team22_jupyter_notebook

In [1]:
```
import pandas as pd
import numpy as np
import itertools

from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score, roc_cur
ve
from sklearn.linear_model import LogisticRegression
from imblearn.under_sampling import RandomUnderSampler

import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
df_profile  = pd.read_csv('dataset/user_profile.csv')
df_profile = df_profile.drop(df_profile.columns[0], axis=1)
df_profile.head()
```

```
/anaconda3/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2785: DtypeWarnin
g: Columns (4) have mixed types. Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

Out[2]:

	user_id	user_signup_timestamp	state	zipcode	is_homeowner	gender
0	50991631a5e7fafd8b5856fc15e3d1a3af5dcf98	2018-07-25 21:06:12	AR	72762	True	Female
1	18db173b8b0fb250985a4db2f3f8593ee9658707	2018-07-01 22:01:56	NE	68111	False	NaN
2	cabee62f0c4f26bb088f4a48d9ca5efa3a4f96e3	2018-07-02 08:47:21	AL	36078	False	Male
3	bb34f48b56a57e834c5c612b835d5a691f7357e8	2018-07-02 02:07:53	MT	59923	True	Unisex
4	6da929725c76c01aa151d97060df2e6bd051e31e	2018-07-03 17:36:42	PA	19040	False	Female

5 rows × 38 columns

In [3]:
```
df_engagement = pd.read_csv('dataset/user_engagement.csv')
df_engagement.head()
```

Out[3]:

	Unnamed: 0	session_id	user_id	sess
0	0	0e0808b9c2f0ee6367e1b2a2956ce964e25b726e	09a33bca3fa1f49f784b9c417e77294737bccab9	187
1	1	9407da7db039a2cafbae0970fcf8feb4766e15c6	6f8353af26427d39c9dd3ce84740df54479896dd	359
2	2	cc7df3be90aba49cf438bec126f76570ca8626ef	60513e969b461d15bc6f91a7a822177b9126c5f4	307
3	3	3b1fdedea217865b461f180b011a56af6505a43a	531600a9890794688120be32259c356057a2207a	0
4	4	1e83196264ebeb9db5bc35c50f9f0462b5c24b36	d72ab2f9299e7c1db705ab1159825ada25d9dad6	469

5 rows × 42 columns

Data Aggregation

In [4]:
```
#### total logins per user
total_logins = df_engagement.groupby(['user_id'])['session_id'].count()
df_profile['total_logins'] = df_profile['user_id'].map(total_logins)
df_profile['total_logins'] = df_profile['total_logins'].fillna(0)
df_profile['total_logins'].head()
```

Out[4]:
```
0     1.0
1     2.0
2     3.0
3    16.0
4     2.0
Name: total_logins, dtype: float64
```

In [5]:
```
#### total session length per user
total_session_length = df_engagement.groupby(['user_id'])['session_length'].sum()
df_profile['total_session_length'] = df_profile['user_id'].map(total_session_length)
df_profile['total_session_length'] = df_profile['total_session_length'].fillna(0)
df_profile['total_session_length'].head()
```

Out[5]:
```
0       0.0
1     673.0
2     806.0
3    2347.0
4     260.0
Name: total_session_length, dtype: float64
```

In [6]:
```
#### average session length per user
avg_session_length = df_engagement.groupby(['user_id'])['session_length'].mean()
df_profile['avg_session_length'] = df_profile['user_id'].map(avg_session_length)
df_profile['avg_session_length'] = df_profile['avg_session_length'].fillna(0)
df_profile['avg_session_length'].head()
```

Out[6]:
```
0      0.000000
1    336.500000
2    268.666667
3    146.687500
4    130.000000
Name: avg_session_length, dtype: float64
```

In [7]:
```
#### total page views per user
total_page_views = df_engagement.groupby(['user_id'])['view_count'].sum()
df_profile['total_page_views'] = df_profile['user_id'].map(total_page_views)
df_profile['total_page_views'] = df_profile['total_page_views'].fillna(0)
df_profile['total_page_views'].head()
```

Out[7]:
```
0     2.0
1     5.0
2    13.0
3    69.0
4     8.0
Name: total_page_views, dtype: float64
```

In [8]:
```
#### average session length per user
avg_page_views = df_engagement.groupby(['user_id'])['view_count'].mean()
df_profile['avg_page_views'] = df_profile['user_id'].map(avg_page_views)
df_profile['avg_page_views'] = df_profile['avg_page_views'].fillna(0)
df_profile['avg_page_views'].head()
```

Out[8]:
```
0    2.000000
1    2.500000
2    4.333333
3    4.312500
4    4.000000
Name: avg_page_views, dtype: float64
```

In [9]:
```
#### total click counts per user
total_click_counts = df_engagement.groupby(['user_id'])['click_count'].sum()
df_profile['total_click_counts'] = df_profile['user_id'].map(total_click_counts)
df_profile['total_click_counts'] = df_profile['total_click_counts'].fillna(0)
df_profile['total_click_counts'].head()
```

Out[9]:
```
0     0.0
1     6.0
2    43.0
3    38.0
4    11.0
Name: total_click_counts, dtype: float64
```

In [10]:
```
#### average click counts per user
avg_click_counts = df_engagement.groupby(['user_id'])['click_count'].mean()
df_profile['avg_click_counts'] = df_profile['user_id'].map(avg_click_counts)
df_profile['avg_click_counts'] = df_profile['avg_click_counts'].fillna(0)
df_profile['avg_click_counts'].head()
```

Out[10]:
```
0     0.000000
1     3.000000
2    14.333333
3     2.375000
4     5.500000
Name: avg_click_counts, dtype: float64
```

In [11]:
```
