How to enable Natural Language Understanding in many languages

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Babelscape

Joint work with…

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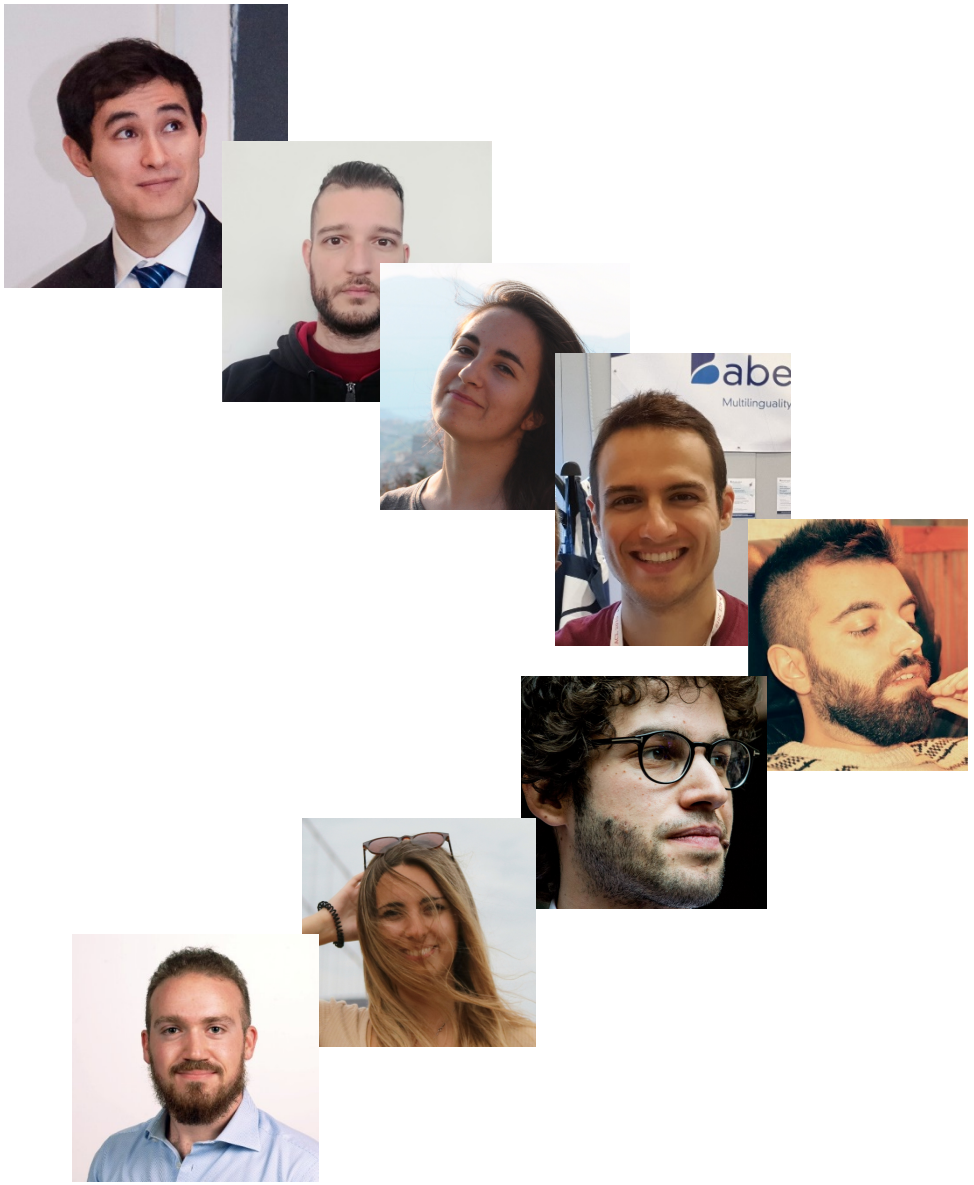
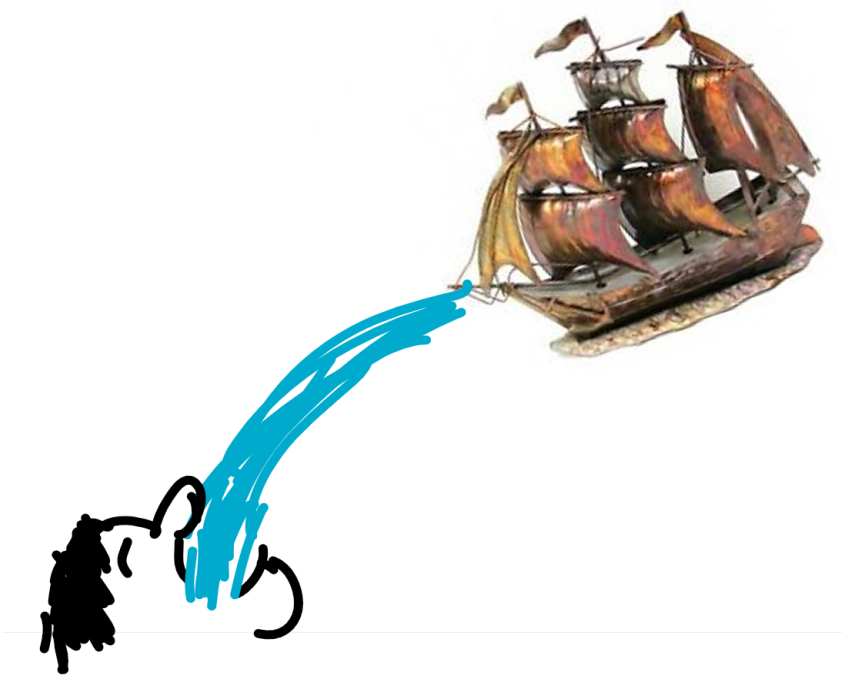


Machine Translation «does not understand»

- **EN** Is it healthy to drink from a copper vessel?
- **IT** È salutare bere da una nave di **rame**?
- **EN** Is it healthy to drink from a **copper** ship?



3 tasks to enable Natural Language Understanding at the semantic level

- Word Sense Disambiguation
  - Associating meanings with words occurring in context

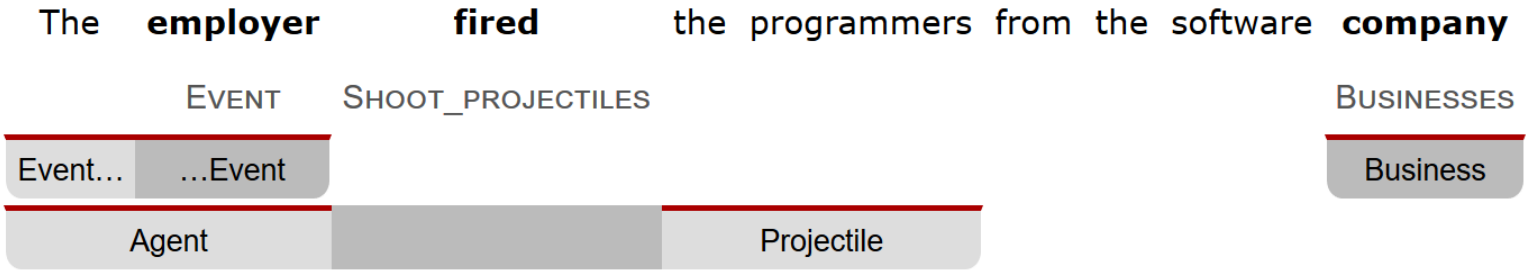
The employer fired the programmers from the software company .





