# Word Embeddings

## Past, Present and Future

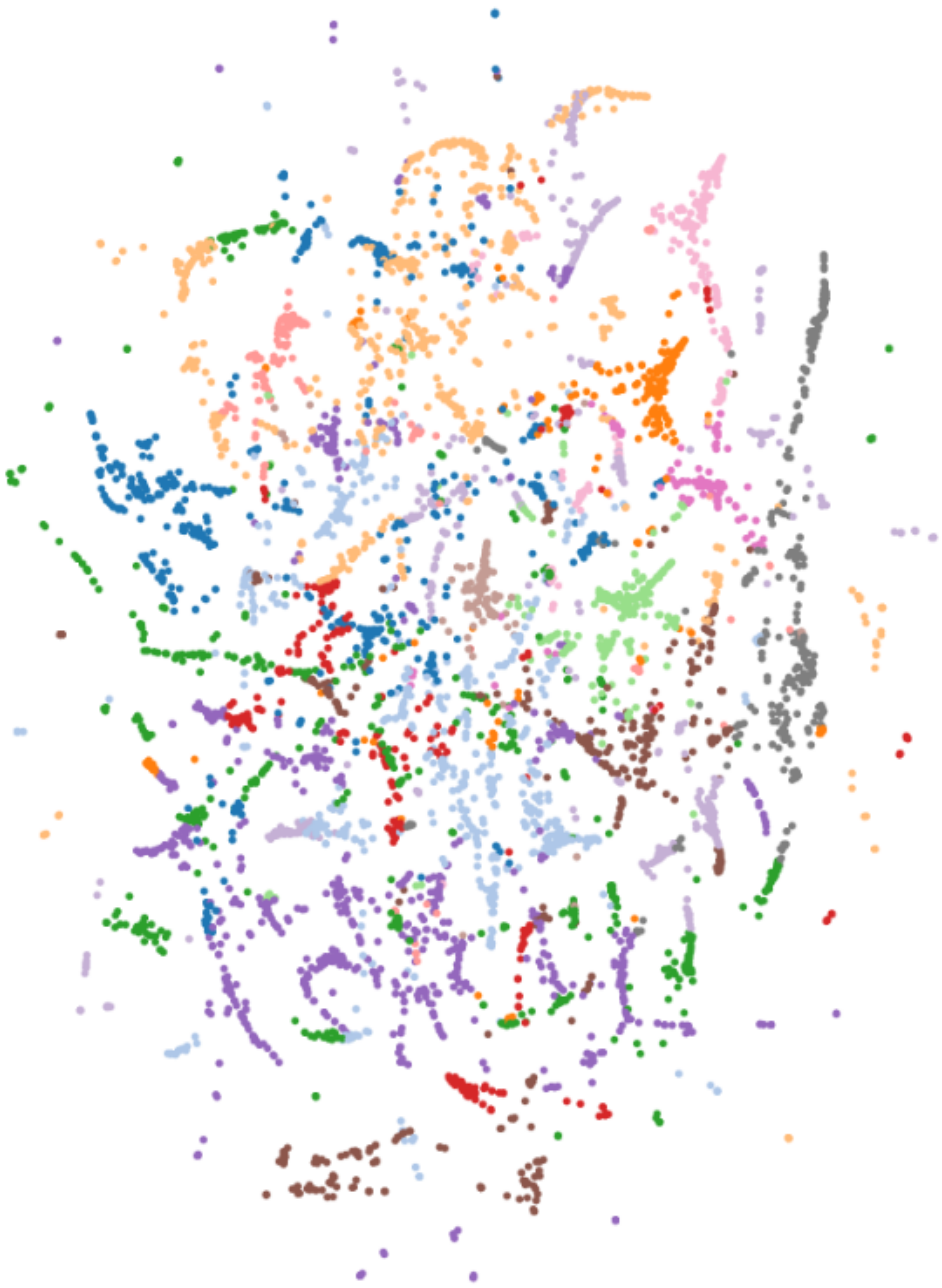
**Piero Molino**

# Motivation

Word Embeddings: **hot trend** in NLP (Post-word2vec era, 2013+)

Many researchers and practitioner are **oblivious of previous work** in computer science, cognitive science and computational linguistics (Pre-word2vec era: up to 2013)

**Delays progress** due to reinventing the wheel + <u>many lessons to be learned</u>



# Goal

Overview* of the **history** of the field to
start **building** on **existing knowledge**

Give **some hints** on **future directions**

*__Not complete overview__, but a useful **starting point** for exploration

# Outline

1. Linguistic background: Structuralism
2. Distributional Semantics
3. Methods overview
4. Open issues and current trends

# Terminology

**Word Embeddings**, Distributed Representations, **Word Vectors**, **Distributional Semantic Models**, Distributional Representations, **Semantic Vector Space**, Word Space, Semantic Space, Geometrical model of Meaning, Context-theoretic models, Corpus-based semantics, Statistical semantics

They all **mean** (almost) the **same thing**

Distributional Semantic Models → Computational Linguistics literature

Word Embeddings → Neural Networks literature

# Structuralism

# Structuralism

“The belief that phenomena of human life are **not intelligible <u>except</u>** through their **interrelations**.
These relations constitute a **structure**,
and behind local variations in the surface phenomena
there are constant laws of abstract culture”

*- Simon Blackburn, Oxford Dictionary of Philosophy, 2008*

# Origins of Structuralism

Ferdinand de Saussure, *Cours de linguistique générale*, 1916

Published posthumous from notes of his students

Previous ideas close to structuralism:

- Wilhelm von Humboldt, *Über den Dualis*, 1828
- Wilhelm von Humboldt, *Über die Verschiedenheit des menschlichen Sprachbaues*, 1836
- Ferdinand de Saussure, *Mémoire sur le système des primitif voyelles dans les langues indo-européennes*, 1879

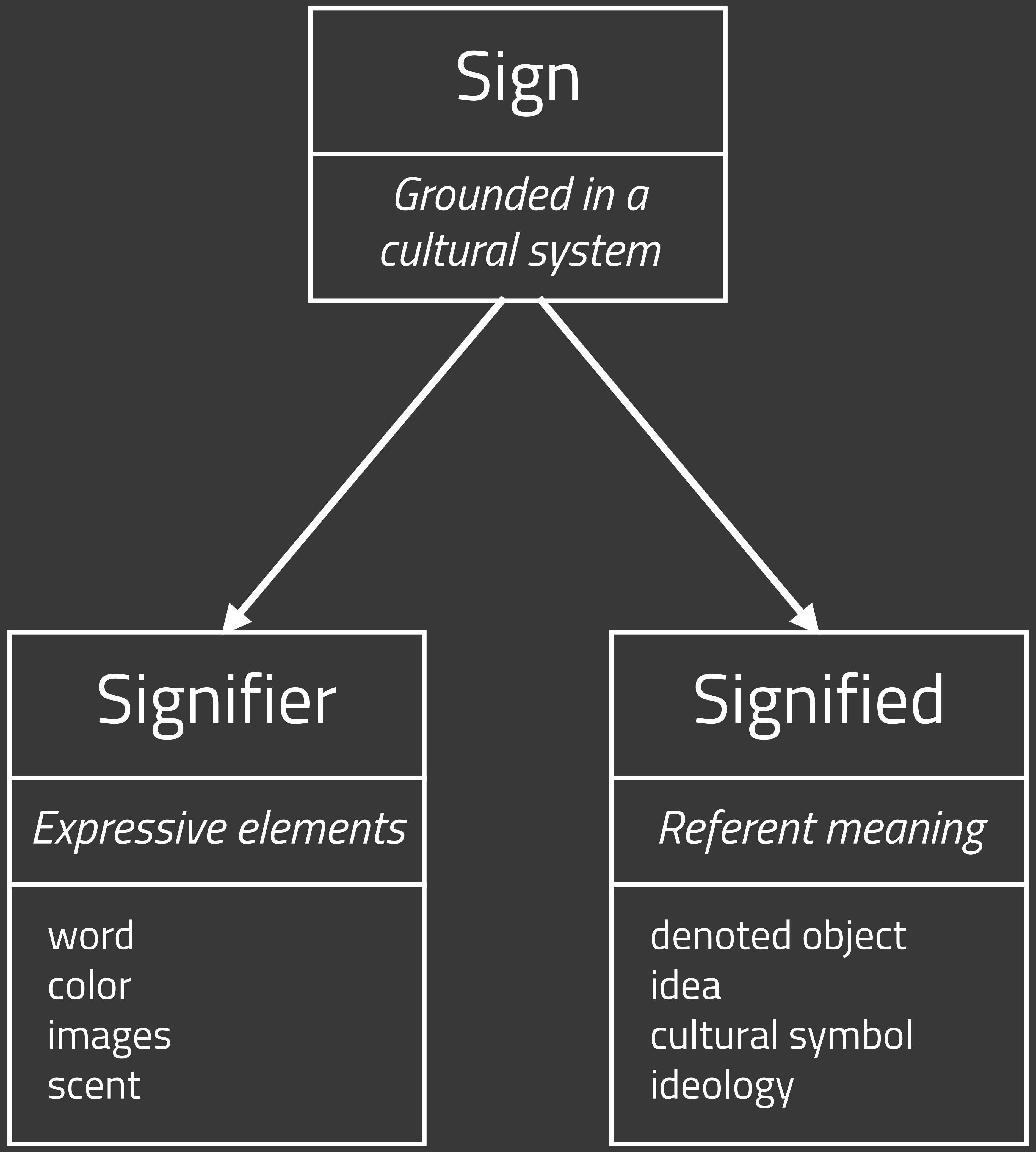
# Structuralism and Semiotics

*Langue* vs *Parole*

Sign, Signifier, Signified

Different languages use **different signifiers** for the **same signified** → the choice of signifiers is **arbitrary**

**Meaning of signs** is **defined** by their **relationships** and **contrasts** with **other signs**



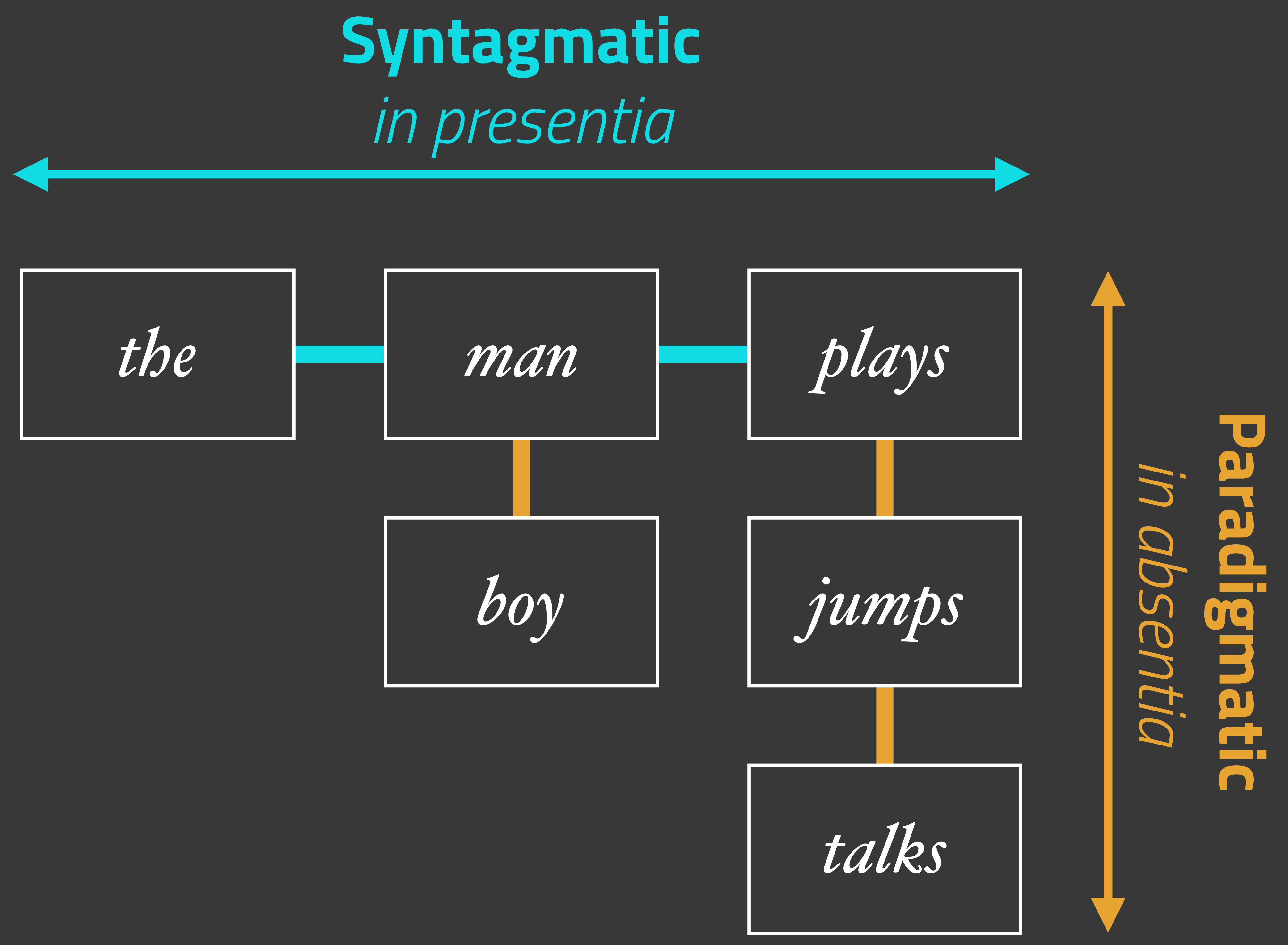
**Meaning of signs** is **defined** by their **relationships** and **contrasts** with **other signs**

# Linguistic relationships

**Paradigmatic**: relationship between words that can be **substituted** for each other in the same position within a given sentence

**Syntagmatic**: relationship a word has with other words that **surround** it

Originally de Saussure used the term *'associative'*, the term *'paradigmatic'* was introduced by Louis Hjelmslev, *Principes de grammaire générale*, 1928



# Paradigmatic

## Synonymy

| | | |
|---|---|---|
| *Bubbling* | *Effervescent* | *Sparkling* |

## Antonymy

*Hot* ⟷ *Cold*

## Hyponymy

*Feline* — Hypernym

*Tiger* *Lion* — Hyponym

# Syntagmatic

## Collocation

| | | |
|---|---|---|
| *against the* | ***law*** | |
| | ***law*** | *enforcement* |
| *become* | ***law*** | |
| | ***law*** | *is passed* |

## Colligation

normal

| | |
|---|---|
| *VERB past* | ***time*** |
| *saved* | |
| *spent* | |
| *wasted* | |

sport

| | |
|---|---|
| *ADJECTIVE* | ***time*** |
| *half* | |
| *extra* | |
| *full* | |

# Distributionalism

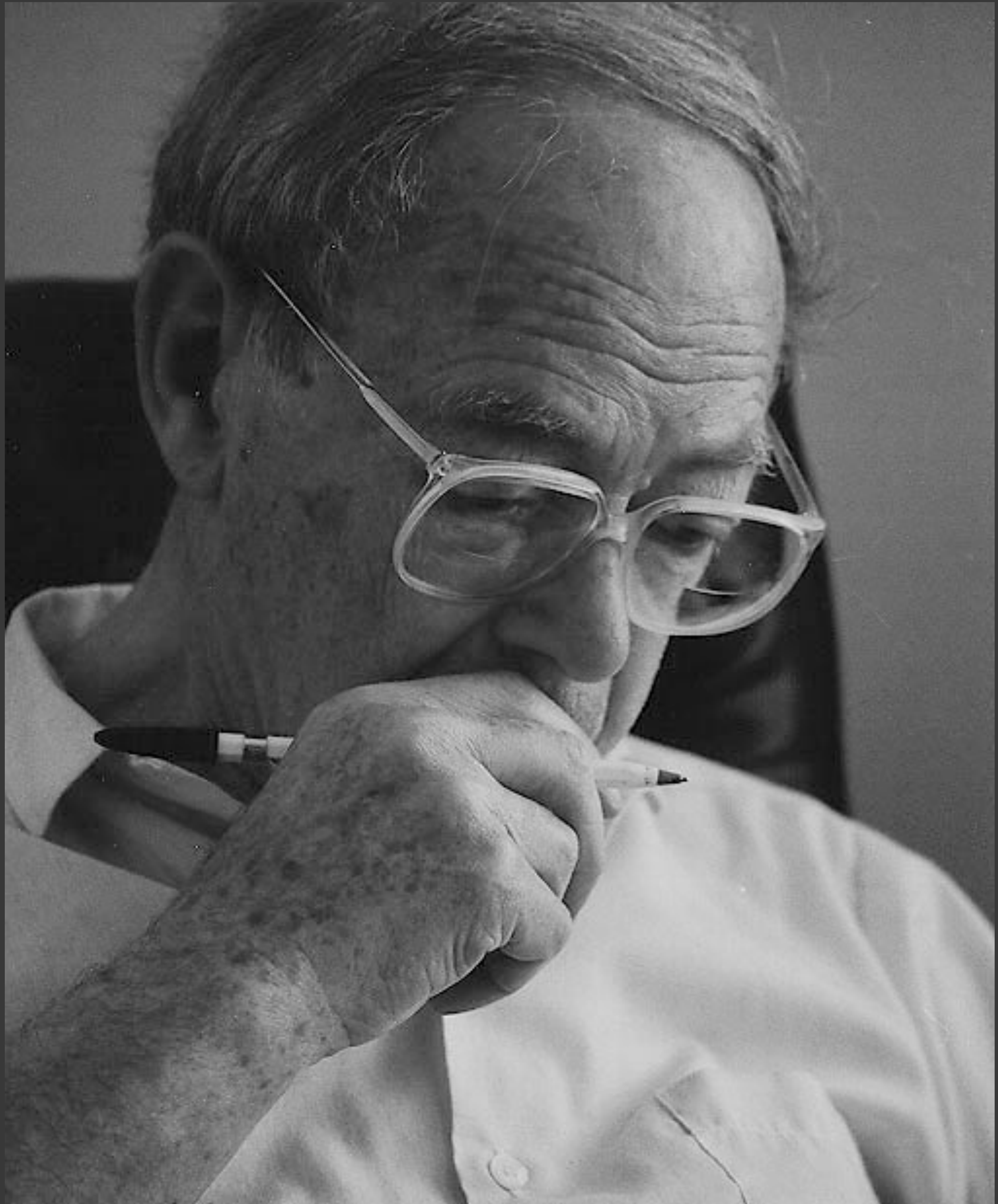
American structuralist branch

Leonard Bloomfield, *Language*, 1933

Zellig Harris. *Methods in Structural Linguistics*, 1951

Zellig Harris, *Distributional Structure*, 1954

Zellig Harris, *Mathematical Structure of Language*, 1968



# Philosophy of Language

"The **meaning of a word**
is its **use** in the language"

*- Ludwig Wittgenstein, Philosophical Investigation, 1953*

# Corpus Linguistics

"You shall know a **word**
by the **company it keeps**"

*- J.R. Firth, Papers in Linguistics, 1957*

# Other relevant work

Willard Van Orman Quine,
*Word and Object*, 1960

Margaret Masterman,
*The Nature of a Paradigm*,
1965

# Distributional Semantics

# Distributional Hypothesis

The degree of **semantic similarity** between two linguistic expressions *A* and *B* is a function of the **similarity** of the **linguistic contexts** in which *A* and *B* can appear

First formulation by Harris, Charles, Miller, Firth or Wittgenstein?

