
Bertrand Le Nézet - October 2018
MODEL RISK in AI/ML
WEAPONS OF MATH DESTRUCTION
ABOUT ME
INTRO
BLACK BOX
FAST BACKWARD
CREDIT SCORING
LIME
WRAP-UP

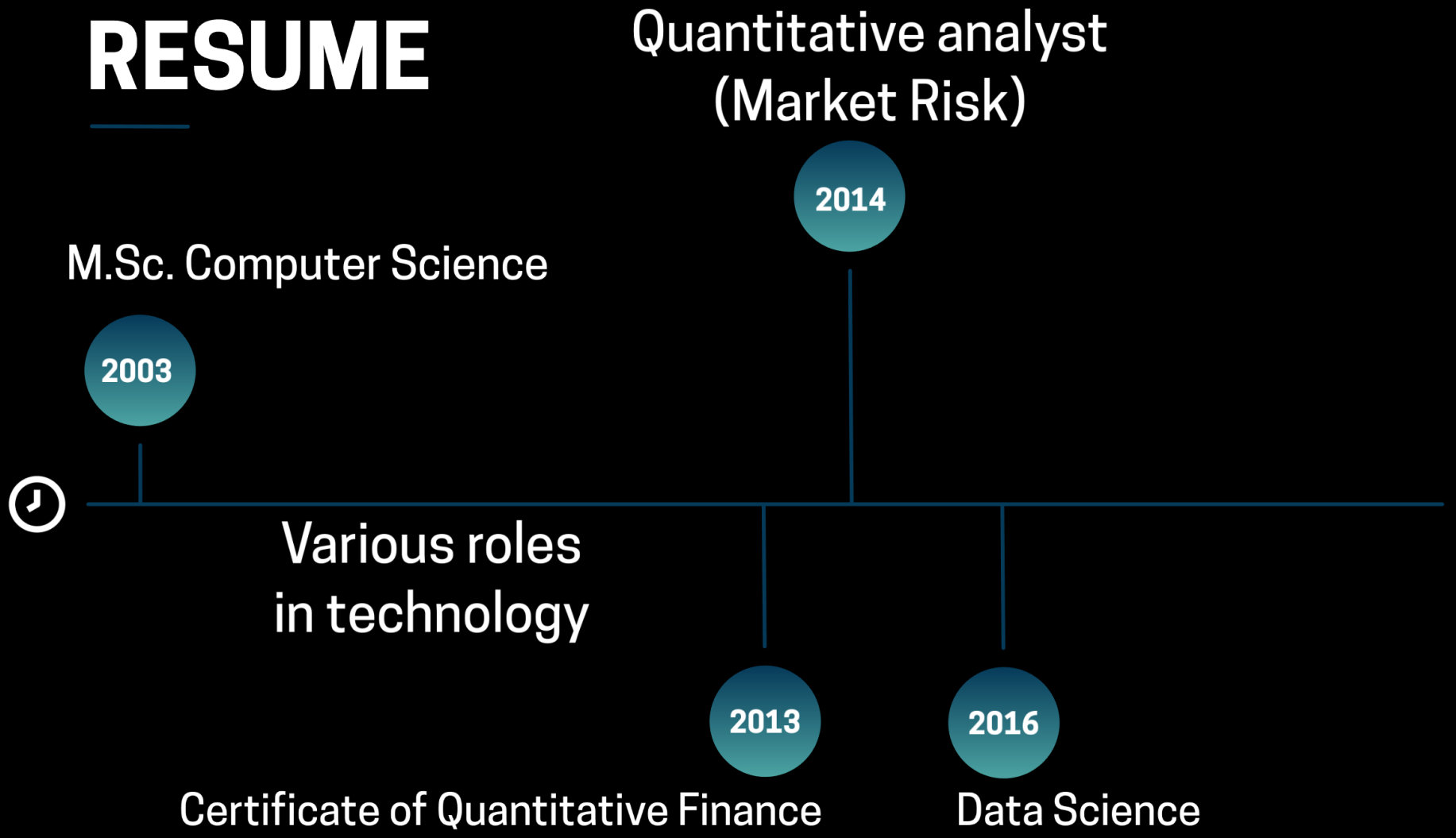
ABOUT ME

RESUME

KEY INTERESTS

HOBBIES

RESUME


Quantitative analyst
(Market Risk)
2014
M.Sc. Computer Science
2003
Various roles
in technology
2013
2016
Certificate of Quantitative Finance
Data Science

KEY INTERESTS

- Quantitative investment
- Systematic trading
- Machine learning
- Blockchain
- System development

HOBBIES

- Traveling
- Acting (Theater)
- Squash
- Cooking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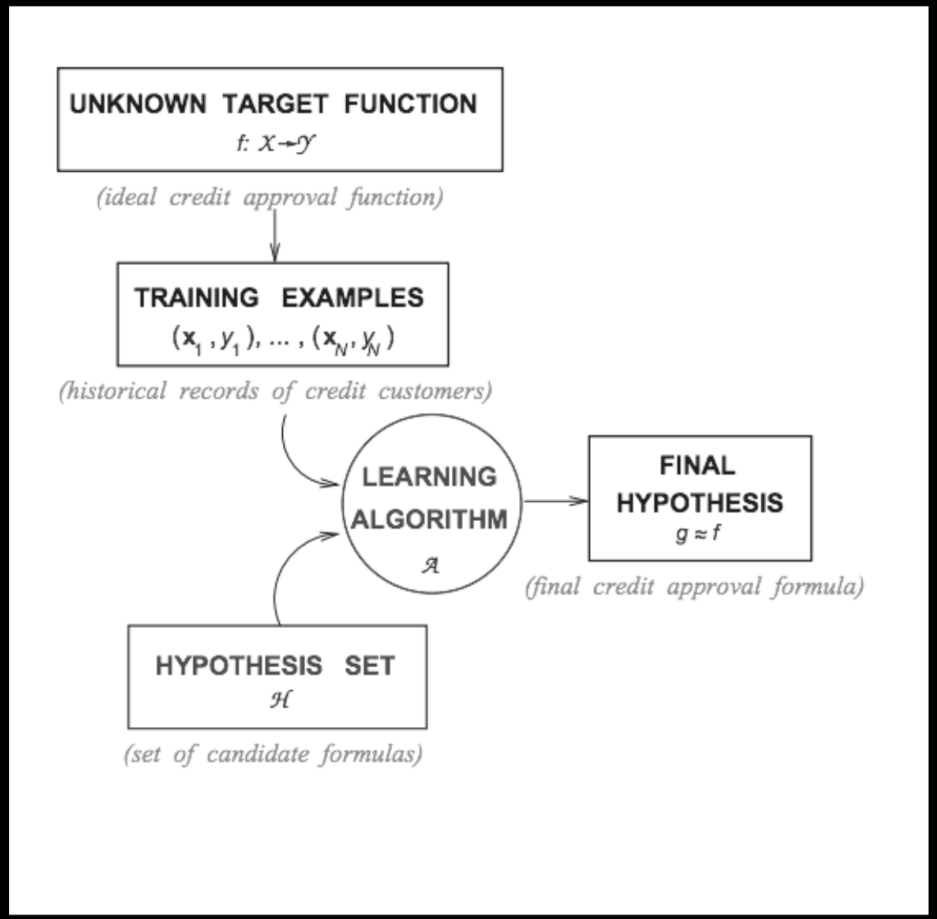
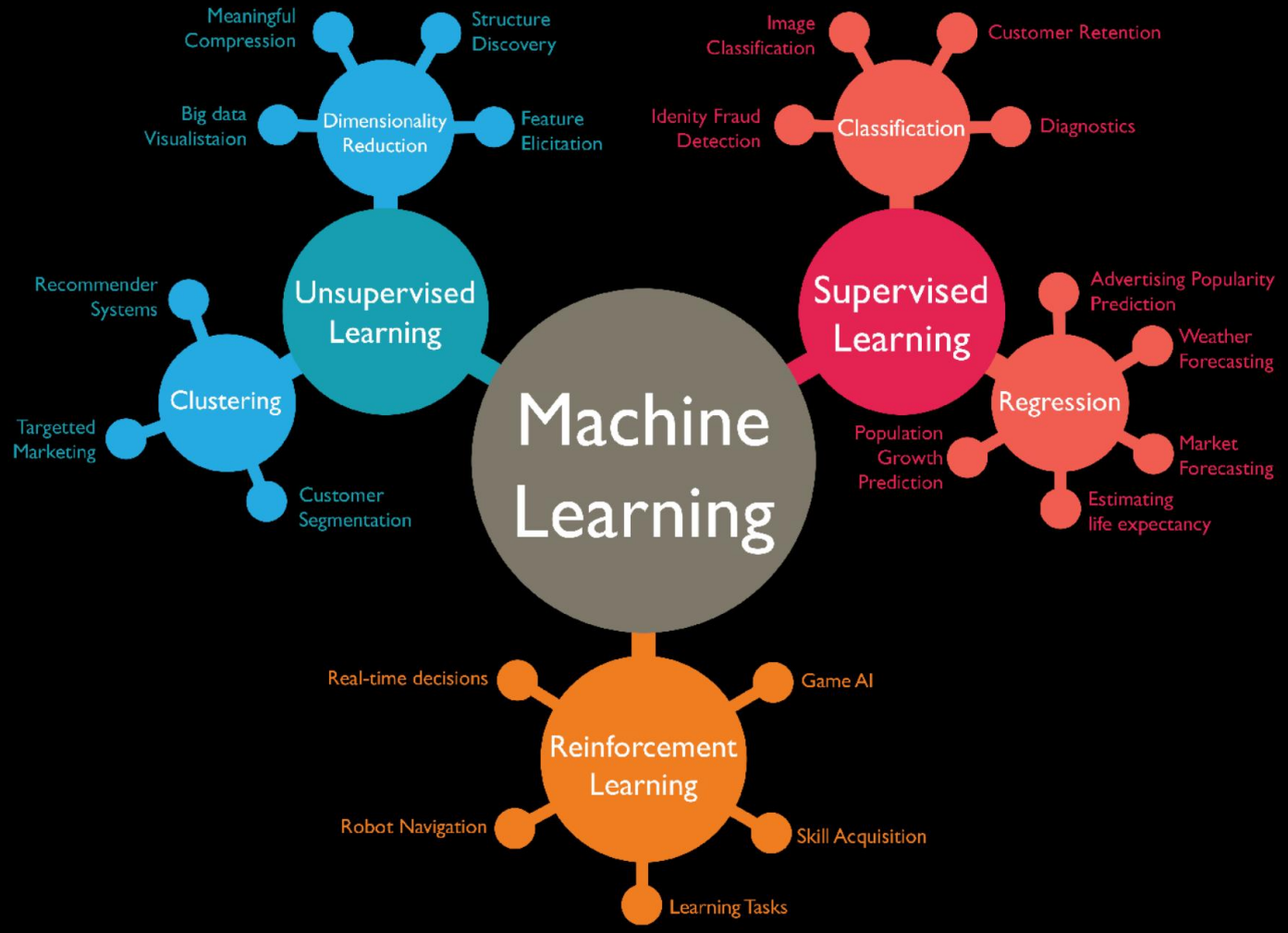
INTRO
MODEL
TECHNIQUES
AI IN FINANCE

WHAT IS A MODEL?

Machine learning (ML) models are algorithm that allows software applications to become more accurate in predicting outcomes without being explicitly programmed. The basic premise of machine learning is to build algorithms that can be trained with data and use statistical analysis to predict an outcome.



