

S5 - HOPE SVM-V2

December 15, 2020

1 Import data from DB.

```
[1]: import pandas as pd
import numpy as np
```

```
[2]: dfOrg = pd.read_csv('hope_dataset_cleaned.csv')

print(dfOrg.shape[0])
```

1243

```
[3]: dfOrg.head(10)
```

```
[3]:  pedido.data.attributes.age  pedido.data.attributes.diagnostic_main  \
0                75.0                FISTULA PERITONEAL
1                75.0                FISTULA PERITONEAL
2                75.0                FISTULA PERITONEAL
3                75.0                FISTULA PERITONEAL
4                75.0                FISTULA PERITONEAL
5                75.0                FISTULA PERITONEAL
6                75.0                FISTULA PERITONEAL
7                75.0                FISTULA PERITONEAL
8                75.0                FISTULA PERITONEAL
9                75.0                FISTULA PERITONEAL

    pedido.data.attributes.gender  articulo  respuesta.articlesRevisedYear  \
0                male  27395425                2018
1                male  28560554                2018
2                male  28641726                2017
3                male  26245344                2016
4                male  28942543                2018
5                male  24782153                2014
6                male  28002229                2018
7                male  27505109                2017
8                male  24850546                2015
9                male  29371050                2019
```

	respuesta.articlesRevisedMonth \
0	1
1	4
2	12
3	12
4	6
5	6
6	9
7	4
8	1
9	4

	respuesta.pubmed_keys	utilidad
0	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu...	1.0
1	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu...	NaN
2	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu...	NaN
3	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu...	NaN
4	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu...	NaN
5	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu...	NaN
6	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu...	NaN
7	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu...	NaN
8	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu...	NaN
9	Abdomen,Adenocarcinoma,Antiemetics,Blood Cultu...	NaN

Expand pubmed_keys attribute

```
[4]: dfOrg['respuesta.pubmed_keys'] = dfOrg['respuesta.pubmed_keys'].apply(lambda x :
    ↪ str(x).split(','))

dfOrg = dfOrg.explode('respuesta.pubmed_keys').reset_index(drop=True)

dfOrg.head(10)
```

	pedido.data.attributes.age	pedido.data.attributes.diagnostic_main \
0	75.0	FISTULA PERITONEAL
1	75.0	FISTULA PERITONEAL
2	75.0	FISTULA PERITONEAL
3	75.0	FISTULA PERITONEAL
4	75.0	FISTULA PERITONEAL
5	75.0	FISTULA PERITONEAL
6	75.0	FISTULA PERITONEAL
7	75.0	FISTULA PERITONEAL
8	75.0	FISTULA PERITONEAL
9	75.0	FISTULA PERITONEAL

	pedido.data.attributes.gender	articulo	respuesta.articlesRevisedYear \
0	male	27395425	2018

1	male	27395425	2018
2	male	27395425	2018
3	male	27395425	2018
4	male	27395425	2018
5	male	27395425	2018
6	male	27395425	2018
7	male	27395425	2018
8	male	27395425	2018
9	male	27395425	2018

	respuesta.articlesRevisedMonth	respuesta.pubmed_keys	utilidad
0	1	Abdomen	1.0
1	1	Adenocarcinoma	1.0
2	1	Antiemetics	1.0
3	1	Blood Culture	1.0
4	1	Catharsis	1.0
5	1	Diuresis	1.0
6	1	Fistula	1.0
7	1	Gastrectomy	1.0
8	1	Incisional Hernia	1.0
9	1	Intestines	1.0

2 Transform (factorize) from Categories to continuous atributes

Transform 'pedido.data.attributes.diagnostic_main' attribute

```
[5]: dataDiagnosticMain, categoriesDiagnosticMain = pd.factorize(dfOrg['pedido.data.
    ↳attributes.diagnostic_main'])

dfOrg['pedido.data.attributes.diagnostic_main'] = dataDiagnosticMain
```

Transform 'gender' attribute

```
[6]: dataGender, categoriesGender = pd.factorize(dfOrg['pedido.data.attributes.
    ↳gender'])

dfOrg['pedido.data.attributes.gender'] = dataGender
```

