IFRS9 Survival Analysis with an Application in Apache Spark

Credit Scoring and Credit Control XV Conference

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Introduction

Introduction

Expected credit losses

Macroeconomic modelling

Probability of default

IFRS 9 aspects

IFRS 9
Expected credit losses

B5.5.3: …an entity shall measure the loss allowance for a financial instrument at an amount equal to the *lifetime* expected credit losses if the credit risk on that financial instrument has increased significantly since initial recognition.

5.5.11. If reasonable and supportable forward-looking information is available without undue cost of effort, an entity cannot rely solely on past due information when determining whether credit risk has increased significantly since initial recognition.

B5.5.17. An entity shall measure expected credit losses of a financial instrument in a way that reflects:

a) an unbiased and probability-weighted amount that is determined by evaluating a range of possible outcomes;
b) the time value of money; and
c) reasonable and supportable information that is available without undue cost or effort at the reporting date about past events, current conditions and forecasts of future economic conditions.

Lifetime forecasts

Forward-looking information

Probability – weighted estimates

Goal

Produce ECL forecasts

Account-classification

Include macroeconomic data

Build upon existing models

Calibrate behavior scores

Methodology

Building blocks

Survival model

Maturity effects

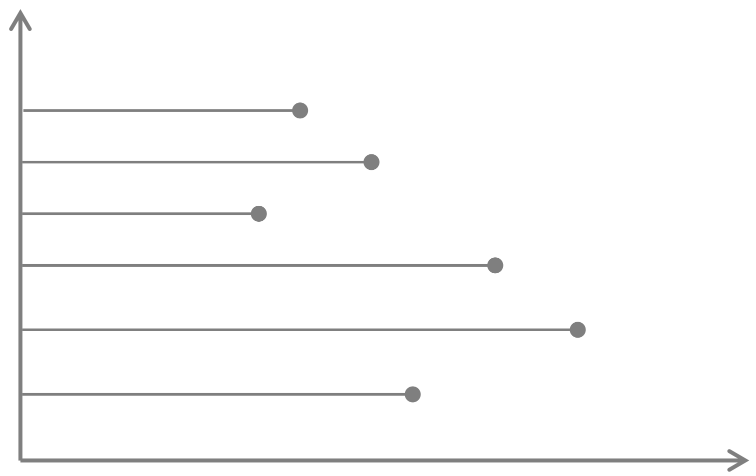
Error correction

Survival analysis

Account level model – PD prediction for each account (similarly for other events)

Models not **if** but **when** an account will enter default

- Better estimates of expected losses
- Strong framework for IFRS 9



Duration (t) Time to default

Easily accommodates IFRS 9 framework

Expected credit losses

Constant (or structural) account characteristics

Time-varying account characteristics (e.g. maturity; current status; behaviour data and scores)

Time-varying internal factors (policy changes etc.)

Time-varying external factors (economics, etc.)

Time specifications

Continuous-time

Often proportional hazard assumption

Individual hazard functions differ proportionately based on a function of observed covariates

Parametric estimation

- Assume distribution
  - eg. Log-logistic hazard
- Maximum likelihood estimation

Non-parametric estimation

Cox PH

Discrete time

Application of continuous-time models is not recommended to discrete survival data due to the large number of ties that result more natural in social and behavioural applications where time is measured discretely.
Discrete-time models can easily accommodate time-varying covariates.
Do not require a hazard-related proportionality assumption. These models allow for unstructured, as well as structured estimation of the hazard function at each discrete time point.

