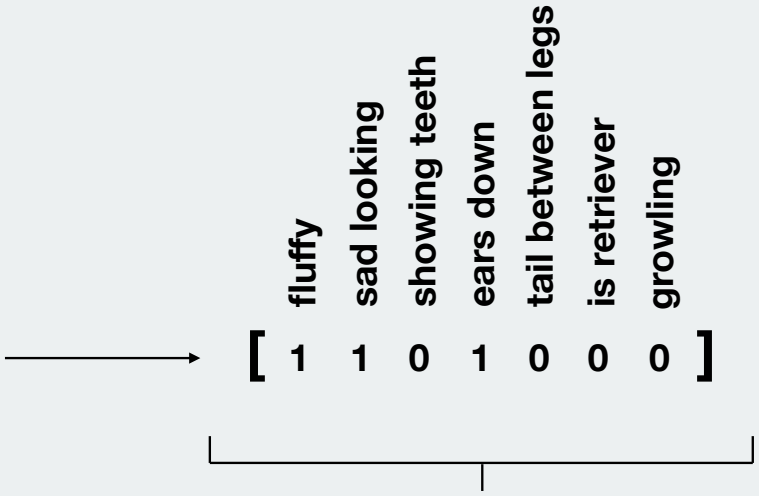
Computational Analysis of Big Data

Week 5

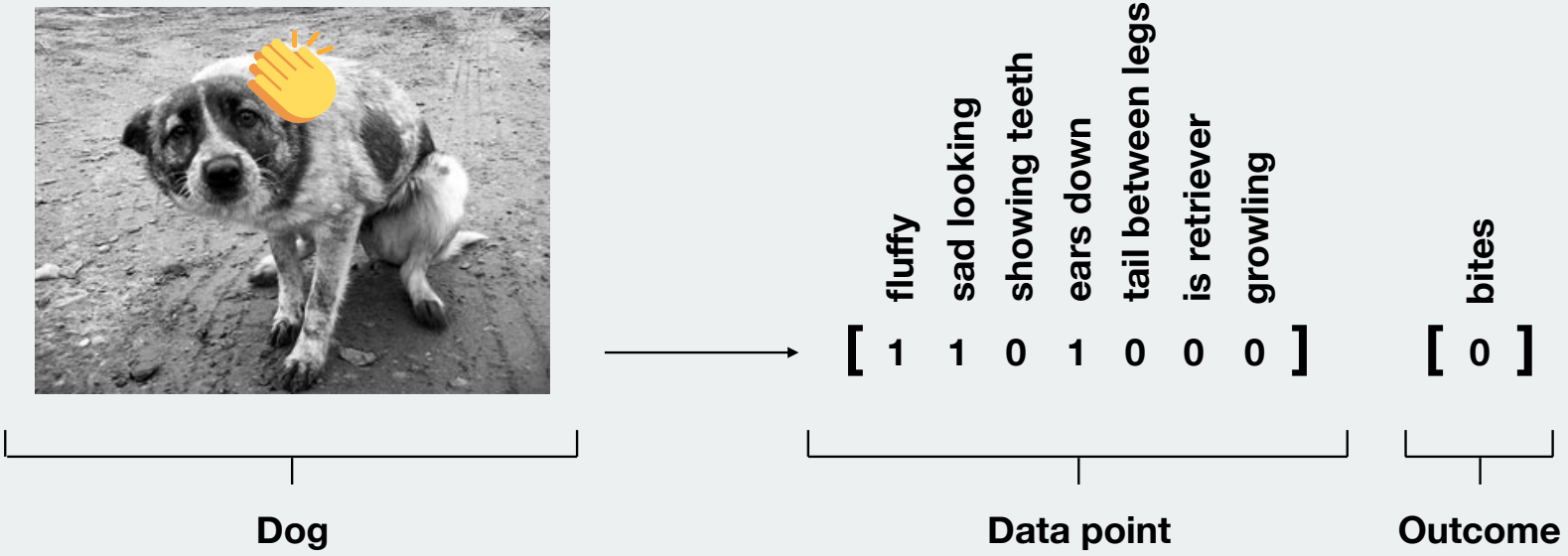
Machine Learning 2

Recap: Machine Learning

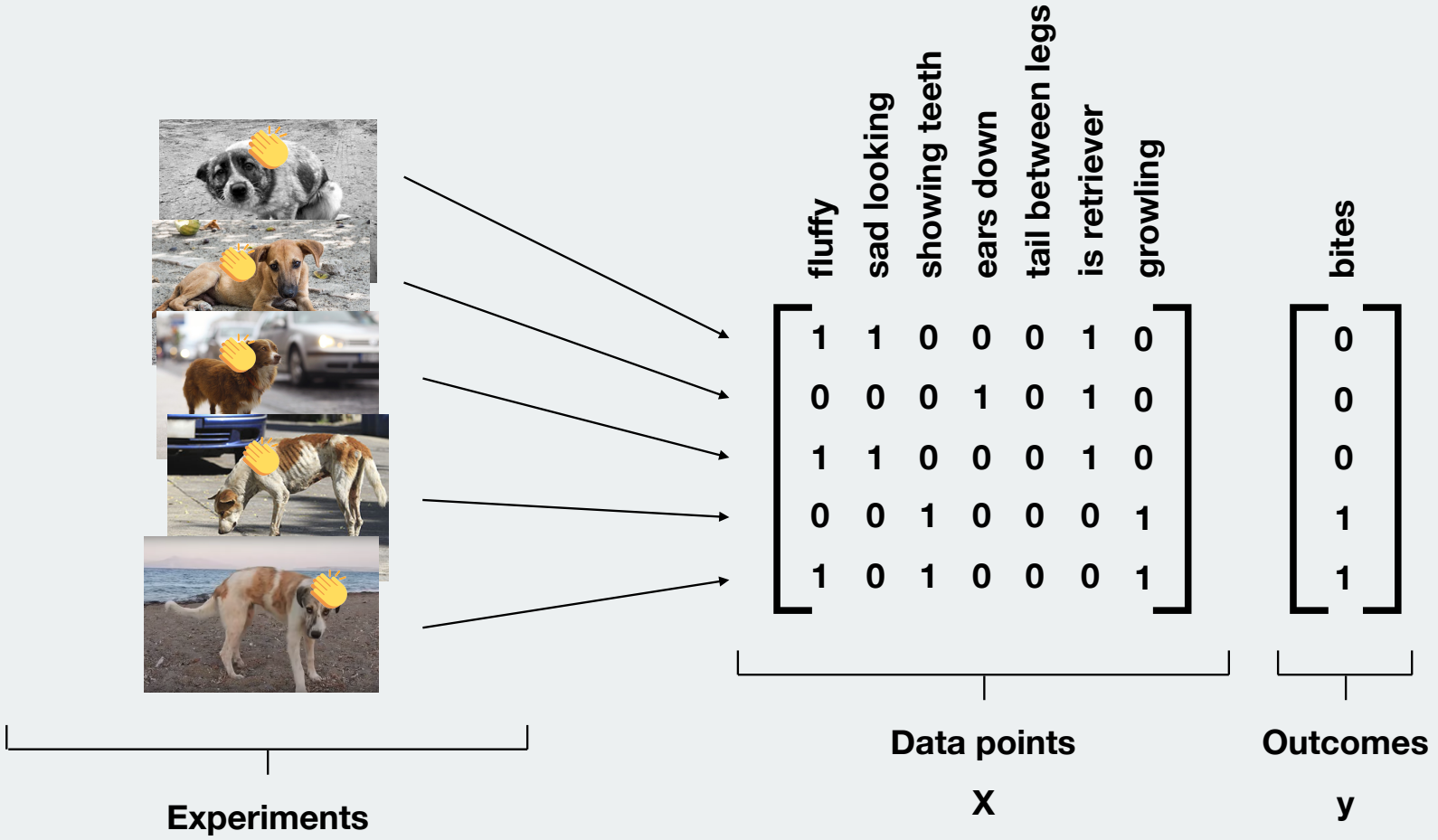
Canonical example



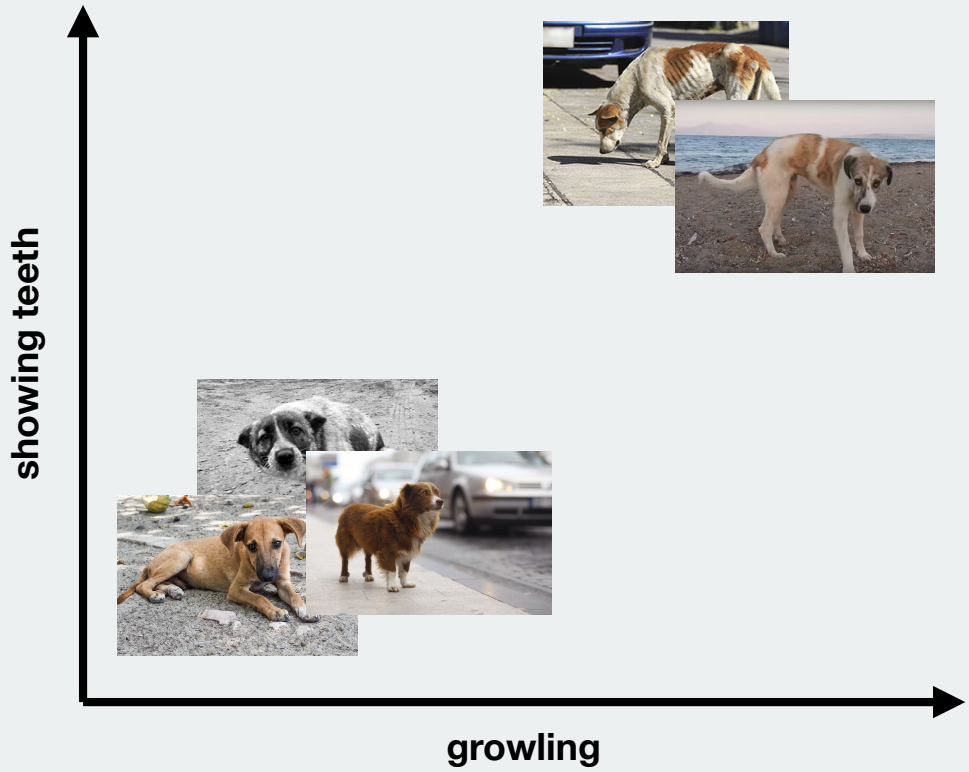
Canonical example



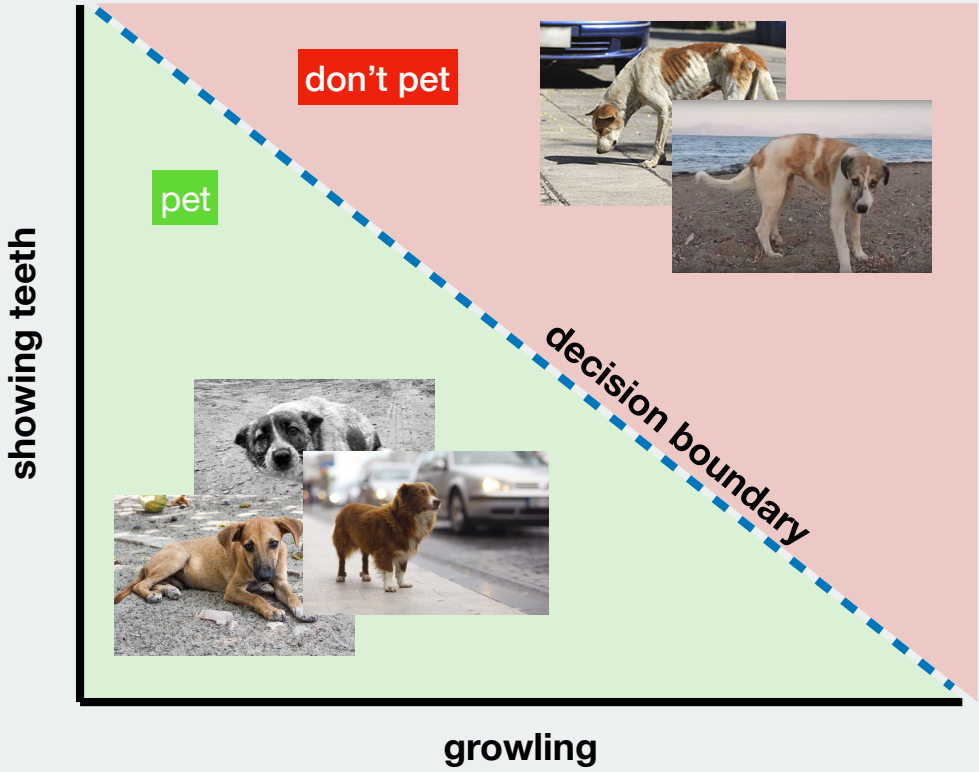
Canonical example



Canonical example



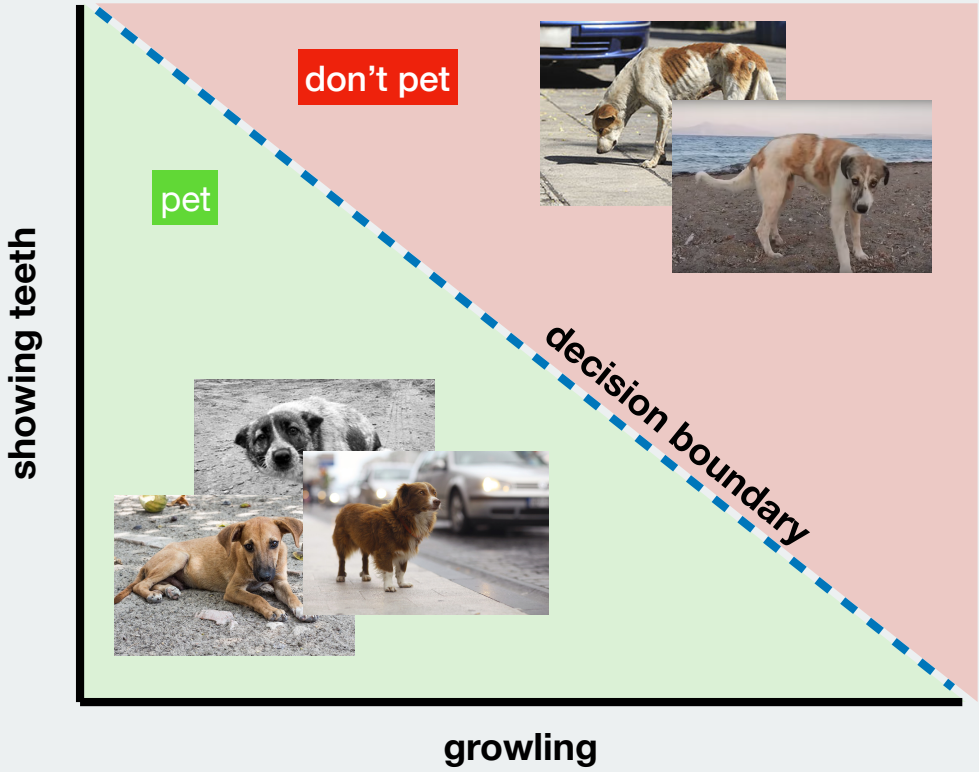
Canonical example



Canonical example

