Text classification

Classification & Evaluation

Ayoub Bagheri

Outline

- Text classification
- Algorithms
- Evaluation

Bag-of-Words representation

Doc1: Text mining is to identify useful information.

Doc2: Useful information is mined from text.

Doc3: Apple is delicious.

Document-Term matrix (DTM):

	text	information	identify	mining	mined	is	useful	to	from	apple	delicious
Doc1	1	1	1	1	0	1	1	1	0	0	0
Doc2	1	1	0	0	1	1	1	0	1	0	0
Doc3	0	0	0	0	0	1	0	0	0	1	1

Text classification

- **Supervised learning**: Learning a function that maps an input to an output based on example input-output pairs.
  - infer a function from labeled training data
  - use the inferred function to label new instances

- Human experts annotate a set of text data
  - Training set

Document	Class
Email1…..	Not spam
Email2….	Not spam
Email3….	Spam
…	…

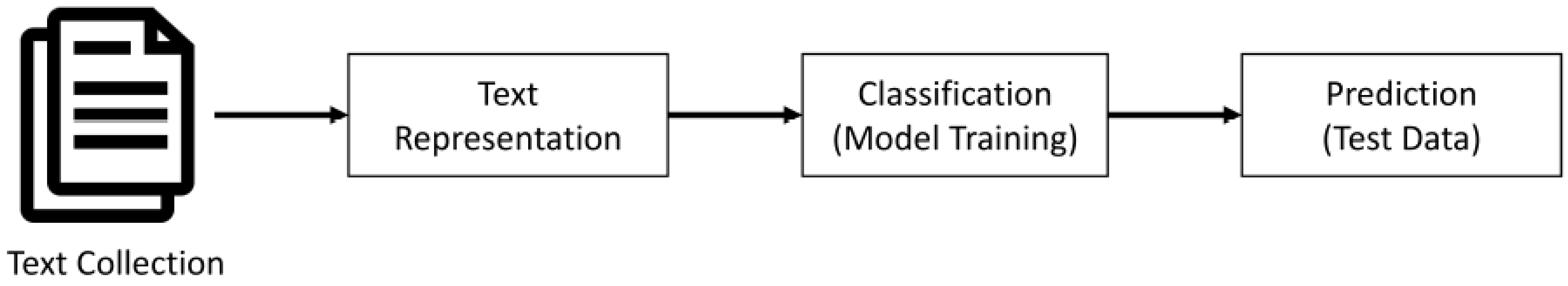
Applications

- Assigning subject categories, topics, or genres
- Spam detection
- Authorship identification
- Age/gender identification
- Language Identification
- Sentiment analysis

Quiz?

- Which one **is not** a text classification task? (less likely to be)
  - Author's gender detection from text
  - Finding about the smoking conditions of patients from clinical letters
  - Grouping similar news articles
  - Classifying reviews into positive and negative sentiment

