

Automatic Identification of Aspectual Classes across Verbal Readings

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Aspectual Polysemy of Verbs

A **same verb** can instantiate different aspectual classes across its different **readings**

élargir 'widen'

Cette veste élargit Paul aux épaules.	~> ATElic
<i>This jacket widens Paul 'at the' shoulders</i>	no completion
On a élargi le débat à la politique étrangère.	~> TELic
<i>They extended the debate to foreign policy.</i>	completion

Objectives

- ▶ investigate verbal aspectual polysemy
- ▶ verb readings as delineated in a French valency lexicon (LVF)
- ▶ use of machine learning method

Approach

- ▶ **automatical** extraction of **verbal readings** from lexicon
- ▶ **manual** assignment of **aspectual value** for each reading
- ▶ **automatical** classification of readings
 - ▶ according to aspectual value (**telic**, **atelic**, **variable**)
 - ▶ based on **features automatically** extracted from **lexicon**
- ▶ exploration of the results:
 - ▶ comparison with annotations
 - ▶ check whether they improve performance in related tasks

Outline

- 1 Motivation
- 2 Related Work
- 3 The Data
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Related Work

1. [Siegel and McKeown, 2000]
2. [Zarcone and Lenci, 2008]
3. [Friedrich and Palmer, 2014]

Similarities

- ▶ classify corpus clauses
- ▶ into 2-4 aspectual classes, related to Vendlerian categories:
states, activities, accomplishments, achievements
- ▶ based on features extracted from corpus
 - ▶ derived from linguistic diagnostics/ tests

Specificities

Siegel and McKeown, 2000

- ▶ **type-based features**
 - ~> same aspectual value across all readings

Zarcone and Lenci, 2008

- ▶ **include syntactic properties**
 - ~> to some extent account for linguistic context of verb

Friedrich and Palmer, 2014

- ▶ **include clause-based syntactic and semantic features**
 - ~> account for linguistic context of verb
 - ~> but corpus only partly reflects the verb's aspectual variability

This study

systematically exploits correlations between

- ▶ syntactic and semantic properties encoded **in the lexicon** and
- ▶ the verb's **aspectual value** in context

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The Lexicon

LVF, Les Verbes français [Dubois and Dubois-Charlier, 1997]
≈12 300 verbs, ≈25 610 readings, ≈4190 polysemous verbs

Detailed morpho-syntactic and semantic description:

- ▶ syntactic frames and argument structure,
- ▶ semantic features of main arguments
 - ▶ human/ non-human, thematic roles, etc.
- ▶ semi-formal predicate decomposition,
- ▶ semantic classes (*e.g.* psych-verbs, change of state verbs, etc.)
- ▶ derivational family:
 - ▶ (adjectival or nominal) category of the verbal base;
 - ▶ nominal and adjectival derivations

Sample entries: *élargir* 'widen'

Semantic description

id	example	sem. decomposition	sem. class
01	On élargit une route/ La route s'élargit .	r/d+qt large	Change of state
02	Cette veste élargit Paul aux épaules.	d large	Change of state
03	On élargit ses connaissances.	r/d large abs	Change of state
04	On élargit le débat à la politique étrangère.	f.i.re abs VRS	Enter/Leave

Syntactic description

id	schema	encoded information
01	A30	intransitive with adjunct, inanimate subject
	T1308	transitive, human subject, inanimate direct object, instrumental adjunct
	P3008	reflexive, inanimate subject, instrumental adjunct
02	N1i	intransitive, animate subject, prep. phrase headed by <i>de</i> (<i>of</i>)
	A90	intransitive with adjunct, subject human or thing
	T3900	transitive, inanimate subject, object human or thing

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- ▶ 167 verbs
- ▶ approx. same number for each Vendlerian class
- ▶ 1199 readings from LVF
- ▶ ≈ 15 readings per verb
- ▶ 50% more than 13 readings
- ▶ only 16 verbs unambiguous

Manually annotated

according to fine-grained aspectual scale of 8 values (from the least to the most telic predicates)

Fine-grained Aspectual Classification: Motivation

- ▶ Theoretical linguistics:
[Hay et al., 1999, Piñón, 2006, Mittwoch, 2013] among many others
- ▶ Interesting opportunities for NLP applications:

Eg. the inference of **event completion**:

is **defeasible** with ‘weak’ accomplishments:

cf. *She filled the truck... but not completely*

is an **entailment** with ‘strong’ accomplishments:

cf. *She filled her with joy...?but not completely*

Annotation Scheme

Label-Class	Type of telos		Example
1 – S-STA	none	ATE	<i>be French</i>
2 – STA-ACT	none		<i>sit in the garden</i>
3 – S-ACT	none		<i>play in the garden</i>
4 – VAR	optional	VAR	<i>widen</i>
5 – W-ACC	context-dep or max. telos	TEL	<i>empty, eat an apple</i>
6 – S-ACC	max. telos		<i>eat up an apple</i>
7 – Q-ACH	max. telos		<i>kill the cat</i>
8 – ACH	max. telos		<i>find the key</i>

Aspectual distribution of 1199 annotated readings

1	2	3	4	5	6	7	8
S-STA	STA-ACT	S-ACT	VAR	W-ACC	S-ACC	Q-ACH	ACH
182	67	175	195	172	227	29	152

1-3	4	5-8
ATE	VAR	TEL
424	195	580

- ▶ considerable aspectual variability across readings
 - 8 way:** 66% of polysemous verbs (types) vary
 - 3 way:** 50% of polysemous verbs (types) vary

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Classification Setting

Objective

- ▶ classify 1199 annotated readings
- ▶ into aspectual classes **ATE**, **TEL** and **VAR**
- ▶ using features extracted from LVF lexicon

Corpus based

Features in previous work:

- ▶ based on linguistic diagnostics
- ▶ mostly available in corpus data
- ▶ but only partly available in lexicon

LVF vs. corpus based

Most corpus based features have LVF equivalents:

Siegel and McKeown, 2000

6 features ✓ equivalents in LVF

5 features ✗

Zarcone and Lenci, 2008

13 features ✓ equivalents in LVF

2 features ✗

✗ LVF equivalents for corpus based features:

- ▶ tense
- ▶ adverbials

Lexical Features

LVF **lexical** features determine the aspectual class:

Semantic class:

- ▶ **'enter/exit'** \rightsquigarrow telic,
- ▶ **change of state** \rightsquigarrow never atelic only

Semantic decomposition:

- ▶ **result** \rightsquigarrow mostly accomplishments,
- ▶ **manner** but no **result** \rightsquigarrow mostly activities, etc.

Syntax:

- ▶ **intransitivity with human subject** \rightsquigarrow atelic

Derivational pattern:

- ▶ **intransitive + no transitive frame** \rightsquigarrow **unaccusative (telic)** or **unergative (atelic)**
- ▶ **But: + -eur nominalisation** \rightsquigarrow **atelic** (**tombeur/*faller*)

38 Features:

- semantics:** semantic decomposition, semantic class, agentivity indicators, semantic roles (manner, location, temporal, etc.), ...
- syntax:** subject only, direct object, reflexive, passive, ...
- derivation:** has a nominal or adjectival derivation, ...
- polysemy:** relative number of readings per lemma

The Classification

- ▶ using Weka [Hall et al., 2009]
- ▶ 38 features
- ▶ **evaluation**: accuracy in 10 fold cross-validation
- ▶ **baseline**: always assigns majority class (**telic**)
- ▶ **linear forward feature selection**: best feature set of 9 features

Results

Algorithm	<i>complete</i>	<i>selected</i>
trees.j48	61.80	63.00
rules.jrip	63.89	61.56
lazy.kstar	62.89	67.47
functions.libsvm	62.72	61.13
bayes.naivebayes	60.22	65.80
baseline	48.37	48.37

- ▶ best setting outperforms baseline by $\approx 20\%$
- ▶ most helpful features:
 - ▶ semantic decomposition
 - ▶ polysemy
 - ▶ 2 derivational properties
 - ▶ 2 agentivity indicators
 - ▶ temporal and manner semantic roles
 - ▶ reflexive reading

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Aspectual Indicators

- ▶ type level
- ▶ reflect “aspectual behaviour” across readings of same verb
- ▶ computed from
 1. predictions
 2. manual annotations

v.	var	> 1 telicity value for same lemma?	1.	%tel	Proportion of telic readings
m.	maj	Telicity value of majority	2.	%ate	Proportion of atelic readings
t.	tel	Any telic reading?	3.	%var	Proportion of flexible readings
a.	ate	Any atelic reading?	4.	probest.max	Max of probability estimates
			5.	probest.min	Min of probability estimates
			6.	probest.avg	Average of probability estimates

Nominal and binary

Numeric

Evaluation

Compare aspectual indicators from 1 and 2

based on manual annotations

lemma	m	t	a	%tel	%ate	%var
casser	TEL	1	0	95.00	0	0.05
'break'	TEL	1	1	95.65	4.35	0
mourir	TEL	1	1	75.00	25.00	0
'die'	TEL	1	1	75.00	25.00	0
remplir	TEL	1	1	70.00	30.00	0
'fill'	TEL	1	1	80.00	20.00	0

