Perceptual Relational Attributes: Navigating and Discovering Shared Perspectives from User-Generated Reviews

Manuel Valle, Christoph Lofi, Mengmeng Ye
Modelling the video-store clerk: what do we need?

• Users’ perception of the movie
  – Viewer: “I liked the story, it’s a lovely adaptation of the book”

• Major consensus groups in perceptions
  – Some people think it’s nice and slow, while others think it’s a great novel adaptation with a beautiful story

• Use one of the multiple shared views to find similar movies
  – Store clerk: “You want something like X with respect to good story and book adaptation, so I think you will love Y”
Challenges:

• Perceptual Features are inherently subjective, different and even contradicting
  – How can we model such a schema?
• There are hundreds of individual perceptions
  – Single/movie representation can’t tell the whole story
• Constructing queries for perceptions is difficult, especially if the user doesn’t know their target
  – How can we simplify this process?
How to get there:

• Infer customer’s perception from available sources
  – Extract representation from social judgements: reviews

• Group similar perceptions together
  – Apply clustering algorithms to inferred representations

• Use Query by Example to find similar movies with respect to a specific perspective
  – Explore iteratively until the user finds the implicit target: “I’ll know it when I see it”
Concepts: From Perception to Perceptual Attributes and Shared Perspectives

- Perception
- Perceptual Attribute
- Perceptual Tuple
- Shared Perspective

emotionality, funniness, action, romanticism

9, 0, 5, 8

9, 0, 5, 8
8, 1, 5, 7
10, 0, 4, 9
5, 2, 5, 1
6, 1, 5, 0
5, 0, 4, 1
User Application
Social Judgements: Reviews

- Rich perceptions
- Important for online decisions
- Commonly used in research
  - Analysis per item, feature, review
- Our dataset:
  - 375K reviews
  - 2041 movies
  - 100-300 reviews per movie
Ok, so it did not deserve best picture. It was still excellent. It has great performances in it. Particularly the guy who never was very famous Michael Jeter or whatever his name is. I love the visuals. I cried at the end. Michael Clarke Duncan is great.
Perceptual Attributes - Explicit vs Implicit

Acting: 3.43/5
Directing: None
Scenery: 3.12/5
Character: 3.43/5
Storyline: None

Ok, so it did not deserve best picture. It was still excellent. It has great performances in it. Particularly the guy who never was very famous Michael Jeter or whatever his name is. I love the visuals. I cried at the end. Michael Clarke Duncan is great.
Ok, so it did not deserve best picture. It was still excellent. It has great performances in it. Particularly the guy who never was very famous Michael Jeter or whatever his name is. I love the visuals. I cried at the end. Michael Clarke Duncan is great.

**Perceptual Attributes - *Explicit vs Implicit***

- **Acting:** 3.43/5
- **Directing:** None
- **Scenery:** 3.12/5
- **Character:** 3.43/5
- **Storyline:** None

Modelling perceptual attributes is hard!

- Subjective
- Usually contradictory
- Constantly changing

...
Movie Modelling Experiment

• 180 second year university BSc students (in pairs)
• Create a ranked list of perceptual attributes for movies – What is IMDB missing?
• Results:
  – 6.5 average attributes per team (min 4 – max 10)
  – 74 teams mentioned “storyline”
  – 72 mentioned “acting”
  – Roughly 50% “scenery”, “character”, or “directing”
Movie Modelling Experiment

- 180 second year university BSc students (in pairs)
- Create a ranked list of perceptual attributes for movies – *What is IMDB missing?*
- Results:
  - 6.5 average att
  - 74 teams mentioned
  - 72 mentioned ‘
  - Roughly 50% ‘
  - 4 – max 10)
  - Lots of complaints or “directing”
Ok, so it did not deserve best picture. It was still excellent. It has great performances in it. Particularly the guy who never was very famous, Michael Jeter or whatever his name is. I love the visuals. I cried at the end. Michael Clarke Duncan is great.

\[
\begin{align*}
d_0 &: 0.00548 \\
d_1 &: -1.02489 \\
&\vdots \\
d_{98} &: 0.58937 \\
d_{99} &: 1.25607
\end{align*}
\]
Ok, so it did not deserve best picture. It was still excellent. It has great performances in it. Particularly the guy who never was very famous Michael Jeter or whatever his name is. I love the visuals. I cried at the end. Michael Clarke Duncan is great.

- Hundreds of perceptions
- Implicit values have no meaning for humans
- Impossible to query

\[
d_0: 0.00548 \\
d_1: -1.02489 \\
\ldots \\
d_{98}: 0.58937 \\
d_{99}: 1.25607
\]
Constructing Shared Perspectives

• Current - Single representation, seems counterintuitive
  – Twilight: powerful romance or shame to vampires?

• Proposal - Group together similar perceptions = with similar *perceptual tuples*
  – Twilight: Why not both?

• Algorithm that can leverage similarity between Perceptual Tuples to create groups, use centers
  – Cool...still un-queryable
A supernatural tale set on death row in a Southern prison, where gentle giant John Coffey possesses the mysterious power to heal people’s ailments. When the warden’s head guard, Paul Edgecomb, recognizes Coffey’s miraculous gift, he tries desperately to help stave off the condemned man’s execution.

