Keyword Extraction using Word Co-occurrence

TIR 2010, Bilbao 31 August 2010

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Problem description

- Keywords used for organising and retrieval of documents (including non textual ones)
- Problem:

$\boxed{\text{Determine keywords automatically}}$

- Operational problem:
  - Define relevance measure of terms
  - Select collection of terms based on relevance
    - Here, just rank

Keywords, world knowledge, informativity

- Relevance of term as keyword depends on:
  - **Importance** of term for the *document*
  - **Discriminative power** of term within *document collection*
  - **A priori criteria**
    - in a thesaurus
    - right word class,
    - non stopword,
    - …

World knowledge from statistics

- Problem: What can we do if we **do** have access to large document collection ?
  - assuming it is a natural document collection
- Importance in the doc collection is (hopefully) a proxy for the importance of terms in “the world”.
  - Importance w.r.t. everything
- Statistics of the collection becomes a source of world knowledge
  - OK to use broad external world knowledge
    - E.g. word class of terms

Predicting the term distribution

- **keyword** is short summary of content of a document
- Use **term distribution** of the document as proxy for the content
  - Bag words model.
  - Distributional hypothesis (Harris 1954)
- Good keywords should **predict** the term distribution of the document

Everything is a distribution

- **Term distribution** of a document:
  - $q_d(t)$ is the term distribution of *d*
  - *“*The fraction of term occurences found in *d,* matching *t*”
- **Document distribution** of a term
  - $Q_z(d)$ is the document distribution of *z*
  - “The fraction of term occurences matching z, found in *d*”
- **Background distribution** of the corpus
  - $q(t)$ is the fraction of term occurences matching *t*

Co-occurrence distribution of a term

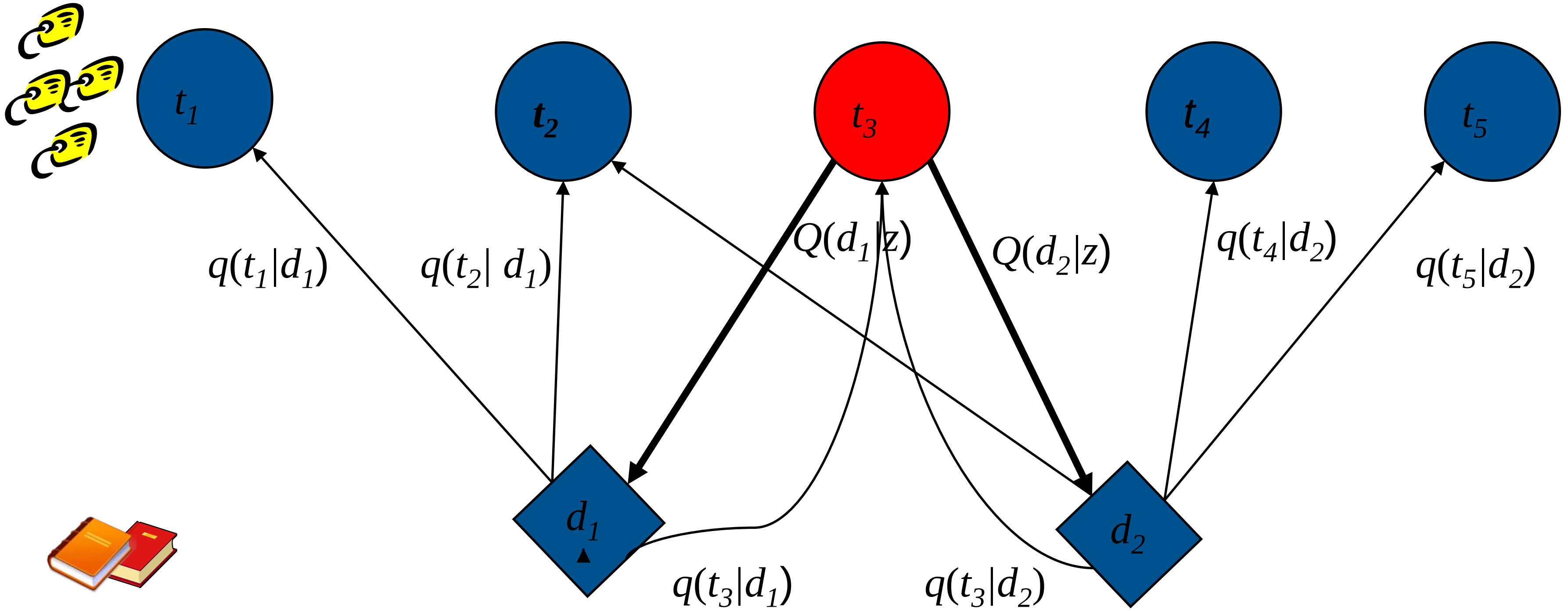
- Co-occurrence distribution of a term

$$\overline{p_z}(t) = \sum_d Q_z(d) q_d(t)$$

.

