

A Semi-supervised Type-based Classification of Adjectives: Distinguishing Properties and Relations

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Motivation: Using Adjectives for Ontology Learning (1)

1. Learning Ontological Knowledge from Adjectives:

- **attributes**

grey donkey \equiv COLOR(donkey)=grey

- **roles**, i.e. "founded" attributes (cf. Guarino, 1992)

fast car \equiv SPEED(car)=fast

- **relations**

economic crisis \equiv AFFECT(crisis, economy)

Different types of adjectives require different ontological representations !

Motivation: Using Adjectives for Ontology Learning (2)

2. Using Adjectives for Clustering Nouns into Concepts:

Clustering Features (pattern-based):

- attribute nouns:
the ATTR of the NOUN
- adjectives denoting properties of the noun:
the ADJ NOUN

Results:

- best results by combination of attribute and adjective features
- problem: attributive position is too unrestrictive for identifying property-denoting adjectives

(Almuhareb, 2006)

Adjective Classification for Ontology Learning

- **Hypothesis:** Classification is a prerequisite for ontology learning from adjectives.
- We adopt an adjective classification scheme from the literature that reflects the ontological information we are interested in:
 - attributes \equiv **basic** adjectives
e.g.: *grey donkey*
 - roles \equiv **event-related** adjectives
e.g.: *fast car*
 - relations \equiv **object-related** adjectives
e.g.: *economic crisis*

(Boleda 2007; Raskin & Nirenburg 1998)

Overview

- 1 Background & Motivation
- 2 Annotation Experiment
 - Initial Classification Scheme: BEO
 - Task Description
 - First Results
 - Results after Re-Analysis
- 3 Automatic Classification
 - Methodology
 - Experimental Settings
 - Evaluation Results
- 4 Conclusions

BEO Classification Scheme (1)

Basic Adjectives

- adjective denotes a value of an attribute exhibited by the noun
- values are either discrete or predications over a range of several values (depending on the concept being modified)

Examples

- *red carpet* \Rightarrow COLOR(carpet)=red
- *oval table* \Rightarrow SHAPE(table)=oval
- *young bird* \Rightarrow AGE(bird)=[?,?]

BEO Classification Scheme (2)

Event-related Adjectives

- there is an event the referent of the noun takes part in
- adjective functions as a modifier of this event

Examples

- good knife \Rightarrow knife that **cuts** well
- fast horse \Rightarrow horse that **runs** fast
- interesting book \Rightarrow book that is interesting to **read**

BEO Classification Scheme (3)

Object-related Adjectives

- adjective is morphologically derived from a noun N/ADJ
- N/ADJ refers to an entity that acts as a semantic dependent of the head noun N

Examples

- environmental destruction _{N}
⇒ destruction _{N} [of] the environment _{N/ADJ}
⇒ destruction(e, AGENT: x, PATIENT: environment)
- political debate _{N}
⇒ debate _{N} [about] politics _{N/ADJ}
⇒ debate(e, AGENT: x, TOPIC: politics)

Annotation Study: Task Description and Methodology

Data Set

- list of 200 high-frequency adjectives from the British National Corpus
- random extraction of five example sentences from the written part of the BNC for each of the 200 adjectives

Methodology

- three annotators
- task: label each of the 1000 items with BASIC, EVENT, OBJECT or IMPOSSIBLE
- instructions: short description of the classes plus examples

BEO Classification: Fundamental Ambiguities

BASIC vs. EVENT

- fast horse
 - BASIC reading: SPEED(horse)=fast
 - EVENT reading: *horse that runs fast*
- good knife
 - BASIC reading: QUALITY(knife)=good
 - EVENT reading: *knife that cuts well*

Additional Instructions: Differentiation Patterns

If one of the following patterns holds for an ambiguous item, this indicates a property that is **founded** on an EVENT:

- ENT's property of being ADJ is due to ENT's ability to EVENT.
- If ENT was unable to EVENT, it would not be an ADJ ENT.

Category-wise Annotator Agreement

	BASIC	EVENT	OBJECT
κ	0.368	0.061	0.700

Table: Category-wise κ -values for all annotators

- overall agreement: $\kappa = 0.4$ (Fleiss 1971)
- separating the OBJECT class is quite feasible
- Can poor overall agreement be traced back to the ambiguities between BASIC and EVENT class ?

