Text Mining for Creative Cross-Domain Knowledge Discovery

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with contributors

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JOTA, FRI, 29.3.2016

Talk outline

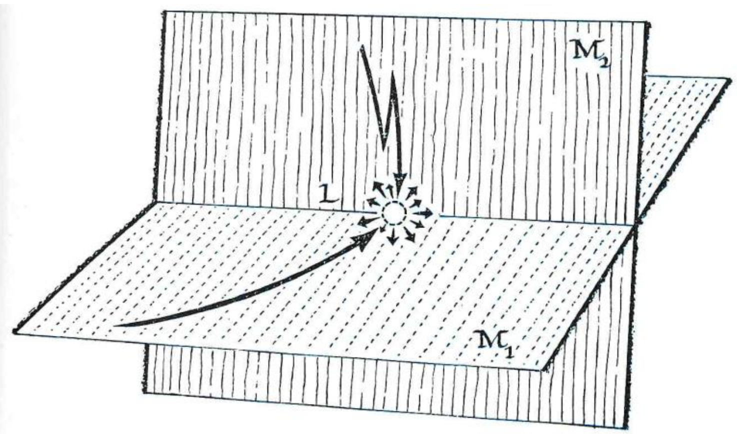
- Background and motivation
- Literature-based discovery
- Cross-domain literature mining approaches
  - Outlier detection for cross-domain knowledge discovery
  - Cross-domain knowledge discovery with CrossBee
- TextFlows text mining platform
- Summary and conclusions

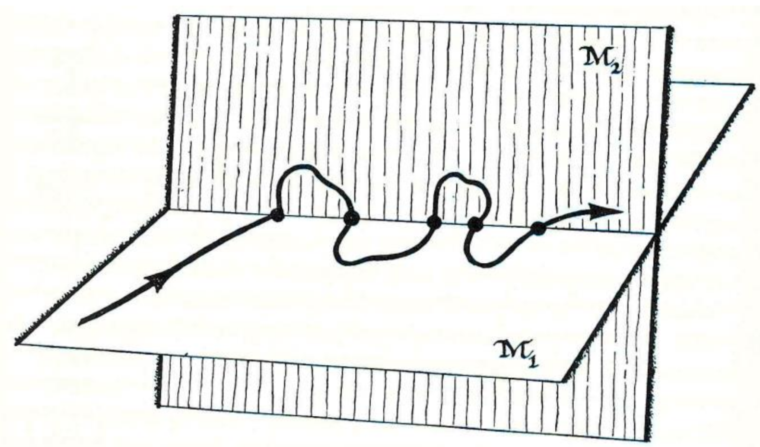
The BISON project

- Explore the idea of bisociation (Arthur Koestler, The act of creation, 1964):
  - The mixture - in one human mind – of **different contexts** or **different categories of objects,** that are normally considered **separate categories** by the processes of the mind.
  - The **thinking process** that is the functional basis of **analogical or metaphoric thinking** as compared to logical or associative thinking.

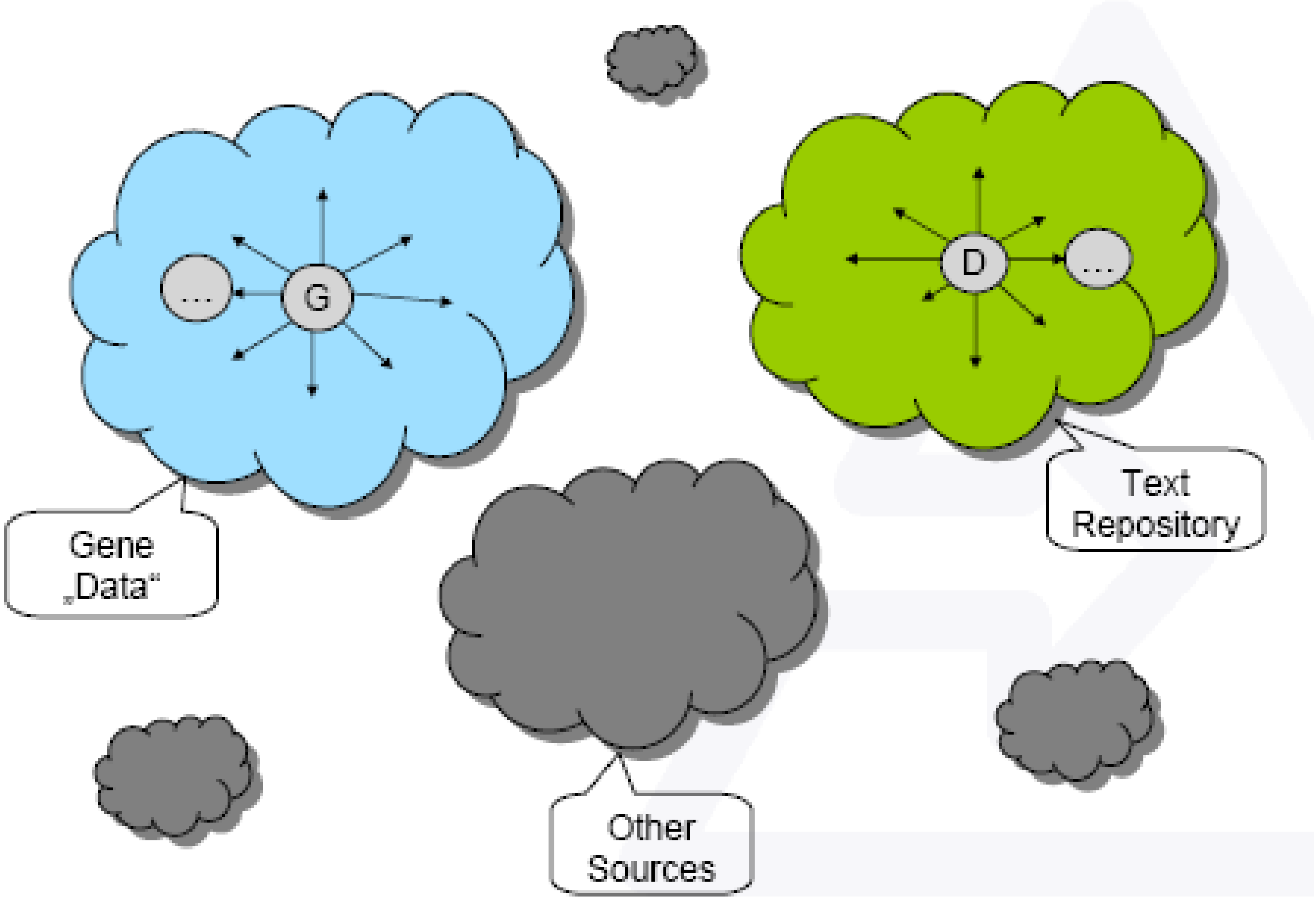
Bisociation discovery in BISON

- BISON challenge:
  - Find new insights: new **bisociations,** i.e., interesting new links **accross domains**
- Two concepts are bisociated if and only if:
  - There is no direct, obvious evidence linking them
  - One has to cross contexts to find the link
  - This new link provides some novel insight



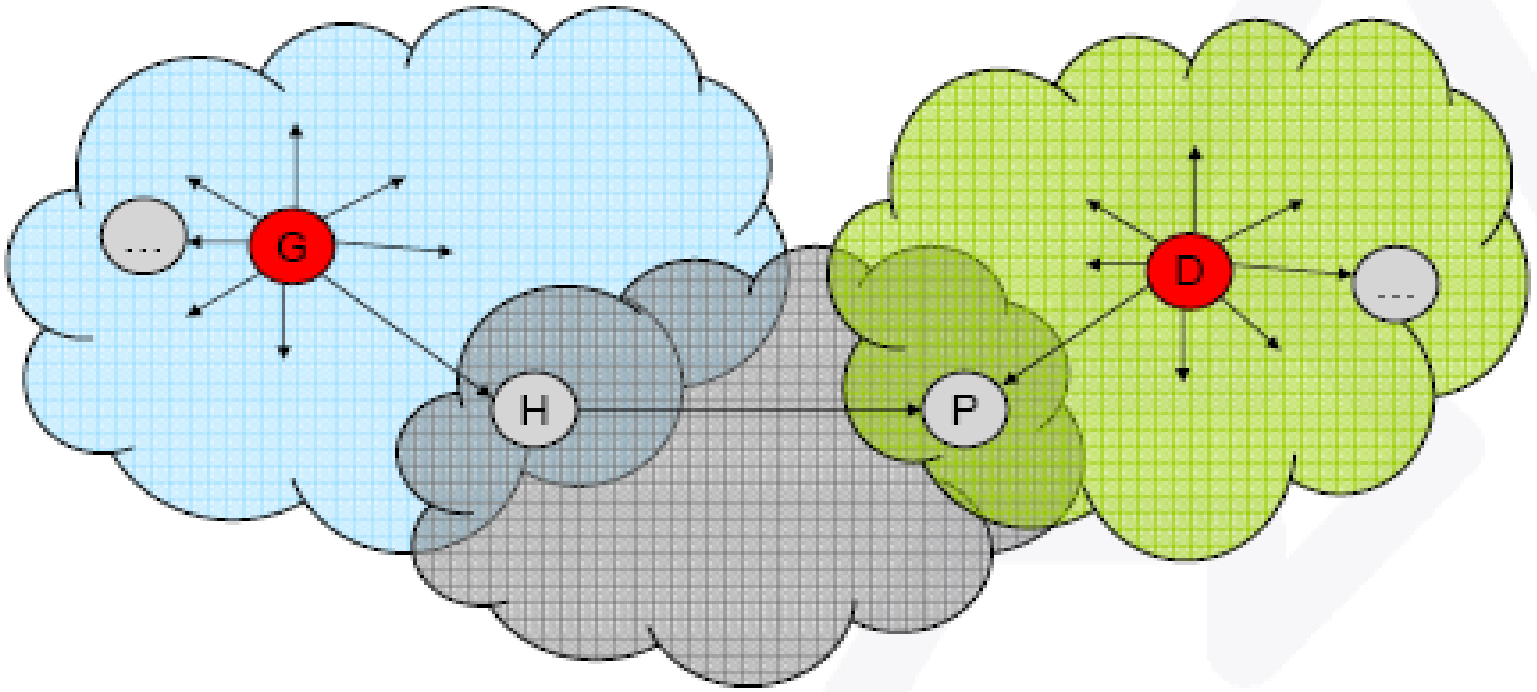


Heterogeneous data sources
(BISON, M. Berthold, 2008)

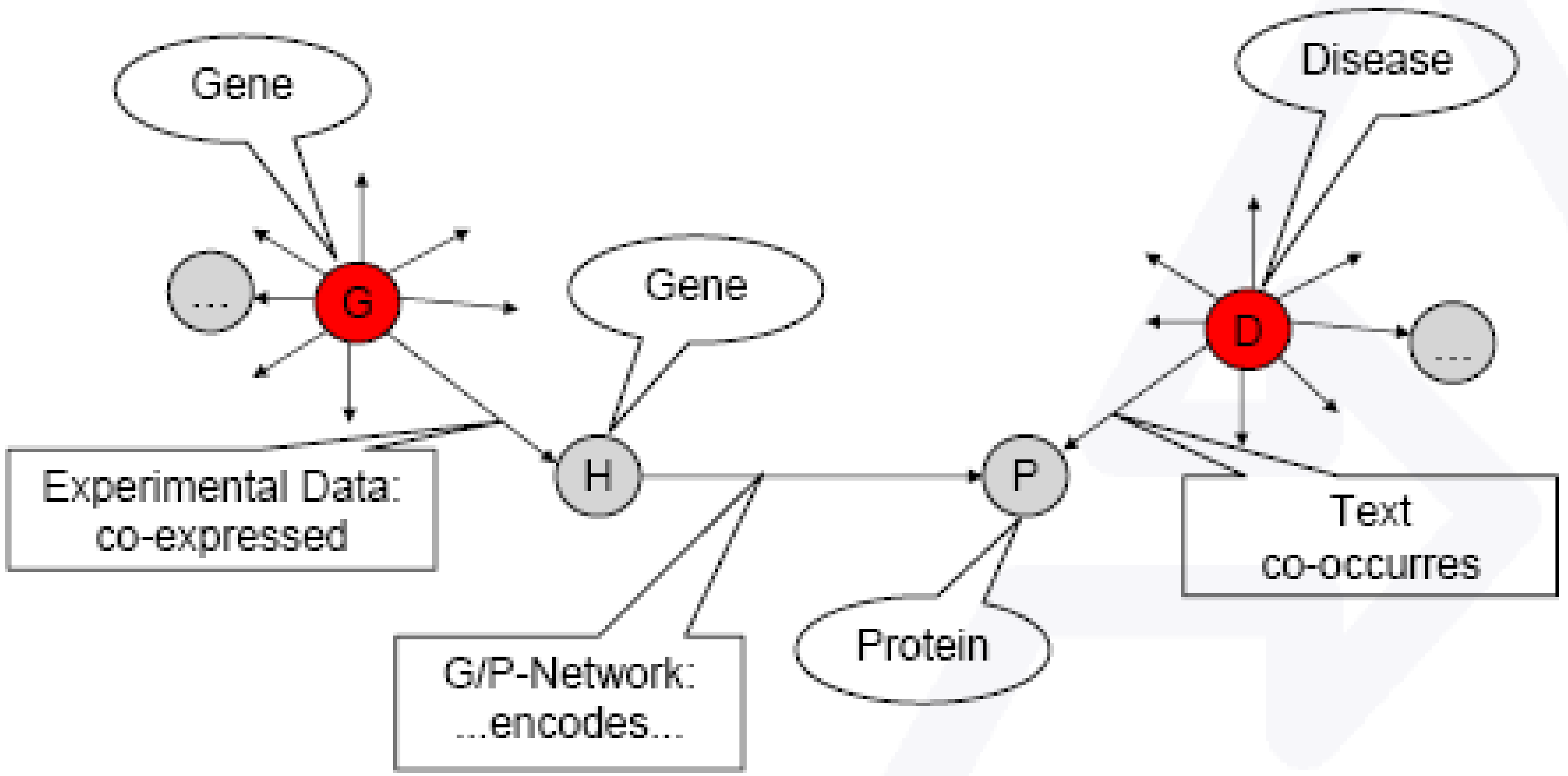


Bridging concepts

(BISON, M. Berthold, 2008)



Chains of associations across domains (BISON, M. Berthold, 2008)



Main BISON approach

- Main approach: graph exploration
  - Find yet unknown links in a graph, crossing different contexts (domains)
- Open problems:
  - Crossing different contexts (domains): Finding unexpected, previously unknown links between BisoNet nodes belonging to different contexts
  - Crossing different types of data and knowledge sources: Fusion of heterogeneous data/knowledge sources into a joint representation format - a large information network named BisoNet (consisting of nodes and relatioships between nodes)

Complementary BISON approach

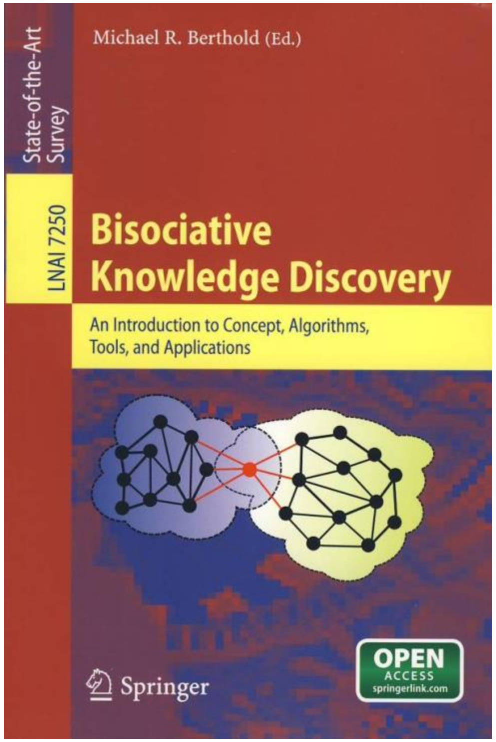
- Complementary approach: text mining
  - Find yet unknown terms in the intersection of documents, crossing different contexts (domains/literatures)
- Early related work: literature-based discovery (LBD)
  - Swanson (1988, 1990)
  - Smalheiser, Swanson (1998): ARROWSMITH
  - Weeber et al. (2001)
  - Hristovski et al. (2001): BITOLA
- Recent work: cross-domain literature mining
  - Petrič et al. (2007, 2009): RaJoLink
  - Juršič et al. (2012): CrossBee
  - …

The BISON project

- BISON: Bisociation Networks for Creative Information Discovery, European 7FP project, www.bisonet.eu
- 12 partners (2008-2011)
- Open access book (Springer 2012):

