

# Media of Langue: Exploring Word Translation Network

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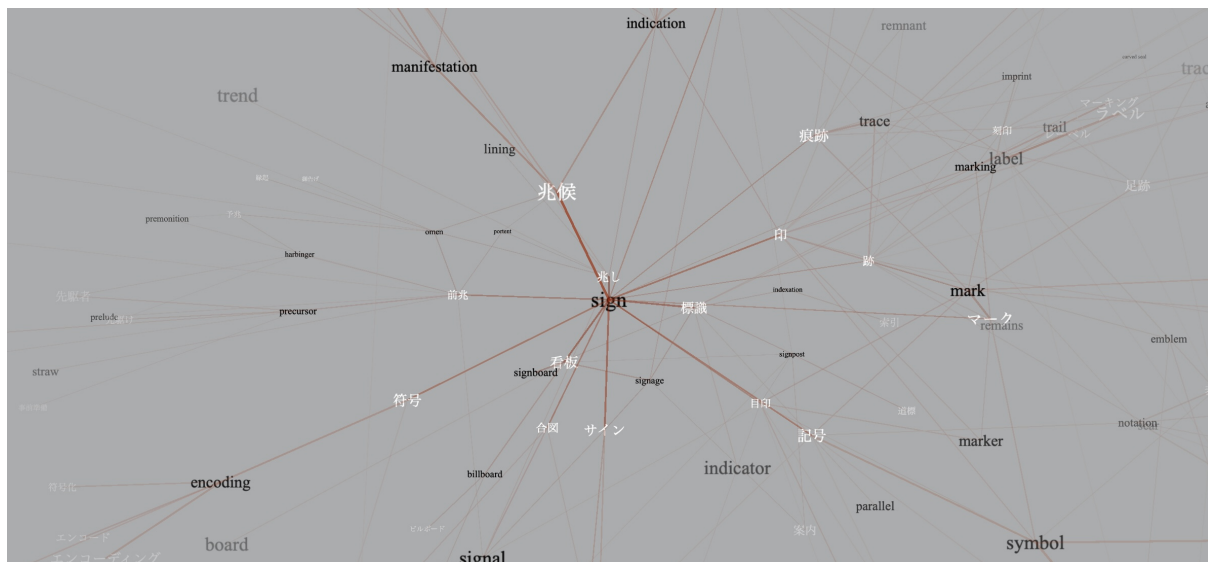


Figure 1: *Word Translation Network* visualized by Media of Langue

## Abstract

In the human activity of word translation, two languages face each other, mutually searching their own language system for the semantic place of words in the other language. We discover the huge network formed by the chain of these mutual translations as *Word Translation Network*, a network where words are nodes, and translation volume is represented as edges, and propose *Word Translation Map*, a novel interface for exploring this network. *Word Translation Map* points to the semantic configurations of many words in multiple languages at once, containing the information of existing dictionaries such as bilingual and synonym dictionaries. We have also implemented and published this interface as a web application, focusing on seven language pairs. This paper first defines the *Word Translation Network* and describes how to actually construct the network from bilingual corpora, followed by an analysis of the properties of the network. Next, we explain how to design a *Word Translation Map* using this network, and finally, we analyze the features of the *Word Translation Map* as a dictionary. The web application is publicly accessible at [www.media-of-langue.org](http://www.media-of-langue.org).

## 1 Introduction

This word was translated into that word.

That word was translated into that one.

That one was...

What a vast network could be formed by collecting and connecting the countless word translations that have occurred in the past.

Language exhibits both universality and diversity. We have faced this seemingly ordinary fact many times through the problem that “translation is neither completely possible nor completely impossible.” Researchers have theoretically examined the balance between the possibility and impossibility of translation. The rejection of the notion that concepts precede names (Jowett et al., 1892; De Saussure, 1989) and the acknowledgment of linguistic relativity—in which language itself shapes perception (Von Humboldt, 1999; Boas, 1938; Sapir, 2004; Whorf, 2012)—have rendered the impossibility of translation a scientific issue that extends beyond everyday intuition. In particular, Quine raised the question of the “indeterminacy of translation,”

believing that translation is necessarily polysemic and that it is impossible to transfer the meaning of one language exactly to another (Quine, 2013).

Conversely, the intrinsic and creative value of the fact that the universality and diversity of language, as well as the possibility and impossibility of translation, maintain a balance has also been highlighted in translation theory in philosophy of language. For example, Benjamin argued that translation is not a perfect reproduction of the original text but rather an act that seeks to approach the “pure language” underlying both the original and translation, supplementing and revealing the implicit in the original (Benjamin, 2016), while Derrida pointed out that the inherent *différance* and impossibility of exact equivalence open up space for new meanings and interpretations in translation act (Derrida et al., 1985). These studies suggest that the presence of multiple intrinsically different languages in the world may bring new and richer knowledge.

In the field of computational linguistics, however, the impossibility of translation is primarily regarded as an issue that requires resolution, with a paucity of studies exploring the creative dimensions of this phenomenon itself. Since the advent of computing, researchers have been developing methodologies to perform as much of the translation process as possible, which is inherently imperfect, using rule-based approaches (Hutchins, 2007), statistical methods (Lopez, 2008), and neural network techniques (Stahlberg, 2020) modeled on the human act of translation. Some studies have implicitly leveraged translation indeterminacy for specific tasks. For example, Helge Dyvik proposed that the two language models influence each other and act as a mirror (Dyvik, 2004), and studies have sought to address the scarcity of data in a few languages by complementing each other’s knowledge and by aggregating the knowledge of each language to obtain information beyond that of the language with the most information (Navigli and Ponzetto, 2010; Etzioni et al., 2007). However, their emphasis is on the variability of data across languages, and there are few examples that demonstrate a proactive approach to leveraging the intrinsic and unavoidable diversity of languages as a valuable asset, which we mentioned at the outset of this paper. Moreover, recent studies analyzing the impact of linguistic differences in cross-language activities (e.g., cross-language transfer and language acquisition) also focus primarily on overcoming these differences

rather than embracing them as valuable aspects of linguistic diversity (Philippy et al., 2023; Nieder and List, 2024).

This research proposes a map to explore the huge network formed by the fact that word translations do not have a one-to-one correspondence, which is the fact that represents the impossibility of translation. Overall, our contributions are as follows: 1. We propose *Word Translation Network* directly formed from the history of human word translation. This is a network where words are nodes, and translation volume is represented as edges. 2. We propose *Word Translation Map*, a framework for visualizing and exploring *Word Translation Network*. This dictionary provides rich and intuitive linguistic and cultural knowledge that cannot be reduced to existing synonym and bilingual dictionaries while providing the functionality of existing synonym and bilingual dictionaries. 3. We release a web application as an implementation of the *Word Translation Map*, focusing on seven language pairs: Chinese-English, English-French, English-German, English-Japanese, English-Korean, English-Spanish, and French-Japanese. Users can access the *Word Translation Network* from it at no additional cost.

This paper first defines a *Word Translation Network* and introduces a method for constructing this network from a bilingual corpus and its unitary analysis. Next, we describe the interface so that users can explore *Word Translation Network*. Finally, we describe how the proposed dictionary proposes new dictionary categories, highlighting unique features not found in existing dictionaries, and describe user experience scenarios written based on actual user usage.

## 2 Related Works

### 2.1 Multilingual Semantic Network

In the field of semantic networks, many works have been conducted to design a network with semantic relations as edges, bringing “meaning” to computers. The key challenge lies in determining the source of semantic relations and how they are defined as edges. Most methods extract information about semantic relationships between words from human-authored texts or databases, partition them into pre-categorized semantic relationships, and construct edges (Richens, 1956; Chandrasekaran and Mago, 2021; Ji et al., 2021). Then, the constructed semantic networks are applied in a vari-

