NYU FRE 7773 - Week 6

Machine Learning in Financial Engineering

Ethan Rosenthal

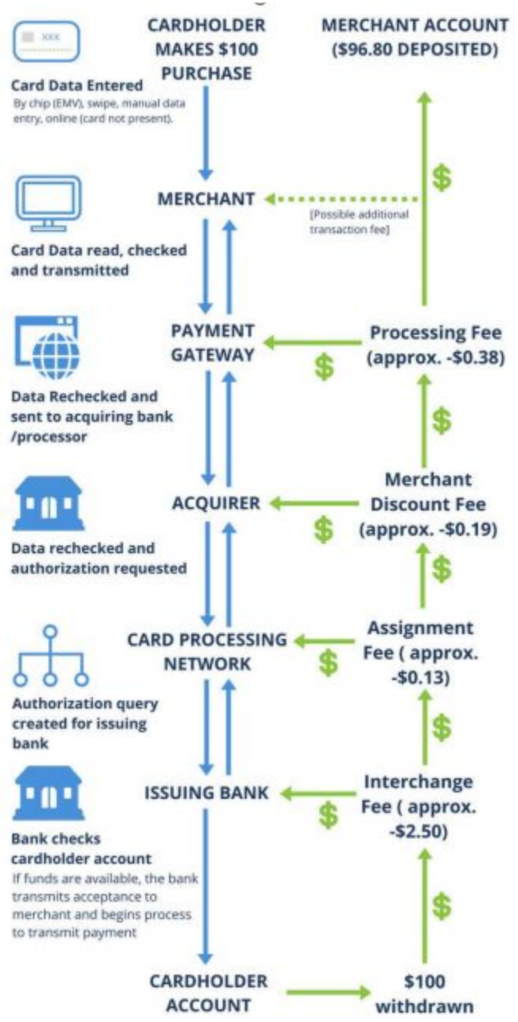
Case Study: Fraud Detection

Machine Learning in Financial Engineering

Ethan Rosenthal

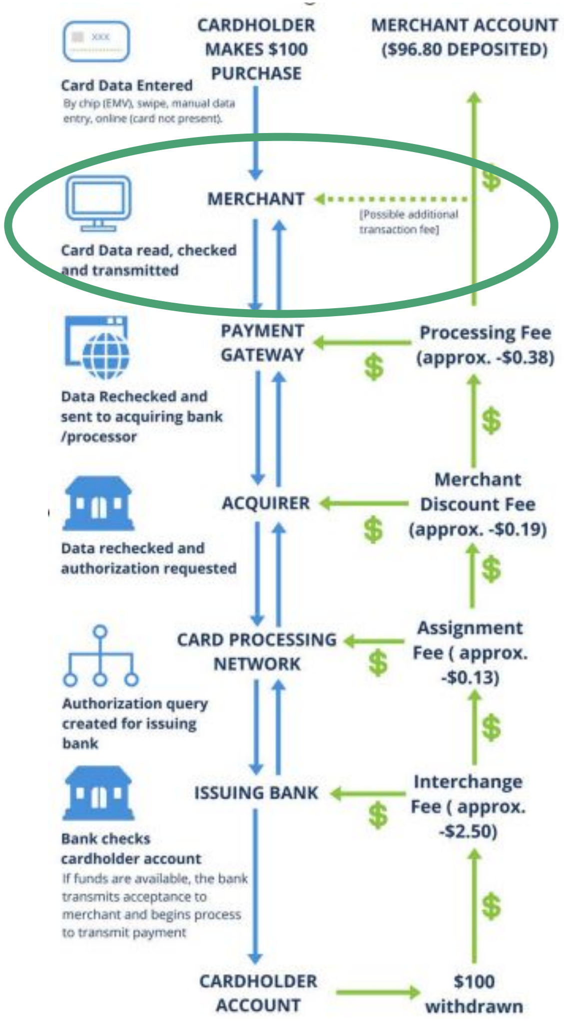
Risk

Square



https://go.wepay.com/collateral/payment-processing-basics/

Square

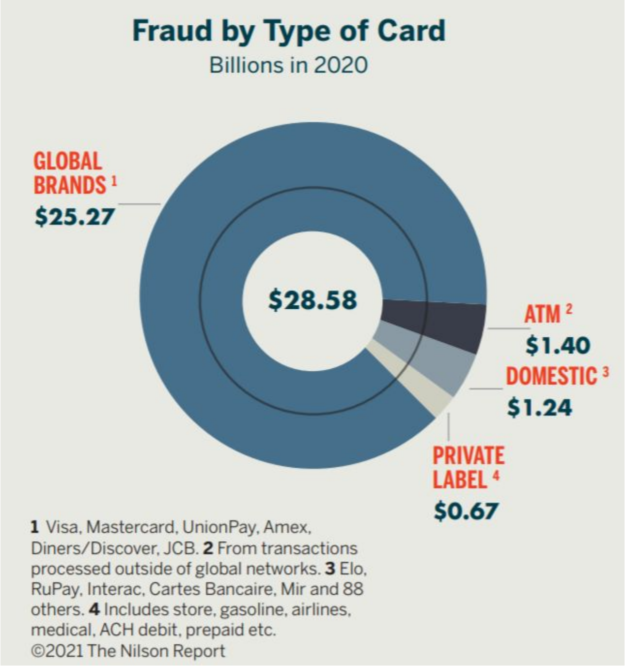


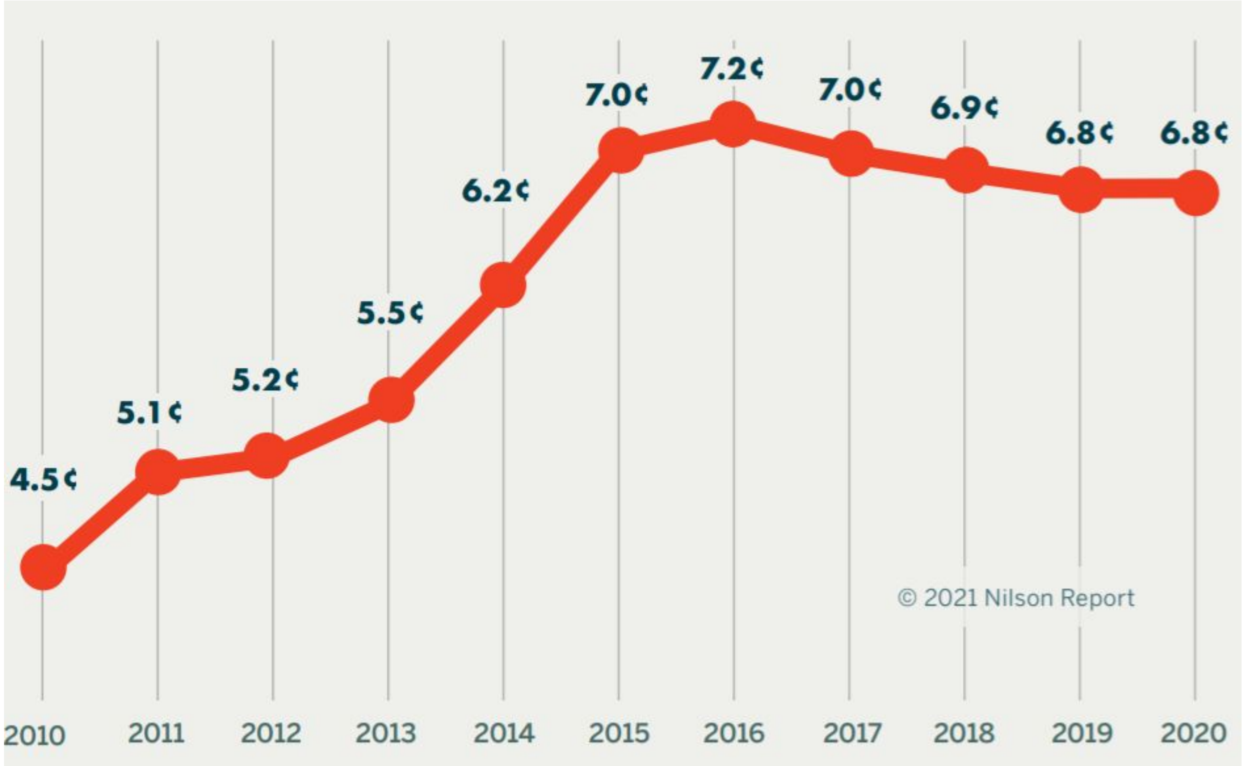
https://go.wepay.com/collateral/payment-processing-basics/

Square Launches On-Demand and Instant Payments for Square Payroll Customers

Square introduced two new features this week to help its customers using Square Payroll – as well as their employees – manage their cash flow.

