349: Machine Learning

Fall 2024

Machine Learning in a Nutshell

What is Machine Learning?

ZA What is machine learning?

ChatGPT

Machine learning, a subset of artificial intelligence, involves the development of algorithms enabling computers to learn and improve performance without explicit programming. Unlike traditional programming, machine learning relies on data-driven learning, where models are trained on labeled datasets for supervised learning or discover patterns in unlabeled data for unsupervised learning. Reinforcement learning involves decision-making through interaction with an environment. The process includes training the model, testing its performance, and refining it to make accurate predictions on new data. Widely applied in image recognition, natural language processing, recommendation systems, and more, machine learning has become essential for solving complex problems and extracting insights from diverse datasets across various domains.

What is Machine Learning?

- “A set of methods that can automatically detect patterns in data, then use the uncovered patterns to predict future data.”

- “Using experience to gain expertise.”

- “Fitting a function to data.”

Source: Murphy, *Machine Learning: A Probabilistic Perspective*
Shalev-Shwartz and Ben-David, *Understanding Machine Learning*

What is Machine Learning?

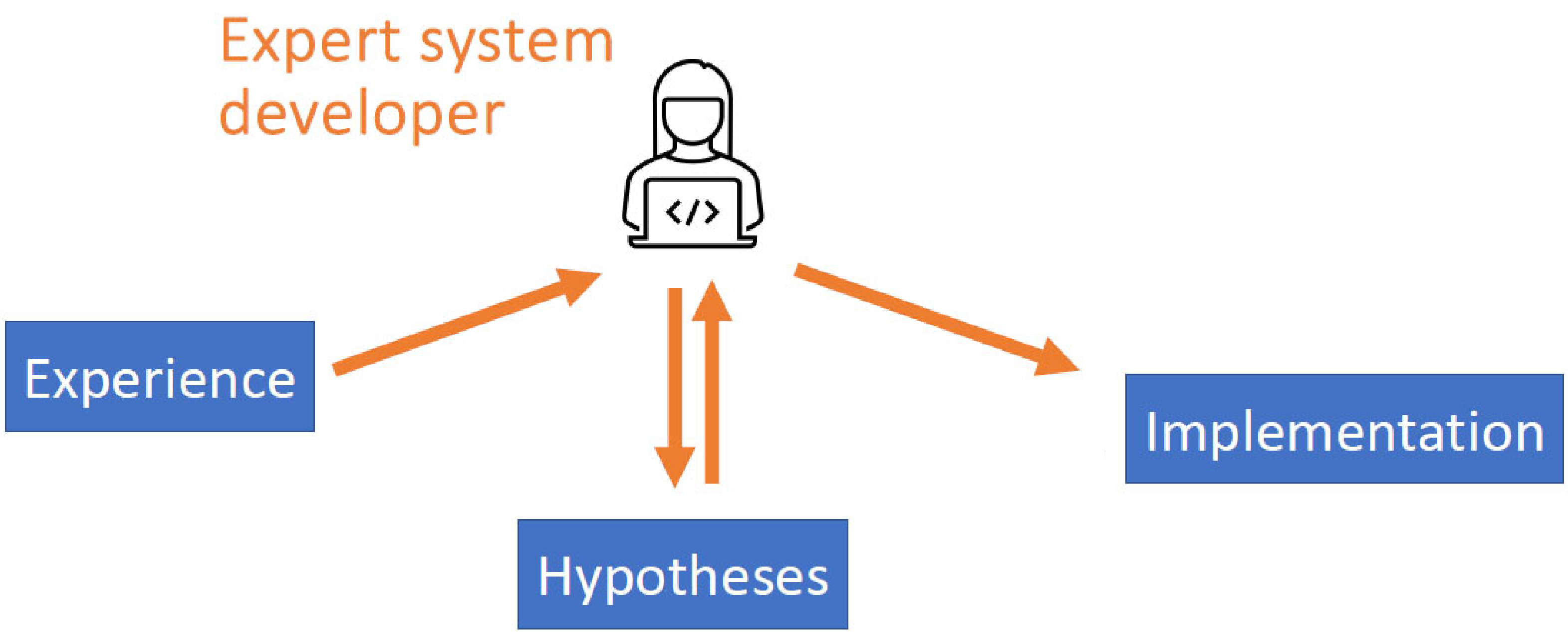
Is Machine Learning different from an Expert System?

- "Expert system" for predicting your grade:

```
if points >= 93.0:
  return "A"
elif points >= 90.0:
  return "A-"
elif points >= 87.0:
  return "B+"
elif points >= 83.0:
  return "B"
...
```

What is Machine Learning?

Is Machine Learning different from an Expert System?



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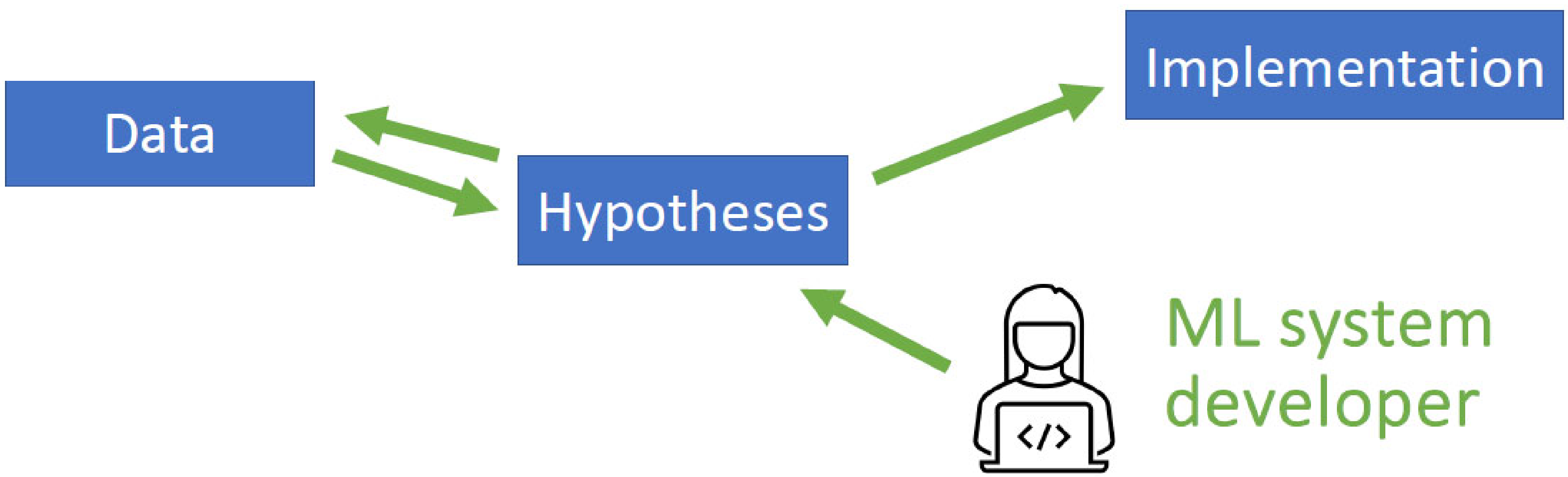
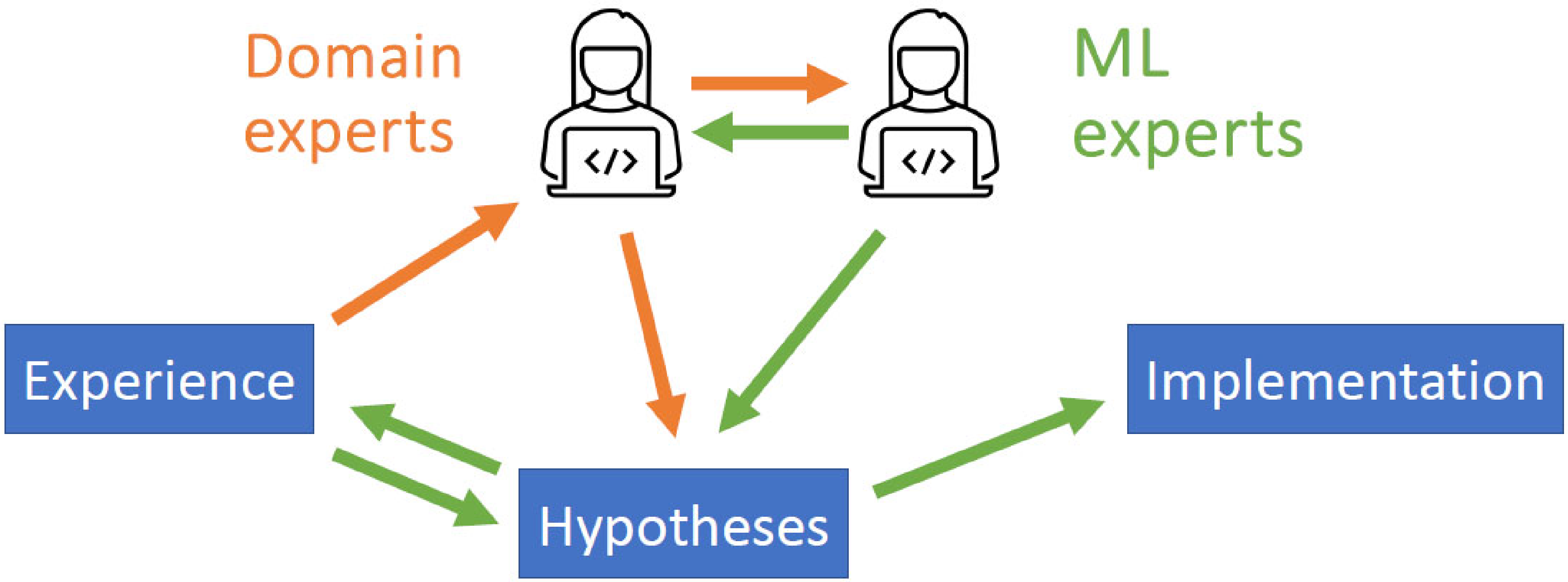
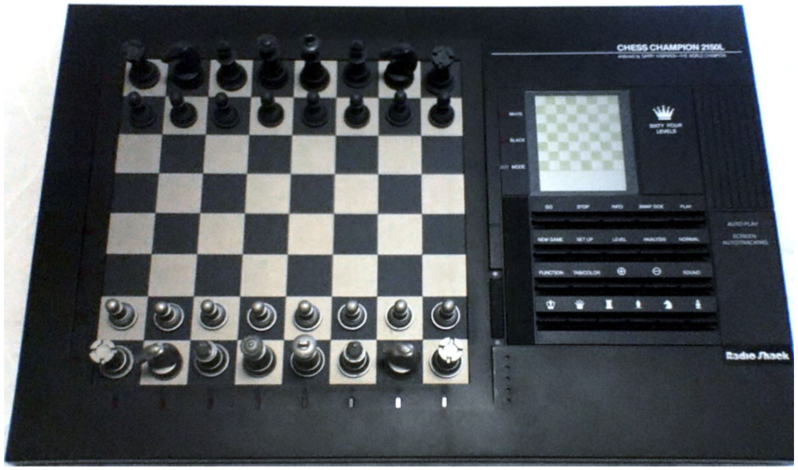


