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Context-Aware Sentiment Detection

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Agenda

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  - Indicators for Missing Context
- Method
  - Context-Aware Sentiment Detection
  - Creation of Contextualized Sentiment Lexicons
  - Example
  - Cross-corpus Contextualized Sentiment Lexicons
- Evaluation
- Outlook and Conclusions

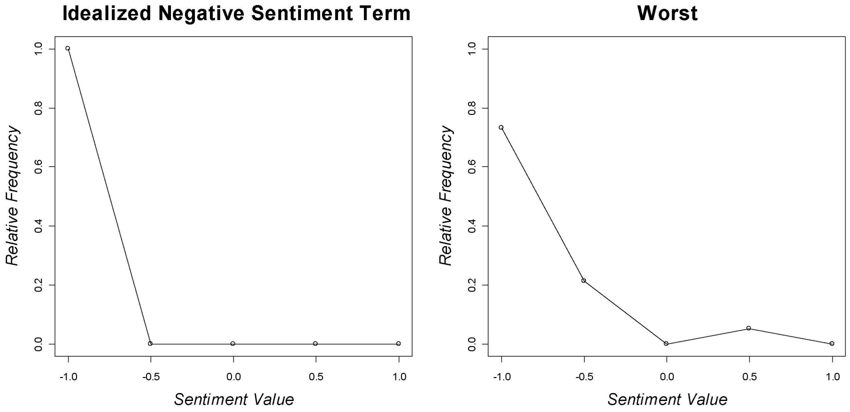
Motivation

- Pang et. al (2002): state of the art machine learning approaches do not unfold their full potential when applied to sentiment detection
- Lexicon-based approach
  - no labeled training corpus necessary
  - applicable *across* domains
  - throughput

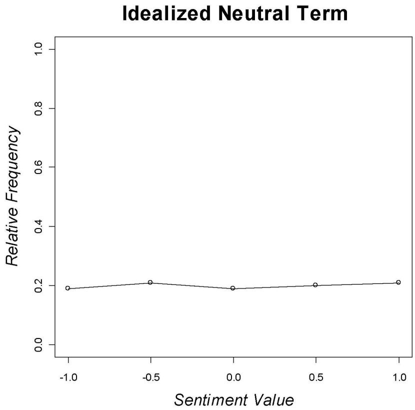
On the Need for Contextualization

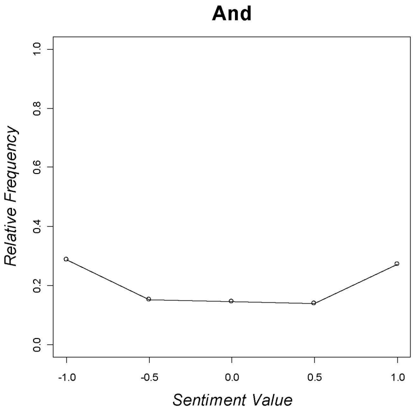
Positive	Negative
The repair of my car was satisfying.	I had many complaints after my camera's repair.
This movie's plot is unpredictable.	The breaks of this car are unpredictable.
The long peace brought wealth and safety to the people.	This peace is a lie.

Frequency Diagram



Frequency Diagram





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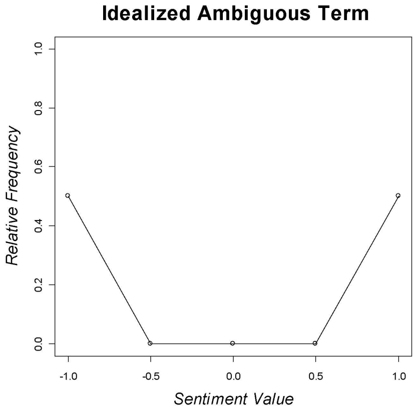

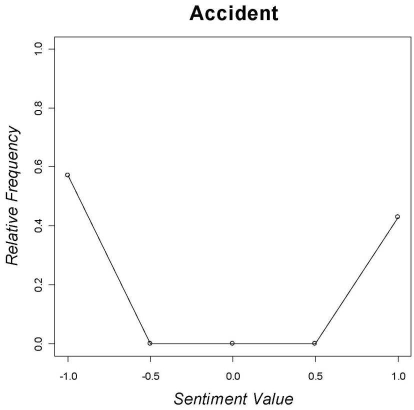

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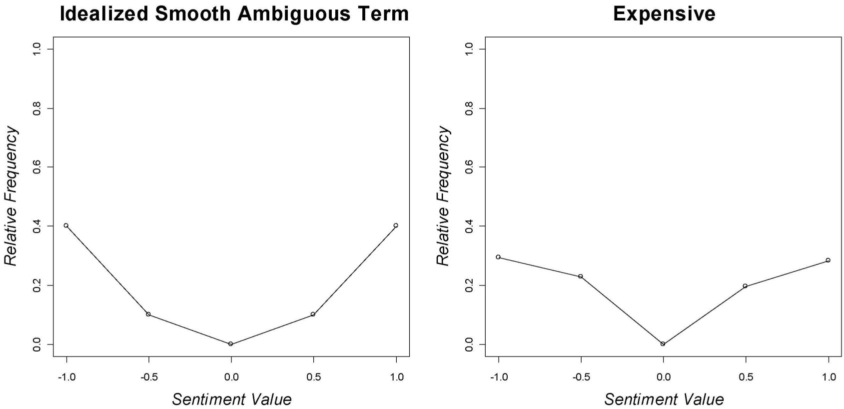

Method - Contextualized Sentiment Lexicon

- Use a contextualized sentiment lexicon
  - Based on ordinary sentiment lexicons
  - Contains stable sentiment terms and ambiguous terms
  - Uses context terms for disambiguation
- Derived from online reviews (Amazon, TripAdvisor)

Method - Context Aware Sentiment Detection

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Refined Sentiment Detection

$$s_{total} = \sum_{t_i \in doc} n(t_i)[s(t_i) + s'(t_i|\mathbf{c})] \quad \text{with} \tag{1a}$$

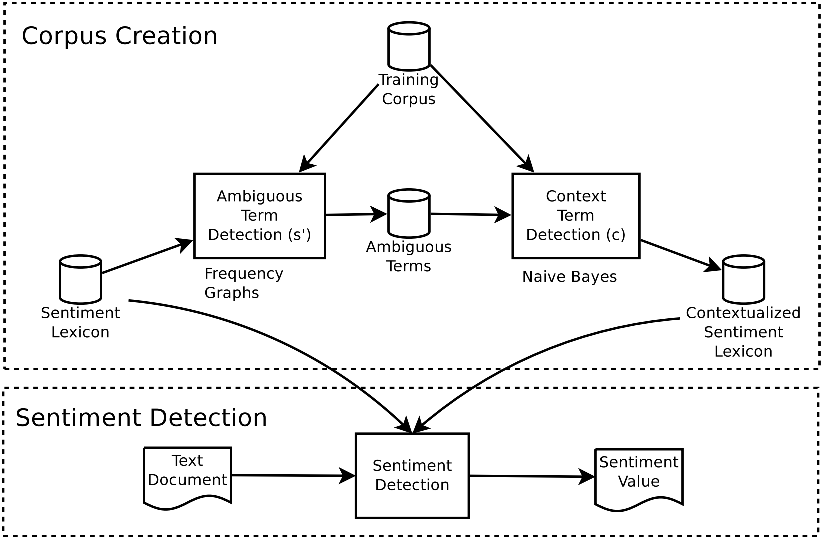
$$n(t_i) = \begin{cases} -1.0 & \text{if } t_i \text{ has been negated} \\ +1.0 & \text{otherwise.} \end{cases} \tag{1b}$$

Context Detection

$$\mathbf{c} = \{c_1, \ldots c_n\} \tag{2a}$$

$$p(C_+|\mathbf{c}) = \frac{p(C_+) \cdot \prod_{i=1}^{n} p(c_i|C_+)}{\prod_{i=1}^{n} p(c_i)} \tag{2b}$$

Method - Contextualized Sentiment Lexicon



Method - Contextualized Sentiment Lexicon

- Identify ambiguous terms (s')
  $\rightarrow$ frequency diagrams

$$\sigma_i \geq v \tag{3}$$

$$\mu_i + \sigma_i \geq w \tag{4a}$$

$$\mu_i - \sigma_i \leq -w \tag{4b}$$

- Learn context terms (c) for disambiguation
  $\rightarrow$ conditional probabilities
- Recalculate the sentiment value of the contextualized sentiment terms

Example

The service staff was *friendly*. They accomplished the **repair** of my car's motor very *quickly*. After driving it for another three months I can say that the motor is as *reliable* as it was before.

positive context terms	negative context terms
reliable	slowly
long-lasting	re-do
affordable	unreliable
pick-up-service	waiting
replacement-car	expensive
cooperative	cheater
...	...

