Mining Rhetorical Devices by means of Natural Language Processing

Bauhaus-Universität Weimar

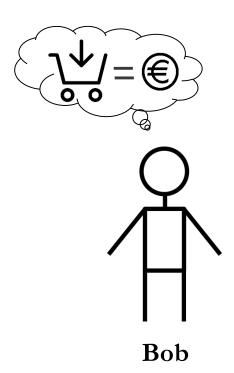
Viorel Morari viorel.morari@uni-weimar.de

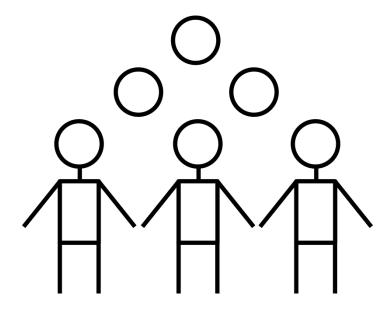
Chair of Web Technology and Information Systems
Prof. Dr. Benno Stein

Advisor: Khalid Al-Khatib

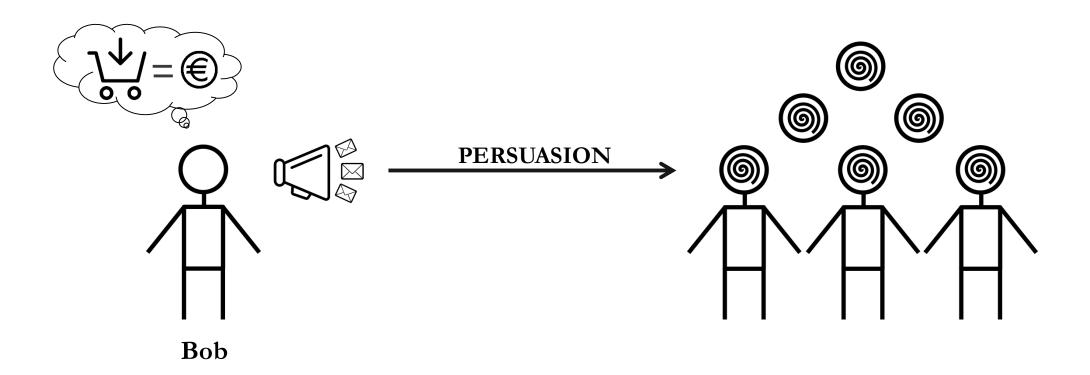
Master Thesis Defense January 23rd, 2018

What is Rhetoric?

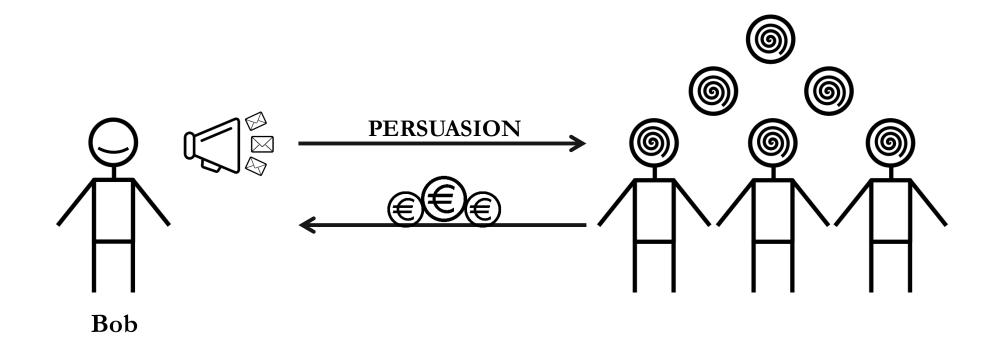




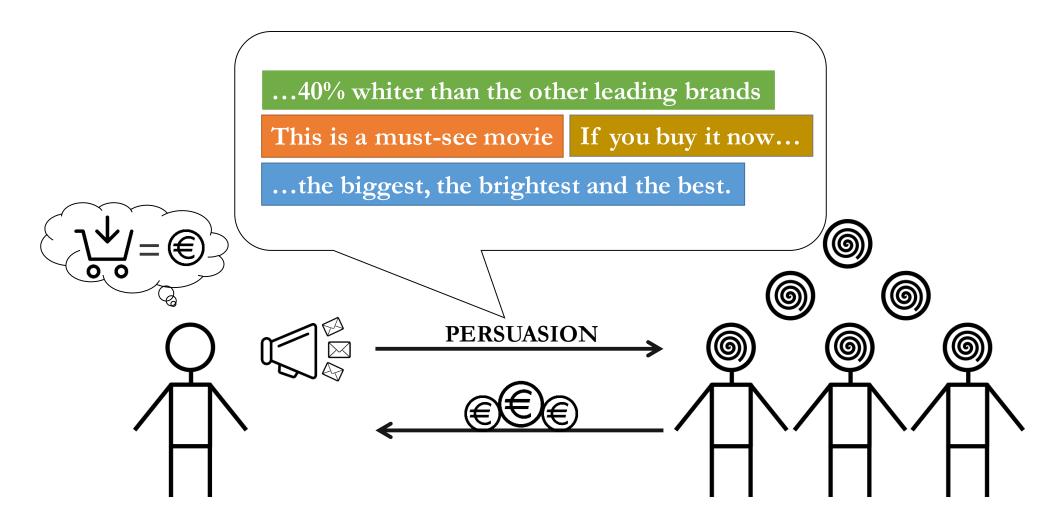
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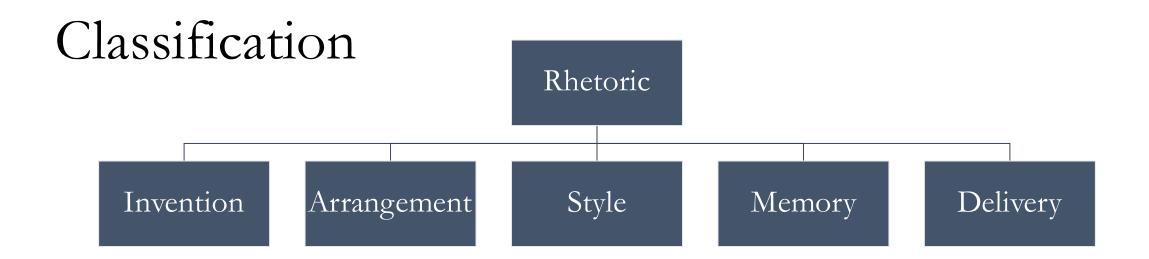


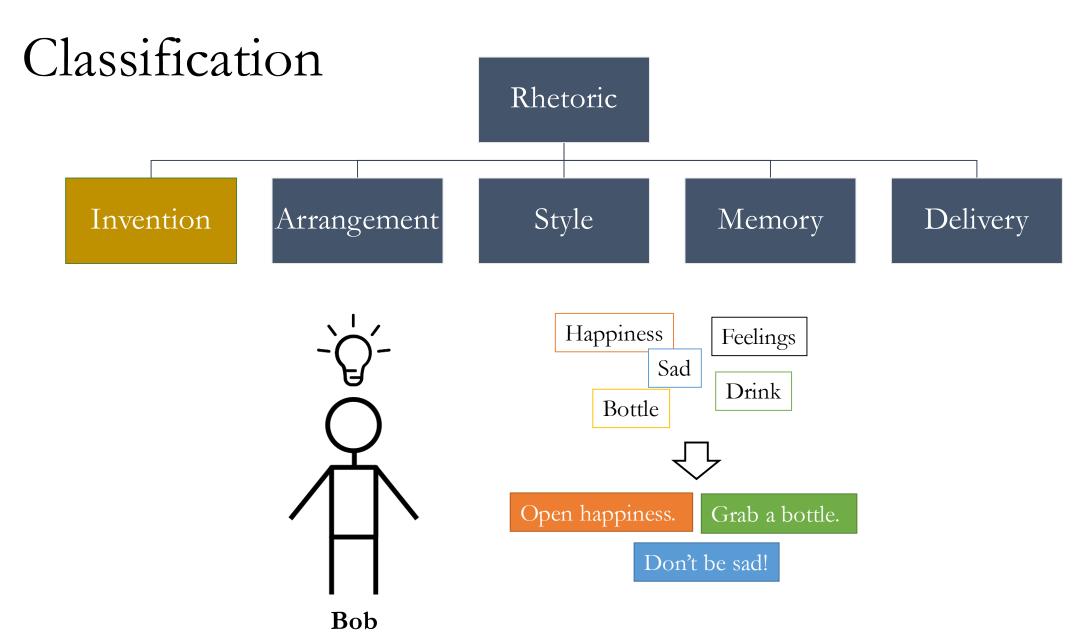
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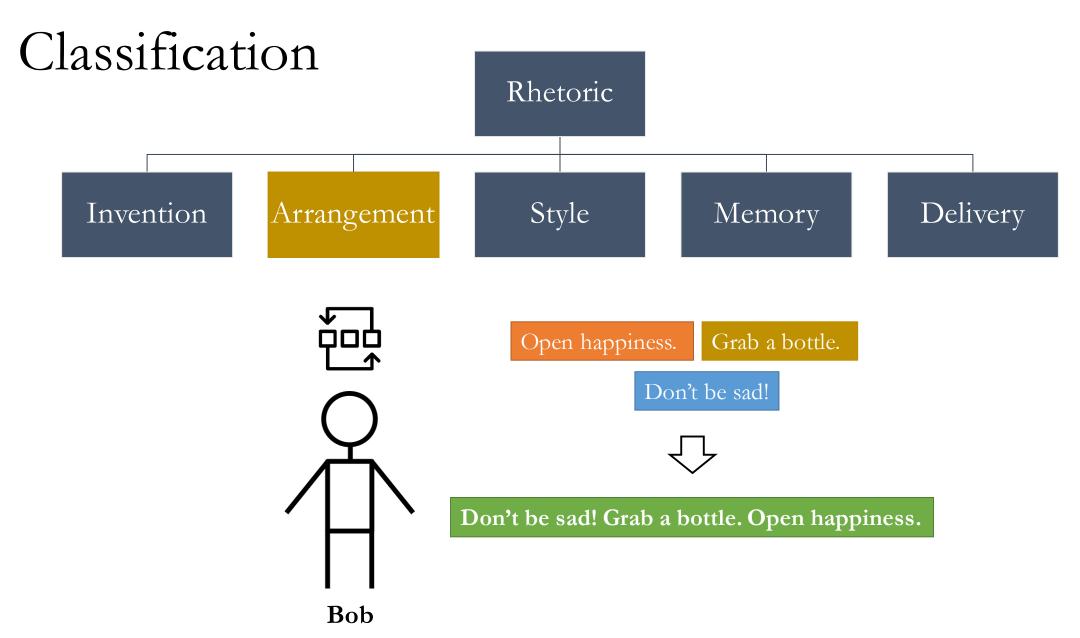


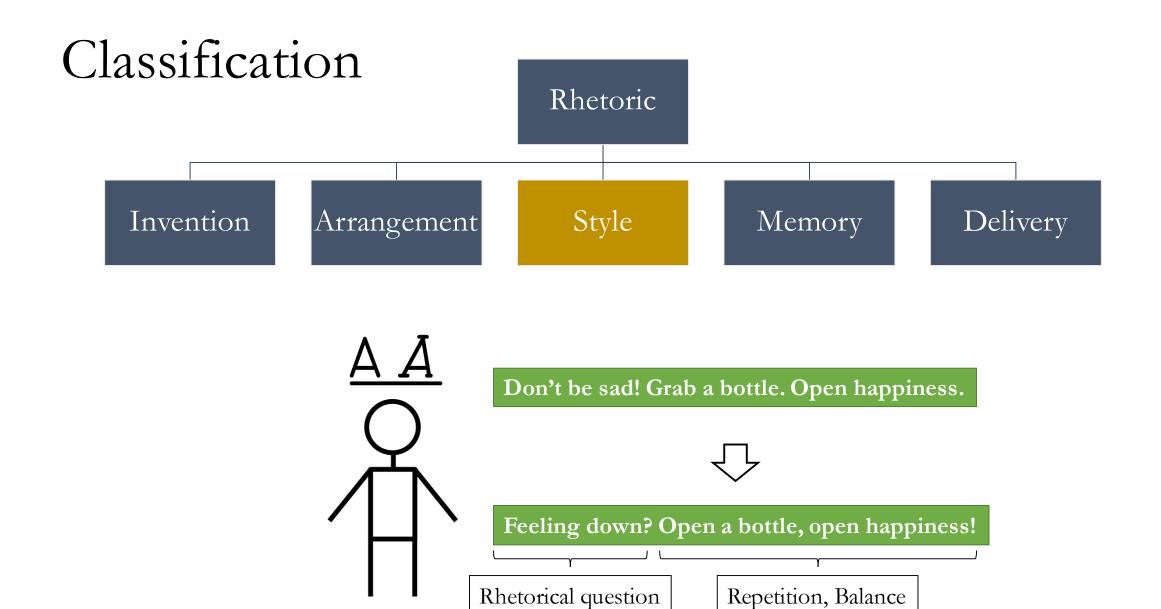
What is a Rhetorical Device?



