02_ForestProject-Modeling&Presentation

August 19, 2020

1 Prediciton (Classification) the Types of Trees.

1.0.1 This Jupyter Notebook contains;

- Classification Models for Predicting the Types of Trees,
- Visualization of the Result.

1.0.2 What I Plan to implement in terms of ML models :

- SVM (I will use `LinearSVC` model from`sklearn.svm` module),
- XGBoost (I will use `XGBClassifier` model from`xgboost` module)
- Additionally :
  - Decision Tree (I will use `DecisionTreeClassifier` model from `sklearn.tree` module)
  - KNN (I will use `KNeighborsClassifier` model from `sklearn.neighbors` module)
  - LGBM (I will usem `LGBMClassifier` model from `lightgbm` module).

1.0.3 I will use `yellowbrick`, `seaborn` and `matplotlib` modules to visualize the model results.

1.0.4 Importing `covtype1.csv` dataset for modelling and required libraries.

[58]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sqlalchemy import create_engine
import warnings
from IPython.core.pylabtools import figsize
from scipy.stats import zscore
from scipy import stats
from numpy import percentile
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
```

```
from statsmodels.formula.api import ols
from scipy.stats import zscore
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier , GradientBoostingClassifier
import seaborn as sns
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from sklearn.model_selection import TimeSeriesSplit
from yellowbrick.classifier import ClassificationReport
from yellowbrick.datasets import load_occupancy
from sklearn.metrics import f1_score
font_title = {'family': 'times new roman', 'color': 'darkred',
              'weight': 'bold', 'size': 14}

warnings.filterwarnings('ignore')
sns.set_style("whitegrid")

plt.rcParams['figure.dpi'] = 100
```

1.0.5 Reading dataset with pandas

[135]:
```
df = pd.read_csv("covtype1.csv")
```

[8]:
```
df.head()
```

[8]:
```
   Elevation  Aspect  Slope  Horizontal_Distance_To_Roadways  Hillshade_9am  \
0       2596      51      3                              510            221
1       2590      56      2                              390            220
2       2804     139      9                             3180            234
3       2785     155     18                             3090            238
4       2595      45      2                              391            220

   Hillshade_Noon  Horizontal_Distance_To_Fire_Points  Wilderness_Area1  \
0             232                                6279                 1
1             235                                6225                 1
2             238                                6121                 1
3             238                                6211                 1
4             234                                6172                 1

   Wilderness_Area2  Wilderness_Area3  …  Soil_Type33  Soil_Type34  \
0                 0                 0  …            0            0
1                 0                 0  …            0            0
```

```
2                  0                   0  ...             0             0
3                  0                   0  ...             0             0
4                  0                   0  ...             0             0

   Soil_Type35  Soil_Type38  Soil_Type39  Soil_Type40  Cover_Type  \
0            0            0            0            0           5
1            0            0            0            0           5
2            0            0            0            0           2
3            0            0            0            0           2
4            0            0            0            0           5

   Square_Hypo_Distance  Average_Dist_Road_Hydro  Average_Elevation_Hydro
0                 66564                      384                     1298
1                 44980                      301                     1292
2                 76049                     1724                     1434
3                 72488                     1666                     1451
4                 23410                      272                     1297

[5 rows x 46 columns]
```

1.0.6 Modeling

[23]:
```
X = df.drop("Cover_Type", axis = 1)
```

[24]:
```
y = df["Cover_Type"]
```

- Splitting the data set into two pieces : Test split - Train split

[25]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=101)
```

1.0.7 XGBoost Classifer

[26]:
```
xgb_classifier = XGBClassifier()
xgb_classifier.fit(X_train , y_train)
```

[26]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=0, num_parallel_tree=1,
              objective='multi:softprob', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=None, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

[27]:
```
y_predicted = xgb_classifier.predict(X_test)
```

[31]:
```
y_predicted
```

[31]:
```
array([7, 3, 3, …, 1, 3, 2], dtype=int64)
```

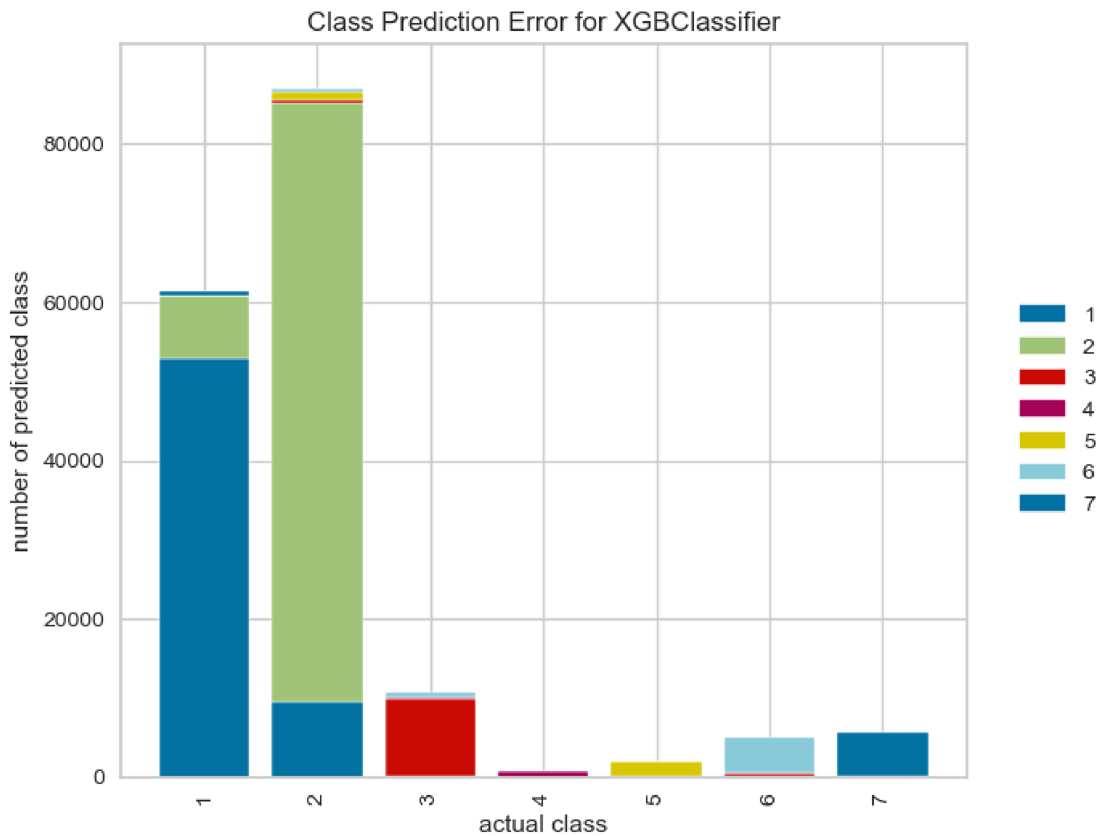
[44]:
```
xgb_accuracy = accuracy_score(y_test, y_predicted)
```

[45]:
```
# Very good!

xgb_accuracy
```

[45]:
```
0.8714599602298091
```

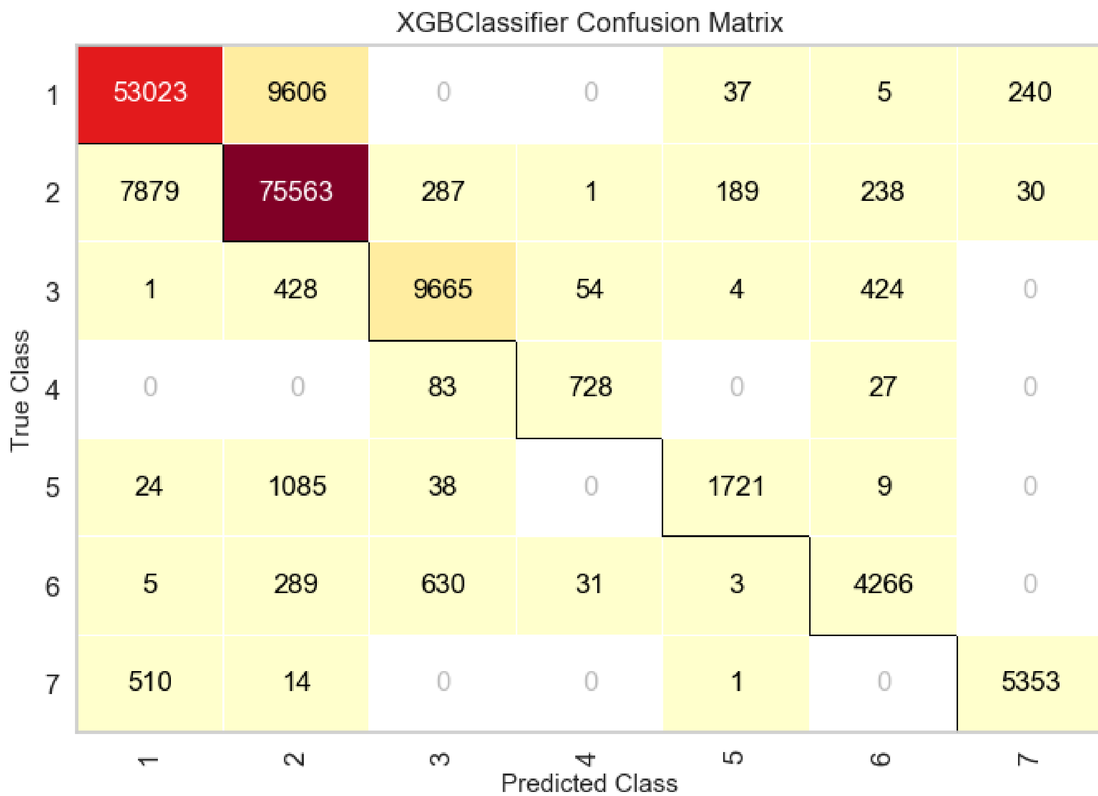
Now, I would like to show three plots for the results. - Class Prediction Error Bar Plot - Confusion Matrix - Classification Report

[42]:
```
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from yellowbrick.classifier import ClassPredictionError

visualizer = ClassPredictionError(xgb_classifier)

# Fit the training data to the visualizer
visualizer.fit(X_train, y_train)

# Evaluate the model on the test data
visualizer.score(X_test, y_test)

# Draw visualization
visualizer.show()
```



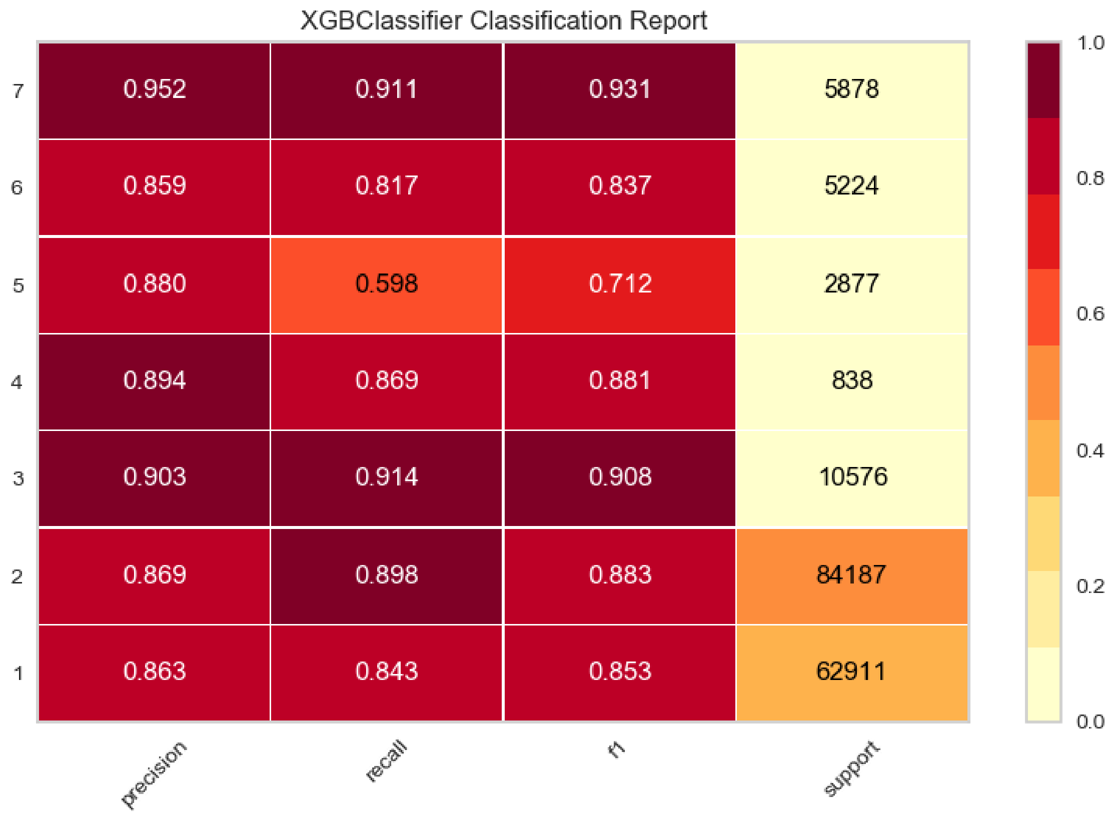
[42]: <matplotlib.axes._subplots.AxesSubplot at 0x2030637a048>

[41]:
```
from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split as tts
from sklearn.linear_model import LogisticRegression
from yellowbrick.classifier import ConfusionMatrix

# The ConfusionMatrix visualizer taxes a model
cm = ConfusionMatrix(xgb_classifier)

# Fit fits the passed model. This is unnecessary if you pass the visualizer a␣
↪pre-fitted model
cm.fit(X_train, y_train)

# To create the ConfusionMatrix, we need some test data. Score runs predict()␣
↪on the data
# and then creates the confusion_matrix from scikit-learn.
cm.score(X_test, y_test)

cm.show()
```



[41]: <matplotlib.axes._subplots.AxesSubplot at 0x203062dc390>

[43]:
```
from sklearn.model_selection import TimeSeriesSplit
from sklearn.naive_bayes import GaussianNB

from yellowbrick.classifier import ClassificationReport
from yellowbrick.datasets import load_occupancy

visualizer = ClassificationReport(xgb_classifier, support=True)

visualizer.fit(X_train, y_train)        # Fit the visualizer and the model
visualizer.score(X_test, y_test)        # Evaluate the model on the test data
visualizer.show()
```



[43]: <matplotlib.axes._subplots.AxesSubplot at 0x203065f2668>

- There is a little bit low `recall` score of the class `5`. I concleuded that it is caused by the values in the data set. %59.8 of the class `5` is predicted true. Although the `recall` score level of class `5` is a little bit low, `precision` and `f1` score is quite well.

1.0.8 LinearSVC

[111]:
```
modelSVM = LinearSVC()
```

[112]:
```
modelSVM.fit(X_train , y_train)
```

[112]:
```
LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True,
          intercept_scaling=1, loss='squared_hinge', max_iter=1000,
          multi_class='ovr', penalty='l2', random_state=None, tol=0.0001,
          verbose=0)
```

[114]:
```
pred = modelSVM.predict(X_test)
```

[115]:
```
SVM_accuracy = accuracy_score(pred, y_test)
```

[116]:
```
SVM_accuracy
```

[116]:
```
0.23831968044709578
```

- It seems the model is failed. I decided to drop additional columns ('Average_Dist_Road_Hydro', 'Average_Elevation_Hydro') and re-split the dataset.

[68]:
```
df['Square_Hypo_Distance'] = np.sqrt(df['Square_Hypo_Distance'])
df1 = df.drop(['Average_Dist_Road_Hydro','Average_Elevation_Hydro'], axis = 1)
X1 = df1.drop("Cover_Type", axis = 1)
y1 = df1["Cover_Type"]
```

- Splitting the data set into two pieces : Test split - Train split

[96]:
```
X1_train, X1_test, y1_train, y1_test = train_test_split(X1, y1, test_size=0.3,␣
↪random_state=101)
```

[118]:
```
modelSVM1 = LinearSVC()
```

[119]:
```
modelSVM1.fit(X1_train , y1_train)
```

[119]:
```
LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True,
          intercept_scaling=1, loss='squared_hinge', max_iter=1000,
          multi_class='ovr', penalty='l2', random_state=None, tol=0.0001,
          verbose=0)
```

[120]:
```
pred1 = modelSVM1.predict(X1_test)
```

[121]:
```
SVM_accuracy1 = accuracy_score(pred1, y1_test)
```

[122]:
```
SVM_accuracy1
```

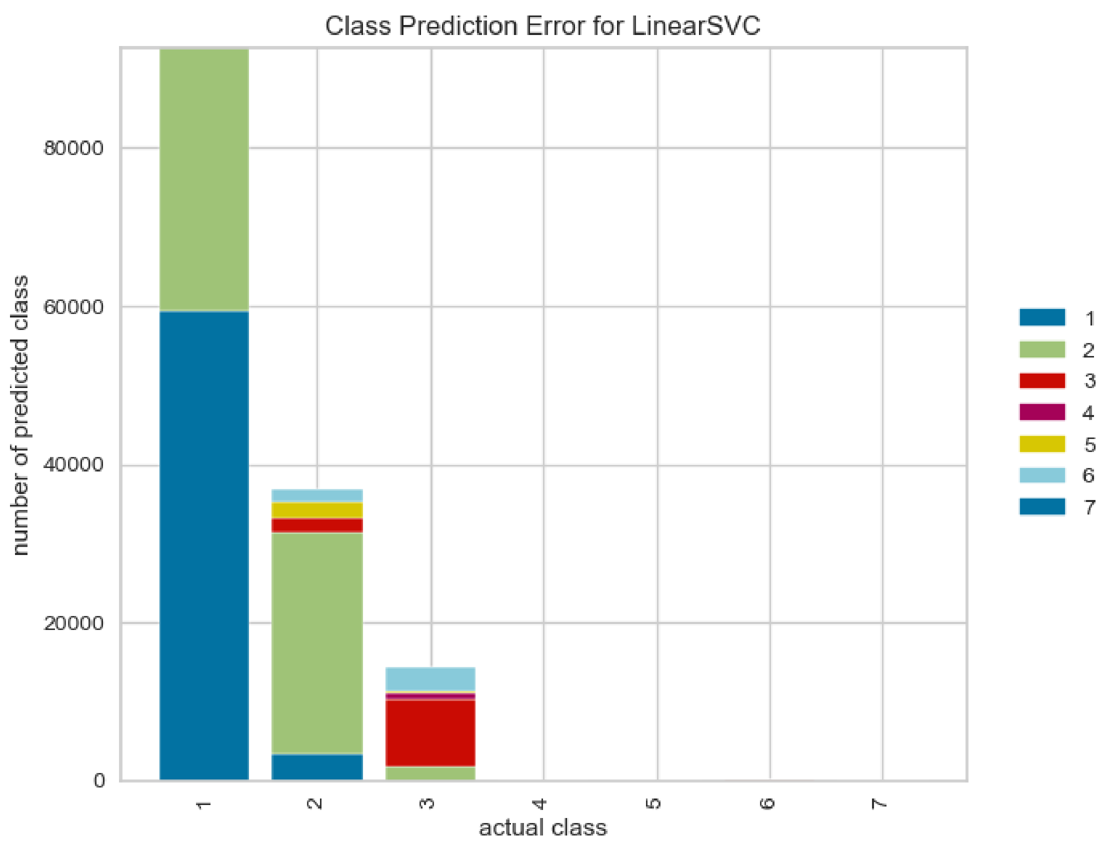
[122]:
```
0.5566145480054032
```

- I've doubled the **accuracy score** but it's still insufficient. SVM Classifier ;
  - SVM has been widely used in finance. For example, predicting stock price via SVM has been a acknowledged application in the industry.
  - In classification of text and handwritten objects, SVM performs well.
  - It may not be very successful in datasets with more than 100,000 data.

Now, I would like to show three plots for the results. - Class Prediction Error Bar Plot - Confusion Matrix - Classification Report

[123]:
```
visualizer = ClassPredictionError(modelSVM1)

# Fit the training data to the visualizer
visualizer.fit(X1_train, y1_train)
```

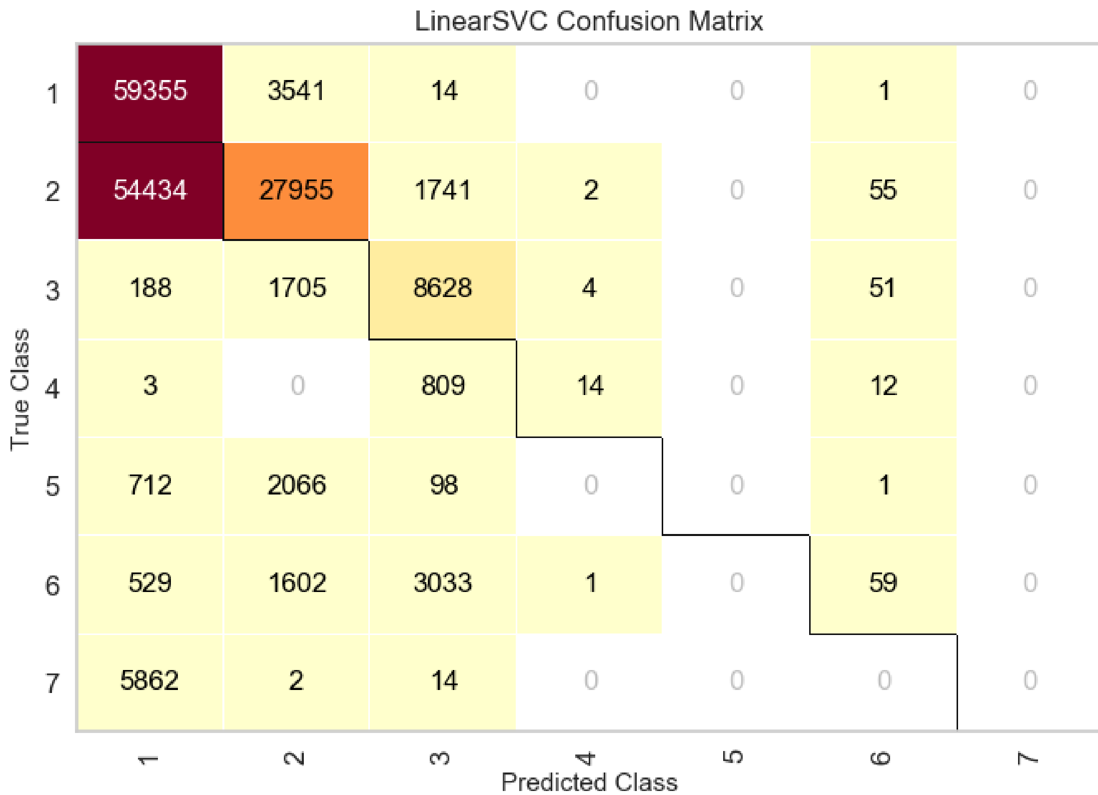
```
# Evaluate the model on the test data
visualizer.score(X1_test, y1_test)

# Draw visualization
visualizer.show()
```



[123]: <matplotlib.axes._subplots.AxesSubplot at 0x2030b33fe10>

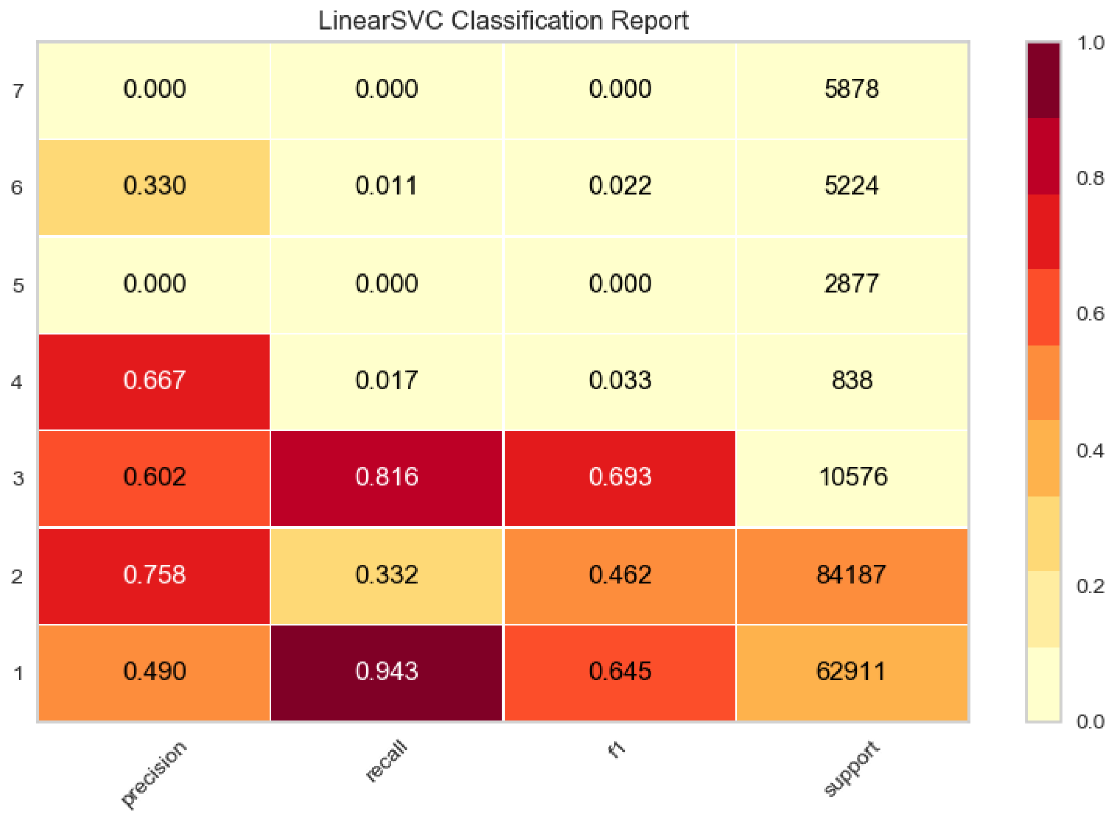
[125]:
```
# The ConfusionMatrix visualizer taxes a model
cm = ConfusionMatrix(modelSVM1)

# Fit fits the passed model. This is unnecessary if you pass the visualizer a␣
↪pre-fitted model
cm.fit(X1_train, y1_train)

# To create the ConfusionMatrix, we need some test data. Score runs predict()␣
↪on the data
# and then creates the confusion_matrix from scikit-learn.
cm.score(X1_test, y1_test)
```

```
cm.show()
```



[125]: <matplotlib.axes._subplots.AxesSubplot at 0x2030c4c5198>

[126]:
```
visualizer = ClassificationReport(modelSVM1, support=True)

visualizer.fit(X1_train, y1_train)        # Fit the visualizer and the model
visualizer.score(X1_test, y1_test)        # Evaluate the model on the test data
visualizer.show()
```



[126]: <matplotlib.axes._subplots.AxesSubplot at 0x2030c5a59e8>

- We can see from the plots that more than half of the classes are predicted correctly. But the model predicted 5 classes although there are 7. Class 5 and 7 could not detected.

1.0.9 DecisionTreeClassifier

[47]:
```
modelTree = DecisionTreeClassifier()
```

[48]:
```
modelTree.fit(X_train , y_train)
```

[48]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

[49]:
```
pred = modelTree.predict(X_test)
```

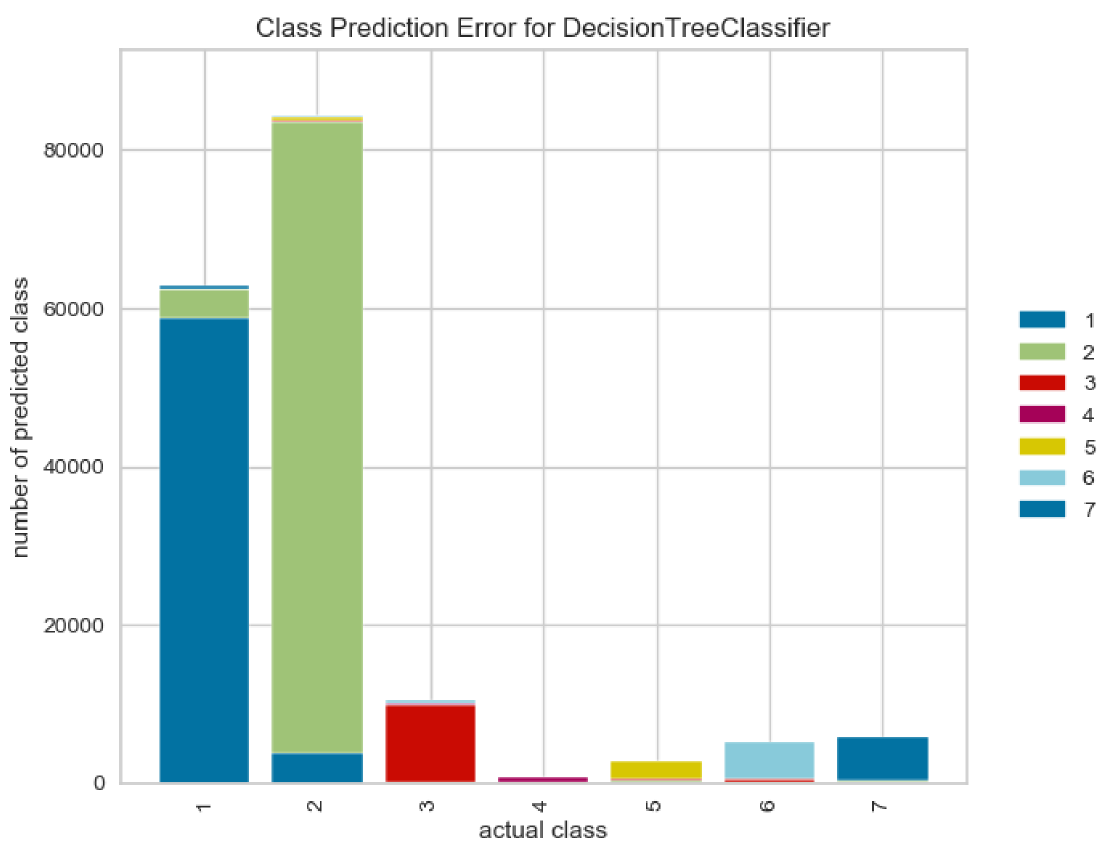
[50]:
```
tree_accuracy = accuracy_score(pred, y_test)
```

[51]:
```
# Quite well!

tree_accuracy
```

[51]: 0.9354517047266234

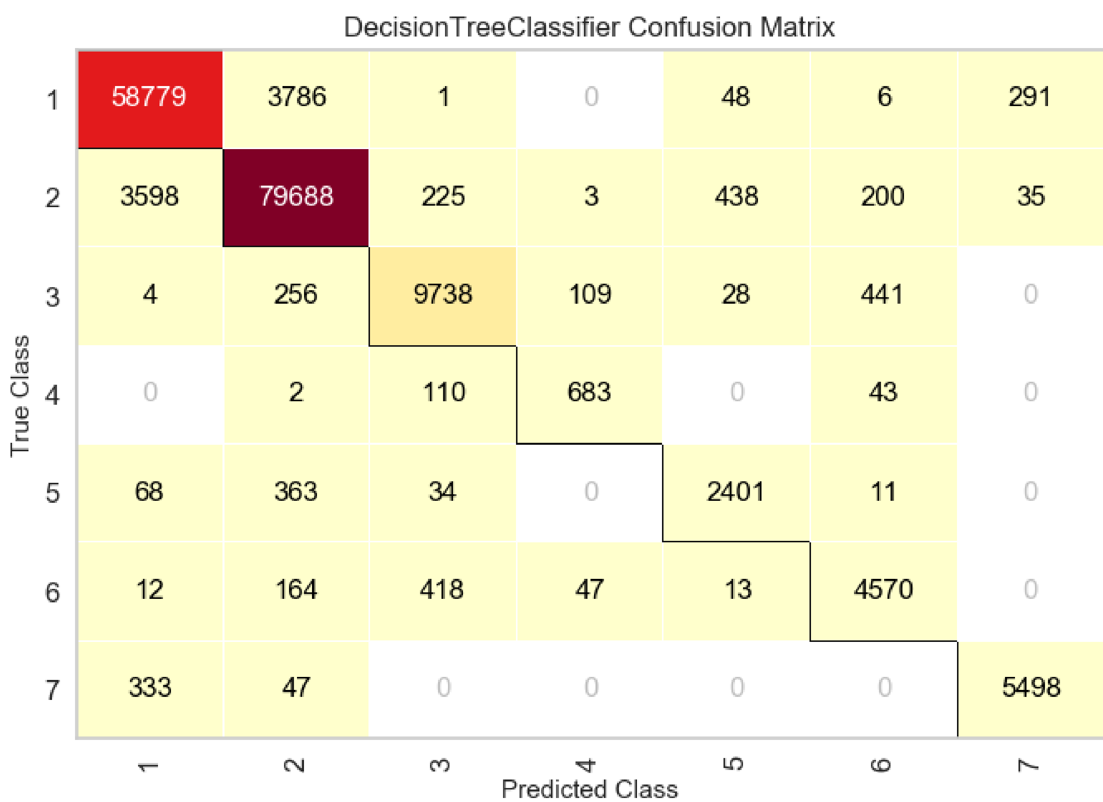
Now, I would like to show three plots for the results. - Class Prediction Error Bar Plot - Confusion Matrix - Classification Report

[54]:
```
visualizer = ClassPredictionError(modelTree)

# Fit the training data to the visualizer
visualizer.fit(X_train, y_train)

# Evaluate the model on the test data
visualizer.score(X_test, y_test)

# Draw visualization
visualizer.show()
```



```
[54]: <matplotlib.axes._subplots.AxesSubplot at 0x203097713c8>
```

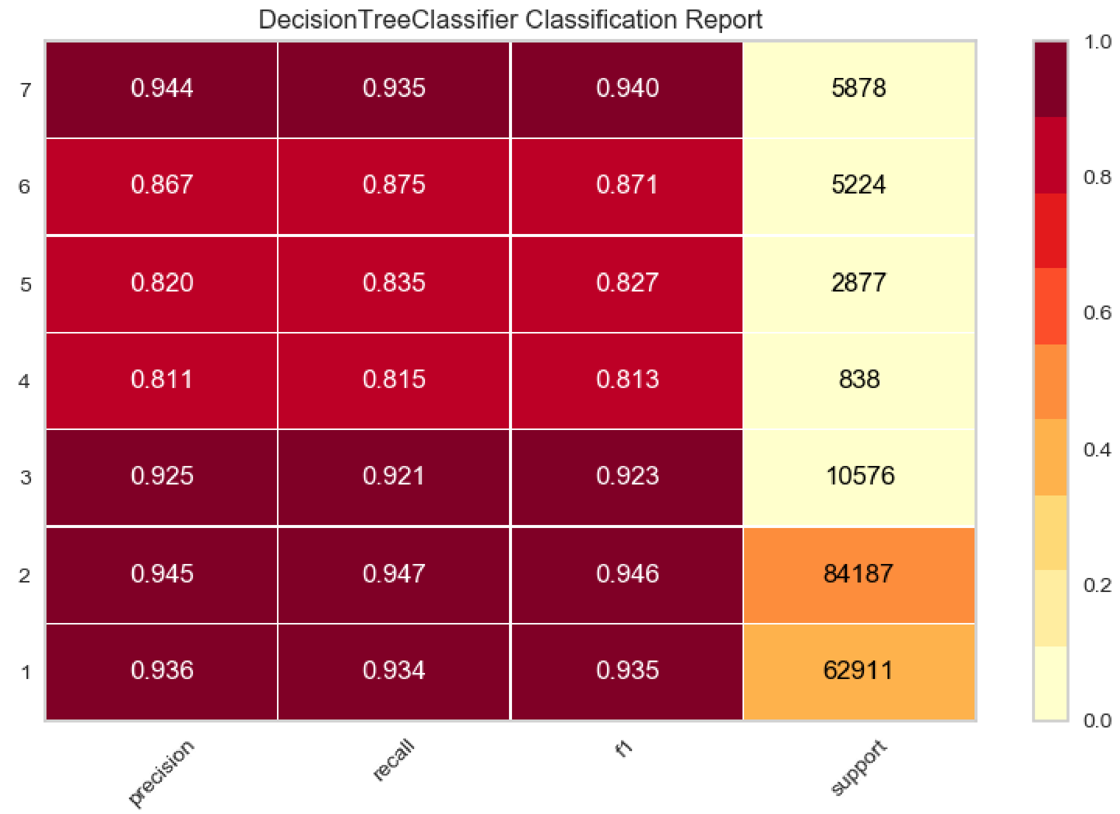
```
[53]: # The ConfusionMatrix visualizer taxes a model
cm = ConfusionMatrix(modelTree)

# Fit fits the passed model. This is unnecessary if you pass the visualizer a␣
↪pre-fitted model
cm.fit(X_train, y_train)

# To create the ConfusionMatrix, we need some test data. Score runs predict()␣
↪on the data
# and then creates the confusion_matrix from scikit-learn.
cm.score(X_test, y_test)

cm.show()
```




```
[53]: <matplotlib.axes._subplots.AxesSubplot at 0x20309c15a20>
```

```
[52]: visualizer = ClassificationReport(modelTree, support=True)
```

```
visualizer.fit(X_train, y_train)        # Fit the visualizer and the model
visualizer.score(X_test, y_test)        # Evaluate the model on the test data
visualizer.show()
```



[52]: <matplotlib.axes._subplots.AxesSubplot at 0x20309c15940>

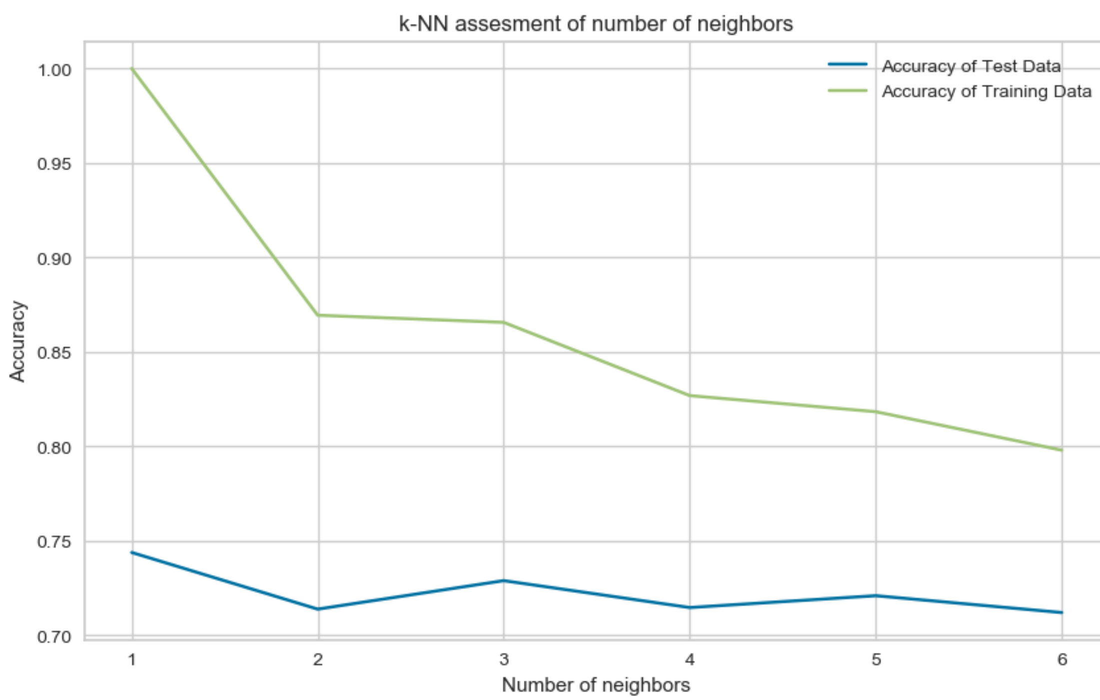
1.0.10 KNeighborsClassifer

- Deciding the number of neighbors

[55]:
```
neighbors = np.arange(1, 7)
train_accuracy =np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))

for i,k in enumerate(neighbors):
    #Setup a knn classifier with k neighbors
    knn = KNeighborsClassifier(n_neighbors = k)

    #Fit the model
    knn.fit(X_train, y_train)
```

```
    #Compute accuracy on the training set
    train_accuracy[i] = knn.score(X_train, y_train)

    #Compute accuracy on the test set
    test_accuracy[i] = knn.score(X_test, y_test)
```

[56]:
```
plt.figure(figsize=(10,6))
plt.title('k-NN assesment of number of neighbors')
plt.plot(neighbors, test_accuracy, label='Accuracy of Test Data')
plt.plot(neighbors, train_accuracy, label='Accuracy of Training Data')
plt.legend()
plt.xlabel('Number of neighbors')
plt.ylabel('Accuracy')
plt.show()
```



- **The graph lines stabilize around 5. So, Let's try 5 neighbors**. Let's prepare the train and test data for KNN Model.

[101]:
```
knn5 = KNeighborsClassifier(n_neighbors = 5)
```

[102]:
```
knn5.fit(X1_train,y1_train)
```

[102]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=5, p=2,
```

```
weights='uniform')
```

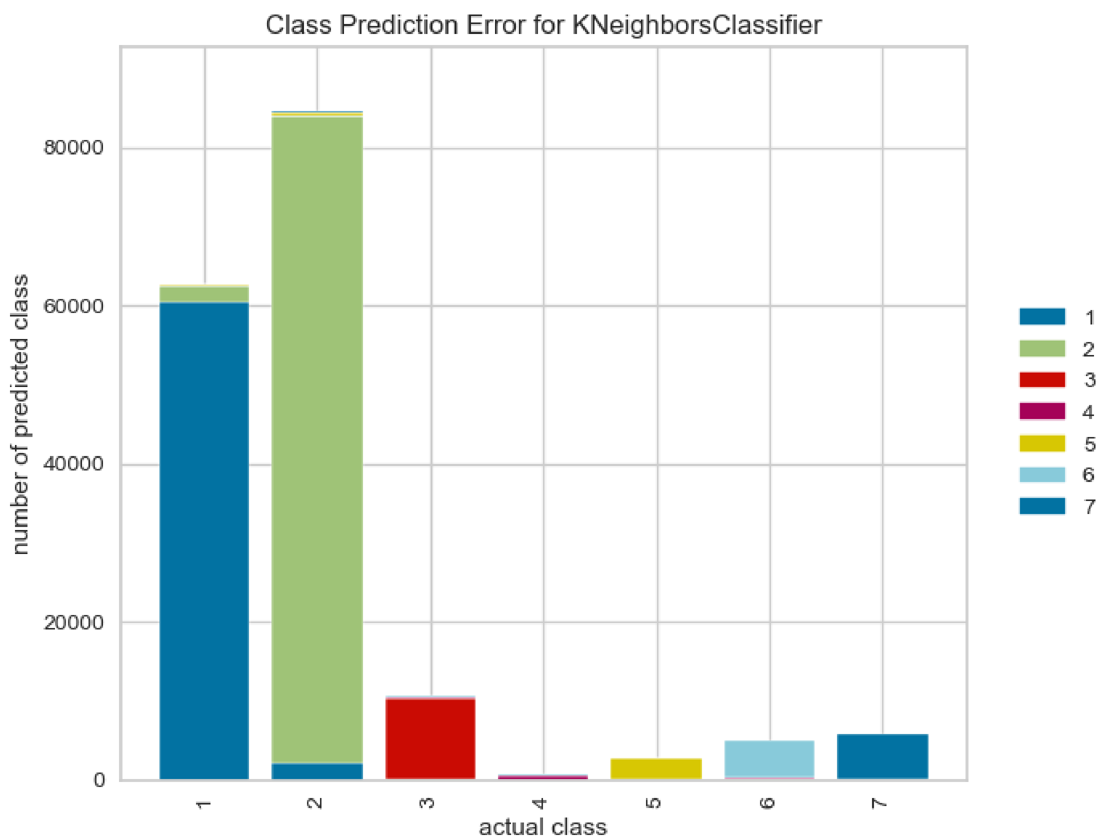
[103]:
```
knn_accuracy = knn5.score(X1_test,y1_test)
```

[104]:
```
# Excellent!

knn_accuracy
```

[104]: 0.962745882393864

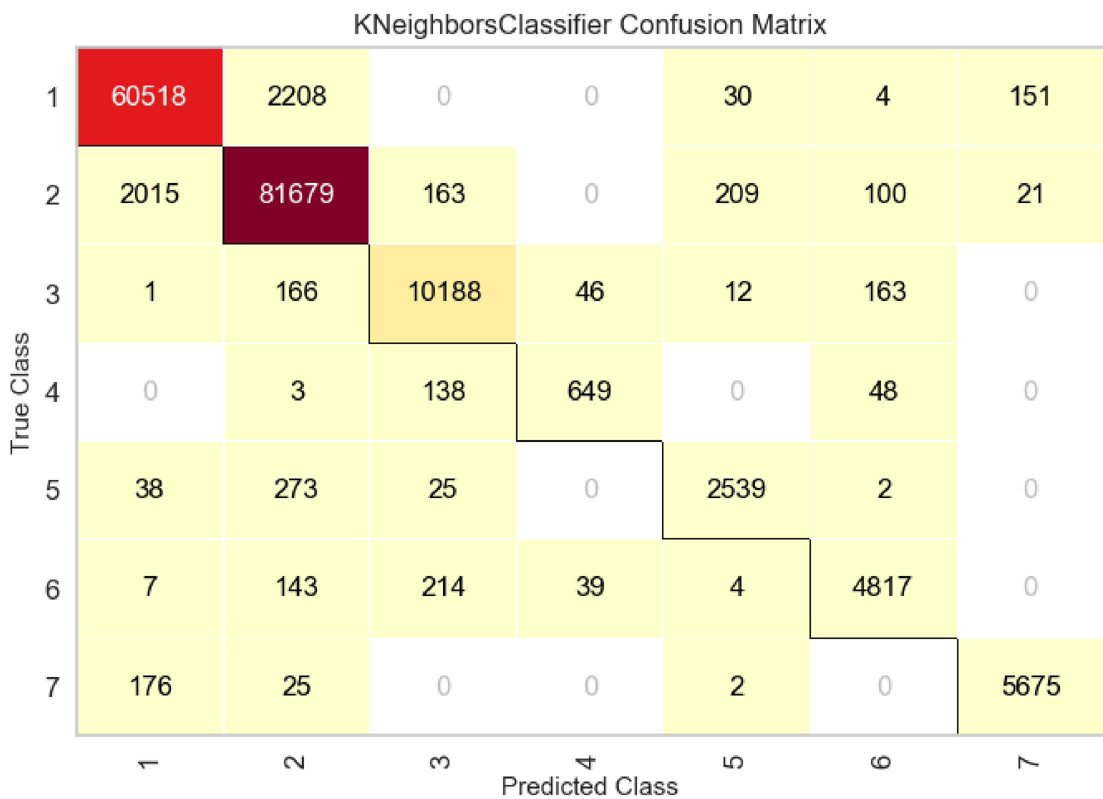
Now, I would like to show three plots for the results. - Class Prediction Error Bar Plot - Confusion Matrix - Classification Report

[108]:
```
visualizer = ClassPredictionError(knn5)

# Fit the training data to the visualizer
visualizer.fit(X1_train, y1_train)

# Evaluate the model on the test data
visualizer.score(X1_test, y1_test)

# Draw visualization
visualizer.show()
```



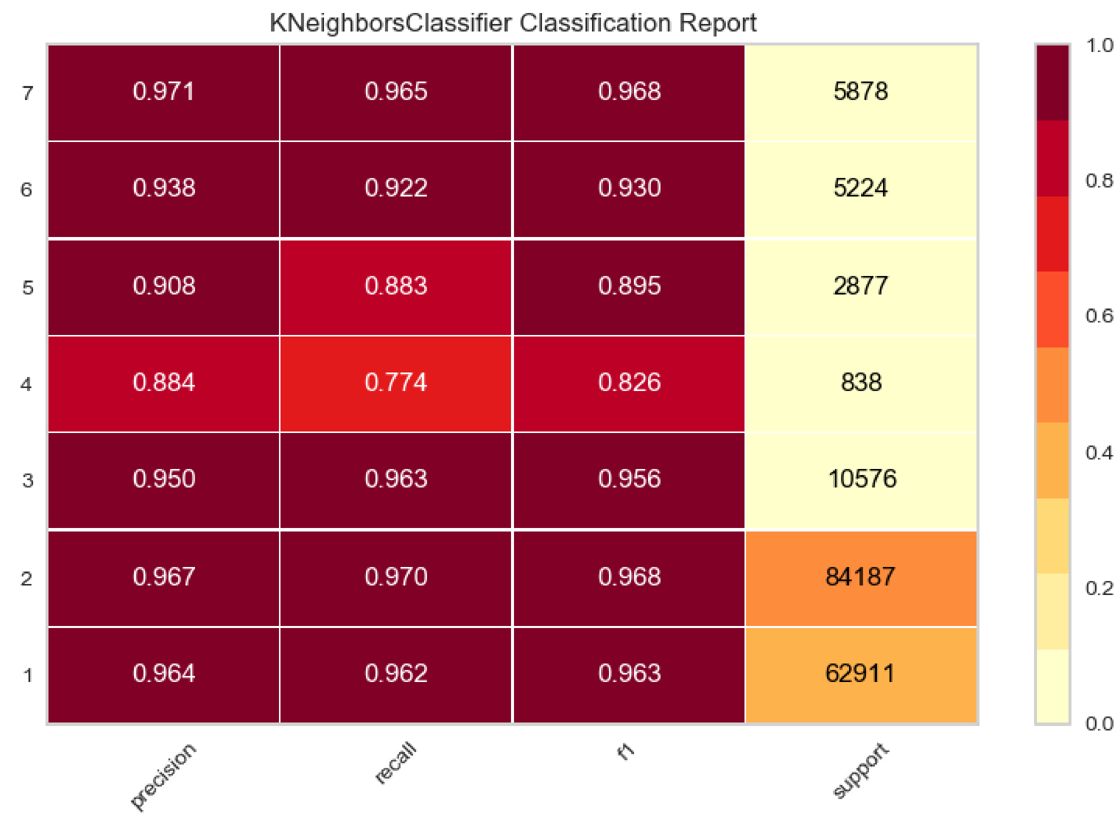
```
[108]: <matplotlib.axes._subplots.AxesSubplot at 0x20306be8358>
```

```
[109]: # The ConfusionMatrix visualizer taxes a model
cm = ConfusionMatrix(knn5)

# Fit fits the passed model. This is unnecessary if you pass the visualizer a␣
 ↪pre-fitted model
cm.fit(X1_train, y1_train)

# To create the ConfusionMatrix, we need some test data. Score runs predict()␣
 ↪on the data
# and then creates the confusion_matrix from scikit-learn.
cm.score(X1_test, y1_test)

cm.show()
```




```
[109]: <matplotlib.axes._subplots.AxesSubplot at 0x203000f5358>
```

[110]:
```
visualizer = ClassificationReport(knn5, support=True)

visualizer.fit(X1_train, y1_train)        # Fit the visualizer and the model
visualizer.score(X1_test, y1_test)        # Evaluate the model on the test data
visualizer.show()
```



[110]: <matplotlib.axes._subplots.AxesSubplot at 0x2030708e400>

1.0.11 LGBMClassifier

[77]:
```
from lightgbm import LGBMClassifier
```

[80]:
```
lgbm_classifier = LGBMClassifier()
```

[81]:
```
lgbm_classifier.fit(X_train, y_train)
y_predicted = lgbm_classifier.predict(X_test)
```

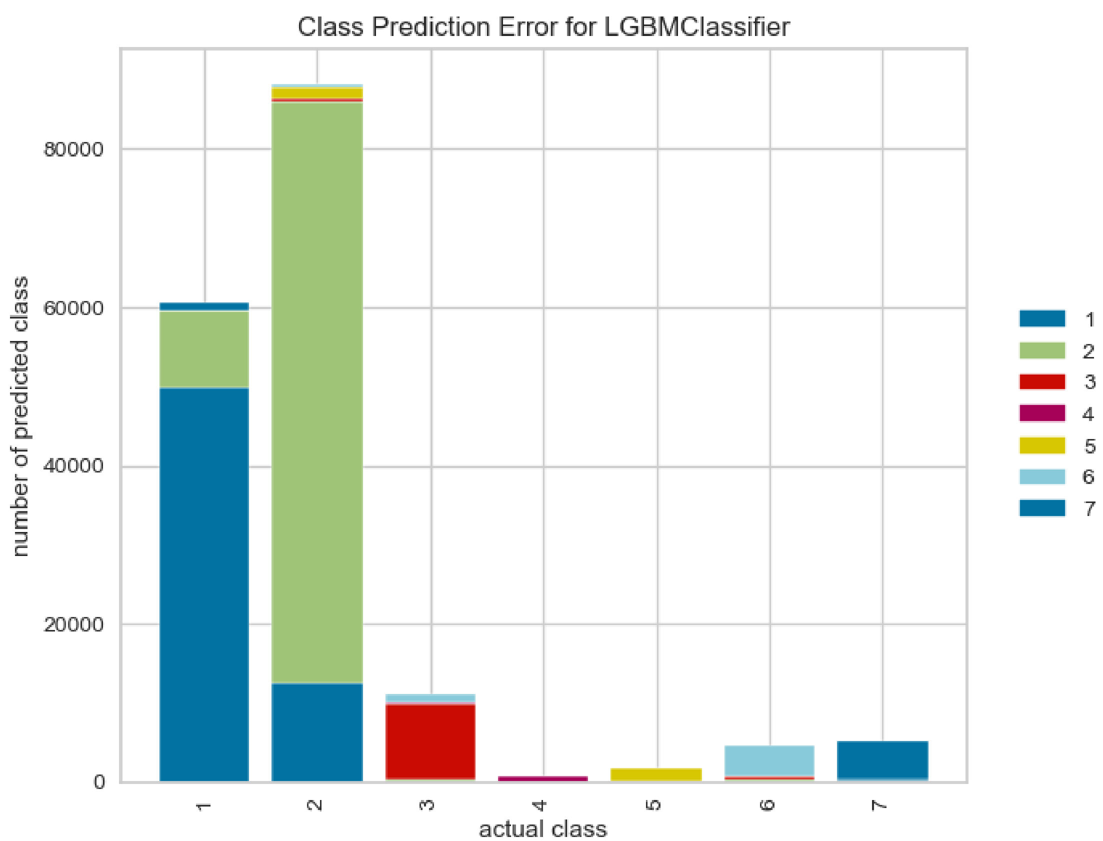
[127]:
```
lgbm_accuracy = accuracy_score(y_test, y_predicted)
```

[128]:
```
# Very good..

lgbm_accuracy
```

[128]: 0.8332782579960694

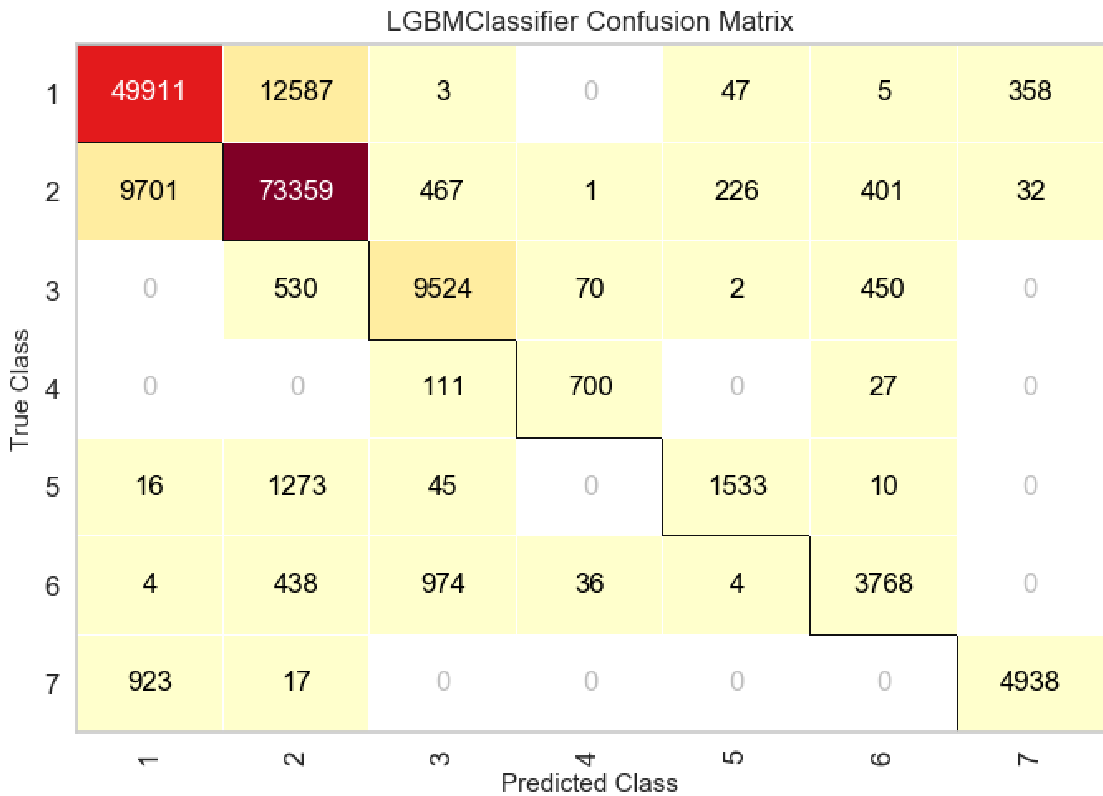
Now, I would like to show three plots for the results. - Class Prediction Error Bar Plot - Confusion Matrix - Classification Report

[130]:
```
visualizer = ClassPredictionError(lgbm_classifier)

# Fit the training data to the visualizer
visualizer.fit(X_train, y_train)

# Evaluate the model on the test data
visualizer.score(X_test, y_test)

# Draw visualization
visualizer.show()
```



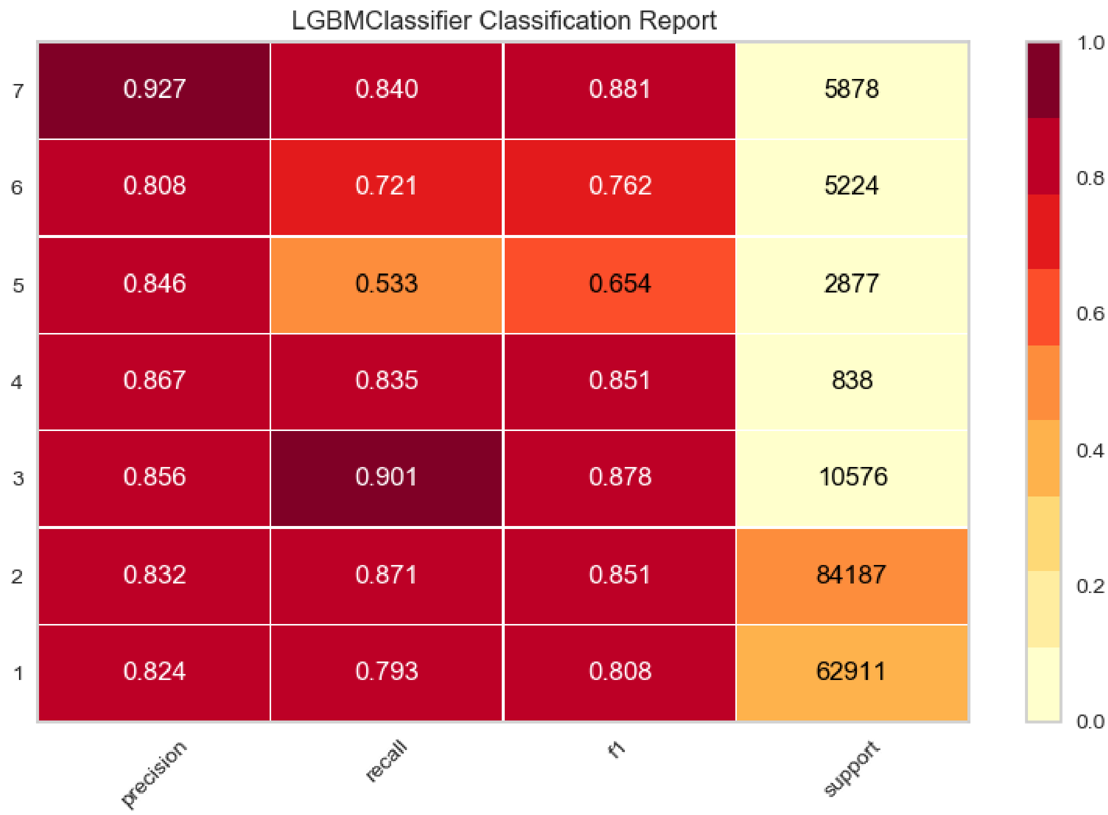
[130]: <matplotlib.axes._subplots.AxesSubplot at 0x2030c5a5b38>

[131]:
```
# The ConfusionMatrix visualizer taxes a model
cm = ConfusionMatrix(lgbm_classifier)

# Fit fits the passed model. This is unnecessary if you pass the visualizer a␣
↪pre-fitted model
cm.fit(X_train, y_train)

# To create the ConfusionMatrix, we need some test data. Score runs predict()␣
↪on the data
# and then creates the confusion_matrix from scikit-learn.
cm.score(X_test, y_test)

cm.show()
```



[131]: <matplotlib.axes._subplots.AxesSubplot at 0x203096c2278>

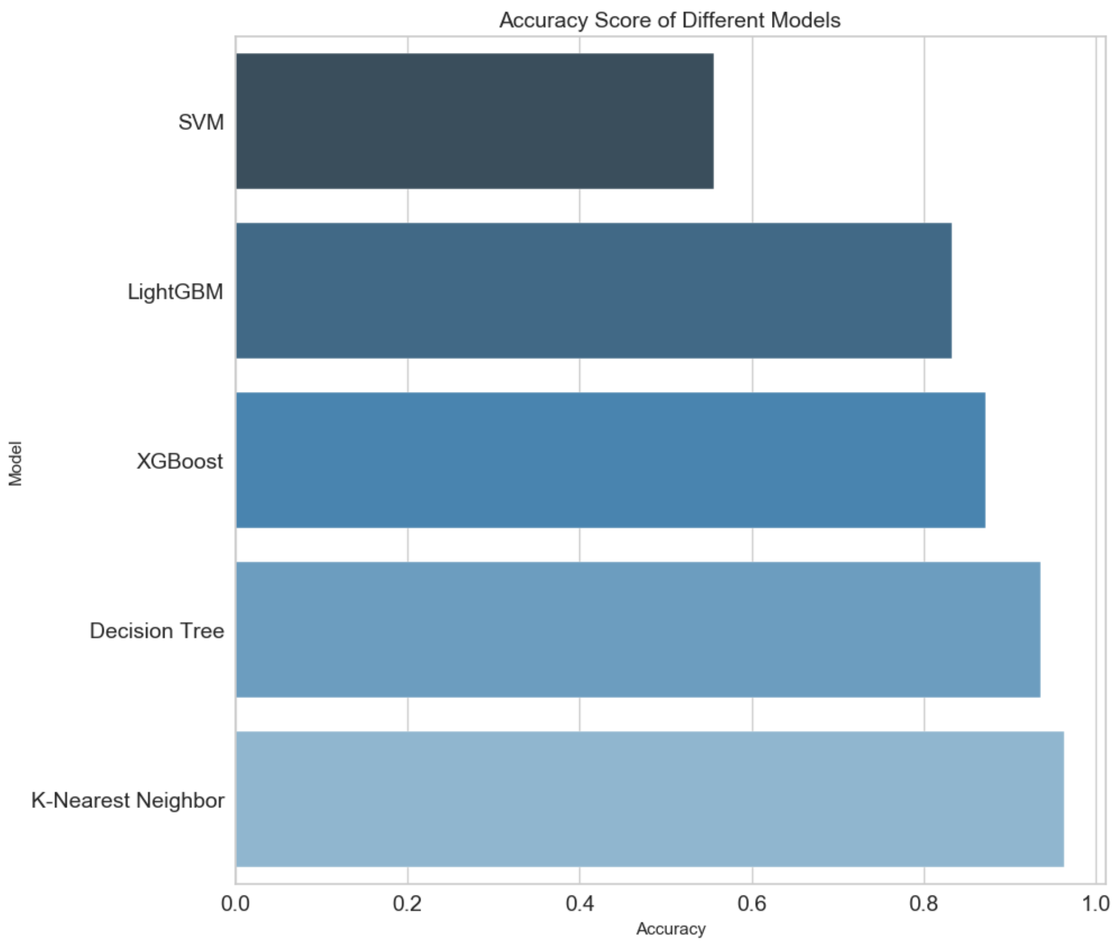
[132]:
```
visualizer = ClassificationReport(lgbm_classifier, support=True)

visualizer.fit(X_train, y_train)        # Fit the visualizer and the model
visualizer.score(X_test, y_test)        # Evaluate the model on the test data
visualizer.show()
```



[132]: <matplotlib.axes._subplots.AxesSubplot at 0x2032c4635f8>

[134]:
```
compare = pd.DataFrame({"Model": ["K-Nearest Neighbor", "LightGBM", "XGBoost",␣
↪"Decision Tree", "SVM"],
                        "Accuracy": [knn_accuracy, lgbm_accuracy, xgb_accuracy,␣
↪tree_accuracy, SVM_accuracy1]})

compare = compare.sort_values(by="Accuracy", ascending=True)

plt.figure(figsize=(10,10))
ax = sns.barplot(x="Accuracy", y="Model", data=compare, palette="Blues_d")

plt.yticks(size = 14)
plt.xticks(size = 14)
plt.title("Accuracy Score of Different Models", size=14)
```

[134]: Text(0.5, 1.0, 'Accuracy Score of Different Models')



1.0.12 Overall Results :

- The overall evaluation in terms of `accuracy scores` is displayed above.
- The model with the least performance is SVM.
  - SVM has been widely used in finance. For example, predicting stock price via SVM has been a acknowledged application in the industry.
  - In classification of text and handwritten objects, SVM performs well.
  - It may not be very successful in datasets with more than 100,000 data (We have half a million).
  - It also doesn't perform well against unstable data (`Cover_Type`).
- `XGBoost` has performed well enough. As in `linear regression` models, it has proven its success in `clasification` once again.
  - There is a little bit low `recall` score of the class `5`.
  - I concluded that it is caused by the values in the data set. %59.8 of the class `5` is predicted true.
  - Although the `recall` score level of class `5` is a little bit low, `precision` and `f1` score is quite well.

- All the other Models (`K-Nearest Neighbor`, `LightGBM`, `Decision Tree`) are quite well. They all have performed well and given high accuracy scores.
- Multi Class Classification is `KNN`'s job...

Best Regards..