The evolution of the Scientific Community through the Peer Review Dynamics in a Multidisciplinary Journal

(Content-Bias in the Peer Review Process at JASSS)

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Aim of the study and research question

Using the **JASSS dataset**, our aim is to investigate if/to which extent the content of a submitted paper can be predictive of the outcome of the peer review processes.

Research question:

Can the content of a paper predict its acceptance? e.g. Is a paper similar to previously accepted papers more likely to be accepted and vice-versa?

***With **content** we mean an analysis of the terms used in the document, we do not consider its quality, correctness or sematic structure.

Methodology

We tried to reconstruct the terms/topics associated to paper accepted/rejected over the time @ JASSS

We defined **a terms-based similarity measure** between documents and we wonder if being similar to an accepted paper increase the likelihood of received a positive review and viceversa.

Similarity measure = two papers are similar if they use the same terms (or combination of terms) with the same frequency and importance. Similar documents would be together in a search engine output. Similar documents they (loosely) share topic. The similarity does not include style, correctness, semantic structures or quality. It is a purely terms-based similarity.

Possible uses (besides Research)

For the Editors:

- It can spot trendy topics, helping editors to monitor topics dynamic over time or compare their journal topics to other journals
- It can detect a bias if classifier performance changes
- Editors could use it to automatically cluster/classify/catalog papers

For the Authors:

- Authors can have their paper pre-processed to see if they fit the scope of the journal

Health Warning!

All models are wrong but some are useful

George Box

Technical Fundamentals

- In this presentation we are going to base our analysis on the distance/similarity between papers

- The methodology used is a vector-space representation of documents, using the TF-IDF metrics to weight each term in a document

Technicalities - Text Normalization

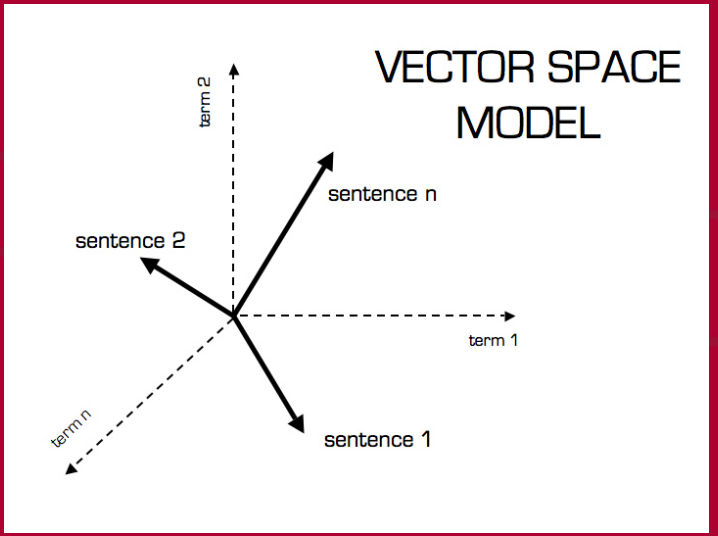
Starting Sentence	`We are a group of brilliant researchers studying peer review, I suppose..`
Tokenize (smaller case)	`[we, are, a, group, of, brilliant, researchers, studying, peer, review, i, suppose]`
Stopwords	`[group, brilliant, researchers, studying, peer, review, suppose]`
Stemming (Porter algorithm)	`[group, brilliant, research, studi, peer, review, suppos]`

- Stopwords and Stemming are needed to reduce the number of distinct terms used in the corpus (dimensionality reduction)
- Each document is represented as a "bag of words" after text normalization. This representation is used to build a vector space model

Representing Text: Vector Space Model

- Every document is represent by a vector. Each dimension of the vector represent the presence of absence of a word (the value could be weighted)
- The space has *n* dimension, where *n* is the number of distinct words in all the corpus

	Documents	I	like	apples	lemons	too
Doc1	*I like apples*	1	1	1	0	0
Doc2	*I like lemons*	1	1	0	1	0
Doc3	*I like apples too*	1	1	1	0	1



Weighting Word Counts (TF-IDF)

- TF-IDF is used to measure importance of terms in a document
  - A term has high TD-IDF if it is very frequent in a paper and infrequent in the other papers. High TF-IDF means that the term is highly significant for the paper

