modeling

October 28, 2021

[40]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from category_encoders import TargetEncoder
from sklearn.metrics import roc_auc_score, recall_score, f1_score,␣
 ↪confusion_matrix, precision_score
from xgboost import XGBClassifier
import xgboost as xgb
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.feature_selection import SelectFromModel

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

[2]:
```
# ! pip install imbalanced-learn
```

1 Loading Data

[3]:
```
df = pd.read_csv('dataset.csv', sep=';')
```

[4]:
```
df_final_uotput = df[df['default'].isna()]
```

[5]:
```
df = df[~df['uuid'].isin(df_final_uotput['uuid'])]
```

2 Missing Values

[6]:
```
# with zero to anotate missing category
df['account_status']  = df['account_status'].fillna(0)

# replacing with 1 because the split by target variable looks very similar to␣
 ↪the one from cat=1
df['account_worst_status_0_3m']  = df['account_worst_status_0_3m'].fillna(1)
```

```python
df['account_worst_status_3_6m']  = df['account_worst_status_3_6m'].fillna(1)
df['account_worst_status_6_12m']  = df['account_worst_status_6_12m'].fillna(1)
df['account_worst_status_12_24m']  = df['account_worst_status_12_24m'].fillna(1)

# replacing with 1 because the split by target variable looks very similar to␣
↪the one from cat=1
df['worst_status_active_inv'] = df['worst_status_active_inv'].fillna(1)

# with zero because the distribution has a long-tail (most values are close to␣
↪0)
df['account_days_in_dc_12_24m']  = df['account_days_in_dc_12_24m'].fillna(0)
df['account_days_in_rem_12_24m']  = df['account_days_in_rem_12_24m'].fillna(0)
df['account_days_in_term_12_24m']  = df['account_days_in_term_12_24m'].fillna(0)

# replacing with 0 because cat = 1 and 2 result in default=0 most of the time
# unlike users with NaN values
df['num_arch_written_off_0_12m']  = df['num_arch_written_off_0_12m'].fillna(0)
df['num_arch_written_off_12_24m']  = df['num_arch_written_off_12_24m'].fillna(0)

df['num_active_div_by_paid_inv_0_12m']  =␣
↪df['num_active_div_by_paid_inv_0_12m'].fillna(0)

# using median because the distribution is slightly skewed to the right
df['avg_payment_span_0_3m'] = df['avg_payment_span_0_3m'].median()
df['avg_payment_span_0_12m'] = df['avg_payment_span_0_12m'].median()

# no particular signal and to many values to replace
df = df.drop(['account_incoming_debt_vs_paid_0_24m'], axis=1)

# this is assuming that other fields can not have missing values
df = df.drop(['uuid'], axis=1)
```

3 Test, Val, Train Split

[7]:
```python
X_train, X_test, y_train, y_test = train_test_split(df, df['default'],␣
↪test_size=0.2, random_state=1)
```

[8]:
```python
# X_train['time_hours'].head()
```

[9]:
```python
X_train, X_val, y_train, y_val = train_test_split(df, df['default'],␣
↪test_size=0.25, random_state=1)
```

4 Target encoding of categorical features

[10]:
```
COLS_TO_ENCODE = ['merchant_group', 'merchant_category', 'name_in_email']

encoder = TargetEncoder()
encoder = encoder.fit(X_train[COLS_TO_ENCODE], X_train['default'])

X_train[COLS_TO_ENCODE] = encoder.transform(X_train[COLS_TO_ENCODE])
X_test[COLS_TO_ENCODE] = encoder.transform(X_test[COLS_TO_ENCODE])
X_val[COLS_TO_ENCODE] = encoder.transform(X_val[COLS_TO_ENCODE])
```

```
/home/svujovic/anaconda3/lib/python3.7/site-packages/pandas/core/frame.py:2963:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self[k1] = value[k2]
```

