



# Predictive Model for Prosper.com

## **BIDM Group 4**

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## What is prosper.com

- Prosper is the world's largest peer-to-peer lending marketplace, with more than 1,020,000 members and over \$213 million in funded loans.”
- Borrowers list loan requests between \$2,000 and \$25,000 and individual lenders invest as little as \$25 in each loan listing they select.

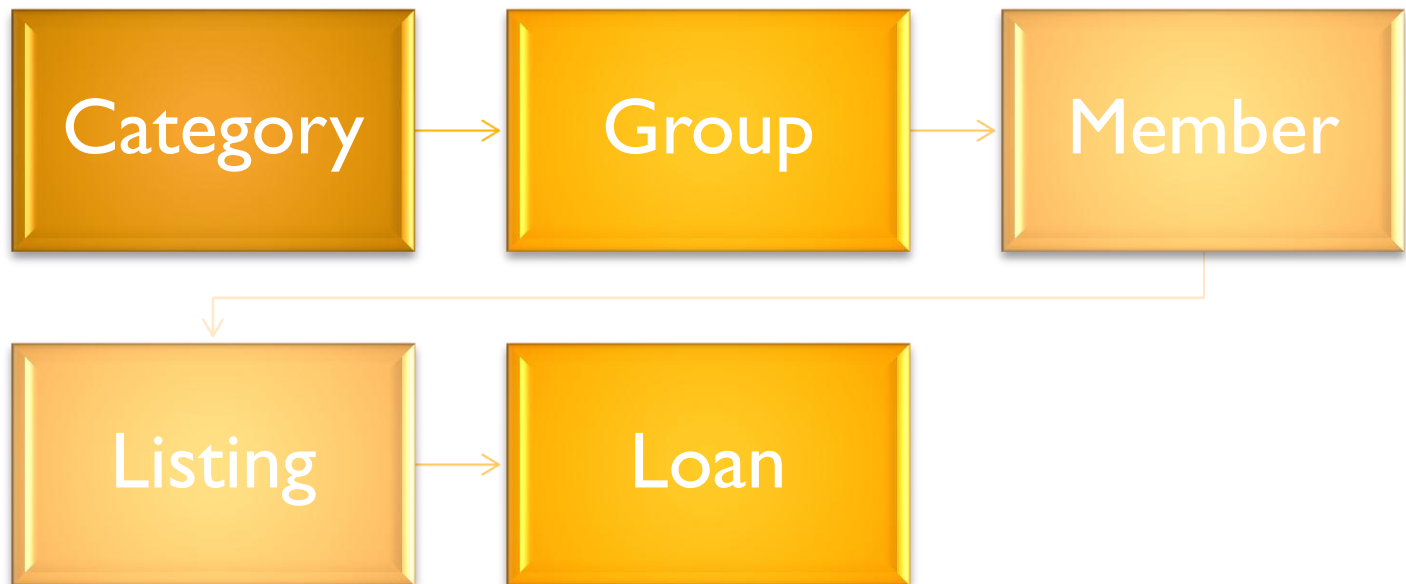
## Objectives

- Build a predictive model for investors to be able to classify “Success” loans vs “Probable Default” Loans

