Classification

JELENA JOVANOVIĆ

Email: jeljov@gmail.com

Web: http://jelenajovanovic.net

OUTLINE

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- Binary and multiclass classification
- Classification algorithms
- Naïve Bayes (NB) algorithm
  - Bayes rule
  - Text classification with the NB algorithm
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- Performance measures for classifier

What is classification?

- A supervised learning task of determining the class of an instance; it is assumed that:
  - feature values for the given instance are known
  - the set of possible classes is known and given
- Classes are given as nominal values; for instance:
  - classification of email messages: spam, not-spam
  - classification of news articles: politics, sport, culture i sl.

BINARY AND MULTICLASS CLASSIFICATION

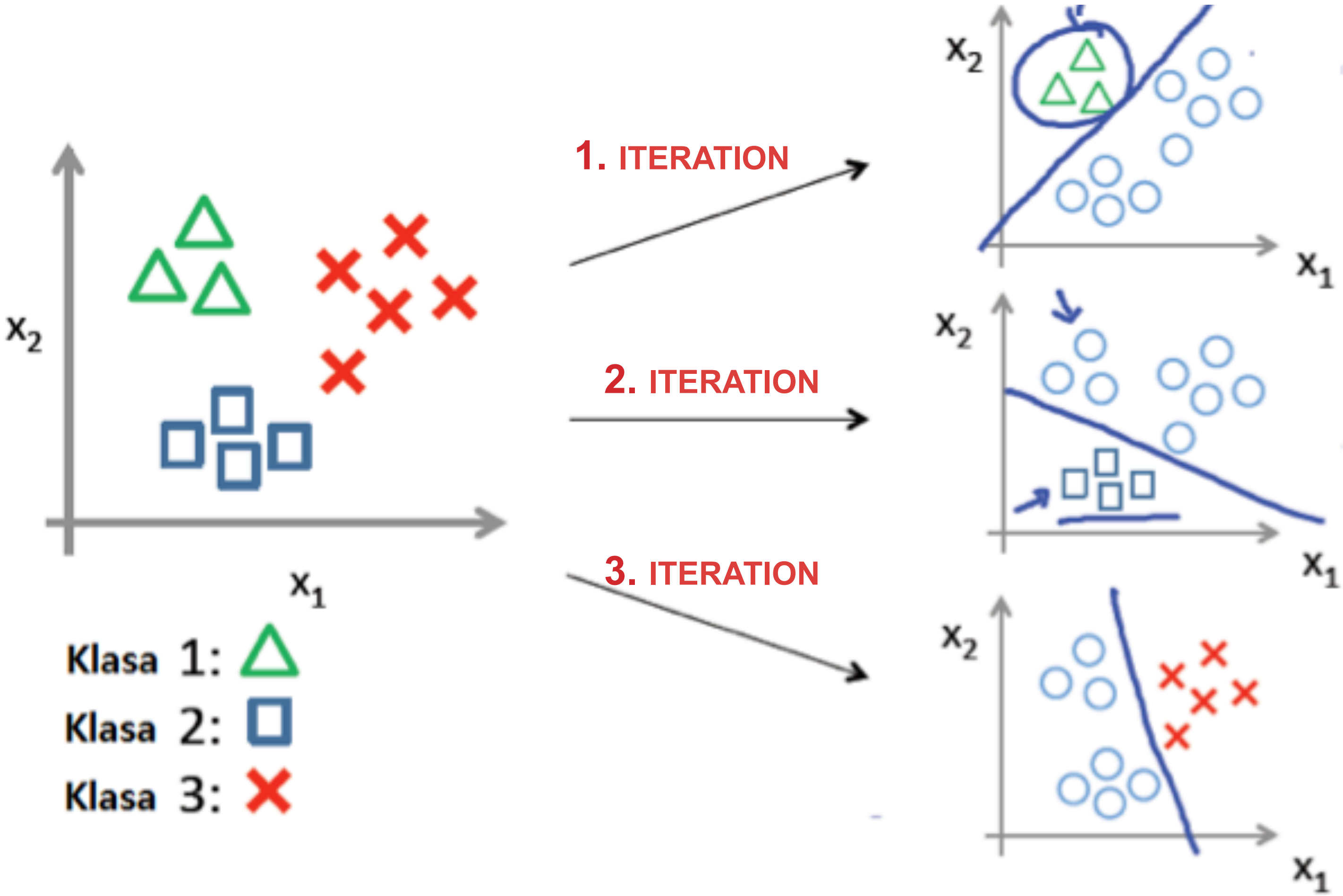
Based on the number of classes, classification can be:

