CBD'S DEVELOPMENT OF AN END TO END MACHINE LEARNING (ML) ECOSYSTEM

WITH CREDIT UNDERWRITING CASE STUDY

January 2020

OBJECTIVE OF USING ML IN CREDIT UNDERWRITING

Reduce charge off rates and optimize credit portfolio risk/return.

Optimize financial institution’s cost structure with wider use of ML/AI technologies.

Increase lending volumes without necessarily increasing risk. Increase access to credit!

Reduce risk of human bias during the risk assessment process. Consistent Approach

Improve performance while ensuring regulatory compliance

MACHINE LEARNING PREREQUISITES

- Be interpretable in order to meet regulatory and ethical Requirements
- Be reproducible and scalable
- Be able to show Tangible Business Benefits to the stakeholders.
- Be periodically re-trained and updated depending on data inflow volume.
- Be part of a wider AI ecosystem and appropriate data/information architecture which itself must be part of a concise data strategy.
- Be Handled By Domain Experts With Constant Feedback From Stakeholders.

BIG DATA SURVEYS SHOW THAT

85% of Companies Trying To be Data Driven in North America.

Less Than 40% of Those Have Claimed To Be Successful

90% of Companies Invested in AI tech but 1 in 3 Succeeded

MACHINE LEARNING DEVELOPMENT IS HARD

ISSUES TO CONTEND WITH
EXPERT KNOWLEDGE IMPERATIVE FOR SUCCESS

- Lack of Strategy
  - Lack data strategy aligned to business strategy
  - Lack of Proper data governance processes
- Siloed Approach
  - Siloed people, processes and systems
  - No Proper Data Lake
- Too Many Tools
  - Complex Web of Analytics Tools
  - Integrating it All
- Unaddressed Gaps
  - Technology gaps and skills gaps hinder cooperation across ecosystem
  - Challenging landscape in terms of cost for smaller firms
- Complex Environments
  - Complex legacy data architectures and scalability
  - Hard To Provision Resources For Analytics especially on prem

