

CapstoneProject

September 26, 2019

```
[3]: from sklearn import metrics, ensemble
from sklearn.model_selection import cross_validate, GridSearchCV, train_test_split
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')
```

```
[4]: train = pd.read_csv('input/train.csv')
train = train.sample(frac=0.5)
```

```
[5]: songs = pd.read_csv('input/songs.csv')
train = pd.merge(train, songs, on='song_id', how='left')
del songs

members = pd.read_csv('input/members.csv')
train = pd.merge(train, members, on='msno', how='left')
del members

song_extra_info = pd.read_csv('input/song_extra_info.csv')
train = pd.merge(train, song_extra_info, on='song_id', how='left')
del song_extra_info
```

```
[6]: train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 750000 entries, 0 to 749999
Data columns (total 20 columns):
msno                750000 non-null object
song_id            750000 non-null object
source_system_tab  747638 non-null object
source_screen_name 715503 non-null object
source_type        747944 non-null object
target             750000 non-null int64
```

```

song_length      749988 non-null float64
genre_ids        738949 non-null object
artist_name      749988 non-null object
composer         587570 non-null object
lyricist         437793 non-null object
language         749984 non-null float64
city             750000 non-null int64
bd               750000 non-null int64
gender           452950 non-null object
registered_via    750000 non-null int64
registration_init_time 750000 non-null int64
expiration_date   750000 non-null int64
name             749934 non-null object
isrc             691080 non-null object
dtypes: float64(2), int64(6), object(12)
memory usage: 120.2+ MB

```

```
[7]: train.describe()
```

```

[7]:
      count  target  song_length  language  city \
count  750000.000000  7.499880e+05  749984.000000  750000.000000
mean      0.665844  2.454337e+05      18.477625      7.567128
std       0.471695  5.928003e+04      21.163488      6.585206
min       0.000000  2.716000e+03     -1.000000      1.000000
25%       0.000000  2.152020e+05      3.000000      1.000000
50%       1.000000  2.423110e+05      3.000000      5.000000
75%       1.000000  2.727180e+05     52.000000     13.000000
max       1.000000  7.371499e+06     59.000000     22.000000

      bd  registered_via  registration_init_time  expiration_date
count  750000.000000    750000.000000          7.500000e+05    7.500000e+05
mean     17.460075         6.775365          2.012778e+07    2.017149e+07
std     21.108548         2.296369          2.978766e+04    3.869867e+03
min     -43.000000         3.000000          2.004033e+07    2.004102e+07
25%       0.000000         4.000000          2.011071e+07    2.017091e+07
50%      21.000000         7.000000          2.013102e+07    2.017093e+07
75%      28.000000         9.000000          2.015101e+07    2.017101e+07
max     1030.000000        13.000000          2.016121e+07    2.020102e+07

```

```
[8]: train.head(10)
```

```

[8]:
      msno \
0  Z1TSQ1AkVZHsqjmxT9LY720XxNAqkDyHspt2lpjZMm0=
1  BAN2f6KT+KXSbD3Tnau6aKDDAIF/tiBo4kMRfArFXc=
2  UjuPJcQo/YoGVR/yJ+CocmWUk2czJE0BBKqaPpVYV64=
3  qv24DyXUmZVHzxcgPJRY7qFeni3fdd2q47kxiCekjs=
4  lGDH18s6FJTqb5a957xraHq7Z6t000sDVMidb584ZjM=
5  1R7ML18C0c/LyqGfeQiCojiuTgQ4a11/XIznJ58e9kQ=
6  6Zfzj07RYXWvEQEQmXrC+Tqpy1QqgErMbbK6S5gN86M=

```

7 KP9C2DhtapjZuDpH3VNvtKQlI3LraMhMnkHw470H7XE=
8 SyjAw0JwRtBznliPX/ujk5jXlzMkiNxZ3taAHDWa3pY=
9 bIAx0XsFcmkAEftfvVu1lxywiAigZEsmjhFPmzWZ78U=

