LendingClub Analysis

by Charla Gaddy

About LendingClub

Established in 2007, LendingClub is an online peer-to-peer lending company that brings borrowers and investors together transforming the way borrowers access credit. They provided personal loans, auto refinance, small business loans and patient care loans.

If you want to become an investor you have the choice of a taxable or retirement account. To do this you open an account, browse loans and purchase notes (a fraction of loan with increments as low as $25).

The Purpose

The purpose of this project is to create a product which can be used by LendingClub to detect customers who are most likely to not pay back the loan.

The Plan

- First, we will use Random Forest and XGBoost to predict the bad loans.
- Second, use Kmeans on the top ten features to see if there are any unknown clusters.
- Third, use SARIMA time series, predict 8 weeks of bad loans and forecast 12 weeks.
- Finally, LSTM will predict 8 weeks of bad loans.

The Data

All data was downloaded from the LendingClub website: https://www.lendingclub.com/info/download-data.action.
There are links for approved and rejected loan applications. I will be using both datasets.

Approved Loan Dataset
This dataset has 610,917 rows and 144 columns. Each row represents a loan and the 144 columns are the various attributes used to determine if you are eligible for a loan. After cleaning the data, such as removing missing values and then applying label encoding to the categorical data, the final dataset has 87,932 rows and 42 columns. For this dataset Random Forest and XGBoost will do the predictions. The accuracy, ROC and other metrics will be evaluated to see which model is better at predictions. Kmeans and Mean Shift will cluster the top 10 features of the Random Forest model to see if there are any unknown features that can help determine loan status.

Rejected Loan Dataset
This dataset has 19,158,655 rows and 2 columns. The data is from the years 2017, 2018 and 2019Q1. Each row represents a loan and the two columns are 1.) date of the loan application 2.) the number of loans for that day. This dataset was converted in to weeks. The final dataset now has 117 rows and 2 columns. SARIMA will predict 8 weeks of loans as well as forecast 12 weeks out. LSTM will also predict 8 weeks of loans

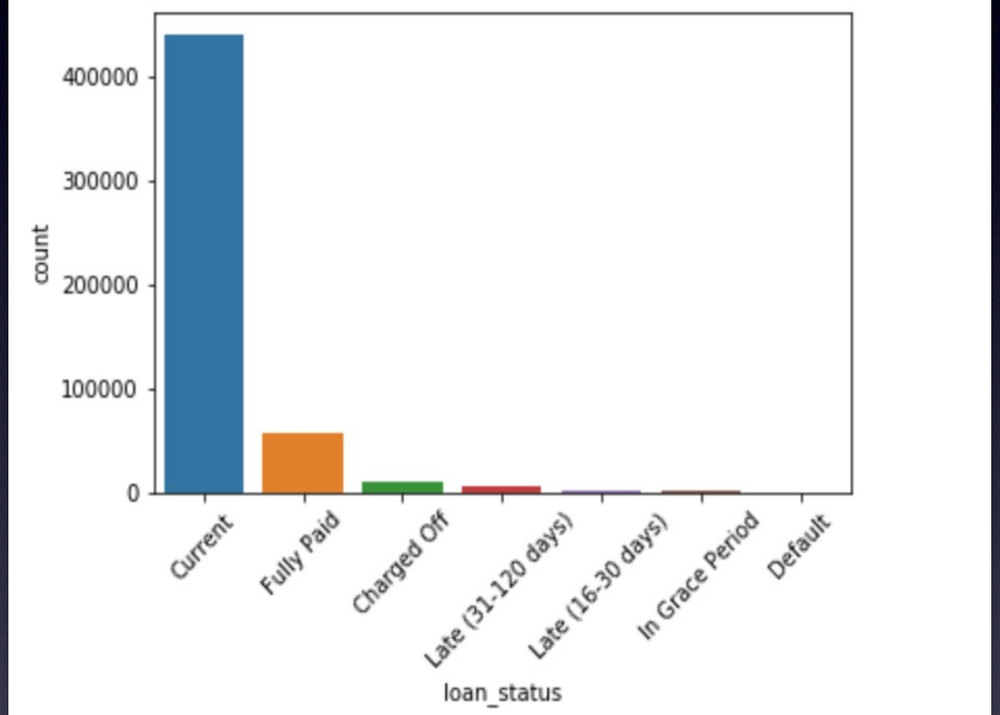
```
DatetimeIndex(['2017-01-02', '2017-01-09', '2017-01-16', '2017-01-23',
               '2017-01-30', '2017-02-06', '2017-02-13', '2017-02-20',
               '2017-02-27', '2017-03-06',
               ...
               '2019-01-21', '2019-01-28', '2019-02-04', '2019-02-11',
               '2019-02-18', '2019-02-25', '2019-03-04', '2019-03-11',
               '2019-03-18', '2019-03-25'],
              dtype='datetime64[ns]', name='Application_Date', length=117, freq=None)
```

Target Variable

- A new Feature ‘bad_loan’ was created from the categorical feature ‘loan_status’.
- A bad loan is: Charged Off, Late(31-120 days) and Default.
- A good loan is: Fully Paid
- The other values will be discarded: Current, Late(16-30 days) and In Grace Period because they are not considered good or bad.

```
1 loan_stat = df["loan_status"]
2 sns.countplot(loan_stat)
3 stat_temp = df.loan_status.value_counts().sum()
4 plt.xticks(rotation=45)
```

```
(array([0, 1, 2, 3, 4, 5, 6]), <a list of 7 Text xtickla
```

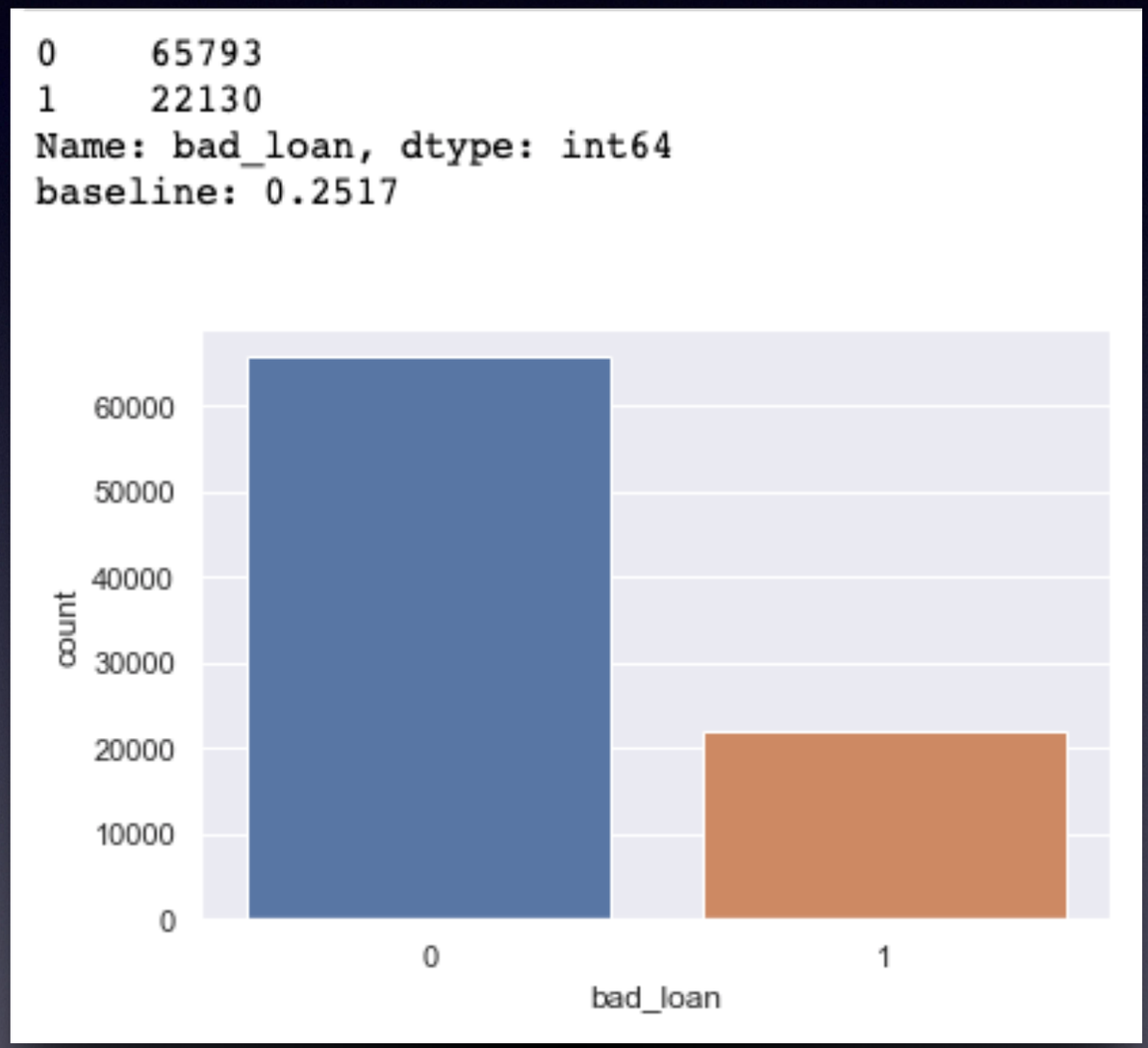



```
1 df = df[df['loan_status'] != 'Current']
2 df = df[df['loan_status'] != 'In Grace Period']
3 df = df[df['loan_status'] != 'Late (16-30 days)']
```

Target variable

- About 74.83% of the remaining loans have been fully paid and 25% have been charged off, late or in default, so we have an unbalanced classification problem.
- If we gave all the customers loans, 25% of them would not pay back the loan.

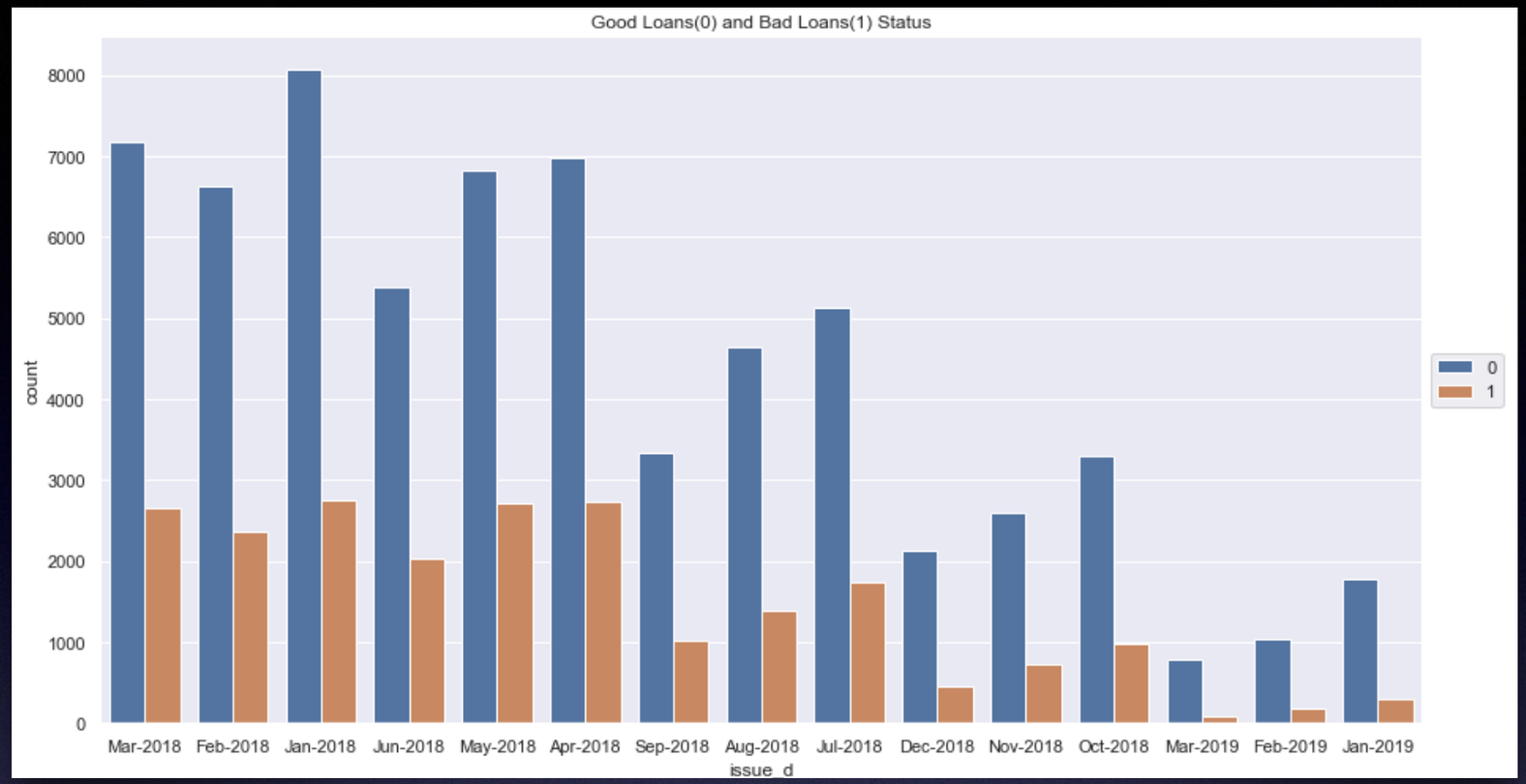
```
0    65793
1    22130
Name: bad_loan, dtype: int64
baseline: 0.2517
```

