SVM

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1 Support Vector Machines

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1.1.1 Using the notebook from https://www.kaggle.com/azzion/svm-for-beginners-tutorial to understand how to use SVM

This notebook essentially covers a basic tutorial for Support Vector Machine. I am going to use the mobile prediction data for this excerise.

Note: 1) This data set is not a great data set to practise SVM classification on, I used it to simple try out the SVM. 2) If you have a better data set then I would recommend use that or IRIS Data set is great for this problem.

The below topics are covered in this Kernal. - Data prepocessing - Target value Analysis - SVM - Linear SVM - SV Regressor - Non Linear SVM with kernal - RBF (note: you can also try poly) - Non Linear SVR

[2]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap


import os
print(os.listdir("../mobile-price-classification"))

# Any results you write to the current directory are saved as output.
```

```
['test.csv', 'train.csv']
```

DATA PREPROCESSING

[4]:
```
df = pd.read_csv('../mobile-price-classification/train.csv')
test = pd.read_csv('../mobile-price-classification/test.csv')
df.head()
```

[4]:
```
   battery_power  blue  clock_speed  dual_sim  fc  four_g  int_memory  m_dep  \
0            842     0          2.2         0   1       0           7    0.6
1           1021     1          0.5         1   0       1          53    0.7
2            563     1          0.5         1   2       1          41    0.9
```

```
3             615      1           2.5          0    0         0           10     0.8
4            1821      1           1.2          0   13         1           44     0.6

   mobile_wt  n_cores  ...  px_height  px_width   ram  sc_h  sc_w  talk_time  \
0        188        2  ...         20       756  2549     9     7         19
1        136        3  ...        905      1988  2631    17     3          7
2        145        5  ...       1263      1716  2603    11     2          9
3        131        6  ...       1216      1786  2769    16     8         11
4        141        2  ...       1208      1212  1411     8     2         15

   three_g  touch_screen  wifi  price_range
0        0             0     1            1
1        1             1     0            2
2        1             1     0            2
3        1             0     0            2
4        1             1     0            1

[5 rows x 21 columns]
```

[5]:
```
# checking if there is any missing value
df.isnull().sum().max()
df.columns
```

[5]:
```
Index([u'battery_power', u'blue', u'clock_speed', u'dual_sim', u'fc',
       u'four_g', u'int_memory', u'm_dep', u'mobile_wt', u'n_cores', u'pc',
       u'px_height', u'px_width', u'ram', u'sc_h', u'sc_w', u'talk_time',
       u'three_g', u'touch_screen', u'wifi', u'price_range'],
      dtype='object')
```

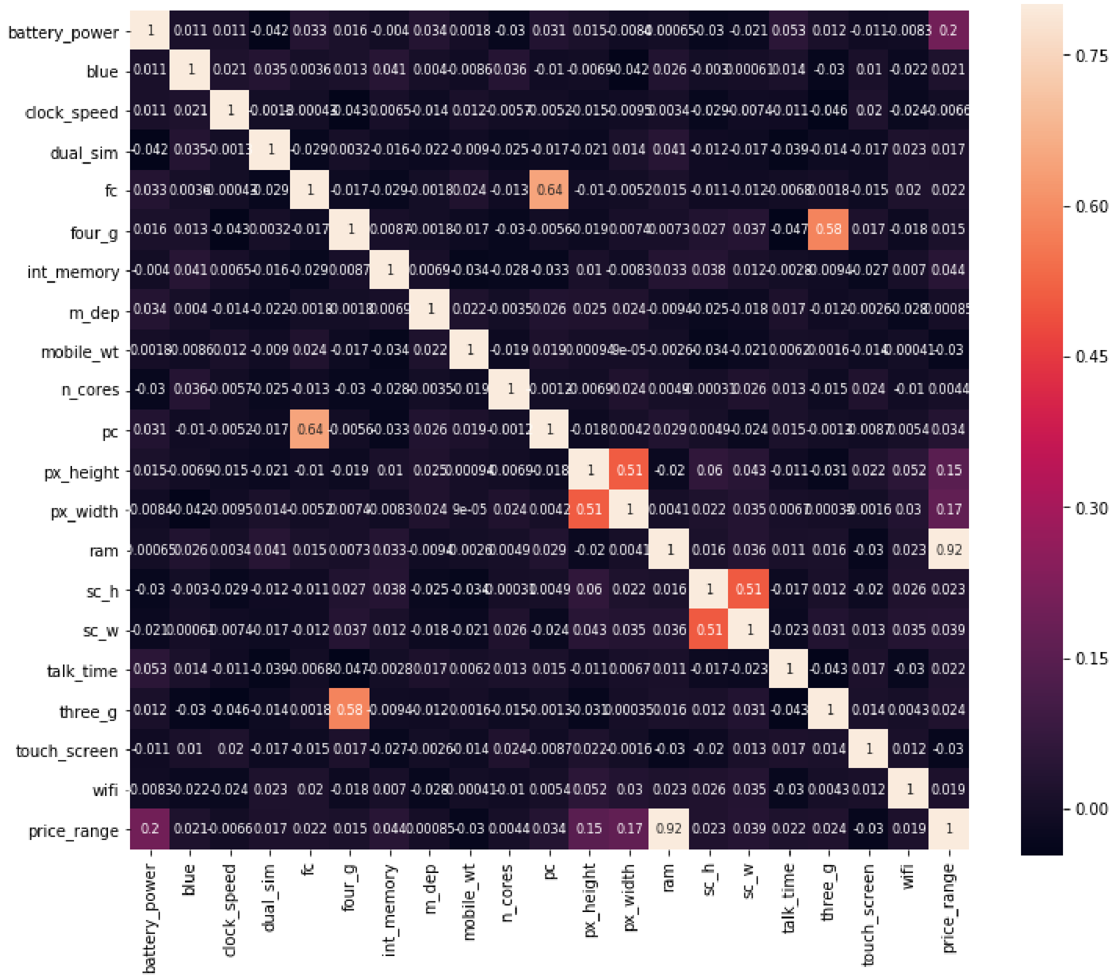
TARGET VALUE ANALYSIS

[6]:
```
#understanding the predicted value - which is hot encoded, in real life price␣
↪won't be hot encoded.
df['price_range'].describe(), df['price_range'].unique()

