Latent Aspect Rating Analysis

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Online opinions cover all kinds of topics

**Topics:**
- People
- Events
- Products
- Services, ...

**Sources:**
- 45M reviews
- 53M blogs
- 340M msgs/day
- 115M users
- 1307M posts
- 10M groups

...
Reviews: helpful resource for decision making
However, it’s not easy for users to make use of the online opinions

• Too much information!
However, it’s not easy for users to make use of the online opinions

- Inconsistent opinion!
Information overload

How can I collect all opinions?

How can I digest them all?

What should I do based on their options?

How can I ...?
Opinion mining in review text data

• Sentiment orientation identification
  • E.g., Pang et.al 2002, Turney 2002
  • Solution
    • Supervised: classification/regression problem
    • Unsupervised: domain-specific sentiment lexicon

“Location good, everything else bad - avoid”

Reviewed May 24, 2011

Pros - About 2 blocks from Tien an men square & Forbidden city - Close to shopping including (near the square, across street into underground mall, or on pedestrian street next to hotel) Cons The lobby looks promising but it ends there. This is not a 4 or 5 star hotel by world standards. Closer to a 2 star -...
Opinion mining in review text data

• Aspect-based sentiment analysis
  • E.g., Hu and Liu KDD’04, Liu et al. WWW’05
  • Solution
    • Frequent pattern mining based on syntax analysis for aspect identification
    • Sentiment lexicon for opinion orientation prediction

Comparison of opinions between two digital cameras
How do we identify the latent aspects and decompose overall ratings into aspect ratings?

Existing work:

Sentiment polarity identification [Pang et. al EMNLP'02, Pang et. al ACL'02, Turney ACL'02]
How do we infer the preferences that the reviewers have put onto the aspects?

No existing work
“A lot of history in this comfortable hotel”
Ambassador East Hotel

Overall Rating: ★★★★★
candostill 47 contributions
Western Michigan, USA
Dec 28, 2010

The bathrooms are small with little counter space and the hotel is on the edge of needing some updating, but I have found each of my 3 trips to this hotel comfortable with a reasonable price. The Pump Room is a treat and breakfast has always been excellent. The hotel staff is friendly and helpful. The hotel is situated within walking distance to many restaurants and bars. I wouldn't recommend the hotel to families with small children but great for couples.
Latent Aspect Rating Analysis (LARA) [KDD’10/KDD’11]

“A lot of history in this comfortable hotel”
Ambassador East Hotel
Overall Rating: 5

The bathrooms are small with little counter space and the hotel is on the edge of needing some updating, but I have found each of my 3 trips to this hotel comfortable with a reasonable price. The Pump Room is a treat and breakfast has always been excellent. The hotel staff is friendly and helpful. The hotel is situated within walking distance to many restaurants and bars. I wouldn’t recommend the hotel to families with small children but great for couples.

Aspect ratings and weights predicted for this hotel:
- Value: 4 (0.41)
- Location: 2 (0.11)
- Rooms: 4 (0.32)
- Service: 3 (0.16)

Text Content
Aspect Identification
Aspect Rating Prediction
Aspect Weight Prediction
Excellent location in walking distance to Tiananmen Square and shopping streets. That’s the best part of this hotel! The rooms are getting really old. Bathroom was nasty. The fixtures were falling off, lots of cracks and everything looked dirty. I don’t think it worth the price. Service was the most disappointing part, especially the door men. This is not how you treat guests, this is not hospitality.
Latent Aspect Rating Analysis Model

• Unified framework

“Spend your money elsewhere”
Reviewed September 19, 2010
Excellent location in walking distance to Tiananmen Square and shopping streets. That’s the best part of this hotel! The rooms are getting really old. Bathroom was nasty. The fixtures were falling off, lots of cracks and everything looked dirty. I don’t think it worth the price. Service was the most disappointing part, especially the door men. this is not how you treat guests, this is not hospitality.

