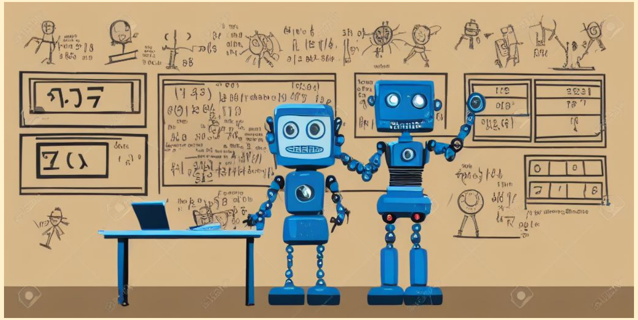


Advanced Workshop on Machine Learning

Lecture 5: Ensemble Methods

Danylo Vashchilenko

2022

Agenda

Part 1

Why ensembles work?

Types of ensembles

Case Study: Gaussian Circles

Part 2

Case Study: Tesla AutoPilot

Assignment 5

Part 3

Course Summary

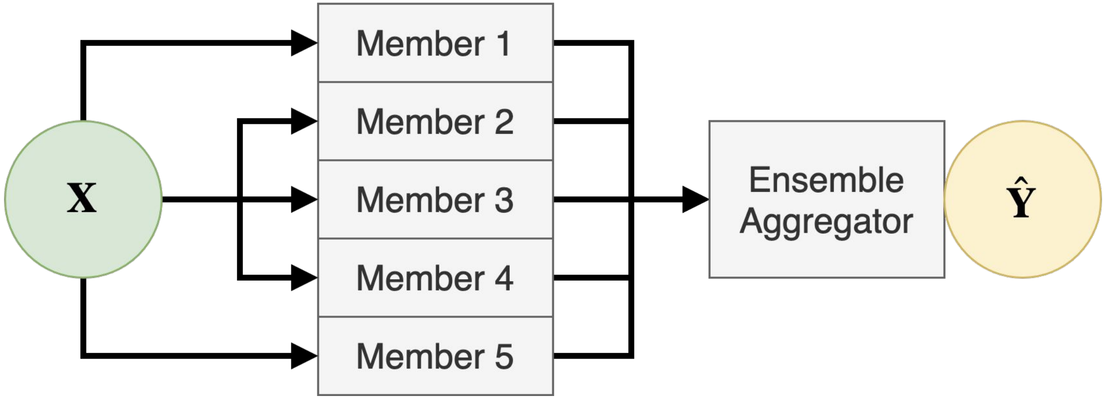
(Image by a Stable Diffusion model)

Ensemble Inference

Ensemble is a collection of models whose output is aggregated together.

Under certain conditions, aggregated output is better than any member output.

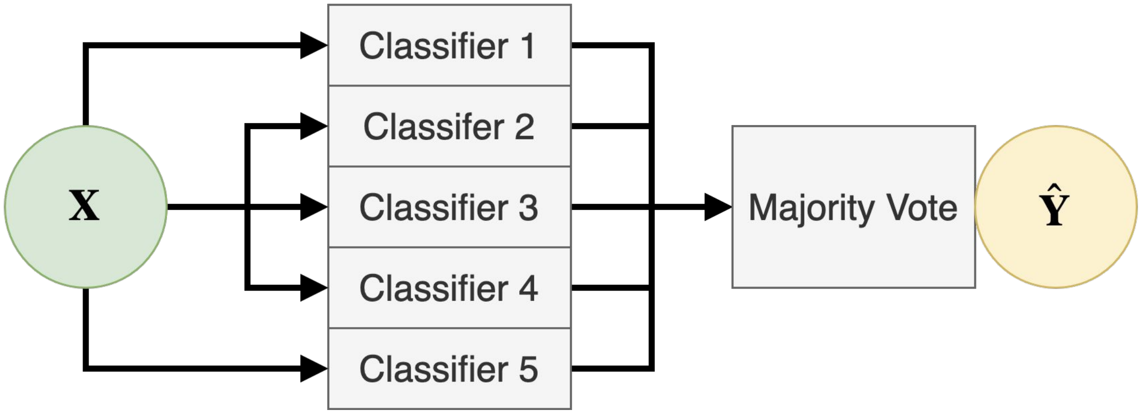
Members may or may not communicate.



Binary Classification

Ensemble output is the class predicted by the majority of member classifiers.

In case of probabilities, the average probability will be consistent with discrete majority vote.

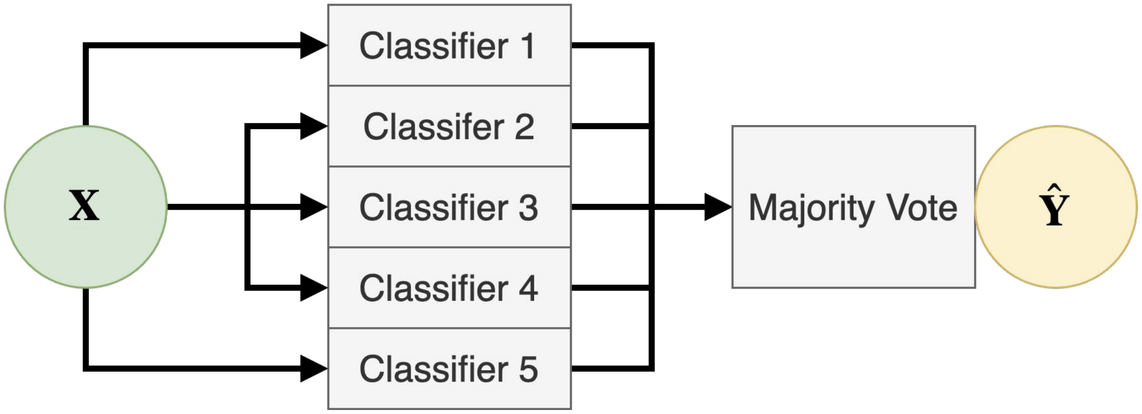


Ensemble Properties

Ensemble performance depends on:

1. Member strength
2. Ensemble size
3. Member independence

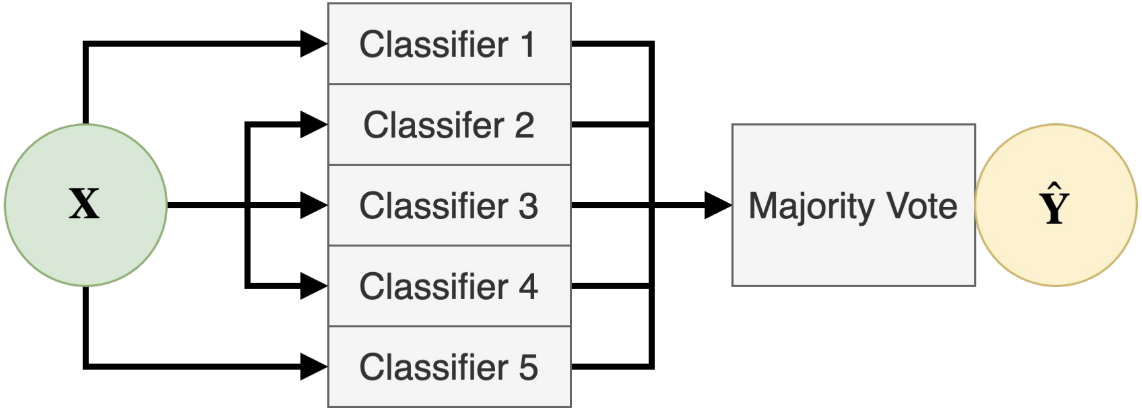
Ensemble performance may or may not be better than its best member.



Ensemble Performance

Method 1: Analytical
Mathematical analysis of the statistical distribution and its properties.

Assumptions:
Binary classification



Evaluation Method 1: Analytical

Member i

$$x \sim p_{data}$$

$$e_i(x) \in \mathbb{R}^n \rightarrow \{0, 1\}$$

$$e_i(x) \sim \text{Bernoulli}(a_i)$$

$$\mathop{\mathbb{E}}_{x}[\ e_i(x)\ ] = a_i$$

Ensemble of s members:

$$e(x) = \lceil \sum_{i=0}^{s} \frac{e_i(x)}{s} \rfloor$$

$$\mathop{\mathbb{E}}_{x}[\ e(x)\ ] = a_e$$

Assumption
Member independence

Evaluation Method 2: Monte Carlo

Approximate the distribution properties
using a finite batch of random samples.

Steps (given member accuracies)

1. Sample the errors for each member
2. Compute the ensemble error
3. Repeat 1-2 for N iterations
4. Average the ensemble errors

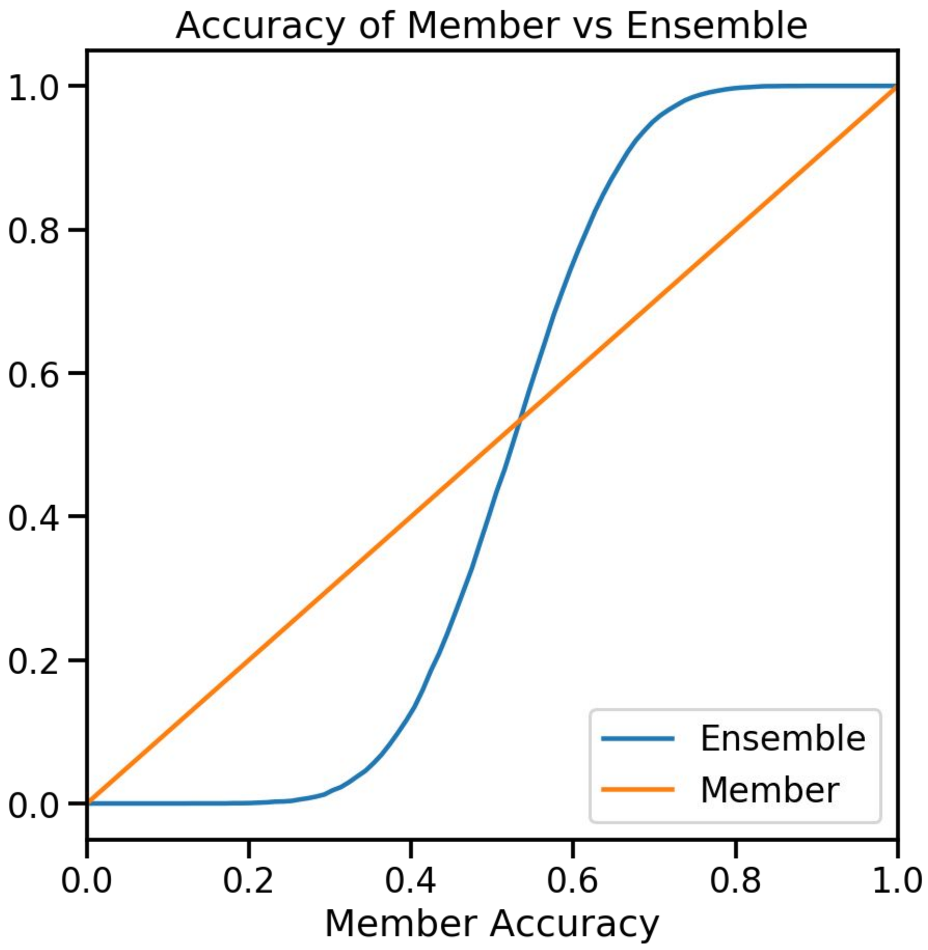
See MonteCarlo.ipynb for NumPy implementation.

Member Strength

Simulation
Ensemble of 20 independent binary classifiers.

Inference
Ensemble strength increases with member strength.

Ensemble members must be better than random.

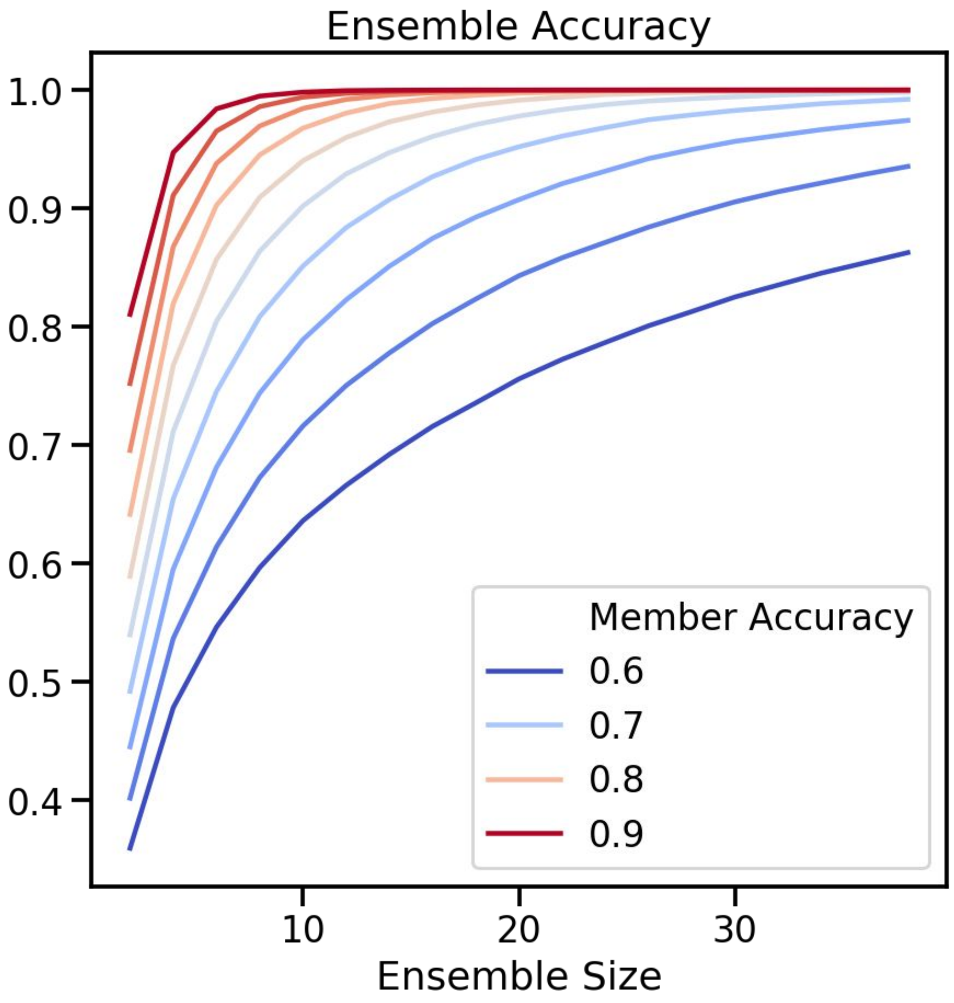


Ensemble Size

Simulation
Ensemble of independent binary classifiers.

Inference
Ensemble strength increases with size.

Marginal value of an additional member decreases with its accuracy and ensemble size.