  Bisociative Knowledge Discovery

  edited by M. Berthold



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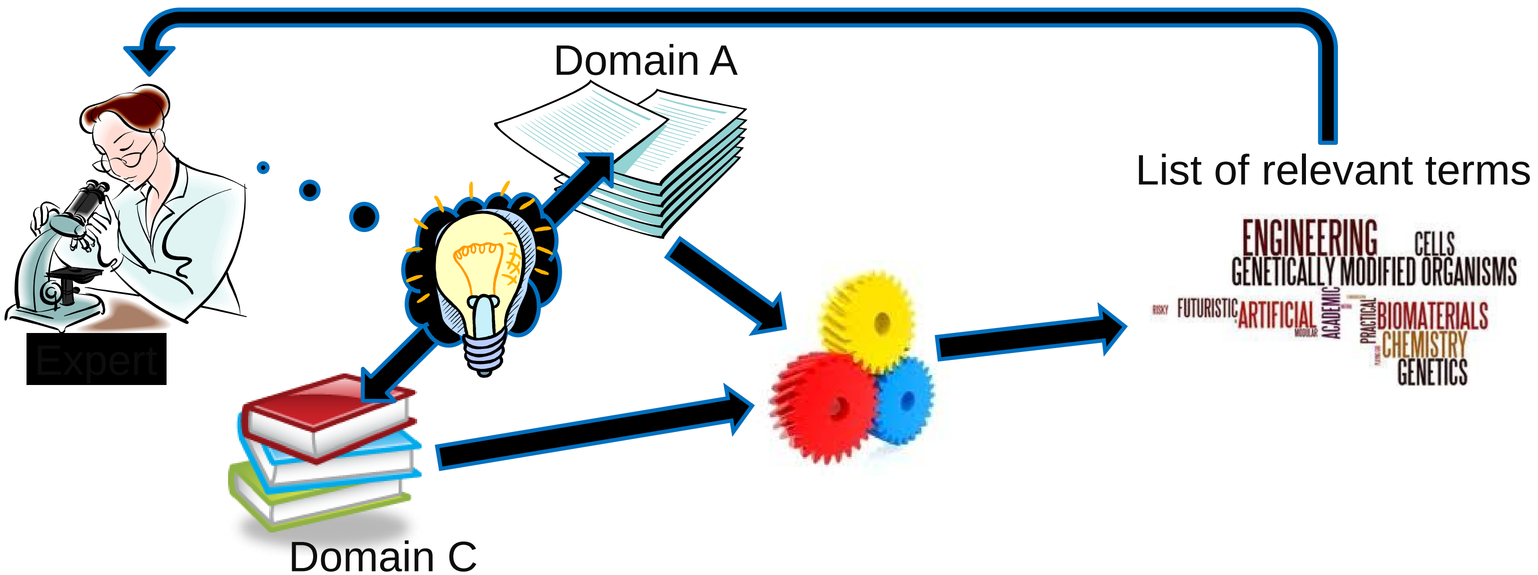
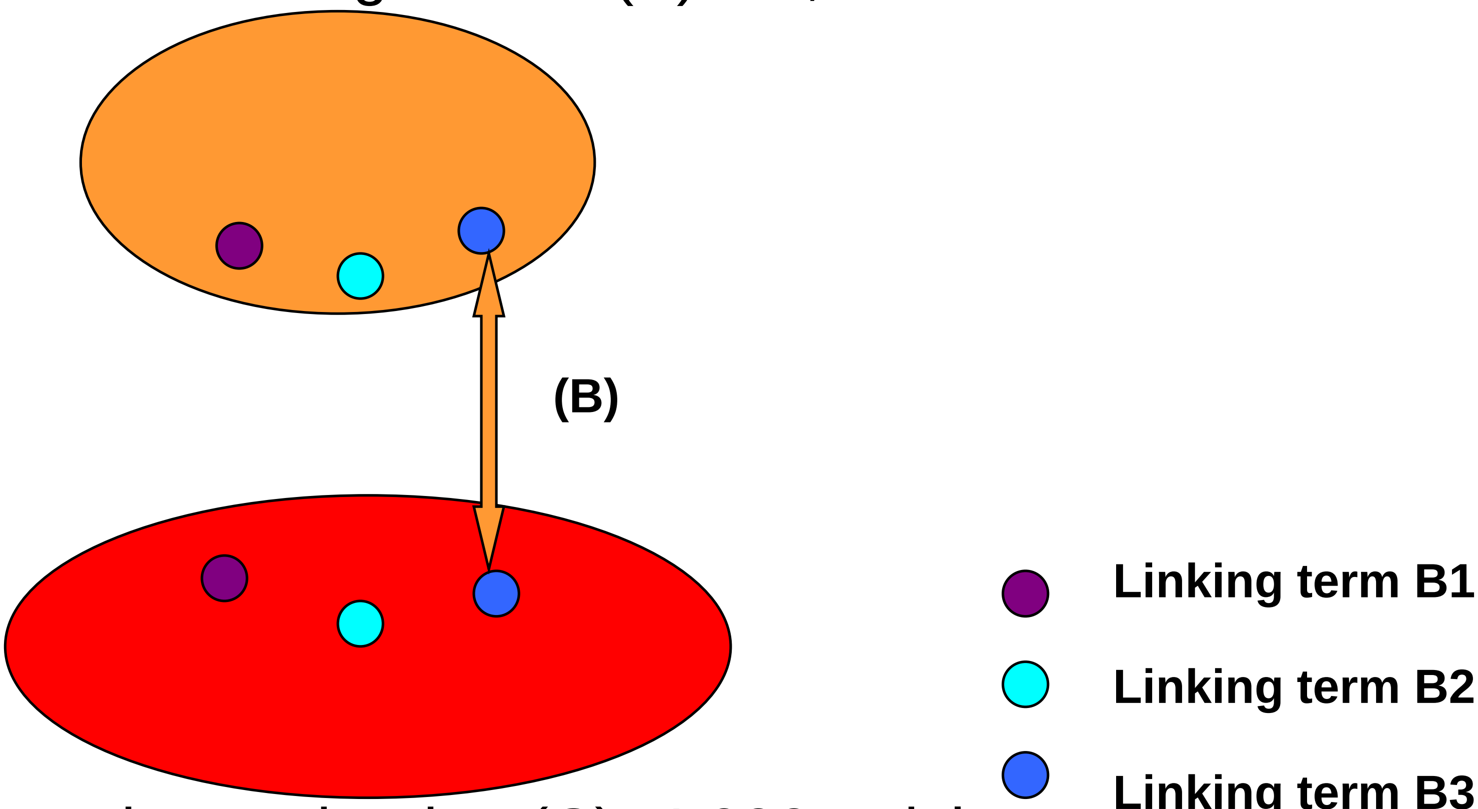
Literature-based discovery

- Help experts in cross-domain discovery for unknown facts/new findings
  - Closed discovery setting
  - Early work by Swanson: Medical literature as a potential source of new knowledge, 1990



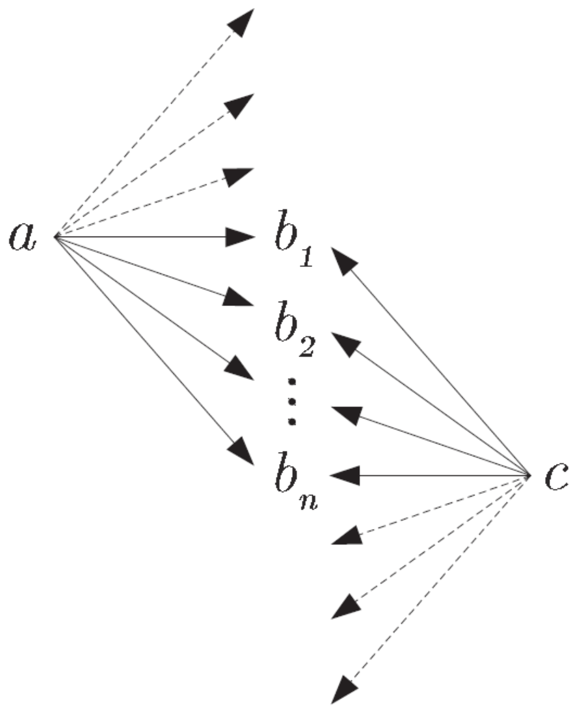
Closed discovery setting: Finding linking (bridging) terms

Literature about magnesium (A): 38,000 articles



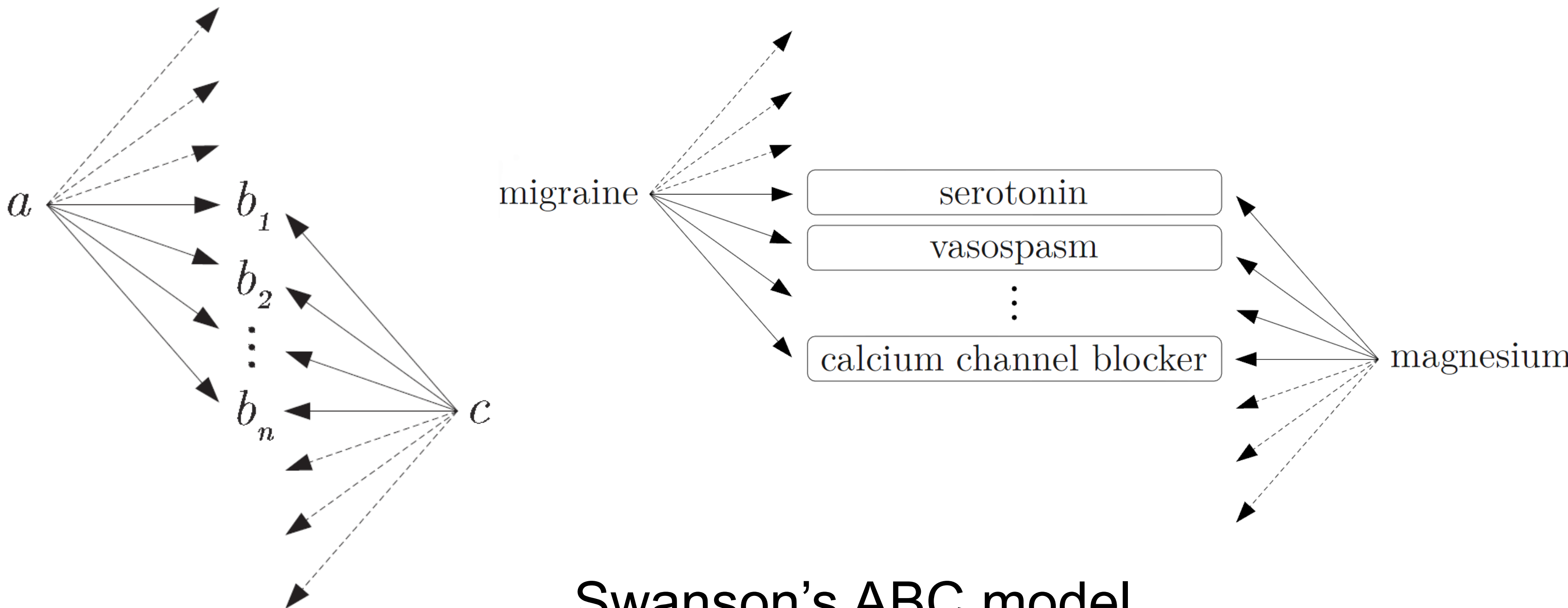
Literature about migraine (C): 4,600 articles

Closed discovery setting: Finding linking (bridging) terms



Swanson's ABC model

Closed discovery setting: Finding linking (bridging) terms



Swanson's ABC model
B-terms: calcium channel blocker, …

Closed discovery setting: Finding linking (bridging) terms

Argument 1 (magnesium literature)

- Mg is a natural calcium channel blocker.
- Stress and Type A behavior can lead to body loss of Mg.
- Magnesium has anti-inflammatory properties.
- . . .

Argument 2 (migraine literature)

- Calcium channel blockers can prevent migraine attacks.
- Stress and Type A behavior are associated with migraine.
- Migraine may involve sterile inflammation of the cerebral blood vessels.
- . . .

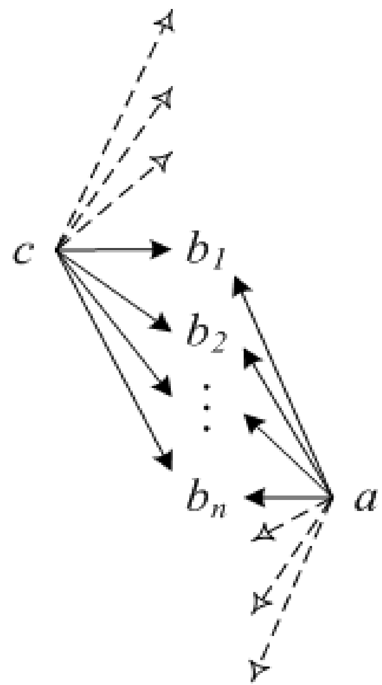
Scientific literature as a source of knowledge

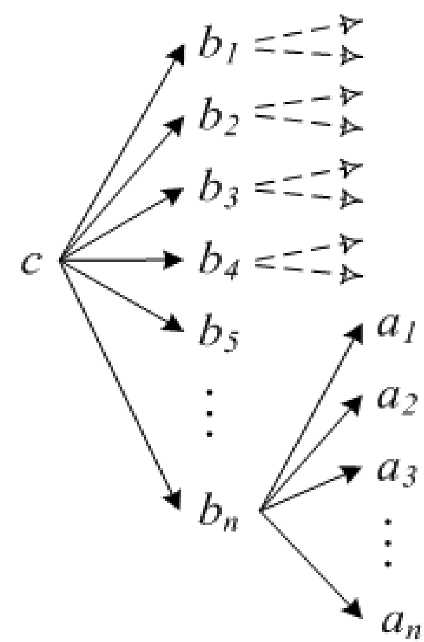
Example:

- Biomedical bibliographical database PubMed
- US National Library of Medicine
- More than 21M citations
- More than 5,600 journals
- 2,000 – 4,000 references added each working day!

Closed vs. open discovery (Weeber et al. 2001)

- **Closed discovery:**
  - A and C are known: Given two separate literatures A and C, find bridging terms B
- **Open discovery:**
  - Only C is known: Given literature C, how do we find A?





Closed vs. open discovery (Weeber et al. 2001)

- **Closed discovery:**
  - A and C are known: Given two separate literatures A and C, find bridging terms B
- **Open discovery:**
  - Only C is known: Given literature C, how do we find A?
  - Swanson: “Search proceeds via some intermediate literature (B) toward an unknown destination A. … Success depends entirely on the knowledge and ingenuity of the searcher.”
- **Text mining for cross-domain knowledge discovery:**
  - Can we provide systematic support to the closed and open discovery process ?

Text mining for coss-domain knowledge discovery

- **Situation:**
  - Growing speed of knowledge growth, huge ammounts of literature available on-line
  - High specialization of researchers
  - Potentially useful connections between “islands” of knowledge may remain hidden
- **Research objective:**
  - To develop methods and text mining tools to support researchers in the discovery of new knowledge from literature

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Outlier detection

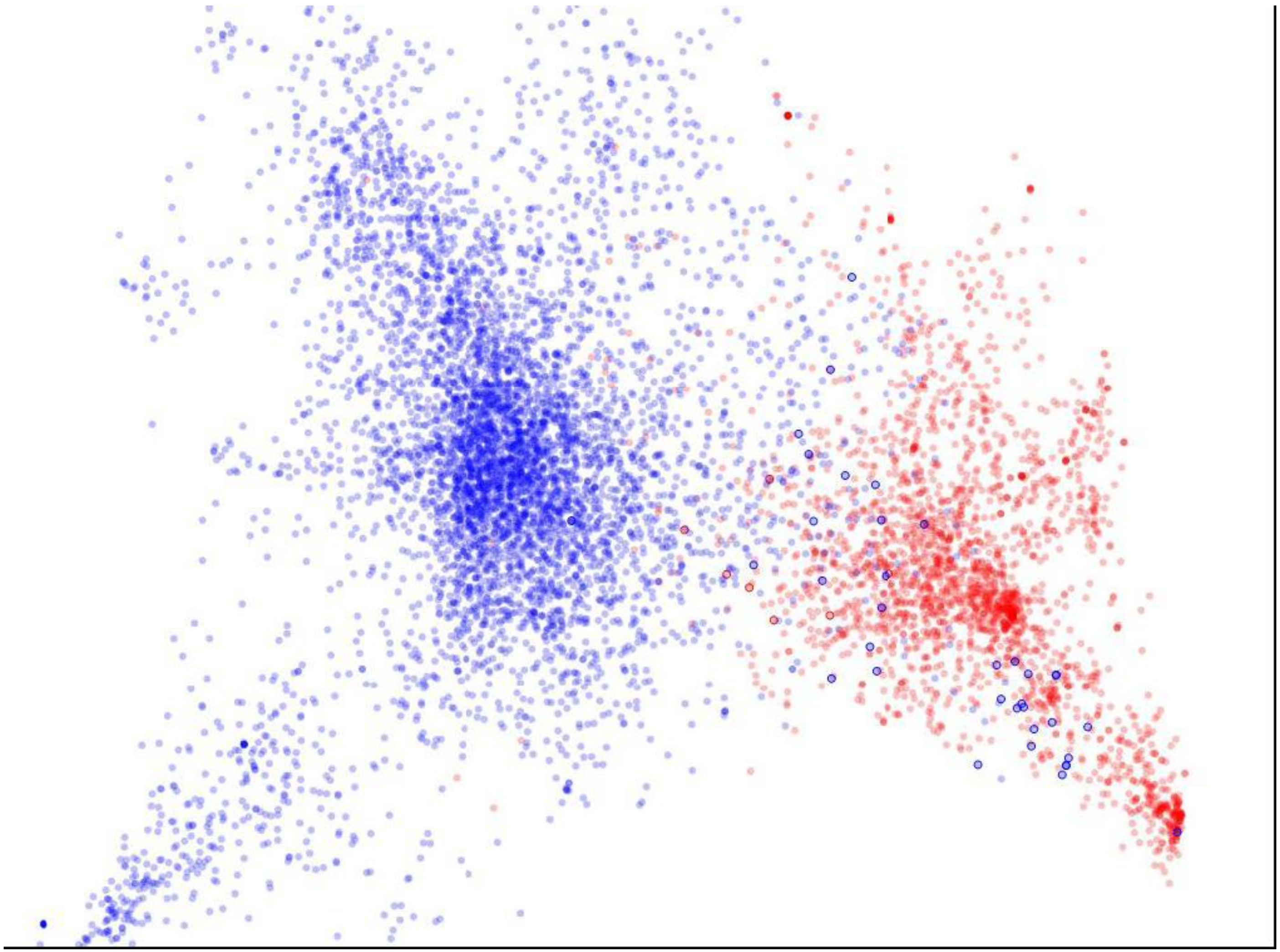
Outlier detection for cross-domain knowledge discovery

- The goal is to identify interesting **terms** or **concepts** which relate or link separate domains.

