Language Modelling Makes Sense

BERT-based Word Sense Disambiguation and Medical Entity Linking

Daniel Loureiro, 12th Dec 2019

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Sense Embeddings

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

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

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)

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

(k-NN)
(over NLM reprs.)

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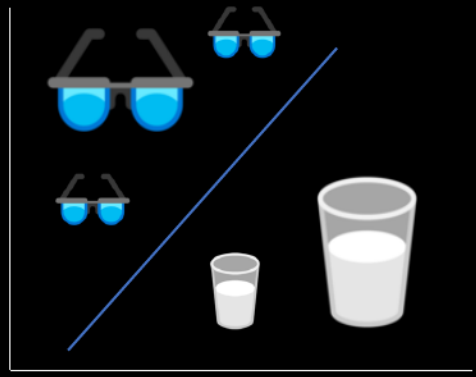
Bag-of-Features Classifiers

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 (!)

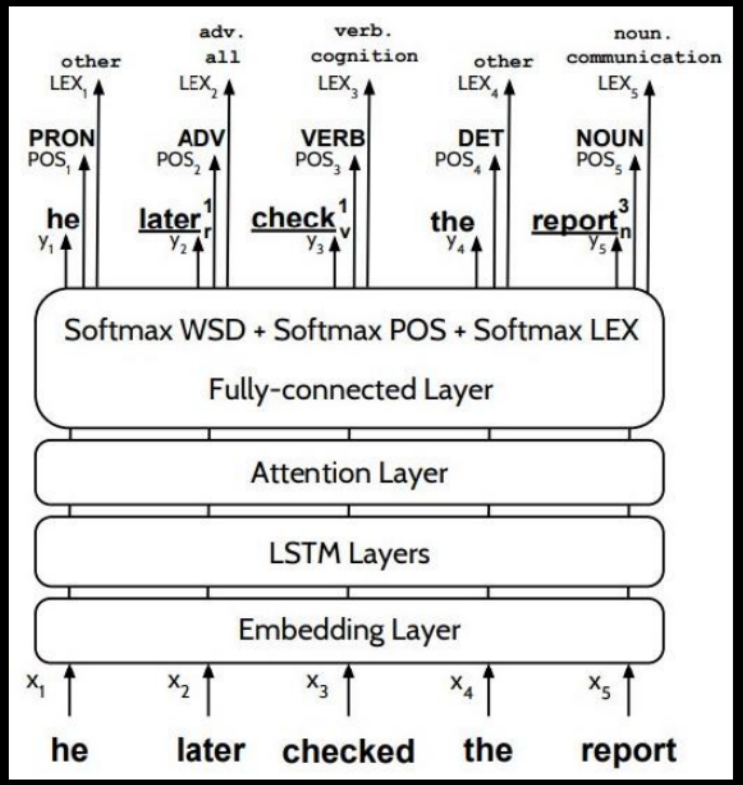


"glasses"

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…

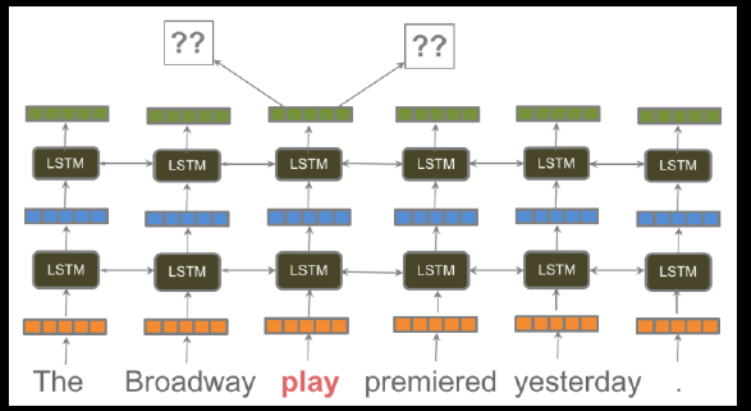


[Raganato et al. (2017)]

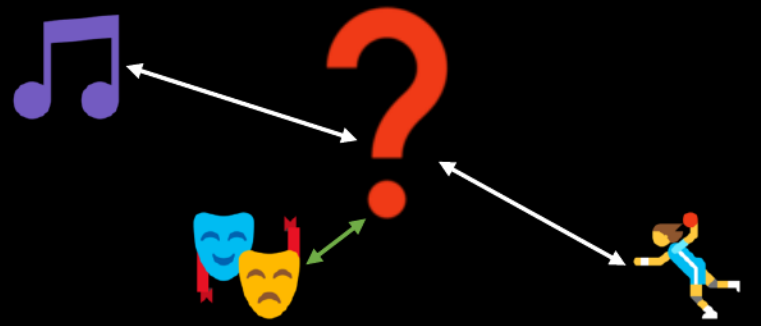
Contextual k-NN

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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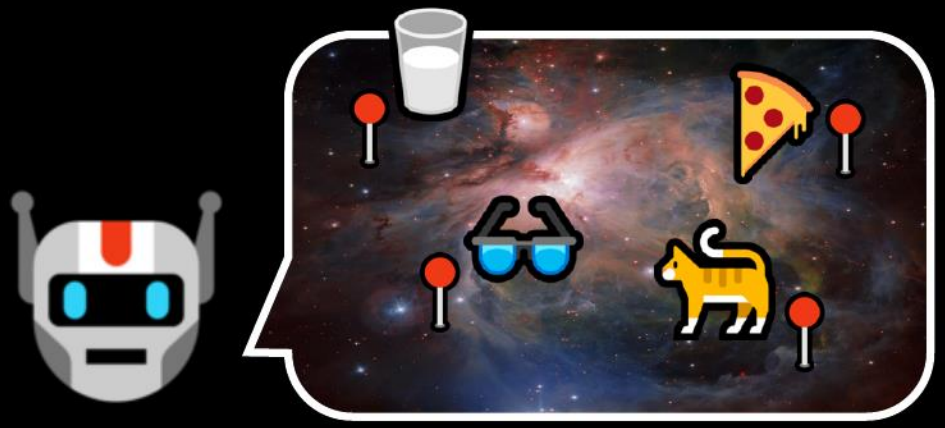

Challenges

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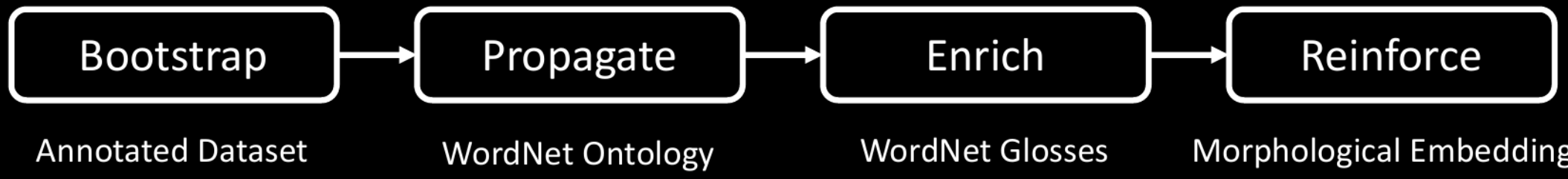
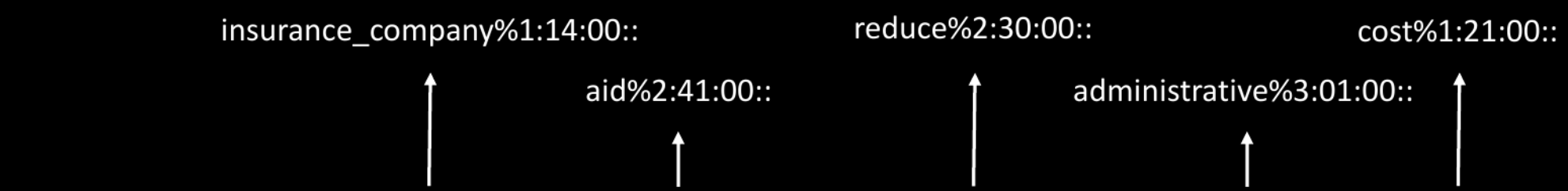


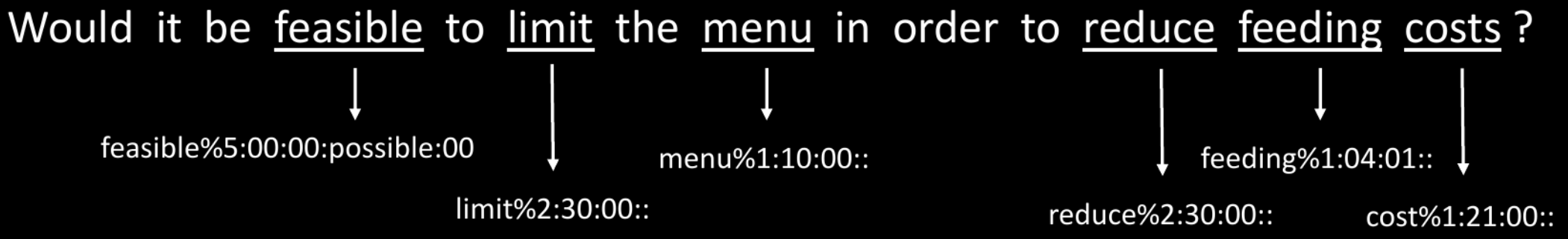
Bootstrapping Sense Embeddings

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





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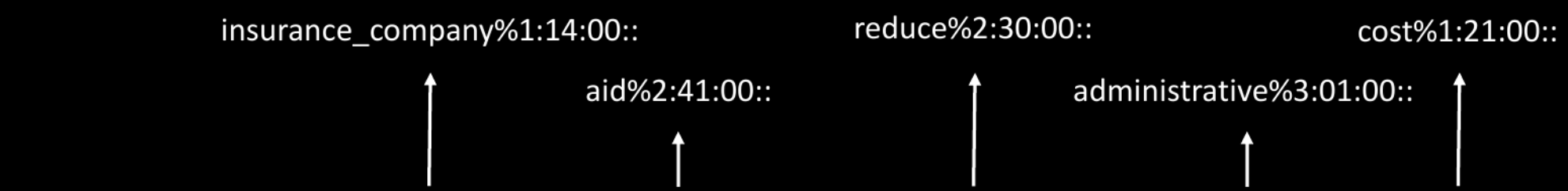
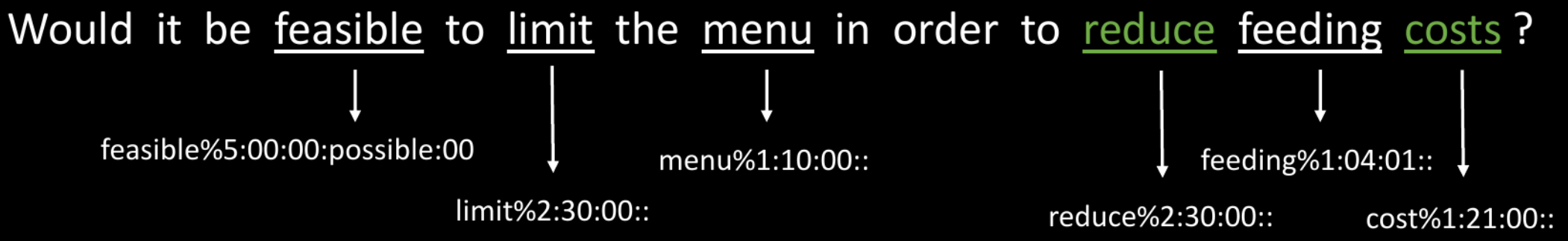