He filled the **wampimuk**, passed it around and we all drunk some

---

We found a little, hairy **wampimuk** sleeping behind the tree

*– McDonald and Ramscar, 2001*

He filled the **wampimuk**, passed it around and we all drunk some

---

We found a little, hairy **wampimuk** sleeping behind the tree

*– McDonald and Ramscar, 2001*

# Distributional Semantic Model

1. Represent words through *vectors* recording their **co-occurrence counts** with **context elements** in a **corpus**

2. *(Optionally)* Apply a **re-weighting scheme** to the resulting co-occurrence matrix

3. *(Optionally)* Apply **dimensionality reduction** techniques to the co-occurrence matrix

4. Measure **geometric distance** of word vectors as **proxy** to **semantic similarity / relatedness**

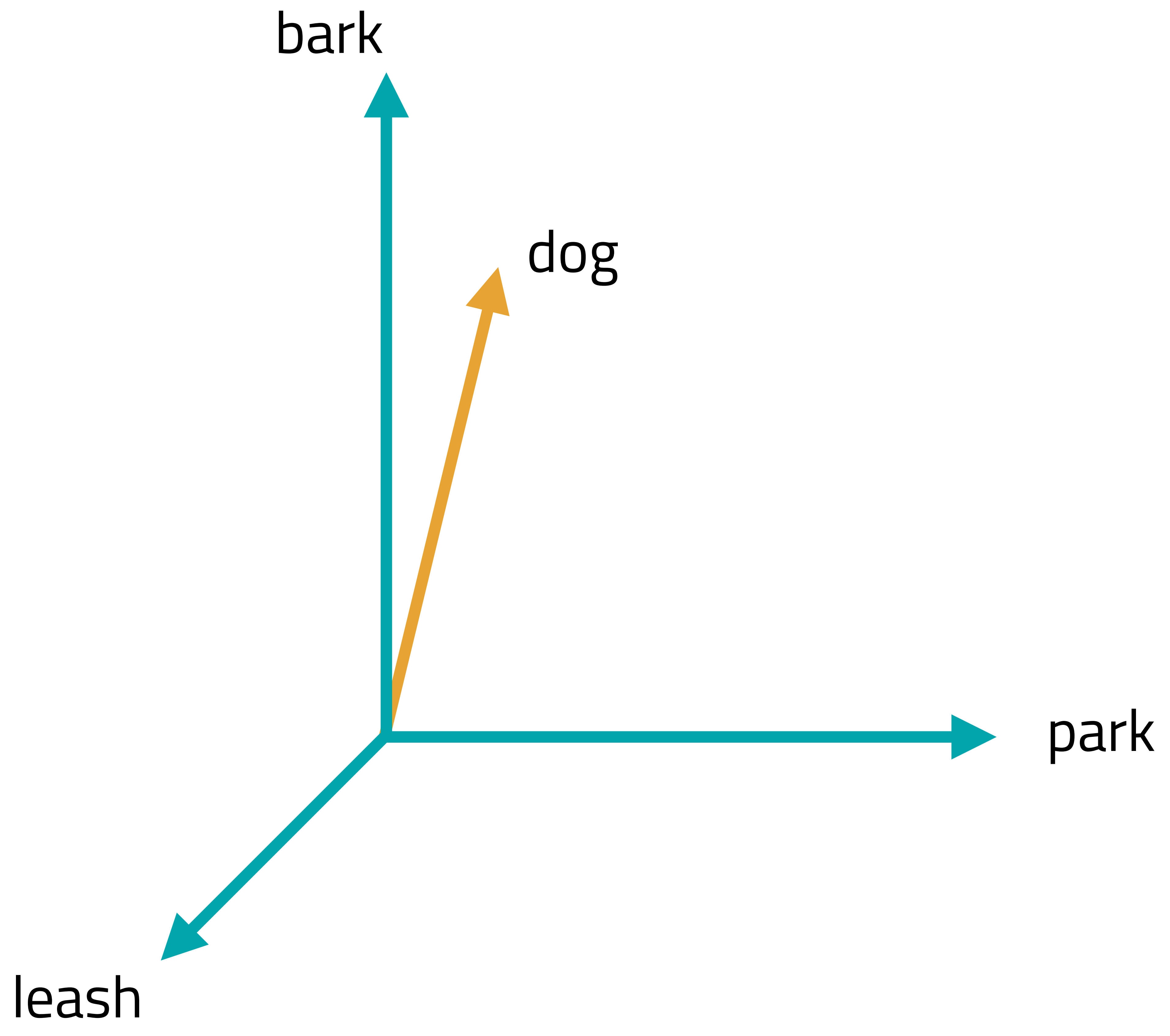
# Example

**Target**: a specific word

**Context**: noun and verbs in the same sentence

*The **dog** **barked** in the **park**. The **owner** of the **dog** put him on the **leash** since he **barked**.*

| word | count |
|---|---|
| bark | 2 |
| park | 1 |
| leash | 1 |
| owner | 1 |



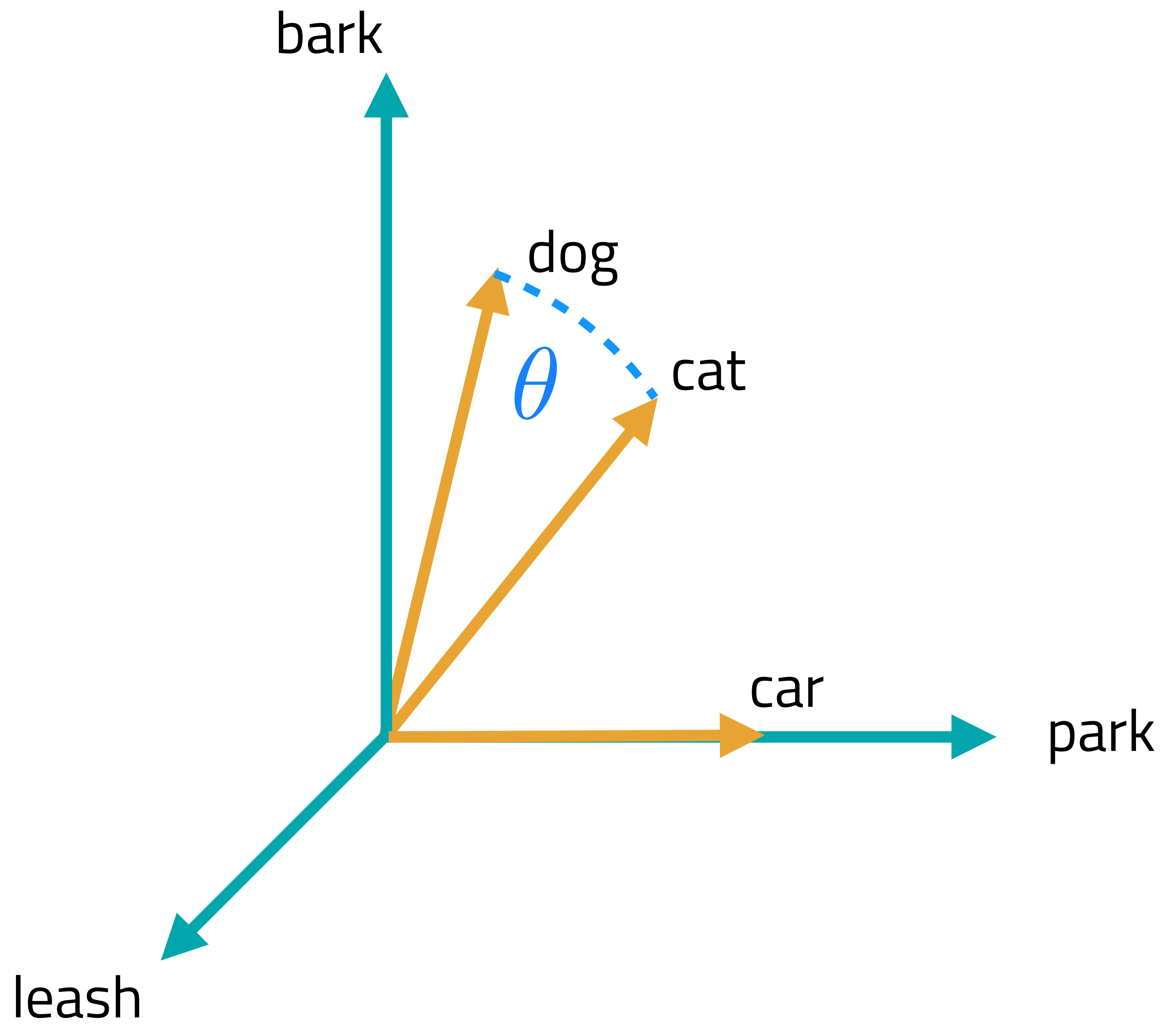
# Example

| | | Contexts | | | | | |
|---|---|---|---|---|---|---|---|
| | | leash | walk | run | owner | leg | bark |
| Targets | dog | 3 | 5 | 1 | 5 | 4 | 2 |
| | cat | 0 | 3 | 3 | 1 | 5 | 0 |
| | lion | 0 | 3 | 2 | 0 | 1 | 0 |
| | light | 0 | 0 | 1 | 0 | 0 | 0 |
| | dark | 1 | 0 | 0 | 2 | 1 | 0 |
| | car | 0 | 0 | 4 | 3 | 0 | 0 |

# Example

Use **cosine similarity** as a measure of **relatedness**

$$\cos\theta = \frac{x \cdot y}{\|x\|\|y\|} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=0}^{n} x_i^2}\sqrt{\sum_{i=0}^{n} y_i^2}}$$



# Similarity and Relatedness

## Semantic similarity

*words sharing salient attributes / features*

- synonymy (car / automobile)
- hypernymy (car / vehicle)
- co-hyponymy (car / van / truck)

## Semantic relatedness

*words semantically associated without being necessarily similar*

- function (car / drive)
- meronymy (car / tyre)
- location (car / road)
- attribute (car / fast)

(Budansky and Hirst, 2006)

# Context

The **meaning of a word** can be **defined** in terms of its **context** (properties, features)

- Other words in the same document / paragraph / sentence
- Words in the immediate neighbors
- Words along dependency paths
- Linguistic patterns
- Predicate-Argument structures
- Frames
- Hand crafted features

  First attempt in 1960s in Charles Osgood's *semantic differentials*, also used in first connectionist AI approaches in the 1980s

Any process that builds a **structure** on **sentences** can be used as a **source for properties**

# Context Examples

## *Document*

**DOC1**: The silhouette of the **sun**[1] beyond a wide-open bay on the lake; the **sun**[2] still glitters although evening has arrived in Kuhmo. It's midsummer; the living room has its instruments and other objects in each of its corners.

# Context Examples

## *Wide window*

**DOC1**: The silhouette of the **sun**[1] beyond a wide-open bay on the lake; the **sun**[2] still glitters although evening has arrived in Kuhmo. It's midsummer; the living room has its instruments and other objects in each of its corners.

# Context Examples

## *Wide window (content words)*

**DOC1**: [1 The silhouette of the **sun** [1] beyond a [2 wide-open bay on the lake; the **sun** [2] still glitters although evening has arrived in Kuhmo. 1] It's midsummer; the living room has its instruments and other objects in each of its corners. 2]

# Context Examples

## *Small window (content words)*

**DOC1**: The silhouette of the **sun** beyond a wide-open bay on the lake; the **sun** still glitters although evening has arrived in Kuhmo. It's midsummer; the living room has its instruments and other objects in each of its corners.

# Context Examples

## *PoS coded content lemmas*

**DOC1**: [1]The silhouette/N of the **sun**[1] beyond a wide-open/A [2]bay/N on the lake/N[1]; the **sun**[2] still glitters/V although evening/N has arrive/V[2] in Kuhmo. It's midsummer; the living room has its instruments and other objects in each of its corners.

# Context Examples

## *PoS coded content lemmas filtered by syntactic path*

PPDEP

**DOC1**: The silhouette/N of the **sun** beyond a wide-open bay on the lake; the

SUBJ

**sun** still glitters/V although evening has arrived in Kuhmo. It’s midsummer;

the living room has its instruments and other objects in each of its corners.

# Context Examples

## *Syntactic path coded lemmas*

PPDEP

**DOC1**: The silhouette/N_PPDEP of the **sun** beyond a wide-open bay on the lake;

SUBJ

the **sun** still glitters/V_SUBJ although evening has arrived in Kuhmo. It's midsummer; the living room has its instruments and other objects in each of its corners.

