Department of Linguistics
Franklin College of Arts and Sciences
UNIVERSITY OF GEORGIA

Quantifying Discourse Support for Omitted Pronouns

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CRAC 2022

Introduction

(1)	这	是	我	给	他	后来	画	出来	最好	的	一 幅	画像。
	zhe	shi	wo	gei	ta	houlai	hua	chulai	zuihao	de	yi fu	huaxiang
	This	is	I	for	he	later	draw	out	best	DE	one	drawing

“This is the best portrait I drew for him later on.”

(2)	[我]	六	岁	时，	大人们	使	我	对	我的	画家	生涯	失去	了	勇气。
	wo	liu	sui	shi	darenmen	shi	wo	dui	wode	huajia	shengya	shiqu	le	yongqi
	[I]	Six	year	old	grown-ups	make	I	towards	my	painter	career	lose	LE	courage

“When I was six, grown-ups made me lose courage in my painter career.”

(3)	[我]	除了	画	过	开着	肚皮	和	闭着	肚皮	的	蟒蛇，
	wo	chule	hua	guo	kaizhe	dupi	he	bizhe	dupi	de	mangshe
	[I]	except	draw	PASS	opening	belly	and	closing	belly	DE	boa

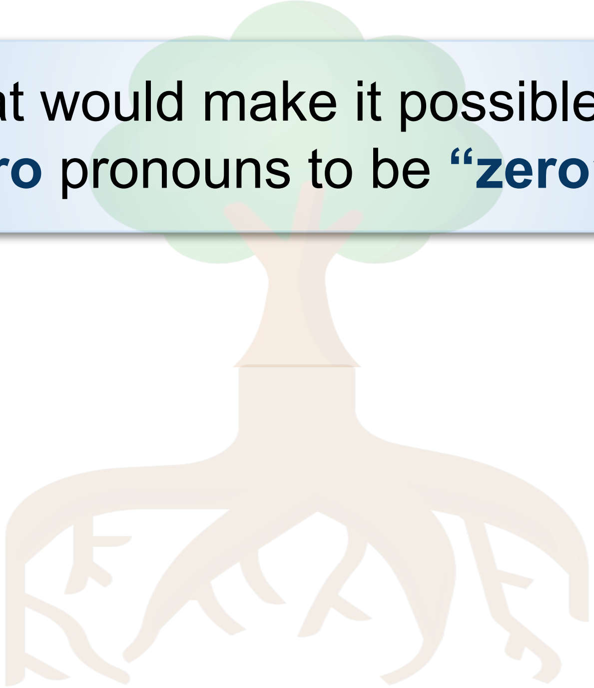
“Except that I had drawn boas with opening and closing belly,”

(4)	[我]	后来	再	没有	学	过	画。
	wo	houlai	zai	meiyou	xue	guo	hua
	[I]	afterwards	again	not	learn	PASS	draw

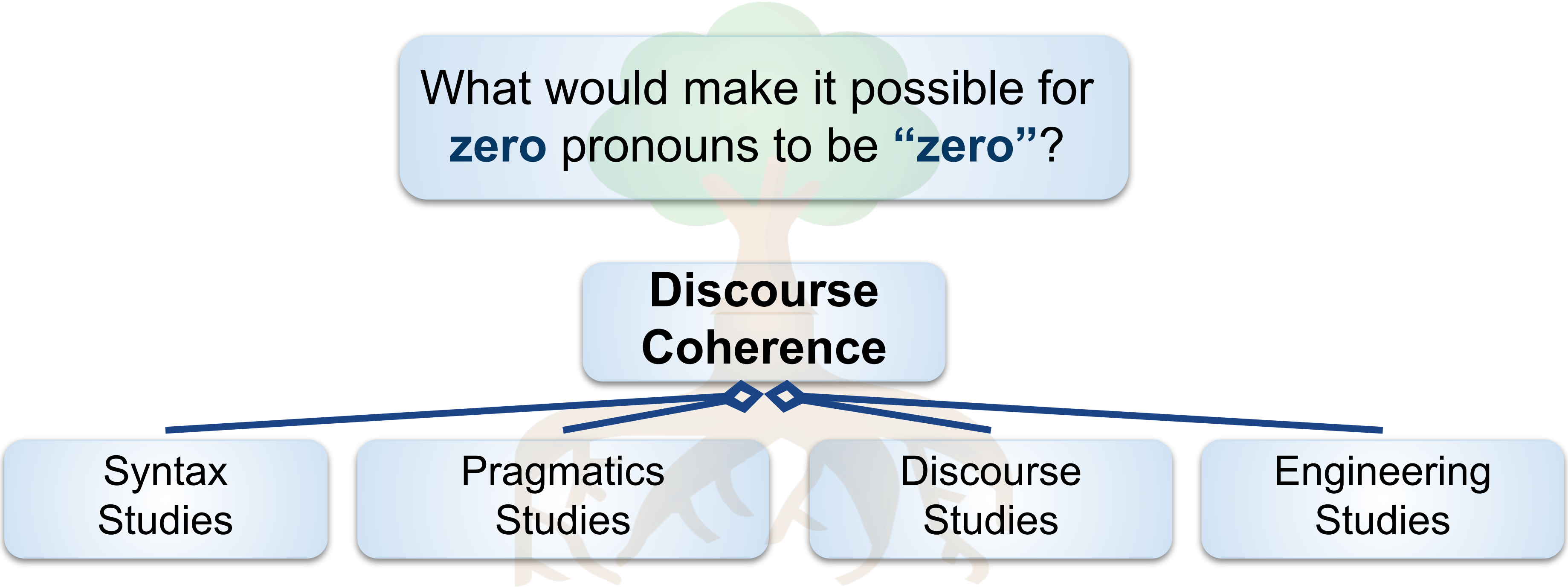
“I had never learned drawing afterwards.”

Introduction

What would make it possible for **zero** pronouns to be “**zero**”?



Introduction



What would make it possible for **zero** pronouns to be **“zero”**?

Discourse Coherence

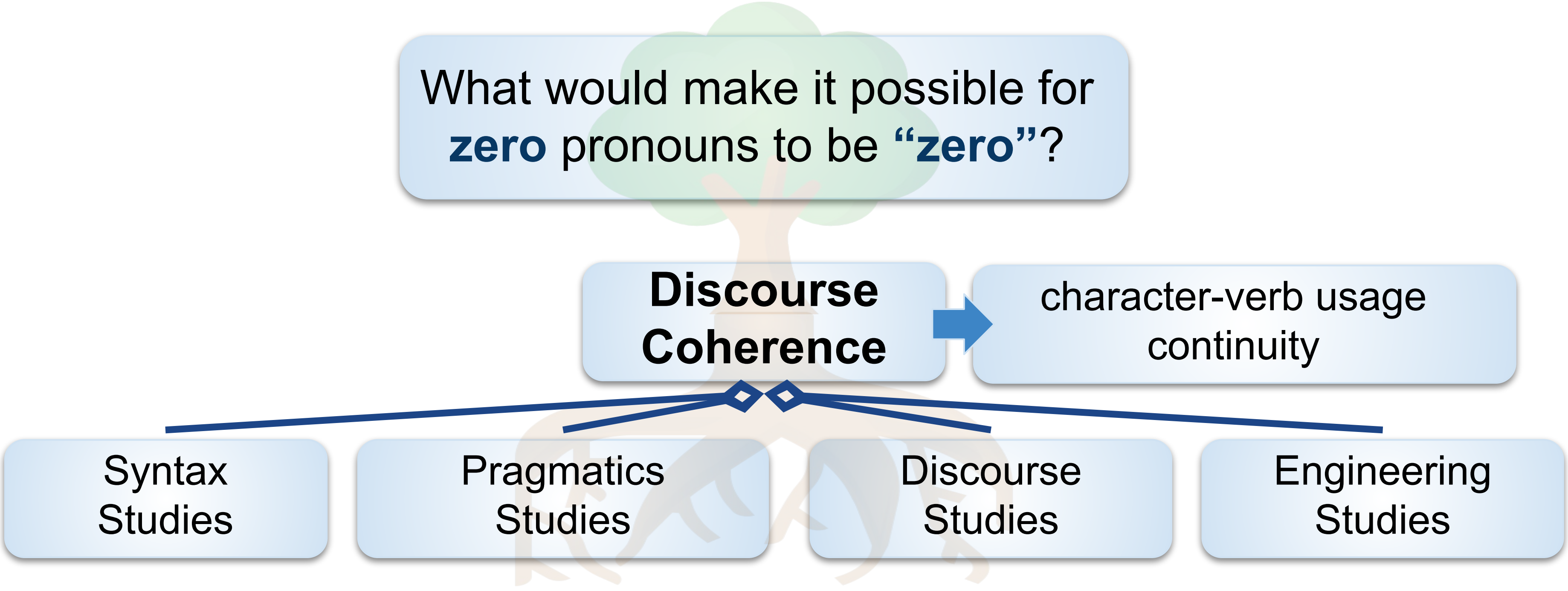
Syntax Studies

Pragmatics Studies

Discourse Studies

Engineering Studies

Introduction



What would make it possible for **zero** pronouns to be "**zero**"?

Discourse Coherence

character-verb usage continuity

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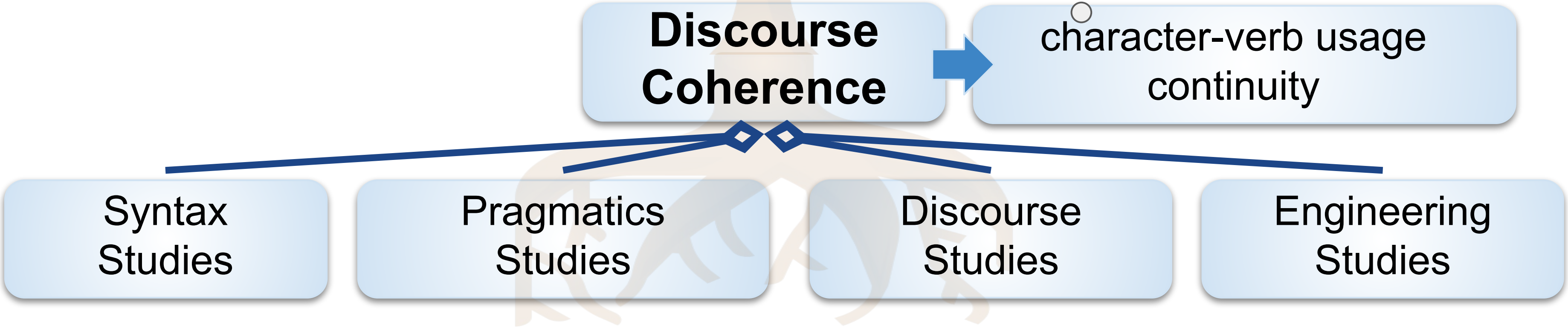
Intro

To compare *zero vs. non-zero*, Is there a **numerical** way to **quantify** the level of **Discourse Coherence**?

for

zer to be “**zero**”?