What is Machine Learning?

Is Machine Learning different from an Expert System?

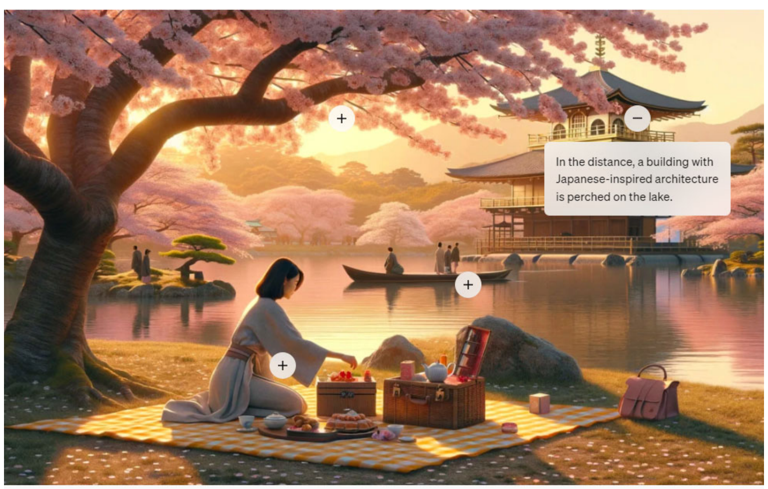


What Can Machine Learning Do?



Computer Chess

Computer Go



DALL·E 3

Self-Driving Car

What Can Machine Learning Do?

- Recognizing patterns:
  - o Facial identities or facial expressions
  - o Handwritten or spoken words, sentiment
  - o Medical images
- Recognizing anomalies:
  - o Unusual credit card transactions
  - o Unusual patterns of sensor readings in a nuclear power plant
- Prediction:
  - o Next word in a sequence of natural language text
  - o Future stock prices or currency exchange rates
- Generating patterns
  - o Generating text, images or audio
  - o Question answering (factual recall, reasoning, planning)?

Types of Learning

Supervised (inductive) learning

- training data + desired outputs (labels)

Unsupervised learning

- training data (without desired outputs)

Semi-supervised learning

- training data + a few desired outputs

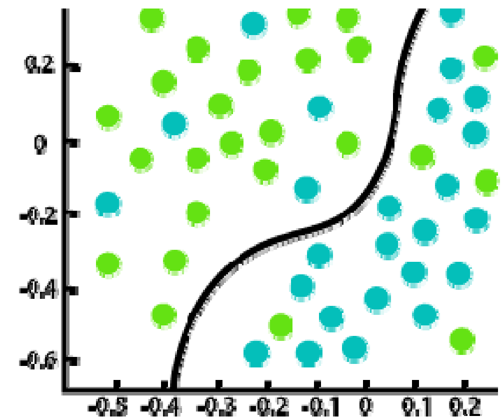
Reinforcement learning

- rewards from sequence of actions

Types of Learning

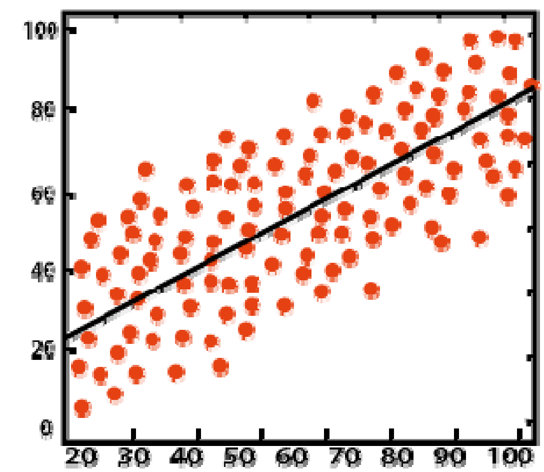
- Classification:

  Learning a function to map from a n-tuple to a ***discrete*** value from a finite set



- Regression:

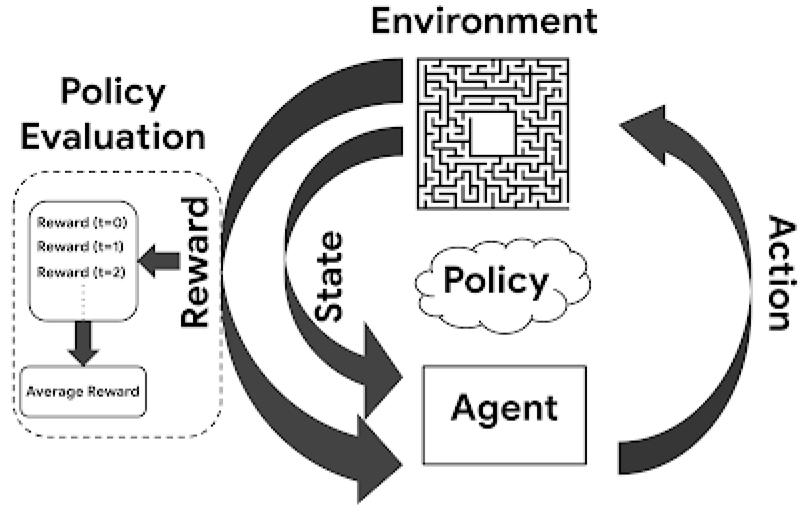
  Learning a function to map from a n-tuple to a ***continuous*** value



Types of Learning

- Reinforcement Learning:

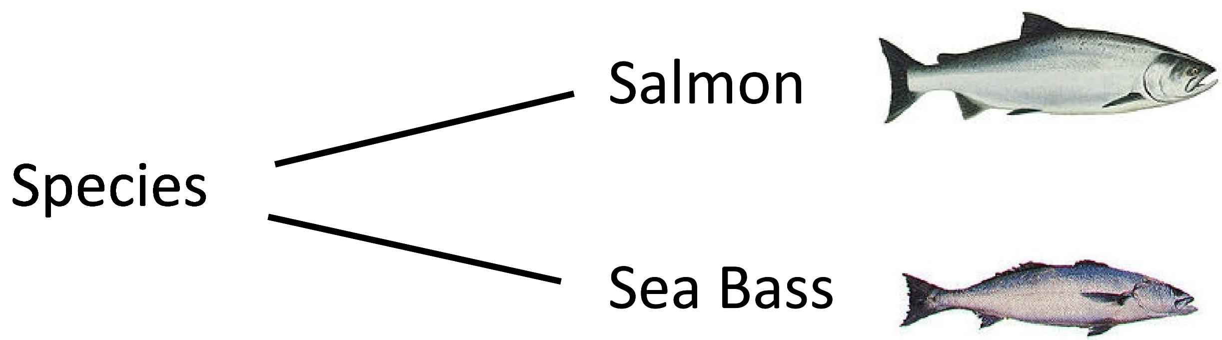
  Learning a ***policy*** to maximize a reward from an agent interacting with its environment through actions and state transitions



Source: Google Research

Fish Example: Task

"Sorting incoming fish on a conveyor according to species using optical sensing"



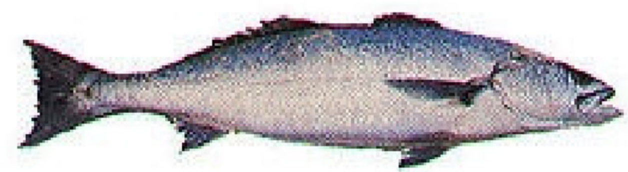
Risk: Finding sea bass in a package of salmon annoys customers!

