# Designing Machine Learning Workflows



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### Overview

End-to-end machine learning workflows

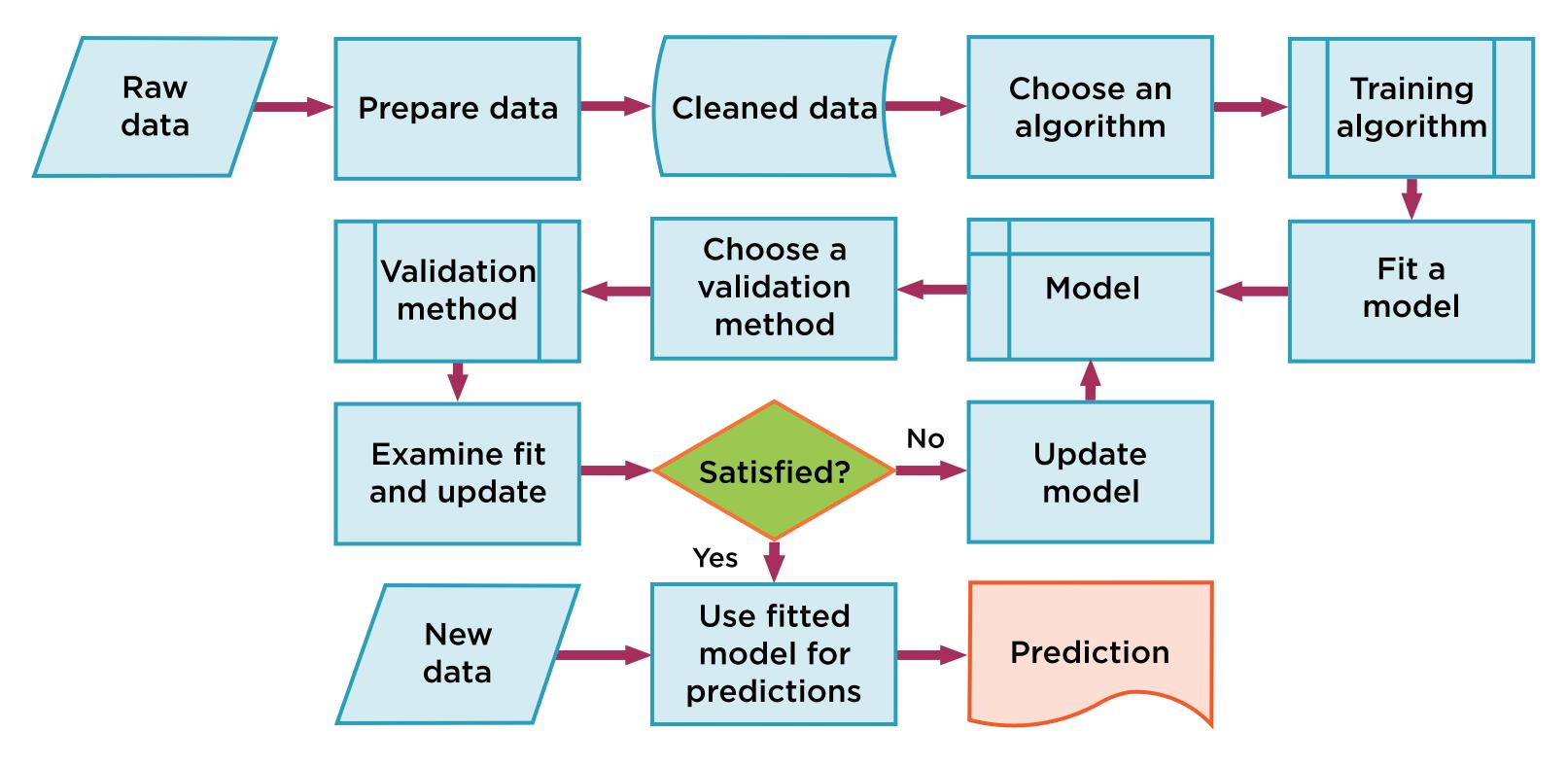
Local, distributed, and cloud-based training and prediction

Understanding the need for ensemble techniques

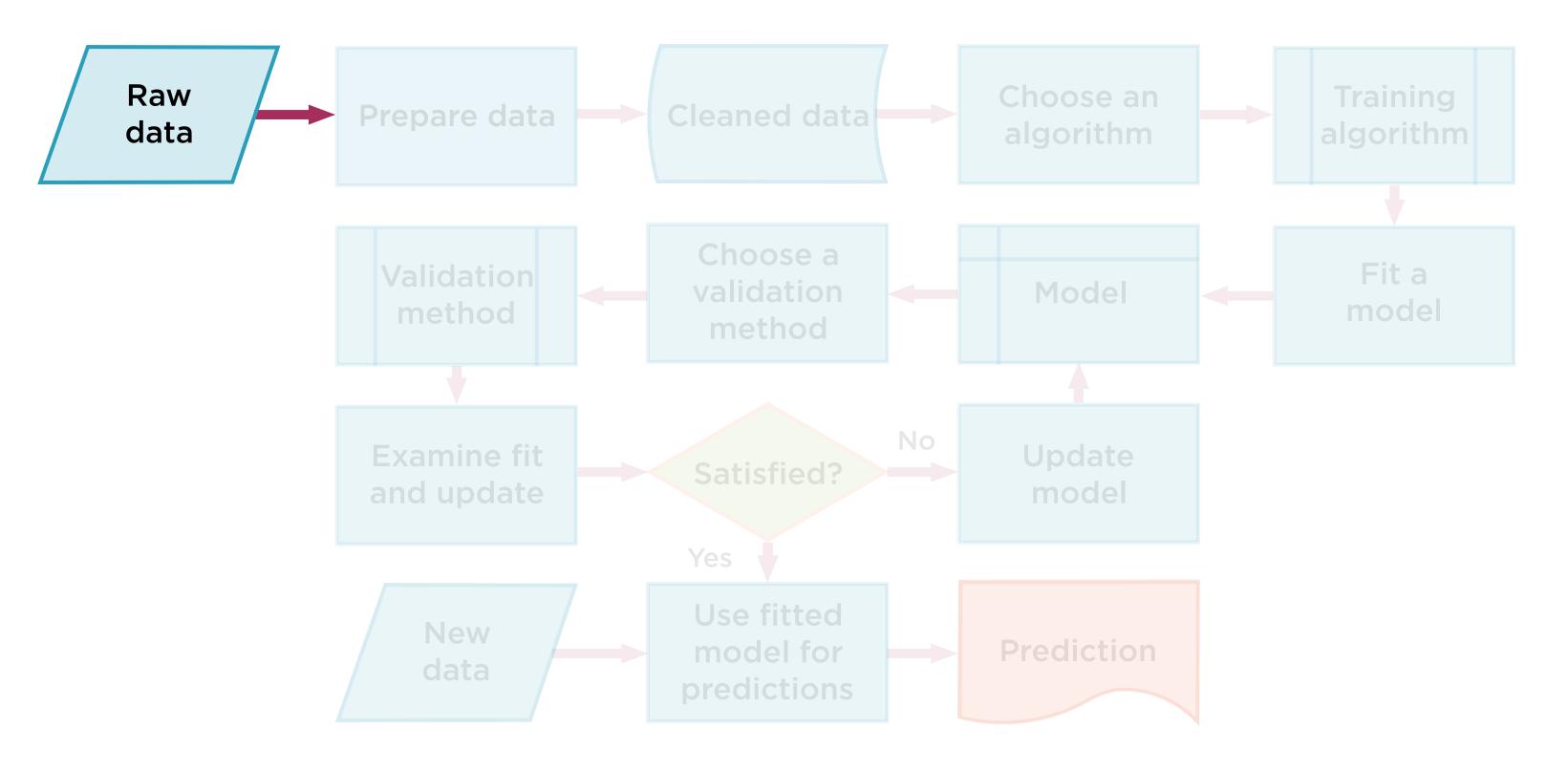
Choosing the right neural network based on the problem