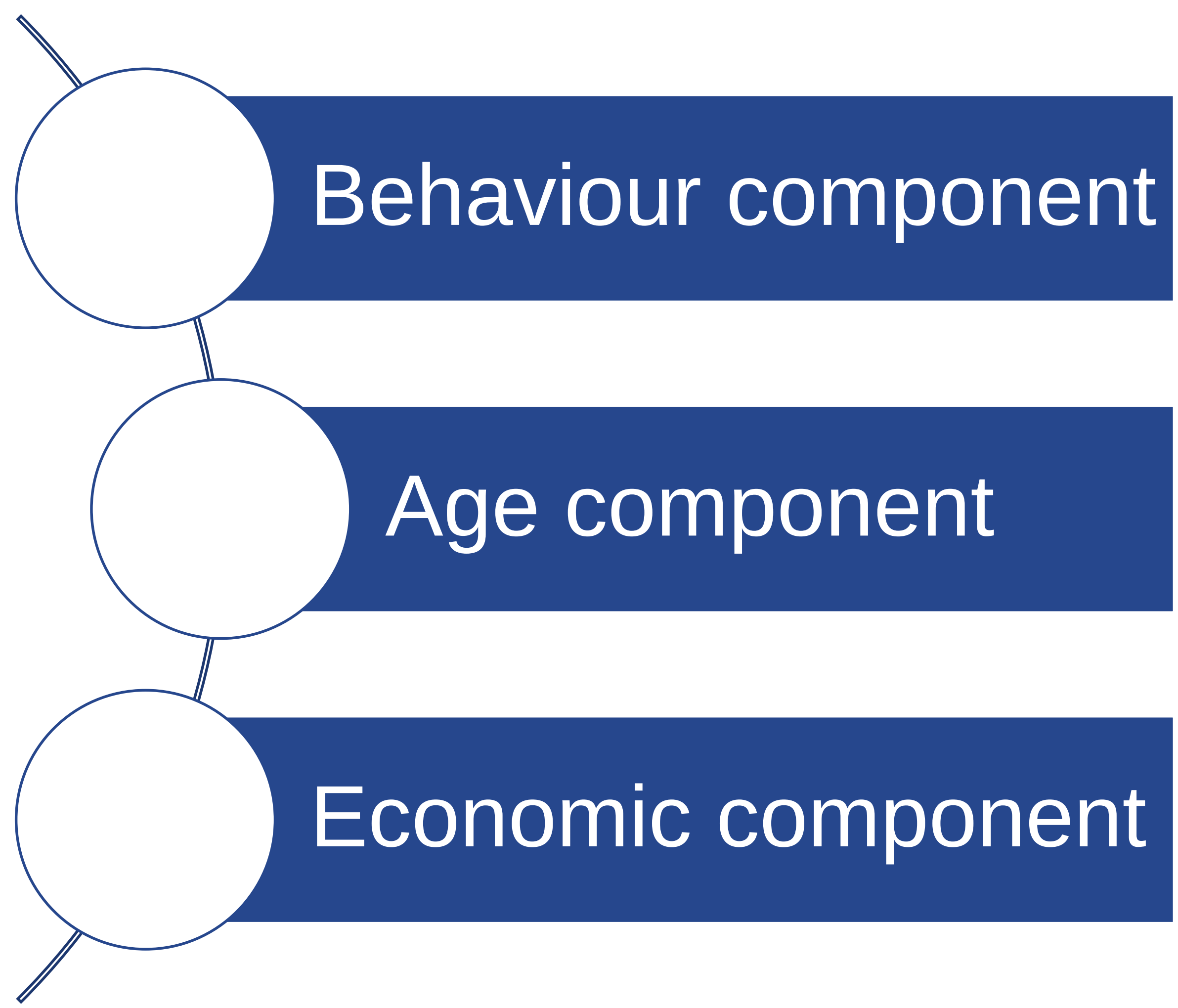
Objective

Estimate

$$P\left(y_{t+\tau} \mid y_t = 0, S_t, A_{t+\tau}, \{E_i\}_{i=-\infty}^{t+\tau}\right)$$

Where

- y_t- account status at time t
- S_t- behaviour score at time t
- A_t- age of account at time t
- E_t- economics variables at time t



Recursive representation

Let define

$$p_{t,k,S,A,E} = P\left(y_{t+k} | y_{t+k-1} = 0, S_t, A_t, \{E_i\}_{i=-\infty}^{t+k}\right)$$

Then

$$P\left(y_{t+\tau} | y_t = 0, S_t, A_t, \{E_i\}_{i=-\infty}^{t+\tau}\right) = \sum_{i=1}^{\tau}\left(p_{t,i,S,A,E}\prod_{j=1}^{i-1}\left(1 - p_{t,j,S,A,E}\right)\right)$$

Therefore it is enough to calculate $p_{t,k,S,A,E}$ for $\mathrm{k} = 1, \dots, \tau$

Probability decomposition

We will focus on the following form

$$p_{t,k,S,A,E} = h\left(g\left(p_{t,k,A}, p_{t,k,S}, p_{t,k,E}\right)\right)$$

Where

- $p_{t,k,S} = P(y_{t+k} | y_{t+k-1} = 0, S_t)$- account behaviour component
- $p_{t,k,A} = P(y_{t+k} | y_{t+k-1} = 0, A_{t+k})$ - account maturity component
- $p_{t,k,E} = P\left(y_{t+k} | y_{t+k-1} = 0, \{E_i\}_{i=-\infty}^{t+k}\right)$- economics environment component
- $h(x) = \frac{1}{1+e^{-x}}$
- $g(x, y, z) = \alpha_1 + \alpha_2 x + \alpha_3 y + \alpha_4 z$

Account behaviour component

Include calibrated behaviour score to behaviour probabilities

Standard scorecard development approach

- Fine/Coarse classing per score and forecasting window
- Incorporate interaction terms as well
- Logistic regression estimates

How to create a forecast

Modelling stage	$PD_{t+1} = f(behaviour\ score_t)$
Forecasting stage	Behaviour score needs to be forecasted

How to create a forecast
Multiple-horizon model

Modelling stage

$PD_{t+1} = f(behaviour\ score_t)$

$PD_{t+2} = f(behaviour\ score_t)$

...

