Similarity between French words based on their phonetic transcription using Needleman-Wunsch & graph clustering

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Abstract

This project is part of the GP-GPU Computing course at UGA by Christophe Picard. Lorem ipsum dolor sit amet, consetetur sadipscing elitr. Lorem ipsum dolor sit amet, consetetur sadipscing elitr, sed diam nonumy eirmod tempor invidunt ut labore et dolore magna aliquyam erat, sed diam voluptua. At vero eos et accusam et justo duo dolores et ea rebum. Stet clita kasd gubergren, no sea takimata sanctus est Lorem ipsum dolor sit amet. Lorem ipsum dolor sit amet, consetetur sadipscing elitr, sed diam nonumy eirmod tempor invidunt ut labore et dolore magna aliquyam erat, sed diam voluptua. At vero eos et accusam et justo duo dolores et ea rebum. Stet clita kasd gubergren, no sea takimata sanctus est Lorem ipsum dolor sit amet. Lorem ipsum dolor sit amet, consetetur sadipscing elitr, sed diam nonumy eirmod tempor invidunt ut labore et dolore magna aliquyam erat, sed diam voluptua. At vero eos et accusam et justo duo dolores et ea rebum. Stet clita kasd gubergren, no sea takimata sanctus est Lorem ipsum dolor sit amet.

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1 Introduction

The International Phonetic Alphabet (IPA) uses special symbols[1] to represent the sound of a spoken language. This is useful for language learners since the pronunciation of a word can be significantly different from its written form. For example, the French word *renseignement* (information) is pronounced /ʁɑ̃.sɛɲ.mɑ̃/. Based on this alphabet, one might wonder if we can construct a metric that quantifies the **distance between two words based on their phonetic transcription**. This would allow to construct a graph where nodes are words and undirected edges are weighted by the distance between the words. This graph could then be used to find neighbors of a word based on their phonetic similarity. This opens up the possibility to apply clustering algorithms and other methods stemming from graph

theory in order to analyze the phonetic structure of a language.

Calculating the distance between each pair of words corresponds to a fully-connected graph. Our dataset consist of around 600,000 French words and their IPA transcription, alongside their frequency in the French language. Excluding self-loops, we find a vast number of edges (14):

$$\#\text{nodes} = 600,000 \tag{1}$$

$$\#\text{edges} = \frac{600,000 \cdot 599,999}{2} \approx 1.8 \times 10^{11} \tag{2}$$

This high number and the independent nature of the distance calculation for each pair of words makes the problem well-suited for parallelization. In section 2, we present the Needleman-Wunsch algorithm used to calculate the distance between two words. In section 4, we discuss how to parallelize this algorithm on a CPU using the *Rayon* library in Rust and on a consumer Nvidia GPU using the CUDA framework with the *cudarc* Rust library. Finally, we provide visualizations of the obtained graphs in 5 and conclude in **??**.

In the following, by *word* we always refer to its phonetic transcription. That is, homophones like the French words *vert* /vɛʁ/ (green) and *verre* /vɛʁ/ (glass) are considered the same word.

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[1]See for example the French list here.

2 Needleman-Wunsch

The Needleman-Wunsch algorithm (developed by Saul B. Needleman and Christian D. Wunsch in 1970) calculates the global alignment of two strings and was originally used in bio-informatics to compare DNA sequences. For our purposes, the alphabet will instead consist of the phonetic IPA symbols. Out of all possible alignments of two words (including gaps), the Needleman-Wunsch algorithm finds the one with the smallest distance, i.e. the alignment with the highest "score". The algorithm is based on dynamic programming and has a time complexity of $\mathcal{O}(\text{len}(A) \cdot \text{len}(B))$, where A and B are the two words to be compared.

Algorithm 2.1 features the pseudo-code of the score computation[2]. In Figure 1, we see the resulting score matrix that the algorithm constructed for the French words *puissance* and *nuance*. Follow the indicated path (red tiles) from the bottom right to the top left to find the (reversed) optimal alignment (see Table 1);

puissance	p	ɥ	i	s	ɑ̃	s
nuance	n	ɥ	–	–	ɑ̃	s

Table 1: The optimal alignment yields a score of -2. See the path in Figure 1.