Supervised Machine Learning

When the input data has outcome labels



Decision trees

Decision trees

Lays eggs	Cold blooded	Mammal
0	0	1
0	0	1
0	0	1
0	0	1
0	0	1
1	0	0
1	0	0
1	1	0
1	1	0
1	1	0
1	1	0
1	1	0
1	1	0
1	1	0
1	1	0
1	1	0

features

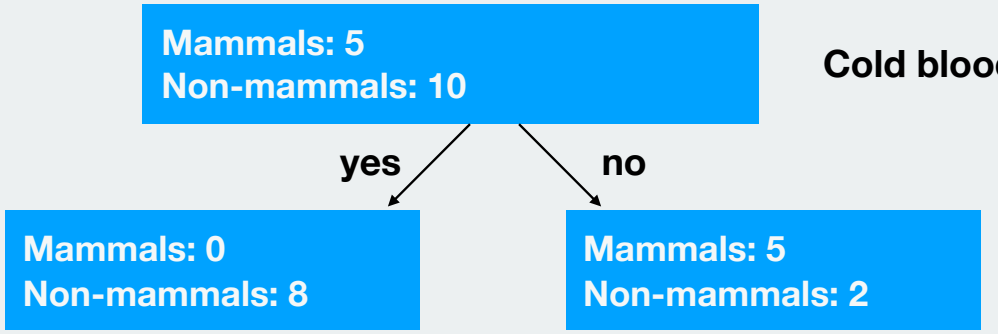
target

Mammals: 5
Non-mammals: 10

Decision trees

Lays eggs	Cold blooded	Mammal
0	0	1
0	0	1
0	0	1
0	0	1
0	0	1
1	0	0
1	0	0
1	1	0
1	1	0
1	1	0
1	1	0
1	1	0
1	1	0
1	1	0