- *binary* – instances should be classified into 2 classes
- *multiclass* – more than 2 classes are used for classifying instances

In both cases, a classifier works in a rather similar manner:

In multiclass classification, the classifier learns iteratively, so that in each iteration, it learns to differentiate instances of one class from all the other instances

MULTICLASS CLASSIFICATION



Source: https://www.coursera.org/course/ml

CLASSIFICATION ALGORITHMS

There are numerous classification models/algorithms:

- Logistic regression
- Naïve Bayes
- Algorithms from the Decision trees family
- Algorithms from the Neural networks family
- k-Nearest Neighbor (kNN)
- Support Vector Machines (SVN)
- …

NAÏVE BAYES

Why Naïve Bayes?

Naïve Bayes (NB) is often cited as an algorithm that is among the first to be considered for any classification task

Rationale:

- Simplicity
- Good performance
- High scalability
- Adaptable to almost any kind of classification task

Occam's Razor:
"Other things being equal, simple theories are preferable to complex ones"

To recall: Bayes rule

$$P(H|E) = P(E|H) * P(H) / P(E)$$

- H – hypothesis
- E – evidence related to the hypothesis H, i.e., the data to be used for validating (accepting/rejecting) the hypothesis H
- P (H) – probability of the hypothesis (*prior probability*)
- P (E) – probability of the evidence i.e., the state of the world described by the gathered data
- P (E | H) – (conditional) probability of evidence E given that the hypothesis H holds
- P (H | E) – (conditional) probability of the hypothesis H given the evidence E

Bayes Rule – An Example

Let us suppose the following:

- one morning, you wake up with a high temperature
- the previous day, you heard that some virus infection had started spreading through the city, though the infection rate was still rather low, namely 2.5%
- you've also heard that in 50% of cases, the virus went with a high temperature
- you typically have a high temperature only a couple of times over a year, so the probability that you have a high temp. is 6.5%

Question: what is the probability that, since you have a high temperature, you've caught the virus?

Bayes rule

Theory	Example
Hypothesis (H)	One has caught a virus infection
P(H)	0.025
Evidence (E)	One has a high temperature
P(E)	0.065
(conditional) probability of E given H P(E|H)	Probability that the virus infection causes high temperature 0.50
(conditional) probability of H given E: P(H|E)	Probability that given one has a high temperature, he/she also has the virus ?

$$P(H|E) = P(E|H) * P(H) / P(E)$$

$$P(H|E) = 0.50 * 0.025 / 0.065 = 0.19$$

Naïve Bayes in text classification

NB is one of the most frequently used algorithms for text classification

Text classification task: for the given text, determine its class, based on the given (annotated) training set

Examples:

- topical classification of news articles, or
- classification of tweets based on the expressed opinion

Features (attributes) the algorithm relies upon are words from the given text

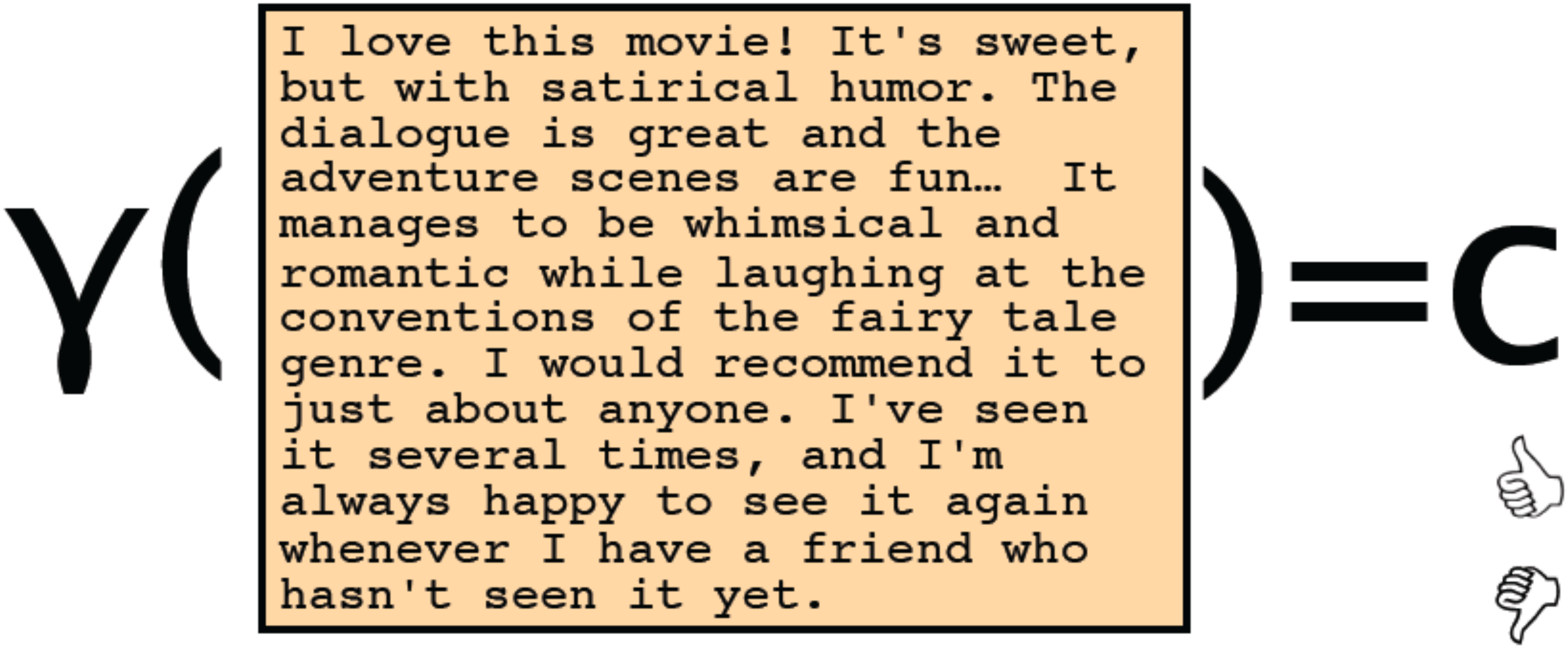
- the text to be classified is represented as a simple bag-of-words

Feature vector formation

There are different approaches for defining a feature vector for the given piece of text; the approach that is often cited as the best one:

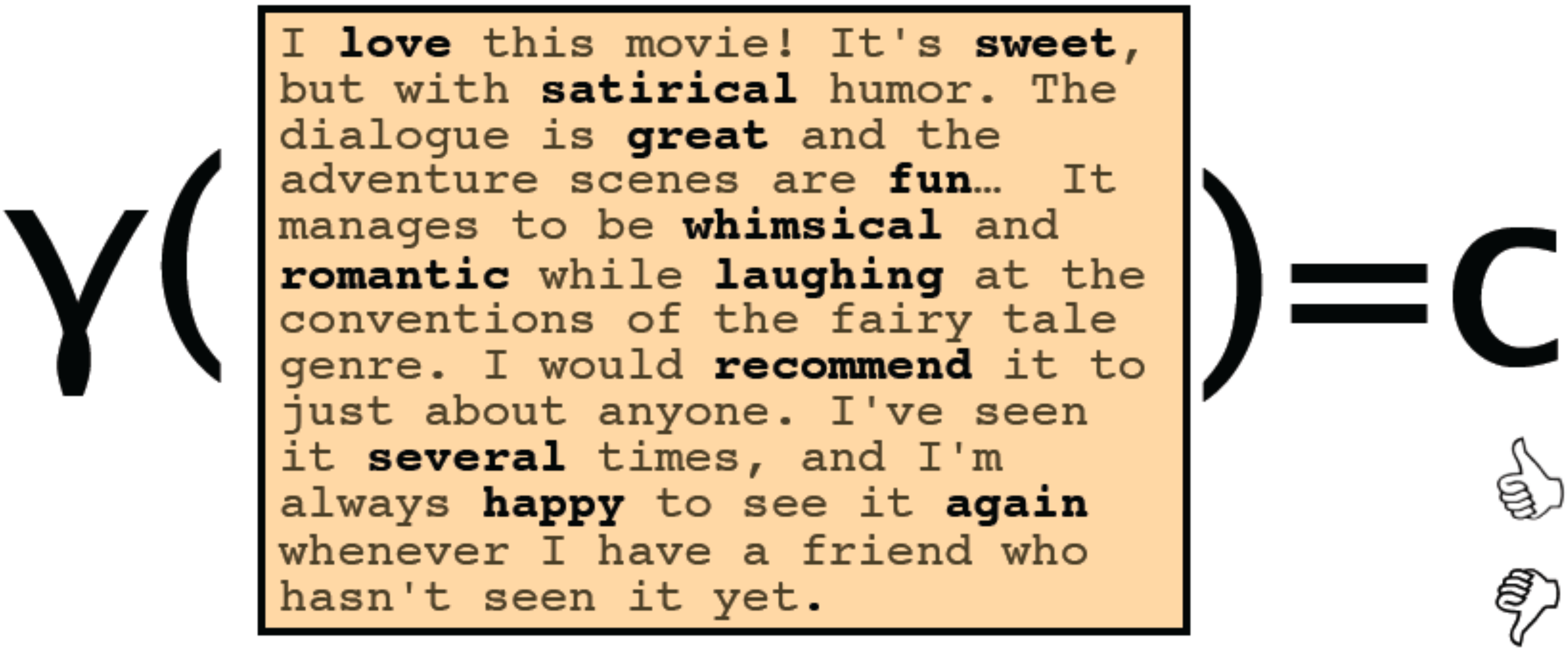
- Create a *Dictionary* by extracting words from documents that form the training set (*Corpus*);
- For each document ***d*** from the *Corpus,* define a feature vector by using words from ***d***:
  - For each word $\boldsymbol{w_i}$ from document ***d****,* introduce a feature $\boldsymbol{x_i}$ with the value equal to the index of the word $\boldsymbol{w_i}$ in the *Dictionary*;
  - Features can be created for all the words from the document ***d*** or only for those words that are considered relevant for the given classification task

Feature vector formation – An example



Source: http://www.stanford.edu/class/cs124/lec/naivebayes.pdf

FEATURE VECTOR FORMATION – AN EXAMPLE



Source: http://www.stanford.edu/class/cs124/lec/naivebayes.pdf

Feature vector formation – An example

$Y($

words (w_i)	features (x_i)
w_1 = love	x_1 = 04567
w_2 = sweet	x_2 = 14321
w_3 = satirical	x_3 = 14007
…	
w_{11} = happy	x_{11} = 02364
w_{12} = again	x_{12} = 00012

$) = C$

Index of the word ***w**ᵢ* in the *Dictionary*

NB IN TEXT CLASSIFICATION

If there is a class ***c*** and a document ***d***, the probability that ***c*** is the class of the document ***d*** is given as:

$$P\,(c|d) = P(d|c) * P(c) \,/\, P(d) \qquad (1)$$

For the given set of classes ***C*** and the document ***d***, we want to find the class ***c***, from the set ***C***, with the highest conditional probability for the document ***d***; this leads to the function:

$$f = \mathrm{argmax}_{c \text{ iz } C}\, P(c|d) \qquad (2)$$

By applying the Bayes rule, we get:

$$f = \mathrm{argmax}_{c \text{ iz } C}\, P(d|c) * P(c) \qquad (3)$$

NB IN TEXT CLASSIFICATION

$$f = \text{argmax}_{c \text{ iz } C} P(d|c) * P(c) \qquad (3)$$

Now, we need to *estimate* the probabilities P(c) and P(d|c)

P(c) can be computed rather easily: by counting the number of occurrences of the class ***c*** in the training set (*Corpus*)

P(d|c) – probability that in the class ***c*** one “finds” the document ***d*** – not that easy to determine, so we introduce assumptions for which this algorithm got the epithet “naïve”

NB IN TEXT CLASSIFICATION

How do we determine P(d|c)?

- we represent document ***d*** as a feature vector $(x_1, x_2, ..., x_n)$
- so, instead of P(d|c), we'll have $P(x_1, x_2, x_3, ...x_n|c)$
- to compute $P(x_1, x_2, x_3, ...x_n|c)$, we introduce 2 naïve assumptions:
  - document ***d*** is treated as a simple bag-of-words; i.e., the position and order of words in the text are considered unimportant
  - the presence of a certain word in the given class ***c*** is independent of the presence of any other word in the same class

NB IN TEXT CLASSIFICATION

The introduced assumptions

- lead to a significant loss of information that could have been derived from the data, *but*,
- simplify the computation of $P(x_1, x_2, ..., x_n|c)$, and thus simplify the overall classification task

NB IN TEXT CLASSIFICATION

Based on the introduced assumptions, $P(x_1, x_2,\ldots,x_n | c)$ can be represented as a product of individual conditional probabilities

$$P(x_1, x_2,\ldots,x_n | c) = P(x_1|c) * P(x_2|c) * \ldots * P(x_n|c)$$

Thus, we arrive to the general equation of the NB algorithm:

$$f = \text{argmax}_{c \text{ iz } C}\ P(c) * \prod_{i=1,n} P(x_i|c)$$

NB IN TEXT CLASSIFICATION

The probabilities are estimated on the training set, based on the following equations:

$P(c)$ = # docs of the class ***c*** / total # docs in the training set

$P(x_i|c)$ = # occurrences of the word $\boldsymbol{w_i}$ in docs of the class ***c*** / total # words from the Dictionary that are in docs of the class ***c***

means "number of"

Characteristics of the NB algorithm

- Very fast and efficient
- Often produces good results
  - often turns out to be better or at least equally good as other, more sophisticated algorithms
- Does not require much memory
- Has low affinity for over-fitting
- Suitable when we do not have much training data

Characteristics of the NB algorithm

- "Resistant" to the low-importance attributes
  - attributes that are equally distributed through the overall training set, and thus do not have significant impact on the class label
- Primarily suitable for use with nominal attributes; in the case of numerical attributes
  - Discretize the attribute values, or
  - Use probability distribution of the attributes (typically, Normal dist.) to estimate the probability of each attribute value

Applying the NB algorithm for text classification using the WEKA framework: an example

PRIMER PRIMENE NB ALGORITMA KORIŠĆENJEM WEKA FRAMEWORK-A

Primer je preuzet iz GitHub projekta TMWeka:

https://github.com/jmgomezh/tmweka

i raspoloživ je na sledećoj adresi:
https://github.com/jmgomezh/tmweka/tree/master/FilteredClassifier

U okviru TMWeka projekta, ima jos nekoliko interesantnih primera klasifikacije teksta primenom ML algoritama

PERFORMANCE MEASURES

The most frequently used metrics:

- Confusion Matrix
- Accuracy
- Precision and Recall
- F measure
- Area Under the ROC Curve

Confusion Matrix

Serves as the basis for calculating other performance measures

		Predicted Class	
		Yes	No
Actual Class	Yes	TP	FN
	No	FP	TN

TP = True Positive

FP = False Positive

TN = True Negative

FN = False Negative

ACCURACY

Accuracy is the percentage of correctly classified instances

Accuracy = (TP + TN) / N

where:

- TP – True Positive; TN – True Negative
- N – the total number of instances in the dataset

		Predicted Class	
		Yes	No
Actual Class	Yes	TP	FN
	No	FP	TN

ACCURACY

In the case of highly unequal distribution of instances across classes (so called skewed classes), this measure is unreliable

An example:

- in the case of message classification as spam vs. not-spam, the training set might contain 0.5% of spam messages
- if we apply a biased classifier that classifies each message as not-spam, we get very high accuracy – 99.5%
- obviously, this metric is unreliable and in the case of skewed classes, other metrics are needed

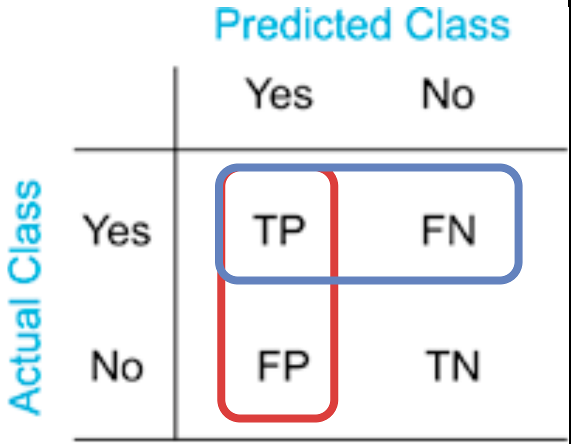
Precision and Recall

Precision = TP / # predicted positive = TP / (TP + FP)

Example: out of all the messages *marked as spam*, the percentage of those that are *really spam* messages

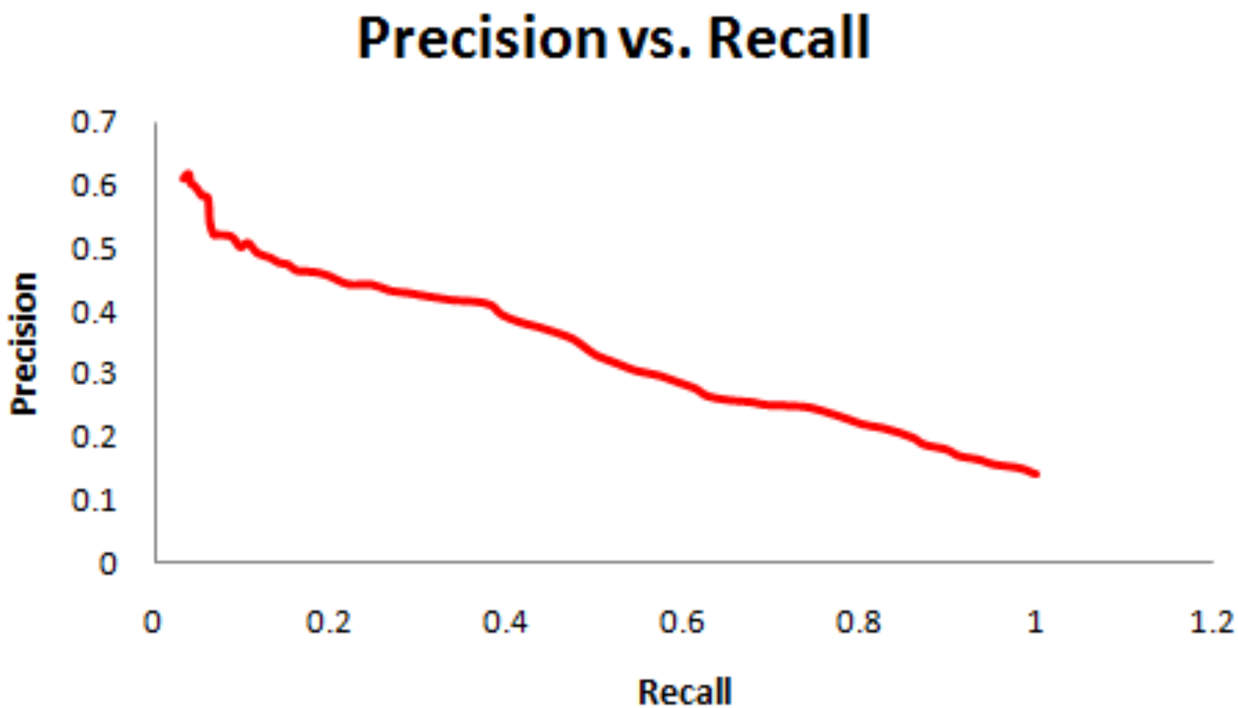
Recall = TP / # actual positive = TP/ (TP + FN)

Example: out of all the messages that are *really spam*, the percentage of those that have been *detected/classified as spam*



Precision vs. Recall

In practice, one always needs to make a compromise between these two metrics: by increasing Recall, we decrease (though unwillingly) Precision, and vice versa



Source:
http://groups.csail.mit.edu/cb/struct2net/webserver/images/prec-v-recall-v2.png

F MEASURE

F measure combines Precision and Recall and allows for easier comparison of two or more algorithms

$$F = (1 + \beta^2) * Precision * Recall / (\beta^2 * Precision + Recall)$$

Parameter β controls the extent to which we want to favor Recall over Precision

In practice, F1 measure is typically used; it is called “balanced“ F measure as it equally weights Precision and Recall:

$$F1 = 2 * Precision * Recall / (Precision + Recall)$$

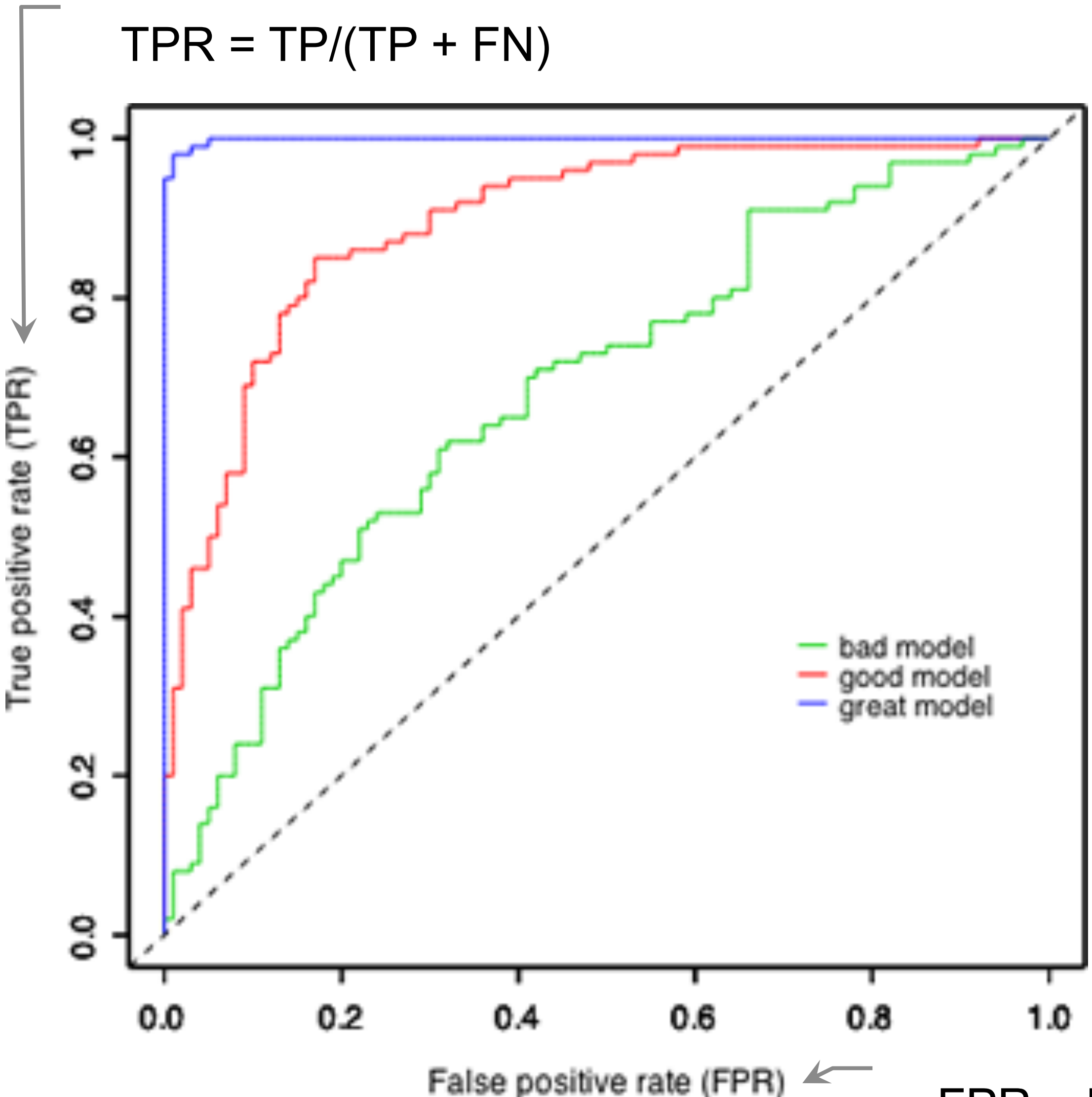
Area Under the ROC* Curve (AUC)

- It measures discriminatory power of a classifier, i.e., its ability to correctly differentiate instances of different classes
- It is used for measuring performance of binary classifiers
- It takes values from the 0-1 interval
- In the case of random classification, AUC = 0.5; so, as the AUC value is greater than 0.5, the classifier is better
  - 0.7–0.8 is considered fair; 0.8–0.9 good; > 0.9 excellent

*ROC = Receiver Operating Characteristic;
http://en.wikipedia.org/wiki/Receiver_operating_characteristic

AREA UNDER THE ROC* CURVE

TPR = TP/(TP + FN)



FPR = FP/(FP + TN)

Source: http://goo.gl/Aeauuh

ACKNOWLEDGEMENTS AND RECOMMENDATIONS

Acknowledgements and Recommendations

Machine Learning @ Stanford

- Coursera: https://www.coursera.org/course/ml
- Stanford YouTube channel:
  http://www.youtube.com/view_play_list?p=A89DCFA6ADACE599

Machine Learning @ Carnegie Melon University

- Lectures by Andrew W. Moore, especially, the lecture on Bayes Rule and Bayes Classifiers:
  http://www.autonlab.org/tutorials/prob_and_naive_bayes.pdf

Recommendations

Data Stories podcasts

- http://datastori.es/
- especially podcast #27 on Big Data Skepticism
- the Cambridge study mentioned in podcast #27 – using FB Likes to determine people's demographic traits: http://www.pnas.org/content/early/2013/03/06/1218772110.full.pdf

(Anonymous) questionnaire for your critiques, comments, suggestions:

http://goo.gl/cqdp3I