	song_id	source_system_tab	\
0	fWtBf0GSJnwaWiNisVGnnZjFAT8vmZ8n1SB7FAIlmOQ=	my library	
1	fEAlgFRWmhXmo6m3ukQeqRksZCc0/7CjkqNckRHiVQo=	discover	
2	WDhQhbbq+bwhBY642Fx3e5eGBdvqzzXmwioCaVIO0=	my library	
3	4m+cvkd9Y5L16enj9nRufbfV+HxYguQ7FgvazLQ3I8=	my library	
4	+W5WCJFc7k7UJLArWZKMYmkr03Ro0m6VrmD7yJfVKRI=	my library	
5	o+fLXtu2auUsQNTfB141c7dPE5HnkvVF9wjBK5dHSjk=	my library	
6	5nsq4I7YcXGj0DKwMsuanz70IO9xrCn80mIJ6127pqg=	my library	
7	Fzq070TM1QVVssM6J7PHtA2l8MFKD7qeJkSPcdqw03o=	my library	
8	kg0SHwInwdvDK0rUu80XvPDITvzPKfeNl2pA96PJBfs=	radio	
9	Of6g3RC1YKF1eqWm0oAP81ao6HmB2zWvXzCUzwUdG1o=	my library	

	source_screen_name	source_type	target	song_length	genre_ids	\
0	Local playlist more	local-playlist	1	225280.0	465	
1	Unknown	online-playlist	1	179258.0	458	
2	Local playlist more	local-library	0	252000.0	458	
3	Local playlist more	local-library	0	206576.0	465	
4	Local playlist more	local-library	0	162168.0	465	
5	Local playlist more	local-playlist	1	239258.0	1259	
6	Local playlist more	local-library	1	195999.0	458	
7	NaN	local-library	1	218801.0	465	
8	Radio	radio	0	292989.0	465	
9	Local playlist more	local-playlist	1	260969.0	458	

	artist_name	\
0	(Claire Kuo)	
1	(MISS KO)	
2	(Stanly Hsu)	
3	(Show Lo)	
4	Fergie	
5	Machine Gun Kelly Camila Cabello	
6	(Joanna Wang)	
7	(Aaron Yan)	
8	(Leehom Wang)	
9	(Rainie Yang)	

	composer	\
0	Victor/	
1	Miss Ko Razor 'n Guido	
2	/	
3	NaN	
4	J. Donald Jamal Jones Stacy Ferguson J. Sol...	
5	Camila Cabello Colson Baker pka "MGK" for EST...	

```

6      Peter Sven Kvint| Vincent Paul Degiorgio
7                                     JerryC
8
9      Ying-Jian Chen

```

```

                                lyricist  language  city  bd  gender  \
0                                /           3.0      1   0    NaN
1                                NaN          3.0     15  20    male
2                                3.0       13  23    female
3                                NaN          3.0      1   0    NaN
4                                NaN          52.0      4  22    female
5                                NaN          52.0      1   0    NaN
6  Peter Sven Kvint| Vincent Paul Degiorgio      3.0      1   0    NaN
7                                3.0       13  43    female
8                                ///          3.0      1   0    NaN
9                                Zhuo-Xiong Li      3.0      4  28    female

```

```

    registered_via  registration_init_time  expiration_date  \
0                7          20131011          20170911
1                9          20100208          20170906
2                9          20130518          20171202
3                9          20151125          20170914
4                7          20110624          20171005
5                4          20151024          20171004
6                7          20150714          20170930
7                9          20151001          20170911
8                4          20161130          20161207
9                4          20151031          20180127

```

```

                                name          isrc
0  (Sorry to Say Goodbye)  TWA211551801
1                        TWUM71600104
2                        TWCG31600001
3                        TWEM31211002
4      M.I.L.F. $  USUM71604730
5      Bad Things  USUM71609854
6  (You Ni De Quai Le)  TWA470722014
7                        TWD951446201
8      Forever Love  TWA470473005
9  (Ni Ming De Hao You)  TWA470915006

```

```
[9]: train.isnull().sum()
```

```

[9]: msno              0
     song_id           0
     source_system_tab  2362
     source_screen_name 34497
     source_type        2056

```

```

target                0
song_length           12
genre_ids             11051
artist_name           12
composer             162430
lyricist              312207
language              16
city                  0
bd                    0
gender                297050
registered_via         0
registration_init_time 0
expiration_date        0
name                  66
isrc                  58920
dtype: int64

```

```

[10]: for i in train.select_dtypes(include=['object']).columns:
        train[i][train[i].isnull()] = 'unknown'
train = train.fillna(value=0)

```

```

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

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

del train['registration_init_time']
del train['expiration_date']
train.head(10)

