THE UNIVERSITY of EDINBURGH

SICSS Edinburgh

Text Classification

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Outlines

- Nature of text
  - Zipf's law
- Text Classification
  - Why you might need classification in CSS?
  - Feature Extraction
  - Feature Selection/Synthesis
  - Feature Weighting (e.g. TFIDF)
  - Classification process setup (train and test)
  - Evaluation

Why Text Classification?

- Text → Most of social communication online *.. so far*
- CSS → Mostly analyse online data on large scale
- Data are not always labelled to be analysed on scale
- Some classifiers are available to use
  - E.g. Sentiment
- Sometimes you need to build specific classifier for a specific task
  - E.g. Stance classifier for Pro-choice vs Pro-life
- Today: How to build a text classifier
  Tomorrow: How to build a general classifier

Words' Nature

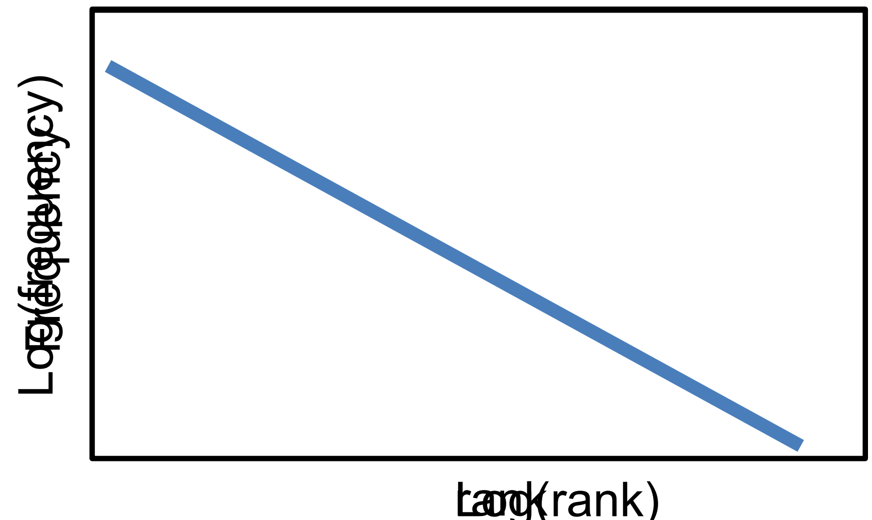
- Word → basic unit to represent text
- Certain characteristics are observed for the words we use!
- These characteristics are very consistent, that we can apply laws for them
- These laws apply for:
    - Different languages
    - Different domains of text

You can try with me …

- Shell commands: cat, sort, uniq, grep
- Python (or alternative)
- Excel (or alternative)
- Download the following:
  - Bible: http://www.gutenberg.org/cache/epub/10/pg10.txt

Frequency of words

- Some words are very frequent
  e.g. “the”, “of”, “to”
- Many words are less frequent
  e.g. “schizophrenia”, “bazinga”
- ~50% terms appears once
- Frequency of words has
  hard exponential decay



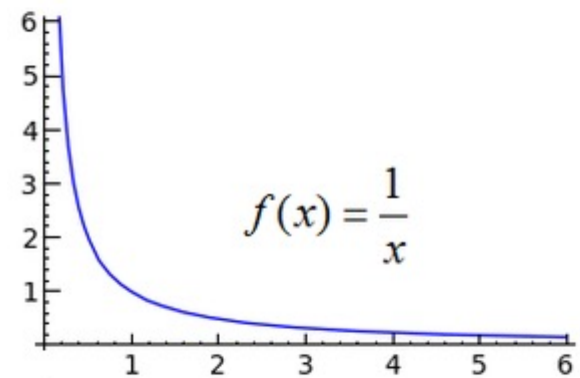
Zipf's Law:

- For a given collection of text, ranking unique terms according to their frequency, then:

$$r \times P_r \cong const$$

- r, rank of term according to frequency
- P_r, probability of appearance of term

- $P_r \cong \frac{const}{r} \rightarrow f(x) \cong \frac{1}{x}$



Zipf's Law:

Wikipedia abstracts

→ 3.5M En abstracts

$$r \times P_r \cong const \rightarrow$$

$$r \times freq_r \cong const$$

Term	Rank	Frequency	r x freq
the	1	5,134,790	5,134,790
of	2	3,102,474	6,204,948
in	3	2,607,875	7,823,625
a	4	2,492,328	9,969,312
is	5	2,181,502	10,907,510
and	6	1,962,326	11,773,956
was	7	1,159,088	8,113,616
to	8	1,088,396	8,707,168
by	9	766,656	6,899,904
an	10	566,970	5,669,700
it	11	557,492	6,132,412
for	13	493,374	5,970,456
as	14	480,277	6,413,862
on	15	471,544	6,723,878
from	16	412,785	7,073,160

Practical

Collection	# words	File size
Bible	824,054	4.24 MB
Wiki abstracts	80,460,749	472 MB

```
cat bible.txt | tr "A-Z" "a-z" | tr -c "a-z" " " | tr " " "\n" | sort | uniq -c | sort -n -r | perl -p -e "s/^ +//" | tr " " "\t" > zipf.txt
```

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)

Classification is and is not

- Different from clustering, where the groups ("clusters") and their number are not known in advance
- The membership of a data item into a class must not be determinable with certainty
  - 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

Types of Classification

- **Binary**:
  item to be classified into <u>one of two</u> classes
  $h : D \rightarrow C, \quad C = \{c_1, c_2\}$
  - 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.
  $h : D \rightarrow C, \quad C = \{c_1 \ldots. c_n\}$, 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
  $h : D \rightarrow 2^C, \quad C = \{c_1 \ldots. c_n\}$, where n>1
  - e.g., Assigning CS articles to classes in the ACM Classification System
  - Usually be solved as *n* independent binary classification problems

