Spoken document retrieval using extended query model and web documents

Kiichi Hasegawa, Masanori Takehara, Satoshi Tamura, Satoru Hayamizu,
Gifu University

Overview of this talk

- (1) Language modeling approach
  - Query model, and Smoothing
- (2) Smoothing using dynamic documents
  - Weighting web pages for query model
- (3) Topic modeling for spoken documents
  - Latent Dirichlet Allocation
- (4) Experiments
  - Dry-run and formal-run
- (5) Conclusion

Our approach

- Our basic framework is a query model.
- Two types of extension:
  - 1) One is to use web documents to expand the corpus as dynamic documents.
  - 2) The other is to use a topic model (LDA) to estimate similarities between web documents and the corpus in the test collection.
- These two extensions are incorporated in a smoothing formula with Dirichlet smoothing.

Query model

- The probabilities where q is a given query and d is a document.

$$P(d|q) = \frac{P(q|d)P(d)}{P(q)} \propto P(q|d)$$

- In language modeling of multinomial model, each term is assumed to be independent.

$$P(q|\theta_d) = \prod_{w_i \in V} P(w_i|\theta_d)^{C(w_i,q)}$$

$$w_i \in V = \{w_1, w_2, ..., w_{|V|}\}$$

- Relative frequency of each term;

$$P(w_i|\theta_d) = \frac{C(w_i, q)}{|d|}$$

Dirichlet smoothing

- The Dirichlet smoothing is given by;

$$P(w_i|\theta_d,\mu) = \frac{|d|}{|d|+\mu} \cdot P(w_i|\theta_d) + \frac{\mu}{|d|+\mu} \cdot P(w_i|\theta_c)$$

- with a parameter μ and,
- the probability for all the collection $P(w_i|\theta_c)$
- For a long document, the smoothing effect becomes smaller.