# Effect of Context

## Neighbors of ***dog*** in *BNC Corpus*

| | 2-word window | 30-word window | |
|---|---|---|---|
| **More paradigmatic** | cat | <u>kennel</u> | **More syntagmatic** |
| | horse | puppy | |
| | fox | pet | |
| | pet | bitch | |
| | rabbit | terrier | |
| | pig | rottweiler | |
| | animal | canine | |
| | mongrel | cat | |
| | sheep | <u>bark</u> | |
| | pigeon | alsatian | |

# Effect of Context

## Neighbors of ***Turing*** in *Wikipedia*

| | Syntactic dependencies | 5-word window | |
|---|---|---|---|
| **Co-hyponyms Paradigmatic** | Pauling | nondeterministic | **Topically related Syntagmatic** |
| | Hotelling | non-deterministic | |
| | Heting | computability | |
| | Lessing | deterministic | |
| | Hamming | finite-state | |

# Weighting Schemes

So far we used **raw counts**

**Several other options** for populating the *target* x *context* matrix are available

In most cases **Positive Pointwise Mutual Information** is the best choice

Kiela and Clark, *A systematic study of Semantic Vector Space Parameters*, 2014, is a good review

| Scheme | Definition |
|---|---|
| None | $w_{ij} = f_{ij}$ |
| TF-IDF | $w_{ij} = \log(f_{ij}) \times \log(\frac{N}{n_j})$ |
| TF-ICF | $w_{ij} = \log(f_{ij}) \times \log(\frac{N}{f_j})$ |
| Okapi BM25 | $w_{ij} = \frac{f_{ij}}{0.5+1.5\times\frac{f_j}{\frac{f_j}{j}}+f_{ij}} \log \frac{N-n_j+0.5}{f_{ij}+0.5}$ |
| ATC | $w_{ij} = \frac{(0.5+0.5\times\frac{f_{ij}}{max_f})\log(\frac{N}{n_j})}{\sqrt{\sum_{i=1}^{N}[(0.5+0.5\times\frac{f_{ij}}{max_f})\log(\frac{N}{n_j})]^2}}$ |
| LTU | $w_{ij} = \frac{(\log(f_{ij})+1.0)\log(\frac{N}{n_j})}{0.8+0.2\times f_j\times\frac{j}{f_j}}$ |
| MI | $w_{ij} = \log \frac{P(t_{ij}\|c_j)}{P(t_{ij})P(c_j)}$ |
| PosMI | $\max(0, \mathrm{MI})$ |
| T-Test | $w_{ij} = \frac{P(t_{ij}\|c_j)-P(t_{ij})P(c_j)}{\sqrt{P(t_{ij})P(c_j)}}$ |
| $\chi^2$ | see (Curran, 2004, p. 83) |
| Lin98a | $w_{ij} = \frac{f_{ij}\times f}{f_i \times f_j}$ |
| Lin98b | $w_{ij} = -1 \times \log \frac{n_j}{N}$ |
| Gref94 | $w_{ij} = \frac{\log f_{ij}+1}{\log n_j+1}$ |

# Similarity Measures

So far we used **cosine similarity**

**Several other options** for computing similarity are available

In most cases **Correlation** is the best choice (cosine similarity of vectors normalized by their mean)

Kiela and Clark, *A systematic study of Semantic Vector Space Parameters*, 2014, is a good review

| Measure | Definition |
|---|---|
| Euclidean | $\frac{1}{1+\sqrt{\sum_{i=1}^{n}(u_i-v_i)^2}}$ |
| Cityblock | $\frac{1}{1+\sum_{i=1}^{n}\lvert u_i-v_i\rvert}$ |
| Chebyshev | $\frac{1}{1+\max_i \lvert u_i-v_i\rvert}$ |
| Cosine | $\frac{u\cdot v}{\lvert u\rvert\lvert v\rvert}$ |
| Correlation | $\frac{(u-\mu_u)\cdot(v-\mu_v)}{\lvert u\rvert\lvert v\rvert}$ |
| Dice | $\frac{2\sum_{i=0}^{n} min(u_i,v_i)}{\sum_{i=0}^{n} u_i+v_i}$ |
| Jaccard | $\frac{u\cdot v}{\sum_{i=0}^{n} u_i+v_i}$ |
| Jaccard2 | $\frac{\sum_{i=0}^{n} min(u_i,v_i)}{\sum_{i=0}^{n} max(u_i,v_i)}$ |
| Lin | $\frac{\sum_{i=0}^{n} u_i+v_i}{\lvert u\rvert+\lvert v\rvert}$ |
| Tanimoto | $\frac{u\cdot v}{\lvert u\rvert+\lvert v\rvert-u\cdot v}$ |
| Jensen-Shannon Div | $1-\frac{\frac{1}{2}(D(u\lvert\lvert\frac{u+v}{2})+D(v\lvert\lvert\frac{u+v}{2}))}{\sqrt{2\log 2}}$ |
| $\alpha$-skew | $1-\frac{D(u\lvert\lvert\alpha v+(1-\alpha)u)}{\sqrt{2\log 2}}$ |

# Evaluation

## Intrinsic

- evaluate **word pairs similarities** → compare with **similarity judgments** given by humans *(WordSim, MEN, Mechanical Turk, SImLex)*
- evaluate on **analogy tasks** *'Paris is to France as Tokyo is to* ***x****' (MSR analogy, Google analogy)*

## Extrinsic

- use the vectors in a **downstream task** *(classification, translation, …)* and evaluate the **final performance** on the task

# Best parameters configuration?

(context, similarity measure, weighting, ...)

# Depends on the task!

# Methods overview

# Methods

Semantic Differential *(Osgood at al. 1957)*

Semantic features *(Smith at al. 1974)*

Mechanisms of sentence processing assigning roles to constituents *(McLelland and Kawamoto 1986)*

Learning Distributed Representations of Concepts *(Hinton et al. 1986)*

Forming Global Representations with Extended Back-Propagation [FGREP] *(Mikkulainen and Dyer 1987)*

Sparse Distributed Memory [SDM] *(Kanerva 1988)*

**Latent Semantic Analysis** [LSA] *(Deerwester et al. 1988-1990)*

**Hyperspace Analogue to Language** [HAL] *(Lund and Burgess 1995)*

Probabilistic Latent Semantic Analysis [pLSA] *(Hoffman et al. 1999)*

**Random Indexing** *(Kanerva et al. 2000)*

**Latent Dirichlet Allocation** [LDA] *(Blei et al. 2003)*

A neural probabilistic language model *(Bengio et al. 2003)*

Infomap *(Widdows et al. 2004)*

Correlated Occurrence Analogue to Lexical Semantic [COALS] *(Rohde et al. 2006)*

Dependency Vecotrs *(Padó and Lapata 2007)*

**Explicit Semantic Analysis** *(Gabrilovich and Markovich 2007)*

Distributional Memory *(Baroni and Lenci 2009)*

Non-Negative Matrix Factorization [NNMF] *(Van de Cruys et al. 2010) originally: (Paatero and Tapper 1994)*

**JoBimText** *(Biemann and Riedl 2013)*

**word2vec** [SGNS and CBOW] *(Mikolov et al. 2013)*

vLBL and ivLBL *(Mnih and Kavukcuoglu 2013)*

Hellinger PCA (HPCA) *(Lebret and Collobert 2014)*

**Global Vectors** [GloVe] *(Pennington et al. 2014)*

Infinite Dimensional Word Embeddings *(Nalisnick and Ravi 2015)*

**Gaussian Embeddings** *(Vilnis and McCallum 2015)*

Diachronic Word Embeddings *(Hamilton et al. 2016)*

WordRank *(Ji et al. 2016)*

Exponential Family Embeddings *(Rudolph et al. 2016)*

**Multimodal Word Distributions** *(Athiwaratkun and Wilson 2017)*

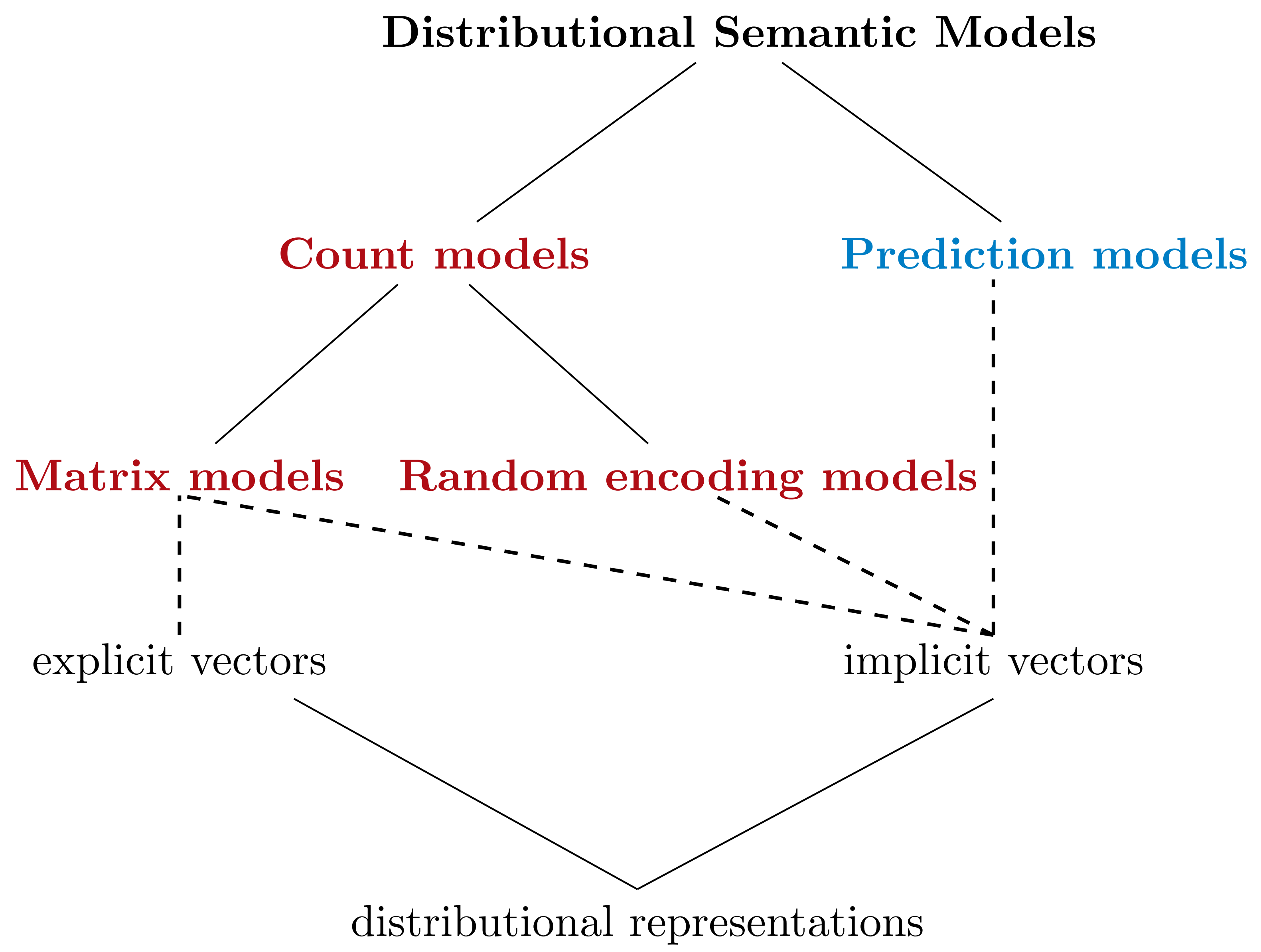
# Explicit vs Implicit

**Explicit** vectors: **big sparse** vectors with **interpretable** dimensions

**Implicit** vectors: **small dense** vectors with **latent** dimensions

**Count** vs **Prediction**

Alessandro Lenci, *Distributional models of word meaning*, 2017



# Hyperspace Analogue to Language [HAL]

**Target**: a specific word

**Context**: window of ten words

**Weighting**: (10 - distance from target) for each occurrence

**Similarity**: euclidean distance

**Dimensionality reduction**: sort **contexts** (columns of the matrix) by variance and keep top 200

**the dog barked at the cat**

weight $_{\text{dog barked}}$ = 10 *(no gap)*

weight $_{\text{dog cat}}$ = 7 *(3 words gap)*

| | $c_2$ | $c_7$ | ... | $c_3$ | $c_5$ | ... | ... | $c_6$ |
|---|---|---|---|---|---|---|---|---|
| $w_1$ | 54 | 23 | ... | 8 | 4 | ... | ... | 1 |
| $w_1$ | 21 | 82 | ... | 10 | 6 | ... | ... | 0 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... |
| $w_n$ | 32 | 47 | ... | 9 | 3 | ... | ... | 1 |
| variance | 30 | 25 | ... | 5 | 3 | ... | ... | 0,5 |

top 200 keep | 201+ discard

# Hyperspace Analogue to Language

## Advantages

- Simple
- Fast *O(n)*

## Disadvantages

- No higher order interactions (only direct co-occurrence)

# Latent Semantic Analysis [LSA]

**Target**: a specific word

**Context**: document id

**Weighting**: tf-idf *(term frequency - inverse document frequency), but can use others*

**Similarity**: cosine

**Dimensionality reduction**: Singular Value Decomposition (SVD)

**TF** **IDF**

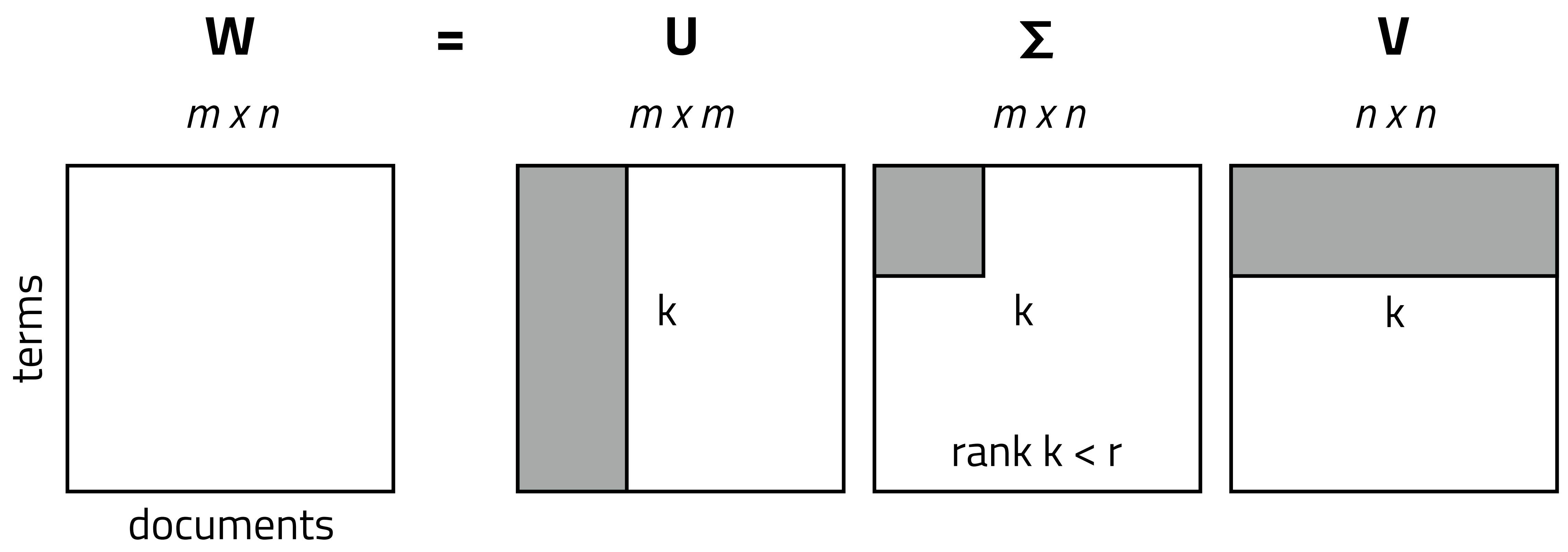
$$weight_{ij} = \log(f_{ij}) \cdot \log(\frac{N}{n_j})$$

frequency of word *j* in document *i*

total documents over documents containing word j

**Intuition**: the more frequency in the document, the better. The less frequent in the corpus, the better

# SVD in a nutshell

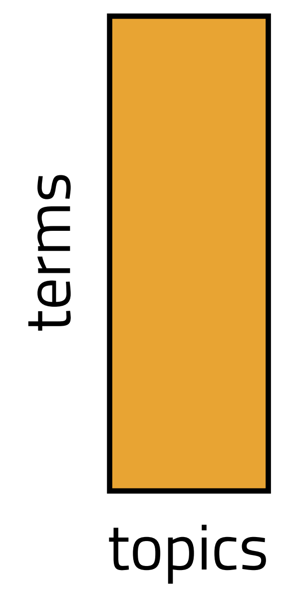



$$W = U_k \Sigma_k V_k^\top$$

**Intuition**
keep top *k* singular values as they contain most of the variance
*k* can be interpreted as the number of topics

**Target matrix**

**T**
*m x k*



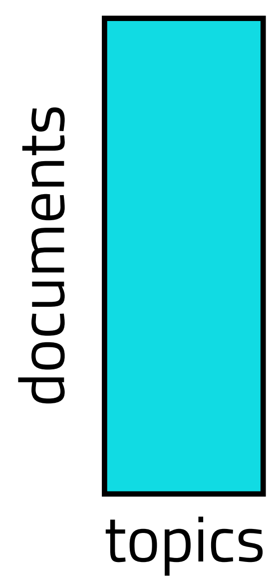

$$T^{SVD} = U_k \Sigma_k$$

Trick from *(Levy at al. 2015)*: throw **Σ** away for better performance

$$T^{SVD} = U_k$$

**Context matrix**

**C**
*n x k*




$$C^{SVD} = V_k^\top$$

# Latent Semantic Analysis

## Advantages

- Reduced dimension *k* can be interpreted as topics
- Reducing the number of columns unveils higher order interactions

## Disadvantages

- Static → can't easily add new documents, words and topics
- SVD is one time operation, without intermediate results
- Expensive in terms of memory and computation $O(k^2m)$

