LIAAD at SemDeep-5 Challenge

Word-in-Context (WiC)

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Sense Embeddings

Exploiting the latest Neural Language Models (NLMs) for sense-level representation learning.

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Exploiting the latest Neural Language Models (NLMs) for sense-level representation learning.

- Beat SOTA for English Word Sense Disambiguation (WSD).
- Full WordNet in NLM-space (+100K common sense concepts).
- Concept-level analysis of NLMs. [ACL 2019 – LMMS Paper]

Related Work

Related Work

[Iacobacci et al. (2016)]
[Zhong and Ng (2010)]

Bag-of-Features Classifiers

(SVM)

[Luo et al. (2018b)]
[Luo et al. (2018a)]
[Vial et al. (2018)]
[Raganato et al. (2017)]

Deep Sequence Classifiers

(BiLSTM)

[Loureiro and Jorge (2019)]
[Peters et al. (2018)]
[Melamud et al. (2016)]
[Yuan et al. (2016)]

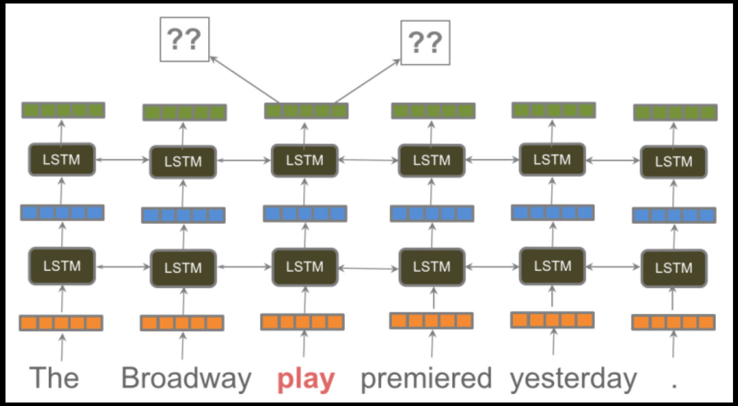
Sense-level Representations

(k-NN)
(over NLM reprs.)

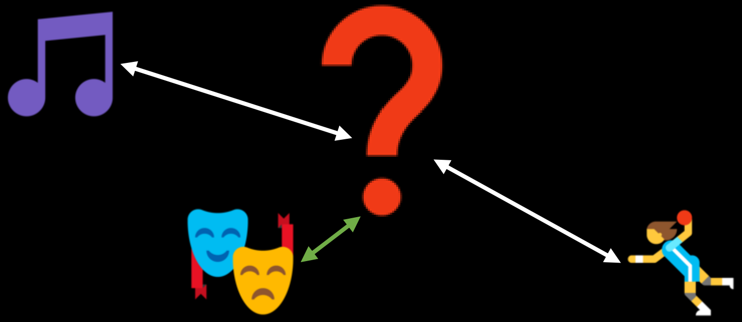
Contextual k-NN

Matching Contextual Word Embeddings:

- Produce Sense Embeddings from NLMs (averaging).
- Sense embs. can be compared with contextual embs.
- Disambiguation = Nearest Neighbour search (1-NN).
- Annotations have limited coverage (16% of WordNet).
- Promising, but early attempts.



[Ruder (2018)]



Our Approach

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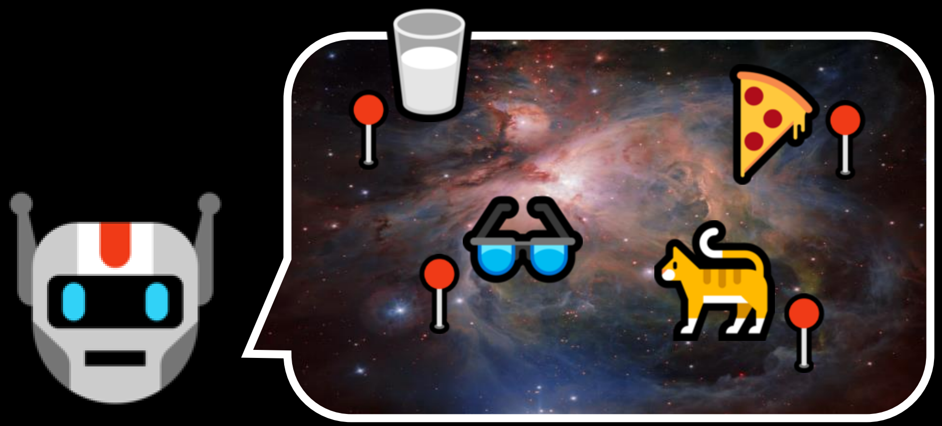

Challenges

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- Overcome very limited sense annotations (covers 16% senses).
- Infer missing senses correctly so that task performance improves.
- Rely only on sense embeddings, no lemma or POS features.*

Bootstrap →	Propagate →	Enrich →	Reinforce*
Annotated Dataset	WordNet Ontology	WordNet Glosses	Morphological Embeddings

*Covered on our ACL 2019 Paper

Bootstrapping Sense Embeddings

Can your insurance company aid you in reducing administrative costs ?

Would it be feasible to limit the menu in order to reduce feeding costs ?

Bootstrapping Sense Embeddings

insurance_company%1:14:00::
aid%2:41:00::
reduce%2:30:00::
administrative%3:01:00::
cost%1:21:00::

Can your <u>insurance company</u> <u>aid</u> you in <u>reducing</u> <u>administrative</u> <u>costs</u> ?

Would it be <u>feasible</u> to <u>limit</u> the <u>menu</u> in order to <u>reduce</u> <u>feeding</u> <u>costs</u> ?

feasible%5:00:00:possible:00
limit%2:30:00::
menu%1:10:00::
reduce%2:30:00::
feeding%1:04:01::
cost%1:21:00::

Bootstrapping Sense Embeddings

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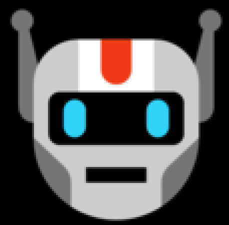

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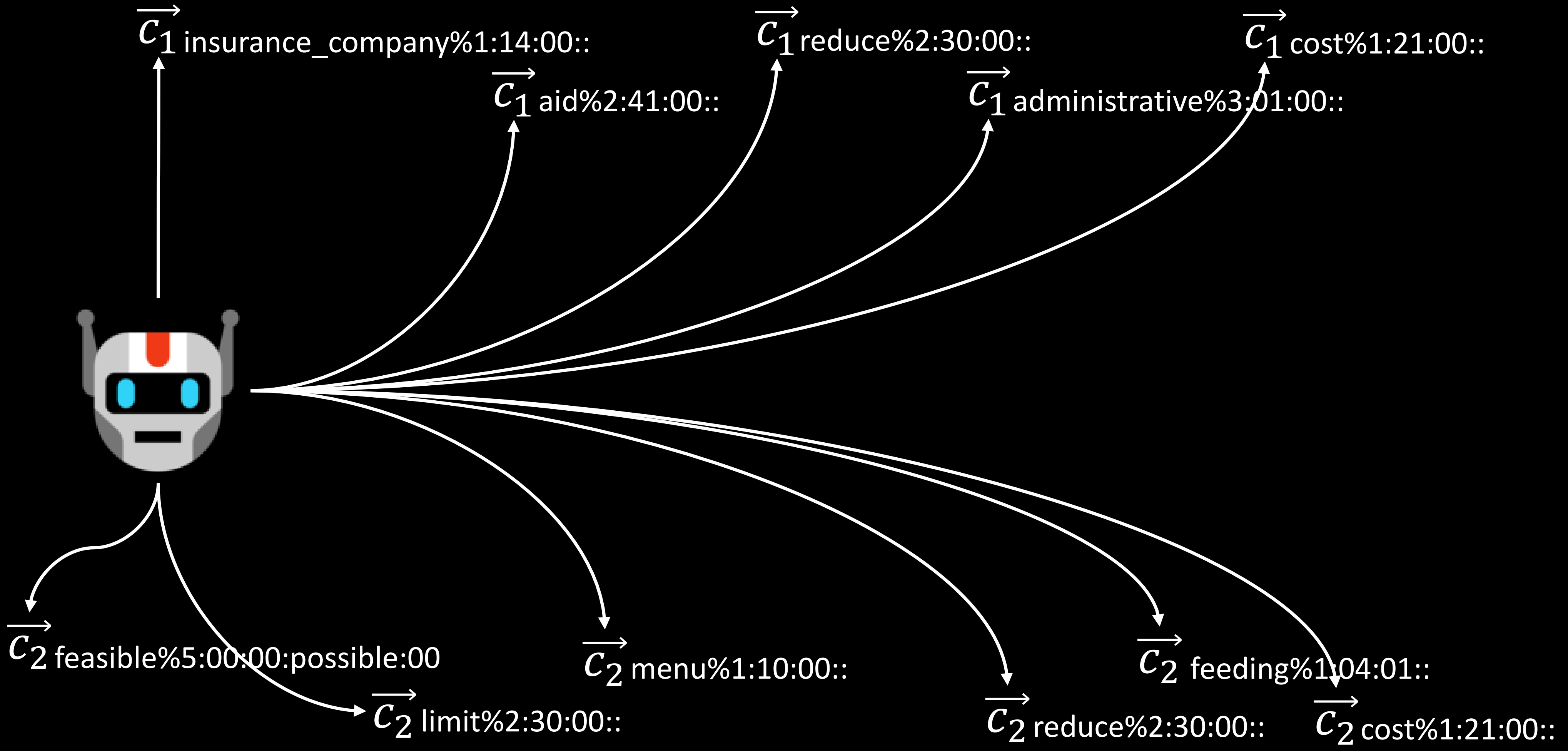