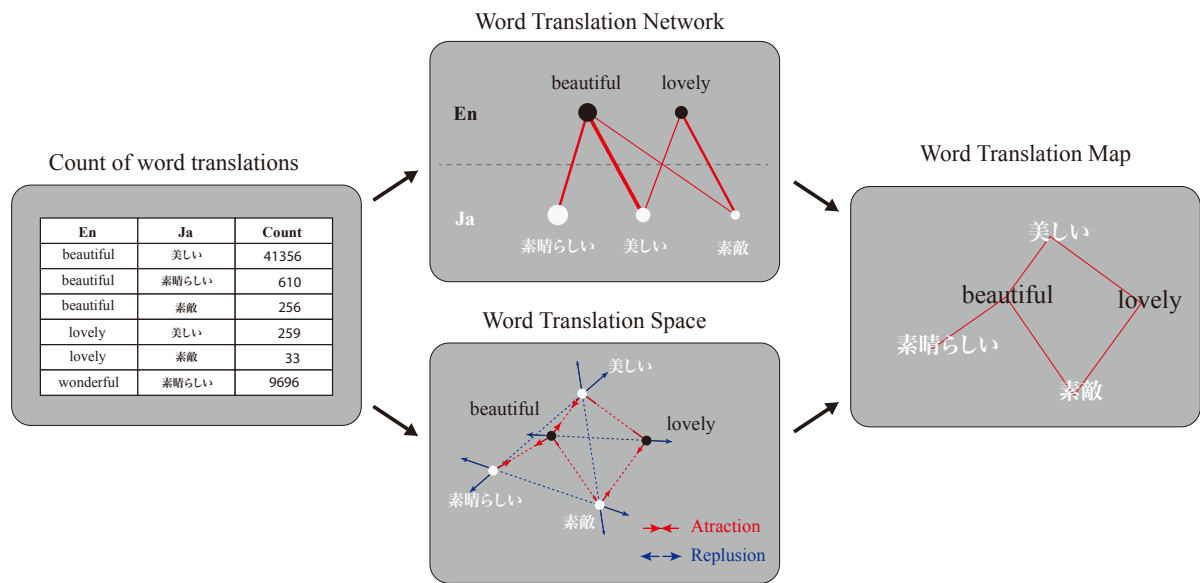


Figure 2: *Word Translation Network* and *Word Translation Space* are formed only from information about the number of translations and then visualized in *Word Translation Map*

ety of situations, including recommendation systems (Zhang et al., 2016; Wang et al., 2018; Guo et al., 2020), question answering systems (Huang et al., 2019; Bauer et al., 2018; Song et al., 2023), and search engines (Xiong et al., 2017).

Some studies have focused on developing a consistent semantic network across multiple languages using translation, primarily by composing monolingual semantic knowledge (Navigli and Ponzetto, 2010; Etzioni et al., 2007). Such a multilingual semantic network is expected to contribute to the conversion, interchange, and mutual complementation of languages on the computer. Here, we emphasize that our *Word Translation Network* differs from these multilingual semantic networks in that it is not a network created by composing the semantic knowledge assumed in advance for their interchange but a network that arises directly from their interchanges themselves only and translated words are connected directly.

## 2.2 Dictionary Interface

*Tout un dictionnaire s'offre, immense, effrayant.* (Stéphane Mallarmé (Mallarmé, 2003))

A word/symbol does not exist alone: it has its “place” in a huge system. Here, the tool that collects words/symbols and points to this “place” for each one can be called a dictionary. This tool has variations based on how they point to the “place” or, in other words, how they describe the address. Lexical dictionaries attempt to point to a “place”

using descriptive sentences, synonym dictionaries attempt to point to a “place” based on a word’s similarity to a nearby word, and translation dictionaries attempt to point to a “place” using translation relations with words in different languages.

After the advent of the computer, the variations of the way of pointing is expanded. In the early days of computers, they imitated the design of paper dictionaries, but the cross-referencing feature that existed in paper dictionaries was accelerated by computers as hypertext and became more than a quantitative extension (Urdang, 1984; Boguraev and Briscoe, 1989). In a slightly later generation, on the other hand, the idea of a freer digital dictionary that took advantage of the characteristics of computers developed significantly. (Klemenc et al., 2017) explained this development by the fact that in digital dictionaries, the database layer could be separated from the presentation layer. While the presentation layer is subject to the limitations of human cognition, the database layer does not necessarily need to be in a form that is directly recognizable to humans, but only if it is properly filtered, rearranged, and displayed in the process of transferring it to the presentation layer. These implementation approaches are unique to computer technology, but most of them still mimic the layout of traditional paper dictionaries in their presentation layers. Some projects, on the other hand, have not only a database structure optimized for computers but also a presentation layer with a dynamically changing

map interface designed to take advantage of the strengths of digital displays (Lohmann et al., 2015; Mendes, 2009; Khan and Khan, 2011; Smilov et al., 2016). Their dictionary arranges words spatially by drawing the existing network/space (e.g., WorkNet (Miller, 1995)) using computer-based network rendering technology (Bannister et al., 2013). Here, we emphasize that our dictionary differs from them in that it draws the new network, i.e., *Word Translation Network*, in the new manner of spatial arrangement, i.e., *Inter-lingual semantic space*. This realizes a new category of dictionaries, *Word Translation Map* providing users with a new experience that is not found in existing dictionaries, which is described in Section 5.

### 3 Word Translation Network

In this section, we introduce *Word Translation Network*. First, in Section 3.1, we provide a definition of *Word Translation Network*. Next, in Section 3.2, we explain the automatic extraction of data for constructing the *Word Translation Network* from bilingual corpora. Finally, in Section 3.3, we present a quick analysis of *Word Translation Network*.

#### 3.1 Definition

We define the network with the following nodes and edges as *Word Translation Network*.

- Each node corresponds to a single word that appears in the corpora.

The weight of the node depends on the frequency of the word in the corpora.

- Each edge connects two words (i.e., nodes) that appear as translation pairs in the corpora<sup>1</sup>.

The weight of the edge depends on the frequency of the translation pair in the corpora.

This network can be defined for multiple language systems (i.e., all the systems in which we can believe the arbitrariness that Saussure named (De Saussure, 1989)) where an adequate amount of translations/communications between them has been accumulated.

This network forms large connected components due to the fact that one word can be translated into several words instead of just one. We believe that

<sup>1</sup>The edges of *Word Translation Network* can also be directed edges if the directionality of the translation is bound to the corpora.

all words other than proper names potentially belong to a fairly large *Word Translation Network*. As a stronger hypothesis, we also consider the possibility that all two words in the same grammatical category (except proper names) belong to the same huge network.

Here, we emphasize that this is not a network created by the compromise of several monolingual knowledge but a network that arises directly from their interchanges between languages only. Therefore, this “inter-lingual” network should be distinguished from the existing “multi-lingual” networks in the field of semantic networks.

Incidentally, we can extract networks representing monolingual semantic similarity relations from *Word Translation Network*. Virtual edges can be created between same-language nodes in *Word Translation Network* when the two words share a common translation in another language, for example when “beautiful” and “lovely” share the Japanese translation “utsukushi.” Note that this is a network that changes depending on which language is paired in the generation. In general, when semantic networks address non-categorical relations, such as nuances of semantic similarity, they encounter limitations in their expressive granularity due to the need to use categorical relations indirectly (Miller, 1995). On the contrary, the virtual edges in *Word Translation Network* express horizontal semantic similarity based on the fact they have the same translation.

#### 3.2 Data Preparation

The data needed for *Word Translation Network* is the huge counts of the events “that word was translated into this word.” In order to obtain this data, we prepared a function, Word Translation Counter (WTC). WTC takes bilingual corpora as an input and outputs a table that stores the number of times a word (from language 1) is translated into a word (into language 2).

WTC works by calling a morphological function, an alignment function, and a normalization function for each pair of two sentences in a translation relationship (Figure 3). Currently, WTC is implemented for seven languages and seven language pairs. The libraries used for each function are summarized in Table 1. We used ParaCrawl (Esplà-Gomis et al., 2019), JParaCrawl (Morishita et al., 2019), and Kittajaf (R.Blin, 2023) as the bilingual corpus. The bilingual corpus and the number of used parallel sentences are summarized in Table 2.



Table 1: Libraries used for WTC.

Function	Library	Language / Language pair
Morphological function	Jieba (Junyi, 2024)	Zh
	Juman++ (Tolmachev et al., 2018)	Ja
	Komoran (Junsoo Shin, 2024)	Ko
	NLTK (Bird et al., 2009)	En
	SpaCy (Honnibal et al., 2024)	De, Fr, Es
Alignment function	AwesomeAlign (Dou and Neubig, 2021)	De-En, En-Fr, En-Ja, En-Zh, Fr-Ja
	M-BERT (Devlin et al., 2019)	En-Es, En-Ko
Normalization function	French LEFFF Lemmatizer (Coulombe, 2024)	Fr
	Germalemma (Konrad, 2024)	De
	Juman++ (Tolmachev et al., 2018)	Ja
	Komoran (Junsoo Shin, 2024)	Ko
	NLTK (Bird et al., 2009)	En
	SpaCy (Honnibal et al., 2024)	Es

Table 2: Bilingual corpus used for WTC.

Bilingual corpus	Language pair (number of used parallel sentences)
ParaCrawl (Esplà-Gomis et al., 2019)	De-En (20,000,000), En-Es (20,000,000), En-Fr (20,000,000), En-Ko (4,000,000), En-Zh (20,000,000)
JParaCrawl (Morishita et al., 2019)	En-Ja (20,000,000)
kittajaf (R.Blin, 2023)	Fr-Ja (6,000,000)

Our use of these libraries and bilingual corpora is consistent with their license and intended use. WTC is openly available, and we expect that it will continue to be improved, including the addition of languages, by contributors from different linguistic backgrounds.

### 3.3 Quick Analysis

Now, we present the results of a quick analysis of data obtained from WTC. This analysis focuses on the *Word Translation Network* with English and Japanese nouns (refer to the Appendix C for a more detailed and comprehensive analysis).