$PD_{t+s} = f(behaviour\ score_t)$

Forecasting stage

Behaviour score does not need to be forecasted

Multiple-horizon model
Exploded panel

Modelling stage

$$PD_{t+1} = f(behaviour\ score_t)$$

$$PD_{t+2} = f(behaviour\ score_t)$$

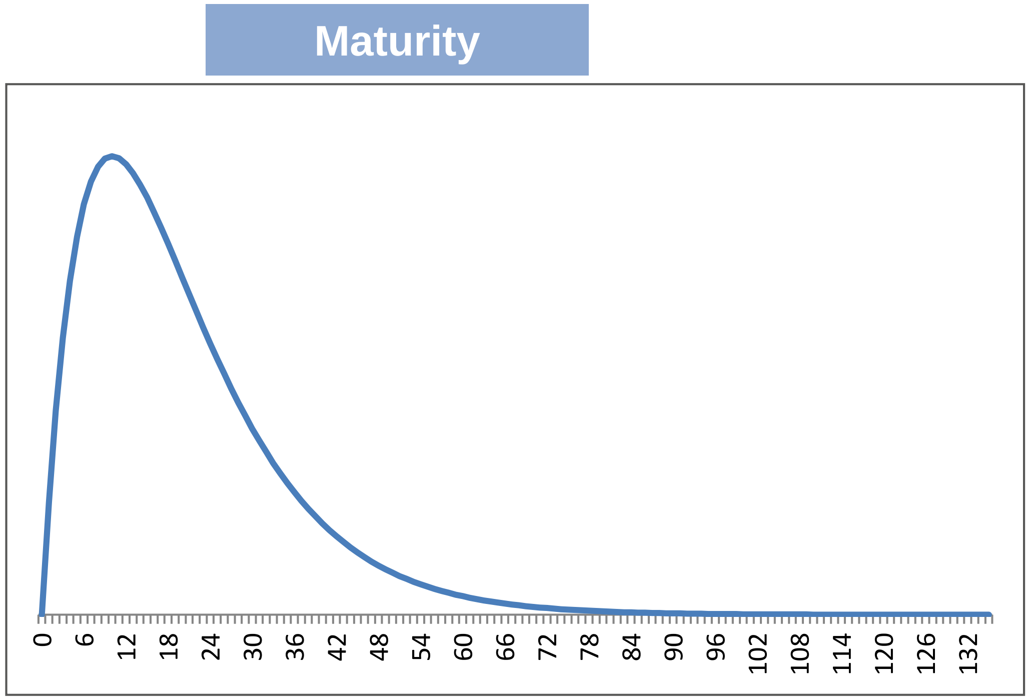
...

$$PD_{t+s} = f(behaviour\ score_t)$$

Exploded panel

Account maturity component

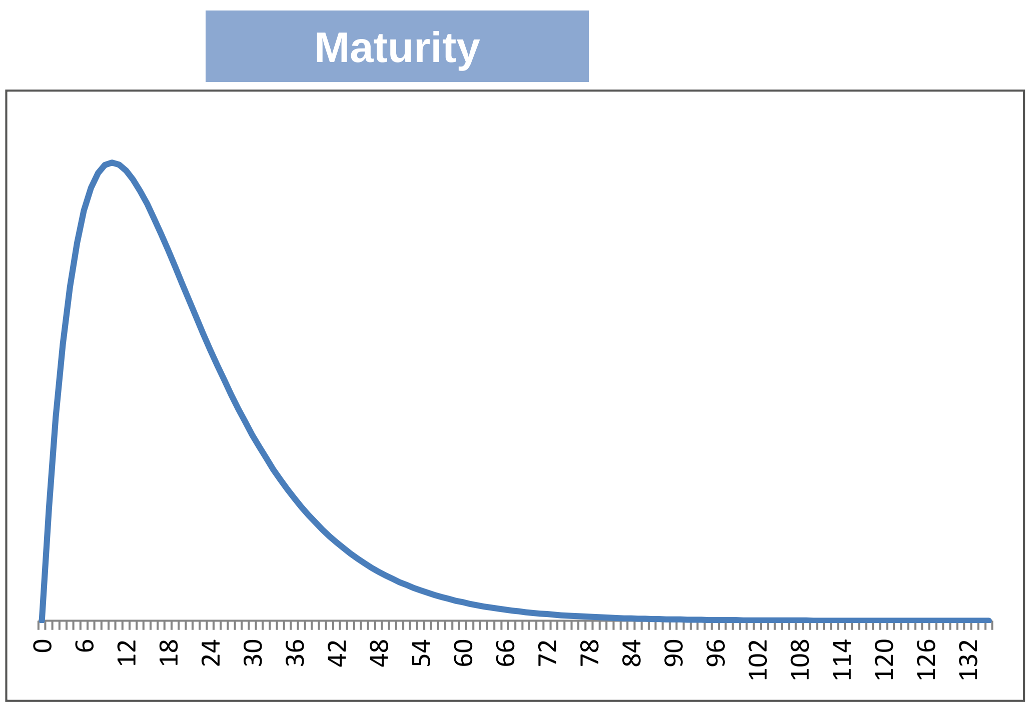
Motivated by age-cohort analysis / EMV models