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
- ……

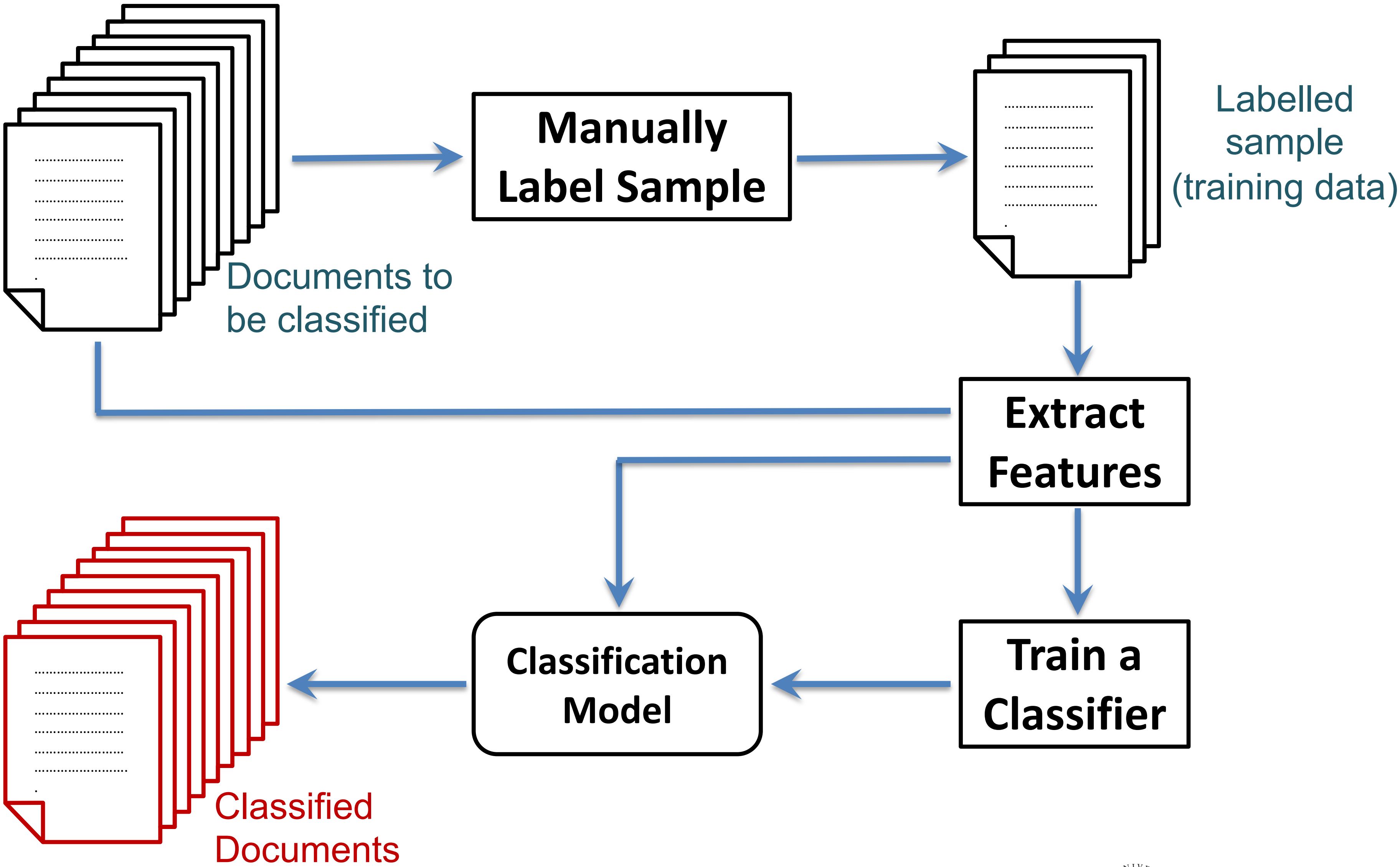
Rule-based classification

- 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)

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



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: 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 (NLP):
  - POS (part-of-speech tags)
  - Syntactic tree structure
- Topic-based features (NLP):
  - 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:
  - Start with Cap, All Cap
  - Repeated characters “congraaaaaats” “help!!!!!!!!”
  - LIWC: Linguistic Inquiry and Word Count
- Which to choose?
  - Classification task/application

Step 2: Feature Selection

- Number of distinctive features = feature space = length of feature vector.
- Vector can be of length $O(10^6)$, and might be sparse
  → High computational cost
  → Overfitting
- What are the most important features among those?
  - e.g. Reduce $O(10^6)$ to $O(10^4)$
- 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 term t_k appear in class c_i compared to other classes
  - Highly 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

