A Neural Embedding Compressor for Scalable Document Search

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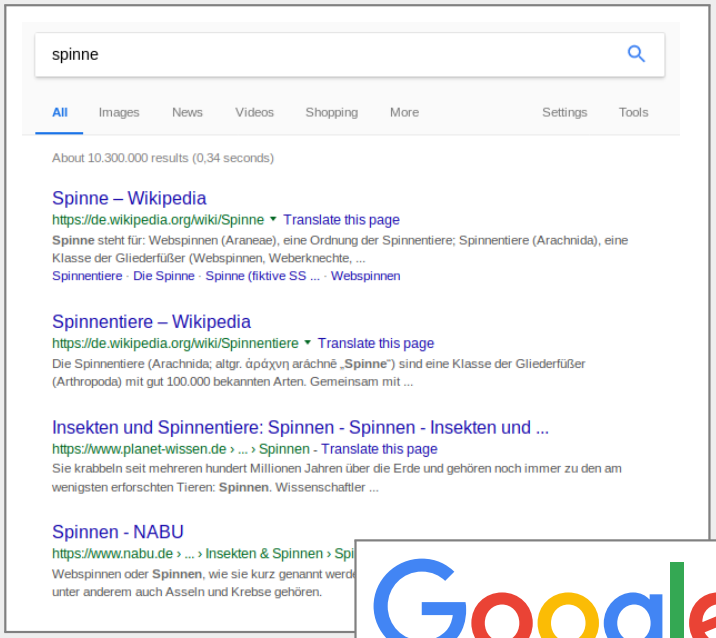
Contents

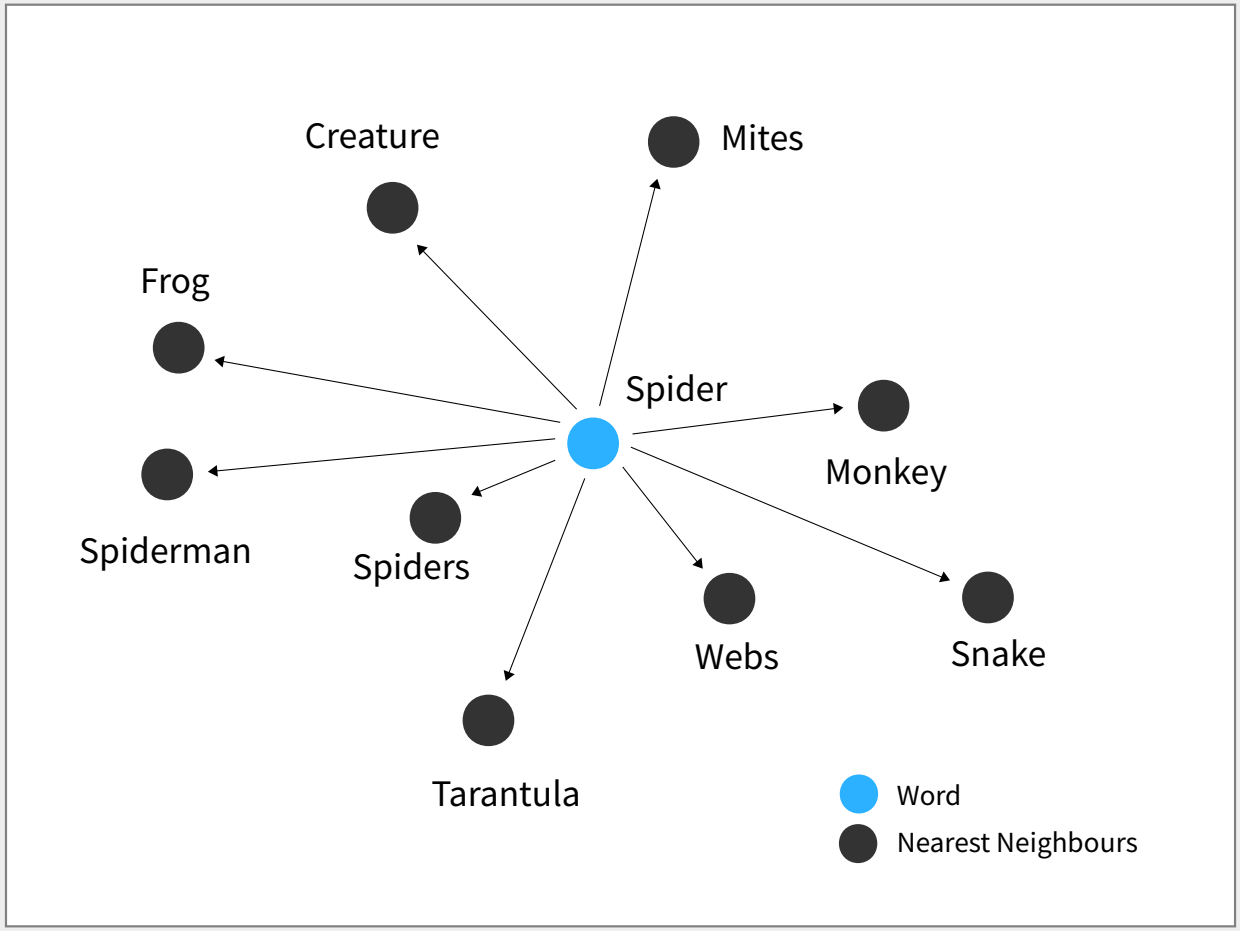
IR and Document Similarity

Information Retrieval

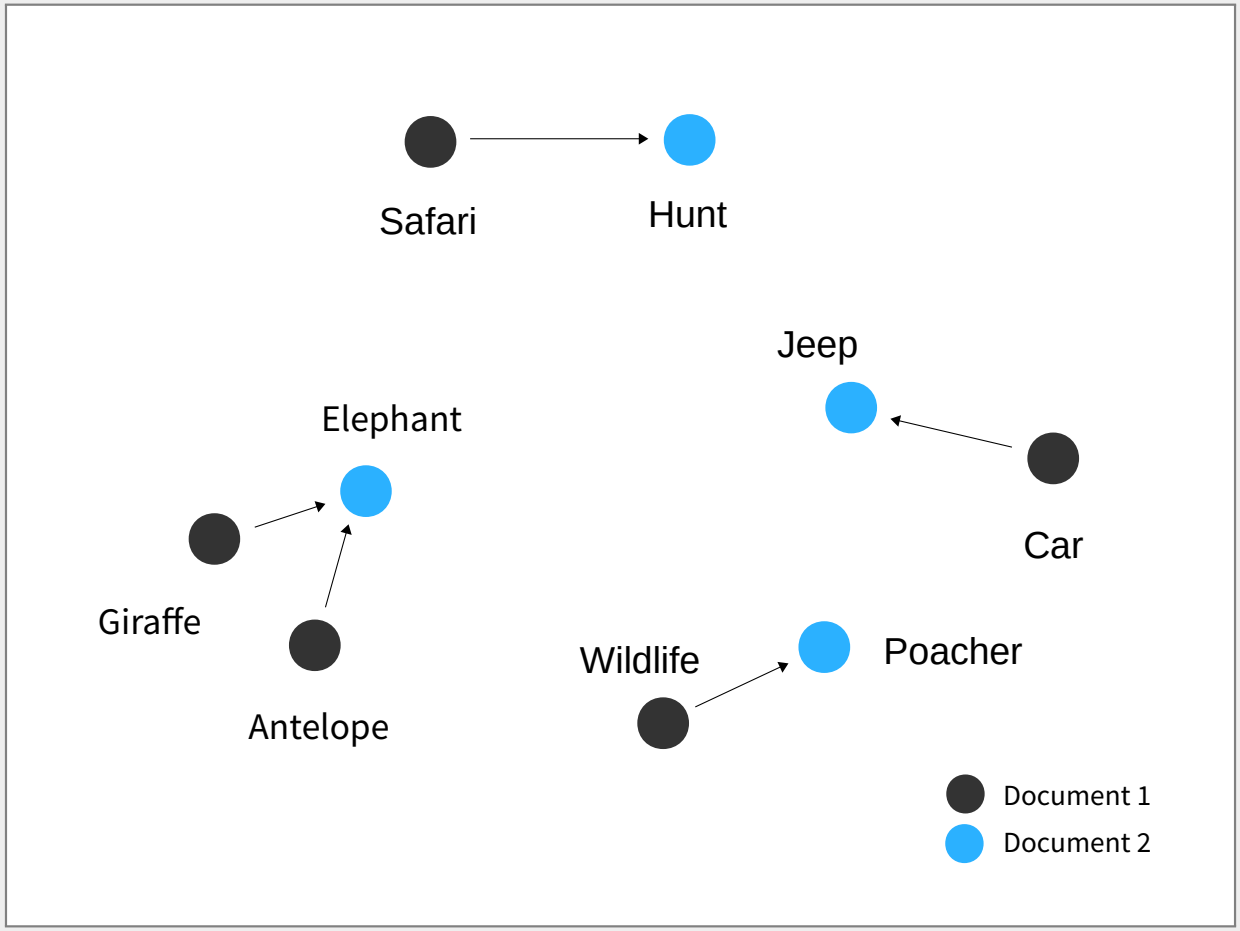
- Here: Searching for text documents given a text query
- Good IR systems:
  - Sort results by relevance effectively
  - Handle large amounts of data
  - Are fast