# Machine Learning Workflow

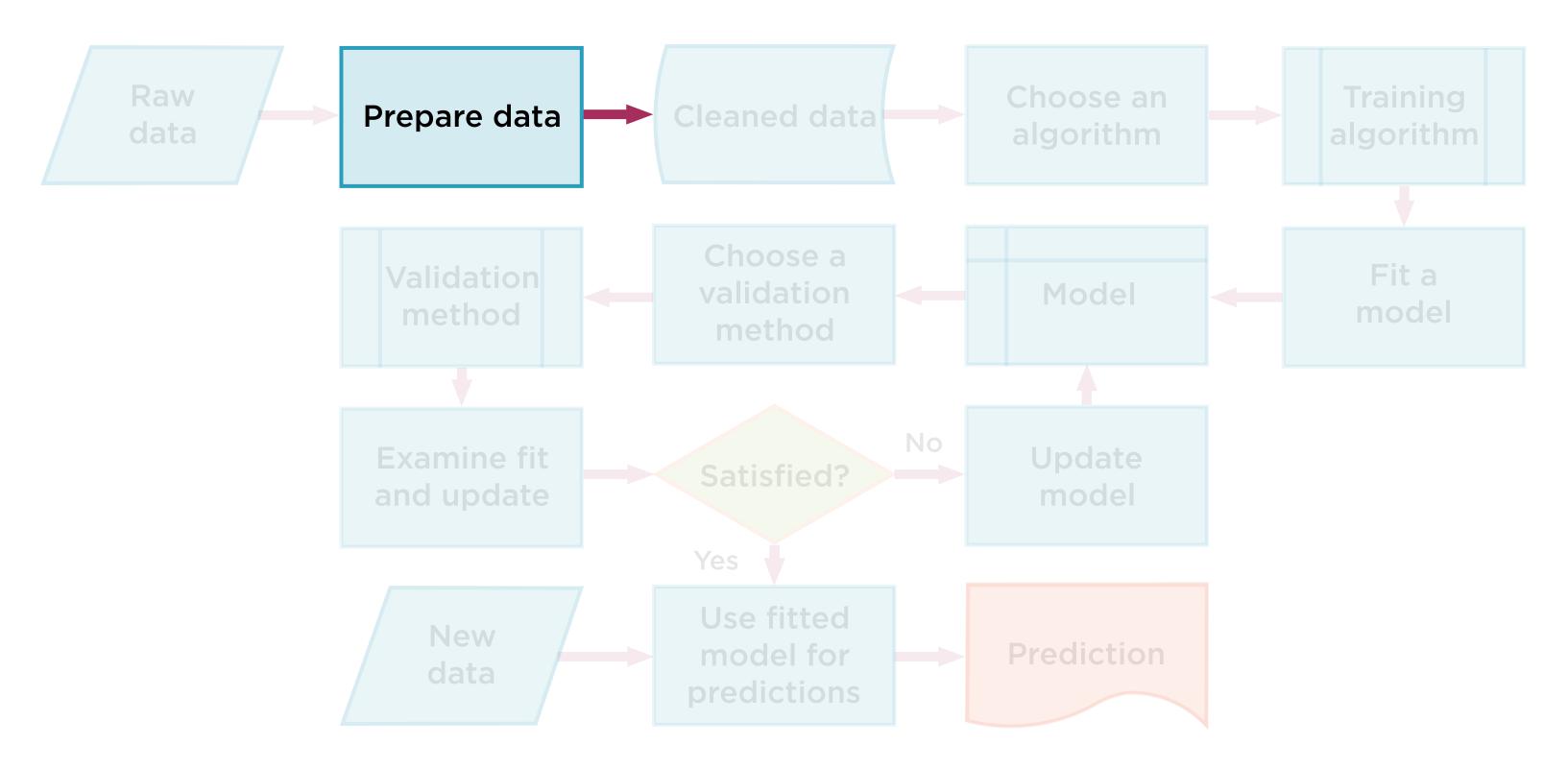
# Basic Machine Learning Workflow



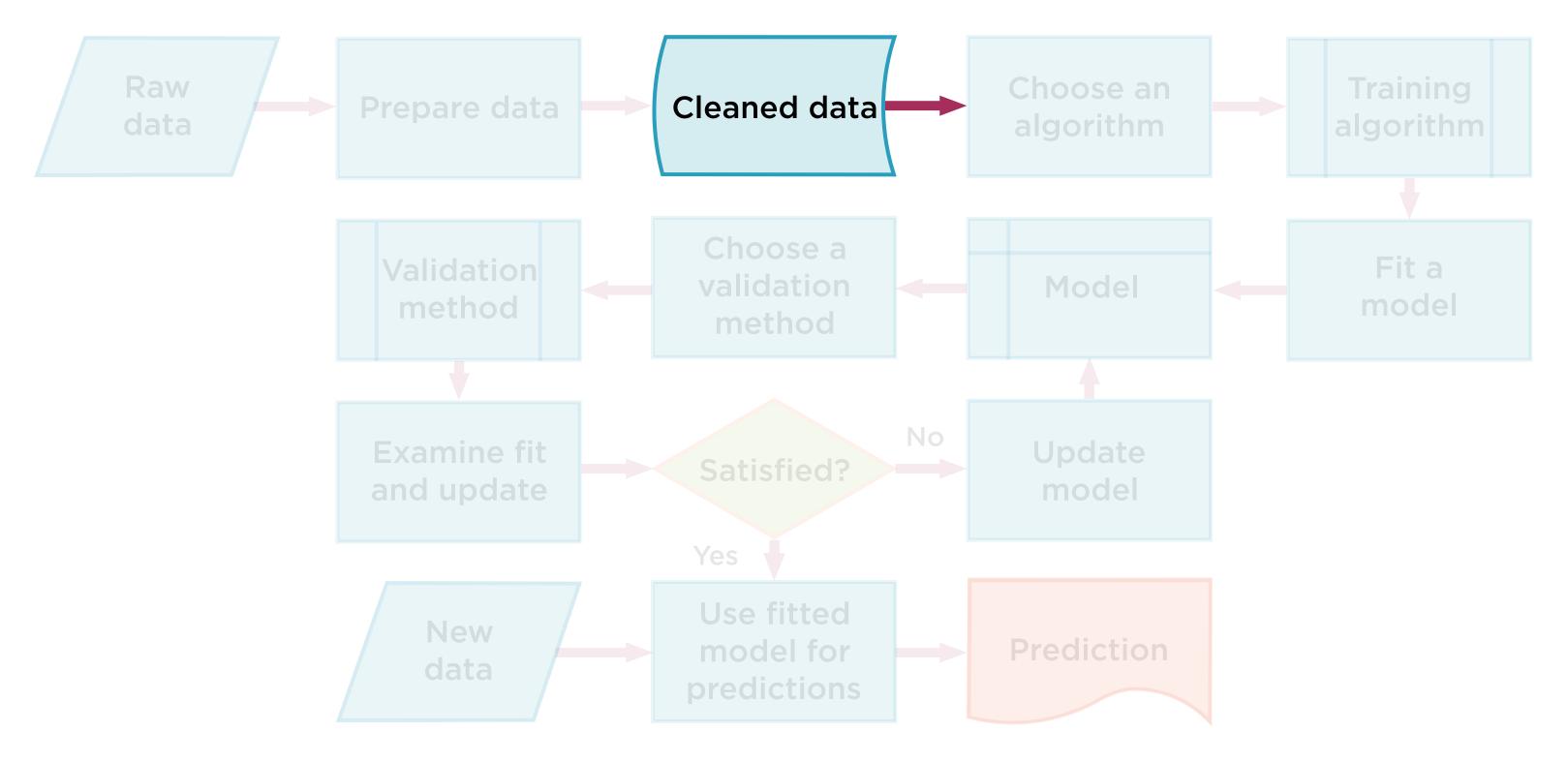
# What Data Do You Have to Work With?



