CreditScore Data Set

Models will be fitted

- 1. Logistic Regression
- 2 SVM
- 3. Random Forest
- 4. ElasticNet
- 5. Ensumble These 4 Models

```
In [1]: #Import Libraries
        import csv
        import numpy as np
        import pandas as pd
        ### Import Descision Tree Classifier
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.linear model import ElasticNet
        from sklearn.linear model import LogisticRegression
        from sklearn.svm import SVC
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.ensemble import GradientBoostingClassifier
        from sklearn.preprocessing import scale
        from sklearn.decomposition import PCA
        from sklearn import svm
        from sklearn.ensemble import VotingClassifier
        from sklearn.model_selection import train_test split
        from sklearn.model_selection import cross_val_score
        from sklearn.model selection import GridSearchCV
        from sklearn.metrics import roc auc score
        from sklearn.pipeline import Pipeline
        from sklearn.metrics import accuracy score
        from sklearn.metrics import classification report
        from sklearn.metrics import confusion matrix
        # Perform the necessary imports
        import matplotlib.pyplot as plt
        ## for pearsonr correlation just feed x and y to this
        from scipy.stats import pearsonr
        pd.options.display.max columns=60
        #Change the Number Fromat of DATA frame
        pd.options.display.float_format = '{:,.4f}'.format
```

```
In [2]: ### Load the Data
seed=42
path="C:\\Users\\fbaharkoush\\IE 598 Machine Learning\\Homework\\Group Project\\"
df_credit=pd.read_csv(path+"MLF_GP1_CreditScore.csv")
if df_credit.isnull().sum().sum()==0:
    print("No Missing Values in the dataset")
```

```
In [3]:
         ### Get the dummy variables of Rating and merge it with the dataset
         df_credit_dummies=pd.merge(df_credit.reset_index(),
                  pd.get dummies(df credit["Rating"]).reset index(),
                  left on="index",right on="index",how="left").drop("index",axis=1)
         df credit dummies.head(2)
In [4]:
Out[4]:
                                                     Net
                                                                                                Free
                            Gross
                                          EBITDA Income
                                                           Total
                                                                    Net
                                                                            LT
                                                                                   ST
                                  EBITDA
            Sales/Revenues
                                                                                         Cash
                                                                                               Cash
                           Margin
                                           Margin
                                                   Before
                                                                                                      De
                                                            Debt
                                                                   Debt
                                                                           Debt
                                                                                  Debt
                                                                                                Flow
                                                   Extras
         0
                                                   0.1468 -0.0297 -0.0193 -0.0426 0.0499
                   -0.0055
                           0.0308
                                   0.0189
                                           0.0245
                                                                                      -0.1337
                                                                                              0.3530
         1
                   -0.0055 0.0308
                                   0.0887
                                           0.0947
                                                   0.1468 -0.0297 -0.0193 -0.0426 0.0499 -0.1337 0.3530
In [5]:
         ### X and y
         X=scale(df_credit_dummies.drop(['InvGrd', 'Rating'],axis=1).values)
         y=df_credit_dummies["InvGrd"].values
         ### Train and Test
         X train,X test,y train,y test=train test split(X,y,test size=0.25,random state=seed)
```

PCA with Dummy Variables

```
In [6]: # Create PCA instance: model
        pca_model = PCA()
        ### Fit the Features value to PCA
        pca model.fit transform(X)
Out[6]: array([[-1.15248335e-01, 3.04056439e-02, -5.73625149e-02, ...,
                -1.98683295e-03, 1.21401142e-03, -2.07682906e-15],
               [-1.06970414e-01, 4.46568712e-02, -1.00024599e-02, ...,
                -2.10264952e-03, 4.68145873e-05, -1.09291666e-15],
               [-1.00726759e-01, 4.49912941e-02, 2.03696419e-02, ...,
                -7.42464244e-04, 4.08196549e-04, 4.80258635e-15],
               [-1.64284497e-01, -6.88637238e-01, -5.71696306e-01, ...,
                -1.00729677e-03, 1.42029979e-03, 1.05203267e-15],
               [-1.02581361e-01, -7.12270022e-01, -6.22364252e-01, ...,
                 7.70699272e-04, -1.54993582e-03, 4.80073863e-16],
               [-2.14992750e-01, -6.88032028e-01, -6.28300064e-01, ...,
                 2.69455000e-03, -8.46058966e-04, 9.73895010e-17]])
        X_features=list(df_credit_dummies.drop(['InvGrd', 'Rating'],axis=1).columns)
In [7]:
In [8]:
       df_pca_exp_var=pd.DataFrame({"Features":X_features,
                      "PCA_Exp_Var":pca_model.explained_variance_ratio_}).sort_values("PCA_Exp_V
```

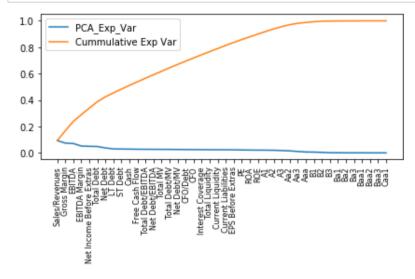
df_pca_exp_var["Cummulative Exp Var"]=df_pca_exp_var["PCA_Exp_Var"].cumsum()

```
In [9]: df_pca_exp_var
```

Out[9]:

	Features	PCA_Exp_Var	Cummulative Exp Var
0	Sales/Revenues	0.0936	0.0936
1	Gross Margin	0.0737	0.1673
2	EBITDA	0.0707	0.2381
3	EBITDA Margin	0.0517	0.2897
4	Net Income Before Extras	0.0495	0.3392
5	Total Debt	0.0481	0.3873
6	Net Debt	0.0372	0.4245
7	LT Debt	0.0298	0.4543
8	ST Debt	0.0288	0.4831
9	Cash	0.0282	0.5113
10	Free Cash Flow	0.0272	0.5385

```
In [10]: plotX = df_pca_exp_var.iloc[:, 0]
    plotY1 = df_pca_exp_var.iloc[:, 1]
    plotY2 = df_pca_exp_var.iloc[:, 2]
    plt.xticks(rotation=90)
    plt.plot(plotX, plotY1)
    plt.plot(plotX, plotY2)
    plt.legend(['PCA_Exp_Var', 'Cummulative Exp Var'])
    plt.tick_params(axis='x', which='major', labelsize=8)
    plt.tight_layout()
```



1.1 Logistic Regression

Target Vaiable: InvGrd with Duummy Variables

```
In [11]: ## Fit the Model
    logReg_model=LogisticRegression(solver='lbfgs')
    logReg_model.fit(X_train,y_train)
    ### Predict
    y_pred_train=logReg_model.predict(X_train)
    y_pred_test=logReg_model.predict(X_test)
```

In [12]: print("Accuracy Score of Logistic Regression Model with dummy variables on Train Set", log print("Accuracy Score of Logistic Regression Model with dummy variables on Test Set", log print("ROC_AUC of Logistic Regression Model with dummy variables on Train Set", roc_auc_s print("ROC_AUC of Logistic Regression Model with dummy variables on Test Set", roc_auc_s

Accuracy Score of Logistic Regression Model with dummy variables on Train Set 1.0 Accuracy Score of Logistic Regression Model with dummy variables on Test Set 1.0 ROC_AUC of Logistic Regression Model with dummy variables on Train Set 1.0 ROC_AUC of Logistic Regression Model with dummy variables on Test Set 1.0

As we noticed creating the dummy variables is boosting the model accuracy. In the following code we are going to remove "Rating" dummy variables and run the logistic regression model again and see what happens to the result.

```
In [14]: X=scale(df_credit_dummies.drop(list_to_drop,axis=1).values)
    y=df_credit_dummies["InvGrd"].values
    ### Train and Test
    X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25,random_state=seed)
```

```
In [15]: del y_pred_train , y_pred_test
```

PCA without Dummy Variables

```
In [16]: # Create PCA instance: model
         pca model = PCA()
         ### Fit the Features value to PCA
         pca model.fit transform(X)
Out[16]: array([[-0.15189997, 0.0235405, -0.06845795, ..., -0.00784368,
                 -0.00442878, -0.00160618],
                [-0.14272847, 0.03249937, -0.01855342, ..., -0.00370066,
                 -0.00426299, -0.00279038],
                [-0.13566313, 0.02783463, 0.00923416, ..., -0.00908331,
                 -0.00279016, -0.00242822],
                [-0.13568104, -0.43058978, -0.44130577, ..., 0.02968121,
                 -0.00582438, 0.00059085],
                [-0.0733207, -0.4424719, -0.4753796, ..., -0.00732613,
                 -0.00338393, -0.00238864],
                [-0.18756961, -0.4270099, -0.50309818, ..., -0.0221842]
                 -0.00134203, -0.00167871]])
```

```
X features=list(df credit dummies.drop(list to drop,axis=1).columns)
In [17]:
In [18]:
            df_pca_exp_var=pd.DataFrame({"Features":X_features,
                               "PCA Exp Var":pca model.explained_variance_ratio_}).sort_values("PCA_Exp_V
            df pca exp var["Cummulative Exp Var"]=df pca exp var["PCA Exp Var"].cumsum()
            PCA Report Without Dummy Variables
In [19]:
            df_pca_exp_var
Out[19]:
                                 Features
                                           PCA Exp Var Cummulative Exp Var
               0
                           Sales/Revenues
                                                   0.1443
                                                                          0.1443
               1
                             Gross Margin
                                                   0.1185
                                                                          0.2628
                                  EBITDA
               2
                                                   0.1126
                                                                          0.3754
                                                                          0.4573
               3
                           EBITDA Margin
                                                   0.0819
                  Net Income Before Extras
                                                   0.0769
                                                                          0.5342
               5
                                Total Debt
                                                   0.0755
                                                                          0.6097
               6
                                 Net Debt
                                                   0.0575
                                                                          0.6672
               7
                                  LT Debt
                                                   0.0420
                                                                          0.7092
               8
                                  ST Debt
                                                   0.0390
                                                                          0.7482
               9
                                     Cash
                                                   0.0382
                                                                          0.7864
             10
                           Free Cash Flow
                                                   0.0377
                                                                          0.8241
In [20]:
            plotX = df_pca_exp_var.iloc[:, 0]
            plotY1 = df_pca_exp_var.iloc[:, 1]
            plotY2 = df pca exp var.iloc[:, 2]
            plt.xticks(rotation=90)
            plt.plot(plotX, plotY1)
            plt.plot(plotX, plotY2)
            plt.legend(['PCA_Exp_Var', 'Cummulative Exp Var'])
            plt.tick_params(axis='x', which='major', labelsize=8)
            plt.tight_layout()
              1.0
              0.8
              0.6
                                                                PCA_Exp_Var
                                                                Cummulative Exp Var
              0.4
              0.2
              0.0
                                         Cash .
Free Cash Flow .
                                  Net Debt
LT Debt
ST Debt
                                                          GO/Debt
GO
                          EBITDA Margin
                                                   Total MV
                                                                         EPS Before Extras
                             Net Income Before Extras
                                Total Debt
                                              otal Debt/EBITDA
                                                 Net Debt/EBITDA
                                                      Total Debt/MV
                                                        Net Debt/MV
                                                               Interest Coverage
                                                                  Total Liquidity
                                                                       Current Liabilities
```

1.2 Logistic Regression

Target Vaiable: InvGrd without Duummy Variables

```
In [21]: ## Fit the Model
    logReg_model=LogisticRegression(solver='lbfgs')
    logReg_model.fit(X_train,y_train)
    ### Predict
    y_pred_train=logReg_model.predict(X_train)
    y_pred_test=logReg_model.predict(X_test)
```

In [22]: print("Accuracy Score of Logistic Regression Model WITHOUT dummy variables on Train Set"
 print("Accuracy Score of Logistic Regression Model WITHOUT dummy variables on Test Set",
 print("ROC_AUC of Logistic Regression Model WITHOUT dummy variables on Train Set",roc_au
 print("ROC_AUC of Logistic Regression Model WITHOUT dummy variables on Test Set",roc_au

Accuracy Score of Logistic Regression Model WITHOUT dummy variables on Train Set 0. 7717647058823529

Accuracy Score of Logistic Regression Model WITHOUT dummy variables on Test Set 0.7 529411764705882

ROC_AUC of Logistic Regression Model WITHOUT dummy variables on Train Set 0.5353135 034645935

ROC_AUC of Logistic Regression Model WITHOUT dummy variables on Test Set 0.5291506 017058067

In [24]: df_models_summary

Out[24]:

	Model	Accuracy Train	Accuracy Test	ROC Train	ROC Test
0	Logistic Regression	0.7718	0.7529	0.5353	0.5292

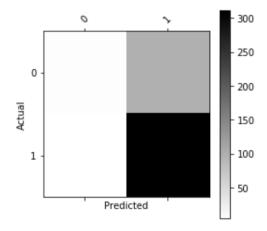
Classification Report on Test Set

In [25]: print(classification_report(y_test,y_pred_test))

	precision	recall	f1-score	support
0	0.62	0.07	0.13	108
1	0.76	0.98	0.86	317
accuracy			0.75	425
macro avg	0.69	0.53	0.49	425
weighted avg	0.72	0.75	0.67	425

```
In [28]: import matplotlib.pyplot as plt
def plot_confusion_matrix(df_confusion, title='Confusion matrix', cmap=plt.cm.gray_r):
    plt.matshow(df_confusion, cmap=cmap) # imshow
    #plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(df_confusion.columns))
    plt.xticks(tick_marks, df_confusion.columns, rotation=45)
    plt.yticks(tick_marks, df_confusion.index)
    #plt.tight_layout()
    plt.ylabel(df_confusion.index.name)
    plt.xlabel(df_confusion.columns.name)

plot_confusion_matrix(df_confusion)
```



2. Random Forest with 10 Cross Validation without dummy variables

Target Vaiable: InvGrd

Out[31]: 0.7819607843137255

In [32]: print("Best Random Forest Model is the one with the following Parameters", random_forest_

Best Random Forest Model is the one with the following Parameters {'criterion': 'gini', 'n estimators': 100}

Selecting Best Random Forest Model

```
In [33]: random_forest_classsifier_model_with_best_param=random_forest_classsifier_model_gridcv.t
random_forest_classsifier_model_gridcv.best_estimator_
```

In Sample Accuracy (Train)

```
In [34]: ### Fit to the best Model
    random_forest_classsifier_model_with_best_param.fit(X_train,y_train)
    ### Training set prediction
    y_pred_train=random_forest_classsifier_model_with_best_param.predict(X_train)
    ### Training set ROC Score and Accuracy Score
    print("ROC AUC Sccore of the best RF model on Train Set",roc_auc_score(y_train,y_pred_tr
    print("Accuracy score of best RF on Train",accuracy_score(y_train,y_pred_train))
```

ROC AUC Sccore of the best RF model on Train Set 0.5925046476254859 Accuracy score of best RF on Train 0.8023529411764706

Out Sample Accuracy (Test)

```
In [35]: ### Test set ROC Score and Accuracy Score
         y_pred_test=random_forest_classsifier_model_with_best_param.predict(X_test)
         print("ROC AUC Sccore of the best RF model on Test Set", roc auc score(y test, y pred test
         print("Accuracy score of best RF on Test",accuracy_score(y_test,y_pred_test))
         ROC AUC Sccore of the best RF model on Test Set 0.5693422128753359
         Accuracy score of best RF on Test 0.7764705882352941
In [36]:
         pd.DataFrame({"Model":["Random Forest"],"Accuracy Train":[accuracy_score(y_train,y_pred]
                       "Accuracy Test": [accuracy score(y test, y pred test)],
                       "ROC Train":roc_auc_score(y_train,y_pred_train),
                      "ROC Test":roc auc score(y test,y pred test)})
Out[36]:
                   Model Accuracy Train Accuracy Test ROC Train ROC Test
            Random Forest
                                0.8024
                                             0.7765
                                                       0.5925
                                                                0.5693
In [37]:
         df_models_summary=pd.concat([df_models_summary,pd.DataFrame(
              {"Model":["Random Forest"],"Accuracy Train":[accuracy_score(y_train,y_pred_train)],
                       "Accuracy Test": [accuracy score(y test, y pred test)],
                       "ROC Train":roc_auc_score(y_train,y_pred_train),
                      "ROC Test":roc_auc_score(y_test,y_pred_test)})])
In [38]: random_forest_classsifier_model_with_best_param.feature_importances_
Out[38]: array([0.06977861, 0.05635957, 0.07123801, 0.03276124, 0.04432367,
                 0.00851944, 0.01474779, 0.00761444, 0.008769 , 0.04213864,
                 0.06794936, 0.02860935, 0.01448993, 0.05124046, 0.02644558,
                 0.01713333, 0.06076943, 0.07945242, 0.00880084, 0.00610081,
                 0.03229257, 0.00272128, 0.05465327, 0.06158875, 0.07671441,
                 0.0547878 1)
In [39]: importances_rf=pd.Series(random_forest_classsifier_model_with_best_param.feature_importal
                    index = X_features)
         # Sort importances rf
          sorted importances rf = importances rf.sort values()
         # Make a horizontal bar plot
          sorted importances rf.plot(kind='barh', color='lightgreen')
          plt.show()
                EPS Before
           Net Income Before
                     ST Debi
Total Debt
LT Debt
```

0.01

0.00

0.02

0.03

0.04

0.05

0.06

0.07

0.08

Target Vaiable: InvGrd

```
1. kernel='linear'
```

2. kernel='rbf

```
del y_pred_train , y_pred_test
In [40]:
In [41]:
         ### Linear SVM
         svm linear classification=svm.SVC(C=1,gamma='scale',kernel='linear')
         svm linear classification.fit(X train,y train)
         ### Linear SVM Prediction
         y pred train=svm linear classification.predict(X train)
         y_pred_test=svm_linear_classification.predict(X_test)
In [42]: print("Accuracy Score of Linear SVM Model WITHOUT dummy variables on Train Set",
               svm_linear_classification.score(X_train,y_train))
         print("Accuracy Score of Linear SVM Model WITHOUT dummy variables on Test Set",
               svm linear classification.score(X test,y test))
         print("ROC AUC of Linear SVM Model WITHOUT dummy variables on Train Set",
               roc_auc_score(y_train,y_pred_train))
         print("ROC AUC of Linear SVM Model WITHOUT dummy variables on Test Set",
               roc auc score(y test,y pred test))
         Accuracy Score of Linear SVM Model WITHOUT dummy variables on Train Set 0.7686274509803
         922
         Accuracy Score of Linear SVM Model WITHOUT dummy variables on Test Set 0.74823529411764
         ROC AUC of Linear SVM Model WITHOUT dummy variables on Train Set 0.5175173229677201
         ROC_AUC of Linear SVM Model WITHOUT dummy variables on Test Set 0.5076819721930131
In [43]:
         ### Models Summary
         df_models_summary=pd.concat([df_models_summary,pd.DataFrame({"Model":["SVM Linear"],"Acd
                       "Accuracy Test":[svm linear classification.score(X test,y test)],
                      "ROC Train":roc_auc_score(y_train,y_pred_train),
                      "ROC Test":roc auc score(y test,y pred test)})])
In [44]: del y_pred_train , y_pred_test
In [45]:
         ### RBF SVM
         svm_rfb_classification=svm.SVC(C=2,gamma='scale',kernel='rbf')
         svm_rfb_classification.fit(X_train,y_train)
         ### RBF SVM prediction
         y pred train=svm rfb classification.predict(X train)
         y_pred_test=svm_rfb_classification.predict(X_test)
```

Accuracy Score of RBF SVM Model WITHOUT dummy variables on Train Set 0.8258823529411765 Accuracy Score of RBF SVM Model WITHOUT dummy variables on Test Set 0.7623529411764706 ROC_AUC of RBF SVM Model WITHOUT dummy variables on Train Set 0.6439327361838769 ROC AUC of RBF SVM Model WITHOUT dummy variables on Test Set 0.5629308330412431

Ensumbling for InvGrd

4 Models were fitted for InvGrd as Target Variable

```
In [49]: ### Iterate over the difined list of tuple containing the classifiers
for clf_nam, clf in classifiers:
    ### Fit clt to the traning set
    clf.fit(X_train,y_train)
    ### Predict test
    y_pred_test=clf.predict(X_test)
    ### Evaluate the accuracy of the clf on the test set
    print((clf_nam,accuracy_score(y_test,y_pred_test)))
```

```
('Logistic Regression', 0.7529411764705882)
('SVM RBF', 0.7623529411764706)
('SVM Linear', 0.7482352941176471)
('Decision Tree Classifier', 0.7764705882352941)
```

```
In [50]: ### Instatitate a VotingClassifier 'vc'
    vc=VotingClassifier(estimators=classifiers)
    ### Fit the VotingClassifier
    vc.fit(X_train,y_train)
    y_pred_train=vc.predict(X_train)
    y_pred_test=vc.predict(X_test)
    print("Accuracy of Voting Classifier Ensumbled Train", vc.score(X_train,y_train))
    print("Accuracy of Voting Classifier Ensumbled Test", vc.score(X_test,y_test))
```

Accuracy of Voting Classifier Ensumbled Train 0.8023529411764706 Accuracy of Voting Classifier Ensumbled Test 0.7670588235294118

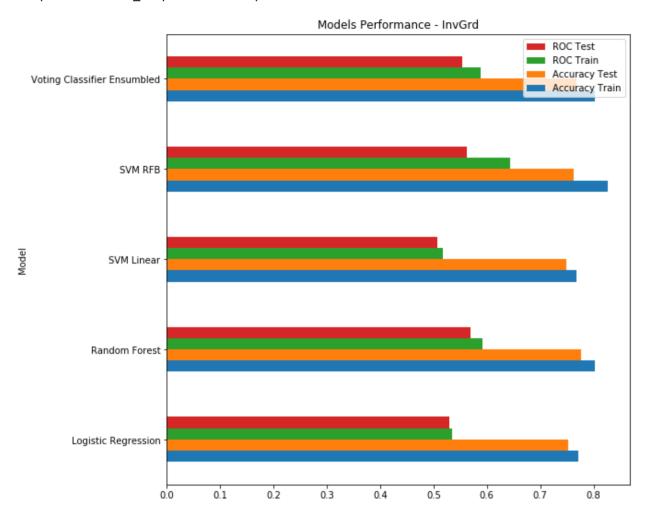
In [52]: df_models_summary

Out[52]:

	Model	Accuracy Train	Accuracy Test	ROC Train	ROC Test
0	Logistic Regression	0.7718	0.7529	0.5353	0.5292
0	Random Forest	0.8024	0.7765	0.5925	0.5693
0	SVM Linear	0.7686	0.7482	0.5175	0.5077
0	SVM RFB	0.8259	0.7624	0.6439	0.5629
0	Voting Classifier Ensumbled	0.8024	0.7671	0.5880	0.5539

In [53]: df_models_summary.plot("Model",kind='barh',title="Models Performance - InvGrd",figsize=(

Out[53]: <matplotlib.axes._subplots.AxesSubplot at 0x162e45c5978>



Conclusion

```
In [ ]:

In [ ]:
```

1 Logistic Regression

Target Vaiable: Rating

```
In [54]: del X_train,X_test,y_train, y_test , y_pred_test, y_pred_train , logReg_model
```

```
In [55]: y=df_credit["Rating"].values
    ### Train and Test
    X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25,random_state=seed)
```

```
In [56]: ## Fit the Model
    logReg_model=LogisticRegression(solver='newton-cg',multi_class ='multinomial')
    logReg_model.fit(X_train,y_train)
    ### Predict
    y_pred_train=logReg_model.predict(X_train)
    y_pred_test=logReg_model.predict(X_test)
```

```
In [57]: print("Accuracy Score of Logistic Regression Model WITHOUT dummy variables on Train Set"
print("Accuracy Score of Logistic Regression Model WITHOUT dummy variables on Test Set",
```

Accuracy Score of Logistic Regression Model WITHOUT dummy variables on Train Set 0. 2627450980392157

Accuracy Score of Logistic Regression Model WITHOUT dummy variables on Test Set 0.2 023529411764706

2 Random Forest

Target Vaiable: Rating

```
In [59]: del y_pred_test, y_pred_train
```

```
In [60]:
         del random forest classsifier model gridcv, random forest classsifier model
In [61]:
         ### Random Forest Parameters
         prameters_for_rfc={'n_estimators': [100,200,300,400,500],
                    'criterion':['gini','entropy'],
                            'max depth':[1,2,3,4,5,6,7,8,9,10,11,12,13,14]}
In [62]:
         ### Initiate Random Forest Model With Max Depth=2
         random forest classsifier model=RandomForestClassifier(random state=seed)
         ### Initiate Random Forest Model with 10 Fold Cross Validation
         random forest classsifier model gridcv=GridSearchCV(estimator=random forest classsifier
                                                          cv=2,iid=False,
                                                         scoring='accuracy')
         ### Fit Random Forest Model with Cross Validation
         random forest classsifier model gridcv.fit(X train, v train)
         ### Get the Best Score of the cross validate model
         random_forest_classsifier_model_gridcv.best_score_
Out[62]: 0.48464144926252384
In [63]: print("Best Random Forest Model is the one with the following Parameters\n",
               random_forest_classsifier_model_gridcv.best_params_)
         Best Random Forest Model is the one with the following Parameters
          {'criterion': 'entropy', 'max depth': 14, 'n estimators': 500}
         Selecting best Random Forest model
In [64]:
         random forest classsifier model with best param=random forest classsifier model gridcv.
         random_forest_classsifier_model_gridcv.best_estimator_
Out[64]: RandomForestClassifier(bootstrap=True, class weight=None, criterion='entropy',
                                max_depth=14, max_features='auto', 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, n_estimators=500,
                                n_jobs=None, oob_score=False, random_state=42, verbose=0,
                                warm start=False)
         In Sample Accuracy (Train)
In [65]: | ### Fit to the best Model
         random forest classsifier model with best param.fit(X train,y train)
         ### Training set prediction
         y pred train=random forest classsifier model with best param.predict(X train)
         ### Training set ROC Score
         print("Accuracy Sccore of the best model on Training Set",
               random_forest_classsifier_model_with_best_param.score(X_train,y_train))
```

Accuracy Sccore of the best model on Training Set 1.0

Out Sample Accuracy (Test)

Accuracy Score of the best model on Test Set 0.6447058823529411

Are we overfitting?

It seems we may be overfitting the model by selecting high number of max depth (more than 10) for the trees and the big diffrence between in sample accuracy vs out of sample accuracy. So we are investiating that here below

Random Models Fitted Preformance

```
In [69]: df_models_summary_rating_rf.head(2)
```

Out[69]:

```
        criterion
        max_depth
        n_estimators
        mean_test_score
        Model

        0
        gini
        1
        100
        0.1945
        Random Forest

        1
        gini
        1
        200
        0.1961
        Random Forest
```

```
In [71]: df_models_summary_rating_rf["Train Accuracy Score"]=list_of_train_score
```

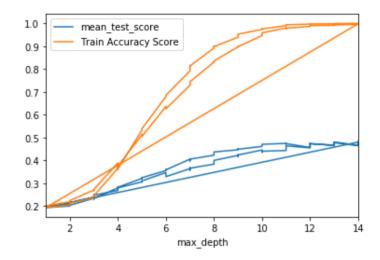
In [72]: df_models_summary_rating_rf.sort_values(["mean_test_score"],ascending=False).head()

Out[72]:

	criterion	max_depth	n_estimators	mean_test_score	Model	Train Accuracy Score
139	entropy	14	500	0.4846	Random Forest	1.0000
134	entropy	13	500	0.4807	Random Forest	0.9992
69	gini	14	500	0.4799	Random Forest	0.9984
64	gini	13	500	0.4776	Random Forest	0.9929
133	entropy	13	400	0.4768	Random Forest	0.9992

In [73]: df_models_summary_rating_rf.plot(y=["mean_test_score","Train Accuracy Score"],x="max_der

Out[73]: <matplotlib.axes._subplots.AxesSubplot at 0x162e30e0cf8>



Our analysis shows its the nature of the data that requiers lagre number of max depth for improvment and we are not overfitting as we the accurcy of the train and test are increasing together as the number of max depth are growing.

SVM

Target Vaiable: Rating

```
In [74]: del y_pred_train , y_pred_test
```

```
In [75]: ### RBF SVM
svm_classification=svm.SVC(gamma='auto')
```

```
In [76]:
         ### RBF Parameters
         prameters_for_SVM={'C':range(1,10),
                    'kernel':['rbf','linear']}
          ### Fit the model
          svm classification gridcv=GridSearchCV(estimator=svm classification,param grid=prameters
                                                           cv=2.
                                                          scoring='accuracy')
          svm_classification_gridcv.fit(X_train,y_train)
          print("Best SVM Model is",svm_classification_gridcv.best_estimator_)
         Best SVM Model is SVC(C=9, cache size=200, class weight=None, coef0=0.0,
              decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
              max iter=-1, probability=False, random state=None, shrinking=True,
              tol=0.001, verbose=False)
In [77]: | df models summary rating=pd.concat([df models summary rating,pd.DataFrame({"Model":"SVM"
                        "Train Accuracy Score":[svm classification gridev.score(X train,y train)],
                       "Test Accuracy Score":[svm_classification_gridcv.score(X_test,y_test)]})])
In [78]: df models summary rating
Out[78]:
                      Model Train Accuracy Score Test Accuracy Score
          0 Logistic Regression
                                        0.2627
                                                          0.2627
          0
                Random Forest
                                        1.0000
                                                          0.6447
```

0.4235

Ensumbling for Rating

O

SVM

3 Models were fitted for Rating as Target Variable

0.2800

```
('Logistic Regression', 0.2023529411764706)
('SVM Classification', 0.28)
('Decision Tree Classifier', 0.6447058823529411)
```

In [81]: ### Instatitate a VotingClassifier 'vc' vc=VotingClassifier(estimators=classifiers) ### Fit the VotingClassifier vc.fit(X_train,y_train) y pred train=vc.predict(X train) y pred test=vc.predict(X test) print("Accuracy of Voting Classifier Ensumbled Rating Train", vc.score(X_train,y_train)) print("Accuracy of Voting Classifier Ensumbled Rating Test", vc.score(X_test,y_test))

Accuracy of Voting Classifier Ensumbled Rating Train 0.6603921568627451 Accuracy of Voting Classifier Ensumbled Rating Test 0.4211764705882353

In [86]: df_models_summary_rating=pd.concat([df_models_summary_rating,pd.DataFrame({"Model":["Vot "Train Accuracy Score":[vc.score(X_train,y_tr "Test Accuracy Score":[vc.score(X_test,y_test)]})],sort=False) df models summary rating

Out[86]:

	Model	Train Accuracy Score	Test Accuracy Score
0	Logistic Regression	0.2627	0.2627
0	Random Forest	1.0000	0.6447
0	SVM	0.4235	0.2800
0	Voting Classifier Ensumbled Rating	0.6604	0.4212

In [87]: df_models_summary_rating.plot("Model",kind='barh',title="Models Performance - Rating",fi

Out[87]: <matplotlib.axes._subplots.AxesSubplot at 0x162f2db2438>

