“You are no Jack Kennedy”: On Media Selection of Highlights from Presidential Debates

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Joint work with Hao Peng and Noah Smith
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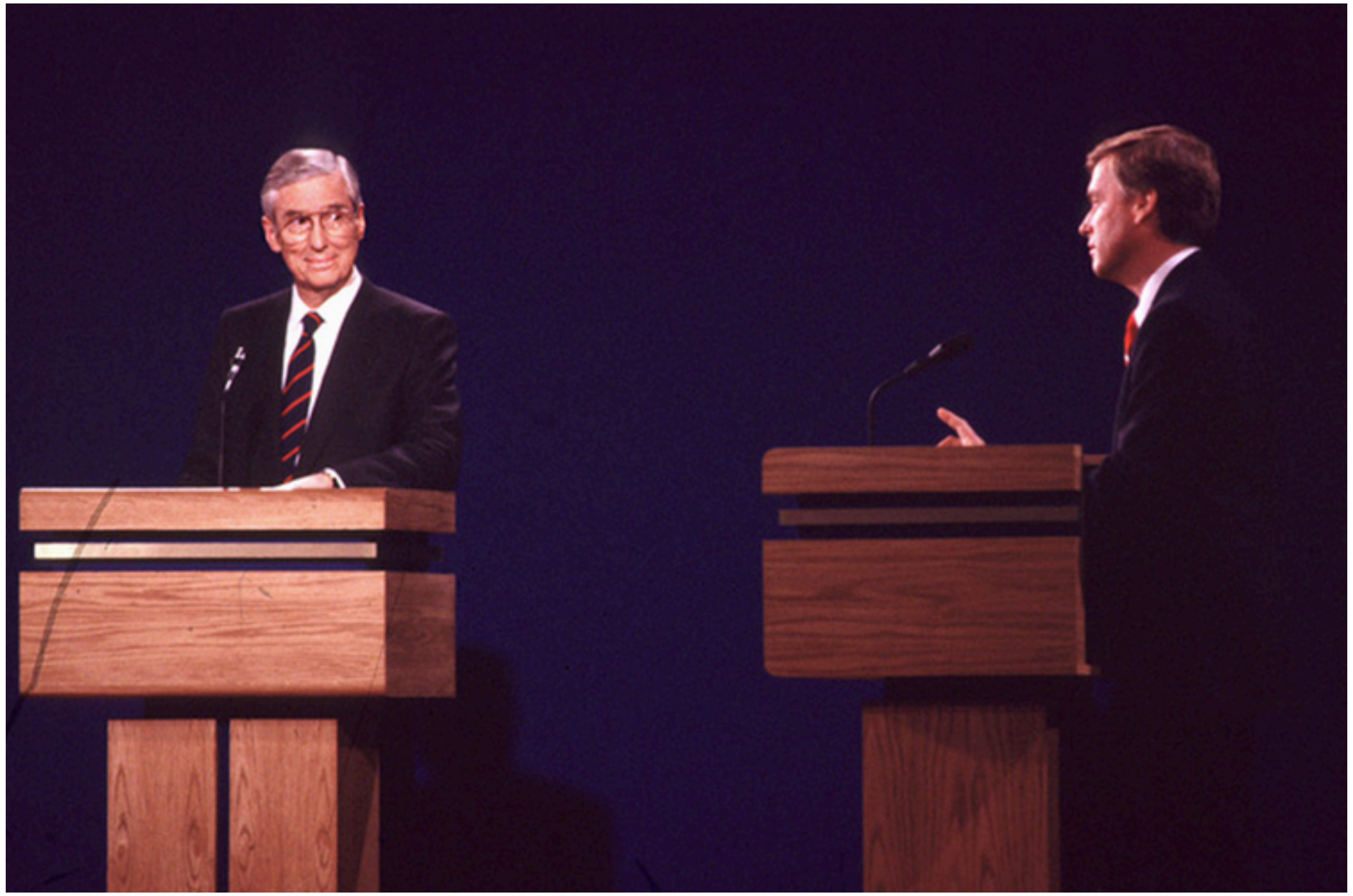
Presidential debates have become a focal point of election campaigns

The first 2016 Presidential debates set the record as the most-watched debate in television history, with 84 million viewers

Presidential debates have become a focal point of election campaigns

"Senator, you are no Jack Kennedy"



News media select highlights from presidential debates

"Yes, I did. And you know what else I prepared for? I prepared to be president." —Clinton

"you've been doing this for 30 years. Why haven't you been able to implement any of these ideas?" —Trump

"He tried to change from looks to stamina, but this is a man who has called women pigs, slobs and dogs," —Clinton

News media select highlights from presidential debates

These highlights can play an important role in shaping the public's opinion of presidential debates and candidates

