

Generating Summary Keywords for Emails Using Topics

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(Joint work with M. Dredze, D. Puller, F. Pereira)

Email Triage

- ▶ Email triage: deciding how to handle incoming email
- ▶ User has a limited amount of information about each email:

```
1 Oct 06 Debian Bug Tracking ( 1.7K) Processed: merging 44256
2 Oct 07 Jonathan Keeling ( 3.3K) Some questions
3 Oct 09 Randy Bunnao ( 20K) SEWS3 - Speaker Invitati
4 Oct 10 Robin Wallach ( 2.1K) Re: Hi!
```

sender

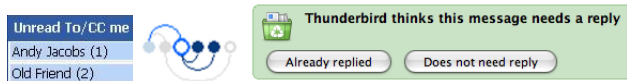
subject line

- ▶ Decisions made using available information
- ▶ Goal: provide user with additional concise information

Incorporating Information

Previous work:

- ▶ Social information, thread indicators, reply prediction

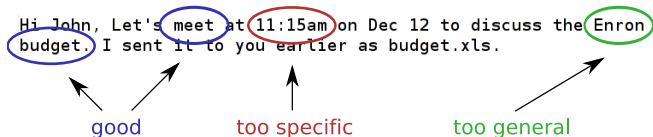


- ▶ Message snippets, full-sentence summaries, summary keywords

Our approach: generate a concise summary of the message's contents – summary keywords – in an unsupervised fashion

Good Summary Keywords

- ▶ Prepare user for message contents
- ▶ Cannot be too specific or too general



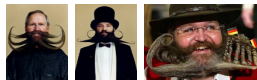
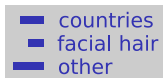
- ▶ Represent the gist of the email
- ▶ Should be associated with coherent user concepts

Our Approach

- ▶ Unsupervised framework for choosing summary keywords
 - ▶ No annotated training data required
- ▶ Use latent concept models to represent topics in user's mailbox
 - ▶ A good summary keyword relates the message to other topically similar messages in the user's mailbox
- ▶ Two ways of selecting keywords, analogous to:
 - ▶ Query-document similarity
 - ▶ Word association

Latent Concept Models

- ▶ Documents are assumed to have latent semantic structure
- ▶ Latent structure is inferred from word-document co-occurrences



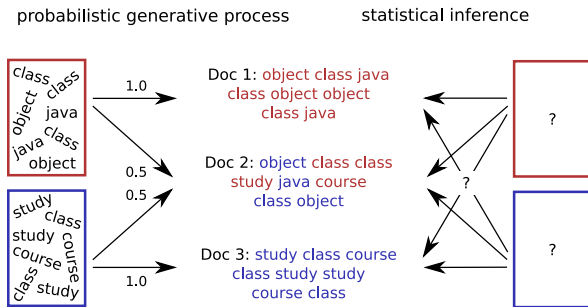
... Germany hosted the World Beard and Mustache Championships ^[1]

- ▶ Relates words to concepts and concepts to documents
- ▶ Used in information retrieval, classification, collaborative filtering

[1] <http://www.worldbeardchampionships.com>

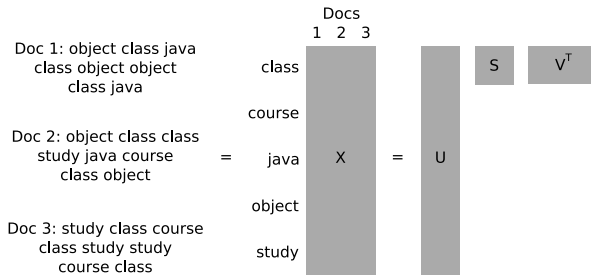
Latent Dirichlet Allocation (Blei et al., '03)

Models documents as mixtures of latent topics. Topics inferred from word correlations, independent of word order: “bag-of-words”



Latent Semantic Analysis (Deerwester et al., '90)

LSA decomposes the word-document co-occurrence count matrix into a set of orthogonal factors that represent latent concepts



Query-Document Similarity

Treat candidate keywords as one-word queries, compute similarity between each keyword and the email, choose those that are most similar

- ▶ Latent Dirichlet allocation:

$$P(\text{keyword } k \mid \text{email } d) = \sum_{\text{topics } t} P(k \mid t)P(t \mid d)$$

- ▶ Latent semantic analysis:

$$\text{score}(\text{keyword } k, \text{email } d) = U_k \cdot V_d$$

Word Association

Compute the association between each candidate keyword and each of word in the email, choose those that are most closely associated

- ▶ Latent Dirichlet allocation:

$$P(\text{keyword } k \mid \text{email } d) = \prod_{w \text{ in } d} \sum_{\text{topics } t} P(k \mid t)P(t \mid w, d)$$