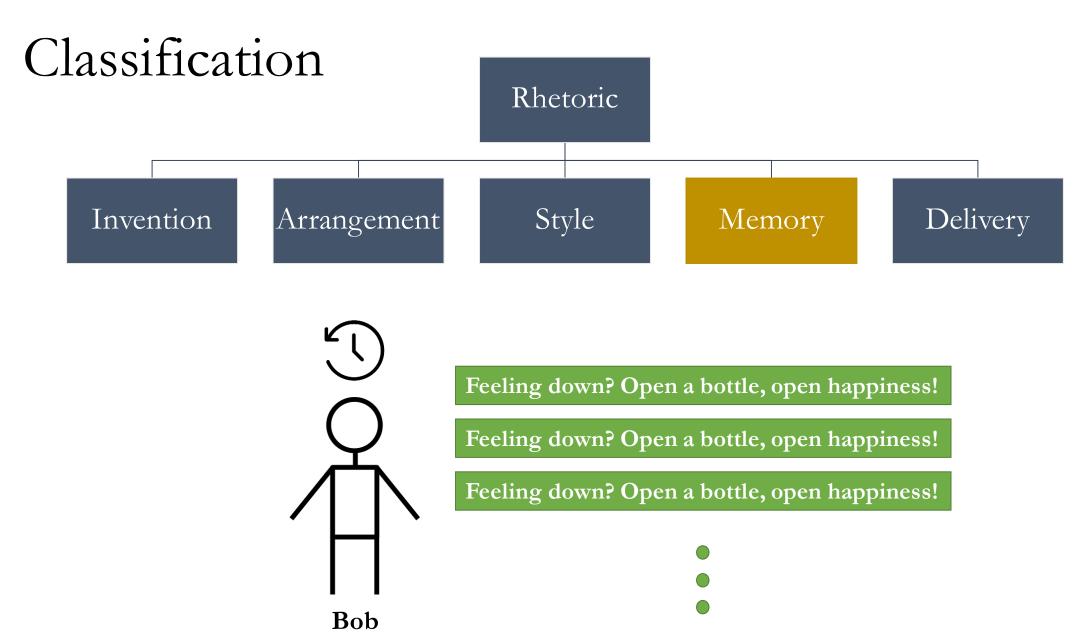


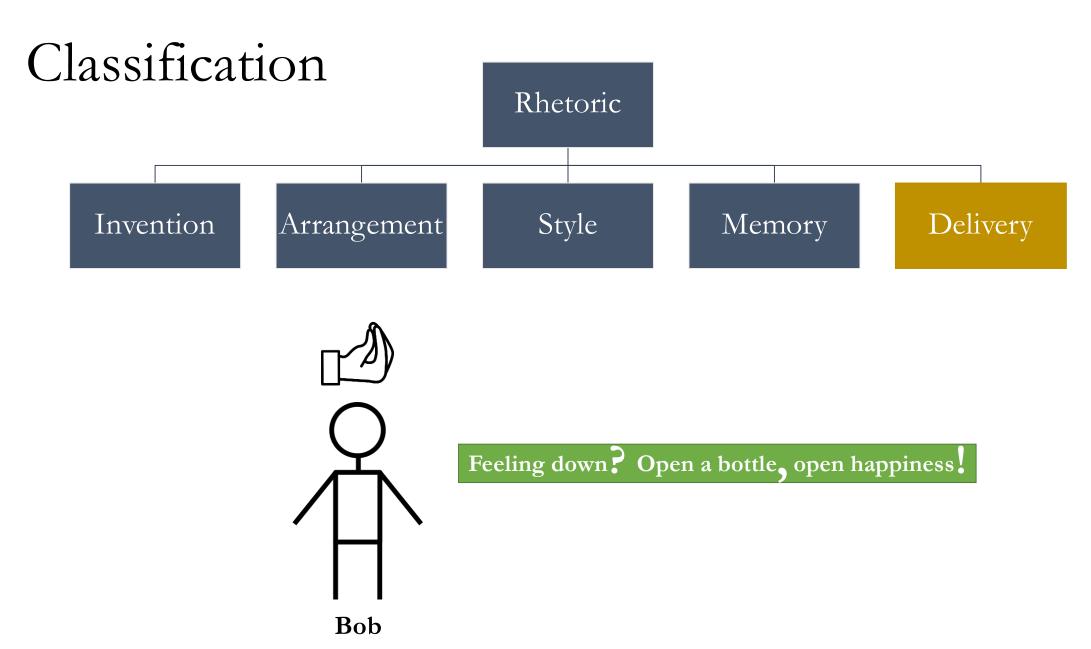


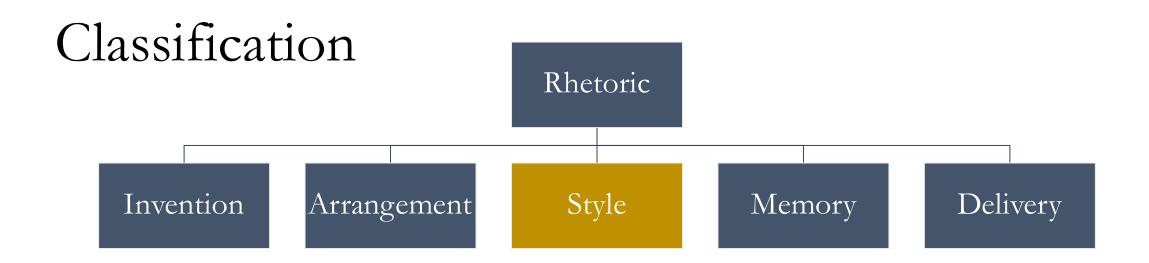


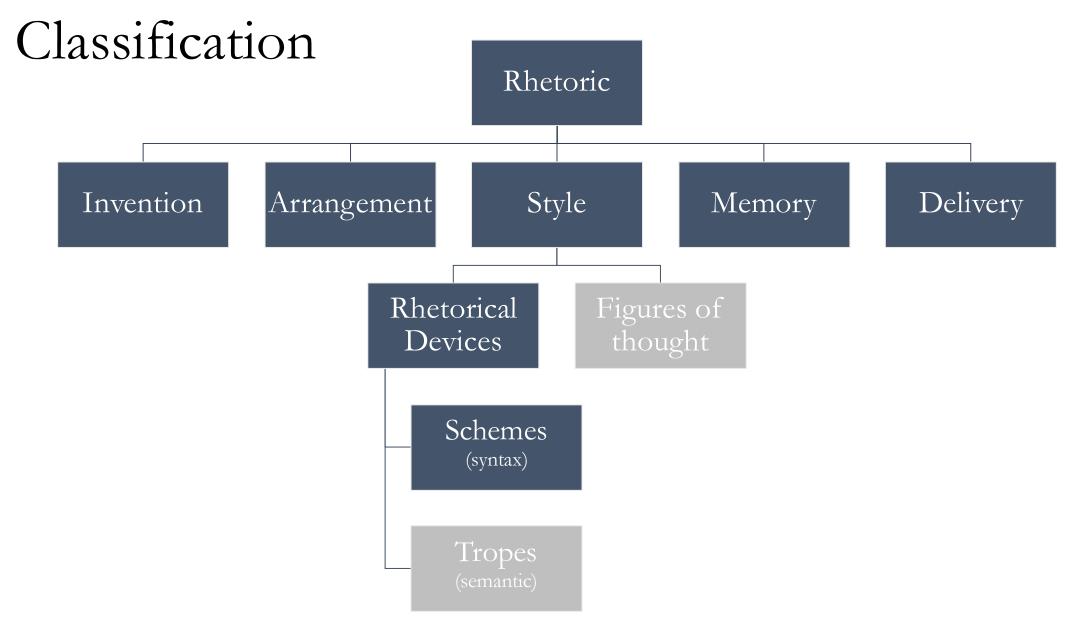


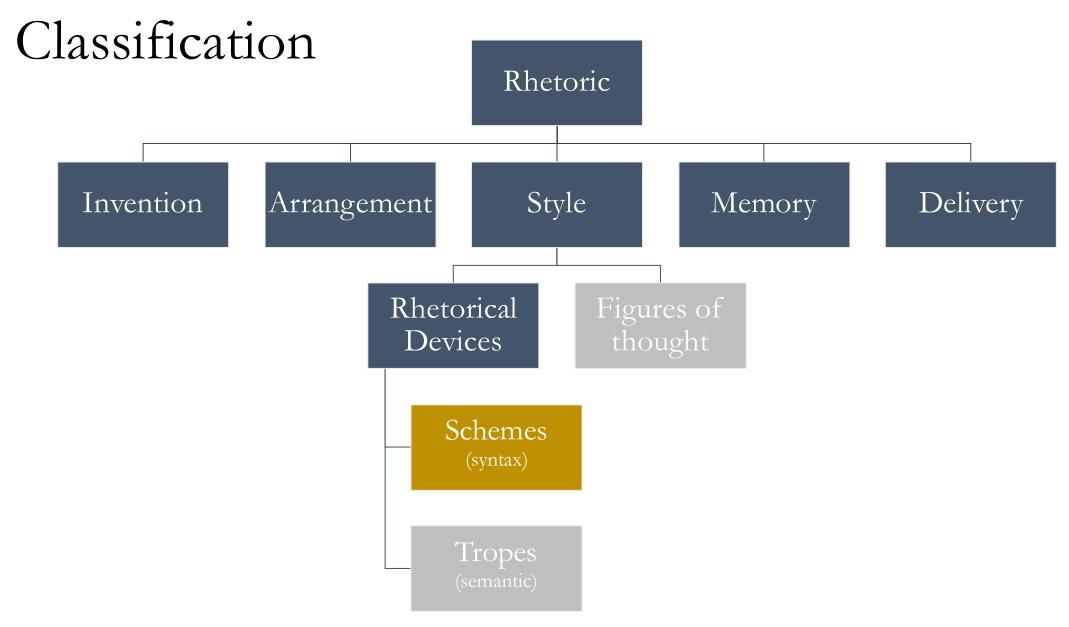
Bob





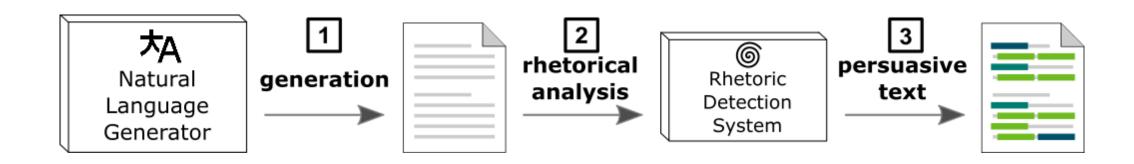






Envisioned Applications

Rhetoric-based NLG system

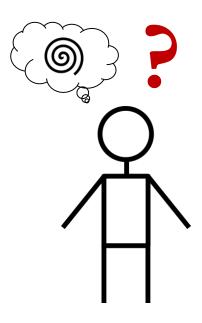


Envisioned Applications

Rhetorical style suggestion system

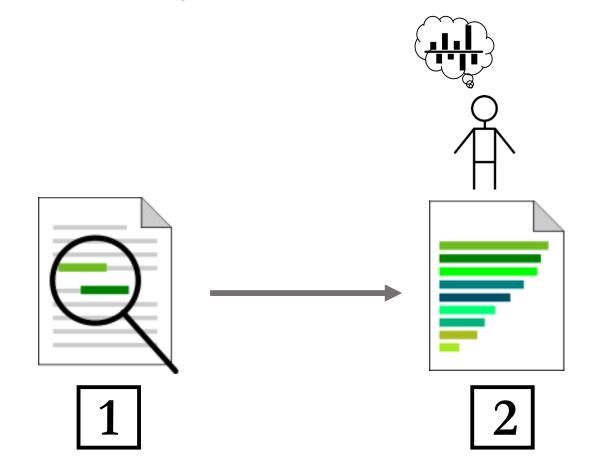
detection analysis suggestion

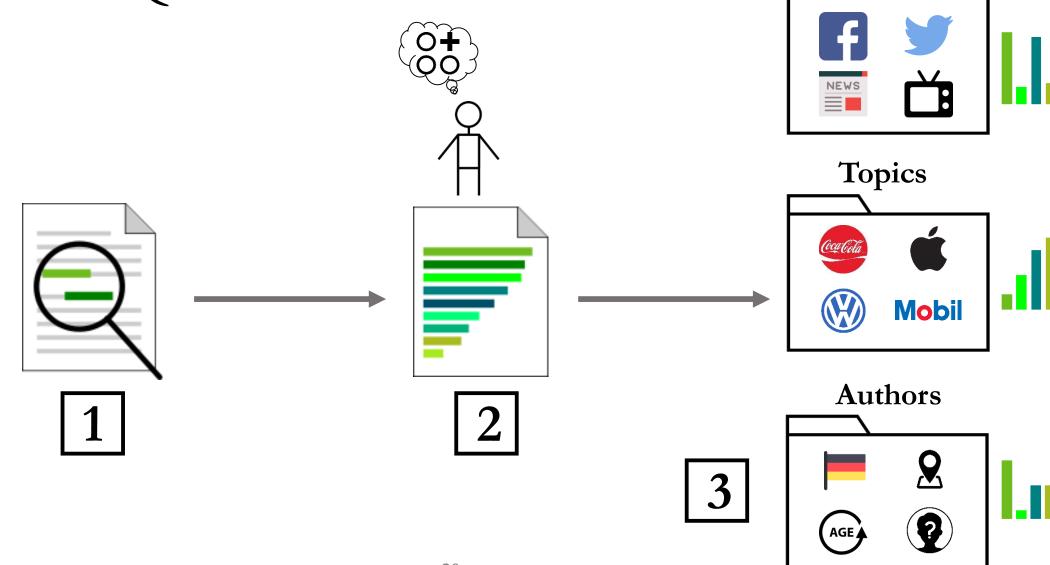
text identification of rheorical patterns suggestion (output)