  $\Rightarrow$ *bridging terms (b-terms) / bridging concepts*

- We explore the utility of *outlier detection* in the task of *cross-domain bridging term discovery*

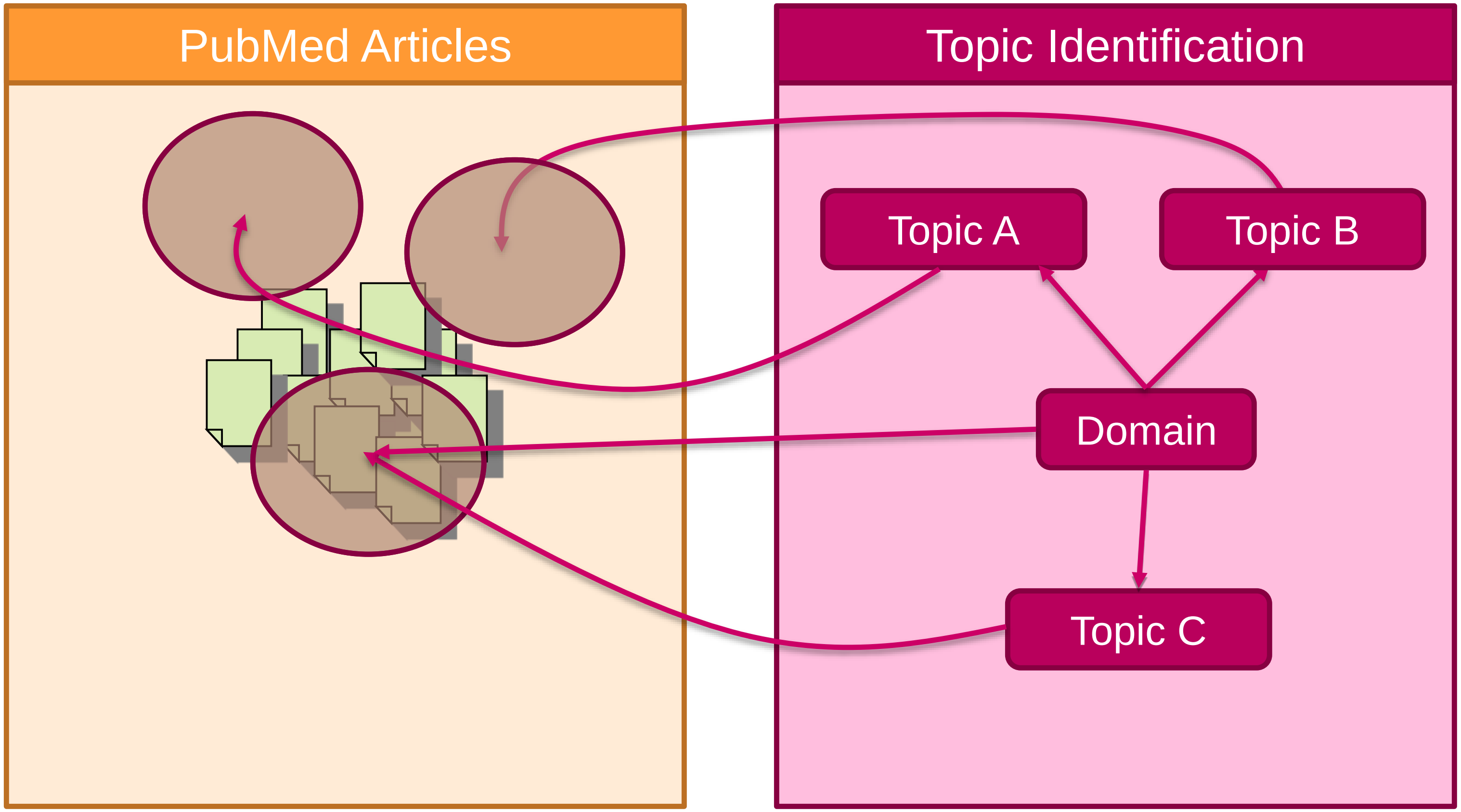
Outlier detection for cross-domain knowledge discovery



2-dimensional projection of documents (about autism (red) and calcineurin (blue). Outlier documents are bolded for the user to easily spot them.

Our research has shown that most domain bridging terms appear in outlier documents.
(Lavrač, Sluban, Grčar, Juršič 2010)

Outlier detection by clustering of PubMed articles



Slide adapted from D. Mladenić, JSI

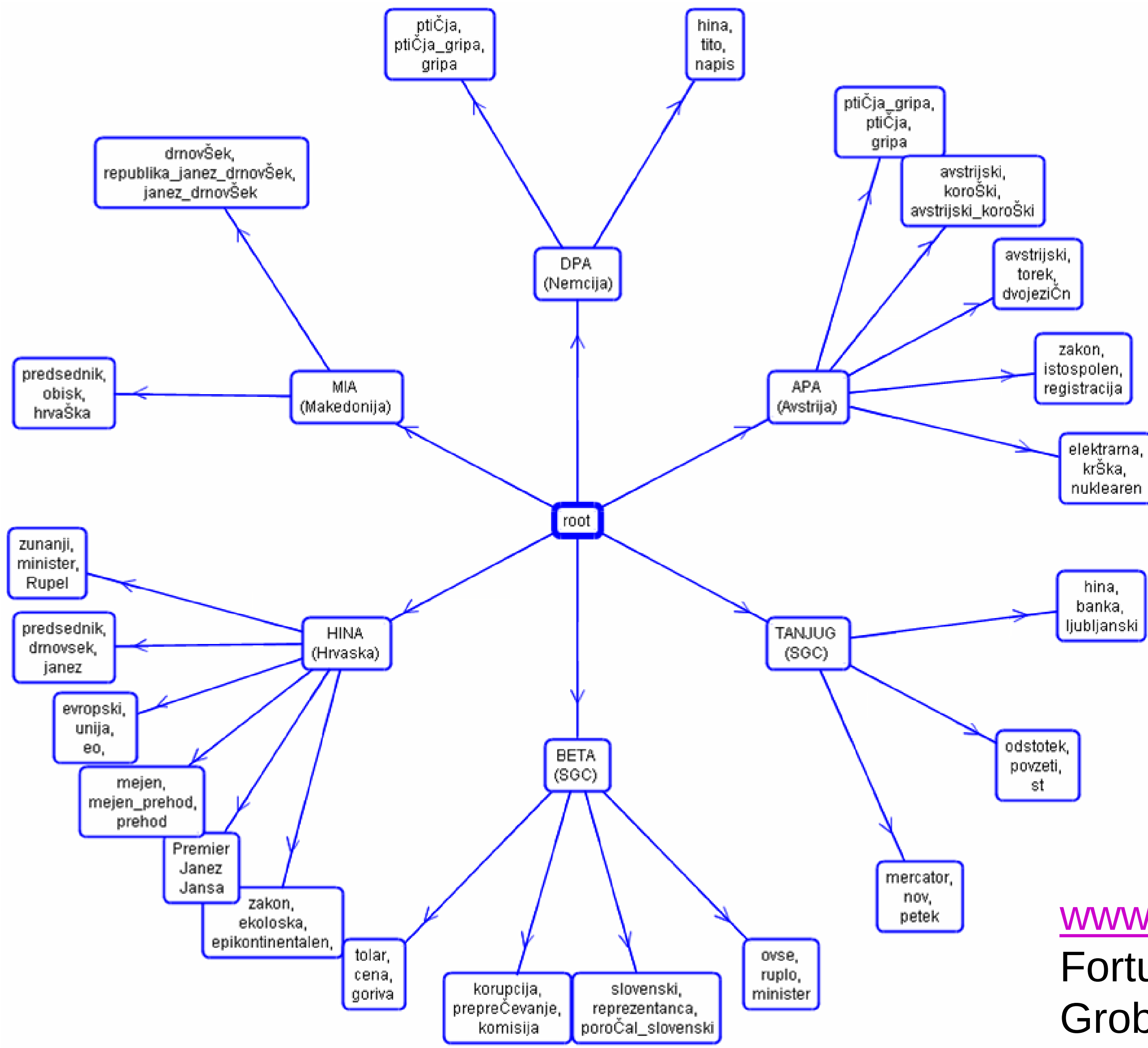
Illustrative example: Input to OntoGen clustering - STA news about Slovenia from foreign press

All.txt - Notepad

File Edit Format View Help

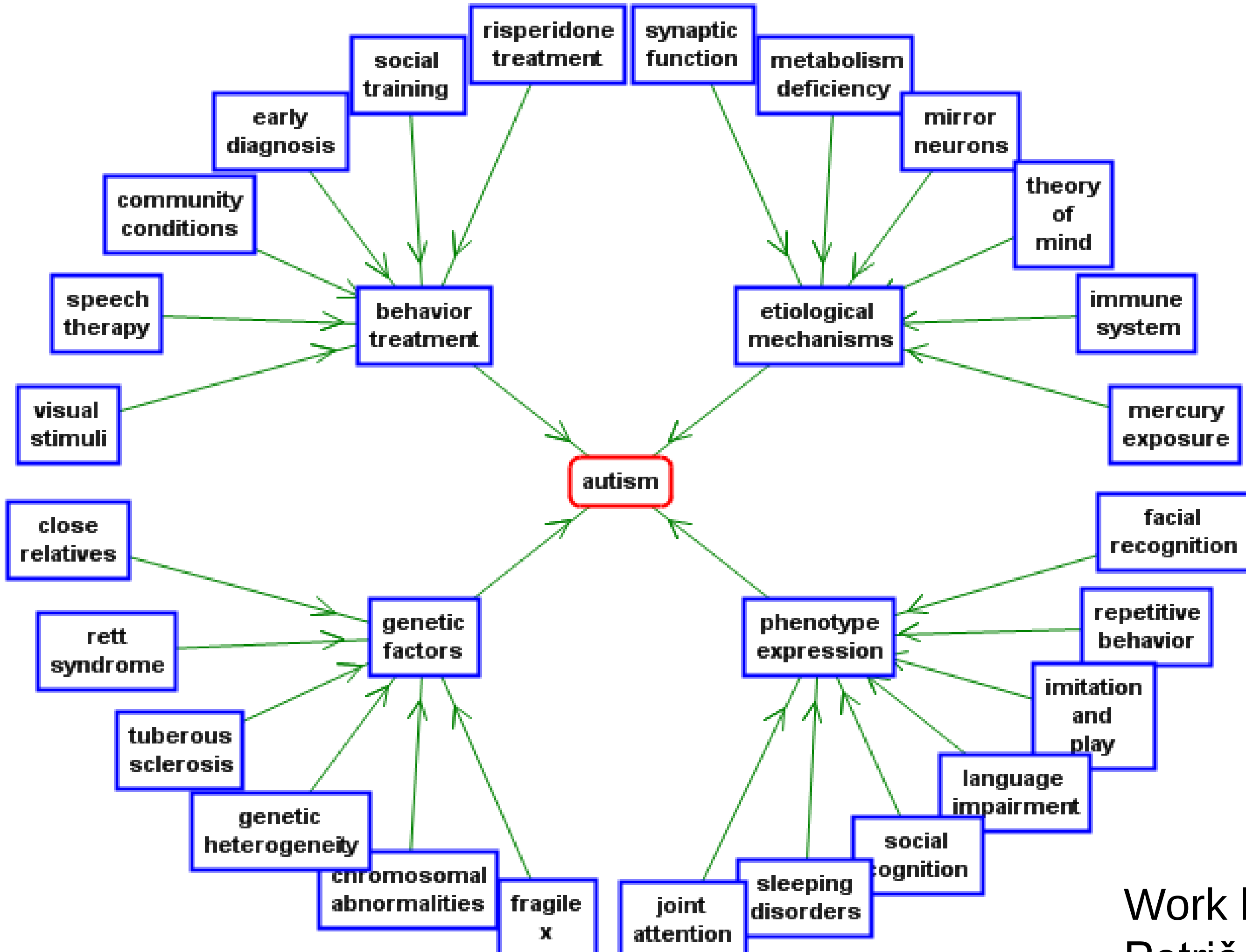
```
#016138= Nemška tiskovna agencija dpa je pisala, da se bo ameriški bogataš Donald Trump
#016139= Tiskovna agencija SÈG Tanjug je po STA povzela vest o odzivu zunanjega ministra
#016140= Tanjug je po Delu povzel izjavo rektorja ljubljanske univerze Jožeta Mencingerj
#016141= Tanjug je namenil pozornost vesti o stopnji registrirane brezposelnosti v Slove
#016142= LJUBLJANA - Ena izmed glavnih tem poroèanja tujih agencij o Sloveniji so bile s
#016143= Avstrijska tiskovna agencija APA je poroèala, da je predsednik republike Janez
#016144= Beograjska tiskovna agencija Beta je poroèala, da je v 69. letu starosti umrla
#016145= Beograjska Beta je še poroèala, da, na podlagi pregleda želja slovenskih poslan
#016146= Beta je tudi poroèala, da so slovenski cariniki Luke Koper odkrili kar 8,86 mil
#016147= Tiskovna agencija Federacije BiH Fena je poroèala, da je bilo v Sloveniji velik
#016148= Agencija Fena je še poroèala, da se je pregledna fotografska razstava o veè kot
#016149= Hrvaška tiskovna agencija Hina je poroèala, da se bo predsednik vlade Janez Jan
#016150= Hrvaška Hina je še poroèala, da je slovenska vlada razpravljala o uresnièitvi n
#016151= Tiskovna agencija SÈG Tanjug je poroèala, da se bo v beograjskem hipermarketu M
#016152= LJUBLJANA - Tuje tiskovne agencije so v petek najveè pozornosti namenile prvemu
#016153= Avstrijska tiskovna agencija APA je objavila vest o obisku slovaškega zunanjega
#016154= APA je tudi poroèala, da je Slovenska nacionalna stranka (SNS) v ljubljanskem m
#016155= APA je še poroèala, da bo ta konec tedna v Mariboru potekalo tekmovanje za Zlat
#016156= Hrvaška tiskovna agencija Hina je poroèala, da sta predsednika vlad Slovenije i
#016157= Ruska tiskovna agencija Itar-Tass je poroèala, da slovenski zunanji minister in
#016158= LJUBLJANA - Tuje tiskovne agencije so v soboto in nedeljo najveè pozornosti nam
#016159= Ameriška tiskovna agencija AP je poroèala, da je slovenska smuèarka Tina Maze v
#016160= Hrvaška tiskovna agencija Hina je poroèala, da je v soboto na novinarski konfer
#016161= Hina je v loèeni vesti še poroèala, da je hrvaški predsednik Stipe Mesiè v pogo
#016162= Hina pa je tudi pisala, da se je ameriški gradbeni mogotec in televizijski zvez
#016163= Èrnogorska tiskovna agencija Mina je poroèala, da so iz slovenskega Mercatorja
#016164= Madžarska tiskovna agencija MTI je pisala, da bo v zaèetku februarja v Koper pr
#016165= LJUBLJANA - Avstrijska tiskovna agencija APA je poroèala o odprtih vprašanjih m
#016166= Avstrijska tiskovna agencija APA je poroèala, da je prvo delovno sreèanje slove
#016167= Avstrijska APA je tudi poroèala, da je predsednik nove slovenske vlade Janez Ja
#016168= Beograjska tiskovna agencija Beta je poroèala, da bi naj slovensko podjetje Ter
```

OntoGen clustering for STA news analysis



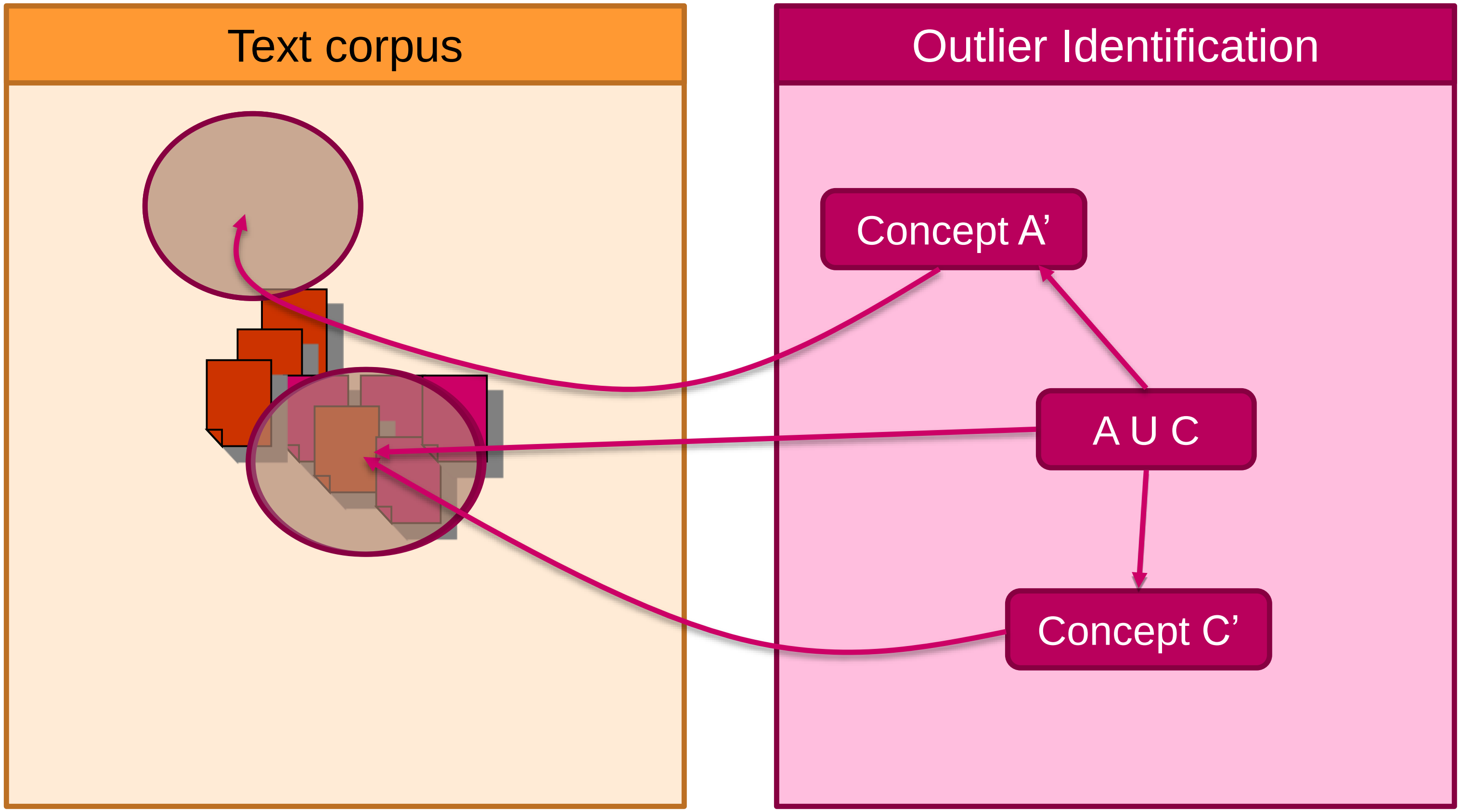
www.ontogen.si
Fortuna, Mladenić, Grobelnik 2006