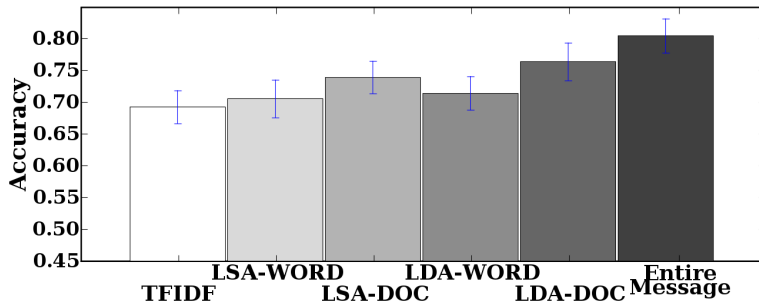
- ▶ Latent semantic analysis:

$$\text{score}(\text{keyword } k, \text{email } d) = \sum_{w \text{ in } d} \sum_{\text{factors } f} U_{k,f} U_{w,f} V_{f,d}$$

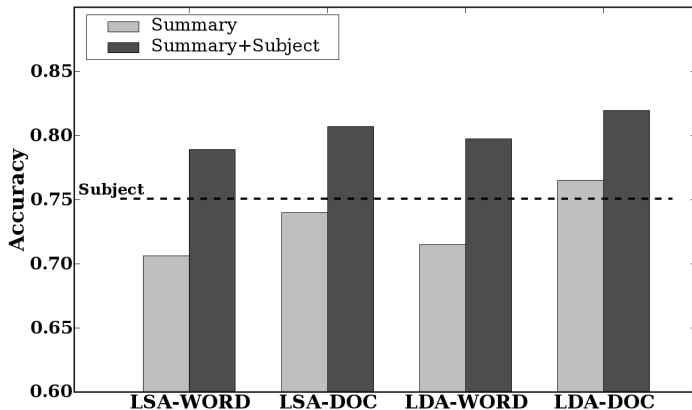
Evaluation

- ▶ Summaries evaluated using two proxy tasks
 - ▶ Automated foldering
 - ▶ Recipient prediction
- ▶ Compared on users from the Enron data set
- ▶ Length of each summary was set to nine keywords
- ▶ Two baselines:
 - ▶ Term frequency-inverse document frequency (TF-IDF) keywords
 - ▶ Full message contents

Automated Foldering: Prediction Accuracy



Automated Foldering: Improvement Over Subject



Summary Keywords

Sally -

Attached are the hypertexts from the final report out at yesterday's ASE Studio Workshop. The CD is finished and on its way to Houston. The files are organized by [team](#):

[Hammer](#) - Sales and Marketing, Vision Stmt, Mission [Stmt](#), Target Market, How to Approach, Pricing, SLA

[Pliers](#) - [Productst](#) and Services - Consulting Based

Saw - Infrastructure Transition Plan

[Wrench](#) - [Productst](#) and [Services](#) - Basic Outsourcing

I hope these help with your [meeting](#) tomorrow. Let me know if there is anything else I can do to help.

[Lisa P](#)

- ▶ TF-IDF: [productst](#) [pliers](#) [stmt](#) [hammer](#) [wrench](#)
- ▶ LDA-doc: [team](#) [meeting](#) [services](#) [lisa](#) [ase](#)

Findings and Future Work

Key finding:

- ▶ Summary keywords generated using topic models are a good approximation of message content and provide additional information over the message subject line

Future work:

- ▶ Other latent concept models, *e.g.*, topical n -gram model
- ▶ Incorporating person-specific information
- ▶ Research on incorporation of keywords into user interfaces

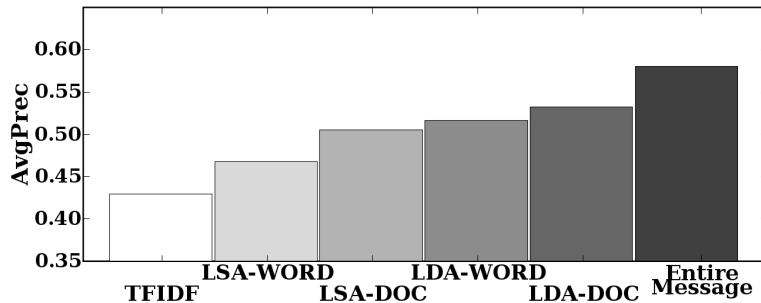
Questions?

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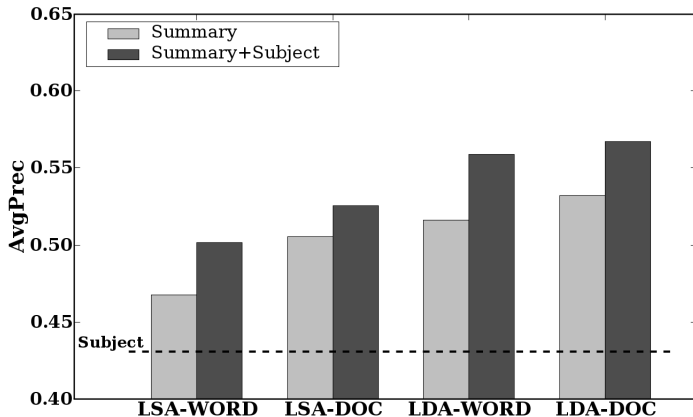
<http://www.inference.phy.cam.ac.uk/hmw26/>

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Recipient Prediction: Average Precision



Recipient Prediction: Improvement Over Subject



User Interface Design

1. Display keywords with subject and sender entries in mailbox listing
2. Separate visualization, such as a tag cloud:

ase attached
meeting lisa
outsourcing report
services studio team

Each word is scaled according to its relevance as a keyword