Music Recommendation -- Random Forest, XGboost

```
# Load Python libraries
from sklearn import cross_validation, grid_search, metrics, ensemble
import xgboost as xgb
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib as mpl
import warnings
warnings.filterwarnings('ignore')
plt.style.use('ggplot')
```

```
/opt/conda/lib/python3.6/site-packages/sklearn/cross_validation.py:41:
DeprecationWarning: This module was deprecated in version 0.18 in
favor of the model_selection module into which all the refactored
classes and functions are moved. Also note that the interface of the
new CV iterators are different from that of this module. This module
will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
/opt/conda/lib/python3.6/site-packages/sklearn/grid_search.py:42:
DeprecationWarning: This module was deprecated in version 0.18 in
favor of the model_selection module into which all the refactored
classes and functions are moved. This module will be removed in 0.20.
  DeprecationWarning)
```

Data Preparation

I merged 3 datasets (train, songs, members), replaced NAs, created 6 columns (days, months, years of registration_init_time and expiration_date), droped correlating columns.

1% of Data is used in the kernel.

```
# Load data
df = pd.read_csv('../input/train.csv')

# 1% sample of items
df = df.sample(frac=0.01)

# Load and join songs data
songs = pd.read_csv('../input/songs.csv')
df = pd.merge(df, songs, on='song_id', how='left')
del songs

# Load and join songs data
members = pd.read_csv('../input/members.csv')
df = pd.merge(df, members, on='msno', how='left')
del members
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 73774 entries, 0 to 73773
Data columns (total 18 columns):
msno                    73774 non-null object
song_id                 73774 non-null object
source_system_tab       73527 non-null object
source_screen_name      69577 non-null object
source_type             73563 non-null object
target                  73774 non-null int64
song_length             73773 non-null float64
genre_ids               72613 non-null object
artist_name             73773 non-null object
composer                57028 non-null object
lyricist                41929 non-null object
language                73772 non-null float64
city                    73774 non-null int64
bd                      73774 non-null int64
gender                  44196 non-null object
registered_via          73774 non-null int64
registration_init_time  73774 non-null int64
expiration_date         73774 non-null int64
dtypes: float64(2), int64(6), object(10)
memory usage: 10.7+ MB
```

```
# Count Na in %
df.isnull().sum()/df.isnull().count()*100
```

```
msno                     0.000000
song_id                  0.000000
source_system_tab        0.334806
source_screen_name       5.688996
source_type              0.286009
target                   0.000000
song_length              0.001355
genre_ids                1.573725
artist_name              0.001355
composer                22.699054
lyricist                43.165614
language                 0.002711
city                     0.000000
bd                       0.000000
gender                  40.092716
registered_via           0.000000
registration_init_time   0.000000
expiration_date          0.000000
dtype: float64
```