Transform 'respuesta.pubmed_keys' attribute

```
[7]: categoriesORGPubMedKeys = dfOrg['respuesta.pubmed_keys'].value_counts()

print("total: " + str(categoriesORGPubMedKeys.size))
```

total: 353

```
[8]: dataPubMedKeys, categoriesPubMedKeys = pd.factorize(dfOrg['respuesta.
      ↳pubmed_keys'])

dfOrg['respuesta.pubmed_keys'] = dataPubMedKeys
```

```
[9]: dfOrg.head(10)
```

```
[9]: pedido.data.attributes.age  pedido.data.attributes.diagnostic_main  \
0                                75.0                                0
1                                75.0                                0
2                                75.0                                0
3                                75.0                                0
4                                75.0                                0
5                                75.0                                0
6                                75.0                                0
7                                75.0                                0
8                                75.0                                0
9                                75.0                                0

      pedido.data.attributes.gender  articulo  respuesta.articlesRevisedYear  \
0                                0  27395425                                2018
1                                0  27395425                                2018
2                                0  27395425                                2018
3                                0  27395425                                2018
4                                0  27395425                                2018
5                                0  27395425                                2018
6                                0  27395425                                2018
7                                0  27395425                                2018
8                                0  27395425                                2018
9                                0  27395425                                2018

      respuesta.articlesRevisedMonth  respuesta.pubmed_keys  utilidad
0                                1                        0      1.0
1                                1                        1      1.0
2                                1                        2      1.0
3                                1                        3      1.0
4                                1                        4      1.0
5                                1                        5      1.0
6                                1                        6      1.0
7                                1                        7      1.0
8                                1                        8      1.0
9                                1                        9      1.0
```

```
[10]: print("age NaN => " + str(dfOrg[pd.isnull(dfOrg['pedido.data.attributes.age'])].
      ↳shape[0]))
print("diagnostic_main NaN => " + str(dfOrg[pd.isnull(dfOrg['pedido.data.
      ↳attributes.diagnostic_main'])].shape[0]))
```

```

print("gender NaN => " + str(dfOrg[pd.isnull(dfOrg['pedido.data.attributes.
↳gender'])].shape[0]))
print("articulo NaN => " + str(dfOrg[pd.isnull(dfOrg['articulo'])].shape[0]))
print("articlesRevisedYear NaN => " + str(dfOrg[pd.isnull(dfOrg['respuesta.
↳articlesRevisedYear'])].shape[0]))
print("articlesRevisedMonth NaN => " + str(dfOrg[pd.isnull(dfOrg['respuesta.
↳articlesRevisedMonth'])].shape[0]))
print("pubmed_keys NaN => " + str(dfOrg[pd.isnull(dfOrg['respuesta.
↳pubmed_keys'])].shape[0]))
print("utilidad NaN => " + str(dfOrg[pd.isnull(dfOrg['utilidad'])].shape[0]))

```

```

age NaN => 10
diagnostic_main NaN => 0
gender NaN => 0
articulo NaN => 0
articlesRevisedYear NaN => 0
articlesRevisedMonth NaN => 0
pubmed_keys NaN => 0
utilidad NaN => 14758

```

Remove row with age eq NaN

```
[11]: dfOrg = dfOrg[pd.notnull(dfOrg['pedido.data.attributes.age'])]
```

3 Standardize the Data

Chooosed “age”, “diagnostic_main”, “month” and “pubmed_keys” attributes (based on PCA_V3 study)

```

[12]: from sklearn.preprocessing import StandardScaler

features = ["pedido.data.attributes.age",
            "pedido.data.attributes.diagnostic_main",
            "respuesta.articlesRevisedMonth",
            "respuesta.pubmed_keys",
            "utilidad"
]

# Separating out the features
x = dfOrg.loc[:, features].values

featuresTransformed = StandardScaler().fit_transform(x)

dfStandarized = pd.DataFrame(featuresTransformed, index=dfOrg.index,
↳columns=features)
dfStandarized['utilidad'] = dfOrg['utilidad']

```

```
dfStandarized
```

```
[12]: pedido.data.attributes.age  pedido.data.attributes.diagnostic_main  \
0          1.285887          -1.503163
1          1.285887          -1.503163
2          1.285887          -1.503163
3          1.285887          -1.503163
4          1.285887          -1.503163
...          ...          ...
15583      -0.607930          -0.586347
15584      -0.607930          -0.586347
15585      -0.607930          -0.586347
15586      -0.607930          -0.586347
15587      -0.607930          -0.586347

      respuesta.articlesRevisedMonth  respuesta.pubmed_keys  utilidad
0          -1.463658          -1.089722          1.0
1          -1.463658          -1.080463          1.0
2          -1.463658          -1.071203          1.0
3          -1.463658          -1.061944          1.0
4          -1.463658          -1.052684          1.0
...          ...          ...          ...
15583      -1.178433          -0.330441          NaN
15584      -1.178433          -0.978608          NaN
15585      -1.178433          0.891817          NaN
15586      -1.178433          -0.876753          NaN
15587      -1.178433          0.901077          NaN

[15578 rows x 5 columns]
```

