Modernizing credit risk modelling:

Using machine learning to challenge industry norms:

Loss Given Default (LGD) Models

CS 890ES Winter 2020

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University of Regina

Outline

1. About the presenter
2. Problem Statement
3. Introduction & Background
4. Solution overview
5. Data, Modelling, & Analysis
6. Outcomes – conclusions & impacts
7. Next steps

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1. About the presenter

- Adam Kehler
- PhD student – statistics (computational)
- Director, Portfolio Modelling & Data Science @ Farm Credit Canada (FCC)

2. Problem Statement

Use **modern data science** and **machine learning** techniques to benchmark, **challenge**, refine, and enhance the more **traditional statistical modelling** methods employed currently at my organization for processes related to certain **accounting standards** and **banking regulations**.

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3. Introduction & Background

Constrained by standards & regulations:

IFRS®

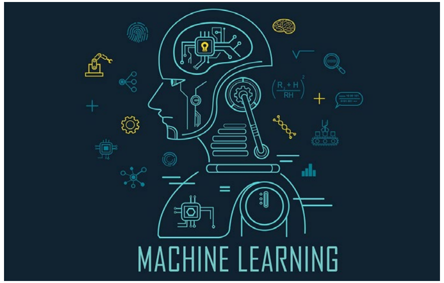
Basel Committee on Banking Supervision

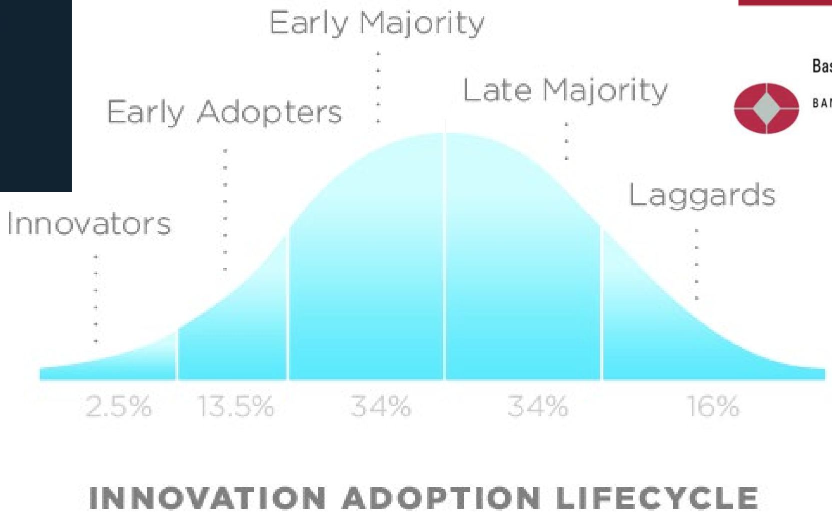
BANK FOR INTERNATIONAL SETTLEMENTS

OSFI
BSIF

3. Introduction & Background

Resulting in slower adoption:





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3. Introduction & Background

Initial opportunity:

- Model Performance
- Model benchmarking
- “Challenger” models
- Alternative models

4. Solution Overview

Scope:

4. Solution Overview

Scope:

Allowance for Credit Losses (ACL) = Expect lifetime credit loss (ECL)

$$ACL = \sum \left[\frac{PD_i \times LGD_i \times EAD_i}{(1+r)^n} \right]$$

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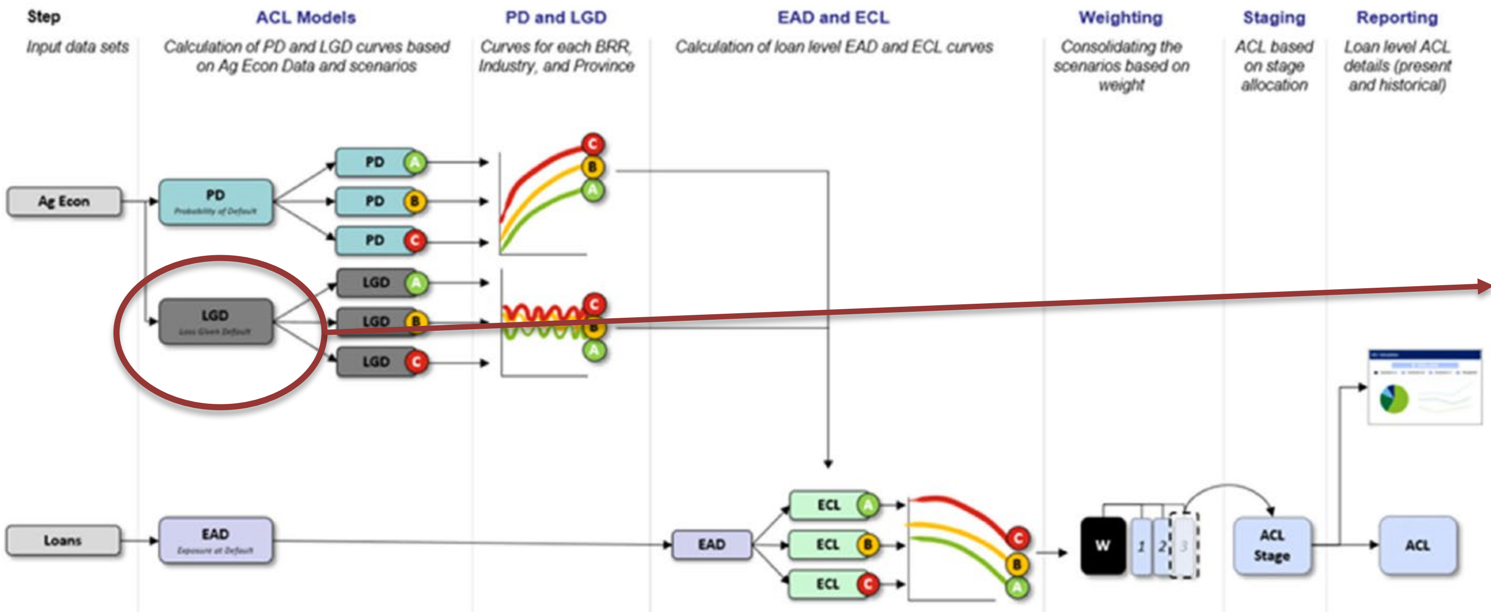
4. Solution Overview