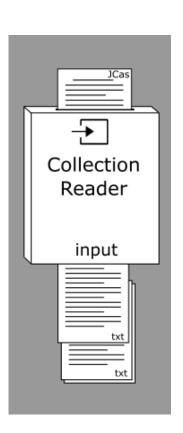


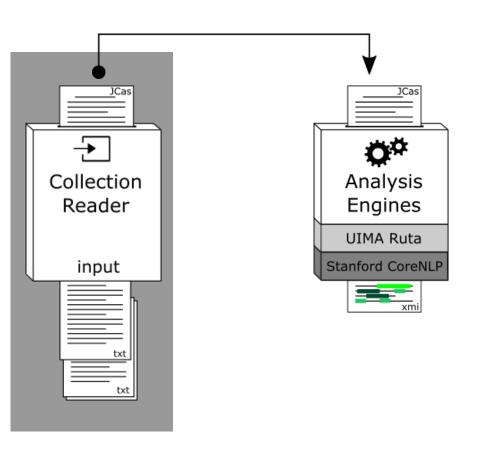
Genres

Detection of Rhetorical Devices

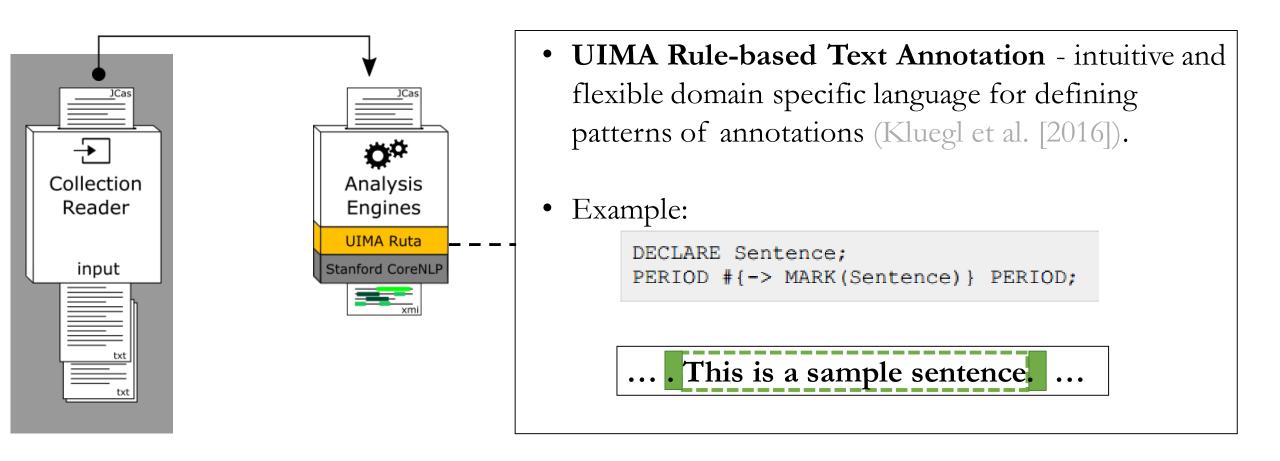


input

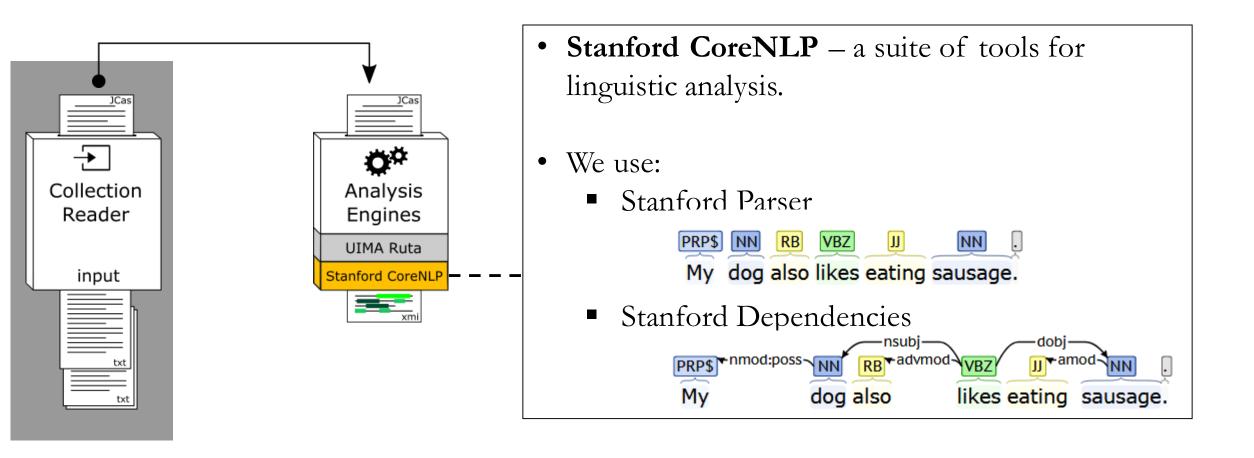


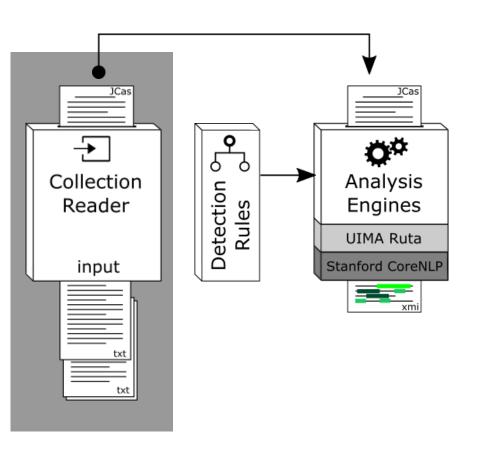


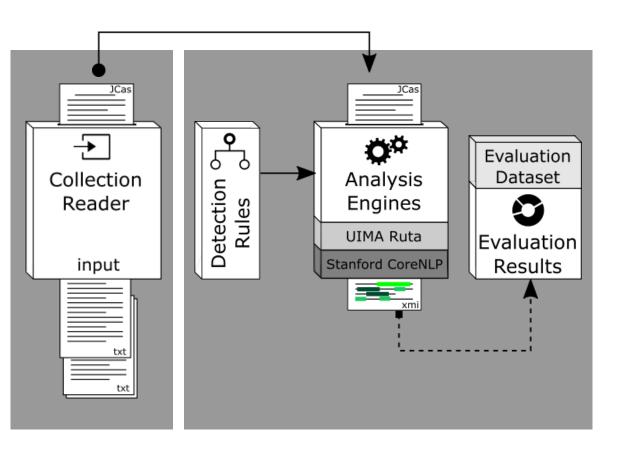
Pipeline – UIMA Ruta

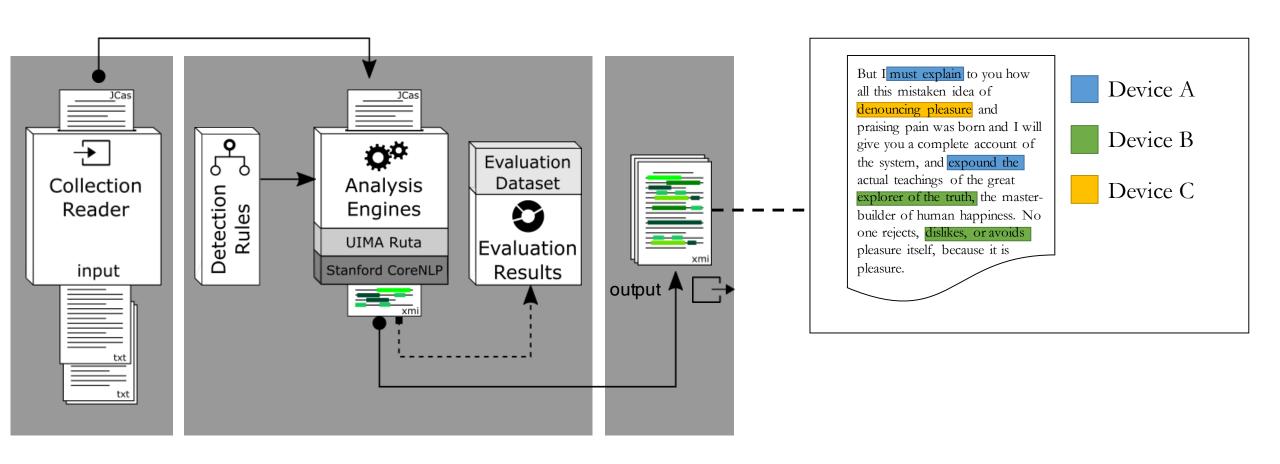


Pipeline – Stanford CoreNLP

















Interplay between equivalent ideas

Control the rhythm of thought



Interplay between equivalent ideas

Control the rhythm of thought



Deliberate omission of intuitive words

Cause incompleteness







Interplay between equivalent ideas

Control the rhythm of thought



Omission schemes

Deliberate omission of intuitive words

Cause incompleteness



Repetition of key words/ideas

Used for emphasis or amplification

Key to persuasion (according to Aristotle)





Interplay between equivalent ideas

Control the rhythm of thought



Omission schemes

Deliberate omission of intuitive words

Cause incompleteness



Repetition of key words/ideas

Used for emphasis or amplification

Key to persuasion (according to Aristotle)



Informal rhetorical devices

Strong emotional effect

Includes causality, comparatives and voice



- Enumeration
- Pysma
- Isocolon
 - -bicolon
 - -tricolon
 - -tetracolon



Omission schemes

- Asyndeton
- Hypozeugma
- Epizeugma



- Epanalepsis
- Mesarchia
- Epiphoza
- Mesodiplosis
- Anadiplosis
- Diacope
- Epizeuxis
- Polysyndeton



- If-conditional 0
- If-conditional 1
- If-conditional 2
- If-conditional 3
- If-counterfactual
- Unless-cond.
- Whether-cond.
- Comparative Adjectives/Adverbs
- Superlative Adjectives/Adverbs



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Omission schemes

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- Hypozeugma
- Epizeugma



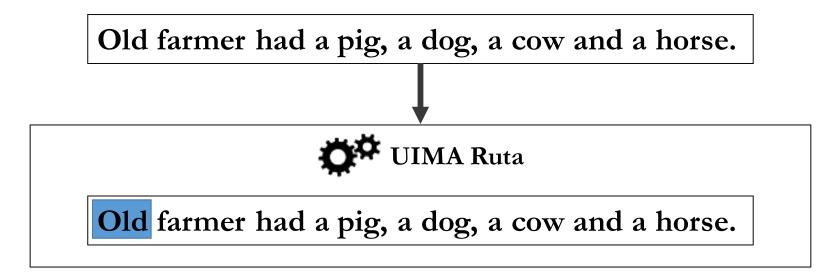
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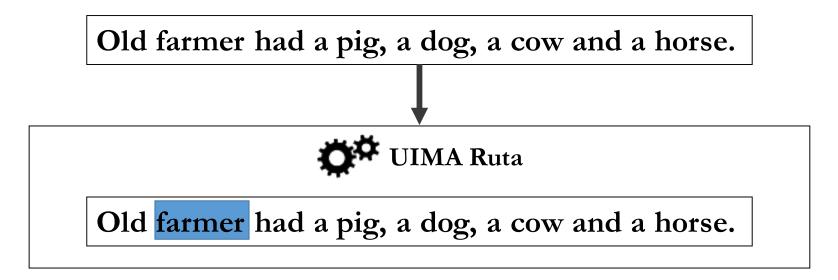


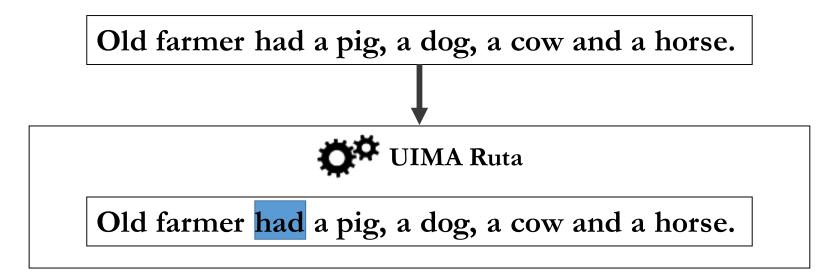
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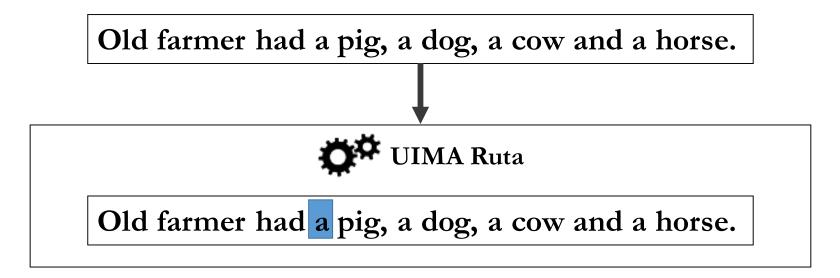
Balance: Enumeration

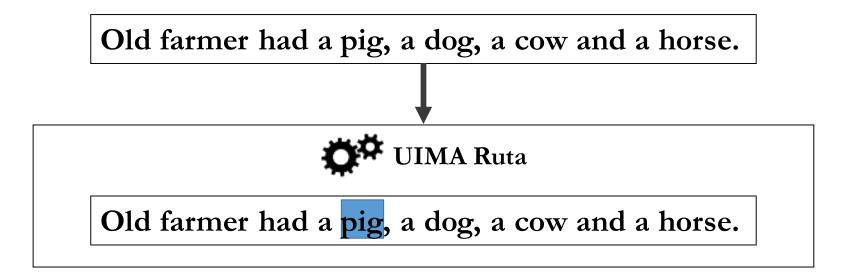
Enumeration - a rhetorical device used to list a series of details, words or phrases. (literarydevices.net)