Account maturity component

Standard scorecard development approach

- Fine/Coarse classing per age of account
- Logistic regression estimates
- No problem in forecasting



Economics component
Error-correction models

Long-term dynamics	Short-term dynamics
Equilibrium state – no inherent tendency to change The system tends to return to this state after deviations Entails a systematic co-movement among economic variables	“Errors” in the short-term Transitory deviations from the long-term relationship due to shocks

Economics component

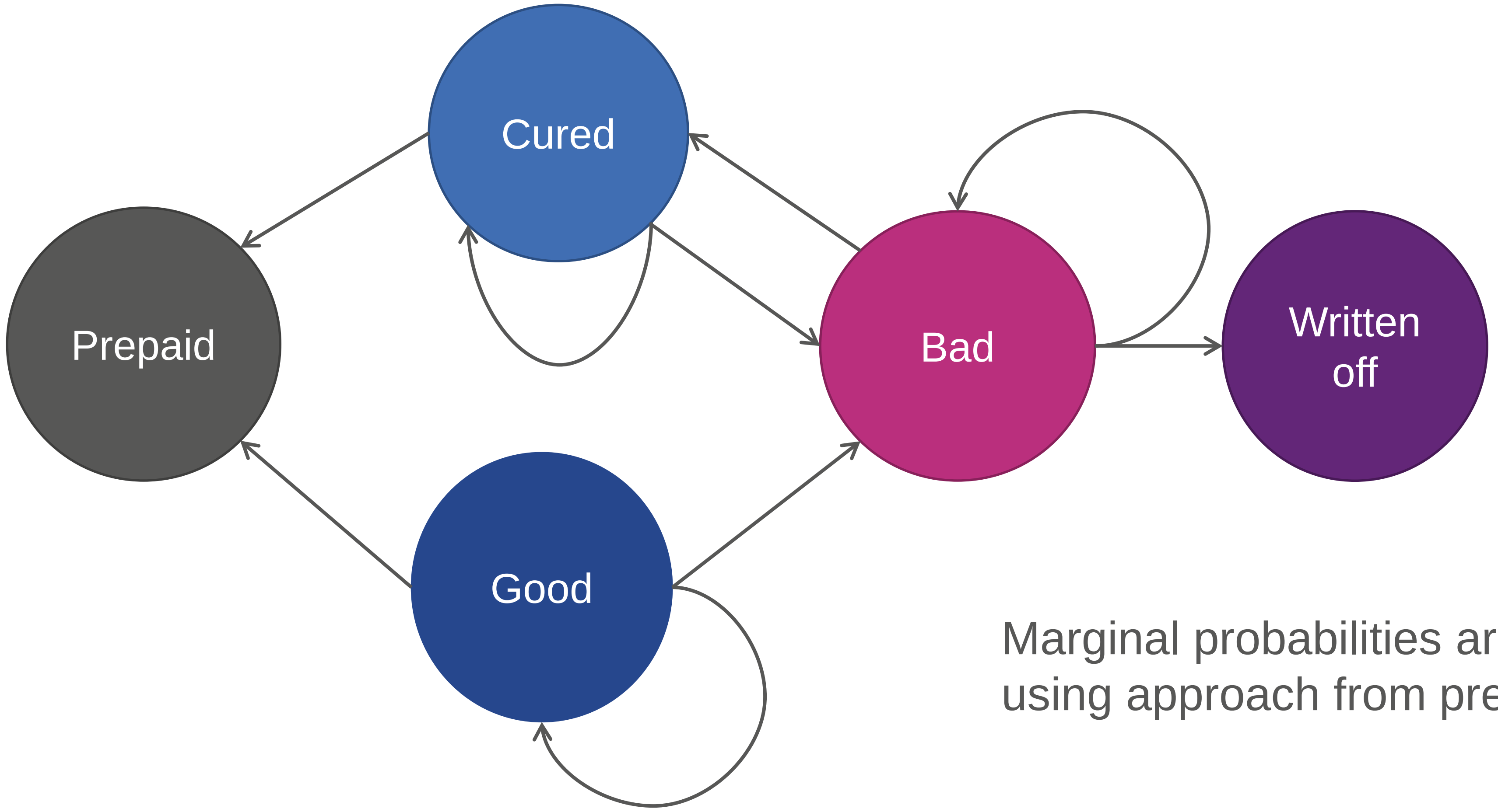
Error correction equation:

$$\Delta(y_t) = \alpha + \beta\Delta x_t - \gamma(\, y_{t-1} - \beta x_{t-1})$$

γ – speed of error correction

Include more lags

Account states



Marginal probabilities are estimated by using approach from previous section

Technical aspects

Account level models

- Millions observations
- Hundreds of variables
- 10-20 years of history
- Multiple-horizon forecast