We first discuss the meaning of the different steps (arrows) in the score matrix (Figure 1) to then explain how to construct this matrix.

- In a **diagonal step**, both symbols that indicate the current position in the two words change. Such a step corresponds to either a match or a mismatch between the two symbols. In the example, the /s/ symbols in the bottom-right corner match, which is why the step beforehand is a *diagonal* step from the field -3 to -2. The score increases by 1 since we defined the match score to be $+1$ (and a mismatch score as -1).

- In a **vertical** or **horizontal step**, only one of the two symbols changes. We interpret this as a gap in the alignment, i.e. one symbol aligns to a gap in the other word. In the example, this is the case two times when we move from the red field 0 down to -2 and then down to -4. The score decreases by 2 each time, as we defined the gap penalty as $p := -2$ in this example. The gap is indicated by "–" in the alignment (see Table 1). As we are still in the column of /ɥ/ of the word /nɥɑ̃s/, we insert two "–" symbols after the /ɥ/ in Table 1. This step is sometimes also referred to as **deletion** or **insertion**.

To find the score matrix for given input words A and B, we follow Algorithm 2.1. First, the score matrix of dimension $(\text{len}(A) + 1) \times (\text{len}(B) + 1)$ is initialized[3]. Then, in lines 3 to 6, the blue-bordered tiles of Figure 1 are filled with the gap penalty p times the index. This is necessary since the only possible step for these tiles is either a vertical or horizontal step (blue arrows), thus leading to a gap in the alignment as discussed beforehand that we punish with the gap penalty p.

Figure 1: Needleman-Wunsch score matrix for the words $A := $ *puissance* /pɥisɑ̃s/ (power, strength) and $B := $ *nuance* /nɥɑ̃s/ (nuance, shade). The arrows indicate which steps locally maximize the score. The red tiles trace the path of the optimal alignment. Match Score: 1, Mismatch Score: -1, Gap Penalty: $p = -2$.
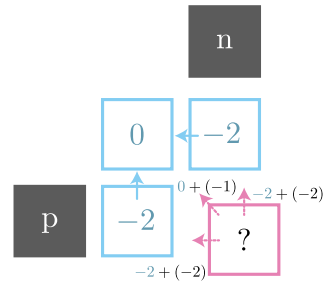

Figure 2: Calculations for one element of the Needleman-Wunsch score matrix.

In the nested loops (lines 7 and 8), we then iterate over the remaining fields of the score matrix (index now starts at 1, not 0) which corresponds to traversing the matrix row-wise. To each field, we assign the maximum of three values:

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[2]The respective Wikipedia page also provides a good introduction. Furthermore, the score matrix is interactively explained in the Global Alignment App.

[3]This does not necessarily involve setting all fields to 0 as will become clear.

Algorithm 2.1: Needleman-Wunsch

Input: $A = \{ A_0, \ldots, A_{\texttt{len}(A)-1} \}$, $B = \{ B_0, \ldots, B_{\texttt{len}(B)-1} \}$,
  similarity: similarityScoreFunc, p: GapPenalty