Fraud





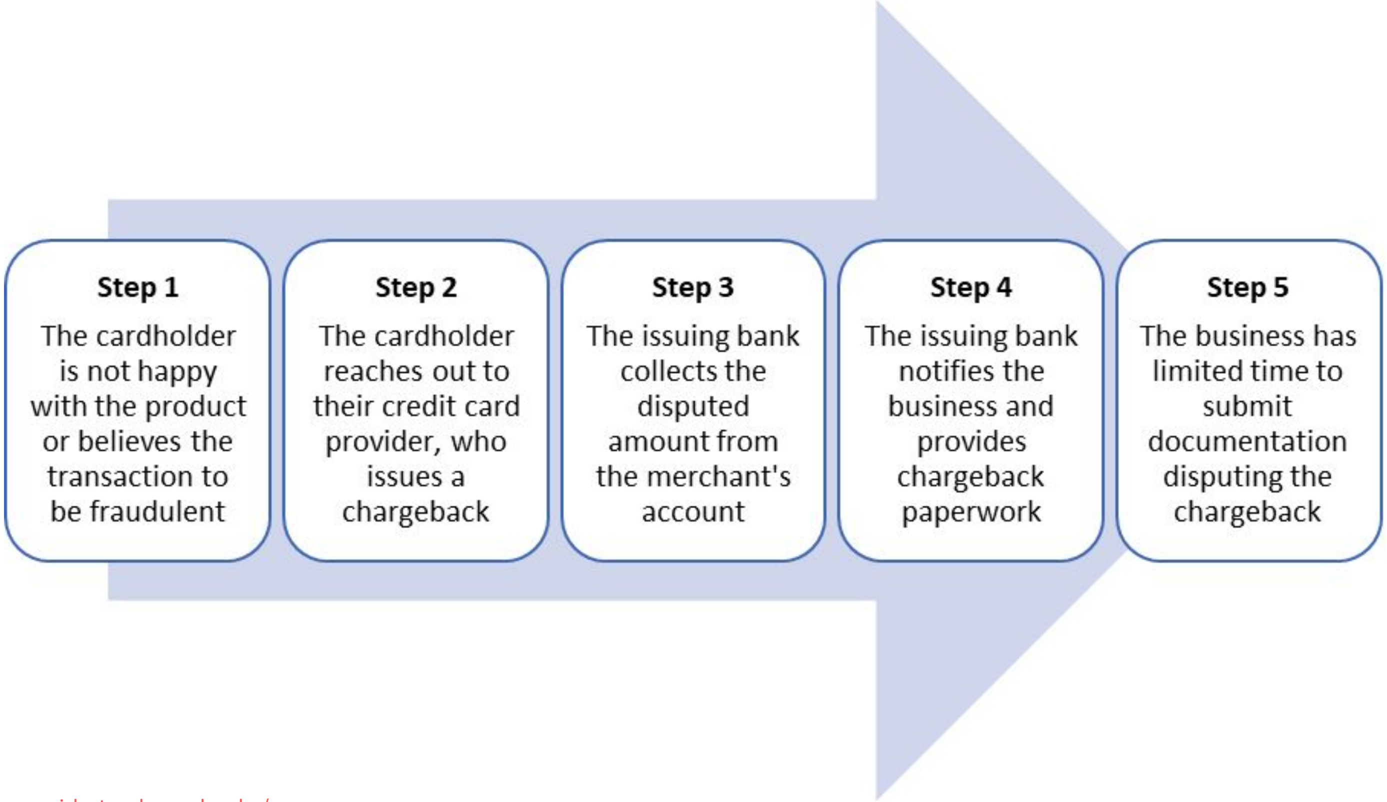
Nilson Report Issue 1209 https://nilsonreport.com/upload/content_promo/NilsonReport_Issue1209.pdf

Card Fraud Projected through 2030

YEAR	Total Volume (TRIL.)	Fraud (BIL.)	Cents per $100 VOLUME
2020	$41.962	$28.58	6.81
2021	$47.229	$32.20	6.82
2022	$50.868	$34.36	6.75
2023	$54.061	$36.13	6.68
2024	$57.323	$38.07	6.64
2025	$60.583	$39.89	6.58
2026	$64.038	$41.73	6.52
2027	$67.570	$43.76	6.48
2028	$71.221	$45.54	6.39
2029	$75.111	$47.50	6.32
2030	$79.140	$49.32	6.23

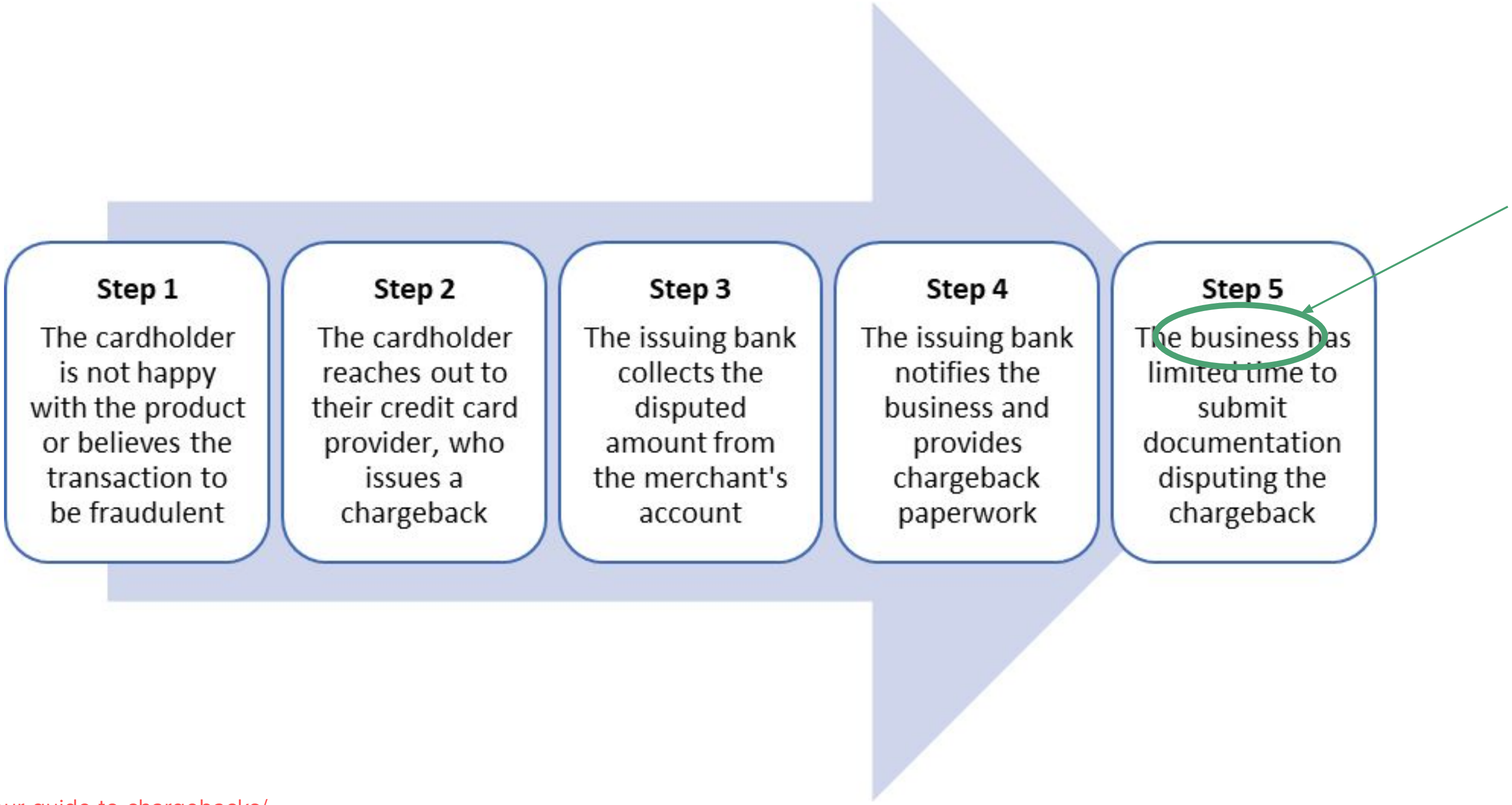
Nilson Report Issue 1209 https://nilsonreport.com/upload/content_promo/NilsonReport_Issue1209.pdf

Chargebacks



https://basyspro.com/your-guide-to-chargebacks/

Chargebacks



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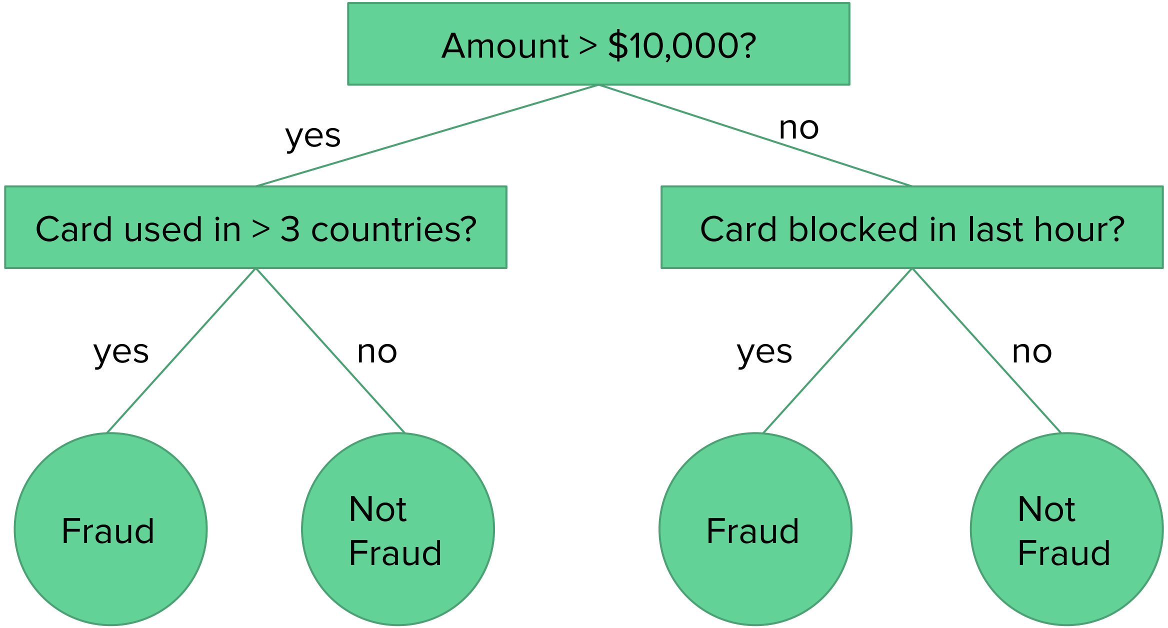
Fraud Detection

Rules

- A manual decision tree
- Ideally, high precision, low recall
- Quick and dirty.
- Lots of manual work and tuning.

