NICF - TEXT ANALYTICS

MODULE 6: TEXT CATEGORIZATION

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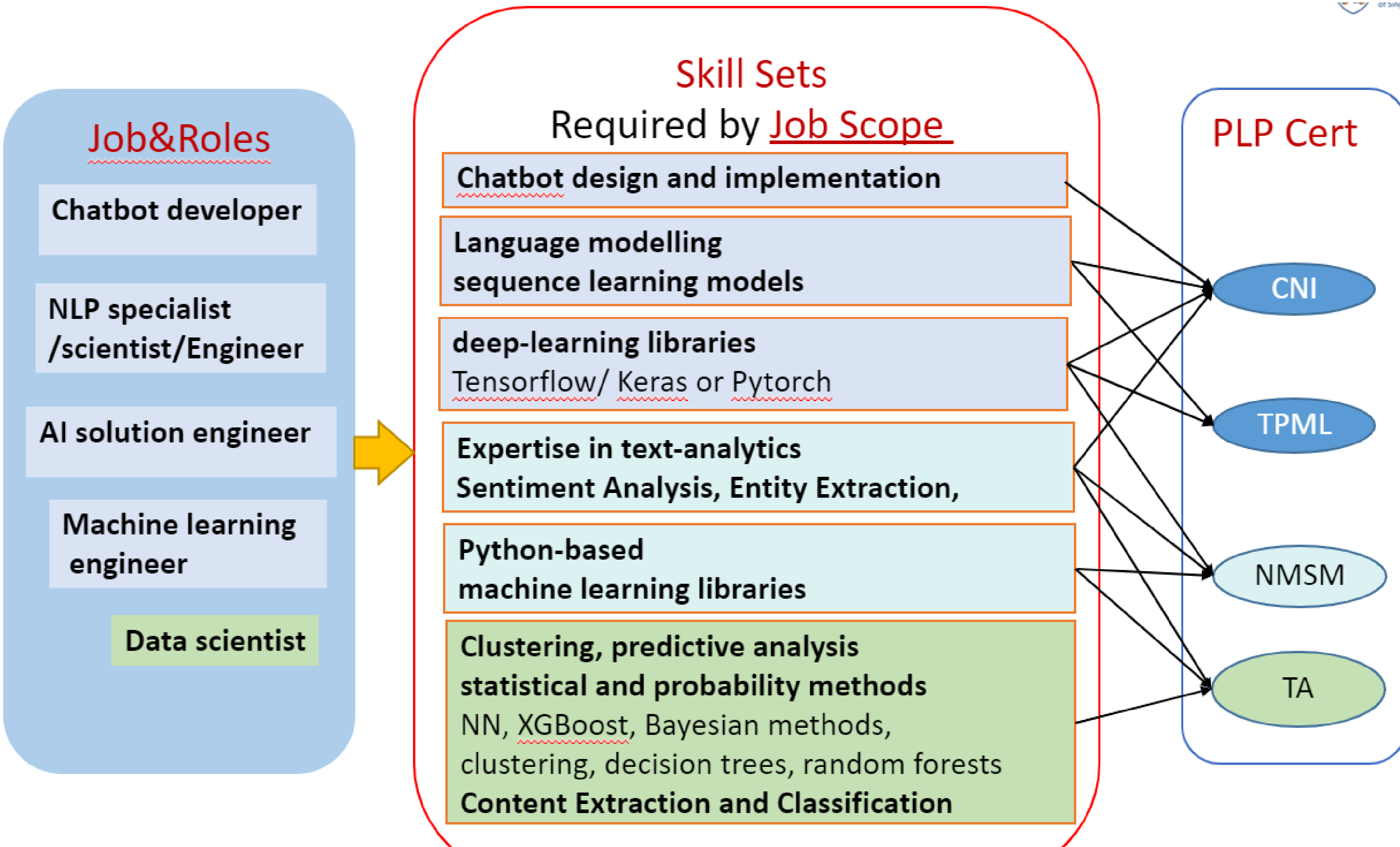
Objectives of this module

At the end of this module, you can:

- Describe what is text categorization and how text categorization systems work
- Evaluate a text categorization system with respect to a business scenario
- Understand how supervised and unsupervised text categorization works
- Understand what is topic modeling

PLP Cert


Job&Roles
Chatbot developer
NLP specialist /scientist/Engineer
AI solution engineer
Machine learning engineer
Data scientist
Skill Sets
Required by Job Scope
Chatbot design and implementation
Language modelling
sequence learning models
deep-learning libraries
Tensorflow/ Keras or Pytorch
Expertise in text-analytics
Sentiment Analysis, Entity Extraction,
Python-based
machine learning libraries
Clustering, predictive analysis
statistical and probability methods
NN, XGBoost, Bayesian methods,
clustering, decision trees, random forests
Content Extraction and Classification
PLP Cert
CNI
TPML
NMSM
TA

Outline for this module

- **What is text categorization?**
- **How does supervised text categorization work?**
  - Document data set
  - Building a classifier
  - Evaluation (*quiz*)
  - Running the classifier (*workshop*)
- **Text categorization application examples**
- **Unsupervised text categorization**
  - Document clustering
- **Topic Modeling**
  - LDA (*workshop*)

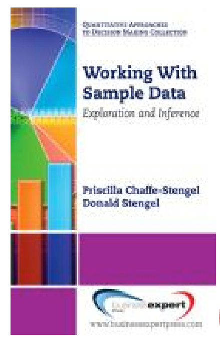
WHAT IS TEXT CATEGORIZATION?

Contrast with a library catalog

- **Example to right**
  - Subject: Statistics
- **Assigned by a cataloger**
- **Slow, tedious**
- **May be inconsistent**

Record 1 of 381 in National Library Board **Search type:** Search by Subjects
Search was: Statistics

Next



Annotation

Title	Working with sample data : exploration and inference / Priscilla Chaffe-Stengel, Donald N. Stengel.
Author	Chaffe-Stengel, Priscilla M.
Publisher	New York : Business Expert Press, c2012.
Physical Description	151 p. : ill. ; 23 cm.
Notes	Includes index. "The quantitative approaches to decision making collection"--Cover. Originally published in 2011.
Other Contributors	Stengel, Donald N.
Search by Subjects	Commercial statistics. **Statistics.**

MESH index of a single journal paper

Below is an example of a **complete reference** in Medline (OvidSP) showing the journal article details and the list of MeSH headings (some with subheadings) assigned to it by the NLM Indexers:

Unique Identifier	20980007
Record Owner	From MEDLINE, a database of the U.S. National Library of Medicine.
Status	MEDLINE
Authors	Asejczyk-Widlicka M. Srodka W. Schachar RA. Pierscionek BK.
Authors Full Name	Asejczyk-Widlicka, M. Srodka, W. Schachar, R A. Pierscionek, B K.
Institution	Institute of Physics, Wroclaw University of Technology, Wybrzeze Wyspianskiego 27, 50-370 Wrocl Poland.
Title	Material properties of the cornea and sclera: a modelling approach to test experimental analysis
Source	Journal of Biomechanics. 44(3):543-6, 2011 Feb 3.
Abbreviated Source	J Biomech. 44(3):543-6, 2011 Feb 3.
NLM Journal Name	Journal of biomechanics
Publishing Model	Journal available in: Print-Electronic Citation processed from: Internet
NLM Journal Code	0157375, hjf
Country of Publication	United States
MeSH Subject Headings	Computer Simulation *Cornea / ph [Physiology] Finite Element Analysis Humans *Intraocular Pressure / ph [Physiology] Muscle Rigidity *Sclera / ph [Physiology] Visual Acuity / ph [Physiology]
Abstract	Material prope… es of cornea and sclera are important for maintaining the shape of the eye and the requisite … ce curvatures for optics. They also need to withstand the forces of external and inte… sculature and fluctuations in intraocular pressure (IOP). These properties are difficult tc … iable results have been reported. A previously published experimental procedure, … material properties of the eyeball coats were obtained, has been modelled in this … te Element Analysis, in order to test the accuracy of the experiment. Material … e calculated from the model and the resulting relationships between stress and … rnea and sclera compared to their experimentally obtained counterparts. The … ween model and experiment was close for the sclera but more varied for the corne… The pressure vessel model can be applied for measuring the material properties of the sclera but is less accurate for the cornea. Copyright Copyright 2010 Elsevier Ltd. All rights reserved.

Journal article details

MeSH descriptors assigned by indexers- taken from the list of preferred terms used to describe topics

The indexers have assigned the subheading Physiology to this MeSH descriptor

From: http://library.ulster.ac.uk/sci/mesh/

Automatic text categorization (also known as “classification”)

- **Hard Classification**

  The process of assigning text documents uniquely into two or more categories (a document cannot be in more than one category)

  E.g., spam filtering – binary decision: “spam” or “not spam”

- **Soft Classification**

  The process of assigning one or more category labels to a text document (a document may have more than one category)

  E.g., news filtering – which category to assign to news articles:
  - Sports, Olympics, Football (natural class)
  - Political, Business, Home,… (news sections)
  - Asian, Europe, Middle-East, …(geographical)

Some Examples of Text Classification

- Email spam detection
- Identifying fraud (anomaly detection)
- Sentiment analysis (e.g., positive/negative reviews)
- Identify fake news
- Study financial news by industries
- Etc.

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HOW DOES AUTOMATIC TEXT CATEGORIZATION WORK?

Text Categorization Phases

Two Phases for supervised method

1. **Training – creating the text "classifier" (automatic categorization engine)**
   - You need a set of documents, already categorized
   - Divide the set into training (typically 70%) and testing (30%)
   - Train your classifier such that it's able to accurately classify the training set of documents to your level of comfort
     - "level of comfort" depends on how hard is the task! ☺
   - Evaluate your classifier on the test set; ensure sufficient accuracy

2. **Running – using your classifier on new sets of documents**
   - You will not know how well it performs
   - Need to "audit" the results occasionally (use an assessor)
     - Assess random sample of the documents against the predicted categories

DOCUMENT DATA SET

Movie reviews classified as “good” and “bad”

POSITIVE POLARITY (GOOD)

-a mesmerizing cinematic poem from the first frame to the last .”
-a well-put-together piece of urban satire .
-one can't deny its seriousness and quality .
-hard to resist .
-a naturally funny film , home movie makes you crave chris smith's next movie .
-a true-blue delight .
-a fun ride .
-a surprisingly funny movie .
-the script is smart and dark - hallelujah for small favors .
-a flick about our infantilized culture that isn't entirely infantile .

-unfortunately the story and the actors are served with a hack script .
-too slow for a younger crowd , too shallow for an older one .
-terminally brain dead production .
-one lousy movie .
-this movie . . . doesn't deserve the energy it takes to describe how bad it is .
-a cleverly crafted but ultimately hollow mockumentary .
-it's an 88-minute highlight reel that's 86 minutes too long .
-the whole affair is as predictable as can be .

NEGATIVE POLARITY (BAD)

From: http://karpathy.ca/mlsite/lecture2.php

Movie reviews classified as "good" and "bad"

POSITIVE POLARITY (GOOD)

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5000 reviews

-unfortunately the story and the actors are served with a hack script .
-too slow for a younger crowd , too shallow for an older one .
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-one lousy movie .
-this movie . . . doesn't deserve the energy it takes to describe how bad it is .
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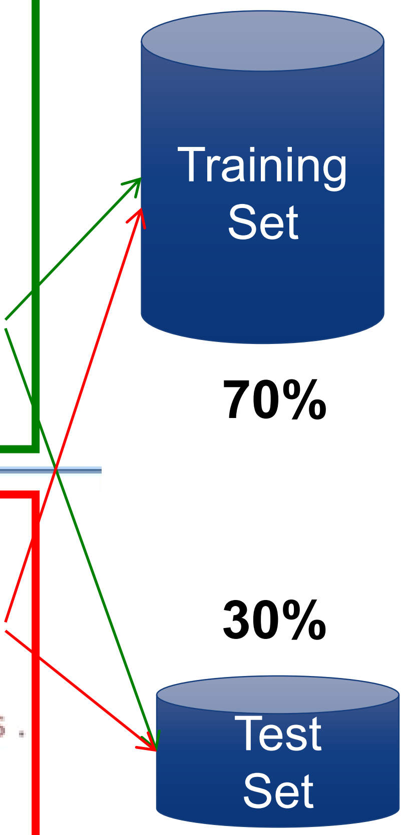
5000 reviews



From: http://karpathy.ca/mlsite/lecture2.php

BUILDING A CLASSIFIER

JUST SOME EXAMPLES (NOT EXHAUSTIVE)

Creating classifiers

- **Hand-coded classifiers (the “good old days!”)**
  - If <conditions> then <category> else NOT<category>, where conditions are normally in disjunctive normal form

If	((wheat & farm)	**or**	
	(wheat & commodity)	**or**	
	(bushels & export)	**or**	
	(wheat & tonnes)	**or**	
	(wheat & winter & ¬soft))	**then**	WHEAT else ¬ WHEAT

From: F. Aiolli, *Text Categorization*, http://www.math.unipd.it/~aiolli/corsi/SI-0607/Lez09.251006.pdf

Generative Classifiers

- **Naïve Bayes Model**

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

- Basically, we are trying to find probability of event A, given the event B is true. Event B is also termed as observations.

