Language Modelling Makes Sense

Propagating Representations through WordNet for Full-Coverage Word Sense Disambiguation

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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.

Related Work

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[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)

[Peters et al. (2018)]
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Sense-level Representations

(k-NN)
(over NLM reprs.)

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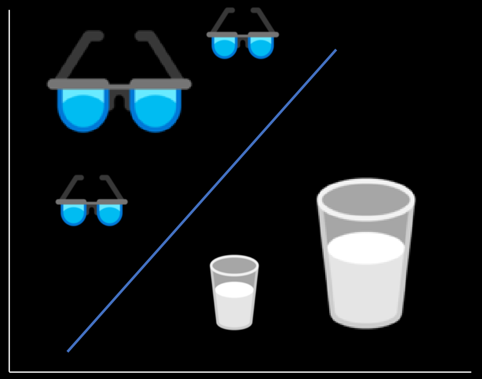
Bag-of-Features Classifiers

It Makes Sense (IMS) **[Zhong and Ng (2010)] :**

- POS tags, surrounding words, local collocations.
- SVM for each word type in training.
- Fallback: Most Frequent Sense (MFS).
- Improved with word embedding features. [Iacobacci et al. (2016)]
- Still competitive (!)

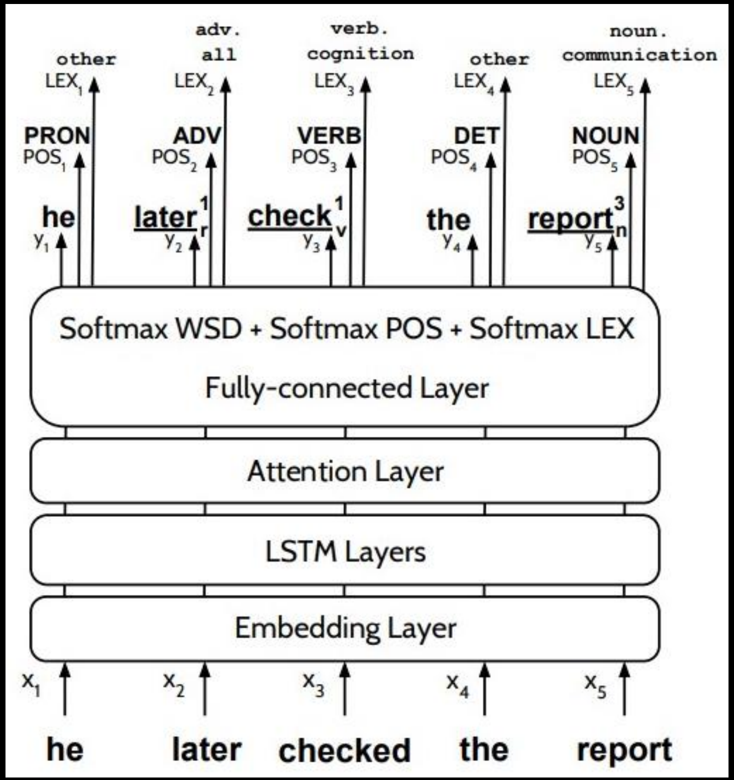


“glasses”

Deep Sequence Classifiers

Bi-directional LSTMs (BiLSTMs):

- Better with:
  - Attention (as everything else).
  - Auxiliary losses. (POS, lemmas, lexnames) [Raganato et al. (2017)]
  - Glosses, via co-attention mechanisms. [Luo et al. (2018)]
- Still must fallback on MFS.
- Not that much better than bag-of-features…

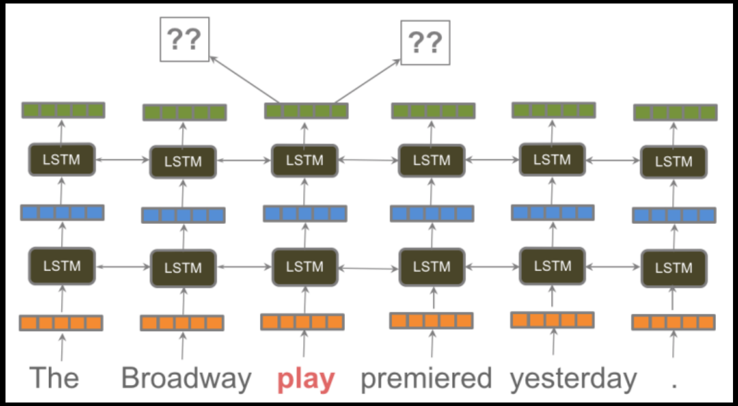


[Raganato et al. (2017)]

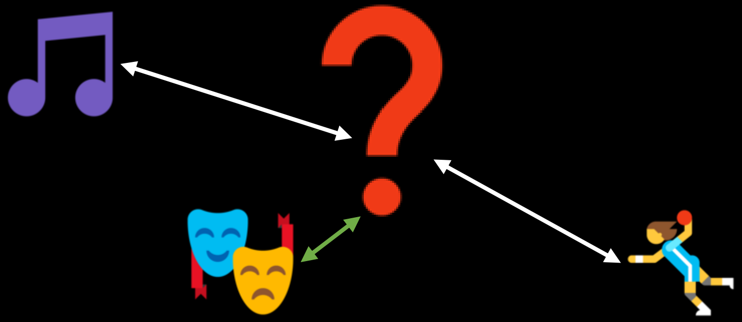
Contextual k-NN

Matching Contextual Word Embeddings:

- Produce Sense Embeddings from NLMs (averaging).
- Sense embs. can be compared with contextual embs.
- Disambiguation = Nearest Neighbour search (1-NN).
- Sense embs. limited to annotations. MFS required.
- Promising, but early attempts.



[Ruder (2018)]



Our Approach

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- Expand the k-NN approach to full-coverage of WordNet.

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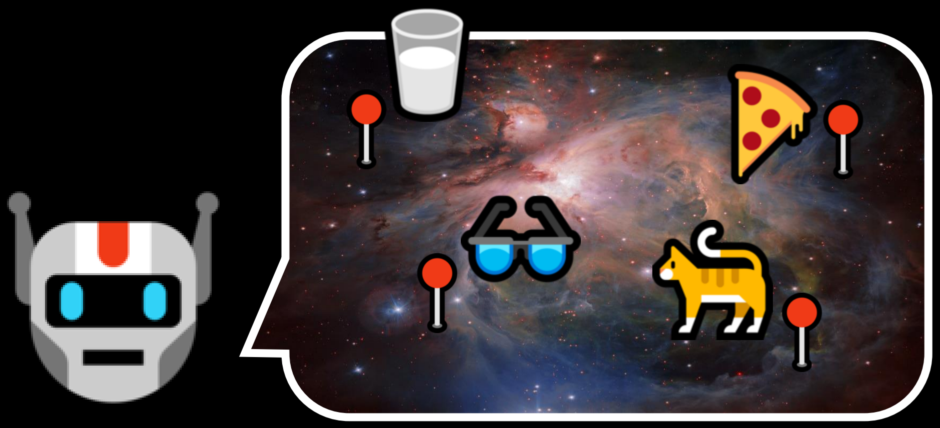

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Bootstrap → Propagate → Enrich → Reinforce

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

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:: reduce%2:30:00:: cost%1:21:00::

aid%2:41:00:: administrative%3:01:00::

Can your insurance company aid you in reducing administrative costs ?