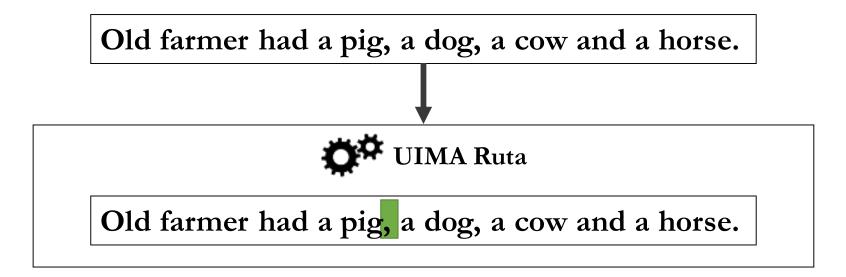


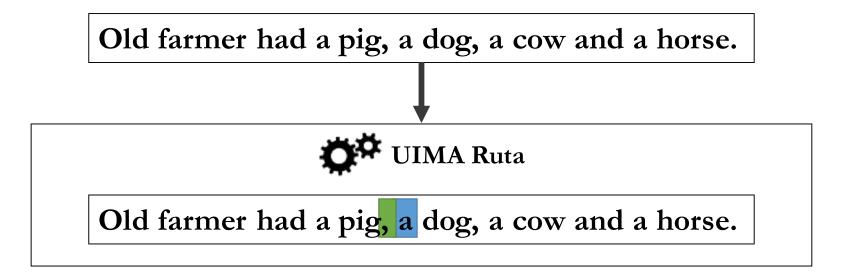


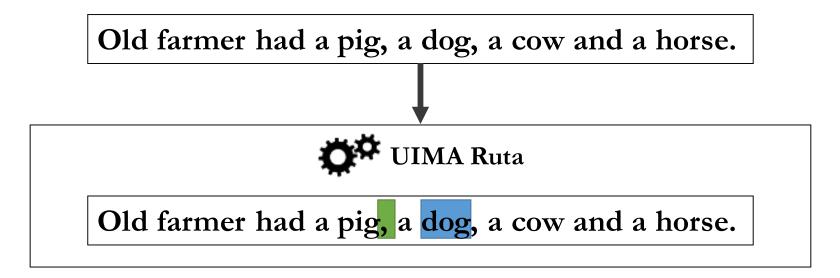


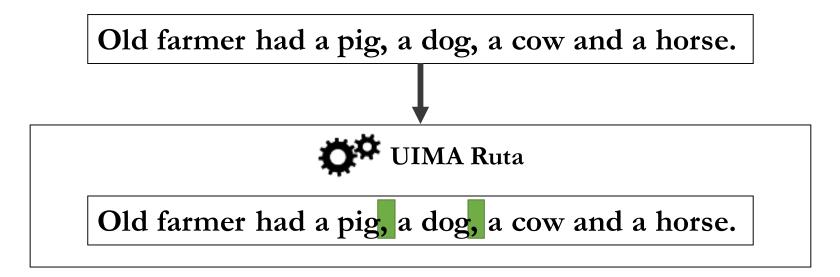


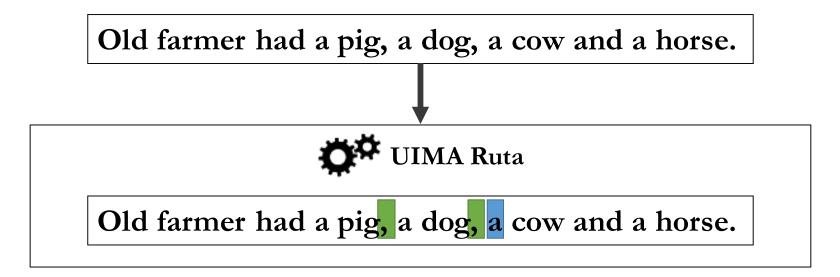


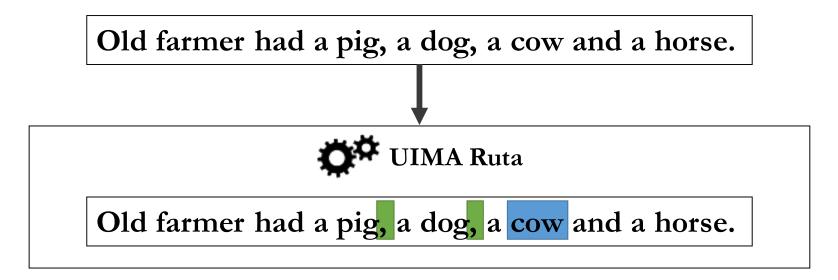








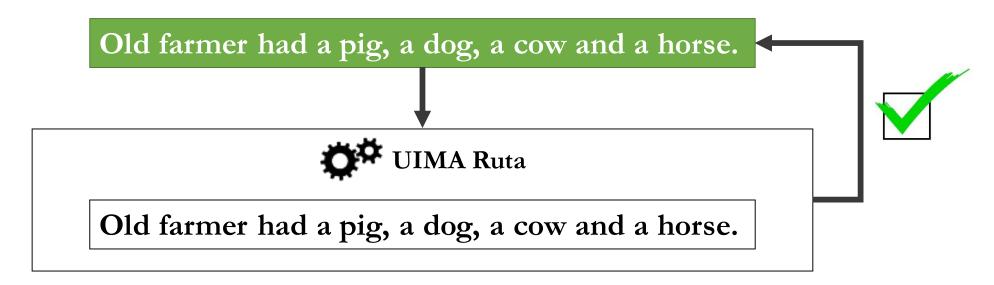




Old farmer had a pig, a dog, a cow and a horse.

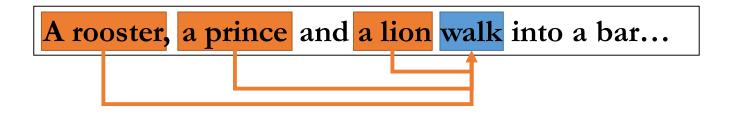
UIMA Ruta

Old farmer had a pig, a dog, a cow and a horse.



Hypozeugma - placing last, in a construction containing several words or phrases of equal value, the word or words on which all of them depend. (Silva Rhetoricae)

A rooster, a prince and a lion walk into a bar...

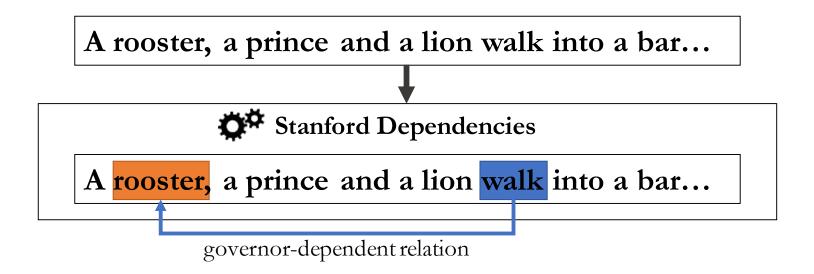


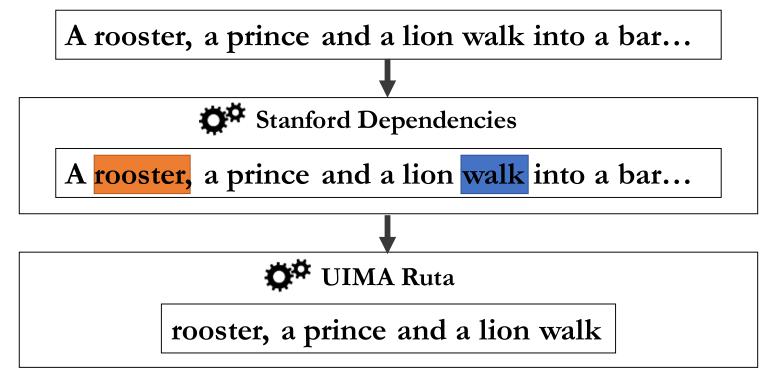
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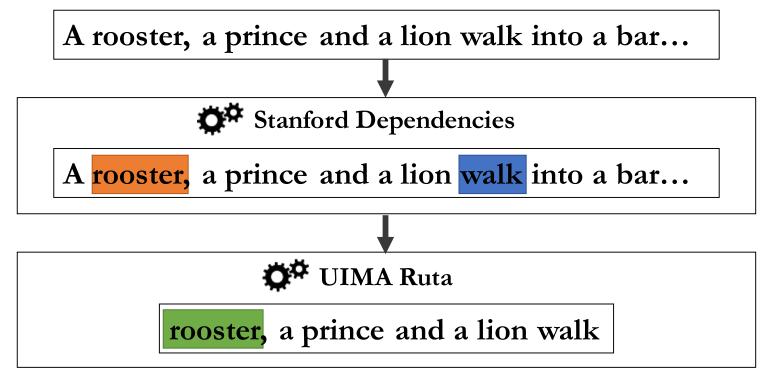
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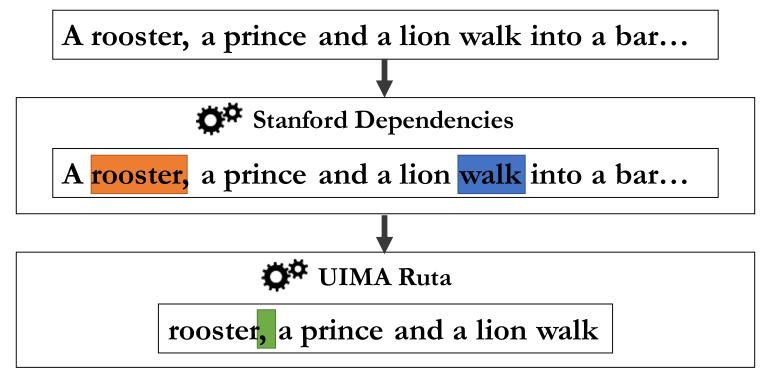
Stanford Dependencies

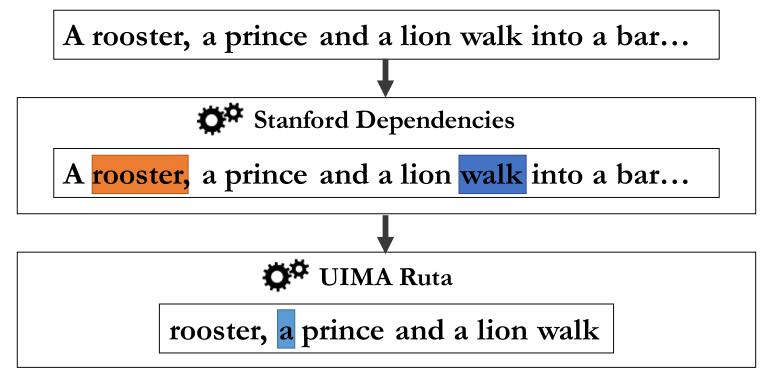
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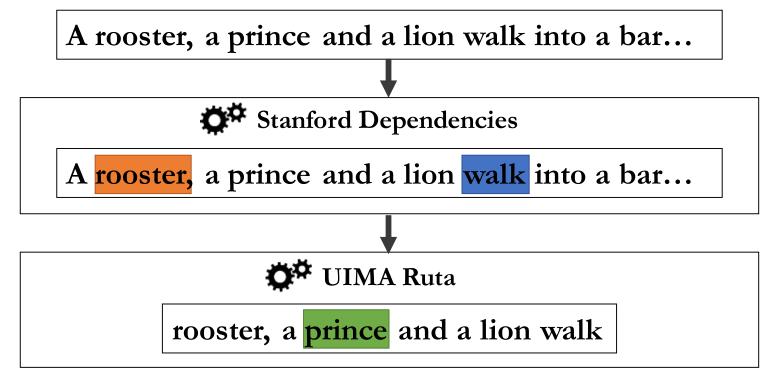


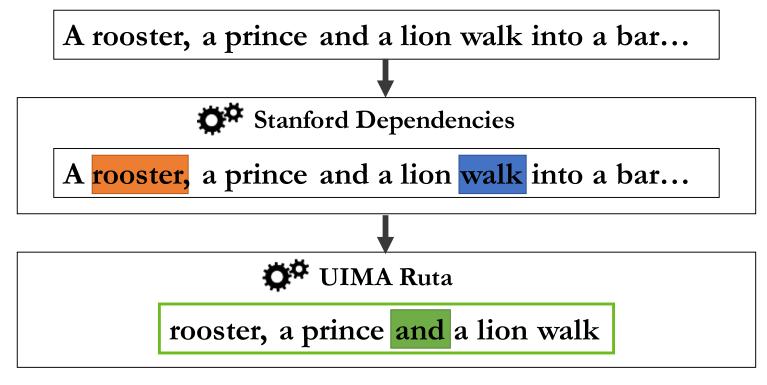


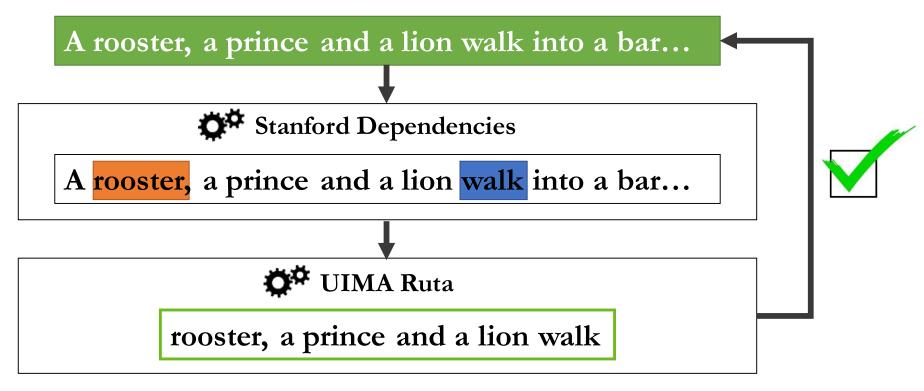










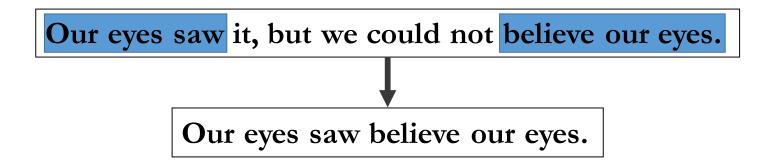


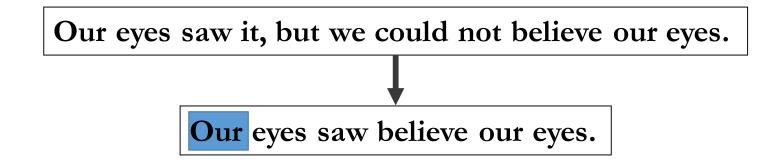
Epanalepsis - repeats the beginning word of a sentence at the end.

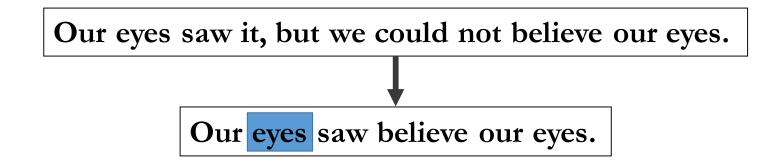
Our eyes saw it, but we could not believe our eyes.