Bootstrapping Sense Embeddings

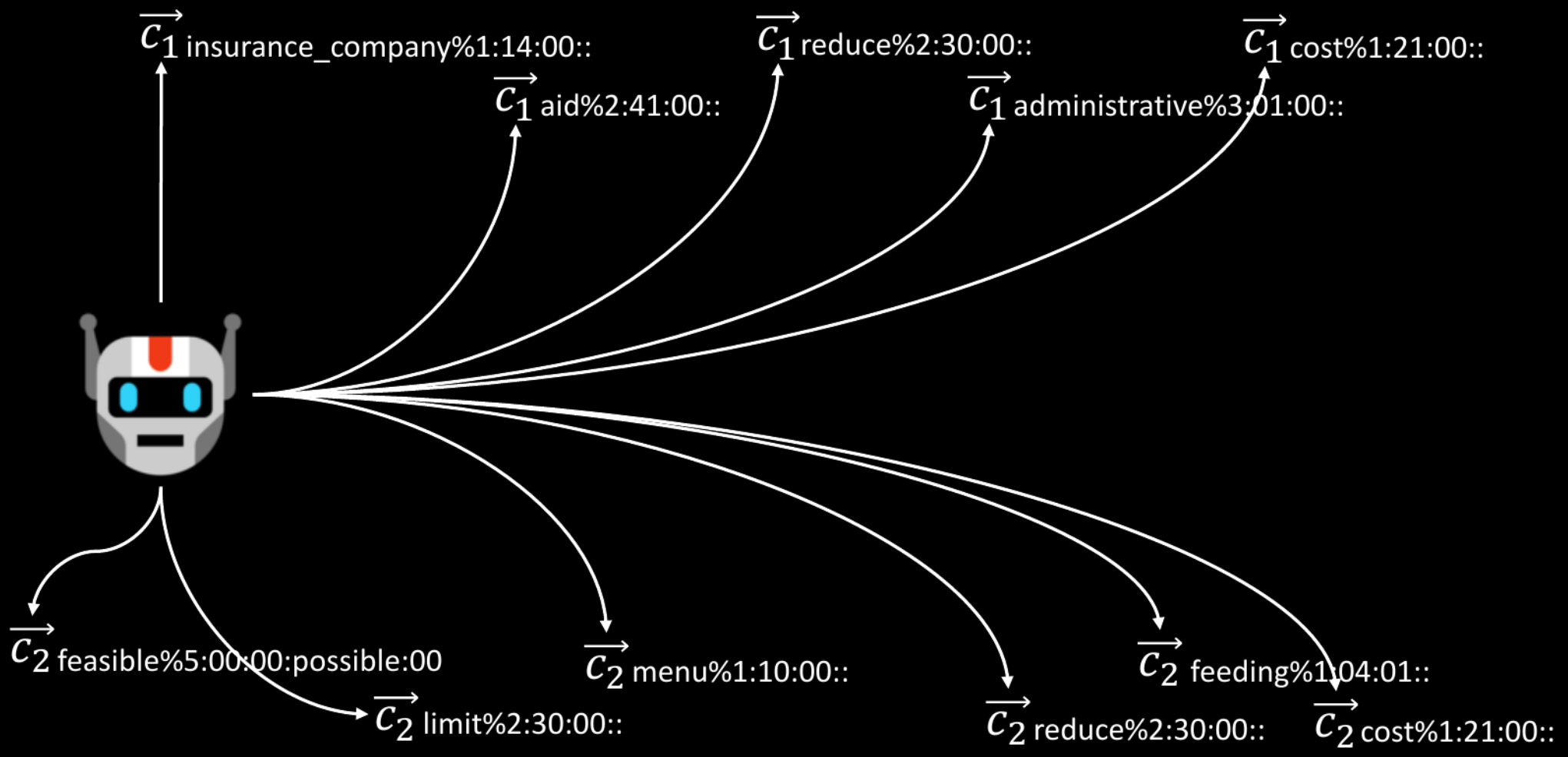
insurance_company%1:14:00:: aid%2:41:00:: reduce%2:30:00:: administrative%3:01:00:: cost%1:21:00::

Can your 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 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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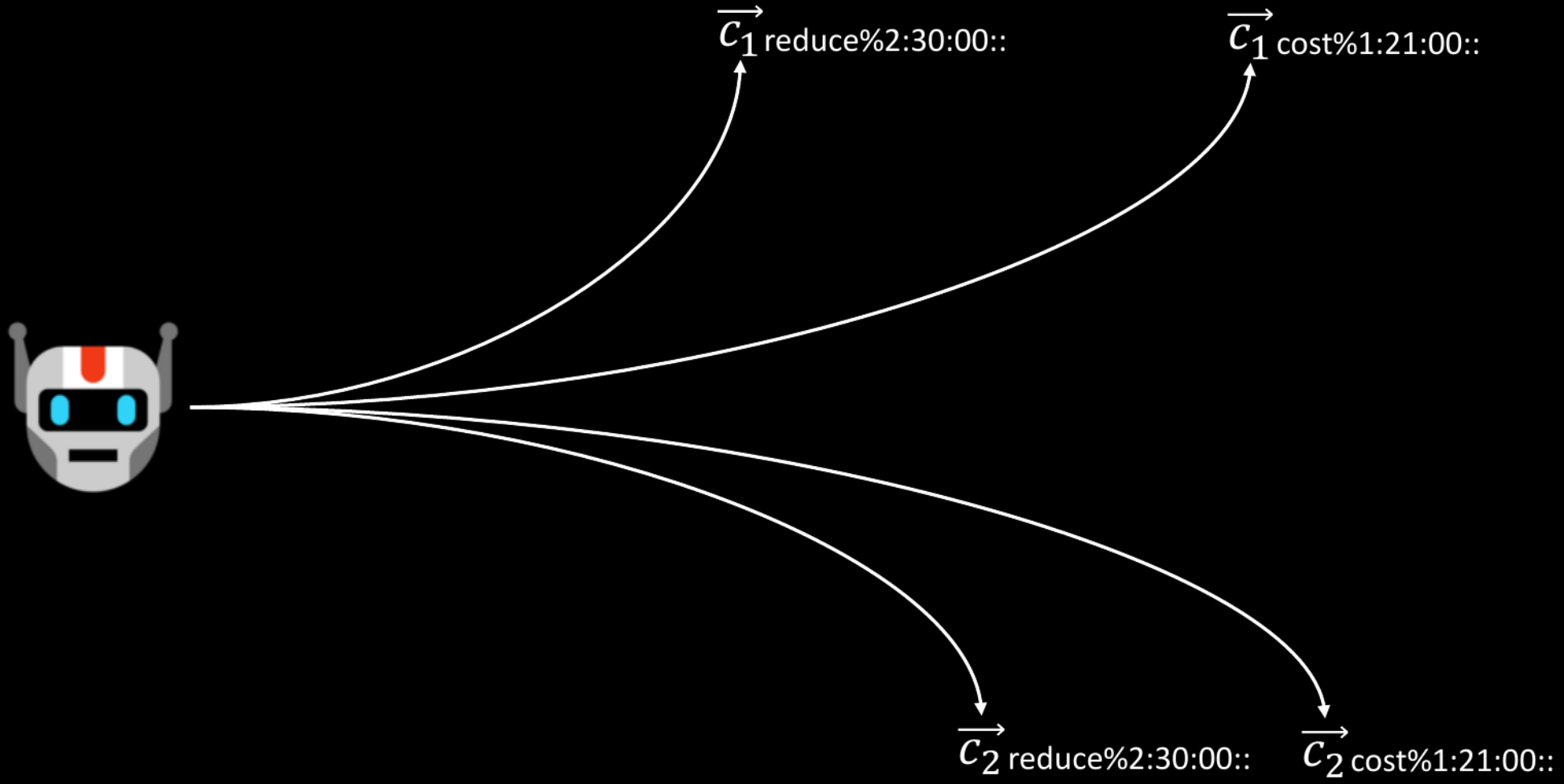

