Modeling

September 30, 2018

1 Modeling

We will establish a baseline with relatively hands-off machine-learning classifiers before using a more easily interpretable model.

```
In [1]: import pandas as pd
        import numpy as np
        import seaborn as sns
        import os
        import pickle

        hmda = pd.read_parquet("processed_data.pqt")
        with open("concordance.pkl", "rb") as f:
            concordances = pickle.load(f)
```

```
/usr/lib/python3.6/importlib/_bootstrap.py:219: RuntimeWarning: numpy.dtype size changed, may in
  return f(*args, **kwds)
/usr/lib/python3.6/importlib/_bootstrap.py:219: RuntimeWarning: numpy.dtype size changed, may in
  return f(*args, **kwds)
```

```
In [2]: %pylab inline
```

```
Populating the interactive namespace from numpy and matplotlib
```

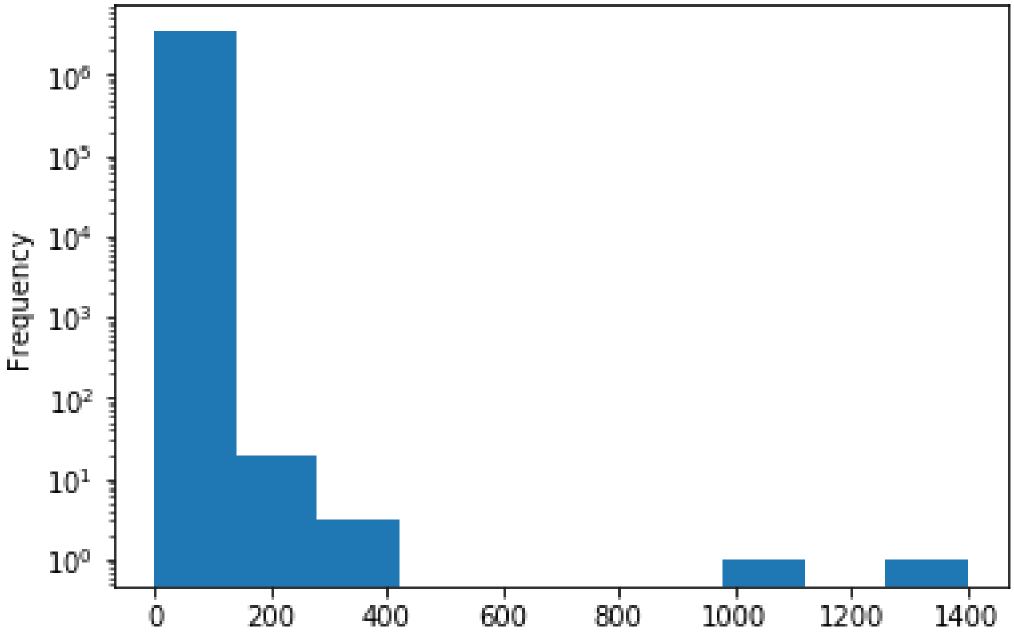
```
/home/cnaylor/env/tensorflow/lib/python3.6/site-packages/IPython/core/magics/pylab.py:160: UserW
`%matplotlib` prevents importing * from pylab and numpy
  "\n`%matplotlib` prevents importing * from pylab and numpy"
```

2 Transformations

We may want to add additional factors later, but for now we definitely want to transform income and hud_median_income to ratios, of the loan amount and of income, respectively.