Fish Example: Problem Analysis

Set up a camera and take some sample images

Extract characteristics that make distinction between species possible

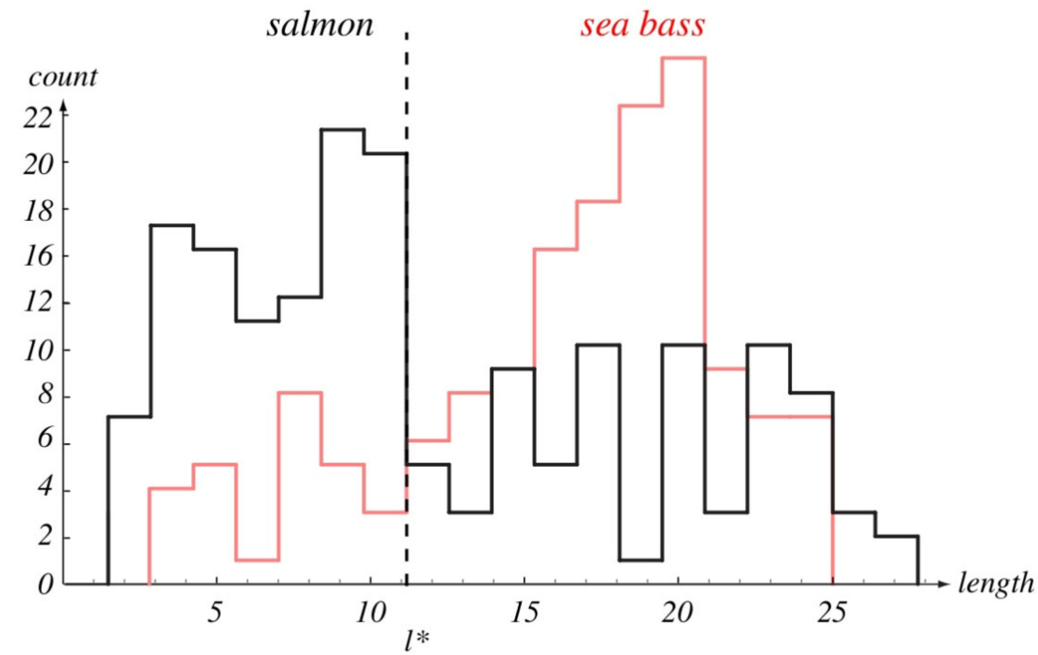
- Length
- Lightness
- Width
- Number and shape of fins
- Position of the mouth, etc.



This is the set of all suggested features to explore for use in our classifier!

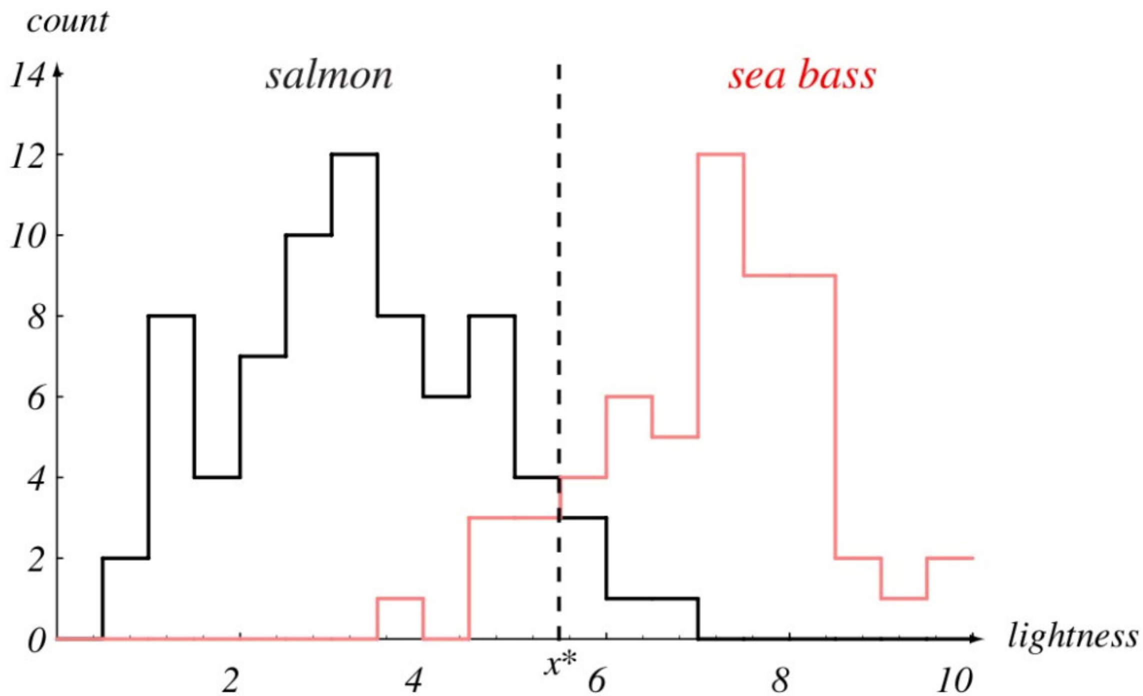
Fish Example: Feature Extraction

Possible feature for discrimination: length of a fish



Fish Example: Consider other Features

Another possible feature: lightness of a fish



Relationship between decision boundary and costs!

- Move decision boundary in response to lightness to reduce costs
- Reduces number of sea bass that are classified as salmon

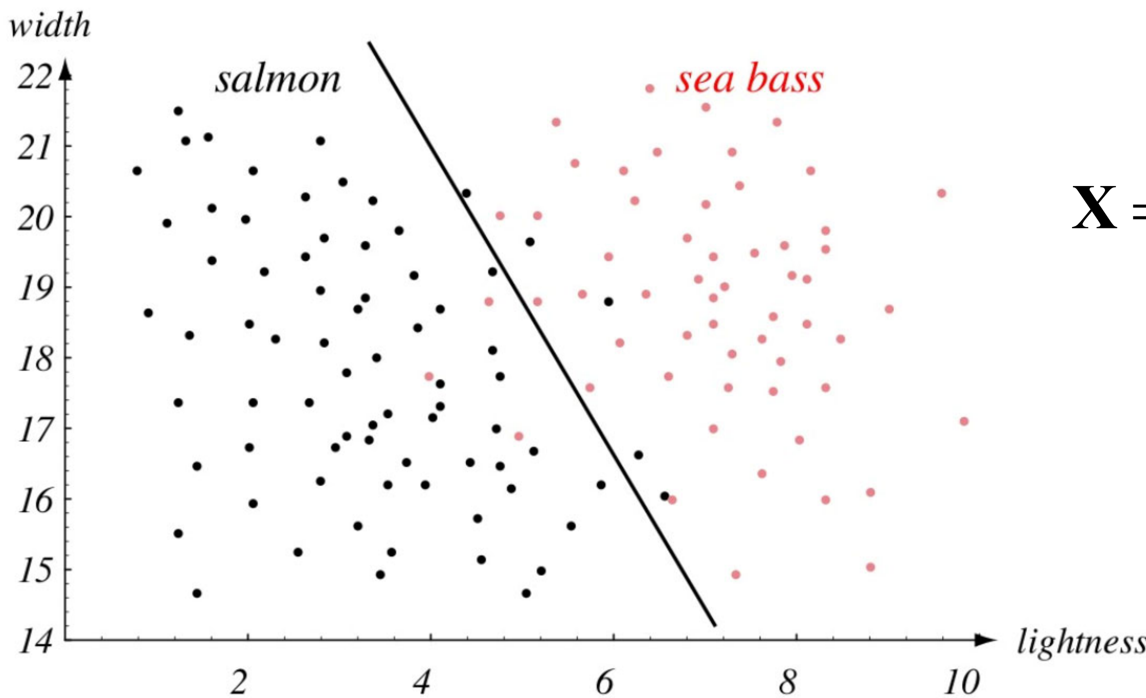
Fish Example: Use Two Features

Adopt lightness (x_1) and width of the fish (x_2)

$$\vec{\mathbf{x}} = \begin{bmatrix} 1.8 & 14.5 \end{bmatrix}$$

$$\text{Fish} \longrightarrow \boldsymbol{x} = [x_1, x_2]$$

$$\mathbf{X} = \begin{bmatrix} 1.8 & 14.5 \\ 2.5 & 15.6 \\ 3.6 & 15.4 \\ 4.5 & 15.5 \\ 5.0 & 14.8 \\ \vdots & \vdots \\ 6.7 & 21.9 \end{bmatrix}$$