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

feasible%5:00:00:possible:00 menu%1:10:00:: feeding%1:04:01::

limit%2:30:00:: reduce%2:30:00:: cost%1:21:00::

Bootstrapping Sense Embeddings

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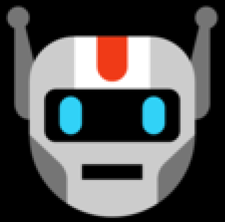

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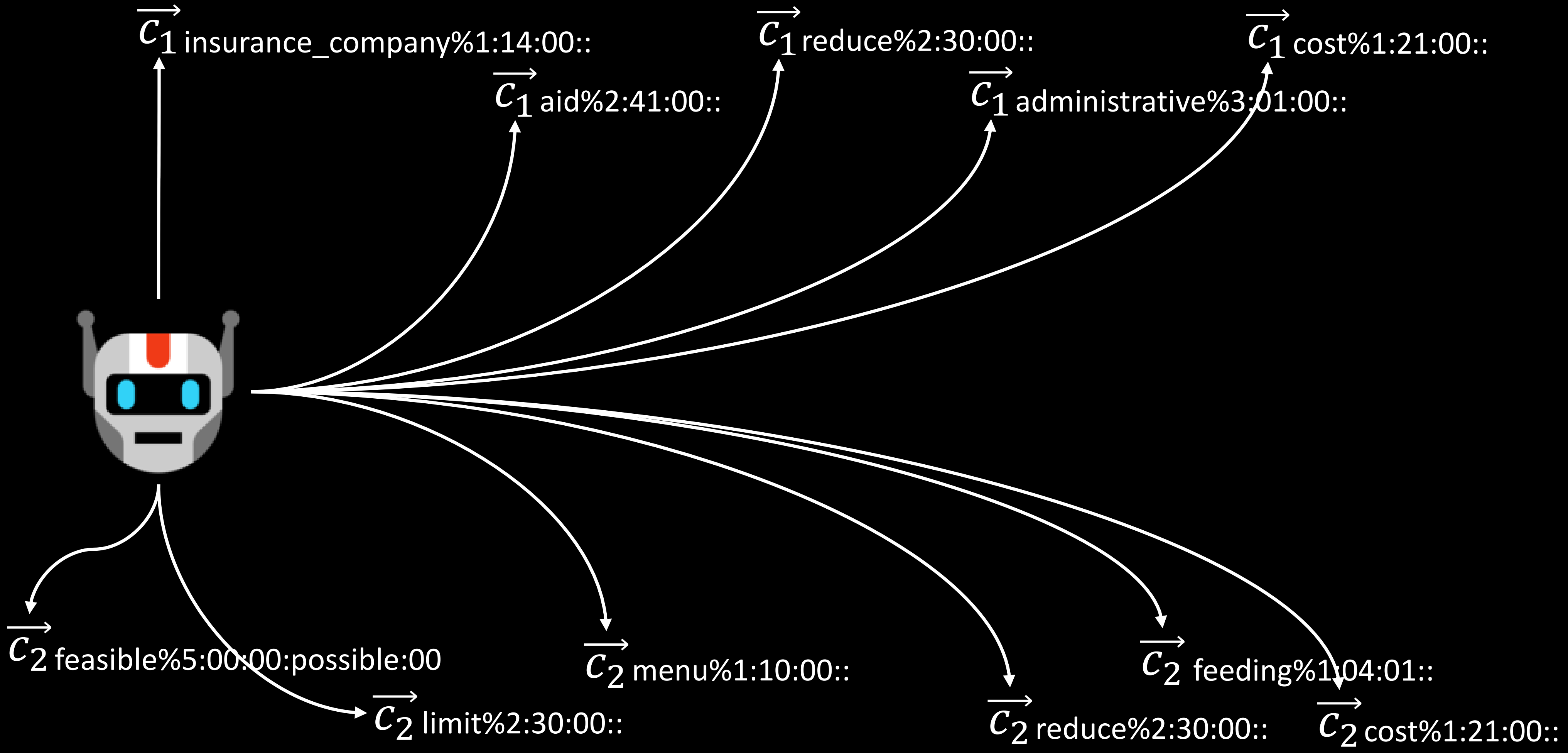

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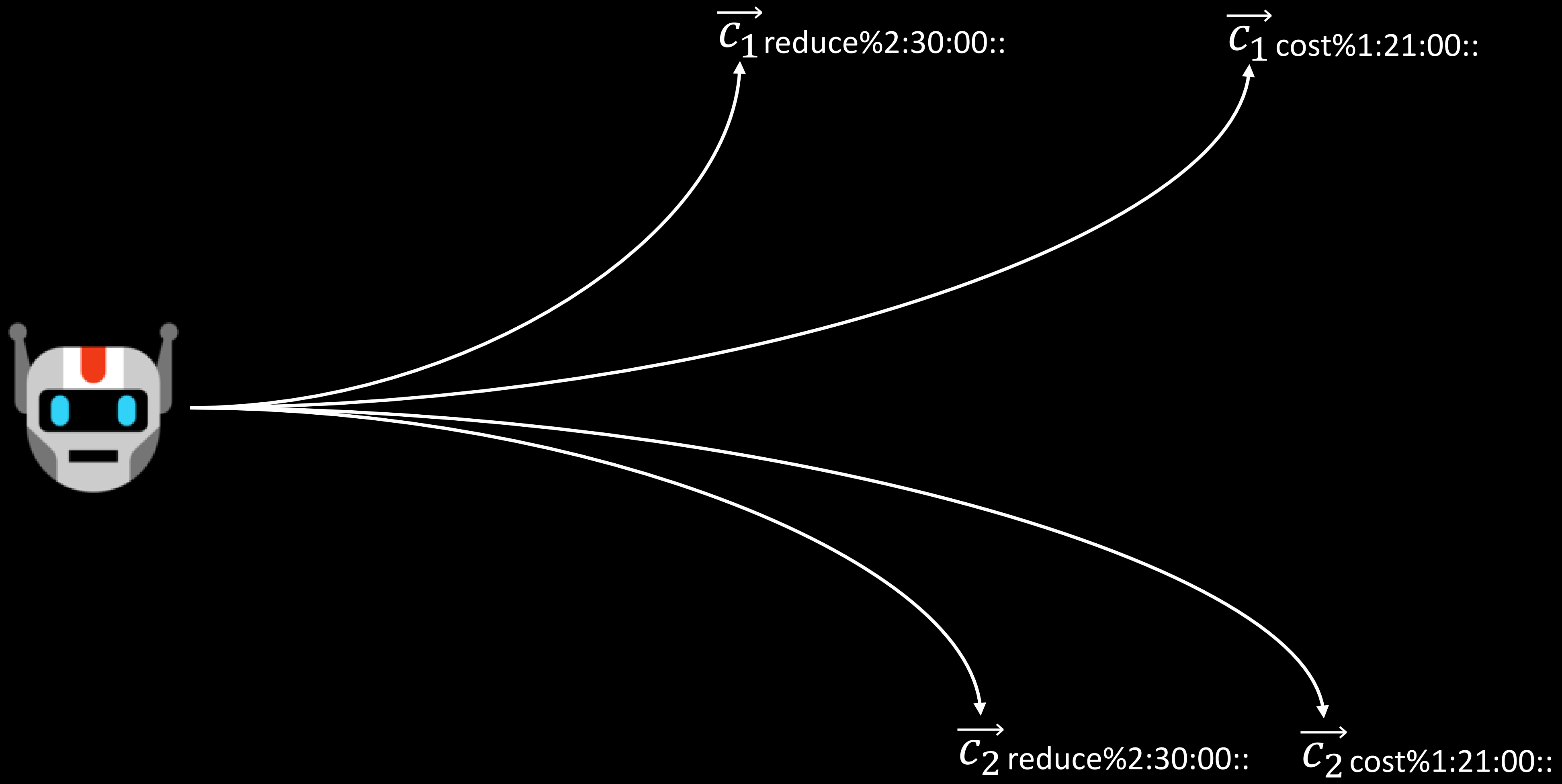

