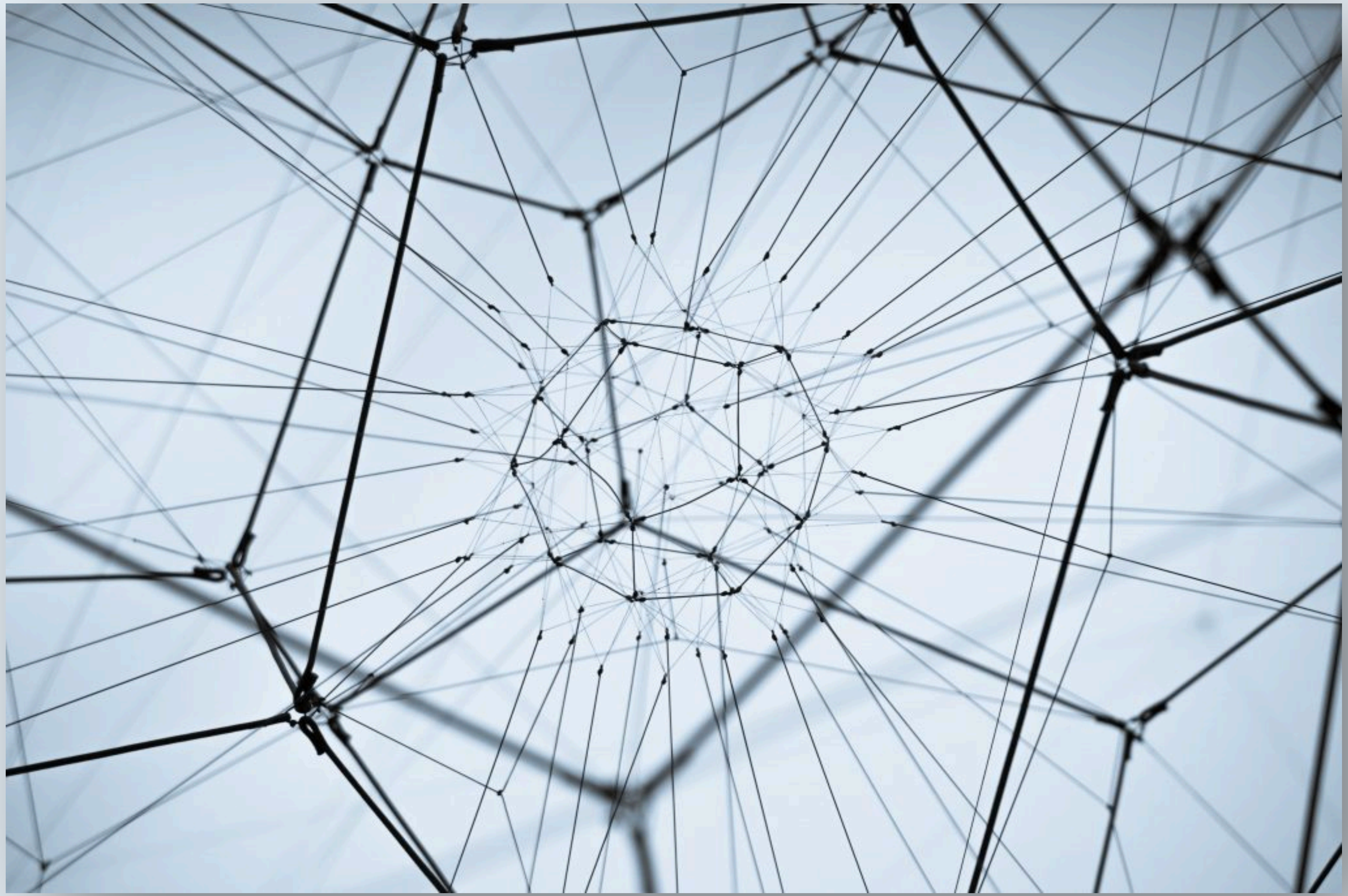
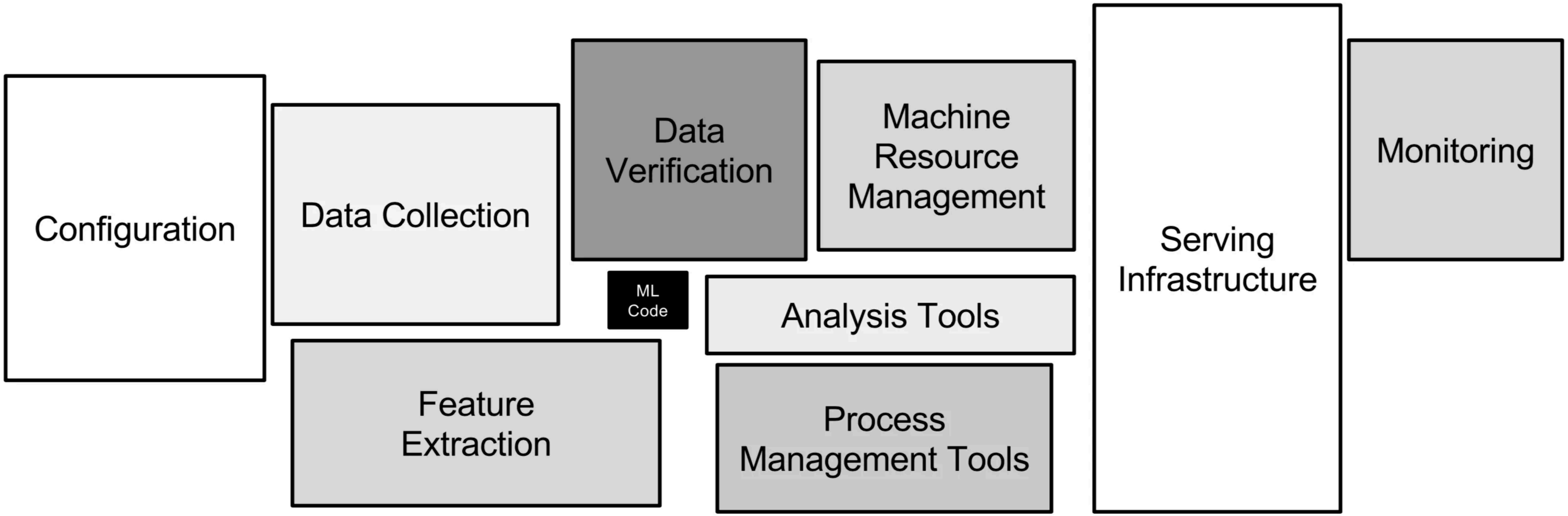


Machine Learning Systems for Engineers

Where Data Science Meets Engineering

Who Am I?

- I'm Cameron!
  - LinkedIn - https://www.linkedin.com/in/cameron-joannidis/
  - Twitter - @CamJo89
- Consult across a range of areas and have built many big data and machine learning systems
- Buzz Word Bingo
  - Big Data
  - Machine Learning
  - Functional Programming


Configuration
Data Collection
Data Verification
Machine Resource Management
Serving Infrastructure
Monitoring
ML Code
Analysis Tools
Feature Extraction
Process Management Tools

Agenda

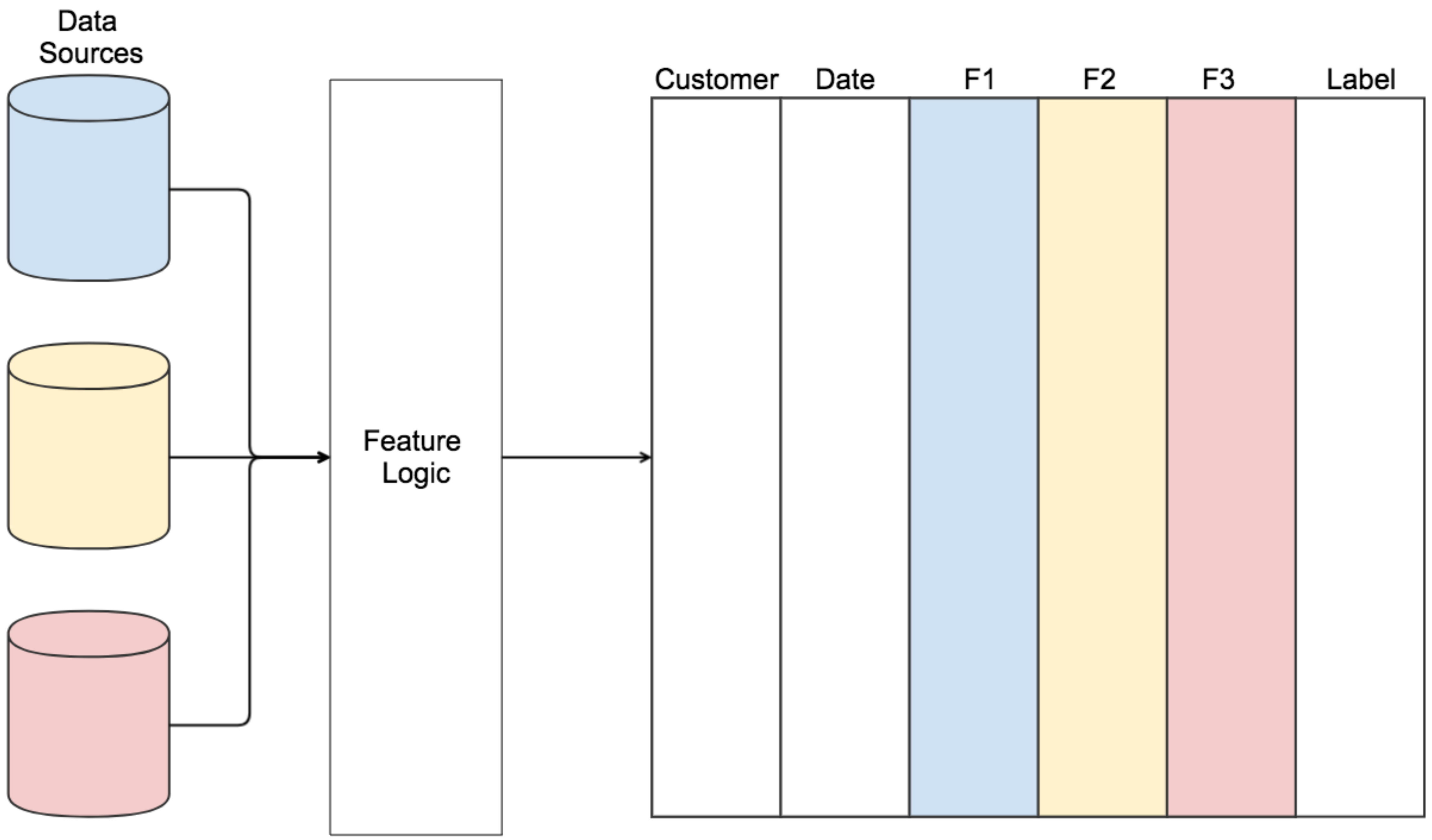
- Data
- Deployment
- Metrics
- Big Data Iteration Speed