Step 2: Feature Selection Functions

Function	Denoted by	Mathematical form
Document frequency	$\#(t_k, c_i)$	$P(t_k \vert c_i)$
DIA association factor	$z(t_k, c_i)$	$P(c_i \vert t_k)$
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	$\chi^2(t_k, c_i)$	$\frac{\vert Tr\vert \cdot [P(t_k, c_i) \cdot P(\overline{t}_k, \overline{c}_i) - P(t_k, \overline{c}_i) \cdot P(\overline{t}_k, c_i)]^2}{P(t_k) \cdot P(\overline{t}_k) \cdot P(c_i) \cdot P(\overline{c}_i)}$
NGL coefficient	$NGL(t_k, c_i)$	$\frac{\sqrt{\vert Tr\vert} \cdot [P(t_k, c_i) \cdot P(\overline{t}_k, \overline{c}_i) - P(t_k, \overline{c}_i) \cdot P(\overline{t}_k, c_i)]}{\sqrt{P(t_k) \cdot P(\overline{t}_k) \cdot P(c_i) \cdot P(\overline{c}_i)}}$
Relevancy score	$RS(t_k, c_i)$	$\log \frac{P(t_k \vert c_i) + d}{P(\overline{t}_k \vert \overline{c}_i) + d}$
Odds Ratio	$OR(t_k, c_i)$	$\frac{P(t_k \vert c_i) \cdot (1 - P(t_k \vert \overline{c}_i))}{(1 - P(t_k \vert c_i)) \cdot P(t_k \vert \overline{c}_i)}$
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, LSA) can be used to synthesize new features that replace the features discussed above
- These techniques are based on the principles of distributional semantics, which states that the semantics of a word "is" the words it co-occurs with in corpora of language use
  - **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

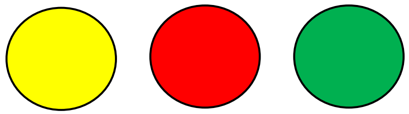
Step 2: Feature Synthesis

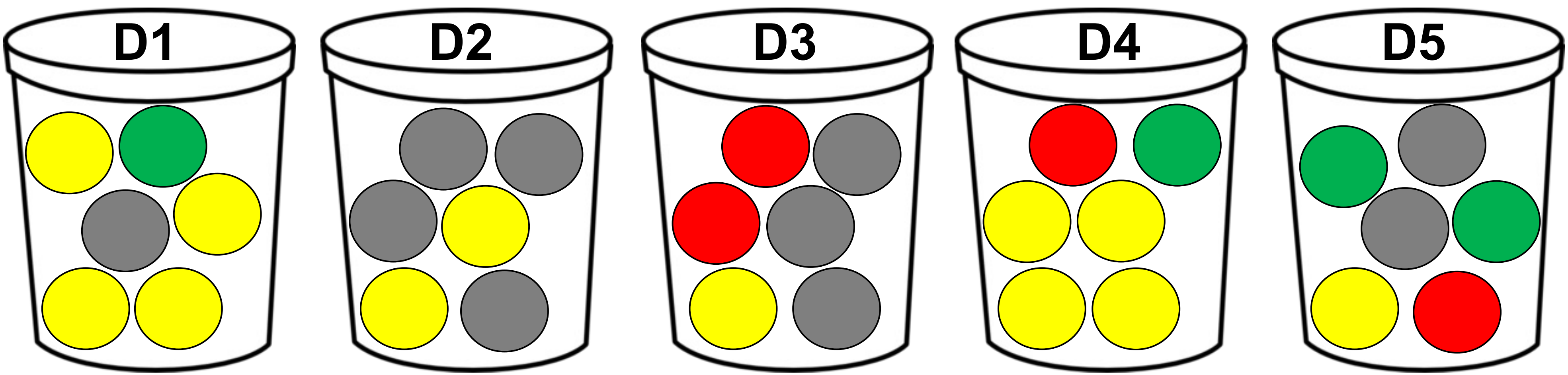
- Deep learning?
- Language modelling "features"
  - Tokenize text and pass to neural network layer
    - E.g., recurrent layer, convolutional layer, self-attention layer
  - Stack on 3+ more layers
  - Train a model to predict the next word (or a missing word) given previous words
  - Penultimate layer of network can be used to generate features for other language-based tasks
  - Basis for many state-of-the-art text classifiers
    - BERT, GPT, Electra, 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
- The similarity between two vectors may be computed via cosine similarity; if these vectors are pre-normalized, this is equivalent to computing the dot product between them

Should terms be weighted the same?

- Collection of 5 documents (balls = terms)
- Query 
- Which is the least relevant document?
- Which is the most relevant document?



TFIDF

- **TFIDF**:
  Term Frequency, Inverse Document Frequency
- ***tf(t,d)***:
  number of times term ***t*** appeared in document ***d***
  - As $tf(t,d)$ ↑↑ → importance of *t* in *d* ↑↑
  - Document about IR, contains "retrieval" more than others
- ***df(t)***:
  number of documents term ***t*** appeared in
  - As d$f(d)$ ↑↑ → importance if *t* in a collection ↓↓
    - "the" appears in many document → not important
    - "FT" is not important word in financial times articles

DF, CF, & IDF

- **DF ≠ CF** (collection frequency)
  - ***cf(t)*** = total number of occurrences of term ***t*** in a collection
  - ***df(t)*** ≤ ***N*** (***N***: number of documents in a collection)
  - ***cf(t)*** can be ≥ ***N***
- **DF** is more commonly used in IR than **CF**
  - **CF** is still used
- ***idf(t)***: inverse of ***df(t)***
  - As $\mathrm{i}df(t)$ ↑↑ → rare term → importance ↑↑
  - ***idf(t)*** → measure of the informativeness of *t*

IDF: formula

$$\mathrm{i}df(t) = log_{10}(\frac{N}{df(t)})$$

- ***idf(t)***: inverse of ***df(t)***
  - As $\mathrm{i}df(t)$ ↑↑ → rare term → importance ↑↑
  - ***idf(t)*** → measure of the informativeness of *t*

- Suppose *N* = 1 million →

term	*df(t)*	*idf(t)*
calpurnia	1	**6**
animal	100	**4**
sky	1,000	**3**
fly	10,000	**2**
under	100,000	**1**
the	1,000,000	**0**

TFIDF term weighting

- One the best known term weights schemes
  - Increases with the number of occurrences within a document
  - Increases with the rarity of the term in the collection
- Combines TF and IDF to find the weight of terms

$$w_{t.d} = \left(1 + log_{10} tf(t,d)\right) \times log_{10}\left(\frac{N}{df(t)}\right)$$

- With current ML techniques, new models learn term weight automatically

Should terms be treaded the same?

