```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.linear_model import LinearRegression
        from sklearn.model_selection import train_test_split
        import statsmodels.api as sm
        from sklearn.preprocessing import StandardScaler
        from sklearn.model_selection import KFold
        import time
        import itertools
        from sklearn.tree import DecisionTreeRegressor
        from sklearn import tree
        import lightgbm as lgb
        import xgboost as xgb
        from sklearn.ensemble import RandomForestRegressor
        from sklearn.neural_network import MLPRegressor
        from sklearn.neighbors import KNeighborsRegressor
        from catboost import CatBoostRegressor
        from sklearn.linear_model import LogisticRegression
        from sklearn.model_selection import StratifiedKFold
        from sklearn.metrics import accuracy_score
        from catboost import CatBoostClassifier
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.neural_network import MLPClassifier
        from sklearn.neighbors import KNeighborsClassifier
```

1. Data Cleaning

1.1 Import the Data

In [2]:	<pre>data = pd.read_csv("option_train.csv")</pre>								
In [3]:	da	data.head(5)							
Out[3]:		Value	s	K	tau	r	BS		
	0	21.670404	431.623898	420.0	0.341270	0.03013	Under		
	1	0.125000	427.015526	465.0	0.166667	0.03126	Over		
	2	20.691244	427.762336	415.0	0.265873	0.03116	Under		
	3	1.035002	451.711658	460.0	0.063492	0.02972	Over		
	4	39.553020	446.718974	410.0	0.166667	0.02962	Under		

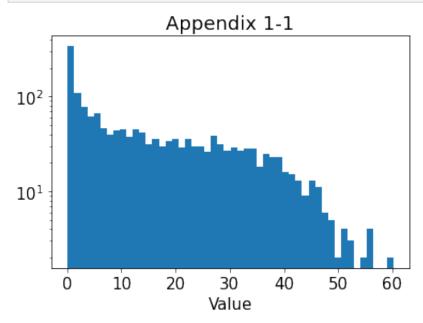
1.2 Data Exploring

data.	data.describe()									
	Value	S	K	tau	r					
count	1678.000000	1679.000000	1678.000000	1679.000000	1680.000000					
mean	15.068709	464.402535	438.241955	0.437519	0.030235					
std	14.040023	973.652179	23.408989	7.057555	0.000557					
min	0.125000	0.000000	375.000000	0.003968	0.029510					
25%	2.255001	433.863864	420.000000	0.119048	0.029820					
50%	11.190967	442.634081	440.000000	0.202381	0.030130					
75%	25.747434	447.320414	455.000000	0.285714	0.030540					
max	60.149367	40333.000000	500.000000	250.000000	0.031880					
	count mean std min 25% 50% 75%	count 1678.000000 mean 15.068709 std 14.040023 min 0.125000 25% 2.255001 50% 11.190967 75% 25.747434	Value S count 1678.000000 1679.000000 mean 15.068709 464.402535 std 14.040023 973.652179 min 0.125000 0.000000 25% 2.255001 433.863864 50% 11.190967 442.634081 75% 25.747434 447.320414	Value S K count 1678.000000 1679.000000 1678.000000 mean 15.068709 464.402535 438.241955 std 14.040023 973.652179 23.408989 min 0.125000 0.000000 375.000000 25% 2.255001 433.863864 420.000000 50% 11.190967 442.634081 440.000000 75% 25.747434 447.320414 455.000000	Value S K tau count 1678.000000 1679.000000 1678.000000 1679.000000 mean 15.068709 464.402535 438.241955 0.437519 std 14.040023 973.652179 23.408989 7.057555 min 0.125000 0.000000 375.000000 0.003968 25% 2.255001 433.863864 420.000000 0.119048 50% 11.190967 442.634081 440.000000 0.202381 75% 25.747434 447.320414 455.000000 0.285714					

1.2.1 Explore Extreme Value

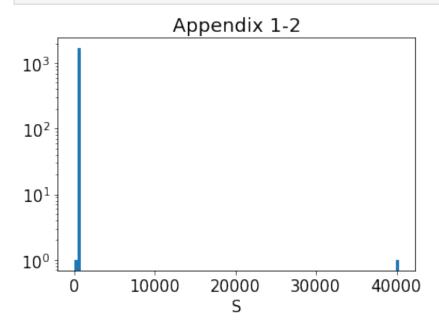
1.2.1.1 Value: current option value

```
In [5]: plt.rcParams.update({'figure.figsize':(6,4)})
    plt.rcParams.update({'font.size':15})
    plt.hist(data['Value'], bins = 50)
    plt.yscale('log')
    plt.xlabel('Value')
    plt.title ('Appendix 1-1')
    plt.show()
```



1.2.1.2 S: current asset value

```
In [6]: plt.hist(data['S'], bins = 100)
   plt.yscale('log')
   plt.xlabel('S')
   plt.title ('Appendix 1-2')
   plt.show()
```



```
In [7]: data[data['S'] > 5000]

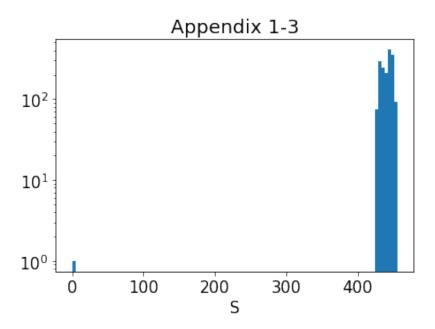
Out[7]: Value S K tau r BS

47 11.451273 40333.0 425.0 0.043651 0.03147 Under
```

When the asset value is extremely high, we examine the observation carefully and think the difference between asset value and strike price is extremely high and the value of option doesn't match the difference. Therefore we treat the observation as an outlier.

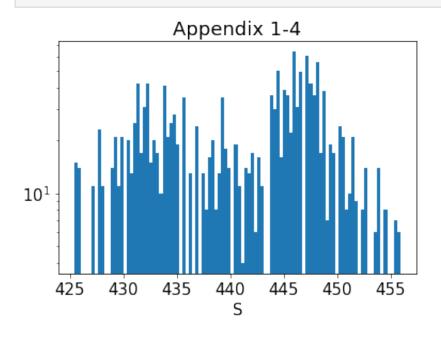
```
In [8]: data.drop(labels = data[data['S'] > 5000].index, axis = 0, inplace = True)

In [9]: plt.hist(data['S'], bins = 100)
    plt.yscale('log')
    plt.xlabel('S')
    plt.title ('Appendix 1-3')
    plt.show()
```



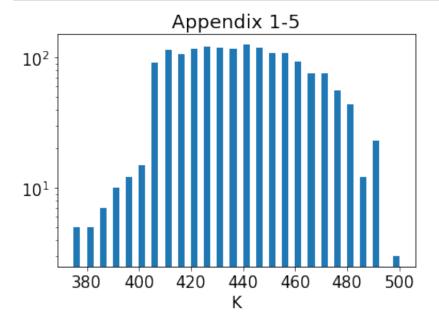
```
In [11]: data.drop(labels = data[data['S'] == 0].index, axis = 0, inplace = True)

In [12]: plt.hist(data['S'], bins = 100)
    plt.yscale('log')
    plt.xlabel('S')
    plt.title ('Appendix 1-4')
    plt.show()
```



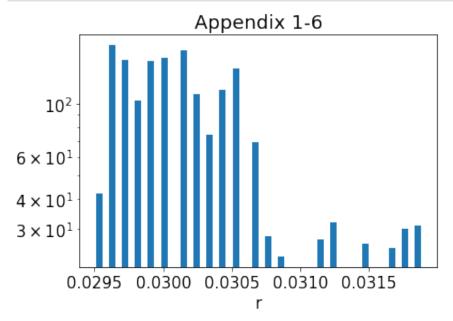
1.2.1.3 K: strike price of option

```
In [13]: plt.hist(data['K'], bins = 50)
    plt.yscale('log')
    plt.xlabel('K')
    plt.title ('Appendix 1-5')
    plt.show()
```



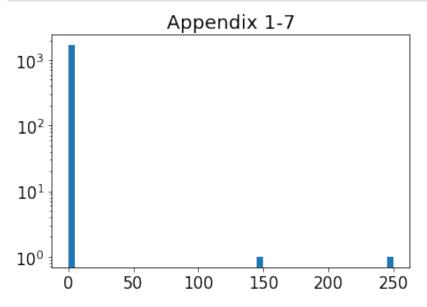
1.2.1.4 r: annual interest rate

```
In [14]: plt.hist(data['r'], bins = 50)
    plt.yscale('log')
    plt.xlabel('r')
    plt.title ('Appendix 1-6')
    plt.show()
```



1.2.1.5 tau: time to maturity

```
In [15]: plt.hist(data['tau'], bins = 50)
    plt.yscale('log')
    plt.title ('Appendix 1-7')
    plt.show()
```



33 2.565000 445.042240 455.0 146.0 0.03003 Over

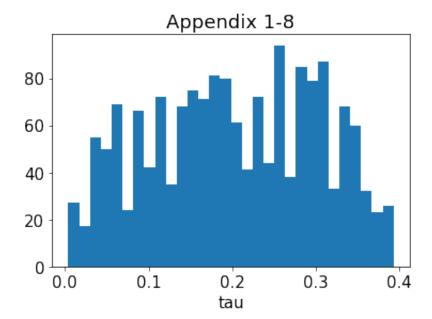
```
In [16]: data[data['tau'] > 1]

Out[16]: Value S K tau r BS

12 2.315001 448.688109 470.0 250.0 0.03013 Over
```

