4_3_Models

April 20, 2020

1 FE + Dimension Reduction + Standardization + ML Classification Model

- 1. No oversampling techniques applied
- 2. feature engineering applied

2 1. Import Necessary Libraries

```
[1]: # For Computational and random seed purpose
     import numpy as np
     np.random.seed(42)
     # To read csv file
     import pandas as pd
     # To Split data into train and cv data
     from sklearn.model_selection import train_test_split
     # To compute AUROC score
     # For AUROC Score (Ref: https://scikit-learn.org/stable/modules/generated/
      \hookrightarrow sklearn.metrics.roc_auc_score.html)
     from sklearn.metrics import roc_curve, auc
     # For Hyperparameter and CV Fold
     from sklearn.model_selection import GridSearchCV, RepeatedStratifiedKFold, u
      ⇔cross_val_score
     # For plot AUROC graph
     import matplotlib.pyplot as plt
     \# Data is umbalance, we need Calibrated Model to ive confidence probabilities \sqcup
      \rightarrow result
     from sklearn.calibration import CalibratedClassifierCV
     # For heatmap
     import seaborn as sns
     # To ignore warninga
     import warnings
     warnings.filterwarnings('ignore')
     # To stndardize the data
     from sklearn.preprocessing import StandardScaler
     import tqdm
     # Dimension reduction
```

3 2. Read train data

```
[2]: # Locate parent directory
    data_dir = "./"
     # Read csv file and display top 5 rows
    df_train = pd.read_csv(data_dir+'/train.csv')
    df train.head(5)
                                     2
[2]:
                                            3
                                                   4
                                                         5
       id
          target
              1.0 -0.098 2.165 0.681 -0.614 1.309 -0.455 -0.236
    1
        1
                  1.081 -0.973 -0.383  0.326 -0.428  0.317  1.172
                                                                   0.352
    2
              1.0 -0.523 -0.089 -0.348 0.148 -0.022 0.404 -0.023 -0.172
    3
              1.0 0.067 -0.021 0.392 -1.637 -0.446 -0.725 -1.035
        3
                                                                   0.834
    4
              1.0 2.347 -0.831 0.511 -0.021 1.225 1.594 0.585
                                                                   1.509 ...
         290
                291
                              293
                                     294
                                            295
                                                   296
                                                         297
                                                                298
                       292
                                                                       299
       0.867
              1.347 0.504 -0.649
                                  0.672 - 2.097
                                                1.051 -0.414
                                                              1.038 -1.065
    1 -0.165 -1.695 -1.257 1.359 -0.808 -1.624 -0.458 -1.099 -0.936
    2 0.013 0.263 -1.222 0.726 1.444 -1.165 -1.544 0.004 0.800 -1.211
    3 -0.404 0.640 -0.595 -0.966 0.900 0.467 -0.562 -0.254 -0.533 0.238
    4 0.898 0.134 2.415 -0.996 -1.006 1.378 1.246 1.478 0.428 0.253
    [5 rows x 302 columns]
[3]: df_test = pd.read_csv(data_dir+'/test.csv')
    df_test.head(5)
[3]:
        id
                       1
                              2
                                     3
                                            4
                                                   5
                                                         6
                                                                7
                                                                             \
       250
           0.500 -1.033 -1.595 0.309 -0.714
                                              0.502
                                                     0.535 -0.129 -0.687
    1
       251 0.776 0.914 -0.494
                                1.347 - 0.867
                                              0.480 0.578 -0.313 0.203
    2 252 1.750 0.509 -0.057 0.835 -0.476
                                              1.428 -0.701 -2.009 -1.378
       253 -0.556 -1.855 -0.682 0.578 1.592
                                              0.512 -1.419 0.722 0.511
       254 0.754 -0.245 1.173 -1.623 0.009 0.370 0.781 -1.763 -1.432
         290
                291
                       292
                              293
                                     294
                                            295
                                                   296
                                                         297
                                                                298
                                                                       299
    0 -0.088 -2.628 -0.845 2.078 -0.277 2.132 0.609 -0.104 0.312 0.979
    1 -0.683 -0.066 0.025 0.606 -0.353 -1.133 -3.138 0.281 -0.625 -0.761
    2 -0.094 0.351 -0.607 -0.737 -0.031 0.701 0.976 0.135 -1.327 2.463
    3 -0.336 -0.787 0.255 -0.031 -0.836 0.916 2.411
                                                       1.053 -1.601 -1.529
    4 2.184 -1.090 0.216 1.186 -0.143 0.322 -0.068 -0.156 -1.153 0.825
     [5 rows x 301 columns]
```