Bootstrapping Sense Embeddings

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

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

Bootstrapping Sense Embeddings

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

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

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

Propagating Sense Embeddings

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

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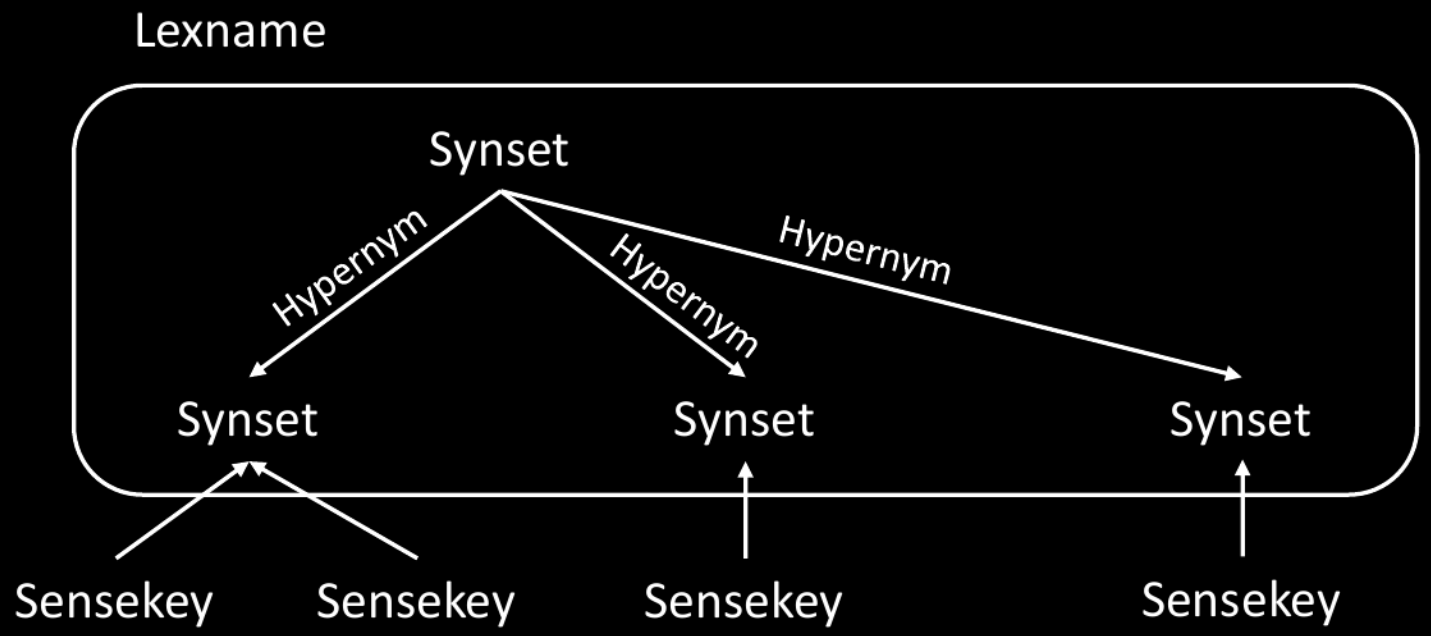

Propagating Sense Embeddings

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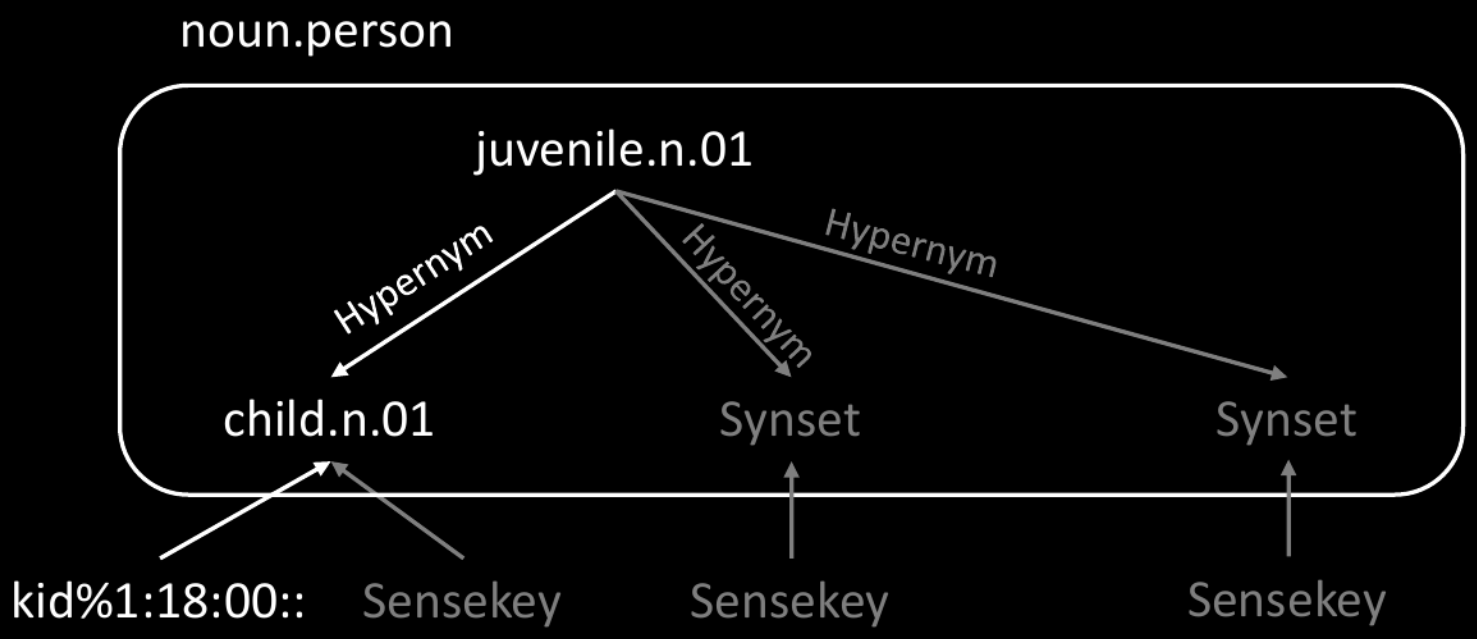


Propagating Sense Embeddings

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::

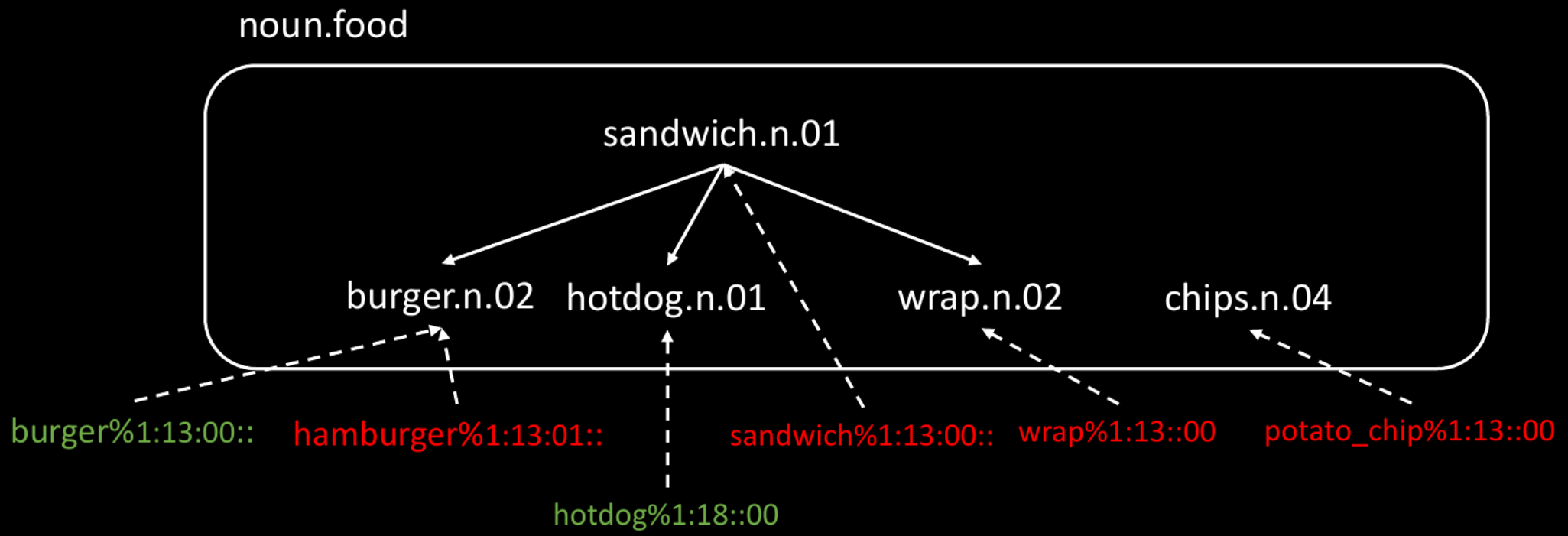
sandwich%1:13:00::

wrap%1:13:00::

potato_chip%1:13:00::

