

Creating a General Russian Sentiment Lexicon

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Abstract

The paper describes the new Russian sentiment lexicon - RuSentiLex. The lexicon was gathered from several sources: opinionated words from domain-oriented Russian sentiment vocabularies, slang and curse words extracted from Twitter, objective words with positive or negative connotations from a news collection. The words in the lexicon having different sentiment orientations in specific senses are linked to appropriate concepts of the thesaurus of Russian language RuThes. All lexicon entries are classified according to four sentiment categories and three sources of sentiment (opinion, emotion, or fact). The lexicon can serve as the first version for the construction of domain-specific sentiment lexicons or be used for feature generation in machine-learning approaches. In this role, the RuSentiLex lexicon was utilized by the participants of the SentiRuEval-2016 Twitter reputation monitoring shared task and allowed them to achieve high results.

Keywords: sentiment analysis, sentiment lexicon, connotation, lexical ambiguity, thesaurus

1. Introduction

Automatic sentiment analysis is useful in many practical applications, such as analysis of users' reviews, posts in social networks, newspaper articles, etc. Sentiment lexicons are important components of sentiment analysis systems. They can be applied in lexicon-based approaches (Taboada et al., 2011) or be sources of features in the machine-learning framework (Mohammad et al., 2013; Severyn & Moschitti, 2015).

For English, there are many sentiment lexicons, which were manually created by experts (Wilson et al., 2005) or by crowdsourcing (Mohammad & Turney, 2013). For other languages, automatic approaches for generating sentiment lexicons have been proposed (Chetviorkin & Loukachevitch, 2012; Perez-Rosas et al., 2012; San Vicente et al., 2014; Yang et al., 2013).

It is well-known that sentiment vocabularies can depend on a specific domain, therefore, a lot of works are devoted to extraction of domain-specific sentiment lexicons (Blitzer et al., 2007; Choi & Cardie, 2009; Lau et al., 2011).

But some works (Mansour et al., 2013) show that the combination of multi-domain training data in supervised sentiment analysis improves the performance of a classifier in each domain under study. It proves the existence of a relatively stable set of general sentiment words and expressions with relatively stable sentiment orientations. Besides, as was shown in (Mohammad et al., 2013), features based on publicly available sentiment vocabularies are useful for improvement of supervised sentiment analysis systems. Thus, for any natural language it is useful to have a publicly available, manually crafted general sentiment lexicon, which can be later adapted to specific domains.

In this paper we present a new manually created general Russian Sentiment Lexicon – RuSentiLex. The lexicon contains more than ten thousand Russian sentiment-related words and expressions. Ambiguous words that have different sentiment polarity in different senses are provided with links to appropriate concepts of the Thesaurus of Russian language RuThes

(Loukachevitch & Dobrov, 2014), which can help disambiguate sentiment ambiguity in specific domains or contexts.

The rest of this paper is organized as follows. In the second section we consider related work on sentiment lexicons. The third section presents the structure of the created general Russian sentiment RuSentiLex. The fourth section describes several techniques to extract sentiment-oriented words of different types for inclusion to RuSentiLex. The fifth section presents the results of the participants of the SentiRuEval-2016 evaluation.

2. Related Work

Manual sentiment-oriented vocabularies can be presented as simple lists of words with specialized fields or can be labeled according to word senses.

The manual lexicon MPQA (Wilson et al., 2005) was compiled from several sources (manual and automatically generated lists of sentiment-oriented words) and contains over 8,000 single words. The entries are marked with polarity labels (positive, negative, or neutral) and subjective words are provided with reliability scores (strong or weak).

The manually created sentiment list AFINN (Nielsen, 2009) was specially enriched with obscene and slang words to adapt it to automatic analysis of messages in social nets. It contains about 2,400 words marked with sentiment strength scores ranged from -5 (very negative) to +5 (very positive).

In (Baccianella et al., 2010) SentiWordNet resource is described. It is the result of the automatic annotation of all the synsets of WordNet where each synset is associated to three numerical scores that indicate how positive, negative, or neutral the terms contained in the synset are. Different senses of the same term may thus have different opinion-related properties.