Figure 4a shows the degree distribution of this *Word Translation Network*. In this analysis, too infrequent translation pairs have been removed, and the network is treated as an unweighted, undirected graph. The points align in a straight line on the logarithmic plot, suggesting that the network exhibits scale-free properties (Barabási and Albert, 1999).

Figure 4b presents the distribution of shortest path lengths in the *Word Translation Network*. For comparison, we also include the shortest path length distribution of a bipartite random graph with the same number of nodes and edges. It can be observed that the shortest path lengths in the *Word Translation Network* tend to be shorter than those

in the random graph. Additionally, after calculating the bipartite clustering coefficient (Latapy et al., 2008) for both networks, we found that the *Word Translation Network* had a clustering coefficient of 0.291, whereas the random network had a slightly lower value of 0.252. These results show that the *Word Translation Network* has a relatively short path length and high clustering characteristics, suggesting that it exhibits small-world characteristics (Watts and Strogatz, 1998).

## 4 Word Translation Map

We propose *Word Translation Map* as the framework for exploring *Word Translation Network*. In this section, we explain the visualization of the network (Section 4.1), then explain the design of the dictionary interface (Section 4.2).

### 4.1 Network Visualization (Word Translation Space)

In the visualization of *Word Translation Network*, the nodes (i.e., words) are positioned according to the following algorithm:

1. Two forces are defined:
  - Repulsion between words in the same language system.

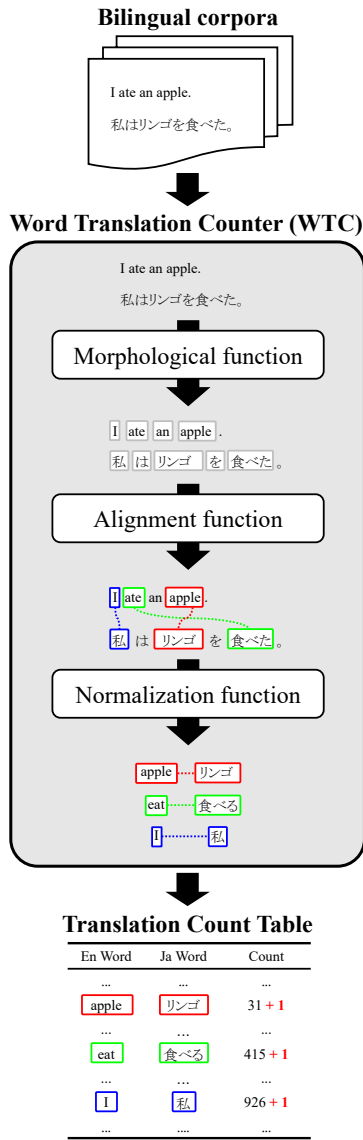


Figure 3: The workflow of our WTC. Note that WTC is defined only by its inputs and outputs; its internals are implementation-dependent.

- Attraction between translated words in different language systems.
2. The positions of words are determined by minimizing the energy associated with these forces.

Although this method is similar to previous work on network visualization (Bannister et al., 2013), the two forces can be explained by linguistic intuition as follows: Repulsion corresponds to the force of a word to secure its value by its difference from other words, or the fact that “words (or translations for a word) with the same meaning are not needed,” and attraction corresponds to the force of a translation to suppress differences from the target

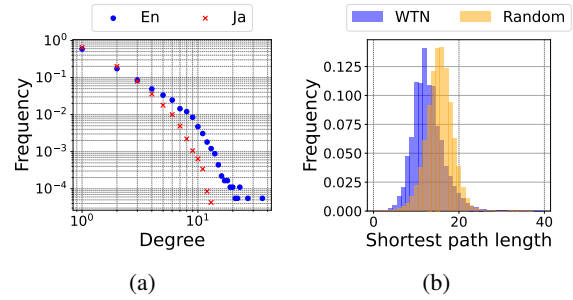


Figure 4: (a) Degree distribution and (b) Shortest path length distribution of *Word Translation Network* with English and Japanese nouns.

word, or the fact that “translation should preserve meaning.”

The magnitude of each force is set based on the frequency of occurrence in the corpora. Repulsion is stronger for words that appear frequently, and attraction is stronger for translation relations that occur frequently. To refine these magnitudes, we apply three adjustments: (i) normalization to account for differences in corpus size between language pairs, (ii) normalization to account for substantial differences in word frequency, and (iii) a weighting system to emphasize words related to the user-searched word. A detailed formulation is provided in Appendices A and B.

Here, we emphasize that this is not a space created by the compromise of several monolingual knowledge but a space that arises directly from their interchanges between languages only. Therefore, this “inter-lingual” space should be distinguished from the existing “multi-lingual” spaces in the field of semantic spaces and could be termed *Word Translation Space*, or *Inter-Lingual Semantic Space*. However, it is a future task to analyze the characteristics of this space as a semantic space through comparison with existing monolingual/multilingual semantic spaces.

Based on the coordinates of this space, network nodes are drawn as the text of the corresponding word, and edges as lines. The word size and line width inherit the node and edge weights, respectively.

## 4.2 User Interface Design

The UI of *Word Translation Map* consists of two parallel layers: the *Word Translation Network* layer, which visualizes the *Word Translation Network*, and the material corpora layer, which displays the bilingual parallel corpus in response to the other layer. Note that these two layers can be seen as

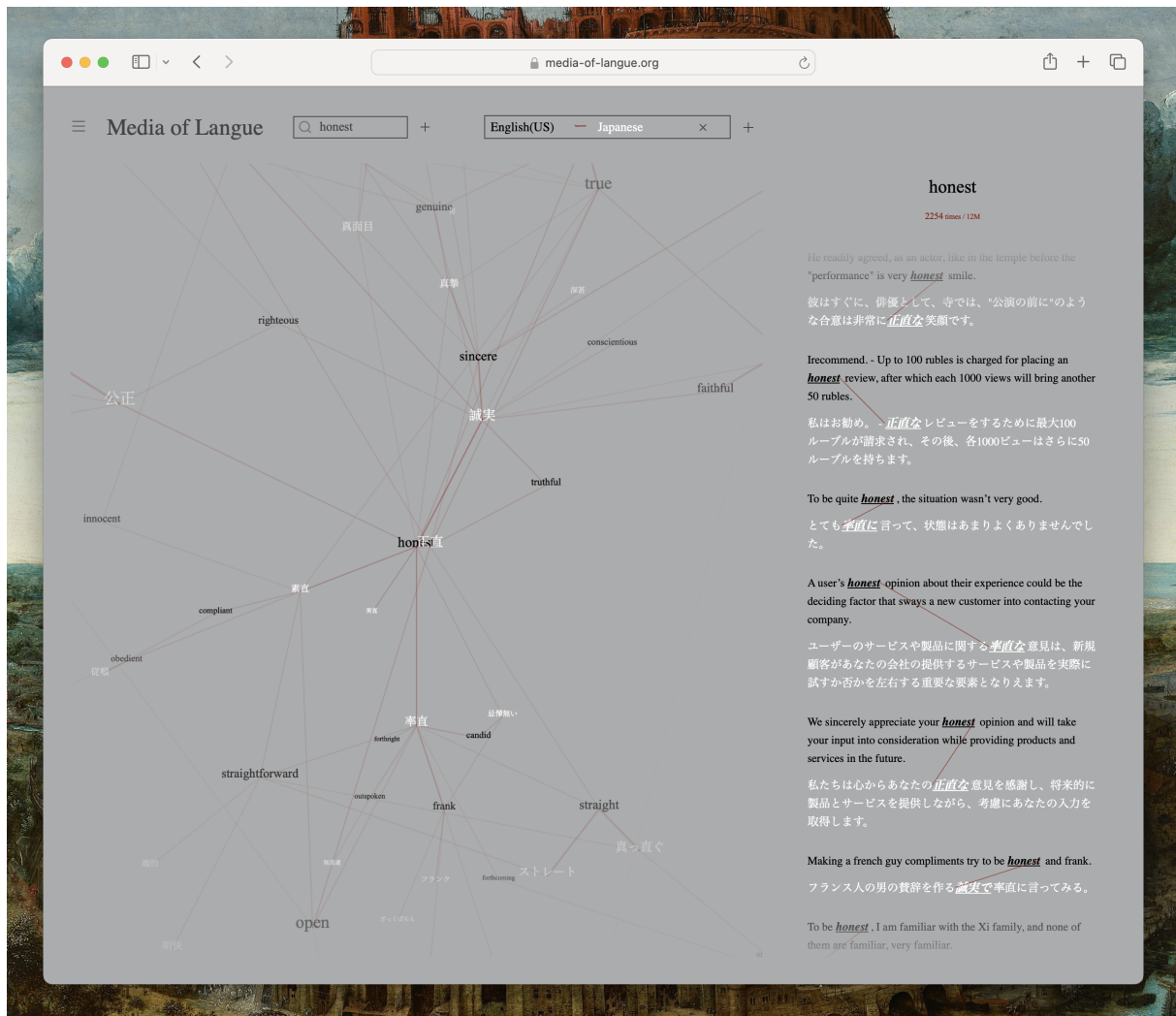


Figure 5: Media of Language: Our implementation of *Word Translation Map*

extensions of the concept of “langue” and “parole” (De Saussure, 1989). The explanations in this section are based on the actual *Word Translation Map* we have implemented as a web page.