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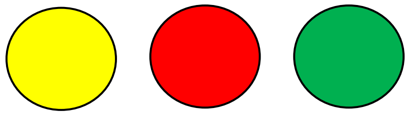
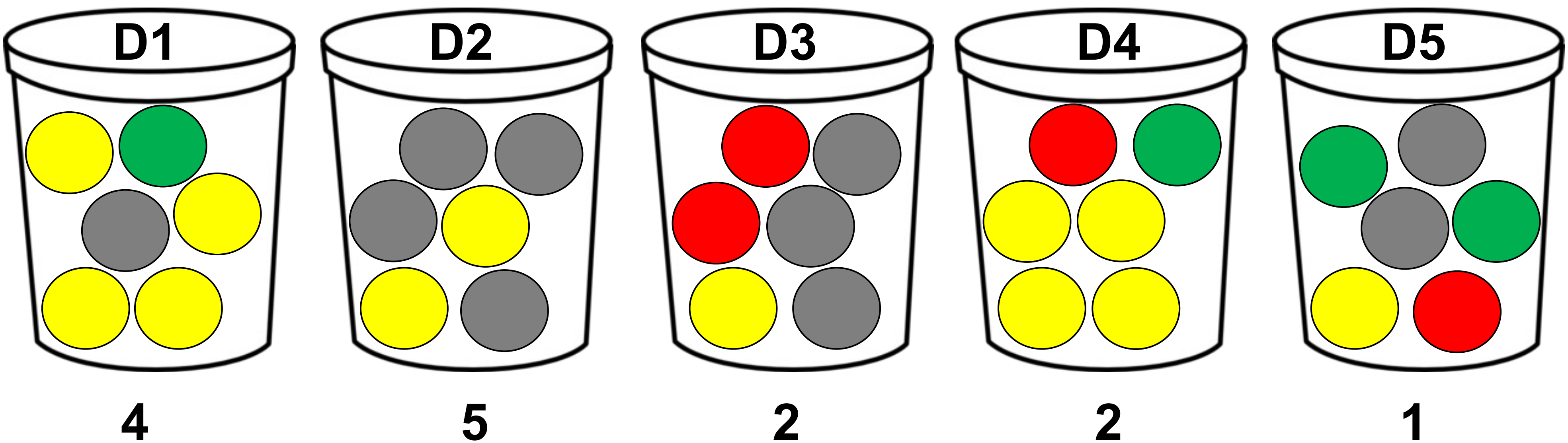
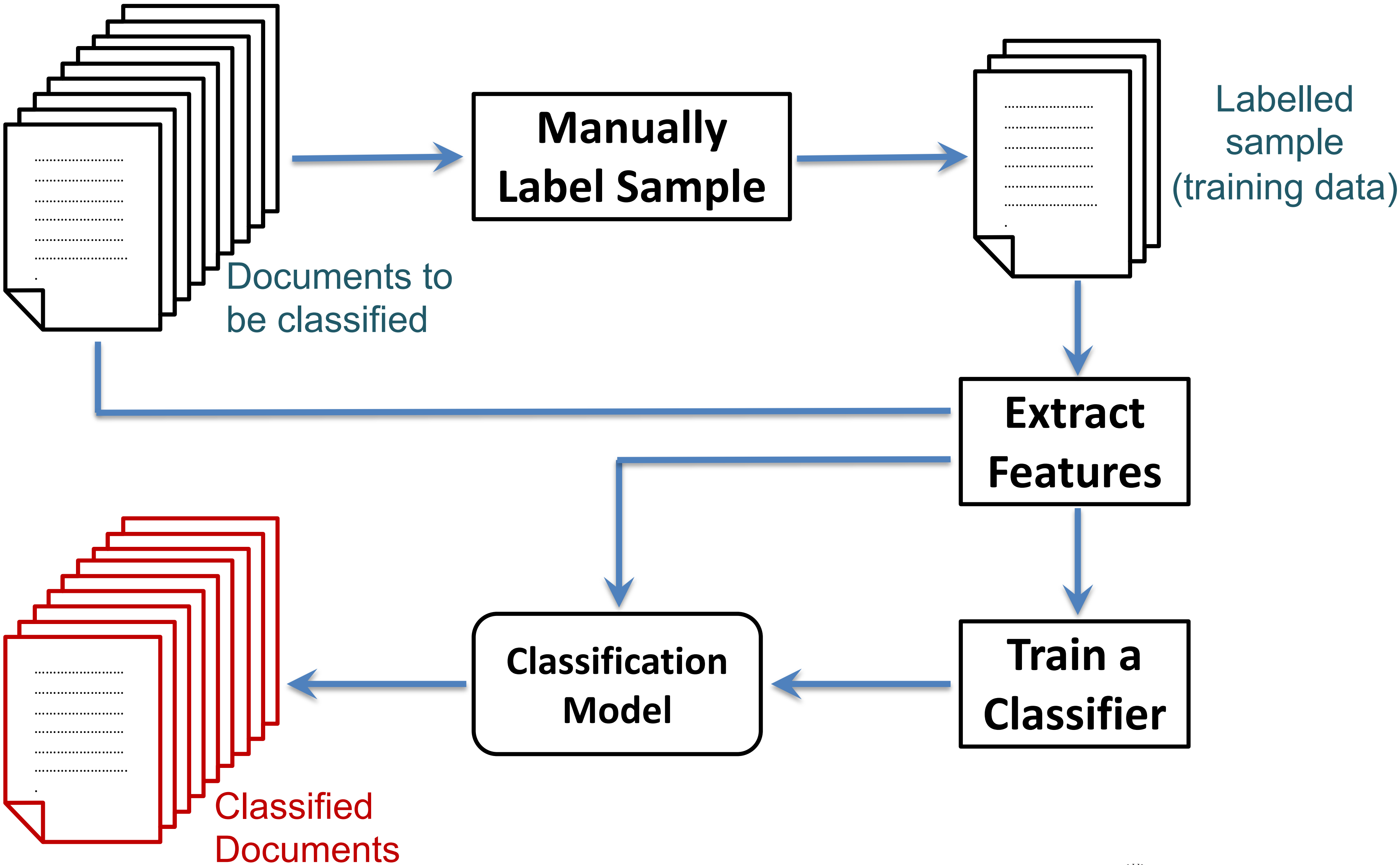
- Query  the destructive storm
- Which is the least relevant document?
- Which is the most relevant document?



