion para mostrar los resultados
def mostrar_resultados(y_test, pred_y):
```

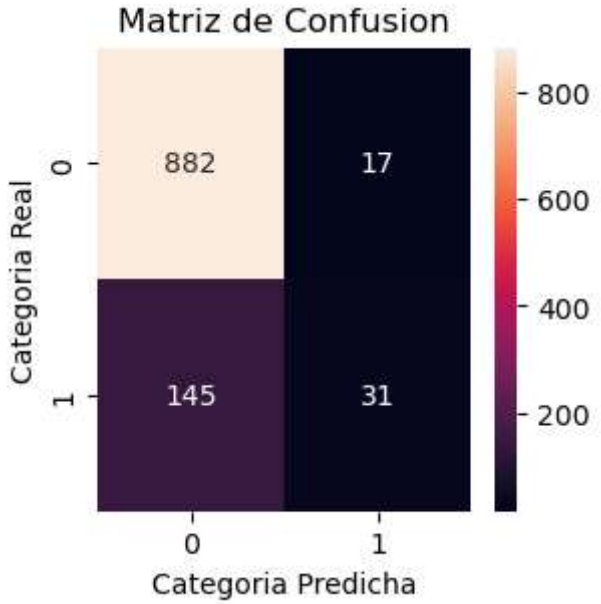
```
    conf_matrix = confusion_matrix(y_test, pred_y)
    plt.figure(figsize=(3, 3))
    sns.heatmap(conf_matrix, annot=True, fmt="d");
    plt.title("Matriz de Confusion")
    plt.ylabel('Categoria Real')
    plt.xlabel('Categoria Predicha')
    plt.show()
    print (classification_report(y_test, pred_y))
```

In [15]:

```
#Definimos funcion para medidas de comparación
def metricas_comparacion(y_test, pred_test, y_train, pred_train):
    #Accuracy
    accuracy_comparacion = metrics.accuracy_score(y_test, pred_test)
    print("Accuracy: ",accuracy_comparacion)

    #AUC test
    fpr, tpr, _ = metrics.roc_curve(y_test,  pred_test)
    auc_test = metrics.roc_auc_score(y_test, pred_test)
    print("AUC test: ",auc_test)

    #AUC train
    fpr_train, tpr_train, _train = metrics.roc_curve(y_train,  pred_train)
    auc_train = metrics.roc_auc_score(y_train, pred_train)
    print("AUC train: ",auc_train)

    #Delta AUC
    print("Delta AUC (overfitting): ",abs(auc_test-auc_train))
```

In [100…

```
#Resultados de prediccion
pred_y = logreg_model.predict(X_test)
mostrar_resultados(y_test, pred_y)
#Recall de attrition de 18% a mejorar, activos en 98%
```



	precision	recall	f1-score	support
0	0.86	0.98	0.92	899
1	0.65	0.18	0.28	176
accuracy			0.85	1075
macro avg	0.75	0.58	0.60	1075
weighted avg	0.82	0.85	0.81	1075

Aplicando SMOTE sobre la base (oversampling)

In [16]:
```
sm = SMOTE(sampling_strategy='auto', k_neighbors=5, random_state=1)
X_sm, y_sm = sm.fit_resample(X, y)
```

In [17]:
```
#Nuevos registros por categoria
print(y_sm.shape)
y_sm.value_counts()
```

Out[17]:
```
(7210,)
0    3605
1    3605
Name: Desercion_Si, dtype: int64
```

In [18]:
```
#Dividir la base en train y test de SMOTE
X_train_sm, X_test_sm, y_train_sm, y_test_sm = train_test_split(X_sm, y_sm, test_size=0.25, random_state=28)
```

Aplicando ADASYN sobre la base (oversampling)

In [19]:
```
ada = ADASYN(sampling_strategy='auto', n_neighbors=5, random_state=1)
X_ada, y_ada = ada.fit_resample(X, y)
```

In [20]:
```
#Nuevos registros por categoria
print(y_ada.shape)
y_ada.value_counts()
```

Out[20]:
```
(7096,)
0    3605
1    3491
Name: Desercion_Si, dtype: int64
```

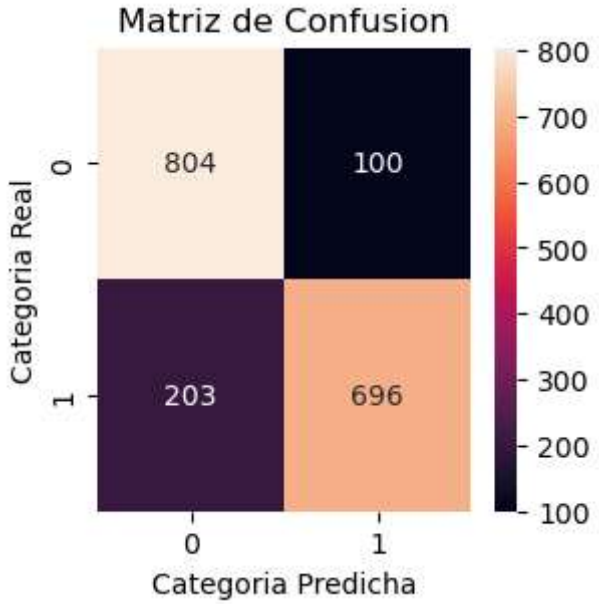
In [21]:
```
#Dividir la base en train y test de ADASYN
X_train_ada, X_test_ada, y_train_ada, y_test_ada = train_test_split(X_ada, y_ada, test_size=0.25, random_state=28)
```

Entrenamiento SMOTE Logistic Regression

In [107…
```
#Modelo de Regresion Logistica SMOTE
logreg_model_sm = LogisticRegression(C=1.0,penalty='l2',random_state=1,max_iter=10000)
logreg_model_sm.fit(X_train_sm, y_train_sm)
```

Out[107]:
```
LogisticRegression(max_iter=10000, random_state=1)
```

In [108…
```
#Prediccion sobre el test
pred_y_log_sm = logreg_model_sm.predict(X_test_sm)
mostrar_resultados(y_test_sm, pred_y_log_sm)
#Recall de attrition de 77%, activos en 89%

#Prediccion sobre el train
pred_y_log_sm_train = logreg_model_sm.predict(X_train_sm)
```



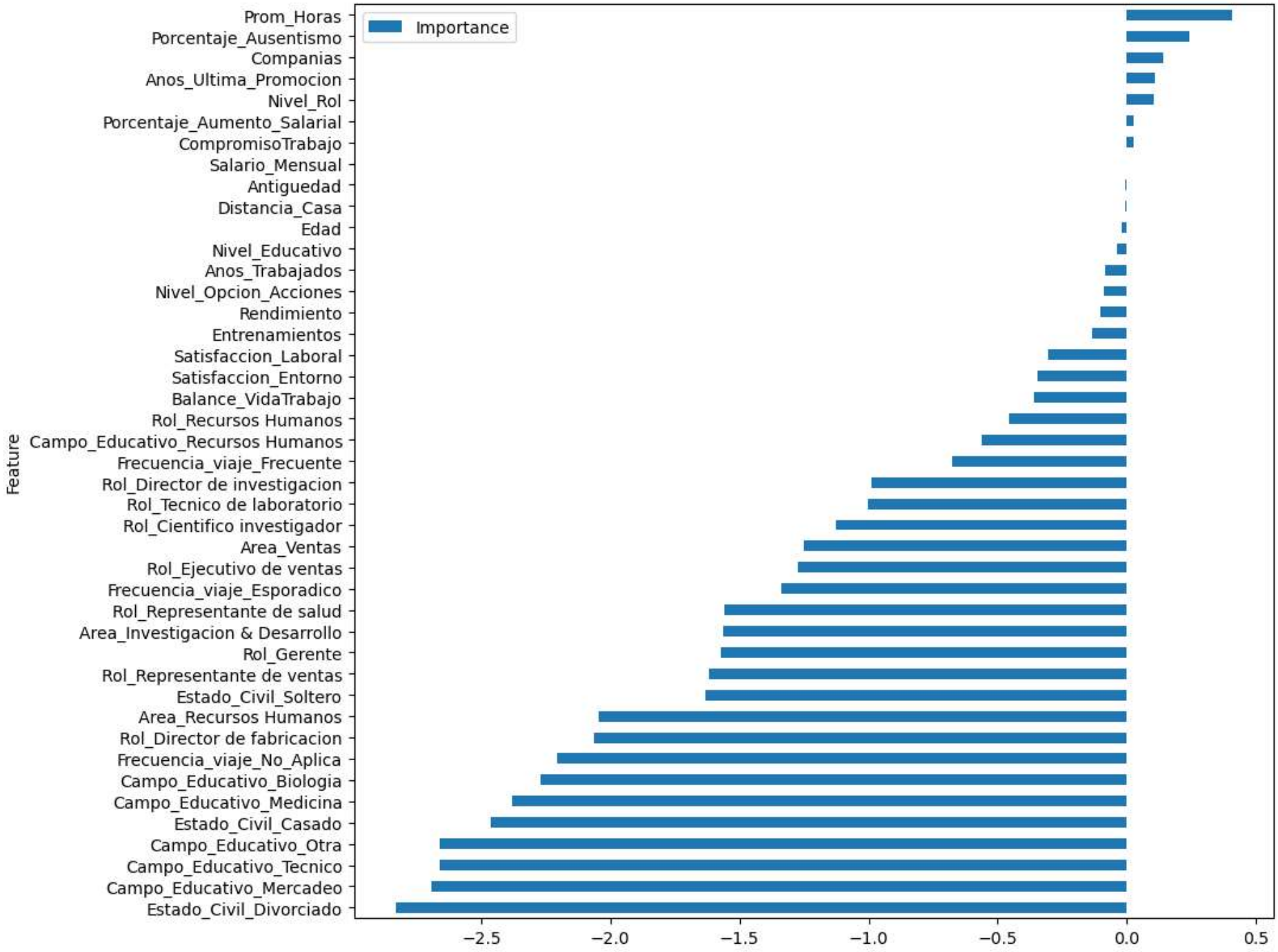
	precision	recall	f1-score	support
0	0.80	0.89	0.84	904
1	0.87	0.77	0.82	899
accuracy			0.83	1803
macro avg	0.84	0.83	0.83	1803
weighted avg	0.84	0.83	0.83	1803

In [109…
```
metricas_comparacion(y_test_sm, pred_y_log_sm, y_train_sm, pred_y_log_sm_train)
```

```
Accuracy:  0.831946755407654
AUC test:  0.831787039680274
AUC train:  0.8323102664064909
Delta AUC (overfitting):  0.0005232267262168522
```

In [111…
```
#Importancia de las variables
coefficients_log_sm = logreg_model_sm.coef_[0]

ft_importance_log_sm = pd.DataFrame({'Feature': X_sm.columns, 'Importance': coefficients_log_sm})
ft_importance_log_sm = ft_importance_log_sm.sort_values('Importance', ascending=True)
ft_importance_log_sm.plot(x='Feature', y='Importance', kind='barh', figsize=(10, 10))
```

Out[111]:
```
<AxesSubplot:ylabel='Feature'>
```



In [112…

```
#Modelo de Regresion Logistica SMOTE (solo importantes)

#Quitar columnas con menos importancia
```

```
cols_del_imp = ['Porcentaje_Aumento_Salarial','CompromisoTrabajo','Salario_Mensual','Antiguedad','Distancia_Casa']

X_train_sm_imp = X_train_sm.loc[:, [name for name in X_train_sm.columns if name not in cols_del_imp]]
X_test_sm_imp = X_test_sm.loc[:, [name for name in X_test_sm.columns if name not in cols_del_imp]]
```

In [113…

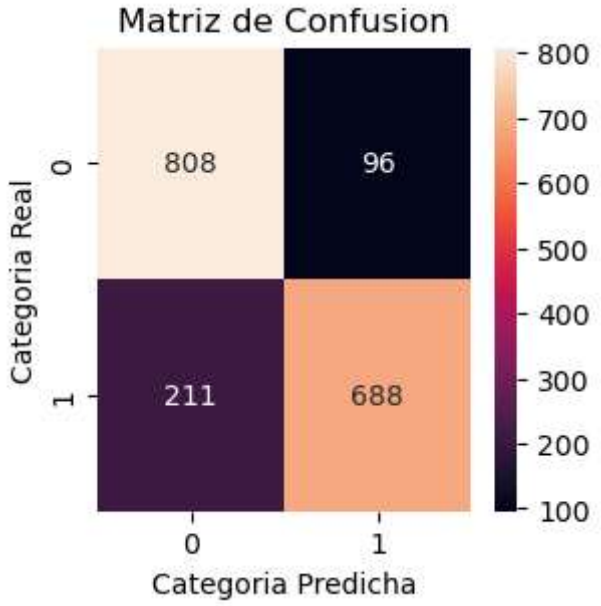
```
#Entrenar de nuevo
logreg_model_sm_imp = LogisticRegression(C=1.0,penalty='l2',random_state=1,max_iter=10000)
logreg_model_sm_imp.fit(X_train_sm_imp, y_train_sm)
```

Out[113]:

```
LogisticRegression(max_iter=10000, random_state=1)
```

In [114…

```
#Prediccion sobre el test
pred_y_log_sm_imp = logreg_model_sm_imp.predict(X_test_sm_imp)
mostrar_resultados(y_test_sm, pred_y_log_sm_imp)
#Recall de attrition de 77%, activos en 89%

#Prediccion sobre el train
pred_y_log_sm_train_imp = logreg_model_sm_imp.predict(X_train_sm_imp)
```



	precision	recall	f1-score	support
0	0.79	0.89	0.84	904
1	0.88	0.77	0.82	899
accuracy			0.83	1803
macro avg	0.84	0.83	0.83	1803
weighted avg	0.84	0.83	0.83	1803

In [115…
```
metricas_comparacion(y_test_sm, pred_y_log_sm_imp, y_train_sm, pred_y_log_sm_train_imp)
```

```
Accuracy:  0.8297282307265669
AUC test:  0.8295500408516838
AUC train:  0.8260279308558626
Delta AUC (overfitting):  0.0035221099958212543
```

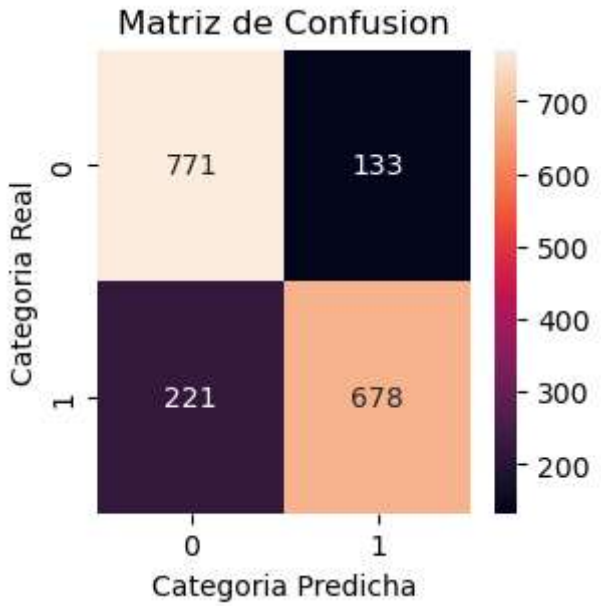
In [39]:
```
#Importancia de las variables
#coefficients_log_sm_imp = logreg_model_sm_imp.coef_[0]

#ft_importance_log_sm_imp = pd.DataFrame({'Feature': X_train_sm_imp.columns, 'Importance': coefficients_log_sm_imp})
#ft_importance_log_sm_imp = ft_importance_log_sm_imp.sort_values('Importance', ascending=True)
#ft_importance_log_sm_imp.plot(x='Feature', y='Importance', kind='barh', figsize=(10, 10))
```

Entrenamiento SMOTE Decision Tree

In [35]:
```
#Arbol de Decision individual SMOTE
dectree_model_sm = DecisionTreeClassifier(max_depth= 5, random_state = 1)
dectree_model_sm.fit(X_train_sm,y_train_sm)
```

Out[35]:
```
DecisionTreeClassifier(max_depth=5, random_state=1)
```

In [36]:
```
#Prediccion sobre el test
pred_y_dectree_sm = dectree_model_sm.predict(X_test_sm)
mostrar_resultados(y_test_sm, pred_y_dectree_sm)
#Recall de attrition de 75%, activos en 85%