Variables of interest
1. word-aspect assignment \( z \)
2. aspect rating \( s_i \)
3. aspect weight \( \alpha \)
Posterior inference

• Variational inference
  • Maximize lower bound of log-likelihood function

\[
\log p(r, W | \epsilon, \gamma, \beta, \mu, \Sigma, \delta^2) \\
= \log p(W | \epsilon, \gamma) + \log p(r | W, \beta, \mu, \Sigma, \delta^2) \\
\geq E_q[\log p(z, \theta, W | \epsilon, \gamma)] - E_q[\log q(z, \theta | \phi, \eta)] \\
+ E_q[\log p(r, \alpha, z | W, \beta, \mu, \Sigma, \delta^2)] - E_q[\log q(\alpha, z | \epsilon, \gamma, \phi, \eta)]
\]

• Insight: bridge - aspect assignment \( \{z_n\}_{n=1}^{d} \)

\[
\hat{\phi}_n = \arg \max \sum_{i=1}^{k} w_n^i \phi_{ni} [\psi(\eta_i) - \psi(\sum_{j=1}^{k} \eta_j) + w_n^i \log \epsilon_{ij} - \log \phi_{ni}] \\
- \frac{1}{2\delta^2}(\lambda^T \bar{s} - r)^2 - \frac{1}{2\delta^2} \sum_{i=1}^{k} \left[ (\lambda_i^2 + \sigma_i^2) Var[s_i] + \sigma_i^2 \bar{s}_i^2 \right]
\]

As aspect modeling part

Rating prediction part

LARA

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Model estimation

• Expectation Maximization
  • E-step: constrained posterior inference
  • M-step: maximizing log-likelihood of whole corpus

• Insight

\[
\hat{\beta} = \arg\max_{\beta} \log p(r, W|\epsilon, \gamma, \beta, \mu, \Sigma, \delta^2) \\
\geq E_q[\log p(z, \theta, W|\epsilon, \gamma)] - E_q[\log q(z|\phi, \eta)] \\
+ E_q[\log p(r, \alpha, z|W, \beta, \mu, \Sigma, \delta^2)] - E_q[\log q(\alpha, z|\epsilon, \gamma, \phi, \eta)]
\]

Alternative understanding of EM: coordinate ascent optimization
Model discussion

• Aspect modeling part
  • Identify word usage pattern
  • Leverage opinion ratings to analyze text content

• Rating analyzing part
  • Model uncertainty from aspect segmentation
  • Informative feedback for aspect segmentation
Comparison with Bing Shopping

SCORECARD: SCREEN (See all)

23 positive reviews | 6 negative reviews

The touch screen is easier to use than we expected, and the multimedia performs well.

SCORECARD: CAMERA (See all)

18 positive reviews | 18 negative reviews

Critics aside, the iPhone display is remarkable for its multitouch technology, which allows you to move your finger in a variety of ways to manipulate what's on the screen.
Experiment results

• Data Set
  • Hotel reviews from TripAdvisor.com
  • MP3 player reviews from Amazon.com

<table>
<thead>
<tr>
<th></th>
<th>#Item</th>
<th>#Review</th>
<th>#Reviewer</th>
<th>Avg. Len</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hotel</td>
<td>2,232</td>
<td>37,181</td>
<td>34,187</td>
<td>96.5</td>
<td>3.92±1.23</td>
</tr>
<tr>
<td>MP3</td>
<td>686</td>
<td>16,680</td>
<td>15,004</td>
<td>87.3</td>
<td>3.76±1.41</td>
</tr>
</tbody>
</table>
Identifying mostly commented aspects

- Amazon MP3 player reviews: no guidance

<table>
<thead>
<tr>
<th>In Low Overall Rating Reviews</th>
<th>In High Overall Rating Reviews</th>
</tr>
</thead>
<tbody>
<tr>
<td>unit</td>
<td>jack</td>
</tr>
<tr>
<td>usb</td>
<td>headphone</td>
</tr>
<tr>
<td>battery</td>
<td>warranty</td>
</tr>
<tr>
<td>charger</td>
<td>replacement</td>
</tr>
<tr>
<td>reset</td>
<td>problem</td>
</tr>
<tr>
<td>time</td>
<td>player</td>
</tr>
<tr>
<td>hours</td>
<td>back</td>
</tr>
<tr>
<td>work</td>
<td>months</td>
</tr>
<tr>
<td>thing</td>
<td>buy</td>
</tr>
<tr>
<td>wall</td>
<td>amazon</td>
</tr>
</tbody>
</table>

**Selected Terms:**
- battery life
- accessory
- service
- file format
- volume
- video
Quantitative evaluation of identified aspects