$$ACL = \sum \left[\frac{PD_i \times LGD_i \times EAD_i}{(1+r)^n} \right]$$

Allowance for Credit Loss Calculation | Model



Loss Given Default (LGD) Model

4. Solution Overview

Current Approach

- Two-stage micro-structure
- Likelihood X Severity
- Assumes independence

$$E(LGD) = E(PWOD \times ELWO) = E(PWOD) \times E(ELWO)$$

- Scorecard approaches based on logistic regression

Proposed Approaches

1. Two-step models
    a) RF class with RF regress
    b) RF class with k-NN regress

2. Two-step models
    a) RF regression
    b) k-NN regression
    c) Multi-layer neural network
    d) Simulation-based

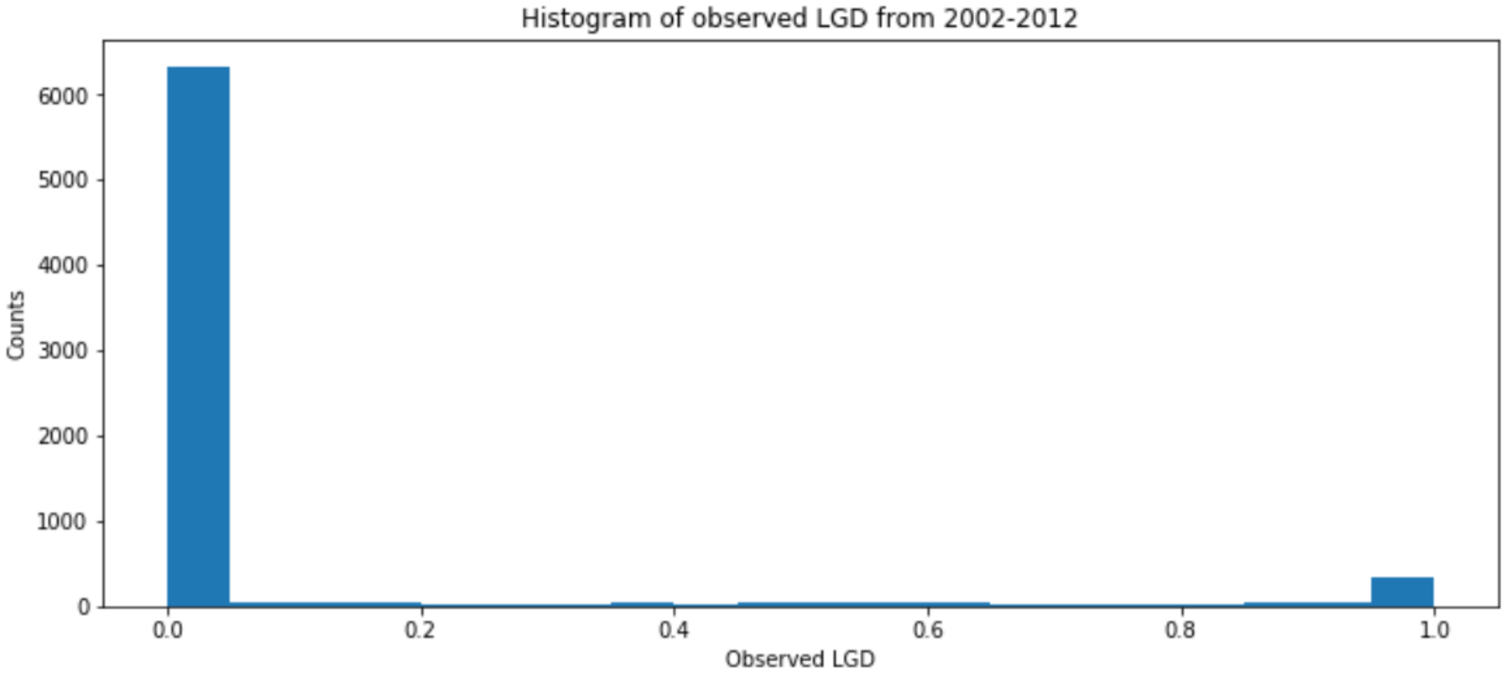
5. Data, Modelling, & Analysis

LGD Data:

- Observed loss data from 2002 to 2012
- 7,264 instances with 172 features (~1.25 M)
- Narrowed to 21 useful & quality features (~150 K)
- From SAP, Oracle DBs, Teradata DBs, and Excel (combined using SQL in SAS)
- Due to system access limitations, CSV into Python JN