#Prediccion sobre el train
pred_y_dectree_sm_train = dectree_model_sm.predict(X_train_sm)
```



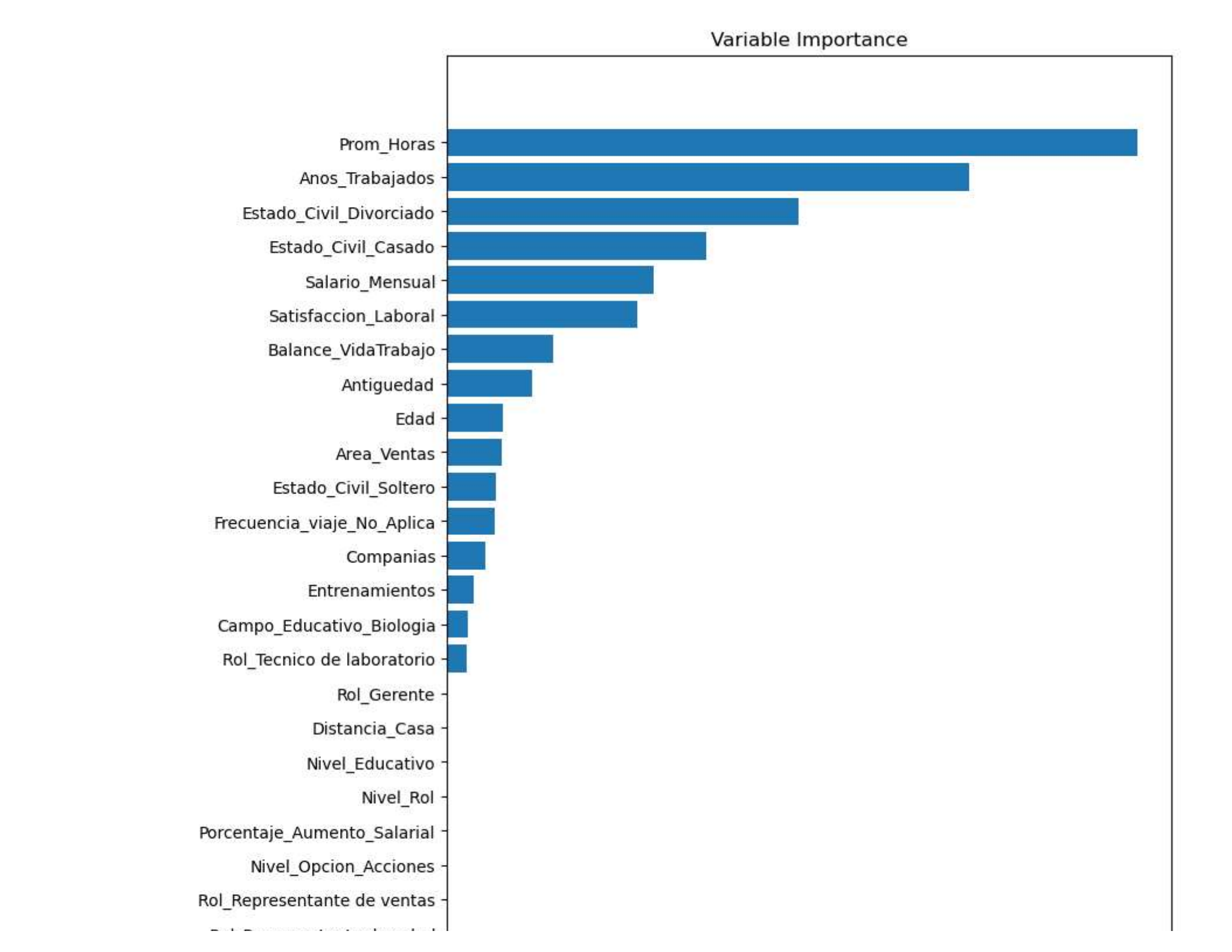
	precision	recall	f1-score	support
0	0.78	0.85	0.81	904
1	0.84	0.75	0.79	899
accuracy			0.80	1803
macro avg	0.81	0.80	0.80	1803
weighted avg	0.81	0.80	0.80	1803

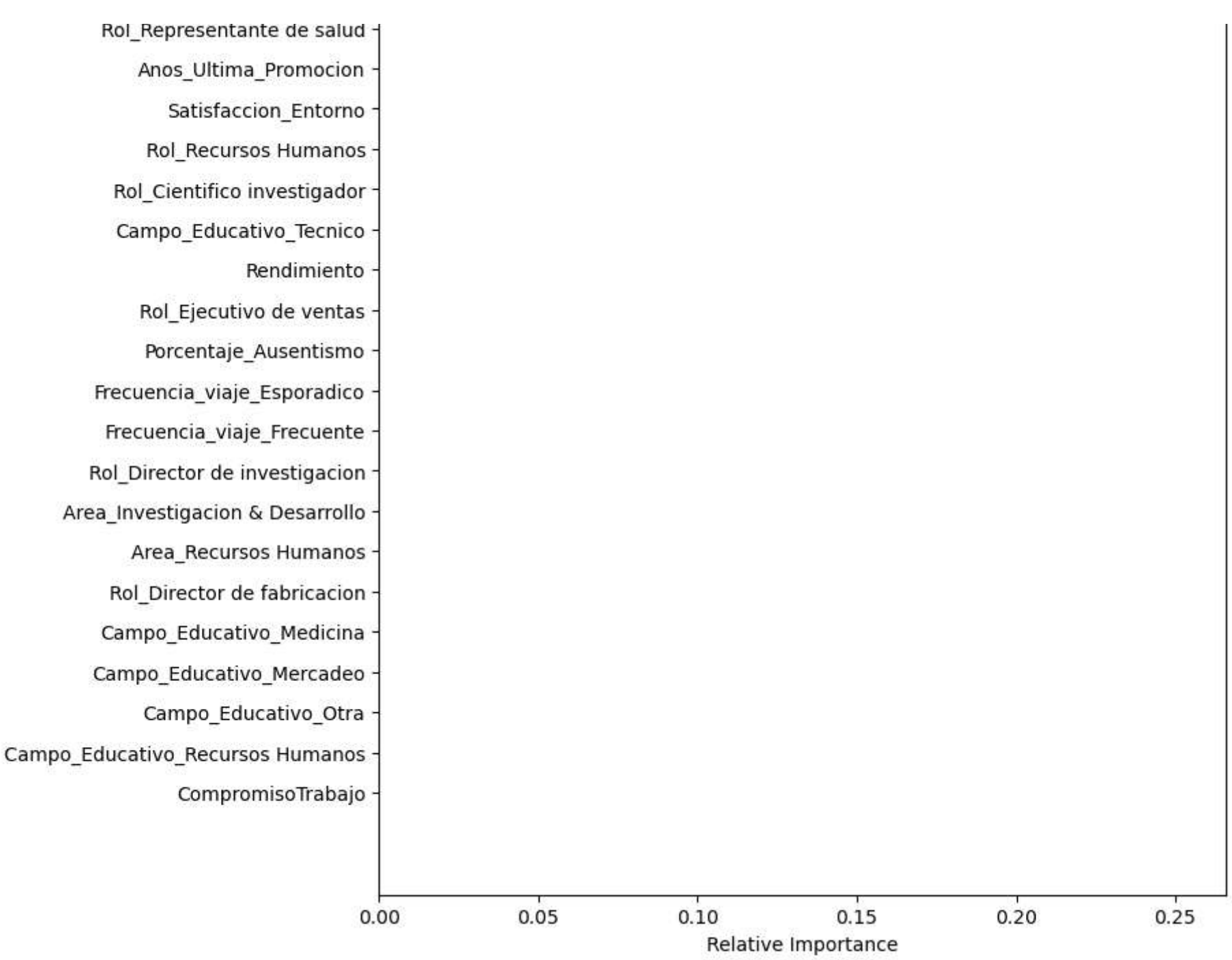
In [37]:
```
metricas_comparacion(y_test_sm, pred_y_dectree_sm, y_train_sm, pred_y_dectree_sm_train)
```

```
Accuracy:  0.8036605657237936
AUC test:  0.8035237038203706
AUC train:  0.8036363444816503
Delta AUC (overfitting):  0.00011264066127969485
```

In [38]:
```
feature_importance = dectree_model_sm.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                             #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5

plt.figure(figsize=(8, 18))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_sm.keys()[sorted_idx])
plt.xlabel('Relative Importance')
```

```
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Prom_Horas
Anos_Trabajados
Estado_Civil_Divorciado
Estado_Civil_Casado
Salario_Mensual
Satisfaccion_Laboral
Balance_VidaTrabajo
Antiguedad
Edad
Area_Ventas
Estado_Civil_Soltero
Frecuencia_viaje_No_Aplica
Companias
Entrenamientos
Campo_Educativo_Biologia
Rol_Tecnico de laboratorio
Rol_Gerente
Distancia_Casa
Nivel_Educativo
Nivel_Rol
Porcentaje_Aumento_Salarial
Nivel_Opcion_Acciones
Rol_Representante de ventas



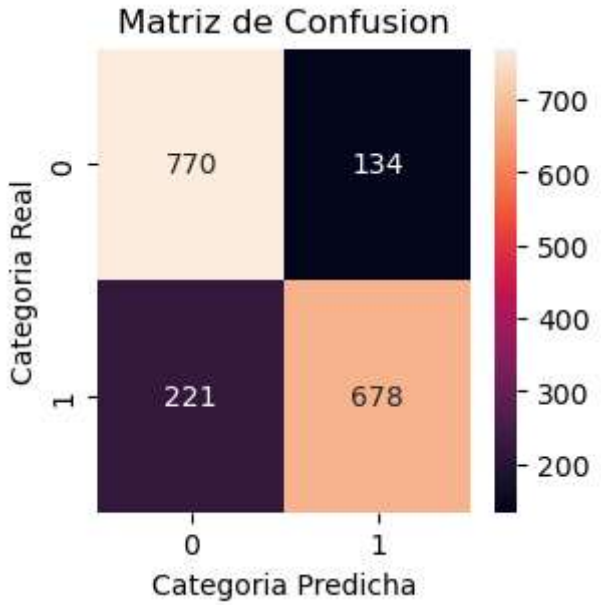
In [39]:
```
#Modelo de Decision Tree SMOTE (solo importantes)

#Quitar columnas con menos importancia
```

```
cols_del_imp = ['CompromisoTrabajo','Campo_Educativo_Recursos Humanos','Campo_Educativo_Otra','Campo_Educativo_Mercadeo',
                'Campo_Educativo_Medicina','Rol_Director de fabricacion','Area_Recursos Humanos',
                'Area_Investigacion & Desarrollo','Rol_Director de investigacion','Frecuencia_viaje_Frecuente',
                'Frecuencia_viaje_Esporadico','Porcentaje_Ausentismo','Rol_Ejecutivo de ventas','Rendimiento',
                'Campo_Educativo_Tecnico','Rol_Cientifico investigador','Rol_Recursos Humanos','Satisfaccion_Entorno',
                'Anos_Ultima_Promocion','Rol_Representante de salud','Rol_Representante de ventas','Nivel_Opcion_Acciones',
                'Porcentaje_Aumento_Salarial','Nivel_Rol','Nivel_Educativo','Distancia_Casa','Rol_Gerente',
                'Rol_Tecnico de laboratorio','Campo_Educativo_Biologia']

X_train_sm_imp = X_train_sm.loc[:, [name for name in X_train_sm.columns if name not in cols_del_imp]]
X_test_sm_imp = X_test_sm.loc[:, [name for name in X_test_sm.columns if name not in cols_del_imp]]
```

In [40]:
```
#Entrenar de nuevo Arbol de Decision individual SMOTE
dectree_model_sm_imp = DecisionTreeClassifier(max_depth= 5, random_state = 1)
dectree_model_sm_imp.fit(X_train_sm_imp,y_train_sm)
```

Out[40]:
```
DecisionTreeClassifier(max_depth=5, random_state=1)
```

In [42]:
```
#Prediccion sobre el test
pred_y_dectree_sm_imp = dectree_model_sm_imp.predict(X_test_sm_imp)
mostrar_resultados(y_test_sm, pred_y_dectree_sm_imp)
#Recall de attrition de 75%, activos en 85%

#Prediccion sobre el train
pred_y_dectree_sm_train_imp = dectree_model_sm_imp.predict(X_train_sm_imp)
```



	precision	recall	f1-score	support
0	0.78	0.85	0.81	904
1	0.83	0.75	0.79	899
accuracy			0.80	1803
macro avg	0.81	0.80	0.80	1803
weighted avg	0.81	0.80	0.80	1803

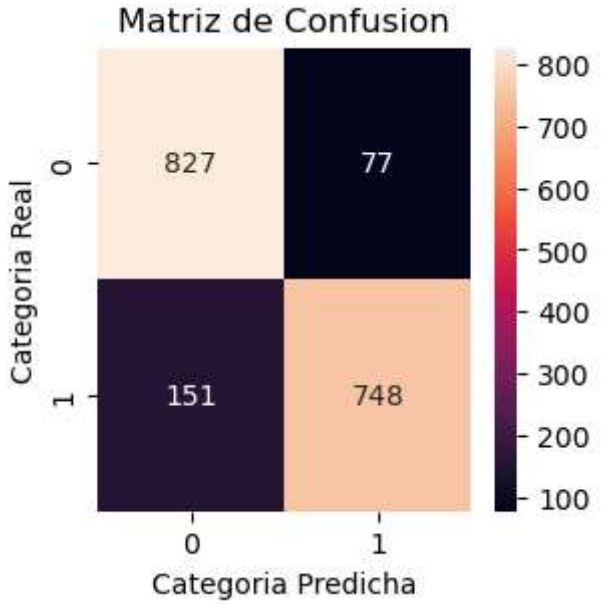
In [43]:
```
metricas_comparacion(y_test_sm, pred_y_dectree_sm_imp, y_train_sm, pred_y_dectree_sm_train_imp)
```

```
Accuracy:  0.8031059345535219
AUC test:  0.802970606475238
AUC train:  0.8032661112347047
Delta AUC (overfitting):  0.00029550475946671373
```

Entrenamiento SMOTE Random Forest

In [22]:
```
#Random Forest con SMOTE
rf_model_sm =RandomForestClassifier(max_depth=5,random_state=1, class_weight = 'balanced')
rf_model_sm.fit(X_train_sm,y_train_sm)

#Prediccion sobre test
y_pred_rf_sm = rf_model_sm.predict(X_test_sm)
```

In [23]:
```
mostrar_resultados(y_test_sm, y_pred_rf_sm)
```



	precision	recall	f1-score	support
0	0.85	0.91	0.88	904
1	0.91	0.83	0.87	899
accuracy			0.87	1803
macro avg	0.88	0.87	0.87	1803
weighted avg	0.88	0.87	0.87	1803

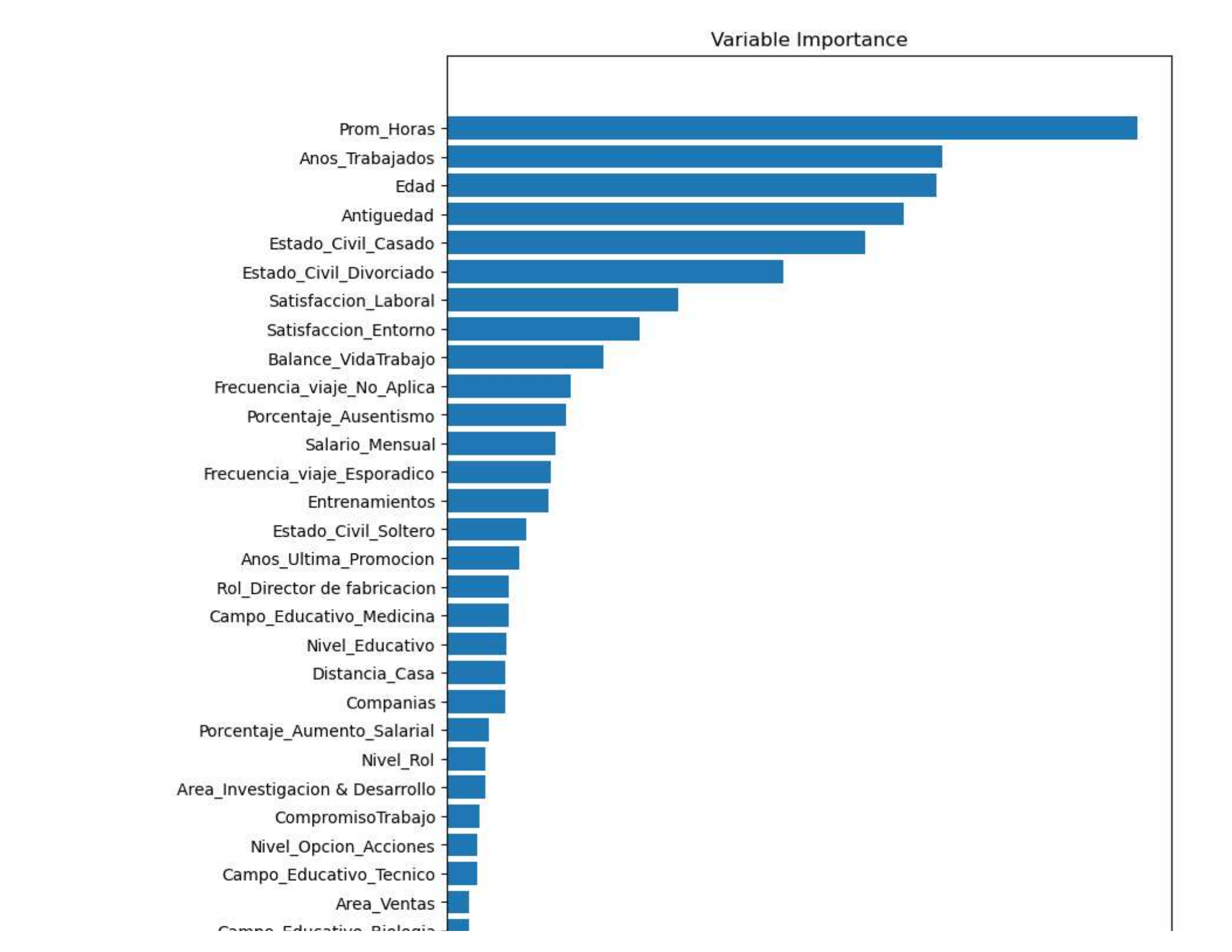
In [24]:
```
#Prediccion sobre el train
y_pred_rf_sm_train = rf_model_sm.predict(X_train_sm)
```

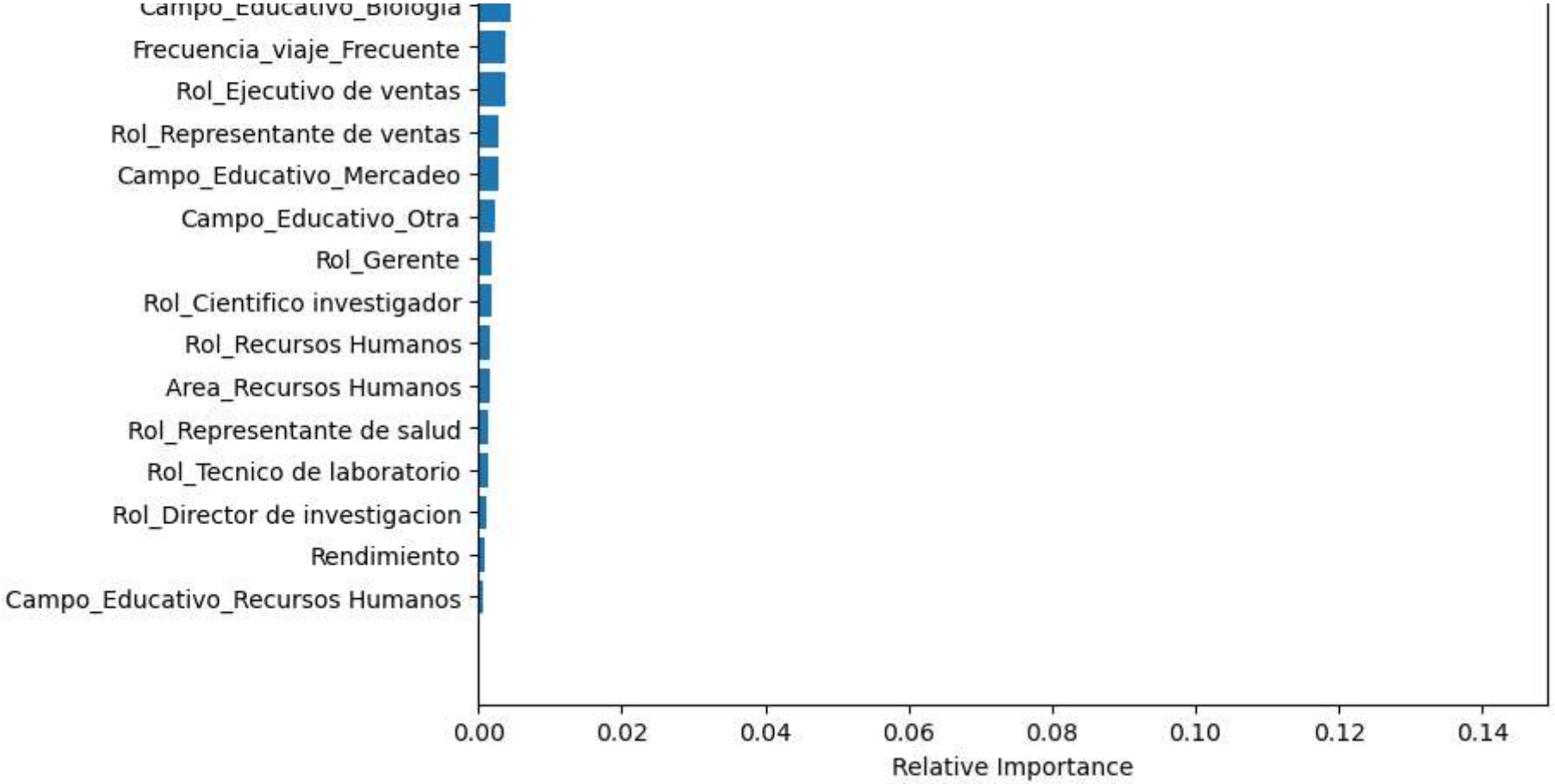
In [25]:
```
metricas_comparacion(y_test_sm, y_pred_rf_sm, y_train_sm, y_pred_rf_sm_train)
```

```
Accuracy:  0.8735440931780366
AUC test:  0.8734293019776151
AUC train:  0.8752039634933052
Delta AUC (overfitting):  0.001774661515690057
```