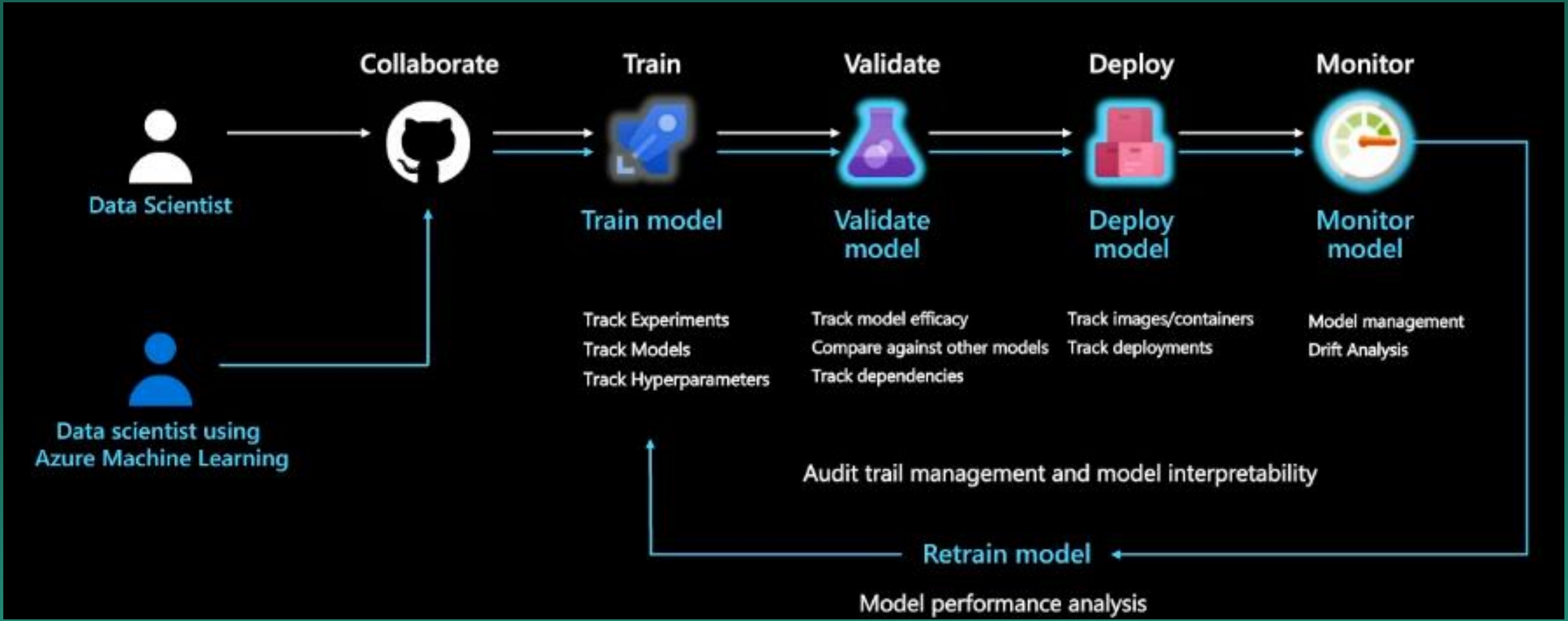
THE RIGHT APPROACH

Define strategies, policies, standards, architecture, and processes

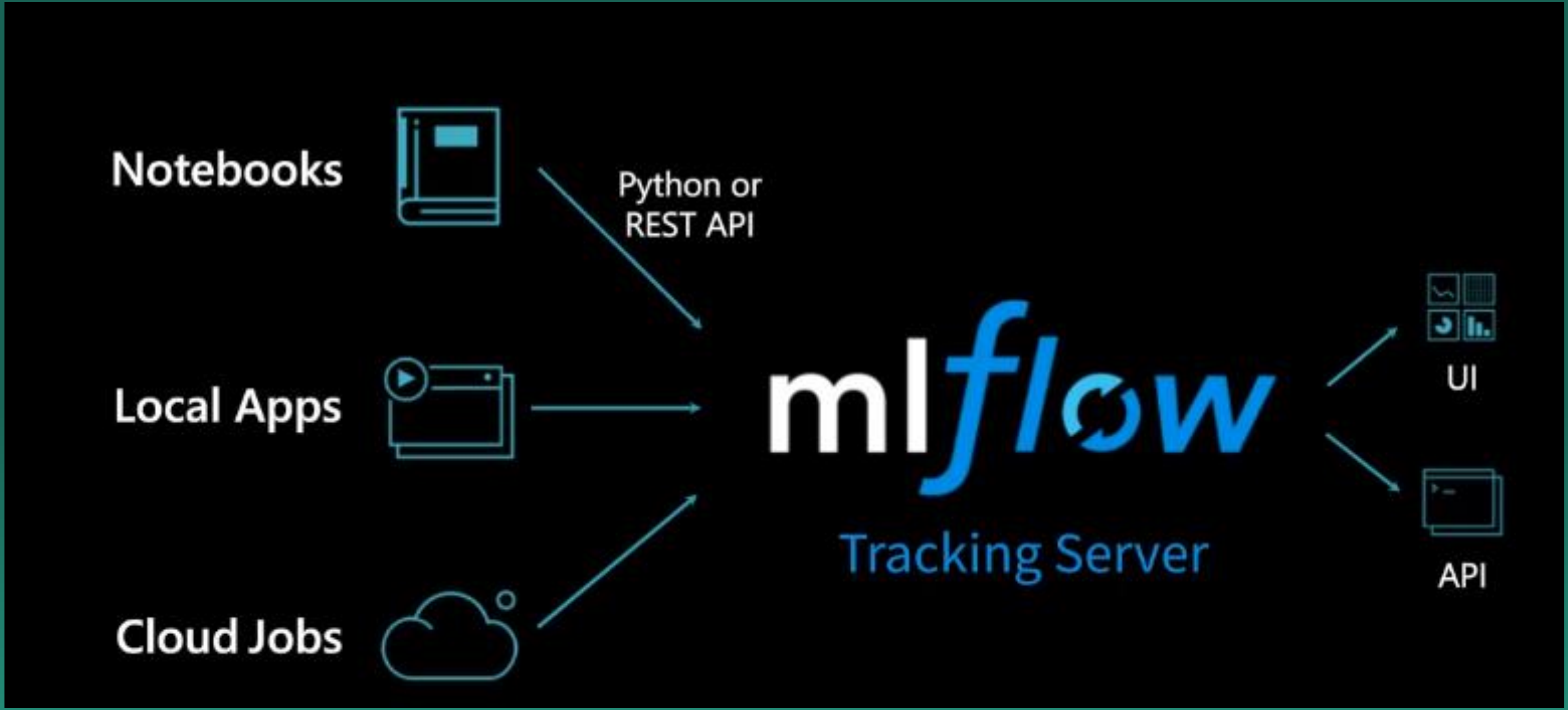
Enforce compliance and conformance to policies, standards, processes, and architecture.

