Information Extraction

Seminar – Bottom-Up Sentiment Analysis

CIS, LMU München

Winter Semester 2021-2022

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Today

- Today we will take a tangent and look at another problem in information extraction: sentiment analysis
  - Today I will cover **bottom-up** sentiment analysis
- I will leave time to make a few comments about the seminar and resolve any open issues

Sentiment Analysis

- Determine if a sentence/document expresses positive/negative/neutral sentiment towards some object

Slide from Koppel/Wilson

Some Applications

- **Review classification:** Is a review positive or negative toward the movie?
- **Product review mining:** What features of the ThinkPad T43 do customers like/dislike?
- **Tracking sentiments toward topics over time:** Is anger ratcheting up or cooling down?
- **Prediction (election outcomes, market trends):** Will Romney or Obama win?

Slide from Koppel/Wilson

Social media

- Twitter most popular
- Short (140 characters) and very informal text
- Abbreviations, slang, spelling mistakes
- 500 million tweets per day
- Tons of applications

Level of Analysis

We can inquire about sentiment at various linguistic levels:

- Words – objective, positive, negative, neutral
- Clauses – "*going out of my mind*"
- Sentences – possibly multiple sentiments
- Documents

Words

- Adjectives
  - objective: red, metallic
  - positive: honest important mature large patient
  - negative: harmful hypocritical inefficient
  - subjective (but not positive or negative): curious, peculiar, odd, likely, probable

Slide from Koppel/Wilson

Words

- Verbs
  - positive: **praise, love**
  - negative: **blame, criticize**
  - subjective: **predict**
- Nouns
  - positive: **pleasure, enjoyment**
  - negative: **pain, criticism**
  - subjective: **prediction, feeling**

Slide from Koppel/Wilson

Clauses

- Might flip word sentiment
  - *“not good at all”*
  - *“not all good”*
- Might express sentiment not in any word
  - *“convinced my watch had stopped”*
  - *“got up and walked out”*

Slide from Koppel/Wilson

Sentences/Documents

- Might express multiple sentiments
  - *"The acting was great but the story was a bore"*
- Problem even more severe at document level

Slide from Koppel/Wilson

Some Special Issues

- Whose opinion?

(Writer)

(writer, Xirao-Nima, US)

(writer, Xirao-Nima)

"The US fears a spill-over", said Xirao-Nima, a professor of foreign affairs at the Central University for Nationalities.

Some Special Issues

- Whose opinion?
- Opinion about what?

Slide from Koppel/Wilson

Laptop Review

- I should say that I am a normal user and this laptop satisfied all my expectations, the screen size is perfect, its very light, powerful, bright, lighter, elegant, delicate... But the only think that I regret is the Battery life, barely 2 hours... some times less... it is too short... this laptop for a flight trip is not good companion...
  Even the short battery life I can say that I am very happy with my Laptop VAIO and I consider that I did the best decision. I am sure that I did the best decision buying the SONY VAIO

Slide from Koppel/Wilson

Some Special Issues

- Identify expressed sentiment towards several aspects of the text
  - Different features of a laptop
- Sentiment towards a specific entity
  - Person, product, company
- Emotion Analysis
  - Identify emotions in text (love, joy, anger…)
- Sarcasm

Two Approaches to Classifying Documents

- Bottom-Up
  - Assign sentiment to words
  - Derive clause sentiment from word sentiment
  - Derive document sentiment from clause sentiment

- Top-Down
  - Get labeled documents
  - Use text categorization methods to learn models
  - Derive word/clause sentiment from models

Slide modified from Koppel/Wilson

Word Sentiment

Let's try something simple

- Choose a few seeds with known sentiment
- Mark synonyms of good seeds: good
- Mark synonyms of bad seeds: bad
- Iterate

Word Sentiment

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Not quite.