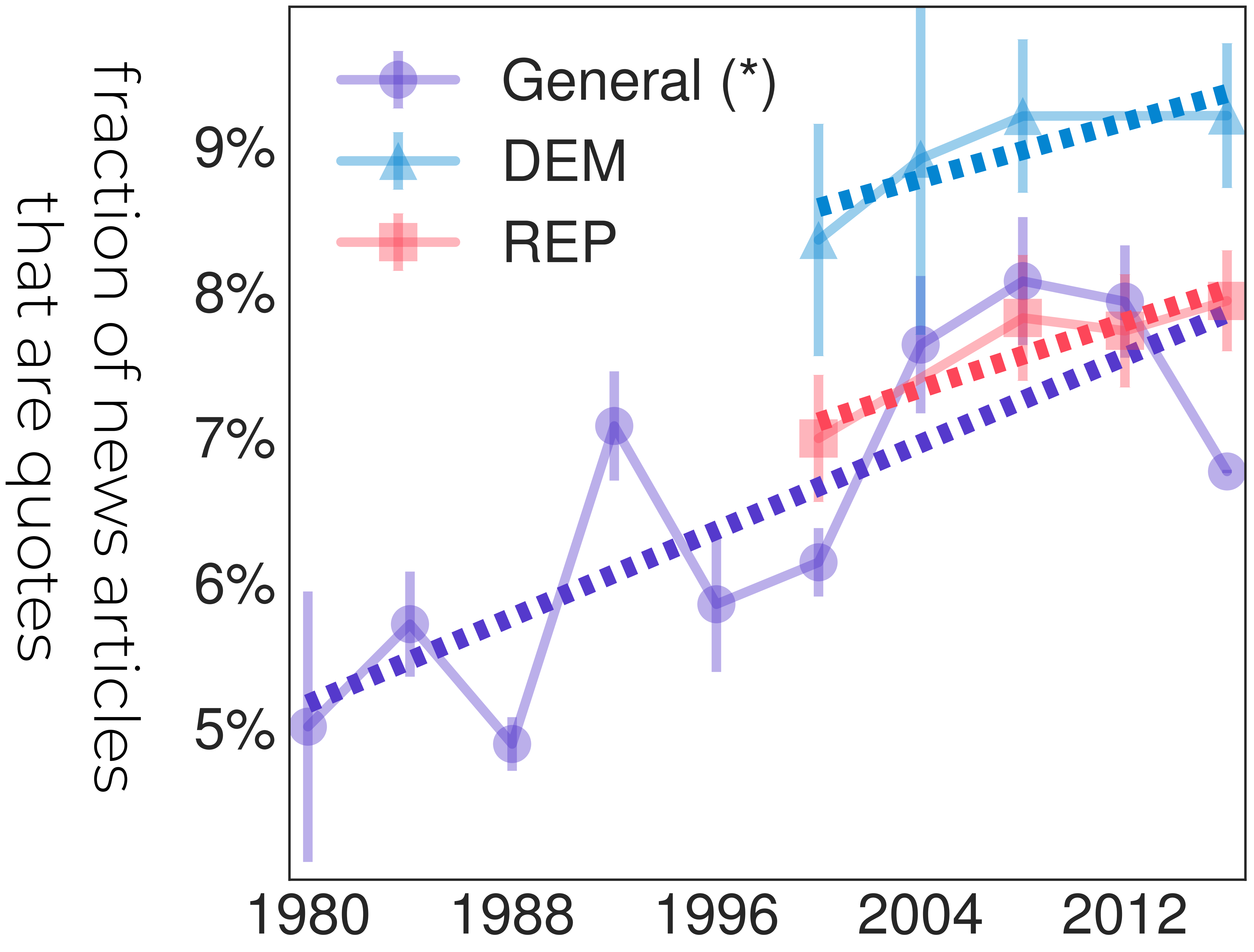
(Fridkin et al, 2008; Hillygus and Jackman, 2003; Hwang et al., 2007)

Media selection of highlights

- The effect of wording on media choices
  - How well can **humans/machines** predict highlights based on texts?
- Media preferences over time

Dataset

- Debate transcripts from 1980-2016 (the American Presidency Project)
  - both primary and general debates
- Quotes in newspapers from 1980-2016 (LexisNexis)



Debate quotes are increasingly used in news articles

A binary classification framework

- Control for the speaker
- Control for the situation in the debate
- Control for the length

SANDERS: **Do I consider myself part of the casino capitalist process by which so few have so much and so many have so little by which Wall Street's greed and recklessness wrecked this economy?** [...]

CLINTON: [...] I think what Senator Sanders is saying certainly makes sense in the terms of the inequality that we have. [...]

SANDERS: [...] So what we need to do is support small and medium-sized businesses, the backbone of our economy, but we have to make sure that every family in this country gets a fair shake [...]