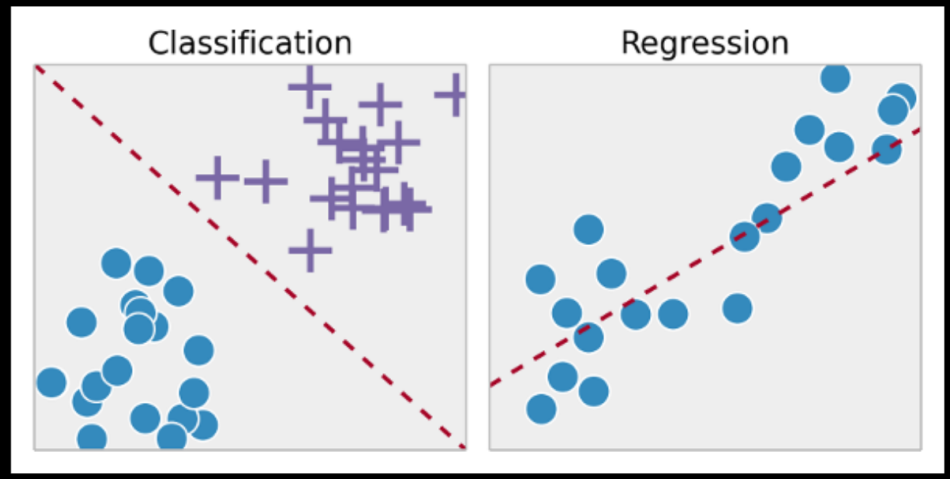
TECHNIQUES



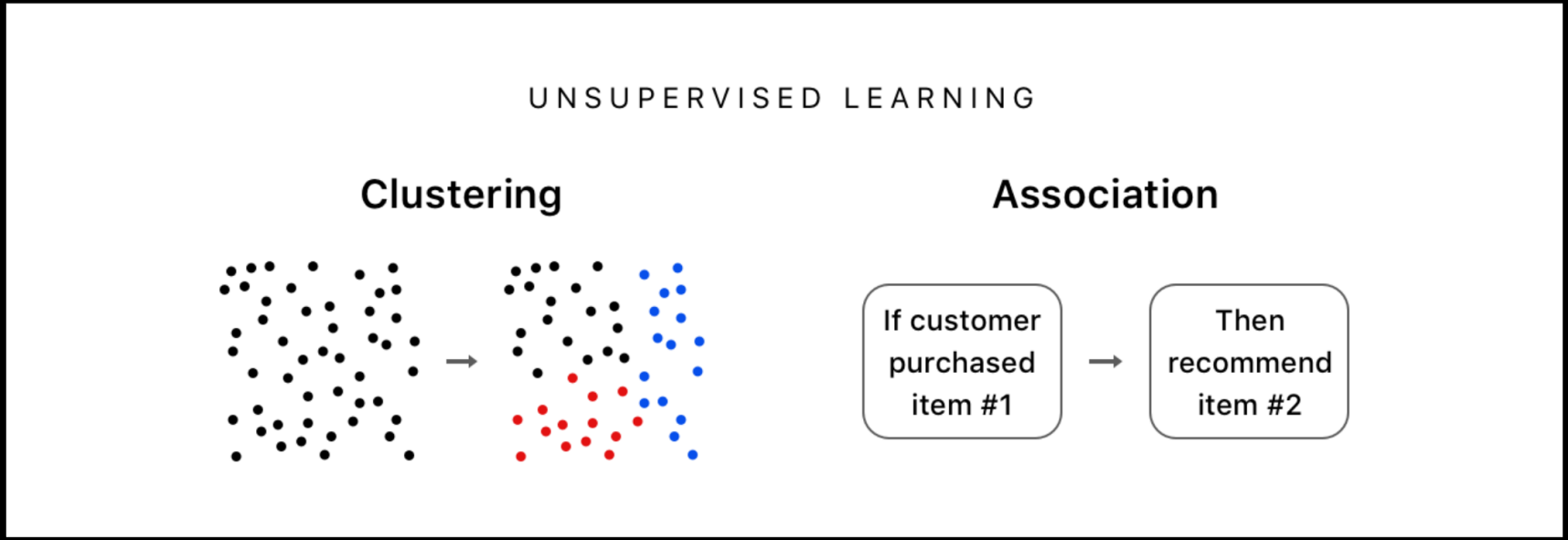
Presenter view

SUPERVISED LEARNING OUTCOME

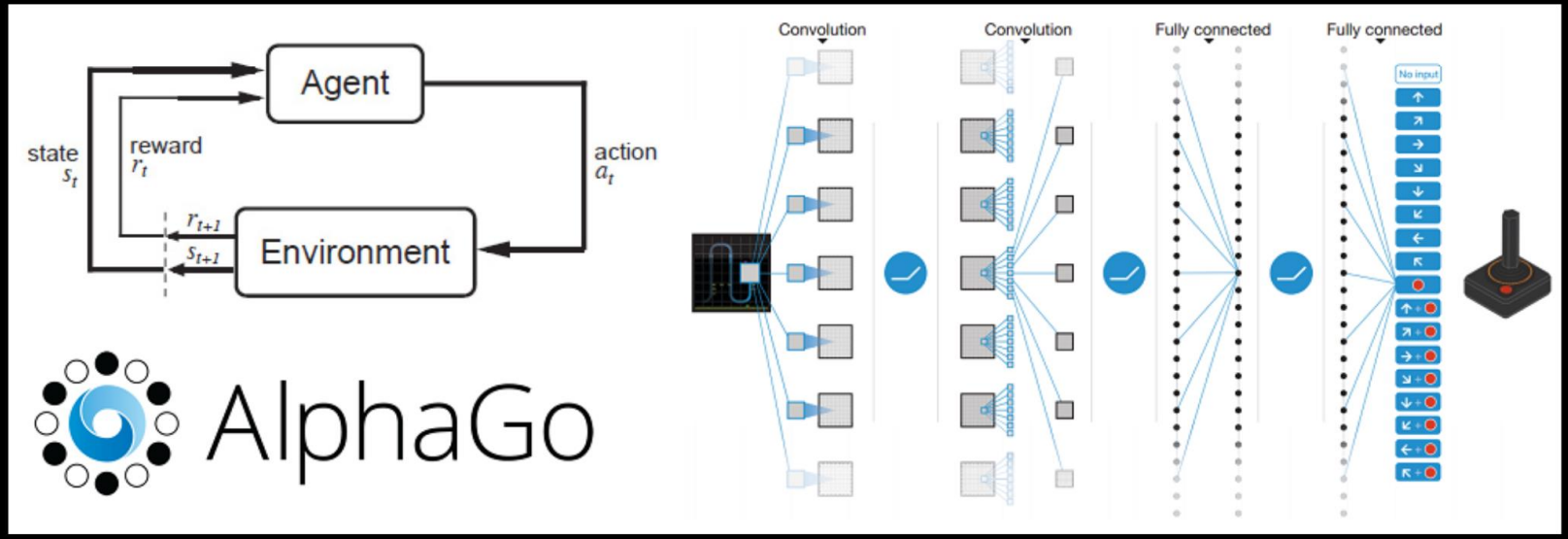
- A classification is the problem of predicting a discrete class label output. For an example, predict if the stock price of Microsoft will go up or down tomorrow. Result is often expressed as probabilities (e.g. 10% down, 90% up). Accuracy = correct predictions / total predictions.
- A regression is the problem of predicting a continuous quantity output. For example, predict the stock price of Microsoft tomorrow. Many ways to estimate accuracy. RMSE is probably most common