In SenticNet (Cambria et al., 2010), words and expressions are labeled with scores in four dimensions: pleasantness, attention, sensitivity, aptitude. To obtain these scores, Cambria et al. used the sentiment keywords and the corresponding values defined in the Hourglass of

Emotions (Cambria et al., 2012) as seeds to derive the sentiment values of other concepts. The authors of the SenticNet lexicon pay special attention to expressions containing gradual adjectives without prior polarity (*big, large, etc.: big monument, big road, big mouse*). Last version of SenticNet contains about 30,000 words and expressions.

Zasko-Zielinska et al. (2015) describe the sentiment-oriented annotation process of lexical units for Polish WordNet (plWordNet). A lexical unit in this case is a pair (lemma, sense_number). About 30,000 lexical units (nouns and adjectives) were annotated with polarity labels (positive, negative, neutral) together with intensity scores (strong or weak). Besides, the lexical units were assigned to basic emotions (joy, trust, fear, surprise, sadness, disgust, anger, or anticipation). It was found that approximately 30% of labeled lexical units were positive or negative.

The NRC Word-Emotion Association Lexicon was created with crowdsourcing technologies and contains words and phrases having associations with a specific sentiment or emotion (Mohammad & Turney, 2013). The set of six emotions was applied.

So far, several Russian sentiment lexicons have been created and published. In (Chetviorkin & Loukachevitch, 2012) automatically generated Russian sentiment lexicon in the domain of products and services (ProductSentiRus¹) is described. The ProductSentiRus is obtained by application of a supervised model to several domain review collections. It is presented as a list of 5,000 words ordered by the decreased probability of their sentiment orientation without any positive or negative labels.

The NRC Emotion Lexicon was automatically translated into Russian by Google Translate² (Mohammad & Turney, 2013). The Russian Sentiment Lexicon Linis-Crowd³ was created by crowd-sourcing (Alexeeva et al., 2015).

The RuSentiLex lexicon described in this paper differs from the existing Russian sentiment lexicons with the coverage and expert quality. Besides, the sentiment ambiguity of Russian words is described.

3. RuSentiLex Lexicon

The RuSentiLex lexicon is an alphabet-ordered Russian sentiment vocabulary. It contains the following types of Russian sentiment-related words:

- words from general Russian for that at least one sense has a positive or negative polarity what means that it conveys negative/positive opinion (*excellent*) or negative/positive emotion, (*sadness*);
- non-opinionated words with negative or positive connotations (Feng et al., 2013) such as *unemployment, terrorism, disease, cancer, explosion, spam* etc. Further we will call them *facts*;
- slang and curse words from Twitter.

¹ <http://www.cir.ru/SentiLexicon/ProductSentiRus.txt>

² NRC Emotion Lexicon translated in Russian via Google Translate (NRC)

³ <http://linis-crowd.org/>

Thus, in RuSentiLex all words and their senses are considered from three points of views:

- polarity: negative, positive or neutral
- source: opinion, emotion or non-opinionated fact,
- sentiment differences between word senses. If a word has different sentiment orientations or sources in its different senses then links between the senses and RuThes concepts are established.

RuThes Thesaurus⁴ of Russian language is a linguistic ontology for natural language processing, i.e. an ontology, where the majority of concepts are introduced on the basis of actual language expressions. The publicly available version of RuThes contains around 100 thousand Russian words and expressions.

If compared to WordNet-style resources, RuThes is organized as a united semantic net where different parts of speech (nouns, verbs, adjectives) can be text entries of the same concepts. Each concept has a unique unambiguous name. Concepts can be connected with several types of conceptual relations (Loukachevitch & Dobrov, 2014).

In contrast to SentiWordNet and other sense-based sentiment resources, we found that a lot of Russian ambiguous words have the same polarity in all available senses. Therefore it is simpler to assign the sentiment polarity information to such a word and not to enumerate all senses of a word with the same sentiment information.