- Q: What is A and B in documents Classification context?

Naïve Bayes Model

Probabilistic Classifiers

Represent the probability that a document d_i belongs to category c_j by

$$P(c_j|d_i) = P(c_j)P(d_i|c_j) / \cancel{P(d_i)}$$

$$class_{MAP} \approx \boldsymbol{argmax}_{\boldsymbol{class \in C}}\, P(doc|class) * \mathrm{P}(class)$$

$$\approx \boldsymbol{argmax}_{\boldsymbol{class \in C}}\, P(w_1, w_2, \ldots w_n|class) * \mathrm{P}(class)$$

$$\approx \boldsymbol{argmax}_{\boldsymbol{class \in C}}\, P(w_1|class) * P(w_2|class) * \cdots * P(w_n|class) * \mathrm{P}(class)$$

Naïve Bayes Model

$$class_{MAP} \approx \boldsymbol{argmax}_{class \in C}\, P(doc|class) * \mathrm{P}(class)$$
$$\approx \boldsymbol{argmax}_{class \in C}\, P(w_1, w_2, \ldots w_n|class) * \mathrm{P}(class)$$
$$\approx \boldsymbol{argmax}_{class \in C}\, P(w_1|class) * P(w_2|class) * \cdots * P(w_n|class) * \mathrm{P}(class)$$

- **Example**
  - For sentiment detection problem: $\boldsymbol{class} \in \{+, -\}$
  - **Training**: calculate and keep all the likelihood of vocabulary words *wrt.* classes: $P(w|-)$, $P(w|+)$, $\mathrm{P}(+)$, $\mathrm{P}(-)$

$P(w|-)$ = *count (neg docs having w) / count (neg docs)*

$P(-)$ = ***count (neg doc) / count(total docs)***

  - **Testing**: calculate, compare and select the class offering bigger result

$$P(w_1|-) * P(w_2|-) * \cdots * P(w_n|-) * \mathrm{P}(-)$$
$$P(w_1|+) * P(w_2|+) * \cdots * P(w_n|+) * \mathrm{P}(+)$$

Naïve Bayes Model

$$class_{MAP} \approx \boldsymbol{argmax}_{class \in C}\, P(doc|class) * \mathrm{P}(class)$$
$$\approx \boldsymbol{argmax}_{class \in C}\, P(w_1, w_2, \dots w_n|class) * \mathrm{P}(class)$$
$$\approx \boldsymbol{argmax}_{class \in C}\, P(w_1|class) * P(w_2|class) * \cdots * P(w_n|class) * \mathrm{P}(class)$$

- **Example**
  - For sentiment detection problem: $\boldsymbol{class} \in \{+, -\}$
  - **Training**: calculate and keep all the likelihood of vocabulary words *wrt.* classes: $P(w|-)$, $P(w|+)$, $\mathrm{P}(+)$, $\mathrm{P}(-)$
  - **Testing**: calculate, compare and select the class offering bigger result

$$P(w_1|-) * P(w_2|-) * \cdots * P(w_n|-) * \mathrm{P}(-)$$
$$P(w_1|+) * P(w_2|+) * \cdots * P(w_n|+) * \mathrm{P}(+)$$

$$Dnew = "I\ hated\ the\ poor\ acting"$$

$$P(+|D_{new}) = P(I|+) * P(hated|+) * \cancel{P(the|+)} * P(poor|+) * P(acting|+) * P(+)$$
$$= \mathrm{a}$$

$$P(-|D_{new}) = P(I|-) * P(hated|-) * \cancel{P(the|-)} * P(poor|-) * P(acting|-) * P(-)$$
$$= \mathrm{b}$$

Discriminative Classifiers

- ## Decision Tree Classifiers

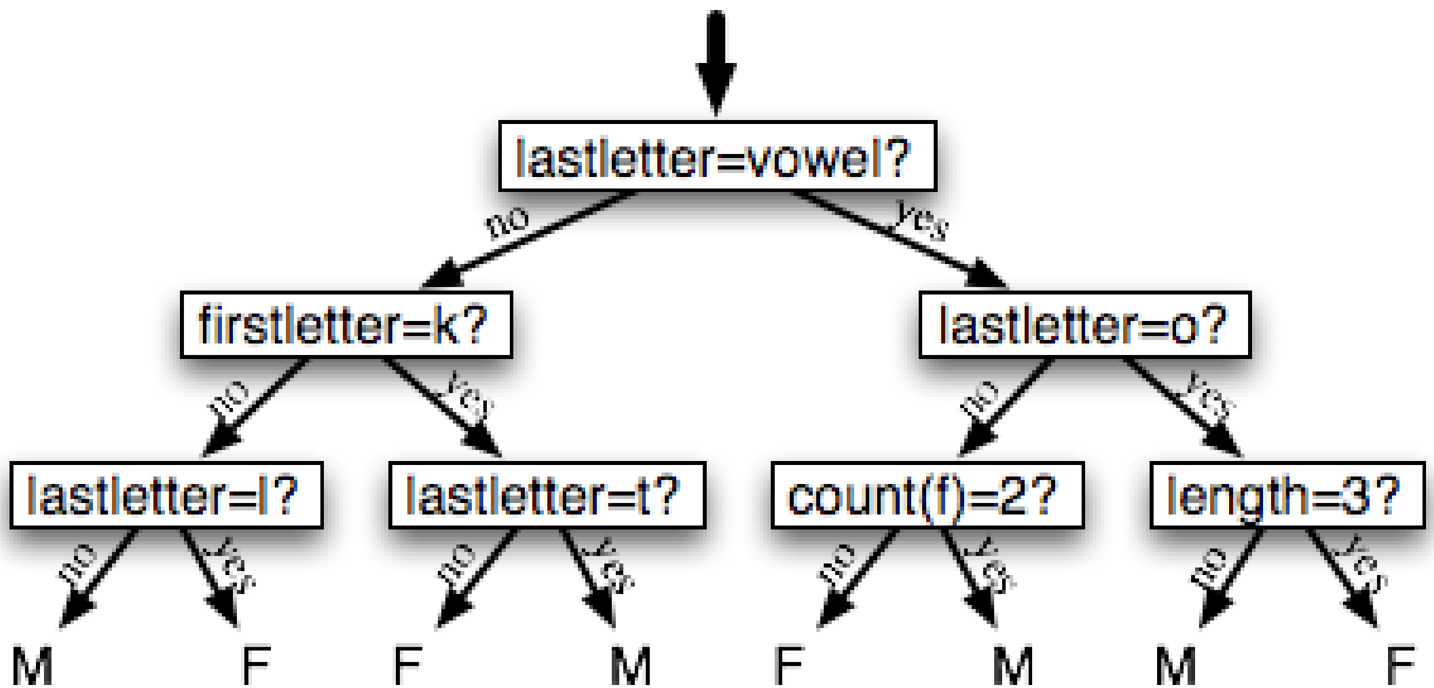
- List of boys names
  - Alan
  - Barry
  - Colin
  - Dexter
  - Edward
  - Frederick
  - Howard
  - ….

- List of girls names
  - Anna
  - Betty
  - Chelsea
  - Doris
  - Elizabeth
  - Fanny
  - Hortense
  - ….

Q: What is inside the leaf node?

Q: What is inside the internal node?

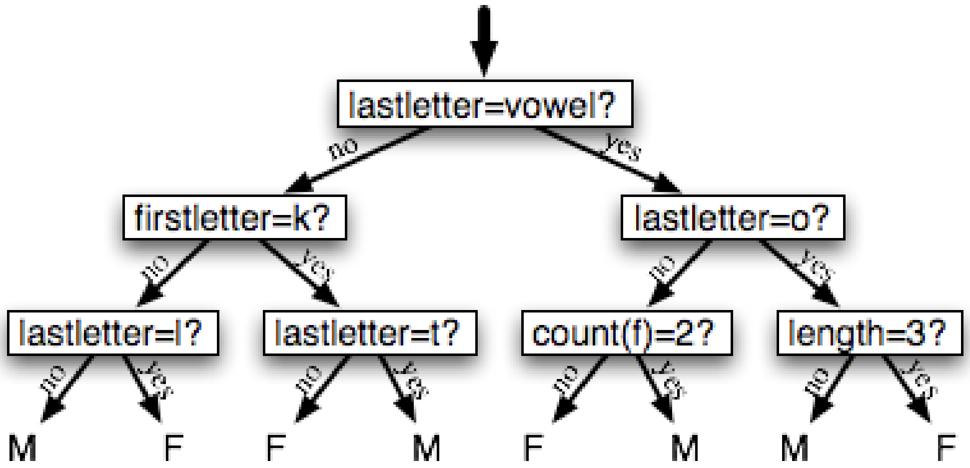
Example of a decision tree to decide if a name is male or female



From: http://nltk.googlecode.com/svn/trunk/doc/book/ch06.html

Example of a decision tree to decide if a name is male or female

	Lastletter ="vowel"	Firstletter= "k"	Lastletter ="t"	Lastletter ="o"	Count(f)	length
Fanny	0	0	0	0	1	5
Kate	0	0	0	0	0	4
Howard	0	0	0	0	0	6

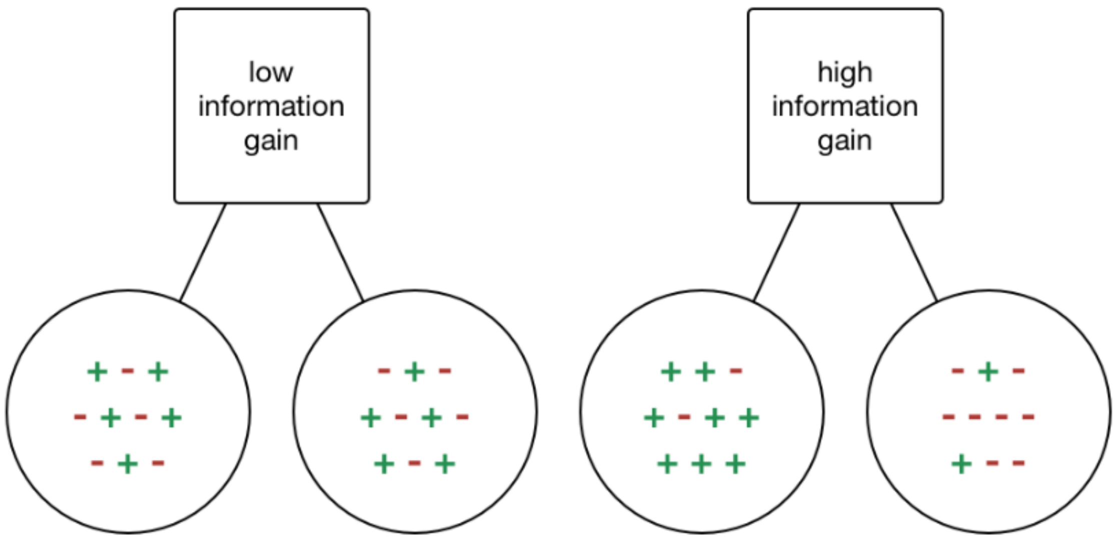


Information Gain

$$IG(D_p, f) = I(D_p) - \frac{N_{left}}{N} I(D_{left}) - \frac{N_{right}}{N} I(D_{right})$$

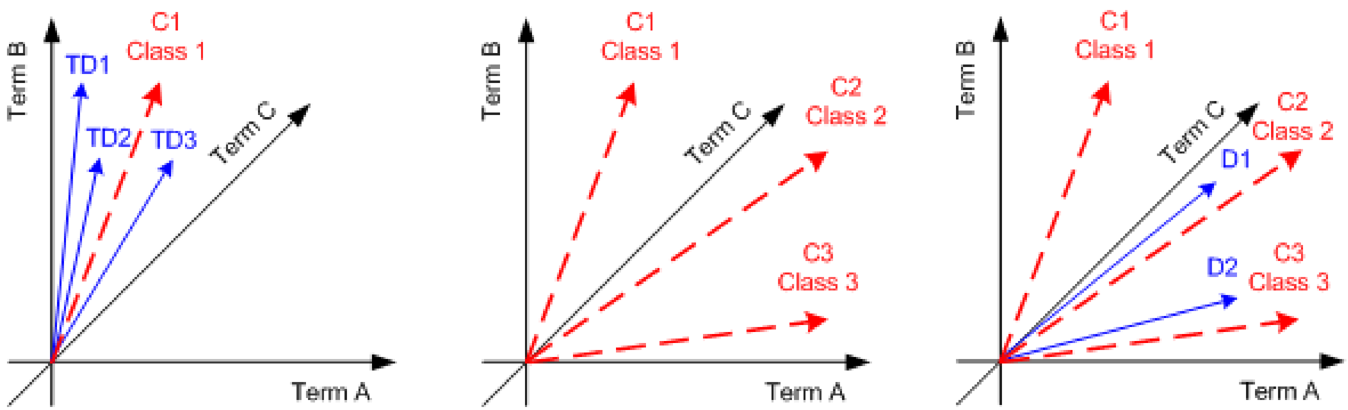
f: feature split on
D_p: dataset of the parent node
D_{left}: dataset of the left child node
D_{right}: dataset of the right child node
I: impurity criterion (Gini Index or Entropy)
N: total number of samples
N_{left}: number of samples at left child node
N_{right}: number of samples at right child node

$$\mathrm{H}(T) = \mathrm{I}_E(p_1, p_2, \ldots, p_J) = -\sum_{i=1}^{J} p_i \log_2 p_i$$