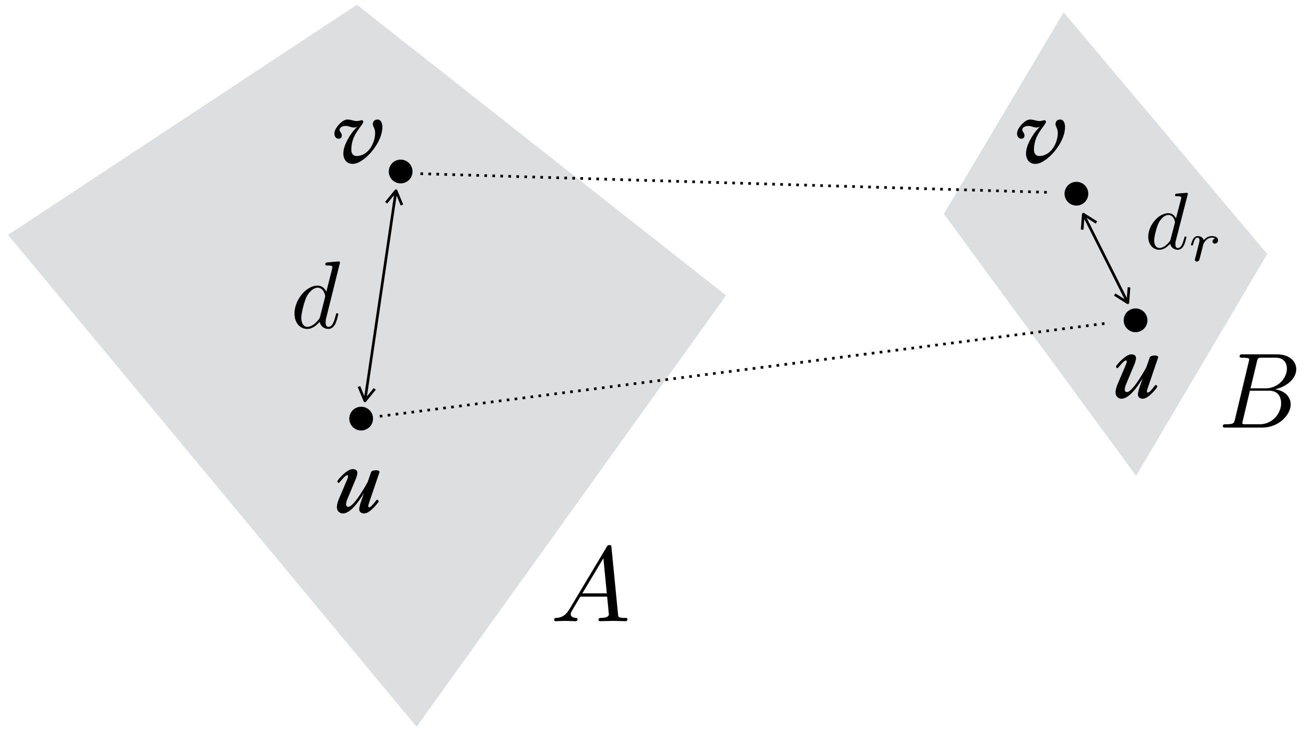
# Random Indexing [RI]

**Locality-sensitive hashing** method that **approximates** the **distance** between points

Generates ***random matrix R*** and projects the ***original matrix A*** to it to obtain a ***reduced matrix B***

***Reduced space B*** preserves the *euclidean distance* between points in ***original space A*** *(Johnson-Lindenstrauss lemma)*

$$B^{n,k} \approx A^{n,m} R^{m,k} \quad k \ll m$$




$$(1-\epsilon)d_r(v,u) \leq d(v,u) \leq (1+\epsilon)d_r(v,u)$$

# Random Indexing [RI]

## Algorithm

- For every word in the corpus create a **sparse random context** vector with values in *{-1, 0, 1}*
- **Target** vectors are the **sum** of the **context** vectors of the words they co-occur with multiplied by the **frequency** of the co-occurrence

### Dataset

I drink beer
You drink a glass of beer

### Context Vectors

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| I | 1 | 0 | 0 | 0 | 0 | -1 | 0 |
| drink | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| beer | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| you | 0 | -1 | 0 | 0 | 0 | 0 | 1 |
| glass | -1 | 0 | 0 | 0 | 1 | 0 | 0 |

### Target Vectors

$$tv_{beer} = 1cv_i + 2cv_{drink} + 1cv_{you} + 1cv_{glass}$$

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| beer | 0 | -1 | 2 | 0 | 1 | -1 | 1 |

# Random Indexing

## Advantages

- Fast *O(n)*
- Incremental → can add new words any time, just create a new **context** vector

## Disadvantages

- In many intrinsic tasks doesn't perform as well as other methods
- Stochasticity in the process → random distortion
- Negative similarity scores

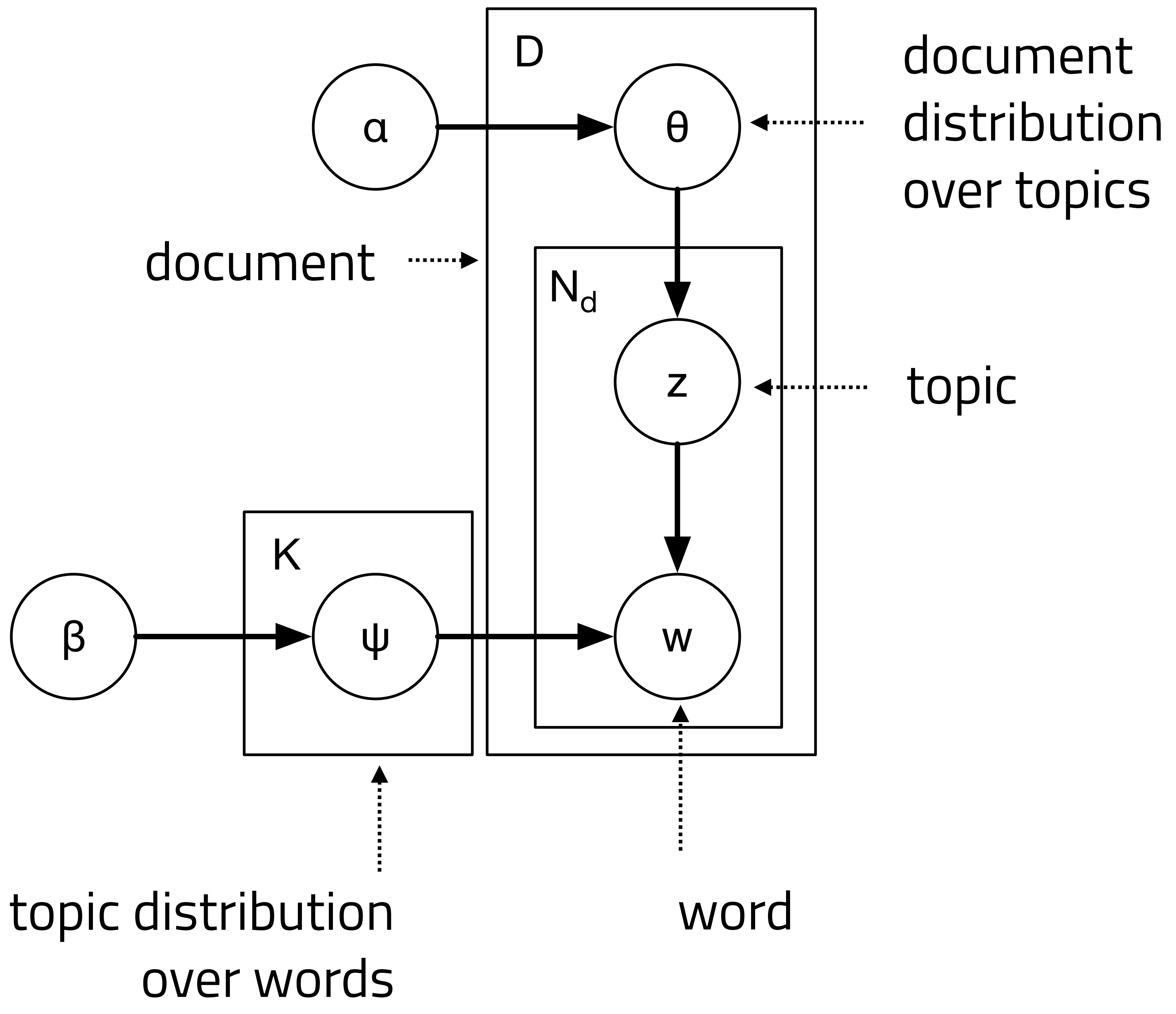
# Latent Dirichlet Allocation [LDA]

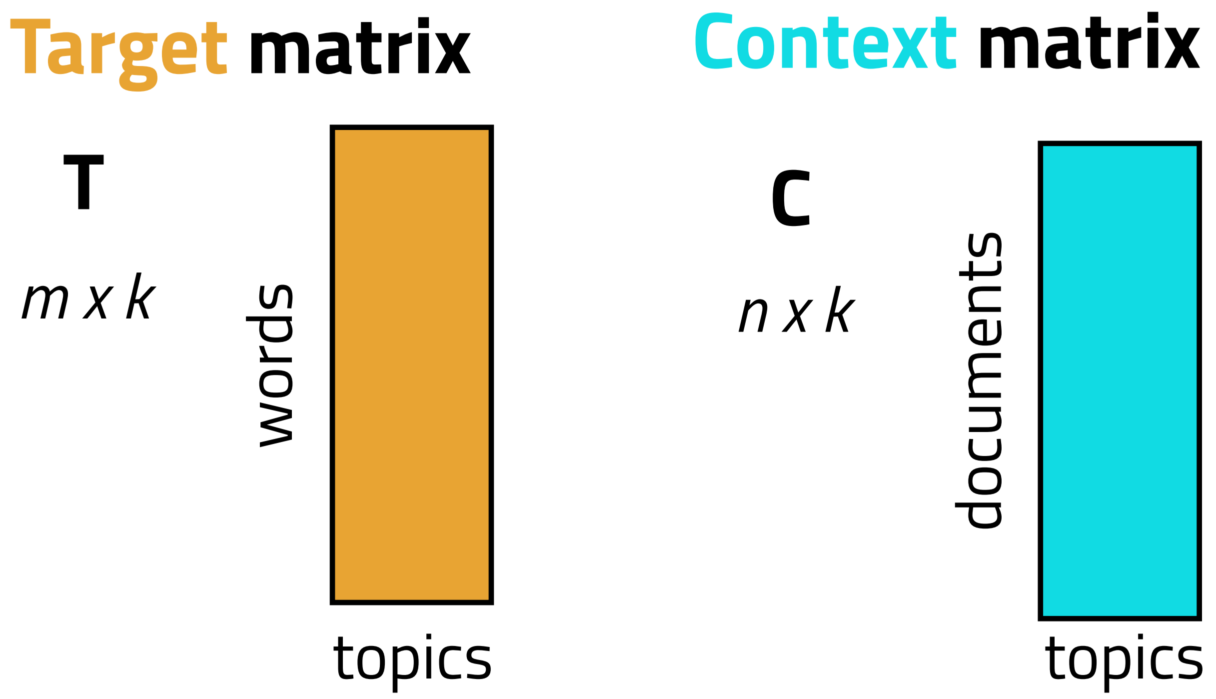
**Target**: a specific word

**Context**: document id

**Assumptions**:

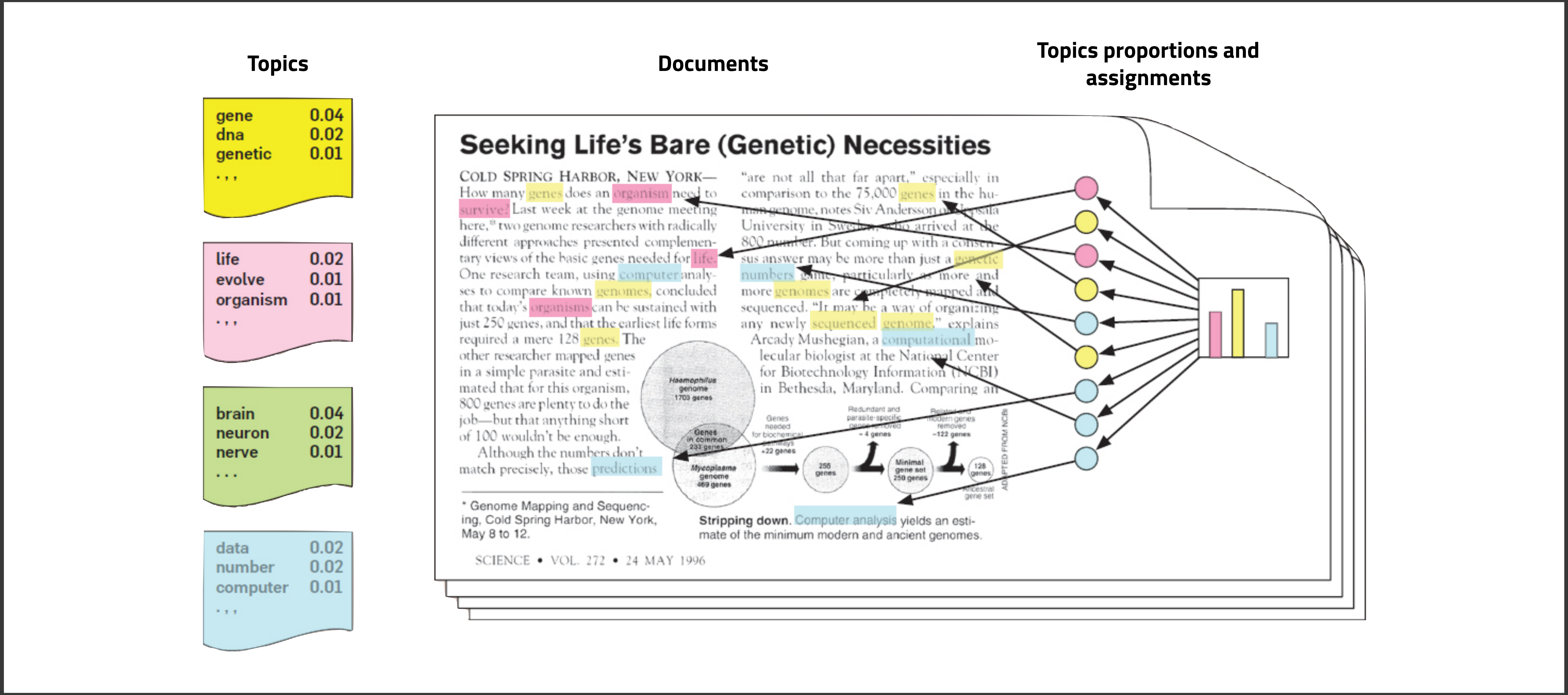
- **Latent topics** (same idea as *k* in LSA)
- Each <u>topic</u> is a **Dirichlet distribution** over words
- Each <u>document</u> is a **mixture** of corpus-wide **topics**
- Each <u>word</u> is drawn from one of the **topics**




The values of **T** and **C** are probabilities

# Latent Dirichlet Allocation



# Latent Dirichlet Allocation

## Advantages

- Dirichlet prior → each document is about few topic
- Easy to interpret

## Disadvantages

- Expensive to compute $O(nk^2)$
- Static → can't easily add new documents, words and topics (although some extensions do it)

# Explicit Semantic Analysis [ESA]

**Target**: a specific word

**Context**: Wikipedia article

**Assumption**: Wikipedia articles are **explicit topics**

**Weighting**: tf-idf

**Similarity**: cosine

**Dimensionality Reduction**: discard *too short* articles and articles with few other articles *linking* them

| | Mouse [Rodent] | Mouse [computing] | Mickey Mouse | Button | Janson Button | Drag and Drop |
|---|---|---|---|---|---|---|
| mouse | **0,95** | **0,89** | **0,81** | 0,50 | 0,01 | 0,60 |
| button | 0,10 | **0,81** | 0,20 | **0,95** | **0,89** | **0,70** |
| mouse button | 0,50 | **0,85** | 0,50 | **0,72** | 0,45 | **0,65** |

average of 2 vectors → emerges disambiguated meaning

| | cat | leopard | jaguar | car | animal | button |
|---|---|---|---|---|---|---|
| Panther | **0,83** | **0,72** | **0,65** | 0,3 | **0,92** | 0,01 |

# Explicit Semantic Analysis

## Advantages

- Simple
- Fast *O(n)*
- Interpretable

## Disadvantages

- The assumption doesn't always hold
- Doesn't perform as good as other methods
- Vectors are really high dimensional, although quite sparse

# JoBimText

Generic holing **@** operation

Apply it to any tuple to obtain **targets** (jo) and **contexts** (bim)

**Weighting**: custom measure similar to Lin

**Similarity**: Lexicographer Mutual Information *(PMI x Frequency)* (Kilgarriff et al. 2004)

| Input tuple |
|---|
| (nsubj, gave, I) |
| (det, book, a) |
| (dobj, gave, book) |
| (det girl, the) |
| (prep_to, gave, girl) |

| target | context |
|---|---|
| I | (nsubj, gave, @) |
| gave | (nsubj, @, I) |
| a | (det, book, @) |
| book | (det, @, a) |
| ... | ... |
| girl | (prep_to, gave, @) |
| gave | (prep_to, @, girl) |

| Input tuple |
|---|
| (I, gave, a, book) |
| (gave, a, book, to) |
| (a, book, to, the) |
| (book, to, the, girl) |

| target | context |
|---|---|
| I | (@, gave, a, book) |
| gave | (I, @, a, book) |
| a | (I, gave, @, book) |
| book | (I, gave, a, @) |
| ... | ... |
| the | (book, to, @, girl) |
| girl | (book, to, the, @) |

# JoBimText

## Advantages

- Generic preprocessing operation deals with many context representations and types of data
- Deals with complex contexts (example: several steps in a tree)

## Disadvantages

- No dimensionality reduction → vectors are high dimensional
- No uncovering of higher order relations
- MapReduce implementation only effective on clusters