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character-verb usage continuity

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	[I]	except	draw	PASS	opening	belly	and	closing	belly	DE	boa

“Except that I had drawn boas with opening and closing belly,”

(4)	[我]	后来	再	没有	学	过	画。
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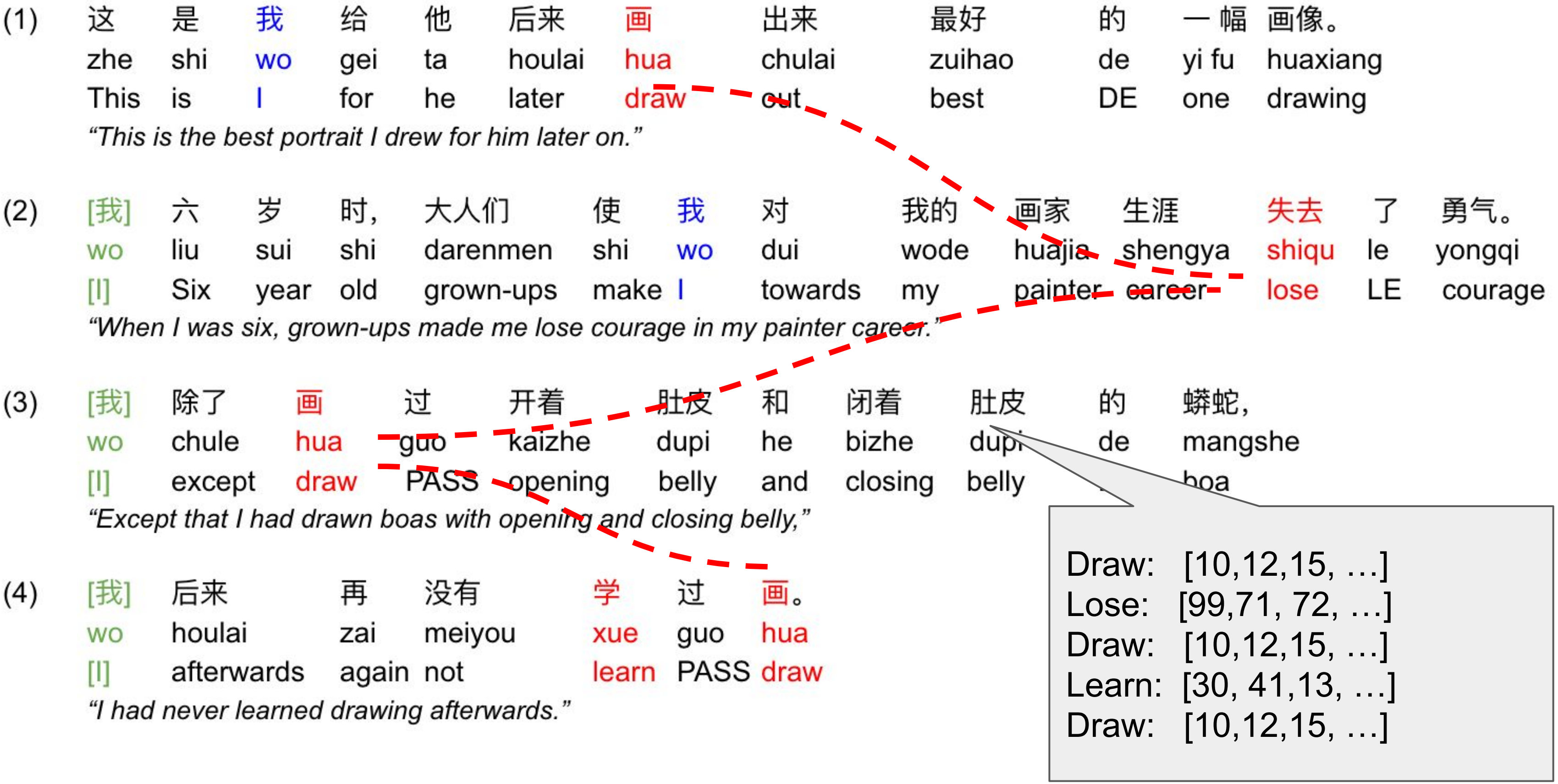
“I had never learned drawing afterwards.”

Introduction



(1)

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[I]	afterwards	again	not	learn	PASS	draw

“I had never learned drawing afterwards.”

Draw: [10,12,15, …]
Lose: [99,71, 72, …]
Draw: [10,12,15, …]
Learn: [30, 41,13, …]
Draw: [10,12,15, …]

Introduction

Assumption:

Compared to non-zero pronouns, zero pronouns have higher discourse coherence supporting them to be resolvable, so that we would expect their verb-usage continuity to be higher than the non-zero cases.

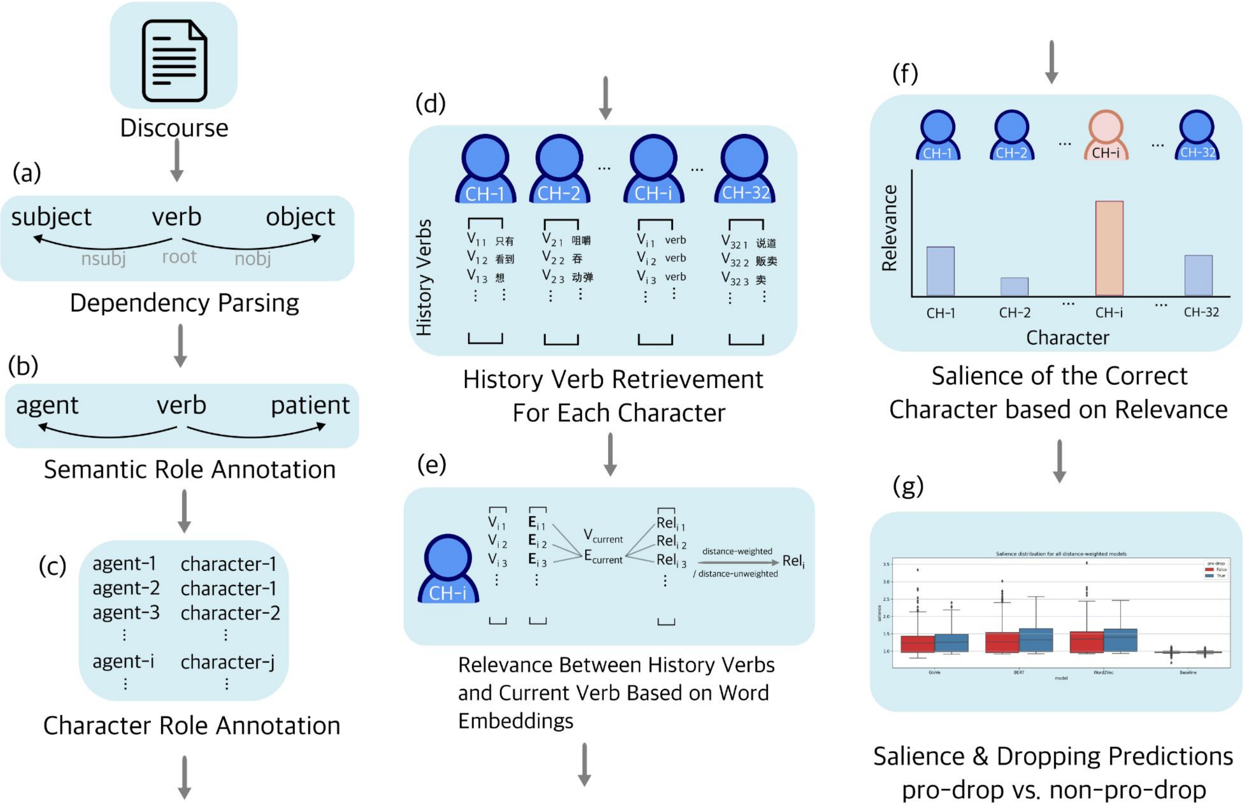
Method

	BERT “Bidirectional Encoder Representations from Transformers”	**GloVe** “Global Vectors for word representation”	**Word2Vec** “Word to vector”
Vector size	768 base model	300	300
Training task	Masked LM, Next sentence prediction	Aggregated global word-word co-occurrence statistics from a corpus	Local statistics, whether words appear in similar contexts (Window size = 5)
Feature catching	Bidirectional and contextual features	Global statistical features	Local statistical features

https://spacy.io/models/zh

https://github.com/Embedding/Chinese-Word-Vectors

Roadmap



Dependency Parsing

Semantic Role Annotation

Character Role Annotation

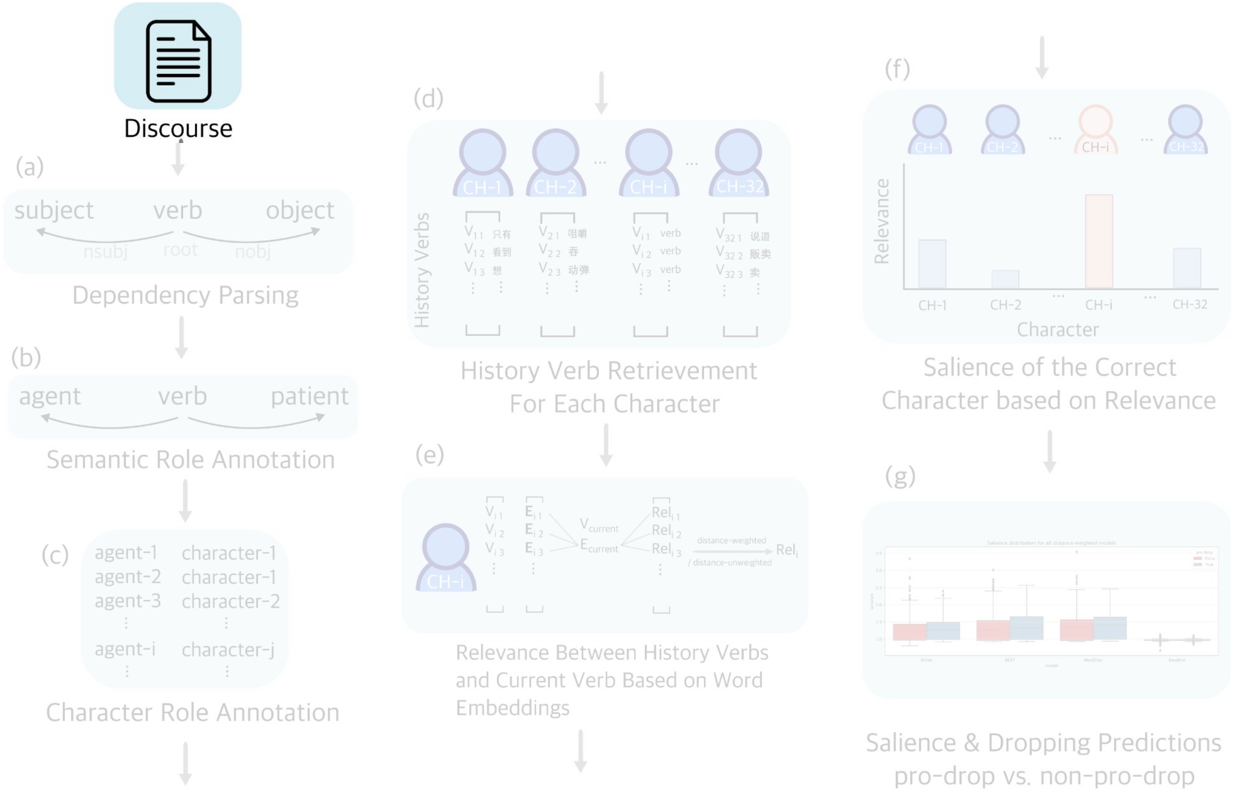
History Verb Retrievement For Each Character

