

Comparing Natural Language Embeddings for Libc Functions as Rich Labels

Bachelor's Thesis Defense

Ruben Triwari

Ludwig Maximilian University Munich

February 17, 2025

Outline

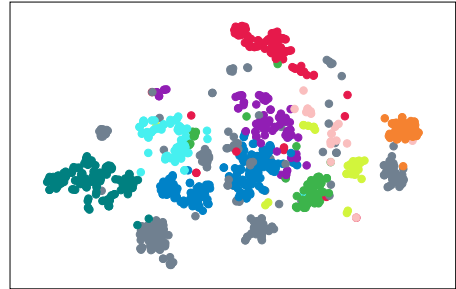
Motivation & Research Objective

Methodology

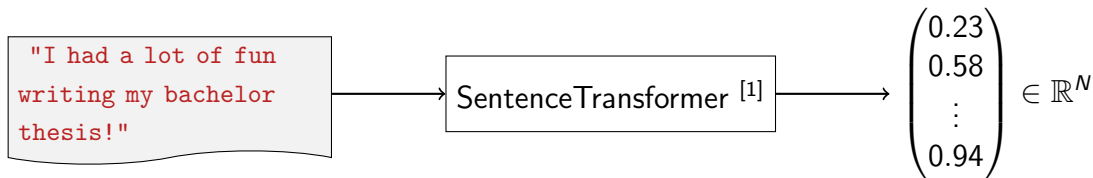
Results

Limitations

Conclusion & Future Work



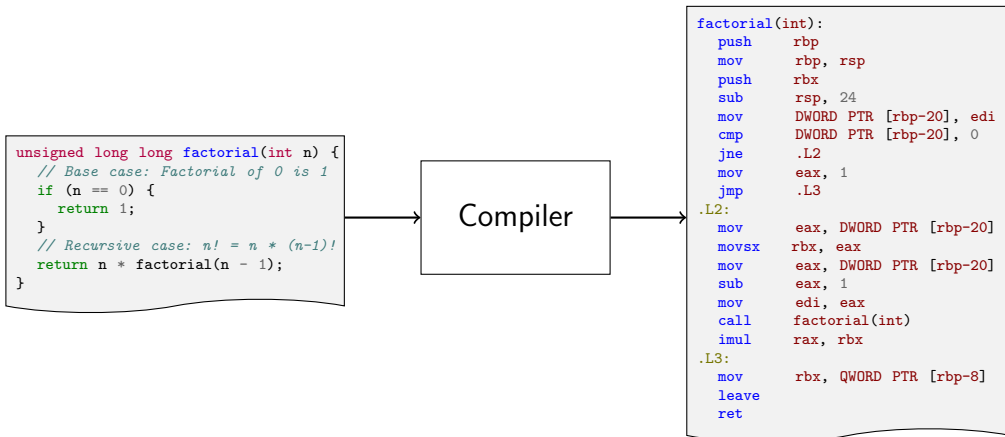
Motivation



- ↪ Encoding natural language had an important role in recent NLP advancements
- ↪ Information described as a vector can be used in many downstream tasks
- ↪ That serves as an motivation for encoding binary code as vector
- ↪ That motivates using NLP tools to encode binary code

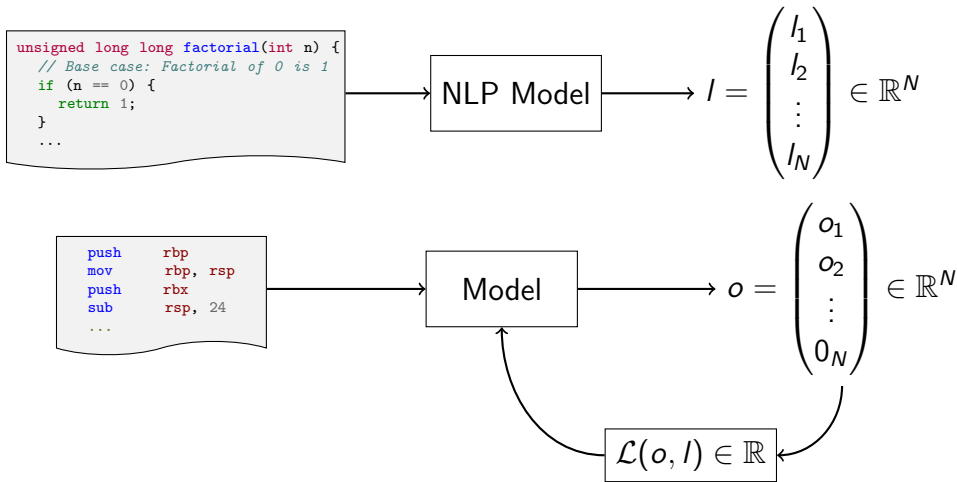
[1]Reimers and Gurevych: Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks, EMNLP'19

