Multi-aspect Sentiment Analysis with Topic Models

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- 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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- **Restaurant 1:**
  - OK service
  - OK food
  - Avg. overall rating: 3/5
- **Restaurant 2:**
  - Slow service
  - Great food
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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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  2. Service
  3. Food
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- **User 2**:
  1. Food
  2. Price
  3. Service
  4. Ambiance

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

Approach / Models

- **Topic modeling**:
  - Based on Latent Dirichlet Allocation (Blei et al., 2003).
  - Uncovers latent ‘topics’ in a document collection.
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Approach / Models

- **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*.

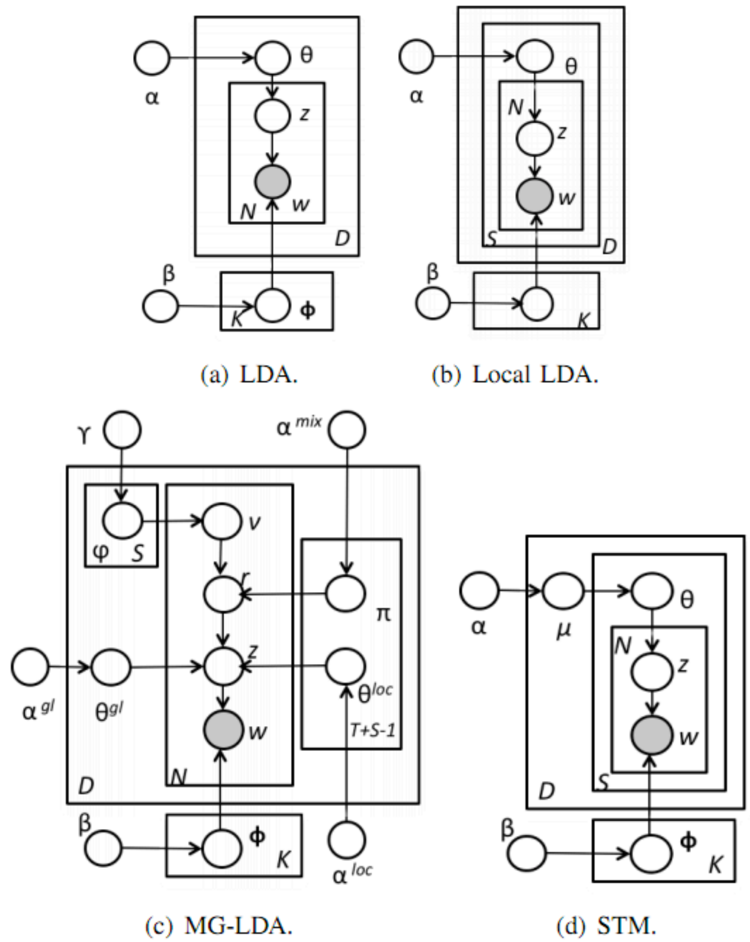
Approach / Models

- **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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  - Identify and extract relevant aspects for a rated entity.
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- **Seed words**:
  - Food: *food, chicken, beef, steak.*
  - Service: *service, staff, waiter, reservation.*
  - Ambiance: *ambiance, atmosphere, room, experience.*