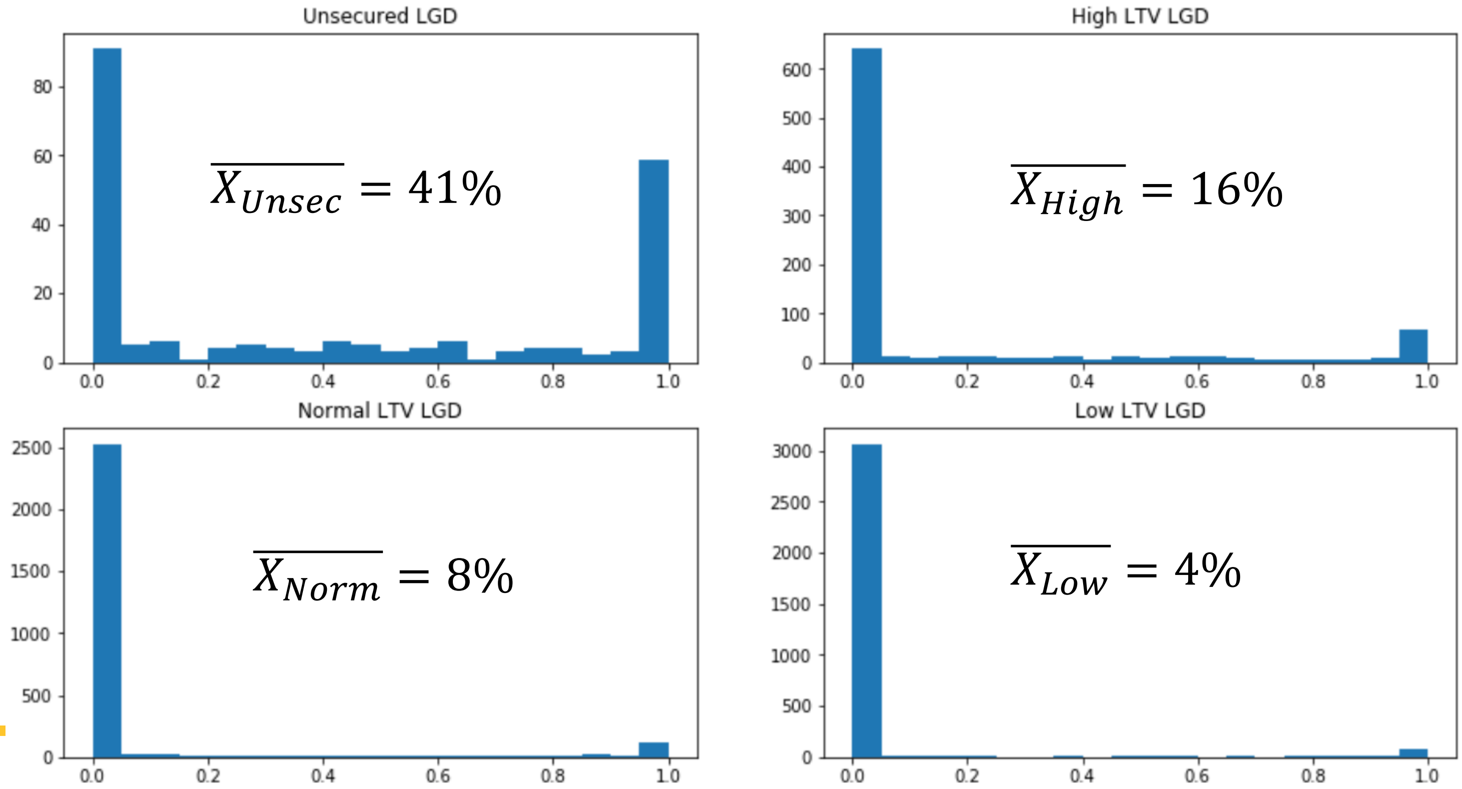
5. Data, Modelling, & Analysis

LGD Data:



5. Data, Modelling, & Analysis

LGD Data:



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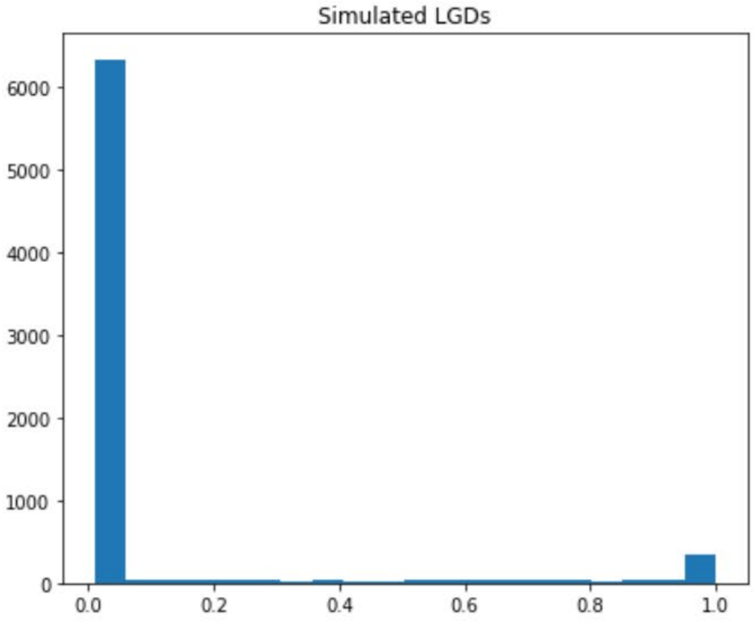
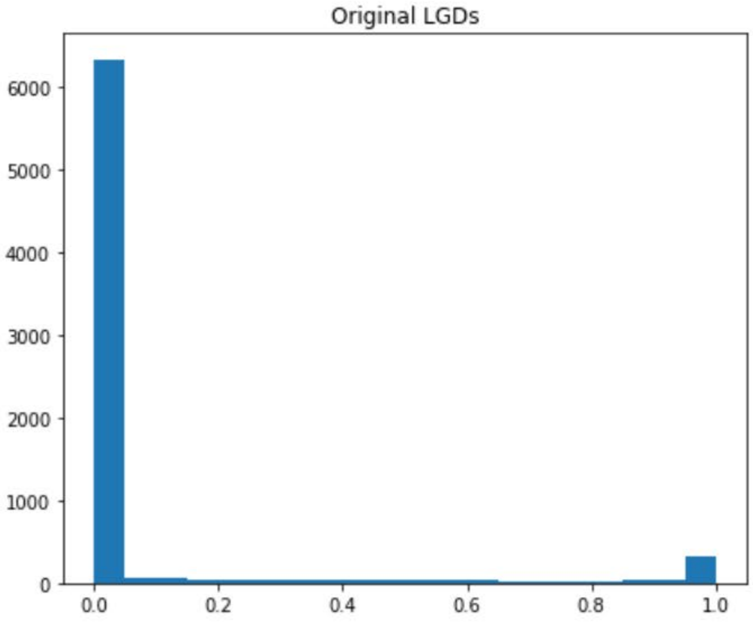
5. Data, Modelling, & Analysis