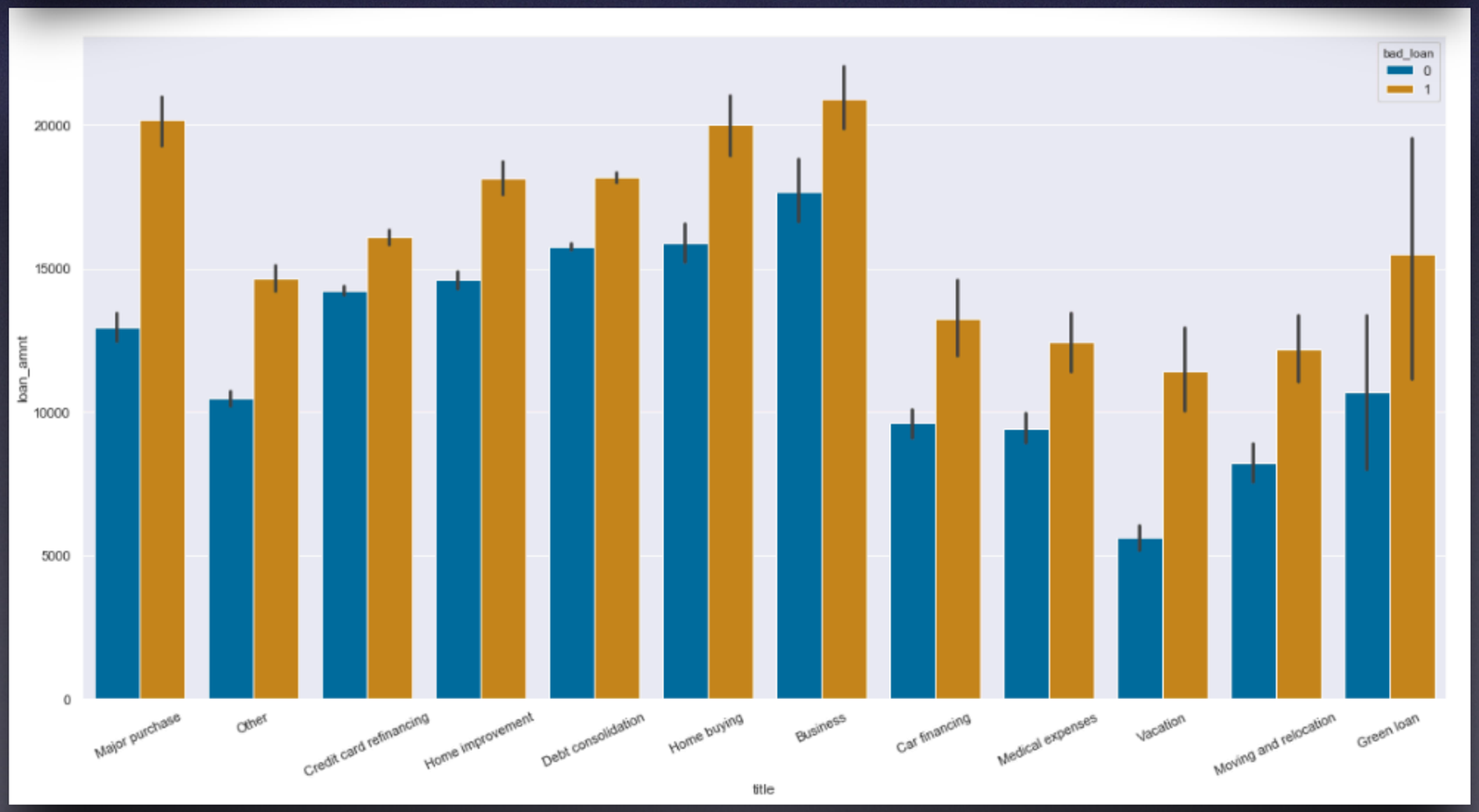


A few feature plots of good(0) vs bad loans(1)

Months January - June have the most defaulted loans.

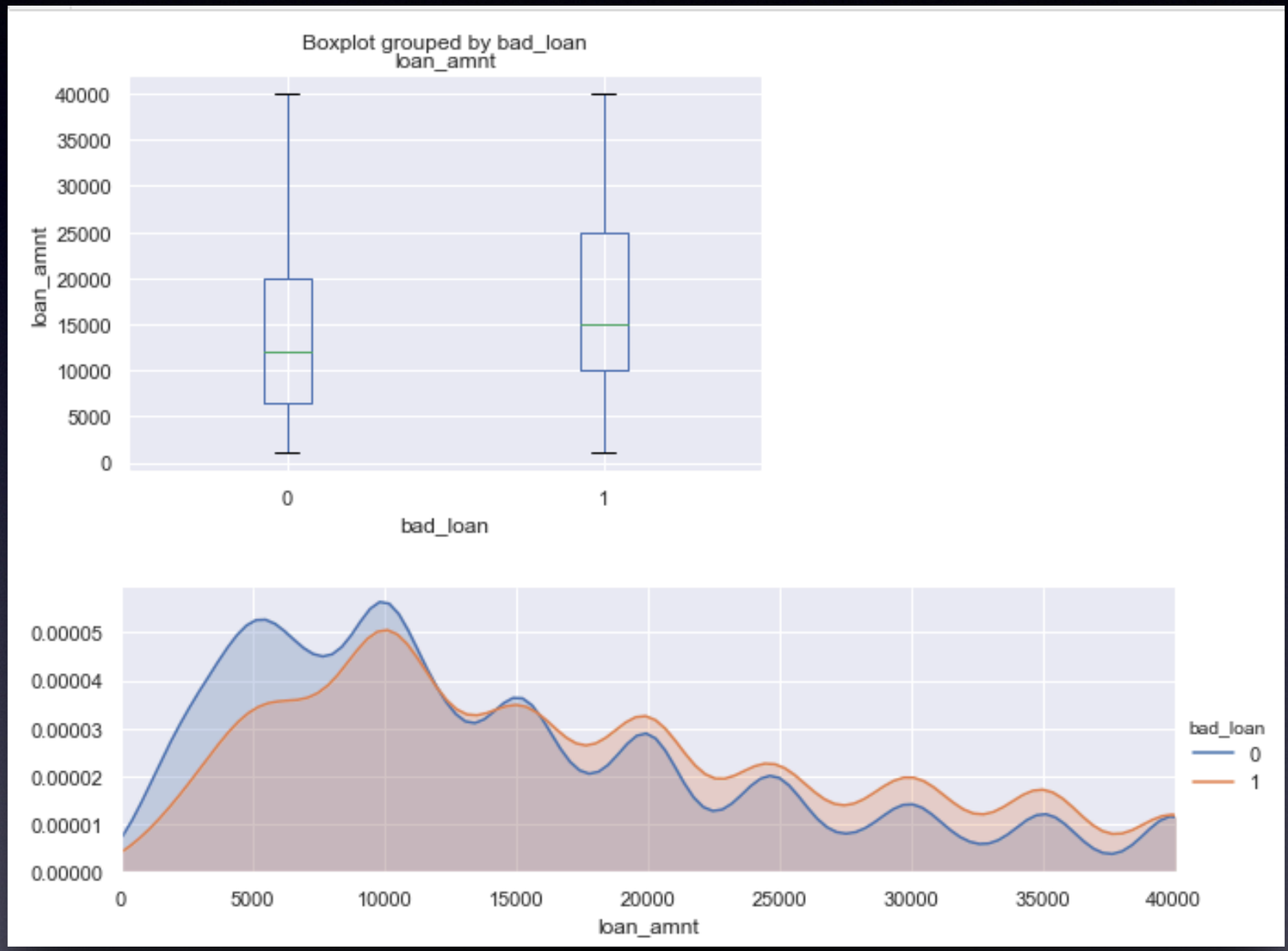
Business loans are the top defaulters and they have the highest loan amounts.





good(0) vs bad loans(1)

$15k is the average loan amount for customers who default.



Supervised Learning

Random Forest, ADABoost Random Forest and XGBoost are the algorithms used to determine the percentage of good loans that will be issued. Grid-search was used to find the best hyper-parameters for each model. Below is the result.

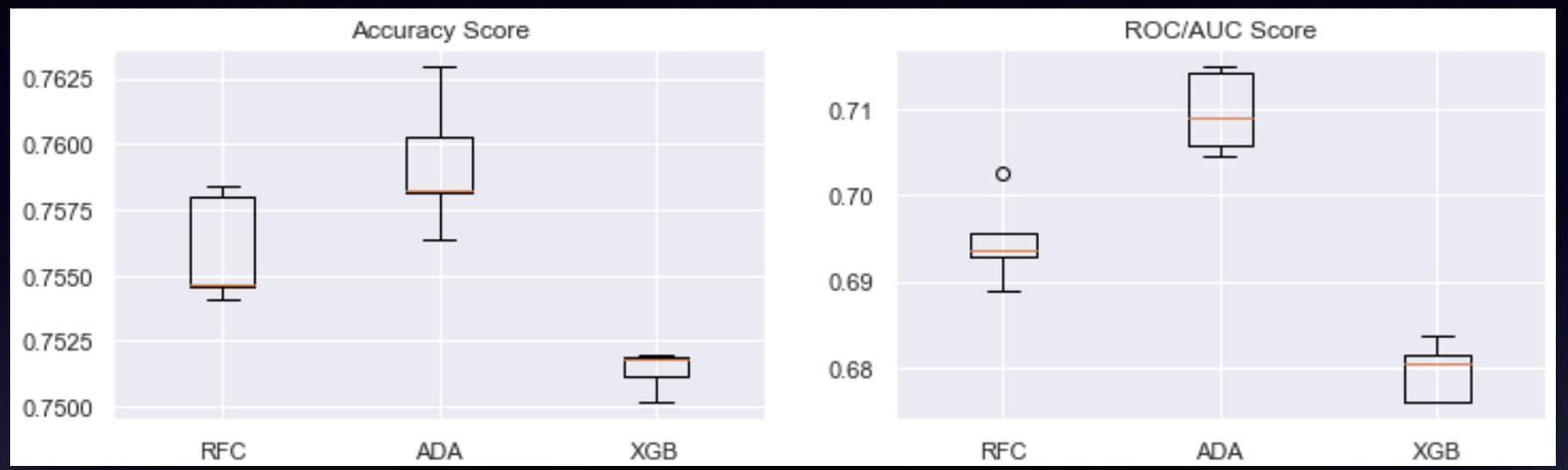
```
rf_final = RandomForestClassifier(max_depth=15,
min_samples_leaf=10,
min_samples_split=10,
max_features=2,
n_estimators=18)
```

```
ada_final = AdaBoostClassifier(base_estimator=rf_final,
n_estimators=7)
```

```
xgb_final = XGBClassifier(max_depth=12,
n_estimators=20,
learning_rate=0.03,
subsample=0.1,
colsample_bytree=0.5,
colsample_bylevel=0.5)
```

Results

Random Forest, ADABoost Random Forest and XGBoost accuracy scores are all approximately 0.75. XGB is the most stable and ADABoost has the better AUC score.



	Accuracy	ROC
	score (std)	score (std)
RFC	0.7559 (0.0019)	0.6947 (0.0045)
ADA	0.7592 (0.0022)	0.7096 (0.0043)
XGB	0.7514 (0.0007)	0.6795 (0.0030)
	baseline 0.7483	

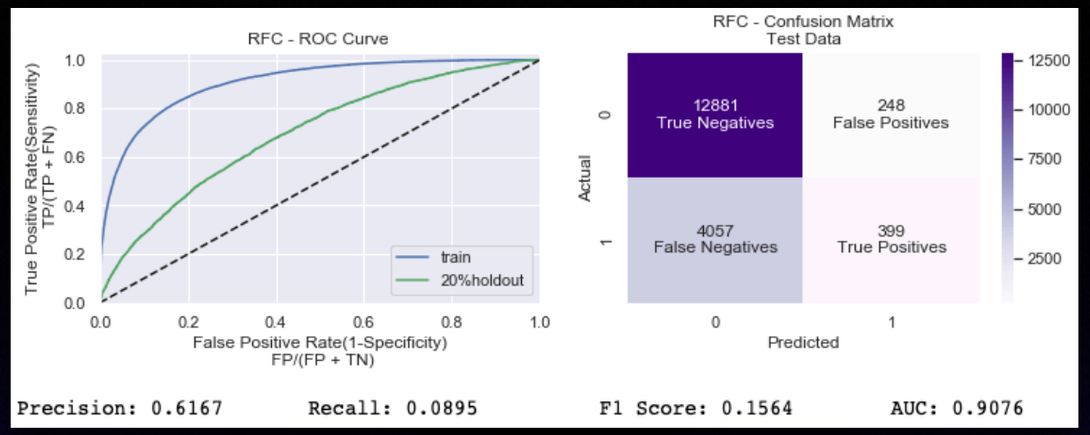
target variable bad loans=1

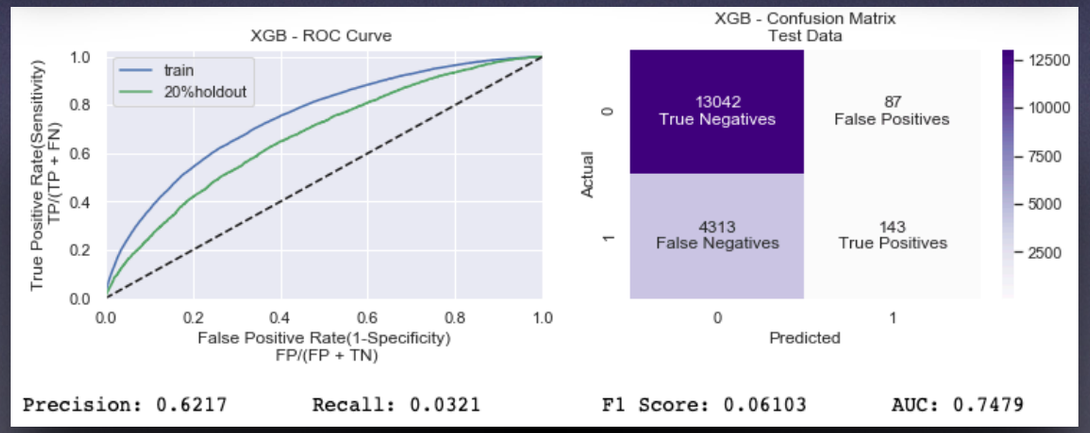
- Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. The question that this metric answers is of all loans that are labeled as bad, how many actually were bad? All models have a ~60% precision.

