EXTRACTING ASPECTS HIERARCHIES USING RHETORICAL STRUCTURE THEORY

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ABSTRACT

We propose a novel approach to generate aspect hierarchies that proved to be consistently correct compared with human-generated hierarchies. We present an unsupervised technique using Rhetorical Structure Theory and graph analysis. We evaluated our approach based on 100,000 reviews from Amazon and achieved an astonishing 80% coverage compared with human-generated hierarchies coded in ConceptNet. The method could be easily extended with a sentiment analysis model and used to describe sentiment on different levels of aspect granularity. Hence, besides the flat aspect structure, we can differentiate between aspects and describe if the *charging* aspect is related to *battery* or *price*.

1 Introduction

Aspect-based sentiment analysis deals with classifying sentiment towards a given aspect in documents. Most of the time sentiment classification approaches work on whole documents, and they do not distinguish between the various aspects mentioned in the text. Imagine that you have a sentence such as *the wall charger works, but the car one does not*. This example expresses two attitudes toward two different aspects of the phone charging process. Firstly, we spot positivity for the *wall charger*, and secondly negativity for the *car charger*. Such an analysis is not feasible with standard sentiment analysis tools. We used the discourse analysis as the text segmentation tool and extracted with it the basic units called Elementary Discourse Units (EDUs). Moreover, the discourse analysis extracts the connection between EDUs and determine its semantic relations. We conduct analysis separately for each review to get Discourse Trees (DTs) such as in Figure 2. Beside the flat aspect structure sometimes we want to know how different aspects are related to each other. For example, if the *charging* is related to *battery* or price *aspect*? This approach needs relation or hierarchies between aspects to be derived. To deal with such problems we need hierarchical aspect-based sentiment models.

We are working on a comprehensive pipeline for analysing texts containing opinions and generating user-friendly descriptive, abstractive reports in natural language (Figure 1). In this paper, we describe extending our previous work [1] and present a prototype implementation of aspect hierarchy extraction.

The paper presents in Section 1 an introduction to hierarchical aspect-based sentiment analysis. Then in Section 2 we present related work from the areas of rhetorical and aspect-based sentiment analysis. In the Section 3 we described our method. Then the implementation and the data are described in Section 4. The Section 5 contains the results and thier description. The last Section 6 covers our conclusions and future work.

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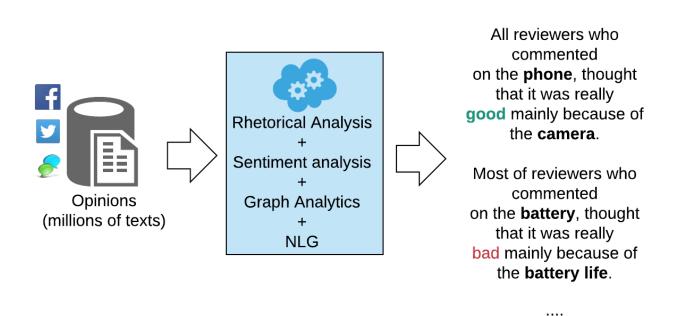


Figure 1: The Workflow for Sentiment Analysis Summarization using Rhetorical Structure Theory.

2 Related Work

2.1 Rhetorical Structure Theory

Rhetorical Structure Analysis (RSA) tries to uncover the coherence structure of the texts. This technique has been shown to be beneficial for many Natural Language Processing (NLP) applications such as sentiment analysis [2], text summarization [3] or machine translation [4]. There exist various theories for RSA, such as Martin [5] and discourse relations based on discourse connectives, words such as *because* or *but*. Beside that, Danlos [6] extended sentence grammar and formalized discourse structure analysis.

However, we use the Rhetorical Structure Theory (RST) by Mann and Thompson [7]. This method is probably the most influential theory of discourse analysis in computational linguistics. It was constructed especially for the text generation tasks. Then it became popular for text parsing [8]. Rhetorical Structure Theory represents documents as tree structures with relations between different parts of the text. Based on RST we can generate tree structures called Discourse Trees (DTs). An exemplification of a DT is presented at Figure 2.

2.2 Aspect hierarchies in Sentiment Analysis

As far as we know, there are only a couple of works on the hierarchy extraction of aspects for sentiment analysis purposes. Kim et al. [9] proposed a hierarchical aspect sentiment model (HASM) and tried to discover a hierarchical structure of aspects from unlabeled documents. The HASM represents the whole structure as a tree. Secondly, Wei and Gulla [10] proposed a Sentiment Ontology Tree, but unfortunately, they analyzed the reviews of one product by manually labeling the product's aspects with sentiments.