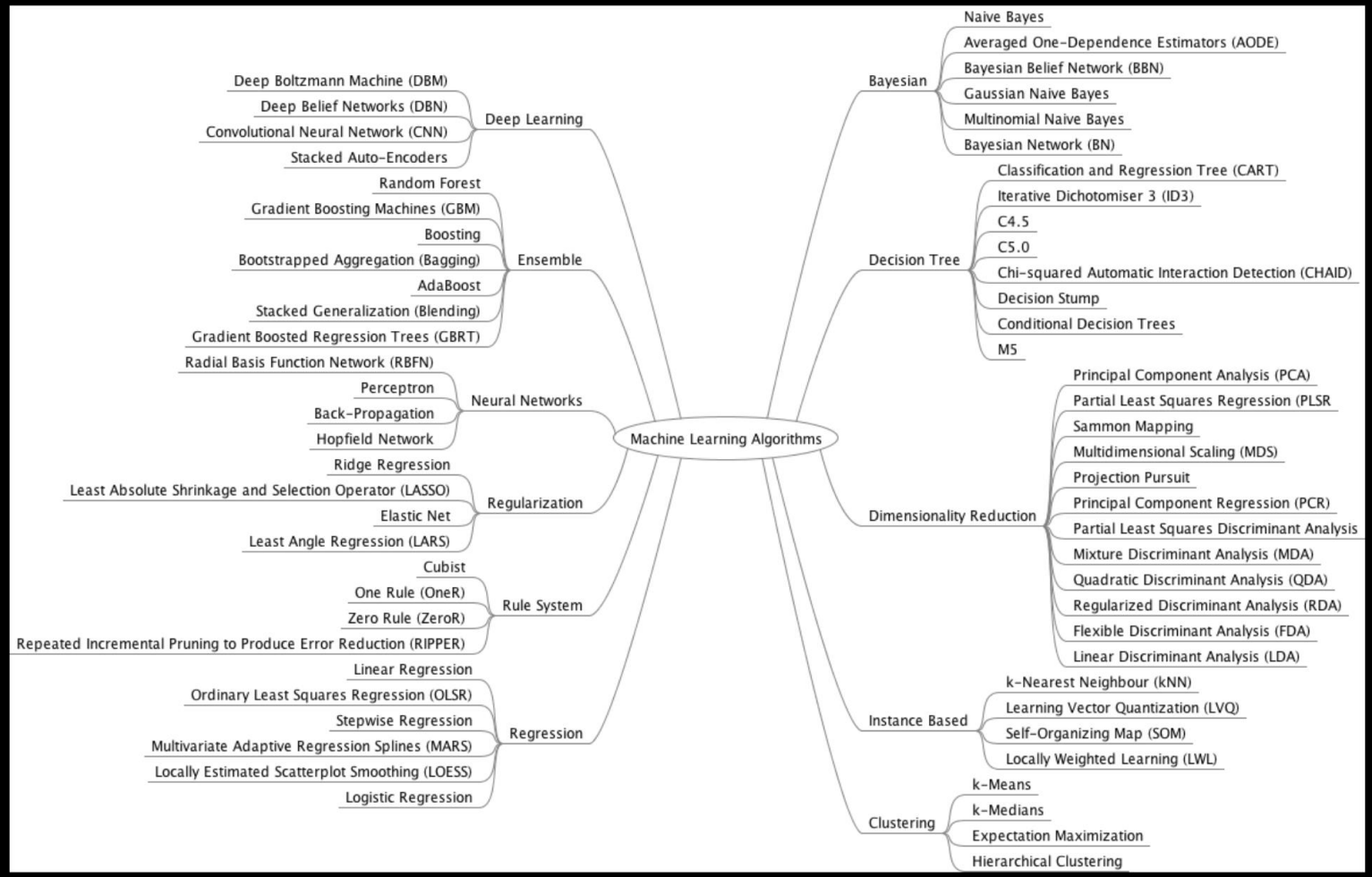
UNSUPERVISED LEARNING



REINFORCEMENT LEARNING

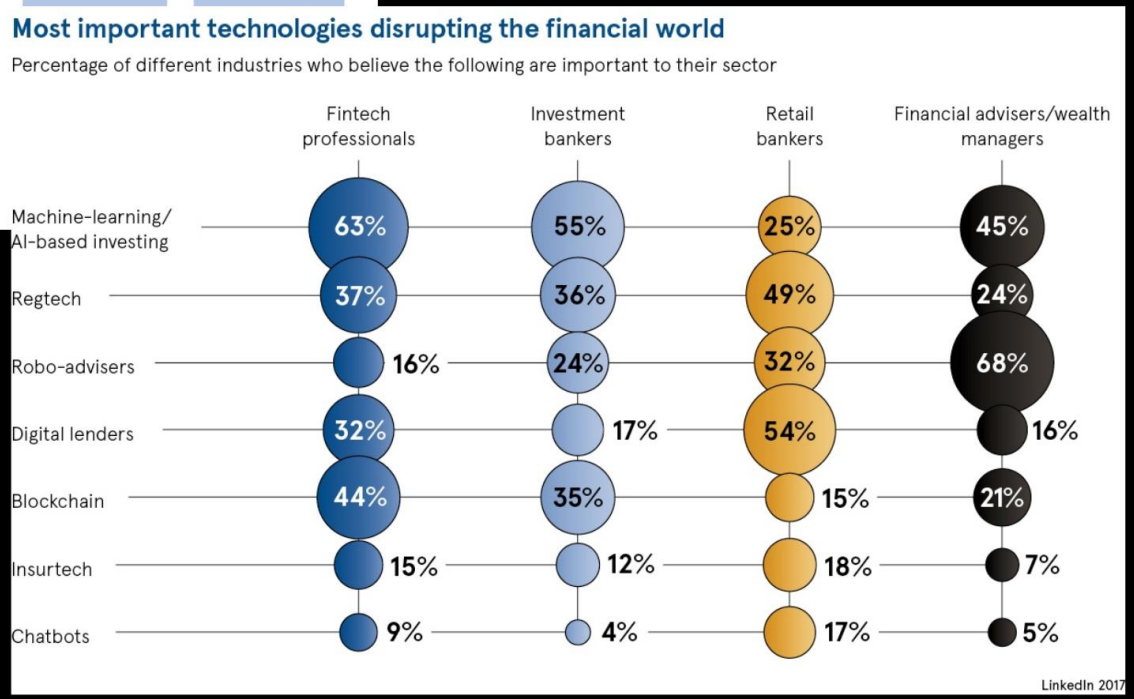


TECHNIQUES


Machine Learning Algorithms
Deep Learning
Deep Boltzmann Machine (DBM)
Deep Belief Networks (DBN)
Convolutional Neural Network (CNN)
Stacked Auto-Encoders
Ensemble
Random Forest
Gradient Boosting Machines (GBM)
Boosting
Bootstrapped Aggregation (Bagging)
AdaBoost
Stacked Generalization (Blending)
Gradient Boosted Regression Trees (GBRT)
Neural Networks
Radial Basis Function Network (RBFN)
Perceptron
Back-Propagation
Hopfield Network
Regularization
Ridge Regression
Least Absolute Shrinkage and Selection Operator (LASSO)
Elastic Net
Least Angle Regression (LARS)
Rule System
Cubist
One Rule (OneR)
Zero Rule (ZeroR)
Repeated Incremental Pruning to Produce Error Reduction (RIPPER)
Regression
Linear Regression
Ordinary Least Squares Regression (OLSR)
Stepwise Regression
Multivariate Adaptive Regression Splines (MARS)
Locally Estimated Scatterplot Smoothing (LOESS)
Logistic Regression
Bayesian
Naive Bayes
Averaged One-Dependence Estimators (AODE)
Bayesian Belief Network (BBN)
Gaussian Naive Bayes
Multinomial Naive Bayes
Bayesian Network (BN)
Decision Tree
Classification and Regression Tree (CART)
Iterative Dichotomiser 3 (ID3)
C4.5
C5.0
Chi-squared Automatic Interaction Detection (CHAID)
Decision Stump
Conditional Decision Trees
M5
Dimensionality Reduction
Principal Component Analysis (PCA)
Partial Least Squares Regression (PLSR
Sammon Mapping
Multidimensional Scaling (MDS)
Projection Pursuit
Principal Component Regression (PCR)
Partial Least Squares Discriminant Analysis
Mixture Discriminant Analysis (MDA)
Quadratic Discriminant Analysis (QDA)
Regularized Discriminant Analysis (RDA)
Flexible Discriminant Analysis (FDA)
Linear Discriminant Analysis (LDA)
Instance Based
k-Nearest Neighbour (kNN)
Learning Vector Quantization (LVQ)
Self-Organizing Map (SOM)
Locally Weighted Learning (LWL)
Clustering
k-Means
k-Medians
Expectation Maximization
Hierarchical Clustering

ARTIFICIAL INTELLIGENCE IN FINANCE

Marketing	Process automation	Security	Underwriting and credit scoring	Algorithmic trading	Asset Management
- Client profiling - Recommendation of financial products	- Chatbots - Call-center automation - Paperwork automation (e.g. Damage estimation for insurance) - Gamification of employee training, and more. - Virtual recruiter	- Financial monitoring (Money laundering, etc.) - Network security	- Credit scoring - Current account / Mortgage portfolio modeling	- AI trading - Market prediction with alternative data (satelite)	- Robo-Advisor / ETFs / - Sentiment Analysis

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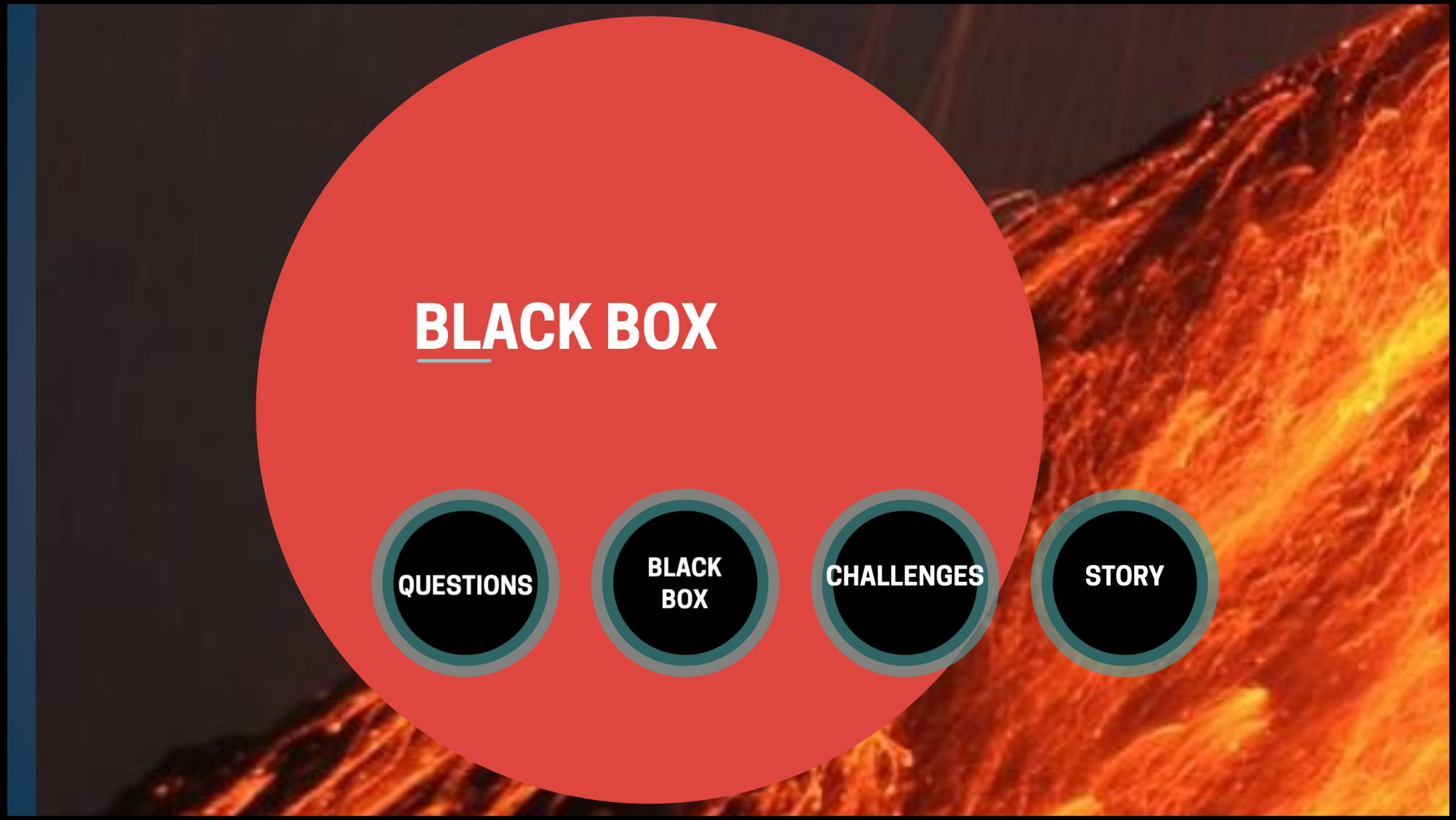
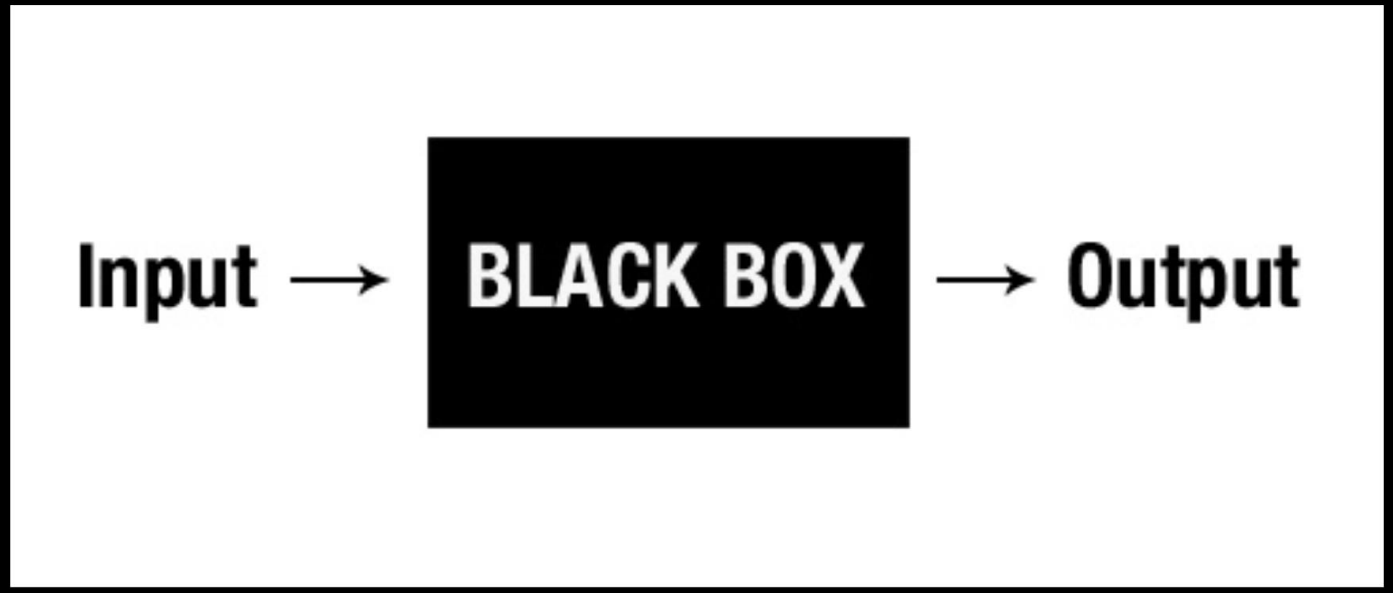