Output: score

1 **Function** `calculateScore()`:
2   Init scoreMatrix with dimensions
     $(\texttt{len}(A) + 1) \times (\texttt{len}(B) + 1)$
3   **for** $i \in \{0, \ldots, \texttt{len}(A)\}$ **do**
4   scoreMatrix$[i][0] \leftarrow p \cdot i$
5   **for** $j \in \{0, \ldots, \texttt{len}(B)\}$ **do**
6   scoreMatrix$[0][j] \leftarrow p \cdot j$
7   **for** $i \in \{1, \ldots, \texttt{len}(A)\}$ **do**
8   **for** $j \in \{1, \ldots, \texttt{len}(B)\}$ **do**
9   cost $\leftarrow$ similarity(A_{i-1}, B_{j-1})
10   matchScore $\leftarrow$ scoreMatrix$[i-1][j-1] + $ cost
11   deleteScore $\leftarrow$ scoreMatrix$[i-1][j] + p$
12   insertScore $\leftarrow$ scoreMatrix$[i][j-1] + p$
13   scoreMatrix$[i][j] \leftarrow$
        max(matchScore, deleteScore, insertScore)
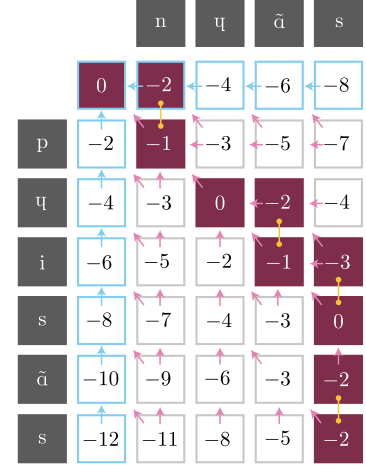14   **return** scoreMatrix$[\texttt{len}(A)][\texttt{len}(B)]$

Figure 3: Needleman-Wunsch score matrix and the path (in red) for a non-optimal alignment. Orange strokes indicate non-optimal steps. Parameters as in Figure 1.

- The **match score** is calculated by checking the step to the upper left diagonal (line 10). In the example of Figure 2, this would result in a value $0 + (-1) = -1$, where 0 is the value in the upper left diagonal field and -1 is the cost of the mismatch between /p/ and /n/. In case of a match, the new value would be $0 + 1 = 1$. In the algorithm, we also consider the case where costs for a match and a mismatch depend on the symbols themselves, which is why we introduce the function `similarity` that returns the cost of aligning two symbols. This is especially useful when comparing phonetic symbols, as the similarity between two symbols can be defined in a more sophisticated way than just 1 or -1 (e. g. replacing a vowel with a consonant might be more costly than replacing a vowel with another vowel).

- The **delete score** refers to the step from the field above (line 11). In the example, we find $(-2) + (-2) = -4$ as new value (-2 is the value in the field above and $p = -2$ is the gap penalty). This steps signifies that a symbol in word A aligns to a gap in word B (here: /i/ and /s/ of *puissance* align to gaps in *nuance*).

- The **insert score** refers to the step from the left (line 12). In the example, we find $(-2) + (-2) = -4$ as new value (-2 is the value in the field to the left and $p = -2$ is the gap penalty). This steps signifies that a symbol in word B aligns to a gap in word A (this does not occur in the example).

The new value of the current field is assigned the maximum of these values (line 13), such that we locally maximize the score: $\max(-1, -4, -4) = -1$. In Figure 1, we additionally kept track of the steps that led to the optimal alignment by means of the rose arrows (here only the diagonal step that yields the new maximal score of -1). For our purposes, we don't want to reconstruct the exact alignment that led to the optimal score, but only the score itself. Thus, we can omit the backtracking step and don't need to store the rose arrows.

By construction, **the bottom-right field of the score matrix contains the score of the optimal alignment**. This is ensured by the Principle of Optimality (Bellman), which states that an optimal solution to a problem can be constructed from optimal solutions to its subproblems. In the context of the Needleman-Wunsch algorithm, this means that the optimal alignment score for two sequences (words) can be derived by considering the optimal alignment scores of progressively smaller subsequences. Each cell in the score matrix represents the optimal score for the corresponding prefixes of the two words up to that point, since we take the maximum of the three possible steps (match, delete, insert) at each cell. This ensures that the final cell (in the bottom right) contains the optimal score for the entire sequences.