Motivation



⇒ Compiler removes all information that is in natural language

Motivation



Research Objectives

- ▶ Compare different approaches encoding additional information in the source code into machine readable format
 1. Embed function names with SentenceTransformer
 2. Embed function comments with SentenceTransformer
 3. Embed Code Llama ^[2] code summaries with SentenceTransformer

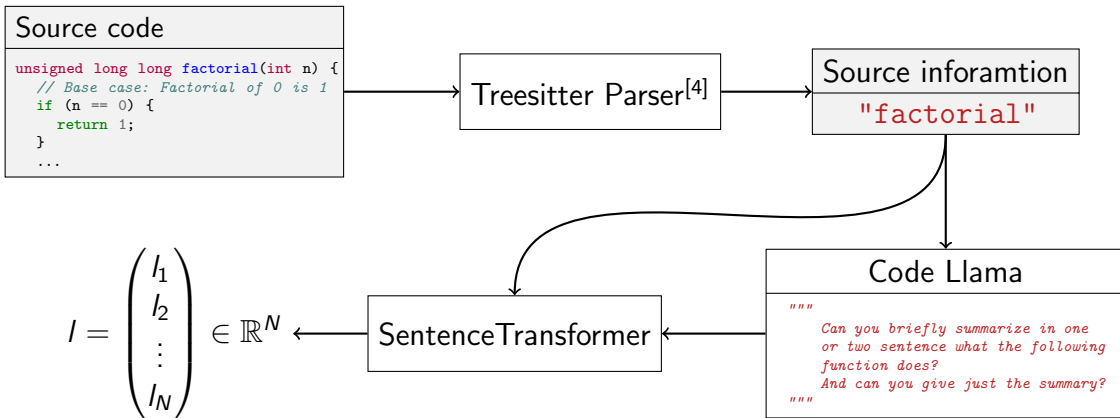
↪ Intuition is that Code Llama explanation will yield "good" embeddings
- ▶ Compare NLP approach to the existing Code2Vec ^[3] Model
- ▶ Propose a new way comparing embedding spaces.

↪ To prove intuition

[2]Rozière et al.: Code Llama: Open Foundation Models for Code, 24

[3]Alon et al.: code2vec: Learning Distributed Representations of Code, POPL'19

Architecture



[4] Official website: <https://tree-sitter.github.io/tree-sitter/>

Evaluation with t-SNE

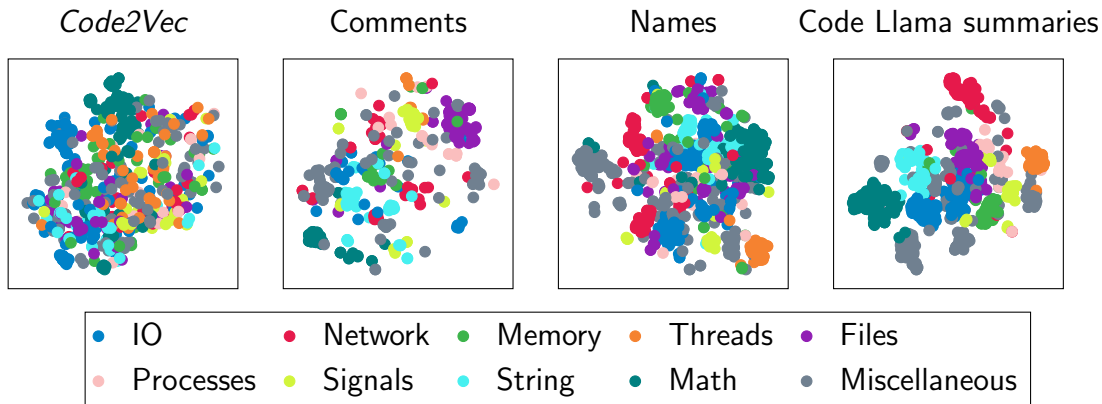


Figure: Depicted are the t -SNE output vectors with perplexity $P = 30$.