- Recall is the ratio of correctly predicted positive observations to the all observations. The question recall answers is: Of all the loans that are truly bad, how many did the model label correctly? The recall for all the models is very low.

- To make sure LendingClub doesn't lose lots of money, customers who don't pay back their loan, we need to decrease the number of False Negatives.

- By decreasing the False Negatives (loans predicted as being paid back that are actually not paid) the recall score will increase.





XGBoost weighted model

- In an attempt to increase the Recall score, the parameter scale_pos_weight was added to XGBoost.
- The parameter scale_pos_weight controls the balance of positive and negative weights which is useful for unbalanced classes.
- There will be a trade off in the accuracy score when the weight is applied. The accuracy will decrease but it is better to have less borrowers who don't pay back the loan than a high accuracy score for this model.
- The weight of 5.5 was chosen as the 'best'. It decreased the False Negatives from 4313 to 1749, increased the False Positives.

```
weights = [1, 3.5, 4, 4.5 ,5, 5.5, 6, 6.5, 14]
for x in weights:
    xgb_bal = XGBClassifier(max_depth=12,
                            n_estimators=20,
                            learning_rate=0.03,
                            subsample=0.1,
                            colsample_bytree=0.5,
                            colsample_bylevel=0.5,
                            scale_pos_weight=x)
    xgb_bal.fit(X_train, y_train)
    predictions = xgb_bal.predict(X_test)
```

Weight of 1
Recall Score: 0.03
Accuracy Score: 0.75
Confusion Matrix
[[13042 87]
[**4313** 143]]

Weight of 3.5
Recall Score: 0.43
Accuracy Score: 0.70
Confusion Matrix
[[10379 2750]
[**2541** 1915]]

Weight of 5.5
Recall Score: 0.61
Accuracy Score: 0.62
Confusion Matrix
[[8151 4978]
[**1749** 2707]]

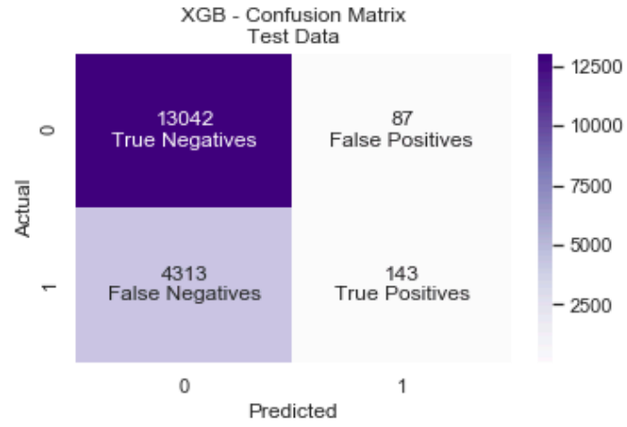
Weight of 14
Recall Score: 0.91
Accuracy Score: 0.39
Confusion Matrix
[[2884 **10245**]
[**417** 4039]]

XGBoost with and without weight

- The Recall increased by 18.93%, F1 score increased by 7.3% and Precision decrease by 56.65% as expected.

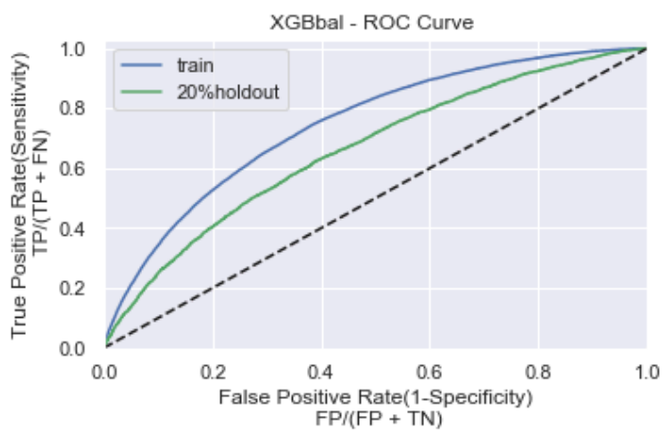
- The False Negatives decrease from 4313 to 1749. So instead of 4313 loans as a LendingClub write off only 1749 loans will be written off.

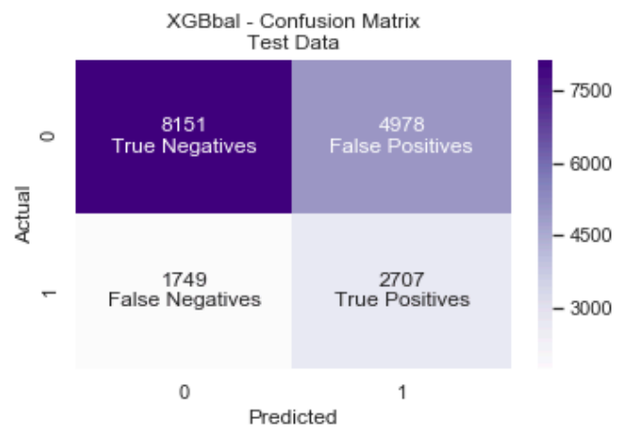
No Weight



Precision: 0.6217 Recall: 0.0321 F1 Score: 0.06103 AUC: 0.7479

Weighted Model

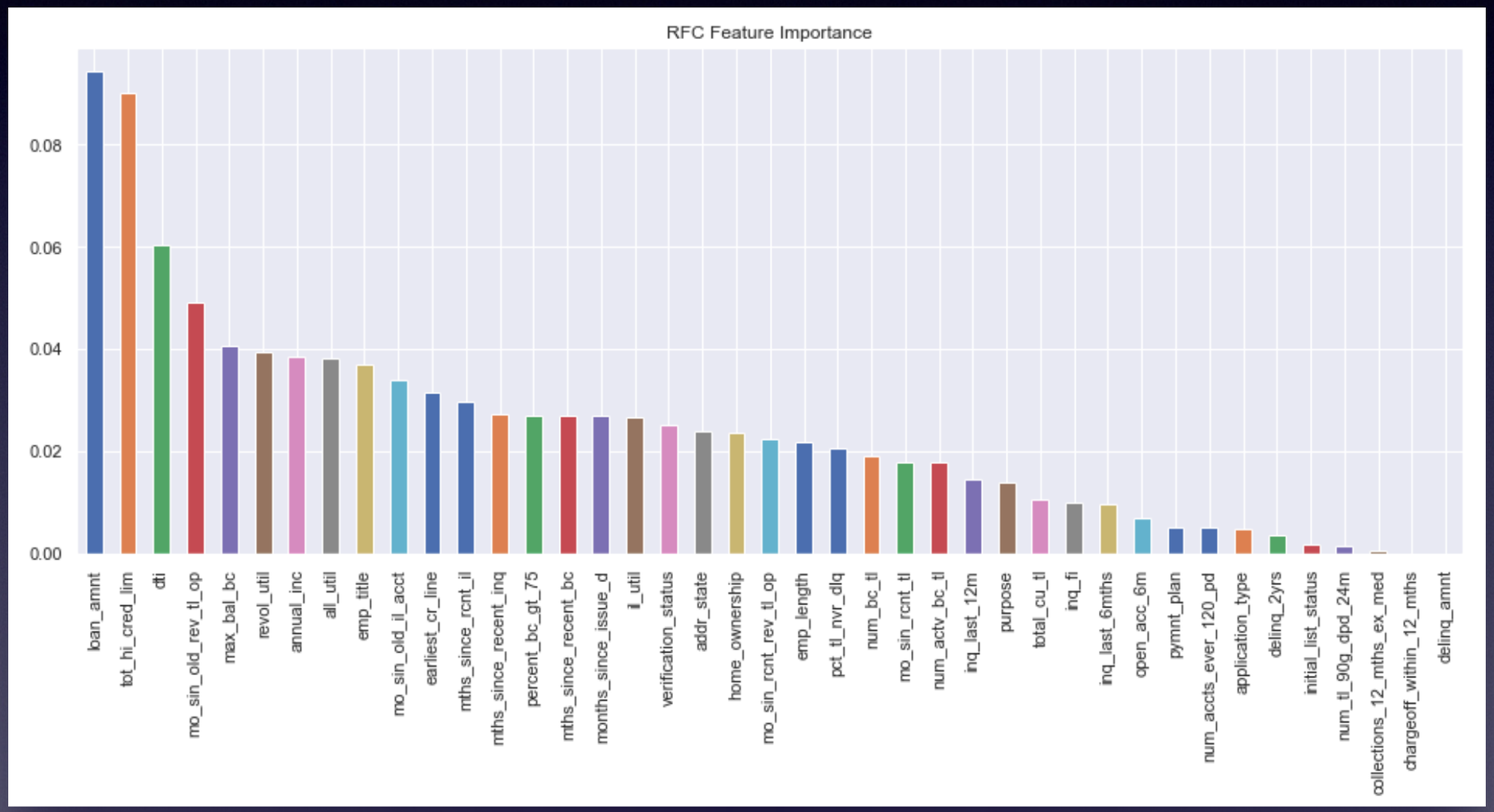




Precision: 0.3522 Recall: 0.6075 F1 Score: 0.4459 AUC: 0.7453

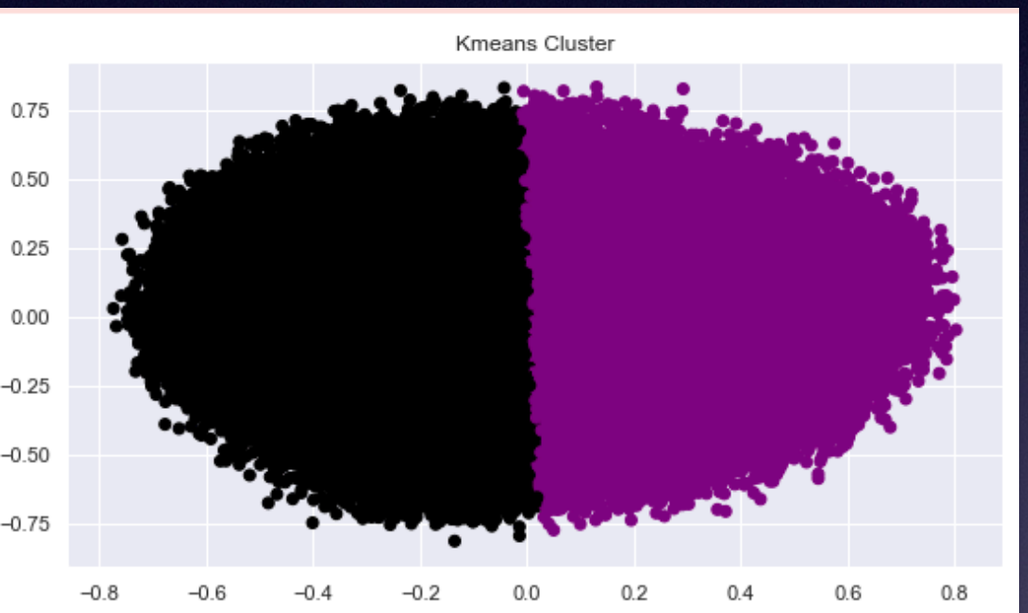
Feature Importance

The top 10 features will be used for Kmeans & Mean Shift clustering.