Bootstrapping Sense Embeddings

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

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

Bootstrapping Sense Embeddings

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

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

Propagating Sense Embeddings

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

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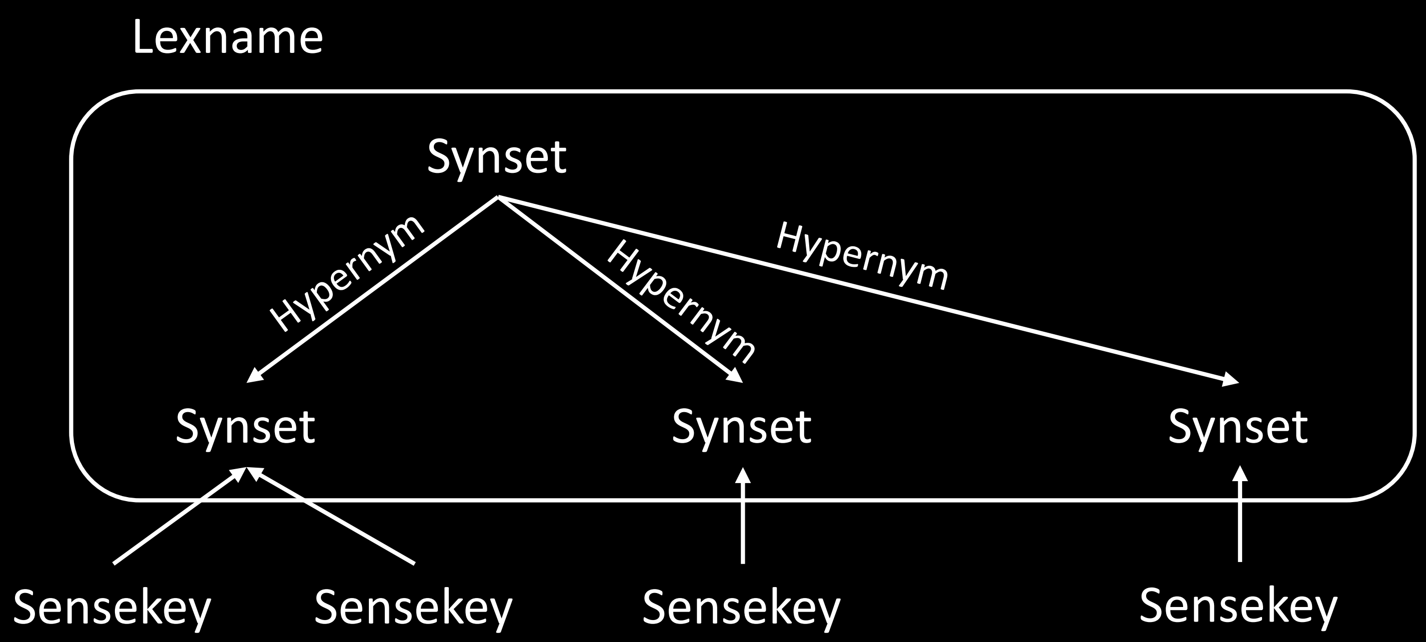

Propagating Sense Embeddings

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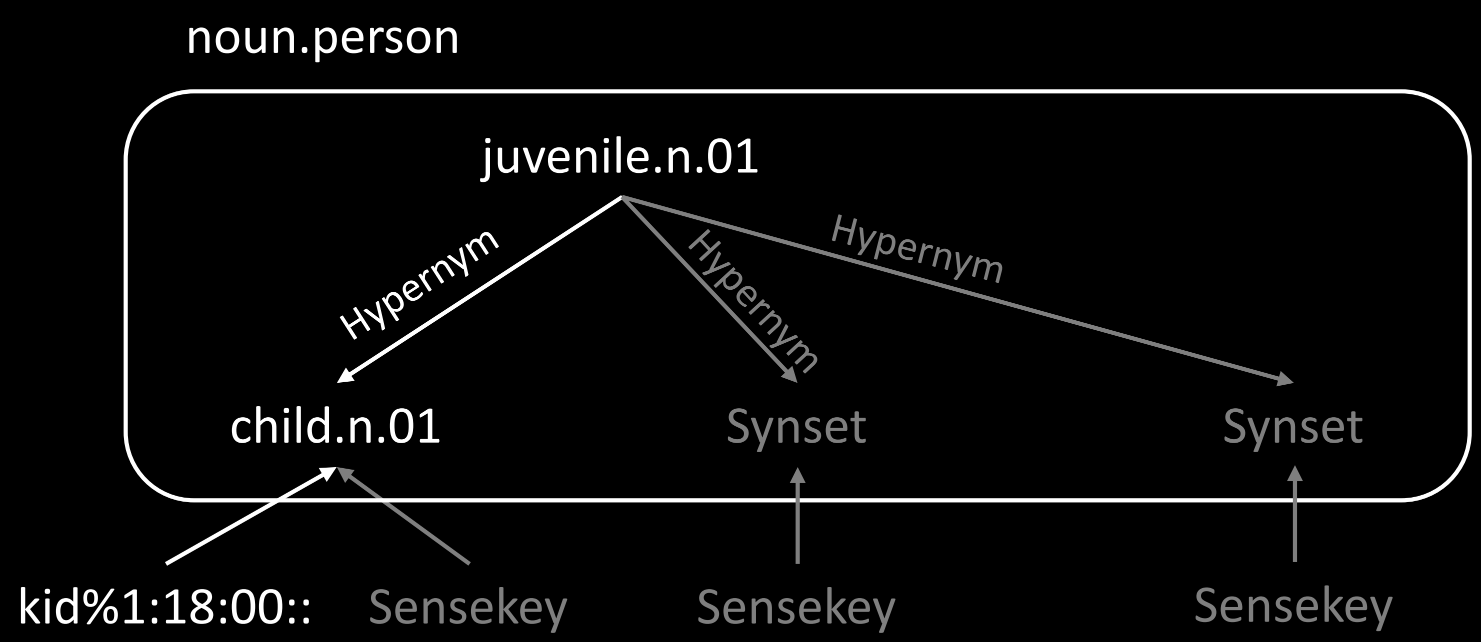


Propagating Sense Embeddings

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::

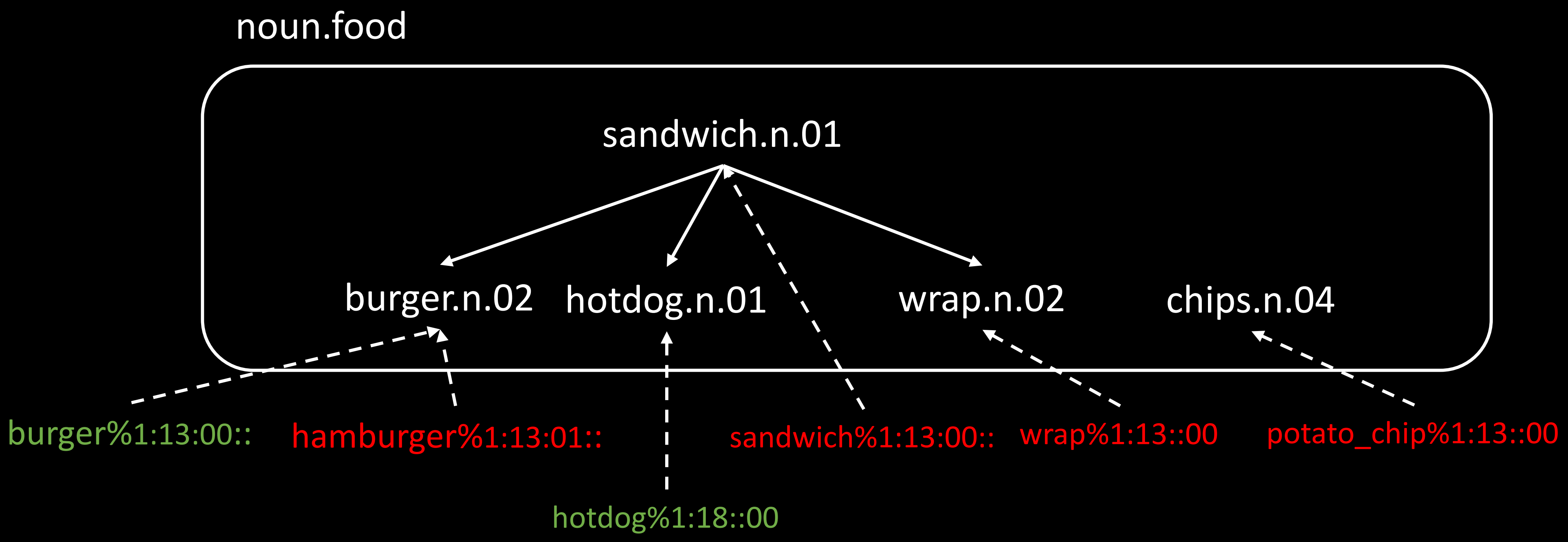
sandwich%1:13:00::

wrap%1:13:00::

potato_chip%1:13:00::

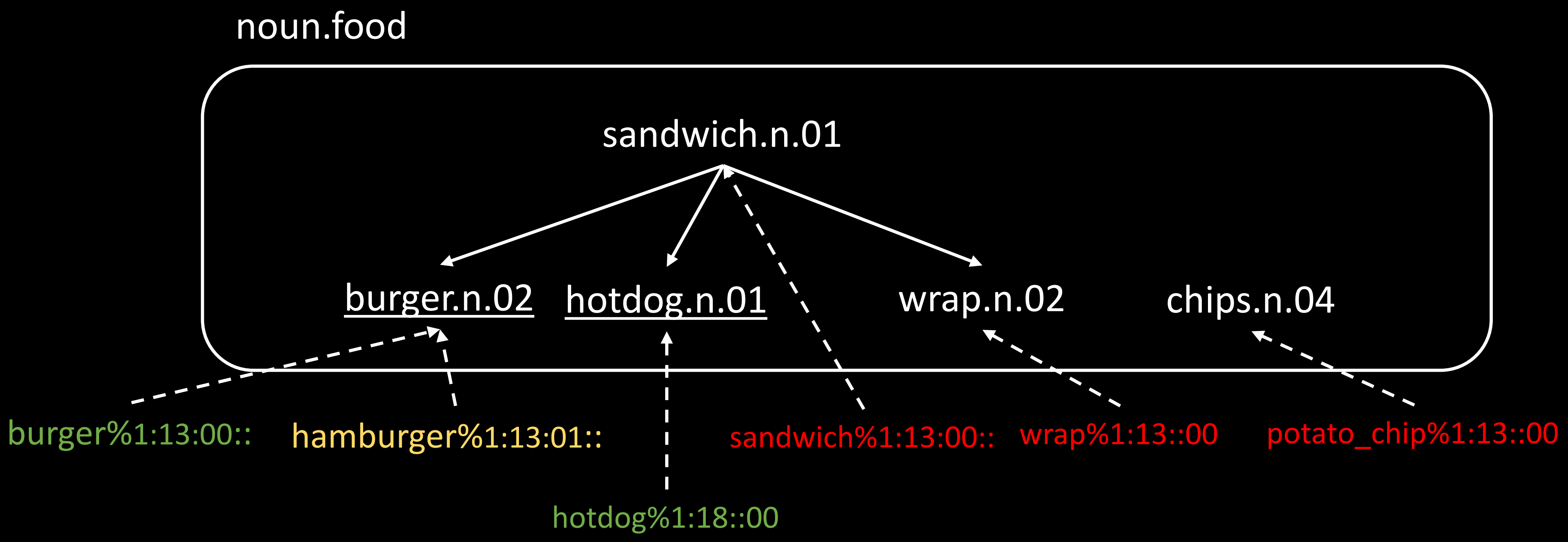
Propagating Sense Embeddings

Retrieve Synsets, Relations and Categories



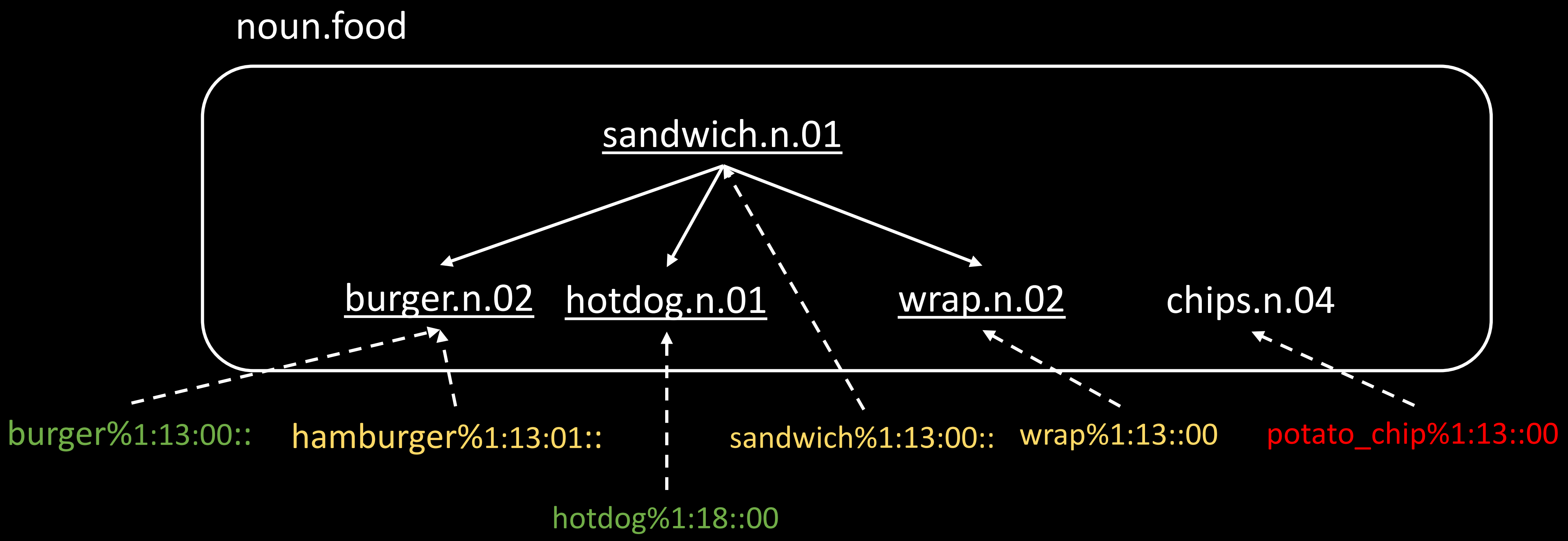
Propagating Sense Embeddings

1st stage: Synset Embeddings



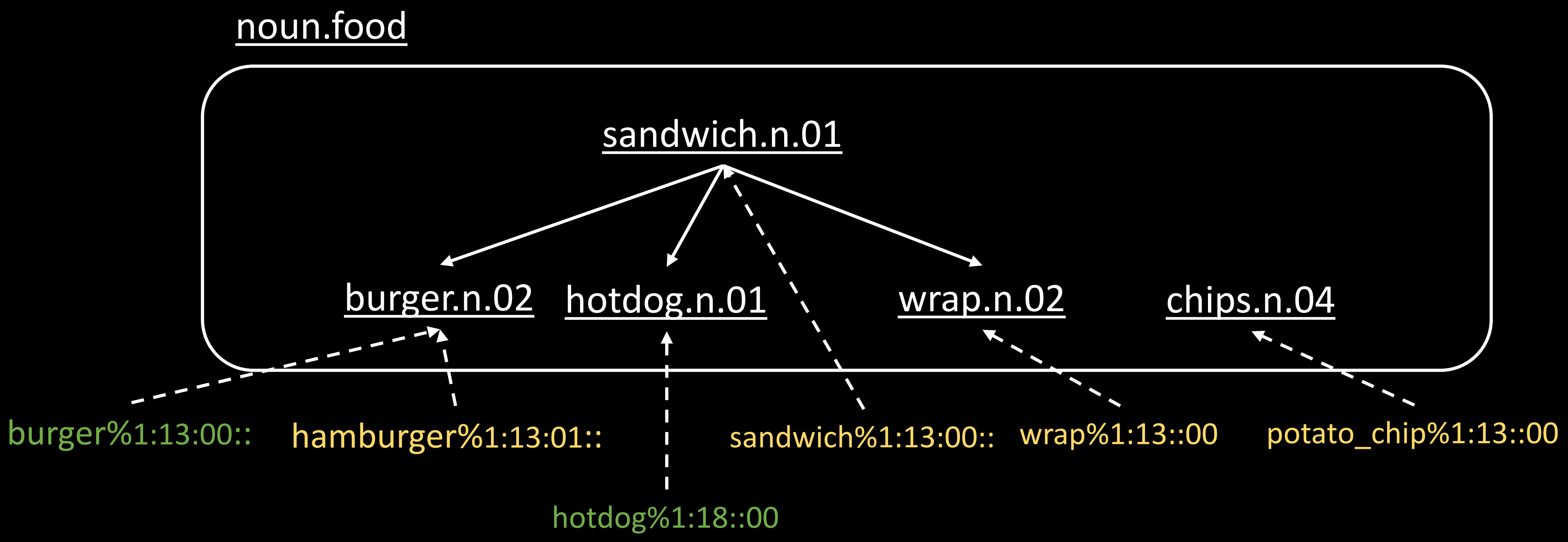
Propagating Sense Embeddings

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



Propagating Sense Embeddings

3rd Stage: Lexname Embeddings



Propagating Sense Embeddings

But  !=  …

noun.food

sandwich.n.01

burger.n.02 hotdog.n.01 wrap.n.02 chips.n.04

burger%1:13:00:: hamburger%1:13:01:: **sandwich%1:13:00::** **wrap%1:13::00** potato_chip%1:13::00

hotdog%1:18::00

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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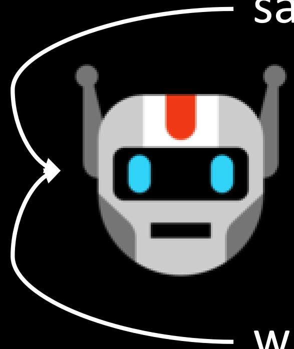


wrap%1:13:00::

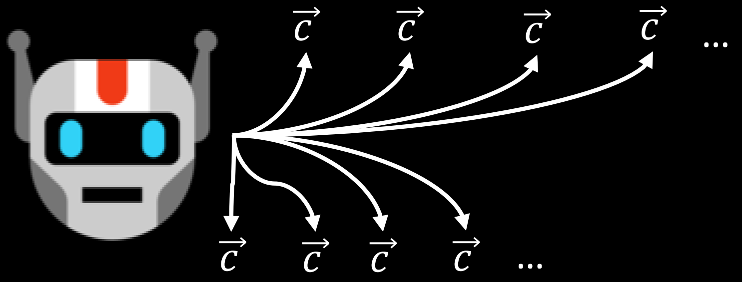
wrap - wrap, tortilla - a sandwich in which the filling is rolled up in a soft tortilla

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

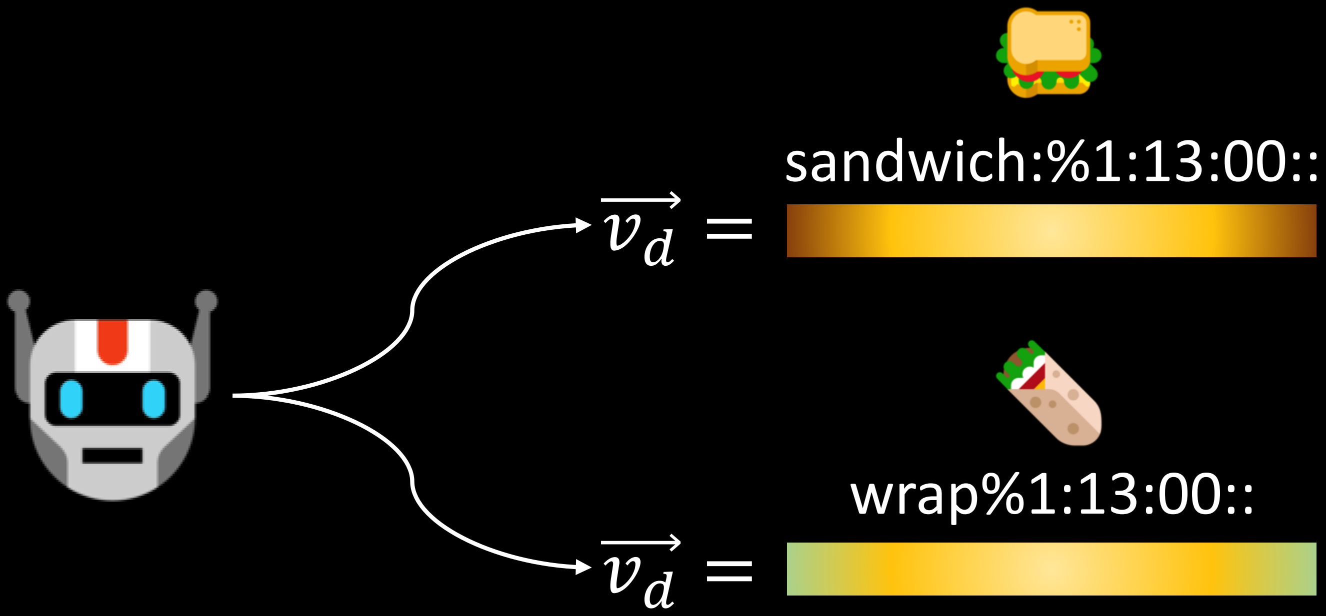


wrap%1:13:00::