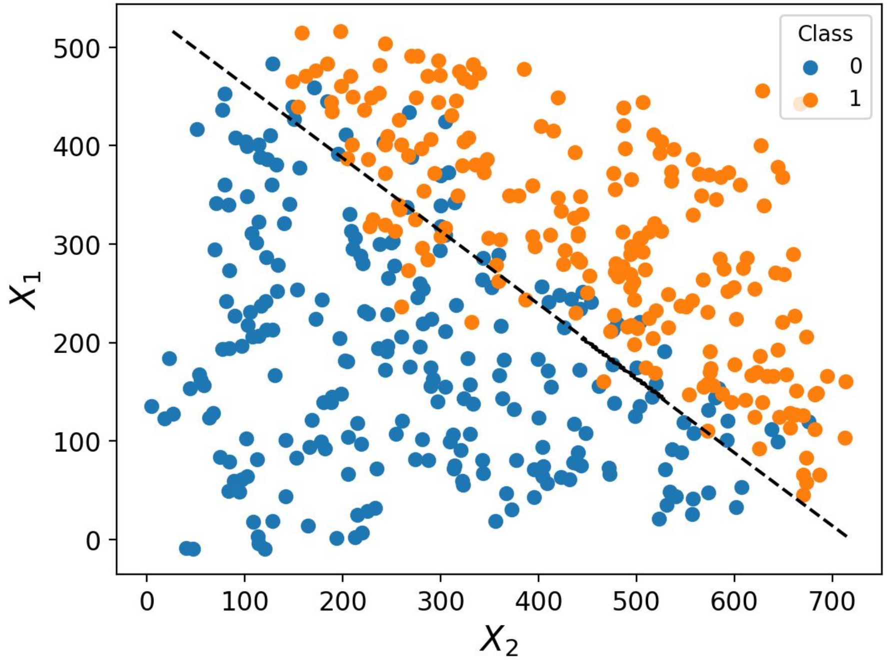


Machine Learning Models

- Binary classification: fraud vs. not fraud
- Sample -> often an **event** (e.g. payment transaction, bank withdrawal).
- **X** -> event features + auxiliary features
- **y** -> was event “associated” with fraud or not
- Train model on historical events, predict on real time events.

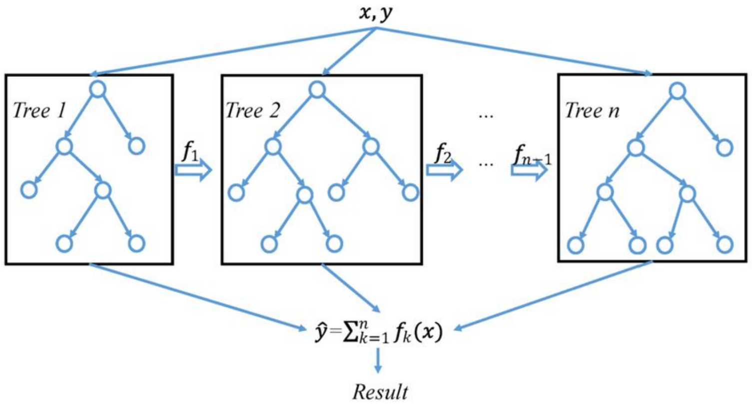
Machine Learning Models

- Logistic regression is simple and can be extremely fast for low latency applications.



Machine Learning Models

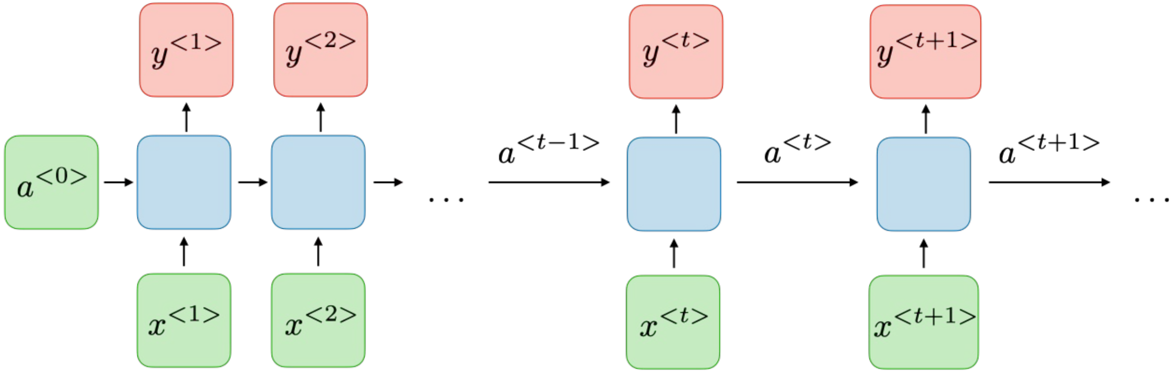
- Tree-based models work particularly well.
- Domain naturally lends itself to if/else statements.
- Easy to tune.
- Relatively fast to train and predict.
- Somewhat interpretable.



https://link.springer.com/article/10.1007/s10509-019-3602-4

Machine Learning Models

- Deep learning models can handle sequences of events.
- Much trickier to model and tune.



TensorFlow

PyTorch

https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-recurrent-neural-networks

Fraud Detection Difficulties


KEANU REEVES DENNIS HOPPER SANDRA BULLOCK
GET READY FOR RUSH HOUR.
SPEED
TWENTIETH CENTURY FOX PRESENTS A MARK GORDON PRODUCTION KEANU REEVES DENNIS HOPPER SANDRA BULLOCK "SPEED"
JOE MORTON AND JEFF DANIELS MUSIC BY MARK MANCINA FILM EDITOR JOHN WRIGHT, A.C.E. PRODUCTION DESIGNER JACKSON DeGOVIA DIRECTOR OF PHOTOGRAPHY ANDRZEJ BARTKOWIAK EXECUTIVE PRODUCER IAN BRYCE WRITTEN BY GRAHAM YOST
R RESTRICTED
UNDER 17 REQUIRES ACCOMPANYING PARENT OR ADULT GUARDIAN
JUNE 10
PRODUCED BY MARK GORDON DIRECTED BY JAN DeBONT

Speed – Realtime Features

- Payment Amount
- Transaction Country
- …

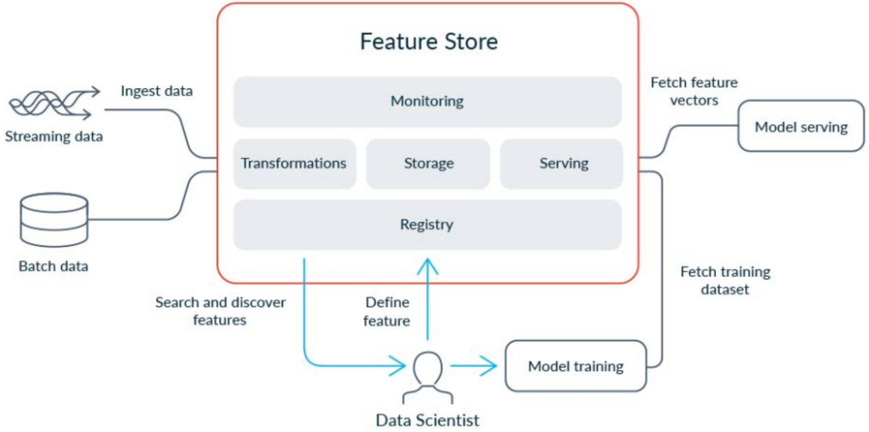
Speed – Realtime Features

- Standard deviation of milliseconds between transaction attempts over the last 30 seconds.

Speed – Realtime Features

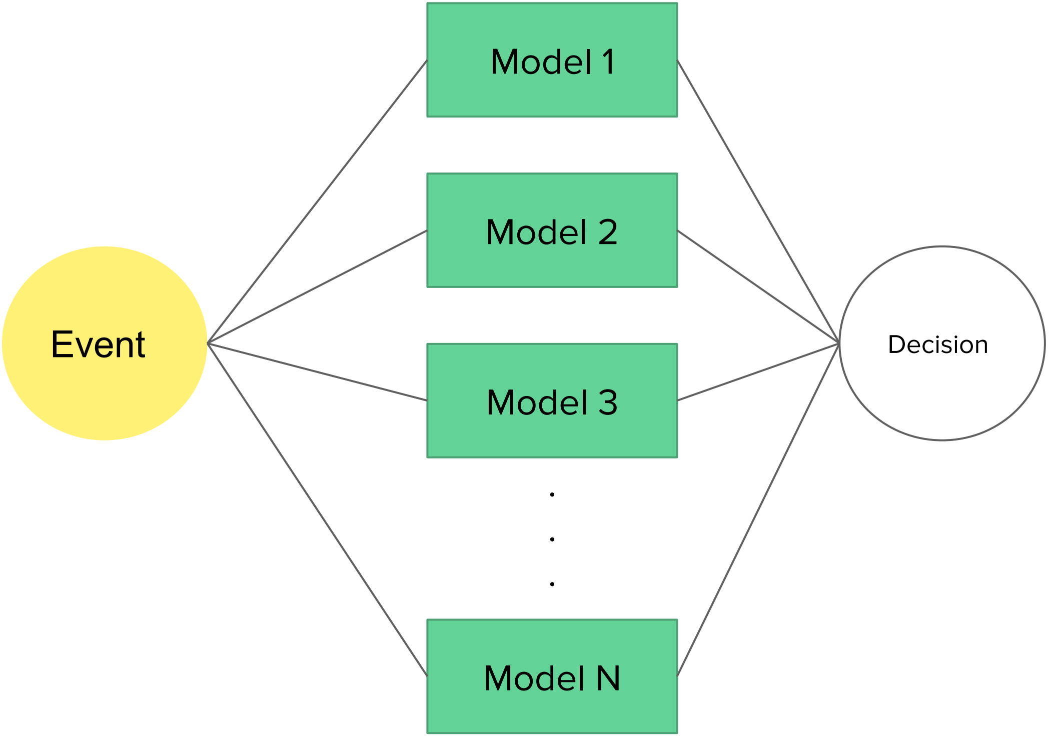
Feature Stores are systems for ingesting streams of events and converting them into features, *quickly*.

Tradeoff between feature *accuracy* and *latency*.