$$w_{x,y} = tf_{x,y} \times \log\left(\frac{N}{df_x}\right)$$

TF-IDF

Term x within document y

$tf_{x,y}$ = frequency of x in y

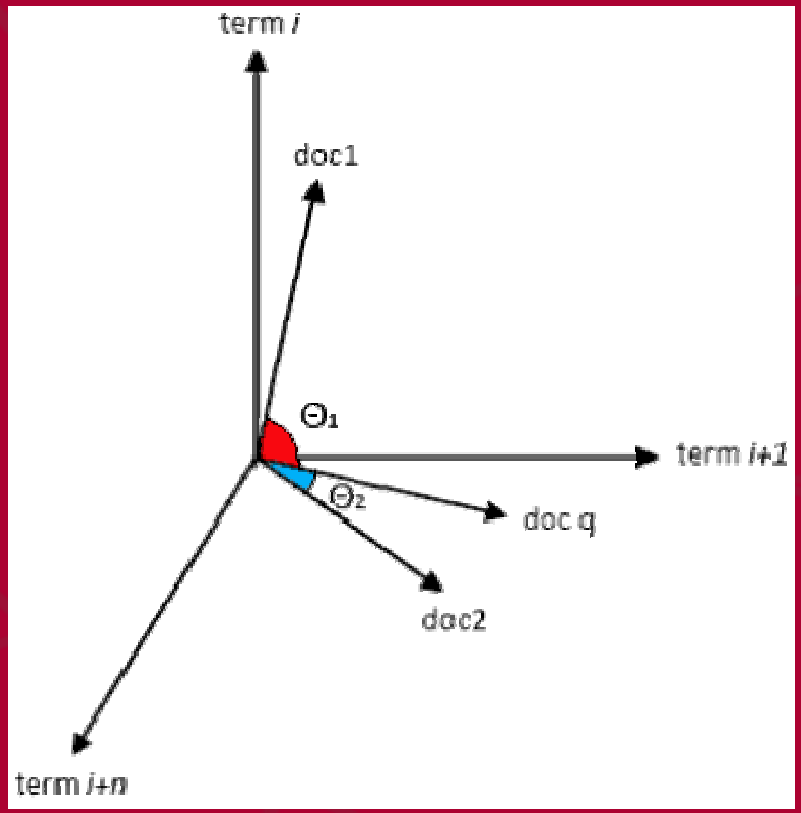
df_x = number of documents containing x

N = total number of documents

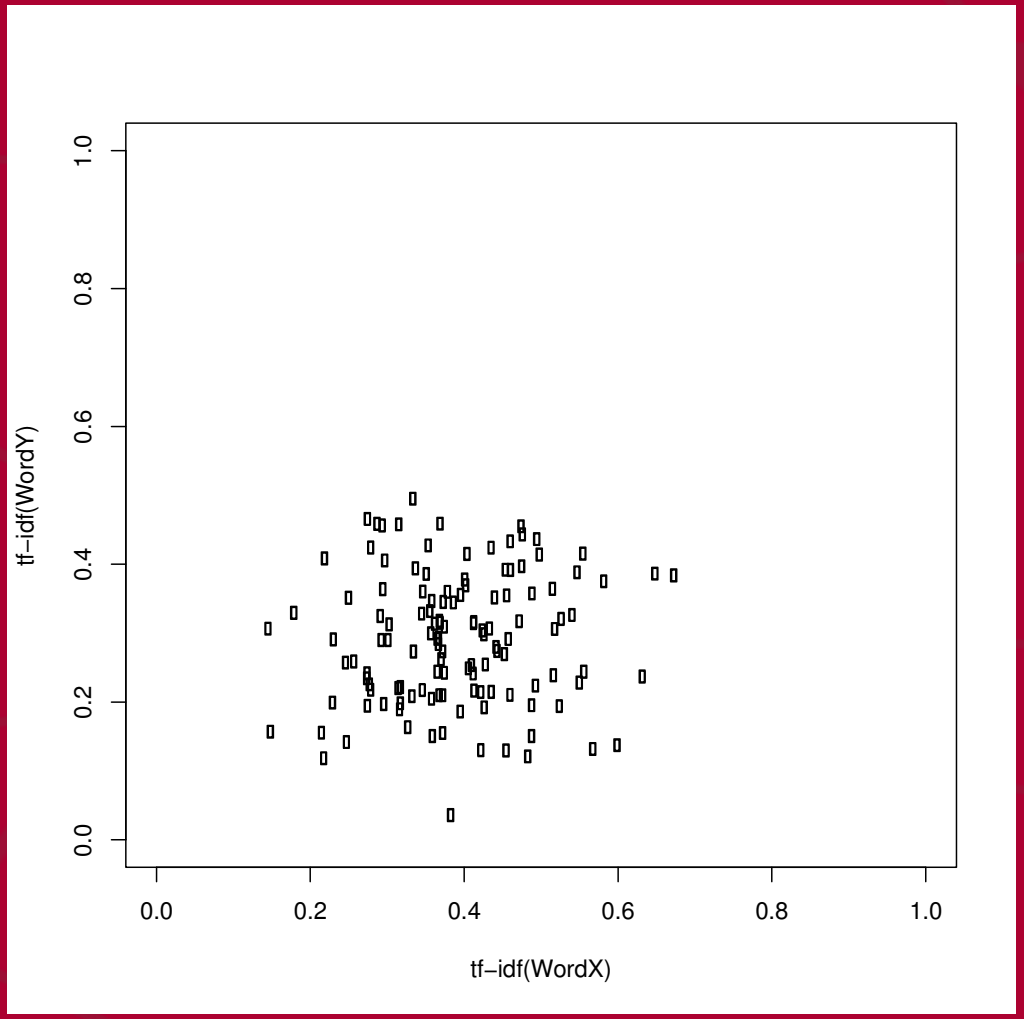
Measuring Text Similarity

- We know that we can represent a text as a vector of tf-idf scores.
- Now we need to decide on how to compute the distance/similarity between texts.

Cosine similarity illustrated



- It measures the angle between 2 vectors.
- It uses ratios
- Each vector represent a document in the vector space model
- Each dimension is a term
- A value of 1 means perfect matching, a value of 0 means no terms in common