Researchers use several approaches to aspect-based sentiment analysis. From still commonly used rule-based methods (POS [1, 11] or dependency-based [12]), through standard supervised learning (e.g., SVMs and CRF [13]) to deep learning-based approaches with CNNs or LSTMs. There is an interesting approach proposed by Ruder et al. [14]. He used a hierarchical, bidirectional LSTM model to leverage both intra and inter-sentence relations. Poria et al. [11] proposed a seven-layer convolutional neural network to tag each word in opinionated sentences as either an aspect or non-aspect word. However, these approaches only extract a flat structure of aspects from the text.

There exist several models for discovering topic hierarchies from textual data such as [15, 16], but they are not designed for aspect-based hierarchies.

I love my new phone. I am amazed at the battery quality that it is charging so fast.

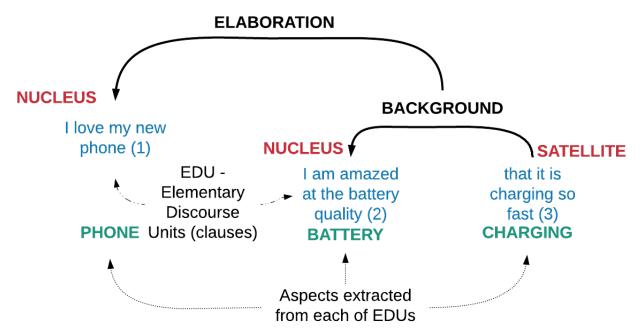


Figure 2: An Exemplary Discourse Tree Based on Rhetorical Structure Theory.

3 Method for aspect hierarchies generation

Our hierarchy extraction model consists of the following sub-tasks.

- 1. Rhetorical analysis of documents, segmentation of the text into the basic units of discourse structures: EDUs (Elementary Discourse Units).
- 2. Aspect detection for each of the EDUs, creating Aspect Discourse Trees (ADTs).
- 3. Hierarchy generation based on RST relations and extracted aspects.

We hypothesize that when aggregating aspects and the rhetorical relation between these aspects for many documents we get aspect hierarchical relationships such as that the *phone* is a precedent for the *battery* and the *battery* is precedent for *battery life*. Why do we need a lot of documents? Each separate document and its aspects can be rather noisy because of (1) the low level of formality of the language of the reviews and (2) inaccuracies from automatic discourse segmentation tools. Hence, by aggregating a lot of documents we may spot more reliable and general information. It is worth mentioning that in the most similar approach to ours, Joty et al. [17] extracted only single aspect relations from every document. Hence, they may potentially miss some of the informative value.

3.1 Rhetorical Analysis and Aspect Hierarchy Generation

We used the discourse analysis as the text segmentation tool and extracted the basic units called Elementary Discourse Units (EDUs). Moreover, the discourse analysis extracts the connection between EDUs and determine its semantic relations. We conduct analysis separately for each review to get Discourse Trees (DTs) such as in Figure 2.

3.2 Aspect detection in textual data

Then we extracted aspects and created aspect-based discourse trees (ADTs). Aspect detection from textual data is based commonly on detection of names or noun-phrases [18] and we used exactly this approach. We replace EDUs with aspects extracted from them, while also skipping all nucleus-nucleus relations (these relations do not show the hierarchical dependency between aspects). At the end of this step, we get trees as in Figure 3.

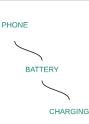


Figure 3: An exemplary Aspect Hierarchical Relation extracted from a single Aspect Discourse Tree.