Using OntoGen for clustering PubMed articles on autism



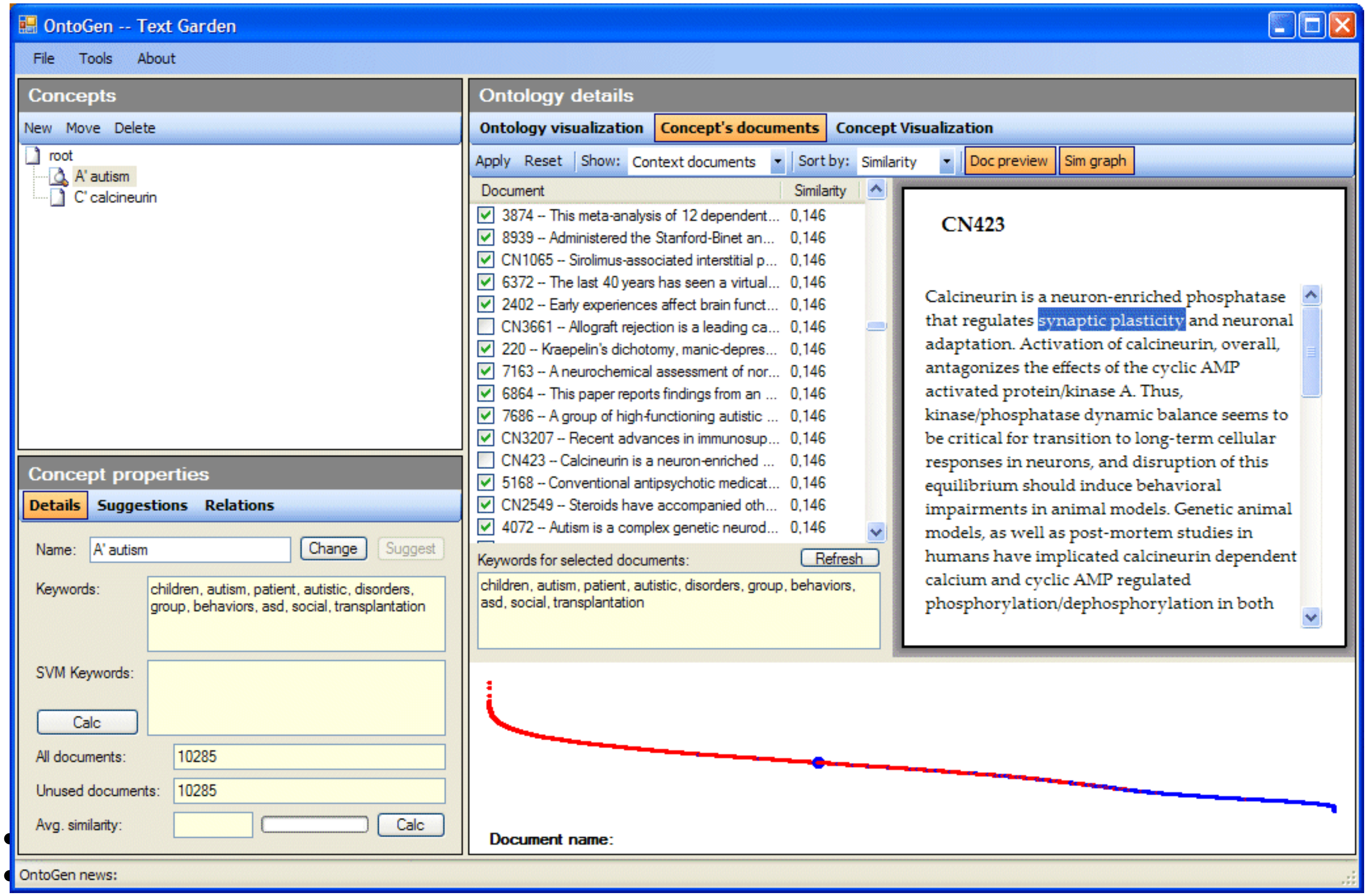
Work by
Petrič et al. 2009

Using OntoGen for outlier document identification



Slide adapted from D. Mladenić, JSI

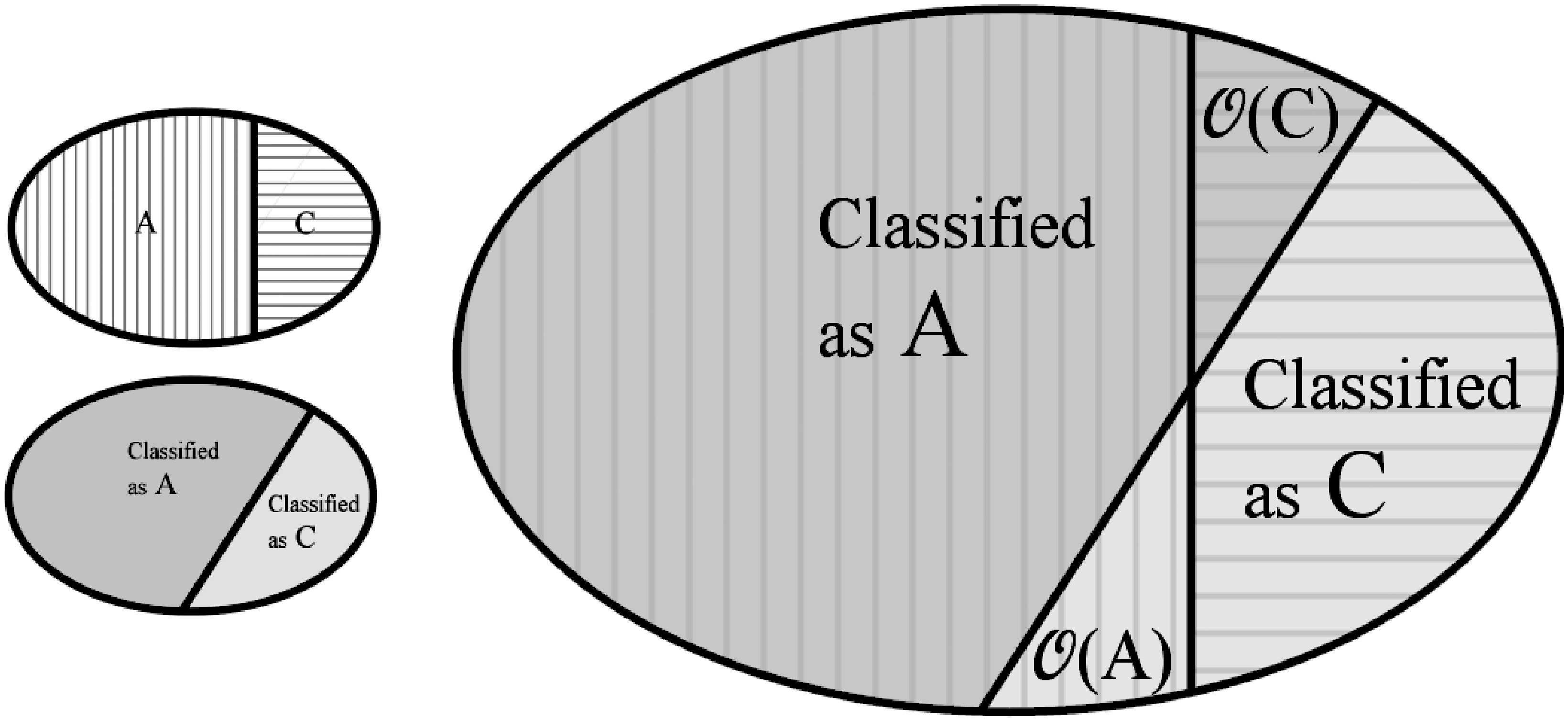
Results on autism-calcineurin: Outlier calcineurin document CN423



Work by
Petrič et al. 2010

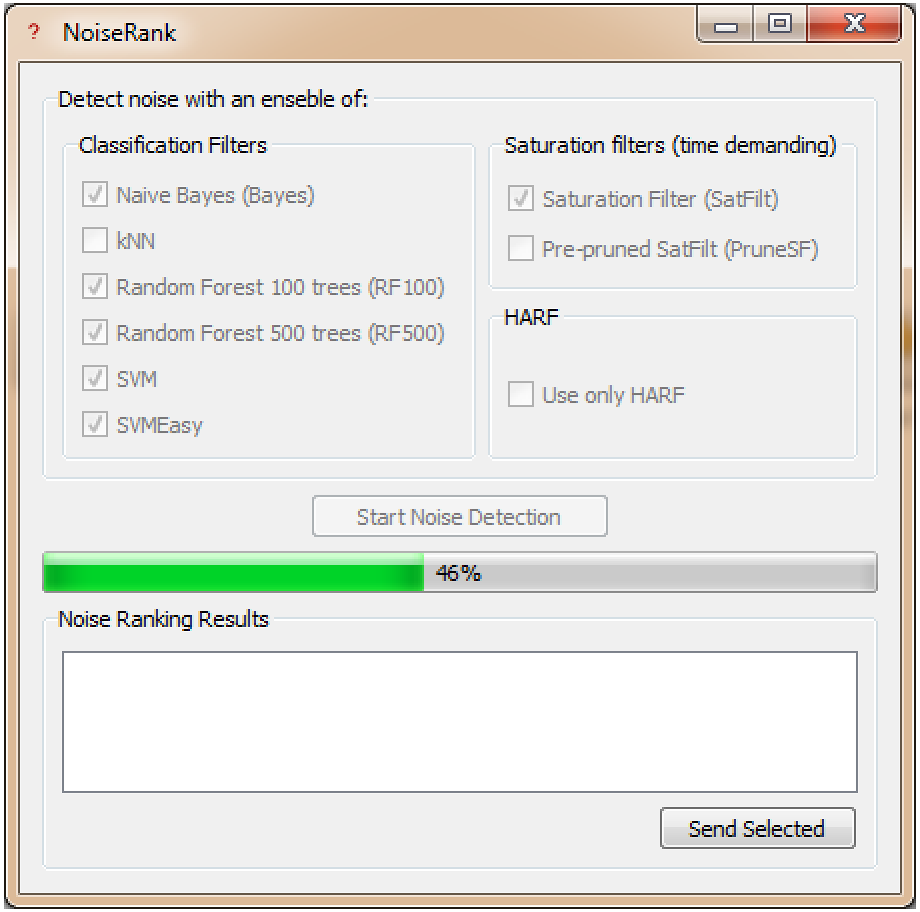
Detecting outlier documents

- By classification noise detection on a domain pair dataset, assuming two separate document corpora



NoiseRank: Ensemble-based noise and outlier detection

- Misclassified document detection by an ensemble of diverse classifiers (e.g., *Naive* ***Bayes***, ***Random Forest***, ***SVM***, … classifiers)
- Ranking of misclassified documents by "voting" of classifiers



NoiseRank on news articles

Articles on Kenyan elections: local vs. Western media

```
Rank | Class | ID | Detected by:
-------------------------------------------------------------------------|------
 1.        WE    352  __Bayes____RF100____RF500_____SVM____SVMEasy__SatFilt_  #HARF#
-------------------------------------------------------------------------|------
 2.        LO     25  __Bayes____RF100____RF500_____SVM____SVMEasy_           #HARF#
 3.        LO    101  __Bayes____RF100____RF500_____SVM____SVMEasy_           #HARF#
 4.        LO    173  __Bayes____RF100____RF500_____SVM____SVMEasy_           #HARF#
 5.        WE    348  __Bayes____RF100____RF500_____SVM____SVMEasy_           #HARF#
 6.        WE    326  __Bayes____RF100____RF500_____SVM____SVMEasy_
 7.        WE    357  __Bayes____RF100____RF500_____SVM____SatFilt_
 8.        WE    410  __Bayes____RF100____RF500_____SVM____SVMEasy_
-------------------------------------------------------------------------|------
 9.        LO     21  __RF100____RF500_____SVM____SVMEasy_                    #HARF#
10.        LO      4  __Bayes____RF500_____SVM____SVMEasy_
11.        LO     68  __RF100____RF500_____SVM____SVMEasy_
12.        LO    162  __Bayes____RF500_____SVM____SVMEasy_
13.        WE    358  __Bayes____RF100____RF500_____SVM___
14.        WE    464  __RF100____RF500_____SVM____SVMEasy_
-------------------------------------------------------------------------|------
15.        LO    153  __Bayes_____SVM____SVMEasy_
16.        LO    201  __RF100____RF500___SatFilt_
17.        WE    238  __RF100____RF500_____SVM___
18.        WE    364  __Bayes____RF500_____SVM___
19.        WE    370  __Bayes____RF100_____SVM___
20.        WE    379  __RF100____RF500___SVMEasy_
```

NoiseRank on news articles

- **Article 352: Out of topic**
  The article was later indeed removed from the corpus used for further linguistic analysis, since it is not about Kenya(ns) or the socio-political climate but about British tourists or expatriates' misfortune.
- **Article 173: Guest journalist**
  Wrongly classified because it could be regarded as a "Western article" among the local Kenyan press. The author does not have the cultural sensitivity or does not follow the editorial guidelines requiring to be careful when mentioning words like tribe in negative contexts. One could even say that he has a kind of "Western" writing style.

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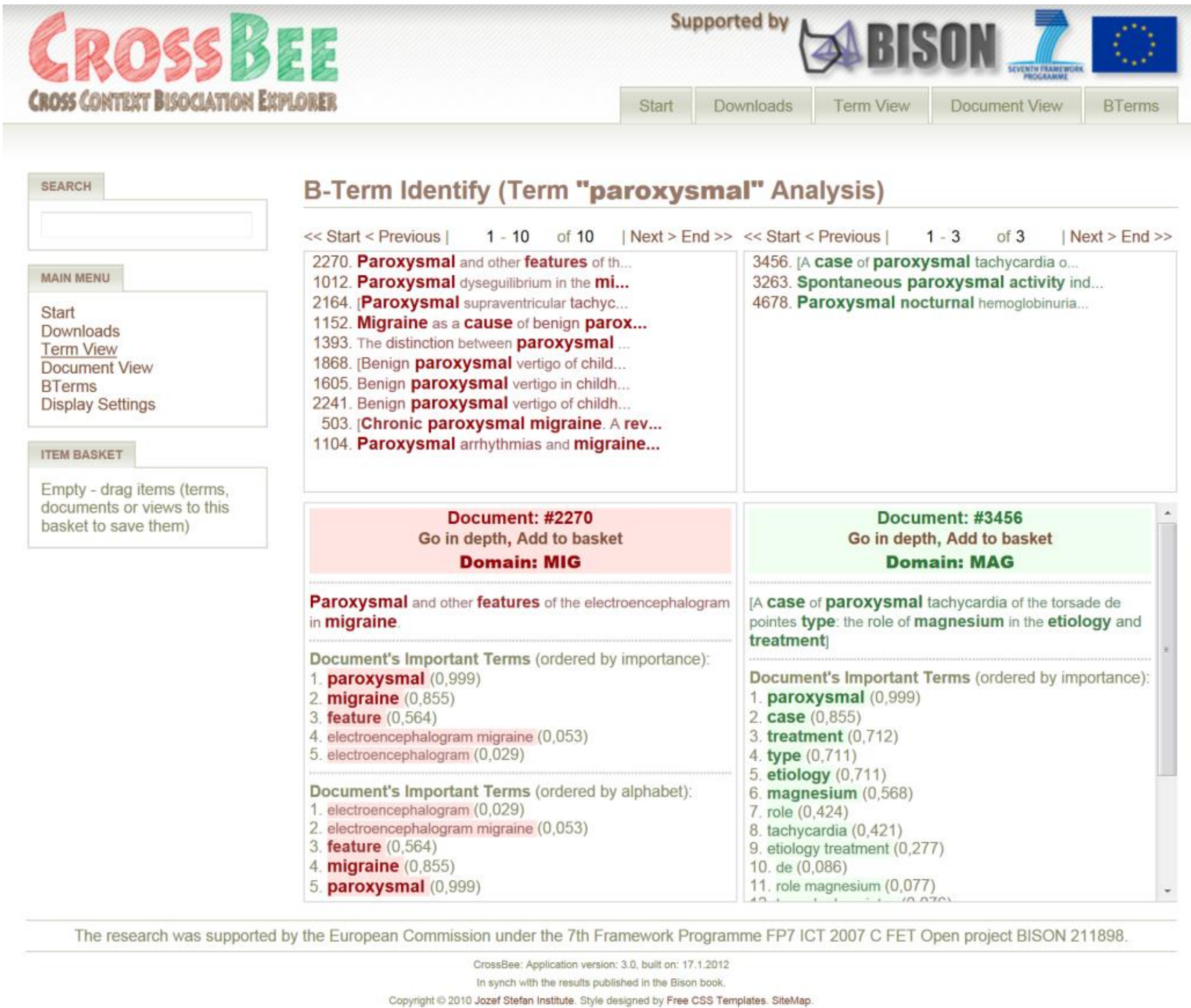
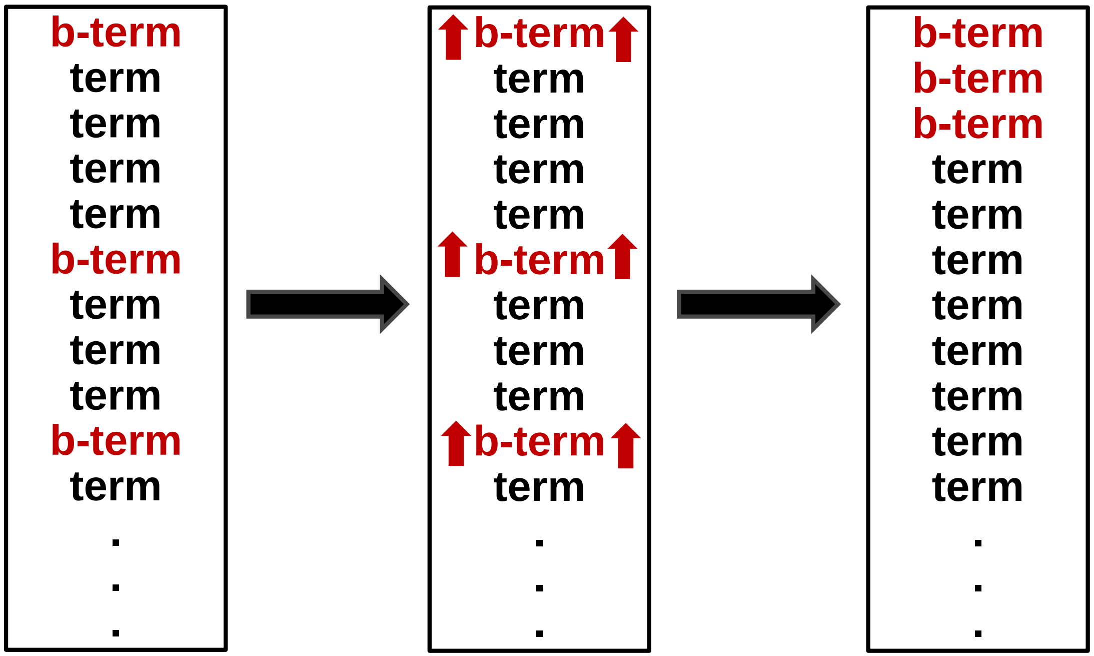
CrossBee: Cross Context Bisociation Explorer