Member Independence

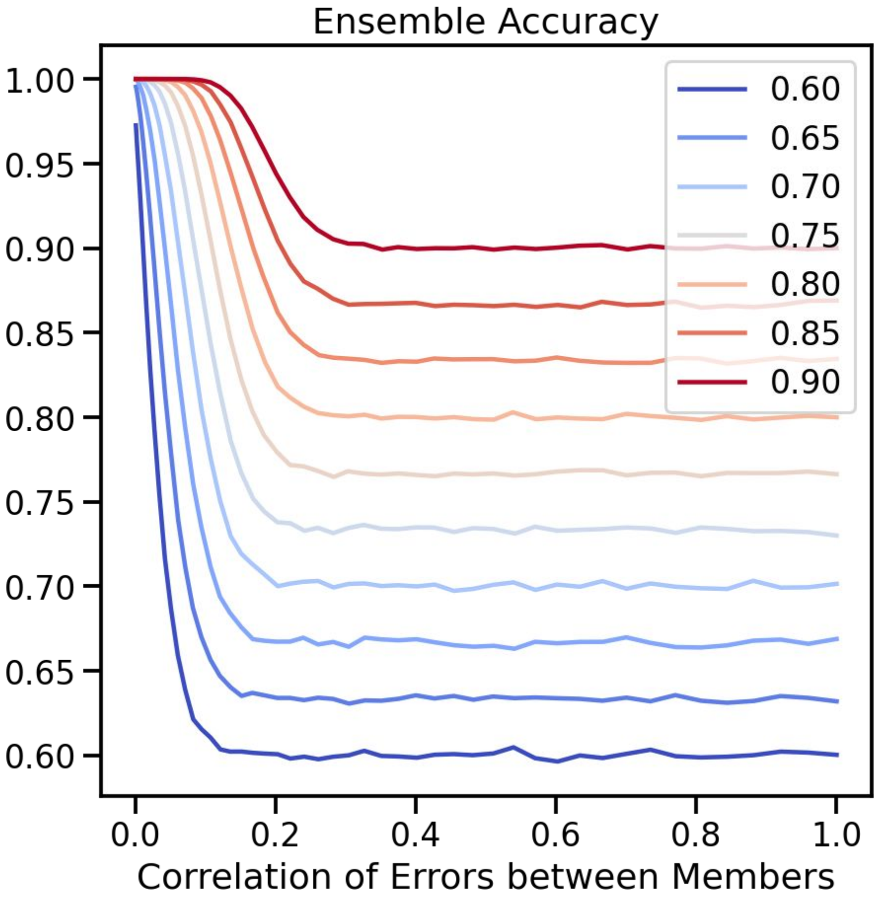
Simulation

Ensemble of 100 binary classifiers with correlated errors.

Inference

Ensemble strength decreases with correlation between members.

Sensitivity to correlation decrease with member strength.

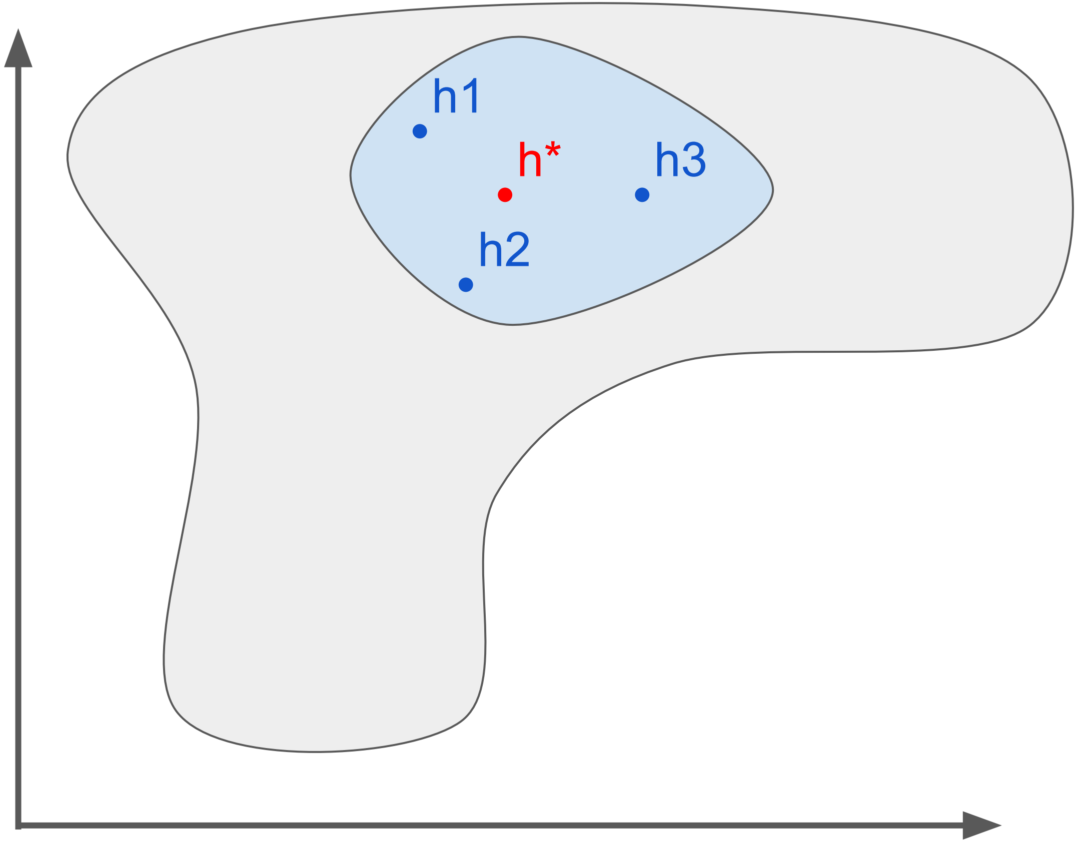


See MonteCarlo.ipynb for NumPy implementation.

Statistical

When datasets are small relative to the hypothesis space, multiple hypotheses may minimize the estimate of the cost.

However, under all possible datasets, there should be a single optimal hypothesis.

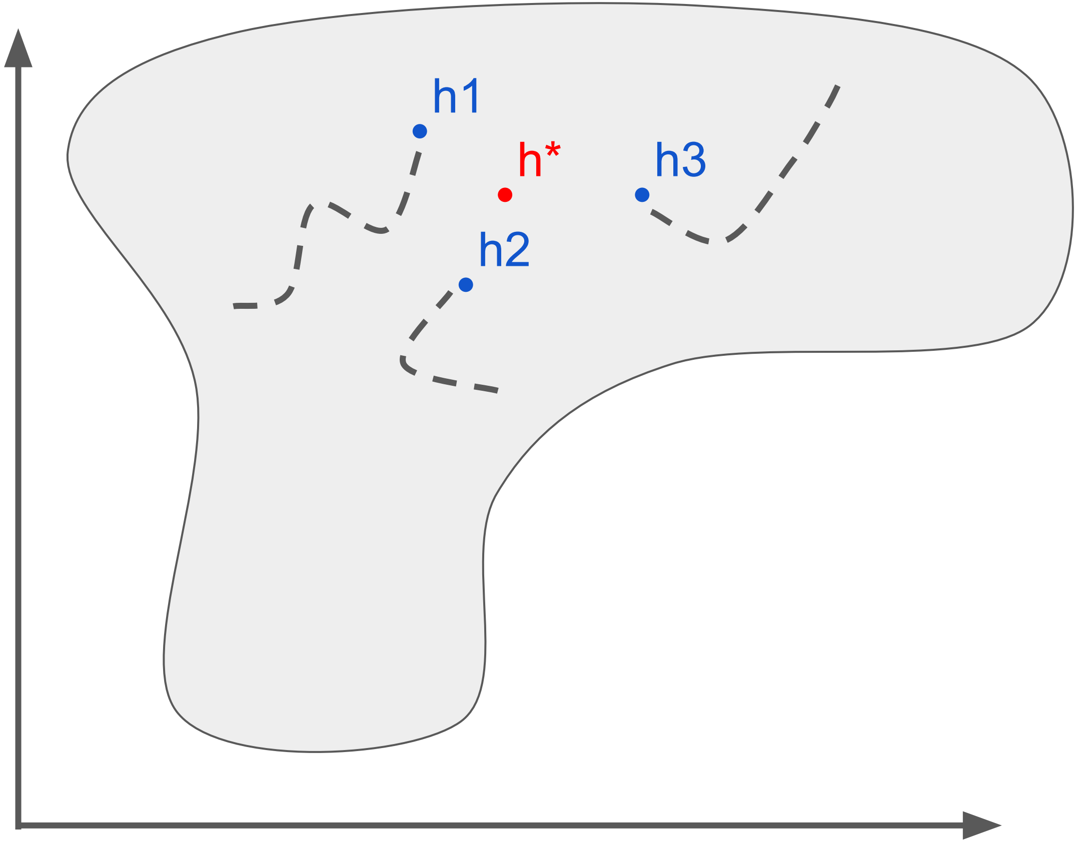


Diettrich, T. G. (2000)

Computational

Iterative learning algorithms (e.g. gradient descent) may converge to different local minima.

An average of multiple hypotheses may be close to the global minimum.

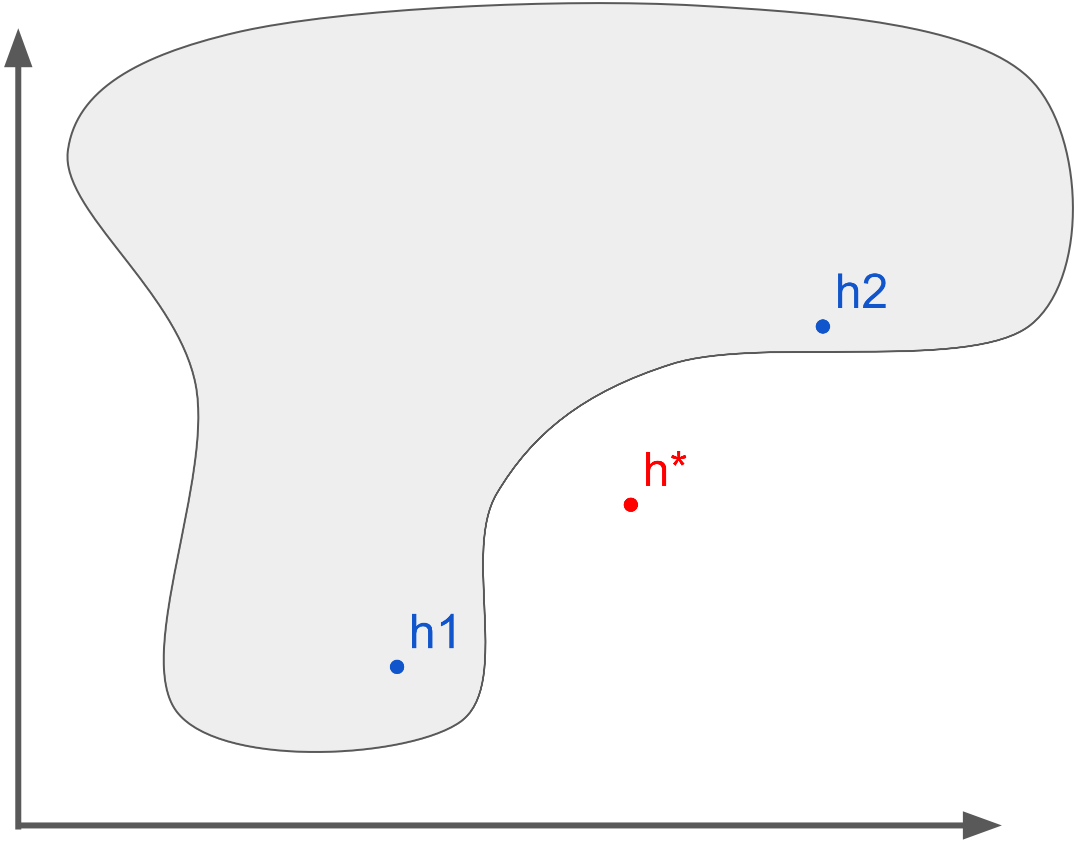


Diettrich, T. G. (2000)

Representational

The optimal hypothesis may be outside of the effective hypothesis space that is searched over using a finite dataset.

An average of multiple hypotheses may be outside of the effective hypothesis space and closer to the optimal hypothesis.



Diettrich, T. G. (2000)

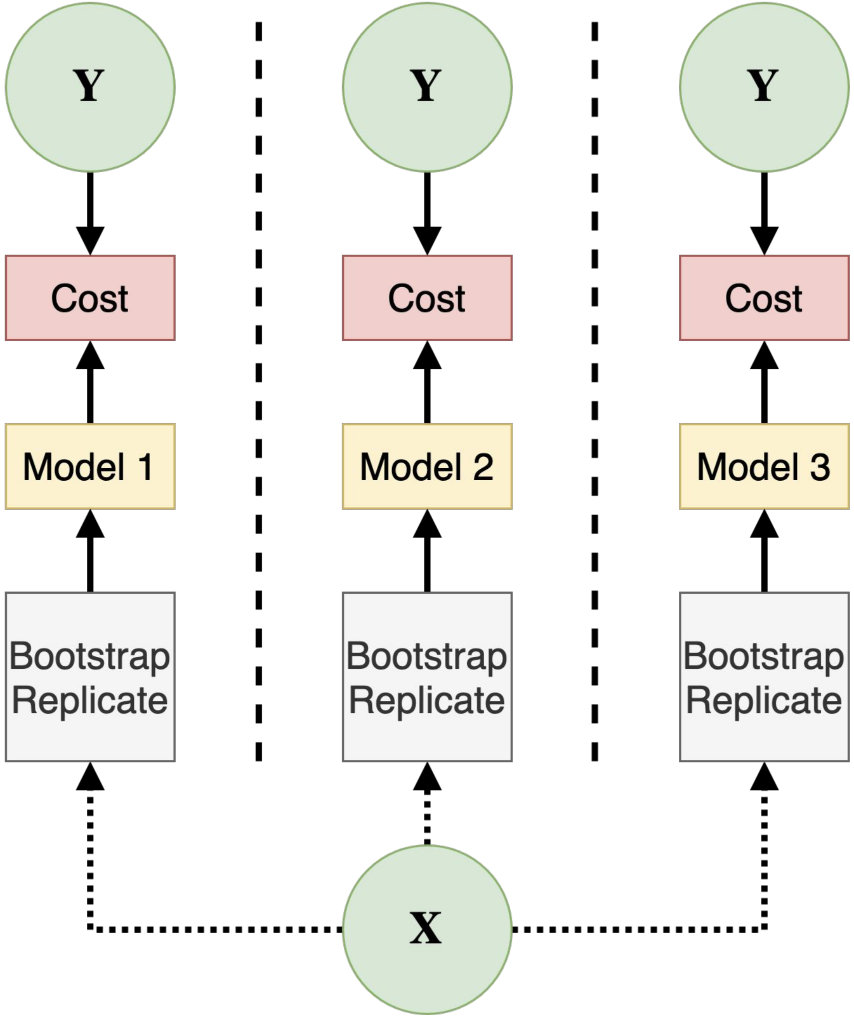
Bagging

Bootstrap replicate = random resampling of the dataset with replacement.

Bootstrap aggregation = an ensemble of models trained on different bootstrap replicates.

On average ~60% of data present in every replicate.

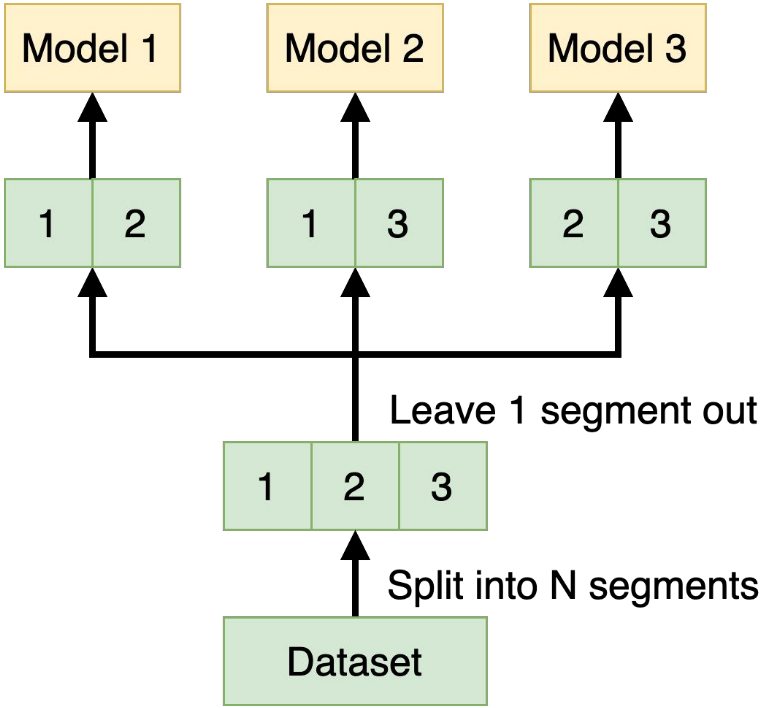
Diettrich, T. G. (2000)



Cross-validated Committee

Segments = N disjoint subsets of the dataset.