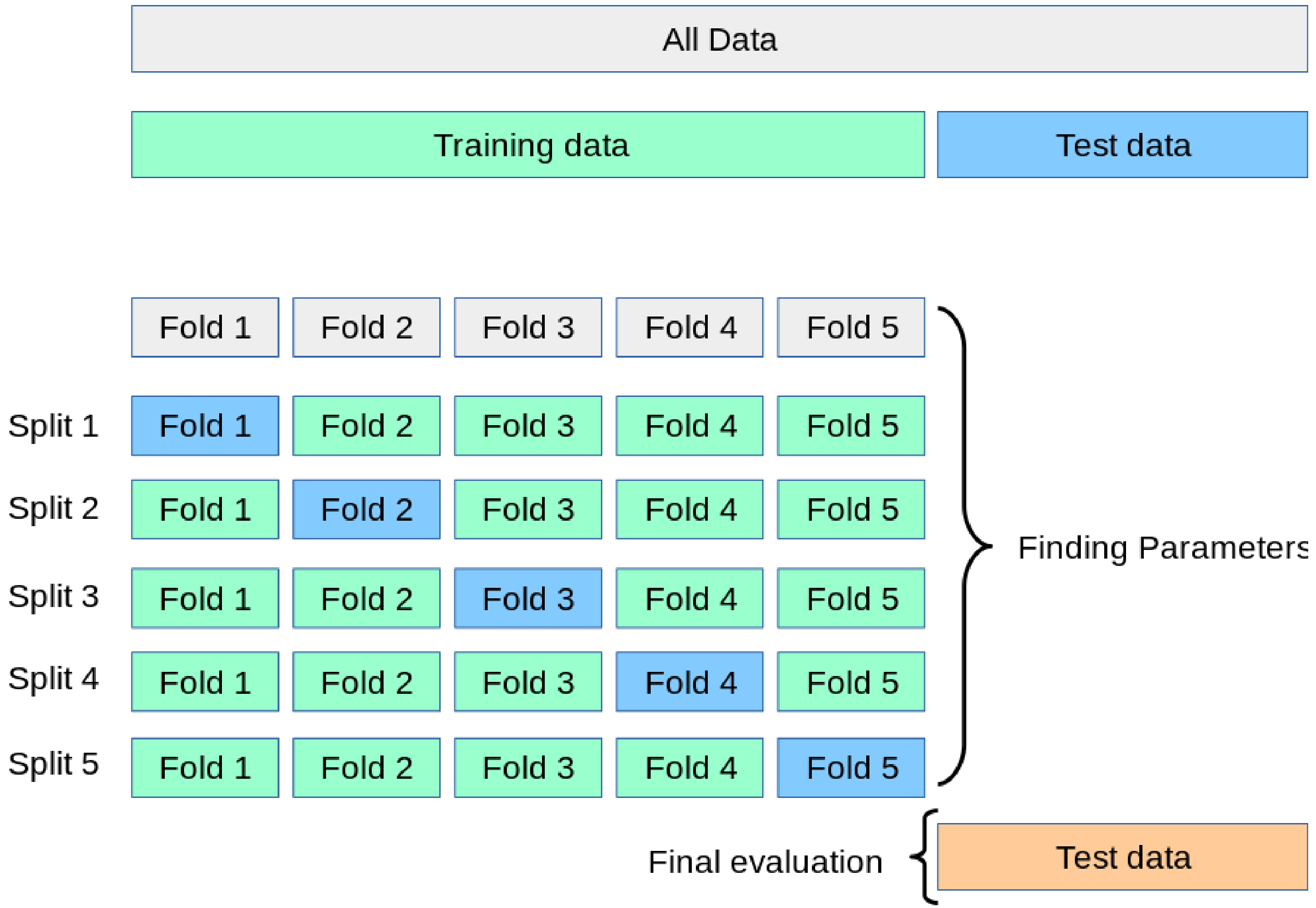
Simple pipeline



Preparing data

- Text preprocessing
- Data splitting
  - Training
  - Validation (development)
    - to tune the hyperparameters
  - Test
- Text representation

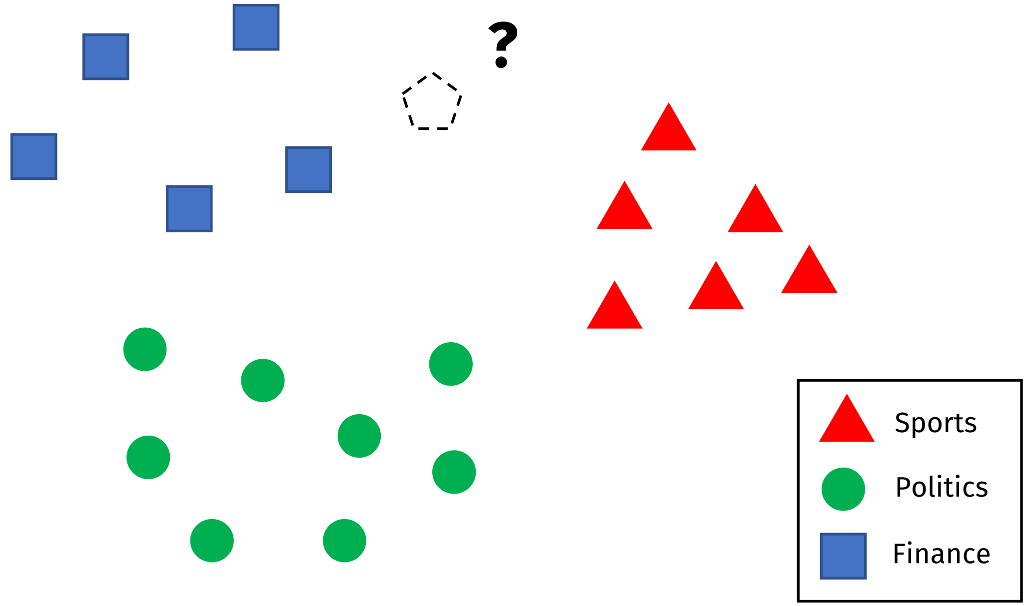
K-fold cross validation



https://scikit-learn.org/stable/modules/cross_validation.html

How to classify this document?

Documents by vector space representation



Text Classification: definition

- *Input*:
  - a document d
  - a fixed set of classes $C = \{c_1, c_2, \ldots, c_J\}$

- *Output*: a predicted class $c \in C$

Classification Algorithms

Hand-coded rules

- Rules based on combinations of words or other features
- Accuracy can be high: If rules carefully refined by expert
- But building and maintaining these rules is expensive
- Data/Domain specifics