[11]:
```
# COLS_TO_NUMERIC = X_train.select_dtypes(include=['object', 'category']).
↪columns

# X_train[COLS_TO_NUMERIC] = X_train[COLS_TO_NUMERIC].apply(pd.to_numeric)
# X_test[COLS_TO_NUMERIC] = X_test[COLS_TO_NUMERIC].apply(pd.to_numeric)
# X_val[COLS_TO_NUMERIC] = X_val[COLS_TO_NUMERIC].apply(pd.to_numeric)
```

[12]:
```
# COLS_TO_NUMERIC
```

[13]:
```
X_train = X_train.drop(['default'], axis=1)
X_test = X_test.drop(['default'], axis=1)
X_val = X_val.drop(['default'], axis=1)
```

5 Baseline

[14]:
```
model = XGBClassifier(max_depth=2)
model.fit(X_train, y_train, eval_metric="auc")
y_pred = model.predict(X_test)

print('ROC-AUC:', roc_auc_score(y_test,y_pred))
print(confusion_matrix(y_test, y_pred))
print('R:', recall_score(y_test, y_pred))

print('P:', precision_score(y_test, y_pred))
```

```
ROC-AUC: 0.528231232195541
[[17720    14]
 [  247    15]]
R: 0.05725190839694656
P: 0.5172413793103449
```

I don't consider ACCURRACY because of the massive class disbalance.

I am looking at ROC-AUC, RECAL and the CONFUSION MATRIX mainly.

This looks terrible, but kinda what I expected. However, that can be treated.

6 Early stopping Train and Val

I did not do any hyper-param tuning. I would leave that for a later stage.

The param `scale_pos_weight=100` is passed because of the class imbalance. And it significantly improves the evaluation metrics.

I tried `oversampling`, which gave similar results, but I decided to go with `scale_pos_weight=100` because it is less complex.

[15]:
```
model = XGBClassifier(max_depth=2, scale_pos_weight=100)
eval_set = [(X_val, y_val)]
model.fit(X_train, y_train, eval_metric="auc", eval_set=eval_set, verbose=False)

y_pred = model.predict(X_test)

print('ROC-AUC:', roc_auc_score(y_test,y_pred))
print(confusion_matrix(y_test, y_pred))
print('R:', recall_score(y_test, y_pred))

print('P:', precision_score(y_test, y_pred))
```

```
ROC-AUC: 0.8213323352649028
[[13563  4171]
 [   32   230]]
R: 0.8778625954198473
P: 0.052260849806862075
```

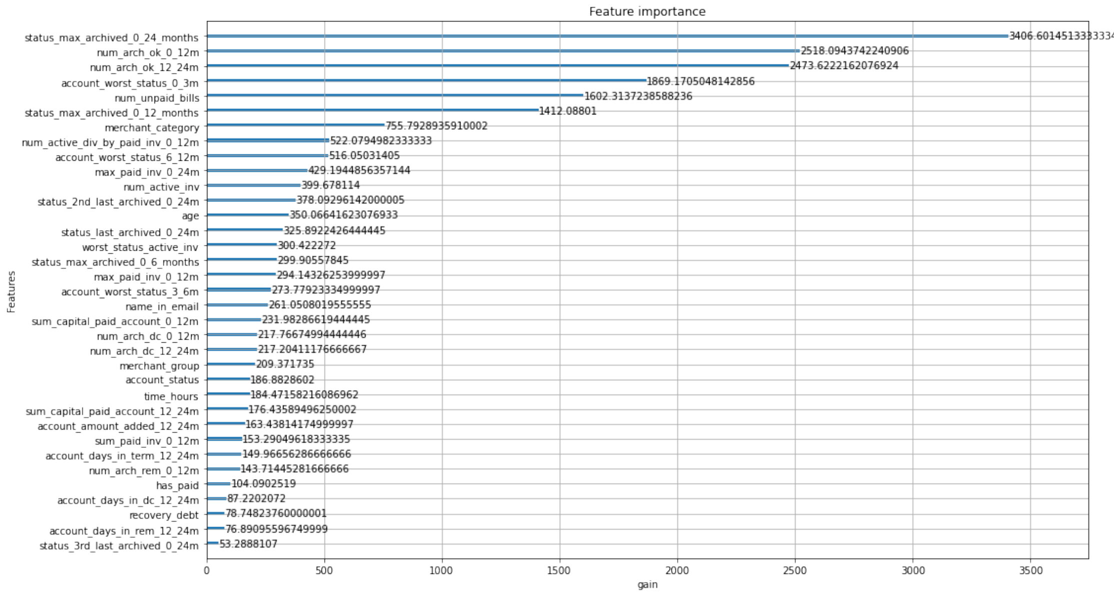
Much better! However, we still have a lot of false positives.