```

```

[11]:                                     msno \
0  Z1TSQ1AkVZHsqjmxT9LY720XxNAqkDyHspt2lpjZMm0=
1  BAN2f6KT+KXSbD3Tnau6aKDDAIF/tiBo4kMRFdArFXc=
2  UjuPJCQo/YoGVR/yJ+CocmWUk2czJE0BBKqaPpVYV64=
3  qv24DyXUmZVHzxcwcpJRy7qFeni3fdd2q47kxiCekjs=
4  lGDH18s6FJTqb5a957xraHq7Z6t000sDVMidb584ZjM=
5  1R7ML18C0c/LyqGfeQiCojiuTgQ4a11/XIznJ58e9kQ=
6  6Zfzj07RYXWvEQEQmXrC+Tqpy1QqgErMbbK6S5gN86M=
7  KP9C2DhtapjZuDpH3VNvtKQlI3LraMhMnkHw470H7XE=
8  SyjAw0JWrTbZnliPX/ujk5jXIzMkiNxZ3taAHDWa3pY=
9  bIAx0XsFcmkAEftfvVullxywiAigZESmjhFPmzWZ78U=

```

	song_id	source_system_tab	\
0	fWtBf0GSJnwaWiNisVGnnZjFAT8vmZ8n1SB7FAIlmOQ=	my library	
1	fEAlgFRWmhXmo6m3ukQeqRksZCc0/7CjkqNckRHIVQo=	discover	
2	WDhQhhbq+bwhBY642Fx3e5eGBdvqzzXmwioCaVIORO=	my library	
3	4m+cvkd9Y5L16enj9nRufbfV+HxYguQ7FgvazLQ3I8=	my library	
4	+W5WCJFc7k7UJLArWZKMYmkr03Ro0m6VrmD7yJfVKRI=	my library	
5	o+fLXtu2auUsQNTfB141c7dPE5HnkVVF9wjBK5dHSjk=	my library	
6	5nsq4I7YcXGjODKwMsuanz70IO9xrCn80mIJ6127pqg=	my library	
7	Fzq070TM1QVVssM6J7PHtA2l8MFKD7qejKSPcdqw03o=	my library	
8	kg0SHwInwDvDK0rUu80XvPDITvzPKfeNl2pA96PJBfs=	radio	
9	0f6g3RC1YKF1eqWm0oAP81ao6Hmb2zWvXzCUzwUdG1o=	my library	

	source_screen_name	source_type	target	song_length	genre_ids	\
0	Local playlist more	local-playlist	1	225280.0	465	
1	Unknown	online-playlist	1	179258.0	458	
2	Local playlist more	local-library	0	252000.0	458	
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5	Local playlist more	local-playlist	1	239258.0	1259	
6	Local playlist more	local-library	1	195999.0	458	
7	unknown	local-library	1	218801.0	465	
8	Radio	radio	0	292989.0	465	
9	Local playlist more	local-playlist	1	260969.0	458	

	artist_name	\
0	(Claire Kuo)	
1	(MISS KO)	
2	(Stanly Hsu)	
3	(Show Lo)	
4	Fergie	
5	Machine Gun Kelly Camila Cabello	
6	(Joanna Wang)	
7	(Aaron Yan)	
8	(Leehom Wang)	
9	(Rainie Yang)	

	composer	...	gender	\
0	Victor/	...	unknown	
1	Miss Ko Razor 'n Guido	...	male	
2	/	...	female	
3	unknown	...	unknown	
4	J. Donald Jamal Jones Stacy Ferguson J. Sol...	...	female	
5	Camila Cabello Colson Baker pka "MGK" for EST...	...	unknown	
6	Peter Sven Kvint Vincent Paul Degiorgio	...	unknown	
7	JerryC	...	female	
8	unknown	