Define clear approach to resolve data related issues

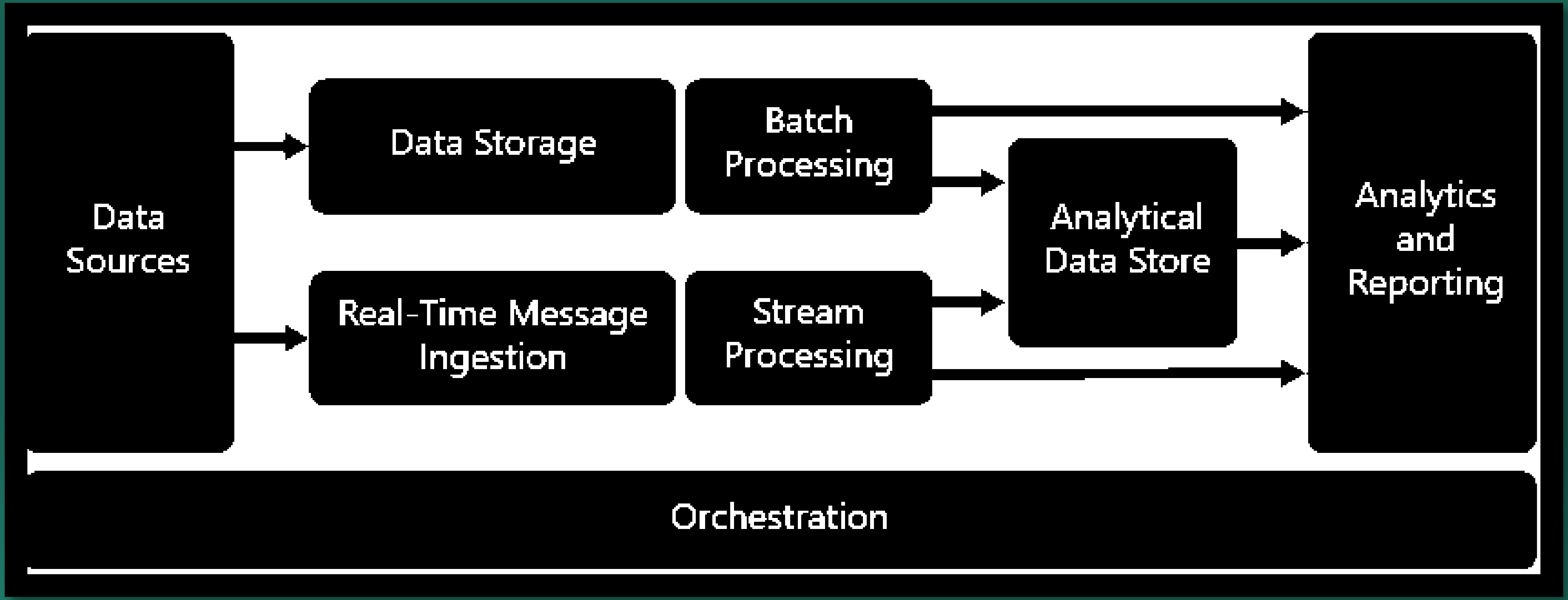
EXAMPLE TYPICAL MACHINE LEARNING LIFE CYCLE ON CLOUD & ON PREMESIS



NEED ABILITY TO TRACK ML EXPERIMENTS



MODERN END TO END ML ARCHITECTURE



CLOUD STRATEGY – PRIVATE / PUBLIC? WHY NOT BOTH!

Private Cloud

- More flexibility—your organization can customize its cloud environment to meet specific business needs.
- Improved security—resources are not shared with others, so higher levels of control and security are possible.
- High scalability—private clouds still afford the scalability and efficiency of a public cloud.
- Down Side – Expensive to run and maintain.

Public Cloud

- Lower costs—no need to purchase hardware or software, and you pay only for the service you use.
- No maintenance—your service provider provides the maintenance.
- Near-unlimited scalability—on-demand resources are available to meet your business needs.
- High reliability—a vast network of servers ensures against failure.
- Down Side – Shared resources – Less security

Hybrid Cloud

- Control—your organization can maintain a private infrastructure for sensitive assets.
- Flexibility—you can take advantage of additional resources in the public cloud when you need them.
- Cost-effectiveness—with the ability to scale to the public cloud, you pay for extra computing power only when needed.
- Ease—transitioning to the cloud doesn't have to be overwhelming because you can migrate gradually—phasing in workloads over time.