4 3. Apply Feature Engg

```
[4]: # We already saw in 2 FE.ipynb file that we created a feat enng function. We
     → just put it here
     def feature_engg(df, if_test = False):
         Perform Feature Engg in Basic Stats, Trigometrics, Hyperbolic and □
      \hookrightarrow Exponential Function
         Parameters:
         df: Pass DataFrame (all features much be in numric values)
         if_test: If the DataFrame is test data or train data. Ig it is test data, ⊔
      \hookrightarrow put \ if\_test=True
         Return:
         DataFrame with feature engineering appended
         if if_test:
             temp = df.drop(['id'], axis=1)
         else:
             temp = df.drop(['id', 'target'], axis=1)
         # Mean and Std FE
         df['mean'] = np.mean(temp, axis=1)
         df['std'] = np.std(temp, axis=1)
         # Trigometric FE
         sin_temp = np.sin(temp)
         cos_temp = np.cos(temp)
         tan_temp = np.tan(temp)
         df['mean_sin'] = np.mean(sin_temp, axis=1)
         df['mean_cos'] = np.mean(cos_temp, axis=1)
         df['mean_tan'] = np.mean(tan_temp, axis=1)
         # Hyperbolic FE
         sinh_temp = np.sinh(temp)
         cosh_temp = np.cosh(temp)
         tanh_temp = np.tanh(temp)
         df['mean_sinh'] = np.mean(sin_temp, axis=1)
         df['mean_cosh'] = np.mean(cos_temp, axis=1)
         df['mean_tanh'] = np.mean(tan_temp, axis=1)
         # Exponents FE
         exp_temp = np.exp(temp)
         expm1_temp = np.expm1(temp)
```

```
exp2\_temp = np.exp2(temp)
        df['mean_exp'] = np.mean(exp_temp, axis=1)
        df['mean_expm1'] = np.mean(expm1_temp, axis=1)
        df['mean_exp2'] = np.mean(exp2_temp, axis=1)
        # Polynomial FE
        # X**2
        df['mean_x2'] = np.mean(np.power(temp,2), axis=1)
        df['mean_x3'] = np.mean(np.power(temp,3), axis=1)
        # X**4
        df['mean_x4'] = np.mean(np.power(temp,4), axis=1)
        return df
[5]: df_train = feature_engg(df_train)
    df train.head(5)
[5]:
       id
           target
                                           3
                                                         5
                                                                      7 ...
              1.0 -0.098 2.165 0.681 -0.614 1.309 -0.455 -0.236 0.276
    0
        0
    1
        1
              0.0 1.081 -0.973 -0.383 0.326 -0.428 0.317 1.172 0.352 ...
    2
              1.0 -0.523 -0.089 -0.348  0.148 -0.022  0.404 -0.023 -0.172
    3
              1.0 0.067 -0.021 0.392 -1.637 -0.446 -0.725 -1.035 0.834
        3
              1.0 2.347 -0.831 0.511 -0.021 1.225 1.594 0.585
                                                                  1.509 ...
       mean_tan mean_sinh mean_cosh mean_tanh mean_exp mean_expm1 mean_exp2 \
                -0.010536
    0 -0.315591
                             0.537968 -0.315591 1.760647
                                                             0.760647
                                                                        1.315869
    1 0.607457
                 0.075490
                             0.611600
                                      0.607457 1.712292
                                                             0.712292
                                                                        1.324817
    2 0.104777 -0.005509
                             0.599358
                                       0.104777 1.749107
                                                             0.749107
                                                                        1.313960
    3 0.891722
                                                             0.752101
                 0.046067
                             0.645721
                                       0.891722 1.752101
                                                                        1.326229
    4 0.274261 0.059548
                           0.643508
                                      0.274261 1.861741
                                                             0.861741
                                                                       1.377569
                 mean_x3
        mean_x2
                           mean_x4
    0 1.182425 0.015243 3.584848
    1 0.976056 0.047272 2.766570
    2 1.023024 0.266454 3.092631
    3 0.887980 0.371308 2.553467
    4 0.901115 0.613952 2.671541
    [5 rows x 316 columns]
[6]: df_test = feature_engg(df_test, True)
    df test.head(5)
[6]:
                0
                              2
                                    3
                                           4
                                                  5
        id
                       1
                                                         6
                                                                7
    0 250 0.500 -1.033 -1.595 0.309 -0.714 0.502 0.535 -0.129 -0.687 ...
    1 251 0.776 0.914 -0.494 1.347 -0.867 0.480 0.578 -0.313 0.203 ...
```

```
2 252 1.750 0.509 -0.057 0.835 -0.476 1.428 -0.701 -2.009 -1.378 ...
3 253 -0.556 -1.855 -0.682 0.578
                                         0.512 -1.419 0.722 0.511
                                  1.592
4 254 0.754 -0.245 1.173 -1.623
                                  0.009
                                         0.370 0.781 -1.763 -1.432
  mean_tan
           mean_sinh mean_cosh mean_tanh mean_exp mean_expm1
                                                                 mean_exp2 \
0 0.565830
             0.094378
                        0.609398
                                  0.565830
                                            1.904397
                                                        0.904397
                                                                  1.404195
1 -1.641918
           -0.018425
                        0.570495 -1.641918 1.642217
                                                        0.642217
                                                                  1.265487
2 -0.516155
           -0.012641
                        0.611053 -0.516155 1.517775
                                                        0.517775
                                                                  1.214393
3 -0.816079
            0.002689
                        0.610619 -0.816079 1.566765
                                                        0.566765
                                                                  1.243412
4 -1.547172
             0.067329
                        0.611907 -1.547172 1.849024
                                                        0.849024
                                                                  1.374870
   mean_x2
             mean_x3
                      mean_x4
0 0.985912 0.477020 2.913247
1 1.094274 -0.128315 3.281111
2 0.994294 -0.330590
                      3.062801
3 0.956136 -0.076546
                      2.382968
4 0.988710 0.371320 3.079160
[5 rows x 315 columns]
```

5 4. Take train and test values from DataFrame

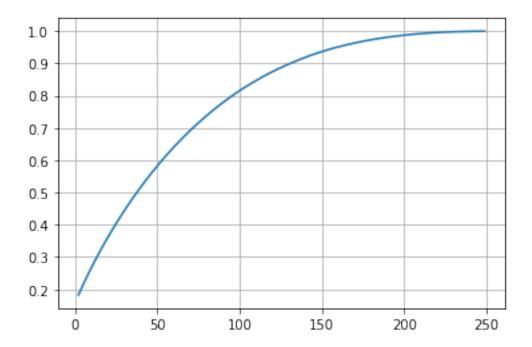
```
[7]: # Take separate for features value
tr_X = df_train.drop(['id','target'], axis=1)
# Take separate for class value
tr_y = df_train['target'].values
# Take test feature value
ts_X = df_test.drop(['id'], axis=1)
```

Note: Don't worry about splitting train data into train and cv. I apply Stratify CV technique while modelling

6 5. PCA - Principal Components Analysis

```
[8]: exp_rat = []
    for i in range(2,min(tr_X.shape[0],tr_X.shape[1])):
        pca = PCA(n_components=i)
        pca.fit(tr_X,tr_y)
        exp_rat.append(np.sum(pca.explained_variance_ratio_))

[9]: plt.plot(np.arange(2,min(tr_X.shape[0],tr_X.shape[1])),exp_rat)
    plt.grid()
    plt.show()
```