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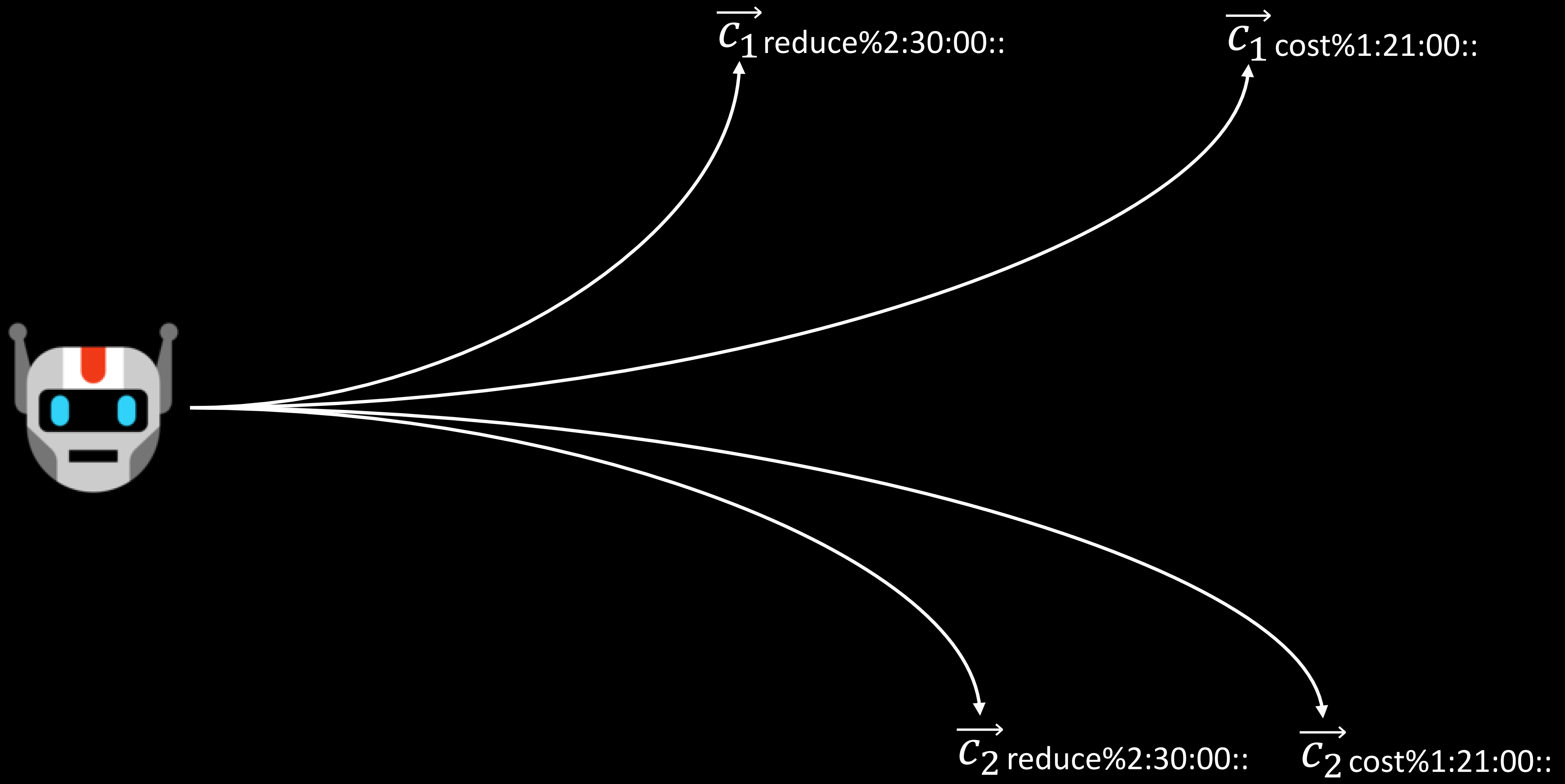

Bootstrapping Sense Embeddings

$$\vec{v}_{\text{reduce\%2:30:00::}} = \frac{\vec{c_1}_{\text{reduce\%2:30:00::}} + \vec{c_2}_{\text{reduce\%2:30:00::}} + \ldots + \vec{c_n}_{\text{reduce\%2:30:00::}}}{n}$$

$$\vec{v}_{\text{cost\%1:21:00::}} = \frac{\vec{c_1}_{\text{cost\%1:21:00::}} + \vec{c_2}_{\text{cost\%1:21:00::}} + \ldots + \vec{c_n}_{\text{cost\%1:21:00::}}}{n}$$

Bootstrapping Sense Embeddings

$$\vec{v}_{\text{reduce\%2:30:00::}} = \frac{\vec{c_1}_{\text{reduce\%2:30:00::}} + \vec{c_2}_{\text{reduce\%2:30:00::}} + \ldots + \vec{c_n}_{\text{reduce\%2:30:00::}}}{n}$$

$$\vec{v}_{\text{cost\%1:21:00::}} = \frac{\vec{c_1}_{\text{cost\%1:21:00::}} + \vec{c_2}_{\text{cost\%1:21:00::}} + \ldots + \vec{c_n}_{\text{cost\%1:21:00::}}}{n}$$

Outcome: 33,360 sense embeddings (16% coverage)

Propagating Sense Embeddings

WordNet’s units, synsets, represent concepts at different levels.

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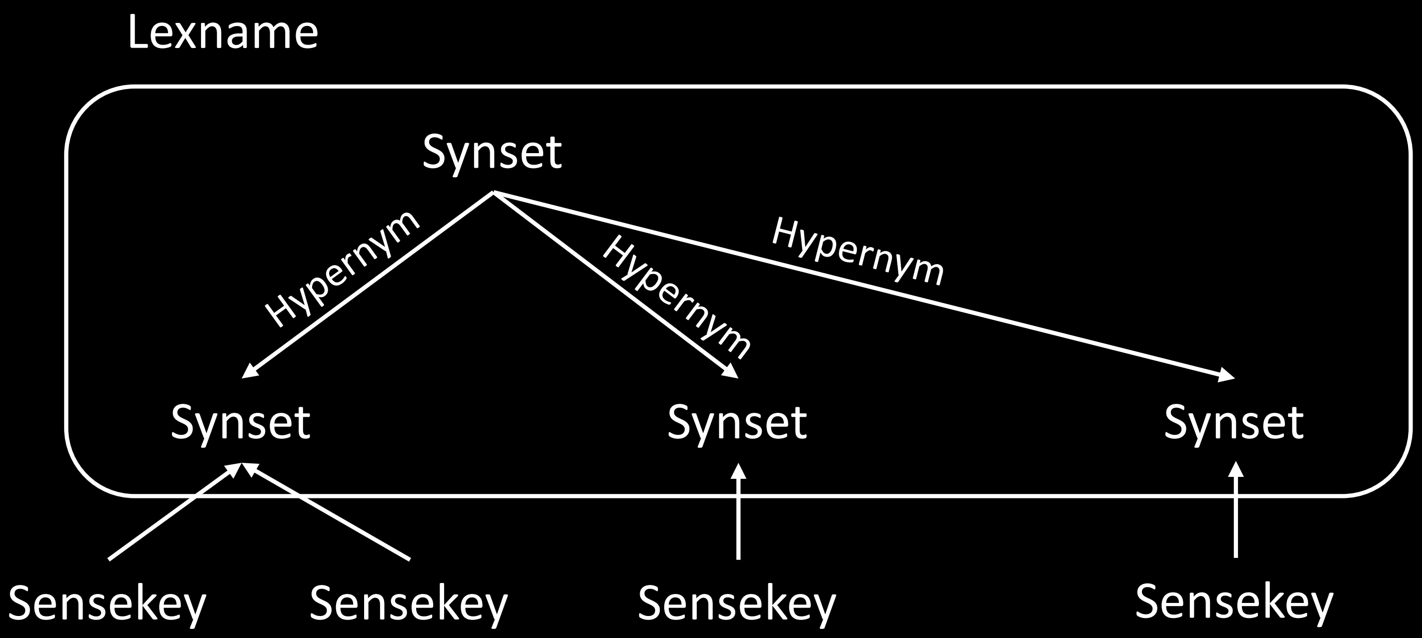