**Word Translation Network layer** This layer (the left side of Figure 5) visualizes *Word Translation Network* based on the method described in Section 4.1. *Word Translation Network* consisting of several hundred words centered on the words that the user is focusing on is visualized, helping the user to recognize the network. Users can choose to view the network in either 2D or 3D. In 2D, they can quickly get an overview of the network at a glance, while in 3D, they can more accurately perceive the semantic distances and network structure between words by rotating the network.

**Material Corpus layer** The parallel corpora that served as material for the *Word Translation Network* layer are displayed (the right side of Fig-

ure 5). In a pair of vertically aligned sentences of the corpora, the words in the focused translation relationship are emphasized by being connected with lines, just as they were in *Word Translation Network*. When users click on a word or translation line in the *Word Translation Network* layer, the corresponding sentences from the corpora immediately flow into this layer. These corpora serve as the so-called example sentences of the dictionary. This feature ensures the transparency of this dictionary, as it means that the sole basis of the dictionary is always displayed in the interface.

**Exploration** There were two types of search methods. The first was a word search. When a word of interest was entered in the search window, a map centered on the word expanded. The users could select language pairs, part of speech, dimension, and initial language. The second was a search that moved sequentially by interacting with the

map. When the user clicks on a word, the map moves so that the word is in the center. The map can also be zoomed in and out. These two methods allow users to explore the vast landform that exists at the boundary between languages in the same way that anyone can explore virtually anywhere on earth from a personal display.

## 5 Feature Analysis

*Word Translation Map* is the first interface to explore the huge network formed by past translation practices based on translation indeterminacy. Here, however, we explain how the ability to explore this network inevitably gives rise to properties that other dictionaries do not have, based on their framework and implementation.

### 5.1 Structural Features

*Word Translation Map* has the following structural features based on the described implementation.

**Consolidation and extension of existing multiple dictionaries** *Word Translation Map* encompasses multiple types of dictionaries and simultaneously provides information equivalent to multiple entries in each dictionary. For example, when a map is created using two languages, it serves as both the two synonym dictionaries for each language and the bilingual dictionary between the two languages; thus, it plays the role of three dictionaries at the same time. In addition, the content covered by multiple entries in the three dictionaries is now contained on a single screen so that the information can be viewed at a glance without having to flip through pages. This not only saves time and effort but also brings richer knowledge that can only be gained from a global perspective.

**Coordinate space embedded with familiar linguistic senses** In *Word Translation Map*, words in one language can be captured relative to their network/spatial distances from multiple words in the other language. This allows users to capture the nuances of the foreign language using the linguistic senses of their native language. In addition, users who are proficient in multiple languages can capture the nuances of an unfamiliar language while using multiple familiar languages.

### Direct reflection of the actual state of translation

The paths connecting words on the map can be interpreted as a “translation traffic network” that records translation events, and the width of the path

can be interpreted as a “translation traffic volume”. This map gives the user a realistic picture of the translation traffic, not only which translations are considered appropriate, but also how words in the two languages are actually being translated into each other around the world.

**Uncovering implicit and global semantic continuities** The *Word Translation Map* does not use explicit knowledge, but reflects the translator’s non-verbal understanding of the meaning behind the translation activities. This allows the dictionary to expose a continuum of meanings based on latent human universals beyond languages. It can suggest words that are out of scope at the usual synonym but actually have a continuity of meaning as synonyms in the broadest sense, or it can tell us how one concept is connected to another.

### 5.2 Illustrative Examples for User Experience

Here we describe the user experience scenario written based on actual user usage. This scenario is a longer experience (1-3 minutes) designed to give an overview of many of the possible experiences of *Word Translation Map*, and in fact, any part of this scenario can be omitted. This scenario was created by the authors by asking 50 users of the app how they use it, reconstructing them.

Assume a user who is an English speaker and a learner of Japanese.

Interested in the difference between “正直” and “誠実,” both of which translations of “honest,” she goes to *Word Translation Map*, and types “honest” in the search window. The map containing words such as “honest,” “sincere,” “truthful,” “frank,” “straightforward,” “正直,” “誠実,” “素直,” “率直,” “真摯” then unfolds. At this point, the basic functions of a normal bilingual dictionary are fulfilled by looking up words directly linked with lines to “honest,” such as “正直,” “誠実,” “素直,” “率直.” The dictionary also fulfills the basic functions of an English synonym dictionary for “honest” by focusing only on English, and a Japanese synonym dictionary for “正直/誠実,” too.

Looking at the map, she first notices that “正直” is quite close to “honest” (the translation is a relatively one-to-one correspondence), whereas there is no English word that corresponds exactly to “誠実.” Seeing that “誠実” is located near the center of the triangle of “honest,” “sincere,” and “truthful” (slightly closer to “honest”), she imagines the nuance of “誠実” as a new blended nuance from the



nuances of three words that have already acquired a rich linguistic sense in the appropriate proportions. Then, to check the actual usage of the word, she clicks on the thickest line near the center, between “honest” and “誠実”, then actual sentences in which “honest” and “誠実” are translated appear on the right side of the screen. She then clicks on other lines to check the usage, confirming that the nuances she understands spatially match the usage, and adding a dependency on the situation to her knowledge, such as the fact that “正直” tends to be used in more casual situations than “誠実.”

Furthermore, looking down, she notices that in the direction of “frank,” words containing the nuance of simplicity such as “frank,” “素直,” and “straightforward” are spreading, while toward “sincere,” words with nuances related to truth such as “truthful,” “true,” and “genuine,” are spreading. When she clicks on the word “素直,” a space appears in which words related to obedience, such as “compliant,” “obedient,” and “docile,” float. It reminds her that “honesty,” which is often required and valued, is next to “obedience,” which is often betrayed, deceived, and criticized.

In addition to the cases examined in detail above, many other situations can be considered.

- A user who has only thought of the word “implication” as a synonym for “meaning” will find through *Word Translation Map* not only the usual synonym dictionary words such as “signification” and “context” but also the words that are seemingly distant concepts such as “sense,” “importance,” and “consciousness,” via the Japanese words.
- A user familiar with English and Japanese can acquire the nuance of “beau” in French, a third language, based not only on the relationship with “beautiful,” “cute,” and “lovely” in English but also on the relationship with “美しい,” “綺麗,” and “素敵” in Japanese.

## 6 Conclusion

This paper presented *Word Translation Map*, a framework for exploring *Word Translation Network*. *Word Translation Network* is a huge network where words are nodes, and translation volume is represented as edges, which was formed by past language translations on the balance between language universality and diversity.

We defined this network, explained the method of constructing it from a parallel corpus, and performed a preliminary analysis of the network we had created. We then explained that we can form a new kind of dictionary that refers to the semantic place of many words at once with a chain of mutual translation by creating a map that explores this network. This map serves as a panoramic and nuanced bilingual and synonym dictionary but also suggests our unique engagement with language and meaning, which is not reducible to the traditional use of dictionaries.

“Media of Langue” is a “medium” between *langue* and *langue* but, therefore, a “medium” between humans and *langue*. We hope that this dictionary will be used across the world and that it will become an open platform that continues to reflect the possibilities/impossibilities of communication, and the universality/diversity of humanity.

## 7 Limitations

Since this paper focuses on the proposal of a new dictionary category, *Word Translation Map*, a detailed analysis of *Word Translation Network*, which we also propose, has not been carried out. In particular, it is important to evaluate, under specific tasks, how the novelty of focusing only on the translation history between languages, without using inter-lingual information, quantitatively differs from the existing multilingual semantic network/space. Also, regarding the evaluation of the interface, this paper focused on the structurally generated features of this new dictionary category, but a qualitative analysis of the actual user experience with this application is a future task. There are still technical limitations with regard to the stage of obtaining the history of word translations, i.e., “that word was translated into this word,” which depend on the insufficient amount of parallel corpora and the accuracy of the alignment libraries. However, future contributions of the NLP community to corpus collection and alignment methods will greatly improve the number of language-pair and the quality of the map can be improved. We hope that the map will eventually become huge one that reflects many of the myriad translations that exist around the world.

## 8 Potential Risks

The example sentences in *Word Translation Map* displayed in the corpus layer are the corpus data

itself, which is the raw material for the map, unlike most existing dictionaries that use example sentences selected by experts. As such, they are not necessarily representative of a given translation and may contain slang or direct expressions. However, the security gained by filtering these out is a trade-off for how well the dictionary reflects actual language traffic. The latter is also an important feature of this category of dictionaries. Careful decisions about this policy will need to be made in future distributions of this dictionary. On the other hand, while the project confronts the fact that there exist multiple languages and re-proposes its value, it relies on the quantity and quality of the translations that are actually done, which leads to a bias towards languages with high speaker and recognition levels. In fact, all of the seven languages currently deployed are English on one side, with the exception of Japanese-French. It is possible to form a map between languages for which there is no actual translation data by adding English, but this is not *Word Translation Map* based on actual direct translations between the two languages, but an indirect one, heavily influenced by English and its culture, which is problem with the English pivot in general. For the dictionary to fully realise its multilingualist nature, there needs to be a conscious effort to actively focus on the languages of minority speakers, or more precisely, between the languages of minority traffic.