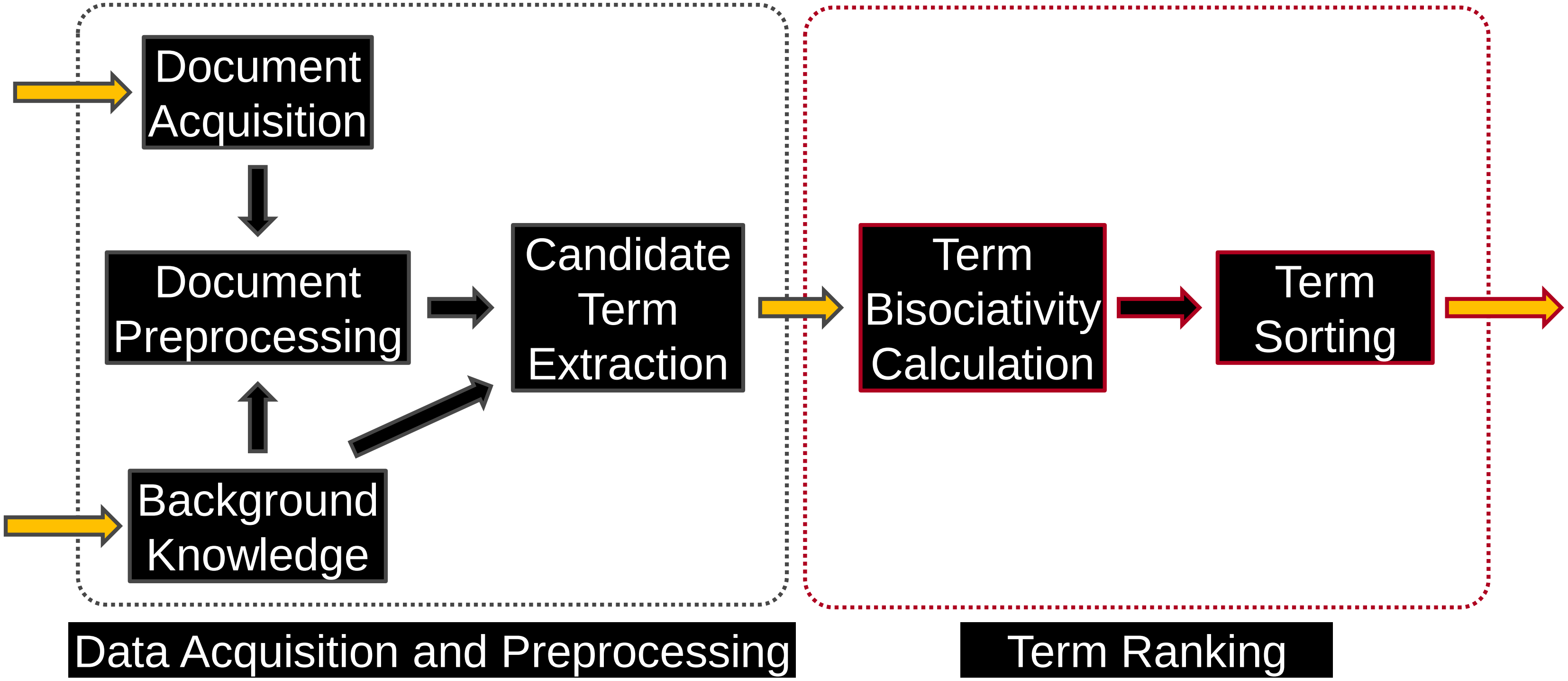


Problem definition

Goal: Develop a term ranking methodology that ranks high all the terms which have high bisociation potential (denoted as *bridging* terms or *b-terms*)



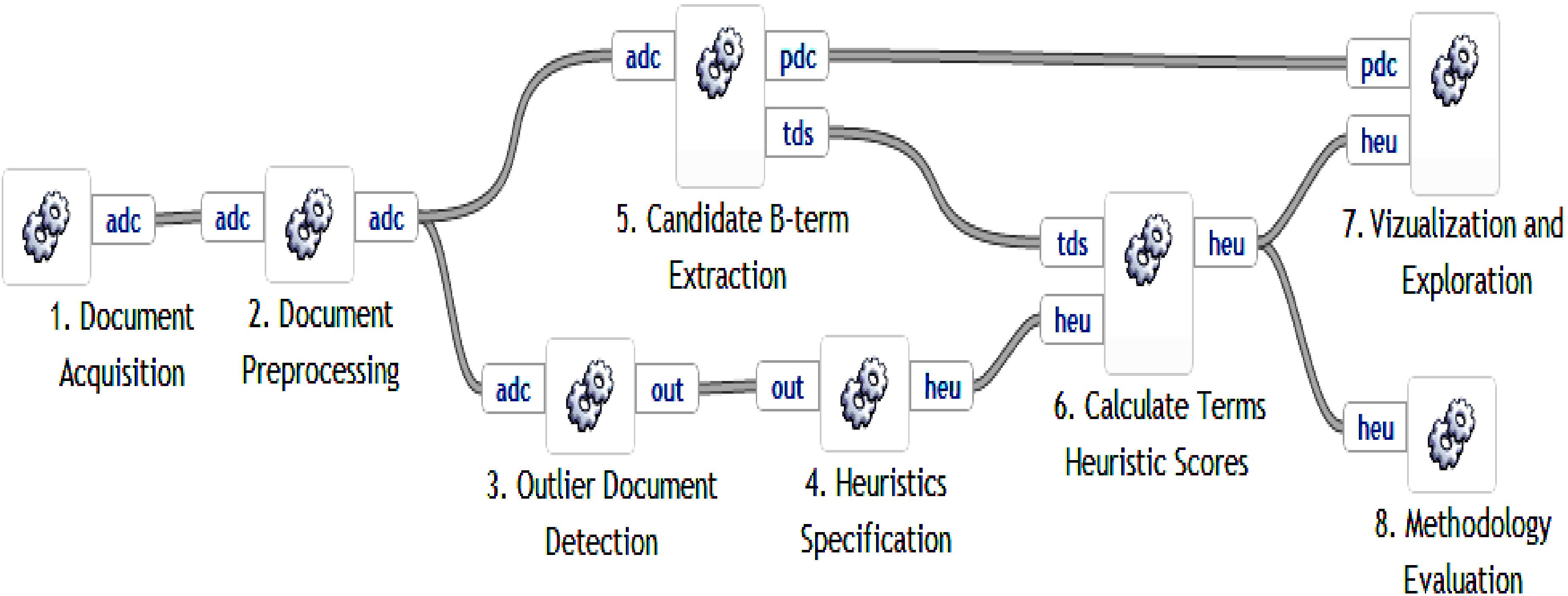
CrossBee: Methodology overview



Incorporating available background knowledge

- Vocabularies: e.g. for word/term filtering
- Ontologies: e.g. for enriching documents term sets

Methodology implementation



Data acquisition and preprocessing

- Document acquisition from the Web
  - Acquiring documents from. PubMed
  - Snippets returned from web search engines
  - Crawling the Internet and gathering documents from web pages
- Document preprocessing
  - Tokenization
  - Stopwords removal
  - Stemming or lemmatization: LemmaGen
  - Part of speech tagging or syntactic parsing
- Candidate term extraction
  - Frequent n-grams in preprocessed documents

Term ranking

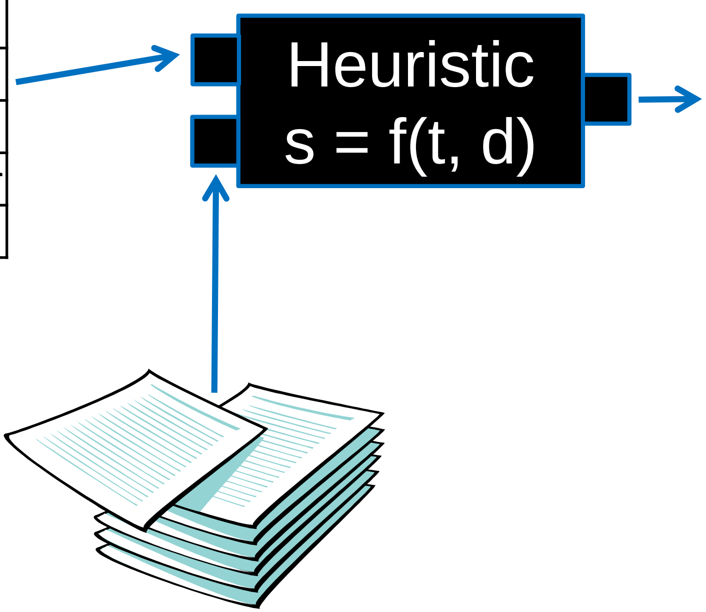
- Term ranking:
  - Assign scores to all the terms
  - Sort the terms according to the assigned scores
- How to assign scores to terms?
  - Using a heuristic function that estimates the probability that a term is b-term
- How to construct the "optimal" heuristic using training data?
  1. Create several promising heuristics
  2. Evaluate the constructed heuristics on a training dataset
  3. Construct the ensemble heuristic using the best individual heuristics
  4. Use the ensemble heuristic for scoring the terms

Heuristic function

- Input: a term with its statistic properties calculated from texts
- Output: a number [0,1] which ranks the term (its probability of being a b-term)

Ideal heuristic: such that ranks all true b-terms very high and all the others lower

combination
associate
cortical spread depression
efficacy safety
5 hydroxytryptamine receptor
accumulate



combination	0.154
associate	0,759
cortical spread depression	0,666
efficacy safety	0,311
5 hydroxytryptamine receptor	0,900
accumulate	0,486

Bisociation potential heuristics

- Heuristics can be grouped based on:
  - frequency (variations of the term occurrences)
    - $freqTerm(t) = countTerm_{D_u}(t)$: term frequency across both domains
  - tf-idf (combinations of tf-idf weights of a term)
    - $tfidfDomnProd(t) = tfidf_{D_1}(t) \cdot tfidf_{D_2}(t)$: product of a term's importance in both domains
  - similarity (similarity of a term to the average terms)
  - outliers (frequency of a term in documents at the border of the two domains)
    - $outFreqRelRF(t) = \frac{countTerm_{D_{RF}}(t)}{countTerm_{D_u}(t)}$: relative frequency in RF outlier set

Ensemble heuristic

$$\left.\begin{array}{l}\textbf{heuristic 1}\\ \textbf{heuristic 2}\\ \textbf{heuristic 3}\end{array}\right\}\ \textbf{ensemble heuristic}$$

heuristic 1

term 1	0,149
term 2	0,759
term 3	0,900
term 4	0,666
term 5	0,311
term 6	0,071
term 7	0,175
term 8	0,637
term 9	0,429
.	.
.	.
.	.

heuristic 2

term 1	0,429
term 2	0,149
term 3	0,071
term 4	0,175
term 5	0,637
term 6	0,759
term 7	0,970
term 8	0,636
term 9	0,311
.	.
.	.
.	.

heuristic 3

term 1	0,680
term 2	0,311
term 3	0,071
term 4	0,175
term 5	0,637
term 6	0,429
term 7	0,149
term 8	0,759
term 9	0,980
.	.
.	.
.	.

Ensemble heuristic

heuristic 1	heuristic 2	heuristic 3	ensemble heuristic	
term 3	term 7	term 7	term 1	2
term 2	term 6	term 8	term 2	1
term 1	term 5	term 1	term 3	1
term 8	term 8	term 5	term 4	0
term 9	term 1	term 6	term 5	2
term 5	term 9	term 2	term 6	1
term 7	term 4	term 4	term 7	2
term 4	term 2	term 7	term 8	3
term 6	term 3	term 9	term 9	0
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.

Ensemble heuristic

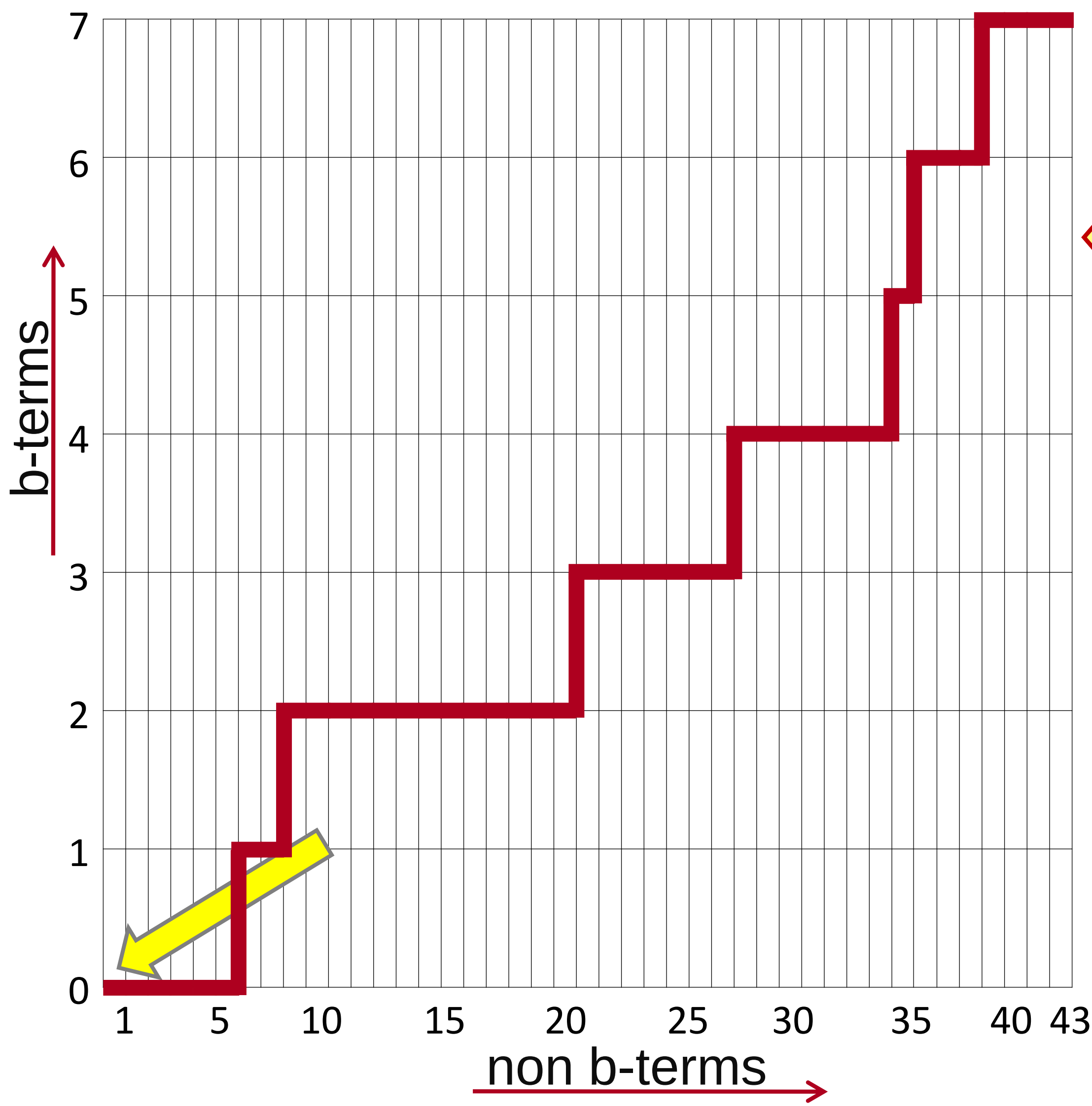
final ensemble heuristic

term 8	heuristic 1, heuristic 2, heuristic 3	term 8
term 1	heuristic 1, heuristic 3	term 1
term 5	heuristic 2, heuristic 3	term 5
term 7	heuristic 2, heuristic 3	term 7
term 2	heuristic 1	term 2
term 3	heuristic 1	term 3
term 6	heuristic 2	term 6
term 7	-	term 7
term 9	-	term 9
.	.	.
.	.	.
.	.	.

Domains and datasets

- Training dataset: migraine-magnesium
  - 8,058 documents (2,425- 5,633), 13,433 distinct terms
  - 43 expert identified b-terms (work by Swanson, D. R., Smalheiser, N. R., Torvik, V. I.: Ranking indirect connections in literature-based discovery : The role of Medical Subject Headings (MeSH))
- Test dataset: autism-calcineurin
  - 22,262 documents (14,890-7,372), 17,514 distinct terms
  - 12 expert identified b-terms (work by Petric, I., Urbancic, T., Cestnik, B., Macedoni-Luksic, M.: Literature mining method RaJoLink for uncovering relations between biomedical concepts)

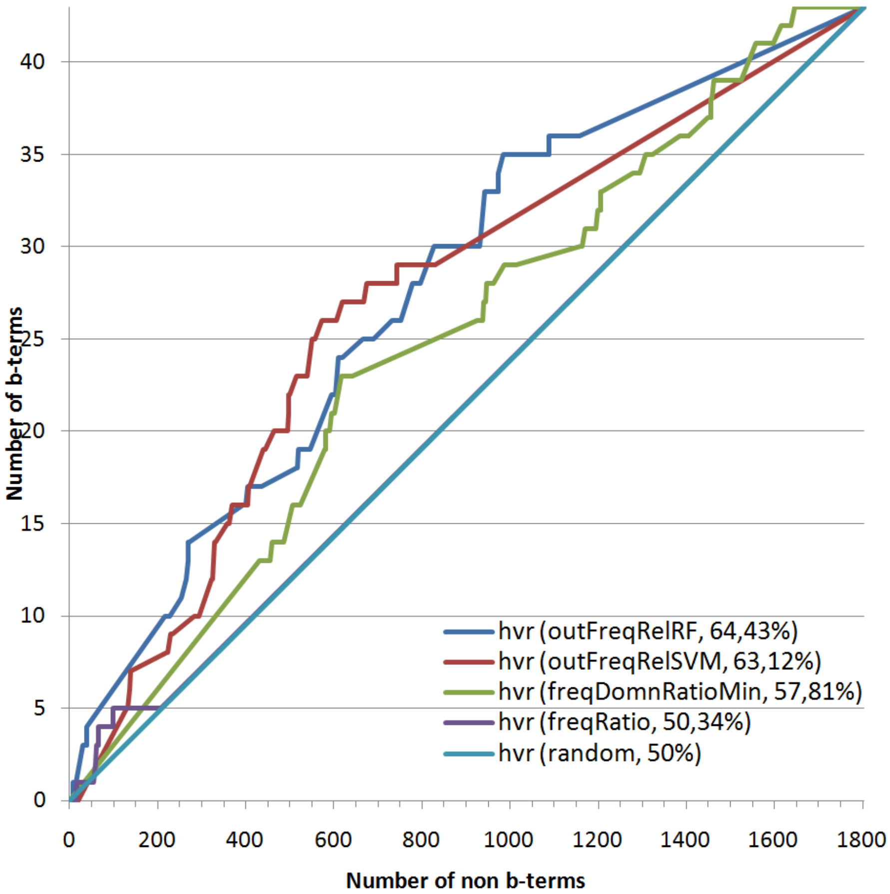
Evaluation ROC curve construction

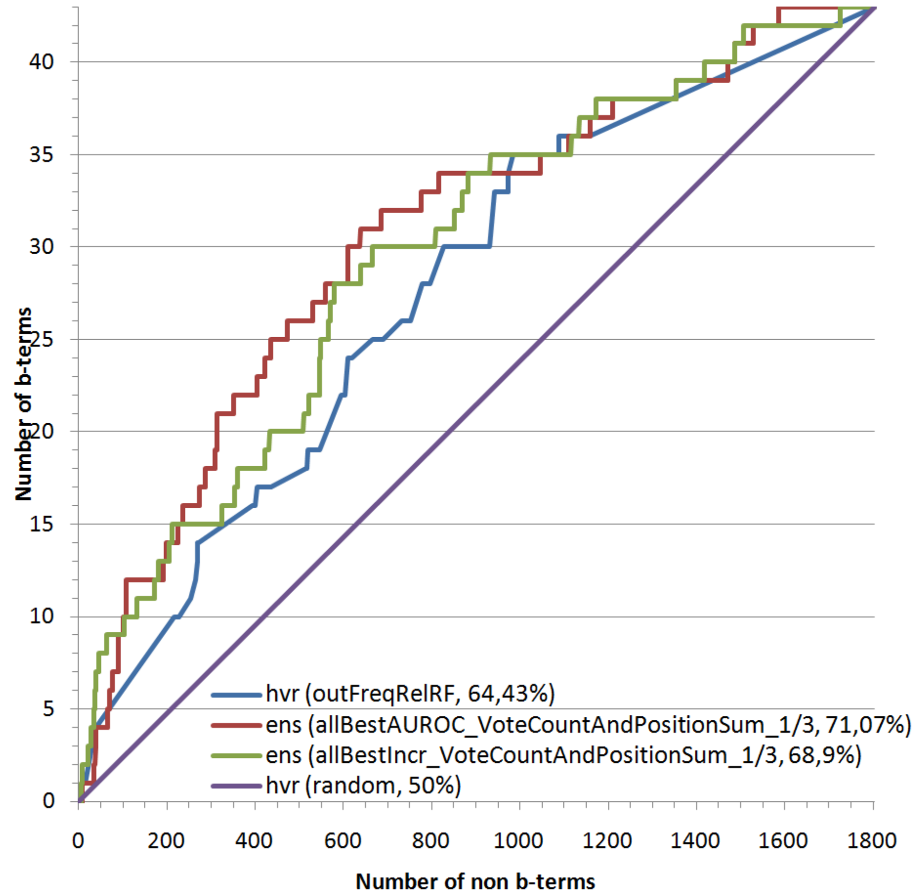


[redacted]