4 Separe data by utilidad is defined

```
[13]: dfDataSetComplete = dfStandarized[pd.notnull(dfStandarized['utilidad'])]

print(dfDataSetComplete.shape[0])

dfDataSetToPredict = dfStandarized[pd.isnull(dfStandarized['utilidad'])]

print(dfDataSetToPredict.shape[0])
```

```
830
14748
```

5 SVM

We check the number of results

```
[14]: dfDataSetComplete.groupby('utilidad').size()
```

```
[14]: utilidad
      0.0    346
      1.0    484
      dtype: int64
```

Separate “utilidad” attribute from data to train

```
[15]: X = np.array(dfDataSetComplete.drop(['utilidad'],1))
      y = np.array(dfDataSetComplete['utilidad'])
      X.shape
```

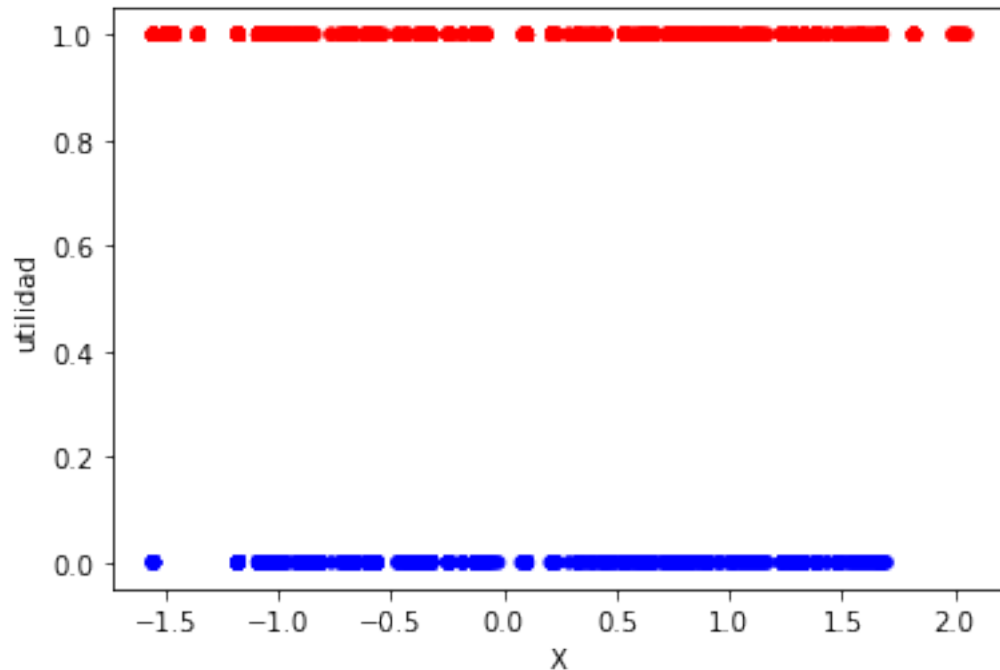
```
[15]: (830, 4)
```

```
[16]: from sklearn.model_selection import train_test_split

      X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
```

```
[17]: ax = dfDataSetComplete.plot.scatter(x="pedido.data.attributes.age",
      ↪y="utilidad", c=dfDataSetComplete.utilidad.map({0:'b', 1:'r'}))
      dfDataSetComplete.plot.scatter(x="pedido.data.attributes.diagnostic_main",
      ↪y="utilidad", c=dfDataSetComplete.utilidad.map({0:'b', 1:'r'}), ax=ax)
      dfDataSetComplete.plot.scatter(x="respuesta.articlesRevisedMonth",
      ↪y="utilidad", c=dfDataSetComplete.utilidad.map({0:'b', 1:'r'}), ax=ax)
      dfDataSetComplete.plot.scatter(x="respuesta.pubmed_keys", y="utilidad",
      ↪c=dfDataSetComplete.utilidad.map({0:'b', 1:'r'}), ax=ax)
      ax.set_xlabel('X')
```

```
[17]: Text(0.5, 0, 'X')
```



A simple vista no podemos crear un hiperplano lineal (división de valores) que nos ayude a poder clasificar los valores del campo utilidad en base los atributos del data set, ya que los resultados del campo “utilidad” están distribuidos sobre todo el plano de X. Exploraremos con los kernel methods, que método nos ayuda a poder crear el hiperplano más optimo para la clasificación.

6 Exploring Hiper Parameters

- C: El valor de penalización de los errores en la clasificación. Indica el compromiso entre obtener el hiperplano con el margen más grande posible y clasificar el máximo número de ejemplos correctamente. Probaremos valores aleatorios distribuidos uniformemente entre 1 y 500.

<https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html>

https://scikit-learn.org/stable/auto_examples/svm/plot_rbf_parameters.html

```
[18]: from sklearn.model_selection import RandomizedSearchCV
from sklearn import svm
from scipy.stats import uniform as sp_rand
from time import time

clf = svm.SVC()

kernels = ['rbf', 'sigmoid']

param_dist = {
    "C": sp_rand(loc=1, scale=500),
```



```

    "gamma": sp_rand(loc=1e-3, scale=1e3)
}

best_score = []

for k in kernels:
    param_dist['kernel'] = [k]
    n_iter_search = 10
    random_search = RandomizedSearchCV(clf, param_distributions=param_dist,
    ↪n_iter=n_iter_search, cv=4)

    start = time()
    random_search.fit(X_train, y_train)
    end = time()
    print("El entrenamiento a durado {} segundos".format(end - start))

    means = random_search.cv_results_["mean_test_score"]
    stds = random_search.cv_results_["std_test_score"]
    params = random_search.cv_results_['params']
    ranks = random_search.cv_results_['rank_test_score']
    best_score.append({'kernel':k, 'score':random_search.best_score_, 'params':
    ↪random_search.best_params_})

    for rank, mean, std, pms in zip(ranks, means, stds, params):
        print("{} Precisión media: {:.2f} +/- {:.2f} con parámetros {}".
        ↪format(rank, mean*100, std*100, pms))

```

El entrenamiento a durado 0.6093668937683105 segundos

10) Precisión media: 76.21 +/- 3.94 con parámetros {'C': 360.85775701024386, 'gamma': 907.3825530117131, 'kernel': 'rbf'}

2) Precisión media: 82.15 +/- 3.10 con parámetros {'C': 317.80497788196783, 'gamma': 119.40946797705895, 'kernel': 'rbf'}

6) Precisión media: 76.69 +/- 4.23 con parámetros {'C': 87.01059367021347, 'gamma': 806.2789163354661, 'kernel': 'rbf'}

5) Precisión media: 77.98 +/- 3.45 con parámetros {'C': 149.54484171124932, 'gamma': 564.5199301320216, 'kernel': 'rbf'}

6) Precisión media: 76.69 +/- 4.23 con parámetros {'C': 118.97768424072203, 'gamma': 793.486590684318, 'kernel': 'rbf'}

6) Precisión media: 76.69 +/- 4.23 con parámetros {'C': 150.02147952417772, 'gamma': 737.8299797134209, 'kernel': 'rbf'}

6) Precisión media: 76.69 +/- 4.23 con parámetros {'C': 363.8370243112447, 'gamma': 848.9827977113308, 'kernel': 'rbf'}

3) Precisión media: 79.74 +/- 2.79 con parámetros {'C': 423.45666708016336, 'gamma': 277.59190556966644, 'kernel': 'rbf'}

1) Precisión media: 86.33 +/- 1.48 con parámetros {'C': 169.2424566596866, 'gamma': 21.685491125386175, 'kernel': 'rbf'}

4) Precisión media: 78.62 +/- 3.45 con parámetros {'C': 56.26738061340281, 'gamma': 313.7065587800348, 'kernel': 'rbf'}

El entrenamiento a durado 0.2546238899230957 segundos

7) Precisión media: 48.38 +/- 4.50 con parámetros {'C': 391.1677890243306, 'gamma': 497.20459077927774, 'kernel': 'sigmoid'}

7) Precisión media: 48.38 +/- 4.50 con parámetros {'C': 492.9377695700987, 'gamma': 453.0399489373676, 'kernel': 'sigmoid'}

4) Precisión media: 48.54 +/- 4.64 con parámetros {'C': 330.13037526527904, 'gamma': 724.4299745866858, 'kernel': 'sigmoid'}

1) Precisión media: 48.86 +/- 4.52 con parámetros {'C': 141.66423772199033, 'gamma': 964.081623637728, 'kernel': 'sigmoid'}

7) Precisión media: 48.38 +/- 4.50 con parámetros {'C': 277.89947393631587, 'gamma': 499.06800915767286, 'kernel': 'sigmoid'}

4) Precisión media: 48.54 +/- 4.64 con parámetros {'C': 339.4193364446046, 'gamma': 849.8383579899024, 'kernel': 'sigmoid'}

1) Precisión media: 48.86 +/- 4.52 con parámetros {'C': 8.782687504322816, 'gamma': 965.8092683063094, 'kernel': 'sigmoid'}

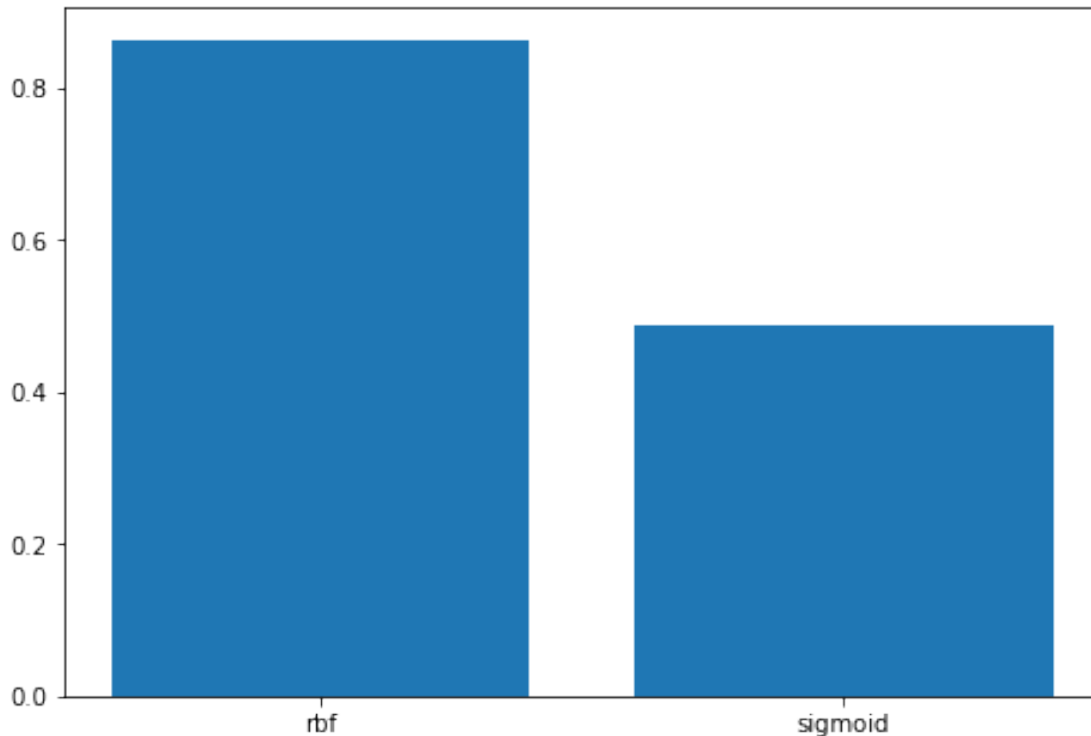
4) Precisión media: 48.54 +/- 4.64 con parámetros {'C': 232.84344873561824, 'gamma': 200.82390241386747, 'kernel': 'sigmoid'}

7) Precisión media: 48.38 +/- 4.50 con parámetros {'C': 340.8373827954047, 'gamma': 346.17465054874623, 'kernel': 'sigmoid'}

1) Precisión media: 48.86 +/- 4.52 con parámetros {'C': 491.55519979656776, 'gamma': 857.6069742445022, 'kernel': 'sigmoid'}

```
[19]: import matplotlib.pyplot as plt

fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar([dic['kernel'] for dic in best_score], [dic['score'] for dic in
↪ best_score])
plt.show()
```



```
[20]: pd.DataFrame(best_score)
```

```
[20]:
```

	kernel	score	params
0	rbf	0.863327	{'C': 169.2424566596866, 'gamma': 21.685491125...}
1	sigmoid	0.488617	{'C': 141.66423772199033, 'gamma': 964.0816236...}

Vemos que el kernel que mejor se ajusta al modelo es el radial (rbf). Utilizaremos este kernel con sus correspondientes parámetros para entrenar el modelo predictivo.

