Lending Club – Data Analysis Net/Net:

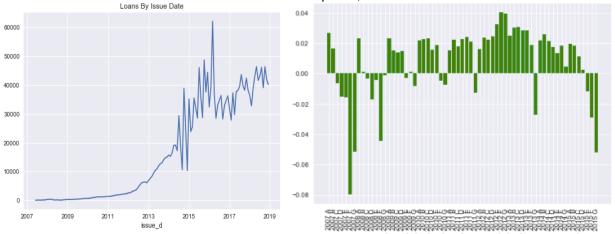
- **Data Exploration:** The primary feature that needs adjustment is income, which is handled by removing nulls as well as the 1st and 99th percentiles. The variable must then be logged as to make it normally distributed. Small changes are also made to other variables (i.e. enforce DTI > 0).
- Business Analysis
 - 1. What percent of loans has been fully paid? 86.05%
 - 2. When bucketed by year of origination and grade which cohort has the highest rate of defaults? 2015-G
 - 3. When bucketed by year of origination and grade, what annualized rate of return have the loans generated on average? Full Data: 1.90%, Average of Individual Year of Origination X Grade Cohorts: 0.79%

Model

- Pre-Model Evaluation
 - The grade assigned by Lending Club has the highest correlation with the default indicator.
 EDA showed the lending club grade did a good job assigning grades to relative default rates.
 - Grade and interest rate are closely related due to the underlying factors that are likely modeling both features.
 - Funding is largely related to income levels
 - The credit revolver is related to both income levels and the dti ratio
 - There is not a strong relationship between income and dti
- Logistic Regression Formulation
 - Because defaulted loans are under-represented in the dataset leverage SMOTE (Synthetic Minority Oversampling Technique)
 - Check the relative ranking of features using RFE (Recursive Feature Elimination)
 - Following testing, build the logistic regression with the following 4 variables: ['int_rate','grade_cat','log_inc','dti']
 - The variables' signs have practical interpretations
 - Worse grade leads to a higher likelihood of default
 - · Higher interest rates lead to a higher likelihood of default
 - · Higher income leads to a lower likelihood of default
 - Higher Debt to Income ratios lead to a higher likelihood of default

Model Performance

The model is of low quality (r-squared: 0.064) classifying 63% of cases correctly (note: this is much
improved compared to without using SMOTE). The robustness of results is confirmed with a K-Fold
Cross Validation. While far from optimal, this could be the start of a model.

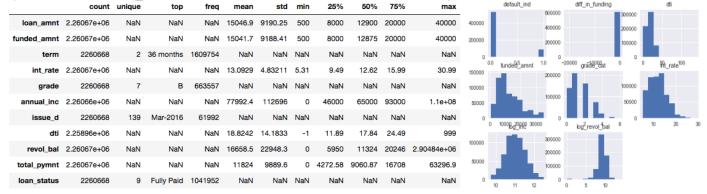


Origination_Year	defaulted	loans	default_rate	Origination_Year	annualized_rate_of_return	grade	defaulted	loans	default_rate	grade	annualized_rate_of_return
2015	41532	277908	14.94	2007	-0.010923	G	248	627	39.55	Α	0.020342
2014	21926	159947	13.71	2008	-0.003214	F	1408	4234	33.25	В	0.022933
2013	12186	99225	12.28	2009	0.014982		1400	4204	55.25		0.022333
2012	5820	42843	13.58	2010	0.021042	E	6033	20990	28.74	С	0.017801
2011	1458	13796	10.57	2011	0.018909	D	17542	74799	23.45	D	0.013222
2010	948	8889	10.66	2012	0.021747	С	28685	159824	17.95	Е	0.005222
2009	692	5114	13.53	2013	0.028977						
2008	480	2335	20.56	2014	0.022106	В	23517	209313	11.24	F	0.000699
2007	133	534	24.91	2015	0.013473	Α	7742	140804	5.50	G	-0.020074

Part 1: Data Exploration and Evaluation

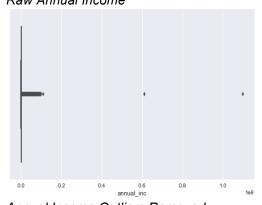
The data represents a point in time snapshot of individual loans (rows)...initial exploration of the data reveals:

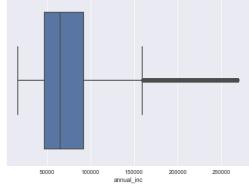
- 1) There are nulls in the annual income and dti fields
- 2) There are outliers in income (both low (0) and high) as well as dti (values < 0) and revol bal
- 3) Fields such as loan status must be unified to a common outcome description or default indicator



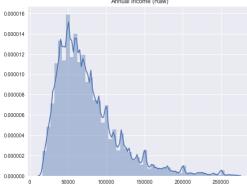
Total Rows: 2260668

Annual Income: 1) remove outliers on the low end (i.e. 0 – unreported) and high-end (i.e. fat finger error or intentional over statement) by using data between the 1st and 99th percentiles 2) Log the variable to create a normal distribution Raw Annual Income Annual Income Outliers Removed

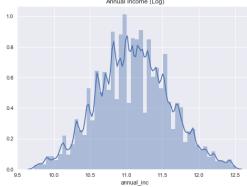




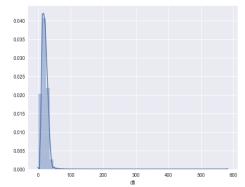
Annual Income Outliers Removed

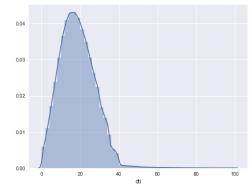


Annual Income after log



DTI: 1) enforce DTI > 0, 2) aware of DTIs > 100 but do not enforce a restriction (high DTI possible, though unlikely) Raw DTI DTI filtered between 0 and 100





Part 2: Business Analysis

While marked as fully paid or charged off, the 2016-2018 loan cohorts likely do not have full 36-month term data as evidenced by their origination date and returns below reasonable expectations. Further unify the loan status into a simpler hierarchy; note: there is a small subset of loans that are still in process (i.e. late).