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

Enriching Sense Embeddings

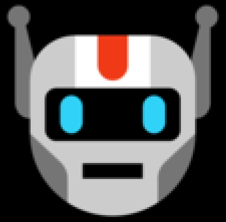
Sentence Embedding from avg. of Contextual Embeddings



$d = 1024$

Enriching Sense Embeddings

Merge Sentence Embedding with previous Sense Embedding



sandwich:%1:13:00::

$\overrightarrow{v_d} =$

sandwich:%1:13:00::

$\overrightarrow{v_s} =$

wrap%1:13:00::

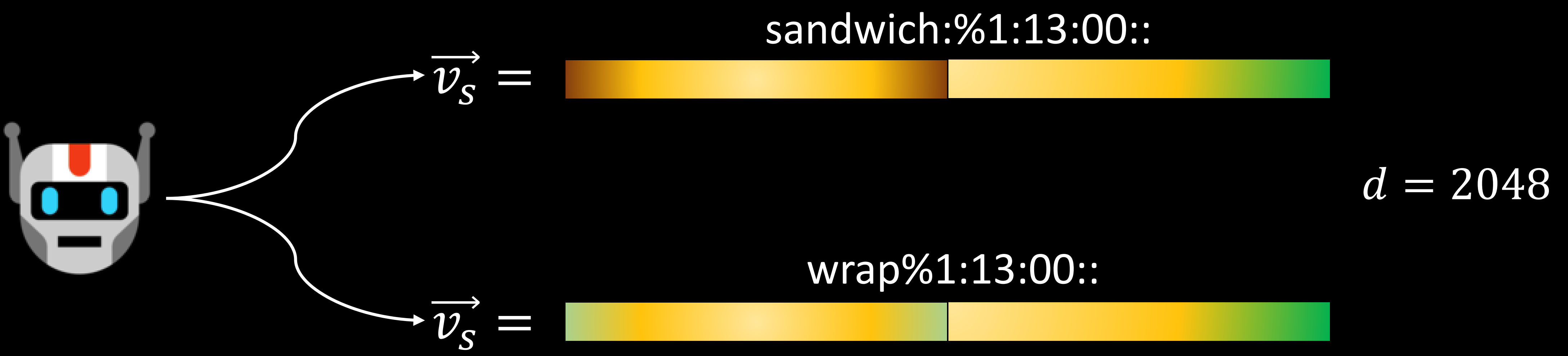
$\overrightarrow{v_d} =$

wrap:%1:13:00::

$\overrightarrow{v_s} =$

Enriching Sense Embeddings

Merge Sentence Embedding with previous Sense Embedding



Reinforcing Sense Embeddings

Contextual Embeddings aren’t good at preserving morphological relatedness

Reinforcing Sense Embeddings

Retrieve char-ngram embeddings (static) for lemmas

sandwich:%1:13:00::

$\vec{v_l} =$

wrap%1:13:00::

$\vec{v_l} =$

Reinforcing Sense Embeddings

Merge with previous sense embeddings

sandwich:%1:13:00::

$\overrightarrow{v_s} =$ $\overrightarrow{v_l} =$

wrap%1:13:00::

$\overrightarrow{v_s} =$ $\overrightarrow{v_l} =$

Reinforcing Sense Embeddings

Merge with previous sense embeddings

sandwich:%1:13:00::

$\overrightarrow{v_s} =$ 

$d = 2348$

wrap%1:13:00::

$\overrightarrow{v_s} =$ 

Matching Sense Embeddings

The glasses are in the cupboard.

Matching Sense Embeddings

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

Matching Sense Embeddings

$$\overrightarrow{v_t} = \begin{array}{|c|c|c|}\hline \vec{c} & \vec{c} & \vec{v} \\ \hline \end{array}$$

$\longrightarrow \vec{v}$

$\longrightarrow \vec{c}$

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

Matching Sense Embeddings

drinking_glass%1:06:00::

$\overrightarrow{v_s}$	$\overrightarrow{v_d}$	$\overrightarrow{v_l}$

glass%1:27:00::

$\overrightarrow{v_s}$	$\overrightarrow{v_d}$	$\overrightarrow{v_l}$

spectacles%1:06:00::