Speed – Realtime Detection

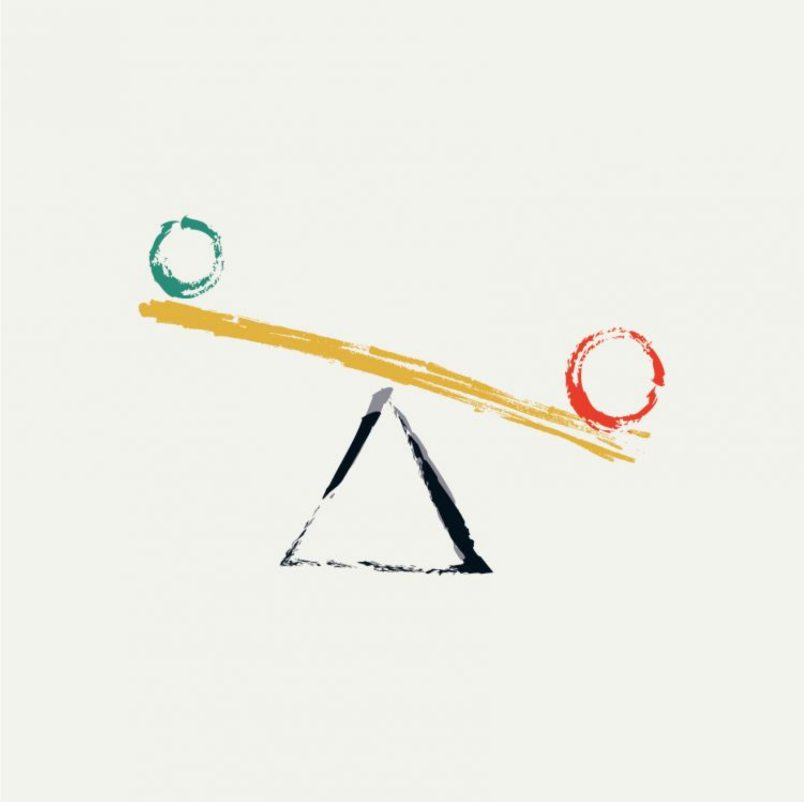
- Thousands or rules and models for a given event.
- Limited time that each can take.
- Sync vs. async workflows.



Fraud Decisioning

Tradeoffs

- Automation vs. Confidence
  - Block high fraud likelihood transactions.
  - Manually review when not sure.
- Friction vs. Risk
  - Verify via SMS vs. providing bank documents.
- **False Positives vs. False Negatives**



lil du bois🌺
@_lildubois

well, well, well, if it isn't the consequences of my own actions

1:25 AM · Sep 29, 2018 · Twitter for Android

133.7K Retweets **5,164** Quote Tweets **297K** Likes

Training Models

Machine Learning Models

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Speed – ~~Realtime~~ Historical Features

- Standard deviation of milliseconds between transaction attempts over the last 30 seconds at the time the Fraud model would make its prediction.

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- Don't leak the future into the past!

Speed – ~~Realtime~~ Historical Features

- Standard deviation of milliseconds between transaction attempts over the last 30 seconds at the time the Fraud model would make its prediction.
- Don't leak the future into the past!
- Historical features must match realtime features ("train/test skew")

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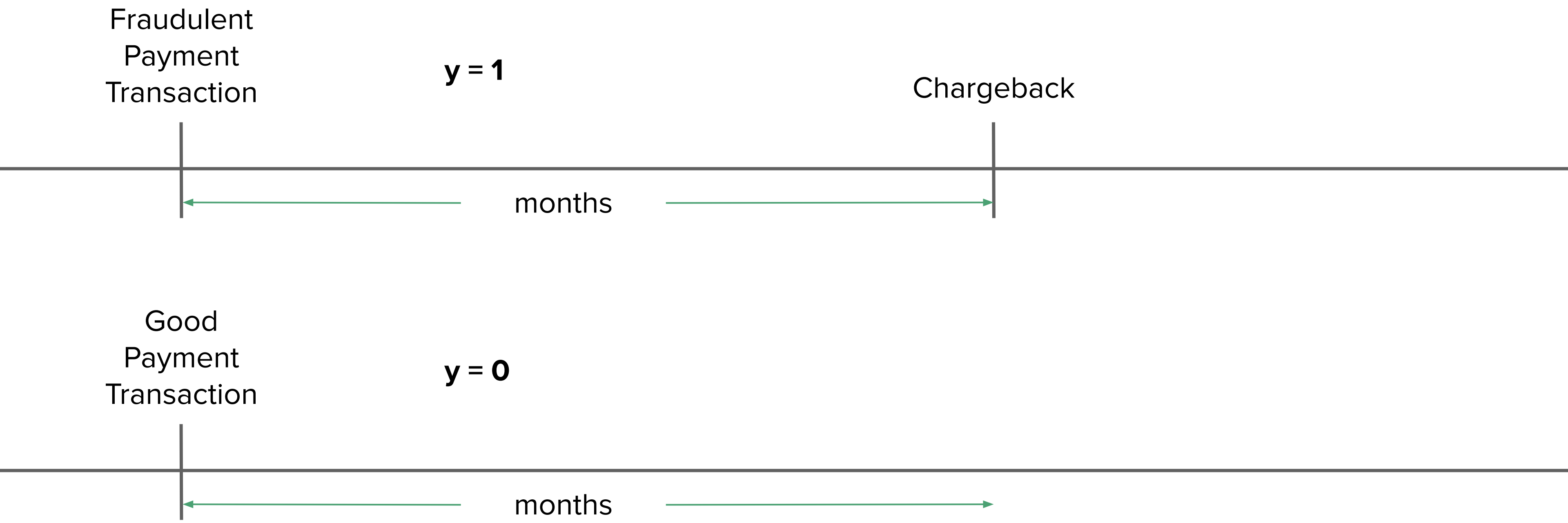
Life of Ground Truth



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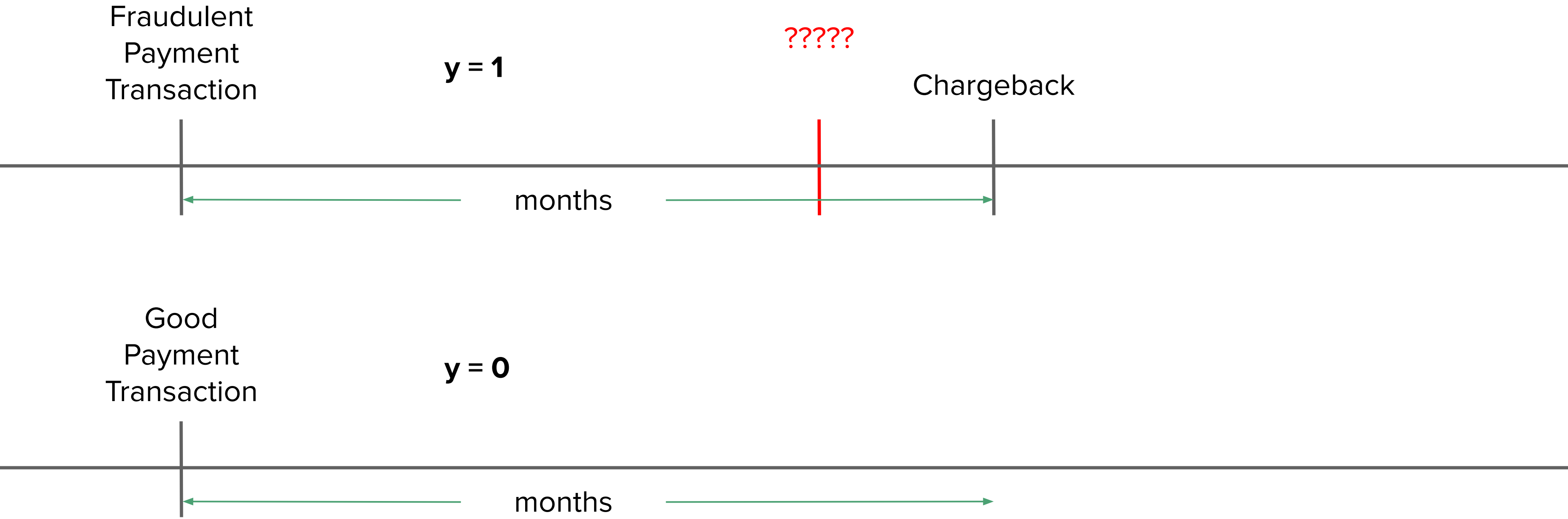
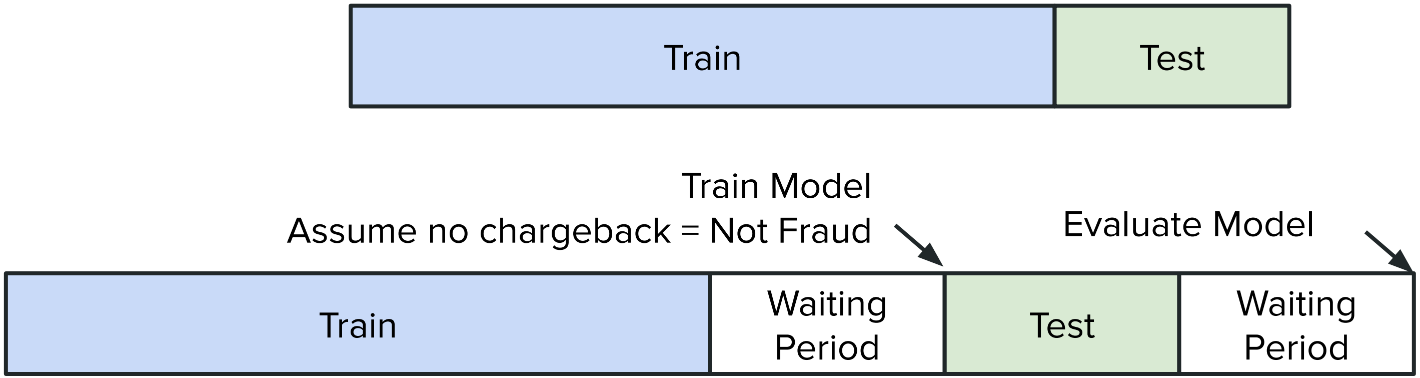
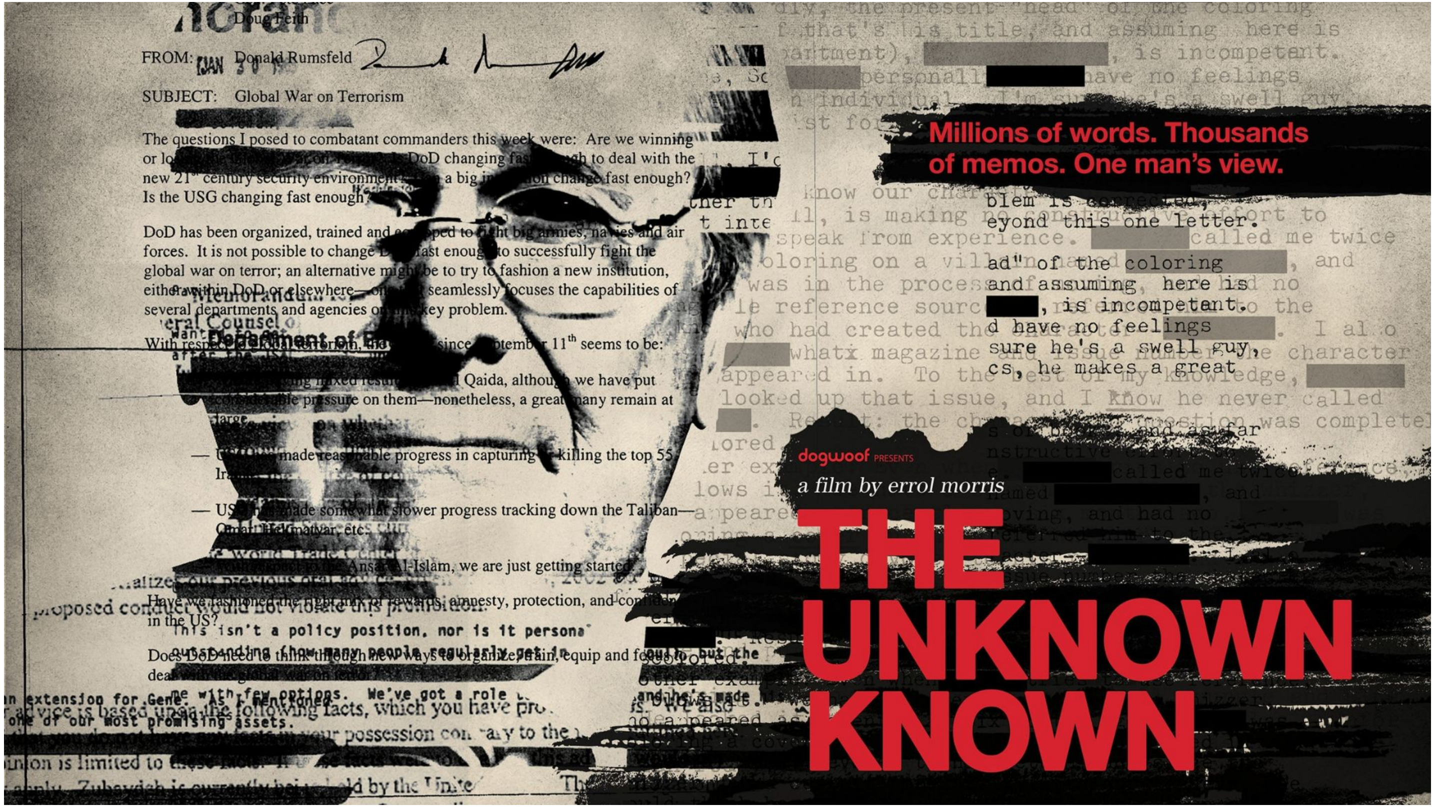