ML AND APPLICATION CREDIT SCORING

A STATISTICAL METHOD OF ANALYZING PRIOR APPLICANT CHARACTERISTICS TO PREDICT THE FUTURE CREDIT BEHAVIOR OF NEW APPLICANTS. IN ML LANGUAGE, THIS IS A CLASSIFICATION TASK AND TYPICALLY IN THE DOMAIN OF SUPERVISED LEARNING

CLEARLY DEFINED OBJECTIVES

Identify 'GOOD' and 'BAD' accounts from historical data based on application, bureau and alternative data source. Applicant deemed willing and able to pay or not as first screen

For applicant willing and able to pay, identify deal characteristics that impact his/her ability to pay using the sample historical data. Allows clients to set loan amount and risk price (rates)

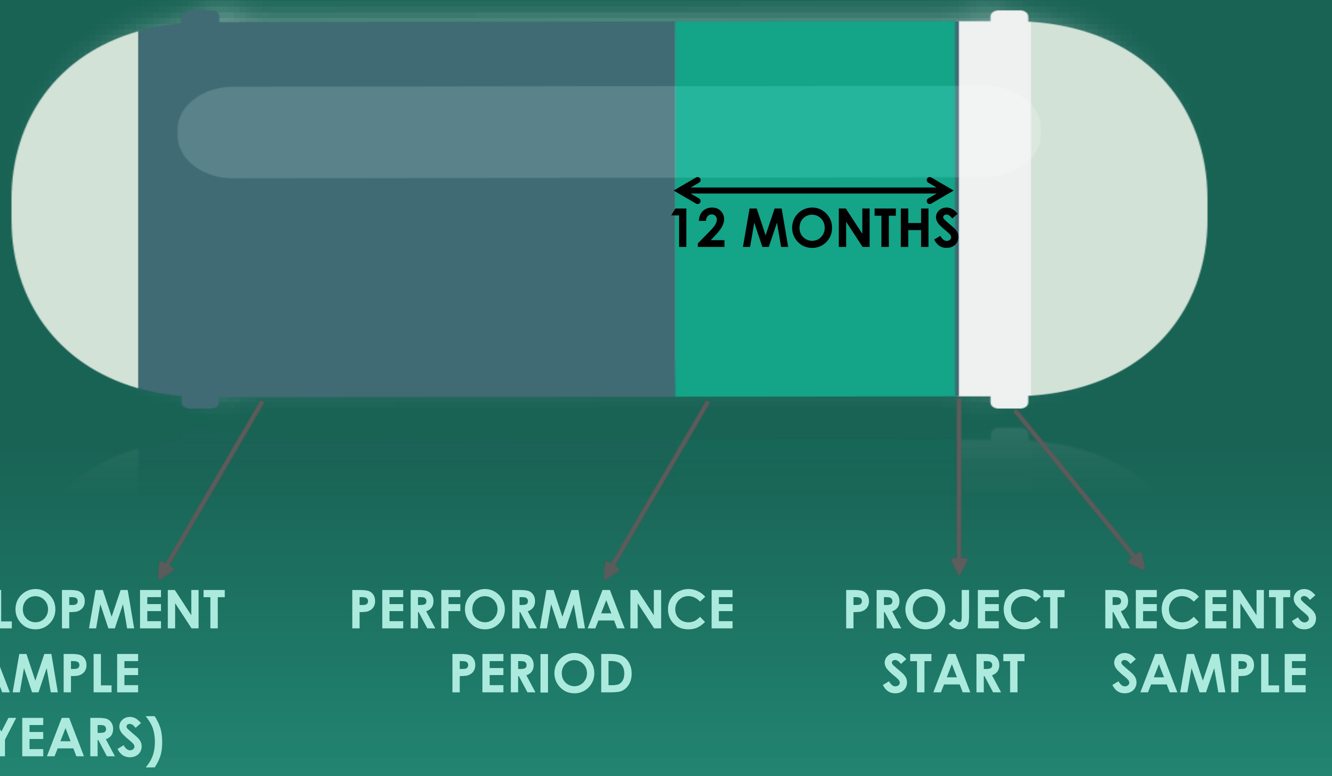
Usual Definition of Creditworthy (GOOD) and Uncreditworthy (BAD)

- **DELINQUENCY BASED :**

GOOD	-	At most once 30 days past due
BAD	-	90 days past due or worse
GREY	-	All others

- **ALTERNATIVE DEFINITIONS CAN BE STATED.**

The Development Time Capsule



CBD'S DOMAIN EXPERTISE FOR FEATURE ENGINEERING

WITH MORE THAN 800 VARIABLES CREATED

We Use Application Level Data such as income, home ownership, job etc. obtained at time of application

