Remembering the 2016 Election Campaign:

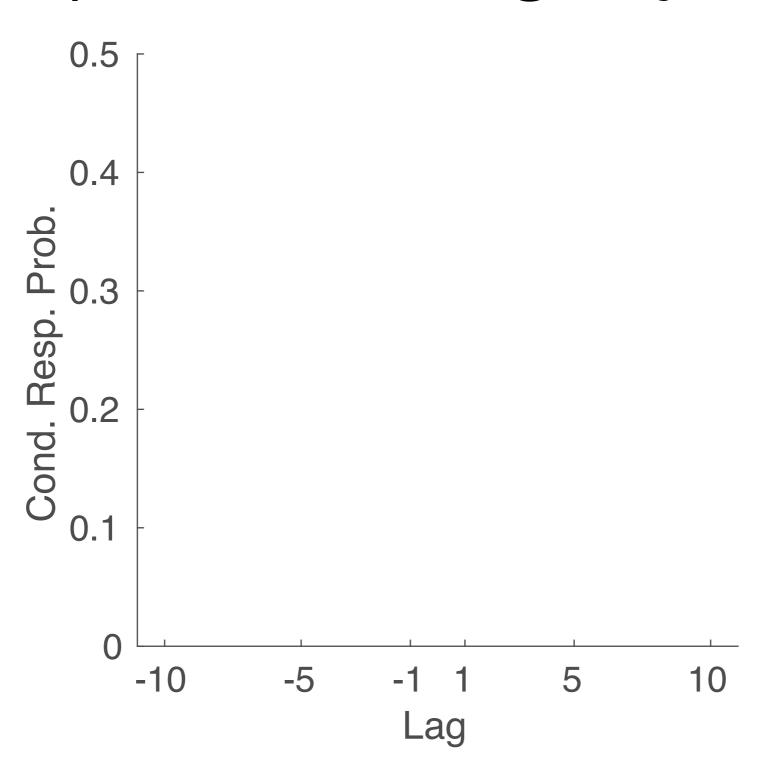
Temporal Proximity Predicts Free Recall Order

Mitchell G Uitvlugt and M Karl Healey

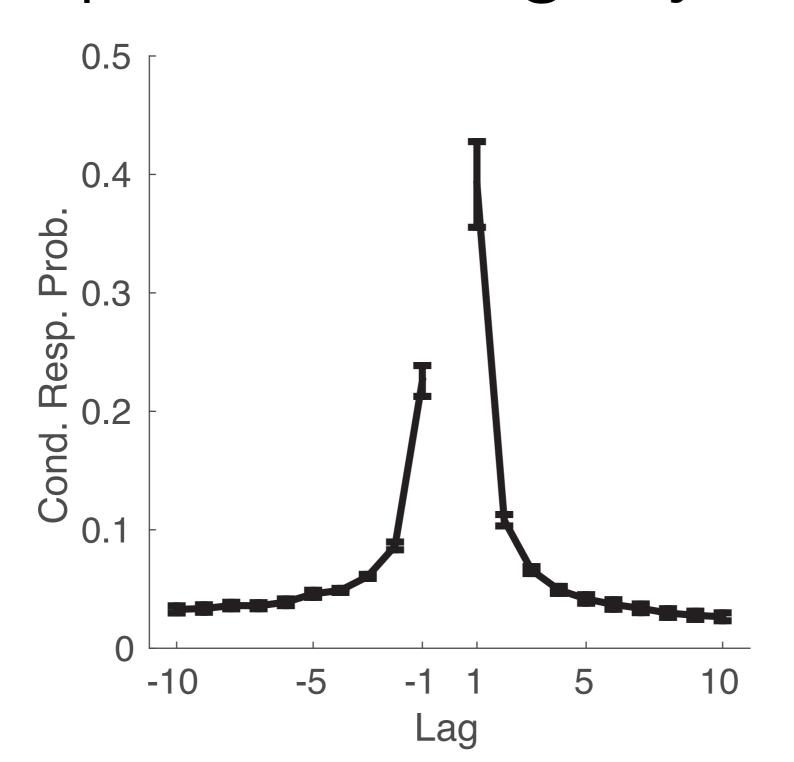


Last year I talked about the Temporal Contiguity Effect

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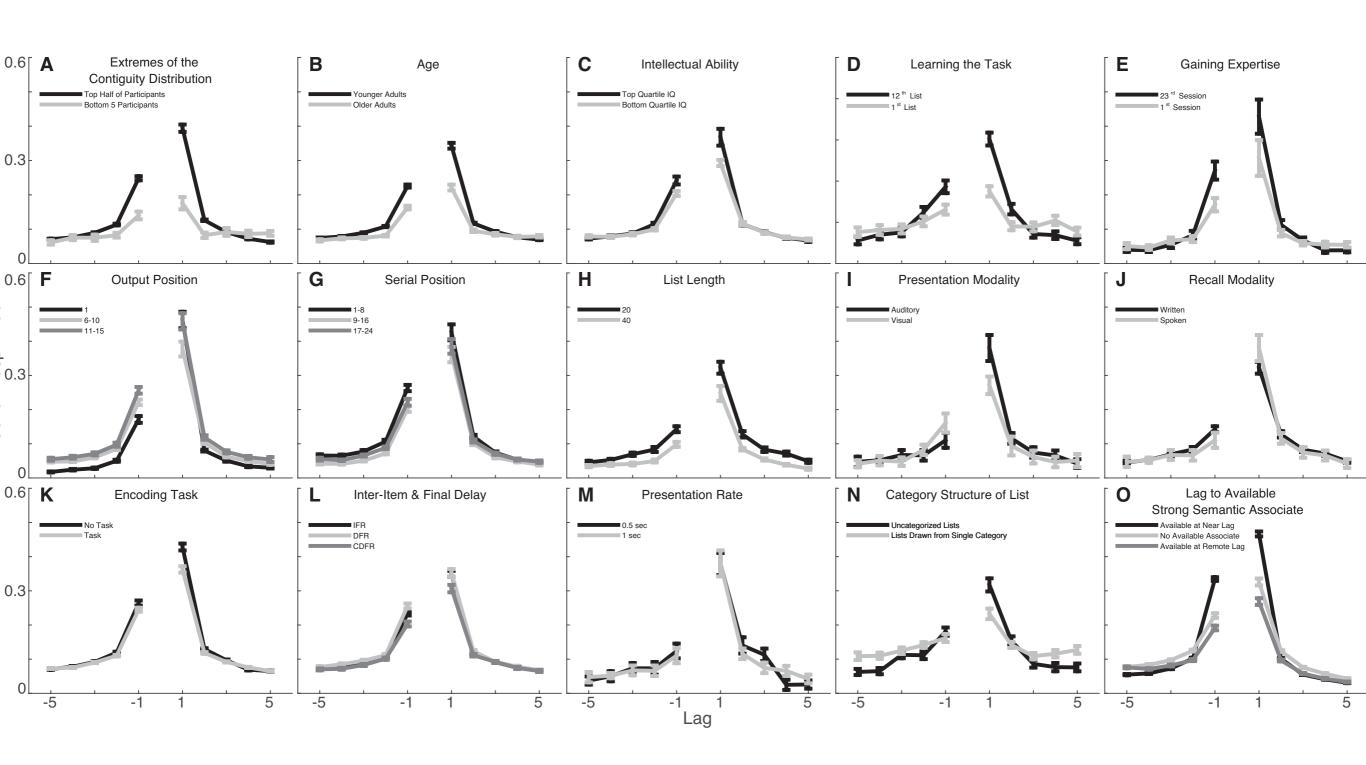


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I showed that it is extremely robust in free recall and other lab tasks

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I argued that temporal contiguity supports particular models

 Models that directly encode information about temporal distance (e.g., TCM, SIMPLE)

Does temporal contiguity really emerge outside the lab?