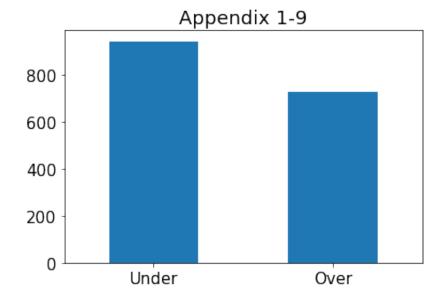
We notice that time to maturity of 2 observations extremely exceeds 1 year (250 years and 146 years respectively). In reality, time to maturity of options usually won't exceed 1 year. Therefore, we identify these two observations as outliers and remove them from the dataset.

```
In [17]: data.drop(labels = data[data['tau'] > 1].index, axis = 0, inplace = True)
In [18]: plt.hist(data['tau'], bins =30)
    plt.xlabel("tau")
    plt.title ('Appendix 1-8')
    plt.show()
```



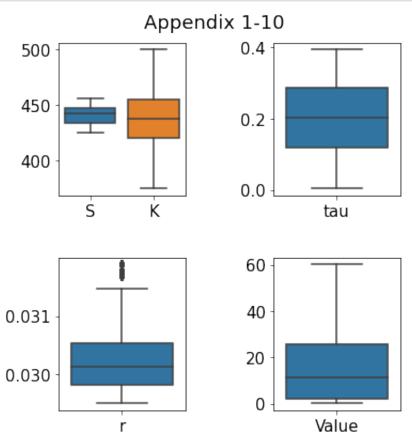
1.2.1.6 BS: Black-Scholes

```
In [19]: data['BS'].value_counts().plot(kind = 'bar')
    plt.xticks(rotation=0)
    plt.title ('Appendix 1-9')
    plt.show()
```



1.2.1.7 Boxplot of Each Variable

```
In [20]: fig, axs = plt.subplots(2,2, figsize = (6,6))
    fig.tight_layout(pad = 2)
    sns.boxplot(ax = axs[0,0], data = data[['S', 'K']])
    sns.boxplot(ax = axs[0,1], data = data[['tau']])
    sns.boxplot(ax = axs[1,0], data = data[['r']])
    sns.boxplot(ax = axs[1,1], data = data[['Value']])
    fig.suptitle ('Appendix 1-10')
    plt.show()
```



1.2.2 Remove Missing Value

```
In [21]: np.sum(data.isnull())
```

```
Out[21]:
         tau
         r
         BS
                  0
         dtype: int64
In [22]: data.drop(labels = data[data['Value'].isnull()].index, axis = 0, inplace = True)
         data.drop(labels = data[data['S'].isnull()].index, axis = 0, inplace = True)
         data.drop(labels = data[data['K'].isnull()].index, axis = 0, inplace = True)
         data.drop(labels = data[data['tau'].isnull()].index, axis = 0, inplace = True)
```

1.2.3 Encoding Categorical Variable

Value

Encoding BS into categorical variable where 1 = Over, 0 = Under

```
In [23]: mapping = {'Under': 0, 'Over': 1}
         data['BS'] = data['BS'].map(mapping)
In [24]:
         data.set_index(pd.Series([x for x in range(data.shape[0])]), inplace = True)
```

2. Feature Engineering

2.1 Non-Linear and Interaction Variables

```
\frac{S}{K}, log(\frac{S}{K}), r*tau, (\frac{S}{K})^2, (1+r)*tau, \sqrt{tau}
```

```
In [25]: data['S/K'] = data['S']/data['K']
         data['log(S/K)'] = np.log(data['S/K'])
         data['(S/K)^2'] = data['S/K']**2
         data['r*tau'] = data['r']*data['tau']
         data['(1+r)*tau'] = data['tau'] + data['r*tau']
         data['(tau)^1/2'] = data['tau']**2
```

2.2 Future Value

(S-K), (S-K)/(r*tau), (S-K)/tau, 1/(1 + r/tau), K/discount rate

```
In [26]: | data['(S-K)'] = data['S'] - data['K']
         data['(S-K)*(r*tau)'] = data['(S-K)']*data['r*tau']
         data['discount rate'] = 1 + data['r*tau']
         data['K*discount rate'] = data['K']*data['discount rate']
         data['(S-K)*discount rate'] = data['(S-K)']*data['discount rate']
```

3. Model Exploration - With Initial Variables

3.1 For Value (C)

3.1.1 Linear Regression

```
In [27]: y = data[['Value', 'BS']]
         y_value = data['Value']
         y_BS = data['BS']
         X = data.drop(['Value', 'BS', 'discount rate'], axis = 1)
         kfolds = KFold(n_splits = 10, random_state = 1, shuffle = True)
         value_score = pd.DataFrame(columns = ['Training CV', 'Testing CV',
                                                'Training Validation Set Approach', 'Testing Validation Set Approach'])
         value_compare = pd.DataFrame(columns = ['model', 'Training', 'Testing'])
```

```
original_var = ['K', 'S', 'tau', 'r']
         for train_index, test_index in kfolds.split(X, y_value):
             X1 = X.iloc[train_index][original_var]
             X1 = sm.add_constant(X1)
             y_train = y_value.iloc[train_index]
             X_test = X.iloc[test_index][original_var]
             X_test = sm.add_constant(X_test)
             y_test = y_value.iloc[test_index]
             # Train the model
             model = sm.OLS(y_train, X1)
             regression = model.fit()
             # Return the score
             r2 train = regression.rsquared
             TSS_test = ((y_test - y_test.mean())**2).sum()
             RSS_test = ((regression.predict(X_test) - y_test)**2).sum()
             r2_test = (TSS_test - RSS_test)/TSS_test
             cv_score_train.append(r2_train)
             cv_score_test.append(r2_test)
In [29]: # Use Train Test Split to test the model performance
         X_train, X_test, y_train, y_test = train_test_split(X, y_value, test_size=0.2,random_state=5)
         X1 = sm.add_constant(X_train[original_var])
         X2 = sm.add constant(X test[original var])
         # Train the model
         model = sm.OLS(y train, X1)
         regression = model.fit()
         # Return the score
         r2_train = regression.rsquared
         TSS\_test = ((y\_test - y\_test.mean())**2).sum()
         RSS_test = ((regression.predict(X2) - y_test)**2).sum()
         r2_test = (TSS_test - RSS_test)/TSS_test
In [30]: # store score for each model
         value_score.loc['Linear Regression'] = [np.mean(cv_score_train), np.mean(cv_score_test), r2_train, r2_test]
         df = pd.DataFrame({'model': ['Linear Regression']*10,
                        'Training': cv_score_train,
                        'Testing': cv_score_test})
         value_compare = pd.concat([value_compare, df])
```

3.1.2 Decision Tree Regression

In [28]: # Use cross validation to get Mean out of sample R-squared

cv_score_train = []
cv_score_test = []

```
In [31]: def tree_cost_complexity_pruning(X, y_value):
             clf_tree = DecisionTreeRegressor(random_state=0)
             path = clf_tree.cost_complexity_pruning_path(X, y_value)
             ccp_alphas = path.ccp_alphas
             score = []
             ccp_alphas = ccp_alphas[ccp_alphas >=0]
             for ccp_alpha in ccp_alphas:
                 score_for_alpha = []
                 for train_index, test_index in kfolds.split(X, y_value):
                     X_train = X.iloc[train_index][original_var]
                     y_train = y_value.iloc[train_index]
                     X_test = X.iloc[test_index][original_var]
                     y_test = y_value.iloc[test_index]
                     clf = DecisionTreeRegressor(random_state=0, ccp_alpha=ccp_alpha)
                     clf.fit(X_train, y_train)
                     TSS\_test = ((y\_test - y\_test.mean())**2).sum()
                     RSS test = ((clf.predict(X test) - y test)**2).sum()
                     r2_test = (TSS_test - RSS_test)/TSS_test
                     score_for_alpha.append(r2_test)
                 score.append(sum(score_for_alpha)/len(score_for_alpha))
             alpha_cv = ccp_alphas[np.argmax(score)]
             return alpha_cv
```

```
In [32]: def cv(var, model):
             cv_score_train = []
             cv_score_test = []
             model_name = model
             if model == 'Random Forest':
                 model = RandomForestRegressor(random_state=9, n_estimators =100, max_depth = 100, min_samples_split=10,
                                                min_samples_leaf=10)
             if model == 'Decision Tree':
                 model = DecisionTreeRegressor(random_state=9, max_depth = 100, min_samples_split=30, min_samples_leaf=20,
                                                ccp_alpha = alpha_cv)
             elif model == 'Linear':
                 model = LinearRegression()
             elif model == 'LGBM':
                 model = lgb.LGBMRegressor(random_state = 5, num_leaves=20,n_estimators=100, max_depth = 50)
             elif model == 'NN':
                 model = MLPRegressor(random_state = 5, hidden_layer_sizes=(18,18,18), activation = 'relu', solver = 'adam'
                                       learning_rate= 'constant',
                                    learning_rate_init = 0.01)
             elif model == 'KNeighbors':
                 model = KNeighborsRegressor(n_neighbors=3)
             elif model == 'XGBoost':
                 model = xgb.XGBRegressor(random_state = 5,max_depth=25, n_estimators=30)
             elif model == 'CatBoost':
                 model = CatBoostRegressor(random_state = 5,verbose=0, max_depth=8, iterations=200, learning_rate = 0.1)
             for train_index, test_index in kfolds.split(X, y_value):
                 X_train = X.iloc[train_index][list(var)]
                 y_train = y_value.iloc[train_index]
                 X_test = X.iloc[test_index][list(var)]
                 y_test = y_value.iloc[test_index]
                 # Train the model
                 regression = model.fit(X_train, y_train)
                 # Return the score
                 # rsquared for train data
                 TSS_train = ((y_train - y_train.mean())**2).sum()
                 RSS_train = ((regression.predict(X_train) - y_train)**2).sum()
                 r2_train = (TSS_train - RSS_train)/TSS_train
                 # rsquared for test data
                 TSS\_test = ((y\_test - y\_test.mean())**2).sum()
                 RSS_test = ((regression.predict(X_test) - y_test)**2).sum()
                 r2_test = (TSS_test - RSS_test)/TSS_test
                 cv score train.append(r2 train)
                 cv_score_test.append(r2_test)
             value_score.loc[model_name,['Training CV', 'Testing CV']] = [np.mean(cv_score_train), np.mean(cv_score_test)
             return {"model": model, "r2_train": cv_score_train, "r2_test": cv_score_test, "variable": var}
In [33]: def validation_set_approach(var, model):
             # Use Train Test Split to test the model performance
             X_train, X_test, y_train, y_test = train_test_split(X[var], y_value, test_size=0.2,random_state=5)
             model_name = model
             if model == 'Random Forest':
                 model = RandomForestRegressor(random_state=9, n_estimators =100, max_depth = 100, min_samples_split=10,
                                                min_samples_leaf=10)
             if model == 'Decision Tree':
                 model = DecisionTreeRegressor(random_state=9, max_depth = 100, min_samples_split=30,min_samples_leaf=20,
                                                ccp_alpha = alpha_cv)
             elif model == 'Linear':
                 model = LinearRegression()
             elif model == 'LGBM':
                 model = lgb.LGBMRegressor(random_state = 5, num_leaves=20,n_estimators=100, max_depth = 50)
             elif model == 'NN':
                 model = MLPRegressor(random_state = 5, hidden_layer_sizes=(18,18,18), activation = 'relu', solver = 'adam'
                                       learning_rate= 'constant',
                                    learning_rate_init = 0.01)
             elif model == 'KNeighbors':
                 model = KNeighborsRegressor(n_neighbors=3)
             elif model == 'XGBoost':
                 model = xgb.XGBRegressor(random_state = 5,max_depth=25, n_estimators=30)
             elif model == 'CatBoost':
                 model = CatBoostRegressor(random_state = 5, verbose=0, max_depth=8, iterations=200, learning_rate = 0.1)
             # Train the model
             regression = model.fit(X_train, y_train)
             # Return the score
             # rsquared for train data
             TSS_train = ((y_train - y_train.mean())**2).sum()
             RSS_train = ((regression.predict(X_train) - y_train)**2).sum()
             r2_train = (TSS_train - RSS_train)/TSS_train
             # rsquared for test data
             TSS_test = ((y_test - y_test.mean())**2).sum()
             RSS test = ((regression.predict(X test) - y test)**2).sum()
             r2 test = (TSS test - RSS test)/TSS test
             value_score.loc[model_name,['Training Validation Set Approach', 'Testing Validation Set Approach']] /=
                 [r2_train, r2_test]
```

