```
In [1]: # import warnings
        # warnings.filterwarnings('ignore')
In [2]: # import libraries
        import pandas as pd
        import numpy as np
        import seaborn as sns
        import matplotlib.pyplot as plt
        from scipy import sparse
        %matplotlib inline
        from sklearn.model selection import RandomizedSearchCV
        from scipy.stats import uniform
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.svm import LinearSVC
        from sklearn.calibration import CalibratedClassifierCV
        from sklearn.linear model import LogisticRegression
        from sklearn.ensemble import RandomForestClassifier
        from xgboost import XGBClassifier
        from catboost import CatBoostClassifier
        import pickle
        Amazon Employee Access Challenge
In [3]: train = pd.read csv('data/train.csv')
        test = pd.read csv('data/test.csv')
In [4]: train.shape
Out[4]: (32769, 10)
In [5]: test.shape
```

```
Out[5]: (58921, 10)
In [6]: y train = train['ACTION']
In [7]: y_train.shape
Out[7]: (32769,)
In [8]: train data = train.drop('ACTION', axis=1)
         train data.shape
Out[8]: (32769, 9)
In [9]: test data = test.drop('id', axis=1)
         test data.shape
Out[9]: (58921, 9)
         Common Variables
In [10]: # define variables
         random state = 42
         cv = 5
         scoring = 'roc auc'
         verbose=2
         Common functions
In [11]: def save_submission(predictions, filename):
             Save predictions into csv file
             global test
             submission = pd.DataFrame()
```

```
submission["Id"] = test["id"]
             submission["ACTION"] = predictions
             filepath = "result/sampleSubmission "+filename
             submission.to csv(filepath, index = False)
In [12]: def print graph(results, param1, param2, xlabel, ylabel, title='Plot sh
         owing the ROC AUC score for various hyper parameter values'):
             Plot the graph
             plt.plot(results[param1], results[param2]);
             plt.grid();
             plt.xlabel(xlabel);
             plt.ylabel(ylabel);
             plt.title(title);
In [13]: def get_rf_params():
             Return dictionary of parameters for random forest
             params = {
                   'n estimators':[10,20,50,100,200,500,700,1000],
                   'max depth':[1,2,5,10,12,15,20,25],
                   'max features':[1,2,3,4,5],
                   'min samples split':[2,5,7,10,20]
             }
             return params
In [14]: def get_xgb_params():
             Return dictionary of parameters for xgboost
             params = {
                  'n estimators': [10,20,50,100,200,500,750,1000],
                  'learning rate': uniform(0.01, 0.6),
                  'subsample': uniform(),
                  'max depth': [3, 4, 5, 6, 7, 8, 9],
```

```
'colsample_bytree': uniform(),
    'min_child_weight': [1, 2, 3, 4]
}
return params
```

## We will try following models

- 1. KNN
- 2. SVM
- 3. Logistic Regression
- 4. Random Forest
- 5. Xgboost

## **Build Models on the raw data**

## 1.1 KNN with raw features

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	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_n_neighbors	param
0	0.083934	0.007898	0.265385	0.036920	1	{'n_neighbors
3	0.240013	0.066697	0.500296	0.106391	6	{'n_neighbors (
7	0.226630	0.185183	0.727930	0.213502	16	{'n_neighbors 16
5	0.243259	0.052800	0.871988	0.100550	26	{'n_neighbors 26
4	0.183503	0.043958	0.783068	0.125342	41	{'n_neighbors 4'
6	0.228750	0.048025	1.059379	0.235010	56	{'n_neighbors 56
2	0.311753	0.040799	1.216632	0.265773	76	{'n_neighbors 70
9	0.270957	0.199804	0.948423	0.458374	81	{'n_neighbors 8'
1	0.168152	0.078784	1.293272	0.219475	86	{'n_neighbors 86
8	0.108329	0.024517	1.590826	0.059955	91	{'n_neighbors 9'
4						•

In [17]: print\_graph(results, 'param\_n\_neighbors', 'mean\_test\_score', 'Hyperpara
meter - No. of neighbors', 'Test score')

## Plot showing the ROC\_AUC score for various hyper parameter values 0.68 0.67 0.66 0.65 0.64

40

Hyperparameter - No. of neighbors

```
In [18]: best_c=best_model.best_params_['n_neighbors']
best_c
```

60

80

Out[18]: 6

In [19]: model = KNeighborsClassifier(n\_neighbors=best\_c,n\_jobs=-1)
model.fit(train\_data,y\_train)

Out[19]: KNeighborsClassifier(n\_jobs=-1, n\_neighbors=6)

20

In [20]: predictions = model.predict\_proba(test\_data)[:,1]
 save\_submission(predictions, "knn\_raw.csv")

knn-raw

0.63

## 1.2 SVM with raw feature

In [21]: C\_val = uniform(loc=0, scale=4)

```
model= LinearSVC(verbose=verbose,random state=random state,class weight
='balanced', max iter=2000)
parameters={'C':C val}
clf = RandomizedSearchCV(model,parameters,random_state=random_state,cv=
cv,verbose=verbose,scoring=scoring,n jobs=-1)
best model = clf.fit(train data,y train)
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
ers.
[Parallel(n jobs=-1)]: Done 25 tasks | elapsed: 1.3min
[Parallel(n jobs=-1)]: Done 50 out of 50 | elapsed: 2.0min finished
```

### [LibLinear]

/home/auw-mayank/.local/lib/python3.6/site-packages/sklearn/svm/ base.p y:977: ConvergenceWarning: Liblinear failed to converge, increase the n umber of iterations.

"the number of iterations.", ConvergenceWarning)

```
In [22]: best c=best model.best params ['C']
         best c
```

Out[22]: 1.49816047538945

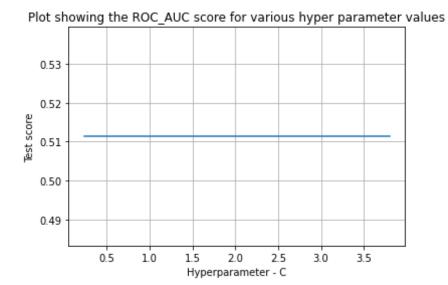
```
In [23]: results = pd.DataFrame.from dict(best model.cv results )
         results=results.sort values('param C')
         results
```

## Out[231:

params	param_C	std_score_time	mean_score_time	std_fit_time	mean_fit_time	
{'C': 0.23233444867279784}	0.232334	0.000217	0.009284	0.499781	18.684481	6
{'C': 0.6239780813448106}	0.623978	0.000904	0.009752	0.305372	19.870518	5
{'C': 0.6240745617697461}	0.624075	0.001661	0.011202	0.358008	19.918902	4

params	param_C	std_score_time	mean_score_time	std_fit_time	mean_fit_time	
{'C': 1.49816047538945}	1.49816	0.000190	0.009220	0.216182	19.442288	0
{'C': 2.3946339367881464}	2.39463	0.000562	0.009917	0.560751	19.357509	3
{'C': 2.404460046972835}	2.40446	0.001407	0.008356	0.356759	18.831271	8
{'C': 2.832290311184182}	2.83229	0.001171	0.006211	5.223100	14.130057	9
{'C': 2.9279757672456204}	2.92798	0.000543	0.009577	0.453250	18.946967	2
{'C': 3.4647045830997407}	3.4647	0.000678	0.009629	0.394303	18.603018	7
{'C': 3.8028572256396647}	3.80286	0.000622	0.009244	0.234885	19.380741	1
<b>+</b>						4
{ 2.927975767245620 { 3.464704583099740 {	3.4647	0.000678	0.009629	0.394303	18.603018	7

In [24]: print\_graph(results, 'param\_C', 'mean\_test\_score', 'Hyperparameter - C'
 , 'Test score')



## In [25]: #https://stackoverflow.com/questions/26478000/converting-linearsvcs-dec ision-function-to-probabilities-scikit-learn-python model = LinearSVC(C=best\_c,verbose=verbose,random\_state=random\_state,cl ass\_weight='balanced',max\_iter=2000) model = CalibratedClassifierCV(model) model.fit(train\_data,y\_train)

## [LibLinear]

/home/auw-mayank/.local/lib/python3.6/site-packages/sklearn/svm/\_base.p y:977: ConvergenceWarning: Liblinear failed to converge, increase the n umber of iterations.

"the number of iterations.", ConvergenceWarning)

## [LibLinear]

/home/auw-mayank/.local/lib/python3.6/site-packages/sklearn/svm/\_base.p y:977: ConvergenceWarning: Liblinear failed to converge, increase the n umber of iterations.

"the number of iterations.", ConvergenceWarning)

## [LibLinear]

/home/auw-mayank/.local/lib/python3.6/site-packages/sklearn/svm/\_base.p y:977: ConvergenceWarning: Liblinear failed to converge, increase the n umber of iterations.

"the number of iterations.", ConvergenceWarning)

## [LibLinear]

/home/auw-mayank/.local/lib/python3.6/site-packages/sklearn/svm/\_base.p y:977: ConvergenceWarning: Liblinear failed to converge, increase the n umber of iterations.

"the number of iterations.", ConvergenceWarning)

## [LibLinear]

/home/auw-mayank/.local/lib/python3.6/site-packages/sklearn/svm/\_base.p y:977: ConvergenceWarning: Liblinear failed to converge, increase the n umber of iterations.

"the number of iterations.", ConvergenceWarning)

```
Out[25]: CalibratedClassifierCV(base estimator=LinearSVC(C=1.49816047538945,
                                                        class weight='balance
         d',
                                                        max iter=2000, random s
         tate=42,
                                                        verbose=2))
In [26]: predictions = model.predict proba(test data)[:,1]
         save submission(predictions, 'svm raw.csv')
         svm-raw
         1.3 Logistic Regression with Raw Feature
In [27]: C val = uniform(loc=0, scale=4)
         lr= LogisticRegression(verbose=verbose, random state=random state, class
         weight='balanced',solver='lbfgs',max iter=500,n jobs=-1)
         parameters={'C':C val}
         clf = RandomizedSearchCV(lr,parameters,random state=random state,cv=cv,
         verbose=verbose,n iter=100,scoring=scoring,n jobs=-1)
         best model = clf.fit(train data,y train)
         Fitting 5 folds for each of 100 candidates, totalling 500 fits
         [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
         ers.
         [Parallel(n jobs=-1)]: Done 25 tasks
                                                     elapsed:
                                                                 1.2s
         [Parallel(n jobs=-1)]: Done 146 tasks
                                                     elapsed:
                                                                 6.1s
         [Parallel(n jobs=-1)]: Done 349 tasks
                                                     elapsed:
                                                                14.3s
         [Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed:
                                                               20.5s finished
         [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
         ers.
         [Parallel(n jobs=-1)]: Done 1 out of 1 | elapsed:
                                                                  0.3s finished
In [28]: best c=best model.best params ['C']
```

best\_c Out[28]: 1.49816047538945 In [29]: results = pd.DataFrame.from\_dict(best\_model.cv\_results\_)
results=results.sort\_values('param\_C') results Out[29]: mean\_fit\_time std\_fit\_time mean\_score\_time std\_score\_time param C parai 72 0.305453 0.042840 0.007123 0.001411 0.0220885 0.02208846849440959 10 0.299544 0.043052 0.009865 0.001636 0.082338 0.0823379771832097 98 0.324737 0.029356 0.009632 0.001840 0.101677 0.1016765069763807 42 0.322684 0.047769 0.008097 0.001223 0.137554 0.137554084460873 58 0.312479 0.040692 0.010287 0.003491 0.180909 0.1809091556421522 1 0.330116 0.064433 0.008579 0.001581 3.80286 3.802857225639664 34 0.307352 0.038496 0.009020 0.000806 3.86253 3.862528132298237 50 0.286139 0.050608 0.008554 0.001624 3.87834 3.878338511058234 11 0.311766 0.046068 0.009899 0.002444 3.87964 3.879639408647977 69 0.288068 0.009172 0.001290 0.053532 3.94755 3.94754774640206 100 rows × 14 columns