9 Ying-Jian Chen ... female

	registered_via	name	isrc \
0	7	(Sorry to Say Goodbye) TWA211551801	
1	9	TWUM71600104	
2	9	TWCG31600001	
3	9	TWEM31211002	
4	7	M.I.L.F. \$ USUM71604730	
5	4	Bad Things USUM71609854	
6	7	(You Ni De Quai Le) TWA470722014	
7	9	TWD951446201	
8	4	Forever Love TWA470473005	
9	4	(Ni Ming De Hao You) TWA470915006	

	registration_init_time_year	registration_init_time_month \
0	2013	10
1	2010	2
2	2013	5
3	2015	11
4	2011	6
5	2015	10
6	2015	7
7	2015	10
8	2016	11
9	2015	10

	registration_init_time_day	expiration_date_year	expiration_date_month \
0	11	2017	9
1	8	2017	9
2	18	2017	12
3	25	2017	9
4	24	2017	10
5	24	2017	10
6	14	2017	9
7	1	2017	9
8	30	2016	12
9	31	2018	1

	expiration_date_day
0	11
1	6
2	2
3	14
4	5
5	4
6	30
7	11

```
8          7
9         27
```

```
[10 rows x 24 columns]
```

```
[12]: categorical_feature = train.dtypes==object
categorical_cols = train.columns[categorical_feature].tolist()
categorical_cols
```

```
[12]: ['msno',
       'song_id',
       'source_system_tab',
       'source_screen_name',
       'source_type',
       'genre_ids',
       'artist_name',
       'composer',
       'lyricist',
       'gender',
       'name',
       'isrc']
```

```
[13]: from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

train[categorical_cols] = train[categorical_cols].apply(lambda col: le.
    ↪fit_transform(col))
train[categorical_cols].head(10)
```

```
[13]:
```

	msno	song_id	source_system_tab	source_screen_name	source_type	\
0	10936	68005	3	7	4	
1	3719	67546	0	18	5	
2	9380	53392	3	7	3	
3	15924	10620	3	7	3	
4	14257	849	3	7	3	
5	14293	81085	3	7	4	
6	2409	12182	3	7	3	
7	6371	28068	3	19	3	
8	8816	75977	5	13	6	
9	11402	41703	3	7	4	

	genre_ids	artist_name	composer	lyricist	gender	name	isrc
0	210	14186	20985	12416	2	49880	37792
1	206	13843	15145	8755	1	64765	56749
2	206	13977	26146	10446	0	50621	49012
3	210	13664	22429	8755	2	71965	51044
4	210	3451	8979	8755	0	22776	74163
5	53	6322	3318	8755	2	3721	74347
6	206	13434	16599	6394	2	60923	41091

7	210	13334	9999	9689	0	44809	49990
8	210	13384	25339	11928	2	12372	40825
9	206	13094	21808	8621	0	49193	41253

```
[14]: #train.to_csv('train_data.csv')
train.head(10)
```

```
[14]:    msno  song_id  source_system_tab  source_screen_name  source_type  target  \
0  10936   68005                3                7          4          1
1   3719   67546                0               18          5          1
2   9380   53392                3                7          3          0
3  15924   10620                3                7          3          0
4  14257    849                3                7          3          0
5  14293   81085                3                7          4          1
6   2409   12182                3                7          3          1
7   6371   28068                3               19          3          1
8   8816   75977                5               13          6          0
9  11402   41703                3                7          4          1
```

	song_length	genre_ids	artist_name	composer	...	gender	registered_via	\
0	225280.0	210	14186	20985	...	2	7	
1	179258.0	206	13843	15145	...	1	9	
2	252000.0	206	13977	26146	...	0	9	
3	206576.0	210	13664	22429	...	2	9	
4	162168.0	210	3451	8979	...	0	7	
5	239258.0	53	6322	3318	...	2	4	
6	195999.0	206	13434	16599	...	2	7	
7	218801.0	210	13334	9999	...	0	9	
8	292989.0	210	13384	25339	...	2	4	
9	260969.0	206	13094	21808	...	0	4	

	name	isrc	registration_init_time_year	registration_init_time_month	\
0	49880	37792	2013	10	
1	64765	56749	2010	2	
2	50621	49012	2013	5	
3	71965	51044	2015	11	
4	22776	74163	2011	6	
5	3721	74347	2015	10	
6	60923	41091	2015	7	
7	44809	49990	2015	10	
8	12372	40825	2016	11	
9	49193	41253	2015	10	

	registration_init_time_day	expiration_date_year	expiration_date_month	\
0	11	2017	9	
1	8	2017	9	
2	18	2017	12	
3	25	2017	9	