Human performance

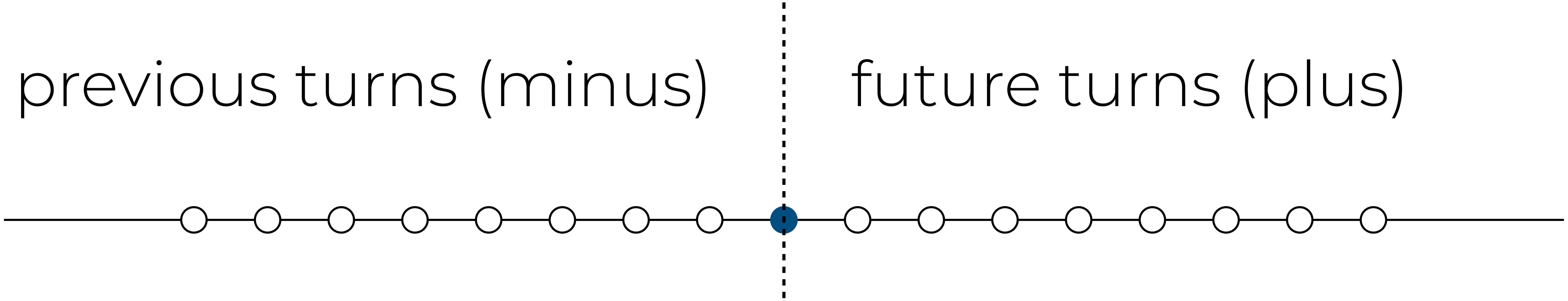
- Human accuracy is 60%
- Top factors do not directly align with existing theories (narrative relevance, conspicuousness, extractability) (Clayman, 1995)
- Only 3% of the participants mentioned that context matters

Rationale for choices	%subjects
circular (sound bite, newsworthy)	30.0%
provocative, sensational	25.5%
surprising, funny	17.0%
issues, informative	16.0%

Quantitative Representation

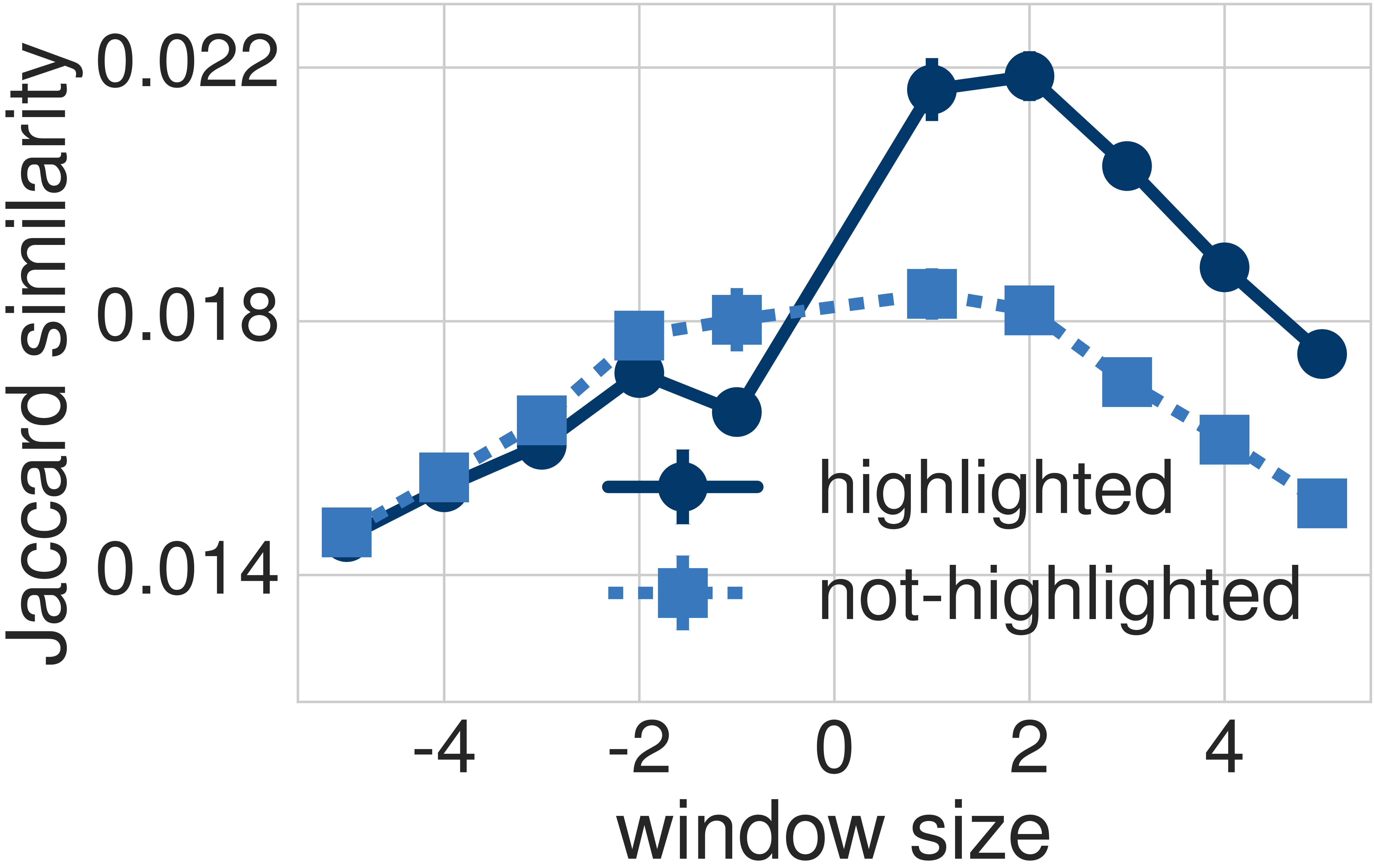
- Modeling conversations
- Sentence-alone features