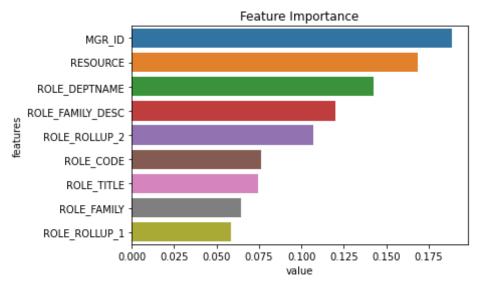
```
In [30]: print_graph(results, 'param_C', 'mean_test_score', 'Hyperparameter - C'
         , 'Test score')
          Plot showingsthe RQC1AUC score for various hyper parameter values
             44
             42
             38
                              1.5
                                   2.0
                                       2.5
                                                3.5
                    0.5
                         1.0
                                            3.0
                              Hyperparameter - C
In [31]: model = LogisticRegression(C=best c,verbose=verbose,n jobs=-1,random st
         ate=random state,class weight='balanced',solver='lbfgs')
         model.fit(train data,y train)
         [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
         ers.
         [Parallel(n jobs=-1)]: Done 1 out of 1 | elapsed:
                                                                    0.3s finished
Out[31]: LogisticRegression(C=1.49816047538945, class weight='balanced', n jobs=
         -1,
                             random state=42, verbose=2)
In [32]: predictions = model.predict proba(test data)[:,1]
         save submission(predictions, 'lr raw.csv')
```

## 1.4 Random Forest with Raw Feature

```
In [33]: rfc = RandomForestClassifier(random state=random state,class weight='ba
         lanced',n jobs=-1)
         clf = RandomizedSearchCV(rfc,get rf params(),random state=random state,
         cv=cv,verbose=verbose,n iter=100,scoring=scoring,n jobs=-1)
         best model = clf.fit(train data,y train)
         Fitting 5 folds for each of 100 candidates, totalling 500 fits
         [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
         ers.
         [Parallel(n jobs=-1)]: Done 25 tasks
                                                      | elapsed:
                                                                   21.1s
         /home/auw-mayank/.local/lib/python3.6/site-packages/joblib/externals/lo
         ky/process executor.py:691: UserWarning: A worker stopped while some jo
         bs were given to the executor. This can be caused by a too short worker
         timeout or by a memory leak.
           "timeout or by a memory leak.", UserWarning
         [Parallel(n jobs=-1)]: Done 146 tasks
                                                      | elapsed: 4.6min
          [Parallel(n jobs=-1)]: Done 349 tasks
                                                      | elapsed: 10.3min
          [Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed: 15.1min finished
In [34]: results = pd.DataFrame(best model.cv results )
         results.sort values('mean test score',ascending=False,inplace=True)
         param keys=['param '+str(each) for each in get rf params().kevs()]
         param keys.append('mean test score')
         results[param keys].head(10)
Out[34]:
             param n estimators param max depth param max features param min samples split mean
          78
                         700
                                        25
                                                          2
                                                                              7
          62
                         500
                                         25
                                                          3
                                                                              5
          79
                         500
                                        25
                                                                             10
          55
                                                          2
                                                                              5
                         200
                                         25
          22
                         200
                                        25
                                                                             10
```

	param_	_n_estimators	param_max_depth	param_max_features	param_min_samples_split	mean			
	20	1000	25	3	2				
	85	1000	20	3	7				
	33	700	25	4	2				
	84	1000	25	5	2				
	27	50	25	2	10				
	4					<b>&gt;</b>			
In [35]:	max_featumax_deptl	ures=clf.best_ les_split=		ax_features']					
Out[35]:	35]: (700, 2, 25, 7)								
In [36]:	[36]: model=RandomForestClassifier(n_estimators=n_estimators,max_depth=max_pth,max_features=max_features,								
	<pre>model.fit(train_data,y_train)</pre>								
Out[36]:	RandomFor	restClassi <sup>.</sup>			max_depth=25, max_fe timators=700, n_jobs				
	1,		random_sta	random_state=42)					
In [37]:	important features	=pd.DataFr	eature_importa ame({' <mark>features</mark>	nces_ ':features,' <mark>valu</mark> <mark>alue'</mark> ,ascending=					





## **Features Observations:**

1. MGR\_ID is the most important feature followed by RESOURCE and ROLE\_DEPTNAME

```
In [38]: predictions = model.predict_proba(test_data)[:,1]
save_submission(predictions, 'rf_raw.csv')
```



## 1.5 Xgboost with Raw Feature

```
In [39]: xgb = XGBClassifier()
clf = RandomizedSearchCV(xgb,get_xgb_params(),random_state=random_state
```

```
,cv=cv,verbose=verbose,n iter=100,scoring=scoring,n jobs=-1)
          best model=clf.fit(train data,y train)
          Fitting 5 folds for each of 100 candidates, totalling 500 fits
          [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
          ers.
          [Parallel(n jobs=-1)]: Done 25 tasks
                                                           elapsed:
                                                                        7.2s
          [Parallel(n jobs=-1)]: Done 146 tasks
                                                           elapsed:
                                                                     1.5min
          [Parallel(n jobs=-1)]: Done 349 tasks
                                                          elapsed: 4.1min
          [Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed: 6.9min finished
In [40]:
          results = pd.DataFrame(best model.cv results )
          results.sort values('mean test score', ascending=False, inplace=True)
          param keys=['param '+str(each) for each in get xgb params().keys()]
          param keys.append('mean test score')
          results[param keys].head(10)
Out[40]:
              param_n_estimators param_learning_rate param_subsample param_max_depth param_colsan
           18
                                                       0.665922
                                                                            9
                          1000
                                        0.048135
           44
                          1000
                                        0.060484
                                                       0.606429
                                                                            6
           97
                           750
                                        0.232385
                                                       0.907694
                                                                            6
                                                                            7
           96
                           500
                                       0.0979629
                                                        0.98664
                                                                            9
           62
                           500
                                       0.0663892
                                                       0.328153
                                                                            8
           49
                           500
                                        0.160277
                                                       0.393098
           84
                           200
                                        0.571989
                                                       0.967581
                                                                            6
           53
                           200
                                        0.540096
                                                       0.928319
                                                                            6
                                                                            9
           86
                          1000
                                        0.475848
                                                       0.858413
                                                       0.683264
                                                                            6
           8
                           750
                                       0.0686033
In [41]: colsample bytree = clf.best params ['colsample bytree']
          learning_rate=clf.best params ['learning rate']
```

```
max depth=clf.best params ['max depth']
         min child weight=clf.best params ['min child weight']
         n estimators=clf.best params ['n estimators']
         subsample=clf.best params ['subsample']
         colsample by tree, learning rate, max depth, min child weight, n estimators,
         subsample
Out[41]: (0.3308980248526492, 0.04813501017161418, 9, 2, 1000, 0.665922356617496
         7)
In [42]: model = XGBClassifier(colsample bytree=colsample bytree,learning rate=l
         earning rate, max depth=max depth,
                              min child weight=min child weight,n estimators=n e
         stimators,subsample=subsample,n jobs=-1)
         model.fit(train data,y train)
Out[42]: XGBClassifier(base score=0.5, booster='gbtree', colsample bylevel=1,
                       colsample bynode=1, colsample bytree=0.3308980248526492,
         gamma=0,
                       gpu id=-1, importance type='gain', interaction constraint
         s='',
                       learning rate=0.04813501017161418, max delta step=0, max
         depth=9,
                       min child weight=2, missing=nan, monotone constraints
         ='()',
                       n estimators=1000, n jobs=-1, num parallel tree=1, random
         state=0,
                       reg alpha=0, reg lambda=1, scale pos weight=1,
                       subsample=0.6659223566174967, tree method='exact',
                       validate parameters=1, verbosity=None)
In [43]: features=train data.columns
         importance=model.feature importances
         features=pd.DataFrame({'features':features,'value':importance})
         features=features.sort values('value',ascending=False)
         sns.barplot('value', 'features', data=features);
         plt.title('Feature Importance');
```



+	-+	+	.+	+
KNN	Raw	0.67224	0.68148	İ
j SVM	j Raw	0.50286	0.5139	İ
Logistic Regression	j Raw	0.53857	0.53034	İ
Random Forest	Raw	0.87269	0.87567	Ĺ
Xgboost	Raw	0.86988	0.87909	İ
+	-+	+	.+	+

## **Observations:**

- 1. Xgboost perform best on the raw features
- 2. Random forest also perform good on raw features
- 3. Tree based models performs better than linear models for raw features

## Build model on one hot encoded features

## 2.1 KNN with one hot encoded features

```
In [46]: train_ohe = sparse.load_npz('data/train_ohe.npz')
    test_ohe = sparse.load_npz('data/test_ohe.npz')
    train_ohe.shape, test_ohe.shape, y_train.shape

Out[46]: ((32769, 4500), (58921, 4500), (32769,))

In [47]: parameters={'n_neighbors':np.arange(1,100, 5)}
    clf = RandomizedSearchCV(KNeighborsClassifier(n_jobs=-1),parameters,ran
    dom_state=random_state,cv=cv,verbose=verbose,scoring=scoring,n_jobs=4)
    best_model = clf.fit(train_ohe,y_train)

Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=4)]: Using backend LokyBackend with 4 concurrent worke
```

```
rs.
          [Parallel(n jobs=4)]: Done 50 out of 50 | elapsed: 3.2min finished
          results = pd.DataFrame.from_dict(best_model.cv_results_)
In [48]:
          results=results.sort values('param n neighbors')
          results
Out[48]:
              mean_fit_time std_fit_time mean_score_time std_score_time param_n_neighbors
                                                                                       param
                                                                                1 {'n_neighbors
           0
                  0.008579
                            0.000699
                                           12.889389
                                                         1.630046
                                                                                6 {'n_neighbors
           3
                  0.218653
                            0.141987
                                           13.355838
                                                         1.399583
                                                                               16 {'n_neighbors
           7
                  0.014216
                            0.010986
                                           11.480899
                                                         0.587346
                                                                               26 {'n_neighbors
           5
                  0.007408
                                                         0.072001
                            0.000506
                                           11.399296
                                                                               41 {'n_neighbors
           4
                  0.029331
                            0.037009
                                                         0.352833
                                           11.730860
                                                                               56 {'n_neighbors
           6
                  0.017152
                            0.013375
                                                         0.940570
                                           12.010613
                                                                               76 {'n_neighbors
           2
                  0.325559
                            0.159848
                                           31.339497
                                                        13.256170
                                                                               81 {'n_neighbors
           9
                  0.013539
                                            9.540637
                                                         2.054831
                            0.006507
                                                                               86 {'n_neighbors
           1
                  0.103347
                            0.155776
                                           24.211115
                                                         9.506957
                                                                               91 {'n_neighbors
           8
                                           11.831052
                                                         0.749635
                  0.016657
                            0.008175
In [49]:
          print_graph(results, 'param_n_neighbors', 'mean_test_score', 'Hyperpara
          meter - No. of neighbors', 'Test score')
```

# Plot showing the ROC\_AUC score for various hyper parameter values 0.800 0.775 0.750 0.725 0.700 0.675 0.650 Hyperparameter - No. of neighbors

```
In [50]: best_c=best_model.best_params_['n_neighbors']
best_c
```

Out[50]: 16

```
In [51]: model = KNeighborsClassifier(n_neighbors=best_c,n_jobs=-1)
model.fit(train_ohe,y_train)
```

Out[51]: KNeighborsClassifier(n\_jobs=-1, n\_neighbors=16)

knn-ohe

## 2.2 SVM with one hot encoded features

```
In [53]: C_val = uniform(loc=0, scale=4)
```

```
model= LinearSVC(verbose=verbose, random_state=random_state, class_weight
='balanced', max_iter=2000)
parameters={'C':C_val}
clf = RandomizedSearchCV(model, parameters, random_state=random_state, cv=
cv, verbose=verbose, scoring=scoring, n_jobs=-1)
best_model = clf.fit(train_ohe, y_train)
```