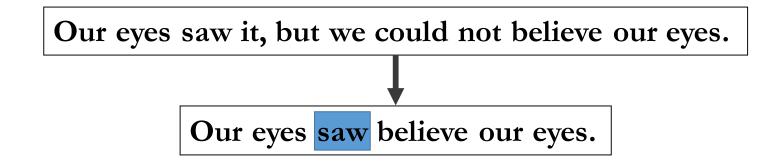
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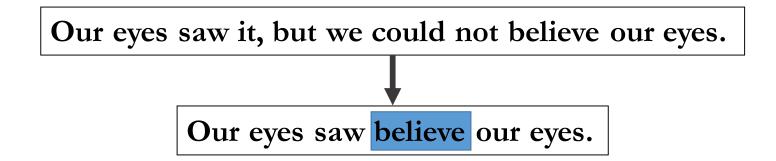
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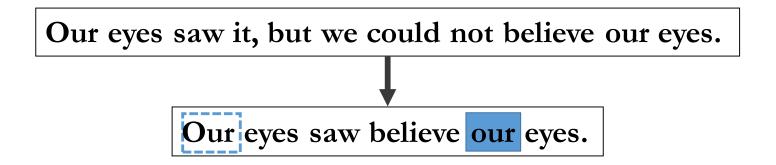


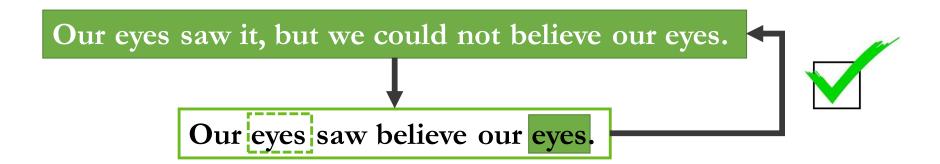








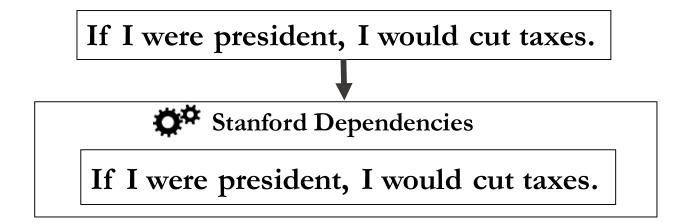




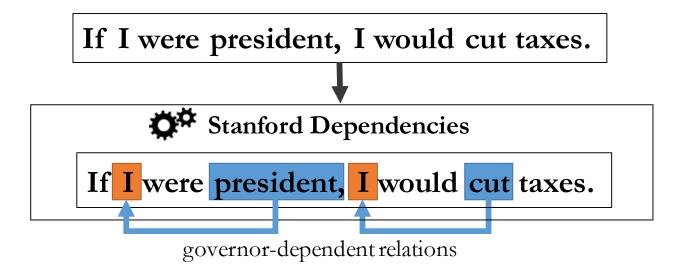
If-conditional 2 - expresses consequences that are totally unrealistic or will not likely happen in the future.

If I were president, I would cut taxes.

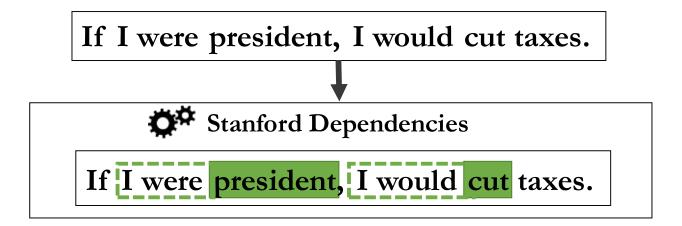
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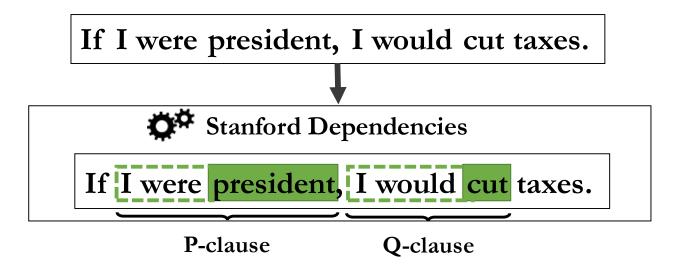


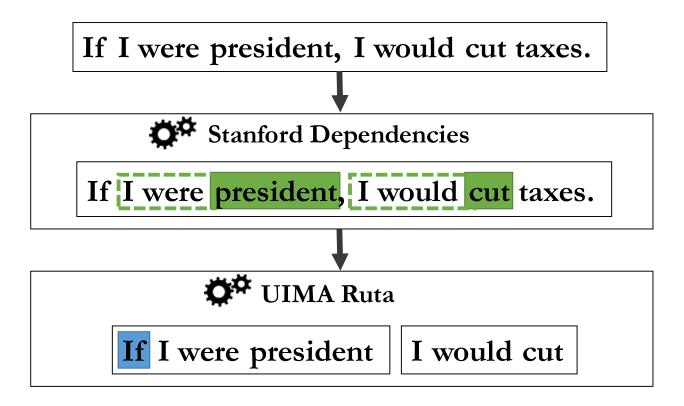
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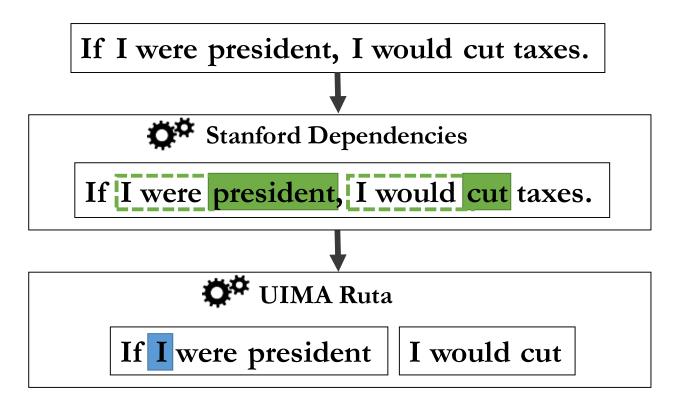


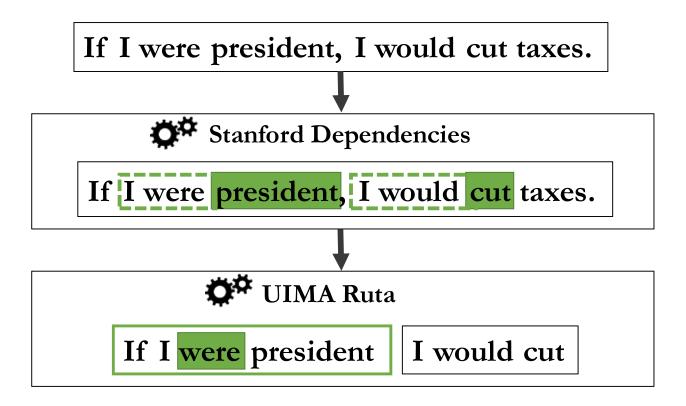
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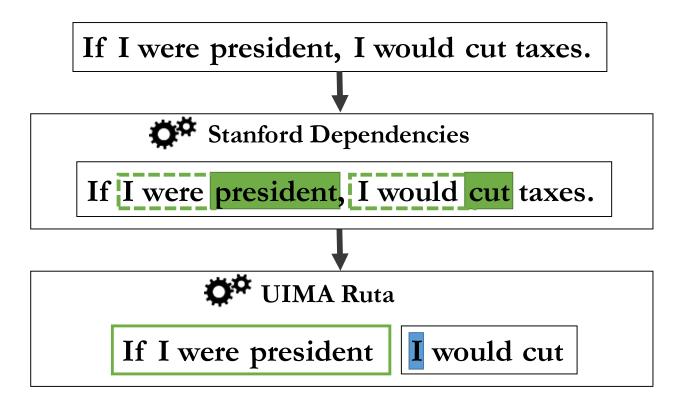


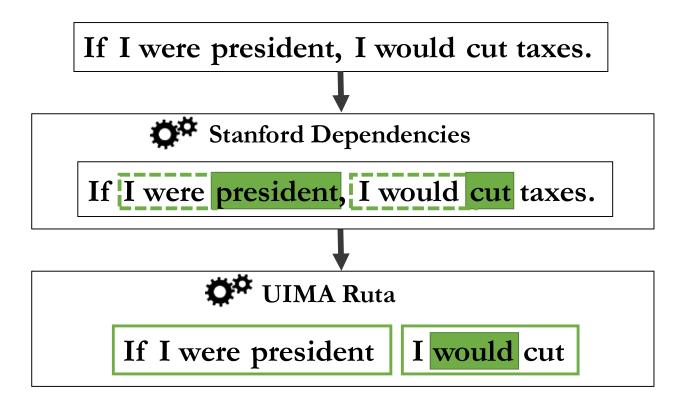


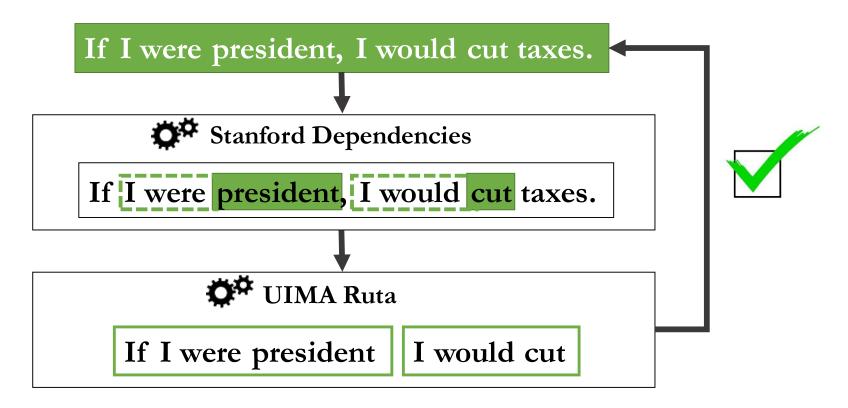




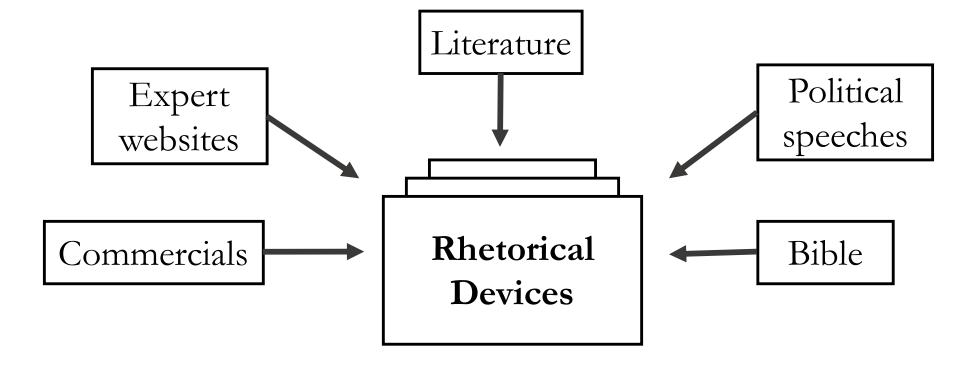




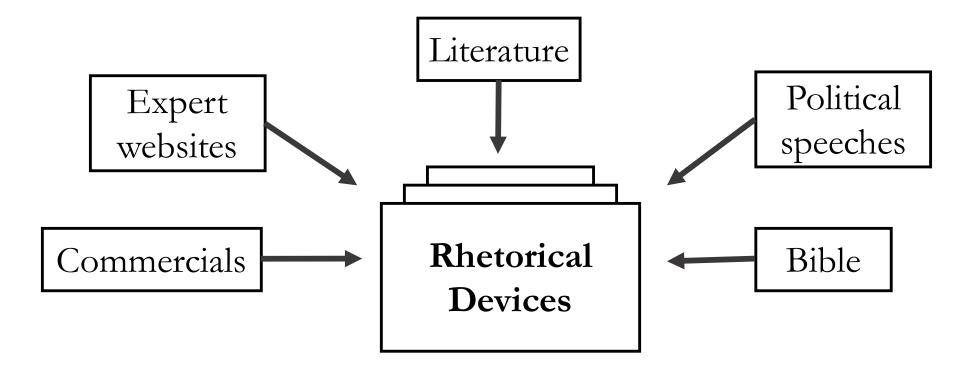




Evaluation dataset

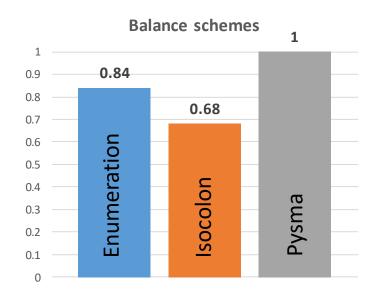


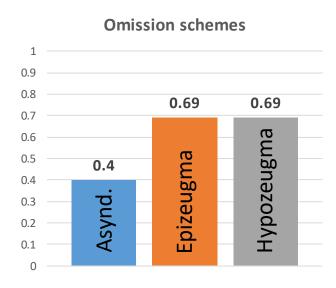
Evaluation dataset

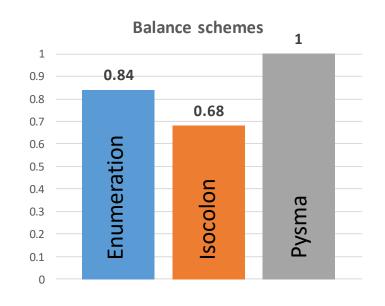


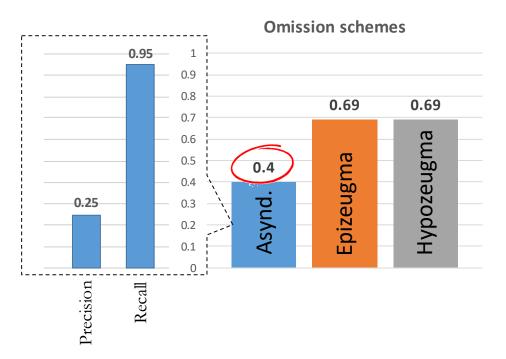
Evaluation measures

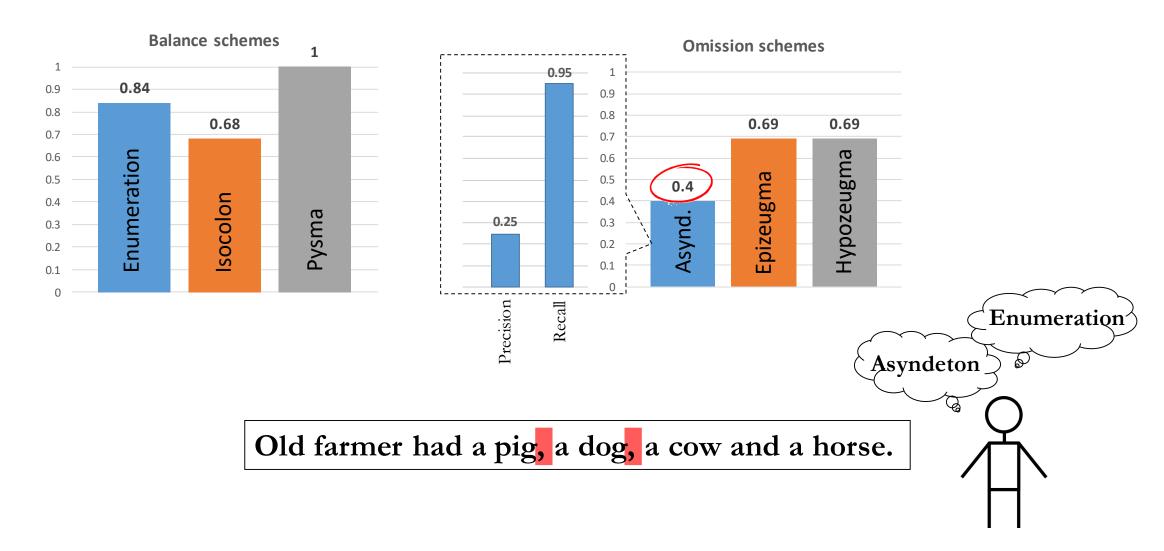
$$Precision = \frac{tp}{tp + fp} \qquad Recall = \frac{tp}{tp + fn} \qquad F1 \ score = \ 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

