Impact of Lexical Filtering on Overall Opinion Polarity Identification

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The Problem

- Opinion Polarity – thumbs up or down
- Supervised machine learning approach
- Impact of Lexical Filtering of the training set

The Data

- 27,000 movie reviews (Internet Movie Database)
- Extract 1500/1500 clearly positive/negative
- Test set of size 100/100 reviews
- Training set: 100–1500 reviews

Unigrams (Naïve Bayes)

- POS tagged data
- data containing only the adjectives
- data containing only the WordNet synsets of the adjectives

Unigram filters

Consider *"It does run long and the plot was weak"*:

- *All-POS*:

it	does	run	long	and	the	plot	was	weak
/PRP	/VBZ	/VB	/JJ	/CC	/DT	/NN	/VBD	/JJ

- *JJ*:

long	weak
/JJ	/JJ

- *JJ Synsets*:

{long,lengthy. . . }	{weak,anemic,adynamic,. . . }
/JJ	/JJ

Results with Unigrams

Training Size	All-POS	JJ	Synsets on JJ
100	.615	.640	.650
400	.740	.700	.730
700	.775	.715	.710
1000	.765	.755	.720
1500	.795	.730	.735

Bigrams (Markov Model)

- POS tagged data
- Tagged data with POS filters
- Tagged data with WordNet filters

POS Filtering

Rule	Example		
Keep	`good/JJ`	$\longrightarrow$	`good/JJ`
Discard	`and/CC`	$\longrightarrow$	
Generalize	`movies/NNS`	$\longrightarrow$	`/NN`

Keep Discard Generalize

Example:

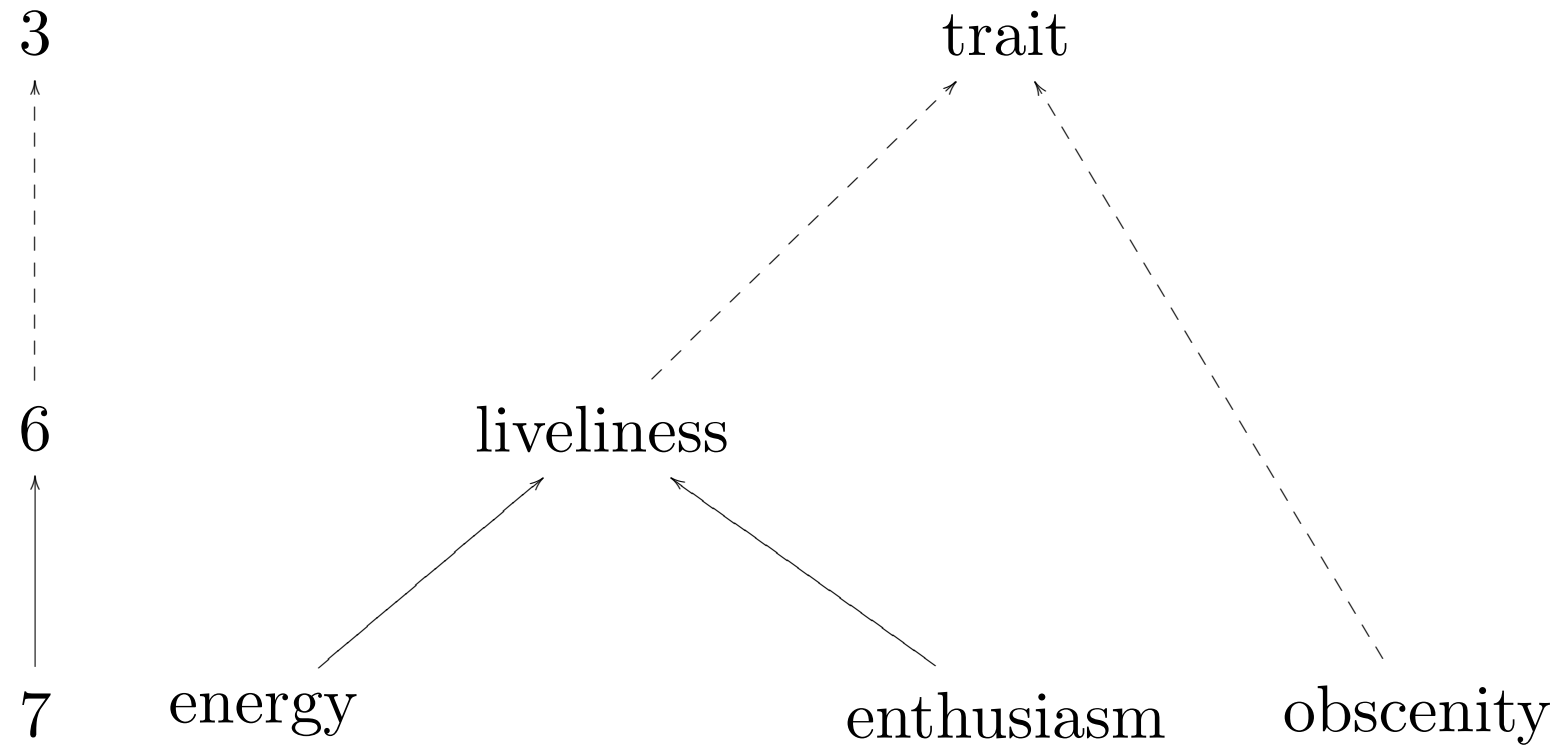
JJ	RB	VBG	VBN	NN	VBZ	CC	DT	COP
K	K	K	K	G	D	D	D	K

"The/DT character/NN is/VBZ written/VBN thinly/RB"
becomes
"/NN is/COP written/VBN thinly/RB"

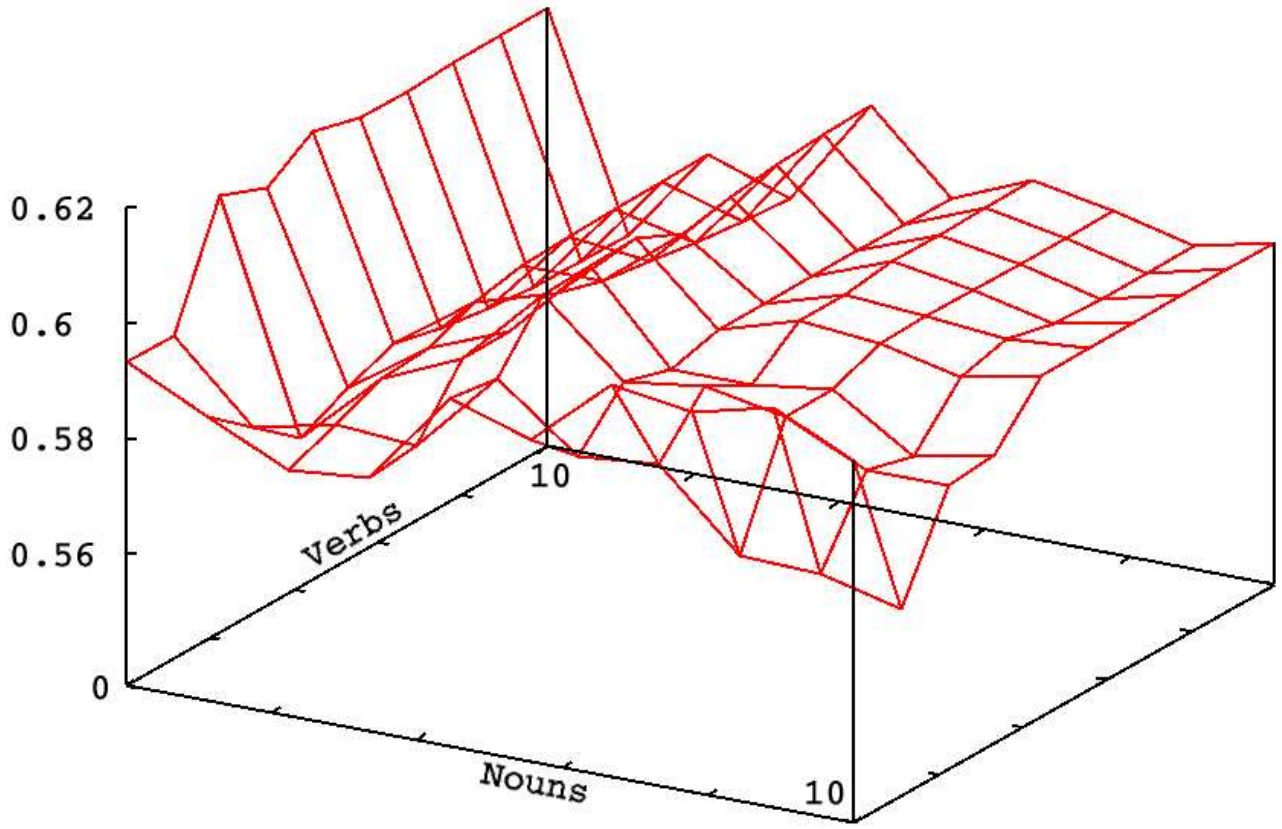
POS filtering with Bigram classifier

Training Size	$Rule_1$	$Rule_2$	$Rule_3$	$Rule_4$	$Rule_5$	All-POS
100	.555	.625	.625	.630	.630	.575
400	.700	.660	.660	.685	.685	.710
700	.705	.700	.700	.690	.690	.735
1000	.730	.745	.745	.730	.730	.765
1500	.725	.730	.730	.750	.750	.770

Hypernym Generalization in WordNet



WordNet Generalization – small training set



Score by Odds Ratio

- $score = \log P\,(\texttt{+}|\texttt{review}) - \log P\,(\texttt{-}|\texttt{review})$
- $P\,(\texttt{+}|\texttt{review})$: Probability of `review` being positive
- $P\,(\texttt{-}|\texttt{review})$: Probability of `review` being negative

Rank by Score

- The reviews are sorted by $score$ (e.g. odds ratio)
- Label the first N reviews `positive` and the last N `negative`

N	precision	recall
10	1.000	.100
30	.900	.270
70	.830	.580
90	.780	.680

Conclusions

- Filtering improves results on small training sets
- Semantic compression does not degrade accuracy
- Ranking gives 100% accuracy if we accept 10% recall

Questions. . .

. . . thank you.

Preprocessing Filtering

Rule	**Example**		
Copula	`is/VB`	$\longrightarrow$	`is/COP`
Copula	`seems/VBZ`	$\longrightarrow$	`seems/COP`
Negation	`not/RB`	$\longrightarrow$	`/NEG`

Hypernymy in WordNet: 3000 reviews