- Average distribution of terms co-occuring with *t* .

Co-occurrence of tags
“average tag cloud”



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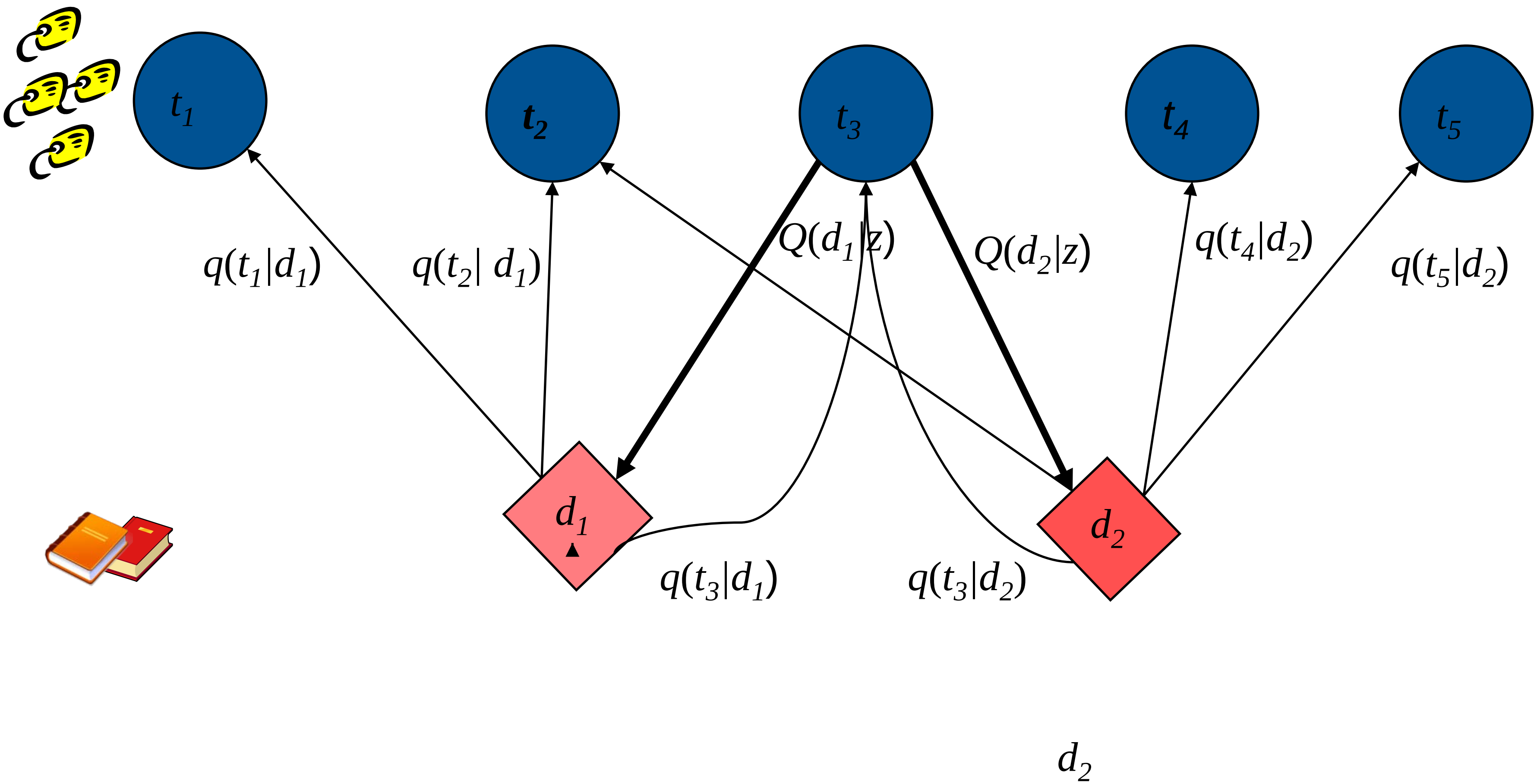