BLACK BOX
QUESTIONS
BLACK BOX
CHALLENGES
STORY

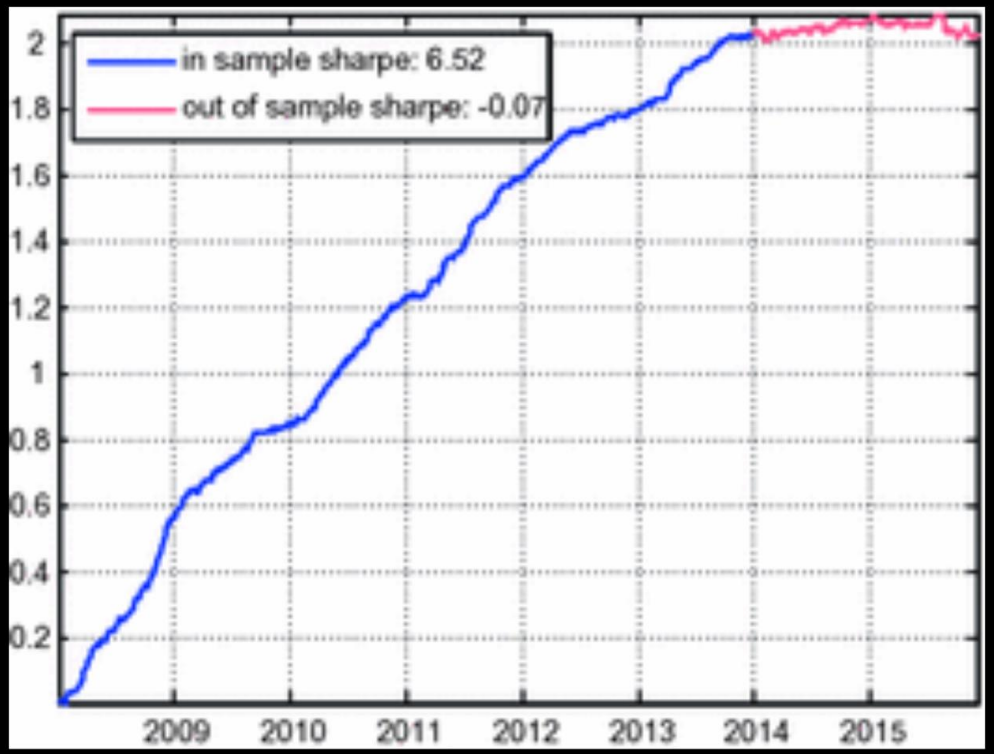
QUESTIONS WE NEED TO ANSWER

- Should I offer a loan to this customer?
- What should be the insurance premium for this customer?
- Is this transaction related to terrorism financing?

BLACK BOX



BLACK BOX


in sample sharpe: 6.52
out of sample sharpe: -0.07
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
2009
2010
2011
2012
2013
2014
2015

CHALLENGES

- Is this model robust?
- Do i understand this model?
- Can i trust this model?
- How can i explain this model?

STORY

Education

‘Creative … motivating’ and fired

Sarah Wysocki was out of work for only a few days after she was fired by DCPS last year. She is now teaching at Hybla Valley Elementary School in Fairfax County. (Jahi Chikwendiu/The Washington Post)

By **Bill Turque**
March 6, 2012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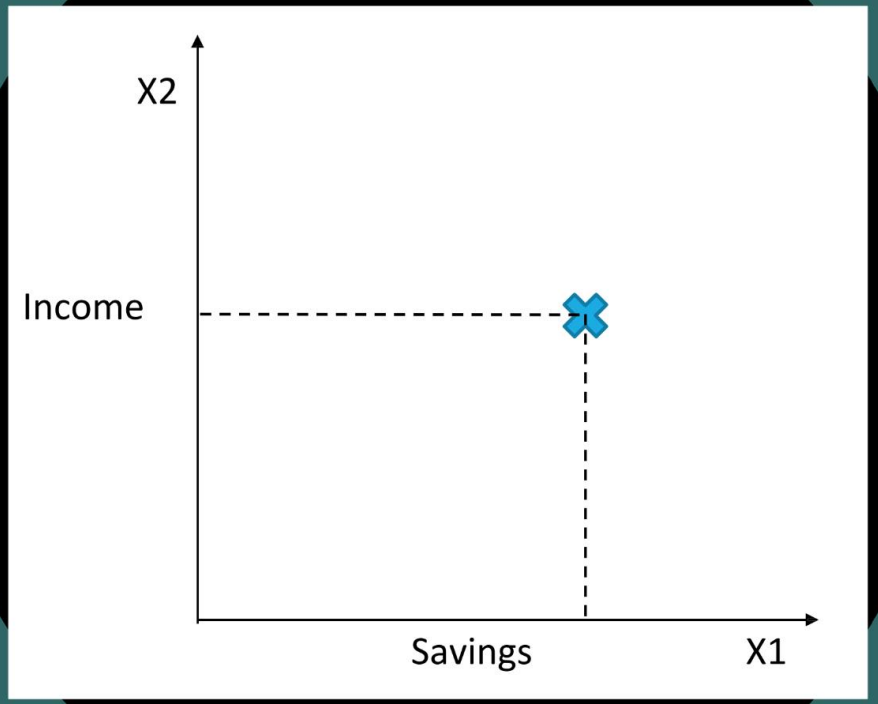
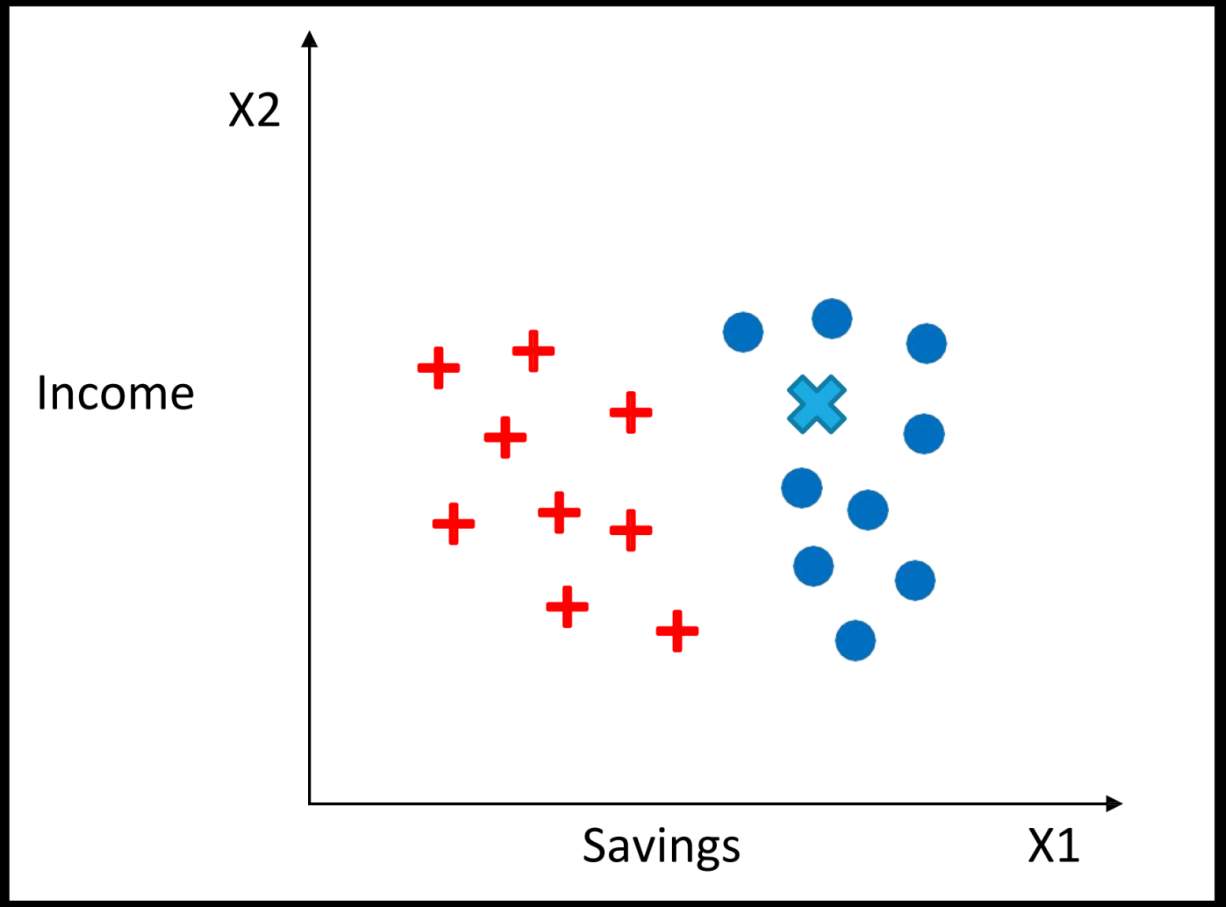
HOW DID WE GET THERE?

- MODEL
- SIMPLE MODEL
- TREE
- MORE COMPLEX
- ACCURACY / INTERPRETABILITY
- NEXT?

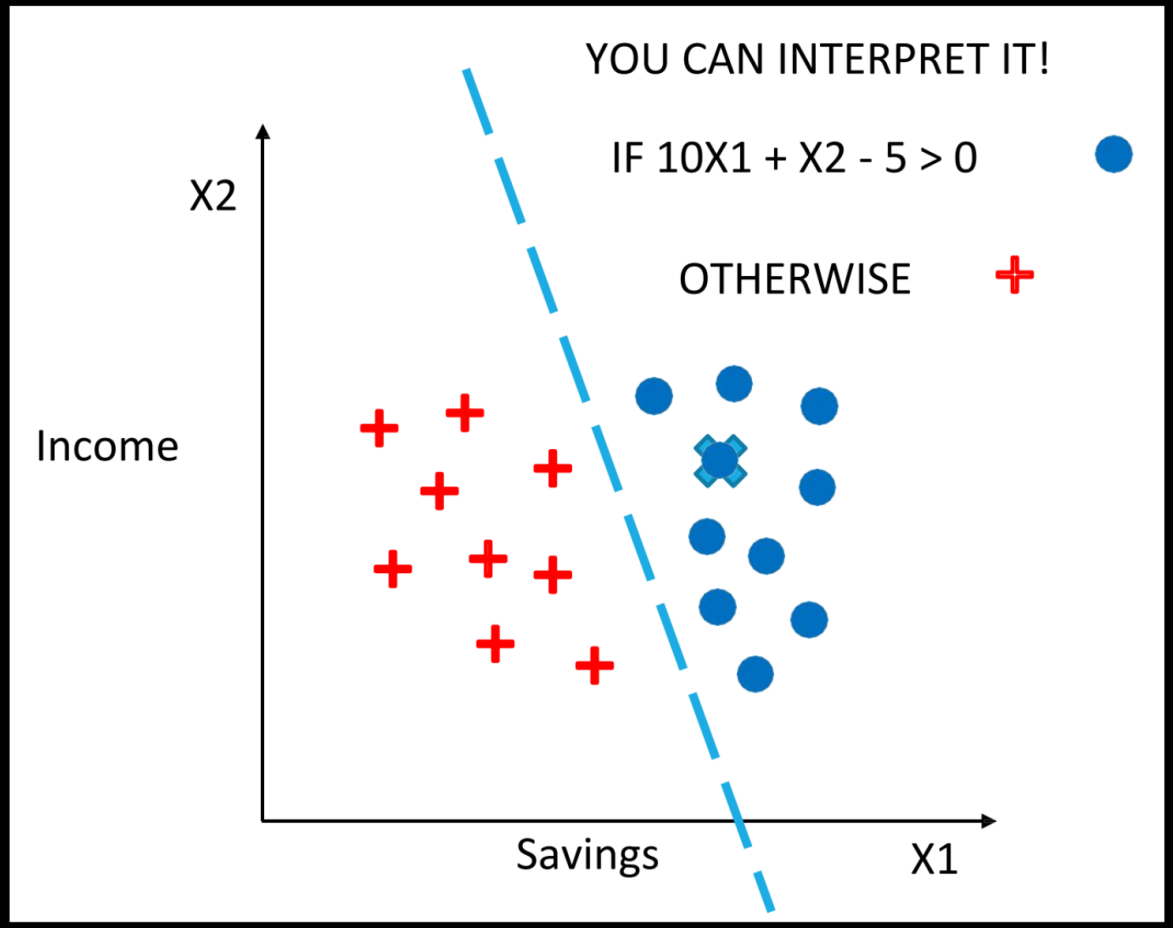
WILL THE LOAN DEFAULT?



