Incorporating Statistical Word Senses in Topic Model

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Outlines

- Introduction
- Related Work
- Topic Models Incorporating Statistical Word Senses
- Inference
- Evaluation
- Conclusion

Introduction(1/4)

- Topic model
  - Use document-level co-occurrence information to group semantically related words into a single topic.
- LDA
  - The topic distribution of the document
  - The probability of the topic to emit this word

Introduction(2/4)

- The probability of the topic to the word has some limitations.
  - Traditional LDA treats word as surface string,
- Example:
  - *Robot*
    - Usually mean an electro-mechanical machine
    - In a film review, it may refer to the name of a film
  - In LDA
    - The probability of topic *electronics technology* to emit the word is much higher than the topic *film*.
    - With word sense information
      - Probability of topic *film* to this word sense *film name* is higher than that of topic *electronics technology*

Introduction(3/4)

- We thus hypothesize that, if word senses are incorporated in topic models, a stronger indication of topic will be obtained.
- Topic models with word senses from lexical resources
  - *WordNet* (Boyd-Graber et al., 2007; Chemudugunta et al., 2008; Guo and Diab, 2011).
  - costly and hardly be complete.
- Word Sense Induction (WSI)
  - Discover word senses from unannotated text
  - Have been integrated in information retrieval to resolve senses of query words (Schutze and Pedersen, 1995; Navigli and Crisafulli, 2010).

Introduction(4/4)

- Two manners, i.e., sequential and co-inference, are proposed to incorporate the statistical word senses in the LDA framework.

- Hierarchical Dirichlet Process (HDP) (Teh et al., 2004) to induce statistical word senses from corpora

Related work(1/2)

- Semantic Document Representation Models
  - VSM
    - Ignore sematic relations.
  - Explicit Sematic Representation
    - The lexical ontologies are difficult to construct and can hardly be complete.
  - Latent Sematic Representation(Topic model)
    - Those models treat word as surface string.
    - One word may contain different meanings in different contexts
  - Integrate semantics from lexical resources into topic model framework
    - (Boyd-Graber et al., 2007; Chemudugunta et al., 2008; Guo and Diab, 2011).
    - The coverage issue again leads to performance bottleneck.

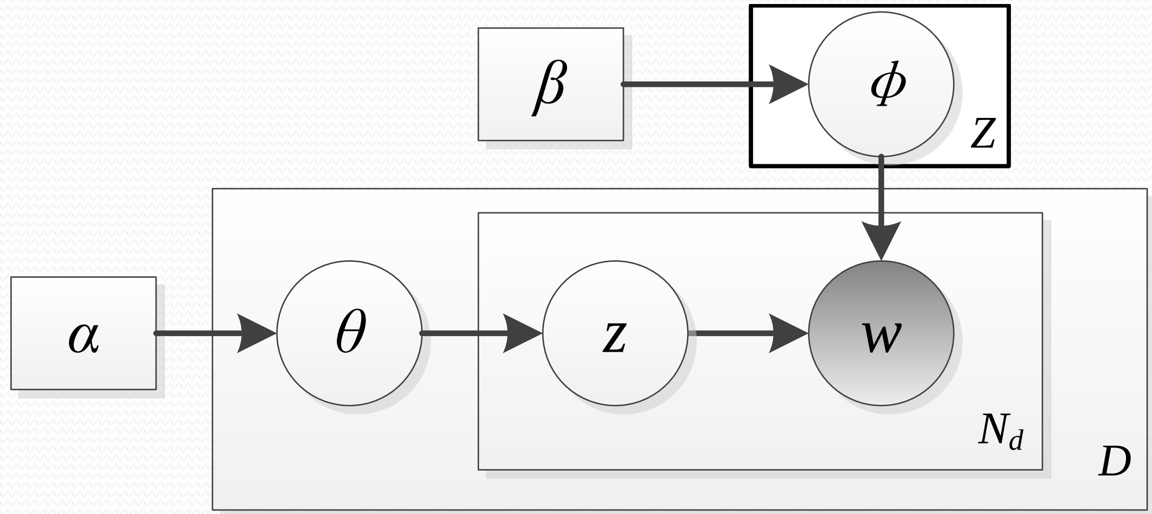
Related work(2/2)

- Word sense disambiguation and word sense induction.
  - The use of word sense
    - Information retrieval (Stokoe, 2003) and text classification (Tufi and Koeva, 2007).
    - Drawbacks:
      - Large, manually compiled lexical resources such as the WordNet database are required.
      - It is hard to decide the proper granularity of the word sense.
  - In this work, word sense induction (WSI) algorithm is adopted in automatically discovering senses of each word in the test dataset.
    - The Bayesian model (Yao and Durme ,2011)
      - HDP: find topic number automatically
      - It outperforms the state-of-the-art systems in SemEval-2007 evaluation (Agirre and Soroa, 2007).
    - Word sense induction algorithms have been integrated in information retrieval (Schutze and J. Pedersen, 1995; Navigli and Crisafulli, 2010).
      - The above researches only consider senses of words and do not investigate connection between words.