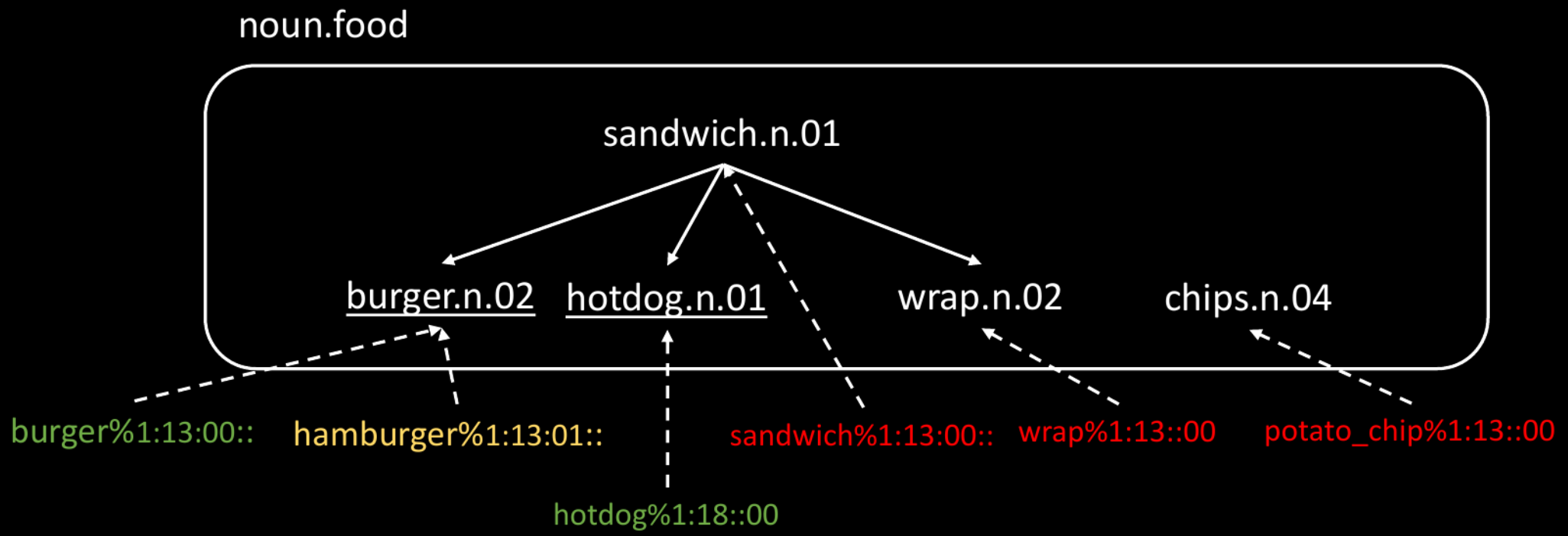
Propagating Sense Embeddings

Retrieve Synsets, Relations and Categories



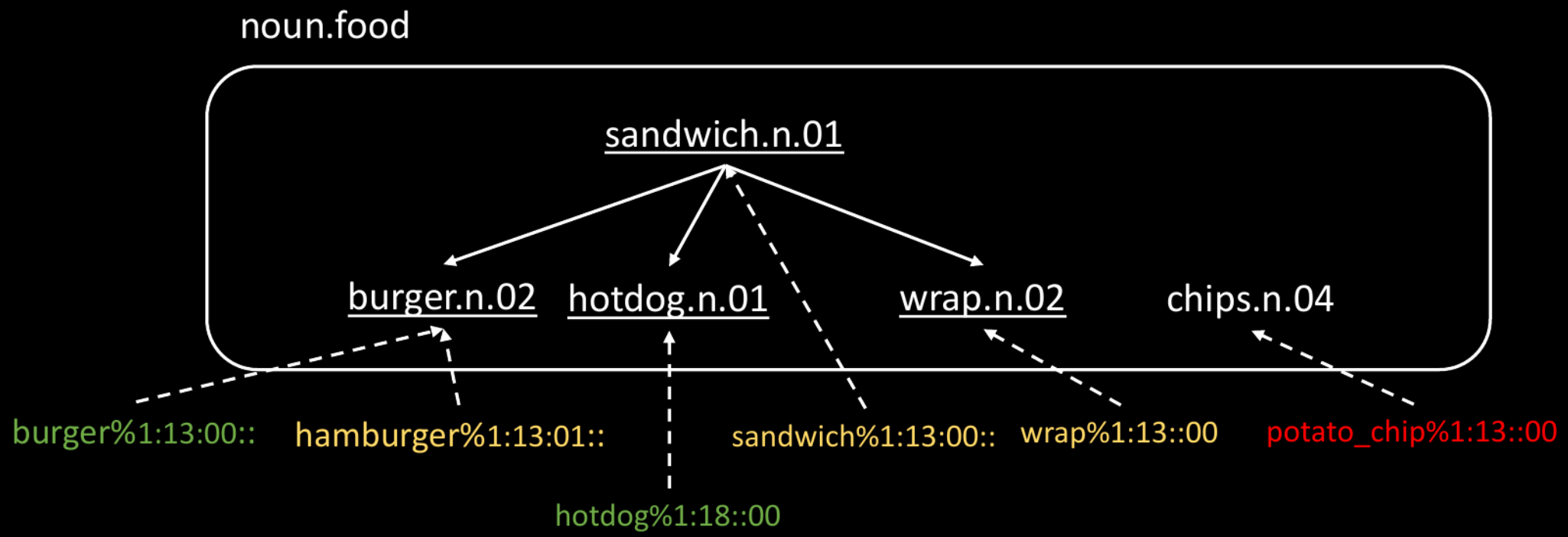
Propagating Sense Embeddings

1st stage: Synset Embeddings



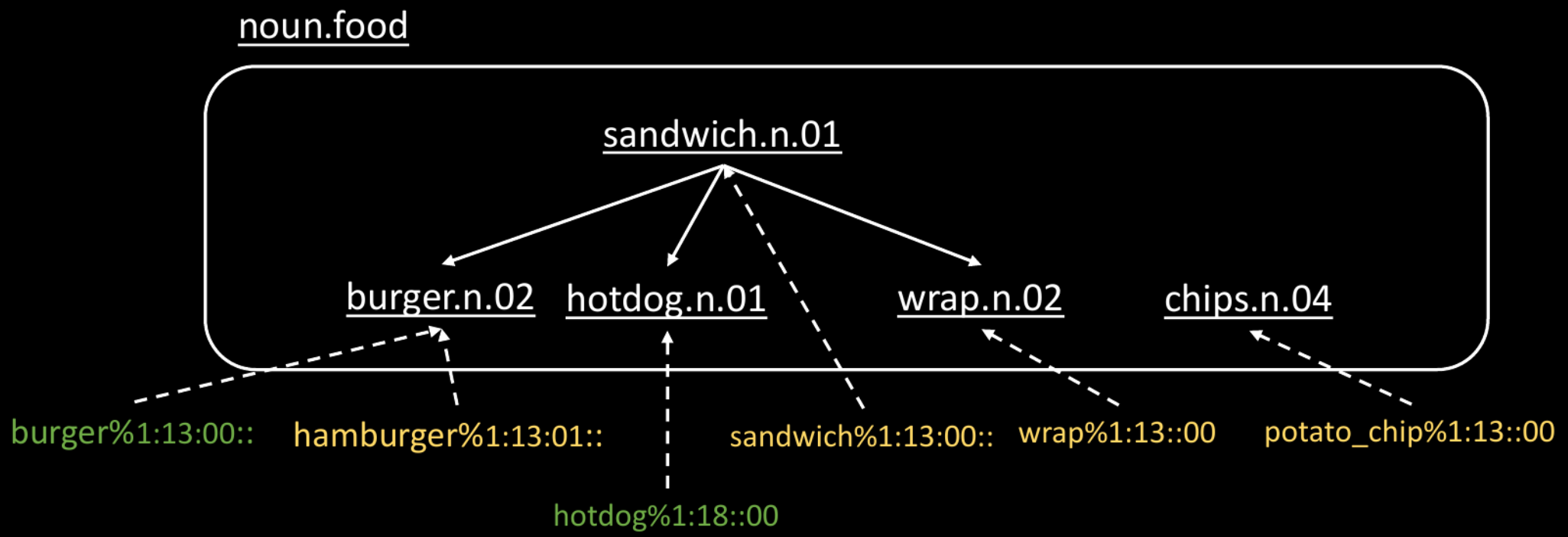
Propagating Sense Embeddings

2nd Stage: Hypernym Embeddings (ind. Synsets)



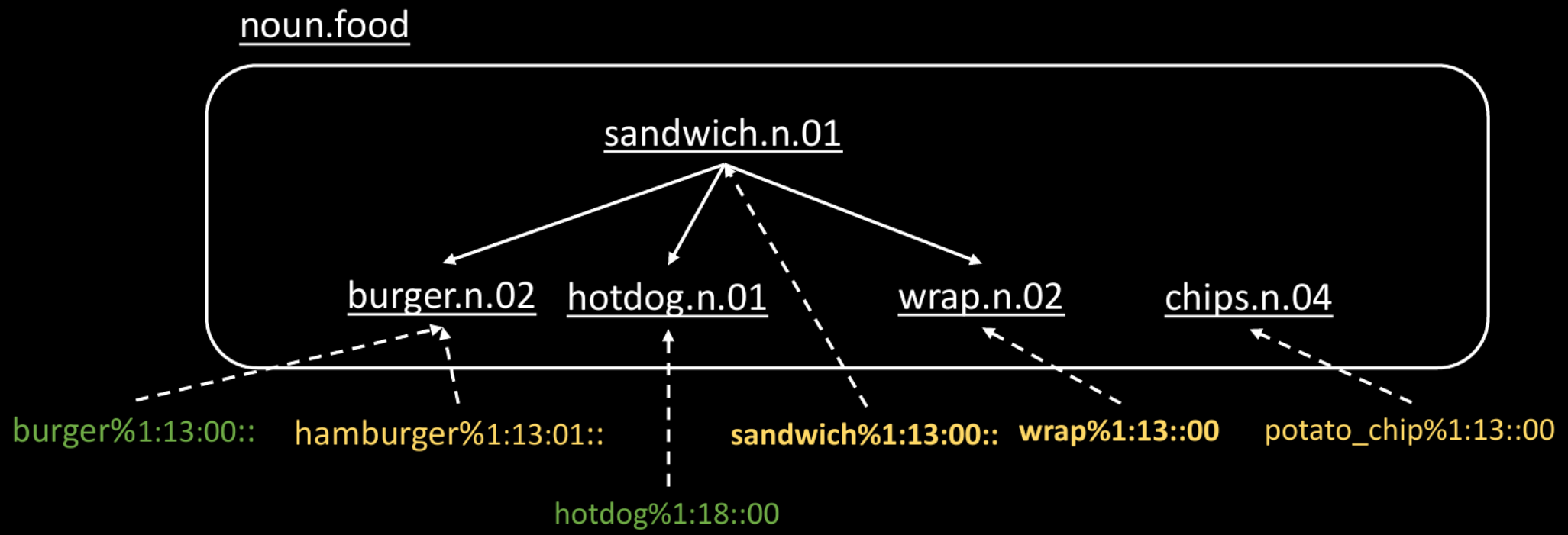
Propagating Sense Embeddings

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)

sandwich:%1:13:00::

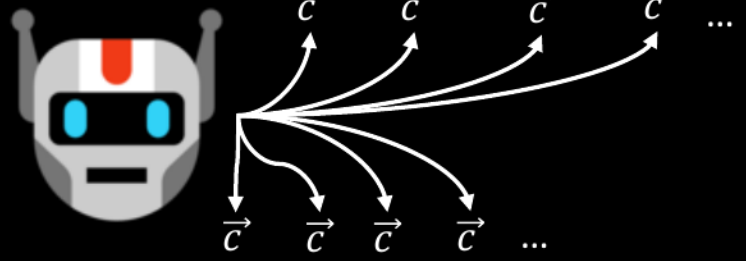
sandwich - sandwich - two (or more) slices of bread with a filling between them

wrap%1:13:00::