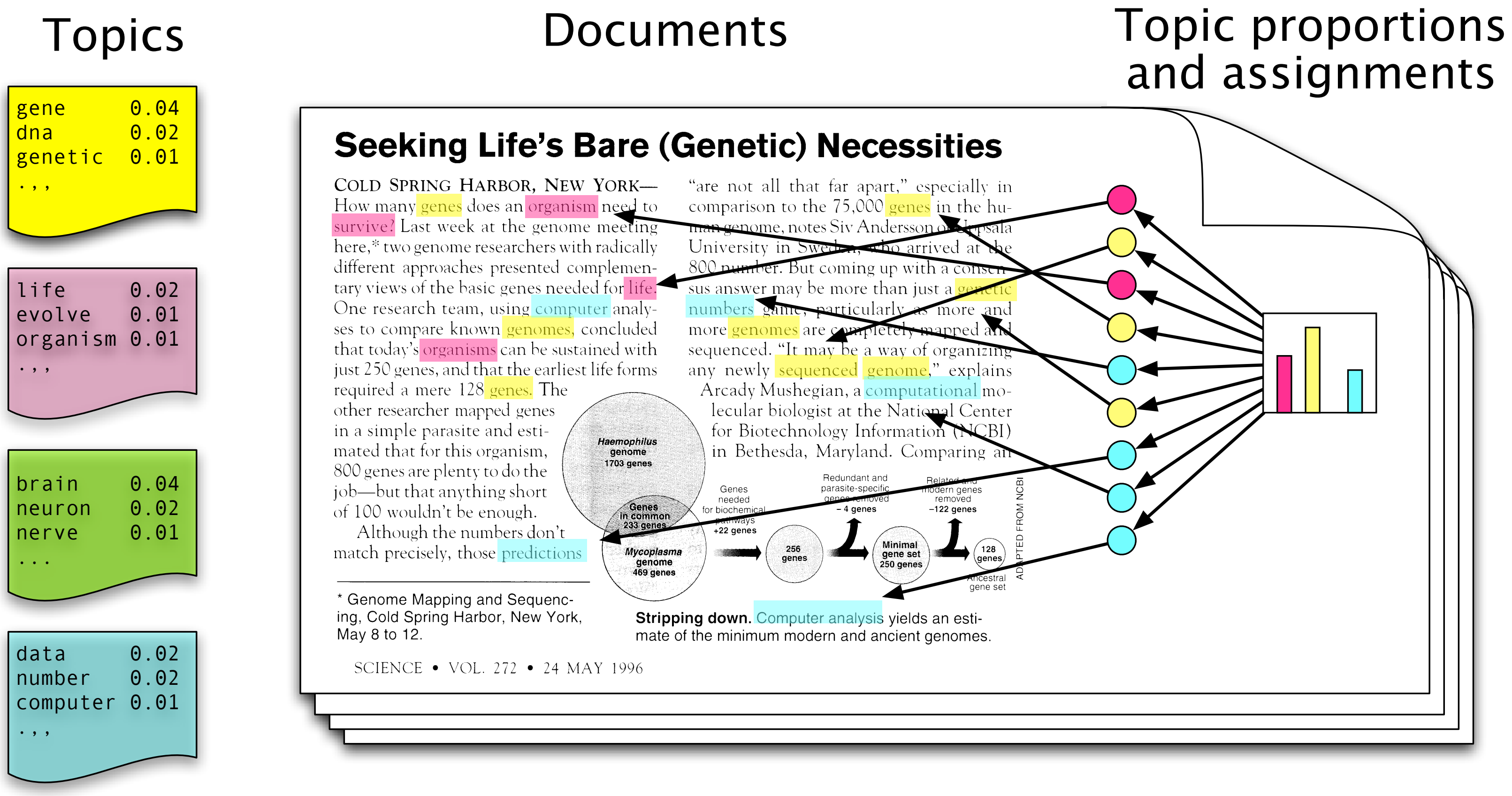
Smoothing using dynamic documents

- Dynamic documents are web pages obtained according to given queries.
- Dirichlet smoothing is extended as follows:

$$
\begin{aligned}
P(w_i|\theta_d,\mu,\nu) = & \frac{|d|}{|d|+\mu+\nu}\cdot P(w_i|\theta_d) \\
& +\frac{\mu}{|d|+\mu+\nu}\cdot P(w_i|\theta_c) \\
& +\frac{\nu}{|d|+\mu+\nu}\cdot P(w_i|\theta_W)
\end{aligned}
$$

- where $P(w_i|\theta_W)$ is for the dynamic documents (web pages) and μ and ν are the smoothing parameters.

LDA (latent Dirichlet allocation)