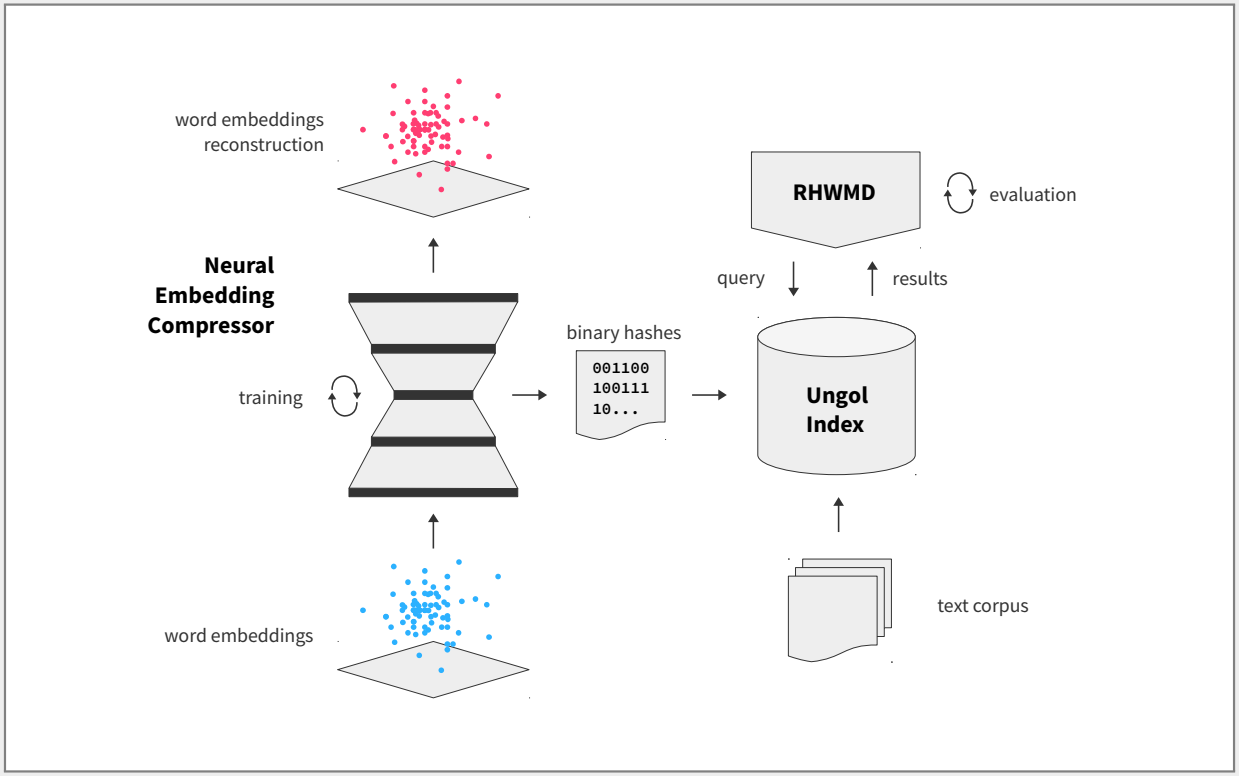


Word Embeddings: Relatedness by distance



(Relaxed) Word Movers Distance (R)WMD: Idea




word embeddings
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The Embedding Compressor

Compressor: Starting Point and Requirements

What we have:

- Real-valued word embeddings in Euclidean space
- Spatial word similarity structure

What we do with it:

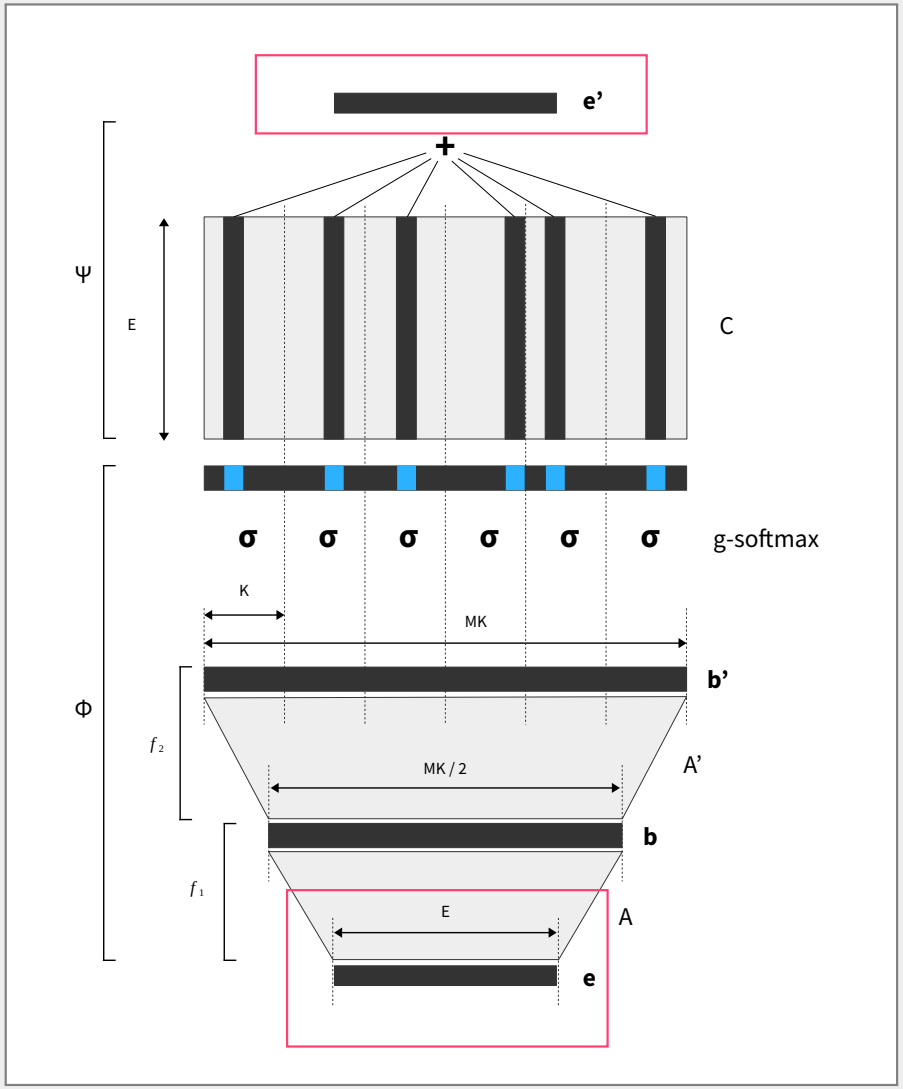
- Training a neural auto-encoder model to reconstruct word embeddings
- Use the encoder to create binary hash codes
- Examine whether the spatial properties are transferred into Hamming space

- Training objective: reduce reconstruction loss

$$L(\mathbf{e}_t, \mathbf{e}'_t) := \frac{1}{2}||\mathbf{e}_t - \mathbf{e}'_t||_2^2$$

$$(\psi_\theta \circ \phi_\theta)(\mathbf{e}_t) := \mathbf{e}'_t$$

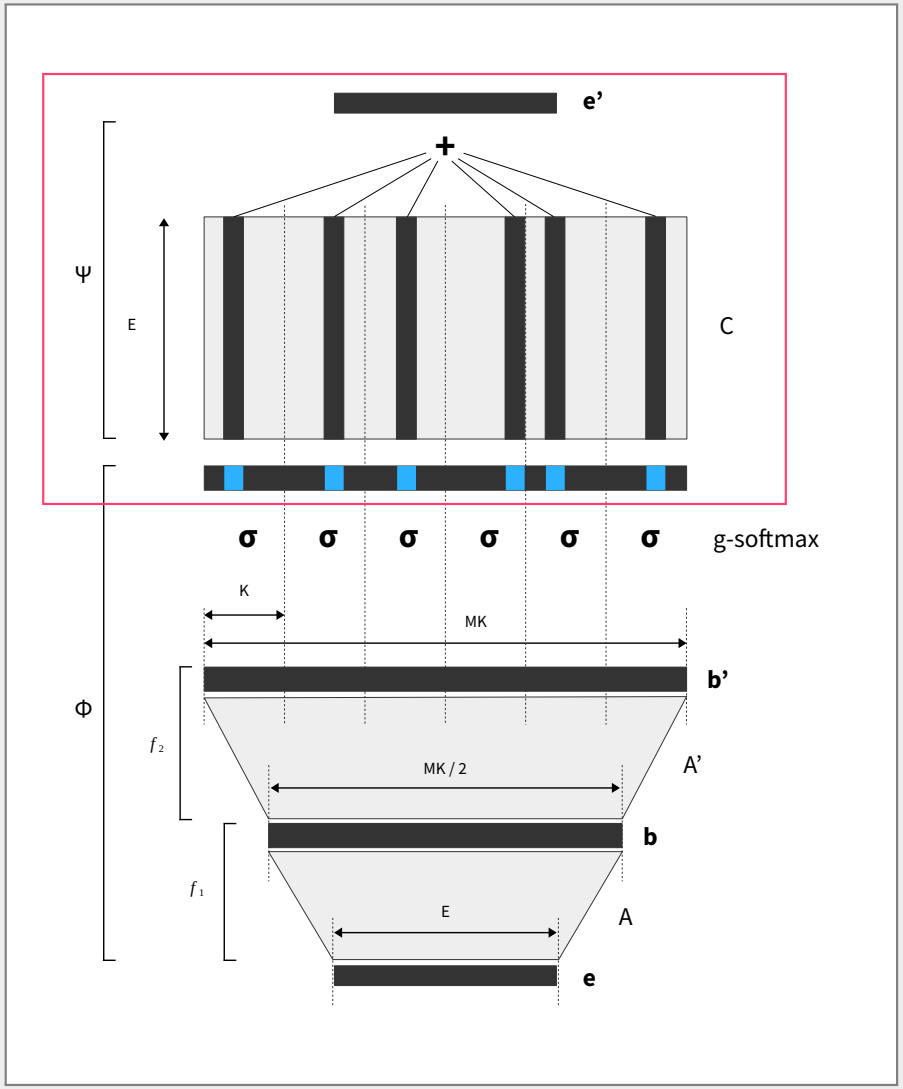
$$\theta := \{A, \mathbf{b}, A', \mathbf{b}', C\}$$



