Syntax Matters for Rhetorical Structure: The Case of Chiasmus

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Introduction

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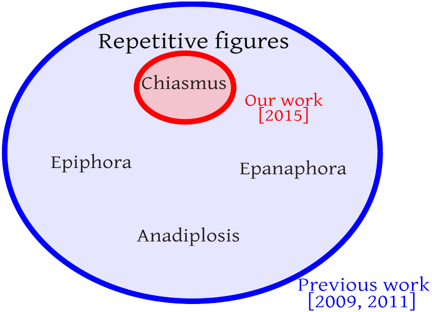
Previous research dealt with several figures and/or aim: ontology constitution, classification, detection.



Our research targets one figure, one task.

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Chiasmus/Antimetabole: Adapting definition to computer

A rhetorical figure in which two words with same lemma are repeated in reverse order.

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Example

Twist **facts** to suit **theories**,

not **theories** to suit **facts**.

 

Our aim: building a chiasmus retrieval engine (CRE)

chiasmus in corpus.txt

Results:

1. **First** should be **last** and **last** should be **first**
2. **Begining** of the **end**, the **end** of the **begining**
3. **Failing** to **prepare** is **preparing** to **fail**

...

99,999. **I** like beer from **time** to **time** but **I** prefer wine

Why Finding Chiasmus? 

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- Practical: Text mining of master pieces and literature
- Linguistic: Improve our general knowledge of the figure?
- Proof of concept: If we can make it for chiasmus, you can hope to make it for more devices.

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State of the Art

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The research on chiasmus

- Gawryjolek [2009]: Test the criss-cross pattern
  Chuck **Norris** does not fear **death**, **death** fears Chuck **Norris**
  - Good for finding the candidates! 100% recall
  - Very low precision
- Hromada [2011]: Introduce discriminative features: 3 words pattern.
  Love makes time pass, **time makes love** pass.
  - Very high precision
  - Recall incomplete

State of the Art 

Problem

There are criss-cross patterns that are not chiasmi such as:

'**I** like beer from **time** to **time** but **I** prefer wine'

They are frequent but chiasmi are rare.

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This is the problem of the needle in the haystack!

(Re-)Defining the Task

Human: nuanced but slow, computer: fast but coarse

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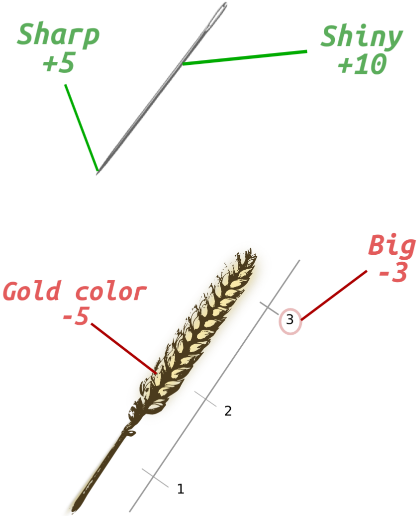
...Why not outputting chiasmi in a sorted manner?

Dubremetz & Nivre [2015]

Features



Our Model 

A standard linear model

So far only shallow ranking features have been successfully tested:

Feature	Description	Weight
Basic		
#punct	Number of hard punctuation marks and parentheses	−10
#softPunct	Number of commas in C_{ab} and C_{ba}	−10
#centralPunct	Number of hard punctuation marks and parentheses in C_{bb}	−5
isInStopListA	W_a is a stopword	−10
isInStopListB	W_b is a stopword	−10
#mainRep	Number of additional repetitions of W_a or W_b	−5
Size		
#diffSize	Difference in number of tokens between C_{ab} and C_{ba}	−1
#toksInBC	Position of W'_a minus position of W_b	−1
Similarity		
exactMatch	True if C_{ab} and C_{ba} are identical	5
#sameTok	Number of identical lemmatized tokens in C_{ab} and in C_{ba}	1
simScore	#sameTok but normalised	10
#sameBigram	Number of bigrams that are identical in C_{ab} and C_{ba}	2
#sameTrigram	Number of trigrams that are identical in C_{ab} and C_{ba}	4
#sameCont	Number of tokens that are identical in C_{Left} and C_{bb}	1
Lexical clues		
hasConj	True if C_{bb} contains one of the conjunctions 'and', 'as', 'because', 'for', 'yet', 'nor', 'so', 'or', 'but'	2
hasNeg	True if the chiasmus candidate contains one of the negative words 'no', 'not', 'never', 'nothing'	2
hasTo	True if the expression "from … to" appears in the chiasmus candidate or 'to' or 'into' are repeated in C_{ab} and C_{ba}	2

All the features tested in previous research (2015).

What about:

- PoS-Tags? Parsing?

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Feature	Description	Weight
PoS-Tag		
#sameDep W_b W_a'	Number of incoming dependency types shared by W_b and W_a'.	$+10$
Positive Dependency		
#sameDep W_b W_a'	Number of incoming dependency types shared by W_b and W_a'.	$+5$
#sameDep W_a W_b	Same but for W_a and W_b'	$+5$
Negative Dependency		
#sameDep W_a W_a'	Same but for W_a and W_a'	-5
#sameDep W_a W_a'	Same but for W_b and W_b'	-5

List of syntax related features added to previous shallow features.