6.1 Evaluating the Algorithm

```
[21]: from sklearn.metrics import accuracy_score

print("Valor óptimo para C: {}".format(best_score[0]['params']['C']))
print("Valor óptimo para gamma: {}".format(best_score[0]['params']['gamma']))

modelSVM = svm.SVC(kernel=best_score[0]['kernel'],
    ↪gamma=best_score[0]['params']['gamma'], C=best_score[0]['params']['C']).
    ↪fit(X_train, y_train)
predict = modelSVM.predict(X_test)

accuracy = np.true_divide(np.sum(predict == y_test), predict.shape[0])*100
print("Precisión en el conjunto de test: {:.2f}%".format(accuracy))
```

Valor óptimo para C: 169.2424566596866
Valor óptimo para gamma: 21.685491125386175
Precisión en el conjunto de test: 89.42%

```
[22]: from sklearn.metrics import confusion_matrix
import itertools

cnf_matrix = confusion_matrix(y_test, predict)

def plot_confusion_matrix(cm, classes):
    cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

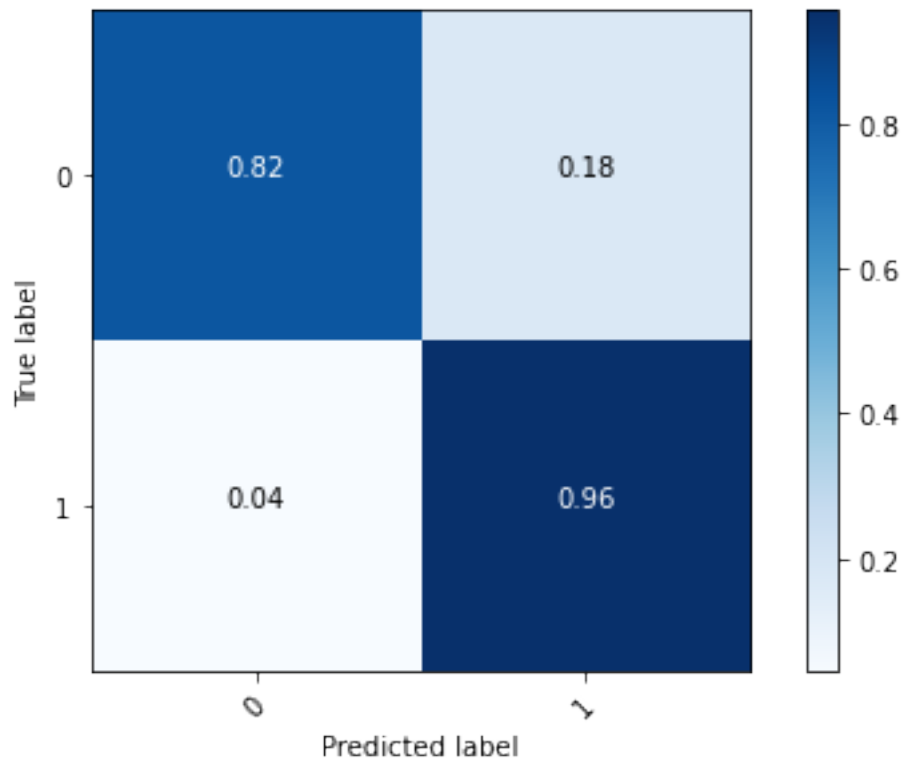
    cmap=plt.cm.Blues

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], ".2f"),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

n_classes=["0","1"]
plot_confusion_matrix(cnf_matrix, classes=n_classes)
```



7 Run Prediction

```
[23]: result = modelSVM.predict(dfDataSetToPredict[["pedido.data.attributes.age",
    "pedido.data.attributes.diagnostic_main",
    "respuesta.articlesRevisedMonth",
    "respuesta.pubmed_keys"
]])

result
```

```
[23]: array([1., 1., 1., ..., 1., 1., 1.])
```

```
[ ]:
```