KMeans & KMeans Minibatch

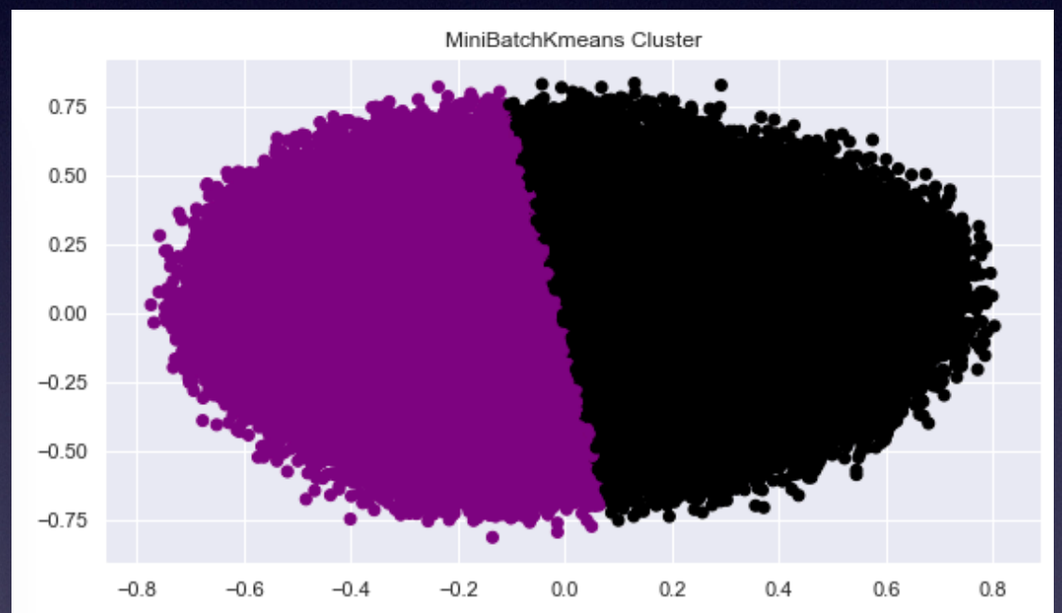
44,298 (10701+33684) correctly classified
43,625 (32109+11429) mis-classified



Comparing k-means clusters against the data:

bad_loan	0	1
row_0		
0	33684	11429
1	32109	10701

43,207 (11015+33352) correctly classified
44,716 (32441+11115) mis-classified

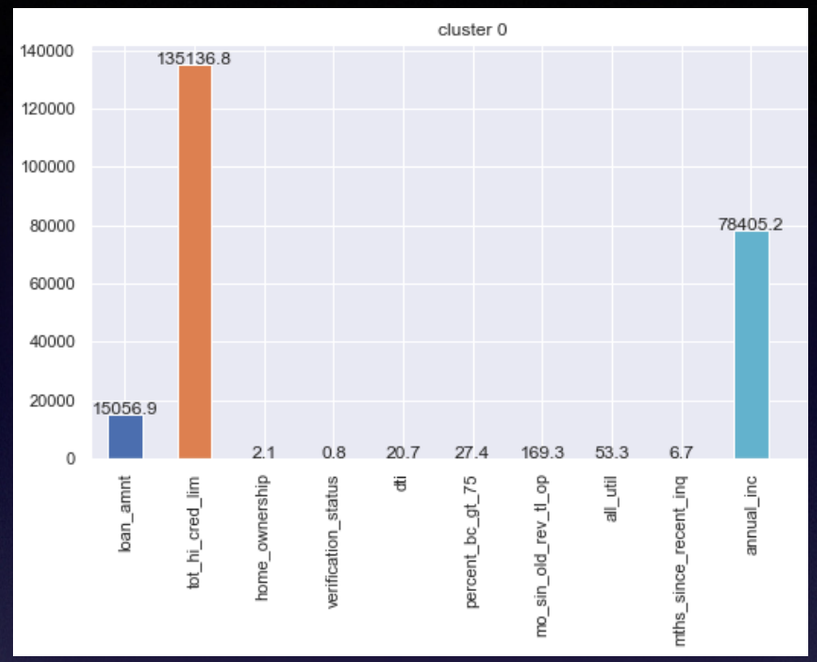


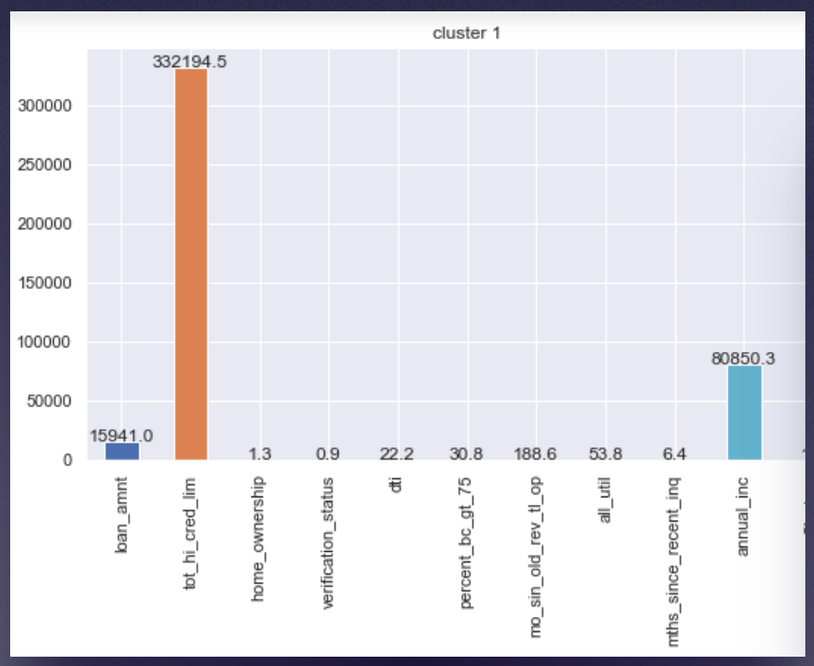
Comparing k-means and mini batch k-means solutions:

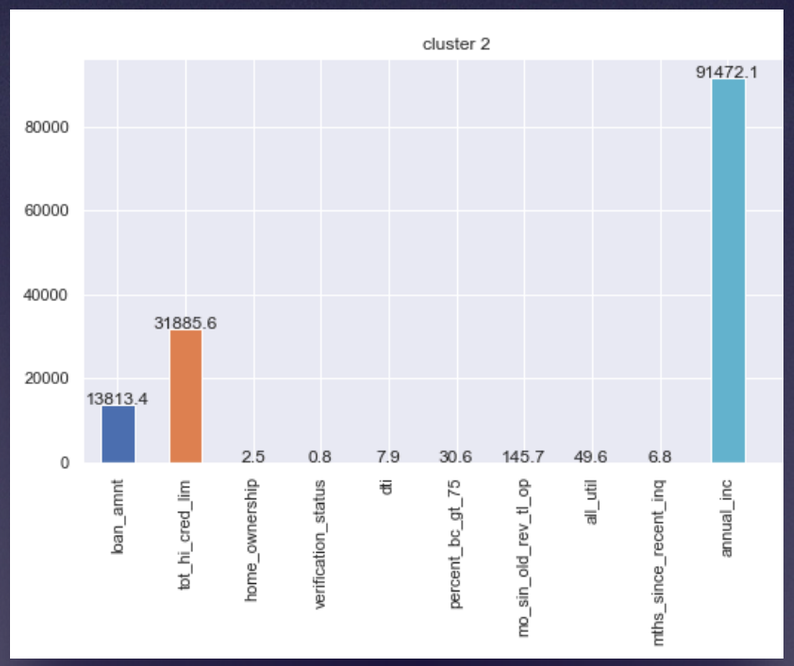
bad_loan	0	1
row_0		
0	33352	11115
1	32441	11015

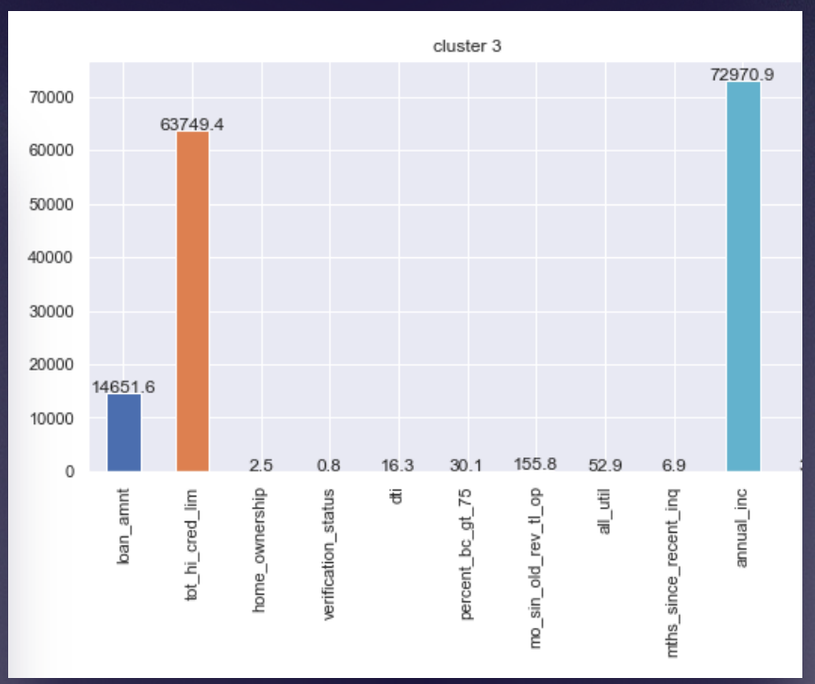
Kmeans Clusters on RFC Features

- Cluster 0 - people who have **high credit limit of 135k, annual income of 78k** and 15k loan amount
- Cluster 1 - people who have **high credit limit of 332k** and an **annual income of 80k.**
- Cluster 2 - people **annual income 91k**, **high credit limit of 32k** and loan amount 14k.
- Cluster 3 -**annual income 73k**, **high credit limit 32k** and loan amount of 14k
- So for potential customers who have a high credit limit that is over 30% of their income they will most likely default on the loan.









Time Series

- For time series we are using the rejected loan application dataset. The original dataset has 19158655 rows but after converting the date to weeks, it is reduced to 117 rows.

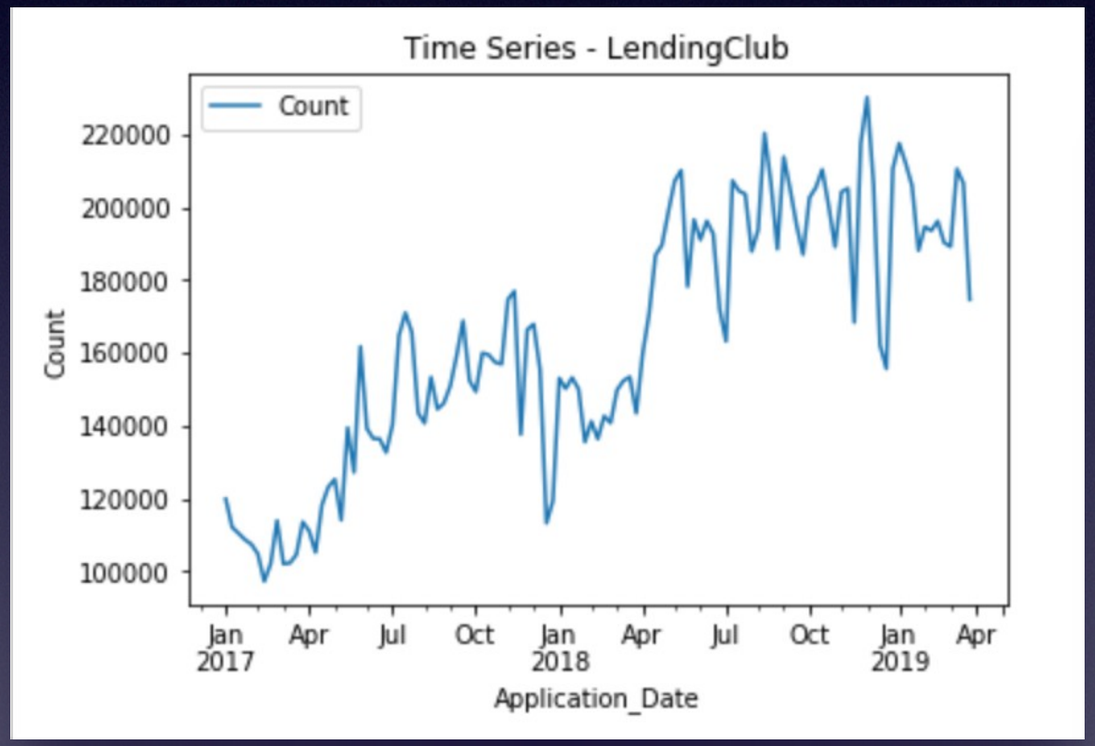
- SARIMA will predict 8 weeks of rejections as well as forecast rejection 12 weeks out. LSTM will also predict 8 weeks of loans using the same data.

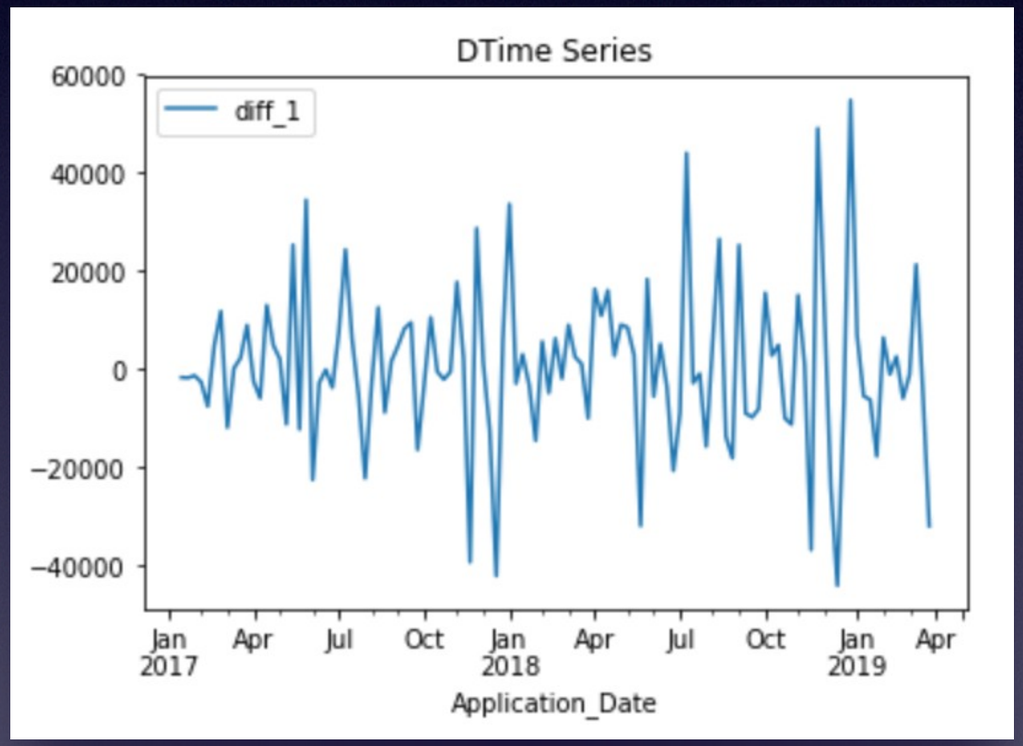
Rejected Loans (weekly)

Application_Date	Count
2017-01-02	119903
2017-01-09	112116
2017-01-16	110457
2017-01-23	108717
2017-01-30	107435

Original and Differenced time series

- The data is not stationary therefore a difference of one is done to make it stationary.

