

# Notes - CRR Models

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2:32 PM

Creditor ----(% interest)--- Lender, banks make profit out of this interest rate

What is a credit risk?

- The likelihood that a borrower would not repay their loan to lender
- When a borrower fails to replay loan
- The lender will have to sustain substantial cost in an effort to recover outstanding debt - cost

Risk based pricing

- Based on credit risk associated with the particular client, banks decide the % interest rate collateral
- Lending to borrowers with high probability default is one of the main reasons of financial crisis 2008,
  - o Factor - high default rate of sub-prime mortgages; low interest rate; loans were provided for 100% or more value of the home; demand for homes increased -> selling price increased
  - o Mortgage backed securities lost value
  - o Big banks holding these instruments got affected - Lehman Brothers

Regulatory rule

- Lender must assess credit risk associated with each borrower
- Lenders know certain amount of credit risks is always associated with each/every client
- It is important to estimate expected loss - amt of money a lender loses by lending to a borrower
- There are many models but established credit risk model has 3 components
  - o PD (Probability of default)
  - o LGD (Loss given default)
  - o EAD (Exposure at default)

**PD (Probability of default):**

- The borrower's inability to repay his/her debt in full or on-time
- Estimate of a borrower's likelihood the borrower will default

**Loss given default (LGD)**

- Loss of an asset due to borrower's default

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- The proportion of the total exposure that cannot be recovered by the lender once a default occurs

### **EAD (Exposure at default)**

- Total value that a lender is exposed to when a borrower defaults i.e. maximum amount that lender will lose if a borrower defaults

Example: A borrower wants to buy a house

Price = \$500,000

(Agreement) Bank funds 80% (loan to value) = \$400,000

Borrower repaid = \$40,000

Outstanding balance = \$400,000 - \$40,000 = \$360,000

When a borrower defaults, total value that a lender is exposed to is \$360,000. This is **Exposure at Default (EAD)**

Assume that the banks can sell the house is at \$342,000, then

**Loss given default = (EAD - \$342,000)/EAD**

- Assume that there is an empirical evidence that one in four homeowners have defaulted

$$PD = 1/4$$

- Expected Loss (EL) = PD \* LGD \* EAD, i.e. 25% \* 5% \* \$360,000 = \$4,500

### Capital Adequacy/Regulations and Basel III accord

- Govt. regulators impose certain requirements for banks to make sure bank conduct their business without risking the stability of the economy system
- Regulators set rules
  - o Regulate bank operations & hence reduce bank risky behaviour
  - o Guarantee to the public that banking system is in good health
- Capital Adequacy: Banks require to hold sufficient capital to absorb capital losses from default. This obligation is called "**Capital Requirement**"
- CAR(Capital Adequacy ratio) = Capital / Risk-weighted assets (loans)
- Basel III accord - primary objective is to ensure capital allocation. Greater the risk the bank holds, the greater amount of capital it needs to hold
  - o Three pillars of Basel III -
    1. Market discipline
    2. Supervisory review
    3. **Minimum Capital Requirement**

Two approaches

- Standardized approach
- Internal ratings based approach (IRB)
  - ◇ Foundation internal rating based (F-IRB)
  - ◇ Advanced internal rating based (A-IRB)

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- Basel III accord prescribes regulators should allow banks to choose from 3 different approaches to calculate/modelling credit risk i.e. calculating & modelling each of the three components of credit loss
  - o Standardized approach
  - o Foundation internal rating based (F-IRB)
  - o Advanced internal rating based (A-IRB)

- Capital requirements are calculated differently in 3 approaches

	SA	F-IRB	A-IRB
PD	External data	Internally calculated	Internally calculated
LGD	External data	External data	Internally calculated
EAD	External data	External data	Internally calculated

- External data comes from credit rating agencies such as FICO, S&P, Moody's, Fitch (for firms)
- Two major credit reporting agency that collects data from FICO
  - o Equifax
  - o TransUnion
- Credit score ranges from 300 to 800
- For firms, credit cards & consumer loans, banks should hold around 75% of the total exposure (Capital adequacy ratio)
- For secured residential property, banks should hold around 35% of the total exposure \* (Capital adequacy ratio)
- The more precise banks estimate expected -- Less capital is needed to hold -- more new loans can generate
- IRB approaches
  - o Allows bank to establish their own credit rating
  - o Precise calculations about the held capital for each individual exposure
  - o Allocate resources to cover losses
  - o Be more profitable

#### Characteristics of the data for individual clients

Biological info	External data	Characteristic of data
Age	Credit rating	Fix term consumer loan
Sex	No. of recent enquiries	Life-span of product
Marital status		Purpose of the loan
Education		Interest rate

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closure \* CAR

CAR (Capital

business bank

Income		
Zip-code		

- Credit limit utilization - the proportion of money spent on the credit card

#### Data availability

- Most of the variables are available at time of application
- Many of the variable/information is available after loan is granted & behaviour of the loan borrower can be obtained for long sufficient

Application models	Behaviour models
Most of the variables are available at time of application	<ul style="list-style-type: none"> <li>- Most of the variables are available at time of application</li> <li>- Many of the variable/information is available after loan is granted &amp; behaviour of the loan borrower can be obtained for long sufficient</li> </ul>

- Behaviour model is used to calculate probability of default or expected loss after loan is granted
- If a customer holds credit card, banks can use behaviour model to grant or reject loan application

#### Understanding the data

Dependent variables

Independent variables - predictor/features

PD model : Logistic regression

- Non-statistically savvy user example: front office workers, present in a simplified manner credit cards

LGD model: Beta regression

- How much loan has been recovered after the client defaulted

EAD model: Beta regression

Different data types

- Discrete
- Continuous

Based on data types data-preprocessing technique varies

**Distinctive feature of PD model** is --- all the independent variables have to be categorical - the model is much easier to present a model in a simplified form and turn into score card - we transform independent variable into categorical variable/dummy variable

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**Fine Classing:** We slice the independent variable into equally sized intervals or classes

**Coarse classing:** we find how well each of the intervals discriminate b/w defaulted and non-defaulted. If adjacent discrete variables discriminate each other very well, then we can merge them.

