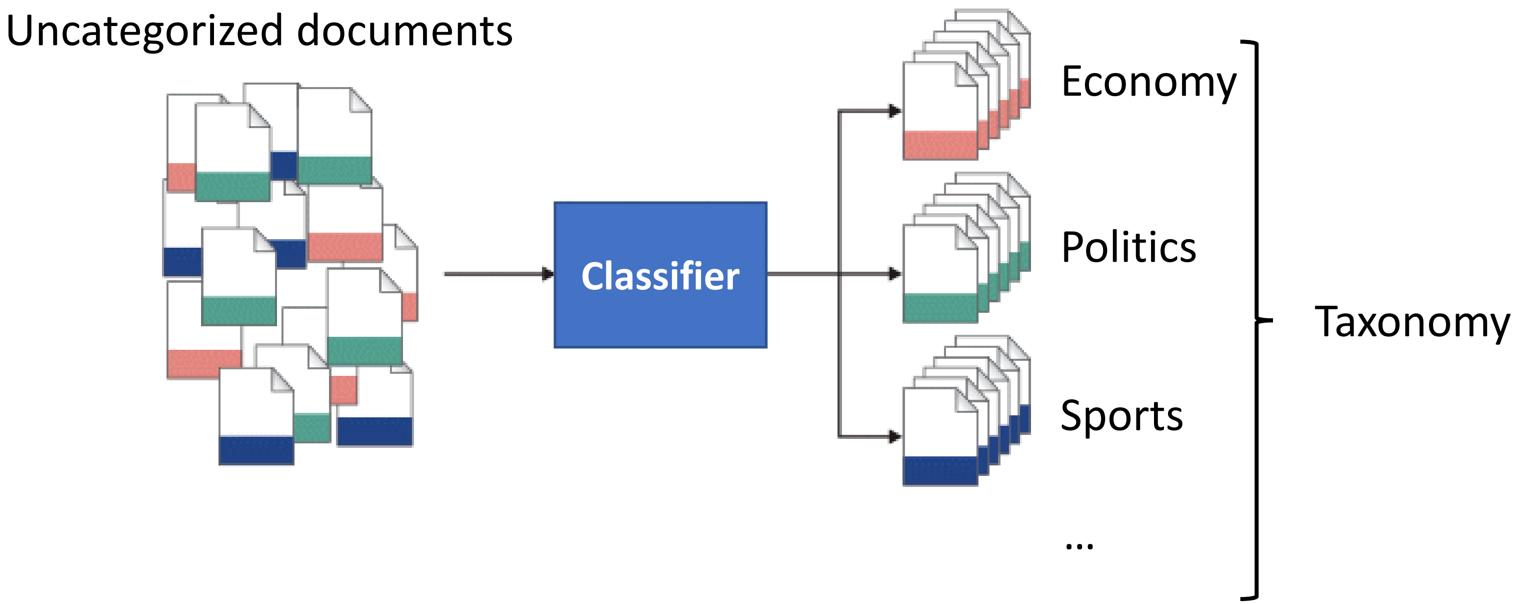
Document Categorization

Perceptron, Topic Detection, Sentiment Classification

Information Retrieval

Document Topic Categorization



Spam filtering: Another text classification task

From: "" <takworlld@hotmail.com>
Subject: real estate is the only way... gem oalvgkay

Anyone can buy real estate with no money down

Stop paying rent TODAY !

There is no need to spend hundreds or even thousands for similar courses

I am 22 years old and I have already purchased 6 properties using the methods outlined in this truly INCREDIBLE ebook.

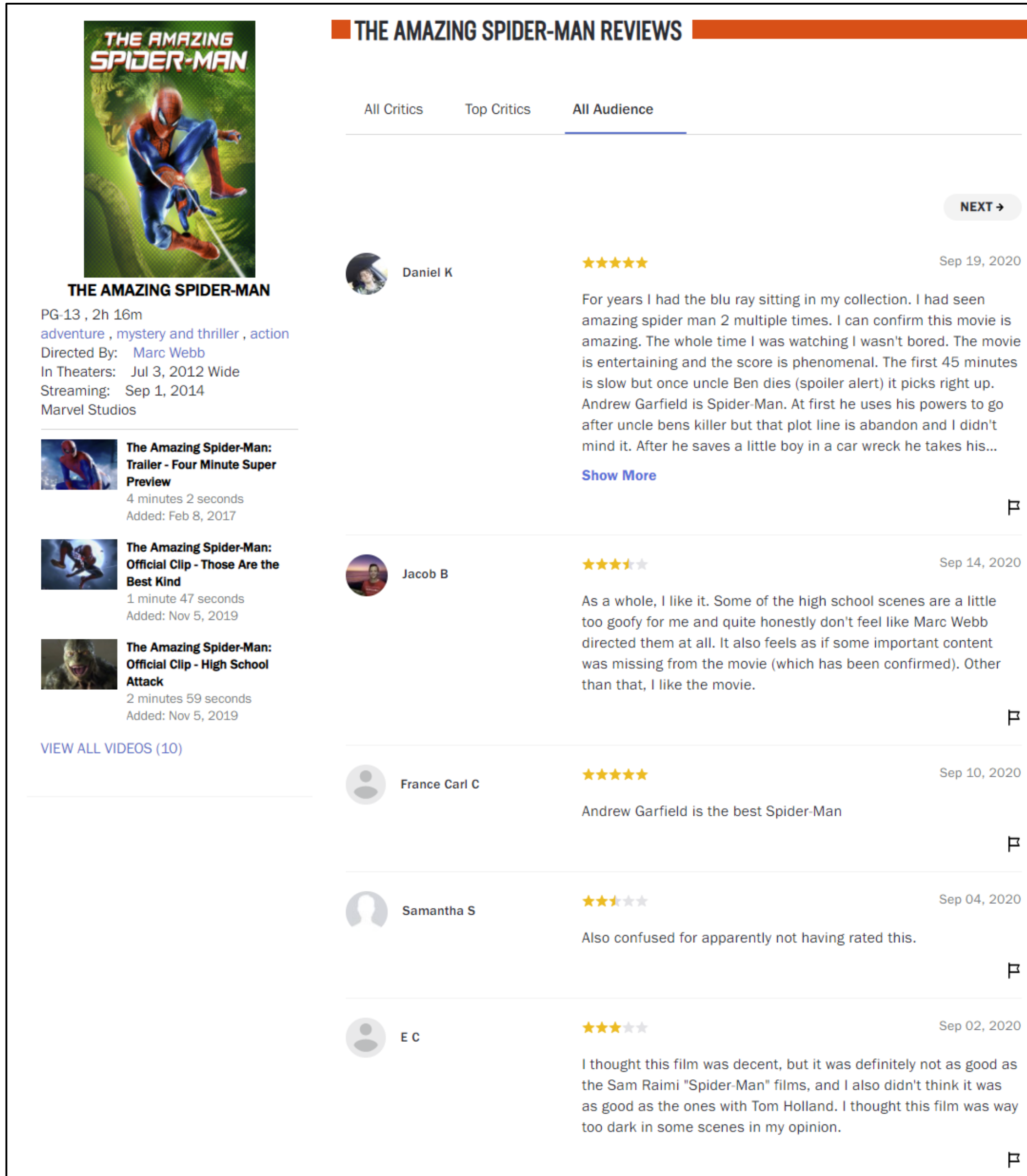
Change your life NOW !