Discriminative Classifiers

- **The Rocchio Classifiers**
  - Each category is represented by a prototypical document, i.e., profile vector
  - Documents are classified by similarity to the profile vector



A) Training Document Representations in Vector Space define Class Representation (Centroid)

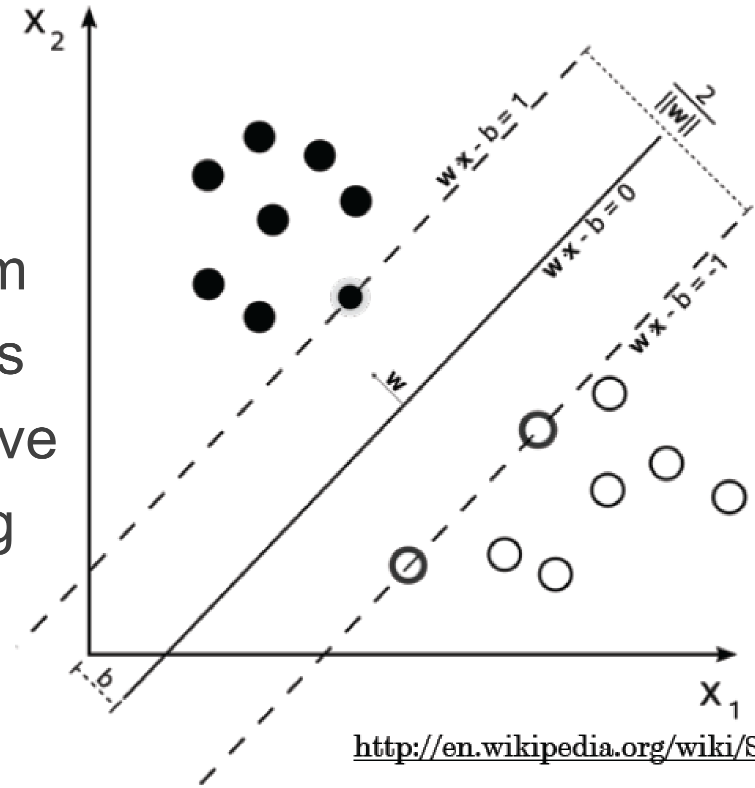
B) Class Representation by Class Vectors (CentroidS)

C) Classification of Documents by similarity between Document Vector and Class Vector

From: http://www.iicm.tugraz.at/about/Homepages/cguetl/courses/isr/opt/classification/Vector_Space_Model.html

Discriminative Classifiers

- **Support Vector Machines (SVMs)**
  - SVMs divide the term space in hyperplanes separating the positive and negative training samples.
  - The surface that provides the widest separation between the support surfaces is selected



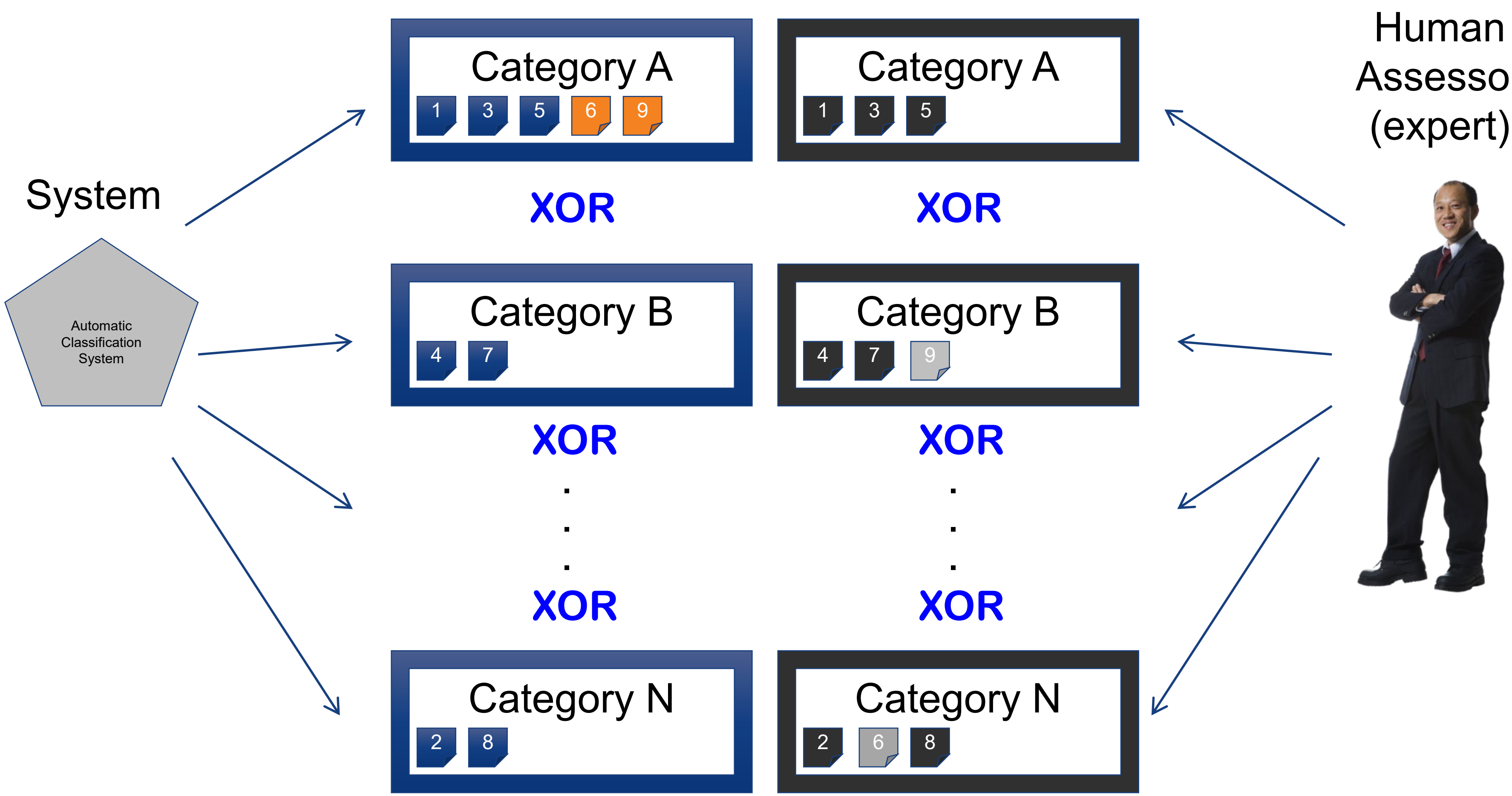
http://en.wikipedia.org/wiki/Support_vector_machines

EVALUATION

ACCURACY

EVALUATION

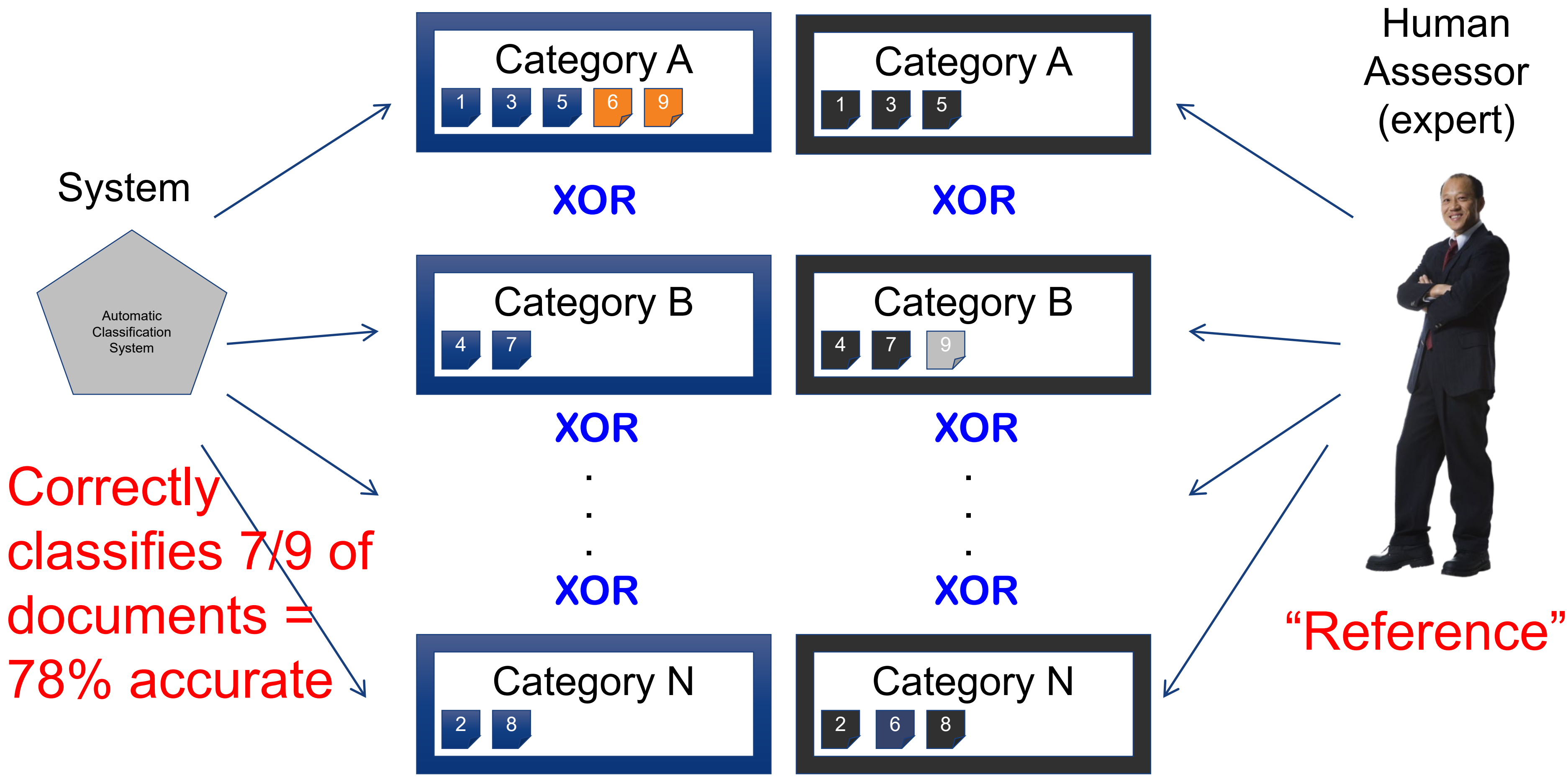
What is “accuracy”?



What do we mean by "Accuracy"

- **You measure an automatic categorization system by:**
  - How well it classifies a set of documents against a "reference"
  - This "reference" is normally a human expert
- **Reference**
  - Gold standard – accepted as being the best available
    - May not be perfect, e.g., tumour board for oncology
  - Good enough
    - Human expert(s), typically 80% agreement, good methodology
  - Better than nothing
    - "your boss tells you to do this, so you recruit your friends, family,…"
- **Most of the time, no such thing as "absolute truth"**

One measure of accuracy



Discussion

- **Weather prediction (system predicts one week in advance)**

	Mon	Tue	Wed	Thu	Fri	Sat	Sun
System	Sunny	Drizzle	Rain	Sunny	Cloudy	Thunderstorms	Sunny
Actual	Sunny	Rain	Cloudy	Sunny	Drizzle	Thunderstorms	Cloudy

- **Questions:**
  - How “accurate” is the weather prediction system?
  - Do you have a tolerance for error? +/- margin of error?
  - How about outcomes – will I get wet if I use the system to decide whether or not to carry an umbrella? Will I get angry?

