Sentiment Aggregation using ConceptNet Ontology

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7th International Joint Conference on Natural Language Processing (IJCNLP 2013), Nagoya, Japan
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Sentiment Analysis
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• Classify a review as positive, negative or objective

• I bought a phone
• The audio quality of the phone is awesome
• The picture quality of its camera is bad

• The audio quality of my new phone is absolutely awesome but the picture taken by the camera is a bit grainy
  • A bag-of-words model will classify it as neutral
  • Feature-specific SA finds polarity w.r.t audio as positive and that w.r.t picture as negative
  • But does not say how to aggregate the polarities
Sentiment Analysis

- Classify a review as *positive*, *negative* or *objective*

- I bought a phone 😞
- The audio quality of the phone is awesome 😊
- The picture quality of its camera is bad 😞

- The **audio** quality of my new phone is absolutely awesome but the **picture** taken by the camera is a bit grainy
  - A bag-of-words model will classify it as *neutral*
  - Feature-specific SA finds polarity w.r.t **audio** as *positive* and that w.r.t **picture** as *negative*
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Example Review

- I bought a Canon EOS 7D (DSLR). It's very small, sturdy, and constructed well. The handling is quite nice with a powder-coated metal frame. It powers on quickly and the menus are fairly easy to navigate. The video modes are nice, too. It works great with my 8GB Eye-Fi SD card. A new camera isn't worth it if it doesn't exceed the picture quality of my old 5Mpixel SD400 and this one doesn't. The auto white balance is poor. I'd need to properly balance every picture taken so far with the ELPH 300. With 12 Mpixels, you'd expect pretty good images, but the problem is that the ELPH 300 compression is turned up so high that the sensor's acuity gets lost (softened) in compression.
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Analyzing Reviews
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- Reviewer happy with camera size, structure, easy use, video modes, SDHC support etc.

- However, the auto-white balance, high compression leading to sensor acuity seems to disappoint him

- Picture, video quality, resolution, color balance etc. are of primary importance to a camera whereas size, video mode, easy use etc. are secondary

- Overall review polarity is negative as the reviewer shows concerns about the most important features of the camera

- Traditional works in sentiment analysis view a review as a flat structure where the association between features of a product is largely ignored

- How to capture the association between features of a product?
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• How to capture the association between features of a product?
Camera Ontology Tree Snapshot

Camera
- body
  - accessories
  - card
  - handling
  - menus
  - size
- lens
  - glass
  - shutter
  - magnify
- flash
- picture
  - light
  - resolution
  - color
  - compression
- delay
- video
  - time
  - capture
  - image resolution
  - mode
Ontology
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- Ontology is a knowledge base of structured list of concepts, relations and individuals

- Hierarchical relationship between the product attributes can be best captured by an Ontology Tree

- Ontology creation is expensive, highly domain-specific

- In this work, we use ConceptNet (Hugo et al., 2004) to automatically construct a domain-specific ontology tree for product reviews

- ConceptNet is a very large semantic network of common sense knowledge

- Largest, machine-usable common sense resource consisting of more than 250,000 propositions
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ConceptNet Relations Contd…
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• We categorize ConceptNet relations into 3 primary categories: **hierarchical**, **synonymous** and **functional**

• *Hierarchical* relations represent parent-child relations
  • Transitive, used to construct tree *top-down*

• *Synonymous* relations identify related concepts
  • Similar nodes merged during tree construction

• *Functional* relations identify property of interest of a concept
  • The relation categorization helps to weigh various relations differently
We categorize ConceptNet relations into 3 primary categories: \textit{hierarchical, synonymous} and \textit{functional}.

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ConceptNet Relations

- Closed class of 24 primary relations expressing connections between various concepts

<table>
<thead>
<tr>
<th>camera UsedFor take_picture</th>
</tr>
</thead>
<tbody>
<tr>
<td>camera IsA tool_for_take_picture</td>
</tr>
<tr>
<td>camera AtLocation store</td>
</tr>
<tr>
<td>tripod UsedFor keep_camera_steady</td>
</tr>
<tr>
<td>camera CapableOf record_image</td>
</tr>
<tr>
<td>camera IsA device</td>
</tr>
<tr>
<td>flash PartOf camera</td>
</tr>
<tr>
<td>lens AtLocation camera</td>
</tr>
<tr>
<td>tripod AtLocation camera_shop</td>
</tr>
<tr>
<td>camera IsA photo_device</td>
</tr>
<tr>
<td>cannon ConceptuallyRelatedTo camera</td>
</tr>
<tr>
<td>photograph ConceptuallyRelatedTo camera</td>
</tr>
<tr>
<td>picture ConceptuallyRelatedTo camera</td>
</tr>
</tbody>
</table>

Table 1. ConceptNet Relation Examples
Ontology Creation using ConceptNet
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- Mining information from ConceptNet can be difficult due to one-to-many relations, noisy data and redundancy.