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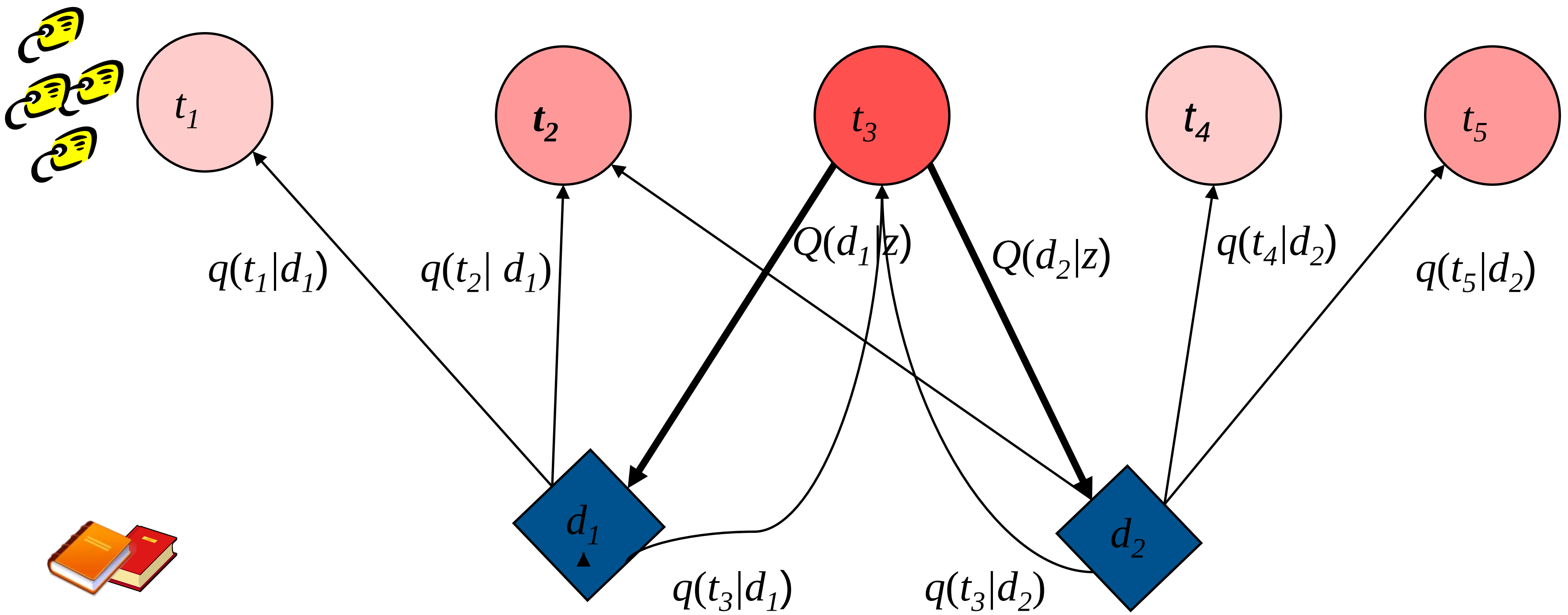


Relevance measure for terms:

- Relevance measure for term *z*
- importance:
  - Closeness of $\overline{p_z}$ to document distribution q_d
- Specifity
  - Awayness of $\overline{p_z}$ from background q

- → need to specify distance measure!

Different distance measures for distributions

- Kullback Leibler divergence D(p||q)
  - #bits per term saved by compression on a term stream using true distribution p instead of estimate q.
    - Infinite if p is not divisible by q!
- Jensen Shannon divergence JSD(p,q)
  - #bits per term saved by compression using streams distributed like p and q seperately instead of mixture
- Naive correlation coefficient r(p,p';q)
  - Cosine similarity of (p-q) and (p'-q)

Relevance measures for terms

- Only weigh closeness of term to document distribution

$$jsd(z,d) = JSD(\overline{p}_z, q_d)$$

- Weigh closeness of term to document and awayness to corpus

$$\Delta(z,d) = D(\overline{p}_z \,\|\, \overline{q}_d) - D(\overline{p}_z \,\|\, q) = \sum_t \overline{p}_z(t) \log\left(\frac{\overline{q}_d(t)}{q(t)}\right)$$

- Correlate differences

$$r(z,d) = r(\overline{p}_z, q_d; q)$$

Evaluation

- Use 11000 ACM abstracts with keywords.
  - #keywords = 1—10, av = 4.5
  - 27336 distinct keywords,
  - 21634 used only once,
  - 2 used more than 100 times.
  - **21642, consists of more than one word**.