## Data Properties

- 1.5 GB of Data
- Over 2 MM rows
- 5 Tables of user data

## Data Schema

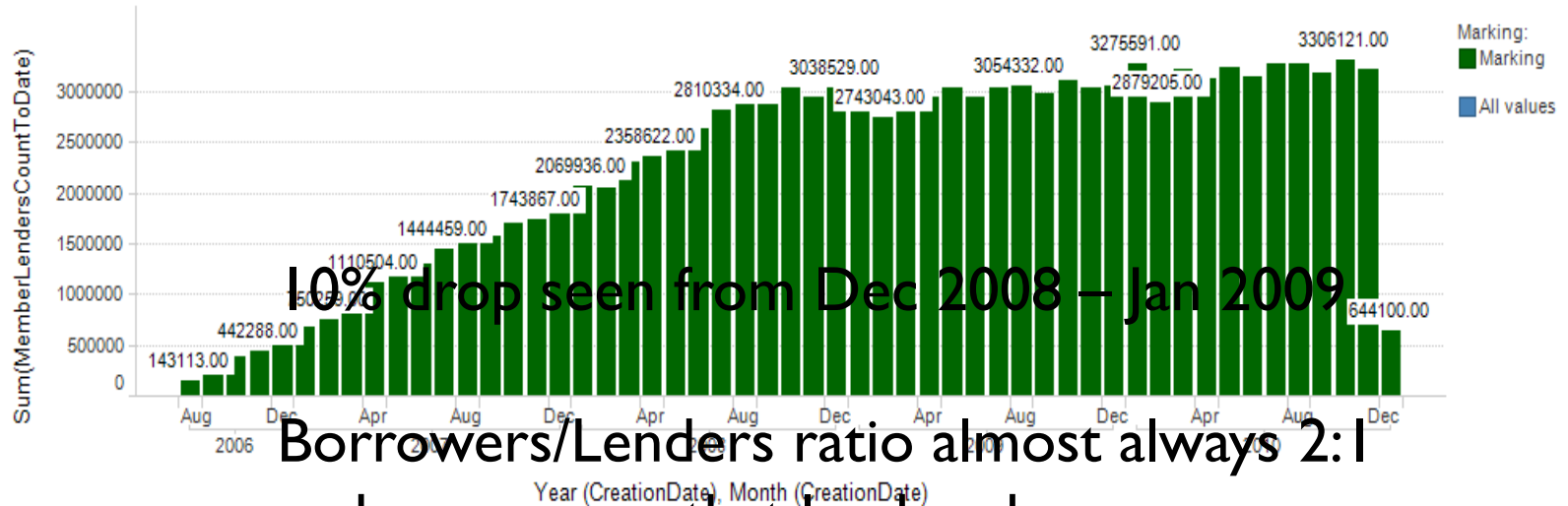


# Data Processing

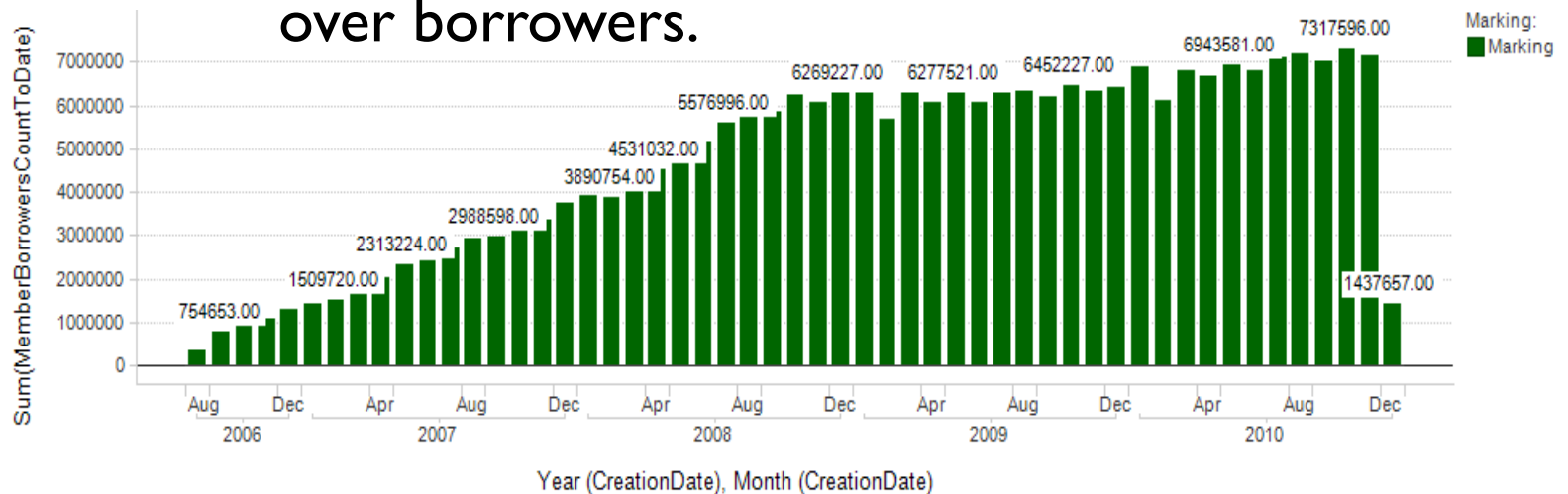
- Merging of data; Account Foreign Key Constraints
- Inner Join / Left Outer / Full Outer
- Random Sample from Data Set
- Random No generator
- Pick ~50k Rows (limitation with XLMiner)
- Working Data Sets
  - Listings – Members - Loans
  - Listings – Members – Groups
- Missing Data Values
- Data Binning
- Merging Columns ( Credit Grade , Prosper Rating )