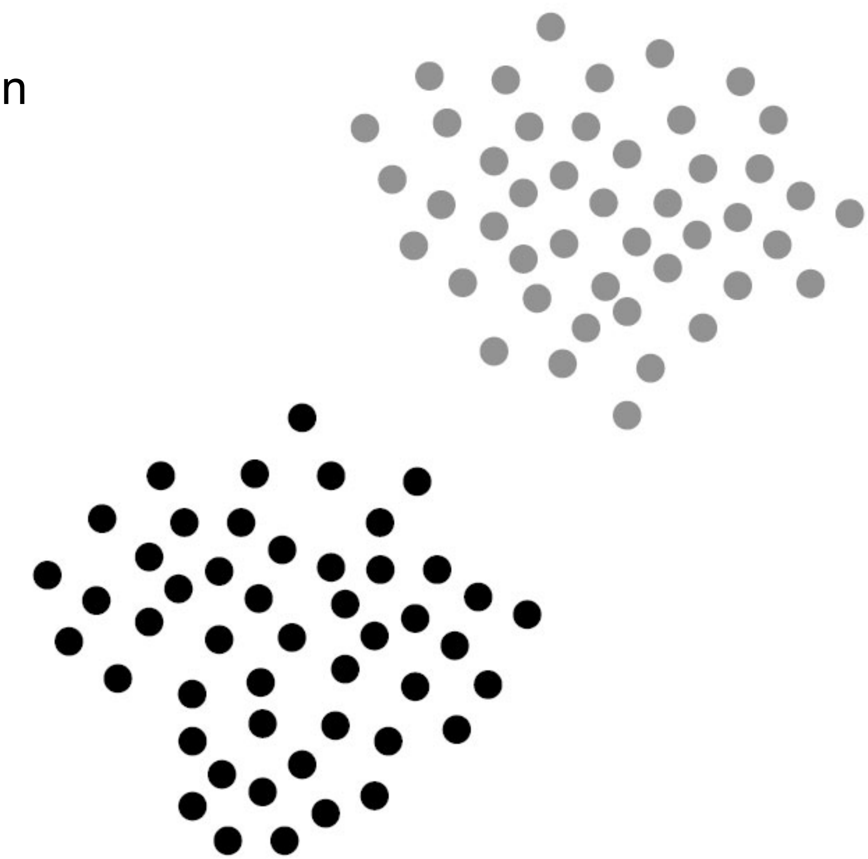
Machine Learning in One Slide

1. Pick data **D**, model **M(w)** and an objective function **J(D,w)**.
2. Initialize model parameters **w** somehow.
3. Measure model performance with the objective function **J(D,w)**.
4. Modify the parameters **w** somehow, hoping to improve **J(D,w)**.
5. Repeat steps 3 and 4 until you stop improving (or run out of time).

Machine Learning in More than One Slide

Supervised machine learning in more than one slide:

- Data **D:** the black and gray dots
- **Goal**: based upon location, classify whether a dot is black or gray



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Supervised machine learning in more than one slide:

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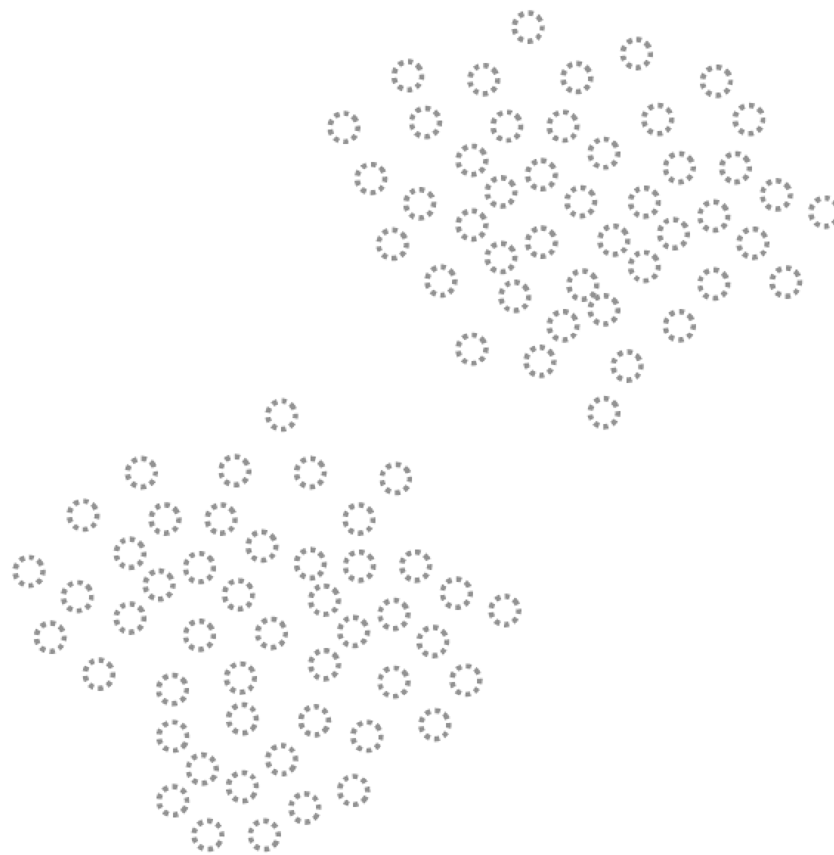

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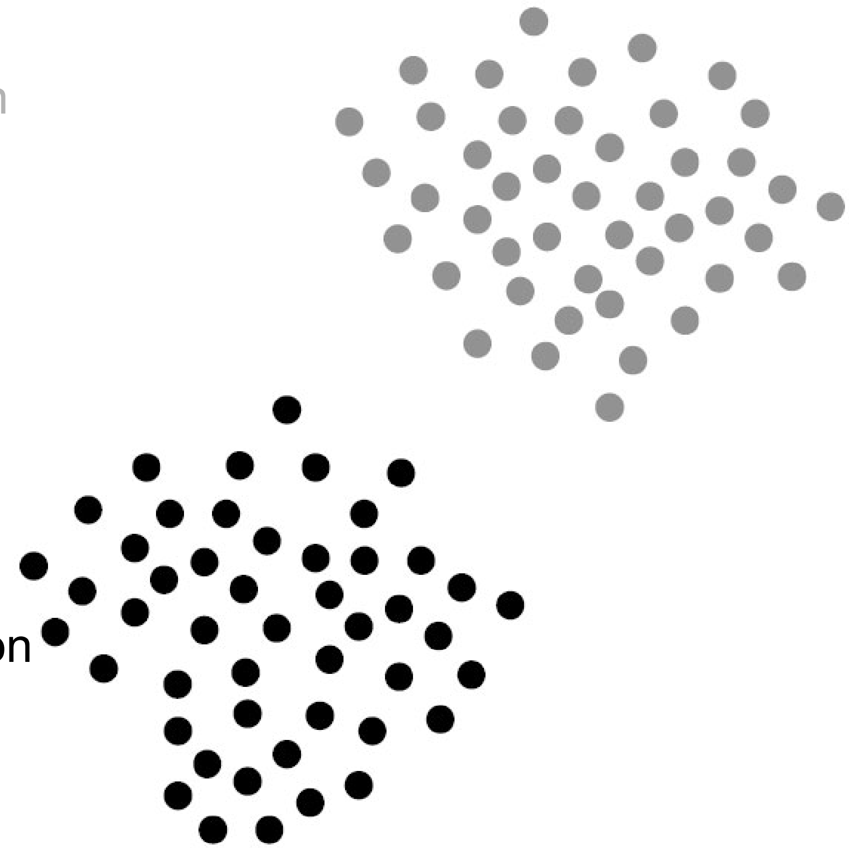
- Dots can be an abstract representation of anything



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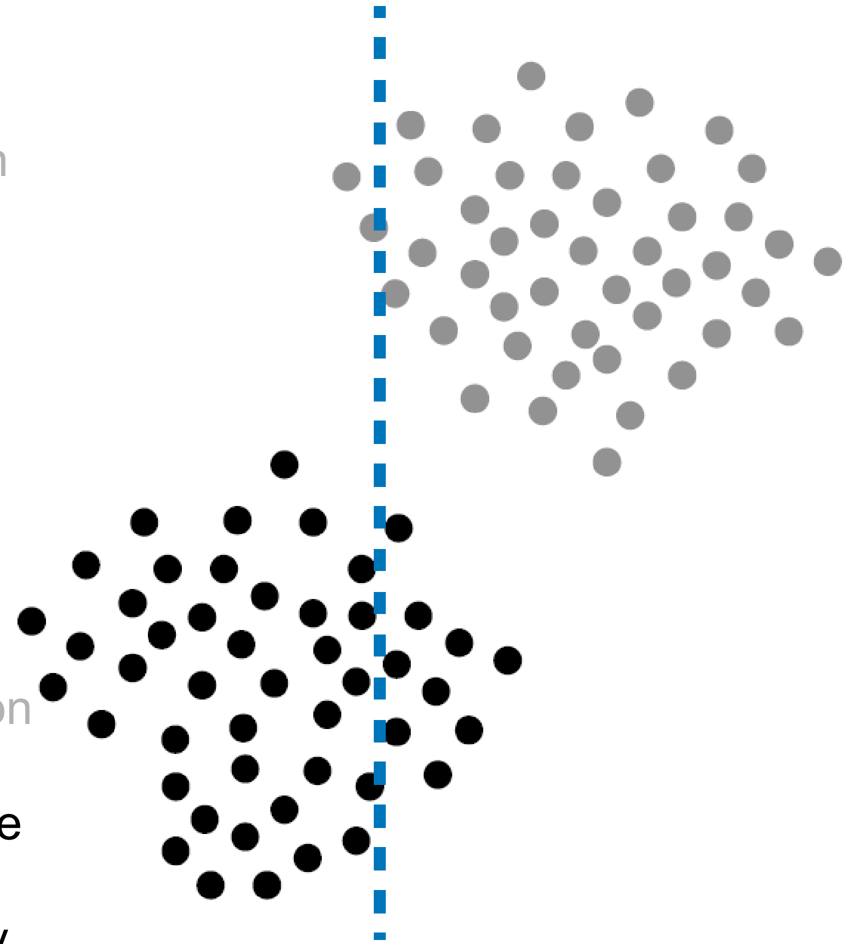
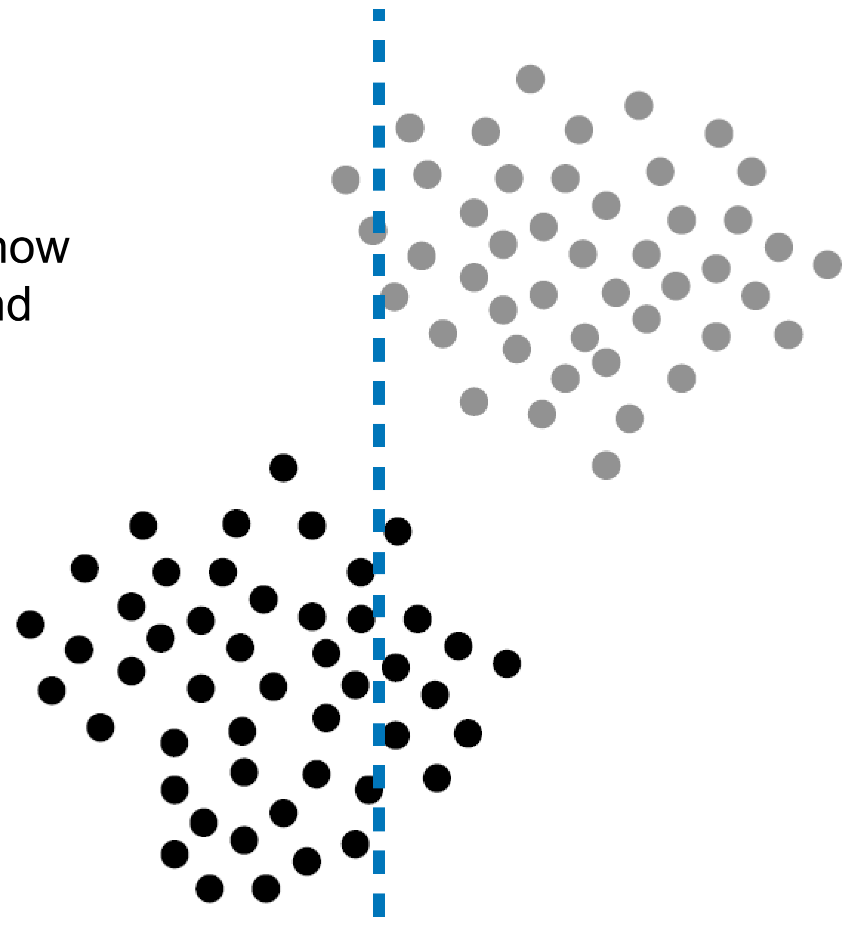
- For learning the model **M(w)**, we do have access to color
- Dots can be an abstract representation of anything
- Our initialize model **M(w)** can be a line through the data
- Dots to the right are classified as gray, otherwise dots are classified as black