Cross-validated committee = an ensemble of N models trained on the dataset with different segments missing.

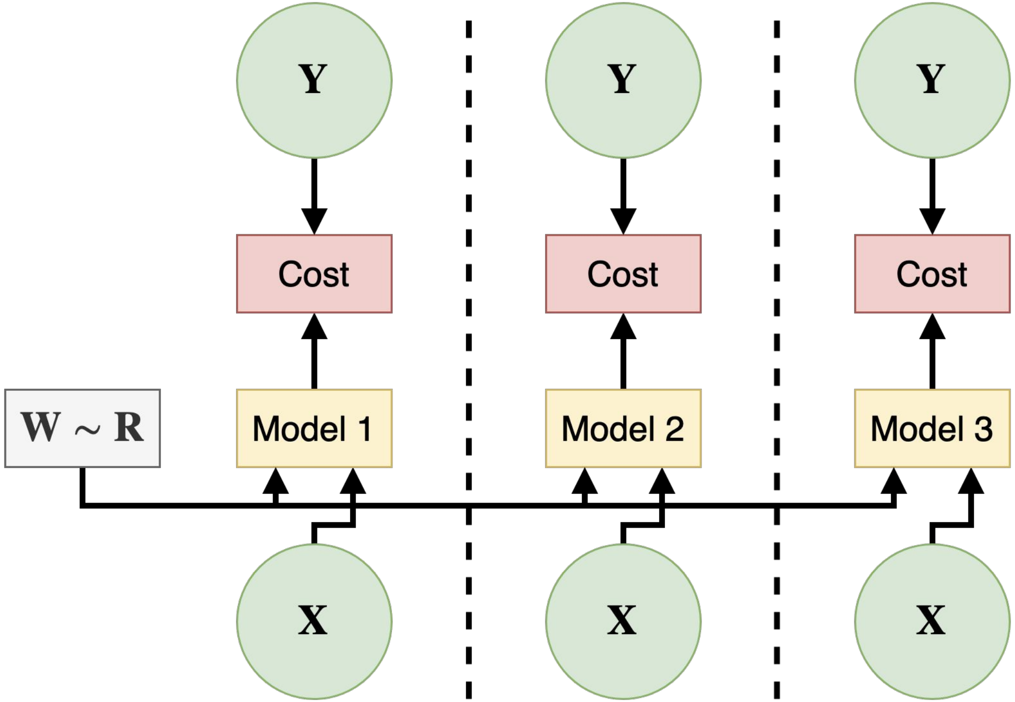


Diettrich, T. G. (2000)

Noise Injection: Initialization

Create multiple neural networks with different initial parameters.

After training, the networks will arrive at different hypotheses.



Diettrich, T. G. (2000)

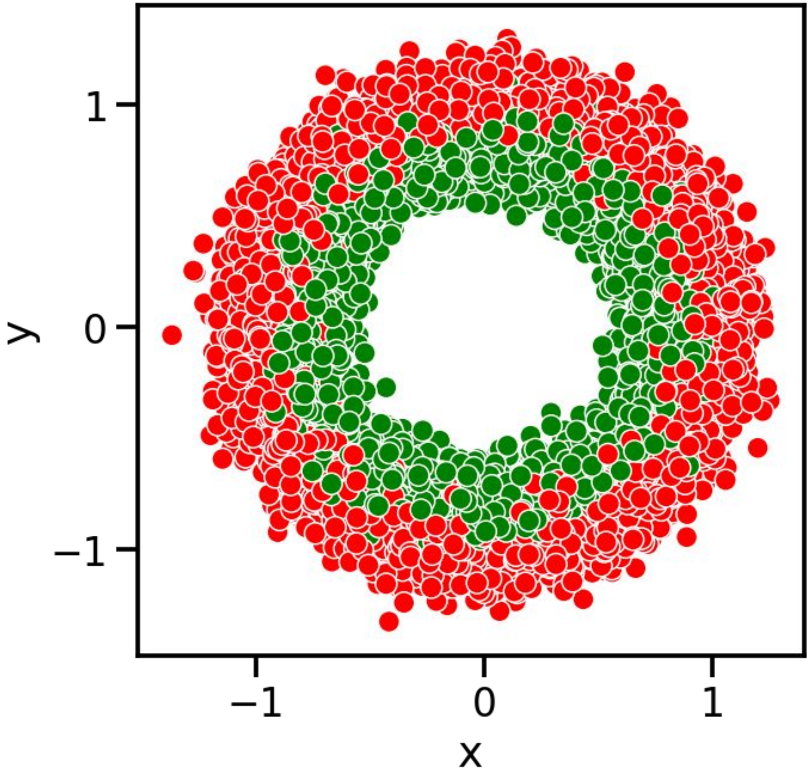
Case Study: Gaussian Circles

Dataset

Collection of 10K points in 2D space arranged as two circles with Gaussian noise.

Task

Classify a point as either green or red given its coordinates.



See GaussianCircles.ipynb for implementation.

Logistic Regression #1

Features

Coordinates X, Y, and constant

Target

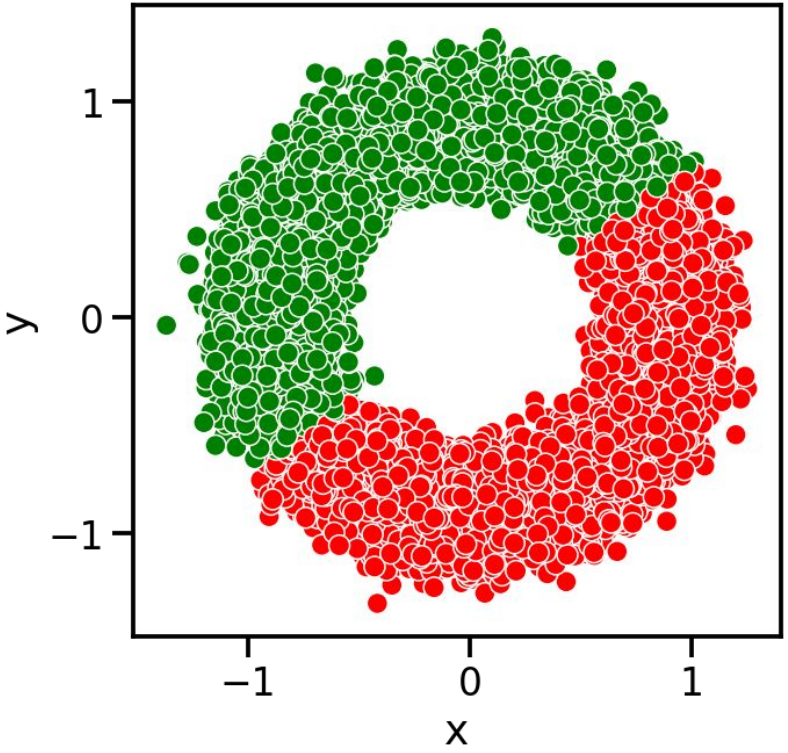
Red = 0, green = 1

Accuracy

0.50

Log Loss

0.693

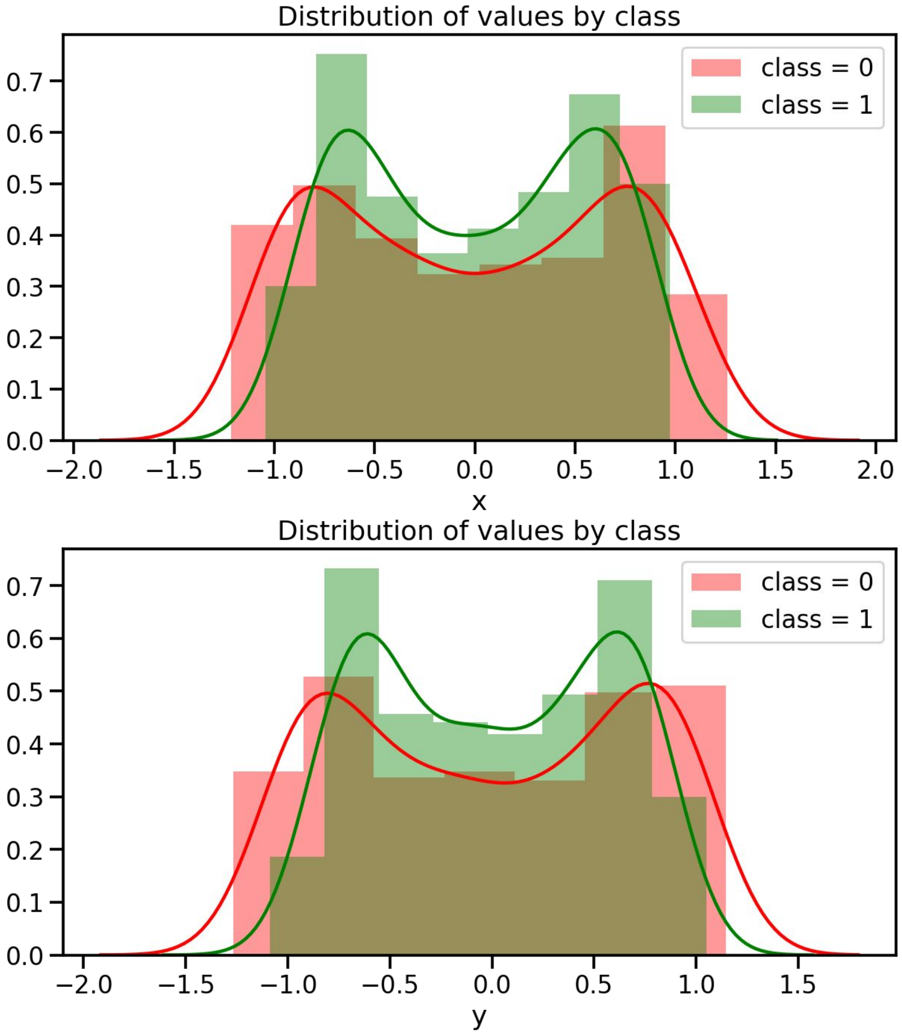


See GaussianCircles.ipynb for implementation.

Distribution by X and Y

Inference from Distributions
There is no way to separate classes with a straight line in either X or Y space.

How to construct **a feature which can separate the two circles** with a line?

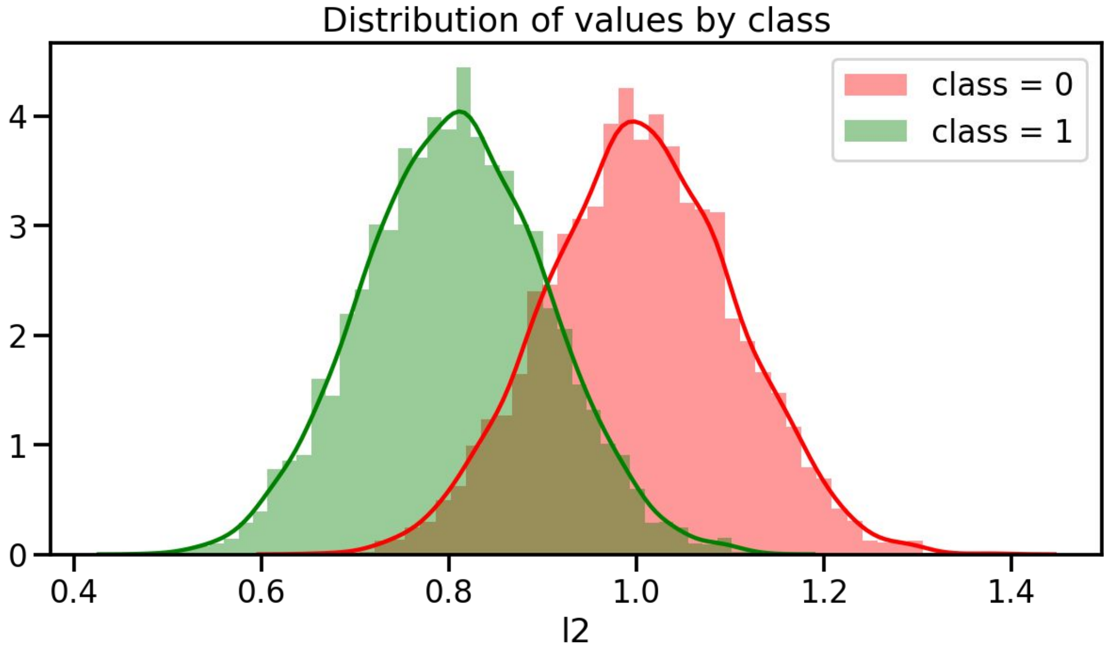


Distribution by L2 Norm

L2 Norm of X and Y = distance from the center.

Distributions **partially separated** from each other.

Overlapping area implies that a **perfectly accurate classifier is not possible**.