7 Feature importance

[16]:
```
plt.rcParams["figure.figsize"] = (16, 10)
```

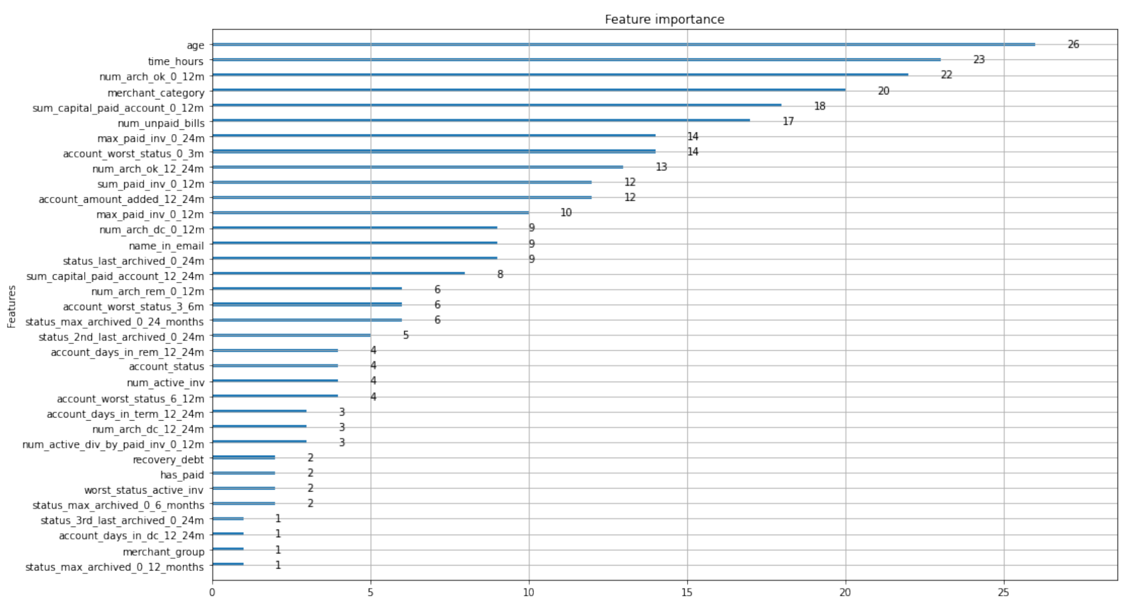
[17]:
```
xgb.plot_importance(model, importance_type='gain', xlabel='gain')
```

[17]: <AxesSubplot:title={'center':'Feature importance'}, xlabel='gain', ylabel='Features'>



[18]:
```
xgb.plot_importance(model, importance_type='weight', xlabel='weight')
```

[18]: <AxesSubplot:title={'center':'Feature importance'}, xlabel='weight', ylabel='Features'>



8 Preparing feature sets for feature selection

Top features based on information gain

[19]:
```
fim = model.get_booster().get_score(importance_type="gain")
feature_gain = pd.DataFrame({
    'feature': list(fim.keys()),
    'importance': list(fim.values())
}).sort_values('importance', ascending=False)
```

[20]:
```
XGB_F_GAIN_TOP_30 = feature_gain['feature'].head(30).values
XGB_F_GAIN_TOP_25 = feature_gain['feature'].head(25).values
XGB_F_GAIN_TOP_20 = feature_gain['feature'].head(20).values
```