## Fitting 5 folds for each of 10 candidates, totalling 50 fits

## [LibLinear]

```
In [54]: best_c=best_model.best_params_['C']
best_c
```

## Out[54]: 0.23233444867279784

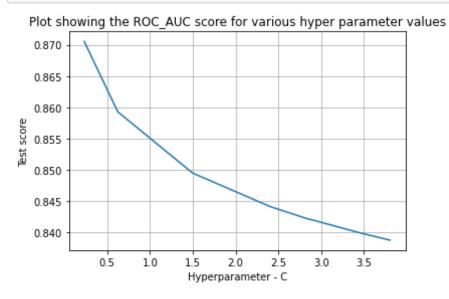
```
In [55]: results = pd.DataFrame.from_dict(best_model.cv_results_)
    results=results.sort_values('param_C')
    results
```

## Out[55]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_C	params
6	1.730894	0.069332	0.005605	0.000029	0.232334	{'C': 0.23233444867279784}
5	3.315943	0.201073	0.005879	0.000622	0.623978	{'C': 0.6239780813448106}
4	3.583880	0.365580	0.005711	0.000297	0.624075	{'C': 0.6240745617697461}
0	5.492834	0.287928	0.006418	0.000139	1.49816	{'C': 1.49816047538945}
3	4.961631	0.298074	0.005662	0.000146	2.39463	{'C': 2.3946339367881464}

params	param_C	std_score_time	mean_score_time	std_fit_time	mean_fit_time	
{'C': 2.404460046972835}	2.40446	0.000888	0.004830	0.644881	4.833444	8
{'C': 2.832290311184182}	2.83229	0.000362	0.003652	0.360801	3.986315	9
{'C': 2.9279757672456204}	2.92798	0.000985	0.006166	0.174700	4.873211	2
{'C': 3.4647045830997407}	3.4647	0.000099	0.005635	0.265487	4.817450	7
{'C': 3.8028572256396647}	3.80286	0.000241	0.006274	0.254005	4.685154	1
						4

In [56]: print\_graph(results, 'param\_C', 'mean\_test\_score', 'Hyperparameter - C'
, 'Test score')



In [57]: #https://stackoverflow.com/questions/26478000/converting-linearsvcs-dec
 ision-function-to-probabilities-scikit-learn-python
 model = LinearSVC(C=best\_c,verbose=verbose,random\_state=random\_state,cl

## svm-ohe

## 2.3 Logistic Regression with one hot encoded features

```
In [59]: C val = uniform(loc=0, scale=4)
         lr= LogisticRegression(verbose=verbose,random state=random state,class
         weight='balanced',solver='lbfgs',max iter=500,n jobs=-1)
         parameters={'C':C val}
         clf = RandomizedSearchCV(lr,parameters,random state=random state,cv=cv,
         verbose=verbose,n iter=100,scoring=scoring,n jobs=-1)
         best model = clf.fit(train ohe,y train)
         Fitting 5 folds for each of 100 candidates, totalling 500 fits
         [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
         ers.
         [Parallel(n jobs=-1)]: Done 25 tasks
                                                      elapsed:
                                                                  7.2s
                                                                 32.8s
         [Parallel(n jobs=-1)]: Done 146 tasks
                                                      elapsed:
         [Parallel(n jobs=-1)]: Done 349 tasks
                                                      elapsed: 1.4min
         [Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed: 2.0min finished
```

```
[Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
            ers.
            [Parallel(n jobs=-1)]: Done 1 out of 1 | elapsed:
                                                                                    0.8s finished
           best c=best model.best params ['C']
In [60]:
            best c
Out[60]: 0.6820964947491661
           results = pd.DataFrame.from_dict(best_model.cv_results_)
results=results.sort_values('param_C')
            results
Out[61]:
                mean_fit_time std_fit_time mean_score_time std_score_time
                                                                            param C
                                                                                                   parai
                                                                  0.000959 0.0220885
            72
                     0.439680
                                 0.041474
                                                  0.006678
                                                                                     0.02208846849440959
             10
                     0.650064
                                 0.051074
                                                  0.006208
                                                                  0.001374
                                                                            0.082338
                                                                                      0.0823379771832097
             98
                     0.776743
                                 0.046280
                                                  0.006456
                                                                  0.000961
                                                                            0.101677
                                                                                      0.1016765069763807
             42
                     0.886947
                                 0.055574
                                                  0.008943
                                                                  0.003785
                                                                            0.137554
                                                                                       0.137554084460873!
                     0.928974
                                 0.072238
             58
                                                  0.006947
                                                                  0.000977
                                                                            0.180909
                                                                                       0.1809091556421522
             1
                     2.534207
                                 0.214963
                                                  0.006663
                                                                  0.000782
                                                                             3.80286
                                                                                        3.802857225639664
             34
                     2.376340
                                                                             3.86253
                                 0.051137
                                                  0.006265
                                                                  0.000269
                                                                                       3.862528132298237
             50
                     2.498738
                                 0.052591
                                                  0.007061
                                                                  0.000964
                                                                             3.87834
                                                                                        3.878338511058234
             11
                     2.401271
                                 0.107580
                                                  0.006628
                                                                             3.87964
                                                                  0.001671
                                                                                        3.879639408647977
```

```
mean_fit_time std_fit_time mean_score_time std_score_time
                                                                  param_C
                                                                                       parai
           69
                  2.674097
                             0.153710
                                            0.007042
                                                         0.000979
                                                                   3.94755
                                                                              3.94754774640206
          100 rows × 14 columns
In [62]:
          print graph(results, 'param C', 'mean test score', 'Hyperparameter - C'
          , 'Test score')
           Plot showing the ROC AUC score for various hyper parameter values
             0.87
             0.86
             0.85
             0.84
             0.83
                      0.5
                           1.0
                                1.5
                                      2.0
                                           2.5
                                                3.0
                                                     3.5
                                                          4.0
                                Hyperparameter - C
In [63]: model = LogisticRegression(C=best c,verbose=verbose,n jobs=-1,random st
          ate=random state,class weight='balanced',solver='lbfgs')
          model.fit(train ohe,y train)
          [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
          ers.
          [Parallel(n jobs=-1)]: Done 1 out of 1 | elapsed:
                                                                         0.5s finished
Out[63]: LogisticRegression(C=0.6820964947491661, class weight='balanced', n job
          s = -1,
                               random state=42, verbose=2)
```

```
In [64]:
         predictions = model.predict proba(test ohe)[:,1]
         save submission(predictions, 'lr ohe.csv')
         Ir-ohe
         2.4 Random Forest with one hot encoded features
In [65]: rfc = RandomForestClassifier(random state=random state, class weight='ba
         lanced',n jobs=-1)
         clf = RandomizedSearchCV(rfc,get rf params(),random state=random state,
         cv=cv, verbose=verbose, n iter=100, scoring=scoring, n jobs=-1)
         best model = clf.fit(train ohe,y train)
         Fitting 5 folds for each of 100 candidates, totalling 500 fits
         [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
         ers.
         [Parallel(n jobs=-1)]: Done 25 tasks
                                                       elapsed:
                                                                    9.8s
         [Parallel(n jobs=-1)]: Done 146 tasks
                                                       elapsed:
                                                                1.6min
         [Parallel(n jobs=-1)]: Done 349 tasks
                                                      | elapsed: 3.6min
         [Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed: 5.3min finished
         results = pd.DataFrame(best model.cv results )
In [66]:
         results.sort values('mean test score', ascending=False, inplace=True)
         param keys=['param '+str(each) for each in get rf params().keys()]
         param keys.append('mean test score')
         results[param keys].head(10)
Out[66]:
             param n estimators param max depth param max features param min samples split mean
          78
                         700
                                        25
                                                         2
                                                                             7
          85
                        1000
                                        20
                                                         3
          62
                         500
                                        25
                                                         3
                                                                             5
           6
                                                         2
                                                                             5
```

20

500

	param	_n_estimators	param_max_depth	param_max_features	param_min_samples_split	mean			
	11	1000	15	3	7				
	25	700	15	4	7				
	19	700	15	4	5				
	22	200	25	4	10				
	79	500	25	1	10				
	82	700	20	5	20				
	4					•			
In [67]:	<pre>n_estimators=clf.best_params_['n_estimators'] max_features=clf.best_params_['max_features'] max_depth=clf.best_params_['max_depth'] min_samples_split=clf.best_params_['min_samples_split'] n_estimators,max_features,max_depth,min_samples_split</pre>								
Out[67]:	(700, 2, 25, 7)								
In [68]:	<pre>model=RandomForestClassifier(n_estimators=n_estimators,max_depth=max_de pth,max_features=max_features,</pre>								
Out[68]:		restClassi	fier(class_weig	ght='balanced', r	max_depth=25, max_fe	eatu			
	res=2,		min samnle	es split=7. n es	timators=700, n jobs	S=-			
	1,					•			
			random_sta	ate=42)					
In [69]:	<pre># features=train_ohe.columns # importance=model.feature_importances_ # features=pd.DataFrame({'features':features,'value':importance}) # features=features.sort_values('value',ascending=False)</pre>								

```
# sns.barplot('value', 'features', data=features);
         # plt.title('Feature Importance');
In [70]: predictions = model.predict proba(test ohe)[:,1]
         save submission(predictions, 'rf ohe.csv')
         rf-ohe
         2.5 Xgboost with one hot encoded features
In [71]: xab = XGBClassifier()
         clf = RandomizedSearchCV(xgb,get xgb params(),random state=random state
          , cv=cv, verbose=verbose, n iter=100, scoring=scoring, n jobs=-1)
         best model=clf.fit(train ohe, v train)
         Fitting 5 folds for each of 100 candidates, totalling 500 fits
         [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
         ers.
         [Parallel(n jobs=-1)]: Done 25 tasks
                                                        elapsed:
                                                                    8.0s
          [Parallel(n jobs=-1)]: Done 146 tasks
                                                       elapsed: 1.6min
         [Parallel(n jobs=-1)]: Done 349 tasks
                                                      I elapsed: 4.3min
          [Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed: 7.1min finished
In [72]: results = pd.DataFrame(best model.cv results )
         results.sort values('mean test score', ascending=False, inplace=True)
         param keys=['param '+str(each) for each in get xgb params().keys()]
         param keys.append('mean test score')
         results[param_keys].head(10)
Out[72]:
             param_n_estimators param_learning_rate param_subsample param_max_depth param_colsan
                                                                        6
          97
                         750
                                      0.232385
                                                    0.907694
                                                                        3
          80
                         1000
                                      0.385564
                                                    0.905351
          86
                         1000
                                      0.475848
                                                    0.858413
                                                                        9
```

	param_n_esti	mators	param_learning_rate	param_subsample	param_max_depth	param_colsan		
	84	200	0.571989	0.967581	6			
	14	200	0.374221	0.802197	7			
	50	500	0.388683	0.645103	4			
	53	200	0.540096	0.928319	6			
	92	200	0.478778	0.49442	9			
	96	500	0.0979629	0.98664	7			
	22	1000	0.391846	0.695516	6			
	4					•		
In [73]:	<pre>colsample_bytree = clf.best_params_['colsample_bytree'] learning_rate=clf.best_params_['learning_rate'] max_depth=clf.best_params_['max_depth'] min_child_weight=clf.best_params_['min_child_weight'] n_estimators=clf.best_params_['n_estimators'] subsample=clf.best_params_['subsample'] colsample_bytree,learning_rate,max_depth,min_child_weight,n_estimators, subsample</pre>							
Out[73]:	(0.3742707957 3)	561203	, 0.23238528824	013455, 6, 1,	750, 0.9076937	96348546		
In [74]:	<pre>model = XGBClassifier(colsample_bytree=colsample_bytree,learning_rate=learning_rate,max_depth=max_depth,</pre>							
0+[74].				+ lab+				
out[/4]:	gamma=0,		score=0.5, boos mple_bynode=1,					
		gpu_i	d=-1, importanc	e_type='gain',	interaction_c	onstraint		
	S='',	learn	ing_rate=0.2323	8528824013455,	max_delta_ste	p=0, max_		

```
depth=6,
                       min child weight=1, missing=nan, monotone constraints
         ='()',
                       n estimators=750, n jobs=-1, num parallel tree=1, random
         state=0,
                       reg alpha=0, reg lambda=1, scale pos weight=1,
                       subsample=0.9076937063485463, tree method='exact',
                       validate parameters=1, verbosity=None)
In [75]: # features=train ohe.columns
         # importance=model.feature importances
         # features=pd.DataFrame({'features':features,'value':importance})
         # features=features.sort values('value',ascending=False)
         # sns.barplot('value', 'features', data=features);
         # plt.title('Feature Importance');
In [76]: predictions = model.predict proba(test ohe)[:,1]
         save submission(predictions, 'xqb ohe.csv')
         xgb-ohe
         kaggle-submission-ohe
In [77]: from prettytable import PrettyTable
         x = PrettyTable(['Model', 'Feature', 'Private Score', 'Public Score'])
         x.add row(['KNN','ohe', 0.81657, 0.81723])
         x.add row(['SVM', 'ohe', 0.87249, 0.87955])
         x.add row(['Logistic Regression', 'ohe', 0.87436, 0.88167])
         x.add row(['Random Forest', 'ohe', 0.84541, 0.84997])
         x.add row(['Xgboost', 'ohe', 0.84717, 0.85102])
         print(x)
                               | Feature | Private Score | Public Score |
                  Model
```