We pull credit bureau reports and pull inquiries, collections, trade records etc. obtained at time of application

Pull Alternative Data such as utility bill payments, bank transaction records where approved etc. via alt data providers

The Credit Approval Process

← Willingness-To-Pay Evaluation →

EXTERNAL INFORMATION ↓

APPLICATION → PRESCREEN → DEMOGRAPHIC CRITERIA → DEMOGRAPHIC AND EXTERNAL CRITERIA → OVERRIDES →

PRESCREEN ↓	DEMOGRAPHIC CRITERIA ↓	DEMOGRAPHIC AND EXTERNAL CRITERIA ↓	OVERRIDES ↓
DECLINE	DECLINE	DECLINE	DECLINE

EXAMPLE CRITERIA FOR DECLINE

- INCOME < $6,000	- NON-HOMEOWNER	- BANKRUPTCY
- AGE < 18	- NO BANK ACCOUNT	- EVER 90+ DAYS DELINQUENT
- UNEMPLOYED	- LISTED MANY DEPENDENTS	

The Credit Approval Process

Ability To Pay Evaluation

DEAL ANALYSIS

DECLINE

APPROVE

DECLINE WITH COUNTEROFFER

APPROVE AND CROSS-SELL

REJECT INFERENCE APPROACH KEY

Past Declined Applications Must Be Included in Development Sample

Must Infer behavior of declined applicant had credit facility been granted

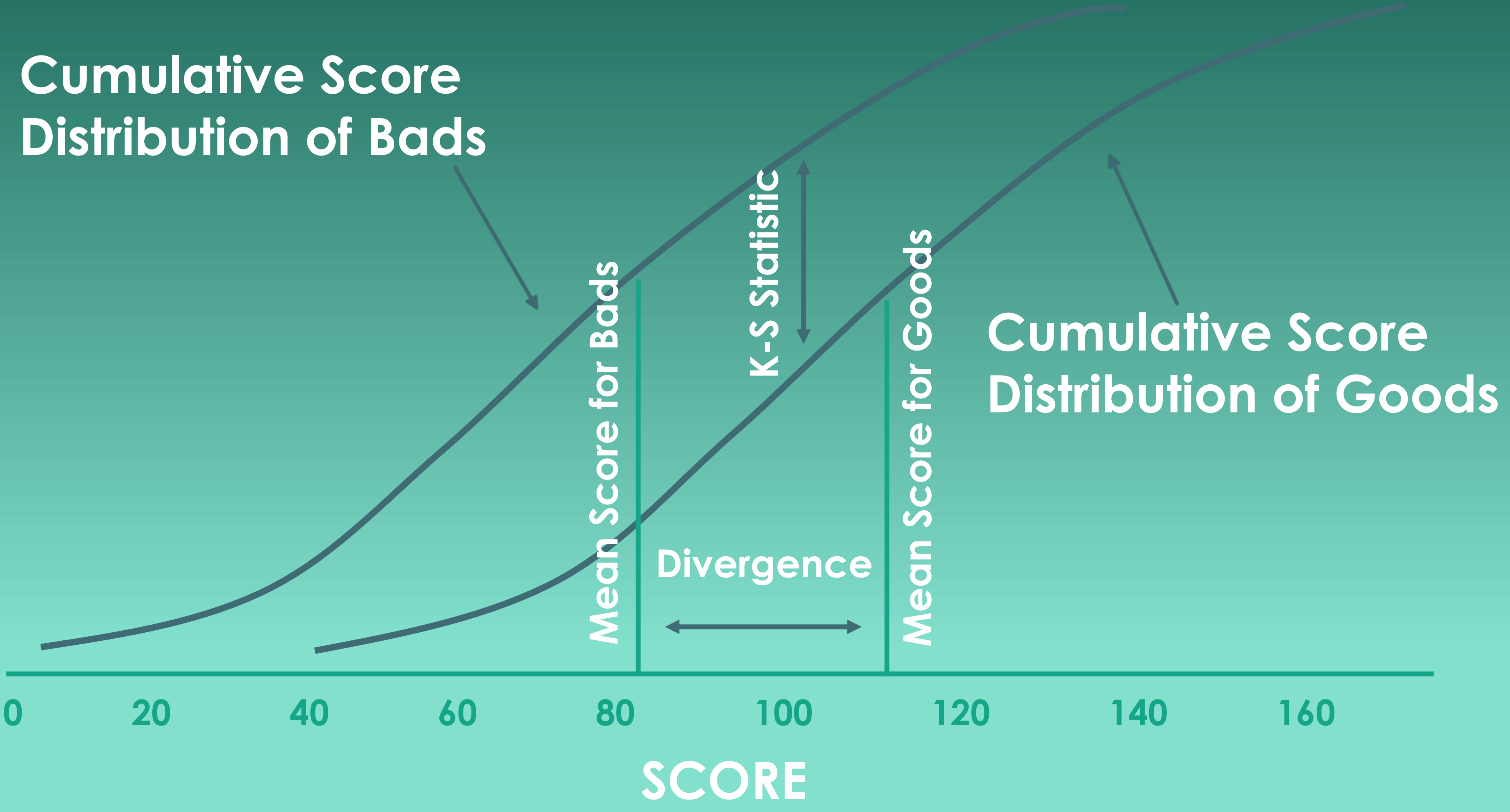
MACHINE LEARNING MODELS USED IN CREDIT UNDERWRITING

