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Text Technologies for Data Science

INFR11145

Text Classification

Instructor:
Björn Ross

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Pre-Lecture

- Today
  - Lecture 1 (Text classification): Theory
  - Coursework 2 overview
  - Lecture 2 (Text classification): Practical

Lecture Objectives

- Learn about text basics of text classification
  - Definition
  - Types
  - Methods
  - Evaluation

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Text Classification

- **Text classification** is the process of classifying documents into predefined categories based on their content.

- Input: Text (document, article, sentence)
- Task: Classify into predefined one/multiple categories
- Categories:
  - Binary: relevant/irrelevant, spam .. etc.
  - Few: sports/politics/comedy/technology
  - Hierarchical: patents

Classification is and is not

- Classification (a.k.a. "categorization"): a common technology in data science; studied within pattern recognition, statistics, and machine learning.
- Definition:
  the activity of predicting to which among a predefined finite set of groups ("classes", or "categories") a data item belongs to
- Formulated as the task of generating a hypothesis (or "classifier", or "model")

$$h : D \rightarrow C$$

where $D = \{\mathbf{x}_1, \mathbf{x}_2, \ldots\}$ is a domain of data items and
$C = \{c_1, \ldots, c_n\}$ is a finite set of classes (the classification scheme)

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Classification is and is not

- Different from clustering, where the groups ("clusters") and their number are not known in advance
- Unsuitable when class membership can be determined with certainty (relatively easily)
  - e.g., predicting whether a natural number belongs to *Prime* or *Non-Prime* is not classification
- In text classification, data items are
  - **Textual**: e.g., news articles, emails, sentences, queries, etc.
  - **Partly textual**: e.g., Web pages

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Types of Classification

- **Binary**:
  item to be classified into <u>one of two</u> classes
  $h : D \rightarrow C, \;\; C = \{c_1, c_2\}$
  - e.g., Spam/not spam, offensive/not offensive, rel/irrel
- **Single-Label Multi-Class** (SLMC)
  item to be classified into <u>only one of *n*</u> possible classes.
  $h : D \rightarrow C, \;\; C = \{c_1 \ldots . c_n\}$, where n>2
  - e.g., Sports/politics/entertainment, positive/negative/neutral
- **Multi-Label Multi-Class** (MLMC)
  item to be classified into none, one, two, or more classes
  $h : D \rightarrow 2^C, \;\; C = \{c_1 \ldots . c_n\}$, where n>1
  - e.g., Assigning CS articles to classes in the ACM Classification System
  - Usually be solved as *n* independent binary classification problems

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Dimension of Classification

- Text classification may be performed according to several dimensions ("axes") orthogonal to each other
- by topic; by far the most frequent case, its applications are global
- by sentiment; useful in market research, online reputation management, social science and political science
- by language (a.k.a. "language identification"); useful, e.g., in query processing within search engines
- by genre; e.g., AutomotiveNews vs. AutomotiveBlogs, useful in website classification and others;
- by author (a.k.a. "authorship attribution"), by native language ("native language identification"), or by gender; useful in forensics and cybersecurity
- by usefulness; e.g., product reviews
- ……

Rule-based classification

- An old-fashioned way to build text classifiers was via knowledge engineering, i.e., manually building classification rules
  - E.g., (Viagra or Sildenafil or Cialis) → Spam
  - E.g. (#MAGA or America great again) → support Trump
- Common type: dictionary-based classification
- Disadvantages:
  - Expensive to setup and to maintain
  - Depends on few keywords → bad coverage (recall)

Zero-shot classification

- Using machine learning models for classification without giving training examples
  - A modern approach that can work well and requires little human effort
  - Depends highly on black-box models, limited opportunities for customisation and error analysis (but this is an active research area)
  - Often used as a baseline for performance comparisons

You

Consider the following sentence: "I love the book." What sentiment is it? Your reply must be one of the following words: positive, neutral, or negative.