- UIMA and GATE based pipeline

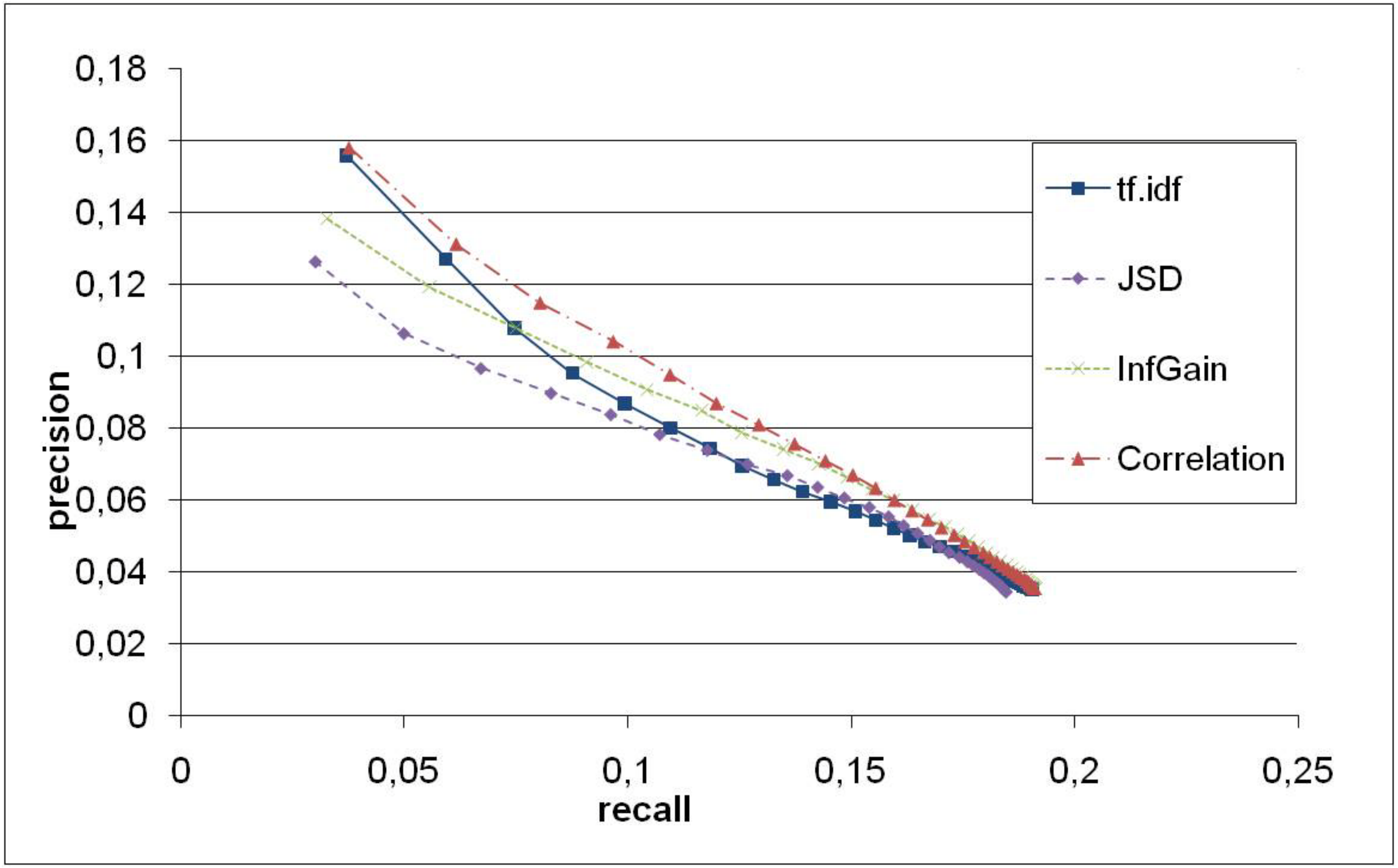
Multiword detection

- Imperative to detect multiwords as candidate terms!
  - Algorithm: detect superabundant combinations taking word class into account using t-test (see Manning and Schütze)
  - detection algorithm identified 4817 multiwords.
  - Results sensitive to multiword extraction algorithm ☹, but all methods evaluated suffer ☺.
  - Only 52% of articles has a keyword that is selected as a candidate term after preprocessing. 52% is optimal!
  - Selected terms may be perfectly acceptable keywords