Logistic Regression #2

Features

L2 norm, and constant

Target

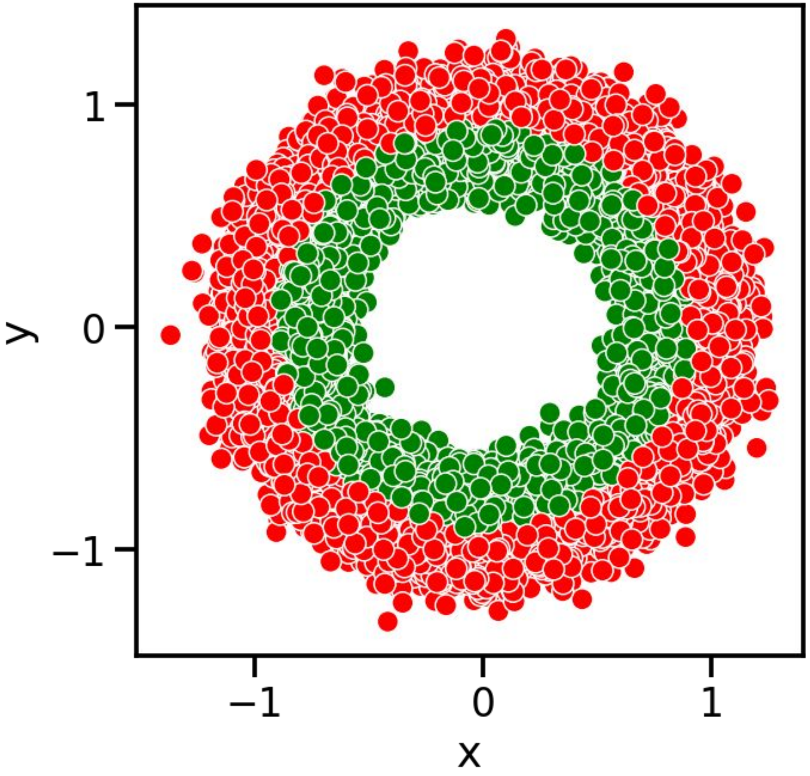
Red = 0, green = 1

Accuracy

0.84

Log Loss

0.36



Neural Network

Layers

1. FC with 10 nodes, tanh
2. FC with 1 node, sigmoid

Features

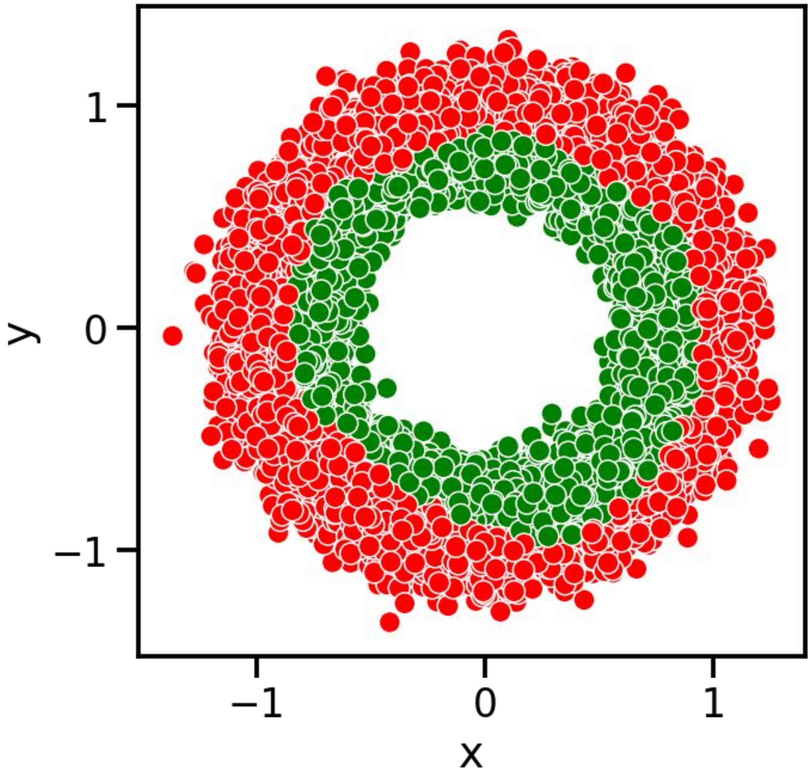
Coordinates of X and Y

Target

Red = 0, green = 1

Log Loss

0.435

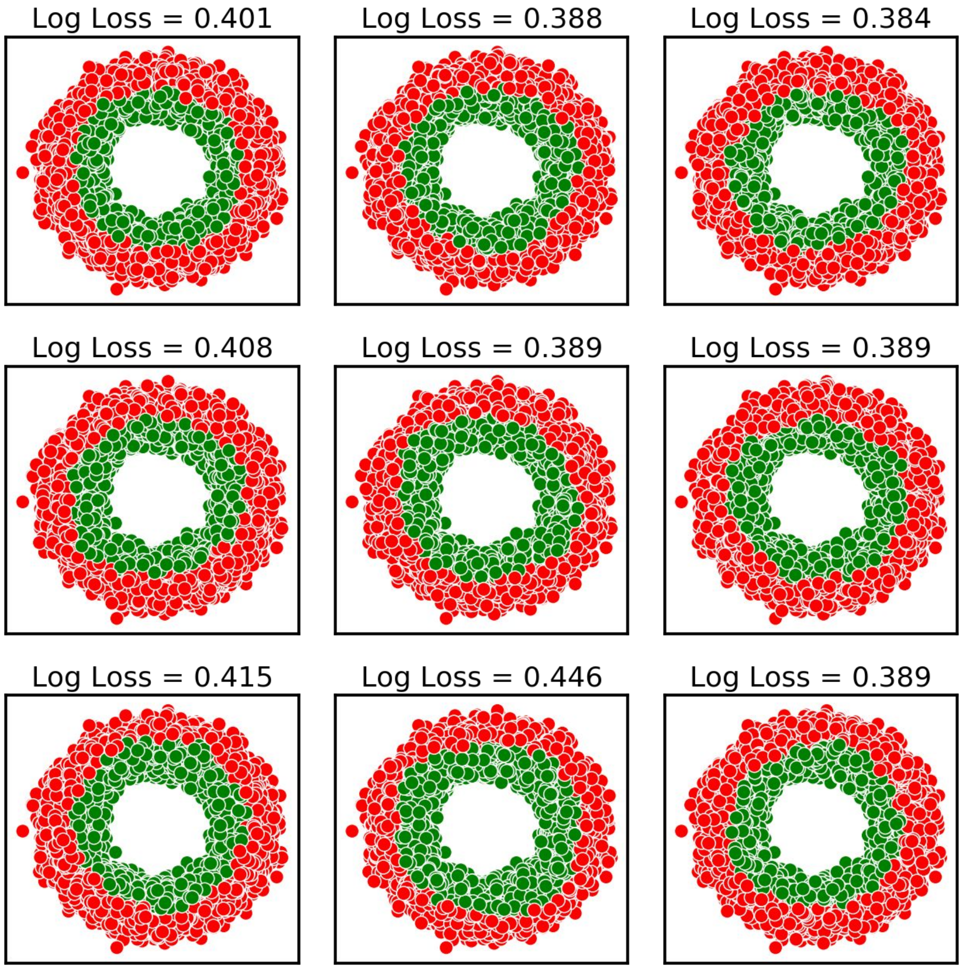


Example: Bagging

1. Sample 20 different bootstrap replicates of the training dataset

2. Train each model for 10 epochs

3. Compare performance on the training dataset



Demo

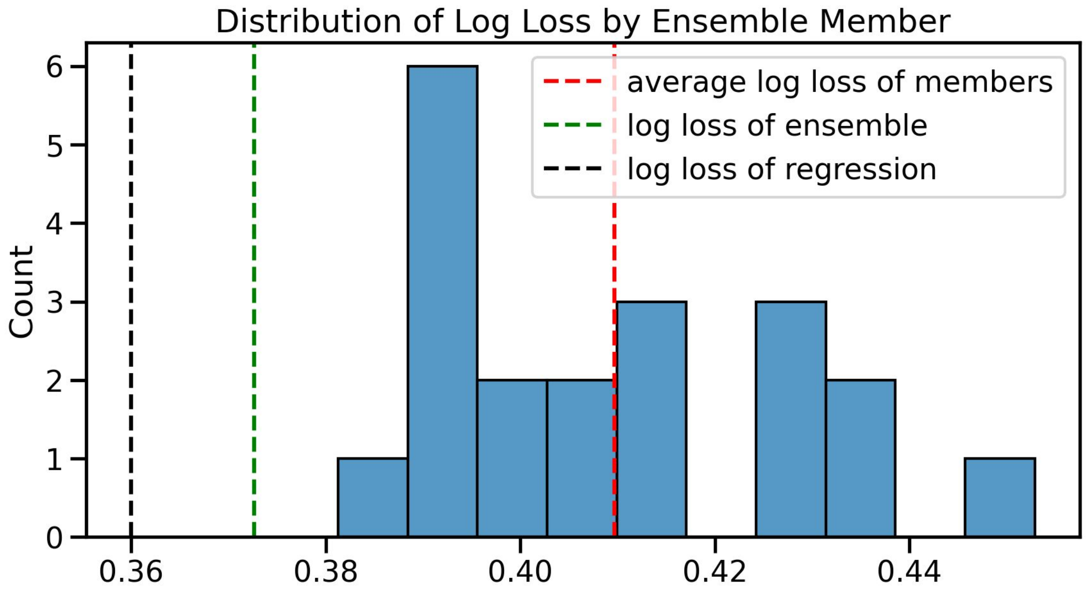
Gaussian Circles

Ensemble: Bagging

Members of Ensemble
20 neural networks with different training bags

Aggregation Method
Average of Probability

Log Loss of Ensemble
0.373

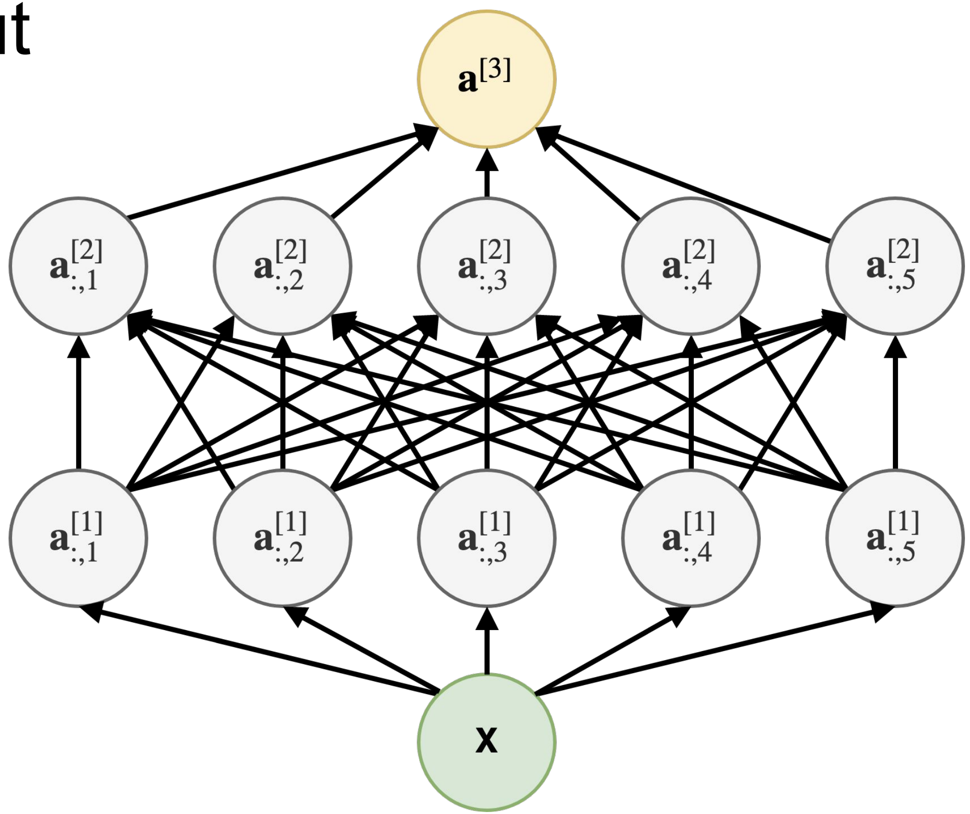


See GaussianCircles.ipynb for implementation.

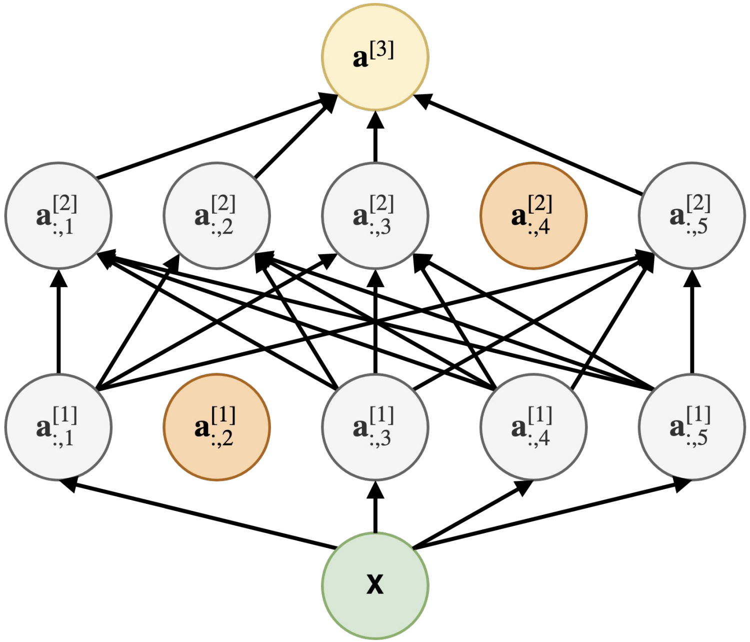
Noise Injection: Dropout

During training
On each iteration, randomly choose and disable nodes with fixed probability.

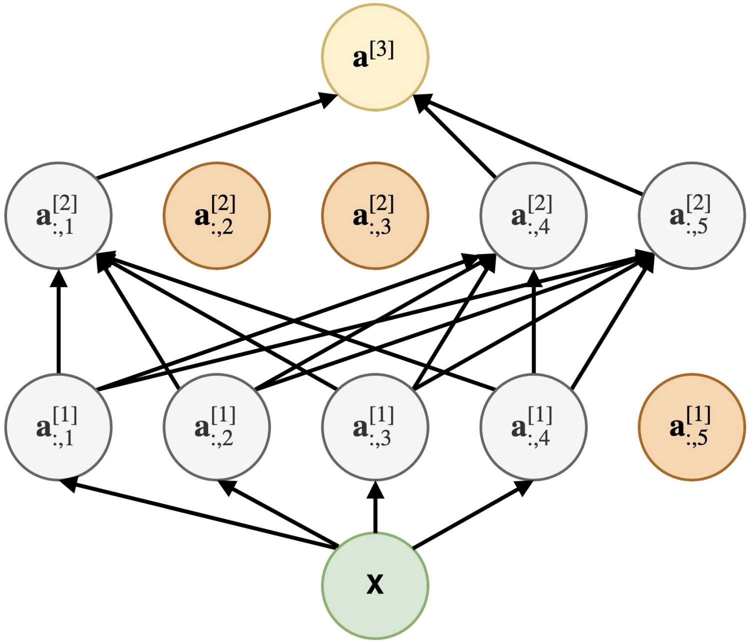
During inference
Use all nodes



Noise Injection: Dropout



Iteration 1



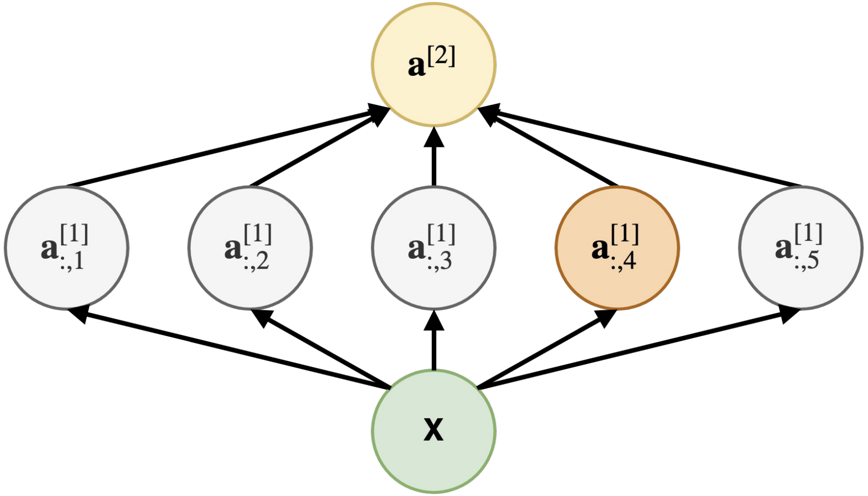
Iteration 2

Noise Injection: Dropout

Let's define:

- p = probability of keeping a node
- $\mathbf{d}$ = vector of random variables ~ Bernoulli(p)

$$\tilde{\mathbf{a}}^{[1]}_{:,m} = \frac{\mathbf{a}^{[1]}_{:,m} \odot \mathbf{d}_m}{p}$$

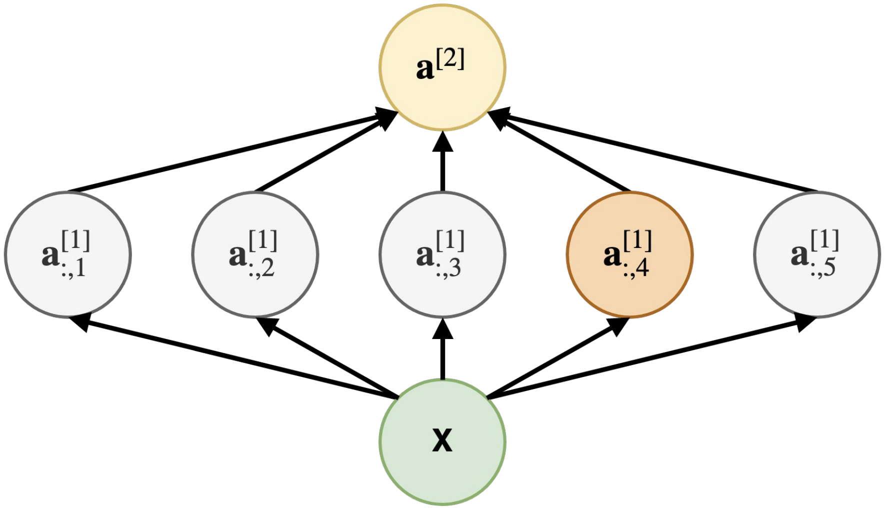


Srivastava, N, et al. (2014)

Noise Injection: Dropout

$$\tilde{\mathbf{a}}^{[1]}_{:,m} = \frac{\mathbf{a}^{[1]}_{:,m} \odot \mathbf{d}_m}{p}$$

$$\begin{aligned}
\mathbb{E}[\tilde{\mathbf{a}}^{[1]}_{s,:}] &= \frac{\mathbb{E}[\mathbf{a}^{[1]}_{s,:}] \cdot \mathbb{E}[\mathbf{d}]}{p} \\
&= \frac{\mathbb{E}[\mathbf{a}^{[1]}_{s,:}] \cdot p}{p} \\
&= \mathbb{E}[\mathbf{a}^{[1]}_{s,:}]
\end{aligned}$$



Srivastava, N, et al. (2014)

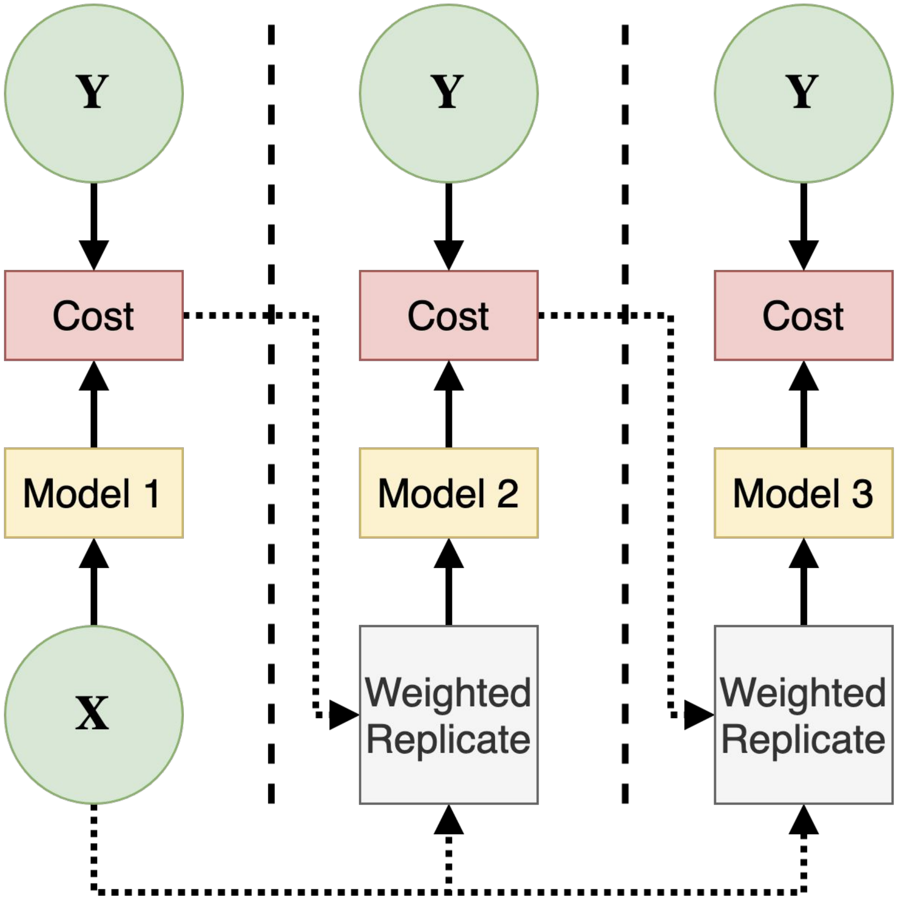
See Dropout.ipynb for discussion, and Keras implementations.

AdaBoost: Training #1

Sequential model training on different datasets.

Each dataset resampled with probabilities depending on the per-sample cost of the previous model.

Each subsequent model is trained with higher focus on hard training samples.



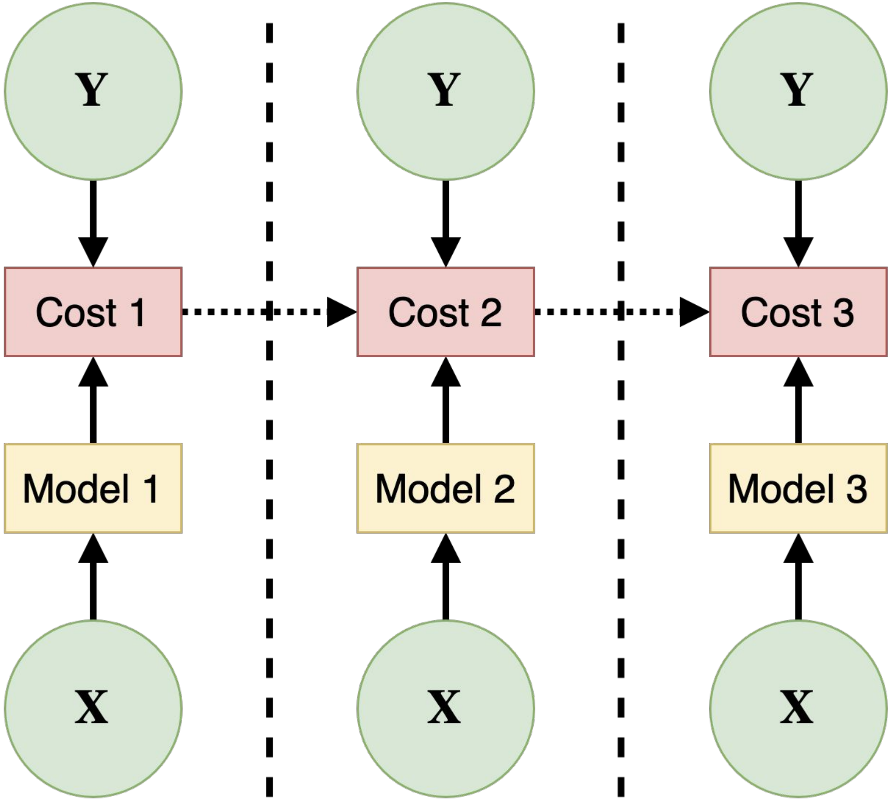
Shwenk, H., Bengio, Y. (2000)

AdaBoost: Training #2

Sequential model training on the same dataset.

Cost = average of this model's per-example cost weighted by per-example cost from the previous model.

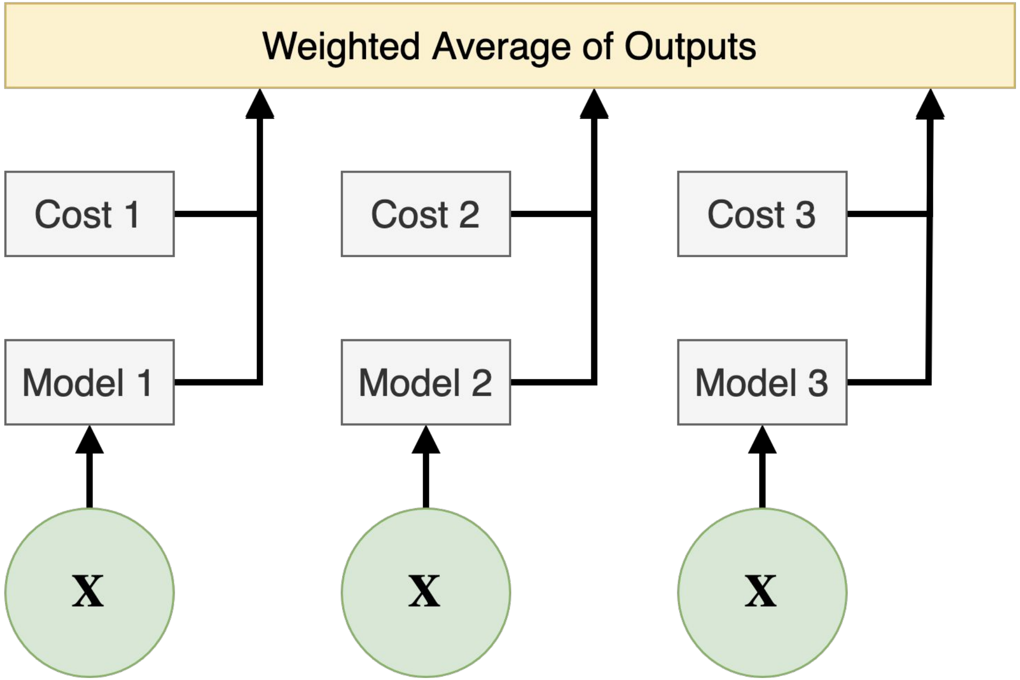
Each subsequent model is trained with higher focus on hard training examples.



Shwenk, H., Bengio, Y. (2000)

AdaBoost: Inference

Ensemble output is the average over each model's output weighted by the performance on the training dataset.

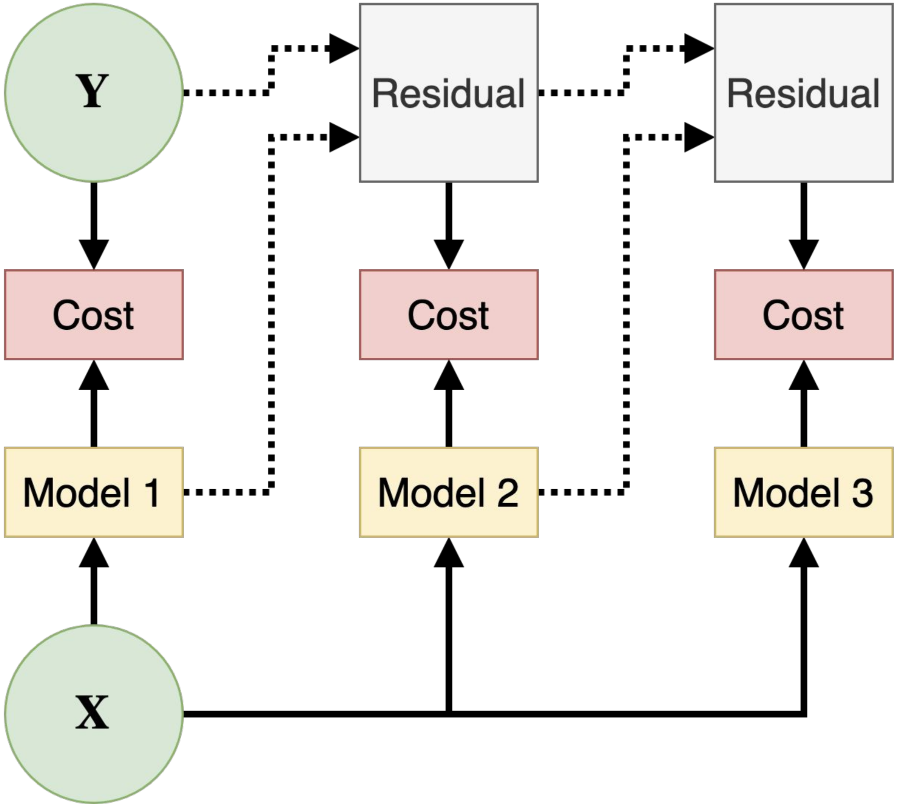


Shwenk, H., Bengio, Y. (2000)

Gradient Boosting: Training

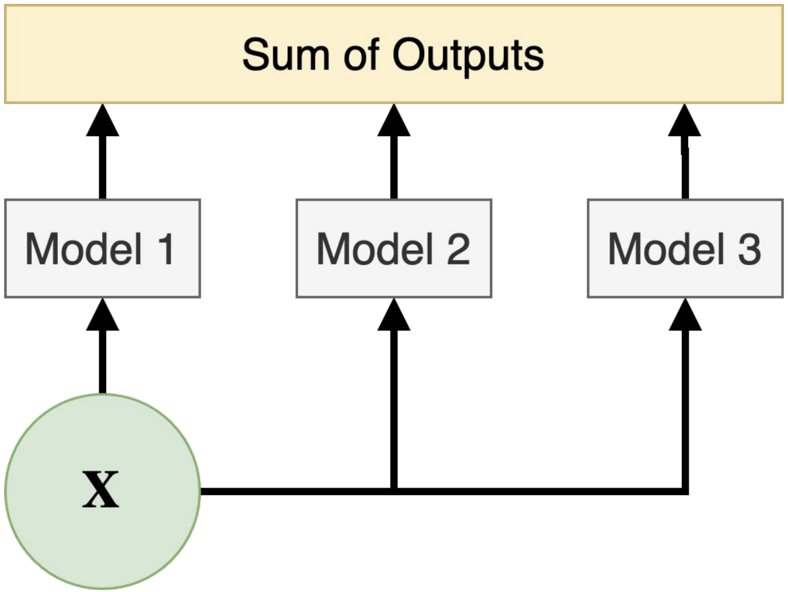
Sequential model training on the same dataset.

Each subsequent model is trained to output the residual of the previous model.



Gradient Boosting: Inference

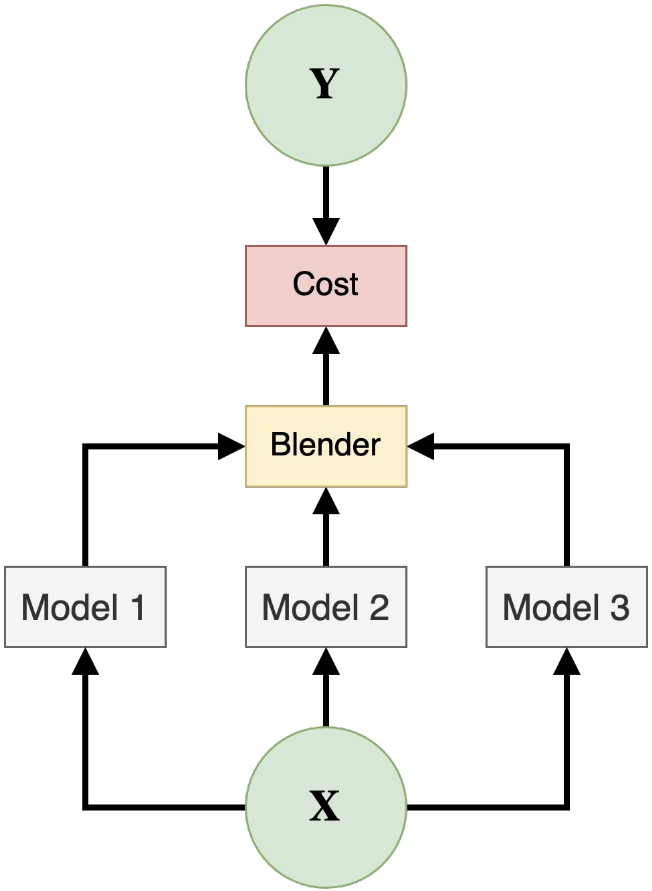
Ensemble output is the sum of outputs of each of the models.



Stacking: Forward Pass

Instead of taking a simple average, the aggregation step can be an independent model taking outputs of ensemble members as input.

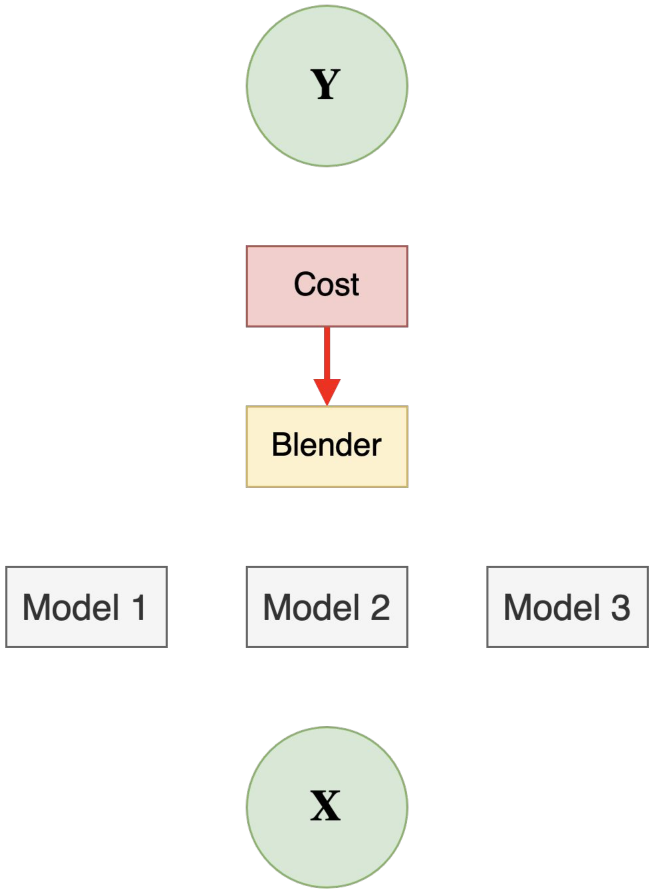
Blender is trained after the ensemble models have been trained.



Stacking: Backward Pass

Instead of taking a simple average, the aggregation step can be an independent model taking outputs of ensemble members as input.

Blender is trained after the ensemble models have been trained.

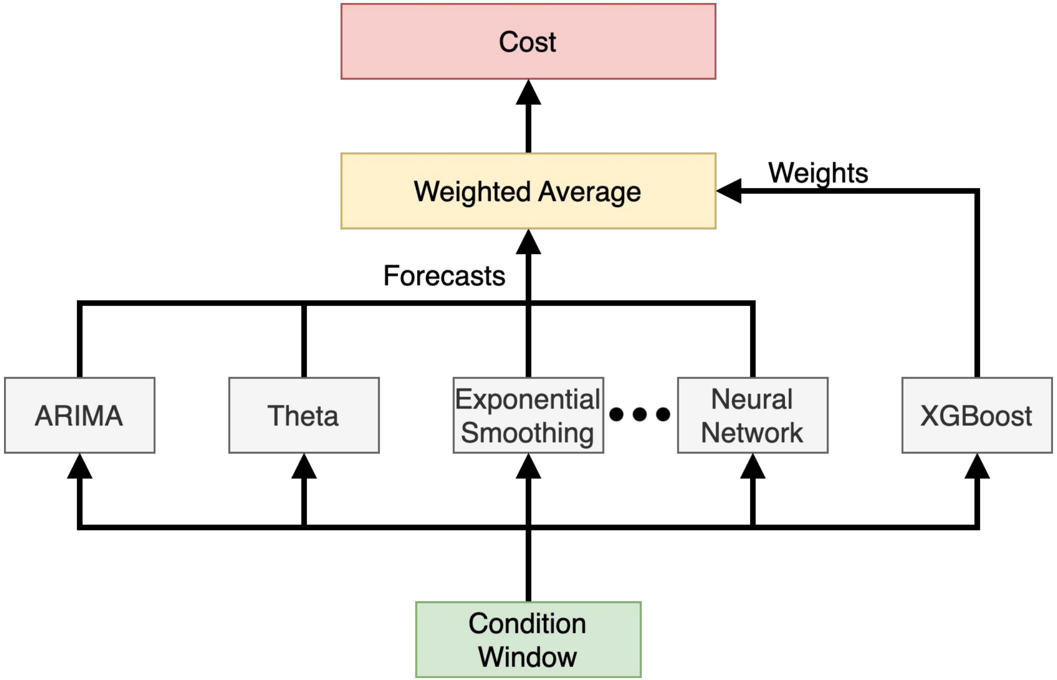


Case Study: FFORMA

Top-2 in M4 Competition

Blender
Weighted average
with weights predicted by XGBoost

XGBoost Features
Training-time errors by each member
Length of time-series
Strength of trend
Curvature
Autocorrelation



Source: FFORMA: Feature-based forecast model averaging (Monterto-Manso, P., et al, 2020)

Part 2

CarNet

(Image by a Stable Diffusion model)

Case Study: Tesla AutoPilot

Source

Tesla AI Day 2022

Neural Network sub-tasks

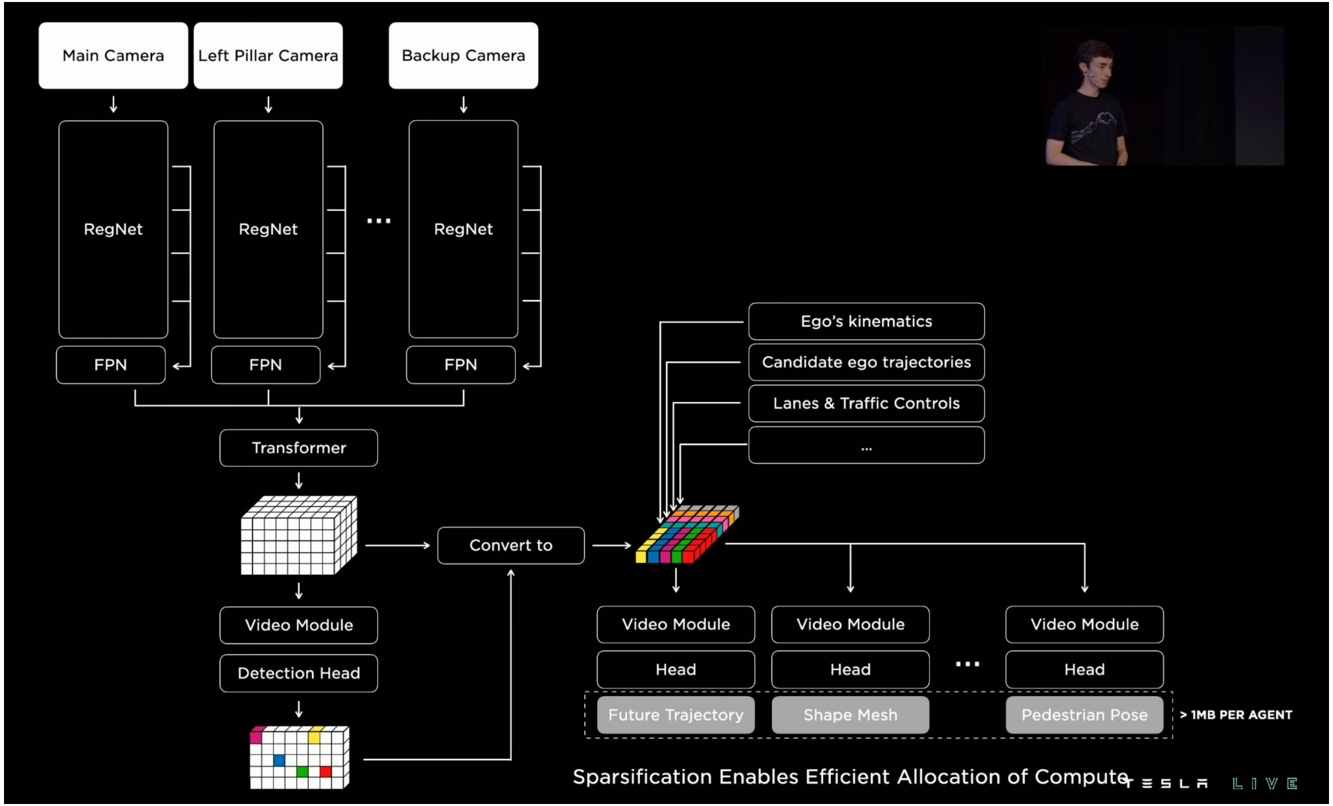
Object detection

Occupancy detection

Lane detection

AutoPilot - Object Detection

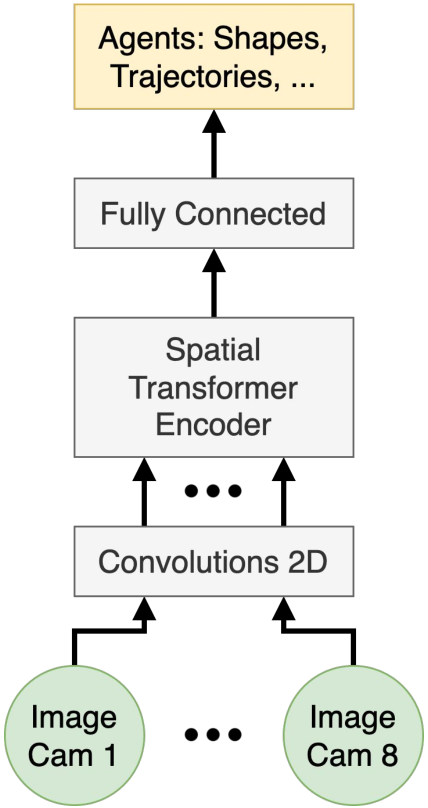
Source: Tesla AI Day 2022



AutoPilot - Object Detection

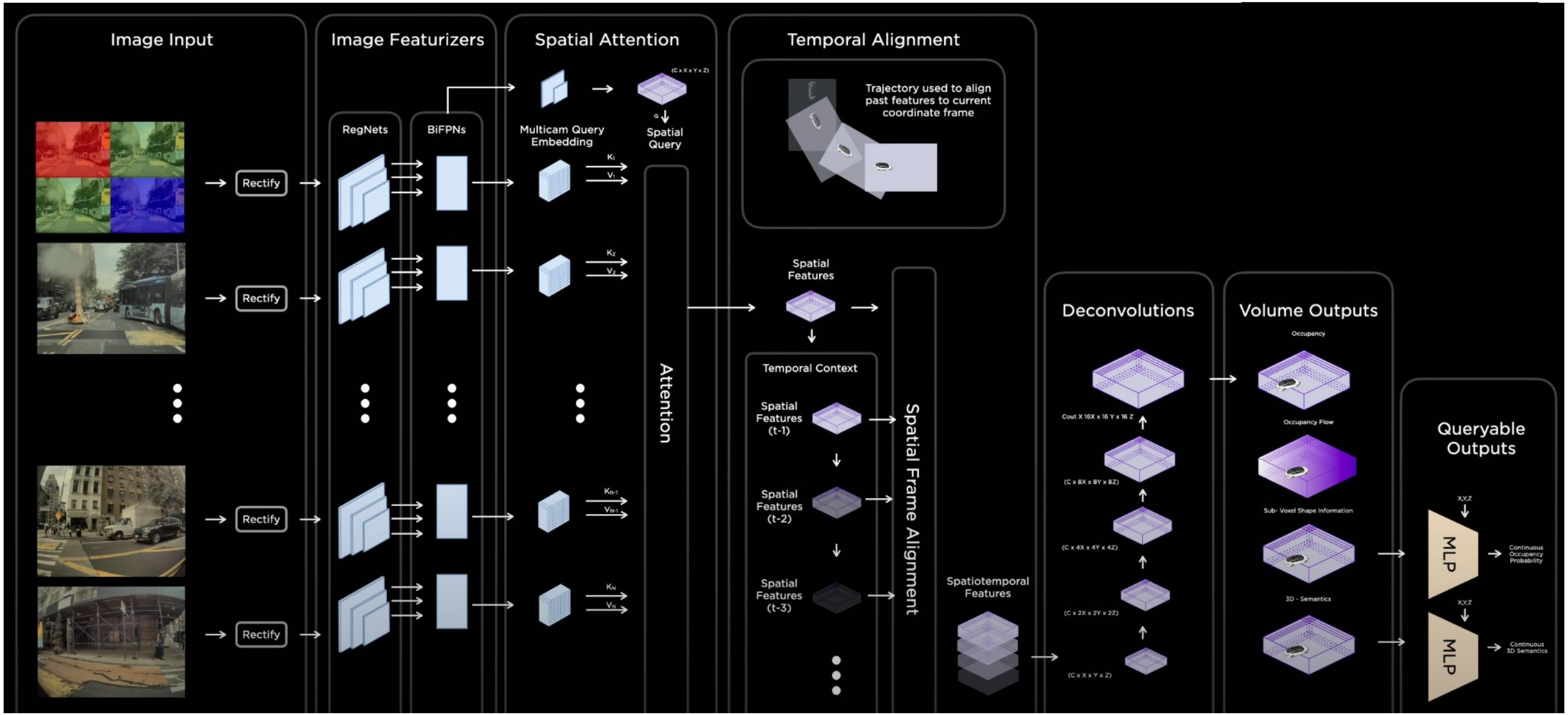
Task
Detect agents: vehicles, people, etc.
Per-agent attributes: velocity, shape, etc.

Other parts of the system make decisions based on the detected objects and attributes.



Source: Tesla AI Day 2022

Tesla AutoPilot - Occupancy Detection



Source: Tesla AI Day 2022

AutoPilot - Occupancy Detection

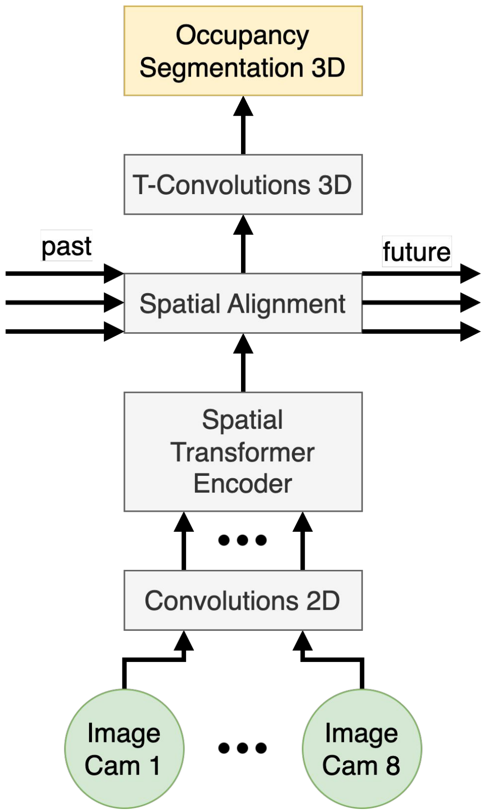
Task

Segmentation in 3D space

Per-voxel classification:

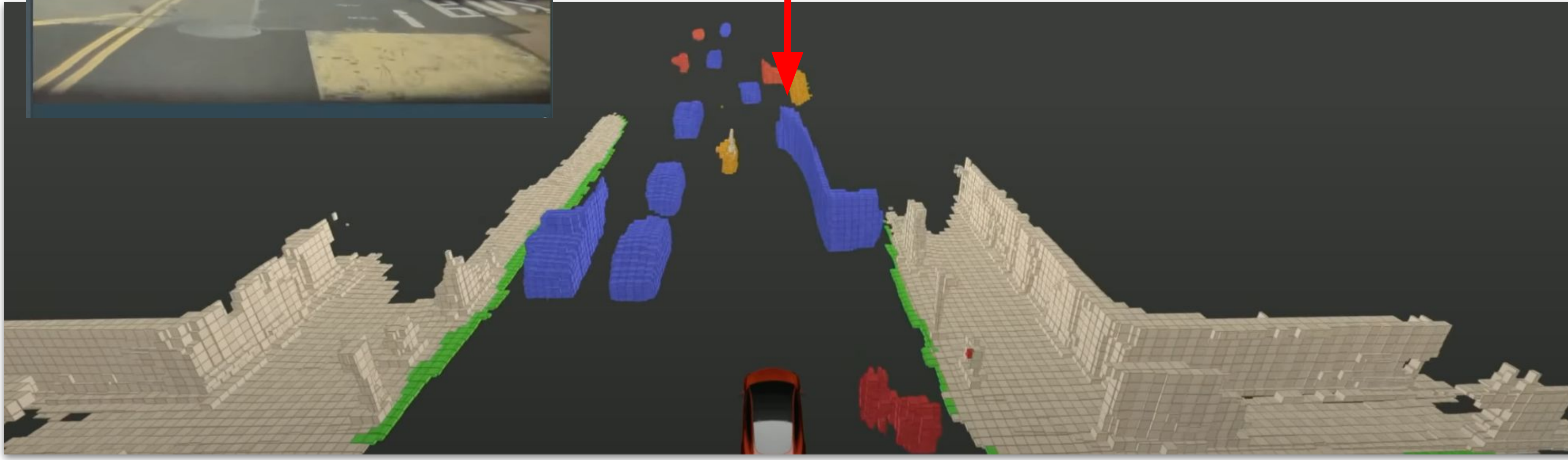
- Occupied by a static object
- Occupied by a moving object
- Free space

Voxel = a pixel in 3D



Source: Tesla AI Day 2022

Bus in 2D on Camera
Bus in 3D in Occupancy Detection



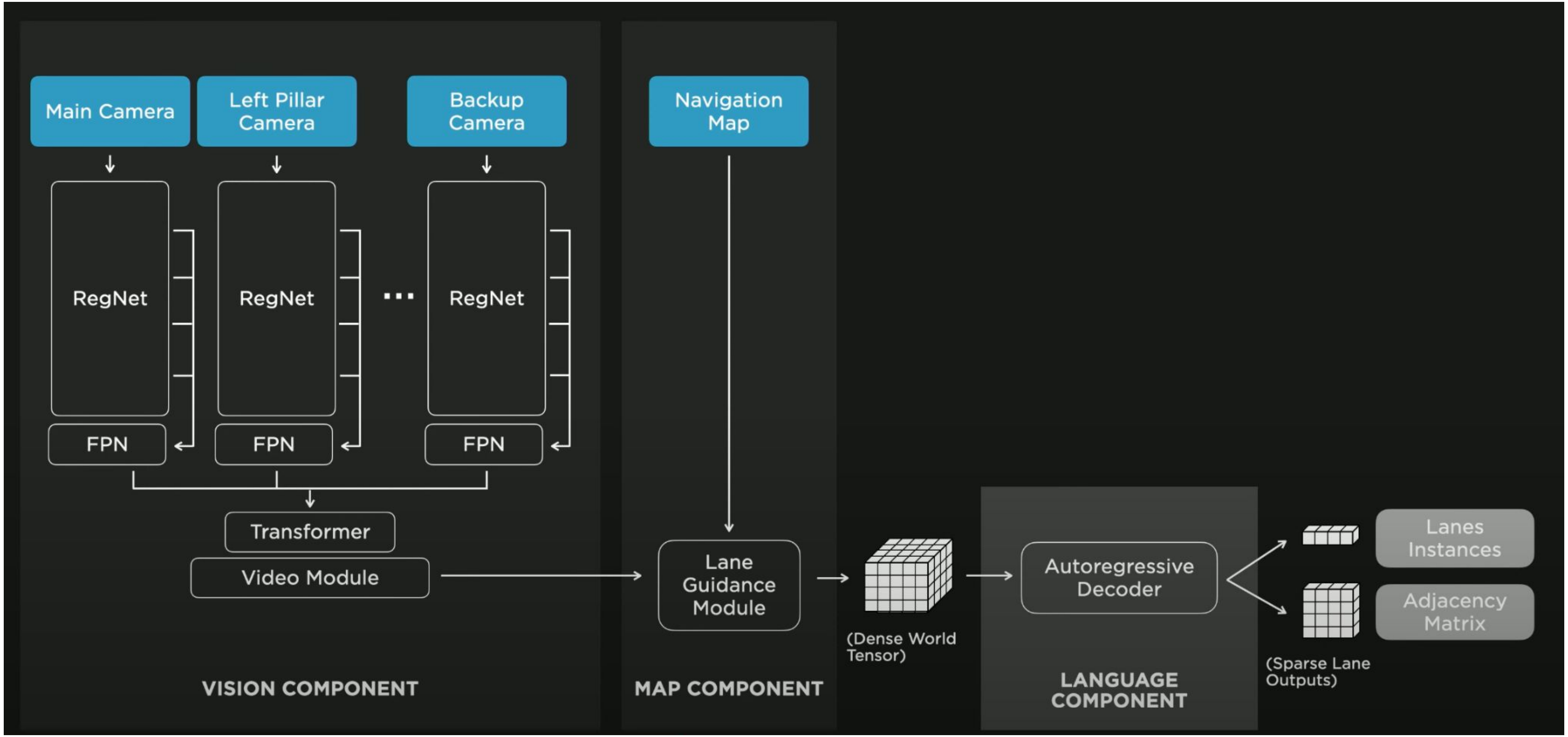
Car

Source: Tesla AI Day 2022

https://youtu.be/ODSJsviD_SU?t=4358

AutoPilot - Lane Detection

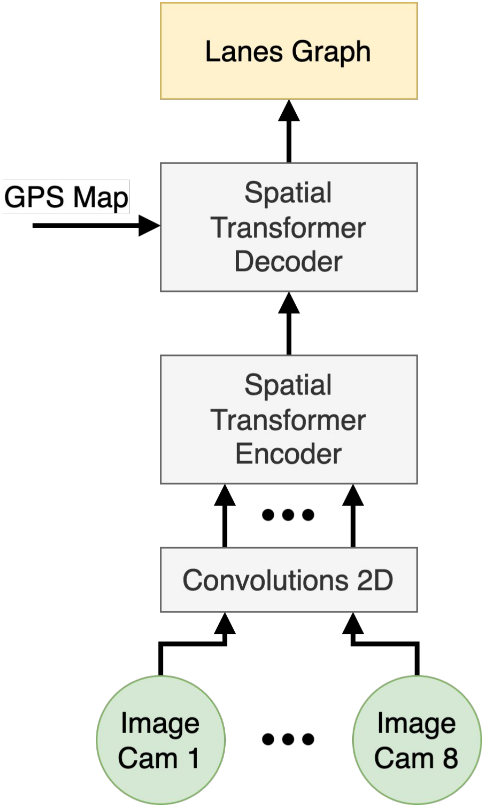
Source: Tesla AI Day 2022



AutoPilot - Lane Detection

Task
Detect lane instances
and connections between lanes.

Details
Utilizes a navigation map and GPS location.
Graph is encoded with a “language of lanes”.



Source: Tesla AI Day 2022

Assignment 5: CarNet

Dataset

~30K images

228 x 228 x 3

Task

1. Count signals (traffic lights, street signs)
2. Count vehicles (cars, planes, bikes, …)

Loss

Average MSE =

½ MSE(signals) + ½ MSE(vehicles)

CarNet: Baseline MSE

backbone	signal	vehicle	average
vanilla cnn	1.81	9.65	5.73
mobile net	1.41	9.77	5.59
mean model	1.91	13.23	7.57

CarNet: Grading

Any neural network architecture, training procedure, and ensemble method.

Grading

15 points = percentile of Average MSE

5 points = description of the solution

Demo

Assignment Template

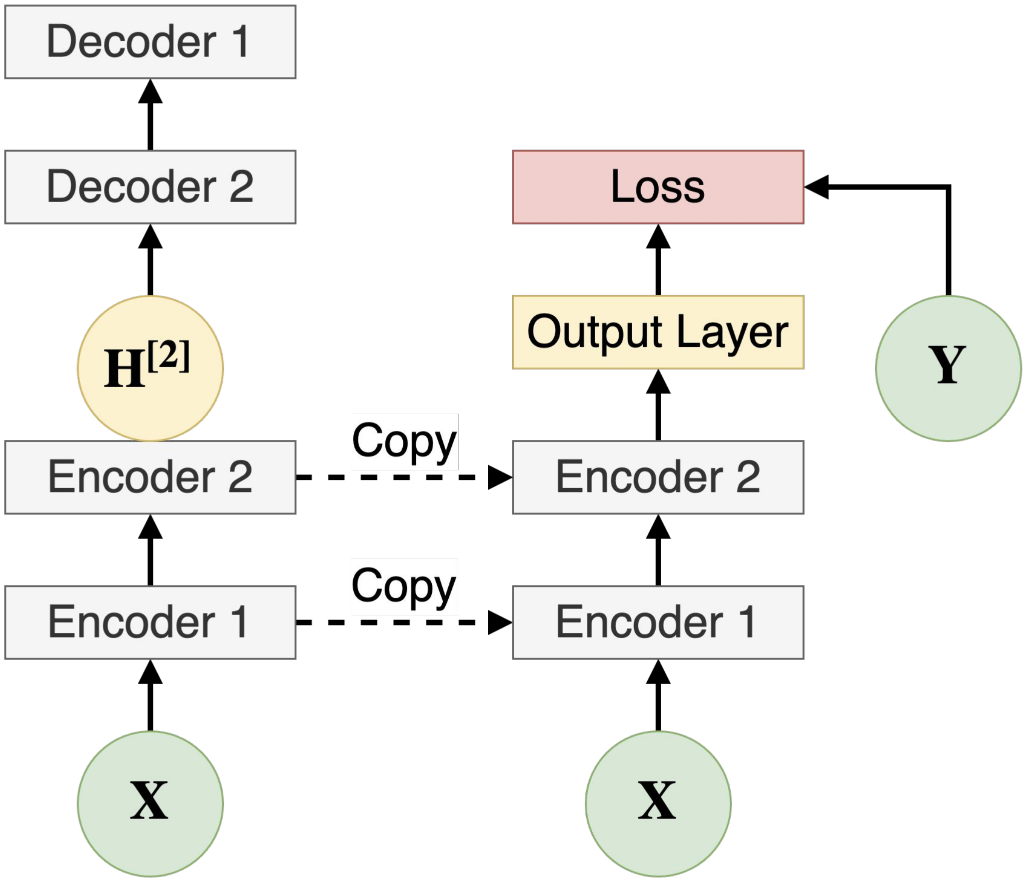
Part 3

Course Summary

Managerial Economics of Deep Learning

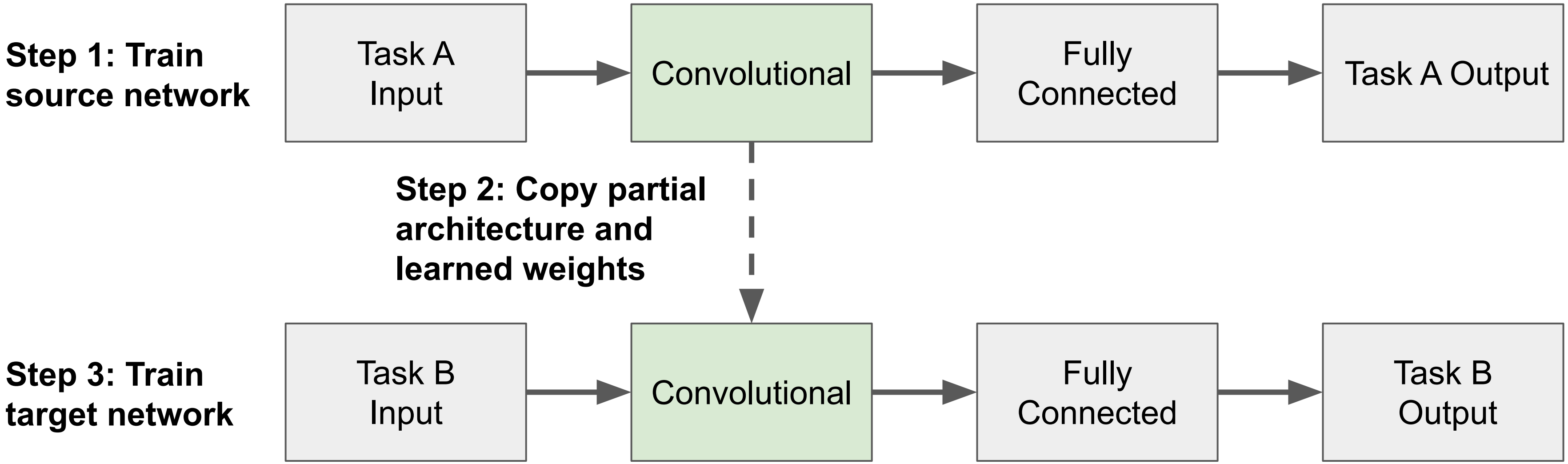
Project Methodology	Project Duration	Fixed Cost	Variable Cost	Required Training
Design new architecture and train from scratch	Months	High	Medium	Machine Learning Researcher
Use existing architecture and transfer learning	**Weeks**	**Medium**	**Medium**	**Machine Learning Engineer**
Find a fully-trained model or buy Inference as a Service API	Days	Nearly zero	High	Software Engineer

Lecture 1: Unsupervised Pre-training



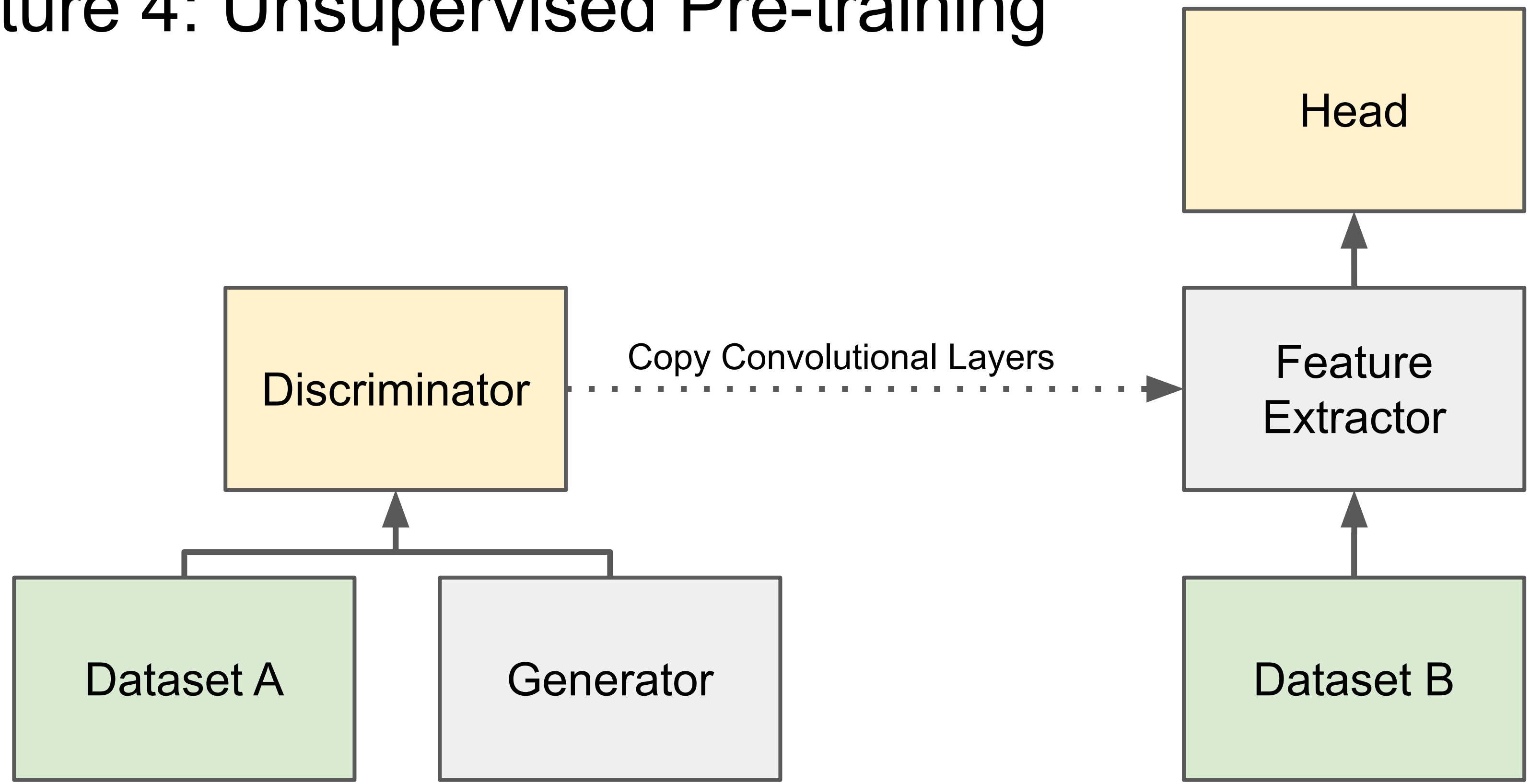
Bengio, Y., et al. (2007)