In [26]:
```
#Importancia variables
feature_importance = rf_model_sm.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                              #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5
```

```
plt.figure(figsize=(8, 15))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_ada.keys()[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Prom_Horas
Anos_Trabajados
Edad
Antiguedad
Estado_Civil_Casado
Estado_Civil_Divorciado
Satisfaccion_Laboral
Satisfaccion_Entorno
Balance_VidaTrabajo
Frecuencia_viaje_No_Aplica
Porcentaje_Ausentismo
Salario_Mensual
Frecuencia_viaje_Esporadico
Entrenamientos
Estado_Civil_Soltero
Anos_Ultima_Promocion
Rol_Director de fabricacion
Campo_Educativo_Medicina
Nivel_Educativo
Distancia_Casa
Companias
Porcentaje_Aumento_Salarial
Nivel_Rol
Area_Investigacion & Desarrollo
CompromisoTrabajo
Nivel_Opcion_Acciones
Campo_Educativo_Tecnico
Area_Ventas

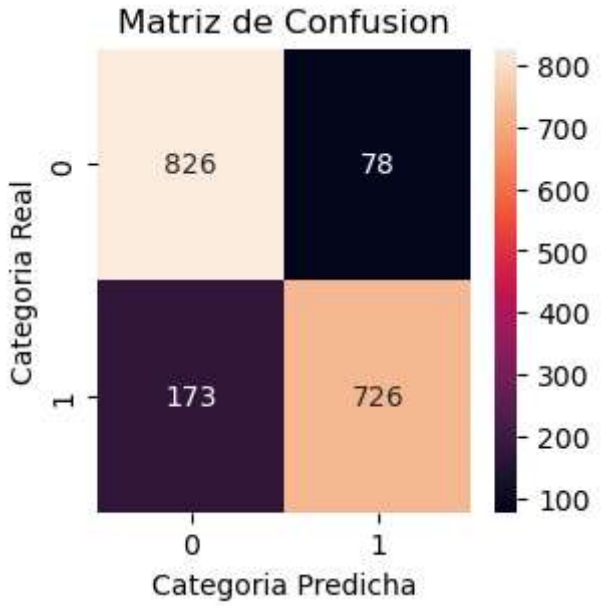


In [27]:

```
#Modelo de Random Forecast SMOTE (solo importantes)
# Segun la grafica las varaibles de rol, campo educativo, compromiso trabajo, nivel de acciones,
# rendimiento no son importantes, se deja frecuencia de viaje frecuente porque las demas estan arriba
# se quitan todos los roles y areas para ser consistentes

#Quitar columnas con menos importancia
cols_del_imp = ['Area_Investigacion & Desarrollo','CompromisoTrabajo','Nivel_Opcion_Acciones','Campo_Educativo_Tecnico',
                'Area_Ventas','Campo_Educativo_Biologia','Rol_Ejecutivo de ventas','Rol_Representante de ventas',
                'Campo_Educativo_Mercadeo','Campo_Educativo_Otra','Rol_Gerente','Rol_Cientifico investigador',
                'Rol_Recursos Humanos','Area_Recursos Humanos','Rol_Representante de salud','Rol_Tecnico de laboratorio',
                'Rol_Director de investigacion','Rendimiento','Campo_Educativo_Recursos Humanos',
                'Rol_Director de fabricacion','Campo_Educativo_Medicina']

X_train_sm_imp = X_train_sm.loc[:, [name for name in X_train_sm.columns if name not in cols_del_imp]]
X_test_sm_imp = X_test_sm.loc[:, [name for name in X_test_sm.columns if name not in cols_del_imp]]
```

In [28]:
```
#Entrenar modelo de nuevo
rf_model_sm_imp =RandomForestClassifier(max_depth=5,random_state=1, class_weight = 'balanced')
rf_model_sm_imp.fit(X_train_sm_imp,y_train_sm)

#Prediccion sobre test
y_pred_rf_sm_imp = rf_model_sm_imp.predict(X_test_sm_imp)
```

In [29]:
```
mostrar_resultados(y_test_sm, y_pred_rf_sm_imp)
```



	precision	recall	f1-score	support
0	0.83	0.91	0.87	904
1	0.90	0.81	0.85	899
accuracy			0.86	1803
macro avg	0.86	0.86	0.86	1803
weighted avg	0.86	0.86	0.86	1803

In [30]:
```
#Prediccion sobre el train
y_pred_rf_sm_train_imp = rf_model_sm_imp.predict(X_train_sm_imp)
```

In [31]:
```
metricas_comparacion(y_test_sm, y_pred_rf_sm_imp, y_train_sm, y_pred_rf_sm_train_imp)
```

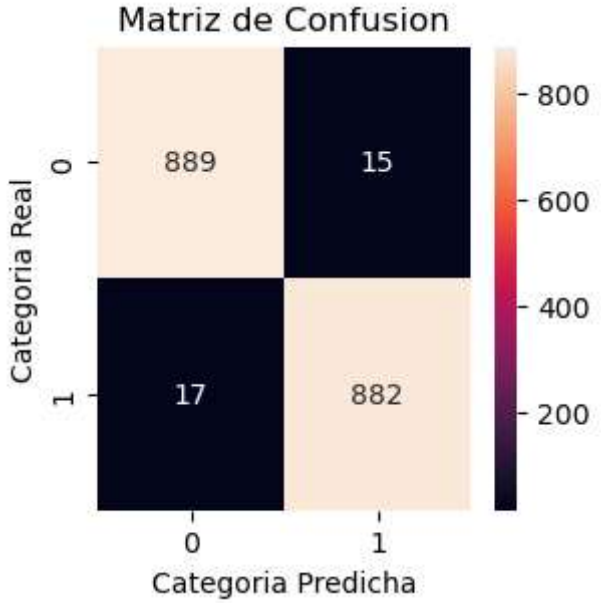
```
Accuracy:  0.8607875762617859
AUC test:  0.8606403870573991
AUC train:  0.8581964934287019
Delta AUC (overfitting):  0.0024438936286972357
```

Entrenamiento SMOTE Gradient Boosting

In [26]:
```
#Gradient Boosting individual
gbm_model_sm = GradientBoostingClassifier(max_depth = 5,max_features = 'auto',random_state = 1)
gbm_model_sm.fit(X_train_sm,y_train_sm)
```

Out[26]:
```
GradientBoostingClassifier(max_depth=5, max_features='auto', random_state=1)
```

In [27]:
```
#Prediccion sobre el test
pred_y_gbm_sm = gbm_model_sm.predict(X_test_sm)
mostrar_resultados(y_test_sm, pred_y_gbm_sm)
#Recall de attrition de 98%, activos en 98%

#Prediccion sobre el train
pred_y_gbm_sm_train = gbm_model_sm.predict(X_train_sm)
```

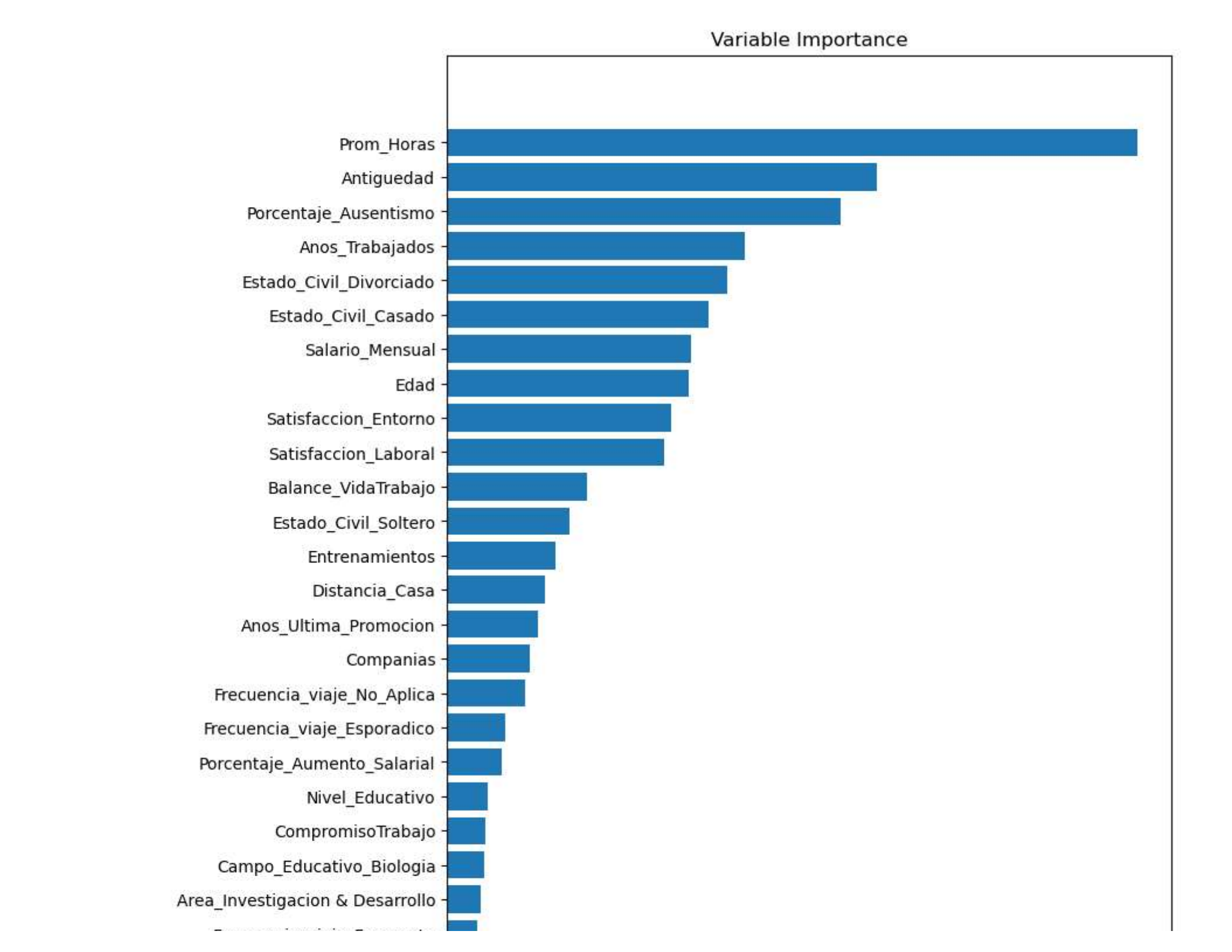


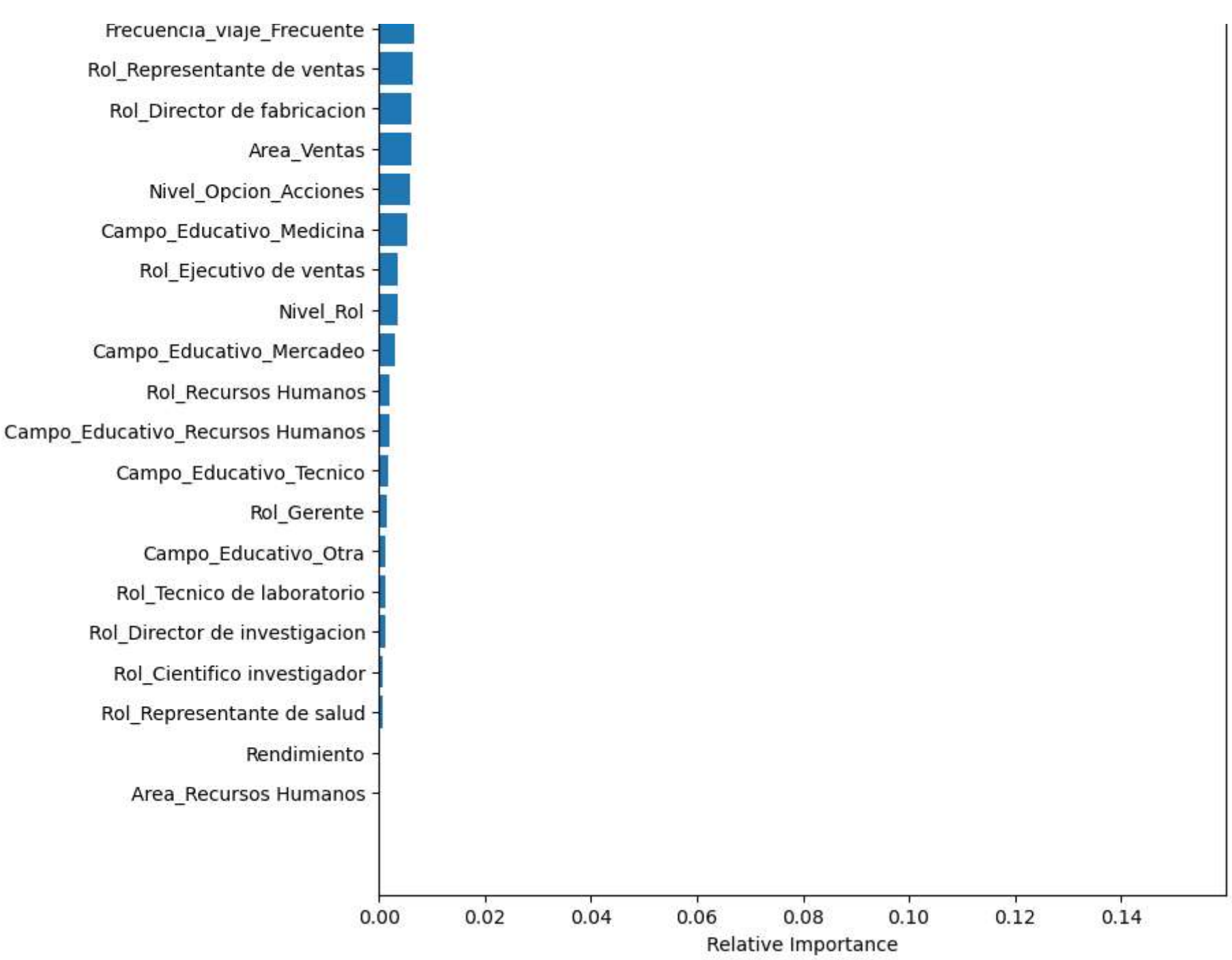
```
              precision    recall  f1-score   support

           0       0.98      0.98      0.98       904
           1       0.98      0.98      0.98       899

    accuracy                           0.98      1803
   macro avg       0.98      0.98      0.98      1803
weighted avg       0.98      0.98      0.98      1803
```

In [28]:
```
metricas_comparacion(y_test_sm, pred_y_gbm_sm, y_train_sm, pred_y_gbm_sm_train)
```

```
Accuracy:  0.9822518025513034
AUC test:  0.9822485898786262
AUC train:  0.9972273552293599
Delta AUC (overfitting):  0.014978765350733725
```

In [29]:
```
feature_importance = gbm_model_sm.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                              #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5

plt.figure(figsize=(8, 18))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_sm.keys()[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Prom_Horas
Antiguedad
Porcentaje_Ausentismo
Anos_Trabajados
Estado_Civil_Divorciado
Estado_Civil_Casado
Salario_Mensual
Edad
Satisfaccion_Entorno
Satisfaccion_Laboral
Balance_VidaTrabajo
Estado_Civil_Soltero
Entrenamientos
Distancia_Casa
Anos_Ultima_Promocion
Companias
Frecuencia_viaje_No_Aplica
Frecuencia_viaje_Esporadico
Porcentaje_Aumento_Salarial
Nivel_Educativo
CompromisoTrabajo
Campo_Educativo_Biologia
Area_Investigacion & Desarrollo



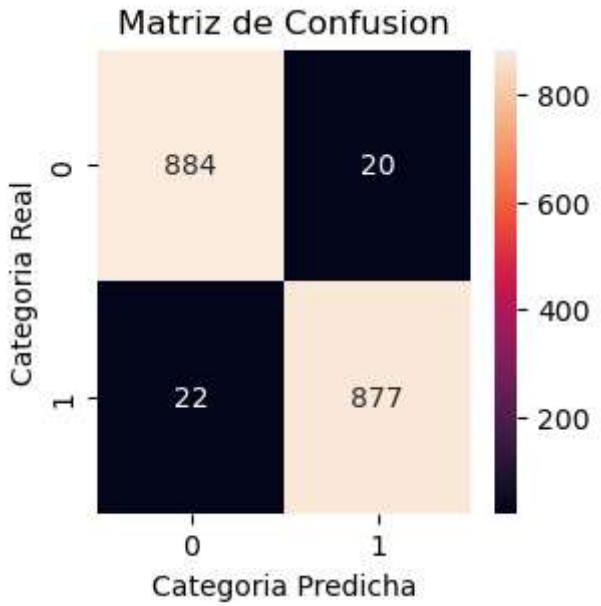
In [30]:
```
#Modelo de Gradient Boosting SMOTE (solo importantes)

#Quitar columnas con menos importancia
```

```
cols_del_imp = ['Area_Recursos Humanos','Rendimiento','Rol_Representante de salud',
                'Rol_Cientifico investigador','Rol_Director de investigacion','Rol_Tecnico de laboratorio',
               'Campo_Educativo_Otra','Rol_Gerente','Campo_Educativo_Tecnico','Campo_Educativo_Recursos Humanos',
               'Rol_Recursos Humanos','Campo_Educativo_Mercadeo','Nivel_Rol','Rol_Ejecutivo de ventas',
               'Campo_Educativo_Medicina','Nivel_Opcion_Acciones','Area_Ventas','Rol_Director de fabricacion',
               'Rol_Representante de ventas','Frecuencia_viaje_Frecuente','Area_Investigacion & Desarrollo',
               'Campo_Educativo_Biologia']

X_train_sm_imp = X_train_sm.loc[:, [name for name in X_train_sm.columns if name not in cols_del_imp]]
X_test_sm_imp = X_test_sm.loc[:, [name for name in X_test_sm.columns if name not in cols_del_imp]]
```

In [31]:
```
#Entrenar de nuevo
gbm_model_sm_imp = GradientBoostingClassifier(max_depth = 5,max_features = 'auto',random_state = 1)
gbm_model_sm_imp.fit(X_train_sm_imp,y_train_sm)
```

Out[31]:
```
GradientBoostingClassifier(max_depth=5, max_features='auto', random_state=1)
```

In [32]:
```
#Prediccion sobre el test
pred_y_gbm_sm_imp = gbm_model_sm_imp.predict(X_test_sm_imp)
mostrar_resultados(y_test_sm, pred_y_gbm_sm_imp)
#Recall de attrition de 98%, activos en 98%

#Prediccion sobre el train
pred_y_gbm_sm_train_imp = gbm_model_sm_imp.predict(X_train_sm_imp)
```



```
              precision    recall  f1-score   support

           0       0.98      0.98      0.98       904
           1       0.98      0.98      0.98       899

    accuracy                           0.98      1803
   macro avg       0.98      0.98      0.98      1803
weighted avg       0.98      0.98      0.98      1803
```

In [34]:
```
metricas_comparacion(y_test_sm, pred_y_gbm_sm_imp, y_train_sm, pred_y_gbm_sm_train_imp)
```

```
Accuracy:  0.9767054908485857
AUC test:  0.9767022355222617
AUC train:  0.9950062977961408
Delta AUC (overfitting):  0.01830406227387915
```