4	24	2017	10
5	24	2017	10
6	14	2017	9
7	1	2017	9
8	30	2016	12
9	31	2018	1

	expiration_date_day
0	11
1	6
2	2
3	14
4	5
5	4
6	30
7	11
8	7
9	27

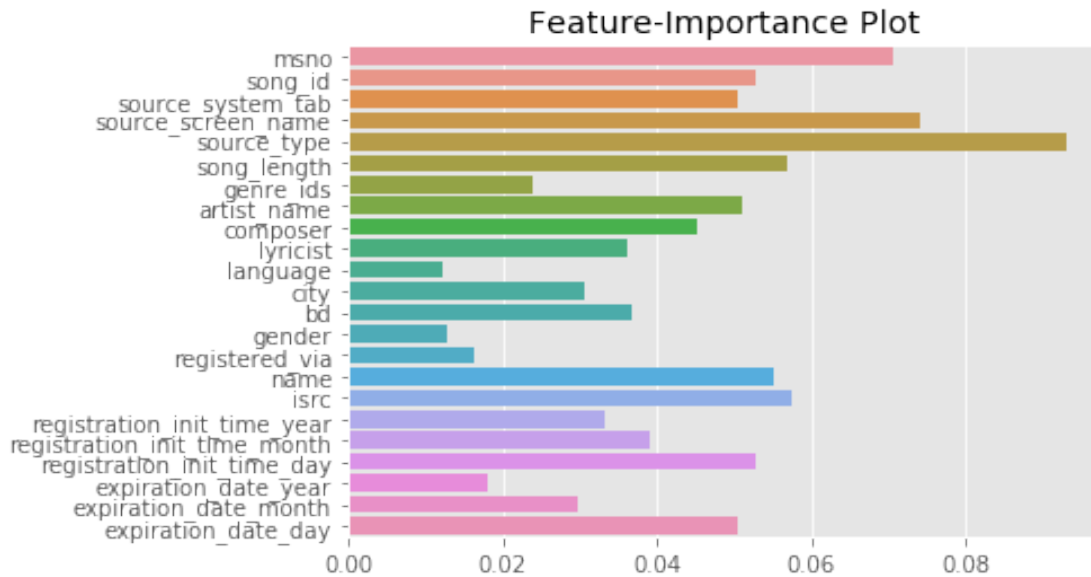
[10 rows x 24 columns]

```
[15]: X = train[train.columns[train.columns != 'target']]
      y = train.target

      model = ensemble.RandomForestClassifier(n_estimators=100, max_depth=25)
      model.fit(X, y)

      features = train.columns[train.columns != 'target']
      importance_values = model.feature_importances_

      sns.barplot(x = importance_values, y = features )
      plt.title('Feature-Importance Plot')
      plt.show()
```