Method - Context Lookup

The service staff was *friendly*. They accomplished the **repair** of my car's motor very *quickly*. After driving it for another three months I can say that the motor is as *reliable* as it was before.

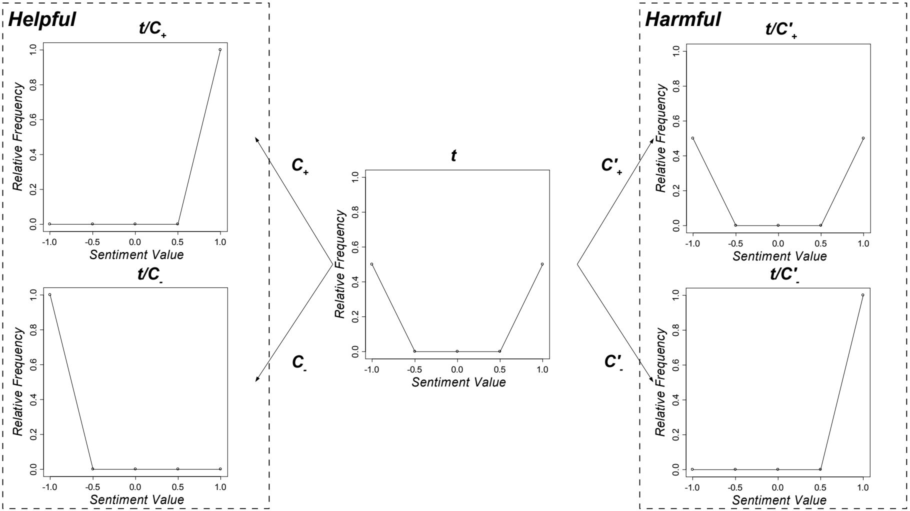
repair	
Context Term (c_i)	$P(C_+ \mid c_i)$
reliable	0.80
friendly	0.70
quickly	0.65

$\Rightarrow$ repair is used in a positive context $\rightarrow$ positive sentiment

Method - Real World Examples

Ambiguous Term	**SV$_{orig}$**	**Example**
busy	1	The hotel is located on a **busy** *road*.
complaint	-1	My *only* **complaint** would be the service.
cool	-1	Our room felt like a *really* **cool** European apartment with a rooftop terrace.
expensive	-1	The room was one of the more **expensive** hotels in Vienna but still *excellent*.
quality	1	*Poor* **quality** copies with one edge always dark.
better	1	Let's *hope* they work **better**.
cost	-1	Toner **cost** is way *behind* competitors.

Cross-corpus Contextualized Sentiment Lexicons

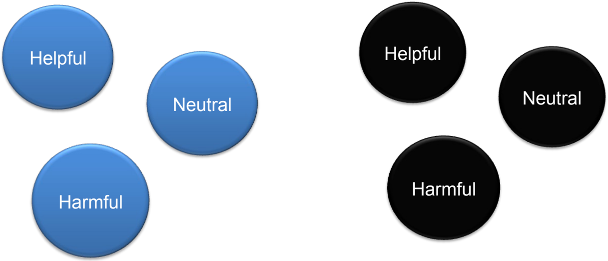


Cross-corpus Contextualized Sentiment Lexicons

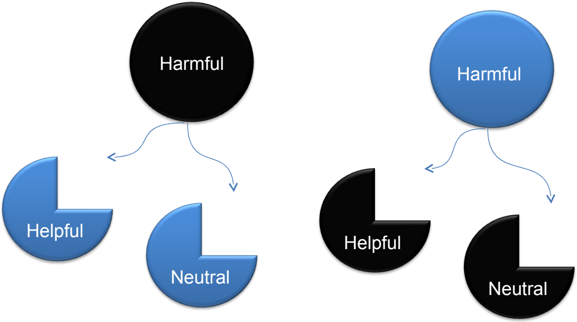
Three-step process

- Determine the helpfulness of all context terms
- Discard harmful context terms
- Merge remaining context terms into a large contextualized lexicon

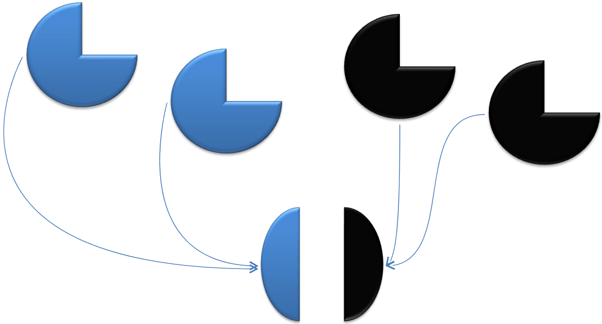
Step 1 - Determine the helpfulness of context terms



Step 2 - Discard harmful context terms



Step 3 - Merging



Evaluation - Approach

Evaluations

1. Comparison to a baseline
   – Do we outperform a lexicon-based approach which does not consider context?
2. Intra-domain sentiment detection
   – Does the removal of unstable sentiment terms has a positive effect?
3. Cross-domain sentiment detection
   – Determine the cross-domain performance of a *generic* contextualized sentiment lexicon.
4. Comparison to a machine learning approach
   – Intra-domain and cross-domain performance.

Evaluation - Setting

- Method: 10-fold cross validation
- Test corpora:
  - Equal number of positive and negative reviews.
  - Amazon: 2,500 reviews
  - TripAdvisor: 1,800 reviews

Evaluation - Context Aware Sentiment Detection

Corpus: Amazon

	Baseline			Context Aware		
	$\overline{R}$	$\overline{P}$	$\overline{F}_1$	$\overline{R}$	$\overline{P}$	$\overline{F}_1$
Pos	0.80	0.64	0.71	0.75	0.75	0.74
Neg	0.53	0.74	0.62	0.71	0.79	0.73

Corpus: TripAdvisor

	Baseline			Context Aware		
	$\overline{R}$	$\overline{P}$	$\overline{F}_1$	$\overline{R}$	$\overline{P}$	$\overline{F}_1$
Pos	0.96	0.60	0.74	0.97	0.66	0.79
Neg	0.34	0.90	0.49	0.46	0.95	0.61

Evaluation - Intra-Domain Performance

Test corpus: Amazon

	Domain-specific (Amazon)			Generic		
	$\overline{R}$	$\overline{P}$	$\overline{F}_1$	$\overline{R}$	$\overline{P}$	$\overline{F}_1$
Pos	0.75	0.75	0.74	0.77	0.72	0.74
Neg	0.71	0.79	0.73	0.67	0.77	0.72

Test corpus: TripAdvisor

	Domain-specific (TripAdvisor)			Generic		
	$\overline{R}$	$\overline{P}$	$\overline{F}_1$	$\overline{R}$	$\overline{P}$	$\overline{F}_1$
Pos	0.97	0.66	0.79	0.89	0.74	0.81
Neg	0.46	0.95	0.61	0.66	0.87	0.75

Evaluation - Cross Domain Performance

Test corpus: Amazon

	Domain-specific (TripAdvisor)			Generic		
	$\overline{R}$	$\overline{P}$	$\overline{F}_1$	$\overline{R}$	$\overline{P}$	$\overline{F}_1$
Pos	0.76	0.67	0.71	0.77	0.72	0.74
Neg	0.58	0.73	0.64	0.67	0.77	0.72

Test corpus: TripAdvisor

	Domain-specific (Amazon)			Generic		
	$\overline{R}$	$\overline{P}$	$\overline{F}_1$	$\overline{R}$	$\overline{P}$	$\overline{F}_1$
Pos	0.84	0.69	0.75	0.89	0.74	0.81
Neg	0.58	0.8	0.66	0.66	0.87	0.75

Evaluation - Naïve Bayes (NLTK)

			Test	
			TripAdvisor	*Amazon*
Training	*TripAdvisor*	$\oplus$	87	32
		$\ominus$	89	70
	Amazon	$\oplus$	75	81
		$\ominus$	60	77

Summary

- Lexicon-based approaches:
  - Simple, no labelled data required
  - Applicable across domains
  - High throughput
  - Can serve as a baseline
- Machine Learning approaches:
  - Powerful, but *domain-specific*
  - Require labelled training data

$\rightarrow$ The introduced approach combines these advantages (cross-domain, high throughput, high performance)

Outlook and Conclusions

- Considering context in sentiment detection
- Creation cross-domain contextualized sentiment lexicons
- Outperforms generic approaches
- Future work:
  - Different context scopes (paragraph, documents, text windows)
  - Consider other machine learning approaches