KNN	ohe	0.81657	0.81723
SVM	ohe	0.87249	0.87955
Logistic Regression	ohe	0.87436	0.88167
Random Forest	ohe	0.84541	0.84997
Xgboost	ohe	0.84717	0.85102
+	+	+	+

## **Observations:**

- 1. One hot encoding features performs better than other encoding technique
- 2. Linear models (Logistic Regression and SVM) performs better on higher dimension

## 3 Build Model on frequency encoding feature

## 3.1 KNN with frequency encoding

```
In [78]: train_df_fc = pd.read_csv('data/train_df_fc.csv')
    test_df_fc = pd.read_csv('data/test_df_fc.csv')

In [79]: train_df_fc.shape, test_df_fc.shape, y_train.shape

Out[79]: ((32769, 9), (58921, 9), (32769,))

In [80]: parameters={'n_neighbors':np.arange(1,100, 5)}
    clf = RandomizedSearchCV(KNeighborsClassifier(n_jobs=-1),parameters,ran dom_state=random_state,cv=cv,verbose=verbose,scoring=scoring,n_jobs=-1)
    best_model = clf.fit(train_df_fc,y_train)

Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent work ers.
```

```
[Parallel(n jobs=-1)]: Done 25 tasks
                                                              | elapsed:
                                                                               5.8s
           [Parallel(n_jobs=-1)]: Done 50 out of 50 | elapsed:
                                                                             10.4s finished
           results = pd.DataFrame.from dict(best model.cv results )
In [81]:
           results=results.sort values('param n neighbors')
           results
Out[81]:
              mean fit time std fit time mean score time std score time param n neighbors
                                                                                             param
                                                                                     1 {'n_neighbors
                  1.245504
                                                             0.057236
            0
                              0.191884
                                              0.444588
                                                                                     6 {'n_neighbors
                                                             0.082150
            3
                   0.966955
                              0.192374
                                              0.425104
                                                                                    16 {'n_neighbors
           7
                   0.915347
                                                             0.062272
                              0.088786
                                              0.510648
                                                                                       {'n_neighbors
            5
                   0.910787
                              0.067158
                                              0.587300
                                                             0.075423
                                                                                    41 {'n_neighbors
            4
                   0.867675
                              0.145174
                                              0.647190
                                                             0.063128
                                                                                    56 {'n_neighbors
                  0.877225
                                                             0.113621
            6
                              0.208047
                                              0.709570
                                                                                    76 {'n_neighbors
            2
                   0.947447
                              0.128830
                                              0.768725
                                                             0.107211
                                                                                    81 {'n_neighbors
            9
                   0.934347
                              0.100315
                                              0.597521
                                                             0.257969
                                                                                    86 {'n_neighbors
            1
                   1.011318
                              0.326486
                                              0.772521
                                                             0.073501
                                                                                       {'n_neighbors
            8
                   0.832900
                              0.196410
                                              0.861454
                                                             0.065058
In [82]:
           print graph(results, 'param n neighbors', 'mean test score', 'Hyperpara
           meter - No. of neighbors', 'Test score')
```

# Plot showing the ROC\_AUC score for various hyper parameter values 0.78 0.76 0.72 0.70

40

Hyperparameter - No. of neighbors

```
In [83]: best_c=best_model.best_params_['n_neighbors']
best_c
```

60

80

Out[83]: 16

```
In [84]: model = KNeighborsClassifier(n_neighbors=best_c,n_jobs=-1)
model.fit(train_df_fc,y_train)
```

Out[84]: KNeighborsClassifier(n\_jobs=-1, n\_neighbors=16)

20

```
In [85]: predictions = model.predict_proba(test_df_fc)[:,1]
    save_submission(predictions, "knn_fc.csv")
```

knn-fc

## 3.2 SVM with frequency encoding

```
In [86]: C_val = uniform(loc=0, scale=4)
```

```
model= LinearSVC(verbose=verbose, random_state=random_state, class_weight
='balanced', max_iter=2000)
parameters={'C':C_val}
clf = RandomizedSearchCV(model, parameters, random_state=random_state, cv=
cv, verbose=verbose, scoring=scoring, n_jobs=-1)
best_model = clf.fit(train_df_fc, y_train)
```

## Fitting 5 folds for each of 10 candidates, totalling 50 fits

## [LibLinear]

```
In [87]: best_c=best_model.best_params_['C']
best_c
```

## Out[87]: 3.4647045830997407

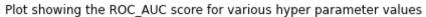
```
In [88]: results = pd.DataFrame.from_dict(best_model.cv_results_)
    results=results.sort_values('param_C')
    results
```

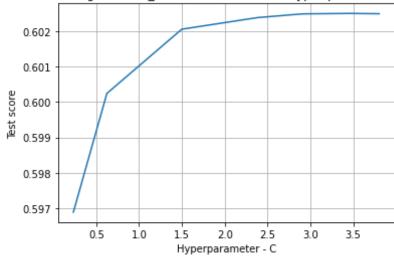
## Out[88]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_C	params
6	0.707697	0.038330	0.009112	0.000330	0.232334	{'C': 0.23233444867279784}
5	1.619894	0.069040	0.009326	0.000816	0.623978	{'C': 0.6239780813448106}
4	1.579539	0.025513	0.008887	0.000250	0.624075	{'C': 0.6240745617697461}
0	3.577643	0.097967	0.009332	0.000580	1.49816	{'C': 1.49816047538945}
3	5.732613	0.118254	0.009076	0.000258	2.39463	{'C': 2.3946339367881464}

params	param_C	std_score_time	mean_score_time	std_fit_time	mean_fit_time	
{'C': 2.404460046972835}	2.40446	0.001280	0.009409	0.136819	5.664490	8
{'C': 2.832290311184182}	2.83229	0.000641	0.005462	0.630964	5.364426	9
{'C': 2.9279757672456204}	2.92798	0.000407	0.009158	0.140802	6.995208	2
{'C': 3.4647045830997407}	3.4647	0.000114	0.009016	0.706659	8.412424	7
{'C': 3.8028572256396647}	3.80286	0.000069	0.008899	0.661829	9.626733	1
•						4

In [89]: print\_graph(results, 'param\_C', 'mean\_test\_score', 'Hyperparameter - C'
, 'Test score')





In [90]: #https://stackoverflow.com/questions/26478000/converting-linearsvcs-dec
 ision-function-to-probabilities-scikit-learn-python
 model = LinearSVC(C=best\_c,verbose=verbose,random\_state=random\_state,cl

```
ass weight='balanced', max iter=2000)
         model = CalibratedClassifierCV(model)
         model.fit(train df fc,y train)
         [LibLinear][LibLinear][LibLinear][LibLinear]
Out[90]: CalibratedClassifierCV(base estimator=LinearSVC(C=3.4647045830997407,
                                                        class weight='balance
         d',
                                                        max iter=2000, random s
         tate=42.
                                                        verbose=2))
In [91]:
         predictions = model.predict proba(test df fc)[:,1]
         save submission(predictions, 'svm fc.csv')
```

svm-fc

#### 3.3 Logistic Regression with frequency encoding

```
In [92]: C val = uniform(loc=0, scale=4)
         lr= LogisticRegression(verbose=verbose,random state=random state,class
         weight='balanced',solver='lbfgs',max iter=500,n jobs=-1)
         parameters={'C':C val}
         clf = RandomizedSearchCV(lr,parameters,random state=random state,cv=cv,
         verbose=verbose, n iter=100, scoring=scoring, n jobs=-1)
         best model = clf.fit(train df fc,y train)
```

Fitting 5 folds for each of 100 candidates, totalling 500 fits

```
[Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
ers.
[Parallel(n jobs=-1)]: Done 25 tasks
                                             elapsed:
                                                         1.7s
[Parallel(n jobs=-1)]: Done 146 tasks
                                                         8.3s
                                             elapsed:
[Parallel(n jobs=-1)]: Done 349 tasks
                                            elapsed:
                                                      20.2s
[Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed:
                                                       29.2s finished
[Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
```

```
ers.
           [Parallel(n jobs=-1)]: Done 1 out of 1 | elapsed:
                                                                                  0.4s finished
In [93]:
           best c=best model.best params ['C']
           best c
Out[93]: 3.947547746402069
           results = pd.DataFrame.from_dict(best_model.cv_results_)
In [94]:
           results=results.sort values('param C')
           results
Out[94]:
                mean fit time std fit time mean score time std score time
                                                                                                 parai
            72
                     0.182546
                                0.056575
                                                 0.010424
                                                                0.001924 0.0220885
                                                                                   0.02208846849440959
            10
                     0.230978
                                0.011034
                                                 0.010079
                                                                0.002740
                                                                          0.082338
                                                                                    0.0823379771832097
            98
                     0.246538
                                0.040240
                                                 0.008149
                                                                0.000789
                                                                          0.101677
                                                                                     0.1016765069763807
            42
                     0.264855
                                0.051649
                                                 0.007584
                                                                0.001100
                                                                          0.137554
                                                                                     0.137554084460873
            58
                     0.294973
                                0.058159
                                                                          0.180909
                                                 0.009848
                                                                0.001887
                                                                                     0.1809091556421522
             1
                     0.544588
                                0.077972
                                                 0.010987
                                                                0.002171
                                                                           3.80286
                                                                                      3.802857225639664
                     0.517311
            34
                                0.047540
                                                 0.010529
                                                                0.004522
                                                                           3.86253
                                                                                      3.862528132298237
                     0.546014
                                0.078366
                                                                           3.87834
            50
                                                 0.011045
                                                                0.001893
                                                                                      3.878338511058234
            11
                     0.487671
                                0.048548
                                                 0.010200
                                                                0.002548
                                                                           3.87964
                                                                                      3.879639408647977
            69
                     0.589011
                                0.053345
                                                 0.010957
                                                                0.001444
                                                                           3.94755
                                                                                       3.94754774640206
```

```
100 rows × 14 columns
                                                                                      •
          print graph(results, 'param C', 'mean test score', 'Hyperparameter - C'
In [95]:
          , 'Test score')
            Plot showing the ROC AUC score for various hyper parameter values
             0.600
             0.595
             0.590
          Est score
             0.585
             0.580
             0.575
                  0.0
                       0.5
                           1.0
                                1.5
                                     2.0
                                         2.5
                                               3.0
                                                    3.5
                                Hyperparameter - C
In [96]:
         model = LogisticRegression(C=best c,verbose=verbose,n jobs=-1,random st
          ate=random state,class weight='balanced',solver='lbfgs')
          model.fit(train df fc,y train)
          [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
          ers.
          [Parallel(n jobs=-1)]: Done 1 out of 1 | elapsed:
                                                                       0.5s finished
Out[96]: LogisticRegression(C=3.947547746402069, class weight='balanced', n jobs
          =-1,
                              random state=42, verbose=2)
In [97]:
          predictions = model.predict proba(test df fc)[:,1]
          save submission(predictions, 'lr fc.csv')
```