Modeling conversations



- Similarity with neighboring turns from the speaker
- Similarity with neighboring turns from other participants

Highlights are "locally" distinct from one's own turns and get echoed more



Similarity with one's own turns

Sentence-alone features

- Informativeness
- Emotions
- Contrast
- Personal pronouns
- Uncertainty
- Strong emphasis
- Generality
- Language model
- Parallelism

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Feature set	Related theories/intuitions and brief description	Significance	
Informative-ness	We use length as a proxy of informativeness. Longer sentences are more likely to be highlighted despite our control on length as discussed in §3.1. This echoes findings in Tan et al. [54, 55].	length	↑↑↑↑
Emotions	We consider positive and negative words in Pennebaker et al. [40]. Highlighted sentences use significantly more negative words, while there is no difference in positive words. This is consistent with negativity bias [44] and the negativity found in the news media [18].	posemo negemo	 ↑↑↑↑
Contrast	We use negations and negative conjunctions (e.g., *not*, *but*, *although*) to capture contrast. Our result echoes Atkinson [1], which demonstrates the importance of contrast.	negation negative conj.	↑↑↑↑ ↑↑↑↑
Personal pronouns	In general, highlighted sentences use more personal pronouns except first person plural and third person plural. One explanation for the contrast between *I* and *we* is that media outlets prefer statements about candidates themselves to unifying statements using *we*.	i, you, she, he they we	↑↑↑↑ ↓↓↓↓
Uncertainty/ subjectivity	Hedging is a common way to express uncertainty [30] and we use a dictionary from Tan and Lee [53]. In the debate context, hedges may also represent subjectivity.	hedges	↑↑↑↑
Strong emphasis	Superlatives represent the extreme form of an adjective or an adverb and can be used to put emphasis on a statement. Surprisingly, highlighted sentences do not use more superlatives.	superlatives	
Generality	We count indefinite articles to measure generality. Our findings are consistent with Danescu-Niculescu-Mizil et al. [13], Shahaf et al. [45], Tan et al. [54].	indef. articles	↑↑↑
Language model	To capture surprise or conspicuousness, we compute language model scores based on NYT texts and part-of-speech (POS) tags in the WSJ portion of Penn Treebank. However, the only significant feature is that highlighted sentences are more similar to NYT texts in unigram usage. This finding is consistent with message sharing [54] but is different from memorable movie quotes [13].	unigram bi-, trigram POS {1, 2, 3}-gram	↑↑
Parallelism	Using parallel sentence structure is a rhetorical technique, e.g, the first sentence in Table 1 and "I've never wilted in my life, and I've never wavered in my life". We use average longest common sequences between sub-sentences to measure it [48].	parallelism	↑

Table 3: Testing results of sentence-alone features. Upward arrows indicate that highlighted sentences have larger scores in that feature, while downward arrows suggest the other way around (↑↑↑↑: $p < 0.0001$, ↑↑↑: $p < 0.001$, ↑↑: $p < 0.01$, ↑: $p < 0.05$, the same for downward arrows; p refers to the p-value after the Bonferroni correction).

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- Emotions
- Contrast
- Personal pronouns
- **Uncertainty**
- **Strong emphasis**
- Generality
- Language model
- Parallelism