#### total apply counts per user
total_apply_counts = df_engagement.groupby(['user_id'])['click_apply_count'].sum()
df_profile['total_apply_counts'] = df_profile['user_id'].map(total_apply_counts)
df_profile['total_apply_counts'] = df_profile['total_apply_counts'].fillna(0)
df_profile['total_apply_counts'].head()
```

Out[11]:
```
0    0.0
1    0.0
2    0.0
3    0.0
4    1.0
Name: total_apply_counts, dtype: float64
```

In [12]:
```
#### average apply counts per user
avg_apply_counts = df_engagement.groupby(['user_id'])['click_apply_count'].mean()
df_profile['avg_apply_counts'] = df_profile['user_id'].map(avg_apply_counts)
df_profile['avg_apply_counts'] = df_profile['avg_apply_counts'].fillna(0)
df_profile['avg_apply_counts'].head()
```

Out[12]:
```
0    0.0
1    0.0
2    0.0
3    0.0
4    0.5
Name: avg_apply_counts, dtype: float64
```

Login Platform

In [13]:
```
df_engagement['dummy_mobile_web'] = [1 if i == 'Mobile Web' else 0 for i in df_engagement[
'login_platform']]
df_engagement['dummy_mobile_app'] = [1 if i == 'Mobile App' else 0 for i in df_engagement[
'login_platform']]
df_engagement['dummy_web'] = [1 if i == 'Web' else 0 for i in df_engagement['login_platfor
m']]
df_engagement.head()
```

Out[13]:

	Unnamed: 0	session_id	user_id	sess
0	0	0e0808b9c2f0ee6367e1b2a2956ce964e25b726e	09a33bca3fa1f49f784b9c417e77294737bccab9	187
1	1	9407da7db039a2cafbae0970fcf8feb4766e15c6	6f8353af26427d39c9dd3ce84740df54479896dd	359
2	2	cc7df3be90aba49cf438bec126f76570ca8626ef	60513e969b461d15bc6f91a7a822177b9126c5f4	307
3	3	3b1fdedea217865b461f180b011a56af6505a43a	531600a9890794688120be32259c356057a2207a	0
4	4	1e83196264ebeb9db5bc35c50f9f0462b5c24b36	d72ab2f9299e7c1db705ab1159825ada25d9dad6	469

5 rows × 45 columns

In [14]:
```
#### mobile_web login counts
mobile_web_logins = df_engagement.groupby(['user_id'])['dummy_mobile_web'].sum()
df_profile['mobile_web_logins'] = df_profile['user_id'].map(mobile_web_logins)
df_profile['mobile_web_logins'] = df_profile['mobile_web_logins'].fillna(0)
df_profile['mobile_web_logins'].head()
```

Out[14]:
```
0     1.0
1     2.0
2     2.0
3    15.0
4     0.0
Name: mobile_web_logins, dtype: float64
```

In [15]:
```
#### mobile_app login counts
mobile_web_logins = df_engagement.groupby(['user_id'])['dummy_mobile_app'].sum()
df_profile['dummy_mobile_app'] = df_profile['user_id'].map(mobile_web_logins)
df_profile['dummy_mobile_app'] = df_profile['dummy_mobile_app'].fillna(0)
df_profile['dummy_mobile_app'].head()
```

Out[15]:
```
0    0.0
1    0.0
2    0.0
3    0.0
4    0.0
Name: dummy_mobile_app, dtype: float64
```

In [16]:
```
#### dummy_web login countds
web_logins = df_engagement.groupby(['user_id'])['dummy_web'].sum()
df_profile['web_logins'] = df_profile['user_id'].map(web_logins)
df_profile['web_logins'] = df_profile['web_logins'].fillna(0)
df_profile['web_logins'].head()
```

Out[16]:
```
0    0.0
1    0.0
2    1.0
3    1.0
4    2.0
Name: web_logins, dtype: float64
```

In [17]:
```
df_profile.head()
```

Out[17]:

	user_id	user_signup_timestamp	state	zipcode	is_homeowner	gender
0	50991631a5e7fafd8b5856fc15e3d1a3af5dcf98	2018-07-25 21:06:12	AR	72762	True	Female
1	18db173b8b0fb250985a4db2f3f8593ee9658707	2018-07-01 22:01:56	NE	68111	False	NaN
2	cabee62f0c4f26bb088f4a48d9ca5efa3a4f96e3	2018-07-02 08:47:21	AL	36078	False	Male
3	bb34f48b56a57e834c5c612b835d5a691f7357e8	2018-07-02 02:07:53	MT	59923	True	Unisex
4	6da929725c76c01aa151d97060df2e6bd051e31e	2018-07-03 17:36:42	PA	19040	False	Female

5 rows × 50 columns

Binary Outcome Variation

In [18]:
```
df_profile['binary_apply_counts'] = [1 if i > 0 else 0 for i in df_profile['total_apply_cou
nts']]
df_profile.head(10)
```

Out[18]:

	user_id	user_signup_timestamp	state	zipcode	is_homeowner	gende
0	50991631a5e7fafd8b5856fc15e3d1a3af5dcf98	2018-07-25 21:06:12	AR	72762	True	Female
1	18db173b8b0fb250985a4db2f3f8593ee9658707	2018-07-01 22:01:56	NE	68111	False	NaN
2	cabee62f0c4f26bb088f4a48d9ca5efa3a4f96e3	2018-07-02 08:47:21	AL	36078	False	Male
3	bb34f48b56a57e834c5c612b835d5a691f7357e8	2018-07-02 02:07:53	MT	59923	True	Unisex
4	6da929725c76c01aa151d97060df2e6bd051e31e	2018-07-03 17:36:42	PA	19040	False	Female
5	e8a6717452a88ec8d699c0a4181637c67d247e84	2018-07-02 16:11:42	NC	28138	False	Female
6	03c209fbb349633c40826a83874f92e302382b13	2018-07-05 13:53:15	FL	33136	False	Female
7	ae0ebe7492c5af1fec00c8ecd59f83cc5a659fb2	2018-07-05 04:59:37	UT	84020	False	Male
8	6bee222d2814703172bbf78bcef85761c4764d90	2018-07-05 11:45:08	TN	38139	False	Female
9	e88601d9dfeb0ffa8016ef0e6fa81094643ae8ab	2018-07-05 18:37:29	MS	39520	True	NaN

10 rows × 51 columns

Dropping Variables

In [19]:
```
for var, count in df_profile.isna().sum().iteritems():
    if count >0:
        print (var, count)
        df_profile = df_profile.drop(columns=[var])
df_profile = df_profile.drop(columns = ['total_apply_counts', 'avg_apply_counts'])
```

