
# 3 Algorithms for Sense Embedding

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**TALia seminar**
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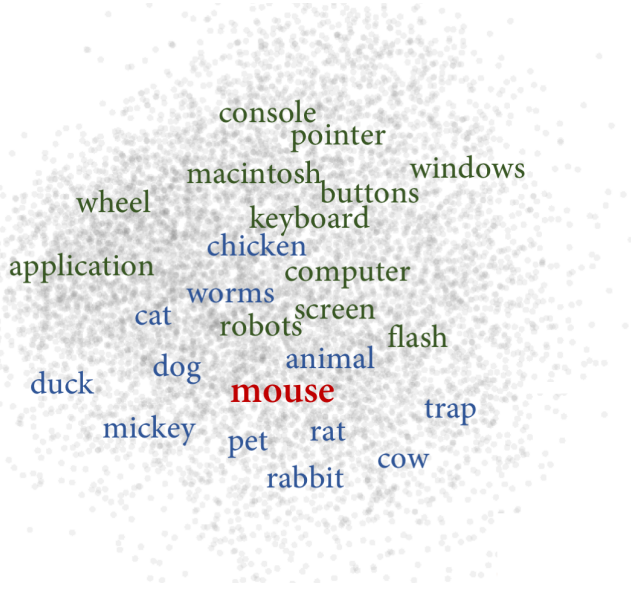
# Bibliography


- From word to sense embeddings: A survey on vector representations of meaning[1]
  Camacho-Collados & Pilehvar 2018
- Multi-prototype vector-space models of word meaning
  Reisinger & Mooney 2010
- Efficient non-parametric estimation of multiple embeddings per word in vector space
  Neelakantan, Shankar, Passos & McCallum 2014
- A unified model for word sense representation and disambiguation
  Chen, Liu & Sun 2014