Relevance Between History Verbs and Current Verb Based on Word Embeddings

Salience of the Correct Character based on Relevance

Salience & Dropping Predictions pro-drop vs. non-pro-drop

Roadmap



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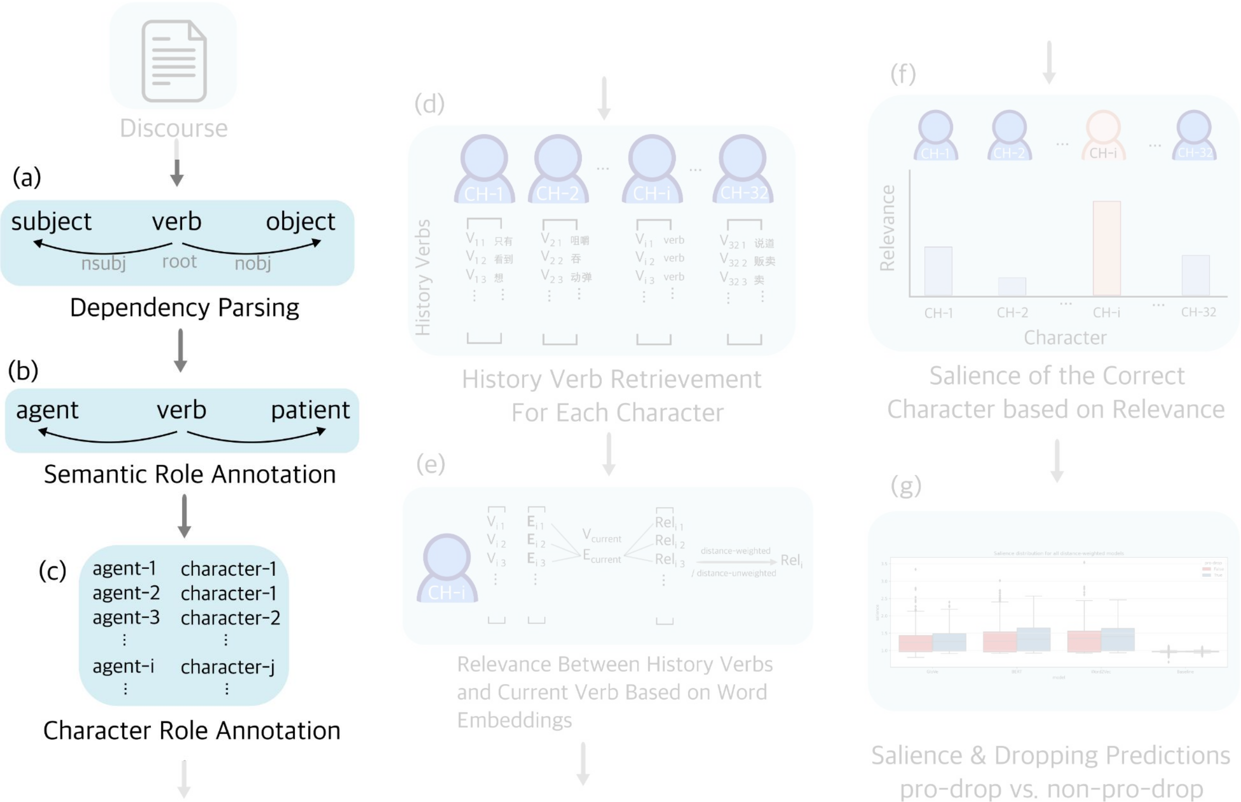
Method

- Discourse material:
    - Chinese translation of Saint-Exupéry's The Little Prince
    - 2802 clauses, 16010 words
        - Each of the clauses includes a main verb, and they were divided by ending with punctuations (i.e. “, . ; ? !”)

Roadmap



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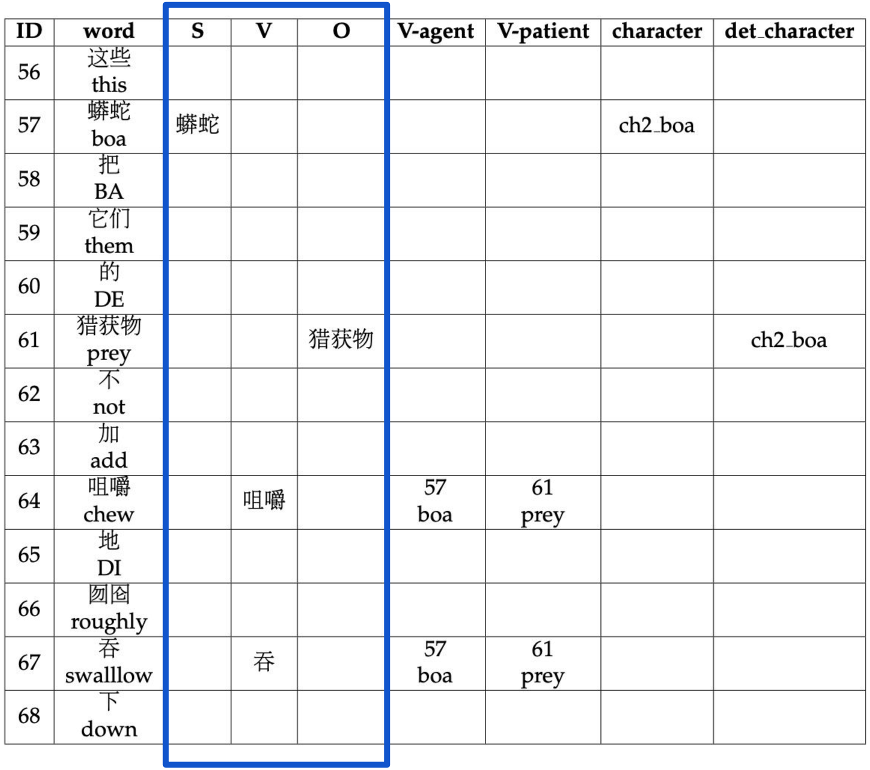
- Dependency parsing

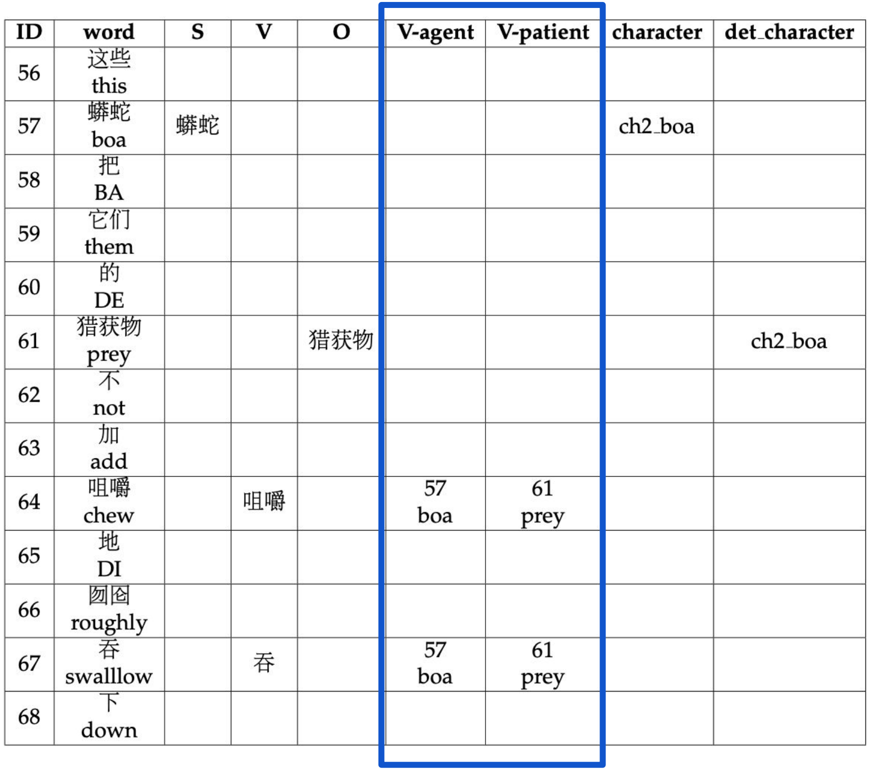


ID	word	S	V	O	V-agent	V-patient	character	det_character
56	这些 this							
57	蟒蛇 boa	蟒蛇					ch2_boa	
58	把 BA							
59	它们 them							
60	的 DE							
61	猎获物 prey			猎获物				ch2_boa
62	不 not							
63	加 add							
64	咀嚼 chew		咀嚼		57 boa	61 prey		
65	地 DI							
66	囫囵 roughly							
67	吞 swalllow		吞		57 boa	61 prey		
68	下 down							

Table 1: Annotation columns

Method

- Semantic Role annotation



ID	word	S	V	O	V-agent	V-patient	character	det_character
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Table 1