# there are 4 classes in the predicted value
```

[6]:
```
(count    2000.000000
 mean        1.500000
 std         1.118314
 min         0.000000
 25%         0.750000
 50%         1.500000
 75%         2.250000
 max         3.000000
 Name: price_range, dtype: float64, array([1, 2, 3, 0]))
```

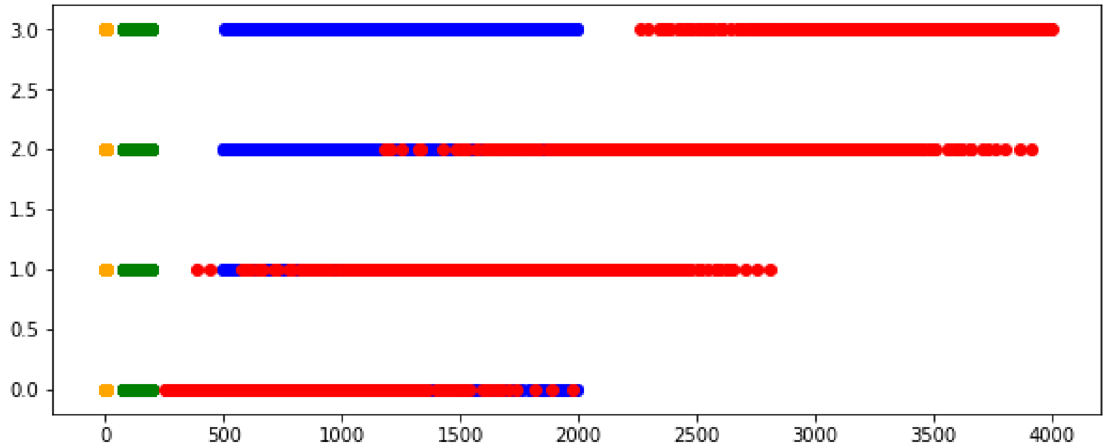
[7]:
```
corrmat = df.corr()
f,ax = plt.subplots(figsize=(12,10))
sns.heatmap(corrmat,vmax=0.8,square=True,annot=True,annot_kws={'size':8})
```

[7]: <matplotlib.axes._subplots.AxesSubplot at 0x1a1fb8f590>



[8]:
```
f, ax = plt.subplots(figsize=(10,4))
plt.scatter(y=df['price_range'],x=df['battery_power'],color='blue')
plt.scatter(y=df['price_range'],x=df['ram'],color='red')
plt.scatter(y=df['price_range'],x=df['n_cores'],color='orange')
plt.scatter(y=df['price_range'],x=df['mobile_wt'],color='green')
# clearly we can see that each of the category has different set of value␣
 ↪ranges
```

[8]: <matplotlib.collections.PathCollection at 0x1a1f86c510>

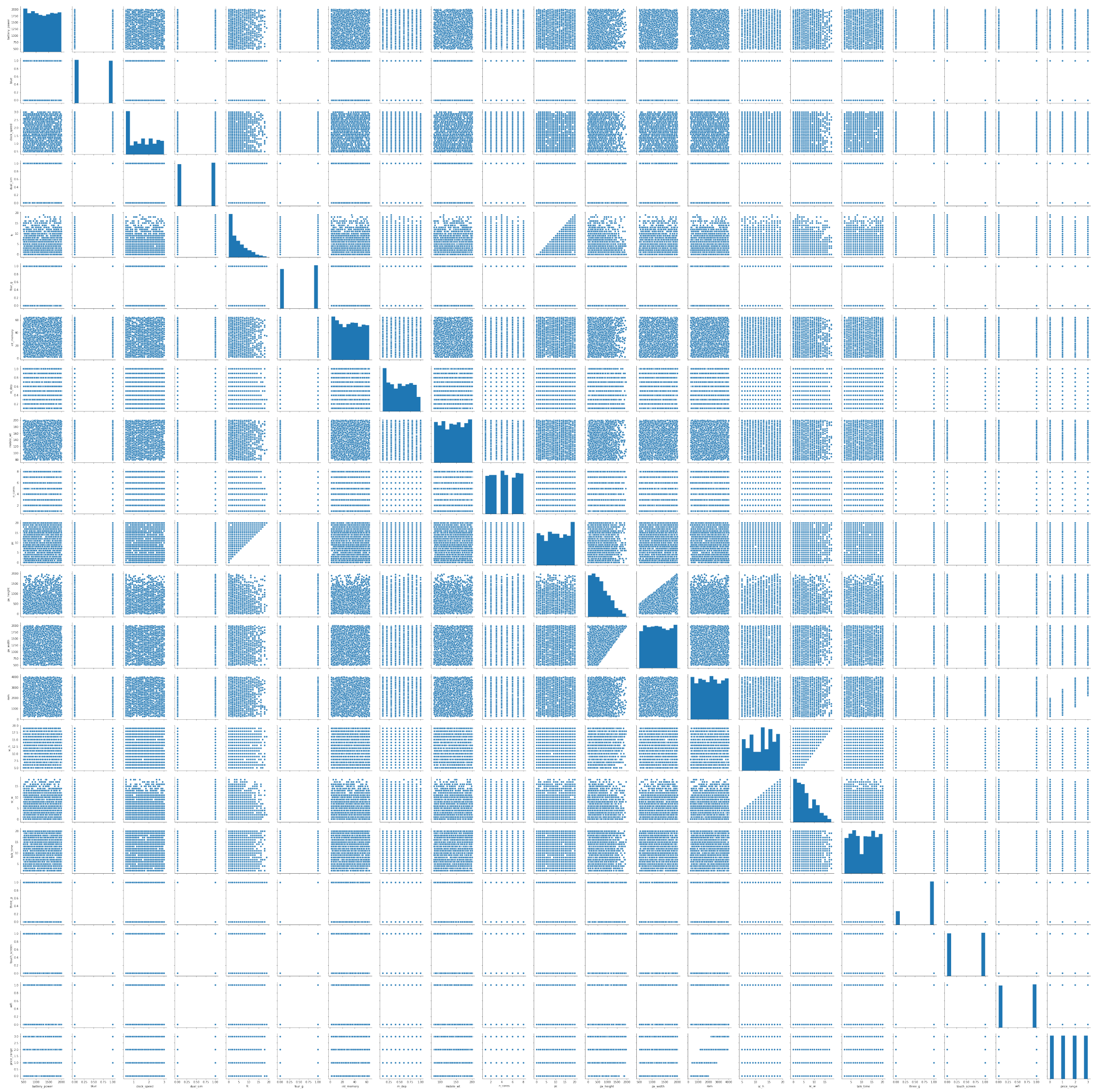


[10]:
```
# Using seaborn to plot
sns.swarmplot(x='battery_power',y='ram',data=df,hue='price_range')
plt.show()
```

[11]:
```
sns.pairplot(df,size=2.5)
plt.show()
```

