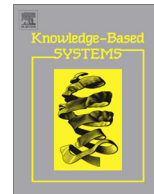




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Enriching semantic knowledge bases for opinion mining in big data applications

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ABSTRACT

This paper presents a novel method for contextualizing and enriching large semantic knowledge bases for opinion mining with a focus on Web intelligence platforms and other high-throughput big data applications. The method is not only applicable to traditional sentiment lexicons, but also to more comprehensive, multi-dimensional affective resources such as SenticNet. It comprises the following steps: (i) identify ambiguous sentiment terms, (ii) provide context information extracted from a domain-specific training corpus, and (iii) ground this contextual information to structured background knowledge sources such as ConceptNet and WordNet. A quantitative evaluation shows a significant improvement when using an enriched version of SenticNet for polarity classification. Crowdsourced gold standard data in conjunction with a qualitative evaluation sheds light on the strengths and weaknesses of the concept grounding, and on the quality of the enrichment process.

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1. Introduction

Communication experts and decision makers aim to understand how stakeholders perceive their announcements and actions, and how news coverage and social media channels affect these perceptions. To address these questions, this article describes the integration and automated extension of semantic knowledge repositories. Building upon a novel approach to contextualized sentiment analysis [19], we introduce methods that can ground and enrich identified concepts. This integration of semantic knowledge repositories is an important stepping stone towards making sense of big data. Extracting factual and affective knowledge from these repositories will provide a deeper understanding of opinions expressed in user-generated content from social media platforms, news articles, scientific publications, etc.

The knowledge extraction tools that analyze the Social Web typically provide frequency and sentiment metrics on either a document or sentence level. Sentiment is an important and insightful indicator. However, even when it is measured accurately, this single metric often cannot address fundamental questions posed by decision makers. Communication experts who are responsible for marketing and public outreach campaigns, for example, want to

know if their message reaches intended groups, how their communication strategy impacts observable patterns in online coverage, and which portion of the identified sentiment actually refers to their organization. The U.S. National Oceanic and Atmospheric Administration (NOAA) is a good example. The NOAA Climate Program Office has adopted the authors' previous work on opinion mining as an essential part of its online evaluation strategy. Fig. 1 shows a screenshot of the system, which is based on the webLyzard big data and Web intelligence platform [15]. The dashboard uses color coding to embed sentiment information into various interface components including a relevance-ranked list of search results, trend charts, and a range of other interactive visualizations such as tag clouds, keyword graphs, word trees and geographic maps. Communication experts at NOAA use the system to track whether social media users associate NOAA with "climate change", for example, which is an important aspect of their communication and outreach goals. With regard to sentiment analysis, this poses an interesting challenge because the term "climate change" typically carries a negative connotation. In such cases, it is imperative to differentiate the sentiment of concepts that are merely co-referenced in a document ("NOAA", "climate change"), and opinions that are directed towards an organization.

User-generated product reviews are another example illustrating the importance of identifying specific opinion targets when analyzing the Social Web. Users tend to comment not only on a product in general (e.g., digital camera), but also on its various

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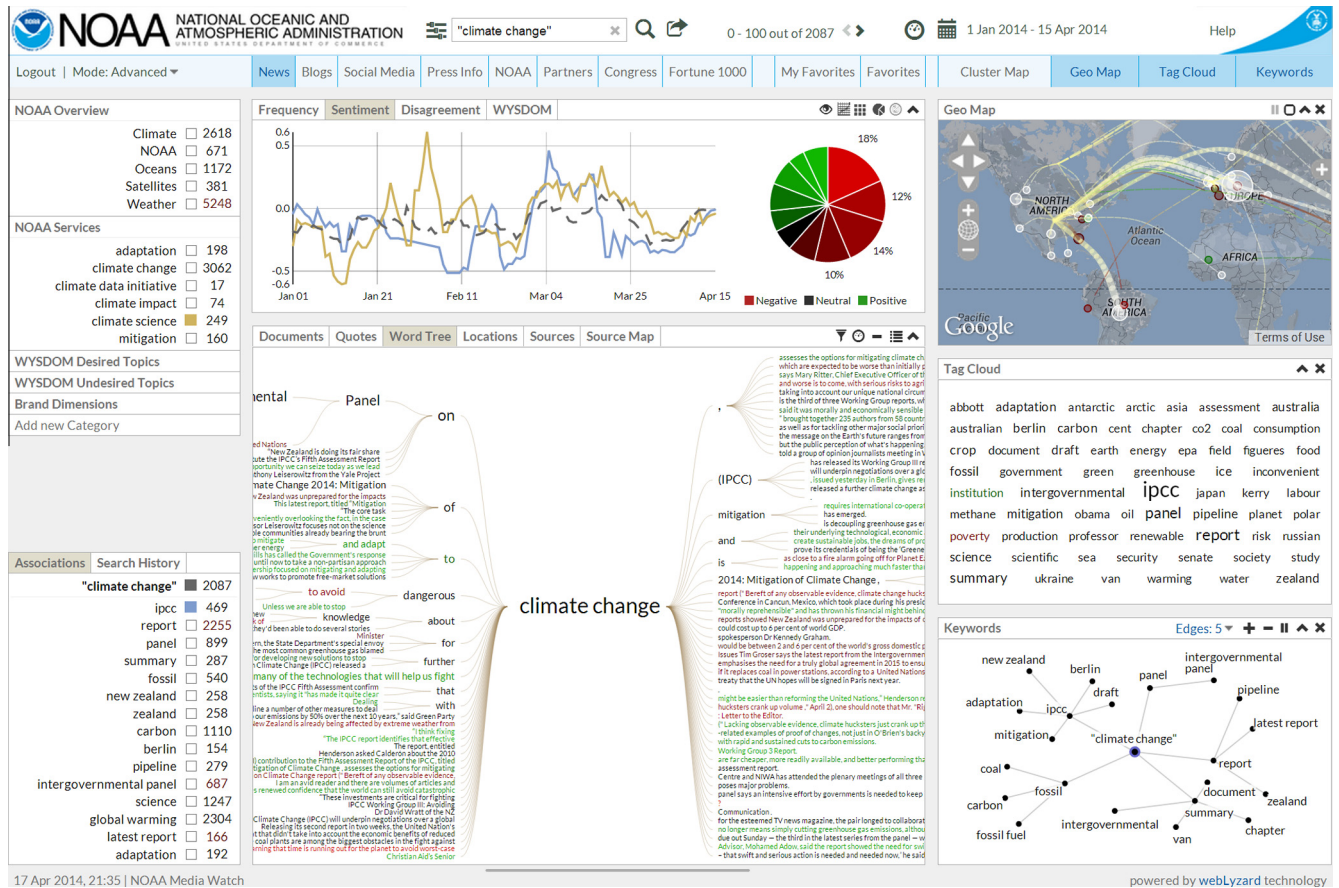


Fig. 1. Screenshot of a Web intelligence portal built for the NOAA Climate Program Office, showing results for a query on "climate change" based on news media coverage between January and April 2014.

85 aspects – shutter speed, quality of the lens, retail price, etc. The
 86 observable preference of users to compare features across products
 87 rather than assessing them in isolation underscores the need for
 88 flexible approaches to concept grounding and enrichment, which
 89 are granular enough to distinguish between the specific aspects
 90 of an entity. For evaluation purposes, therefore, this paper uses
 91 reviews from Amazon.com about electronics and software prod-
 92 ucts as well as reviews from the Internet Movie Database
 93 (www.imdb.com) in the categories comedy, crime and drama.

94 2. Related work

95 Many opinion mining tools rely on sentiment lexicons as lin-
 96 guistic resources that attach polarity values and strengths to senti-
 97 ment terms. Static polarity values may serve as a good baseline,
 98 but a closer examination reveals the need for more differentiated
 99 approaches. Cambria and White emphasize the need for a shift
 100 from simple syntactic (bag-of-words) approaches to semantic
 101 (bag-of-concept) or even pragmatic (bag-of-narratives) ones in
 102 their extensive review on natural language processing [5]. Depend-
 103 ing on the context, a term might lose its opinionated characteristic,
 104 or its polarity might change – e.g., "good" expressing a positive
 105 emotion versus "good" as the cargo of a freight train.

106 Gangemi et al. [9] emphasize the importance of sentiment con-
 107 textualization as one of seven major challenges in the area of opin-
 108 ion holder and target detection. Existing approaches handle it in
 109 different ways – e.g., by vector space modeling [6], by invoking lan-
 110 guage models [11], or by applying sentence- and discourse-based
 111 context shifters [20], rule-based approaches [7] or linguistic

112 patterns [21]. Xia et al. [22] address the problem of contextual
 113 polarity change by employing an ensemble of part-of-speech
 114 (POS) features combined with a sample selector. The sample selec-
 115 tor uses principal component analysis to select samples from the
 116 source domain that are similar to the target domain. Enriching senti-
 117 ment lexicons with context knowledge is another research avenue
 118 being pursued [12]. Gindl et al. [10] separate ambiguous
 119 sentiment terms from terms with stable polarity, a process that
 120 yields contextualized sentiment lexicons. Embedding context
 121 information into the lexicon allows adapting an ambiguous term's
 122 polarity if the context indicates a polarity shift.

123 Structured knowledge contained in external linguistic reposi-
 124 tories can support this contextualization process. Efforts to extend
 125 the well-known WordNet repository [8] have resulted in language
 126 resources such as SentiWordNet [1] and WordNetAffect [17]. The
 127 former attaches objectivity and polarity values to WordNet syn-
 128 sets, while the latter enriches WordNet with labels for affective
 129 language resources. They apply iterative regression and a random
 130 walk strategy to label ConceptNet [16] elements with sentiment
 131 values. Poria et al. [13] merge SenticNet [3] and WordNetAffect
 132 to provide emotive labels for SenticNet. SenticNet itself uses Con-
 133 ceptNet by blending its knowledge with WordNetAffect, and infer-
 134 ring concept polarities from the Hourglass of Emotion [2].

135 Our previous work extended this line of research by accom-
 136 plishing cross-domain contextualization [10]. Complementing
 137 related work that applies common and common-sense knowledge
 138 to improve sentiment analysis [4], this paper specifically targets
 139 the problem of correctly interpreting ambiguous sentiment terms.
 140 We ground such terms depending on their actual usage to
 141

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