1	1	0
1	1	0

features **target**

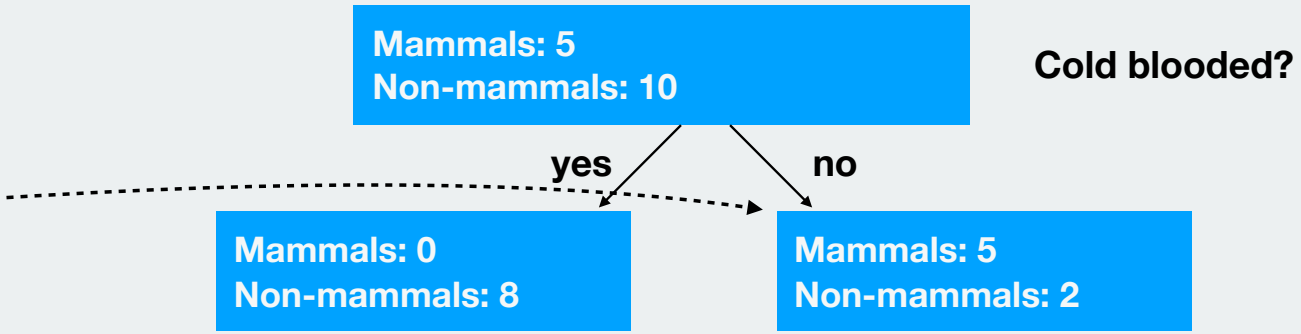


Decision trees

	Lays eggs	Cold blooded	Mammal
no	0	0	1
	0	0	1
	0	0	1
	0	0	1
	0	0	1
	1	0	0
	1	0	0
yes	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0

features

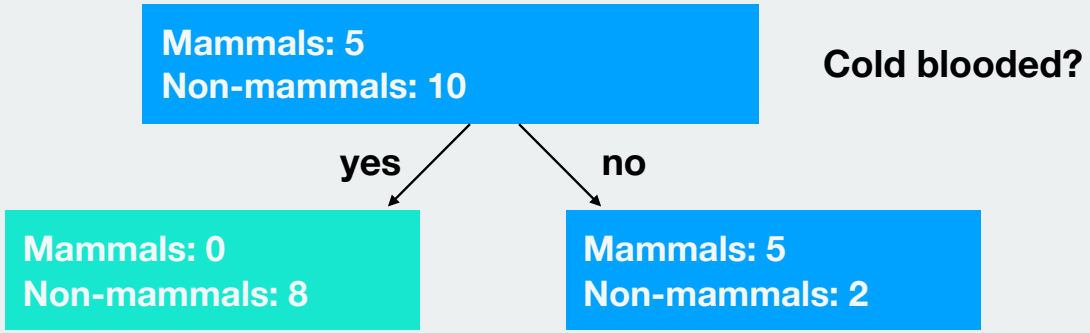
target



Decision trees

	Lays eggs	Cold blooded	Mammal
no	0	0	1
	0	0	1
	0	0	1
	0	0	1
	0	0	1
	1	0	0
	1	0	0
yes	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0