- Linear Classifiers such as Logistic Regression, Lasso, Ridge, Elastisnet Regression, SVM with Linear Kernel
- Non Linear Tree Based Classifiers such as Decision Trees, Random Forest, Gradient Boosted Trees family
- Deep Learning Models such as Multi Layer Perceptron's
- Ensemble of Models or Ensemble of Best of Breed Models for Wisdom of Crowd.

Typical Model Strength Measures

- Kolmogorov-Smirnov Statistic
- Area Under The Curve
- F1 or a customized weighted F1 score
- Business Specific Metric

The Higher the KS The Better



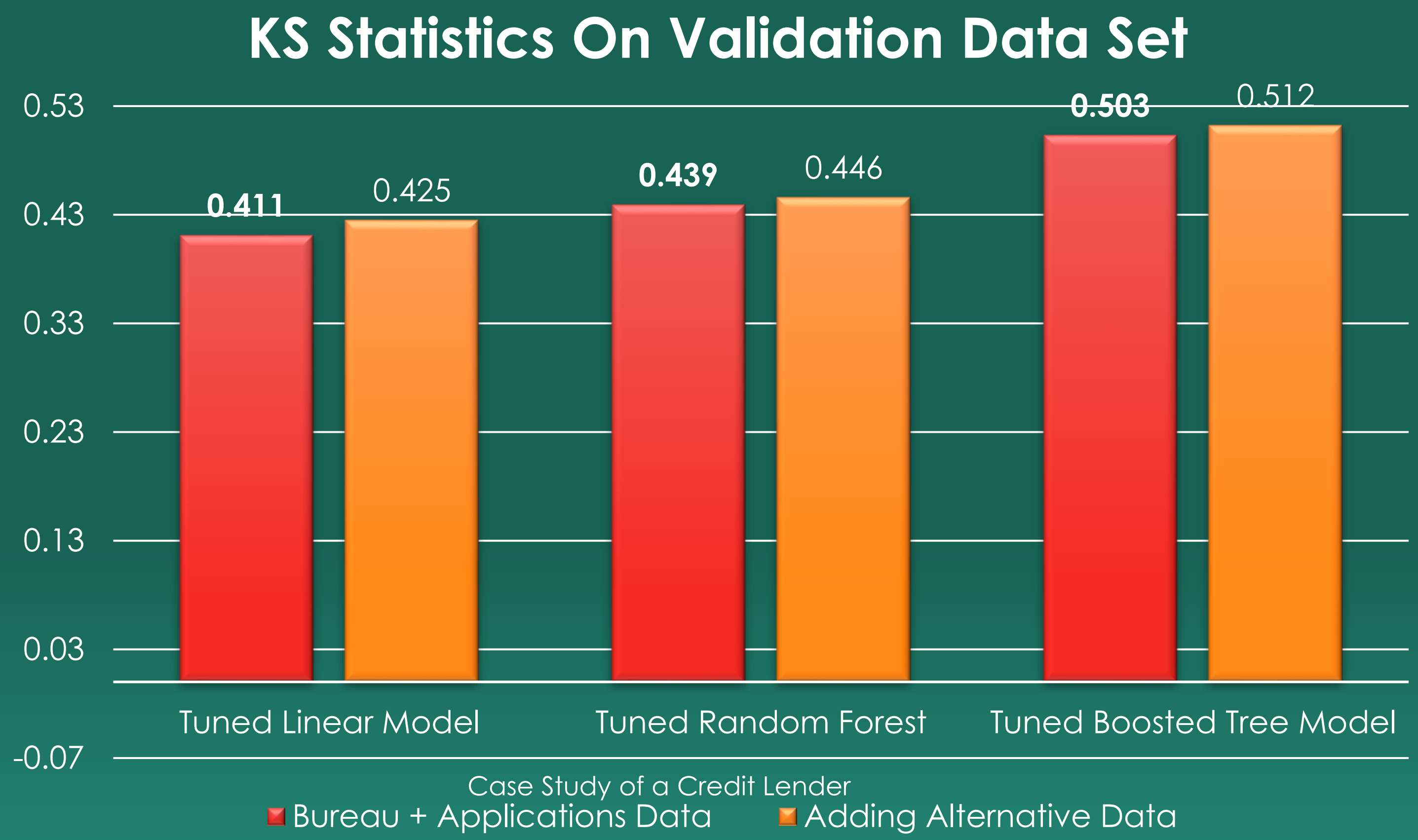
WHEN TO USE WHAT?