Propagating Sense Embeddings

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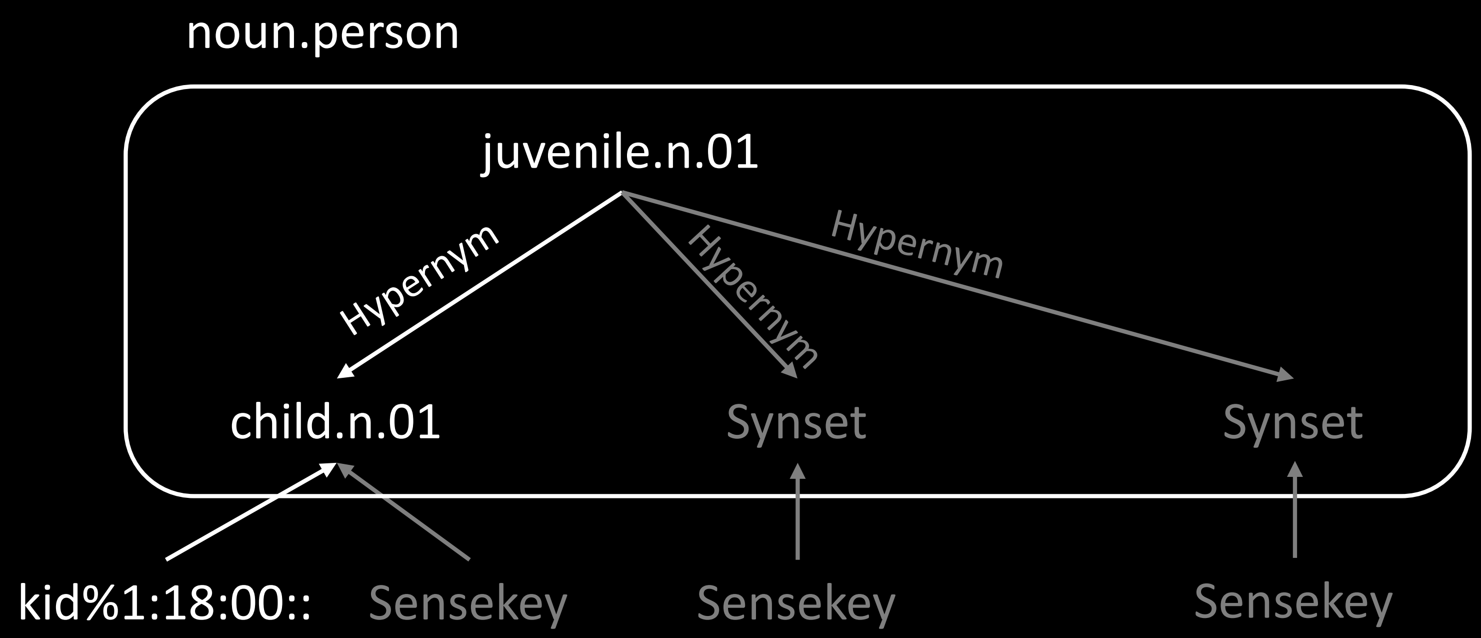


Propagating Sense Embeddings

burger%1:13:00::

hotdog%1:18:00::

hamburger%1:13:01::

sandwich%1:13:00::

wrap%1:13:00::

potato_chip%1:13:00::

Propagating Sense Embeddings

burger%1:13:00::

hotdog%1:18:00::

hamburger%1:13:01::

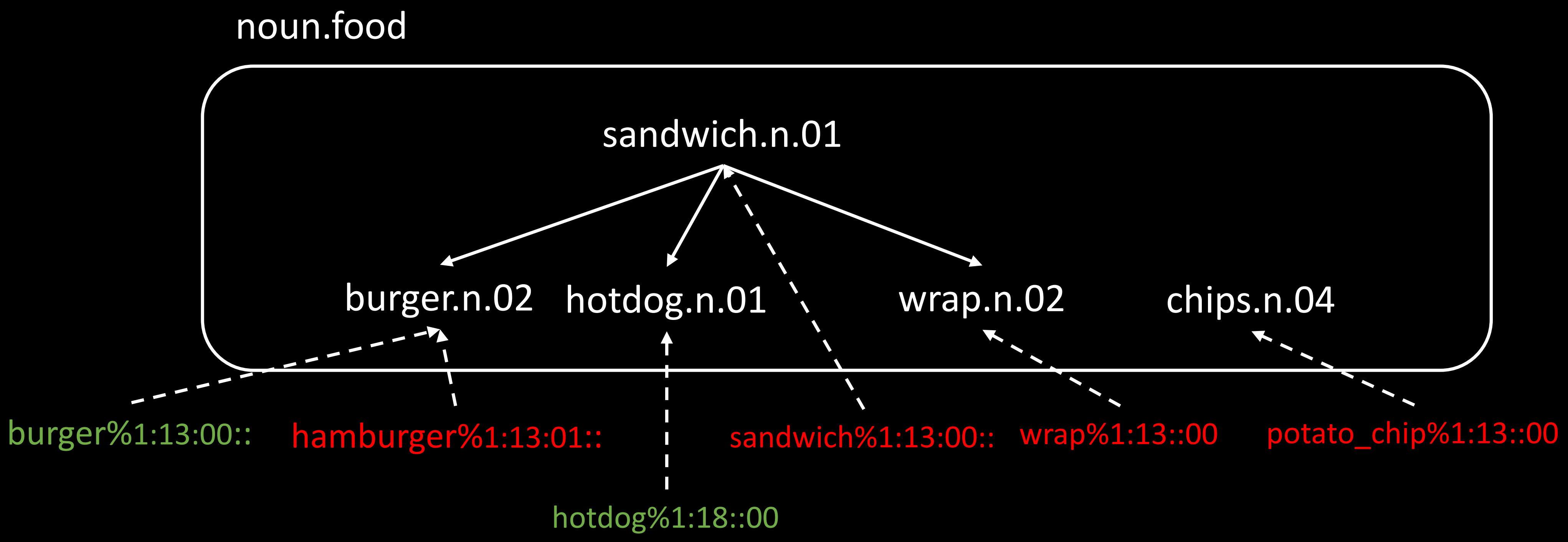
sandwich%1:13:00::

wrap%1:13:00::

potato_chip%1:13:00::