Let take n_components = 100 which retain 80-85% data

```
[10]: # Fit and transform on train data and transform on cv and test data
pca = PCA(n_components=100)
tr_X = pca.fit_transform(tr_X,tr_y)
ts_X = pca.transform(ts_X)
```

7 6. Standardization

```
[11]: stand_vec = StandardScaler()
     tr_X = stand_vec.fit_transform(tr_X)
     pd.DataFrame(tr_X).head(5)
[11]:
             0
                      1
                               2
                                        3
                                                           5
     0 -0.166673  0.716303  1.061006  0.283135  0.765347  1.253518 -1.967637
     1 0.031105 0.688296 -0.679376 -1.075485 1.484971 -1.484536 -0.954770
     2 -0.037655 0.759798 0.240590 -1.494130 0.680533 -1.507534 -1.475887
     3 0.089884 -0.794913 0.652919 -0.124737 -1.415833 0.182715 1.361817
     4 -0.048058   0.464460   0.932549   0.062235   1.730730 -0.003666 -1.875208
                               9
                                           90
                                                    91
                                                             92
                                                                       93 \
     0 1.739057 -1.551768 2.025589 ... -0.595692 -0.318748 -1.337064 2.628657
     0.900612
     2 1.563435 -0.133188 1.023150 ... 1.752939 1.005274 -0.664277 0.933295
     3 -0.364036 1.076568 -0.197581 ... 0.693881 0.713162 -0.981445 -1.106564
```

```
4 0.016811 0.794978 1.687170 ... -1.366679 -0.379423 0.101277 -0.234361
              94
                        95
                                  96
                                            97
                                                      98
                                                                99
     0 0.170896 1.266913 -0.725125 -0.328609 -0.029965 -0.067125
     2 0.279115 0.701745 0.674709 -0.358302 -1.274508 -1.814593
     3 -1.178461 0.141677 -2.065266 -1.978613 -1.559254 -0.184509
     4 -1.180351 -0.475823 -1.364242 0.418845 -0.064071 -0.862030
     [5 rows x 100 columns]
[12]: ts_X = stand_vec.transform(ts_X)
     pd.DataFrame(ts X).head(5)
[12]:
                                  2
                                            3
     0 0.019110 0.276096 -0.061850 -0.436308 0.152002 -0.063529 0.282660
     1 - 0.361623 - 0.459394 \quad 0.611061 - 0.043825 - 0.601051 - 0.794353 - 0.333588
     2 -0.174794 0.385567 -0.876048 0.592629 0.129279 -0.328676 -0.401293
     3 -0.220446 0.983462 -0.596268 0.007514 -0.104571 0.285299 -0.541471
     4 -0.327378 -0.630620 -1.088273 -1.305239 -0.065958 0.116384 -0.027180
              7
                        8
                                  9
                                               90
                                                         91
                                                                   92
                                                                             93 \
     1 \quad 0.045550 \quad 0.197833 \quad 0.466416 \quad \dots \quad -1.227608 \quad -0.117458 \quad -0.640373 \quad -0.619610
     2 1.146829 -0.305653 -0.500269 ... 0.998926 1.647119 -0.347204 -0.904379
     3 0.045604 -0.163915 0.472175 ... 1.487871 0.153404 -0.337140 -1.482203
     4 \quad 0.027114 \quad -0.500452 \quad -0.846949 \quad \dots \quad 0.249169 \quad 0.517964 \quad 0.206816 \quad -0.102744
                                  96
                                            97
                                                      98
                        95
     0 -1.211555 0.123960 -1.542254 0.698954 0.393598 -0.215651
     1 \quad 0.566481 \quad 0.970761 \quad -0.286684 \quad 1.293203 \quad -0.134996 \quad -0.749521
     2 0.172312 -0.845432 -1.661443 1.292290 2.376381 -0.957758
     3 -0.039025 -1.118181 -0.131397 0.612306 -0.730028 -0.996033
     4 -0.936385 1.129054 -0.643586 0.104072 -0.879719 0.345509
     [5 rows x 100 columns]
```

8 7. Apply ML Models (with hyperparameter)

9 7.1 kNN

```
# List of params

params = {'n_neighbors':np.arange(3,51,2).tolist(), 'algorithm': ['kd_tree', □

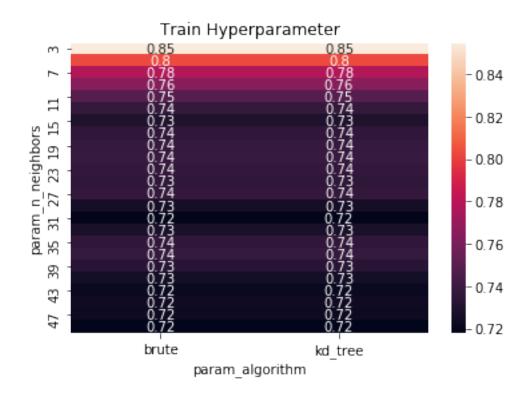
→'brute']}

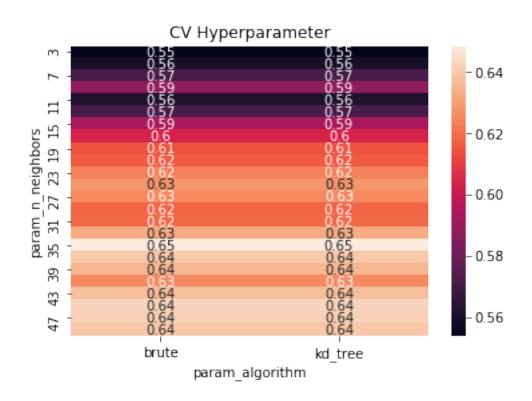
# Instance of knn model

knn_model = KNeighborsClassifier()

# Call hyperparameter for find the best params as possible

knn_clf = hyperparameter_model(knn_model, params)
```





```
[17]: print(knn_clf.best_params_)
     {'algorithm': 'kd_tree', 'n_neighbors': 35}
[18]: clf = CalibratedClassifierCV(knn_clf, cv=3)
      clf.fit(tr_X,tr_y)
[18]: CalibratedClassifierCV(base_estimator=GridSearchCV(cv=RepeatedStratifiedKFold(n_
      repeats=5, n_splits=10, random_state=42),
                                                           error_score=nan,
      estimator=KNeighborsClassifier(algorithm='auto',
        leaf_size=30,
        metric='minkowski',
        metric_params=None,
        n_jobs=None,
        n_neighbors=5,
        p=2,
        weights='uniform'),
                                                           iid='deprecated',
                                                           n_jobs=None,
                                                           param_grid={'algorithm':
      ['kd_tree',
      'brute'],
                                                                        'n_neighbors':
      [3,
      5,
      7,
      9,
      11,
      13,
      15,
      17,
      19,
      21,
      23,
      25,
      27,
      29,
      31,
      33,
      35,
      37,
      39,
      41,
      43,
      45,
      47,
```