Table 2 shows an example of a non-optimal alignment of the two words, yielding a score of -15 (compared to -2 for the optimal path). Figure 3 depicts the corresponding score matrix. Note how the indicated path includes 4 non-optimal choices (orange strokes).

puissance	–	p	ɥ	–	i	–	s	ɑ̃	s
nuance	n	–	ɥ	ɑ̃	–	s	–	–	–

Table 2: This non-optimal alignment yields a score of -15. See the path in Figure 3.

$$\begin{array}{c} \begin{matrix} 0 & 1 & 2 & 3 & & n-2 & & n-1 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ \\ \\ n-2 \\ n-1 \end{matrix} \begin{pmatrix} (0,0) & (0,1) & (0,2) & (0,3) & \cdots & (0,n-2) & (0,n-1) \\ & (1,1) & (1,2) & (1,3) & \cdots & (1,n-2) & (1,n-1) \\ & & (2,2) & (2,3) & \cdots & (2,n-2) & (2,n-1) \\ & & & (3,3) & \cdots & (3,n-2) & (3,n-1) \\ & & & & \ddots & \vdots & \vdots \\ & & & & & (n-2,n-2) & (n-2,n-1) \\ & & & & & & (n-1,n-1) \end{pmatrix} \begin{matrix} S_0 \\ S_1 \\ S_2 \\ S_3 \\ \\ \\ S_{n-2} \\ S_{n-1} \end{matrix} \end{array}$$
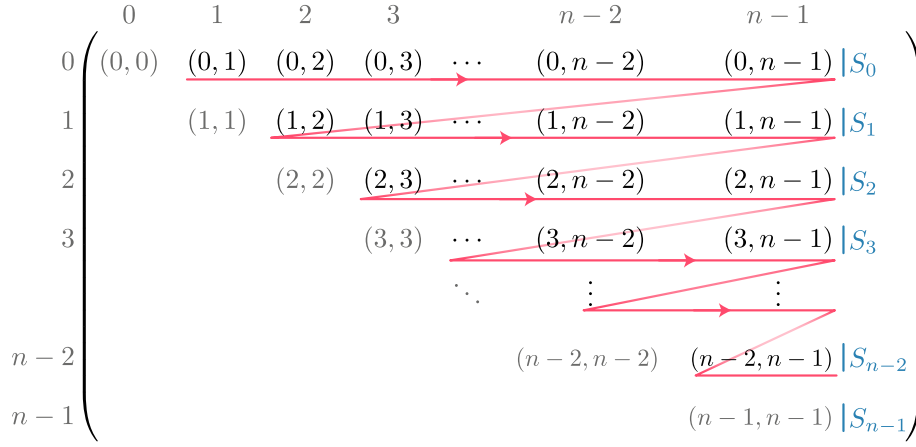
Figure 4: Row-major traversal of the adjacency matrix. n is the total number of words (i. e. nodes).

3   Data Preparation

We use the **french-words** dataset (frodonh, 2020), which contains 691,969 French words. It is compiled from several sources including (among others) the Debian package wfrench (used for spell checking), Lexique 3.83 (Boris New & Christophe Pallier), the DELA dictionary from the University of Marne-la-Vallée as well as the French-Dictionary (Hussem Ben Belgacem). The words also include Part-of-Speech (POS) tagging information, e.g. whether it is a noun, verb, adjective, preposition etc. It also comprises the usage frequency according to Lexique.org and Google Ngrams. We use the average of both sources (or just one if the other is missing).

Since the french-words dataset does not include the phonetic transcriptions, we consult the **wiki-pronunciation-dict** (Daniel Wolf, 2021) extracted from the French Wiktionnaire. We merge both datasets to obtain 611,786 words with their IPA transcription. If multiple phonetic transcription are available, we only store the first one. For easy access, we store the data in a dataclass and serialize it to a pickle file of around 60 MB.

Additionally, we extract all used phonetic symbols and assign integer IDs to them. This enables us to store the transcription as a list of integers. For our examples, we obtain Table 3. The Needleman-Wunsch algorithm will then work on these integer lists. Note that we consider /dʒ/ as one symbol, even though it is a combination of /d/ and /ʒ/. The same applies to /tʃ/. This is to account for the different pronunciation of the combined symbols compared to the individual ones.

Word	IPA	Encoding
puissance	/pɥisɑ̃s/	$[0, 18, 16, 11, 26, 11]$
nuance	/nɥɑ̃s/	$[29, 18, 26, 11]$

Table 3: Example of two words with their phonetic transcription and encoding.