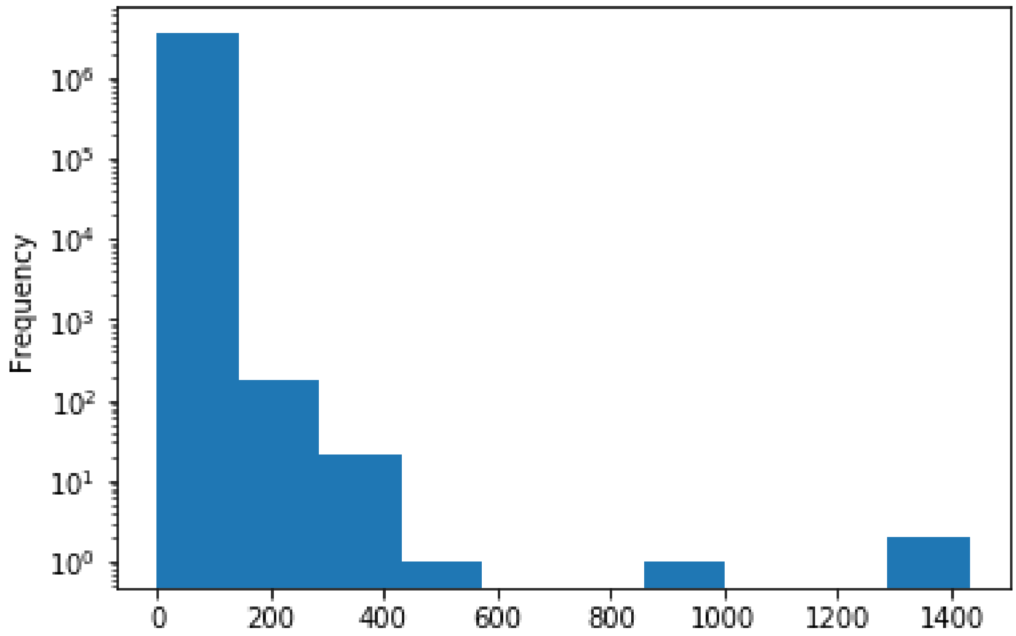
```
In [3]: hmda.loc[:, 'income_to_loan'] = hmda['applicant_income_000s'].div(hmda['loan_amount_000s
        hmda.loc[:, 'income_to_med_income'] = hmda['loan_amount_000s'].mul(1000).div(hmda['hud_m
        hmda.loc[:, 'income_to_loan'].dropna().plot(kind='hist', logy=True)
```

```
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0x7fde345ce978>
```




```
In [4]: hmda.loc[:, 'income_to_med_income'].dropna().plot(kind='hist', logy=True)
```

```
Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x7fde346a3160>
```



All of the action we care about is in the ratio < 1, I expect.

2.1 Testing and Training samples.

```
In [5]: from sklearn.model_selection import train_test_split
        hmda_train, hmda_test = train_test_split(hmda.dropna(), test_size=0.99) #high proportion
        hmda_train.shape

Out[5]: (31743, 33)
```

2.2 SVM

We need to convert the continuous or high-category data into a few factors, but otherwise we should be able to run a support vector machine without much trouble. I'm going to try a linear kernel on normalized data. With a linear kernel, we can look at coefficients to determine what was important to the fit.

```
In [17]: from sklearn.preprocessing import StandardScaler, KBinsDiscretizer, Binarizer, OneHotEn
         from sklearn_pandas import DataFrameMapper
         from sklearn.pipeline import make_pipeline
         from sklearn.svm import SVC, LinearSVC

In [35]: mapper = DataFrameMapper([
             (['population'], KBinsDiscretizer(n_bins=3)),
             (['applicant_income_000s'], KBinsDiscretizer(n_bins=5)),
             (['loan_amount_000s'], Binarizer(threshold=700)), # > ~700 are non-conforming loans
             (['minority_population'], KBinsDiscretizer(n_bins=3)),
```

```
        (['income_to_loan'], KBinsDiscretizer(n_bins=5)),
        (['income_to_med_income'], KBinsDiscretizer(n_bins=3)),
        (['applicant_ethnicity'], OneHotEncoder()),
        (['applicant_race_1'], OneHotEncoder()),
        (['applicant_sex'], OneHotEncoder()),
        (['as_of_year'], OneHotEncoder()),
        (['loan_purpose'], OneHotEncoder())
         ])
    pipe = make_pipeline(mapper, StandardScaler(), SVC(kernel='linear', class_weight='balan
    pipe.fit(hmda_train, hmda_train.approved.astype("float"))
```

```
/home/cnaylor/env/tensorflow/lib/python3.6/site-packages/sklearn/preprocessing/_encoders.py:363:
```

```
Out[35]: Pipeline(memory=None,
              steps=[('dataframemapper', DataFrameMapper(default=False, df_out=False,
                 features=[(['population'], KBinsDiscretizer(encode='onehot', n_bins=3, strategy
          shrinking=True, tol=0.001, verbose=False))])
```

```
In [116]: concordances['applicant_race_1'][7] = "NA"
```

```
In [155]: coef_names = []
          for (nm, transformer) in pipe.named_steps['dataframemapper'].features:
              if isinstance(transformer, KBinsDiscretizer):
                  coef_names.extend([f"{nm[0]}_{v}" for v in transformer.bin_edges_[0][:-1]])
              elif isinstance(transformer, Binarizer):
                  coef_names.extend([f"{nm[0]}"])
              elif isinstance(transformer, OneHotEncoder):
                  if nm[0] in concordances:
                      coef_names.extend(["{}_{}".format(nm[0],concordances[nm[0]][int(v[3])]) fo
                  else:
                      coef_names.extend(transformer.get_feature_names())
```

```
In [156]: pd.DataFrame({'names':coef_names, 'coefficient':pipe.named_steps['svc'].coef_.ravel()}
```