$\overrightarrow{v_s}$	$\overrightarrow{v_d}$	$\overrightarrow{v_l}$

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

$\longrightarrow \vec{v}$

$\longrightarrow \vec{c}$

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WSD Results

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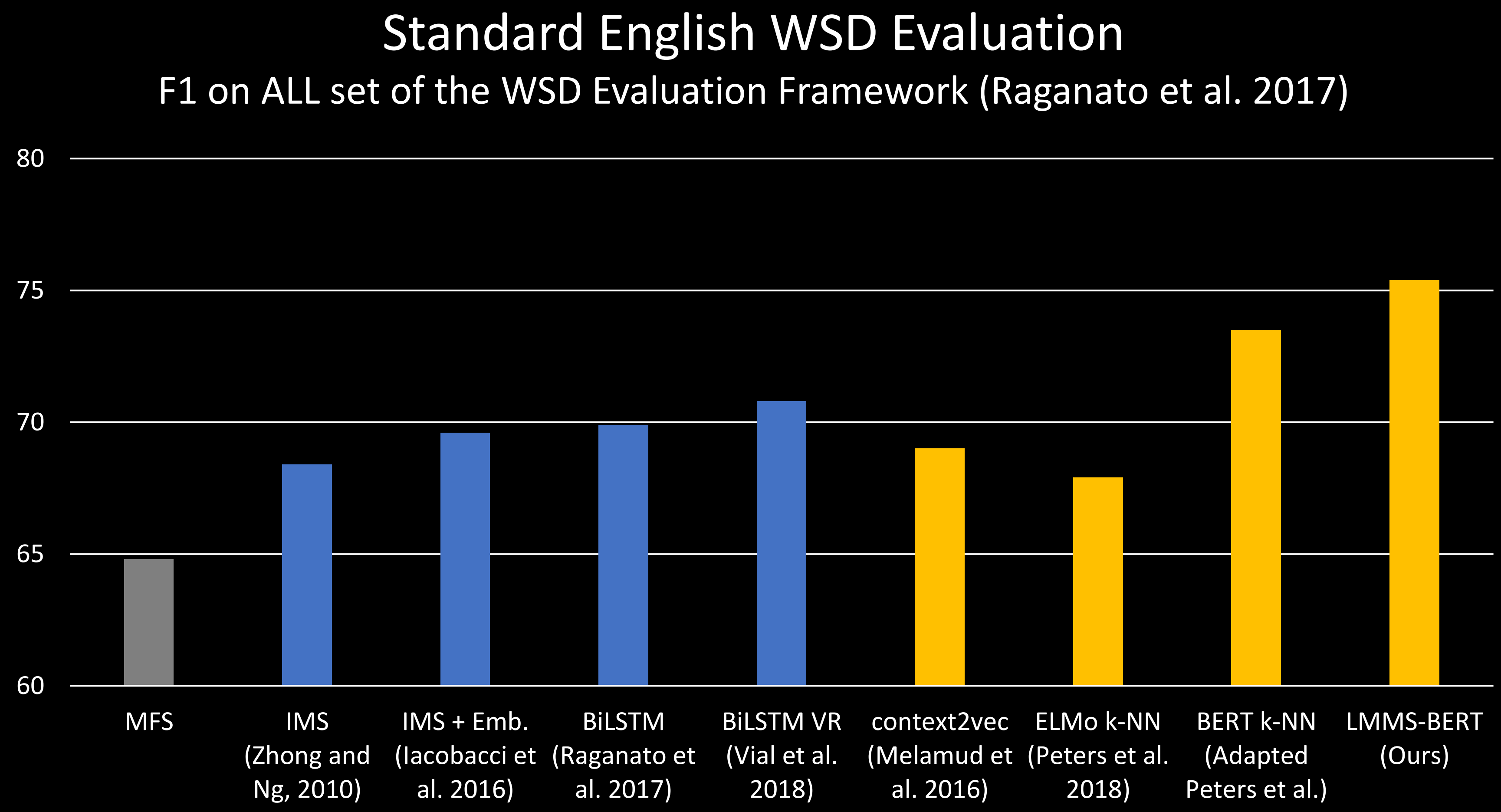
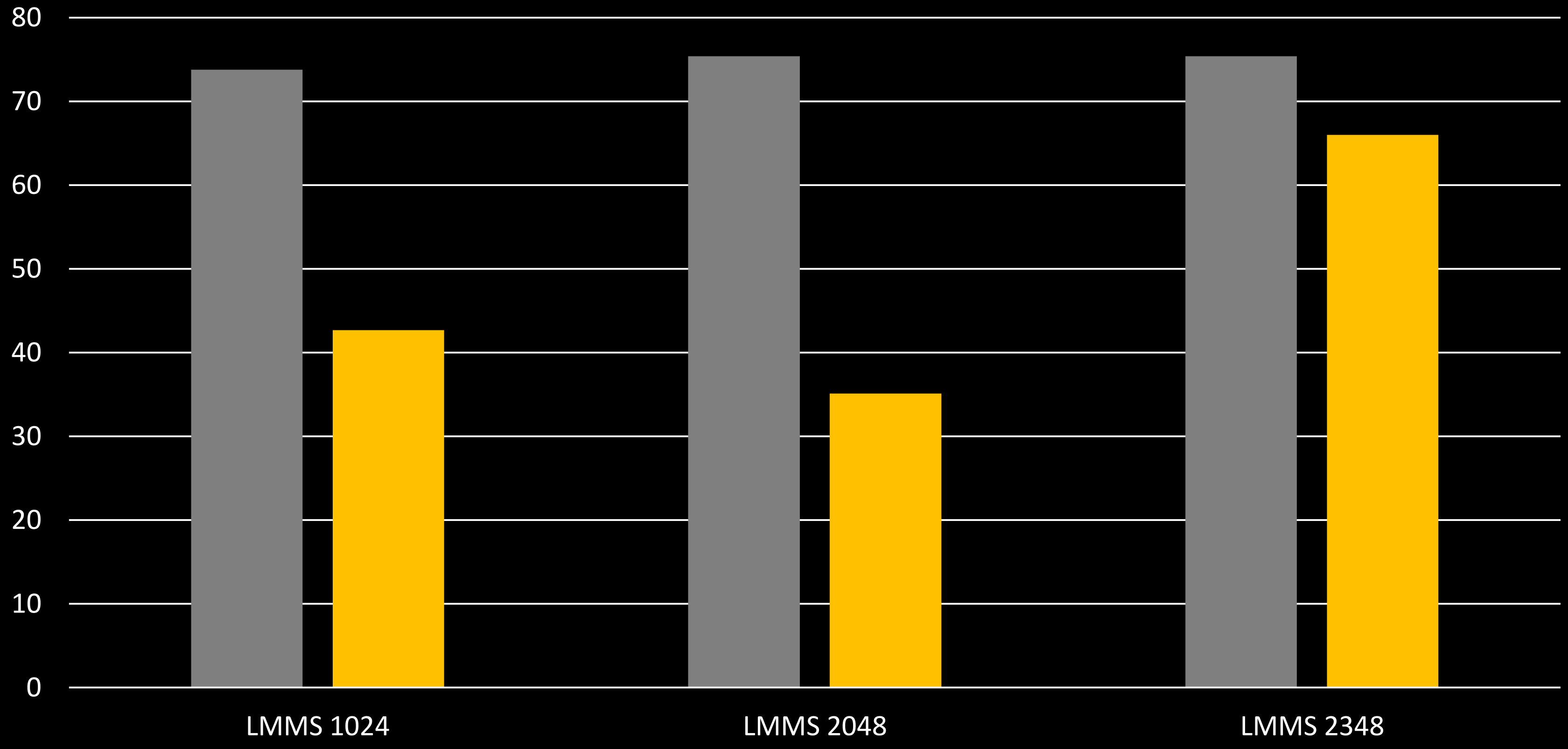


Standard English WSD Evaluation
F1 on ALL set of the WSD Evaluation Framework (Raganato et al. 2017)
80
75
70
65
60
MFS
IMS (Zhong and Ng, 2010)
IMS + Emb. (Iacobacci et al. 2016)
BiLSTM (Raganato et al. 2017)
BiLSTM VR (Vial et al. 2018)
context2vec (Melamud et al. 2016)
ELMo k-NN (Peters et al. 2018)
BERT k-NN (Adapted Peters et al.)
LMMS-BERT (Ours)