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- Does temporal contiguity really emerge outside the lab?
 - Evidence is almost exclusively from list learning tasks (Moreton & Ward, 2010)
 - List have obvious chain-like structure. Could encourage subjects to recall items as a chain
 - Places claims of universality on shaky ground (Hintzman, 2016)

 In the weeks following the 2016 presidential election we looked for temporal contiguity when people recalled details of the election campaign.

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 - Except not studied one after another in a chain.
 - Instead, interwoven with other events separated by irregularly spaced intervals of days to months.

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- 7,931 headlines (M = 7.55, SD = 4.82)
- 5,776 transitions (M = 5.50, SD = 4.36)

"Trump's Access Hollywood hot mic"

"Trump's Access Hollywood hot mic"

• October 7, 2016

"Trump's Access Hollywood hot mic" "FBI re-opens Clinton's e-mail investigation"

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October 28, 2016

"Trump's Access Hollywood hot mic"

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October 28, 2016

$$Lag = 599 - 578 = +21$$

"Trump won't accept the results of election"

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• ?

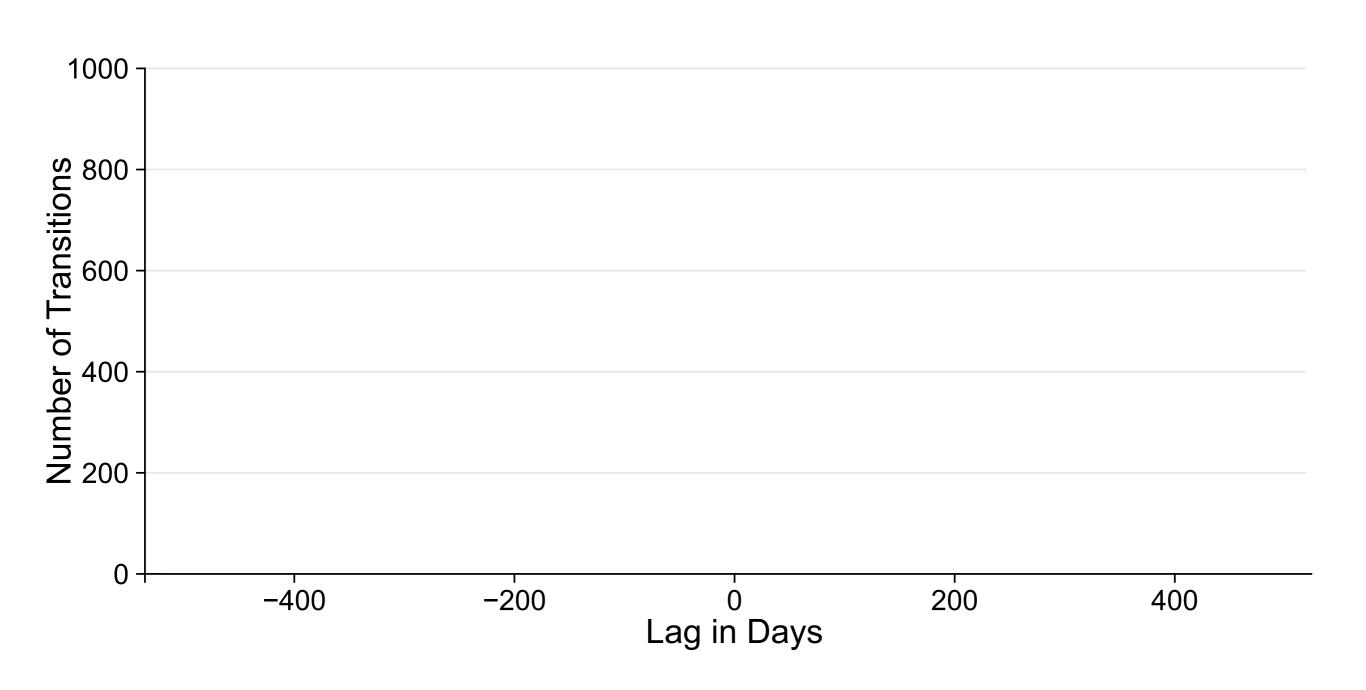
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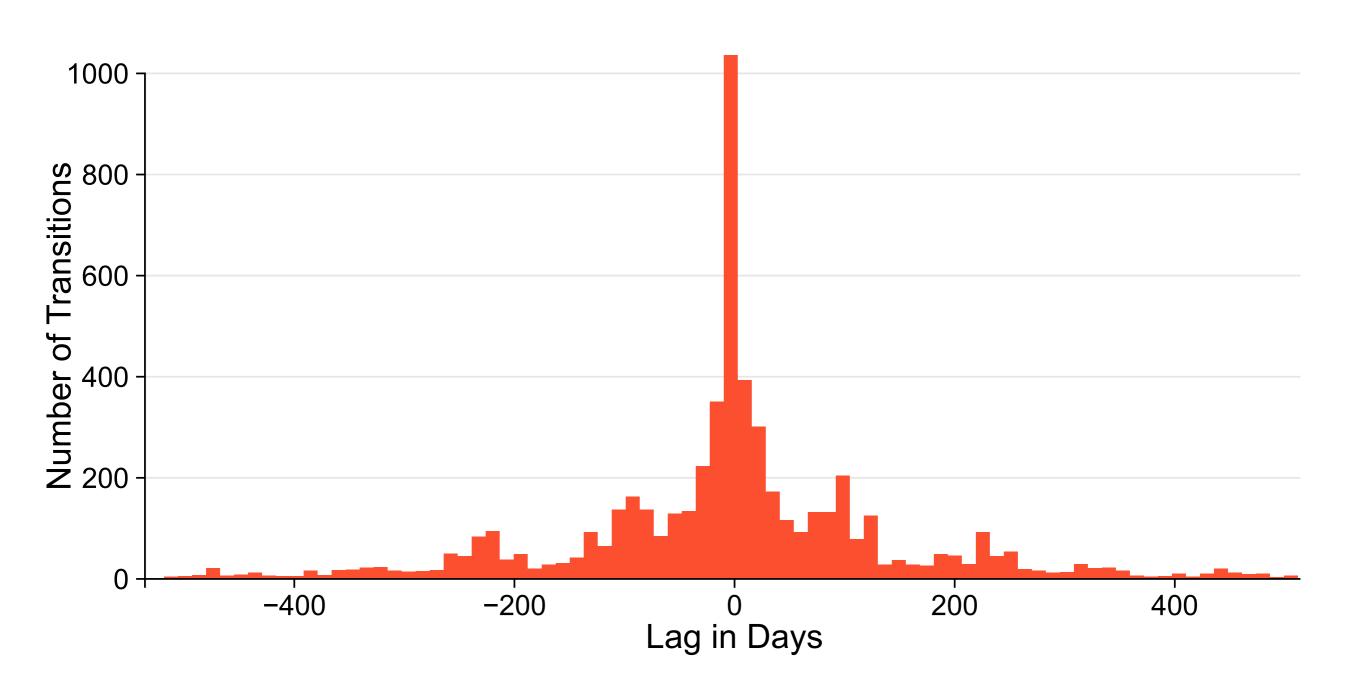
• ?