Method

- Character Role annotation

ID	word	S	V	O	V-agent	V-patient	character	det_character
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66	囫囵 roughly							
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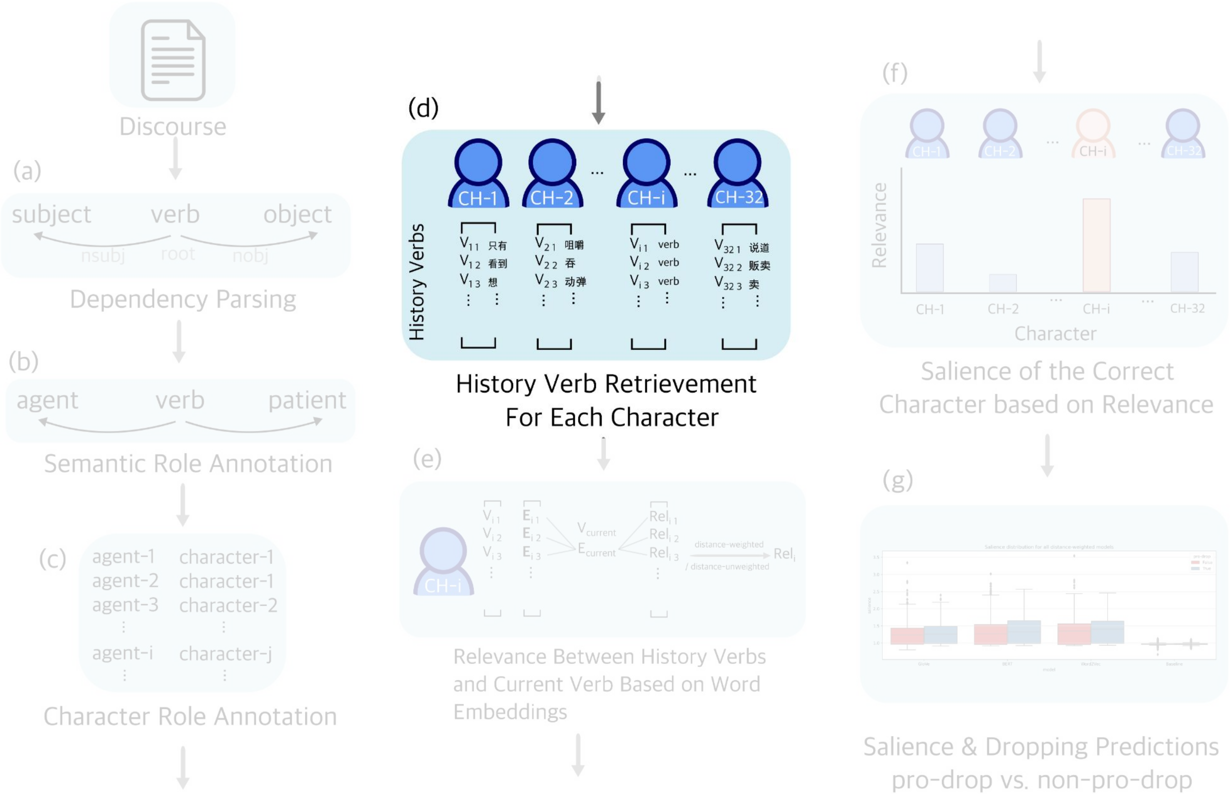
68	下 down							

Table 1: Annotation columns

Method

- Character Role annotation
- Pro-drop annotation
  - Among all agent cases, 422 of them are dropped; only 16 cases of patient were dropped.
  - In the following analyses, we focused on the agent cases.

Roadmap



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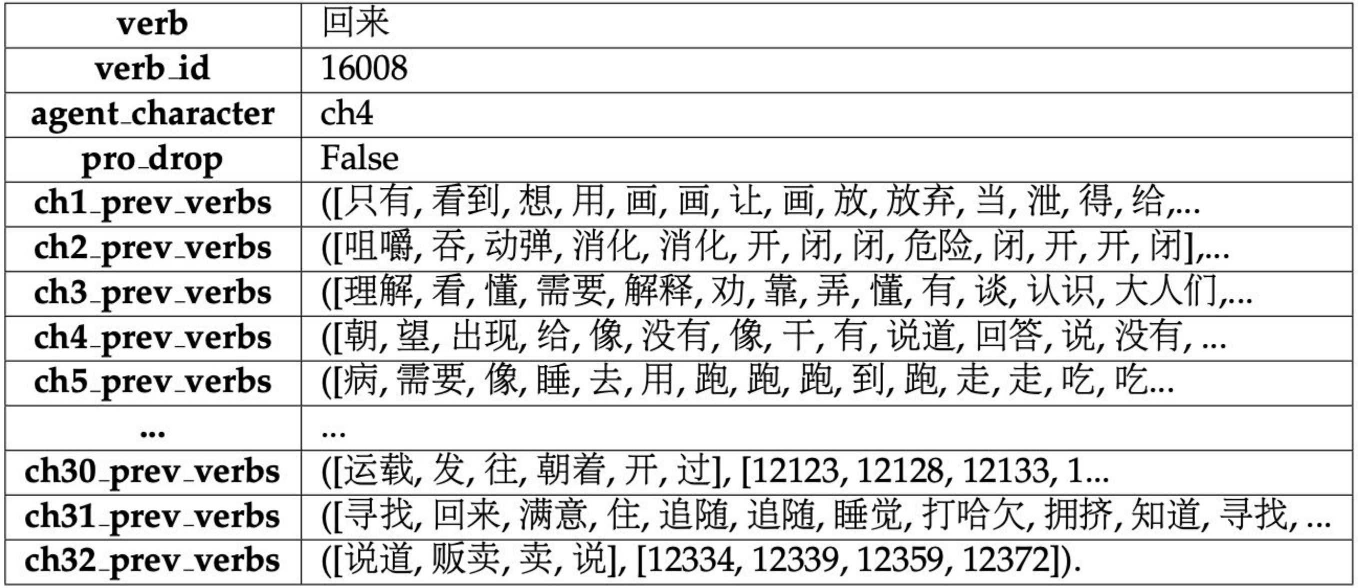
Method

- Dynamic Character-Verb Usage Table



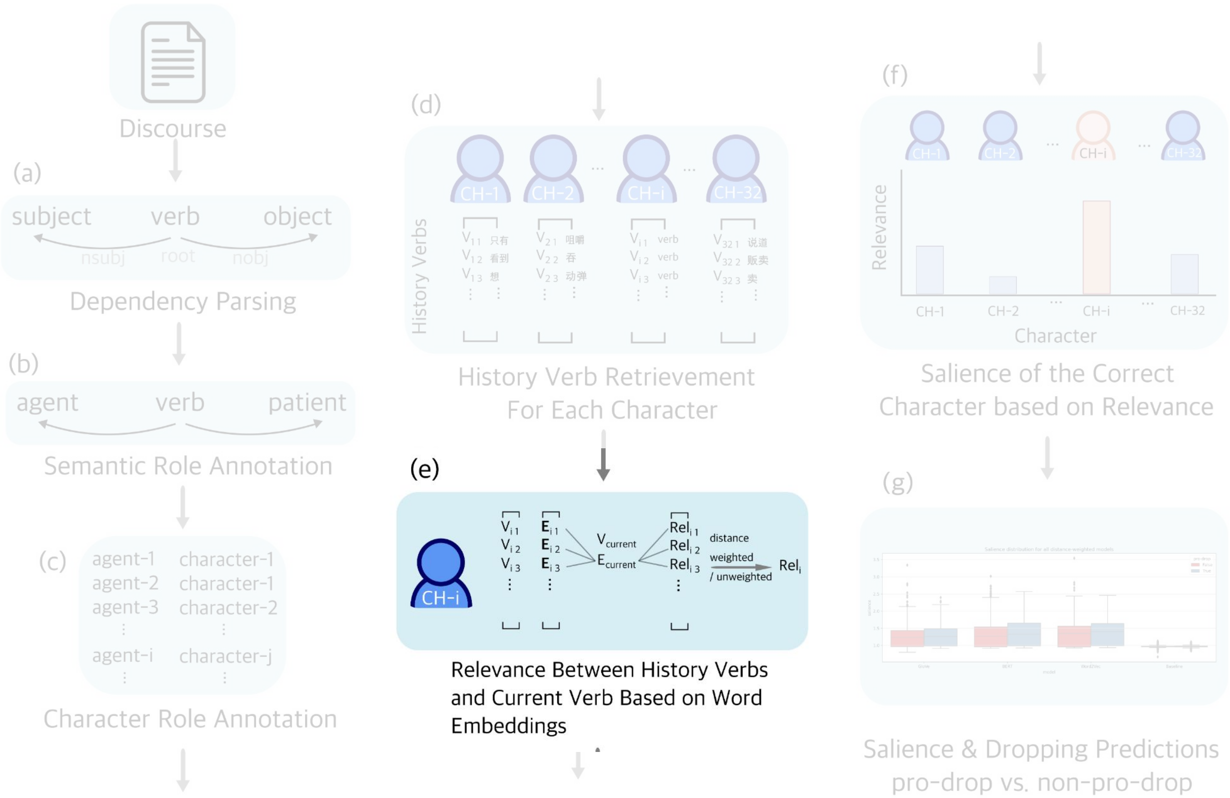
verb	回来
verb_id	16008
agent_character	ch4
pro_drop	False
ch1_prev_verbs	([只有, 看到, 想, 用, 画, 画, 让, 画, 放, 放弃, 当, 泄, 得, 给,...
ch2_prev_verbs	([咀嚼, 吞, 动弹, 消化, 消化, 开, 闭, 闭, 危险, 闭, 开, 开, 闭],...
ch3_prev_verbs	([理解, 看, 懂, 需要, 解释, 劝, 靠, 弄, 懂, 有, 谈, 认识, 大人们,...
ch4_prev_verbs	([朝, 望, 出现, 给, 像, 没有, 像, 干, 有, 说道, 回答, 说, 没有, ...
ch5_prev_verbs	([病, 需要, 像, 睡, 去, 用, 跑, 跑, 跑, 到, 跑, 走, 走, 吃, 吃...
...	...
ch30_prev_verbs	([运载, 发, 往, 朝着, 开, 过], [12123, 12128, 12133, 1...
ch31_prev_verbs	([寻找, 回来, 满意, 住, 追随, 追随, 睡觉, 打哈欠, 拥挤, 知道, 寻找, ...
ch32_prev_verbs	([说道, 贩卖, 卖, 说], [12334, 12339, 12359, 12372]).

Table 3: Example of Verb-Character table

Method

verb	Come back
verb_id	16008
agent_character	ch4
pro_drop	False - Non-pro-drop
ch1_prev_verbs	Only have, see, want, use, draw, draw, let, …
ch2_prev_verbs	chew , swallow, move, digest, digest, open, …
ch3_prev_verbs	Understand, see, understand, need, explain, advise,...
ch4_prev_verbs	Towards, watch, show up, give, alike, not have, alike, …
ch5_prev_verbs	Sick, need, alike, sleep, go, use, run, run, run, walk, walk, eat, eat...
…	
ch30_prev_verbs	Carry, send, towards, drive, pass
ch31_prev_verbs	Seek, come, back, satisfy, live, follow,...
ch32_prev_verbs	Say, sell, sell, say