===

Click Below to order:
http://www.wholesaledaily.com/sales/nmd.htm

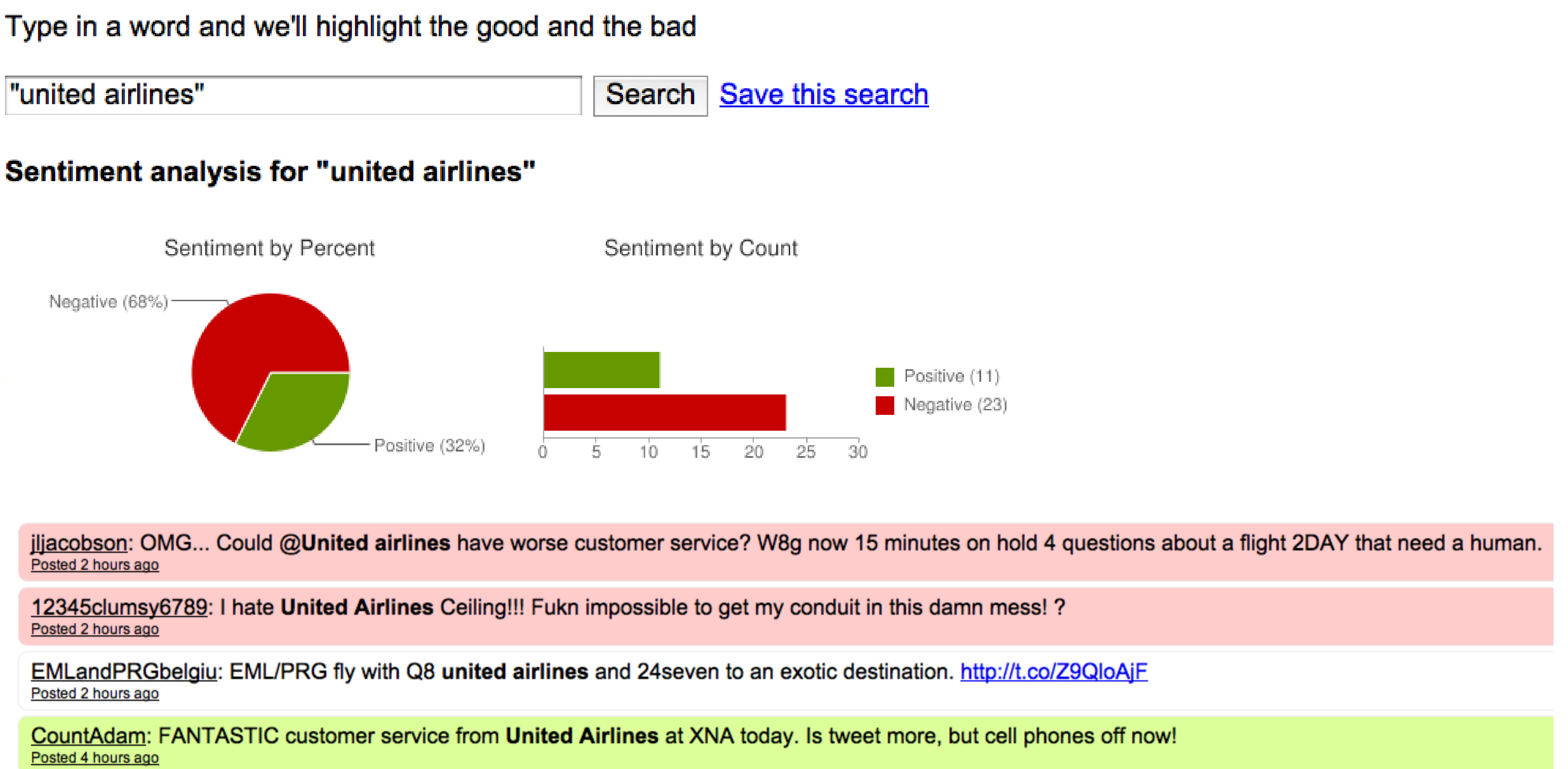
===

Sentiment Classification



Target Sentiment on Twitter

- [Twitter Sentiment App]
- Alec Go, Richa Bhayani, Lei Huang. 2009. Twitter Sentiment Classification using Distant Supervision



Importance of information categorization

P. Jackson and I. Moulinier. 2002. *Natural Language Processing for Online Applications*

- "There is no question concerning the commercial value of being able to classify documents automatically by content. There are myriad potential applications of such a capability for corporate intranets, government departments, and Internet publishers"

- "Understanding the data is one of the keys to successful categorization, yet this is an area in which most categorization tool vendors are extremely weak. Many of the 'one size fits all' tools on the market have not been tested on a wide range of content types."

Categorization/Classification

- Given:
  - A description of an instance, $d \in X$
    - X is the *instance language* or *instance space*.
      - Issue: how to represent text documents.
      - Usually some type of high-dimensional space
  - A fixed set of classes:
    $C = \{c_1, c_2,\ldots, c_J\}$
- Determine:
  - The category of d: $\gamma(d) \in C$, where $\gamma(d)$ is a *classification function* whose domain is X and whose range is C.
    - We want to know how to build classification functions ("classifiers").

Supervised Classification

- Given:
  - A description of an instance, $d \in X$
    - X is the *instance language* or *instance space*.
  - A fixed set of classes:

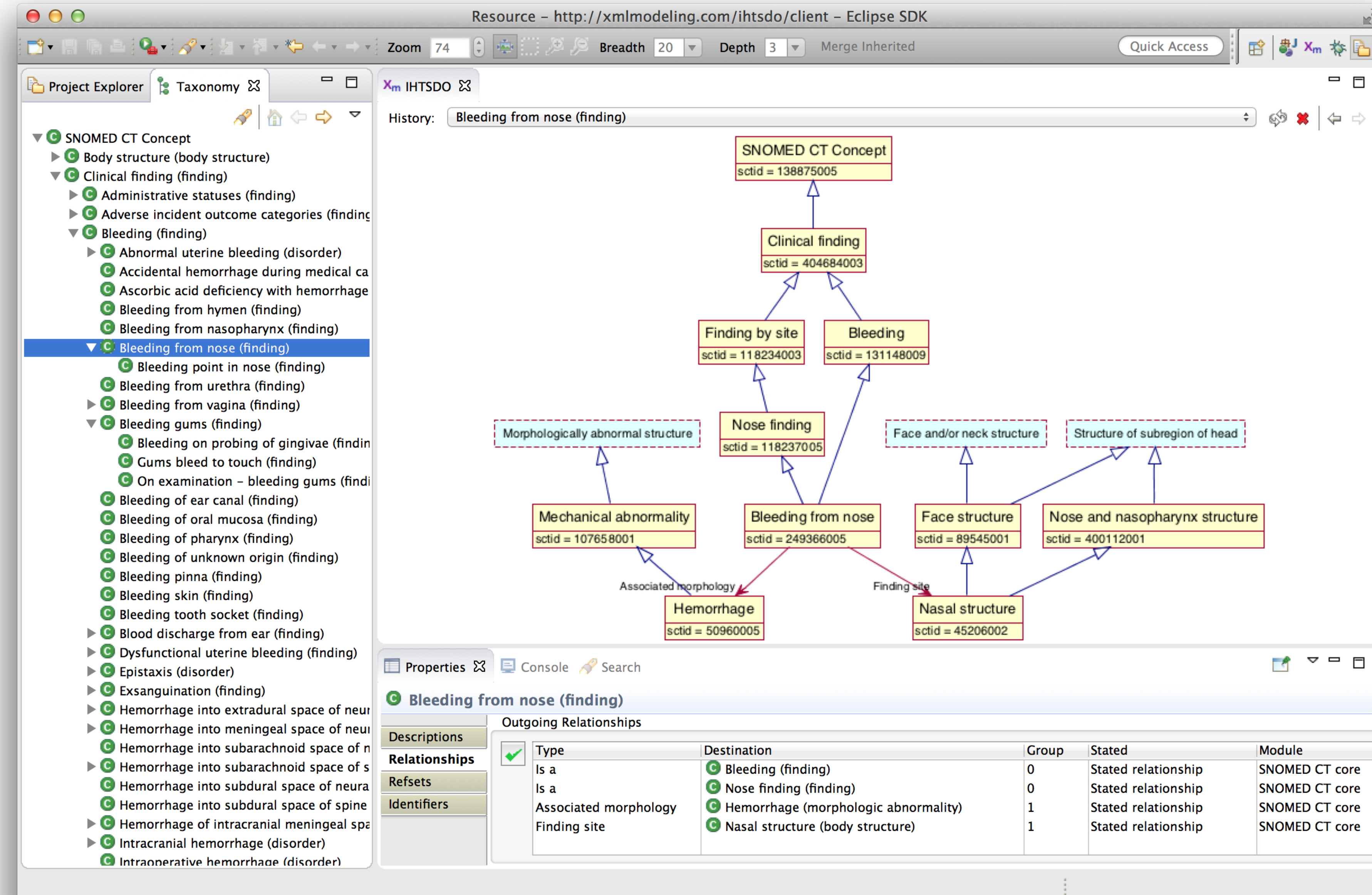
    $C = \{c_1, c_2,\ldots, c_J\}$
  - A training set D of labeled documents with each labeled document $\langle d,c \rangle \in X \times C$
- Determine:
  - A learning method or algorithm which will enable us to learn a classifier $\gamma: X \rightarrow C$
  - For a test document d, we assign it the class $\gamma(d) \in C$

Domain specific taxonomies

- Domain specific terminologies are curated by domain experts and are designed with specific tasks and workflows in mind.