```
/Users/enzo/anaconda2/lib/python2.7/site-packages/seaborn/axisgrid.py:2065:
UserWarning: The `size` parameter has been renamed to `height`; pleaes update
```

```
your code.
  warnings.warn(msg, UserWarning)
```



Now in the data set there is no need to create dummy variables or handle missing data as data set doesn't have any missing data

SUPPORT VECTOR MACHINES AND METHODS :

[12]:
```python
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split

y_t = np.array(df['price_range'])
X_t = df
X_t = df.drop(['price_range'],axis=1)
X_t = np.array(X_t)
```

```python
print("shape of Y :"+str(y_t.shape))
print("shape of X :"+str(X_t.shape))

from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_t = scaler.fit_transform(X_t)
```

```
shape of Y :(2000,)
shape of X :(2000, 20)
```

[13]:
```python
X_train,X_test,Y_train,Y_test = train_test_split(X_t,y_t,test_size=.
 ↪20,random_state=42)
print("shape of X Train :"+str(X_train.shape))
print("shape of X Test :"+str(X_test.shape))
print("shape of Y Train :"+str(Y_train.shape))
print("shape of Y Test :"+str(Y_test.shape))
```

```
shape of X Train :(1600, 20)
shape of X Test :(400, 20)
shape of Y Train :(1600,)
shape of Y Test :(400,)
```

[14]:
```python
for this_C in [1,3,5,10,40,60,80,100]:
    clf = SVC(kernel='linear',C=this_C).fit(X_train,Y_train)
    scoretrain = clf.score(X_train,Y_train)
    scoretest  = clf.score(X_test,Y_test)
    print("Linear SVM value of C:{}, training score :{:2f} , Test Score: {:2f}␣
 ↪\n".format(this_C,scoretrain,scoretest))
```

```
Linear SVM value of C:1, training score :0.953750 , Test Score: 0.960000

Linear SVM value of C:3, training score :0.961875 , Test Score: 0.977500

Linear SVM value of C:5, training score :0.968125 , Test Score: 0.975000

Linear SVM value of C:10, training score :0.977500 , Test Score: 0.967500

Linear SVM value of C:40, training score :0.981250 , Test Score: 0.962500

Linear SVM value of C:60, training score :0.981250 , Test Score: 0.962500

Linear SVM value of C:80, training score :0.981875 , Test Score: 0.970000

Linear SVM value of C:100, training score :0.980625 , Test Score: 0.967500
```

[15]:
```python
from sklearn.model_selection import cross_val_score,StratifiedKFold,LeaveOneOut
clf1 = SVC(kernel='linear',C=20).fit(X_train,Y_train)
scores = cross_val_score(clf1,X_train,Y_train,cv=5)
strat_scores =␣
 ↪cross_val_score(clf1,X_train,Y_train,cv=StratifiedKFold(5,random_state=10,shuffle=True))
#Loo = LeaveOneOut()
#Loo_scores = cross_val_score(clf1,X_train,Y_train,cv=Loo)
print("The Cross Validation Score :"+str(scores))
print("The Average Cross Validation Score :"+str(scores.mean()))
print("The Stratified Cross Validation Score :"+str(strat_scores))
print("The Average Stratified Cross Validation Score :"+str(strat_scores.
 ↪mean()))
#print("The LeaveOneOut Cross Validation Score :"+str(Loo_scores))
#print("The Average LeaveOneOut Cross Validation Score :"+str(Loo_scores.
 ↪mean()))
```

```
The Cross Validation Score :[0.95015576 0.96261682 0.94392523 0.92789969
0.97169811]
The Average Cross Validation Score :0.9512591238085129
The Stratified Cross Validation Score :[0.95327103 0.96884735 0.95015576
0.96551724 0.95597484]
The Average Stratified Cross Validation Score :0.9587532454897574
```

[16]:
```python
from sklearn.dummy import DummyClassifier

for strat in ['stratified', 'most_frequent', 'prior', 'uniform']:
    dummy_maj = DummyClassifier(strategy=strat).fit(X_train,Y_train)
    print("Train Stratergy :{} \n Score :{:.2f}".format(strat,dummy_maj.
 ↪score(X_train,Y_train)))
    print("Test Stratergy :{} \n Score :{:.2f}".format(strat,dummy_maj.
 ↪score(X_test,Y_test)))
```