Out[156]:

	names	coefficient
47	loan_purpose_Refinancing	-0.46014
46	loan_purpose_Home improvement	-0.18000
28	applicant_race_1_White	-0.00031
29	applicant_race_1_Information not provided by a...	-0.00024
26	applicant_race_1_Black or African American	-0.00019
25	applicant_race_1_Asian	-0.00017
24	applicant_race_1_American Indian or Alaska Native	-0.00004
27	applicant_race_1_Native Hawaiian or Other Paci...	-0.00004
3	applicant_income_000s_1.0	-0.00003
12	income_to_loan_0.0024390243902439024	-0.00003
19	income_to_med_income_3.851351351351351	-0.00002
36	x0_2008.0	-0.00001
4	applicant_income_000s_51.0	-0.00001
2	population_5524.0	-0.00001

```
35                                     x0_2007.0     -0.00001
42                                     x0_2014.0     -0.00001
0                                population_68.0     -0.00001
21        applicant_ethnicity_Not Hispanic or Latino     -0.00001
11            minority_population_23.979999542236328     -0.00001
8                               loan_amount_000s     -0.00001
22  applicant_ethnicity_Information not provided b...     -0.00001
14                 income_to_loan_0.3693181818181818     -0.00000
39                                     x0_2011.0     -0.00000
15                income_to_loan_0.49030993278566104     -0.00000
32                          applicant_sex_Female     -0.00000
10             minority_population_8.460000038146973     -0.00000
37                                     x0_2009.0     -0.00000
34                  applicant_sex_Not applicable      0.00000
33  applicant_sex_Information not provided by appl...      0.00000
31                            applicant_sex_Male      0.00000
43                                     x0_2015.0      0.00000
40                                     x0_2012.0      0.00000
23                applicant_ethnicity_Not applicable      0.00001
9             minority_population_0.3400000035762787      0.00001
18           income_to_med_income_2.0071303373528733      0.00001
6                      applicant_income_000s_100.0      0.00001
41                                     x0_2013.0      0.00001
5                       applicant_income_000s_74.0      0.00001
44                                     x0_2016.0      0.00001
17         income_to_med_income_0.009416195856873822      0.00001
38                                     x0_2010.0      0.00001
13                 income_to_loan_0.2753369863013698      0.00002
1                              population_3896.0      0.00002
16                 income_to_loan_0.7101943346508566      0.00002
20          applicant_ethnicity_Hispanic or Latino      0.00002
7                      applicant_income_000s_149.0      0.00002
30                            applicant_race_1_NA      0.02509
45                     loan_purpose_Home purchase      0.53449
```

- Very few coefficients were significant. This is not a good fit.
- Loan purpose turned up as inordinately important, with home purchases being much more likely to be approved.
- Non-conforming (>$700k) loans actually were more likely to be approved.
- Race and ethnicity show up as some of the most important factors, but the pattern is not what might be expected. Hispanics were more likely to be approved, and Whites were significantly less likely. This is a big surprise.