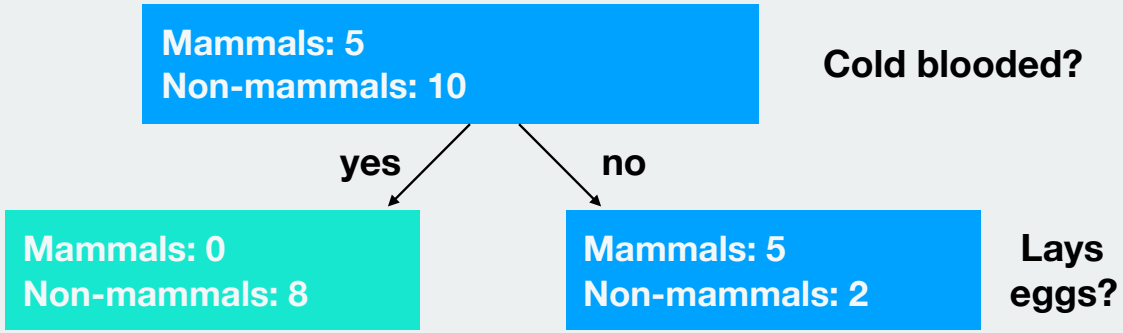
features **target**



Decision trees

	Lays eggs	Cold blooded	Mammal
no	0	0	1
	0	0	1
	0	0	1
	0	0	1
	0	0	1
	1	0	0
	1	0	0
yes	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0

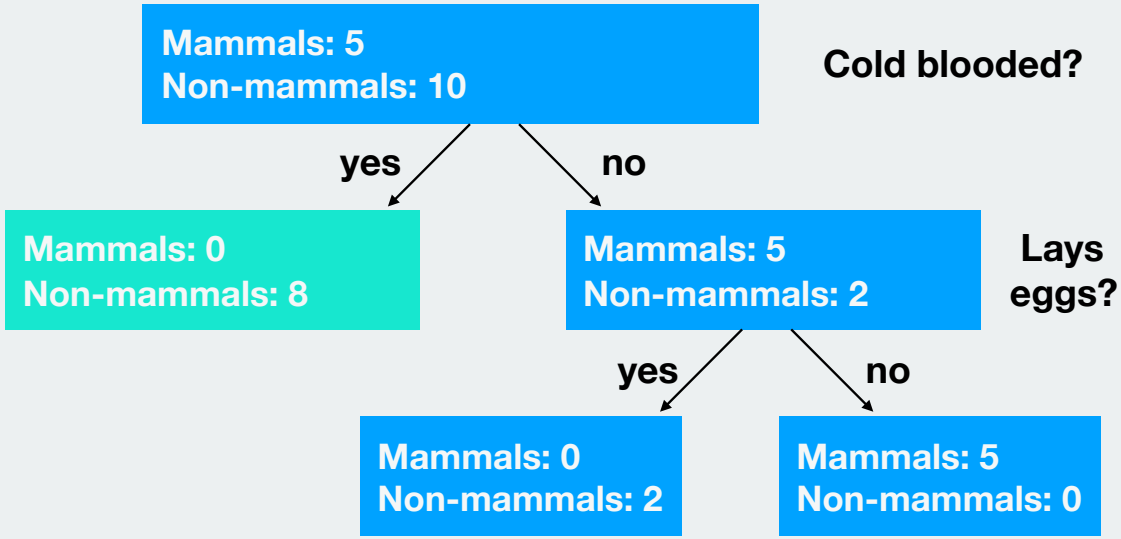
features **target**



Decision trees

	Lays eggs	Cold blooded	Mammal
no	0	0	1
no	0	0	1
no	0	0	1
no	0	0	1
no	0	0	1
yes	1	0	0
yes	1	0	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0

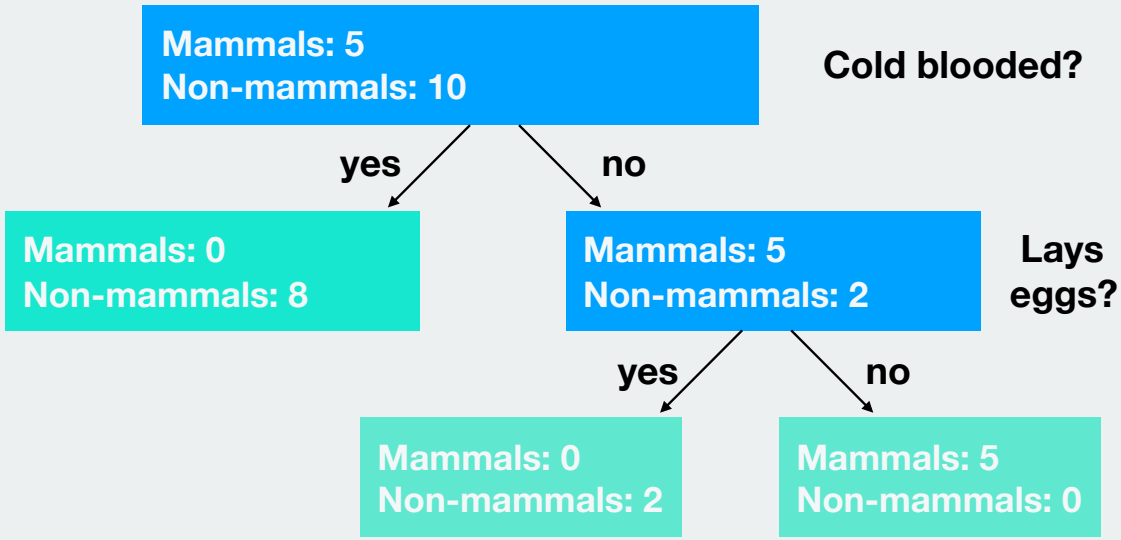
features **target**



Decision trees

	Lays eggs	Cold blooded	Mammal
no	0	0	1
no	0	0	1
no	0	0	1
no	0	0	1
no	0	0	1
yes	1	0	0
yes	1	0	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0