3.1.3 Random Forest Regression

3.1.4 LGBM Regression

3.1.5 Nerual Network Regression

3.1.6 KNeighbors Regression

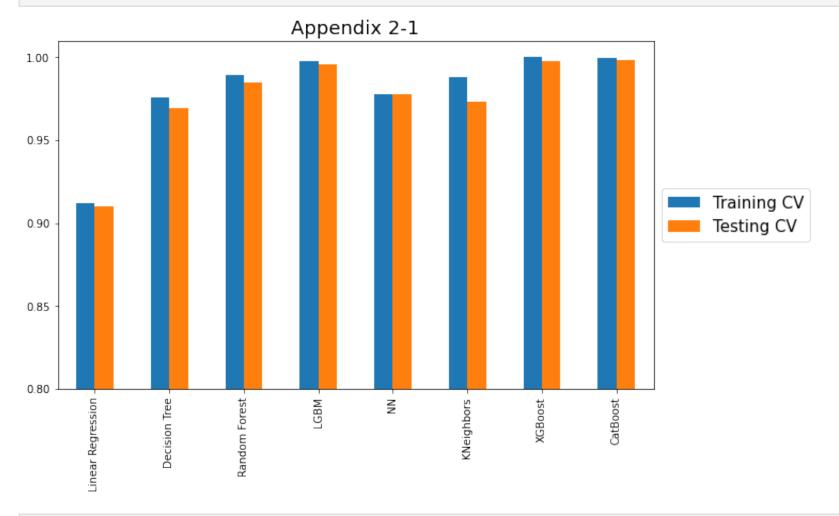
3.1.7 XGBoost Regression

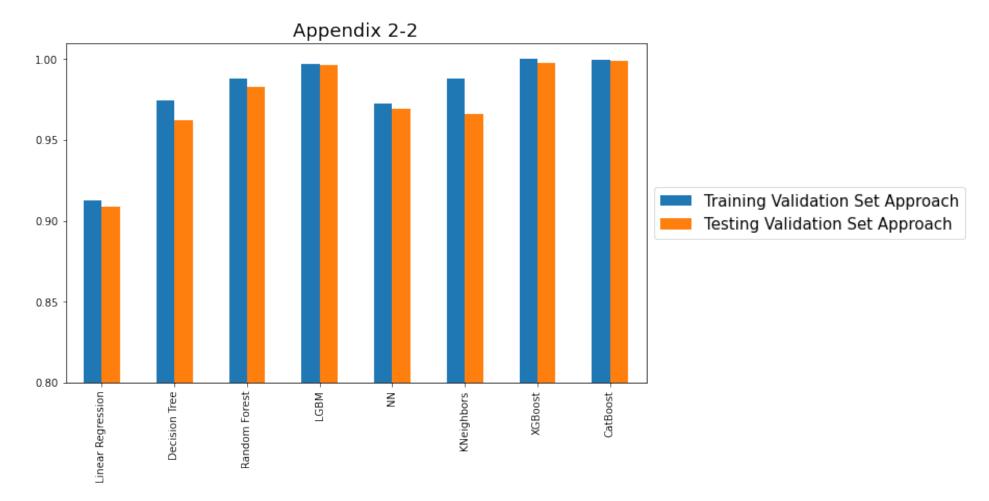
value_compare = pd.concat([value_compare, df])

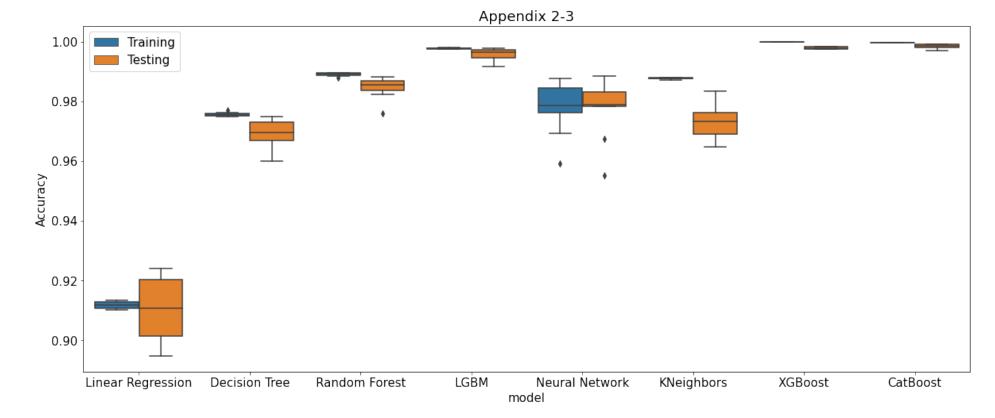
3.1.8 CatBoost Regression

```
In [46]: result = cv(original_var, model = 'CatBoost')
          validation_set_approach(original_var, 'CatBoost')
          cv_score_train = result['r2_train']
          cv_score_test = result['r2_test']
          # store score for each model
In [47]:
          df = pd.DataFrame({'model': ['CatBoost']*10,
                          'Training': cv_score_train,
                          'Testing': cv_score_test})
          value_compare = pd.concat([value_compare, df])
In [48]:
          value_score
                           Training CV Testing CV Training Validation Set Approach Testing Validation Set Approach
Out[48]:
                              0.911910
                                         0.910002
          Linear Regression
                                                                      0.912325
                                                                                                   0.908975
              Decision Tree
                             0.975635
                                        0.969149
                                                                      0.974508
                                                                                                   0.962396
            Random Forest
                             0.989055
                                        0.984696
                                                                      0.987830
                                                                                                   0.982893
                    LGBM
                             0.997700
                                        0.995823
                                                                      0.997175
                                                                                                   0.996120
                             0.977895
                                        0.977544
                                                                      0.972457
                                                                                                   0.969199
                       NN
                KNeighbors
                             0.987691
                                        0.973050
                                                                      0.987685
                                                                                                   0.966178
                  XGBoost
                             0.999999
                                        0.997885
                                                                      0.999999
                                                                                                   0.997799
                 CatBoost
                             0.999615
                                        0.998490
                                                                      0.999629
                                                                                                   0.998905
```

```
In [49]: value_score[['Training CV', 'Testing CV']].plot(kind = 'bar', figsize = (10,6), fontsize = 10)
    plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
    plt.ylim(0.8, 1.01)
    plt.yticks([0.8, 0.85, 0.9, 0.95,1.0])
    plt.title ('Appendix 2-1')
    plt.show()
```

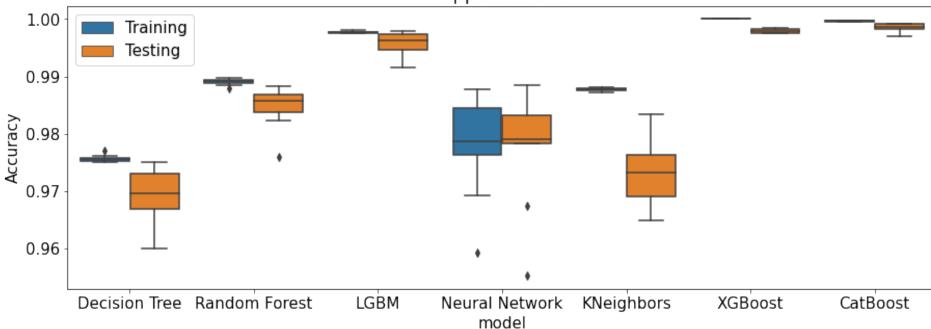






```
In [53]: plt.figure(figsize = (15,5))
    sns.boxplot(x='model',y='value',hue='variable', data = value_compare[value_compare['model'] != 'Linear Regression
    plt.ylabel('Accuracy')
    plt.legend(title = '')
    plt.title ('Appendix 2-4')
    plt.show()
```