```
Train Stratergy :stratified
 Score :0.26
Test Stratergy :stratified
 Score :0.27
Train Stratergy :most_frequent
 Score :0.26
Test Stratergy :most_frequent
 Score :0.23
Train Stratergy :prior
 Score :0.26
Test Stratergy :prior
 Score :0.23
Train Stratergy :uniform
 Score :0.25
```

```
Test Stratergy :uniform
 Score :0.27
```

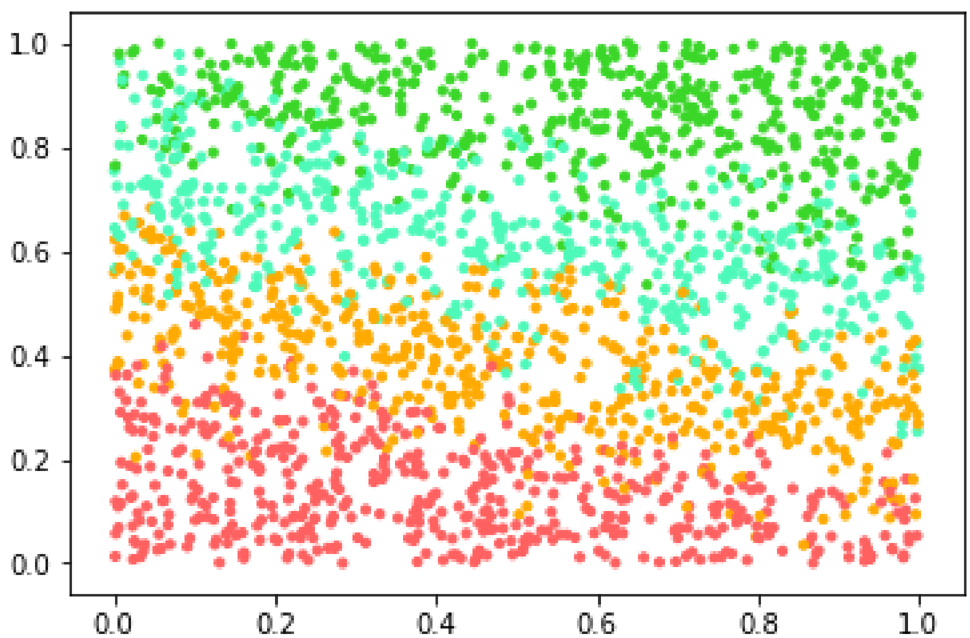
[17]:
```
# plotting the decision boundries for the data
#converting the data to array for plotting.
X = np.array(df.iloc[:,[0,13]])
y = np.array(df['price_range'])
print("Shape of X:"+str(X.shape))
print("Shape of y:"+str(y.shape))
X = scaler.fit_transform(X)
```

```
Shape of X:(2000, 2)
Shape of y:(2000,)
```

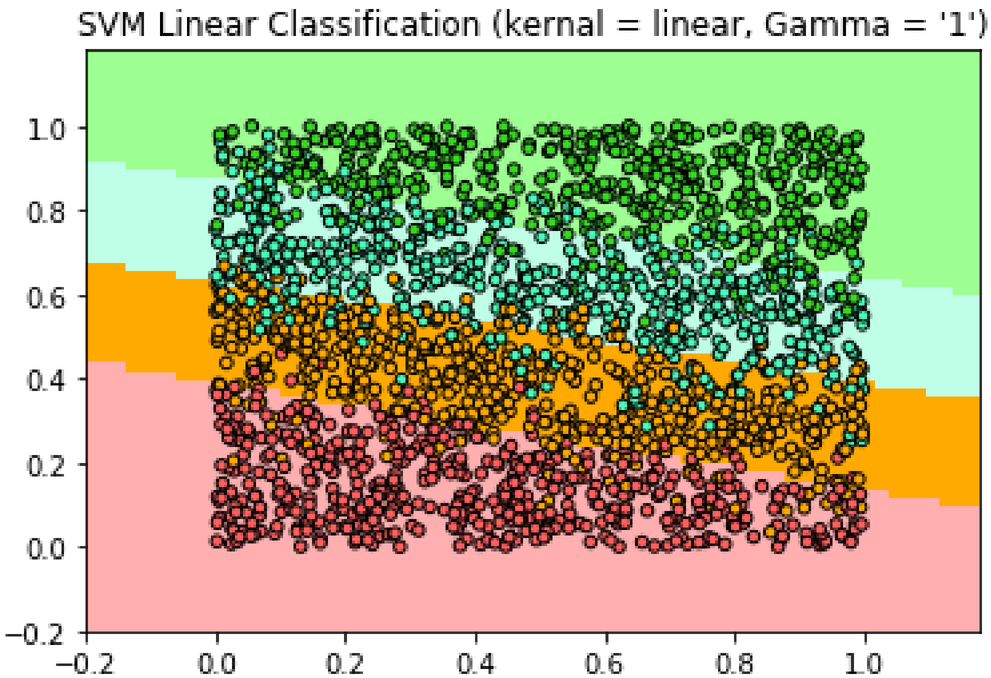
```
/Users/enzo/anaconda2/lib/python2.7/site-
packages/sklearn/utils/validation.py:595: DataConversionWarning: Data with input
dtype int64 was converted to float64 by MinMaxScaler.
  warnings.warn(msg, DataConversionWarning)
```

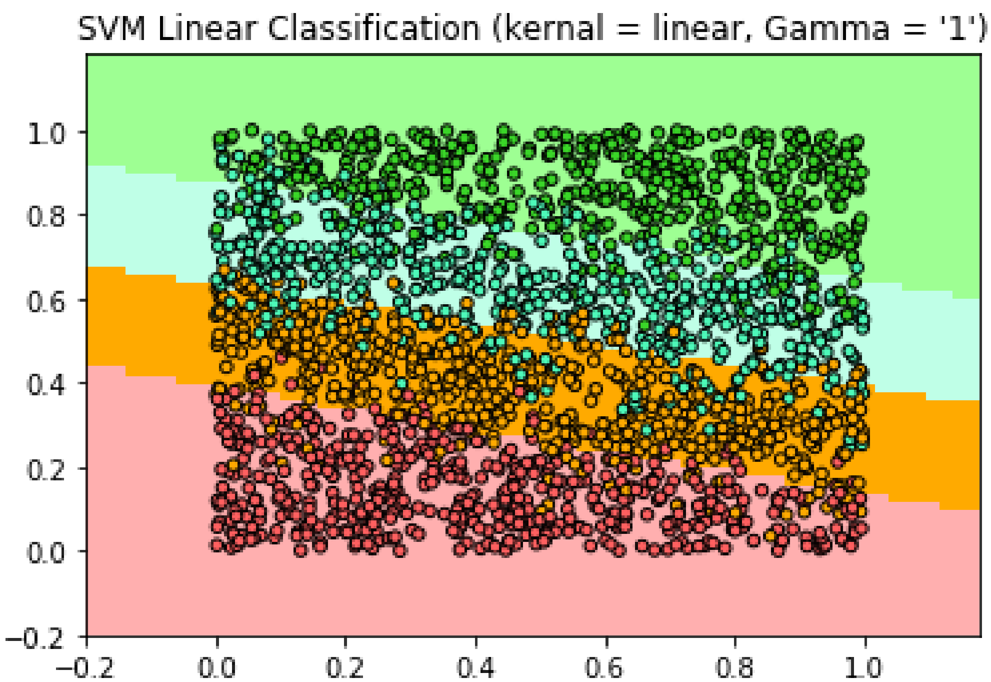
[18]:
```
# custome color maps
cm_dark = ListedColormap(['#ff6060',␣
 ↪'#8282ff','#ffaa00','#fff244','#4df9b9','#76e8fc','#3ad628'])
cm_bright = ListedColormap(['#ffafaf',␣
 ↪'#c6c6ff','#ffaa00','#ffe2a8','#bfffe7','#c9f7ff','#9eff93'])
```

[19]:
```
plt.scatter(X[:,0],X[:,1],c=y,cmap=cm_dark,s=10,label=y)
plt.show()
```



[20]:
```
h = .02  # step size in the mesh
C_param = 1 # No of neighbours
for weights in ['uniform', 'distance']:
    # we create an instance of Neighbours Classifier and fit the data.
    clf1 = SVC(kernel='linear',C=C_param)
    clf1.fit(X, y)