10 7.1.1 Kaggle Score

[20]: <matplotlib.image.AxesImage at 0x209091d11c8>



10.1 7.2 Logistic Regression

```
[21]: # Import Logistic Regression from sklearn.linear_model import LogisticRegression
```

```
[22]: # LogisticRegression (See Docs: https://scikit-learn.org/stable/modules/

→ generated/sklearn.linear_model.LogisticRegression.html)

# List of hyperparameter that has to be tuned

params = {'penalty':['11', '12', 'elasticnet'], 'C':[10**i for i in_

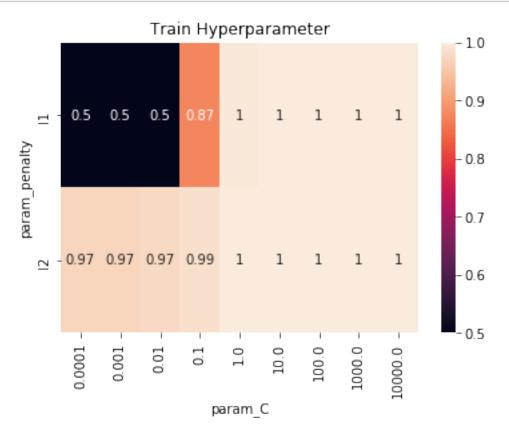
→ range(-4,5)], 'solver':['liblinear','sag']}

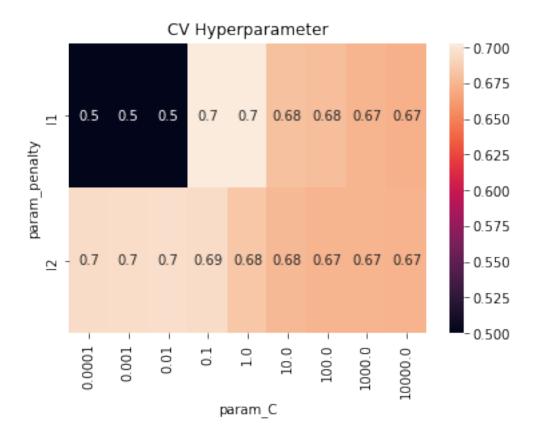
# Instance of Logistic Regression

log_model = LogisticRegression(random_state=42, class_weight='balanced')

# Call hyperparameter to get the best parameters of this model
```

log_clf = hyperparameter_model(log_model, params)





```
[24]: print(log_clf.best_params_)
     {'C': 0.1, 'penalty': 'l1', 'solver': 'liblinear'}
[25]: clf = CalibratedClassifierCV(log_clf, cv=3)
      clf.fit(tr_X,tr_y)
[25]: CalibratedClassifierCV(base_estimator=GridSearchCV(cv=RepeatedStratifiedKFold(n_
      repeats=5, n_splits=10, random_state=42),
                                                          error_score=nan,
      estimator=LogisticRegression(C=1.0,
      class_weight='balanced',
      dual=False,
      fit_intercept=True,
      intercept_scaling=1,
      11_ratio=None,
      max_iter=100,
     multi_class='auto',
      n_jobs=None,
      penalty='12',
      random_state=42,
```

```
solver='lbfgs',
tol=0.0001,
verbose=0,
warm_start=False),
                                                      iid='deprecated',
                                                      n_jobs=None,
                                                      param_grid={'C': [0.0001,
                                                                         0.001,
                                                                         0.01, 0.1,
                                                                         1, 10, 100,
                                                                         1000.
                                                                         10000],
                                                                   'penalty': ['11',
                                                                               '12',
'elasticnet'],
                                                                   'solver':
['liblinear',
'sag']},
                                                      pre_dispatch='2*n_jobs',
                                                      refit=True,
                                                      return_train_score=True,
                                                      scoring='roc_auc',
                                                      verbose=0),
                        cv=3, method='sigmoid')
```

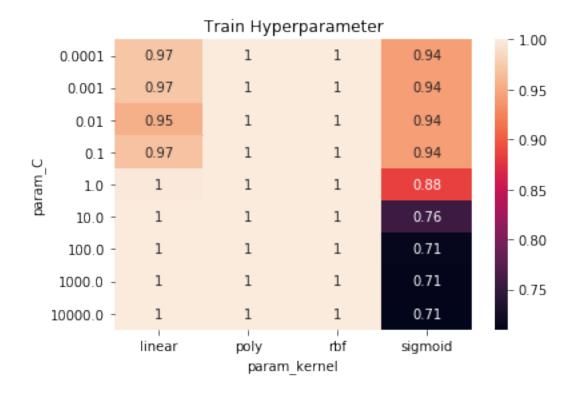
11 7.2.1 Kaggle Score

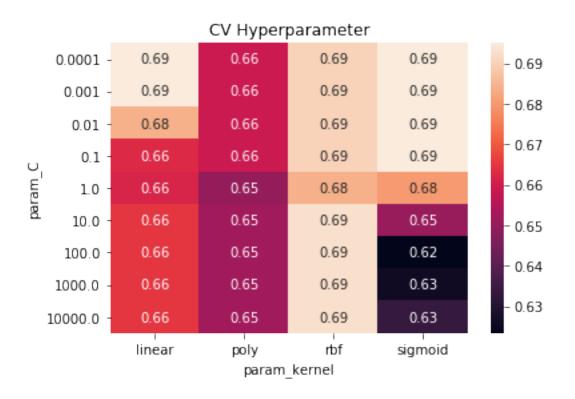
[27]: <matplotlib.image.AxesImage at 0x2090934f388>