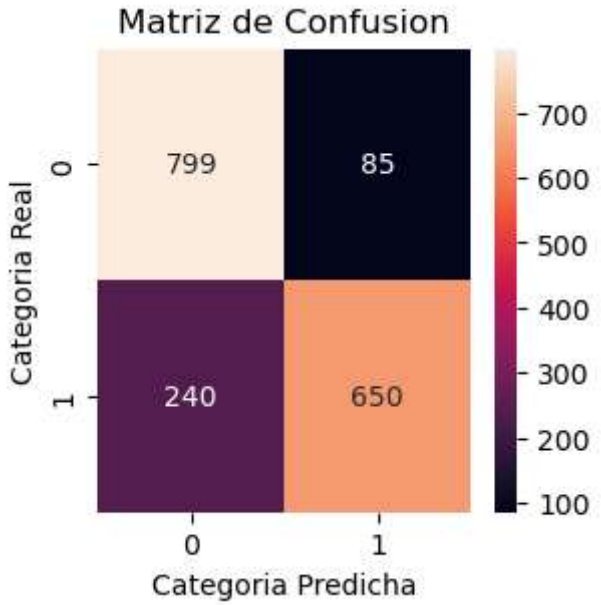
In [62]:
```
#feature_importance = gbm_model_sm_imp.feature_importances_
##Importancia relativa a la importancia maxima
#feature_importance = 100.0 * (feature_importance / 100)
#                             #feature_importance.max())
#sorted_idx = np.argsort(feature_importance)
#pos = np.arange(sorted_idx.shape[0]) + .5
#
#plt.figure(figsize=(8, 18))
#plt.barh(pos, feature_importance[sorted_idx], align='center')
#plt.yticks(pos, X_train_sm_imp.keys()[sorted_idx])
#plt.xlabel('Relative Importance')
#plt.title('Variable Importance')
#plt.show()
```

Entrenamiento ADASYN Logistic Regression

In [44]:
```
#Modelo de Regresion Logistica ADASYN
logreg_model_ada = LogisticRegression(C=1.0,penalty='l2',random_state=1,max_iter=10000)
logreg_model_ada.fit(X_train_ada, y_train_ada)
```

Out[44]:
```
LogisticRegression(max_iter=10000, random_state=1)
```

In [45]:
```
#Prediccion sobre el test
pred_y_log_ada = logreg_model_ada.predict(X_test_ada)
mostrar_resultados(y_test_ada, pred_y_log_ada)
#Recall de attrition de 73%, activos en 90%

#Prediccion sobre el train
pred_y_log_ada_train = logreg_model_ada.predict(X_train_ada)
```



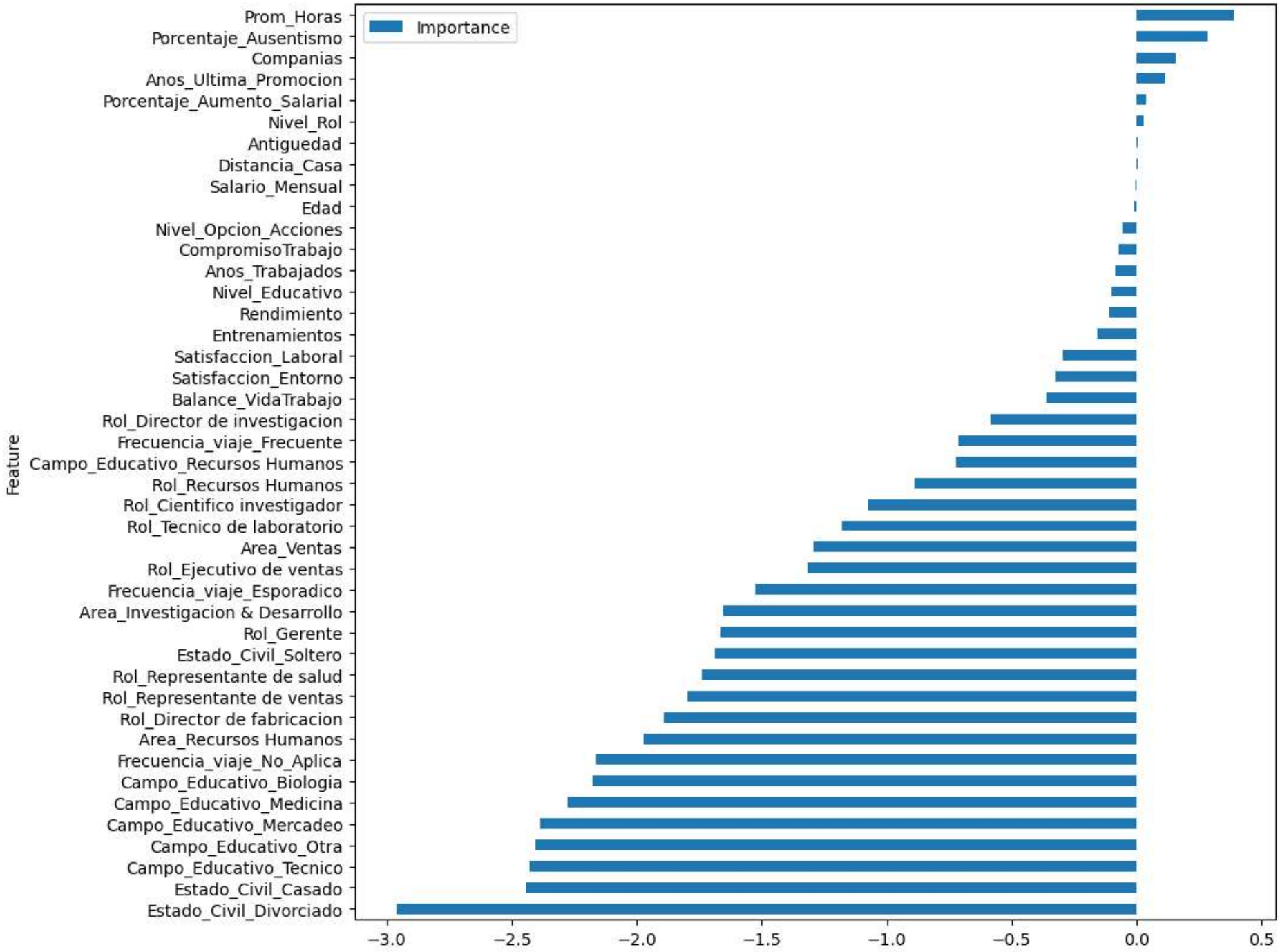
	precision	recall	f1-score	support
0	0.77	0.90	0.83	884
1	0.88	0.73	0.80	890
accuracy			0.82	1774
macro avg	0.83	0.82	0.82	1774
weighted avg	0.83	0.82	0.82	1774

In [46]:
```
metricas_comparacion(y_test_ada, pred_y_log_ada, y_train_ada, pred_y_log_ada_train)
```

```
Accuracy:  0.8167981961668546
AUC test:  0.8170916162489197
AUC train:  0.8267456711374261
Delta AUC (overfitting):  0.009654054888506458
```

In [47]:
```
#Importancia de las variables
coefficients_log_ada = logreg_model_ada.coef_[0]

ft_importance_log_ada = pd.DataFrame({'Feature': X_ada.columns, 'Importance': coefficients_log_ada})
ft_importance_log_ada = ft_importance_log_ada.sort_values('Importance', ascending=True)
ft_importance_log_ada.plot(x='Feature', y='Importance', kind='barh', figsize=(10, 10))
```

Out[47]:
```
<AxesSubplot:ylabel='Feature'>
```



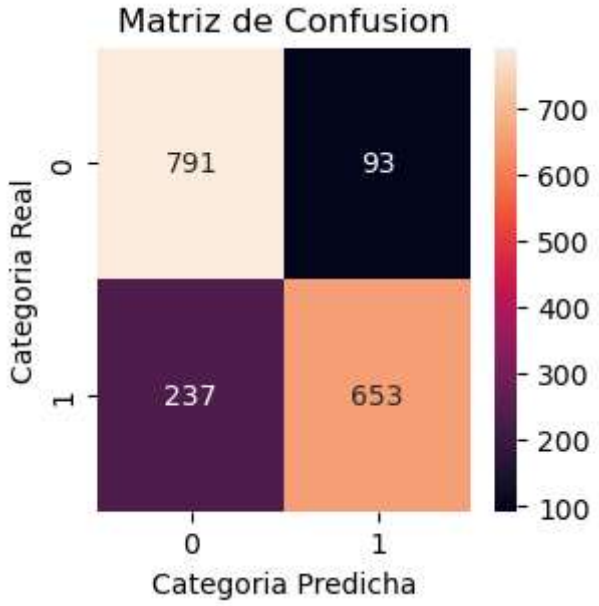
In [48]:
```
#Modelo de Regresion Logistica ADASYN (solo importantes)

#Quitar columnas con menos importancia
```

```
cols_del_imp = ['Porcentaje_Aumento_Salarial','Nivel_Rol','Antiguedad','Distancia_Casa','Salario_Mensual','Edad']

X_train_ada_imp = X_train_ada.loc[:, [name for name in X_train_ada.columns if name not in cols_del_imp]]
X_test_ada_imp = X_test_ada.loc[:, [name for name in X_test_ada.columns if name not in cols_del_imp]]
```

In [49]:
```
#Entrenar de nuevo
logreg_model_ada_imp = LogisticRegression(C=1.0,penalty='l2',random_state=1,max_iter=10000)
logreg_model_ada_imp.fit(X_train_ada_imp, y_train_ada)
```

Out[49]:
```
LogisticRegression(max_iter=10000, random_state=1)
```

In [50]:
```
#Prediccion sobre el test
pred_y_log_ada_imp = logreg_model_ada_imp.predict(X_test_ada_imp)
mostrar_resultados(y_test_ada, pred_y_log_ada_imp)
#Recall de attrition de 77%, activos en 89%

#Prediccion sobre el train
pred_y_log_ada_train_imp = logreg_model_ada_imp.predict(X_train_ada_imp)
```



```
              precision    recall  f1-score   support

           0       0.77      0.89      0.83       884
           1       0.88      0.73      0.80       890

    accuracy                           0.81      1774
   macro avg       0.82      0.81      0.81      1774
weighted avg       0.82      0.81      0.81      1774
```

In [51]:
```
metricas_comparacion(y_test_ada, pred_y_log_ada_imp, y_train_ada, pred_y_log_ada_train_imp)
```

```
Accuracy:  0.8139797068771139
AUC test:  0.8142521226295186
AUC train:  0.8253010567134088
Delta AUC (overfitting):  0.011048934083890183
```

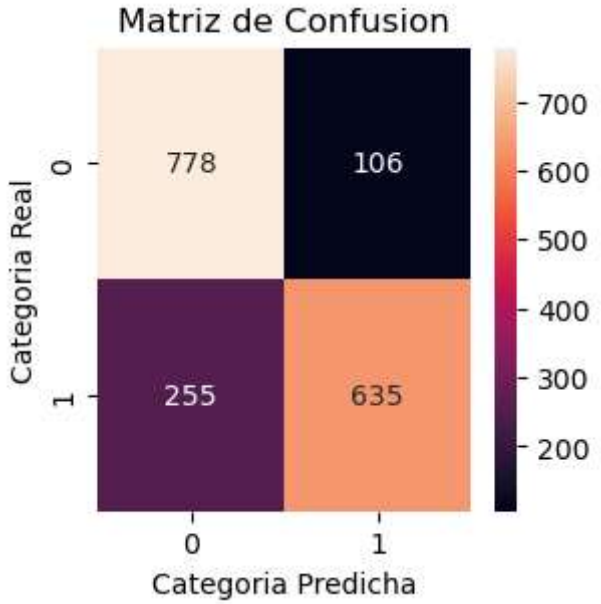
In [39]:
```
#Importancia de las variables
#coefficients_log_ada_imp = logreg_model_ada_imp.coef_[0]

#ft_importance_log_ada_imp = pd.DataFrame({'Feature': X_train_ada_imp.columns, 'Importance': coefficients_log_ada_imp})
#ft_importance_log_ada_imp = ft_importance_log_ada_imp.sort_values('Importance', ascending=True)
#ft_importance_log_ada_imp.plot(x='Feature', y='Importance', kind='barh', figsize=(10, 10))
```

Entrenamiento ADASYN Decision Tree

In [41]:
```
#Arbol de Decision individual ADASYN
dectree_model_ada = DecisionTreeClassifier(max_depth= 5, random_state = 1)
dectree_model_ada.fit(X_train_ada,y_train_ada)
```

Out[41]:
```
DecisionTreeClassifier(max_depth=5, random_state=1)
```

In [42]:
```
#Prediccion sobre el test
pred_y_dectree_ada = dectree_model_ada.predict(X_test_ada)
mostrar_resultados(y_test_ada, pred_y_dectree_ada)
#Recall de attrition de 71%, activos en 88%

#Prediccion sobre el train
pred_y_dectree_ada_train = dectree_model_ada.predict(X_train_ada)
```



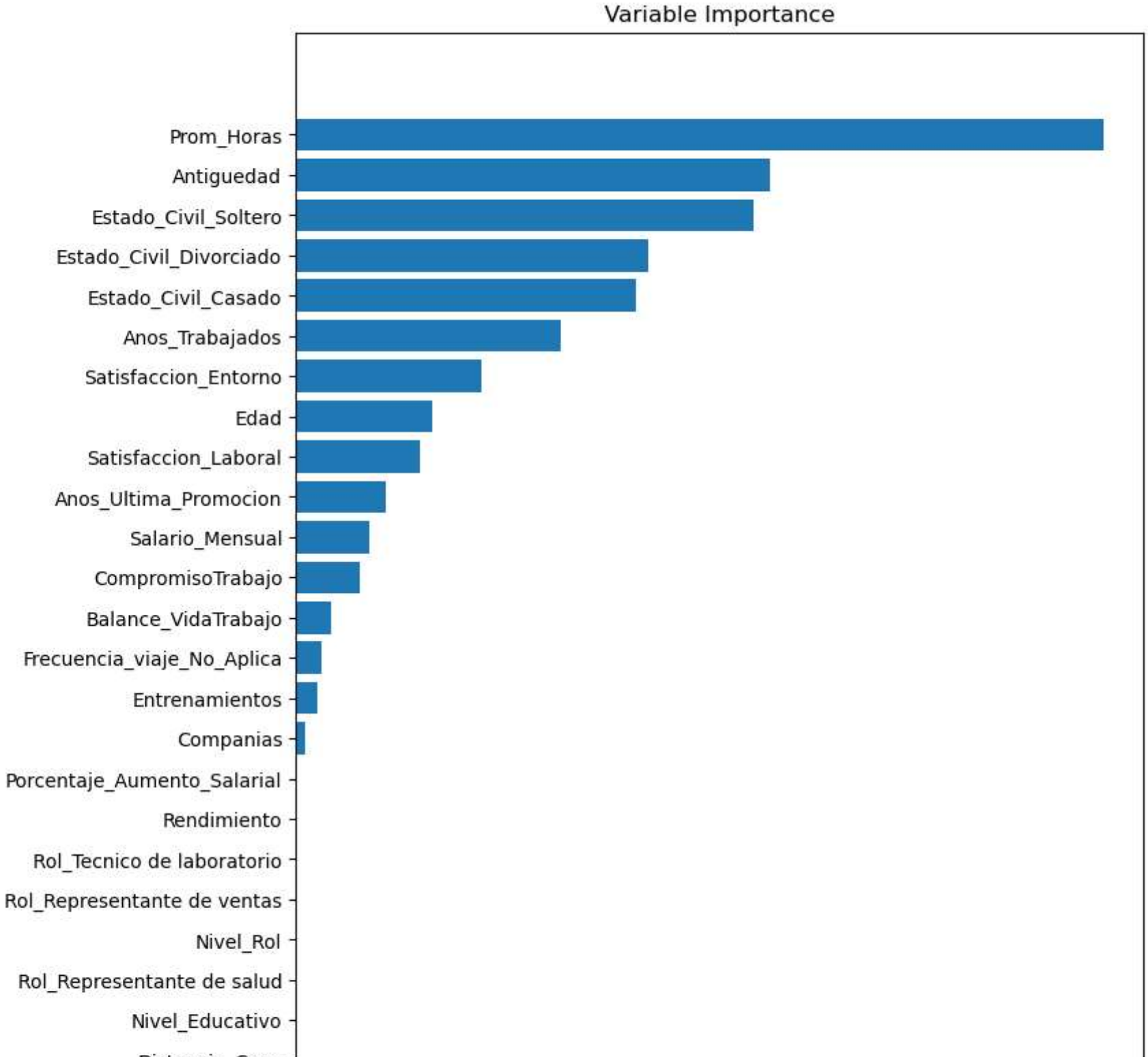
	precision	recall	f1-score	support
0	0.75	0.88	0.81	884
1	0.86	0.71	0.78	890
accuracy			0.80	1774
macro avg	0.81	0.80	0.80	1774
weighted avg	0.81	0.80	0.80	1774

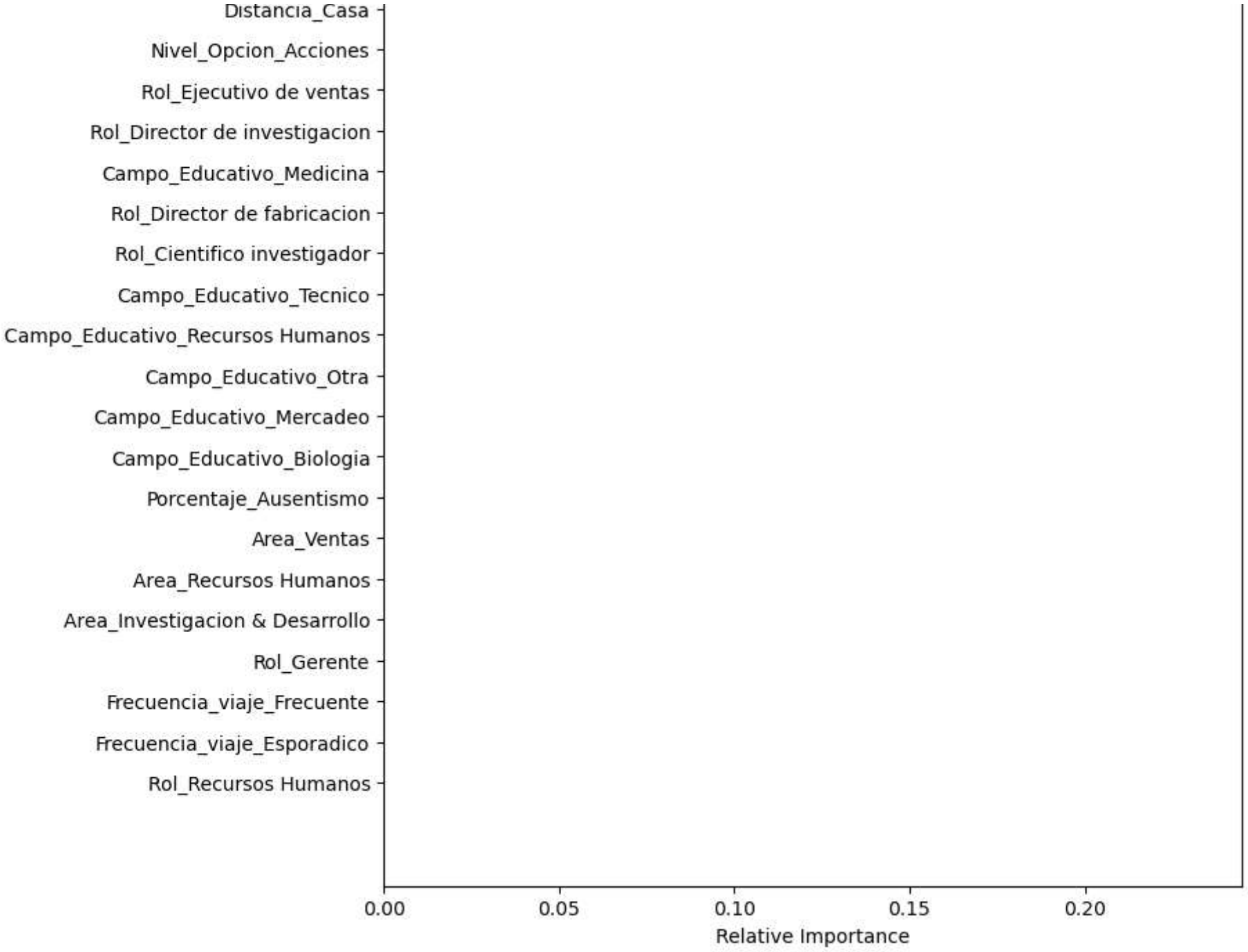
In [43]:
```
metricas_comparacion(y_test_ada, pred_y_dectree_ada, y_train_ada, pred_y_dectree_ada_train)
```

```
Accuracy:  0.7965050732807215
AUC test:  0.7967868219024861
AUC train:  0.8051023120189122
Delta AUC (overfitting):  0.008315490116426183
```