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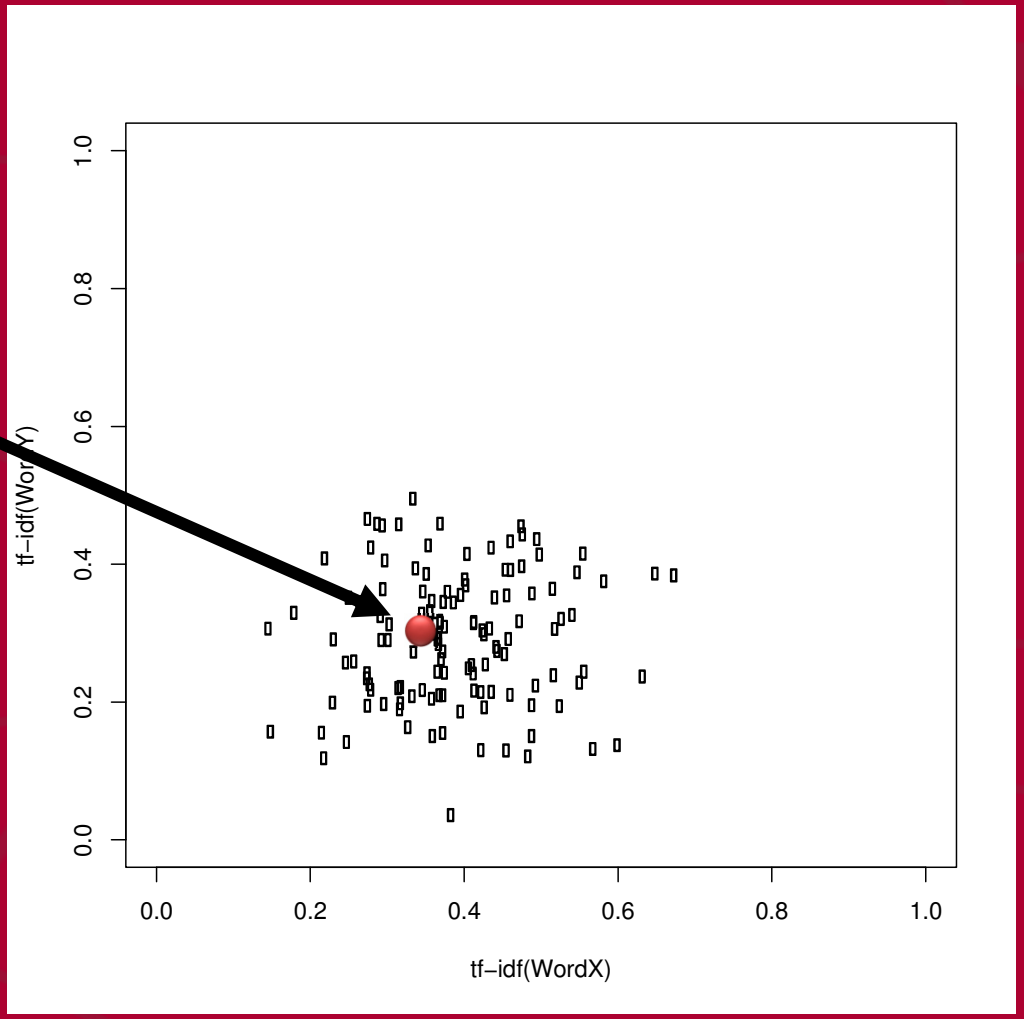
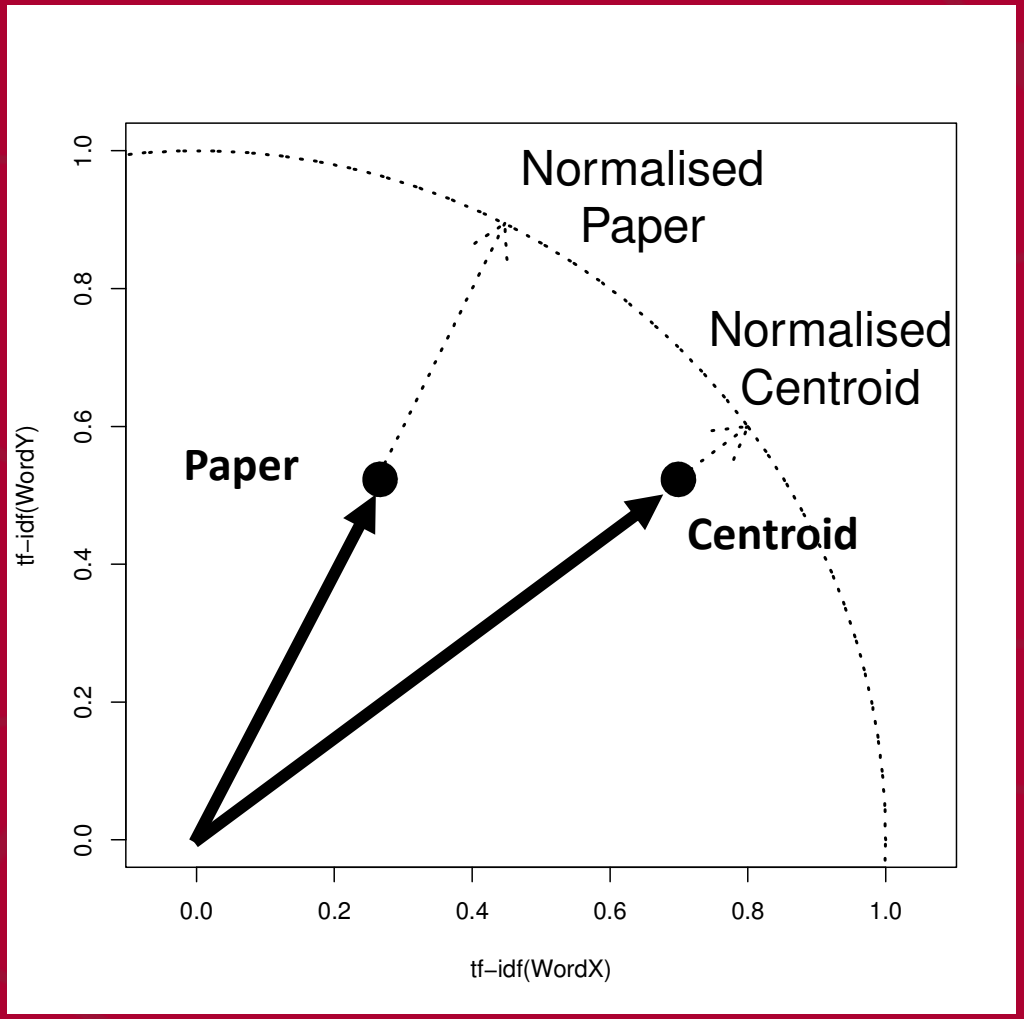
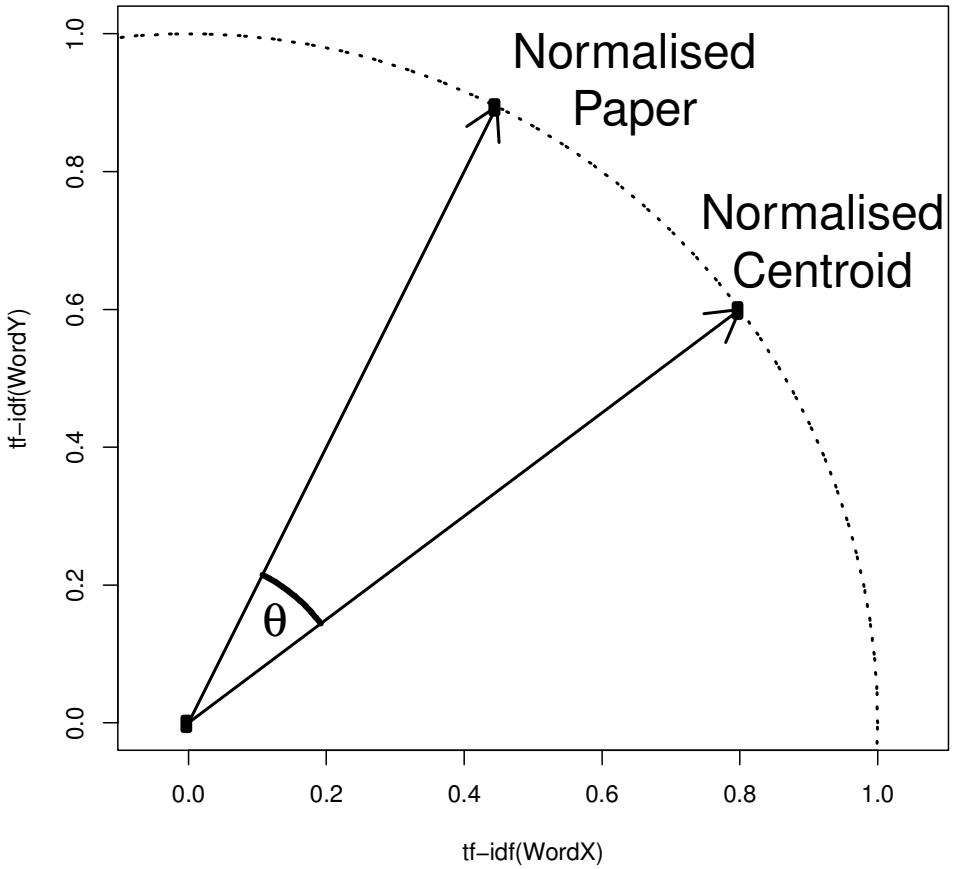
CENTROID



$$C = \frac{1}{|S|}\sum_{d \in S} d$$


Normalised
Paper
Normalised
Centroid
Paper
Centroid
tf−idf(WordY)
tf−idf(WordX)
0.0
0.2
0.4
0.6
0.8
1.0



The Dataset

We had the following data for 681 Papers submitted to JASSS:

- Full text of submitted manuscript
  doc, docx, pdf, tex, rtf, html
- Decision of the Editor
  accept or minor revision are considered positive decisions, rejected or major revision are considered negative decisions
- Time of the submission

Pre-processing JASSS Corpus

We needed to reduce the dimensionality of the dataset (reduce the distint terms!)

- Basic text normalization, removal of stopwords
- numeric tokens were removed
- we expanded few common used acronyms using . For instance, “abm” was expanded into agent-based models
- we extracted the root of each term
- we introduced a time windows w of n years (n=1,2,5).

The tokenization generated **11145** unique terms. The application of the Porter stemmer algorithm reduced it to **9705**. The use of a time window of 2 years reduce the terms count to **6921**.