12 7.3 SVC

```
[28]: # Import SVC
     from sklearn.svm import SVC
[29]: # SVC (See Docs: https://scikit-learn.org/stable/modules/generated/sklearn.sum.
      \hookrightarrow SVC.html)
      # List of hyperparameter that has to be tuned
     params = {'C':[10**i for i in range(-4,5)], 'kernel':
      →['linear','poly','sigmoid','rbf']}
     # Instance of SVC
     svc_model = SVC(class_weight='balanced', random_state=42, probability=True)
      # Call hyperparameter to find the best parameters
     svc_clf = hyperparameter_model(svc_model, params)
[30]: cv_pvt = pd.pivot_table(pd.DataFrame(svc_clf.cv_results_),__
      columns='param_kernel')
     tr_pvt = pd.pivot_table(pd.DataFrame(svc_clf.cv_results_),__
      →values='mean_train_score', index='param_C', \
                          columns='param_kernel')
     plt.title('Train Hyperparameter')
     sns.heatmap(tr_pvt, annot=True)
     plt.show()
     plt.title('CV Hyperparameter')
     sns.heatmap(cv_pvt, annot=True)
     plt.show()
```





```
[31]: print(svc_clf.best_params_)
     {'C': 0.0001, 'kernel': 'sigmoid'}
[32]: | svc_model = SVC(**svc_clf.best_params_, class_weight='balanced',__
      →random_state=42, probability=True)
      svc_model.fit(tr_X, tr_y)
      clf = CalibratedClassifierCV(svc_clf, cv=3)
      clf.fit(tr_X,tr_y)
[32]: CalibratedClassifierCV(base_estimator=GridSearchCV(cv=RepeatedStratifiedKFold(n_
      repeats=5, n_splits=10, random_state=42),
                                                          error_score=nan,
                                                          estimator=SVC(C=1.0,
      break_ties=False,
                                                                         cache_size=200,
      class_weight='balanced',
                                                                         coef0=0.0,
      decision_function_shape='ovr',
                                                                         degree=3,
                                                                         gamma='scale',
                                                                         kernel='rbf',
                                                                         max_iter=-1,
      probability=True,
      random_state=42,
                                                                         shrinking=True,
                                                                         tol=0.001,
                                                                         verbose=False),
                                                          iid='deprecated',
                                                          n jobs=None,
                                                          param_grid={'C': [0.0001,
                                                                             0.001,
                                                                             0.01, 0.1,
                                                                             1, 10, 100,
                                                                             1000,
                                                                             10000],
                                                                       'kernel':
      ['linear',
      'poly',
      'sigmoid',
      'rbf']},
                                                          pre_dispatch='2*n_jobs',
                                                          refit=True,
                                                          return_train_score=True,
                                                          scoring='roc_auc',
                                                          verbose=0),
```

```
cv=3, method='sigmoid')
```

13 7.3.1 Kaggle Score

```
[33]: # Create a submssion format to make submission in Kaggle

temp_id = df_test['id']

svc_csv = clf.predict_proba(ts_X)[:,1]

svc_df = pd.DataFrame(np.column_stack((temp_id,svc_csv)),

columns=['id','target'])

svc_df['id'] = svc_df['id'].astype('int32')

svc_df.to_csv(data_dir+'/submission_svc_pca100.csv', index=False)
```

```
[34]: image = plt.imread(data_dir+'/submission_svc_pca100.png')
   plt.figure(figsize=(18,5))
   plt.imshow(image)
```

[34]: <matplotlib.image.AxesImage at 0x209006f2908>



14 7.4 RandomForest

```
[35]: # Impoer Random Forest
from sklearn.ensemble import RandomForestClassifier

[36]: # RandomForest (See Docs: https://scikit-learn.org/stable/modules/generated/
```

```
# RandomForest (See Docs: https://scikit-learn.org/stable/modules/generated/

⇒sklearn.ensemble.RandomForestClassifier.html)

# List of hyperparameter that has t be tuned

params = {'n_estimators':[10,20,30,40,50,100,200,300,400],'max_depth':[2,3,5,7]}

# Instance of randomforest

rf_model = RandomForestClassifier(random_state=42)

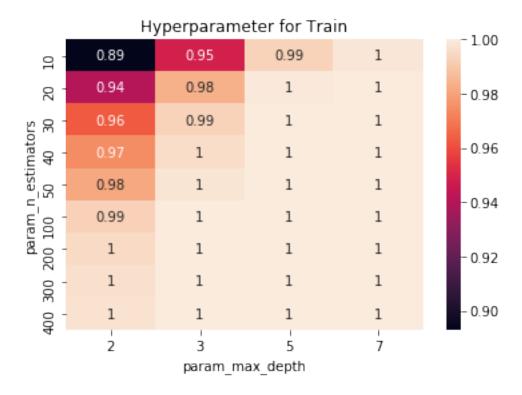
# Perform GridSearchCV to find best parameters

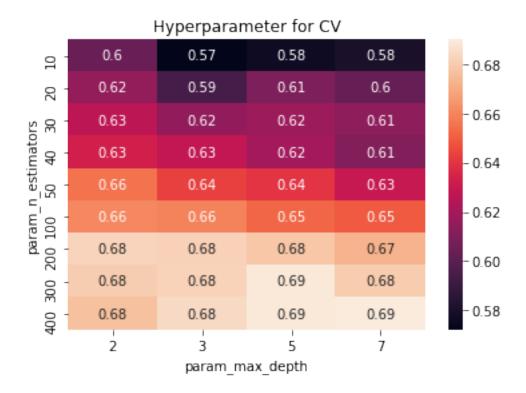
rf_clf = hyperparameter_model(rf_model, params)
```

```
[37]: # Ref: https://stackoverflow.com/questions/48791709/

→how-to-plot-a-heat-map-on-pivot-table-after-grid-search

# Plotting of hyperpameter of train and cv score
```





```
[38]: print(rf_clf.best_params_)
     {'max_depth': 7, 'n_estimators': 400}
[39]: # Calibrate the model
      clf = CalibratedClassifierCV(rf_clf, cv=3)
      clf.fit(tr_X, tr_y)
[39]: CalibratedClassifierCV(base_estimator=GridSearchCV(cv=RepeatedStratifiedKFold(n_
      repeats=5, n_splits=10, random_state=42),
                                                          error_score=nan,
      estimator=RandomForestClassifier(bootstrap=True,
          ccp_alpha=0.0,
          class_weight=None,
          criterion='gini',
          max_depth=None,
          max_features='auto',
          max_leaf_nodes=None,
          max_samples=None,
          min_impurity_decrease=0.0,
          min_impurity_split=N...
          min_samples_split=2,
          min_weight_fraction_leaf=0.0,
```