Cases of Disagreement

	BASIC	EVENT	OBJECT
2:1 agreement	283	21	66
3:0 agreement	486	5	62

Table: Cases of Agreement vs. Disagreement

		1 voter		
		BASIC	EVENT	OBJECT
2 voters	BASIC	–	172	16
	EVENT	18	–	1
	OBJECT	54	10	–

Table: Distribution of Disagreement Cases over Classes

BASIC/EVENT ambiguity is the **primary source of disagreement** !

Re-Analysis of the Annotated Data

- People have substantial difficulties in distinguishing BASIC from EVENT adjectives !
- Re-analysis: **binary classification scheme**
 - adjectives denoting **properties** (BASIC & EVENT)
 - adjectives denoting **relations** (OBJECT)
- overall agreement after re-analysis: $\kappa = 0.69$

	BASIC+EVENT	OBJECT
κ	0.696	0.701

Table: Category-wise κ -values for all annotators (after re-analysis)

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Methodology

- task: automatically classify adjectives according to their denotation: **properties** (ATTR) vs. **relations** (REL)
- features: set of **lexico-syntactic patterns** capturing systematic differences of these adjective classes in certain grammatical constructions
- overcome feature sparsity:
 - classification on the **type level**
 - **semi-supervised** approach: acquire enough training material on the type level by heuristic annotation projection

Features for Classification

Group	Feature	Pattern
I	as comparative-1 comparative-2 superlative-1 superlative-2	as JJ as JJR NN RBR JJ than JJS NN the RBS JJ NN
II	extremely incredibly really reasonably remarkably very	an extremely JJ NN an incredibly JJ NN a really JJ NN a reasonably JJ NN a remarkably JJ NN DT very JJ
III	predicative-use static-dynamic-1 static-dynamic-2	NN (WP WDT)? is was are were RB? JJ NN is was are were being JJ be RB? JJ .
IV	one-proform	a/an RB? JJ one
V	see-catch-find	see catch find DT NN JJ <i>they saw the sanctuary desolate</i> <i>Baudouin's death caught the country unprepared</i>
VI	morph	adjective is morphologically derived from noun <i>economic ← economy</i>

Table: Set of features used for classification

Experimental Settings

Data Set

- manually annotated seed data (\mathbf{A}_s): 164 property-denoting, 18 relational adjective types
- heuristic annotation projection:
 - extract 5.000 sentences per type from ukWaC corpus (\mathbf{A}_{acq})
 - for every adjective **token** in \mathbf{A}_{acq} : project unanimous class label from the corresponding **type** in \mathbf{A}_s

Evaluation

- several feature configurations:
 - all-feat: all features individually
 - all-grp: all features, collapsed into groups
 - no-morph: all features individually, without morph feature
- 10-fold cross validation
- baseline: label all instances with majority class (ATTR)

Experimental Results

	ATTR			REL			Acc
	P	R	F	P	R	F	
all-feat	0.96	0.99	0.97	0.79	0.61	0.69	0.95
all-grp	0.96	0.99	0.97	0.85	0.61	0.71	0.95
no-morph	0.95	0.96	0.95	0.56	0.50	0.53	0.91
<i>Baseline</i>	<i>0.90</i>	<i>1.00</i>	<i>0.95</i>	<i>0.00</i>	<i>0.00</i>	<i>0.00</i>	<i>0.90</i>

Table: Precision, recall and accuracy scores for Boosted Learner (10-fold cross-validation)

- high precision for both classes
- recall on the REL class lags behind
- morph-feature is highly valuable for REL class
- boosting benefits from collapsing sparse features into groups

Selective Evaluation of Class Volatility

Type	ATTR Tokens	REL Tokens	IMPOSS Tokens
beautiful (ATTR)	50	0	0
black (ATTR)	35	7	8
bright (ATTR)	45	1	4
heavy (ATTR)	42	0	8
new (ATTR)	50	0	0
civil (REL)	0	49	1
commercial (ATTR)	5	44	1
cultural (REL)	2	48	0
environmental (REL)	0	48	2
financial (REL)	0	46	4

Table: Volatility of prototypical class members

- average class volatility on the token level: 8.6%
- rough estimate of the error introduced by raising the classification task to the type level

Conclusions

Prospects of adjective classification for ontology learning:

- attribute/role distinction on the basis of adjectives alone is difficult even for human judges
- property-denoting and relational adjectives can be automatically distinguished at high precision for both classes
 - even with small and skewed training data
 - even in the absence of a morphological lexicon (see paper)

What else ?

- classification on the type level is justified by tolerable degree of class volatility
- shallow feature set should be easily applicable to specialized domains and adaptable to different languages

Thank you for your attention !
Any questions ?