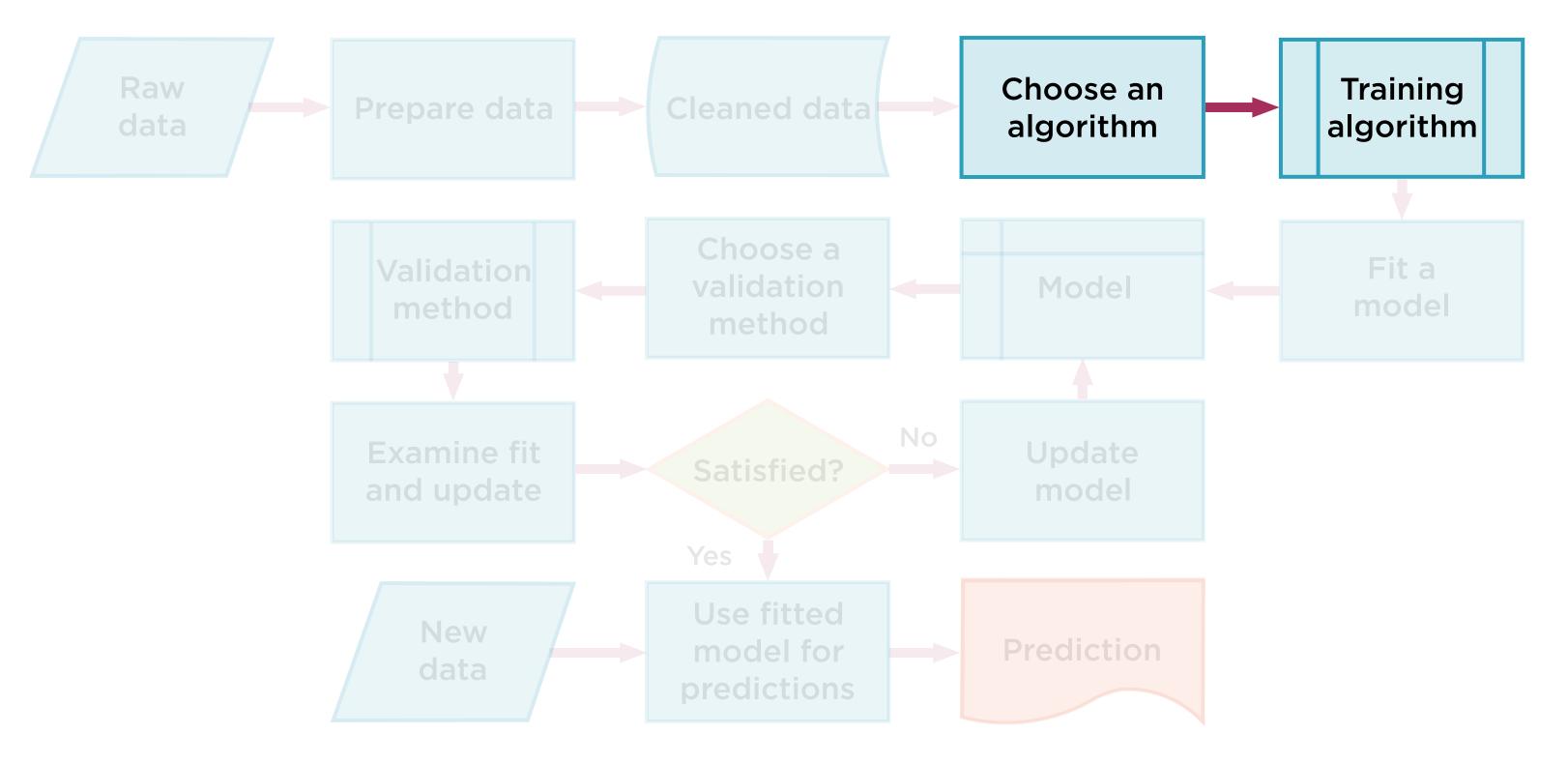
# Load and Store Data



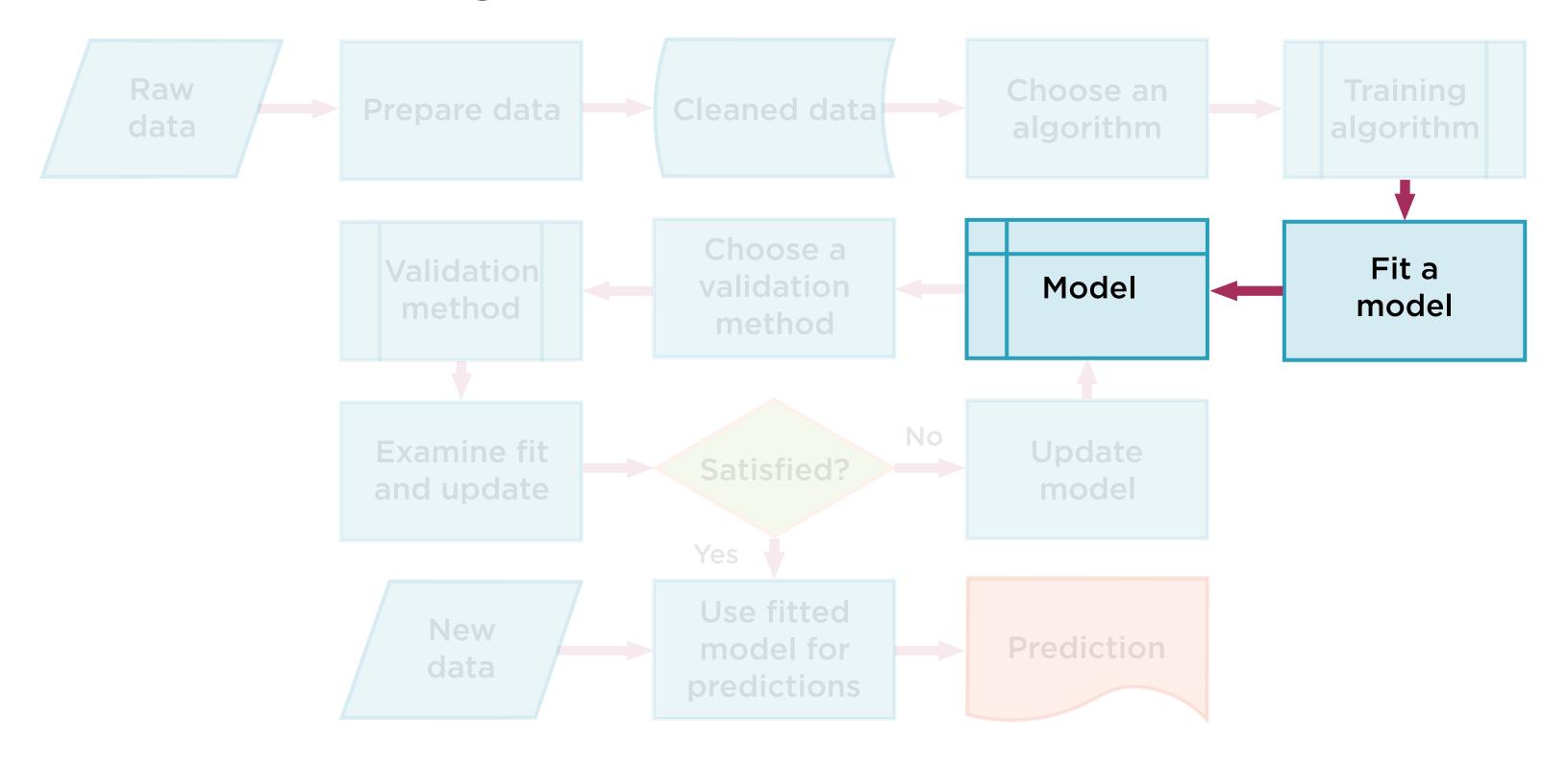
# Data Preprocessing



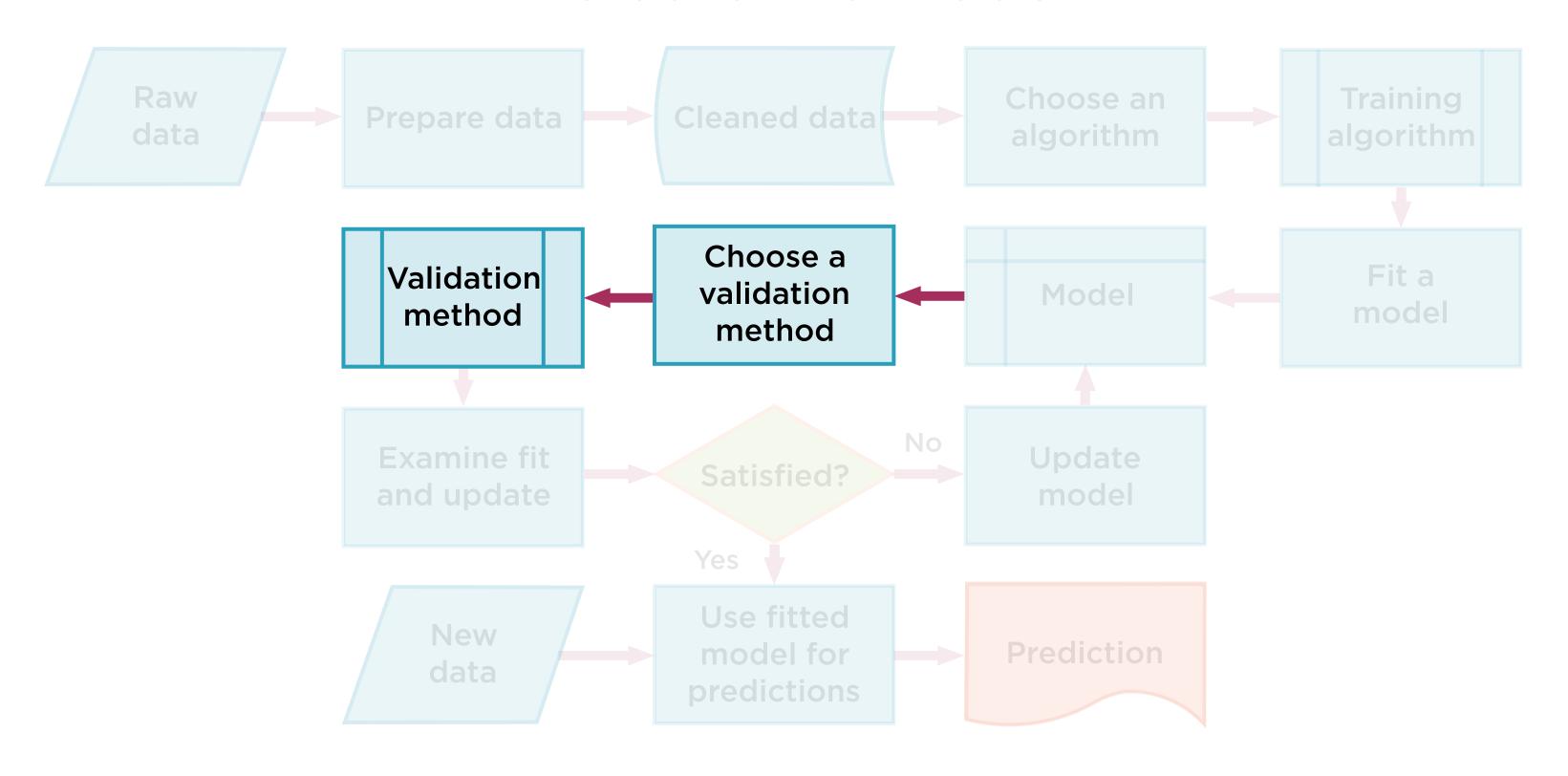
# Decision Trees, Support Vector Machines?



