Using K-NN ML model predicting S&P LT ratings for sovereign CDS

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0.1 Data

The dataset has sovereign credit default swaps (CDS) from 81 countries and their prices for 3 year, 5 year, 7 year and 10 year swaps - which will be considered as features in our machine learning algorithm. It also has S&P LT ratings - which reflects S&P's opinions about the capacity and willingness of the obligor to meet its financial commitments on an obligation; For example, an obligation rated 'AAA' has the highest rating assigned by S&P Global Ratings and the obligor's capacity to meet its financial commitments on the obligation is extremely strong. I decide to use and categorize S&P LT rating as follows to best train and evalute the model using this dataset: 1. combine 'AAA'/'AA+' as 'Investment Grade' 2. combine 'A-'/'BBB+'/'BBB' as 'High Yield' 3. combine 'B'/'B-' as 'Junk'

0.2 Algorithm

K-nearest-neighbor (K-NN) machine learning model will be trained and evaluated. In K-NN classification, the output is a class membership - predicted S&P LT ratings for these CDS. An object is classified by a majority vote of its neighbors. If k = 1, then the object is simply assigned to the class of the nearest neighbor. Here, the goal is to predict the classification of S&P LT ratings:'Investment Grade','High Yield' and 'Junk' as I categorized earlier using the majority vote of 3 nearest neighbors (**K**=3). If the 3 nearest neighbor for X country's CDS are "Investment Grade', 'Investment Grade' and 'High Yield' then X is classified as 'Investment Grade' rating in this pattern recognition process.

0.3 Application

0.4 Machine Learning Steps 1-9

STEP 1 Import the data. Data is downloaded from FactSet Research Systems Inc - A company provides financial information and analytic software for investment professionals.

```
In [30]: import numpy as np
         import pandas as pd
         import xlrd
         import matplotlib
```

```
df = pd.read_excel('/Users/lesliesmac/Desktop/CdsAndRatings.xlsx', sheet_name='sheet1

print("Column headings:")
print(df.columns)
```

```
Column headings:
Index(['Country CDS', '1 Year', '3 Year', '5 Year', '7 Year', '10 Year',
       'S&P LT Rating*', 'Last Change', 'Rating Reason'],
      dtype='object')
```

STEP 2 Look at the data type. The features are all numeric, and the label is a categorical string variable.

```
In [31]: df.dtypes
```

```
Out[31]: Country CDS        object
         1 Year             object
         3 Year            float64
         5 Year            float64
         7 Year            float64
         10 Year           float64
         S&P LT Rating*     object
         Last Change        object
         Rating Reason      object
         dtype: object
```

STEP 3 Categorize the label. Find the count of each category in 'S&P LT Rating*'. Assign new S&P ratings as **'my_rating'**: 1. combine 'AAA'/'AA+' as 'Investment Grade' 2. combine 'A-'/'BBB+'/'BBB' as 'High Yield' 3. combine 'B'/'B-' as 'Junk'

```
In [32]: rating= df[['S&P LT Rating*']]
         spread = [['3 Year', '5 Year', '7 Year', '10 Year']]
         df['S&P LT Rating*'] = rating
```

```
In [33]: df['count'] = 1
         df[['S&P LT Rating*', 'count']].groupby('S&P LT Rating*').count()
```

```
Out[33]:                 count
         S&P LT Rating*
         A                   4
         A+                  4
         A-                  5
         AA                  6
         AA+                 5
         AA-                 5
         AAA                 8
         B                   8
```

```
B+                  6
B-                  6
BB                  3
BB+                 1
BB-                 3
BBB                 8
BBB+                2
BBB-                7
```

combining groups as below:

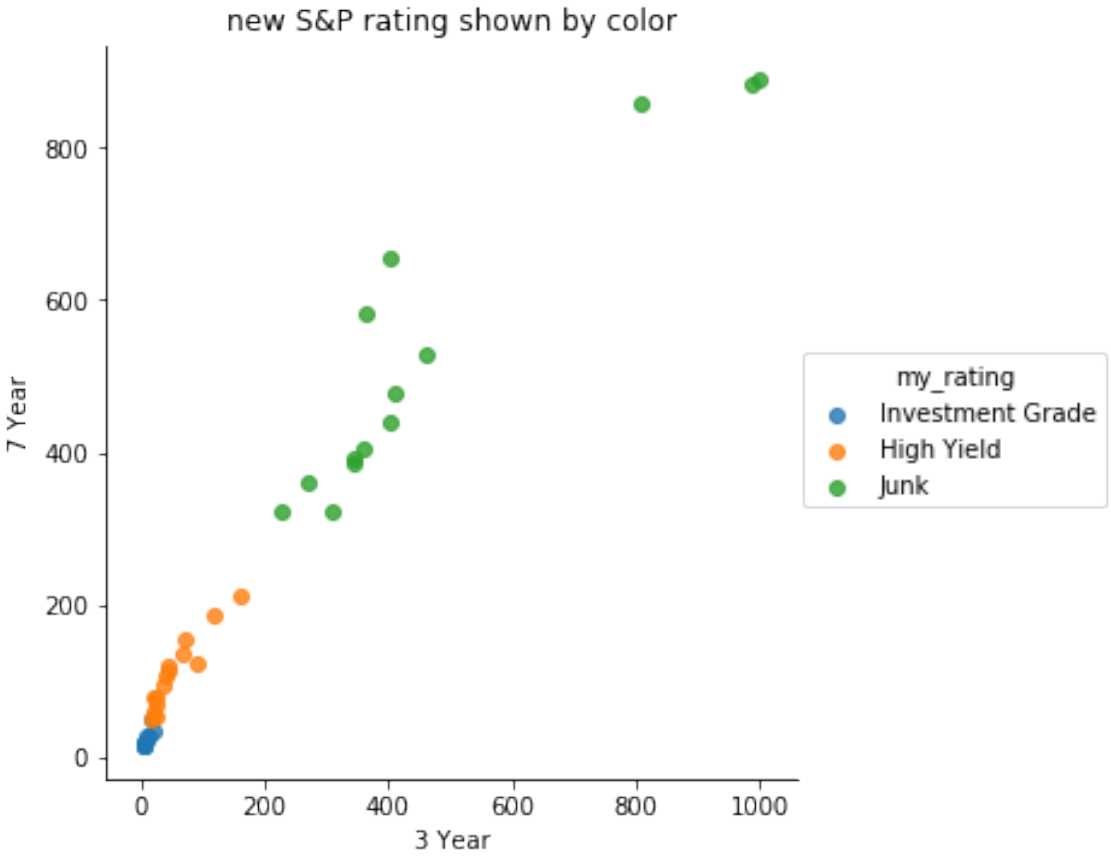
```
In [34]: def set_myrating(row):
             if row["S&P LT Rating*"] == "AAA" or row["S&P LT Rating*"] == "AA+":
                 return "Investment Grade"
             elif row["S&P LT Rating*"] == "BBB+" or row["S&P LT Rating*"] == "A-" or row["S&P
                 return "High Yield"
             elif row["S&P LT Rating*"] == "B" or row["S&P LT Rating*"] == "B-":
                 return "Junk"
             else:
                 return "NA"

         df = df.assign(my_rating=df.apply(set_myrating, axis=1))
         df_final = df.loc[df['my_rating'] != 'NA', :]
         df_final.head()
```

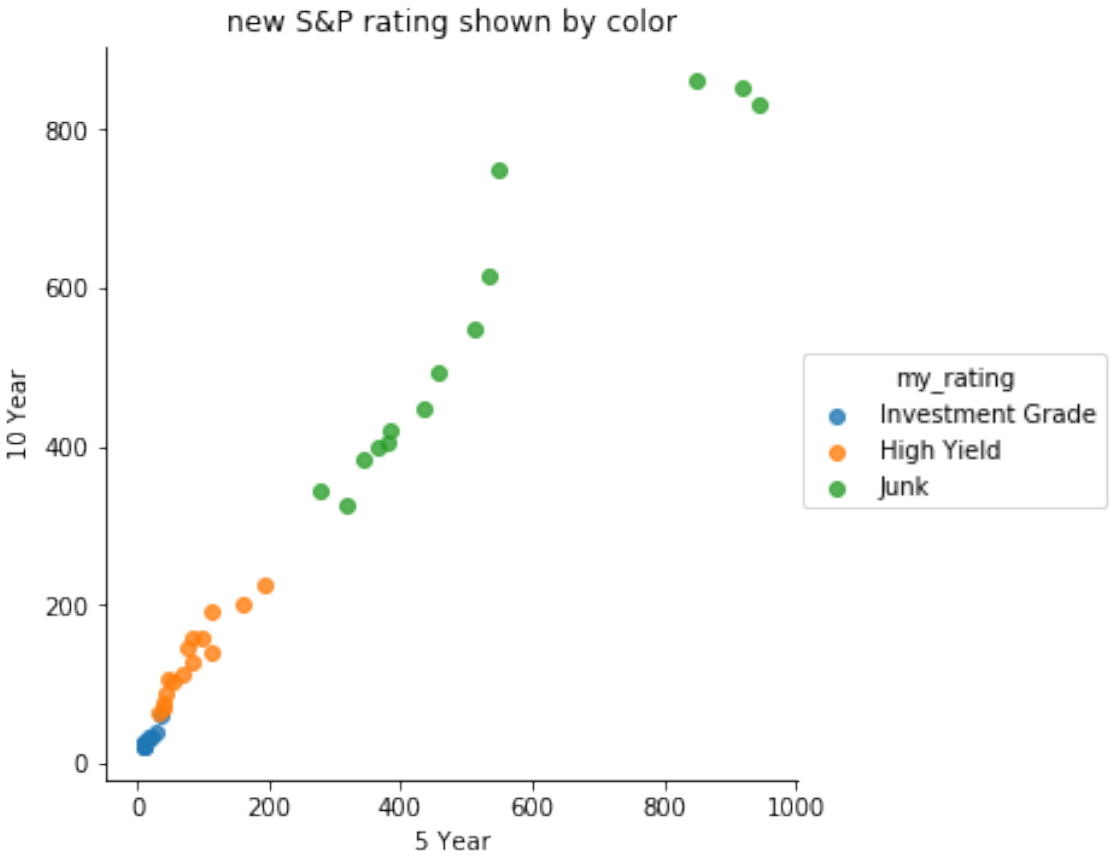
```
Out[34]:      Country CDS 1 Year  3 Year  5 Year  7 Year  10 Year S&P LT Rating*  \
         0  United States   7.79   10.31   15.88   22.11    27.21            AA+
         2         Russia  40.17   65.77   99.88  134.99   157.24            BBB
         4          Italy  52.62  116.82  159.94  187.62   202.11            BBB
         5        Germany   2.02    5.86   10.52   14.96    20.94            AAA
         7         Canada  15.07   20.11   27.28   32.88    38.31            AAA

           Last Change Rating Reason  count         my_rating
         0  10 Jun '13           NaN      1  Investment Grade
         2  23 Feb '18       Upgrade      1        High Yield
         4  26 Oct '18           NaN      1        High Yield
         5  13 Jan '12           NaN      1  Investment Grade
         7  14 Oct '92           New      1  Investment Grade
```

STEP 4 Plot features & label Create some plots to see how the classes might, or might not, be separated by the value of the features. In an ideal case, the label classes will be perfectly separated by one or more of the feature pairs, e.g. '3 Year' and '7 year' spread. Here we see there's some overlapping area among 'Good' and 'OK' groups; 'OK' and 'Not good' groups are separated more clearly.

```
In [35]: %matplotlib inline
         def plot_cds(df_final, col1, col2):
             import seaborn as sns
             import matplotlib.pyplot as plt
```

```
    sns.lmplot(x = col1, y = col2,
               data = df_final,
               hue = "my_rating",
               fit_reg = False)
    plt.xlabel(col1)
    plt.ylabel(col2)
    plt.title('new S&P rating shown by color')
    plt.show()
plot_cds(df_final, '3 Year', '7 Year')
plot_cds(df_final, '5 Year', '10 Year')
```





STEP 5 Scale / normalize the numeric values of the features A normalized dataset should ~ N (0,1); checked the mean & sd

```
In [36]: from sklearn.preprocessing import scale

         num_cols = ['3 Year', '5 Year', '7 Year', '10 Year']
         df_scaled = scale(df_final[num_cols])
         df_scaled = pd.DataFrame(df_scaled, columns = num_cols)
         print(df_scaled.describe().round(3))
```

```
       3 Year  5 Year  7 Year  10 Year
count  42.000  42.000  42.000   42.000
mean    0.000  -0.000   0.000   -0.000
std     1.012   1.012   1.012    1.012
min    -0.692  -0.773  -0.829   -0.870
25%    -0.661  -0.727  -0.776   -0.813
50%    -0.542  -0.499  -0.452   -0.421
75%     0.607   0.602   0.611    0.624
max     3.204   2.876   2.628    2.488
```

In order to use sklearn pkg, the strings indicting S&P ratings must be re-coded as numbers. Here we re-coded as {'Investment Grade':0, 'High Yield':1, 'Junk':2}

```
In [37]: levels = {'Investment Grade':0, 'High Yield':1, 'Junk':2}
         df_scaled['my_rating'] = [levels[x] for x in df_final['my_rating']]
         df_scaled.head()
```

Out[37]:

	3 Year	5 Year	7 Year	10 Year	my_rating
0	-0.670380	-0.750773	-0.800690	-0.845245	0
1	-0.453055	-0.422562	-0.354148	-0.325474	1
2	-0.253011	-0.187891	-0.145949	-0.146115	1
3	-0.687818	-0.771716	-0.828975	-0.870308	0
4	-0.631978	-0.706230	-0.758085	-0.800875	0

STEP 6 Split the dataset Split the dataset **df_scaled** into randomly sampled training datasets **df_train_** and evaluation datasets **df_test_**. Checked the shape of splited datasets.

```
In [38]: ## Split the data into a training and test set
         from sklearn.model_selection import train_test_split
         #set seed
         np.random.seed(129)
         df_final_split = train_test_split(np.asmatrix(df_scaled), test_size = 21)
         df_train_features = df_final_split[0][:, :4]
         df_train_labels = np.ravel(df_final_split[0][:, 4])
         df_test_features = df_final_split[1][:, :4]
         df_test_labels = np.ravel(df_final_split[1][:, 4])
         #print the shape to check the split
         print(df_train_features.shape)
         print(df_train_labels.shape)
         print(df_test_features.shape)
         print(df_test_labels.shape)
```

```
(21, 4)
(21,)
(21, 4)
(21,)
```

STEP 7 Define and train the K-NN model. **K=3**

```
In [39]: from sklearn.neighbors import KNeighborsClassifier
         KNN_mod = KNeighborsClassifier(n_neighbors = 3)
         KNN_mod.fit(df_train_features, df_train_labels)
```

```
Out[39]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=1, n_neighbors=3, p=2,
                    weights='uniform')
```

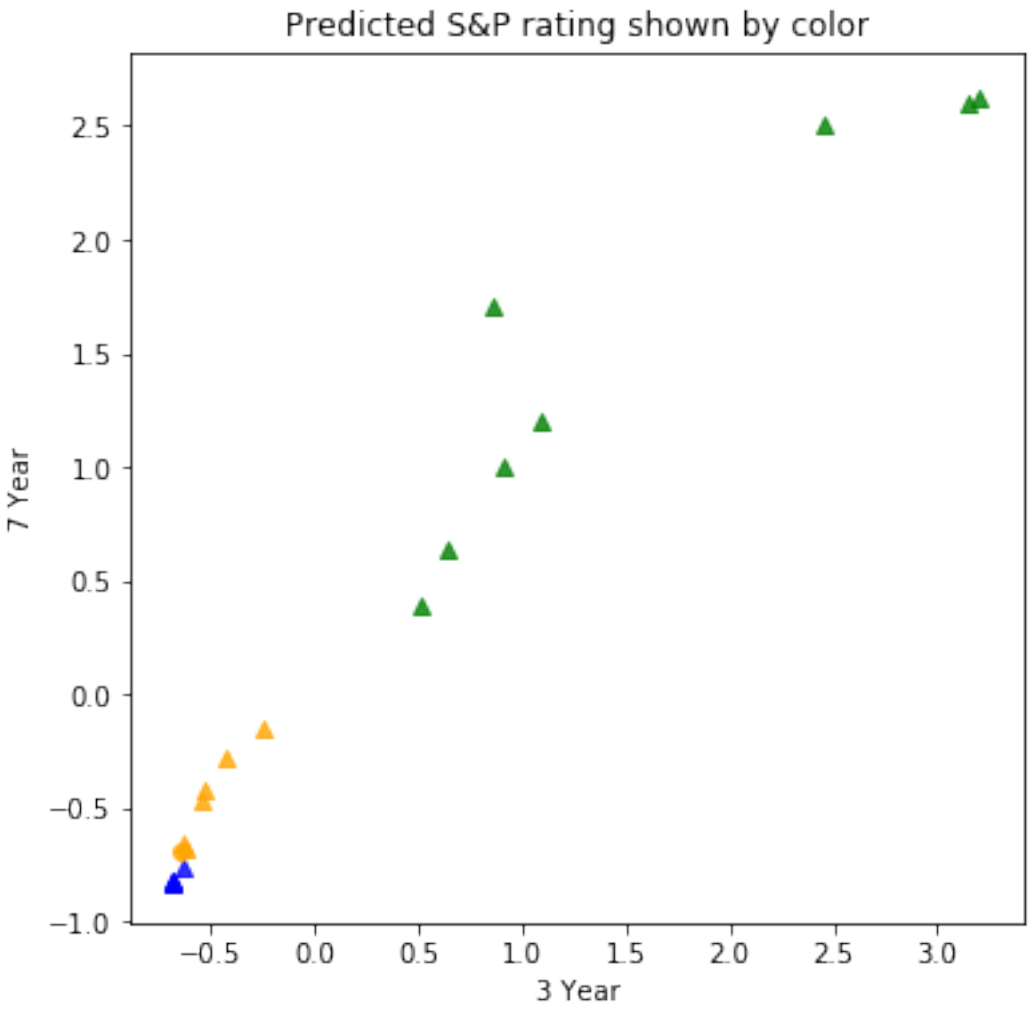
STEP 8 Evaluate this model

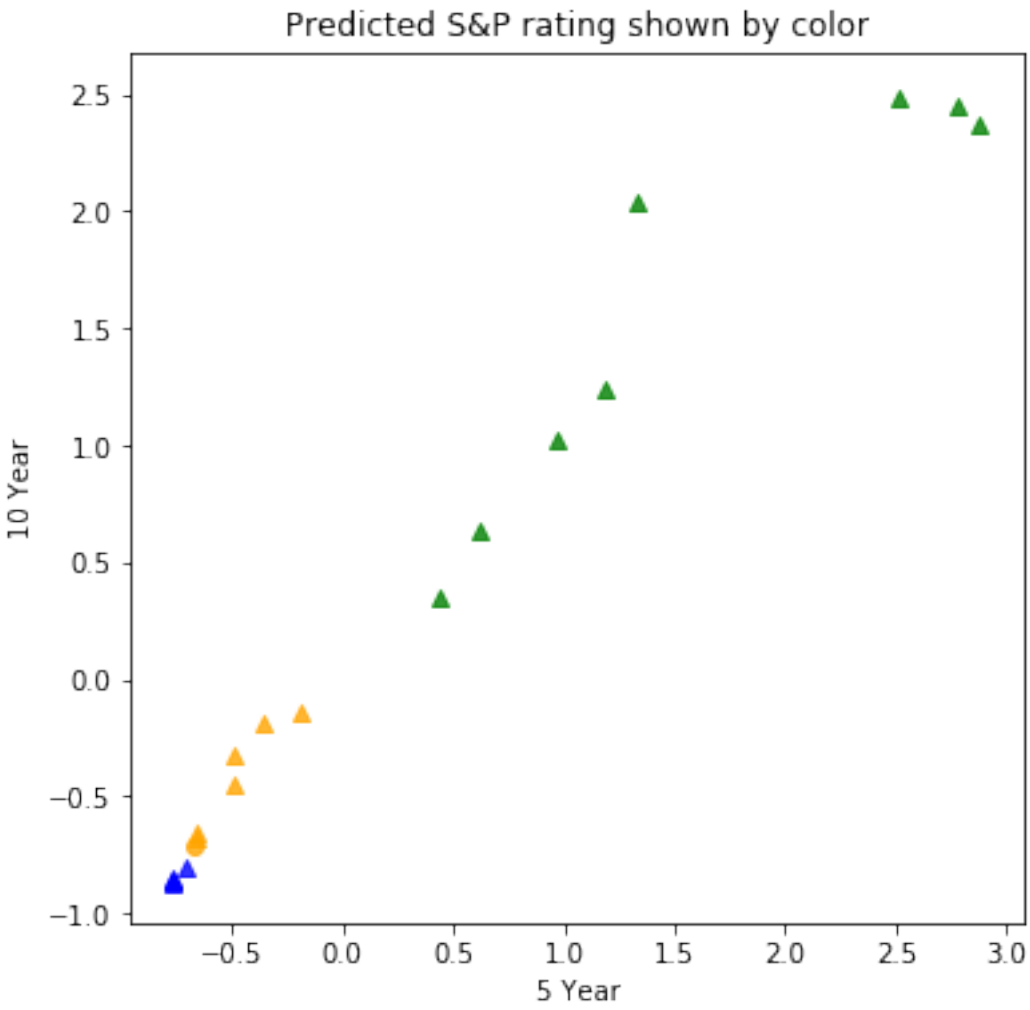
1. using the accuracy statistic

```
In [40]: df_test = pd.DataFrame(df_test_features, columns = num_cols)
         df_test['predicted'] = KNN_mod.predict(df_test_features)
         df_test['correct'] = [1 if x == z else 0 for x, z in zip(df_test['predicted'], df_tes
         accuracy = 100.0 * float(sum(df_test['correct'])) / float(df_test.shape[0])
         print('Accuracy =' + str(accuracy))

Accuracy =95.23809523809524
```

2. using 'true vs predicted' plot

```
In [41]: levels = {0:'Investment Grade', 1:'High Yield', 2:'Junk'}
         df_test['my_rating'] = [levels[x] for x in df_test['predicted']]
         markers = {1:'^', 0:'o'}
         colors = {'Investment Grade':'blue', 'High Yield':'orange', 'Junk':'green'}
         def plot_shapes(df, col1,col2,  markers, colors):
             import matplotlib.pyplot as plt
             import seaborn as sns
             ax = plt.figure(figsize=(6, 6)).gca() # define plot axis
             for m in markers: # iterate over marker dictioary keys
                 for c in colors: # iterate over color dictionary keys
                     df_temp = df[(df['correct'] == m)  & (df['my_rating'] == c)]
                     sns.regplot(x = col1, y = col2,
                                 data = df_temp,
                                 fit_reg = False,
                                 scatter_kws={'color': colors[c]},
                                 marker = markers[m],
                                 ax = ax)
             plt.xlabel(col1)
             plt.ylabel(col2)
             plt.title('Predicted S&P rating shown by color')
             return 'How many S&P ratings are misclassified?'
         plot_shapes(df_test, '3 Year', '7 Year', markers, colors)
         plot_shapes(df_test, '5 Year', '10 Year', markers, colors)

Out[41]: 'How many S&P ratings are misclassified?'
```


Predicted S&P rating shown by color
7 Year
3 Year
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0



0.5 Summary

Based on Step 8, our machine learning model achieved an accuracy of 95.24%. Based on Step 9's plots, correctly classified cases are shown by triangles and incorrectly classified cases are shown by circles. only one S&P rating is not classified correctly, which located in the 'overlapping' area between 'Investment Grade' and 'High Yield' types of CDS. I think it is forgivable: 1. limit of our sample size - sample size & Number of features; 2. inherent difficulty of clearly classification of S&P LT ratings.

Overall, I think K-NN machine learning model is a great tool to predict the S&P LT ratings. It can served as a reference in credit ratings. As more features and more data come in, the accuracy of the model will be improved.