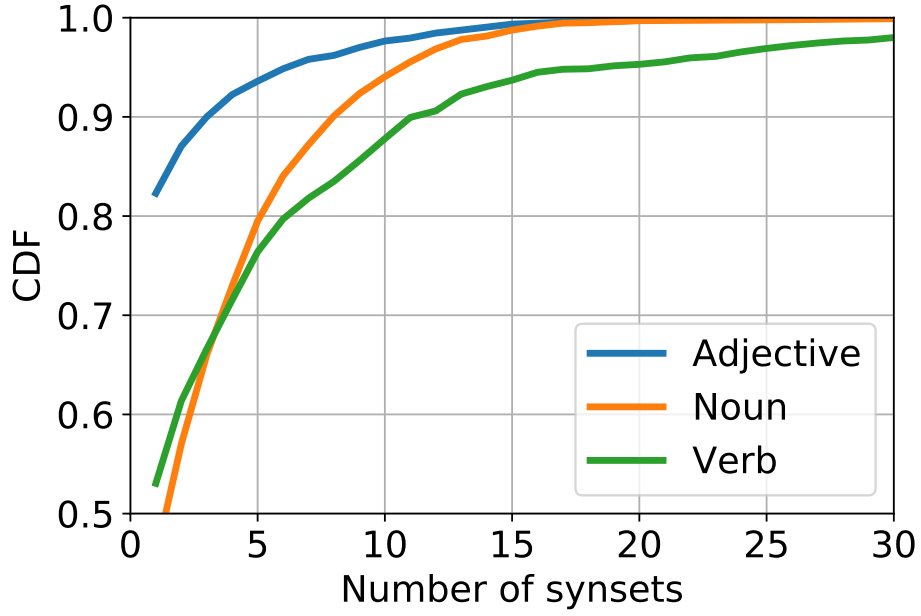

[1] Source for illustrations

# Motivation




Confusion due to the polysemy of the word **mouse**

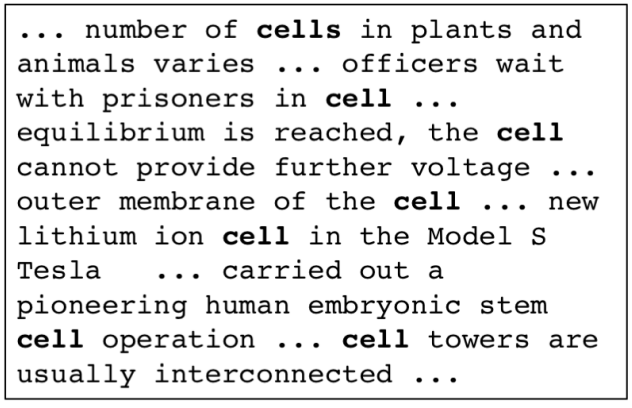
# Polysemy



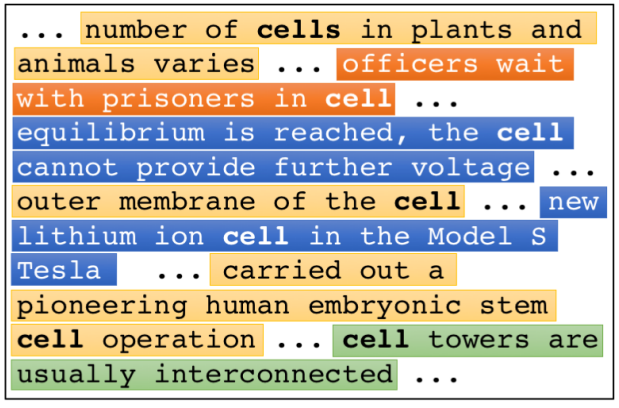

Distribution of the number of synsets per word
(Wordnet, 2,000 most frequent words)

# Sense embedding

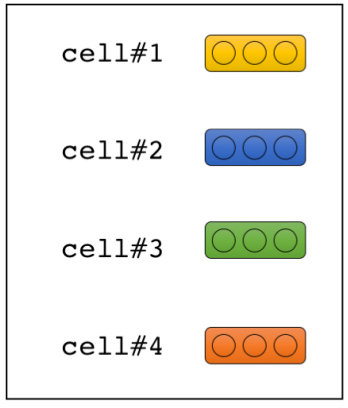
Learn the representation of **senses** instead of **words**




(1) Get occurrences of a word from text corpora




(2) Analyze contexts and induce senses of the word




(3) Compute sense representation

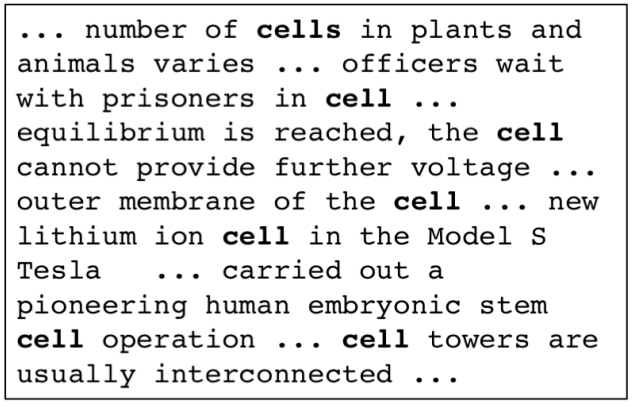
## Note

A **single** vector per sense

Different from contextual embedding (e.g., BERT)

# 2 main issues

1. The **number** of senses is not well defined
2. The **context** itself becomes ambiguous...

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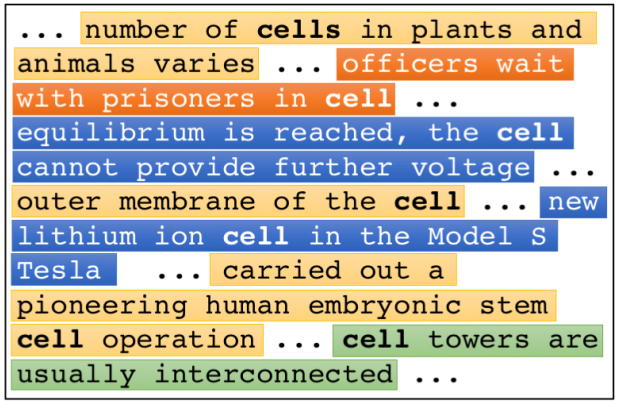


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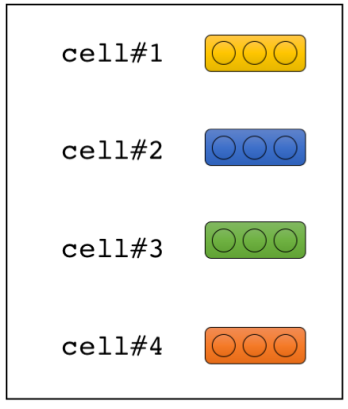