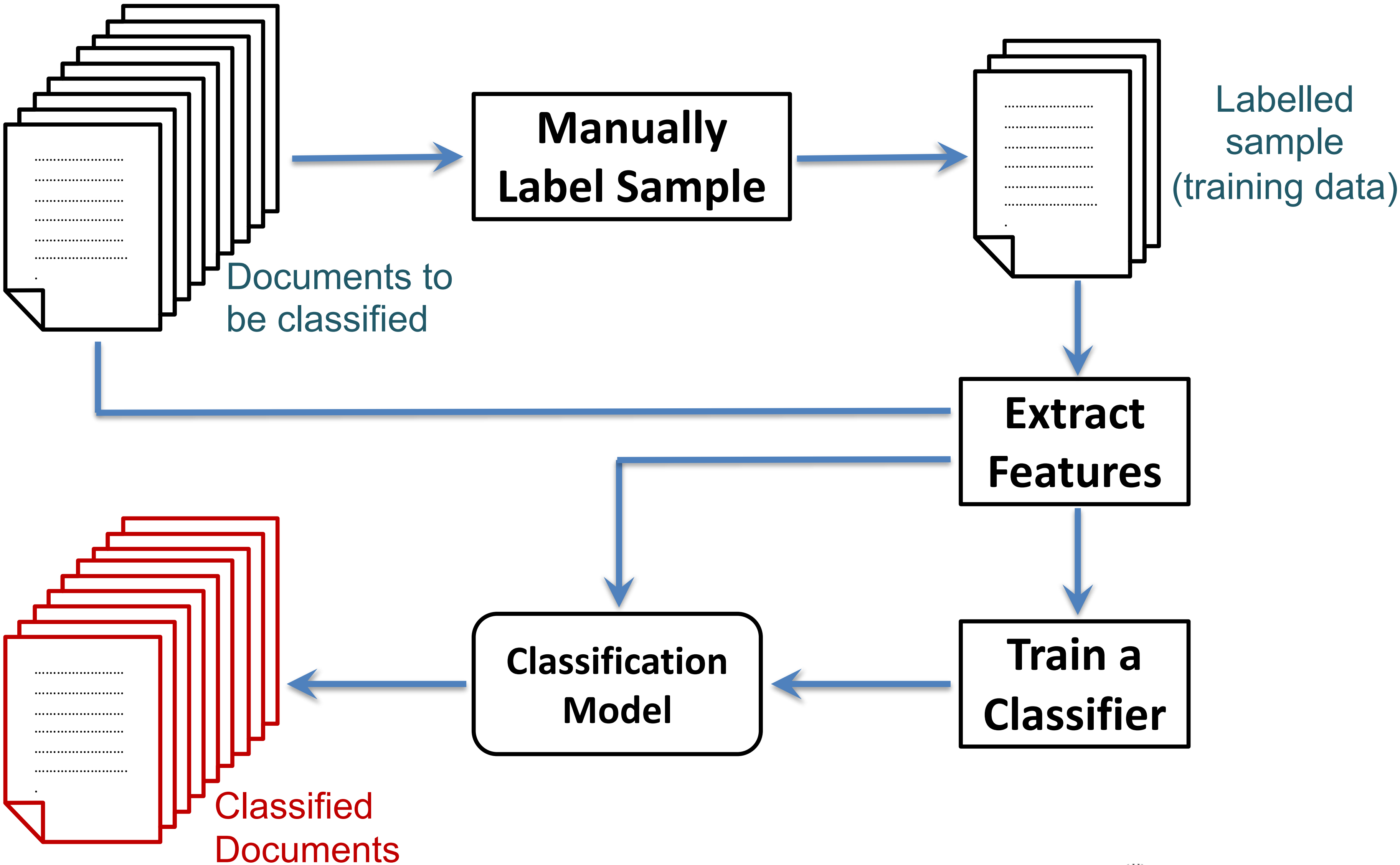
ChatGPT

Positive.

Supervised-learning classification

- A generic (task-independent) learning algorithm is used to train a classifier from a set of manually classified examples
- The classifier learns, from these training examples, the characteristics a new text should have in order to be assigned to class *c*
- Advantages:
  - Generating training examples cheaper than writing classification rules
  - Easy update to changing conditions (e.g., addition of new classes, deletion of existing classes, shifted meaning of existing classes, etc.)

Supervised-learning classification



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Extract Features

- In order to be input to a learning algorithm (or a classifier), all training (or unlabeled) documents are converted into vectors in a common vector space
- The dimensions of the vector space are called features
- In order to generate a vector-based representation for a set of documents *D*, the following steps need to be taken
    1. Feature Extraction
    2. Feature Selection or Feature Synthesis (optional)
    3. Feature Weighting

Step 1: Feature Extraction

- What are the features that should be different from one class to another?
- Simplest form: Bag-of-words (BOW)
  - Each term in a document is a feature
  - Feature space size = vocabulary in all docs
  - Standard IR preprocessing steps are usually applied
    - Tokenisation, stopping, stemming
- Other simple features forms:
  - Word n-grams (bigrams, trigrams, ….)
    - Much larger + more sparse
  - Sometimes char n-grams are used
    - Especially for degraded text (OCR or ASR outputs)

Step 1: Feature Extraction

- What other text features could be used?
- Sentence structure:
  - POS (part-of-speech tags)
  - Syntactic tree structure
- Topic-based features:
  - LDA topics
  - NEs (named entities) in text
  - Links / Linked terms
- Non-textual features:
  - Average doc\sentence\word length
  - % of words start with upper-case letter
  - % of links/hashtags/emojis in text

Step 1: Feature Extraction

- What preprocessing to apply?
  - Case-folding? really vs Really vs REALLY
  - Punctuation? "?", "!", "@", "#"
  - Stopping? "he", "she", "what", "but"
  - Stemming? "replaced" vs "replacement"
- Other Features:
  - Starts with capital letter, all caps
  - Repeated characters "congraaaaaats" "help!!!!!!!!"
  - Scores from dictionaries and lexicons (e.g. LIWC)
- Which to choose?
  - Classification task/application

Step 2: Feature Selection

- Number of distinctive features = length of feature vector
- Vector can be of length in the order of 10^6, and might be sparse
  → High computational cost
  → Overfitting
- What are the most important features among those?
  - e.g. Reduce from 10^6 to 10^4
- For each class, find the top representative *k* features for it → get the Union over all classes → reduced feature space

Step 2: Feature Selection Functions

- Document frequency
  - % of docs in class c_i that contain the term t_k
  - Very basic measure. Will select stop words as features

$$\#(t_k, c_i) = P(t_k | c_i)$$

- Mutual Information
  - How much we learn from the presence or absence of term t_k about whether or not a document is in class c_i
  - Often used in feature selection in text classification

$$MI(t_k, c_i) = \sum_{c \in \{c_i, \bar{c}_i\}} \sum_{t \in \{t_k, \bar{t}_k\}} P(t, c) \cdot log_2 \frac{P(t, c)}{P(t) \cdot P(c)}$$