    # Plot the decision boundary. For that, we will assign a color to each
    # point in the mesh [x_min, x_max]x[y_min, y_max].
    x_min, x_max = X[:, 0].min()-.20, X[:, 0].max()+.20
    y_min, y_max = X[:, 1].min()-.20, X[:, 1].max()+.20
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                         np.arange(y_min, y_max, h))
    Z = clf1.predict(np.c_[xx.ravel(), yy.ravel()])   # ravel to flatten the␣
 ↪into 1D and c_ to concatenate

    # Put the result into a color plot
    Z = Z.reshape(xx.shape)
    plt.figure()
    plt.pcolormesh(xx, yy, Z, cmap=cm_bright)

    # Plot also the training points
    plt.scatter(X[:, 0], X[:, 1], c=y, cmap=cm_dark,
                edgecolor='k', s=20)
    plt.xlim(xx.min(), xx.max())
    plt.ylim(yy.min(), yy.max())
    plt.title("SVM Linear Classification (kernal = linear, Gamma = '%s')"%␣
 ↪(C_param))

plt.show()
```





[21]:
```
print("The score of the above :"+str(clf1.score(X,y)))
```

```
The score of the above :0.825
```

[22]:
```python
# Linear Support vector machine with only C Parameter
from sklearn.svm import LinearSVC

for this_C in [1,3,5,10,40,60,80,100]:
    clf2 = LinearSVC(C=this_C).fit(X_train,Y_train)
    scoretrain = clf2.score(X_train,Y_train)
    scoretest  = clf2.score(X_test,Y_test)
    print("Linear SVM value of C:{}, training score :{:2f} , Test Score: {:2f}
 \n".format(this_C,scoretrain,scoretest))
```

```
Linear SVM value of C:1, training score :0.846250 , Test Score: 0.840000


/Users/enzo/anaconda2/lib/python2.7/site-packages/sklearn/svm/base.py:931:
ConvergenceWarning: Liblinear failed to converge, increase the number of
iterations.
  "the number of iterations.", ConvergenceWarning)

Linear SVM value of C:3, training score :0.864375 , Test Score: 0.855000

Linear SVM value of C:5, training score :0.867500 , Test Score: 0.872500

Linear SVM value of C:10, training score :0.874375 , Test Score: 0.877500

Linear SVM value of C:40, training score :0.818125 , Test Score: 0.835000

Linear SVM value of C:60, training score :0.857500 , Test Score: 0.855000

Linear SVM value of C:80, training score :0.846250 , Test Score: 0.827500

Linear SVM value of C:100, training score :0.813125 , Test Score: 0.807500
```

Apparently we got better scores with SVC where we defined the kernal as linear than with just LinearSVC

The LinearSVC class is based on the liblinear library, which implements an optimized algorithm for linear SVMs. 1. It does not support the kernel trick, but it scales almost linearly with the number of training instances and the number of features: its training time complexity is roughly O(m Œ n).

The SVC class is based on the libsvm library, which implements an algorithm that supports the kernel trick. 1. The training time complexity is usually between O(m2 Œ n) and O(m3 Œ n). 1. LinearSVC is much faster than SVC(kernel="linear")

[23]:
```python
from sklearn.svm import SVR

svr = SVR(kernel='linear',C=1,epsilon=.01).fit(X_train,Y_train)
```

```
print("{:.2f} is the accuracy of the SV Regressor".format(svr.
↪score(X_train,Y_train)))
```