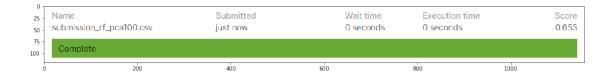
```
n_estimators=100,
    n_jobs=None,
    oob_score=False,
    random_state=42,
    verbose=0,
    warm_start=False),
                                                      iid='deprecated',
                                                      n_jobs=None,
                                                      param_grid={'max_depth': [2,
                                                                                 5,
                                                                                 7],
                                                                   'n estimators':
[10,
20,
30,
40,
50,
100,
200,
300,
400]},
                                                      pre_dispatch='2*n_jobs',
                                                      refit=True,
                                                      return_train_score=True,
                                                      scoring='roc auc',
                                                      verbose=0),
                        cv=3, method='sigmoid')
```

15 7.4.1 Kaggle Score

```
[40]: # Create a submission file format to submit in kaggle
  temp_id = df_test['id']
  rf_csv = clf.predict_proba(ts_X)[:,1]
  rf_df = pd.DataFrame(np.column_stack((temp_id,rf_csv)), columns=['id','target'])
  rf_df['id'] = rf_df['id'].astype('int32')
  rf_df.to_csv(data_dir+'/submission_rf_pca100.csv', index=False)

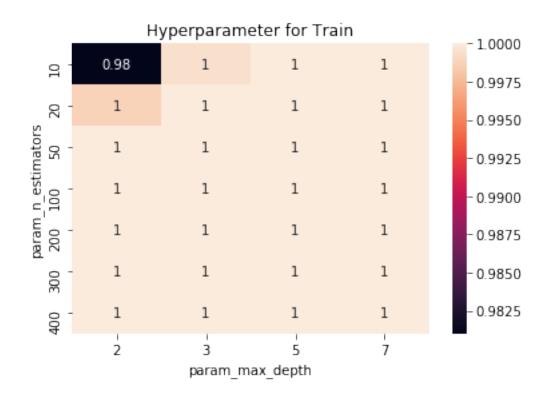
[41]: image = plt.imread(data_dir+'/submission_rf_pca100.png')
  plt.figure(figsize=(18,5))
  plt.imshow(image)
```

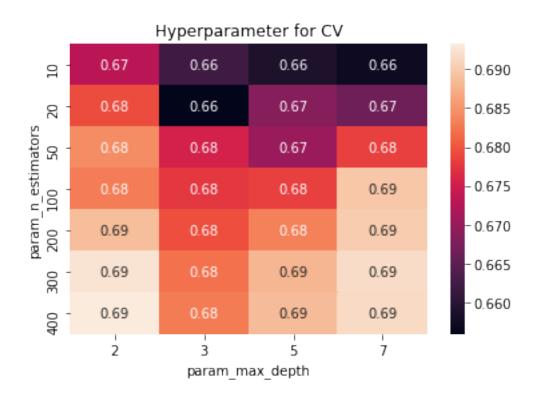
[41]: <matplotlib.image.AxesImage at 0x209023dc1c8>



16 7.5 XGBoost

```
[42]: # Import Xaboost
     from xgboost import XGBClassifier
[43]: # Xgboost (See Docs: https://xgboost.readthedocs.io/en/latest/python/python_api.
      \rightarrow html)
      # List of hyperparameter that has to be tuned
     params = {'max_depth':[2,3,5,7], 'n_estimators':[10,20,50,100,200,300,400]}
     # Instance of XGBoost Model
     xgb_model = XGBClassifier(scale_pos_weight=0.5)
     # Call hyperparameter to find the best parameters
     xgb_clf = hyperparameter_model(xgb_model, params)
[44]: # Ref: https://stackoverflow.com/questions/48791709/
      \rightarrow how-to-plot-a-heat-map-on-pivot-table-after-grid-search
      # Plotting of hyperpameter of train and cv score
     pvt_tr = pd.pivot_table(pd.DataFrame(xgb_clf.cv_results_),__
      →values='mean_train_score', index='param_n_estimators',
      pvt_cv = pd.pivot_table(pd.DataFrame(xgb_clf.cv_results_),__
      →values='mean_test_score', index='param_n_estimators',
      plt.figure(1)
     plt.title('Hyperparameter for Train')
     sns.heatmap(pvt_tr, annot=True)
     plt.figure(2)
     plt.title('Hyperparameter for CV')
     sns.heatmap(pvt cv, annot=True)
     plt.show()
```