In [45]:
```
from sklearn.metrics import confusion_matrix
svm_hat = pipe.predict(hmda_test.iloc[:100000,:])
confusion_matrix(hmda_test.approved.astype("float").iloc[:100000], svm_hat)
```

Out[45]:
```
array([[19488,  7616],
       [36713, 36183]])
```

Not a particularly effective fit, with as many false negatives as true positives. It looks as though the SVM wasn't able to handle the unbalanced outcome.

2.2.1 PCA (Again)

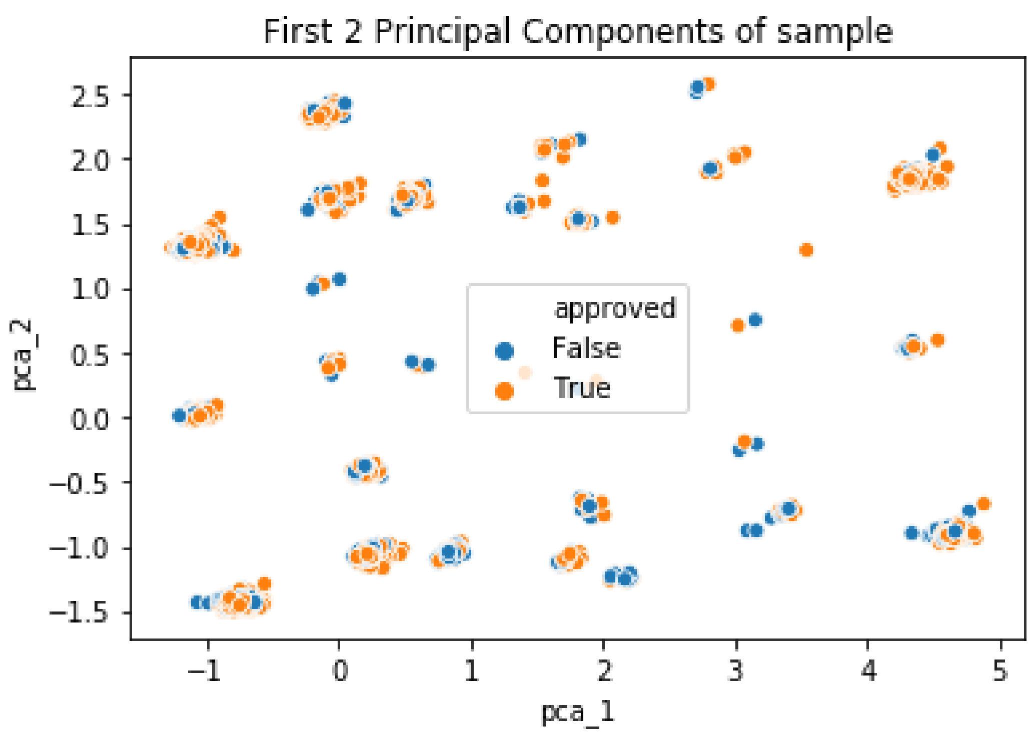
Having done all that work on proper encoding of features, let's just check if a Principal Components Analysis is more effective now.

```
In [144]: from sklearn.decomposition import PCA
          pca_pipe = make_pipeline(mapper, StandardScaler(), PCA(n_components=5))
          pca_pipe.fit(hmda_train)
          pca = pca_pipe.named_steps['pca']
          print(pca.explained_variance_ratio_)
```

```
[0.17828983 0.11431848 0.10865586 0.09033409 0.07278618]
```

A bit better than before.

```
In [150]: pca_hat = pd.DataFrame(pca_pipe.transform(hmda_train)[:5000,:2], columns=['pca_1', 'pc
          pca_hat.loc[:, 'approved'] =  hmda_train.iloc[:5000,:].approved.values
          ax = sns.scatterplot(x='pca_1', y='pca_2', hue='approved', data=pca_hat)
          ax.set_title("First 2 Principal Components of sample")
          plt.show()
```



That's what we get for using discretized data everywhere.

2.3 Logit Regression

We'll try only one other model as we have time constraints: a traditional logistic regression, with parameter choice informed by the SVM above.