```
0.92 is the accuracy of the SV Regressor
```

- SVM supports linear and nonlinear regression.
- SVM Regression tries to fit as many instances as possible on the decision boundary while limiting margin violations.
- The width of the decision boundary is controlled by a hyperparameter .

NON LINEAR SVM

A method to Handle Non linear relationships in our data set is to use polynomial Kernal or using a similarity function with our SVM.

We will use the Gaussian Radial Basis Function(RBF) function for the same. to handle this in Sklearn there is a Gamma hyperparameter. Check the Gausian RBF Function - for more info.

Technically, the gamma parameter is the inverse of the standard deviation of the RBF kernel (Gaussian function), which is used as similarity measure between two points. Intuitively, a small gamma value define a Gaussian function with a large variance. In this case, two points can be considered similar even if are far from each other. **In the other hand, a large gamma value means define a Gaussian function with a small variance and in this case, two points are considered similar just if they are close to each other.**

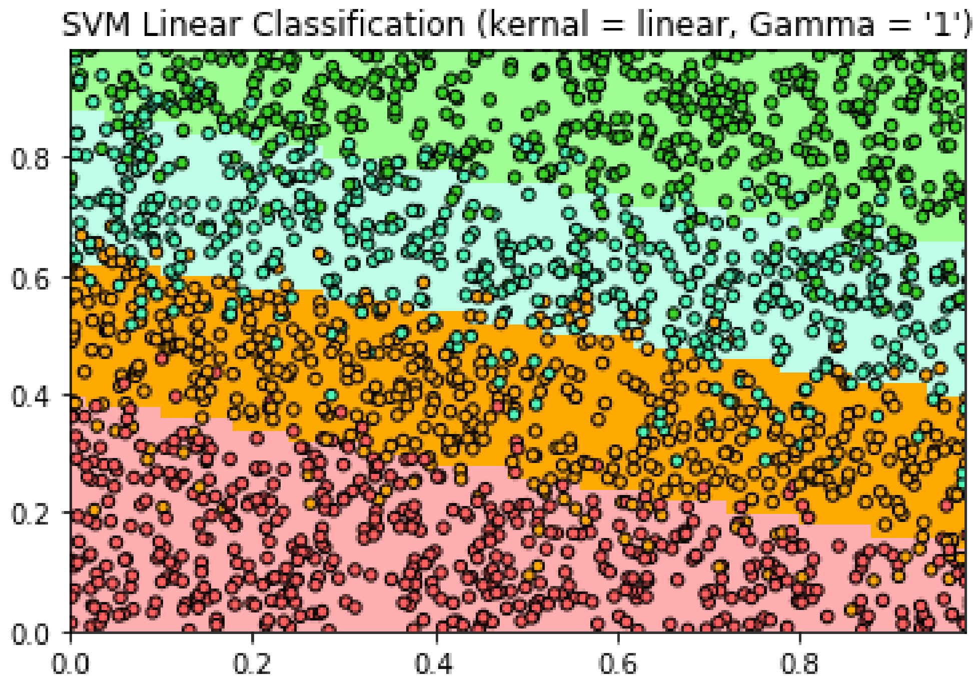
Initution : we create different landmarks and then check how far the training examples are from the landmark. In practise, if we have n training examples then we will have n landmarks and we will thus create a feature set of n values with n landmarks. When the training example is closest to a landmark the value the variance will be small and when far the value will be large and hence we will associate the close to the landmark example with a 1 and those that are far with a 0. This ability makes the SVM very powerful.

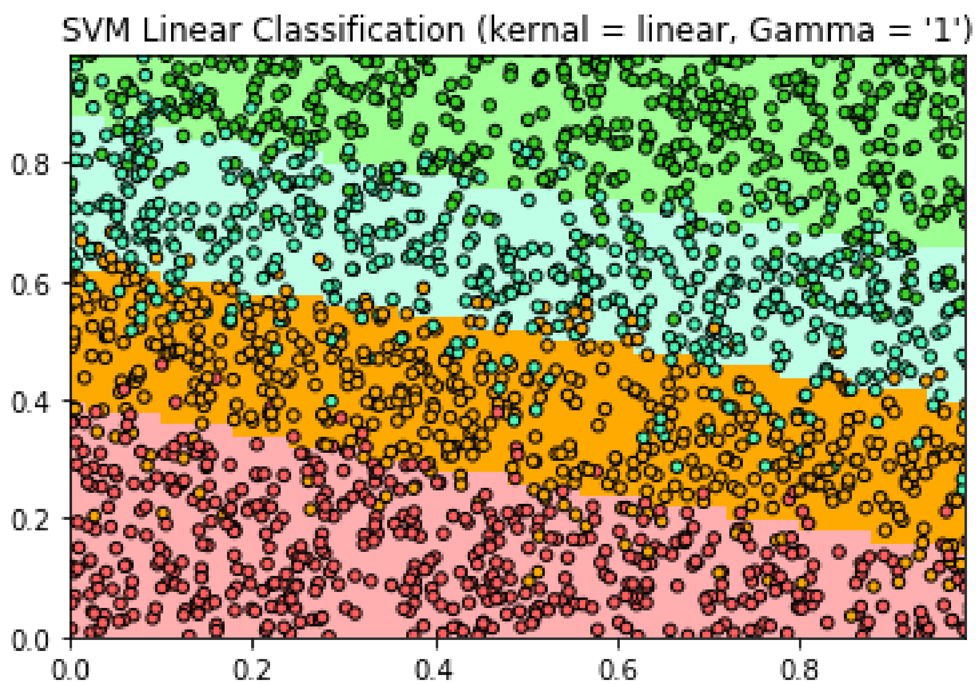
[24]:
```
# SMV with RBF KERNAL AND ONLY C PARAMETER

for this_C in [1,5,10,25,50,100]:
    clf3 = SVC(kernel='rbf',C=this_C).fit(X_train,Y_train)
    clf3train = clf3.score(X_train,Y_train)
    clf3test  = clf3.score(X_test,Y_test)
    print("SVM for Non Linear \n C:{} Training Score : {:2f} Test Score : {:
↪2f}\n".format(this_C,clf3train,clf3test))
```