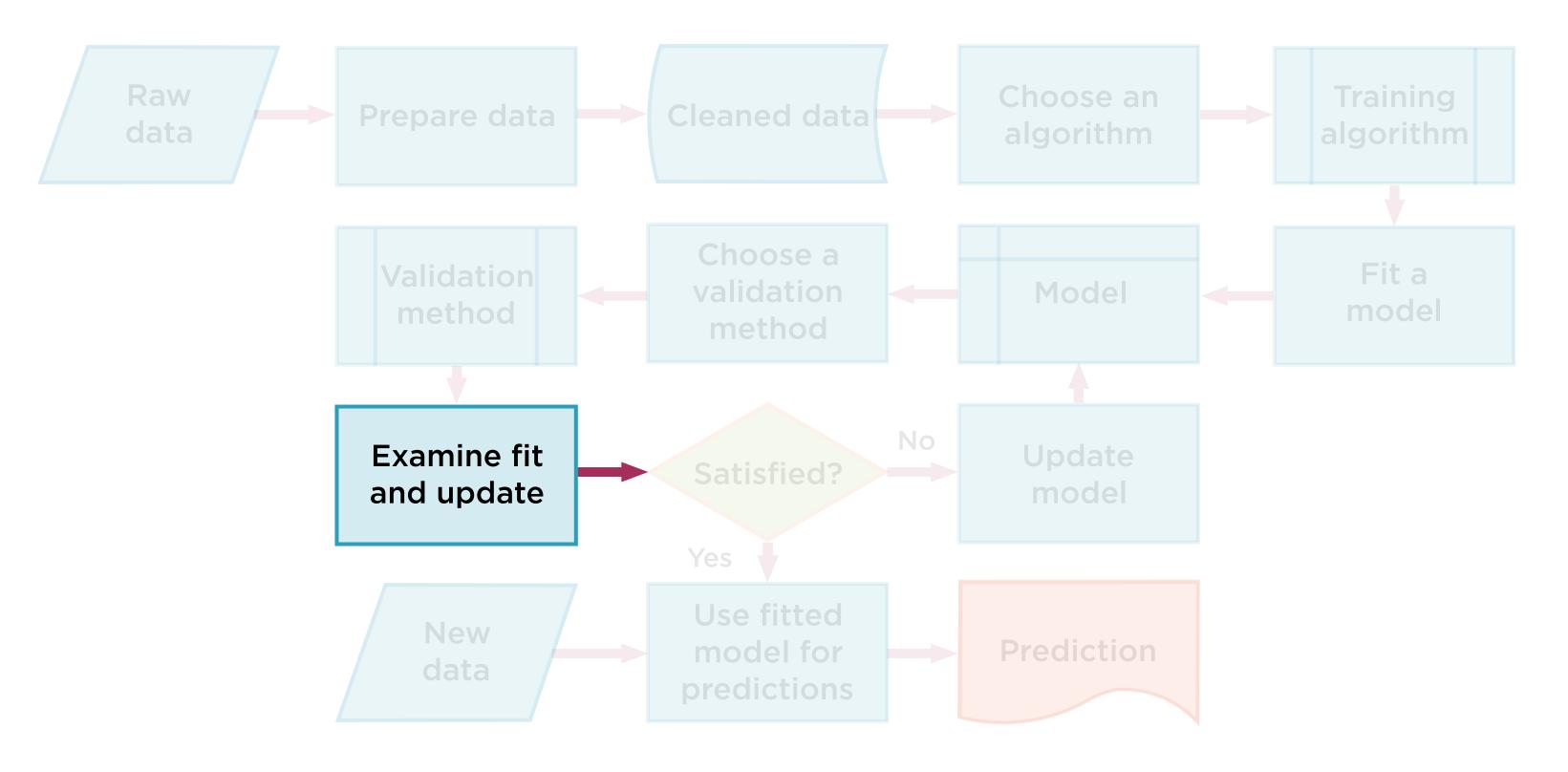
# Training to Find Model Parameters



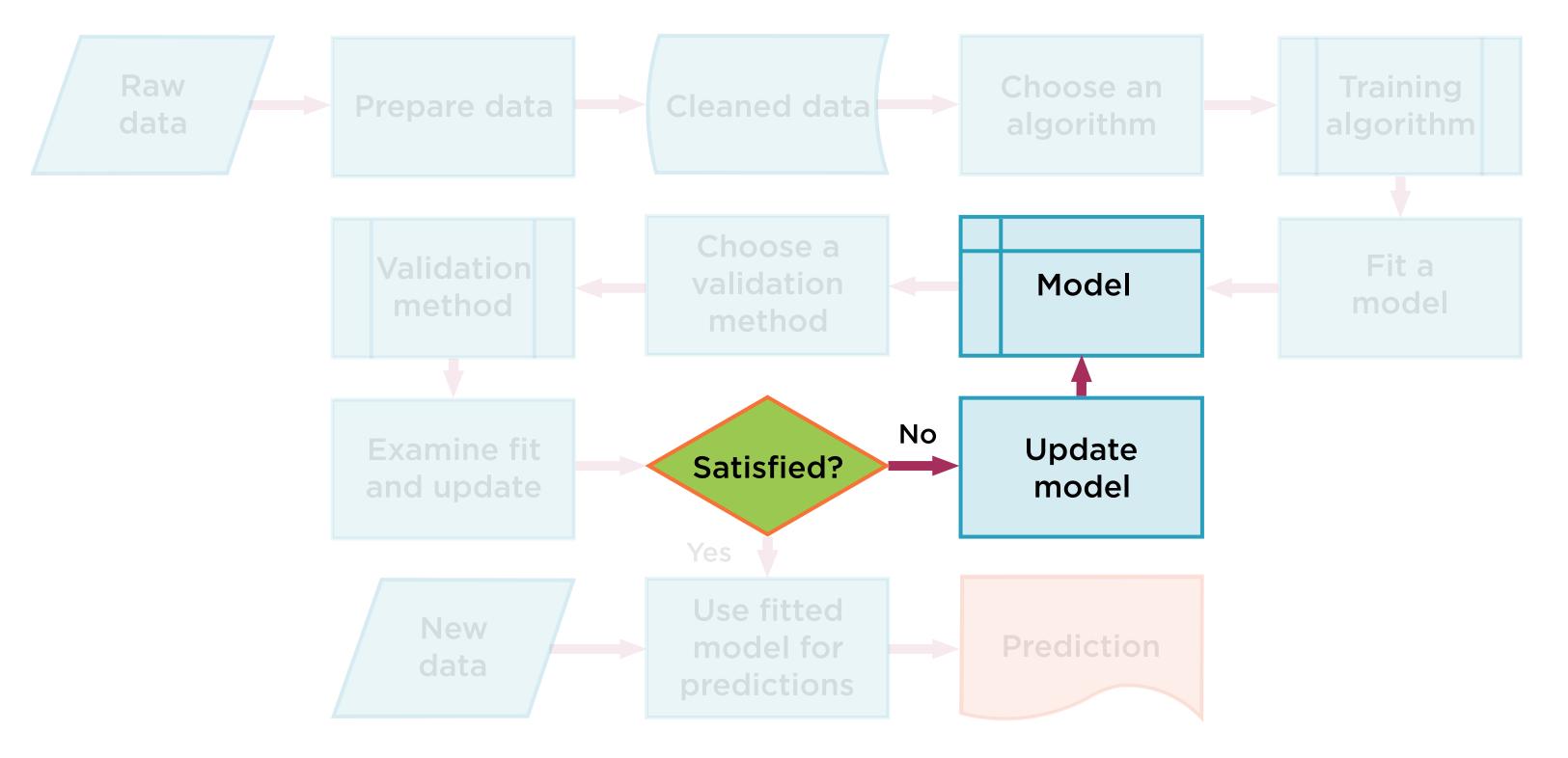
# Evaluate the Model



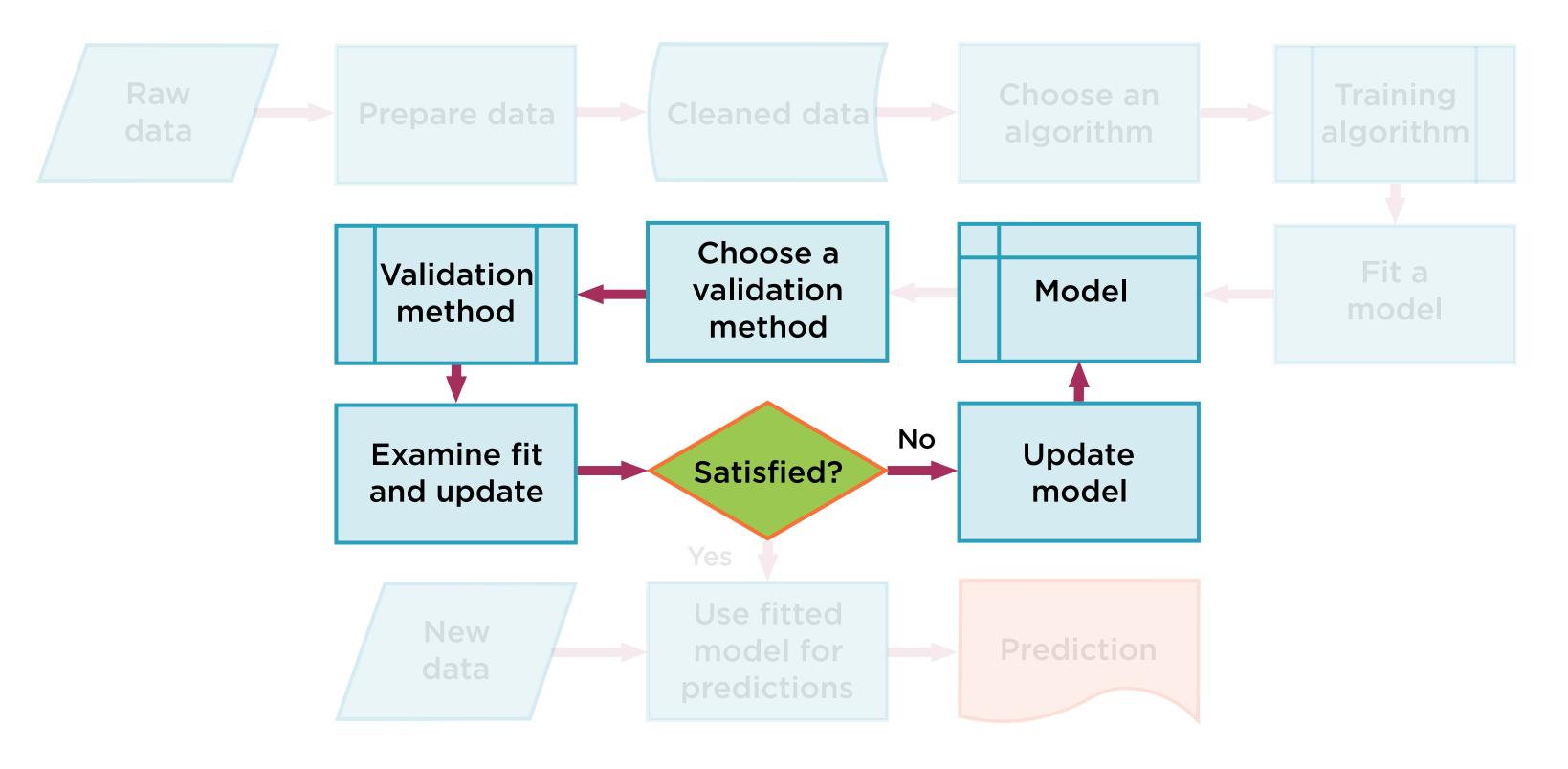
# Score the Model



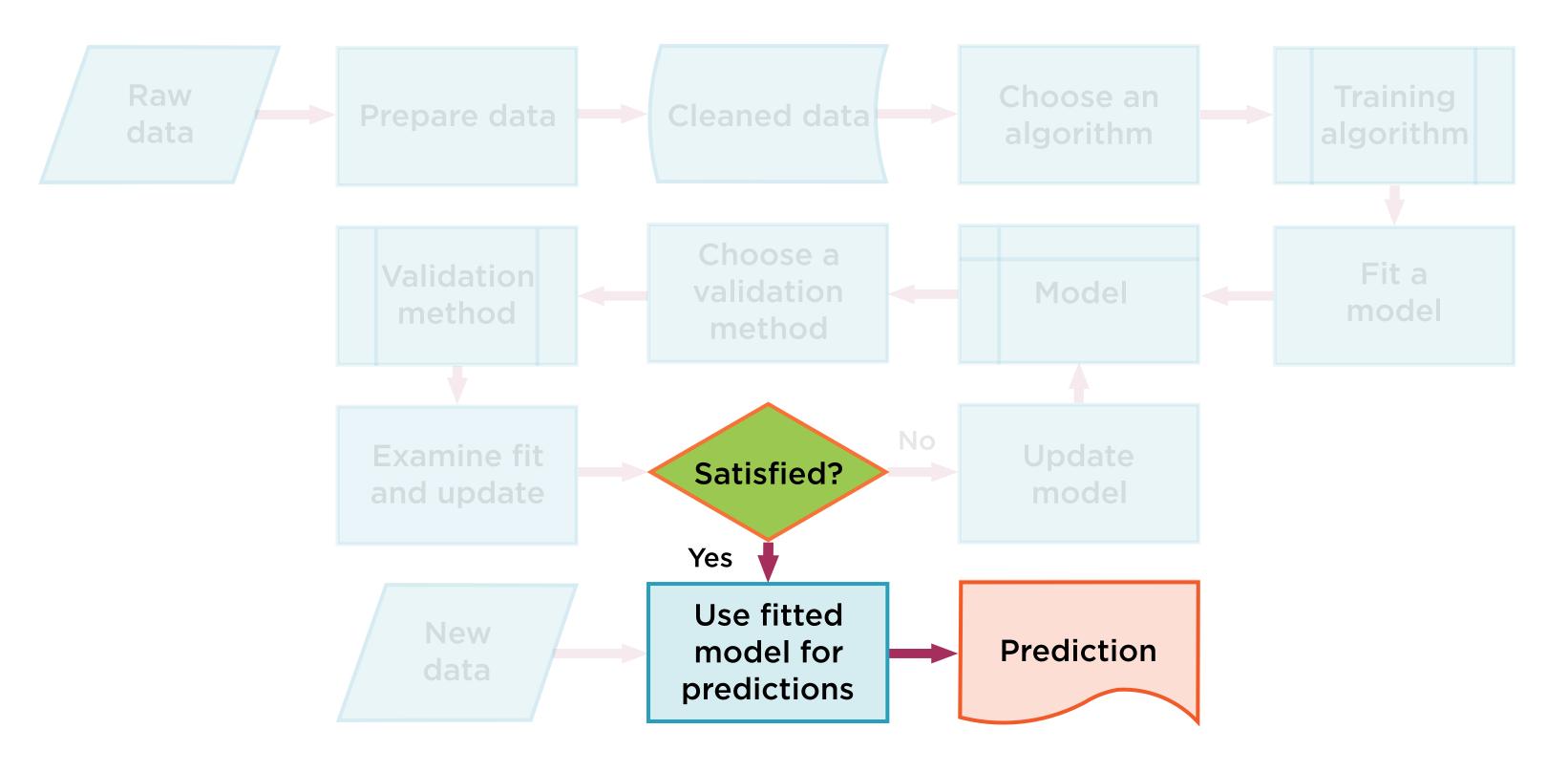
# Different Algorithm, More Data, More Training?