The Neural Embedding Compressor: Decoder

- Given MK basis vectors $C \in \mathbb{R}^{E \times MK}$
- Accepts vector $\mathbf{x} \in \{0, 1\}^{MK}$ of concatenated one-hot encodings
- Combination by additive vector quantization

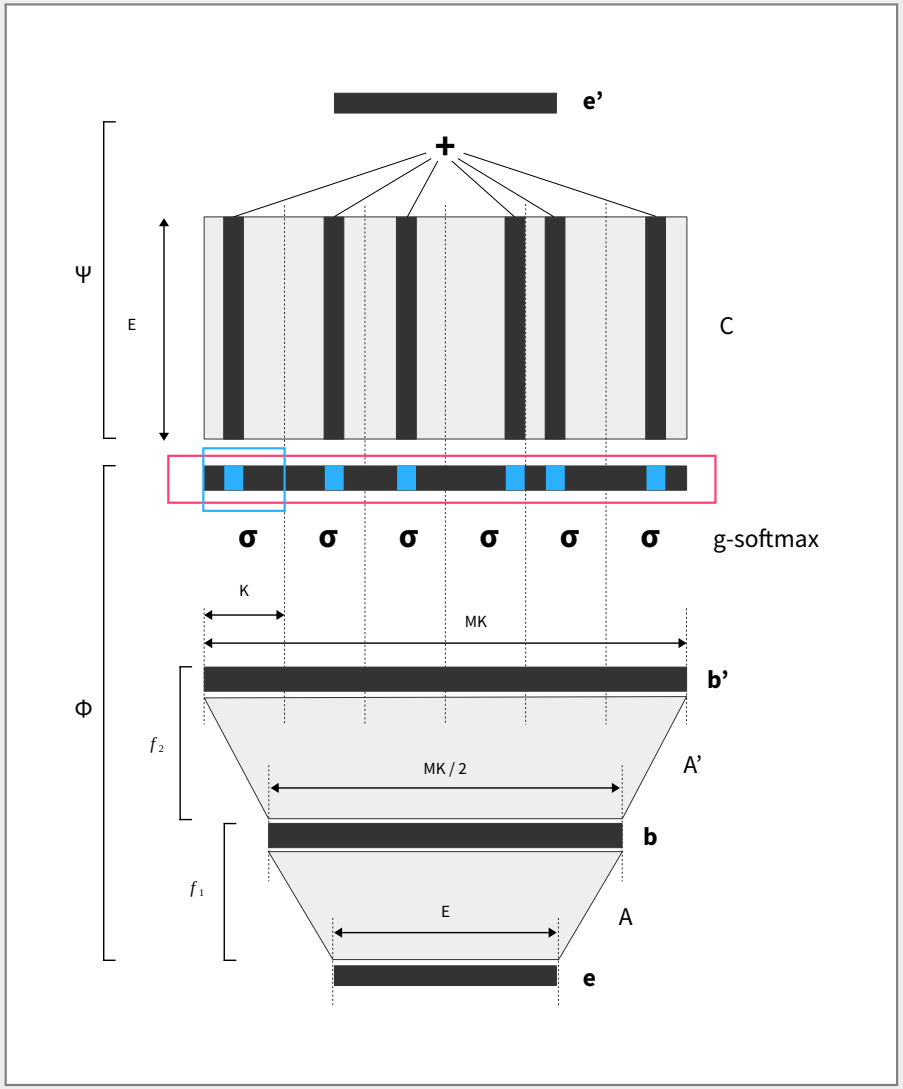
$$\psi_\theta(\mathbf{x}) := C\mathbf{x} = \mathbf{e}'$$



The Neural Embedding Compressor: One-Hot Encoding

- Encoder output are one-hot encodings
- Here: $M = 6, K = 5$
- Code: $(1, 3, 2, 4, 1, 3)$

$$X = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{ccccc} 0 & 1 & 2 & 3 & 4 \end{array} \\ \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \end{array}$$



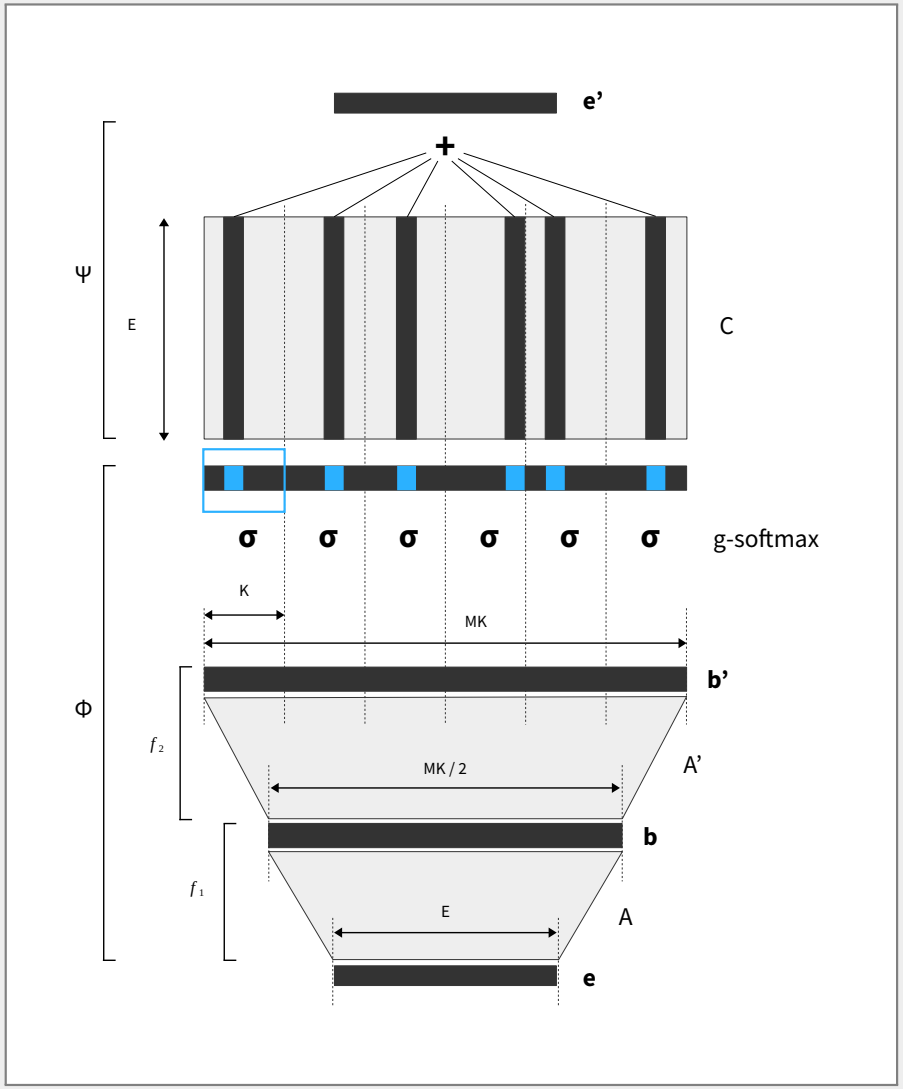
The Neural Embedding Compressor: Gumbel Softmax I