Data

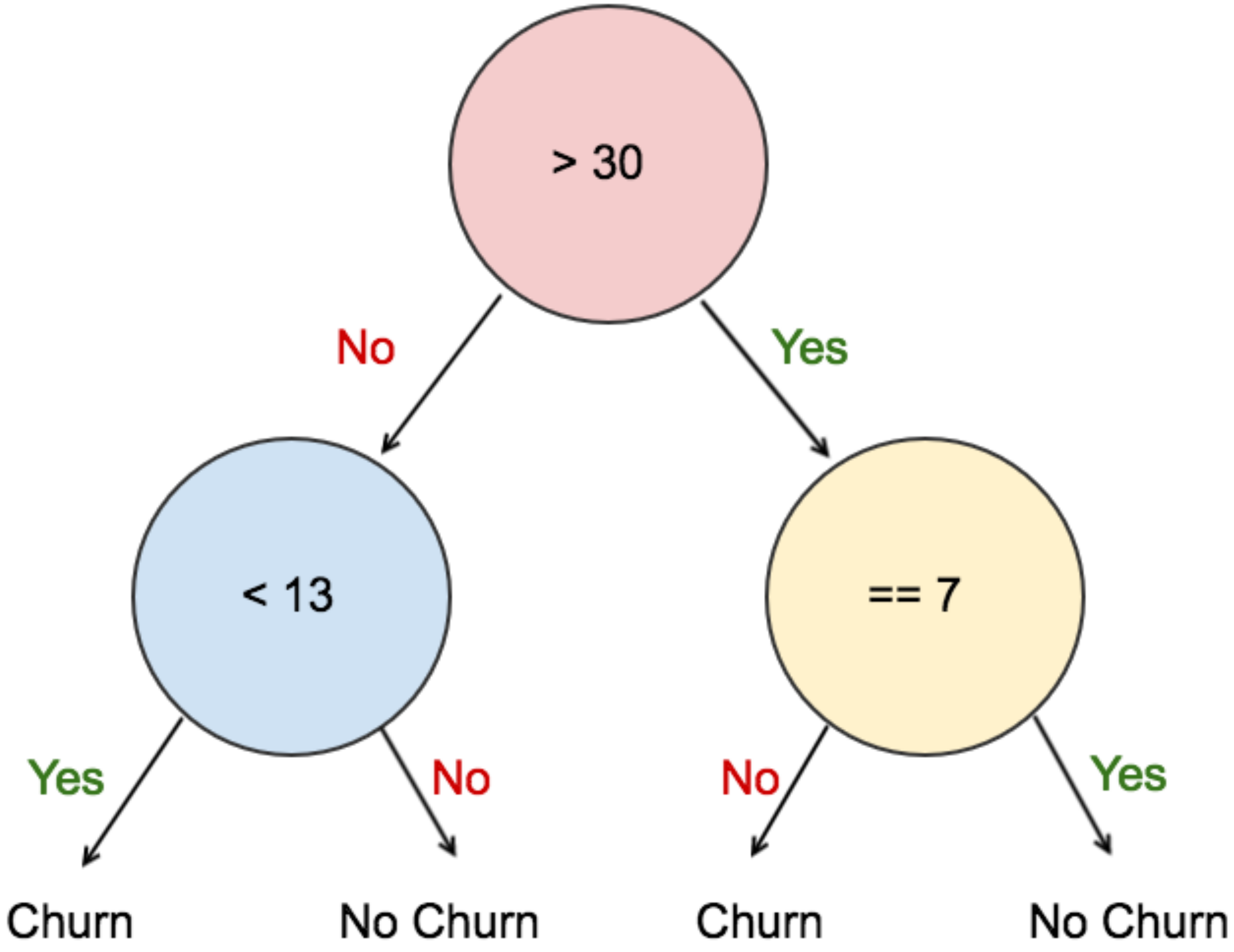
Example Use Case: Churn Prediction

We want to predict which users are likely to leave our service soon so that we can try and give them reasons to stay

Training Data Creation

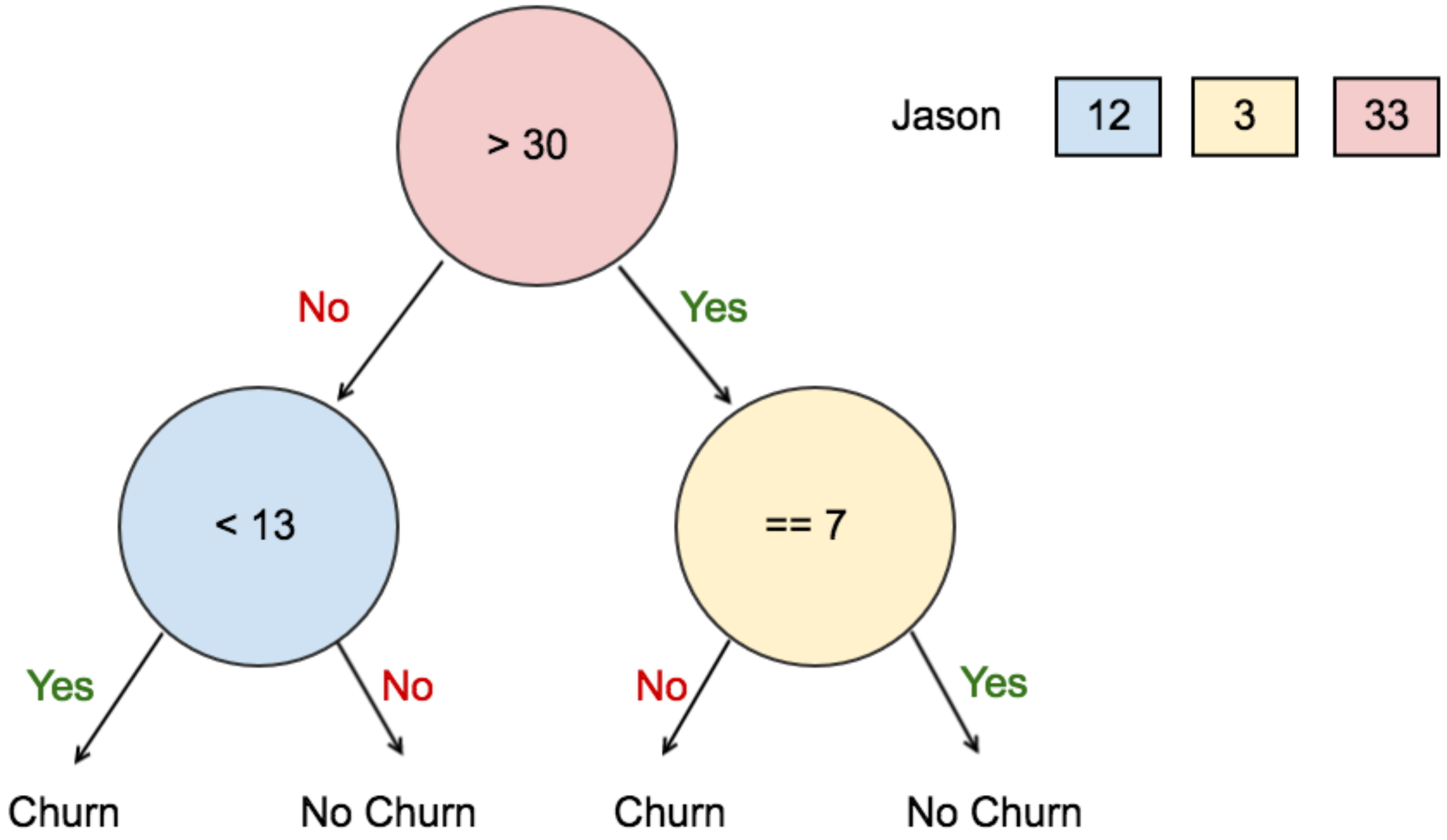


- Historical Data (need actual churn events as examples)
- We know the labels at train time
- Produce Features to try and predict the label



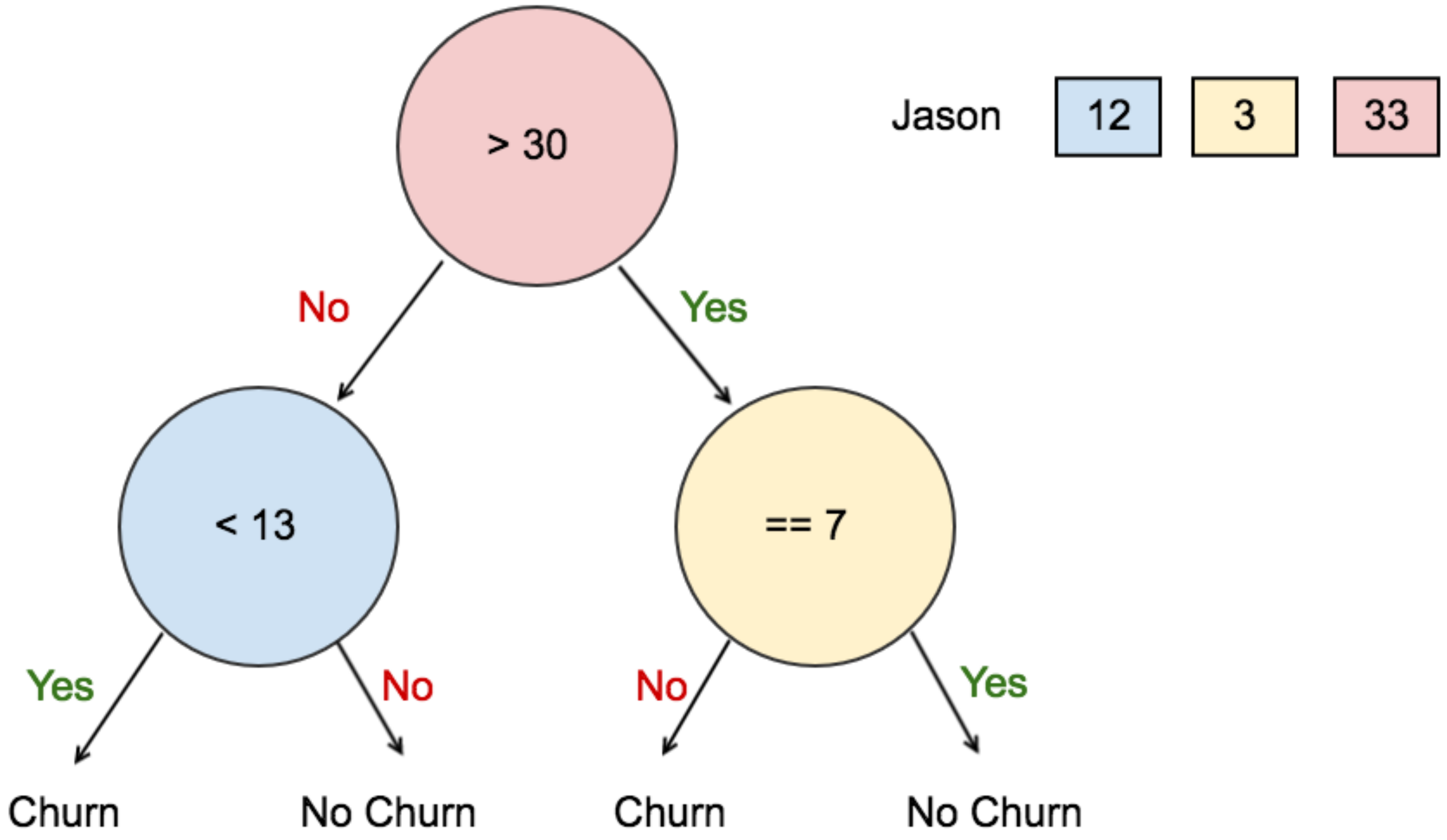
Train Our Model

- Minimise our loss function to best predict our labels (Churn/No Churn)



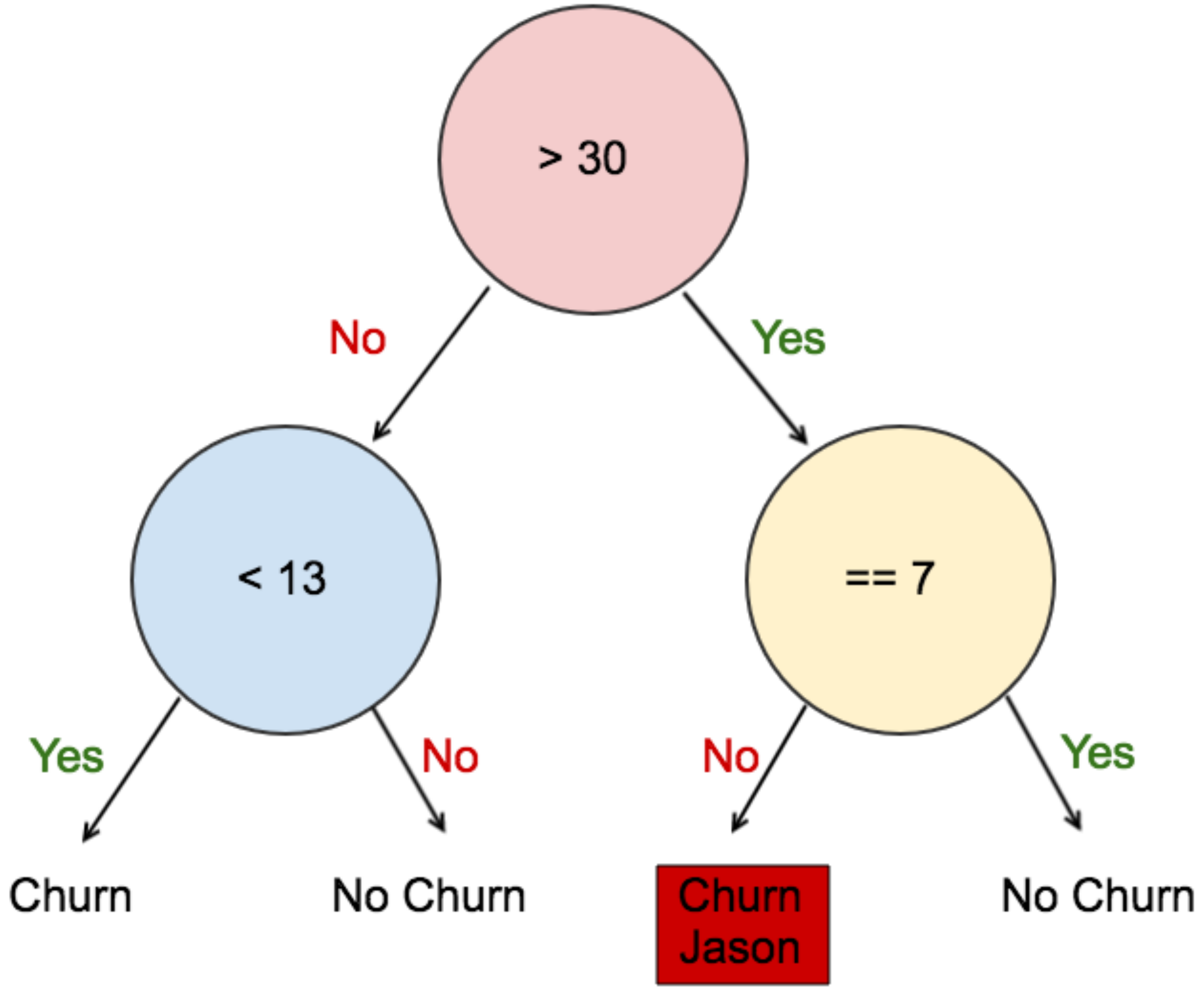
Prediction Time

- Jason's red feature value > 30



Prediction Time

- Jason's red feature value > 30
- Jason's yellow feature value != 7

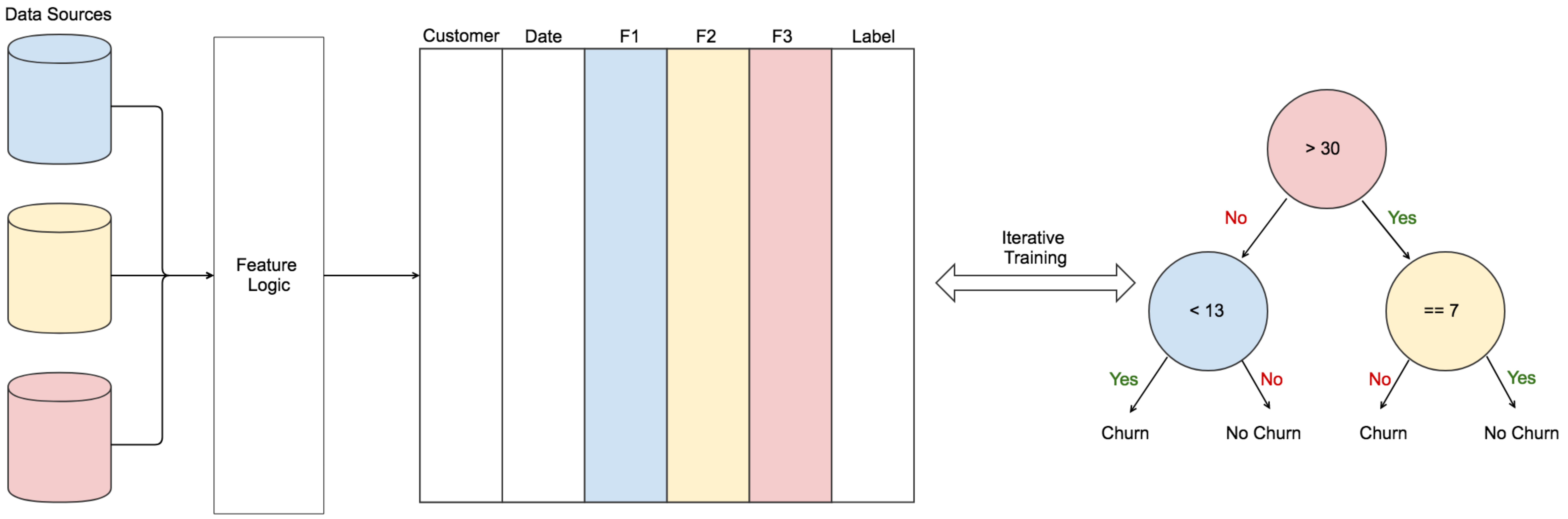


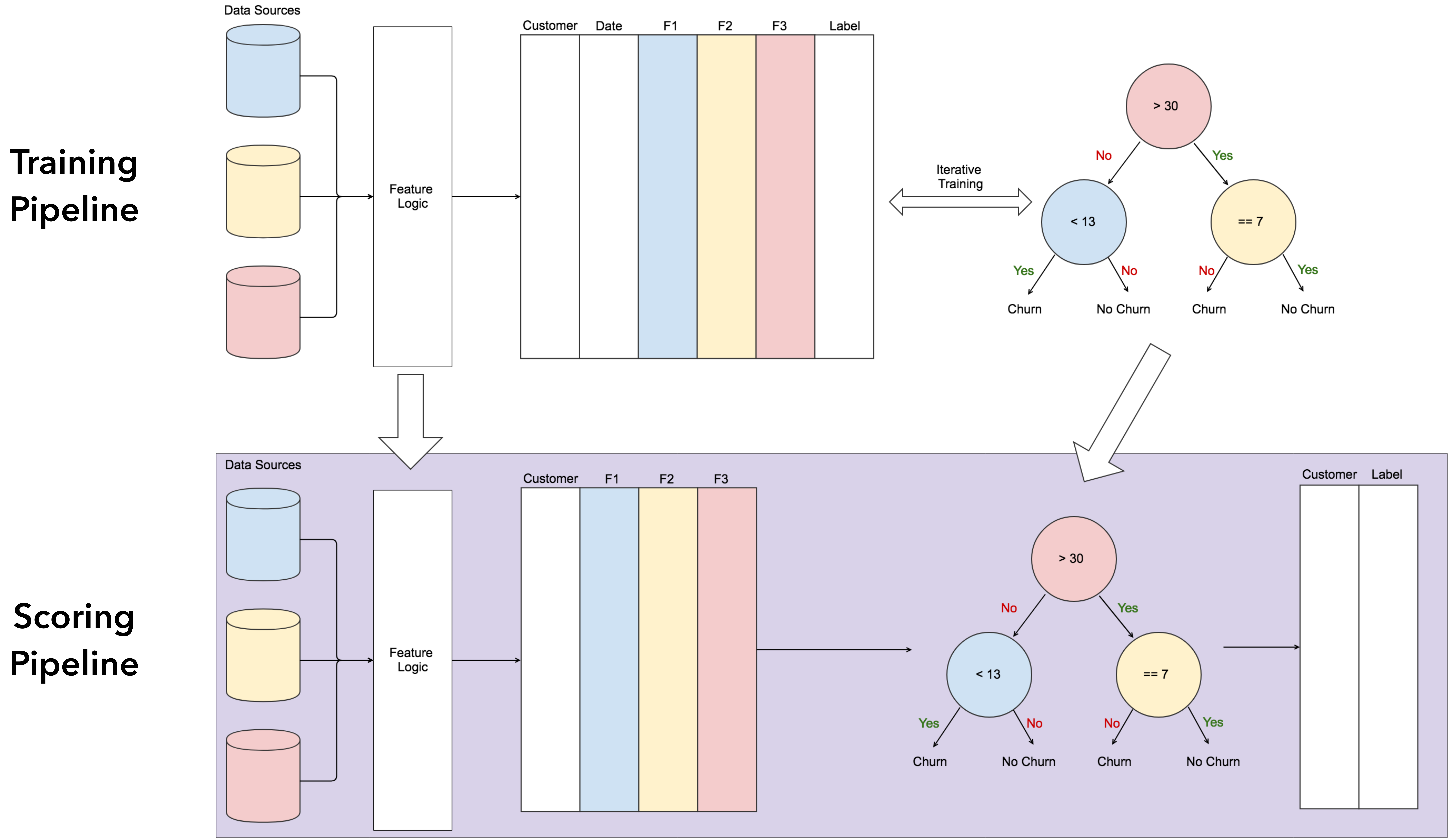
Prediction Time

- Jason's red feature value > 30
- Jason's yellow feature value != 7
- We predict Jason will churn

Moving to Production

Training Pipeline





Training Pipeline
Data Sources
Feature Logic
Customer
Date
F1
F2
F3
Label
Iterative Training
> 30
No
Yes
< 13
== 7
Yes
No
No
Yes
Churn
No Churn
Churn
No Churn
Scoring Pipeline
Data Sources
Feature Logic
Customer
F1
F2
F3
> 30
No
Yes
< 13
== 7
Yes
No
No
Yes
Churn
No Churn
Churn
No Churn
Customer
Label

Data Issues

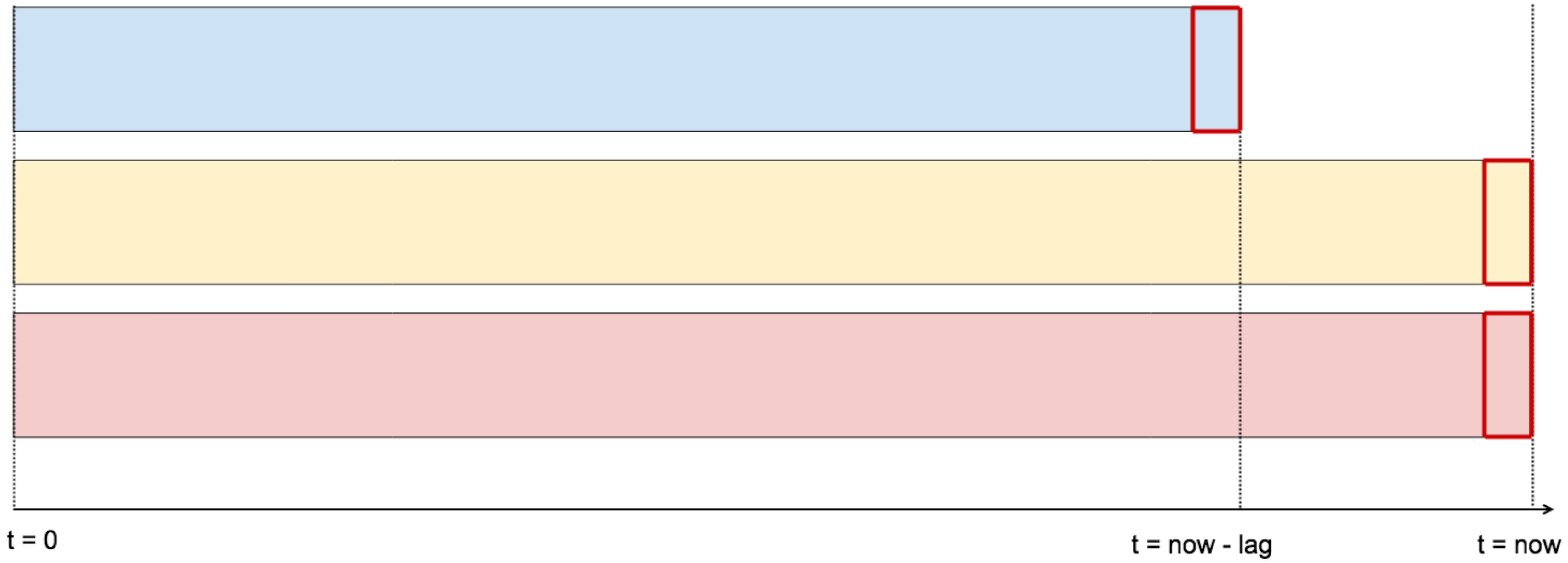
- Data ingestion lags (systematic) or failures (random)
- Data is incorrect

Data Issues

- Data ingestion lags (systematic) or failures (random)
- Data is incorrect

Before We Change the System

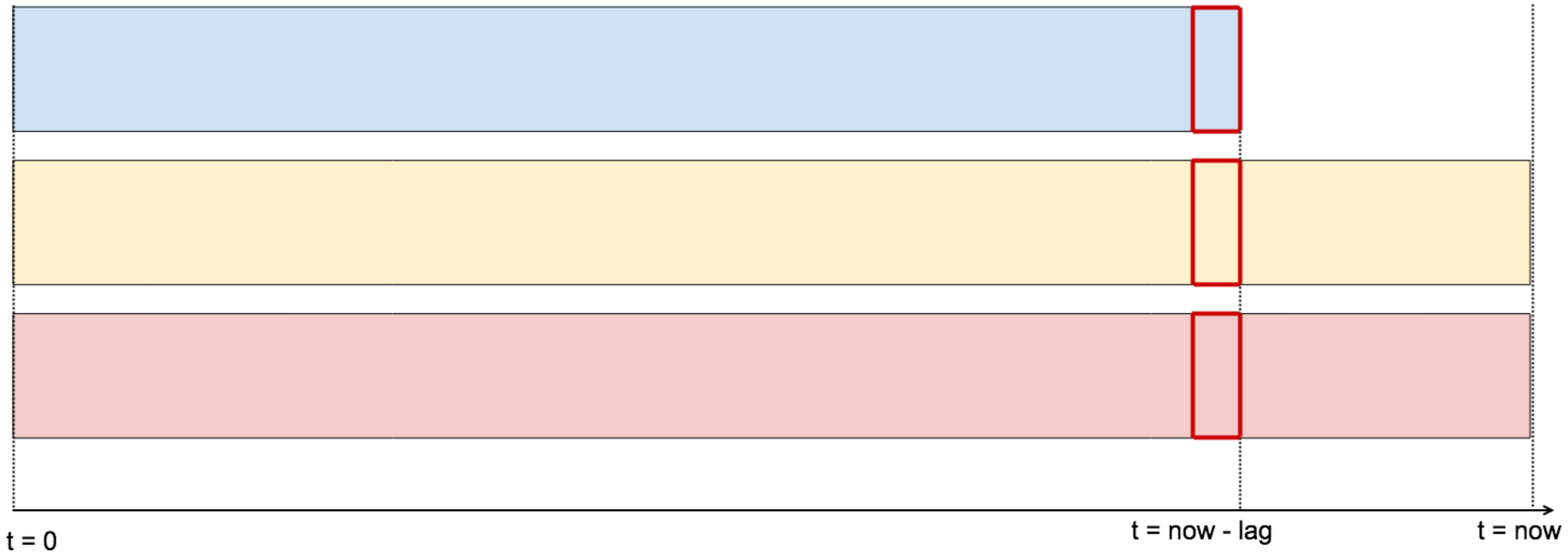
- Fix the data source if that’s and option
- Measure the importance of the feature in the model to quantify the cost/effort



Naive Best Effort

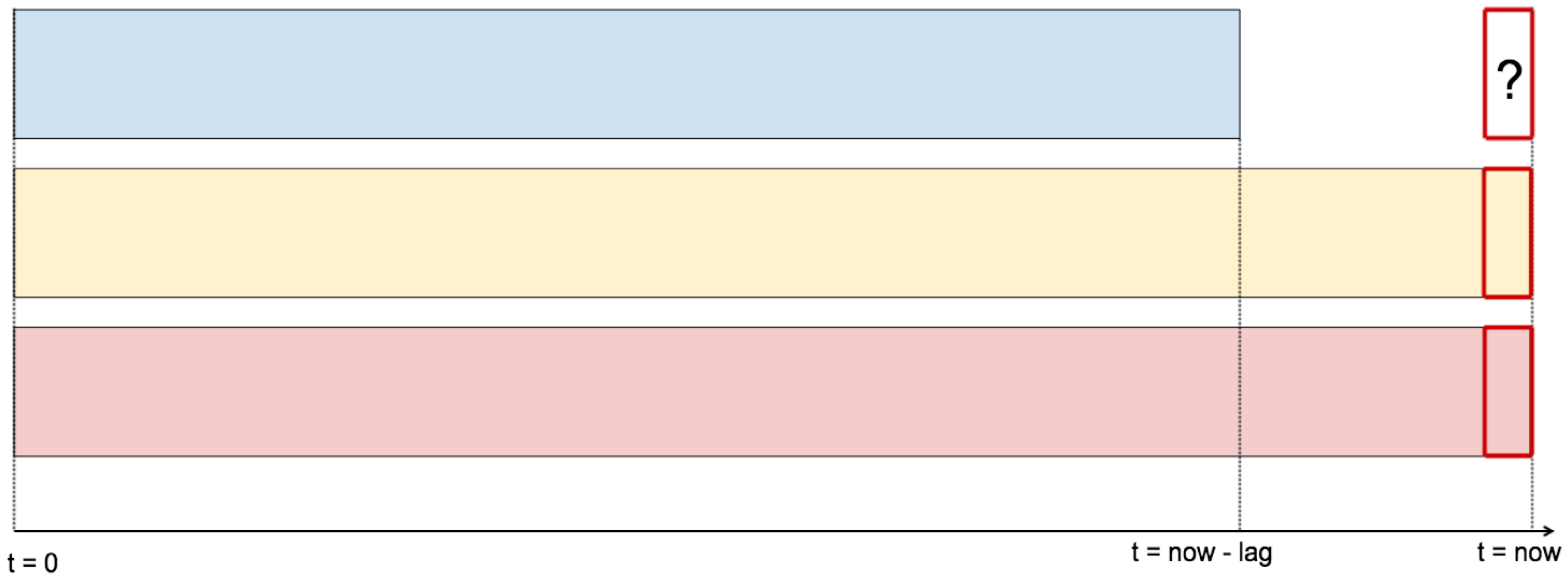
- Use most recent data for all features
  - *Inconsistent customer view*
- Retrain model with data lag in mind
  - *Tightly couple model*

Consistently Lagged



- Get a consistent snapshot at the time of the most lagged data source
    - *Predictions will be outdated equal to the slowest data source lag*

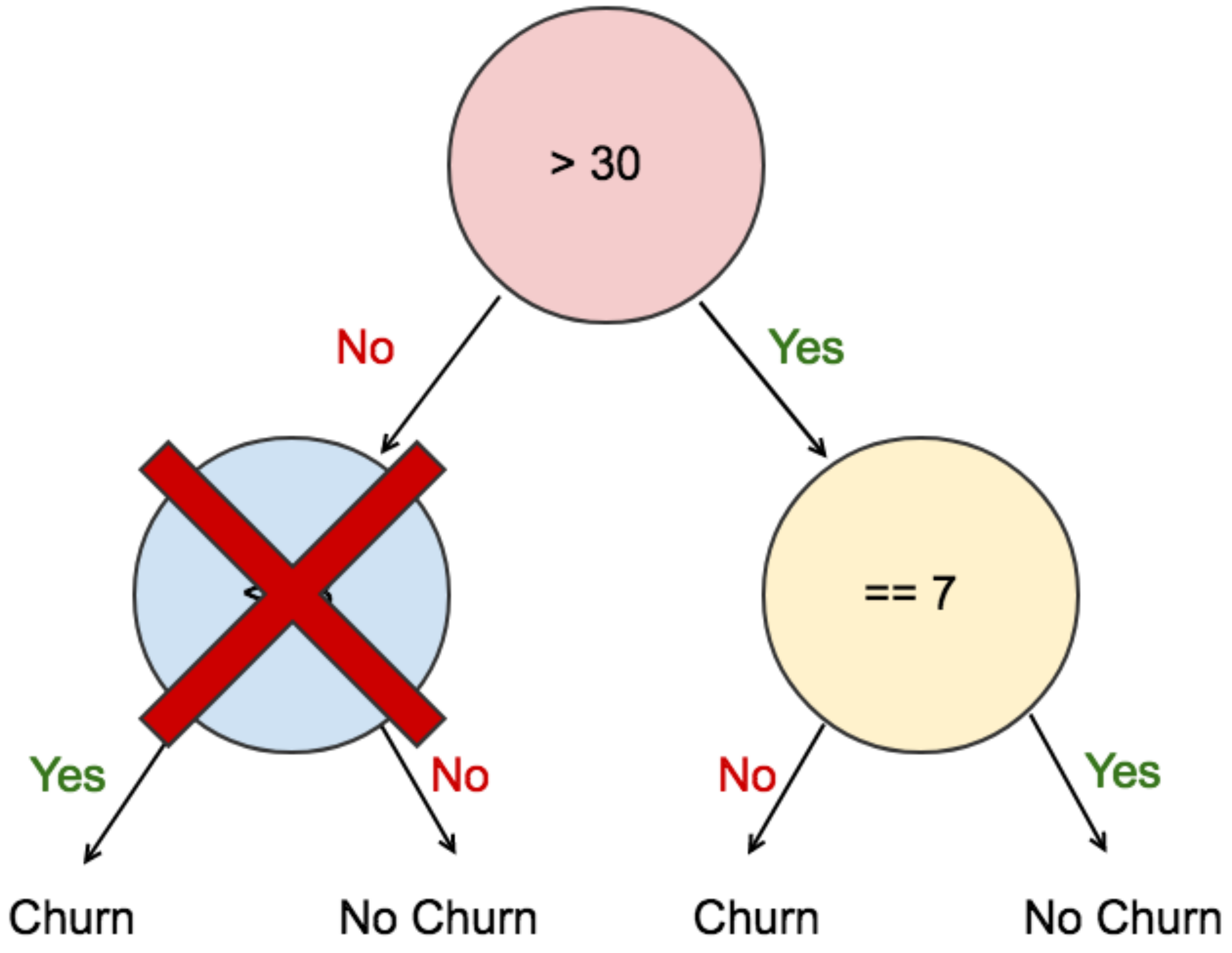
Imputation



- Fill in missing values with median for numerical, mode for continuous
  - *Every users experience is the median experience? Not useful.*
- Contextual Imputing (e.g. Median male height for men, median female height for women)
  - *Lots of custom model specific code necessary*

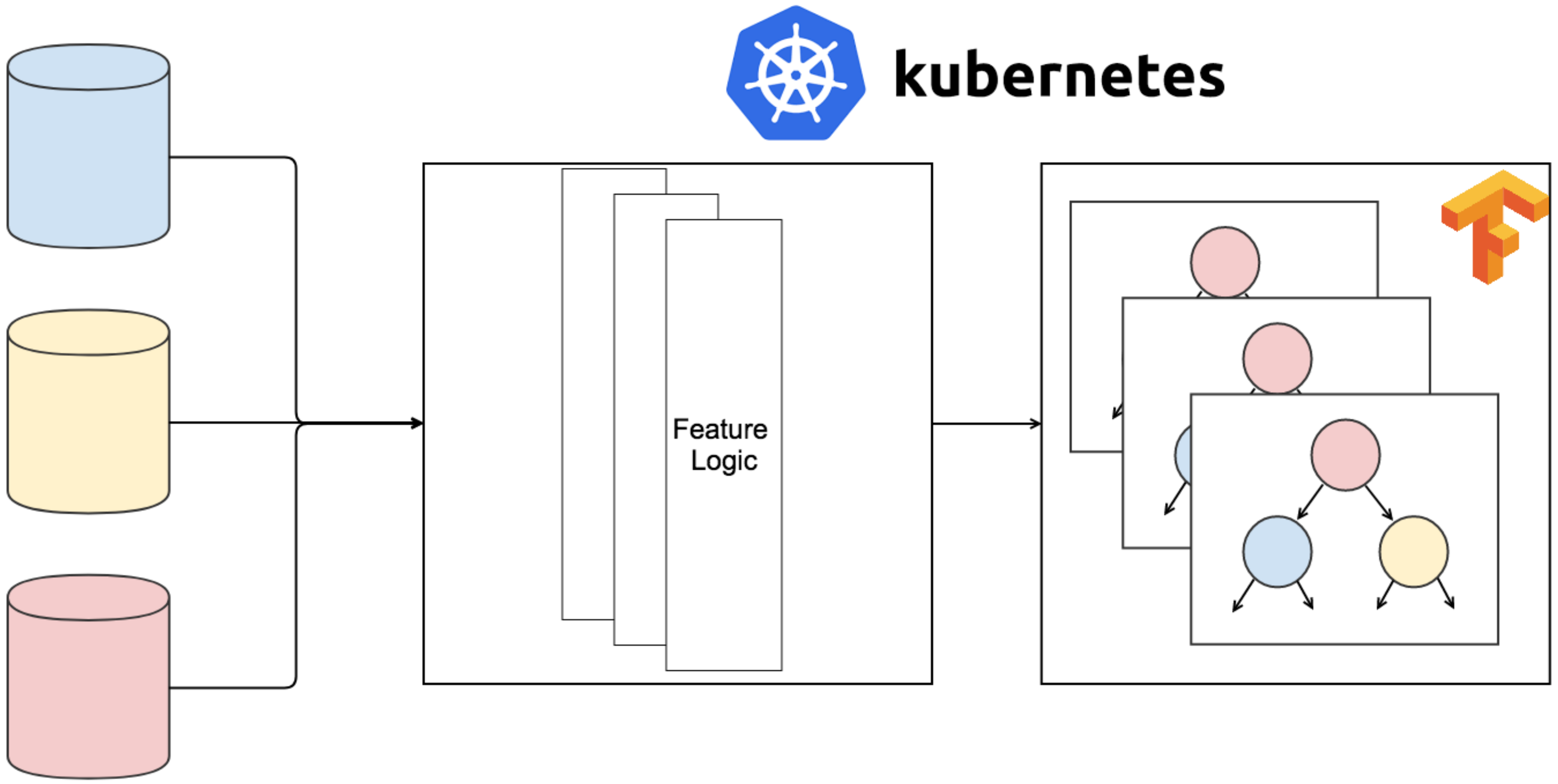
Graceful Model Degradation

- Model Specific fallback to give a best guess from the distribution given the current inputs
  - *Doesn't come out of the box in most cases*

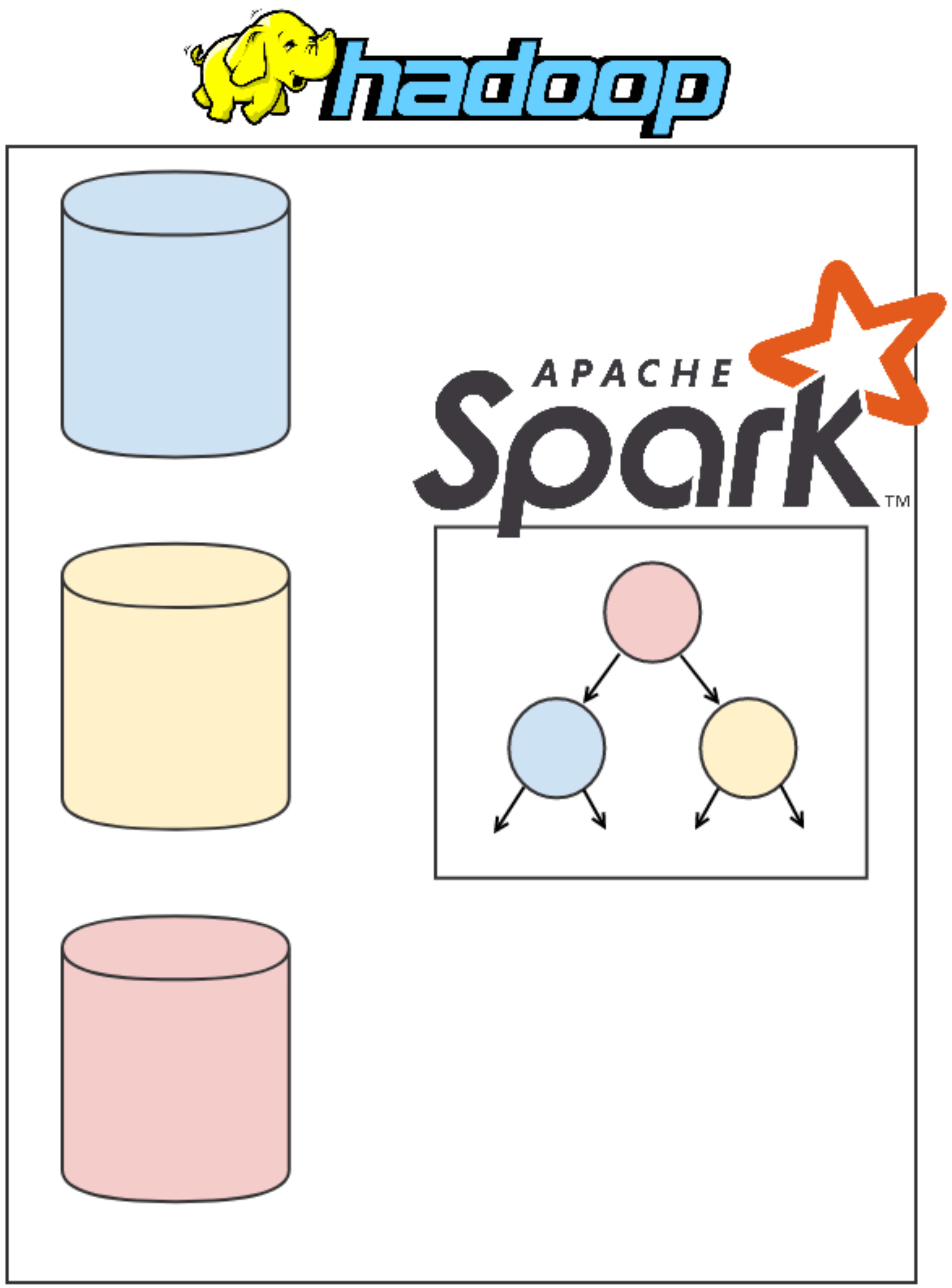


Deployment

Data to Model Deployments



- Containerised model exposing scoring API
- Clean and simple model management semantics
- Send your data to your models
  - *Network shuffle costs can be substantial for larger datasets*



Model to Data Deployment

- Distributed processing framework performs scoring (e.g. Spark)
- Send your models to your data
  - *Efficient but less portable*
  - *Model lifecycle more difficult to manage*

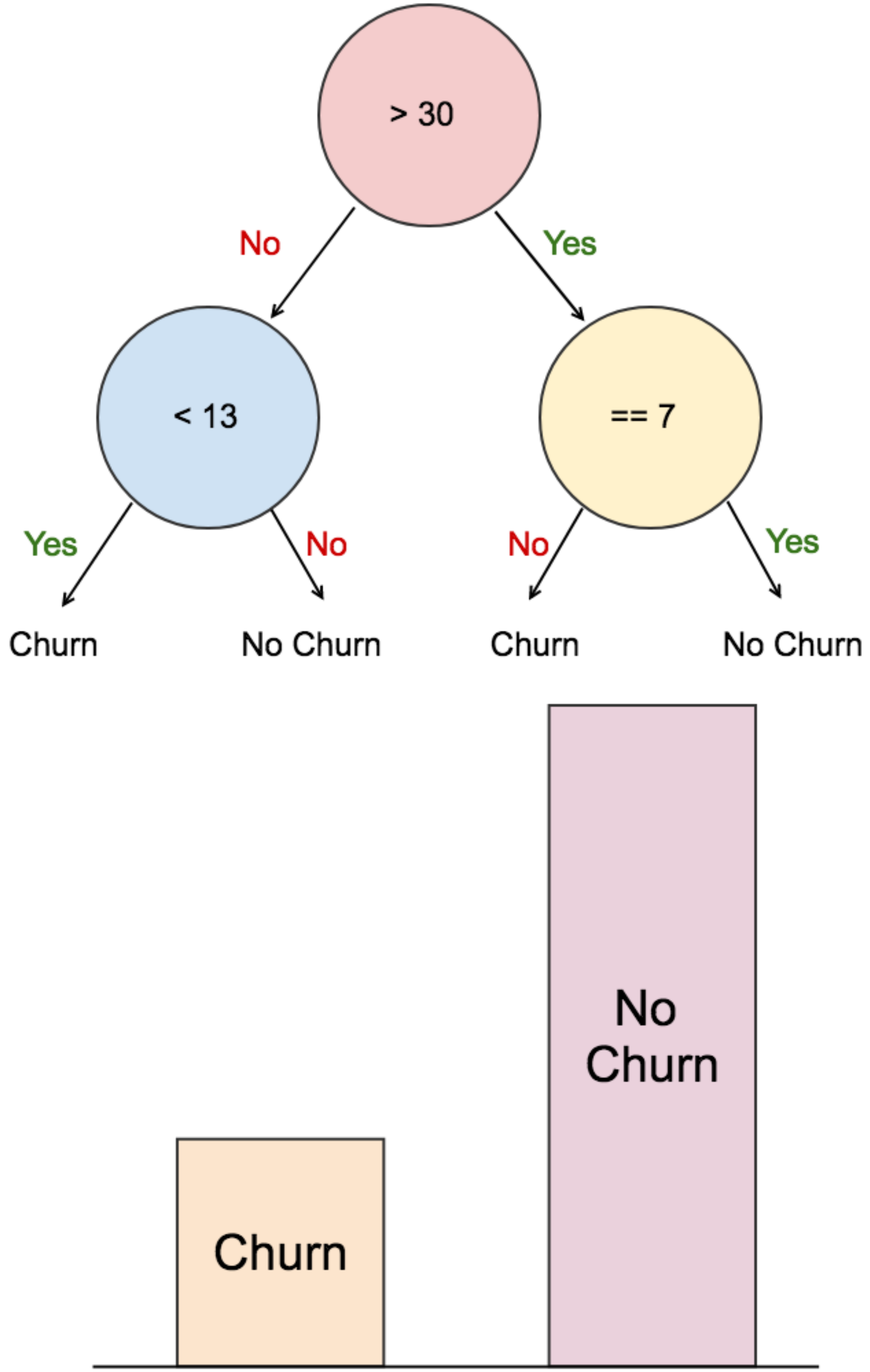
Future Solutions

- Spark on Kubernetes
  - Models and Executors colocated in pods with data locality.
  - Model lifecycle management through Kubernetes
    - Rollouts
    - Rollbacks
    - Canary Testing
    - A/B testing
  - Managed cloud solutions
    - Complexity hidden from users

Metrics

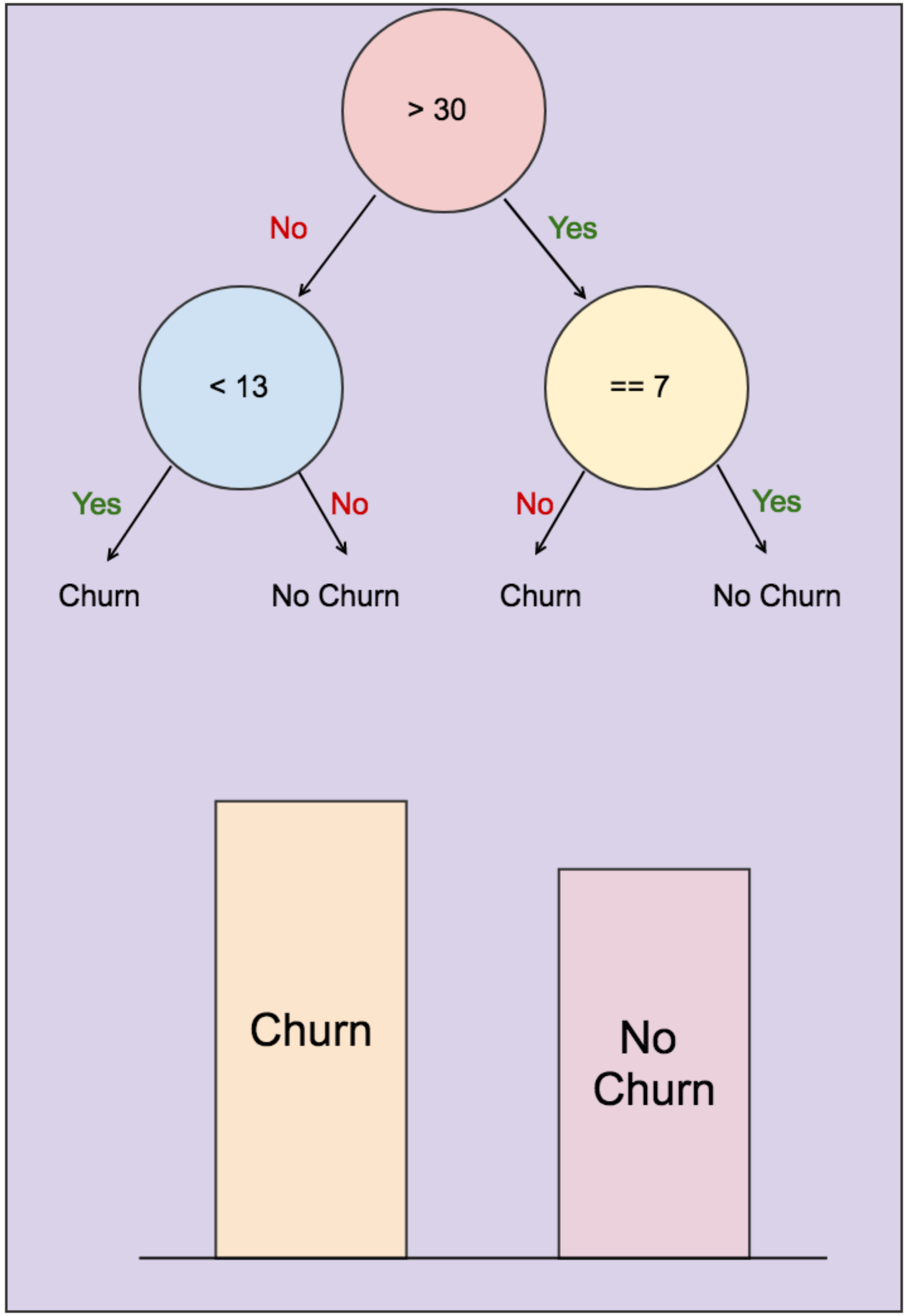
A Few ML System Metrics

- Data Distribution
- Effectiveness in Market



Data Distribution

Your training data will have some distribution of labels



Data Distribution

- In production, your data distribution may be significantly different
- This can happen over time as these systems tend to be dynamic

Possible Causes

- Changes to the domain you're modelling
- Seasonality or external effects
- Changes to the customers themselves or the way the customers are using your service
- Problems with the data collection pipelines (corrupted data feeds etc)

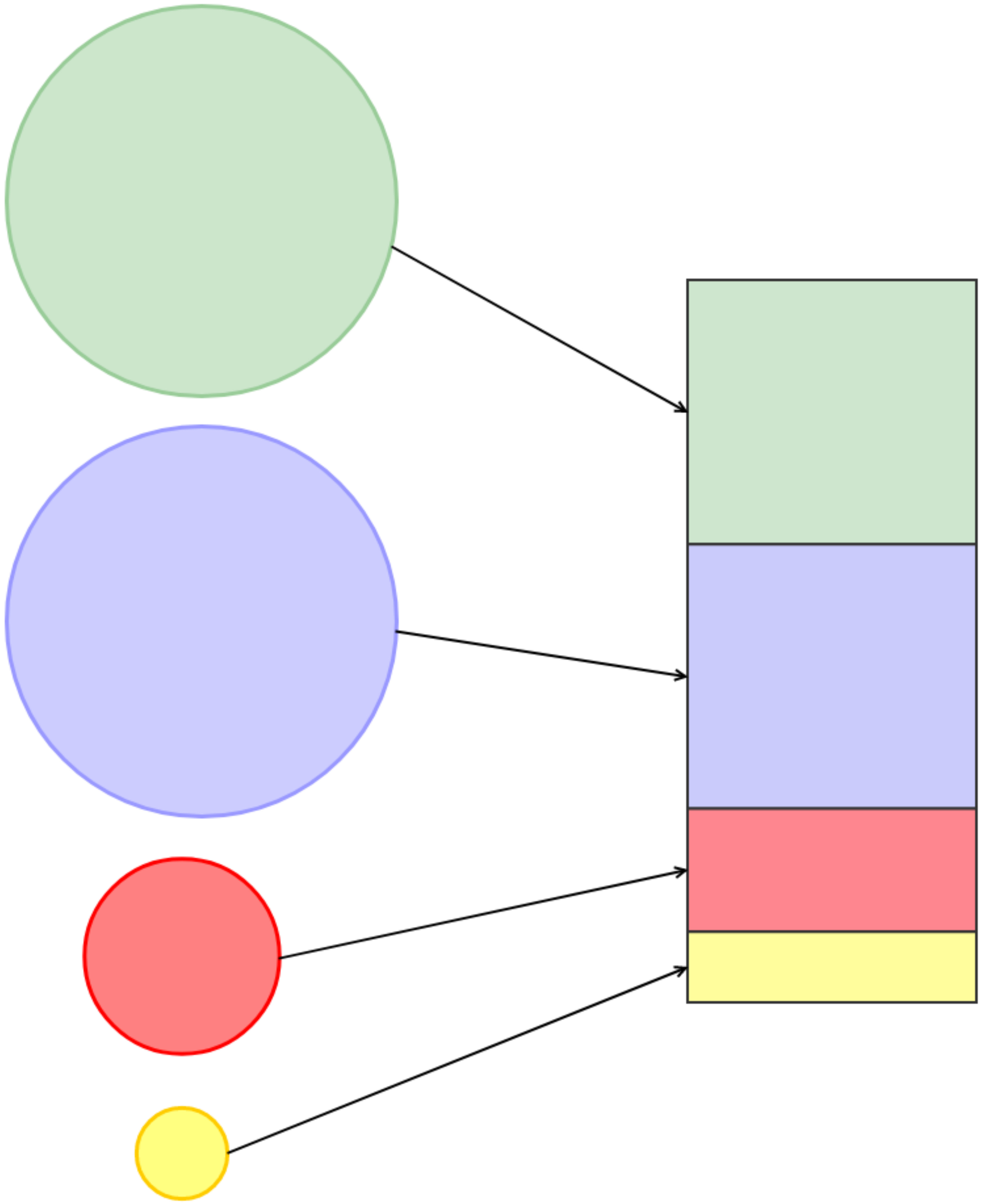
Effectiveness in Market

- Production is the first real test
- Need to capture metrics to measure the effect of the model for its intended purpose
- Paves the road towards;
  - Effective A/B testing
  - Incremental model improvement
  - Measurability of ROI

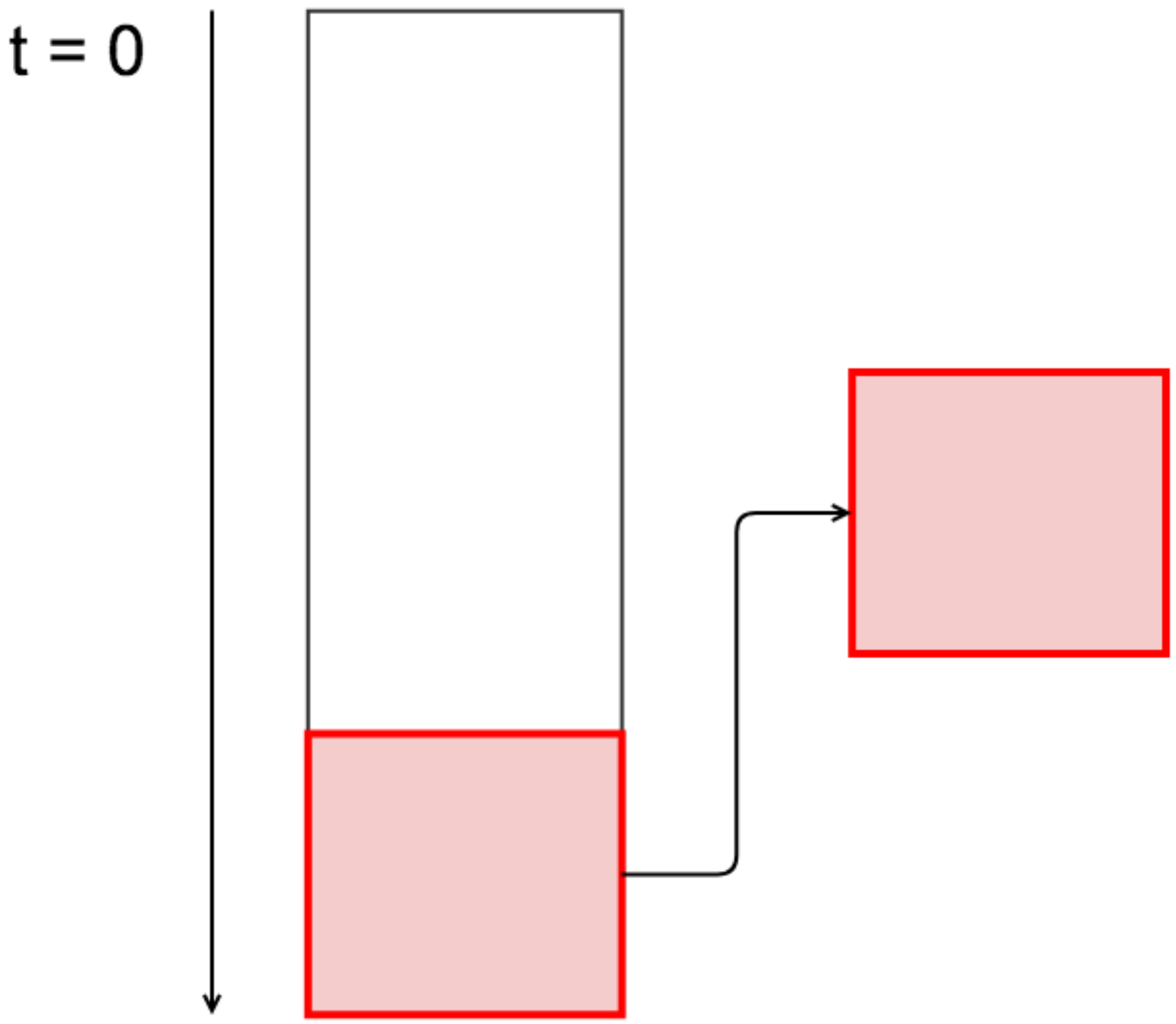
Big Data Iteration Speed

Training Models on Big Data is Slow

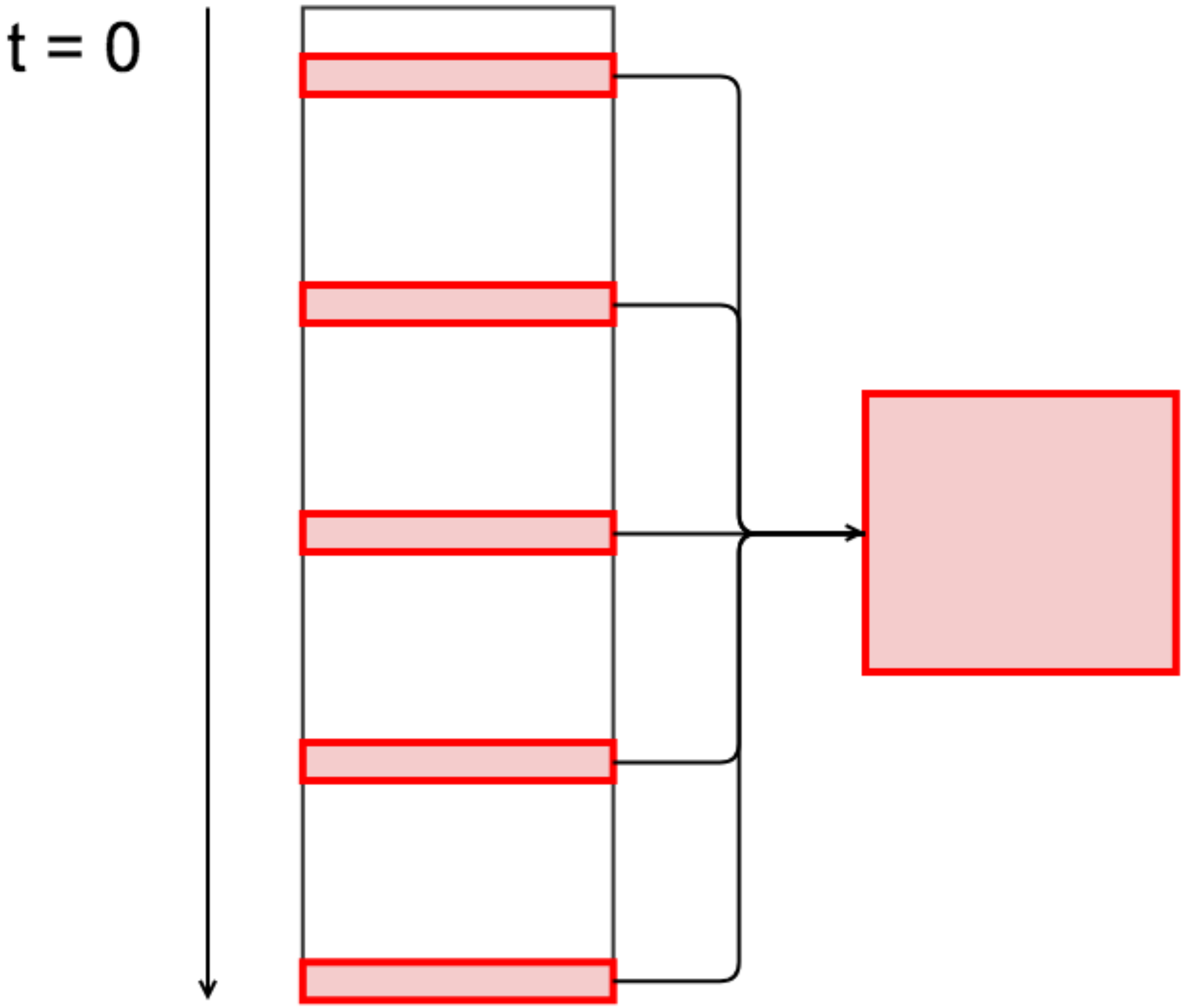
- Not all algorithms scale linearly as data/model complexity increases
- Hit computation/memory bottlenecks
- Number of hypothesis we can test is reduced
- Generating new features can become prohibitively expensive



Stratified Sampling



Sampling History



Customer Subset Sampling

Know Where to Spend Your Time

- Bad performance on training data = Bias Problem
  - Improve features
  - More complex model
  - Train longer
- Good performance on training data and bad performance on test set = Variance Problem
  - Get more data for training
  - Regularisation

Choice of Framework / Technology

- Modelling in R/Python and rewriting in production in Scala/Spark is an expensive process
- Choose a tech stack that allows engineers and data scientists to work together and productionise things quickly. Leads to faster feedback loops

What We’ve Covered

- Data issues can be be a central issue to ML systems are require a lot of up front design thought
- There are several modes of deployment, each with their own tradeoffs for different scenarios
- Production is not the end of the process for ML models. Metrics are a fundamental part of enabling improvement and growth.
- Ways to improve iteration speed on ML projects

Thank You

Questions?