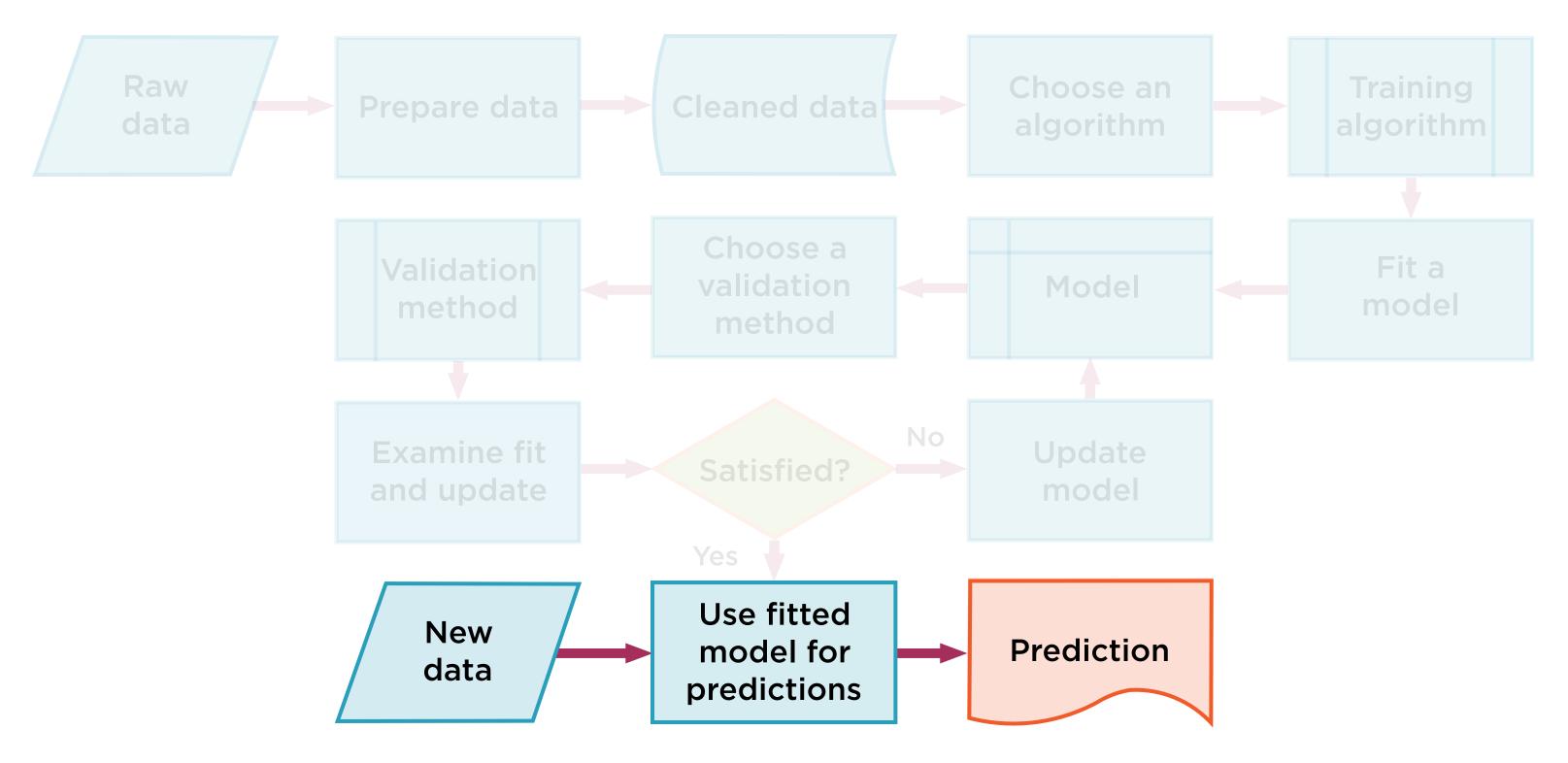
# Iterate Till Model Finalized



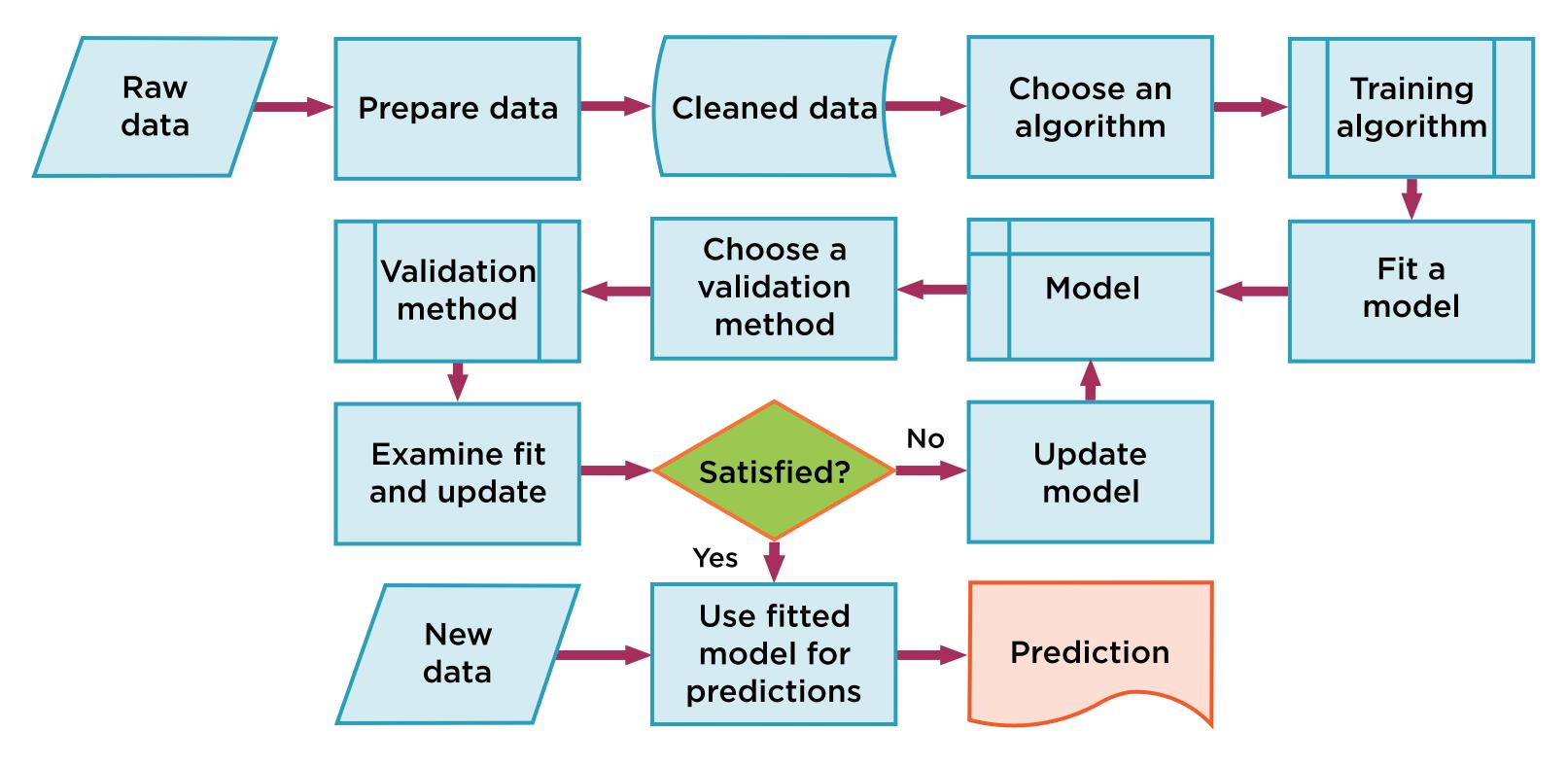
# Model Used for Predictions



# Retrained Using New Data



# Basic Machine Learning Workflow



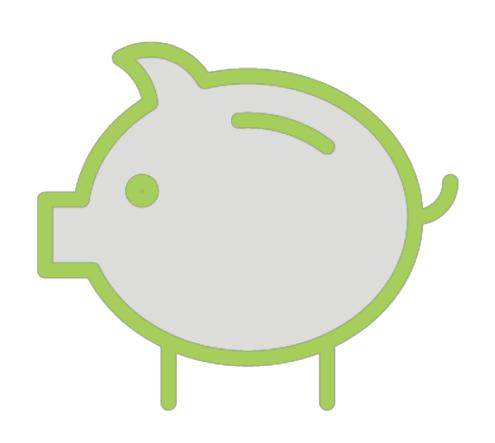
# Case Study: PyTorch on the Cloud

# PyTorch

A deep learning framework for fast, flexible experimentation.

https://pytorch.org/

# Tight Python Integration



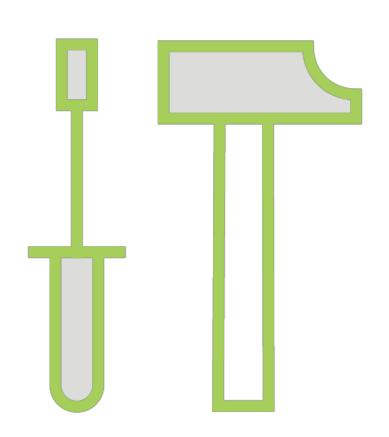
Deeply tied to Python

Approach similar to NumPy/scikit-learn

Create neural networks in Python

Use existing Python libraries and debuggers

# GPU-ready Tensor Library



Tensors for either CPU or GPU
Powerful, fast NumPy-like functionality

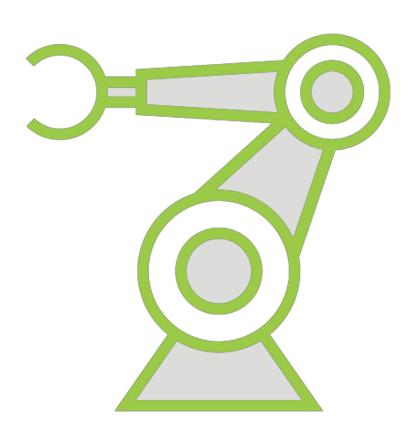
- slicing
- indexing
- reductions
- linear algebra

# GPU (Graphics Processing Unit)

Specialized chips with highly parallel architecture that makes them an order of magnitude faster than CPUs for some deep learning applications

# PyTorch Tensors have been architected to make optimal use of GPUs for massively parallel computations

# GPUs for ML

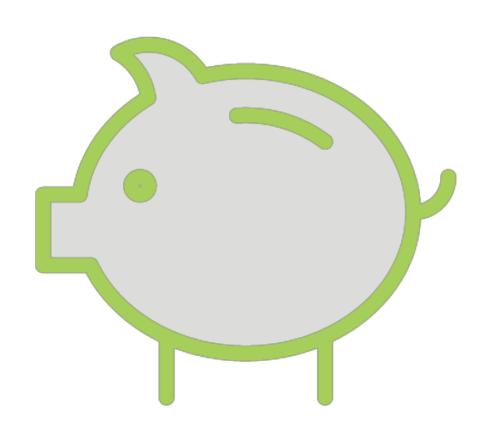


Usage of GPUs has gone far beyond video/graphics processing

Widely used in Big Data and Machine Learning applications

Speedup of 10-50X where parallelization yields big wins

# Training Options



Local training as starter option

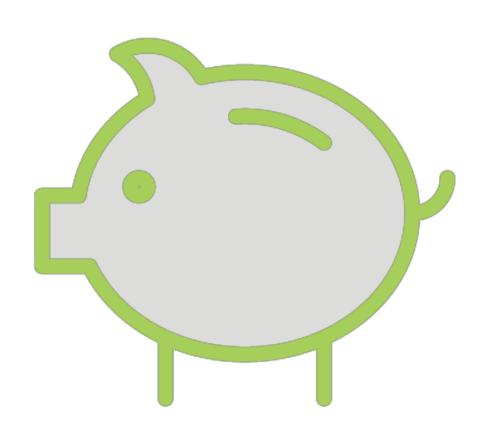
Fine for prototyping

Can not leverage GPUs

**Out-of-memory issues** 

Hours and hours for training

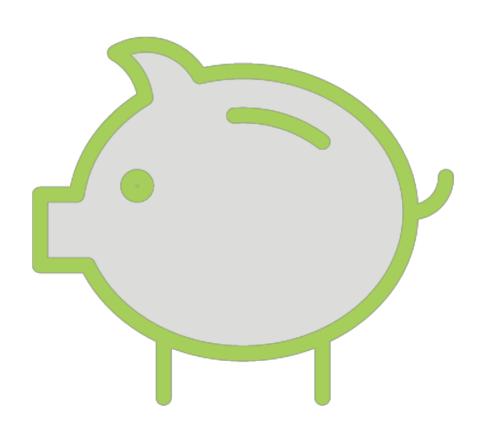
# Training Options



### Distributed training

- More epochs
- Performance dramatically rises
- Scaling needs additional hardware

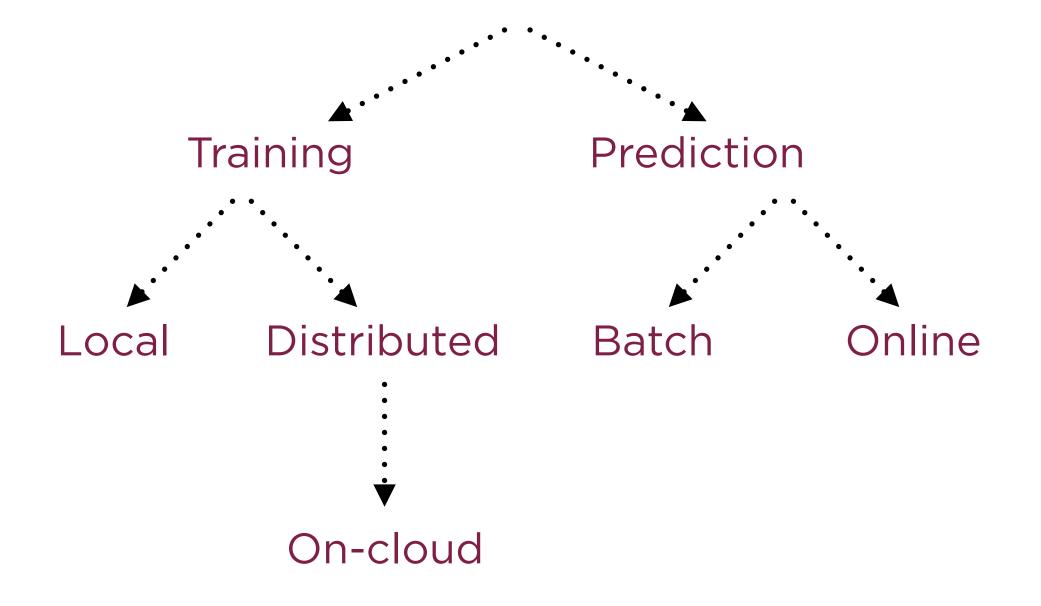
# Training Options



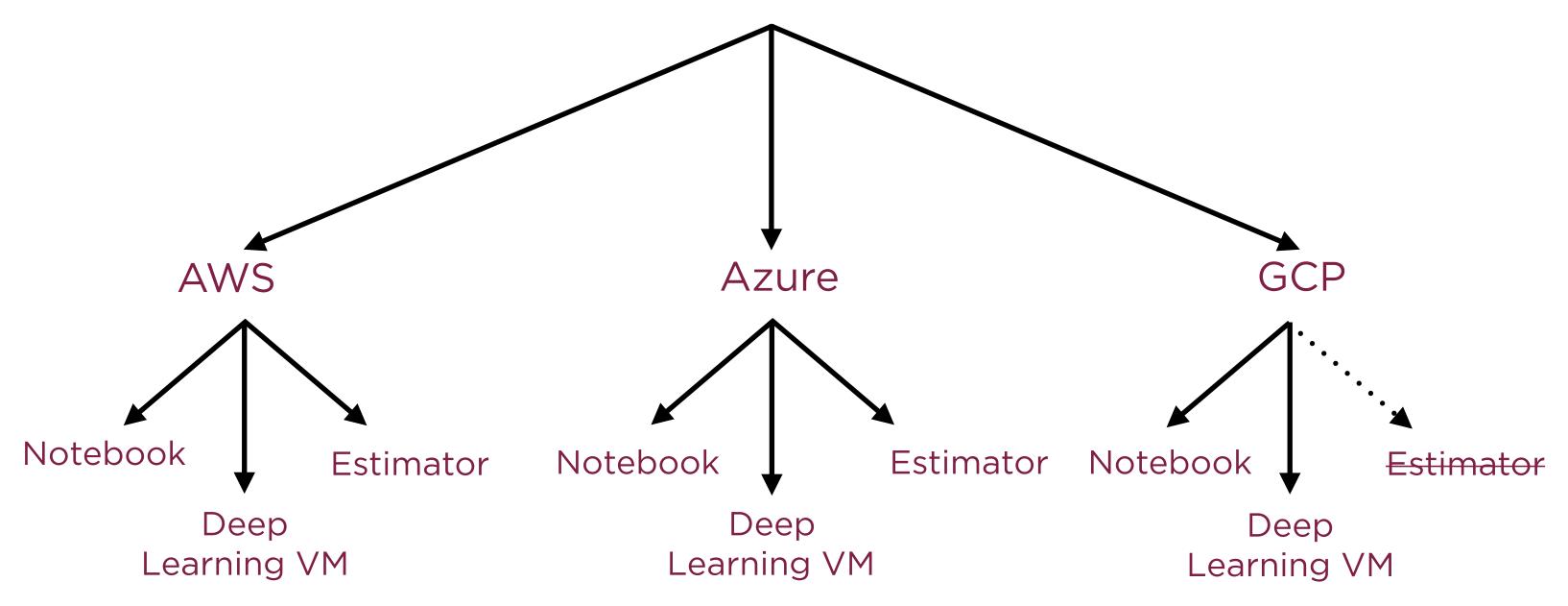
### **On-cloud training**

- Pay-as-you-go
- Elastic and scalable
- CUDA and GPU support
- Frameworks and platform support

