Multi-aspect Sentiment Analysis with Topic Models

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Motivation

• User reviews are rapidly growing in quantity and popularity.

• Typically:
  – Users write reviews and assign overall ratings.
  – Products are ranked based on their average overall rating.
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• Overall ratings can be too coarse.

• Restaurant 1:
  – OK service
  – OK food
  – Avg. overall rating: 3/5

• Restaurant 2:
  – Slow service
  – Great food
  – Avg. overall rating: 3/5
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Multi-aspect Sentiment Analysis with Topic Models
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• Users have different priorities.

• User 1:
  1. Ambiance
  2. Service
  3. Food
  4. Price

• User 2:
  1. Food
  2. Price
  3. Service
  4. Ambiance

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• **User 2:**
  1. Food
  2. Price
  3. Service
  4. Ambiance

Multi-aspect Sentiment Analysis with Topic Models
Motivation

• **MULTI-ASPECT SENTIMENT ANALYSIS:** Takes into account multiple, potentially related aspects often discussed within a single review.
  – e.g., food, service and ambiance for a restaurant review.
Motivation

“The food was very good, but it took over half an hour to be seated, ... and the service was terrible. The room was very noisy and cold wind blew in from a curtain next to our table. Desserts were very good, but because of [the] poor service, I’m not sure we’ll ever go back!”

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Outline

- Motivation
- **Approach / Models**
- Sentence Labeling
- Rating Prediction
- Conclusion

Multi-aspect Sentiment Analysis with Topic Models
Approach / Models

• Topic modeling:
  – Based on Latent Dirichlet Allocation (Blei et al., 2003).
  – Uncovers latent ‘topics’ in a document collection.
  – Topics are (kind of) like aspects.
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• Topic modeling:
  – Popular choice for multi-aspect sentiment analysis tasks.
  – Many models have been proposed.
  – We consider 4.
Approach / Models

• Original LDA (Blei et al., 2003):
  – An aspect is a distribution over words.
  – Each review is generated from a distribution over aspects.
Approach / Models

• Local LDA (Brody and Elhadad, 2010):
  – An aspect is a distribution over words.
  – Each sentence is generated from a distribution over aspects.
Approach / Models

• **Segmented Topic Model (Du et al., 2010):**
  – Each *review* is generated from a distribution over *aspects*.
  – Each *sentence* is generated from a distribution over *aspects*.
  – Pitman-Yor Process.
Approach / Models

• Multi-grain LDA (Titov and McDonald, 2008):
  – Each *sentence* is generated from a distribution over *global* topics and *local* aspects:
    • e.g., 10% Vancouver (global *topic*), 30% food, service and ambiance (local *aspects*).
Approach / Models

- (a) LDA.
- (b) Local LDA.
- (c) MG-LDA.
- (d) STM.

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- Multi-aspect sentence labeling:
  - Identify and extract relevant aspects for a rated entity.
  - Useful for creating aspect-specific comparative summaries.
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  - Label sentences according to topic distributions.
  - Need to map topics to aspects:
    - Not trivial.
    - Inform the prior with seed words.
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Multi-aspect Sentiment Analysis with Topic Models
Sentence Labeling

• Seed words:
  – Food: *food, chicken, beef, steak*.
  – Service: *service, staff, waiter, reservation*.
  – Ambiance: *ambiance, atmosphere, room, experience*.
Sentence Labeling

• Dataset:
  – 1,490 manually labeled sentences, from 652 restaurant reviews on CitySearch.com (Ganu et al., 2009).
  – Aspects: food, service, ambiance.
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  – Assign ratings (e.g., 1-5 ‘stars’) to each aspect of each review.
  – Useful for aspect-specific ranking.
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• Multi-aspect rating prediction:
  – Indirect supervision:
    • No gold-standard aspect ratings.
    • Assume overall ratings given.
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    • Train supervised SVM to predict overall ratings.
  • Apply to aspect-labeled sentences.
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• **Dataset:**
  – 66,512 reviews from TripAdvisor with overall, and 7 aspect ratings.
  – Not every review discusses every aspect:
    • Group reviews by hotel.

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• **Metrics:**
  
  – $\rho_{\text{aspect}}$: For a given hotel, how good is the relative ranking of aspects?
  
  – $\rho_{\text{hotel}}$: For a given aspect, how good is the relative ranking of hotels?
  
  – **Mean Average Precision @ K**: How well do we keep the top K hotels in the top K spots?
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• Seed words can be incorporated into topic models to accurately label sentences according to aspect.
• Topic models can help predict aspect-ratings given only overall ratings.
• Features derived from topic models contribute little to a fully supervised support-vector regression learner.
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Thank you. Questions?

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• Topic models can help predict aspect-ratings given only overall ratings.
• Features derived from topic models contribute little to a fully supervised support-vector regression learner.