Current Expected Credit Loss (CECL)
Loss Rates & PD Modeling

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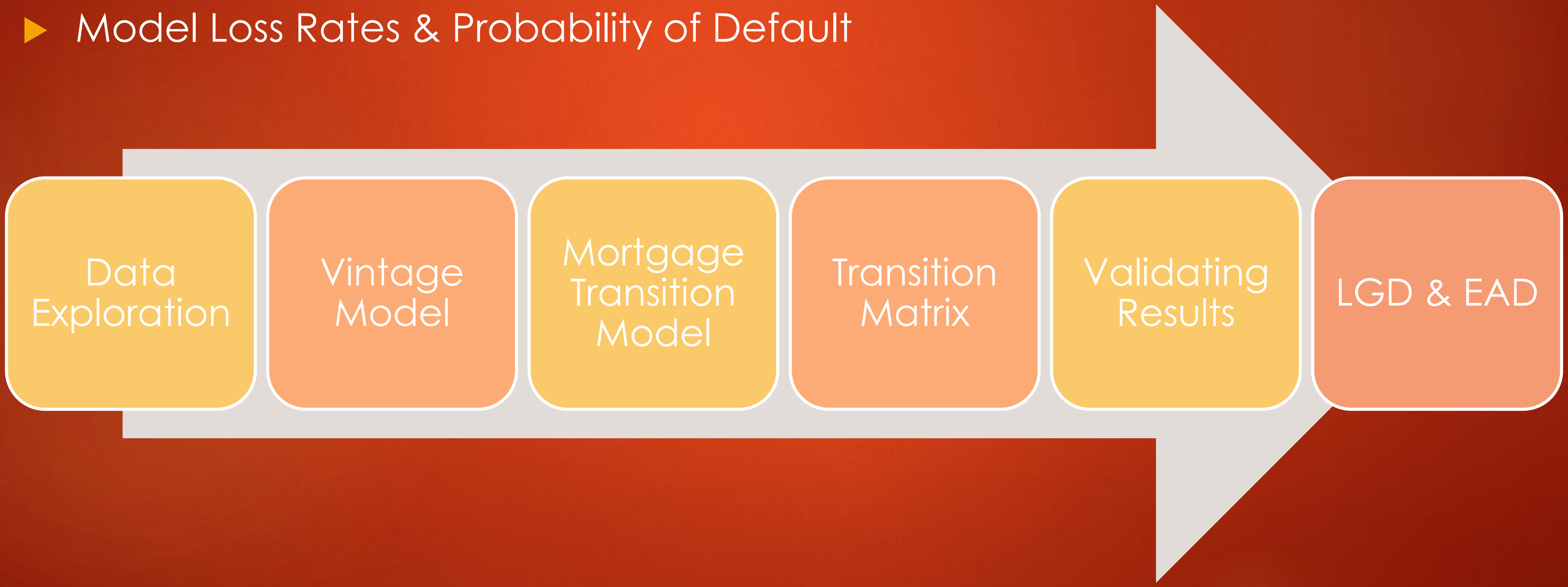
Objective & Methodology

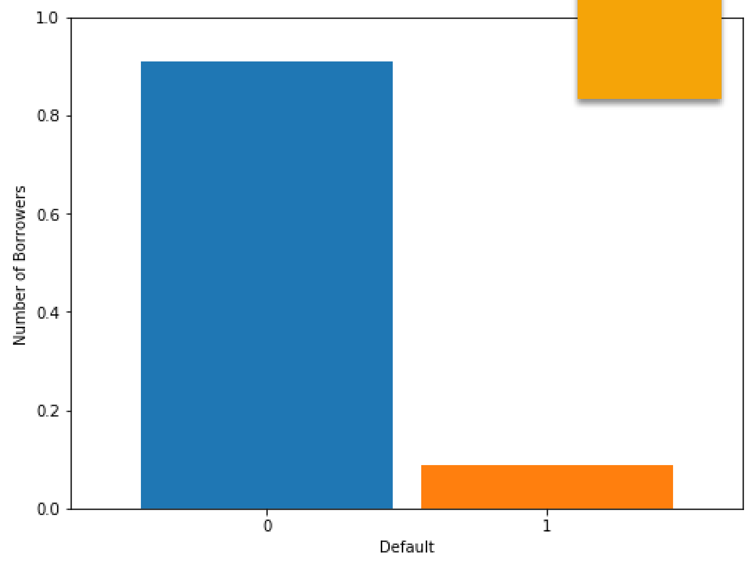
- Understand the need for CECL
- Data Exploration & Preparation
- Model Loss Rates & Probability of Default