4   Parallelized algorithms

In the following implementations, we always use a similarity matrix with 1 on its diagonal (symbols match) and -1 elsewhere (symbols do not match). The gap penalty is set to $p = -1$ (instead of -2 beforehand in the examples in section 2).

4.1   On the CPU

First, we implement the Needleman-Wunsch algorithm in Python using `numpy`. This implementation serves well to deepen the understanding of the algorithm and to eliminate index errors. However, it is very slow, making it unsuitable for the whole dataset. We then translate the code to an unparallelized Rust version and confirm correct output by direct comparison with the Python implementation. To make use of all CPU cores, we **parallelize the Rust implementation** employing the `rayon` library to parallelize the outer for-loop (line 7): for every word A, we consider all other words B and calculate the similarity between A and B. Since words lengths differ, the core calculation takes different times for different word pairs. Therefore, every thread appends its result to a vector that is wrapped in a `Mutex` (avoid data races by mutual exclusion) and an `Arc` (thread-safe reference pointer to deallocate data at the end).

Since comparing A to B yields the same score as the comparison of B to A, we deal with *undirected* edges and thus the adjacency matrix is symmetric. Furthermore, we are not interested in self-loops, but only in the similarity between *different* words. For these two reasons, **we only consider the upper triangular part of the adjacency matrix** in Figure 4. To store the resulting edge weights in a binary file, we traverse the matrix in row-major order (red path): $(0,1), (0,2), \dots, (0,n-1), (1,2), \dots, (1,n-1), (2,3), \dots, (n-2,n-1)$, where n is the total number of words. Note that in the parallelized Rust implementation, we have to also

return the indices of the words since the order in which the threads terminate is not deterministic (from point of view of the Rust code). After all threads are finished, the results are sorted according to row-major ordering to match the traversal order. When saving the edge weights in a file, we drop the indices and only store the similarity scores as 8-bit signed integers (range $[-128, 127]$). This is sufficient since word lengths are typically small and match/mismatch score as well as gap penalty p are likewise chosen to be small.

4.2 On the GPU

We implement the algorithm in the CUDA framework. We consult the `cudarc` Rust library, which provides Rust wrappers around the CUDA driver API as well as the NVRTC API (among others). The latter makes available a method to compile our C++ kernel to Parallel Thread Execution (PTX) code during runtime and to launch it afterwards.

Subtasks. Foster's methodology can help in designing parallel algorithms. The first step is to partition the problem at hand into small tasks. At the level of the adjacency matrix (Figure 4), such a task would be to compute the similarity score between two words A and B at the respective row and column. On a finer granularity, we can also refer to Figure 2 and consider the calculation of one element of the score matrix. However, we realize that calculations of elements in the score matrix are highly dependent on each other since the score of a cell depends on the scores of its up, left and up-left (diagonal) neighbors (example of a *stencil computation*). Additionally, words length differ, so the size of the score matrix varies. Due to the data dependencies and the varying problem size, we decide to focus on parallelizing the for-loops in the Needleman-Wunsch algorithm (lines 7 and 8 in Algorithm 2.1) making this a *pleasingly parallel* problem, namely that of parallelizing score calculation for entries in the adjacency matrix.

Grid. The maximum number of blocks in a grid (grid size) is limited to $2^{16} - 1 = 65535$ in y and z direction. Starting with CUDA compute capability 3.0, the limit in the x direction is raised to $2^{31} - 1 = 2,147,483,647$ blocks. Furthermore, we only consider the upper triangular part of the adjacency matrix, while a grid is always rectangular. These constraints motivate the choice of using a one-dimensional grid and spawning blocks only in the x direction. Likewise, we only employ one-dimensional blocks, i.e. a block is a one-dimensional array of threads. The exact number of threads we use inside a block (block dimension) is discussed later. With this configuration, we calculate (in every thread) an **index** ranging from 0 to a number great than that of entries in the upper

triangular part of the adjacency matrix:

$$\text{idx} = \text{blockDim.x} \cdot \text{blockIdx.x} \cdot \text{threadIdx.x} \quad (3)$$