- Alter softmax function
- Add Gumbel noise
- Forces the model to approach categorical distribution

$$\text{g-softmax}(\mathbf{x}_i) := \frac{\exp(f(\mathbf{x}_i))}{\sum_{k=1}^{K} \exp(f(\mathbf{x}_k))}$$

$$f_\tau(\mathbf{x}_k) = \frac{1}{\tau} \cdot (\mathbf{x}_k + \mathbf{g}_k)$$

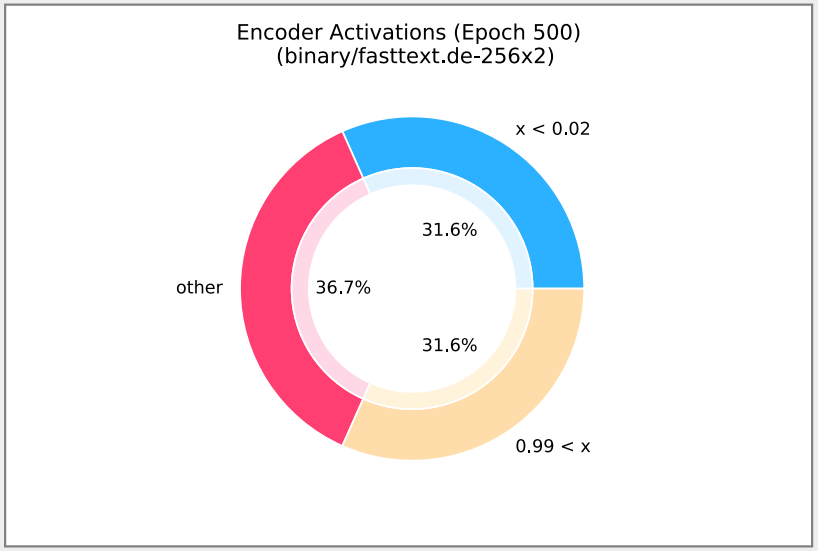
$$\mathbf{g} = (g_1, \ldots, g_K); g_i \sim G$$



The Neural Embedding Compressor: Gumbel Softmax II

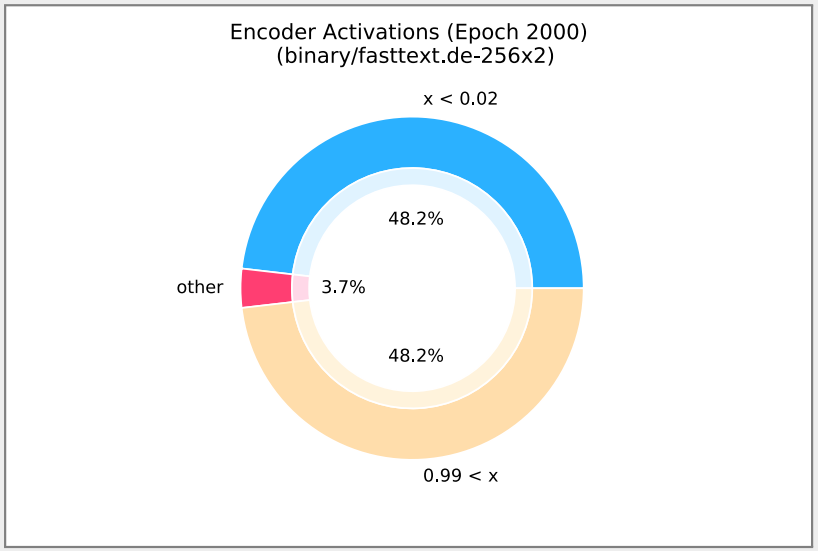
- After a few epochs:

training	0.505	0.001	0.003	0.186	0.305
validation	1	0	0	0	0



- End of training:

training	0.993	0.001	0.003	0.002	0.001
validation	1	0	0	0	0



- Training excerpt for $K = 2$
- Good loss and entropy for $M = 256$

		GloVe		fasttext.de	
M	$\lvert\Theta\rvert$	Loss	Entropy	Loss	Entropy
32	19200	16.82	0.972	8.037	**0.960**
64	38400	14.99	0.981	6.809	0.932
128	76800	11.72	**0.985**	5.319	0.909
256	153600	6.986	0.961	3.682	0.873
512	307200	6.921	0.970	3.762	0.849

$$\text{entropy}(\mathbf{x}) := \frac{1}{log_2 K} \sum_{i=1}^{K} \begin{cases} 0 & \text{if } p(\mathbf{x}_i) = 0 \\ -p(\mathbf{x}_i) \cdot \log_2 p(\mathbf{x}_i) & \text{else} \end{cases}$$

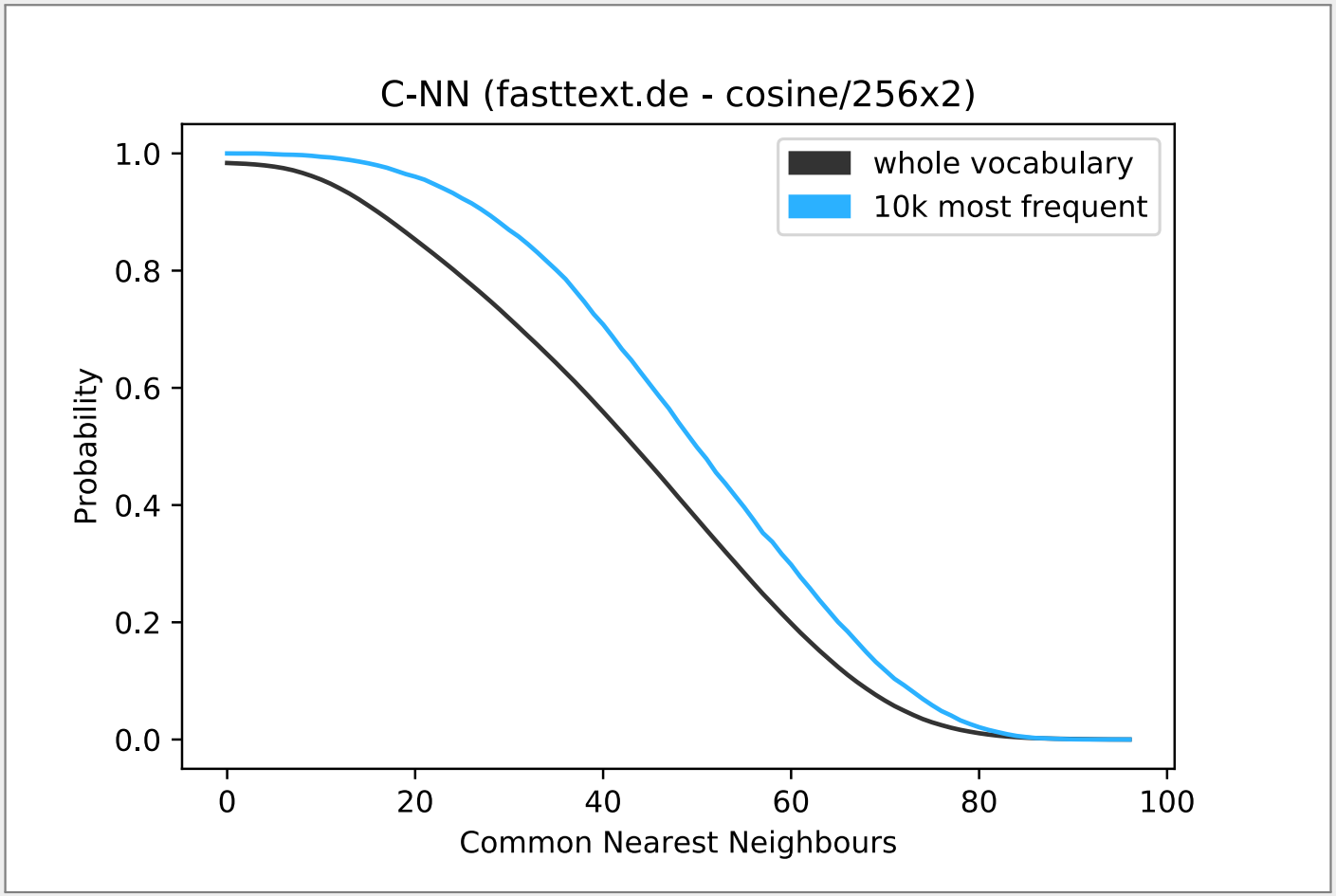
The Embedding Compressor: Nearest Neighbours (exemplary)

Nearest Neighbours of **Compressor**

	Cosine - *C*				**Hamming** - *H*			
idx	**word**	**dist**$_C$	**dist**$_H$	**idx**$_H$	**word**	**dist**$_C$	**dist**$_H$	**idx**$_C$
1	compressors	0.694	60	2	turbine	0.693	60	2
2	turbine	0.693	60	1	compressors	0.694	60	1
3	supercharger	0.541	78	11	valve	0.440	72	25
4	high-pressure	0.541	75	8	engine	0.415	73	40
5	nozzle	0.524	82	19	combustion	0.503	74	8
6	turbocharger	0.513	80	16	cylinder	0.483	75	14
7	turbines	0.504	75	7	turbines	0.504	75	7
8	combustion	0.503	74	5	high-pressure	0.541	75	4
9	conditioner	0.501	89	54	engines	0.384	77	56
10	piston	0.495	85	23	cylinders	0.438	78	27

dist$_H$ is the count of unequal bits of two hash codes

The Embedding Compressor: Nearest Neighbours (quantitatively)