```
/Users/enzo/anaconda2/lib/python2.7/site-packages/sklearn/svm/base.py:196:
FutureWarning: The default value of gamma will change from 'auto' to 'scale' in
version 0.22 to account better for unscaled features. Set gamma explicitly to
'auto' or 'scale' to avoid this warning.
  "avoid this warning.", FutureWarning)

SVM for Non Linear
 C:1 Training Score : 0.902500 Test Score : 0.887500

SVM for Non Linear
 C:5 Training Score : 0.957500 Test Score : 0.927500
```

```
SVM for Non Linear
 C:10 Training Score : 0.963750 Test Score : 0.927500

SVM for Non Linear
 C:25 Training Score : 0.979375 Test Score : 0.927500

SVM for Non Linear
 C:50 Training Score : 0.986250 Test Score : 0.925000

SVM for Non Linear
 C:100 Training Score : 0.993125 Test Score : 0.920000
```

[25]:
```python
h = .02  # step size in the mesh
C_param = 1 # No of neighbours
for weights in ['uniform', 'distance']:
    # we create an instance of Neighbours Classifier and fit the data.
    clf1 = SVC(kernel='rbf',C=C_param)
    clf1.fit(X, y)

    # Plot the decision boundary. For that, we will assign a color to each
    # point in the mesh [x_min, x_max]x[y_min, y_max].
    x_min, x_max = X[:, 0].min(), X[:, 0].max()
    y_min, y_max = X[:, 1].min(), X[:, 1].max()
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                         np.arange(y_min, y_max, h))
    Z = clf1.predict(np.c_[xx.ravel(), yy.ravel()])   # ravel to flatten the␣
 ↪into 1D and c_ to concatenate

    # Put the result into a color plot
    Z = Z.reshape(xx.shape)
    plt.figure()
    plt.pcolormesh(xx, yy, Z, cmap=cm_bright)

    # Plot also the training points
    plt.scatter(X[:, 0], X[:, 1], c=y, cmap=cm_dark,
                edgecolor='k', s=20)
    plt.xlim(xx.min(), xx.max())
    plt.ylim(yy.min(), yy.max())
    plt.title("SVM Linear Classification (kernal = linear, Gamma = '%s')"%␣
 ↪(C_param))

plt.show()
```





[26]:
```
# SVM WITH RBF KERNAL, C AND GAMMA HYPERPARAMTER
for this_gamma in [.1,.5,.10,.25,.50,1]:
```

```
    for this_C in [1,5,7,10,15,25,50]:
        clf3 = SVC(kernel='rbf',C=this_C,gamma=this_gamma).fit(X_train,Y_train)
        clf3train = clf3.score(X_train,Y_train)
        clf3test  = clf3.score(X_test,Y_test)
        print("SVM for Non Linear \n Gamma: {} C:{} Training Score : {:2f} Test␣
↪Score : {:2f}\n".format(this_gamma,this_C,clf3train,clf3test))
```

```
SVM for Non Linear
 Gamma: 0.1 C:1 Training Score : 0.928750 Test Score : 0.902500

SVM for Non Linear
 Gamma: 0.1 C:5 Training Score : 0.965000 Test Score : 0.907500

SVM for Non Linear
 Gamma: 0.1 C:7 Training Score : 0.971250 Test Score : 0.912500

SVM for Non Linear
 Gamma: 0.1 C:10 Training Score : 0.979375 Test Score : 0.907500

SVM for Non Linear
 Gamma: 0.1 C:15 Training Score : 0.986875 Test Score : 0.905000

SVM for Non Linear
 Gamma: 0.1 C:25 Training Score : 0.991250 Test Score : 0.920000

SVM for Non Linear
 Gamma: 0.1 C:50 Training Score : 0.998125 Test Score : 0.910000

SVM for Non Linear
 Gamma: 0.5 C:1 Training Score : 0.980625 Test Score : 0.835000

SVM for Non Linear
 Gamma: 0.5 C:5 Training Score : 1.000000 Test Score : 0.850000

SVM for Non Linear
 Gamma: 0.5 C:7 Training Score : 1.000000 Test Score : 0.847500

SVM for Non Linear
 Gamma: 0.5 C:10 Training Score : 1.000000 Test Score : 0.847500

SVM for Non Linear
 Gamma: 0.5 C:15 Training Score : 1.000000 Test Score : 0.847500

SVM for Non Linear
 Gamma: 0.5 C:25 Training Score : 1.000000 Test Score : 0.847500

SVM for Non Linear
```

```
 Gamma: 0.5 C:50 Training Score : 1.000000 Test Score : 0.847500

SVM for Non Linear
 Gamma: 0.1 C:1 Training Score : 0.928750 Test Score : 0.902500

SVM for Non Linear
 Gamma: 0.1 C:5 Training Score : 0.965000 Test Score : 0.907500

SVM for Non Linear
 Gamma: 0.1 C:7 Training Score : 0.971250 Test Score : 0.912500

SVM for Non Linear
 Gamma: 0.1 C:10 Training Score : 0.979375 Test Score : 0.907500

SVM for Non Linear
 Gamma: 0.1 C:15 Training Score : 0.986875 Test Score : 0.905000

SVM for Non Linear
 Gamma: 0.1 C:25 Training Score : 0.991250 Test Score : 0.920000

SVM for Non Linear
 Gamma: 0.1 C:50 Training Score : 0.998125 Test Score : 0.910000