Experiments with 2 Text-Mining Classifiers

1. Centroid-based Global Classifier

Given a paper **p**, if the paper is closer to the group of previously accepted papers it will be accepted , otherwise rejected

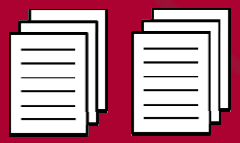
2. KNN Local Classifier

Given a paper **p**, if the most similar paper to **p** was accepted, then **p** will be accepted, otherwise rejected

(*) all the experiments use the time variable

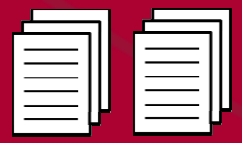
Global Centroid Classifier

Submitted Paper
01-01-2007



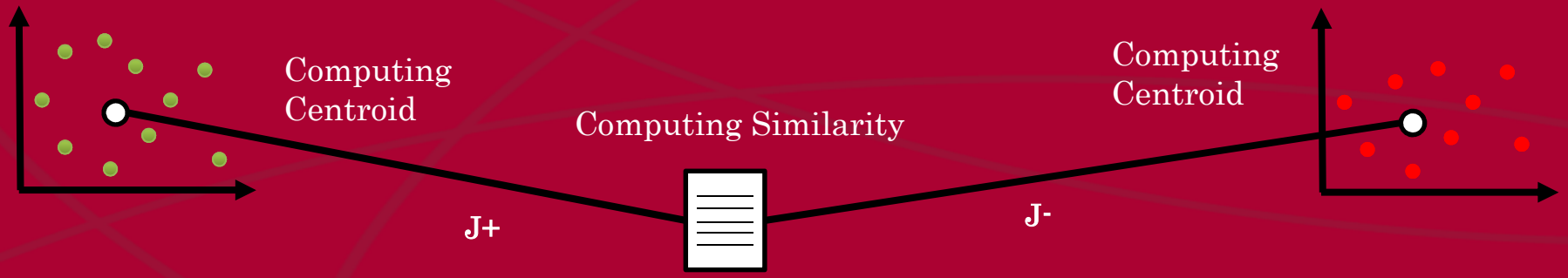
Corpus of Accepted Papers
prior to 01-01-2007