Confusion Matrix

		Predicted Categories					
		A	B	C		. . .	N
Actual Categories	A						
	B						
	C						
	:						
	N						

Example (using #)

Automatic Classification System

		Predicted Categories						
		A	B	C		. . .	N	
Actual Categories	A	143	34	17		. . .	2	= Tot(A) docs
	B	67	1289	44		. . .	239	= Tot(B) docs
	C	980	234	3454		. . .	88	= Tot(C) docs
						. . .		
	:					. . .		
	N	87	24	63		. . .	650	= Tot(N) docs

Example (using %)

Automatic Classification System

Actual Categories	Predicted Categories						
	A	B	C		. . .	N	
A	87%	2%	5%		. . .	1%	= 100%
B	6%	90%	0%		. . .	2%	= 100%
C	12%	2%	77%		. . .	4%	= 100%
					. . .		
:					. . .		
N	21%	0%	4%		. . .	65%	= 100%

Consider the simple 2x2 matrix (1200 documents were classified)

Desired positive prediction

False negative

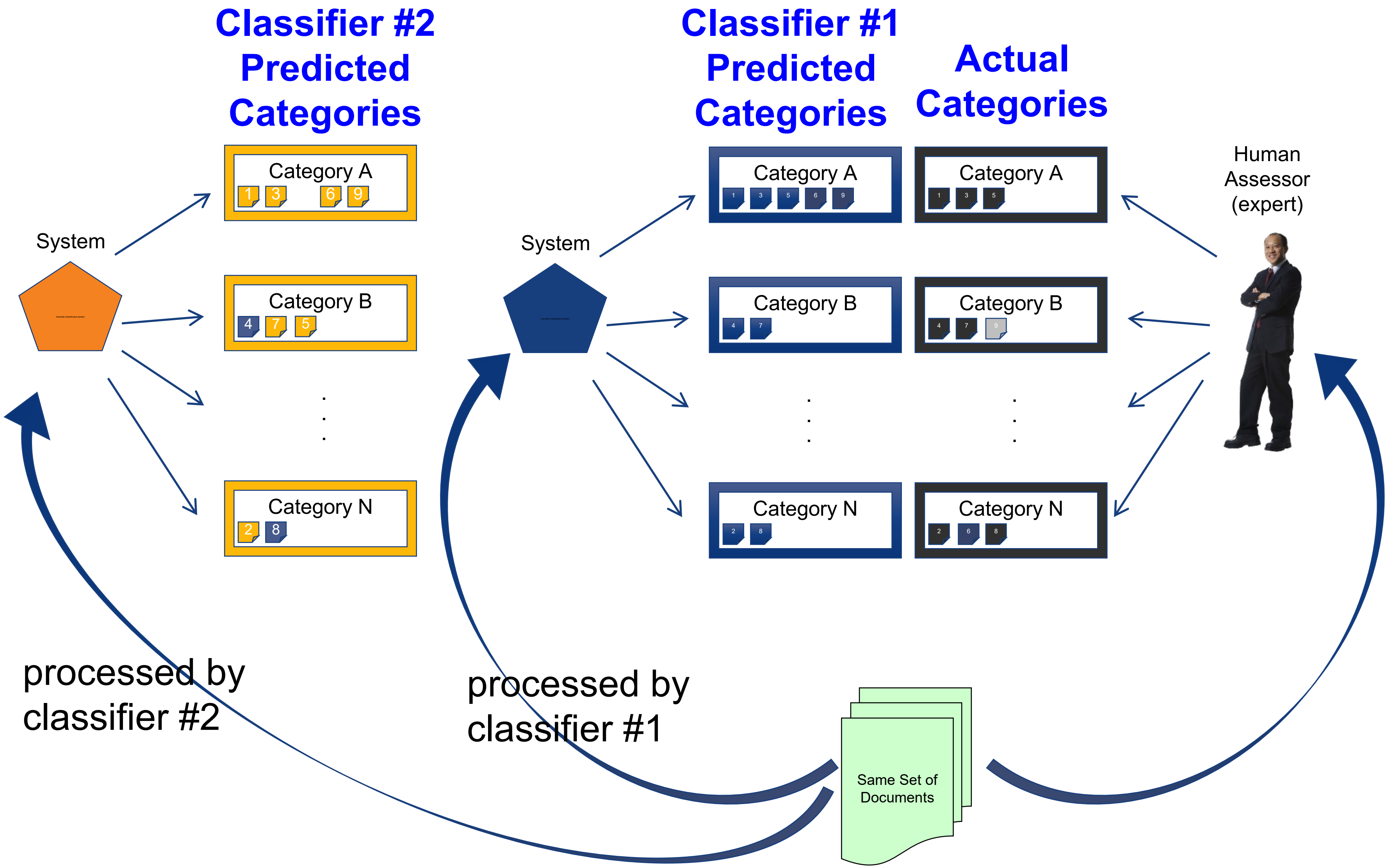
		Predicted	
		Yes	No
Actual	Yes	1110	10
	No	40	40

False positive

Desired negative prediction

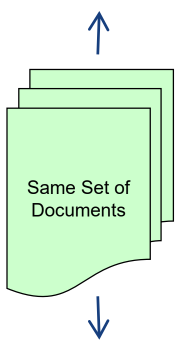
EVALUATING MULTIPLE CLASSIFIERS

What happens with 2 classifiers?



Comparing models: e.g. 2x2 matrix (actual numbers of documents)

Classifier #1



Classifier #2

		Predicted	
		Y	N
Actual	Y	900	100
	N	40	410

Seems quite good for both predictions

		Predicted	
		Y	N
Actual	Y	700	300
	N	2	448

Reduced the false positives but false negatives increased

? Which classifier is better?

Adding the semantics – the courtroom

Classifier #1

Actual \ Predicted	Guilty	Innocent
Guilty	900	100
Innocent	40	410

Let 100 guilty go free
Convict 40 innocent persons

Testimony of witnesses

? Which classifier is better?

Classifier #2

Actual \ Predicted	Guilty	Innocent
Guilty	700	300
Innocent	2	448

Let 300 guilty go free
Convict 2 innocent persons

Adding a cost function – fraud investigation

Classifier #1

Actual	Predicted		
		Honest	Fraud
	Honest	900	100
	Fraud	40	410

Insurance Claim Statements

Classifier #2

Actual	Predicted		
		Honest	Fraud
	Honest	700	300
	Fraud	2	448

? Which classifier is better?

The average fraud costs the company $2000
It costs the company $500 to investigate each suspected fraud

Adding a cost function – fraud investigation

- The average fraud costs the company $2000
- It costs the company $500 to investigate each suspected fraud

Company loses $80k in fraud
Company pays $255k in costs

	Predicted		
Actual		Honest	Fraud
	Honest	900	100
	Fraud	40	410

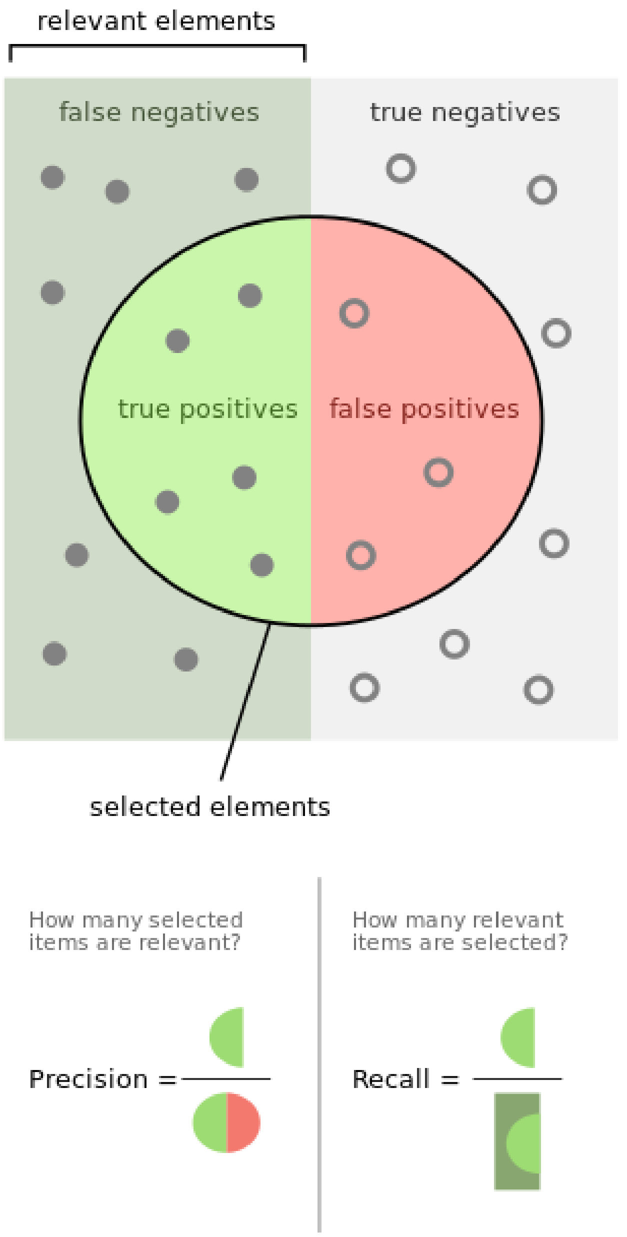
Company loses $4k in fraud
Company pays $374k in costs

	Predicted		
Actual		Honest	Fraud
	Honest	700	300
	Fraud	2	448

- ***Consider Doing nothing (don't act to identify fraud):***
  - *Predicted fraud = 0 cases @$500 per case costs $0k for investigation.*
  - *Undetected fraud is 450 cases @$2k/fraud loses $900k.*
  - *Overall -$0k -$900k = -$900k*
- ***Analysis for classifier #1:***
  - *Predicted fraud = 510 cases @$500 per case costs $255k for investigation.*
  - *Undetected fraud is 40 cases @$2k/fraud loses $80k.*
  - *Overall -$255k -$80k = -$335k*
- ***Analysis for classifier #2:***
  - *Predicted fraud = 748 cases @$500 per case costs $374k for investigation.*
  - *Undetected fraud is 2 cases @$2k/fraud loses $4k.*
  - *Overall -$374k -$4k = -$378k*

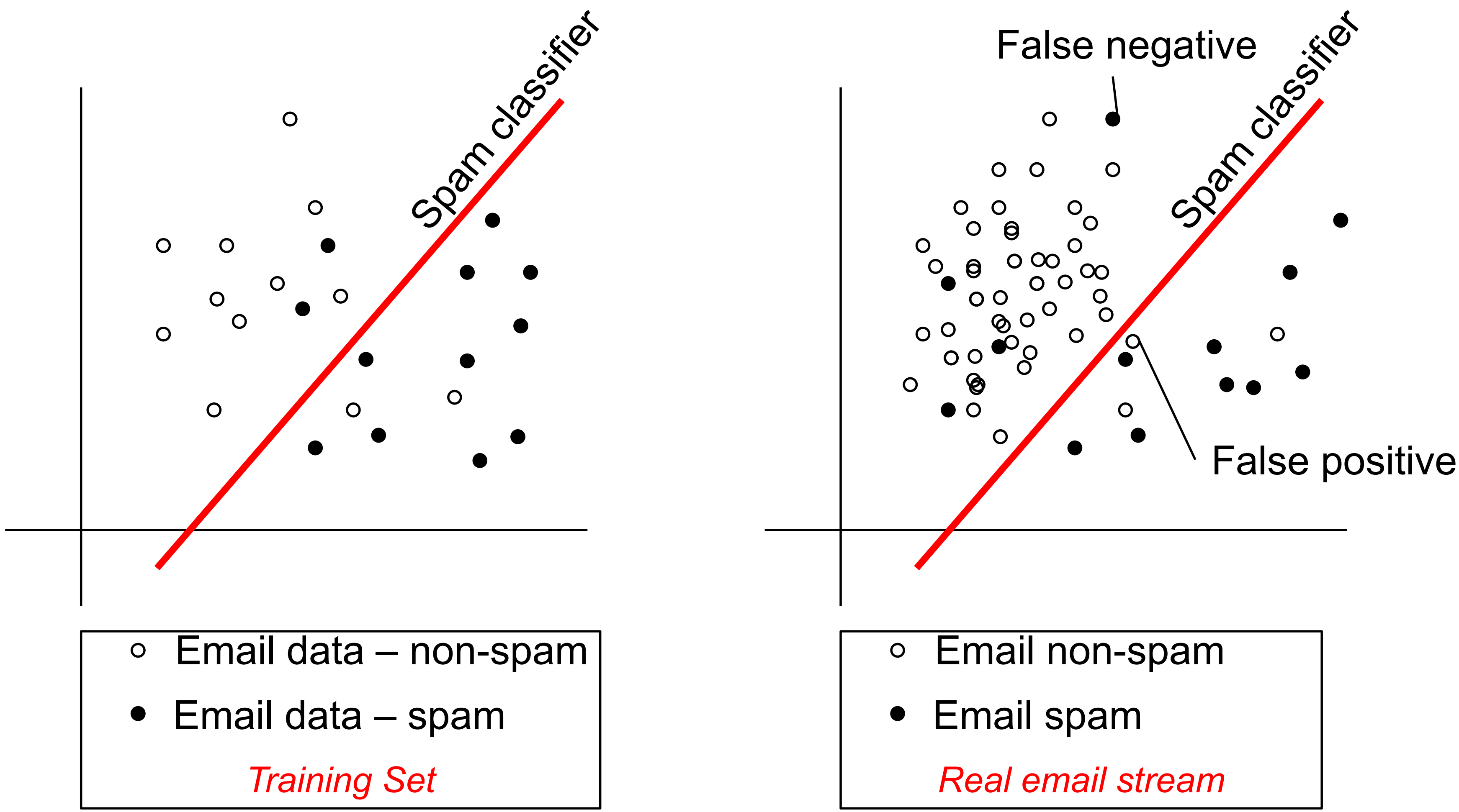
Classifier evaluation

- Evaluation of classifiers is done with respect to a ***business context***
- Experimental evaluation focuses on ***effectiveness***