## References

- Michael J Bannister, David Eppstein, Michael T Goodrich, and Lowell Trott. 2013. Force-directed graph drawing using social gravity and scaling. In *Graph Drawing: 20th International Symposium, GD 2012, Redmond, WA, USA, September 19-21, 2012, Revised Selected Papers 20*, pages 414–425.
- Albert-László Barabási and Réka Albert. 1999. Emergence of scaling in random networks. *science*, 286(5439):509–512.
- Lisa Bauer, Yicheng Wang, and Mohit Bansal. 2018. Commonsense for generative multi-hop question answering tasks. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics.
- Walter Benjamin. 2016. The task of the translator: An introduction to the translation of baudelaire’s tableaux parisiens. In *Readings in the theory of religion*, pages 131–139. Routledge.
- Steven Bird, Ewan Klein, and Edward Loper. 2009. *Natural language processing with Python: analyzing text with the natural language toolkit*. " O’Reilly Media, Inc."
- Franz Boas. 1938. *Handbook of American indian languages*. 40. US Government Printing Office.
- Bran Boguraev and Ted Briscoe. 1989. *Computational lexicography for natural language processing*. Longman Publishing Group.
- Dhivya Chandrasekaran and Vijay Mago. 2021. Evolution of semantic similarity—a survey. *ACM Computing Surveys (CSUR)*, 54(2):1–37.
- Claude Coulombe. 2024. French lefff lemmatizer. <https://github.com/ClaudeCoulombe/FrenchLefffLemmatizer>. Accessed: 2024-01-23.
- Ferdinand De Saussure. 1989. *Cours de linguistique générale*, volume 1. Otto Harrassowitz Verlag.
- Jacques Derrida et al. 1985. Des tours de babel. *Difference in translation*, 167.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In *North American Chapter of the Association for Computational Linguistics (NAACL)*.
- Zi-Yi Dou and Graham Neubig. 2021. Word alignment by fine-tuning embeddings on parallel corpora. In *Conference of the European Chapter of the Association for Computational Linguistics (EACL)*.
- Helge Dyvik. 2004. Translations as semantic mirrors: from parallel corpus to wordnet. In *Advances in corpus linguistics*, pages 309–326. Brill.
- Miquel Esplà-Gomis, Mikel L Forcada, Gema Ramírez-Sánchez, and Hieu Hoang. 2019. Paracrawl: Web-scale parallel corpora for the languages of the eu. In *Proceedings of Machine Translation Summit XVII: Translator, Project and User Tracks*, pages 118–119.
- Oren Etzioni, Kobi Reiter, Stephen Soderland, and Marcus Sammer. 2007. Lexical translation with application to image searching on the web. In *Proceedings of Machine Translation Summit XI: Papers*.
- Qingyu Guo, Fuzhen Zhuang, Chuan Qin, Hengshu Zhu, Xing Xie, Hui Xiong, and Qing He. 2020. A survey on knowledge graph-based recommender systems. *IEEE Transactions on Knowledge and Data Engineering*, 34(8):3549–3568.
- M. Honnibal, I. Montani, S. Van Landeghem, and A. Boyd. 2024. spacy: Industrial-strength natural language processing in python. <https://github.com/explosion/spaCy>. Accessed: 2024-01-22.
- Xiao Huang, Jingyuan Zhang, Dingcheng Li, and Ping Li. 2019. Knowledge graph embedding based question answering. In *Proceedings of the twelfth ACM international conference on web search and data mining*, pages 105–113.

- John Hutchins. 2007. Machine translation: A concise history. *Computer aided translation: Theory and practice*, 13(29-70):11.
- Shaoxiong Ji, Shirui Pan, Erik Cambria, Pekka Marttinen, and S Yu Philip. 2021. A survey on knowledge graphs: Representation, acquisition, and applications. *IEEE transactions on neural networks and learning systems*, 33(2):494–514.
- Benjamin Jowett et al. 1892. *Charmides. Lysis. Laches. Protagoras. Euthydemus. Cratylus. Phaedrus. Ion. Symposium*, volume 1. Oxford University Press, American branch.
- Geunho Lee Junsoo Shin, Junghwan Park. 2024. Komoran: Korean morphological analyzer. <https://github.com/shineware/KOMORAN>. Accessed: 2024-01-22.
- Sun Junyi. 2024. Jieba. <https://github.com/fxsjy/jieba>. Accessed: 2024-01-22.
- Muzammil Khan and Sarwar Shah Khan. 2011. Data and information visualization methods, and interactive mechanisms: A survey. *International Journal of Computer Applications*, 34(1):1–14.
- Bojan Klemenc, Marko Robnik Šikonja, Luka Fürst, Ciril Bohak, and Simon Krek. 2017. Technological design of a state-of-the-art digital dictionary. *Dictionary of Modern Slovene: Problems and Solutions*, pages 10–22.
- M. Konrad. 2024. Germalemma. <https://github.com/WZBSocialScienceCenter/germalemma>. Accessed: 2024-01-22.
- Matthieu Latapy, Clémence Magnien, and Nathalie Del Vecchio. 2008. Basic notions for the analysis of large two-mode networks. *Social networks*, 30(1):31–48.
- Steffen Lohmann, Vincent Link, Eduard Marbach, and Stefan Negru. 2015. Webvowl: Web-based visualization of ontologies. In *Knowledge Engineering and Knowledge Management: EKAW 2014 Satellite Events, VISUAL, EKM1, and ARCOE-Logic, Linköping, Sweden, November 24-28, 2014. Revised Selected Papers*. 19, pages 154–158. Springer.
- Adam Lopez. 2008. Statistical machine translation. *ACM Computing Surveys (CSUR)*, 40(3):1–49.
- Stéphane Mallarmé. 2003. *Œuvres complètes*, volume 65. Gallimard.
- Olga Bessa Mendes. 2009. Following the path between conceptual maps and visual thesauri. In *Actes de la conférence*.
- George A Miller. 1995. Wordnet: a lexical database for english. *Communications of the ACM*, 38(11):39–41.
- Makoto Morishita, Jun Suzuki, and Masaaki Nagata. 2019. Jparacrawl: A large scale web-based english-japanese parallel corpus. *arXiv preprint arXiv:1911.10668*.
- Roberto Navigli and Simone Paolo Ponzetto. 2010. Babelnet: Building a very large multilingual semantic network. In *Proceedings of the 48th annual meeting of the association for computational linguistics*, pages 216–225.
- Jessica Nieder and Johann-Mattis List. 2024. A computational model for the assessment of mutual intelligibility among closely related languages. In *Proceedings of the 6th Workshop on Research in Computational Linguistic Typology and Multilingual NLP*.
- Fred Philippy, Siwen Guo, and Shohreh Haddadan. 2023. Identifying the correlation between language distance and cross-lingual transfer in a multilingual representation space. In *Proceedings of the 5th Workshop on Research in Computational Linguistic Typology and Multilingual NLP*.
- Willard Van Orman Quine. 2013. *Word and object*. MIT press.
- R.Blin. 2023. kittajfr-v4.0.4-c.1. <https://sharedocs.huma-num.fr/wl/?id=eMoQjZUyrthaXtP5EKw5ZQI5h77gzIDa>. Accessed: 2024-01-22.
- Richard H Richens. 1956. Preprogramming for mechanical translation. *Mech. Transl. Comput. Linguistics*, 3(1):20–25.
- Edward Sapir. 2004. *Language: An introduction to the study of speech*. Courier Corporation.
- Daniel Smilkov, Nikhil Thorat, Charles Nicholson, Emily Reif, Fernanda B Viégas, and Martin Wattenberg. 2016. Embedding projector: Interactive visualization and interpretation of embeddings. *arXiv preprint arXiv:1611.05469*.
- Yiqing Song, Wenfa Li, Guiren Dai, and Xinna Shang. 2023. Advancements in complex knowledge graph question answering: a survey. *Electronics*, 12(21):4395.
- Felix Stahlberg. 2020. Neural machine translation: A review. *Journal of Artificial Intelligence Research*, 69:343–418.
- Arseny Tolmachev, Daisuke Kawahara, and Sadao Kurohashi. 2018. Juman++: A morphological analysis toolkit for scriptio continua. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*.
- Laurence Urdang. 1984. A lexicographer’s adventures in computing. *Dictionaries: Journal of the Dictionary Society of North America*, 6(1):150–165.
- Wilhelm Von Humboldt. 1999. *Humboldt: ‘On language’: On the diversity of human language construction and its influence on the mental development of the human species*. Cambridge University Press.
- Hongwei Wang, Fuzheng Zhang, Xing Xie, and Minyi Guo. 2018. Dkn: Deep knowledge-aware network for news recommendation. In *Proceedings of the 2018 world wide web conference*, pages 1835–1844.