3 tasks to enable Natural Language Understanding at the semantic level

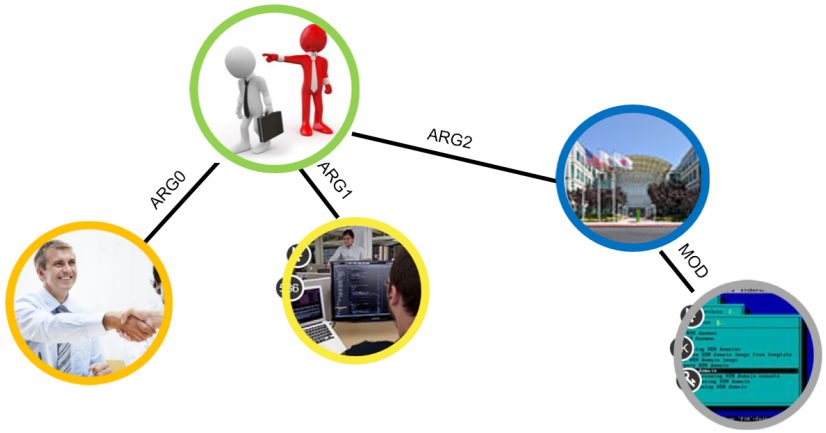
- Word Sense Disambiguation
- Semantic Role Labeling
  - «Shallow semantic parsing» which performs predicate-argument annotations



3 tasks to enable Natural Language Understanding at the semantic level

- Word Sense Disambiguation
- Semantic Role Labeling
- Semantic Parsing
  - Transforming the text into a structured semantic representation

The employer fired the programmers from the software company .



A Key Goal of AI – Multilingual Machine Reading

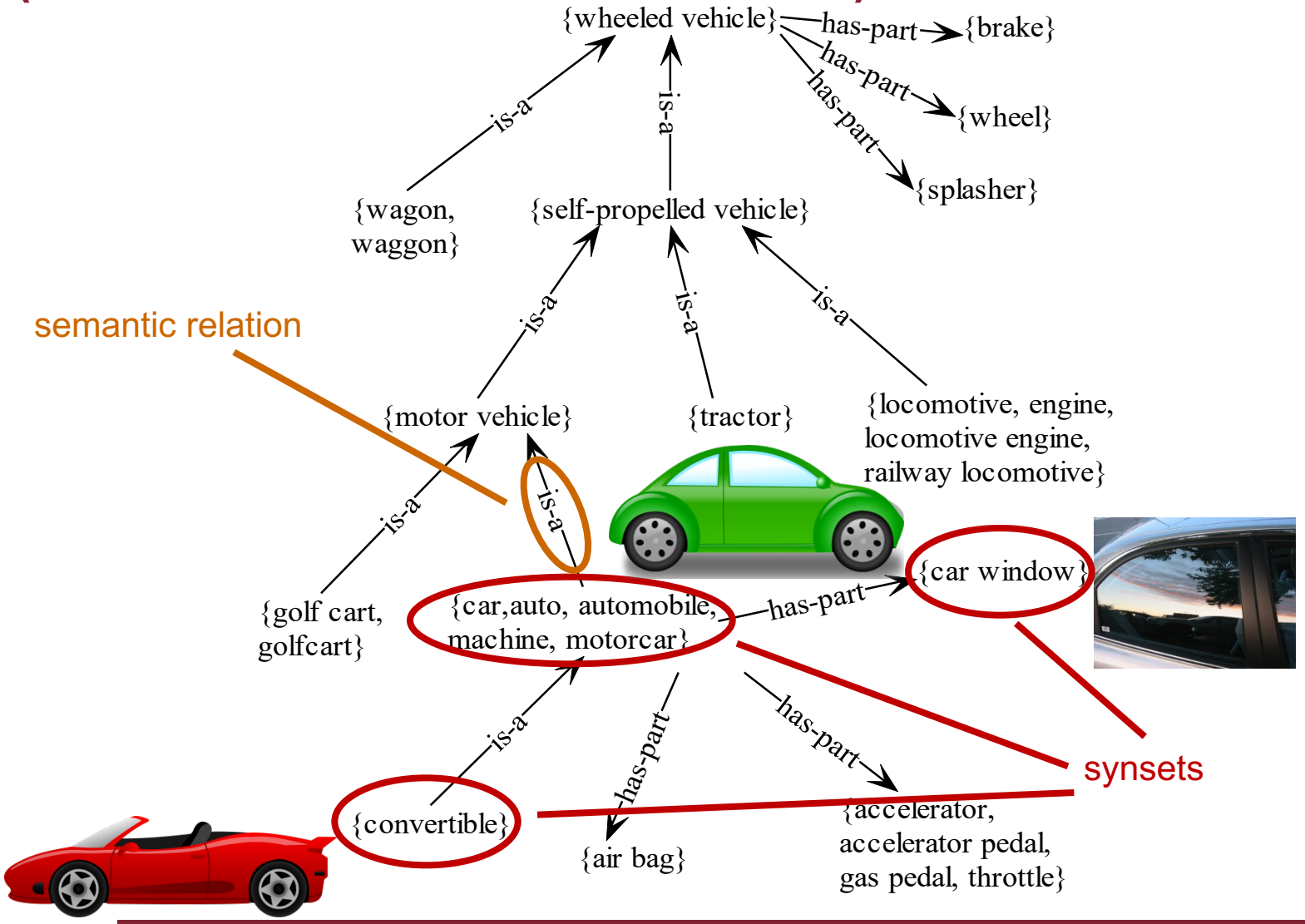
- Why? Machines could potentially **"read" the entire Web**
- Answer all kinds of questions, summarize, translate, etc.

Key question: deriving meaning from natural language by **overcoming its inherent complexities**

