In [8]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pylab as pl
import scipy.optimize as opt
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings('ignore')
```

In [148]:
```
rh_df = pd.read_csv('C:/Users/Isaac/Desktop/IHD/EBAC DT/M22 DS/recursos_humanos.csv')
rh_df.head()
```

Out[148]:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	left	promotion_last_5years	sales	salary
0	0.38	0.53	2	157	3	0	1	0	sales	low
1	0.80	0.86	5	262	6	0	1	0	sales	medium
2	0.11	0.88	7	272	4	0	1	0	sales	medium
3	0.72	0.87	5	223	5	0	1	0	sales	low
4	0.37	0.52	2	159	3	0	1	0	sales	low

In [10]:
```
rh_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   satisfaction_level     14999 non-null  float64
 1   last_evaluation        14999 non-null  float64
 2   number_project         14999 non-null  int64
 3   average_montly_hours   14999 non-null  int64
 4   time_spend_company     14999 non-null  int64
 5   Work_accident          14999 non-null  int64
 6   left                   14999 non-null  int64
 7   promotion_last_5years  14999 non-null  int64
 8   sales                  14999 non-null  object
 9   salary                 14999 non-null  object
dtypes: float64(2), int64(6), object(2)
memory usage: 1.1+ MB
```

In [11]:
```
pd.unique(rh_df['left'])
```

Out[11]:
```
array([1, 0], dtype=int64)
```

In [14]:
```
dummies_sales = pd.get_dummies(rh_df['sales'], prefix = 'sales')
dummies_sales = dummies_sales.astype(int)
dummies_salary = pd.get_dummies(rh_df['salary'], prefix = 'salary')
dummies_salary = dummies_salary.astype(int)
```

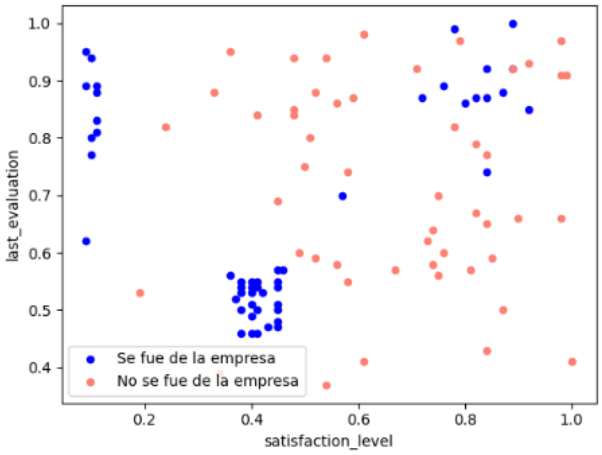
In [16]:
```
rh_df = pd.concat([rh_df, dummies_sales], axis = 1)
rh_df = pd.concat([rh_df, dummies_salary], axis = 1)
rh_df
```

Out[16]:

alary	...	sales_hr	sales_management	sales_marketing	sales_product_mng	sales_sales	sales_support	sales_technical	salary_high	salary_low	salary_medium
low	...	0	0	0	0	1	0	0	0	1	0
edium	...	0	0	0	0	1	0	0	0	0	1
edium	...	0	0	0	0	1	0	0	0	0	1
low	...	0	0	0	0	1	0	0	0	1	0
low	...	0	0	0	0	1	0	0	0	1	0

In [19]:
```
rh_df.drop(['sales', 'salary'], axis = 1, inplace = True)
```

In [31]:
```
ax = rh_df[rh_df['left']== 1][0:50].plot(kind = 'scatter', x = 'satisfaction_level', y = 'last_evaluation', color= 'blue', label
ax = rh_df[rh_df['left']== 0][0:50].plot(kind = 'scatter', x = 'satisfaction_level', y = 'last_evaluation', color= 'salmon', lab
plt.show()
```



In [57]:
```
# Asignamos valores a nuestras variables 'x' y 'y'

rh1 = rh_df[['satisfaction_level','last_evaluation','number_project','average_montly_hours','time_spend_company','Work_accident',
             'promotion_last_5years','sales_IT','sales_RandD','sales_accounting','sales_hr','sales_management','sales_marketing',
             'sales_product_mng','sales_sales','sales_support','sales_technical','salary_high','salary_low','salary_medium']]
x = np.asarray(rh1)
x
```

Out[57]:
```
array([[0.38, 0.53, 2.  , ..., 0.  , 1.  , 0.  ],
       [0.8 , 0.86, 5.  , ..., 0.  , 0.  , 1.  ],
       [0.11, 0.88, 7.  , ..., 0.  , 0.  , 1.  ],
       ...,
       [0.37, 0.53, 2.  , ..., 0.  , 1.  , 0.  ],
       [0.11, 0.96, 6.  , ..., 0.  , 1.  , 0.  ],
       [0.37, 0.52, 2.  , ..., 0.  , 1.  , 0.  ]])
```

In [58]:
```
rh_df['left']= rh_df['left'].astype('int')
y = np.asarray(rh_df['left'])
y[0:5]
```

Out[58]:
```
array([1, 1, 1, 1, 1])
```

In [59]:
```
# normalizamos los datos

#x = (x1 - np.min(x1)) / (np.max(x1) - np.min(x1))
#x
```

CREAMOS GRUPOS DE ENTRENAMIENTO Y PRUEBAS

In [60]:
```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size= 0.2, random_state = 1)

# revisamos la dimension de las bases

print('Grupo de entrenamiento', X_train.shape, y_train.shape)
print('Grupo de prueba', X_test.shape, y_test.shape)
```

```
Grupo de entrenamiento (11999, 20) (11999,)
Grupo de prueba (3000, 20) (3000,)
```

Modelo SVM ¶

In [61]:
```
from sklearn import svm
```

KERNEL RBF

In [62]:
```
rbf = svm.SVC(kernel = 'rbf')

# entrenamos el modelo

rbf.fit(X_train, y_train)
```

Out[62]:
```
SVC()
```

In [63]:
```
# realizamos predicciones

rbf_pred = rbf.predict(X_test)
rbf_pred[0:5]
```

Out[63]:
```
array([0, 0, 0, 0, 0])
```

In [64]:
```
# creamos la matriz de confucion

from sklearn.metrics import confusion_matrix
```

In [70]:
```
m_cnof = rbf.predict(x)
cm = confusion_matrix(y_test, rbf_pred)
cm
```

Out[70]:
```
array([[2287,    0],
       [ 663,   50]], dtype=int64)
```

In [71]:
```
y_test
```

Out[71]:
```
array([0, 0, 0, ..., 0, 0, 0])
```

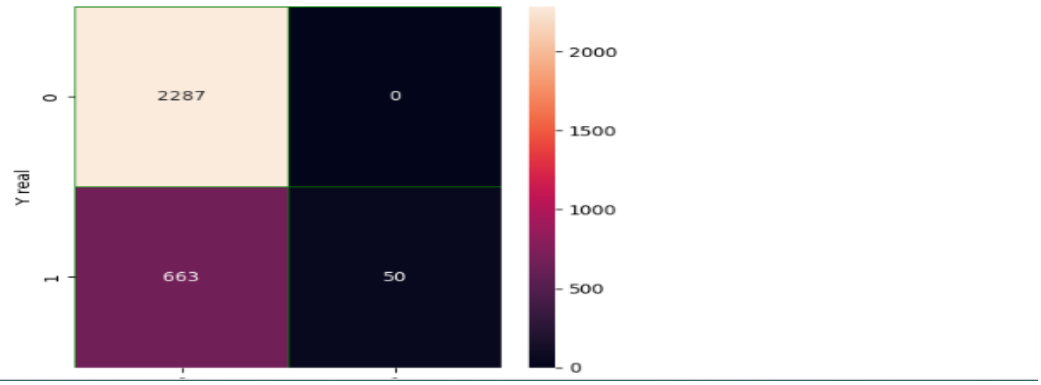
In [72]:
```
rbf_pred
```

Out[72]:
```
array([0, 0, 0, ..., 0, 0, 0])
```

In [69]:
```
# visualizamos la MC

import seaborn as sns
```

In [74]:
```
f, ax = plt.subplots(figsize = (5,5))
sns.heatmap(cm, annot = True, linewidths = 0.5, linecolor= 'green', fmt= '.0f', ax = ax)
plt.xlabel('Y pronosticada')
plt.ylabel('Y real')
plt.show
```

Out[74]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



- Se pronosticaron 2950 casos acertando 2287 y 663 errores
- Se pronosticaron 50 casos acertando todos los pronosticos

In [75]:
```
# Revisamos las estadisticas de desempeño

from sklearn.metrics import classification_report
```

In [77]:
```
cm_matirx = confusion_matrix(y_test, rbf_pred, labels = [0,1])
print(classification_report(y_test, rbf_pred))
```

```
              precision    recall  f1-score   support

           0       0.78      1.00      0.87      2287
           1       1.00      0.07      0.13       713

    accuracy                           0.78      3000
   macro avg       0.89      0.54      0.50      3000
weighted avg       0.83      0.78      0.70      3000
```

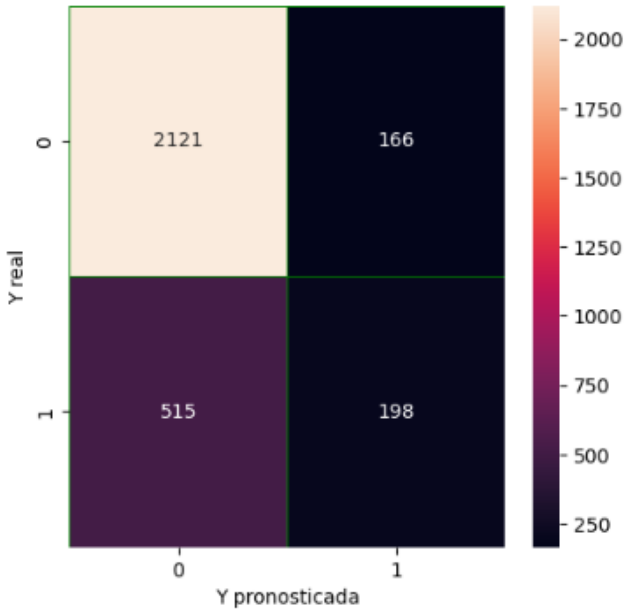
SVM con Kernel Lineal ¶

In [91]:
```
svm_lineal = svm.SVC(kernel = 'linear')

# entrenamos el algoritmo

svm_lineal.fit(X_train, y_train)

# realizamos predicciones

svm_lineal_pred = svm_lineal.predict(X_test)

# matriz de confusion

from sklearn.metrics import confusion_matrix
m_conf = svm_lineal.predict(x)
cm = confusion_matrix(y_test, svm_lineal_pred)
cm
```

Out[91]:
```
array([[2121,  166],
       [ 515,  198]], dtype=int64)
```

In [92]:
```
f, ax = plt.subplots(figsize = (5,5))
sns.heatmap(cm, annot = True, linewidths = 0.5, linecolor= 'green', fmt= '.0f', ax = ax)
plt.xlabel('Y pronosticada')
plt.ylabel('Y real')
plt.show
```

Out[92]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [93]:
```
from sklearn.metrics import classification_report
cm_matrix = confusion_matrix(y_test, svm_lineal_pred, labels = [0,1])
print(classification_report(y_test, svm_lineal_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.93      0.86      2287
           1       0.54      0.28      0.37       713

    accuracy                           0.77      3000
   macro avg       0.67      0.60      0.61      3000
weighted avg       0.74      0.77      0.74      3000
```

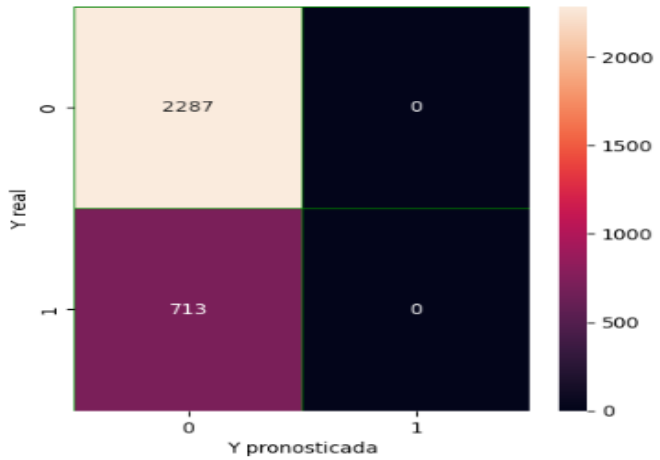
SVM con kernel Polinomial

In [94]:
```
svm_pll = svm.SVC(kernel = 'poly')

# entrenamos el modelo

svm_pll.fit(X_train, y_train)

# hacemos predicciones

svm_pll_pred = svm_pll.predict(X_test)

# matriz de confusion

from sklearn.metrics import confusion_matrix

cm_matrix = svm_pll.predict(x)
cm = confusion_matrix(y_test, svm_pll_pred)
cm
```

Out[94]:
```
array([[2287,    0],
       [ 713,    0]], dtype=int64)
```

In [95]:
```
f, ax = plt.subplots(figsize = (5,5))
sns.heatmap(cm, annot = True, linewidths = 0.5, linecolor= 'green', fmt= '.0f', ax = ax)
plt.xlabel('Y pronosticada')
plt.ylabel('Y real')
plt.show
```

Out[95]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [96]:
```
from sklearn.metrics import classification_report

cm_matrix = confusion_matrix(y_test, svm_pll_pred, labels = [0,1])
print(classification_report(y_test, svm_pll_pred))
```