Non linear models may need more data to converge

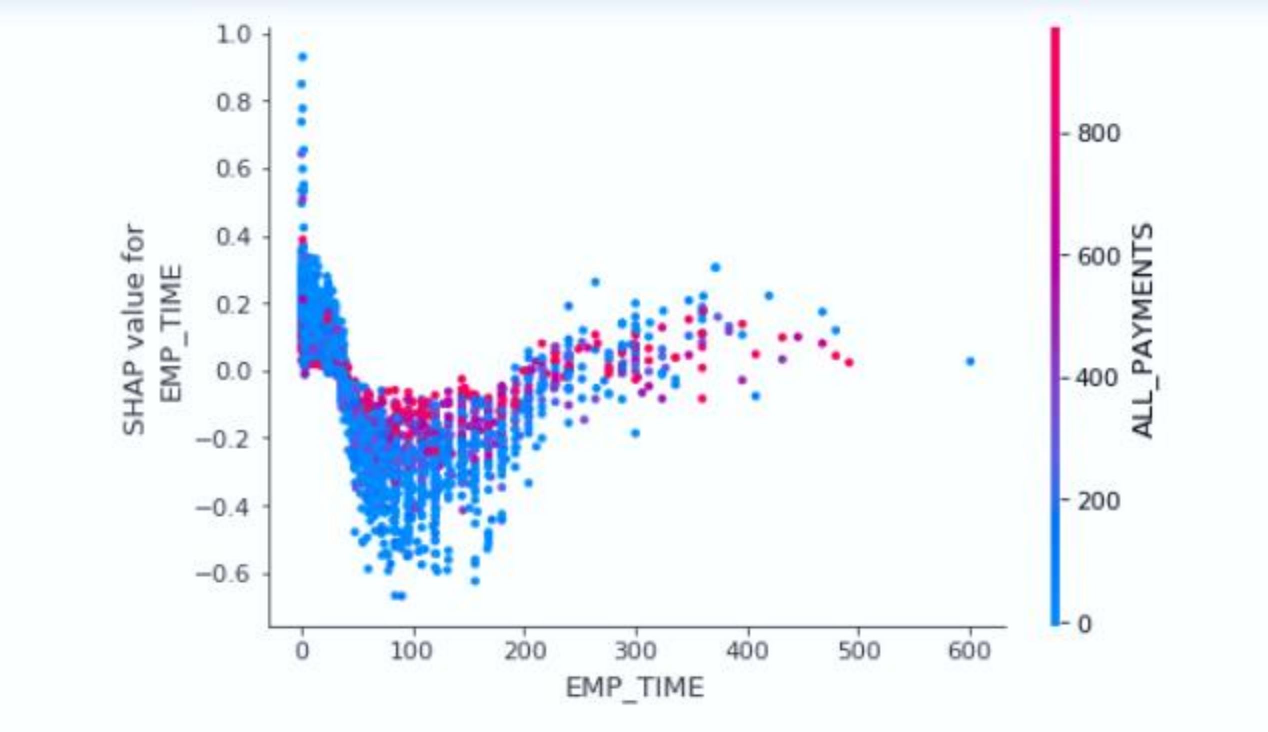
Non linear models may need more computational resources especially for model hyper-parameter tuning

Mix of Expert Judgement and Experimenting With Different Models picking one of the top models

NON LINEAR MODELS + INCLUSION OF ALTERNATIVE DATA = PERFORMANCE BOOST IN SOME CASES



NON LINEAR MODELS CAN DO BETTER WHEN FEATURE INTERACTIONS ARE NON LINEAR



In this example, the length of applicant being employed reduces risk but the relationship depends on the all monthly payments variable. High payments and long employment history does not mean lower risk