- In the medical domain, the SNOMED-CT is intended to describe medical conditions, procedures, admin, etc.
  - http://browser.ihtsdotools.org/

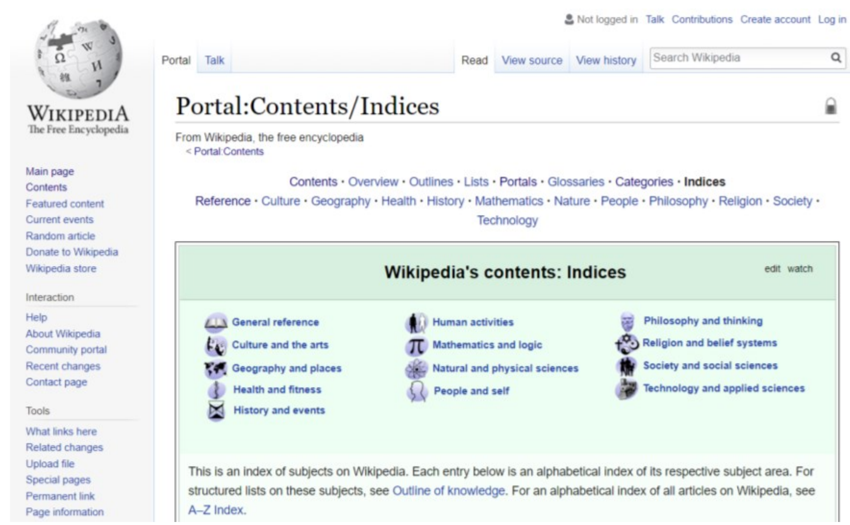
- In the computer science domain the ACM Computing Classification Scheme is widely used to classify published articles.
  - https://dl.acm.org/ccs/ccs.cfm


Resource – http://xmlmodeling.com/ihtsdo/client – Eclipse SDK
Zoom 74
Breadth 20
Depth 3
Merge Inherited
Quick Access
Project Explorer
Taxonomy
SNOMED CT Concept
Body structure (body structure)
Clinical finding (finding)
Administrative statuses (finding)
Adverse incident outcome categories (finding
Bleeding (finding)
Abnormal uterine bleeding (disorder)
Accidental hemorrhage during medical ca
Ascorbic acid deficiency with hemorrhage
Bleeding from hymen (finding)
Bleeding from nasopharynx (finding)
Bleeding from nose (finding)
Bleeding point in nose (finding)
Bleeding from urethra (finding)
Bleeding from vagina (finding)
Bleeding gums (finding)
Bleeding on probing of gingivae (findin
Gums bleed to touch (finding)
On examination – bleeding gums (findi
Bleeding of ear canal (finding)
Bleeding of oral mucosa (finding)
Bleeding of pharynx (finding)
Bleeding of unknown origin (finding)
Bleeding pinna (finding)
Bleeding skin (finding)
Bleeding tooth socket (finding)
Blood discharge from ear (finding)
Dysfunctional uterine bleeding (finding)
Epistaxis (disorder)
Exsanguination (finding)
Hemorrhage into extradural space of neu
Hemorrhage into meningeal space of neu
Hemorrhage into subarachnoid space of n
Hemorrhage into subarachnoid space of s
Hemorrhage into subdural space of neura
Hemorrhage into subdural space of spine
Hemorrhage of intracranial meningeal spa
Intracranial hemorrhage (disorder)
Intraoperative hemorrhage (disorder)
IHTSDO
History: Bleeding from nose (finding)
SNOMED CT Concept
sctid = 138875005
Clinical finding
sctid = 404684003
Finding by site
sctid = 118234003
Bleeding
sctid = 131148009
Morphologically abnormal structure
Nose finding
sctid = 118237005
Face and/or neck structure
Structure of subregion of head
Mechanical abnormality
sctid = 107658001
Bleeding from nose
sctid = 249366005
Face structure
sctid = 89545001
Nose and nasopharynx structure
sctid = 400112001
Associated morphology
Finding site
Hemorrhage
sctid = 50960005
Nasal structure
sctid = 45206002
Properties
Console
Search
Bleeding from nose (finding)
Descriptions
Relationships
Refsets
Identifiers
Outgoing Relationships
Type
Destination
Group
Stated
Module
Is a
Bleeding (finding)
0
Stated relationship
SNOMED CT core
Is a
Nose finding (finding)
0
Stated relationship
SNOMED CT core
Associated morphology
Hemorrhage (morphologic abnormality)
1
Stated relationship
SNOMED CT core
Finding site
Nasal structure (body structure)
1
Stated relationship
SNOMED CT core

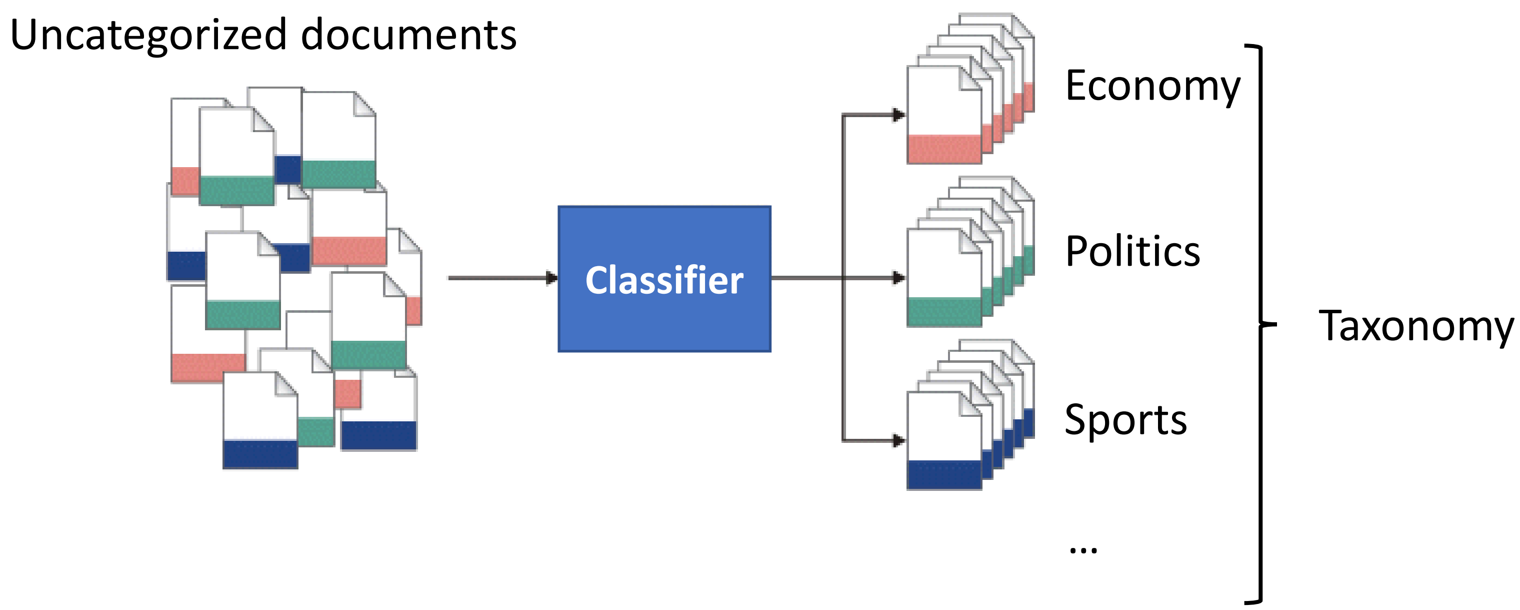
Wikipedia as a database

- Wikipedia contains large amounts of information largely unstructured but structured as a taxonomy.
- **DBPedia** aims to create a rigorous database out of Wikipedia.
- A key application is to link data to Wikipedia entries.