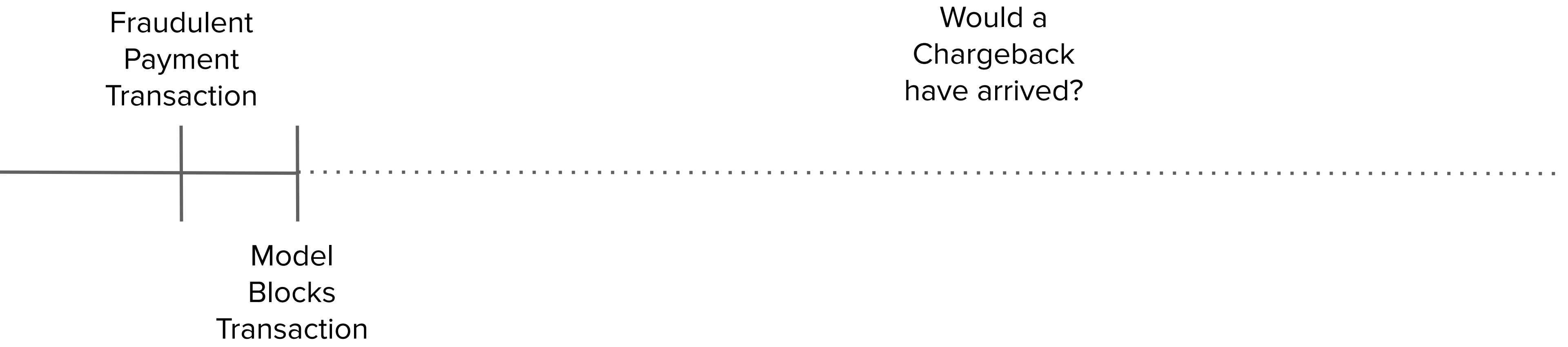
Train/Test Split

Train/Test Split




FROM: Donald Rumsfeld
SUBJECT: Global War on Terrorism
Millions of words. Thousands of memos. One man's view.
dogwoof PRESENTS
a film by errol morris
THE UNKNOWN KNOWN

Life of Ground Truth



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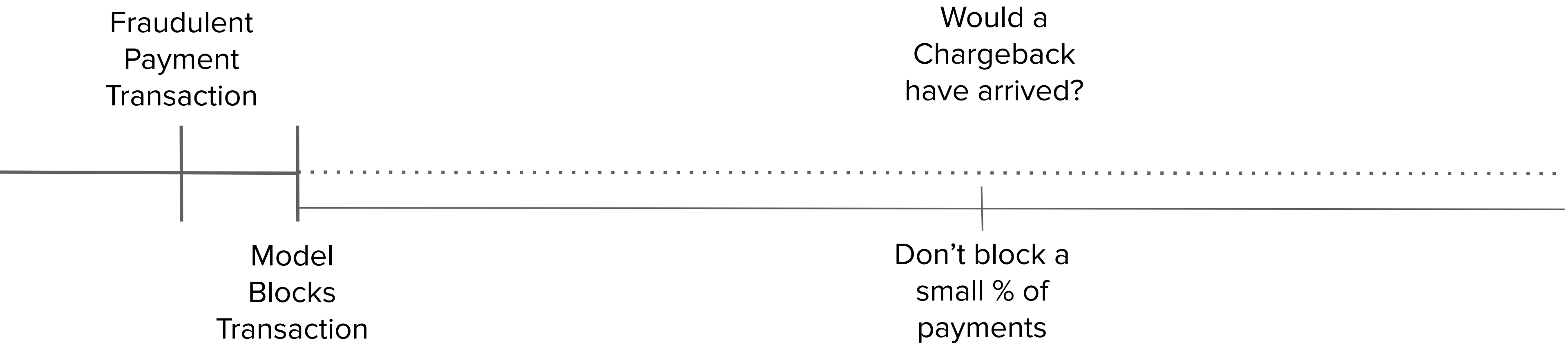

Optimization

What are we optimizing for?

False Positive

- Miss out on a sale
- Churn – long term risk
- Difficult to measure!

False Negative

- Straightforward financial loss
- Could be unbounded

Capacity

- Limited capacity for human review
- Capacity has a cost

What are we optimizing for?

False Positive Precision

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Capacity Support / Positive Prediction Rate

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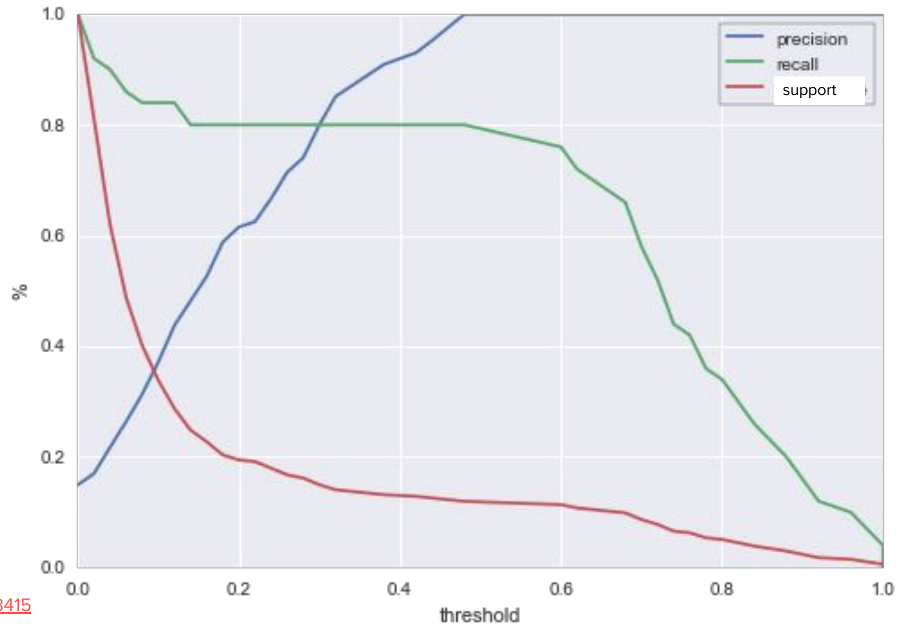

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https://blog.insightdatascience.com/visualizing-machine-learning-thresholds-to-make-better-business-decisions-4ab07f823415

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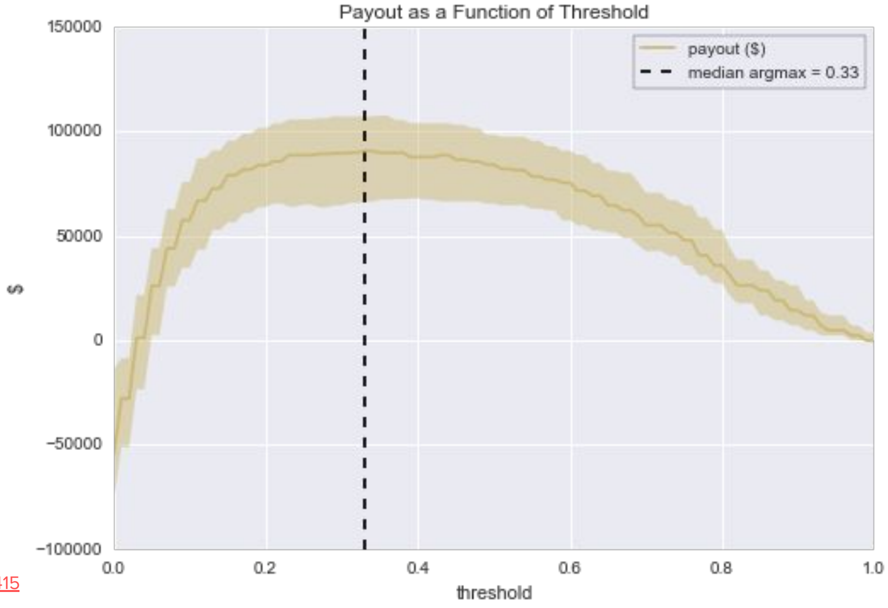