- Huge datasets
- Difficult to process

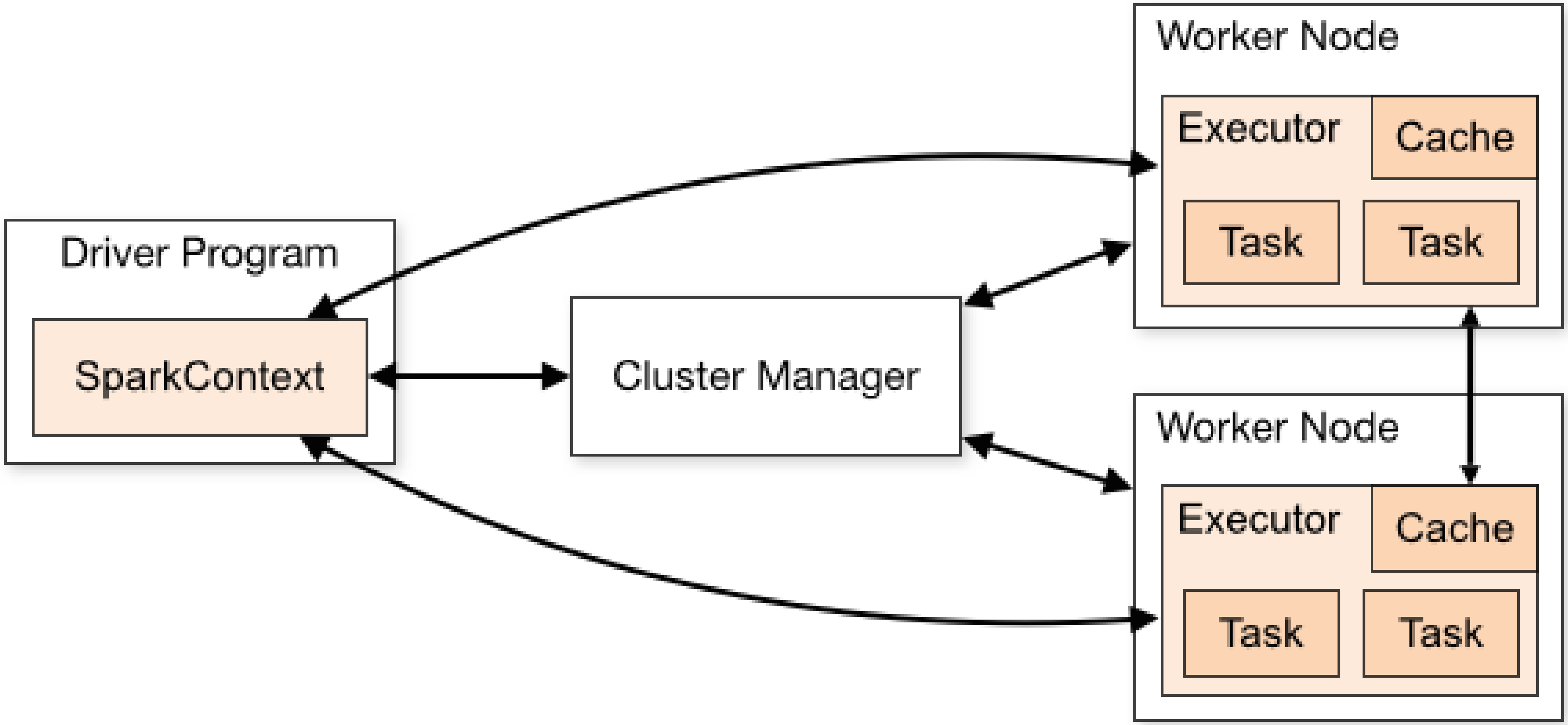
Sample size

Time series	Accounts	Observations	Exploded panel
• 100 historic months	1	32	704
	100 000	32 mn	704 mn

What is Apache Spark?

1. Powerful **open source** engine for **large-scale** data processing
2. Started as a research project in **UC Berkeley AMPLab in 2009**
3. The **largest** Apache Foundation project
4. Sorts **100TB** of data in **23 minutes**