- Pearson's Chi-squared (x^2)
  - used more in comparisons between classes

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Step 2: Feature Selection Functions

Function	Denoted by	Mathematical form
Document frequency	$\#(t_k, c_i)$	$P(t_k \mid c_i)$
DIA association factor	$z(t_k, c_i)$	$P(c_i \mid t_k)$
Information gain	$IG(t_k, c_i)$	$\sum_{c \in \{c_i, \overline{c}_i\}} \sum_{t \in \{t_k, \overline{t}_k\}} P(t, c) \cdot \log \frac{P(t, c)}{P(t) \cdot P(c)}$
Mutual information	$MI(t_k, c_i)$	$\log \frac{P(t_k, c_i)}{P(t_k) \cdot P(c_i)}$
Chi-square	$\chi^2(t_k, c_i)$	$\frac{\lvert Tr\rvert \cdot [P(t_k, c_i) \cdot P(\overline{t}_k, \overline{c}_i) - P(t_k, \overline{c}_i) \cdot P(\overline{t}_k, c_i)]^2}{P(t_k) \cdot P(\overline{t}_k) \cdot P(c_i) \cdot P(\overline{c}_i)}$
NGL coefficient	$NGL(t_k, c_i)$	$\frac{\sqrt{\lvert Tr\rvert} \cdot [P(t_k, c_i) \cdot P(\overline{t}_k, \overline{c}_i) - P(t_k, \overline{c}_i) \cdot P(\overline{t}_k, c_i)]}{\sqrt{P(t_k) \cdot P(\overline{t}_k) \cdot P(c_i) \cdot P(\overline{c}_i)}}$
Relevancy score	$RS(t_k, c_i)$	$\log \frac{P(t_k \mid c_i) + d}{P(\overline{t}_k \mid \overline{c}_i) + d}$
Odds Ratio	$OR(t_k, c_i)$	$\frac{P(t_k \mid c_i) \cdot (1 - P(t_k \mid \overline{c}_i))}{(1 - P(t_k \mid c_i)) \cdot P(t_k \mid \overline{c}_i)}$
GSS coefficient	$GSS(t_k, c_i)$	$P(t_k, c_i) \cdot P(\overline{t}_k, \overline{c}_i) - P(t_k, \overline{c}_i) \cdot P(\overline{t}_k, c_i)$

Step 2: Feature Synthesis

- Matrix decomposition techniques (e.g., PCA, SVD, LSI) can be used to synthesize new features that replace the features discussed above
- Principle of distributional semantics: semantics of a word "is" the words it co-occurs with
  - **Pros**: the synthetic features in the new vector representation do not suffer from problems such as polysemy and synonymy
  - **Cons**: computationally expensive
- Word embeddings: the new wave of distributional semantics, modern approaches are based on neural networks

- PCA: Principle component analysis
- SVD: Singular value decomposition
- LSA: latent semantic analysis

Step 2: Feature Synthesis

- Deep learning?
- Language modelling "features"
  - Tokenize text and pass to neural network layer
    - E.g., recurrent layer, convolutional layer, self-attention layer
  - Stack on 3+ more layers
  - Train a model to predict the next word (or a missing word) given previous words
  - Penultimate layer of network can be used to generate features for other language-based tasks
  - Basis for many state-of-the-art text classifiers
    - e.g. BERT (DistilBERT, RoBERTa..), XLNet, etc.

Step 3: Feature Weighting

- Attributing a value to feature t_k in document d_i
  This value may be
  - binary (representing presence/absence of t_k in d_i);
  - numeric (representing the importance of t_k for d_i);
    obtained via feature weighting functions in the following two classes:
    - unsupervised: e.g., tfidf or BM25,
    - supervised: e.g., *tf* * MI, *tf* * x^2
- Similarity between two vectors may be computed e.g. via cosine similarity
- Scaling can be important!