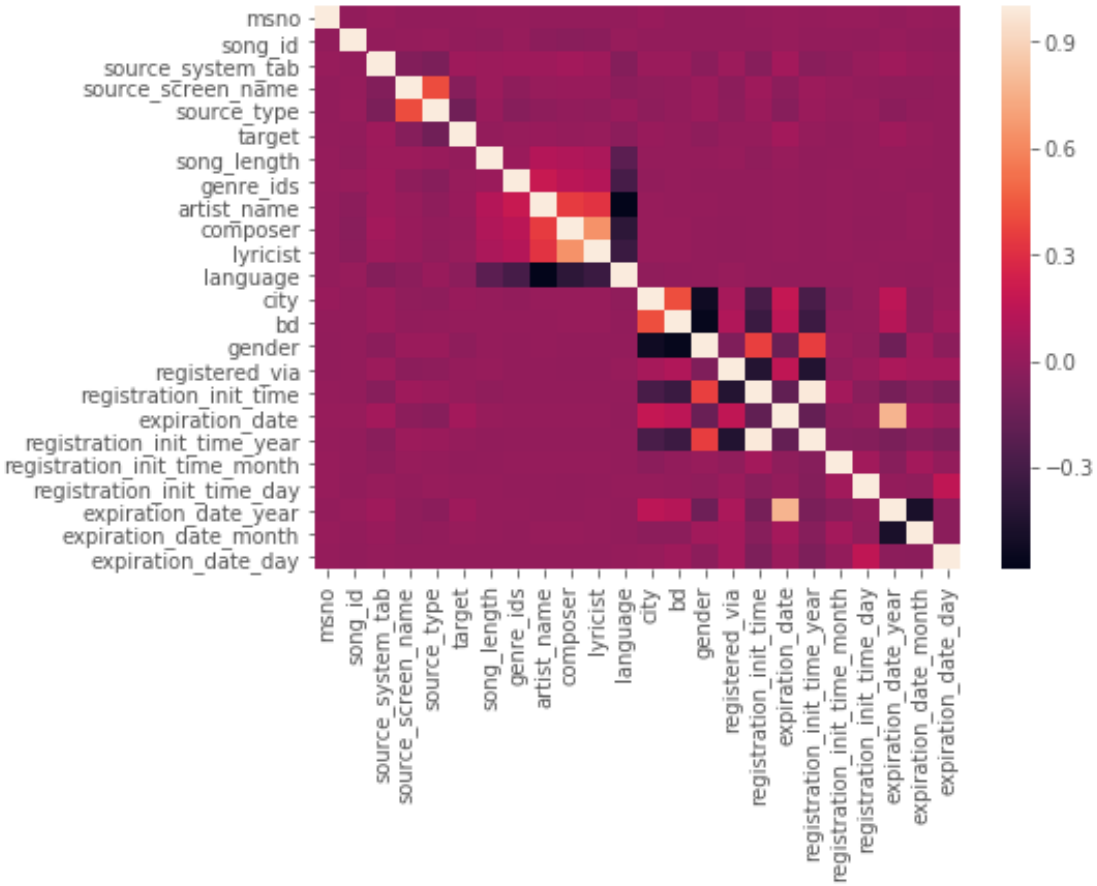
```
# Replace NA
for i in df.select_dtypes(include=['object']).columns:
```

```
    df[i][df[i].isnull()] = 'unknown'
df = df.fillna(value=0)

# Create Dates

# registration_init_time
df.registration_init_time = pd.to_datetime(df.registration_init_time,
format='%Y%m%d', errors='ignore')
df['registration_init_time_year'] =
df['registration_init_time'].dt.year
df['registration_init_time_month'] =
df['registration_init_time'].dt.month
df['registration_init_time_day'] = df['registration_init_time'].dt.day

# expiration_date
df.expiration_date = pd.to_datetime(df.expiration_date,  format='%Y%m
%d', errors='ignore')
df['expiration_date_year'] = df['expiration_date'].dt.year
df['expiration_date_month'] = df['expiration_date'].dt.month
df['expiration_date_day'] = df['expiration_date'].dt.day

df.head()
```

```
                                           msno  \
0  crUeQ6DYDHHRNYmn+n5Kodfvu9ki0IdHfXHNlZEUPHs=
1  rNJWIl2uvL2o+m5xP6Wbu4Pzokslrb2eQlGYe82r7fA=
2  lbJHQba4aEMJUFDFgDE7PwTdR1UoY/iLj+XkofWMsik=
3  B14Thl6p2fkkE10+Jq2KXliDLa7LLQX6b5kEvkVzylw=
4  wGUfULxf/bZwNgo7+2KxcQSKOp+86YtlLJTty1/fp+M=

                                        song_id source_system_tab  \
0  d9Flpsyq/y8CR3F213pnXUkrfK1fMClvhYH37pFSc7s=          discover
1  TRe3/tOgqw/x4a8nhG/qe88tQQXd2P7yem3Ub61D0CQ=        my library
2  AJQOsWR+d8TYfx8K3IngAs9/GSQE5ujDqBx/8PYm6zo=          discover
3  RxCEvZAXgnh1ZDlQBuVb/J9xpnopFSJBaBxLqGZIXSs=        my library
4  ot7ZDLrguBLIG2TiXjT0VGawAzmSlgcDZv6+UkKeOHo=          discover

     source_screen_name      source_type  target  song_length
genre_ids  \
0        Discover Genre  online-playlist       1     295497.0
465
1   Local playlist more    local-library       1     274176.0
458
2  Online playlist more  online-playlist       0     285600.0
458
3   Local playlist more   local-playlist       0     297482.0
458
4  Online playlist more  online-playlist       0     264777.0
2022
```

```
      artist_name                    composer         ...
gender  \
0           Adele  Adele Adkins| Greg Kurstin         ...
male
1  徐佳瑩(Lala Hsu)                          黃建為    ...
male
2  林宥嘉(Yoga Lin)                          張葉帆    ...
male
3  周杰倫(Jay Chou)                          周杰倫    ...
male
4      旺福(Wonfu)                          姚小民    ...
unknown

   registered_via  registration_init_time  expiration_date  \
0               9              2014-06-14       2017-09-07
1               7              2013-11-19       2017-10-03
2               9              2008-11-29       2017-07-17
3               9              2005-08-13       2017-10-06
4               7              2013-11-21       2017-09-23

  registration_init_time_year  registration_init_time_month  \
0                        2014                             6
1                        2013                            11
2                        2008                            11
3                        2005                             8
4                        2013                            11

  registration_init_time_day expiration_date_year
expiration_date_month  \
0                         14                 2017
9
1                         19                 2017
10
2                         29                 2017
7
3                         13                 2017
10
4                         21                 2017
9

   expiration_date_day
0                    7
1                    3
2                   17
3                    6
4                   23

[5 rows x 24 columns]
```

```
# Dates to categoty
df['registration_init_time'] =
df['registration_init_time'].astype('category')
df['expiration_date'] = df['expiration_date'].astype('category')

# Object data to category
for col in df.select_dtypes(include=['object']).columns:
    df[col] = df[col].astype('category')

# Encoding categorical features
for col in df.select_dtypes(include=['category']).columns:
    df[col] = df[col].cat.codes

# Correlation matrix
plt.figure(figsize=[7,5])
sns.heatmap(df.corr())
plt.show()
```




```
# Drop columns
df = df.drop(['expiration_date', 'lyricist'], 1)
```