Lecture 2: Transfer of Supervised Learning



Tan, C., et al. (2018)

Lecture 4: Unsupervised Pre-training



Radford, A., et al. (2016)

Lecture 4: Zero-Shot Prediction

Source Task

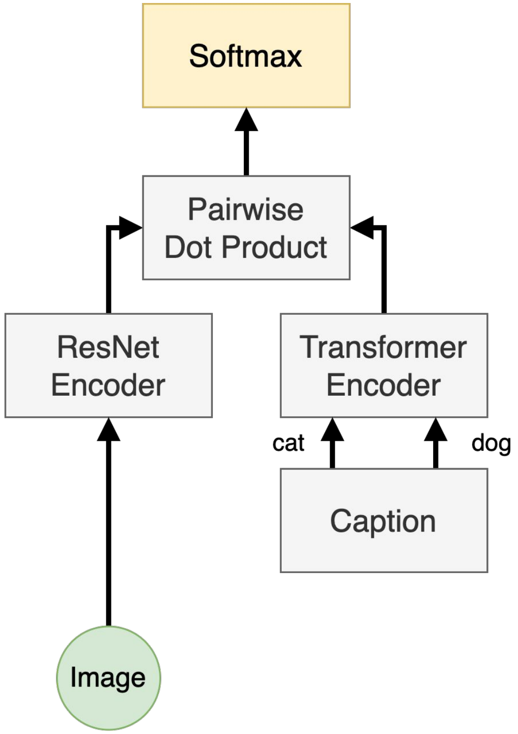
Image-caption similarity

Target Task

Image classification

1. Create per-class English captions
2. Pass similarity scores to softmax

No training!



Source: Learning Transferable Visual Models From Natural Language Supervision (Radford, A., et al., 2021)

Model Stores

In this Course

Keras Applications

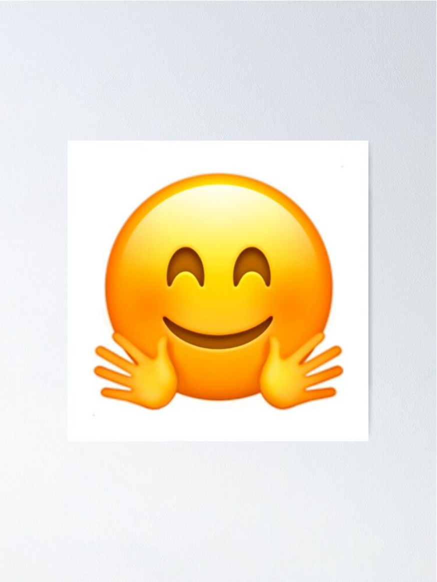
TensorFlow Hub

HuggingFace Hub

Other

PapersWithCode.com

TensorFlow Model Garden



AWS Rekognition

Product

~ $0.001 / image

Available as a convenient API

Features

Custom model training

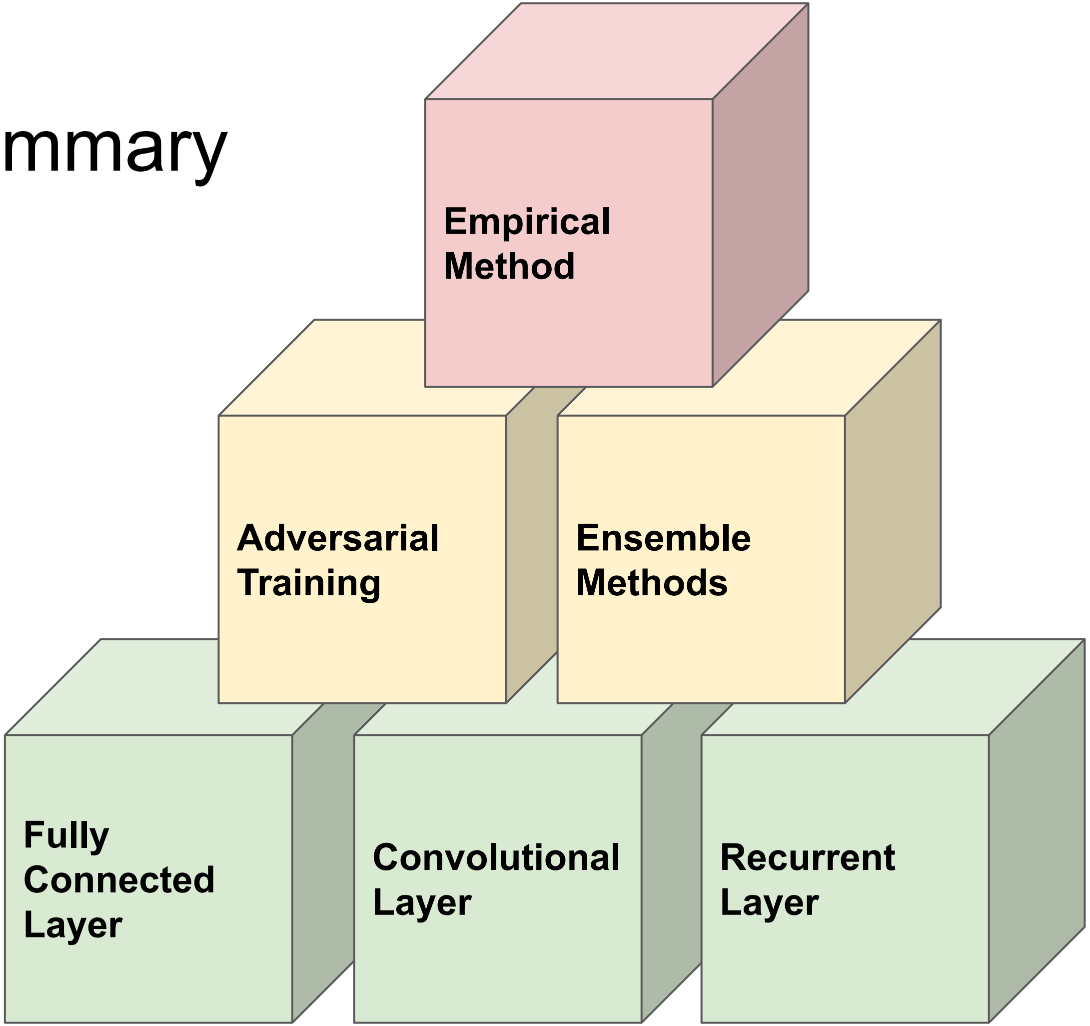
Object/scene detection

Face recognition and analysis

Both photo and video input

Image to text

Course Summary



BodyX

Input:

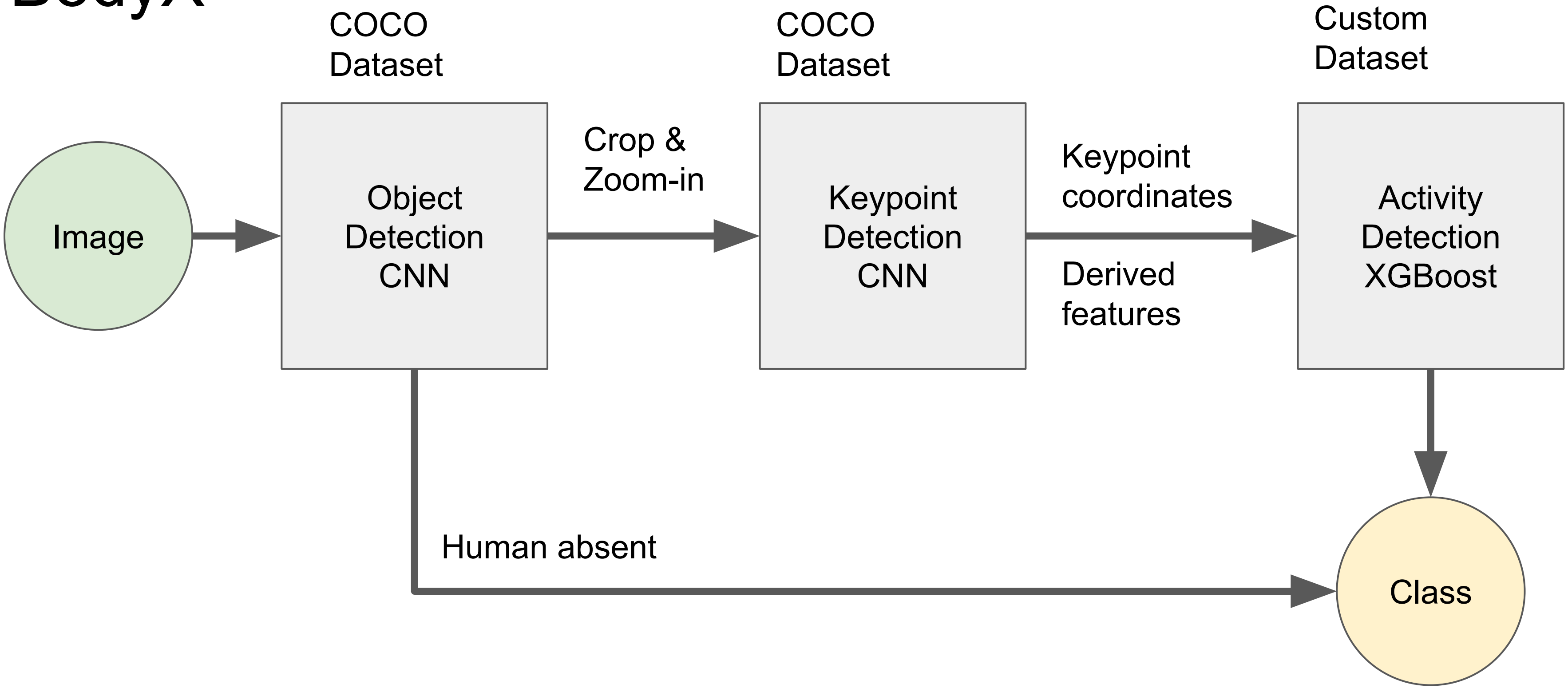
- Image RGB

Output:

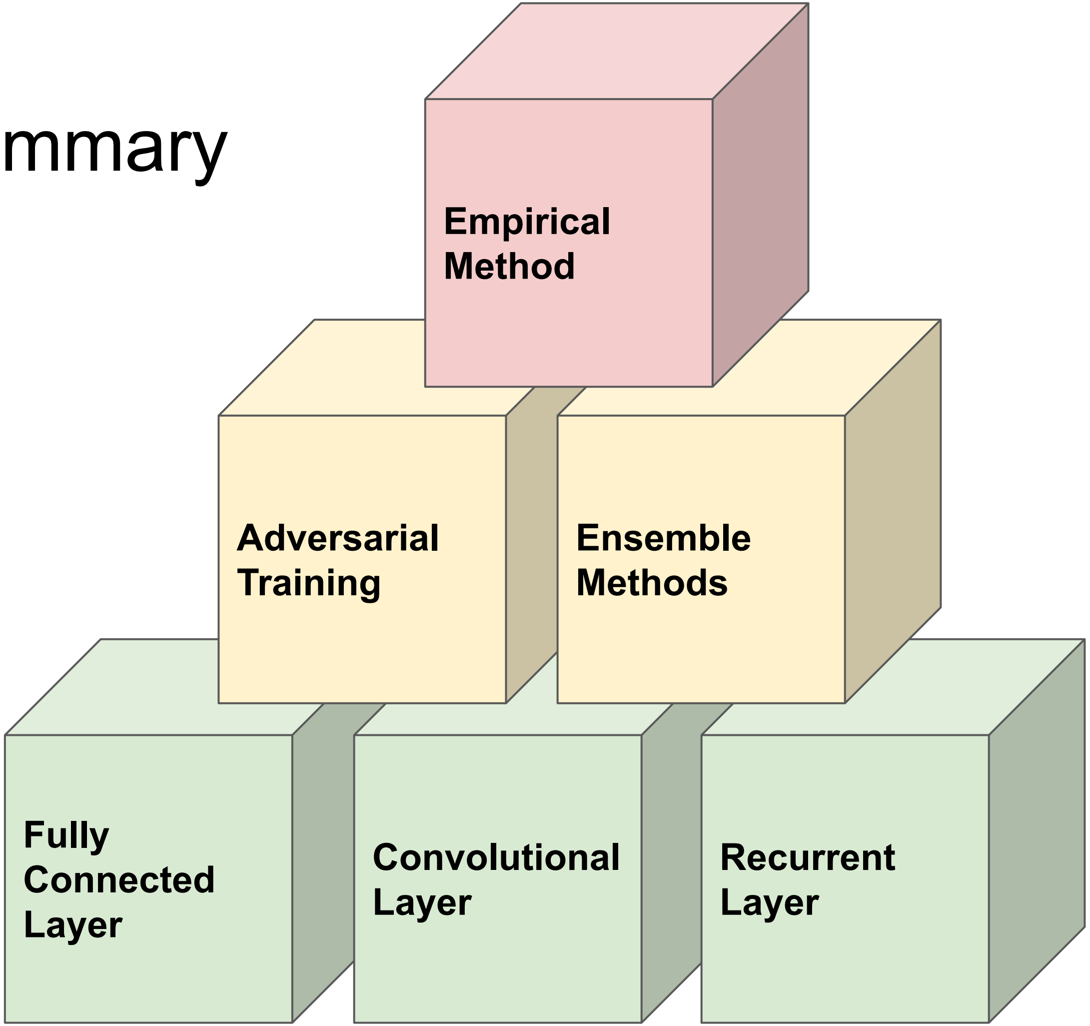
- 4-way classification
  - Human absent
  - Human present, sitting
  - Human present, standing
  - Human present, unknown pose

Present & Sitting

BodyX


COCO
Dataset
COCO
Dataset
Custom
Dataset
Image
Object
Detection
CNN
Crop &
Zoom-in
Keypoint
Detection
CNN
Keypoint
coordinates
Derived
features
Activity
Detection
XGBoost
Human absent
Class

Course Summary



References

- A Short Introduction to Boosting (Fruend, Y., and Schapire, R. E., 1999)
- Dropout: A Simple Way to Prevent Neural Networks from Overfitting (Srivastava, N., et al., 2014)
- Ensemble Methods in Machine Learning (Diettrich, T. G., 2000)
- FFORMA: Feature-based forecast model averaging (Monterto-Manso, P., et al, 2020)
- Tesla AI Day 2022: https://youtube.com/watch?v=ODSJsviD_SU

Thank you

(Really) Final Q&A Time