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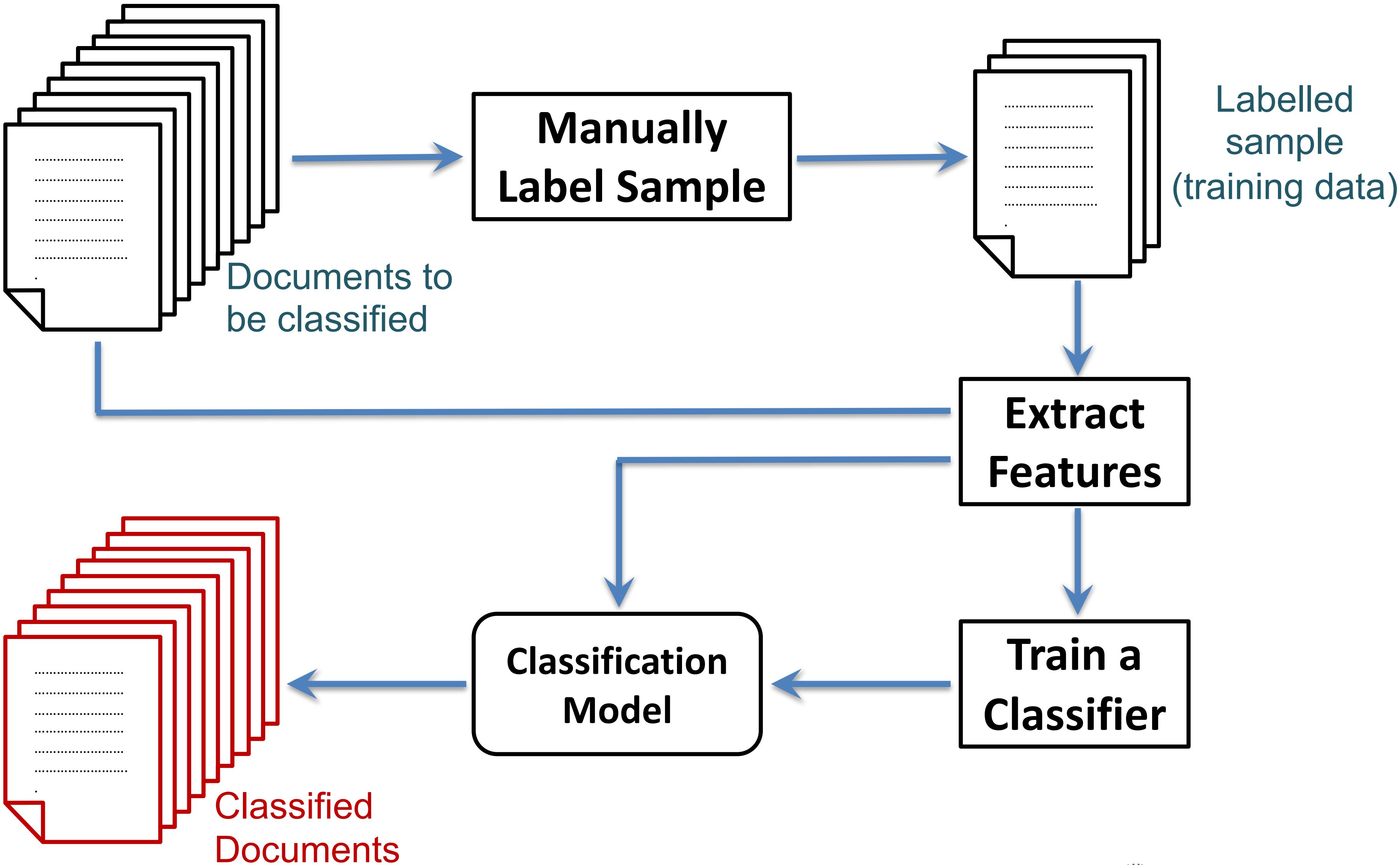
Supervised-learning classification



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Training a Classifier

- For binary classification, essentially any supervised learning algorithm can be used for training a classifier; classical choices include
  - Support vector machines (SVMs)
  - Random forests
  - Naïve Bayesian methods
  - Lazy learning methods (e.g., k-NN)
  - Logistic Regression
  - ….
- The “No-free-lunch principle” (Wolpert, 1996) → *there is no learning algorithm that can outperform all others in all contexts*
- Implementations need to cater for
  - the very high dimensionality
  - the sparse nature of the representations involved

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Training a Classifier

- For Multiclass classification, some learning algorithms for binary classification are "SLMC-ready"; e.g.
  - Decision trees
  - Random forests
  - Naive Bayesian methods
  - Lazy learning methods (e.g., k-NN)
  - Neural networks
- For other learners (notably: SVMs) to be used for SLMC classification, combinations / cascades of the binary versions need to be used
  - e.g. multi-class classification SVM
  - Could be directly used for MLMC as well

Holding out test data

- It’s important to avoid overfitting
- Labelled data could be split into two parts
  - Training: used to train the classifier (e.g. **80%** of the data)
  - Test: used to test the performance of the trained classifier on unseen data (e.g. **20%** of the data)

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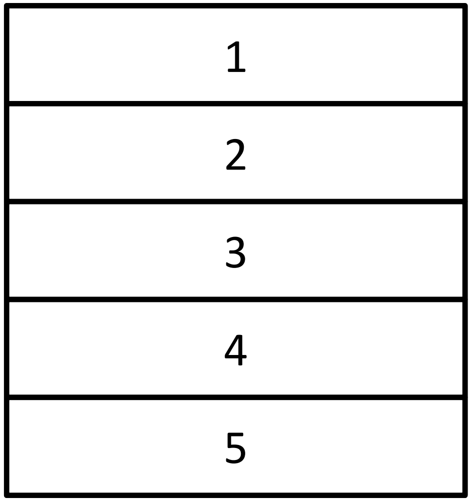
Hyperparameter optimisation

- Most classifiers have some hyperparameters to be optimized (we will usually refer to the ones we set manually as “hyperparameters” to distinguish from the ”learned” parameters/weights of the model)
  - The *C* parameter in soft-margin SVMs
  - The *r*, *d* parameters of non-linear kernels
  - Decision threshold for binary SVM
- Usually labelled data is split into three parts
  - Training: used to train the classifier (typically **80%** of the data)
  - Development: used to optimise hyperparameters. Apply the classifier on this data with different values of the hyperparameters and report the one that achieves the highest results (usually **10%** of the data)
  - Test: used to test the performance of the trained classifier with the optimal hyperparameters on these unseen data (usually **10%** of the data)
- Optimising the hyperparameters on test data is cheating!