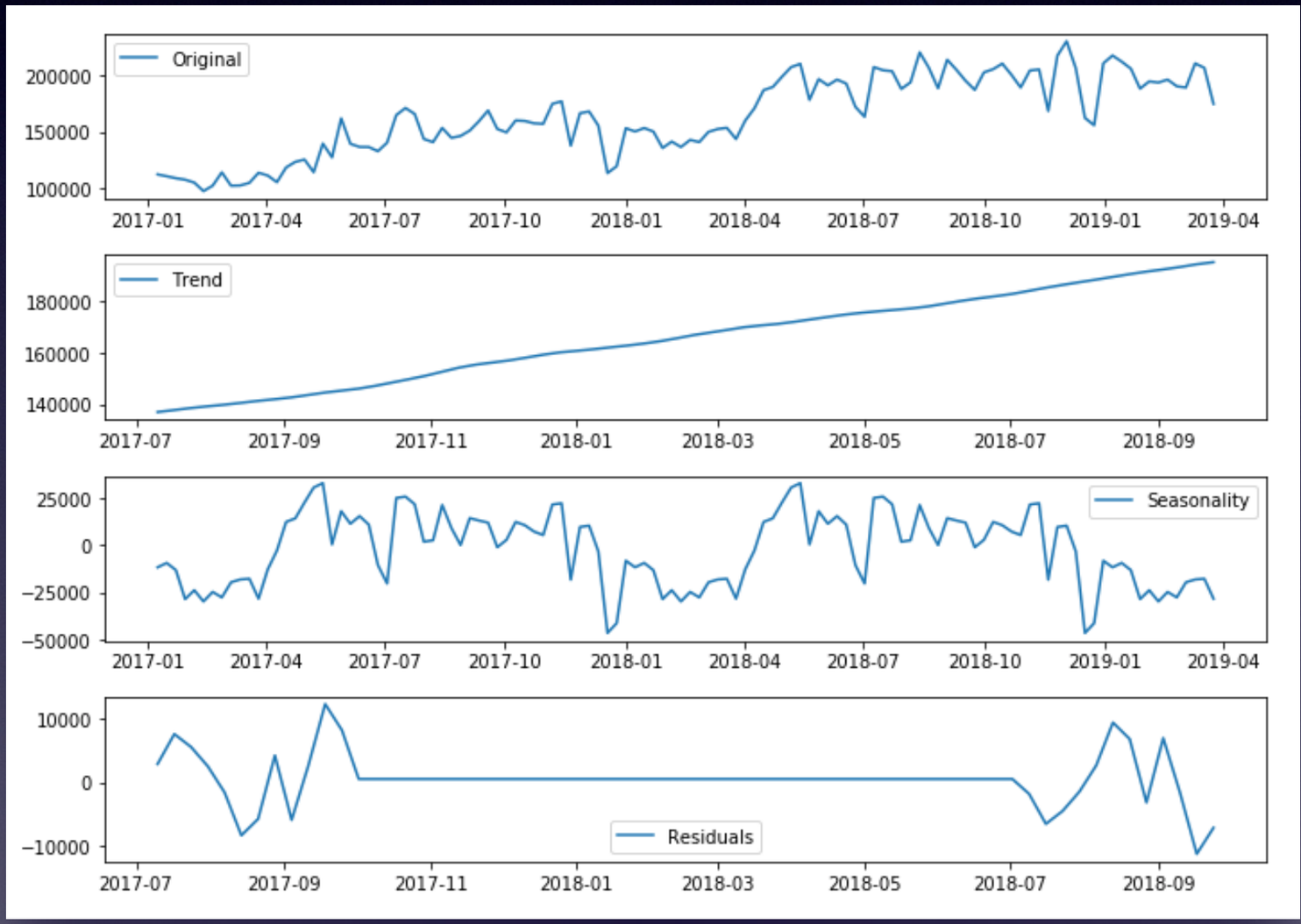




Decompose Seasonality

A statistical task that deconstructs a time series into several components.

Here we can see that the trend and seasonality are separated out from data and we can model the residuals.



Augmented Dickey-Fuller test

The null hypothesis for this test is that there is a unit root.
The basic alternate is that the time series is stationary.

A large p-value (> 0.05) indicates weak evidence against the null hypothesis, so you fail to reject the null hypothesis. The p-value is greater than 0.05, this is an indication that the model is not stationary and we have to take a difference to make it stationary.

raw data

Test Statistic	-1.653998
p-value	0.454956
#lags used	3.000000
#nobs used	112.000000

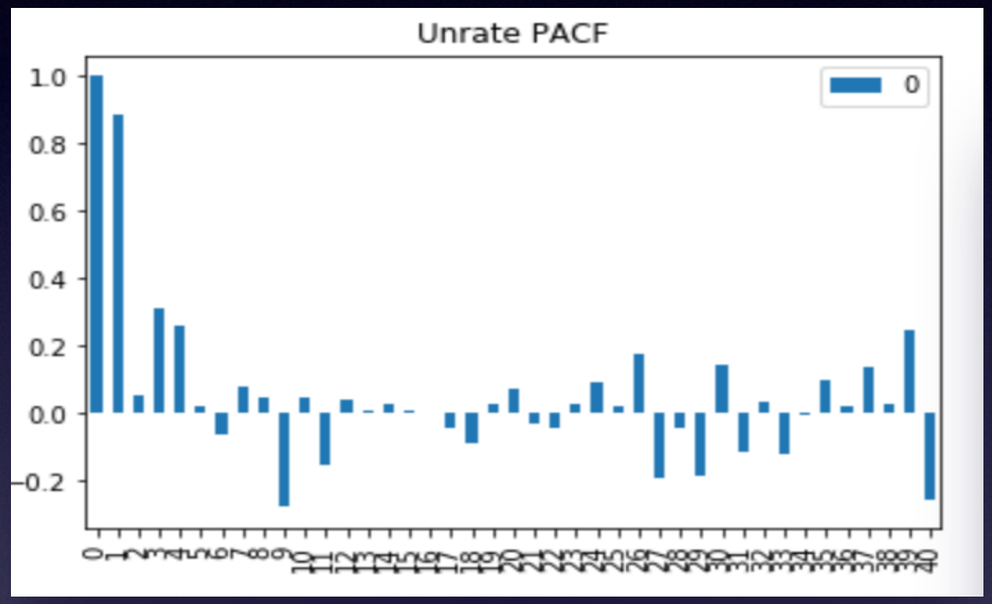
1%	-3.4901313156261384
5%	-2.8877122815688776
10%	-2.5807296460459184

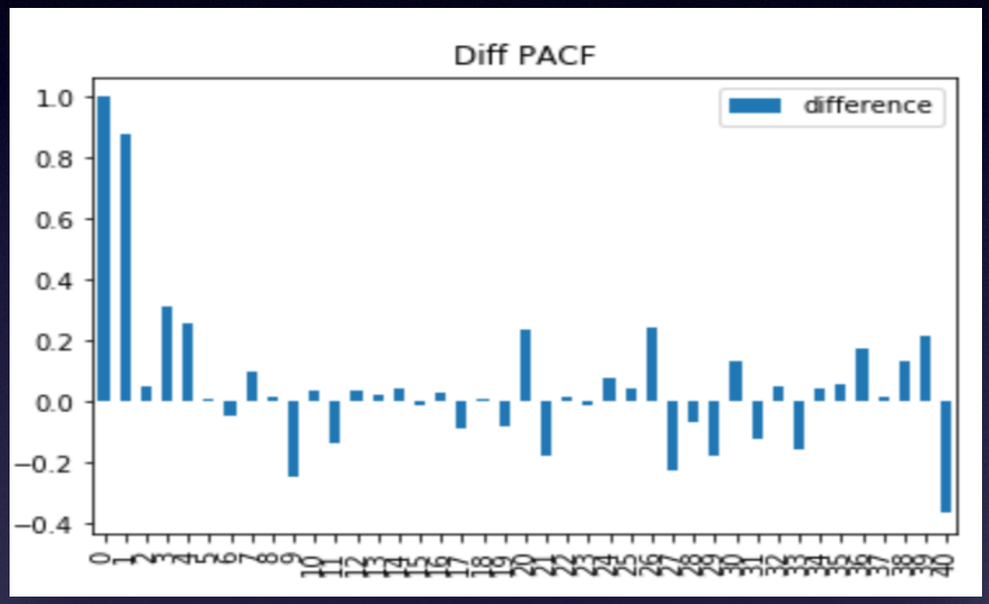
PACF original and differenced **time** series

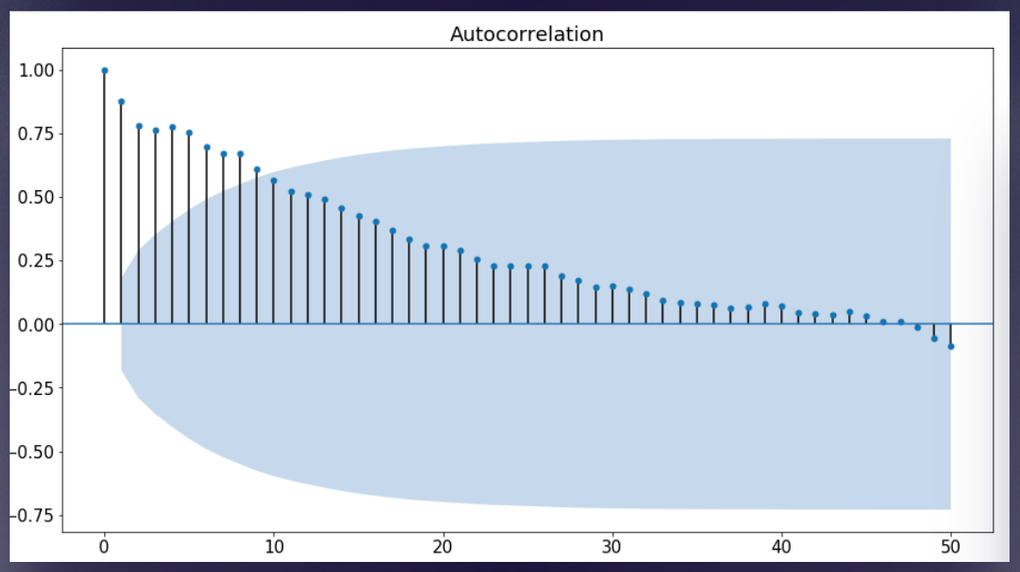
The initial and the differenced plots both have a strong autocorrelation at 1.

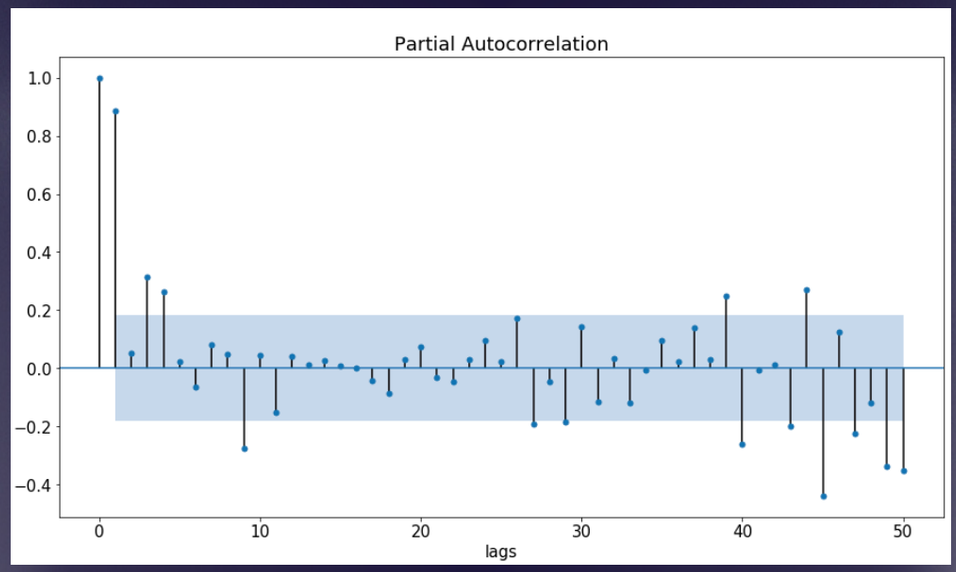
The Autocorrelation plot says the value in time ’t’ has some correlation with the previous.
The partial autocorrelation plot ask’s the question 'how many lags do you need?’