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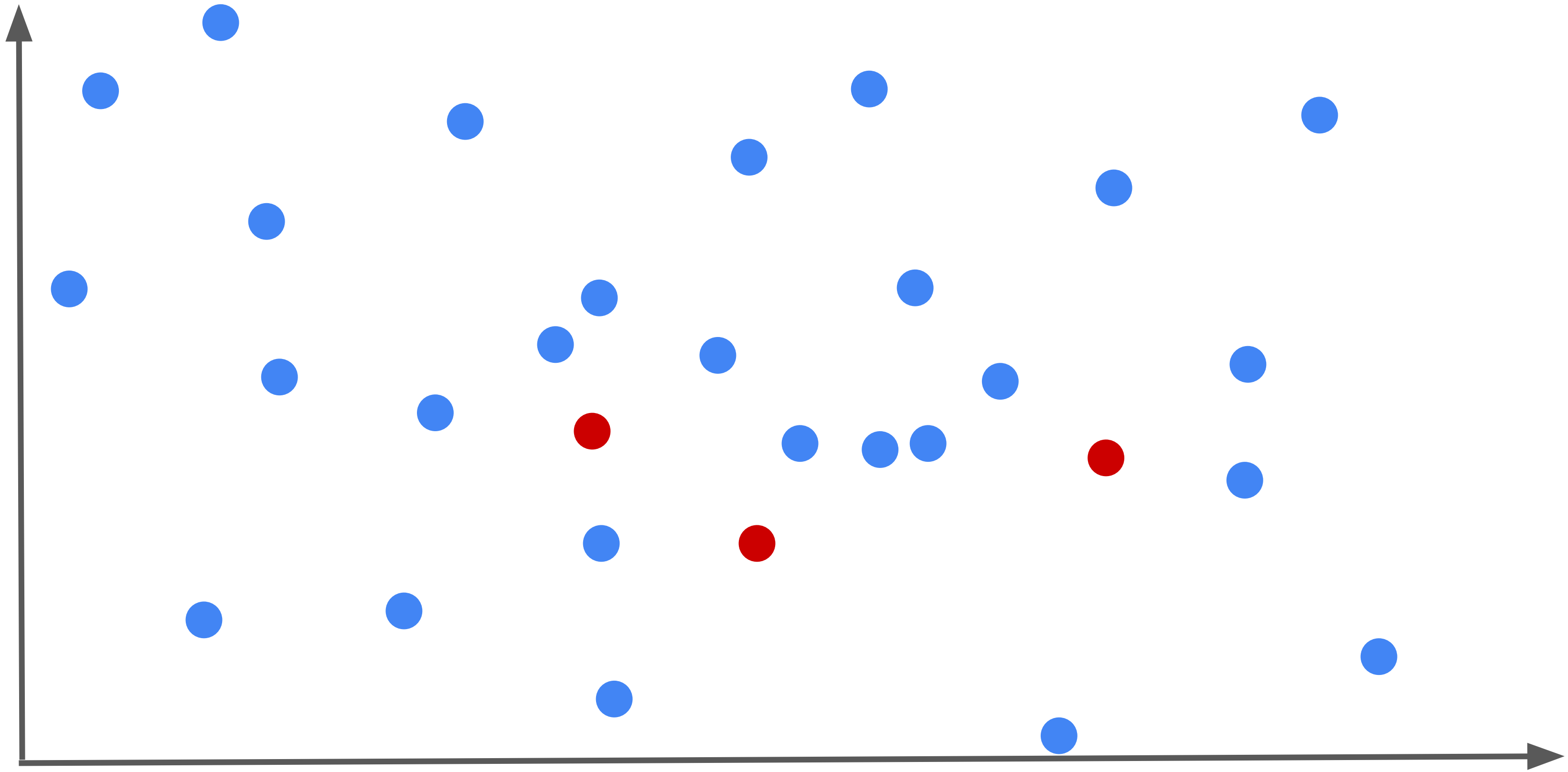
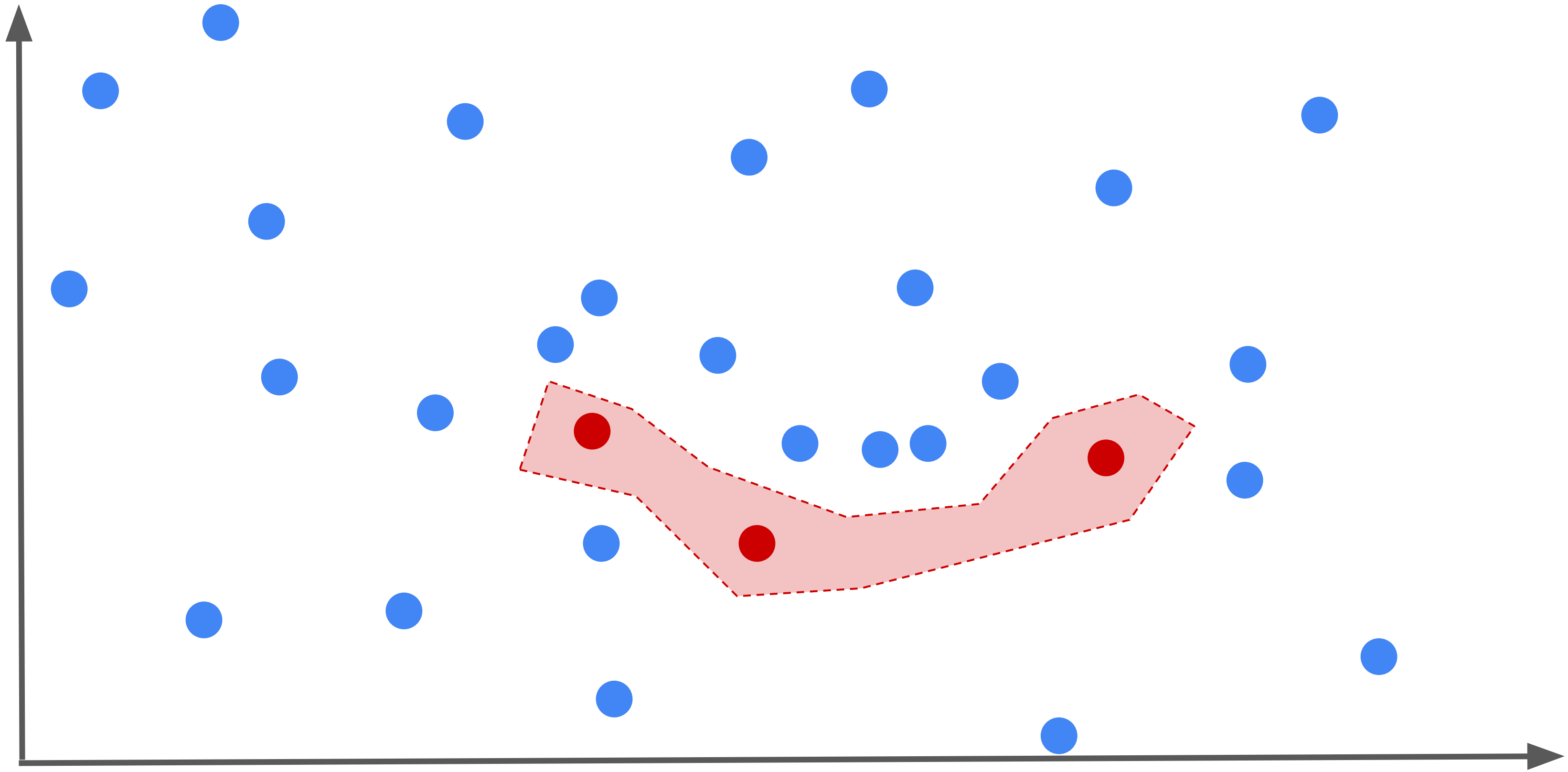