How Do We score? An Example of Features 

Twist **facts** to suit **theories** ,

theories to suit **facts.**

I weighted them with the

only **weight I** could find.

How Do We Score? An Example of Features

Different word
Same role
+5

Twist **facts** to suit **theories** , dobj

Same PoS-Tag
+10

NOUN NOUN

theories to suit **facts.**

NOUN NOUN

I weighted them with the

only **weight I** could find.

How Do We Score? An Example of Features

Different word
Same role
+5

Same PoS-Tag
+10

Twist **facts** to suit **theories** ,
NOUN *NOUN*

dobj

theories to suit **facts.**
NOUN *NOUN*

Same word
Same role
-5

I weighted them with the

nsubj

only **weight I** could find.

Experimental Set Up

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- Corpus 
  - Parliament proceedings 
  - Training: 4 M words
  - Test:2 M words
- Evaluation
  - 200 chiasmus candidates
  - 2 annotators 
- Techniques and Tools
  - Manual tuning on train corpus
  - Stanford Parser and Tagger (CoreNLP)

Results

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Model	Average Precision	Compared to Baseline
Baseline	42.54	NA
Tag features	59.48	+14
Dependency features	64.27	+22
All features	67.65	+25

Table: Average precision for chiasmus detection (test set).

Parsing and Tagging features help the detection.

κ=0.69

Generalisation 

Can this algorithm work on something else than political proceedings? The check on Sherlock Holmes.

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Model	**Average Precision**	**Difference**
Baseline	53.00	NA
All features	70.35	$+17$

Table: Average precision for chiasmus detection (Sherlock Holmes set).

Without any tune specific to literature genre we managed to find more chiasmi in Sherlock Holmes!

Discussion and Perspectives

Discussion 

Our research is complementary:

- Hromada [2011] + Gawryjolek [2009] are the detection pioneer that offer multilingual algorithms
- Whereas our research focus on performance issue, and value the use of English NLP resources (lemmatiser, parser...)

Future Work 

- More annotation with more annotators
- Apply our method to other devices? Anaphora? Anadiplosis?
- Apply machine learning

Contributions 

1. Computational Linguistics
   - Test of new features
   - More than 400 annotations by two annotators
2. Linguistics
   - More liberty to linguists to select borderline cases (2015)
   - Chiasmus vs random criss-cross concept is more than individually defined (2016)
3. Concretely
   - A system that works on both political discourse and novel.

Demo online: `http://bit.do/chiasmus`

Bonus: a Chiasmus Viewed by a Computer

***If the mountain won't come to Mohammed, then let's take Mohammed to the mountain.* (In binary.)**

01001001 01100110 00100000 01110100 01101000 01100101 00100000 01101101 01101111 01110101 01101110
01110100 01100001 01101001 01101110 00100000 01110111 01101111 01101110 00100111 01110100 00100000
01100011 01101111 01101101 01100101 00100000 01110100 01101111 00100000 01001101 01101111 01101000
01100001 01101101 01101101 01100101 01100100 00101100 00100000 01110100 01101000 01100101 01101110
00100000 01101100 01100101 01110100 00100111 01110011 00100000 01110100 01100001 01101011 01100101
00100000 01001101 01101111 01101000 01100001 01101101 01101101 01100101 01100100 00100000 01110100
01101111 00100000 01110100 01101000 01100101 00100000 01101101 01101111 01110101 01101110 01110100
01100001 01101001 01101110 00101110

By Model	**Ranked at**
Baseline	188
Tag features	33
Tag + Dependency features	24

Thank You!

Questions?

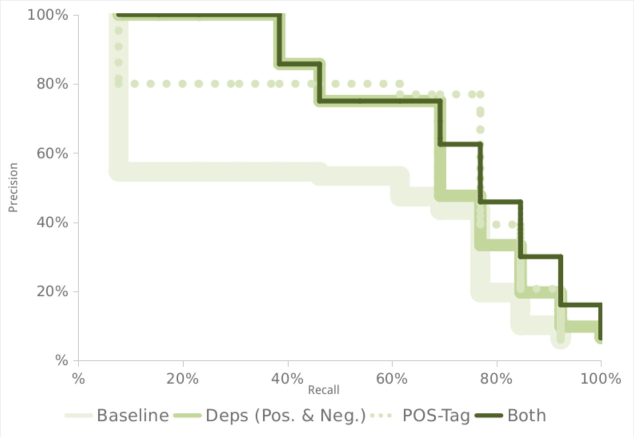
References

Dubremetz, M. & Nivre, J. (2015). Rhetorical Figure Detection: the Case of Chiasmus. In *Proceedings of the Fourth Workshop on Computational Linguistics for Literature*, (pp. 23–31)., Denver, Colorado, USA. Association for Computational Linguistics.

Gawryjolek, J. J. (2009). *Automated Annotation and Visualization of Rhetorical Figures*. Master thesis, Universty of Waterloo.

Hromada, D. D. (2011). Initial Experiments with Multilingual Extraction of Rhetoric Figures by means of PERL-compatible Regular Expressions. In *Proceedings of the Second Student Research Workshop associated with RANLP 2011*, (pp. 85–90)., Hissar, Bulgaria.

Results



13 True Pos. / 466 annotated candidates

Top 5 all true positives!