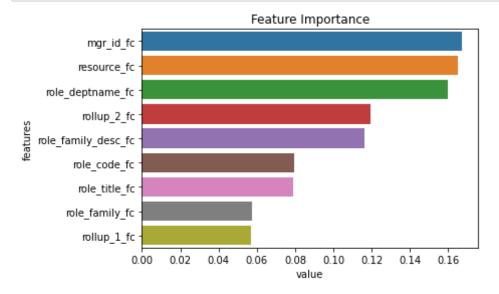


#### 3.4 Random Forest with frequency encoding

```
In [98]: rfc = RandomForestClassifier(random state=random state, class weight='ba
         lanced',n jobs=-1)
         clf = RandomizedSearchCV(rfc,get rf params(),random state=random state,
         cv=cv, verbose=verbose, n iter=100, scoring=scoring, n jobs=-1)
         best model = clf.fit(train df fc,y train)
         Fitting 5 folds for each of 100 candidates, totalling 500 fits
         [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
         ers.
         [Parallel(n jobs=-1)]: Done 25 tasks
                                                       elapsed:
                                                                 18.9s
         [Parallel(n jobs=-1)]: Done 146 tasks
                                                       elapsed: 3.5min
         [Parallel(n jobs=-1)]: Done 349 tasks
                                                      I elapsed: 8.3min
         /home/auw-mayank/.local/lib/python3.6/site-packages/joblib/externals/lo
         ky/process executor.py:691: UserWarning: A worker stopped while some jo
         bs were given to the executor. This can be caused by a too short worker
         timeout or by a memory leak.
           "timeout or by a memory leak.", UserWarning
         [Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed: 12.3min finished
In [99]: results = pd.DataFrame(best model.cv results )
         results.sort values('mean test score', ascending=False, inplace=True)
         param keys=['param '+str(each) for each in get rf params().keys()]
         param keys.append('mean test score')
         results[param keys].head(10)
Out[991:
             param n estimators param max depth param max features param min samples split mean
          78
                         700
                                        25
                                                         2
                                                                             7
          79
                         500
                                        25
                                                                             10
          85
                        1000
                                        20
```

	paran	n_n_estimators	param_max_depth	param_max_features	param_min_samples_split	mean	
	55	200	25	2	5		
	27	50	25	2	10		
	62	500	25	3	5		
	22	200	25	4	10		
	6	500	20	2	5		
	76	50	25	1	5		
	84	1000	25	5	2		
	4					•	
In [100]:	<pre>n_estimators=clf.best_params_['n_estimators'] max_features=clf.best_params_['max_features'] max_depth=clf.best_params_['max_depth'] min_samples_split=clf.best_params_['min_samples_split'] n_estimators,max_features,max_depth,min_samples_split</pre>						
Out[100]:	(700, 2,	25, /)					
In [101]:	<pre>model=RandomForestClassifier(n_estimators=n_estimators,max_depth=max_de pth,max_features=max_features,</pre>						
Out[101]:	RandomFo	restClassif	fier(class_weig	jht='balanced', i	max_depth=25, max_fe	eatu	
	res=2, 1,		min_sample		timators=700, n_jobs	5=-	
In [103]:		s=train_df_1 nce=model.fe	fc.columns eature_importar	nces_			

```
features=pd.DataFrame({'features':features,'value':importance})
features=features.sort_values('value',ascending=False)
sns.barplot('value','features',data=features);
plt.title('Feature Importance');
```



```
In [106]: predictions = model.predict_proba(test_df_fc)[:,1]
    save_submission(predictions, 'rf_fc.csv')
```



#### 3.5 Xgboost with frequency encoding

```
In [107]: xgb = XGBClassifier()
clf = RandomizedSearchCV(xgb,get_xgb_params(),random_state=random_state
,cv=cv,verbose=verbose,n_iter=100,scoring=scoring,n_jobs=-1)
best_model=clf.fit(train_df_fc,y_train)
```

Fitting 5 folds for each of 100 candidates, totalling 500 fits

[Parallel(n\_jobs=-1)]: Using backend LokyBackend with 8 concurrent work

```
ers.
           [Parallel(n jobs=-1)]: Done 25 tasks
                                                                         8.5s
                                                            elapsed:
           [Parallel(n jobs=-1)]: Done 146 tasks
                                                            elapsed: 1.6min
           [Parallel(n jobs=-1)]: Done 349 tasks
                                                            elapsed:
                                                                       4.4min
           [Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed: 7.3min finished
In [108]: results = pd.DataFrame(best model.cv results )
           results.sort values('mean test score', ascending=False, inplace=True)
           param keys=['param '+str(each) for each in get xgb params().keys()]
           param keys.append('mean test score')
           results[param keys].head(10)
Out[108]:
               param n estimators param learning rate param subsample param max depth param colsan
            18
                           1000
                                         0.048135
                                                        0.665922
                                                                             9
            96
                            500
                                        0.0979629
                                                         0.98664
                                                                             7
            44
                           1000
                                         0.060484
                                                        0.606429
                                                                             6
                                         0.232385
                                                                             6
            97
                            750
                                                        0.907694
                                                                             9
            86
                           1000
                                         0.475848
                                                        0.858413
            53
                            200
                                         0.540096
                                                        0.928319
                                                                             6
            84
                                                                             6
                            200
                                         0.571989
                                                        0.967581
            49
                            500
                                         0.160277
                                                        0.393098
                                                                             8
            62
                            500
                                        0.0663892
                                                        0.328153
                                                                             9
                                                                             7
            14
                            200
                                         0.374221
                                                        0.802197
           colsample bytree = clf.best params ['colsample bytree']
In [109]:
           learning rate=clf.best params ['learning rate']
           max depth=clf.best params ['max depth']
           min child weight=clf.best params ['min child weight']
           n estimators=clf.best params ['n estimators']
           subsample=clf.best params ['subsample']
```

```
colsample bytree, learning rate, max depth, min child weight, n estimators,
          subsample
Out[109]: (0.3308980248526492, 0.04813501017161418, 9, 2, 1000, 0.665922356617496
          7)
In [110]: model = XGBClassifier(colsample bytree=colsample bytree,learning rate=l
          earning rate, max depth=max depth,
                               min child weight=min child weight,n estimators=n e
          stimators, subsample=subsample, n jobs=-1)
          model.fit(train df fc,y train)
Out[110]: XGBClassifier(base score=0.5, booster='gbtree', colsample bylevel=1,
                        colsample bynode=1, colsample bytree=0.3308980248526492,
          qamma=0,
                        gpu id=-1, importance type='gain', interaction constraint
          s='',
                        learning rate=0.04813501017161418, max delta step=0, max
          depth=9,
                        min child weight=2, missing=nan, monotone constraints
          ='()',
                        n estimators=1000, n jobs=-1, num parallel tree=1, random
          state=0,
                        reg alpha=0, reg lambda=1, scale pos weight=1,
                        subsample=0.6659223566174967, tree method='exact',
                        validate parameters=1, verbosity=None)
In [111]: features=train df fc.columns
          importance=model.feature importances
          features=pd.DataFrame({'features':features,'value':importance})
          features=features.sort values('value',ascending=False)
          sns.barplot('value', 'features', data=features);
          plt.title('Feature Importance');
```



KNN   fc   0.79715   SVM   fc   0.60085   Logistic Regression   fc   0.59896   Random Forest   fc   0.87299   Xgboost   fc   0.86987
--

#### **Observations:**

- 1. Tree based models performs better for this feature than linear models
- 2. KNN is doing good for every feature

# 4 Build Model using response encoding feature

```
In [114]: train_df_rc = pd.read_csv('data/train_df_rc.csv')
    test_df_rc = pd.read_csv('data/test_df_rc.csv')

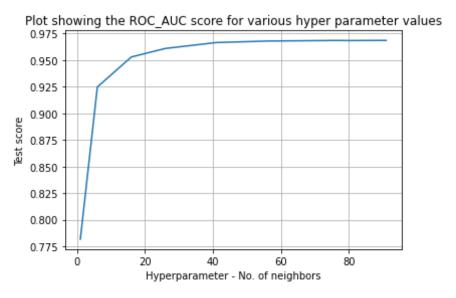
In [115]: train_df_rc.shape, test_df_rc.shape, y_train.shape
Out[115]: ((32769, 9), (58921, 9), (32769,))
```

# 4.1 KNN with response encoding

```
In [116]: parameters={'n_neighbors':np.arange(1,100, 5)}
    clf = RandomizedSearchCV(KNeighborsClassifier(n_jobs=-1),parameters,ran
    dom_state=random_state,cv=cv,verbose=verbose,scoring=scoring,n_jobs=-1)
    best_model = clf.fit(train_df_rc,y_train)
```

Fitting 5 folds for each of 10 candidates, totalling 50 fits

```
[Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
            ers.
            [Parallel(n jobs=-1)]: Done 25 tasks
                                                               | elapsed:
                                                                               5.2s
            [Parallel(n jobs=-1)]: Done 50 out of 50 | elapsed:
                                                                              10.7s finished
In [117]:
           results = pd.DataFrame.from dict(best model.cv results )
            results=results.sort values('param n neighbors')
            results
Out[117]:
               mean fit time std fit time mean score time std score time param n neighbors
                                                                                             param
                                                                                     1 {'n_neighbors
                                                             0.118324
             0
                    0.087703
                               0.003754
                                               0.270912
                                                                                     6 {'n_neighbors
             3
                    0.161678
                               0.063581
                                               0.749612
                                                             0.191282
                                                                                    16 {'n_neighbors
            7
                    0.365460
                               0.149200
                                               1.097595
                                                             0.234131
                                                                                    26 {'n_neighbors
             5
                    0.274667
                               0.128723
                                               1.106008
                                                             0.062541
                                                                                    41 {'n_neighbors
             4
                    0.196924
                               0.091312
                                               1.247186
                                                             0.043935
                                                                                       {'n_neighbors
             6
                    0.121391
                               0.037696
                                               1.616742
                                                             0.078125
                                                                                    76 {'n_neighbors
             2
                    0.257782
                               0.047633
                                               1.718469
                                                             0.251959
                                                                                       {'n_neighbors
             9
                    0.259518
                               0.169725
                                               1.463110
                                                             0.571909
                                                                                    86 {'n_neighbors
            1
                    0.166987
                               0.110239
                                               2.083340
                                                             0.073632
                                                                                    91 {'n_neighbors
             8
                    0.215055
                               0.138284
                                               2.578594
                                                             0.120702
            print graph(results, 'param_n_neighbors', 'mean_test_score', 'Hyperpara
In [118]:
            meter - No. of neighbors', 'Test score')
```



```
In [119]: best_c=best_model.best_params_['n_neighbors']
best_c

Out[119]: 91

In [120]: model = KNeighborsClassifier(n_neighbors=best_c,n_jobs=-1)
    model.fit(train_df_rc,y_train)

Out[120]: KNeighborsClassifier(n_jobs=-1, n_neighbors=91)

In [121]: predictions = model.predict_proba(test_df_rc)[:,1]
    save_submission(predictions, "knn_rc.csv")
```

## 4.2 SVM with response encoding

```
In [122]: C_val = uniform(loc=0, scale=4)
```

```
model= LinearSVC(verbose=verbose, random_state=random_state, class_weight
='balanced', max_iter=2000)
parameters={'C':C_val}
clf = RandomizedSearchCV(model, parameters, random_state=random_state, cv=
cv, verbose=verbose, scoring=scoring, n_jobs=-1)
best_model = clf.fit(train_df_rc, y_train)
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent work
ers.
[Parallel(n_jobs=-1)]: Done 25 tasks | elapsed: 59.3s
[Parallel(n_jobs=-1)]: Done 50 out of 50 | elapsed: 1.6min finished
```

