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Support Vector Machine - SVM - Diabetes

Disponível em [https://www.kaggle.com/uciml/pima-indians-diabetes-database (https://www.kaggle.com/uciml/pima-indians-diabetes-database)](https://www.kaggle.com/uciml/pima-indians-diabetes-database)

Attributes:

Pregnancies: Number of times pregnant - Gravidez

Glucose: Plasma glucose concentration a 2 hours in an oral glucose tolerance test - Glicose

BloodPressure: Diastolic blood pressure (mm Hg) - Pressão Arterial

SkinThickness: Triceps skin fold thickness (mm) - Espessura do tríceps

Insulin: 2-Hour serum insulin (mu U/ml) - Insulina

BMI: Body mass index (weight in kg/(height in m)^2) - IMC

DiabetesPedigreeFunction: Diabetes pedigree function - Função que leva em conta doenças na familia

Age: Age (years)

Outcome: Class variable (0 or 1) - 0 : Não tem Diabetes, 1: Possui Diabetes

In [1]:

```
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
df = pd.read_csv("diabetes.csv")
df.rename(columns={"Outcome": "Class"} , inplace=True)
df.head()
```

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunc
0	6	148	72	35	0	33.6	0
1	1	85	66	29	0	26.6	0
2	8	183	64	0	0	23.3	0
3	1	89	66	23	94	28.1	0
4	0	137	40	35	168	43.1	2

In [3]:

```
df.describe().T
```

Out[3]:

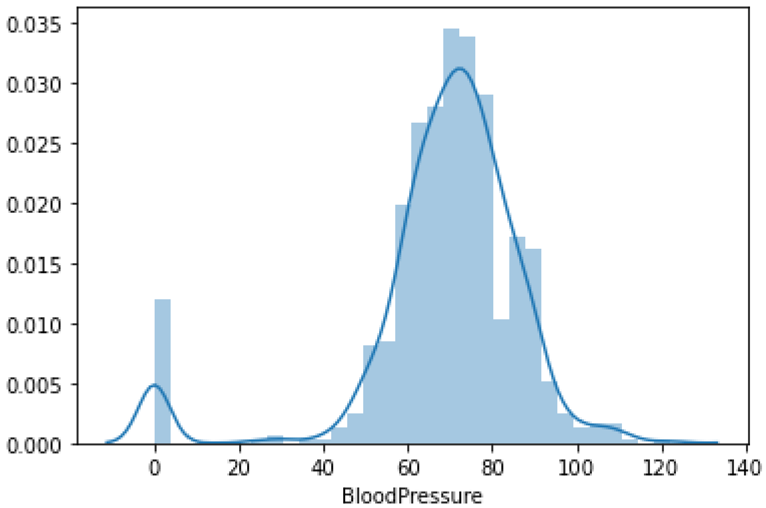
	count	mean	std	min	25%	50%	7
Pregnancies	768.0	3.845052	3.369578	0.000	1.00000	3.0000	6.00(
Glucose	768.0	120.894531	31.972618	0.000	99.00000	117.0000	140.25(
BloodPressure	768.0	69.105469	19.355807	0.000	62.00000	72.0000	80.00(
SkinThickness	768.0	20.536458	15.952218	0.000	0.00000	23.0000	32.00(
Insulin	768.0	79.799479	115.244002	0.000	0.00000	30.5000	127.25(
BMI	768.0	31.992578	7.884160	0.000	27.30000	32.0000	36.60(
DiabetesPedigreeFunction	768.0	0.471876	0.331329	0.078	0.24375	0.3725	0.62(
Age	768.0	33.240885	11.760232	21.000	24.00000	29.0000	41.00(
Class	768.0	0.348958	0.476951	0.000	0.00000	0.0000	1.00(

In [4]:

```
import seaborn as sns
sns.distplot(df.BloodPressure)
```

Out[4]:

<matplotlib.axes._subplots.AxesSubplot at 0x25a1fa7a220>

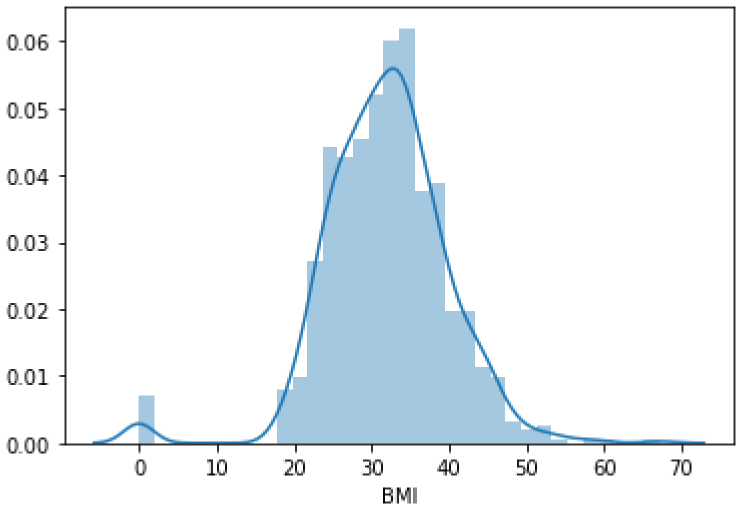


In [5]:

```
sns.distplot(df.BMI)
```

Out[5]:

<matplotlib.axes._subplots.AxesSubplot at 0x25a20219e20>

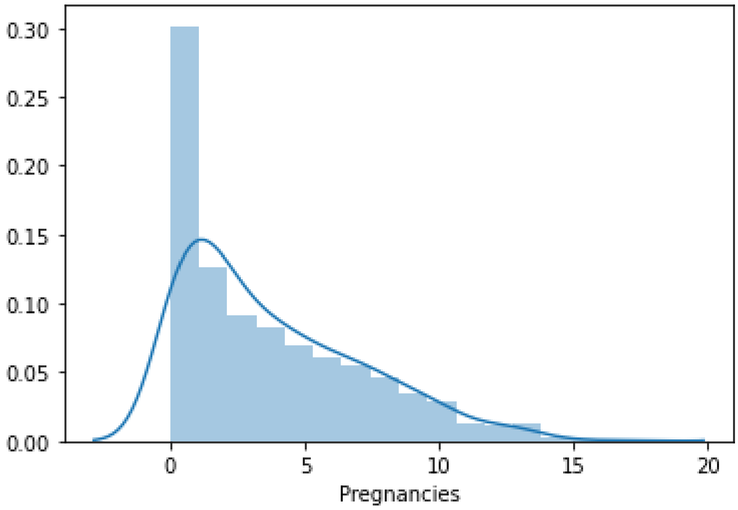


In [6]:

```
sns.distplot(df.Pregnancies)
```

Out[6]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x25a202cd0a0>
```



Preparação dos dados

In [7]:

```
# particionar os conjuntos de treino e teste
from sklearn.model_selection import train_test_split

df2 = df.copy()

diabetes_data = df2.loc[:,["Pregnancies", "Glucose", "BloodPressure", "SkinThick
ness", "Insulin",
                       "BMI", "DiabetesPedigreeFunction", "Age"]]
diabetes_target = df2["Class"]
```

In [8]:

