

# On opinion summarization with textual entailment recognition

(and how I got here..)

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# Outline

- Previous work
  - Sentiment Analysis
- Phd topic – Opinion Summarization with Textual Entailment Recognition
  - Textual entailment
- Current ongoing work

# Sentiment Analysis – ABSA task

**Task:** SemEval 2014 – Task4 Aspect-Based Sentiment Analysis

→ Determine sentiments or opinions on different aspects of entities (fine-grained SA)

- Aspect term and aspect term polarity detection
- Aspect category and aspect category polarity detection
  - Polarity = {positive, negative, neutral, conflict}
  - Categories = {food, service, price, ambience, anecdotes}

**Example:** Restaurant review:

“Their pizza was **great**, yet the lasagna that my friend had was **awful**.”

Aspect terms: pizza, lasagna

Aspect term polarity: pizza – positive, lasagna – negative

Aspect category: food

Aspect category polarity: food – conflict

# Sentiment Analysis – ABSA method

*Existing opinion detection system:*

- Based on a robust dependency parser (Xerox Incremental Parser - XIP)
- Additional component extracting sentiments relations (Brun, 2012): Polar lexicon (1265 negative words, 1082 positive words)

## **Term detection**

Goal: sentence → aspect terms

Method: Domain lexicon + hand-crafted rules to detect multiword terms

## **Term polarity detection**

Goal: aspect term → aspect term polarity

Method: Additional sentiment extraction rules

## **Category detection**

Goal: sentence → aspect categories

Method: logistic regression, bag-of-words (lemma forms + adjusted term freq)

## **Category polarity detection**

Goal: 1 sentence, 1 category → aspect category polarity

Method: SVM, 5 models, bag-of-words, polarities

# Sentiment Analysis – ABSA results

## Data:

Training corpus: 3044 sentences annotated for all subtasks:

3699 aspect term occurrences, 3714 aspect categories occurrences

Test corpus : 800 sentences annotated for all subtasks:

1134 aspect term occurrences, 1025 aspect category occurrences

## Phase A : Term & Category Detection

	Method	Prec.	Recall	F-Meas	Rank
<b>Terms</b>	Baseline	0.63	0.37	0.47	2
	XRCE	0.86	0.82	0.84	
<b>Categories</b>	Baseline	0.64	0.48	0.55	3
	XRCE	0.83	0.81	0.82	

## Phase B: Term and Category Polarity Detection

	Method	Accuracy	Rank
<b>Term Polarity</b>	Baseline	0.58	4
	XRCE	0.78	
<b>Categ. Polarity</b>	Baseline	0.59	3
	XRCE	0.78	

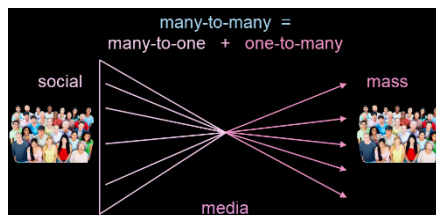
Label	F-measure	# of examples
Conflict	0.23	52
Negative	0.70	222
Positive	0.87	657
Neutral	0.48	94

# Phd outline and goals

**Goal:** Investigate methods for producing abstract summaries\* of opinionated statements

→ **range** and **quantitative distribution** of opinions

**Motivation:** \* to \* communication



**A 3-steps approach:**

Starting from a large collection of text statements expressing opinions on the same topic

1. Choose candidate statements
2. Estimate the **pattern of agreement** between opinions and statements
3. Select the statements to be included in the summary

\*Summary = List of statements with % of opinions that agree to each statement

# Phd focus

## ***Pattern of agreement***

→ Predict whether / to what extent a person who wrote an opinion would agree to a given statement

### **- Develop models of textual entailment**

Particular focus and preference towards distributional semantics vector-space models.

### **- Train on labelled agreement-prediction data**

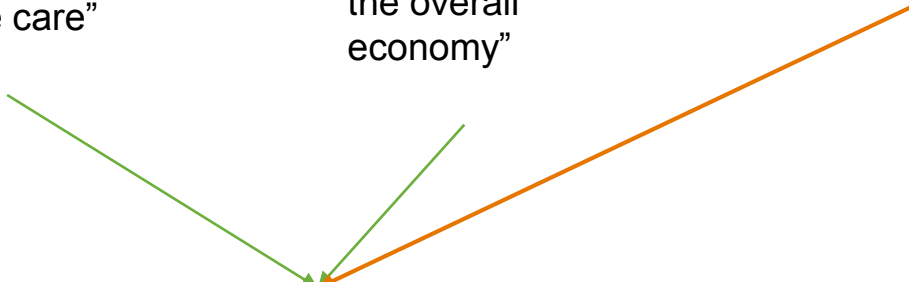
Identify agreement/disagreement in linked social media posts → supervised learning setting (refinement on top of the unsupervised methods)

# Phd focus - example

“Universal health care systems have lower long-term health costs as they encourage patients to seek preventative care”

“Public insurance is less costly than private insurance to the overall economy”

“Public insurance will help protect the uninsured from economic calamity”



Public healthcare is less expensive

The diagram consists of three arrows pointing towards a central point. Two green arrows originate from the left and middle text blocks, and one orange arrow originates from the right text block. All three arrows converge at a point above the central text 'Public healthcare is less expensive'.



# Textual entailment

**Textual entailment (TE)** - directional relation between text fragments: T - the entailing “Text”, and H - the entailed “Hypothesis”

*T entails H if, typically, a human reading T would infer that H is most likely true.*

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A man inspects the uniform of a figure in some East Asian country.	<b>contradiction</b> C C C C C	The man is sleeping
An older and younger man smiling.	<b>neutral</b> N N E N N	Two men are smiling and laughing at the cats playing on the floor.
A black race car starts up in front of a crowd of people.	<b>contradiction</b> C C C C C	A man is driving down a lonely road.
A soccer game with multiple males playing.	<b>entailment</b> E E E E E	Some men are playing a sport.
A smiling costumed woman is holding an umbrella.	<b>neutral</b> N N E C N	A happy woman in a fairy costume holds an umbrella.

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# Textual entailment

**Challenge:** Variability of semantic expression; \*-to-\* mapping between language expressions and meanings.

**Usefulness:** NLP applications: QA, IE, (multi-document) summarization, MT

**Attempts:** Pascal RTE challenges (2006 →)

**Methods:** pattern-based models, distributional models

**State-of-the-art: 84% (2014)**

# Textual entailment

## Lexical entailment

- Different types of lexical semantic relationships

**Hypernymy:** X is a type of Y. *example: dog/animal*

**Co-hyponymy:** X and Y share the same hypernym. *example: dog/cat*

**Meronymy:** X is a part of Y. *example: paws/dog*

**How to distinguish between them?**

# Textual entailment

- Extensive use of lexical resources (WordNet, FrameNet)
- Asymmetric measures
- Distributional Semantic Models (vector-space models)
- Distributional Inclusion Hypothesis

*If  $u$  is semantically narrower term than  $v$ , then a significant number of salient distributional features of  $u$  is included in the feature vector of  $v$  as well.*

$$\text{WeedsPrec}(u, v) = \frac{\sum_{f \in F_u \cap F_v} w_u(f)}{\sum_{f \in F_u} w_u(f)}$$

$$\text{cosWeeds}(u, v) = \sqrt{\text{WeedsPrec}(u, v) * \cos(u, v)}$$

$F(x)$  = set of distributional features of a term  $x$

$w_x(f)$  = weight of feature  $f$  for  $x$

- Operations on word2vec/ GloVe embeddings

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**! Entailment vector space !**

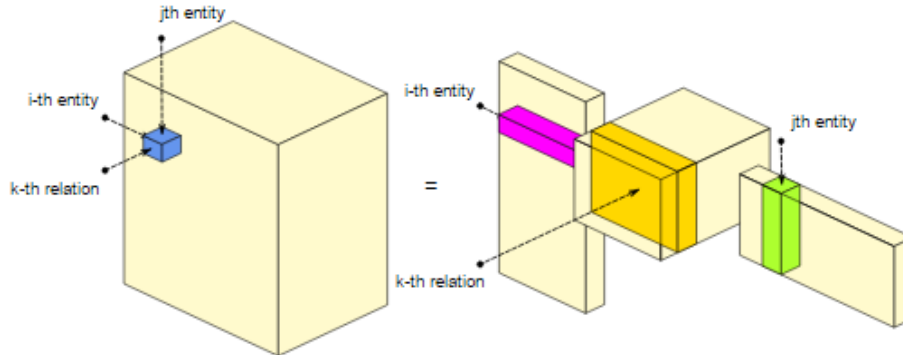
# Ongoing work

## Factorization Model - RESCAL

$X$  = adjacency tensor representing a multigraph of sentences

$X \approx R \times A \times A$ , or equivalently in elementwise notation

$$x_{ijk} \approx a_i^T R_k a_j$$



# Thank you!



# More on Phd outline and goals

## 1. Choose a set of candidate statements

- **List the candidate statements** before seeing the opinions
- **Use the input opinions** as candidate statements
- **Apply paraphrasing** models to **extend** the set of **opinions** with simpler versions
- **Apply lexical entailment** to **substitute** terms in the set of input opinions

## 2. Estimate the pattern of agreement between opinions and statements

## 3. Select the subset of statements to be included in the summary

- Data = opinions, cluster labels = summary statements