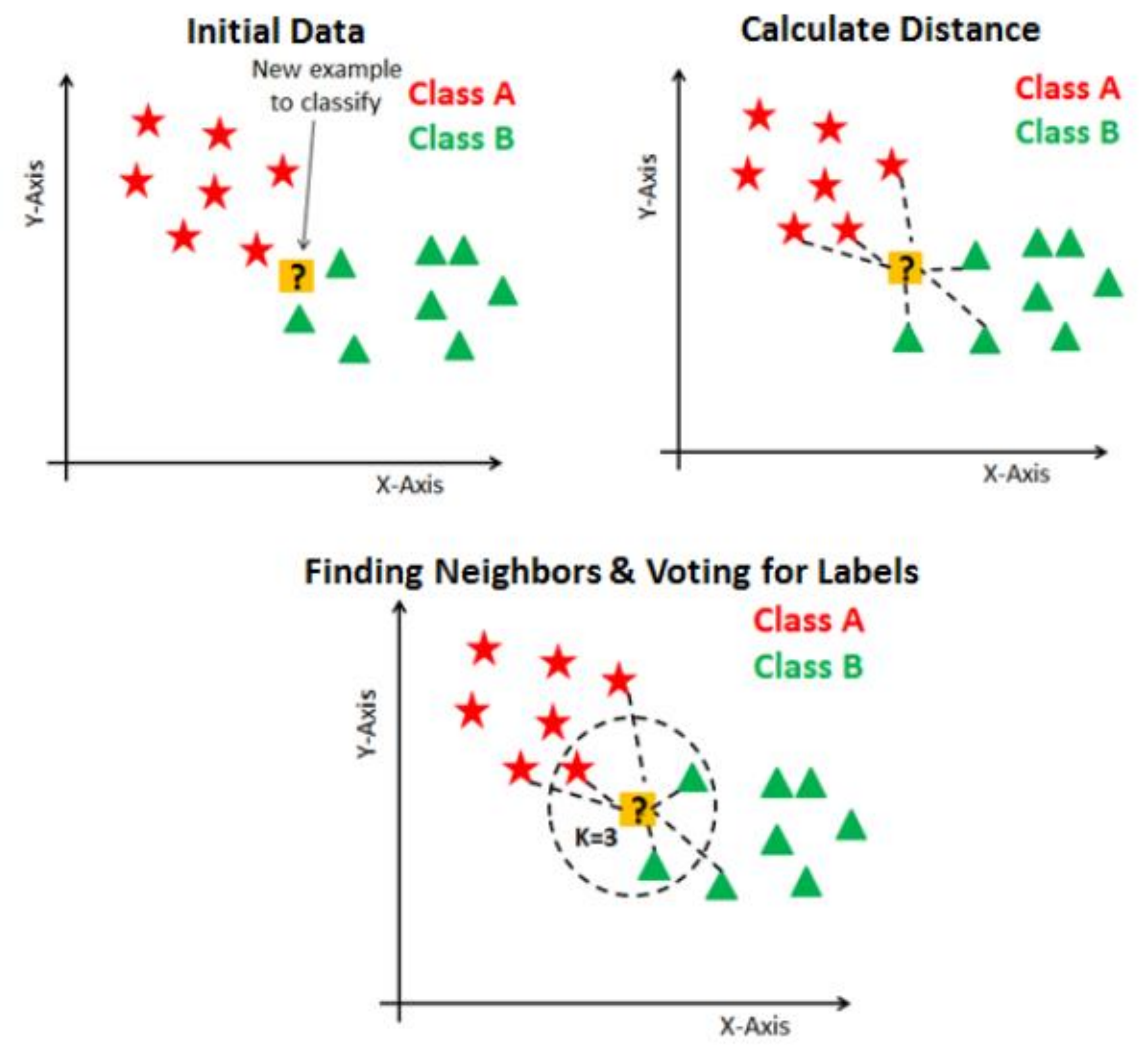
Supervised Machine Learning

- *Input:*
  - a document d
  - a fixed set of classes $C = \{c_1, c_2,\ldots, c_J\}$
  - A training set of m hand-labeled documents $(d_1,c_1),\ldots,(d_m,c_m)$
- *Output:*
  - a learned classifier $y{:}d \rightarrow c$

Outline

- Naïve bayes
- Logistic regression
- Support-vector machines
- K-nearest neighbors
- Neural networks
- Deep learning

K-nearest neighbor



Naïve Bayes

$y($

great	2
love	2
recommend	1
laugh	1
happy	1
...	...

$)=c$

Bayes' rule

- For a document *d* and a class *c*

$$P(c \mid d) = \frac{P(d \mid c)P(c)}{P(d)}$$

Learning naïve Bayes

$$c_{MAP} = \underset{c \in C}{\operatorname{argmax}} P(c \mid d)$$

MAP is "maximum a posteriori" = most likely class

$$= \underset{c \in C}{\operatorname{argmax}} \frac{P(d \mid c)P(c)}{P(d)}$$

Bayes Rule

$$= \underset{c \in C}{\operatorname{argmax}} P(d \mid c)P(c)$$

Dropping the denominator

Learning naïve Bayes

$$c_{MAP} = \underset{c \in C}{\operatorname{argmax}} P(d \mid c) P(c)$$

$$= \underset{c \in C}{\operatorname{argmax}} P(x_1, x_2, \ldots, x_n \mid c) P(c)$$

Document d represented as features x1..xn

Could only be estimated if a very, very large number of training examples was available.

We can just count the relative frequencies in a corpus

Learning naïve Bayes

- Simply use the frequencies in the data

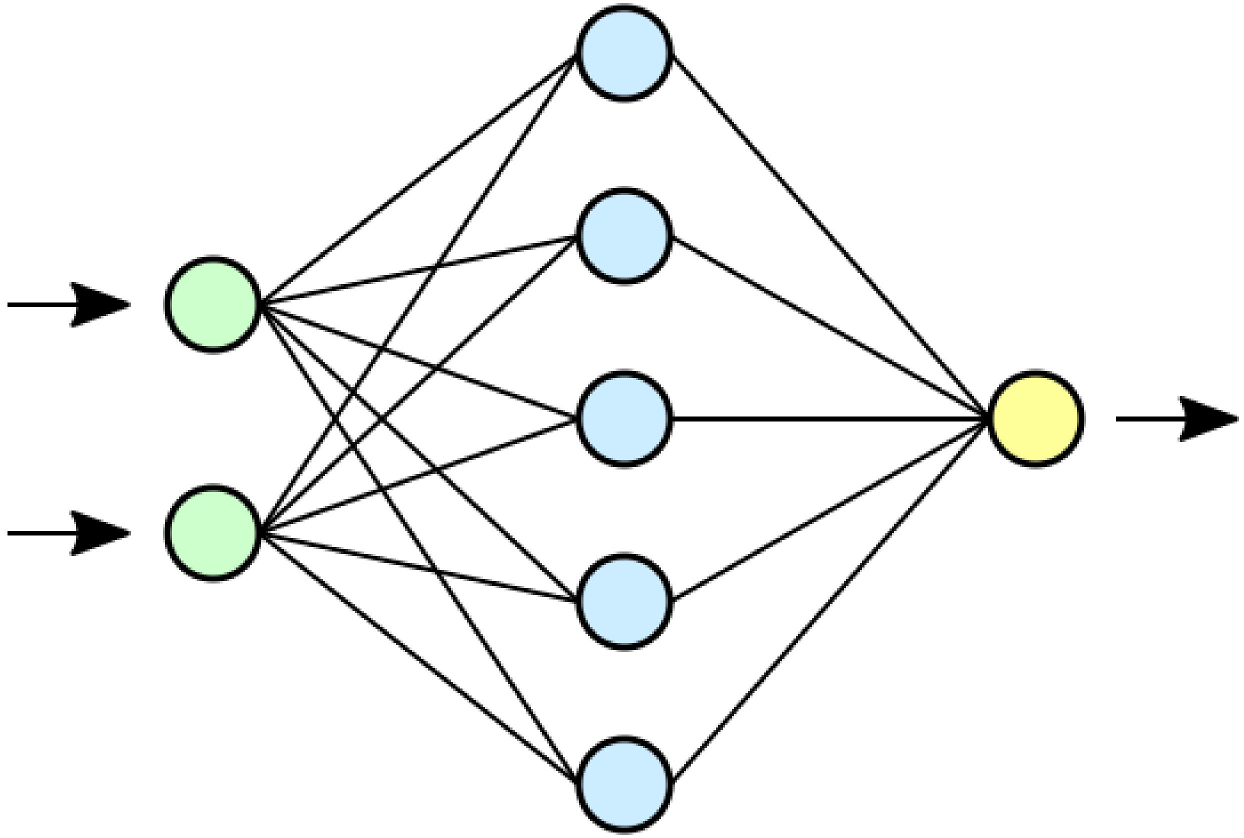
$$\hat{P}(c_j) = \frac{doccount(C = c_j)}{N_{doc}}$$