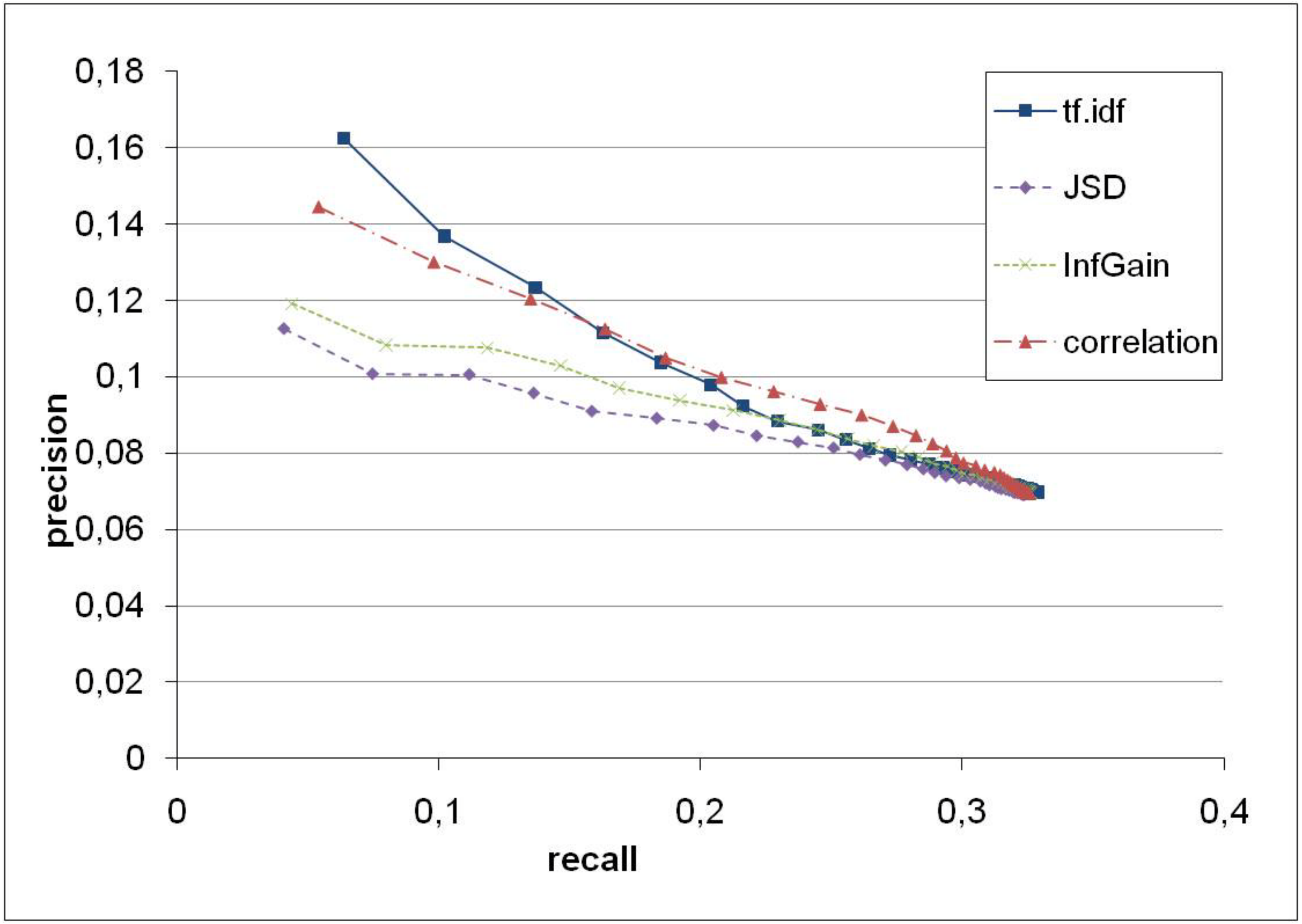
Evaluation BBC dataset

- 2879 BBC Program descriptions (Many very short)
  - #keywords = 1 -- 22 keywords, av = 2.9
  - 1748 distinct keywords,
  - 898 used once
  - 8 used more than a 100 times,
  - 792 keywords consist of multi word.
- Multiword detection algorithm found 168 multiwords.
- 57% of articles has a keyword selected as a candidate term

11000 ACM abstracts



2879 BBC abstracts



Conclusion

- Using co-occurence data improves on tf-idf
- Slightly naive correlation coefficient works best.
- There is room for improvement
  – Christian Wartena has recently gotten good results with recommendation by using some clustering, and with doc retrieval on keywords (CLEF).
  – Good multiword detection is really important.