3.2 For BS

3.2.1 Logistic Regression

```
In [54]: kfolds = StratifiedKFold(n_splits = 10, random_state = 1, shuffle = True)
         BS_score = pd.DataFrame(columns = ['Training CV', 'Testing CV',
                                                'Training Validation Set Approach', 'Testing Validation Set Approach'])
         BS_compare = pd.DataFrame(columns = ['model', 'Training', 'Testing'])
In [55]:
         cv_classification_score_train = []
         cv_classification_score_test = []
         for train_index, test_index in kfolds.split(X, y_BS):
             X1 = X.iloc[train_index][original_var]
             y_train = y_BS.iloc[train_index]
             X_test = X.iloc[test_index][original_var]
             y_test = y_BS.iloc[test_index]
             # Fit the model
             model = LogisticRegression(penalty='none', max_iter=10000).fit(X1,y_train)
             # Store the score
             cv_classification_score_train.append(model.score(X1, y_train))
             cv_classification_score_test.append(model.score(X_test[original_var], y_test))
In [56]:
         # Use Train Test Split to test the model performance
         X_train, X_test, y_train, y_test = train_test_split(X[original_var], y_BS, test_size=0.2,random_state=5)
         # Train the model
         model = LogisticRegression(penalty='none', max_iter=10000)
         model = model.fit(X_train, y_train)
         # Return the score
         # accuracy score for train data
         score train = accuracy score(model.predict(X train), y train)
         # accuracy score for test data
         score test = accuracy score(model.predict(X test), y test)
In [57]: # store accuracy score for each model
         BS_score.loc['Logistic Regression'] = [np.mean(cv_classification_score_train),
                                                 np.mean(cv_classification_score_test),score_train, score_test]
         df = pd.DataFrame({'model': ['Logistic Regression']*10,
                        'Training': cv_classification_score_train,
                        'Testing': cv_classification_score_test})
```

3.2.2 Decision Tree Classification

BS_compare = pd.concat([BS_compare, df])

```
In [58]: from sklearn.tree import DecisionTreeClassifier
```

```
clf_tree = DecisionTreeClassifier(random_state=0)
             path = clf_tree.cost_complexity_pruning_path(X, y_BS)
             ccp_alphas = path.ccp_alphas
             accuracies = []
             ccp_alphas = ccp_alphas[ccp_alphas >=0]
             for ccp_alpha in ccp_alphas:
                 score_for_alpha = []
                 for train_index, test_index in kfolds.split(X, y_BS):
                     clf = DecisionTreeClassifier(random_state=0, ccp_alpha=ccp_alpha)
                     clf.fit(X.iloc[train_index], y_BS.iloc[train_index])
                     y_pred = clf.predict(X.iloc[test_index])
                     score = accuracy_score(y_pred, y_BS.iloc[test_index])
                     score for alpha.append(score)
                 accuracies.append(sum(score_for_alpha)/len(score_for_alpha))
             alpha_cv = ccp_alphas[np.argmax(accuracies)]
             return alpha_cv
In [60]: cv classification score train = []
         cv_classification_score_test = []
         alpha_cv = tree_cost_complexity_pruning(X,y_BS)
         for train_index, test_index in kfolds.split(X, y_BS):
             X1 = X.iloc[train_index][original_var]
             y_train = y_BS.iloc[train_index]
             X_test = X.iloc[test_index][original_var]
             y_test = y_BS.iloc[test_index]
             # Fit the model
             model = DecisionTreeClassifier(random_state=8, max_depth = 80, min_samples_split=10,min_samples_leaf=20,
                                            ccp alpha = alpha cv)
             model.fit(X1,y train)
             # Store the score
             cv_classification_score_train.append(model.score(X1, y_train))
             cv_classification_score_test.append(model.score(X_test[original_var], y_test))
In [61]: # Use Train Test Split to test the model performance
         X_train, X_test, y_train, y_test = train_test_split(X[original_var], y_BS, test_size=0.2,random_state=4)
         # Train the model
         model = DecisionTreeClassifier(random state=8, max_depth = 80, min_samples_split=10,min_samples_leaf=20,
                                        ccp_alpha = alpha_cv)
         model = model.fit(X_train, y_train)
         # Return the score
         # accuracy score for train data
         score_train = accuracy_score(model.predict(X_train), y_train)
         # accuracy score for test data
         score_test = accuracy_score(model.predict(X_test), y_test)
In [62]: BS_score.loc['Decision Tree'] = [np.mean(cv_classification_score_train), np.mean(cv_classification_score_test),
                                                   score_train, score_test]
         df = pd.DataFrame({'model': ['Decision Tree']*10,
                       'Training': cv_classification_score_train,
                       'Testing': cv_classification_score_test})
         BS_compare = pd.concat([BS_compare, df])
         3.2.3 Random Forest Classification
In [63]: cv classification score train = []
         cv_classification_score_test = []
         for train_index, test_index in kfolds.split(X, y_BS):
             X1 = X.iloc[train_index][original_var]
             y_train = y_BS.iloc[train_index]
             X_test = X.iloc[test_index][original_var]
             y_test = y_BS.iloc[test_index]
             # Fit the model
             model = RandomForestClassifier(random_state=3, n_estimators =100, max_depth = 100, min_samples_split= 2,
                                            min_samples_leaf=2).fit(X1,y_train)
             # Store the score
             cv_classification_score_train.append(model.score(X1, y_train))
             cv_classification_score_test.append(model.score(X_test[original_var], y_test))
In [64]: # Use Train Test Split to test the model performance
         X_train, X_test, y_train, y_test = train_test_split(X[original_var], y_BS, test_size=0.2,random_state=4)
         # Train the model
```

model = RandomForestClassifier(random state=3, n estimators =100, max depth = 100, min samples split= 2,

min_samples_leaf=2)

score_train = accuracy_score(model.predict(X_train), y_train)

score_test = accuracy_score(model.predict(X_test), y_test)

model = model.fit(X_train, y_train)

accuracy score for train data

accuracy score for test data

Return the score

In [59]: def tree_cost_complexity_pruning(X, y_BS):

3.2.4 LGBM Classification

```
In [66]: cv_classification_score_train = []
         cv_classification_score_test = []
         for train_index, test_index in kfolds.split(X, y_BS):
             X1 = X.iloc[train_index][original_var]
             y_train = y_BS.iloc[train_index]
             X_test = X.iloc[test_index][original_var]
             y_test = y_BS.iloc[test_index]
             # Fit the model
             model = lgb.LGBMClassifier(num_leaves=25,n_estimators=30, max_depth = 30).fit(X1,y_train)
             # Store the score
             cv_classification_score_train.append(model.score(X1, y_train))
             cv_classification_score_test.append(model.score(X_test[original_var], y_test))
In [67]: # Use Train Test Split to test the model performance
         X_train, X_test, y_train, y_test = train_test_split(X[original_var], y_BS, test_size=0.2,random_state=4)
         # Train the model
         model = lgb.LGBMClassifier(num_leaves=25,n_estimators=30, max_depth = 30)
         model = model.fit(X_train, y_train)
         # Return the score
         # accuracy score for train data
         score_train = accuracy_score(model.predict(X_train), y_train)
         # accuracy score for test data
         score_test = accuracy_score(model.predict(X_test), y_test)
In [68]: BS_score.loc['LGBM'] = [np.mean(cv_classification_score_train), np.mean(cv_classification_score_test),
                                                   score_train, score_test]
         df = pd.DataFrame({'model': ['LGBM']*10,
                       'Training': cv_classification_score_train,
                       'Testing': cv_classification_score_test})
         BS_compare = pd.concat([BS_compare, df])
```

3.2.5 Neural Network Classification

```
In [69]: cv_classification_score_train = []
         cv_classification_score_test = []
         for train_index, test_index in kfolds.split(X, y_BS):
             X1 = X.iloc[train_index][original_var]
             y_train = y_BS.iloc[train_index]
             X_test = X.iloc[test_index][original_var]
             y_test = y_BS.iloc[test_index]
             # Fit the model
             model = MLPClassifier(random_state = 5, hidden_layer_sizes=(15,15,15,15,15), activation = 'relu',
                                   solver = 'adam', learning_rate= 'adaptive',
                                   learning_rate_init = 0.01).fit(X1,y_train)
             # Store the score
             cv_classification_score_train.append(model.score(X1, y_train))
             cv_classification_score_test.append(model.score(X_test[original_var], y_test))
         X_train, X_test, y_train, y_test = train_test_split(X[original_var], y_BS, test_size=0.2,random_state=4)
         # Train the model
```

3.2.6 KNeighbors Classification

cv_classification_score_test = []

In [72]: cv classification score train = []

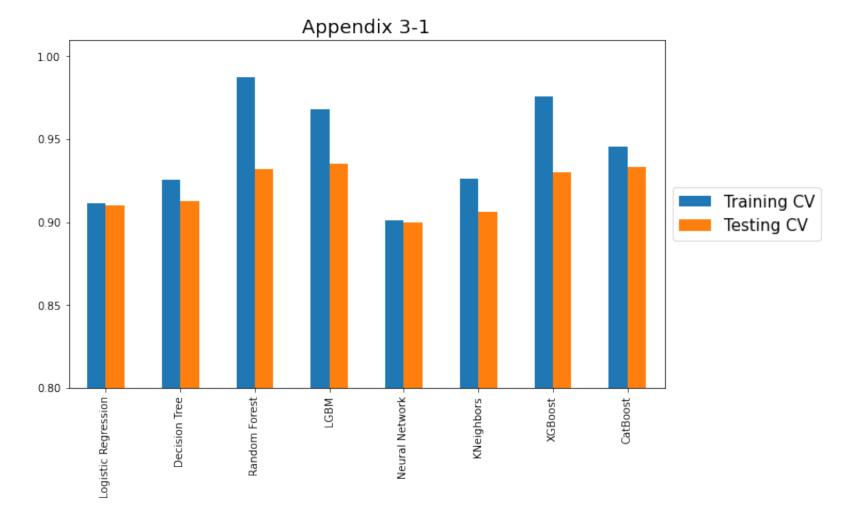
```
for train_index, test_index in kfolds.split(X, y_BS):
             X1 = X.iloc[train_index][original_var]
             y_train = y_BS.iloc[train_index]
             X_test = X.iloc[test_index][original_var]
             y_test = y_BS.iloc[test_index]
             # Fit the model
             model = KNeighborsClassifier(n_neighbors = 8).fit(X1,y_train)
             # Store the score
             cv_classification_score_train.append(model.score(X1, y_train))
             cv_classification_score_test.append(model.score(X_test[original_var], y_test))
In [73]: # Use Train Test Split to test the model performance
         X_train, X_test, y_train, y_test = train_test_split(X[original_var], y_BS, test_size=0.2,random_state=4)
         # Train the model
         model = KNeighborsClassifier(n_neighbors = 8).fit(X_train, y_train)
         # Return the score
         # accuracy score for train data
         score_train = accuracy_score(model.predict(X_train), y_train)
         # accuracy score for test data
         score_test = accuracy_score(model.predict(X_test), y_test)
In [74]: BS_score.loc['KNeighbors'] = [np.mean(cv_classification_score_train), np.mean(cv_classification_score_test),
                                                   score_train, score_test]
         df = pd.DataFrame({'model': ['KNeighbors']*10,
                       'Training': cv_classification_score_train,
                       'Testing': cv_classification_score_test})
         BS_compare = pd.concat([BS_compare, df])
         3.2.7 XGBoost Classification
In [75]: cv classification score train = []
         cv_classification_score_test = []
         for train_index, test_index in kfolds.split(X, y_BS):
             X1 = X.iloc[train_index][original_var]
             y_train = y_BS.iloc[train_index]
             X_test = X.iloc[test_index][original_var]
            y_test = y_BS.iloc[test_index]
             # Fit the model
            model = xgb.XGBClassifier(random_state = 5, max_depth=10, n_estimators=5).fit(X1,y_train)
             # Store the score
             cv_classification_score_train.append(model.score(X1, y_train))
             cv_classification_score_test.append(model.score(X_test[original_var], y_test))
In [76]: # Use Train Test Split to test the model performance
         X train, X test, y train, y test = train test split(X[original var], y BS, test size=0.2,random state=4)
         # Train the model
         model = xgb.XGBClassifier(random_state = 4, max_depth=10, n_estimators=5).fit(X_train, y_train
         # Return the score
         # accuracy score for train data
         score_train = accuracy_score(model.predict(X_train), y_train)
         # accuracy score for test data
         score_test = accuracy_score(model.predict(X_test), y_test)
In [77]: BS_score.loc['XGBoost'] = [np.mean(cv_classification_score_train), np.mean(cv_classification_score_test),
                                                   score_train, score_test]
         df = pd.DataFrame({'model': ['XGBoost']*10,
                        'Training': cv_classification_score_train,
                        'Testing': cv_classification_score_test})
         BS_compare = pd.concat([BS_compare, df])
```

3.2.8 Cathoost Classification

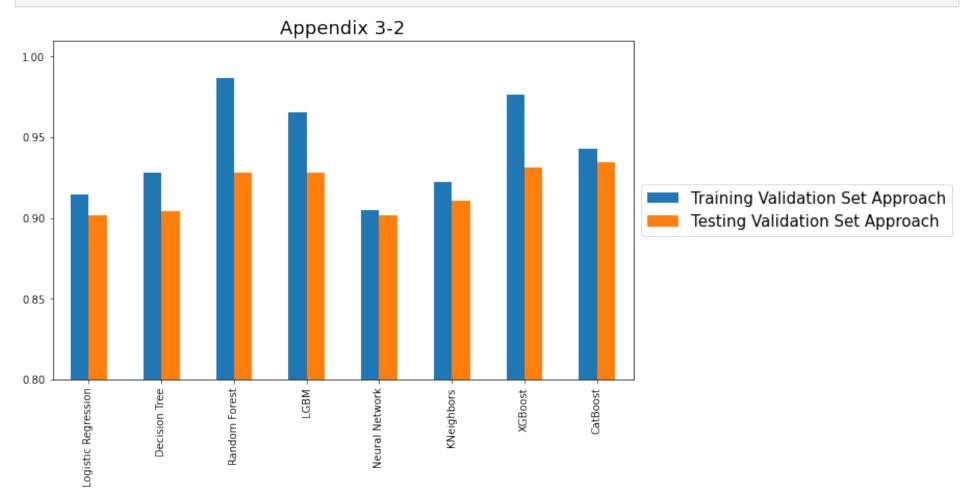
```
In [78]: cv_classification_score_train = []
         cv_classification_score_test = []
         for train_index, test_index in kfolds.split(X, y_BS):
              X1 = X.iloc[train_index][original_var]
              y_train = y_BS.iloc[train_index]
             X_test = X.iloc[test_index][original_var]
              y_test = y_BS.iloc[test_index]
             # Fit the model
             model = CatBoostClassifier(random_state = 5, verbose=0, max_depth=5, iterations=100,
                                          learning_rate = 0.1).fit(X1,y_train)
              # Store the score
              cv_classification_score_train.append(model.score(X1, y_train))
              cv_classification_score_test.append(model.score(X_test[original_var], y_test))
In [79]: # Use Train Test Split to test the model performance
         X_train, X_test, y_train, y_test = train_test_split(X[original_var], y_BS, test_size=0.2,random_state=4)
          # Train the model
         model = CatBoostClassifier(random state = 5, verbose=0, max depth=5, iterations=100,
                                     learning_rate = 0.1).fit(X_train, y_train)
         # Return the score
         # accuracy score for train data
         score_train = accuracy_score(model.predict(X_train), y_train)
          # accuracy score for test data
         score_test = accuracy_score(model.predict(X_test), y_test)
In [80]: BS_score.loc['CatBoost'] = [np.mean(cv_classification_score_train), np.mean(cv_classification_score_test),
                                                     score_train, score_test]
         df = pd.DataFrame({'model': ['CatBoost']*10,
                        'Training': cv classification score train,
                        'Testing': cv_classification_score_test})
         BS compare = pd.concat([BS compare, df])
In [81]: # store score for each model
         value_score.loc['CatBoost'] = [np.mean(cv_score_train), np.mean(cv_score_test), r2_train, r2_test]
          df = pd.DataFrame({'model': ['CatBoost']*10,
                        'Training': cv_score_train,
                        'Testing': cv_score_test})
         value_compare = pd.concat([value_compare, df])
In [82]: BS score
                           Training CV Testing CV Training Validation Set Approach Testing Validation Set Approach
Out[82]:
         Logistic Regression
                              0.911071
                                       0.910340
                                                                   0.914798
                                                                                               0.901493
                             0.925218
              Decision Tree
                                       0.912753
                                                                    0.928251
                                                                                              0.904478
             Random Forest
                             0.987381
                                       0.931890
                                                                   0.986547
                                                                                              0.928358
                     LGBM
                             0.967723
                                       0.934870
                                                                   0.965620
                                                                                              0.928358
             Neural Network
                             0.901109
                                       0.899604
                                                                   0.905082
                                                                                               0.901493
                KNeighbors
                             0.925882
                                       0.906166
                                                                    0.922272
                                                                                               0.910448
                  XGBoost
                             0.975958
                                       0.930101
                                                                   0.976084
                                                                                               0.931343
                  CatBoost
                             0.945142
                                       0.933084
                                                                   0.943199
                                                                                               0.934328
In [83]: BS_score[['Training CV', 'Testing CV']].plot(kind = 'bar', figsize = (10,6), fontsize = 10)
         plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
         plt.ylim(0.8, 1.01)
         plt.yticks([0.8, 0.85, 0.9, 0.95,1.0])
```

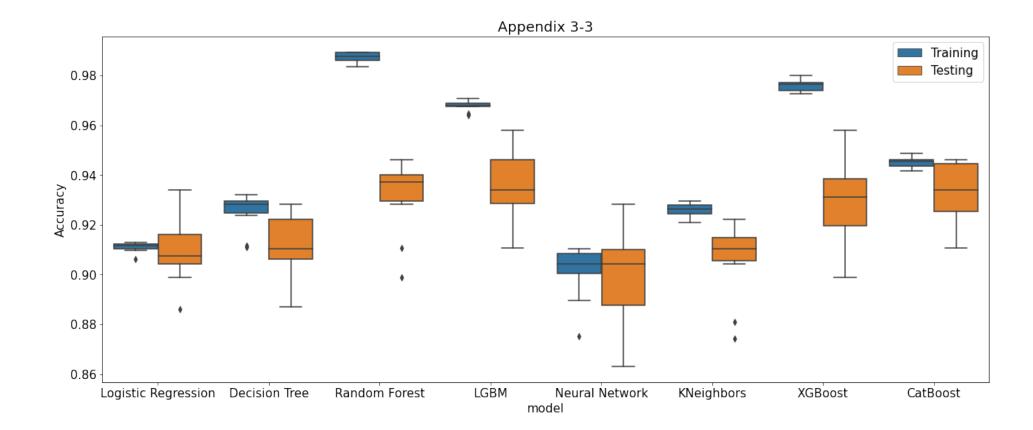
plt.title ('Appendix 3-1')

plt.show()



```
In [84]: BS_score[['Training Validation Set Approach', 'Testing Validation Set Approach']].plot(
          kind = 'bar', figsize = (10,6), fontsize = 10)
    plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
    plt.ylim(0.8, 1.01)
    plt.yticks([0.8, 0.85, 0.9, 0.95,1.0])
    plt.title ('Appendix 3-2')
    plt.show()
```