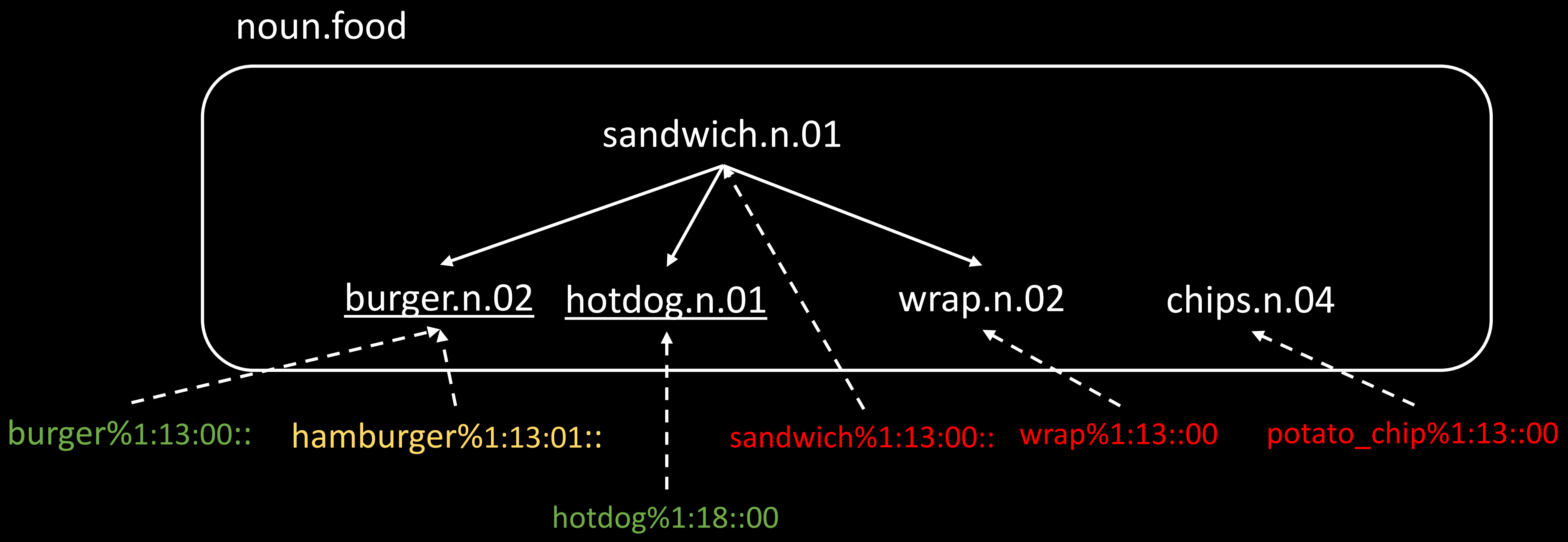
Propagating Sense Embeddings

Retrieve Synsets, Relations and Categories



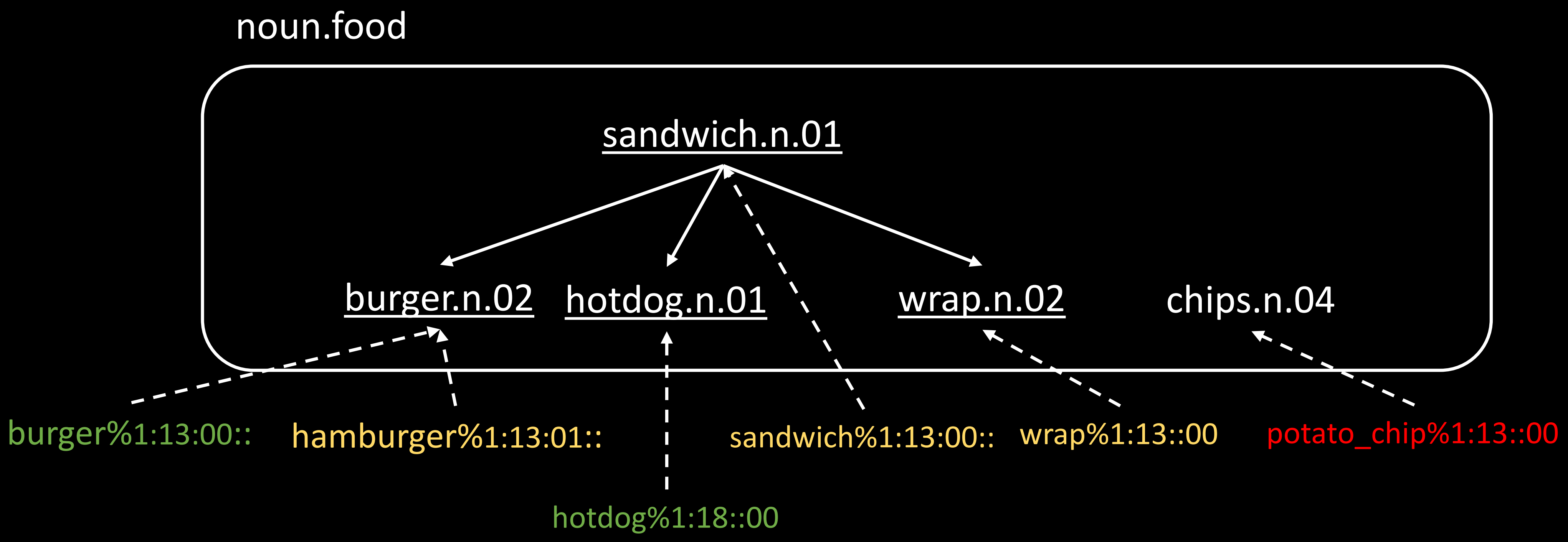
Propagating Sense Embeddings

1st stage: Synset Embeddings



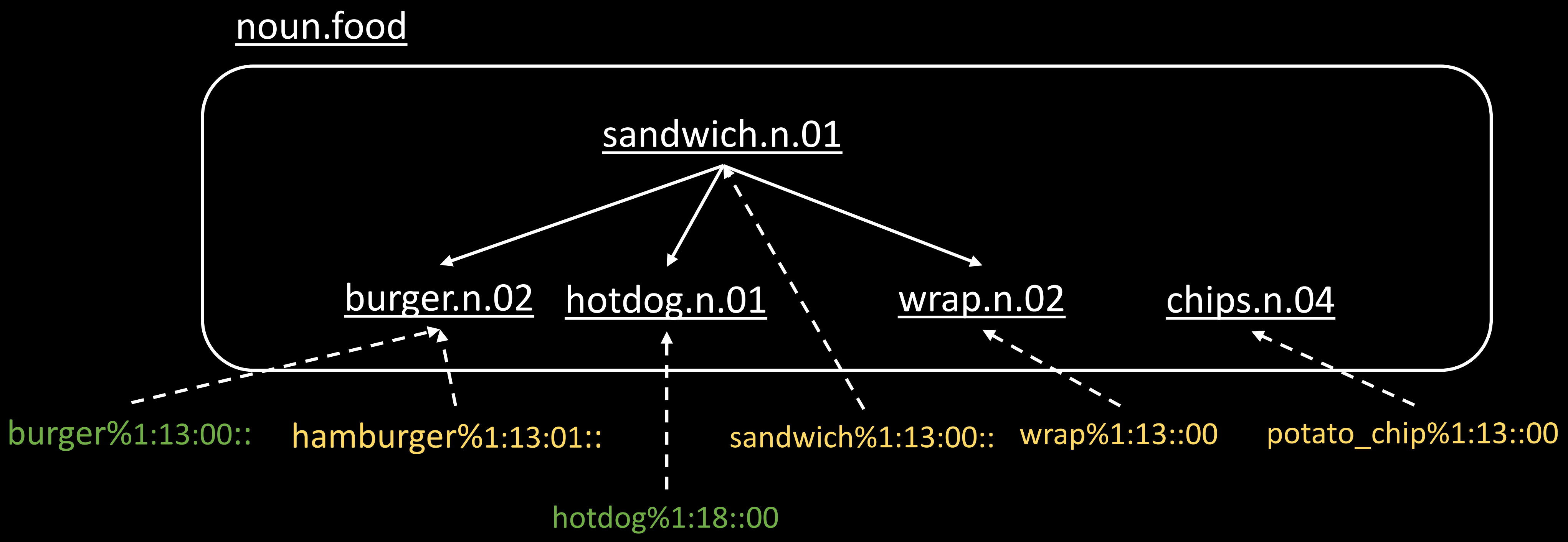
Propagating Sense Embeddings

2^{nd} Stage: Hypernym Embeddings (ind. Synsets)