- Duncan J Watts and Steven H Strogatz. 1998. Collective dynamics of ‘small-world’ networks. *nature*, 393(6684):440–442.
- Benjamin Lee Whorf. 2012. *Language, thought, and reality: Selected writings of Benjamin Lee Whorf*. MIT press.
- Chenyan Xiong, Russell Power, and Jamie Callan. 2017. Explicit semantic ranking for academic search via knowledge graph embedding. In *Proceedings of the 26th international conference on world wide web*, pages 1271–1279.
- Fuzheng Zhang, Nicholas Jing Yuan, Defu Lian, Xing Xie, and Wei-Ying Ma. 2016. Collaborative knowledge base embedding for recommender systems. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, pages 353–362.

## A Formulate *Inter-lingual semantic space*

Here we formulate the *Inter-lingual semantic space*. Let  $\mathcal{L}$  be the set of languages,  $\mathcal{W}_{\text{all}}^{(l)}$  be the set of words of the language  $l$ , and  $\mathbf{x}_w$  be the coordinates of the word  $w$ . The word coordinates are optimized to minimize the loss  $E_{\text{total}} = E_{\text{rep}} + E_{\text{att}}$ , where  $E_{\text{rep}}$  is the energy loss due to repulsive forces between words of the same language, and  $E_{\text{att}}$  is the energy loss due to attractive forces between words of different languages;

$$E_{\text{rep}} = \sum_{l \in \mathcal{L}} \sum_{\substack{u, v \in \mathcal{W}_{\text{all}}^{(l)} \\ u \neq v}} \text{rep}(\mathbf{x}_u, \mathbf{x}_v; u, v), \quad (1)$$

$$E_{\text{att}} = \sum_{\substack{l_1, l_2 \in \mathcal{L} \\ l_1 \neq l_2}} \sum_{\substack{u \in \mathcal{W}_{\text{all}}^{(l_1)} \\ v \in \mathcal{W}_{\text{all}}^{(l_2)}}} \text{att}(\mathbf{x}_u, \mathbf{x}_v; u, v). \quad (2)$$

$\text{rep}$  and  $\text{att}$  are functions that return the energy loss between the two words due to repulsion and attraction, respectively. We used the metaphor of the elastic force of a spring and the repulsive force of an electric charge, referring to previous work in network visualization (Bannister et al., 2013):

$$\text{rep}(\mathbf{x}_u, \mathbf{x}_v; u, v) = \frac{q_u q_v}{\|\mathbf{x}_u - \mathbf{x}_v\|_2}, \quad (3)$$

$$\text{att}(\mathbf{x}_u, \mathbf{x}_v; u, v) = k_{u,v} \|\mathbf{x}_u - \mathbf{x}_v\|_2^2, \quad (4)$$

where  $q_u$  and  $k_{u,v}$  are the “charge” of the word  $u$  and the “spring constant” of the spring connecting the word  $u$  and  $v$ , respectively. Here, note that repulsive forces, which are usually defined for all nodes, only work between nodes of the same language in our method.

## B Exploration of Network

Here, we describe the two algorithms we have developed to enable users to explore *Word Translation Network* composed of the “neighborhood words” of the user-searched word.

### B.1 Computing with a Subset of Words

We have to address the following three important factors to provide users with well-organized *Word Translation Network* of “neighborhood words”: (i) the corpora size varies widely among different language pairs, (ii) the frequency of word occurrences varies widely among different words, (iii) the words particularly relevant to the user-searched word should be highlighted. Here, let  $\mathcal{W}^{(l)}$  be the

“neighborhood words” in language  $l$ , and  $\mathcal{P}$  be the user-specified set of language pairs.

First, to deal with (i), we normalize the number of occurrences of the word  $u$ ,  $c_u$ , and the number of occurrences of the translation between  $u$  and  $v$ ,  $c_{u,v}$ , as follows:

$$\bar{c}_u = \frac{1}{|\mathcal{L}_{\text{pair}}^{(l_u)}|} \sum_{l_v \in \mathcal{L}_{\text{pair}}^{(l_u)}} \sum_{v \in \mathcal{W}_{\text{all}}^{(l_v)}} \frac{c_{u,v}}{T_{l_u, l_v}}, \quad (5)$$

$$\bar{c}_{u,v} = \frac{c_{u,v}}{T_{l_u, l_v}}, \quad (6)$$

where

$$\mathcal{L}_{\text{pair}}^{(l_u)} = \{l \mid (l_u, l) \in \mathcal{P}\}, \quad (7)$$

$$T_{l_u, l_v} = \sum_{s \in \mathcal{W}_{\text{all}}^{(l_u)}} \sum_{t \in \mathcal{W}_{\text{all}}^{(l_v)}} c_{s,t}. \quad (8)$$

The term  $T_{l_u, l_v}$  serves as a normalization factor that accounts for differences in corpus sizes across language pairs. Specifically,  $T_{l_u, l_v}$  represents the total number of translation occurrences between language  $l_u$  and  $l_v$ . By dividing the raw number of appearances  $c_{u,v}$  by  $T_{l_u, l_v}$ , we scale the value to a comparable scale across different language pairs.

Next, to handle (ii), we mitigate the effects of words and translation pairs that appear extremely frequently by applying a nonlinear transformation. We define the “original” charge and spring coefficients,  $\bar{q}_u$  and  $\bar{k}_{u,v}$ , as follows:

$$\bar{q}_u = \frac{f(\bar{c}_u)}{C}, \quad \bar{k}_{u,v} = \frac{f(\bar{c}_{u,v})}{C}, \quad (9)$$

where

$$C = \frac{\sum_{(l_1, l_2) \in \mathcal{P}} \sum_{\substack{s \in \mathcal{W}^{(l_1)} \\ t \in \mathcal{W}^{(l_2)}}} p(s; \mathbf{x}_s) p(t; \mathbf{x}_t) f(\bar{c}_{s,t})}{\sum_{(l_1, l_2) \in \mathcal{P}} \sum_{\substack{s \in \mathcal{W}^{(l_1)} \\ t \in \mathcal{W}^{(l_2)}}} p(s; \mathbf{x}_s) p(t; \mathbf{x}_t)}, \quad (10)$$

$$f(c) = c^\gamma. \quad (11)$$

The function  $p$  weights the “original” charge and spring coefficients according to the relevance to the user-searched word (we define  $p$  later).

The function  $f$  applies a nonlinear transformation to mitigate the impact of highly frequent words and translation pairs ( $\gamma = 0.5$  in our implementation).  $C$  is a normalization constant that ensures the overall scale of the values is appropriately maintained, regardless of the searched word or the selected language pair.



Finally, to address (iii), we define the actual charge and spring coefficients,  $q_u$  and  $k_{u,v}$ , by weighting the “original” charge and spring coefficients:

$$q_u = \bar{q}_u \cdot p(u; \mathbf{x}_u), \quad (12)$$

$$k_{u,v} = \bar{k}_{u,v} \cdot p(u; \mathbf{x}_u)p(v; \mathbf{x}_v). \quad (13)$$

The function  $p(u; \mathbf{x}_u)$  assigns higher importance to words that have been displayed for a longer time and that are closer to the user-searched word. It is defined as:

$$p(u; \mathbf{x}_u) = (1 - \alpha_t^{t_u}) \cdot \alpha_x^{\|\mathbf{x}_u\|^2}. \quad (14)$$

Here,  $t_u$  represents the time elapsed since the word  $u$  is added to  $\mathcal{W}$ , and  $\alpha_t$  and  $\alpha_x$  are positive hyperparameters that adjust the temporal and spatial weighting, respectively. In our implementation, we set  $\alpha_t = 0.9985$  and  $\alpha_x = 0.5$ . By applying this weighting mechanism, words that have been displayed for a longer period and are positioned closer to the user’s focus receive higher importance in the visualization.

## B.2 Selecting Words for Coordinate Calculation

$\mathcal{W}$  is first a set consisting of only one word searched by the user, and then words are successively added to and deleted from this set, following the assumption that “the tentatively computed word coordinates correctly represent (to some extent) the semantic distribution of the words around the central word.” Based on this assumption, words connected to words close to the searched word are added, and words that have moved away from the searched word are deleted.

Algorithm 1 shows the process of the addition and deletion of words to  $\mathcal{W}$ . The word additions and deletions are performed when the word coordinates have approximately converged. Word addition is performed by adding a word that is connected to “tentatively near-centered words”, i.e., “parent” words. Word deletion is performed according to two rules: (i) words that are not “parent” words and are not connected to “parent” words are deleted, (ii) if the number of words exceeds  $N_{\max}$  (150 in our implementation), the words farthest from the center are deleted.