A customer's annual income for 2019 may have a relationship with their income from 2012 but we only need the annual income from 2018 to be accurate.









SARIMA Time Series model results

```
stepwise_model =
auto_arima(dfIndex['Rejected_Loan_Count'],
                        start_p=0, start_q=0,
                        max_p=13, max_q=13, m=13,
                        start_P=0, start_Q=0,
                        seasonal=True,
                        d=1, D=1, trace=True,
                        error_action='ignore',
                        suppress_warnings=True,
                        random_state=42,
                        n_fits=3,
                        stepwise=True)
stepwise_model.summary()
```

SARIMAX(0, 1, 2)x(1, 1, 1, 13)

This was the best fit, the lowest AIC. The seasonality is 13 which is ok as the data is quarterly.

Statespace Model Results

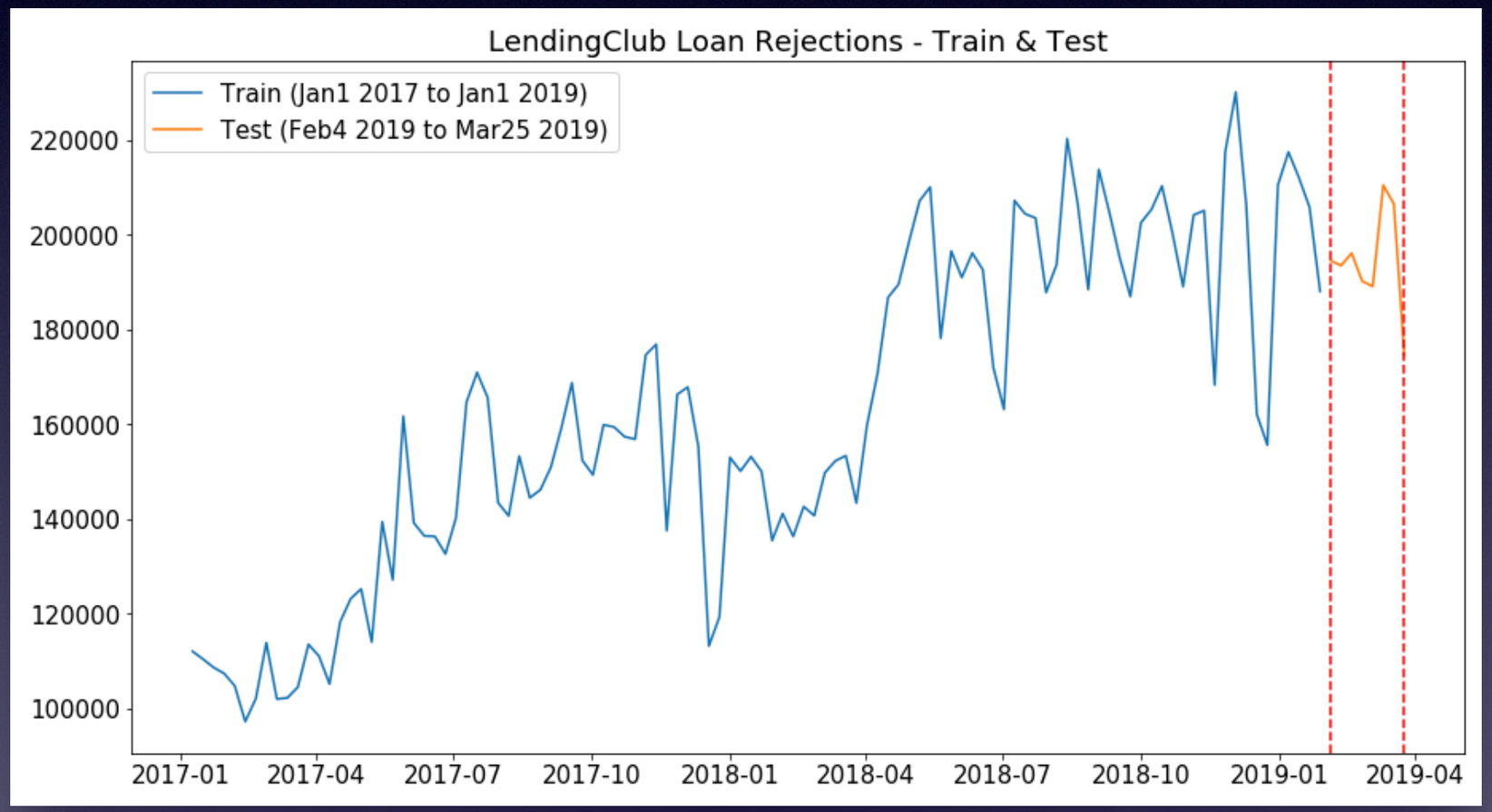
Dep. Variable:	y	**No. Observations:**	116
Model:	SARIMAX(0, 1, 2)x(1, 1, 1, 13)	**Log Likelihood**	-1134.857
Date:	Tue, 16 Jul 2019	**AIC**	2281.713
Time:	16:18:21	**BIC**	2297.463
Sample:	0	**HQIC**	2288.091
	- 116		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	-315.9325	725.235	-0.436	0.663	-1737.367	1105.502
ma.L1	-0.3026	0.238	-1.272	0.204	-0.769	0.164
ma.L2	-0.2153	0.198	-1.086	0.278	-0.604	0.173
ar.S.L13	-0.2300	0.210	-1.096	0.273	-0.641	0.181
ma.S.L13	-0.6329	0.261	-2.428	0.015	-1.144	-0.122
sigma2	4.291e+08	0.001	7.23e+11	0.000	4.29e+08	4.29e+08

Ljung-Box (Q):	38.70	**Jarque-Bera (JB):**	0.85
Prob(Q):	0.53	**Prob(JB):**	0.65
Heteroskedasticity (H):	1.30	**Skew:**	0.14
Prob(H) (two-sided):	0.45	**Kurtosis:**	3.34

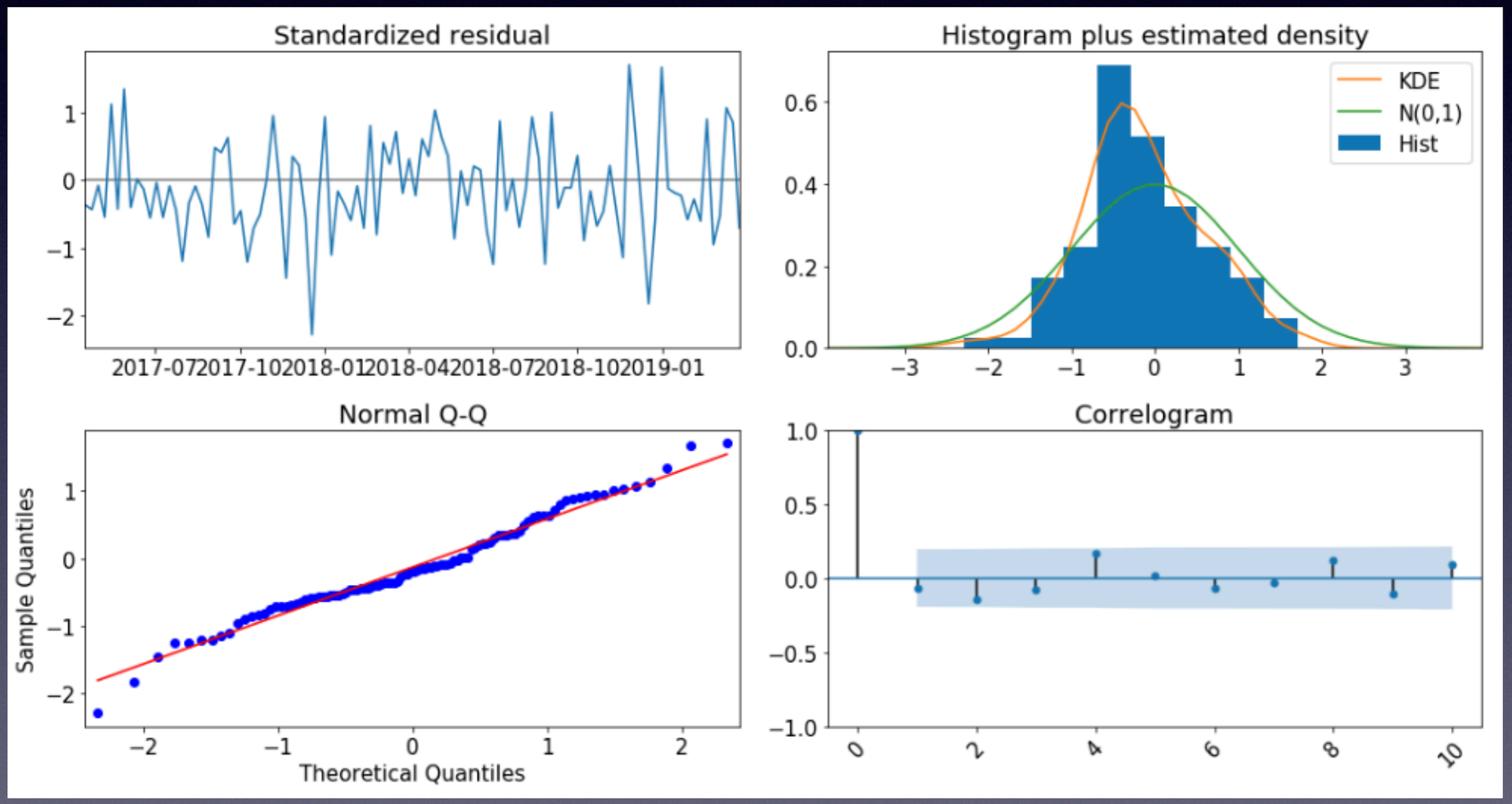
8 week prediction

Loan dataset will have 116 rows.
train, test = dfIndex[:108], dfIndex[108:]
Train: 108 rows weekly loan rejections from Jan1 2017 to Jan1 2019
Test: 8 rows of weekly loan rejections from Feb4 2019 to Mar25 2019



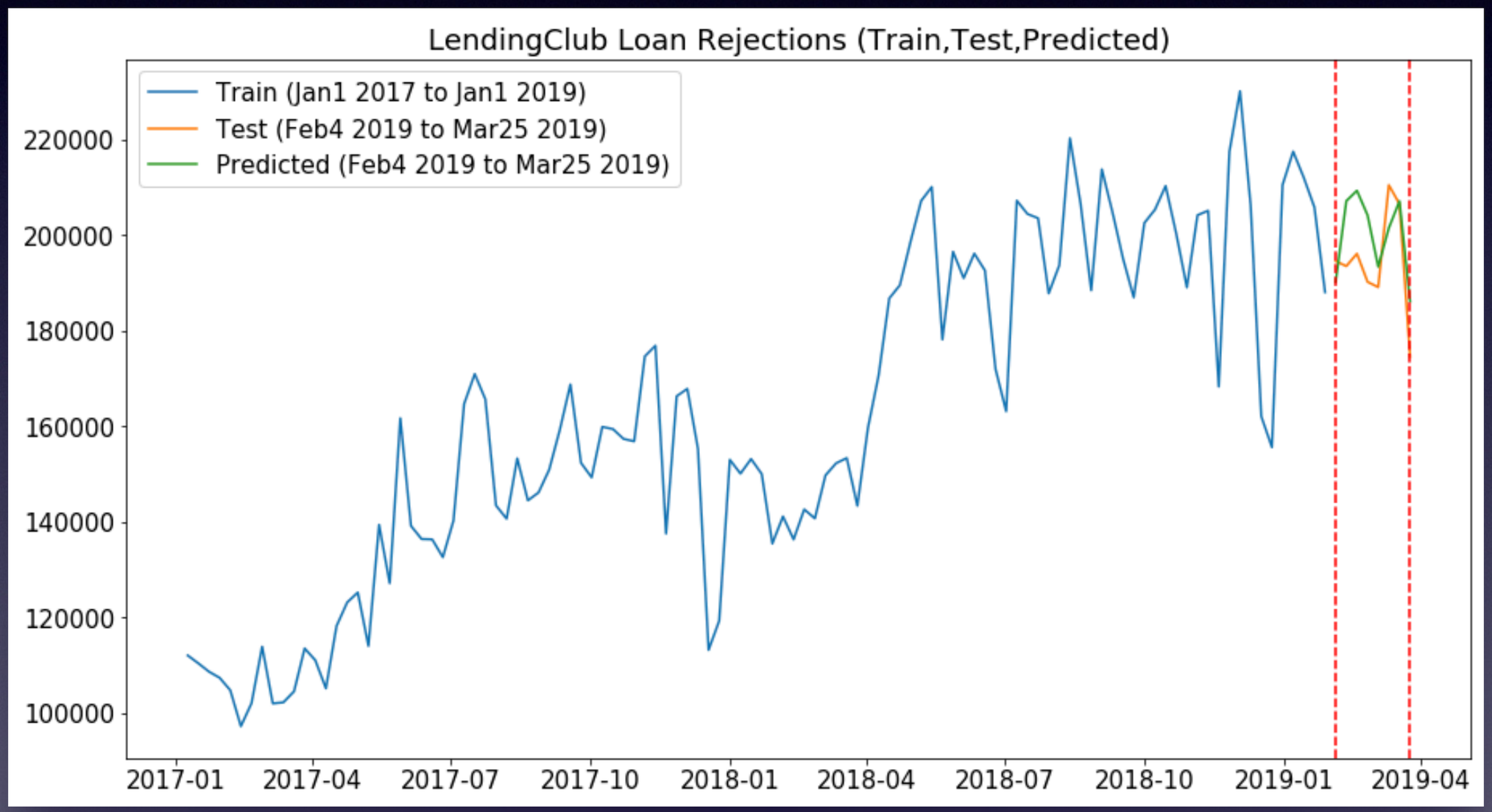
Results

- The residuals look random therefore the model doesn't seem to have any bias.
- The histogram distribution has a Gaussian look.
- The Q-Q plot also shows a normal distribution but with a few outliers.
- There isn’t any obvious autocorrelation trend in the plot.