RUNNING THE CLASSIFIER

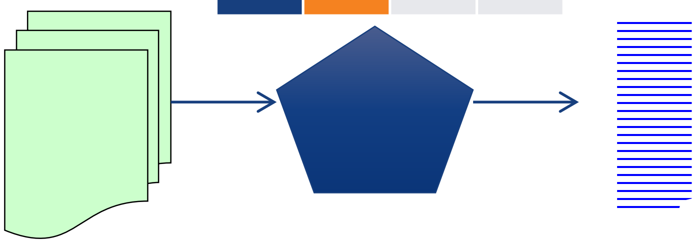
Expect False Results eg: spam filtering



Overfitting the Training Set

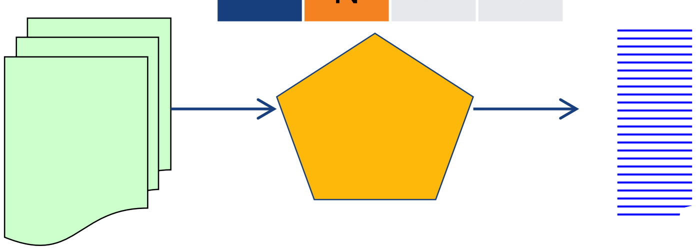
Training Set

		Predicted	
		Y	N
Actual	Y	700	0
	N	0	300



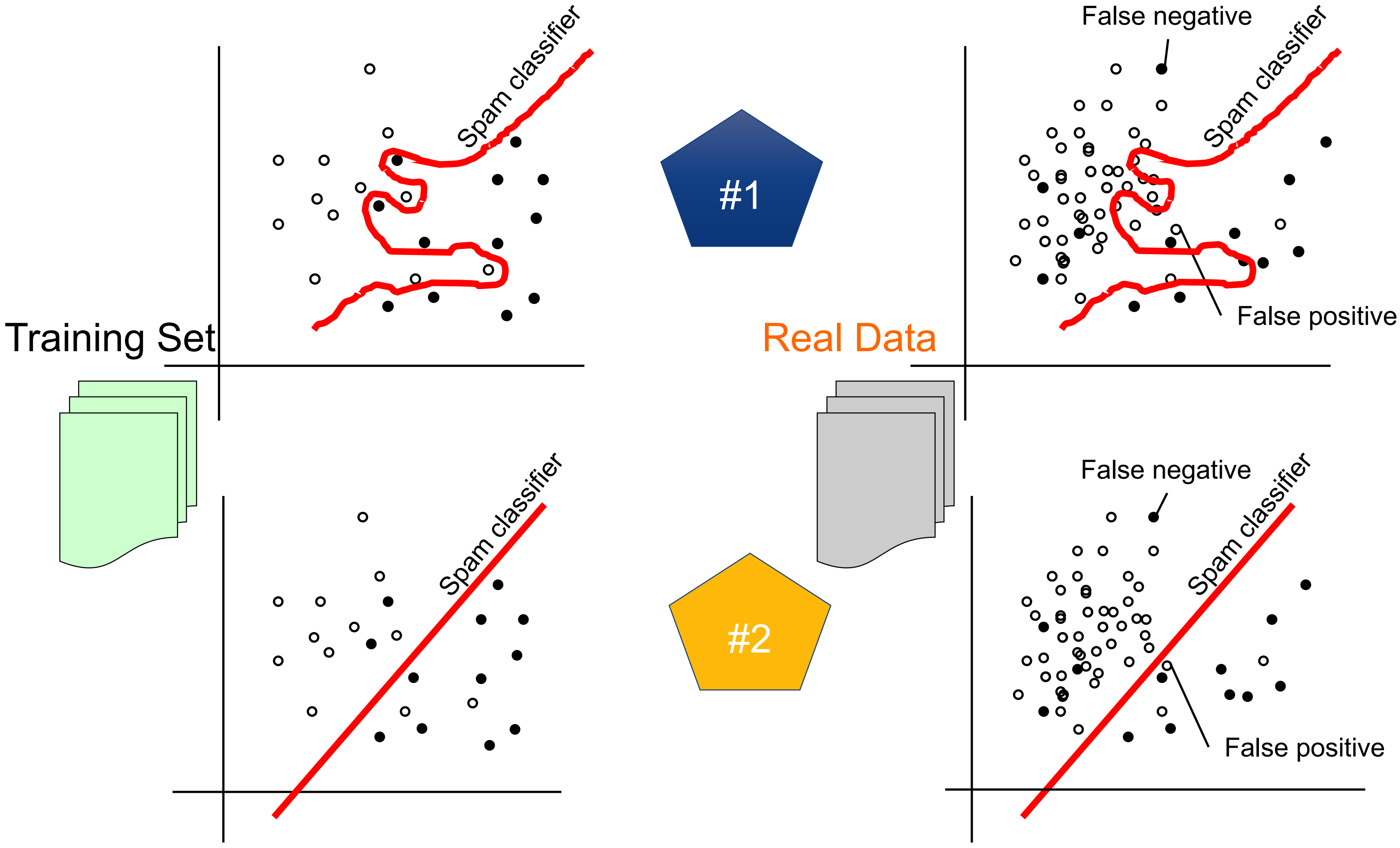
Training Set

		Predicted	
		Y	N
Actual	Y	600	100
	N	50	250



? Which classifier is better?

Overfitting the Training Set – what happened?



Overfitting the Training Set

Training Set

Actual \ Predicted	Y	N
Y	700	0
N	0	300

Training Set

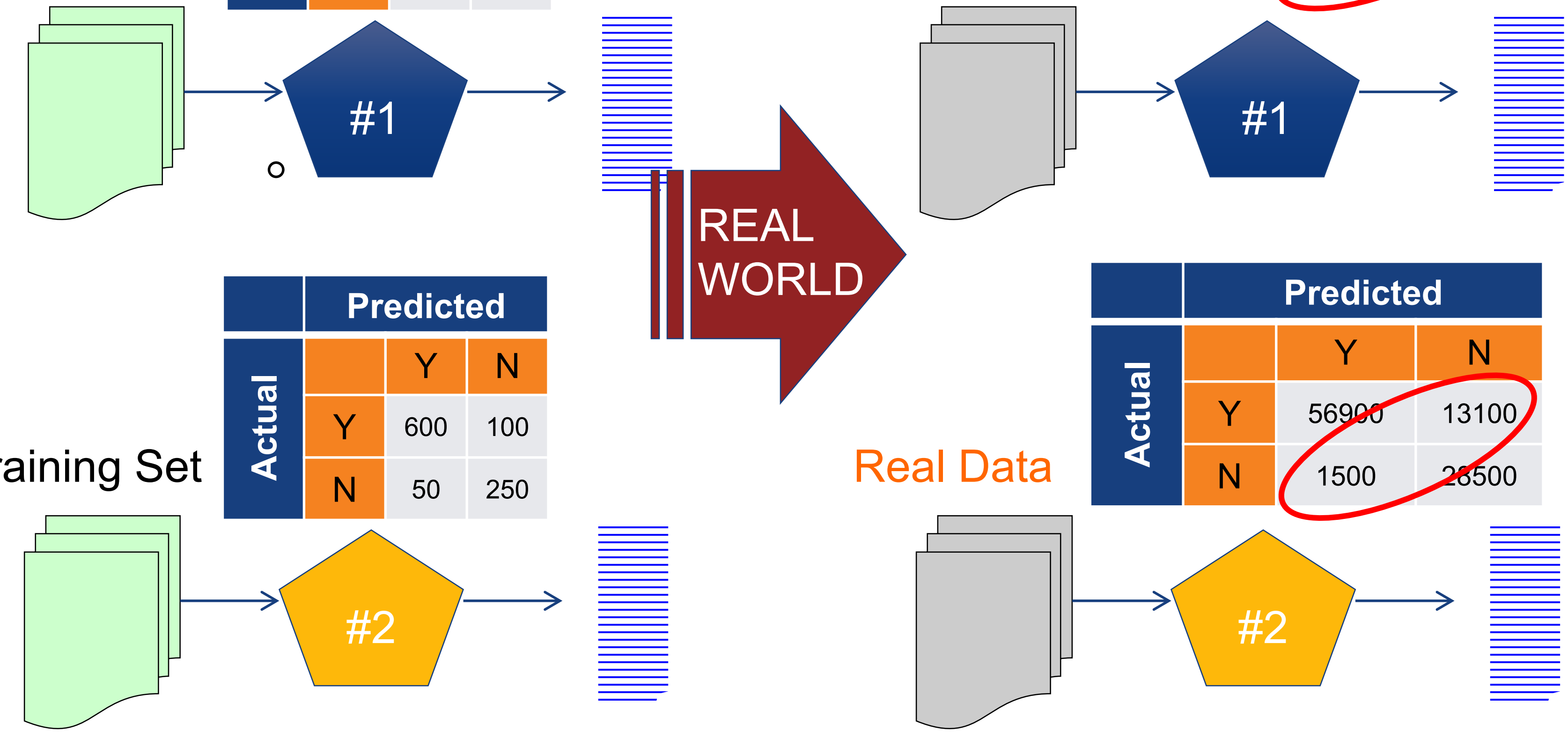
Actual \ Predicted	Y	N
Y	600	100
N	50	250

Real Data

Actual \ Predicted	Y	N
Y	45200	24800
N	13800	16200

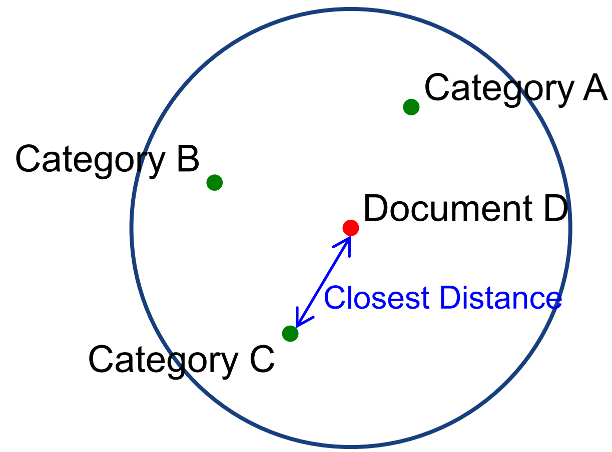
Real Data

Actual \ Predicted	Y	N
Y	56900	13100
N	1500	28500



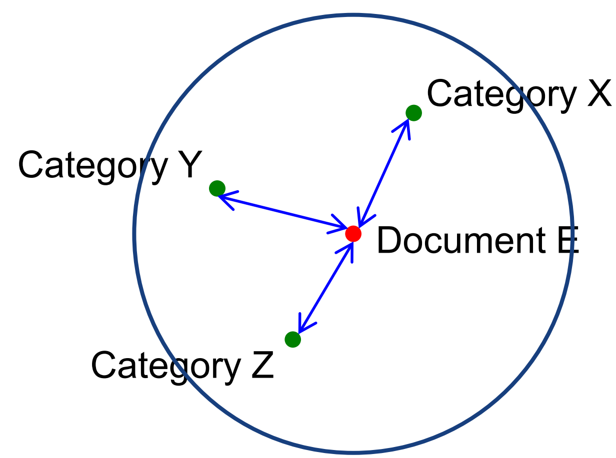
Hard and Soft Categorization

- **Fully automated classifiers make "hard" binary decisions**
  - In example to right, the document, D, is assigned to category C only.