## C Detailed Analysis of Word Translation Network

Here, we provide a more detailed and comprehensive analysis of the *Word Translation Network*.

All analysis was conducted on a Linux machine equipped with an Intel® Core™ i9-11900H CPU @ 2.50 GHz and 62 GB of memory. Our analysis delves into the network structure and key properties, offering insights that were not fully covered in the main text.

As a preliminary, we offer some assumptions. In this analysis, translation pairs that occur too infrequently have been removed, and the network is modeled as an unweighted, undirected graph. Specifically, edges between nodes  $u$ , whose number of occurrences in the corpus is  $c_u$ , and  $v$ , whose number of occurrences in the corpus is  $c_v$ , are omitted if  $c_{u,v}$ , the number of occurrence of their translation in the corpus, satisfies the inequality  $c_{u,v} \leq \alpha \min(c_u, c_v) + \beta$ , where  $\alpha = 0.008$  and  $\beta = 5$ . This filtering process ensures that the analysis focuses on meaningful and frequent word translations.

Additionally, we define the construction method for the bipartite random network used as a comparison throughout this section. This bipartite random network contains the same number of nodes and edges as the *Word Translation Network*. Let the number of nodes in language 1 and language 2 be  $N_1$  and  $N_2$ , respectively, and the number of edges be  $M$ . The random bipartite network is generated by selecting  $M$  edges uniformly at random from the  $N_1 N_2$  possible edges between the two sets of nodes. This random network serves as a baseline for comparison in terms of degree distribution, clustering coefficient, and shortest path lengths.

First, Table 3 displays the proportion of nodes that belong to the largest connected component in each *Word Translation Network*. The values in parentheses show the actual number of nodes in the largest component and the total number of nodes in the network. From this table, it is evident that for most language pairs and parts of speech, more than half of the words are part of the same connected network, indicating a high degree of connectivity.

Next, Figure 6 presents the degree distribution of each *Word Translation Network*. The data points tend to align linearly on a logarithmic plot, suggesting that the degree distribution follows a power-law, which is characteristic of scale-free networks. This observation implies that a few nodes act as hubs, connecting a large number of other nodes, while most nodes have relatively few connections.

Table 4 provides the bipartite clustering coefficients for each *Word Translation Network*. Since the conventional clustering coefficient would yield

Table 3: The proportion of nodes in the largest connected component. The values in parentheses indicate the number of nodes in the largest component and the total number of nodes.

	Adjective	Adverb	Noun	Verb
De-En	0.592 (4,460/7,538)	0.855 (627/733)	0.569 (17,744/31,159)	0.877 (5,872/6,696)
En-Es	0.272 (3,021/11,103)	0.639 (679/1,063)	0.543 (14,458/26,631)	0.748 (7,093/9,480)
En-Fr	0.416 (4,218/10,133)	0.713 (917/1,286)	0.522 (16,769/32,109)	0.773 (5,843/7,561)
En-Ja	0.664 (3,262/4,909)	0.895 (649/725)	0.475 (19,812/41,704)	0.867 (7,643/8,820)
En-Ko	0.651 (164/252)	0.767 (394/514)	0.521 (8,229/15,784)	0.786 (1,137/1,446)
En-Zh	0.622 (2,499/4,020)	0.844 (146/173)	0.685 (9,435/13,776)	0.901 (4,508/5,006)
Fr-Ja	0.671 (1,778/2,649)	0.970 (460/474)	0.614 (11,702/19,067)	0.872 (4,177/4,788)

Table 4: The bipartite clustering coefficient (Latapy et al., 2008) in *Word Translation Network* (approximated). The values in parentheses indicate those in a random network with the same number of nodes and edges.

	Adjective	Adverb	Noun	Verb
De-En	0.28 (0.22 $\pm$ 0.01)	0.28 (0.18 $\pm$ 0.01)	0.26 (0.23 $\pm$ 0.02)	0.25 (0.17 $\pm$ 0.00)
En-Es	0.32 (0.25 $\pm$ 0.02)	0.29 (0.21 $\pm$ 0.01)	0.32 (0.23 $\pm$ 0.01)	0.40 (0.21 $\pm$ 0.00)
En-Fr	0.30 (0.24 $\pm$ 0.02)	0.29 (0.21 $\pm$ 0.00)	0.24 (0.25 $\pm$ 0.02)	0.21 (0.19 $\pm$ 0.01)
En-Ja	0.30 (0.23 $\pm$ 0.01)	0.26 (0.19 $\pm$ 0.01)	0.29 (0.25 $\pm$ 0.01)	0.26 (0.19 $\pm$ 0.01)
En-Ko	0.41 (0.28 $\pm$ 0.03)	0.29 (0.21 $\pm$ 0.01)	0.23 (0.24 $\pm$ 0.01)	0.28 (0.20 $\pm$ 0.00)
En-Zh	0.25 (0.22 $\pm$ 0.01)	0.31 (0.23 $\pm$ 0.01)	0.24 (0.20 $\pm$ 0.01)	0.21 (0.14 $\pm$ 0.00)
Fr-Ja	0.32 (0.22 $\pm$ 0.01)	0.23 (0.13 $\pm$ 0.00)	0.34 (0.23 $\pm$ 0.01)	0.28 (0.18 $\pm$ 0.00)

Table 5: The average shortest path length in the largest connected component of each *Word Translation Network* (approximated). The values in parentheses indicate those in a random network with the same number of nodes and edges.

	Adjective	Adverb	Noun	Verb
De-En	11.67 (11.05 $\pm$ 0.16)	6.92 (6.25 $\pm$ 0.17)	11.22 (13.12 $\pm$ 0.12)	7.70 (7.64 $\pm$ 0.07)
En-Es	13.13 (15.70 $\pm$ 0.30)	8.62 (8.01 $\pm$ 0.21)	12.54 (14.28 $\pm$ 0.15)	9.42 (9.24 $\pm$ 0.15)
En-Fr	12.61 (13.92 $\pm$ 0.45)	9.04 (7.69 $\pm$ 0.20)	11.35 (14.49 $\pm$ 0.30)	8.50 (8.61 $\pm$ 0.09)
En-Ja	9.51 (9.92 $\pm$ 0.20)	6.89 (6.12 $\pm$ 0.12)	12.79 (15.66 $\pm$ 0.20)	8.76 (8.44 $\pm$ 0.09)
En-Ko	5.51 (6.50 $\pm$ 0.45)	6.78 (6.64 $\pm$ 0.20)	10.64 (13.86 $\pm$ 0.24)	6.54 (6.97 $\pm$ 0.13)
En-Zh	7.78 (9.15 $\pm$ 0.12)	4.05 (4.36 $\pm$ 0.21)	7.94 (9.63 $\pm$ 0.11)	6.30 (6.39 $\pm$ 0.04)
Fr-Ja	8.91 (8.77 $\pm$ 0.14)	5.05 (4.39 $\pm$ 0.05)	11.62 (11.24 $\pm$ 0.10)	7.28 (7.11 $\pm$ 0.07)