SARIMA Prediction

- The actual and predicted forecast comparison plots.
- For the first 4 weeks the predicted is higher than the actual but after that the predictions are close to the actual.



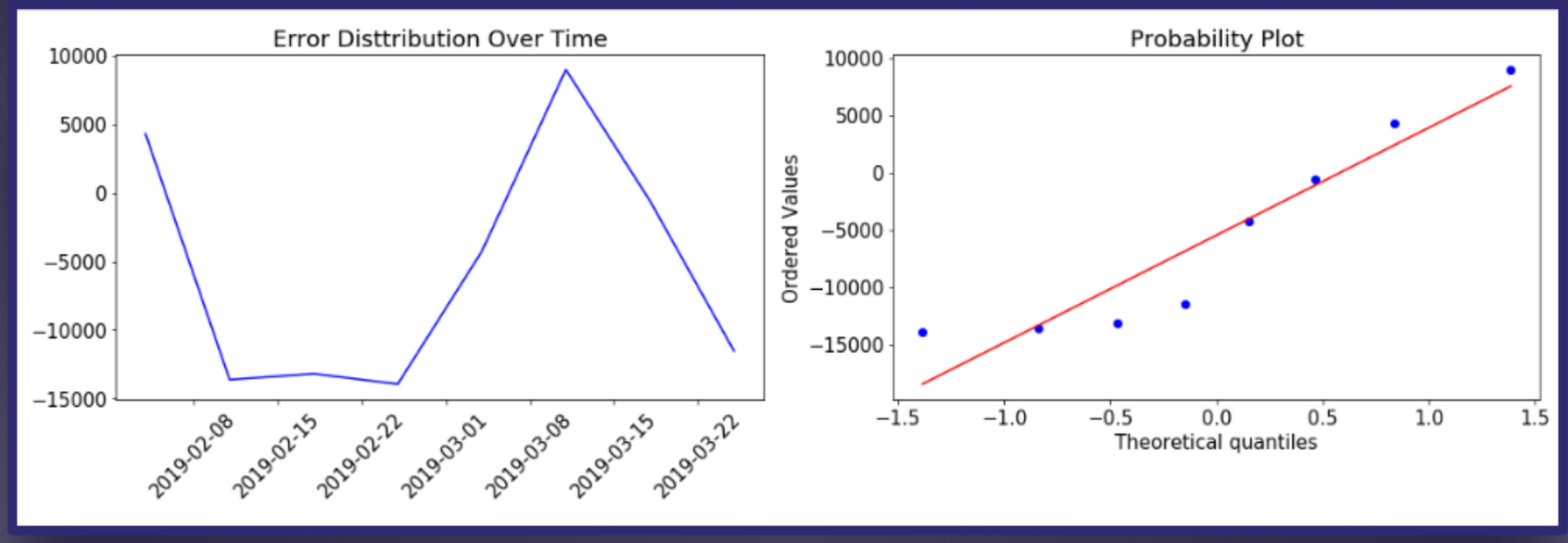
SARIMA prediction Errors

Application_Date	Loan_Count	Predicted_Count	Error	Predictions
2019-02-04	194570	190282.51	4287.49	200641.32
2019-02-11	193545	207165.14	-13620.14	212867.37
2019-02-18	196149	209330.69	-13181.69	191871.74
2019-02-25	190241	204186.00	-13945.00	202893.15
2019-03-04	189141	193419.03	-4278.03	213443.53
2019-03-11	210487	201513.06	8973.94	206000.16
2019-03-18	206549	207129.72	-580.72	190300.88
2019-03-25	174618	186142.10	-11524.10	181063.40

Mean of Number of Loans: 194,412.50

Root Mean Square Error: 10,025.50
Mean Squared Error: 100,510,732.85
Percent Mean Error: 5,483.53

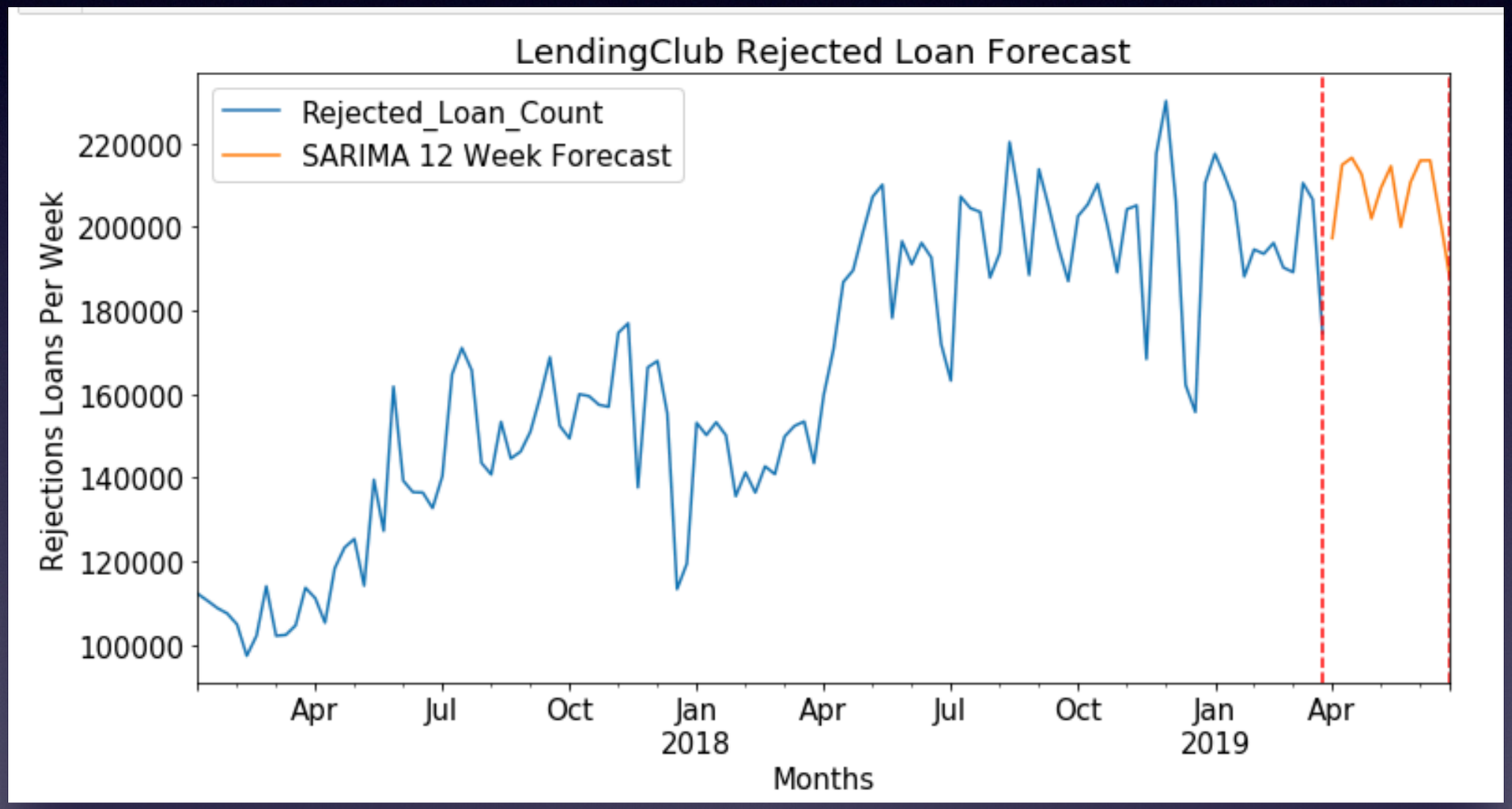
The model is off by 5.16%.
The with the mean number of loan = 194,412.50 and the root mean square error of 10,025.50.



SARIMA 12 week Forecast

- The forecast looks to be on trend at about 200,000 loan applications rejected per week. The forecast is for the weeks of March 26, 2019 to June 24, 2019.

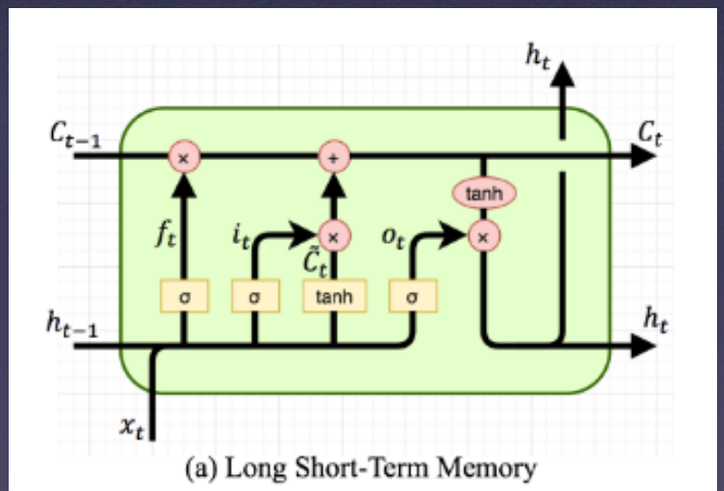
```
model = SARIMAX(dfIndex['Rejected_Loan_Count'], order=(0, 1, 2), seasonal_order=(
                0, 1, 1, 13), enforce_invertibility=False)
                results = model.fit()
fcast = results.predict(len(dfIndex), len(dfIndex)+12,
                        typ='levels').rename('SARIMA 12 Week Forecast')
```



LSTM Time Series

- Long short-term memory(LSTM) is capable of learning long-term dependencies by remembering information for long periods of time.
- It also uses a sigmoid function a value of 0 = let nothing through, 1= let everything through.
- The model needs to know what input shape it should expect. For this reason, the first layer in the model needs to have the input shape.
- A layer consists of a set of recurrent blocks that contains one or more recurrently connected memory cells and three multiplicative units(input(i), output(o), forget gates(f)).
- For this model, LSTM will look at the previous 8 weeks(time steps) to predict the 9th week.

- After many different combinations, this yielded the best result:
  - units = 100
  - dropout = 0.2
  - epochs = 900
  - batch size = 1
  - optimizer = adam
  - loss = mean squared error

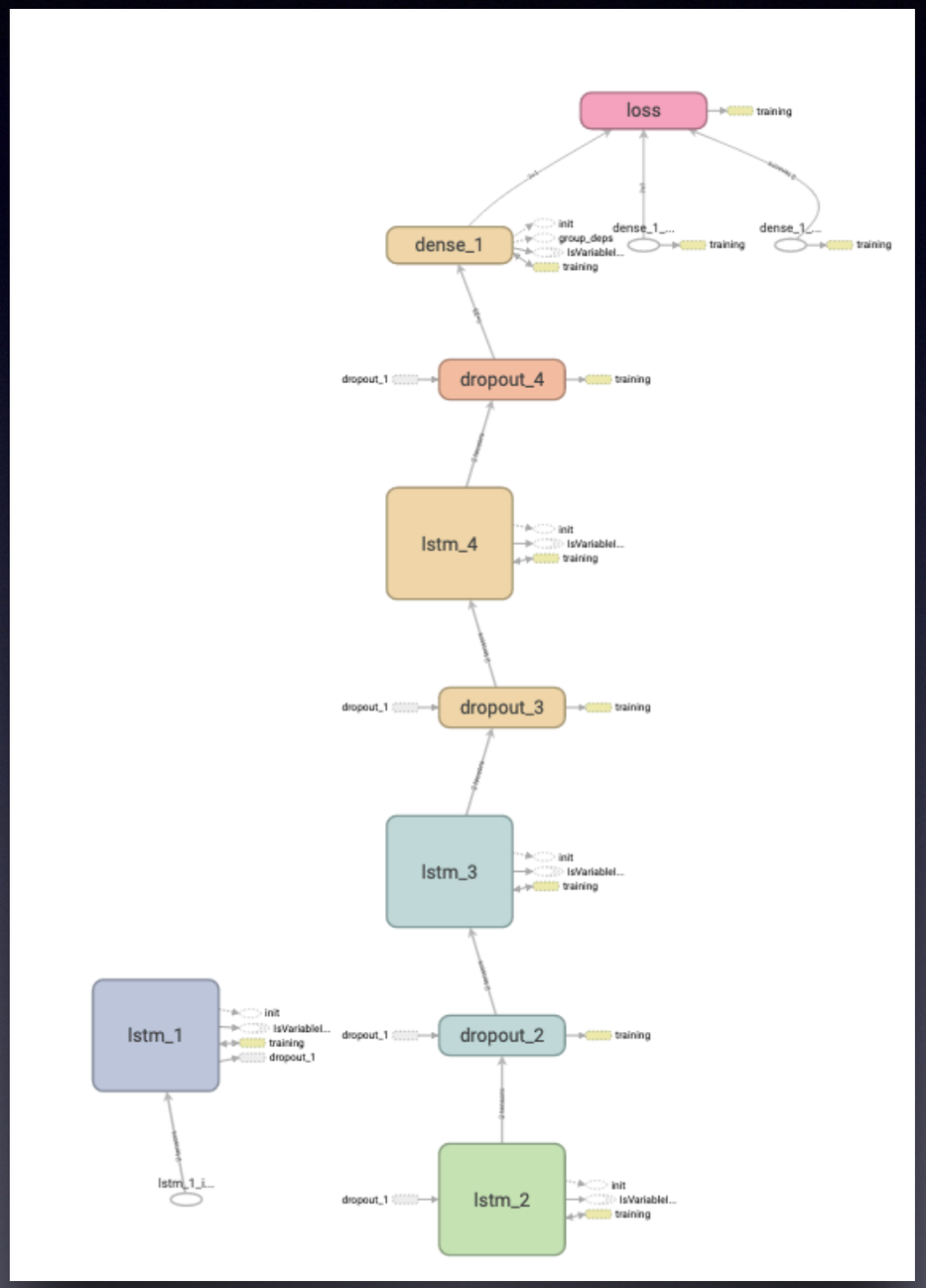


(a) Long Short-Term Memory

references:
https://isaacchanghau.github.io/post/lstm-gru-formula/
https://machinelearningmastery.com/gentle-introduction-long-short-term-memory-networks-experts
https://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM Sequential Model & Summary