# Growth in the member base over the years

## Lenders

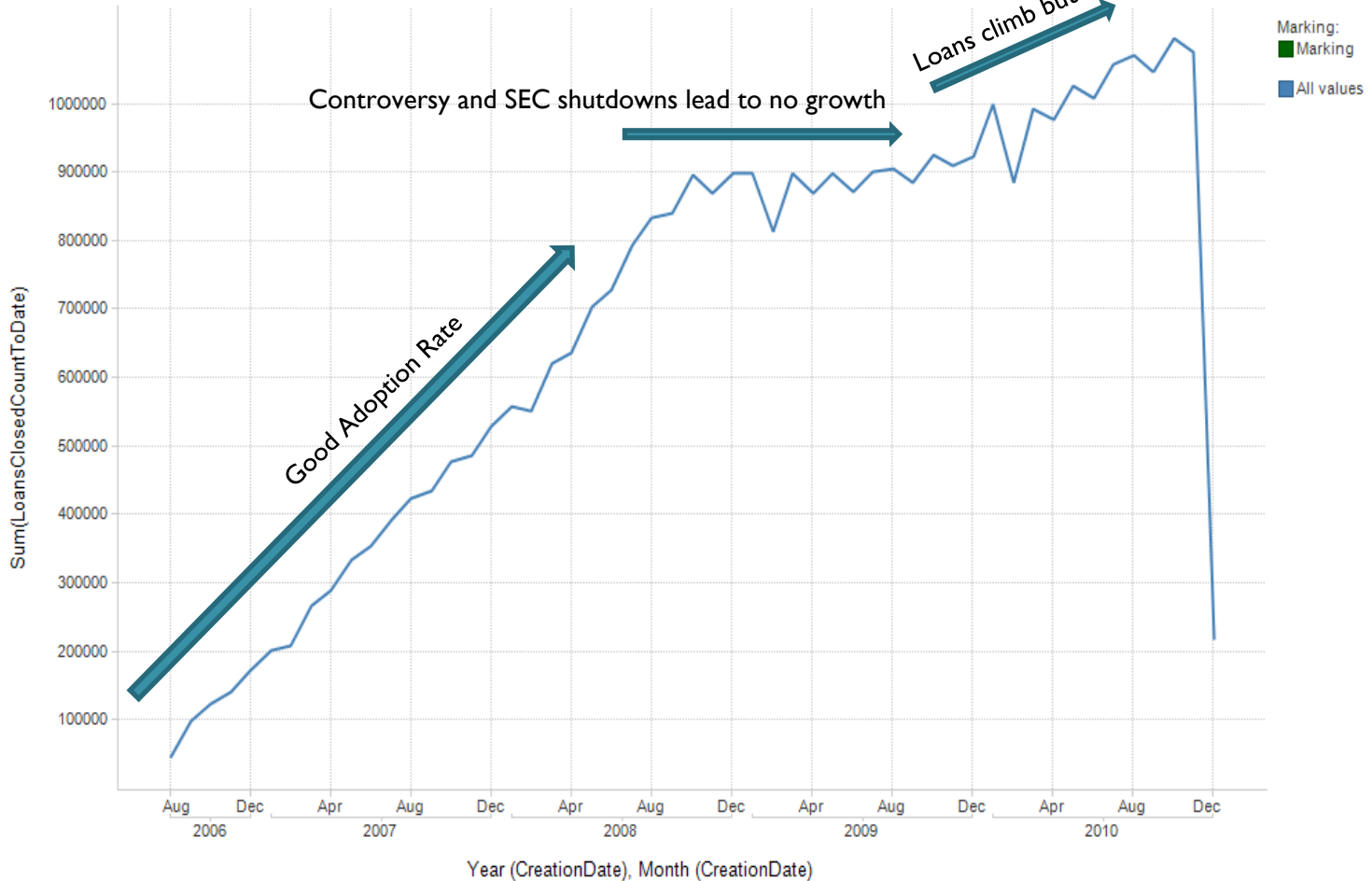


## Borrowers



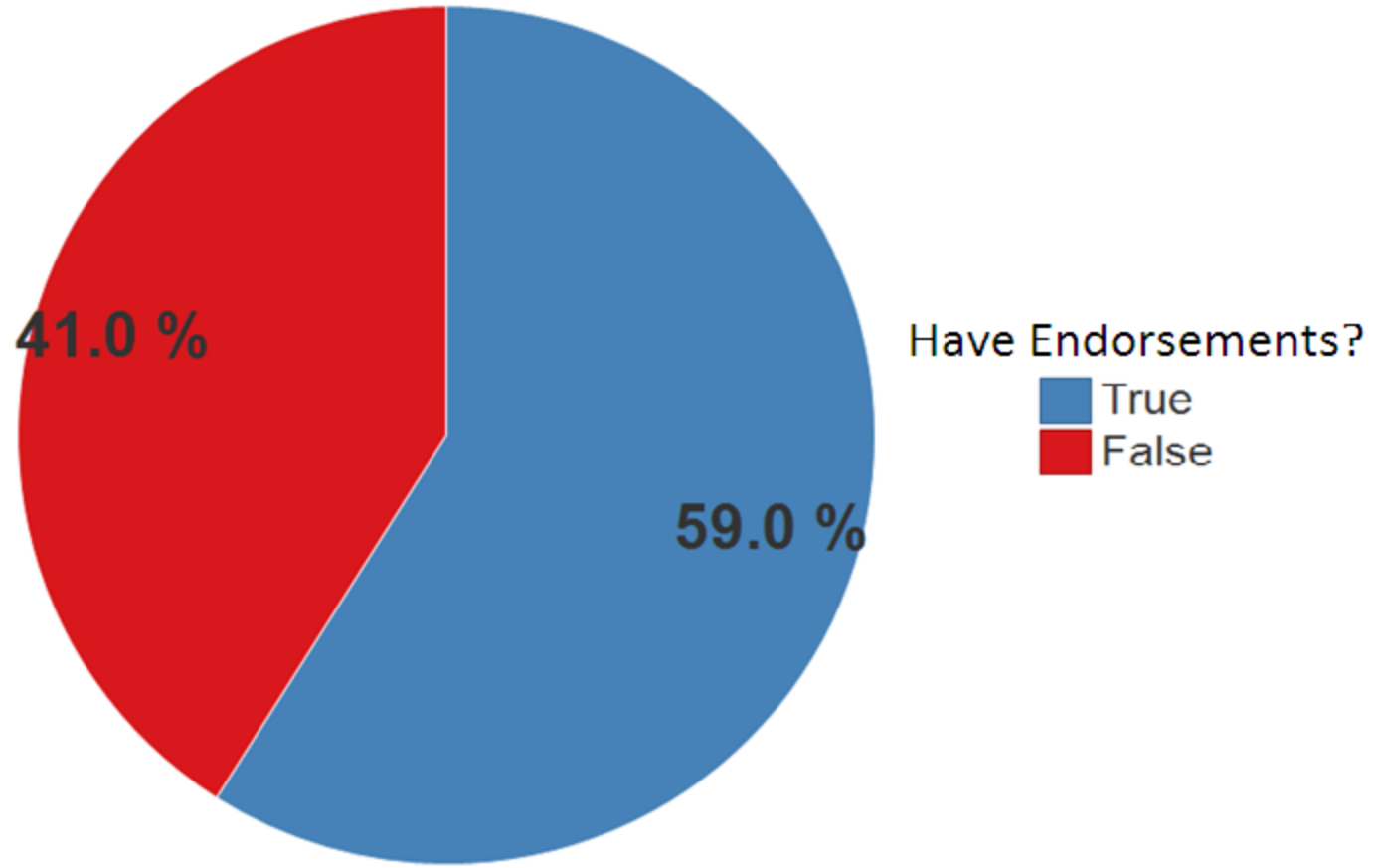
# Loans closed over time

Line Chart



Loans closed rate grew significantly until Nov 2008 which coincides with the class action lawsuit

# Having an endorsement increases your chance of being funded by 18%



# Logistic Regression

- Output : Status ( Default , Late , Paid )
- Predictors
  - Bid Count
  - Borrower rate
  - Lender rate
  - Age in months
  - Amount Borrowed
  - Is Home Owner
  - Debt To Income Ratio
- Co-relation analysis
- Significant predictors
- Goodness of Fit : Performance & Error Rate



# Logistic Regression

Input variables	Coefficient	Std. Error	p-value	Odds
BidCount	0.00045379	0.00028042	0.10560962	1.000454
<b>BorrowerRate</b>	24.77111626	4.57036781	<b>0.00000006</b>	5.727E+10
DebtToIncomeRatio	0.03414476	0.02391896	0.15343051	1.0347344
<b>IsBorrowerHomeowner</b>	0.17194989	0.05088718	<b>0.00072739</b>	1.1876184
<b>LenderRate</b>	-15.33367443	4.61400652	<b>0.00088963</b>	2.2E-07
<b>AgeInMonths</b>	0.05707799	0.0022076	<b>0</b>	1.0587384
<b>AmountBorrowed</b>	0.00003511	0.0000068	<b>0.00000024</b>	1.0000352
<b>Term</b>	-0.141791	0.00396481	<b>0</b>	0.8678026