Roadmap



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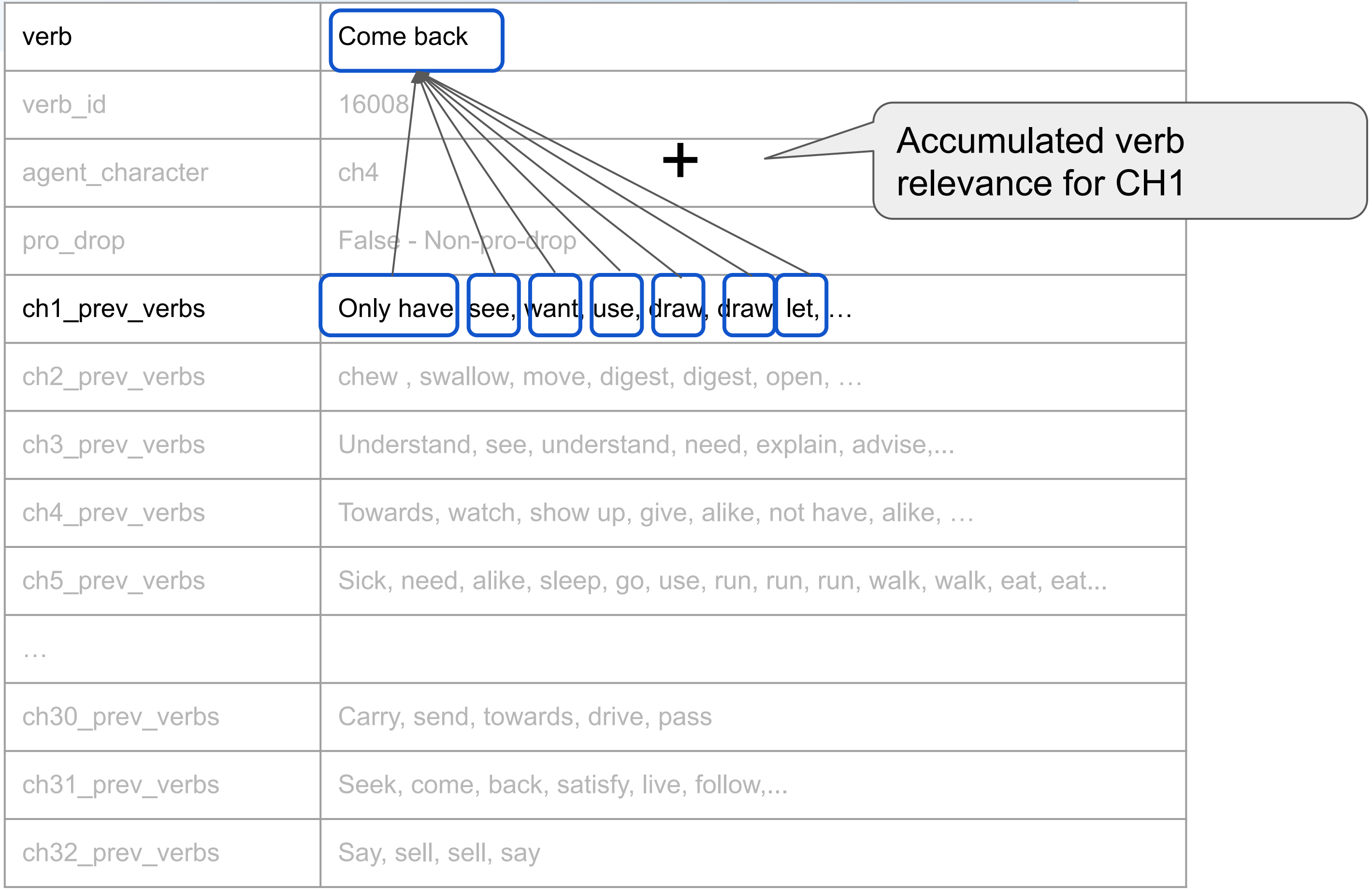

verb	Come back
verb_id	16008
agent_character	ch4
pro_drop	False - Non-pro-drop
ch1_prev_verbs	Only have, see, want, use, draw, draw, let, …
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+

Accumulated verb relevance for CH1

Method

verb	Come back
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agent_character	ch4
pro_drop	False - Non-pro-drop
ch1_prev_verbs	Only have see, want, use, draw, draw, let, …
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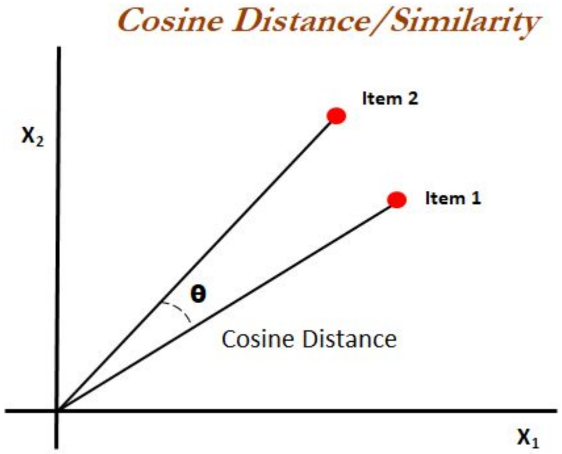
verb similarity

Method

- Verb similarity
    - = cosine similarity between two word embedding vectors

$$R(v_{prev}, v_{curr}) = \frac{v_{prev} \cdot v_{curr}}{||v_{prev}||||v_{curr}||} \qquad (2)$$



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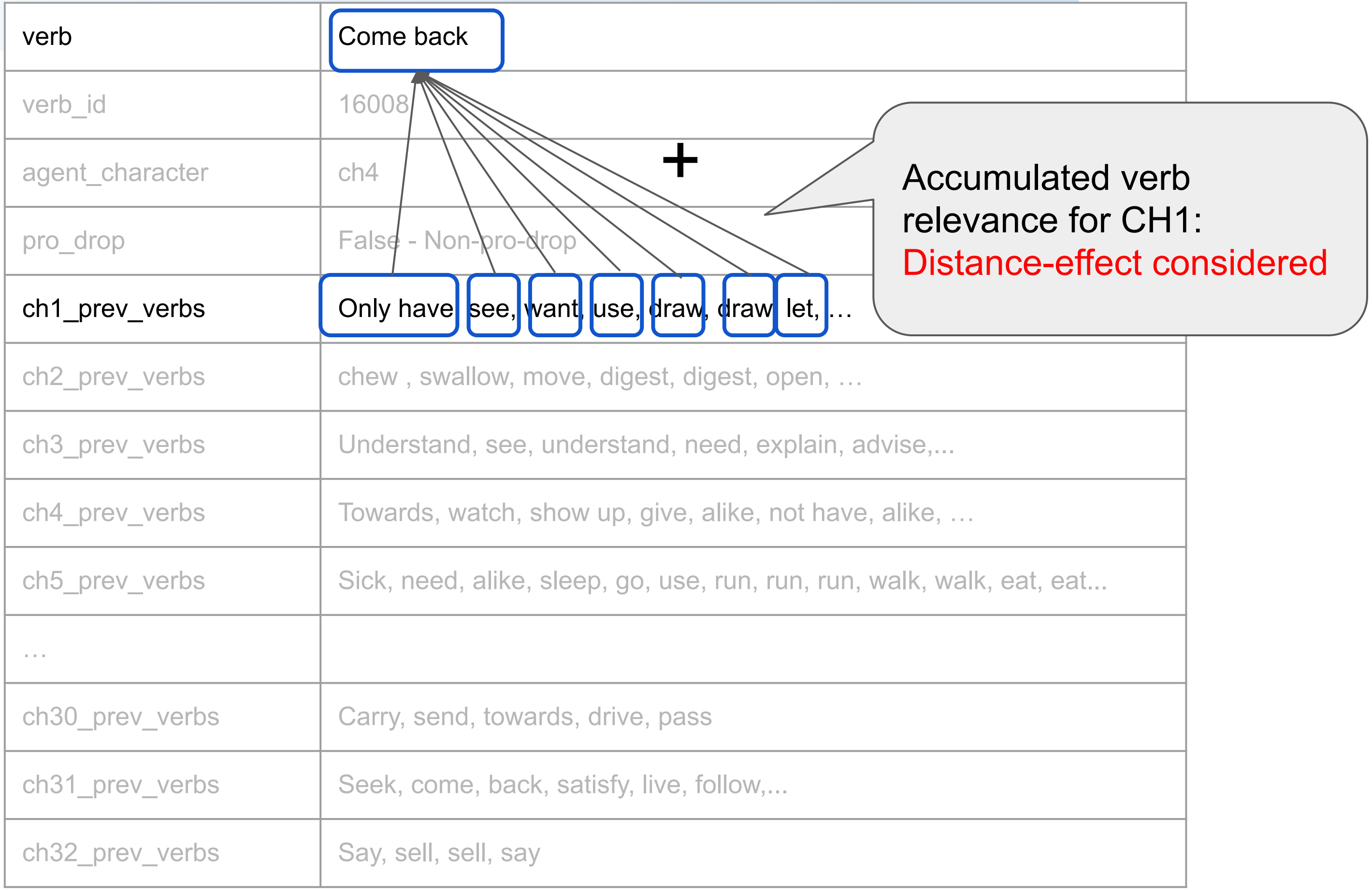

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ch32_prev_verbs	Say, sell, sell, say

Accumulated verb relevance for CH1:
Distance-effect considered

Method

- Verb similarity
  - = cosine similarity between two word embedding vectors

$$R(v_{prev}, v_{curr}) = \frac{v_{prev} \cdot v_{curr}}{||v_{prev}||||v_{curr}||} \quad (2)$$

- Verb-chain similarity

$$R_{weighted}([v_{prev\_1}, ..., v_{prev\_n}], v_{curr}) = \sum_{i=1}^{n} \omega(cl\_prev\_i, cl\_curr) * R(v_{prev\_i}, v_{curr}) \quad (3)$$

Method

- Verb similarity
    - = cosine similarity between two word embedding vectors

$$R(v_{prev}, v_{curr}) = \frac{v_{prev} \cdot v_{curr}}{||v_{prev}||||v_{curr}||} \qquad (2)$$

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Method

- Verb similarity
  - = cosine similarity between two word embedding vectors

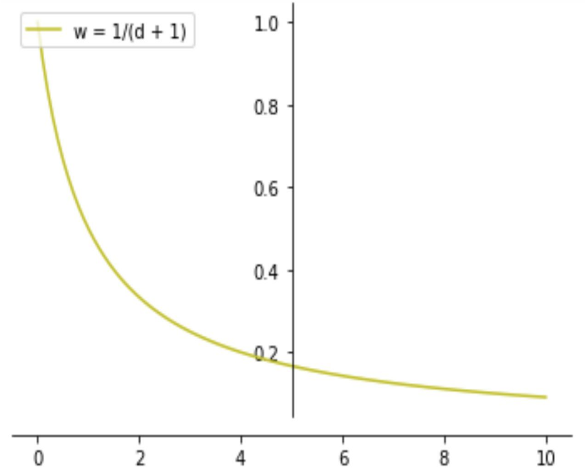
$$R(v_{prev}, v_{curr}) = \frac{v_{prev} \cdot v_{curr}}{||v_{prev}|| \, ||v_{curr}||} \qquad (2)$$

- Verb-chain similarity

$$R_{weighted}([v_{prev\_1}, \ldots, v_{prev\_n}], v_{curr}) = \sum_{i=1}^{n} \boxed{\omega(cl\_prev\_i, cl\_curr)} * R(v_{prev\_i}, v_{curr})$$