Supervised-learning classification



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

Training a Classifier

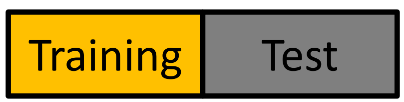
- For Multiclass classification, some learning algorithms for binary classification are “SLMC-ready”; e.g.
  - Decision trees
  - Random forests
  - Naive Bayesian methods
  - Lazy learning methods (e.g., k-NN)
  - Neural networks
- For other learners (notably: SVMs) to be used for SLMC classification,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

Parameter Optimisation of Classifier

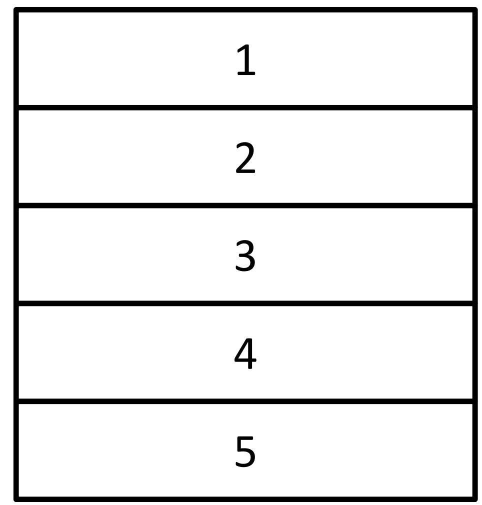
- Most classifiers has some parameters to be optimized:
  (we will usually refer to the ones we set manually as "hyperparameters" to distinguish from the "learned" parameters/weights of the model)
  - The *C* parameter in soft-margin SVMs
  - The *r*, *d* parameters of non-linear kernels
  - Decision threshold for binary SVM
- Optimising the hyperparameters on test data is cheating!
- *Data Split*: Usually labelled data would be split into three parts
  - Training: used to train the classifier (typically **80%** of the data)
  - Validation: 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)

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 being 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



- Extreme case: LOOCV
  LOOCV: leave-one-out cross-validation



Evaluation

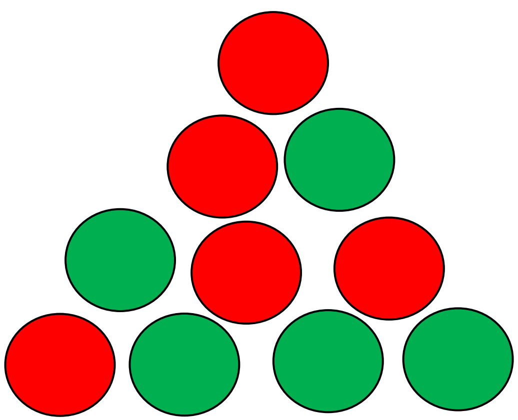
- Efficiency / Effectiveness
- Baselines
- Efficiency:
  - Speed in learning
    - SVM with linear kernel is known to be fast
    - DNNs are known to be much slower (specially with large # layers)
  - Speed in classification
    - K-NNs are known to be one of the slowest
  - Speed in feature extraction
    - BOW vs POS vs Link analysis features
- Effectiveness:
  - Global effectiveness measures
  - Per class effectiveness measures

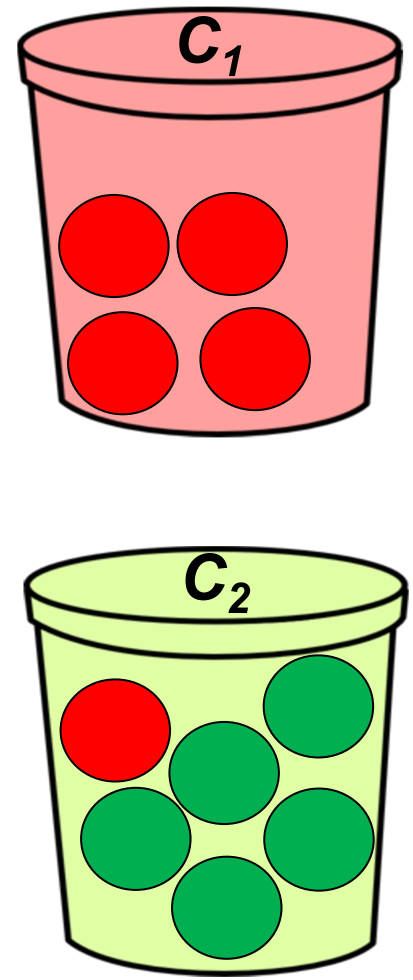
Evaluation: Baselines

- 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
  - Recently: BERT baseline