Corpus of Rejected Papers
prior to 01-01-2007



Computing Vector Representation

Computing Vector Representation

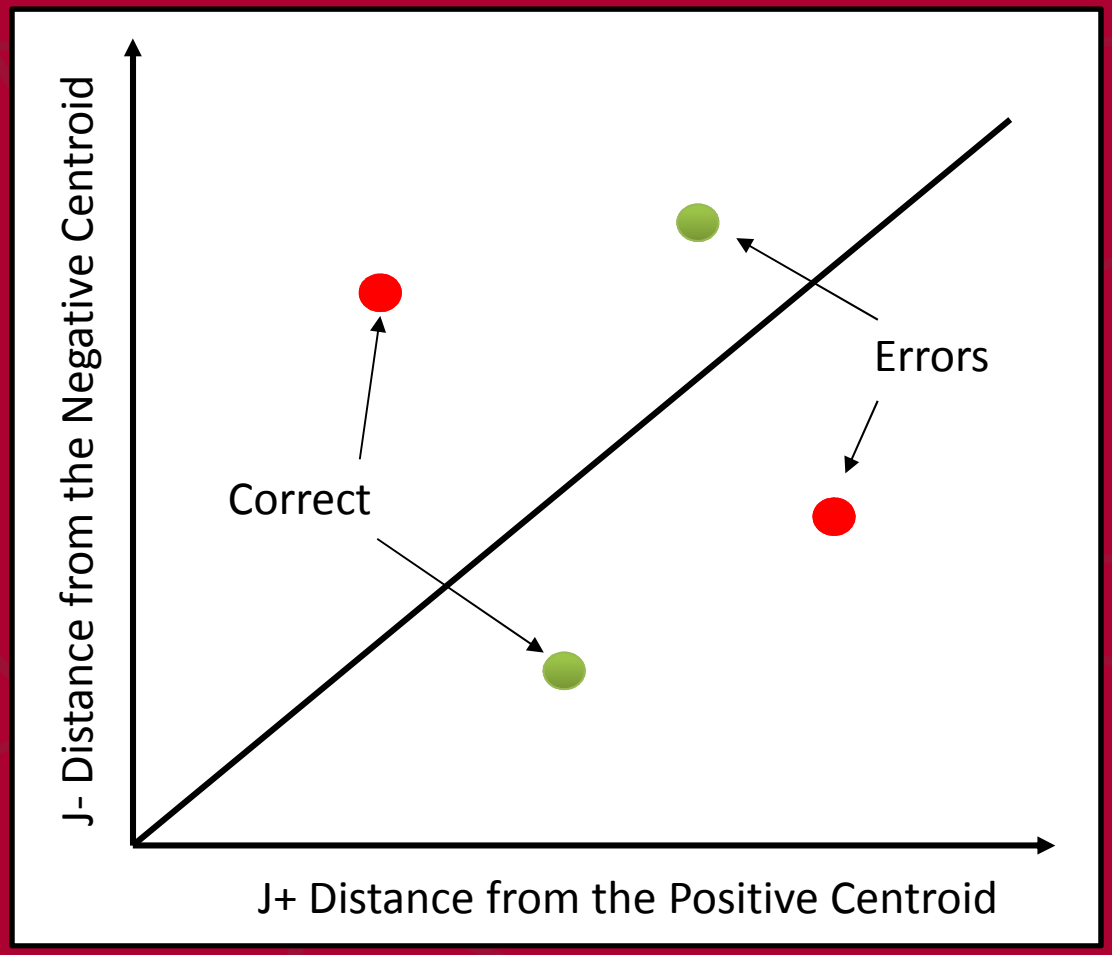


Classification
J+ > J-

POSITIVE

NEGATIVE

Graphical Representation



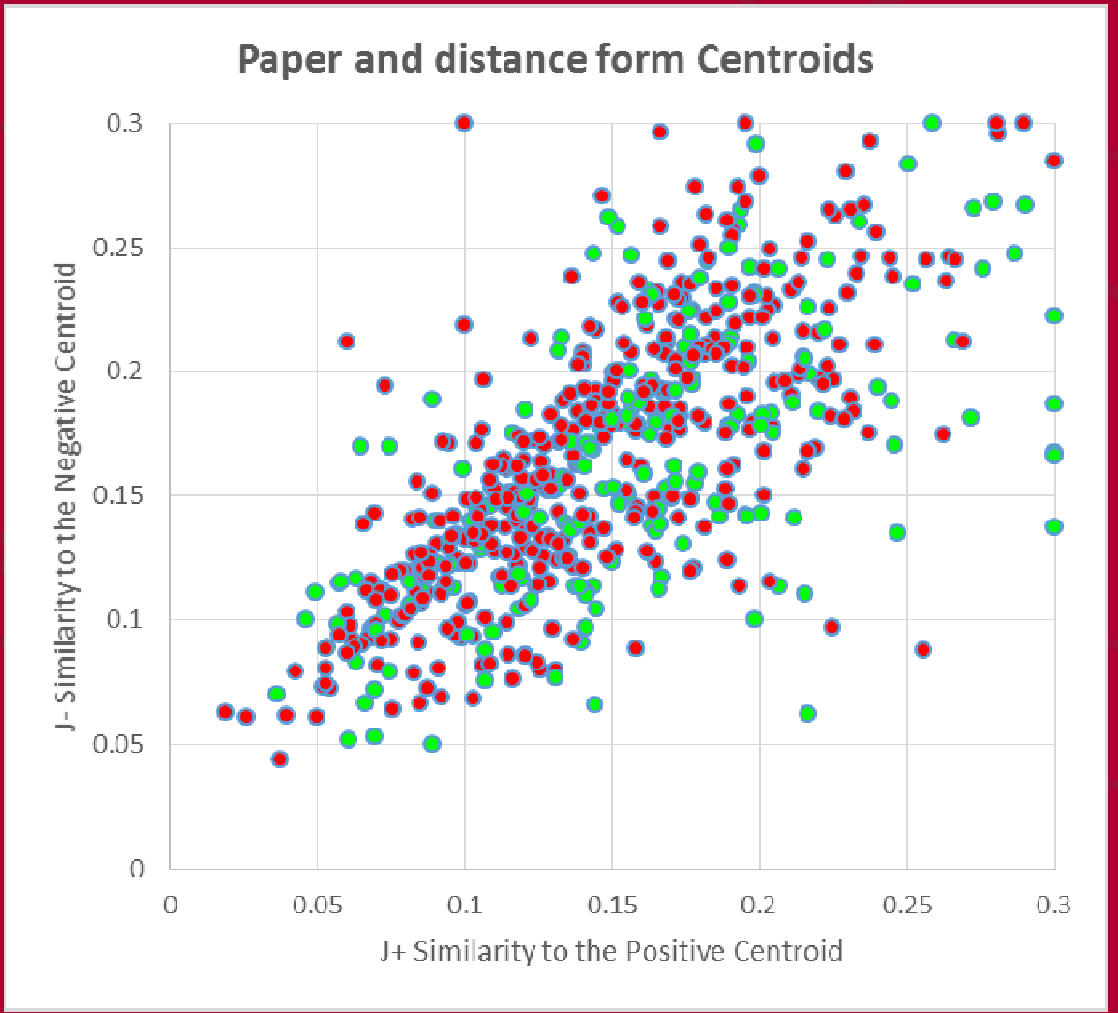
Upper triangle = negative review

Lower triangle = negative review

On the line = equidistant, no decision

Closer to the line = more uncertainty

Any surprise?



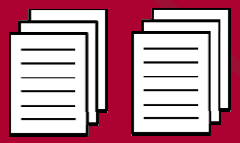
Result – Global Classifier

- Baseline
  - F-score: 0.568
  - Accuracy: 56.9%
  - Based on a random classifier with prior probabilities equals to JASSS dataset: P(accept)=0.315 , P(reject)=0.685

- Global Classifier
  - F-score: 0.613
  - Accuracy: 61.7%
  - Significant but modest gain in performance.
  - J+ more predictive than J-

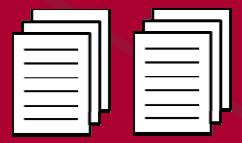
Global Classifier: using a temporal window

Submitted Paper
01-01-2007



Corpus of Accepted Papers
n years before 01-01-2007

Corpus of Rejected Papers
n years before 01-01-2007



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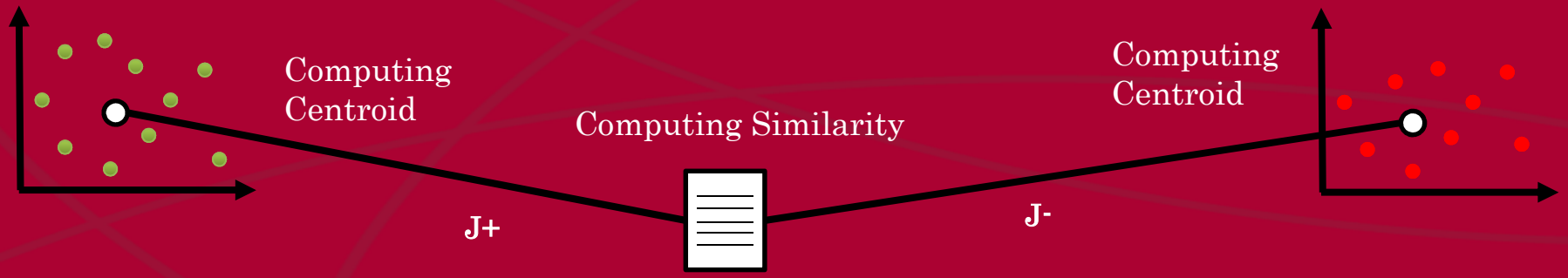


POSITIVE

Classification
J+ > J-

NEGATIVE

Result – Global Classifier

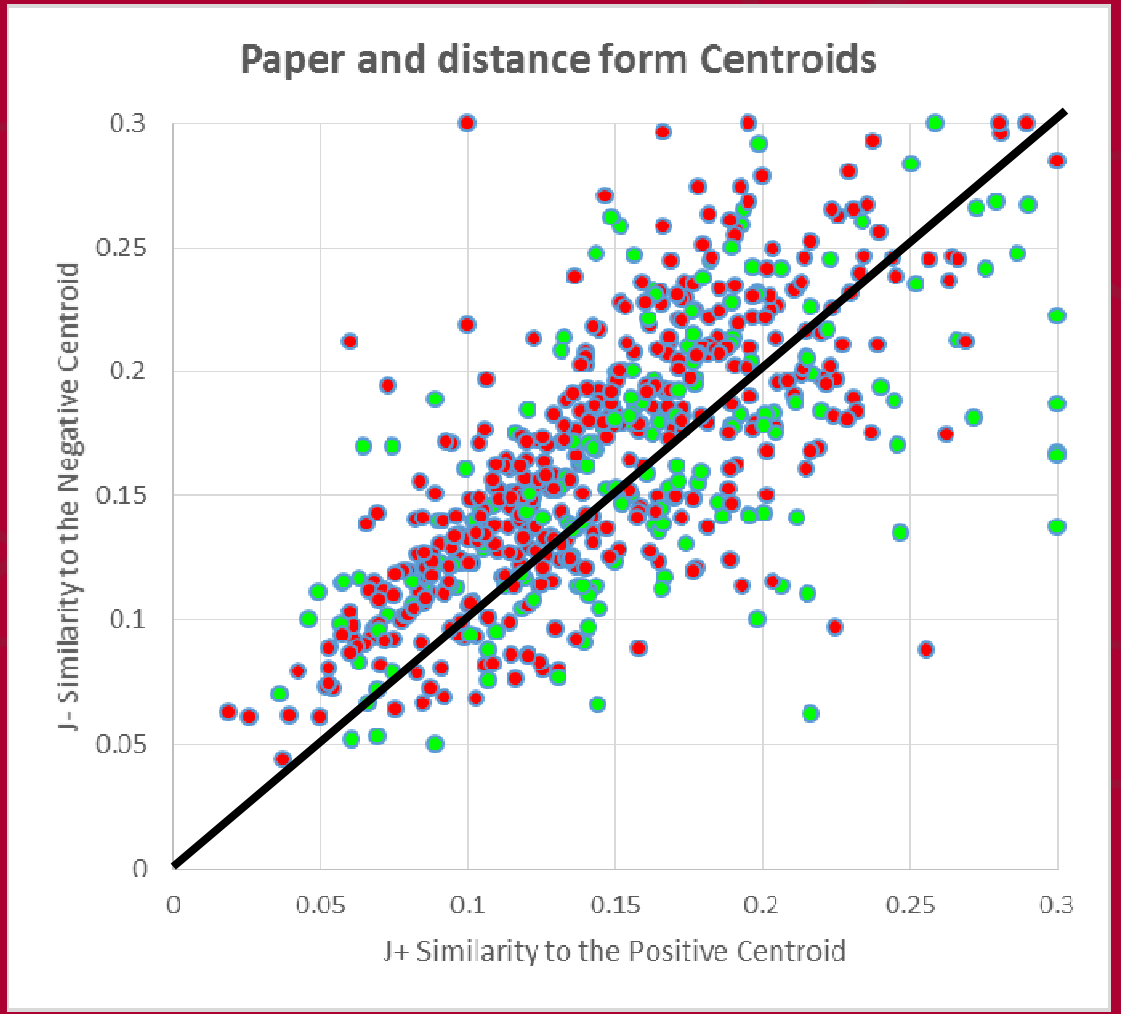
- Do the performance improve by using a time windows?
  Yes, results increase with an maximum around 2-3 years.
  This suggests the presence of a time locality in JASSS, maybe the presence of fashionable topics?