Machine Learning in More than One Slide

How good is the model:

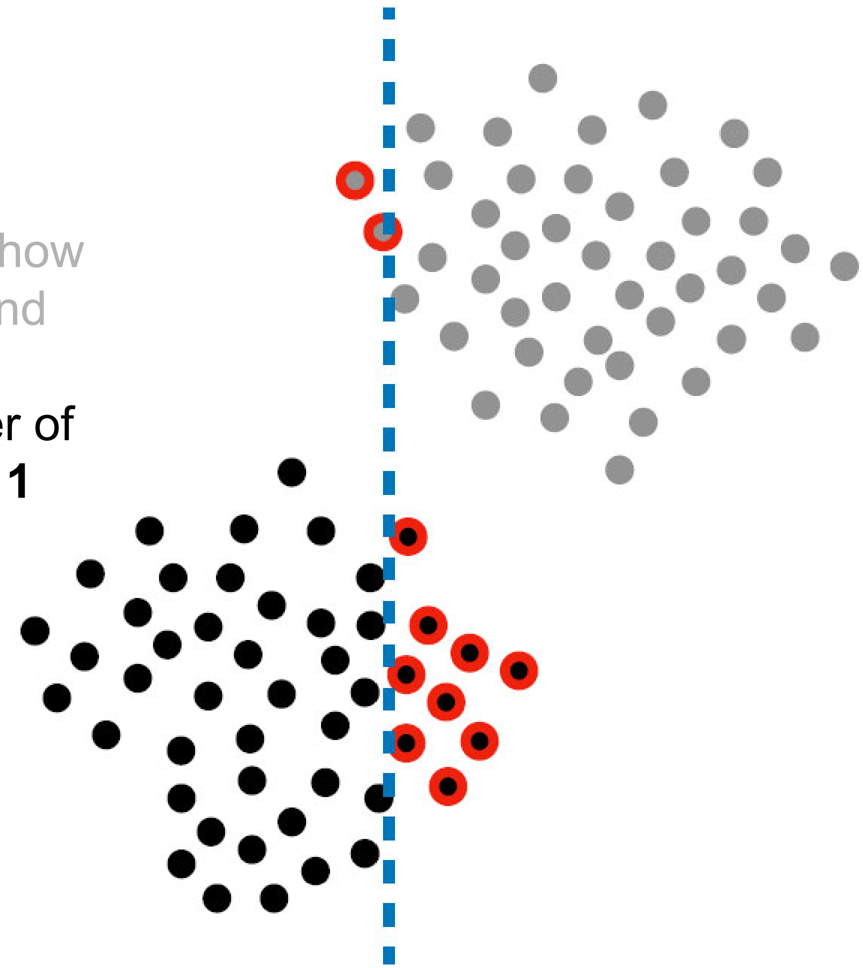
- An objective function **J(D,w)** tells us how good the line is for classifying gray and black dots



Machine Learning in More than One Slide

How good is the model:

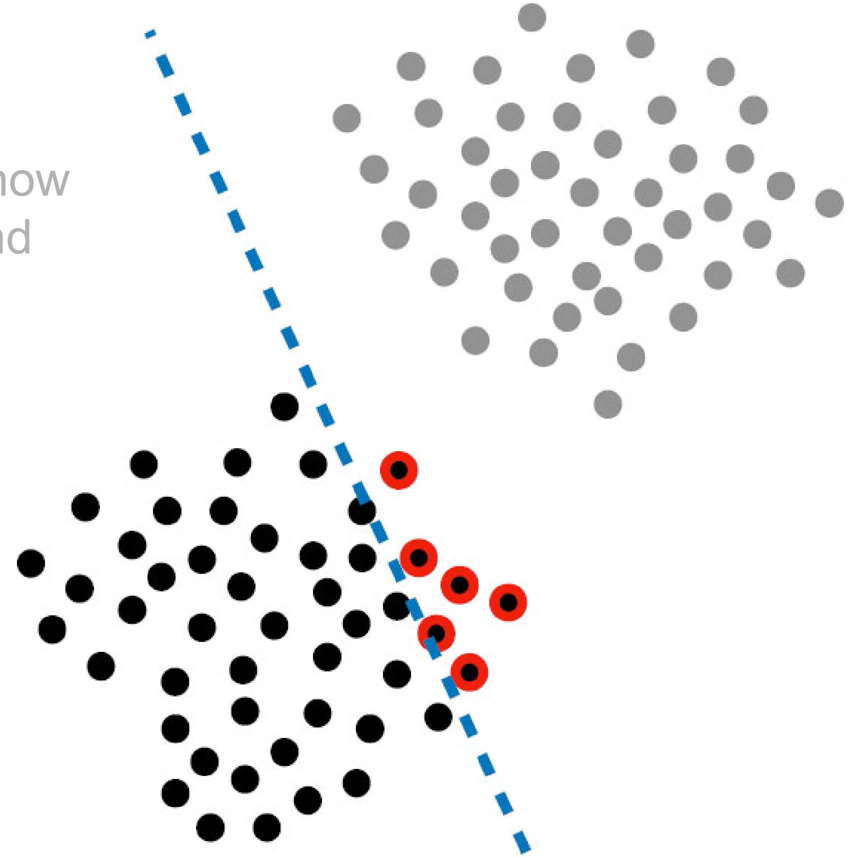
- An objective function **J(D,w)** tells us how good the line is for classifying gray and black dots
- One possibility is to count the number of misclassified dots, so that **J(D,w) = 11**



Machine Learning in More than One Slide

How good is the model:

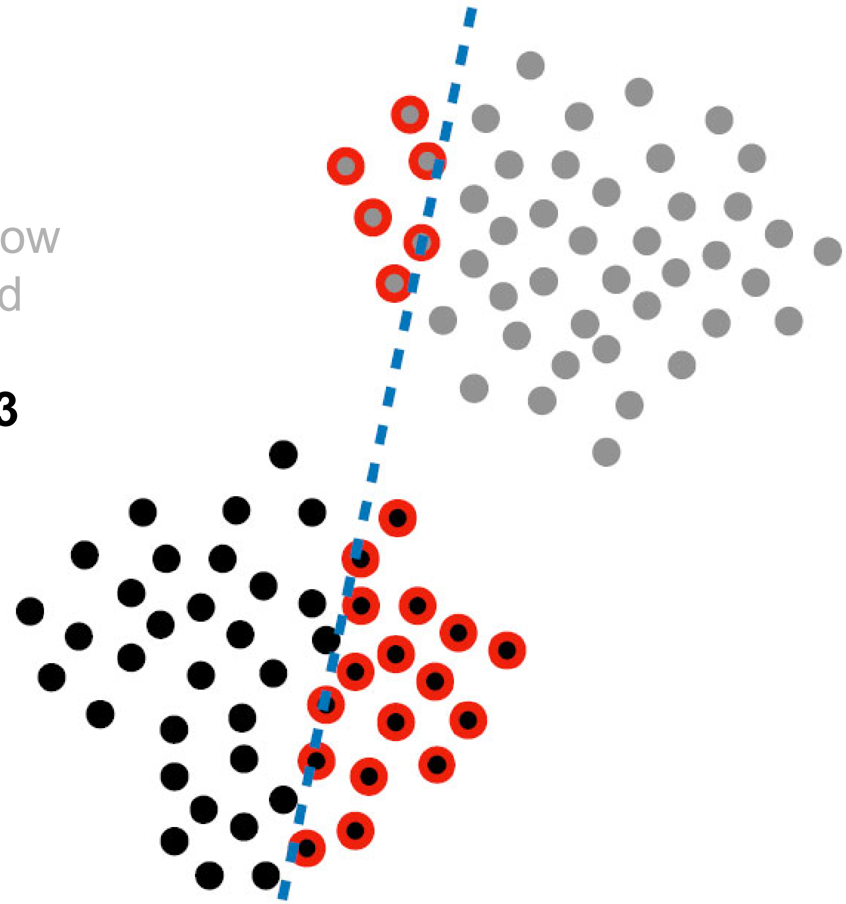
- An objective function **J(D,w)** tells us how good the line is for classifying gray and black dots
- Some lines perform better **J(D,w) = 6**



Machine Learning in More than One Slide

How good is the model:

- An objective function **J(D,w)** tells us how good the line is for classifying gray and black dots
- Some lines perform worse **J(D,w) = 23**



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- An objective function **J(D,w)** tells us how good the line is for classifying gray and black dots
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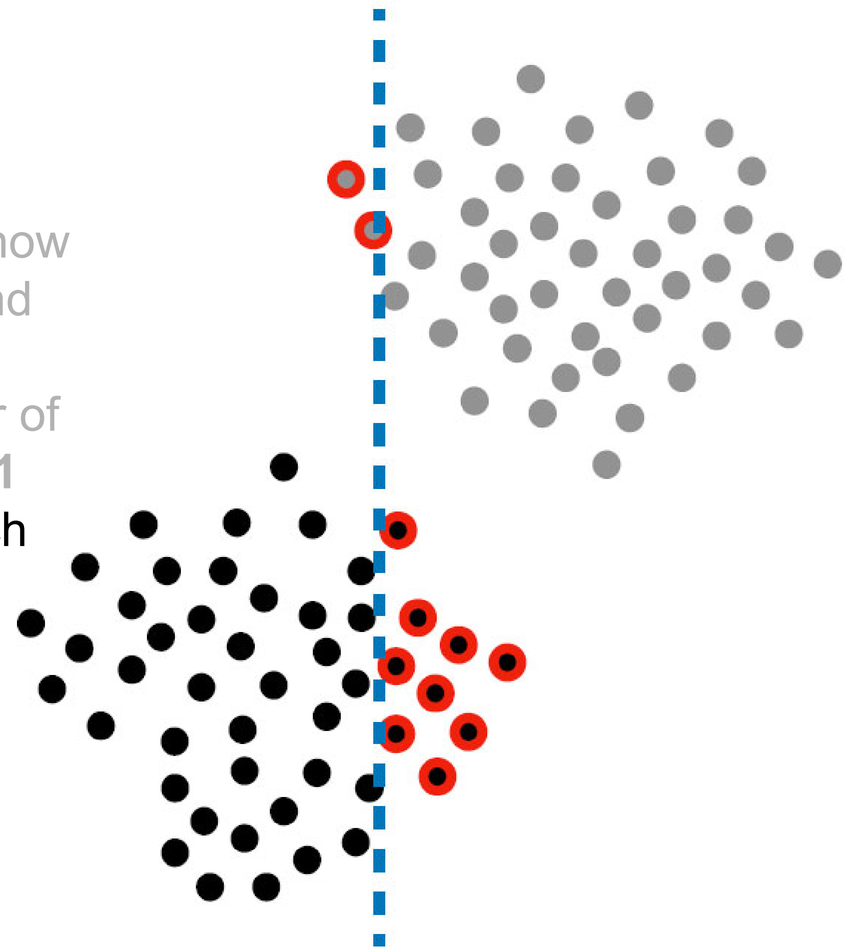
- Our goal is to move the line **M(w)** such that it reduces the objective function



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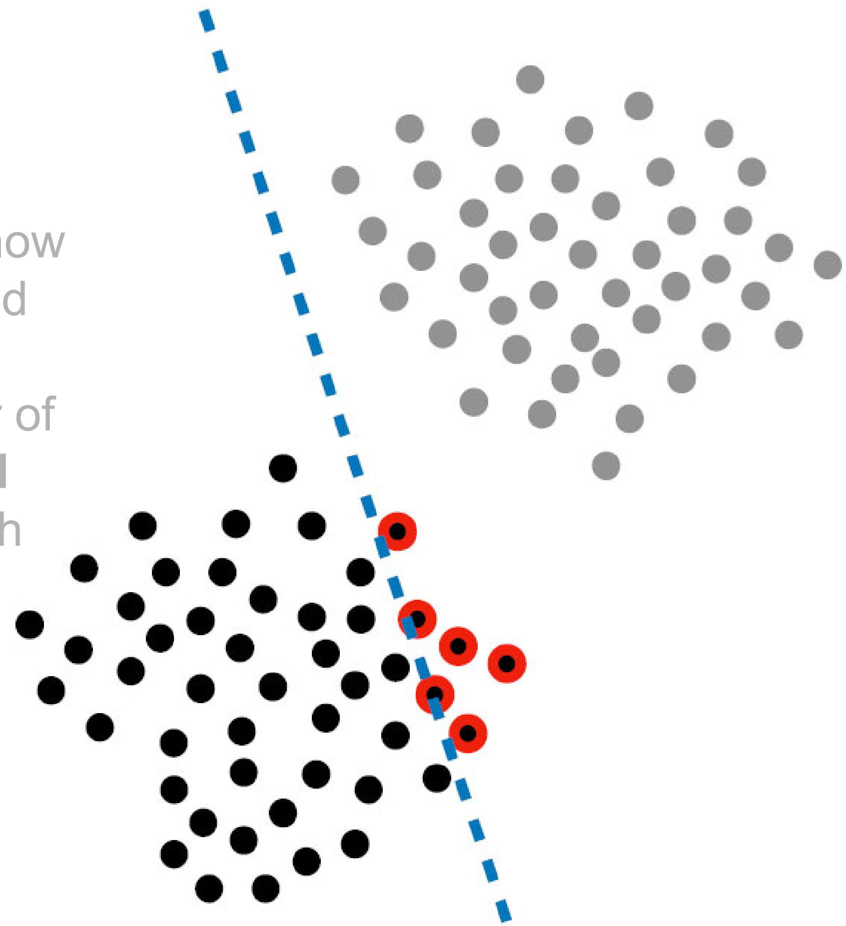
How good is the model:

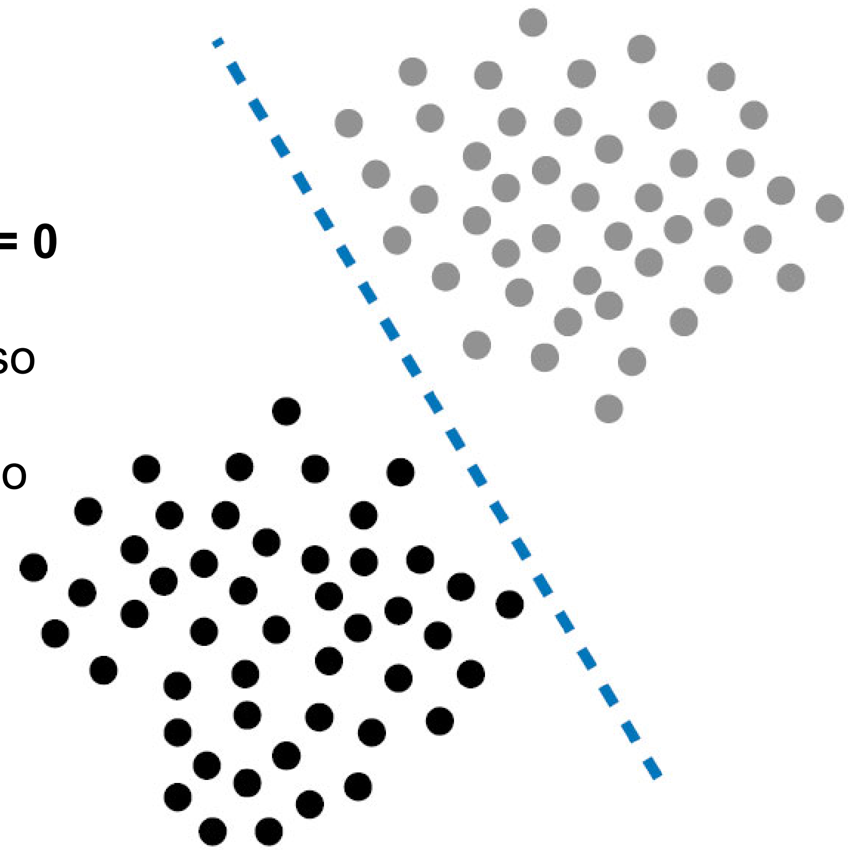
- An objective function **J(D,w)** tells us how good the line is for classifying gray and black dots
- One possibility is to count the number of misclassified dots, so that **J(D,w) = 11**
- Our goal is to move the line **M(w)** such that it reduces the objective function
- Updating **M(w)** is done according to a ***learning algorithm***



Machine Learning in More than One Slide

How good is the model:

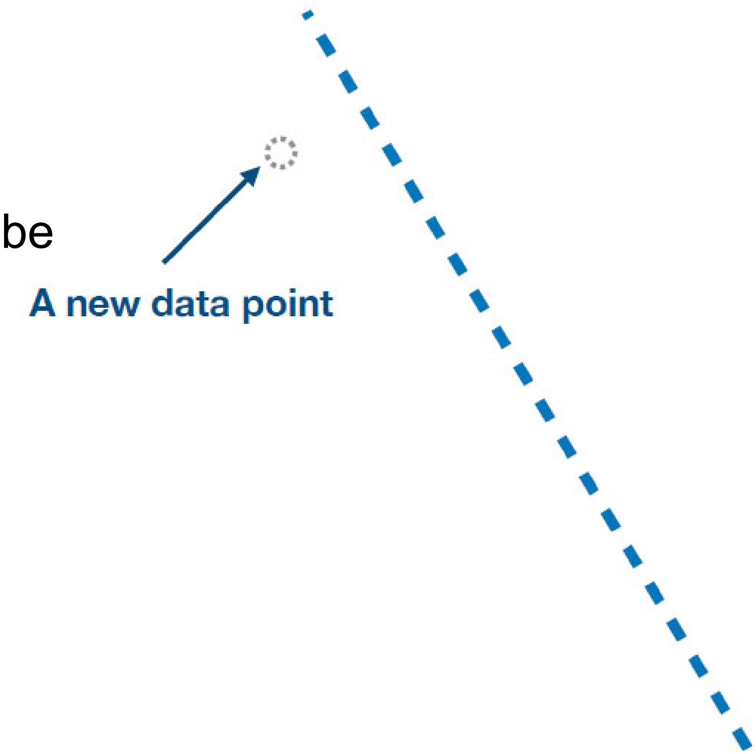
- We have a model **M(w)** that fits the training data **D** perfectly, with **J(D,w) = 0**
- This called a ***minima*** of the objective function **J(D,w)**, and in this case is also a *global* ***minima***
- In most learning algorithms, this is also called ***convergence***



Machine Learning in More than One Slide

Using the model:

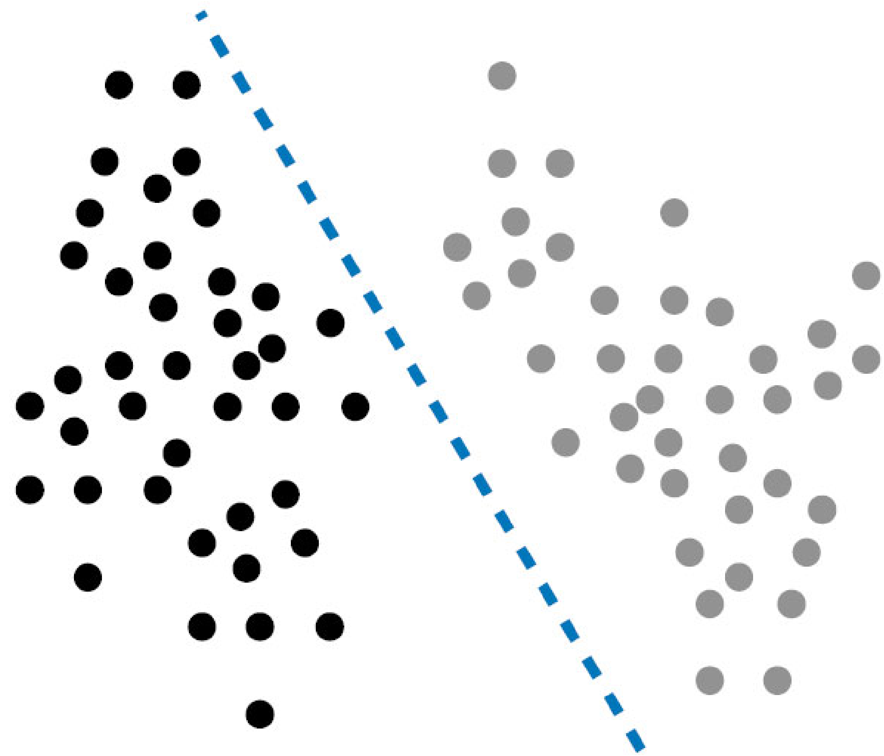
- Once the model is trained, it can be applied to ***unseen*** data
- New data Is classified using the learned line
- This is called ***inference***



Machine Learning in More than One Slide

Using the model:

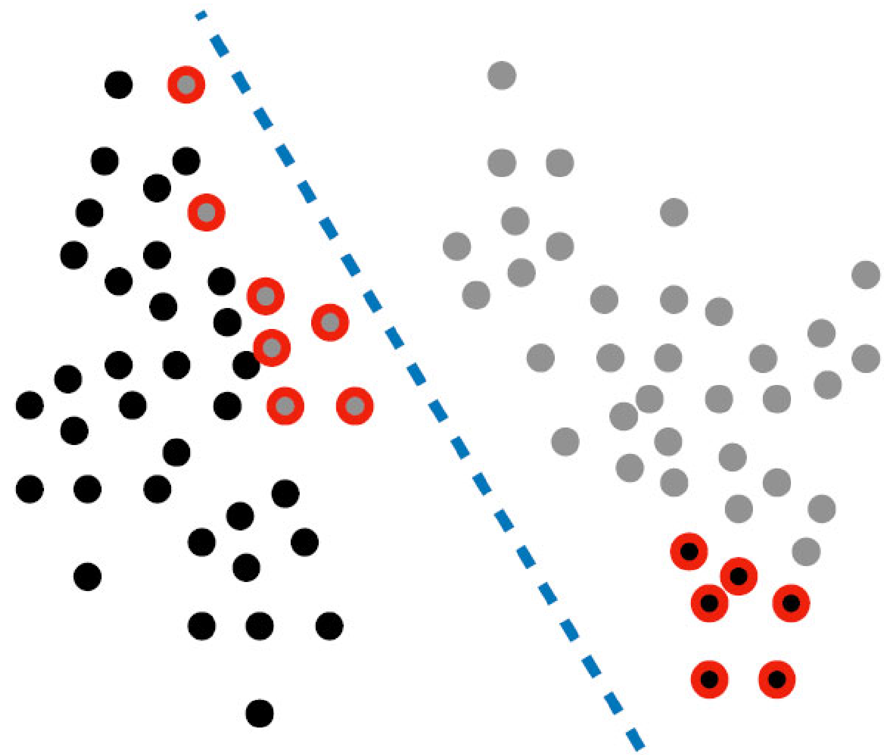
- Once the model is trained, it can be applied to *unseen* data
- New data Is classified using the learned line
- This is called *inference* and generates ***predicted labels***
- The *unseen* data is often called the ***test set***



Machine Learning in More than One Slide

Using the model:

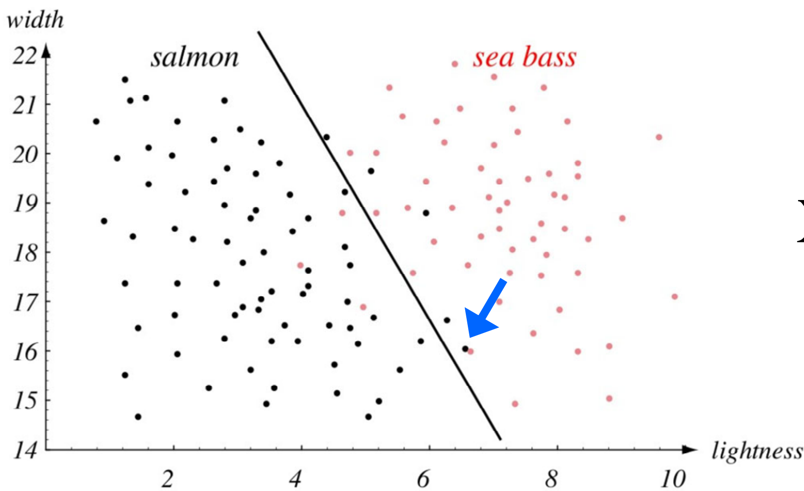
- Once the model is trained, it can be applied to *unseen* data
- New data Is classified using the learned line
- This is called *inference* and generates *predicted labels*
- The *unseen* data is often called the *test set*
- If you know the *actual* labels, then you can measure how well your model ***generalizes***