In [44]:
```
#Hallar variables importantes
feature_importance = dectree_model_ada.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                             #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5

plt.figure(figsize=(8, 18))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_sm.keys()[sorted_idx])
```

```
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Prom_Horas
Antiguedad
Estado_Civil_Soltero
Estado_Civil_Divorciado
Estado_Civil_Casado
Anos_Trabajados
Satisfaccion_Entorno
Edad
Satisfaccion_Laboral
Anos_Ultima_Promocion
Salario_Mensual
CompromisoTrabajo
Balance_VidaTrabajo
Frecuencia_viaje_No_Aplica
Entrenamientos
Companias
Porcentaje_Aumento_Salarial
Rendimiento
Rol_Tecnico de laboratorio
Rol_Representante de ventas
Nivel_Rol
Rol_Representante de salud
Nivel_Educativo



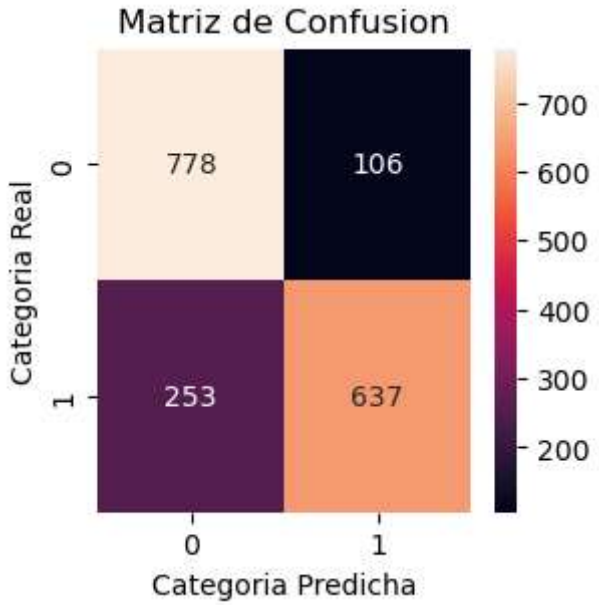
In [45]:
```
#Modelo de Decision Tree ADAYSIN(solo importantes)

#Quitar columnas con menos importancia
```

```
cols_del_imp = [ 'Porcentaje_Aumento_Salarial','Rendimiento','Rol_Tecnico de laboratorio','Rol_Representante de ventas',
                 'Nivel_Rol','Rol_Representante de salud','Nivel_Educativo','Distancia_Casa','Nivel_Opcion_Acciones',
                 'Rol_Ejecutivo de ventas','Rol_Director de investigacion','Campo_Educativo_Medicina',
                 'Rol_Director de fabricacion','Rol_Cientifico investigador','Campo_Educativo_Tecnico',
                 'Campo_Educativo_Recursos Humanos','Campo_Educativo_Otra','Campo_Educativo_Mercadeo',
                 'Campo_Educativo_Biologia','Porcentaje_Ausentismo','Area_Ventas','Area_Recursos Humanos',
                 'Area_Investigacion & Desarrollo','Rol_Gerente','Frecuencia_viaje_Frecuente','Frecuencia_viaje_Esporadico',
                 'Frecuencia_viaje_No_Aplica','Rol_Recursos Humanos']

X_train_sm_imp = X_train_sm.loc[:, [name for name in X_train_sm.columns if name not in cols_del_imp]]
X_test_sm_imp = X_test_sm.loc[:, [name for name in X_test_sm.columns if name not in cols_del_imp]]
```

In [46]:
```
#Arbol de Decision individual ADASYN con variables importantes
dectree_model_ada_imp = DecisionTreeClassifier(max_depth= 5, random_state = 1)
dectree_model_ada_imp.fit(X_train_ada_imp,y_train_ada)
```

Out[46]:
```
DecisionTreeClassifier(max_depth=5, random_state=1)
```

In [47]:
```
#Prediccion sobre el test
pred_y_dectree_ada_imp = dectree_model_ada_imp.predict(X_test_ada_imp)
mostrar_resultados(y_test_ada, pred_y_dectree_ada_imp)
#Recall de attrition de 72%, activos en 88%

#Prediccion sobre el train
pred_y_dectree_ada_train_imp = dectree_model_ada_imp.predict(X_train_ada_imp)
```



```
              precision    recall  f1-score   support

           0       0.75      0.88      0.81       884
           1       0.86      0.72      0.78       890

    accuracy                           0.80      1774
   macro avg       0.81      0.80      0.80      1774
weighted avg       0.81      0.80      0.80      1774
```

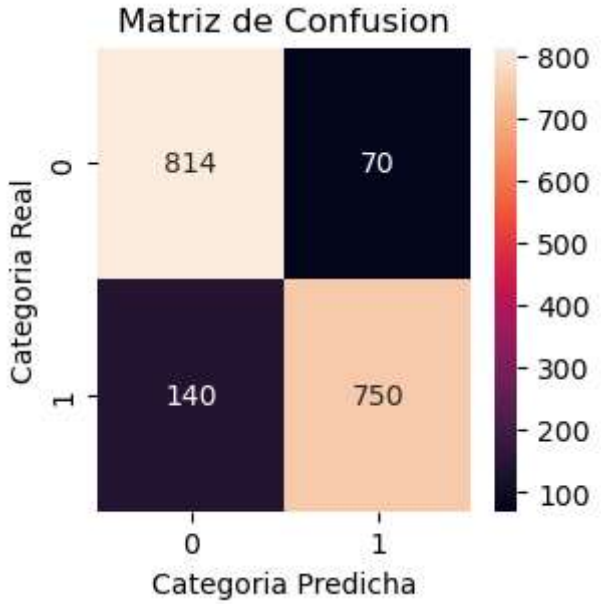
In [48]:
```
metricas_comparacion(y_test_ada, pred_y_dectree_ada_imp, y_train_ada, pred_y_dectree_ada_train_imp)
```

```
Accuracy:  0.7976324689966178
AUC test:  0.7979104174081041
AUC train:  0.8041411432376743
Delta AUC (overfitting):  0.006230725829570183
```

Entrenamiento ADASYN Random Forest

In [32]:
```
#Random Forest con ADASYN
rf_model_ada =RandomForestClassifier(max_depth=5,random_state=1, class_weight = 'balanced')
rf_model_ada.fit(X_train_ada,y_train_ada)

#Prediccion sobre test
y_pred_rf_ada = rf_model_ada.predict(X_test_ada)
```

In [33]:
```
mostrar_resultados(y_test_ada, y_pred_rf_ada)
```



	precision	recall	f1-score	support
0	0.85	0.92	0.89	884
1	0.91	0.84	0.88	890
accuracy			0.88	1774
macro avg	0.88	0.88	0.88	1774
weighted avg	0.88	0.88	0.88	1774

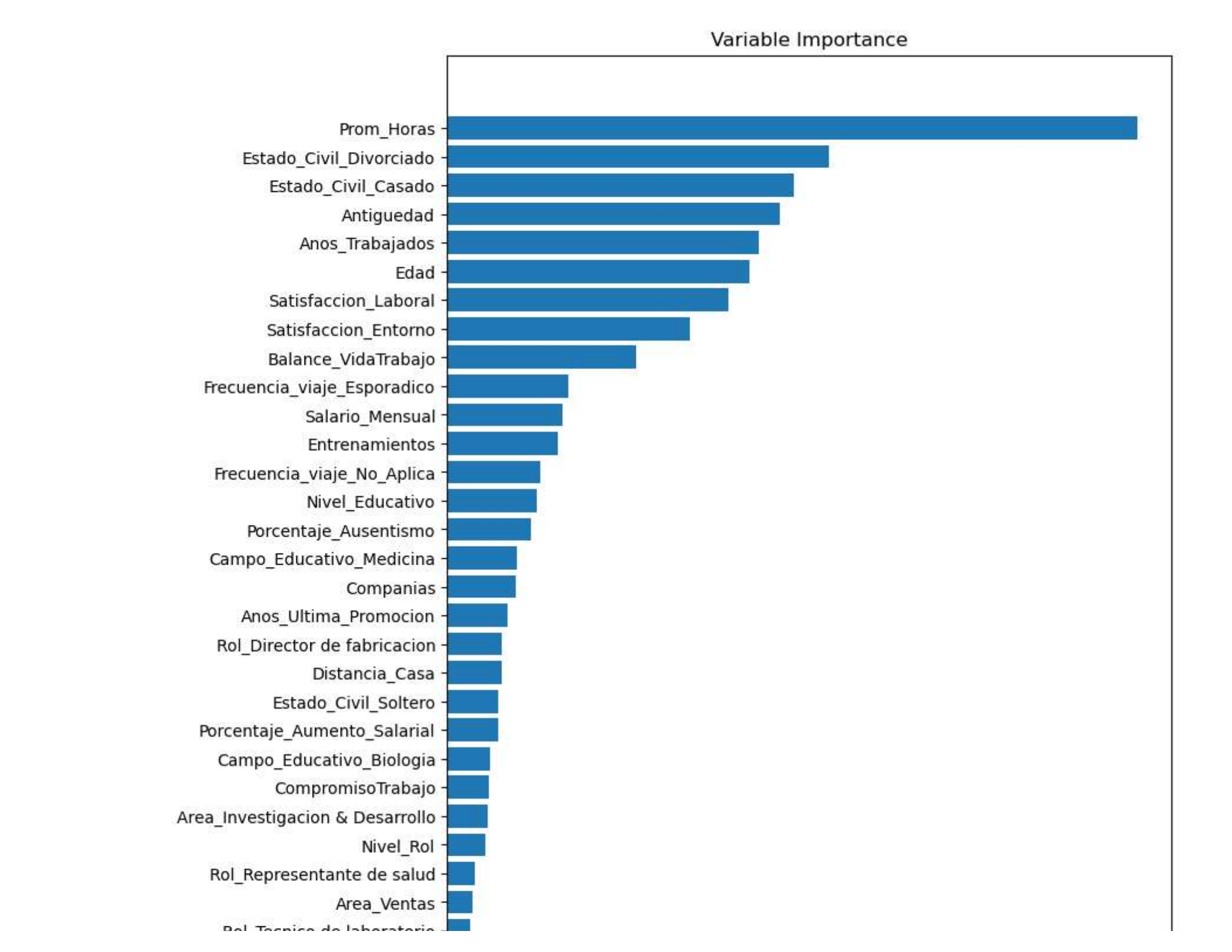
In [34]:
```
#Prediccion sobre el train
y_pred_rf_ada_train = rf_model_ada.predict(X_train_ada)
```

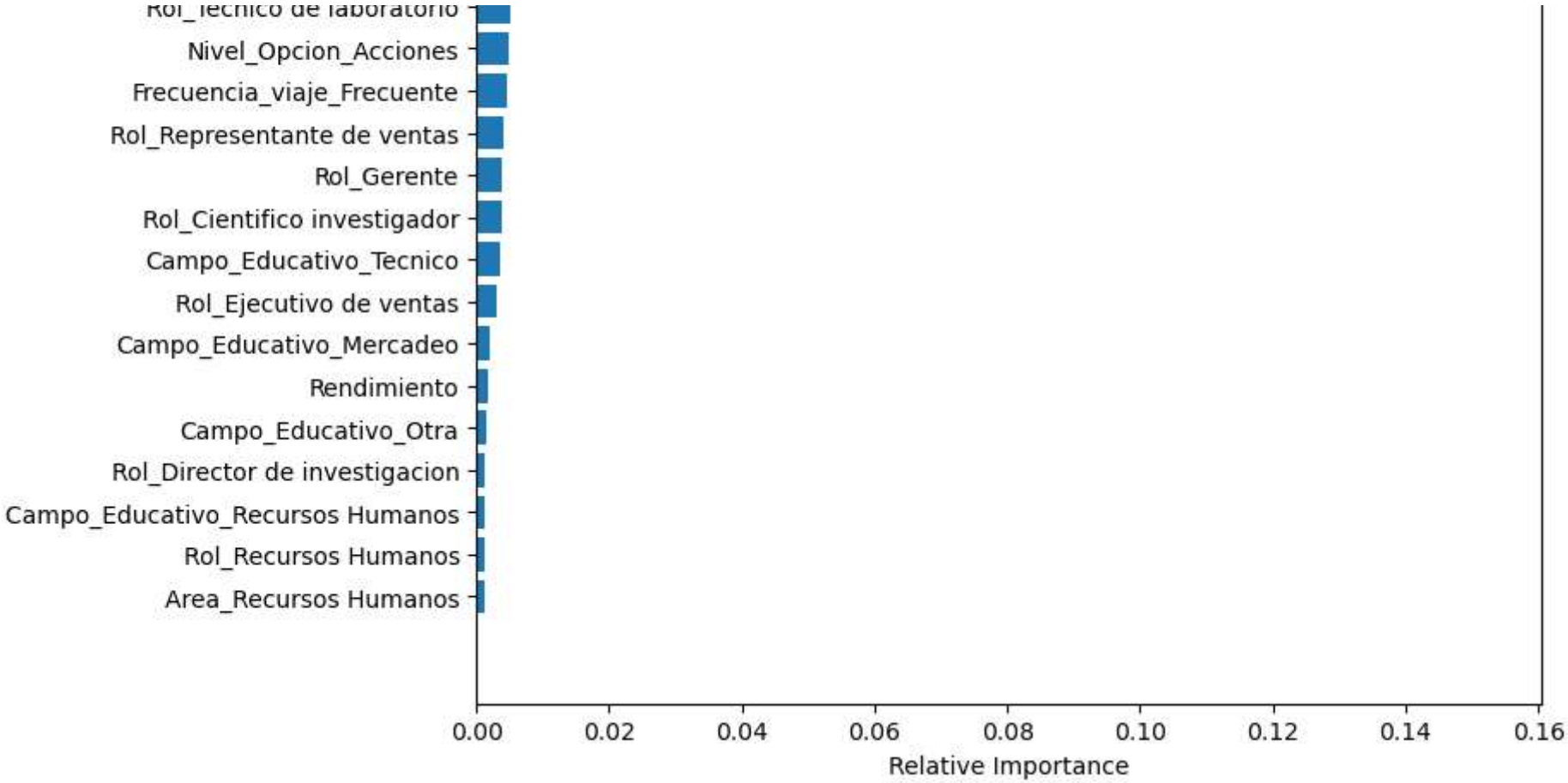
In [35]:
```
metricas_comparacion(y_test_ada, y_pred_rf_ada, y_train_ada, y_pred_rf_ada_train)
```

```
Accuracy:  0.8816234498308907
AUC test:  0.8817555544257463
AUC train:  0.8884471963331888
Delta AUC (overfitting):  0.006691641907442536
```

In [36]:
```
#Importancia variables
feature_importance = rf_model_ada.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                              #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5
```

```
plt.figure(figsize=(8, 15))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_ada.keys()[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Prom_Horas
Estado_Civil_Divorciado
Estado_Civil_Casado
Antiguedad
Anos_Trabajados
Edad
Satisfaccion_Laboral
Satisfaccion_Entorno
Balance_VidaTrabajo
Frecuencia_viaje_Esporadico
Salario_Mensual
Entrenamientos
Frecuencia_viaje_No_Aplica
Nivel_Educativo
Porcentaje_Ausentismo
Campo_Educativo_Medicina
Companias
Anos_Ultima_Promocion
Rol_Director de fabricacion
Distancia_Casa
Estado_Civil_Soltero
Porcentaje_Aumento_Salarial
Campo_Educativo_Biologia
CompromisoTrabajo
Area_Investigacion & Desarrollo
Nivel_Rol
Rol_Representante de salud
Area_Ventas

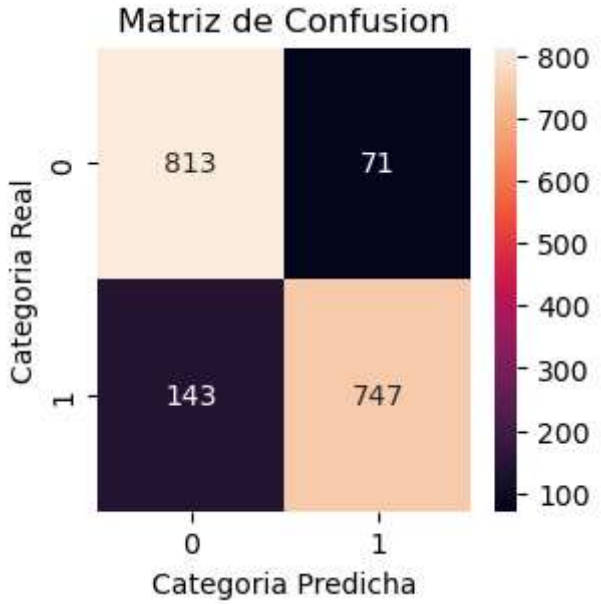


In [37]:

```
#Modelo de Random Forecast ADASYN (solo importantes)
# Segun la grafica las varaibles de rol, campo educativo, compromiso trabajo, nivel de acciones, rendimiento no son importantes
# se deja frecuencia de viaje frecuente porque las demas estan arriba
# se quitan todos los roles y areas para ser consistentes

#Quitar columnas con menos importancia
cols_del_imp = ['Area_Investigacion & Desarrollo','CompromisoTrabajo','Nivel_Opcion_Acciones','Campo_Educativo_Tecnico',
                'Area_Ventas','Campo_Educativo_Biologia','Rol_Ejecutivo de ventas','Rol_Representante de ventas',
                'Campo_Educativo_Mercadeo','Campo_Educativo_Otra','Rol_Gerente','Rol_Cientifico investigador',
                'Rol_Recursos Humanos','Area_Recursos Humanos','Rol_Representante de salud','Rol_Tecnico de laboratorio',
                'Rol_Director de investigacion','Rendimiento','Campo_Educativo_Recursos Humanos',
                'Rol_Director de fabricacion','Campo_Educativo_Medicina']

X_train_ada_imp = X_train_ada.loc[:, [name for name in X_train_ada.columns if name not in cols_del_imp]]
X_test_ada_imp = X_test_ada.loc[:, [name for name in X_test_ada.columns if name not in cols_del_imp]]
```