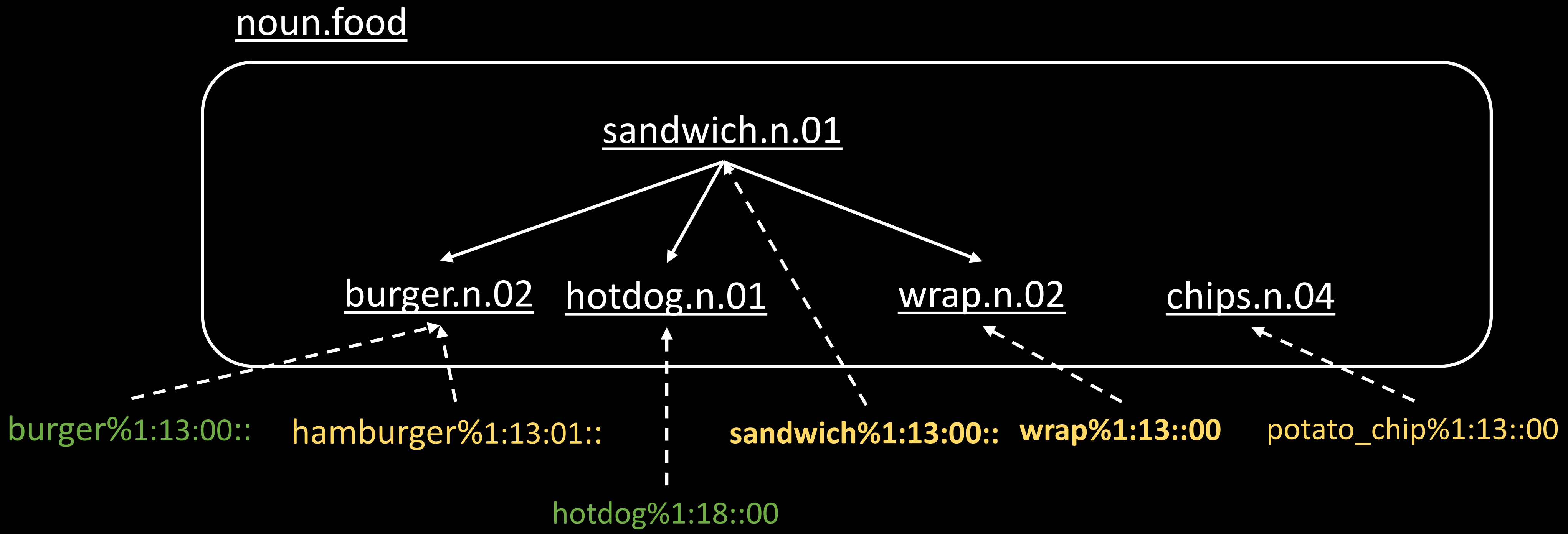
Propagating Sense Embeddings

3rd Stage: Lexname Embeddings



Propagating Sense Embeddings

But  !=  …



Enriching Sense Embeddings

Leverage Synset Definitions and Lemmas for Differentiation

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sandwich:%1:13:00:: (sandwich.n.01)

Definition: two (or more) slices of bread with a filling between them

Lemmas: sandwich

wrap:%1:13:00:: (wrap.n.02)

Definition: a sandwich in which the filling is rolled up in a soft tortilla

Lemmas: wrap, tortilla

Enriching Sense Embeddings

Compose a new context

sandwich:%1:13:00:: (sandwich.n.01)

sandwich - two (or more) slices of bread with a filling between them

wrap:%1:13:00:: (wrap.n.02)

wrap, tortilla - a sandwich in which the filling is rolled up in a soft tortilla

Enriching Sense Embeddings

Make the context specific to sensekey (repeat lemma)

sandwich:%1:13:00::

sandwich - sandwich - two (or more) slices of bread with a filling between them

wrap%1:13:00::

wrap - wrap, tortilla - a sandwich in which the filling is rolled up in a soft tortilla

Enriching Sense Embeddings

Make the context specific to sensekey (repeat lemma)

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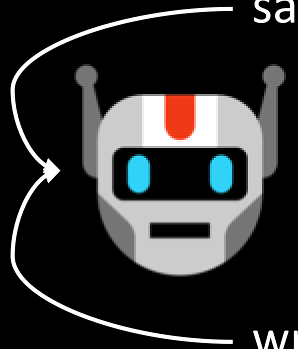


wrap%1:13:00::

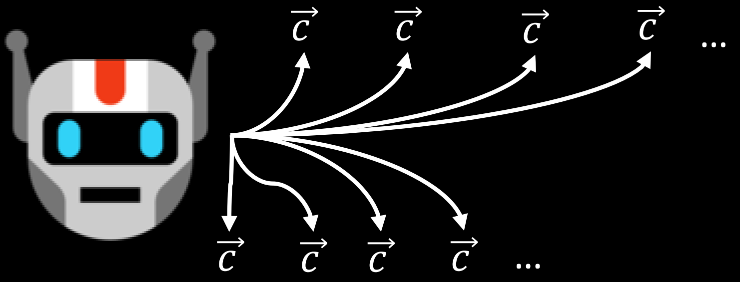
wrap - wrap, tortilla - a sandwich in which the filling is rolled up in a soft tortilla

Enriching Sense Embeddings

Obtain contextual embeddings for every token

sandwich:%1:13:00::

sandwich - sandwich - two (or more) slices of bread with a filling between them

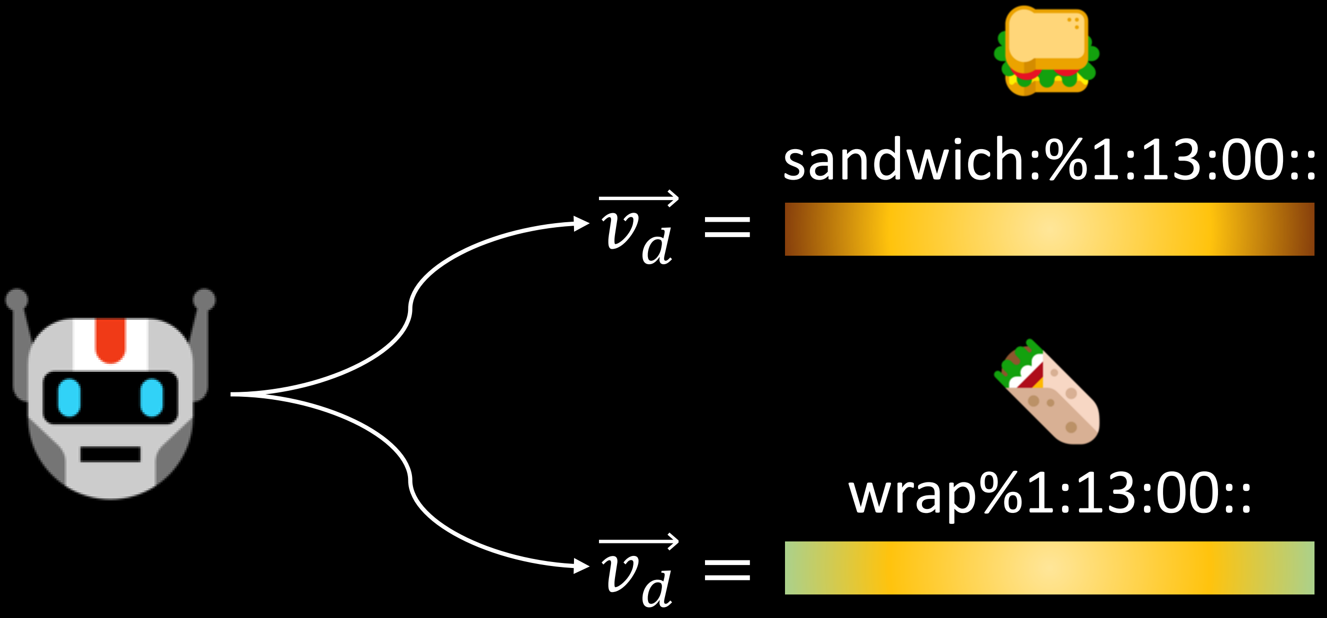


wrap%1:13:00::

wrap – wrap, tortilla - a sandwich in which the filling is rolled up in a soft tortilla