400
animal human
anti inflammatory agent
basal
bruxism
biochemical aspect
brain serotonin
arteriopathy
cerebral artery
cerebral vasospasm
child treatment
clinical comparative
clinical form
clinical statistical
combination treatment
comparative double
[redacted]

Results on training data set





CrossBee system

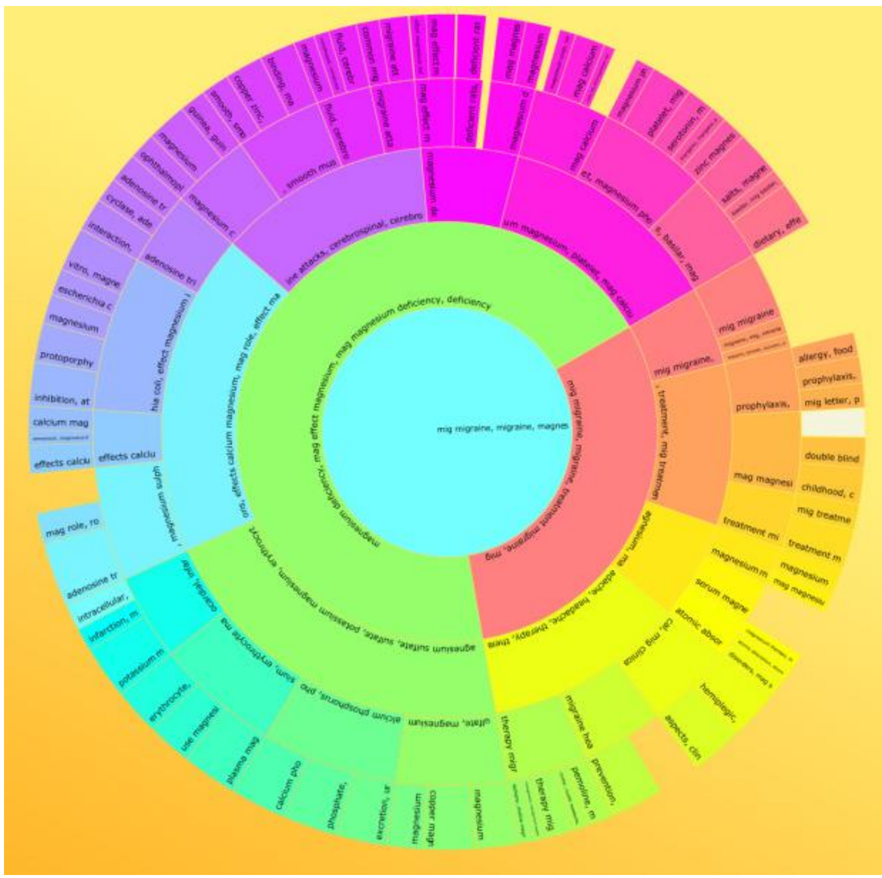
- Cross Context Bisociation Explorer

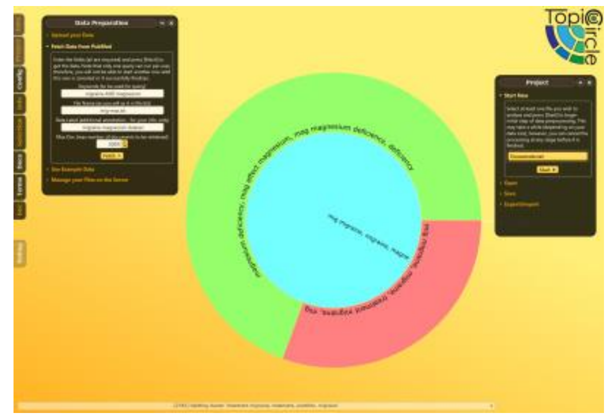
- What is CrossBee?
- Web user interface which fuses multiple approaches developed for discovering bisociations in text

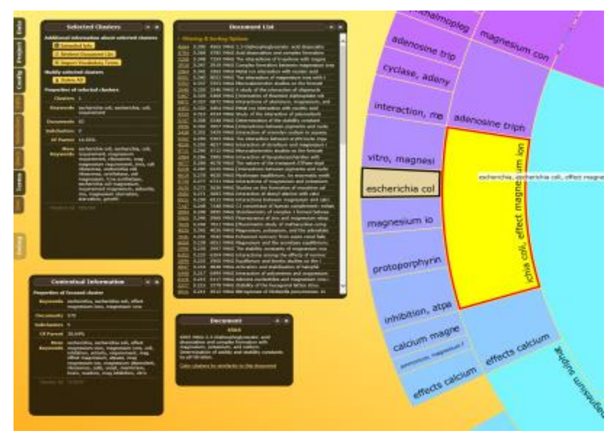
- Why CrossBee?
- Collaborating with domain experts on their data in real time on user friendly system (and thus evaluating their and our hypotheses)

Additional CrossBee functionality

CrossBee Topic Circle for top-down document clustering

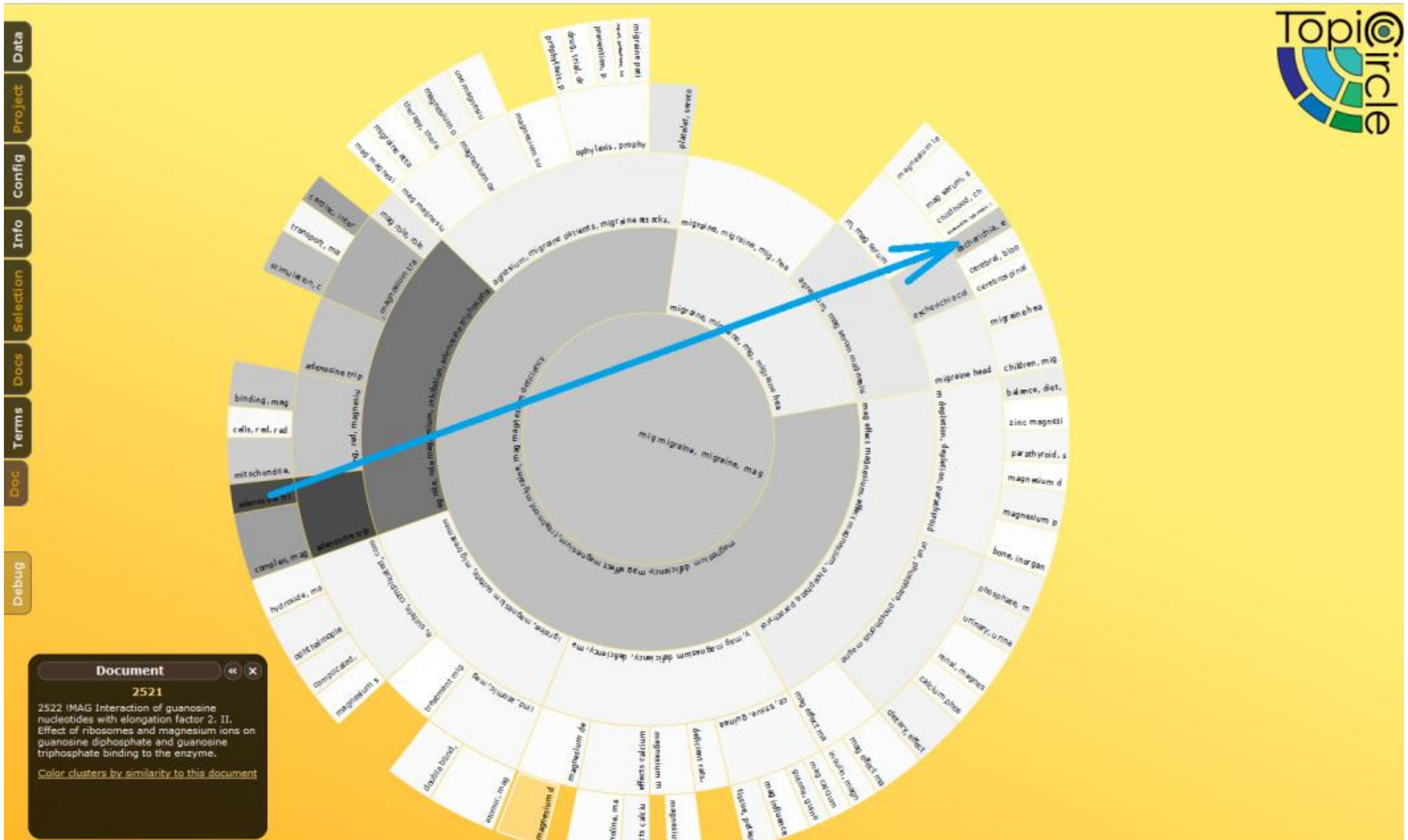






Additional CrossBee functionality

Cluster colors can show e.g., cluster's similarity to a single selected document. The arrow shows similar clusters in two different domains, potentially indicate to a novel bisociative link between the two domains.

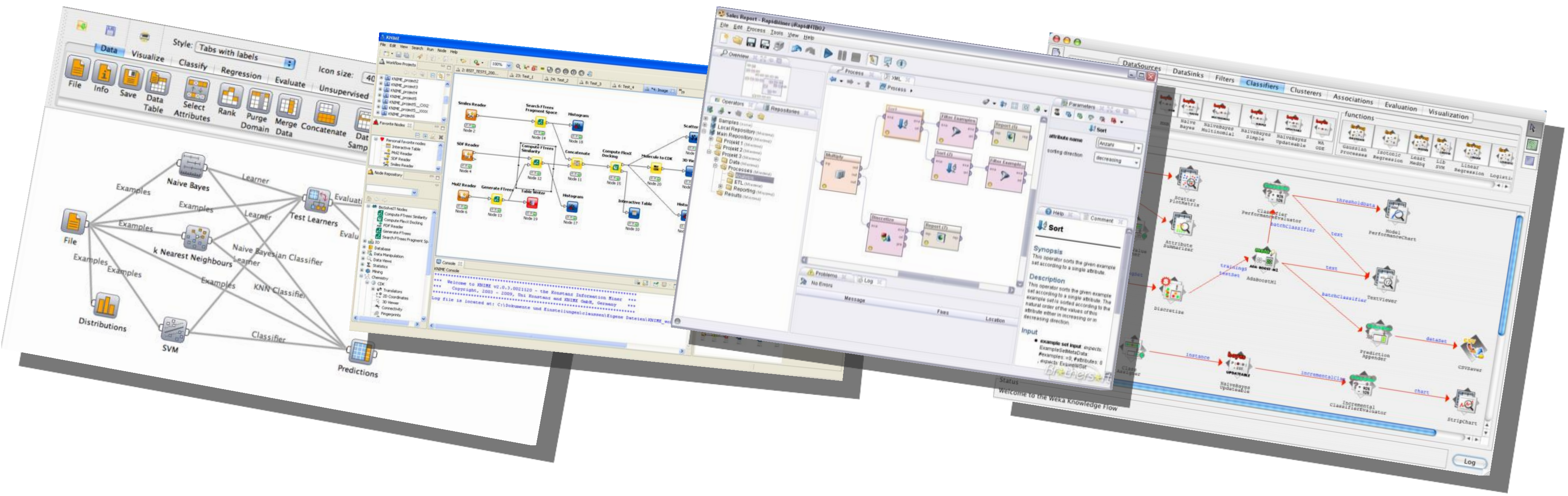


Talk outline

- Background and motivation
- Literature-based discovery
- Cross-domain literature mining approaches
  - Outlier detection for cross-domain knowledge discovery
  - Cross-domain knowledge discovery with CrossBee
- TextFlows text mining platform
- Summary and conclusions

Data mining platforms

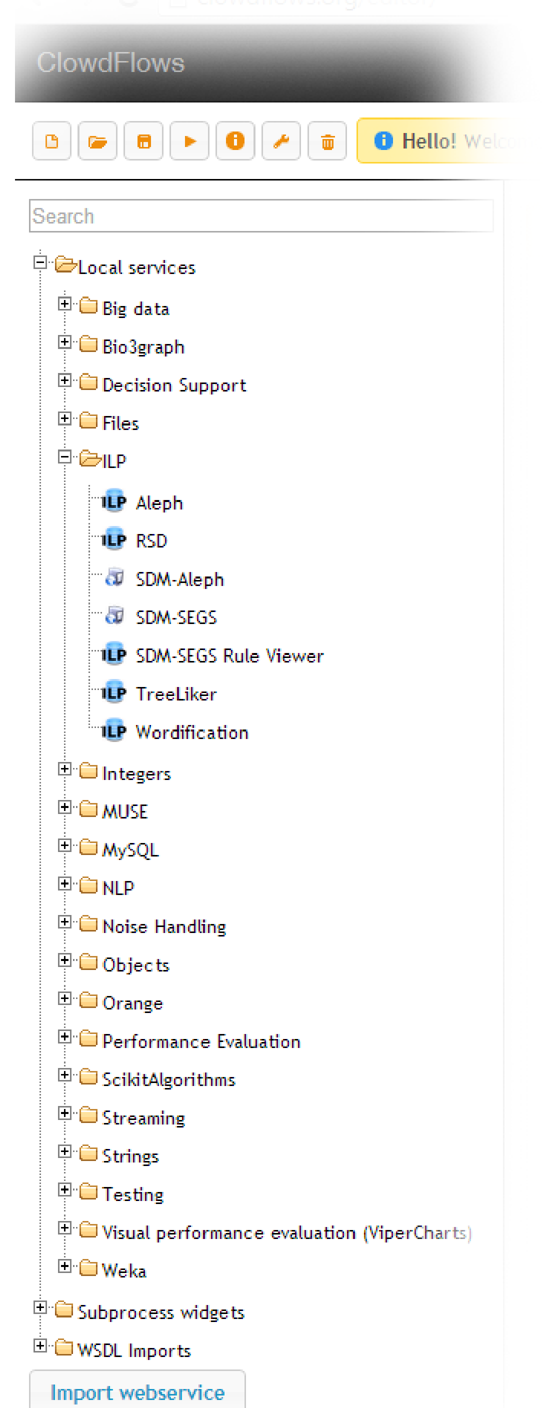
WEKA, KNIME, RapidMiner, Orange (FRI), **Orange4WS (IJS)**



- Incorporate numerous data mining algorithms
- Enable data analysis and visualization
- Enable workflow construction

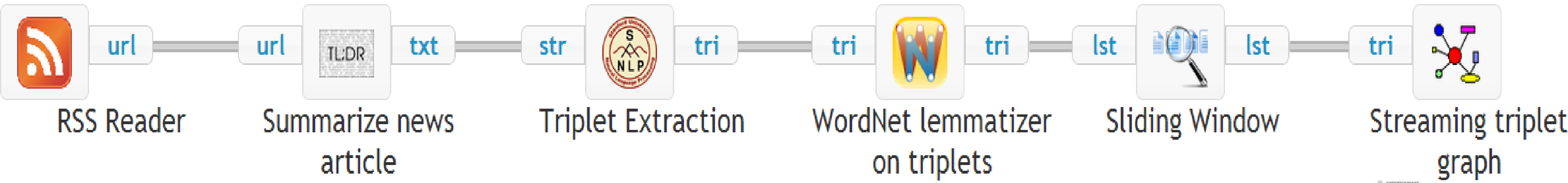
ClowdFlows platform

- **Large algorithm repository**
  - Relational data mining
  - All Orange algorithms
  - WEKA algorithms as web services
  - Data and results visualization
  - Text analysis
  - Social network analysis
  - Analysis of big data streams
- **Large workflow repository**
  - Enables access to our technology heritage



“Big Data” Use Case

- Real-time analysis of big data streams
- Example: semantic graph construction from news streams. http://clowdflows.org/workflow/1729/.