• KL divergency between the identified word-aspect distribution and “ground-truth” distribution in TripAdvisor hotel reviews

<table>
<thead>
<tr>
<th></th>
<th>LDA</th>
<th>sLDA</th>
<th>LARAM</th>
</tr>
</thead>
<tbody>
<tr>
<td>7 topics</td>
<td>5.675</td>
<td>14.878</td>
<td>5.827</td>
</tr>
<tr>
<td>14 topics</td>
<td>8.819</td>
<td>19.074</td>
<td>8.356</td>
</tr>
<tr>
<td>21 topics</td>
<td>12.745</td>
<td>22.411</td>
<td>11.167</td>
</tr>
</tbody>
</table>
Opinion rating decomposition

• Hotels with the same overall rating but different aspect ratings

<table>
<thead>
<tr>
<th>Hotel</th>
<th>Value</th>
<th>Room</th>
<th>Location</th>
<th>Cleanliness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grand Mirage Resort</td>
<td>4.2(4.7)</td>
<td>3.8(3.1)</td>
<td>4.0(4.2)</td>
<td>4.1(4.2)</td>
</tr>
<tr>
<td>Gold Coast Hotel</td>
<td>4.3(4.0)</td>
<td>3.9(3.3)</td>
<td>3.7(3.1)</td>
<td>4.2(4.7)</td>
</tr>
<tr>
<td>Eurostars Grand Marina Hotel</td>
<td>3.7(3.8)</td>
<td>4.4(3.8)</td>
<td>4.1(4.9)</td>
<td>4.5(4.8)</td>
</tr>
</tbody>
</table>

(All 5 Stars hotels, ground-truth in parenthesis.)

• Reveal detailed opinions at the aspect level
Accuracy of aspect rating prediction

• Ground-truth aspect ratings in hotel reviews
  two-step approach: topic model + aspect rating prediction

<table>
<thead>
<tr>
<th></th>
<th>LDA+LRR</th>
<th>sLDA+LRR</th>
<th>LARAM</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MSE</strong></td>
<td>2.130</td>
<td>2.360</td>
<td>1.234</td>
</tr>
<tr>
<td>(\rho_{aspect})</td>
<td>0.080</td>
<td>0.079</td>
<td>0.228</td>
</tr>
<tr>
<td>(\text{Mis}_{aspect})</td>
<td>0.439</td>
<td>0.439</td>
<td>0.387</td>
</tr>
<tr>
<td>(\text{nDCG}_{aspect})</td>
<td>0.860</td>
<td>0.886</td>
<td>0.901</td>
</tr>
<tr>
<td>(\rho_{hotel})</td>
<td>0.558</td>
<td>0.450</td>
<td>0.622</td>
</tr>
<tr>
<td>(\text{MAP}_{hotel@10})</td>
<td>0.427</td>
<td>0.437</td>
<td>0.436</td>
</tr>
</tbody>
</table>

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Corpus-specific word sentimental orientation

• Reveal sentimental information directly from the data

<table>
<thead>
<tr>
<th>Value</th>
<th>Rooms</th>
<th>Location</th>
<th>Cleanliness</th>
</tr>
</thead>
<tbody>
<tr>
<td>resort 22.80</td>
<td>view 28.05</td>
<td>restaurant 24.47</td>
<td>clean 55.35</td>
</tr>
<tr>
<td>value 19.64</td>
<td>comfortable 23.15</td>
<td>walk 18.89</td>
<td>smell 14.38</td>
</tr>
<tr>
<td>excellent 19.54</td>
<td>modern 15.82</td>
<td>bus 14.32</td>
<td>linen 14.25</td>
</tr>
<tr>
<td>worth 19.20</td>
<td>quiet 15.37</td>
<td>beach 14.11</td>
<td>maintain 13.51</td>
</tr>
<tr>
<td>bad -24.09</td>
<td>carpet -9.88</td>
<td>wall -11.70</td>
<td>smelly -0.53</td>
</tr>
<tr>
<td>money -11.02</td>
<td>smell -8.83</td>
<td>bad -5.40</td>
<td>urine -0.43</td>
</tr>
<tr>
<td>terrible -10.01</td>
<td>dirty -7.85</td>
<td>road -2.90</td>
<td>filthy -0.42</td>
</tr>
<tr>
<td>overprice -9.06</td>
<td>stain -5.85</td>
<td>website -1.67</td>
<td>dingy -0.38</td>
</tr>
</tbody>
</table>
Reviewer rating behavior analysis