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

Enriching Sense Embeddings

Obtain contextual embeddings for every token



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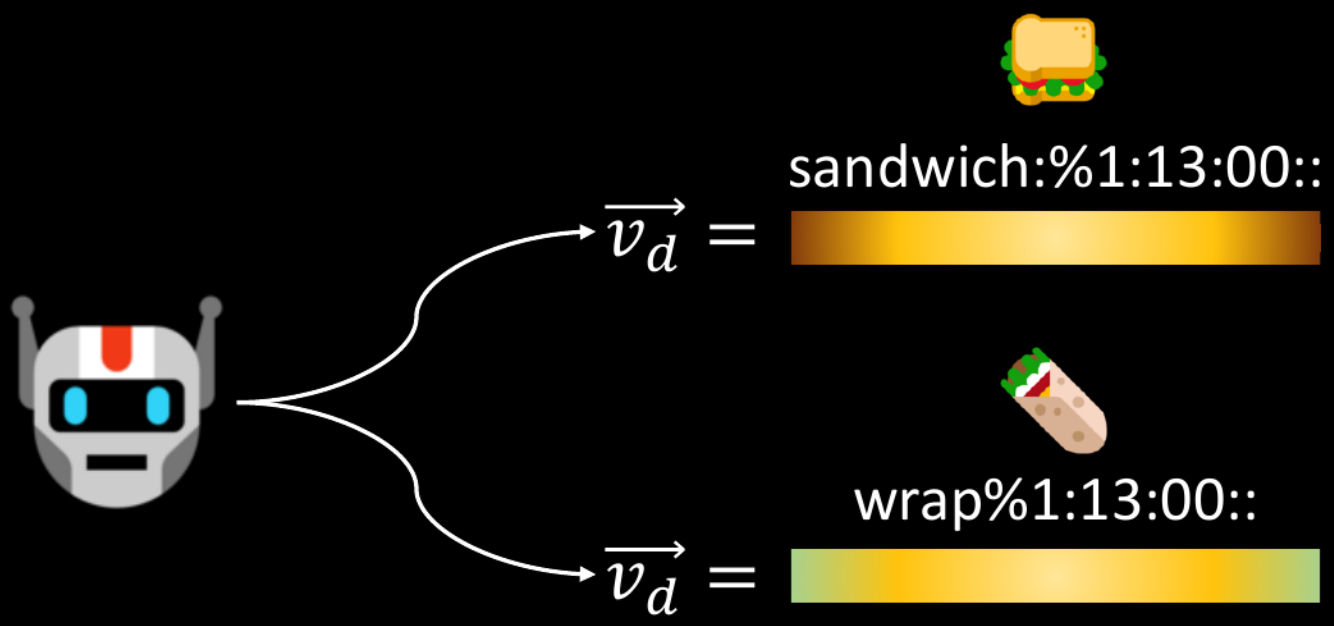
sandwich - sandwich - two (or more) slices of bread with a filling between them

wrap%1:13:00::

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

Enriching Sense Embeddings

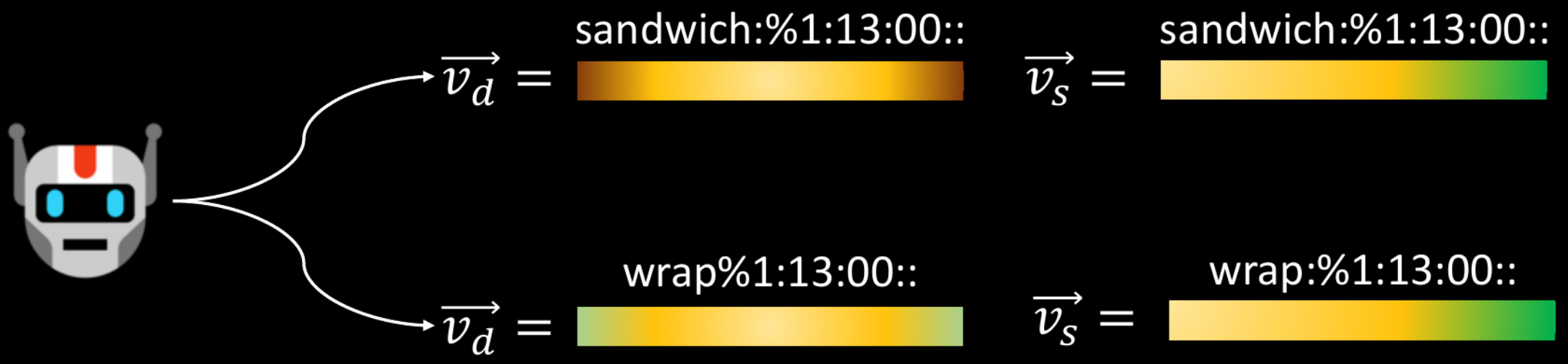
Sentence Embedding from avg. of Contextual Embeddings



$d = 1024$

Enriching Sense Embeddings

Merge Sentence Embedding with previous Sense Embedding



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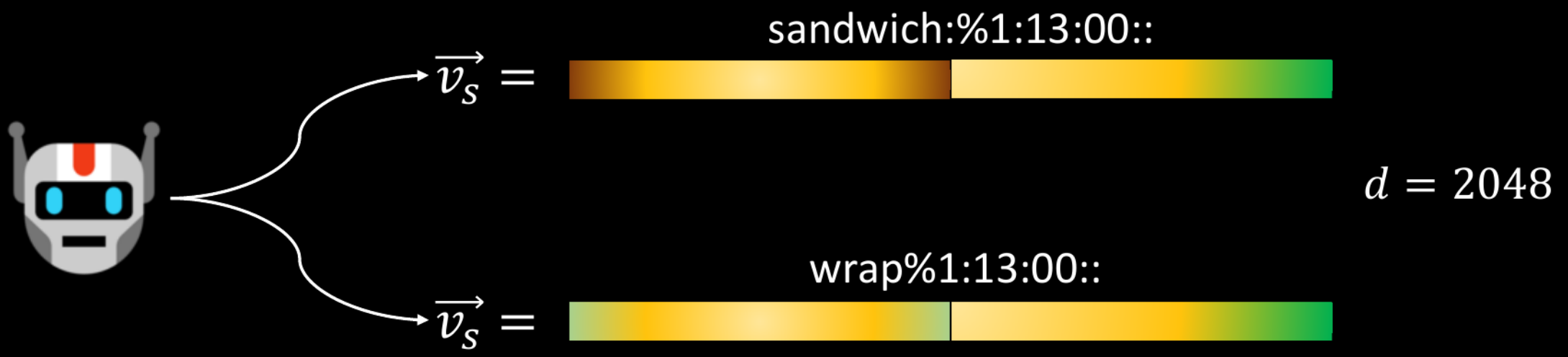
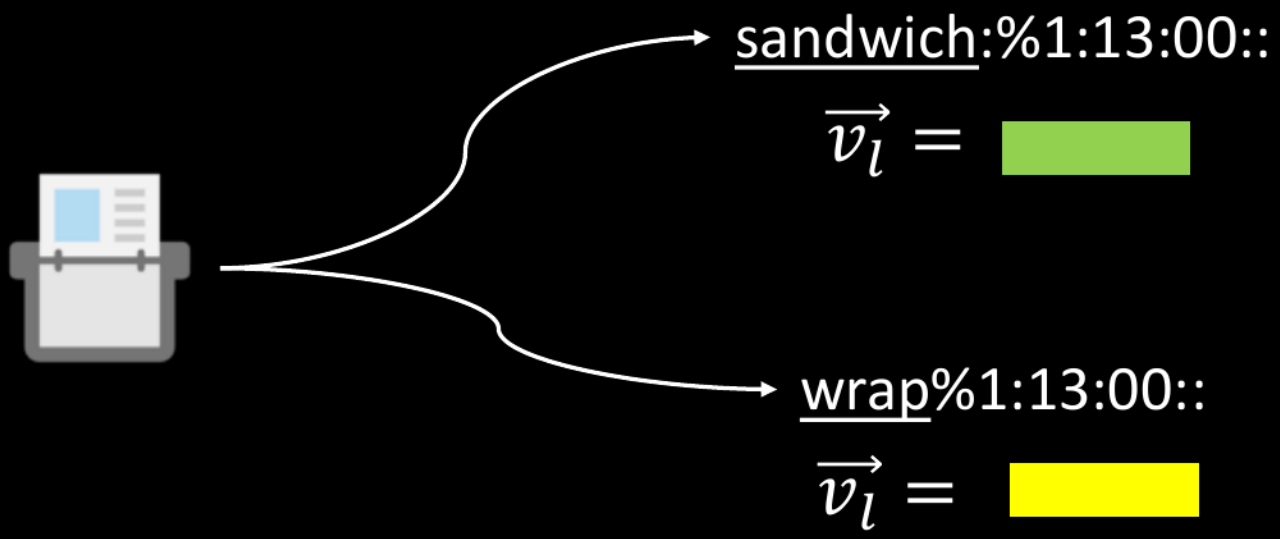


Reinforcing Sense Embeddings

Contextual Embeddings aren’t good at preserving morphological relatedness

Reinforcing Sense Embeddings

Retrieve char-ngram embeddings (static) for lemmas



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

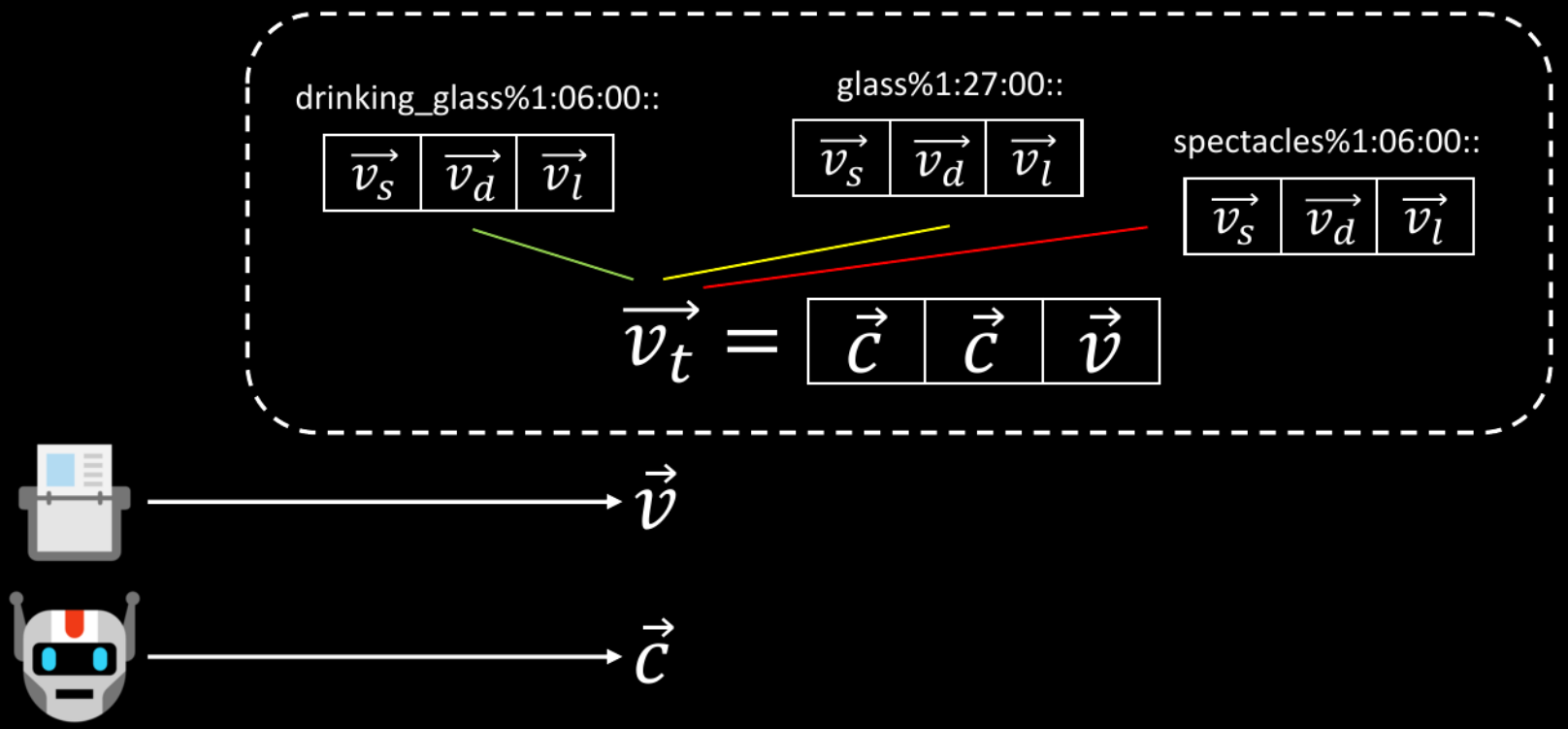
The glasses are in the cupboard.