- **Semi-automated (interactive) classifiers instead are created by allowing "soft" real-value decisions**
  - Rank the categories according to their measure of appropriateness for the document
  - In example to right, the document, E, is assigned 3 possible categories:

Rank	Category	Probability
1	Z	0.76
2	X	0.72
3	Y	0.54



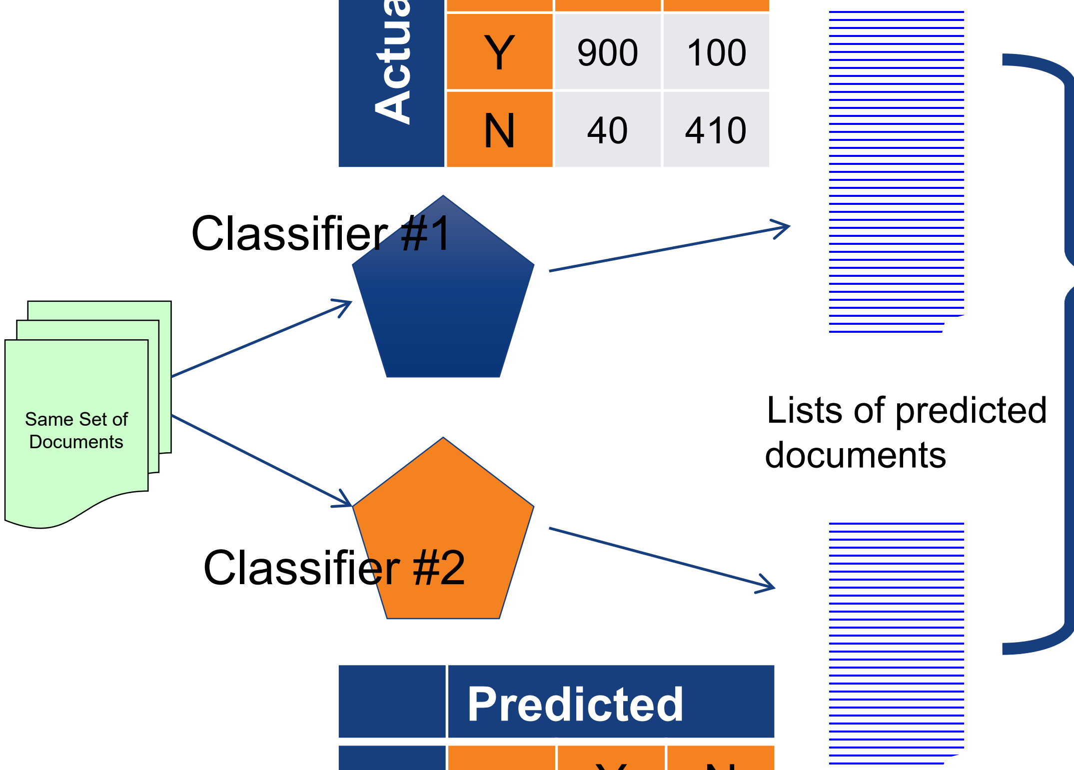
  - Used for computer assisted human decision making
    - For example, in critical applications such as medical diagnosis

Aggregating multiple classifiers

Running with more than one classifier

Classifier #1:

		Predicted	
		Y	N
Actual	Y	900	100
	N	40	410



Classifier #2:

		Predicted	
		Y	N
Actual	Y	700	300
	N	2	448

Aggregate the results

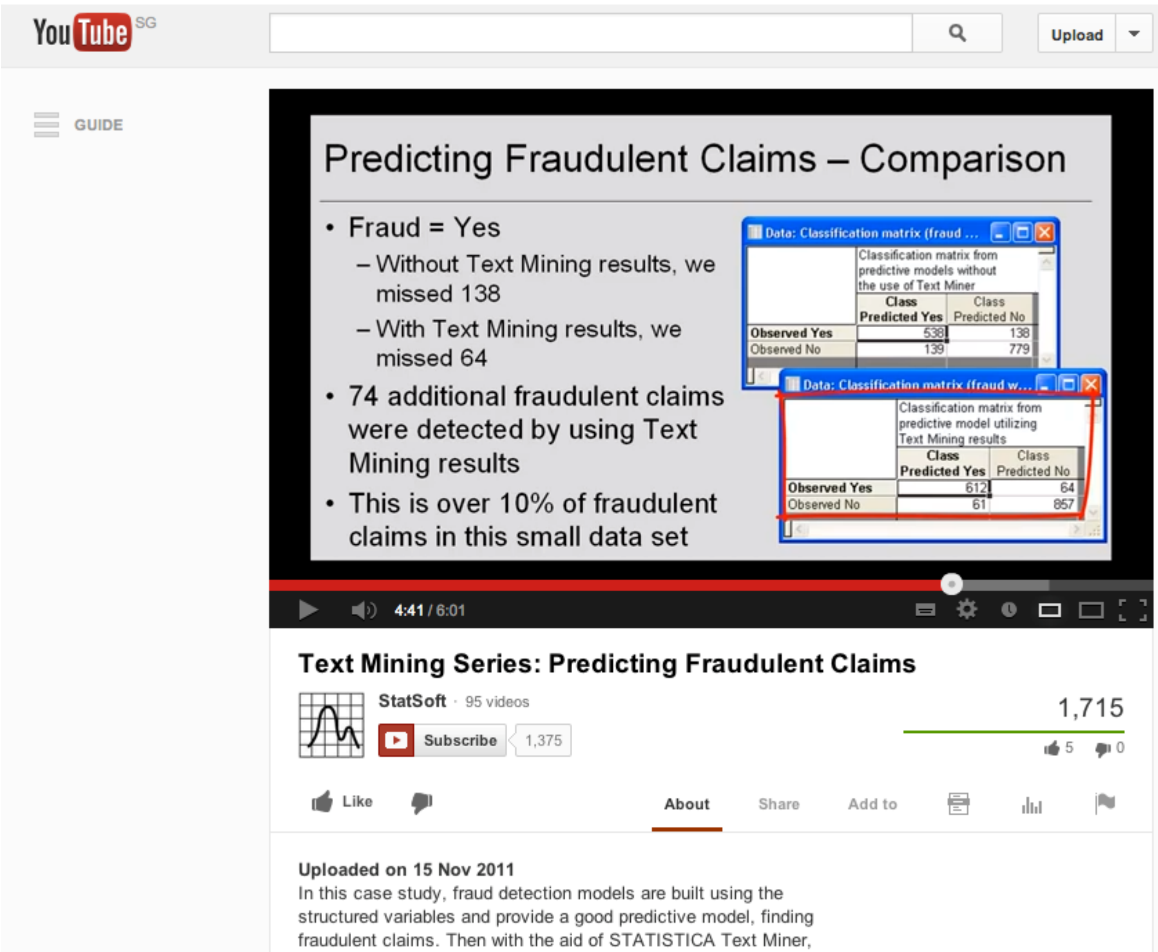
Various methods:

- Union
- Intersection
- Algorithmic
  - Voting
  - By confidence level
  - Etc.

		Predicted	
		Y	N
Actual	Y	880	120
	N	20	430

TEXT CATEGORIZATION APPLICATION EXAMPLES

Boosting Identification of Fraudulent Claims



From: http://www.youtube.com/watch?v=OIQpm8qTog4

UNSUPERVISED TEXT CATEGORIZATION

DOCUMENT CLUSTERING

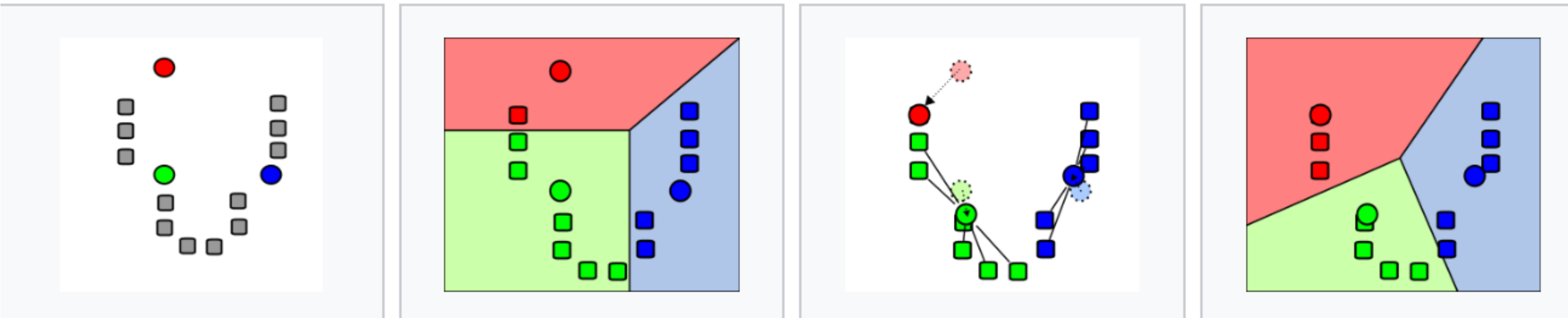
UNSUPERVISED

What is text clustering?

- **Clustering is the task of grouping a set of documents in such a way that the documents in each group are more "similar" to each other than to documents in other groups.**
- **Clustering lets you explore your data**
  - Many tools are interactive
- **You can understand your data better, e.g.:**
  - What groupings exist in your data?
  - How many are there? How big is each group?
  - What are the common terms?
  - Are there anomalies?

Clustering Example

Demonstration of the standard algorithm



1. *k* initial "means" (in this case *k*=3) are randomly generated within the data domain (shown in color).

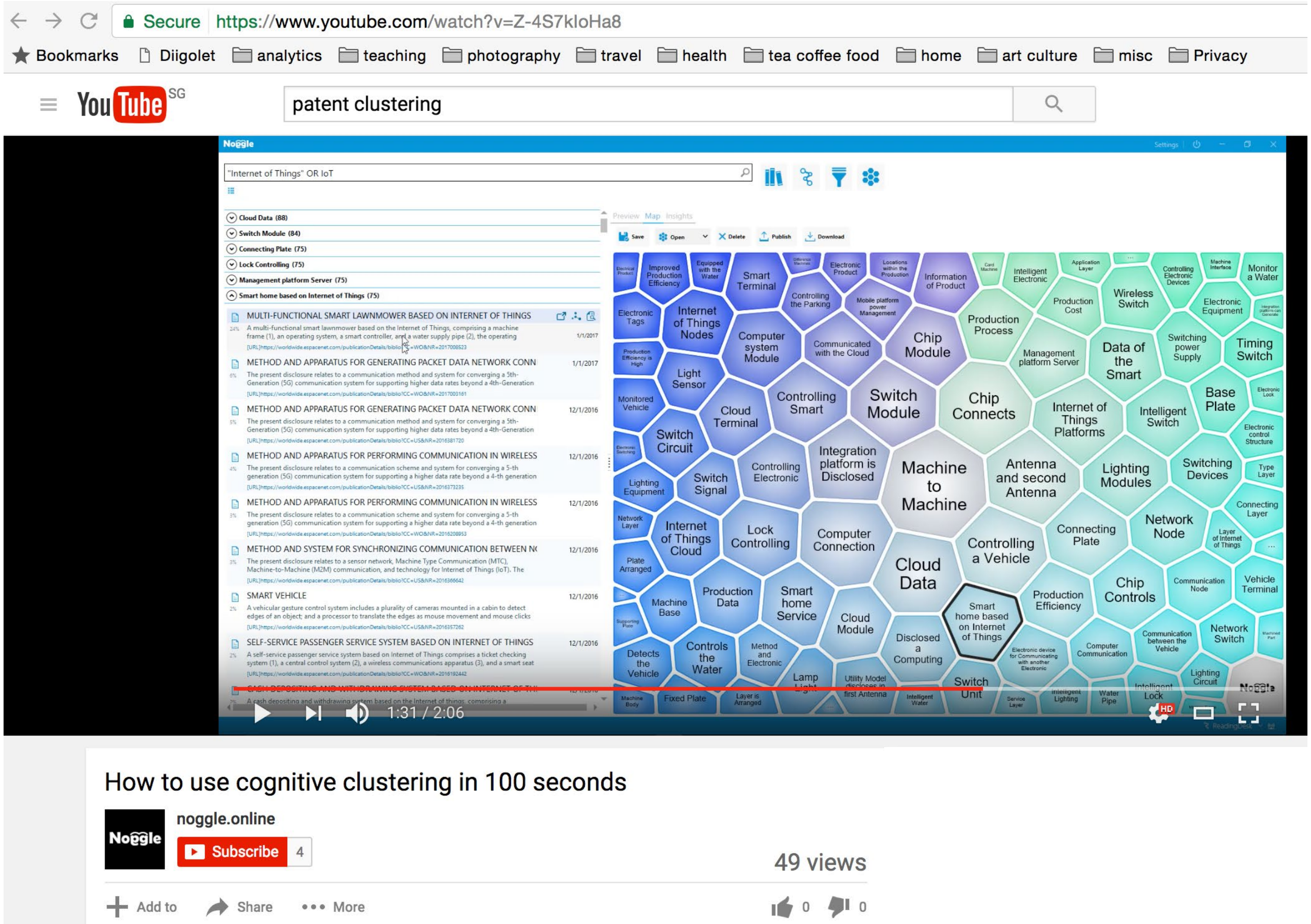
2. *k* clusters are created by associating every observation with the nearest mean. The partitions here represent the Voronoi diagram generated by the means.