Enriching Sense Embeddings

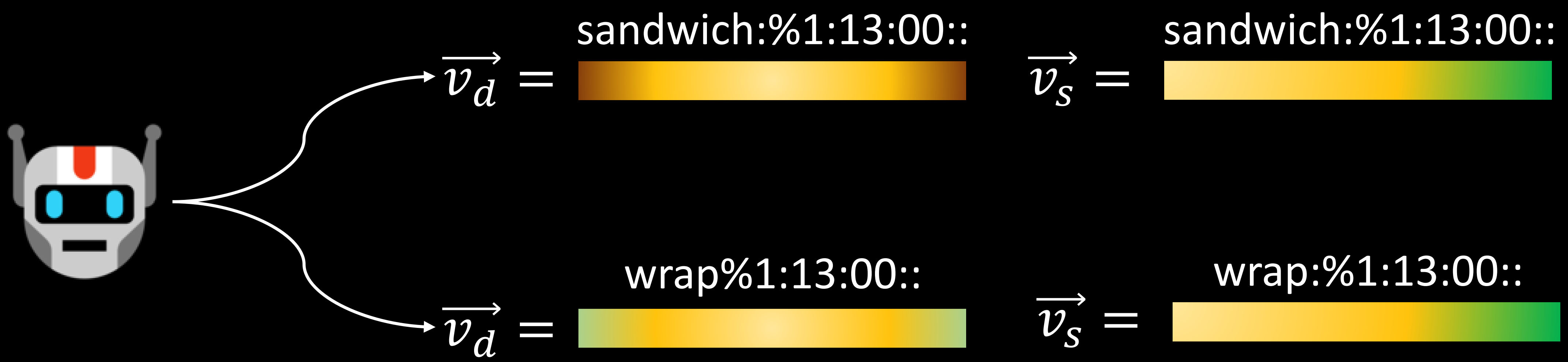
Sentence Embedding from avg. of Contextual Embeddings



$d = 1024$

Enriching Sense Embeddings

Merge Sentence Embedding with previous Sense Embedding



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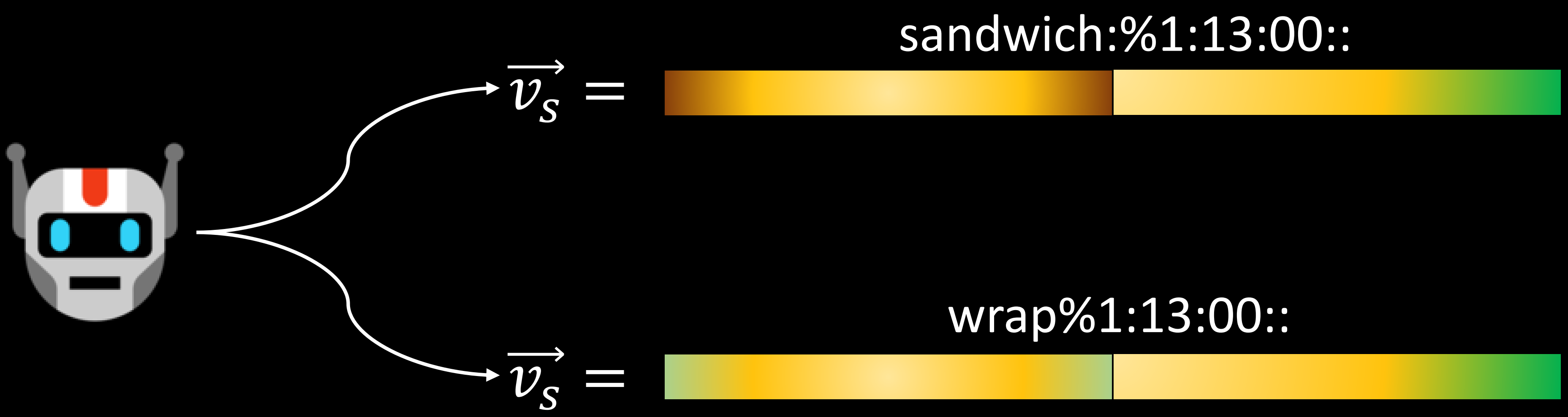


$d = 2048$

Matching Sense Embeddings

The glasses are in the cupboard.

Matching Sense Embeddings

 $\longrightarrow \vec{c}$

The <u>glasses</u> are in the cupboard.

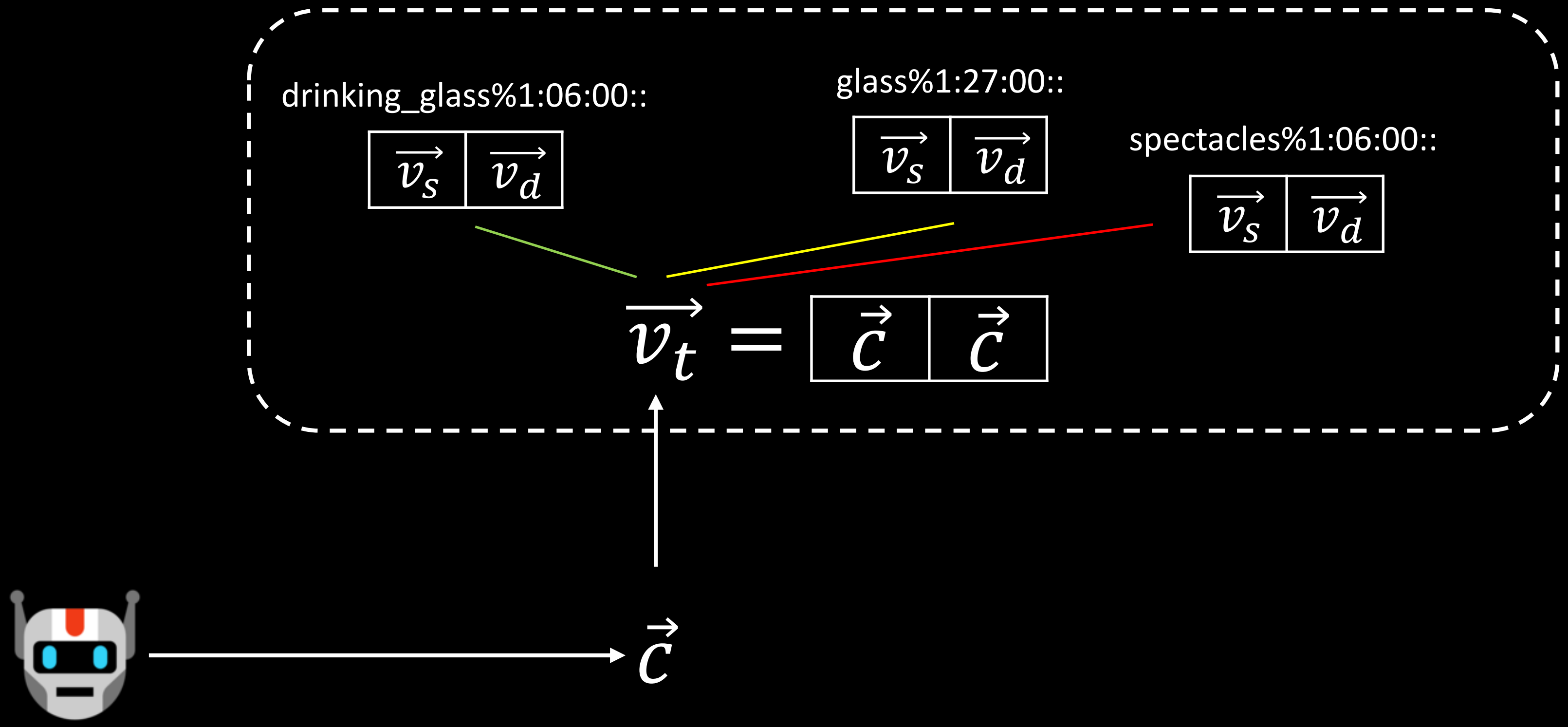
Matching Sense Embeddings

$$\overrightarrow{v_t} = \boxed{\vec{c}}\boxed{\vec{c}}$$

$\vec{c}$

The <u>glasses</u> are in the cupboard.