# word2vec

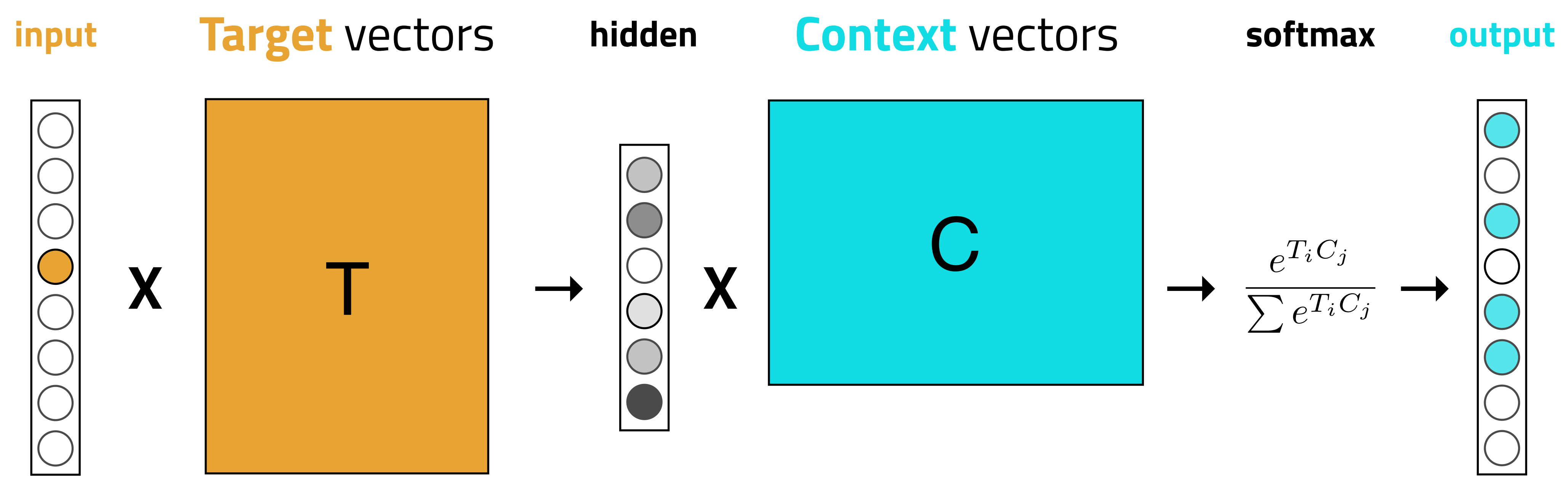
Skip Gram with Negative Sampling (SGNS)

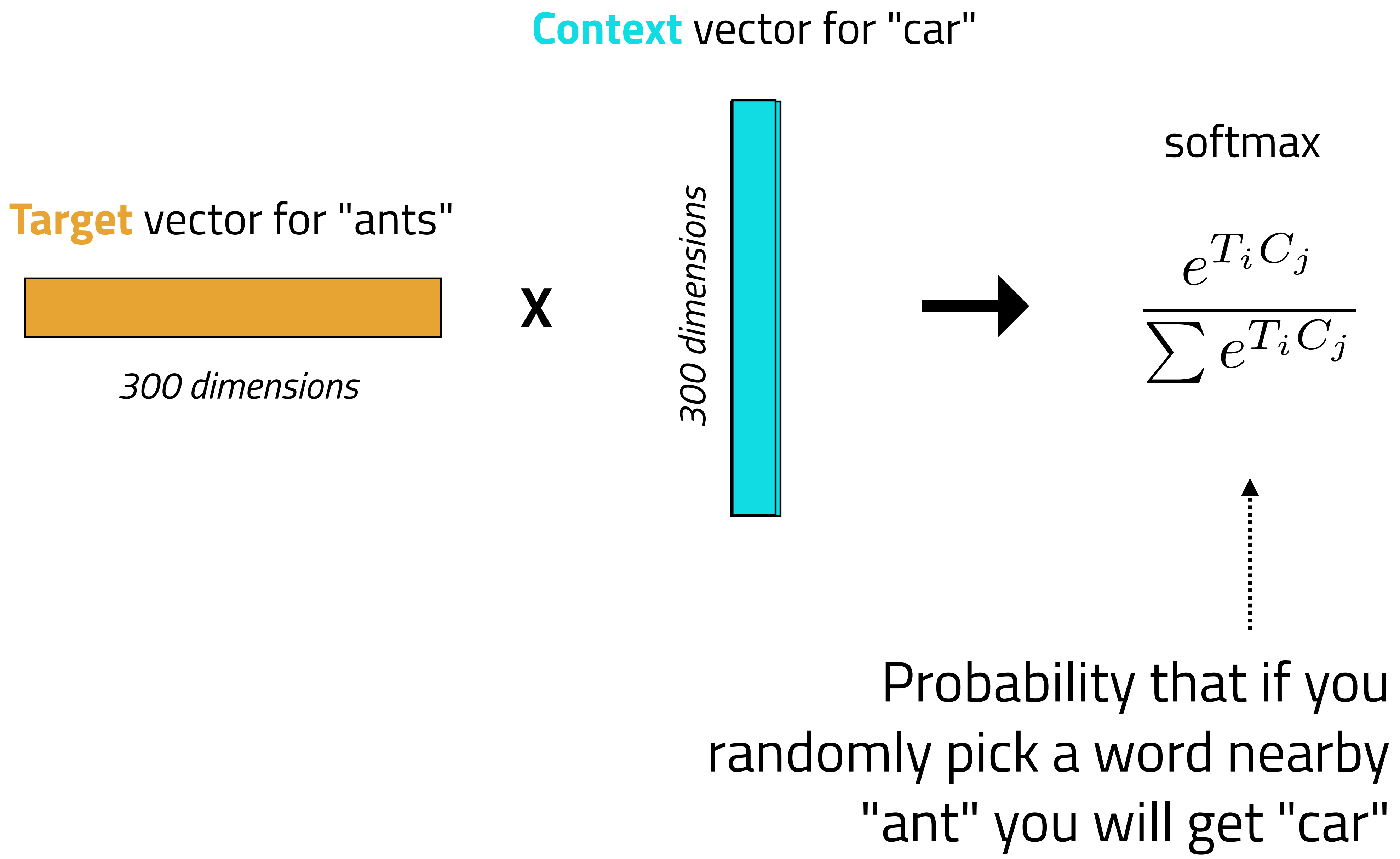
**Target**: a specific word

**Context**: window of *n* words

Vectors are obtained training the model to predict the **context** given a **target**

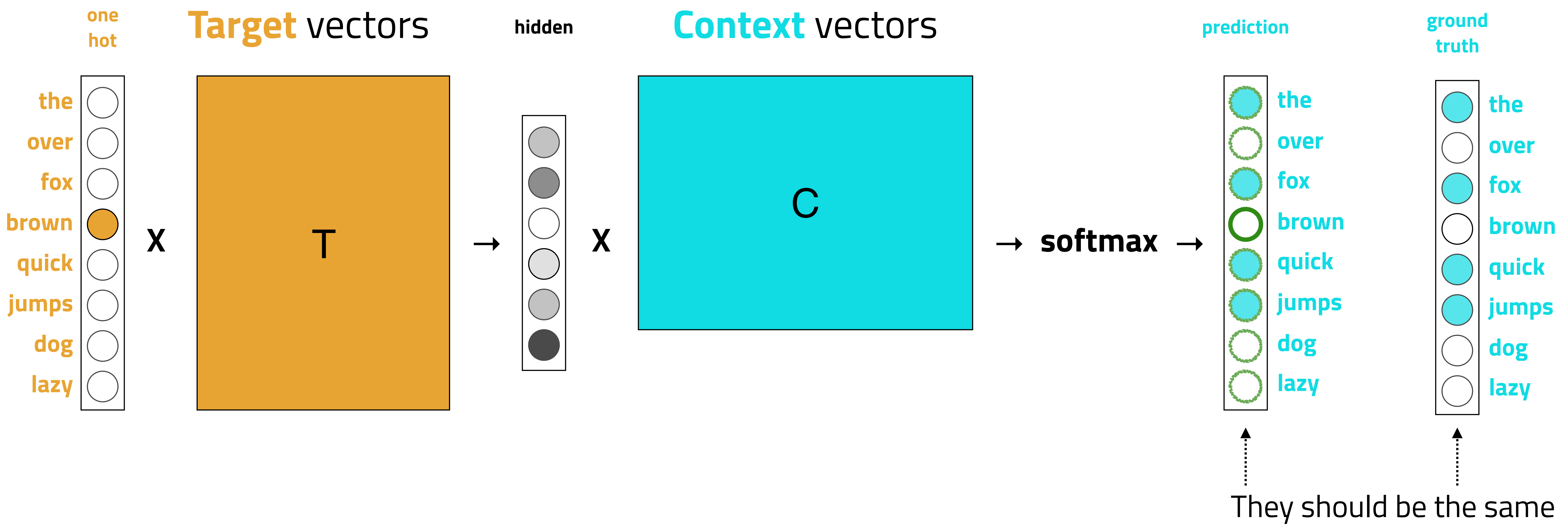
The **error** of the **prediction** is **back-propagated** and the **vectors updated**



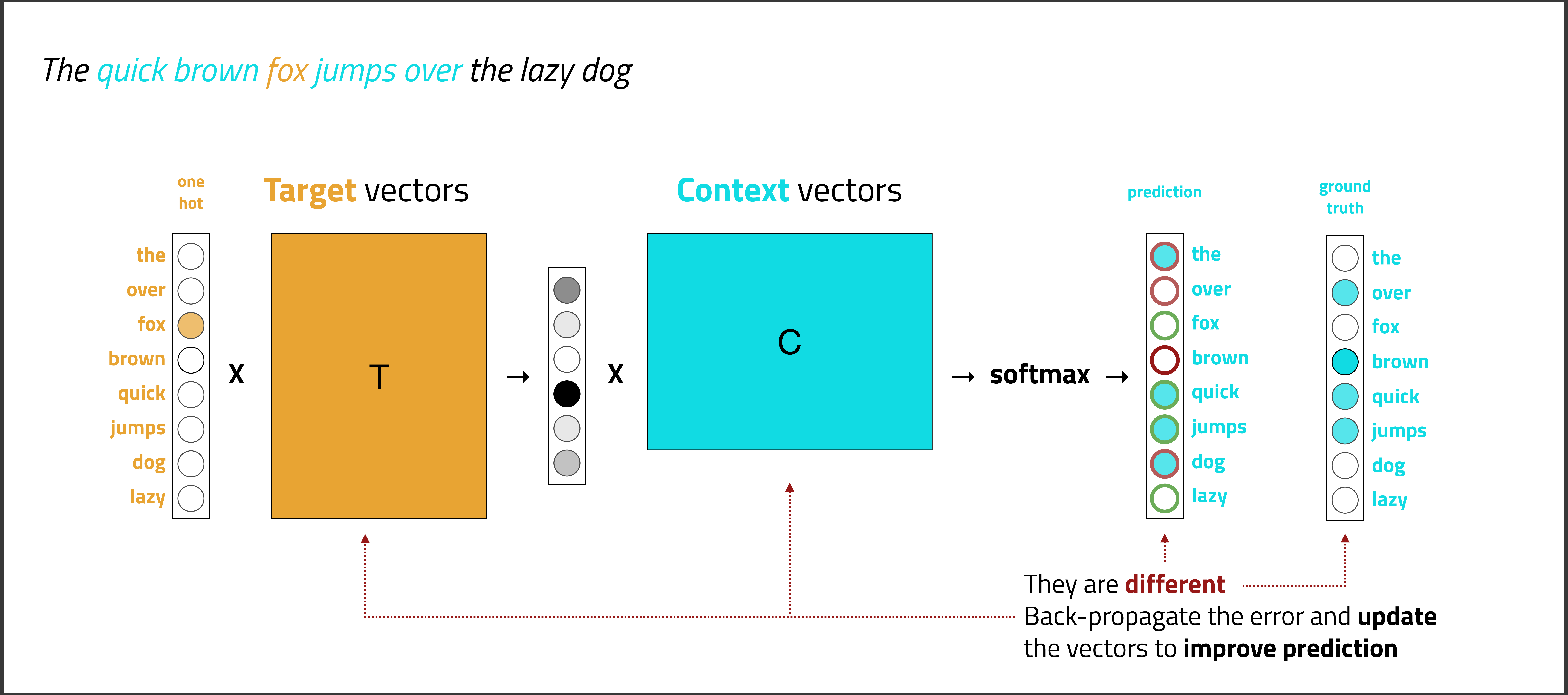



# Example

*The quick brown fox jumps over the lazy dog*



# Example



The quick brown fox jumps over the lazy dog
one hot
Target vectors
Context vectors
prediction
ground truth
the
over
fox
brown
quick
jumps
dog
lazy
X
T
X
C
softmax
They are different
Back-propagate the error and update the vectors to improve prediction

# Model and Loss

$$p(w_j|w_i) = softmax(\boxed{T_i} \cdot \boxed{C_j}) = \frac{e^{\boxed{T_i} \cdot \boxed{C_j}}}{\sum_k e^{\boxed{T_i} \cdot \boxed{C_k}}}$$

context target

$$H(y, \hat{y}) = -\sum_k y_k \log \hat{y}_k$$

Categorical cross entropy

True one hot label

Predicted one hot label

# Example Negative Sampling

Calculating the full softmax is **expensive** because of **large vocabulary**

*The quick brown fox jumps over the lazy dog*

1. Create pairs of **target** and **context** words and predict the probability of them co-occurring to be **1**

   (fox, quick) → **1**
   (fox, brown) → **1**
   (fox, jumps) → **1**
   (fox, over) → **1**

2. Sample **false context** words from their unigram distribution and predict the probability of them co-occurring with **true target** word to be **0**

   (fox, quick) → **1**
   (fox, brown) → **1**
   (fox, jumps) → **1**
   (fox, over) → **1**

   (fox, the) → **0**
   (fox, lazy) → **0**
   (fox, dog) → **0**
   (fox, the) → **0**

# Negative Sampling Loss

$$\log\sigma(\boxed{T_i}\cdot\boxed{C_j}) + \sum^{n}_{k\sim P(w)} \mathbb{E} \log\sigma(-\boxed{T_k}\cdot\boxed{C_j})$$

target

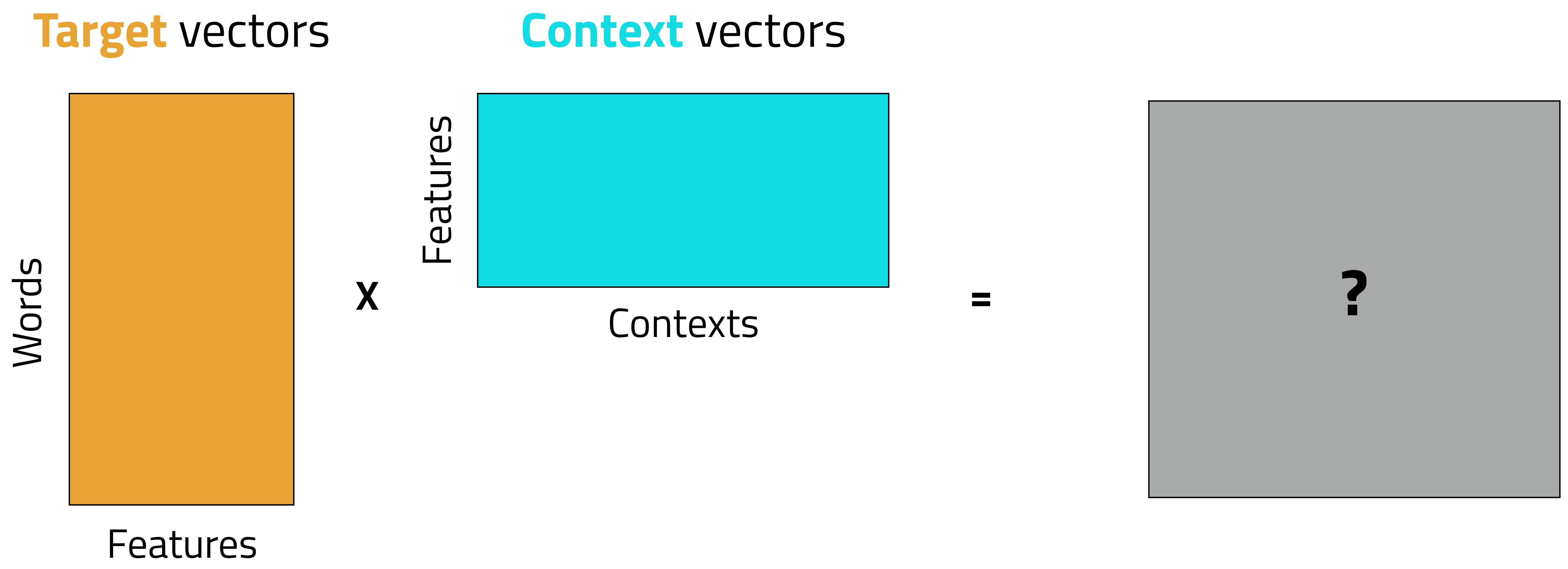
context

Number of negative samples

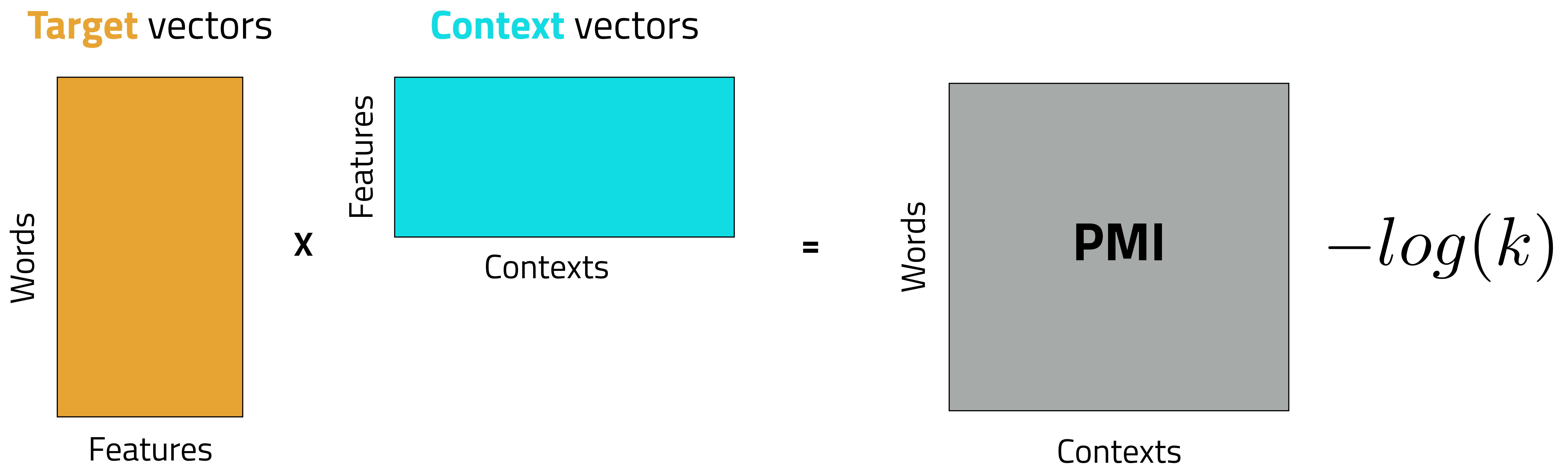
Sample from the distribution of words

Vector of the negative sample

# SGNS as matrix factorization



# SGNS as matrix factorization



# word2vec

## Advantages

- Iterative way for factorizing a matrix
- Fast *O(nm)*, great implementations
- Several parameters to improve performance (negative samples, subsampling of frequent words, ...)
- Default parameters can go a long way