[21]:
```
fim = model.get_booster().get_score(importance_type="weight")
feature_weight = pd.DataFrame({
    'feature': list(fim.keys()),
    'importance': list(fim.values())
}).sort_values('importance', ascending=False)
```

[22]:
```
XGB_F_WEIGHT_TOP_30 = feature_weight['feature'].head(30).values
XGB_F_WEIGHT_TOP_25 = feature_weight['feature'].head(25).values
XGB_F_WEIGHT_TOP_20 = feature_weight['feature'].head(20).values
```

Sanity check

[23]:
```
set(XGB_F_GAIN_TOP_30).difference(XGB_F_WEIGHT_TOP_30)
```

[23]:
```
{'merchant_group', 'status_max_archived_0_12_months'}
```

[24]:
```
set(XGB_F_GAIN_TOP_25).difference(XGB_F_WEIGHT_TOP_25)
```

[24]:
```
{'merchant_group',
 'num_active_div_by_paid_inv_0_12m',
 'num_arch_dc_12_24m',
 'status_max_archived_0_12_months',
 'status_max_archived_0_6_months',
 'worst_status_active_inv'}
```

[25]:
```
set(XGB_F_GAIN_TOP_20).difference(XGB_F_WEIGHT_TOP_20)
```

[25]:
```
{'account_worst_status_6_12m',
 'num_active_div_by_paid_inv_0_12m',
 'num_active_inv',
 'status_max_archived_0_12_months',
 'status_max_archived_0_6_months',
 'worst_status_active_inv'}
```

9 Feature Selection

[26]:
```
def evaluate_xgb(X_train,X_val, X_test, y_train, y_val,y_test, feature_list):
    # this function could be cleaner ofc :D
    X_train = X_train[feature_list]
    X_val = X_val[feature_list]
    X_test = X_test[feature_list]

    model = XGBClassifier(max_depth=2, scale_pos_weight=100)
    eval_set = [(X_val, y_val)]
    model.fit(X_train, y_train, eval_metric="auc", eval_set=eval_set,␣
 ↪verbose=False)

    ypred = model.predict(X_test)

    print('roc_auc', roc_auc_score(y_test, ypred))
    print(f"""Confusion matrix
    {confusion_matrix(y_test, ypred)}
    """)
    print('R:', recall_score(y_test, ypred))
    print('P:', precision_score(y_test, ypred))
```

9.0.1 ALL Features included

[27]:
```
evaluate_xgb(X_train, X_val, X_test, y_train, y_val, y_test, X_train.columns) #␣
 ↪all features
```

```
roc_auc 0.8213323352649028
Confusion matrix
    [[13563  4171]
 [   32   230]]

R: 0.8778625954198473
P: 0.052260849806862075
```

9.0.2 Features based on GAIN

[28]:
```
evaluate_xgb(X_train, X_val, X_test, y_train, y_val, y_test, XGB_F_GAIN_TOP_30)
```

```
roc_auc 0.8230997600675632
Confusion matrix
    [[13558  4176]
 [   31   231]]
```

```
R: 0.8816793893129771
P: 0.05241660993873383
```

[29]:
```
evaluate_xgb(X_train, X_val, X_test, y_train, y_val, y_test, XGB_F_GAIN_TOP_25)
```

```
roc_auc 0.8158802645024823
Confusion matrix
    [[13505  4229]
 [    34   228]]

R: 0.8702290076335878
P: 0.05115548575274848
```

[30]:
```
evaluate_xgb(X_train, X_val, X_test, y_train, y_val, y_test, XGB_F_GAIN_TOP_20)
```

```
roc_auc 0.81483707063759
Confusion matrix
    [[13468  4266]
 [    34   228]]

R: 0.8702290076335878
P: 0.050734312416555405
```

9.0.3 Features based on WEIGHT

[31]:
```
evaluate_xgb(X_train, X_val, X_test, y_train, y_val, y_test,␣
 ↪XGB_F_WEIGHT_TOP_30)
```

```
roc_auc 0.8171208193688407
Confusion matrix
    [[13549  4185]
 [    34   228]]

R: 0.8702290076335878
P: 0.05166553365057784
```