Random LGD Generator:





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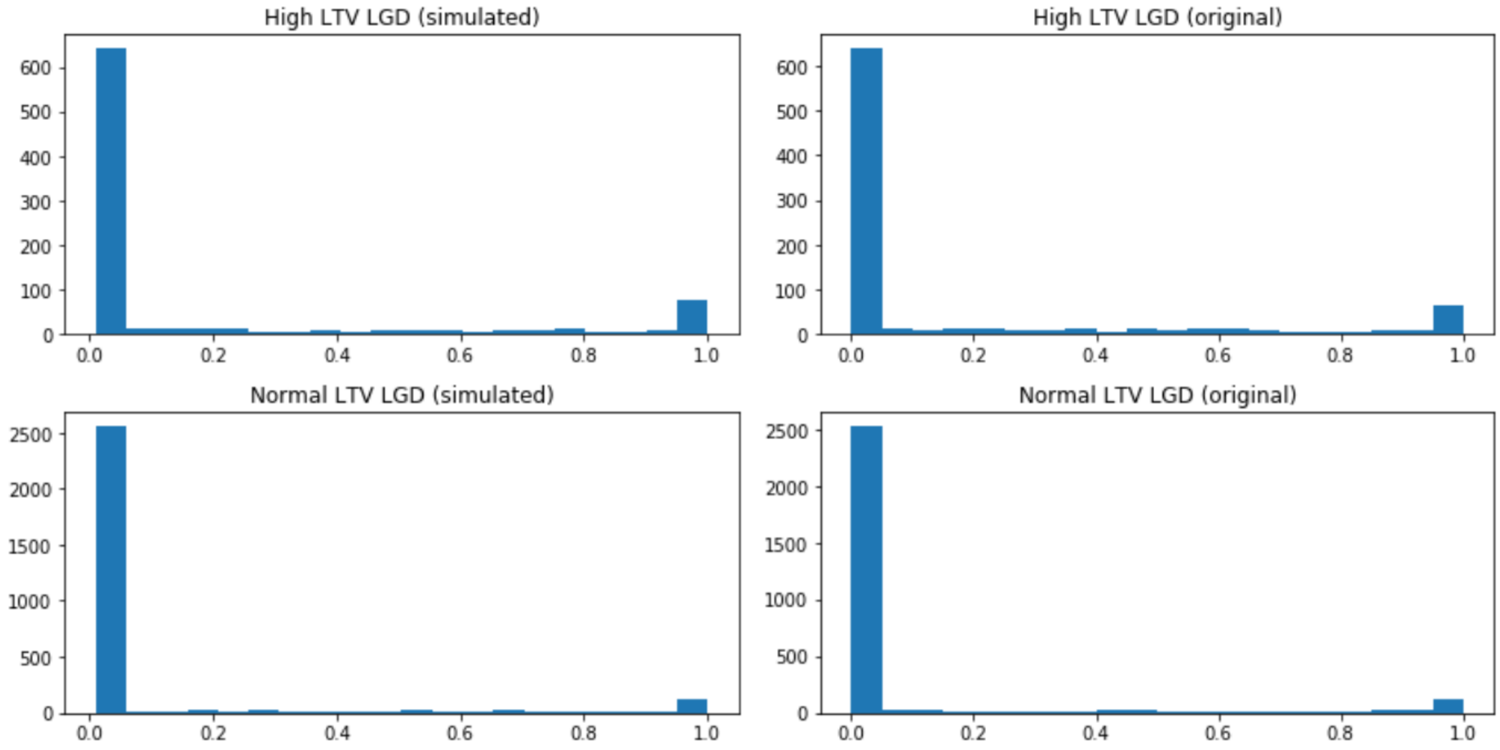
5. Data, Modelling, & Analysis

Random LGD Generator:



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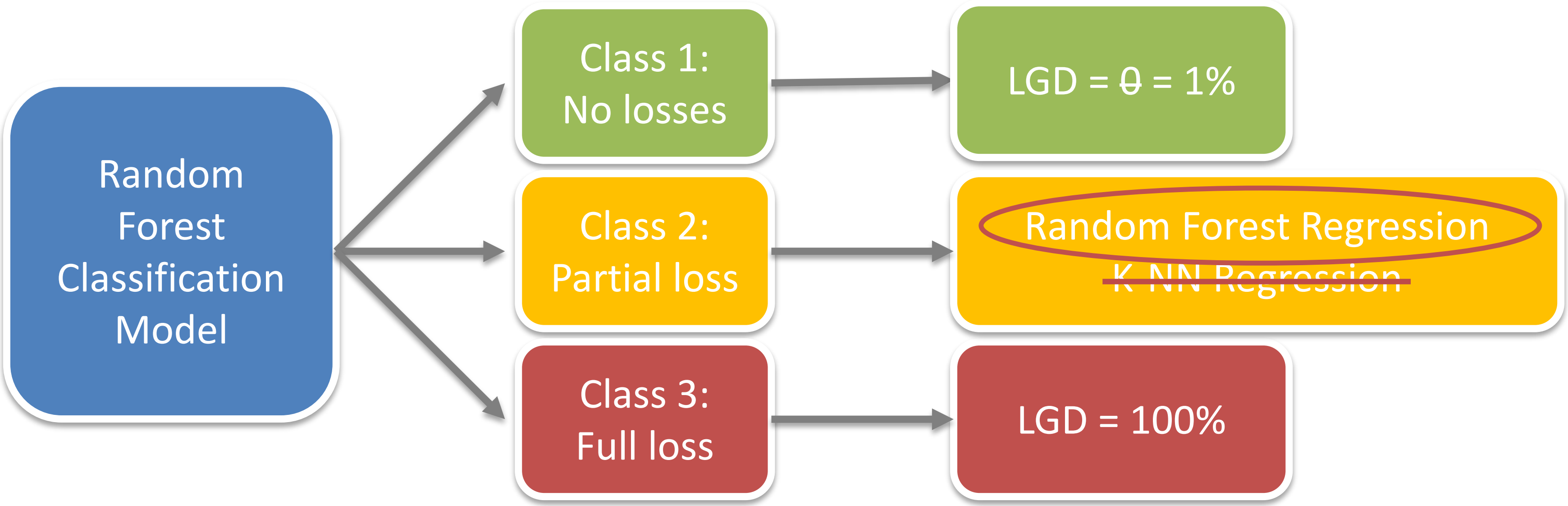
5. Data, Modelling, & Analysis

Predictive model data prep:

- One-hot encoding
- Missing values (set to 0)
- Bin LGDs into 3 groups (0 – no loss, 1 – partial loss, 2 – full loss)
- Split Train-Test (70-30)
- Scale features

5. Data, Modelling, & Analysis

Two-step models:



Classification then severity

5. Data, Modelling, & Analysis

Two-step models:

Random Forest Classification Model

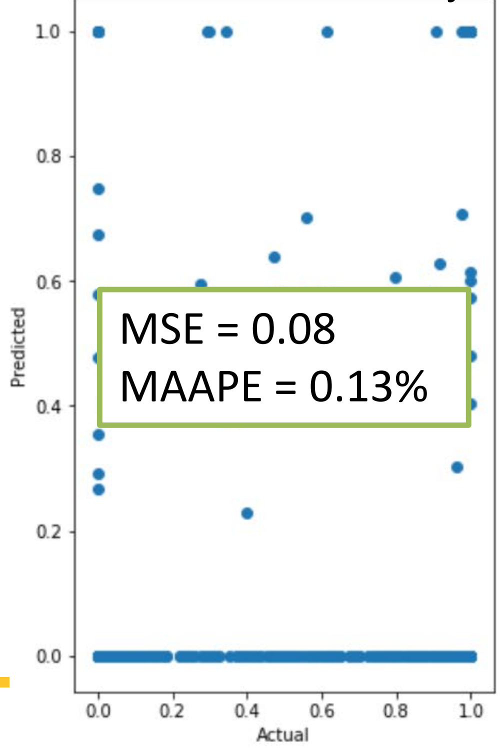
Probability	Severity
Class 1: No losses	LGD = ~~0~~ = 1%
Class 2: Partial loss	RF Regression 1% < LGD < 100%
Class 3: Full loss	LGD = 100%

Probability weighted

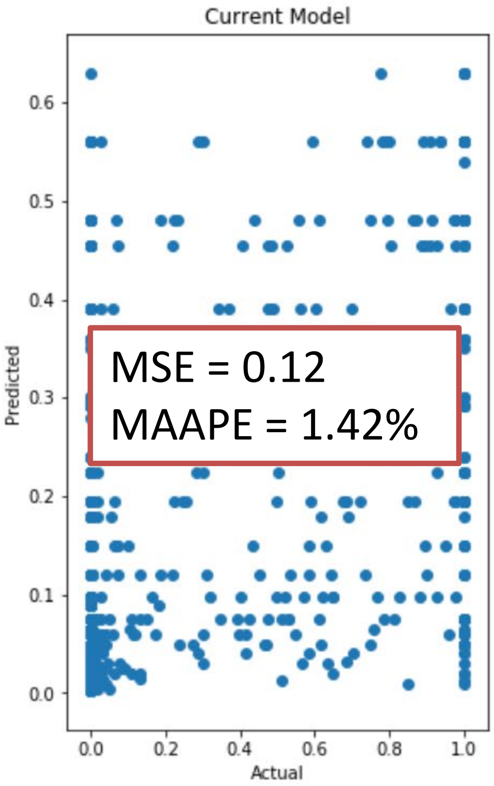
5. Data, Modelling, & Analysis

Two-step models:

Class then severity

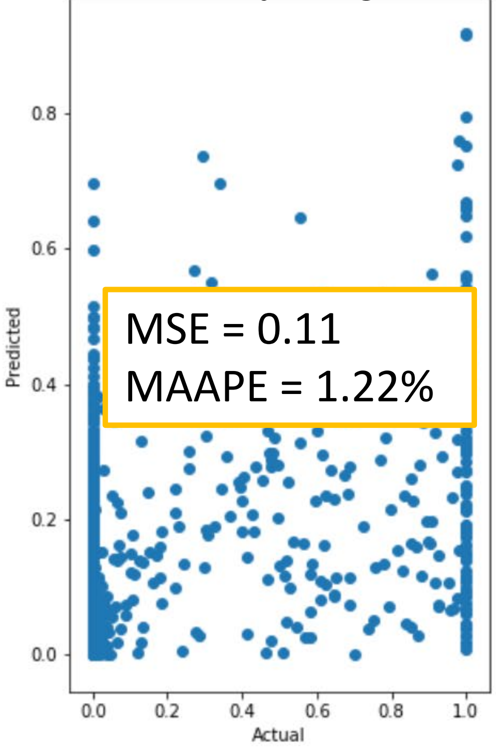


MSE = 0.08
MAAPE = 0.13%



MSE = 0.12
MAAPE = 1.42%

Probability weighted



MSE = 0.11
MAAPE = 1.22%

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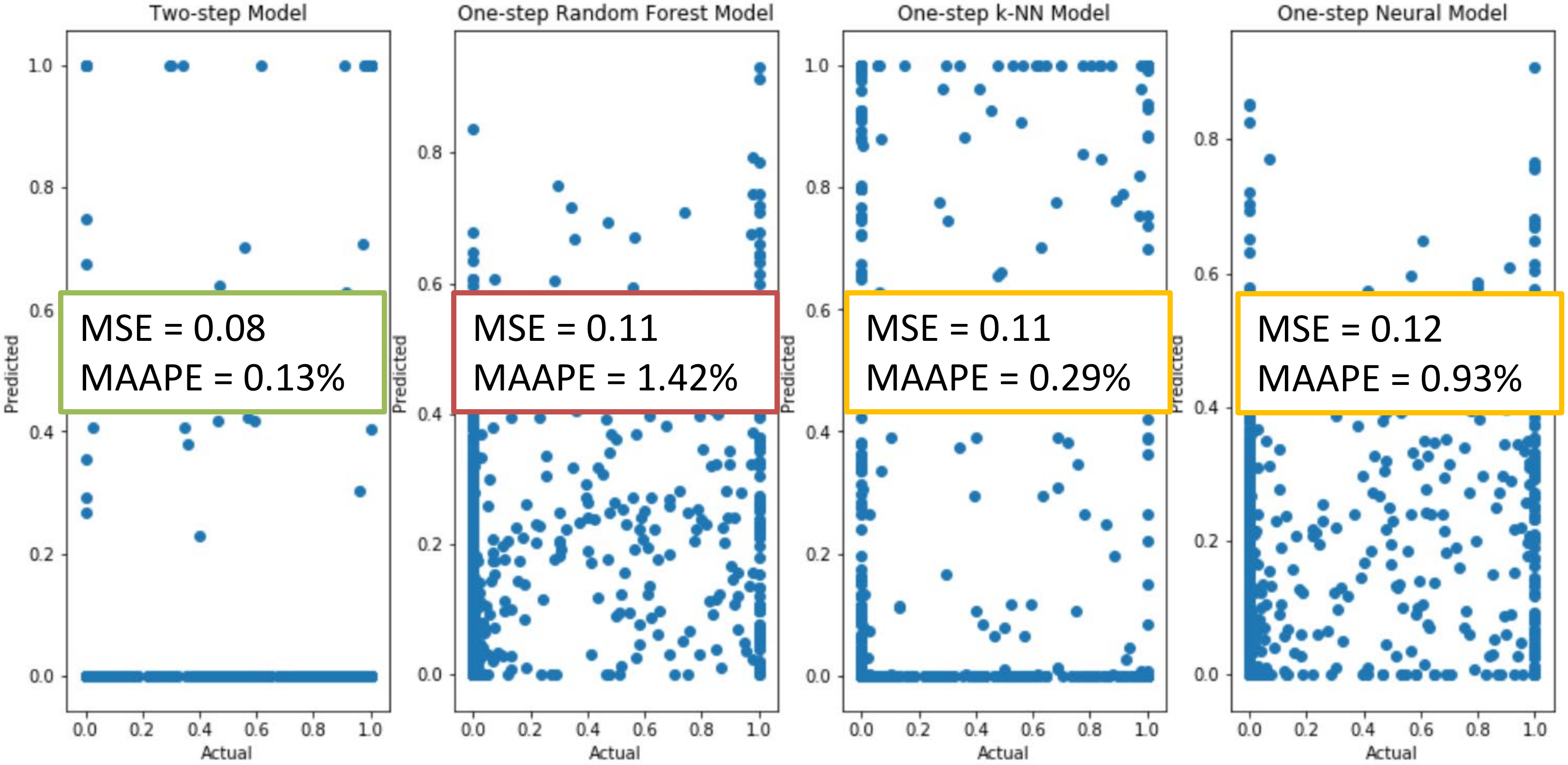
5. Data, Modelling, & Analysis

One-step models:



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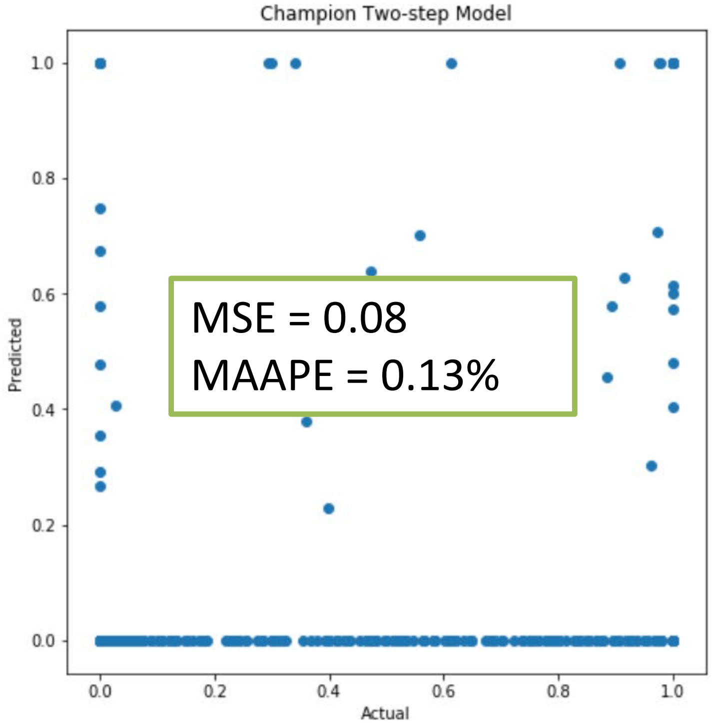
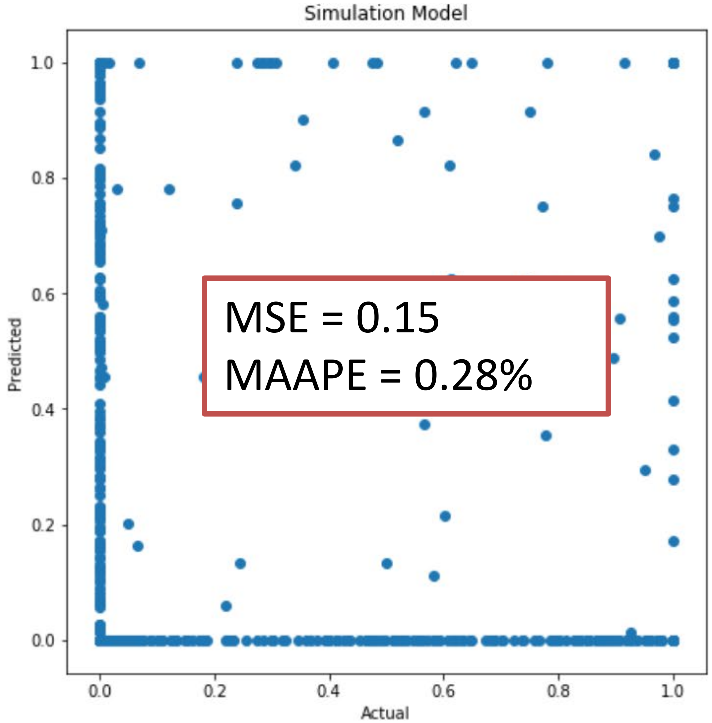
5. Data, Modelling, & Analysis

Simulation-based model:



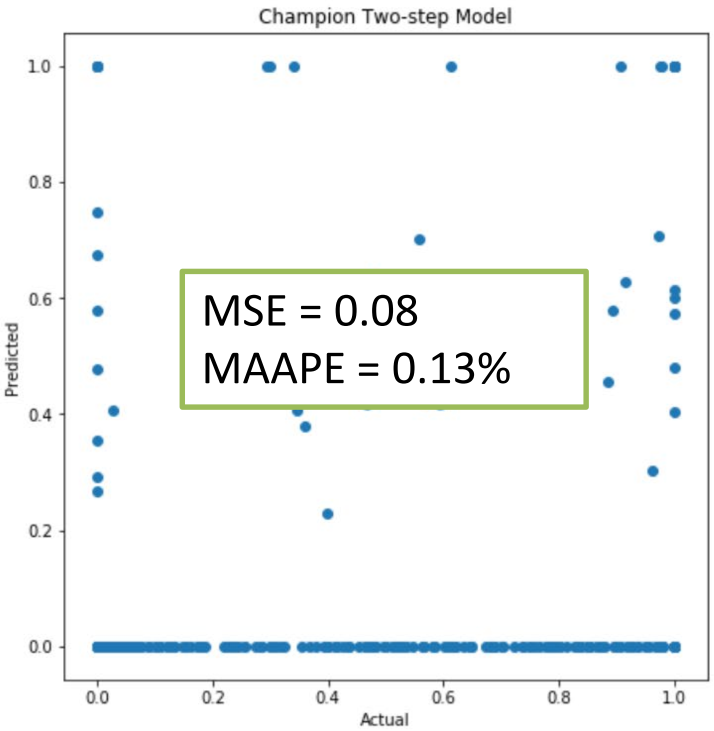
MSE = 0.08
MAAPE = 0.13%

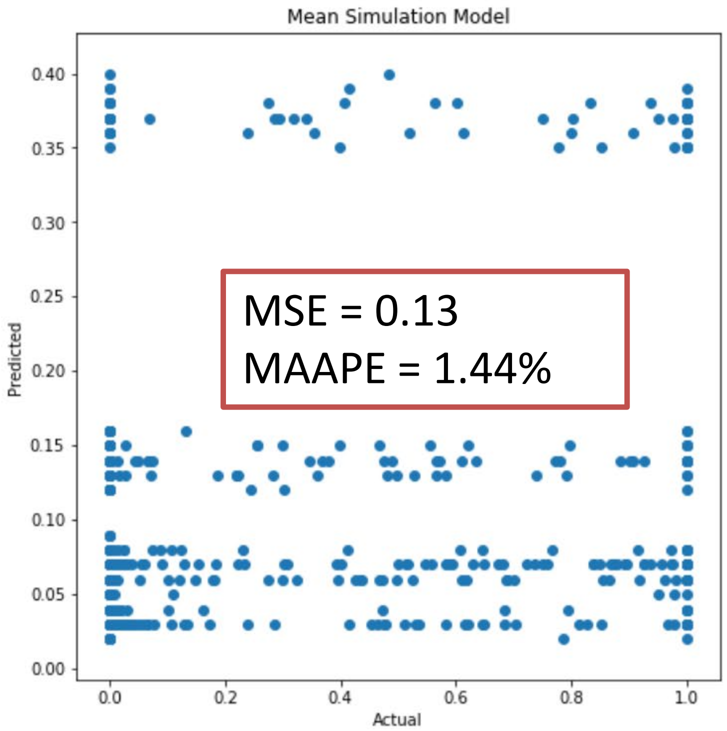


MSE = 0.15
MAAPE = 0.28%

5. Data, Modelling, & Analysis

Simulation-based model:





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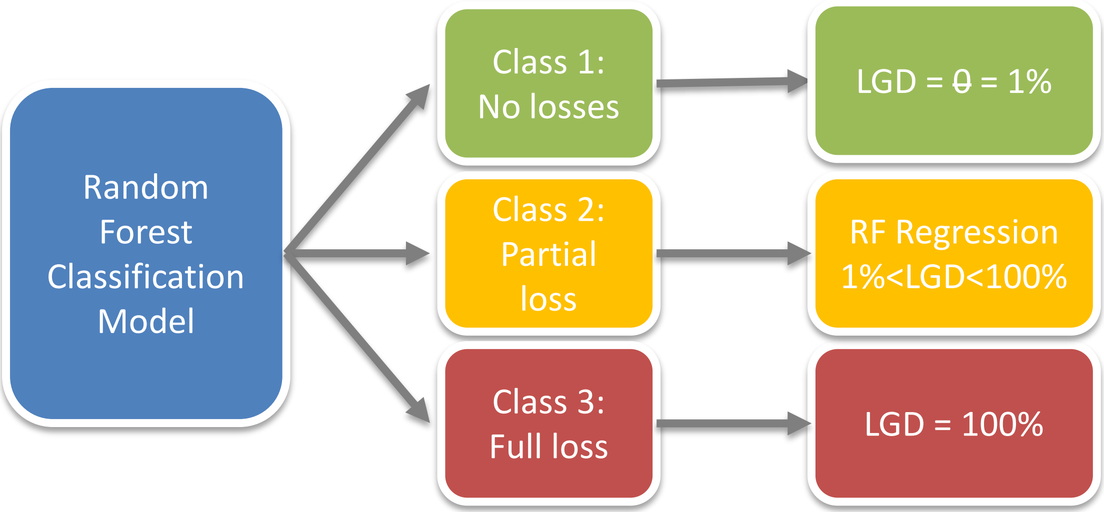
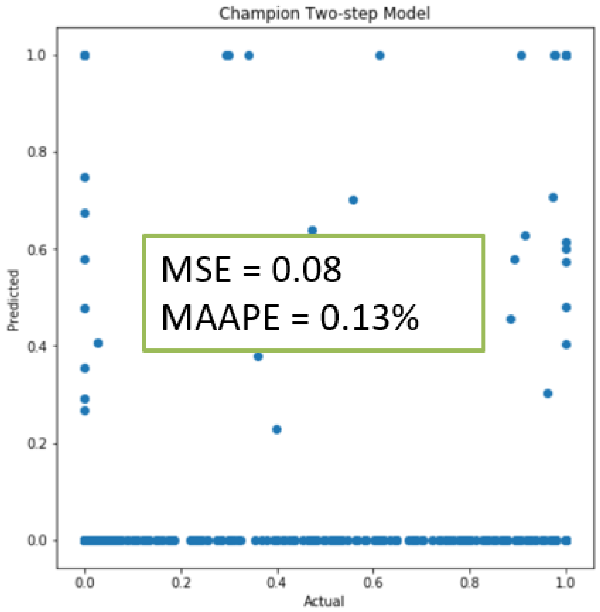
6. Outcomes – conclusions

Champion Model: RF Classification, then RF Severity





6. Outcomes – impacts

- Enables more accurate Financial Statements
- Enables more refined pricing
- Improved Model Performance Monitoring
- Facilitate change management and adoption of new techniques
- Inform next round of model development (this upcoming year)
- Simulation engine will be used in credit economic capital (ECAP) model

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7. Next Steps

1. Partner with Model Development on LGD simulation (for credit ECAP)
2. Work with IT and Finance to get 2013 – 2019 data, then re-run analysis
3. Incorporate "Challenger" model into Model Performance Monitoring
4. Explore enhancements by bringing in macro-economic variables (forward-looking)
5. "Familiarize" stakeholders with new approaches (to help move Challenger to Production)
6. Work with IT and Finance to determine best practices for deployment