Random Forest

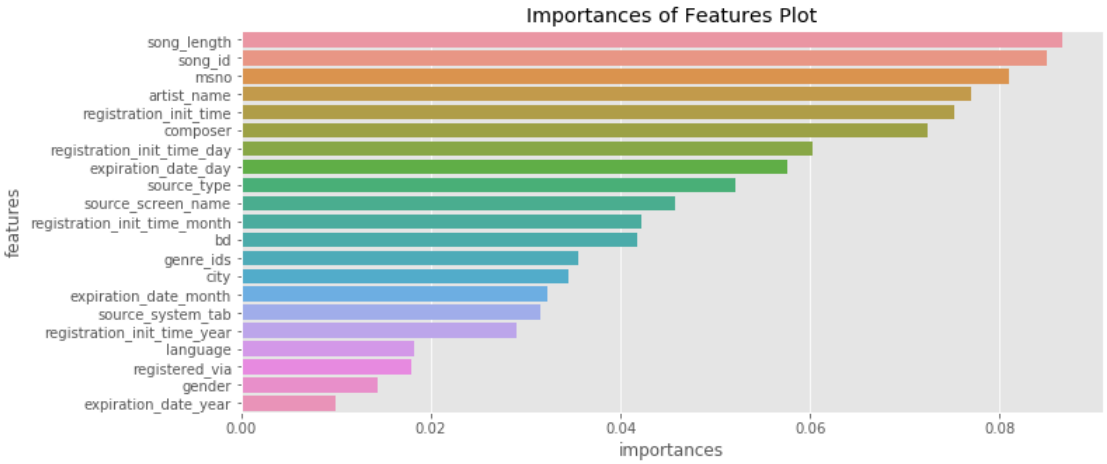
I selected the most informative columns using Random Forest Model.

```
# Model with the best estimator
model = ensemble.RandomForestClassifier(n_estimators=250,
max_depth=25)
model.fit(df[df.columns[df.columns != 'target']], df.target)
```

```
RandomForestClassifier(bootstrap=True, class_weight=None,
criterion='gini',
            max_depth=25, 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=250, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
```

```
df_plot = pd.DataFrame({'features': df.columns[df.columns !=
'target'],
                        'importances': model.feature_importances_})
df_plot = df_plot.sort_values('importances', ascending=False)
```

```
plt.figure(figsize=[11,5])
sns.barplot(x = df_plot.importances, y = df_plot.features)
plt.title('Importances of Features Plot')
plt.show()
```




```
# Drop columns with importances < 0.04
df = df.drop(df_plot.features[df_plot.importances < 0.04].tolist(), 1)
```

```
# Selected columns
df.columns
```

```
Index(['msno', 'song_id', 'source_screen_name', 'source_type',
'target',
       'song_length', 'artist_name', 'composer', 'bd',
       'registration_init_time', 'registration_init_time_month',
       'registration_init_time_day', 'expiration_date_day'],
      dtype='object')
```

XGboost

```
# Train & Test split
target = df.pop('target')
train_data, test_data, train_labels, test_labels =
cross_validation.train_test_split(df, target, test_size = 0.3)

# Delete df
del df
```

The best estimator was selected by Randomized Grid Search with Stratified Shuffle Split Cross Validation.

Create model

model = xgb.XGBClassifier()

Create parameters grid

parameters_grid = { 'learning_rate' : [0.1, 0.2, 0.5], 'max_depth' : [5, 10, 15], 'n_estimators' : [150, 250, 300], 'min_child_weight' : [3, 5, 10] }

Strategy of cross validation

cv = cross_validation.StratifiedShuffleSplit(train_labels, n_iter = 3, test_size = 0.3)

Create Grid search Strategy

grid_cv = grid_search.RandomizedSearchCV(model, parameters_grid, scoring = 'accuracy', cv = cv)

Fit model by Grid

grid_cv.fit(train_data, train_labels)

Model with the best estimator

grid_cv.best_estimator_

```
# Create model
model = xgb.XGBClassifier(learning_rate=0.1, max_depth=15,
min_child_weight=5, n_estimators=250)
model.fit(train_data, train_labels)

XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
       colsample_bytree=1, gamma=0, learning_rate=0.1,
max_delta_step=0,
       max_depth=15, min_child_weight=5, missing=None,
n_estimators=250,
       n_jobs=1, nthread=None, objective='binary:logistic',
random_state=0,
       reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
       silent=True, subsample=1)
```

```
# Predicting
predict_labels = model.predict(test_data)
```

The results of the algorithm

```
print(metrics.classification_report(test_labels, predict_labels))
```

```
             precision    recall  f1-score   support

          0       0.63      0.60      0.61     11129
          1       0.61      0.65      0.63     11004

avg / total       0.62      0.62      0.62     22133
```