We'll use more continuous factors this time, although the extreme right skew in income and associated factors means we should either censor the data or, my preference, do a log transform on it.

```
In [48]: from sklearn.preprocessing import FunctionTransformer
         from sklearn.linear_model import LogisticRegression
         Log = FunctionTransformer(np.log)
         Log1p = FunctionTransformer(np.log1p)
         mapper = DataFrameMapper([
             (['population'], Log),
             (['applicant_income_000s'], Log),
             (['minority_population'], Binarizer(threshold=0.5)), #we know from graphing the dat
             (['income_to_loan'], Log1p), #We'll add one to these ratios as I suspect the thresh
             (['income_to_med_income'], Log1p),
             (['applicant_ethnicity'], OneHotEncoder()),
             (['applicant_race_1'], OneHotEncoder()),
             (['loan_purpose'], OneHotEncoder())
              ])
         pipe_logit = make_pipeline(mapper, LogisticRegression(solver="sag")) #the SAG solver is
         pipe_logit.fit(hmda_train, hmda_train.approved)
```

```
Out[48]: Pipeline(memory=None,
              steps=[('dataframemapper', DataFrameMapper(default=False, df_out=False,
                 features=[(['population'], FunctionTransformer(accept_sparse=False, check_inver
                   func=<ufunc 'log'>, inv_kw_args=None, inverse_func=None,
                   kw_args=None, pass_y='deprecated', validate=None)), (['... penalty='l2', rand
                   tol=0.0001, verbose=0, warm_start=False))])
```

```
In [153]: coef_names = []
          for (nm, transformer) in pipe_logit.named_steps['dataframemapper'].features:
              if isinstance(transformer, (FunctionTransformer, Binarizer)):
                  coef_names.extend([f"{nm[0]}"])
              elif isinstance(transformer, OneHotEncoder):
                  if nm[0] in concordances:
                      coef_names.extend(["{}_{}".format(nm[0],concordances[nm[0]][int(v[3])]) fo
                  else:
                      coef_names.extend(transformer.get_feature_names())
```

```
In [154]: pd.DataFrame({'names':coef_names, 'coefficient':pipe_logit.named_steps['logisticregres
```

Out[154]:

	names	coefficient
4	income_to_med_income	-1.27
3	income_to_loan	-1.06
17	loan_purpose_Home improvement	-0.52
18	loan_purpose_Refinancing	-0.50

```
11         applicant_race_1_Black or African American        -0.46
5              applicant_ethnicity_Hispanic or Latino        -0.46
9    applicant_race_1_American Indian or Alaska Native        -0.45
12   applicant_race_1_Native Hawaiian or Other Paci...        -0.27
7    applicant_ethnicity_Information not provided b...        -0.18
14   applicant_race_1_Information not provided by a...        -0.11
2                                   minority_population        -0.10
10                                applicant_race_1_Asian       -0.05
0                                            population         0.04
6          applicant_ethnicity_Not Hispanic or Latino           0.06
8                   applicant_ethnicity_Not applicable           0.11
13                                applicant_race_1_White        0.17
16                           loan_purpose_Home purchase         0.54
15                                   applicant_race_1_NA        0.69
1                                  applicant_income_000s        1.12
```

```
In [51]: pipe_logit.named_steps['logisticregression'].intercept_
```

```
Out[51]: array([-2.00460545])
```

I'm surprised we wound up with a negative intercept, given that approvals are more common than rejections. Several of the coefficients look intuitively wrong, too. The Income_to_loan and income to median income ratios, for example, both have significant negative effects. There may be too much collinearity between the three income-related features. Race and Ethnicity, on the other hand, are now more or less what I would expect.

Let's check the confusion matrix for this one.

```
In [53]: logit_hat = pipe_logit.predict(hmda_test.iloc[:100000,:])
         confusion_matrix(hmda_test.approved.astype("float").iloc[:100000], logit_hat)
```

```
Out[53]: array([[ 4091, 23013],
                [ 2729, 70167]])
```

That's better, but now we are erring on the side of false positives.