Cross-Validation

- Sometimes the amount of labelled data in hand is limited (e.g. 200 samples). Having evaluation of a set of 20 samples only might be misleading
- Cross-validation is used to train the classifier with all data and test on all data without “cheating”
- Idea:
  - Split the labelled data into ***n* folds**
  - Train classifier on *n*-1 fold and test on the remaining one
  - Repeat *n* times
- 5-fold cross validation



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Evaluation

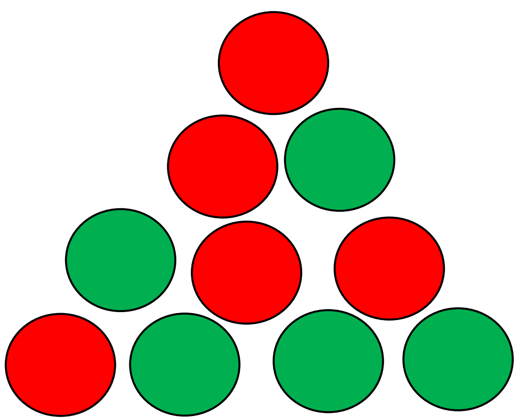
- Effectiveness (e.g. accuracy, precision, recall, F1):
  - Global effectiveness measures
  - Per class effectiveness measures
- Efficiency:
  - Speed in learning
    - SVM with linear kernel is known to be fast
    - DNNs are known to be much slower (specially with large # layers)
  - Speed in classification
    - K-NNs are known to be one of the slowest
  - Speed in feature extraction
    - BOW vs POS vs Link analysis features
- Importance of baselines

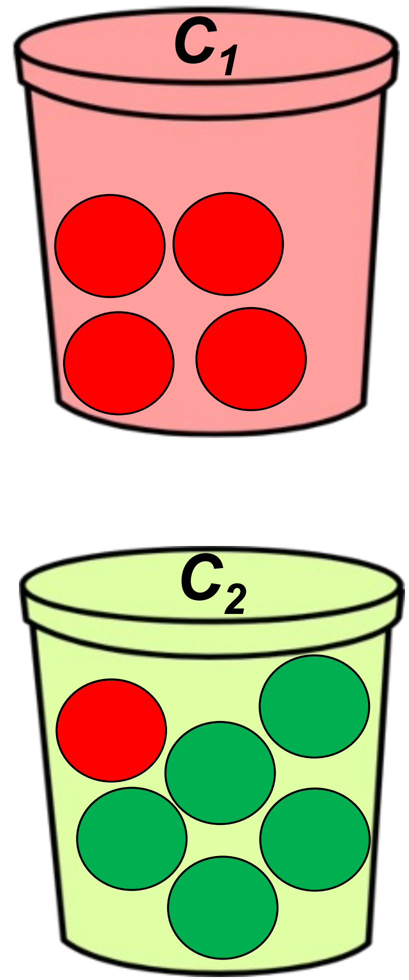
Evaluation: Baselines

- There are standard methods for creating baselines in text classification to compare your classifier with
- Most popular/simplest baselines
  - Random classification
    - Classes are assigned randomly
    - How much better is the classifier doing than random?
  - Majority class baseline
    - Assign all elements to the class that appears the most
    - How much better you are doing than if you always picked the same thing output regardless of input?
  - Simple algorithm, e.g. BOW
    - Usually used when you introduce new interesting features

Evaluation: Binary Classification

- Accuracy:
  - How many of the samples are classified correctly?
- A = (4+5)/10 = 0.9