Matching Sense Embeddings

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

The glasses are in the cupboard.

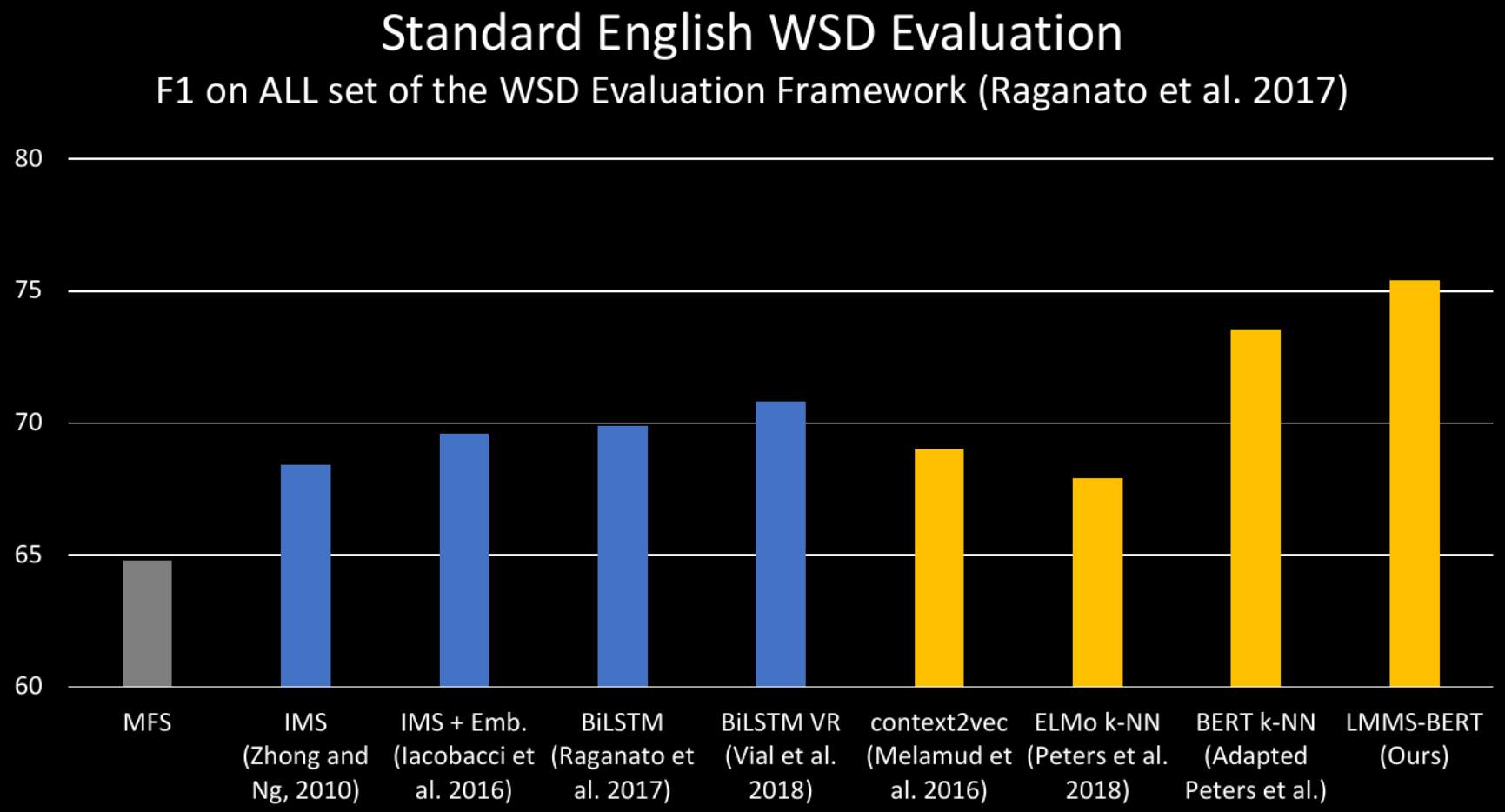
Matching Sense Embeddings



The glasses are in the cupboard.

WSD Results

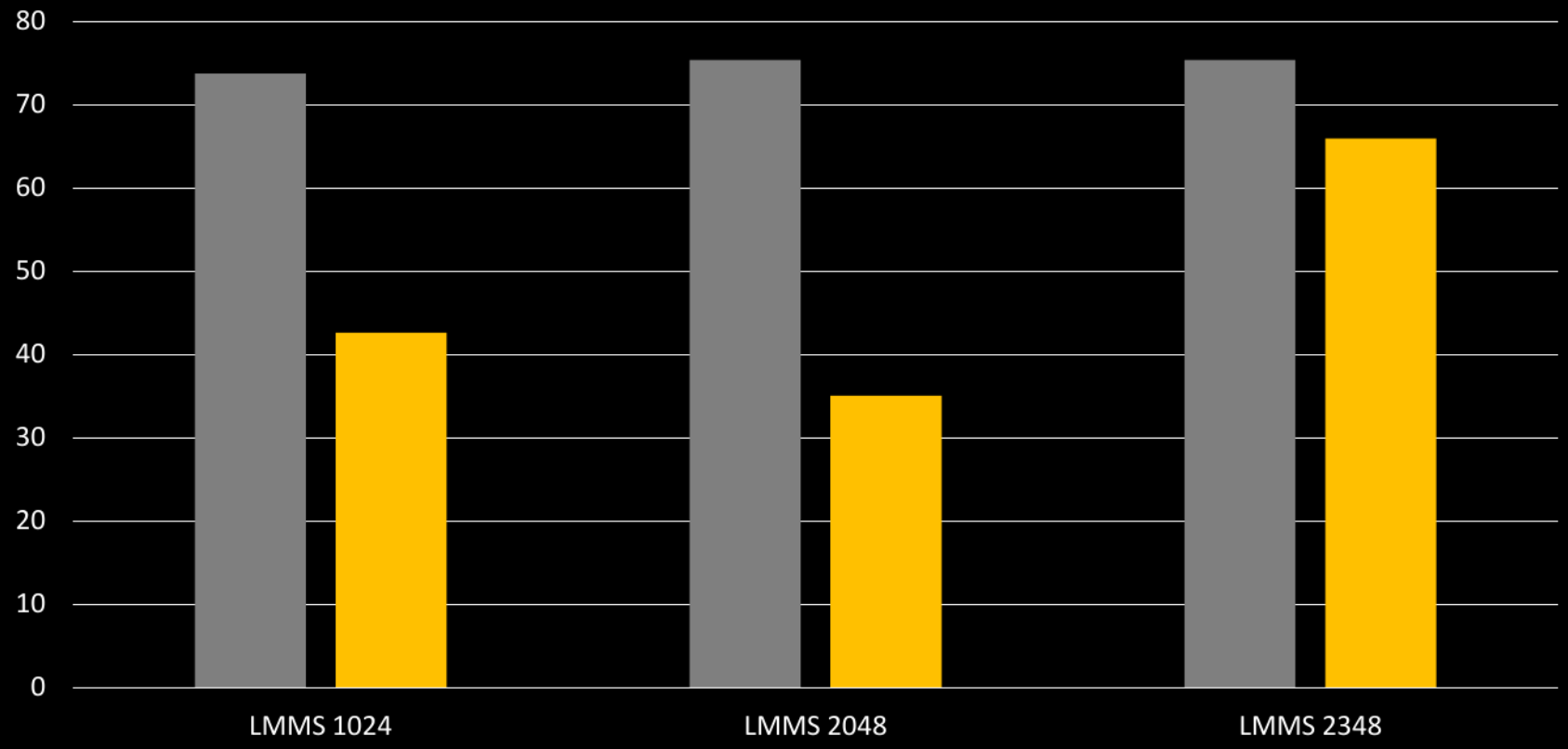
WSD Results


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)

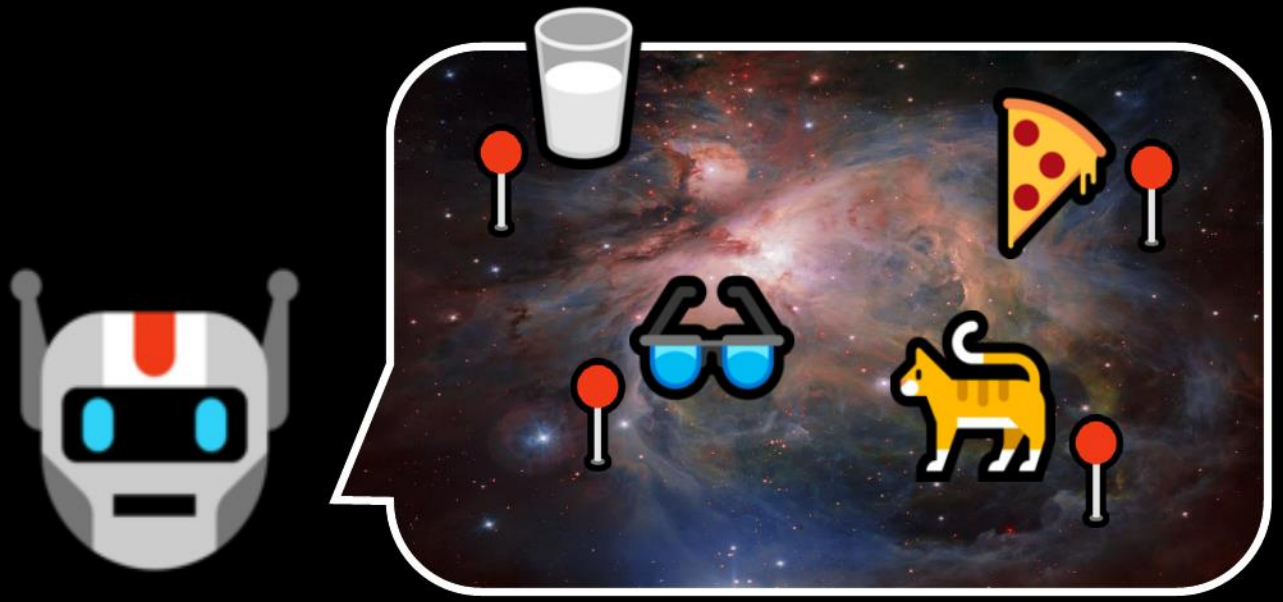
WSD Results

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.