Classifier	F-score	Accuracy	Gain
Random Baseline	0.565	56.9%	
Global	0.613	61.7%	+4.8%
Global with time window	0.659	66.4%	+9.5% (*)

Improving accuracy

$\Delta J = J+ - J-$

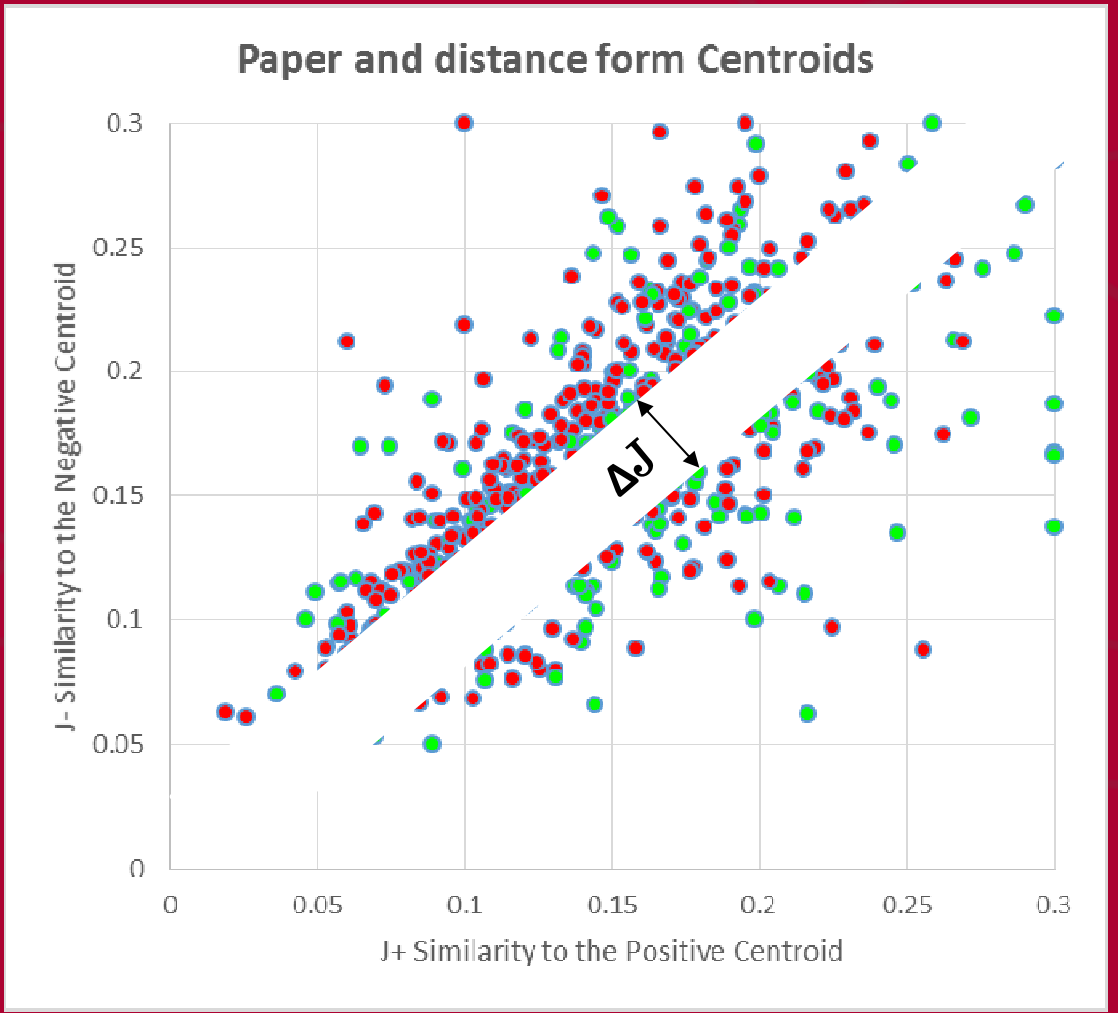
Could be a measure of the certainty of prediction



Smaller but better?

$\Delta J = J+ - J-$

Could be a measure of the certainty of prediction



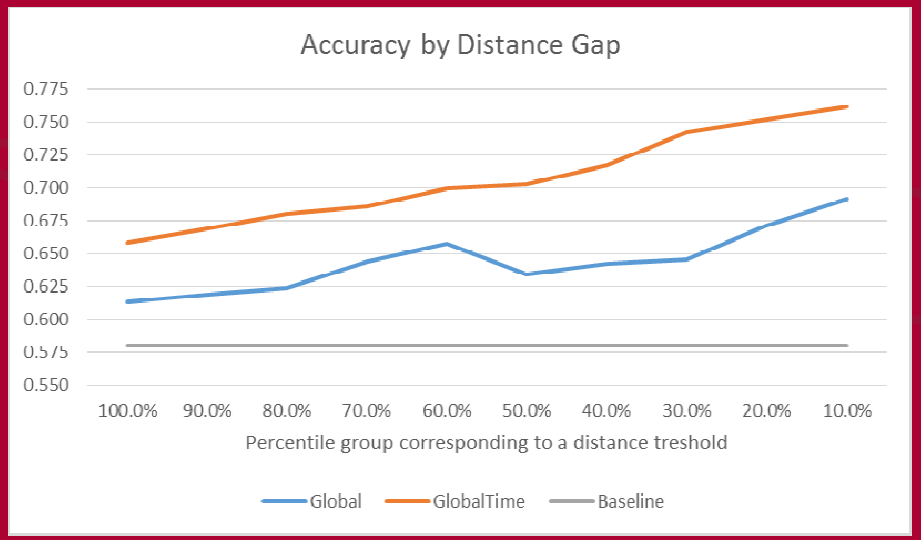
Result – Global Classifier

- Do the performance improve by only take a decision when the model is more certain?