[32]:
```
evaluate_xgb(X_train, X_val, X_test, y_train, y_val, y_test,␣
 ↪XGB_F_WEIGHT_TOP_25)
```

```
roc_auc 0.8193111606032145
Confusion matrix
    [[13559  4175]
 [    33   229]]

R: 0.8740458015267175
P: 0.05199818346957311
```

[33]:
```
evaluate_xgb(X_train, X_val, X_test, y_train, y_val, y_test,␣
 ↪XGB_F_WEIGHT_TOP_20)
```

```
roc_auc 0.8189076143897477
Confusion matrix
     [[13477  4257]
 [   32   230]]

R: 0.8778625954198473
P: 0.05125919322487185
```

9.0.4 Feature group XGB_F_GAIN_TOP_30 seems to slightly incerase ROC AUC, PRECISION and RECAL. It would be useful to cross-validate this at a later stage and maybe try out some othe FS methods.

[34]:
```
#features to drop
set(X_train.columns).difference(XGB_F_GAIN_TOP_30)
```

[34]:
```
{'account_days_in_dc_12_24m',
 'account_days_in_rem_12_24m',
 'account_worst_status_12_24m',
 'avg_payment_span_0_12m',
 'avg_payment_span_0_3m',
 'has_paid',
 'num_arch_written_off_0_12m',
 'num_arch_written_off_12_24m',
 'recovery_debt',
 'status_3rd_last_archived_0_24m'}
```

10 Prediction Distributions (For sanity check)

[35]:
```
model = XGBClassifier(max_depth=2)

X_train = X_train[XGB_F_GAIN_TOP_30]
X_val = X_val[XGB_F_GAIN_TOP_30]
X_test = X_test[XGB_F_GAIN_TOP_30]

model = XGBClassifier(max_depth=2, scale_pos_weight=100)
eval_set = [(X_val, y_val)]
model.fit(X_train, y_train, eval_metric="auc", eval_set=eval_set, verbose=False)

y_pred = model.predict(X_test)
y_pred_proba = model.predict_proba(X_test)
```

[36]:
```
df_predictions = pd.DataFrame({
    'pred': list(y_pred),
    'actual': list(y_test)
})
```

[37]:
```
df_prediction_facts = pd.DataFrame(y_pred_proba,␣
↪columns=['no_default','default']).join(df_predictions)
```

[38]:
```
df_prediction_facts.groupby(['actual'])['default'].describe(percentiles=[.8,.9,.
↪95])
```

[38]:
```
          count      mean       std       min       50%       80%       90%  \
actual
0.0     17734.0  0.261242  0.282908  0.000013  0.140902  0.552735  0.721442
1.0       262.0  0.771425  0.219115  0.004630  0.839382  0.939611  0.972786

             95%       max
actual
0.0     0.822045  0.996326
1.0     0.984168  0.995464
```

[39]:
```
df_prediction_facts[df_prediction_facts['default'] > 0.5].
↪groupby(['actual'])['default'].describe(percentiles=[.1,.2,.8,.9,.95])
```

[39]:
```
         count      mean       std       min       10%       20%       50%  \
actual
0.0     4176.0  0.703193  0.130591  0.500086  0.539679  0.575606  0.690510
1.0      231.0  0.837742  0.121491  0.504810  0.655200  0.731708  0.860252

             80%       90%       95%       max
actual
0.0     0.829040  0.896619  0.936660  0.996326
1.0     0.950055  0.975800  0.985638  0.995464
```

10.0.1 My confidence in precision is higher for items with proba > 0.7. Considering the perspective of reducing false positives.

11 Imporvements?

- Hyper-param tunning
- Adding a Level 2 Model to reduce false positives, combined with oversampling (maybe)
- Feature selection based on other methods(maybe)
- Trying out CatBoost or Light GBM