4.1 For Value (C) - With Created Variables

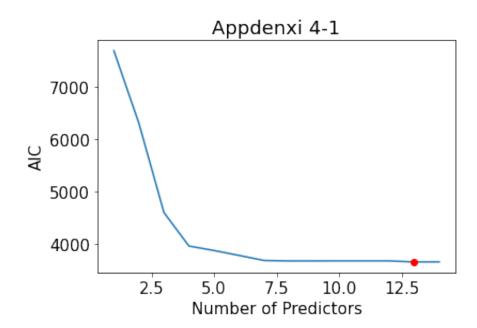
4.1.1 Linear Regression

```
In [87]: from sklearn.linear_model import LinearRegression
    from sklearn.model_selection import train_test_split
    import statsmodels.api as sm
    from sklearn.preprocessing import StandardScaler
    import time
    import itertools
In [88]: value_score = pd.DataFrame(columns = ['r2_train', 'r2_test'])
    kfolds = KFold(n_splits = 10, shuffle = True, random_state = 1)
```

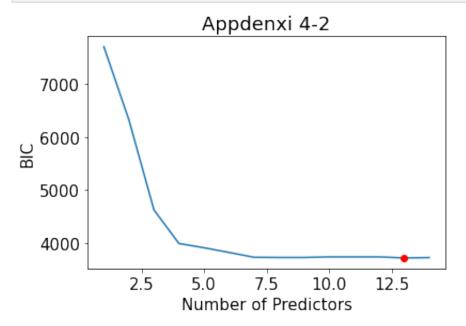
```
In [89]: def cv(var, model):
             cv_score_train = []
             cv score test = []
             if model == 'Random Forest':
                 model = RandomForestRegressor(random_state=9, n_estimators =100, max_depth = 100,
                                                min_samples_split=10,min_samples_leaf=10)
             elif model == 'Linear':
                 model = LinearRegression()
             elif model == 'LGBM':
                 model = lgb.LGBMRegressor(random_state = 5, num_leaves=20,n_estimators=100, max_depth = 50)
             elif model == 'NN':
                 model = MLPRegressor(random_state = 5,hidden_layer_sizes=(18,18,18), activation = 'relu',
                                       solver = 'adam', learning_rate= 'constant',
                                    learning_rate_init = 0.01)
             elif model == 'KNeighbors':
                 model = KNeighborsRegressor(n_neighbors=3)
             elif model == 'XGBoost':
                 model = xgb.XGBRegressor(random state = 5,max depth=25, n estimators=30)
             elif model == 'CatBoost':
                 model = CatBoostRegressor(random_state = 5,verbose=0, max_depth=8, iterations=200, learning_rate = 0.1)
             for train index, test index in kfolds.split(X, y value):
                 X_train = X.iloc[train_index][list(var)]
                 y_train = y_value.iloc[train_index]
                 X_test = X.iloc[test_index][list(var)]
                 y_test = y_value.iloc[test_index]
                 # Train the model
                 regression = model.fit(X_train, y_train)
                 # Return the score
                 # rsquared for train data
                 TSS_train = ((y_train - y_train.mean())**2).sum()
                 RSS_train = ((regression.predict(X_train) - y_train)**2).sum()
                 r2_train = (TSS_train - RSS_train)/TSS_train
                 # rsquared for test data
                 TSS_test = ((y_test - y_test.mean())**2).sum()
                 RSS_test = ((regression.predict(X_test) - y_test)**2).sum()
                 r2_test = (TSS_test - RSS_test)/TSS_test
                 cv_score_train.append(r2_train)
                 cv_score_test.append(r2_test)
             return {"model": model, "r2_train": np.mean(cv_score_train),
                      "r2 test": np.mean(cv score test), "variable": var}
         def subset(var):
             X_train, X_test, y_train, y_test = train_test_split(X, y_value, test_size=0.2,random_state=2)
             X1 = sm.add_constant(X_train[list(var)])
             model = sm.OLS(y_train, X1)
             regression = model.fit()
             #rsquared for train data
             r2_train = regression.rsquared
             # rsquared for test data
             X2_test = sm.add_constant(X_test[list(var)])
             TSS = ((y_test - y_test.mean())**2).sum()
             RSS_test = ((regression.predict(X2_test) - y_test)**2).sum()
             r2\_test = (TSS - RSS\_test)/TSS
             return {"model": regression, "r2_train": r2_train, "r2_test": r2_test, 'variable': var}
         def getBest(k):
             results = []
             for combo in itertools.combinations(X.columns, k):
                 results.append(subset(combo))
             # Wrap everything in a dataframe
             models = pd.DataFrame(results)
             # Choose the model with the smallest RSS
             best_model = models.loc[models['r2_test'].idxmax()]
             return best model
In [90]: models = pd.DataFrame(columns = ["model", "r2_train", "r2_test", 'variable'])
         ct = time.time()
         for i in range(1, X.shape[1]+1):
             models.loc[i] = getBest(i)
In [91]: aic = models.apply(lambda row: row['model'].aic, axis = 1)
         plt.plot(aic)
         plt.plot(aic.idxmin(), aic.min(), "or")
         plt.ylabel('AIC')
         plt.xlabel('Number of Predictors')
```

plt.title("Appdenxi 4-1")

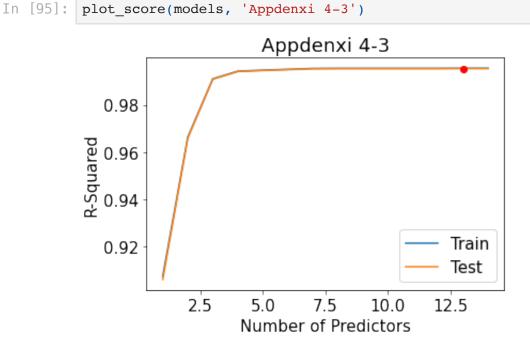
plt.show()



```
In [92]: bic = models.apply(lambda row: row[0].bic, axis = 1)
    plt.plot(bic)
    plt.plot(bic.idxmin(), bic.min(), "or")
    plt.ylabel('BIC')
    plt.xlabel('Number of Predictors')
    plt.title("Appdenxi 4-2")
    plt.show()
```



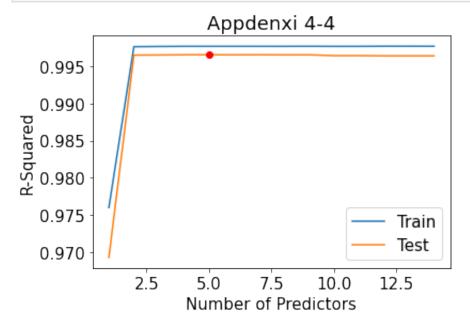
```
In [93]:
         for i in range(1, X.shape[1]+1):
             models.loc[i] = cv(models.loc[i, 'variable'], 'Linear')
         models['r2_test'] = models['r2_test'].astype("float")
         value_score.loc['Linear Regression'] = models.loc[models['r2_test'].idxmax(),['r2_train', 'r2_test']]
In [94]: def plot_score(models,title):
             models['r2_test'] = models['r2_test'].astype("float")
             plt.plot(models['r2_train'])
             plt.plot(models['r2_test'])
             plt.plot(models['r2_test'].idxmax(), models['r2_test'].max(),"or")
             plt.ylabel('R-Squared')
             plt.xlabel('Number of Predictors')
             plt.title("R-Squared for Training/Testing Data")
             plt.legend(['Train', 'Test'])
             plt.title(title)
             plt.show()
```



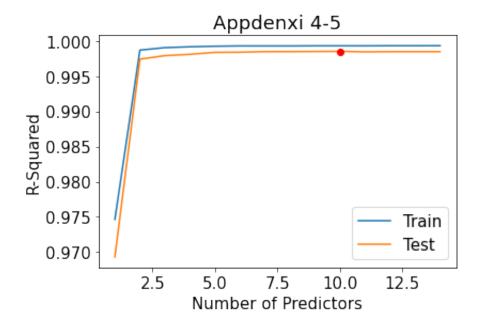
4.1.2 Random Forest Regression

```
In [96]: def subset(var, model):
             X_train, X_test, y_train, y_test = train_test_split(X, y_value, test_size=0.2,random_state=2)
             X1 = X_train[list(var)]
             if model == 'Random Forest':
                 model = RandomForestRegressor(random_state=9, n_estimators =100, max_depth = 100,
                                                min_samples_split=10,min_samples_leaf=10)
             elif model == 'LGBM':
                 model = lgb.LGBMRegressor(random state = 5, num leaves=20, n estimators=100, max depth = 50)
             elif model == 'NN':
                 model = MLPRegressor(random_state = 5, hidden_layer_sizes=(18,18,18), activation = 'relu',
                                       solver = 'adam', learning_rate= 'constant',
                                    learning_rate_init = 0.01, max_iter= 300)
             elif model == 'KNeighbors':
                 model = KNeighborsRegressor(n_neighbors=3)
             elif model == 'XGBoost':
                 model = xgb.XGBRegressor(random_state = 5,max_depth=25, n_estimators=30)
             elif model == 'CatBoost':
                 model = CatBoostRegressor(random_state = 5,verbose=0, max_depth=8, iterations=200, learning_rate = 0.1)
             regression = model.fit(X1, y_train)
             X2_test = X_test[list(var)]
             # rsquared for train data
             TSS = ((y_train - y_train.mean())**2).sum()
             RSS_train = ((regression.predict(X1) - y_train)**2).sum()
             r2_train = (TSS - RSS_train)/TSS
             # rsquared adj for test data
             TSS = ((y_test - y_test.mean())**2).sum()
             RSS_test = ((regression.predict(X2_test) - y_test)**2).sum()
             r2_test = (TSS - RSS_test)/TSS
             return {"model": regression, "r2_train": r2_train, "r2_test": r2_test, "variable": var}
         def forward(predictors, model):
             ct = time.time()
             results = []
             remaining = X.columns.drop(predictors)
             for pred in remaining:
                 results.append(subset(predictors + [pred], model))
             # Wrap everything up in a dataframe
             models = pd.DataFrame(results)
             best_model = models.loc[models['r2_test'].idxmax()]
             return best model
```

```
In [97]: forward_num = X.shape[1]
    models = pd.DataFrame(columns = ["model",'r2_train', "r2_test","variable"])
    predictors = []
    for i in range(1, forward_num + 1):
        models.loc[i] = forward(predictors, model = 'Random Forest')
        models.loc[i] = cv(models.loc[i, 'variable'], 'Random Forest')
        predictors = models.loc[i]['variable']
    plot_score(models,'Appdenxi 4-4')
    value_score.loc['Random Forest'] = models.loc[models['r2_test'].idxmax(),['r2_train', 'r2_test']]
```

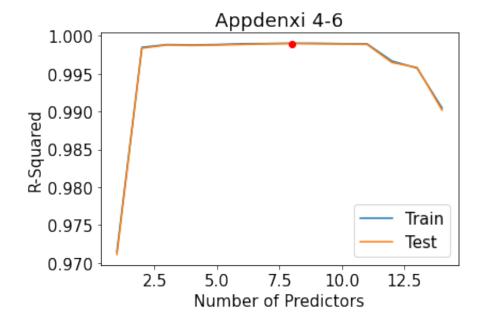


4.1.3 LGBM Regression



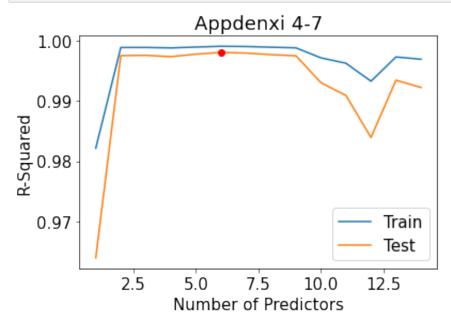
4.1.4 Neural Network Regression

```
In [99]: forward_num = X.shape[1]
    models = pd.DataFrame(columns = ["model",'r2_train', "r2_test","variable"])
    predictors = []
    for i in range(1, forward_num + 1):
        models.loc[i] = forward(predictors, model = 'NN')
        models.loc[i] = cv(models.loc[i, 'variable'], 'NN')
        predictors = models.loc[i]['variable']
    plot_score(models,'Appdenxi 4-6')
    value_score.loc['Neural Network'] = models.loc[models['r2_test'].idxmax(),['r2_train', 'r2_test']]
```



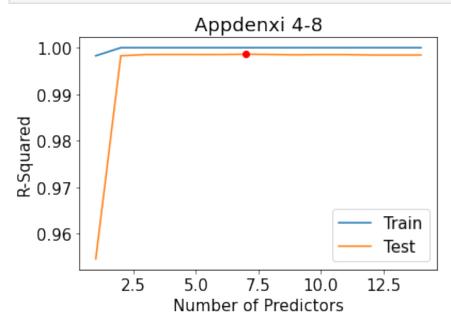
4.1.5 KNeighbors Regression

```
In [100... forward_num = X.shape[1]
    models = pd.DataFrame(columns = ["model",'r2_train', "r2_test","variable"])
    predictors = []
    for i in range(1, forward_num + 1):
        models.loc[i] = forward(predictors, model = 'KNeighbors')
        models.loc[i] = cv(models.loc[i, 'variable'], 'KNeighbors')
        predictors = models.loc[i]['variable']
    plot_score(models,'Appdenxi 4-7')
    value_score.loc['KNeighbors'] = models.loc[models['r2_test'].idxmax(),['r2_train', 'r2_test']]
```



4.1.6 XGBoost Regression

```
In [101... forward_num = X.shape[1]
    models = pd.DataFrame(columns = ["model",'r2_train', "r2_test","variable"])
    predictors = []
    for i in range(1, forward_num + 1):
        models.loc[i] = forward(predictors, model = 'XGBoost')
        models.loc[i] = cv(models.loc[i, 'variable'], 'XGBoost')
        predictors = models.loc[i]['variable']
    plot_score(models,'Appdenxi 4-8')
    value_score.loc['XGBoost'] = models.loc[models['r2_test'].idxmax(),['r2_train', 'r2_test']]
```



4.1.7 CatBoost Regression

```
In [102... forward_num = X.shape[1]
    models = pd.DataFrame(columns = ["model",'r2_train', "r2_test","variable"])
    predictors = []
    for i in range(1, forward_num + 1):
        models.loc[i] = forward(predictors, model = 'CatBoost')
        models.loc[i] = cv(models.loc[i, 'variable'], 'CatBoost')
        predictors = models.loc[i]['variable']
    plot_score(models,'Appdenxi 4-9')
    value_score.loc['CatBoost'] = models.loc[models['r2_test'].idxmax(),['r2_train', 'r2_test']]
```

```
Appdenxi 4-9

1.000

0.995

0.985

0.980

0.975

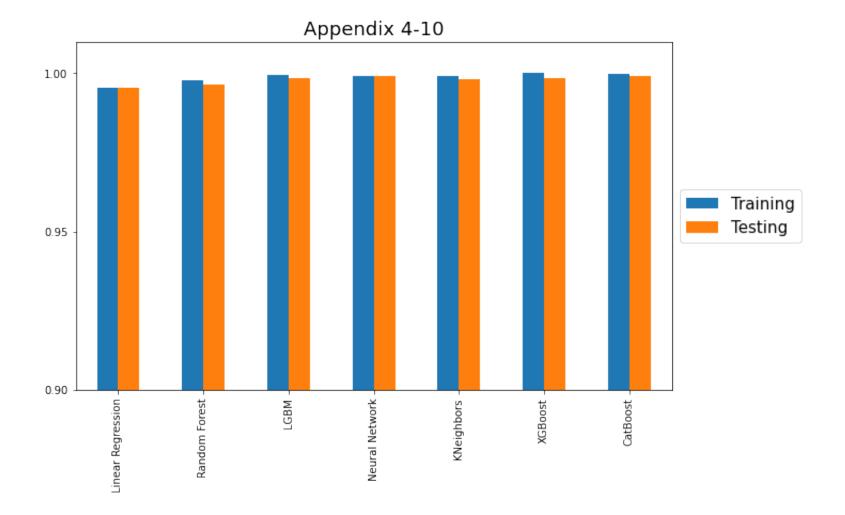
0.970

2.5 5.0 7.5 10.0 12.5

Number of Predictors
```

```
In [103...
          value_score
Out[103]:
                             r2_train
                                       r2_test
           Linear Regression 0.995506
                                     0.995352
                                     0.996568
              Random Forest 0.997706
                      LGBM 0.999313 0.998528
             Neural Network 0.999029
                                      0.99898
                 KNeighbors
                             0.99906 0.998048
                   XGBoost 0.999999 0.998595
                   CatBoost 0.99967
                                       0.99905
```

```
In [104... value_score.plot(kind = 'bar', figsize = (10,6), fontsize = 10)
    plt.legend(['Training', 'Testing'],loc='center left', bbox_to_anchor=(1, 0.5))
    plt.ylim(0.9, 1.01)
    plt.yticks([0.9, 0.95,1.0])
    plt.title ('Appendix 4-10')
    plt.show()
```



4.2 For BS

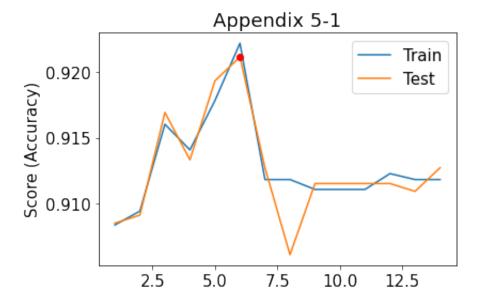
4.2.1 Logistic Regression

```
In [105... kfolds = StratifiedKFold(n_splits = 5, random_state = 1, shuffle = True)
BS_score = BS_score = pd.DataFrame(columns = ['score_train', 'score_test'])
```

```
In [106... def cv(var, model name):
             cv_classification_score_train = []
             cv classification score test = []
             if model_name == 'Logistics':
                 model = LogisticRegression(penalty='none', max_iter=10000)
             elif model_name == 'Random Forest':
                 model = RandomForestClassifier(random_state=3, n_estimators =100, max_depth = 100,
                                                 min_samples_split= 2, min_samples_leaf=2)
             elif model name == 'LGBM':
                 model = lgb.LGBMClassifier(num_leaves=25,n_estimators=30, max_depth = 30)
             elif model_name == 'NN':
                 model = MLPClassifier(random_state = 5, hidden_layer_sizes=(15,15,15,15,15))
                                        activation = 'relu', solver = 'adam', learning_rate= 'adaptive',
                                    learning_rate_init = 0.01)
             elif model_name == 'KNeighbors':
                 model = KNeighborsClassifier(n_neighbors = 8)
             elif model_name == 'XGBoost':
                 model = xgb.XGBClassifier(random state = 5, max depth=10, n estimators=5)
             elif model name == 'CatBoost':
                 model = CatBoostClassifier(random_state = 5, verbose=0, max_depth=5, iterations=100, learning_rate = 0.1)
             elif model name == 'Decision Tree':
                 model = DecisionTreeClassifier(random_state=3, max_depth=20,min_samples_split=20,min_samples_leaf=20)
             for train_index, test_index in kfolds.split(X, y_BS):
                 X1 = X.iloc[train_index][var]
                 y_train = y_BS.iloc[train_index]
                 X_test = X.iloc[test_index][var]
                 y_test = y_BS.iloc[test_index]
                 model = model.fit(X1,y_train)
                 cv classification score train.append(model.score(X1, y train))
                 cv classification score test.append(model.score(X test[var], y test))
             return {"model": model, "score_train": np.mean(cv_classification_score_train),
                      "score_test": np.mean(cv_classification_score_test), "variable": var}
         def subset(var, model_name):
             X_train, X_test, y_train, y_test = train_test_split(X[var], y_BS, test_size=0.2,random_state=4)
             if model_name == 'Logistics':
                 model = LogisticRegression(penalty='none', max_iter=10000)
             elif model name == 'Random Forest':
                 model = RandomForestClassifier(random_state=3, n_estimators =100, max_depth = 100,
                                                 min_samples_split= 2, min_samples_leaf=2)
             elif model_name == 'LGBM':
                 model = lgb.LGBMClassifier(num_leaves=25,n_estimators=30, max_depth = 30)
             elif model_name == 'NN':
                 model = MLPClassifier(random_state = 5, hidden_layer_sizes=(15,15,15,15,15),
                                        activation = 'relu', solver = 'adam', learning_rate= 'adaptive',
                                    learning_rate_init = 0.01)
             elif model_name == 'KNeighbors':
                 model = KNeighborsClassifier(n_neighbors = 8)
             elif model_name == 'XGBoost':
                 model = xgb.XGBClassifier(random_state = 5, max_depth=10, n_estimators=5)
             elif model_name == 'CatBoost':
                 model = CatBoostClassifier(random_state = 5, verbose=0, max_depth=5, iterations=100, learning_rate = 0.1)
             elif model_name == 'Decision Tree':
                 model = DecisionTreeClassifier(random_state=3, max_depth=20,min_samples_split=20,min_samples_leaf=20)
             model = model.fit(X_train, y_train)
             # Return the score
             # accuracy score for train data
             score_train = accuracy_score(model.predict(X_train), y_train)
             # accuracy score for test data
             score_test = accuracy_score(model.predict(X_test), y_test)
             return {"model": regression, "score train": score train, "score test": score test, 'variable': var}
         def forward(predictor, model_name):
             results = []
             remaining = X.columns.drop(predictors)
             for pred in remaining:
                 results.append(subset(predictors + [pred], model_name))
             # Wrap everything up in a dataframe
             models = pd.DataFrame(results)
             best_model = models.loc[models['score_test'].idxmax()]
```