https://en.wikipedia.org/wiki/Portal:Contents

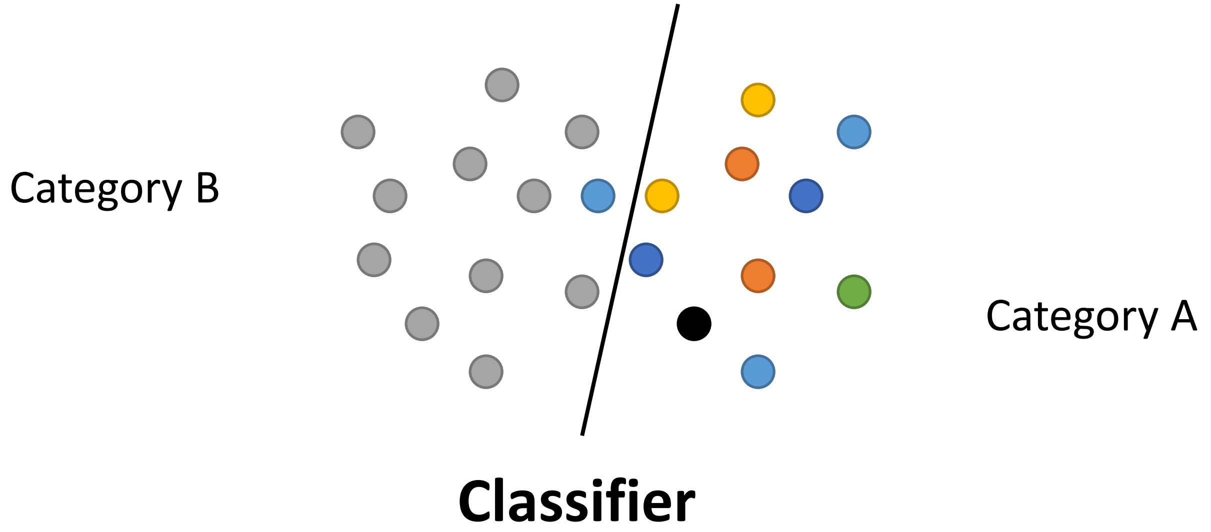


Document Topic Classification



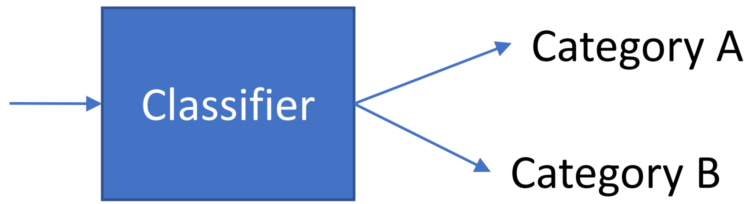
Classification task

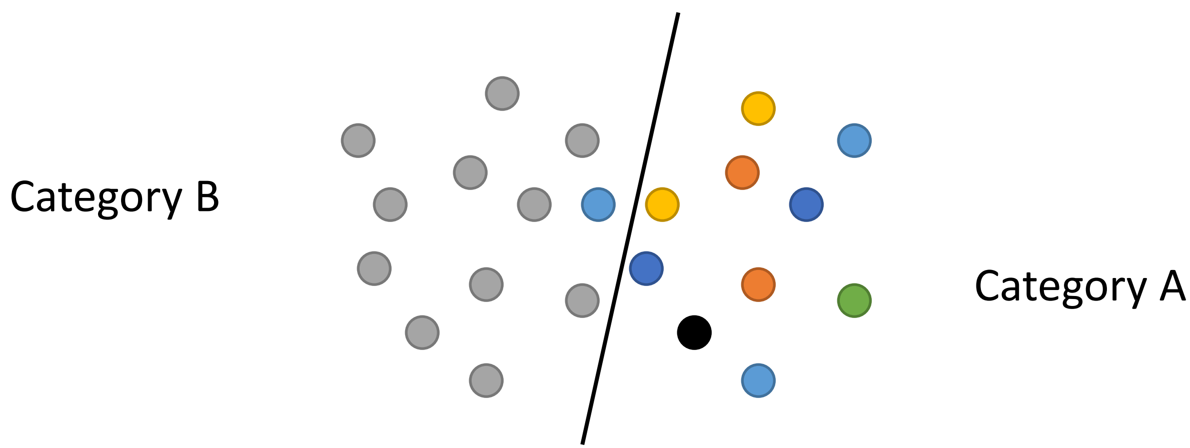
- For new unseen documents, we wish to classify documents with one of the known classes.
- New documents are represented in some feature space and then a machine learning algorithm classifies the new documents.



Input sample *can be* the document word counts

$$d_i = \left(w_1^{d_i}, w_2^{d_i}, \ldots, w_n^{d_i}\right)$$



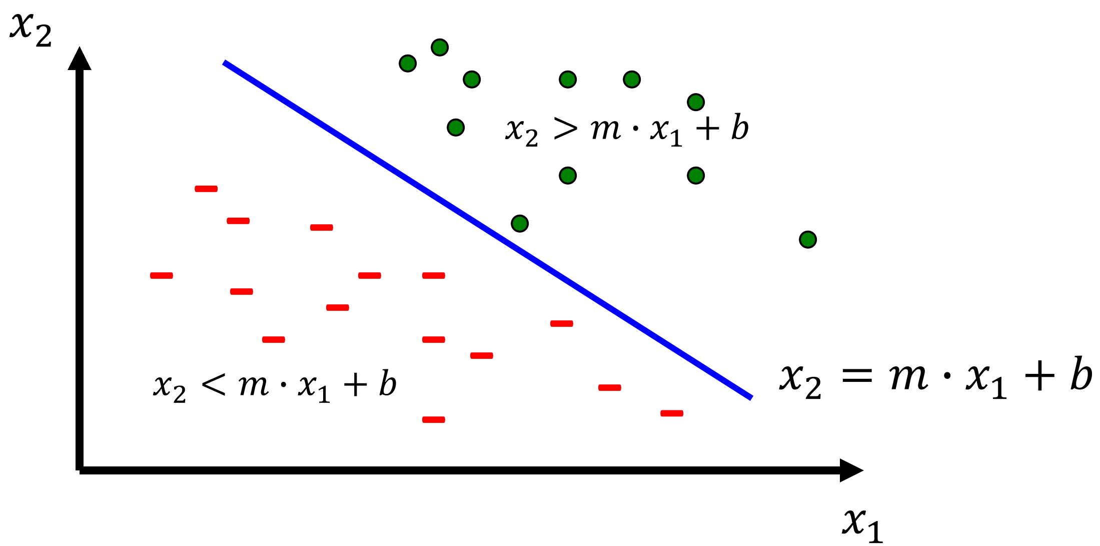


Classifier

Perceptron

- All sample vectors ***x**^(j)^* have their corresponding label ***y**^(j)^ = {+1, -1}*
- **The perceptron performs a binary prediction $\hat{y}$ based on the observed data x :**

$$\hat{y} = f(x) = \begin{cases} +1 & , if\ x_2 \geq m \cdot x_1 + b \\ -1 & , if\ x_2 < m \cdot x_1 + b \end{cases}$$

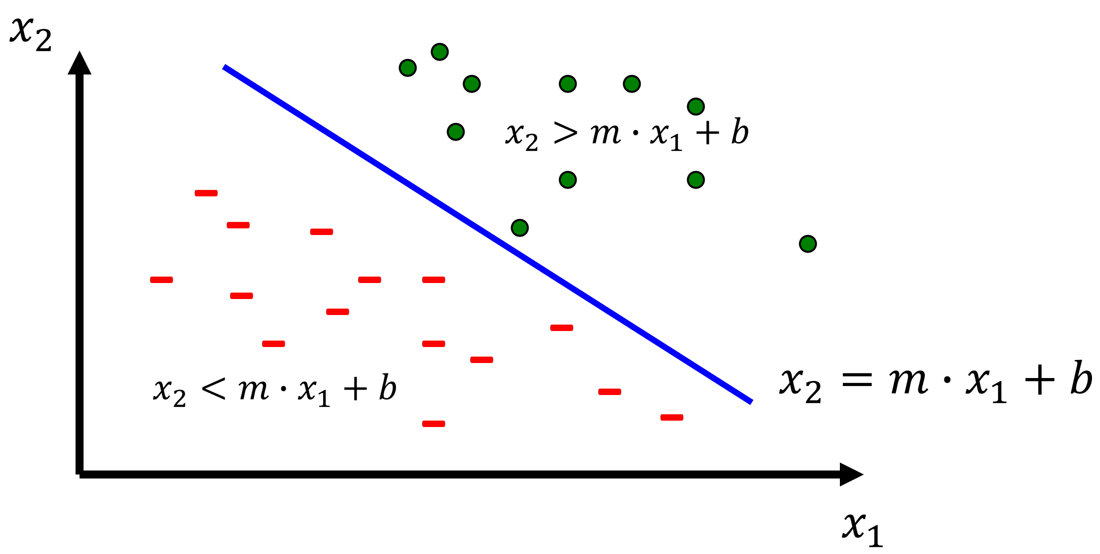


Perceptron

- All sample vectors $\boldsymbol{x}^{(j)}$ have their corresponding label $\boldsymbol{y}^{(j)} = \{+1, -1\}$

- **The perceptron performs a binary prediction $\hat{y}$ based on the observed data x :**

$$\hat{y} = f(x) = \begin{cases} +1 & , if\ x_2 \geq m \cdot x_1 + b \\ -1 & , if\ x_2 < m \cdot x_1 + b \end{cases} = \begin{cases} +1 & , if\ 0 \geq m \cdot x_1 + b - x_2 \\ -1 & , if\ 0 < m \cdot x_1 + b - x_2 \end{cases}$$