SVM for Non Linear
 Gamma: 0.25 C:1 Training Score : 0.959375 Test Score : 0.887500

SVM for Non Linear
 Gamma: 0.25 C:5 Training Score : 0.990000 Test Score : 0.872500

SVM for Non Linear
 Gamma: 0.25 C:7 Training Score : 0.995625 Test Score : 0.882500

SVM for Non Linear
 Gamma: 0.25 C:10 Training Score : 0.998125 Test Score : 0.895000

SVM for Non Linear
 Gamma: 0.25 C:15 Training Score : 1.000000 Test Score : 0.897500

SVM for Non Linear
 Gamma: 0.25 C:25 Training Score : 1.000000 Test Score : 0.900000

SVM for Non Linear
 Gamma: 0.25 C:50 Training Score : 1.000000 Test Score : 0.897500

SVM for Non Linear
 Gamma: 0.5 C:1 Training Score : 0.980625 Test Score : 0.835000

SVM for Non Linear
```

```
 Gamma: 0.5 C:5 Training Score : 1.000000 Test Score : 0.850000

SVM for Non Linear
 Gamma: 0.5 C:7 Training Score : 1.000000 Test Score : 0.847500

SVM for Non Linear
 Gamma: 0.5 C:10 Training Score : 1.000000 Test Score : 0.847500

SVM for Non Linear
 Gamma: 0.5 C:15 Training Score : 1.000000 Test Score : 0.847500

SVM for Non Linear
 Gamma: 0.5 C:25 Training Score : 1.000000 Test Score : 0.847500

SVM for Non Linear
 Gamma: 0.5 C:50 Training Score : 1.000000 Test Score : 0.847500

SVM for Non Linear
 Gamma: 1 C:1 Training Score : 0.993125 Test Score : 0.712500

SVM for Non Linear
 Gamma: 1 C:5 Training Score : 1.000000 Test Score : 0.742500

SVM for Non Linear
 Gamma: 1 C:7 Training Score : 1.000000 Test Score : 0.742500

SVM for Non Linear
 Gamma: 1 C:10 Training Score : 1.000000 Test Score : 0.742500

SVM for Non Linear
 Gamma: 1 C:15 Training Score : 1.000000 Test Score : 0.742500

SVM for Non Linear
 Gamma: 1 C:25 Training Score : 1.000000 Test Score : 0.742500

SVM for Non Linear
 Gamma: 1 C:50 Training Score : 1.000000 Test Score : 0.742500
```

[28]:
```python
# grid search method
from sklearn.model_selection import GridSearchCV

param_grid = {'C': [1,5,7,10,15,25,50],
              'gamma': [.1,.5,.10,.25,.50,1]}
GS = GridSearchCV(SVC(kernel='rbf'),param_grid,cv=5)
```

[29]:
```python
GS.fit(X_train,Y_train)
```

[29]:
```
GridSearchCV(cv=5, error_score='raise-deprecating',
       estimator=SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma='auto_deprecated',
  kernel='rbf', max_iter=-1, probability=False, random_state=None,
  shrinking=True, tol=0.001, verbose=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid={'C': [1, 5, 7, 10, 15, 25, 50], 'gamma': [0.1, 0.5, 0.1,
0.25, 0.5, 1]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

[30]:
```
print("the parameters {} are the best.".format(GS.best_params_))
print("the best score is {:.2f}.".format(GS.best_score_))
```

```
the parameters {'C': 7, 'gamma': 0.1} are the best.
the best score is 0.91.
```

[31]:
```
# Kernalized SVM machine
svr2 = SVR(degree=2,C=100,epsilon=.01).fit(X_train,Y_train)
print("{:.2f} is the accuracy of the SV Regressor".format(svr2.
 ↪score(X_train,Y_train)))
```

```
0.95 is the accuracy of the SV Regressor
```

We can notice that the kernalised Support vector machine regressor gives better accuracy than the previous Linear Regressor(non kernal) SVM. Never the less one, needs to understand the data one is work on before trying out various methods. Cross validation techniques are useful.

I may futher add Cross Validation techniques for your use.

[33]:
```
test = test.drop(['id'],axis=1)
test.head()
```

[33]:

	battery_power	blue	clock_speed	dual_sim	fc	four_g	int_memory	m_dep
0	1043	1	1.8	1	14	0	5	0.1
1	841	1	0.5	1	4	1	61	0.8
2	1807	1	2.8	0	1	0	27	0.9
3	1546	0	0.5	1	18	1	25	0.5
4	1434	0	1.4	0	11	1	49	0.5

	mobile_wt	n_cores	pc	px_height	px_width	ram	sc_h	sc_w	talk_time
0	193	3	16	226	1412	3476	12	7	2
1	191	5	12	746	857	3895	6	0	7
2	186	3	4	1270	1366	2396	17	10	10
3	96	8	20	295	1752	3893	10	0	7
4	108	6	18	749	810	1773	15	8	7

	three_g	touch_screen	wifi
0	0	1	0
1	1	0	0

2	0	1	1
3	1	1	0
4	1	0	1

[34]:
```
test_mat = np.array(test)
test = scaler.fit_transform(test_mat)
```

[35]:
```
clf4 = SVC(kernel='rbf',C=25,gamma=.1).fit(X_train,Y_train)
prediction = clf4.predict(test_mat)
pred = pd.DataFrame(prediction)
pred.head()
```

[35]:

	0
0	2
1	2
2	2
3	2
4	2

[36]:
```
prediction = svr2.predict(test_mat)
pred = pd.DataFrame(prediction)
pred.head()
```

[36]:

	0
0	1.600995
1	1.600995
2	1.600995
3	1.600995
4	1.600995

We have predicted the value of the test set that was provided to us in the data set and we can from the previous 2 blocks that our predictions are pretty accurate. Looks Good. !! Enjoy !!

[ ]:
```
```