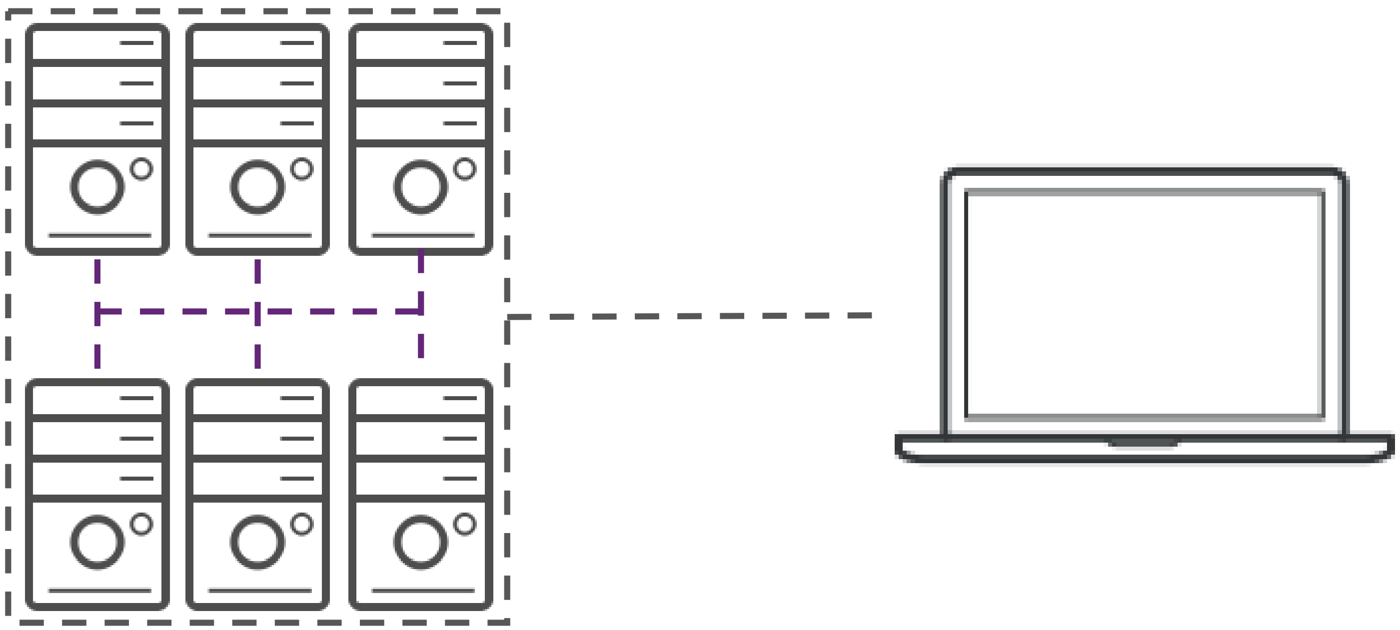
Spark Architecture



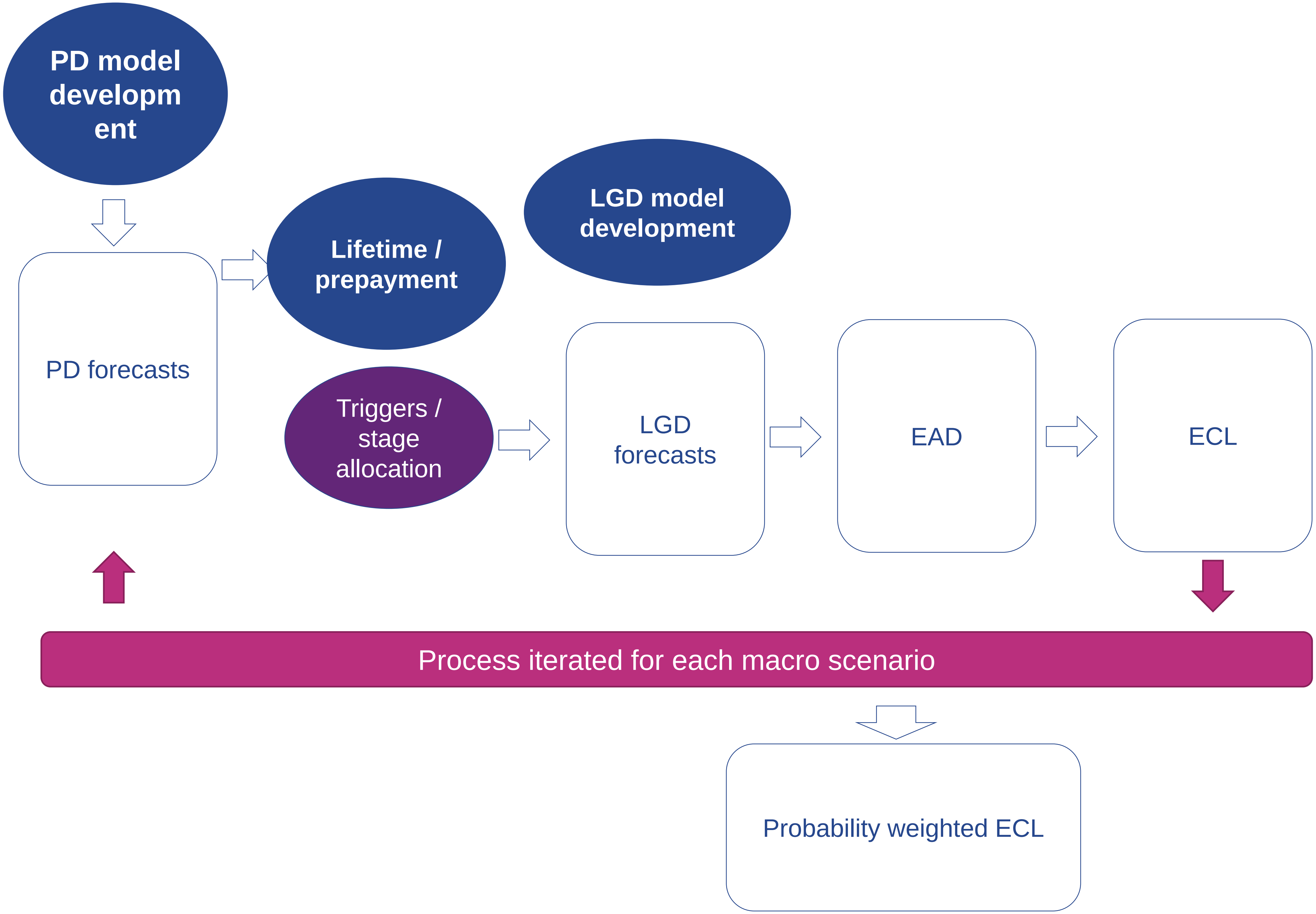
Why Spark?