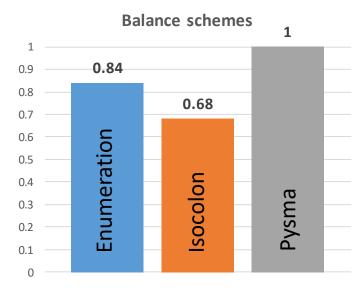




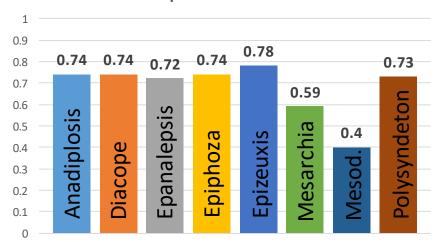




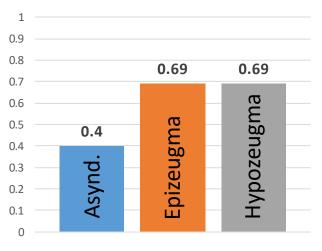




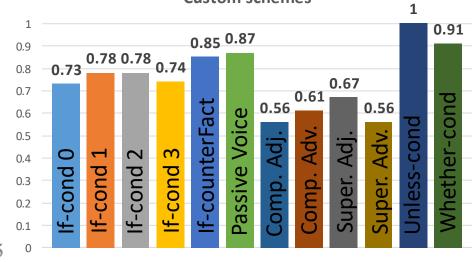
Repetition schemes

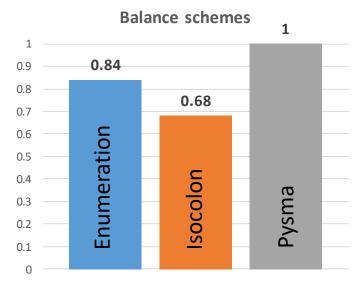




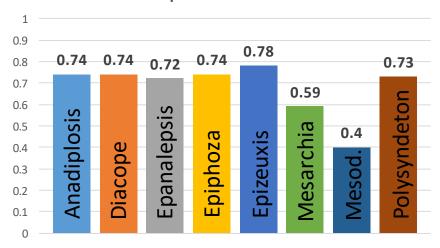


Custom schemes

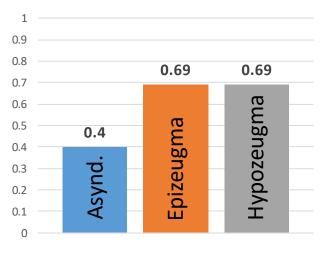


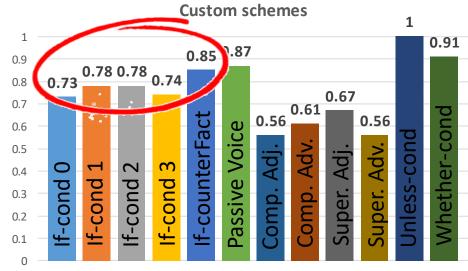


Repetition schemes

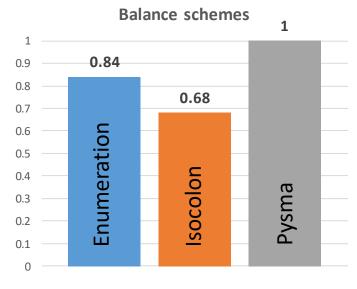




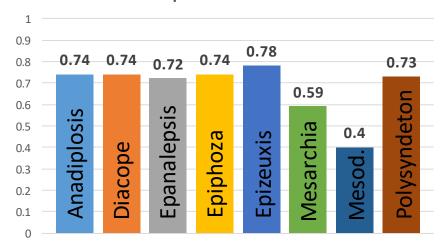


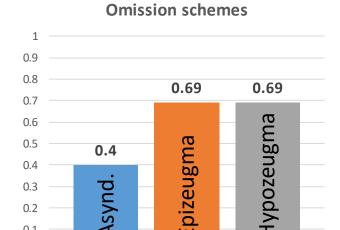


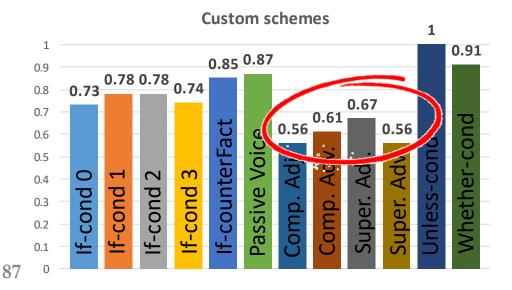
Evaluation Results F1-Score

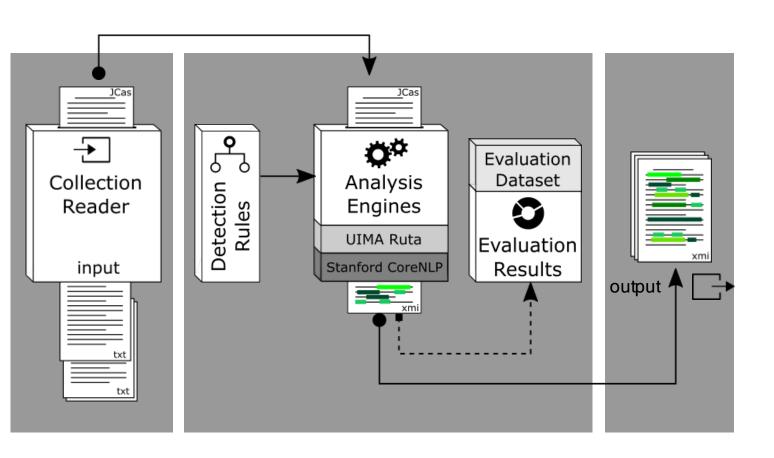


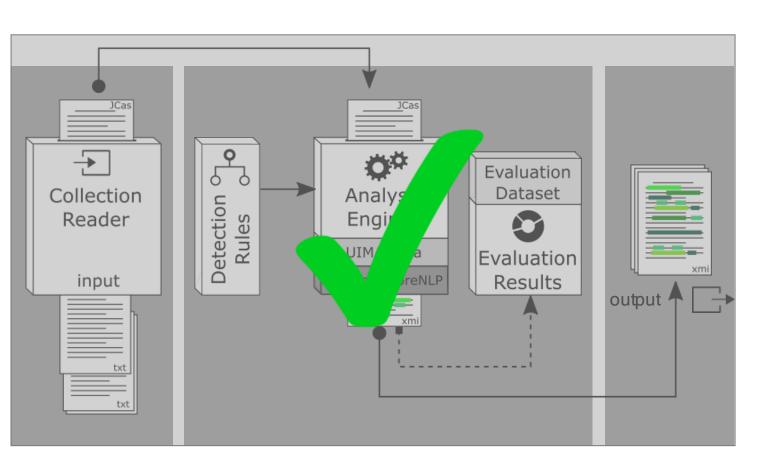
Repetition schemes



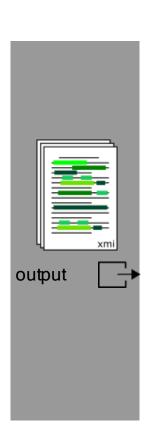


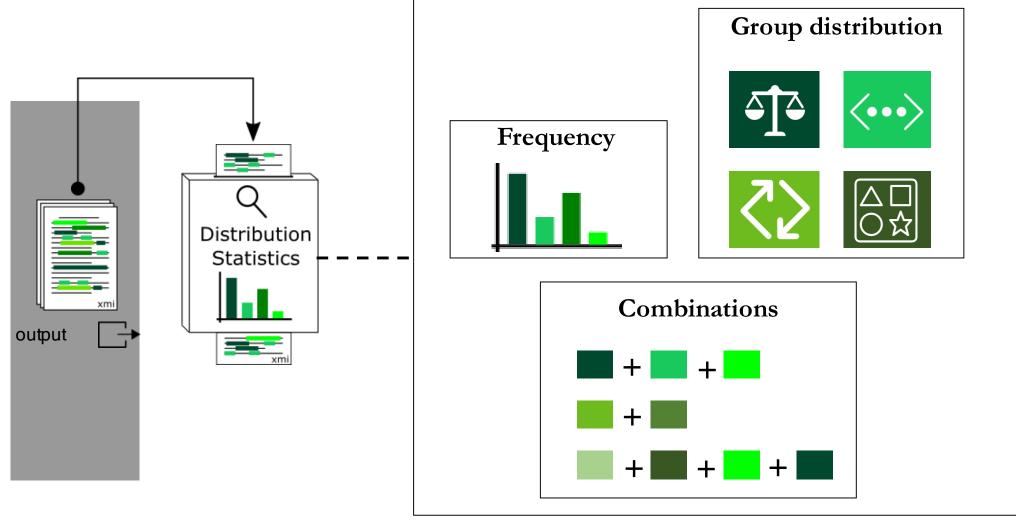


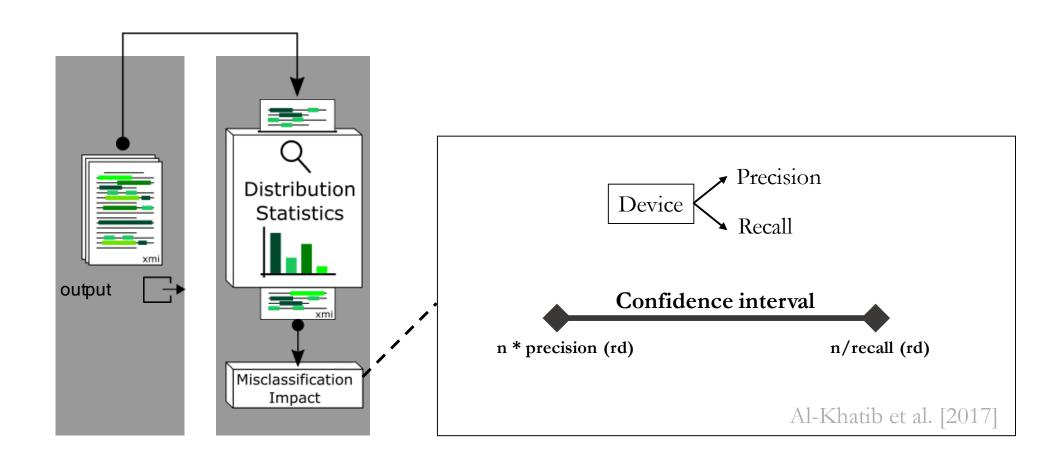


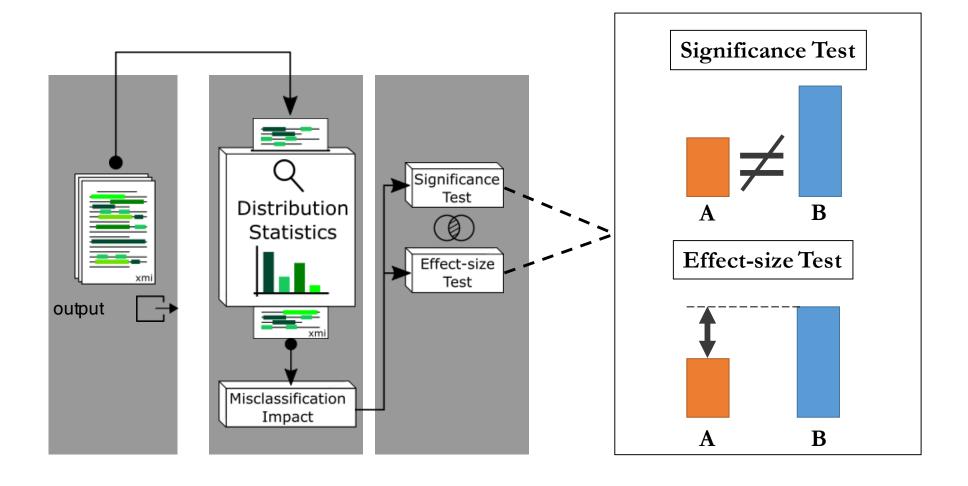


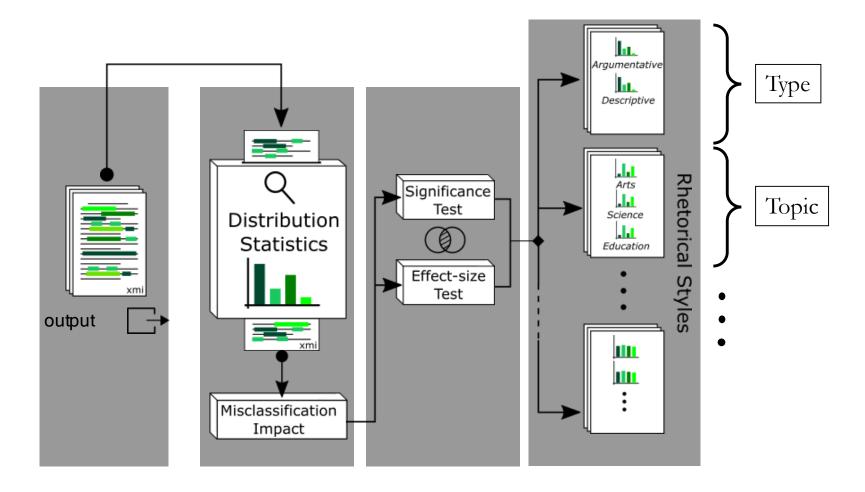
Analysis of Rhetorical Devices

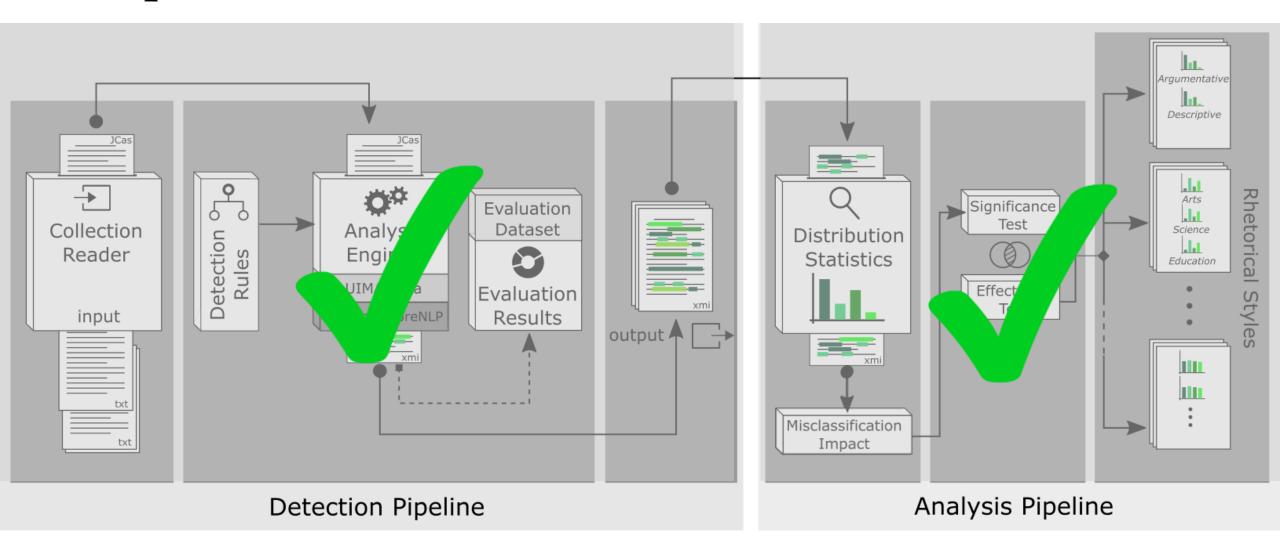












Analysis Experiments

Data Preparation

Experiments: datasets

The New York Times

The New Hork Times

US Presidential Debates 2016

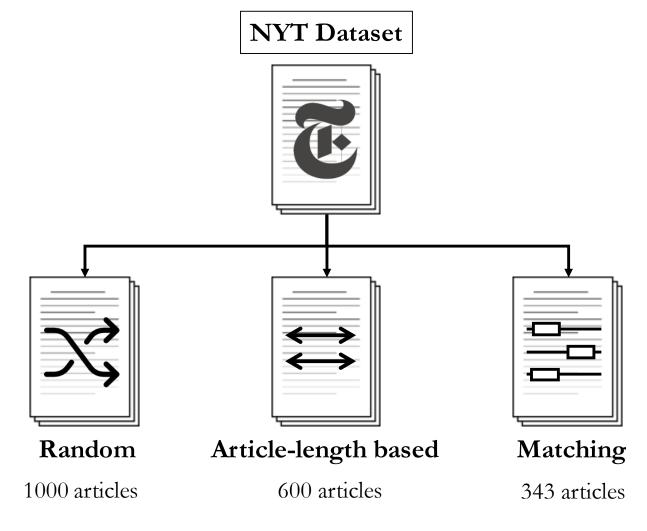


Ben Wiseman [2016]

Data dimensionality

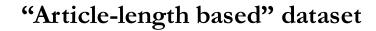
Language M		Mo	de	Communication		Author	hor Audience	
English		Writ	Written		onological	Identity	U.S.	
	Type Descriptive		Genre		Topic	Medium		
			Editorial		Education	Newspaper		
	Argumentative		Review		Science	Presidential Debates		
		Biography		Art				
		Debate		Politics				