## PD Model

- Established dependent variable
- Binary
  - o 0 = Bad loan
  - o 1 = Good loan
- "Default definition": If a borrower is more than 90 days past due on a loan
- Statistical methodology to model PD is a logistic regression where dependent variable is whether customer is defaulter or not
- Logistic regression estimates the relationships b/w 2 things
  - o Odds of an outcome (dependent variable) --- linear combination (Independent  $\sum$  variables) of predictors
- Logistic regression
  - o  $\ln(\text{Non-default/default}) = \sum \beta_j X_j = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$
- **"Weight of evidence"** - The ability of each category to predict the dependent variable.
  - o To what extent an independent variable would predict a dependent variable
  - o  $\ln(\% \text{Good}/\% \text{Bad})$

Variable Categories	Good	Bad	Proportion of good	Proportion of bad	Weight of evidence
Higher education	4000	600	$4000/16000 = 25\%$	$600/4000 = 15\%$	$\ln(25/15) = 0.51$
No Higher education	12000	3400	$12000/16000 = 75\%$	$3400/4000 = 85\%$	$\ln(75/85) = -0.13$
Total	16000	4000			

- **"Information value"** - shows how much information the original independent variable brings in explaining the dependent variable

Range 0 - 1	Predictive power
$IV < 0.02$	No predictive power
$0.02 \leq IV \leq 0.1$	Weak predictive power
$0.1 \leq IV \leq 0.3$	Medium predictive power

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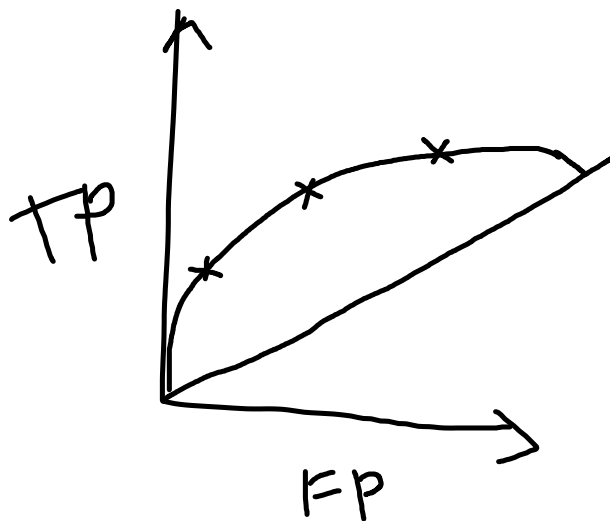
$0.3 \leq IV \leq 0.5$	Strong predictive power
$0.05 < IV$	Suspiciously high, too good to be true

Variable Categories	Good	Bad	Proportion of good	Proportion of bad	Weight of evidence	%good-%bad	Information
Higher education	4000	600	$4000/16000 = 25\%$	$600/4000 = 15\%$	$\ln(25/15) = 0.51$	$0.25 - 0.15 = 0.1$	$0.51 \times 0.1 = 0.051$
No Higher education	12000	3400	$12000/16000 = 75\%$	$3400/4000 = 85\%$	$\ln(75/85) = -0.13$	$0.75 - 0.85 = -0.1$	$0.13 \times 0.1 = 0.013$
Total	16000	4000					$0.064$ pred

**Overfitting:** A substantial issue we might face when statistical model has focused on a particular point so much that it missed the point

**Underfitting:** is under fitting when model fails to capture the underlying logic of data that we learn well so it doesn't know what to do and therefore it provides inaccurate answers

ROC - Receiver operating curve



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fpr, tpr, thresholds = roc_curve(df_actual_predicted_probs['loan_data_targets_test'], df_actu
```

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fpr, tpr, thresholds = roc_curve(df_actual_predicted_probs['loan_data_targets_test'], df_actual_predicted_probs['loan_data_targets_test'])
# Here we store each of the three arrays in a separate variable.

```

Interpretation	Area under the curve
Bad	50-60%
Poor	60-70%
Fair	70-80%
Good	80-90%
Excellent	90-100%

```

from sklearn.metrics import roc_curve, roc_auc_score
AUROC = roc_auc_score(df_actual_predicted_probs['loan_data_targets_test'], df_actual_predicted_probs['loan_data_targets_test'])
Gini = AUROC * 2 - 1

```

### Population Stability Index

Values of PSI: 0-1	Population difference
PSI = 0	No difference
PSI < 0.1	Little no difference
0.1 > PSI > 0.25	Little difference (no action is taken)
PSI > 0.25	Big difference (Action is taken)
PSI = 1	Absolute difference

### LGD and EAD model

#### Dependent variables

RECOVERY RATE =  $\text{amt\_recovered} / \text{total\_fund\_amt}$

CREDIT CONVERSION FACTOR =  $(\text{total\_fund\_amt} - \text{total\_rec\_principal}) / \text{total\_fund\_amt}$

dicted\_probs['y\_hat\_test\_proba'],

dicted\_probs['y\_hat\_test\_proba'])