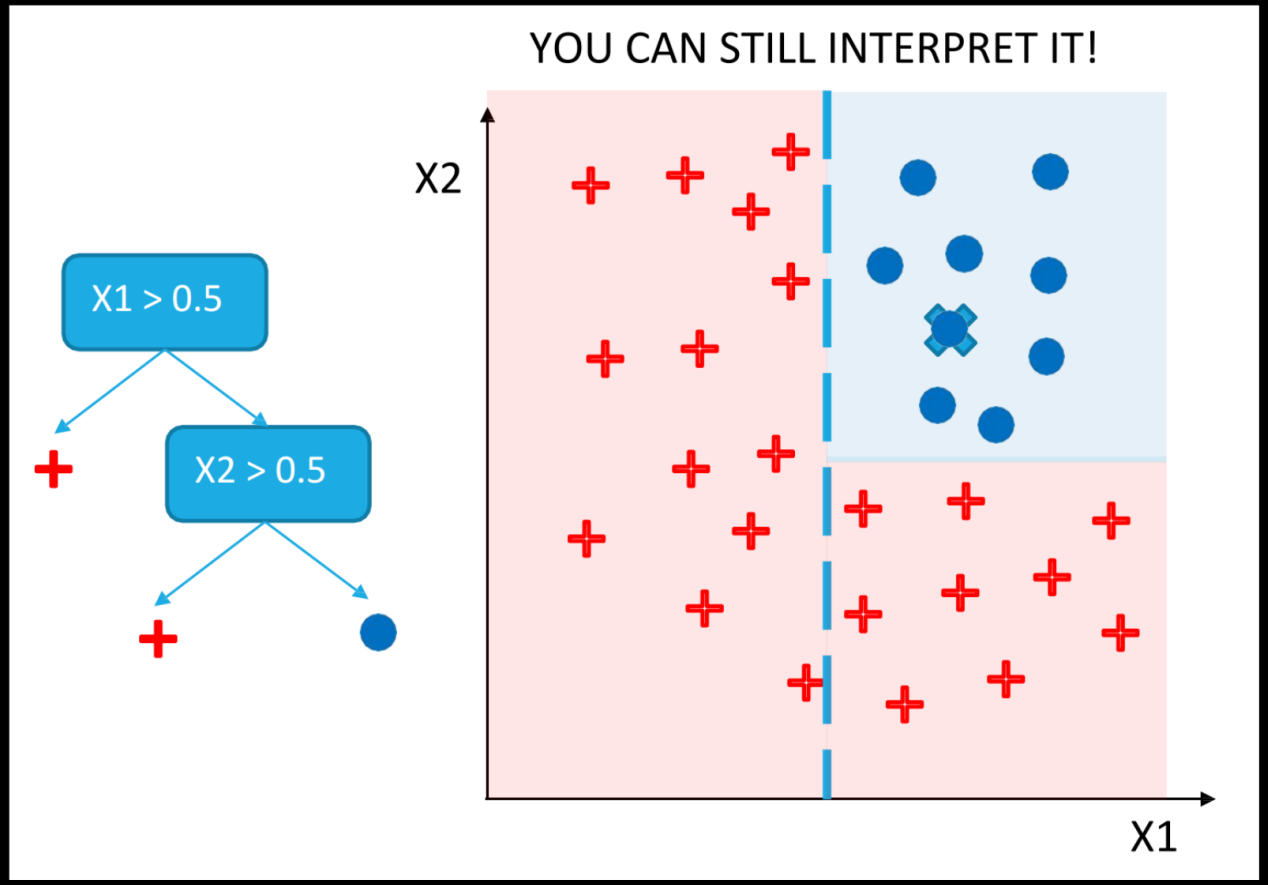
HISTORICAL DATA



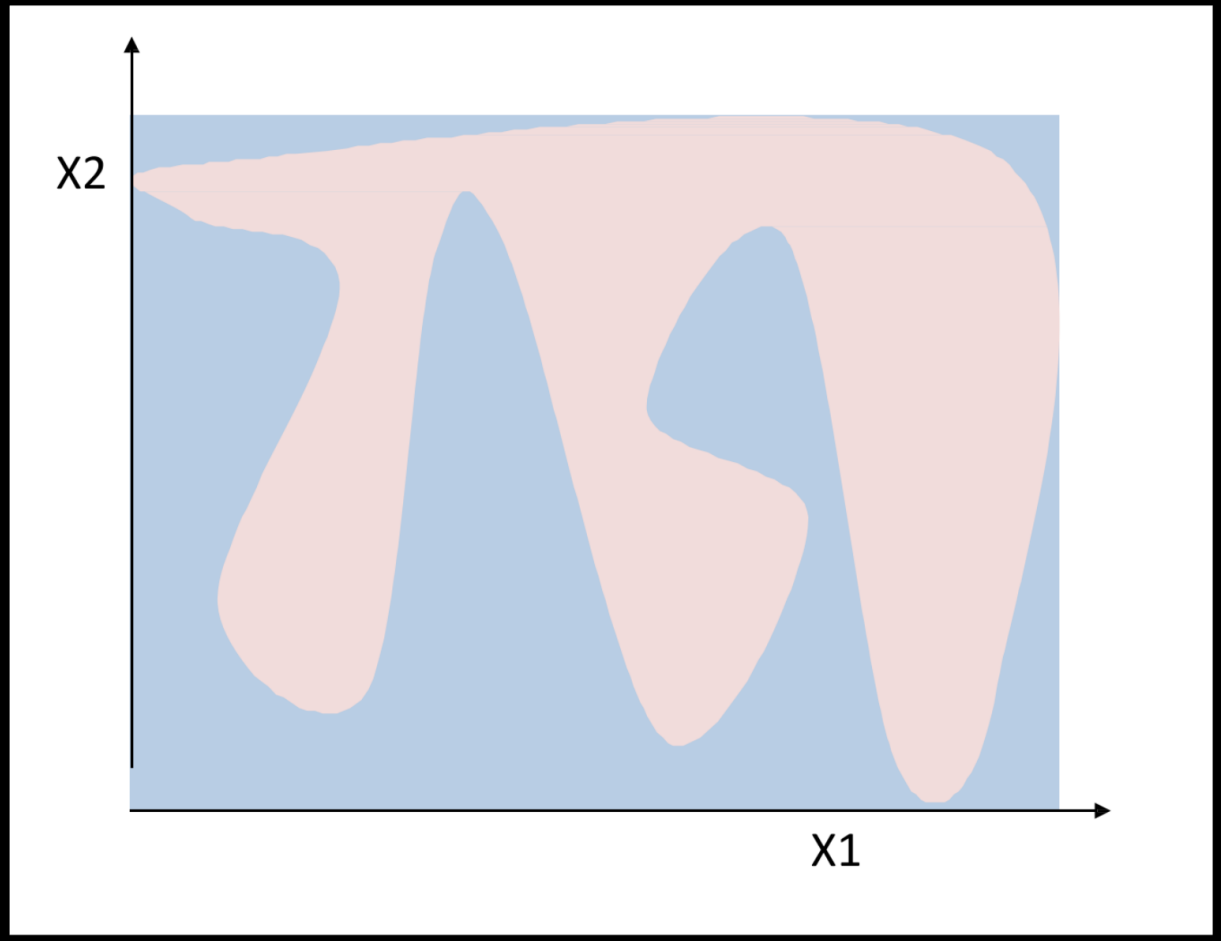
LINEAR CLASSIFIERS



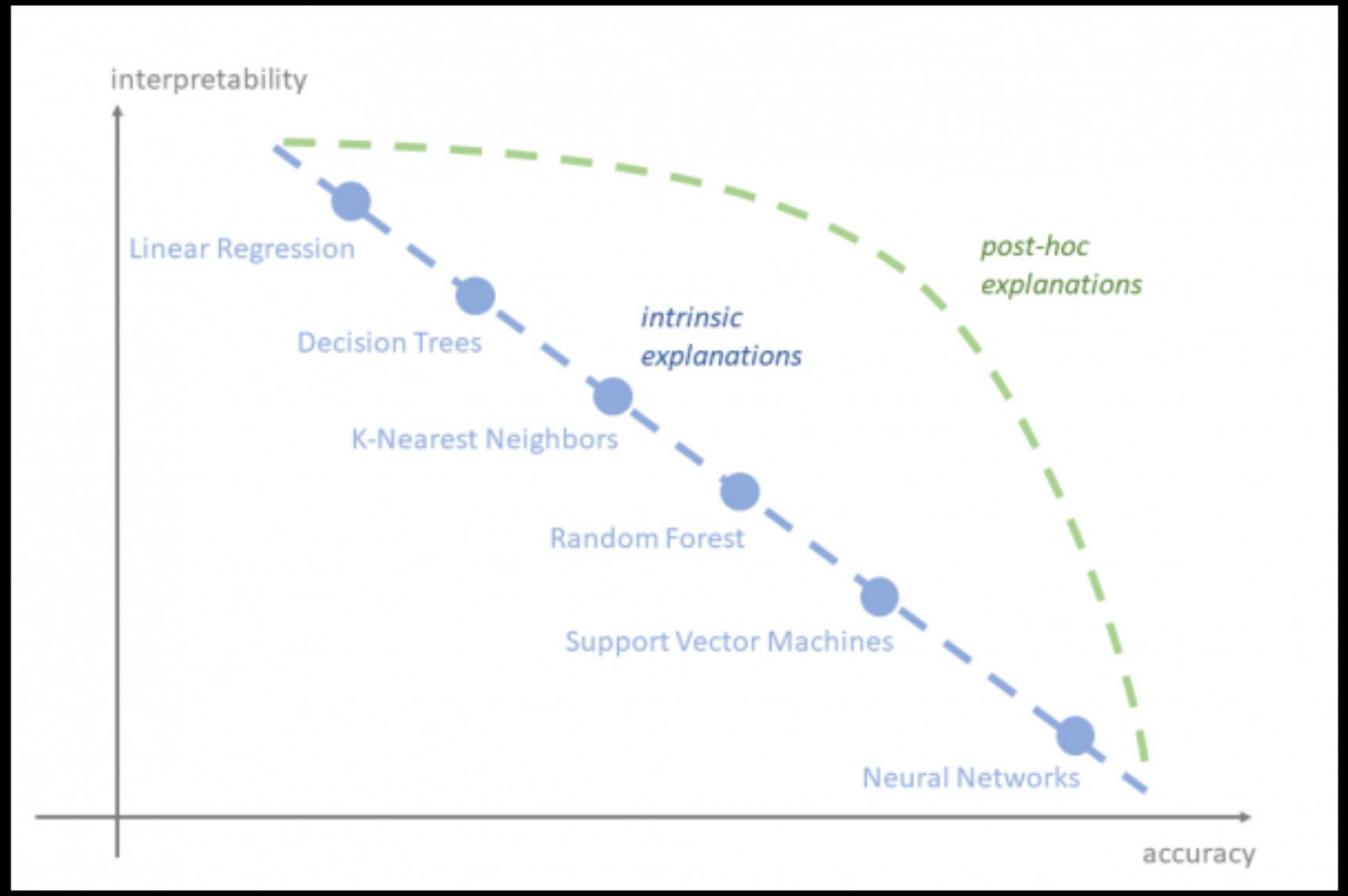
DECISION TREE



More Complexity & More Dimensions

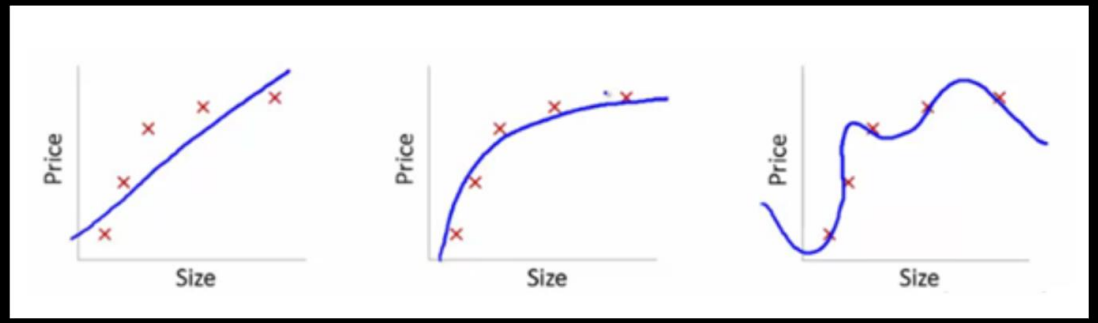


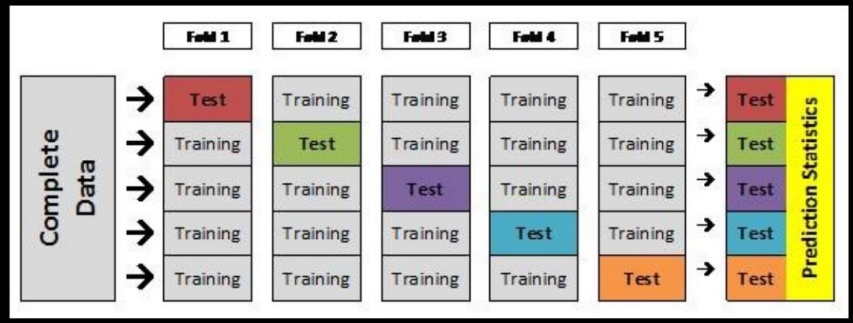
ACCURACY vs INTERPRETABILITY



WHAT PEOPLE DO TO GAIN TRUST?