3.3 Aspect Hierarchy generation

Then we gather relations from all Aspect Discourse Trees and extract general hierarchical relations between aspects. We generate tuples from ADTs (a_i, a_j, r) , a_i and a_j mean aspects, *i* and *j* indicate the aspect's index and $i \neq j$, *r* state the rhetorical relations type. We use a breadth-first search (BFS) [19] algorithm for each Discourse Tree to generate the tuples mentioned. These tuples can be simplified to (a_i, a_j) on the assumption that the first element of tuple a_i is nucleus and the second element a_j means a satellite. As a reminder, the nucleus means the more important part of the RST relation and a satellite is a subsidiary part. We count all such tuples and use the top *n* aspects appearing in these tuples, as in Listing 1. We start with the most common tuple (*phone, case*), where *phone* is the nucleus (hence it is the root node in the hierarchy), and the satellite in this pair *case* will be the first child in the hierarchy for the root node. Then, in the second step, we go to the next element in the sorted pairs (*phone, battery*). The nucleus *phone* is already in the hierarchy hence we will add its child only, *battery*.

```
(NUCLEUS, SATELLITE)
(phone, case)
(phone, battery)
(phone, headset)
(phone, bluetooth)
(price, battery)
(battery, charge)
(headset, bluetooth)
(case, phone)
(phone, price)
....
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Listing 1: Aspects pairs of Nucleus and Satellite

If we find a nucleus aspect that is not already present in the hierarchy such as (*price, battery*) we create a separate hierarchy with the nucleus as a root node of this sub-hierarchy. This subtree could be merged to the main hierarchy in the next steps when in our pair list it will appear tuple with satellite equal to the root node of this sub-hierarchy, and our main hierarchy will contain a nucleus from this aspect's pair such as (*phone, price*). We repeat the step by going over and over pairs of nucleus and satellite until the end of the list.

It is important to mention that we can add repeated aspects to the hierarchy as children. For example, the pairs (*phone, bluetooth*) and (*headset, bluetooth*) contain the same satellite *bluetooth*. This is a very interesting phenomenon related to the local structures of the aspect's sub-hierarchies (see Section 5).

4 Experimental Scenario

We used [20] for Rhetorical Segmentation in our experiments. We used a noun and noun phrase extractor according to the part-of-speech tagger from the Spacy Python library. We implemented our own version of the breadth-first search (BFS) algorithm.

Metric	Value
Total # of reviews	100,000
Average # of words in review	97
Average # of sentences in review	5.27
# of reviews with at least 2 aspects	98,528
# of reviews with at least 10 aspects	35,219

Table 1: Amazon Cell Phones and Accessories dataset statistics.

4.1 Dataset

We used a dataset of Amazon product reviews scraped by Julian McAuley [21]. The dataset consists of review's texts, product metadata, and links written between May 1996 and July 2014. We chose one of the domains of this datasets, to be specific Cell Phones and Accessories, and we sampled randomly 100,000 reviews out of 3,447,249 reviews in total.

As we can see in Table 1, Amazon reviews are rather lengthy, and most of the time they contain more than two aspects. Moreover, several thousands of reviews consist of more than ten aspects. Hence, we want to extract more than just one aspect pair from each review, in contrast to [22].

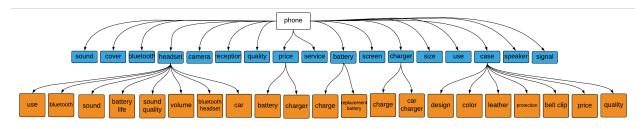


Figure 4: Aspect Hierarchy extracted from Amazon Cell Phones and Accessories dataset.

4.2 Evaluation

This section describes the evaluation metrics of our method. A comprehensive comparison of our method is difficult. To best of our knowledge, there is no prior work where an aspect hierarchy has been described that could easily be compared with our method. Hence, we used a hierarchical relation expressed in ConceptNet [23]. ConceptNet is a graph-based knowledge representation. The ConceptNet contains words and common phrases (both called as concepts) in any written human language. These words and phrases are related via several different types of relations. These relations describe not only lexical definitions but also how concepts are related based on common knowledge. A couple of examples are *keypad PartOf phone, IsA tool for take picture, camera IsA device, flash PartOf camera, camera IsA photo device, car MadeOf metal, car HasA seats, car HasA windows* and others.

Importantly ConceptNet covers relations of a hierarchical nature such as presented by Mukherjee and Joshi in [24] as in *LocatedNear*, *HasA*, *PartOf*, *MadeOf* and *IsA*.

Moreover, ConceptNet also covers relation such as *Synonym* and *RelatedTo*. These two relations were very useful and enabled us to obtain hierarchical relations not expressed directly in ConceptNet. For example, we could find the relation *receiver PartOf telephone*, but there isn't the relation *receiver PartOf phone*, although using *telephone Synonym phone* relation we can derive *receiver PartOf phone*.

We used the coverage metric to evaluate our method

$$coverage = \frac{|A \cap C|}{|A|} \tag{1}$$

where A is a set of aspect hierarchical tuples generated by our method, and C is a set of all hierarchical tuples extracted from ConceptNet within a graph distance up to three hops. Reporting the results with the coverage we show of how many of aspect hierarchical tuples discovered by our method exist in ConceptNet. As an example, the relation between *receiver* and *telephone* is equal to 1, because of the *receiver PartOf telephone* explicit relation, but the distance for *antenna* and *telephone* will be 2, because of the relations *antenna PartOf receiver* and *receiver PartOf telephone*. We chose a distance of up to three because ConceptNet is a crowd-sourced database and it misses a lot of relations that should appear in a complete solution. With a distance up to three we spot reasonable hierarchical relations such as *phone* and *case*, *phone* and *battery*, and others.

5 Results

In this section, we describe and analyze the results of our method.

We designed our model to produce a hierarchical structure of aspects such that this hierarchy can be traversed to find certain aspects. Moreover, it can be easily extended with a sentiment analysis module to enrich aspects with sentiment orientation distribution. The hierarchy of aspects is consistent with our intuition and the root node is the most general aspect/type of the product or service expressed in all documents. With the depth of hierarchy, the aspects become more and more specific features.

Table 2: Coverage values between our Aspect Hierarchical Pairs and ConceptNet Hierarchical Relations.

	Coverage
Top 5	1.00
Top 10	0.90
Top 20	0.78
Top 30	0.75
Top 40	0.82
Top 50	0.80

Table 2 presents results of the coverage calculated for a different number of most frequent tuple hierarchical aspect pairs generated by our method. We tested the top 5, 10, 20, 30, 40, and 50 pairs of aspects. We consistently received a coverage level higher than 75% for every subset of our hierarchical aspect pairs. This proves that our unsupervised method generates aspect hierarchies consistent with human-generated relations coded in ConceptNet. Interestingly, all our top 5 aspect pairs were confirmed by ConceptNet relations. Next, the top 10 pairs proved to be 90% correct which is an astonishing result. Moreover, even the top 30, 40 and 50 pairs achieve a coverage level of about 80%.

Interestingly, we can spot the same aspects in different parts of the hierarchy (see Figure 4). This is related to the contextuality of aspects. We can have aspects such as *battery* or *bluetooth* in several sub-hierarchies and each time this aspect will carry different semantics: on the one hand, the battery could be a battery of the whole phone, on the other hand it could be a battery of the headset. As we can see, aspects should not be unique in the hierarchy and they can carry very interesting insights from sentiment analysis tasks.

6 Conclusions and future Work

We have proposed a novel approach to generate aspect hierarchies that proved to be 80% correct, consistent with the same accuracy levels of human generated hierarchies. The advantages of our method are firstly that it is not limited to the number of aspects, secondly and really importantly, it doesn't need training data (an unsupervised method), and thirdly it is simple to calculate and it could easily be extended with a sentiment analysis model to provide sentiments on different levels of aspect granularity. in future work, we want to improve the aspect extraction phase using sequence tagging approaches with BiLSTM and CRF models. We want to extend our method with other metrics to rank aspect pairs. Moreover, we want to apply the analysis to the Polish language.

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References

- Lukasz Augustyniak, Krzysztof Rajda, and Tomasz Kajdanowicz. Method for aspect-based sentiment annotation using rhetorical analysis. In Ngoc Thanh Nguyen, Satoshi Tojo, Le Minh Nguyen, and Bogdan Trawiński, editors, Intelligent Information and Database Systems, pages 772–781, Cham, 2017. Springer International Publishing.
- [2] Angeliki Lazaridou, Ivan Titov, and Caroline Sporleder. A Bayesian Model for Joint Unsupervised Induction of Sentiment, Aspect and Discourse Representations. *Proceedings of the 51st Annual Meeting of the Association* for Computational Linguistics (Volume 1: Long Papers), pages 1630–1639, 2013.