3. The centroid of each of the *k* clusters becomes the new mean.

4. Steps 2 and 3 are repeated until convergence has been reached.

From: https://www.youtube.com/watch?v=CHIrx4gsoJI

Patent Clustering



From: https://www.youtube.com/watch?v=Z-4S7kIoHa8

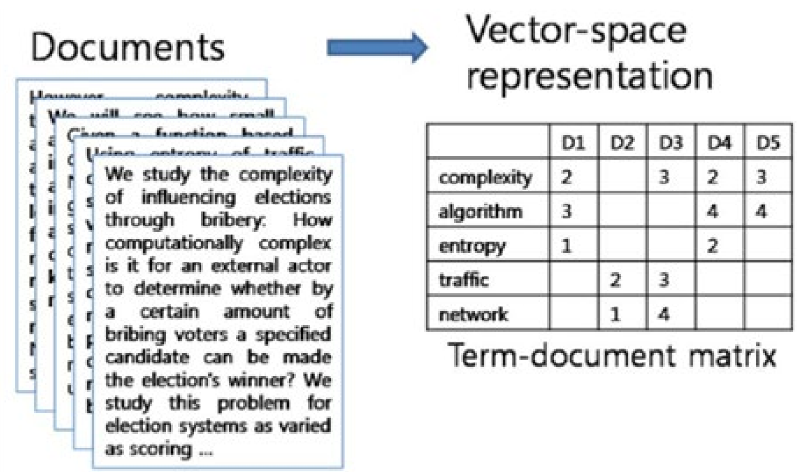
Notes about Clustering

- **Your clusters may surprise you**
  - Documents tend to fall into natural classes (clusters)
  - There will be some surprising ones (worth drilling down!)
- **You can control the number of clusters (depends on the algorithm)**
  - You don’t want too many clusters (overfit!)
  - You don’t want too few clusters (meaningless)
  - **Clusters should lead to fulfilling business outcomes**
- **You don’t need training phase to create clusters**
  - Clustering can be language independent (but monolingual)

DIMENSIONAL REDUCTION

OPTIONAL

Dimensional Reduction



	D1	D2	D3	D4	D5
complexity	2		3	2	3
algorithm	3			4	4
entropy	1			2	
traffic		2	3		
network		1	4		

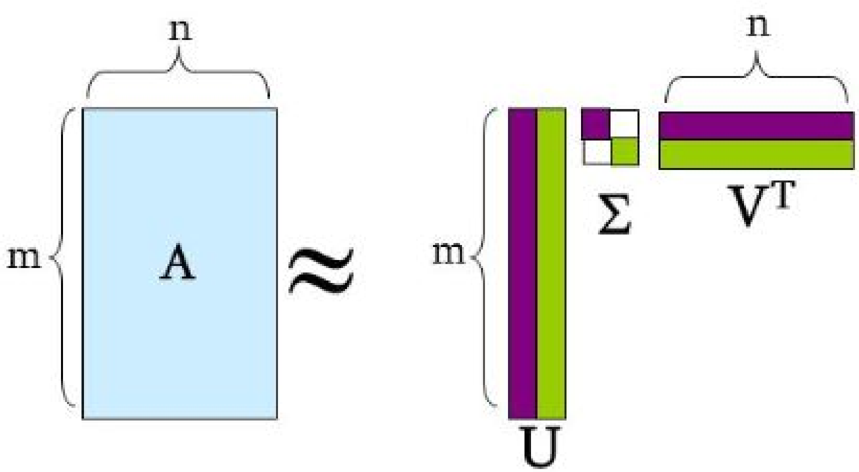
Term-document matrix

- Sparse
- High dimension
- When lots of documents

	T1	T2	T3	T4	T5	T6	T7	T8
Doc1	2	0	4	3	0	1	0	2
Doc2	0	2	4	0	2	3	0	0
Doc3	4	0	1	3	0	1	0	1
Doc4	0	1	0	2	0	0	1	0
Doc5	0	0	2	0	0	4	0	0
Doc6	1	1	0	2	0	1	1	3
Doc7	2	1	3	4	0	2	0	2

Singular Value Decomposition

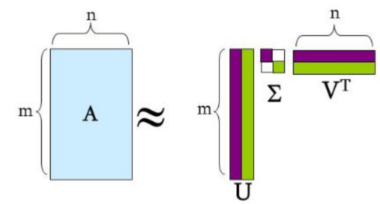
$$\mathbf{A} \approx \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T = \sum_i \sigma_i \mathbf{u}_i \circ \mathbf{v}_i^T$$



- **U,V**
  - Columns are orthogonal and unit vectors
- **Σ**
  - Entries (singular values) are positive and sorted in decreasing order of importance

Singular Value Decomposition

$$\mathbf{A} \approx \mathbf{U}\boldsymbol{\Sigma}\mathbf{V}^T = \sum_i \sigma_i \mathbf{u}_i \circ \mathbf{v}_i^T$$



Original Matrix

		document	error	invalid	message	file	format	unable	to	open	using	path	variable
1	d1	1	1	1	1	1	0	0	0	0	0	0
2	d2	1	0	2	1	0	1	1	1	1	1	0
3	d3	1	0	0	0	1	1	1	0	0	0	1

(3,11)

A ≈

	document	SVD1	SVD2
1	d1	1.63	.49
2	d2	3.14	-.96
3	d3	1.35	1.64

(3,N)

U

×

When N=2

Sorted Singular Values		
12.29		
	6.2	
		...

(N,N)

Σ

×

T

Weights

	U_2	
error	43	.30
invalid	.11	.13
message	.55	-.37
file	.33	-.12
format	.21	.55
unable	.31	.18
to	.31	.18
open	.22	-.25
using	.22	-.25
path	.22	-.25
variable	.09	.42

V^T

($11,N$)^T

Singular Value Decomposition

Original Matrix

	document	error	invalid	message	file	format	unable	to	open	using	path	variable
1	d1	1	1	1	1	1	0	0	0	0	0	0
2	d2	1	0	2	1	0	1	1	1	1	1	0
3	d3	1	0	0	0	1	1	1	0	0	0	1

- **Dimensions reduced from 11 to N=2**

	document	SVD1	SVD2
1	d1	1.63	.49
2	d2	3.14	-.96
3	d3	1.35	1.64

(3,N)

×

Sorted Singular Values		
12.29		
	6.2	
		...

(N,N)

New Matrix

Dense & low

(3,N)

Dimension Reduction

Original Matrix

	document	error	invalid	message	file	format	unable	to	open	using	path	variable
1	d1	1	1	1	1	1	0	0	0	0	0	0
2	d2	1	0	2	1	0	1	1	1	1	1	0
3	d3	1	0	0	0	1	1	1	0	0	0	1

Step1. Apply SVD/PCA

You get SVDs/Concepts.

	document	SVD1	SVD2
1	d1	1.63	.49
2	d2	3.14	-.96
3	d3	1.35	1.64

✖

Sorted Singular Values	
12.29	
	6.2

DataPoint1 = [1,1,1,1,1,0,0,0,0,0,0]

DataPoint2 = [1,1,2,1,0,1,1,1,1,1,0]

DataPoint3 = [1,0,0,0,1,1,1,0,0,0,1]

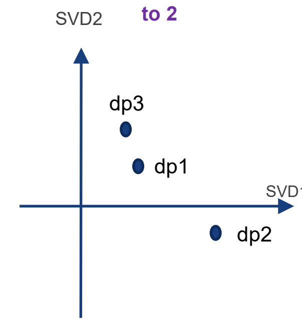
≈

Datapoint1 = [20.1, 3.0]

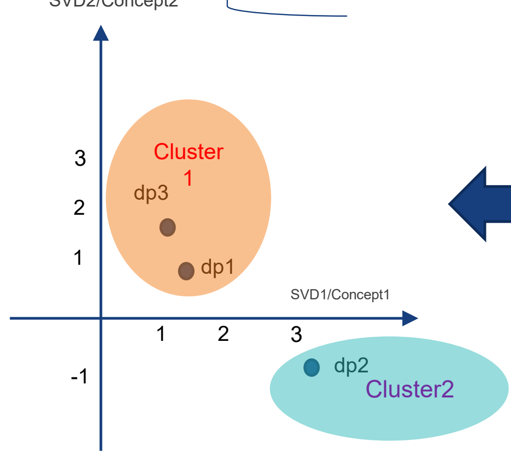
Datapoint2 = [38.6,-5.95]

Datapoint3 = [16.6, 10.2]

Dimensions reduced from 11 to 2



Step 2. Apply KM Or other classifiers



Concept# /SVD# ≠ Cluster#

Singular Value Decomposition

SVD – How Many Dimensions?

- Usually no more than 5 to 20 dimensions extract most of the information from the TDM.
- More dimensions (up to a few hundred) can be retained if the processed data is for subsequent predictive modeling or clustering

Sorted Singular Values		
12.29		
	6.2	
		…

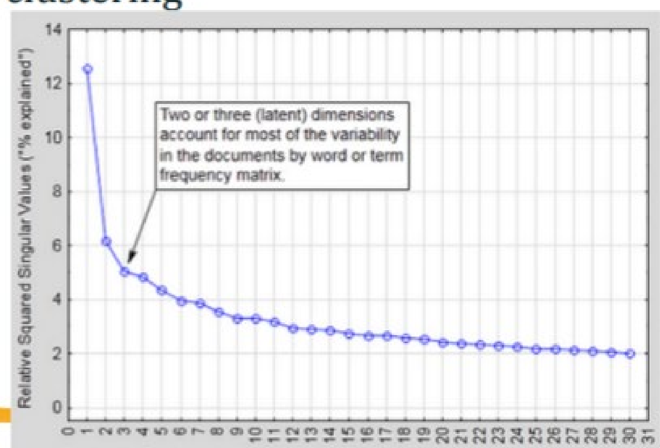
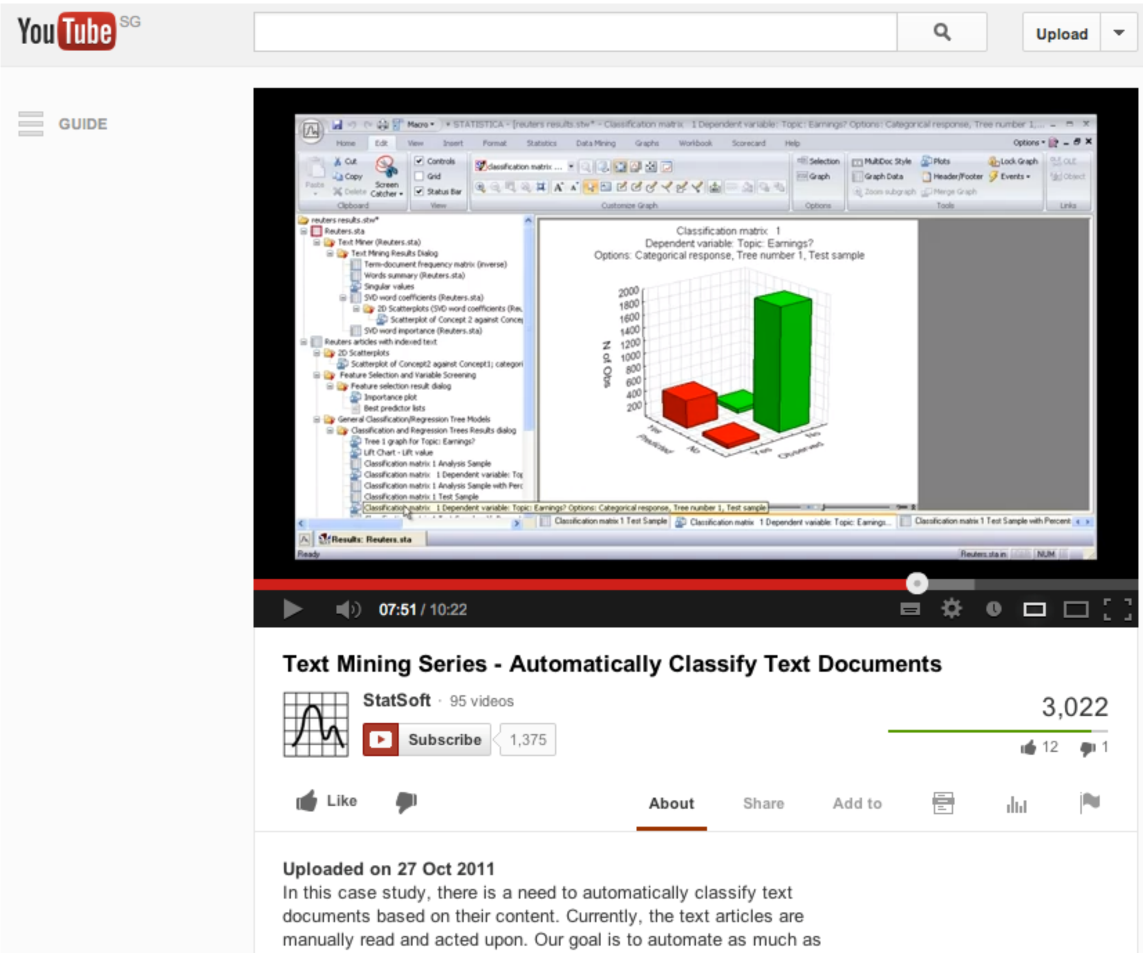


Figure 11.3 Plot of relative squared singular values by number of latent semantic dimensions
From *Practical Text Mining and Statistical Analysis for Non-structured Text data*

Automatic Categorization of Documents



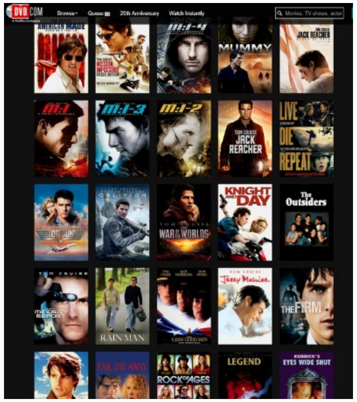
From: http://www.youtube.com/watch?v=Q5K3gyQJkC0

TOPIC MODELING

UNSUPERVISED

Latent Variables

- Actors and their movies are observed inputs



- The potential tags of “Action”, “War” are latent variables

Text Example

- **What's unusual?**
  - Anomaly detection

Date	Amount	Location
2 Mar	$40	Penang
5 Mar	$20	KL
17 Mar	$30	KL
4 Apr	$80	Ipoh
9 Apr	$30	KL
14 Apr	$70	KL
20 May	$100	Johor
25 May	$20	KL
31 May	$3	Kiev
4 Jun	$40	KL
23 Jun	$50	KL
30 Jun	$30	KL
16 Jul	$70	Ipoh
16 Jul	$50	Ipoh

What is topic modeling?