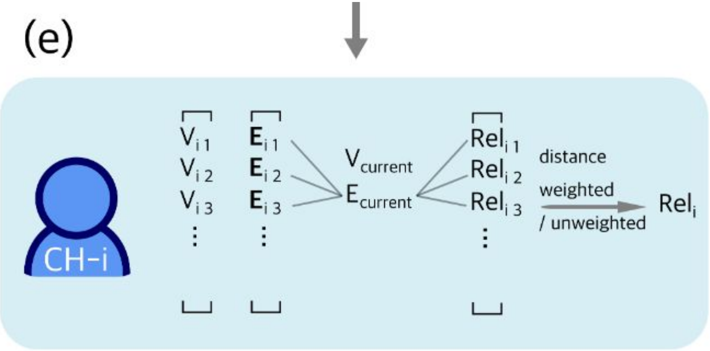
$$\omega(j,k) = 1/(d+1) \qquad (3)$$

$$d = |j - k|$$

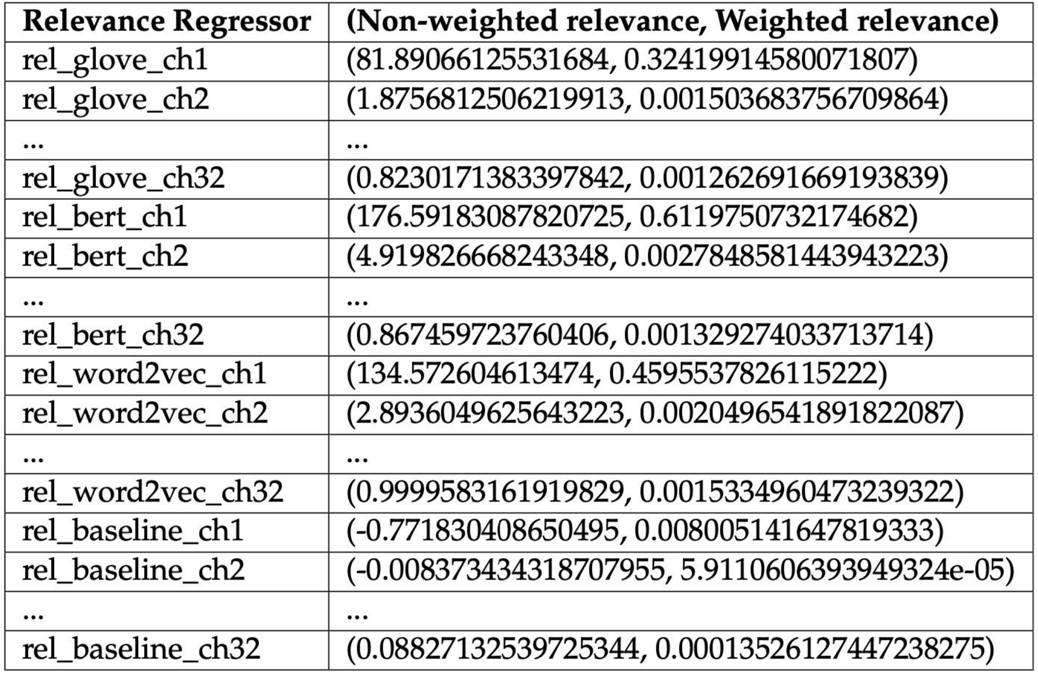


The decay function for weighted relevance

Method



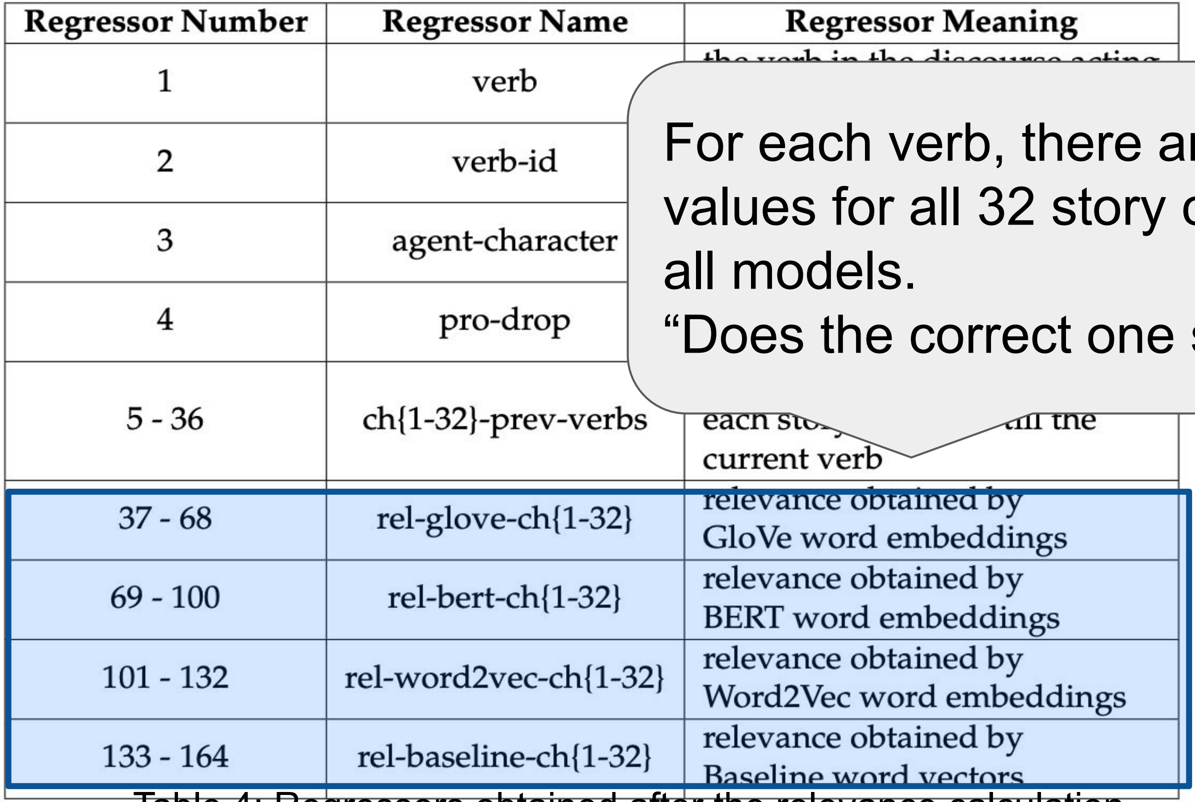
Relevance Between History Verbs and Current Verb Based on Word Embeddings



Relevance Regressor	**(Non-weighted relevance, Weighted relevance)**
rel_glove_ch1	(81.89066125531684, 0.32419914580071807)
rel_glove_ch2	(1.8756812506219913, 0.0015036837567098640)
...	...
rel_glove_ch32	(0.8230171383397842, 0.0012626916691938390)
rel_bert_ch1	(176.59183087820725, 0.6119750732174682)
rel_bert_ch2	(4.919826668243348, 0.002784858144394322 3)
...	...
rel_bert_ch32	(0.867459723760406, 0.0013292740337137140)
rel_word2vec_ch1	(134.572604613474, 0.4595537826115222)
rel_word2vec_ch2	(2.8936049625643223, 0.0020496541891822087)
...	...
rel_word2vec_ch32	(0.9999583161919829, 0.0015334960473239322)
rel_baseline_ch1	(-0.771830408650495, 0.0080051416478193330)
rel_baseline_ch2	(-0.008373434318707955, 5.911060639394932 4e-05)
...	...
rel_baseline_ch32	(0.0882713253972534 4, 0.0001352612744723827 5)

Table A5: Example of relevance results for the last verb

Method

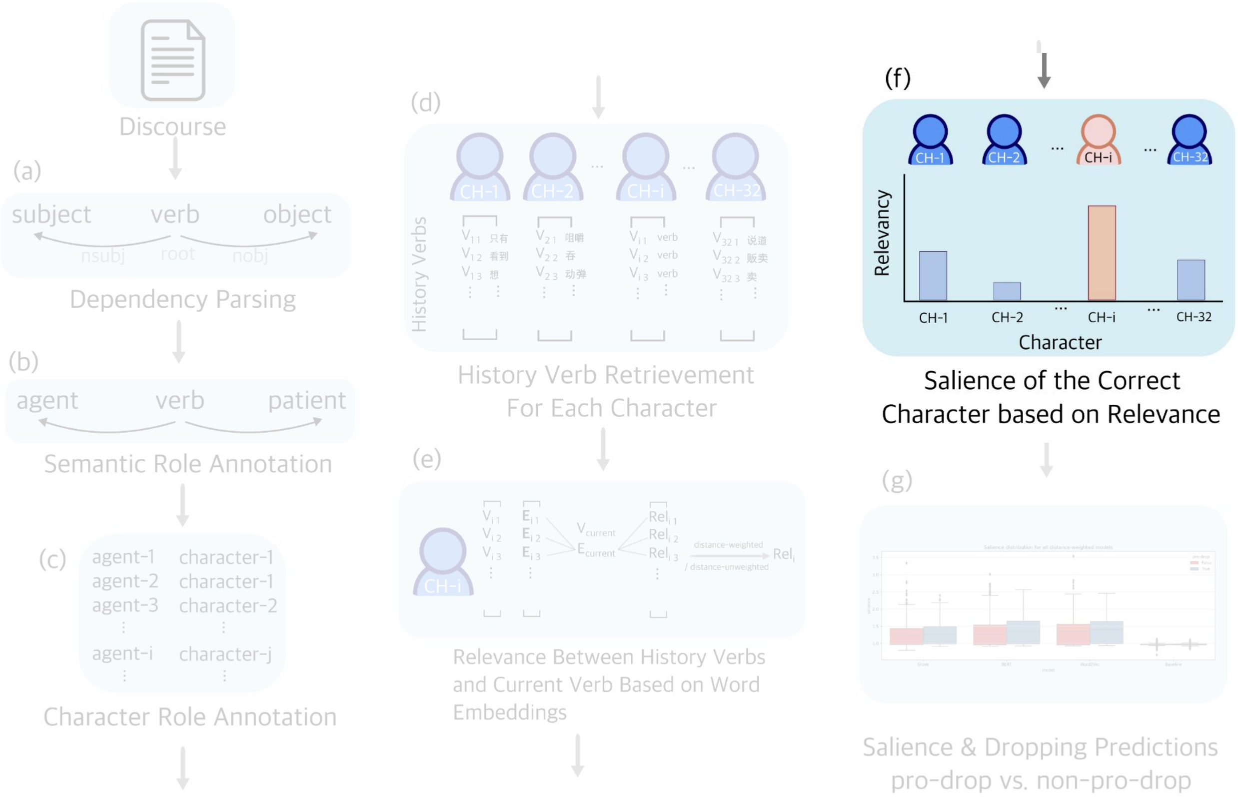


Regressor Number	Regressor Name	Regressor Meaning
1	verb	the verb in the discourse acting
2	verb-id	
3	agent-character	
4	pro-drop	
5 - 36	ch{1-32}-prev-verbs	each sto ill the current verb
37 - 68	rel-glove-ch{1-32}	relevance obtained by GloVe word embeddings
69 - 100	rel-bert-ch{1-32}	relevance obtained by BERT word embeddings
101 - 132	rel-word2vec-ch{1-32}	relevance obtained by Word2Vec word embeddings
133 - 164	rel-baseline-ch{1-32}	relevance obtained by Baseline word vectors

Table 4: Regressors obtained after the relevance calculation

For each verb, there are 32 relevance values for all 32 story characters for all models.
“Does the correct one stand out?”

Roadmap



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Salience & Dropping Predictions pro-drop vs. non-pro-drop

Method

verb	Come back
verb_id	16008
agent_character	ch4
pro_drop	False - Non-pro-drop
ch1_prev_verbs	Only have, see, want, use, draw, draw, let, …
ch2_prev_verbs	chew , swallow, move, digest, digest, open, …
ch3_prev_verbs	Understand, see, understand, need, explain, advise,...
ch4_prev_verbs	Towards, watch, show up, give, alike, not have, alike, …
ch5_prev_verbs	Sick, need, alike, sleep, go, use, run, run, run, walk, walk, eat, eat...
…	
ch30_prev_verbs	Carry, send, towards, drive, pass
ch31_prev_verbs	Seek, come, back, satisfy, live, follow,...
ch32_prev_verbs	Say, sell, sell, say

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ch2_prev_verbs	che
ch3_prev_verbs	U
ch4_prev_verbs	Tow
ch5_prev_verbs	Sic
…	
ch30_prev_verbs	Carry, send, towards, drive, pass
ch31_prev_verbs	Seek, come, back, satisfy, live, follow,...
ch32_prev_verbs	Say, sell, sell, say

$$\begin{aligned}\text{Salience (ch4)} = (&\text{Rel\_ch4} / \text{Rel\_ch1} + \\ &\text{Rel\_ch4} / \text{Rel\_ch2} + \\ &\text{Rel\_ch4} / \text{Rel\_ch3} + \\ &\dots \\ &\text{Rel\_ch4} / \text{Rel\_ch31} + \\ &\text{Rel\_ch4} / \text{Rel\_ch32}\ ) /32\end{aligned}$$

Method

- Correct character ’s verb-chain-similarity salience

$$S(k) = \frac{\sum_{i=1}^{n} \left(\frac{R_{weighted}(k)+1}{R_{weighted}(i)+1} \right)}{n+1} \tag{4}$$

Note: the “+1” s in this function are assigned to keep the division denominator as non-zero, and balanced for the numerator

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Correct character's accumulated Relevance

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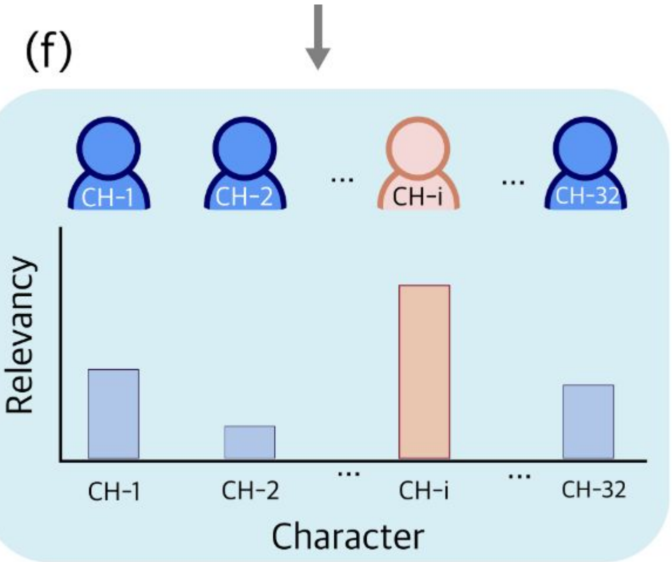
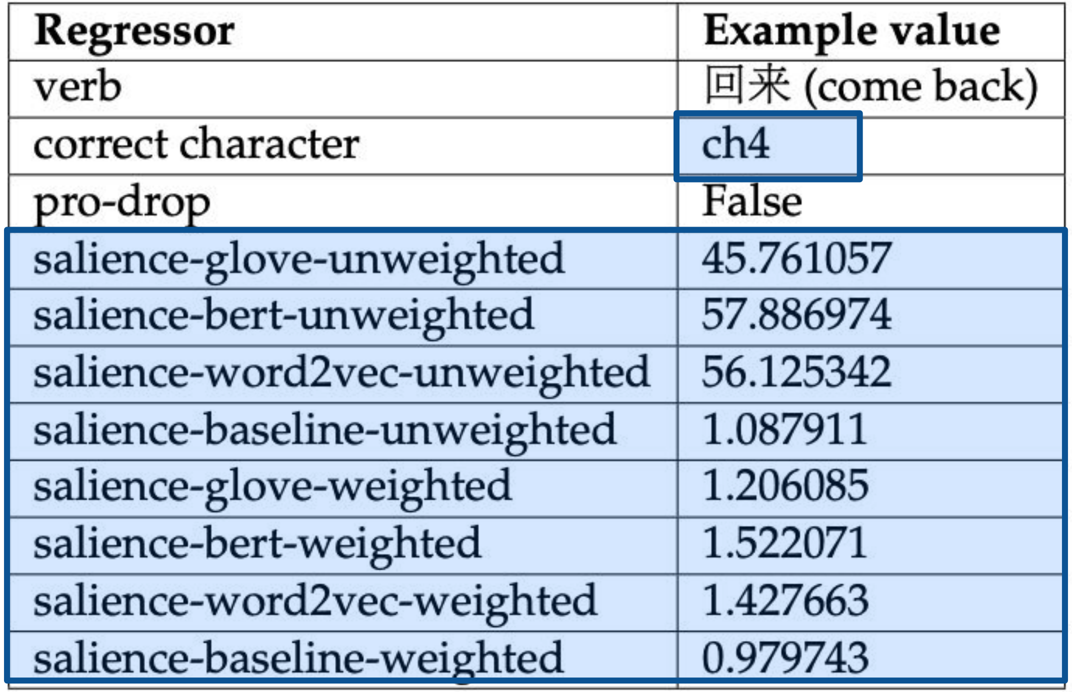
Method



Salience of the Correct Character based on Relevance

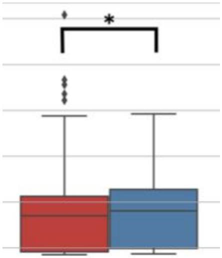


Regressor	Example value
verb	回来 (come back)
correct character	ch4
pro-drop	False
salience-glove-unweighted	45.761057
salience-bert-unweighted	57.886974
salience-word2vec-unweighted	56.125342
salience-baseline-unweighted	1.087911
salience-glove-weighted	1.206085
salience-bert-weighted	1.522071
salience-word2vec-weighted	1.427663
salience-baseline-weighted	0.979743

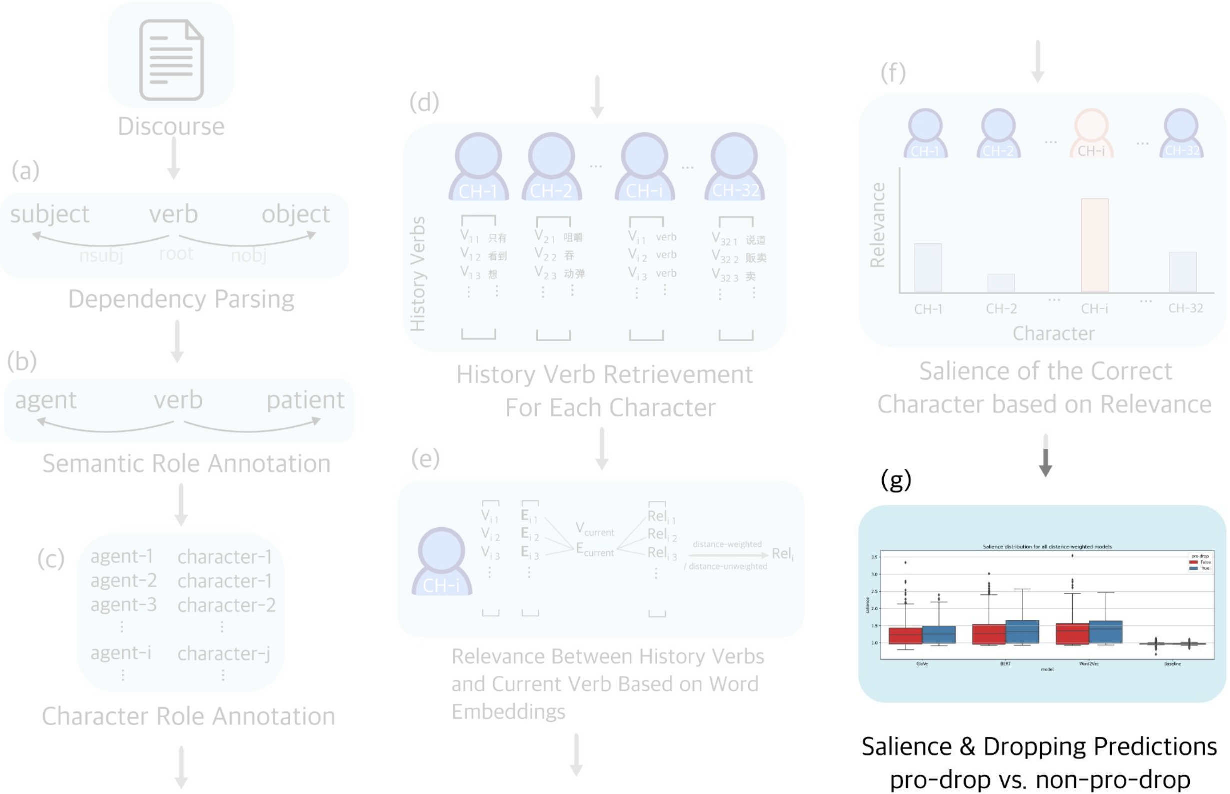
Table A6: Example of salience result of the last verb

Methods

Verb-id	pro-drop	Correct character salience
1	False	1.65
2	True	5.86
3	False	1.22
…		
16007	True	4.12
16008	False	3.51



Roadmap



Dependency Parsing

Semantic Role Annotation

Character Role Annotation

History Verb Retrievement For Each Character

Relevance Between History Verbs and Current Verb Based on Word Embeddings

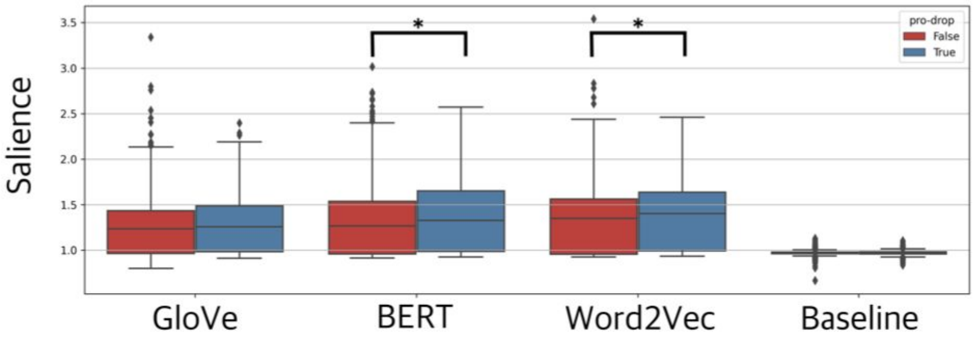
Salience of the Correct Character based on Relevance

Salience & Dropping Predictions
pro-drop vs. non-pro-drop

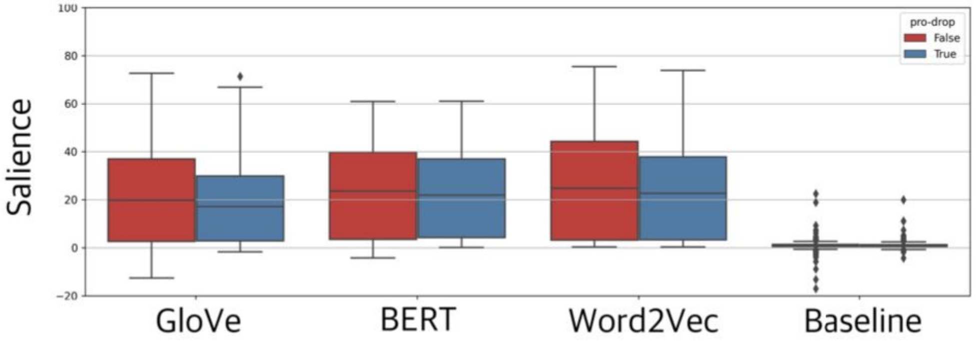
Results

- Character salience distribution:
  - non-pro-drop vs. pro-drop

(a) Salience distribution of word embedding models *with* verb distance weighted

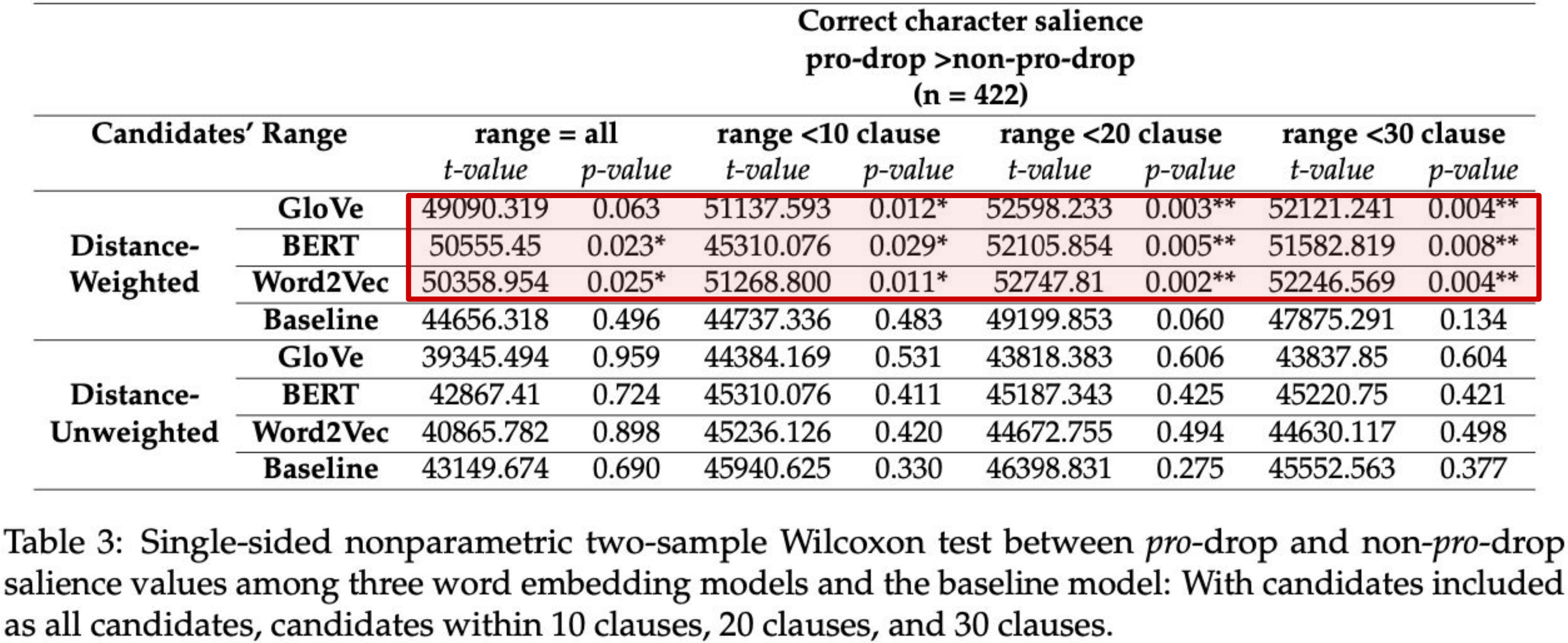


(b) Salience distribution of word embedding models *without* verb distance weighted



Results

- Ranged character salience group comparison:

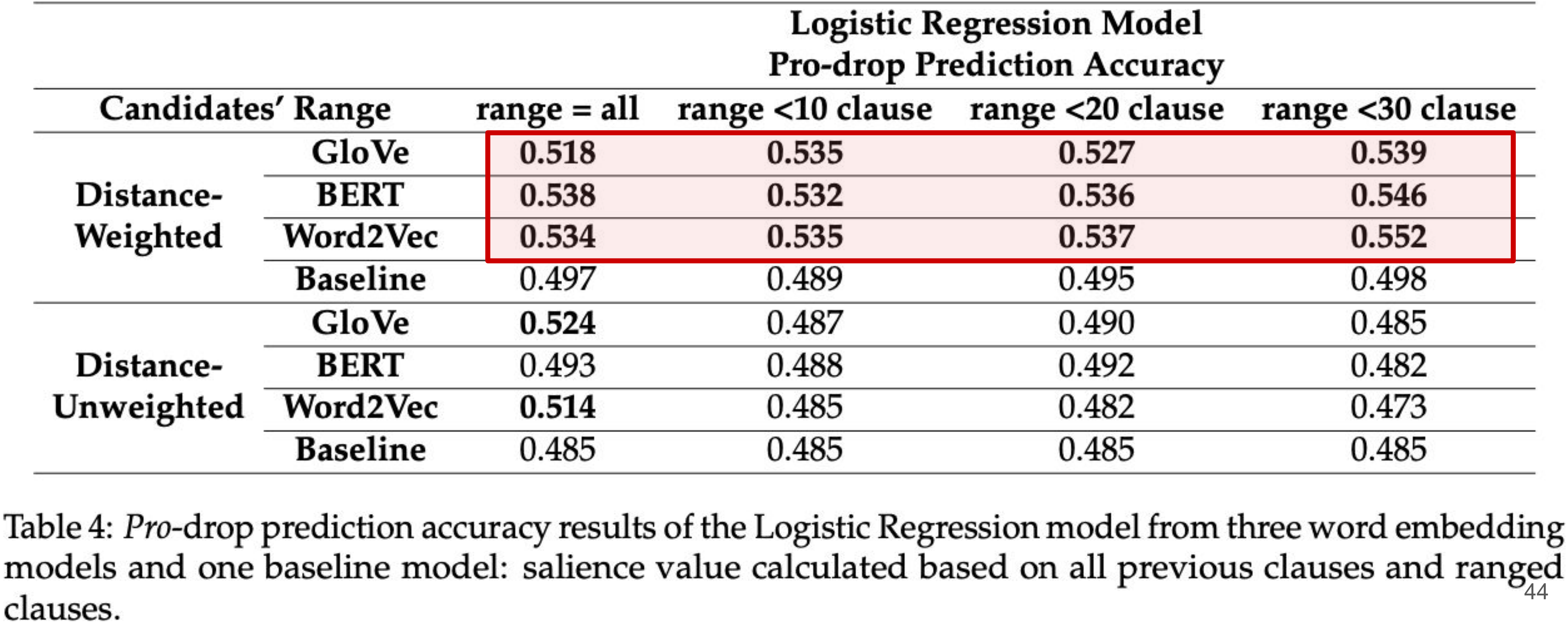


		Correct character salience pro-drop >non-pro-drop (n = 422)							
Candidates' Range		**range = all**		**range <10 clause**		**range <20 clause**		**range <30 clause**	
		t-value	*p-value*	*t-value*	*p-value*	*t-value*	*p-value*	*t-value*	*p-value*
Distance-Weighted	**GloVe**	49090.319	0.063	51137.593	0.012*	52598.233	0.003**	52121.241	0.004**
	BERT	50555.45	0.023*	45310.076	0.029*	52105.854	0.005**	51582.819	0.008**
	Word2Vec	50358.954	0.025*	51268.800	0.011*	52747.81	0.002**	52246.569	0.004**
	Baseline	44656.318	0.496	44737.336	0.483	49199.853	0.060	47875.291	0.134
Distance-Unweighted	**GloVe**	39345.494	0.959	44384.169	0.531	43818.383	0.606	43837.85	0.604
	BERT	42867.41	0.724	45310.076	0.411	45187.343	0.425	45220.75	0.421
	Word2Vec	40865.782	0.898	45236.126	0.420	44672.755	0.494	44630.117	0.498
	Baseline	43149.674	0.690	45940.625	0.330	46398.831	0.275	45552.563	0.377

Table 3: Single-sided nonparametric two-sample Wilcoxon test between *pro*-drop and non-*pro*-drop salience values among three word embedding models and the baseline model: With candidates included as all candidates, candidates within 10 clauses, 20 clauses, and 30 clauses.

Results

- Logistic regression model predicting dropping behaviour: Ranged salience results



		Logistic Regression Model Pro-drop Prediction Accuracy			
Candidates' Range		**range = all**	**range <10 clause**	**range <20 clause**	**range <30 clause**
Distance-Weighted	**GloVe**	**0.518**	**0.535**	**0.527**	**0.539**
	BERT	**0.538**	**0.532**	**0.536**	**0.546**
	Word2Vec	**0.534**	**0.535**	**0.537**	**0.552**
	Baseline	0.497	0.489	0.495	0.498
Distance-Unweighted	**GloVe**	**0.524**	0.487	0.490	0.485
	BERT	0.493	0.488	0.492	0.482
	Word2Vec	**0.514**	0.485	0.482	0.473
	Baseline	0.485	0.485	0.485	0.485

Table 4: *Pro*-drop prediction accuracy results of the Logistic Regression model from three word embedding models and one baseline model: salience value calculated based on all previous clauses and ranged clauses.

Discussion

- Language models and their performances
  - Group t-test and logistic regression results are consistent: showing the performance ordering as: BERT > word2vec > GloVe
    1. BERT: bidirectional and contextual
    2. Word2Vec: local statistical features
    3. GloVe: global statistical features
- Ranged character salience improves t-test significance level and prediction accuracy
- Distance-weighted models show zero > non-zero salience effect; unweighted models do not show this effect

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Conclusions

- This study quantifies character-verb usage continuity as an aspect of discourse that helps comprehenders resolve omitted pronouns. Omitted pronouns tend to show higher verb usage consistency compared to pronounced entities, and this effect is strengthened by clause recency.

Thank you!

Dr. Jixing Li

Prof. John Hale

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