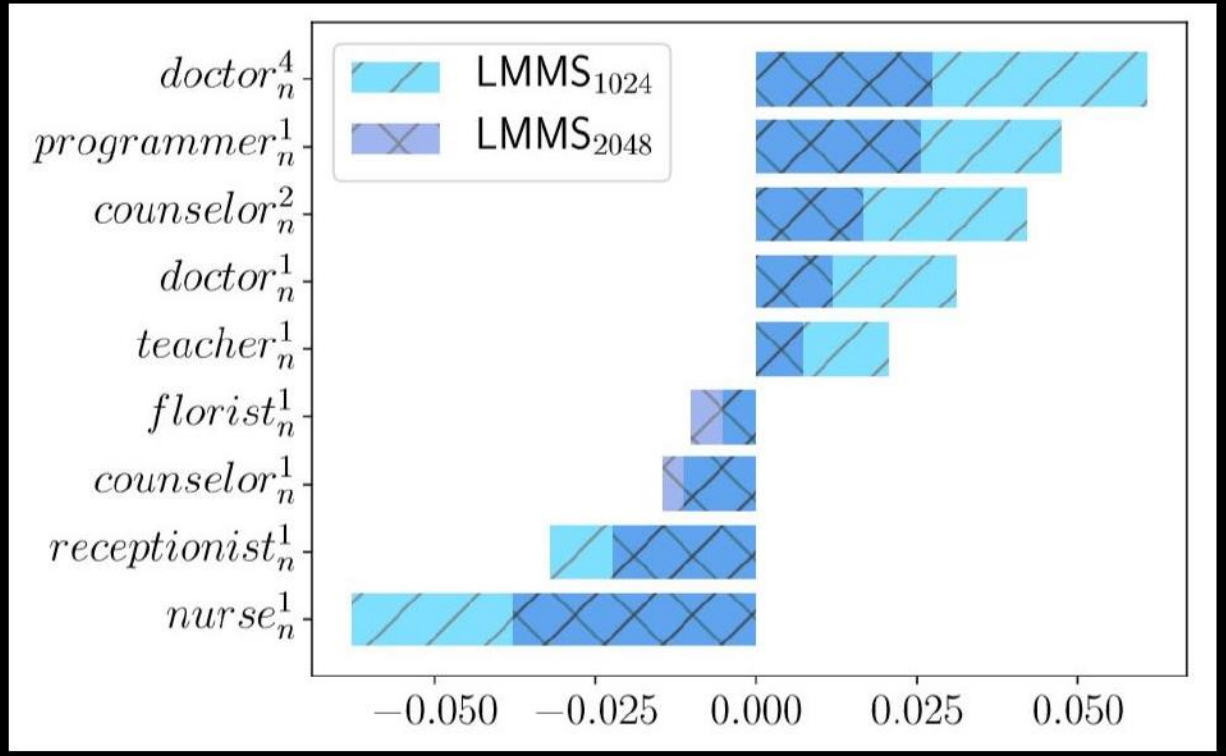
David	**Bowie***	**played**	**Warszawa***	**in**	**Tokyo**
$person_n^1$	$person_n^1$	$play_v^{14}$	$poland_n^1$	$originate\_in_n^1$	$tokyo_n^1$
$amati_n^2$	$folk\_song_n^1$	$play_v^6$	$location_n^1$	in_r^1	$japan_n^1$
$guarnerius_n^3$	$fado_n^1$	$riff_v^2$	$here_n^1$	$take\_the\_field_v^2$	$japanese_a^1$

$\mathbf{play_v^{14}}$: 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

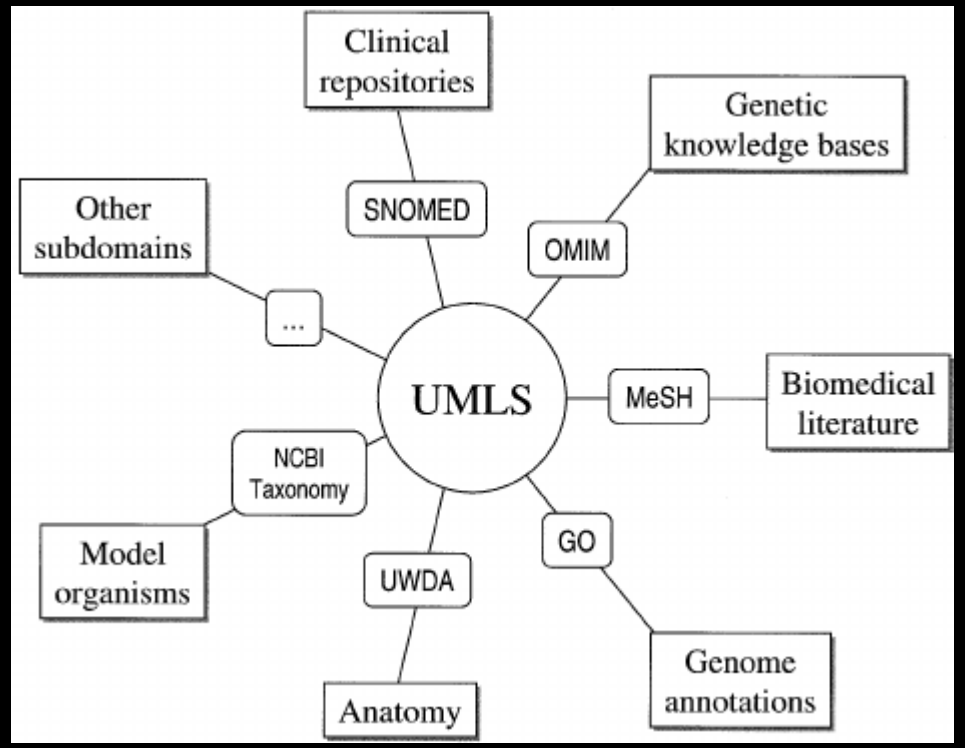
Checking for Biases in NLMs



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

MedLinker: WSD Hard Mode

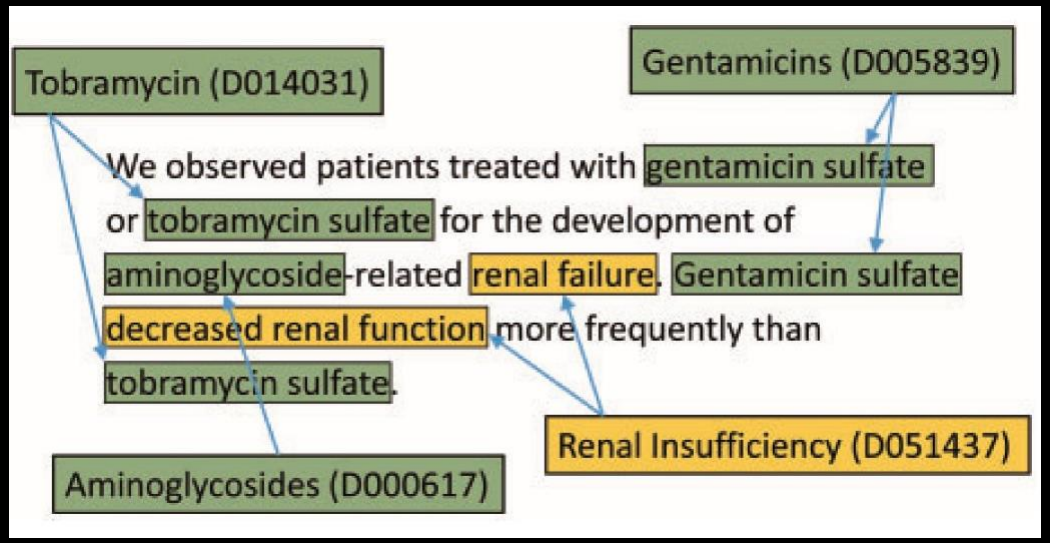
MedLinker: WSD Hard Mode



UMLS Ontology:

- +2M Medical Domain Concepts
- From professions to genes
- 10x size of WordNet

MedLinker: WSD Hard Mode



MedMentions (Mohan and Li, 2019)

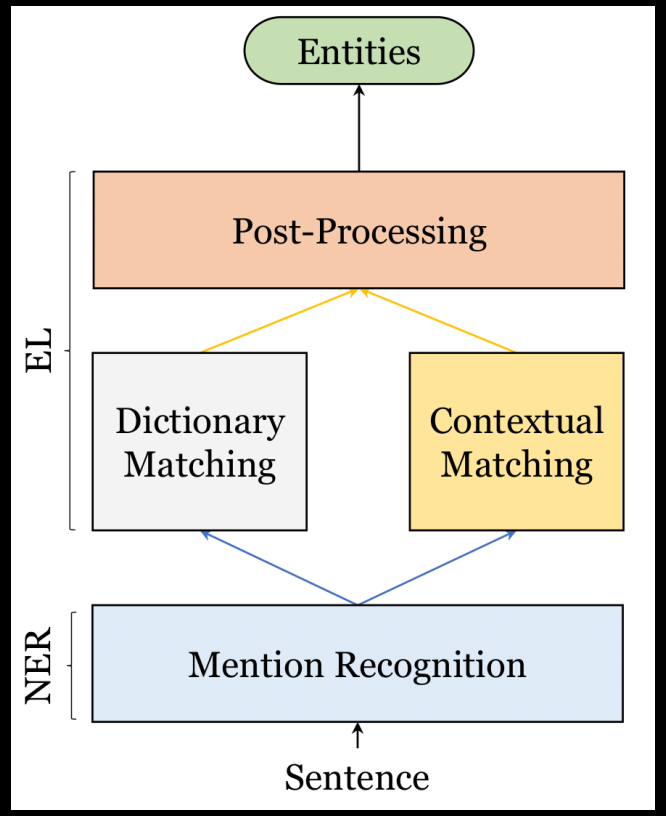
- 200k annotations
- 18k concepts (entities)
- 50% train/test overlap
- 1% coverage