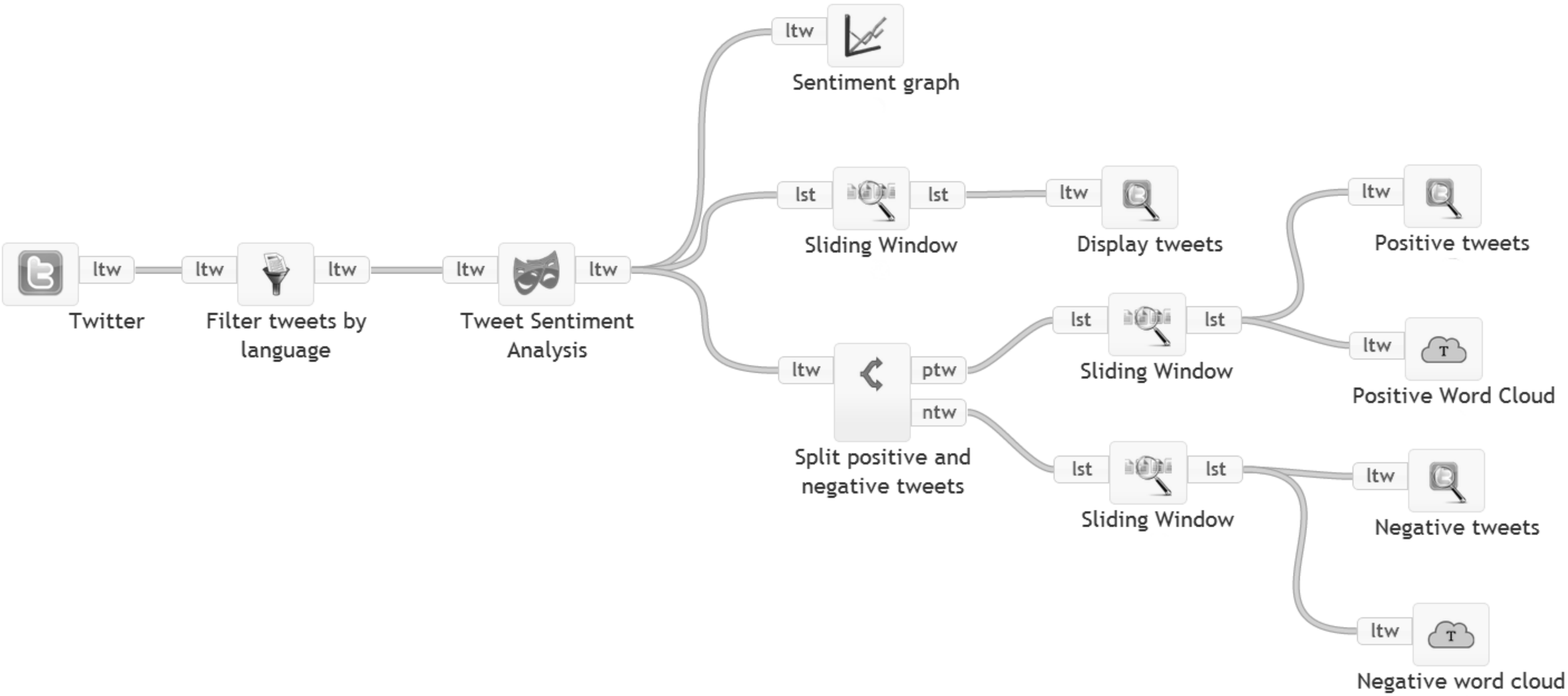


- Example: news monitoring by graph visualization (graph of CNN RSS feeds)

http://clowdflows.org/streams/data/31/1

“Big Data” Use Case

- Analysis of positive/negative sentiment of tweets in real time: http://clowdflows.org/workflow/1041/.



TextFlows

- Motivation:
  - Develop an online text mining platform for composition, execution and sharing of text mining workflows
- TextFlows platform – fork of ClowdFlows.org:
  - Web-based user interface
  - Visual programming
  - Big roster of existing workflow (mostly data mining) components
  - Cloud-based service-oriented architecture

Comparison with ClowdFlows

- ClowdFlows:
  - Roster of not fully compatible widgets, developed separately by each workflow developer, non-systematic approach
  - Missing components for text mining and natural language processing
- TextFlows:
  - Includes numerous text mining and NLP widgets
  - Widgets grouped by their functionality
  - New common text representation structure

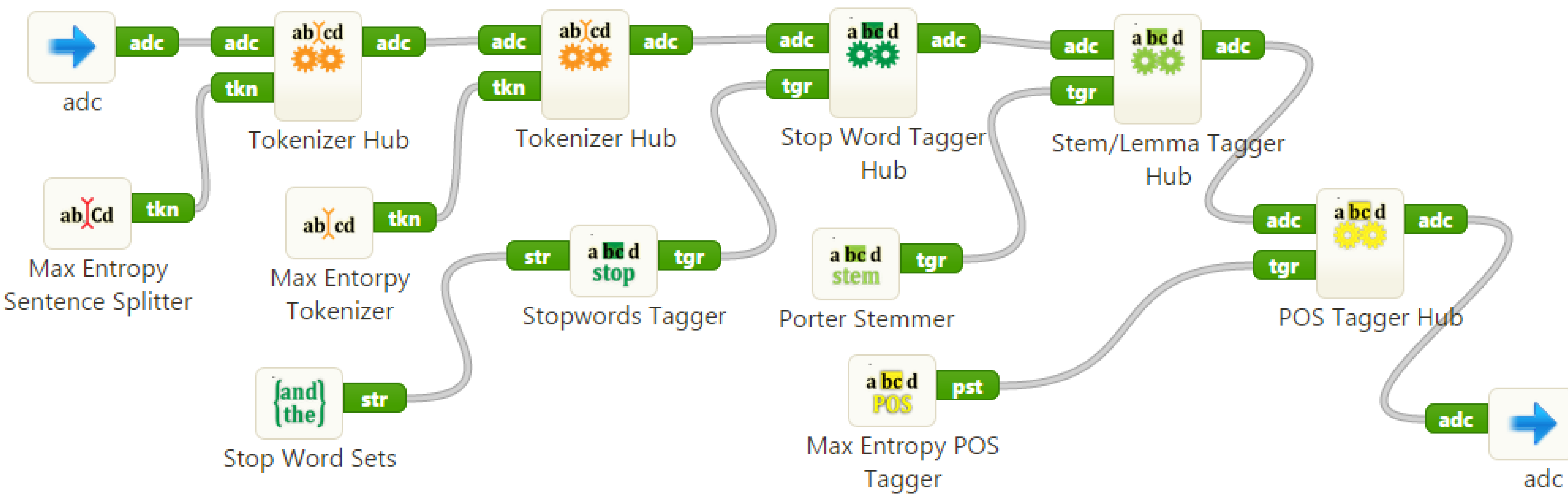
The TextFlows Modules

- Implemented packages:
  - Text preprocessing
    - Latino (Grčar, 2015)
    - NLTK (Bird et. al., 2006)
    - Scikit-learn (Pedregosa et. al., 2011)
  - Text Categorisation
  - Literature based discovery (Juršič et. al., 2012)
  - Noise handling (Sluban et. al., 2012)
  - Visual performance evaluation (Sluban et. al., 2012)
  - Relational data mining through wordification (Perovšek et al., 2015)
- Advanced text processing workflows and use cases developed in this thesis

Advanced workflows in TextFlows

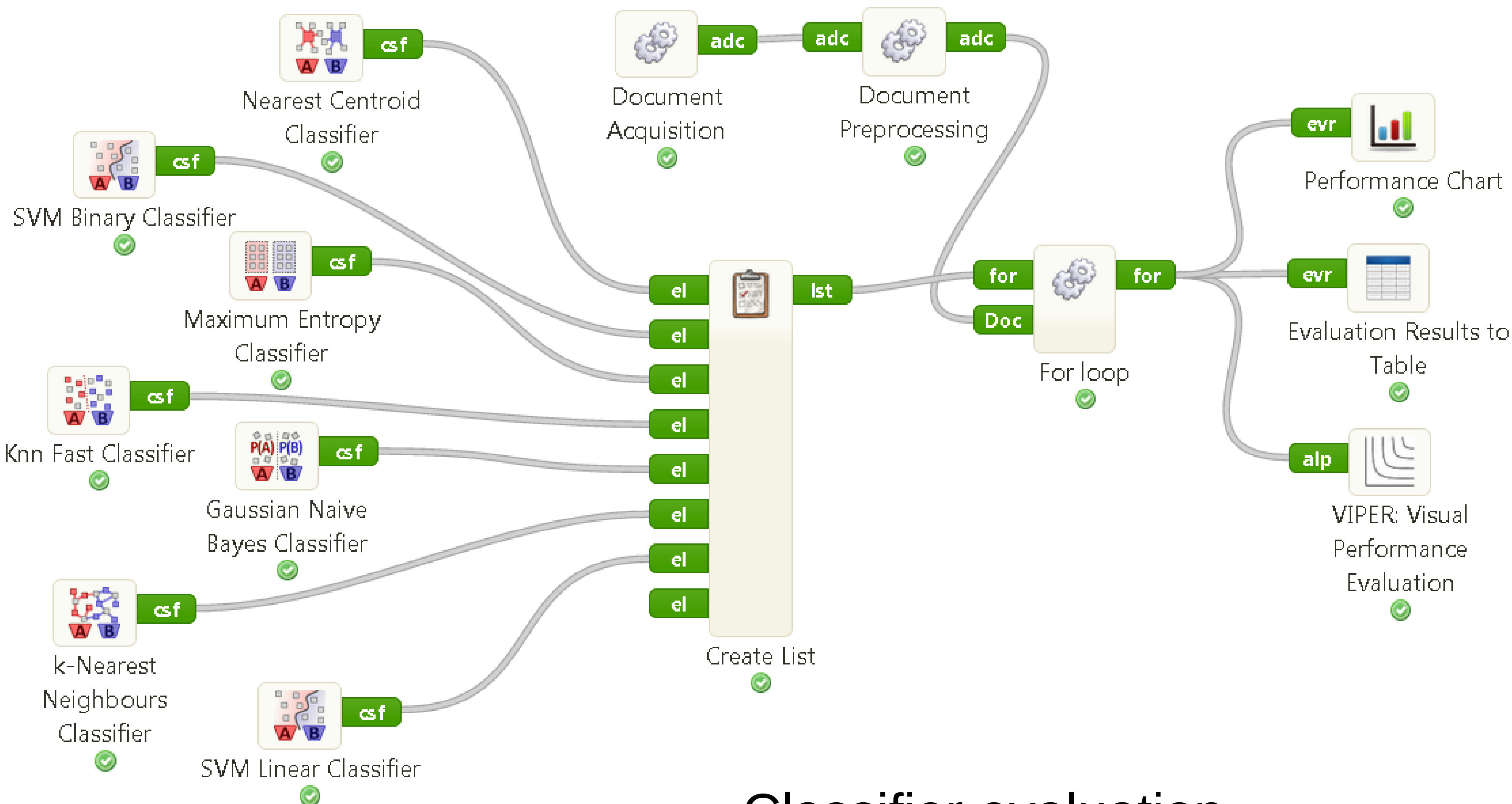
- NLP scenarios
  1. Document preprocessing
  2. Classifier evaluation
  3. POS tagging classification evaluation
  4. Stemming classification evaluation
  5. Outlier document detection
- Complex data/text analysis scenarios
  1. Relational data mining, propositionalization
  2. Literature based cross-context knowledge discovery

1. Document preprocessing



Simple Document Preprocessing
http://textflows.org/workflow/604/

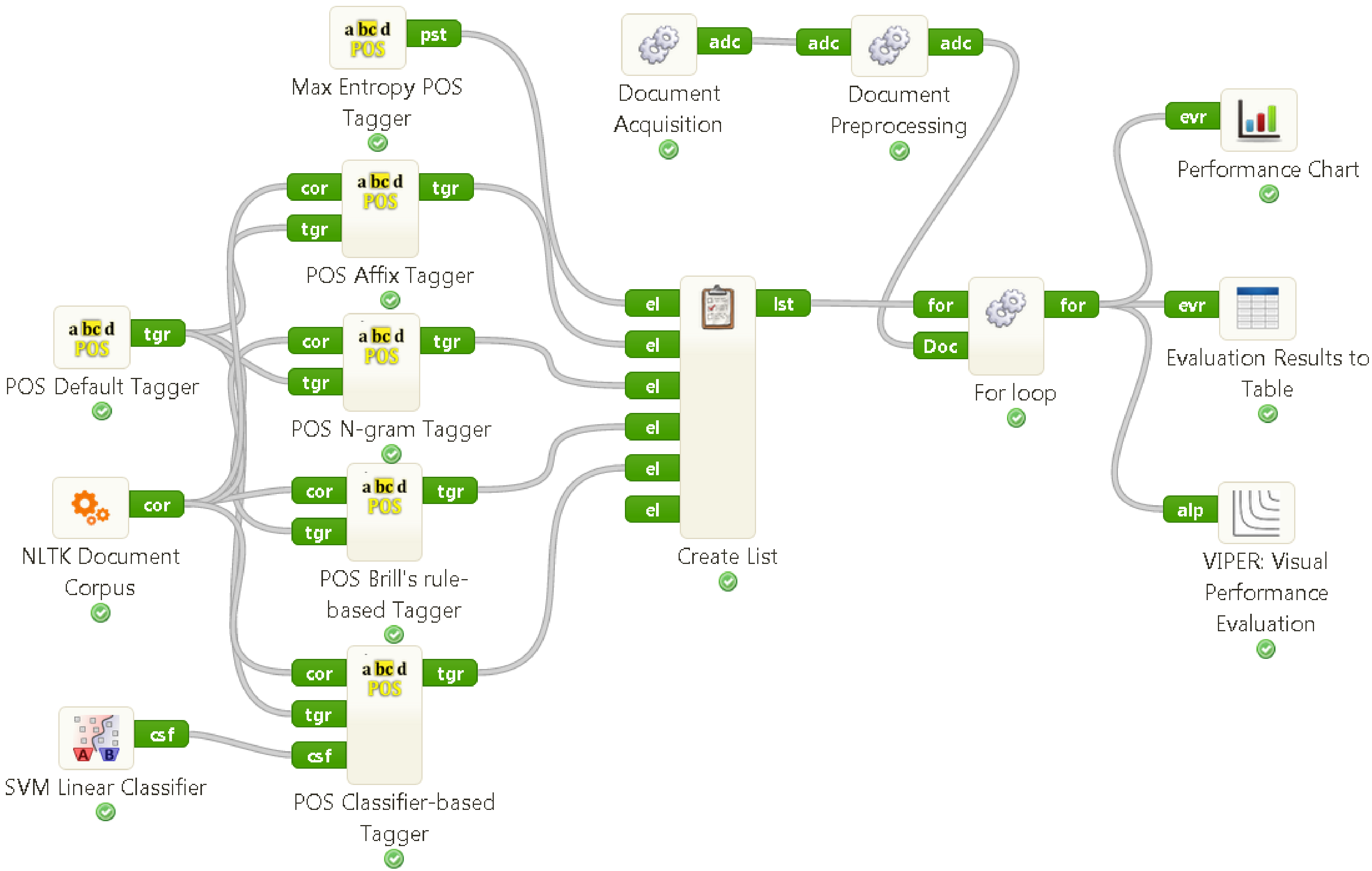
2. Classifier Evaluation



Classifier evaluation

http://textflows.org/workflow/350/

3. POS Tagger Evaluation

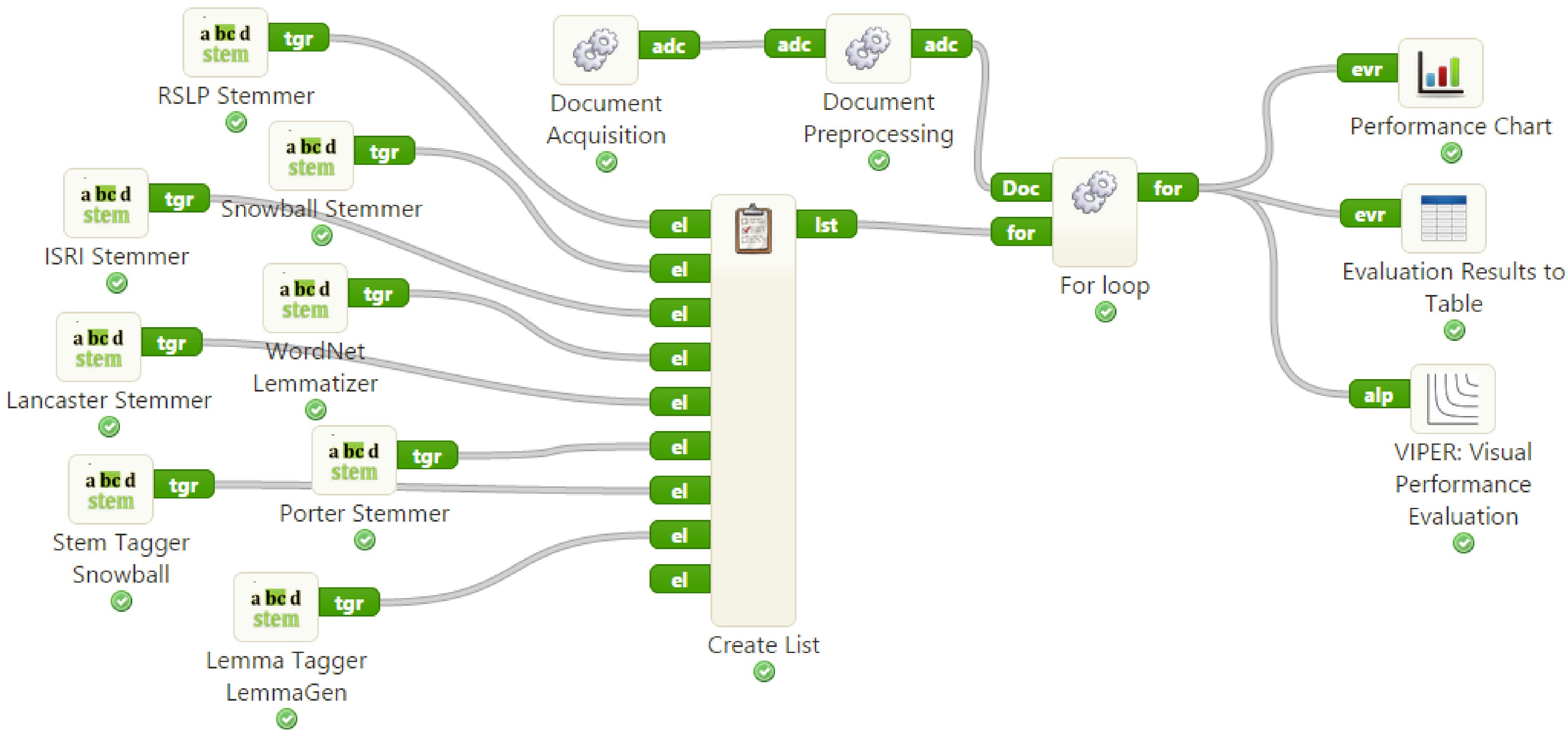


3. POS Tagger Evaluation

Table 2: POS tagger evaluation on the Kenyan elections database.