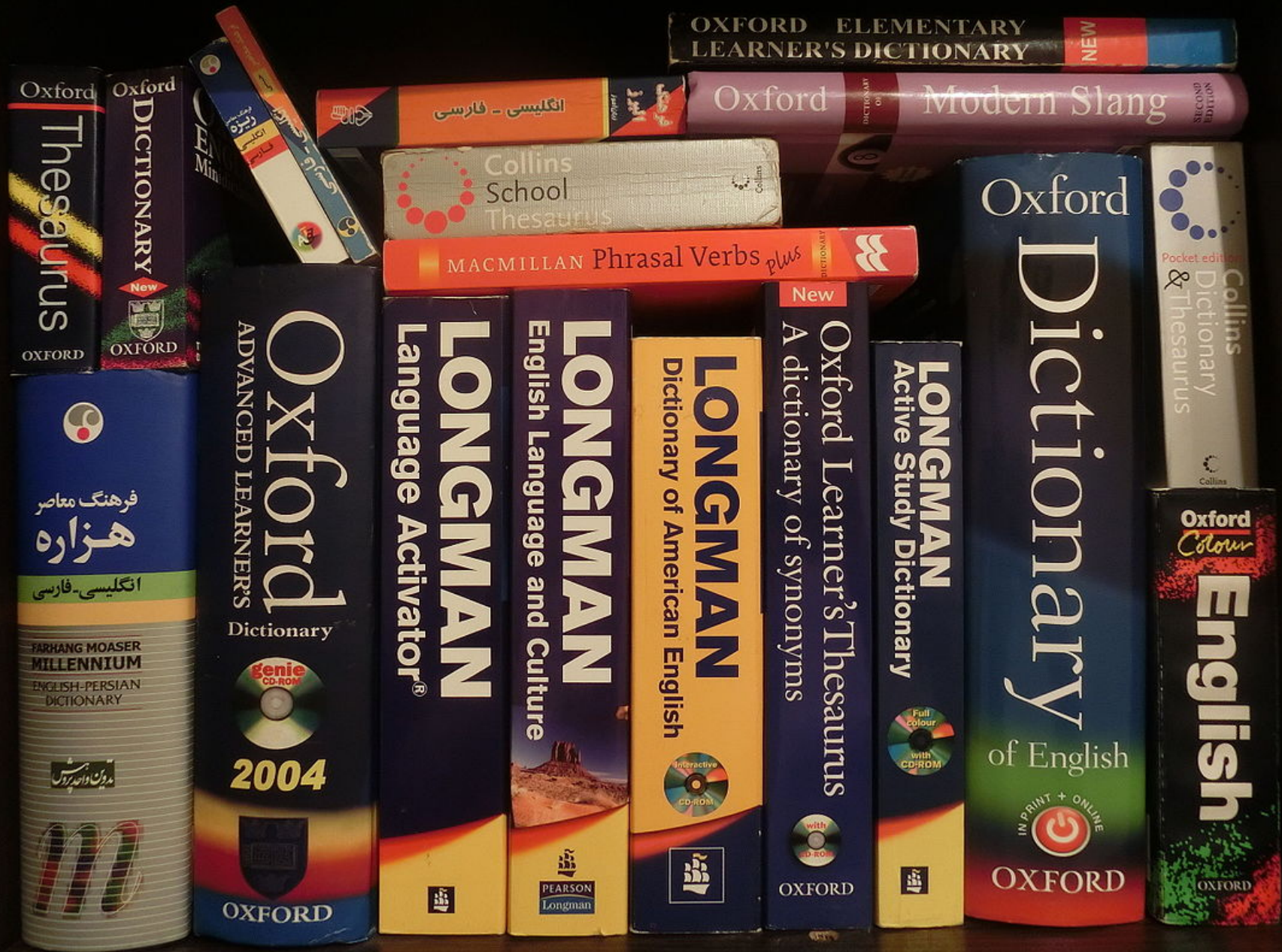
Word Sense Disambiguation

The mouse is eating the cheese .

WordNet is THE sense inventory for English (Miller et al. 1990; Fellbaum, 1998)



The resource diaspora



Word senses: which sense inventory to scale multilingually?

- **BabelNet** (Navigli and Ponzetto, ACL 2010; AIJ 2012): a merger of WordNet, multilingual wordnets, Wikipedia, Wikidata, Wiktionary and many other resources

Word senses: which sense inventory to scale multilingually?

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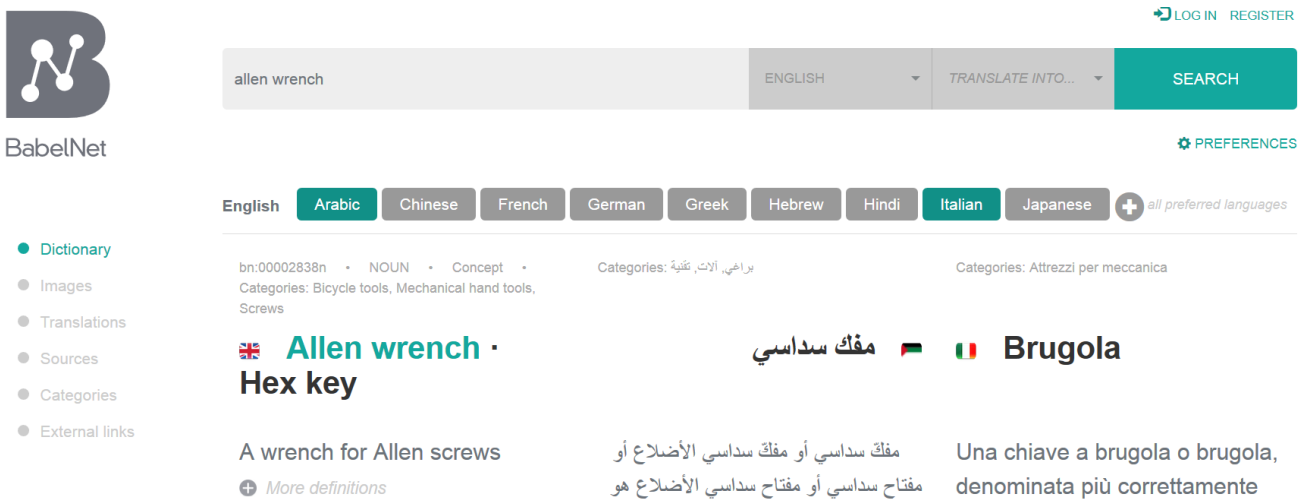
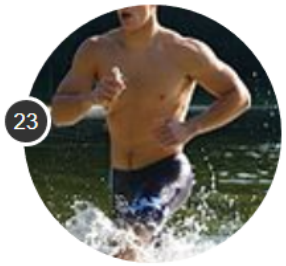


Verb



run

Move fast by using one's feet, with one foot off the ground at any given time

ID: 00093170v | Concept

هَرْوَلَ, جَرَى, رَكَضَ

奔跑, 跑

courir

rennen

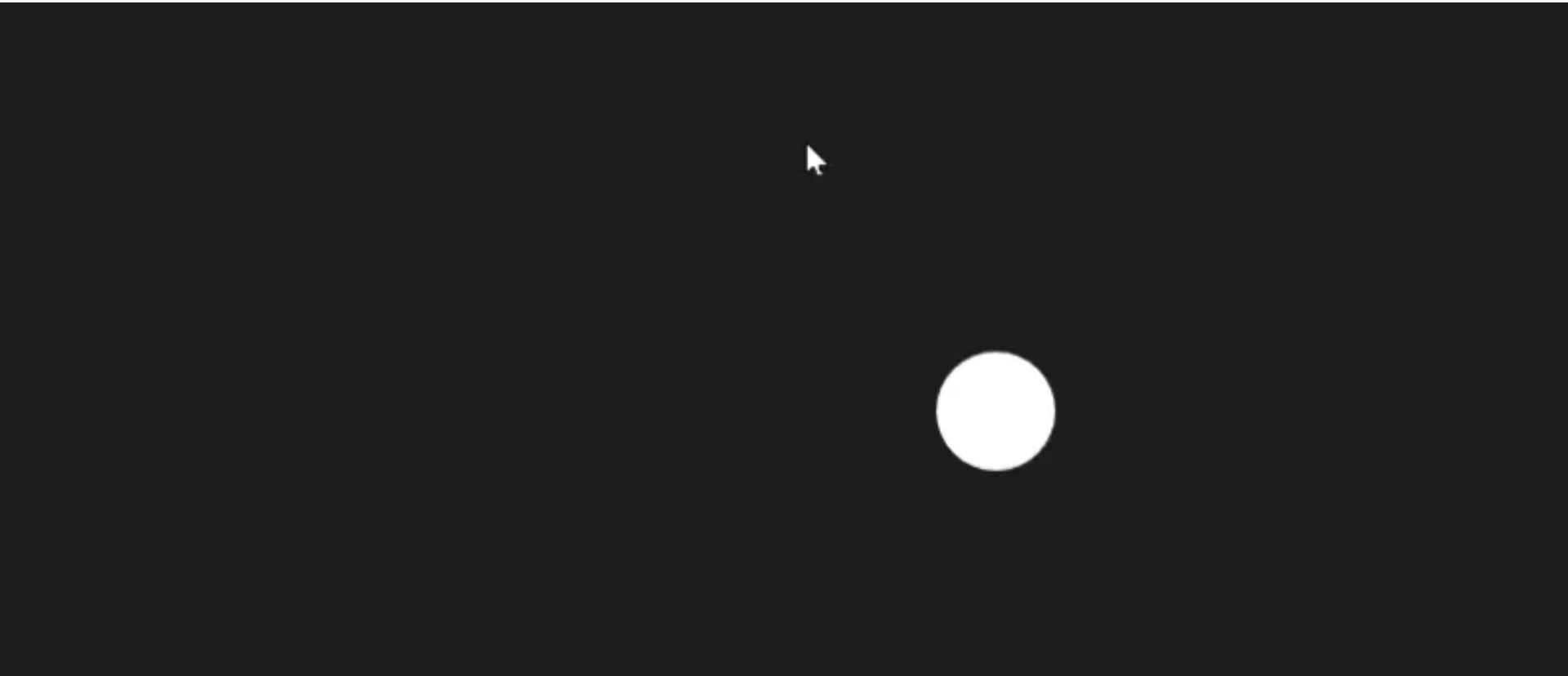
τρέχω, κινούμαι

רץ

correre

Why do we need BabelNet?