[LibLinear]

```
In [123]: best_c=best_model.best_params_['C']
best_c
```

Out[123]: 0.23233444867279784

```
In [124]: results = pd.DataFrame.from_dict(best_model.cv_results_)
    results=results.sort_values('param_C')
    results
```

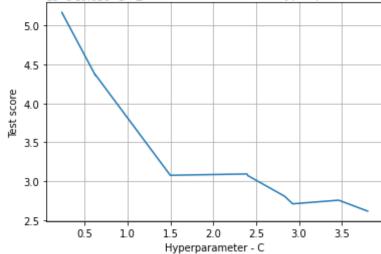
Out[124]:

params	param_C	std_score_time	mean_score_time	std_fit_time	mean_fit_time	· 
{'C': 0.23233444867279784}	0.232334	0.000833	0.009511	0.130475	3.726326	6
{'C': 0.6239780813448106}	0.623978	0.000450	0.009016	0.452051	9.815611	5
{'C': 0.6240745617697461}	0.624075	0.000597	0.009335	0.604710	9.402443	4
{'C': 1.49816047538945}	1.49816	0.000943	0.009698	0.735768	20.009992	0
{'C': 2.3946339367881464}	2.39463	0.008621	0.013516	0.384670	19.451480	3

params	param_C	std_score_time	mean_score_time	std_fit_time	mean_fit_time	
{'C': 2.404460046972835}	2.40446	0.001653	0.008659	1.498897	17.116975	8
{'C': 2.832290311184182}	2.83229	0.001067	0.005841	1.305182	14.348889	9
{'C': 2.9279757672456204}	2.92798	0.002716	0.010328	0.395682	19.717969	2
{'C': 3.4647045830997407}	3.4647	0.000206	0.009083	0.625358	18.970401	7
{'C': 3.8028572256396647}	3.80286	0.000238	0.009152	0.710743	20.206970	1

In [125]: print\_graph(results, 'param\_C', 'mean\_test\_score', 'Hyperparameter - C' , 'Test score')





In [126]: #https://stackoverflow.com/questions/26478000/converting-linearsvcs-dec ision-function-to-probabilities-scikit-learn-python model = LinearSVC(C=best c,verbose=verbose,random state=random state,cl

```
ass weight='balanced', max iter=2000)
          model = CalibratedClassifierCV(model)
          model.fit(train df rc,y train)
          [LibLinear][LibLinear][LibLinear][LibLinear]
Out[126]: CalibratedClassifierCV(base estimator=LinearSVC(C=0.23233444867279784,
                                                         class weight='balance
          d',
                                                         max iter=2000, random s
          tate=42.
                                                         verbose=2))
In [127]:
          predictions = model.predict proba(test df rc)[:,1]
          save submission(predictions, 'svm rc.csv')
          svm-rc
```

# 4.3 Logistic Regression with response encoding

```
In [128]: C val = uniform(loc=0, scale=4)
          lr= LogisticRegression(verbose=verbose,random state=random state,class
          weight='balanced',solver='lbfgs',max iter=500,n jobs=-1)
          parameters={'C':C val}
          clf = RandomizedSearchCV(lr,parameters,random state=random state,cv=cv,
          verbose=verbose, n iter=100, scoring=scoring, n jobs=-1)
          best model = clf.fit(train df rc,y train)
```

Fitting 5 folds for each of 100 candidates, totalling 500 fits

```
[Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
ers.
[Parallel(n jobs=-1)]: Done 25 tasks
                                             elapsed:
                                                         1.8s
[Parallel(n jobs=-1)]: Done 146 tasks
                                                         9.9s
                                             elapsed:
[Parallel(n jobs=-1)]: Done 349 tasks
                                            elapsed:
                                                      24.2s
[Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed:
                                                        34.9s finished
[Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
```

```
ers.
             [Parallel(n jobs=-1)]: Done 1 out of 1 | elapsed:
                                                                                   0.5s finished
In [129]:
            best c=best model.best params ['C']
            best c
Out[129]: 3.8783385110582342
            results = pd.DataFrame.from_dict(best_model.cv_results_)
In [130]:
             results=results.sort values('param C')
            results
Out[130]:
                 mean fit time std fit time mean score time std score time
                                                                           param C
                                                                                                  parai
             72
                      0.419037
                                 0.018913
                                                  0.014351
                                                                 0.004590 0.0220885
                                                                                    0.02208846849440959
             10
                      0.377327
                                 0.053768
                                                  0.012779
                                                                 0.002567
                                                                           0.082338
                                                                                     0.0823379771832097
             98
                      0.375209
                                 0.049318
                                                  0.010560
                                                                 0.000751
                                                                           0.101677
                                                                                      0.1016765069763807
                      0.392769
             42
                                 0.045860
                                                  0.014432
                                                                 0.004220
                                                                           0.137554
                                                                                      0.137554084460873
             58
                      0.438569
                                 0.077177
                                                  0.013336
                                                                           0.180909
                                                                 0.003642
                                                                                      0.1809091556421522
              1
                      0.506320
                                 0.115184
                                                  0.009774
                                                                 0.001500
                                                                            3.80286
                                                                                       3.802857225639664
             34
                      0.435505
                                 0.063518
                                                  0.010841
                                                                 0.001308
                                                                            3.86253
                                                                                       3.862528132298237
                      0.560126
                                 0.144761
                                                                            3.87834
             50
                                                  0.012199
                                                                 0.003007
                                                                                       3.878338511058234
             11
                      0.493065
                                 0.118567
                                                  0.013844
                                                                 0.004191
                                                                            3.87964
                                                                                       3.879639408647977
             69
                      0.649569
                                 0.209739
                                                  0.016016
                                                                 0.005468
                                                                            3.94755
                                                                                        3.94754774640206
```



#### 4.4 Random Forest with response encoding

```
In [134]: | rfc = RandomForestClassifier(random state=random state, class weight='ba
          lanced',n jobs=-1)
          clf = RandomizedSearchCV(rfc,get rf params(),random state=random state,
          cv=cv, verbose=verbose, n iter=100, scoring=scoring, n jobs=-1)
          best model = clf.fit(train df rc,y train)
          Fitting 5 folds for each of 100 candidates, totalling 500 fits
          [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
          ers.
          [Parallel(n jobs=-1)]: Done 25 tasks
                                                         elapsed:
                                                                   19.0s
           [Parallel(n jobs=-1)]: Done 146 tasks
                                                         elapsed: 3.0min
           [Parallel(n jobs=-1)]: Done 349 tasks
                                                        | elapsed: 7.0min
           [Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed: 10.3min finished
In [135]: results = pd.DataFrame(best model.cv results )
          results.sort values('mean test score',ascending=False,inplace=True)
          param keys=['param '+str(each) for each in get rf params().keys()]
          param keys.append('mean test score')
          results[param keys].head(10)
Out[135]:
               param n estimators param max depth param max features param min samples split mean
           68
                          1000
                                          10
                                                           4
                                                                               20
           26
                                                                               20
                          700
                                          12
           64
                          700
                                          10
                                                                               7
                                                                               20
           82
                          700
                                          20
                                                           5
           41
                           500
                                          10
                                                           3
                                                                               7
```

10

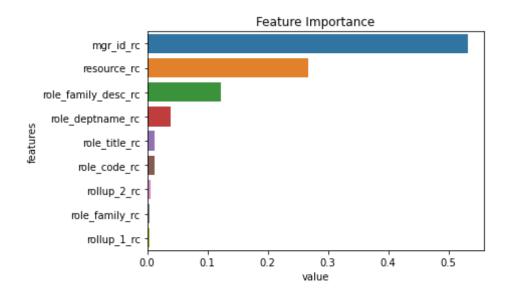
3

10

96

100

```
param_n_estimators param_max_depth param_max_features param_min_samples_split mean
           87
                          200
                                          10
                                                                               2
           11
                                          15
                          1000
                                                           3
           85
                          1000
                                          20
                                                           3
           25
                          700
                                          15
                                                           4
                                                                               7
          n estimators=clf.best params ['n estimators']
In [136]:
          max features=clf.best params ['max features']
          max depth=clf.best params ['max depth']
          min samples split=clf.best params ['min samples split']
          n estimators, max features, max depth, min samples split
Out[136]: (1000, 4, 10, 20)
In [137]: model=RandomForestClassifier(n estimators=n estimators,max depth=max de
          pth, max features = max features,
                                         min samples split=min samples split,
                                         random state=random state, class weight='ba
          lanced',n jobs=-1)
          model.fit(train df rc,y train)
Out[137]: RandomForestClassifier(class weight='balanced', max depth=10, max featu
          res=4,
                                  min samples split=20, n estimators=1000, n jobs=
          -1,
                                  random state=42)
In [138]: features=train df rc.columns
          importance=model.feature importances
          features=pd.DataFrame({'features':features,'value':importance})
          features=features.sort values('value',ascending=False)
          sns.barplot('value', 'features', data=features);
          plt.title('Feature Importance');
```



```
In [139]: predictions = model.predict_proba(test_df_rc)[:,1]
    save_submission(predictions, 'rf_rc.csv')
```