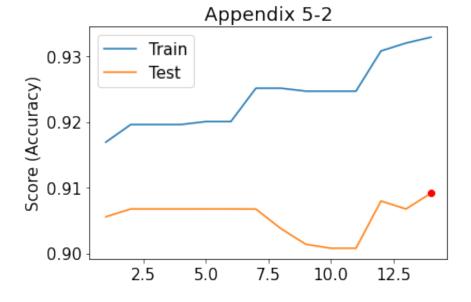
return best_model

```
In [107... forward_num = X.shape[1]
         models2 = pd.DataFrame(columns = ['model', 'score_train', 'score_test', 'variable'])
         predictors = []
         for i in range(1, forward_num + 1):
             models2.loc[i] = forward(predictors, 'Logistics')
             predictors = models2.loc[i]['variable']
             models2.loc[i] = cv(models2.loc[i, 'variable'], 'Logistics')
In [108...
         def plot_score(models2,title):
             models2['score_test'] = models2['score_test'].astype("float")
             plt.plot(models2['score_train'])
             plt.plot(models2['score_test'])
             plt.plot(models2['score_test'].idxmax(), models2['score_test'].max(),"or")
             plt.ylabel('Score (Accuracy)')
             plt.legend(['Train', 'Test'])
             plt.title(title)
             plt.show()
         plot score(models2, 'Appendix 5-1')
         BS_score.loc['Logistic Regression'] = models2.loc[models2['score_test'].idxmax(),['score_train', 'score_test']]
```

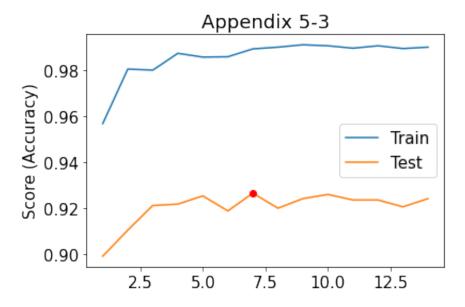


3.2.2 Decision Tree

```
In [109... models2 = pd.DataFrame(columns = ['model', 'score_train', 'score_test', 'variable'])
    predictors = []
    for i in range(1, forward_num + 1):
        models2.loc[i] = forward(predictors, 'Decision Tree')
        predictors = models2.loc[i]['variable']
        models2.loc[i] = cv(models2.loc[i, 'variable'], 'Decision Tree')
    plot_score(models2, 'Appendix 5-2')
    BS_score.loc['Decision Tree'] = models2.loc[models2['score_test'].idxmax(),['score_train', 'score_test']]
```



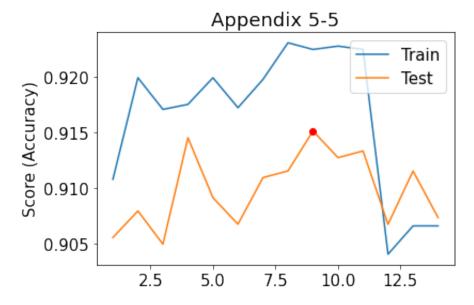
4.2.3 Random Forest



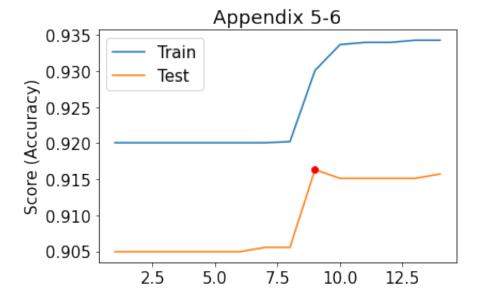
4.2.4 LGBM Classification

Appendix 5-4 Train Test 0.96 0.94 2.5 5.0 7.5 10.0 12.5

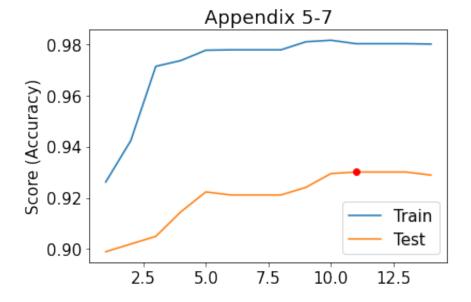
4.2.5 Neural Network Classification



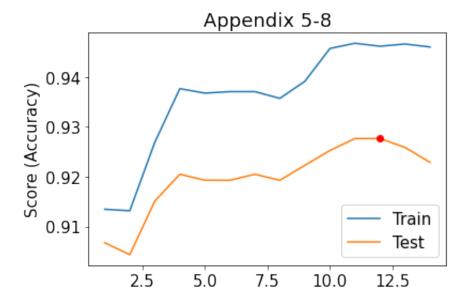
4.2.6 KNeighbors Classification



4.2.7 XGBoost Classification

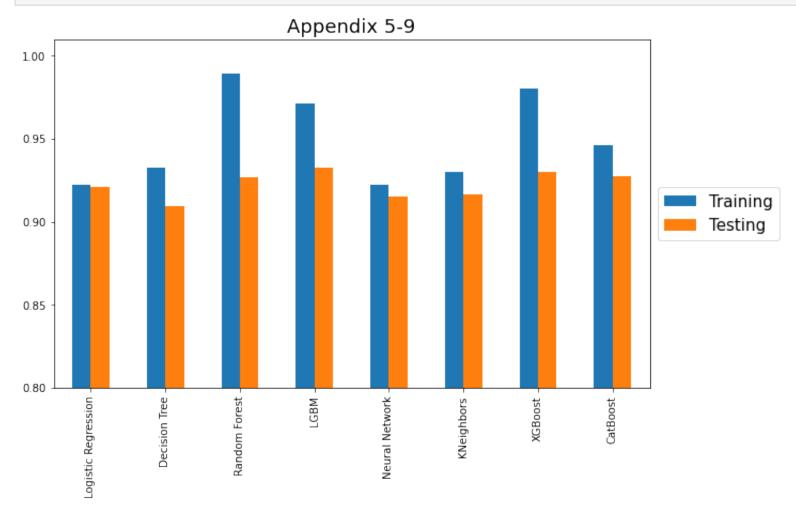


4.2.8 CatBoost Classification



```
In [116...
           BS_score
Out[116]:
                                score_train score_test
            Logistic Regression
                                   0.922146
                                               0.921108
                  Decision Tree
                                  0.932905
                                              0.909148
                                              0.926485
                 Random Forest
                                   0.98939
                         LGBM
                                   0.971309
                                              0.932462
                Neural Network
                                  0.922445
                                               0.915124
                    KNeighbors
                                  0.930067
                                              0.916329
                      XGBoost
                                   0.980124
                                              0.930067
                      CatBoost
                                  0.946204
                                              0.927684
```

```
In [117... BS_score.plot(kind = 'bar', figsize = (10,6), fontsize = 10)
    plt.legend(['Training', 'Testing'],loc='center left', bbox_to_anchor=(1, 0.5))
    plt.ylim(0.8, 1.01)
    plt.yticks([0.8, 0.85, 0.9, 0.95,1.0])
    plt.title ('Appendix 5-9')
    plt.show()
```



5. Predict the Option Value and BS with Selected Models

```
In [118... data_test = pd.read_csv('option_test_wolabel.csv')

In [119... original_var = ['S', 'K', 'tau', 'r']
    model = xgb.XGBRegressor(random_state = 5, max_depth=25, n_estimators=30)
    model = model.fit(X[original_var], y_value)
    test_value = model.predict(data_test)

model = CatBoostClassifier(random_state = 5, verbose=0, max_depth=5, iterations=100, learning_rate = 0.1)
    model = model.fit(X[original_var], y_BS)
    test_BS = model.predict(data_test)
    pd.DataFrame({'Value': test_value, 'BS':test_BS}).to_csv('group_11_prediction.csv')
```