$$\hat{P}(w_i \mid c_j) = \frac{count(w_i, c_j)}{\sum_{w \in V} count(w, c_j)}$$

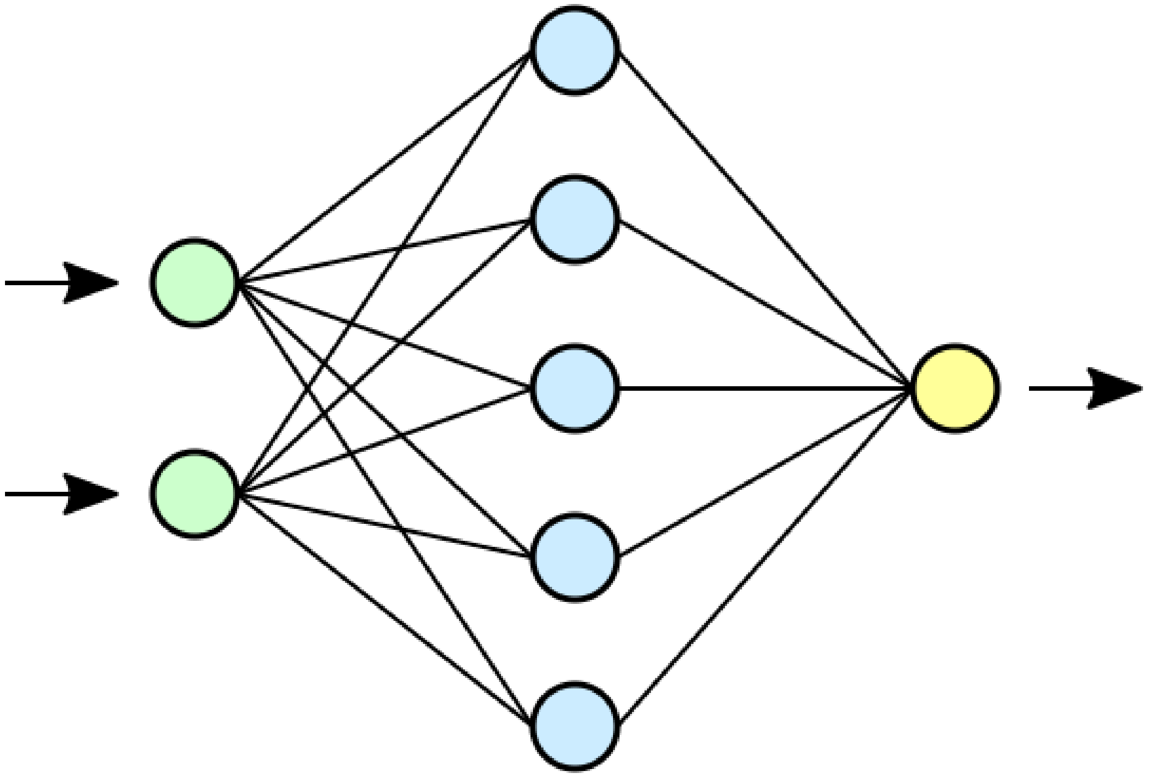
Neural networks, “deep learning”

- Compositional approach to curve-fitting;
- “Biologically inspired”
  (but don’t take that too seriously);
- Sound cool.

Neural network



Neural network



"Hidden" nodes:

Example:

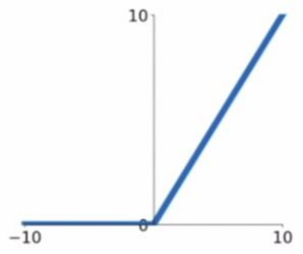
$$h_1 = f(w_{11}x_1 + w_{12}x_2)$$

Output:

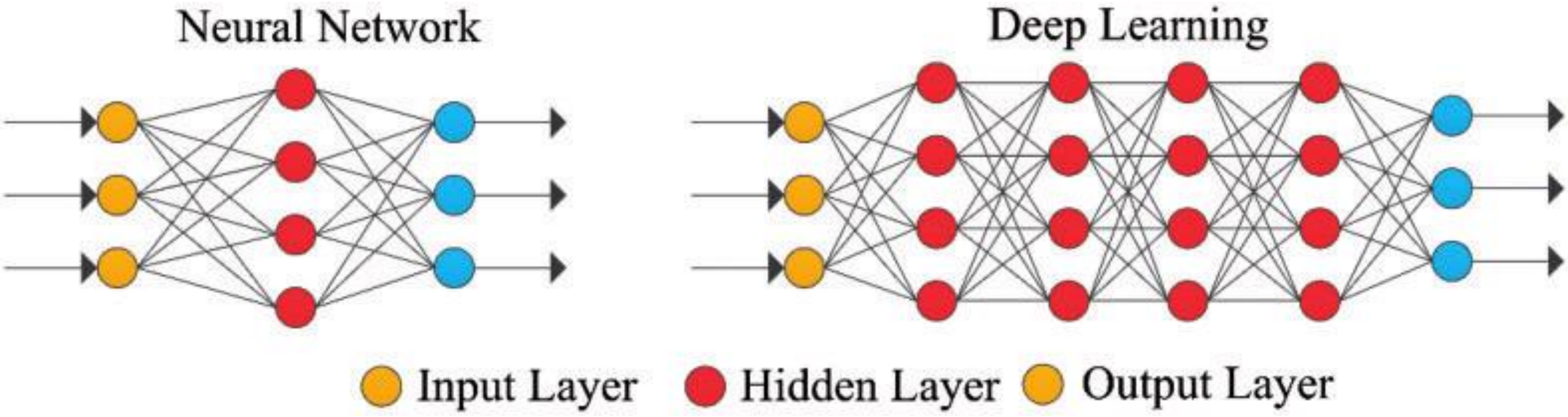
$$y = f(w_{21}h_1 + w_{22}h_2 + \cdots + w_{25}h_5)$$

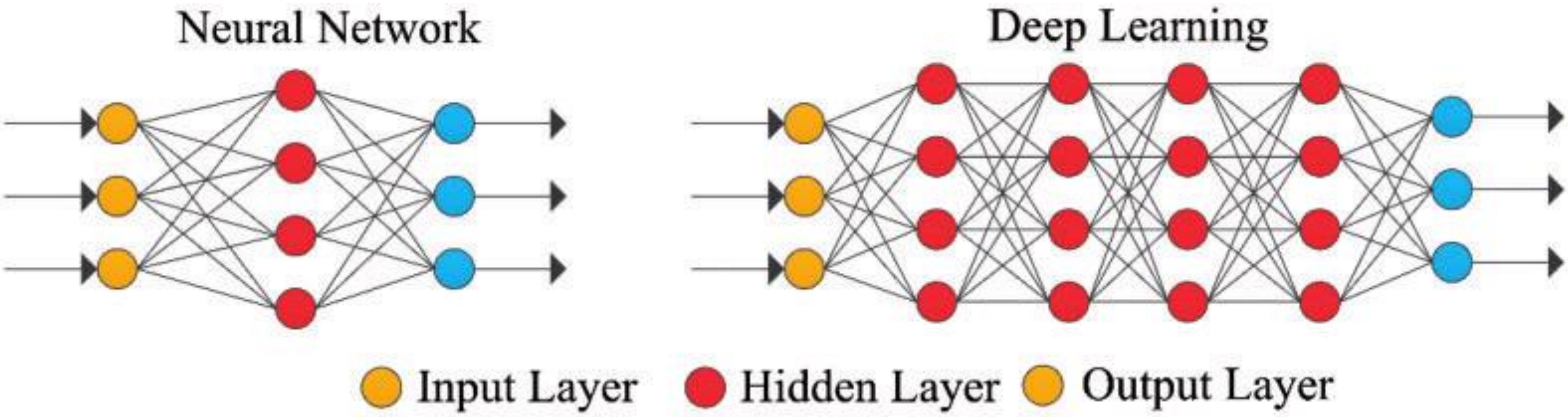
"Activation function":

- REIu $f(z) =$
- …



What makes a neural net “deep”?





Keep doing

$$z = g^{(n_h)}(g^{(\dots)}(g^{(2)}(g^{(1)}(\mathbf{x}))))$$

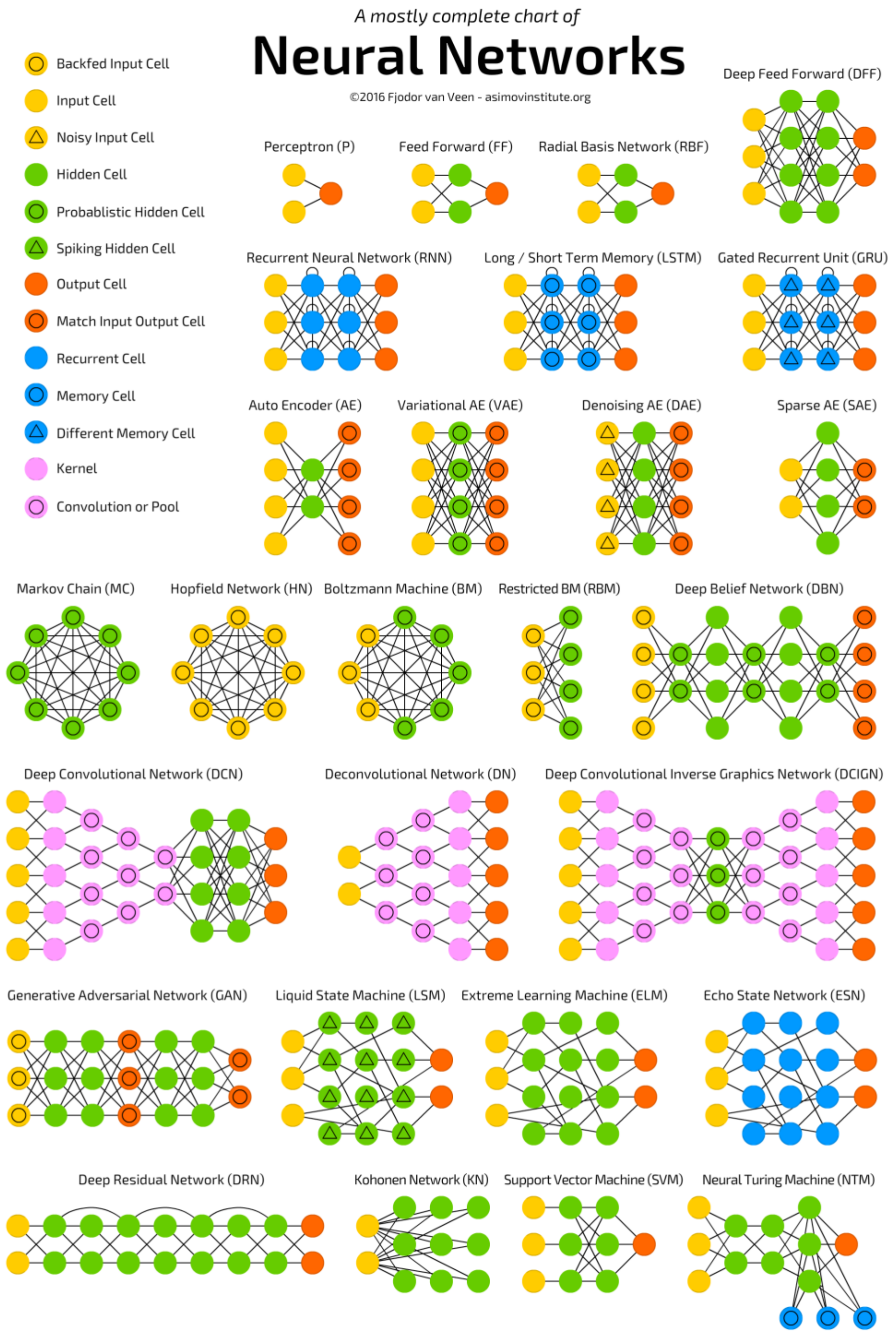
then $y \approx f(z)$.

Deep learning

- Output of each hidden layer is input to subsequent one
- Allow representation learning by building complex features out of simpler ones
- Go deep: exponential advantages, less overfitting
- Aggressive parameterization + aggressive regularization
- Compositional: efficient parametrization
- Learn relevant features: “End-to-end”

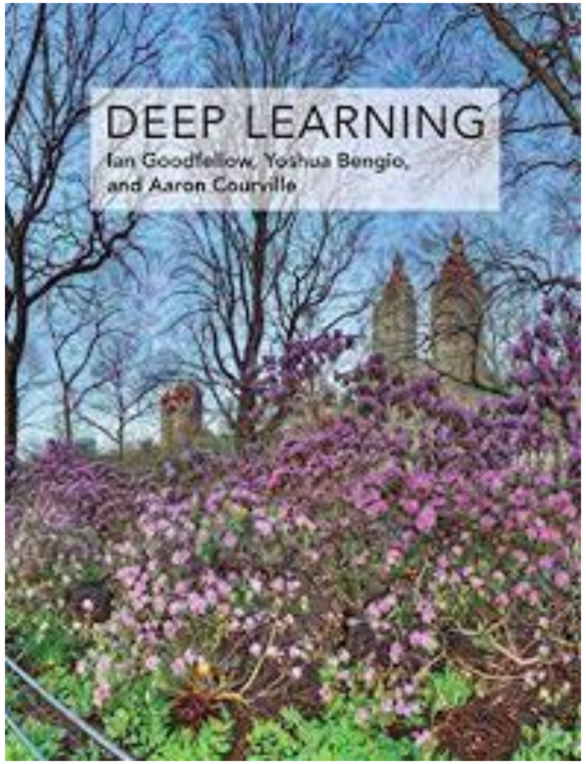
Different architectures

- By adjusting the arrows, layers, and activation functions, you can create models that are tailored to specific data, e.g.
- Convolutional (CNN): images, text, sound
- Recurrent (RNN): time series, text
- Graph (GNN): networks
- …

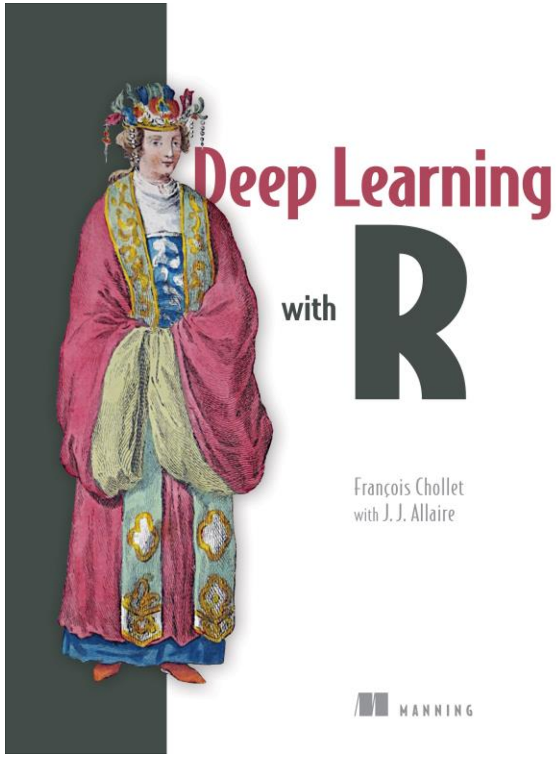


Deep learning in practice

- Good places to start:
  - https://keras.rstudio.com/
- ISLR Chapter 10



Goodfellow et al.



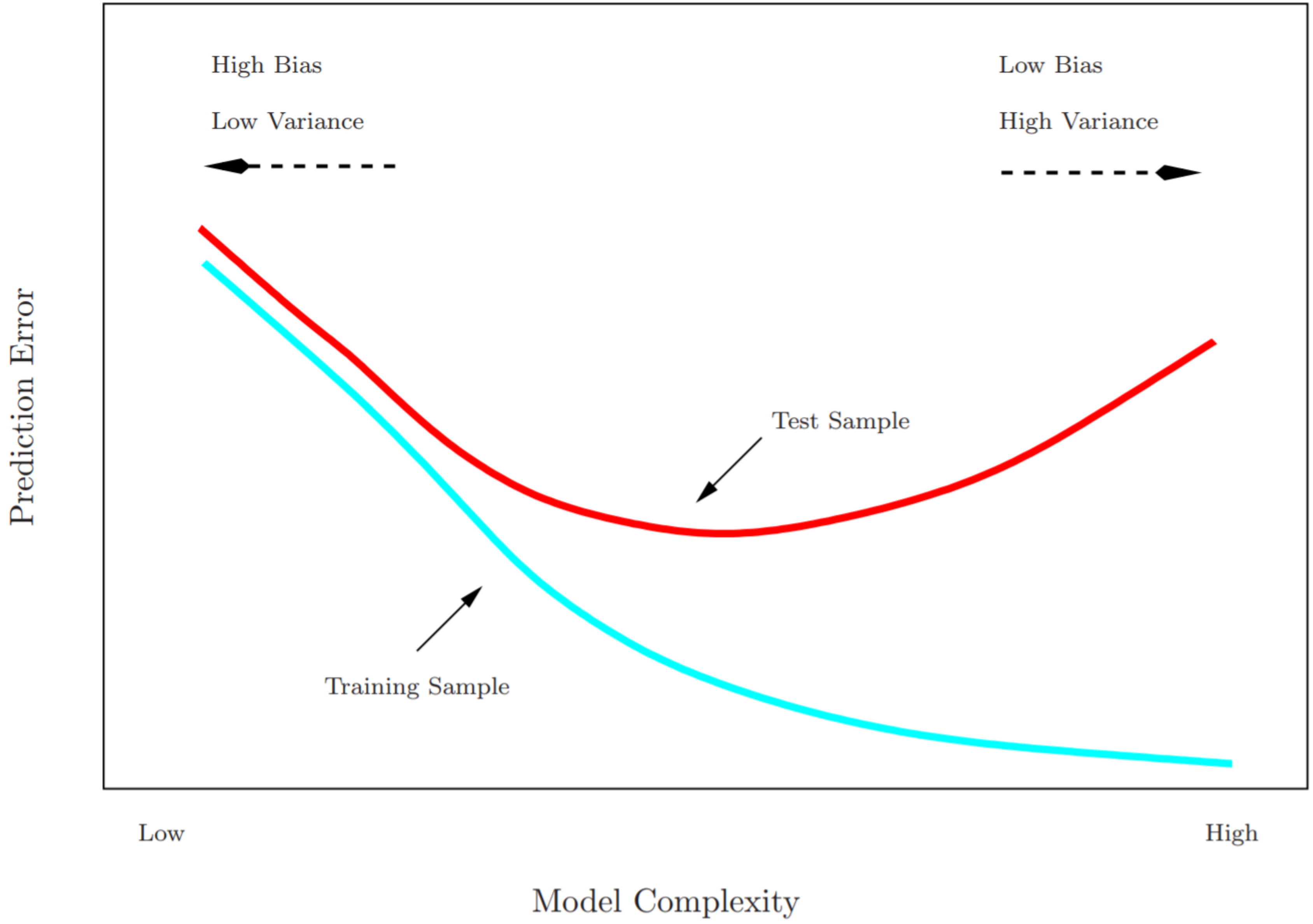
Chollet (R/Python version)

Evaluation

No free lunch

"Any two optimization algorithms are equivalent when their performance is averaged across all possible problems"

(Wolpert & MacReady)


High Bias
Low Variance
Low Bias
High Variance
Test Sample
Training Sample
Prediction Error
Low
High
Model Complexity

Confusion matrix

		Predicted Class: Positive	Predicted Class: Negative	
Actual Class	**Positive**	True Positive (TP)	False Negative (FN) **Type II Error**	**Sensitivity** $\frac{TP}{(TP + FN)}$
Actual Class	**Negative**	False Positive (FP) **Type I Error**	True Negative (TN)	**Specificity** $\frac{TN}{(TN + FP)}$
		Precision $\frac{TP}{(TP + FP)}$	**Negative Predictive Value** $\frac{TN}{(TN + FN)}$	**Accuracy** $\frac{TP + TN}{(TP + TN + FP + FN)}$

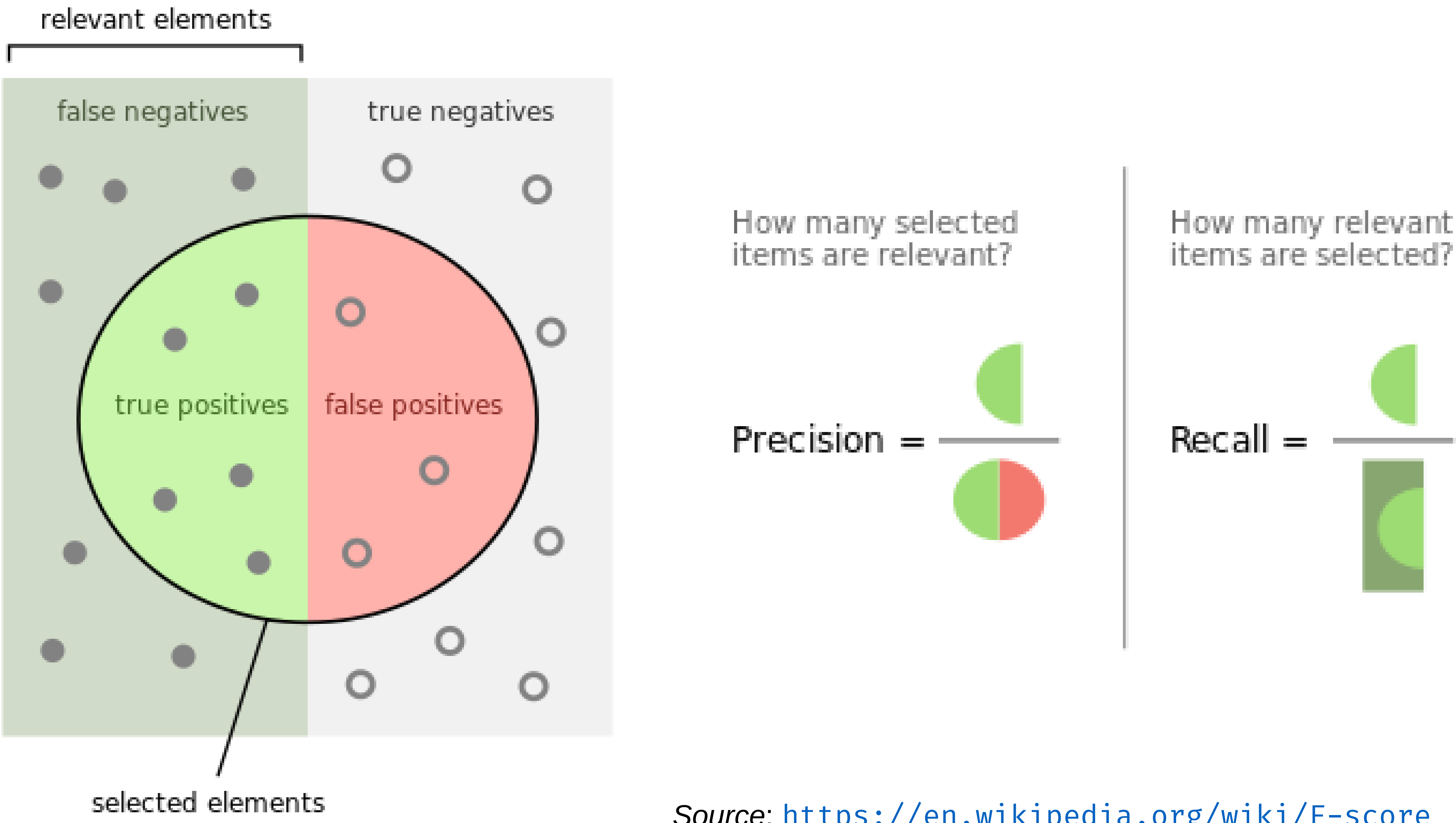
Accuracy

- Accuracy is a valid choice of evaluation for classification problems which are well balanced and not skewed.

Precision and recall

- **Precision**: % of selected items that are correct
  Recall: % of correct items that are selected

- Precision is a valid choice of evaluation metric when we want to be very sure of our prediction.
- Recall is a valid choice of evaluation metric when we want to capture as many positives as possible.



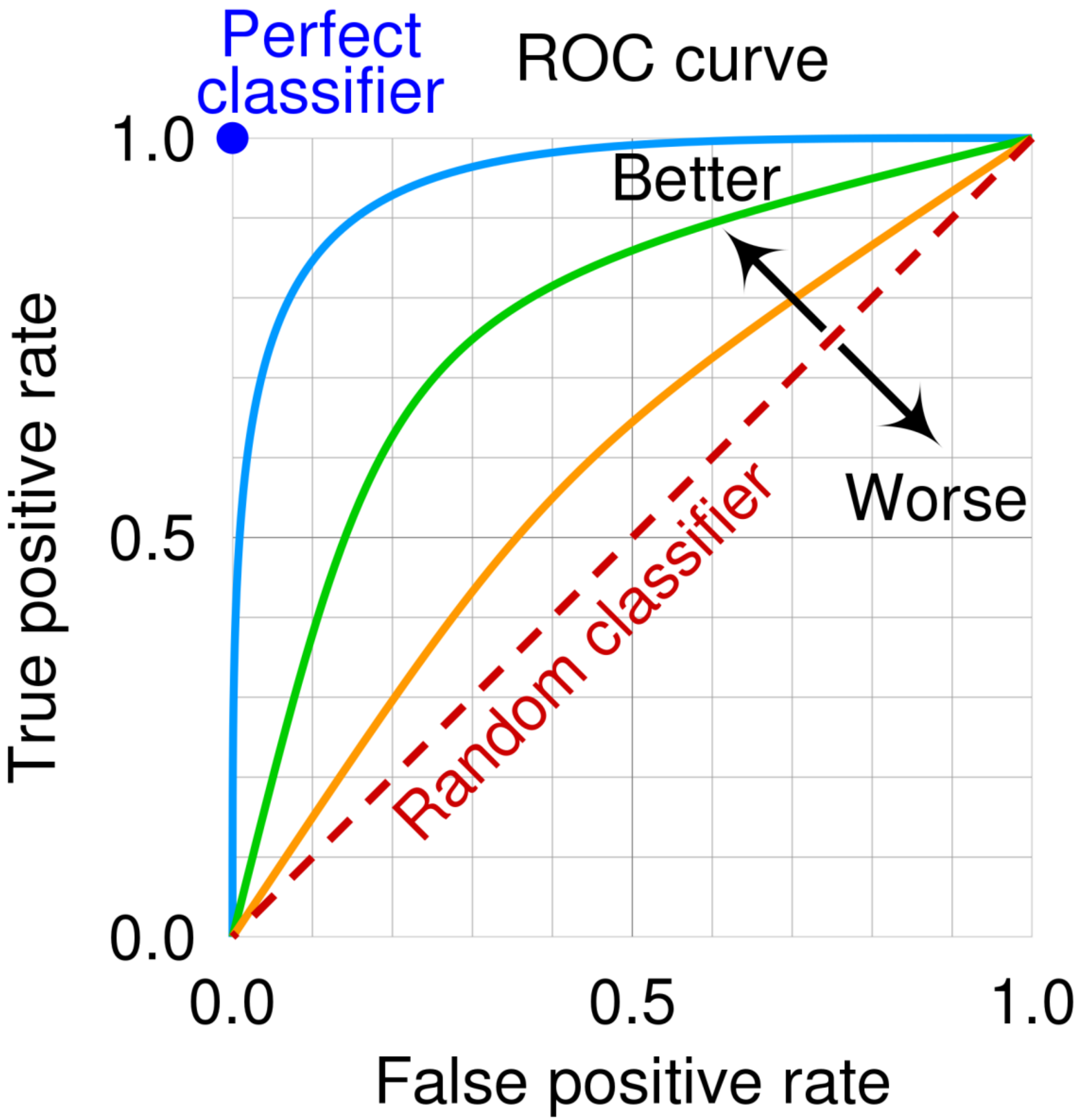
Source: https://en.wikipedia.org/wiki/F-score

A combined measure: F

- A combined measure that assesses the P/R tradeoff is F measure (weighted harmonic mean):

$$F = \frac{1}{a\frac{1}{P} + (1 - a)\frac{1}{R}} = \frac{(b^2 + 1)PR}{b^2 P + R}$$

- The harmonic mean is a very conservative average
- People usually use balanced F1 measure
  - i.e., with $\beta = 1$ (that is, $\alpha = ½$): $F = 2PR/(P+R)$



Perfect classifier
ROC curve
1.0
Better
Worse
0.5
Random classifier
0.0
0.0
0.5
1.0
True positive rate
False positive rate

Practical

Text classification of BBC news articles.

Questions?