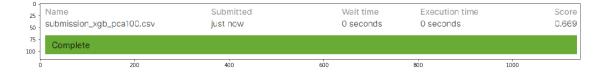


```
[45]: print(xgb_clf.best_params_)
     {'max_depth': 2, 'n_estimators': 400}
[46]: # Calibrate the model
      clf = CalibratedClassifierCV(xgb_clf, cv=3)
      clf.fit(tr_X, tr_y)
[46]: CalibratedClassifierCV(base_estimator=GridSearchCV(cv=RepeatedStratifiedKFold(n_
      repeats=5, n_splits=10, random_state=42),
                                                           error_score=nan,
      estimator=XGBClassifier(base_score=None,
      booster=None,
      colsample_bylevel=None,
      colsample_bynode=None,
      colsample_bytree=None,
      gamma=None,
      gpu_id=None,
      importance_type='gain',
      interaction_constraints=None,
      learning_rate=None,
                                                                                    m...
      random_state=None,
      reg_alpha=None,
      reg_lambda=None,
      scale_pos_weight=0.5,
      subsample=None,
      tree_method=None,
      validate_parameters=False,
      verbosity=None),
                                                           iid='deprecated',
                                                           n jobs=None,
                                                           param_grid={'max_depth': [2,
                                                                                      3,
                                                                                      5,
                                                                                      7],
                                                                        'n_estimators':
      [10,
      20,
      50,
      100,
      200,
      300,
      400]},
                                                           pre_dispatch='2*n_jobs',
                                                           refit=True,
                                                           return_train_score=True,
```

```
scoring='roc_auc',
verbose=0),
cv=3, method='sigmoid')
```

17 7.5.1 Kaggle Score

[48]: <matplotlib.image.AxesImage at 0x2090ae87a88>

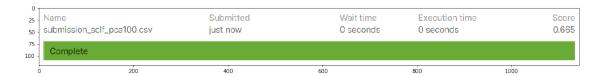


18 7.6 Stacking Classifier

```
clf2.fit(tr_X,tr_y)
      clf2 = CalibratedClassifierCV(clf2, cv=3)
      # Classifier 3: XGBoost with best params
      clf3 = XGBClassifier(max_depth=2, n_estimators=400, scale_pos_weight=0.5)
      clf3.fit(tr_X,tr_y)
      clf3 = CalibratedClassifierCV(clf3, cv=3)
      # Classifier 4: RF with best params
      clf4 = RandomForestClassifier(max_depth=7, n_estimators=400)
      clf4.fit(tr X,tr y)
      clf4 = CalibratedClassifierCV(clf4, cv=3)
      # Stack Classifier
      sclf = StackingClassifier(classifiers=[clf1,clf2,clf3,clf4],__
      →meta_classifier=clf1, use_probas=True)
      # Fit the model
      sclf.fit(tr_X, tr_y)
[50]: StackingClassifier(average_probas=False,
      classifiers=[CalibratedClassifierCV(base_estimator=LogisticRegression(C=0.1,
               class_weight='balanced',
               dual=False,
               fit_intercept=True,
               intercept_scaling=1,
               11_ratio=None,
               max_iter=100,
               multi_class='auto',
               n_jobs=None,
               penalty='11',
               random_state=42,
               solver='liblinear',
               tol=0.0001,
               verbose=0,
               warm_start=False),
                                                              cv=3, method='si...
      meta_classifier=CalibratedClassifierCV(base_estimator=LogisticRegression(C=0.1,
                  class_weight='balanced',
                  dual=False,
                  fit_intercept=True,
                  intercept_scaling=1,
                  11_ratio=None,
                  max_iter=100,
                  multi_class='auto',
                  n_jobs=None,
                  penalty='11',
```

19 7.6.1 Kaggle score

[52]: <matplotlib.image.AxesImage at 0x2090ae78fc8>



20 7.7 Voting Classifier (Without Stack Classifier + no weights)

```
[54]: EnsembleVoteClassifier(clfs=[CalibratedClassifierCV(base_estimator=LogisticRegre
      ssion(C=0.1,
            class weight='balanced',
            dual=False,
            fit intercept=True,
            intercept_scaling=1,
            11 ratio=None,
            max_iter=100,
            multi_class='auto',
            n_jobs=None,
            penalty='11',
            random_state=42,
            solver='liblinear',
            tol=0.0001,
            verbose=0,
            warm_start=False),
                                                            cv=3, method='sigmoid'),
                                    CalibratedClassi...
                max_depth=7,
                max features='auto',
                max leaf nodes=None,
                max samples=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=400,
                n_jobs=None,
                oob_score=False,
                random_state=None,
                verbose=0,
                warm_start=False),
                                                            cv=3, method='sigmoid')],
                              refit=True, verbose=0, voting='hard', weights=None)
```

21 7.7.1 Kaggle Score

```
[56]: image = plt.imread(data_dir+'/submission_eclf_pca100.png')
    plt.figure(figsize=(18,5))
    plt.imshow(image)
```

[56]: <matplotlib.image.AxesImage at 0x2090e4be508>



22 7.8 Voting Classifier (With Stack Classifier + no weights)

```
[57]: # Voting Classifier (See Docs: http://rasbt.github.io/mlxtend/user_guide/
       →classifier/EnsembleVoteClassifier/)
      eclf = EnsembleVoteClassifier(clfs=[clf1, clf2,clf3,clf4,sclf])
      # Fit the train data
      eclf.fit(tr_X,tr_y)
[57]: EnsembleVoteClassifier(clfs=[CalibratedClassifierCV(base_estimator=LogisticRegre
      ssion(C=0.1,
            class_weight='balanced',
            dual=False,
            fit_intercept=True,
            intercept_scaling=1,
            11_ratio=None,
            max_iter=100,
            multi_class='auto',
            n_jobs=None,
            penalty='11',
            random_state=42,
            solver='liblinear',
            tol=0.0001,
            verbose=0,
            warm_start=False),
                                                            cv=3, method='sigmoid'),
                                    CalibratedClassi...
                                                fit_intercept=True,
                                                intercept_scaling=1,
                                                11_ratio=None,
                                                max_iter=100,
                                                multi_class='auto',
                                                n_jobs=None,
                                                penalty='11',
```

23 7.8.1 Kaggle Score

plt.imshow(image)