Library	Tagger	Recall	Precision	F1 score	Classification accuracy	AUC
	no POS tagger	0.98	0.93	0.95	95.24%	0.95
LATINO	Maximum Entropy POS Tagger	0.98	0.94	0.96	96.10%	0.96
NLTK	POS Affix Tagger	0.98	0.94	0.96	95.67%	0.96
NLTK	POS Ngram Tagger	0.98	0.95	0.96	96.10%	0.96
NLTK	POS Brill Tagger	0.97	0.93	0.95	95.24%	0.95
NLTK+ scikit-learn	POS Classifier Based Tagger (using SVM Linear Classifier)	0.98	0.95	0.96	96.32%	0.96

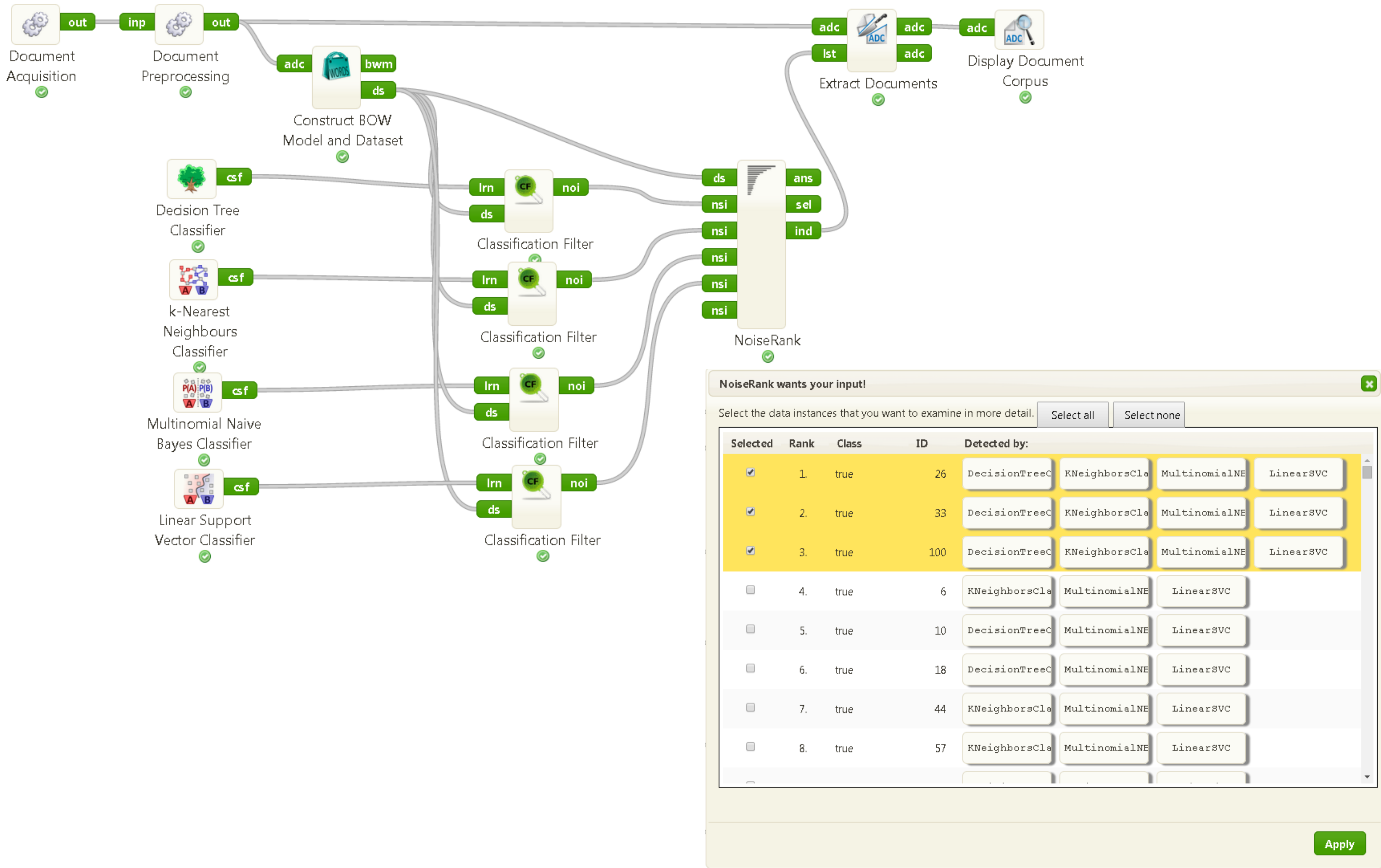
4. Stemmer Evaluation



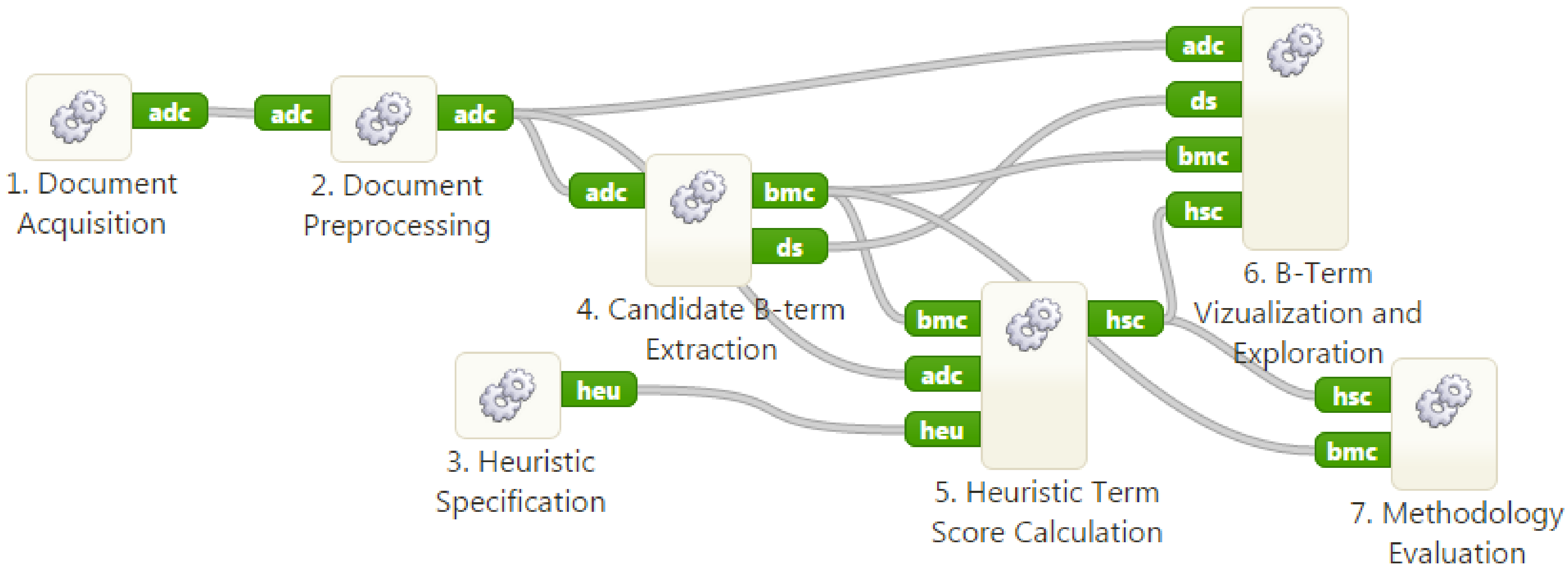
4. Stemmer Evaluation

Library	Stemmer/Lemmatizer	F1 score	Class. accuracy	AUC
	no stemmer	0.94	94.16%	0.94
NLTK	RSLP Stemmer	0.95	95.24%	0.95
NLTK	Snowball Stemmer	0.96	96.10%	0.96
NLTK	ISRI Stemmer	0.96	96.10%	0.96
NLTK	WordNet Lemmatizer	0.96	96.32%	0.96
NLTK	Lancaster Stemmer	0.95	94.81%	0.95
NLTK	Porter Stemmer	0.95	95.24%	0.95
Latino	Stem Tagger Snowball	0.95	95.24%	0.95
Latino	Lemma Tagger LemmaGen	0.95	95.24%	0.95

5. Outlier Document Detection

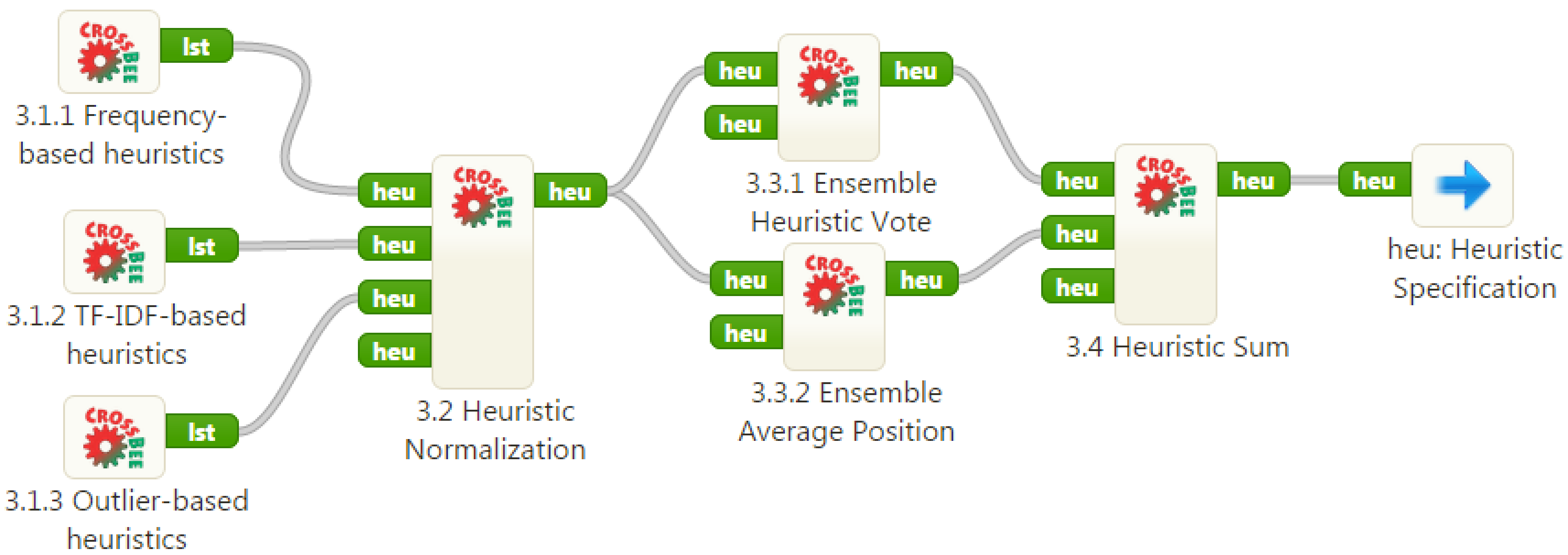


The Methodology Workflow



http://textflows.org/workflow/486/

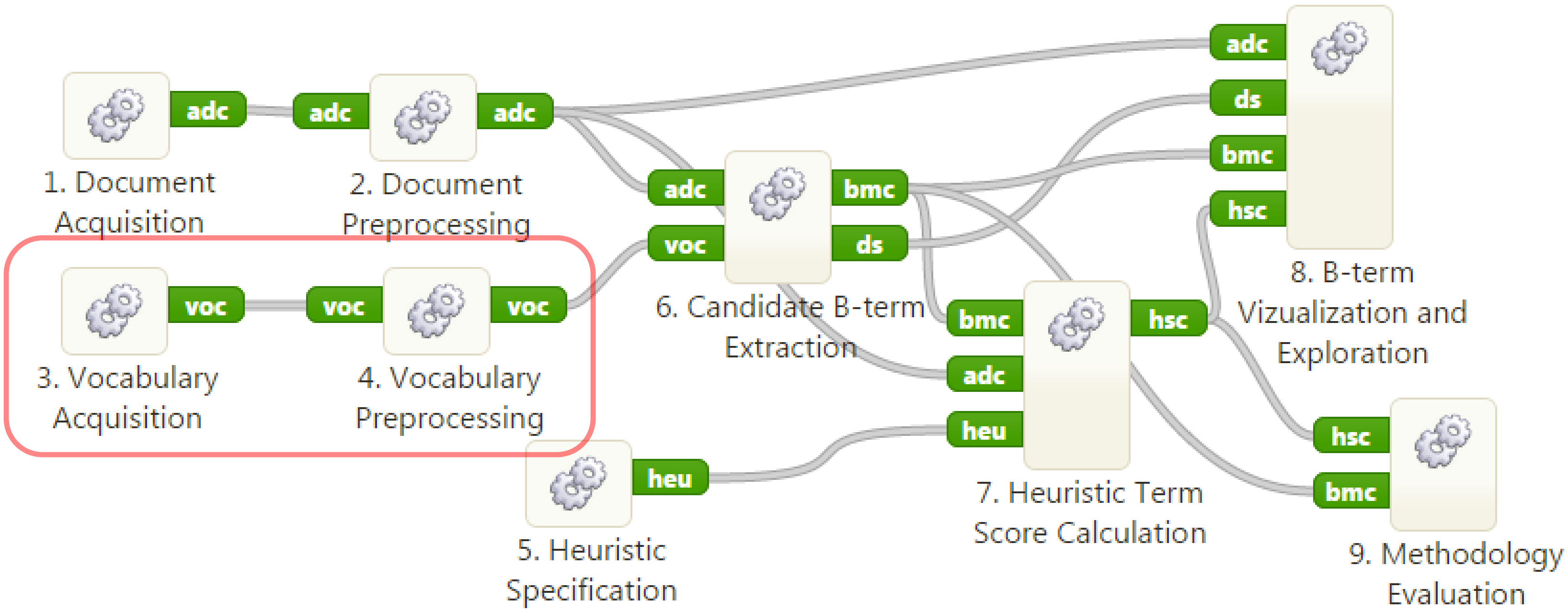
Heuristics Specification Subprocess



Controlled Vocabularies

- TextFlows BoW construction widget accepts synonyms and term whitelist as an additional input
- New lexicology package in TextFlows contains controlled vocabularies:
  - MeSH term filter
  - GO term filter
  - HGNC synonyms

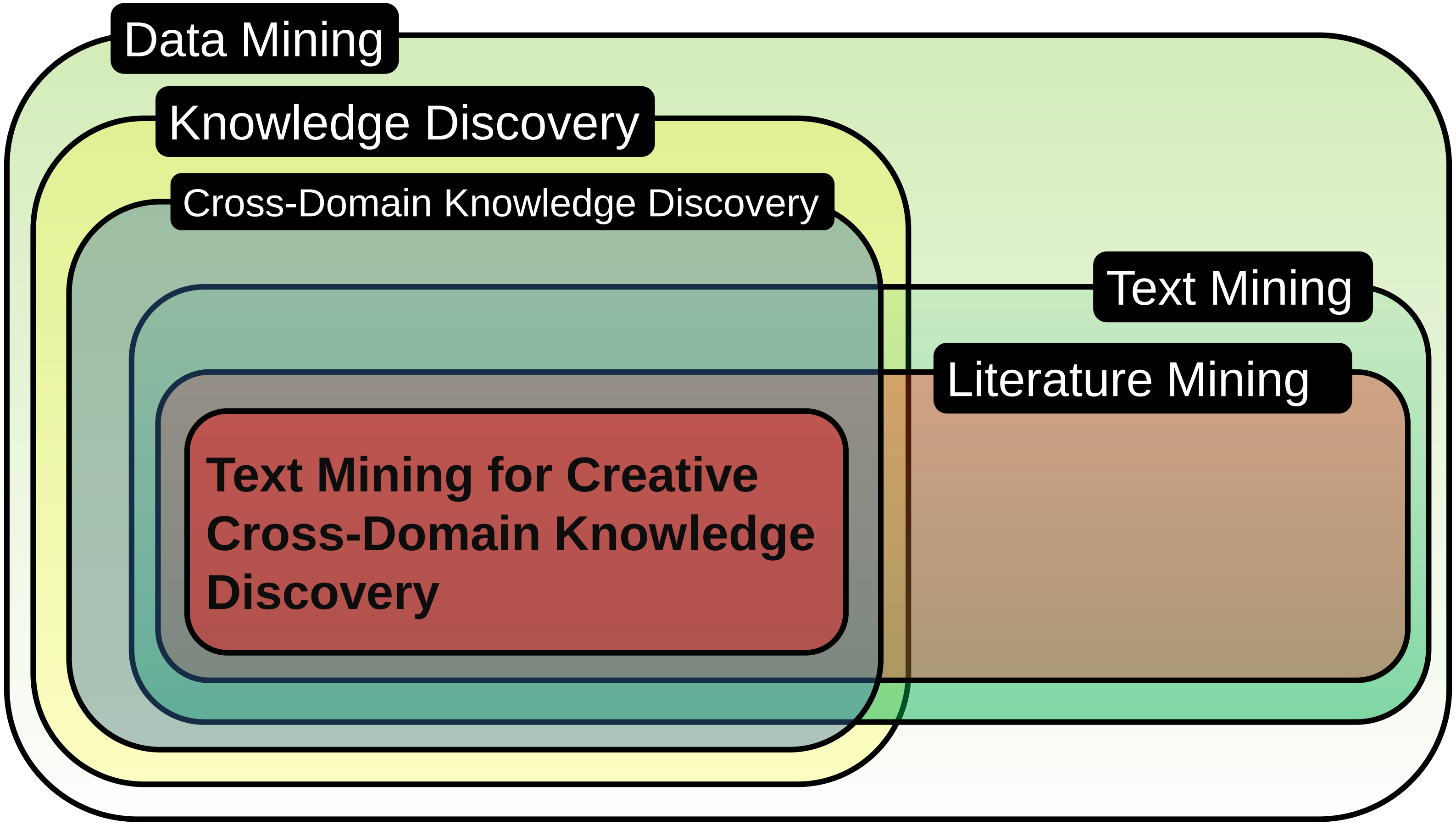
Extended Methodology



Summary and conclusions

- Current literature-based approaches mostly depend on simple associative information search
- Potential of outlier detection for b-term discovery
  - Document outlier detection and ranking by NoiseRank
  - Document outlier detection by OntoGen
- CrossBee: improving computational creativity by supporting the expert in the task of cross-domain literature mining (novelty: ensemble-based bridging term ranking)
- TextFlows text processing and text mining platform

Summary and conclusions



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- M. Berthold (2012): Bisociative Knowledge Discovery, Springer (open access)
- Juršič, M., Cestnik, B., Urbančič, T., Lavrač, N.: Cross-domain literature mining: Finding bridging concepts with CrossBee. In: Proc. 3rd International Conference on Computational Creativity (2012)
- Juršič, M., Cestnik, B., Urbančič, T., Lavrač, N.: HCI empowered literature mining for cross-domain knowledge discovery. In: Proc. HCI-KDD, pp. 124-135, Springer (2013)
- Petrič, I., Urbančič, T., Cestnik, B., Macedoni-Lukšič, M.: Literature mining method RaJoLink for uncovering relations between biomedical concepts. Journal of Biomedical Informatics. vol. 42/2, pp. 219–227 (2009)

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- Petrič, I., Cestnik, B., Lavrač, N., Urbančič, T.: Outlier Detection in Cross-Context Link Discovery for Creative Literature Mining. Computer Journal 55/1, pp. 47–61 (2012)
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- Weeber, M., Vos, R., Klein, H., de Jong-van den Berg, L. T. W.: Using concepts in literature-based discovery: Simulating Swanson's Raynaud–fish oil and migraine–magnesium discoveries. J. Am. Soc. Inf. Sci. Tech. vol. 52/7, pp. 548–57 (2001)