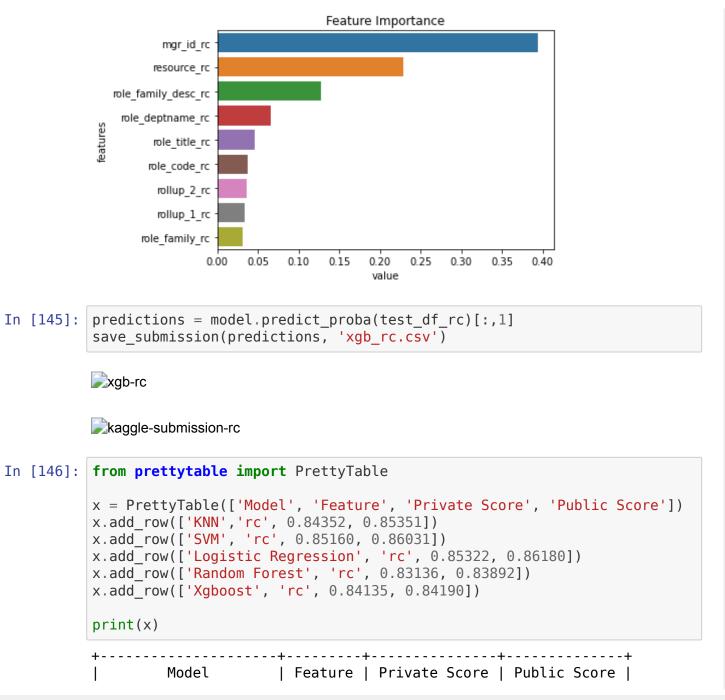


#### 4.5 Xgboost with response encoding

Fitting 5 folds for each of 100 candidates, totalling 500 fits

```
[Parallel(n jobs=-1)]: Done 349 tasks
                                                                       4.0min
                                                          | elapsed:
           [Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed: 6.7min finished
          results = pd.DataFrame(best model.cv results )
In [141]:
           results.sort values('mean test score', ascending=False, inplace=True)
           param keys=['param '+str(each) for each in get xgb params().keys()]
           param keys.append('mean test score')
           results[param keys].head(10)
Out[141]:
               param n estimators param learning rate param subsample param max depth param colsan
            1
                                        0.0699849
                                                        0.601115
                            200
                                                                             5
            28
                            500
                                        0.0141713
                                                        0.222108
                                                                             5
            7
                            500
                                         0.017959
                                                        0.808397
                                                                             3
            98
                            50
                                         0.220131
                                                        0.777147
                                                                             6
                                                                             6
            41
                            20
                                         0.34312
                                                        0.996254
            58
                                                                             3
                            50
                                         0.454461
                                                        0.708911
            33
                            100
                                                        0.447783
                                                                             4
                                         0.153737
            74
                                         0.432195
                                                        0.763364
                                                                             6
                            20
            94
                            20
                                         0.591191
                                                        0.618218
                                                                             3
                                                                             3
            88
                            200
                                         0.307937
                                                        0.895523
In [142]:
           colsample bytree = clf.best params ['colsample bytree']
           learning rate=clf.best params ['learning rate']
           max depth=clf.best params ['max depth']
           min child weight=clf.best params ['min child weight']
           n estimators=clf.best params ['n estimators']
           subsample=clf.best params ['subsample']
           colsample bytree, learning rate, max depth, min child weight, n estimators,
           subsample
Out[142]: (0.44583275285359114, 0.06998494949080172, 5, 4, 200, 0.601115011743208
           8)
```

```
In [143]: model = XGBClassifier(colsample bytree=colsample bytree,learning rate=l
          earning rate, max depth=max depth,
                               min child weight=min child weight,n estimators=n e
          stimators, subsample=subsample, n jobs=-1)
          model.fit(train df rc,v train)
Out[143]: XGBClassifier(base score=0.5, booster='gbtree', colsample bylevel=1,
                        colsample bynode=1, colsample bytree=0.44583275285359114,
          qamma=0,
                        gpu id=-1, importance type='gain', interaction constraint
          s='',
                        learning rate=0.06998494949080172, max delta step=0, max
          depth=5,
                        min child weight=4, missing=nan, monotone constraints
          ='()',
                        n estimators=200, n jobs=-1, num parallel tree=1, random
          state=0,
                        reg alpha=0, reg lambda=1, scale pos weight=1,
                        subsample=0.6011150117432088, tree method='exact',
                        validate parameters=1, verbosity=None)
In [144]: features=train df rc.columns
          importance=model.feature importances
          features=pd.DataFrame({'features':features,'value':importance})
          features=features.sort values('value',ascending=False)
          sns.barplot('value', 'features', data=features);
          plt.title('Feature Importance'):
```



++		+	++
KNN I	rc	0.84352	0.85351
SVM	rc	0.8516	0.86031
Logistic Regression	rc	0.85322	0.8618
Random Forest	rc	0.83136	0.83892
Xgboost	rc	0.84135	0.8419
++		+	++

#### **Observations:**

1. Every model performs good for this feature

In [147]: train svd = pd.read csv('data/train svd.csv')

2. Linear models performs better than Tree based models

#### 5 Build model on SVD feature

```
test_svd = pd.read_csv('data/test_svd.csv')

In [148]: train_svd.shape, test_svd.shape, y_train.shape
Out[148]: ((32769, 72), (58921, 72), (32769,))

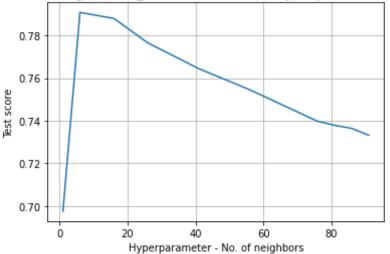
5.1 KNN with SVD

In [149]: parameters={'n_neighbors':np.arange(1,100, 5)}
    clf = RandomizedSearchCV(KNeighborsClassifier(n_jobs=-1),parameters,ran dom_state=random_state,cv=cv,verbose=verbose,scoring=scoring,n_jobs=-1)
    best_model = clf.fit(train_svd,y_train)

Fitting 5 folds for each of 10 candidates, totalling 50 fits
    [Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent wo rkers.
```

```
19.0s
           [Parallel(n jobs=-1)]: Done 50 out of 50 | elapsed:
                                                                           38.0s finishe
           results = pd.DataFrame.from_dict(best_model.cv_results_)
In [150]:
            results=results.sort values('param n neighbors')
           results
Out[150]:
               mean fit time std fit time mean score time std score time param n neighbors
                                                                                         param
                                                                                  1 {'n_neighbors
            0
                   0.526564
                              0.011169
                                             1.004034
                                                           0.149404
                                                                                  6 {'n_neighbors
            3
                   1.944336
                                             1.655248
                                                           0.153292
                              0.551025
                                                                                 16 {'n_neighbors
            7
                   2.016851
                              0.954735
                                             3.149633
                                                           0.351339
                                                                                    {'n_neighbors
            5
                   2.240037
                              0.818733
                                             3.354217
                                                           0.898707
                                                                                 41 {'n_neighbors
                   1.967969
                                                           1.218701
            4
                              0.228458
                                             3.715187
                                                                                 56 {'n_neighbors
                   1.281747
                                                           0.125865
            6
                              0.189357
                                             5.637847
                                                                                 76 {'n_neighbors
            2
                   2.475243
                              0.578326
                                                           0.859254
                                             5.100802
                                                                                 81 {'n_neighbors
            9
                   2.189955
                              1.122140
                                             3.499732
                                                           1.791585
                                                                                    {'n_neighbors
                   1.204084
            1
                              0.808660
                                             5.773037
                                                           0.319467
                                                                                    {'n_neighbors
            8
                                             7.607220
                                                           0.172469
                   0.703830
                              0.153865
In [151]:
           print_graph(results, 'param_n_neighbors', 'mean_test_score', 'Hyperpara
           meter - No. of neighbors', 'Test score')
```

#### Plot showing the ROC\_AUC score for various hyper parameter values



```
In [152]: best_c=best_model.best_params_['n_neighbors']
best_c
```

Out[152]: 6

In [153]: model = KNeighborsClassifier(n\_neighbors=best\_c,n\_jobs=-1)
model.fit(train\_svd,y\_train)

Out[153]: KNeighborsClassifier(n\_jobs=-1, n\_neighbors=6)

In [154]: predictions = model.predict\_proba(test\_svd)[:,1]
 save\_submission(predictions, "knn\_svd.csv")

knn-svd

#### 5.2 SVM with SVD

In [155]: C\_val = uniform(loc=0, scale=4)

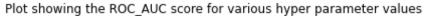
```
model= LinearSVC(verbose=verbose, random state=random state, class weight
          ='balanced',max iter=2000)
          parameters={'C':C val}
          clf = RandomizedSearchCV(model,parameters,random_state=random_state,cv=
          cv,verbose=verbose,scoring=scoring,n jobs=-1)
          best model = clf.fit(train svd,y train)
          Fitting 5 folds for each of 10 candidates, totalling 50 fits
          [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
          ers.
          [Parallel(n jobs=-1)]: Done 25 tasks | elapsed: 1.5min
          [Parallel(n jobs=-1)]: Done 50 out of 50 | elapsed: 2.7min finished
          [LibLinear]
In [156]: best c=best model.best params ['C']
          best c
Out[156]: 3.8028572256396647
In [157]: results = pd.DataFrame.from dict(best model.cv results )
          results=results.sort values('param C')
          results
```

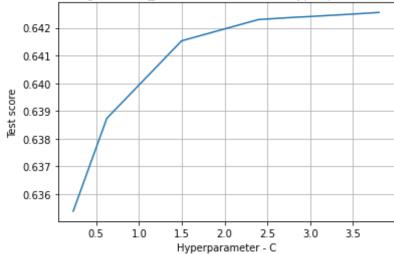
Out[157]:

params	param_C	std_score_time	mean_score_time	std_fit_time	mean_fit_time	
{'C': 0.23233444867279784}	0.232334	0.002776	0.016558	0.150177	2.968880	6
{'C': 0.6239780813448106}	0.623978	0.000876	0.012963	0.301619	6.587434	5
{'C': 0.6240745617697461}	0.624075	0.000442	0.012513	0.065596	6.343227	4
{'C': 1.49816047538945}	1.49816	0.007285	0.016185	1.080804	17.291072	0
{'C': 2.3946339367881464}	2.39463	0.003827	0.015290	0.767611	29.455153	3

params	param_C	std_score_time	mean_score_time	std_fit_time	mean_fit_time	
{'C': 2.404460046972835}	2.40446	0.002009	0.012303	1.952692	29.985117	8
{'C': 2.832290311184182}	2.83229	0.000748	0.007257	2.354661	27.816009	9
{'C': 2.9279757672456204}	2.92798	0.000489	0.012634	2.210566	36.411890	2
{'C': 3.4647045830997407}	3.4647	0.000702	0.012921	1.334583	44.704208	7
{'C': 3.8028572256396647}	3.80286	0.005413	0.016626	2.384907	48.909459	1
						4

In [158]: print\_graph(results, 'param\_C', 'mean\_test\_score', 'Hyperparameter - C'
 , 'Test score')





In [159]: #https://stackoverflow.com/questions/26478000/converting-linearsvcs-dec
 ision-function-to-probabilities-scikit-learn-python
 model = LinearSVC(C=best\_c,verbose=verbose,random\_state=random\_state,cl

#### Sviii-Svu

#### 5.3 Logistic Regression with SVD

Fitting 5 folds for each of 100 candidates, totalling 500 fits

```
ers.
             [Parallel(n jobs=-1)]: Done 1 out of 1 | elapsed: 14.7s finished
In [162]:
            best c=best model.best params ['C']
            best c
Out[162]: 3.947547746402069
In [163]:
            results = pd.DataFrame.from_dict(best_model.cv_results_)
             results=results.sort values('param C')
            results
Out[163]:
                 mean fit time std fit time mean score time std score time
                                                                                                  parai
             72
                     1.042337
                                 0.102578
                                                  0.035350
                                                                 0.017093 0.0220885
                                                                                    0.02208846849440959
             10
                      1.598916
                                 0.145812
                                                  0.029739
                                                                 0.011829
                                                                           0.082338
                                                                                     0.0823379771832097
             98
                      1.946853
                                 0.134926
                                                  0.031715
                                                                 0.005840
                                                                           0.101677
                                                                                     0.1016765069763807
                     1.629183
             42
                                 0.083901
                                                  0.022801
                                                                 0.003346
                                                                           0.137554
                                                                                     0.137554084460873
             58
                      1.859177
                                 0.136240
                                                  0.025097
                                                                 0.007581
                                                                           0.180909
                                                                                     0.1809091556421522
              1
                      7.015733
                                 0.438911
                                                  0.026228
                                                                 0.005973
                                                                            3.80286
                                                                                      3.802857225639664
             34
                      6.146194
                                 0.345854
                                                  0.028273
                                                                 0.008512
                                                                            3.86253
                                                                                      3.862528132298237
                      6.477816
                                                                            3.87834
             50
                                 0.289469
                                                  0.026133
                                                                 0.013208
                                                                                      3.878338511058234
             11
                      6.560687
                                 0.689193
                                                  0.033242
                                                                 0.007402
                                                                            3.87964
                                                                                      3.879639408647977
             69
                      7.289347
                                 0.445322
                                                  0.030326
                                                                 0.003518
                                                                            3.94755
                                                                                       3.94754774640206
```

```
100 rows × 14 columns
                                                                                       •
          print graph(results, 'param C', 'mean test score', 'Hyperparameter - C'
In [164]:
           , 'Test score')
             Plot showing the ROC AUC score for various hyper parameter values
              0.635
              0.630
            Test score
              0.625
              0.620
              0.615
              0.610
                   0.0
                        0.5
                           1.0
                                 1.5
                                      2.0
                                          2.5
                                                3.0
                                                     3.5
                                 Hyperparameter - C
In [165]: model = LogisticRegression(C=best c,verbose=verbose,n jobs=-1,random st
           ate=random state,class weight='balanced',solver='lbfgs')
           model.fit(train svd,y train)
           [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
           ers.
           [Parallel(n jobs=-1)]: Done 1 out of 1 | elapsed:
                                                                        3.5s finished
Out[165]: LogisticRegression(C=3.947547746402069, class weight='balanced', n jobs
           =-1,
                               random state=42, verbose=2)
          predictions = model.predict proba(test svd)[:,1]
In [166]:
           save submission(predictions, 'lr svd.csv')
```