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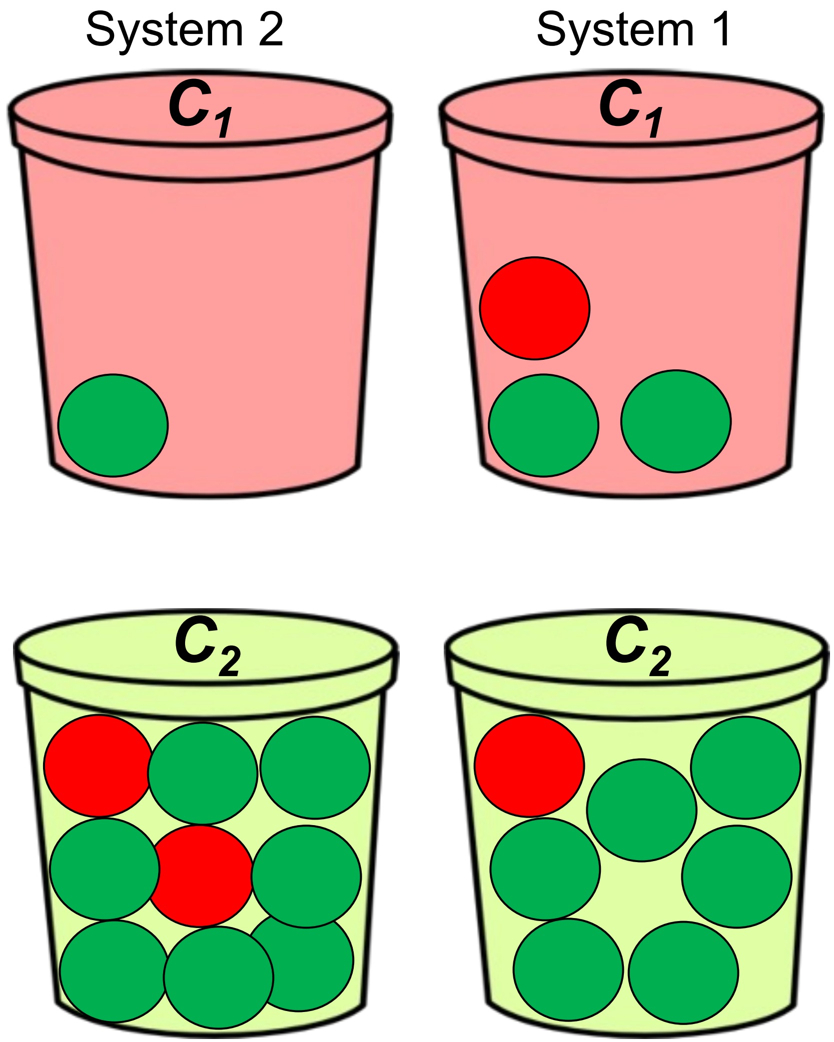
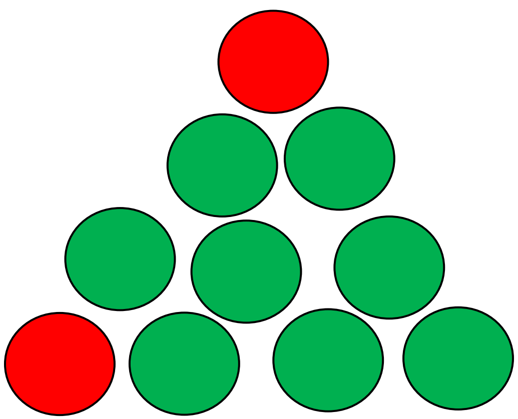
Evaluation: Binary Classification

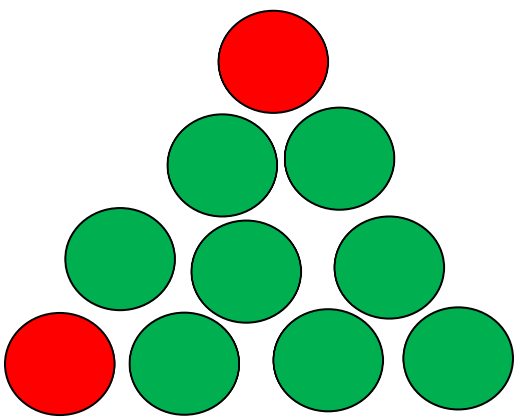
- A = (1+6)/10 = 0.7 System 1
- A = (0+7)/10 = 0.7 System 2
- When classes are highly unbalanced
  - Precision/recall/F1 for the **rare class**
  - e.g. Spam classification (detection)