1. Fast **in-memory** and disk computing
2. Runs **everywhere** – on a cluster or standalone
3. Write Spark applications in **Python, R, Java, Scala**
4. A rich stack of **libraries** – SQL, machine learning, graph analytics, steaming data
5. Batch jobs and **real-time** analytics
6. Lazy evaluations and Catalyst optimizer
7. It’s fault tolerant

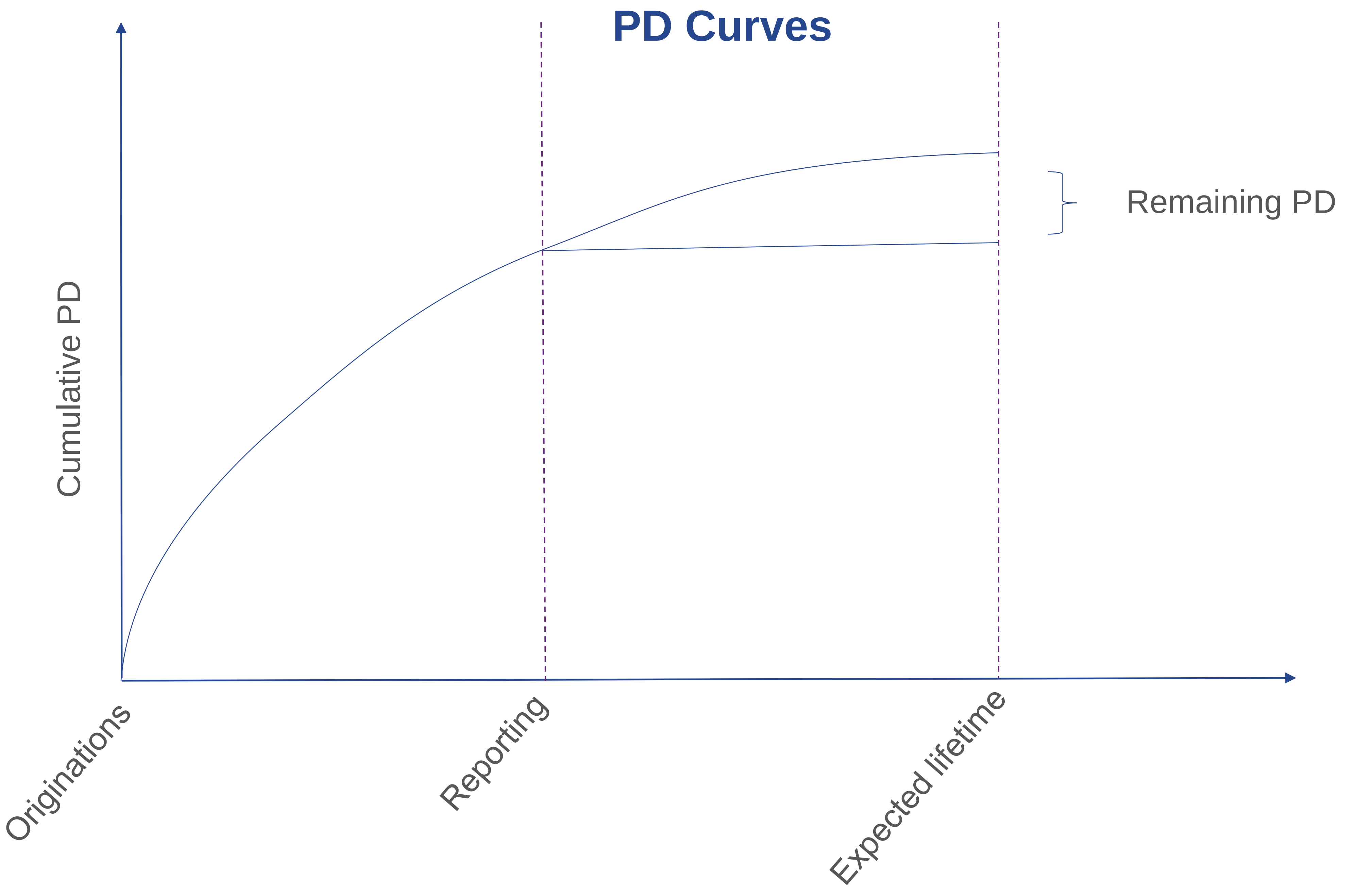