The RuSentiLex vocabulary is presented in the plain text format and contains the following fields:

- initial word or phrase,
- part of speech,
- the word (phrase) in the lemmatized form,
- sentiment orientation. It can be positive, negative, neutral, or positive/negative. The latter value means that a word usually has a sentiment polarity but it is highly dependent on the context;
- the source of the sentiment,
- links to a RuThes sense (the concept name is used) if a word has a different polarities or sources in different senses. In this case, separate entries for each word sense are allocated.

For example, the Russian word *пресный* [*presnyj*] has three different senses. The first sense corresponds to the food-related sense of English word *tasteless*. The second sense is similar to the sense of word *insipid* as *uninteresting*. The third sense is as English *fresh* in the expression *fresh water*. This sense of the word *пресный* is described as a positive fact because it is not-opinionated and people need fresh water.

Thus, description of word *пресный* in the RuSentiLex is as follows (labels in quotes correspond to names of RuThes concepts):

- пресный, Adj, пресный, negative, emotion, "НЕВКУСНЫЙ" [*tasteless*];
- пресный, Adj, пресный, negative, opinion, "НЕИНТЕРЕСНЫЙ" [*insipid*];
- пресный, Adj, пресный, positive, fact, "ПРЕСНАЯ ВОДА" [*fresh water*]

Another opinionated Russian word *грязный* has two senses in RuThes (this word is similar to English word

⁴ <http://www.labinform.ru/pub/ruthes/index.htm>

dirty) but it is described in RuSentiLex without reference to the RuThes senses because in all known senses this word is negative:

- грязный, Adj, грязный, negative, opinion.

Table 1 presents the number of lexicon entries according to their sources and sentiment categories.

Types of entries	Number
Negative	9,499
Positive/negative	241
Positive	3,339
Neutral	1,394
Fact	4,607
Words from Twitter absent in the RuThes thesaurus	798
Different entries	10,467
Senses	14,492

Table 1. Quantitative characteristics of the RuSentiLex vocabulary

4. Extraction of sentiment-oriented words from different sources

RuSentiLex lexicon was obtained from several sources using semi-automatic techniques.

4.1. Gathering general sentiment words from domain-oriented sentiment lists

To obtain an initial list of words and RuThes concepts for RuSentiLex, several sentiment lists created in lexicon-based sentiment-oriented projects in several domains, such as described in (Kuznetsova et al., 2013) were matched with the RuThes entries. All entries of concepts where at least one entry was found in the existing sentiment lists were extracted for further manual analysis to decide about the inclusion of the entry into RuSentiLex and assign relevant labels.

4.2. Extraction of words with negative or positive connotations

Non-opinionated words with connotations usually convey information about negative or positive phenomena (facts) in social life (Feng et al., 2013). Positive phenomena are usually supported, protected. Negative phenomena are struggled with, fought against, etc. Therefore we supposed that words with connotations are mentioned in specific contexts.

To reveal such words or phrases, we created lists of lexical patterns for extracting words with negative (35 patterns) and positive (20 patterns) connotations.

The examples of the negative patterns include: *бороться с (struggle against) W, обвинить в (charge in) W, противостоять (withstand) W,*

The examples of the positive patterns are as follows: *бороться за (struggle for) W, охранять (guard) W, защищать (protect) W.*

These patterns were applied to a news collection of two million news articles. Words and phrases met in the patterns were extracted and ranked in the order of their pattern frequency. The extracted phrases included RuThes

multiword entries and noun groups (Adjective+Noun, Noun+Noun in Genitive, and their combinations).

After processing the collection and the extraction of words and phrases in patterns, it was noted that some words (phrases) were met in both types of the patterns. Therefore, a word was assigned to one (positive or negative) class if its frequency in patterns of this class was at least ten times more than its frequency in patterns of another class. Other words that were met in patterns of both classes were considered as neutral.

Thus, the extracted words and phrases were subdivided into three classes: words with negative connotations (most patterns were negative), words with positive connotations (most patterns were positive), and neutral words without specific connotations (could be equally met in both types of patterns). At last the extracted lists were cut at the frequency threshold equal 5. The created Pattern Connotation Lexicon contains 3,249 positive entries, 4,870 negative entries, and 596 neutral entries. Table 2 shows the most frequent words found in the patterns. Table 3 contains the most frequent phrases.

Connotation classes of words	The most frequent extracted words with connotations (translation from Russian)
Negative class	<i>corruption, terrorism, crime, extremism, drugs, inflation, barrier, threat, crisis, unemployment</i>
Neutral class	<i>government, program, circle, water, club</i>
Positive class	<i>right, population, interest, citizen, child, title, freedom, information, life</i>

Table 2. The most frequent words found in the connotation patterns

Connotation classes of phrases	The most frequent extracted phrases with connotations (translation from Russian)
Negative class	<i>economic crime, international terrorism, forest fire, extremist activity animal disease, global warming</i>
Positive class	<i>consumer right, human right, civil population, own interest, child right, intellectual property, freedom of speech, champion title</i>

Table 3. The most frequent phrases found in the connotation patterns.

The Pattern Connotation Lexicon is not very large. We decided to expand it and to use its entries as seed words for label propagation (Zhu & Ghahramani, 2002) on the basis of the RuThes thesaurus. Besides, we supposed that the neutral seed set should be considerably larger and add all thesaurus entries located on the thesaurus hierarchy levels upper than any word with a connotation.

		Neutral	Positive	Negative	Total number of tweets
Telecom	Training collection	4,870	1,354	2,550	8,643
	Gold standard test collection	1,016	226	1,054	2,247
Banks	Training collection	6,977	704	1,734	9,392
	Gold standard test collection	2,240	312	722	3,313

Table 4. Distribution of messages according to polarity classes in the SentiRuEval-2016 datasets

After the label propagation, the whole volume of the RuThes thesaurus entries obtained positive, negative, or neutral labels. Thus, the Extended Connotation Lexicon was generated.

The Pattern Connotation Lexicon and the most probable entries of the Extended Connotation lexicon were analyzed by a linguist to enrich the RuSentiLex lexicon.

4.3. Extraction of sentiment words from Twitter

To extract sentiment words from Twitter, we applied the supervised model of sentiment word extraction trained on the movie domain (Chetviorkin and Loukachevitch 2012). The size of the Russian tweet collection was 1 M+ of unlabeled tweets.

This model is based on several text collections: a collection with the high concentration of sentiment words, a contrast domain-specific collection, a contrast domain-independent collection (e.g. general news collection). Thus, taking into account statistical distributions of words in such collections, it is possible to distinguish specific sentiment words, used in a collection under analysis (tweets in this case) (Chetviorkin and Loukachevitch, 2013).

As a result, the words extracted from Twitter were ordered in decreasing probability of predicted sentiment orientation. The precision of the obtained list at the level 1,000 first entries was estimated as 78.6%. The first 5,000 words in the list were reviewed by a linguist to add slang and curse words absent in RuSentiLex but useful for analysis of social media posts.

5. Use RuSentiLex in Automatic Sentiment Analysis

RuSentiLex was used as a linguistic resource by several participants of the Russian evaluation of sentiment analysis systems SentiRuEval-2016.

SentiRuEval-2016 is the fourth event in the evaluation series in Russian (Chetviorkin & Loukachevitch, 2013; Loukachevitch et al., 2015). It was devoted to testing the possibility of current sentiment analysis systems to monitor tweets related to the reputation of a company. The SentiRuEval evaluation is in many aspects similar to RepLab evaluation (Amigo et al., 2012).

The task of SentiRuEval-2016 (Loukachevitch & Rubtsova, 2016) was to classify tweets into positive, negative, or neutral in two domains: banks and telecommunication companies. Positive (negative) tweets could contain positive (negative) opinion toward a company or mention a positive (negative) fact about a company.

As a training collection, the data from the previous evaluation SentiRuEval-2015 were used. The test collection was created by crowdsourcing. Each tweet obtained as least four labels from annotators, at least three

of them should vote for a specific label. Table 4 present the distribution of tweets according to polarity classes.

The training data of SentiRueval-2016 was collected during December 2013 and July 2014. The test collections were gathered in two parts: during July 2015 and November 2015. Thus, there is a considerable time gap between training and text collections of SentiRuEval.

This difference in time enhances the difficulty of tweet classification because various events, changes in social life can occur during this time (Loukachevitch & Rubtsova, 2015) and lead to using new sentiment words and expressions. Thus, the time gap was an intentional feature in constructing the training and test collections. The participants should find solutions to overcome the lexical dependence on the training collection. Existing approaches rely on creating word clusters on large text collection, extraction of positive and negative words and phrases from sentiment-oriented texts, or manual sentiment vocabularies (Mohammad et al. 2013; Severyn & Moschitti, 2015).

This year ten participants have submitted 58 runs to the Twitter sentiment analysis task at SentiRuEval-2016. As the main quality measure, macro-average F-measure was used. Macro F-measure is calculated as the average value between F-measure of the positive class and F-measure of the negative class ignoring the neutral class. But this does not reduce the task to the two-class prediction because erroneous labeling of neutral tweets negatively influences Fpos and Fneg. Additionally, micro-average F-measures were calculated for two sentiment classes.

The baselines were calculated with the use of SVM to the Boolean representation of tweet word forms (if a word form is presented in a tweet then the feature is equal to 1, otherwise 0).

The results of the best systems according to macro-F from each participant are presented in Table 5 for telecom tweets and Table 6 for bank tweets.

Run	F-macro	F-micro
SVM Baseline	0.3416	0.5829
1_4	<u>0.5286</u>	<u>0.6632</u>
2_k	0.5594	0.6569
3_1	0.3634	0.3994
4_5	0.4955	0.6252
5_1	0.3499	0.4044
6_con	0.3545	0.5263
7_5_a	0.4842	0.6374
8_533_2	0.4871	0.5745
9_hand_ext_tri	<u>0.5493</u>	0.6813
10_10	<u>0.5055</u>	<u>0.6254</u>

Table 5. The best run from each participant for telecom tweets according Macro F

The underscored results (the second, third, and fourth best results) are achieved with the use of the RuSentiLex lexicon. The participant 9 used SVM over unigrams,

bigrams, and trigrams. Two lexicons were also used: RuSentiLex (9_hand_ext_tri) and the automatically generated Pattern Connotation Lexicon (9_auto_ext_tri) (see section 4.2).

Run	F-macro	F-micro
SVM baseline	0.4555	0.4952
1_4	<u>0.4683</u>	<u>0.5022</u>
2_k	0.5517	0.5881
3_1	0.3423	0.3524
4_1	0.376	0.4108
5_1	0.3859	0.464
6_con	0.2398	0.3127
7_5_a	0.471	0.5128
8_533_2	0.4492	0.4705
9_auto_ext_tri	<u>0.5245</u>	<u>0.5653</u>
10_5	<u>0.4659</u>	<u>0.5053</u>

Table 6. The best run from each participant for banks tweets according Macro F

The participant 2 obtained the best results in both domains. The team utilized the recurrent neural network algorithm and word2vec-based word clusters generated from social network posts and comments.

It can be seen that all methods using additional knowledge (including RuSentiLex) considerably outperformed the SVM baselines.

6. Conclusion

In the paper we described the new Russian sentiment lexicon - RuSentiLex. The current size of the lexicon is more than ten thousand words and phrases. The lexicon was gathered from several sources: opinionated words from general Russian thesaurus RuThes, slang and curse words extracted from Twitter, objective words with positive or negative connotations from a news collection.

The lexicon entries are classified according to four sentiment categories (positive, negative, neutral, or positive/negative) and three sources of sentiment (opinion, emotion, or fact). The words in the lexicon having different sentiment orientations in different senses are linked to appropriate concepts of thesaurus of Russian language RuThes, which can help disambiguate sentiment ambiguity in specific domains or contexts

The lexicon can serve as the first version for the construction of domain-specific sentiment lexicons or be used for feature generation in machine-learning approaches. In this role, the RuSentiLex lexicon was utilized by the participants of the SentiRuEval-2016 Twitter reputation monitoring shared task and allowed them to achieve high results.

The RuSentiLex lexicon is publicly available at <http://www.labinform.ru/pub/rusentilex/index.htm>.

7. Acknowledgements

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8. Bibliographical References

Alexeeva, S., Koltsova, E., Kolcov, S. (2015). Linis-crowd.org: A lexical resource for Russian sentiment analysis of social media [Linis-crowd.org: lexicheskiy resurs dl'a analiza tonal'nosti sotsial'no-politicheskix

tekstov] *Computational Linguistics and computational ontologies: Proceedings of the XVIII joint Conference "Internet and modern society (IMS-2015)"* [Kompyuternaya lingvistika i vyichislitelnyie ontologii: sbornik nauchnyih statey. Trudy XVIII ob'edinennoy konferentsii «Internet i sovremennoe obschestvo» (IMS-2015)], St. Peterburg, pp. 25–34

Amigo, E., Corujo, A., Gonzalo, J., Meij, E., and de Rijke M. (2012). Overview of RepLab 2012: Evaluating Online Reputation Management Systems, *CLEF 2012 Evaluation Labs and Workshop Notebook Papers*, Rome.

Baccianella, S., Esuli, A., and Sebastiani, F. (2010). SentiWordNet 3.0: An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining. In: *LREC-2010*, Vol. 10, pp. 2200-2204.

Blitzer, J., Dredze, M., and Pereira, F. (2007). Biographies, bollywood, boom-boxes and blenders: Domain adaptation for sentiment classification. In: *Proceedings of ACL 2007*, pp. 440-447.

Cambria, E., Livingstone, A., and Hussain, A. (2012). The hourglass of emotions. Cognitive Behavioural Systems, *Lecture Notes in Computer Science*, vol. 7403, Springer, pp. 144-157

Cambria, E., Hussain, A., Havasi, C., and Eckl, C. (2010). Sentic computing: Exploitation of common sense for the development of emotion-sensitive systems. In: Springer, *LNCS*, vol. 5967, pp. 148-156.

Chetviorkin, I., and Loukachevitch, N. (2012). Extraction of Russian Sentiment Lexicon for Product Meta-Domain. In *COLING-2012*, pp. 593-610.

Chetviorkin, I., and Loukachevitch, N. (2013). Evaluating Sentiment Analysis Systems in Russian. In *Proceedings of BSNLP workshop, ACL 2013*. pp. 12-16.

Chetviorkin, I., and Loukachevitch, N. (2014). Two-Step Model for Sentiment Lexicon Extraction from Twitter Streams. In *Proceedings of WASSA workshop in conjugation with ACL-2014*, pp. 67-72.

Choi, Y., and Cardie, C. (2009). Adapting a polarity lexicon using integer linear programming for domain-specific sentiment classification. In *EMNLP '09*, pp. 590-598.

Feng S., Jun S. Kang, Polina Kuznetsova, and Yejin Choi. (2013). Connotation lexicon: a dash of sentiment beneath the surface meaning. *Proceedings of ACL-2013*, pp. 1774-1784.

Kuznetsova, E., Loukachevitch, N., and Chetviorkin, I. (2013). Testing rules for a sentiment analysis system. In *Proceedings of International Conference Dialog-2013*, pp. 71-80.

Lau, R., Lai, C., Bruza, P. and Wong, K. (2011). Pseudo Labeling for Scalable Semi-supervised Learning of Domain-specific Sentiment Lexicons. In *20th ACM Conference on Information and Knowledge Management*.

Loukachevitch, N., and Dobrov, B. (2014). RuThes Linguistic Ontology vs. Russian Wordnets. In *Proceedings of Global WordNet Conference GWC-2014*, Tartu.

Loukachevitch, N., Blinov, P., Kotelnikov, E., Rubtsova Yu., Ivanov, V., and Tutubalina, E. (2015). SentiRuEval: testing object-oriented sentiment analysis systems in Russian. In *Proceedings of International*

- Conference on Computational Linguistics and Intellectual Technologies Dialog-2015*, v.2. p. 3-13.
- Loukachevitch, N., and Rubtsova, Y. (2015). Entity-Oriented Sentiment Analysis of Tweets: Results and Problems. *Proceedings of Text-Speech-Dialog-2015*, LNAI, Springer, 9302, pp.551-559.
- Loukachevitch, N., and Rubtsova, Y. (2016). SentiRuEval-2016: Overcoming Time Gap and Data Sparsity in Tweet Sentiment Analysis. In *Proceedings of International Conference on Computational Linguistics and Intellectual Technologies Dialog-2016*.
- Mansour, R., Refaei, N., Gamon, M., Abdul-Hamid, A., and Sami, K. (2013). Revisiting The Old Kitchen Sink: Do We Need Sentiment Domain Adaptation?. In *Proceedings of RANLP-2013*, pp. 420-427.
- Mohammad, S. M., and Turney, P. D. (2013). Crowdsourcing a word-emotion association lexicon. *Computational Intelligence*, 29(3), 436-465.
- Mohammad, S. M., Kiritchenko, S., and Zhu, X. (2013). NRC-Canada: Building the state-of-the-art in sentiment analysis of tweets. In *Second Joint Conference on Lexical and Computational Semantics (SEM)*, Vol. 2, pp. 321-327.
- Nielsen, F. (2011). A new ANEW: evaluation of a word list for sentiment analysis in microblogs. In *Proceedings of the ESWC2011 Workshop on 'Making Sense of Microposts': Big things come in small packages*, Heraklion, Crete, Greece, May 30, 2011, pages 93-98.
- Perez-Rosas, V., Banea, C., and Mihalcea, R. (2012). Learning Sentiment Lexicons in Spanish. In *LREC-2012*, pp. 3077-3081.
- San Vicente, I., Agerri, R., Rigau, G., and Sebastián, D. S. (2014). Simple, Robust and (almost) Unsupervised Generation of Polarity Lexicons for Multiple Languages. *EACL 2014*, 88.
- Severyn, A., and Moschitti, A. (2015). On the automatic learning of sentiment lexicons. In *Proceedings of the Conference of the North American Chapter of the Association for Computational Linguistics (NAACL HLT 2015)*.
- Taboada, M., Brooke, J., Tofiloski, M., Voll, K., and Stede, M. (2011). Lexicon-based methods for sentiment analysis. *Computational linguistics*, 37(2), pp. 267-307.
- Wilson, T., Wiebe, J., and Hoffmann, P. (2005). Recognizing contextual polarity in phrase-level sentiment analysis. In *Proceedings of the conference on human language technology and empirical methods in natural language processing*, pp. 347-354.
- Ward, C. B., Choi, Y., Skiena, S., and Xavier, E. C. (2011). Empath: A framework for evaluating entity-level sentiment analysis. In *Emerging Technologies for a Smarter World (CEWIT-2011)*, pp. 1-6.
- Yang, A. M., Lin, J. H., Zhou, Y. M., and Chen, J. (2013). Research on building a Chinese sentiment lexicon based on SO-PMI. In *Applied Mechanics and Materials*, Vol. 263, pp. 1688-1693.
- Zasko-Zielinska M., Piasecki M., and Szpakowicz S. (2015). A Large Wordnet-based Sentiment Lexicon for Polish. *Proceedings Recent Advances in Natural Language Processing Conference (RANLP-2015)*. pp. 721-728.
- Zhu, X., and Ghahramani, Z. (2002). Learning from labeled and unlabeled data with label propagation.
- Technical Report CMU-CALD-02-107*, Carnegie Mellon University.