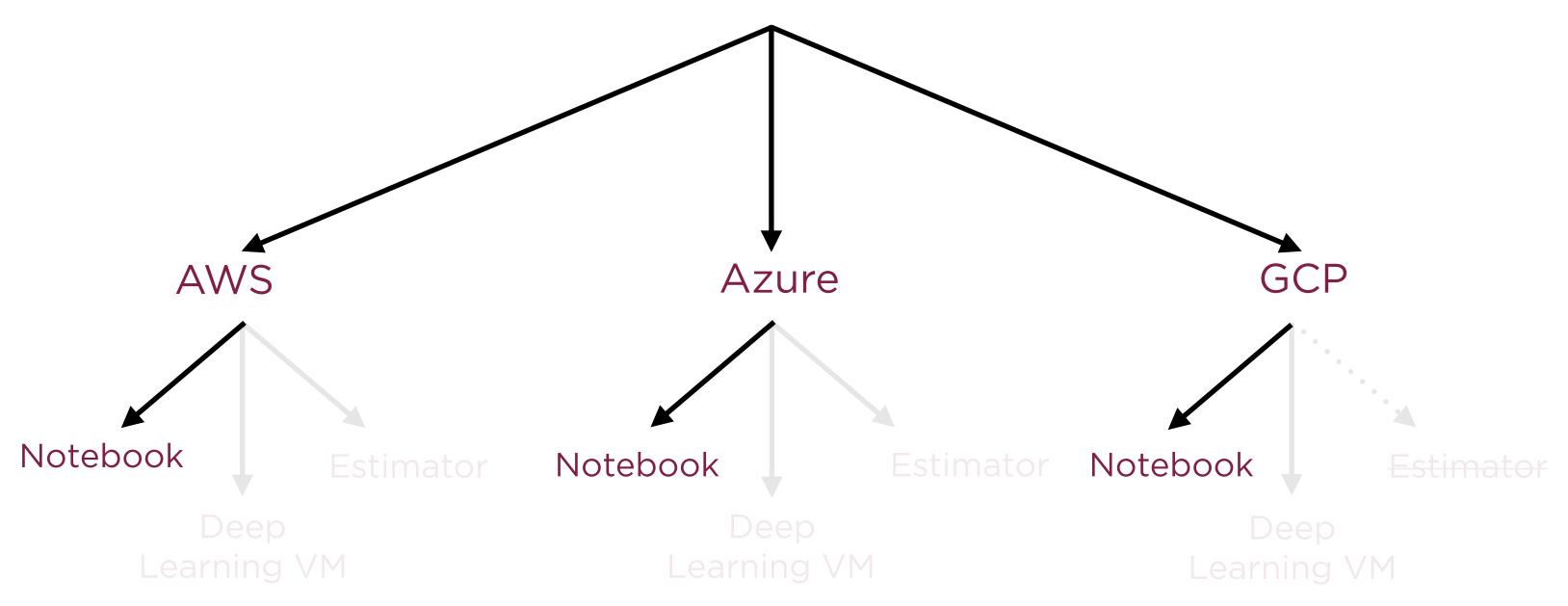
# ML Design Choices



# PyTorch on the Cloud



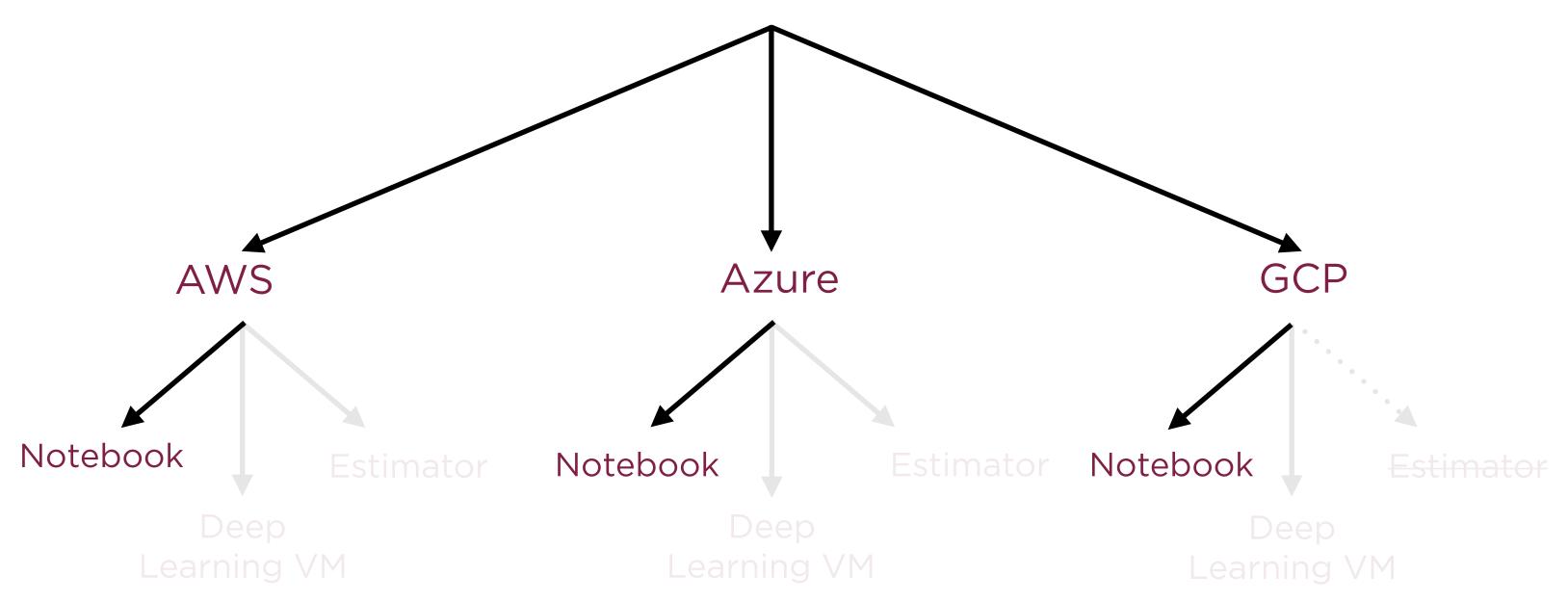
# PyTorch on the Cloud



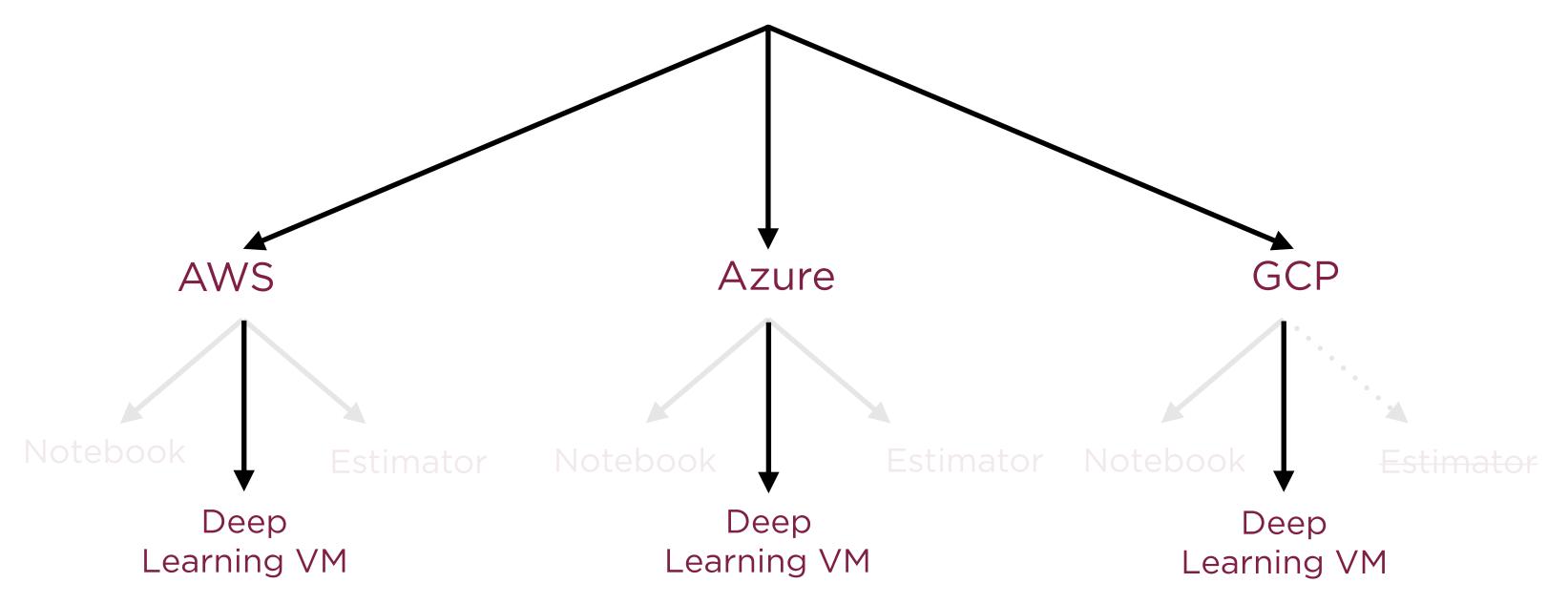
# Notebook

Cloud-hosted Python notebook. Could be platformagnostic (Jupyter) or platform-specific (e.g. Datalab on GCP)

# PyTorch on the Cloud



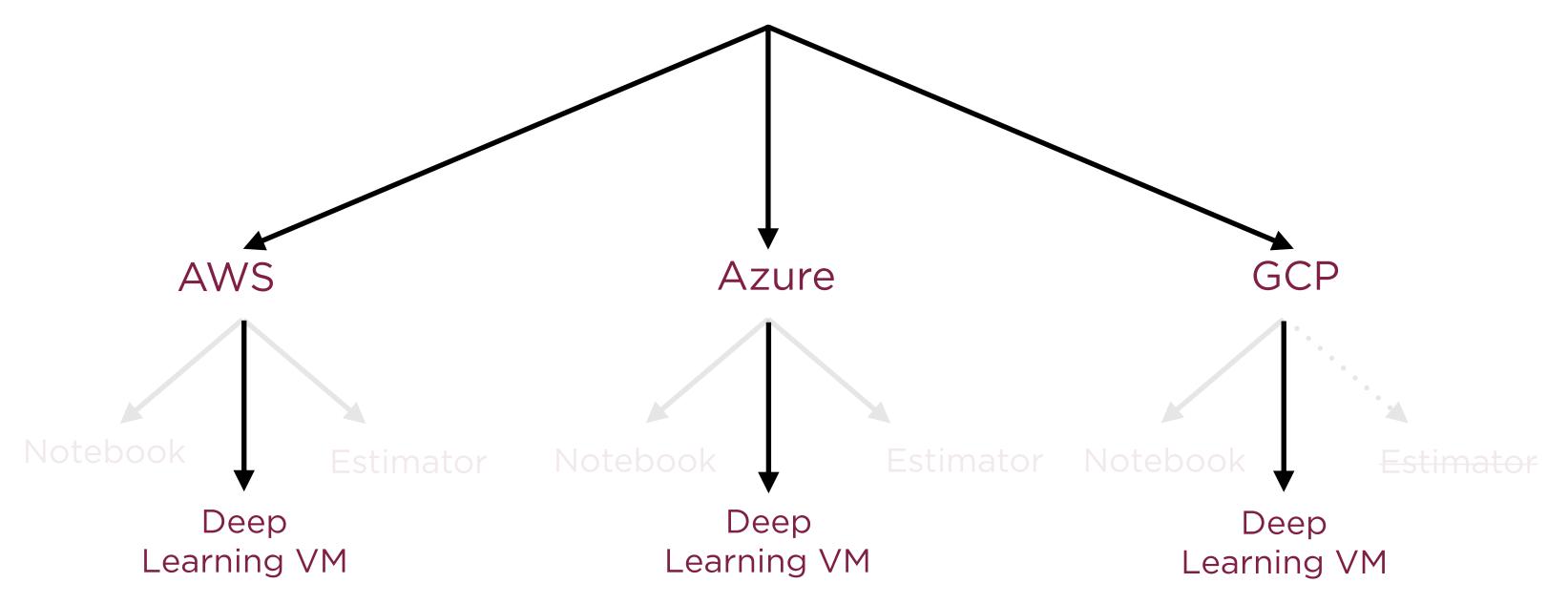
# PyTorch on the Cloud



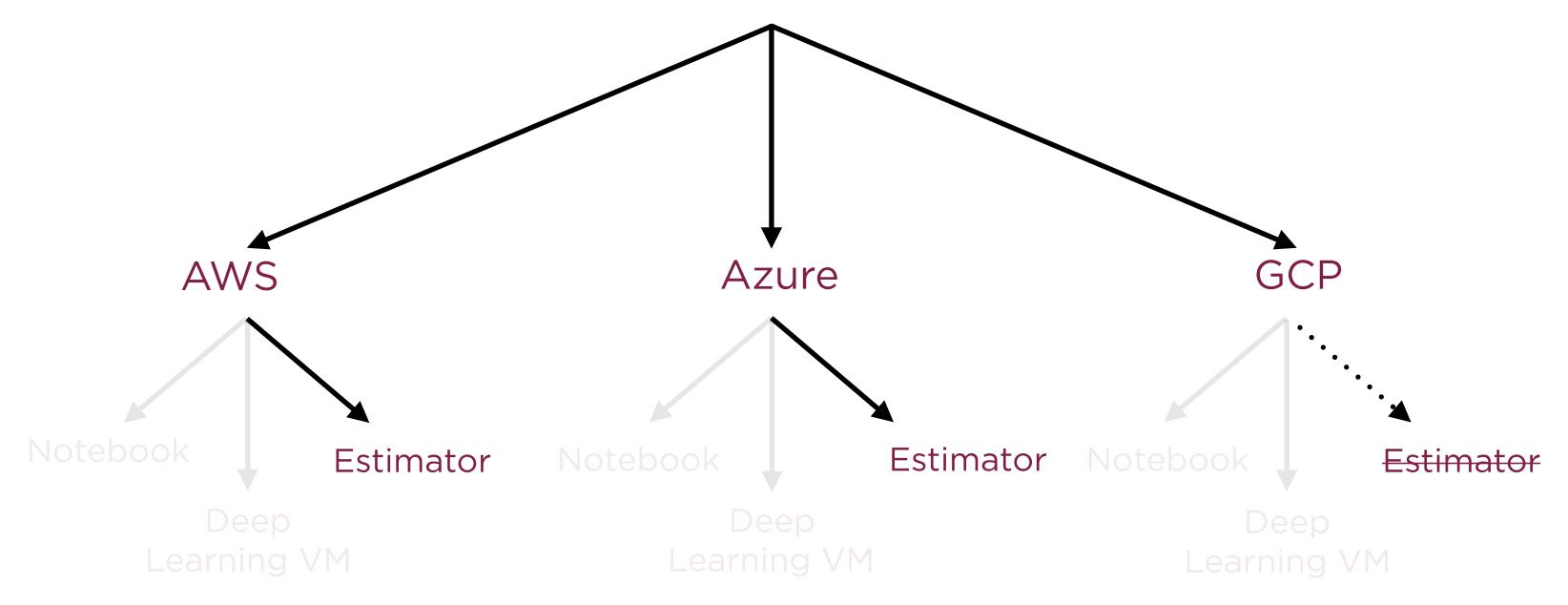
# Deep Learning VM

Cloud-specific virtual machine instance (e.g. EC2 on AWS, GCE on GCP) equipped with GPUs for optimized PyTorch performance

# PyTorch on the Cloud



# PyTorch on the Cloud



# Estimator

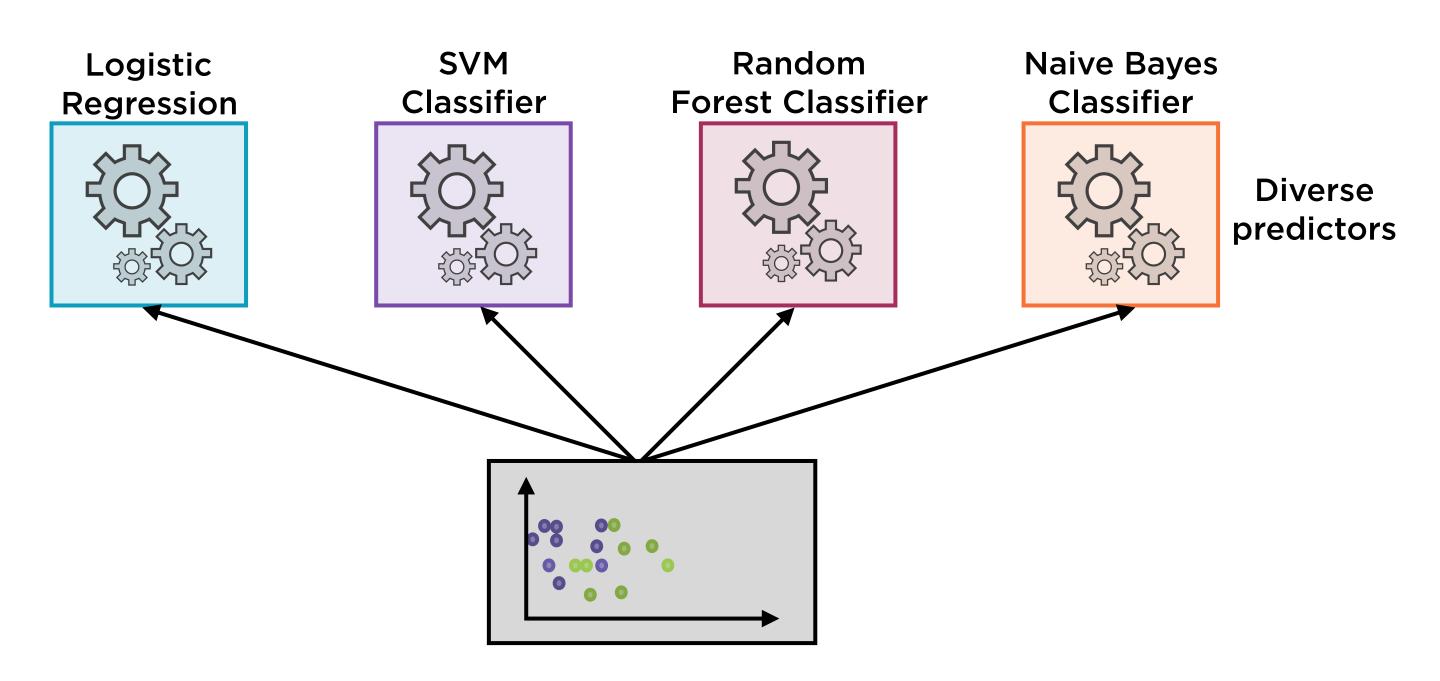
High-level API, specific to a cloud platform, that helps build, train, and deploy PyTorch models

## Quick Overview of Ensemble Learning

Machine learning technique in which several learners are combined to obtain a better performance than any of the learners individually.