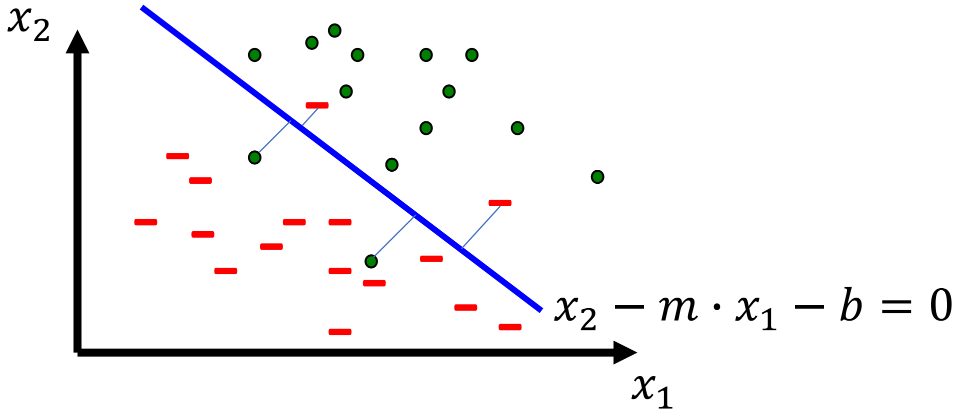


Model error

- The Mean Square Error (MSE) measures the error between the true labels and the predicted labels

$$MSE = \frac{1}{N}\sum_{i}^{N}(error_i)^2$$

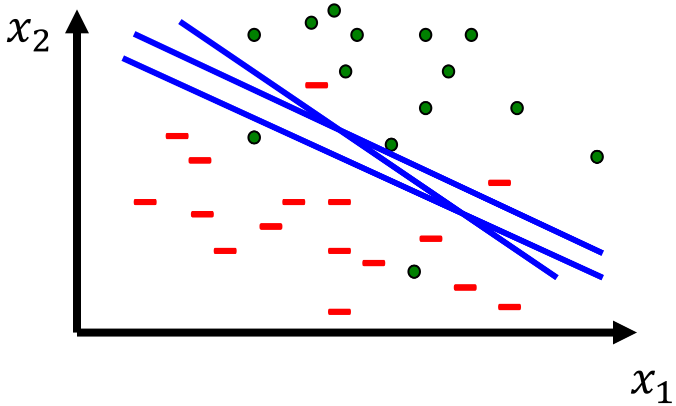
$$error_i = true\_label_i - predictedLabel_i$$

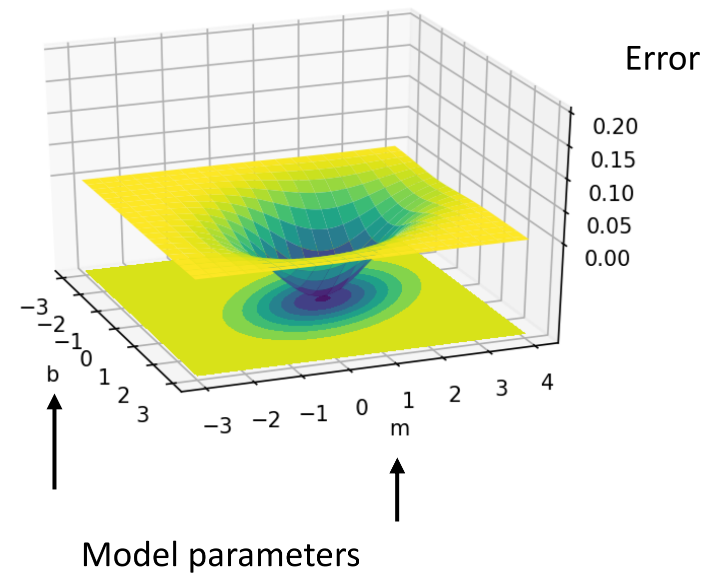


Minimizing the error

$$MeanSquareError = \frac{1}{TotalSamples} \sum_{i}^{TotalSamples} (label_i - predictedLabel_i)^2$$

$$x_2 = x_1 \cdot \boldsymbol{m} + \boldsymbol{b}$$





Learning to minimize the model error

- Initialize the model with random weights
- Compute the model predictions
- Compute the error of each prediction
- Update the model with the samples incorrectly classified.

True label	Predicted label	Error	Update
-1	-1	0	0
-1	+1	-1	-1*x
+1	-1	+1	+1*x
+1	+1	0	0

Learning algorithm

```
[ ]: b=0
     m=0
     model = [m,b]

     max_iters = 30
     mean_square_error = []
     for iter in range(0,max_iters):

         # Compute the model predictions
         predicted_labels = ((observations_x2 - m*observations_x1 - b ) >= 0)*2-1

         # Compute the model error
         error_of_all_samples = (true_labels-predicted_labels)/2

         # Update the model parameters
         update_m = np.mean(error_of_all_samples*observations_x1)
         update_b = np.mean(error_of_all_samples)

         m = m - update_m*0.1
         b = b - update_b*0.1
```

Model predictions

$$\hat{y} = f(x) = \begin{cases} +1 & , if\ x_2 - m \cdot x_1 - b \geq 0 \\ -1 & , if\ x_2 - m \cdot x_1 - b < 0 \end{cases}$$

Model error

$$error = (\mathrm{y} - \hat{y})/2 = \begin{cases} +1 \\ 0 \\ -1 \end{cases}$$

Model parameter update

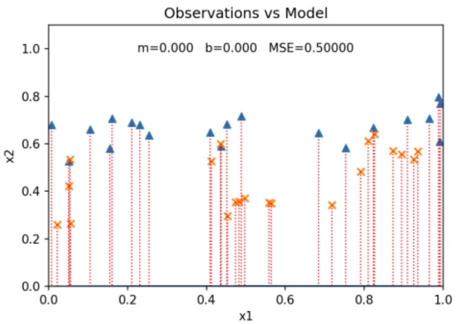
$$update_m = error \cdot x_1$$

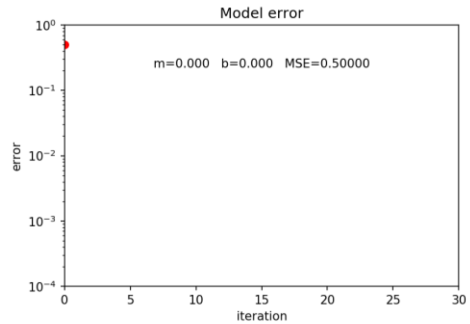
$$m = m - update_m \cdot learning_{rate}$$

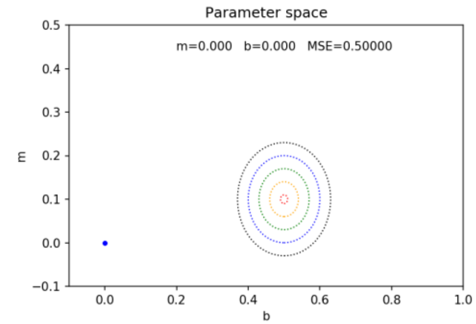
Perceptron learning example

Model predictions | Model error | Model parameter update

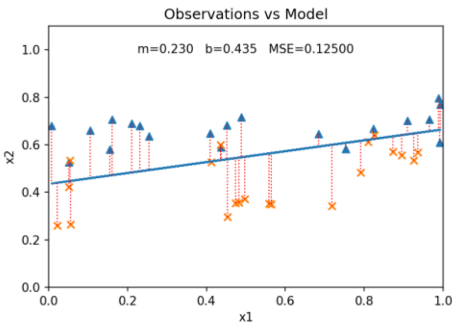
iter = 1

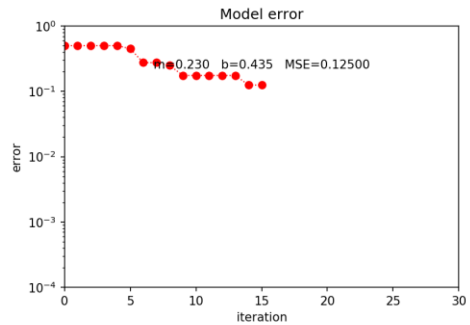


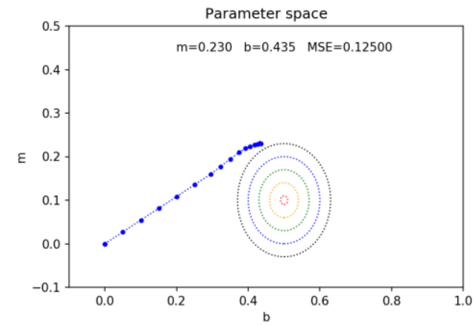




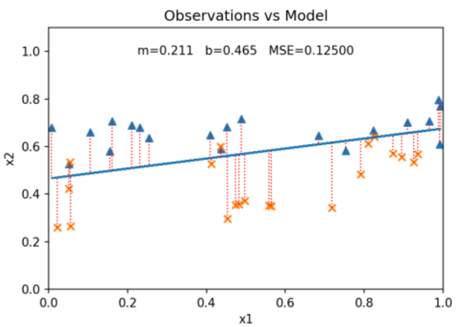
iter = 15

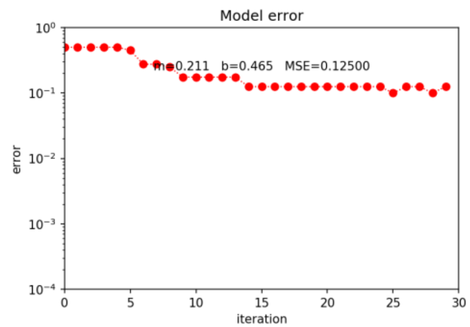


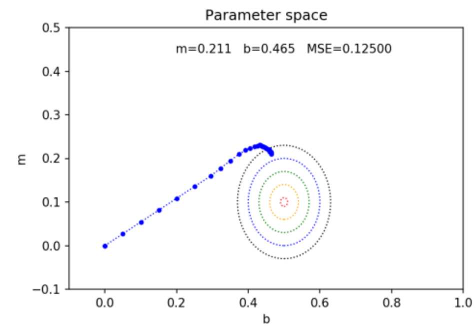




iter = 36





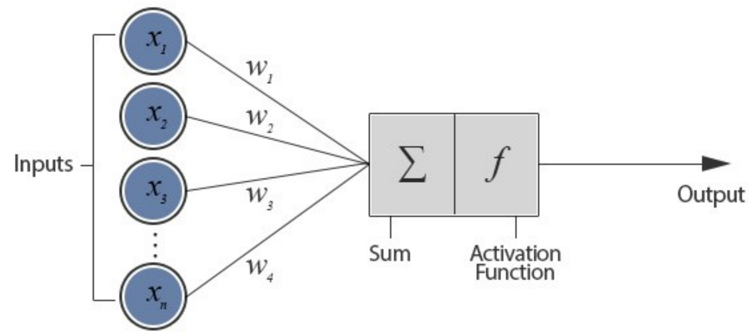


Perceptron: general formulation

- **Binary classification:**

$$z = w_0 + w_1 x_1 + \ \dots + w_n x_n$$

$$\hat{y} = \sigma(z) = \begin{cases} +1 & , if\ z \geq 0 \\ -1 & , if\ z < 0 \end{cases}$$