Expert Survey

"execl"

1. j1l
2. exp10l
3. exp2l
4. expm1l

☐ Yes

☐ No

"fmaximum_numl"

1. fminimum_magl
2. fminimuml
3. fminimum_mag_numl
4. fminimum_numl

☐ Yes

☐ No

Figure: Positive example

Figure: Negative example

Expert survey results				
Method	Code Llama summaries	Function names	Function comments	Code2Vec
Score	0.596	0.532	0.433	0.321

Embedding space comparison

$$\text{compare}(u, v)_k = \frac{1}{G_k} \sum_{i=1}^k \frac{\text{score}_k(u_i, i, v)}{\log_2(i+1)} \in [0, 1]$$

where

$u, v \in \mathbb{N}^k$: Neighbor ranking of the same vector in different spaces,

$$\text{score}_k(l, i, v) = \begin{cases} 1 & , \exists j \in \mathbb{N} : l = v_j \wedge i = j \\ \frac{1}{2} & , \exists j \in \mathbb{N} : l = v_j \wedge i \neq j \\ 0 & , \text{otherwise} \end{cases} \quad , \quad G_k := \sum_{i=1}^k \frac{1}{\log_2(i+1)}.$$

Embedding space comparison

$$\text{CMP}(A, B, k) = \frac{1}{N} \sum_{i=1}^N \text{compare}_k(\text{NN}_k(A_i, A), \text{NN}_k(B_i, B))$$

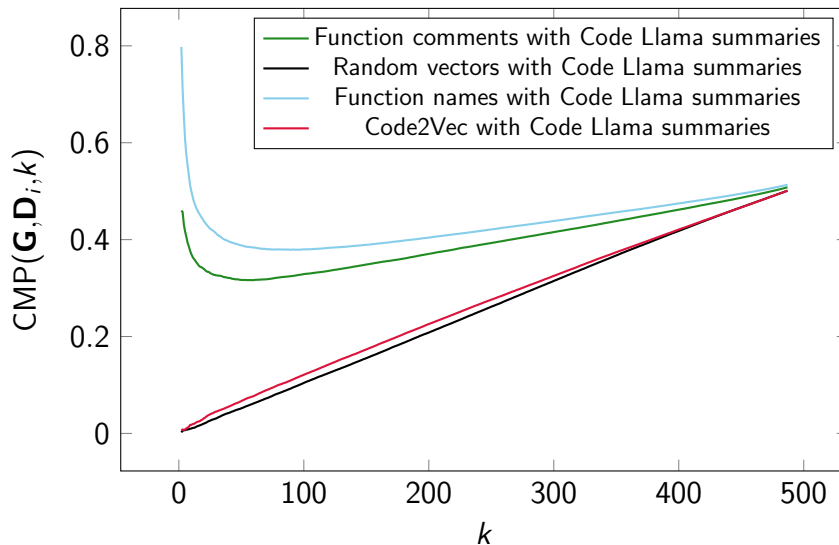
where

$A, B \in \mathbb{R}^{N \times l}$: Embedding space with N vectors of length l

$\text{NN}_k(A_i, A)$: k nearest neighbors from vector with index i in A

$k \in \mathbb{N}$: Amount of vectors we include in one neighborhood relation

Embedding space comparison



Function names

Abbreviations can potentially confuse the SentenceTransformer:

Example function `lchmod`:

`l` \leftrightarrow link, `ch` \leftrightarrow change, `mod` \leftrightarrow file mode.

Nearest neighbors in function space:

`lchmod` \leftrightarrow (`lcong48`, `fchmodat`, `coshl`, `cacoshl`)

\rightsquigarrow In categories:

`files` \leftrightarrow (`math`, `files`, `math`, `math`)

function names

Example function `lchmod`:

`l` ↔ link, `ch` ↔ change, `mod` ↔ file mode.

Nearest neighbors in code llama summary space:

`lchmod`

↔ (`fchmodat`, `fchownat`, `euidaccess`, `__file_change_detection_for_stat`)

↪ In categories:

`files` ↔ (`files`, `files`, `files`, `files`)

function comments

Comments are not always directly about the code:

Example functions `rand` and `rand_r`:

`rand` ↔ Return a random integer between 0 and `RAND_MAX`.

`rand_r` ↔ This algorithm is mentioned in the ISO C standard, here extended for 32 bits.

↪ Cosine distance in comment and llama summary space

$$d_{\text{comment}}(\text{rand}, \text{rand_r}) = 0.8544 \quad d_{\text{llama}}(\text{rand}, \text{rand_r}) = 0.2216.$$

Future Work

► Code Llama

1. Is it necessary to use a large Model with 70B parameters?
2. Can Large Language Models produce deterministic output for this application?
3. Is there a better Prompt?