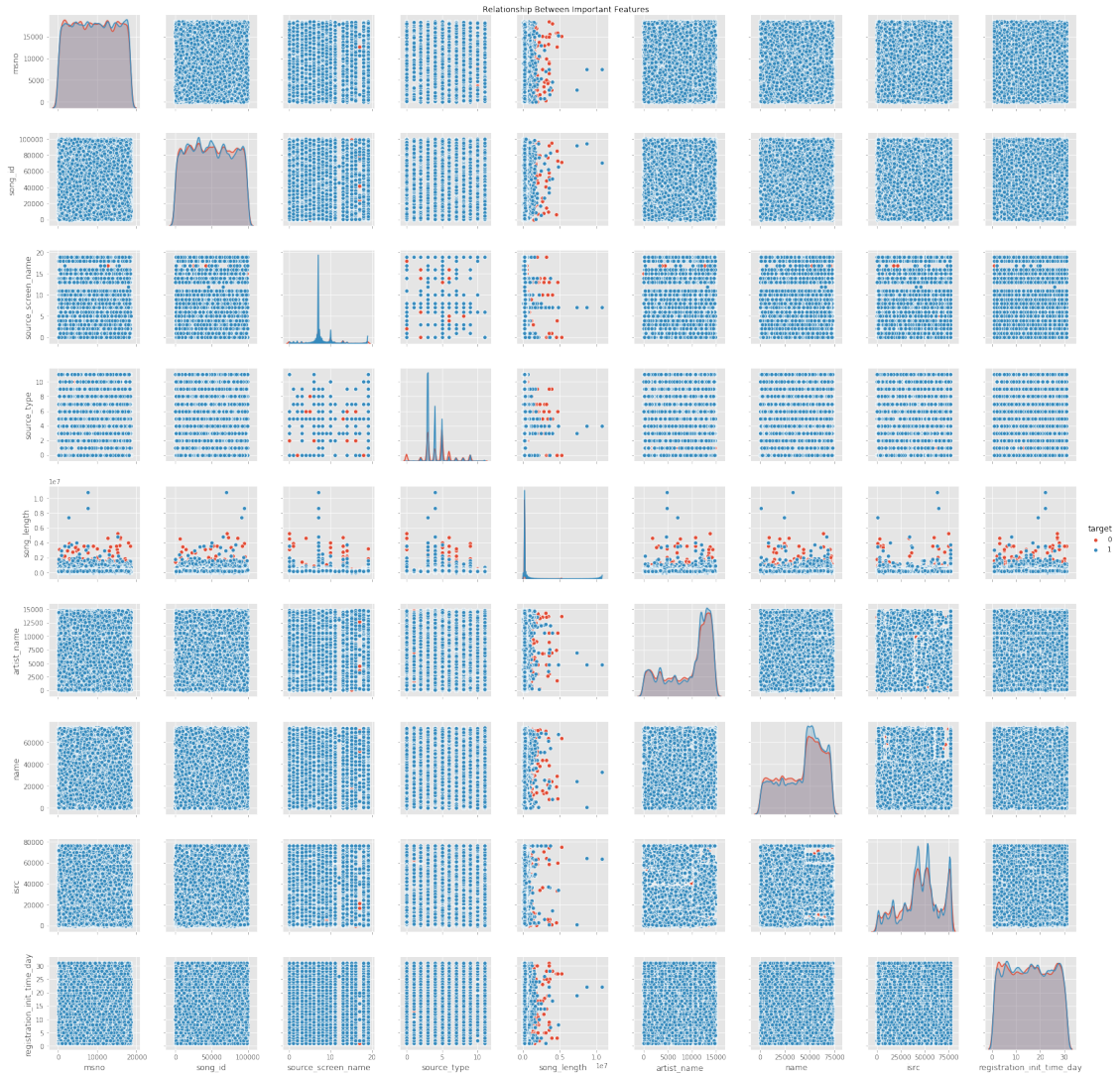
```
[16]: imporant_feat = pd.concat([(features.to_series().reset_index(drop=True)), pd.
    ↳ DataFrame(importance_values)], axis=1)
imporant_feat.columns = ['features', 'importance_values']
imporant_feat[importance_values>0.05]
```

```
[16]:
```