```
gender 34772
tradelines_avg_days_since_opened 10593
tradelines_max_days_since_opened 10593
tradelines_min_days_since_opened 10593
max_cc_utilization_ratio 153646
avg_cc_utilization_ratio 153656
recent_bankruptcy_date 259814
age_bucket 6957
```

In [20]:
```
df_profile.head()
```

Out[20]:

	user_id	user_signup_timestamp	state	zipcode	is_homeowner	count_
0	50991631a5e7fafd8b5856fc15e3d1a3af5dcf98	2018-07-25 21:06:12	AR	72762	True	1
1	18db173b8b0fb250985a4db2f3f8593ee9658707	2018-07-01 22:01:56	NE	68111	False	7
2	cabee62f0c4f26bb088f4a48d9ca5efa3a4f96e3	2018-07-02 08:47:21	AL	36078	False	8
3	bb34f48b56a57e834c5c612b835d5a691f7357e8	2018-07-02 02:07:53	MT	59923	True	8
4	6da929725c76c01aa151d97060df2e6bd051e31e	2018-07-03 17:36:42	PA	19040	False	1

5 rows × 41 columns

Random Forest Classifier

In [21]:
```
df = df_profile.select_dtypes(['number'])
df.head()
```

Out[21]:

	count_tradelines_closed_accounts	count_total_tradelines_opened_24_months	count_tradelines_cc_opened_2
0	1	2	0
1	7	3	1
2	8	2	0
3	8	5	3
4	1	6	1

5 rows × 35 columns

In [22]:
```
X = df.iloc[:, :-1]
y = df.iloc[:, -1]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
cols = X_train.columns
```

Undersample to Balance Classes

Balance binary_apply = 0, and binary_apply = 1

In [23]:
```
usamp = RandomUnderSampler()
us_X_train, us_y_train=usamp.fit_sample(X_train, y_train)
us_X_train = pd.DataFrame(data=us_X_train,columns=cols)
#us_y_train = pd.DataFrame(data=us_y_train,columns=['binary_apply_counts'])
```

In [24]:
```
y_train.value_counts()
```

Out[24]:
```
0    129813
1     98579
Name: binary_apply_counts, dtype: int64
```

In [25]:
```
us_y_train
```

Out[25]:
```
array([0, 0, 0, ..., 1, 1, 1])
```

Random Forest Classifier

In [26]:
```
clf = RandomForestClassifier(n_estimators=200)
clf.fit(us_X_train, us_y_train)
```

Out[26]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=None, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=200, n_jobs=None,
                       oob_score=False, random_state=None, verbose=0,
                       warm_start=False)
```