features **target**



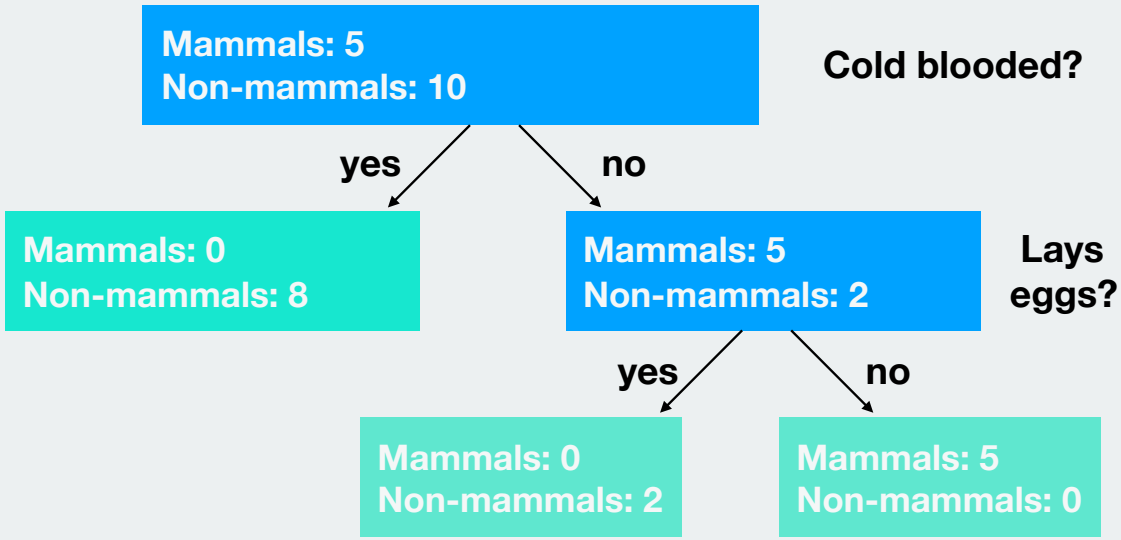
Decision trees

Could we have asked better questions?

Decision trees

	Lays eggs	Cold blooded	Mammal
no	0	0	1
no	0	0	1
no	0	0	1
no	0	0	1
no	0	0	1
yes	1	0	0
yes	1	0	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0

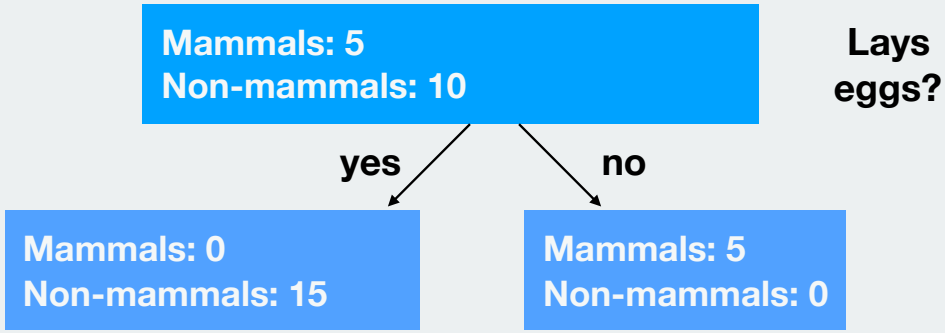
features **target**



Decision trees

	Lays eggs	Cold blooded	Mammal
no	0	0	1
	0	0	1
	0	0	1
	0	0	1
	0	0	1
yes	1	0	0
	1	0	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0

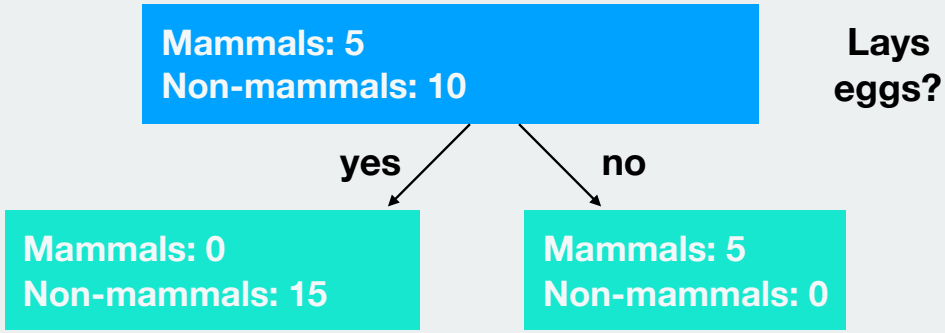
features **target**



Decision trees

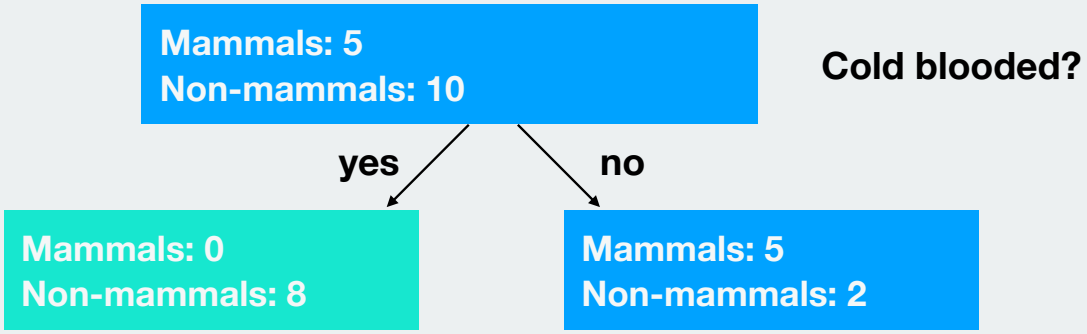
	Lays eggs	Cold blooded	Mammal
no	0	0	1
	0	0	1
	0	0	1
	0	0	1
	0	0	1
yes	1	0	0
	1	0	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0
	1	1	0

features **target**

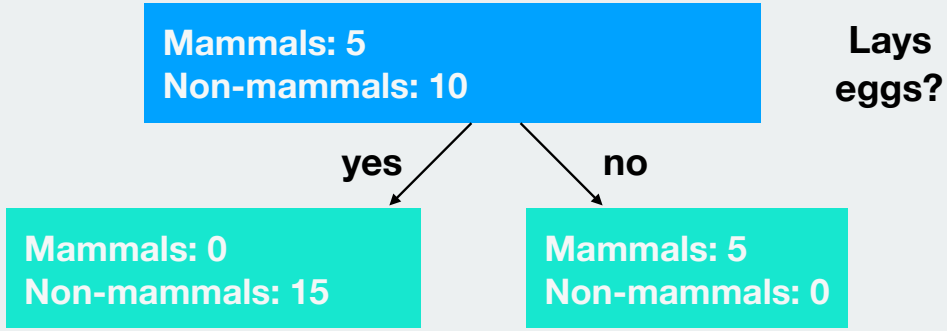


Split selection

Split 1:



Split 2:



Split selection

(Shannon) $$Entropy = -\sum_i p(i) \log_2 p(i)$$

Input: Probability vector (a list of values between 0 and 1, which sums to 1)

Output: Entropy (a measure of how "spread out" the probability distribution is)

Split selection

$$Entropy = -\sum_i p(i) \log_2 p(i)$$

Mammals: 0
Non-mammals: 8

p = [1, 0]

Split selection

$$Entropy = -\sum_i p(i) \log_2 p(i)$$

Mammals: 0
Non-mammals: 8

p = [1, 0]

Entropy = - (1 · $\log_2(1)$ + 0 · $\log_2(0)$) = 0

Split selection

$$Entropy = -\sum_i p(i) \log_2 p(i)$$

Mammals: 0
Non-mammals: 8

p = [1, 0]

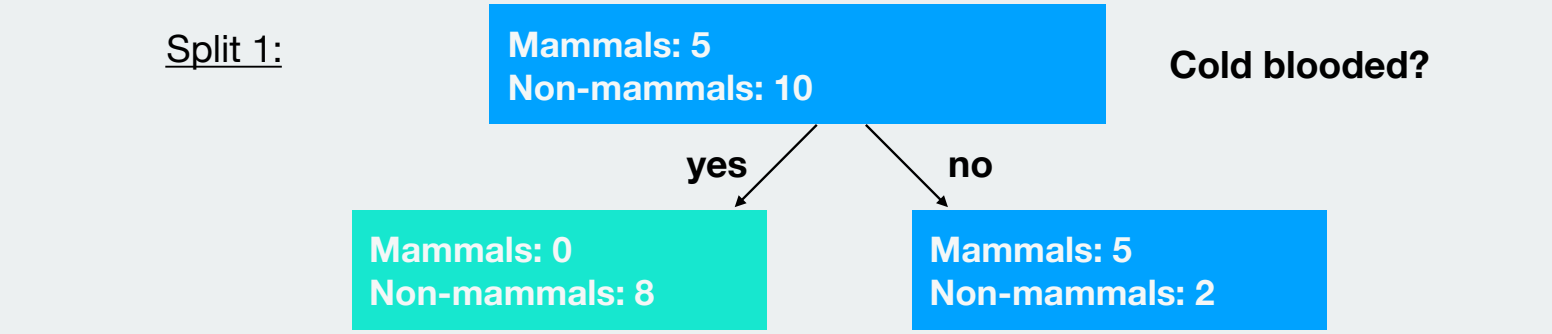
Entropy = - (1 · $\log_2(1)$ + 0 · $\log_2(0)$) = 0

Mammals: 5
Non-mammals: 2

p = [2/7, 5/7]

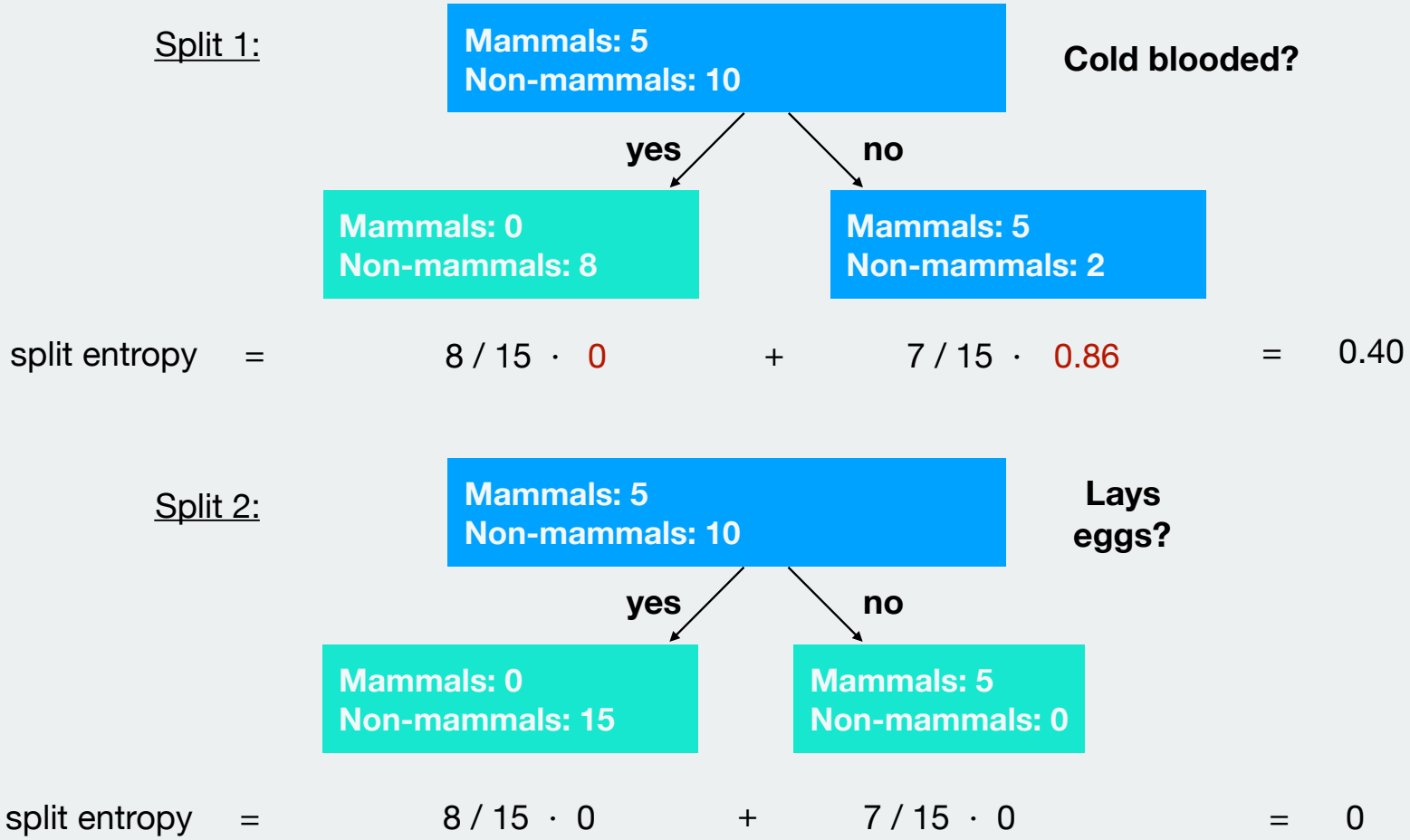
Entropy = - (2/7 · $\log_2(2/7)$ + 5/7 · $\log_2(5/7)$) = 0.86