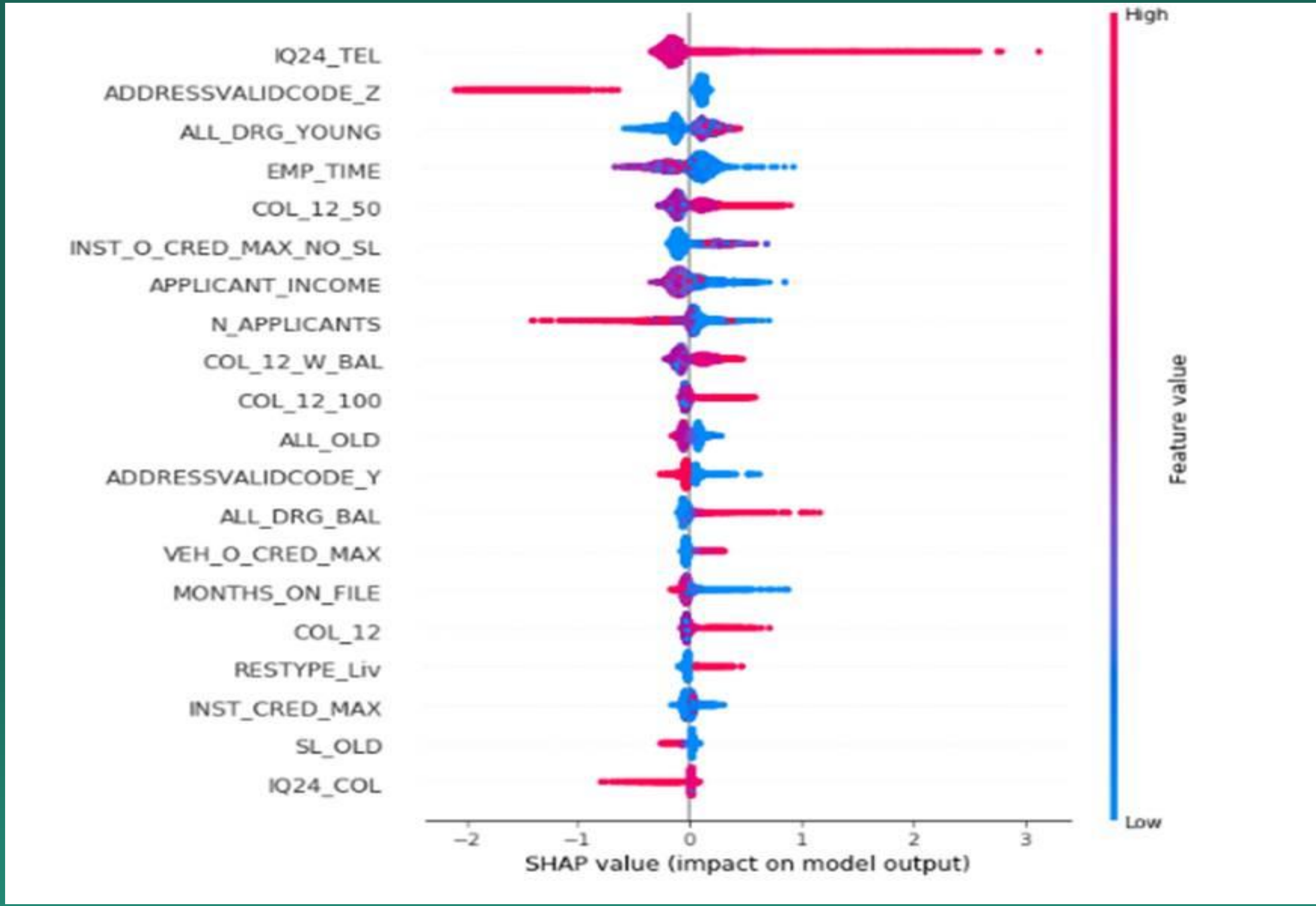
THREE LAYER APPROACH TO BEST MODEL SELECTION

1. Run Multiple Models on Cloud and rank them by metric.
2. Hyper-parameter Tuning of Best Model
3. Sense check model.

INTERPRETING DECISIONS OF NON LINEAR MODELS

SHAP (SHapley Additive exPlanations) is a unified approach to explain the output of any machine learning model. SHAP connects game theory with local explanations, and representing one of the only possible consistent and locally accurate additive feature attribution method based on expectations

GLOBAL MODEL INTERPRETATIONS



LOCAL INTERPRETABILITY IN LOG ODDS

- Why did The Model Predict High Log Odds of a Decline For This Applicant?