In [38]:
```
#Entrenar el modelo de nuevo con variables importantes
#Random Forest individual
rf_model_ada_imp =RandomForestClassifier(max_depth=5,random_state=1, class_weight = 'balanced')
rf_model_ada_imp.fit(X_train_ada_imp,y_train_ada)

#Prediccion sobre test
y_pred_rf_ada_imp = rf_model_ada_imp.predict(X_test_ada_imp)
```

In [39]:
```
mostrar_resultados(y_test_ada, y_pred_rf_ada_imp)
```



	precision	recall	f1-score	support
0	0.85	0.92	0.88	884
1	0.91	0.84	0.87	890
accuracy			0.88	1774
macro avg	0.88	0.88	0.88	1774
weighted avg	0.88	0.88	0.88	1774

In [40]:
```
metricas_comparacion(y_test_ada, y_pred_rf_ada_imp, y_train_ada, y_pred_rf_ada_train)
```

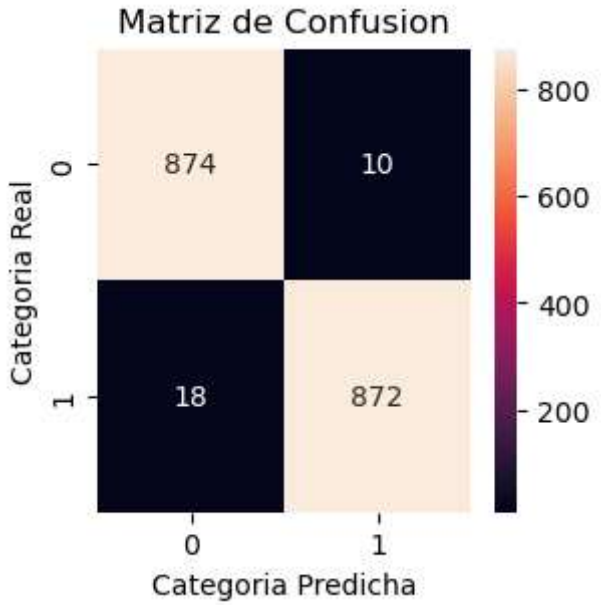
```
Accuracy:  0.8793686583990981
AUC test:  0.8795045503075906
AUC train:  0.8884471963331888
Delta AUC (overfitting):  0.008942646025598244
```

Entrenamiento ADASYN Gradient Boosting

In [52]:
```
#Gradient Boosting individual
gbm_model_ada = GradientBoostingClassifier(max_depth = 5,max_features = 'auto',random_state = 1)
gbm_model_ada.fit(X_train_ada,y_train_ada)
```

Out[52]:
```
GradientBoostingClassifier(max_depth=5, max_features='auto', random_state=1)
```

In [53]:
```
#Prediccion sobre el test
pred_y_gbm_ada = gbm_model_ada.predict(X_test_ada)
mostrar_resultados(y_test_ada, pred_y_gbm_ada)
#Recall de attrition de 98%, activos en 99%

#Prediccion sobre el train
pred_y_gbm_ada_train = gbm_model_ada.predict(X_train_ada)
```



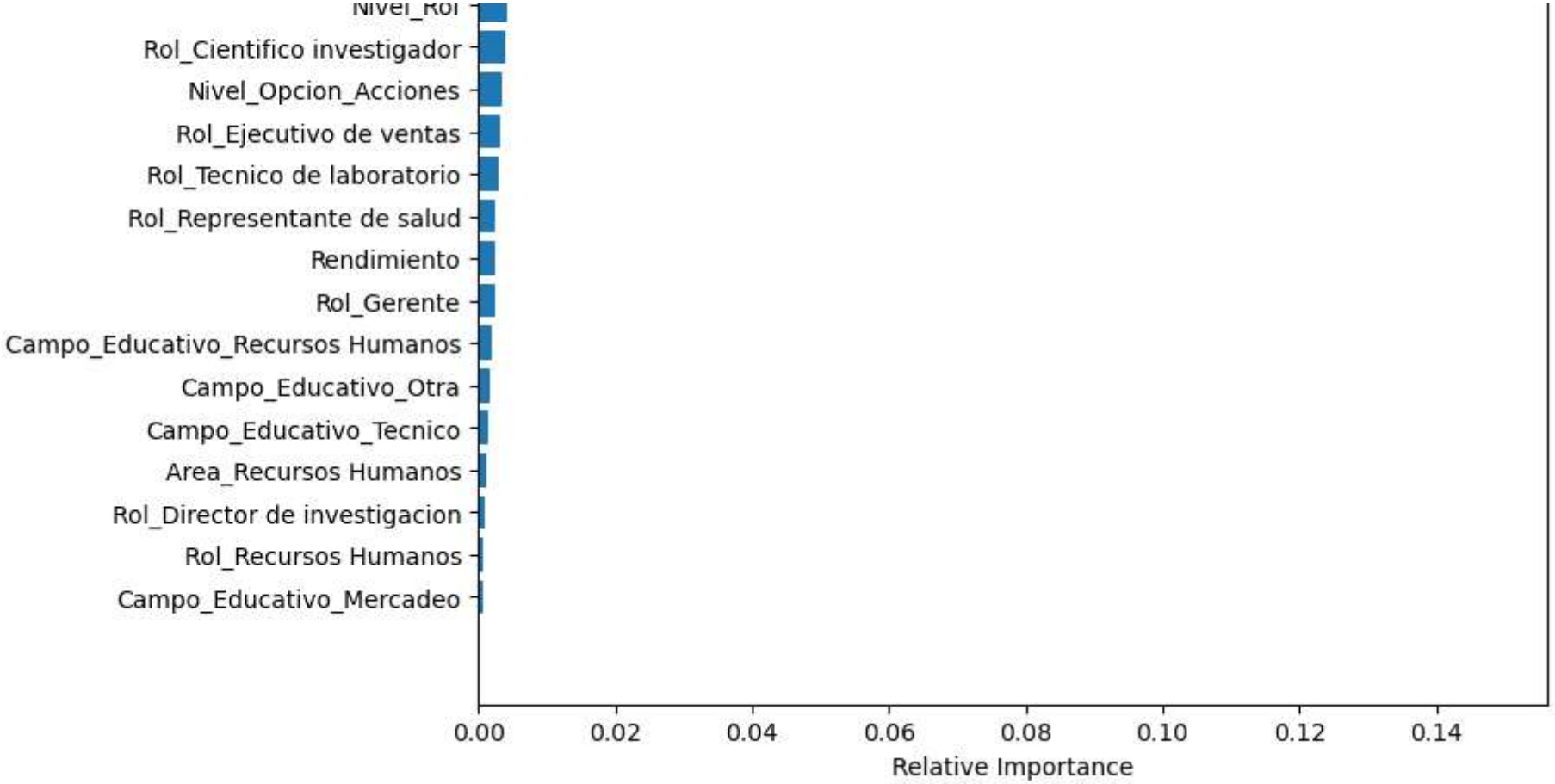
	precision	recall	f1-score	support
0	0.98	0.99	0.98	884
1	0.99	0.98	0.98	890
accuracy			0.98	1774
macro avg	0.98	0.98	0.98	1774
weighted avg	0.98	0.98	0.98	1774

In [54]:
```
metricas_comparacion(y_test_ada, pred_y_gbm_ada, y_train_ada, pred_y_gbm_ada_train)
```

```
Accuracy:  0.9842164599774521
AUC test:  0.9842315318521532
AUC train:  0.9988465974625145
Delta AUC (overfitting):  0.0146150656103613
```

In [60]:
```
feature_importance = gbm_model_ada.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                              #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5

plt.figure(figsize=(8, 15))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_ada.keys()[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Prom_Horas
Porcentaje_Ausentismo
Estado_Civil_Divorciado
Edad
Antiguedad
Anos_Trabajados
Estado_Civil_Casado
Satisfaccion_Laboral
Salario_Mensual
Estado_Civil_Soltero
Satisfaccion_Entorno
Companias
Anos_Ultima_Promocion
Balance_VidaTrabajo
Entrenamientos
Distancia_Casa
Nivel_Educativo
Porcentaje_Aumento_Salarial
Frecuencia_viaje_Esporadico
Frecuencia_viaje_No_Aplica
CompromisoTrabajo
Area_Ventas
Frecuencia_viaje_Frecuente
Campo_Educativo_Biologia
Campo_Educativo_Medicina
Rol_Director de fabricacion
Area_Investigacion & Desarrollo
Rol_Representante de ventas

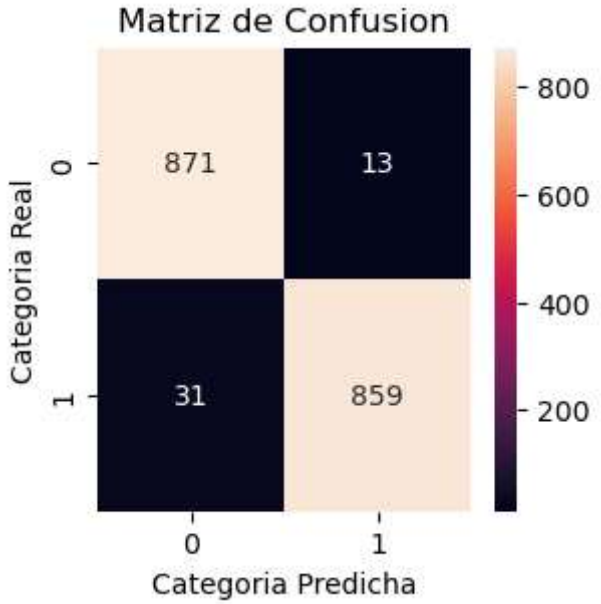


In [56]:
```
#Modelo de Gradient Boosting ADASYN (solo importantes)

#Quitar columnas con menos importancia
cols_del_imp = ['Campo_Educativo_Mercadeo','Rol_Recursos Humanos','Rol_Director de investigacion',
                'Area_Recursos Humanos','Campo_Educativo_Tecnico','Campo_Educativo_Otra','Campo_Educativo_Recursos Humanos',
                'Rol_Gerente','Rendimiento','Rol_Representante de salud','Rol_Tecnico de laboratorio',
                'Rol_Ejecutivo de ventas','Nivel_Opcion_Acciones','Rol_Cientifico investigador','Nivel_Rol',
                'Rol_Representante de ventas','Area_Investigacion & Desarrollo','Rol_Director de fabricacion',
                'Campo_Educativo_Medicina','Campo_Educativo_Biologia']

X_train_ada_imp = X_train_ada.loc[:, [name for name in X_train_ada.columns if name not in cols_del_imp]]
X_test_ada_imp = X_test_ada.loc[:, [name for name in X_test_ada.columns if name not in cols_del_imp]]
```

In [57]:
```
#Entrenar de nuevo
gbm_model_ada_imp = GradientBoostingClassifier(max_depth = 5,max_features = 'auto',random_state = 1)
gbm_model_ada_imp.fit(X_train_ada_imp,y_train_ada)
```

Out[57]:
```
GradientBoostingClassifier(max_depth=5, max_features='auto', random_state=1)
```

In [58]:
```
#Prediccion sobre el test
pred_y_gbm_ada_imp = gbm_model_ada_imp.predict(X_test_ada_imp)
mostrar_resultados(y_test_ada, pred_y_gbm_ada_imp)
#Recall de attrition de 97%, activos en 99%

#Prediccion sobre el train
pred_y_gbm_ada_train_imp = gbm_model_ada_imp.predict(X_train_ada_imp)
```



	precision	recall	f1-score	support
0	0.97	0.99	0.98	884
1	0.99	0.97	0.98	890
accuracy			0.98	1774
macro avg	0.98	0.98	0.98	1774
weighted avg	0.98	0.98	0.98	1774

In [59]:
```
metricas_comparacion(y_test_ada, pred_y_gbm_ada_imp, y_train_ada, pred_y_gbm_ada_train_imp)
```

```
Accuracy:  0.9751972942502819
AUC test:  0.9752313284864508
AUC train:  0.9963899475521882
Delta AUC (overfitting):  0.02115861906573746
```

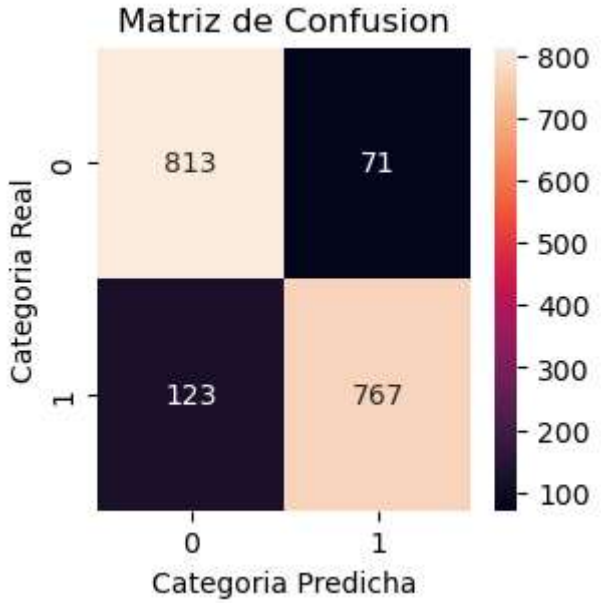
In [62]:
```
#feature_importance = gbm_model_ada_imp.feature_importances_
##Importancia relativa a la importancia maxima
#feature_importance = 100.0 * (feature_importance / 100)
#                             #feature_importance.max())
#sorted_idx = np.argsort(feature_importance)
#pos = np.arange(sorted_idx.shape[0]) + .5
#
#plt.figure(figsize=(8, 18))
#plt.barh(pos, feature_importance[sorted_idx], align='center')
#plt.yticks(pos, X_train_ada_imp.keys()[sorted_idx])
#plt.xlabel('Relative Importance')
#plt.title('Variable Importance')
#plt.show()
```

Búsqueda de mejor semilla sobre modelo elegido: Random Forest (ADASYN) con variables importantes

In [54]:
```
#Almacenamiento inicial de semilla y AUC
mejor_seed = 3996
mejor_auc = 0.890740

#Iterador sobre semillas y predicciones
for i in range(3001,5001):
    #Random Forest individual
    rf_model_ada =RandomForestClassifier(max_depth=5,random_state=i, class_weight = 'balanced')
    rf_model_ada.fit(X_train_ada_imp,y_train_ada)
    #Prediccion sobre test
    y_pred_rf_ada = rf_model_ada.predict(X_test_ada_imp)
    #AUC test
    fpr, tpr, _ = metrics.roc_curve(y_test_ada,  y_pred_rf_ada)
    auc_test = metrics.roc_auc_score(y_test_ada, y_pred_rf_ada)
    if auc_test > mejor_auc:
        mejor_seed = i
        mejor_auc = auc_test

#Imprimir mejores resultados
print("Mejor Seed: ",mejor_seed)
print("Mejor AUC test: ",mejor_auc)

#corriendo hasta 5001
```

```
Mejor Seed:  3996
Mejor AUC test:  0.8907405053637704
```

In [55]:
```
#Resultados Random Forest ADASYN con semilla ganadora
rf_model_ada =RandomForestClassifier(max_depth=5,random_state=3996, class_weight = 'balanced')
rf_model_ada.fit(X_train_ada_imp,y_train_ada)

#Prediccion sobre test
y_pred_rf_ada = rf_model_ada.predict(X_test_ada_imp)

mostrar_resultados(y_test_ada, y_pred_rf_ada)
```



	precision	recall	f1-score	support
0	0.87	0.92	0.89	884
1	0.92	0.86	0.89	890
accuracy			0.89	1774
macro avg	0.89	0.89	0.89	1774
weighted avg	0.89	0.89	0.89	1774

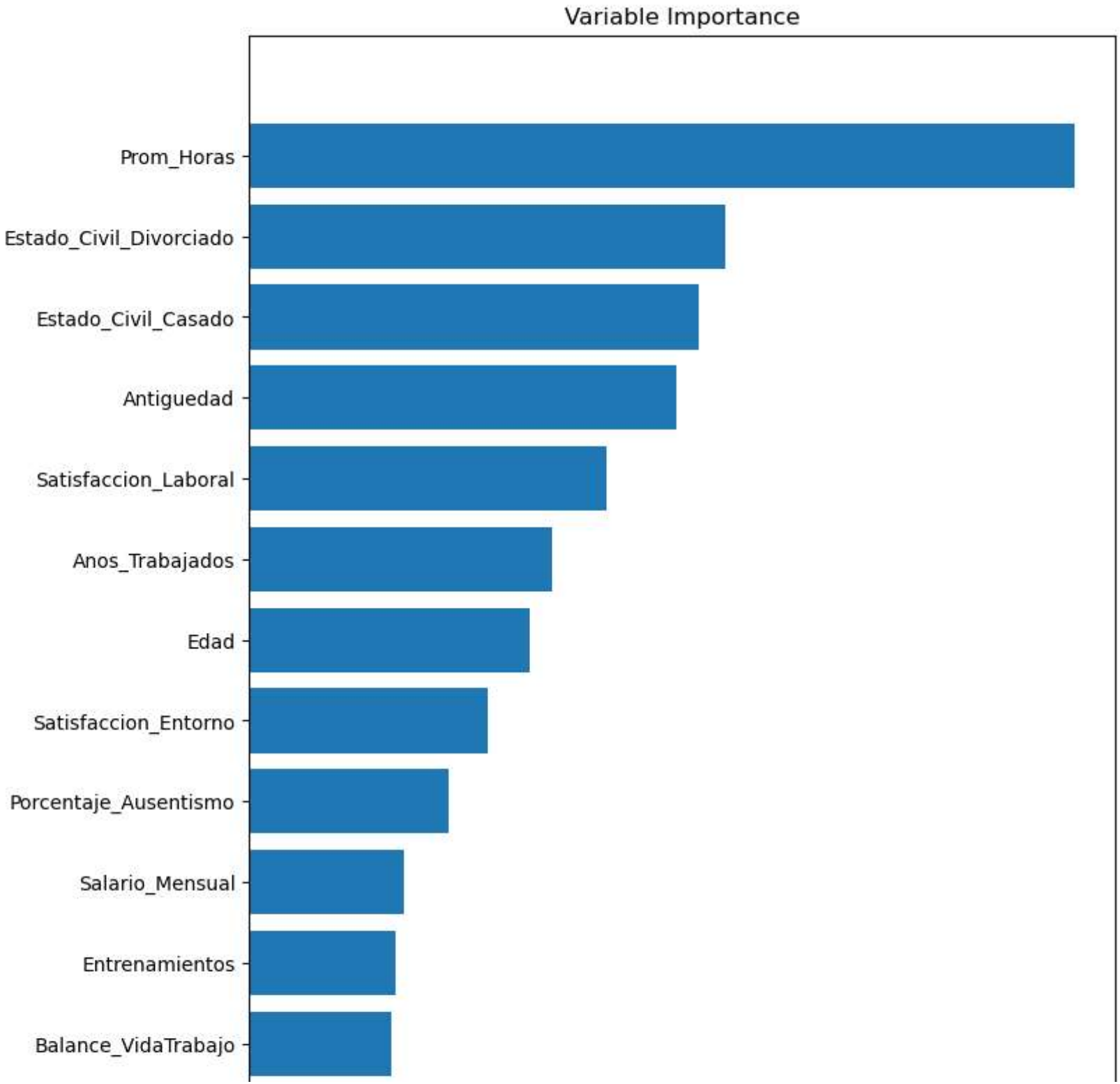
In [58]:
```
#Prediccion sobre el train
pred_y_rf_ada_train = rf_model_ada.predict(X_train_ada_imp)
```

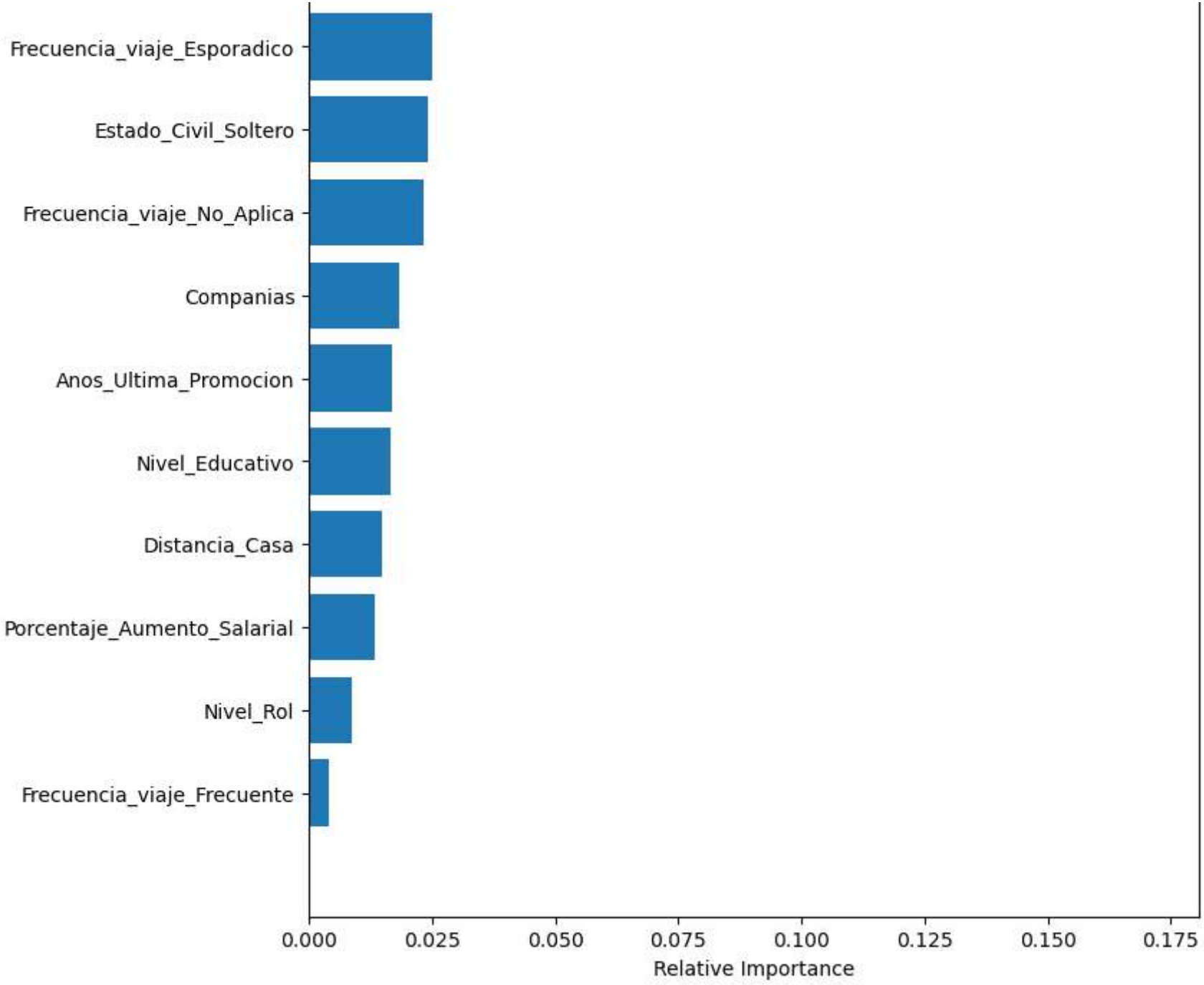
In [59]:
```
metricas_comparacion(y_test_ada, y_pred_rf_ada, y_train_ada, pred_y_rf_ada_train)
```

```
Accuracy:  0.8906426155580609
AUC test:  0.8907405053637704
AUC train:  0.8830928397906496
Delta AUC (overfitting):  0.007647665573120799
```

In [56]:

```python
#Hallar variables importantes
feature_importance = rf_model_ada.feature_importances_
#Importancia relativa a la importancia maxima
feature_importance = 100.0 * (feature_importance / 100)
                              #feature_importance.max())
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5

plt.figure(figsize=(8, 18))
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, X_train_ada_imp.keys()[sorted_idx])
plt.xlabel('Relative Importance')
plt.title('Variable Importance')
plt.show()
```


Variable Importance
Prom_Horas
Estado_Civil_Divorciado
Estado_Civil_Casado
Antiguedad
Satisfaccion_Laboral
Anos_Trabajados
Edad
Satisfaccion_Entorno
Porcentaje_Ausentismo
Salario_Mensual
Entrenamientos
Balance_VidaTrabajo



Predicción sobre base completa para Dashboard

In [60]:
```
#Copia de datos de entrada y llave ID empleado
#De df_raw se sacará la base de dashboard
df_raw = df.copy()
df_raw = df_raw.set_index('ID_empleado')
```

In [61]:
```
df_raw.head()
```

Out[61]:

ID_empleado	Edad	Desercion	Frecuencia_viaje	Area	Distancia_Casa	Nivel_Educativo	Campo_Educativo	Recuento_Empleado	Genero	Nivel_Rol
1	51	No	Esporadico	Ventas	6	2	Biologia	1	Femenino	2
2	31	Si	Frecuente	Investigacion & Desarrollo	10	1	Biologia	1	Femenino	3
3	32	No	Frecuente	Ventas	17	4	Otra	1	Masculino	3
4	38	No	No_Aplica	Recursos Humanos	2	5	Biologia	1	Masculino	3
5	32	No	Esporadico	Ventas	10	1	Medicina	1	Masculino	3

In [62]:
```
#Quitar columnas sobrantes para crear entrada al modelo
#De df_raw_X se sacara entrada al modelo, omitiendo resultado final
cols_del = ['Mayor18','Recuento_Empleado','Horario','Genero','Anos_Lider_Actual','Ausentismo']
df_raw_X = df_raw.loc[:, [name for name in df_raw.columns if name not in cols_del]]

df_raw_X.head()
```

Out[62]:

ID_empleado	Edad	Desercion	Frecuencia_viaje	Area	Distancia_Casa	Nivel_Educativo	Campo_Educativo	Nivel_Rol	Rol	Estado_Civil	Sa
1	51	No	Esporadico	Ventas	6	2	Biologia	2	Representante de salud	Casado	
2	31	Si	Frecuente	Investigacion & Desarrollo	10	1	Biologia	3	Cientifico investigador	Soltero	
3	32	No	Frecuente	Ventas	17	4	Otra	3	Ejecutivo de ventas	Casado	
4	38	No	No_Aplica	Recursos Humanos	2	5	Biologia	3	Recursos Humanos	Casado	
5	32	No	Esporadico	Ventas	10	1	Medicina	3	Ejecutivo de ventas	Soltero	

In [63]:
```
#Dummificar y borrar target redundante
df_raw_X = pd.get_dummies(df_raw_X, columns=['Desercion', 'Frecuencia_viaje', 'Area','Campo_Educativo','Rol',
                                             'Estado_Civil'])
df_raw_X = df_raw_X.drop('Desercion_No', axis=1)
df_raw_X.head()
```

Out[63]:

ID_empleado	Edad	Distancia_Casa	Nivel_Educativo	Nivel_Rol	Salario_Mensual	Companias	Porcentaje_Aumento_Salarial	Nivel_Opcion_Acciones	Anos_Tra
1	51	6	2	2	131.16	1	11	0	
2	31	10	1	3	41.89	0	23	1	
3	32	17	4	3	193.28	1	15	3	
4	38	2	5	3	83.21	3	11	3	
5	32	10	1	3	23.42	4	12	2	

In [64]:
```
#Quitar target principal de la entrada
df_raw_X = df_raw_X.drop('Desercion_Si', axis=1)
df_raw_X.head()
```

Out[64]:

ID_empleado	Edad	Distancia_Casa	Nivel_Educativo	Nivel_Rol	Salario_Mensual	Companias	Porcentaje_Aumento_Salarial	Nivel_Opcion_Acciones	Anos_Tra
1	51	6	2	2	131.16	1	11	0	
2	31	10	1	3	41.89	0	23	1	
3	32	17	4	3	193.28	1	15	3	
4	38	2	5	3	83.21	3	11	3	
5	32	10	1	3	23.42	4	12	2	

In [65]:
```
#Quitar columnas con menos importancia segun analisis previo
cols_del_imp = ['Area_Investigacion & Desarrollo','CompromisoTrabajo','Nivel_Opcion_Acciones','Campo_Educativo_Tecnico',
                'Area_Ventas','Campo_Educativo_Biologia','Rol_Ejecutivo de ventas','Rol_Representante de ventas',
                'Campo_Educativo_Mercadeo','Campo_Educativo_Otra','Rol_Gerente','Rol_Cientifico investigador',
                'Rol_Recursos Humanos','Area_Recursos Humanos','Rol_Representante de salud','Rol_Tecnico de laboratorio',
                'Rol_Director de investigacion','Rendimiento','Campo_Educativo_Recursos Humanos',
                'Rol_Director de fabricacion','Campo_Educativo_Medicina']

df_raw_X = df_raw_X.loc[:, [name for name in df_raw_X.columns if name not in cols_del_imp]]
```

In [66]:
```
df_raw_X.head()
```

Out[66]:

ID_empleado	Edad	Distancia_Casa	Nivel_Educativo	Nivel_Rol	Salario_Mensual	Companias	Porcentaje_Aumento_Salarial	Anos_Trabajados	Entrenamiento
1	51	6	2	2	131.16	1	11	1	
2	31	10	1	3	41.89	0	23	6	
3	32	17	4	3	193.28	1	15	5	
4	38	2	5	3	83.21	3	11	13	
5	32	10	1	3	23.42	4	12	9	

In [67]:
```
#Random Forest individual campeon
rf_model_ada =RandomForestClassifier(max_depth=5,random_state=3996, class_weight = 'balanced')
rf_model_ada.fit(X_train_ada_imp,y_train_ada)
```

Out[67]:
```
RandomForestClassifier(class_weight='balanced', max_depth=5, random_state=3996)
```

In [68]:
```
#Prediccion sobre entrada
y_pred_rf_ada_raw = rf_model_ada.predict(df_raw_X)
```

In [69]:
```
#Convertir prediccion a dataframe con mismo indice de entrada
y_pred_rf_ada_raw_df = pd.DataFrame(data = y_pred_rf_ada_raw, columns = ['y_pred_rf_ada_raw'],
                                    index = df_raw_X.index.copy())

y_pred_rf_ada_raw_df.head()
```

Out[69]:

ID_empleado	y_pred_rf_ada_raw
1	0
2	1
3	0
4	0
5	0

In [70]:
```
#Probabilidades sobre entrada
y_prob_rf_ada_raw = rf_model_ada.predict_proba(df_raw_X)[:,1]
y_prob_rf_ada_raw
```

Out[70]:
```
array([0.3208080212, 0.6122491676, 0.3716451499, ..., 0.1820298632,
       0.3708517273, 0.3106304255])
```

In [71]:
```
#Convertir probabilidades a dataframe con mismo indice de entrada
y_prob_rf_ada_raw_df = pd.DataFrame(data = y_prob_rf_ada_raw, columns = ['y_prob_rf_ada_raw'],
                                    index = df_raw_X.index.copy())

y_prob_rf_ada_raw_df.head()
```

Out[71]:

ID_empleado	y_prob_rf_ada_raw
1	0.320808
2	0.612249
3	0.371645
4	0.195029
5	0.453909

In [72]:
```
#Combinar resultados con entrada cruda
df_out = pd.merge(df_raw, y_pred_rf_ada_raw_df, how = 'left', left_index = True, right_index = True)
df_out = pd.merge(df_out, y_prob_rf_ada_raw_df, how = 'left', left_index = True, right_index = True)
df_out.head()
```

Out[72]:

ID_empleado	Edad	Desercion	Frecuencia_viaje	Area	Distancia_Casa	Nivel_Educativo	Campo_Educativo	Recuento_Empleado	Genero	Nivel_Rol
1	51	No	Esporadico	Ventas	6	2	Biologia	1	Femenino	2
2	31	Si	Frecuente	Investigacion & Desarrollo	10	1	Biologia	1	Femenino	3
3	32	No	Frecuente	Ventas	17	4	Otra	1	Masculino	3
4	38	No	No_Aplica	Recursos Humanos	2	5	Biologia	1	Masculino	3
5	32	No	Esporadico	Ventas	10	1	Medicina	1	Masculino	3

In [73]:
```
#ID empleado nuevamente a columna
df_out.reset_index(inplace=True)
df_out.head()
```

Out[73]:

	ID_empleado	Edad	Desercion	Frecuencia_viaje	Area	Distancia_Casa	Nivel_Educativo	Campo_Educativo	Recuento_Empleado	Genero	Nivel_
0	1	51	No	Esporadico	Ventas	6	2	Biologia	1	Femenino	
1	2	31	Si	Frecuente	Investigacion & Desarrollo	10	1	Biologia	1	Femenino	
2	3	32	No	Frecuente	Ventas	17	4	Otra	1	Masculino	
3	4	38	No	No_Aplica	Recursos Humanos	2	5	Biologia	1	Masculino	
4	5	32	No	Esporadico	Ventas	10	1	Medicina	1	Masculino	

In [74]:

```
#Exportar a csv
ruta = r'C:\Users\Jaime Andres Molina\Documents\Maestria\Proyecto Empresarial\Entrega Semestre 3\all_attrition_prob_v2.csv'
df_out.to_csv(ruta, index = False, sep=';')
```

Calculadora de Riesgo de Deserción para Candidatos

In [1]:
```
#Librerias numericas y graficos
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

#Graficos
import plotly as py
import plotly.graph_objs as go

#Manejo de fechas
import datetime as dt

#Modelos de Arboles
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier

#Medidas
from sklearn import metrics
from sklearn import model_selection
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score

#Split X - y en conjuntos training y testing
from sklearn.model_selection import train_test_split

#Mostrar todas las columnas de frame
pd.set_option('display.max_columns', None)

#Asignar el formato de los decimales
np.set_printoptions(formatter={'float': lambda x: "{0:0.10f}".format(x)})

#Para datos desbalanceados
from pylab import rcParams

from imblearn.under_sampling import NearMiss
from imblearn.over_sampling import RandomOverSampler
from imblearn.combine import SMOTETomek
```

```
from imblearn.ensemble import BalancedBaggingClassifier
from imblearn.over_sampling import SMOTE
from imblearn.over_sampling import ADASYN

from collections import Counter
```

In [2]:
```
#Ejecutar si no esta instalada la libreria tkinter en el equipo
#pip install tk
```

In [3]:
```
#Importar utilidades de tkinter (visualizacion)
import sys
from tkinter import *
from tkinter import ttk
from tkinter import filedialog
import tkinter as tk
#Importar libreria de imagenes
from PIL import ImageTk, Image
import os
```

Inclusión de modelo predictivo

In [4]:
```
#Carga de datos modelo entrenado
ruta = r'C:\Users\Jaime Andres Molina\Documents\Maestria\Proyecto Empresarial\Fuentes\01_Fuentes\all_attrition_modeling.csv'
#CSV
df = pd.read_csv (ruta, sep = ';')
```

In [5]:
```
#Quitar columnas por nombre
cols_del = ['ID_empleado','Mayor18','Recuento_Empleado','Horario','Genero','Anos_Lider_Actual','Ausentismo',
            'Frecuencia_viaje','Porcentaje_Aumento_Salarial','Nivel_Opcion_Acciones','Entrenamientos','Antiguedad',
            'Anos_Ultima_Promocion','Satisfaccion_Entorno','Satisfaccion_Laboral','Balance_VidaTrabajo',
            'CompromisoTrabajo','Rendimiento','Prom_Horas','Porcentaje_Ausentismo']
df_in = df.loc[:, [name for name in df.columns if name not in cols_del]]
```

In [6]:
```
#Dummificar variables seleccionadas
df_in= pd.get_dummies(df_in, columns=['Desercion', 'Area','Campo_Educativo', 'Rol', 'Estado_Civil'])
```

In [7]:
```
#Quitar columnas redundantes
cols_del_in = ['Desercion_No']
df_in = df_in.loc[:, [name for name in df_in.columns if name not in cols_del_in]]
```

In [8]:
```
#Definimos nuestras etiquetas y features
y = df_in['Desercion_Si']
X = df_in.drop('Desercion_Si', axis=1)
```

In [9]:
```
#ADASYN sobre entrenamiento
ada = ADASYN(sampling_strategy='auto', n_neighbors=5, random_state=1)
X_ada, y_ada = ada.fit_resample(X, y)
#Dividir la base en train y test de ADASYN
X_train_ada, X_test_ada, y_train_ada, y_test_ada = train_test_split(X_ada, y_ada, test_size=0.25, random_state=28)
```

In [10]:
```
#Random Forest con ADASYN mejor semilla
rf_model_ada =RandomForestClassifier(max_depth=5,random_state=4455, class_weight = 'balanced')
rf_model_ada.fit(X_train_ada,y_train_ada)
```

Out[10]:
```
RandomForestClassifier(class_weight='balanced', max_depth=5, random_state=4455)
```

Desarrollo de interfaz gráfica

In [11]:
```
#Crear app principal llamada root
root = tk.Tk()
#Se configura un titulo para la ventana
root.title("Calculadora de Probabilidad de Deserción")
#Para evitar que la ventana cambie de tamaño
root.resizable(0, 0)
#Configuracion de tamaño relativo de columnas y filas
#Ultima columna doble de ancho
root.columnconfigure(0, weight=1)
root.columnconfigure(1, weight=1)
root.columnconfigure(2, weight=2)
#Primera y segunda fila doble de ancho
root.rowconfigure(0, weight=2)
root.rowconfigure(1, weight=2)
```

In [12]:
```
#Crear titulo principal en frame con una etiqueta
titulo =Label(root,text="Probabilidad de Deserción para Candidatos",
              font=("Segoe UI",20,"bold"),fg="#005C76",anchor="center",padx=10, pady=10)
#Posicion del titulo
titulo.grid(column=1,row=0,columnspan=2)
```

In [13]:
```
#Insertar logo de farmaceutica
ruta_img = r'C:\Users\Jaime Andres Molina\Documents\Maestria\Proyecto Empresarial\Imagenes\calculadora.png'
img = ImageTk.PhotoImage(Image.open(ruta_img))
logo_empresa = Label(root,image = img,padx=10,pady=20)
logo_empresa.grid(column=0,row=0)
```

In [14]:
```
#Creacion de etiquetas de segmentos generales

#Crear etiqueta Criterio candidato y posicion
```

```
etiqueta_criteriocandidato=Label(root,text="Datos de Candidato",font=("Segoe UI",16,'bold'),fg="#A92E63")
etiqueta_criteriocandidato.grid(column=0,row=3,columnspan=2,padx=10, pady=10)
#Crear etiqueta resultados deserción y posicion
etiqueta_resultadosdesercion=Label(root,text="Resultados deserción",font=("Segoe UI",16,'bold'),fg="#A92E63")
etiqueta_resultadosdesercion.grid(column=2,row=3,padx=10, pady=10)