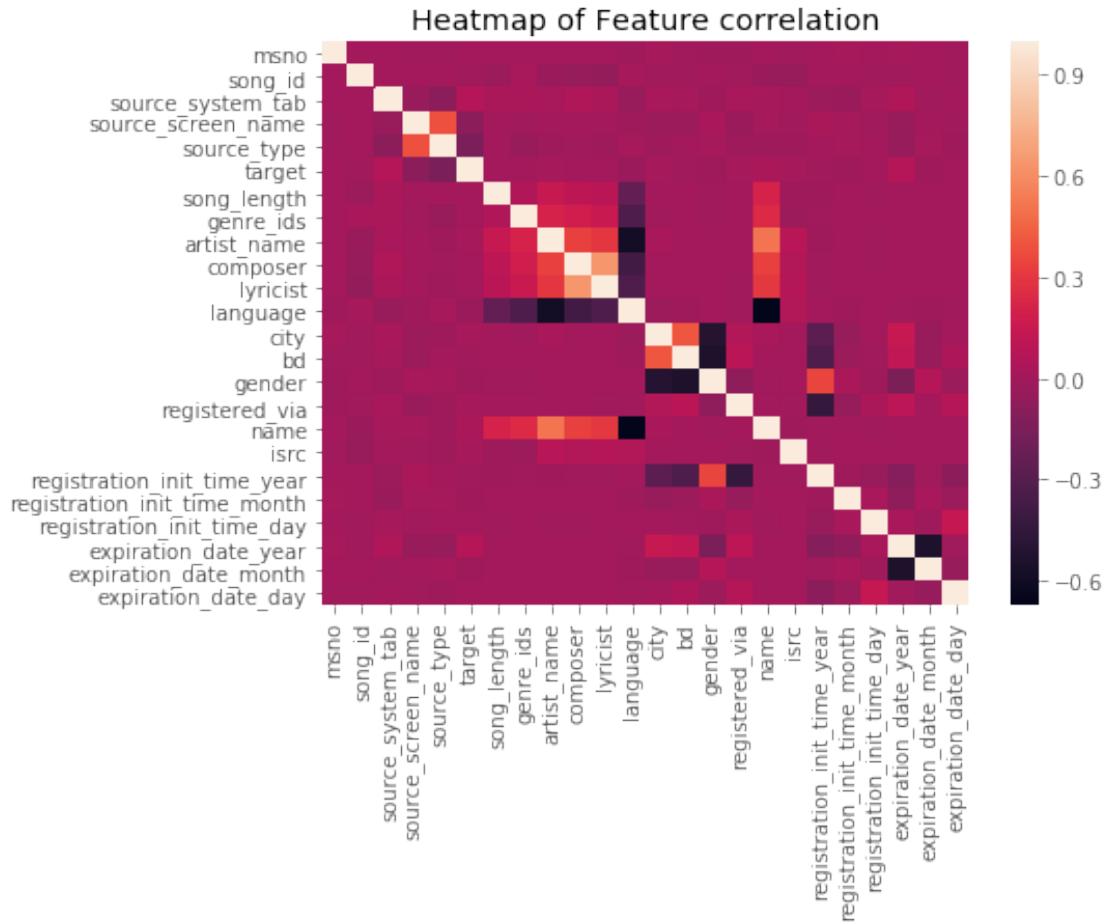
	features	importance_values
0	msno	0.070745
1	song_id	0.052876
2	source_system_tab	0.050610
3	source_screen_name	0.074082
4	source_type	0.093018
5	song_length	0.057001
7	artist_name	0.051044
15	name	0.055021
16	isrc	0.057585
19	registration_init_time_day	0.052867
22	expiration_date_day	0.050392

```
[18]: # To have a look at relationship between the important Features >0.05
imporant_features = ['msno', 'song_id', 'source_screen_name', 'source_type', '
    ↳ 'song_length', 'artist_name', 'name', 'isrc', 'registration_init_time_day']
pair_plot_imp = sns.pairplot(train, vars=imporant_features, hue='target')
pair_plot_imp.fig.suptitle("Relationship Between Important Features", y=1)
```

```
[18]: Text(0.5, 1, 'Relationship Between Important Features')
```



```
[17]: # Heatmap of the Feature correlation
plt.figure(figsize=[7,5])
sns.heatmap(train.corr())
plt.title('Heatmap of Feature correlation')
plt.show()
```



```
[18]: train.columns
      #train.count(axis='columns')
```

```
[18]: Index(['msno', 'song_id', 'source_system_tab', 'source_screen_name',
        'source_type', 'target', 'song_length', 'genre_ids', 'artist_name',
        'composer', 'lyricist', 'language', 'city', 'bd', 'gender',
        'registered_via', 'name', 'isrc', 'registration_init_time_year',
        'registration_init_time_month', 'registration_init_time_day',
        'expiration_date_year', 'expiration_date_month', 'expiration_date_day'],
        dtype='object')
```

```
[19]: target = train.pop('target')
```

```
[20]: train_data, test_data, train_labels, test_labels = train_test_split(train,
    ↪target, test_size = 0.3)
```

```
[21]: import lightgbm as lgb
      d_train = lgb.Dataset(train_data, label= train_labels)
      params = {}
      params['learning_rate']= 0.003
```

```

params['boosting_type']='gbdt'
params['objective']='binary'
params['metric']='binary_logloss'
params['sub_feature']=0.5
params['num_leaves']= 10
params['min_data']=50
params['max_depth']=10
clf= lgb.train(params, d_train, 100)
y_pred = clf.predict(test_data)
y_pred = np.where(y_pred > 0.49, 1, 0)

len(y_pred)

from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_pred, test_labels)
accuracy

#from sklearn import metrics
#fpr, tpr, thresholds = metrics.roc_curve(test_labels, y_pred)
#metrics.auc(fpr, tpr)

```

[21]: 0.66304

```

[22]: from sklearn import model_selection
from sklearn.linear_model import LogisticRegression

from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from mlxtend.classifier import StackingCVClassifier
import numpy as np
import warnings

warnings.simplefilter('ignore')

RANDOM_SEED = 42

clf1 = GradientBoostingClassifier()
clf2 = RandomForestClassifier(random_state=RANDOM_SEED)

lr = LogisticRegression()

sclf = StackingCVClassifier(classifiers=[clf1, clf2],
                           meta_classifier=lr,
                           random_state=RANDOM_SEED)

print('3-fold cross validation:\n')

for clf, label in zip([clf1, clf2, sclf],