Cross Validation

In [27]:
```
scores = cross_val_score(clf, us_X_train, us_y_train, cv=3, scoring='accuracy')
```

In [28]:
```
scores.mean()
```

Out[28]:
```
0.7104656986507781
```

Testing

In [29]:
```
clf.score(X_test, y_test)
```

Out[29]:
```
0.7097322194784497
```

In [30]:
```
coefs = zip(list(X.columns), [round(i, 3) for i in list(clf.feature_importances_)])
coefs = sorted(coefs, key = lambda t: t[1])[::-1]
coefs
```

Out[30]:
```
[('total_session_length', 0.129),
 ('avg_session_length', 0.079),
 ('total_tradelines_open_balance', 0.062),
 ('total_page_views', 0.058),
 ('total_click_counts', 0.049),
 ('avg_click_counts', 0.048),
 ('avg_page_views', 0.047),
 ('mobile_web_logins', 0.041),
 ('count_tradelines_condition_derogatory', 0.04),
 ('count_tradelines_closed_accounts', 0.04),
 ('total_tradelines_amount_past_due', 0.036),
 ('max_cc_limit', 0.034),
 ('count_tradelines_opened_accounts', 0.034),
 ('total_logins', 0.031),
 ('count_total_tradelines_opened_24_months', 0.03),
 ('count_tradelines_open_collection_accounts', 0.029),
 ('count_inquiries_12_months', 0.028),
 ('total_cc_open_balance', 0.028),
 ('total_auto_loans_balance', 0.024),
 ('count_inquiries_6_months', 0.019),
 ('count_inquiries_3_months', 0.015),
 ('total_student_loans_balance', 0.014),
 ('count_open_installment_accounts_24_months', 0.012),
 ('count_tradelines_open_student_loans', 0.011),
 ('count_tradelines_cc_opened_24_months', 0.01),
 ('web_logins', 0.009),
 ('dummy_mobile_app', 0.008),
 ('total_mortgage_loans_balance', 0.008),
 ('total_mortgage_loans_amount', 0.008),
 ('count_bankruptcy', 0.006),
 ('count_tradelines_open_unsecured_loans', 0.005),
 ('count_tradelines_open_secured_loans', 0.005),
 ('count_tradelines_open_mortgages', 0.003),
 ('total_open_cc_amount_past_due', 0.002)]
```