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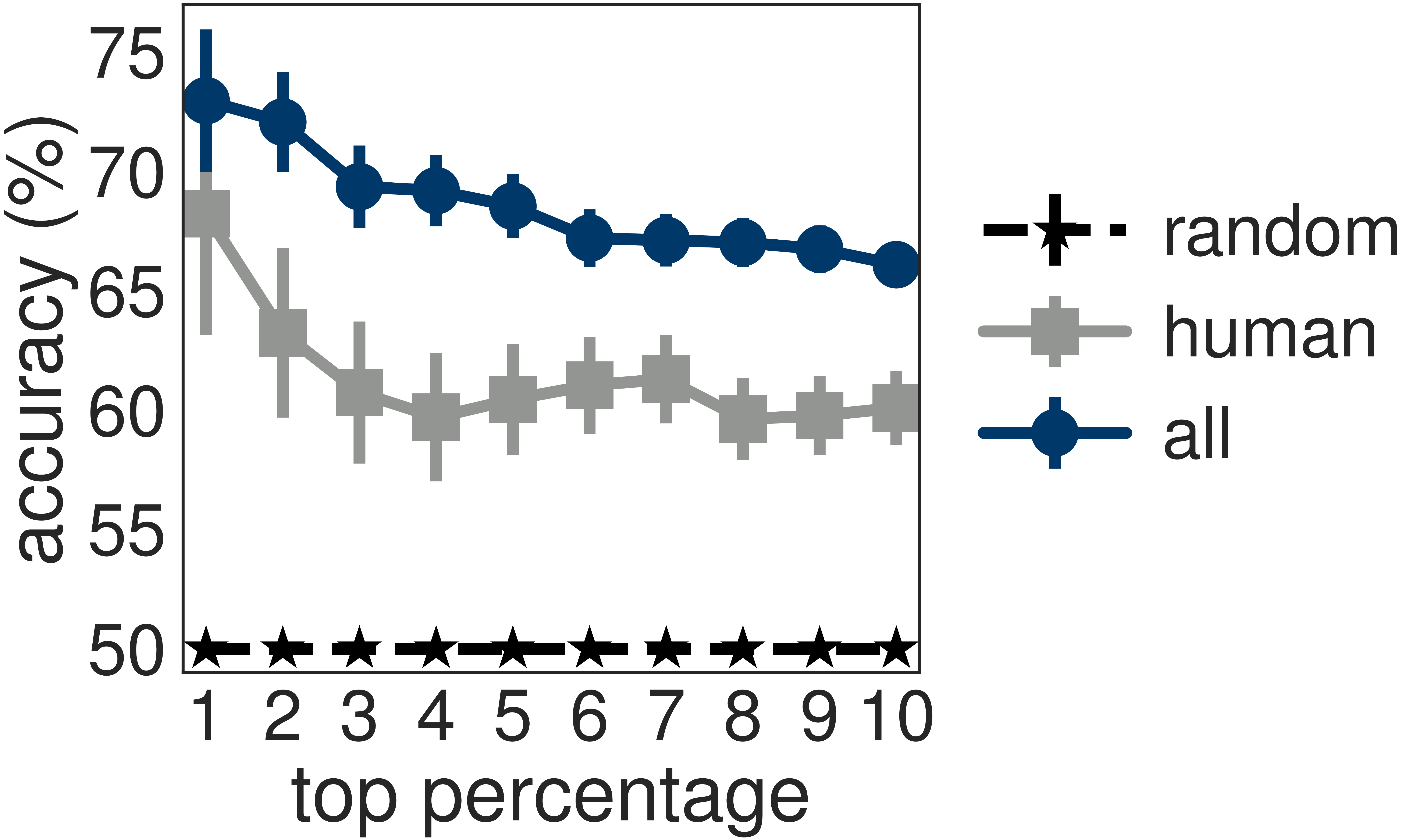
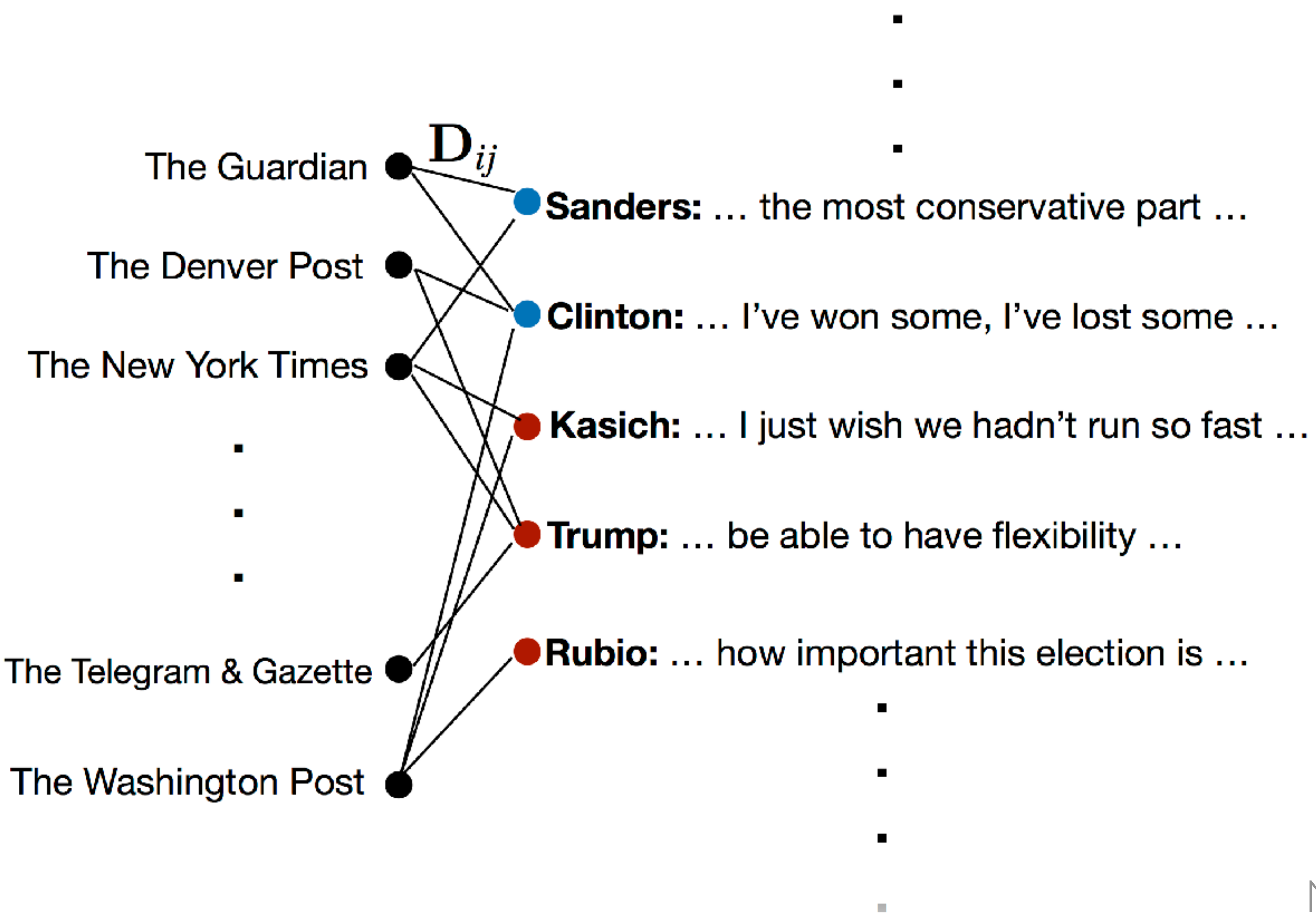
Highlights uses more uncertainty, but not more strong emphasis

Uncertainty (hedges, e.g., I am not sure)	↑↑↑↑
Strong emphasis (superplatives, e.g., greatest)	—

Machines consistently outperform humans



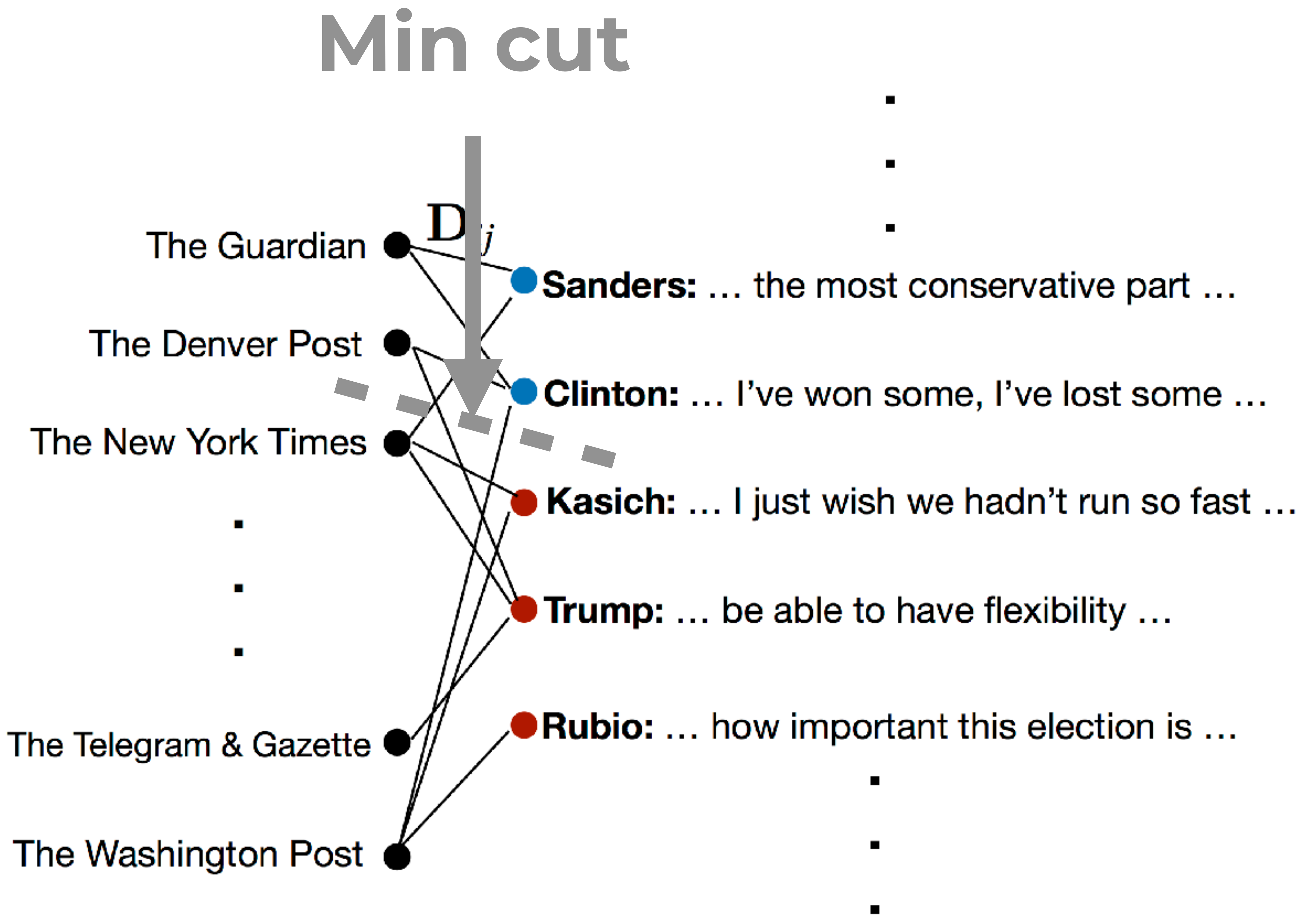
Media preferences over time



Niculae et al., 2015

Media preferences over time

- Min-cut: bipartisan coverage
- Clustering quality: media fragmentation



Media preferences over time

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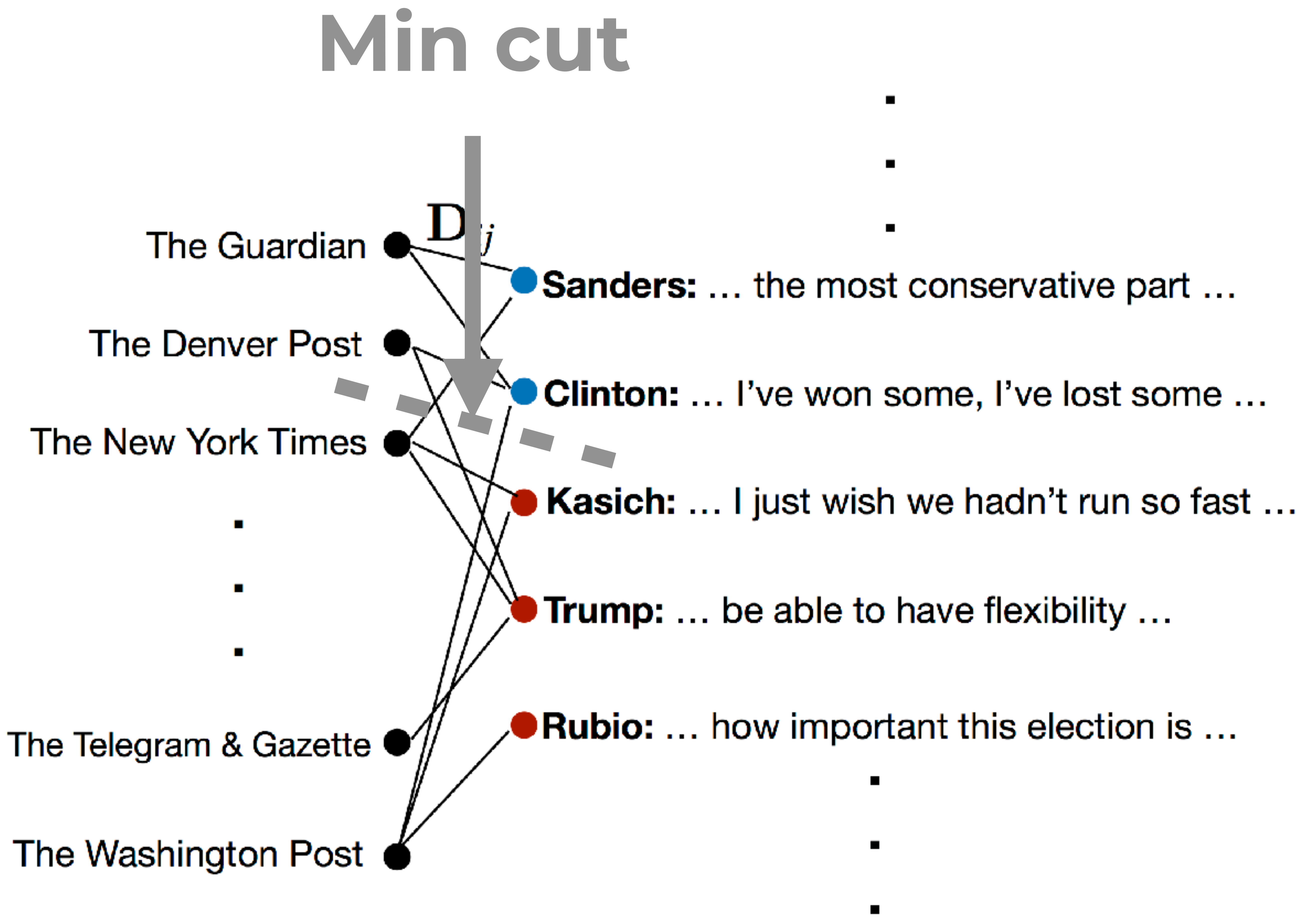
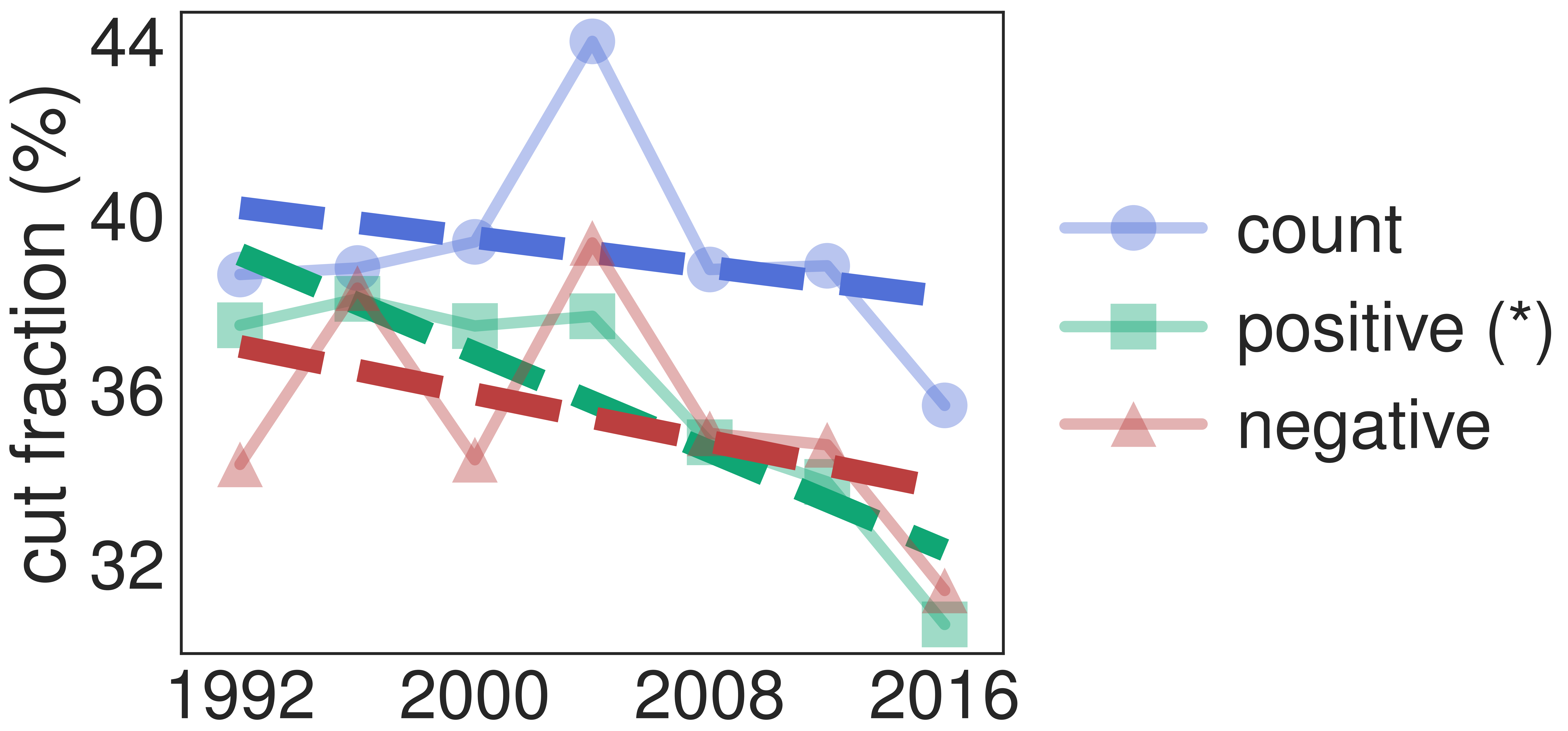


Decreasing bipartisan coverage



Take away

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- It is challenging for the public (at least the turkers) to distinguish highlights from non-highlights.
- Machines can better predict highlights.
- Highlights are locally distinct and get echoed during the debate.
- Bipartisan coverage is decreasing over time.
- Data & more at https://chenhaot.com/papers/debate-quotes.html

Thank you!