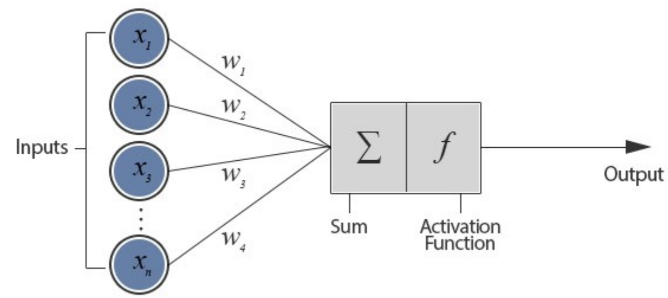


- **Input:** Vectors $x^{(j)}$ and labels $y^{(j)}$
  - Vectors $x^{(j)}$ are real valued where $\|x\|_2 = 1$

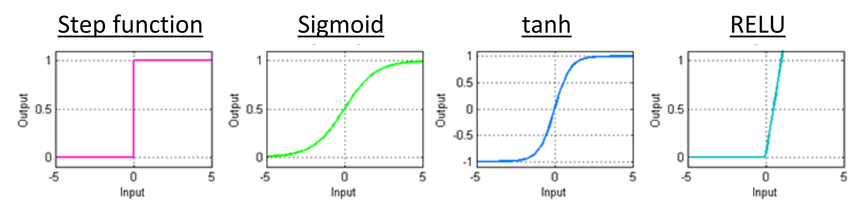
- **Goal:** Find vector $w = (w_1, w_2, \dots, w_d)$
  - Each w_i is a real number

Activation functions

- The perceptron was initially proposed with the step function.
- Historically, other activation functions have been studied.
- It can be shown that the perceptron with the sigmoid activation function corresponds to the logistic regression model.



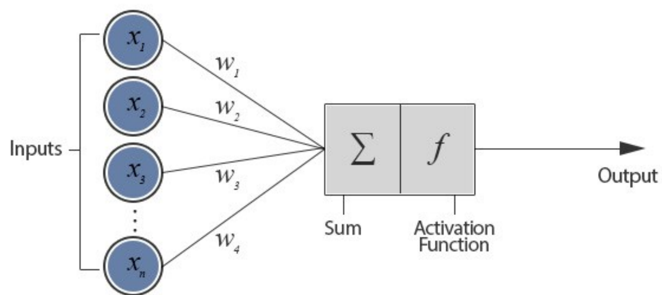
Activation functions



The sigmoid activation function

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \\ x_n \end{bmatrix}$$

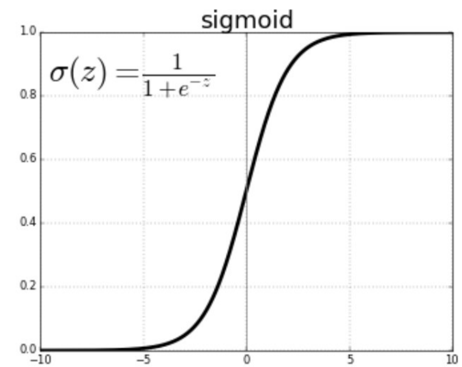
Word frequency counts



$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ \\ w_n \end{bmatrix}$$

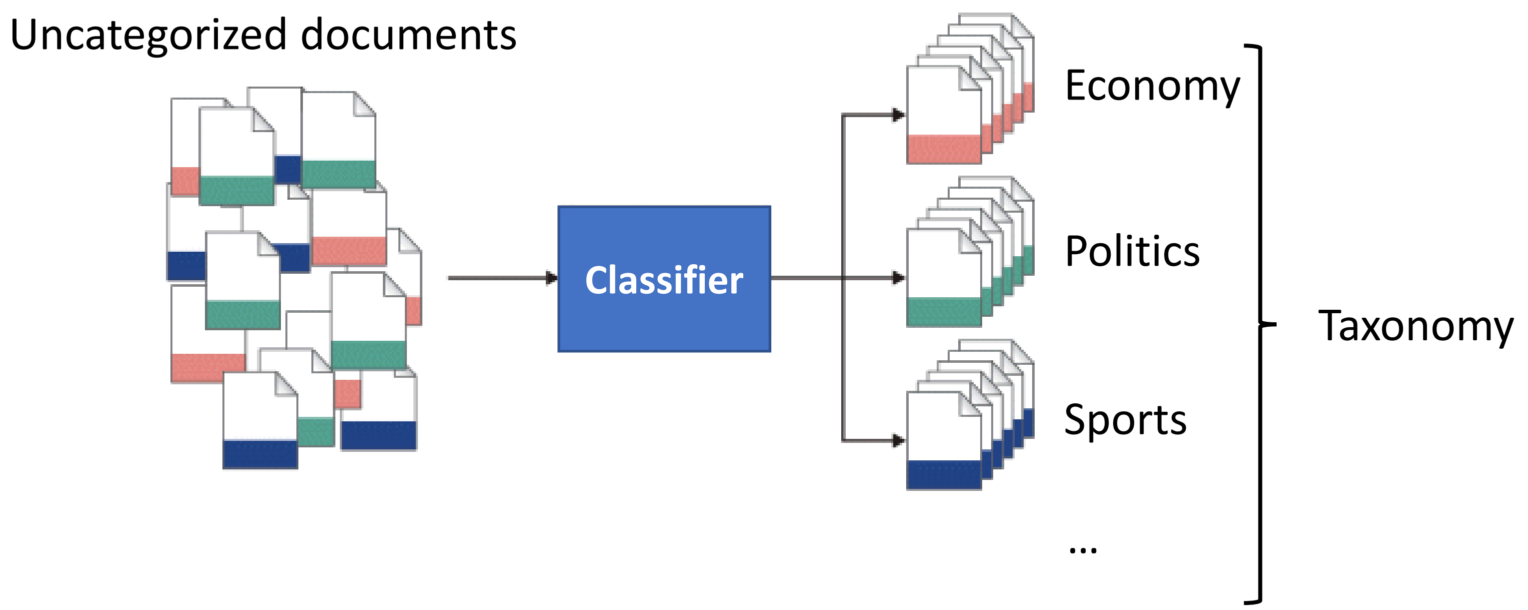
Word weights

$\sigma(z)$



$$z = w_0 + w_1 x_1 + \ \ldots + w_n x_n$$

Training Document Categorizers



Real-world model training

- Robustly training a model for Web data is a complex task.
- In most of the cases, we will use pre-trained models.
- These models were trained on large-scale data.
- These pre-trained models are robust and reliable.

Which and how many categories are detectable?

- An important question to ask is which and how many items of the taxonomy are detectable in data?