## Disadvantages

- Inflexible definition of context
- Doesn't use dataset statistics in a smart way
- Columns are hard to interpret as topics

# Are neural word embeddings better than classic DSMs?

## Yes

**With vanilla parameters**

Baroni et al., *Don't count, predict! A systematic comparison of context-counting vs. context-predicting semantic vectors*, 2014

## No

**With optimal parameters**

Levy et al., *Improving Distributional Similarity with Lessons Learned from Word Embeddings*, 2015

## Maybe

**Trained on 1 billion+ words**

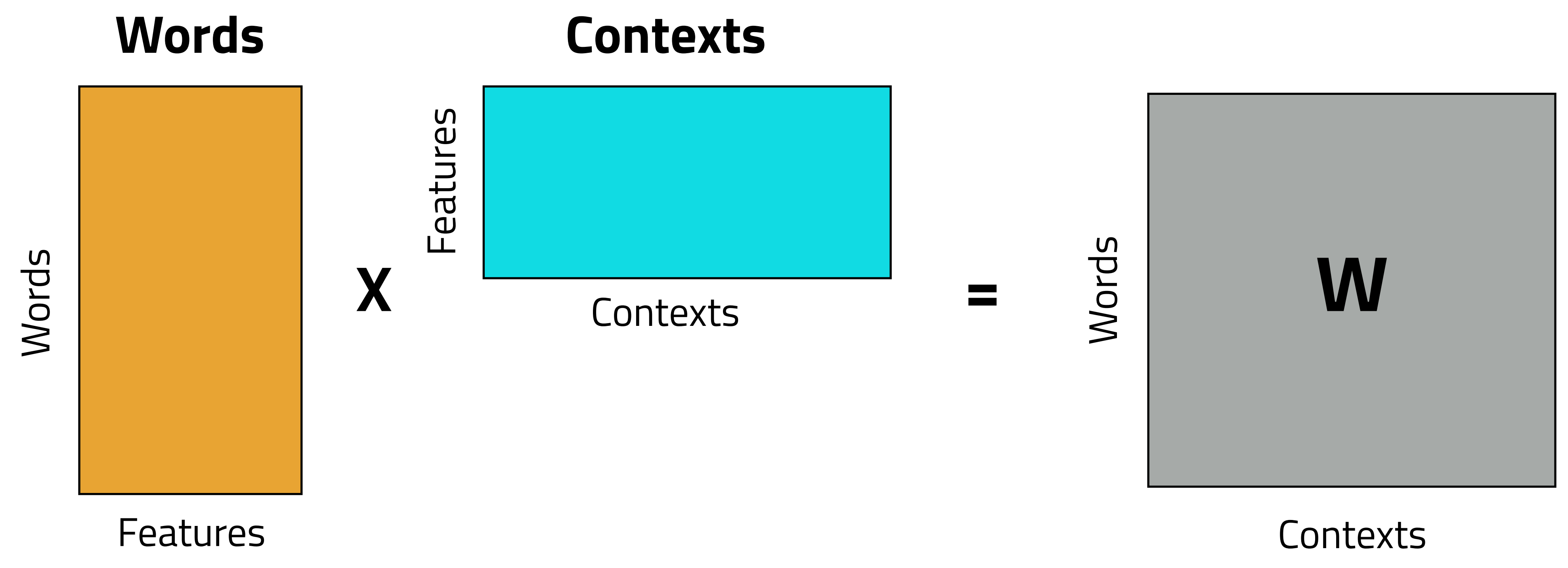
Sahlgren and Lenci, *The Effects of Data Size and Frequency Range on Distributional Semantic Models* , 2016

# GloVe

Explicit factorization of **target** x **contexts** matrix

Precomputes the matrix (unlike SGNS)

Uses **directly** the **statistics** of the dataset (frequencies of co-occurrences)




$$J = \sum_{i,j} f(W_{ij})(w_i^\top \tilde{w}_j - \log W_{ij})^2$$

frequency of word *i* in context *j*

**target**

**context**

like SGNS

# GloVe

## Advantages

- Better use of dataset statistics
- Converges to good solutions with less data
- Simple to apply on different contexts

## Disadvantages

- Recent comparisons show that on many tasks it doesn't perform as well as LSA or SGNS

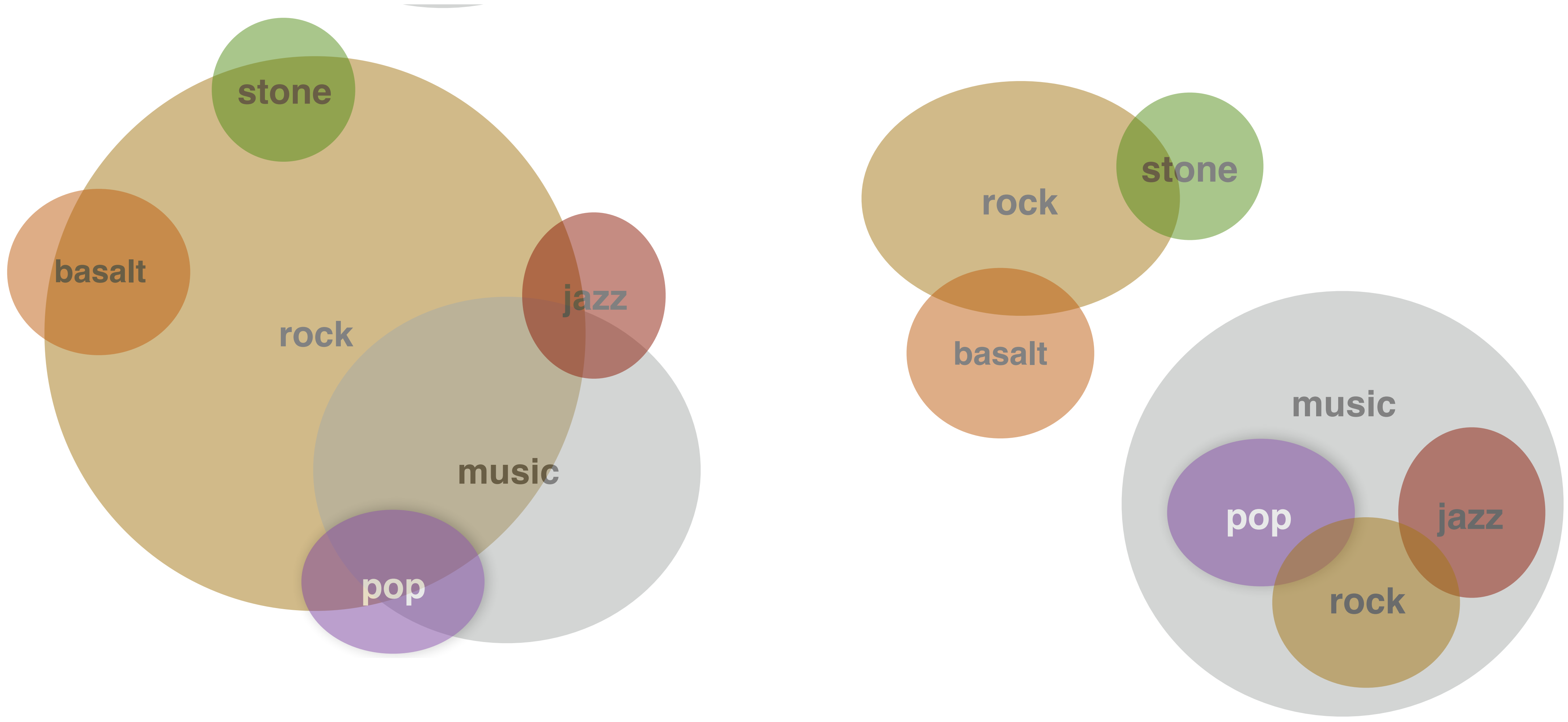
# Gaussian Embeddings and Multimodal Word Distributions

Instead of representing words as points, represent them as **distributions**

**Mean** and **variance** in every dimension

Multimodal **mixes** a **fixed** number of gaussian distributions

**Gaussian Embeddings** **Multimodal Distributions**



# Gaussian Embeddings and Multimodal Word Distributions

## Advantages

- Words as distributions instead of point in a space is a promising direction
- Better treatment of polysemy

## Disadvantages

- More expensive than previous models
- Still brittle → fixed number of mixtures

# Takeaways from literature*

**No single algorithm consistently outperforms the others**: all models in the same ballpark

**SGNS** is only slightly **better** when there is *more than **1 billion words*** in the corpus

**iSVD** is slightly **better** in *most other cases*

**SVD better** on *similarity*, **SGNS better** on *analogy*

**Hyperparameter settings** are **more important than algorithm** choice

Training on a **larger corpus helps**

*Levy, Goldberg and Dagan, *Improving Distributional Similarity with Lesson Learn from Word Embeddings*, 2015

# Recommendations from literature*

**DON'T** use shifted PPMI with SVD

**DON'T** use SVD "correctly", i.e. without eigenvector weighting, throwing away Sigma

**DO** use PPMI and SVD with short contexts (window size of 2)

**DO** use many negative samples with SGNS

**DO** always use *context distribution smoothing* (raise unigram distribution to the power of $\alpha$=0.75)

**DO** use **SGNS** as a **baseline** *(robust, fast and cheap to train)*

**DO** try adding context vectors in SGNS and GloVe

*Levy, Goldberg and Dagan, *Improving Distributional Similarity with Lesson Learn from Word Embeddings*, 2015

# Open questions and current trends

# Compositionality

So far we represented words as vectors, how to represent **sentences**?

Can't use the co-occurrences of sentences in their context as **sentences** are **sparse**, most of them occur once

Should represent their meaning **combining** word representations

*The **meaning of an utterance** is a **function** of the **meaning of its parts** and their **composition rules*** - Gottlob Frege, *Über Sinn und Bedeutung*, 1892

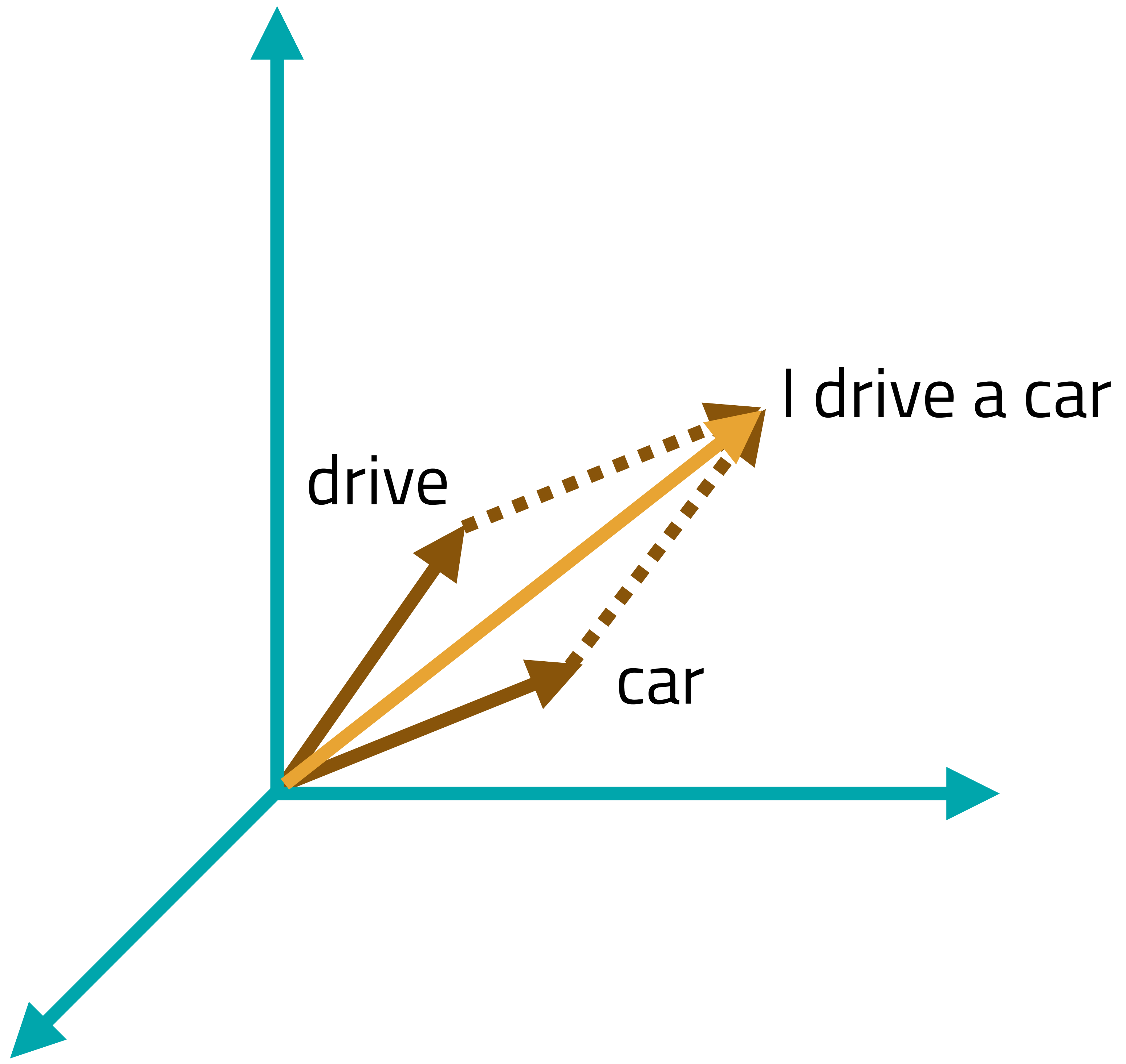
# Composition operators

Simple solution, just **sum** the vectors of the words in a sentence!