Selected Movie

Official movie overview

Emotional and touching

Great acting, good story from book

Long but worth it, good actors

Select next movie below

Next Set
Evaluation: Performance

• Can Shared Perspectives improve the query process of items with Perceptual Attributes?
  – Simulate User Interaction with Current Similarity Search vs Shared Perspectives
Acclaimed prison movie with Tom Hanks that everyone should watch.
Emotional and touching movie

Great acting with good story from a book

Long but worth it, great movie w/ good actors
Evaluation: Performance

• Can Shared Perspectives improve the query process of items with Perceptual Attributes?
  – Evaluate: Simulate User with Current vs Proposed System (not SQL queries or Recommendation)
  – Metric: Query Iterations from Starting movie to Target movie (the only user input)
  – Challenge: Subjectivity, how to define movie pairs?
Evaluation: Performance

- Simulated QBE User Behavior
  - Predefined, random pairs of start and target movie
  - Count the query iterations
  - In average, SPs should outperform SR
Simulated User
Simulated User: Single Representation

Generate display

Select movie most similar to target

Repeat
Simulated User: Shared Perspectives

Generate display

Select movie most similar to target

Repeat
Results – 100 Pairs

- In average, 30% fewer steps from start to target item using Shared Perspectives
- Main issue, pairs with many iterations (up to 200)

<table>
<thead>
<tr>
<th>Pairs</th>
<th>Single Representation</th>
<th>Shared Perspectives</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>40.58</td>
<td>32.54</td>
</tr>
</tbody>
</table>
Qualitative Analysis

• 2 steps from romantic comedy to sci-fi because of “unexpected good acting, refreshing to the genre” ✓

• 96 steps from horror to musical because “it looks better on Blu-ray than VHS” ×

• 200 steps from drama/comedy to romantic comedy because all SP of target “looked good but it’s just alright” ×
Evaluation: Semantic Quality

1. Ask users to rate some SPs to obtain their Usefulness Scores
2. Model this Score as a function of available data
3. Predict the Score of all SPs and Evaluate in Simulation
Usefulness Score: Asking Users
Simulated User: Shared Perspectives

Generate display

Display 

Select movie most similar to target

Display 

New set

Repeat
Simulated User: Shared Perspectives

- Generate display
- Select movie most similar to target
  - Boost ‘high quality’ perspectives
- Repeat
Results – 100 Pairs

• Optimize “selection” step:

<table>
<thead>
<tr>
<th>Pairs</th>
<th>Single Representation</th>
<th>Three Shared Perspectives</th>
<th>Three SP + Usefulness</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>40.58</td>
<td>32.54</td>
<td>31.56</td>
</tr>
</tbody>
</table>

• Improvement for pairs with unusually high results
• More importantly: Implementation
In summary

- Some entity types require **perceptual features** to be effectively queryable
- Perceptual features can be **extracted** from user feedback
- User feedback is often conflicting
  - Current single-representations lose information!
  - Grouping perceptual features into **Shared Perspectives** covers this well
- Shared perspectives can be effectively used for **Query-by-Example similarity queries**
Perceptual Relational Attributes: Navigating and Discovering Shared Perspectives from User-Generated Reviews

Manuel Valle, Christoph Lofi, Mengmeng Ye
## Table of students’ features

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Sum Importance</th>
<th>Avg Importance</th>
<th>mentions</th>
</tr>
</thead>
<tbody>
<tr>
<td>storyline</td>
<td>346</td>
<td>4.67</td>
<td>74</td>
</tr>
<tr>
<td>acting</td>
<td>341</td>
<td>4.73</td>
<td>72</td>
</tr>
<tr>
<td>scenery</td>
<td>197</td>
<td>4.10</td>
<td>48</td>
</tr>
<tr>
<td>character</td>
<td>186</td>
<td>4.53</td>
<td>41</td>
</tr>
<tr>
<td>directing</td>
<td>177</td>
<td>4.43</td>
<td>40</td>
</tr>
<tr>
<td>sound</td>
<td>162</td>
<td>2.74</td>
<td>59</td>
</tr>
<tr>
<td>humor</td>
<td>160</td>
<td>3.01</td>
<td>53</td>
</tr>
<tr>
<td>originality</td>
<td>67</td>
<td>2.48</td>
<td>27</td>
</tr>
<tr>
<td>pace</td>
<td>49</td>
<td>3.06</td>
<td>16</td>
</tr>
<tr>
<td>cinematography</td>
<td>46</td>
<td>2.70</td>
<td>17</td>
</tr>
<tr>
<td>child friendliness</td>
<td>3</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>babes</td>
<td>2</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>morality</td>
<td>2</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>animal friendliness</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Disney’ishness</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
K-MEDOIDS

- Spherical k-medoids for Document Embeddings: Partitions the available tuples into $k$ clusters.
  - Cosine distance: angle between tuples
  - The medoid is the central datapoint
  - Determine $k$ by applying the “elbow method”: 3 clusters in average
  - Same number of clusters for all movies, for consistency