```

```

        ['GradientBoostingClassifier',
         'RandomForestClassifier',
         'StackingClassifier']):

    scores = model_selection.cross_val_score(clf, train_data,
→train_labels, cv=3, scoring='accuracy')
    print("Accuracy: %0.2f (+/- %0.2f) [%s]"
          % (scores.mean(), scores.std(), label))

```

3-fold cross validation:

Accuracy: 0.72 (+/- 0.00) [GradientBoostingClassifier]

Accuracy: 0.74 (+/- 0.00) [RandomForestClassifier]

Accuracy: 0.73 (+/- 0.00) [StackingClassifier]

```

[:]: from sklearn.metrics import accuracy_score, log_loss
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, LinearSVC, NuSVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,
→GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn import metrics

classifiers = [
    KNeighborsClassifier(3),
    #SVC(kernel="rbf", C=0.025, probability=True),
    NuSVC(probability=True),
    DecisionTreeClassifier(),
    RandomForestClassifier(),
    AdaBoostClassifier(),
    GradientBoostingClassifier(),
    GaussianNB(),
    LinearDiscriminantAnalysis(),
    QuadraticDiscriminantAnalysis()]

# Logging for Visual Comparison
log_cols=["Classifier", "Accuracy", "Log Loss"]
log = pd.DataFrame(columns=log_cols)

for clf in classifiers:
    print("="*30)
    name = clf.__class__.__name__
    print(name)
    print('****Results****')

```

```

clf.fit(train_data, train_labels)

train_predictions = clf.predict(test_data)
acc = accuracy_score(test_labels, train_predictions)
print("Accuracy: {:.4%}".format(acc))

fpr, tpr, thresholds = metrics.roc_curve(test_labels, train_predictions)
print(metrics.auc(fpr, tpr))

train_predictions = clf.predict_proba(test_data)
ll = log_loss(test_labels, train_predictions)
print("Log Loss: {}".format(ll))

#log_entry = pd.DataFrame([[name, acc*100, ll]], columns=log_cols)
#log = log.append(log_entry)

print("="*30)

```

```

[ ]: model = xgb.XGBClassifier(max_depth=20,
                             learning_rate=0.1,
                             min_child_weight=3,
                             n_estimators=300,
                             scale_pos_weight=1,
                             seed=1)

model.fit(train_data, train_labels, eval_metric='auc', #verbose=True,
          eval_set=[(test_data, test_labels)], early_stopping_rounds=100)

[ ]: model = xgb.XGBClassifier(learning_rate=0.1, max_depth=15, min_child_weight=5,
                             ↪n_estimators=300)
model.fit(train_data, train_labels)

[ ]: predict_labels = model.predict(test_data)

[ ]: print(metrics.classification_report(test_labels, predict_labels))

[ ]: print(metrics.accuracy_score(test_labels, predict_labels))

[ ]: print(metrics.roc_auc_score(test_labels, predict_labels))

[ ]: from keras.models import Sequential
from keras.layers import Dense, Dropout, MaxPooling1D
from keras.utils.vis_utils import model_to_dot
from IPython.display import SVG
model = Sequential()
model.add(Dense(64, input_dim=23, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.25))

```



```

model.add(Dense(256, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(64, activation='relu'))
model.add(Dense(1, activation='softmax'))

model.summary()
#SVG(model_to_dot(model).create(prog='dot', format='svg'))

[: #model.compile(loss='binary_crossentropy', optimizer='adam',
    ↳metrics=['accuracy'])
model.compile(loss='binary_crossentropy', optimizer='rmsprop',
    ↳metrics=['accuracy'])

[: from keras.callbacks import EarlyStopping
early_stopping_monitor = EarlyStopping(patience=3)
print(train_data.size)
train_data.shape

[: model.fit(train_data, train_labels, epochs=25, batch_size=1000,
    ↳callbacks=[early_stopping_monitor])

[: accuracy = model.evaluate(test_data, test_labels)

[: #print('Accuracy: %.2f' % (accuracy*100))
print(model.metrics_names)
accuracy

```