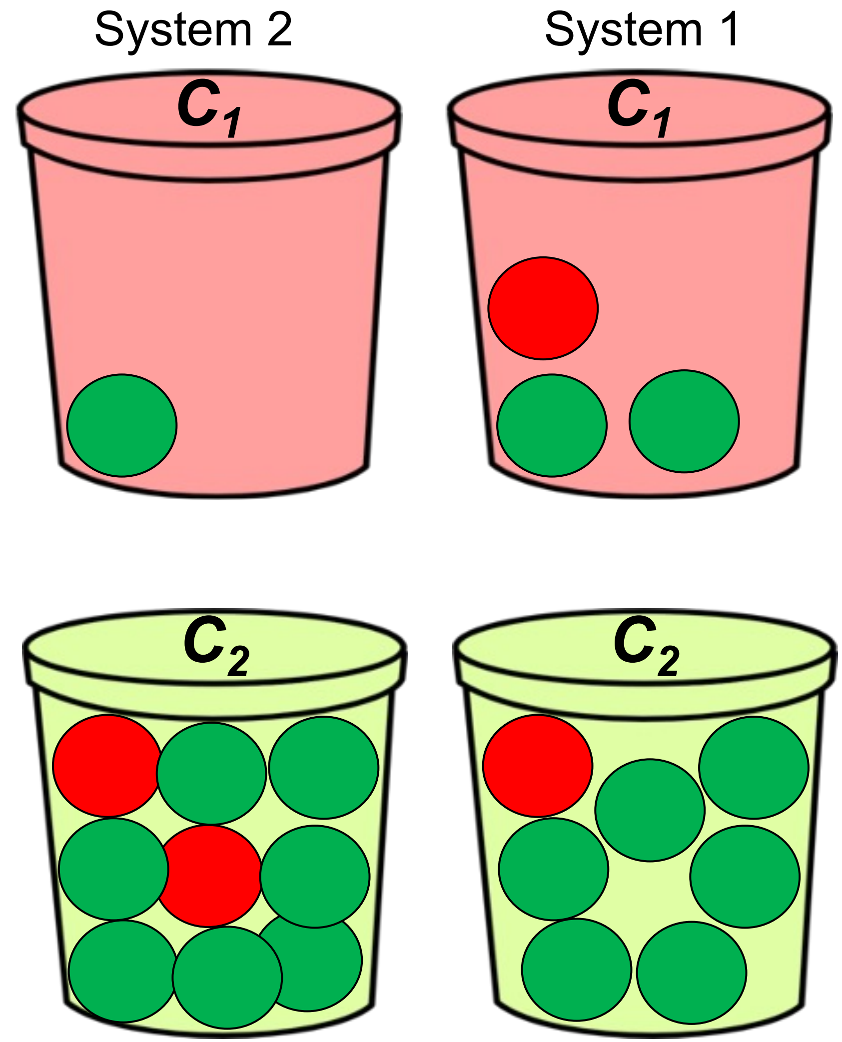




Evaluation: Binary Classification

	System 1	System 2
Precision	1/3 = 0.33	0/1 = 0
Recall	1/2 = 0.5	0/2 = 0
F1	0.4	0



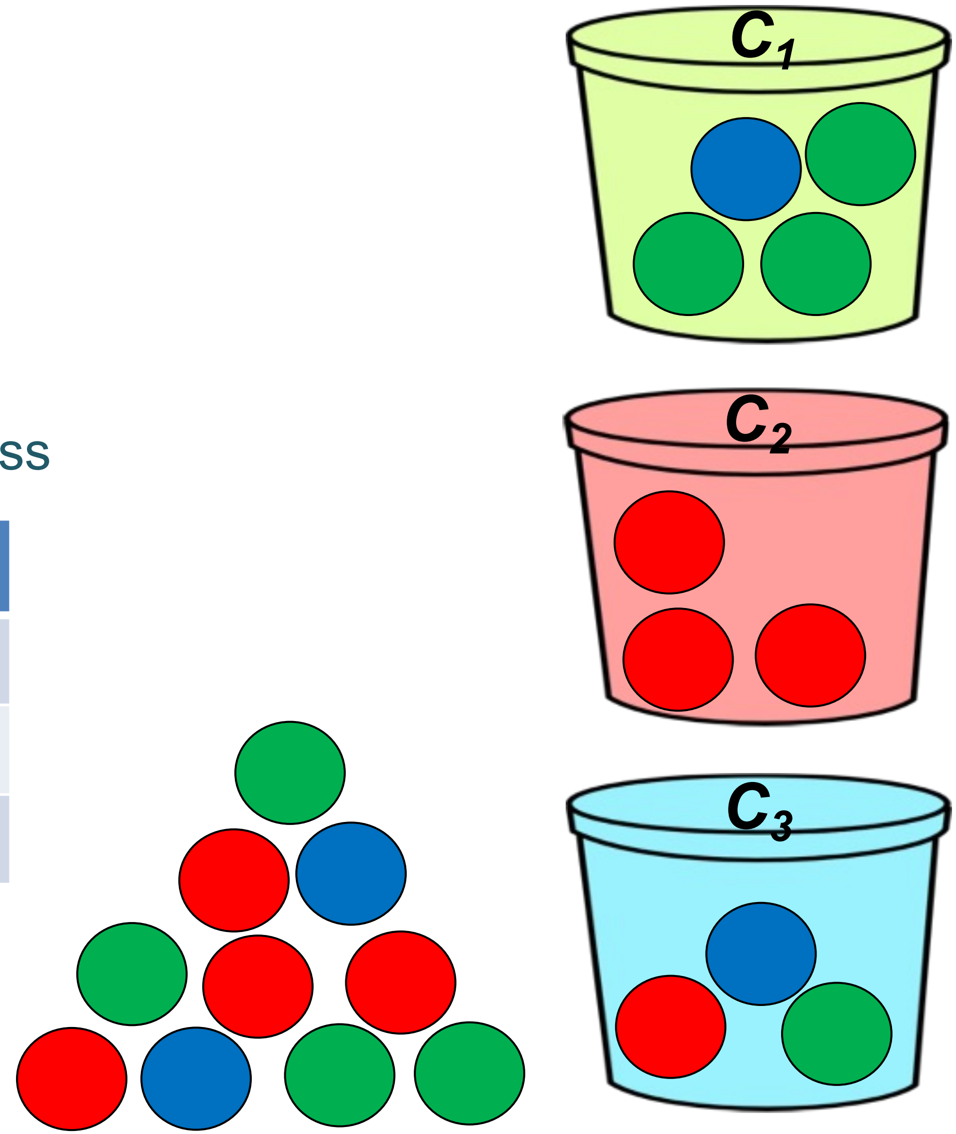


Evaluation: Multi-class

- Accuracy = (3+3+1)/10 = 0.7
- Good measure when
  - Classes are nearly balanced
- Preferred:
  - Precision/recall/F1 for each class