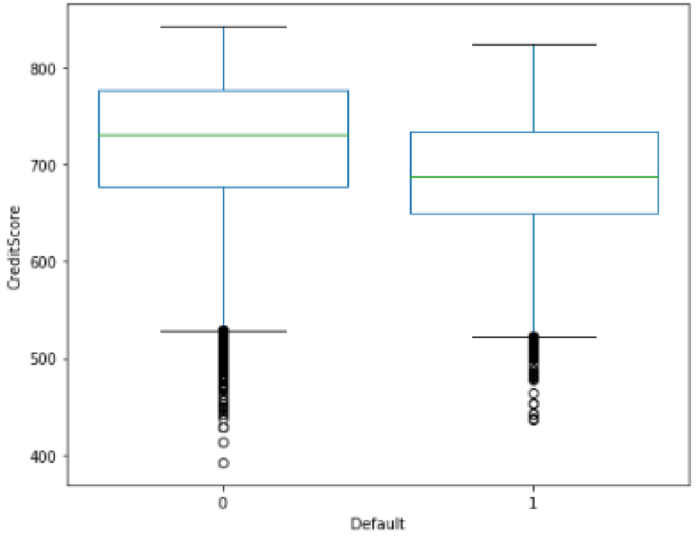


Data Exploration

- Dealing with NULL values
- Selecting relevant variables from Acquisition and Performance data
- Foreclosure Date populated = Default
- Correlation heat map on features to check for multicollinearity
- Findings:

 1. Defaults were very low, data was balanced later
 2. Interest rates on defaults were slightly higher
 3. Lesser defaults on loans with 2 borrowers
 4. Relatively high DTI for default loans
 5. Significant difference between median credit scores





Vintage Model (Loss Rate)

Loss rate model with closed pools

Sorted by origination

Works well with homogenous portfolio

Qualitative factor (Q), enhances the estimates

Projected loss rate is given by,

$$LR_{Proj} = [\ LR_{Avg} / Q_{Avg}\ ]^{*}\ Q_{Proj}$$

Loss Rate Matrix

Loss Rates by Vintage						
	Y1	Y2	Y3	Y4	Y5	Y6
2001	0.00%	0.05%	0.13%	0.13%	0.08%	0.06%
2002	0.00%	0.05%	0.09%	0.08%	0.06%	
2003	0.00%	0.02%	0.05%	0.06%		
2004	0.00%	0.03%	0.07%			
2005	0.00%	0.03%				
2006	0.01%					
Average	0.00%	0.04%	0.09%	0.09%	0.07%	0.06%
Q factor	0.03%	0.67%	1.60%	1.78%	1.44%	1.30%

Q Factor by Vintage-Unemployment Rate						
	Y1	Y2	Y3	Y4	Y5	Y6
2001	4.70%	5.80%	6.00%	5.50%	5.10%	4.60%
2002	5.80%	6%	5.50%	5.10%	4.60%	
2003	6%	5.50%	5.10%	4.60%		
2004	5.50%	5.10%	4.60%			
2005	5.10%	4.60%				
2006	4.60%					
Average	5.28%	5.40%	5.30%	5.07%	4.85%	4.60%

Loss Rates by Vintage (with forecast)						
	Y1	Y2	Y3	Y4	Y5	Y6
2001	0.00%	0.05%	0.13%	0.13%	0.08%	0.06%
2002	0.00%	0.05%	0.09%	0.08%	0.06%	0.06%
2003	0.00%	0.02%	0.05%	0.06%	0.07%	0.08%
2004	0.00%	0.03%	0.07%	0.08%	0.08%	0.12%
2005	0.00%	0.03%	0.07%	0.10%	0.13%	0.13%
2006	0.01%	0.03%	0.09%	0.17%	0.14%	0.12%
Average	0.00%	0.04%	0.08%	0.10%	0.09%	0.09%
Q factor	0.03%	0.67%	1.60%	1.78%	1.44%	1.30%

Reasonable estimate of Q factor (true rates - historical data)						
	Y1	Y2	Y3	Y4	Y5	Y6
2001	4.70%	5.80%	6.00%	5.50%	5.10%	4.60%
2002	5.80%	6%	5.50%	5.10%	4.60%	4.60%
2003	6%	5.50%	5.10%	4.60%	4.60%	5.80%
2004	5.50%	5.10%	4.60%	4.60%	5.80%	9.30%
2005	5.10%	4.60%	4.60%	5.80%	9.30%	9.60%
2006	4.60%	4.60%	5.80%	9.30%	9.60%	8.90%
Average	5.28%	5.27%	5.27%	5.82%	6.50%	7.13%

Improvements

- Qualitative factors can be lagging indicators of loss rates
- Multiple factors like Interest Rates, HPI, etc., can be incorporated into the Q factor

