Tense and Aspect in Distributional Semantic Vector Space Models

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based on joint work with Nathanael Chambers and Mark Steedman

University of Sussex, 25th July 2018 (1532516400)

 Towards a Form-Independent Semantics with Entailment Graphs

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- WTH is Aspect?

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The verbs are all of a different form, however share a substantial amount of meaning.

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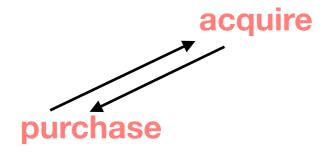
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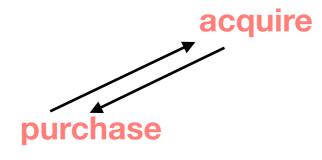
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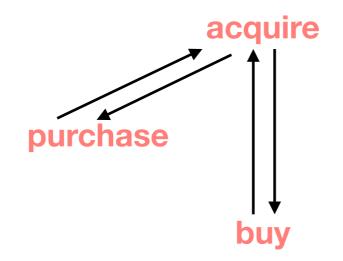


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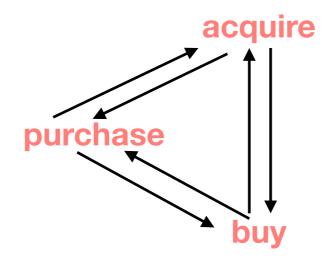


buy

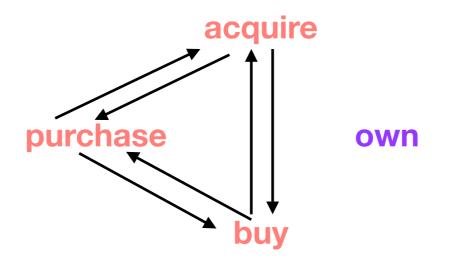
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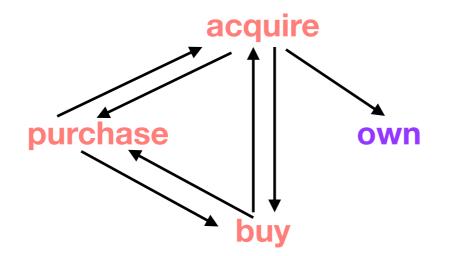
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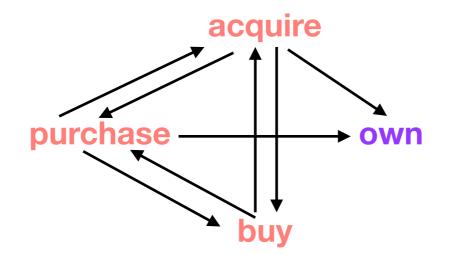
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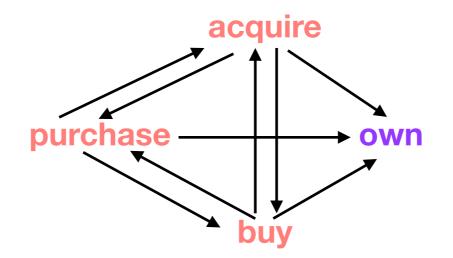
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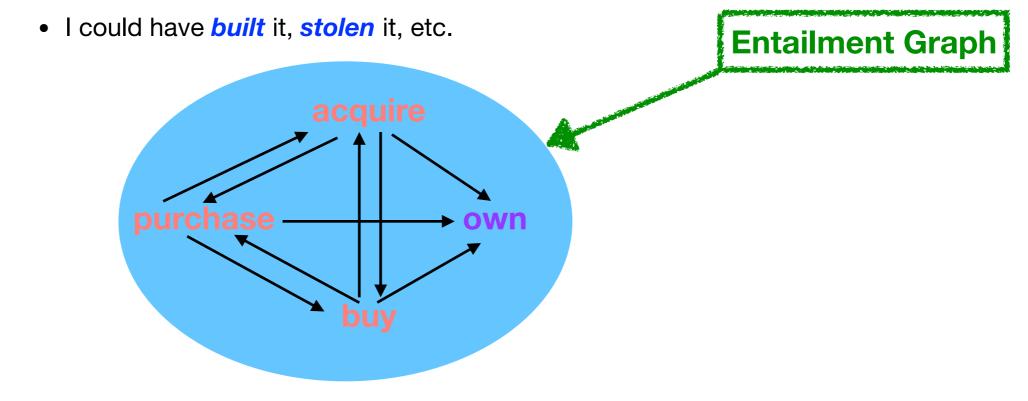
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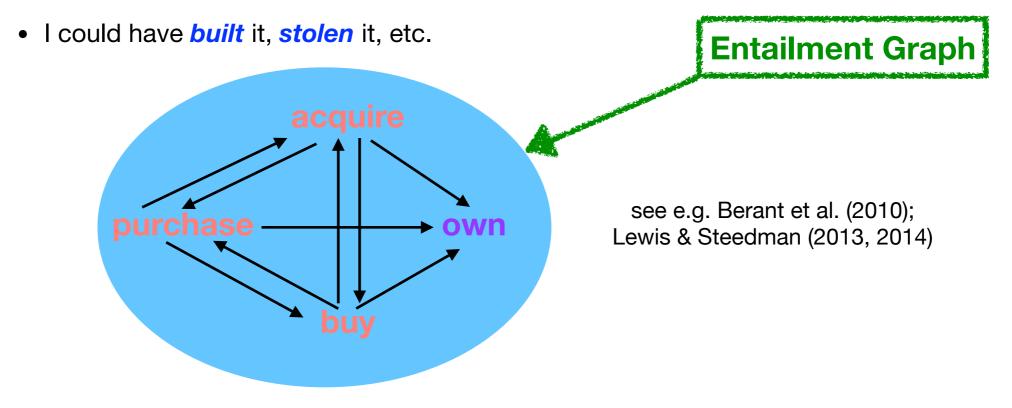
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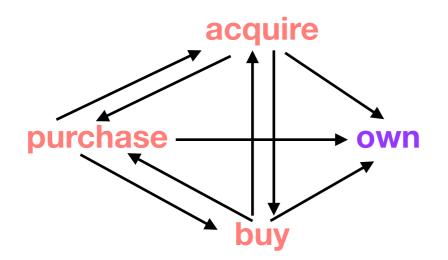
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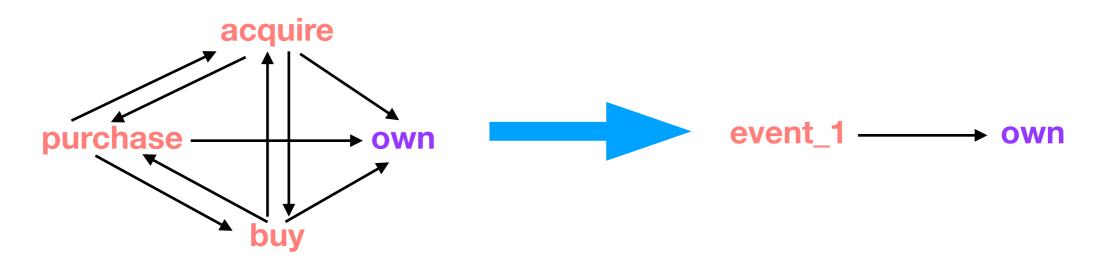
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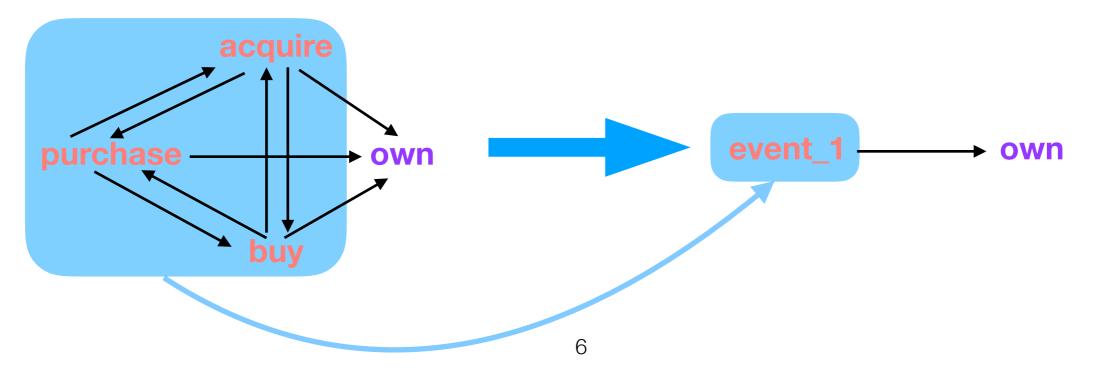
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Outline

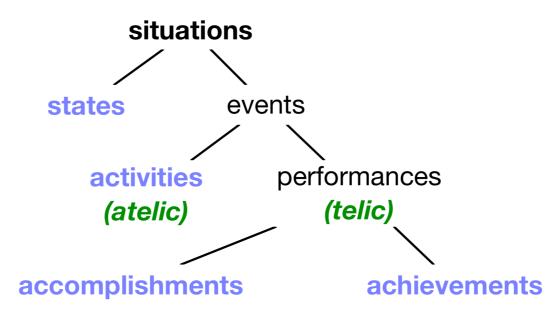
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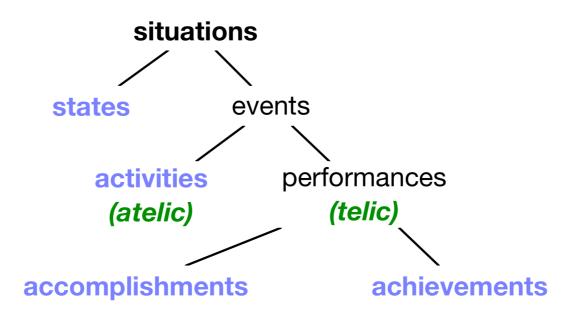
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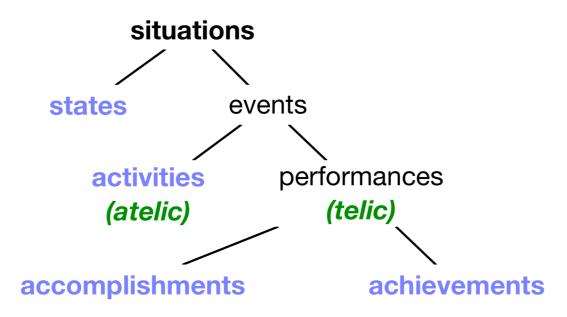


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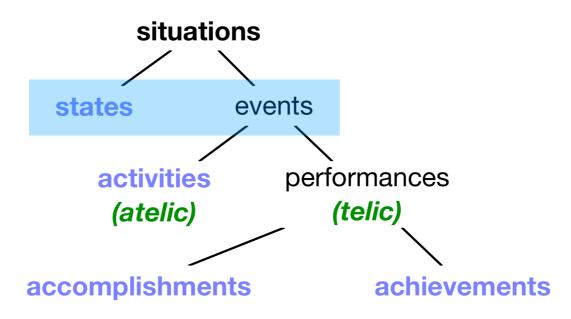
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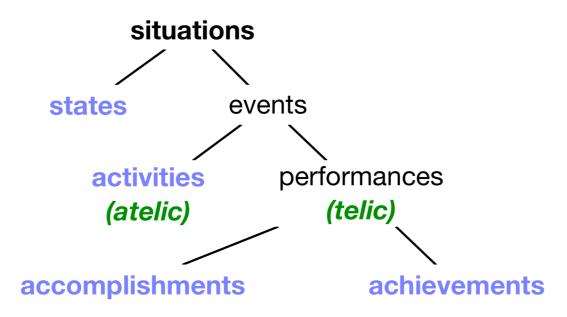
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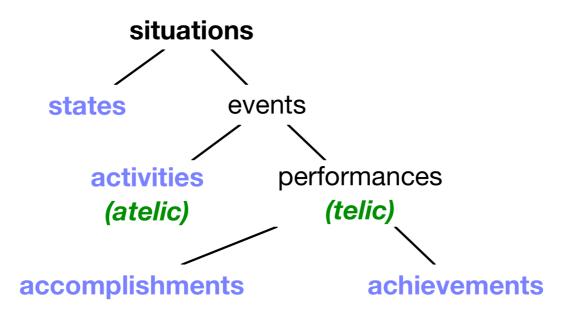
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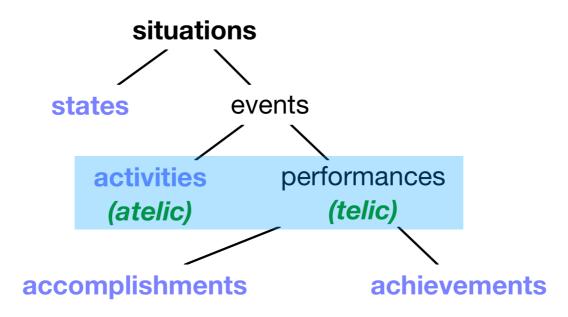
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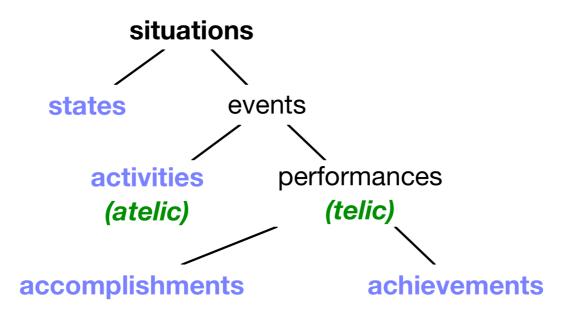
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- In English, we need to rely on **contextual cues** co-occurring with a given verb

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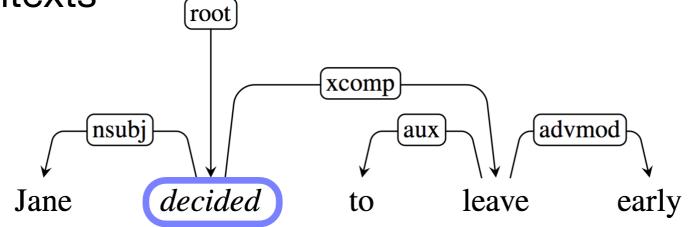
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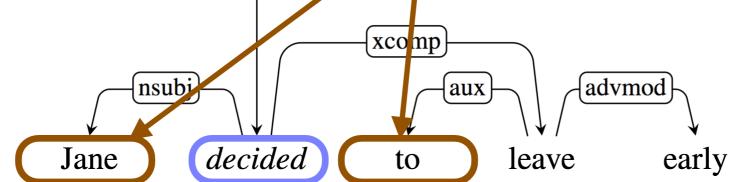
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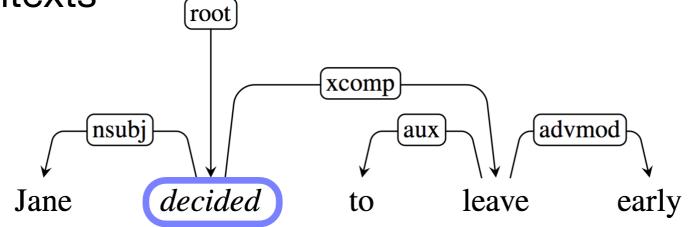
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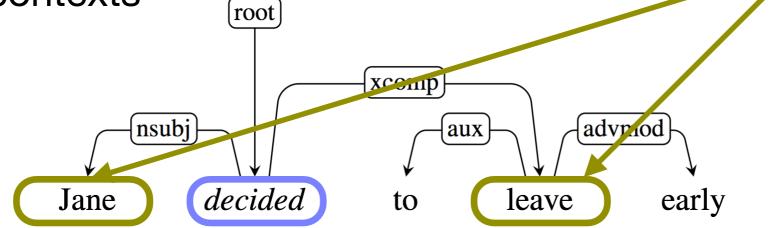
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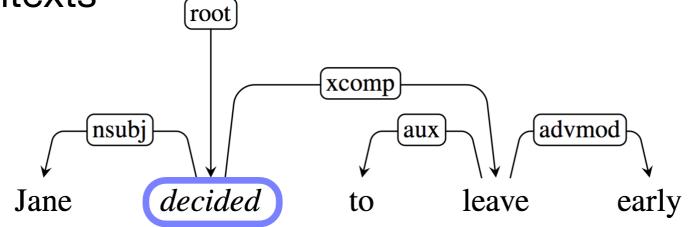
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- We are only relying on distributional representations for words (e.g. from word2vec [Mikolov et al., 2013])



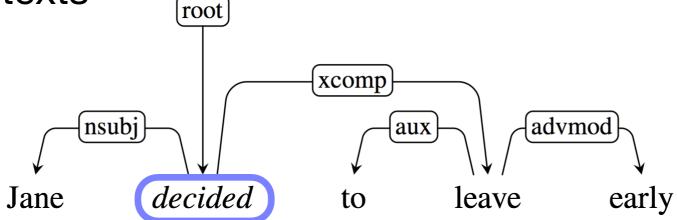




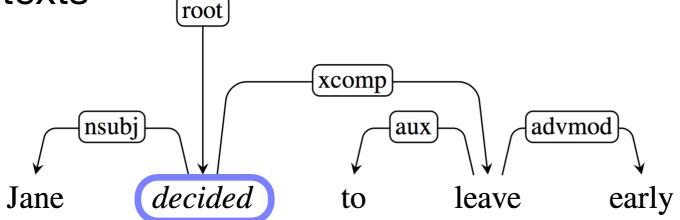




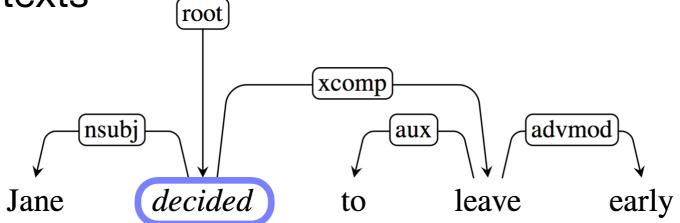
 For each verb we extract window-based and dependencybased contexts



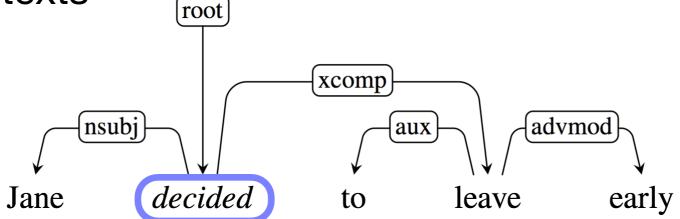
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- Then contextualise (i.e. compose) the target verb with its context through vector addition
 - v(phrase-win) = v(decided) + v(Jane) + v(to)
 - v(phrase-dep) = v(decided) + v(Jane) + v(leave)
- Subsequently use the resulting phrase vector as input to a classifier to predict whether *decided* is a state or an event (or alternatively a telic or an atelic event)

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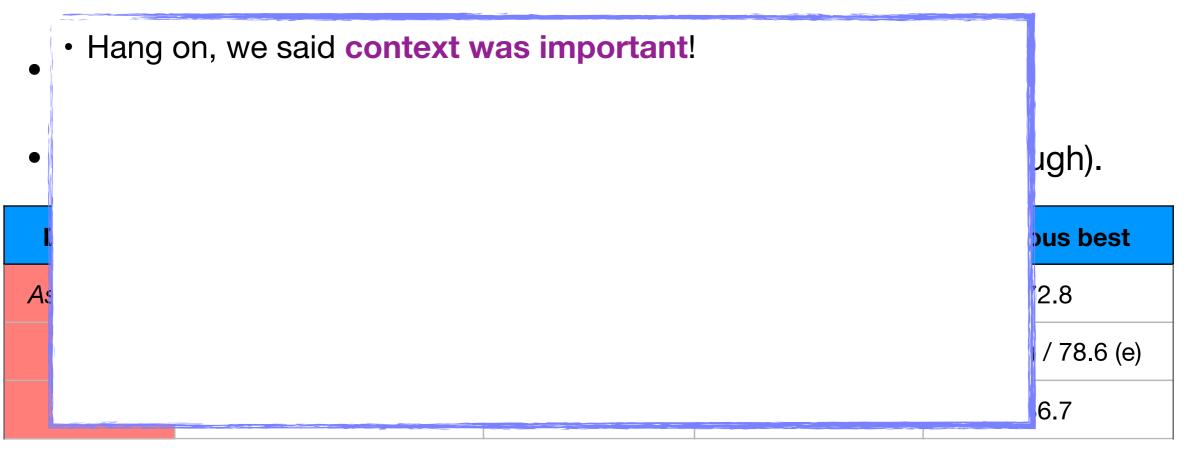
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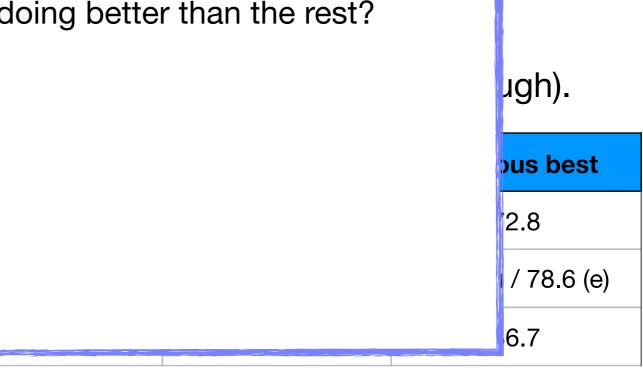
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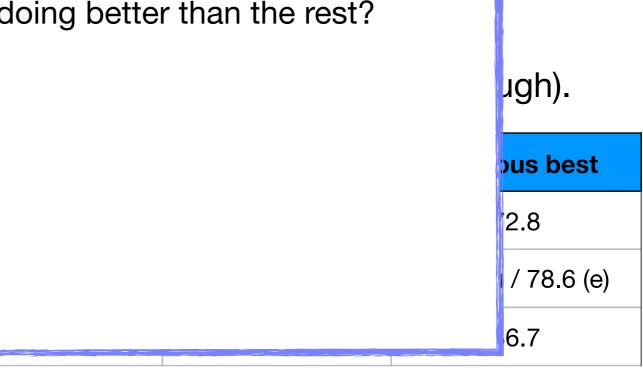
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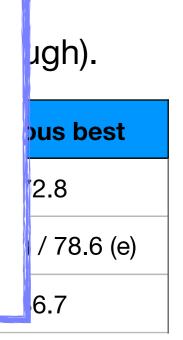
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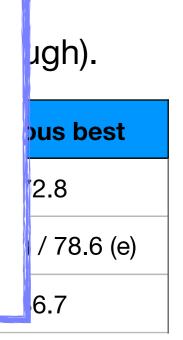
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- So in conclusion, closed class words are really strong indicators of aspect, but they also need to occur in the "right" position (i.e. as preposition, verb particles or subjects)

Modelling Aspect with

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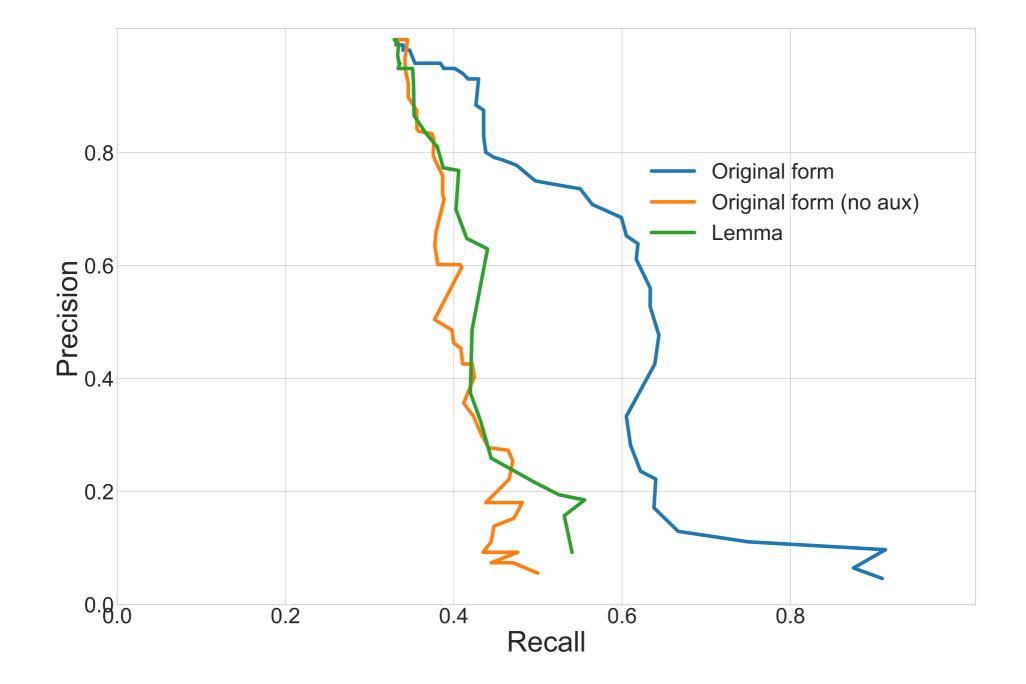
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 - And thats *pretty cool*, actually

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- Distributional Composition can be leveraged to recover even more information

Thats it, I'm done!

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Q & (maybe) A

tkober@inf.ed.ac.uk

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