MedLinker: WSD Hard Mode

Specialized BERT models

- Trained on PubMed, etc.
- NCBI BERT
- BioBert
- SciBERT

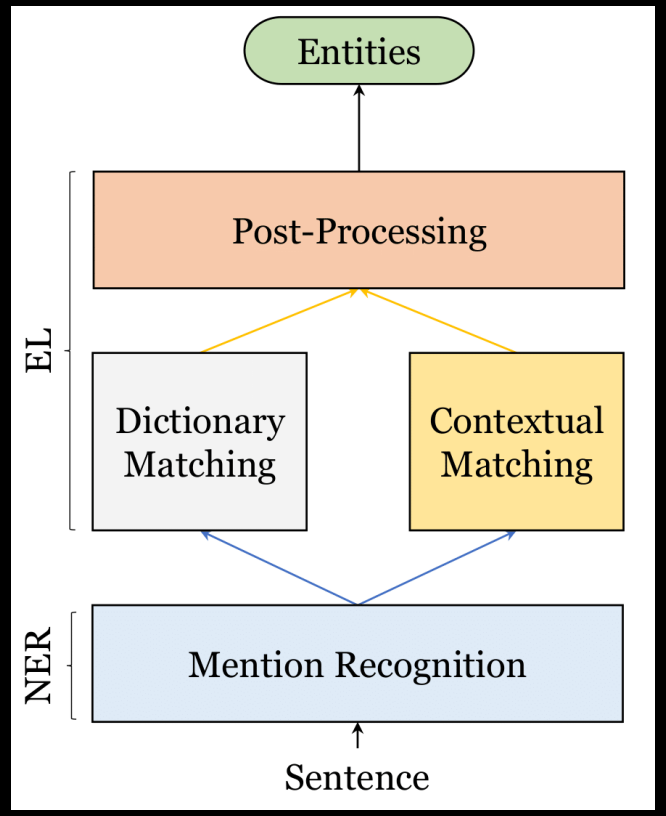
MedLinker: Solution



← NER (no gold spans)

MedLinker: Solution

String Matching →

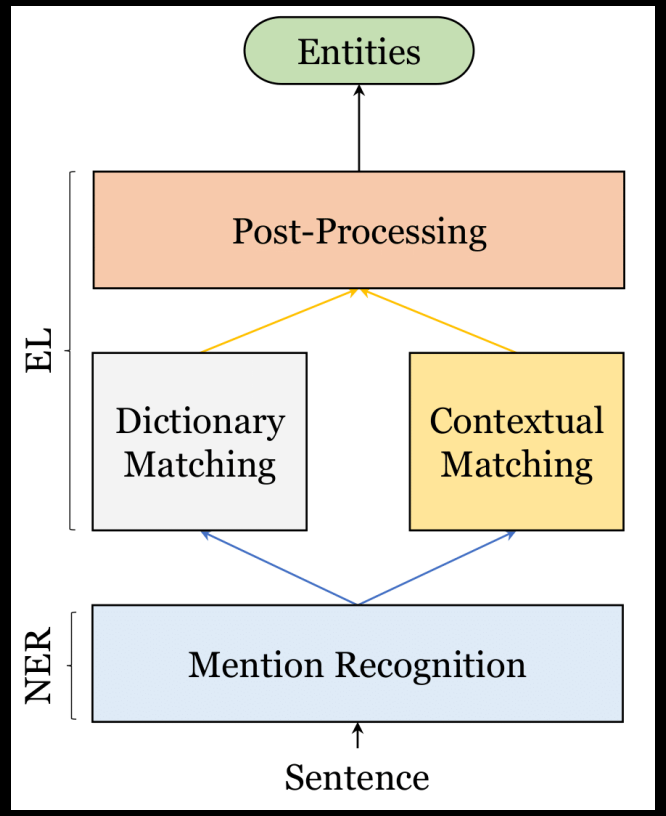


← NER (no gold spans)

MedLinker: Solution

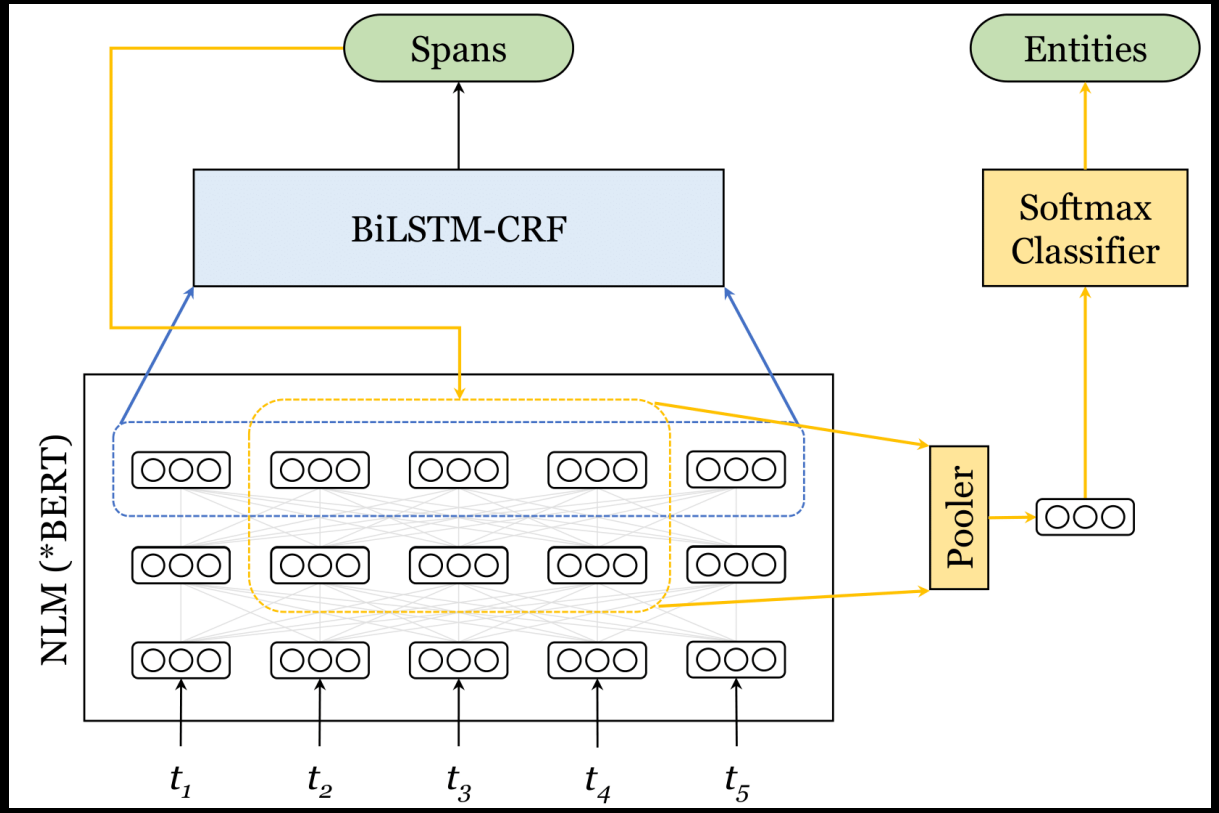
Combine Preds. →

String Matching →



← NER (no gold spans)

MedLinker: Solution



MedLinker: Solution

$$scoreSTR(s,e) = \max_{a \in map(e)} \cos(\hat{s}, \hat{a})$$

$$scoreCLF(s,e) = P(e = j|\overrightarrow{s}) = \frac{\exp^{f(\overrightarrow{s})_j}}{\sum_{i=1}^{|E|} \exp^{f(\overrightarrow{s})_i}}$$

← All aliases(e), for all entities

← Entities in train set

$$scoreSTR\_CLF(s,e) = \max(scoreSTR(s,e), scoreCLF(s,e))$$

MedLinker: Results

Mention Recognition			
Model	**P**	**R**	**F1**
Exact Match	51.32	32.96	40.14
NCBI BERT (Uncased)	69.44	69.38	69.41
BioBERT 1.1 (Cased)	70.00	70.43	70.21
SciBERT (SciVocab)			
- Uncased	69.42	71.81	**70.59**
- Cased	69.16	71.30	70.22

MedLinker: Results

Concept (CUI) Linking			
Model	**P**	**R**	**F1**
Exact Match	47.12	31.11	37.48
TaggerOne [1]	47.10	43.60	45.30
MedLinker			
- scoreSTR	33.03	47.34	38.91
- score1NN	33.61	55.16	41.77
- scoreCLF	32.21	52.66	39.97
- scoreSTR_1NN	40.46	59.69	48.23
- scoreSTR_CLF	40.70	**59.59**	48.37
- scoreSTR_CLF (t=0.70)	**48.43**	50.07	**49.24**

Semantic Type (STY) Linking			
Model	**P**	**R**	**F1**
Exact Match	49.04	31.97	38.71
Fraser et al. 2019 [8]			
- BioBERT	61	66	63
- BioBERT | BERT-base	**63**	65	**64**
MedLinker			
- scoreSTR	48.31	56.81	52.22
- score1NN	46.62	62.67	53.47
- scoreCLF	58.62	64.63	61.48
- scoreSTR_1NN	53.06	65.94	58.80
- scoreSTR_CLF	59.23	**67.81**	63.23
- scoreSTR_CLF (t=0.45)	**63.13**	63.69	63.41

Conclusion

- Recent NLMs allow for unprecedented gains in WSD.
- The same principles show similar improvements in Entity Linking tasks.
- 1NN (and w/softmax) methods are straightforward enough to assume progress should follow with better NLMs.
- Sense/entity embeddings can be useful for probing NLMs for world knowledge and downstream tasks.

Thanks

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

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