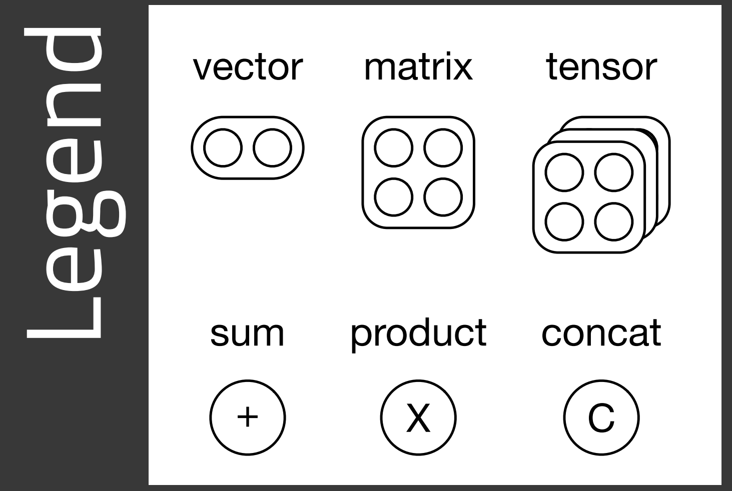
Other **operators**: product, weighted sum, convolution, … (Mitchell and Lapata, 2008)

It's hard to perform better than the simple **sum**

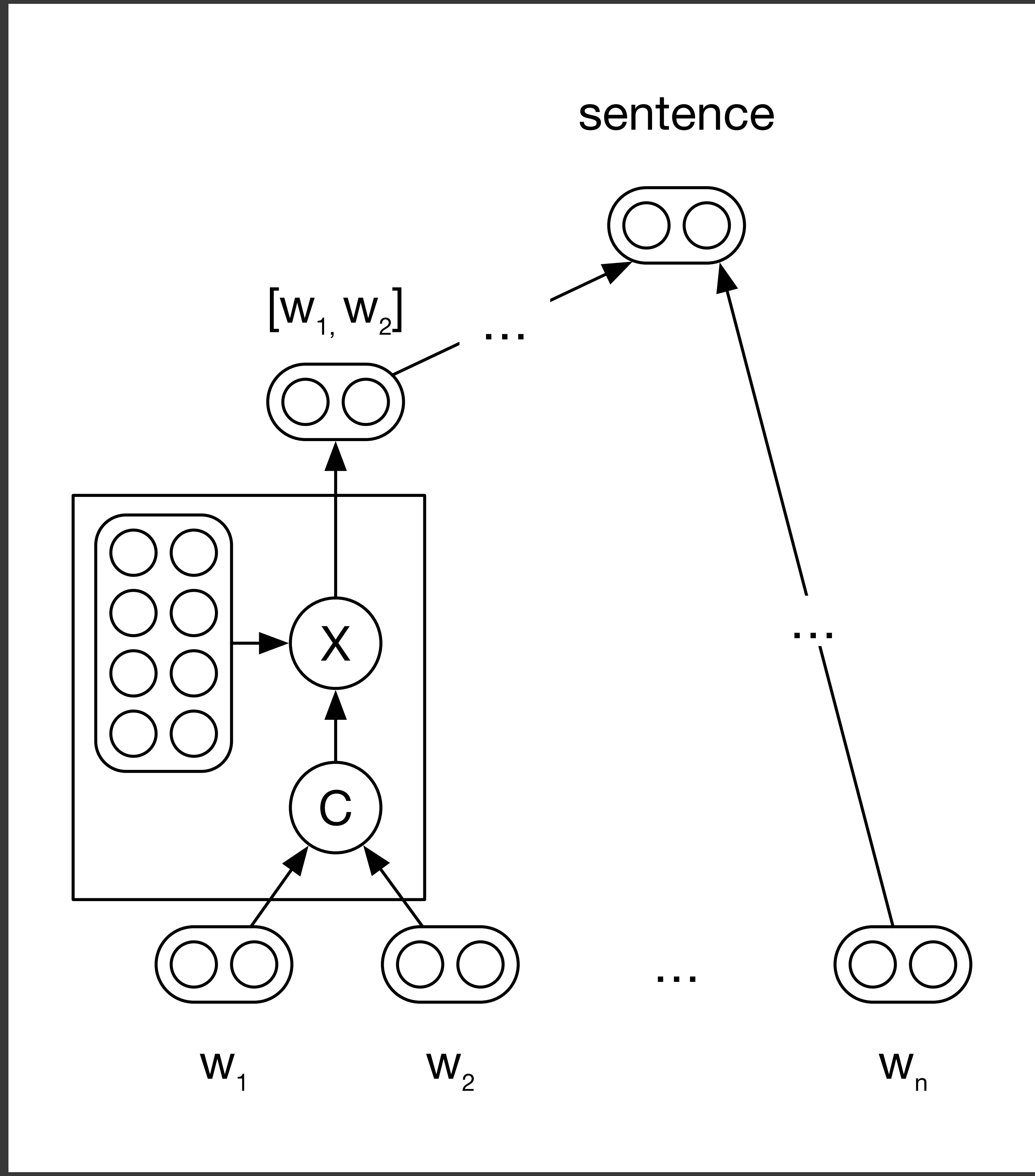
**Sum** can't be the real answer as it's **commutative** → doesn't consider **word order**



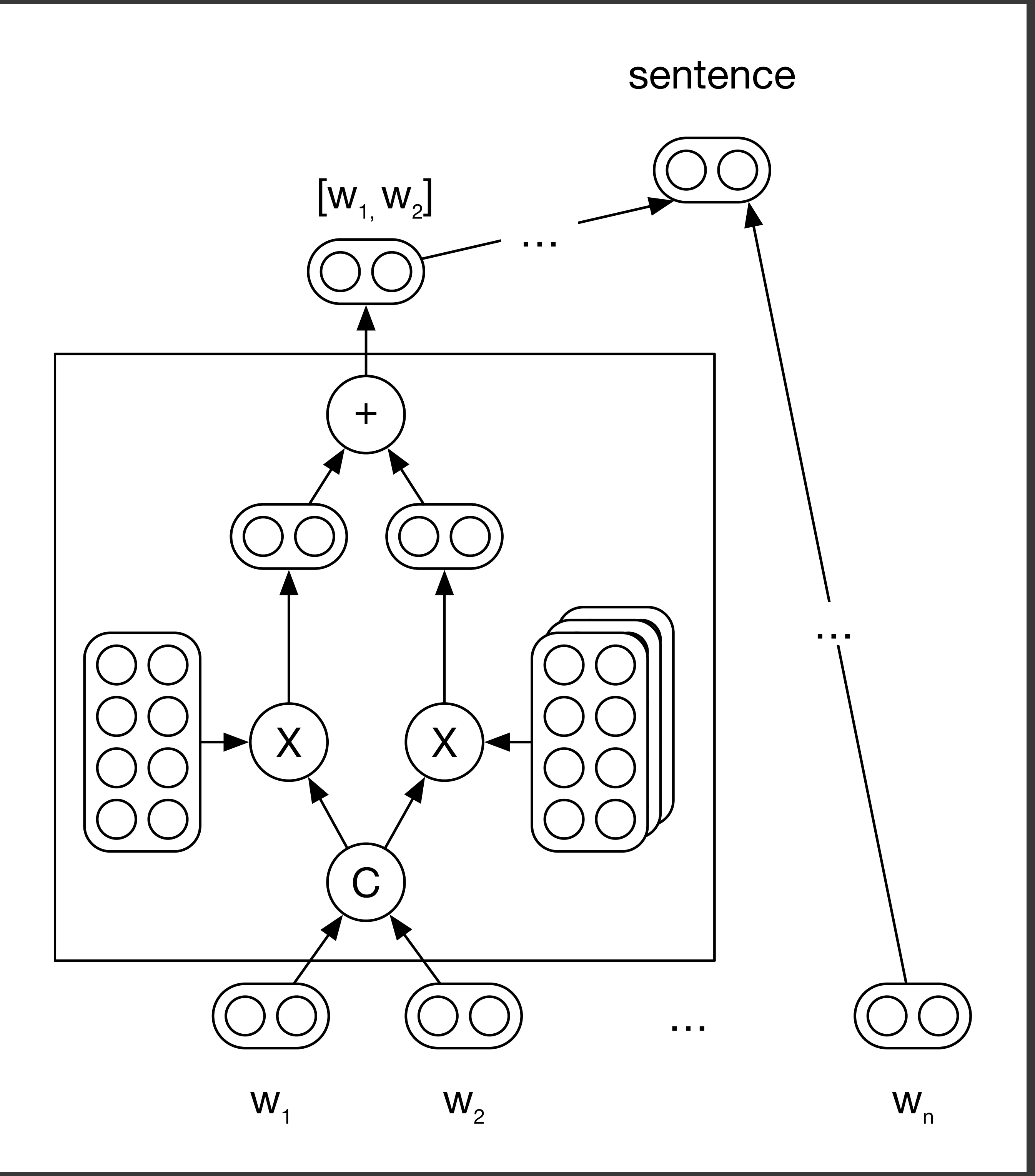
# Learn to compose



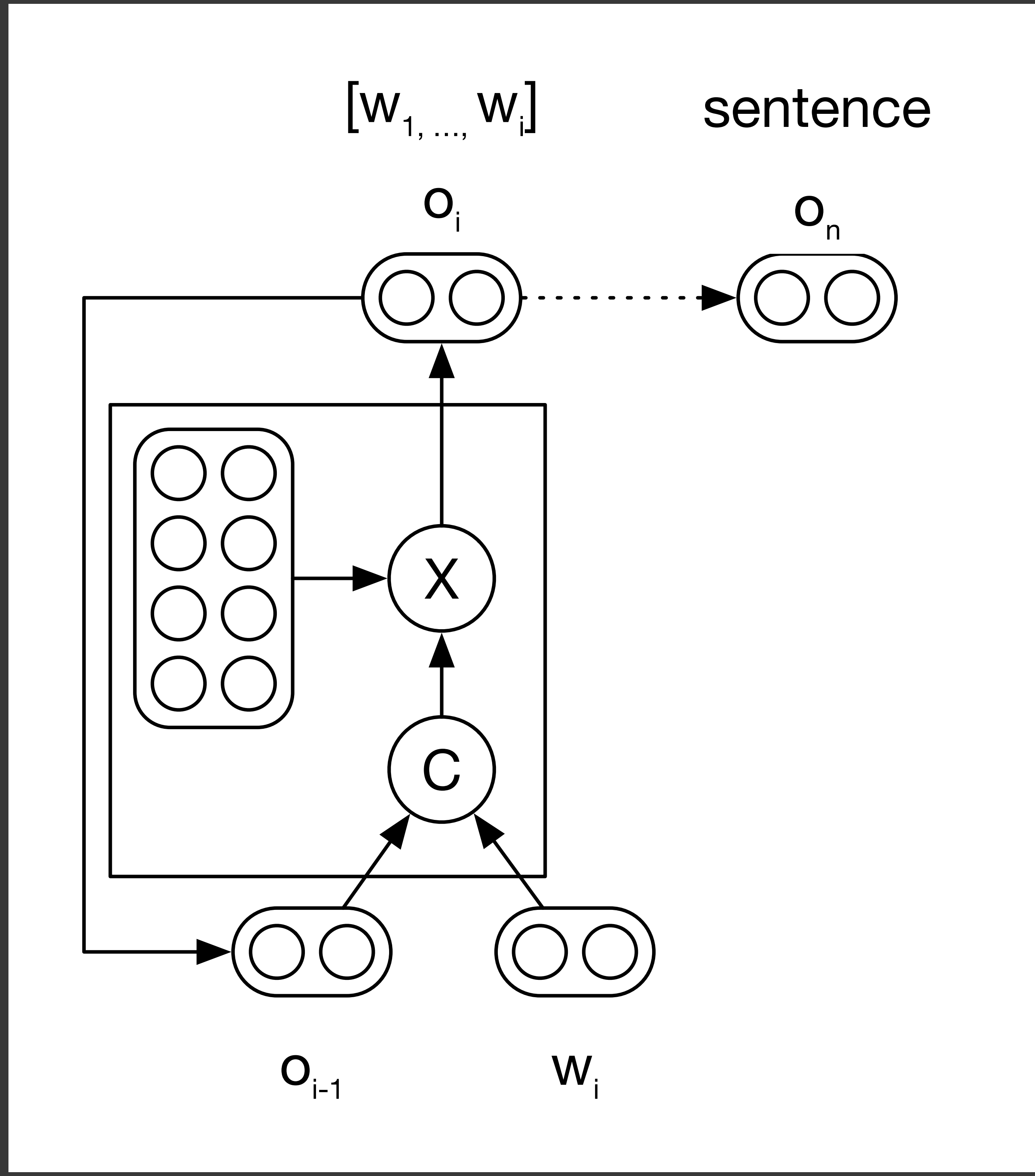

**Recursive Matrix Vector Network** (Socher at al. 2012)




**Recursive Neural Tensor Network** (Socher et al. 2013)




**Recurrent Neural Network** (Elman 1990) and others



# Subword structure

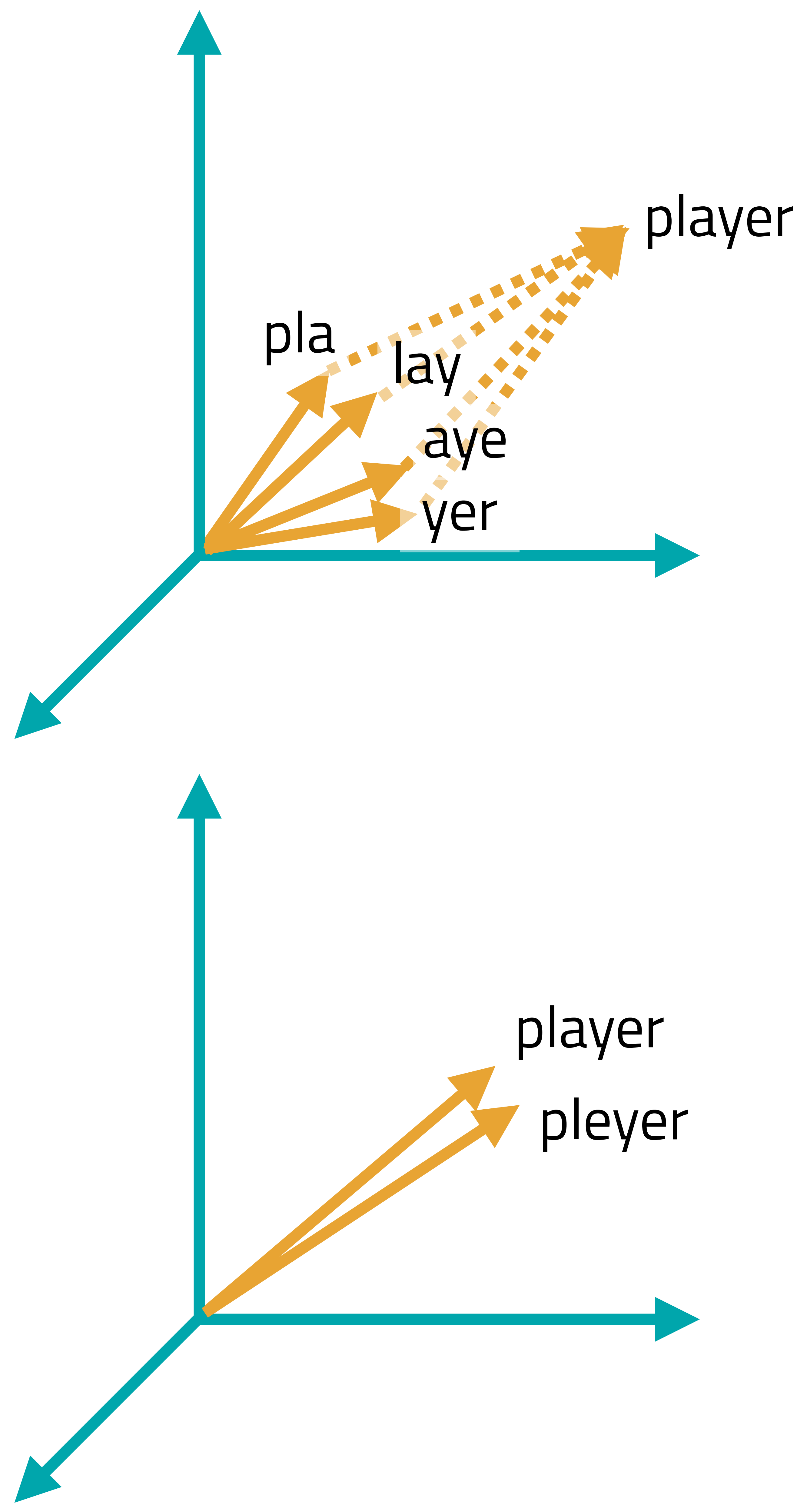
**Assumption**: **similar words** are **similarly spelled** *(player / played)*

Exploit **characters** and **character sequences**

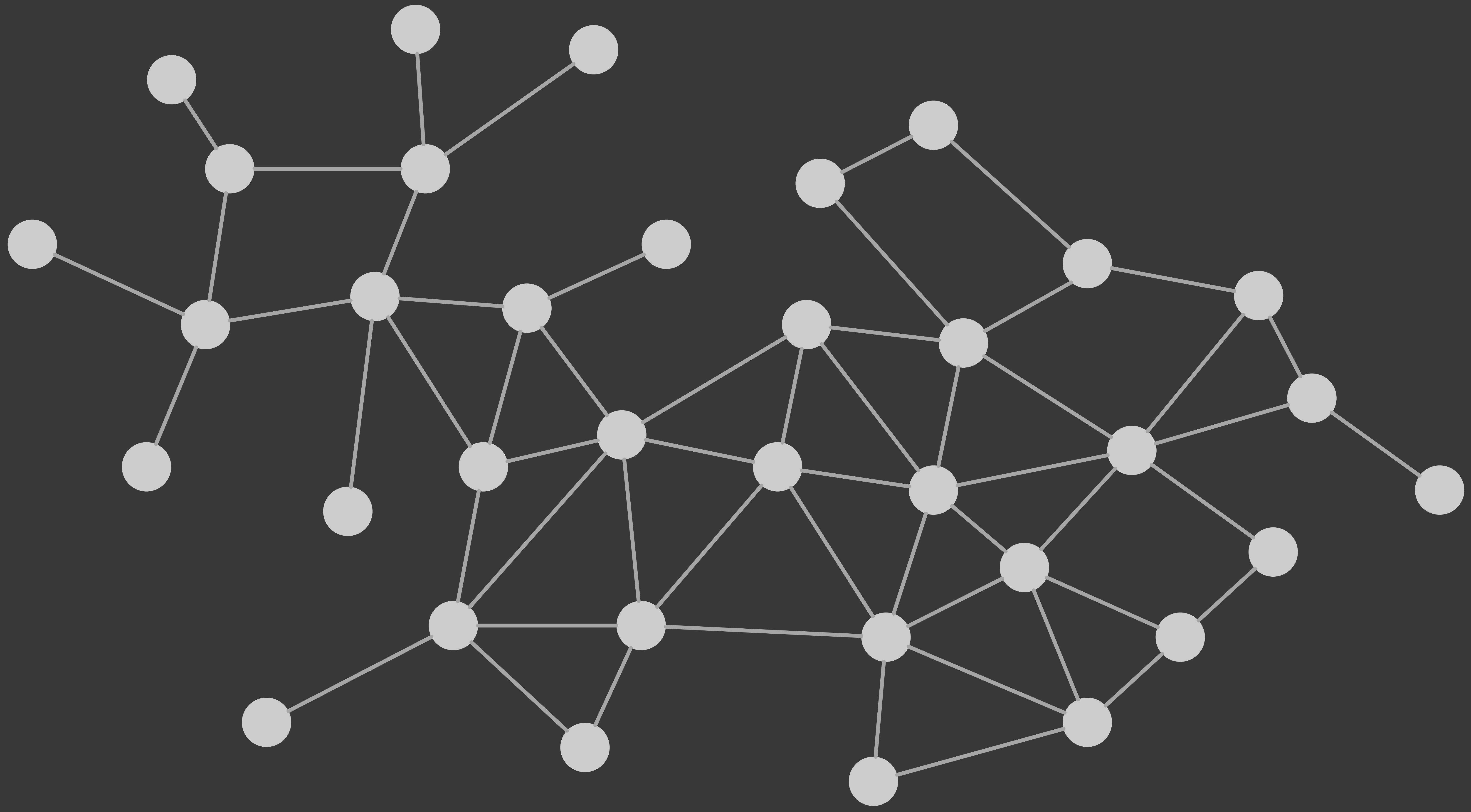
Useful to deal with **misspells** and **rare / new words** *(player ~ pleyer)*