The Relaxed Hamming WMD

RHWMD: Starting Point and Requirements

What we have:

- Binary hash codes of words
- Hamming distance as similarity measure

What we do with it:

- Measure similarity between documents
- Following the RWMD: Select nearest neighbour pairs
- Quantify similarity of documents by using the distance of all nearest neighbour pairs

- Calculate a score s for a document pair:

$$s(d, d') := \sum_{t \in d} \text{n-idf}(t) \cdot \left(1 - \eta(h_t, h_{t'})\right) \tag{1}$$

$$\text{n-idf}(t) := \frac{\text{idf}(t)}{\sum_{t' \in d} \text{idf}(t')} \quad \text{and} \quad \eta(h_t, h_{t'}) := \frac{1}{M} \left| \left\{ i \mid h_{t_i} \neq h_{t'_i} \right\} \right| \tag{2}$$

- $t' \in d'$ is the nearest neighbour token of $t \in d$
- h_{t_i} is the i-th bit of hash code h_t with M bits
- Heuristic normalisation with **n-idf**
- This score is not symmetric:

$$r_{\text{rhwmd}}(d, d') := s(d, d') + s(d', d)$$

RHWMD: Example

- Document 1:
  Auf der Mauer auf der Lauer sitzt ne kleine Wanze.
- Document 2:
  Ein Marienkäfer schläft auf dem Zaun.
- Score: **0.711667**

token	nn	sim	tf	idf	n-idf	weight
wanze	marienkäfer	0.742	0.100	9.335	0.269	0.200
lauer	schläft	0.668	0.100	7.134	0.206	0.137
ne	auf	0.664	0.100	5.561	0.160	0.106
mauer	zaun	0.758	0.100	4.674	0.135	0.102
sitzt	schläft	0.727	0.100	4.361	0.126	0.091
kleine	auf	0.688	0.100	3.290	0.095	0.065
auf	auf	1.000	0.200	0.305	0.009	0.009
der	dem	0.785	0.200	0.033	0.001	0.001

The Ungol Index

RHWMD: Starting Point and Requirements

What we have:

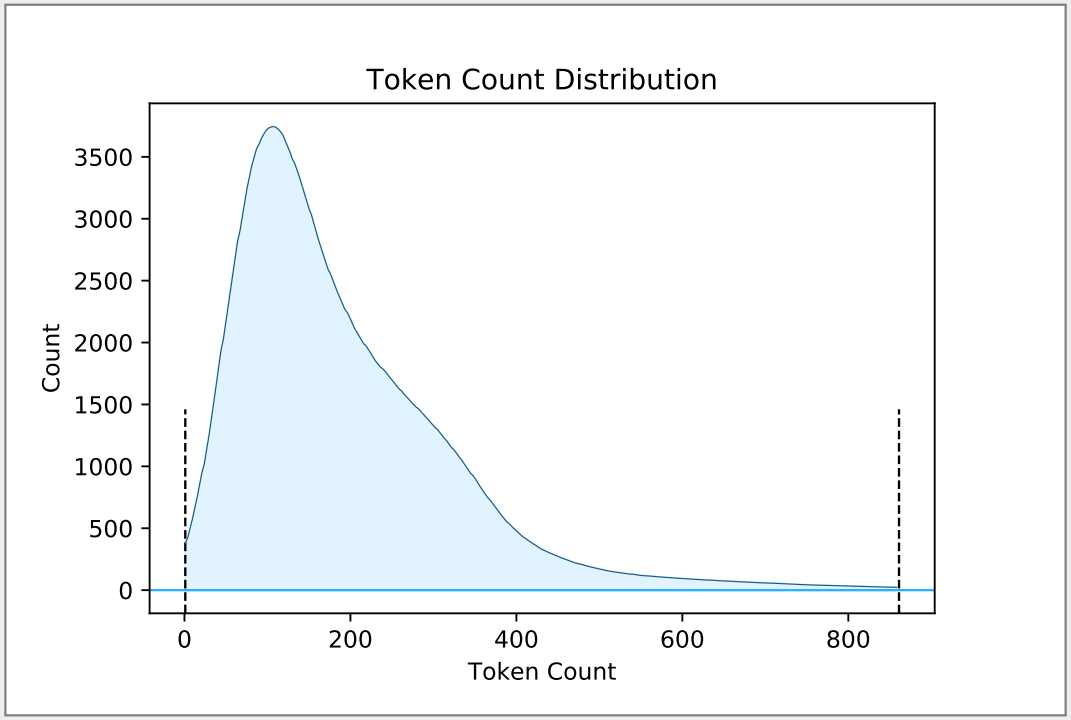
- Binary codes for words
- RHWMD for measuring similarity between documents

What we do with it:

- Evaluation of the RHWMD for Information Retrieval (IR)
- Calculate the RHWMD for query/candidate-documents
- Measure the execution speed of the implementation
- Compare the ranking quality to TF-IDF, BM25 and WMD

The Evaluation: Overview

- Around 300k news articles (Spiegel/SDA/Fr. Rundschau)
- CLEF 2003 Ad-Hoc Monolingual: IR Task
- 56 Topics: 1-226 positives, queries are very short



The Evaluation: Example and Preprocessing

- An example query:
  - *Finde Berichte über den Kruzifixstreit in bayerischen Schulen.*

> *München, 22. Sept. (sda/Reuter) Erstmals seit dem Kruzifix-Urteil des deutschen Bundesverfassungsgerichts sind in zwei bayerischen Schulen Kreuze abgehängt worden. Dies erklärte am Freitag in München der Sprecher des bayerischen Kultusministeriums. (...)*

- Preprocessing includes:
  - tokenizing
  - lower casing
  - compound splitting
  - sanitizing

180921_ungol.db.pickle	
Documents	294659
Vocabulary	400000
Code Size	256
Unique Tokens	258391
Avg. Doc. Length	197
Skipped	8
Memory Footprint	$\sim$ 3 GB

The Algorithm I

- How to calculate the RHMWD fast with Python?
- Problem: $|d| \cdot |d'|$ many token combinations

Approach:

- Create lookup table with each $x_i =$ number of ones for i_2

$$\Xi := (x_0, \dots x_{255}) = (0, 1, 1, 2, 1, \dots)$$

The Algorithm II

- Given two documents (d, d'):
  - Construct two matrices $H, H' \in \{0, \ldots, 255\}^{|d| \times |d'| \times B}$

$$H := \begin{bmatrix} h_1 & \cdots & h_1 \\ \vdots & \ddots & \vdots \\ h_{|d|} & \cdots & h_{|d|} \end{bmatrix} \qquad H' := \begin{bmatrix} h'_1 & \cdots & h'_{|d'|} \\ \vdots & \ddots & \vdots \\ h'_1 & \cdots & h'_{|d'|} \end{bmatrix}$$

  - Use numpy's vectorized XOR implementation $Z := H \oplus^{v} H'$
  - Select from lookup table and collapse last dimension:

$$T_{ij} = \frac{1}{M} \sum_{k=1}^{B} \Xi_{Z_{ijk}}$$

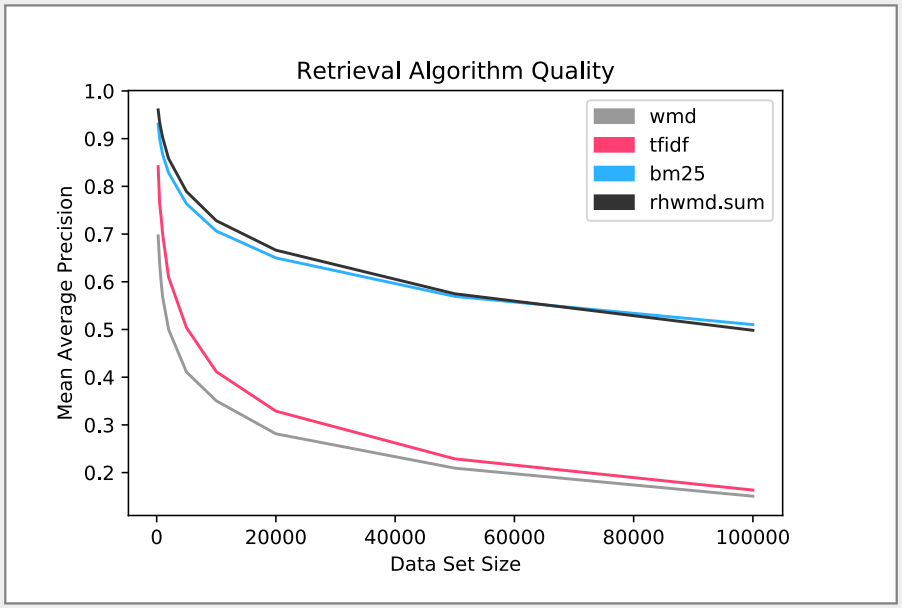
  - Create two vectors with nearest neighbours along each axis:

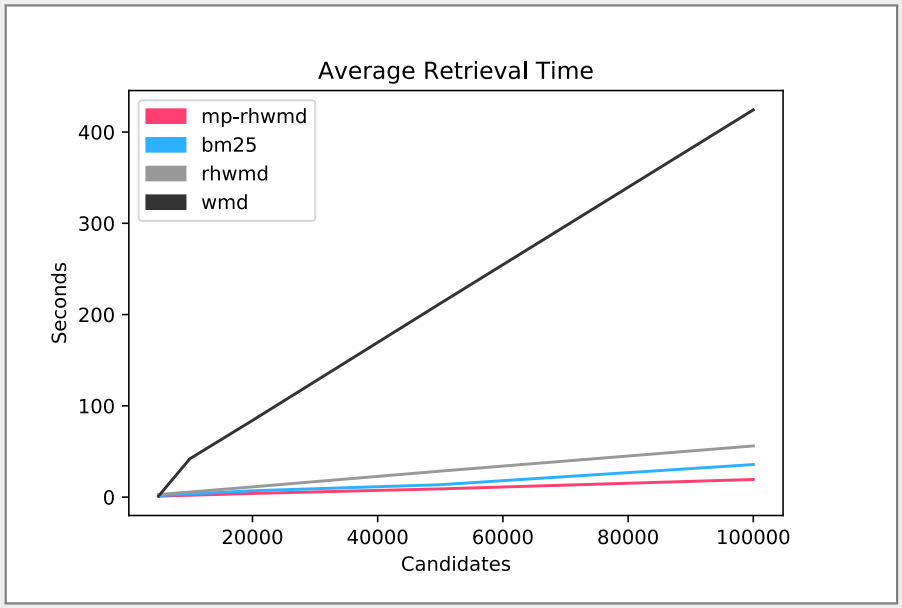
$$\mathbf{v}_d := (v_1, \ldots, v_{|d|}) \qquad \text{with} \quad v_i := \min_j T_{ij}$$

$$\mathbf{v}_{d'} := (v'_1, \ldots, v'_{|d'|}) \qquad \text{with} \quad v'_i := \min_i T_{ij}$$

Experiment I: Baseline Experiment

- Use different corpus subsets (1k, 5k, 10k, ... documents)
- Compare **rhwmd**, **bm25**, **tf-idf** and **wmd**
- Measure execution speed in seconds for a **linear search**
- Measure performance with **Mean Average Precision** μAP



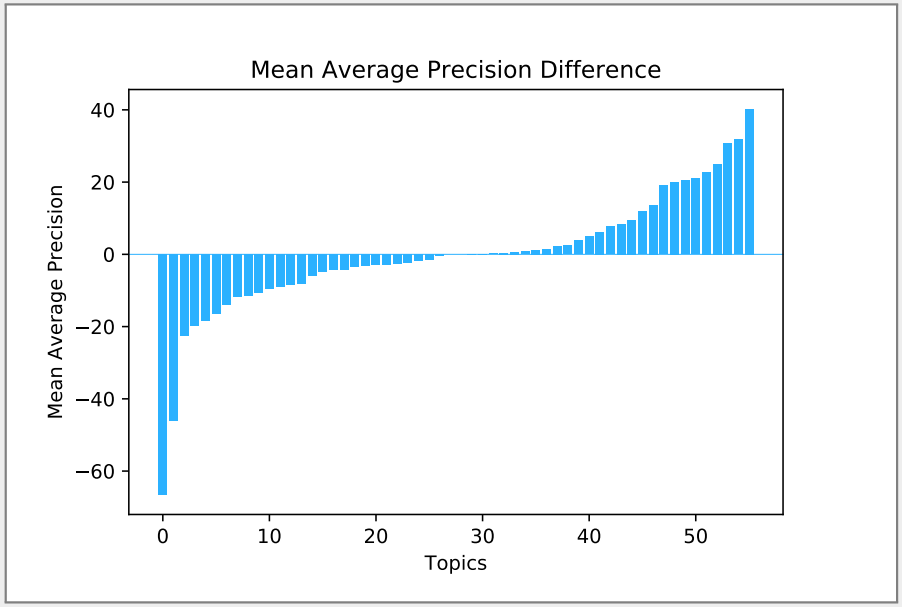


Experiment II: Re-Ranking

- Use an inverted index for candidate pre-selection
- Elasticsearch is used for pre-selection
- Apply the RWMD to the candidate set for re-ranking
- Evaluate whether re-ranking improves the μAP

Algorithm	μAP
rhwmd.sum	38.30
bm25 (Elasticsearch)	38.40
bm25 (Ungol)	**38.65**

- BM25 and RHWMD rank differently $\rightarrow$ room for improvement



RHWMD: Reasonable False Positive

token	nn	sim	idf	weight
zöliakie	erkrankungen	0.738	11.900	0.187
erkrankten	erkrankten	1.000	6.363	0.135
diskutieren	diskutieren	1.000	4.760	0.101
finde	habe	0.758	5.330	0.086
ernährungs	gesundheit	0.754	5.999	0.096
bzw	und	0.770	5.027	0.082
berichte	berichtete	0.809	4.304	0.074
probleme	probleme	1.000	3.020	0.064
von	von	1.000	0.221	0.005
die	die	1.000	0.050	0.001

- Approach works correctly but ranks worse

RHWMD: Nice True Positive

token	nn	sim	idf	weight
irisches	irland	0.742	9.226	0.022
dublin	dublin	1.000	6.225	0.020
freundschaftsspiel	fußball	0.738	7.884	0.019
ausschreitungen	ausschreitungen	1.000	5.782	0.019
krawallen	ausschreitungen	0.781	7.295	0.018
row	finde	0.688	8.211	0.018
randalierer	ausschreitungen	0.777	7.247	0.018
rowdies	ausschreitungen	0.660	8.450	0.018
landfriedensbruchs	ausschreitungen	0.699	7.757	0.018
Birmingham	england	0.738	6.924	0.017

- Ten highest contributors for a document ranked worse with BM25

Conclusion

Summary

- Producing binary hash codes using the compressor model works nicely
- Fast similarity computation: **much** faster than the WMD
- Competitive ranking algorithm even in this state

Ad-Hoc Improvements

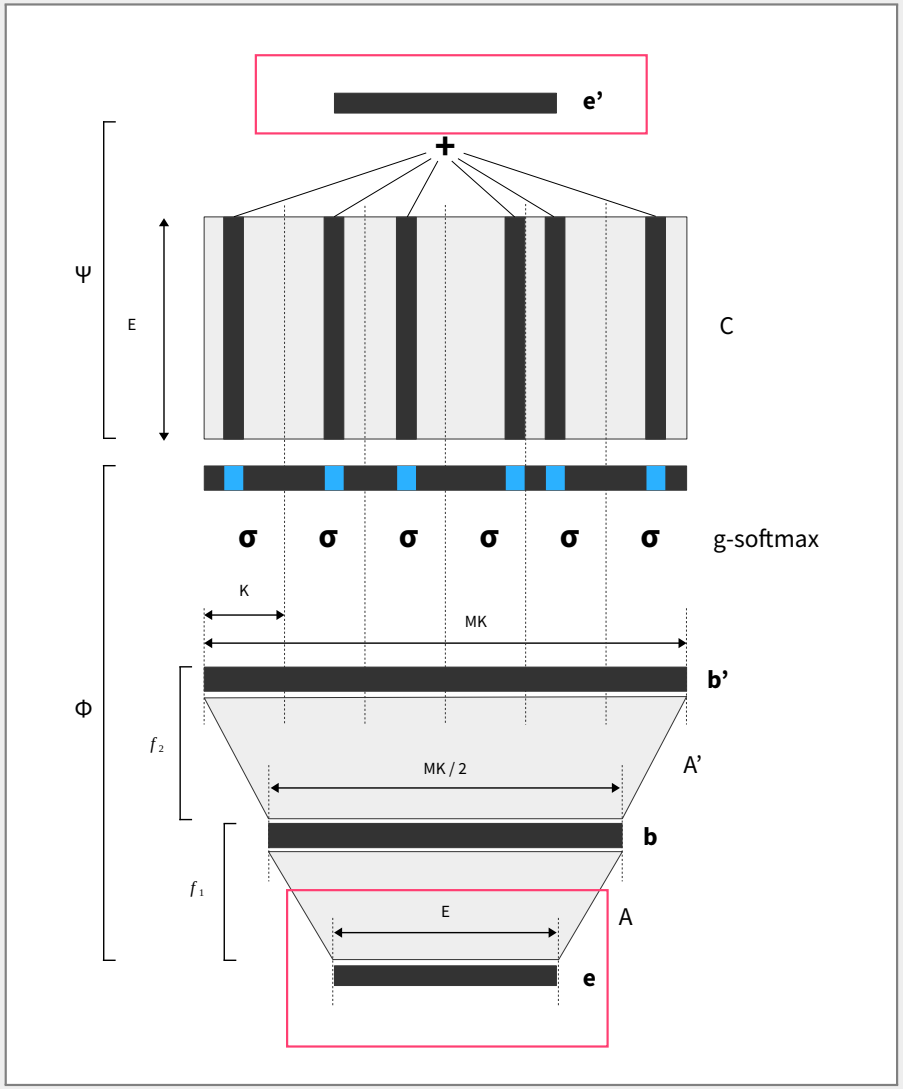
- Faster native implementation for query $\rightarrow$ batch of candidate documents
- Use the rank of the nearest neighbour
- IDF combination (use IDF of NN)

Thank you! Questions?