Row & Column. The index `idx` needs to be mapped to the corresponding row and column in the adjacency matrix, such that a thread knows which words to compare. We take advantage of the row-major traversal path. Let S_r be the number of elements traversed up to the end of row r. In Figure 4, this variable is drawn in blue. Figure 5 provides an example to ease keeping track during following calculations.

$$
\begin{array}{cccc}
0 & 1 & 2 & 3 \\
\end{array}
$$
$$
\begin{array}{c}
0 \\ 1 \\ 2 \\ 3
\end{array}
\begin{pmatrix}
\cdot & 0 & 1 & 2 \\
 & \cdot & 3 & 4 \\
 & & \cdot & 5 \\
 & & & \cdot
\end{pmatrix}
\begin{array}{l}
S_0 = 3 \\
S_1 = 5 \\
S_2 = 6 \\
\end{array}
$$

Figure 5: Example of idx (black) for $n = 4$. S_r is the number of elements traversed up to the end of row r (blue).

$$S_0 = n - 1, \quad S_1 = S_0 + (n - 2), \quad \dots \quad (4)$$

$$S_r = \sum_{k=0}^{r}(n - k - 1) \quad (5)$$

$$= (n - 1) \cdot (r + 1) - \sum_{k=0}^{r} k \quad (6)$$

$$= (n - 1) \cdot (r + 1) - \frac{r \cdot (r + 1)}{2} \quad (7)$$

$$= -\frac{1}{2}r^2 + r\left(n - \frac{3}{2}\right) + (n - 1) \quad (8)$$

For a given row r, we have idx $\in [S_{r-1}, S_r)$. We therefore require $S_{r-1} \overset{!}{=}$ idx and solve for r. After some algebraic manipulations, we obtain:

$$0 = -\frac{1}{2}r^2 + r\underbrace{\left(n - \frac{1}{2}\right)}_{z} - \text{idx} \quad (9)$$

$$\Leftrightarrow 0 = r^2 + r(-2z) + 2 \cdot \text{idx} \quad (10)$$

$$\Rightarrow r(\text{idx}) = z - \sqrt{z^2 - 2 \cdot \text{idx}} \quad (11)$$

We only use the negative branch of the square root since we want the row to increase with increasing index. Furthermore, we require the row index to be an integer, so we round down $\lfloor r(\text{idx}) \rfloor$ such that the row stays the same for a range of increasing indices. We can now also calculate column c:

$$c(\text{idx}) := r + 1 + (\text{idx} - S_{r-1}) \quad (12)$$

$$= \frac{1}{2}r^2 + r\left(\frac{3}{2} - n\right) + (\text{idx} + 1) \quad (13)$$

Finally, note that S_{n-1} conveniently gives us the number of elements in the upper triangular part of the adjacency matrix, i.e. the number of edges in our graph. With (8), we find:

$$\text{num edges} = S_{n-1} = \frac{1}{2}n^2 - \frac{1}{2}n = \frac{n(n-1)}{2} \quad (14)$$

With (11) and (13), we determine the respective row and column in the adjacency matrix for a

given index (3). During this row and column calculation, one should use 64-bit floating point numbers to mitigate precision errors that yield to wrong indices. Furthermore, we deal with graphs of more than 2^{32} edges and thus need to store the `idx` as an 64-bit unsigned integer. The `blockIdx.x` has to be statically cast to `u64` (unsigned long long int), otherwise it is assumed to be `u32` leading to incorrect indices and hard-to-debug errors for big graphs.