Beware of **pitfalls** *(pray / prey)*

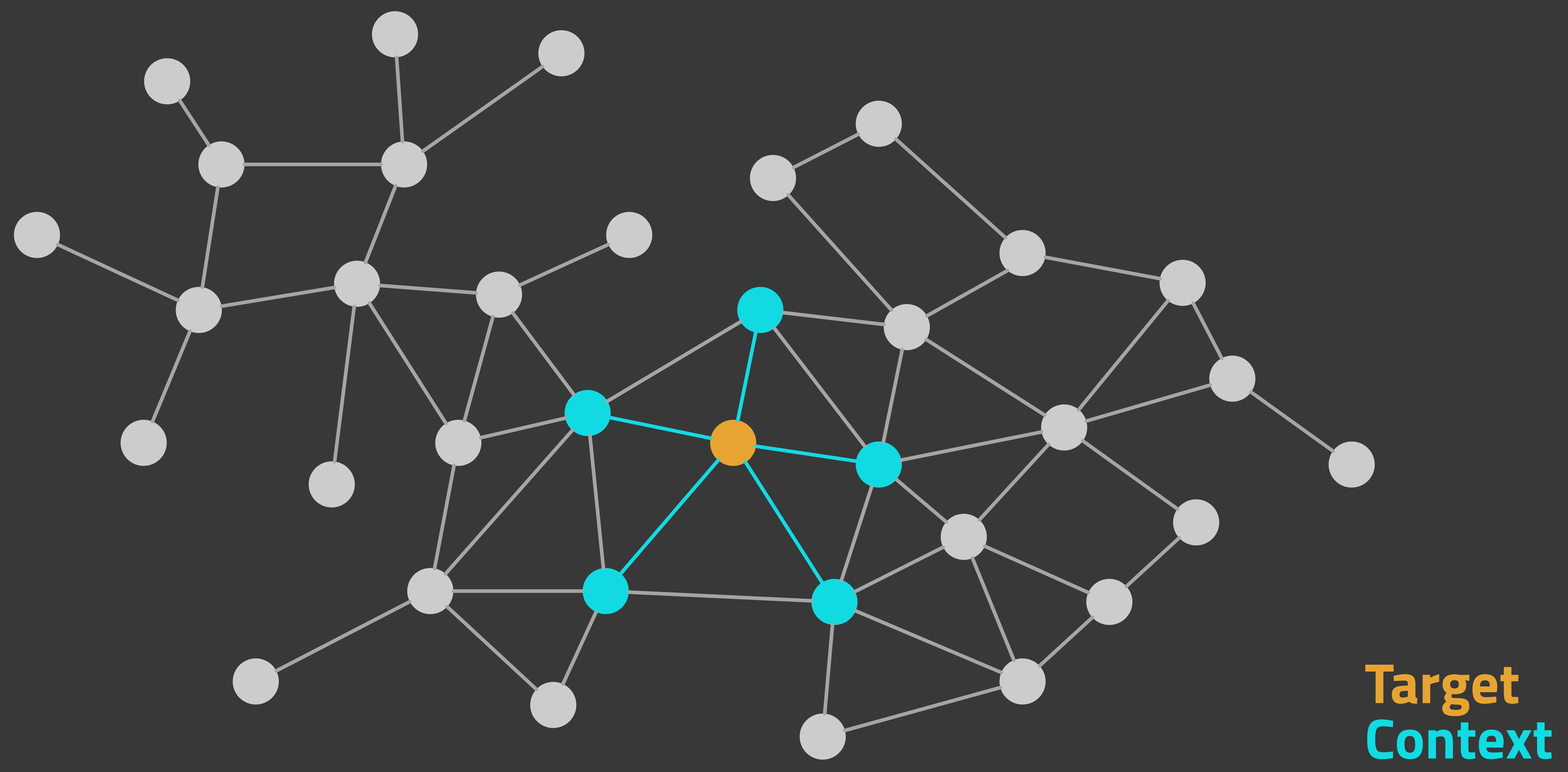
- **CharCNN** (Zhang, Zhao and LeCun 2015)
- **LSTM** with **word CharCNN** (Kim 2016)
- **FastText** (Bojanowski 2016)
- Luong and Manning, *Achieving Open Vocabulary Neural Machine Translation with Hybrid Word-Character Models*, 2016



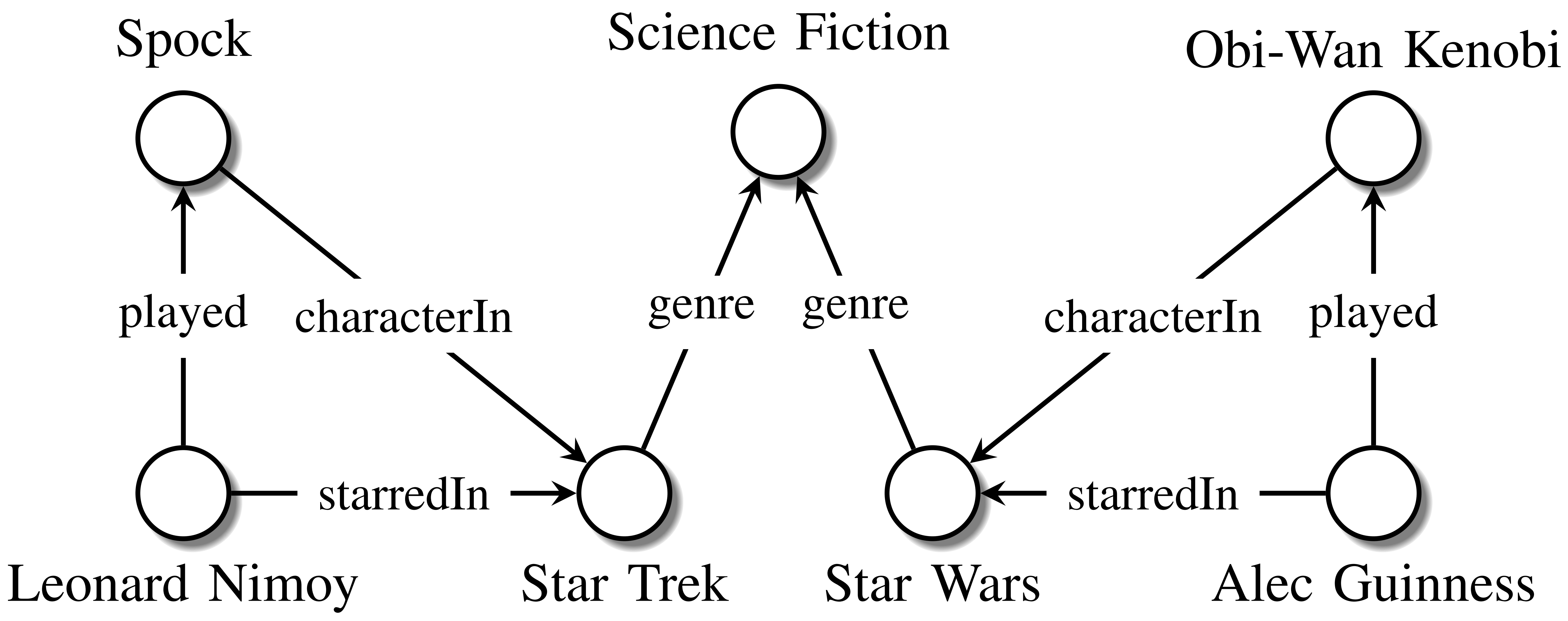
# Embeddings for Graphs



# Embeddings for Graphs



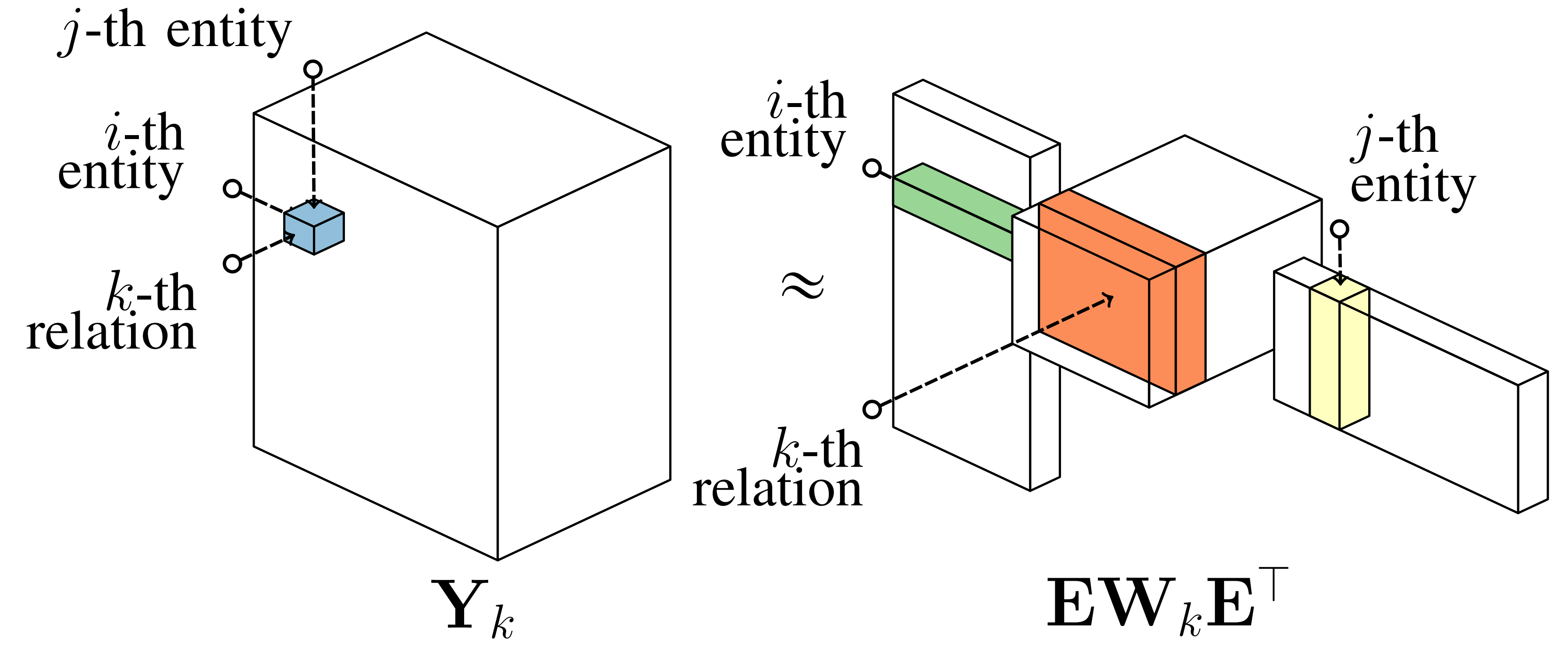
# Knowledge Graph




Node = Entity
Link = Relation

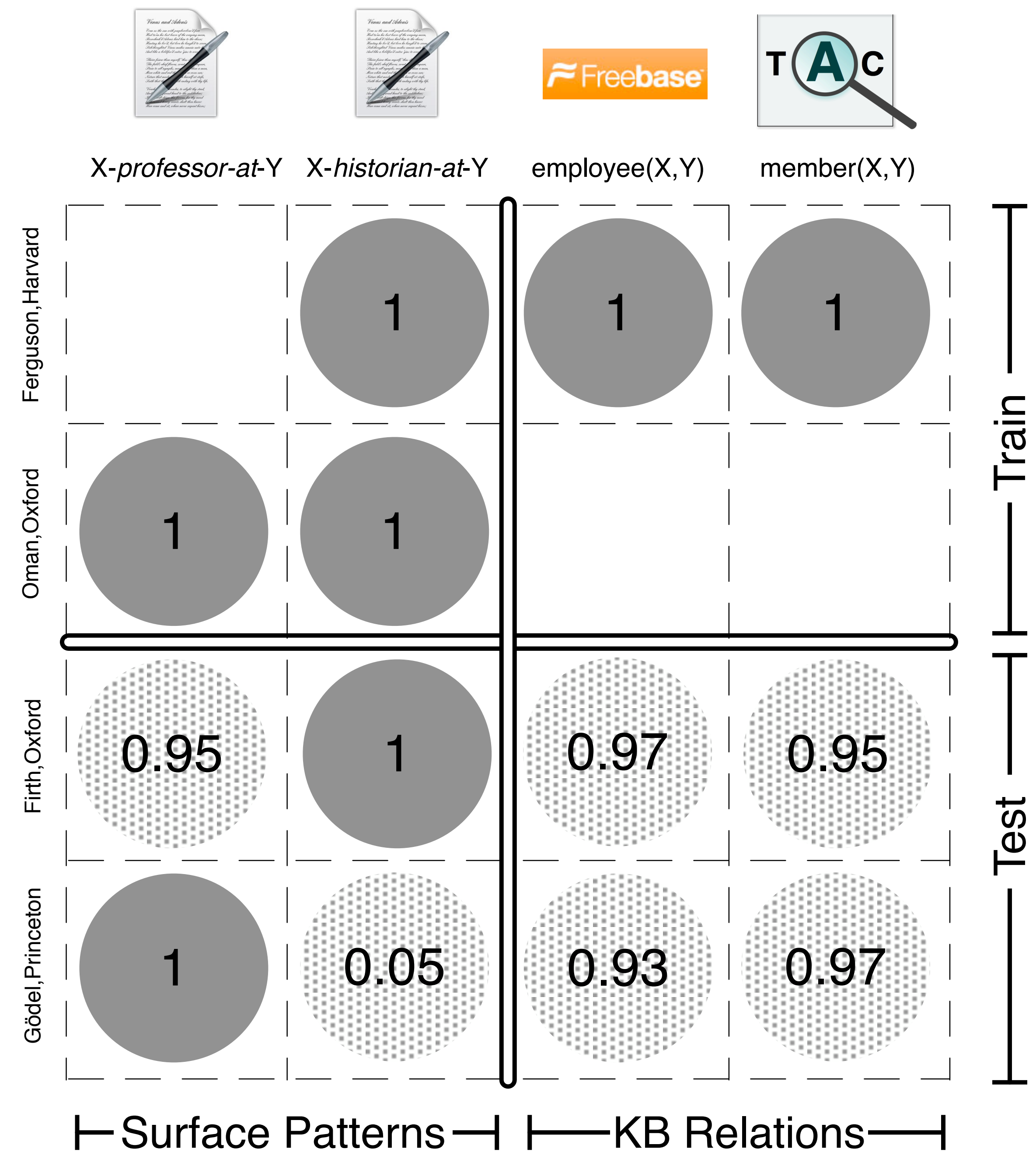
# Knowledge Graphs

**Tensor Factorizations**
(Nickel et al. 2015)




Node = Entity
Link = Relation

**Universal Schema**
(Riedel at al. 2013)



# Exotic applications

item2vec - recommender systems (Barkan and Koenigstein 2016)

node2vec - graph embeddings (Grover and Leskovec 2016)

dna2vec (Ng 2017)

Predicting drug-drug interactions (Fokoue 2016)

Movies, music, playlists, recipes, ...

# Conclusions

**Know the theory** *(structuralism)* and everything **makes sense**

Distributional Semantics and Embeddings have a **long rich history**

**Context is king**

**No algorithm** to *rule them all*, but a **great toolset** to chose from

Many aspects of reality can be seen in terms of **targets** and **contexts**

Go out and apply them to your business!

# Thanks

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Arianna Betti