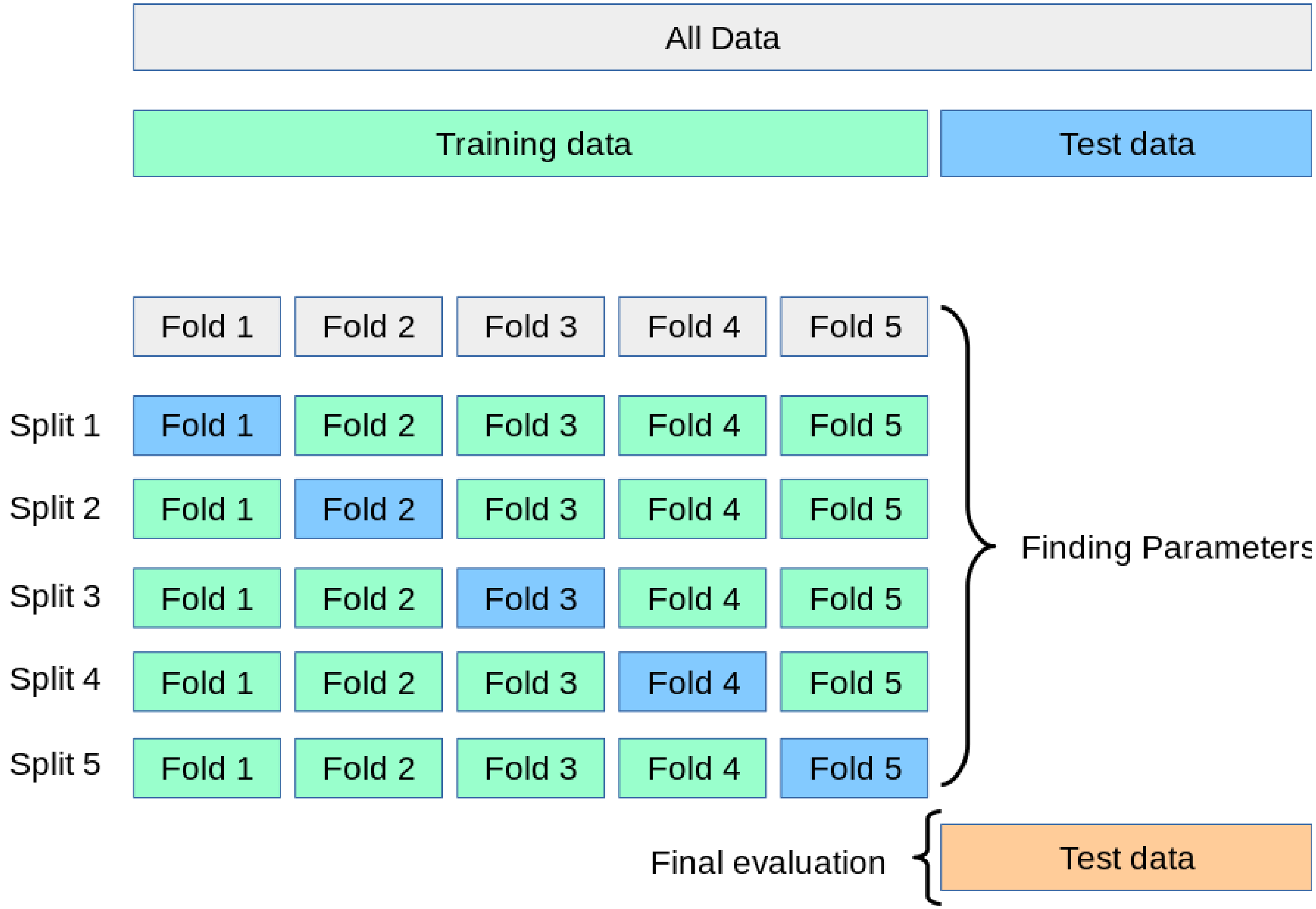
- A few (well separated ones)? -> Easy!

- A zillion closely related ones? -> Not so easy…
  - Think: Yahoo! Directory, Library of Congress classification, legal applications
  - Quickly gets difficult!
    - Classifier combination is always a useful technique
      - Voting, bagging, or boosting multiple classifiers
    - Much literature on hierarchical classification
      - Definitely helps for scalability, even if not in accuracy
    - May need a hybrid automatic/manual solution

Taxonomies and classification

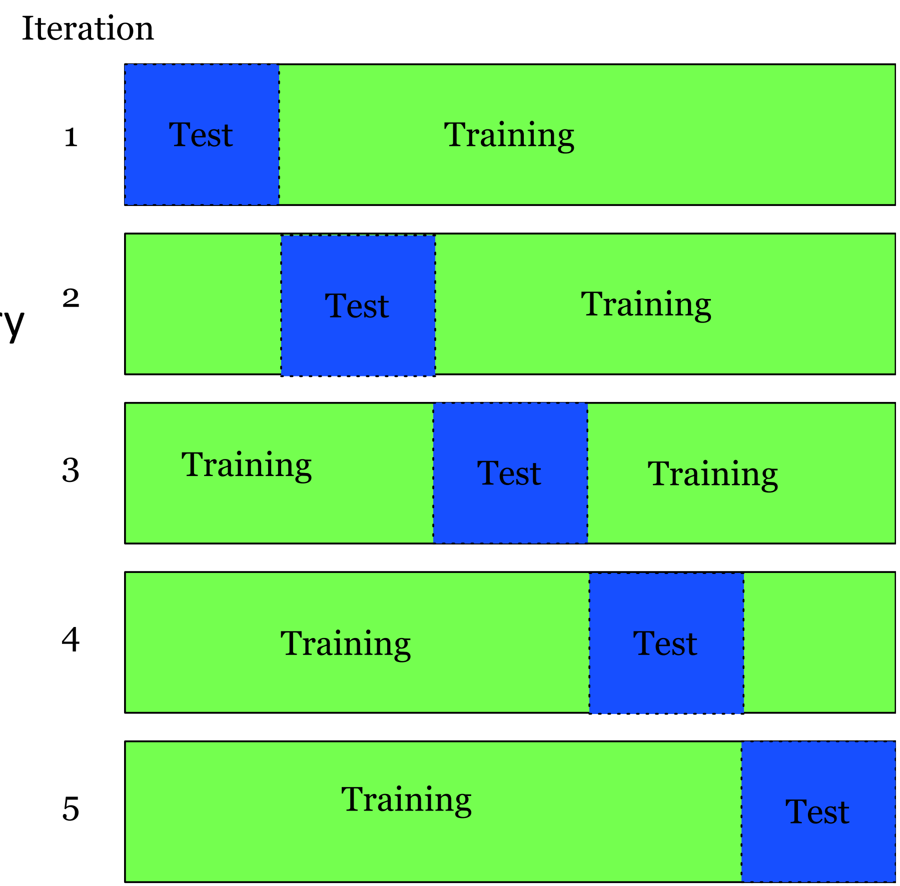
- In practice, only a few elements of the taxonomy should be used as classes for classification
  - Only the ones offering a stable document class representation.
- The ultimate goal is to link information to an entry on a taxonomy capturing the target domain.
- Ultimately more complete domain representation should be used, e.g. an ontology.

Cross-Validation with held-out test data



Cross-Validation with limited data

- Break up data into 10 folds
  - (Equal positive and negative inside each fold?)
- For each fold
  - Choose the fold as a temporary test set
  - Train on 9 folds, compute performance on the test fold
- Report average performance of the 10 runs



Per-class evaluation measures

		Ground-truth	
		True	False
Method	True	True positive	False positive
	False	False negative	True negative

- **Recall**: Fraction of docs in class i classified correctly:

$$Recall = \frac{truePos}{truePos + falseNeg}$$

- **Precision**: Fraction of docs assigned class i that are actually about class i:

$$Precision = \frac{truePos}{truePos + falsePos}$$

- **Accuracy**: Fraction of docs classified correctly:

$$Accuracy = \frac{truePos + trueNeg}{truePos + falsePos + trueNeg + falseNeg}$$

* abragência, precisão e exatidão.

Micro- vs. Macro-Averaging

- If we have more than one class, how do we combine multiple performance measures into one quantity?

- **Macroaveraging**: Compute performance for each class, then average.

- **Microaveraging**: Collect decisions for all classes, compute contingency table, evaluate.

Micro- vs. Macro-Averaging: Example

Class 1

	Truth: yes	Truth: no
Classifier: yes	10	10
Classifier: no	10	970

Class 2

	Truth: yes	Truth: no
Classifier: yes	90	10
Classifier: no	10	890

Micro Ave. Table

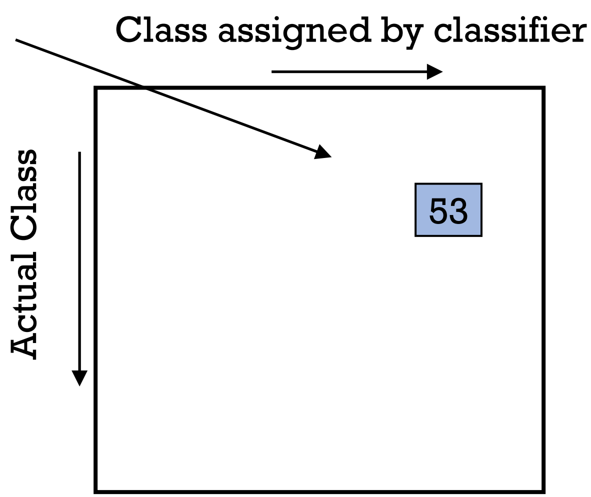
	Truth: yes	Truth: no
Classifier: yes	100	20
Classifier: no	20	1860