Memory. In the first version of our CUDA kernel, for every thread we allocate an array of arrays on the heap inside global GPU memory for the score matrix. We deallocate it after the alignment score is computed. This is very costly and immensely slows down the kernel execution. Instead, we want to use *shared memory* for all threads in a block and let them share one big score matrix as to minimize the number of allocations needed. However, the score matrix dimensions differ in size depending on the word lengths of A and B. Our solution is to look up the maximum word length q before the kernel is launched and allocate enough shared memory, i. e. for every thread, we assume the worst-case scenario of a $(q + 1) \times (q + 1)$ matrix and allocate $(q + 1)^2 \cdot$ blockDim.x chars (`i8`) as linear shared memory. Then, inside each thread, we retrieve a pointer to the start of the memory reserved for this thread by adding threadIdx.x$\cdot(q+1)^2$ to the base pointer. To finally access element (i, j) in the score matrix, we calculate $i \cdot \big(\text{len}(B) + 1\big) + j$. This may not use all allocated memory, but it is a trade-off between memory usage and performance; with our approach we avoid bank conflicts.

Block dimension. This dimension specifies the number of threads inside a block and is limited to 1024. We want to maximize shared memory available per block in order to minimize the number of memory allocations needed. Before the kernel is launched, for each $u \in [1, 1024]$, the resulting shared memory size for one block $(u \cdot (q+1)^2$ bytes) is calculated. The maximum u is chosen such that the maximum available shared memory per block (retrieved from CUDA device properties) is not exceeded.

5 Evaluation

We deploy our GPU code on a consumer Nvidia GeForce GTX 1060[4] with 6GB GDDR5. Every code change related to the GPU code is verified by comparing the resulting binary edge weights file with the one generated by our parallelized Rust implementation on the CPU. This baseline helps to quickly identify errors, which could otherwise remain unnoticed. During our tests, we define a manual threshold to cap the number of words to a user-defined threshold. The words considered are sorted according to their frequency as we are interested in relationships between the most commonly used words.

Performance. A fair comparison between the CPU and GPU implementation is not possible since focus was put in optimizing the GPU code. For example, the CPU implementation currently stores the row and column number alongside the actual edge weight in RAM to be able to order the results to the row-major ordering afterwards. To give an order of magnitude, the parallelized Rust CPU implementation (without the subsequent sorting) takes around 12 s (for 10,000 nodes), 42 s (for 20,000 nodes) and 93 s for 30,000 nodes on a 4-core Intel i7-6700 CPU. The implementation is limited to around 35,000 words when ≈ 20 GB of RAM are available.
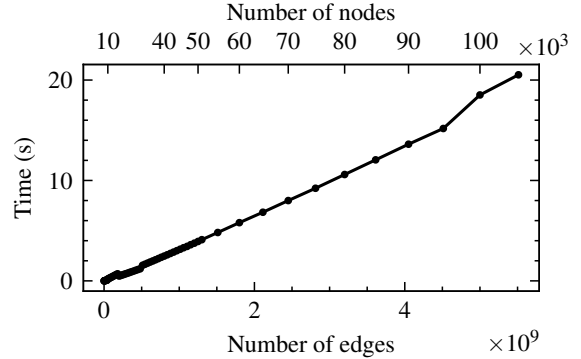

Figure 6: Performance of the GPU code for different number of nodes n. Number of edges via (14).

To test the performance of the GPU code, we measure the kernel execution time (including copying the results back to the host) for a range of number of nodes n in the graph. For every n, we measure the duration 12 times[5] and calculate mean and variance. The results are depicted in Figure 6. The variance is not shown as it is too small to be visible (always less than 1 ms). For 20,000 words, the GPU code takes 484 ms on average, while the CPU implementation needs 42 s. Up to 100,000 nodes (i. e. up to almost 5 billion edges), the GPU implementation takes less than 20 s. Figure 6 also reveals the linear trend of time with increasing

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[4]We use the Driver Version 572.42 and CUDA Toolkit 12.8 inside WSL2 (Ubuntu 22.04 jammy).

[5]After every run, the device is re-initialized. Furthermore, we wait 2 s after every run before a new one starts.

number of edges, which was to be expected since
a thread is launched for every edge.

Glossary

IPA International Phonetic Alphabet. 1, 2, 4

POS Part-of-Speech. 4

PTX Parallel Thread Execution. 5