Mortgage Transition Model

- Estimate losses at loan level
- Expected Credit Loss = PD * LGD * EAD
- Various delinquency states including prepaid and default are considered discrete Markov states
- Estimate Transition Probabilities using Multinomial Logistic Regression
- State space, S = {-1,0,1,2,3,4}

State	Description
-1	Prepaid
0	Current
1	Not performing for 30 days
2	Not performing for 60 days
3	Not performing for 90 days
4	Default

One Step Transition Matrix

- Monthly delinquency transitions are considered
- Transition matrix is represented as follows:
- The corresponding probabilities are calculated using Logistic Regression:
- Covariates:

X1 = Credit Score

X2 = % change in HPI

X3 = % change in Unemployment Rate

X4 = % change in CPI

X5 = 3-month Treasury Rate

$$
\begin{array}{c c}
 & \begin{array}{cccccc} -1 & 0 & 1 & 2 & 3 & 4 \end{array} \\
\begin{array}{c} -1 \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \end{array} &
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
p_{0,-1} & p_{0,0} & p_{0,1} & 0 & 0 & 0 \\
0 & p_{1,0} & 0 & p_{1,2} & 0 & 0 \\
0 & 0 & p_{2,1} & 0 & p_{2,3} & 0 \\
0 & 0 & 0 & p_{3,2} & 0 & p_{3,4} \\
0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix}
\end{array}
$$

$$\log \frac{p_{ij}}{1 - p_{ij}} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5$$

Transition Probabilities and Matrix

$$\log \frac{p_{0-1}}{1-p_{0-1}} = -8.6033 + 0.0112x_1 - 0.6396x_2 + 0.2722x_3 + 0.0886x_4 - 0.2576x_5$$

$$\log \frac{p_{00}}{1-p_{00}} = -4.5249 + 0.005x_1 + 0.2636x_2 + 0.4964x_3 - 0.0153x_4 - 0.0601x_5$$

$$p_{01} = 1 - p_{00} - p_{0-1}$$

$$\log \frac{p_{10}}{1-p_{10}} = -0.1828 - 0.0002x_1 - 0.2284x_2 + 0.0311x_3 - 0.0059x_4 - 0.0043x_5$$

$$p_{12} = 1 - p_{10}$$

$$\log \frac{p_{21}}{1-p_{21}} = -0.2989 - 0.0008x_1 + 0.0237x_2 - 0.0017x_3 - 0.0007x_4 + 0.0035x_5$$

$$p_{23} = 1 - p_{21}$$

$$\log \frac{p_{32}}{1-p_{32}} = -0.3857 - 0.0072x_1 - 0.4520x_2 - 0.3802x_3 + 0.1055x_4 0.0183x_5$$

$$p_{34} = 1 - p_{32}$$

- At baseline credit score 650

$$\begin{array}{c} \\ -1 \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \end{array}
\begin{array}{c} \begin{array}{cccccc} -1 & 0 & 1 & 2 & 3 & 4 \end{array} \\
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 & 0 \\
0.1742 & 0.2781 & 0.5477 & 0 & 0 & 0 \\
0 & 0.6072 & 0 & 0.3928 & 0 & 0 \\
0 & 0 & 0.1592 & 0 & 0.8408 & 0 \\
0 & 0 & 0 & 0.1075 & 0 & 0.8925 \\
0 & 0 & 0 & 0 & 0 & 1
\end{pmatrix} \end{array}$$

State 0

	precision	recall	f1-score	support
0-1	0.54	0.50	0.52	5962
00	0.47	0.31	0.37	6111
01	0.57	0.76	0.65	7716
avg / total	0.53	0.54	0.52	19789

State 1

	precision	recall	f1-score	support
10	0.60	1.00	0.75	17050
12	0.00	0.00	0.00	11440
avg / total	0.36	0.60	0.45	28490

State 2

	precision	recall	f1-score	support
21	0.00	0.00	0.00	1701
23	0.85	1.00	0.92	9324
avg / total	0.72	0.85	0.77	11025

State 4

	precision	recall	f1-score	support
32	0.67	0.01	0.01	666
34	0.90	1.00	0.95	6136
avg / total	0.88	0.90	0.86	6802

Efficiency

Remarks & Limitations

- Credit Score is the only borrower characteristic, updated quarterly
- Need predicted macroeconomic variables for future forecasts
- Unbalanced data set, can adjust feature variable distributions by applying transformations
- Verify cross validation scores and AUC to pick the champion & challenger models

LGD & EAD

- Loss given Default = Unpaid Balance + Expenses – Proceeds
- LGD can be modelled using a linear regression with features like Credit Score, CLTV, HPI, Unemployment Rate, Loan type, etc.
- Exposure at Default = Unpaid balance at Default
- EAD can be modelled using a linear regression with features like Current Unpaid Balance, CLTV, and Balance Clearing Rate from history

Thank You