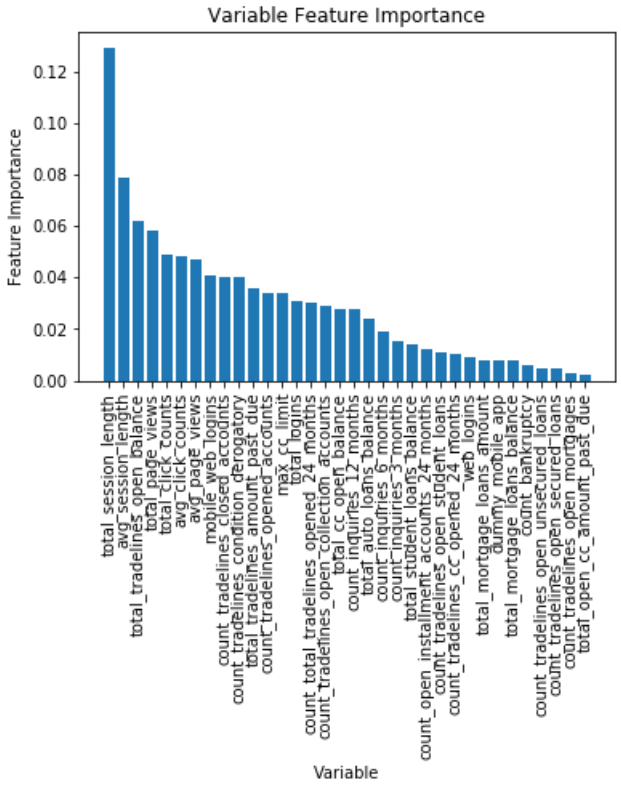
In [31]:
```
df_coefs = pd.DataFrame({'feature': list(X.columns), 'feature_importance': [round(i, 3) for
 i in list(clf.feature_importances_)]})
df_coefs = df_coefs.sort_values(by=['feature_importance'], ascending=False)
df_coefs = df_coefs.set_index('feature')
df_coefs.head(20)
```

Out[31]:

	feature_importance
feature	
total_session_length	0.129
avg_session_length	0.079
total_tradelines_open_balance	0.062
total_page_views	0.058
total_click_counts	0.049
avg_click_counts	0.048
avg_page_views	0.047
mobile_web_logins	0.041
count_tradelines_closed_accounts	0.040
count_tradelines_condition_derogatory	0.040
total_tradelines_amount_past_due	0.036
count_tradelines_opened_accounts	0.034
max_cc_limit	0.034
total_logins	0.031
count_total_tradelines_opened_24_months	0.030
count_tradelines_open_collection_accounts	0.029
total_cc_open_balance	0.028
count_inquiries_12_months	0.028
total_auto_loans_balance	0.024
count_inquiries_6_months	0.019

In [32]:
```
ax = plt.bar(df_coefs.index, df_coefs['feature_importance'])
plt.xticks( rotation='vertical')
plt.title('Variable Feature Importance')
plt.xlabel('Variable')
plt.ylabel('Feature Importance')
```

Out[32]: Text(0,0.5,'Feature Importance')



In [33]:
```
max_coef = coefs[0][1]
max_coef
```

Out[33]: 0.129

In [34]:
```
indexes = []
for i in list(coefs)[:20]:
    indexes.append(i[0])
```

Model Evaluation

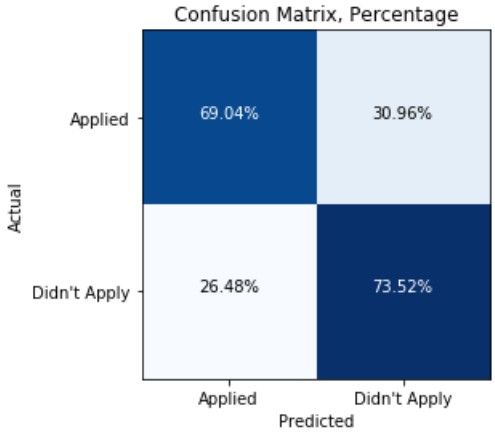
In [35]:
```
con_train = confusion_matrix(us_y_train, pd.DataFrame(clf.predict(us_X_train)))
con_train
```

Out[35]:
```
array([[98579,     0],
       [    1, 98578]])
```

In [36]:
```
con_test = confusion_matrix(y_test, pd.DataFrame(clf.predict(X_test)))
con_test
```

Out[36]:
```
array([[22426, 10055],
       [ 6519, 18099]])
```

In [37]:
```
target_names = ['Applied', "Didn't Apply"]
con = confusion_matrix(y_test, pd.DataFrame(clf.predict(X_test)))
con = con.astype('float')/ con.sum(axis=1)[:, np.newaxis]
plt.imshow(con, interpolation='nearest', cmap=plt.get_cmap('Blues'))
tick_marks = np.arange(len(target_names))
thresh = con.max() / 1.5
for i, j in itertools.product(range(con.shape[0]), range(con.shape[1])):
    plt.text(j, i, "{}%".format(round(con[i, j]*100,2)),
             horizontalalignment="center",
             color="white" if con[i, j] > thresh else "black")
plt.xticks(tick_marks, target_names)
plt.yticks(tick_marks, target_names)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix, Percentage')
plt.show()
```



In [38]:
```
logit_roc_auc = roc_auc_score(y_test, clf.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, clf.predict_proba(X_test)[:,1])
plt.plot(fpr, tpr, label='Random Forest (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([-0.05, 1.05])
plt.ylim([-0.05, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
```