$$Lag = ? - ? = 0$$

Transition lags peak at zero days



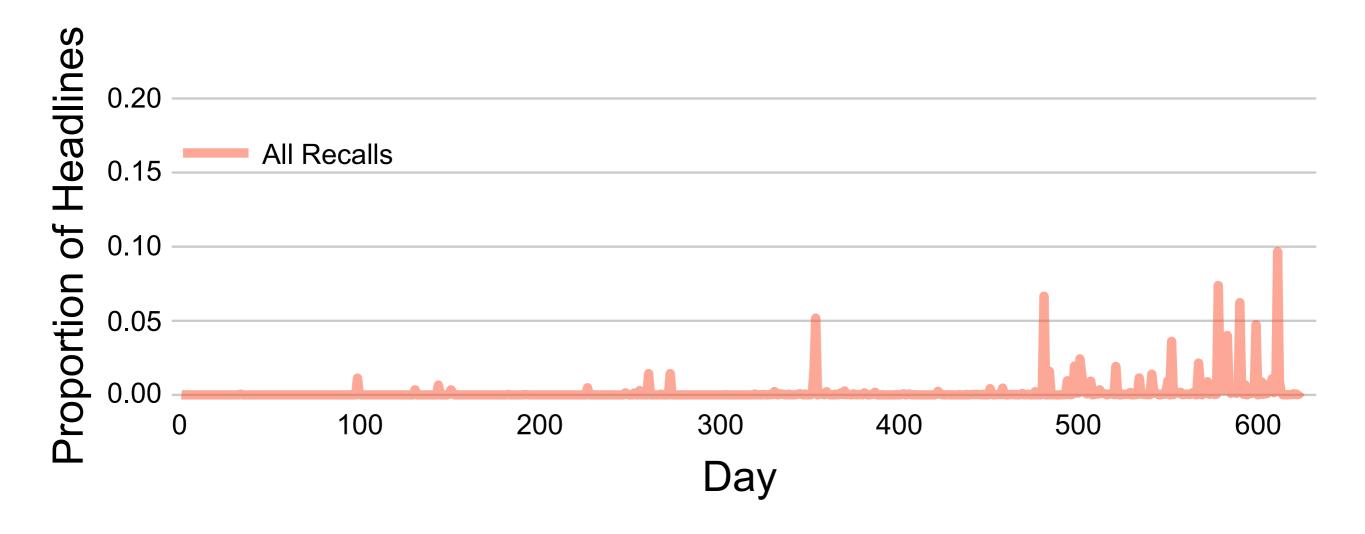
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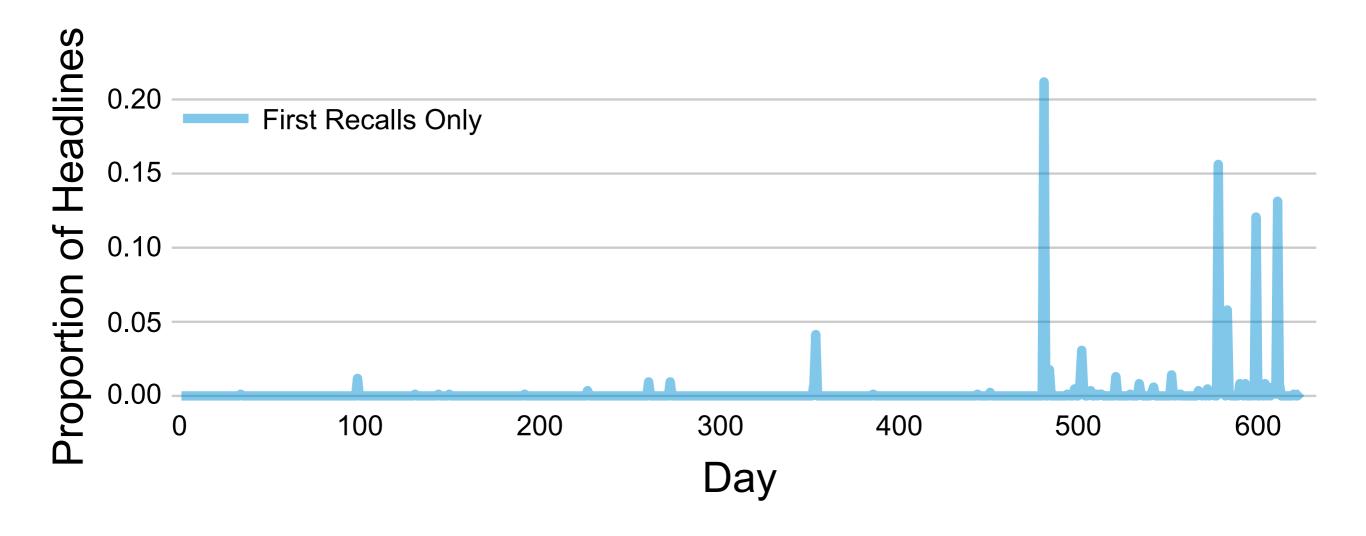


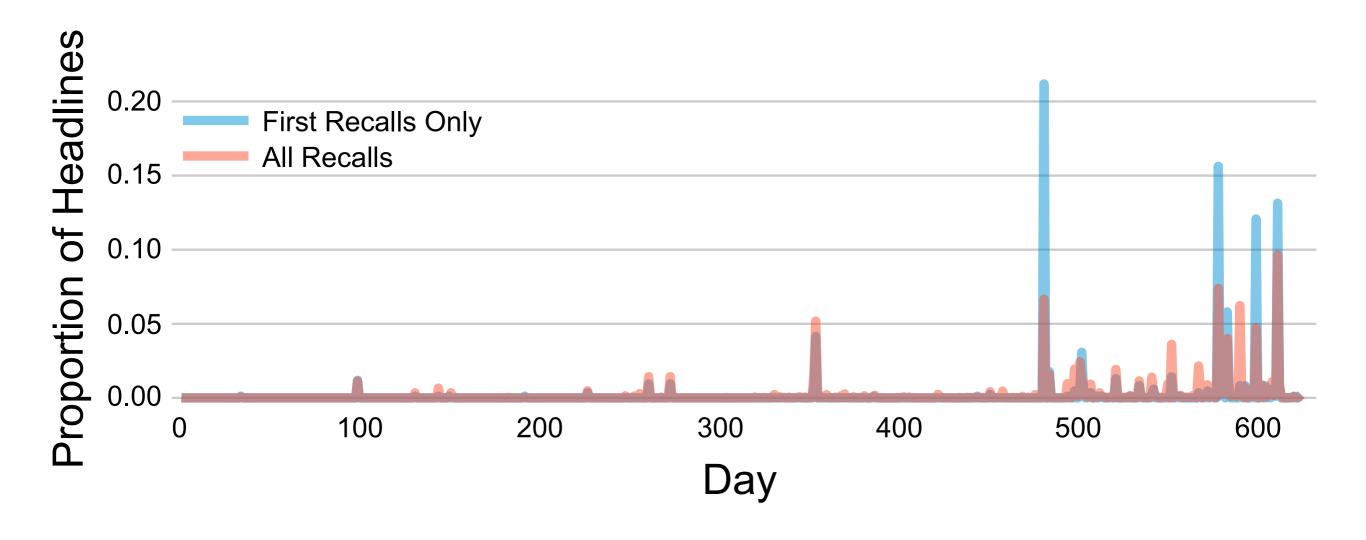
 Imagine if 9 out of every 10 headlines came from a particular day

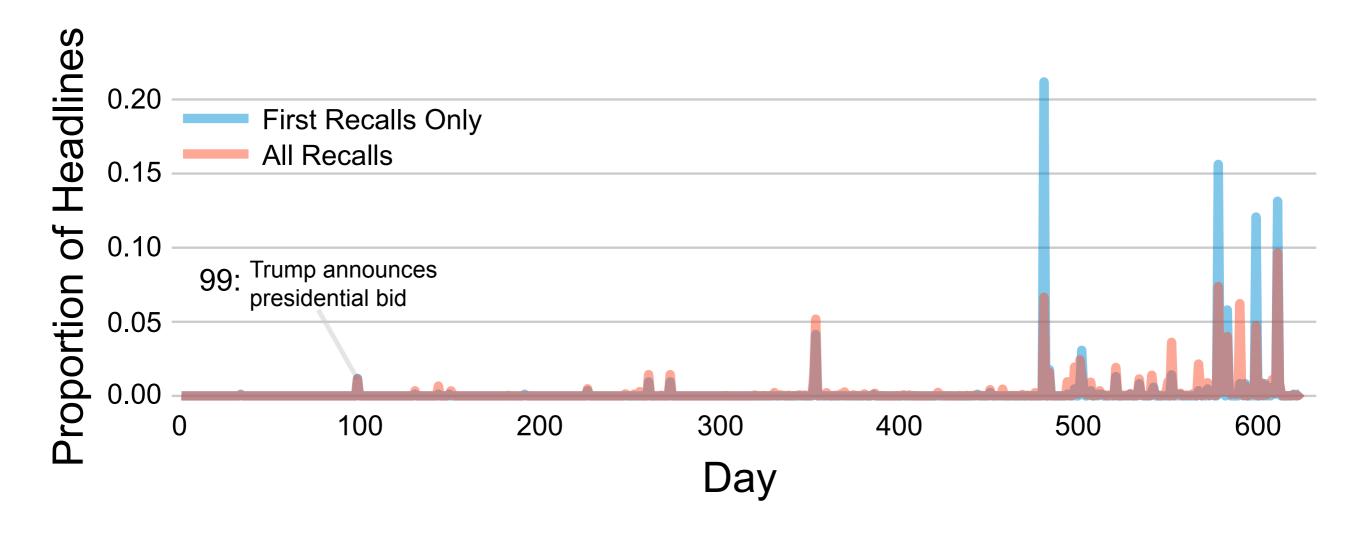
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- There would be many ways to make lag-zero transitions, and few ways to make longer transitions

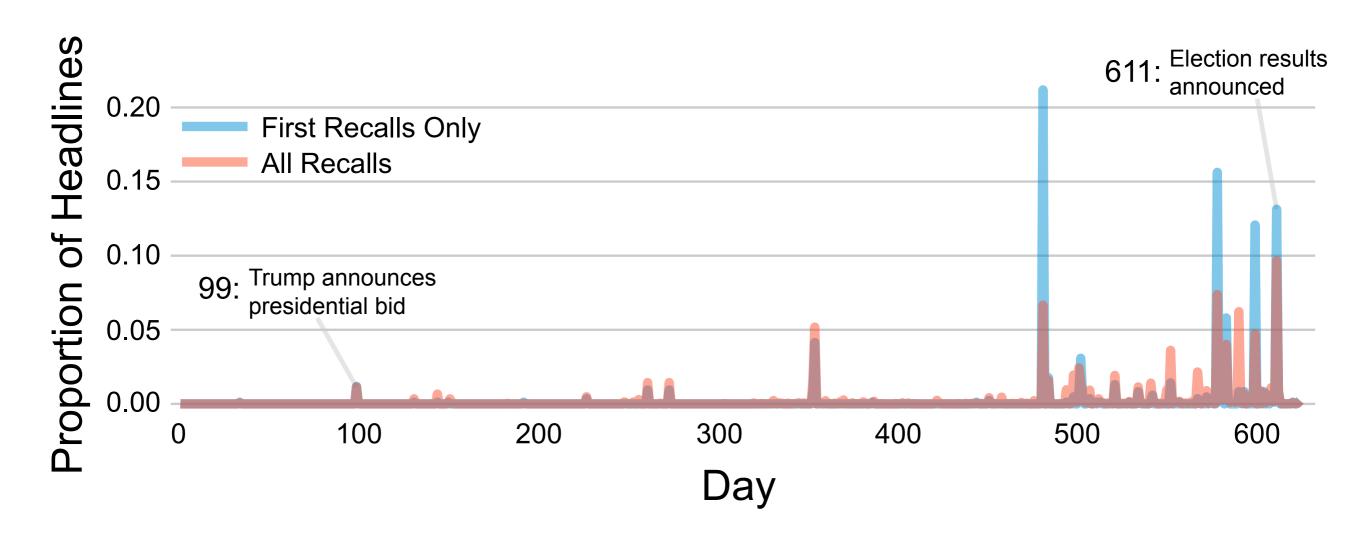
- Imagine if 9 out of every 10 headlines came from a particular day
- There would be many ways to make lag-zero transitions, and few ways to make longer transitions
- We'd expect an artificial contiguity effect

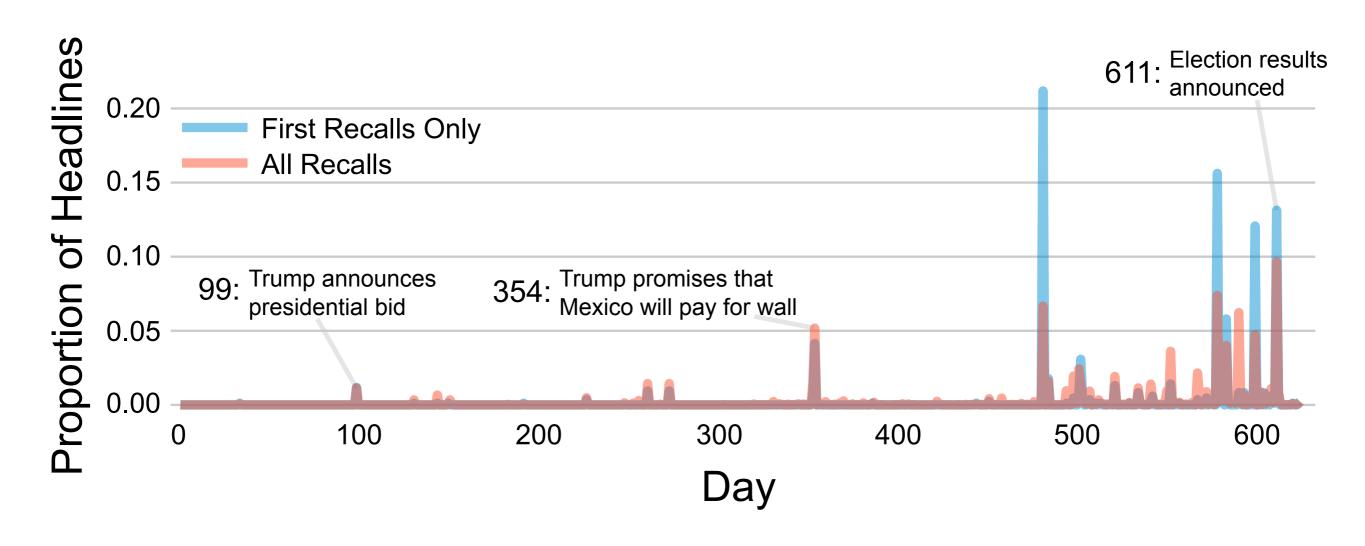


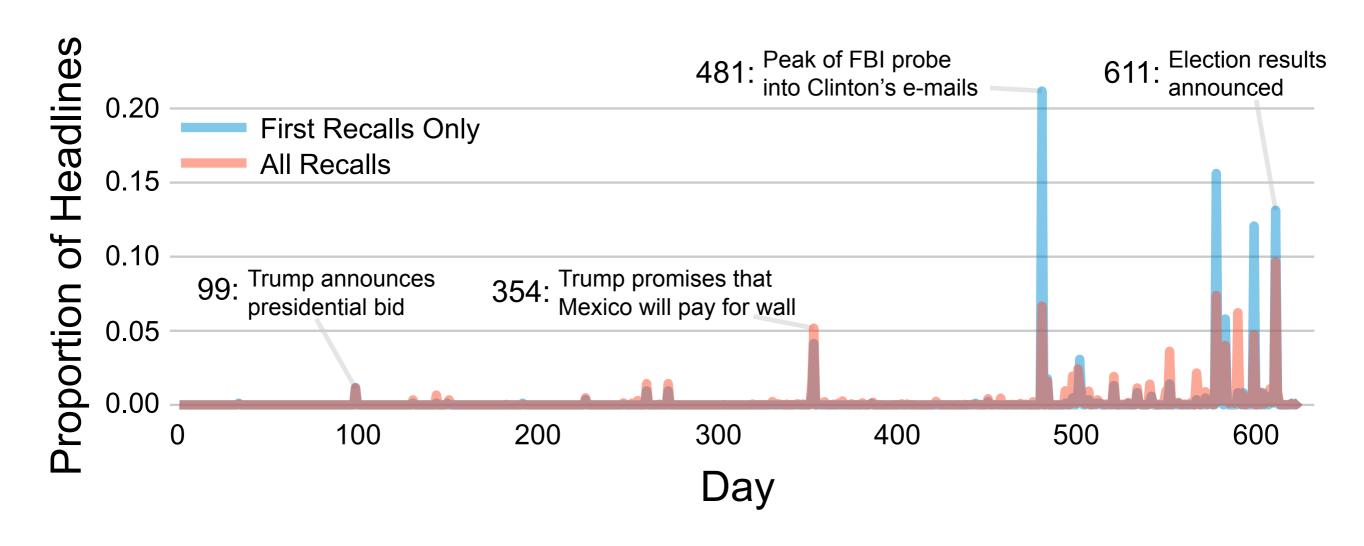


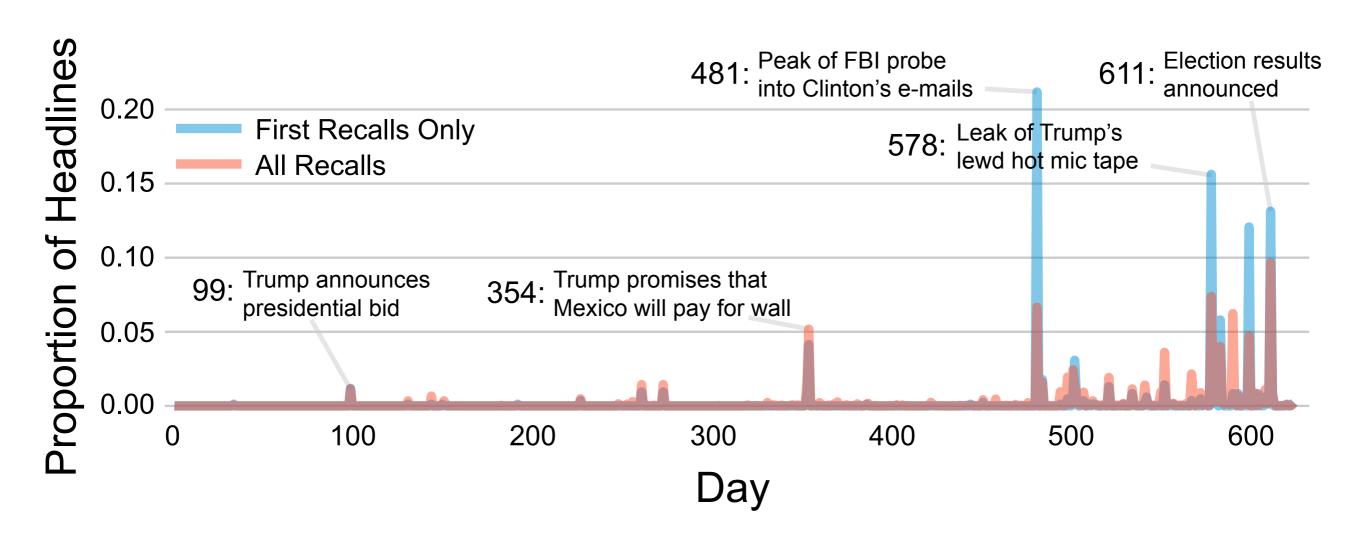


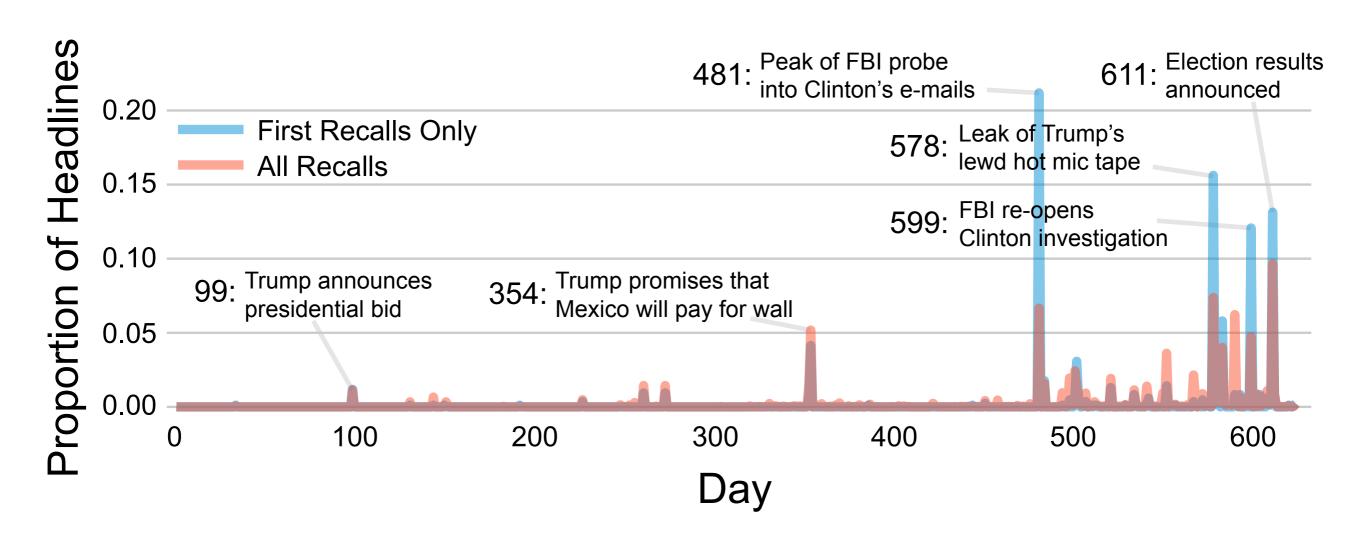












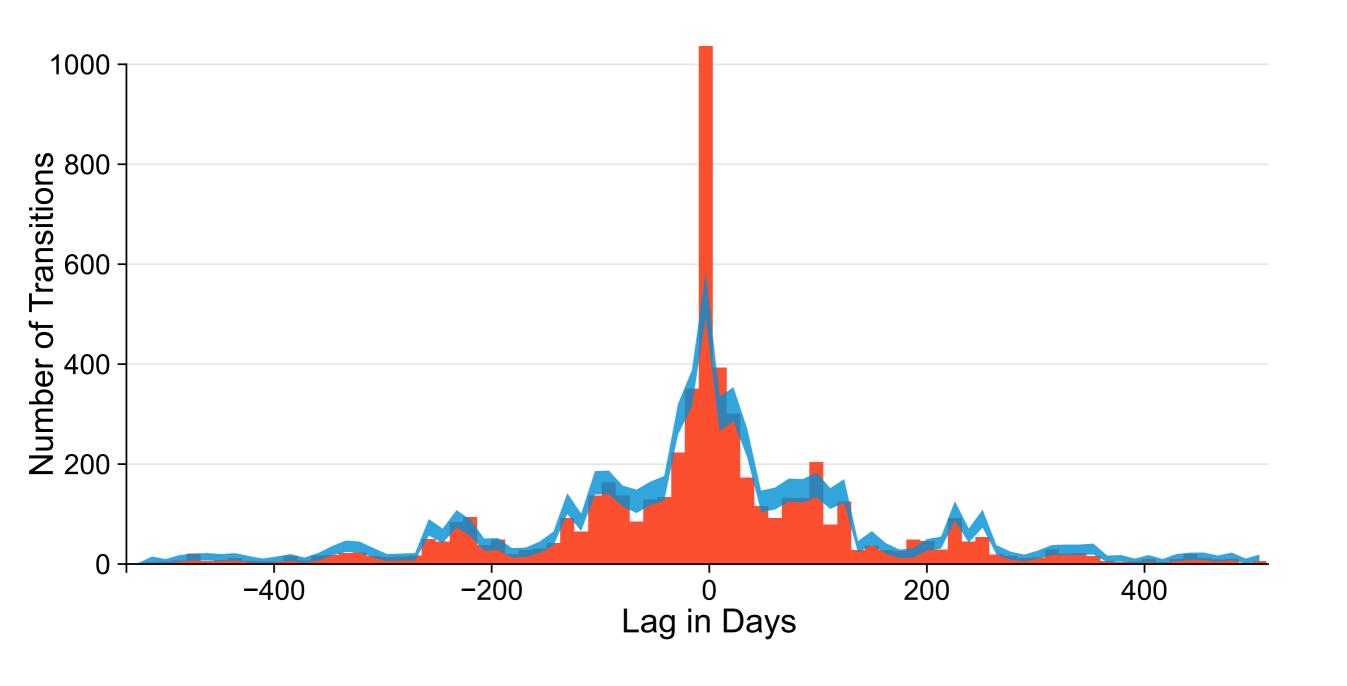
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- Simulated subjects recalled *k* headlines by randomly sampling from:
- Because each draw from the distribution is independent, all links between successive recalls are broken and transition lags depend only on headline-clustering

Near-Lag Transitions More Frequent than Chance



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- For each bin, used the actual and null distributions to calculate a temporal bias score:

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Temporal\ bias\ score = \ ^{actual\ count}
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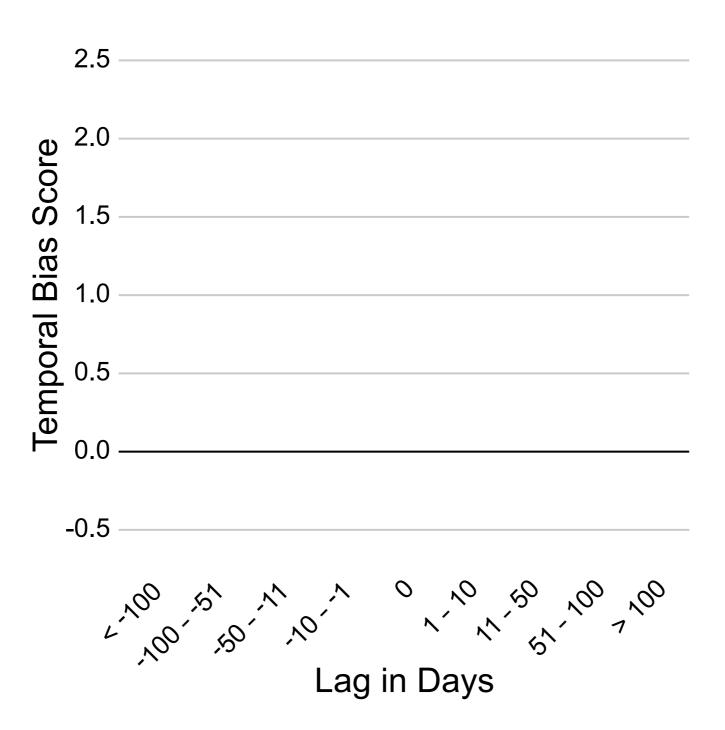
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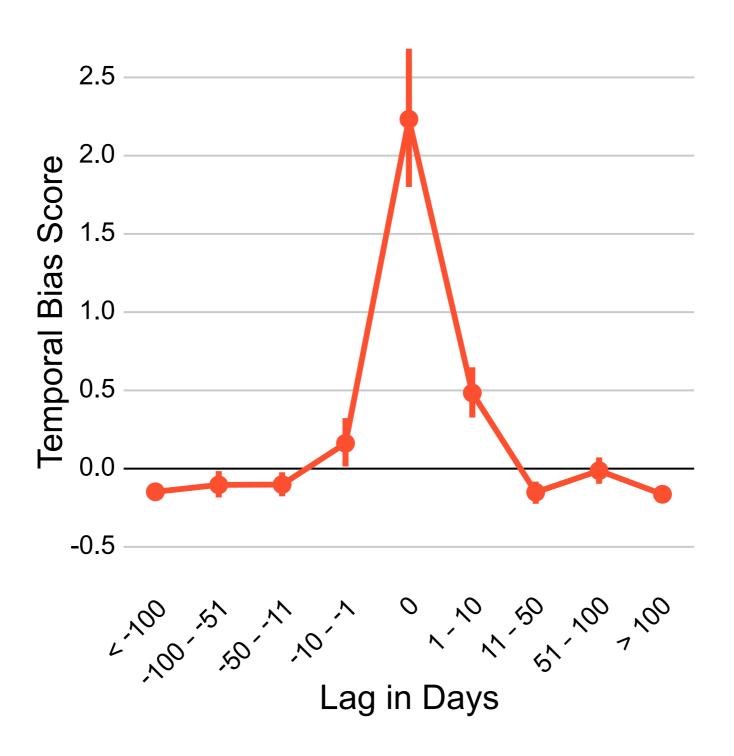
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A Bias Toward Near-Lags



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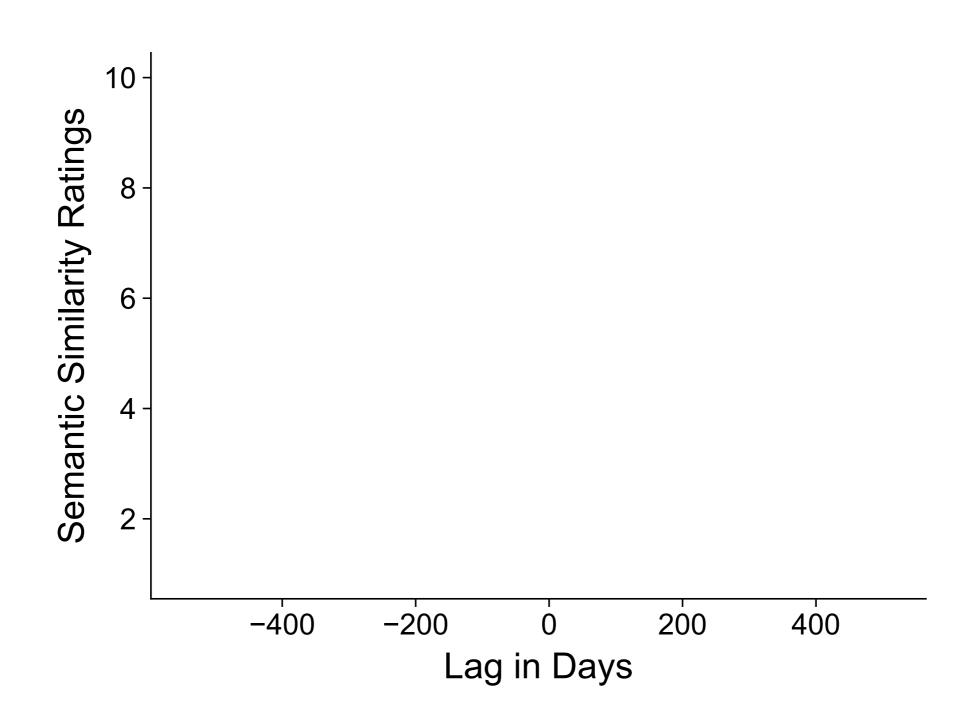


 Items that are semantically related tend to be recalled together (Bousfield, 1953)

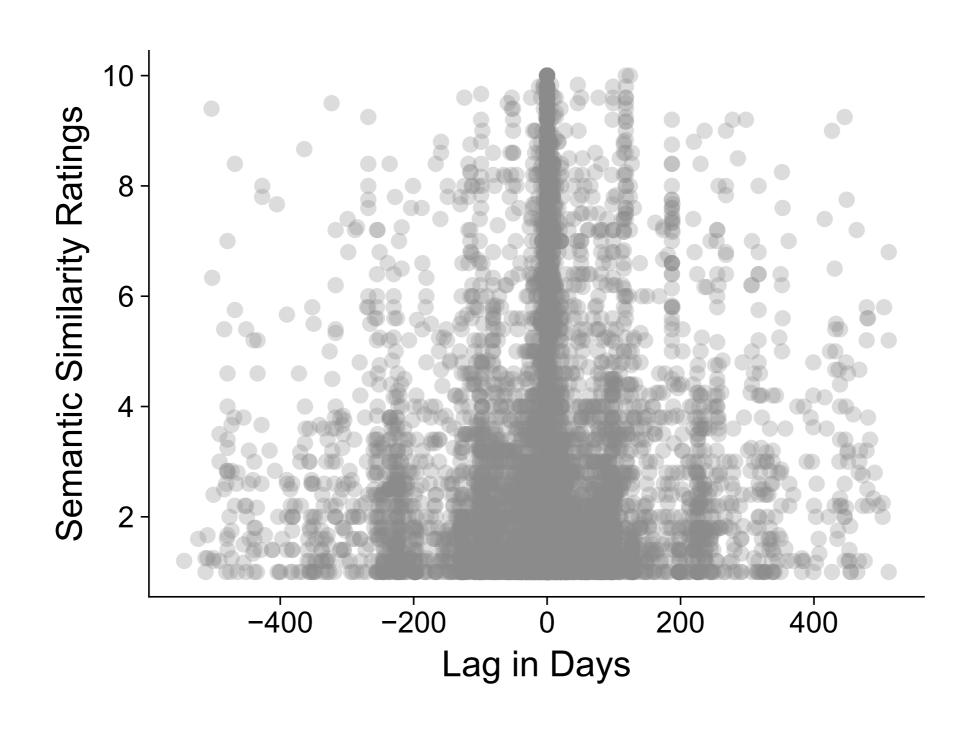
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- Could produce a peak at near-lags if news stories that occur near in time to one another tend to be semantically related
- 4+ raters judged the semantic similarity between the headlines in each of the 5,776 transitions.

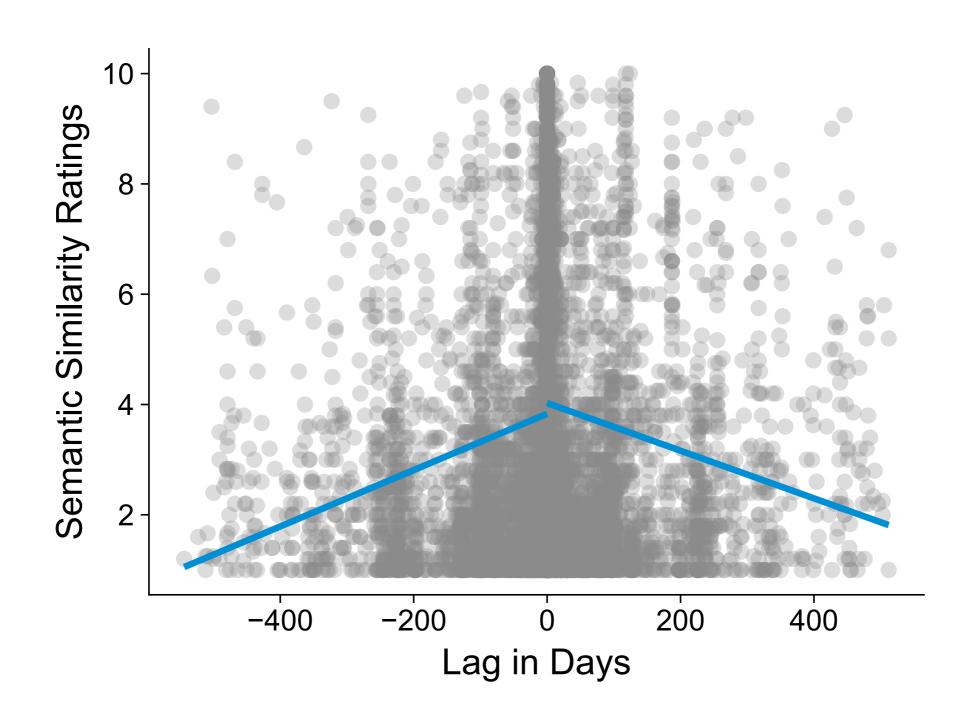
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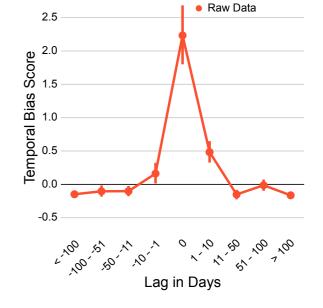


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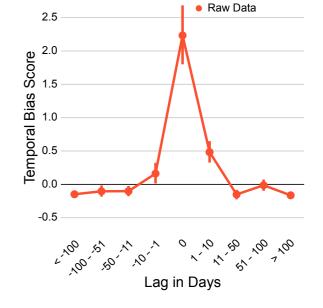
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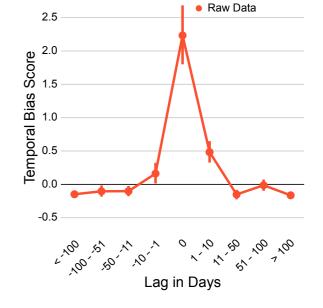
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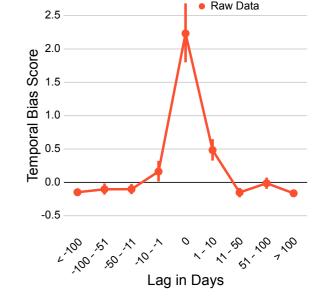
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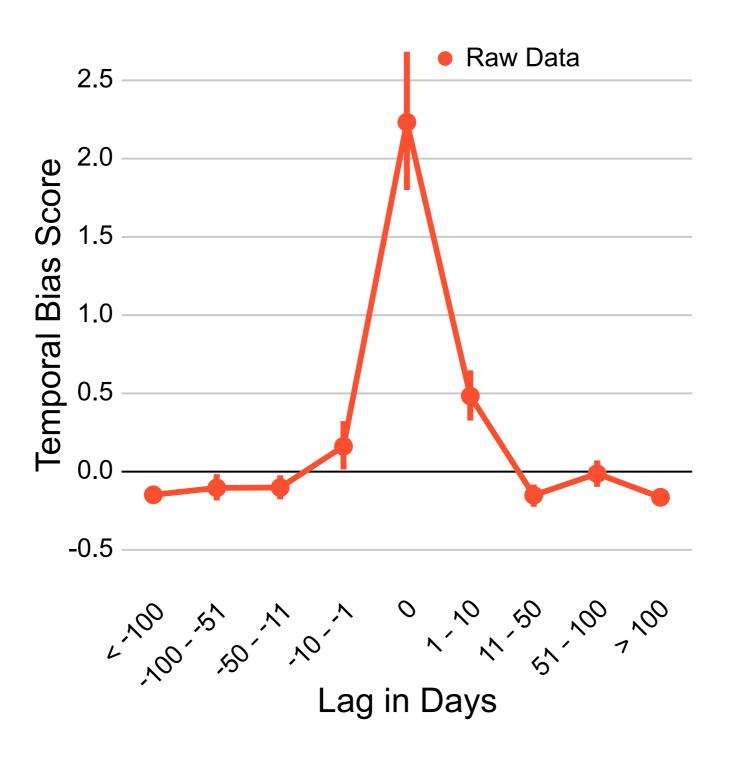
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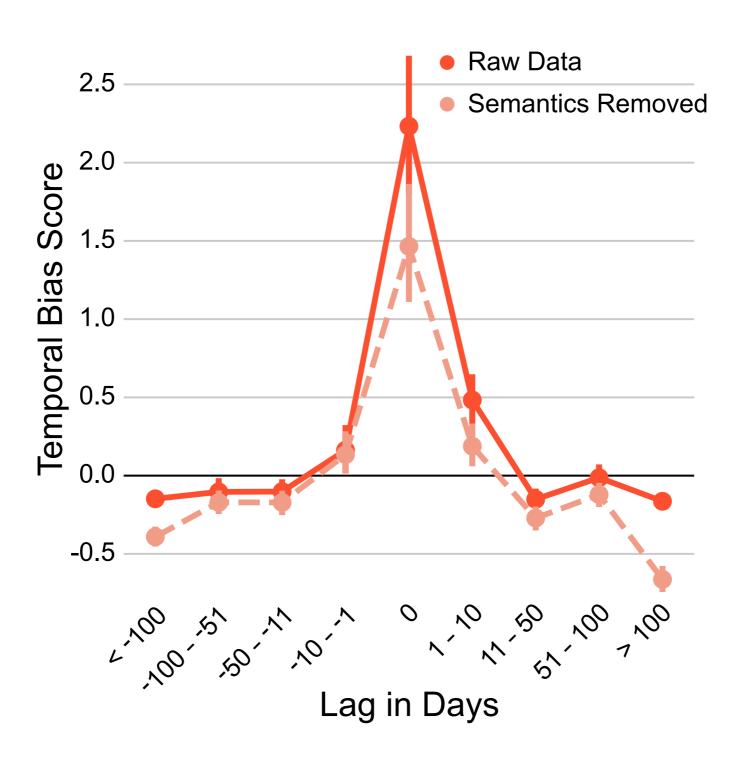


 The residuals give the portion of the temporal bias scores that cannot be predicted by semantic similarity.

A Bias Toward Near-Lags



Even After Removing The Influence of Semantics



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 - Not presented in a chain-like list
 - Separated by long time scales
 - After controlling for clusters of events
 - After controlling for semantic associations

Thanks!



Zero lag transitions

- Different headlines refer to exact same event:
 - "Hillary Clinton Loses the Election"
 - "Donald Trump is New President Elect"
- Different headlines stemming from one event:
 - E.g., 3rd Presidential Debate
 - "Trump won't accept the results of election"
 - "Trump invites Obama's half-brother to third debate"
- Seemingly unrelated:
 - E.g., October 7, 2016
 - "WikiLeaks posts John Podesta's e-mails"
 - "Trump's Access Hollywood video surfaces"

"Trump gets the White House"

"Hillary Clinton loses in a surprise upset"

"Trump gets the White House"

"Hillary Clinton loses in a surprise upset"

November 8, 2017

November 8, 2017

"Trump gets the White House"

"Hillary Clinton loses in a surprise upset"

November 8, 2017

November 8, 2017

Day 611

Day 611

"Trump gets the White House"

"Hillary Clinton loses in a surprise upset"

November 8, 2017

• November 8, 2017

Day 611

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Lag = 611 - 611 = 0

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"Trump's Access Hollywood hot mic"

• October 7, 2016

"FBI re-opens Clinton's e-mail investigation"

October 28, 2016

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Day 578

"FBI re-opens Clinton's e-mail investigation"

October 28, 2016

Day 599

"Trump's Access Hollywood hot mic"

• October 7, 2016

Day 578

"FBI re-opens Clinton's e-mail investigation"

October 28, 2016

Day 599

Lag = 599 - 578 = +21