The Neural Embedding Compressor: Loss

- Training objective: reduce reconstruction loss
- Loss: Mean squared error of the Euclidean distance
- Input: embedding vector $\mathbf{e}_t$ of a token t
- Output: embedding vector $\mathbf{e}'_t$ given $\mathbf{e}_t$

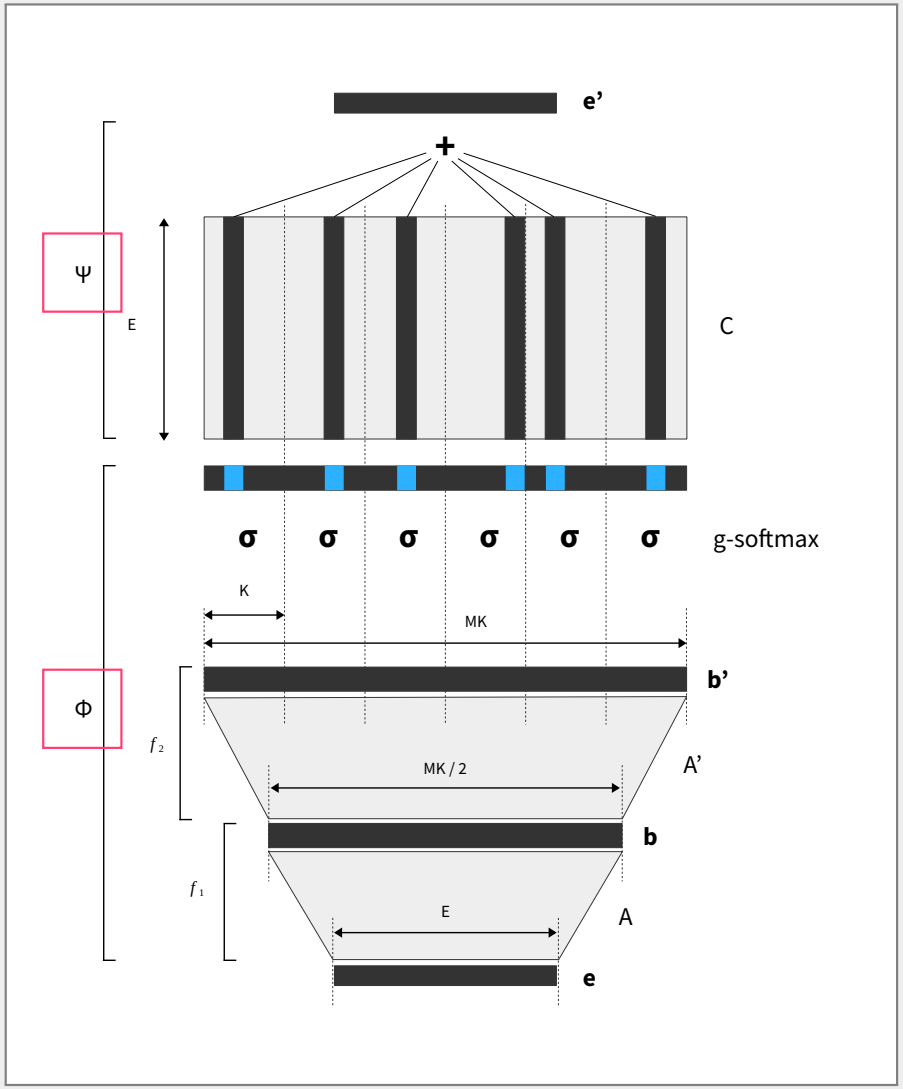
$$L(\mathbf{e}_t, \mathbf{e}'_t) := \frac{1}{2}||\mathbf{e}_t - \mathbf{e}'_t||_2^2$$



The Neural Embedding Compressor: Encoder/Decoder

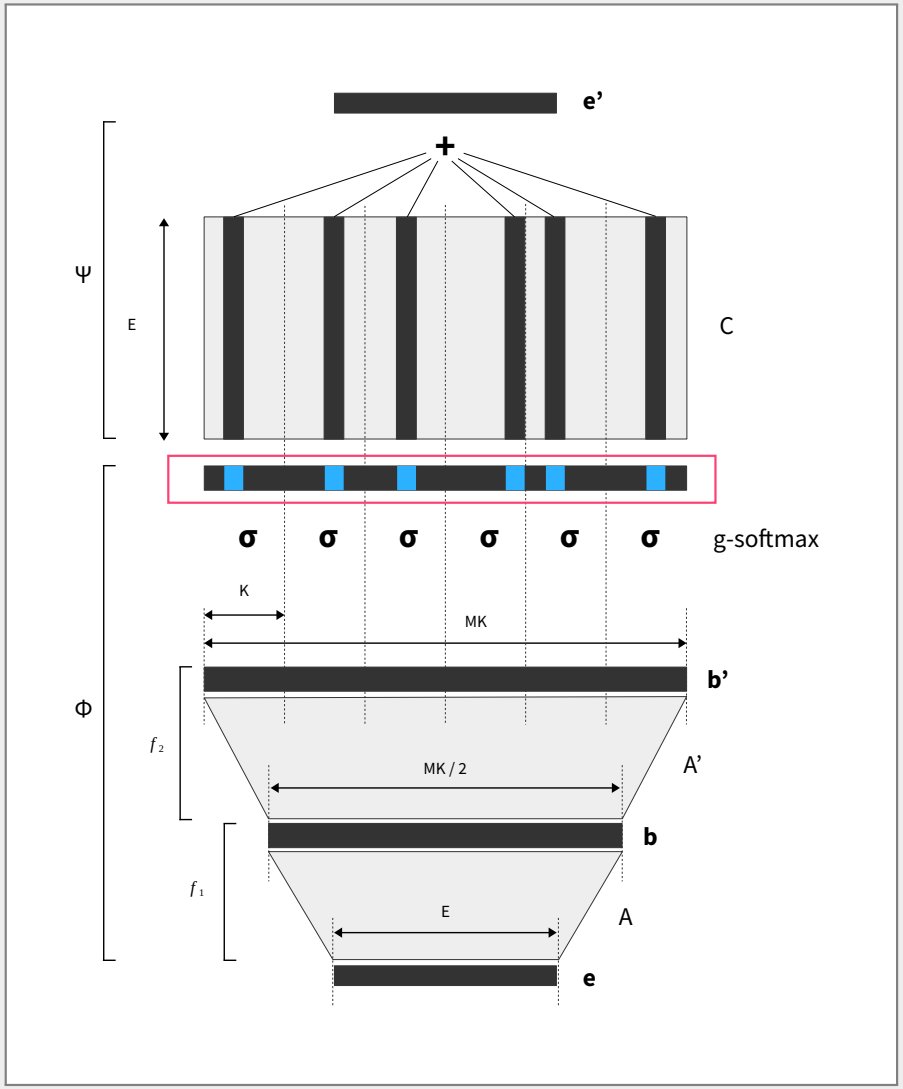
- M: Code components
- K: Code domain
- E: Embedding dims.

- **Encoder**:
  $\phi : \mathbb{R}^E \mapsto \{0,1\}^{MK}$
- **Decoder**:
  $\psi : \{0,1\}^{MK} \mapsto \mathbb{R}^E$
- **Model**:
  $(\psi_\theta \circ \phi_\theta)(\mathbf{e}_t) = \mathbf{e}'_t$



- Encoder output are one-hot encodings
- Here: $M = 6, K = 5$
- Code: $(1, 3, 2, 4, 1, 3)$

$$X = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{ccccc} 0 & 1 & 2 & 3 & 4 \end{array} \\ \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \end{array}$$