```
diabetes_data[:3]
```

Out[8]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunc
0	6	148	72	35	0	33.6	0
1	1	85	66	29	0	26.6	0
2	8	183	64	0	0	23.3	0

In [9]:

```
diabetes_target[:3]
```

Out[9]:

```
0    1
1    0
2    1
Name: Class, dtype: int64
```

In [10]:

```
X_train, X_test, y_train, y_test = train_test_split(
    diabetes_data, diabetes_target, test_size=0.33, random_state=42)

X_train[:3]
```

Out[10]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFu
464	10	115	98	0	0	24.0	
223	7	142	60	33	190	28.8	
393	4	116	72	12	87	22.1	

In [11]:

```
print("# dados de treino = ", len(X_train))
print("# dados de teste = ", len(X_test))
```

```
# dados de treino =  514
# dados de teste =  254
```

In [12]:

```
diabetes_data[:3]
```

Out[12]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunc
0	6	148	72	35	0	33.6	0
1	1	85	66	29	0	26.6	0
2	8	183	64	0	0	23.3	0

In [13]:

```
diabetes = diabetes_data
diabetes["class"] = diabetes_target
diabetes.head()
```

Out[13]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunc
0	6	148	72	35	0	33.6	0
1	1	85	66	29	0	26.6	0
2	8	183	64	0	0	23.3	0
3	1	89	66	23	94	28.1	0
4	0	137	40	35	168	43.1	2

In [14]:

```
# correlação
diabetes.corr()
```

Out[14]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin
Pregnancies	1.000000	0.129459	0.141282	-0.081672	-0.073535
Glucose	0.129459	1.000000	0.152590	0.057328	0.331357
BloodPressure	0.141282	0.152590	1.000000	0.207371	0.088933
SkinThickness	-0.081672	0.057328	0.207371	1.000000	0.436783
Insulin	-0.073535	0.331357	0.088933	0.436783	1.000000
BMI	0.017683	0.221071	0.281805	0.392573	0.197859
DiabetesPedigreeFunction	-0.033523	0.137337	0.041265	0.183928	0.185071
Age	0.544341	0.263514	0.239528	-0.113970	-0.042163
class	0.221898	0.466581	0.065068	0.074752	0.130548

In [15]:

```
diabetes.corr().loc["class"].sort_values()
```

Out[15]:

```
BloodPressure               0.065068
SkinThickness               0.074752
Insulin                     0.130548
DiabetesPedigreeFunction    0.173844
Pregnancies                 0.221898
Age                         0.238356
BMI                         0.292695
Glucose                     0.466581
class                       1.000000
Name: class, dtype: float64
```

In [16]:

```
from sklearn.metrics import confusion_matrix
from sklearn import svm
```

In [17]:

```
classifier = svm.SVC(kernel='linear')
```

In [18]:

```
classifier.fit(X_train, y_train)
```

Out[18]:

```
SVC(kernel='linear')
```

In [19]:

```
prediction_SVM = classifier.predict(X_test)
```

In [20]:

```
#kernel_svm.fit(data_train, targets_train)
#kernel_svm_score = kernel_svm.score(data_test, targets_test)

print("Accuracy on test set (SVM): {:.3f}".format(classifier.score(X_test, y_tes
t)))
```

```
Accuracy on test set (SVM): 0.756
```

In [21]:

```
cm = confusion_matrix(y_test, prediction_SVM)
cm
```

Out[21]:

```
array([[139,  29],
       [ 33,  53]], dtype=int64)
```

comparação com KNN

In [22]:

```
from sklearn.neighbors import KNeighborsClassifier

model = KNeighborsClassifier()
model.fit(X_train, y_train)
#print("Accuracy on training set: {:.3f}".format(tree.score(X_train, y_train)))
print("Accuracy on test set (Knn): {:.3f}".format(model.score(X_test, y_test)))
```

```
Accuracy on test set (Knn): 0.701
```

In [23]:

```
import sklearn.metrics as metrics

metrics.confusion_matrix(y_test, model.predict(X_test))
```

Out[23]:

```
array([[130,  38],
       [ 38,  48]], dtype=int64)
```

mudar os parametros do svm

O parâmetro C é um trade off (escolha) entre a incorreta classificação de exemplos de treinamento contra a simplicidade da superfície de decisão. Um C baixo torna a superfície de decisão suave, enquanto um C alto visa classificar todos os exemplos de treinamento corretamente, dando ao modelo liberdade para selecionar mais amostras como vetores de suporte. O parâmetro gamma define qual é a influência de um único exemplo de treinamento. É um coeficiente de kernel para 'rbf', 'poli' e 'sigmóide'. Se gamma for definido como 'auto' então 1/n_features serão usados. Valores baixos significam 'alta variância' e maior influência do vetor de suporte e valores altos significam 'baixa variância' e os vetores de suporte não possuem grande influência no processo de classificação. Os parâmetros gama podem ser vistos como o inverso do raio de influência de amostras selecionadas pelo modelo como vetores de suporte.

In [108]:

```
def testar_kernels(kernels):
    for kernel in kernels:
        classifier = svm.SVC(kernel=kernel, C = 10.0, gamma = 0.001)
        if kernel == 'linear':
            classifier = svm.SVC(kernel=kernel)
        else:
            classifier = svm.SVC(kernel=kernel, C = 10.0, gamma = 0.001 )
        classifier.fit(X_train, y_train)
        prediction_SVM = classifier.predict(X_test)
        cm = confusion_matrix(y_test, prediction_SVM)
        #cm = confusion_matrix(y_test, prediction_SVM)
        print("kernel",kernel)
        print("confusion matrix:\n",cm)
        print("score:", classifier.score(X_test, y_test))
        print("\n")
kernels = ['linear', 'rbf', 'sigmoid']
#['linear', 'poly', 'rbf', 'sigmoid', 'precomputed']
# o tempo de processamento do kernel polinomial é alto em relação aos demais
testar_kernels(kernels)
```

```
kernel linear
confusion matrix:
 [[139  29]
 [ 33  53]]
score: 0.7559055118110236


kernel rbf
confusion matrix:
 [[135  33]
 [ 38  48]]
score: 0.7204724409448819


kernel sigmoid
confusion matrix:
 [[168   0]
 [ 86   0]]
score: 0.6614173228346457
```

Normalizar os dados

aumenta a acurácia do modelo

valores são transpostos para o intervalo 0-1

In [109]:

```
diabetes_data = diabetes_data.loc[:, ["Pregnancies", "Glucose", "BloodPressure",
"SkinThickness", "Insulin",
                        "BMI", "DiabetesPedigreeFunction", "Age"] ]
diabetes_data.head()
```

Out[109]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunc
0	6	148	72	35	0	33.6	0
1	1	85	66	29	0	26.6	0
2	8	183	64	0	0	23.3	0
3	1	89	66	23	94	28.1	0
4	0	137	40	35	168	43.1	2

In [110]:

```
# normalize the data attributes
from sklearn import preprocessing
min_max_scaler = preprocessing.MinMaxScaler()
np_scaled = min_max_scaler.fit_transform(diabetes_data)
df_normalized = pd.DataFrame(np_scaled)
df_normalized.columns = ["Pregnancies", "Glucose", "BloodPressure", "SkinThickne
ss", "Insulin",
                        "BMI", "DiabetesPedigreeFunction", "Age"]
df_normalized.head()
```

Out[110]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigr
0	0.352941	0.743719	0.590164	0.353535	0.000000	0.500745	
1	0.058824	0.427136	0.540984	0.292929	0.000000	0.396423	
2	0.470588	0.919598	0.524590	0.000000	0.000000	0.347243	
3	0.058824	0.447236	0.540984	0.232323	0.111111	0.418778	
4	0.000000	0.688442	0.327869	0.353535	0.198582	0.642325	

In [111]:

```
diabetes_target[:3]
```

Out[111]:

```
0    1
1    0
2    1
Name: Class, dtype: int64
```

In [112]:

```
X_train, X_test, y_train, y_test = train_test_split(
    df_normalized, diabetes_target, test_size=0.33, random_state=42)
X_train[:3]
```

Out[112]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPed
464	0.588235	0.577889	0.803279	0.000000	0.000000	0.357675	
223	0.411765	0.713568	0.491803	0.333333	0.224586	0.429210	
393	0.235294	0.582915	0.590164	0.121212	0.102837	0.329359	

In [113]:

```
classifier = svm.SVC(kernel='linear', C=10.0, gamma=0.001)
```

In [114]:

```
classifier.fit(X_train, y_train)
```

Out[114]:

```
SVC(C=10.0, gamma=0.001, kernel='linear')
```

In [115]:

```
prediction_SVM = classifier.predict(X_test)
```

In [116]:

```
cm = confusion_matrix(y_test, prediction_SVM)
cm
```

Out[116]:

```
array([[137,  31],
       [ 33,  53]], dtype=int64)
```

kernel linear confusion matrix: [[139 29] [33 53]] score: 0.7559055118110236

In [117]:

```
classifier.score(X_test, y_test)
```

Out[117]:

```
0.7480314960629921
```

In [118]:

```
kernels = ['linear', 'rbf', 'sigmoid']
testar_kernels(kernels)
```

```
kernel linear
confusion matrix:
 [[141  27]
 [ 37  49]]
score: 0.7480314960629921


kernel rbf
confusion matrix:
 [[168   0]
 [ 86   0]]
score: 0.6614173228346457


kernel sigmoid
confusion matrix:
 [[168   0]
 [ 86   0]]
score: 0.6614173228346457
```

SVM - Cancer

In [119]:

```
from sklearn.datasets import load_breast_cancer
data = load_breast_cancer()

list(data.target_names)
```

Out[119]:

```
['malignant', 'benign']
```

'malignant': 0, 'benign':1

Breast Cancer Wisconsin (Diagnostic) Database

Notes

Data Set Characteristics: :Number of Instances: 569

```
:Number of Attributes: 30 numeric, predictive attributes and the class

:Attribute Information:
    - radius (mean of distances from center to points on the perimeter)
    - texture (standard deviation of gray-scale values)
    - perimeter
    - area
    - smoothness (local variation in radius lengths)
    - compactness (perimeter^2 / area - 1.0)
    - concavity (severity of concave portions of the contour)
    - concave points (number of concave portions of the contour)
    - symmetry
    - fractal dimension ("coastline approximation" - 1)

    The mean, standard error, and "worst" or largest (mean of the three
    largest values) of these features were computed for each image,
    resulting in 30 features.  For instance, field 3 is Mean Radius, fiel
d
    13 is Radius SE, field 23 is Worst Radius.

    - class:
            - WDBC-Malignant (0)
            - WDBC-Benign (1)
```

In [120]:

```
df = pd.DataFrame(data.data)
df.columns = ['mean radius', 'mean texture', 'mean perimeter', 'mean area',
       'mean smoothness', 'mean compactness', 'mean concavity',
       'mean concave points', 'mean symmetry', 'mean fractal dimension',
       'radius error', 'texture error', 'perimeter error', 'area error',
       'smoothness error', 'compactness error', 'concavity error',
       'concave points error', 'symmetry error', 'fractal dimension error',
       'worst radius', 'worst texture', 'worst perimeter', 'worst area',
       'worst smoothness', 'worst compactness', 'worst concavity',
       'worst concave points', 'worst symmetry', 'worst fractal dimension']
df["class"] = data.target
df.head()
```

Out[120]:

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	m symm
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1

5 rows × 31 columns

In [121]:

```
len(data.data)
```

Out[121]:

569

In [122]:

```
data.feature_names
```

Out[122]:

```
array(['mean radius', 'mean texture', 'mean perimeter', 'mean area',
       'mean smoothness', 'mean compactness', 'mean concavity',
       'mean concave points', 'mean symmetry', 'mean fractal dimensi
on',
       'radius error', 'texture error', 'perimeter error', 'area err
or',
       'smoothness error', 'compactness error', 'concavity error',
       'concave points error', 'symmetry error',
       'fractal dimension error', 'worst radius', 'worst texture',
       'worst perimeter', 'worst area', 'worst smoothness',
       'worst compactness', 'worst concavity', 'worst concave point
s',
       'worst symmetry', 'worst fractal dimension'], dtype='<U23')
```

In [123]:

```
import numpy as np
np.set_printoptions(suppress=True, precision=3)
data.data
```

Out[123]:

```
array([[ 17.99 ,  10.38 , 122.8  , ...,   0.265,   0.46 ,   0.119],
       [ 20.57 ,  17.77 , 132.9  , ...,   0.186,   0.275,   0.089],
       [ 19.69 ,  21.25 , 130.   , ...,   0.243,   0.361,   0.088],
       ...,
       [ 16.6  ,  28.08 , 108.3  , ...,   0.142,   0.222,   0.078],
       [ 20.6  ,  29.33 , 140.1  , ...,   0.265,   0.409,   0.124],
       [  7.76 ,  24.54 ,  47.92 , ...,   0.   ,   0.287,   0.07 ]])
```

In [124]:

```
data.target_names
```

Out[124]:

```
array(['malignant', 'benign'], dtype='<U9')
```

In [125]:

```
data.target[:20]
```

Out[125]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1])
```

In [126]:

```
df.columns
```

Out[126]:

```
Index(['mean radius', 'mean texture', 'mean perimeter', 'mean area',
       'mean smoothness', 'mean compactness', 'mean concavity',
       'mean concave points', 'mean symmetry', 'mean fractal dimensi
on',
       'radius error', 'texture error', 'perimeter error', 'area err
or',
       'smoothness error', 'compactness error', 'concavity error',
       'concave points error', 'symmetry error', 'fractal dimension
error',
       'worst radius', 'worst texture', 'worst perimeter', 'worst ar
ea',
       'worst smoothness', 'worst compactness', 'worst concavity',
       'worst concave points', 'worst symmetry', 'worst fractal dime
nsion',
       'class'],
      dtype='object')
```

In [127]:

```
df['class'].value_counts()
```

Out[127]:

```
1    357
0    212
Name: class, dtype: int64
```

In [128]:

```
X_train, X_test, y_train, y_test = train_test_split(
    data.data, data.target, test_size=0.33, random_state=42)
```

