

# INTRO TO DATA SCIENCE REVIEW

#### INTRODUCTION

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# INTRO TO DATA SCIENCE REVIEW

## supervised unsupervised

making predictions discovering patterns

## supervised unsupervised

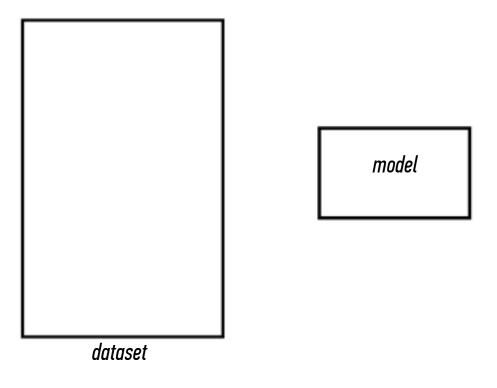
labeled examples no labeled examples

#### TYPES OF ML SOLUTIONS

# supervised<br/>unsupervisedregression<br/>dimension reductionclassification<br/>clustering

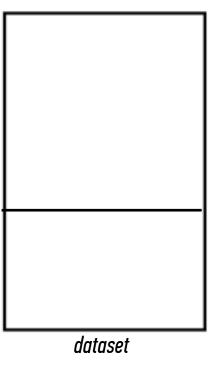
#### INTRO TO DATA SCIENCE

### SUPERVISED LEARNING



Q: What steps does a classification problem require?

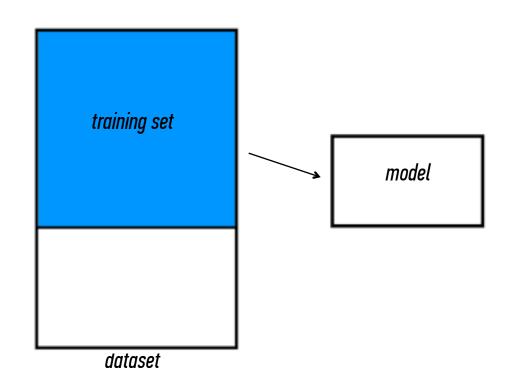
1) split dataset



model

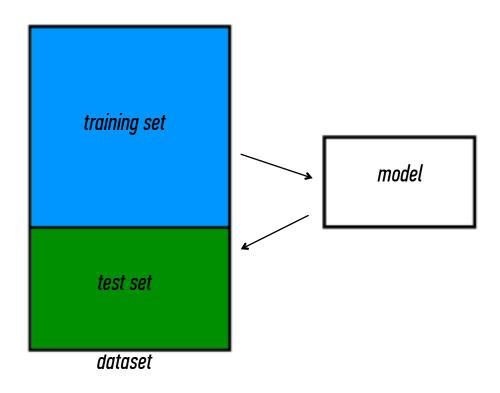
#### **SUPERVISED LEARNING PROBLEMS**

- 1) split dataset
- 2) train model



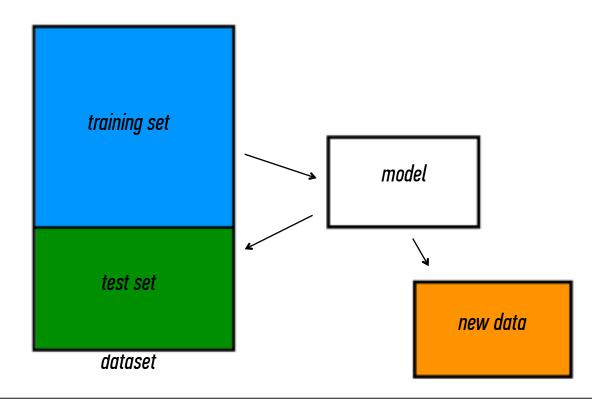
#### **SUPERVISED LEARNING PROBLEMS**

- 1) split dataset
- 2) train model
- 3) test model



#### **SUPERVISED LEARNING PROBLEMS**

- 1) split dataset
- 2) train model
- 3) test model
- 4) make predictions



#### INTRO TO DATA SCIENCE

## LINEAR REGRESSION

#### **REGRESSION PROBLEMS**

# supervised<br/>unsupervisedregression<br/>dimension reductionclassification<br/>clustering

#### INTRO TO REGRESSION

- Q: What is a regression model?
- A: A functional relationship between input & response variables

The simple linear regression model captures a linear relationship between a single input variable x and a response variable y:

$$y = \alpha + \beta x + \varepsilon$$

Q: What do the terms in this model mean?

$$y = \alpha + \beta x + \varepsilon$$

A: y = response variable (the one we want to predict)

x =input variable (the one we use to train the model)

 $\alpha$  = intercept (where the line crosses the y-axis)

 $\beta$  = regression coefficient (the model "parameter")

 $\varepsilon$  = residual (the prediction error)

#### **LEARNING**

```
OLS: min(\|y-x\beta\|^2)
L1 regularization: min(\|y-x\beta\|^2+\lambda\|\beta\|)
L2 regularization: min(\|y-x\beta\|^2+\lambda\|\beta\|^2)
```

#### INTRO TO DATA SCIENCE

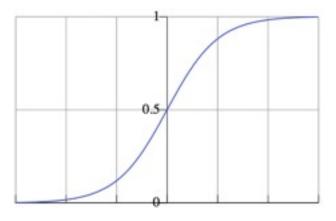
## LOGISTIC REGRESSION

$$E(y|x) = \pi(x) = \frac{e^{\alpha + \beta x}}{1 + e^{\alpha + \beta x}}$$

#### THE LOGISTIC FUNCTION

$$E(y|x) = \pi(x) = \frac{e^{\alpha + \beta x}}{1 + e^{\alpha + \beta x}}$$

We've already seen what this looks like:



#### THE LOGISTIC FUNCTION

The **logit function** is an important transformation of the logistic function. Notice that it returns the linear model!

$$g(x) = ln(\frac{\pi(x)}{1-\pi(x)}) = \alpha + \beta x$$

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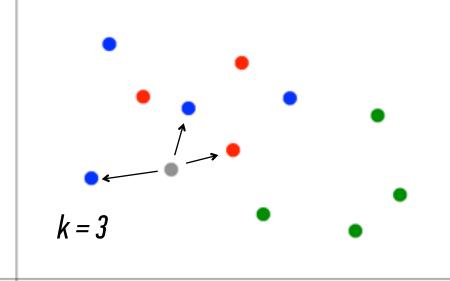
The logit function is also called the log-odds function.

#### INTRO TO DATA SCIENCE

### KNN CLASSIFICATION

#### Suppose we want to predict the color of the grey dot.

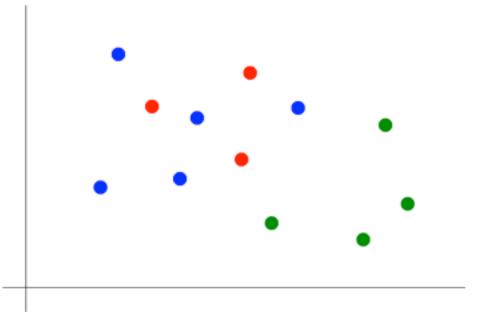
- 1) Pick a value for k.
- 2) Find colors of k nearest neighbors.



#### KNN CLASSIFICATION

#### Suppose we want to predict the color of the grey dot.

- 1) Pick a value for k.
- 2) Find colors of k nearest neighbors.
- 3) Assign the most common color to the grey dot.



#### INTRO TO DATA SCIENCE

## NAÏVE BAYES

#### **BAYESIAN INFERENCE**

Suppose we have a dataset with features  $x_1, ..., x_n$  and a class label C. What can we say about classification using Bayes' theorem?

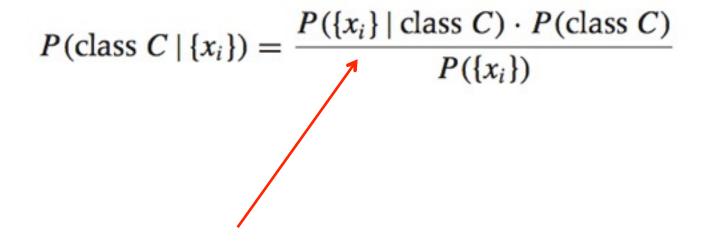
$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

Bayes' theorem can help us to determine the probability of a record belonging to a class, given the data we observe.

source: Data Analysis with Open Source Tools, by Philipp K. Janert. O'Reilly Media, 2011.

#### THE LIKELIHOOD FUNCTION

This term is the likelihood function. It represents the joint probability of observing features  $\{x_i\}$  given that that record belongs to class C.



#### THE PRIOR

This term is the prior probability of C. It represents the probability of a record belonging to class C before the data is taken into account.

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

#### THE NORMALIZATION CONSTANT

This term is the normalization constant. It doesn't depend on C, and is generally ignored until the end of the computation.

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

#### THE POSTERIOR

This term is the posterior probability of C. It represents the probability of a record belonging to class C after the data is taken into account.

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

This term is the posterior probability of C. It represents the probability of a record belonging to class C after the data is taken into account.

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

The goal of any Bayesian computation is to find ("learn") the posterior distribution of a particular variable.

The idea of Bayesian inference, then, is to **update** our beliefs about the distribution of C using the data ("evidence") at our disposal.

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

Then we can use the posterior for prediction.

#### **CLASSIFICATION**

# supervised<br/>unsupervisedregression<br/>dimension reductionclassification<br/>clustering

#### INTRO TO DATA SCIENCE

## COMPARISON

#### **CLASSIFICATION**

scalability

linear

# interpretation configuration feature-select

Wednesday, March 19, 14

overfitting

**37** 

**CLASSIFICATION** 

linear

## KNN

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## KNN

linear scalability

-/-

linear

# **KNN**N +/-

scalability interpretation

\_

	KNN
linear	N
scalability	+/-
interpretation	_
configuration	+

	KNN
linear	N
scalability	+/-
interpretation	-
configuration	+
feature-select	_

### <u>KNN</u>

linear scalability interpretation configuration feature-select overfitting

linear scalability

configuration

KNN

Logistic

interpretation feature-select

overfitting

scalability

interpretation

configuration

feature-select

linear

<u>-</u>

KNN

Logistic

**overfitting**Wednesday, March 19, 14

scalability

configuration

linear

interpretation

Logistic

NB

Prior

feature-select

KNN

overfitting Wednesday, March 19, 14

interpretation

configuration

overfitting

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feature-select

KNN

Logistic

NB

Prior

RF

48 **CLASSIFICATION** KNN Logistic NB SVM RF linear

Prior

n tree

scalability

interpretation

configuration

overfitting

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feature-select

#### QUESTION

## HOW DO YOU REPRESENT YOUR DATA?

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RGB-values

{red, blue}

ratings

color

1 — 10 rating

Good / Bad

#### QUESTION

# HOW DO YOU MEASURE

OF QUALITY?

#### **ASSESSING ML PERFORMANCE**

# supervised unsupervised

## test out your predictions

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#### **ASSESSING ML PERFORMANCE**

# supervised unsupervised

## Accuracy, MAE, AUC