- Multilinguality: the same concept is expressed in tens of languages
- Coverage: 284 languages and 16 million entries!
- Concepts and named entities together: dictionary and encyclopedic knowledge is semantically interconnected



Two ERC projects aimed at automatic text understanding

MOUSSE: ERC Consolidator Grant (2017-2022)

The current limits of Word Sense Disambiguation

- Lack of high-quality knowledge
  - Limited to WordNet, BabelNet, etc.
- Limited to one language
  - English, English, English?
- Fine granularity of the sense inventory
  - WordNet, WordNet, WordNet

The current limits of Word Sense Disambiguation

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What is missing in WordNet and BabelNet?

- WordNet is manually curated, but contains mostly paradigmatic relations (e.g. convertible –is-a-> car)
- BabelNet is very rich, but contains a huge number of unclassified relations (e.g. ERC –> Brussels, screen –> pixel)

- To disambiguate, we need syntagmatic relations
  - open -> door
  - open -> business
  - play -> piano
  - play -> act
  - play -> game
  - door -> window

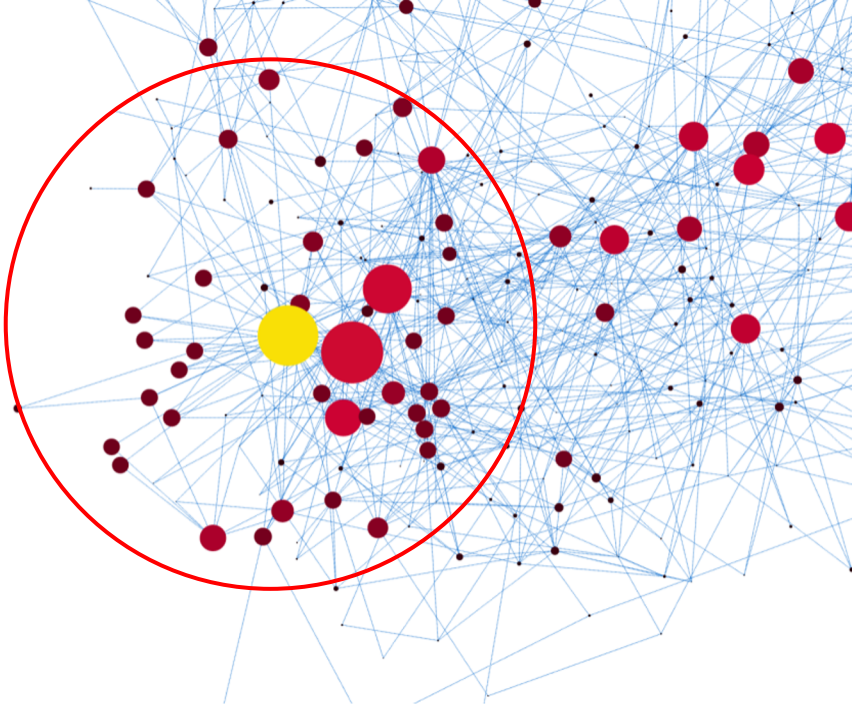
SyntagNet: addressing the lack of syntagmatic knowledge (Maru et al., EMNLP 2019)

- We extracted cooccurrences of nouns and verbs on a large scale from Wikipedia and the British National Corpus

$$score(w_1, w_2) = log_2(1 + n_{w_1 w_2}) \frac{2n_{w_1 w_2}}{n_{w_1} + n_{w_2}}$$

- We disambiguated the cooccurrences with our state-of-the-art WSD system
  - Babelfy (Moro et al., TACL 2014)
- We validated the top-ranking cooccurrences manually
- Minimum agreement between 3 annotators: **κ = 0.71** (substantial agreement)
  - Disagreement instances are valid alternative tags, not factual errors

Knowledge-based WSD



- Personalized PageRank can be used to perform disambiguation of an ambiguous word in context
- The probability of a word sense depends on its direct and indirect interconnections to other senses of words in context
- The quality of disambiguation depends on the **underlying semantic network** which connects meanings

Comparison between different Lexical Knowledge Bases

		English					
resource	**#relations**	**Sens2**	**Sens3**	**Sem07**	**Sem13**	**Sem15**	**All**
WNG (WordNet+PWNG)	671,779	69.2	65.9	54.9	66.8	70.7	67.1
WNG+KnowNet20	520,682	67.2	65.8	53.8	67.3	71.5	66.6
WNG+deepKnowNet95d	522,880	66.9	64.9	53.6	66.9	71.6	66.2
WNG+BabelNet 4.0	9,447,341	67.5	64.1	53.0	67.6	66.9	65.6
WNG+eXtended WordNet	551,551	67.7	65.7	52.3	67.6	71.0	66.7
WNG+ColWordNet	8,424	69.2	65.9	54.1	66.7	70.7	67.1
WNG+SyntagNet	88,019	**71.2**	**71.6**	**59.6**	**72.4**	**75.6**	**71.5**

Underlined results show statistically significant differences from the baseline (χ^2 test, $p < 0.05$)

Comparison with the state of the art in WSD

system	Sens2	Sens3	Sem07	Sem13	Sem15	All
LSTMLP•	**73.8**	71.8	**63.5**	69.5	72.6	**71.5**
IMSC2V$_{+PR}$∞	**73.8**	71.9	63.3	68.2	72.8	71.2
fastSense△	73.5	**73.5**	62.4	66.2	73.2	71.1
UKB+SyntagNet	71.2	71.6	59.6	**72.4**	**75.6**	**71.5**

• Yuan et al., 2016

† Raganato et al. (2017b)

⋆ Gutiérrez Vázquez et al. (2010)

◇ best SUDOKU-RUNk (Manion, 2015)

○ Pasini and Navigli (2017)

∞ Melacci et al. (2018)

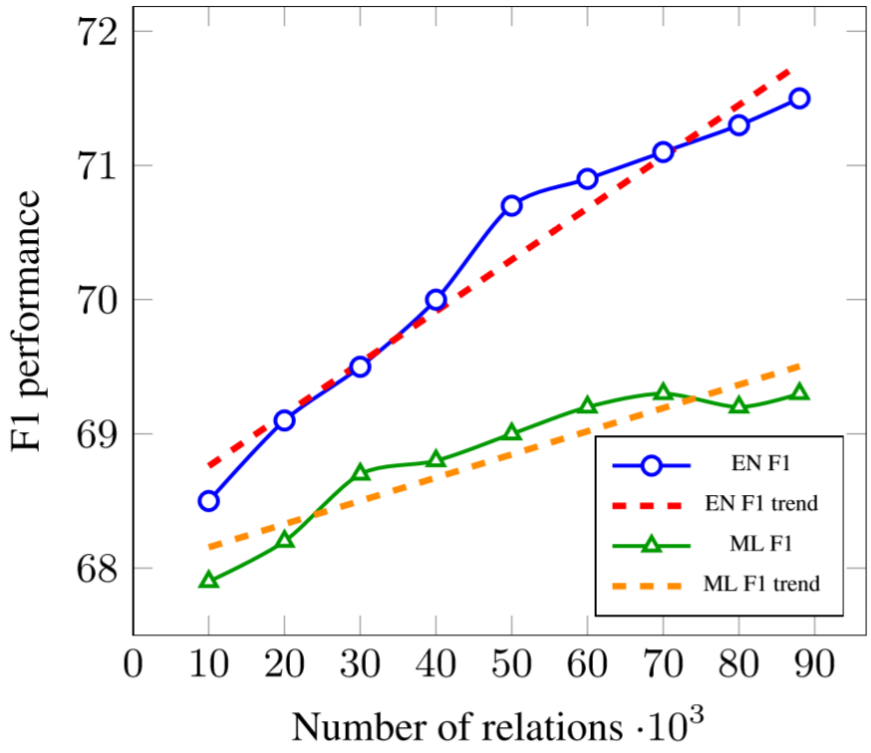
△ Uslu et al. (2018)

‡ result obtained by aggregating the outputs of the best systems across languages

Underlined results show statistically significant differe[illegible] from results (χ^2 test, $p < 0.05$)

Syntagmatic relations rival (and surpass) neural supervised WSD!

