Sentiment Polarity and Polarity Modifiers

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Outline

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Automatic Classification of Facts

- Traditionally, text categorization seeks to classify documents by topic into many possible categories.
- Classification of facts works based on keywords, if a keyword is contained in the document, the document talks about the topic related to that keyword[1].
- Keywords can be determined manually or automatically (i.e. using words as features for a machine learning algorithm).

[1] simplified slightly ...

First Idea: Sentiment Keywords

- In sentiment classification we have relatively few classes representing opposing categories (positive/negative, sometimes neutral).
- First idea: Find a set of keywords for every sentiment category.
- Keywords will be mainly adjectives, but can also be nouns (*"rubbish"*), verbs (*"hate"*) or complete phrases (*"cost someone an arm and a leg"*).

Keyword-based Sentiment Classification

	Proposed word lists	Accuracy	Ties
Human 1	positive: *dazzling, brilliant, phenomenal, excellent, fantastic* negative: *suck, terrible, awful, unwatchable, hideous*	58%	75%
Human 2	positive: *gripping, mesmerizing, riveting, spectacular, cool, awesome, thrilling, badass, excellent, moving, exciting* negative: *bad, cliched, sucks, boring, stupid, slow*	64%	39%

Figure 1: Baseline results for human word lists. Data: 700 positive and 700 negative reviews.

	Proposed word lists	Accuracy	Ties
Human 3 + stats	positive: *love, wonderful, best, great, superb, still, beautiful* negative: *bad, worst, stupid, waste, boring, ?, !*	69%	16%

Figure 2: Results for baseline using introspection and simple statistics of the data (including *test* data).

- Results for classifying documents into positive and negative based on counting positive and negative words.
- Coming up with the right set of keywords is less trivial than one might initially think [PLV02].

Machine Learning for Sentiment Classification

	Features	# of features	frequency or presence?	NB	ME	SVM
(1)	unigrams	16165	freq.	**78.7**	N/A	72.8
(2)	unigrams	"	pres.	81.0	80.4	**82.9**
(3)	unigrams+bigrams	32330	pres.	80.6	80.8	**82.7**
(4)	bigrams	16165	pres.	77.3	**77.4**	77.1
(5)	unigrams+POS	16695	pres.	81.5	80.4	**81.9**
(6)	adjectives	2633	pres.	77.0	**77.7**	75.1
(7)	top 2633 unigrams	2633	pres.	80.3	81.0	**81.4**
(8)	unigrams+position	22430	pres.	81.0	80.1	**81.6**

Figure 3: Average three-fold cross-validation accuracies, in percent. Boldface: best performance for a given setting (row). Recall that our baseline results ranged from 50% to 69%.

- Results for classifying documents into positive and negative using Naive Bayes, Maximum Entropy and Support Vector Machines with unigram features [PLV02]
- Sentiment classification is hard!

Top Machine Learning Features[2]

Positive class:

```
capable: -1.26          trimode: -0.76
amazing: -1.2           value: -0.75
wonderful: -1.14        enabled: -0.75
convenience: -1.06      unlimited: -0.75
tons: -1.05             fits: -0.73
inexpensive: -1.02      imagine: -0.73
telephone: -0.9         love: -0.73
pros: -0.9              reasonably: -0.71
excellent: -0.89        beyond: -0.71
solid: -0.87            provides: -0.71
functional: -0.83       great: -0.7
superb: -0.82           handy: -0.69
pick: -0.81             reasonable: -0.69
via: -0.81              eyes: -0.69
nor: -0.81              ago: -0.69
cool: -0.79             awesome: -0.68
outstanding: -0.79      metal: -0.68
told: -0.78             monthly: -0.68
aim: -0.78              party: -0.67
active: -0.77           pda: -0.66
easy: -0.77             blue: -0.65
holds: -0.76            visible: -0.65
sturdy: -0.76           stores: -0.65
phenomenal: -0.76       everything: -0.65
```

Negative class:

```
lacks: 1.62             lack: 0.79
worst: 1.54             occasional: 0.78
heats: 1.13             awful: 0.77
poor: 1.05              barely: 0.76
horrible: 1.03          remove: 0.76
scratches: 0.98         replaced: 0.76
dislike: 0.94           dont: 0.74
ll: 0.92                organiser: 0.74
fragile: 0.92           poorly: 0.74
concern: 0.88           confusing: 0.73
inconsistent: 0.88      dark: 0.73
uncomfortable: 0.88     frustrating: 0.73
biggest: 0.85           looked: 0.73
bad: 0.84               bugs: 0.73
slow: 0.84              drops: 0.73
requires: 0.83          updated: 0.73
changed: 0.83           issues: 0.73
joke: 0.81              elsewhere: 0.72
happen: 0.81            gave: 0.72
instructions: 0.81      hard: 0.72
none: 0.8               accessing: 0.71
horrid: 0.79            quiet: 0.71
tunes: 0.79             track: 0.71
disable: 0.79           miss: 0.71
```

[2] Stanford classifier trained on sentences from cellphone reviews.

One Word, Two Polarities (1)

One word may have different polarities in **different domains**:

- *"unpredictable"*
  - Movie domain: *"unpredictable plot"* (positive)
  - Automotive domain: *"unpredictable steering"* (negative)
- *"funny"*
  - Movie domain: *"funny movie"* (positive)
  - Food domain: *"funny taste"* (negative)

One Word, Two Polarities (2)

One word may have different polarities in the **same domain** in combination with **different targets**:

- *"long"*, camera domain
  - *"The battery life is long."* (positive)
  - *"The time taken to focus is long."* (negative)
- *"low"*, finance domain
  - *"The price is low."* (positive)
  - *"Their income is low."* (negative)
- *"warm"*, restaurant domain
  - *"They gave me a warm welcome ..."* (positive)
  - *"... and warm beer."* (negative)

Sentiment Words without Sentiment, Sentiment without Sentiment Words

Sentiment words do not always express sentiment:

- *"I am looking for a* **good** *insurance for my family."*
- *"With* **great** *power comes* **great** *responsibility."*

It is possible to express sentiment with no words that are obvious sentiment words:

- *"If you are reading this because it is your darling fragrance, please wear it at home exclusively, and tape the windows shut."* (negative)
- *"The food tasted like my shoes."* (negative)

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Polarity Modifiers

Definition: Polarity Modifiers [PZ04]

Lexical phenomena that can cause the valence of a lexical item to shift from one pole to the other or, less forcefully, to modify the valence towards a more neutral position.

Polarity modifiers are also called valence shifters, contextual sentiment influencers, . . .
[PZ04] give an overview about many sentence-level phenomena.

Polarity Reversers[3]

Polarity reversers can "flip" or "reverse" the polarity of an expression:

- *"I like this book."* (positive)
  → *"I* **don't** *like this book."* (negative)
- *"John is successful at tennis."* (positive)
  → *"John is* **never** *successful at tennis."* (negative)
- *"Peter failed the exam."* (negative)
  → "**Nobody** *failed the exam."* (positive)

But the presence of a reverser in the sentence is no guarantee to flip the polarity of the sentence:

- *"This book is good."* (positive)
- "**No** *wonder this book is good."* (positive)

[3] Negation, negators, . . . , sometimes also polarity shifters

Polarity Shifters[4]

Polarity shifters weaken or intensify the strength of the polarity of the term modified:

- *"efficient"* (positive)
  → "**very** *efficient.*" (more positive)
- *"suspicious"* (negative)
  → "**deeply** *suspicious*" (more negative)
- *"efficient"* (positive)
  → "**slightly** *efficient*" (less positive)
- *"suspicious"* (negative)
  → "**somewhat** *suspicious*" (less negative)

[4] Intensifiers/diminishers, increase/decrease words, degree modifiers, . . .

Presuppositional Items

Definition: Presupposition

Any information which is taken for granted in a discourse situation, for instance the sentence *"Did you enjoy your breakfast?"* assumes that the interlocutor already had breakfast.

Presuppositional items may swap polarity or assign polarity to otherwise neutral/objective statements:

- *"The battery lasts 2 hours."* (objective) → *"The battery* **only** *lasts 2 hours."* (negative, it should have lasted more)
- *"Servings were sufficient."* (positive) → *"Servings were* **barely** *sufficient."* (negative, more was expected)
- *"He succeeded."* (positive) → *"He* **failed** *to succeed."* (negative, he was expected to succeed)

Modal Operators

Definition: Modal operators [PZ04]

Modal operators are used to express possibilities, conditions, or to set up a context in which an attitude is expressed that does not necessarily reflect the actual opinion of the author.

- *"The only gripe I have is that the flash is weak."* (negative)
  → *"The only gripe I* **might** *have is . . ."* (less negative)
- *"The camera is bulky."* (negative)
  → *"Although you* **might** *think the camera is bulky, . . ."* (?)
- *"I just wish they* **would** *come out with a similar camera with bigger optical zoom!"* (neutral? negative?)
- *"The resolution is poor and the autofocus* **would** *constantly hunt."* (negative)

Conditional Sentences

Definition: Conditional sentences [NLC09]

Conditional sentences are sentences that describe implications or hypothetical situations and their consequences.

- "**If** *Sony makes* <u>*good*</u> *cameras, I will buy one.*" (neutral)
- "**If** *you are looking for a camera with* <u>*great*</u> *picture quality, buy Sony.*" (positive)
- "**If** *you are looking for a camera with* <u>*great*</u> *picture quality, don't buy Sony.*" (negative)
- "**If** *this restaurant was* <u>*good*</u>*, I would recommend it.*" (?)

Irony, Sarcasm

Definition: Sarcasm [TDR10]

The activity of saying or writing the opposite of what you mean, or of speaking in a way intended to make someone else feel stupid or show them that you are angry.

- *"As much use as a trapdoor on a lifeboat."* (sarcastic)
- *"All the features you want. Too bad they don't work!"* (sarcastic, the second sentence overrides the first)
- *"Be sure to save your purchase receipt!"* (could just be good advice – but sarcasm if it's the title of a review).
- *"This book was really good – until page 300!"* (not sarcastic)
- *"This book was really good – until page 2!"* (sarcastic)

Outline

Review Relevance

A document may contain off-topic passages that might also contain opinions.

"**The book**, *which is* <u>*terrific*</u>, *[. . .] McCourt's autobiographical account of growing up [. . .] is a* <u>*gut-wrenching*</u> *experience; [. . .]* **His father** *[. . .] wasn't a* <u>*bad*</u> *man, in an* <u>*evil*</u> *sense; he was just no* <u>*good*</u>. **Carlyle**, *a* <u>*fine*</u> *actor [. . .] never seems to get to the core of this admittedly complex character; [. . .]* **His performance** *is* <u>*passable*</u>, *but it's all on the surface. [. . .] Visually,* **the movie** *is* <u>*stunning*</u>, *though; the cinematography successfully captures the* <u>*bleakness*</u> *of* **Limerick** *and the surrounding countryside."*

Opinions about items other than the target should be filtered out.

Aspects[5]

- Opinions can be expressed on an object or on one of its aspects (components or attributes) [Liu10]:
  - *"The Kyocera QCP-2035a is hard to use though."* (object)
  - *"The touch screen of iPhone is really cool".* (component)
  - *"The voice quality on this phone is one of the best that I've ever heard."* (attribute)
- The aspect is not always explicitly mentioned:
  "The S300 is slightly larger than the S100." $\rightarrow$ aspect *"size"*
- Aspects form a hierarchy and are discussed on different levels, e.g., the statement *"the pasta is good"* should count towards the opinion about the aspect *"food"*.

[5] Often called "properties" or "features", but not to be confused with features used for machine learning.

Incorporating Discourse Structure

"I hate the Spice Girls. ... [3 things the author hates about them] ... Why I saw this movie is a really, really, really long story, but I did, and one would think I'd despise every minute of it. But... Okay, I'm really ashamed of it, but I enjoyed it. I mean, I admit it's a really awful movie, ... [they] act wacky as hell...the ninth floor of hell...a cheap [beep] movie...The plot is such a mess that it's terrible. But I loved it."

⇒ Contains a large number of negative sentences, but the overall sentiment towards the movie is positive [PL08, PLV02].

Reviews are Difficult Texts to Analyze

- Creative spelling and punctuation:
  "So im A little miffed.They PROMISED me they would call me back and Ofcourse they havent.. Need less to say if your camera breaks they will blame you so they can try and make more money.."
- Slang, common internet abbreviations, smilies:
  "imo the ice cream is luuurrrrrrvely :))"
- Figures of speech, metaphers, trying to be funny:
  "He is not the sharpest knife in the drawer."
  "if you don't require every last bell and whistle, it is more than enough."

Outline

Summary: Why is it Difficult

- Assigning polarity to words can be difficult:
  - Sentiment words are domain-specific.
  - Some sentiment words can have different polarities depending on the opinion target.
  - Sentiment words don't always express sentiment.
- Polarity modifiers can change the polarities of words:
  - Polarity reversers "flip" word polarity.
  - Polarity shifters influence the strength of sentiment.
  - Modals/conditionals may not express "real" sentiment.
  - Irony/sarcasm may mean the opposite of what is stated.
- Reviews are difficult texts:
  - Reviews often contain non-relevant passages.
  - Sentiments are expressed in a discourse.
  - Reviews are often badly written.

Outline

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