(3) Compute sense representation

# Outline

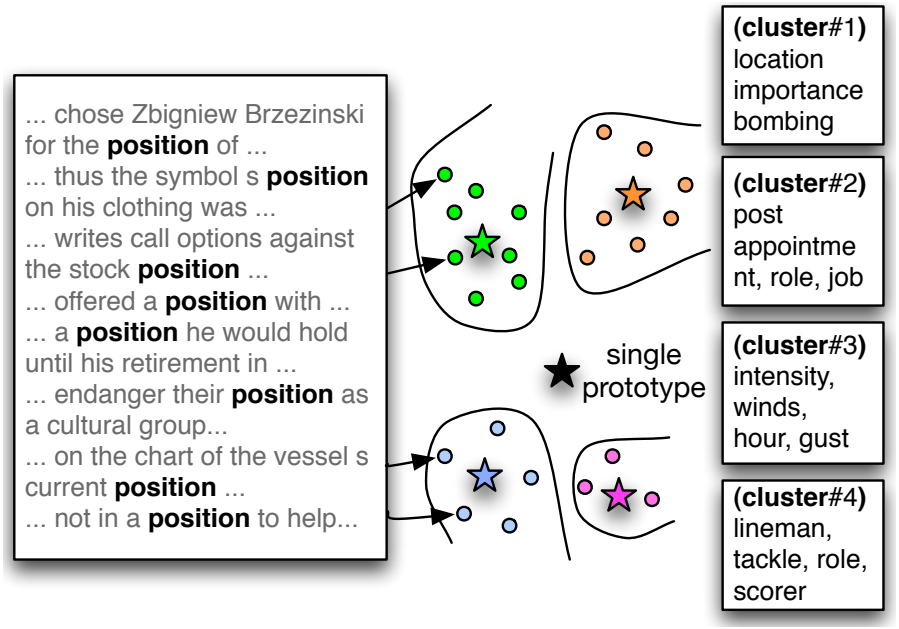
Focus on 3 algorithms:

1. Clustering
   Schutze 1998, Reisinger & Mooney 2010
2. Online matching
   Neelakantan, Shankar, Passos & McCallum 2014
3. Knowledge
   Chen, Liu & Sun 2014

# Clustering

2 steps:

1. For each word, cluster the **contexts** in which this word appears (cosine-similarity in the word space)
2. Learn the representation of each **sense** (= context cluter)

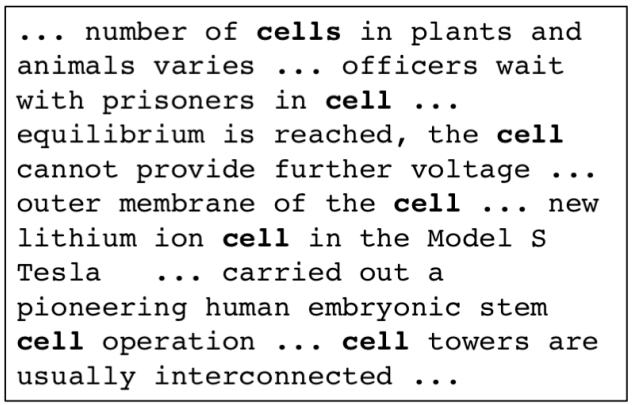



**Idea:** Hierarchical clustering of the word-context bipartite graph

# Online matching

Joint learning of word & sense representations:

- **Context** represented by the average of **word** vectors
- **Sense** induced by the closest **context**
  ($k$ senses per word)

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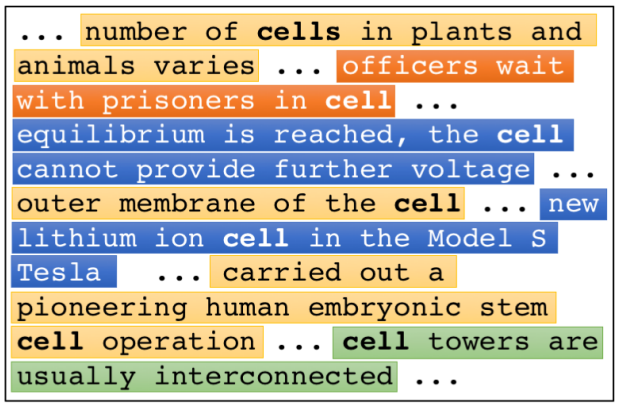