[59]: <matplotlib.image.AxesImage at 0x2090e871408>



24 7.9 Voting Classifier (without Stack Classifier + weights)

```
ssion(C=0.1,
            class weight='balanced',
            dual=False,
            fit intercept=True,
            intercept_scaling=1,
            11 ratio=None,
            max_iter=100,
           multi_class='auto',
            n_jobs=None,
            penalty='11',
            random_state=42,
            solver='liblinear',
            tol=0.0001,
            verbose=0,
            warm_start=False),
                                                          cv=3, method='sigmoid'),
                                   CalibratedClassi...
                max_features='auto',
               max leaf nodes=None,
               max samples=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=400,
                n_jobs=None,
                oob_score=False,
                random_state=None,
                verbose=0,
                warm_start=False),
                                                          cv=3, method='sigmoid')],
                             refit=True, verbose=0, voting='hard',
                             weights=[0.3, 0.3, 0.15, 0.25])
     # 7.9.1 Kaggle Score
[61]: # Create a submission file format to submit in Kaggle
      temp_id = df_test['id']
      eclf csv = eclf.predict proba(ts X)[:,1]
      eclf_df = pd.DataFrame(np.column_stack((temp_id,eclf_csv)),__
      eclf_df['id'] = eclf_df['id'].astype('int32')
      eclf_df.to_csv(data_dir+'/submission_eclf_weights_pca100.csv', index=False)
```

[60]: EnsembleVoteClassifier(clfs=[CalibratedClassifierCV(base_estimator=LogisticRegre

```
[62]: image = plt.imread(data_dir+'/submission_eclf_weights_pca100.png')
    plt.figure(figsize=(18,5))
    plt.imshow(image)
```

[62]: <matplotlib.image.AxesImage at 0x2090eaa8388>



25 7.10 Voting Classifier (with Stack Classifier + weights)

```
[63]: | # Voting Classifier (See Docs: http://rasbt.github.io/mlxtend/user_guide/
       →classifier/EnsembleVoteClassifier/)
      eclf = EnsembleVoteClassifier(clfs=[clf1,clf2,clf3,clf4,sclf], weights=[0.3,0.
       \rightarrow3,0.1,0.1,0.2])
      # Fit the train data
      eclf.fit(tr_X,tr_y)
[63]: EnsembleVoteClassifier(clfs=[CalibratedClassifierCV(base_estimator=LogisticRegre
      ssion(C=0.1,
            class_weight='balanced',
            dual=False,
            fit_intercept=True,
            intercept_scaling=1,
            11_ratio=None,
            max_iter=100,
            multi_class='auto',
            n_jobs=None,
            penalty='11',
            random_state=42,
            solver='liblinear',
            tol=0.0001,
            verbose=0,
            warm_start=False),
                                                            cv=3, method='sigmoid'),
                                    CalibratedClassi...
                                                 intercept_scaling=1,
                                                 11_ratio=None,
                                                 max iter=100,
                                                 multi_class='auto',
                                                 n_jobs=None,
                                                 penalty='11',
```

26 7.10.1 Kaggle Score

```
[64]: # Create a submission file format to submit in Kaggle

temp_id = df_test['id']

eclf_csv = eclf.predict_proba(ts_X)[:,1]

eclf_df = pd.DataFrame(np.column_stack((temp_id,eclf_csv)),

→columns=['id','target'])

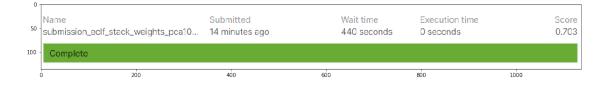
eclf_df['id'] = eclf_df['id'].astype('int32')

eclf_df.to_csv(data_dir+'/submission_eclf_stack_weights_pca100.csv',

→index=False)
```

```
[65]: image = plt.imread(data_dir+'/submission_eclf_stack_weights_pca100.png')
    plt.figure(figsize=(18,5))
    plt.imshow(image)
```

[65]: <matplotlib.image.AxesImage at 0x2090abe0588>



27 6. Summary of All Models

```
[66]: from prettytable import PrettyTable
    x = PrettyTable()
    x.field_names = ['Model','Features','Hyperparameter','Test Score']
    x.add_row(['knn','AF',r"{'algorithm': 'kd_tree', 'n_neighbors': 35}",0.652])
```

```
x.add_row(['Logistic Regression','AF',r"{'C': 0.1, 'penalty': '11', 'solver':
 →'liblinear'}",0.702])
x.add_row(['SVC','AF',r"{'C': 0.0001, 'kernel': 'sigmoid'}",0.707])
x.add_row(['RandomForest','AF',r"{'max_depth': 7, 'n_estimators': 400}",0.653])
x.add_row(['XGBoost','AF',r"{'max_depth': 2, 'n_estimators': 400}",0.669])
x.add row(['Stacking Classifier','AF','-',0.665])
x.add_row(['Voting Classifier(No stacking + no weights)','AF',"-",0.702])
x.add_row(['Voting Classifier(stacking + no weights)','AF',"-",0.697])
x.add_row(['Voting Classifier(no stacking + weights)','AF',"-",0.705])
x.add_row(['Voting Classifier(stacking + weights)','AF',"-",0.703])
print(x)
+----+
                  Model
                                         | Features |
                             | Test Score |
Hyperparameter
-----+
                                                     {'algorithm':
                   knn
                                             AF
'kd_tree', 'n_neighbors': 35} | 0.652
                                                   | {'C': 0.1, 'penalty':
            Logistic Regression
                                             AF
'l1', 'solver': 'liblinear'} |
                            0.702
                   SVC
                                                           {'C': 0.0001,
                                             AF
'kernel': 'sigmoid'}
                             0.707
               RandomForest
                                                         {'max depth':
                                             ΑF
7, 'n_estimators': 400}
                           0.653
                                                         {'max depth':
                 XGBoost
                                             ΑF
2, 'n_estimators': 400}
                               0.669
            Stacking Classifier
                                             AF
                        1
                           0.665
| Voting Classifier(No stacking + no weights) |
                           0.702
   Voting Classifier(stacking + no weights) |
                           0.697
   Voting Classifier(no stacking + weights) |
                          0.705
    Voting Classifier(stacking + weights)
                                             ΑF
                          0.703
   -----+
Notation: 1. AF: All features
```

34

[]: