Information-theoretic locality properties of natural language

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- **Mathematical formalization**: human languages are **solutions** to a **constrained optimization problem** describing communication subject to cognitive constraints.
  - So, what is the objective function that human languages optimize?

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- Key part: **effort is quantified using entropy (average surprisal).**

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Information Locality

- Introduction
- Information Locality
- Study 1: Strength of Dependencies
- Study 2: Adjective Order
- Conclusion

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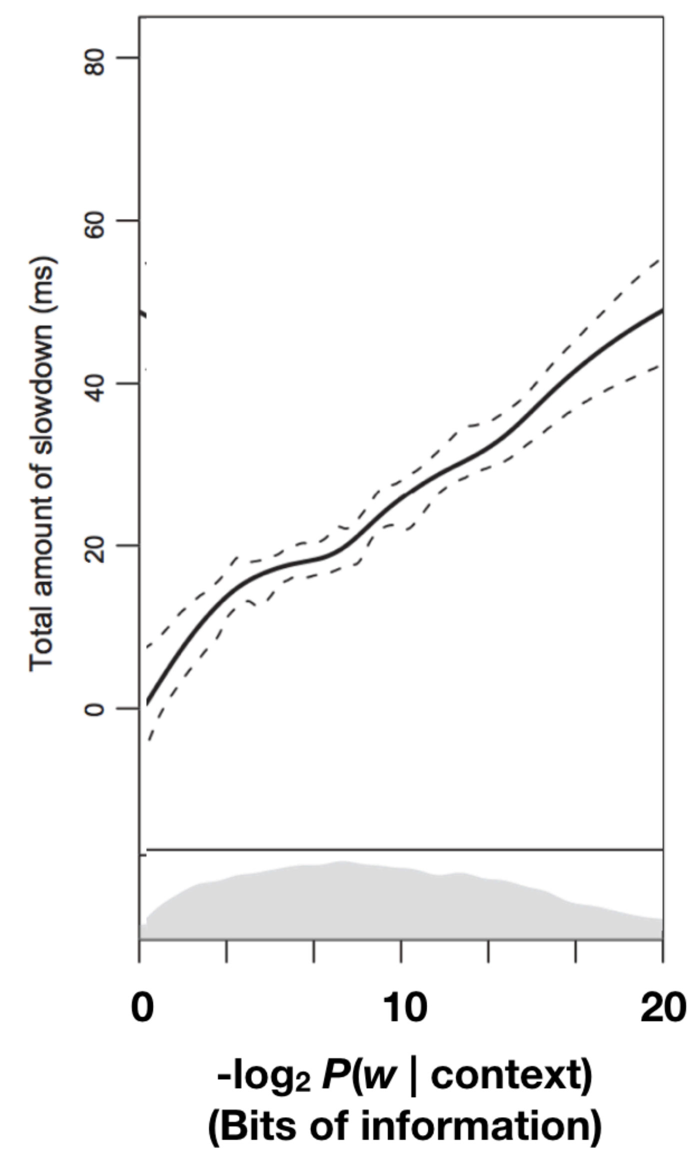

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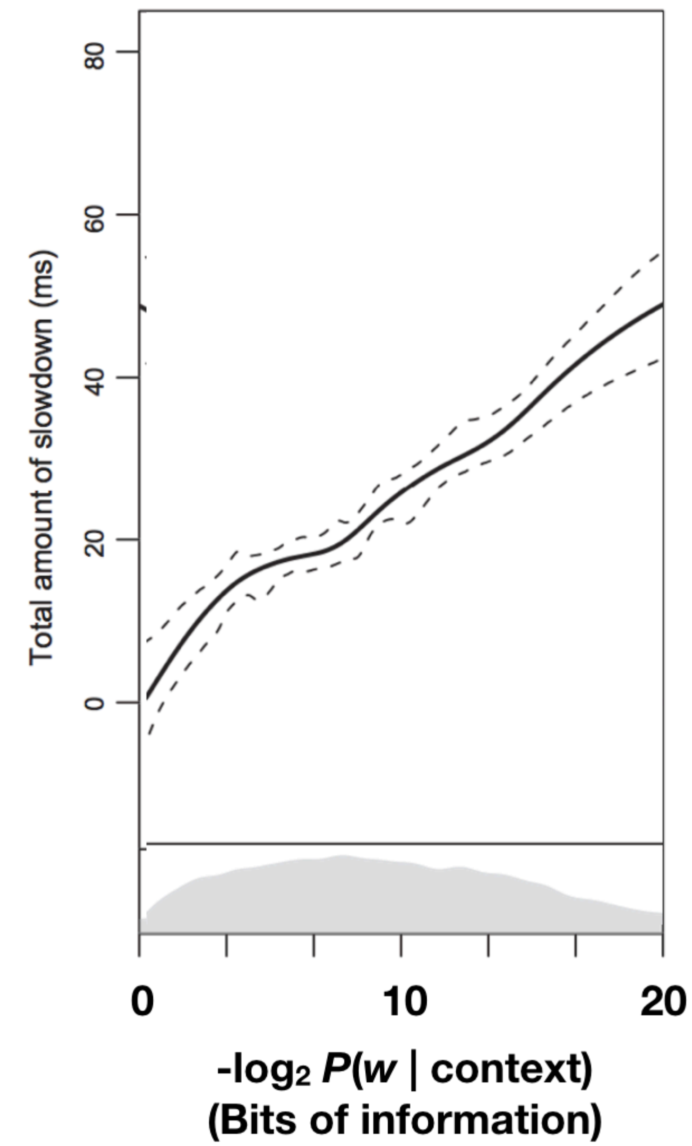

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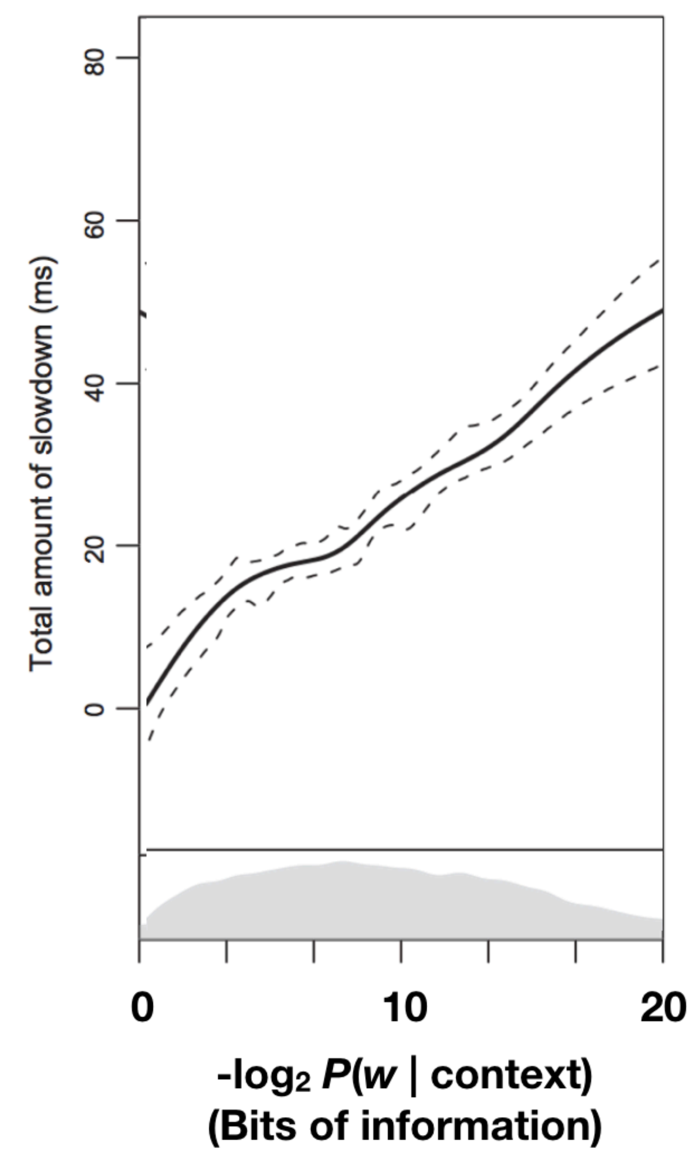

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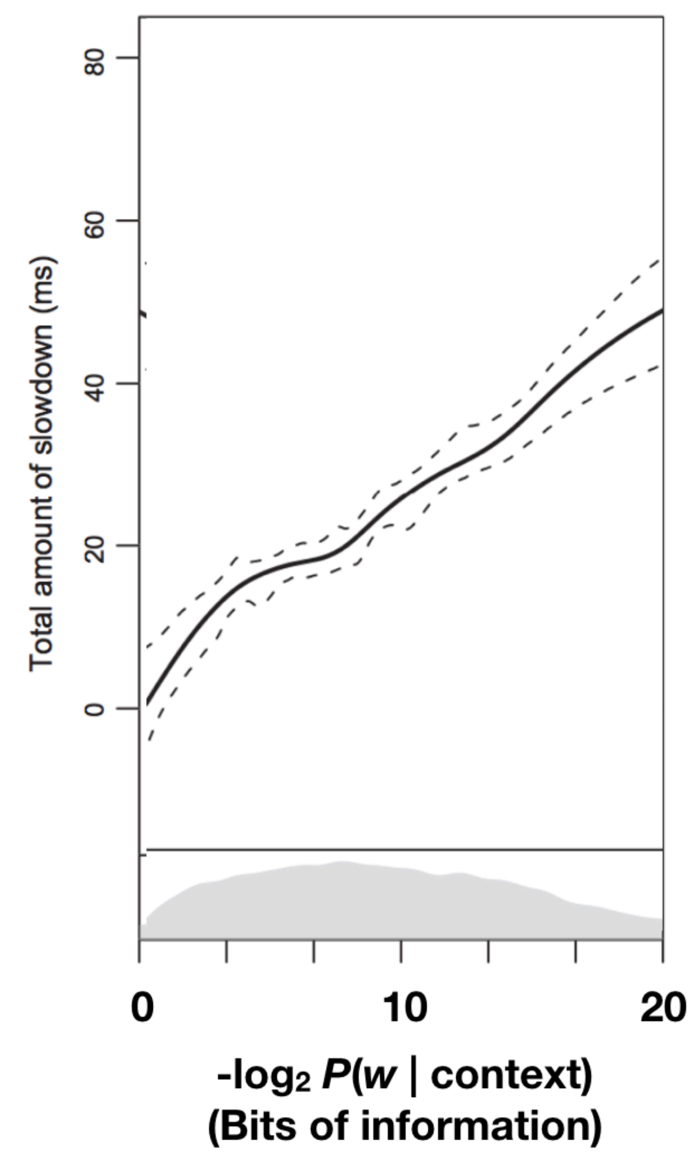

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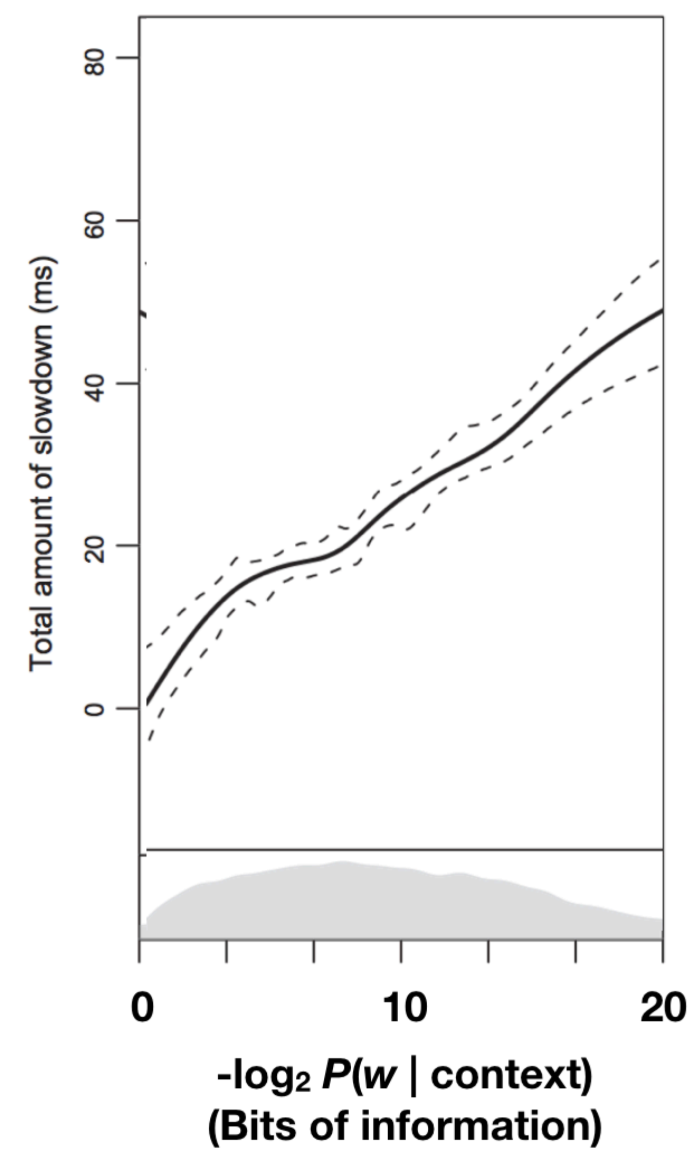

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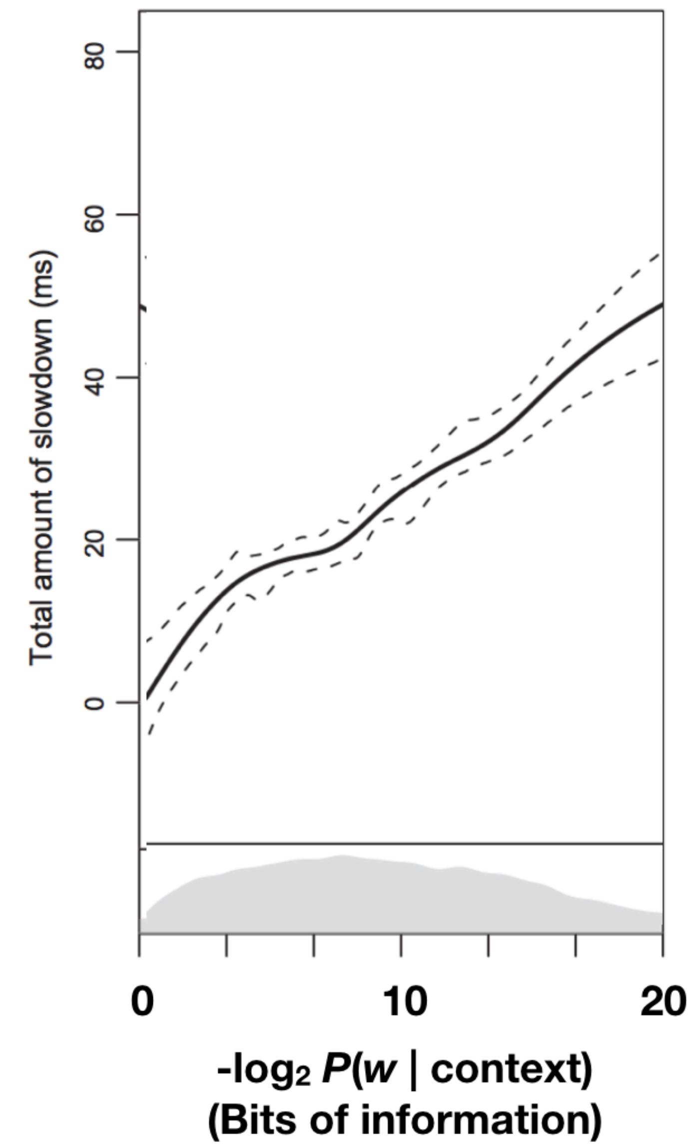

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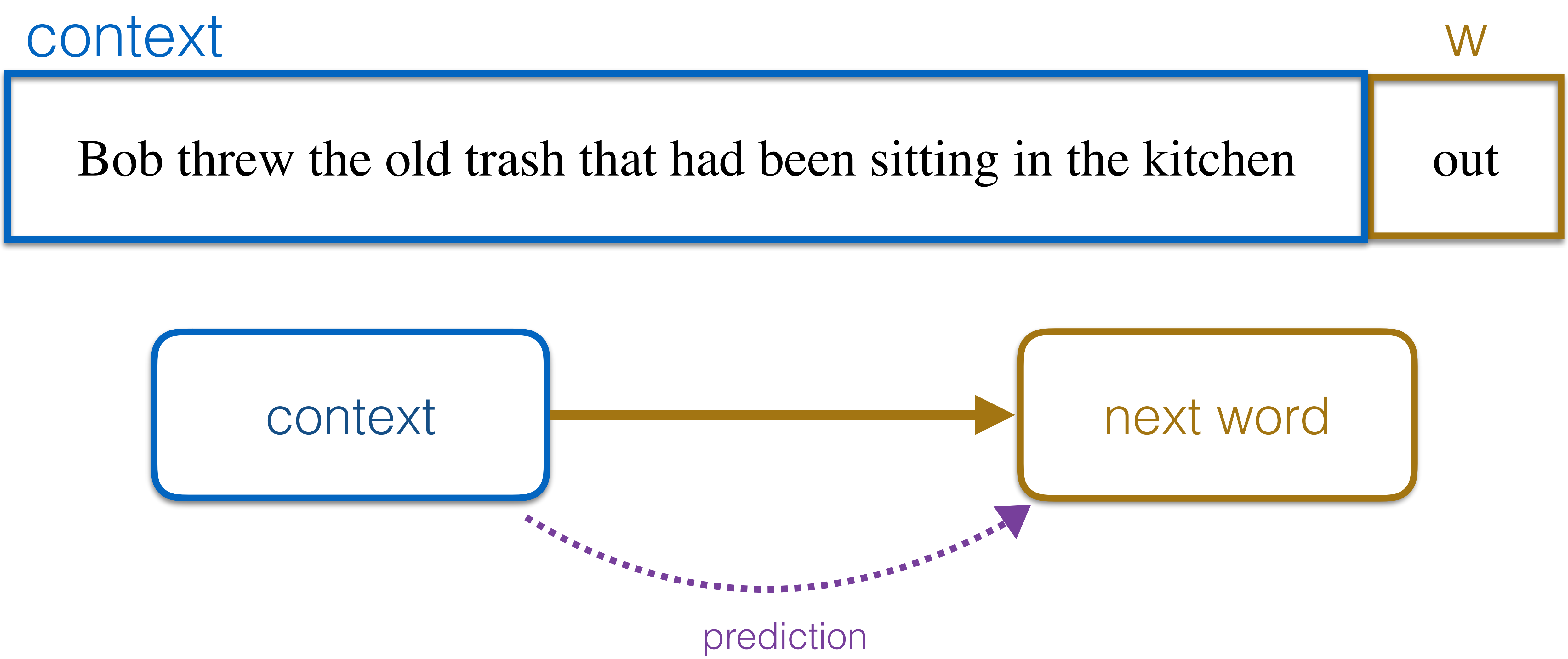

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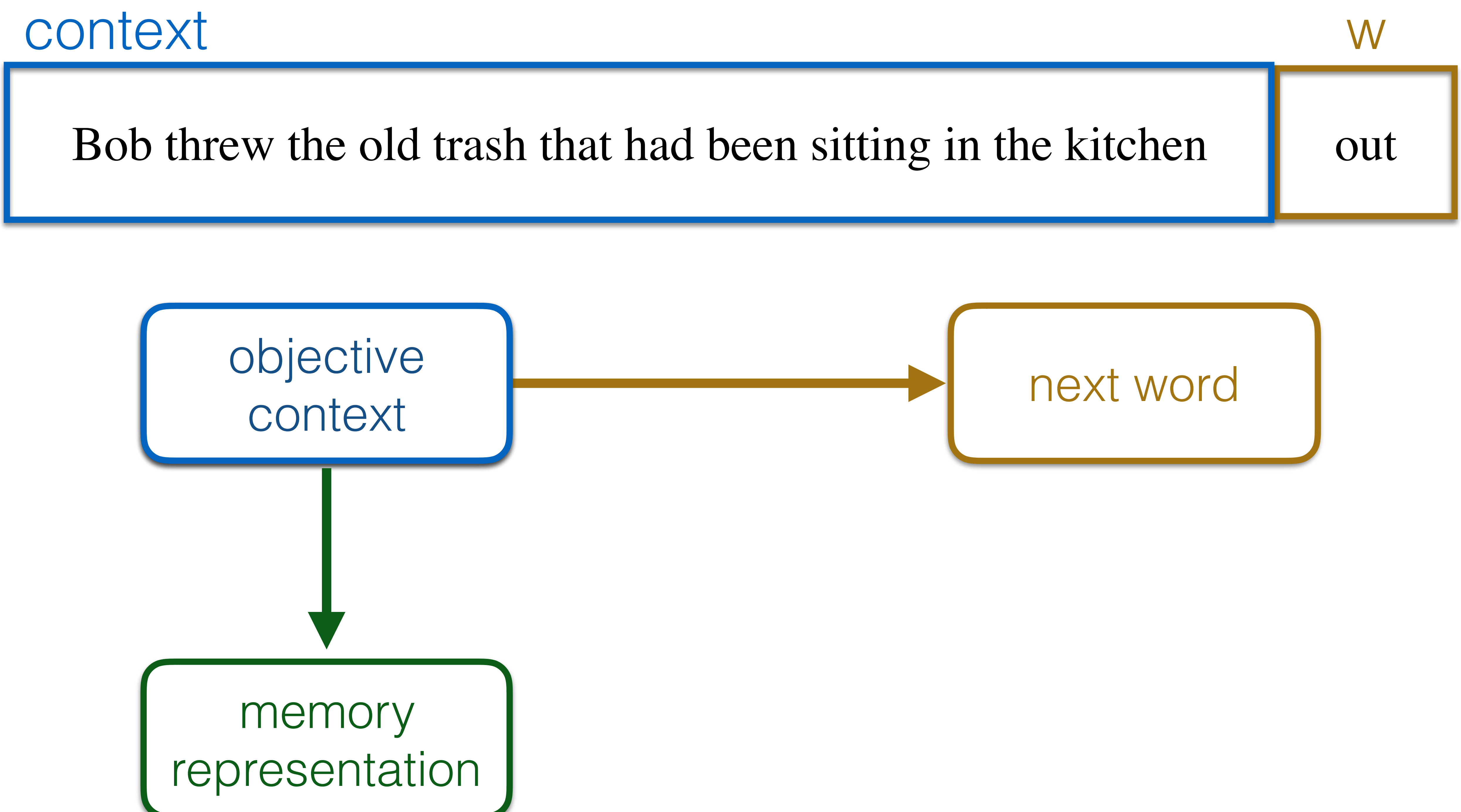

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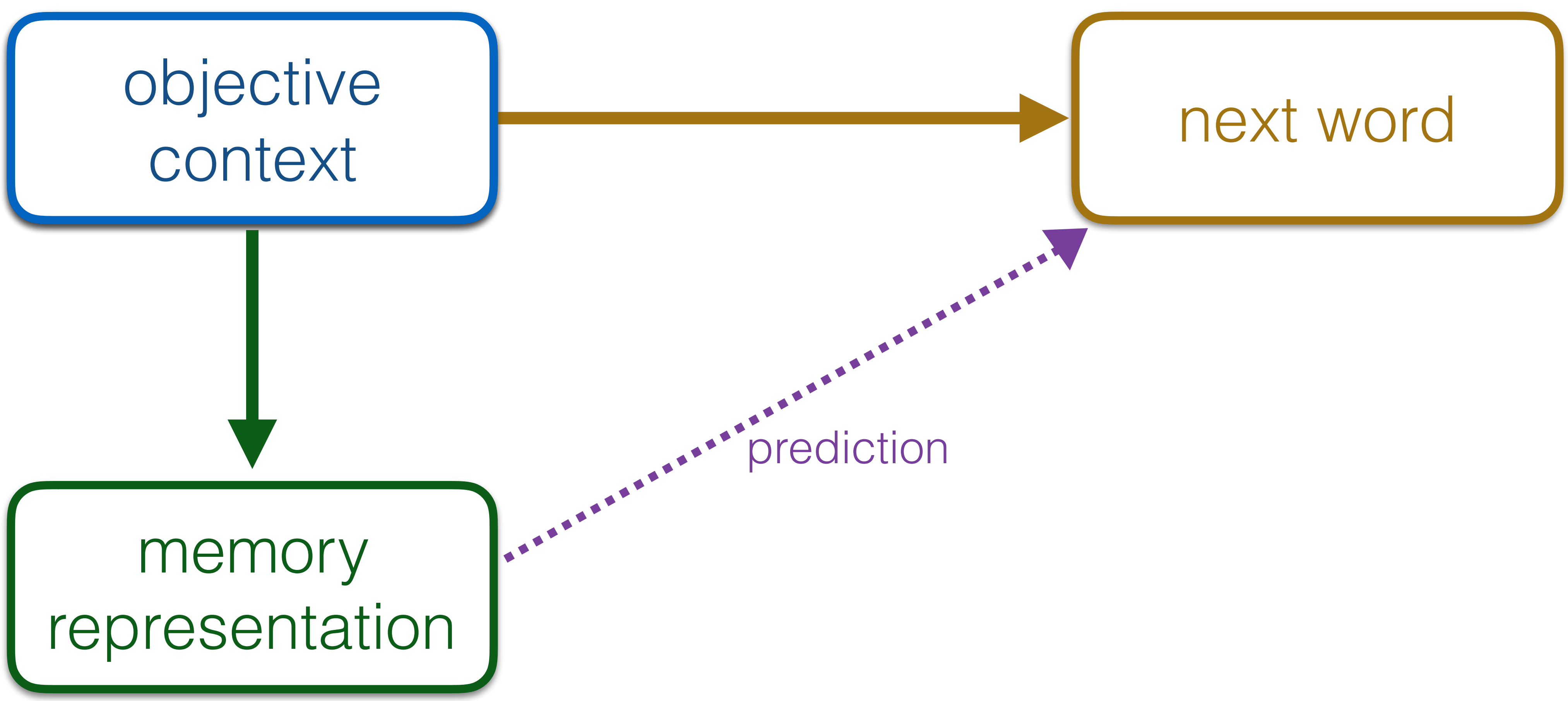

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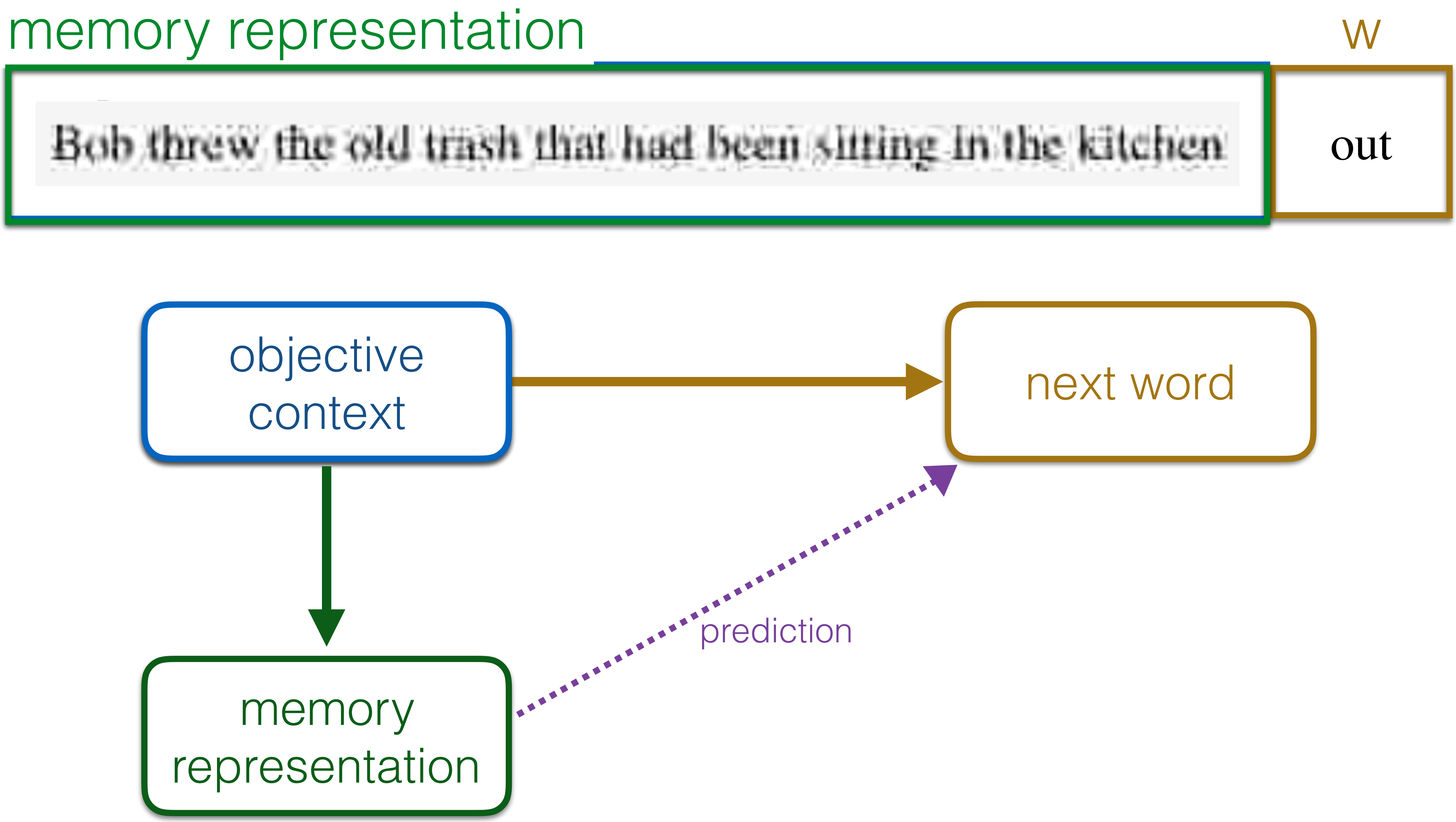

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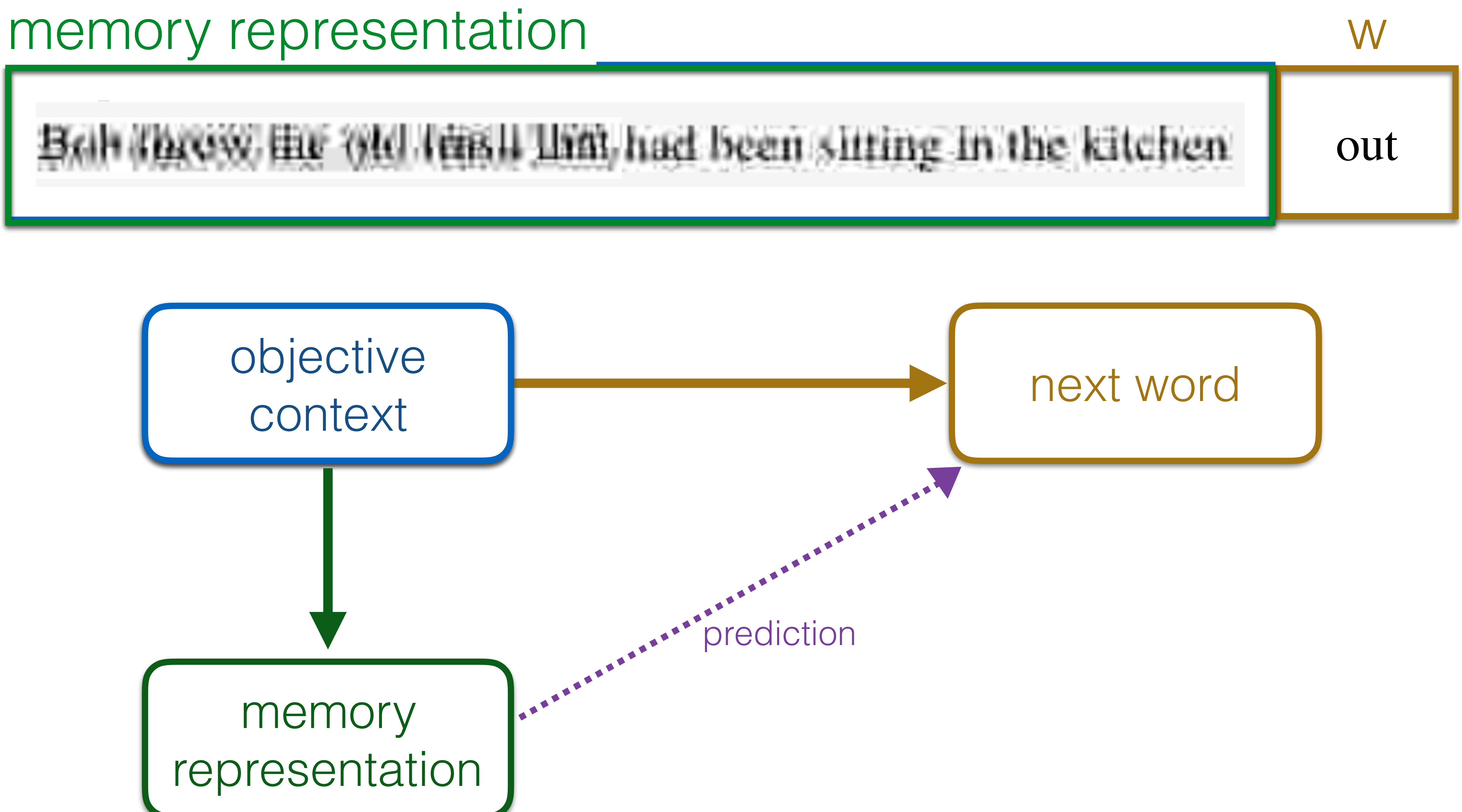

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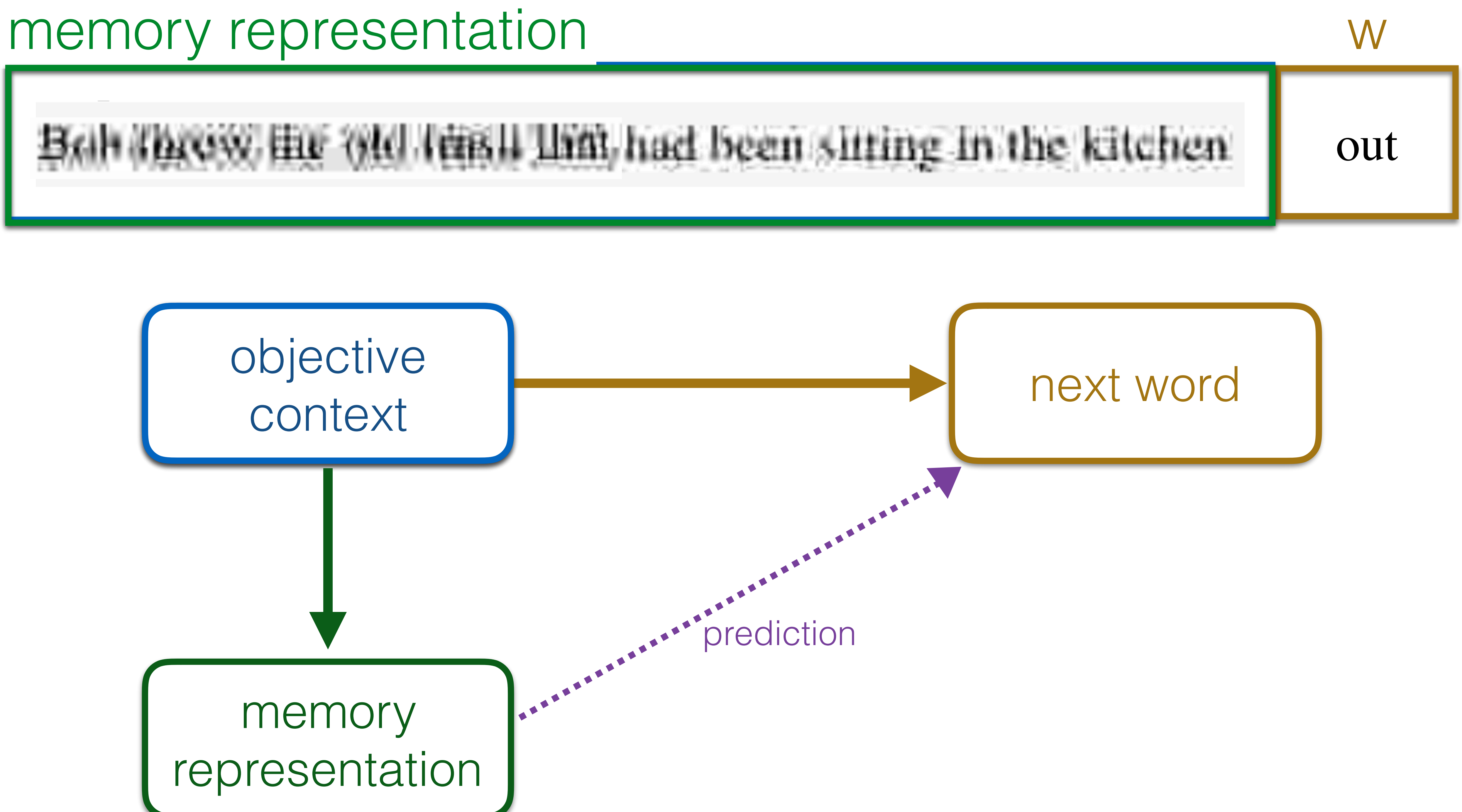

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where $\boldsymbol{m_i}$ **is a lossy compression of the context** $\boldsymbol{w_{1,\ldots,i-1}}$,
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Information Locality

memory representation

Bob threw the old trash sitting in the kitchen	out

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Bob threew the old trash sitting in the kitchen | out

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Pointwise mutual information (pmi) is the most general statistical measure of *how strongly two values predict each other* (Church & Hanks, 1990)

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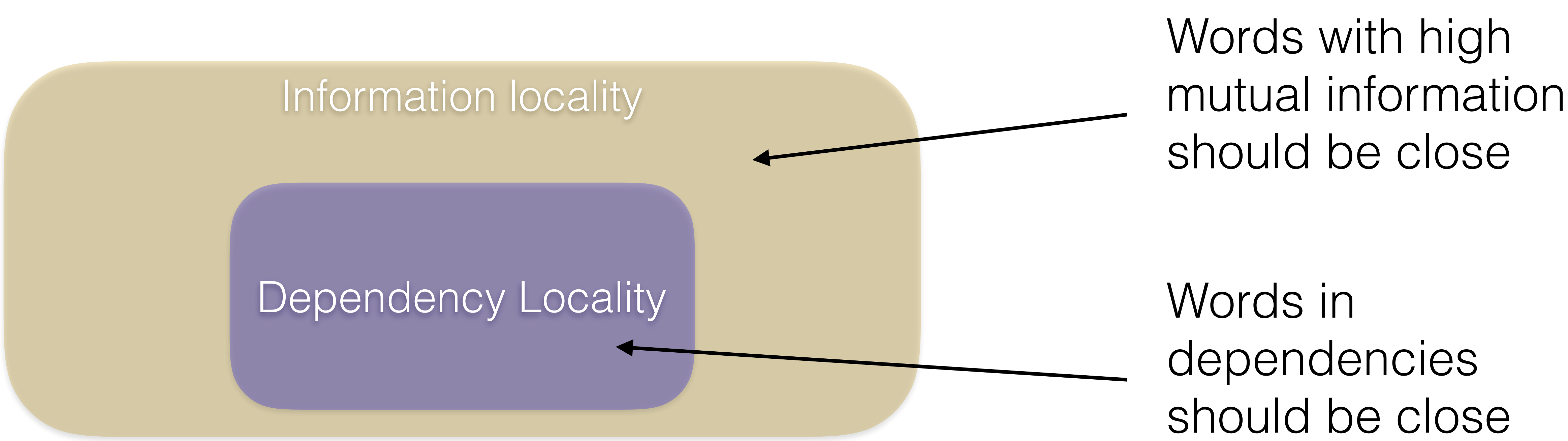

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- I measure pmi between POS tags, not wordforms, because wordform mutual information is hard to estimate for natural language (see my talk tomorrow)

Are words in dependencies with high pmi closer?

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Language	β_{MI}	p
Ancient Greek	-0.18	<.001
Arabic	-0.26	<.001
Basque	-0.22	<.001
Belarusian	-0.20	<.001
Bulgarian	-0.29	<.001
Catalan	-0.29	<.001
Church Slavonic	-0.23	<.001
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Croatian	-0.32	<.001
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Danish	-0.38	<.001
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English	-0.38	<.001
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  - Hahn et al.'s (2018) **Subjective Rational Speech Acts Model**: Involves noisy incremental memory in the computation of meaning.
  - Scontras et al.'s (2019) **Noisy composition model** explains adjective order in terms of noisy hierarchical computation of meaning.

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- Introduction
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Dependency locality happens in this term in the form of information locality

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Thanks all!

- All code is available online at http://github.com/langprocgroup/adjorder and http://github.com/langprocgroup/cliqs
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