Topic Models Incorporating Statistical Word Senses

- Motivation
  - Synonymy
    - different words carrying almost identical or similar meanings.
  - Polysemy
    - one single word carrying two or more senses at the same time.
  - Topic is not able to reflect meaning of word delicately.
  - Incorporating word senses
    - A topic is more directly relevant to a word meaning (i.e., sense) than a word due to polysemy;
    - Word senses are more proper to reflect synonymy than words.

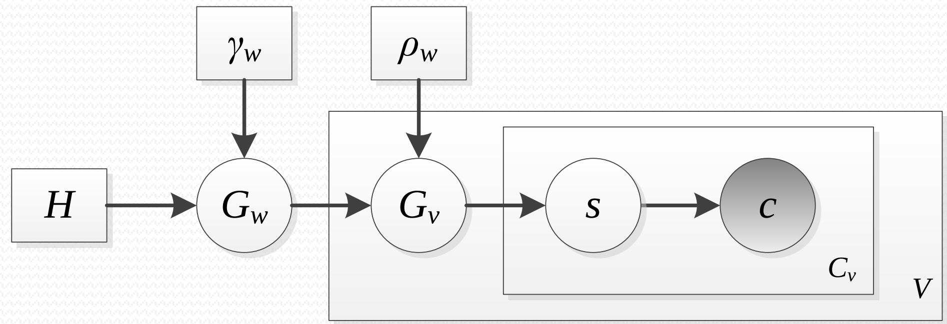
LDA



1. For each topic z:
   a) choose $\phi_z \sim Dir(\beta)$.
2. For each document d_i:
   a) choose $\theta_{d_i} \sim Dir(\alpha)$.
   b) for each word w_{ij} in document d_i:
      i. choose topic $z_{ij} \sim Mult(\theta_{d_i})$.
      ii. choose word $w_{ij} \sim Mult(\phi_{z_{ij}})$.

$$P(z_{ij} = z|\boldsymbol{z_{-ij}}, \boldsymbol{w}) \propto \frac{n^{d_i}_{-ij,z}+\alpha}{n^{d_i}_{-ij}+Z\alpha} \times \frac{n^{w}_{-ij,z}+\beta}{n_{-ij,z}+W\beta}$$

WSI with HDP Algorithm



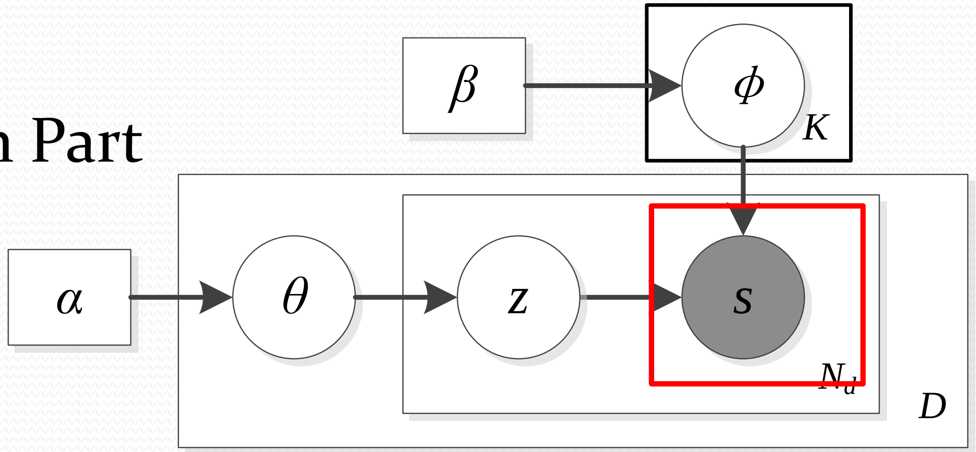
1. Choose $G_w \sim DP(\gamma_w, H)$.
2. For each context window v_i of word w:
   a) choose $G_{v_i} \sim DP(\rho_w, G_w)$.
   b) for each context word c_{ij} of target word w:
      i. choose $s_{ij} \sim G_{v_i}$.
      ii. choose $c_{ij} \sim Mult(\eta_{s_{ij}})$.