- Restrict ourselves to only interpretable models
- Measure Accuracy (held-out data, cross validation)
- A/B testing





WHAT PEOPLE DO TO GAIN TRUST?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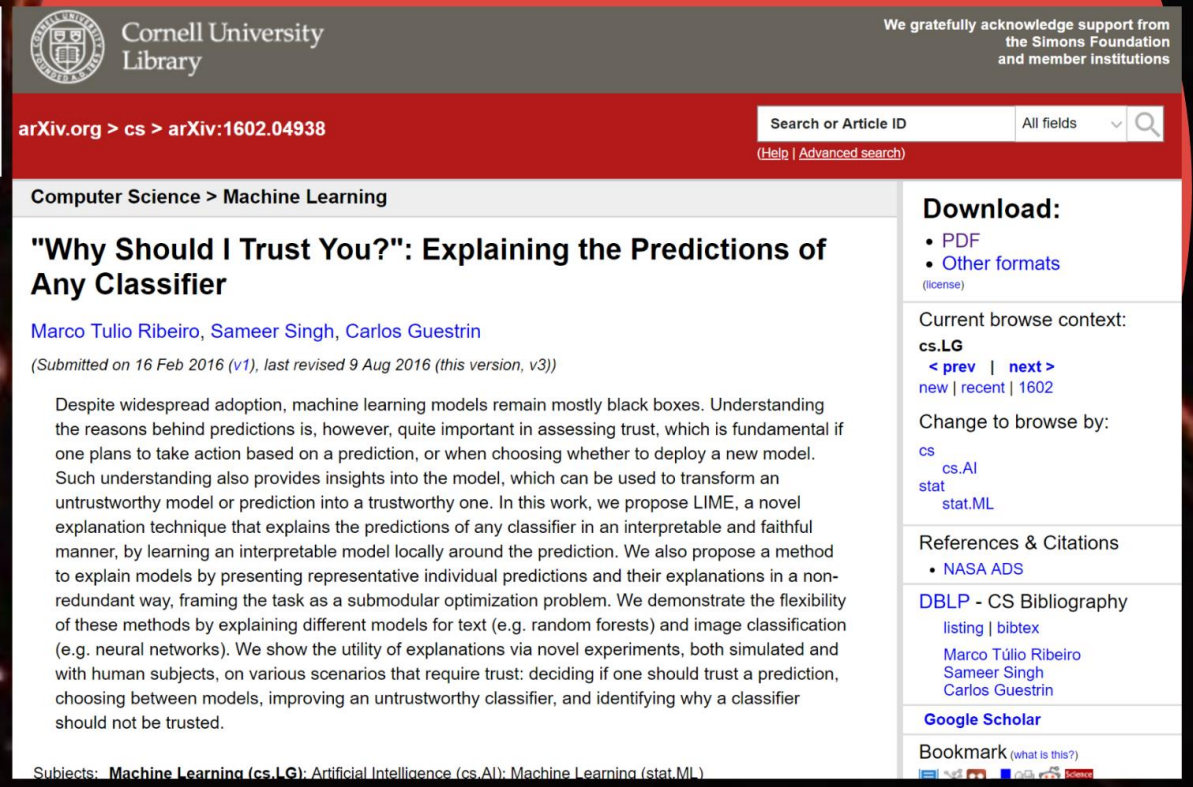
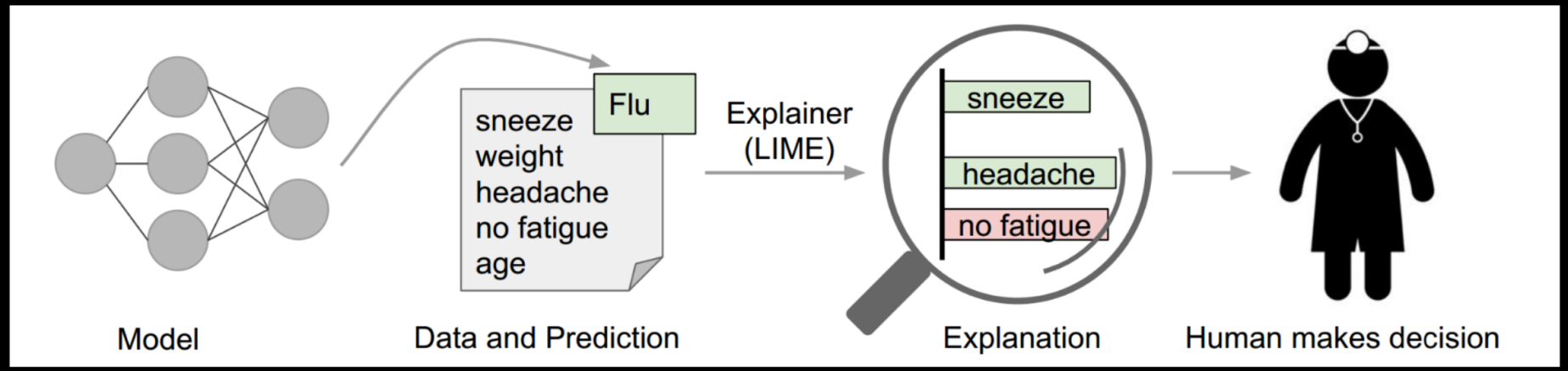
Local Interpretable Model-agnostic Explanations