Evaluation: Binary Classification

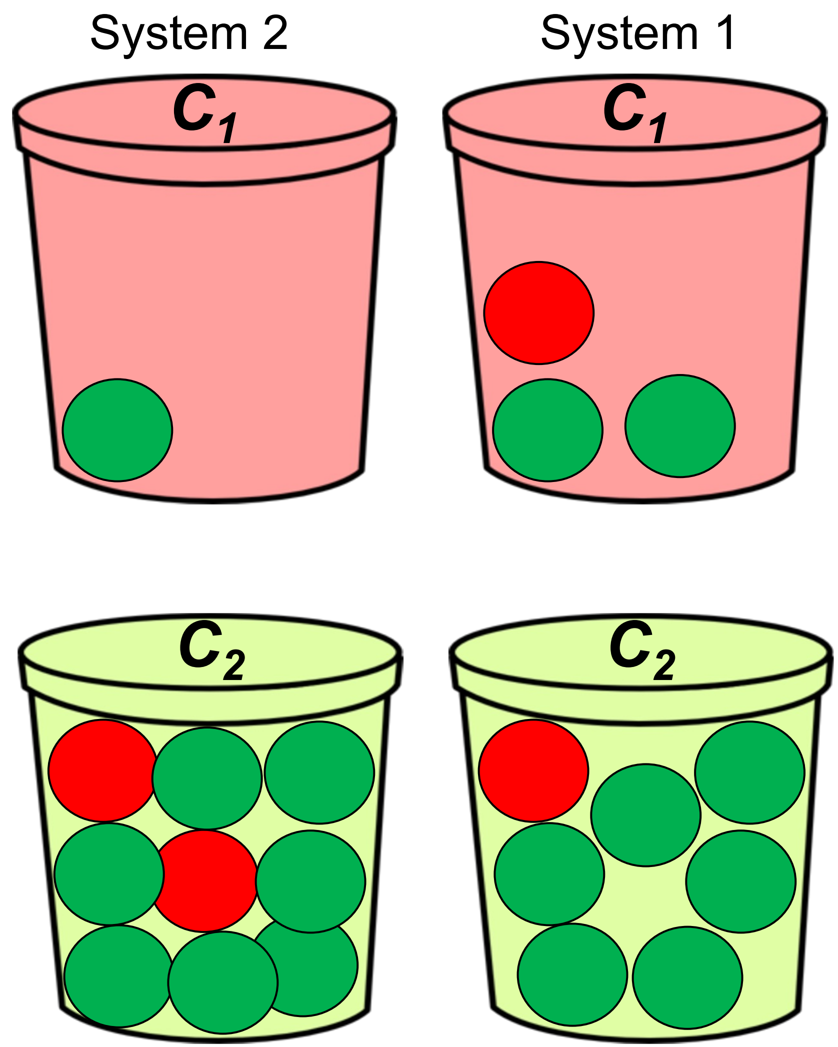
- Accuracy:
  - How many of the samples are classified correctly?
- A = 9/10 = 0.9

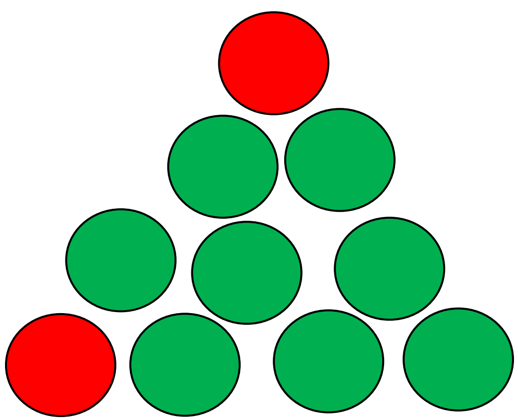




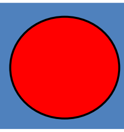
Evaluation: Binary Classification

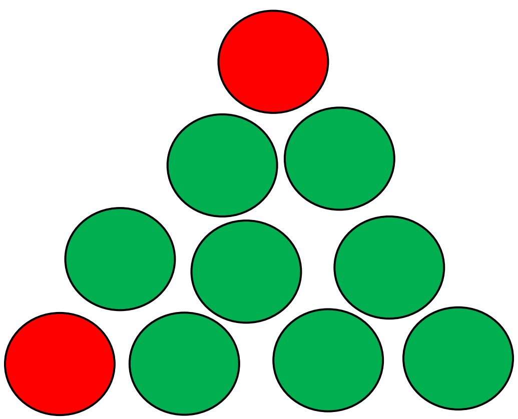
- A = 7/10 = 0.7 System 1
- A = 7/10 = 0.7 System 2
- When classes are highly unbalanced
  - Precision/recall/F1 for the **rare class**
  - e.g. Spam classification (detection)