P	0.75	1	0.333
R	0.75	0.75	0.5
F1	0.75	0.86	0.4

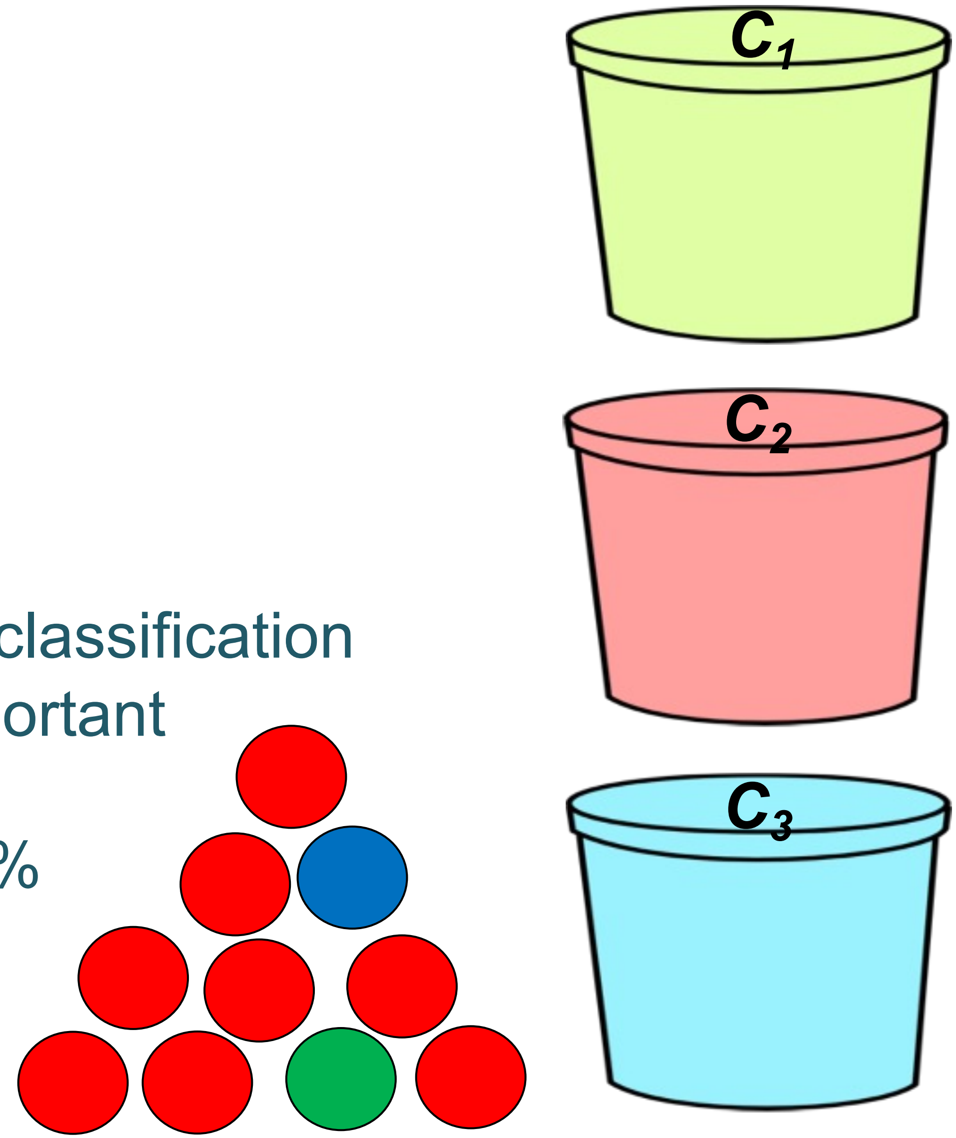
- **Macro-F1**
  = (0.75+0.86+0.4)/3
  = **0.67**



Evaluation: Multi-class

- Majority class baseline
  - Accuracy = 0.8
  - Macro-F1 = 0.296

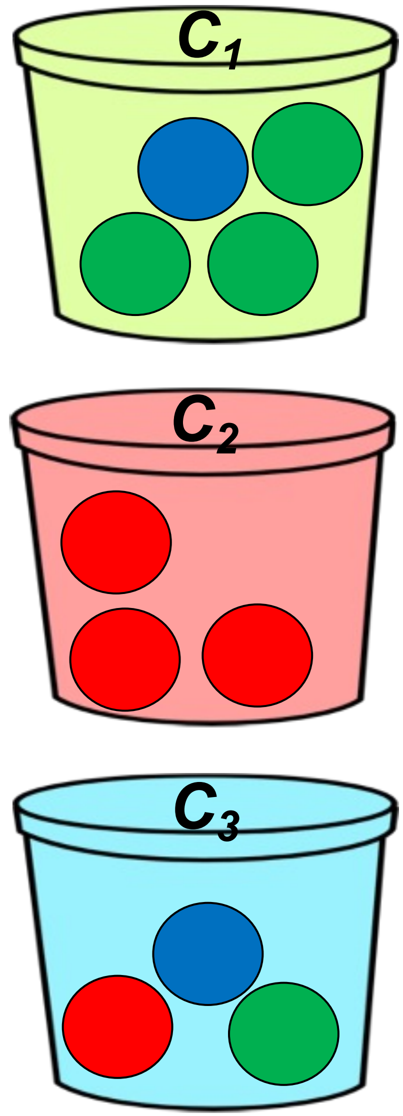
- Macro-F1:
  - Should be used in binary classification when two classes are important
  - e.g.: males/females
    while distribution is 80/20%



Error Analysis

- **Confusion Matrix**

	Predicted class			
Actual class				
		3	0	1
		0	3	1
		1	0	1



- Useful:
  - Find classes that are confused with others
  - Develop better features to solve the problem

Summary

- Text Classification tasks
- Feature extraction/selection/synthesis/weighting
- Learning algorithms
- Baselines
- Evaluation measures
  - Accuracy/precision/recall/Macro-F1

Resources

- *Fabrizio Sebastiani*
  Machine Learning in Automated Text Categorization
  ACM Computing Surveys, 2002
  Link: https://arxiv.org/pdf/cs/0110053
- *Yoav Goldberg*
  A Primer on Neural Network Models for Natural Language Processing
  Link: https://arxiv.org/abs/1510.00726