► Comments

1. Use inline Comments

Future Work

$$\text{CMP}(A, B, k) = \frac{1}{N} \sum_{i=1}^N \text{compare}_k(\text{NN}_k(A_i, A), \text{NN}_k(B_i, B))$$

$$\text{compare}(u, v)_k = \frac{1}{G_k} \sum_{i=1}^k \frac{\text{score}_k(u_i, i, v)}{\log_2(i+1)} \in [0, 1]$$

► $\text{CMP}(A, B, k) \in [0, 1]$ function

1. Is there an optimal value for k ?
2. Is there a better way to generate a neighborhood?
(instead of K-Nearest-Neighbor)
3. Is there a better way to aggregate the compare functions?

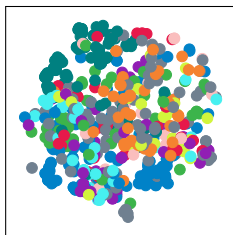
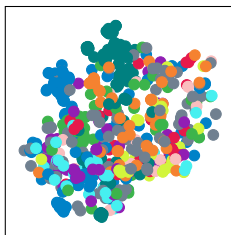
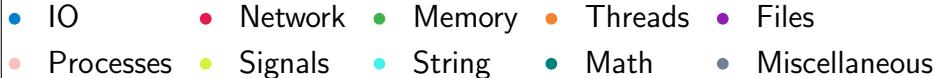
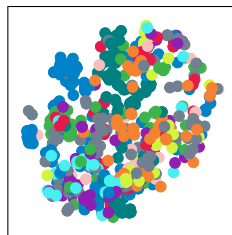
Conclusion

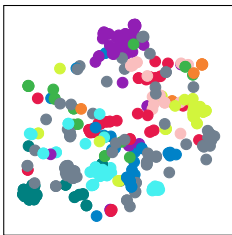
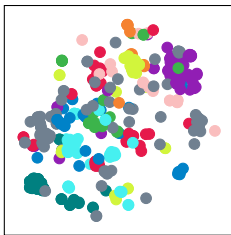
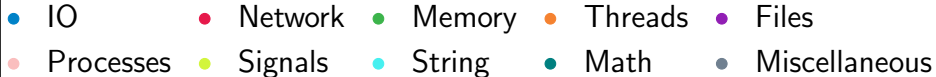
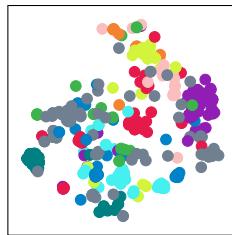
- ▶ Best strategies ranked:
 1. Code Llama summaries
 2. Function names
 3. Function comments
 4. Code2Vec
- ▶ Code Llama summary vectors for C source code downstream tasks
- ▶ Code Llama summary vectors can now be used to train a Model
- ▶ $\text{CMP}(A, B, k)$ function can be used to compare two embedding spaces from the same features Space
- ▶ Evaluation methods can be used to compare different Large Language Models to each other

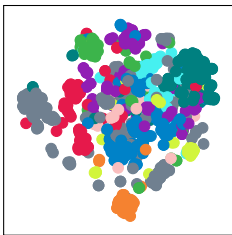
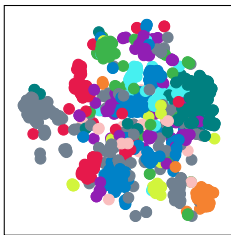
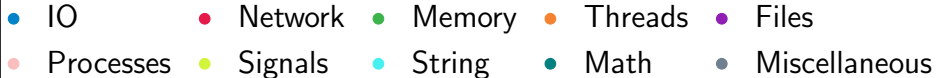
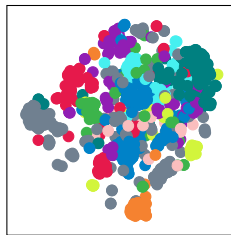
Discussion

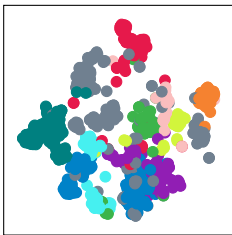
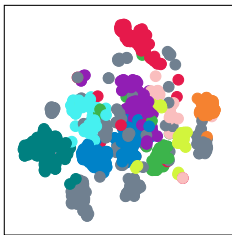
Code2Vec

- ▶ Also dependent on the function names in the data set
- ▶ Bad results could be Explained by:
 1. Small data set
 2. C instead of Java \rightsquigarrow potential engineering mistakes
 3. Quality of names in the data set

Code2Vec $P = 20$ Code2Vec $P = 30$ Code2Vec $P = 40$ 

Comments $P = 20$ Comments $P = 30$ Comments $P = 40$ 

Names $P = 20$ Names $P = 30$ Names $P = 40$ 

Code Llama $P = 20$ Code Llama $P = 30$ Code Llama $P = 40$ 