Statistical Word Sense Improves Document Clustering

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Outlines

- Introduction
- Related work
- Document representation based on word sense
- Evaluation
- Conclusion and future work

Introduction (1/4)

- Document Clustering:
  - Automatically organize a large collection of documents into groups of similar documents
- How to represent document?
  - Vector Space Model(Salton et al., 1975)
- Two linguistic phenomena:
  - Synonymy
    - computer and PC
  - Polysemy
    - apple: ⑴ A pomaceous fruit; ⑵ A computer company founded by Steve Jobs.

Introduction (2/4)

VSM
- Synonymy
- Polysemy

Explicit Sematic Representation
- Need large, general purpose lexical resources
- Tend to over-represent rare word senses while missing corpus-specific senses.

Latent Semantic Representation
- According to previous research Lu et al., (2011) it cannot provide fine granularity discrimination.

Introduction (3/4)

- Our solution: represent document with statistical word sense.
  - Word senses are constructed in two steps:
    - Local word senses are induced from the development dataset by the LDA models (Brody and Lapata, 2009).
    - Local word senses are combined as global word senses by clustering technology
  - Global word senses are used to represent every document after word sense disambiguation on the document.

Introduction (4/4)

- The proposed model aims to well address the synonymy and polysemy issues in document representation.
  - Synonymy: Different words of the same meaning are identified as the same sense.
  - Polysemy: One word in different contexts can be identified as different sense in different contexts.
- Compared with previous researches,
  - Compared with the explicit sematic methods:
    - Word sense can be induced from the raw development dataset
    - It can be easily extended to process documents in other languages
  - Compared with the latent sematic methods:
    - It can achieve finer granularity discrimination in document representation

Related work(1/2)

- Document representation models
  - Classic model
    - VSM(Vector Space Model)
      - Problems: Synonymy Polysemy
  - Improvement:
    - Explicit Sematic Representation(Hotho et al., 2003; Gabrilovich and Markovitch, 2007; Huang and Kuo, 2010)
      - Lexical resources: WordNet and wikipedia
      - Represent documents in the concept space
    - Latent Semantic Representation
      - Probabilistic latent semantic analysis (Puzicha and Hofmann, 1999)
      - Latent Dirichlet Allocation (Blei et al., 2003)

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 (Brody and Lapata ,2009)
      - Use an extended LDA model to induce word senses
      - 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.

Document representation based on word sense

- How to represent word sense?
- How to obtain word sense?
- How to use word sense in document clustering?

How to represent word sense?(1/2)

- Local word sense:
  - A probability distribution over context words

Example #1: word sense arm#1 for word arm
arm: 0.159
sleeve: 0.069
sew: 0.019

Example #2: word sense arm#2 for word arm
arm: 0.116
weapon: 0.039
war: 0.026

How to represent word sense?(2/2)

- Global word sense:
  - A group of similar local word senses

Example #3: sense cluster c#1
{arm#1, sleeve#1}
arm#1={arm: 0.159, sleeve: 0.069, sew: 0.019}
sleeve#1={sleeve:0.179,arm:0.059,sew: 0.029}

How to obtain word sense?(1/2)

- Local word sense:
  - Bayesian word sense introduction model (Brody and Lapata, 2009)

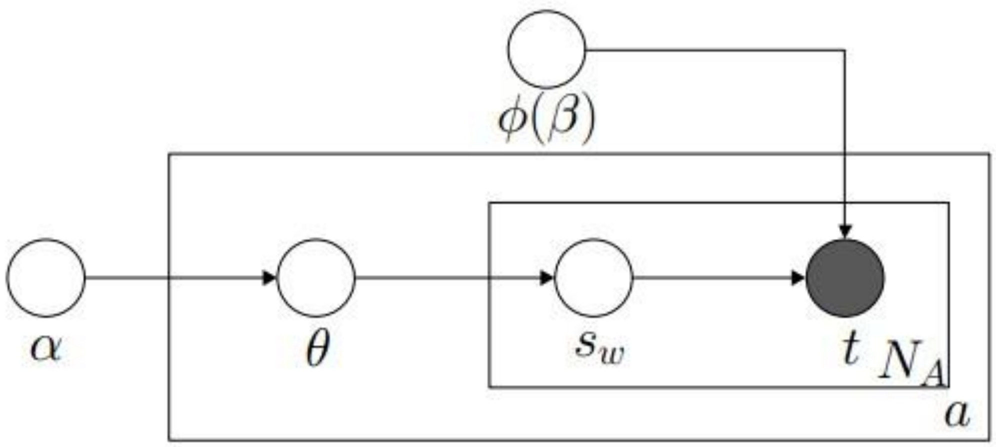


FIGURE 1 – Bayesian sense induction model (Brody and Lapata, 2009).

How to obtain word sense?(2/2)

- Apply clustering algorithm to obtain global word sense.
  - In the clustering algorithms, we take context words of local word senses as features and probabilities of the context words as the weights of features.
  - Bisecting K-Means
    - An extension of K-means, which is proved better than standard K-Means and hierarchical agglomerative clustering (Steinbach et al., 2000). It begins with a large cluster consisting of every element to be clustered and iteratively picks the largest cluster in the set, split it into two.

How to use word sense in document clustering?(1/3)

- Bayesian word sense disambiguation
  - Example:
    - ① There's a tear in the arm of my jacket.
      - P(arm#1| S1)=0.998005.
    - ②The nation must arm its soldiers for battle.
      - P(arm#2| S2)= 0.944096.