Mostly telic

based on predictions

lemma	m	t	a	%tel	%ate	%var
regarder	ATE	0	1	0	91.67	8.33
'look at'	ATE	1	1	16.67	83.33	0
chanter	ATE	0	1	0	66.67	33.33
'sing'	ATE	0	1	0	66.67	33.33
étudier	ATE	1	1	30.00	60.00	10.00
'study'	ATE	1	1	20.00	80.00	0

Mostly atelic

lemma	m	t	a	%tel	%ate	%var
vieillir	VAR	0	1	0	11.11	88.89
'get older'	VAR	0	1	0	22.22	77.78
embellir	VAR	0	1	0	33.33	66.67
'beautify'	VAR	1	0	33.33	0	66.67
élargir	VAR	1	1	25.00	25.00	50.00
'widen'	VAR	1	1	25.00	25.00	50.00

Mostly variable

Dominant aspectual value is correctly assigned in most cases

Idea

- ▶ can we improve performance in related task using our predictions?

If this is the case

- ▶ our predictions are good
- ▶ even for unseen verbs/ readings

Task chosen: TempEval Challenge 2007

- ▶ automatic detection of temporal relation types in TimeBank data
- ▶ aspect is expected to improve the performance

```
<s>In Washington <TIMEX3 tid="t53" type="DATE" value="1998-01-14">today</TIMEX3>, the Federal Aviation Administration
<EVENT eid="e1" class="OCCURRENCE" stem="release" aspect="NONE" tense="PAST" polarity="POS" pos="VERB">
released</EVENT> air traffic control tapes from <TIMEX3 tid="t54" type="TIME" value="1998-XX-XXTNI">the night</
TIMEX3> the TWA Flight eight hundred <EVENT eid="e2" class="OCCURRENCE" stem="go" aspect="NONE" tense="
PAST" polarity="POS" pos="VERB">went</EVENT> down.</s>
<TLINK lid="l1" relType="BEFORE" eventID="e2" relatedToTime="t53"/>
<TLINK lid="l2" relType="OVERLAP" eventID="e2" relatedToTime="t54"/>
```

Task: automatically determine **relType** of time links - <TLINK>

3 types of time links:

Task A: event ↔ time

Task B: event ↔ document creation time

Task C: event ↔ event

Data	French TimeBank		verbs in LVF	
	tlinks	rel. types	lemmas(seen)	readings
A	302	10	164(16)	1597
B	264	5	149(14)	1329
C	1172	15	427(40)	3827

Approach

[Costa and Branco, 2012] – for Portuguese

- ▶ enhance rel. type detection through the use of **aspectual indicators from the web**

Our approach – for French

- ▶ enhance rel. type detection through the use of **LVF aspectual indicators**

Costa and Branco's (2012) method

1. start with base classifiers for temporal relation detection
2. collect aspectual indicators from the web – using *Google Hits*
3. enhance features of base system by aspectual indicators

Results

Performance of

- ▶ 9 out of 15 classifiers could be improved
- ▶ by 1%–3%

Our method

1. start with base classifiers for temporal relation detection
2. compute **LVF aspectual indicators**
3. enhance features of base system by aspectual indicators

Results:

Performance of

- ▶ 8 out of 15 classifiers could be improved
- ▶ by 1%–3%
- ▶ similar to Costa and Branco (2012)

~> good performance of LVF model on unseen verbs

italics: base classifiers, **bold face**: enhanced classifiers

Classifier	A	B	C
trees.j48	<i>0.71</i>	<i>0.81</i>	<i>0.40</i>
	0.73¹	0.82³	0.41^a
rules.jrip	<i>0.71</i>	<i>0.83</i>	<i>0.36</i>
	0.73⁶	0.84⁶	0.37^m
lazy.kstar	<i>0.72</i>	<i>0.82</i>	<i>0.42</i>
		0.85⁵	
functions.libsvm	<i>0.74</i>	<i>0.83</i>	<i>0.40</i>
		0.85⁶	
bayes.naivebayes	<i>0.73</i>	<i>0.84</i>	<i>0.40</i>
baseline	<i>0.72</i>	<i>0.62</i>	<i>0.29</i>

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Conclusion

- ▶ Through the use of
 - ▶ a rich morpho-syntactic and semantic valency lexicon and
 - ▶ a machine learning approachwe could model aspectual variation reasonably well.
- ▶ We gained insights about distribution and behaviour of aspectually polysemous verbs across readings

Future work:

- ▶ Explore behaviour and distribution in corpus data.

Thank you!

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