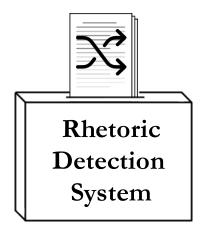
NYT Experiment: data subsampling

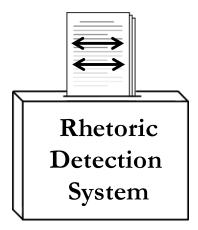


NYT Experiment: Findings

"Random" dataset







Articles cover multiple dimensions

Hard to deduce particular styles

NYT Experiment: Findings

"Random" dataset

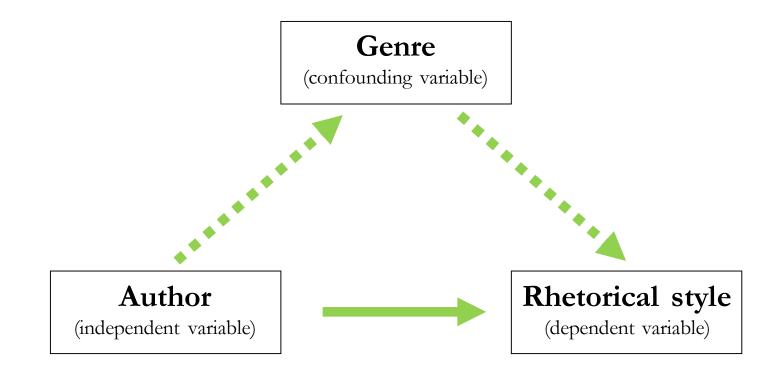
"Article-length based" dataset



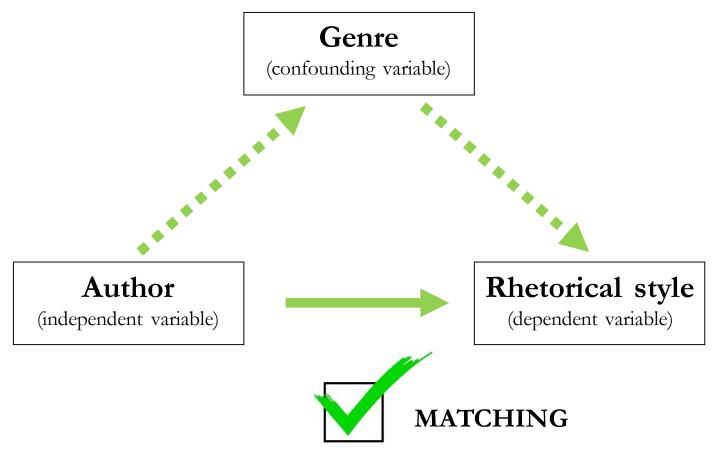
Articles cover multiple dimensions

Hard to deduce particular styles

NYT Experiment: Confounding



NYT Experiment: Confounding



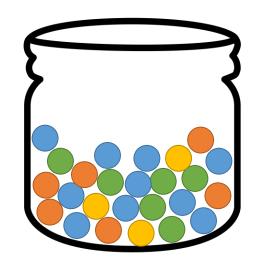


Genre 1

Genre 2

Genre 3

Genre 4

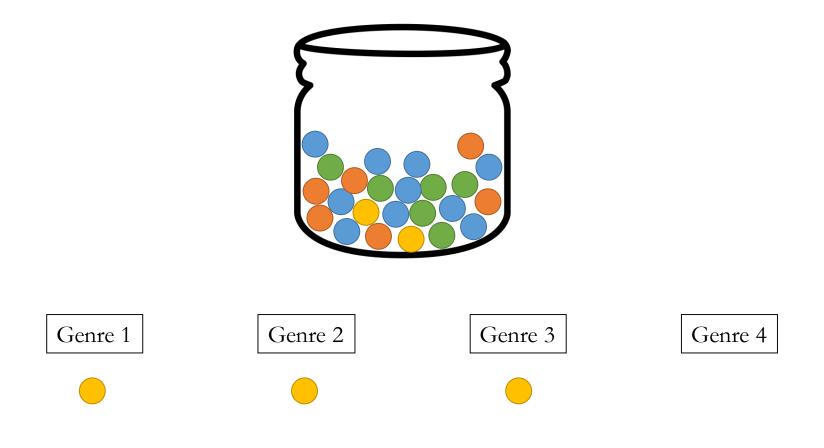


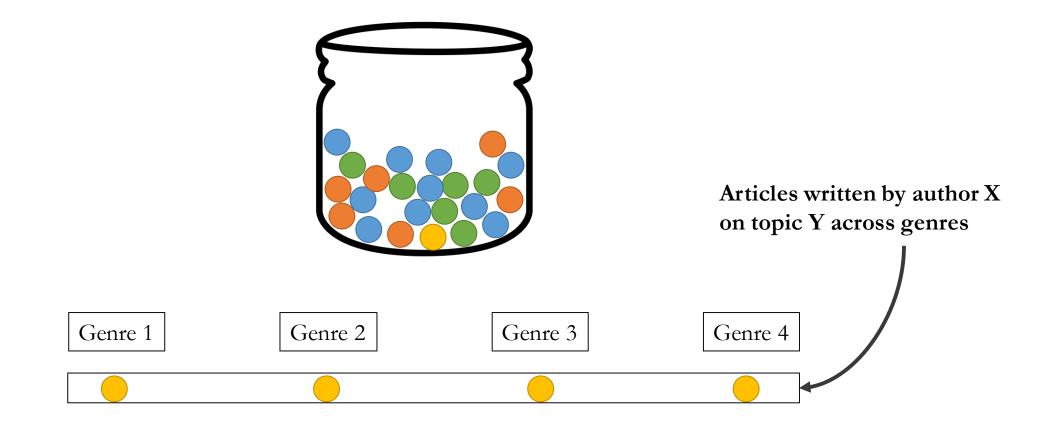
Genre 1

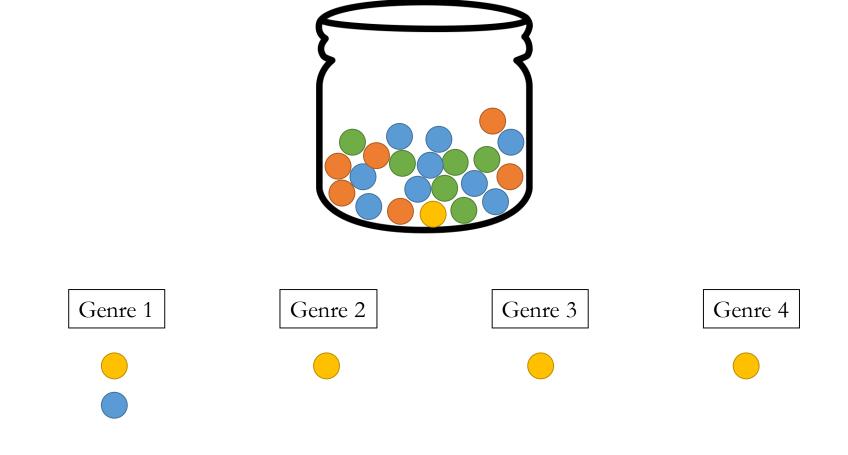
Genre 2

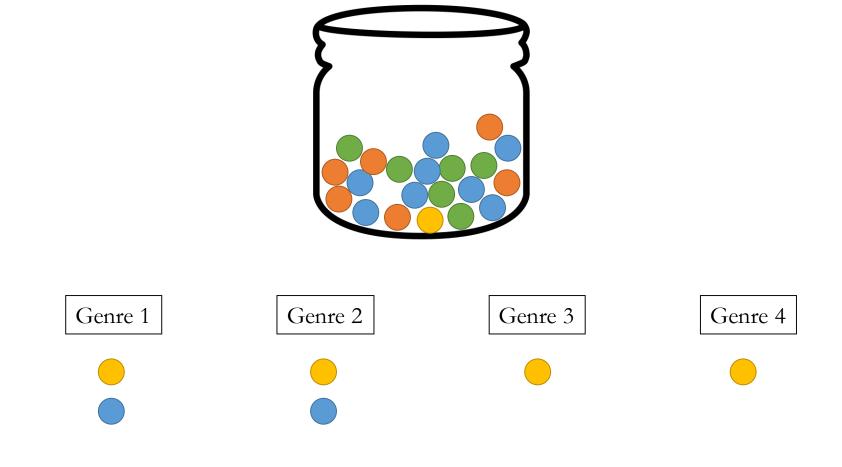
Genre 3

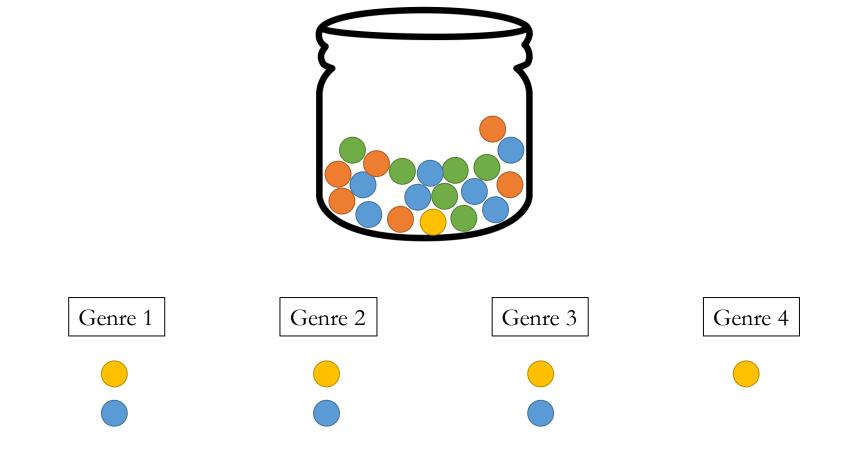
Genre 4

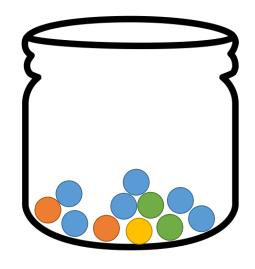


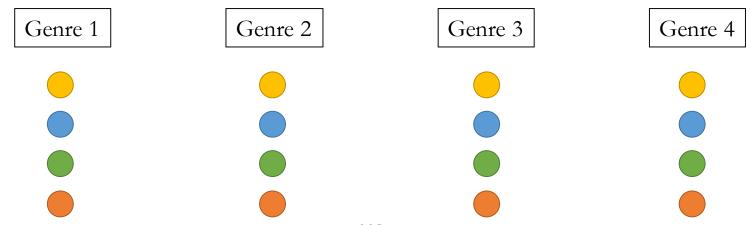




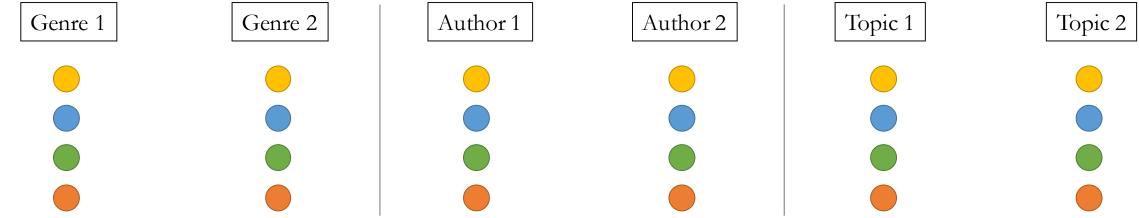








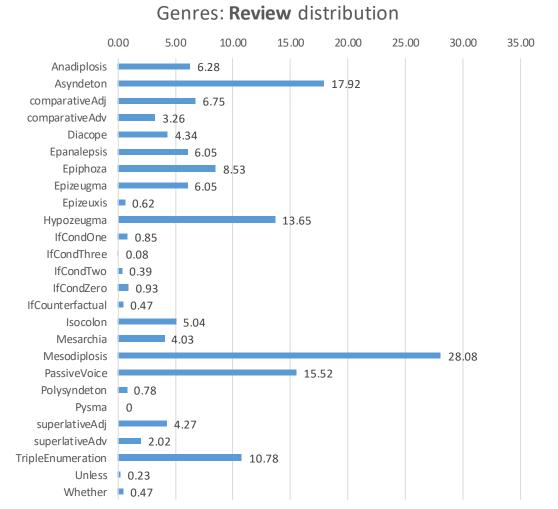




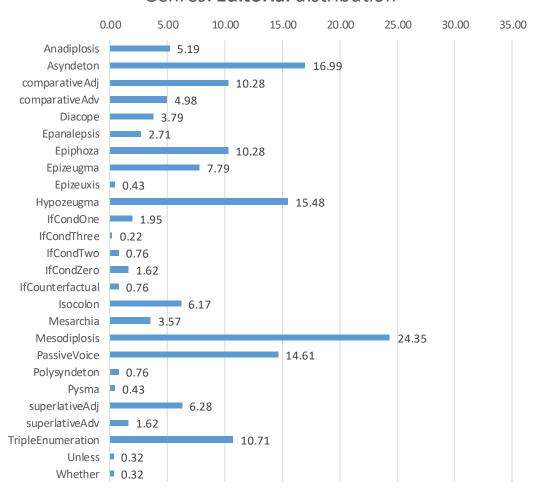
Analysis Experiments

Findings

NYT Experiment: Frequency



Genres: Editorial distribution





Style-based frequency of rhetorical devices
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<u> </u>

	Authors			
	EPIPHOZA	REPETITION SCHEMES		
Author	Distribution (%)	Distribution (%)		
Hevesi Dennis	10.74	70.99		
Lewis Paul	12.99	81.93		
Martin Douglas	6.49	55.49		

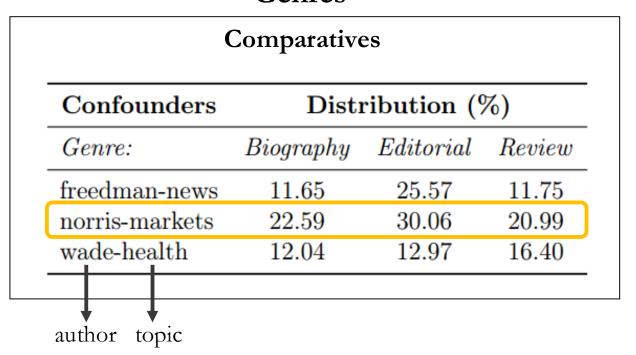
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Good Job, Lewis!

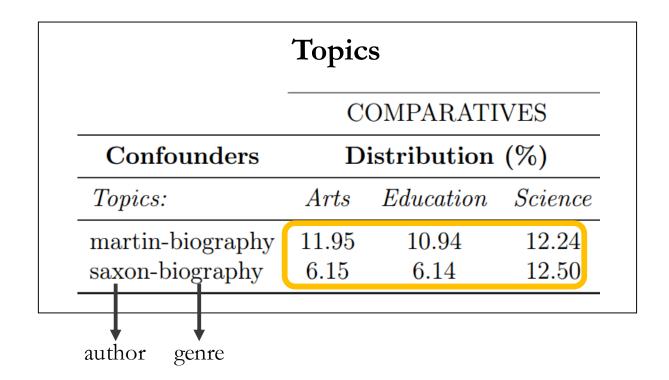
Authors				
SIGNIFICANCE EFFECT-SIZE				
Datasets	P-value	Independence	Cramer's V value	Effect
Hevesi vs. Lewis	0.015	TRUE*	0.1	SMALL
Lewis vs. Martin	~ 0	TRUE	0.15	SMALL
Martin vs. Hevesi	0.017	TRUE*	0.1	SMALL
* for $\alpha > 0.001$				

Genres



	Genres	
	COMPARATIVES	CONDITIONALS
Genre	Distribution (%)	Distribution (%)
Biography Editorial Review	14.07 23.16 16.29	3.45 5.95 3.41

Genres: tests' results				
	SIGN	NIFICANCE	EFFECT-SIZ	E
Datasets	P-value	Independence	Cramer's V value	Effect
Biography vs. Editorial	~0	TRUE	0.16	SMALL
Editorial vs. Review	~ 0	TRUE	0.14	SMALL
Review vs. Biography	(0.68)	FALSE	0.07	SMALL



Style-based frequency of rhetorical devices

Characteristic style patterns within each dimension

Topics: tests' results				
	SIGN	NIFICANCE	EFFECT-SIZ	E
Datasets	P-value	Independence	Cramer's V value	Effect
Science vs. Education	0.70	FALSE	0.09	SMALL
Education vs. Arts	0.26	FALSE	0.10	SMALL
Arts vs. Science	0.19	FALSE	0.10	SMALL

Style-based frequency of rhetorical devices

Characteristic style patterns within each dimension

Style is more author- and genre-dependent

Presidential Debates: Datasets



REST

REST



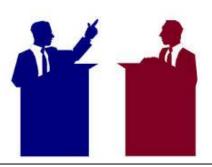
Comparatives			
istribution (%)			
11.00			
7.02			



	ASYNDETON	VOICE	BALANCE SCH.
Debate Type	Distribution (%)	Distribution (%)	Distribution (%)
$Clinton \rightarrow Trump$	15.24	8.07	17.69
Trump \rightarrow Clinton	10.83	5.29	19.92
- Tump / Ciliton	10.00	0.20	10.02



	ASYNDETON	VOICE	BALANCE SCH.	
Debate Type	Distribution (%)	Distribution (%)	Distribution (%)	
$\begin{array}{c} \text{Clinton} \to \text{Trump} \\ \text{Trump} \to \text{Clinton} \end{array}$	15.24 10.83	8.07 5.29	17.69 19.92	
Asyndeton = clarity and rhythm				



	ASYNDETON	VOICE	BALANCE SCH.
Debate Type	Distribution (%)	Distribution (%)	Distribution (%)
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Acceptance Speech Analysis by Huffington Post

Candidate	Sent.	Long Sent. (%)	Passive voice (%)	Grade Level (US)
Hillary Clinton	413	7.26	3.39	5
Donald Trump	341	16.42	8.8	8



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Significance Test

Debate Type	$Clinton \rightarrow Rest$	$ Clinton \rightarrow Trump $	$Trump \rightarrow Clinton$	$Trump \rightarrow Rest$
$Clinton \rightarrow Rest$		$TRUE^*$	TRUE	TRUE
$Clinton \rightarrow Trump$	$TRUE^*$		TRUE	TRUE
$Trump \rightarrow Clinton$	TRUE	TRUE		FALSE^{\dagger}