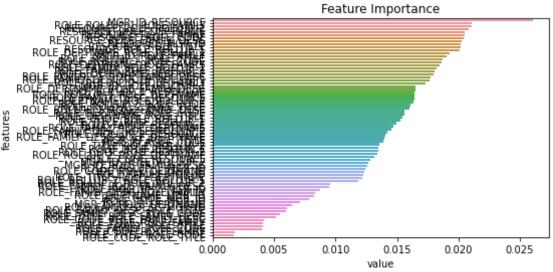


#### 5.4 Random Forest with SVD

```
In [167]: | rfc = RandomForestClassifier(random state=random state, class weight='ba
          lanced',n jobs=-1)
          clf = RandomizedSearchCV(rfc,get rf params(),random state=random state,
          cv=cv, verbose=verbose, n iter=100, scoring=scoring, n jobs=-1)
          best model = clf.fit(train svd,y train)
          Fitting 5 folds for each of 100 candidates, totalling 500 fits
          [Parallel(n jobs=-1)]: Using backend LokyBackend with 8 concurrent work
          ers.
          [Parallel(n jobs=-1)]: Done 25 tasks
                                                       | elapsed:
          /home/auw-mayank/.local/lib/python3.6/site-packages/joblib/externals/lo
          ky/process_executor.py:691: UserWarning: A worker stopped while some jo
          bs were given to the executor. This can be caused by a too short worker
          timeout or by a memory leak.
            "timeout or by a memory leak.", UserWarning
          [Parallel(n jobs=-1)]: Done 146 tasks
                                                       | elapsed: 6.8min
          [Parallel(n jobs=-1)]: Done 349 tasks
                                                       | elapsed: 16.5min
          [Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed: 24.5min finished
In [168]: results = pd.DataFrame(best model.cv results )
          results.sort values('mean test score', ascending=False, inplace=True)
          param keys=['param '+str(each) for each in get rf params().keys()]
          param keys.append('mean test score')
          results[param keys].head(10)
Out[168]:
              param n estimators param max depth param max features param min samples split mean
           84
                         1000
                                         25
                                                           5
                                                                               2
           20
                         1000
                                          25
                                                           3
                                                                               2
           33
                          700
                                         25
```

	param_r	_estimators	param_max_depth	param_max_features	param_min_samples_split	mean		
	22	200	25	4	10			
	78	700	25	2	7			
	85	1000	20	3	7			
	62	500	25	3	5			
	82	700	20	5	20			
	79	500	25	1	10			
	92	500	20	3	2			
	4					•		
In [169]:	<pre>n_estimators=clf.best_params_['n_estimators'] max_features=clf.best_params_['max_features'] max_depth=clf.best_params_['max_depth'] min_samples_split=clf.best_params_['min_samples_split'] n_estimators,max_features,max_depth,min_samples_split</pre>							
Out[169]:	(1000, 5, 25, 2)							
In [170]:	<pre>model=RandomForestClassifier(n_estimators=n_estimators,max_depth=max_de pth,max_features=max_features,</pre>							
	<pre>model.fit(train_svd,y_train)</pre>							
Out[170]:	<pre>RandomForestClassifier(class_weight='balanced', max_depth=25, max_featu res=5,</pre>							
In [171]:	<pre>importance features=</pre>	od.DataFra	ature_importar me({' <mark>features</mark> '	nces_ :features,' <mark>valu</mark> e alue',ascending=I				

```
sns.barplot('value', 'features', data=features);
plt.title('Feature Importance');
```



```
In [172]: predictions = model.predict_proba(test_svd)[:,1]
save_submission(predictions, 'rf_svd.csv')
```



### 5.5 Xgboost with SVD

```
In [173]: xgb = XGBClassifier()
clf = RandomizedSearchCV(xgb,get_xgb_params(),random_state=random_state
    ,cv=cv,verbose=verbose,n_iter=100,scoring=scoring,n_jobs=-1)
best_model=clf.fit(train_svd,y_train)
```

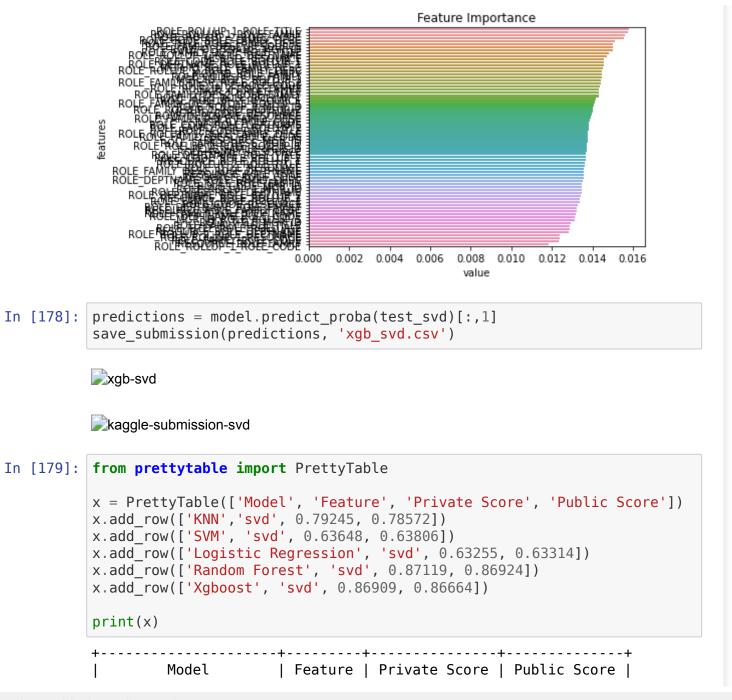
Fitting 5 folds for each of 100 candidates, totalling 500 fits

 $\label{lem:concurrent} \end{subarrante} \begin{subarrantered} [Parallel(n\_jobs=-1)]: Using backend LokyBackend with 8 concurrent work ers. \end{subarrantered}$ 

/home/auw-mayank/.local/lib/python3.6/site-packages/joblib/externals/lo

```
ky/process executor.py:691: UserWarning: A worker stopped while some jo
           bs were given to the executor. This can be caused by a too short worker
           timeout or by a memory leak.
             "timeout or by a memory leak.", UserWarning
           [Parallel(n jobs=-1)]: Done 25 tasks
                                                           elapsed:
                                                                       54.6s
           [Parallel(n jobs=-1)]: Done 146 tasks
                                                           elapsed: 9.9min
           [Parallel(n jobs=-1)]: Done 349 tasks
                                                          | elapsed: 28.0min
           [Parallel(n jobs=-1)]: Done 500 out of 500 | elapsed: 50.8min finished
In [174]:
          results = pd.DataFrame(best model.cv results )
           results.sort values('mean test score', ascending=False, inplace=True)
           param keys=['param '+str(each) for each in get xgb params().keys()]
           param keys.append('mean test score')
           results[param keys].head(10)
Out[174]:
               param_n_estimators param_learning_rate param_subsample param_max_depth param_colsan
            62
                           500
                                        0.0663892
                                                        0.328153
                                                                             9
            18
                           1000
                                        0.048135
                                                        0.665922
                                                                             9
                                                         0.98664
                                                                             7
            96
                           500
                                        0.0979629
            44
                                                                             6
                           1000
                                        0.060484
                                                        0.606429
            8
                           750
                                        0.0686033
                                                        0.683264
                                                                             6
            97
                           750
                                        0.232385
                                                        0.907694
                                                                             6
            49
                            500
                                         0.160277
                                                        0.393098
                                                                             8
                                                                             3
            80
                           1000
                                         0.385564
                                                        0.905351
            53
                           200
                                         0.540096
                                                        0.928319
                                                                             6
            78
                           1000
                                        0.576551
                                                         0.94023
                                                                             6
In [175]: colsample bytree = clf.best params ['colsample bytree']
           learning rate=clf.best params ['learning rate']
           max depth=clf.best params ['max depth']
           min child weight=clf.best params ['min child weight']
```

```
n estimators=clf.best params ['n estimators']
          subsample=clf.best params ['subsample']
          colsample bytree, learning rate, max depth, min child weight, n estimators,
          subsample
Out[175]: (0.375582952639944, 0.06638916390452139, 9, 3, 500, 0.3281526674747319
          model = XGBClassifier(colsample bytree=colsample bytree,learning rate=l
In [176]:
          earning rate, max depth=max depth,
                               min child weight=min child weight,n estimators=n e
          stimators, subsample=subsample, n jobs=-1)
          model.fit(train svd,y train)
Out[176]: XGBClassifier(base score=0.5, booster='qbtree', colsample bylevel=1,
                        colsample bynode=1, colsample bytree=0.375582952639944, q
          amma=0,
                        gpu id=-1, importance type='gain', interaction constraint
          s='',
                        learning rate=0.06638916390452139, max delta step=0, max
          depth=9,
                        min child weight=3, missing=nan, monotone constraints
          ='()',
                        n estimators=500, n jobs=-1, num parallel tree=1, random
          state=0.
                        reg alpha=0, reg lambda=1, scale pos weight=1,
                        subsample=0.32815266747473193, tree method='exact',
                        validate parameters=1, verbosity=None)
In [177]: features=train svd.columns
          importance=model.feature importances
          features=pd.DataFrame({'features':features,'value':importance})
          features=features.sort values('value',ascending=False)
          sns.barplot('value', 'features', data=features);
          plt.title('Feature Importance');
```



+	+	+	+
KNN	svd	0.79245	0.78572
SVM	svd	0.63648	0.63806
Logistic Regression	svd	0.63255	0.63314
Random Forest	svd	0.87119	0.86924
Xgboost	svd	0.86909	0.86664
+	+	+	+

#### **Observations:**

- 1. Tree based models works better than linear model
- 2. KNN is performing overall good

# We have to improve our model to reach into 5-10% on kaggle

```
In [180]: # https://www.kaggle.com/mitribunskiy/tutorial-catboost-overview
In [181]: # https://www.kaggle.com/prashant111/catboost-classifier-tutorial
```

# https://catboost.ai/

# CatBoost is a high-performance open source library for gradient boosting on decision trees

#### **About**

CatBoost is an algorithm for gradient boosting on decision trees. It is developed by Yandex researchers and engineers, and is used for search, recommendation systems, personal assistant, self-driving cars, weather prediction and many other tasks at Yandex and in other

companies, including CERN, Cloudflare, Careem taxi. It is in open-source and can be used by anyone.

#### **Features**

- 1. Reduce time spent on parameter tuning, because CatBoost provides great results with default parameters
- 2. Improve your training results with CatBoost that allows you to use non-numeric factors, instead of having to pre-process your data or spend time and effort turning it to numbers.
- 3. Reduce overfitting when constructing your models with a novel gradient-boosting scheme.
- 4. Apply your trained model quickly and efficiently even to latency-critical tasks using CatBoost's model applier

```
In [182]: params = {
                      'loss function': 'Logloss',
                      'eval metric': 'AUC',
                      'cat features':list(range(train data.shape[1])),
                      'verbose':100,
                      'random seed':random state
In [183]: clf= CatBoostClassifier(**params)
          clf.fit(train data,y train)
          Learning rate set to 0.045713
          0:
                  total: 99.2ms
                                  remaining: 1m 39s
                                  remaining: 20.7s
          100:
                  total: 2.33s
          200:
                  total: 5.6s
                                  remaining: 22.3s
          300:
                  total: 8.79s
                                  remaining: 20.4s
                                  remaining: 17.8s
          400:
                  total: 11.9s
          500:
                  total: 15.2s
                                  remaining: 15.2s
          600:
                  total: 18.4s
                                  remaining: 12.2s
          700:
                  total: 21.7s
                                  remaining: 9.27s
                                  remaining: 6.16s
          800:
                  total: 24.8s
          900:
                  total: 28s
                                  remaining: 3.08s
          999:
                  total: 31.1s
                                  remaining: Ous
```

```
Out[183]: <catboost.core.CatBoostClassifier at 0x7f361d4d8780>

In [184]: predictions = clf.predict_proba(test_data)[:,1]

In [185]: save_submission(predictions, 'catboost.csv')

Catboost

Catboost perform better than all our previous models and it's AUC score is much better than previous models so I am selecting this for predicting future data

In [186]: # Save model on disk pickle.dump(clf, open('models/catboost_model.pkl', 'wb'))

In []:
```