In [129]:

```
classifier = svm.SVC(kernel='linear', C=10.0, gamma=0.001)
```

In [130]:

```
classifier.fit(X_train, y_train)
```

Out[130]:

```
SVC(C=10.0, gamma=0.001, kernel='linear')
```

In [131]:

```
prediction_SVM = classifier.predict(X_test)
```

In [132]:

```
cm = confusion_matrix(y_test, prediction_SVM)
cm
```

Out[132]:

```
array([[ 63,   4],
       [  7, 114]], dtype=int64)
```

In [133]:

```
classifier.score(X_test, y_test)
```

Out[133]:

```
0.9414893617021277
```

In [134]:

```
testar_kernels(kernels)
```

```
kernel linear
confusion matrix:
 [[ 63   4]
 [  4 117]]
score: 0.9574468085106383


kernel rbf
confusion matrix:
 [[ 64   3]
 [ 13 108]]
score: 0.9148936170212766


kernel sigmoid
confusion matrix:
 [[  0  67]
 [  0 121]]
score: 0.6436170212765957
```

normalizar

In [135]:

```
np_scaled = min_max_scaler.fit_transform(data.data)
```

In [136]:

```
data.data
```

Out[136]:

```
array([[ 17.99 ,  10.38 , 122.8  , ...,   0.265,   0.46 ,   0.119],
       [ 20.57 ,  17.77 , 132.9  , ...,   0.186,   0.275,   0.089],
       [ 19.69 ,  21.25 , 130.   , ...,   0.243,   0.361,   0.088],
       ...,
       [ 16.6  ,  28.08 , 108.3  , ...,   0.142,   0.222,   0.078],
       [ 20.6  ,  29.33 , 140.1  , ...,   0.265,   0.409,   0.124],
       [  7.76 ,  24.54 ,  47.92 , ...,   0.   ,   0.287,   0.07 ]])
```

In [137]:

```
np_scaled
```

Out[137]:

```
array([[0.521, 0.023, 0.546, ..., 0.912, 0.598, 0.419],
       [0.643, 0.273, 0.616, ..., 0.639, 0.234, 0.223],
       [0.601, 0.39 , 0.596, ..., 0.835, 0.404, 0.213],
       ...,
       [0.455, 0.621, 0.446, ..., 0.487, 0.129, 0.152],
       [0.645, 0.664, 0.666, ..., 0.911, 0.497, 0.452],
       [0.037, 0.502, 0.029, ..., 0.   , 0.257, 0.101]])
```

In [138]:

```
X_train, X_test, y_train, y_test = train_test_split(
    np_scaled, data.target, test_size=0.33, random_state=42)
```

In [139]:

```
classifier.fit(X_train, y_train)
```

Out[139]:

```
SVC(C=10.0, gamma=0.001, kernel='linear')
```

In [140]:

```
classifier.score(X_test, y_test)
```

Out[140]:

```
0.9840425531914894
```

In [141]:

```
kernel linear
confusion matrix:
 [[ 63   4]
 [  4 117]]
score: 0.9574468085106383
```

```
  File "<ipython-input-141-f84f1215e81c>", line 1
    kernel linear
                ^
SyntaxError: invalid syntax
```

In [142]:

```
testar_kernels(kernels)
```

```
kernel linear
confusion matrix:
 [[ 65   2]
 [  1 120]]
score: 0.9840425531914894


kernel rbf
confusion matrix:
 [[ 51  16]
 [  0 121]]
score: 0.9148936170212766


kernel sigmoid
confusion matrix:
 [[ 40  27]
 [  0 121]]
score: 0.8563829787234043
```

SVM - Carros

In [143]:

```
import pandas as pd

df = pd.read_csv("car.data")
df.columns = ["buying", "maint", "doors", "persons", "lug_boot", "safety", "Clas
s"]
df.head()
```

Out[143]:

	buying	maint	doors	persons	lug_boot	safety	Class
0	vhigh	vhigh	2	2	small	med	unacc
1	vhigh	vhigh	2	2	small	high	unacc
2	vhigh	vhigh	2	2	med	low	unacc
3	vhigh	vhigh	2	2	med	med	unacc
4	vhigh	vhigh	2	2	med	high	unacc

In [144]:

```
len(df)
```

Out[144]:

```
1727
```

In [145]:

```
df.Class.value_counts()
```

Out[145]:

```
unacc    1209
acc       384
good       69
vgood      65
Name: Class, dtype: int64
```

Encoder - Decoder

In [146]:

```
from sklearn.preprocessing import LabelEncoder
import numpy as np

categorias = ["vhigh", "high", "med", "low"]

le = LabelEncoder()

categorias_convertidas_inteiro = le.fit_transform(categorias)
print(categorias_convertidas_inteiro)
```

```
[3 0 2 1]
```

In [147]:

```
# Decodificar
print(le.inverse_transform(categorias_convertidas_inteiro))
```

```
['vhigh' 'high' 'med' 'low']
```

In [148]:

```
lv = [ 1, 0, 0, 3]
#lv = [3, 0, 2, 1]
print(le.inverse_transform(lv))
```

```
['low' 'high' 'high' 'vhigh']
```

In [149]:

```
from sklearn.preprocessing import LabelEncoder
import numpy as np

le_buying = LabelEncoder()
#le_buying.fit(["vhigh", "high", "med", "low"])
print(le.fit_transform(["vhigh", "high", "med", "low"]))

dataset =  [ [1, 1, 1, 0],
             [3, 0, 2, 1]
           ]

dataset = np.array(dataset)

for tupla in dataset:
    print(list(le.inverse_transform(tupla)))
```

```
[3 0 2 1]
['low', 'low', 'low', 'high']
['vhigh', 'high', 'med', 'low']
```

Codificar os dados categóricos para inteiros

In [150]:

```
# codifica todo o dataframe para numérico
from sklearn.preprocessing import LabelEncoder
def codificar_dataframe(df):
    le = LabelEncoder()
    df2 = pd.DataFrame()
    for col in df.columns.values:
        # Encoding only categorical variables
        #print(len(df2[col]))
        if df[col].dtypes=='object':
            data=df[col]
            le.fit(data.values)
            #print (data.values)
            #print(le.fit(data.values))
            df2[col]=le.transform(df[col])

    # gerar os dicionarios das categorias e dos inteiros
    dict_scalar ={}
    dict_to_string = {}
    d = {}
    columns = df.columns.values.tolist()
    #print(type(columns))
    #print(columns)
    for col in columns:
        #print(col)
        values = list(set(df[col]))
        #print (values)
        le = LabelEncoder()
        vt = le.fit_transform(values)
        #print(le.transform(values))
        dict_scalar[col] = {}
        dict_to_string[col] = {}
        d = {}
        ds = {}
        for v, vt in zip(values, vt):
            #print (v,vt)
            d[v] = vt
            ds[vt] = v
        dict_scalar[col] = d
        dict_to_string[col] = ds

    return(df2, dict_scalar, dict_to_string)


def decodificar_dataframe(df2, dict_to_string):
    df3 = pd.DataFrame()
    columns = df2.columns.values.tolist()
    for col in columns:
        df3[col] = df2[col].map(dict_to_string[col])
    return (df3)
```

In [151]:

```
df.head()
```

Out[151]:

	buying	maint	doors	persons	lug_boot	safety	Class
0	vhigh	vhigh	2	2	small	med	unacc
1	vhigh	vhigh	2	2	small	high	unacc
2	vhigh	vhigh	2	2	med	low	unacc
3	vhigh	vhigh	2	2	med	med	unacc
4	vhigh	vhigh	2	2	med	high	unacc

