In [5]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import os
os.chdir('/Users/Lenovo/Desktop/EBAC')
```

In [7]:
```
data = pd.read_csv('recursos_humanos.csv')
data
```

Out[7]:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	left	promo
0	0.38	0.53	2	157	3	0	1	
1	0.80	0.86	5	262	6	0	1	
2	0.11	0.88	7	272	4	0	1	
3	0.72	0.87	5	223	5	0	1	
4	0.37	0.52	2	159	3	0	1	
...	...	...	...	...	...	...	...	
14994	0.40	0.57	2	151	3	0	1	
14995	0.37	0.48	2	160	3	0	1	
14996	0.37	0.53	2	143	3	0	1	
14997	0.11	0.96	6	280	4	0	1	
14998	0.37	0.52	2	158	3	0	1	

14999 rows × 10 columns

In [9]:
```
data = pd.get_dummies(data, columns = ['sales'], prefix = 'Info_Sales', dtype=int)
```

In [11]:
```
data = pd.get_dummies(data, columns = ['salary'], prefix = 'Info_Salary', dtype = int)
```

In [13]:
```
y = data.left.values
x_data = data.drop(['left'], axis = 1)
```

In [15]:
```
#Normalizacion
x = (x_data - np.min(x_data)) / (np.max(x_data) - np.min(x_data))
```

In [17]:
```
# Bases de entrenamiento y prueba
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.30, random_state = 1)
```

In [47]:
```
# Modelo KNN (K vecinos mas cercanos)
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split, cross_val_score
#knn = KNeighborsClassifier(n_neighbors=3)

# Valor Optimo
k_range = range(1, 20)
cv_scores = []

for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, x_train, y_train, cv=5, scoring='accuracy')  # 5-fold CV
    cv_scores.append(scores.mean())

# Crear tabla con los resultados
results_df = pd.DataFrame({
    'K': list(k_range),
    'CV_Accuracy': cv_scores
})

optimal_k = k_range[np.argmax(cv_scores)]
print(f"El valor óptimo de K es: {optimal_k}")
```