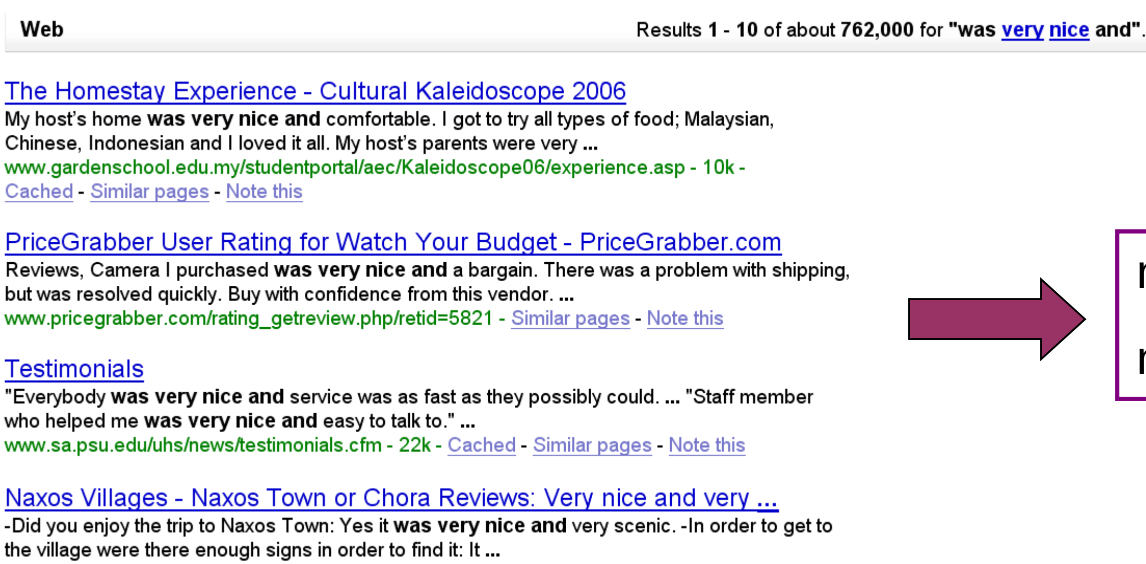
exceptional -> unusual -> weird

Slide from Koppel/Wilson

Better Idea

Hatzivassiloglou & McKeown 1997

1. Build training set: label all adj. with frequency > 20; test agreement with human annotators
2. Extract all conjoined adjectives



Web Results **1** - **10** of about **762,000** for **"was very nice and"**.

The Homestay Experience - Cultural Kaleidoscope 2006
My host's home **was very nice and** comfortable. I got to try all types of food; Malaysian, Chinese, Indonesian and I loved it all. My host's parents were very **...**
www.gardenschool.edu.my/studentportal/aec/Kaleidoscope06/experience.asp - 10k -
Cached - Similar pages - Note this

PriceGrabber User Rating for Watch Your Budget - PriceGrabber.com
Reviews, Camera I purchased **was very nice and** a bargain. There was a problem with shipping, but was resolved quickly. Buy with confidence from this vendor. **...**
www.pricegrabber.com/rating_getreview.php/retid=5821 - Similar pages - Note this

Testimonials
"Everybody **was very nice and** service was as fast as they possibly could. **...** "Staff member who helped me **was very nice and** easy to talk to." **...**
www.sa.psu.edu/uhs/news/testimonials.cfm - 22k - Cached - Similar pages - Note this

Naxos Villages - Naxos Town or Chora Reviews: Very nice and very ...
-Did you enjoy the trip to Naxos Town: Yes it **was very nice and** very scenic. -In order to get to the village were there enough signs in order to find it: It **...**

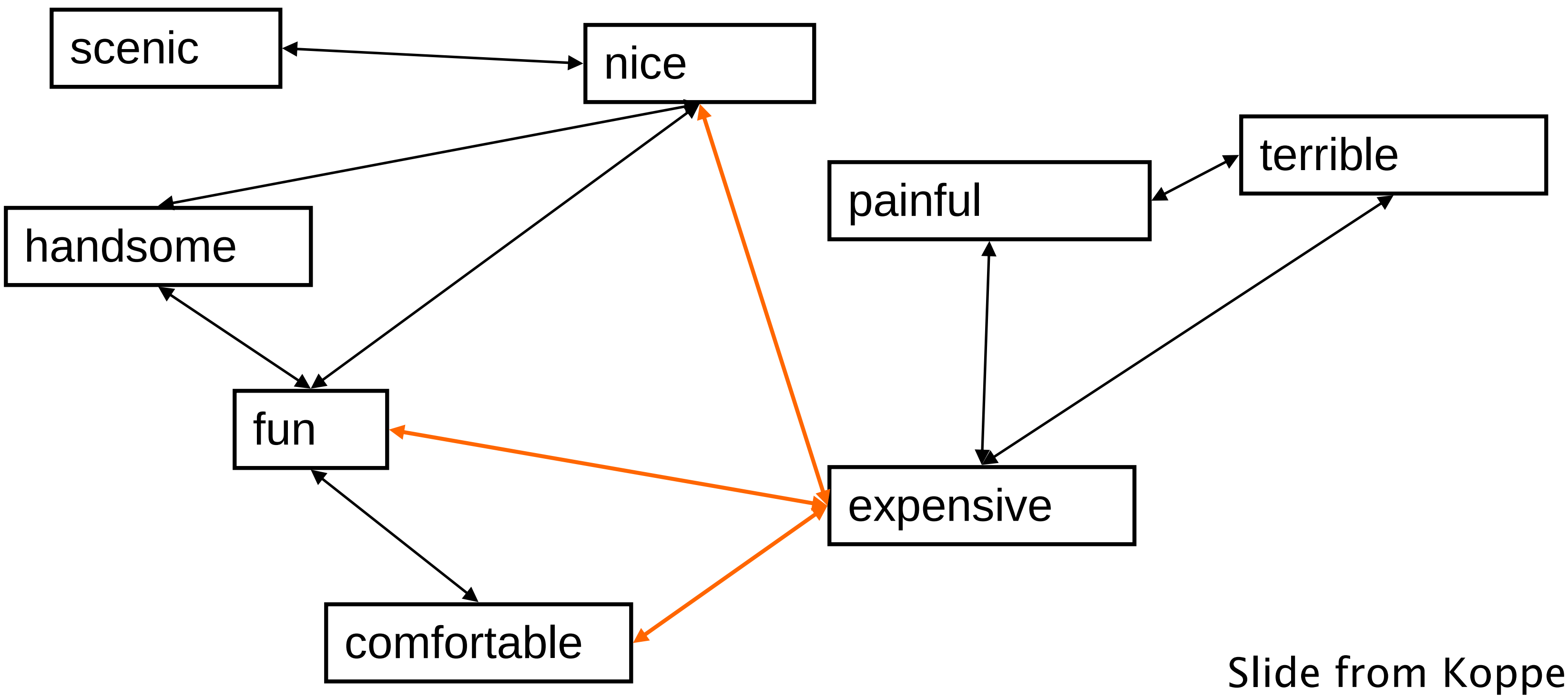
nice and comfortable

nice and scenic

Slide from Koppel/Wilson

Hatzivassiloglou & McKeown 1997

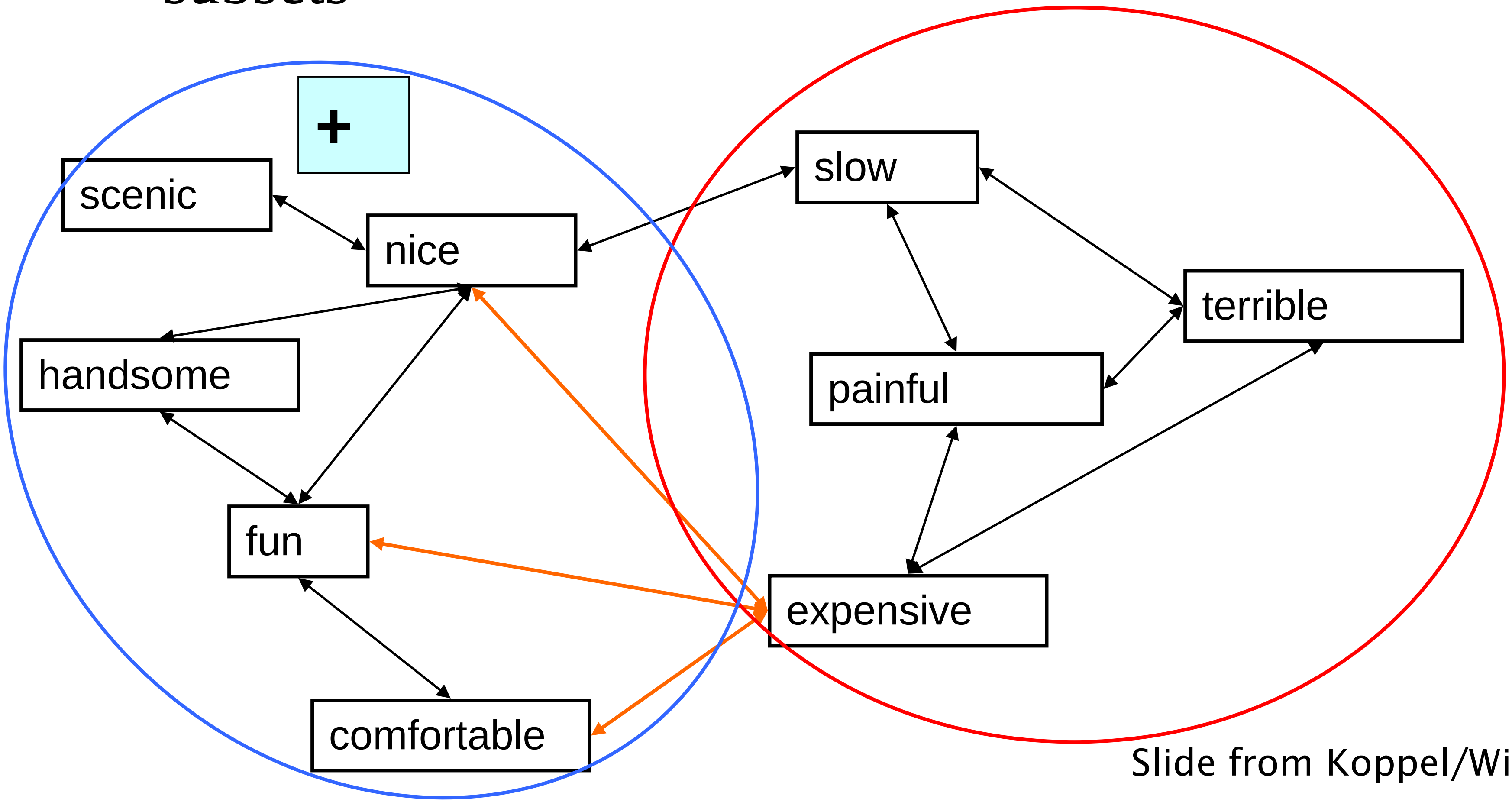
3. A supervised learning algorithm builds a graph of adjectives linked by the same or different semantic orientation



Slide from Koppel/Wilson

Hatzivassiloglou & McKeown 1997

4. A clustering algorithm partitions the adjectives into two subsets



Slide from Koppel/Wilson

Even Better Idea Turney 2001

- Pointwise Mutual Information (Church and Hanks, 1989):

$$\mathrm{PMI}(word_1, word_2) = \log_2\left(\frac{p(word_1 \wedge word_2)}{p(word_1)\, p(word_2)}\right)$$

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- Semantic Orientation:

$$\mathrm{SO}(phrase) = \mathrm{PMI}(phrase, \text{"excellent"}) - \mathrm{PMI}(phrase, \text{"poor"})$$

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- PMI-IR estimates PMI by issuing queries to a search engine

$$\mathrm{SO}(phrase) = \log_2\left(\frac{\mathrm{hits}(phrase\ \mathrm{NEAR}\ \text{"excellent"})\mathrm{hits}(\text{"poor"})}{\mathrm{hits}(phrase\ \mathrm{NEAR}\ \text{"poor"})\mathrm{hits}(\text{"excellent"})}\right)$$

Slide from Koppel/Wilson

Resources

These -- and related -- methods have been used to generate sentiment dictionaries

- Sentinet
- General Enquirer
- …

Slide from Koppel/Wilson

Bottom-Up: Words to Clauses

- Assume we know the “polarity” of a word
- Does its context flip its polarity?

Slide from Koppel/Wilson

Prior Polarity versus Contextual Polarity

Wilson et al 2005

- **Prior polarity**: out of context, positive or negative

  beautiful → positive

  horrid → negative

- A word may appear in a phrase that expresses a different polarity in context

> "Cheers to Timothy Whitfield for the **wonderfully horrid** visuals."

Contextual polarity

Example

Philip Clap, President of the National Environment Trust, sums up well the general thrust of the reaction of environmental movements: there is no reason at all to believe that the polluters are suddenly going to become reasonable.

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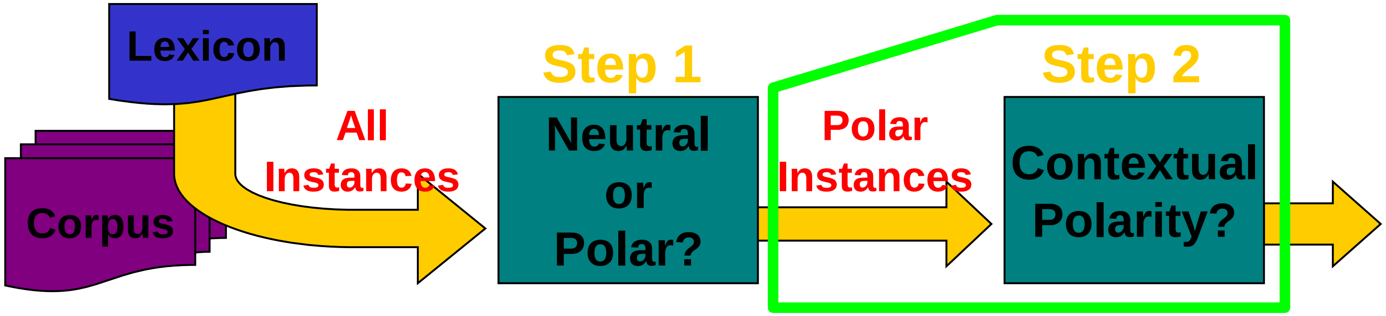
prior polarity

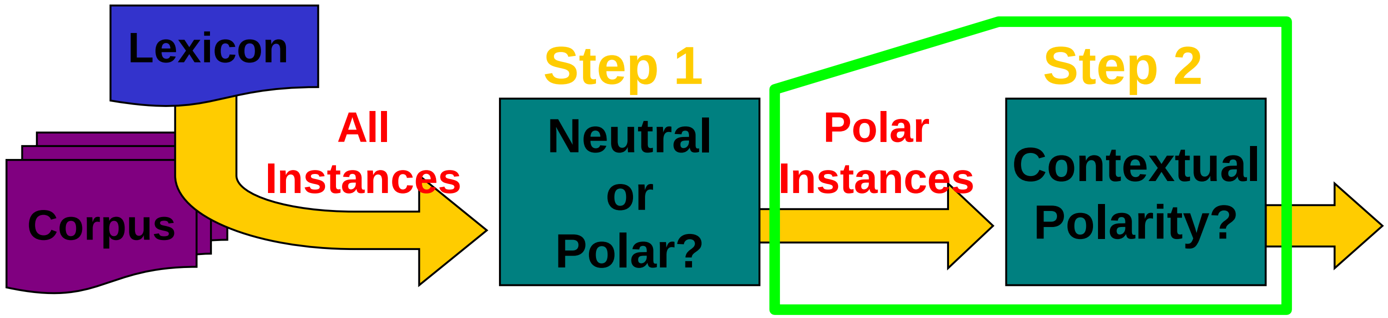
Contextual polarity

Slide from Koppel/Wilson



- Word token
- Word prior polarity
- Negated
- Negated subject
- Modifies polarity
- Modified by polarity
- Conjunction polarity
- General polarity shifter
- Negative polarity shifter
- Positive polarity shifter

Slide from Koppel/Wilson



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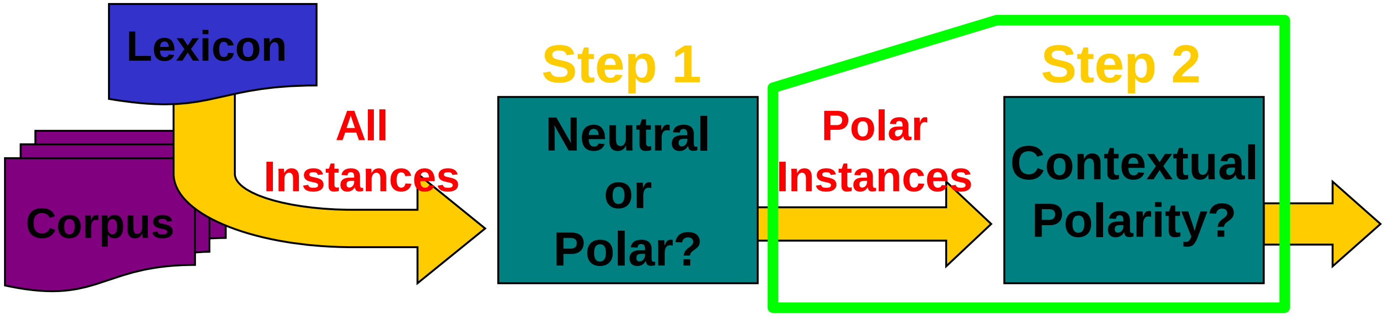
Word token

terrifies

Word prior polarity

negative

Slide from Koppel/Wilson



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Binary features:

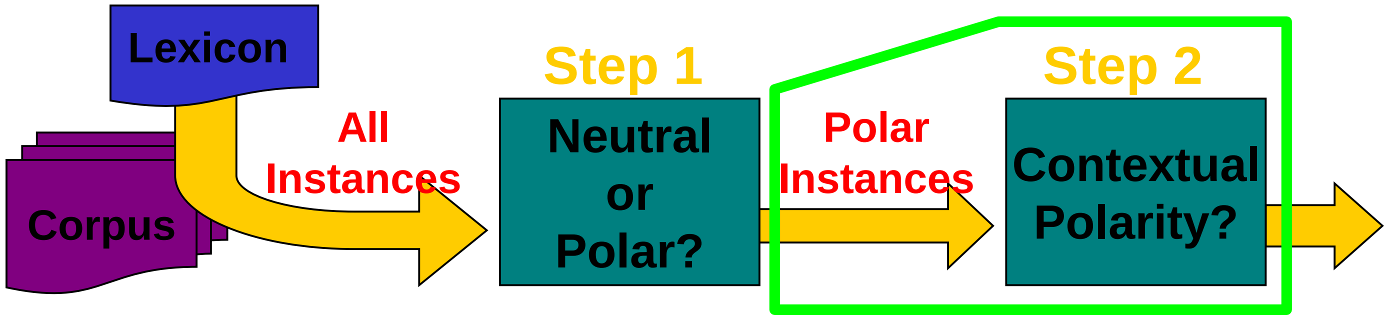
- **Negated**

  For example:
  - ***not*** *good*
  - ***does not*** *look very good*
  - ❖ ***not only*** *good but amazing*

- **Negated subject**

  No politically prudent Israeli *could support either of them.*

Slide from Koppel/Wilson



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- **Modifies polarity**

  5 values: positive, negative, neutral, both, not mod

  ***substantial*: negative**

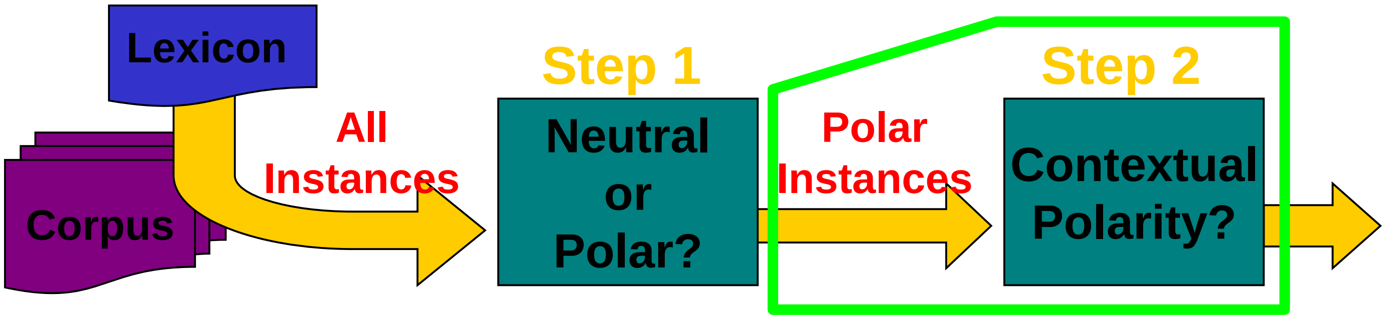
- **Modified by polarity**

  5 values: positive, negative, neutral, both, not mod

  ***challenge*: positive**

substantial (pos) *challenge* (neg)

Slide from Koppel/Wilson



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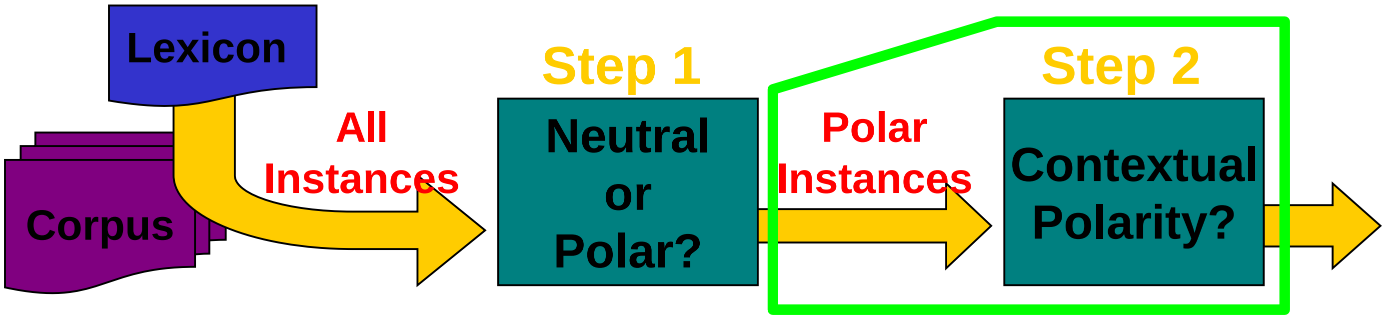
- **Conjunction polarity**

5 values: positive, negative, neutral, both, not mod

***good*: negative**

good (pos) *and* *evil* (neg)

Slide from Koppel/Wilson



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- Modifies polarity
- Modified by polarity
- Conjunction polarity
- **General polarity shifter**
- **Negative polarity shifter**
- **Positive polarity shifter**

- General polarity shifter

  *pose **little** threat*

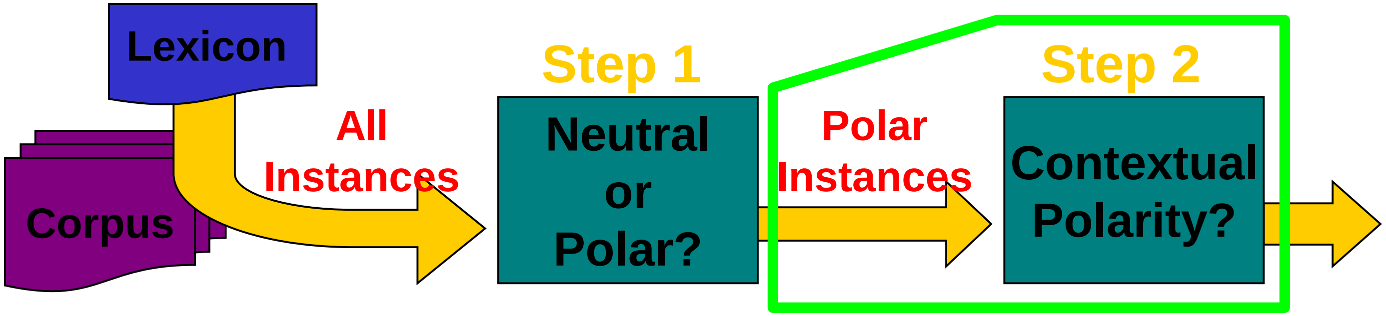
  *contains **little** truth*

- Negative polarity shifter

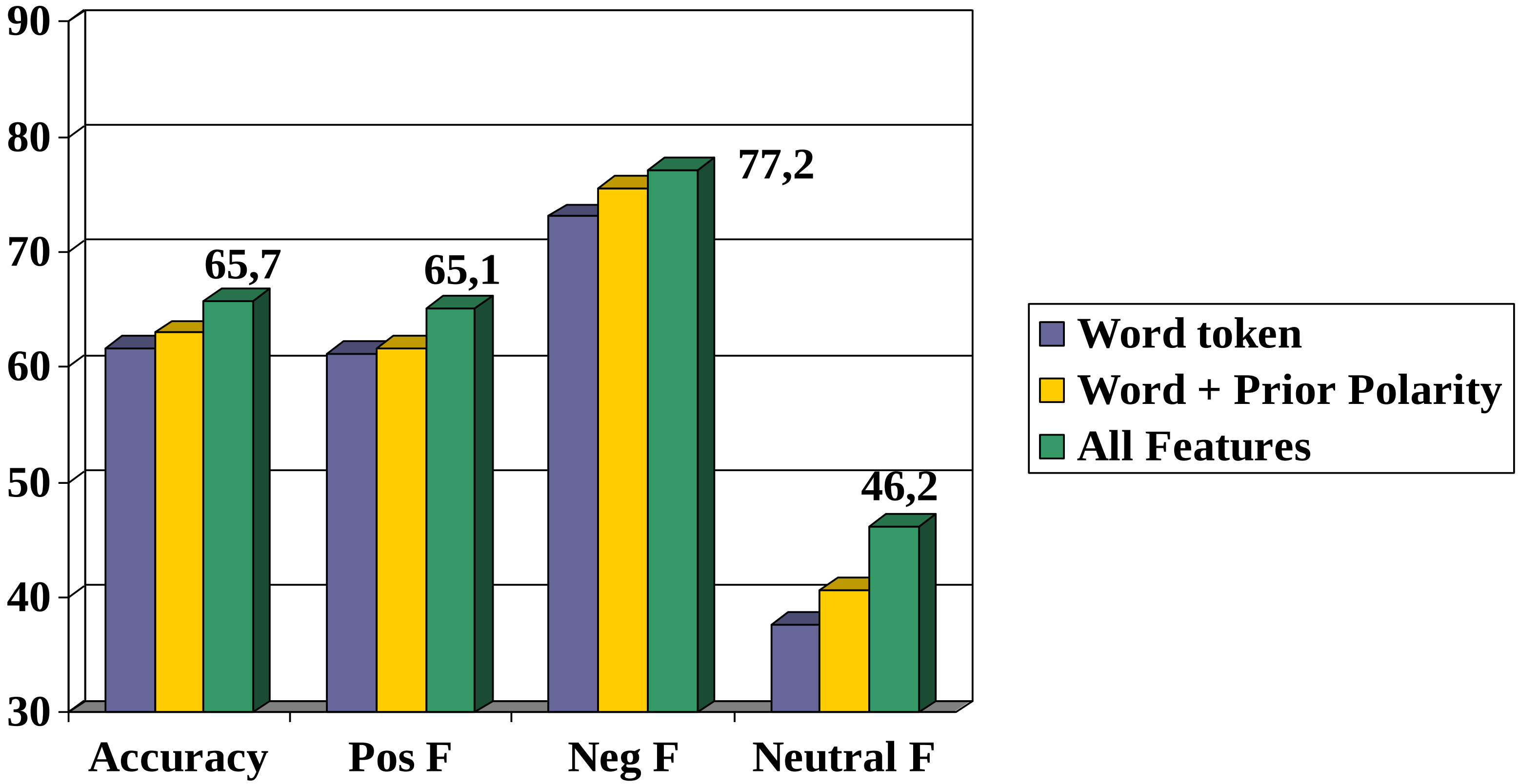
  ***lack** of understanding*

- Positive polarity shifter

  ***abate** the damage*



Results 2a



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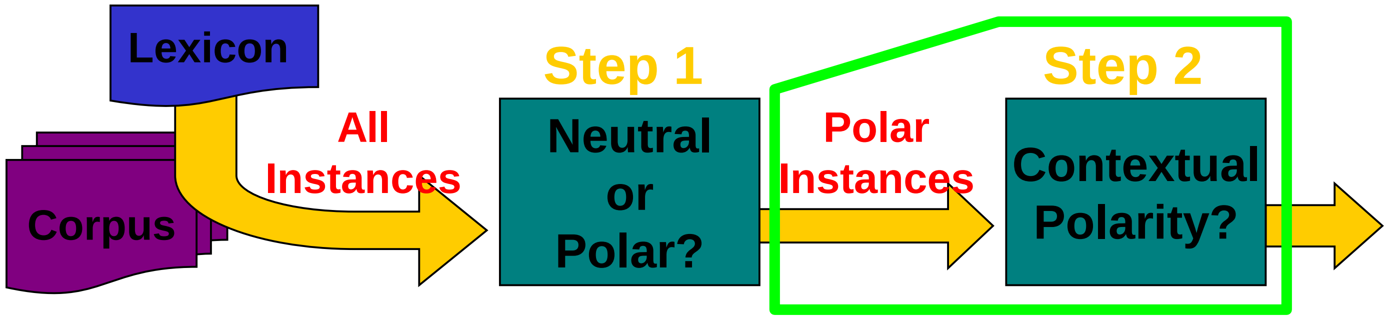

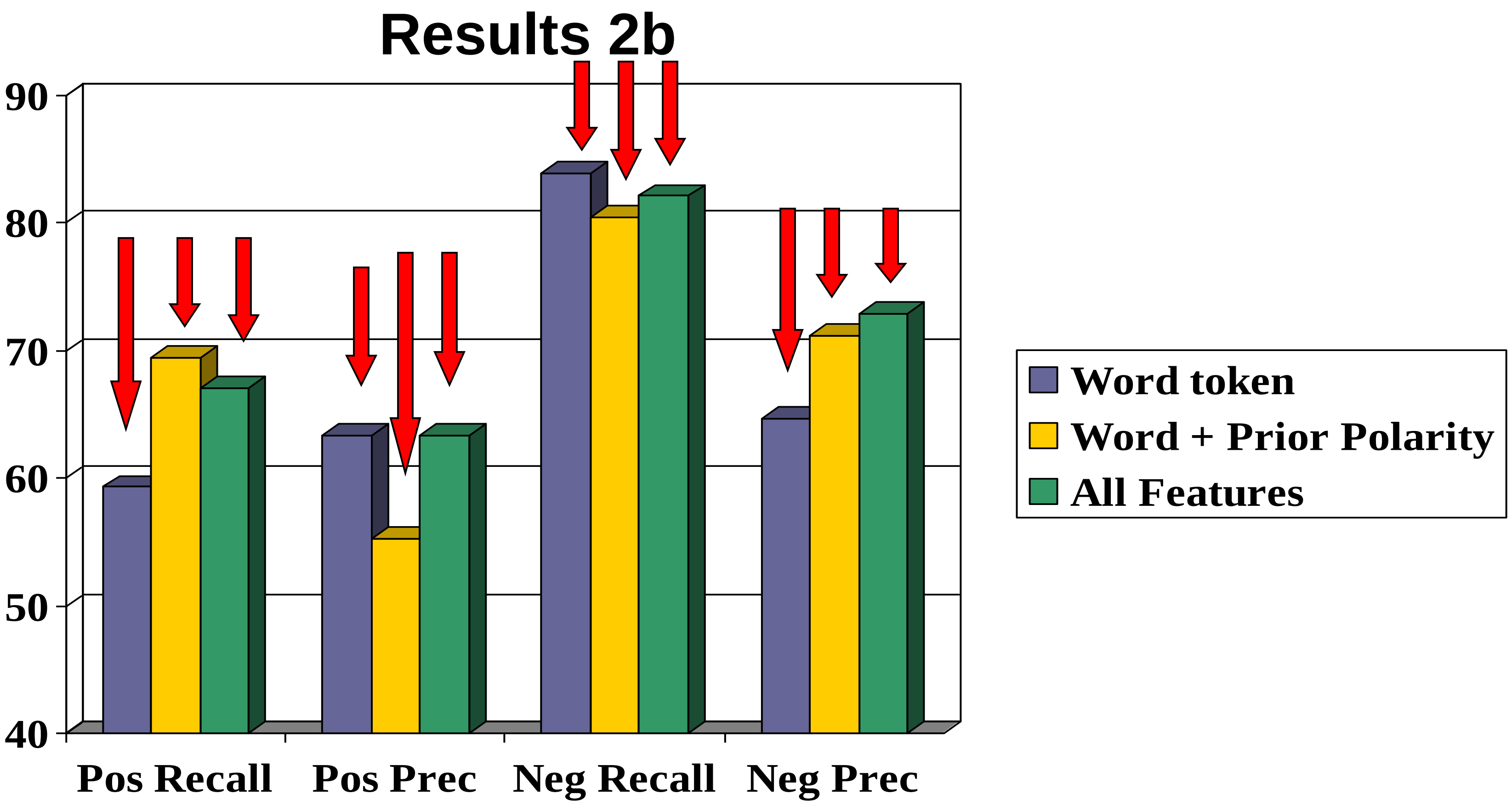

Slide from Koppel/Wilson

Conclusion: Bottom-up sentiment analysis

- We discussed bottom-up sentiment analysis, which critically depends on lexical information
  - Easy to understand, used in some commercial products
- We may discuss top-down later, which uses text classification approaches (including deep learning)
  - This would require as background the lectures on machine learning that are coming up

- Slide sources
  - Nearly all of the slides today are from Prof. Moshe Koppel (Bar-Ilan University)
- Further reading on traditional sentiment approaches
  - 2011 AAAI tutorial on sentiment analysis from Bing Liu (quite technical)

- Thank you for your attention!