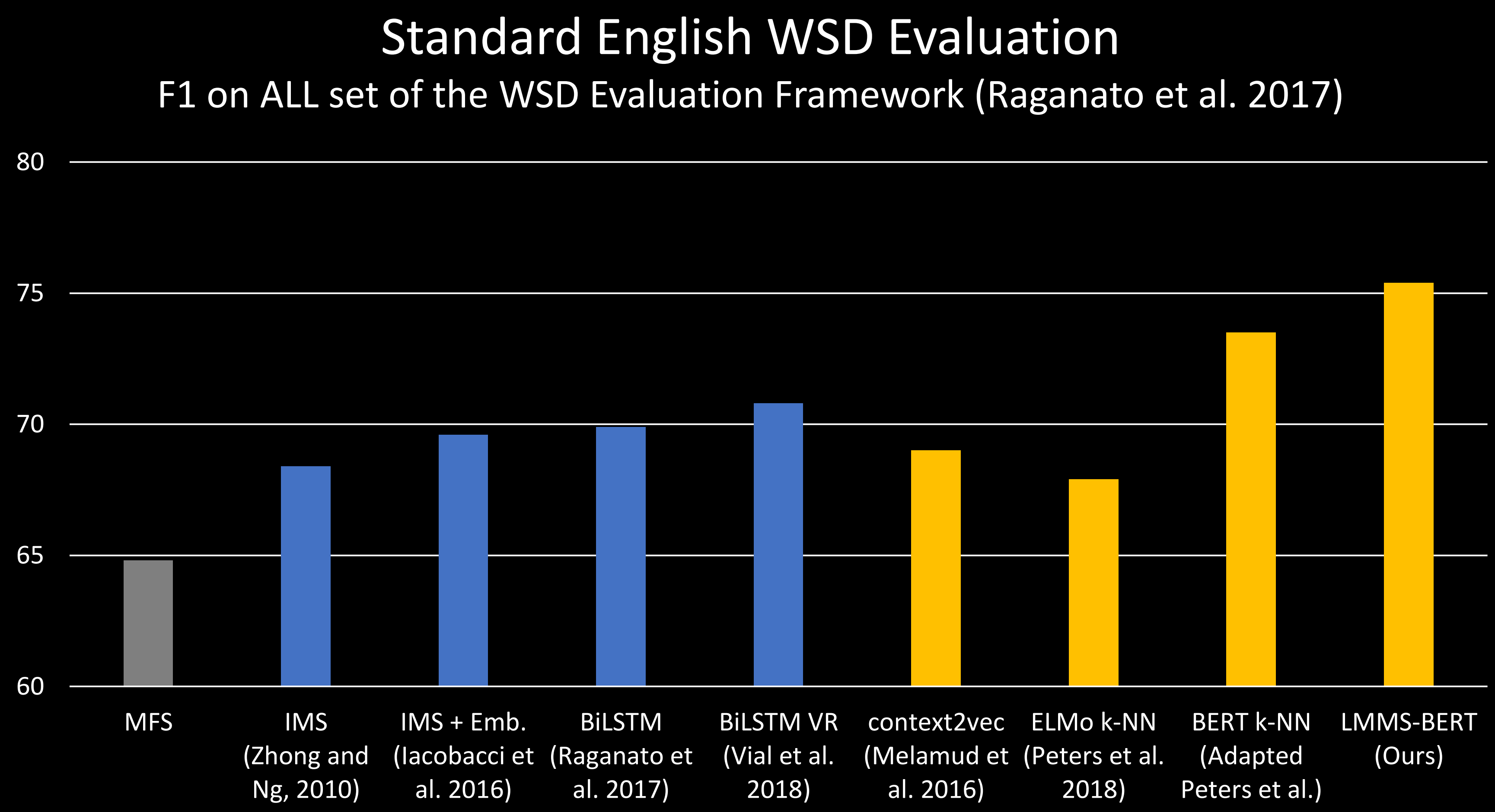
Matching Sense Embeddings



The <u>glasses</u> are in the cupboard.

WSD Results

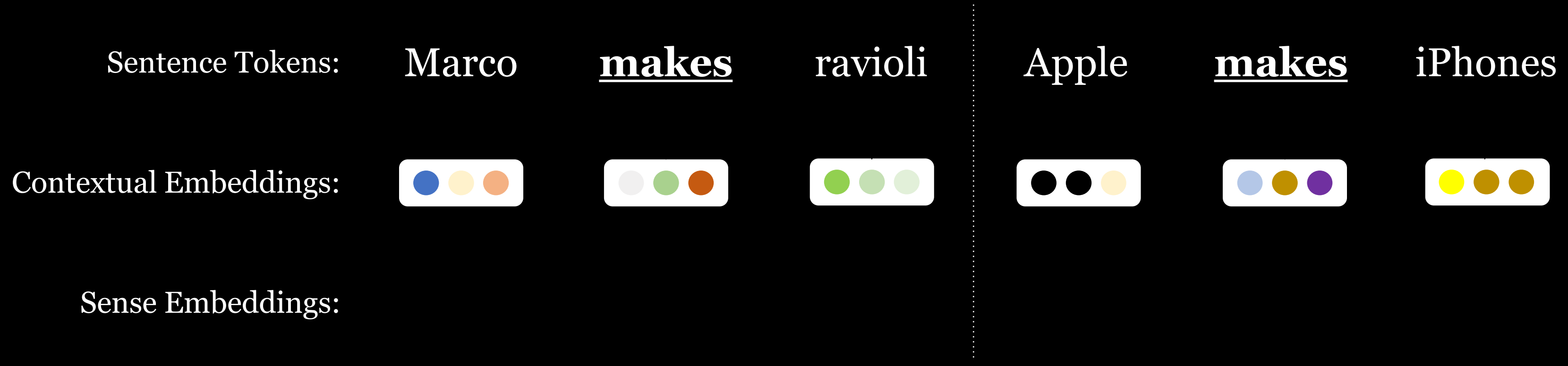
WSD Performance



Classifying Embedding Similarities

Sentence Tokens:	Marco	**makes**	ravioli	Apple	**makes**	iPhones
Contextual Embeddings:						
Sense Embeddings:						

Classifying Embedding Similarities



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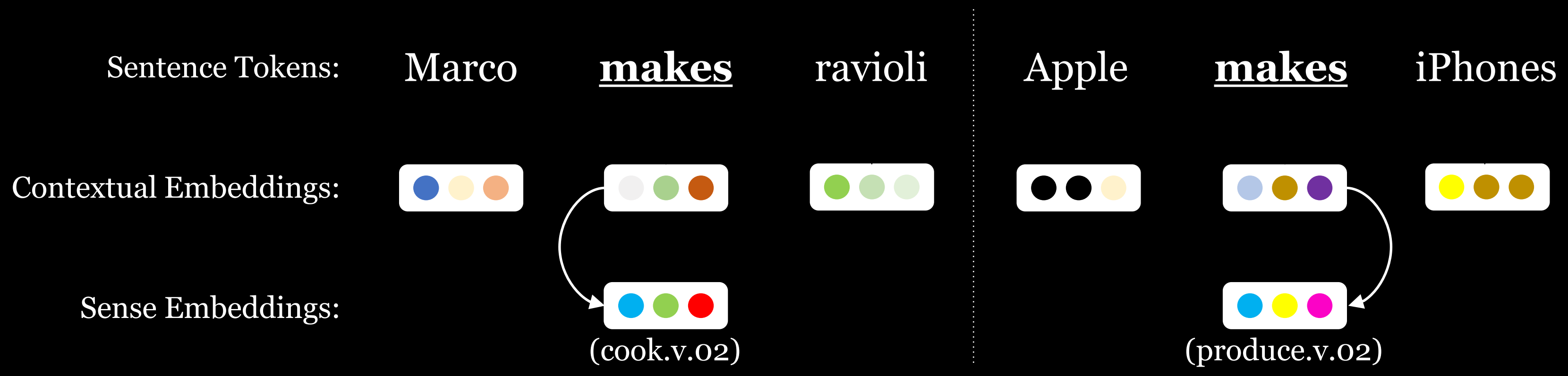
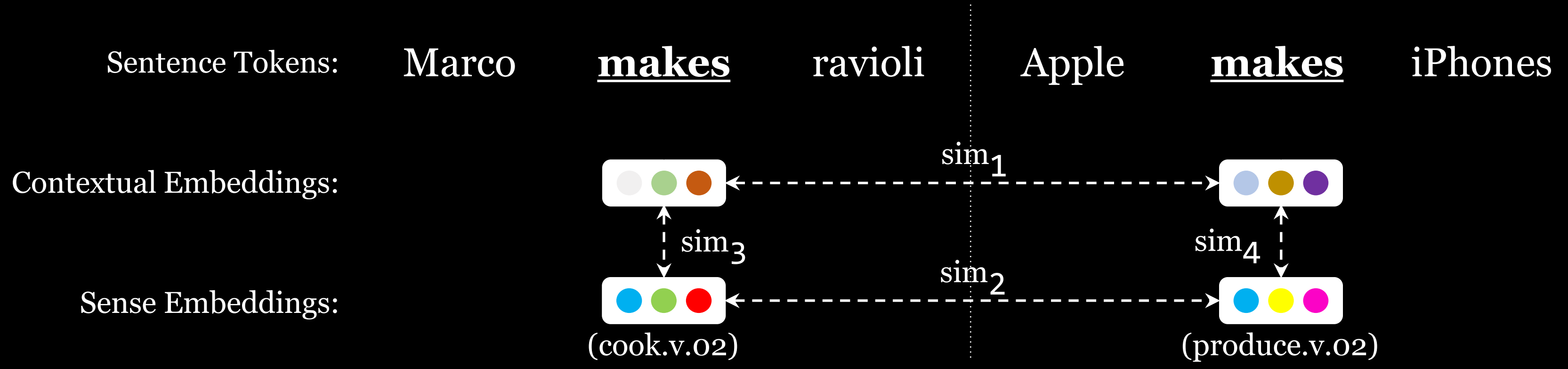