- **“Topic” modeling**
  - Can we figure out what discourses (==latent variables) would generate the collection of documents?
  - These discourses are just bunches of words
    - If done well, the bunches of words would seem naturally to be together, e.g.,
      - “wag”, “bark”, “bone”, “bite”, “dog”
      - ”pilot”, “plane”, “wing”, ”flight”
  - These bunches of words constitute **topics**

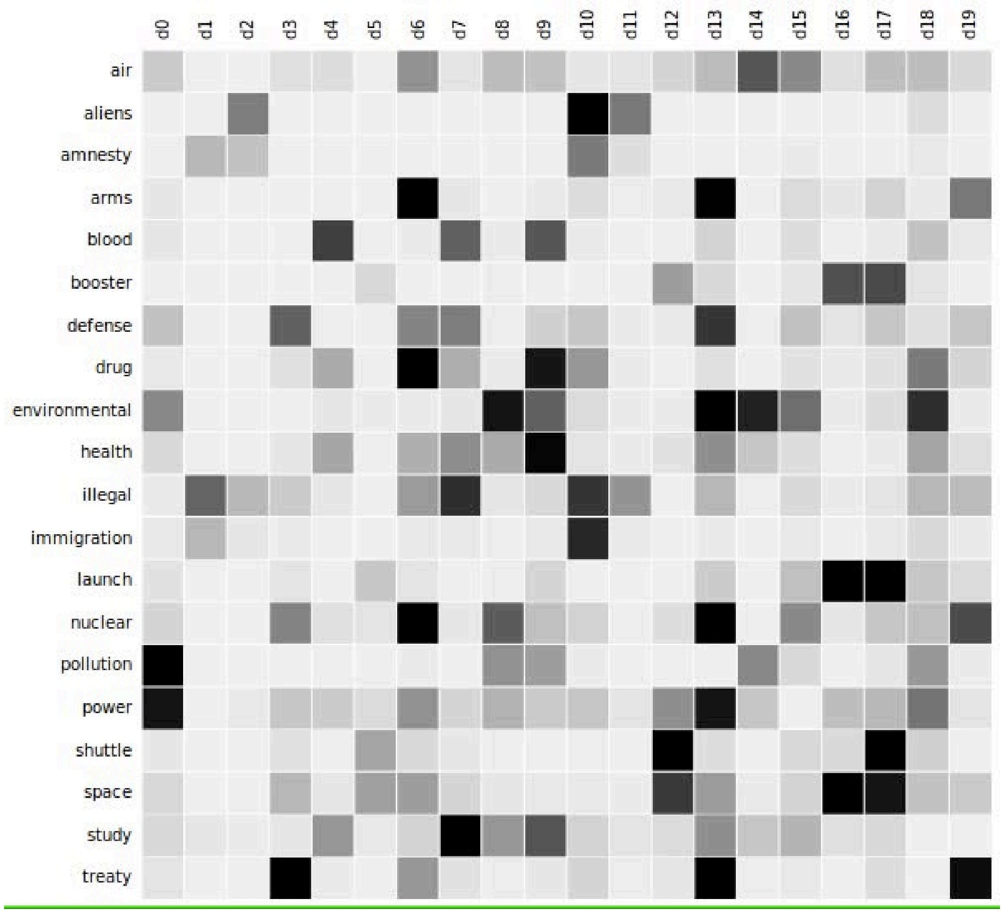
Animation of topic modeling

- **Columns = documents**
- **Rows = words**
- **Squares = frequency**
- **Darker = higher frequency**

- **Group:**
  - Documents using similar words
  - Words which occur in similar documents

  Resulting set of words are "topics"

  Number of Groups are pre-defined

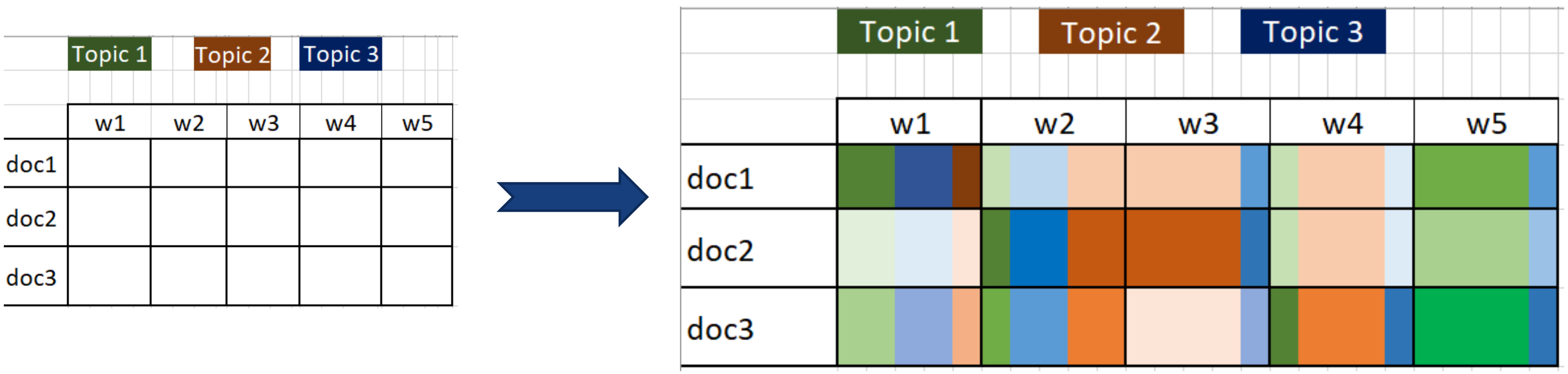


From: http://topicmodels.west.uni-koblenz.de/ckling/tmt/svd_ap.html

Animation of topic modeling

Input

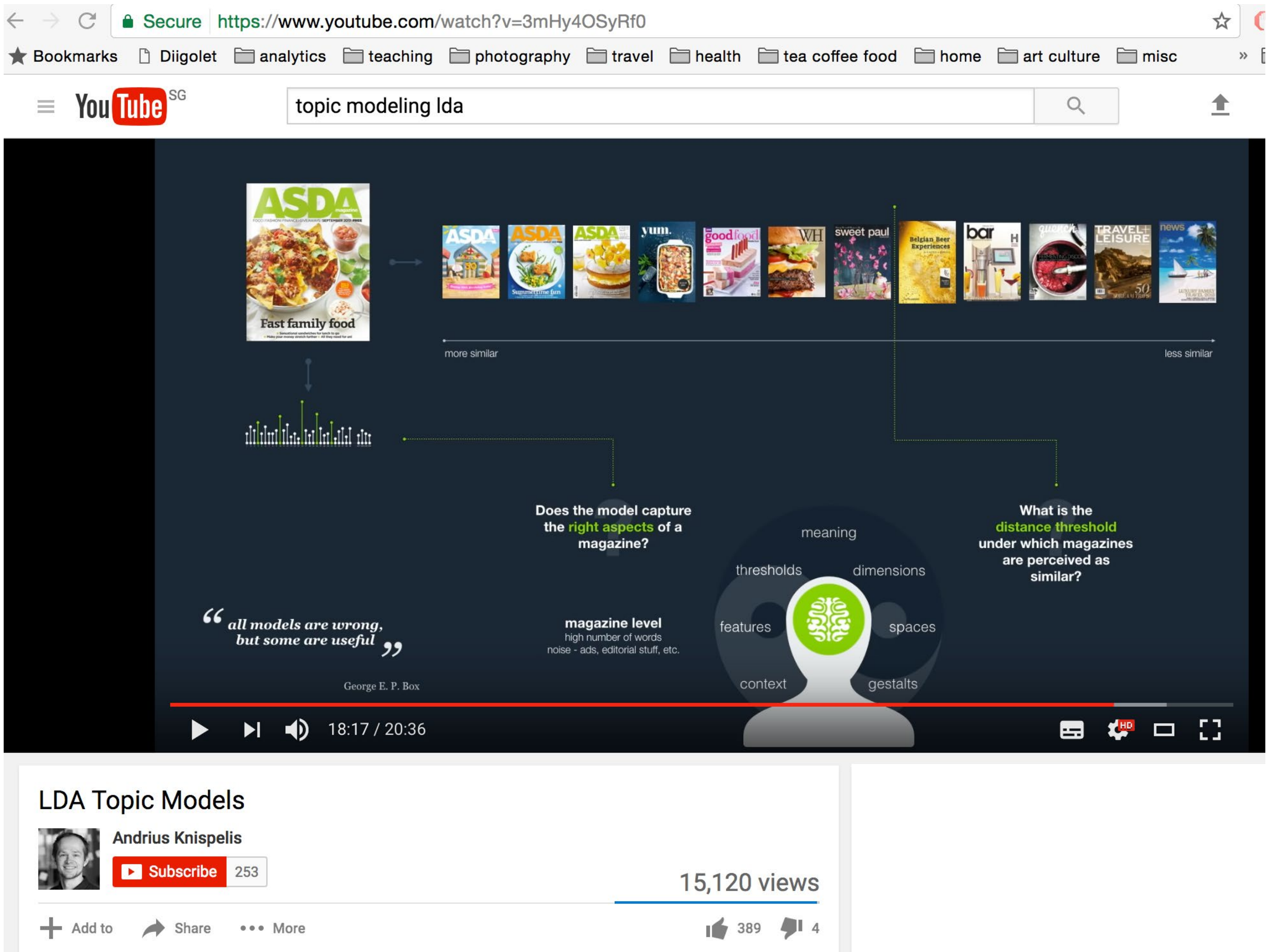
output



- Predefine N=3 topics
- TDM

- Word-Topic distribution
- Doc-Topic distribution
- Topics are indexed with numbers without tags
- Topics are represented by a list of (important) words

LDA Topic Model Explanation



From: https://www.youtube.com/watch?v=3mHy4OSyRf0

More examples of applications

- **Analysis of text, e.g.,**
  - Diachronic analysis:
    - Speeches during election campaign
      - Economy, abortion, build wall, reduce taxes,…
    - Speeches after taking office
      - Reduce taxes, create jobs, immigration, China,…
  - Contrast analysis:
    - Different candidates positions and issues
    - Characteristics of various media publications

Reference & Resources

- Fabrizio Sebastiani, ***A Tutorial on Automated Text Categorization***, web.iiit.ac.in/~jawahar/PRA-03/textCat.pdf
- F. Aiolli, ***Text Categorization***, downloaded from http://www.math.unipd.it/~aiolli/corsi/SI-0607/Lez09.251006.pdf
- John Elder, Gary Miner, Bob Nisbet. ***Practical Text Mining and Statistical Analysis for non-Structured Text Data Applications***, Academic Press, 2012
- Chris Manning & Hinrich Schutze, ***Foundations of Statistical Natural Language Processing***, MIT Press, 1999
- Scott Weingart, ***Topic Modeling for Humanists: A Guided Tour***, downloaded from http://www.scottbot.net/HIAL/index.html@p=19113.html
- Ted Underwood, ***Topic Modeling made just simple enough***, downloaded from https://tedunderwood.com/2012/04/07/topic-modeling-made-just-simple-enough/
- NLP resources: http://nlp.stanford.edu/links/statnlp.html