Fish Example: Use Two Features

Adopt lightness (x_1) and width of the fish (x_2)

$$\text{Fish} \longrightarrow \boldsymbol{x}^T = [x_1, x_2]$$



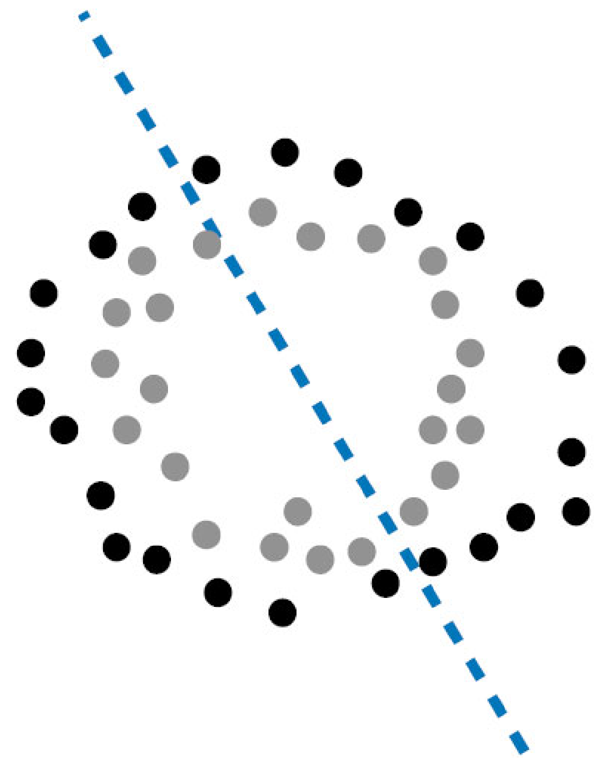
$$\vec{\mathbf{x}} = \begin{bmatrix} 1.8 & 14.5 \end{bmatrix}$$

$$\mathbf{X} = \begin{bmatrix} 1.8 & 14.5 \\ 2.5 & 15.6 \\ 3.6 & 15.4 \\ 4.5 & 15.5 \\ 5.0 & 14.8 \\ \vdots & \vdots \\ 6.7 & 21.9 \end{bmatrix} \quad \mathbf{Y} = \begin{bmatrix} B \\ B \\ B \\ B \\ B \\ \vdots \\ R \end{bmatrix} \quad \hat{\mathbf{Y}} = \begin{bmatrix} B \\ B \\ B \\ B \\ R \\ \vdots \\ R \end{bmatrix}$$

Inductive Bias

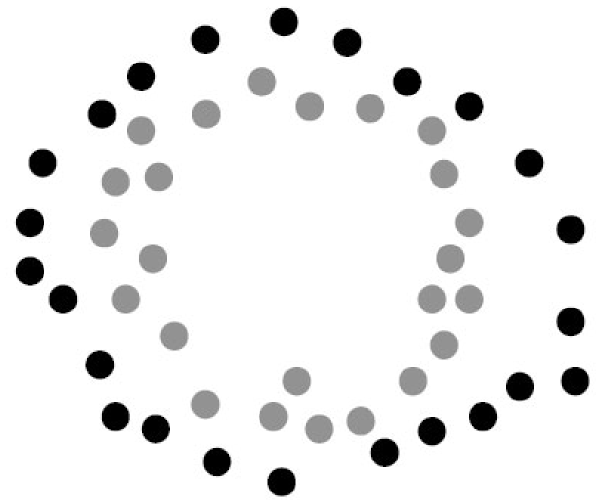
Machine Learning in More than One Slide

What if your data looks like this? Can the “line” model **M(w)** learn to separate this data?



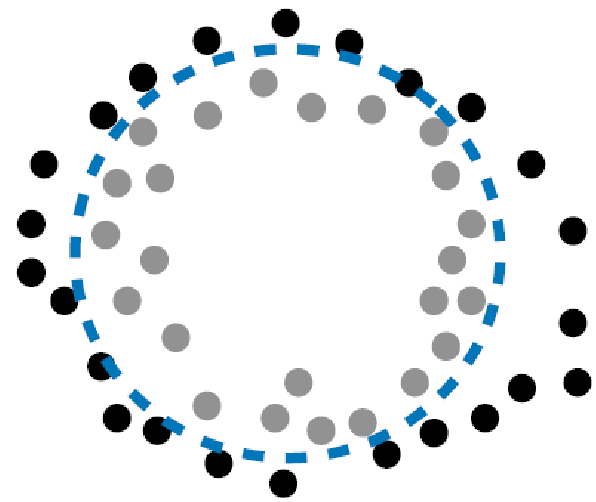
Machine Learning in More than One Slide

What sort of shape should we use to learn this data?



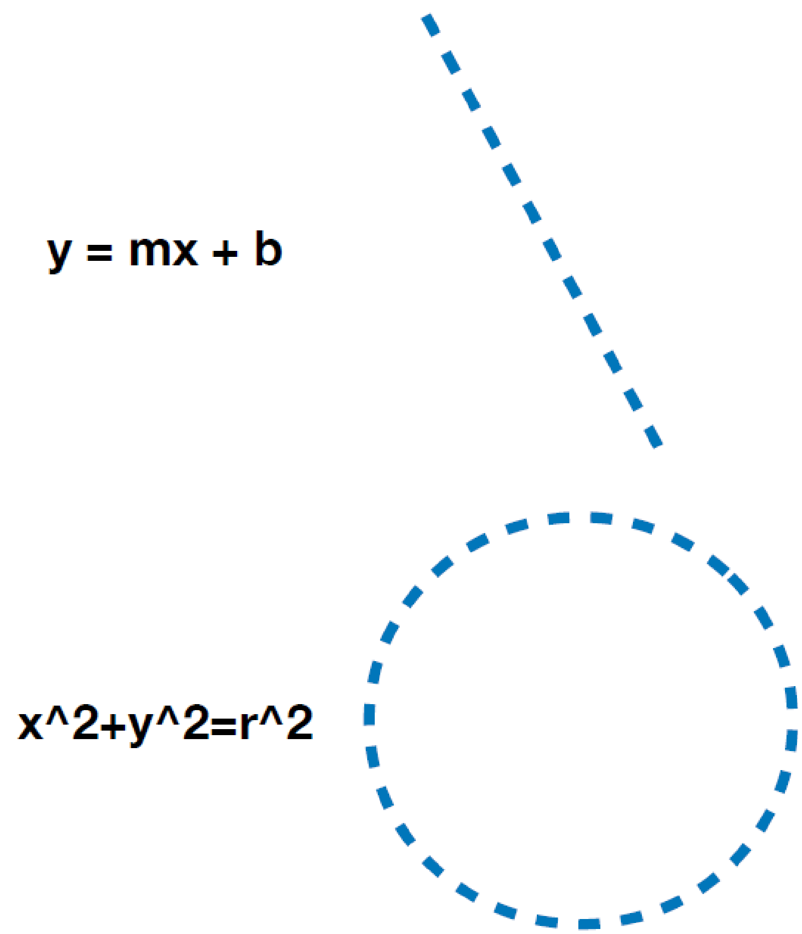
Machine Learning in More than One Slide

A circle!



Machine Learning in More than One Slide

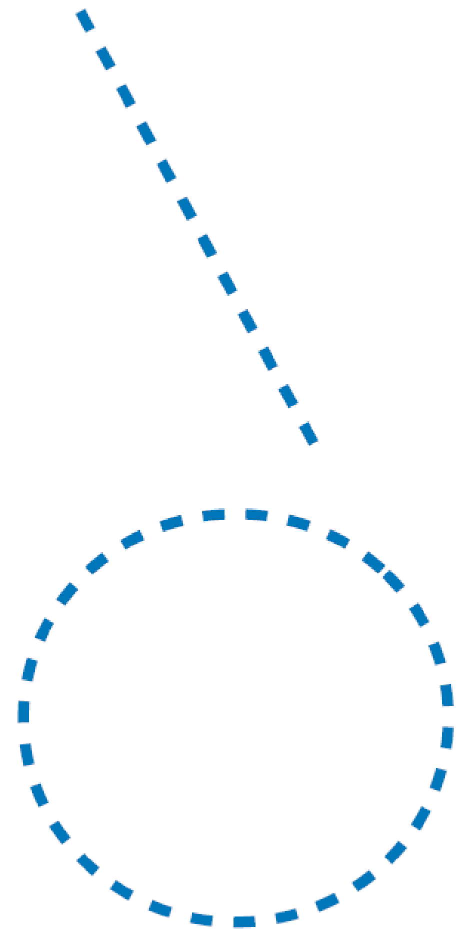
The “shapes” a model can make in the feature space is called the ***hypothesis space***.



Machine Learning in More than One Slide

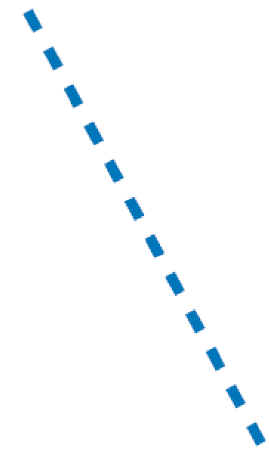
The type of shapes a model can make is a form of ***inductive bias***.

$y = mx + b$



$x^2+y^2=r^2$

Machine Learning in More than One Slide



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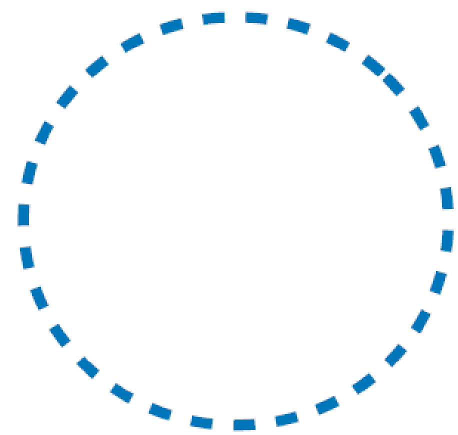
The type of shapes a model can make is a form of ***inductive bias***.

$$r^2 = a\,(x - x_0)^2 + b\,(y - y_0)^2$$



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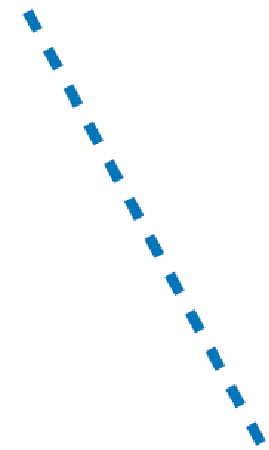

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