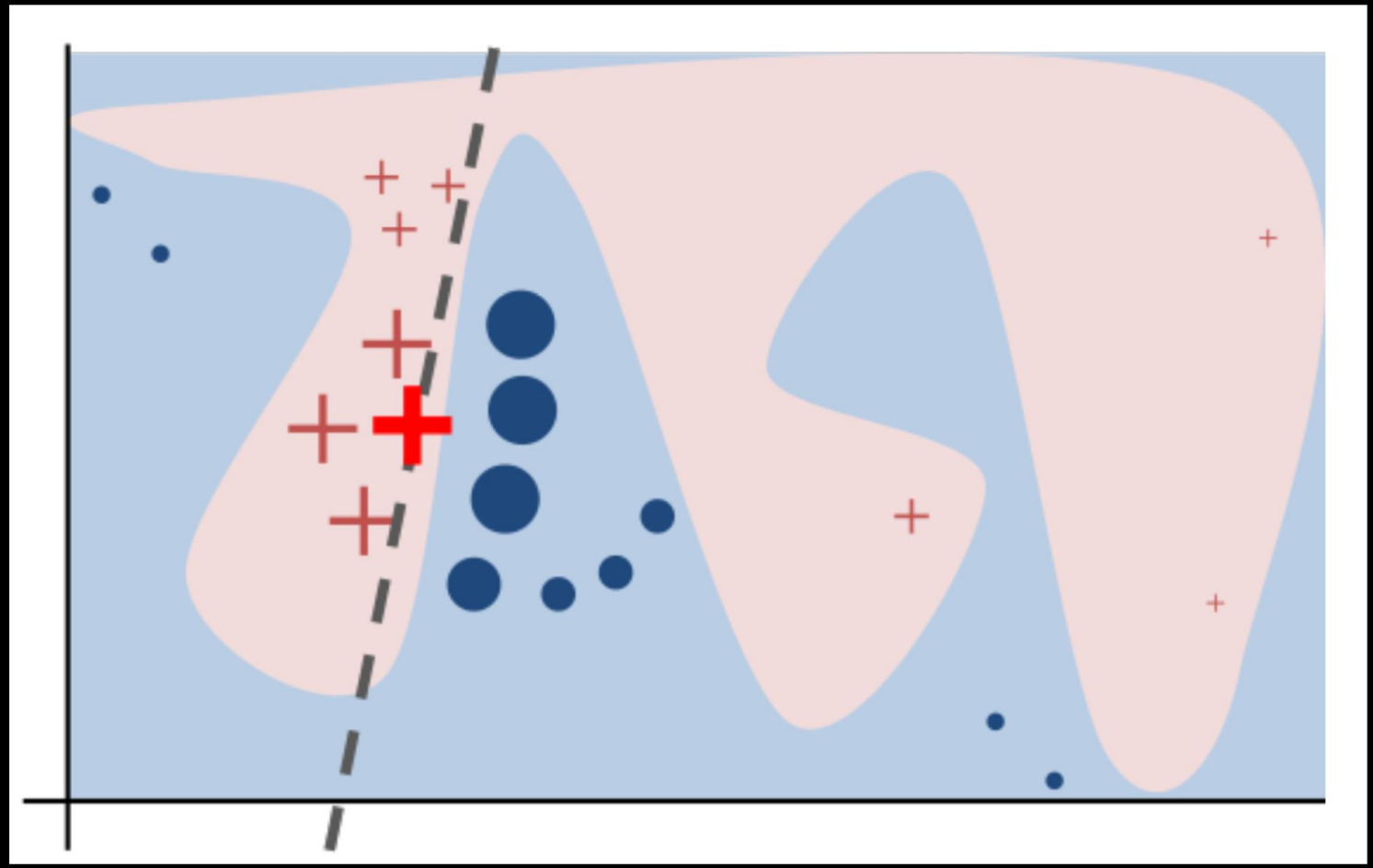


HOW IT WORKS

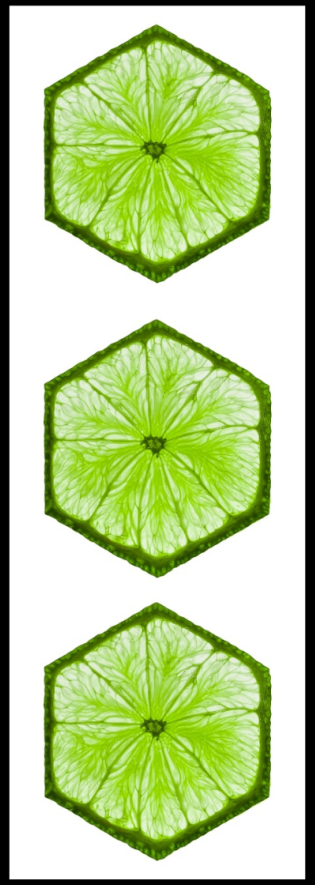
Local Interpretable Model-agnostic Explanations



Local Interpretable Model-agnostic Explanations

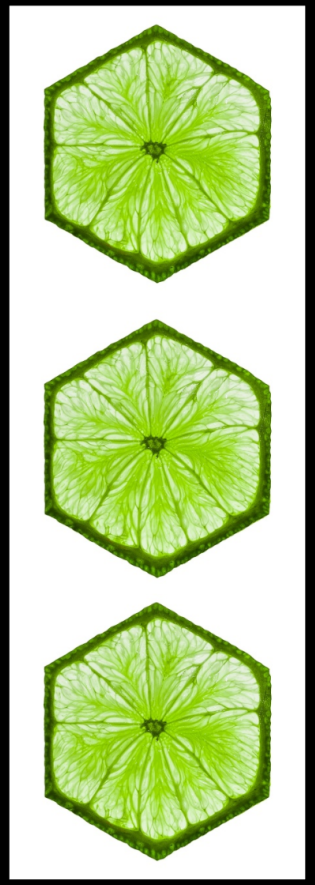


Local Interpretable Model-agnostic Explanations



1. Permute data
2. Calculate distance between permutations and original observations
3. Make predictions on new data using complex model

Local Interpretable Model-agnostic Explanations

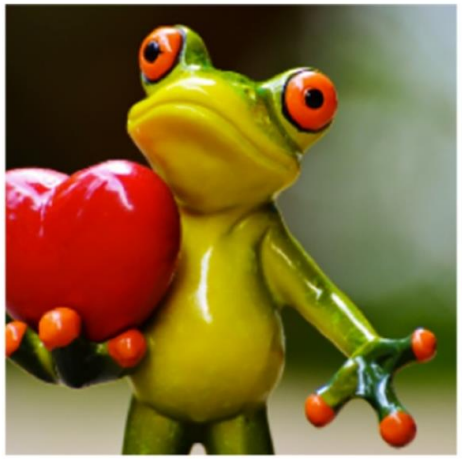


4. Pick m features best describing the complex model outcome from the data

5. Fit a simple model to the data with m features and similarity scores as weights

6. Feature weights from the simple model make explanations for the complex models local behavior

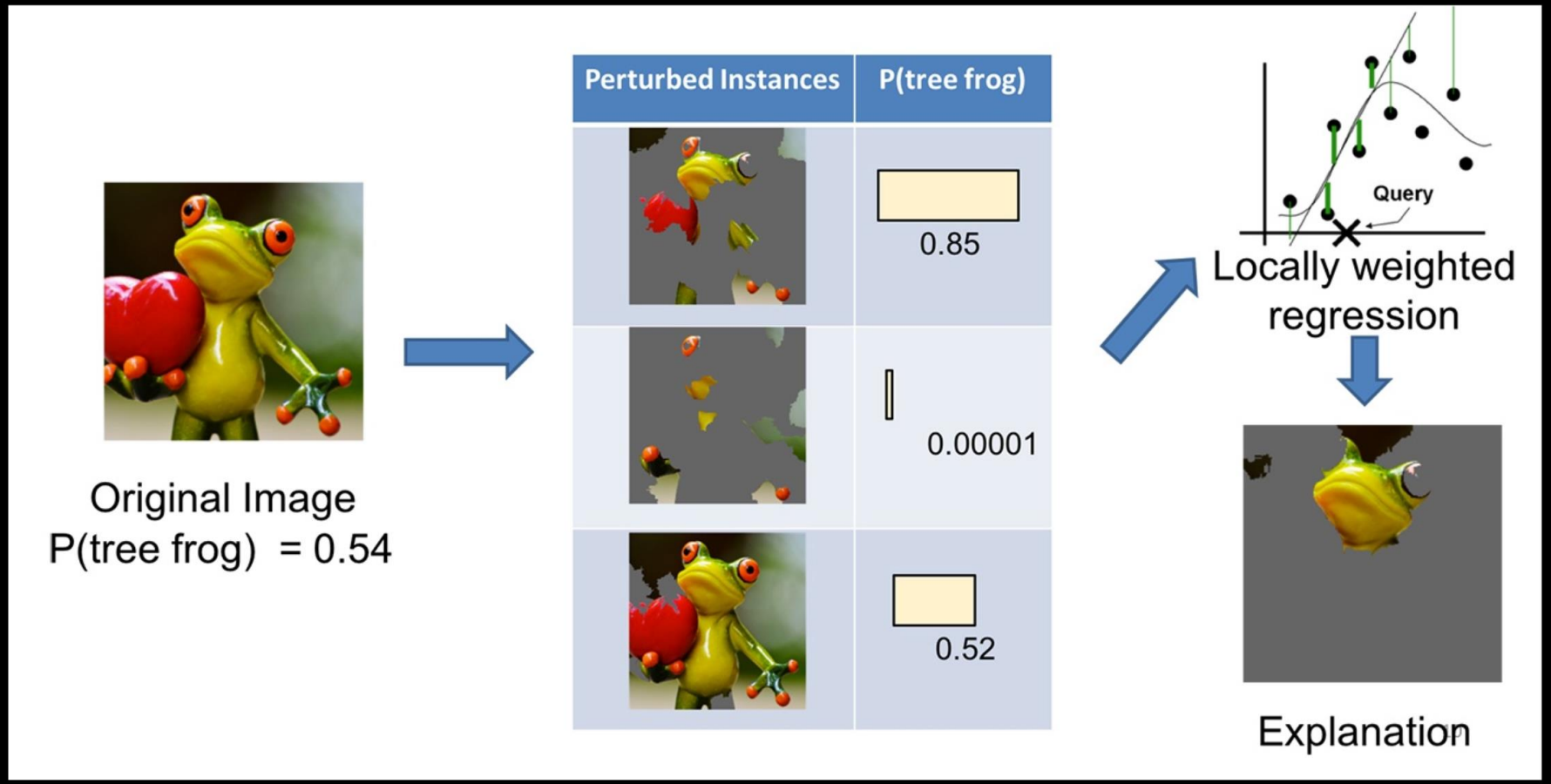
Local Interpretable Model-agnostic Explanations



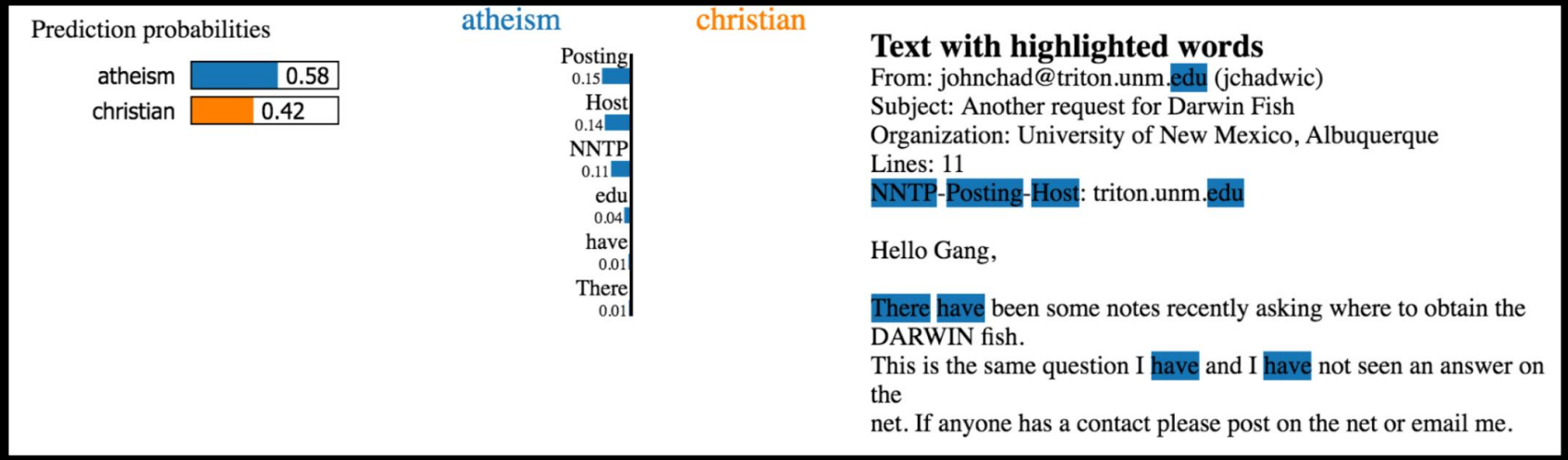
Original Image

Interpretable Components

Local Interpretable Model-agnostic Explanations



Local Interpretable Model-agnostic Explanations

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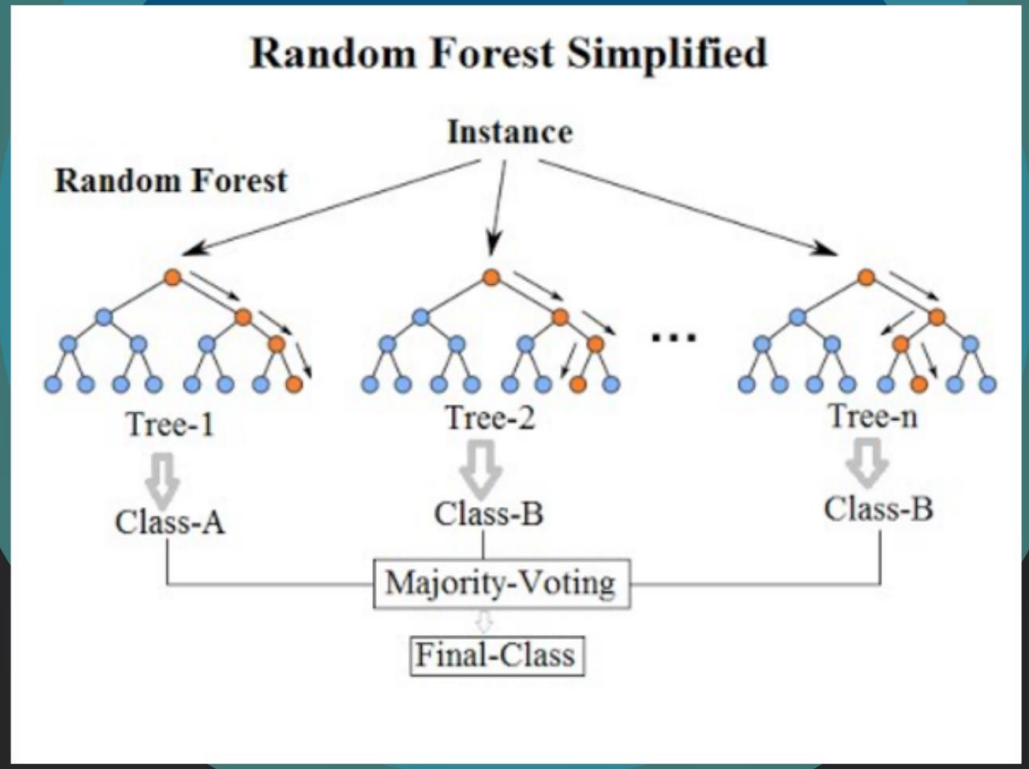
CREDIT SCORING