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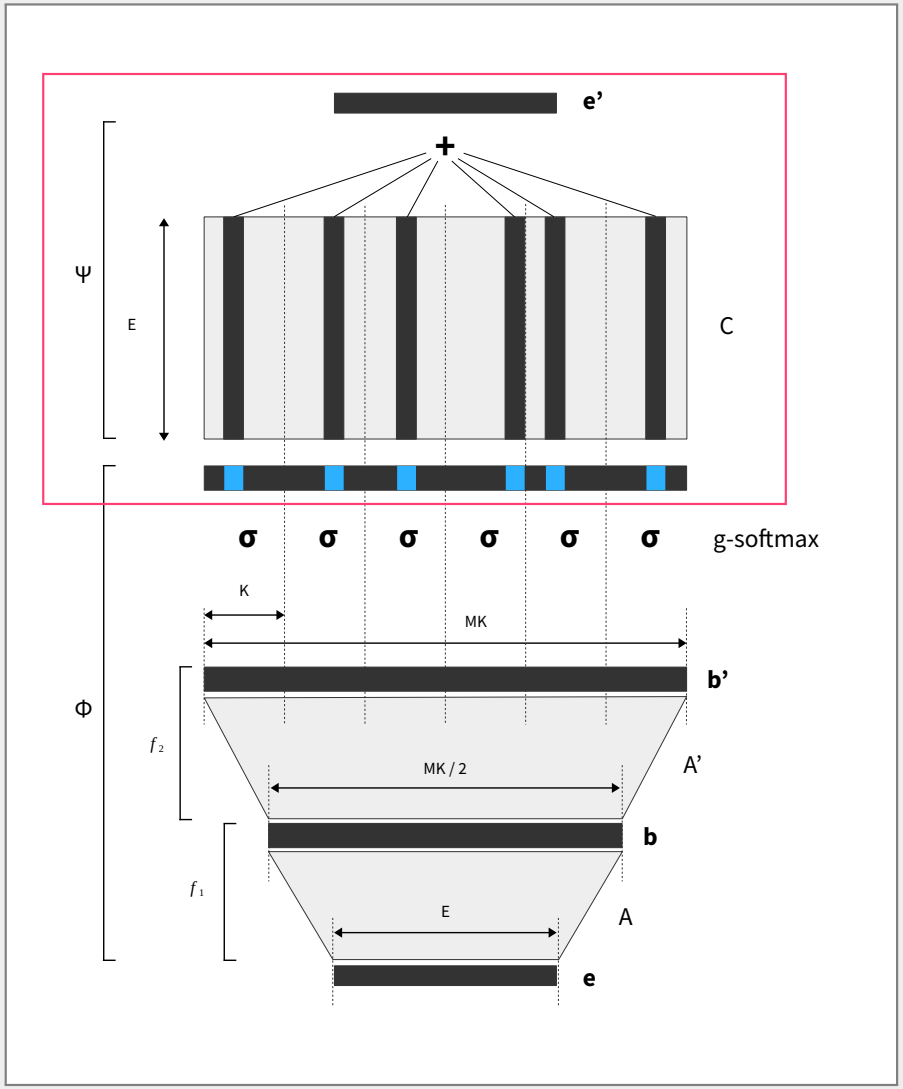
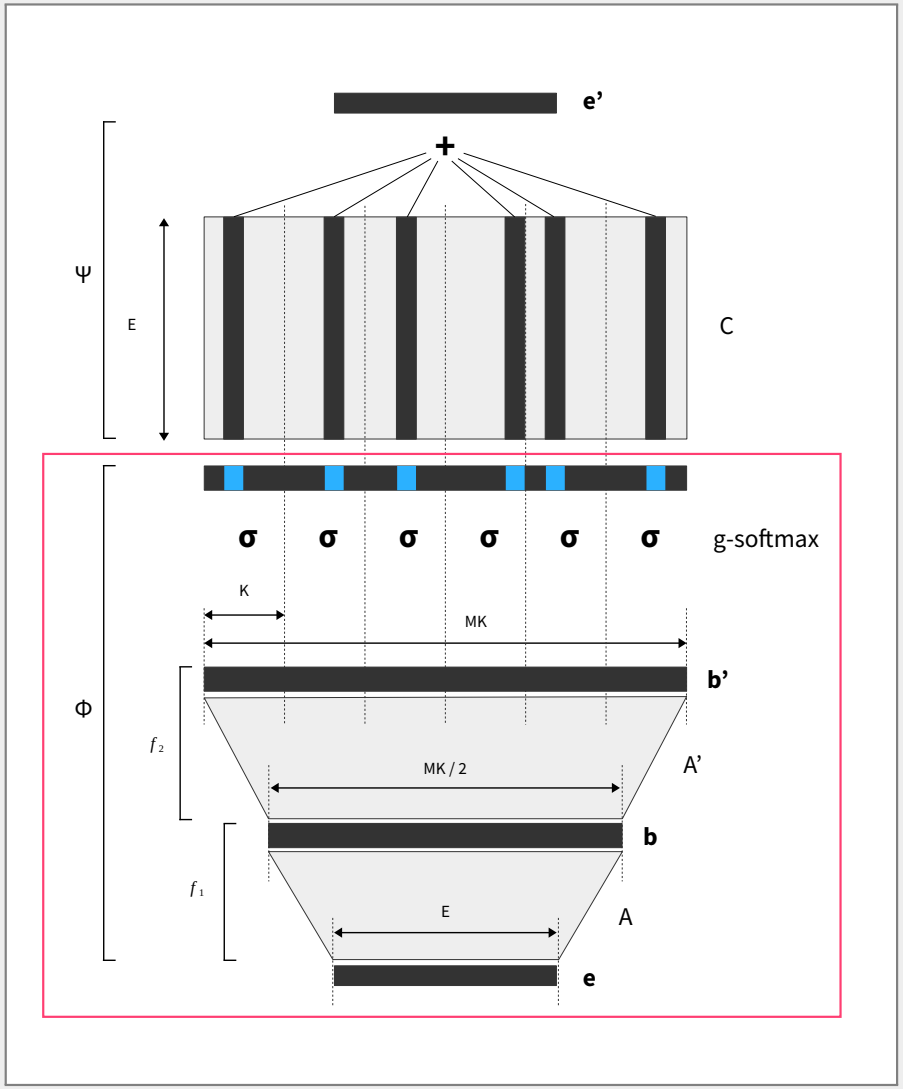


The Neural Embedding Compressor: Encoder (MLP)

$$\phi_\theta(\mathbf{e}_t) := \sigma(f_2 \circ f_1)(\mathbf{e}_t)$$
$$f_1(\mathbf{x}) := \tanh(A \cdot \mathbf{x} + \mathbf{b})$$
$$f_2(\mathbf{x}) := \text{softplus}(A' \cdot \mathbf{x} + \mathbf{b}')$$

- Encoder ϕ_θ: Two fully connected layers
- Select the $\arg\max$ per codebook
- Problem: gradient!



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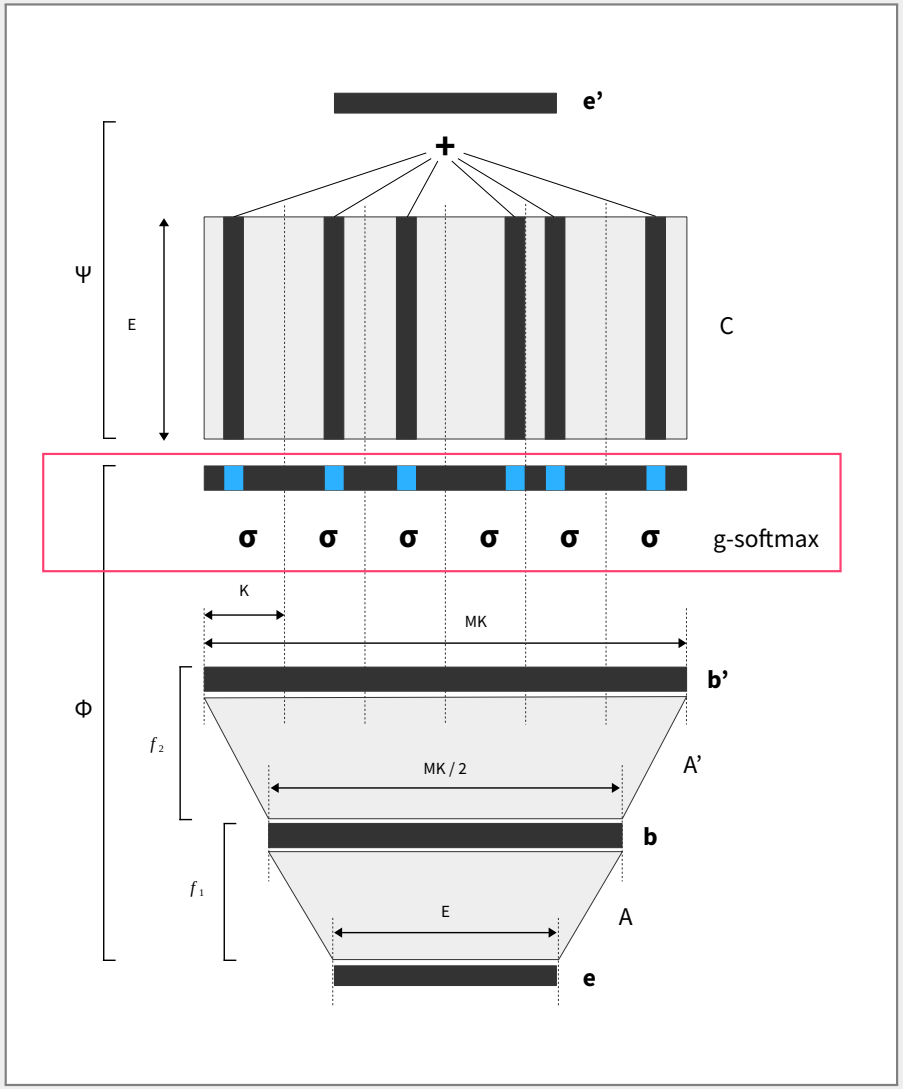

The Index

- No redundant information
- Allow for multiprocessing

Index used for evaluation:

180921_ungol.db.pickle	
Documents	294659
Vocabulary	400000
Code Size	256
Unique Tokens	258391
Avg. Doc. Length	197
Skipped	8
Memory Footprint	$\sim$ 3 GB