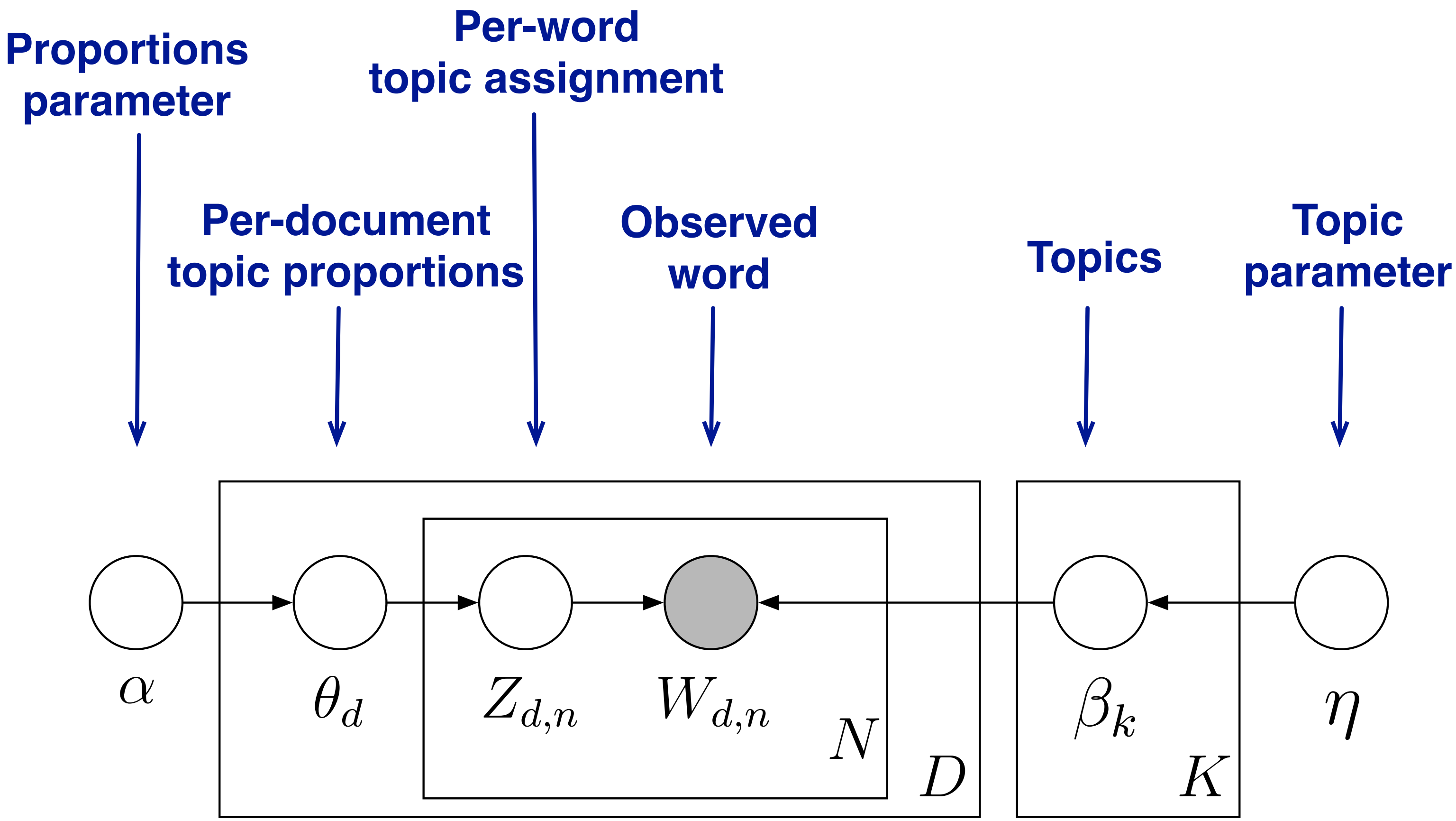


- LDA posits that each document is a mixture of topics, and that each word's creation is attributable to one of the document's topics.

from David M. Blei, KDD2011, tutorial

graphical model of LDA

$$\prod_{i=1}^{K} p(\beta_i|\eta) \prod_{d=1}^{D} p(\theta_d|\alpha) \left(\prod_{n=1}^{N} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n}) \right)$$



from David M. Blei, KDD2011, tutorial

Weighting method

- Weighted score is used for probability of the web page which is extracted by the query.
- Its weight is average similarity between the web page and documents in the collection.

$$P(w_i|\theta_W) = \frac{\sum_{j=1}^{|W|} \delta(p_j, C) \cdot C(w_i, p_j)}{\sum_{j=1}^{|W|} \sum_{k=1}^{N_j} \delta(p_j, C) \cdot C(w_k, p_j)}$$

- where

$$\delta(p, C) = \frac{1}{|C|} \sum_{m=1}^{|C|} \delta(p, d_m)$$

p: extracted web page

d_m: m-th document

$$C = \{d_1, d_2, ..., d_{|C|}\}$$

Similarity by topic mixture

- Similarity between a document and a web page is defined as cosine distance between topic mixture ratio vectors.