Sequential LSTM cannot remember more of the past, but only the recent past (short term memory) and this is considered as a shortcoming of these networks. The model input, layers and output had the summary of
The model has 3 layers




```
lstm_model = Sequential()

lstm_model.add(LSTM(units=100,return_sequences=True, input_shape=(X_train.shape[1], 1)))
lstm_model.add(Dropout(0.2))

lstm_model.add(LSTM(units=100, return_sequences=True))
lstm_model.add(Dropout(0.2))

lstm_model.add(LSTM(units=100, return_sequences=True))
lstm_model.add(Dropout(0.2))

lstm_model.add(LSTM(units=100))
lstm_model.add(Dropout(0.2))

lstm_model.add(Dense(units=1))

lstm_model.compile(optimizer='adam', loss='mean_squared_error')

history = lstm_model.fit(X_train, y_train, epochs=900,batch_size=1,callbacks=[tensorboard])
```

Layer(type)	Output Shape	Param#
lstm_29 (LSTM)	(None,8 (Dense)	40800
dropout_29 (Dropout)	(None,8 (Dense)	0
lstm_30 (LSTM)	(None,8 (Dense)	80400
dropout_30 (Dropout)	(None,8 (Dense)	0
lstm_31 (LSTM)	(None,8 (Dense)	80400
dropout_31 (Dropout)	(None,8 (Dense)	0
lstm_32 (LSTM)	(None,100)	80400
dropout_32 (Dropout)	(None,100)	0
dense_8 (Dense)	(None,1)	101
Total params: 282,101		
Traina ble params: 282,101		
Non-tr ainable params: 0		

LSTM Prediction Result

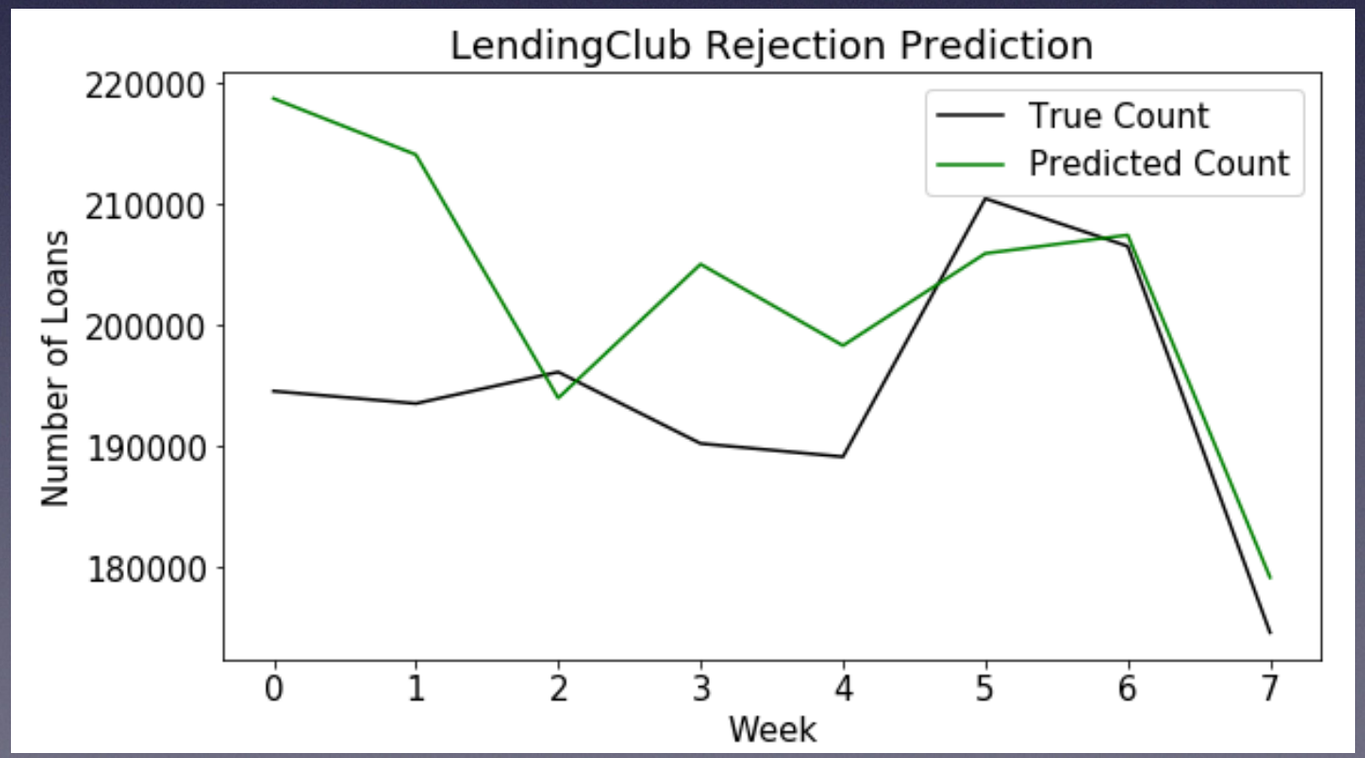
- The first 5 months the predicted number of rejected loans is a lot greater than the actual number of loans.

- The 5th thru the 8th month predictions were a lot better.

- RMSE Test Score: 13,033.17
- MSE Test Score: 169,863,469.53

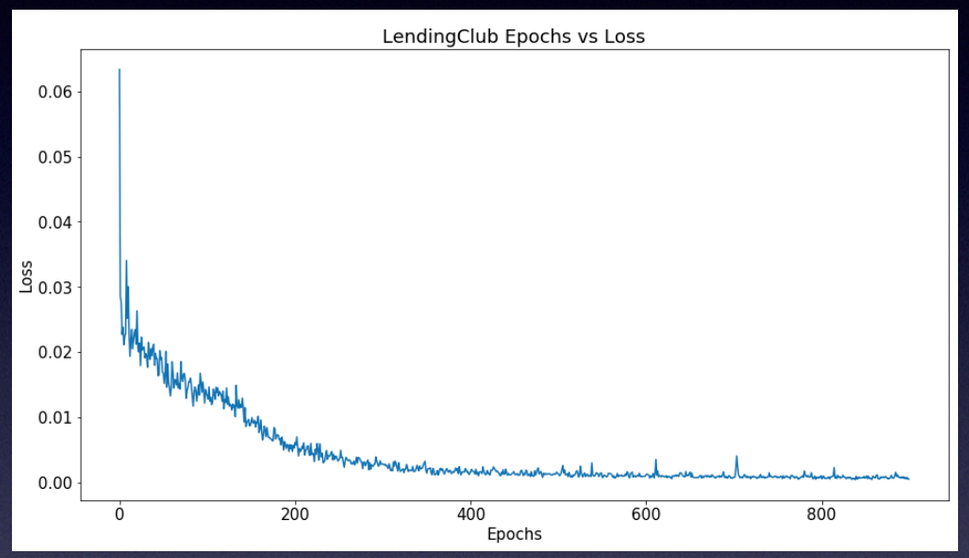
- The model is off by 6.70%.
- The with the mean number of loan = 194,412.50
- and the root mean square error of 13,033.17

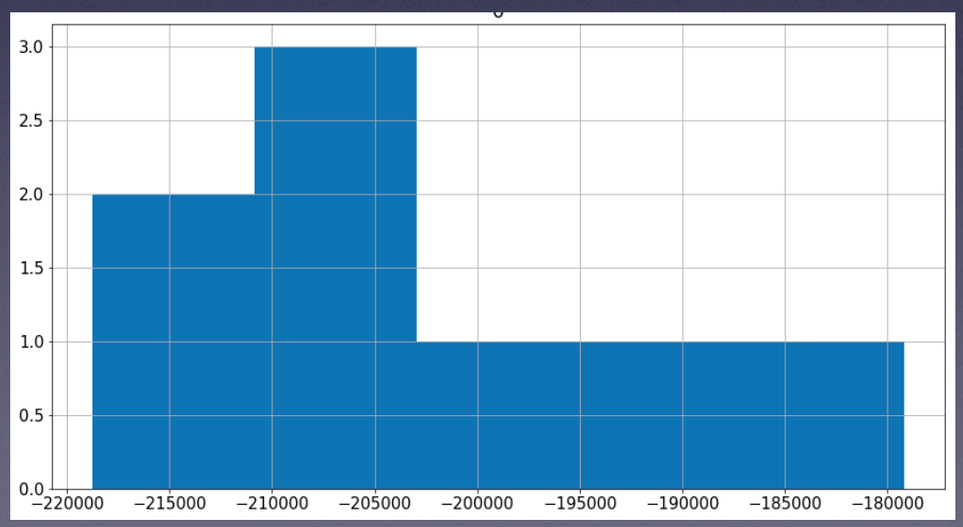
- SARIMA predicted the 8 weeks of loans better than LSTM by 1.54%.

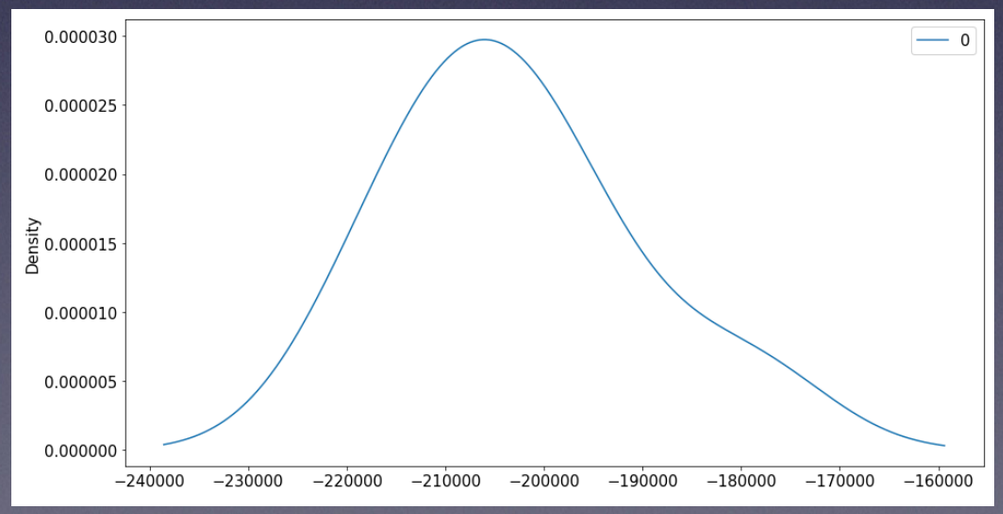


Loss, Residuals and Density Plots

- There is a sharp drop off for the loss at the start and then it tries to level out
- For the residual plot, the distribution does look Gaussian with right skewness (the mean is to the right of the median)







Summary

- The supervised learning models predicted too many False Negatives (applications which were predicted as good but they were actually bad loans). Using a weighted XGB model decrease the False Positives which therefore increased the recall score from 3% to 60% but the penalty was the accuracy score decreased from 75% to 62%.

- For future work, it is worth testing the model using different sampling(up/down) methods to balance the target variable.

- The top 10 features from Random Forest were analyzed with KMeans and Mean Shift. Kmeans found 4 clusters and Mean Shift didn’t find any clusters. The clusters can be used as new features that may help to boost the prediction to catch bad loans.

Summary

- SARIMA predicted 8 weeks and forecasted 12 weeks of rejected loan applications. The model had an RMSE of 10,025 which is not bad as there are an average of 200k loans per week. To test the model, I would like to get the July loan data to see if the forecast was accurate.

- LSTM predicted the 8 weeks of loans too, and had a RMSE of 13,033.

- SARIMA model was 1.54% better at predicting bad loans than LSTM.

- Lastly, it would be interesting to use my own information to see wha category I would fall into.

Conclusion

The model would give more time to LendingClub to look at the loans that were predicted as bad but were actually not bad which would increase revenue.

LendingClub would know the number of weekly loans predicted to be paid off therefore making sure they have resources to handle the collection processes.

Knowing the predicted outcome for 8 week and a forecast of 12 weeks would give them a good resource to show the investors which would increase their revenue.

They would find potentially new attributes of customers that are not likely to pay off their loans, the 4 new Kmeans clusters. customers who have a high credit limit that is over 30% of their income.

Questions & Suggestion?