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  - 1,490 manually labeled sentences, from 652 restaurant reviews on CitySearch.com (Ganu et al., 2009).
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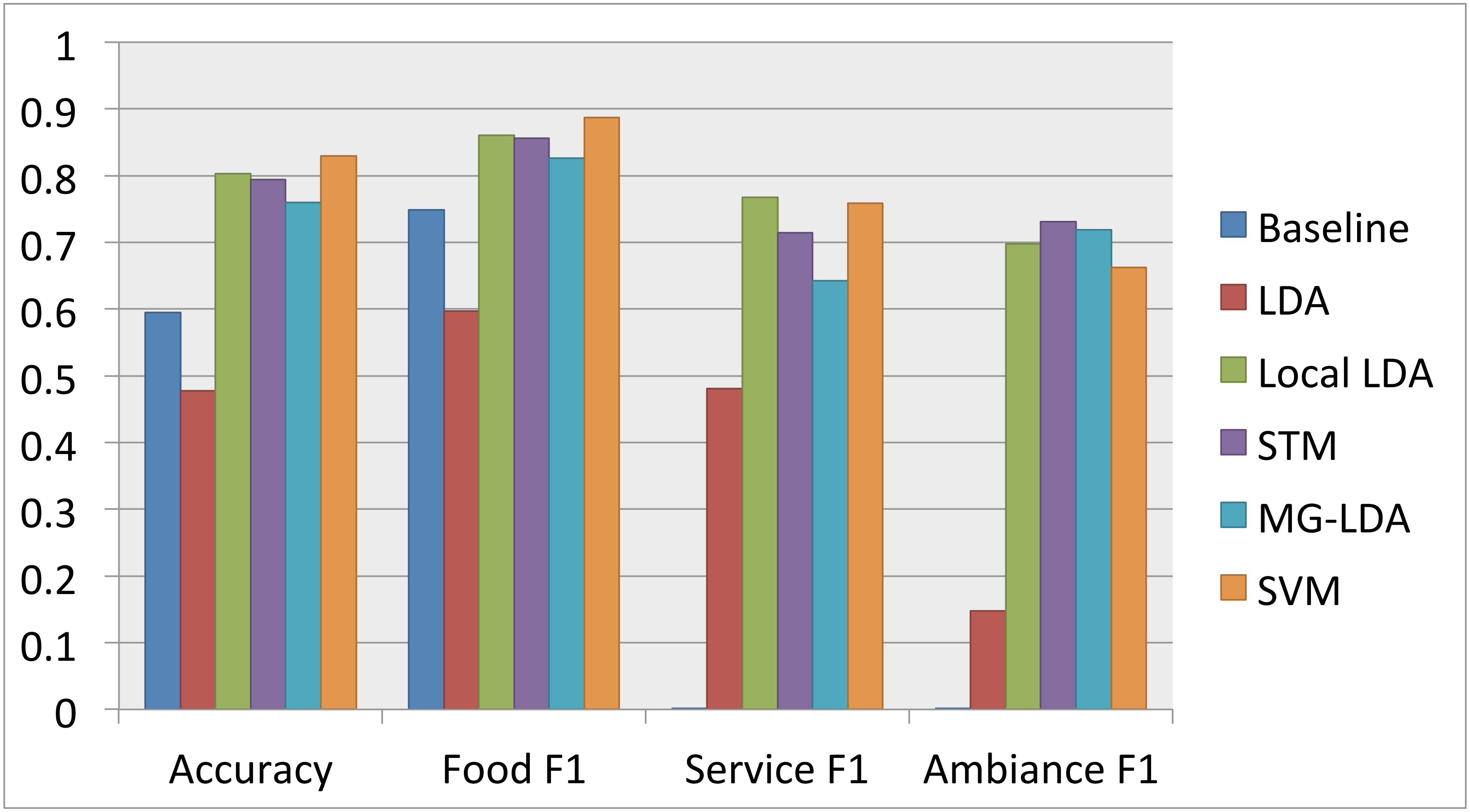

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  - Indirect supervision:
    - No gold-standard aspect ratings.
    - Assume overall ratings given.

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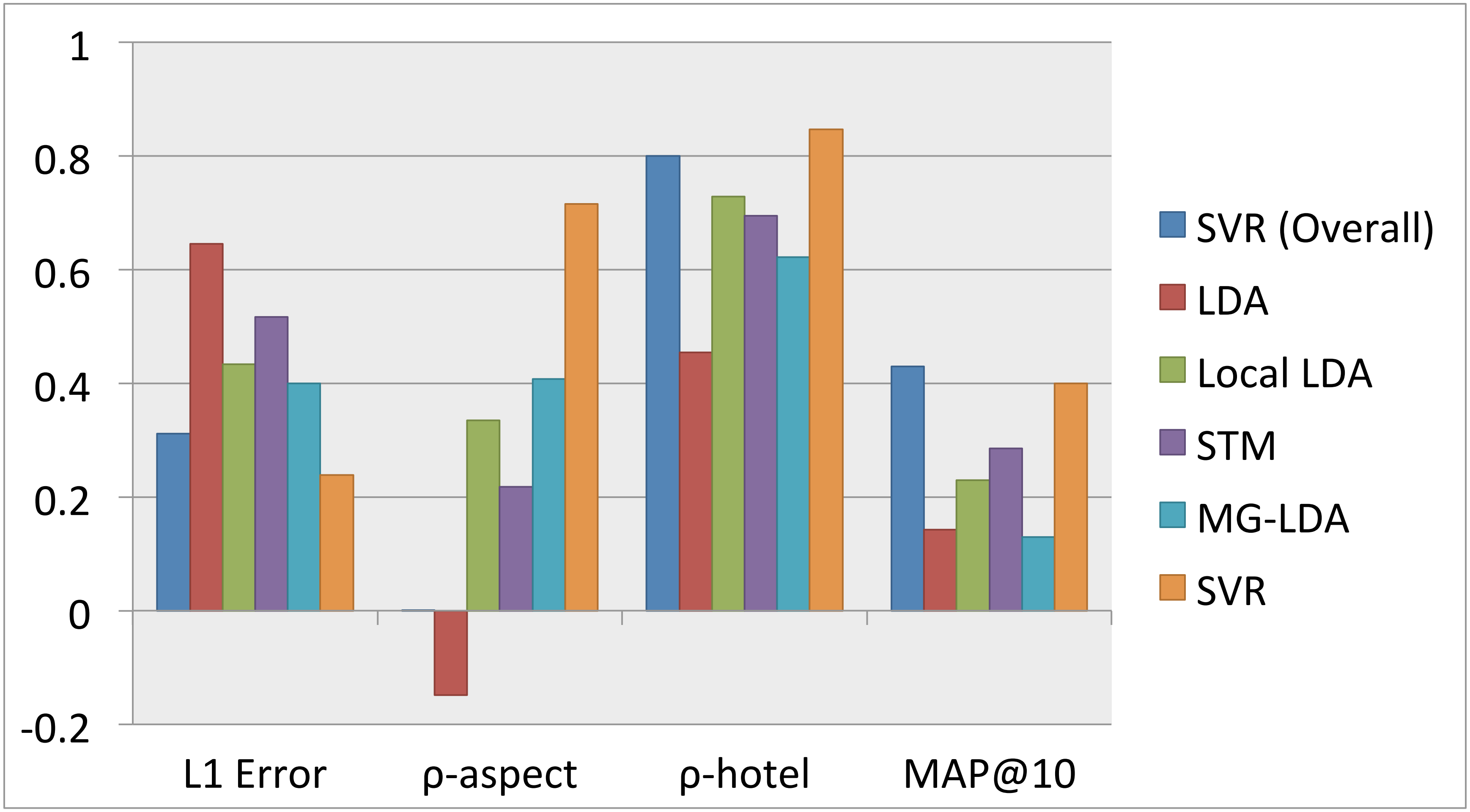