```
El valor óptimo de K es: 1
```

In [49]:
```
results_df
```

Out[49]:

	K	CV_Accuracy
0	1	0.946376
1	2	0.943804
2	3	0.934756
3	4	0.942566
4	5	0.937232
5	6	0.942756
6	7	0.937041
7	8	0.941137
8	9	0.934565
9	10	0.938089
10	11	0.933422
11	12	0.937899
12	13	0.934946
13	14	0.937613
14	15	0.934565
15	16	0.935708
16	17	0.933803
17	18	0.936185
18	19	0.933518

In [51]:
```
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(x_train, y_train)
prediction = knn.predict(x_test)
print('Score: ', knn.score(x_test, y_test))
```

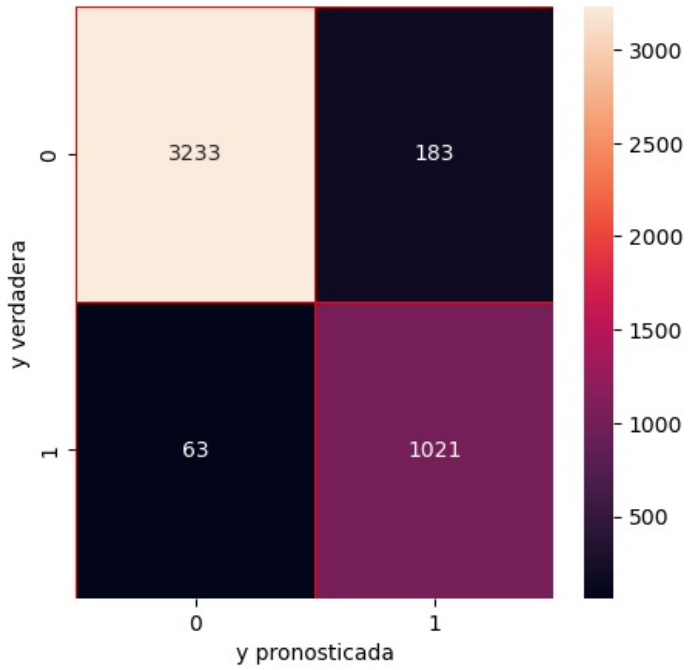
```
Score:  0.9453333333333334
```

In [53]:
```
y_pred = prediction
y_true = y_test
```

In [55]:
```
# Creacion de la matriz de confusion
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_true, y_pred)
cm
```

Out[55]:
```
array([[3233,  183],
       [  63, 1021]], dtype=int64)
```

In [57]:
```
# Visualizacion de la matriz de confusion
import seaborn as sns
f, ax = plt.subplots(figsize = (5,5))
sns.heatmap(cm, annot = True, linewidths = 0.5, linecolor = 'red', fmt = '.0f', ax = ax)
plt.xlabel('y pronosticada')
plt.ylabel('y verdadera')
plt.show()
```



Para el primer caso podemos concluir que cuando predecimos que un empleado no dejara la compañia, tenemos un 98% de acertividad.
Para el segundo caso podemos concluir que cuando predecimos que un empleado dejara la compañia, tenemos un 84% de acertividad.

In [59]:
```
# Calculo de la precision global
Correctos = cm[0,0] + cm[1,1]
Incorrectos = cm[0,1] + cm[1,0]
PrecisionGlobal = Correctos / (Correctos + Incorrectos)
PrecisionGlobal
```

Out[59]: 0.9453333333333334

In [61]:
```
PrecisionNoLeft = cm[0,0] / (cm[0,0] + cm[1,0])
PrecisionNoLeft
```

Out[61]: 0.9808859223300971

In [63]:
```
PrecisionLeft = cm[1,1] / (cm[1,1] + cm[0,1])
PrecisionLeft
```

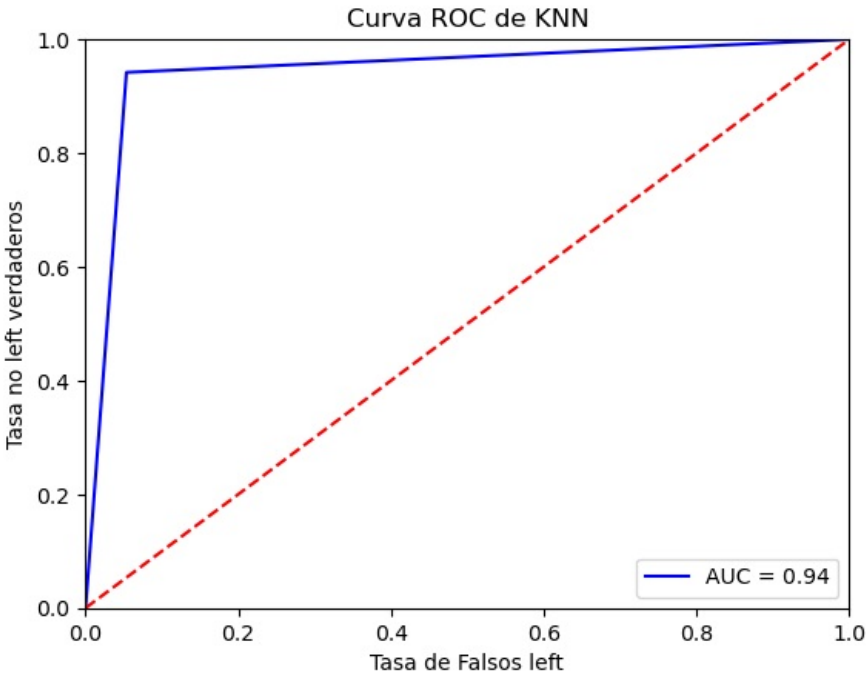
Out[63]: 0.8480066445182725

In [67]:
```
from sklearn.metrics import roc_curve
from sklearn.metrics import auc

y_scores = knn.predict_proba(x_test)

fpr, tpr, threshold = roc_curve(y_test, y_scores[:,1])
roc_auc = auc(fpr, tpr)

plt.title('Receiver Operation Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0,1], [0,1], 'r--')
plt.xlim([0,1])
plt.ylim([0,1])
plt.ylabel('Tasa no left verdaderos')
plt.xlabel('Tasa de Falsos left')
plt.title('Curva ROC de KNN')
plt.show()
```



Tenemos una tasa baja de personal que se pronostico que dejara la compañia y si la dejara. Y al tener la grafica AUC muy cerca del cero en el eje X, podemos determinar que la tasa de empleados predecidos que no dejaran la compañia, efectivamente no lo dejara.

In [ ]: