Concepts of Text Classification

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Introduction (1/4)

Text classification is the task of assigning a textual object (e.g., a document) to a class.

Is not new … we are dealing with text classification every day.

- Every morning, you wake up …
  - Examine the GF/BF messages you missed last night to know if she/he is happy
  - Check emails and move them to different categories
  - Reading finance news to predict up or down of stock market

In these cases … **you are a classifier**.

- **Trained** by all the emails, messages, news you've read and experienced.

Introduction (2/4)

If we can do classification on our own **WHY SHOULD WE LEARN THIS TOPIC?**

You may not be a good classifier …

- You probably mis-classified a lot of your GF/BF's messages.
- You definitely cannot handle too many texts.
  - Say that more that 500 finance new articles per day.

Hence, we need an agent (classification model) to do classification

Introduction (3/4)

Classification is a **classic** data mining problem, and can be applied to various data and domains:

- Images – image classification
- Human Resource records – churn prediction
- Atmosphere data – weather forecast

Here, we focus on **text** classification which is applicable to different business tasks:

- Customer service message – knowing which service
- Product reviews – sentiment analysis (positive or negative)

Introduction (4/4)

Here, we first introduce the basis of text classification.

- Definition, procedure of model construction, evaluation, and so on.

Then, we learn and **PRACTICE** well-known classification methods:

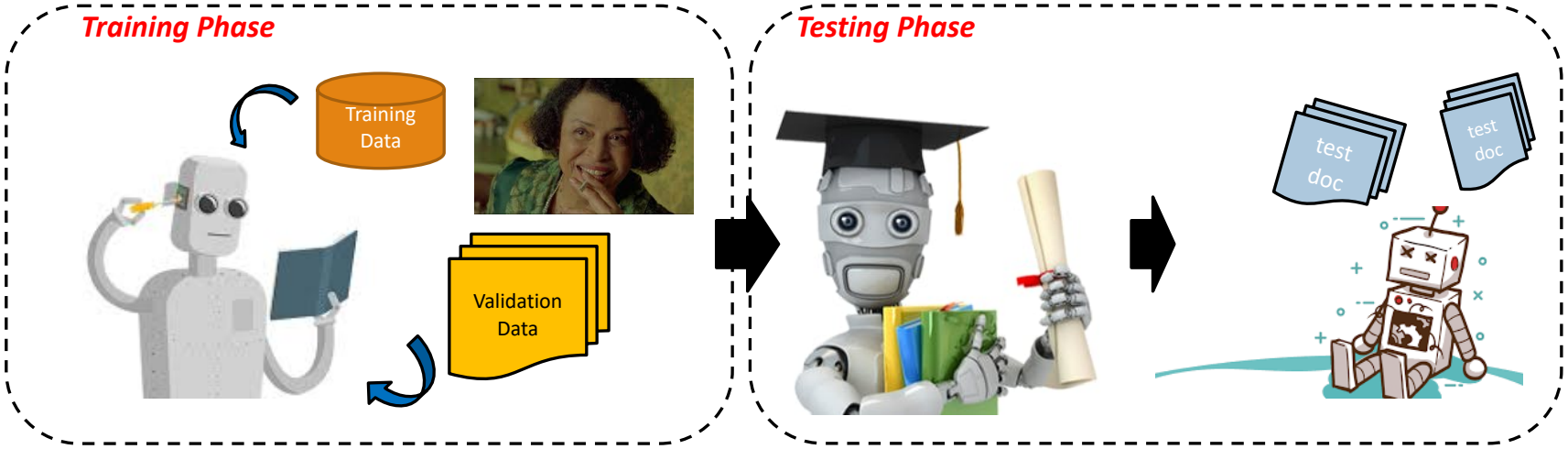
- Naïve Bayes method
- Rocchio method
- K nearest neighbor
- Support vector machine

Definition (1/2)

Text classification is a type of **supervised learning**.

- A **supervisor** (oracle) serves as a **teacher** directing the learning process.
  - Defining the classes and labeling training documents.

Consist of two phases:



Definition (2/2)

Definition:

- **Document space *X***:
  - High-dimensional space.
  - Dimensions – terms.
- **Classes *C***:
  - Also called *categories* or *labels*.
  - $C = \{c_1, c_2, \ldots, c_J\}$.
  - **A fixed set**, defined by human experts for the needs of an application.
  - E.g., C = {positive, negative,}.
- **Training set *D***:
  - $D = \{\langle d, c\rangle\}$, where $\langle d, c\rangle \in X \times C$.
  - E.g., $\langle d, c\rangle$ = <'I don't like the room service …', negative>

Training Phase

A ***learning algorithm*** ***Γ*** is adopted to learn a ***classifier*** (classification model) γ from the **training data** *D*.

- The learning method *Γ* takes the training set *D* as input and return the learned classifier γ.
- Mathematically, $\Gamma(D) = \gamma$

Γ can be *Naïve Bayes method*, *SVM algorithm, KNN …*

different learning algorithms
different classification behavior

Testing Phase (1/2)

Once we obtain an **appropriate** classifier γ, we apply it to new document and predict the document's class

- Mathematically, the classifier γ acts a function that $\gamma: X \rightarrow C$

In many cases, we also need to report the performance of the classifier.

- In addition to training data, we need **test data** to evaluate model performance.

Testing Phase (2/2)

Test set (or test data)

- Evaluate a model's performance.
- Chosen **independently** of the training data!!
  - To know how good (generalized) the classifier is, when dealing with **unseen** data.
- Otherwise, classification performance is **overestimated**

Remember … when starting to train/test with labeled data

- Always separate data into a training portion and a testing portion.
- The testing data is normally a small percentage (5~10%) of the total data.

Validation Phase (1/2)

Sometimes, **parameter tuning** is required if there are model parameters.

- Classification performance depends on parameter settings.
- E.g., assign (classify) a document to a category against a **similarity threshold**.

IT IS WRONG to tune model parameters to maximize performance on the test data!!

- This way, again, performance of the model is overestimated.

We require one data set called ***validation set*** (or development test collection).

- Tune model parameters against the validation dataset.
- And report the performance results on the test dataset in an unbiased manner.

Validation Phase (2/2)

The validation data needs to be **independent** of both the training data and the testing data.

- Normally, we collect 10% of the training data to form the validation data.
- Again, to keep training data as big as possible!!

In practice … once the evaluation process is done, the validation and testing data can be bundled back into the training data to produce a new model.

- To maximize the amount of data used to generate models.

K-Fold Cross Validation (1/3)

The amount of data that can be used for training and testing is limited.

- So, it is possible that the sample used for training (or testing) may not be representative!!

K-fold cross-validation:

- A frequently-used approach to obtain reliable performance results.
- Decide on a fixed number (i.e., *k*) of ***folds*** and **randomly** split the data into **approximately equal partitions**.
- Each partition **in turn** is used for testing while the remainder is used for training.
  - Every labeled instance has been used exactly once for testing.
- *K* is 10, usually.

K-Fold Cross Validation (2/3)

Note that sometimes people use *K*-fold cross validation for **parameter tuning**.

First, split data into training and testing portions.

Training:

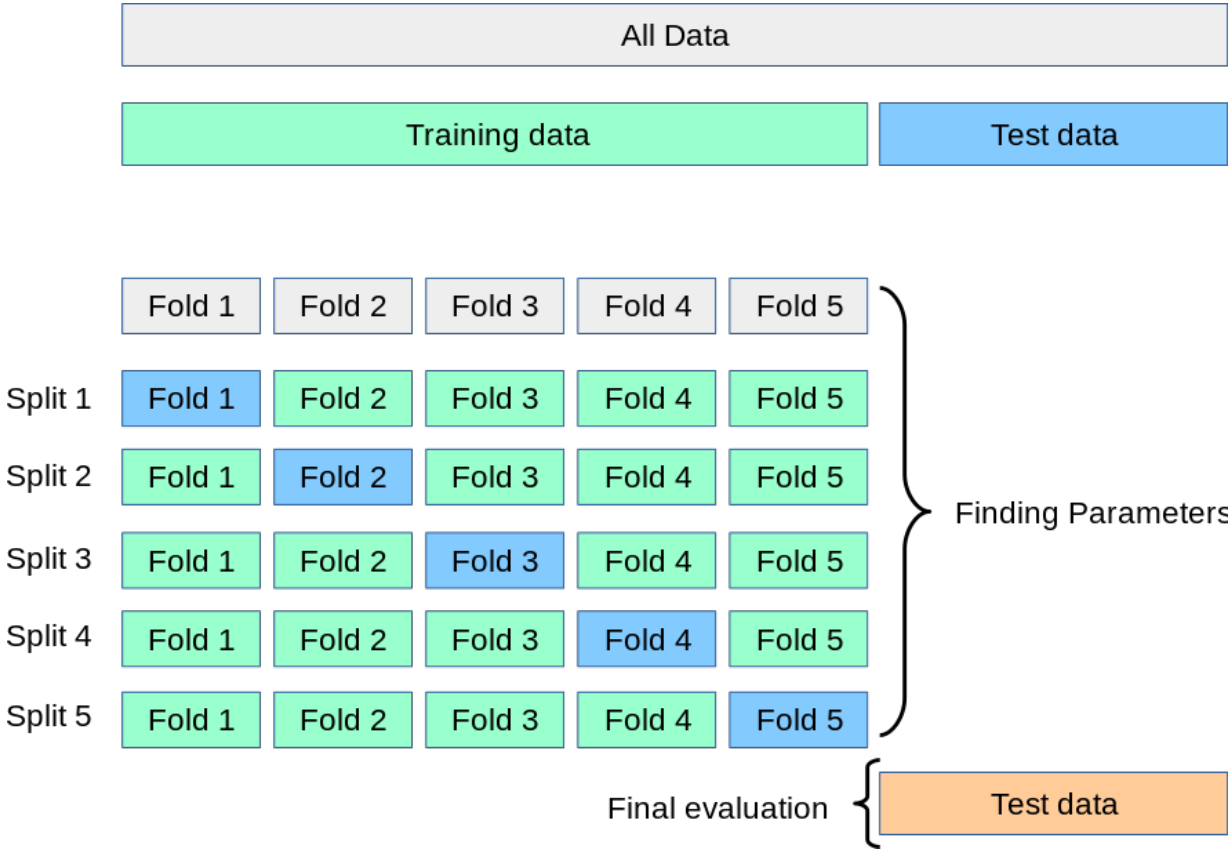
- Divide **training data** into *K* folds.
- For each parameter setting, average the K-fold validation results.
- Compare the performances of different settings to determine the final parameter values.
- Re-train the model using the whole training data and the parameter values.

Testing:

- Apply the new model to the testing data and report the final performance result.

The computation cost of this procedure is very very very high …

K-Fold Cross Validation (3/3)



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

Performance Metrics (1/12)

Three important metrics: **precision, recall, and F1**

	class 1	
	truth yes	truth no
model yes	# of true positives (tp)	# of false positives (fp)
model no	# of false negatives (fn)	# of true negatives (tn)

- Precision = tp / (tp+fp)
- Recall = tp / (tp+fn)

Example:

	class 1	
	truth yes	truth no
model yes	15	5
model no	10	970

- Precision: 15/20 = 0.75
- Recall : 15/25 = 0.6

Performance Metrics (2/12)

Different circumstances prefer different metrics:

- High precision: classify spam mails.
- High recall: Identify negative reviews about a certain product.

Generally, precision and recall trade off against one another.

- That makes model comparisons harder!!
- Is that fair to say “my precision is better than your recall”??

To compare models in a fair manner, we need to average them into a single value.

- F_1 – the **harmonic mean** of precision and recall

Performance Metrics (3/12)

$$F_1 = \frac{1}{(0.5\frac{1}{P} + 0.5\frac{1}{R})}$$

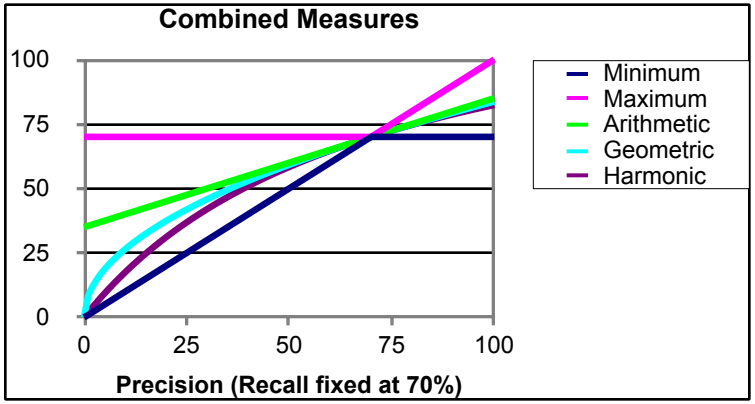
$$= \frac{2PR}{(P+R)}$$

Why F_1 measure?

- F1 is a **conservative** approach, and consider the two measures.

Note that precision, recall, and F1 are all between 0 and 1.

- The higher the better.



The F_1 measure is often quite **close to the minimum** of the two numbers.

Performance Metrics (4/12)

In data mining, one popular metrics is **accuracy**

- accuracy = (tp + tn) / (tp+fp+fn+tn)

	class 1	
	truth yes	truth no
model yes	# of true positives (tp)	# of false positives (fp)
model no	# of false negatives (fn)	# of true negatives (tn)

Accuracy sometimes is **not** a good metrics if data is so skew…

- E.g. classifying spam mail.

	class 1	
	truth yes	truth no
model yes	0	0
model no	25	975

- In this case, the accuracy of the mode is:

  (975) / (0+0+25+975) = **0.975**

- A model that always says no can achieve 0.975 accuracy rate!!

Performance Metrics (5/12)

Classification decisions are usually with a score.

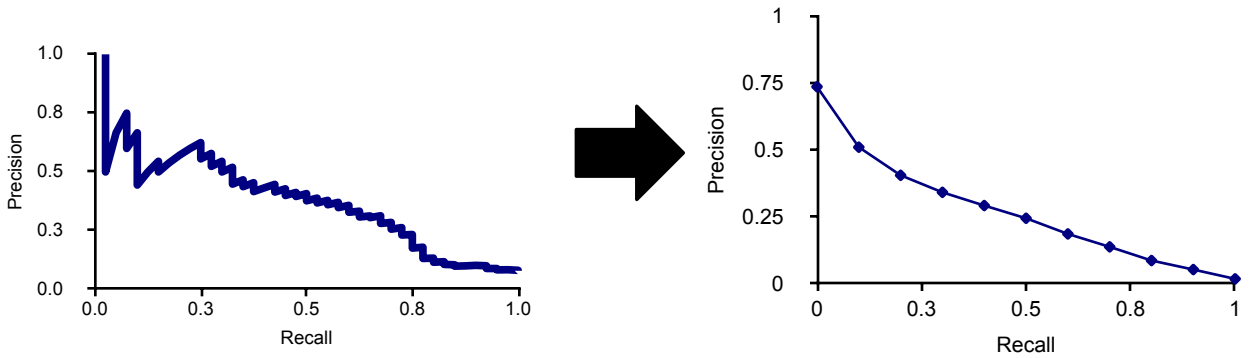
- For instance, Naïve Bayes classification model predicts the probability that a document belongs to a class.

Performance curves can be plotted by ranking the classification decisions according to their scores.

- ***Precision-recall curves***
- ***ROC curves***

Performance Metrics (6/12)

Precision-recall curve



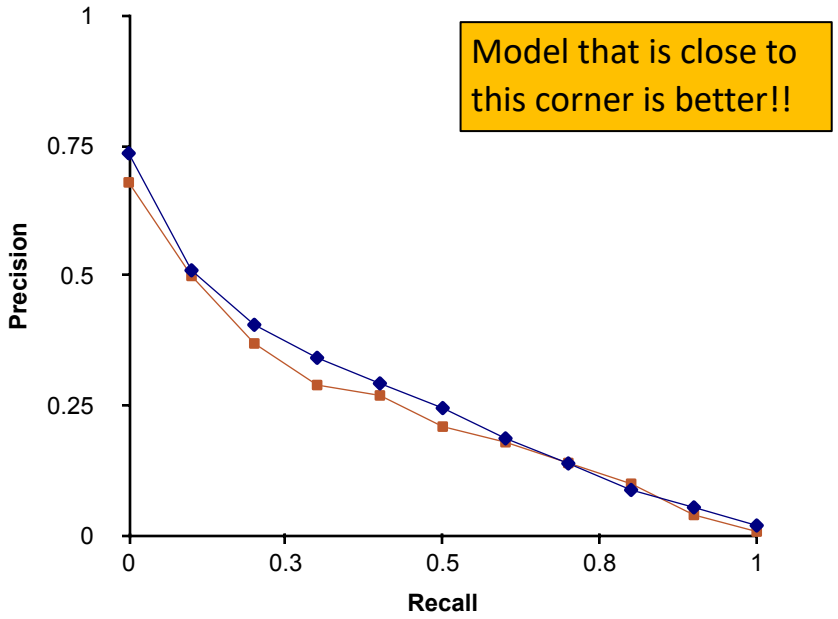
- Often have a saw-tooth shape, and hard to read (compare).

11-point (interpolated average) precision-recall curve:

- The interpolated precision is measured at the 11 recall levels of 0.0, 0.1, 0.2, …, 1.0.
- For each recall level, **arithmetic mean** of the interpolated precision is calculated.

Performance Metrics (7/12)

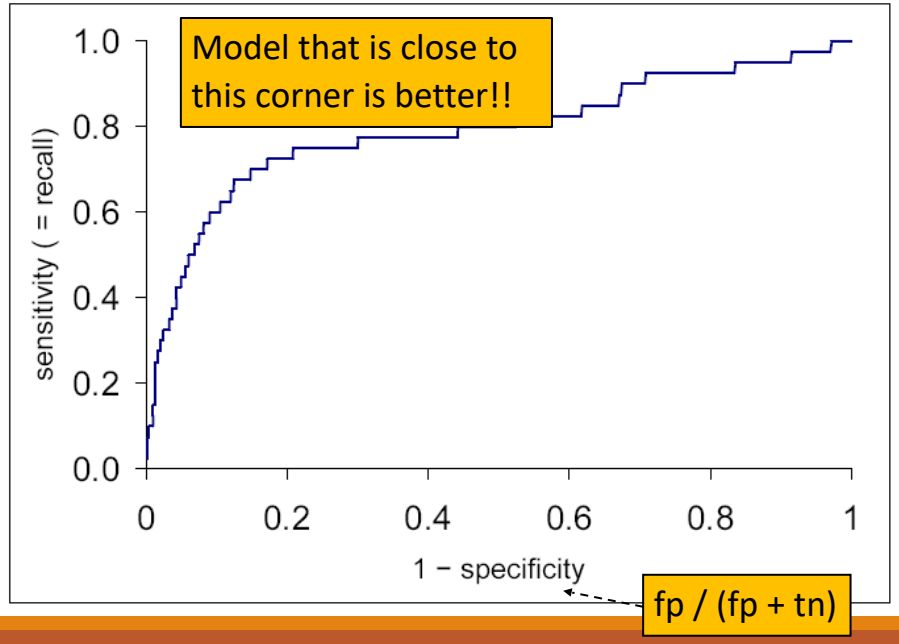
11-point precision-recall curve is useful to model comparisons



Performance Metrics (8/12)

ROC curve:

- Plot the true positive rate (recall) against the false positive rate.
- **AUC** (Area Under the Curve) is also a measure for model comparisons
  - The range is [0, 1]



Performance Metrics (9/12)

Multi-class classification:

- Many text classification tasks are multi-class.
  - E.g., news documents classification – sports, entertainment, stock, …

Confusion Matrix: a tool for analyzing a classification model under multi-class classification problems.

true class \ assigned class	*money-fx*	*trade*	*interest*	*wheat*	*corn*	*grain*
money-fx	95	0	10	0	0	0
trade	1	1	90	0	1	0
interest	13	0	0	0	0	0
wheat	0	0	1	34	3	7
corn	1	0	2	13	26	5
grain	0	0	2	14	5	10

Indicate how many documents from c_x were **incorrectly** assigned to c_y.

Help know the strength/weakness of a model

Performance Metrics (10/12)

For model comparisons, we often want to compute a single score the combines the results of different classes.

Two kinds of average for doing this:

- ***Macro-averaging***:
  - Compute a simple average over classes.
  - E.g., $precision_{avg} = 1/m\ (precision_1 + precision_2 + \ldots + precision_m)$.

- ***Micro-averaging***:
  - First aggregation the decisions across classes.
  - Then compute a measure on the pooled contingency table.

Performance Metrics (11/12)

Example:

	class 1	
	truth yes	truth no
model yes	10	10
model no	10	970

Precision: 0.5
Recall: 0.5

	class 2	
	truth yes	truth no
call yes	90	10
call no	10	890

Precision: 0.9
Recall: 0.9

Macro-averaging precision: (0.5+0.9)/2=0.7
Macro-averaging recall: (0.5+0.9)/2=0.7

Micro-averaging precision: 100/(100+20)=0.833
Micro-averaging recall: 100/(100+20)=0.833

	pooled table	
	truth yes	truth no
call yes	100	20
call no	20	1860

Performance Metrics (12/12)

The differences between micro and macro can be large!!

In micro-averaging, large classes usually dominate small classes.

- For example, the micro-averaging precision of the last example is 0.833, much closer to the precision of class 2.

To get a sense of effectiveness on small classes, you should compute macro-averaged results.

One/Any-of Classification (1/2)

Classification involved more than two classes can be **one-of** or **any-of**!!

Any-of classification – a document can belong to several classes, a single class, or none!!

- Training:
  - Build a two-class classifier γ_j **for each class** c_j, that returns either c_j or $not\text{-}c_j$.
  - Training set consists of the set of documents in c (positive) and its complement (negative).
- Testing:
  - Given the test document, apply each classifier separately.

One/Any-of Classification (2/2)

One-of classification – a document must belong to **exactly one** of the classes.

Many classification models can handle multi-class problem directly.

Some classification methods can only produce binary classifiers.

- Training:
  - Build a classifier for each class.
  - The training set consists of the set of documents in the class (positive) and its complement (negative).
- Testing:
  - Apply the test document to each classifier separately.
  - Assign the document to the class with the maximum score.