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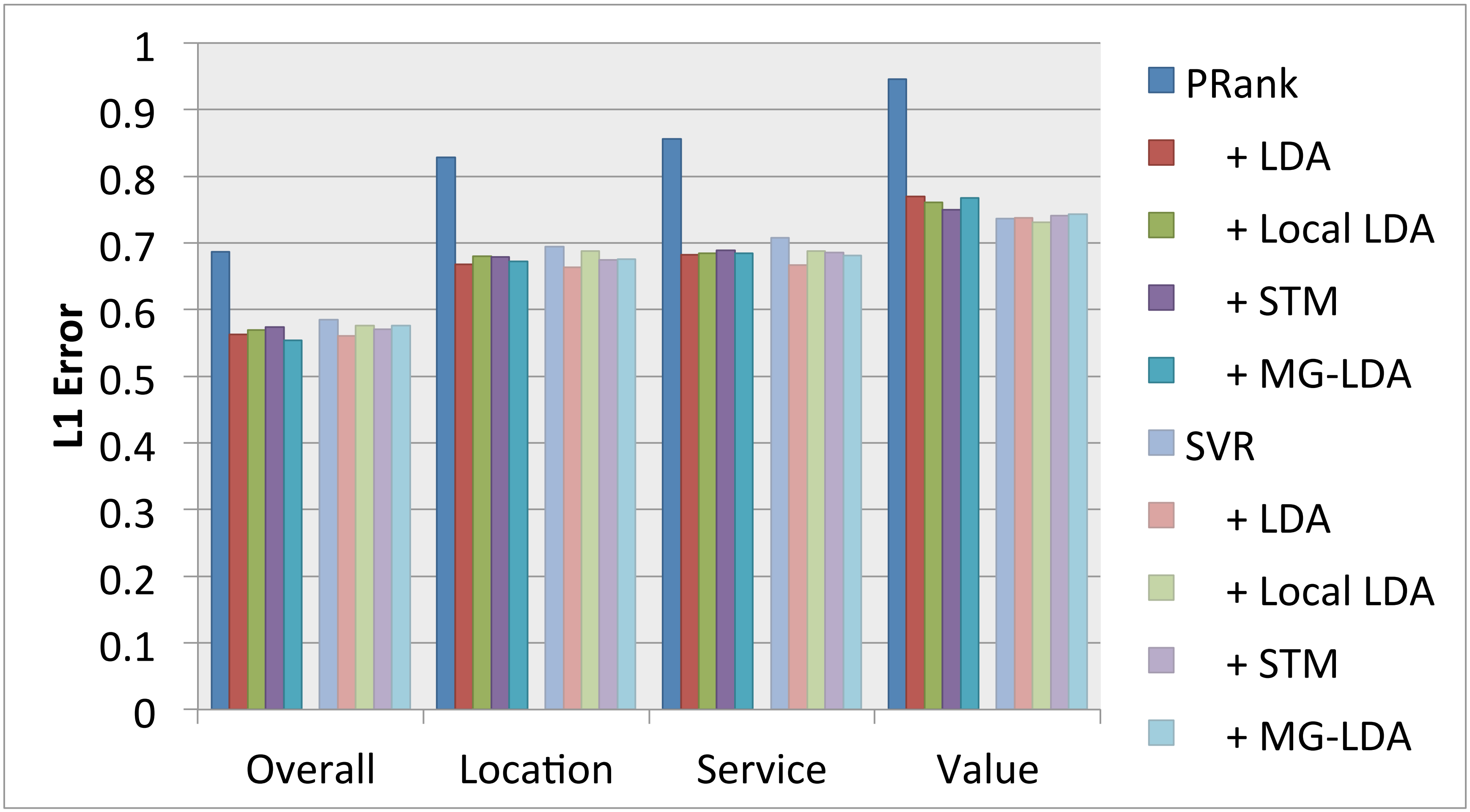

Multi-aspect Sentiment Analysis with Topic Models

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Thank you. Questions?

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- Features derived from topic models contribute little to a fully supervised support-vector regression learner.