• Reviewers focus differently on ‘expensive’ and ‘cheap’ hotels

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Expensive Hotel</th>
<th>Cheap Hotel</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>5 Stars</td>
<td>3 Stars</td>
</tr>
<tr>
<td>Value</td>
<td>0.134</td>
<td>0.148</td>
</tr>
<tr>
<td>Room</td>
<td>0.098</td>
<td>0.162</td>
</tr>
<tr>
<td>Location</td>
<td>0.171</td>
<td>0.074</td>
</tr>
<tr>
<td>Cleanliness</td>
<td>0.081</td>
<td>0.163</td>
</tr>
<tr>
<td>Service</td>
<td>0.251</td>
<td>0.101</td>
</tr>
</tbody>
</table>
Inferring user aspect preferences

- Reviewers emphasize ‘value’ aspect would prefer ‘cheap’ hotels

<table>
<thead>
<tr>
<th>City</th>
<th>AvgPrice</th>
<th>Group</th>
<th>Value/Location</th>
<th>Value/Room</th>
<th>Value/Service</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amsterdam</td>
<td>$241</td>
<td>top-10</td>
<td>$190</td>
<td>$214</td>
<td>$221</td>
</tr>
<tr>
<td></td>
<td></td>
<td>bot-10</td>
<td>$270</td>
<td>$333</td>
<td>$236</td>
</tr>
<tr>
<td>San Francisco</td>
<td>$261</td>
<td>top-10</td>
<td>$214</td>
<td>$249</td>
<td>$225</td>
</tr>
<tr>
<td></td>
<td></td>
<td>bot-10</td>
<td>$321</td>
<td>$311</td>
<td>$311</td>
</tr>
<tr>
<td>Florence</td>
<td>$272</td>
<td>top-10</td>
<td>$269</td>
<td>$248</td>
<td>$220</td>
</tr>
<tr>
<td></td>
<td></td>
<td>bot-10</td>
<td>$298</td>
<td>$293</td>
<td>$292</td>
</tr>
</tbody>
</table>
User profiling

• Inferred aspect weight as user profile
  • Similar users give same entity similar overall rating
  • Cluster users by the inferred aspect weight
Analysis

• Limitation: bag-of-words assumption

hotel_100587Parsed_TravelGirl222 5 4.32456

Value 5: 4.23087 Room 5: 4.62536 Location 5: 4.78819 Cleanliness 5: 4.21941
Check-in 5: 4.14636 Service 5: 3.98103 Business Service 3: 3.8463

Great Boutique Hotel - Loved It! I stayed at Hotel Max for a week during a business trip to Seattle. I really enjoyed my stay - the service was REALLY good and everyone was very friendly. Whenever I asked for anything, I got it in 15 minutes or less. The hotel is artsy and fun, a vast improvement over the generic mega-chains available nearby for 2x the price. My room was smaller but perfectly adequate, the decor was contemporary and I LOVED the bed - excellent quality on par with the Westin 'heavenly' bed. Location was also excellent - just around the corner from the retail core and walking distance to any of the major tourist attractions in downtown Seattle. Really a great deal for downtown Seattle.
Review Miner system

1) 27K hotels with 2M reviews
2) 15K products with 472K reviews
3) 12K restaurants with 230K reviews
4) 129 medications with 15k reviews
System architecture

1. Data crawling module, evoke periodically

2. Natural language query parser

3. Multi-modal opinion analysis and display

4. User behavior logging

5. Aspect-based user modeling

LARA

LARA

LARA
Conclusions

• Latent Aspect Rating Analysis
  • Unified framework for exploring review text data with companion overall ratings
  • Simultaneously discover latent topical aspects, aspect ratings and weights
  • A multi-modal opinion analysis and decision support system

• Limitation
  • Bag-of-words assumption

• Future work
  • Incorporate sentence boundary/proximity information
  • Address aspect sparsity in review content
References


• Hu, M., & Liu, B. Mining and summarizing customer reviews. In Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 168-177). ACM.


Thank you!

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