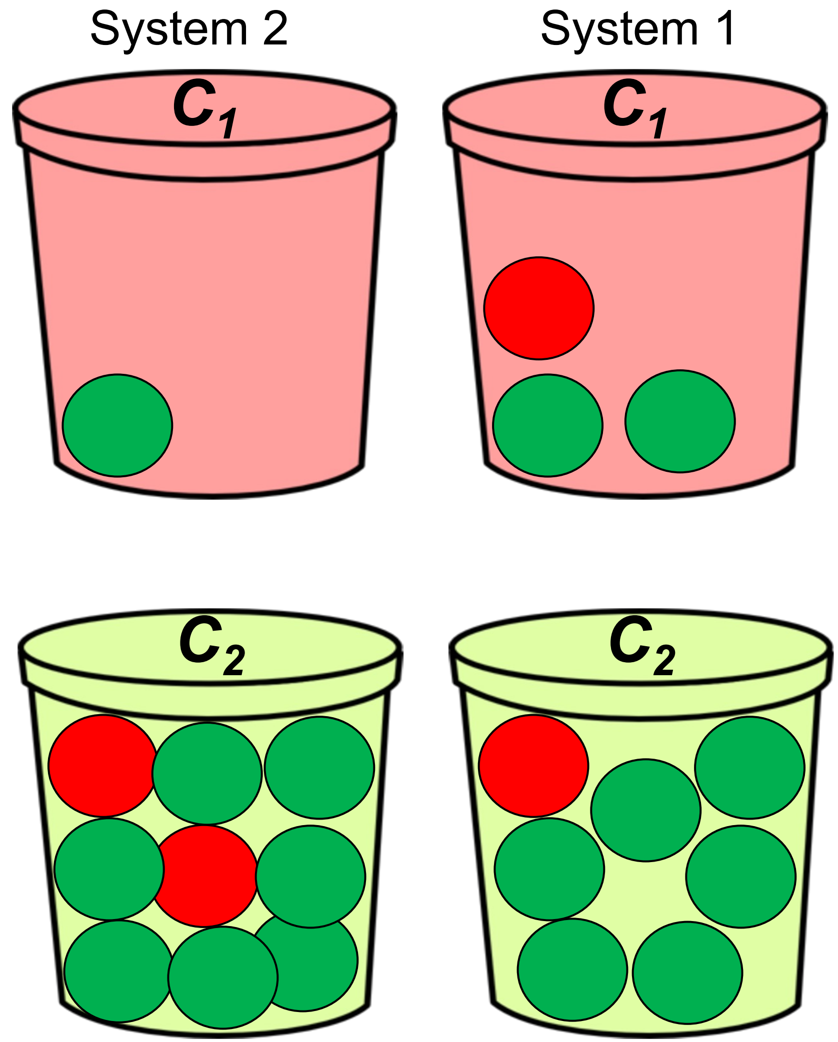




Evaluation: Binary Classification

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



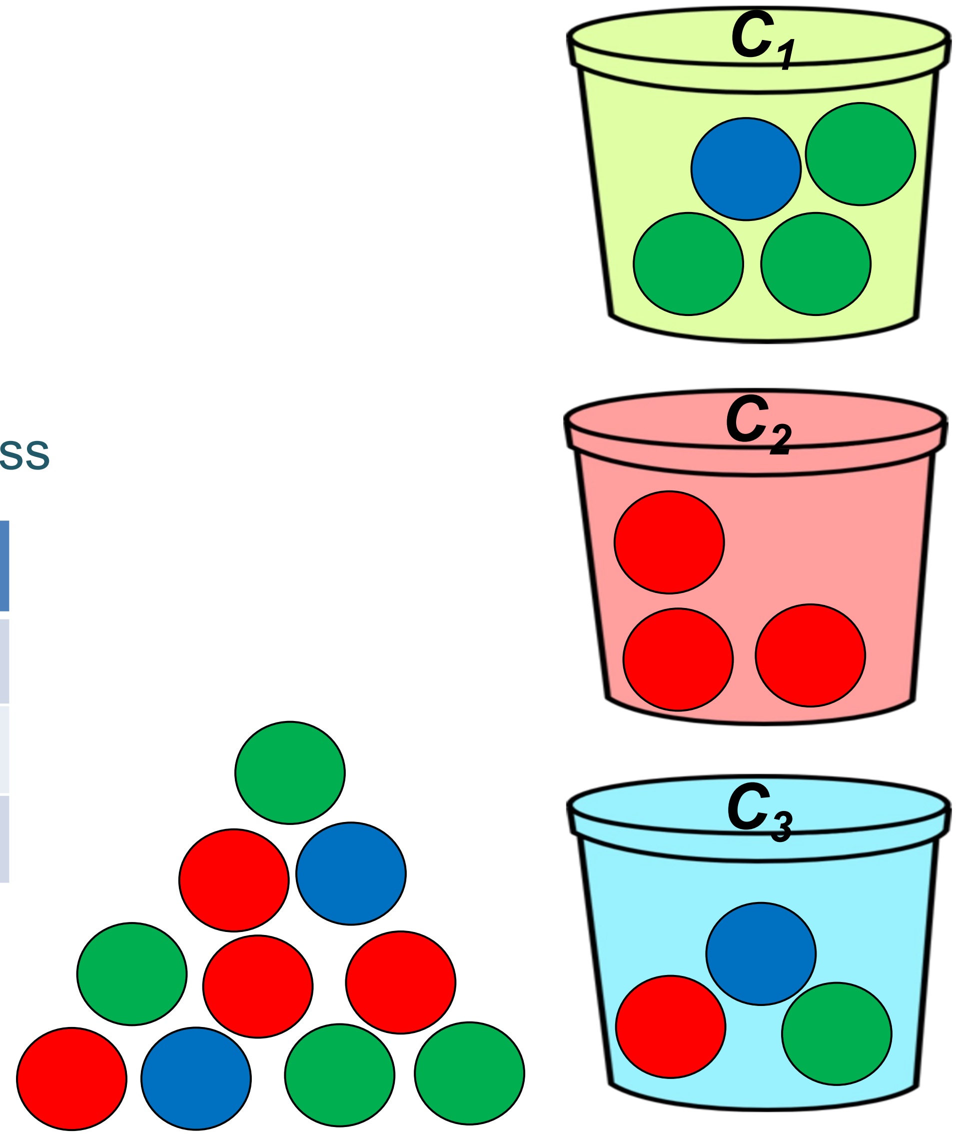


Evaluation: Multi-class

- 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

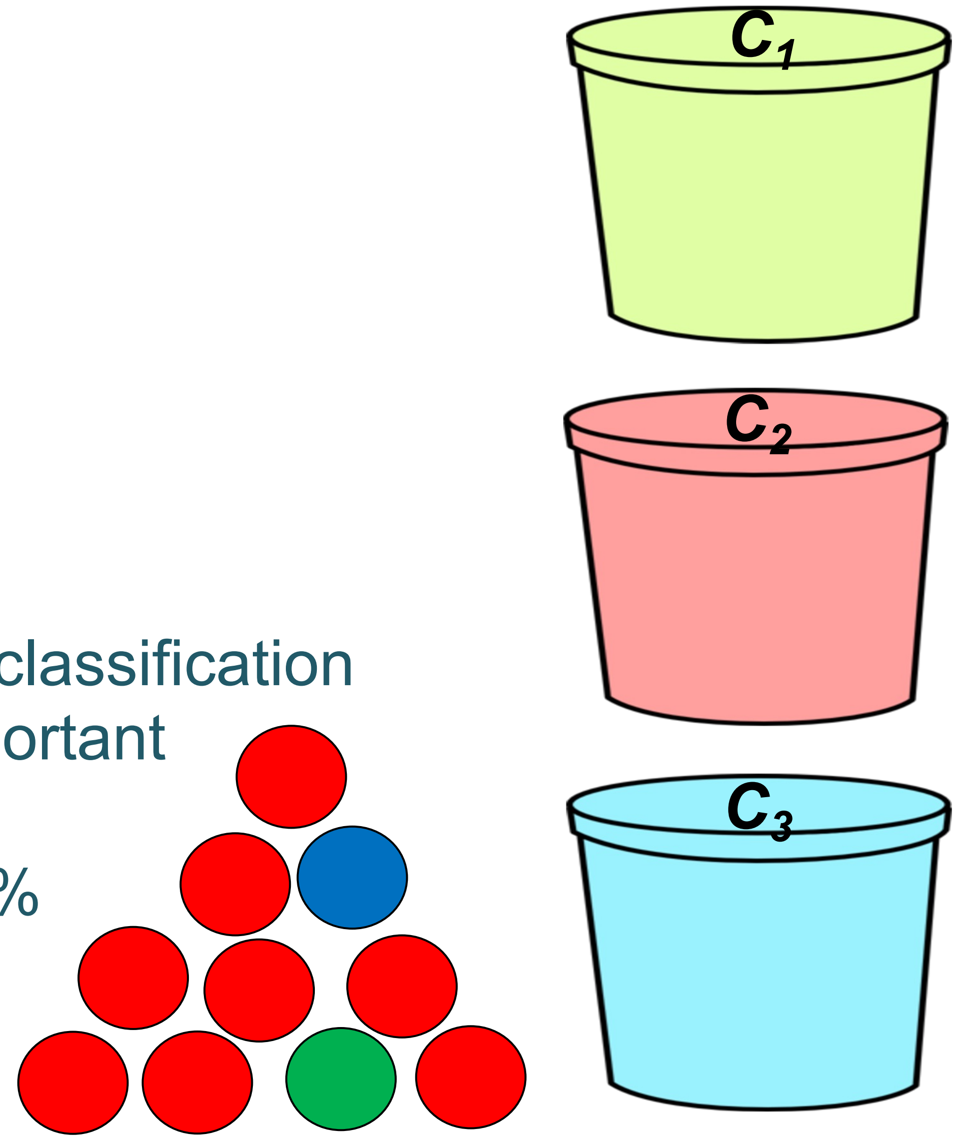
- **Macro-F1**
  = (0.75+0.86+0.4)/3
  = **0.67**



Evaluation: Multi-class

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

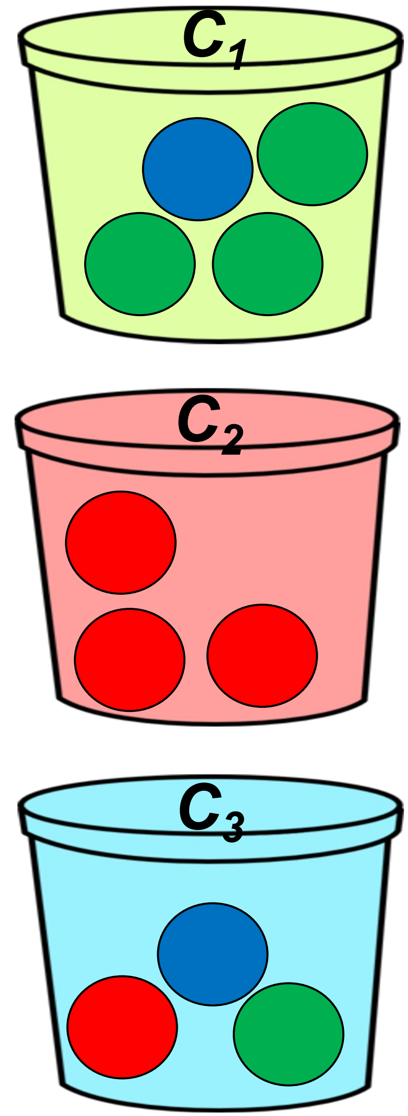
- Macro-F1:
  - Should be used in binary classification when two classes are important
  - e.g.: males/females while distribution is 80/20%



Error Analysis

- **Confusion Matrix**
  How classes get confused?

	3	0	1
	0	3	1
	1	0	1



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

Summary

- CSS requires classifying data for in-depth analysis
- Zipf's Law
- Text Classification tasks
- Feature extraction/selection/synthesis/weighting
- Learning algorithms
- Cross-validation
- 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

Practice

- **Zipf's distribution:** *https://www.inf.ed.ac.uk/teaching/courses/tts/labs/lab1.html*
- **Text Classification** *https://www.inf.ed.ac.uk/teaching/courses/tts/labs/lab7.html*
- Note: In-class practice tomorrow with Bjorn