  We take a decision only on a subset of papers, but (maybe) a better decision. The gap between J+ and J- is a measure of certainty. We can classify papers only if **ΔJ** is more than a threshold.

  Performance improves almost linearly

Size of the subset of Papers (percentile)	F-score
100	0.659
80	0.680
50	0.703
30	0.743
20	0.75
10	0.762



Result – Global Classifier

- Do performance change over time?

  Yes, overall performance **improves** over time. This suggests that papers are getting easier to classify. Time locality helps.

  This could suggests that JASSS had well defiend its topics?

  However, while rejection is constantly getting easier to predict, acceptance does not show a clear trend even if it has its maximum in 2010 - 2012

Time Period	F-score (for 100% of papers)
04-06	0.56
07-09	0.64
10-12	0.705

Global Classifier -Summary

- Modest results with a standard classifiers
- Good improvements with the introduction of a time windows (time locality)
- It is possible to increase the accuracy of the model by only treating less uncertain cases
  - 50% of cases with accuracy around 70%
  - 30% of cases with accuracy around 75%
- The quality of the classifiers improves over time. However, it seems that negative reviews are easier to predict than positive

Global Classifier -Comments

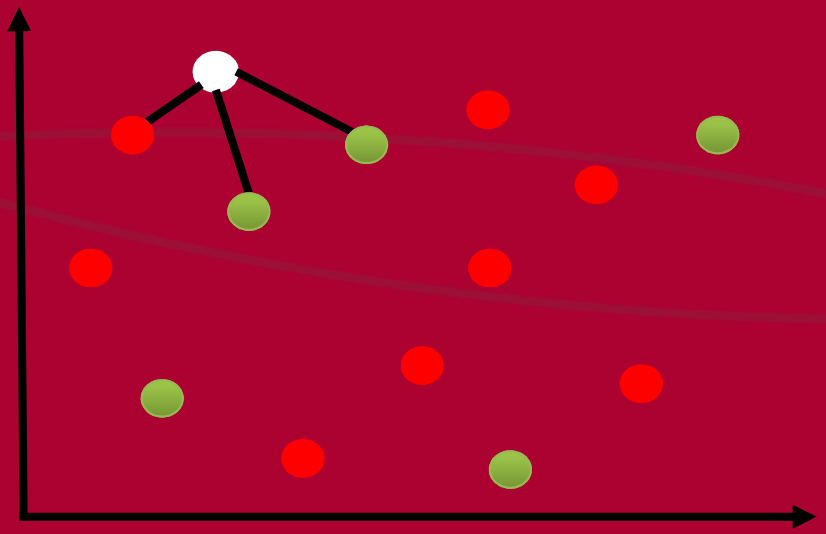
- Making prediction based on documents terms is not trivial, similar papers could have different review outcomes. Topic is not sufficient.
- The presence of time locality suggests that is easier to be accepted if the topic is fashionable
- The increment of performance over time suggest a growing distinction between papers with positive and negative review
- The gap between J+ and J- is an efficient proxy of uncertainty

Local KNN Classifier

Submitted Paper
01-01-2007

Corpus of ALL papers
submitted
prior to 01-01-2007
labelled as Accepted / Rejcted

Vector Representation



K-NN Classifier

- K=1 Assign the label of the closest paper
- K=N Consider the N closest papers and assign the label based on majority rule or minimum quorum
- N cannot be too big when data are unbalanced

Result – Local KNN Classifier

- Baseline
  F-score: 0.568
  Accuracy: 56.9%
  Based on a random classifier with prior probabilities equals to JASSS dataset: P(accept)=0.315 , P(reject)=0.685

- KNN Classifier (K=1)
  F-score: 0.589
  Accuracy: 59.2%
  Performance similar to the baseline.
  Overall, locality does not help. The introduction of a time window improve performances (accuracy up to 64.1% with 2 year window)

Result –Local

- Do the performance improve by only take a decision when the model is more certain?
  - We take a decision only on a subset of papers, but good decision
  - We can increase the number of neighbours N and use a quorum

N	Quorum	% of papers	F-score	Accuracy	Gain
1	1 / 1	100	0.589	59.2%	
2	2 / 2	62.3	0.668	66.8%	+7.6%
3	3 / 3	40.7	0.704	70.5%	+11.3%
4	4 / 4	25.5	0.737	74.1%	+14.9%
5	5 /5	17.7	0.769	77.8%	+18.8%
3	2 /3	100	0.616	62%	+2.8%
5	3 / 5	100	0.658	65.7%	+7.4%
5	4 / 5	54.1	0.708	71.4%	+12.4%

Result – Global vs Local

- Are both the classifiers balanced?

  Let us compare the accuracy of the <u>2 classes separated</u>

Model	% papers	Accuracy NEG
Global 2-yrs	20	77%
Global 2-yrs	50	75.70%
KNN 4 / 4	25.5	74.40%
Global 2-yrs	100	73.60%
KNN 4 / 5	54.1	72.80%
KNN 5 /5	17.7	72.60%
KNN 3 / 5	100	71.60%
KNN 3 / 3	40.7	71.50%
KNN 1	100	65.70%

Model	% papers	Accuracy POS
KNN 5 /5	17.7	86.4%
KNN 4 / 4	25.5	75.5%
KNN 3 / 3	40.7	66.1%
Global 2-yrs	20	64.7%
KNN 4 / 5	54.1	64.6%
Global 2-yrs	50	56.1%
KNN 3 / 5	100	52.4%
KNN 1	100	47.4%
Global 2-yrs	100	41.2%