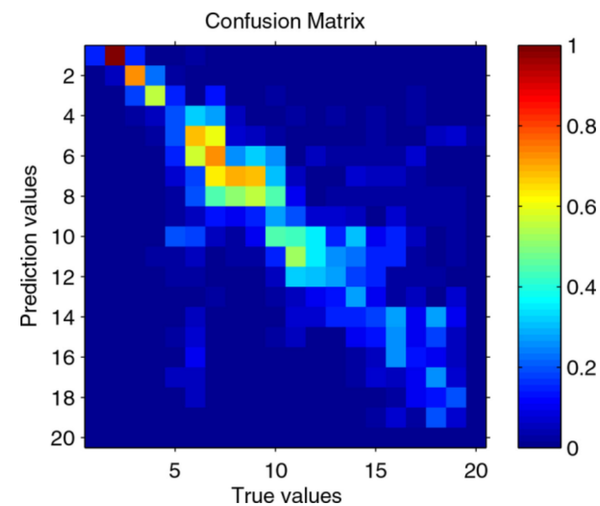
- Macroaveraged precision: (0.5 + 0.9)/2 = 0.7
- Microaveraged precision: 100/120 = .83

- Microaveraged score is dominated by score on common classes

Good practice: Make a confusion matrix

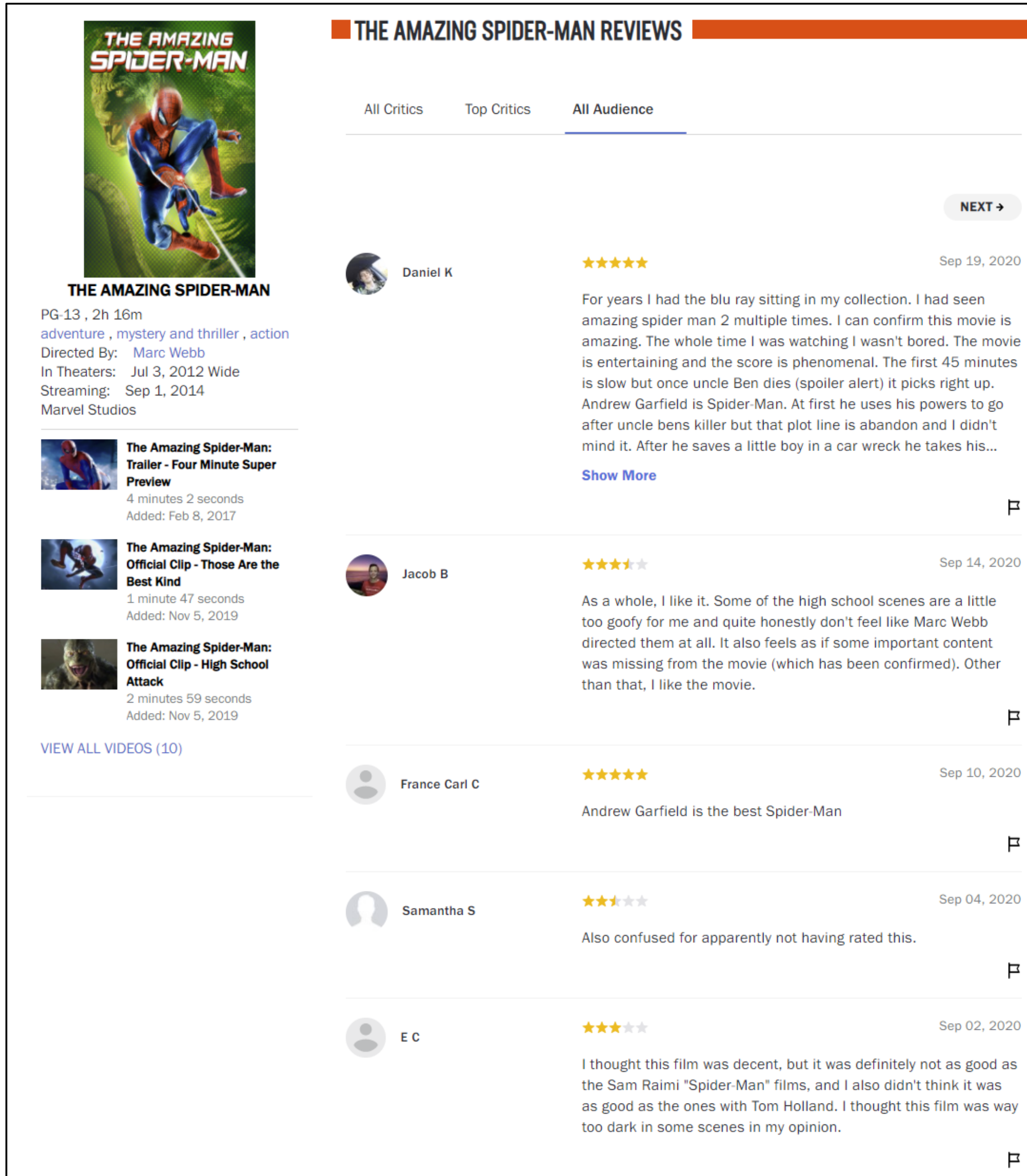
- This (i, j) entry means 53 of the docs actually in class i were put in class j by the classifier.





- In a perfect classification, only the diagonal has non-zero entries
- Look at common confusions and how they might be addressed

Sentiment Classification



Sentiment Classification in Movie Reviews

- Polarity detection:
  - Is an IMDB movie review positive or negative?
- Data: Polarity Data 2.0:
  - http://www.cs.cornell.edu/people/pabo/movie-review-data

Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79—86.

Bo Pang and Lillian Lee. 2004. A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts. ACL, 271-278

IMDB data in the Pang and Lee database

✓

when _star wars_ came out some twenty years ago , the image of traveling throughout the stars has become a commonplace image . [...]

when han solo goes light speed , the stars change to bright lines , going towards the viewer in lines that converge at an invisible point .

cool .

october sky offers a much simpler image–that of a single white dot , traveling horizontally across the night sky . [. . .]

✗

" snake eyes " is the most aggravating kind of movie : the kind that shows so much potential then becomes unbelievably disappointing .

it's not just because this is a brian depalma film , and since he's a great director and one who's films are always greeted with at least some fanfare .

and it's not even because this was a film starring nicolas cage and since he gives a brauvara performance , this film is hardly worth his talents .

Baseline Algorithm

- Tokenization
- Feature Extraction
- Classification using different classifiers
  - Naïve Bayes
  - MaxEnt
  - SVM

Sentiment Tokenization Issues

- Deal with HTML and XML markup
- Twitter mark-up (names, hash tags)
- Capitalization (preserve for words in all caps)
- Phone numbers, dates, emoticons
- Useful code:
  - [Christopher Potts sentiment tokenizer]
  - [Brendan O'Connor twitter tokenizer]

REGEX emoticons

```
[<>]?                          # optional hat/brow
[:;=8]                         # eyes
[\-o\*\']?                     # optional nose
[\)\]\(\[dDpP/\:\}\{@\|\\]     # mouth
|                              #### reverse orientation
[\)\]\(\[dDpP/\:\}\{@\|\\]     # mouth
[\-o\*\']?                     # optional nose
[:;=8]                         # eyes
[<>]?                          # optional hat/brow
```

Extracting Features for Sentiment Classification

- How to handle negation

  *I **didn't** like this movie*

  vs

  I really like this movie

- Which words to use?
  - Only adjectives
  - All words
    - All words turns out to work better, at least on this data

Negation

Add NOT_ to every word between negation and following punctuation:

`didn't like this movie , but I`

`didn't NOT_like NOT_this NOT_movie but I`

Das, Sanjiv and Mike Chen. 2001. Yahoo! for Amazon: Extracting market sentiment from stock message boards. In Proceedings of the Asia Pacific Finance Association Annual Conference (APFA).
Bo Pang, Lillian Lee, and Shivakumar Vaithyanathan. 2002. Thumbs up? Sentiment Classification using Machine Learning Techniques. EMNLP-2002, 79—86.

Word representations

- Binary seems to work better than full word counts

- **Sentiment lexicons** (e.g. SentiWordNet http://sentiwordnet.isti.cnr.it/)
  - All WordNet synsets automatically annotated for degrees of positivity, negativity, and neutrality/objectiveness
  - [estimable(J,3)] “may be computed or estimated”
  - Pos 0 Neg 0 Obj 1
  - [estimable(J,1)] “deserving of respect or high regard”
  - Pos .75 Neg 0 Obj .25

- **Affective lexicons**
  - joy–sadness
  - anger–fear
  - trust–disgust
  - anticipation–surprise

Problems:
What makes reviews hard to classify?

- Subtlety:
  - Perfume review in Perfumes: the Guide:
    - “If you are reading this because it is your darling fragrance, please wear it at home exclusively, and tape the windows shut.”
  - Dorothy Parker on Katherine Hepburn
    - “She runs the gamut of emotions from A to B”

Thwarted Expectations and Ordering Effects

- "This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it **can't hold up**."
- Well as usual Keanu Reeves is nothing special, but surprisingly, the very talented Laurence Fishbourne is **not so good** either, I was surprised.

Summary

- Document topic categorization
- Perceptron and sigmoid function
- Model training
- Sentiment classification