```
              precision    recall  f1-score   support

           0       0.76      1.00      0.87      2287
           1       0.00      0.00      0.00       713

    accuracy                           0.76      3000
   macro avg       0.38      0.50      0.43      3000
weighted avg       0.58      0.76      0.66      3000
```

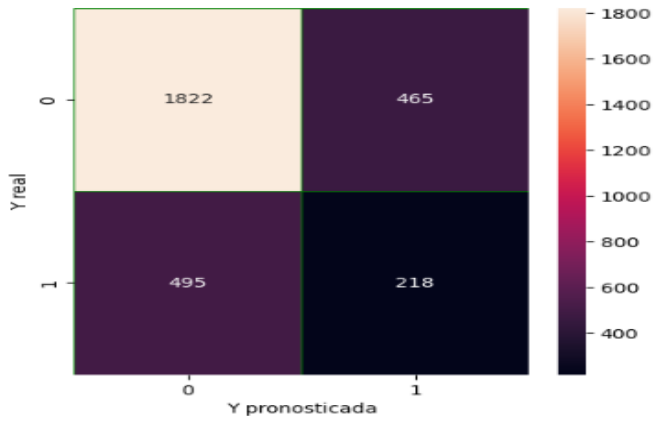
SVM con kernel Sigmoide

In [97]:
```
svm_sig = svm.SVC(kernel = 'sigmoid')

# entrenamos el algoritmo

svm_sig.fit(X_train, y_train)

# hacemos predicciones

svm_sig_pred = svm_sig.predict(X_test)

# matriz de confusion

from sklearn.metrics import confusion_matrix
cm_matrix = svm_sig.predict(x)
cm = confusion_matrix(y_test, svm_sig_pred)
cm
```

Out[97]:
```
array([[1822,  465],
       [ 495,  218]], dtype=int64)
```

In [98]:
```
f, ax = plt.subplots(figsize = (5,5))
sns.heatmap(cm, annot = True, linewidths = 0.5, linecolor= 'green', fmt= '.0f', ax = ax)
plt.xlabel('Y pronosticada')
plt.ylabel('Y real')
plt.show
```

Out[98]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [99]:
```
from sklearn.metrics import classification_report
cm_matrix = confusion_matrix(y_test, svm_sig_pred, labels = [0,1])
print(classification_report(y_test, svm_sig_pred))
```

```
              precision    recall  f1-score   support

           0       0.79      0.80      0.79      2287
           1       0.32      0.31      0.31       713

    accuracy                           0.68      3000
   macro avg       0.55      0.55      0.55      3000
weighted avg       0.68      0.68      0.68      3000
```

¿Cuál resultó ser el modelo predictivo más adecuado? ¶

- RBF

  precision recall f1-score support

```
0       0.78      1.00      0.87      2287
1       1.00      0.07      0.13       713
```

Revisando los resultados de los reportes de clasificacion de cada modelo, el mas optimo en esta caso es el modelo de RBF.

Los otros 3 modelos sus predicciones no fueron tan acertivas lo que se reflejaba en los reportes donde indicaban valores cercanos a 0, recordando que un valor cercano a 0 o igual a 0 es un nodelo No confiable.

¿Qué resultado pronosticaría para un empleado con los siguientes indicadores?

satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	promotion_last_5years	sales	salary
0.5.	0.75	4	200	4	0	0	sales	medium

PREDICCION CON VALORES ESPECIFICOS. ¿ SE VA O SE QUEDA EL EMPLEADO?

In [129]:
```
# cREAMOS UN NUEVO DF CON LOS VALORES INDICADOS
empleado_pronos = pd.DataFrame({'satisfaction_level': [0.5],
                                'last_evaluation': [0.75],
                                'number_project':[4],
                                'average_montly_hours':[200],
                                'time_spend_company':[4],
                                'Work_accident':[0],
                                'left':[1],
                                'promotion_last_5years':[0],
                                'sales_IT':[0],
                                'sales_RandD':[1],
                                'sales_accounting':[0],
                                'sales_hr':[0],
                                'sales_management':[1],
                                'sales_marketing':[1],
                                'sales_product_mng':[0],
                                'sales_sales':[1],
                                'sales_support':[1],
                                'sales_technical':[0],
                                'salary_high':[0],
                                'salary_low':[1],
                                'salary_medium':[1]})
```

```
empleado_pronos
```

Out[129]:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	left	promotion_last_5years	sales_IT	sales_f
0	0.5	0.75	4	200	4	0	1	0	0	

1 rows × 21 columns

In [134]:
```
ampleado_pronos = empleado_pronos.drop('left', axis = 1, inplace = True)
```

In [147]:
```
rbf.fit(X_train, y_train)
prediccion = rbf.predict(empleado_pronos)
prediccion
```

Out[147]:
```
array([0])
```

- USANDO EL MODELO RBF(EL QUE MEJORES RESULTADOS ARROJO) Y SUANDO LOS VALORES ESPECIFICOS, LA PREDICCION DEL MODELO ES 0 LO QUE INDICA QUE EL EMPLEADO SE QUEDA EN EL TRABAJO.