- DATA
- RANDOM FOREST
- NEURAL NET
- EXPLAIN

DATA

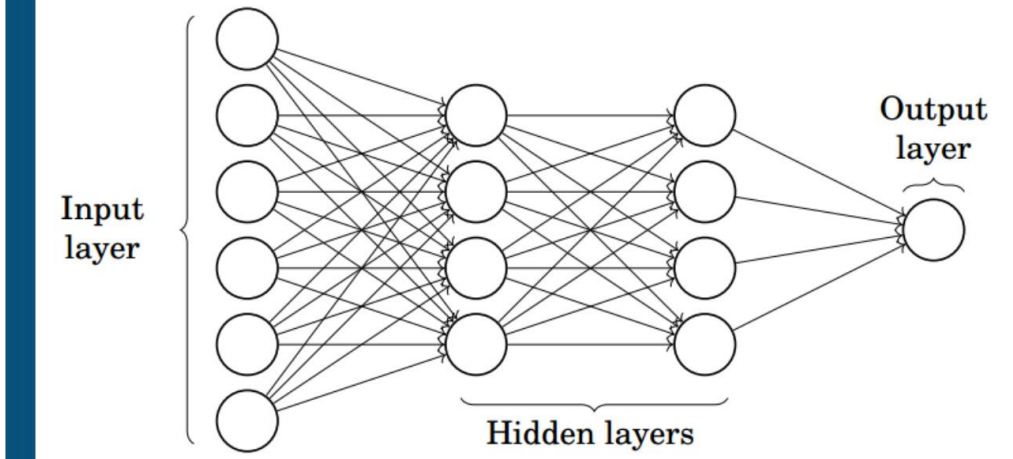
Field	Data	Description
Status	bad,good	Credit status
Home	ignore, other, owner, parents, priv, rent	Type of home ownership
Marital	divorced, married, separated, single, widow	Marital status
Records	no_rec, yes_rec	Existance of records
Job	fixed, freelance, others, partime	Type of job
Age		Client's age
Seniority		Job seniority (years)
Time		Maturity of requested loan (years)
Expenses		Expenses (in thousands $)
Income		Income (in thousands $)
Assets		Assets (in thousands $)
Debt		Debt
Amount		Loan Amount (in thousands $)
Price		Property price (in thousands $)
FinRat		Financing Ratio
Savings		(Income - Expenses - (Debt/100)) / (Amount / Time)

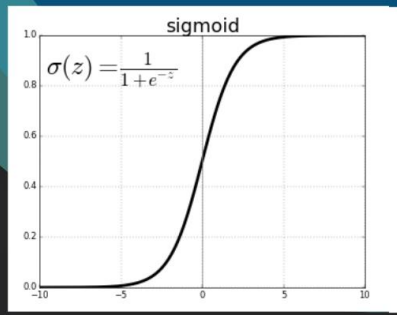
RANDOM FOREST

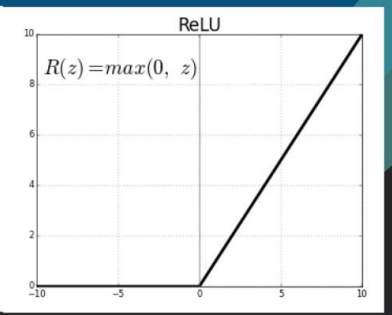


NEURAL NETWORK

dense_1: Dense	input:	(None, 15)
	output:	(None, 12)
dense_2: Dense	input:	(None, 12)
	output:	(None, 12)
dense_3: Dense	input:	(None, 12)
	output:	(None, 12)
dense_4: Dense	input:	(None, 12)
	output:	(None, 1)

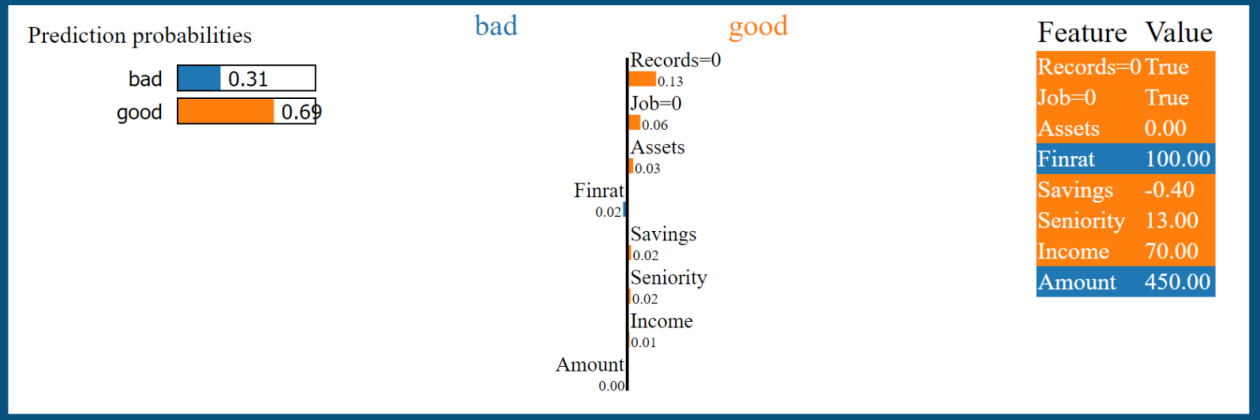






EXPLAIN - Random Forest vs Neural Net

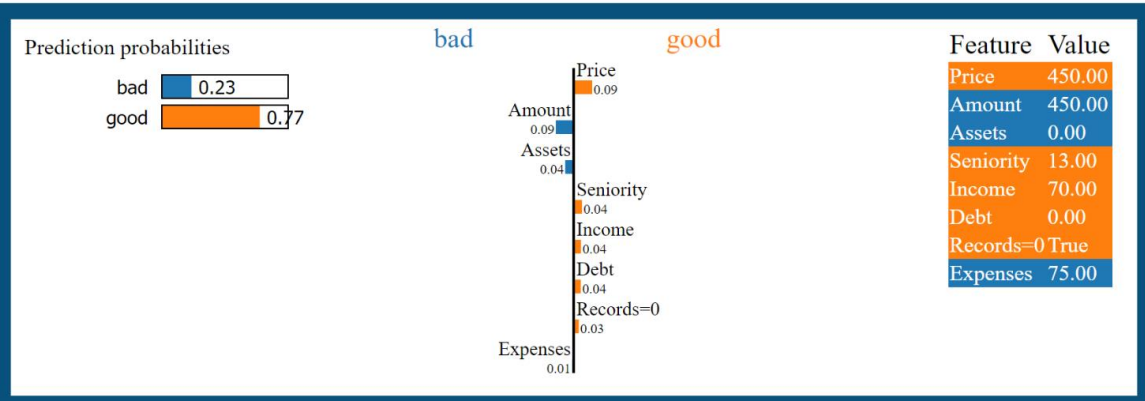
Random Forest



Neural Net (MLP)

EXPLAIN - Compare Predictions

Status	Seniority	Home	Time	Age	Marital	Records	Job	Expenses	Income	Assets	Debt	Amount	Price	Finrat	Savings
bad	13	other	36	35	married	no_rec	fixed	75	70	0	0	450	450	100	-0.4
bad	13	other	36	35	married	no_rec	fixed	75	70	0	0	1200	1200	100	-0.4

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WRAP-UP

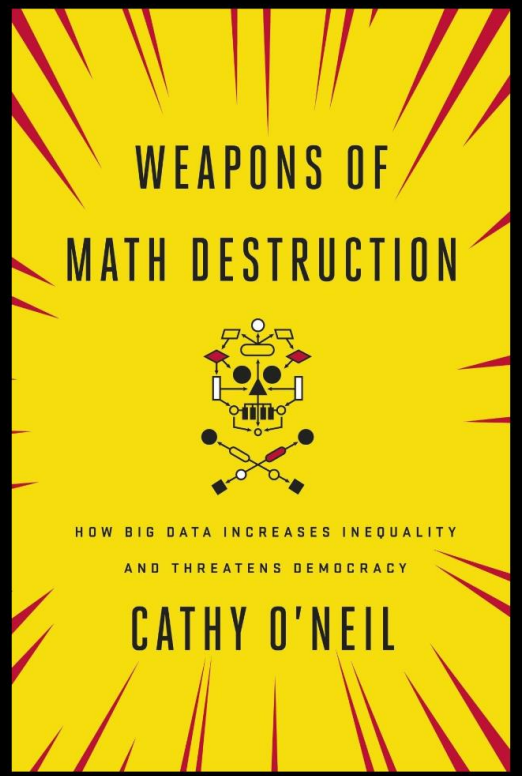
- TRUST PREDICT IMPROVE
- ETHICS IN AI
- GDPR
- OCBC
- LET'S CONNECT

TRUST, PREDICT, IMPROVE

Trust	Predict	Improve
How can we trust the predictions are correct?	How can we understand and predict the behavior?	How do we improve it to prevent potential mistakes?
Being able to interpret the explanations and compare classifiers based on them	Improved prediction of model behavior and time to make that assessment when explanations were provided	Non-ML experts with explanations vs ML experts without explanations

ETHICS IN AI

- Privacy
- Transparency
- Eliminate biases (gender, races, etc.)
- Explainability
- Accountability



GENERAL DATA PROTECTION REGULATION

Individual have now the right to demand an explanation of how an AI system made a decision that affects them

THE OPEN VAULT AT OCBC

Committed to being ethical and responsible

To both our customers and staff in our pursuit of being an AI enabled organisation

Ethical use of data & AI

OCBC is founding member of the MAS' committee to promote responsible and ethical use of AI

People & skillsets

OCBC's FutureSmart program trains and develops the digital skills of all employees of the OCBC Group

Committed to fair and transparent practices

Committed to developing our staff

LETS CONNECT!

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https://github.com/lampalork/model_risk_ai_oct2018