- Locality helps to predict papers with a positive review

Comparing Classifiers

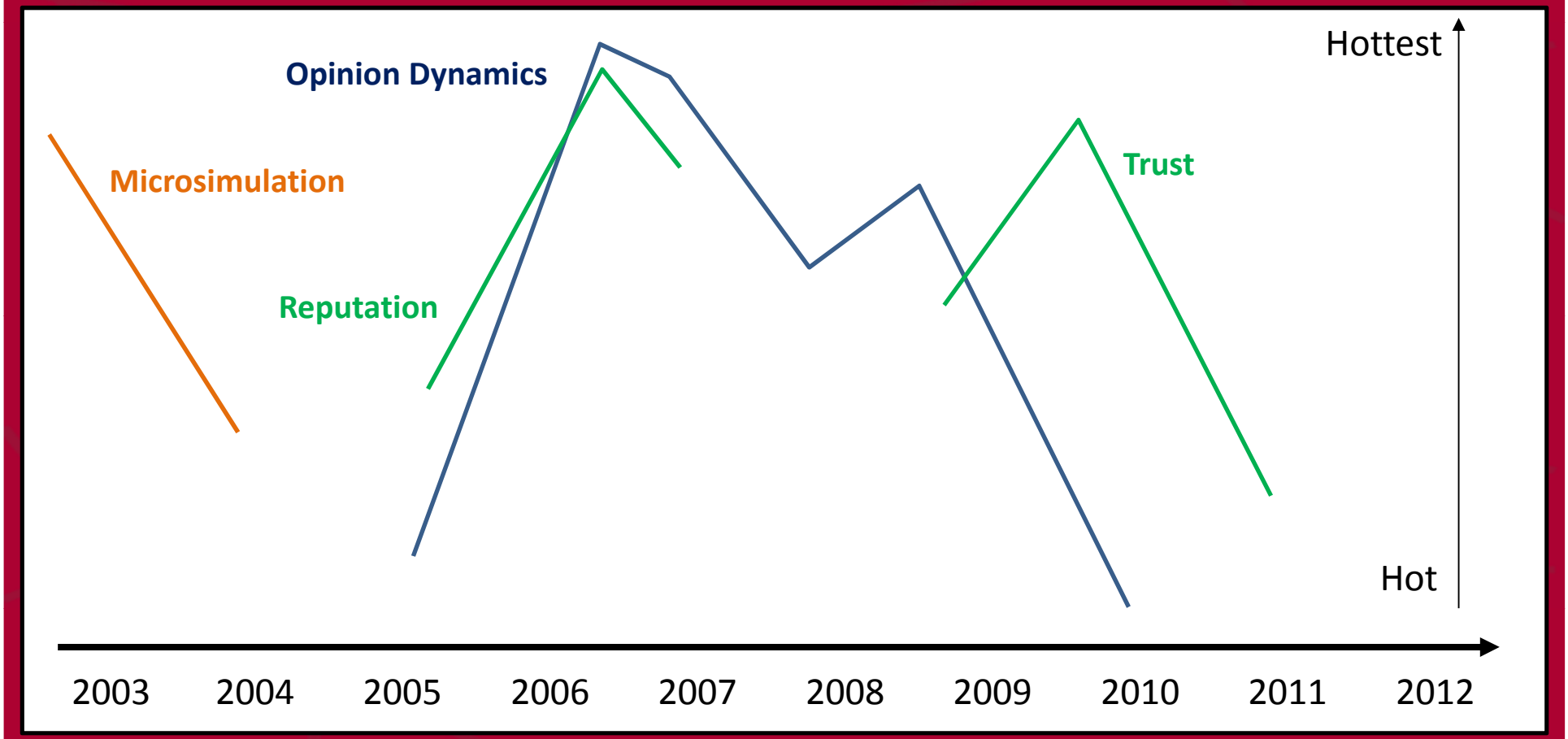
Overall, the classifiers have similar baseline performance but both of them improve by introducing a time windows and by classifying only a subset of less uncertain cases

Both of the classifiers can predict referee review outcome of 50% of the papers with accuracy around **70%**, and 1/3 of the papers with accuracy around **74%**

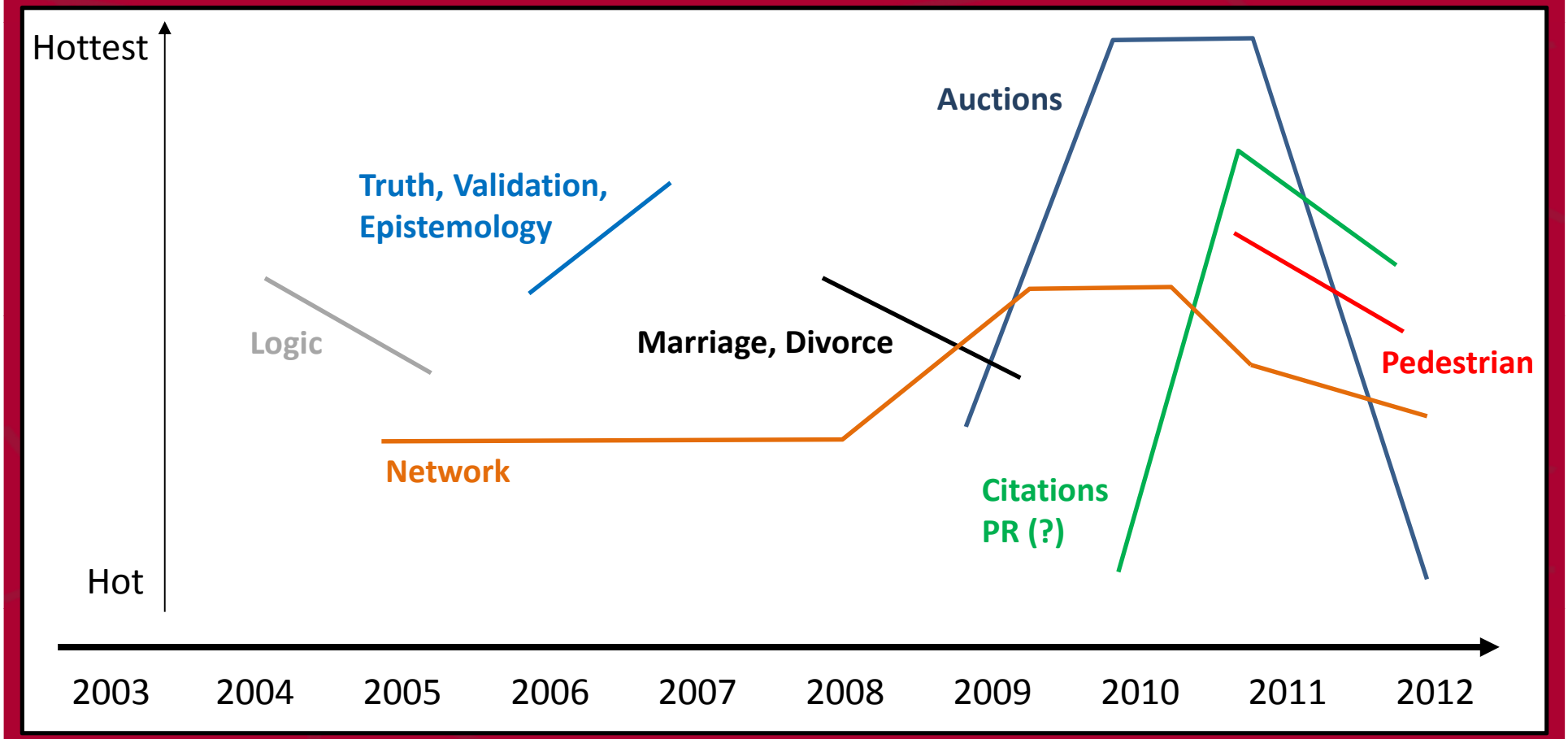
- However

The KNN classifiers are more balanced (they can predict negative and positive outcomes), while the global classifiers predict the negative outcome better than the positive ones

Hot Topics examples



Hot Topics examples



Conclusions & Future Works

- Can we automatically predict review outcome by text similarity?

  Overall, we obtained an improvement compared to the baseline, but modest, that improves by considering the time dimension

  However, for a subset of papers the accuracy of the classification is interestingly high (70%-75%)

  The study has also collected interesting experimental evidence of a dynamic change in JASSS topics

Next Step on JASSS dataset:

- LSA Analysis to name and discover changing and trending topics