Split selection



split entropy = 8 / 15 · 0 + 7 / 15 · 0.86 = 0.40

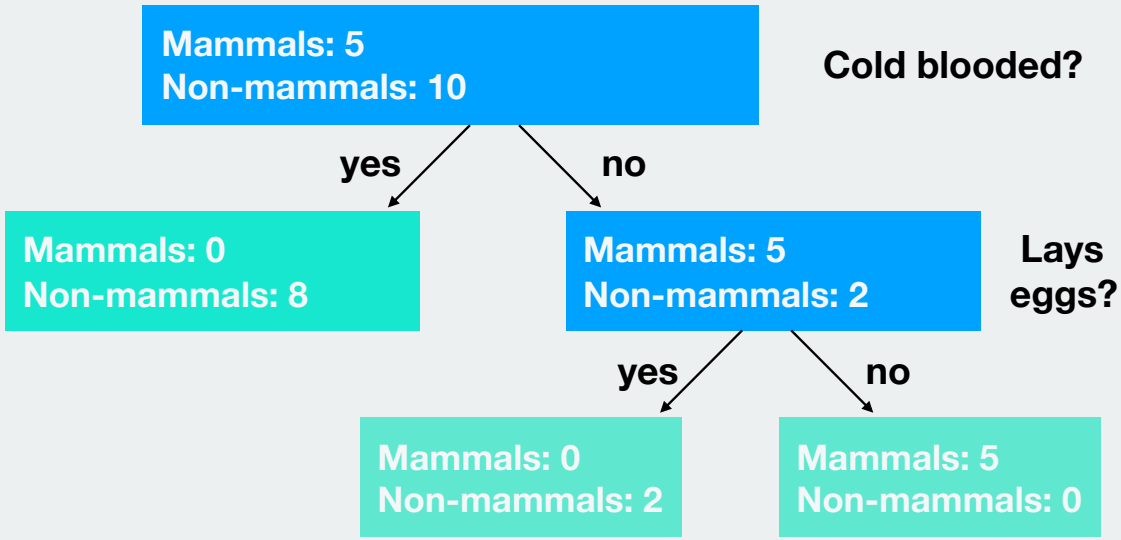
Automatic split selection



Decision trees

	Lays eggs	Cold blooded	Mammal
no	0	0	1
no	0	0	1
no	0	0	1
no	0	0	1
no	0	0	1
yes	1	0	0
yes	1	0	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0
yes	1	1	0

features **target**



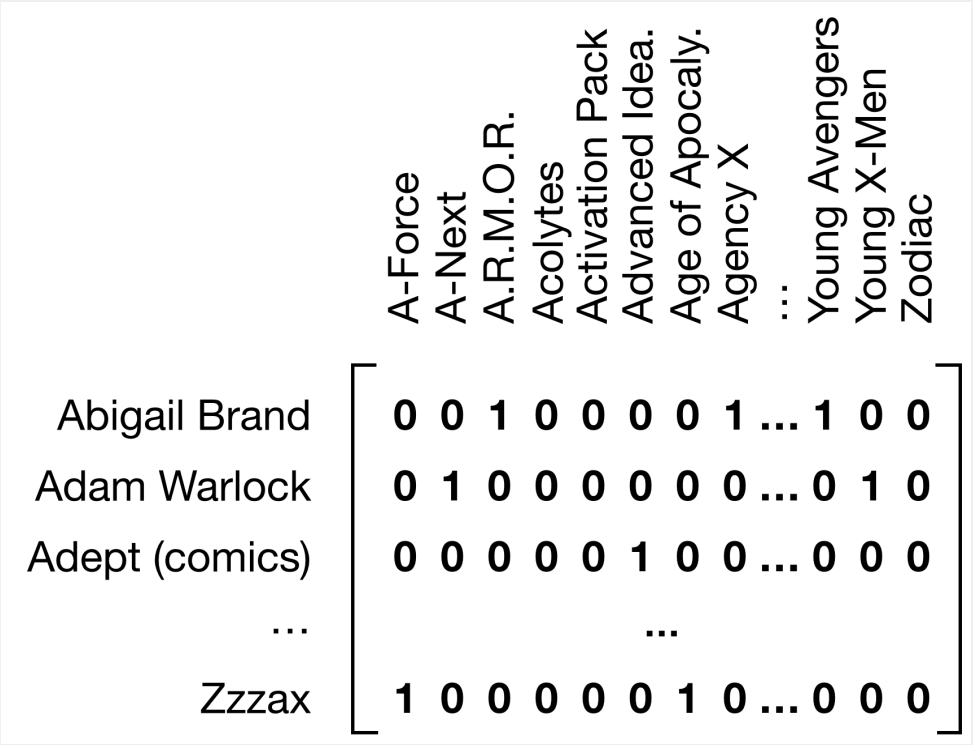
Decision trees

- Each node is split based on the attribute with the **best** split entropy
- Leafs = decisions (majority vote)
- To classify a new input, start at the root and make your way down through the tree by answering attribute questions at each node

Decision trees

What do we do when we have Big(ger) Data?

Decision trees



On steroids:

Ensemble Learning

Ensemble Learning

- Create and train many classification models
- Treat each model as a “voter”
- For each datapoint, classify it according to what models predicts it to be

Random Forest

model1

	Pclass1	Pclass2	Pclass3	Sexfemale	Sexmale	Embarkednan	EmbarkedC	EmbarkedQ	EmbarkedS	CabinFalse	CabinTrue	PassengerId	Age	SibSp	Parch	Fare	Survived
0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	1	22.0	1	0	7.2500	0
1	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	2	38.0	1	0	71.2833	1
2	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	3	26.0	0	0	7.9250	1
3	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	4	35.0	1	0	53.1000	1
4	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	5	35.0	0	0	8.0500	0
5	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	6	NaN	0	0	8.4583	0
6	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	1.0	7	54.0	0	0	51.8625	0
7	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	8	2.0	3	1	21.0750	0
8	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	9	27.0	0	2	11.1333	1
9	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	10	14.0	1	0	30.0708	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
881	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	882	33.0	0	0	7.8958	0
882	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	883	22.0	0	0	10.5167	0
883	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	884	28.0	0	0	10.5000	0
884	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	885	25.0	0	0	7.0500	0
885	0.0	0.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	886	39.0	0	5	29.1250	0
886	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	887	27.0	0	0	13.0000	0
887	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	888	19.0	0	0	30.0000	1
888	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	889	NaN	1	2	23.4500	0
889	1.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	890	26.0	0	0	30.0000	1
890	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	891	32.0	0	0	7.7500	0

Random Forest

model2

	Pclass1	Pclass2	Pclass3	Sexfemale	Sexmale	Embarkednan	EmbarkedC	EmbarkedQ	EmbarkedS	CabinFalse	CabinTrue	PassengerId	Age	SibSp	Parch	Fare	Survived
0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	1	22.0	1	0	7.2500	0
1	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	2	38.0	1	0	71.2833	1
2	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	3	26.0	0	0	7.9250	1
3	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	4	35.0	1	0	53.1000	1
4	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	5	35.0	0	0	8.0500	0
5	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	6	NaN	0	0	8.4583	0
6	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	1.0	7	54.0	0	0	51.8625	0
7	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	8	2.0	3	1	21.0750	0
8	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	9	27.0	0	2	11.1333	1
9	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	10	14.0	1	0	30.0708	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
881	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	882	33.0	0	0	7.8958	0
882	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	883	22.0	0	0	10.5167	0
883	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	884	28.0	0	0	10.5000	0
884	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	885	25.0	0	0	7.0500	0
885	0.0	0.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	886	39.0	0	5	29.1250	0
886	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	887	27.0	0	0	13.0000	0
887	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	888	19.0	0	0	30.0000	1
888	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	889	NaN	1	2	23.4500	0
889	1.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	890	26.0	0	0	30.0000	1
890	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	891	32.0	0	0	7.7500	0