- Relational predicates in ConceptNet have an inherent structure suitable for building ontology.

- ConceptNet has a closed class of well-defined relations which can be weighed for different purposes.

- Continual expansion of the knowledge resource through crowdsourcing incorporates new data and enriches the ontology.

- Ontology creation using ConceptNet does not require any labeling of product reviews.
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ConceptNet Relations Contd…
Consider the *functional* relation “a camera is used for taking picture” to be of more interest to someone than the *hierarchical* relation “a camera has a tripod”

A product which takes good pictures but lacks a tripod will have a high positive polarity

- Subjective and can be used to personalize the ontology tree.
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<table>
<thead>
<tr>
<th>Hierarchical</th>
<th>LocatedNear, HasA, PartOf, MadeOf, IsA, InheritsFrom</th>
</tr>
</thead>
<tbody>
<tr>
<td>Synonymous</td>
<td>Synonym, ConceptuallyRelatedTo</td>
</tr>
<tr>
<td>Functional</td>
<td>UsedFor, CapableOf, HasProperty, DefinedAs</td>
</tr>
</tbody>
</table>

Table 2. ConceptNet Relation Type Categorization
ConceptNet Relations  Contd...
One-to-many relations exist between concepts

- E.g. `camera` and `picture` related with camera `UsedFor` `take_picture`, camera `HasA` `picture`, picture `ConceptuallyRelatedTo` camera, picture `AtLocation` camera `etc.`

Hierarchical relations in ConceptNet

- Definitive, less topic drift and used to ground the ontology tree
- Preferred over other relations during a relational conflict
  - camera `HasA` `picture` > `picture` is `ConceptuallyRelatedTo` camera

- **hierarchical relations > synonymous relations > functional relations**

High degree of *topic drift* during relation extraction

- E.g. camera `HasA` `lens`, lens `IsA` `glass` and glass `HasA` `water` places `water` at a high level in the ontology tree

Ontology feature nodes extracted from ConceptNet constrained to belong to a list of frequently found concepts in the domain, obtained from an unlabeled corpus.
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  - E.g. *camera* and *picture* related with *camera* UsedFor *take_picture*, *camera* HasA *picture*, *picture* ConceptuallyRelatedTo *camera*, *picture* AtLocation *camera* etc.

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1. Part-of-speech tag the reviews and retrieve all *Nouns.*
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4. Every relation tuple $r_{ij}(f_i, f_j) \in R$ is assigned to one of the sets $S, F$ or $H$ with ties being broken as $H > S > F$. 
Algorithm for Ontology Creation Contd…
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Sentiment Annotated Ontology Tree
Feature Specific Opinion Extraction
Hypothesis (Mukherjee et al. 2012)
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Adjective Modifier
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• “I want to use Samsung which is a great product but am not so sure about using Nokia”.

• Here “great” and “product” are related by an adjective modifier relation, “product” and “Samsung” are related by a relative clause modifier relation. Thus “great” and “Samsung” are transitively related.

• Here “great” and “product” are more related to Samsung than they are to Nokia

• Hence “great” and “product” come together to express an opinion about the entity “Samsung” than about the entity “Nokia”
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“More closely related words come together to express an opinion about a feature”
Graph
Graph

I have an iPod.

It is a great buy but I'm probably the only person who dislikes it.

That software is also confusing.
Graph
Graph

I have an ipod it is a

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Graph
Graph
Graph
• Annotating Ontology tree with feature-specific polarities
• View sentiment aggregation as an information propagation problem
Sentiment Aggregation
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- Product attributes at a higher level of the tree dominate those at the lower level.

- Reviewer opinion about a feature at a higher level in the ontology tree (say picture), weighs more than the information of all its children nodes (say light, resolution, color and compression).

- Feature importance captured by height of a feature node in the tree.

- If parent feature polarity is neutral / absent, its polarity is given by its children feature polarities.

- Information at a particular node is given by its self information and the weighted information of all its children nodes.

- Information propagation is done bottom-up to determine the information content of the root node, which gives the polarity of the review.
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- Consider the ontology tree $T(V,E)$
  - $V_i = \{f_i, p_i, h_i\}$ is a product attribute set, where $f_i$ is a product feature, $p_i$ is review polarity score with w.r.t. $f_i$ and $h_i$ is the height of the product attribute in the ontology tree
  - $E_{ij}$ is an attribute relation type connecting $V_i$ and $V_j$ and $u_{ij}$ be the link strength of $E_{ij}$
  - Let $V_{ij}$ be the $j^{th}$ child of $V_i$
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The *positive sentiment weight* (PSW) and *negative sentiment weight* (NSW) of a vertex $V_i$ are defined as,

$$\text{PSW}(V_i) = h_i \times p_i^+ + \sum_j \text{PSW}(V_{ij}) \times u_{ij}$$

$$\text{NSW}(V_i) = h_i \times p_i^- + \sum_j \text{NSW}(V_{ij}) \times u_{ij}$$

where $p_i^+ \in [0,1]$ and $p_i^- \in [-1,0]$.