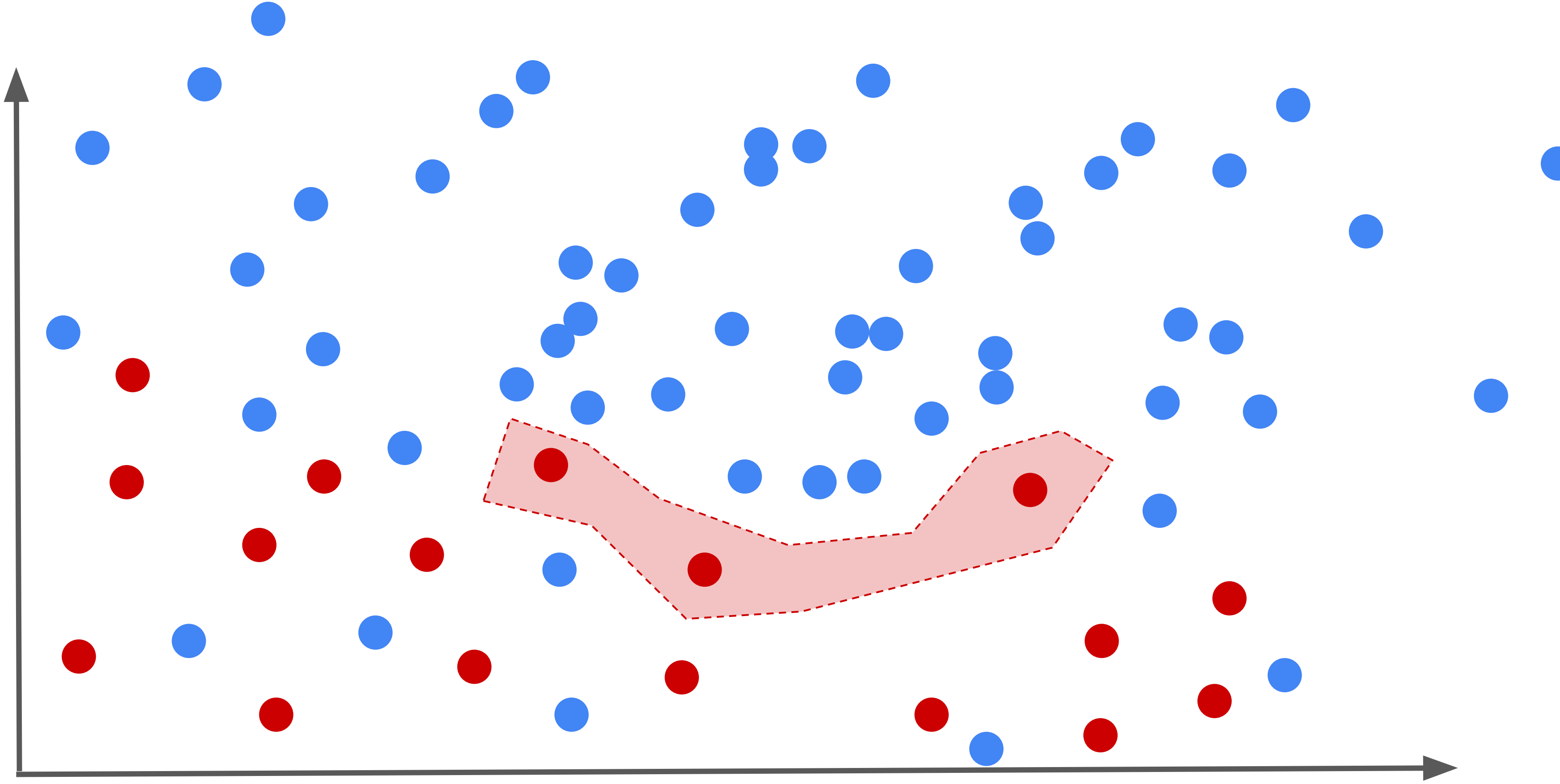
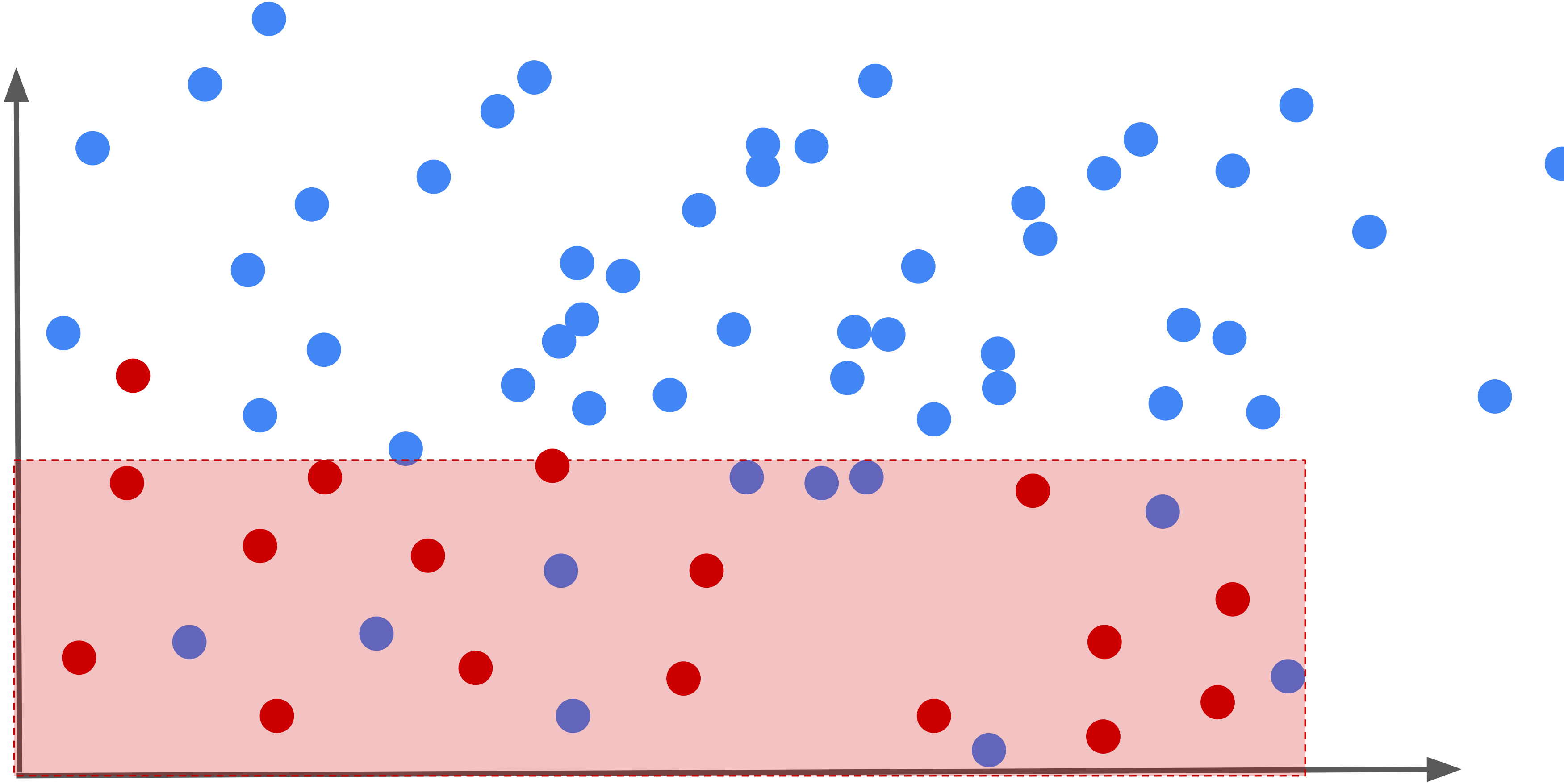
Class Imbalance