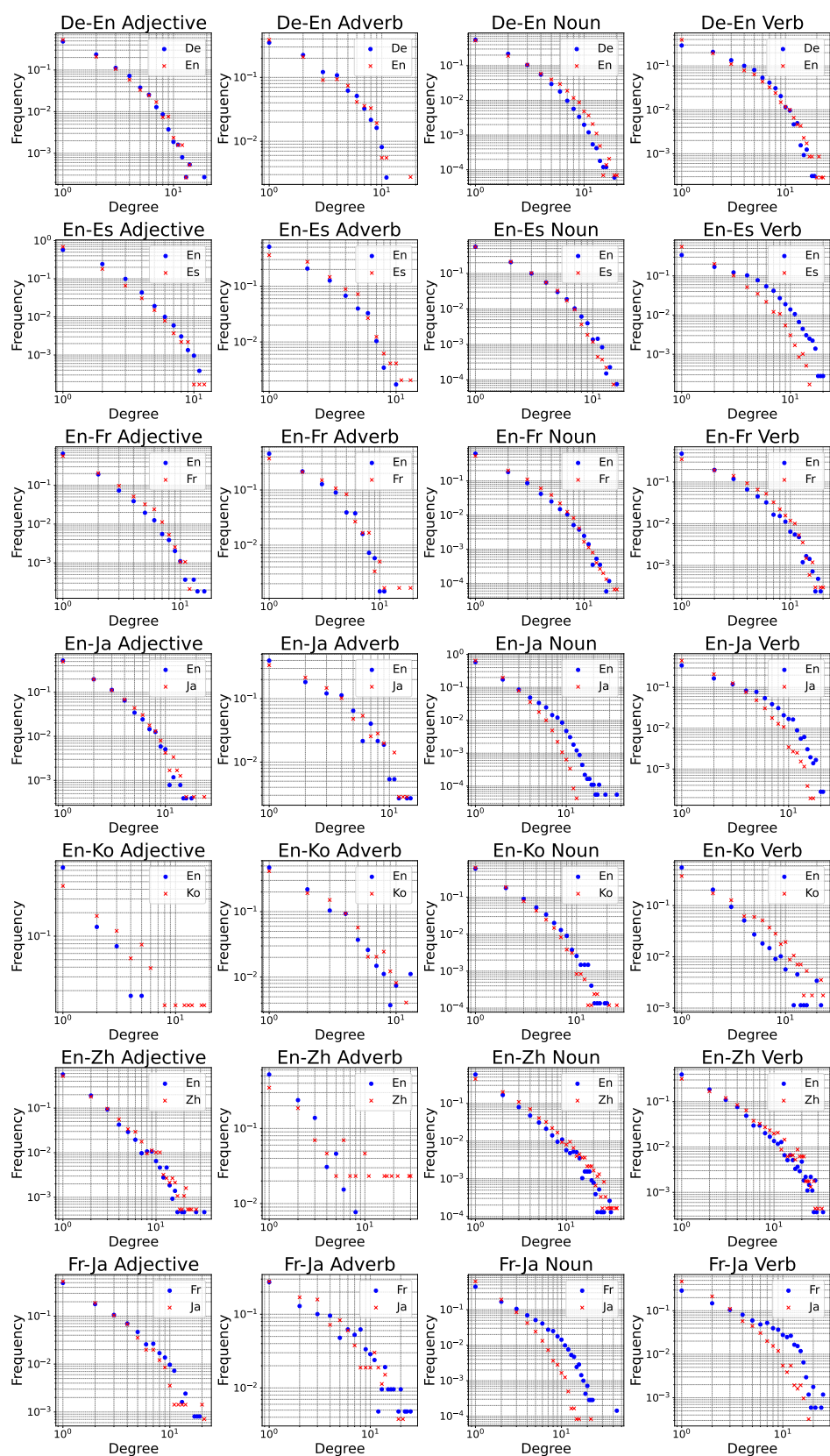


Figure 6: Degree distribution of each *Word Translation Network*.

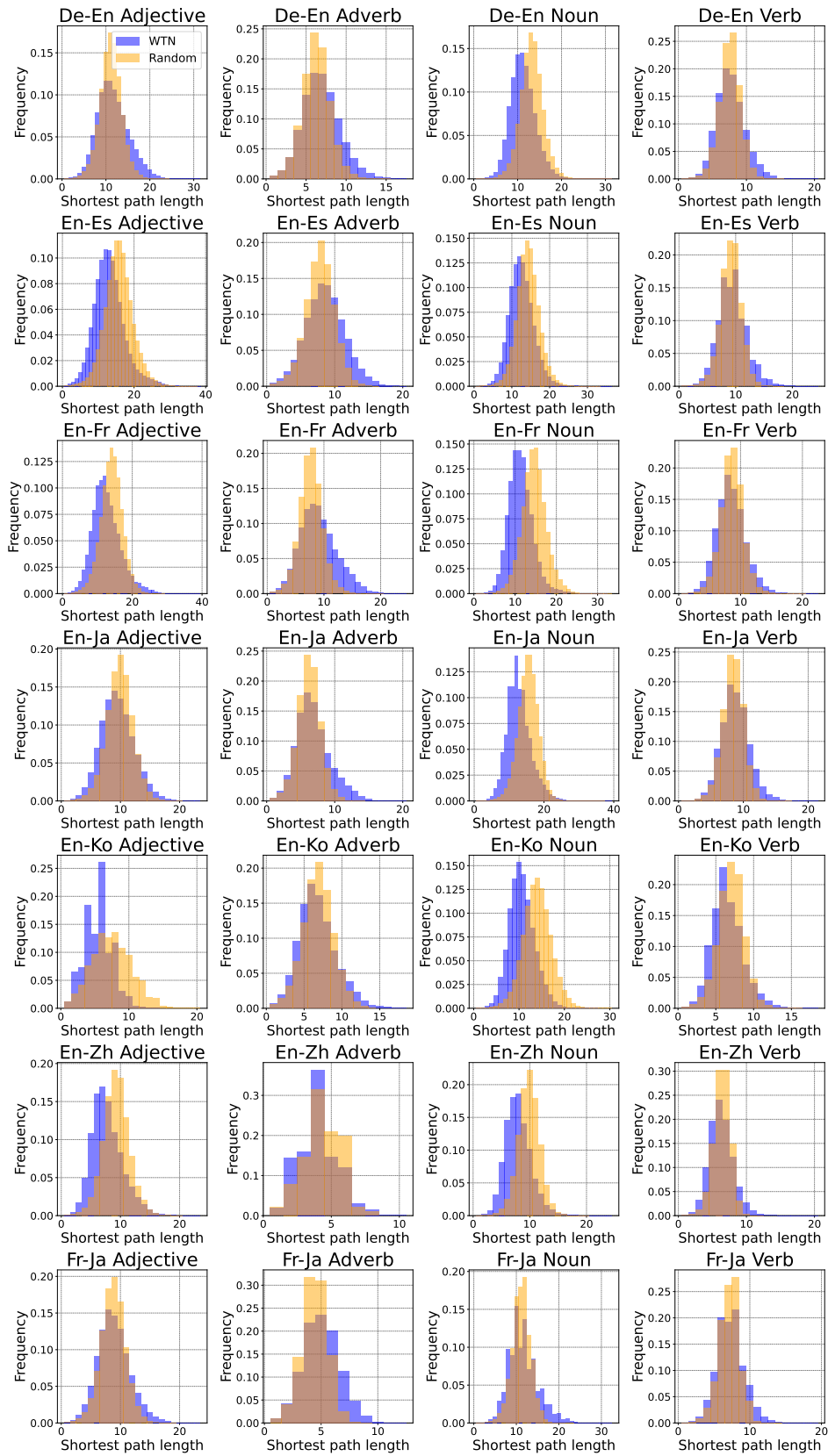


Figure 7: Distribution of shortest path lengths in the largest connected components of each *Word Translation Network* (approximated).

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**Algorithm 1** Word addition/deletion to  $\mathcal{W}$ 

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1: Algorithms:
2: AVERAGECOORDINATE( $w$ ) :
3:   returns the (weighted) average coordinates of the words connected to  $w$ .
4:
5:  $\mathcal{W}_{\text{par}} \leftarrow \{w \mid \|\mathbf{x}_w\|_2 \leq R_{\text{par}}\}$  ▷ Define “parent” words
6:  $\mathcal{C} \leftarrow \{w \in \mathcal{W}_{\text{all}} \mid \exists p \in \mathcal{W}_{\text{par}} \text{ s.t. } c_{w,p} > 0\} \setminus \mathcal{W}$  ▷ Candidate words to add
7:  $c \leftarrow \operatorname{argmin}_{w \in \mathcal{C}} \|\text{AVERAGECOORDINATE}(w)\|$ 
8:  $\mathcal{W} \leftarrow \mathcal{W} \cup \{c\}$  ▷ Add the candidate closest to the center
9:  $\mathcal{W}_{\text{child}} \leftarrow \{w \in \mathcal{W} \mid \exists p \in \mathcal{W}_{\text{par}} \text{ s.t. } c_{w,p} > 0\}$ 
10:  $\mathcal{W} \leftarrow \mathcal{W} \cap (\mathcal{W}_{\text{par}} \cup \mathcal{W}_{\text{child}})$  ▷ Delete “non-parents” not connected to “parents”
11: while  $|\mathcal{W}| > N_{\text{max}}$ 
12:    $f \leftarrow \operatorname{argmax}_{w \in \mathcal{W}} \|\mathbf{x}_w\|_2$ 
13:    $\mathcal{W} \leftarrow \mathcal{W} \setminus \{f\}$  ▷ Delete off-center words to satisfy  $N_{\text{max}}$  condition
```

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a value of zero for bipartite graphs, we use a clustering coefficient specifically designed for bipartite networks (Latapy et al., 2008). For computational efficiency, we approximate this value by averaging the clustering coefficients of a random sample of 100 nodes. The table also shows the average clustering coefficient for 10 randomly generated bipartite networks with the same number of nodes and edges. Notably, the clustering coefficient of the *Word Translation Network* is consistently higher than that of the random bipartite networks. This suggests that words in the *Word Translation Network* tend to form tightly connected clusters, a hallmark of small-world networks.

Table 5 summarizes the average shortest path length in the largest connected component of each *Word Translation Network*, with corresponding values for random bipartite networks. Figure 7 shows the distribution of shortest path lengths. The shortest path lengths of the *Word Translation Networks* tend to be as short as, or shorter than, those of the random networks, further supporting the idea that these networks exhibit small-world properties (Watts and Strogatz, 1998). This indicates that, on average, words are more closely related to each other in translation networks than would be expected by chance.

In conclusion, the detailed analysis of the *Word Translation Network* reveals several key structural properties: the network is scale-free, exhibits small-world characteristics, and forms clusters more densely than random bipartite graphs. These findings provide valuable insights into the organization and efficiency of word translations between languages.