The review polarity is given by the *expected sentiment-weight* (ESW) of the tree defined as,

$$\text{ESW}(\text{root}) = \text{PSW}(\text{root}) + \text{NSW}(\text{root})$$
Feature Weight from Corpus

- **Corpus** assigns weight to each *feature* that distinguishes between attributes that are siblings.

- E.g. Ontology assigns the same weight to the children of *camera* i.e. *body, lens, flash, picture* and *video*.

- But *picture*, in general, is more important than *body* for a *camera* which is captured from the corpus.

- The feature weight $u_i$ of $f_i$ is given by

$$u_i = \frac{df_i}{\sum_{j \in \text{Sibling}(i)} df_j + df_i}$$

$$ESW(V_i) = u_i \times [\mathcal{S}(p_i) \times h_i \times p_i + (1 - \mathcal{S}(p_i)) \times \sum_j ESW(V_{ij})]$$
Feature Weighted SOT
Experimental Evaluation

- Experiments performed in 3 domains, namely *camera*, *automobile* and *software*

<table>
<thead>
<tr>
<th>Domain</th>
<th>Positive Reviews</th>
<th>Negative Reviews</th>
<th>Total Reviews</th>
</tr>
</thead>
<tbody>
<tr>
<td>Automobile</td>
<td>584</td>
<td>152</td>
<td>736</td>
</tr>
<tr>
<td>Camera</td>
<td>986</td>
<td>210</td>
<td>1196</td>
</tr>
<tr>
<td>Software</td>
<td>1000</td>
<td>915</td>
<td>1915</td>
</tr>
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*Table 3. Dataset Statistics*
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1. Lexical bag-of-words baseline
   - Majority voting
   - Sentiment Lexicons used: SentiWordNet, Inquirer, Bing Liu

2. Corpus Feature-Specific baseline
   - Feature-specific polarities extracted using dependency parsing algorithm in Mukherjee et al. (2012)
   - Feature-specific polarities weighed by tf-idf important of the feature in the corpus

3. ConceptNet and Corpus Feature-Specific baseline
   - ConceptNet is used to extract the feature set (H U S U F)
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- All the baselines lack hierarchical aggregation using ontological information
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# Model Feature Comparison

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<thead>
<tr>
<th>Models</th>
<th>Lexical</th>
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<th>Sent. Aggr.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lexical Baseline</td>
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<td></td>
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<td>Y</td>
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*Table 4. Models and Baselines*
<table>
<thead>
<tr>
<th>Domains</th>
<th>Corpus Frequent Features</th>
<th>Ontology Nodes</th>
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<tr>
<td>Automobile</td>
<td>268</td>
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</tr>
<tr>
<td>Camera</td>
<td>768</td>
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<td>333</td>
<td>148</td>
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<tr>
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<td>763</td>
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**Table 5. Ontology Tree Statistics**

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<td>60.88</td>
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<td>60.76</td>
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<td>General Inquirer</td>
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<td>65.25</td>
<td>72.54</td>
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<tr>
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<td>67.15</td>
<td>74.74</td>
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<td>72.90</td>
<td>76.06</td>
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Table 7. Overall Accuracy of All Models
Class-wise Accuracy in Each Domain

Figure 3. Positive and Negative Accuracy of Models in Each Domain
Discussions
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- Difficult to evaluate purity of ontology
  - Qualitative evaluation done
  - 75.75% of concepts in *automobile* domain, 43.49% concepts in *camera* and 74.90% concepts in *software* domain are mapped to respective ontology
  - In camera domain, number of ontology feature nodes << frequently occurring concepts in reviews,
  - But proposed model performs much better than the baseline, which considers all features to be equally relevant
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Ongoing Work - Submitted

- Automatically learning ontology from a raw corpus without any annotation
  - Discovering domain-specific multi-words like Canon SX 160, Samsung Galaxy S IV etc.
  - Discovering domain-specific relations IS-A, Similar-To, Attributes and Methods

- Uses ESG parser features, Random Indexing, HITS etc.

- Domain-specific ontology improves an in-house Question-Answering system (Watson) by upto 7%
- It also improves parser performance by reducing number of incomplete or noisy parses by upto 74%
Ongoing Work - Submitted

- Learn author-specific preferences (edge weights $u_{ij}$ in ontology tree) from reviews

- Size of a camera may be of more importance to someone than a tripod
  - Different feature preference, which cannot be captured by ontology or corpus feature weight

- Generative model using HMM-LDA
  - Jointly learns product features, feature-specific sentiment, author-preference for the features, and overall ratings
  - HMM is used to capture coherence in reviews, author-writing style by capturing semantic-syntactic class transition and topic switch
Thank you