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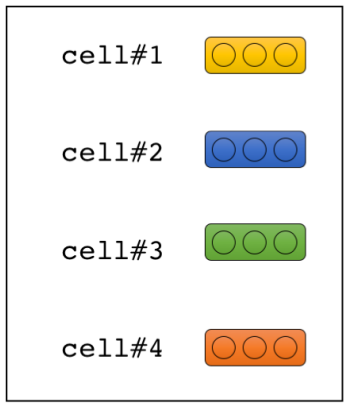
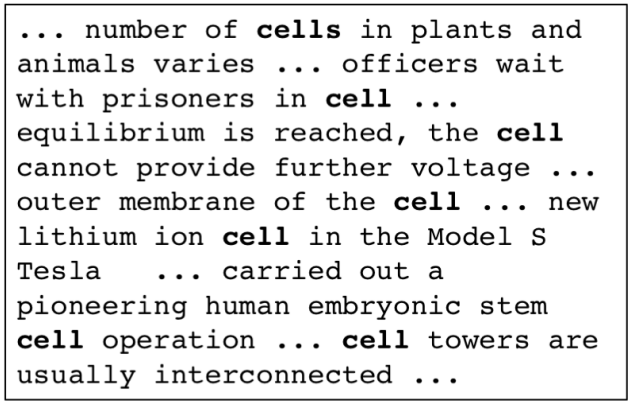



(3) Compute sense representation

# Example

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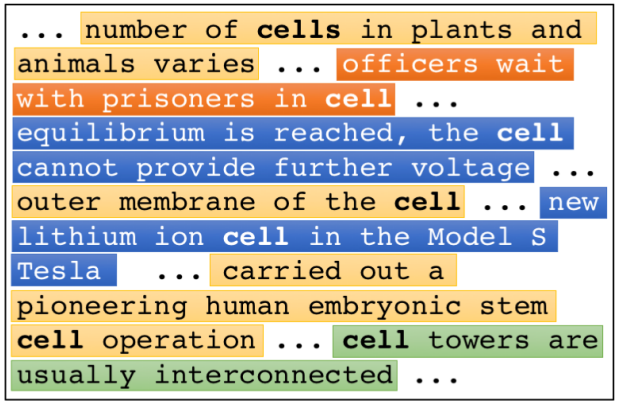


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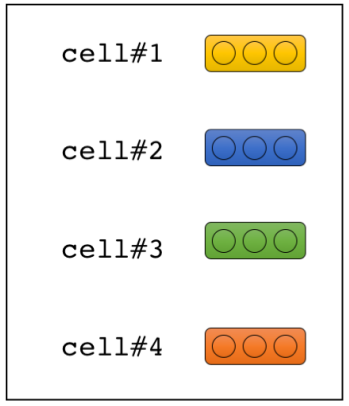
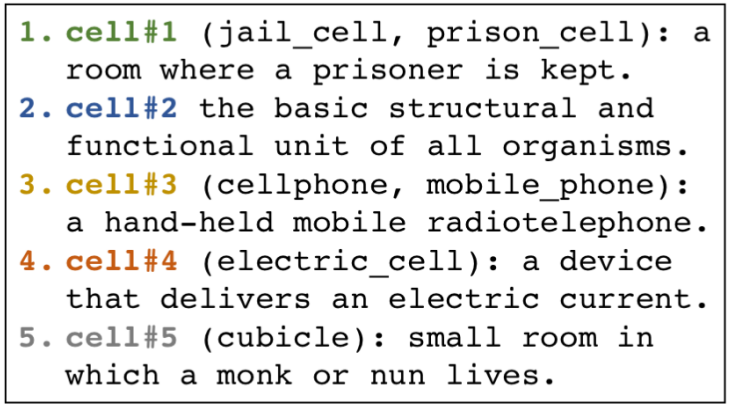



(3) Compute sense representation

# Knowledge

Use of a knowledge base (e.g., Wordnet, Babelnet, Conceptnet)

1. Initialize each **sense** vector as the average of **word** vectors used in the textual definition of this sense
2. **Disambiguate** each word of a large corpus on this basis
3. Joint learning of **word** & **sense** representations