You need a lot of data



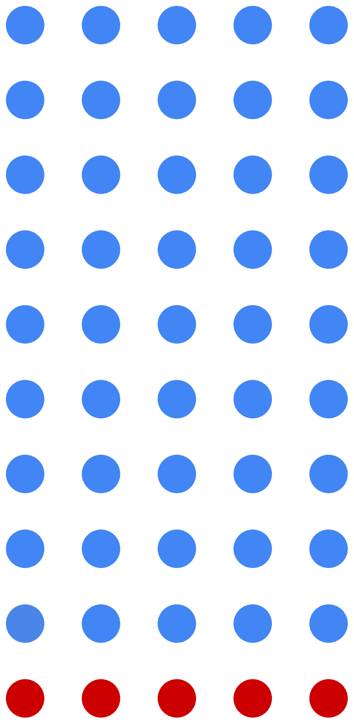


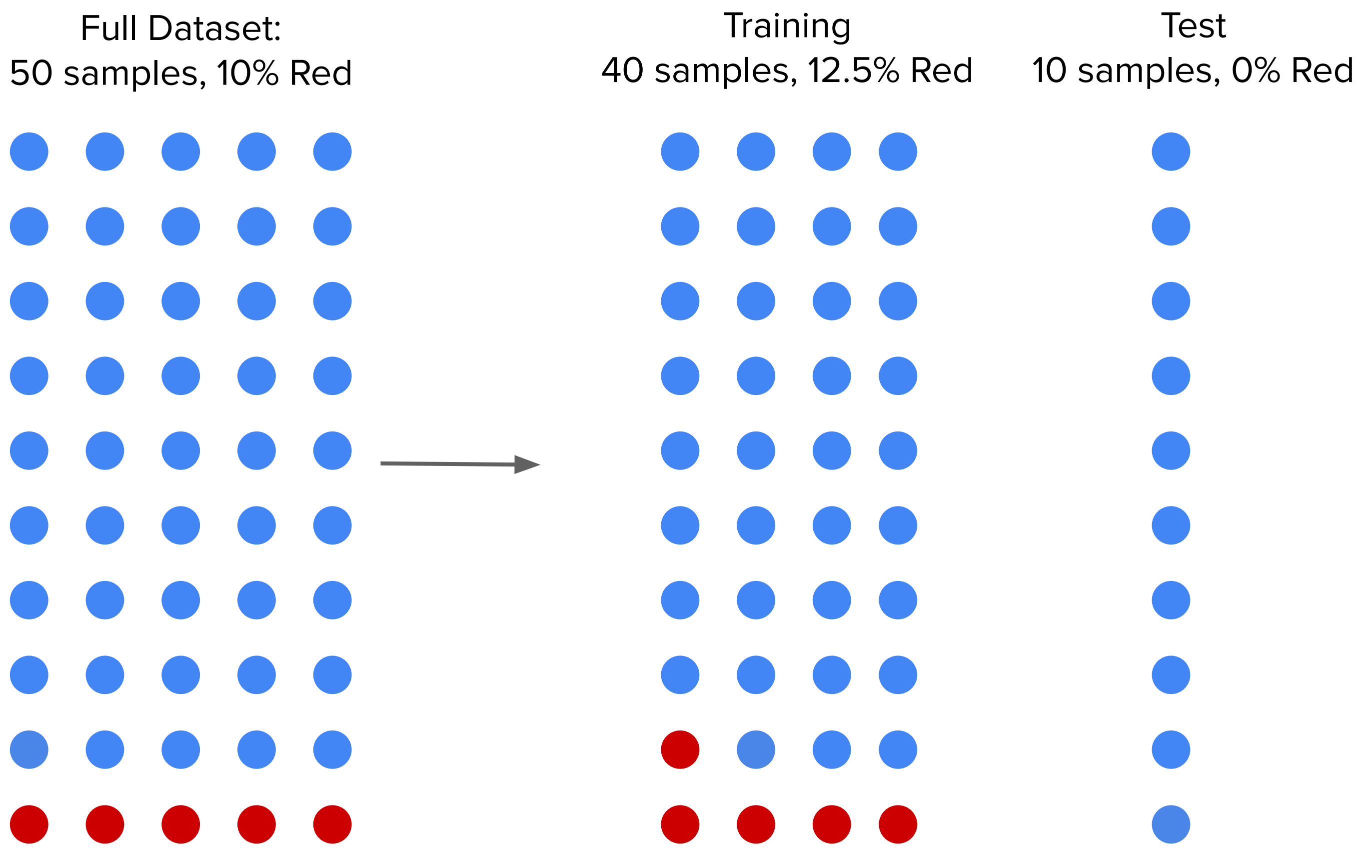


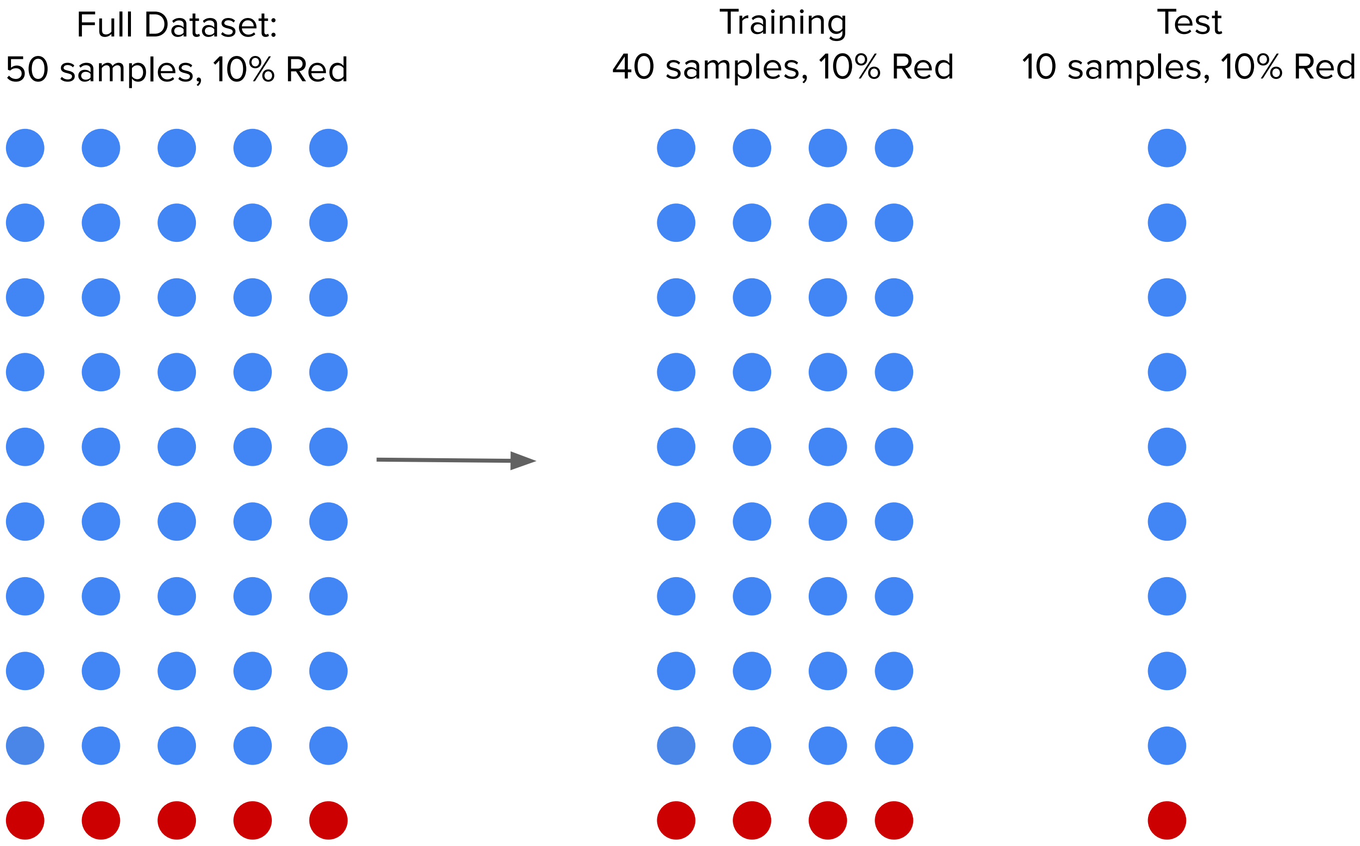


Stratified Sampling

Full Dataset:
50 samples, 10% Red



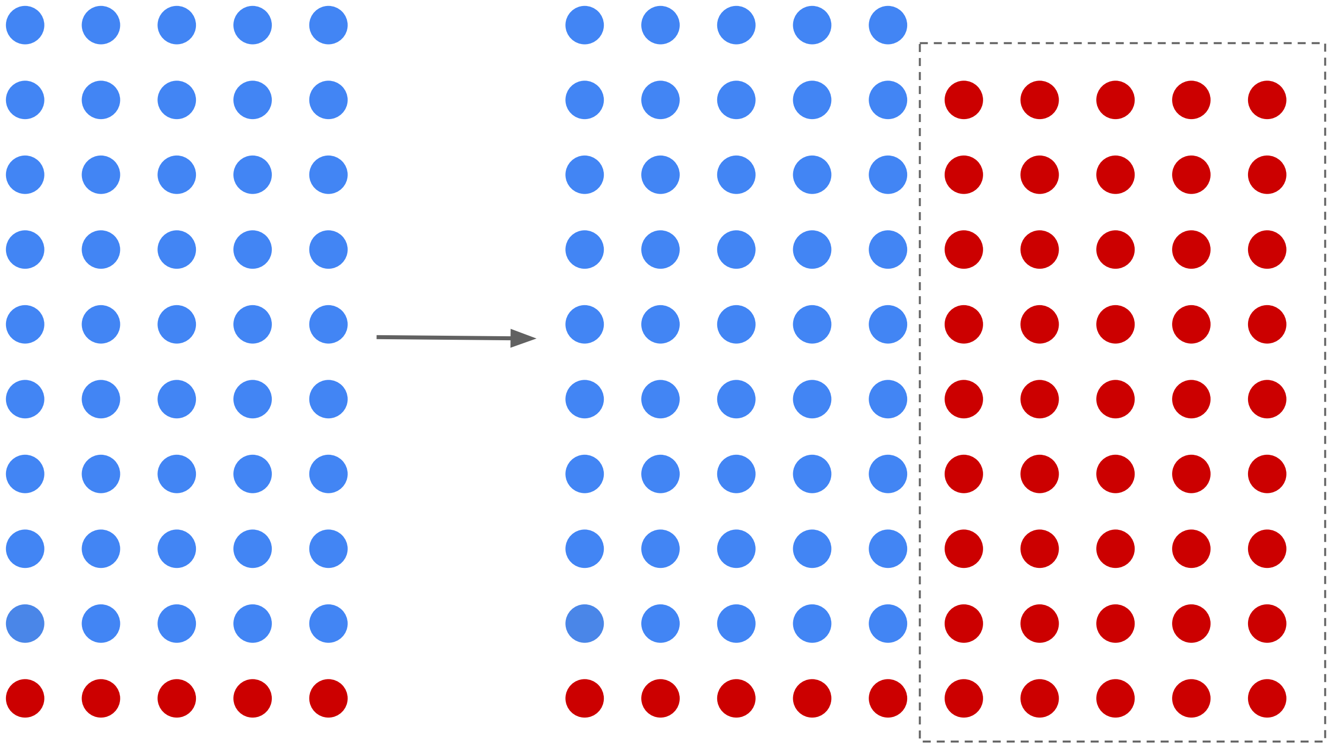

Full Dataset:
50 samples, 10% Red
Training
40 samples, 12.5% Red
Test
10 samples, 0% Red


Full Dataset:
50 samples, 10% Red
Training
40 samples, 10% Red
Test
10 samples, 10% Red

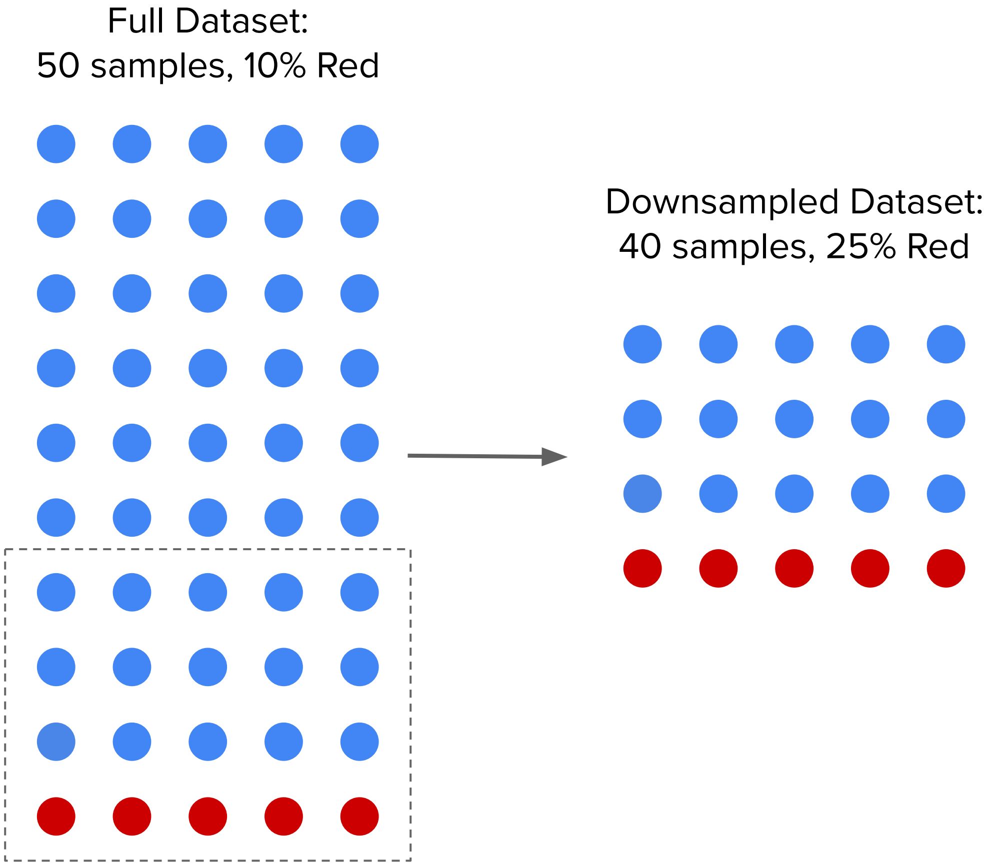
Upsampling

Full Dataset:
50 samples, 10% Red

Upsampled Dataset:
100 samples, 50% Red



Downsampling


Full Dataset:
50 samples, 10% Red
Downsampled Dataset:
40 samples, 25% Red

Class Weighting

Metrics

Imbalanced Metrics

- Accuracy is not good!
- Sampling -> weighted metrics
- Uncertainty