Python application



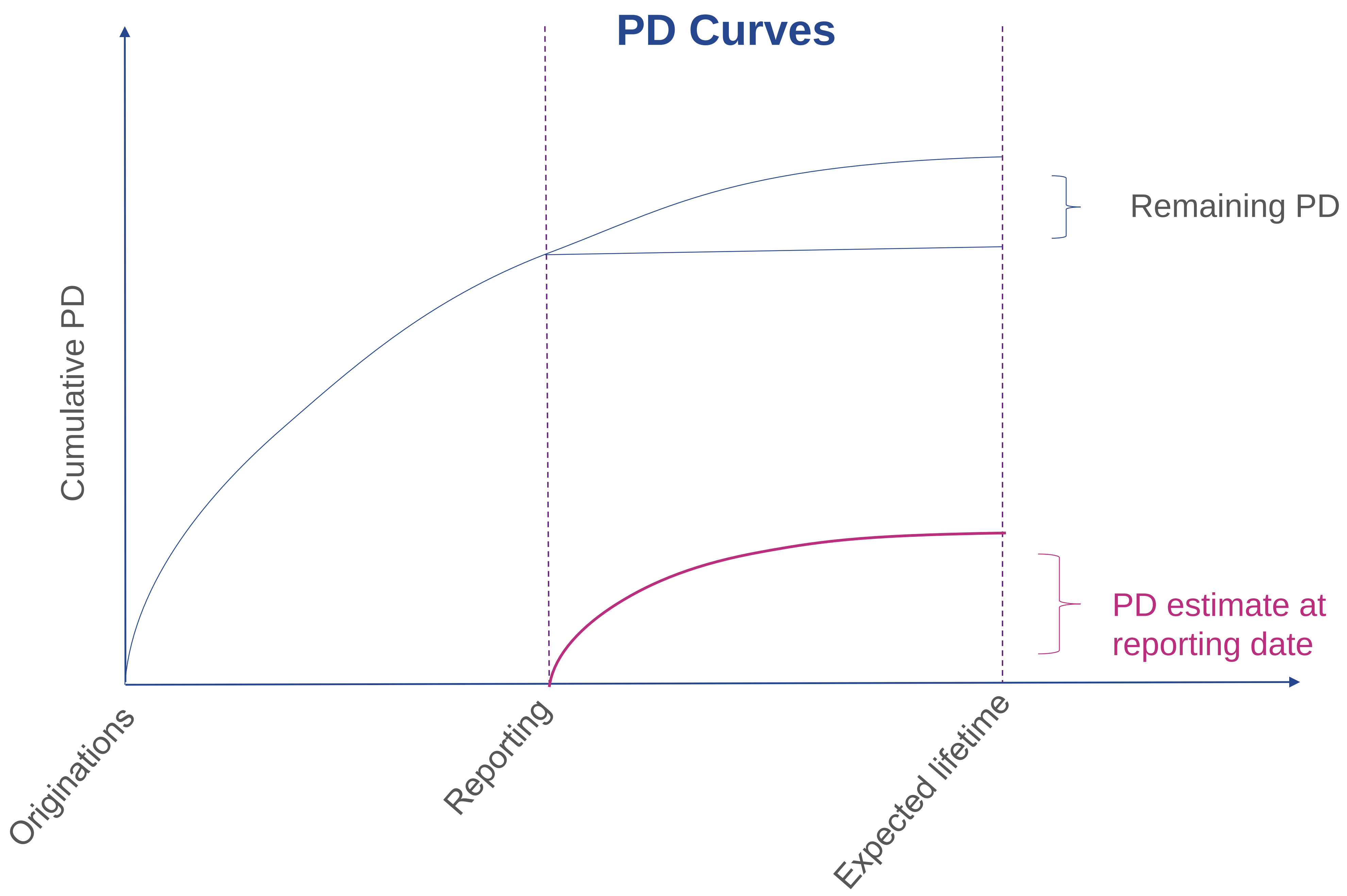
Use


PD model developm ent
PD forecasts
Lifetime / prepayment
LGD model development
Triggers / stage allocation
LGD forecasts
EAD
ECL
Process iterated for each macro scenario
Probability weighted ECL

Significant increase in risk



Significant increase in risk



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