Incorporating Statistical Word Senses into Topic Model

- Sequential Approach (SEQ)
- Co-inference Approach (COI)

Sequential Approach (SEQ)

- Word Sense Induction Part
  - Same as HDP



- Document Presentation Part

1. For each topic z, choose $\phi_z \sim Dir(\beta)$.
2. For each document d_i :
   a) choose $\theta_{d_i} \sim Dir(\alpha)$.
   b) For each word w_j in document d_i:
      i. choose topic $z_{ij} \sim Mult(\theta_{d_i})$.
      ii. choose sense $s_{ij} \sim Mult(\phi_{z_{ij}})$.

Example

- Robot
- Topic1 : film
- Topic2: electronics technique

sense *robot#1*
film: 0.159
role: 0.069
performance: 0.019
...

sense *robot#2*
computer: 0.116
system: 0.039
software: 0.026
...

In the end, it's an inspired performance from Robot that keeps the film fresh

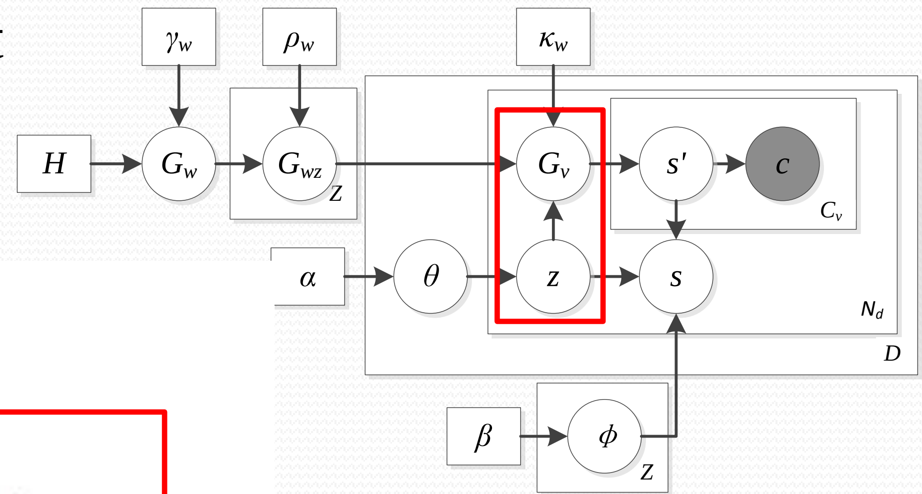
There may be a computer operating system designed mainly for robots

Co-inference Approach (COI)

- Can the topics of words make a positive impact on the indication of senses ?

- Take the topics of words as pseudo feedback and co-infer both topics and senses iteratively.
  - Word *robot* in topic *film* has a higher probability to contain sense *robot#1*.
  - The sense *robot#1* has a higher probability to be assigned topic *film*.

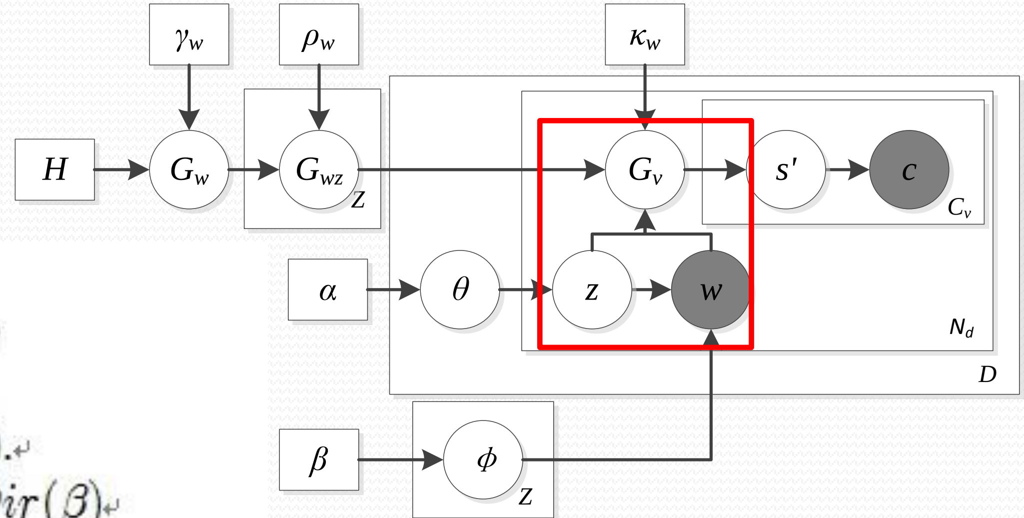
- Document Presentation Part
  - Same as SEQ
- Word Sense Induction Part