- [3] Annie Louis, Aravind Joshi, and Ani Nenkova. Discourse indicators for content selection in summarization. In Proceedings of the 11th Annual Meeting of the Special Interest Group on Discourse and Dialogue, SIGDIAL '10, pages 147–156, Stroudsburg, PA, USA, 2010. Association for Computational Linguistics.
- [4] Francisco Guzmán, Shafiq Joty, Lluis Màrquez, and Preslav Nakov. Using Discourse Structure Improves Machine Translation Evaluation. Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 687–698, 2014.
- [5] J.R. Martin. English Text. John Benjamins Publishing Company, Amsterdam, nov 1992.
- [6] Laurence Danlos. D-STAG: A formalism for discourse analysis based on SDRT and using synchronous TAG. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 5591 LNAI:64–84, 2011.
- [7] William C Mann and Sandra A Thompson. Rhetorical structure theory: Toward a functional theory of text organization. *Text*, 8(3):243–281, 1988.
- [8] Maite Taboada. Discourse markers as signals (or not) of rhetorical relations. *Journal of Pragmatics*, 38(4):567–592, 2006.
- [9] Suin Kim, Jianwen Zhang, Zheng Chen, Alice Oh, and Shixia Liu. A hierarchical aspect-sentiment model for online reviews. In *Proceedings of the Twenty-Seventh AAAI Conference on Artificial Intelligence*, AAAI'13, pages 526–533. AAAI Press, 2013.
- [10] Wei Wei and Jon Atle Gulla. Sentiment learning on product reviews via sentiment ontology tree. *Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics*, pages 404–413, 2010.
- [11] Soujanya Poria, Erik Cambria, and Alexander Gelbukh. Aspect Extraction for Opinion Mining with a Deep Convolutional Neural Network. *Knowledge-Based Systems*, 108:42–49, sep 2016.
- [12] Soujanya Poria, Nir Ofek, Alexander Gelbukh, Amir Hussain, and Lior Rokach. Dependency tree-based rules for concept-level aspect-based sentiment analysis. In Valentina Presutti, Milan Stankovic, Erik Cambria, Iván Cantador, Angelo Di Iorio, Tommaso Di Noia, Christoph Lange, Diego Reforgiato Recupero, and Anna Tordai, editors, *Semantic Web Evaluation Challenge*, pages 41–47. Springer International Publishing, Cham, 2014.
- [13] Zhiqiang Toh and Wenting Wang. Dlirec: Aspect term extraction and term polarity classification system. In Proceedings of the 8th International Workshop on Semantic Evaluation (SemEval 2014), pages 235–240. Association for Computational Linguistics, 2014.
- [14] Sebastian Ruder, Parsa Ghaffari, and John G. Breslin. A hierarchical model of reviews for aspect-based sentiment analysis. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 999–1005. Association for Computational Linguistics, 2016.
- [15] David M. Blei, Thomas L. Griffiths, and Michael I. Jordan. The nested chinese restaurant process and bayesian nonparametric inference of topic hierarchies. J. ACM, 57(2):7:1–7:30, February 2010.
- [16] Joon Hee Kim, Dongwoo Kim, Suin Kim, and Alice Oh. Modeling topic hierarchies with the recursive chinese restaurant process. In *Proceedings of the 21st ACM International Conference on Information and Knowledge Management*, CIKM '12, pages 783–792, New York, NY, USA, 2012. ACM.
- [17] Shafiq Joty, Giuseppe Carenini, and Raymond T. Ng. CODRA : A Novel Discriminative Framework for Rhetorical Analysis. *Computational Linguistics*, 41(January):1–50, sep 2015.
- [18] Maria Pontiki, Dimitrios Galanis, Haris Papageorgiou, Suresh Manandhar and Ion Androutsopoulos. SemEval-2015 Task 12: Aspect Based Sentiment Analysis. Proceedings of the 9th International Workshop on Semantic Evaluation (SemEval 2015), Denver, Colorado., pages 486–495, 2015.
- [19] David Eppstein and David. All maximal independent sets and dynamic dominance for sparse graphs. ACM *Transactions on Algorithms*, 5(4):1–14, oct 2009.
- [20] Vanessa Wei Feng and Graeme Hirst. Two-pass discourse segmentation with pairing and global features. *CoRR*, abs/1407.8215, 2014.

- [21] Ruining He and Julian McAuley. Ups and Downs: : Modeling the Visual Evolution of Fashion Trends with One-Class Collaborative Filtering. In *Proceedings of the 25th International Conference on World Wide Web WWW '16*, pages 507–517, New York, New York, USA, 2016. ACM Press.
- [22] Shima Gerani, Yashar Mehdad, Giuseppe Carenini, Raymond T. Ng, and Bita Nejat. Abstractive summarization of product reviews using discourse structure. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing, EMNLP 2014, October 25-29, 2014, Doha, Qatar, A meeting of SIGDAT, a Special Interest Group of the ACL, pages 1602–1613, 2014.
- [23] Robert Speer and Catherine Havasi. Representing general relational knowledge in conceptnet 5. In *Proceedings of the Eighth International Conference on Language Resources and Evaluation (LREC-2012)*. European Language Resources Association (ELRA), 2012.
- [24] Subhabrata Mukherjee and Sachindra Joshi. Sentiment Aggregation using ConceptNet Ontology. pages 570– 578, 2013.