SVM-BankNoteAuthentication

May 4, 2019

1 Bank Note Authentication

Banknotes are one of the most important assets of a country. Some miscreants introduce fake notes which bear a resemblance to original note to create discrepancies of the money in the financial market. It is difficult for humans to tell true and fake banknotes apart especially because they have a lot of similar features. Fake notes are created with precision, hence there is need for an efficient algorithm which accurately predicts whether a banknote is genuine or not. This paper proposes machine learning techniques to evaluate authentication of banknotes. Supervised learning algorithm Support Vector Machine (SVM) are used for differentiating genuine banknotes from fake ones.

In [172]:
```
%config IPCompleter.greedy=True
```

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
%matplotlib inline

from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report,
```

In [6]:
```
bankdata = pd.read_csv("C:\\MyRWork\\Data\\Bank-Note\\bill_authentication.csv")
```

In [9]:
```
bankdata.describe()
```

Out[9]:

	Variance	Skewness	Curtosis	Entropy	Class
count	1372.000000	1372.000000	1372.000000	1372.000000	1372.000000
mean	0.433735	1.922353	1.397627	-1.191657	0.444606
std	2.842763	5.869047	4.310030	2.101013	0.497103
min	-7.042100	-13.773100	-5.286100	-8.548200	0.000000
25%	-1.773000	-1.708200	-1.574975	-2.413450	0.000000
50%	0.496180	2.319650	0.616630	-0.586650	0.000000
75%	2.821475	6.814625	3.179250	0.394810	1.000000
max	6.824800	12.951600	17.927400	2.449500	1.000000

Data were extracted from genuine and counterfeit banknote images. The dataset has 1372 instances.The target class contains two values: 0 and 1 where 0 represents genuine note and 1 represents fake note.

Variance: Variance finds how each pixel varies from the neighboring pixels and classifies them into different regions

Skewness: Skewness is the measure of the lack of symmetry

Curtosis: Curtosis is a measure of whether the data are heavytailed or light-tailed relative to a normal distribution

Entropy: Image entropy is a quantity which is used to describe the amount of information which must be coded for, by a compression algorithm

Class: 0 representing genuine note and 1 representing fake note

```
In [13]: bankdata.dtypes
```

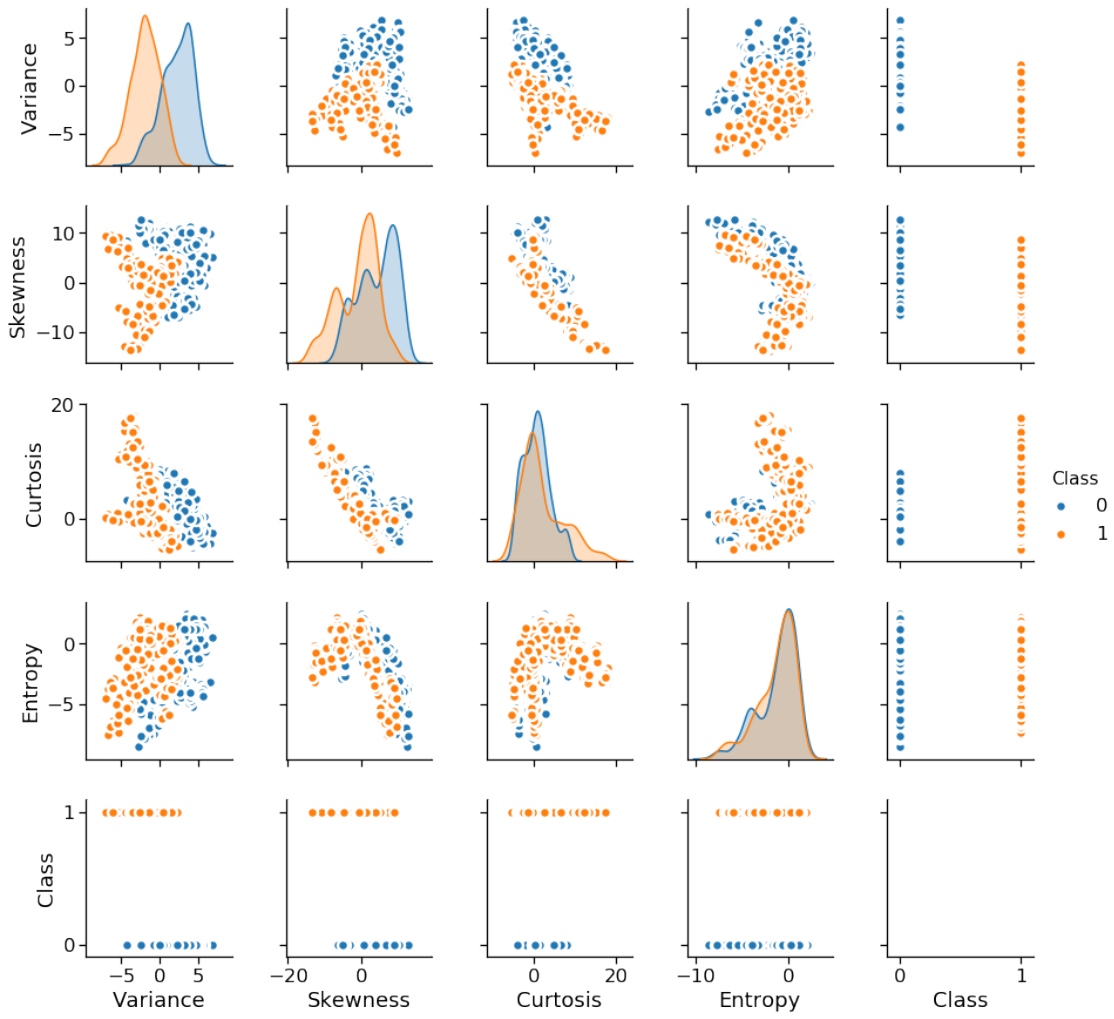
```
Out[13]: Variance    float64
         Skewness    float64
         Curtosis    float64
         Entropy     float64
         Class         int64
         dtype: object
```

```
In [17]: bankdata.head(10)
```

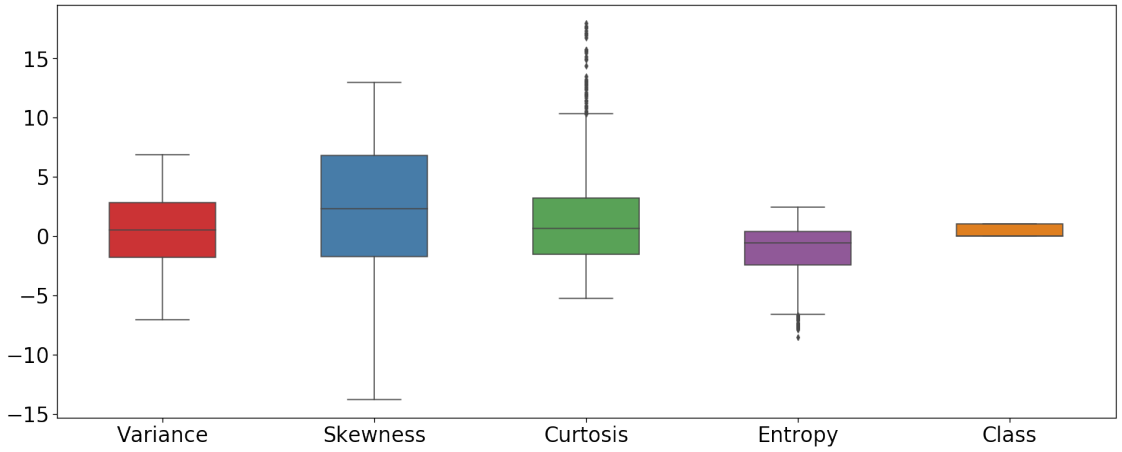
```
Out[17]:    Variance  Skewness  Curtosis  Entropy  Class
         0   3.62160    8.6661  -2.80730 -0.44699      0
         1   4.54590    8.1674  -2.45860 -1.46210      0
         2   3.86600   -2.6383   1.92420  0.10645      0
         3   3.45660    9.5228  -4.01120 -3.59440      0
         4   0.32924   -4.4552   4.57180 -0.98880      0
         5   4.36840    9.6718  -3.96060 -3.16250      0
         6   3.59120    3.0129   0.72888  0.56421      0
         7   2.09220   -6.8100   8.46360 -0.60216      0
         8   3.20320    5.7588  -0.75345 -0.61251      0
         9   1.53560    9.1772  -2.27180 -0.73535      0
```

```
In [107]: sns.pairplot(bankdata, kind="scatter", hue="Class", plot_kws=dict(s=80, edgecolor="wh
          sns.set_context("notebook", font_scale=2.5)
          plt.show()
```

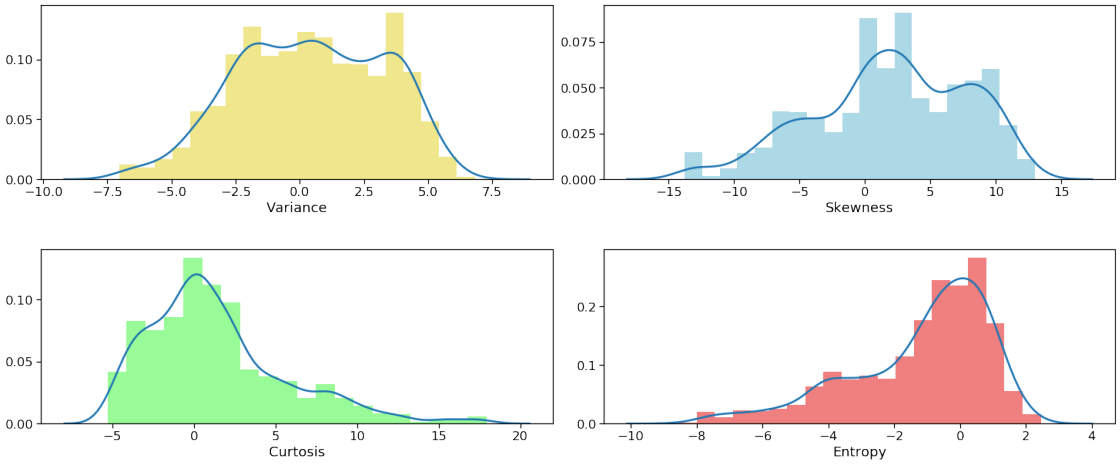
```
C:\Users\rgoyal\Anaconda3\Lib\site-packages\statsmodels\nonparametric\kde.py:488: RuntimeWarnin
  binned = fast_linbin(X, a, b, gridsize) / (delta * nobs)
C:\Users\rgoyal\Anaconda3\Lib\site-packages\statsmodels\nonparametric\kdetools.py:34: RuntimeWa
  FAC1 = 2*(np.pi*bw/RANGE)**2
```



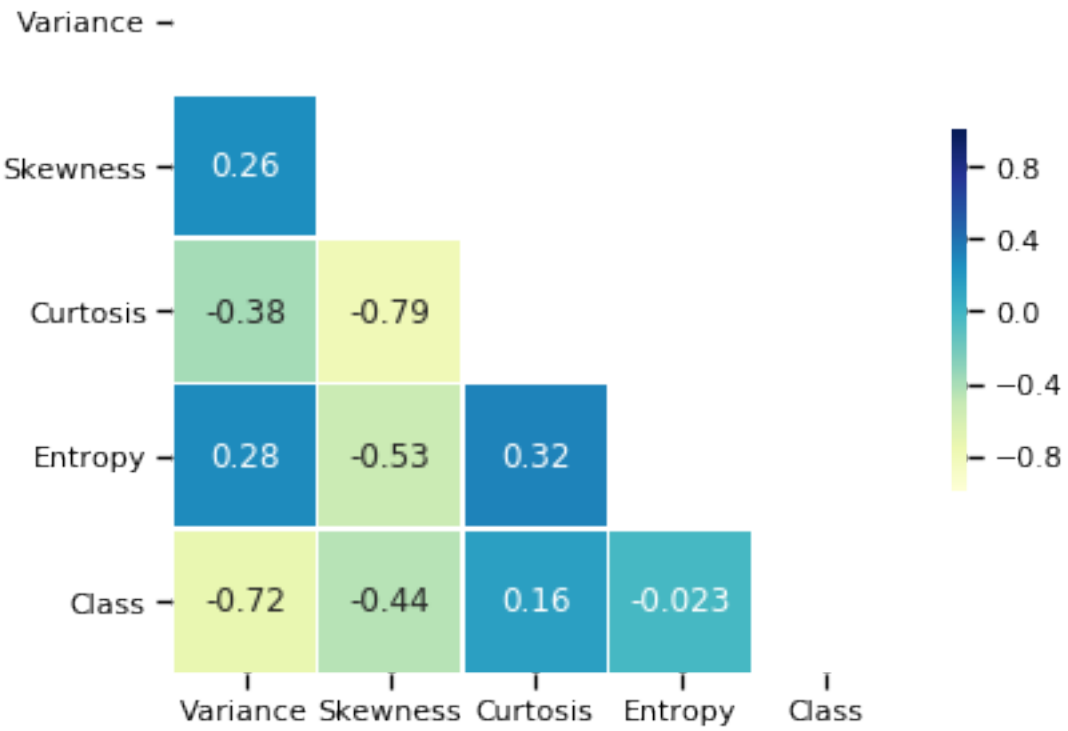

```
In [108]: bxplt = sns.boxplot(data=bankdata, palette="Set1", width=0.5)
          plt.rcParams['figure.figsize']=(25,10)
          sns.set_context("notebook", font_scale=2, rc={"lines.linewidth": 3.5})
          plt.show()
```



In [97]:
```
#sns.distplot(bankdata.Variance, bins=20, hist_kws={"alpha": 1, "color": "khaki", "li

fig = plt.figure()
fig.subplots_adjust(hspace=0.4, wspace=0.1)

ax = fig.add_subplot(2, 2, 1)
sns.distplot(bankdata.Variance, bins=20, hist_kws={"alpha": 1, "color": "khaki", "lin

ax = fig.add_subplot(2, 2, 2)
sns.distplot(bankdata.Skewness, bins=20, hist_kws={"alpha": 1, "color": "lightblue",

ax = fig.add_subplot(2, 2, 3)
sns.distplot(bankdata.Curtosis, bins=20, hist_kws={"alpha": 1, "color": "palegreen",

ax = fig.add_subplot(2, 2, 4)
sns.distplot(bankdata.Entropy, bins=20, hist_kws={"alpha": 1, "color": "lightcoral",

sns.set_context("notebook", font_scale=2.5, rc={"lines.linewidth": 2.5})
plt.show()
```



In [137]:
```
# Compute the correlation matrix
corr = bankdata.corr()

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(7, 5))

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap = "YlGnBu", vmax=1, vmin=-1, center=0, annot = True
            square=True, linewidths=.5, cbar_kws={"shrink": .5})

sns.set_context("notebook", font_scale=1, rc={"lines.linewidth": 2.5})
```




```
In [161]: X = bankdata.iloc[:,0:4]
          y = bankdata.Class

In [164]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25)

In [174]: svcClassifier = SVC(kernel = "linear")
          svcClassifier.fit(X_train, y_train)

Out[174]: SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
            decision_function_shape='ovr', degree=3, gamma='auto', kernel='linear',
            max_iter=-1, probability=False, random_state=None, shrinking=True,
            tol=0.001, verbose=False)

In [175]: svcClassifier.score(X_train, y_train)    ## Probably not overfitting

Out[175]: 0.9902818270165209

In [177]: y_pred = svcClassifier.predict(X_test)

In [181]: print(confusion_matrix(y_test, y_pred))
          print(classification_report(y_test, y_pred))
```

```
[[193   3]
 [  3 144]]
             precision    recall  f1-score   support

          0       0.98      0.98      0.98       196
          1       0.98      0.98      0.98       147

avg / total       0.98      0.98      0.98       343
```