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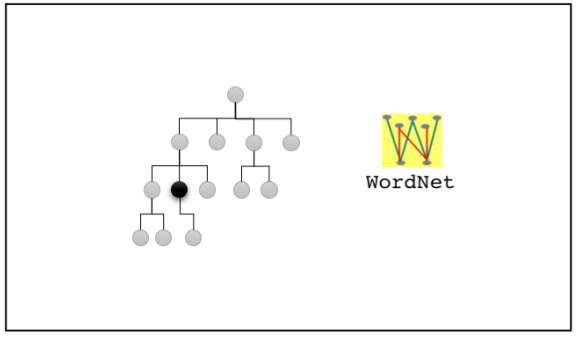
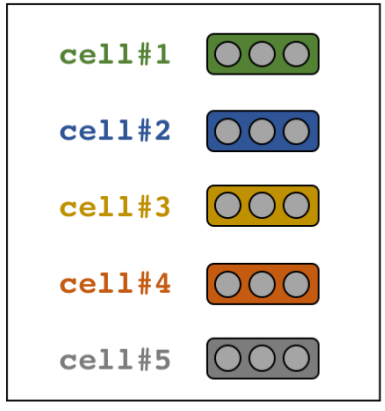



(2) Gather information for each sense (e.g., by exploiting the structural properties of sense inventory's semantic network, and (optionally) then from text corpora)




(3) Compute sense representation

# Example

1. **cell#1** (jail_cell, prison_cell): a room where a prisoner is kept.
2. **cell#2** the basic structural and functional unit of all organisms.
3. **cell#3** (cellphone, mobile_phone): a hand-held mobile radiotelephone.
4. **cell#4** (electric_cell): a device that delivers an electric current.
5. **cell#5** (cubicle): small room in which a monk or nun lives.

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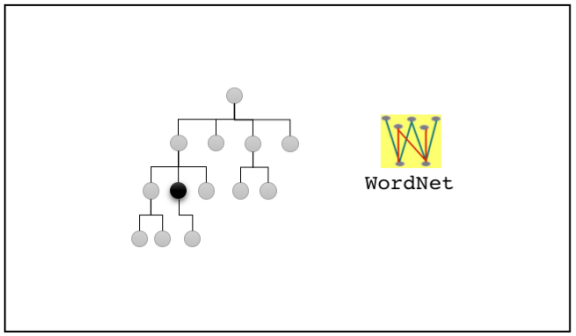


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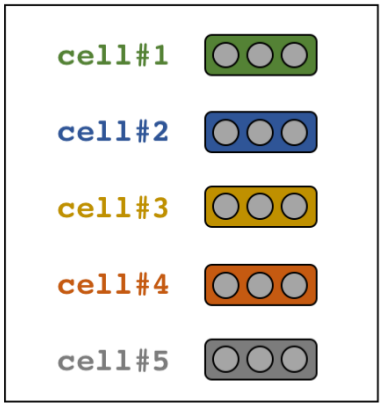
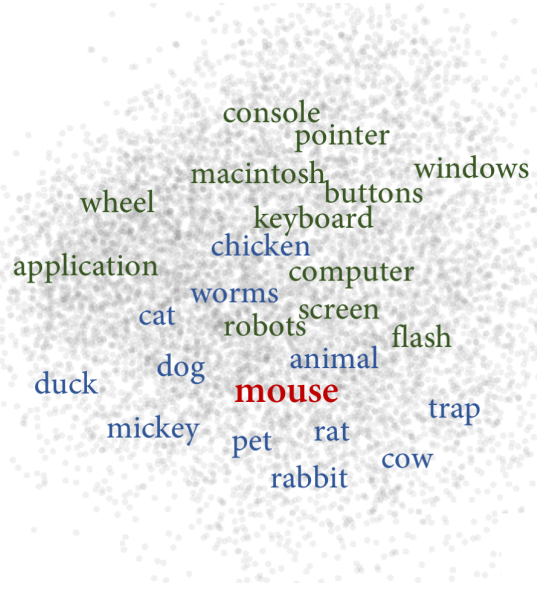



(3) Compute sense representation

# Summary

- Focus on 3 approaches to **sense** embedding
- Potential improvement by **graph techniques**
- Other approaches exist (e.g., multilingual)




"My mouse is broken"