$Trump \rightarrow Rest$	TRUE	TRUE	FALSE^{\dagger}	

^{*} for $\alpha > 0.01$

 $^{^{\}dagger}$ for $\alpha > 0.1$



Significance Test

Debate Type	$Clinton \rightarrow Rest$	$Clinton \rightarrow Trump$	$ Trump \rightarrow Clinton $	$ Trump \rightarrow Rest $
$Clinton \rightarrow Rest$		TRUE*	TRUE	TRUE
$Clinton \rightarrow Trump$	$TRUE^*$		TRUE	TPUE
$Trump \rightarrow Clinton$	TRUE	TRUE		FALSE)
$Trump \rightarrow Rest$	TRUE	TRUE	FALSE	

^{*} for $\alpha > 0.01$

Trump doesn't change his style



 $^{^{\}dagger}$ for $\alpha > 0.1$

Conclusions

System for rhetorical style identification in high-quality text documents

Rule-based algorithms for detection of RD

Vague style patterns across random and articlelength based subsampling: **Confounding**

Better style identification with **Matching**

Rhetorical style depends more on author and genre of writings rather than their topics

Debates: candidates employ different styles

Debates: domain experience trains an adaptive rhetorical style

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Initialization \rightarrow 1.7 sec.

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Future Work

Larger dataset for analysis

Focus of semantical rhetoric

Analysis measures like placement and flows of rhetorical devices

Thank you!

References

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References - Icons and Images

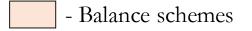
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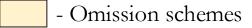
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- https://www.washingtonpost.com/graphics/politics/2016election/presidential-debate-schedule/

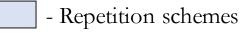
Existing research

- Gawryjołek et al. [2009] authorship identification system based on rhetorical style.
- Strommer [2011] authorial intent detection system based on the anaphora usage.
- Java [2015] machine-learning based authorship identification system using rhetorical devices (based on Gawryjołek et al. [2009])

Device	Total No.	Precision	Recall	F1-score	Device	Total No.	Precision	Recall	F1-score
Anadiplosis	60	0.76	0.73	0.74	If Conditional Two	60	0.82	0.75	0.78
Asyndeton	60	0.25	0.95	0.4	If Conditional Zero	60	0.71	0.76	0.73
Comparative Adjective	67	0.51	0.61	0.56	If Counterfactual	60	0.84	0.87	0.85
Comparative Adverb	71	0.6	0.62	0.61	Isocolon	180	0.57	0.83	0.68
Diacope	60	0.75	0.73	0.74	Mesarchia	20	0.45	0.85	0.59
Enumeration	60	0.76	0.93	0.84	Mesodiplosis	40	0.28	0.68	0.4
Epanalepsis	60	0.63	0.83	0.72	Passive Voice	60	0.79	0.98	0.87
Epiphoza	60	0.61	0.93	0.74	Polysyndeton	60	0.77	0.7	0.73
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Epizeuxis	60	0.79	0.77	0.78	Superlative Adjective	70	0.62	0.73	0.67
Hypozeugma	60	0.61	0.8	0.69	Superlative Adverb	70	0.63	0.5	0.56
If Conditional One	60	0.78	0.78	0.78	Unless Conditional	60	1	1	1
If Conditional Three	60	0.86	0.65	0.74	Whether Conditional	60	1	0.83	0.91

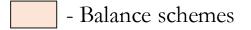


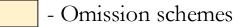


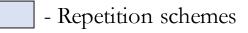


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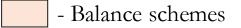


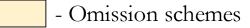


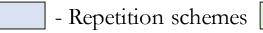


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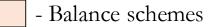
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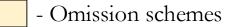


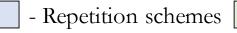




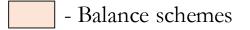
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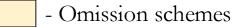


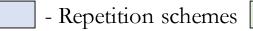




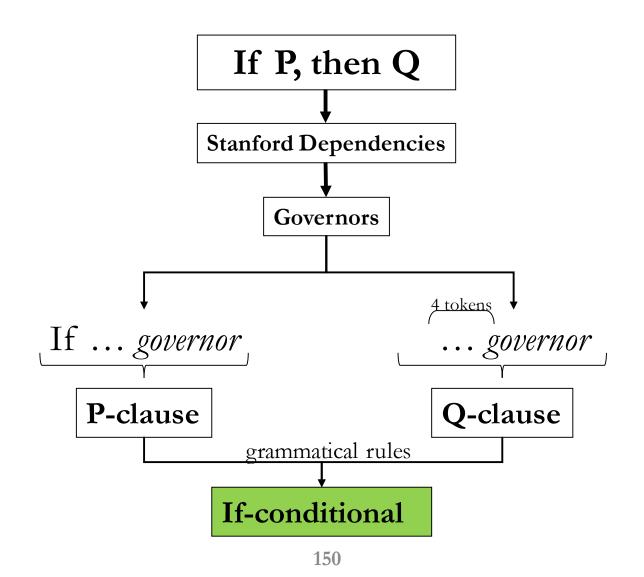
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Hypozeugma	60	0.61	0.8	0.69	Superlative Adverb	70	0.63	0.5	0.56
If Conditional One	60	0.78	0.78	0.78	Unless Conditional	60	1	1	1
If Conditional Three	60	0.86	0.65	0.74	Whether Conditional	60	1	0.83	0.91







If-conditional Detection



If-counterfactual Detection