- 1) What percent of loans has been fully paid? 86.05%
- 2) When bucketed by year of origination and grade which cohort has the highest rate of defaults? 2015-Gerformance by Origination Year

 Performance by Grade

Performance by Origination Year

24
22
20
18
19

Origination_Year	defaulted	loans	default_rate		defaulted		default_rate
2015	41532	277908	14.94	G	248	627	39.55
2014	21926	159947	13.71	F	1408	4234	33.25
2013	12186	99225	12.28				
2012	5820	42843	13.58	E	6033	20990	28.74
2011	1458	13796	10.57	D	17542	74799	23.45
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2009	692	5114	13.53				
2008	480	2335	20.56	В	23517	209313	11.24
2007	133	534	24.91	Α	7742	140804	5.50

Year of Origination X Grade

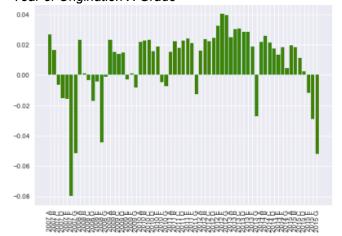
Origination_Year	grade	defaulted	loans	default_rate
2015	G	107	221	48.42
2007	F	24	51	47.06
2007	G	13	29	44.83
2015	F	552	1292	42.72
2009	G	18	49	36.73

3) When bucketed by year of origination and grade, what annualized rate of return have the loans generated on average? Full Data: 1.90%, Average of Individual Year of Origination X Grade Cohorts: 0.79%

Year of Origination

_	annualized_rate_of_return	grade	annualized_rate_of_return
2007	-0.010923	Α	0.020342
2008	-0.003214	В	0.022933
2009	0.014982		
2010	0.021042	С	0.017801
2011	0.018909	D	0.013222
2012	0.021747	E	0.005222
2013	0.028977	F	0.000699
2014	0.022106		0.000699
2015	0.013473	G	-0.020074

Year of Origination X Grade



Part 3: Modeling (Building a Logistic Regression)

Note: For the model further filter to loans with definite outcomes i.e. either Fully Paid or Charged Off Correlation Matrix

	funded_amnt	diff_in_funding	int_rate	grade_cat	log_inc	dti	log_revol_bal	default_ind
funded_amnt	1.000000	0.007680	-0.084115	-0.083594	0.497529	0.011973	0.384587	-0.015184
diff_in_funding	0.007680	1.000000	0.015430	0.006199	-0.010732	0.016266	-0.002447	0.000158
int_rate	-0.084115	0.015430	1.000000	0.939436	-0.214134	0.138035	-0.096716	0.188700
grade_cat	-0.083594	0.006199	0.939436	1.000000	-0.204665	0.145428	-0.105439	0.193332
log_inc	0.497529	-0.010732	-0.214134	-0.204665	1.000000	-0.216139	0.317277	-0.087823
dti	0.011973	0.016266	0.138035	0.145428	-0.216139	1.000000	0.227523	0.080762
log_revol_bal	0.384587	-0.002447	-0.096716	-0.105439	0.317277	0.227523	1.000000	-0.029943
default_ind	-0.015184	0.000158	0.188700	0.193332	-0.087823	0.080762	-0.029943	1.000000

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Logistic Regression Formulation

- Because defaulted loans are under-represented leverage SMOTE (Synthetic Minority Oversampling Technique)
- Check the relative ranking of features using RFE (Recursive Feature Elimination)
- Following testing, build the logistic regression with the following 4 variables: ['int_rate','grade_cat','log_inc','dti'] Optimization terminated successfully.

Current function value: 0.648831 Iterations 5

Results: Logit

Model: Dependent Variable:			Logit	No. 1	teration	s: 5.00	5.0000	
			default_ind	i Pseud	lo R-squa	red: 0.06	0.064	
	Date:		2019-11-17	10:16 AIC:		9550	955061.5852	
	No. Observati	ons:	735980	BIC:		9551	955107.6210	
	Df Model:		3	Log-I	ikelihoo	d: -4.7	-4.7753e+05	
	Df Residuals:		735976	LL-Nu	ill:	-5.1	-5.1014e+05	
	Converged:		1.0000	Scale	:	1.00	1.0000	
		Coef.	Std.Err.	2	P> z	[0.025	0.975]	
	int_rate	0.0834	0.0019	44.8275	0.0000	0.0798	0.0871	
	grade_cat	0.2244	0.0064	34.9122	0.0000	0.2118	0.2370	
	log_inc	-0.1612	0.0014	-117.6452	0.0000	-0.1639	-0.1585	
	dti	0.0186	0.0003	63.3591	0.0000	0.0181	0.0192	

The variables' signs have practical interpretations

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Model Performance

The model is of low quality (r-squared: 0.064) classifying 63% of cases correctly (note: this is much improved compared to without using SMOTE). The robustness of results is confirmed with a K-Fold Cross Validation. While far from optimal, this could be the start of a model.