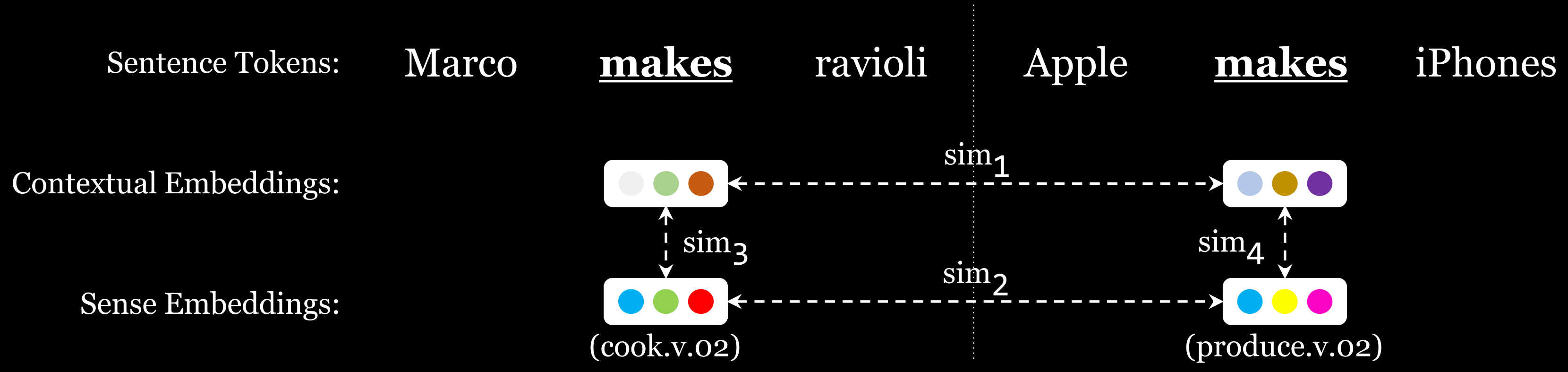
Classifying Embedding Similarities

Sentence Tokens:	Marco	**makes**	ravioli	Apple	**makes**	iPhones
Contextual Embeddings:						
Sense Embeddings:		(cook.v.02)			(produce.v.02)	

Classifying Embedding Similarities

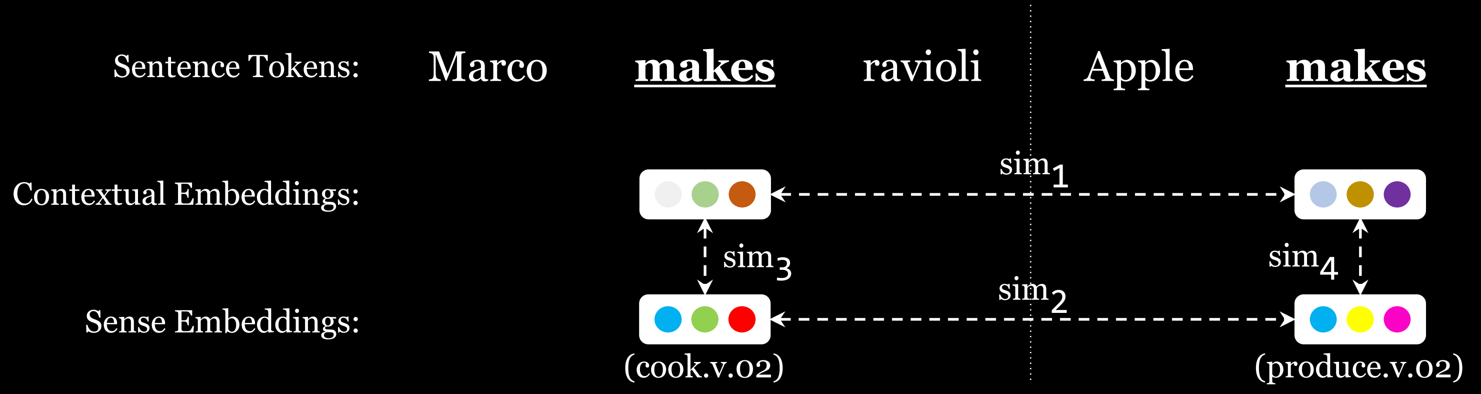


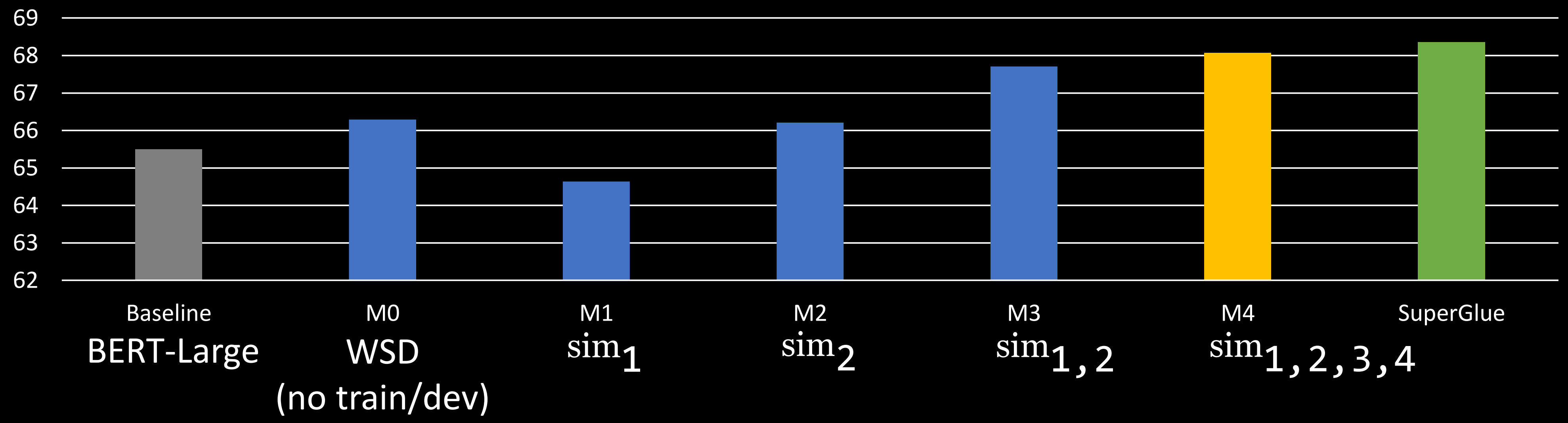
Classifying Embedding Similarities



Now, we classify different similarity combinations using Binary Logistic Regression

Classifying Embedding Similarities





Conclusions

- Systems designed for WSD, without being trained for the WiC task, can perform competitively.
- Sense Embeddings can still benefit from information captured by contextual embeddings, as shown by similarities classifier.
- In future work, progress on the WiC task could lead to better semi-supervised annotations for WSD.

Thanks

Code and Sense Embeddings:
github.com/danlou/LMMS

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