#Crear etiqueta resultado individual y posicion
etiqueta_individual=Label(root,text="Individual",font=("Segoe UI",14,'bold'),fg="#00A981")
etiqueta_individual.grid(column=2,row=5)
#Crear etiqueta resultado grupal y posicion
etiqueta_grupal=Label(root,text="Grupal",font=("Segoe UI",14,'bold'),fg="#00A981")
etiqueta_grupal.grid(column=2,row=10)
```

In [15]:

```
#Crear etiquetas de entrada de datos

#Candidato entrada numerica
entry_candidato=Label(root, text="N° Candidato",font=("Segoe UI",12),fg="#4D4D4D").grid(row=4, column=0,padx=10,pady=5,
                                                                                       sticky='E')
candidatoE =IntVar()
entry_candidato = Entry(root, textvariable=candidatoE,width=22,font=("Segoe UI",12))
entry_candidato.grid(row=4, column=1,padx=10,pady=5,sticky='W')

#Area entrada lista
entry_Area=Label(root, text="Area",font=("Segoe UI",12),fg="#4D4D4D").grid(row=5, column=0,padx=10,pady=5,sticky='E')
comboArea = ttk.Combobox(state="readonly",values=["Investigacion & Desarrollo", "Recursos Humanos", "Ventas"]
                         ,font=("Segoe UI",12))
comboArea.grid(row=5, column=1,padx=10,pady=5,sticky='W')

#Distancia a Casa entrada numerica
entry_Distancia=Label(root, text="Distancia [km]",font=("Segoe UI",12),fg="#4D4D4D").grid(row=6, column=0,padx=10,pady=5,
                                                                                         sticky='E')
dist_e= IntVar()
entry_Distancia=Entry(root, textvariable=dist_e,width=22,font=("Segoe UI",12))
entry_Distancia.grid(row=6, column=1,padx=10,pady=5,sticky='W')

#Nivel de rol entrada lista
entry_NivelRol=Label(root, text="Nivel Rol",font=("Segoe UI",12),fg="#4D4D4D").grid(row=7, column=0,padx=10,pady=5,
                                                                                   sticky='E')
comboNivelR = ttk.Combobox(state="readonly",values=["1","2","3","4","5"],font=("Segoe UI",12))
comboNivelR.grid(row=7, column=1,padx=10,pady=5,sticky='W')

#Rol entrada lista
entry_Rol=Label(root, text="Rol",font=("Segoe UI",12),fg="#4D4D4D").grid(row=8, column=0,padx=10, pady=5,sticky='E')
comboRol = ttk.Combobox(state="readonly",
                        values=["Cientifico investigador", "Director de fabricacion", "Director de investigacion",
                                "Ejecutivo de ventas","Gerente","Recursos Humanos","Representante de salud",
                                "Representante de ventas","Tecnico de laboratorio"]
```

```
                        ,font=("Segoe UI",12))
comboRol.grid(row=8, column=1,padx=10, pady=5,sticky='W')

#Campo Educativo entrada lista
entry_CampoEducativo=Label(root, text="Campo Educativo",font=("Segoe UI",12),fg="#4D4D4D").grid(row=9, column=0,padx=10,
                                                                                                pady=5,sticky='E')
comboCampoE = ttk.Combobox(state="readonly",
                           values=["Biologia", "Medicina", "Mercadeo","Otra","Recursos Humanos","Tecnico"]
                           ,font=("Segoe UI",12))
comboCampoE.grid(row=9, column=1,padx=10,pady=5,sticky='W')

#Nivel Educativo entrada lista
entry_NivelEducativo=Label(root, text="Nivel Educativo",font=("Segoe UI",12),fg="#4D4D4D").grid(row=10, column=0,padx=10,
                                                                                                pady=5,sticky='E')
comboNivelE = ttk.Combobox(state="readonly",values=["1","2","3","4","5"],font=("Segoe UI",12))
comboNivelE.grid(row=10, column=1,padx=10,pady=5,sticky='W')

#Experiencia entrada numerica
entry_exp =Label(root, text="Experiencia [Años]",font=("Segoe UI",12),fg="#4D4D4D").grid(row=11, column=0,padx=10,pady=5,
                                                                                         sticky='E')
exp_e= IntVar()
entry_exp=Entry(root, textvariable=exp_e,width=22,font=("Segoe UI",12))
entry_exp.grid(row=11, column=1,padx=10,pady=5,sticky='W')

#Compañias entrada numerica
entry_companias=Label(root, text="Compañías",font=("Segoe UI",12),fg="#4D4D4D").grid(row=12, column=0,padx=10,pady=5,
                                                                                     sticky='E')
companias_e= IntVar()
entry_companias=Entry(root, textvariable=companias_e,width=22,font=("Segoe UI",12))
entry_companias.grid(row=12, column=1,padx=10,pady=5,sticky='W')

#Salario entrada numerica
entry_salario=Label(root, text="Salario Mensual",font=("Segoe UI",12),fg="#4D4D4D").grid(row=13, column=0,padx=10,pady=5,
                                                                                        sticky='E')
salario_e= IntVar()
entry_salario=Entry(root, textvariable=salario_e,width=22,font=("Segoe UI",12))
entry_salario.grid(row=13, column=1,padx=10,pady=5,sticky='W')

#Estado Civil entrada lista
entry_EstadoCivil=Label(root, text="Estado Civil",font=("Segoe UI",12),fg="#4D4D4D").grid(row=14, column=0,padx=10,pady=5,
                                                                                          sticky='E')
comboEstadoC = ttk.Combobox(state="readonly",values=["Casado", "Divorciado", "Soltero"],font=("Segoe UI",12))
comboEstadoC.grid(row=14, column=1,padx=10,pady=5,sticky='W')

#Edad entrada numerica
entry_edad=Label(root, text="Edad",font=("Segoe UI",12),fg="#4D4D4D").grid(row=15, column=0,padx=10,pady=5,sticky='E')
edad_e= IntVar()
```

```
entry_edad=Entry(root, textvariable=edad_e,width=22,font=("Segoe UI",12))
entry_edad.grid(row=15, column=1,padx=10,pady=5,sticky='W')
```

In [16]:

```
#Label de Resultado prediccion individual e iconos

ruta_alta = r'C:\Users\Jaime Andres Molina\Documents\Maestria\Proyecto Empresarial\Imagenes\Alerta_Alta.png'
ruta_media = r'C:\Users\Jaime Andres Molina\Documents\Maestria\Proyecto Empresarial\Imagenes\Alerta_Media.png'
ruta_baja = r'C:\Users\Jaime Andres Molina\Documents\Maestria\Proyecto Empresarial\Imagenes\Alerta_Baja.png'
#Guardar iconos
img_alta_original = Image.open(ruta_alta)
img_media_original = Image.open(ruta_media)
img_baja_original = Image.open(ruta_baja)
#Cambiar tamaño en pixeles
resize_alta = img_alta_original.resize((100, 100))
resize_media = img_media_original.resize((100, 100))
resize_baja = img_baja_original.resize((100, 100))
#Guardar en tkinter
img_alta = ImageTk.PhotoImage(resize_alta)
img_media = ImageTk.PhotoImage(resize_media)
img_baja = ImageTk.PhotoImage(resize_baja )

resultado_ind=Label(root, text=" - %",font=("Segoe UI",20),fg="#4D4D4D")
resultado_ind.grid(row=6, column=2,padx=10,pady=10,rowspan=4)

#Tabla de resultados grupales top 5

#Cambiar tamaño en pixeles iconos
resize_alta_grupal = img_alta_original.resize((20,20))
resize_media_grupal = img_media_original.resize((20,20))
resize_baja_grupal = img_baja_original.resize((20,20))
#Guardar en tkinter
img_alta_grupal = ImageTk.PhotoImage(resize_alta_grupal)
img_media_grupal = ImageTk.PhotoImage(resize_media_grupal)
img_baja_grupal = ImageTk.PhotoImage(resize_baja_grupal)

#Widget de tabla
treeview = ttk.Treeview(columns=("Candidato", "Probabilidad"),height=5)
#Nombramiento columnas
treeview.heading('#0',text='')
treeview.heading("Candidato", text="Candidato")
treeview.heading("Probabilidad", text="Probabilidad")
#Ajustar el ancho de las columnas
treeview.column('#0',anchor=CENTER,width=50)
treeview.column("# 1",anchor=CENTER, stretch=NO,width=100)
treeview.column("# 2",anchor=CENTER, stretch=NO,width=100)

#Estilo para las líneas y encabezado
```

```
style = ttk.Style()
style.configure("mystyle.Treeview", highlightthickness=10, bd=10, borderwidth=10, font=('Segoe UI', 10))
style.configure("mystyle.Treeview.Heading", font=('Segoe UI',10,'bold'))
#Cambiar el color de las líneas de la tabla a negro
style.configure("mystyle.Treeview", foreground="black", background="white")
#Aplicar el estilo a la tabla
treeview.configure(style="mystyle.Treeview")
#Ubicacion tabla
treeview.grid(row=11, column=2,padx=10,pady=10,rowspan=5)
```

Funciones

In [17]:

```
#Captura de datos y calculo predicción individual
def enviar_datos():
    #Array para almacenar los datos de entrada
    datos = []
    #Copia de datos de entrada al modelo y crea ID empleado, limpieza de frame entrada
    df_raw = X_train_ada.copy()
    df_raw.insert(loc=0, column='ID_empleado',value=0)
    df_raw.drop(df_raw.index,inplace=True)
    #Almacenamiento datos
    datos.append({
            'ID_empleado': entry_candidato.get(),
            'Area': comboArea.get(),
            'Distancia_Casa': entry_Distancia.get(),
            'Nivel_Rol': comboNivelR.get(),
            'Rol':comboRol.get(),
            'Campo_Educativo': comboCampoE.get(),
            'Nivel_Educativo': comboNivelE.get(),
            'Anos_Trabajados': entry_exp.get(),
            'Companias': entry_companias.get(),
            'Salario_Mensual': entry_salario.get(),
            'Edad': entry_edad.get(),
            'Estado_Civil': comboEstadoC.get()
    })

    #Transformar a dataframe
    df_calculadora = pd.DataFrame(datos,columns=['ID_empleado','Edad','Area','Distancia_Casa','Nivel_Educativo',
                                                 'Campo_Educativo','Nivel_Rol','Rol','Estado_Civil','Salario_Mensual',
                                                 'Companias','Anos_Trabajados'])
    #Garantizar tipos de datos numericos entrada
    df_calculadora['ID_empleado'] = pd.to_numeric(df_calculadora['ID_empleado'].str.replace(',','.'))
    df_calculadora['Edad'] = pd.to_numeric(df_calculadora['Edad'].str.replace(',','.'))
    df_calculadora['Distancia_Casa'] = pd.to_numeric(df_calculadora['Distancia_Casa'].str.replace(',','.'))
    df_calculadora['Nivel_Rol'] = pd.to_numeric(df_calculadora['Nivel_Rol'].str.replace(',','.'))
    df_calculadora['Nivel_Educativo'] = pd.to_numeric(df_calculadora['Nivel_Educativo'].str.replace(',','.'))
```

```
df_calculadora['Anos_Trabajados'] = pd.to_numeric(df_calculadora['Anos_Trabajados'].str.replace(',','.'))
df_calculadora['Companias'] = pd.to_numeric(df_calculadora['Companias'].str.replace(',','.'))
df_calculadora['Salario_Mensual'] = pd.to_numeric(df_calculadora['Salario_Mensual'].str.replace(',','.'))
#Dummificar entrada
df_calculadora = pd.get_dummies(df_calculadora, columns=['Area','Campo_Educativo','Rol','Estado_Civil'])

#--------------Funciones de prediccion
#Inserta datos en frame entrada y rellena dummies
for column in df_calculadora:
    df_raw[column] = df_calculadora[column]
df_raw.fillna(0,inplace=True)
#Set de index y creacion entrada modelo
df_raw = df_raw.set_index('ID_empleado')
df_raw_X = df_raw.copy()
#Prediccion sobre entrada
y_pred_rf_ada_raw = rf_model_ada.predict(df_raw_X)

#Convertir prediccion a dataframe con mismo indice de entrada
y_pred_rf_ada_raw_df = pd.DataFrame(data = y_pred_rf_ada_raw, columns = ['y_pred_rf_ada_raw'],
                                    index = df_raw_X.index.copy())
#Probabilidades sobre entrada
y_prob_rf_ada_raw = rf_model_ada.predict_proba(df_raw_X)[:,1]

#Convertir probabilidades a dataframe con mismo indice de entrada
y_prob_rf_ada_raw_df = pd.DataFrame(data = y_prob_rf_ada_raw, columns = ['y_prob_rf_ada_raw'],
                                    index = df_raw_X.index.copy())
#Combinar resultados con entrada cruda
df_out = pd.merge(df_raw, y_pred_rf_ada_raw_df, how = 'left', left_index = True, right_index = True)
df_out = pd.merge(df_out, y_prob_rf_ada_raw_df, how = 'left', left_index = True, right_index = True)
#ID empleado nuevamente a columna
df_out.reset_index(inplace=True)

#Muestra resultado en label

print((df_out['y_prob_rf_ada_raw'].values[:1][0])*100)
print(str(round((df_out['y_prob_rf_ada_raw'].values[:1][0])*100,2))+'%')

resultado_num = round((df_out['y_prob_rf_ada_raw'].values[:1][0])*100,2)
resultado = str(resultado_num)+'%'

resultado_ind.config(text=resultado)

#Color de label segun resultado
if resultado_num >= 55:
    resultado_ind.config(font=("Segoe UI",20,'bold'),fg="#A92E63",image=img_alta,compound='top')
elif resultado_num >= 30:
    resultado_ind.config(font=("Segoe UI",20,'bold'),fg="#EC9A29",image=img_media,compound='top')
```

```
    else:
        resultado_ind.config(font=("Segoe UI",20,'bold'),fg="#0F8B8D",image=img_baja,compound='top')
```

In [18]:

```
#Para manejo de calculo masivo

#Instancia de dataframe para almacenar resultados grupales
df_out = pd.DataFrame()

def exportar_csv():
    ruta_archivo = filedialog.asksaveasfilename(defaultextension=".csv", filetypes=[("Archivo CSV", "*.csv")])
    if ruta_archivo:
        try:
            #Guardar DataFrame como archivo CSV en la ruta especificada
            df_out.to_csv(ruta_archivo, index=False)
            print("Datos exportados exitosamente a:", ruta_archivo)

        except Exception as e:
            print("Error al exportar los datos:", e)

def limpiar_masivo():
    #Limpiar la tabla de calculo masivo
    for i in treeview.get_children():
        treeview.delete(i)

def calculo_masivo(df_grupal):
    global df_out
    #Copia de datos de entrada al modelo y crea ID empleado, limpieza de frame entrada
    df_raw = X_train_ada.copy()
    df_raw.insert(loc=0, column='ID_empleado',value=0)
    df_raw.drop(df_raw.index,inplace=True)

    #Crear base para exportacion con indice nuevo
    df_grupal_export = df_grupal.set_index('ID_empleado')
    #Dummificar entrada
    df_grupal = pd.get_dummies(df_grupal, columns=['Area','Campo_Educativo','Rol','Estado_Civil'])

    #--------------Funciones de prediccion
    #Inserta datos en frame entrada y rellena dummies
    for column in df_grupal:
        df_raw[column] = df_grupal[column]
    df_raw.fillna(0,inplace=True)
    #Set de index y creacion entrada modelo
    df_raw = df_raw.set_index('ID_empleado')
    df_raw_X = df_raw.copy()
    #Prediccion sobre entrada
    y_pred_rf_ada_raw = rf_model_ada.predict(df_raw_X)
```

```
    #Convertir prediccion a dataframe con mismo indice de entrada
    y_pred_rf_ada_raw_df = pd.DataFrame(data = y_pred_rf_ada_raw, columns = ['y_pred_rf_ada_raw'],
                                        index = df_raw_X.index.copy())
    #Probabilidades sobre entrada
    y_prob_rf_ada_raw = rf_model_ada.predict_proba(df_raw_X)[:,1]

    #Convertir probabilidades a dataframe con mismo indice de entrada
    y_prob_rf_ada_raw_df = pd.DataFrame(data = y_prob_rf_ada_raw, columns = ['y_prob_rf_ada_raw'],
                                        index = df_raw_X.index.copy())
    #Combinar resultados con entrada cruda
    df_out = pd.merge(df_grupal_export, y_pred_rf_ada_raw_df, how = 'left', left_index = True, right_index = True)
    df_out = pd.merge(df_out, y_prob_rf_ada_raw_df, how = 'left', left_index = True, right_index = True)
    #ID empleado nuevamente a columna
    df_out.reset_index(inplace=True)
    df_grupal_export.reset_index(inplace=True)

    #Extraer top 5
    df_out_top = df_out.sort_values('y_prob_rf_ada_raw',ascending = True).head()
    #Mostrar top 5 en pantalla
    #Limpiar tabla si ya hay datos
    limpiar_masivo()
    # Insertar datos en la tabla
    for ind in df_out_top.index:
        if df_out_top['y_prob_rf_ada_raw'][ind]*100 >= 55:
            imagen_registro = img_alta_grupal
        elif df_out_top['y_prob_rf_ada_raw'][ind]*100 >= 30:
            imagen_registro = img_media_grupal
        else:
            imagen_registro = img_baja_grupal

        treeview.insert(parent="",index="end", image=imagen_registro,
                        value=(df_out_top['ID_empleado'][ind],
                               str(round(df_out_top['y_prob_rf_ada_raw'][ind]*100,2))+'%'))
    #Habilita exportacion
    boton_exportar["state"] = "normal"
    boton_exportar.config(bg='teal')

#Captura de datos
def cargarArchivo():
    #Lectura
    ruta_archivo = filedialog.askopenfilename(filetypes=[("Archivo XLSX", "*.xlsx")])
    if ruta_archivo:
        try:
            #Cargar el archivo XLSX en un DataFrame
            df_masivo = pd.read_excel(ruta_archivo)
            calculo_masivo(df_masivo)
```

```
        except Exception as e:
            print("Error al cargar el archivo:", e)
```

Accionables de interfaz

In [19]:
```
#Boton evaluar - funcion enviar_datos
boton_evaluar = Button(root, text="Evaluar",font=("Segoe UI",12,'bold'),fg="white",bg="teal",command=enviar_datos)
boton_evaluar.grid(row=18,column=0,columnspan=2,pady=10)

#Boton de cargue masivo
boton_cargar = tk.Button(root, text="Cargar Formato Grupal", font=("Segoe UI",12,'bold'),fg="white",bg="teal",
                         command=cargarArchivo)
boton_cargar.grid(row=18,column=2,pady=10)

#Boton de exportar masivo
boton_exportar = tk.Button(root, text="Exportar resultados", font=("Segoe UI",12,'bold'),fg="white",bg="#4D4D4D",
                         command=exportar_csv,disabledforeground="black")
boton_exportar.grid(row=19,column=2,pady=10)
boton_exportar["state"] = "disabled"
```

Ejecución de Interfaz

In [20]:
```
#Mostrar la ventana (entra en un loop)
root.mainloop()
```

```
63.343023230030774
63.34%
20.815220158606717
20.82%
Datos exportados exitosamente a: C:/Users/Jaime Andres Molina/Documents/Maestria/Proyecto Empresarial/Fuentes/01_Fuentes/Carga Ca
lculadora/resultados.csv
```