In [152]:

```
df_cod, dict_nomes, dict_int = codificar_dataframe(df)
df_cod.head()
```

Out[152]:

	buying	maint	doors	persons	lug_boot	safety	Class
0	3	3	0	0	2	2	2
1	3	3	0	0	2	0	2
2	3	3	0	0	1	1	2
3	3	3	0	0	1	2	2
4	3	3	0	0	1	0	2

In [153]:

```
len(df_cod)
```

Out[153]:

1727

In [154]:

```
df_dec = decodificar_dataframe(df_cod, dict_int)
df_dec.head()
```

Out[154]:

	buying	maint	doors	persons	lug_boot	safety	Class
0	vhigh	vhigh	2	2	small	med	unacc
1	vhigh	vhigh	2	2	small	high	unacc
2	vhigh	vhigh	2	2	med	low	unacc
3	vhigh	vhigh	2	2	med	med	unacc
4	vhigh	vhigh	2	2	med	high	unacc

In [155]:

```
df.head()
```

Out[155]:

	buying	maint	doors	persons	lug_boot	safety	Class
0	vhigh	vhigh	2	2	small	med	unacc
1	vhigh	vhigh	2	2	small	high	unacc
2	vhigh	vhigh	2	2	med	low	unacc
3	vhigh	vhigh	2	2	med	med	unacc
4	vhigh	vhigh	2	2	med	high	unacc

Separar os dados X e Y

In [156]:

```
data_x = df_cod.loc[:,["buying", "maint", "doors", "persons", "lug_boot", "safet
y"]]
data_x.head()
```

Out[156]:

	buying	maint	doors	persons	lug_boot	safety
0	3	3	0	0	2	2
1	3	3	0	0	2	0
2	3	3	0	0	1	1
3	3	3	0	0	1	2
4	3	3	0	0	1	0

In [157]:

```
target_y = df_cod.loc[:,"Class"]
len(target_y)
```

Out[157]:

1727

In [158]:

```
X_train, X_test, y_train, y_test = train_test_split(data_x, target_y, test_size=
0.33, random_state=42)
```

In [159]:

```
classifier = svm.SVC(kernel='linear', C=10.0, gamma=0.001)
```

In [160]:

```
classifier.fit(X_train, y_train)
```

Out[160]:

```
SVC(C=10.0, gamma=0.001, kernel='linear')
```

In [161]:

```
prediction_SVM = classifier.predict(X_test)
```

In [162]:

```
df.Class.value_counts()
```

Out[162]:

```
unacc    1209
acc       384
good       69
vgood      65
Name: Class, dtype: int64
```

In [163]:

```
cm = confusion_matrix(y_test, prediction_SVM)
cm
```

Out[163]:

```
array([[ 23,   0, 104,   0],
       [  0,   0,  18,   0],
       [  6,   0, 393,   0],
       [ 15,   0,  11,   0]], dtype=int64)
```

In [164]:

```
classifier.score(X_test, y_test)
```

Out[164]:

```
0.7298245614035088
```

In [165]:

```
print("Vetores de suporte: ", len(classifier.support_vectors_))
classifier.support_vectors_
```

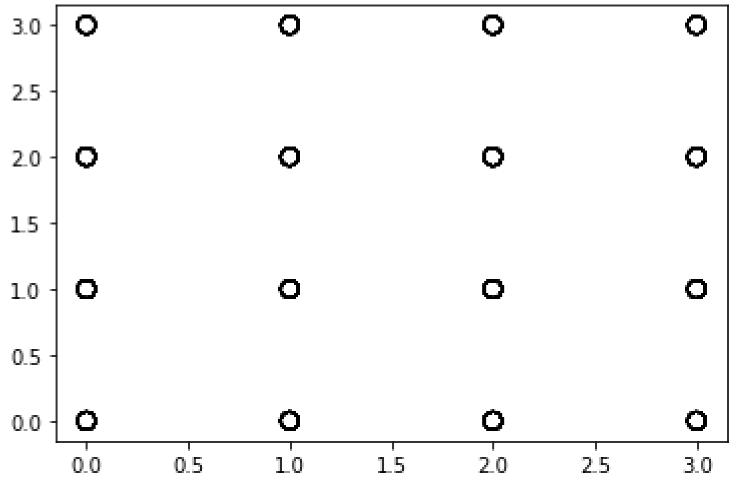
```
Vetores de suporte:  734
```

Out[165]:

```
array([[1., 0., 3., 2., 1., 2.],
       [1., 0., 1., 1., 2., 2.],
       [3., 1., 0., 2., 1., 0.],
       ...,
       [1., 1., 2., 1., 1., 0.],
       [2., 2., 1., 1., 0., 0.],
       [2., 1., 3., 2., 0., 0.]])
```

In [166]:

```
import matplotlib.pyplot as plt
clf = classifier
#plt.clf()
#plt.scatter(clf.support_vectors_[:, 0], clf.support_vectors_[:, 1]) #, s=80, fa
cecolors='none', zorder=10)
plt.scatter(clf.support_vectors_[:, 0], clf.support_vectors_[:, 1], s=80,
                facecolors='none', zorder=10, edgecolors='k')
#plt.scatter(clf.support_, clf.support_)
#plt.scatter(X[:, 0], X[:, 1], c=Y, zorder=10, cmap=plt.cm.Paired)
plt.show()
```



In [167]:

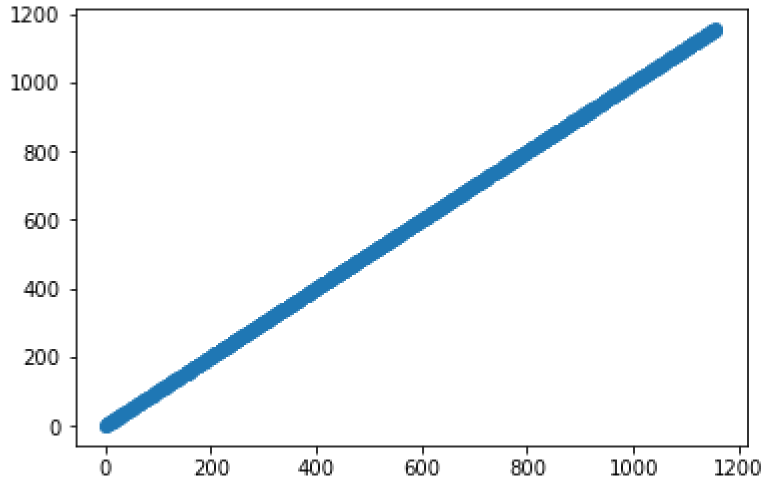
```
clf.support_[:4]
```

Out[167]:

```
array([ 7, 10, 14, 18])
```

In [168]:

```
plt.scatter(clf.support_, clf.support_) #, s=80, facecolors='none', zorder=10)
#plt.scatter(X[:, 0], X[:, 1], c=Y, zorder=10, cmap=plt.cm.Paired)
plt.show()
```



In [169]:

```
testar_kernels(kernels)
```

```
kernel linear
confusion matrix:
 [[ 20   0 107   0]
 [  0   0  18   0]
 [  5   0 394   0]
 [ 13   0  13   0]]
score: 0.7263157894736842


kernel rbf
confusion matrix:
 [[  0   0 127   0]
 [  0   0  18   0]
 [  0   0 399   0]
 [  0   0  26   0]]
score: 0.7


kernel sigmoid
confusion matrix:
 [[  0   0 127   0]
 [  0   0  18   0]
 [  0   0 399   0]
 [  0   0  26   0]]
score: 0.7
```

In [170]:

```
## Normalizar
```

In [171]:

```
np_scaled = min_max_scaler.fit_transform(data_x)
```

In [172]:

```
np_scaled[:3]
```

Out[172]:

```
array([[1. , 1. , 0. , 0. , 1. , 1. ],
       [1. , 1. , 0. , 0. , 1. , 0. ],
       [1. , 1. , 0. , 0. , 0.5, 0.5]])
```

In [173]:

```
X_train, X_test, y_train, y_test = train_test_split(np_scaled, target_y, test_si
ze=0.33, random_state=42)
```

In [174]:

```
testar_kernels(kernels)
```

```
kernel linear
confusion matrix:
 [[  5   0 122   0]
 [  0   0  18   0]
 [  2   0 397   0]
 [  2   0  24   0]]
score: 0.7052631578947368


kernel rbf
confusion matrix:
 [[  0   0 127   0]
 [  0   0  18   0]
 [  0   0 399   0]
 [  0   0  26   0]]
score: 0.7


kernel sigmoid
confusion matrix:
 [[  0   0 127   0]
 [  0   0  18   0]
 [  0   0 399   0]
 [  0   0  26   0]]
score: 0.7
```

Kernels - Plots

In [175]:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import svm


# Atributos e variável target
X = np.c_[(.4, -.7),
          (-1.5, -1),
          (-1.4, -.9),
          (-1.3, -1.2),
          (-1.1, -.2),
          (-1.2, -.4),
          (-.5, 1.2),
          (-1.5, 2.1),
          (1, 1),
          # --
          (1.3, .8),
          (1.2, .5),
          (.2, -2),
          (.5, -2.4),
          (.2, -2.3),
          (0, -2.7),
          (1.3, 2.1)].T
Y = [0] * 8 + [1] * 8

fignum = 1

# Modelo e Fit com 3 kernels
for kernel in ('linear', 'poly', 'rbf'):
    clf = svm.SVC(kernel = kernel, gamma = 2)
    clf.fit(X, Y)

    # Plot da linha com vetores de suporte mais próximos
    print("kernel: ", kernel)
    plt.figure(fignum, figsize=(4, 3))
    plt.clf()

    plt.scatter(clf.support_vectors_[:, 0], clf.support_vectors_[:, 1], s=80, fa
cecolors='none', zorder=10)
    plt.scatter(X[:, 0], X[:, 1], c=Y, zorder=10, cmap=plt.cm.Paired)

    plt.axis('tight')
    x_min = -3
    x_max = 3
    y_min = -3
    y_max = 3

    XX, YY = np.mgrid[x_min:x_max:200j, y_min:y_max:200j]
    Z = clf.decision_function(np.c_[XX.ravel(), YY.ravel()])

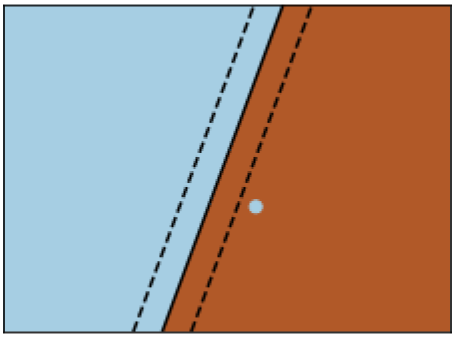
    # Color Plot
    Z = Z.reshape(XX.shape)
    plt.figure(fignum, figsize=(4, 3))
    plt.pcolormesh(XX, YY, Z > 0, cmap=plt.cm.Paired)
    plt.contour(XX, YY, Z, colors=['k', 'k', 'k'], linestyles=['--', '-', '--'],
levels=[-.5, 0, .5])

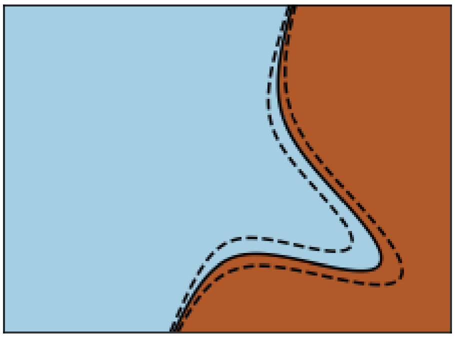
    plt.xlim(x_min, x_max)
    plt.ylim(y_min, y_max)
```

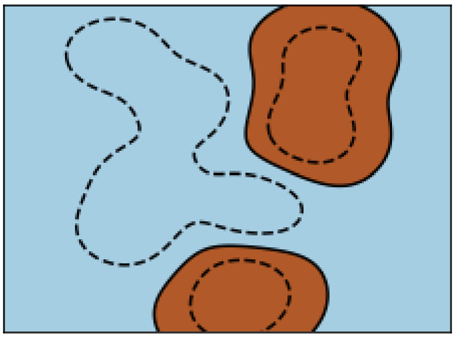
```
    plt.xticks(())
    plt.yticks(())
    fignum = fignum + 1

plt.show()
```

```
kernel:  linear
kernel:  poly
kernel:  rbf
```







Hyperparameter Tuning

A escolha de C e de gamma é importante performance das SVMs. A otimização (tuning) dos hyperparâmetros é uma boa prática para enoontrar bons parâmetros.

In [176]:

```
# dataset diabetes
X = diabetes_data.values
Y = diabetes_target.values
X_train, X_test, y_train, y_test = train_test_split(
    diabetes_data, diabetes_target, test_size=0.33, random_state=42)
```

In [177]:

```
kernel = 'linear'
#classifier = svm.SVC(kernel=kernel, C = 10.0, gamma = 0.001)
classifier = svm.SVC(kernel=kernel)
classifier.fit(X_train, y_train)
prediction_SVM = classifier.predict(X_test)
cm = confusion_matrix(y_test, prediction_SVM)
#cm = confusion_matrix(y_test, prediction_SVM)
print("kernel",kernel)
print("confusion matrix:\n",cm)
print("score:", classifier.score(X_test, y_test))
print("\n")
```

```
kernel linear
confusion matrix:
 [[139  29]
 [ 33  53]]
score: 0.7559055118110236
```

In [178]:

```
kernels = ['linear', 'rbf', 'sigmoid']
kernel = 'rbf'
#classifier = svm.SVC(kernel=kernel, C = 10.0, gamma = 0.001)
classifier = svm.SVC(kernel=kernel,C = 10.0, gamma = 0.001)
classifier.fit(X_train, y_train)
prediction_SVM = classifier.predict(X_test)
cm = confusion_matrix(y_test, prediction_SVM)
#cm = confusion_matrix(y_test, prediction_SVM)
print("kernel",kernel)
print("confusion matrix:\n",cm)
print("score:", classifier.score(X_test, y_test))
print("\n")
```

```
kernel rbf
confusion matrix:
 [[135  33]
 [ 38  48]]
score: 0.7204724409448819
```

In [179]:

```
np.arange(-15, 5, step=2)
```

Out[179]:

```
array([-15, -13, -11,  -9,  -7,  -5,  -3,  -1,   1,   3])
```

In [180]:

```
import numpy as np

2. **  np.arange(-15, 5, step=2)
```

Out[180]:

```
array([0.   , 0.   , 0.   , 0.002, 0.008, 0.031, 0.125, 0.5  , 2.  
,
       8.   ])
```

In [181]:

```
np.set_printoptions(precision=1, suppress=True)
g_range = 2. ** np.arange(-15, 5, step=2)
C_range = 2. ** np.arange(-5, 15, step=2)
g_range
```

Out[181]:

```
array([0. , 0. , 0. , 0. , 0. , 0. , 0.1, 0.5, 2. , 8. ])
```

In [182]:

```
C_range
```

Out[182]:

```
array([   0. ,    0.1,    0.5,    2. ,    8. ,   32. ,  128. ,  512. 
,
       2048. , 8192. ])
```

In [183]:

```
#from sklearn.grid_search import GridSearchCV, RandomizedSearchCV
from sklearn.model_selection import GridSearchCV
#import sklearn.cross_validation as cv
#  gamma and C (Cost)  hyperparametros
  g_range = 2. ** np.arange(-15, 5, step=2)
  C_range = 2. ** np.arange(-5, 15, step=2)

grid = [{'gamma': g_range, 'C': C_range}]

gridcv = GridSearchCV(svm.SVC(kernel='rbf'), param_grid=grid, cv= 5) #cv.KFold(n
=X_train.shape[0], n_folds=5))
gridcv.fit(X_train, y_train)

bestGamma = gridcv.best_params_['gamma']
bestC = gridcv.best_params_['C']

print ("Os melhores paRâmetros: gamma=", bestGamma, " and Cost=", bestC)
```

```
Os melhores paRâmetros: gamma= 3.0517578125e-05  and Cost= 8.0
```

In [192]:

```
classifier = svm.SVC(kernel='rbf', C=8, gamma=3.0517578125e-05)
classifier.fit(X_train, y_train)
prediction_SVM = classifier.predict(X_test)
cm = confusion_matrix(y_test, prediction_SVM)
#cm = confusion_matrix(y_test, prediction_SVM)
print("kernel",kernel)
print("confusion matrix:\n",cm)
print("score:", classifier.score(X_test, y_test))
print("\n")
```

```
kernel rbf
confusion matrix:
 [[143  25]
 [ 39  47]]
score: 0.7480314960629921
```

In [185]:

```
gridcv
```

Out[185]:

```
GridSearchCV(cv=5, estimator=SVC(),
             param_grid=[{'C': array([   0. ,    0.1,    0.5,    2.
,    8. ,   32. ,  128. ,  512. ,
       2048. , 8192. ]),
                          'gamma': array([0. , 0. , 0. , 0. , 0. ,
0. , 0.1, 0.5, 2. , 8. ])}])
```

In [186]:

```
gridcv.cv_results_
```

Out[186]:

```
{'mean_fit_time': array([0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0.
, 0. , 0. , 0. , 0. ,
        0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
0. ,
        0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
0. ,
        0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
0. ,
        0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
0. ,
        0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
0. ,
        0. , 0. , 0. , 0.1, 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ,
0.1,
        0.1, 0. , 0. , 0. , 0. , 0. , 0. , 0. , 0. ]),
 'std_fit_time': array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.]),
 'mean_score_time': array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.]),
 'std_score_time': array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.]),
 'param_C': masked_array(data=[0.03125, 0.03125, 0.03125, 0.03125,
0.03125, 0.03125,
                    0.03125, 0.03125, 0.03125, 0.03125, 0.125, 0.12
5,
                    0.125, 0.125, 0.125, 0.125, 0.125, 0.125, 0.125,
0.125,
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```

In [187]:

```
scores = gridcv.cv_results_['mean_test_score']
```

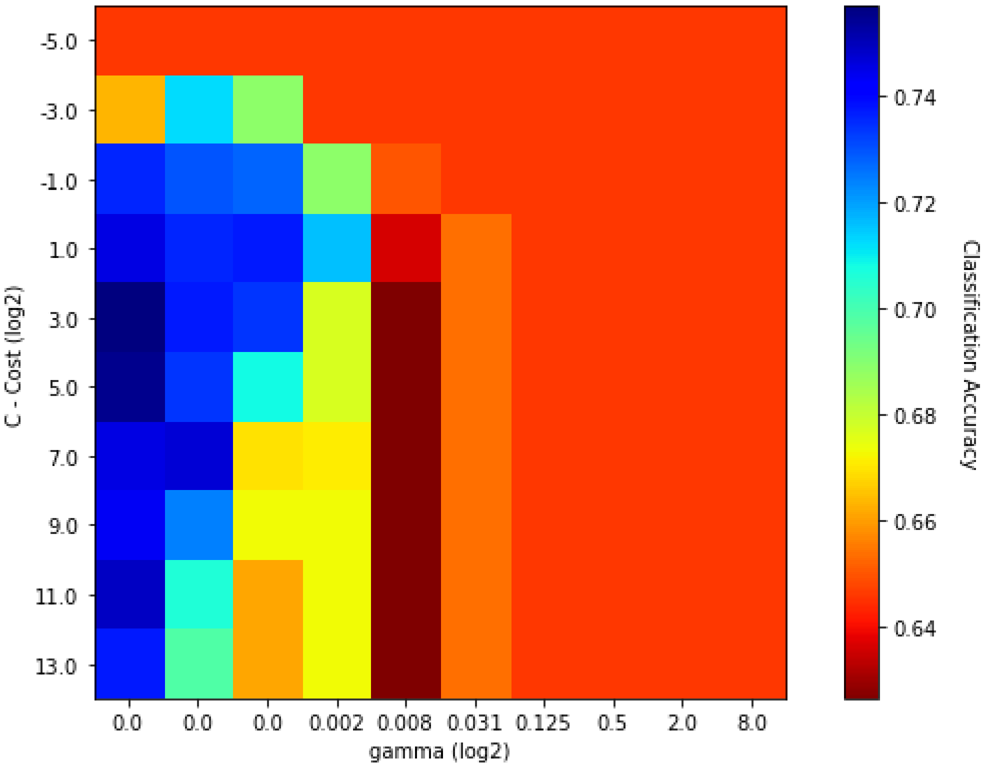
In [188]:

```
# plot the scores of the grid
# grid_scores_ contains parameter settings and scores
scores = np.array(scores).reshape(len(C_range), len(g_range))

# Make a heatmap with the performance
plt.figure(figsize=(10, 6))
plt.subplots_adjust(left=0.15, right=0.95, bottom=0.15, top=0.95)
plt.imshow(scores, interpolation='nearest', origin='upper', cmap=plt.cm.get_cmap
('jet_r')) # higher
plt.xlabel('gamma (log2)')
plt.ylabel('C - Cost (log2)')
plt.xticks(np.arange(len(g_range)), np.round(g_range,3) )
plt.yticks(np.arange(len(C_range)), np.log2((C_range)))

cbar = plt.colorbar()
cbar.set_label('Classification Accuracy', rotation=270, labelpad=20)

plt.show()
```



Exercício: Usar o GridSearch para o gamma e o C e plotar

In [189]:

```
g_range = 1.2 ** np.arange(-15, 5, step=2)
C_range = 1.5 ** np.arange(-5, 15, step=2)
```

In [190]:

```
g_range
```

Out[190]:

```
array([0.1, 0.1, 0.1, 0.2, 0.3, 0.4, 0.6, 0.8, 1.2, 1.7])
```

In [191]:

```
C_range
```

Out[191]:

```
array([  0.1,   0.3,   0.7,   1.5,   3.4,   7.6,  17.1,  38.4,  86.
5,
       194.6])
```

In [200]:

```
#from sklearn.grid_search import GridSearchCV, RandomizedSearchCV
from sklearn.model_selection import GridSearchCV
#import sklearn.cross_validation as cv
#  gamma and C (Cost)  hyperparametros
g_range = 1.2 ** np.arange(-15, 5, step=2)
C_range = 1.5 ** np.arange(-5, 15, step=2)

grid = [{'gamma': g_range, 'C': C_range}]

gridcv = GridSearchCV(svm.SVC(kernel='rbf'), param_grid=grid, cv= 5) #cv.KFold(n
=X_train.shape[0], n_folds=5))
gridcv.fit(X_train, y_train)

bestGamma = gridcv.best_params_['gamma']
bestC = gridcv.best_params_['C']

print ("Os melhores paRâmetros: gamma=", bestGamma, " and Cost=", bestC)
```

```
Os melhores paRâmetros: gamma= 0.0649054715188745  and Cost= 0.13168
724279835392
```

In [201]:

```
classifier = svm.SVC(kernel='rbf', C=8, gamma=3.0517578125e-05)
classifier.fit(X_train, y_train)
prediction_SVM = classifier.predict(X_test)
cm = confusion_matrix(y_test, prediction_SVM)
#cm = confusion_matrix(y_test, prediction_SVM)
print("kernel",kernel)
print("confusion matrix:\n",cm)
print("score:", classifier.score(X_test, y_test))
print("\n")
```

```
kernel rbf
confusion matrix:
 [[143  25]
 [ 39  47]]
score: 0.7480314960629921
```

In [202]:

```
gridcv
```

Out[202]:

```
GridSearchCV(cv=5, estimator=SVC(),
             param_grid=[{'C': array([  0.1,   0.3,   0.7,   1.5,
3.4,   7.6,  17.1,  38.4,  86.5,
       194.6]),
                          'gamma': array([0.1, 0.1, 0.1, 0.2, 0.3,
0.4, 0.6, 0.8, 1.2, 1.7])}])
```

In [203]:

```
gridcv.cv_results_
```

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0.6, 0.6, 0.6, 0.6, 0.6,
```

```
        0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6,
0.6,
        0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6,
0.6,
        0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6,
0.6,
        0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6,
0.6,
        0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6,
0.6,
        0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6,
0.6,
        0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6, 0.6]),
 'std_test_score': array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0., 0., 0., 0., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0., 0.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.]),
 'rank_test_score': array([ 1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
1,  1,  1,  1,  1,  1,  1,
         1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1, 94,  1,
1,  1,
         1,  1,  1,  1,  1,  1, 94,  1,  1,  1,  1,  1,  1,  1,  1,
1, 94,
         1,  1,  1,  1,  1,  1,  1,  1,  1, 94,  1,  1,  1,  1,  1,
1,  1,
         1,  1, 94,  1,  1,  1,  1,  1,  1,  1,  1,  1, 94,  1,  1,
1,  1,
         1,  1,  1,  1,  1, 94,  1,  1,  1,  1,  1,  1,  1,  1,
1])}
```

In [204]:

```
scores = gridcv.cv_results_['mean_test_score']
```

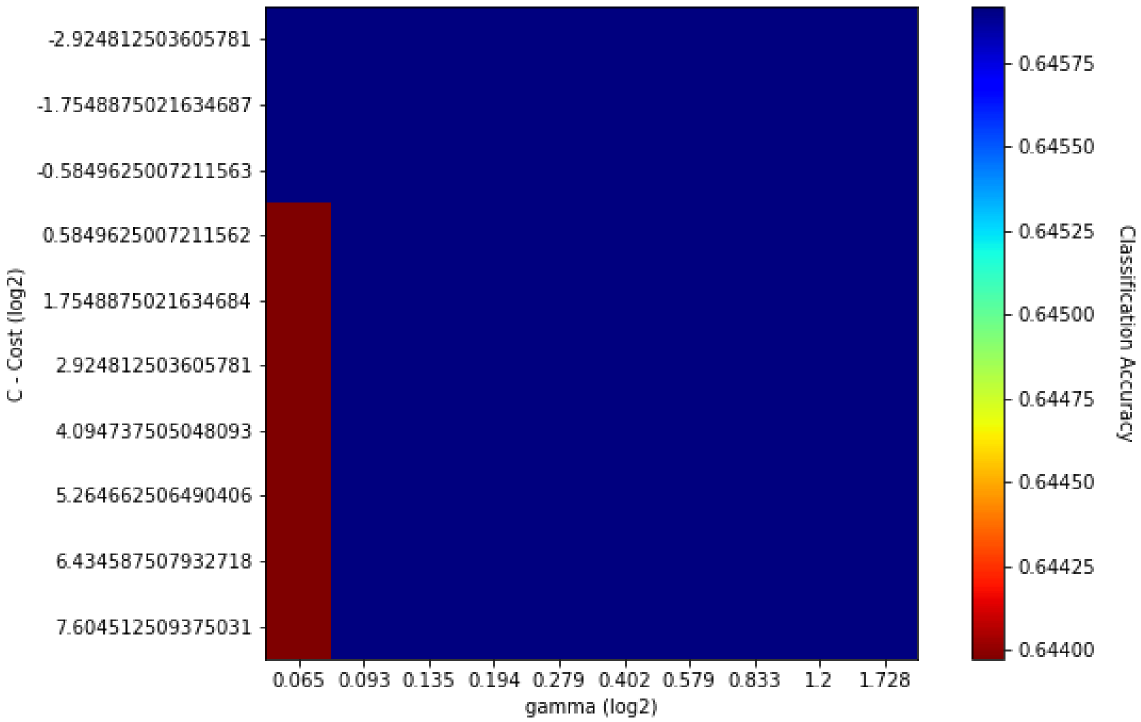
In [205]:

```
# plot the scores of the grid
# grid_scores_ contains parameter settings and scores
scores = np.array(scores).reshape(len(C_range), len(g_range))

# Make a heatmap with the performance
plt.figure(figsize=(10, 6))
plt.subplots_adjust(left=0.15, right=0.95, bottom=0.15, top=0.95)
plt.imshow(scores, interpolation='nearest', origin='upper', cmap=plt.cm.get_cmap
('jet_r')) # higher
plt.xlabel('gamma (log2)')
plt.ylabel('C - Cost (log2)')
plt.xticks(np.arange(len(g_range)), np.round(g_range,3) )
plt.yticks(np.arange(len(C_range)), np.log2((C_range)))

cbar = plt.colorbar()
cbar.set_label('Classification Accuracy', rotation=270, labelpad=20)

plt.show()
```



In [ ]: