

# What is Machine Learning, Anyway

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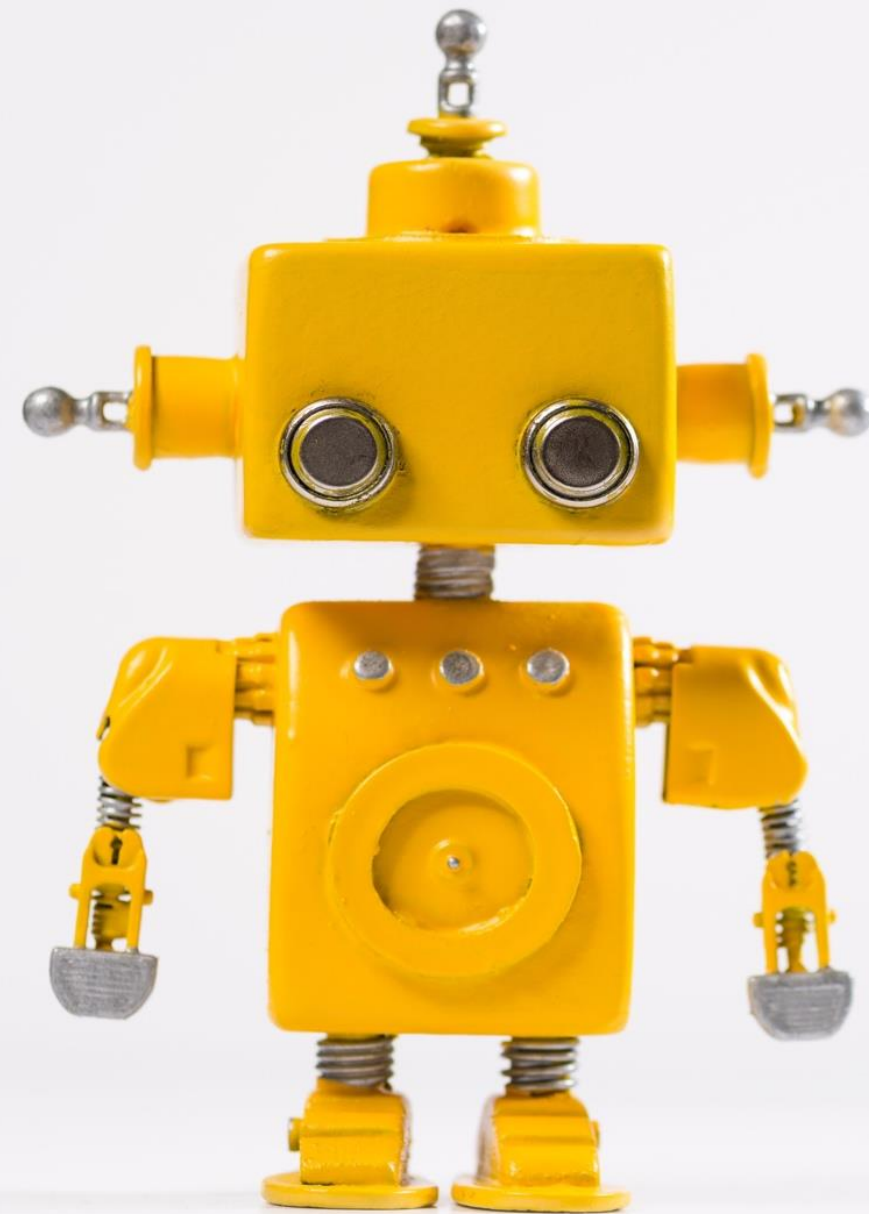
# Let's Start with a Definition

## Machine Learning

- Algorithms that train computer systems to improve their performance on specific tasks without being given explicit rules on how to do that
- The “computer systems” up there is an Artificial Intelligence
- ML is a branch of AI, but can also be used outside an AI application

# Let's Start with a Definition

## Machine Learning



Learning from machines,  
We know what it means,  
To use algorithms that can reason,  
And make decisions with precision.

It is the power of data,  
That can be used to inform,  
To detect patterns and trends,  
And keep us all in the firm.

The ability to recognize,  
The patterns we choose,  
Enables us to take action,  
And respond to the news.

Machine learning is the future,  
It will bring us so far,  
We can build smarter systems,  
That are better by far.

# Machine Learning vs Statistical Inference

## What's the Difference?

	Statistical Inference	Machine Learning
Data	Data has some underlying probability distribution	Wide range of data types
Goals	Test hypotheses / explore relationships	Make predictions / decisions
Approach	Specify a model and estimate parameters	Learn patterns by itself
Scope	Smaller data with a specific question	Large, complex data with many variables
Validation	Check the underlying assumptions about the data	See how the model does on data from a hold-out sample

# Machine Learning Methods

## Learning Types

- **Supervised Learning** – Algorithms are trained on a labeled dataset and work to predict outcomes
- **Unsupervised Learning** – Techniques where data is not labeled or classified, so there is no target to predict
- **Deep Learning** – ML techniques that use multiple layers of nonlinear processing to analyze data and create predictions

# Supervised Learning

Popular Models and Use Cases

# Supervised Learning

## Use Cases

- Generally used for predictive models, mostly binary (Yes/No) predictions
- Can be used for continuous variable predictions
- Data is partitioned into a Training Set (~70%) and a Validation set (~30%) to see how the model does on data it was not exposed to in training -- this is to minimize **overfitting** the model.

# Supervised Learning Models

## Logistic Regression

- Similar to Linear Regression, except you are predicting the **probability** of an outcome
- Produces an equation to predict that probability of success
- Hypothesis tests for each variable's significance
- You must specify a **cutoff point** that determines if the prediction is a success or failure
- Cutoff point selection is critical, but often overlooked
- Case complete model



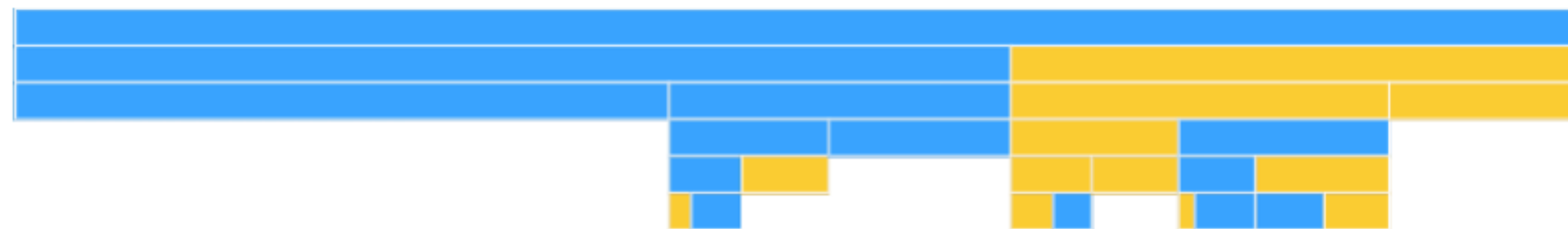
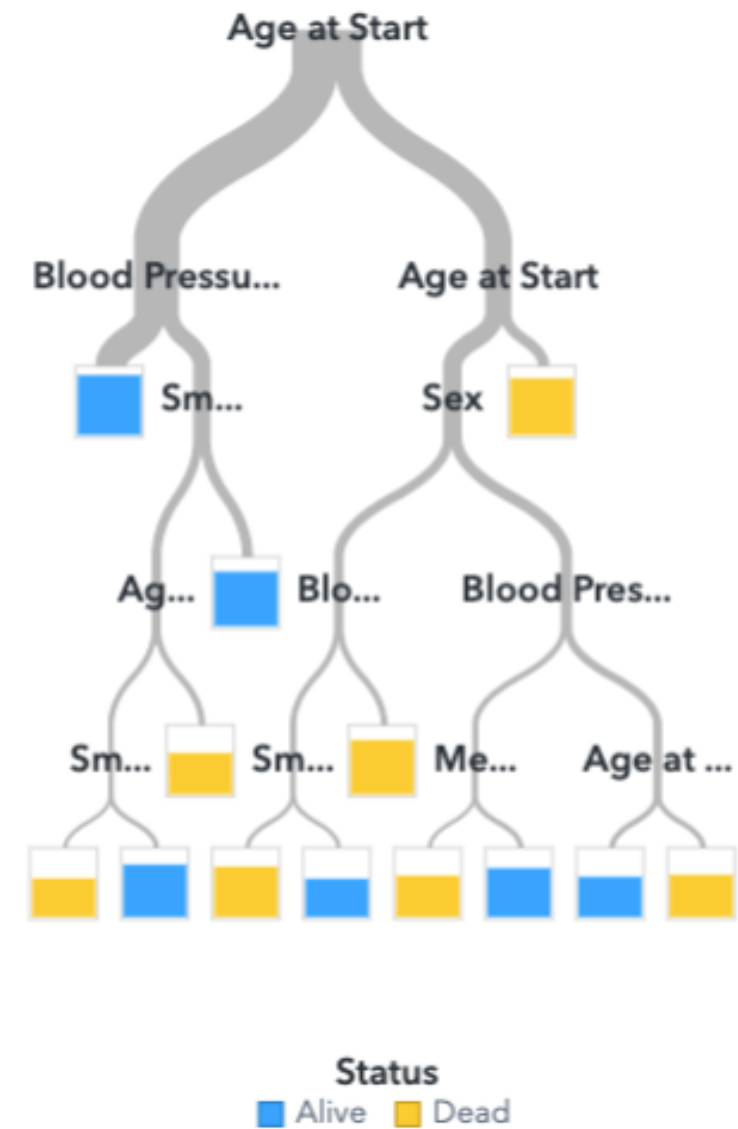
# Supervised Learning Models

## Decision Trees

- Find the values of variables that can split the data into **branches** that lead to **leaves** where there are a high number of success or failures
- Algorithm searches through all values of all variables
- Handles missing values like any other value
- Very easy to interpret and use
- Can limit the numbers of splits in a branch, the number of levels possible and the smallest leaf size

# Supervised Learning Models

## Decision Trees



# Supervised Learning Models

## Random Forests

- Data is sampled (with replacement) to create multiple subsets of observations (**bootstrapped samples**)
- Make a decision tree for each bootstrapped sample, using a random selection of variables
- Once all trees are trained, predictions are made by running new data through each tree. Final prediction is based on majority vote
- Essentially crowdsourcing predictions
- Less prone to overfitting than a single tree

# Supervised Learning Models

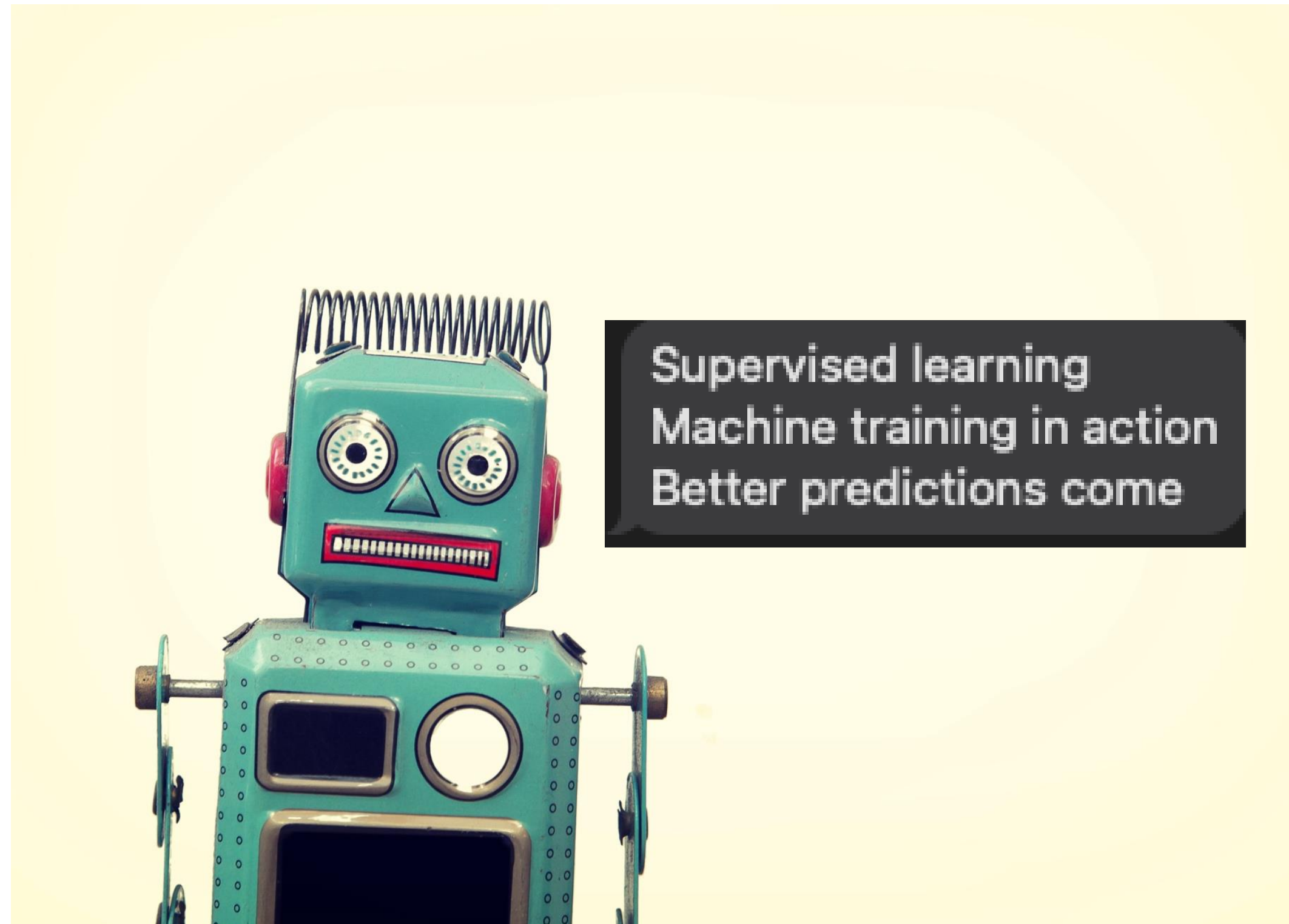
## Gradient Boosting

1. Train a tree to make predictions
2. Calculate errors between predicted and actual value
3. Build a new model to predict errors in step 2
4. Combine the base model and error model to make new predictions and calculate new error rates
5. Repeat 2-4 until error rate stops improving
6. Final version gives prediction

Good for complex relationships between features and targets

# Supervised Learning Models

## Summary



# Unsupervised Learning

Popular Models and Use Cases

# Unsupervised Learning

## Use Cases

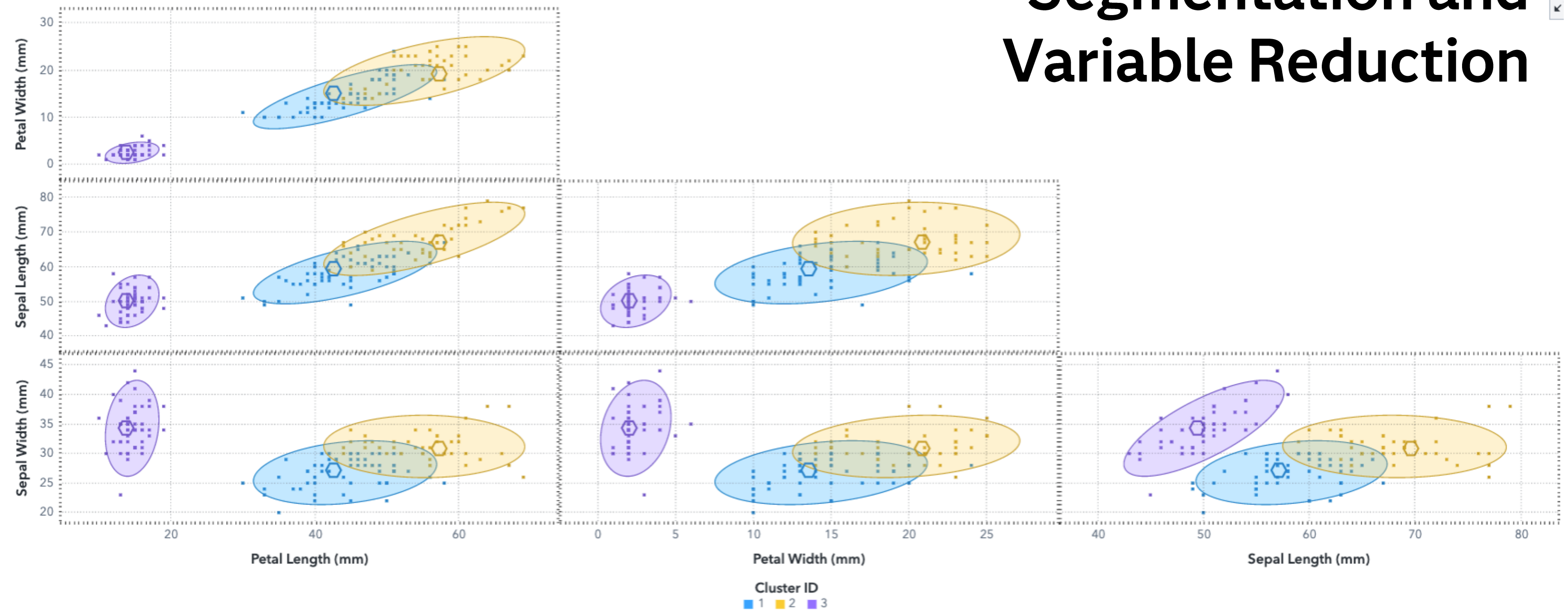
- Goal: Discover patterns, relationships, and structures in the data
- Most Common use cases:
  - Customer Segmentation
  - Anomaly Reduction
  - Variable Reduction
  - Recommendation Systems
  - Fraud Detection
  - Network Analysis

# Unsupervised Learning

## Clustering

# Segmentation and Variable Reduction

Cluster Observations: 150 of 150 Polylines: 110





# Unsupervised Learning

## Clustering

1. Pick a starting number of clusters
2. Randomly assign center points (**centroids**)
3. Determine the distance from each point to each centroid
4. Assign each point to the closest cluster
5. Find the new centroid of points assigned to each cluster
6. Repeat 3-5 until no observations move
7. Repeat the whole process with a different number of clusters

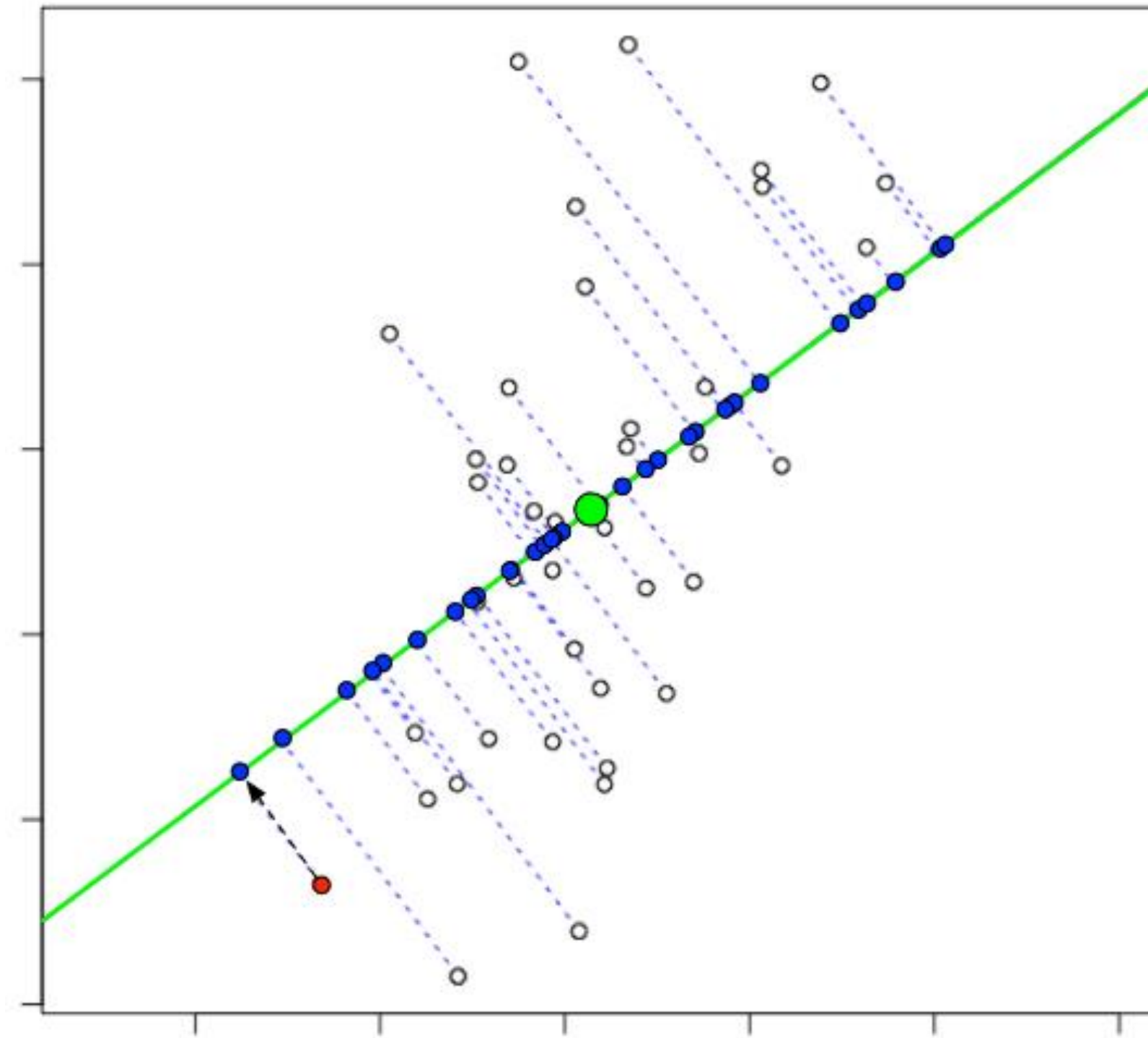
# Unsupervised Learning

## Principal Components Analysis (PCA)

- Reduce the number of variables (features) in a dataset to make modeling smoother (**reducing dimensionality**)
- Basically, instead of needing 12 variables to explain the variance in the data, make a new set of coordinates and only need 3 features

# Unsupervised Learning

## Principal Components Analysis (PCA)



# Unsupervised Learning

## Association Analysis

- Identifies sets of items that are frequently obtained together (Beer and pretzels, milk and cereal, similar types of movies streamed, that sort of thing)
- Generates a bunch of association rules
- Ranks the rules based on how often things are consumed together
- Besides market basket analysis, also used in fraud detection and supply chain optimization



# Unsupervised Learning

## Summary

Unsupervised learning  
Finding patterns in the data  
Reveals secrets hidden



# Deep Learning

Popular Models and Use Cases

# Deep Learning

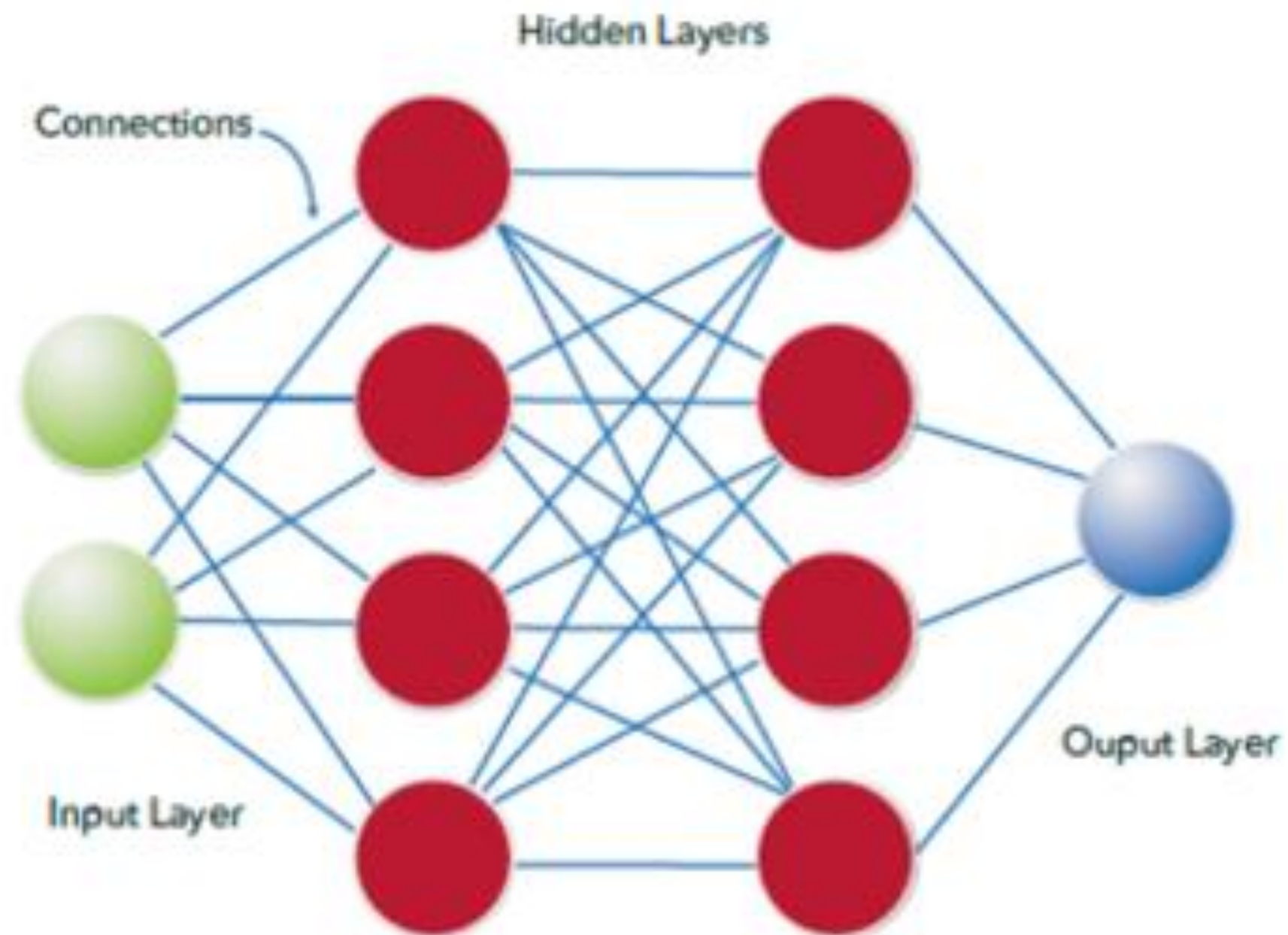
## Definition and Use Cases

- Neural Networks – complex networks of neurons that make many steps of models to get from inputs to predictions
- Computationally intensive and very hard to understand what's happening (black box models)
- Common Use cases:
  - Computer vision & pattern recognition
  - Natural language translation and sentiment analysis
  - Generating new data, such as images or videos



# Deep Learning

## Neural Networks





# Deep Learning

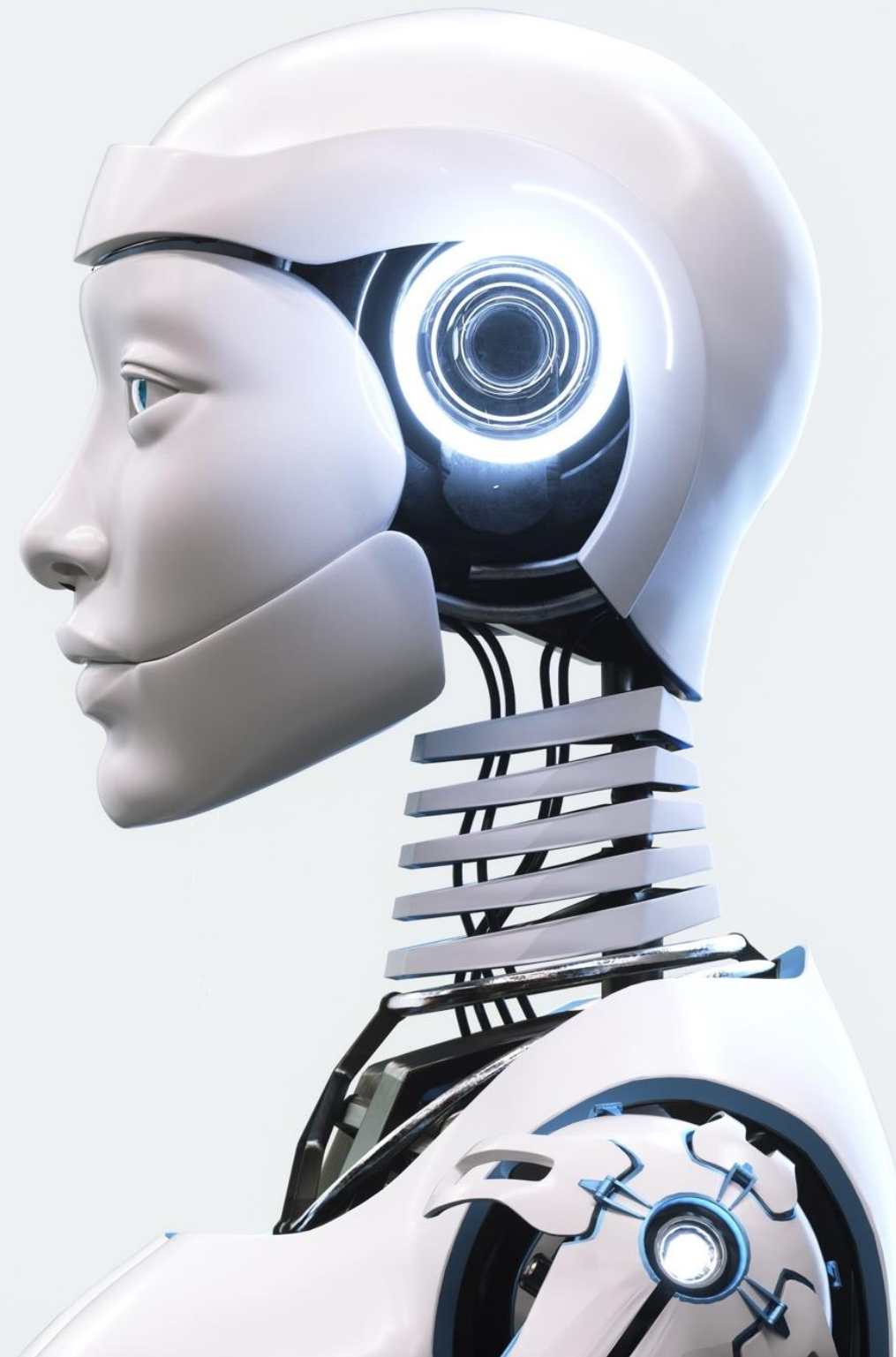
## Summary

Neural networks, a cryptic thing  
A world of ever-changing equations  
The complexity of these wonders ring  
To tease out the data in its relation

We train and tweak, using numbers and math  
To make the network ever-smarter  
And when the data is in its path  
We can unlock insights ever-farther

This web of neurons, so intricate  
It can learn the patterns of the past  
We can use it to keep our fate  
By controlling what will come to pass

The power of this technology  
Should not be underestimated  
We can use it for the good of all  
And make the world ever-updated



# Model Selection

Methods of Evaluation

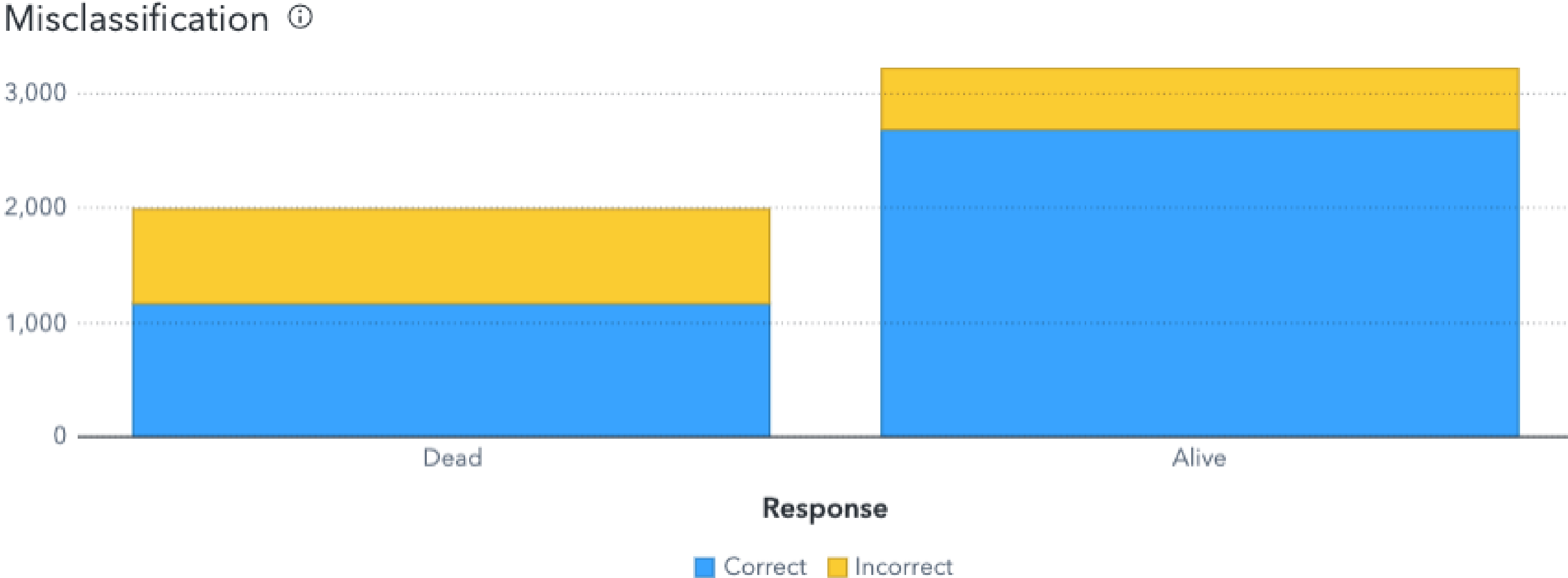
# Model Selection

## Model Process

- **Partition** the data into Training and Validation
- Train a bunch of models in the Training data
- Use the model to generate predictions on the Validation data
- Compare the Predicted values to the Actual Values in the Validation partition
- Use different methods to decide which is the “best” model

# Model Selection

## Misclassification Rate



**Dependent on that Cutoff Point!**

# Model Selection

## Confusion Matrix

Confusion Matrix ⓘ

Observed

Alive	<b>True Positive</b> 2,686	<b>False Negative</b> 532
Dead	<b>False Positive</b> 821	<b>True Negative</b> 1,170
	Alive	Dead

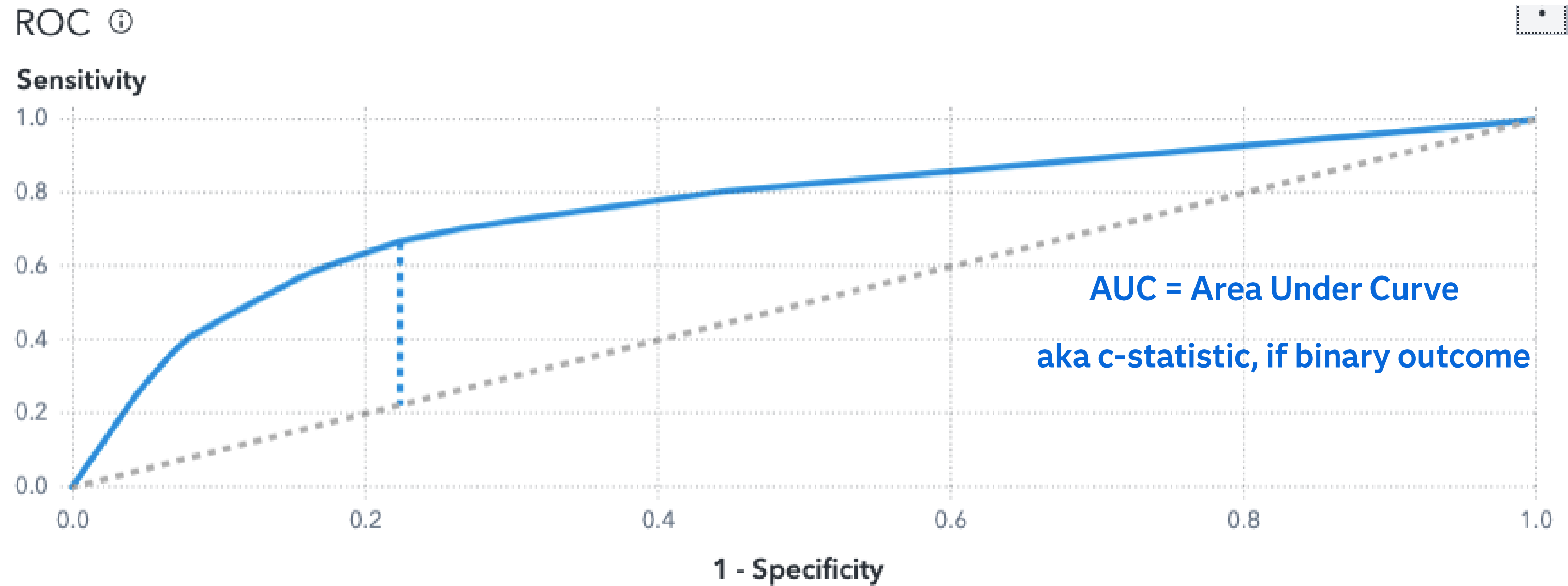
Predicted

- **Sensitivity: True Positive / Actually Positive = .8347**
- **Specificity: True Negative / Actually Negative = .5876**

**Dependent on that Cutoff Point!**

# Model Selection

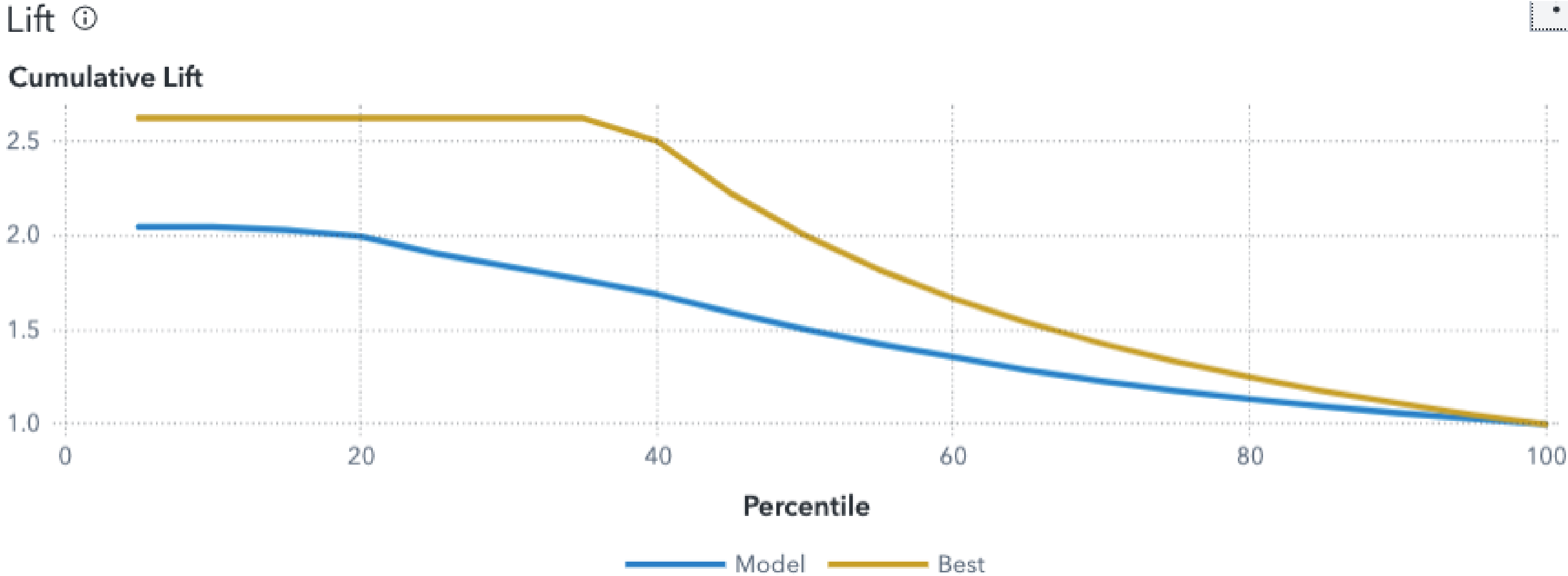
## ROC Curves



**Looks across all possible cutoff points**

# Model Selection

## Lift Curves



**Independent of cutoff points**

# Summary

To the brave warriors of machine learning, may your minds be sharp and your algorithms ever-evolving. May you build models that withstand the test of time, and may your efforts be ever-rewarded. Skål!





# Thanks!

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