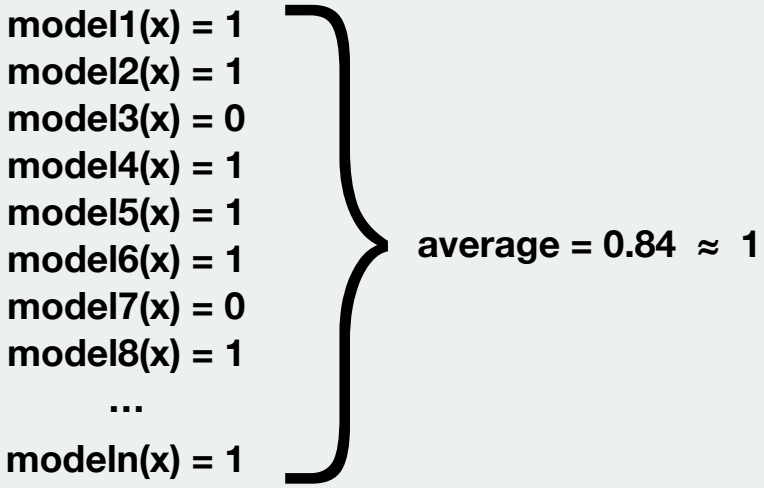
Random Forest

model3

	Pclass1	Pclass2	Pclass3	Sexfemale	Sexmale	Embarkednan	EmbarkedC	EmbarkedQ	EmbarkedS	CabinFalse	CabinTrue	PassengerId	Age	SibSp	Parch	Fare	Survived
0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	1	22.0	1	0	7.2500	0
1	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	2	38.0	1	0	71.2833	1
2	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	3	26.0	0	0	7.9250	1
3	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	4	35.0	1	0	53.1000	1
4	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	5	35.0	0	0	8.0500	0
5	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	6	NaN	0	0	8.4583	0
6	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	1.0	7	54.0	0	0	51.8625	0
7	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	8	2.0	3	1	21.0750	0
8	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	9	27.0	0	2	11.1333	1
9	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	10	14.0	1	0	30.0708	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
881	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	882	33.0	0	0	7.8958	0
882	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	883	22.0	0	0	10.5167	0
883	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	884	28.0	0	0	10.5000	0
884	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	885	25.0	0	0	7.0500	0
885	0.0	0.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	886	39.0	0	5	29.1250	0
886	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	1.0	0.0	887	27.0	0	0	13.0000	0
887	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	888	19.0	0	0	30.0000	1
888	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	889	NaN	1	2	23.4500	0
889	1.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	890	26.0	0	0	30.0000	1
890	0.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	891	32.0	0	0	7.7500	0

Ensemble Learning

- Create and train many classification models
- Treat each model as a “voter”
- For each datapoint, classify it according to what models predicts it to be



Ensemble Learning — benefits

- Very fast training (fewer attributes)
- Pretty good performance
- Very robust to overfitting

So far today

- Decision Trees (DTs) = a ML algorithm
    - Entropy, split decisions
- Ensemble Learning (EL) = using many models (+/- many algorithms)
    - Random Forrest, an example of EL using DTs

Linear (and Logistic) regression

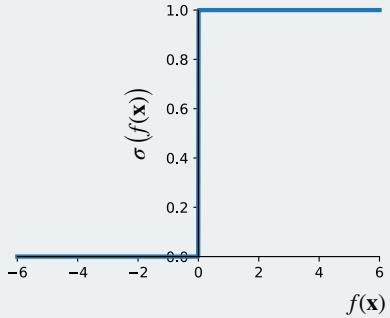
Linear regression

$$w_0 + x_0 w_1 + x_1 w_2 + x_2 w_3 = f(\mathbf{x})$$

Linear regression classifier

$$w_0 + x_0 w_1 + x_1 w_2 + x_2 w_3 = f(\mathbf{x})$$

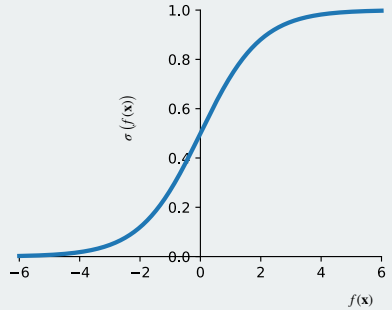
$$\sigma\left(f(\mathbf{x})\right) = \begin{cases} 1, & \textbf{if } f(\mathbf{x}) \geq 0 \\ 0, & \textbf{otherwise} \end{cases}$$



Linear regression regression

$$w_0 + x_0 w_1 + x_1 w_2 + x_2 w_3 = f(\mathbf{x})$$

$$\sigma\left(f(\mathbf{x})\right) = \frac{1}{1 + exp\left(-f(x)\right)}$$

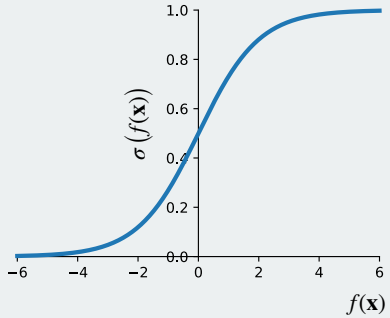


Linear regre ssifier

¡Logistic regression!
classifier

$$w_0 + x_0 w_1 + x_1 w_2 + x_2 w_3 = f(\mathbf{x})$$

$$\sigma\left(f(\mathbf{x})\right) = \frac{1}{1 + exp\left(-f(x)\right)}$$



Logistic regression classifier

(Input)

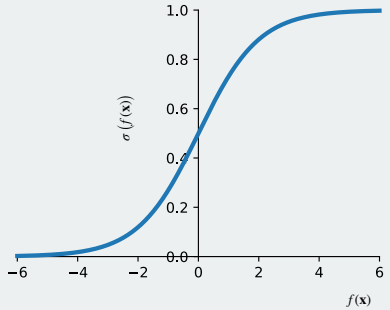
Variables **Weights**

$$w_0 + x_0 w_1 + x_1 w_2 + x_2 w_3 = f(\mathbf{x})$$

Output

$$\sigma\left(f(\mathbf{x})\right) = \frac{1}{1 + exp\left(-f(x)\right)}$$

Activation function



Sum up

- Decision Trees (DTs) = a ML algorithm
    - Entropy, split decisions
- Ensemble Learning (EL) = using many models (+/- many algorithms)
    - Random Forrest, an example of EL using DTs
- Linear/Logistic Regression = a ML algorithm
    - Linear regression outputs 0 or 1
    - Logistic regression gives a probability