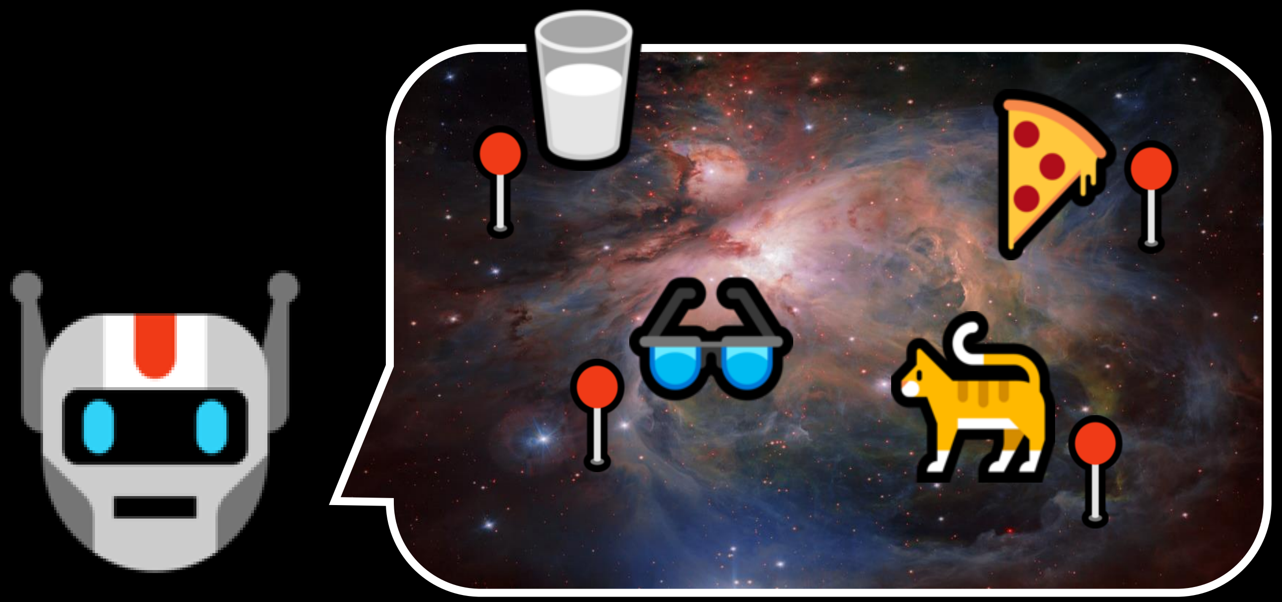
WSD Results

Uninformed Sense Matching (matching +200K)

Same standard but without filtering candidates by lemmas or POS



Applying Sense Embeddings



World Knowledge in NLMs

What's BERT thinking about when he reads?

World Knowledge in NLMs

[E1] played [E2] in [E3]

Marlon★	**Brando**★	**played**	**Corleone**★	**in**	**Godfather**★
$person_n^1$	$person_n^1$	act_v^3	$syndicate_n^1$	$movie_n^1$	$location_n^1$
$womanizer_n^1$	$group_n^1$	$make_v^{42}$	$mafia_n^1$	$telefilm_n^1$	$here_n^1$
$bustle_n^1$	$location_n^1$	$emote_v^1$	$person_n^1$	$final\_cut_n^1$	$there_n^1$

$\mathbf{act_v^3}$: play a role or part; $\mathbf{make_v^{42}}$: represent fictiously, as in a play, or pretend to be or act like; $\mathbf{emote_v^1}$: give expression or emotion to, in a stage or movie role.

Serena★	**Williams**	**played**	**Kerber**★	**in**	**Wimbledon**★
$person_n^1$	$professional\_tennis_n^1$	$play_v^1$	$person_n^1$	win_v^1	$tournament_n^1$
$therefore_r^1$	$tennis_n^1$	$line\_up_v^6$	$group_n^1$	$romp_v^3$	$world\_cup_n^1$
$reef_n^1$	$singles_n^1$	$curl_v^5$	$take\_orders_v^2$	$carry_v^{38}$	$elimination\_tournament_n^1$

$\mathbf{play_v^1}$: participate in games or sport; $\mathbf{line\_up_v^6}$: take one's position before a kick-off; $\mathbf{curl_v^5}$: play the Scottish game of curling.

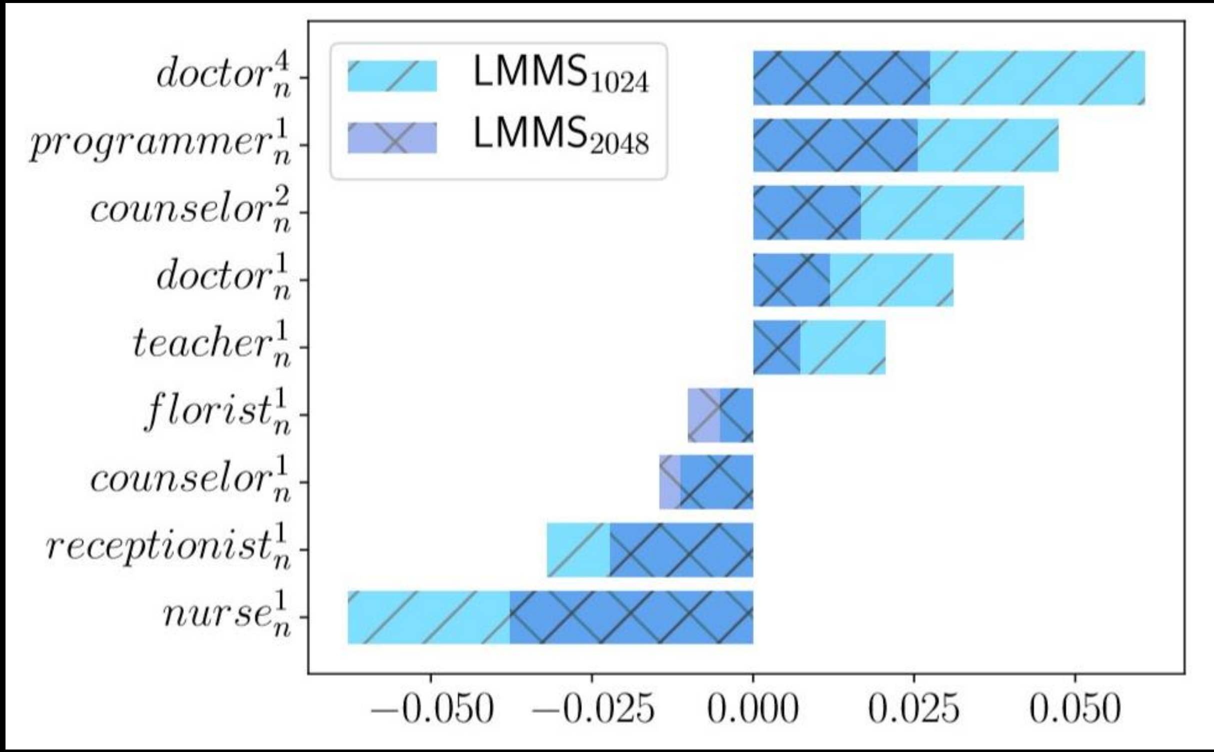
David	**Bowie**★	**played**	**Warszawa**★	**in**	**Tokyo**
$person_n^1$	$person_n^1$	$play_v^{14}$	$poland_n^1$	$originate\_in_v^1$	$tokyo_n^1$
$amati_n^2$	$folk\_song_n^1$	$play_v^6$	$location_n^1$	in_r^1	$japan_n^1$
$guarnerius_n^3$	$fado_n^1$	$riff_v^2$	$here_n^1$	$take\_the\_field_v^2$	$japanese_a^1$

$\mathbf{play_v^{14}}$: perform on a certain location; $\mathbf{play_v^6}$: replay (as a melody); $\mathbf{riff_v^2}$: play riffs.

Checking for Biases in NLMs

Putting BERT on the spot

Checking for Biases in NLMs



$$bias(s) = sim(\vec{v}_{man_n^1}, \vec{v}_s) - sim(\vec{v}_{woman_n^1}, \vec{v}_s)$$

Conclusion

- Powerful NLMs allow for a simple k-NN to perform really well for WSD.
- NLMs are improving very rapidly, progress in WSD should follow.
- Sense embeddings from NLMs are useful not only for WSD, but also for NLM inspection, and other probing or downstream tasks.

Future Work

- Pipeline Improvements: Better NLMs, sentence embeddings, char embeddings, use of WN, etc..

- Multilingual Sense Embeddings.

- Semi-supervised Refinement.

- Formalize inspection (probing task), other applications.

Thanks

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

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