Let's simplify the features we're examining to see if it makes much difference.

```
In [66]: mapper = DataFrameMapper([
             (['population'], Log),
             (['applicant_income_000s'], Log),
             (['minority_population'], Binarizer(threshold=0.5)), #we know from graphing the dat
             (['applicant_ethnicity'], OneHotEncoder()),
             (['applicant_race_1'], OneHotEncoder()),
             (['loan_purpose'], OneHotEncoder())
              ])
         pipe_logit2 = make_pipeline(mapper, LogisticRegression(solver="sag")) #the SAG solver i
         pipe_logit2.fit(hmda_train, hmda_train.approved)
```

```
Out[66]: Pipeline(memory=None,
              steps=[('dataframemapper', DataFrameMapper(default=False, df_out=False,
```

```
          features=[(['population'], FunctionTransformer(accept_sparse=False, check_inver
            func=<ufunc 'log'>, inv_kw_args=None, inverse_func=None,
            kw_args=None, pass_y='deprecated', validate=None)), (['... penalty='l2', rand
            tol=0.0001, verbose=0, warm_start=False))])
```

In [151]:
```python
coef_names = []
for (nm, transformer) in pipe_logit2.named_steps['dataframemapper'].features:
    if isinstance(transformer, (FunctionTransformer, Binarizer)):
        coef_names.extend([f"{nm[0]}"])
    elif isinstance(transformer, OneHotEncoder):
        if nm[0] in concordances:
            coef_names.extend(["{}_{}".format(nm[0],concordances[nm[0]][int(v[3])]) fo
        else:
            coef_names.extend(transformer.get_feature_names())
pd.DataFrame({'names':coef_names, 'coefficient':pipe_logit2.named_steps['logisticregre
```

Out[151]:

	names	coefficient
9	applicant_race_1_Black or African American	-0.52
3	applicant_ethnicity_Hispanic or Latino	-0.51
16	loan_purpose_Refinancing	-0.47
15	loan_purpose_Home improvement	-0.44
7	applicant_race_1_American Indian or Alaska Native	-0.41
10	applicant_race_1_Native Hawaiian or Other Paci...	-0.28
5	applicant_ethnicity_Information not provided b...	-0.16
8	applicant_race_1_Asian	-0.12
12	applicant_race_1_Information not provided by a...	-0.07
2	minority_population	0.01
4	applicant_ethnicity_Not Hispanic or Latino	0.11
0	population	0.13
6	applicant_ethnicity_Not applicable	0.16
11	applicant_race_1_White	0.28
1	applicant_income_000s	0.39
14	loan_purpose_Home purchase	0.51
13	applicant_race_1_NA	0.71

In [143]:
```python
logit_hat = pipe_logit2.predict(hmda_test.iloc[:100000,:])
confusion_matrix(hmda_test.approved.astype("float").iloc[:100000], logit_hat)
```

Out[143]:
```
array([[ 2449, 24655],
       [ 1830, 71066]])
```

The simpler model is not much less accurate.

3 Conclusions

In the final model, we have extracted some basic features for loan approval, mostly squaring with our prior assumptions:

- **White, non-Hispanic** applicants were approved more frequently than other races.

- **Home purchase** loans are more likely to be approved than Home improvement or refinancing loans, both of which are taking equity out of a house, and hence inherently more risky.
- **Wealthier** applicants were more likely to get their loans approved.

We also had some surprises:

- Being **Asian had a negative impact** on mortgage approval. One might guess that Asian applicants' numbers were skewed by foreign purchases of NY real estate, but further study is needed.
- The ratio of the applicant's **income to the size of the loan was not relevant**. The income-to-loan ratio's irrelevance might be due to survival bias; we filtered out incomplete applications, and possibly those applicants with a large imbalance in loan to income and no other mitigating factors didn't get far enough in the process to show up in the data.

There is a great deal more work to be done here. If we could find additional data on these loans, probably the single most important feature currently missing would be the percent down payment being made on each mortgage. The spread of the proposed interest rate over some average would also be informative.

It might also make sense to concentrate in commonalities in loan rejections, as they are less frequent. We could flip the encoding of loan approval to be loan rejection, then fit a zero-inflated poisson model.

We could also use the census tract data to break the applications into regions of NY State, then fit a hierarchical model permitting some different effects depending on region. That would take some work to determine how to aggregate the census tracts, however, as a model with one group for each would be ungainly.