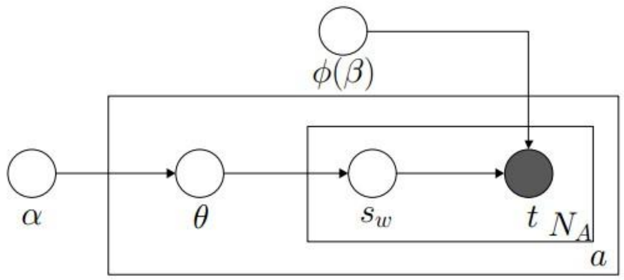


FIGURE 1 – Bayesian sense induction model (Brody and Lapata, 2009).

How to use word sense in document clustering?(2/3)

- Represent document in global word sense space

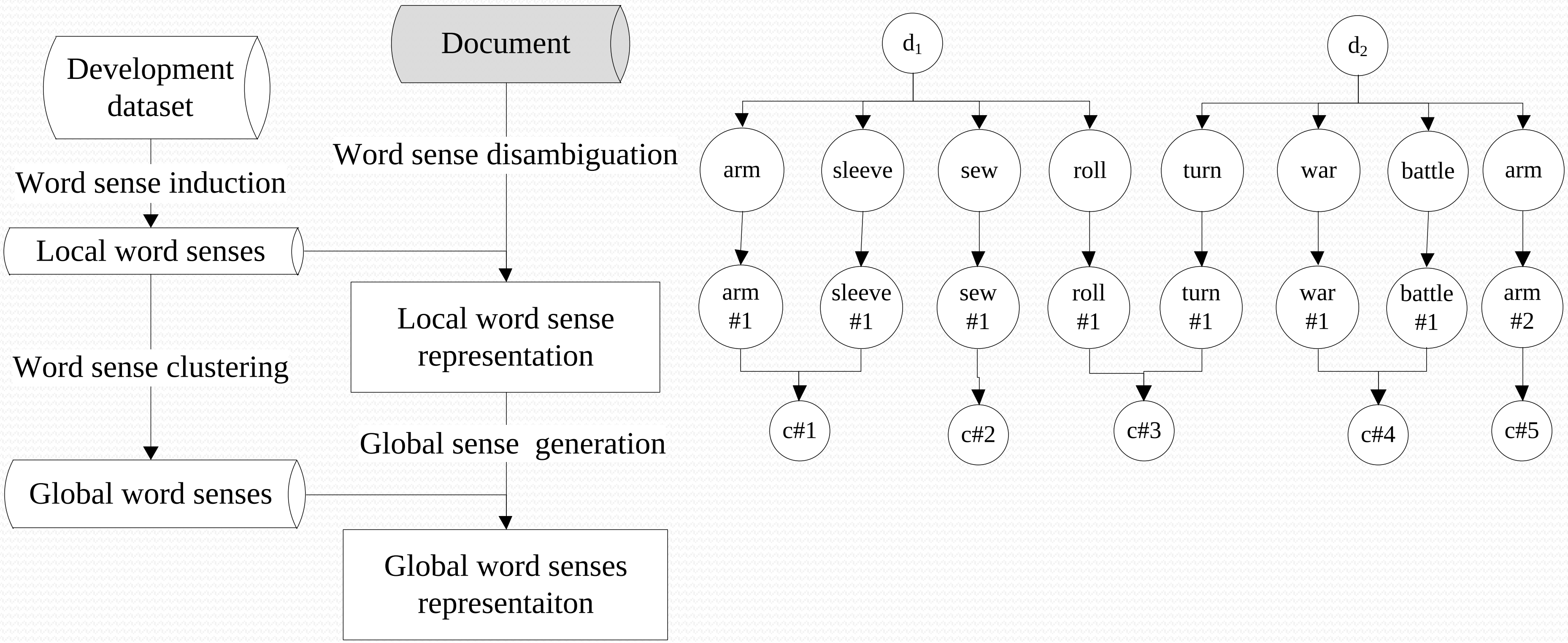
$$n(c,d) = \sum_{w_k \in d} n(c|w_k, d) \quad n(c|w,d) = \sum_{s_w \in c} p(s_w|d)$$

- Sense based TF-IDF

$$tf(c,d) = n(c,d), idf(c) = \sum_{n(c,d)>1} 1$$

- Clustering Methods:
  - Cosine similarity
  - Hierarchical Agglomerative Clustering

How to use word sense in document clustering?(2/3)



Evaluation

- Setup
  - Development Dataset: Giga Word（ 2.1 million English documents and 3.5 million Chinese documents ）
  - Test Dataset: TDT4 and CLTC in both English and Chinese language
  - Evaluation criteria
    - Precision
    - Recall
    - F-Measure

Dataset	**English**	**Chinese**
TDT41	38/1270	37/657
TDT42	33/617	32/560
CLTC1	20/200	20/200
CLTC2	20/600	20/600

Experiment

- Methods:
  - VSM (Vector Space Model)
  - LDA(Latent Dirichlet Allocation)
  - LSSM (Local Sense Space Model)
  - GSSM (Global Sense Space Model)
- Result

Methods	CLTC1	CLTC2	TDT41	TDT42
VSM	0.886	0.898	0.894	0.924
LDA	0.832	0.891	0.789	0.854
LSSM	0.888	0.893	0.922	0.964
GSSM	0.905	0.918	0.926	0.964

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Conclusion and future work

- Our research on addressing synonymy and polysemy issues in document representation shows that document representation can be further improved with word sense.
- In this work, a new document represent model is proposed to make full use of global word sense.
  - The proposed model aims to well address the synonymy and polysemy issues
  - Experiments on four datasets of two language cases show that our proposed SCM model advances both baseline systems and LDA models in document clustering task in both language cases.
- In the future work, we will continue to evaluate the performance of our model with datasets of smaller samples, e.g., SMS messages and tweets.

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Thank you ！

Q&A