Training data			
Class	# Cases	# Errors	% Error
0	2986	1951	65.3
1	7013	688	9.8
Overall	9999	2639	26.4

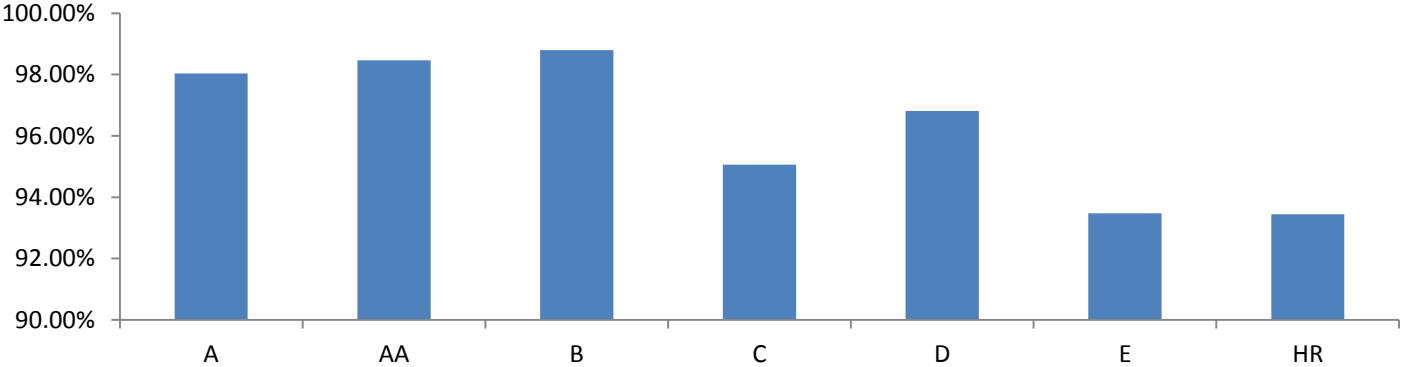
Test data			
Class	# Cases	# Errors	% Error
0	3118	2031	65.1
1	7378	739	10.0
Overall	10496	2770	26.39

# Classification Tree

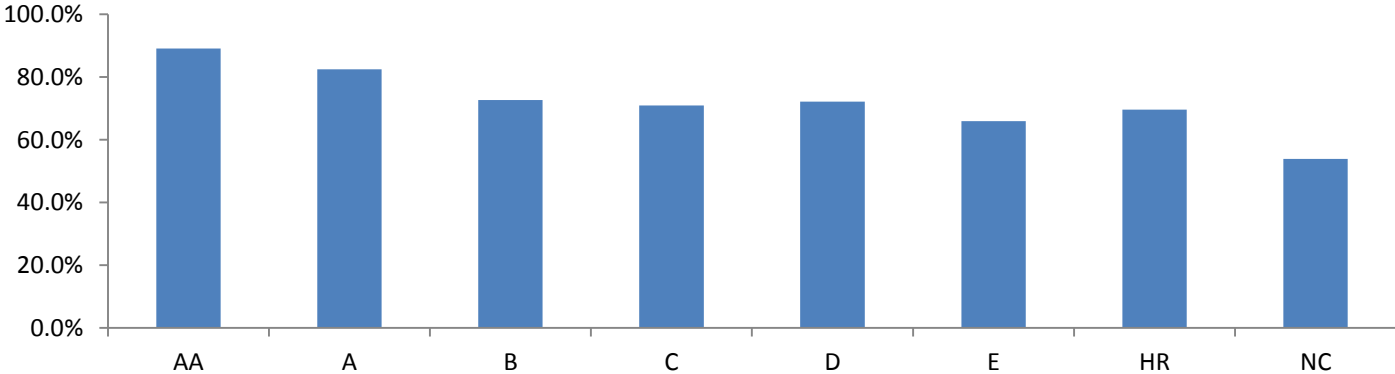
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- Parameters of the tree
  - Best Pruned Tree
  - 100 in the terminal node
- Classification tree top 3 predictors
  - Age in Months
  - Borrower Rate
  - Bid Count

# Prediction accuracy

### Prediction accuracy with Prosper rating



### Prediction accuracy with Prosper & Credit rating



# What We tried ..... but Failed

- Role of Social Network
  - Relation between Member Friends in network and probability of getting a loan
- Some categories better than others
  - Religious / Ethnic ?
- Does time of the year has role to play in role approval
  - Thanks Giving / Christmas time !!!

# Conclusion

- Real use of our model
  - Usage along with Prosper Rating for identifying “Lemons”
  - 50+% opportunities without Prosper Rating can also be lucrative.



# Questions