We are far from reaching a plateau!



- More relation edges are expected to provide further performance increase
- English growth steeper because of cleaner sense inventory

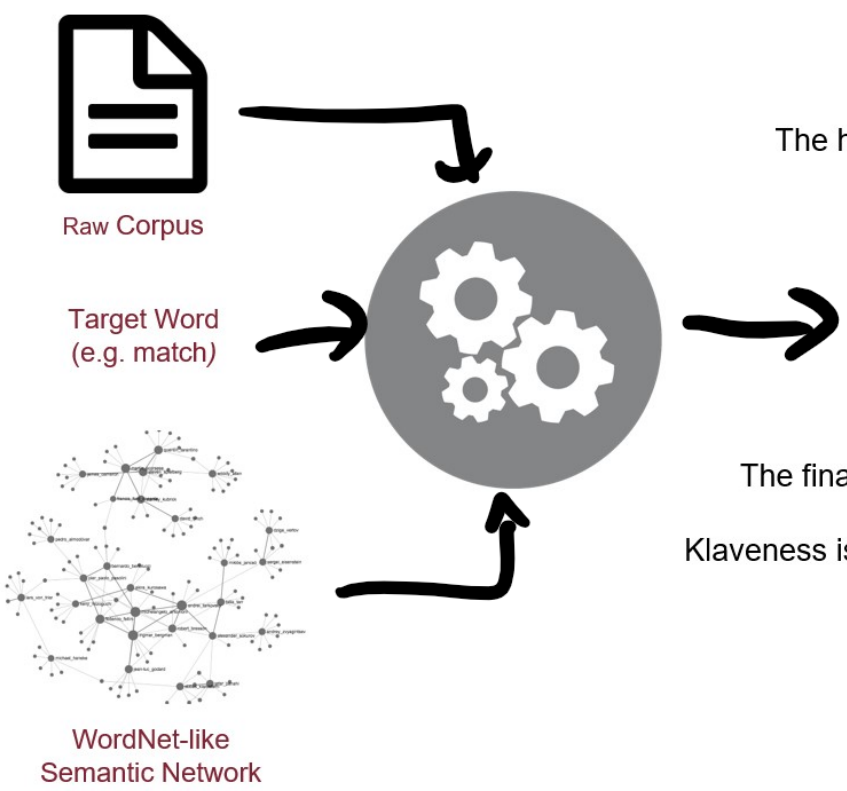
The current limits of Word Sense Disambiguation

- Lack of high-quality knowledge
  - Limited to WordNet, BabelNet, etc.
- Limited to one language (Scarlini et al., AAAI 2020)
  - English, English, English
- Fine granularity of the sense inventory
  - WordNet, WordNet, WordNet


“Language barriers”

Addressing the lack of sense-annotated data

- Goal: overcome the **knowledge acquisition bottleneck**
  - i.e. acquire **large training datasets for supervised WSD**



The head of the **match** consisted of a mixture of potassium

Wooden **matches** are packaged in matchboxes

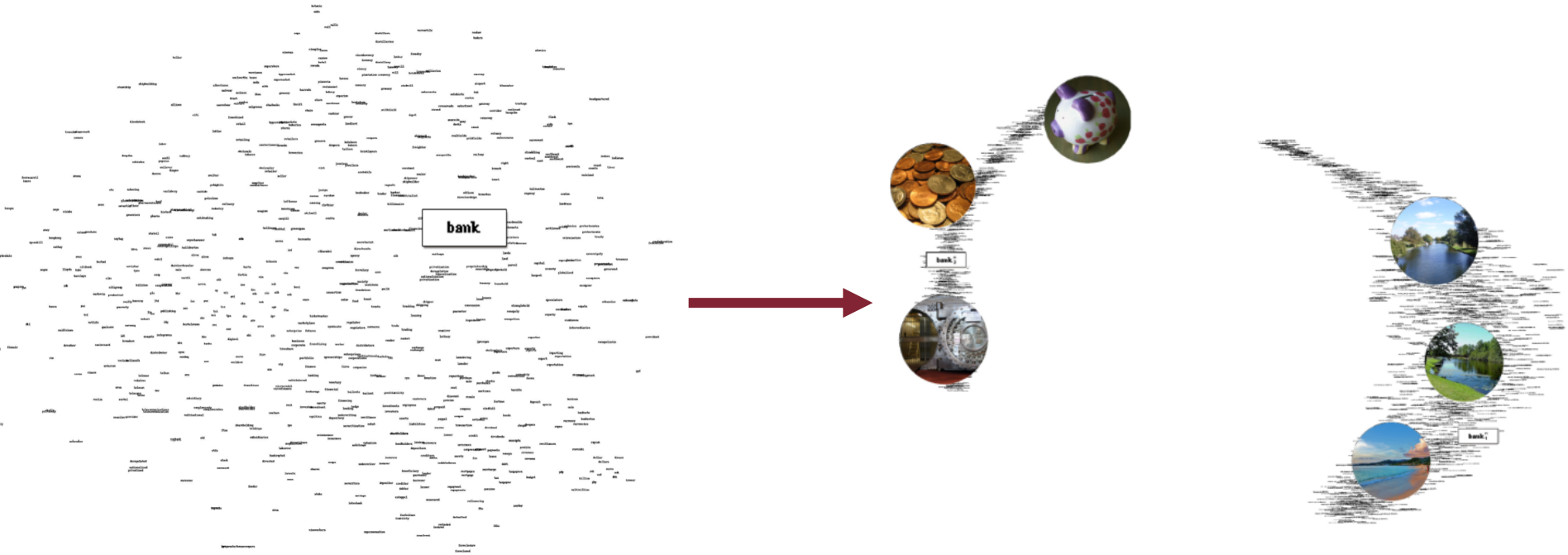
The **match** takes place in a ring

The final tournament **matches** were held in four stadium venues

Klaveness is a Norwegian lawyer and footballer who played 73 **matches**

Training Corpus

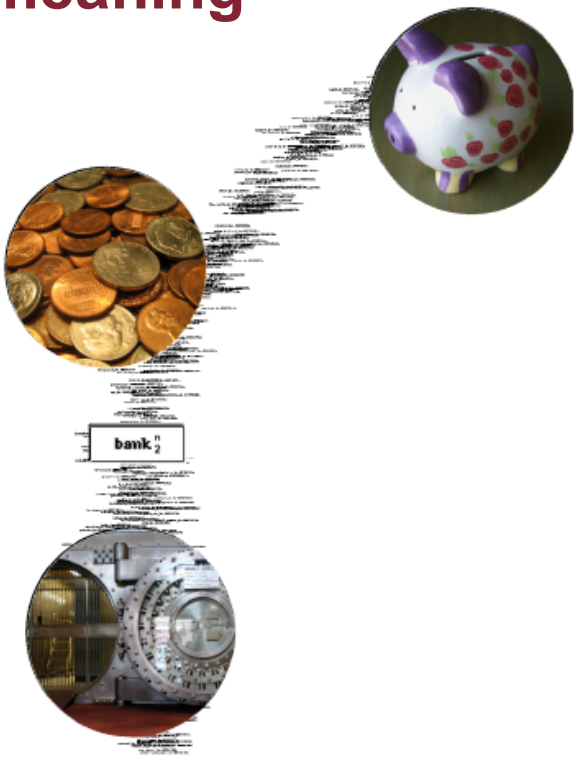
Solution: move from lexical to semantic

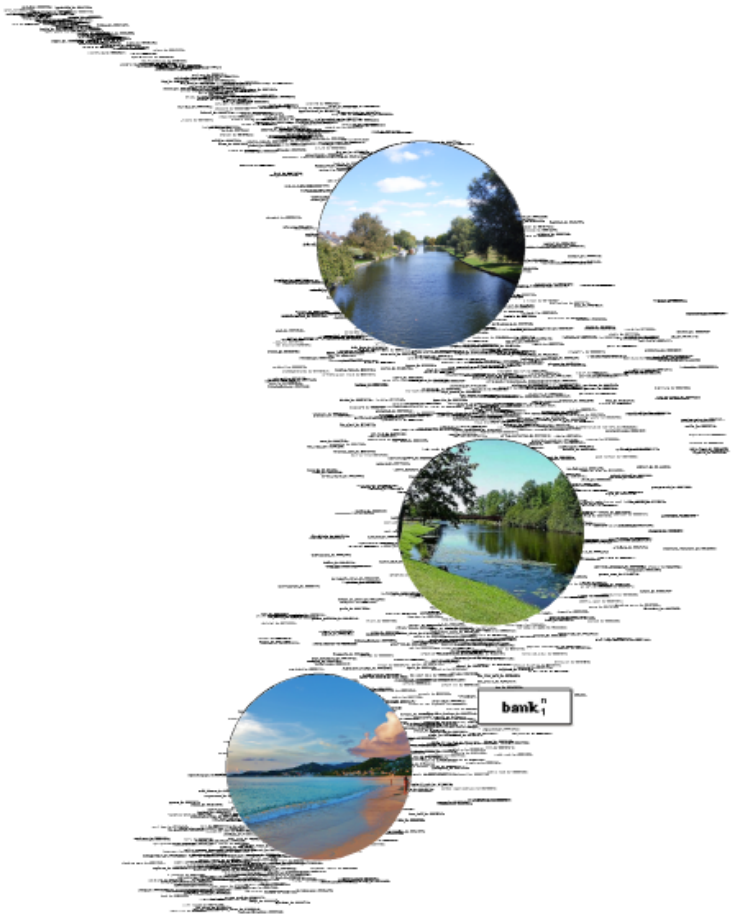


Word vector space model

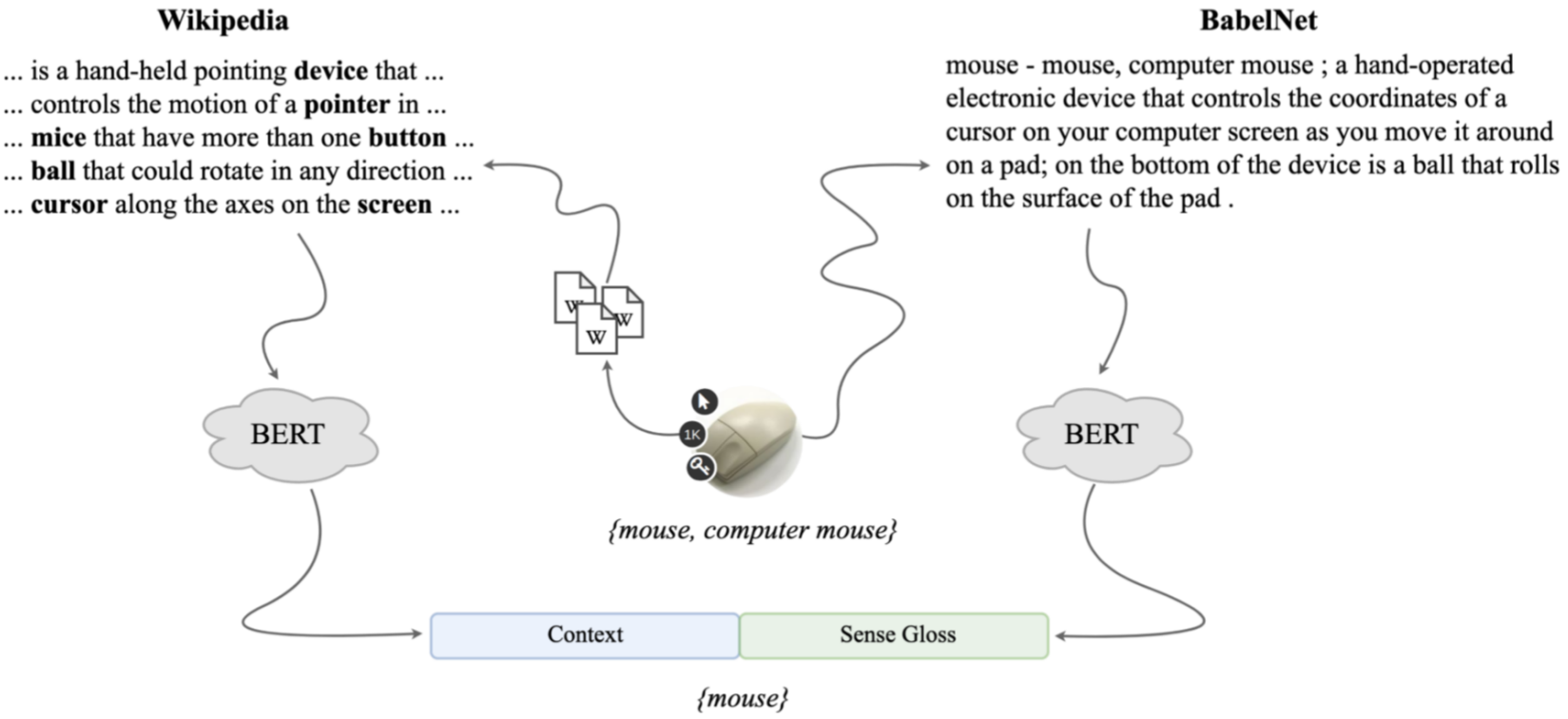
Sense vector space model

Solution: distinct representation for each word's meaning





Sense representations out of contextualized embeddings (AAAI 2020, SensEmBERT)

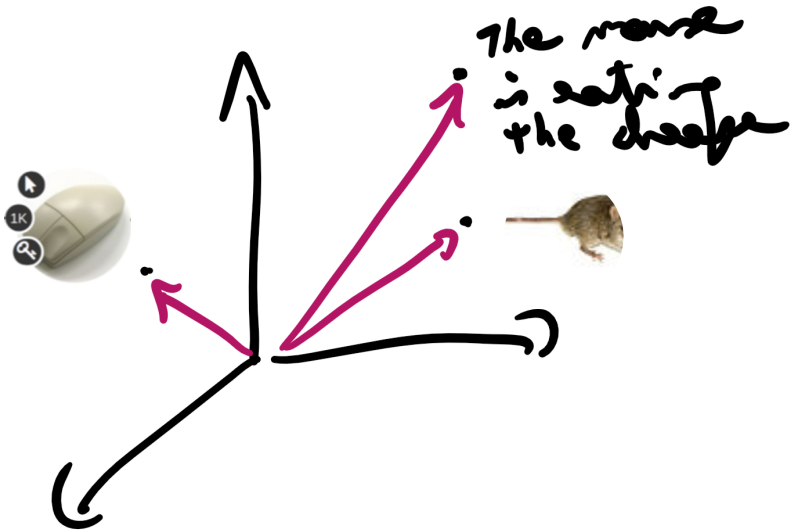


$$v_s = \frac{\sum_{w_i \in W_s} rank(w_i)^{-1} \; v_{w_i}}{\sum_{w_i \in W_s} rank(w_i)^{-1}}$$

How to perform Word Sense Disambiguation?

- Very, very simple: 1-nearest neighbour!

- For a given sentence, e.g. *The **mouse** is eating the cheese*, compare the representations of the meanings of **mouse** with the context vector representation:



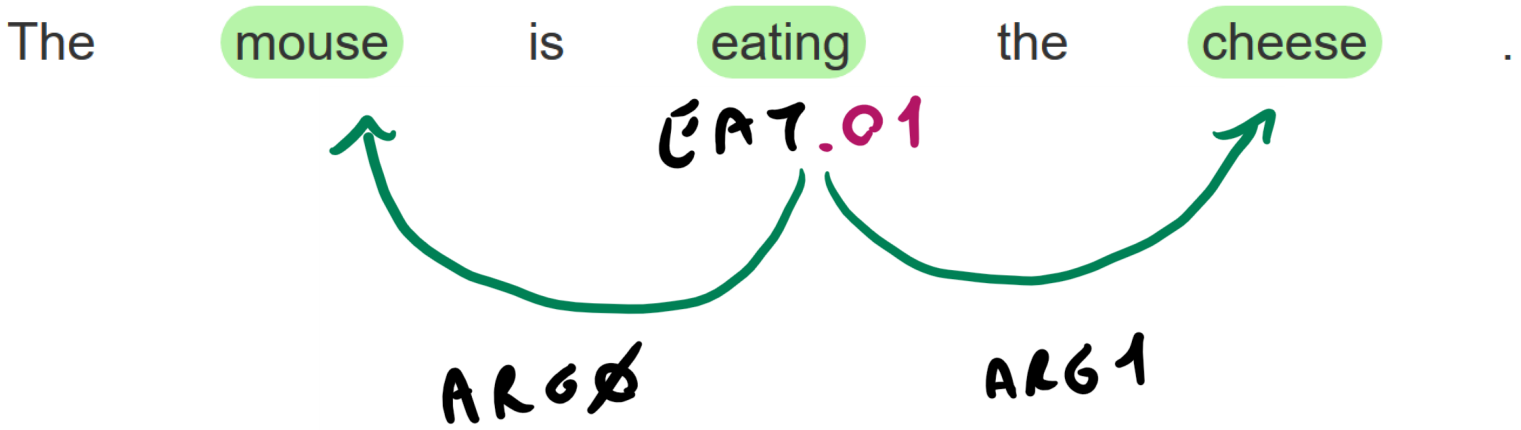
Knowledge-based+Neural achieves 80% accuracy in Word Sense Disambiguation!

	Model	Senseval-2	Senseval-3	SemEval-07	SemEval-13	SemEval-15	ALL
KB	MFS	72.1	72.0	65.4	63.0	66.3	67.6
	Lesk$_{ext}$+emb (2014)	74.6	72.7	66.0	66.2	67.8	69.8
	UKB$_{gloss}$ (2014)	70.6	58.4	56.6	59.0	62.3	62.1
	Babelfy (2014)	74.0	66.7	61.0	66.4	69.9	68.6
Sup	IMS+emb (2016)	79.0	74.6	71.1	65.9	72.1	71.9
	Bi-LSTM (2017)	78.6	72.7	71.1	66.4	73.3	71.6
	HCAN (2018a)	78.3	73.2	70.9	68.5	73.8	72.6
	EWISE$_{ConvE}$ (2019)	-	-	-	69.4	-	74.0
Sup$_{context}$	context2vec (2016)	78.0	73.1	66.7	65.6	71.6	71.0
	LSTM-LP (2016)	79.6	76.3	71.7	69.5	72.8	-
	BERT k-NN (2019)	71.7	73.0	72.9	65.6	68.4	69.3
	BERT k-NN + MFS (2019)	81.4	76.3	73.6	71.8	74.0	75.5
	LMMS (2019)	82.6	77.8	76.7	75.4	76.6	77.9
Ours	SENSEMBERT	79.9	70.0	74.2	75.0	**79.7**	75.7
	SENSEMBERT$_{sup}$	**84.0**	**80.8**	**80.5**	**78.5**	79.5	**80.5**

The current limits of Word Sense Disambiguation

- Lack of high-quality knowledge
  - Limited to WordNet, BabelNet, etc.
- Lack of sense-annotated data
  - Limited to SemCor, MASC, Senseval, SemEval, not much more
- Fine granularity of the sense inventory (Lacerra et al., AAAI 2020)
  - WordNet, WordNet, WordNet
  - **No time in this overview talk, sorry!**

Dependency-based Semantic Role Labeling



Roleset id: eat.01

Roles:

Arg0-PAG: *consumer, eater* (vnrole: 39.1-1-agent)
Arg1-PPT: *meal* (vnrole: 39.1-1-patient)

What are the issues with the current frame inventories?

	Cluster type	#	Argument roles	#	Meaning units	#
FrameNet	Frames	1,224	Frame elements	10,542	Lexical units	5,200
VerbNet	Levin's classes	329	Thematic roles	39	Senses	6,791
PropBank	Verbs	5,649	Proto-roles	6	Framesets	10,687
WordNet	-	-	-	-	Synsets	13,767

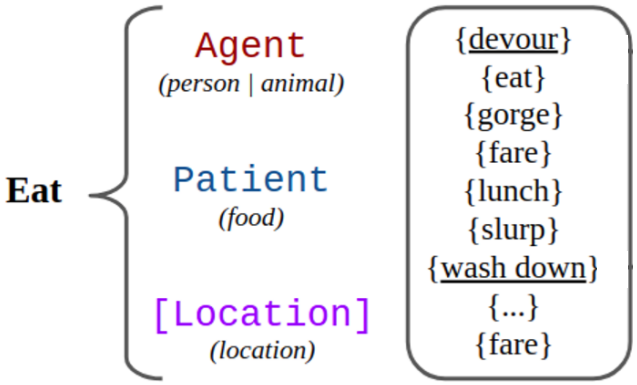
- Low coverage of verbal meanings (FrameNet, VerbNet)
- Low coverage of verbs (all resources, compared to 11.5k distinct verbs in WordNet)
- Unintelligibile argument roles (ARG0, ARG1, PropBank)
- Syntactic organization of verbs (VerbNet)
- Language (English!) specificity (all resources)

VerbAtlas: a new resource for SRL and Semantic Parsing (Di Fabio et al., EMNLP 2019)

- A **manually-crafted inventory of verbs** and **argument structures** with:
  1. full coverage of the verbal lexicon
  2. prototypical argument structures for each cluster of synsets that define a semantically-coherent frame
  3. explicit, cross-domain semantic roles
  4. refined semantic information and selectional preferences for the frame argument structure
  5. scalability: linkage to WordNet and, as a result, to BabelNet
  6. reusability: full mapping to PropBank framesets
  7. effectiveness: ability to improve over PropBank on the CoNLL-2009 dataset

VerbAtlas vs. PropBank

VerbAtlas



PropBank

Roleset id: eat.01

Roles:

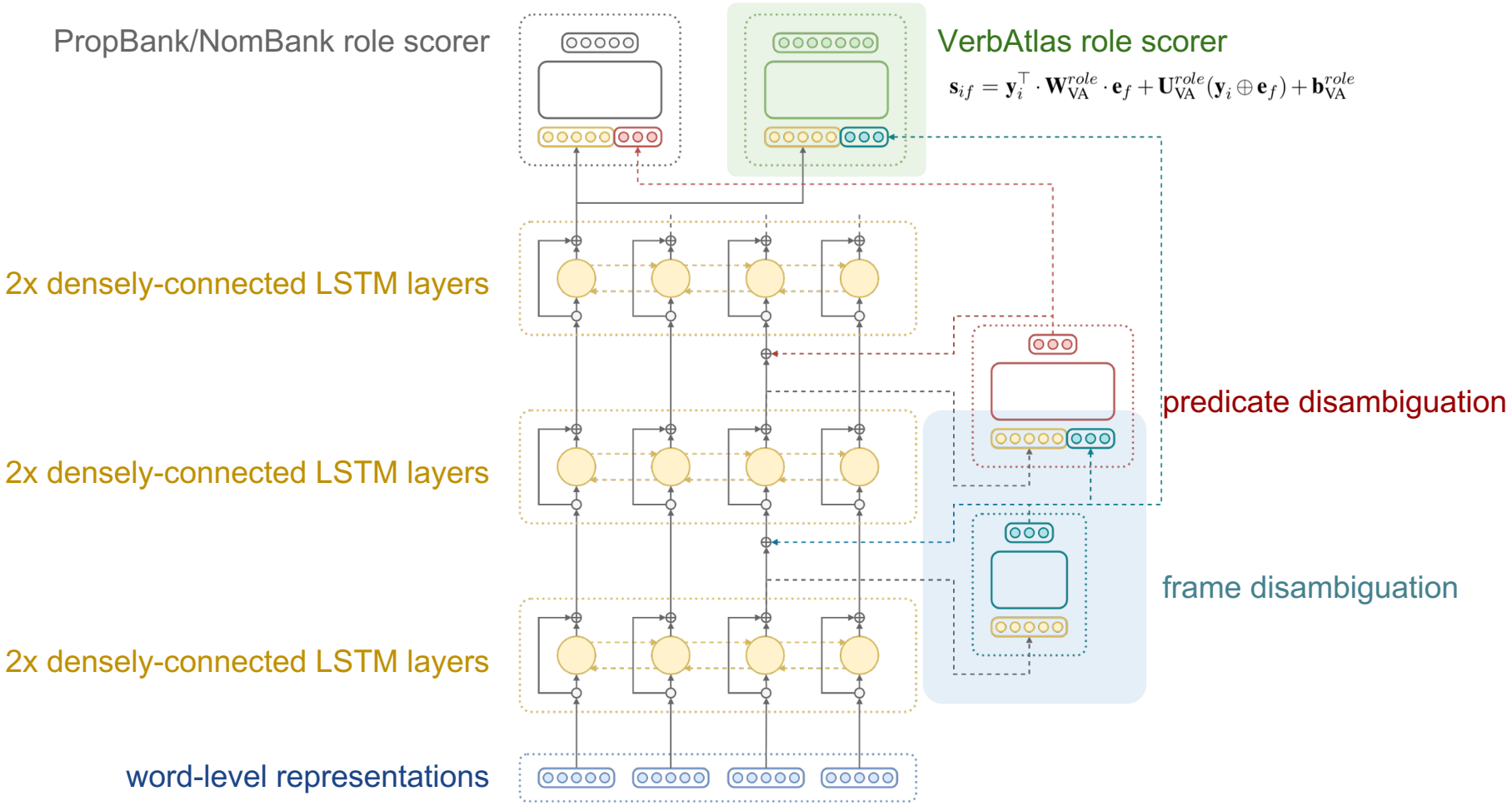
Arg0-PAG: *consumer, eater* (vnrole: 39.1-1-agent)
Arg1-PPT: *meal* (vnrole: 39.1-1-patient)

Roleset id: wash_down.04 ,

Roles:

Arg0-PAG: *Agent of swallowing*
Arg1-PPT: *Thing being swallowed*
Arg2-MNR: *Liquid enabling swallowing*

1. **A Simple SRL Architecture based on Cai et al. (2018)**
2. **Aiding predicate disambiguation with frame disambiguation**
3. **Achieving a deeper understanding thanks to finer-grained semantically-coherent roles**



Results on the CoNLL-2009 dataset

In-domain

Syntax-aware system	P	R	F_1
Roth and Lapata (2016)	88.1	85.3	86.7
Marcheggiani and Titov (2017)	89.1	86.8	88.0
He et al. (2018)	89.7	**89.3**	89.5
Li et al. (2018)	**90.3**	**89.3**	**89.8**
Syntax-agnostic system	P	R	F_1
Marcheggiani et al. (2017)	88.7	86.8	87.7
He et al. (2018)	89.5	87.9	88.7
Cai et al. (2018)	89.9	89.2	89.6
This work	**90.5**	**89.5**	**90.0**

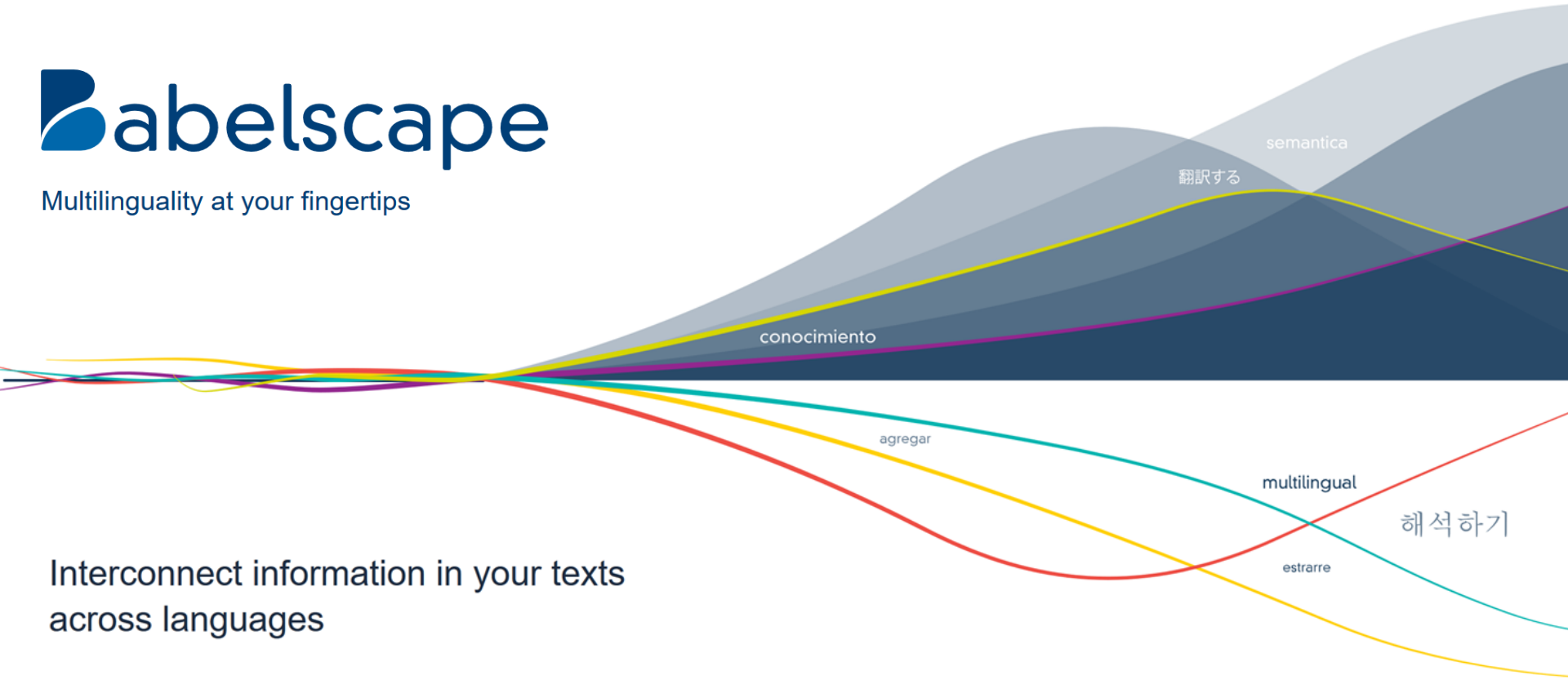
Out-of-domain

Syntax-agnostic system	P	R	F_1
Marcheggiani et al. (2017)	79.4	76.2	77.7
He et al. (2018)	**81.7**	76.1	78.8
Cai et al. (2018)	79.8	78.3	79.0
This work	81.1	**78.4**	**79.7**

- VerbAtlas adds important information already within the domain, and provides robustness across domains

Babelscape: the future of BabelNet and related technologies

- We created a Sapienza spinoff, Babelscape, with the **key objective** of making BabelNet and related technologies sustainable
- Income is reinvested in BabelNet and subsequent projects
- Working for EUIPO and big companies



Demos

- Let's now look at demos of our technologies

Conclusions

- Natural Language Understanding is hampered by the lack of knowledge, annotated data and suitable resources
  - Especially if we want to go multilingual or scale across domains
- We presented approaches to **relieve the knowledge acquisition bottleneck**
  - take the tasks of disambiguation and semantic role labeling beyond the current state of the art
  - make the systems and their outputs more understandable, explainable and scalable
- All of the approaches can **scale across languages thanks to BabelNet**

Thanks or…

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