1. For each word w:
   a) choose $G_w \sim DP(\gamma_w, H)$.
   b) For each topic z,
      choose $G_{wz} \sim DP(\rho_w, G_w)$.
2. For each document d_i,
   a) For each context v_j of word w_j:
      i. choose $G_{ij} \sim DP(\kappa_{wz}, G_{wz})$.
      ii. For each context word c_k of target word w_j:
         1) choose $s'_{ijk} \sim G_{ij}$.
         2) choose $c_{ijk} \sim Mult(\eta_{s_{ijk}})$
         3) set $s_{ij} = \arg\max_s P(s_{ij}|G_{ij})$

Extended Co-inference Approach (COX)

- The standard COI approach takes the sense with the highest probability as the sense of the target word.
- We now consider the whole sense distribution of the target word in its context
  - COX.
- Three factors are considered to determine the topic of a word:
  - The topic distribution of the document
  - The probability of the topic to emit this word
  - The probability of the word and its topic to generate the sense distribution.
    - reflects the meaning contained by its context.
    - considers the sense distribution of the target word which is more precise.
- Example:
  - In ROBOT, the most important character is an electro-mechanical machine whose software was upgraded to give it the ability to comprehend and generate human emotions
    - The illustrative sense distribution of this context is (0.2, 0.8).
    - In SEQ and COI, the sense will be set as robot#2
    - In COX, it will have a probability of robot#1.



1. For each word w:
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2. For each topic z, choose $\phi_z \sim Dir(\beta)$
3. For each document d_i:
   a) choose $\theta_{d_i} \sim Dir(\alpha)$.
   b) For each word w_j in document d_i:
      i. choose topic $z_{ij} \sim Mult(\theta_{d_i})$.
      ii. choose word $w_{ij} \sim Mult(\phi_{z_{ij}})$
      iii. choose $G_{ij} \sim DP(\kappa_{wz}, G_{wz})$.
      iv. For each context word c_k in context v_j of target word w_j:
         1) choose $s'_{ijk} \sim G_{ij}$.
         2) choose $c_{ijk} \sim Mult(\eta_{s_{ijk}})$

Inference

- Sequential Approach

$$P(z_{ij} = z|\boldsymbol{z_{-ij}}, \boldsymbol{s}) \propto \frac{n^{d_i}_{-ij,z} + \alpha}{n^{d_i}_{-ij} + Z\alpha} \times \frac{n^{s}_{-ij,z} + \beta}{n_{-ij,z} + S\beta}$$

- Co-inference Approach
  - variables $\boldsymbol{z} = \{z_{ij}\}$assigning words to topics
  - variables $\boldsymbol{s} = \{s_{ijk}\}$ assigning context words of each target word to senses, base distributions of each target word G_w and $\{G_{wz}\}$.
  - COI
    - given the second kind of variables are fixed, the first kind can be sampled using the same scheme as SEQ.
    - Given the first kind of variables are fixed, the second kind can be sampled using the same scheme as described in (Teh et al., 2004)

COX

- Similarly, given the first kind of variables are fixed, the second kind can be sampled using the same scheme as described in (Teh et al., 2004).
- Hence the key issue is how to sample $z = \{z_{ij}\}$ given sense distributions.

$$P(z_{ij} = z | \boldsymbol{z_{-ij}}, \boldsymbol{s}, \boldsymbol{w})$$
$$\propto \frac{n^{d_i}_{-ij,z} + \alpha}{n^{d_i}_{ij} + Z\alpha} \frac{n^{w}_{-ij,z} + \beta}{n_{-ij,z} + W\beta} \frac{\prod_{s \in \{s_w\}} \prod_{g=0}^{n^{s-1}_{ij}} (\kappa_{wz}\pi_{zs} + g)}{\prod_{g=0}^{C_{ij}-1} (\kappa_{wz} + g)}$$

Evaluation

Dataset	#doc	#topic	#words	#content words
TDT41	1270	38	18511	5457
TDT42	617	33	11782	3548
Reutes20	9101	20	25748	7454

- Setup
  - Test dataset
    - TDT4 datasets
    - Reuters dataset
  - Evaluation task
    - Document clustering task
    - Evaluation criteria
      - Precision
      - Recall
      - F-Measure

Experiment Result

- Different Word Sense Incorporating Approaches

Method	TDT41	TDT42	Reutes20
LDA	0.735	0.852	0.483
K-Means	0.727	0.843	0.501
SEQ	0.776	0.865	0.491
COI	0.825	0.874	0.597
COX	0.864	0.905	0.612

Conclusion

- In this paper, we present three approaches to incorporating word senses in topic models:
  - SEQ approach
  - COI approach
  - COX approach
- Three conclusions can be drawn from the experimental results.
  - Replacing word surfaces with word senses is helpful in topic modeling.
  - The topics of words can make a positive impact on the indication of word senses thus improve word sense induction.
  - Using the regular sense distribution of the target word can get a better topic indication than that uses merely the definite sense with the highest probability.

Reference(1/2)

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Thank you ！

Q&A