$$\boldsymbol{\gamma} = (\gamma_1, \gamma_2, \ldots, \gamma_{|Z|})$$

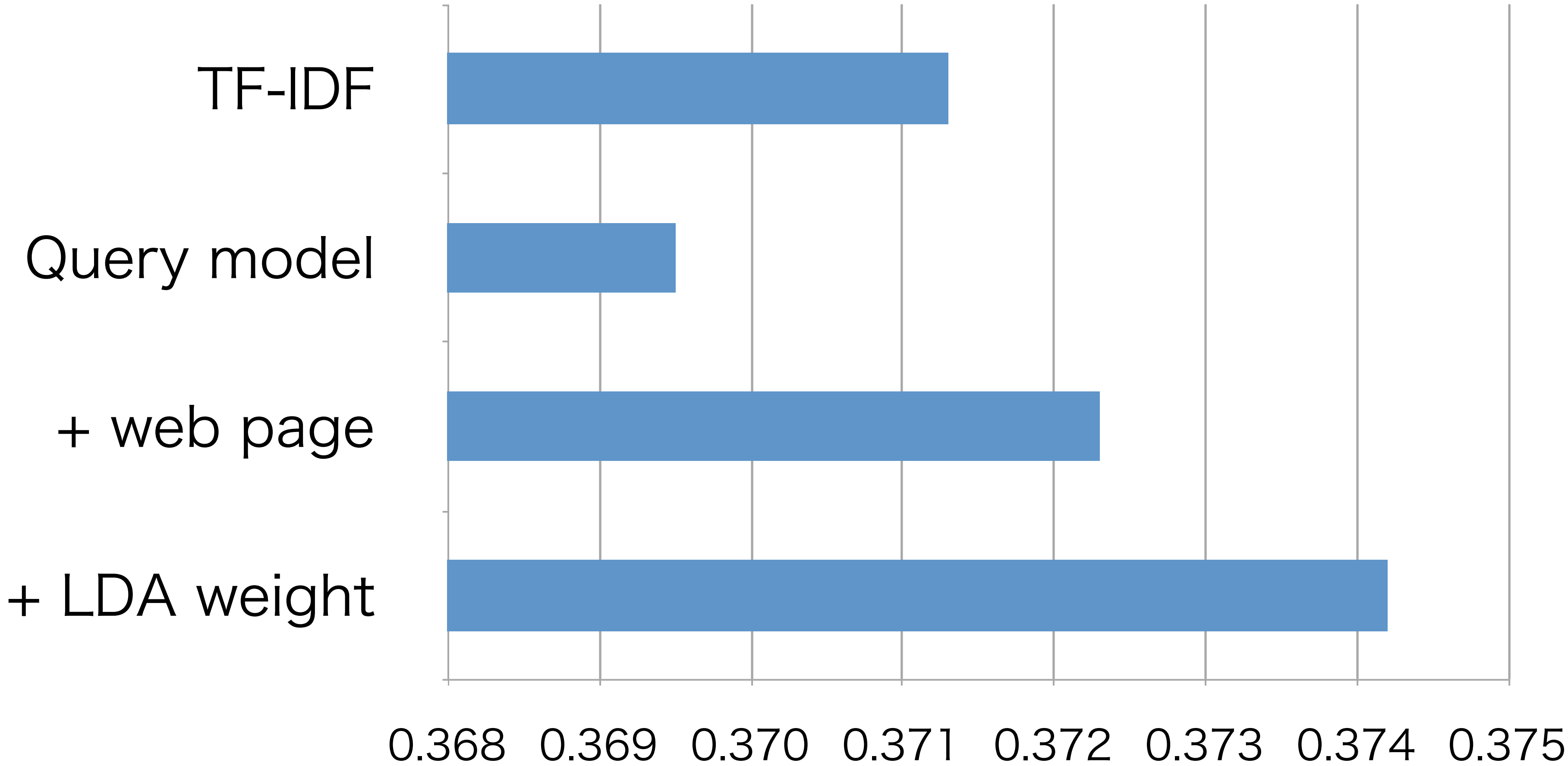
- For each document, a topic mixture ratio vector (topic proportion) is estimated using LDA with the parameters α, β_k from the whole document collection.
- For a web page, a topic mixture ratio vector is estimated using the same parameters α , β_k .
- Finally, cosine distance between two vectors are calculated as the similarity measure.

Experiments

- Experimental setup
- SpokenDoc-2 SCR subtask in NTCIR-10
- Sub-subtask: Lecture retrieval
- Spoken document: Ref-Word-Matched
- LDA training data: Mainichi newspaper corpus (2007-2008)
- Web search engine: Yahoo! API
- Dynamic documents: 30 web pages per query
- Smoothing parameters: μ =4000, ν =50

NTCIR-9 Dry-run results

- Preliminary experiment by NTCIR-9 Dry-run.
- The score is the Mean Average Precision (MAP).



NTCIR-10 Formal-run results

- Table 2. Results for NTCIR-10 SpokenDoc-2 Formal-run.
- Query model + LDA (RunID L36) 0.408
- Query model + Web (RunID L37) 0.399
- Query Expansion (RunID L38) 0.372

- Note: since queries in NTCIR-10 Formal-run were longer than those in NTCIR-9 Dry-run, it seemed that more related and informative web pages were obtained.

Conclusion

- Our spoken document retrieval method uses the language model approach.
- We extend query model in two ways.
- One is to use web page retrieval for dynamic document collection.
- The other is to employ a topic model (latent Dirichlet allocation) for the measure between documents and retrieved web pages.
- We expand the Dirichlet smoothing for dynamic documents and the topic model.
- We showed improvements at NTCIR-9 Dry-run and NTCIR-10 Formal-run.

From teaching staff's view

- NTCIR provides a very good opportunity for students to learn the knowledge and the evaluation skill on language technology.
- It is also good for them to have valuable experiences to be in a research community.
- In general, research purpose defines "what to measure", and then "how to measure" provides research issues to be solved.
- It seems that future design of SpokeDoc tasks needs to be more balanced on the number of participants and diversity of research issues.