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What kind of individual learners to use?

How should individual learners be trained?

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#### Choice of Individual Learners



Individual learners (models) could be of absolutely any type

Each learner should be as different as possible from other learners

#### Choice of Individual Learners



Decision trees are most often used

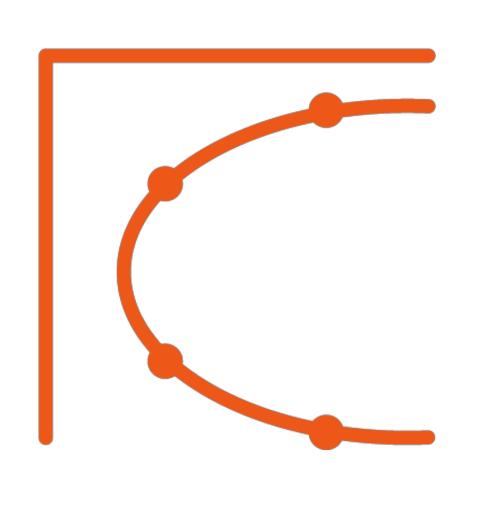
An ensemble of decision trees is a Random Forest

Random forests make it easy to build uncorrelated learners

What kind of individual learners to use?

How should individual learners be trained?

#### Training Individual Learners



If learners are different, each learner can be trained on the entire dataset

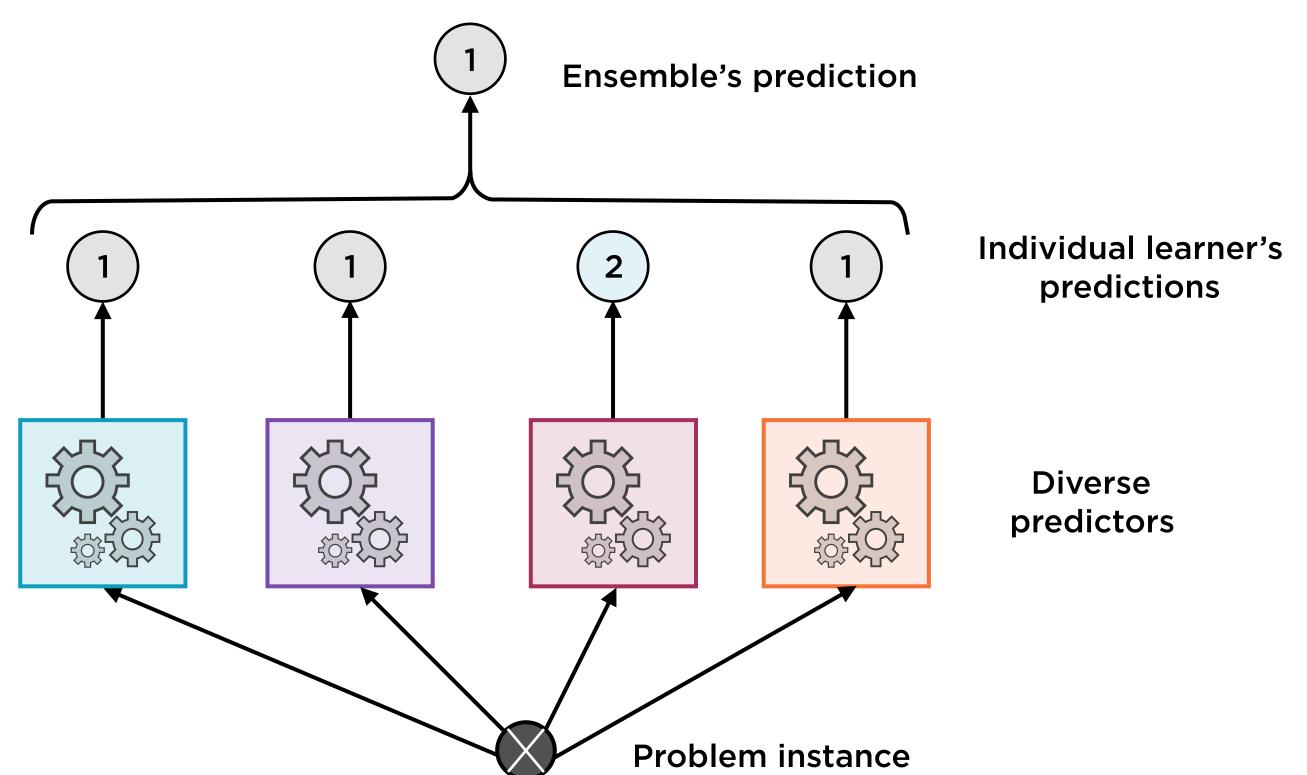
#### For similar learners:

- Each model is trained on random samples of training data
- Can also use random set of features to train different models

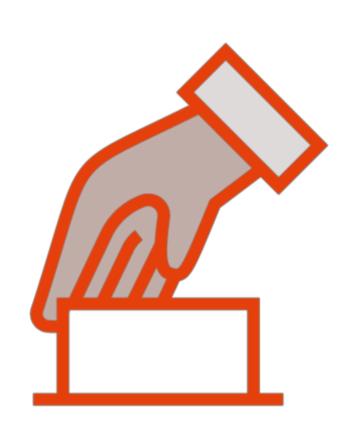
What kind of individual learners to use?

How should individual learners be trained?

# Combining Classifier Predictions



### Combining Individual Learners



Hard voting: Majority vote of individual learners (classification)

Soft voting: Probability-weighted average

Stacking: Train additional model to combine predictions from individual learners

# Ensemble Learning Techniques

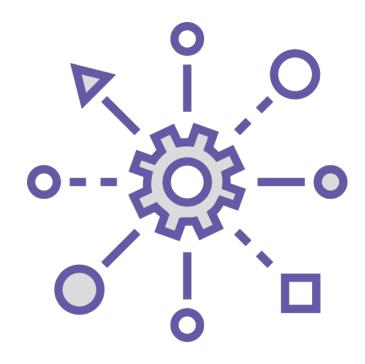
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#### Averaging and Boosting



**Averaging** 

Train predictors in parallel and average scores of individual predictors



**Boosting** 

Train predictors in sequence where each predictor learns from earlier mistakes

### Averaging vs. Boosting

#### Averaging

Individual learners are independent

Can build trees in parallel

Learners do not learn from mistakes of other learners

#### **Boosting**

Individual learners are linked to previous learners

Need to build tree sequentially

Individual learners explicitly configured to learn from previous mistakes

What kind of individual learners to use?

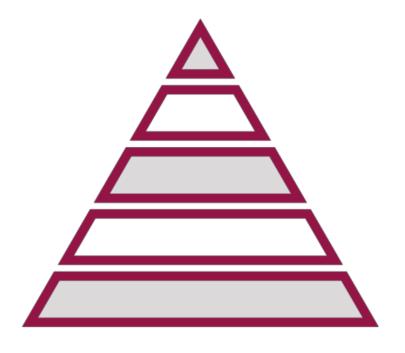
How should individual learners be trained?

## Voting and Stacking



Voting

Majority vote of the individual predictors is the final prediction of the ensemble

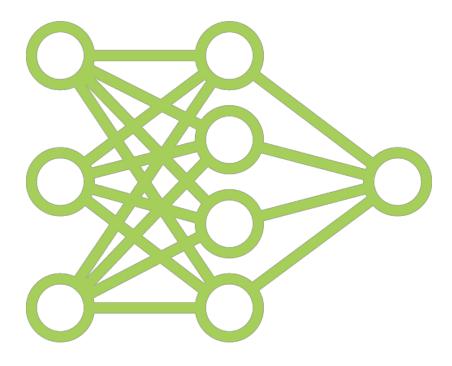


**Stacking** 

Fit a model on the individual predictions to get the final prediction of the ensemble

#### Neural Network Models

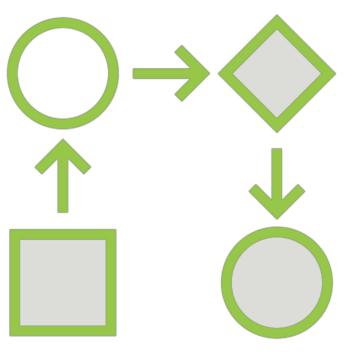
## Deep Learning Models



Fully-connected, dense neural networks

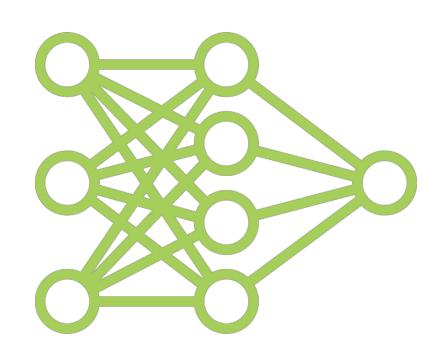


Convolutional neural networks



Recurrent neural networks

#### Dense Neural Networks



Work well with numeric features

Traditional classification, regression

Layers of interconnected neurons

All neurons in one layer connected to neurons in the previous and next layers

#### Convolutional Neural Networks



Specialize in working with image data

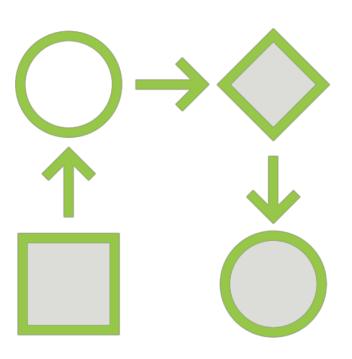
Designed to mimic the visual cortex of the brain

Sparse neural networks

Convolutional layers for feature detection

Pooling layers for subsampling of inputs

#### Recurrent Neural Networks



Specialize in sequential data such as text or time series data

Neurons have "memory" or state

Neural network layers represent instances in time

### Summary

End-to-end machine learning workflows

Local, distributed, and cloud-based training and prediction

Understanding the need for ensemble techniques

Choosing the right neural network based on the problem