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Master Computer Science

Analyzing human navigation using network-based games

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Abstract

This thesis examines human path traversal in complex networks, aiming to understand the impact of individual characteristics on path selection. Today, navigating digital information spaces is an essential part of our lives and it is essential that we understand the way humans navigate such systems. We have created a network-based game using a large network of synonyms which participants are asked to traverse to find a given word. We give an in-depth breakdown on the navigational patterns humans prefer and the impact of personal characteristics on path selection. Firstly, we found people tend to choose words with a higher degree, simplicity score and centrality values in favor of their lower valued counterparts. Furthermore, we found people choose high-degree words in the early stages of a game, while they navigate through low-degree nodes at the end. Moreover, we found that personal characteristics may play a role in human path selection when playing our game. Females exclusively choose higher valued words for all node properties than males do. The same is true for people with a master degree compared to other levels of education. Finally, we found that the self-proclaimed level of English fluency does not appear to have an impact on path selection.

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1 Introduction

Human navigation is one of the most fundamental goal-directed behaviors relevant to humans and has been a topic of interest for a quite some time now. Physical navigation has been studied extensively [1], though with the rising need to navigate information networks, such as the internet, navigational spaces have also become digital. Today, navigating digital information spaces is an essential part of our lives and to be able to design efficient information systems, it is essential that we understand the way humans navigate such systems and find the information they are looking for. One avenue for studying this line of research is the use of network-based games. One game that is often used is the *Wikipedia Game*. For example, a 2012 study by West and Leskovec [2] identified strategies people use when navigating information spaces and a 2014 study by Takes and Kosters [3] looked at the difficulty of paths in information spaces. Furthermore, Iyengar et al. [4] created a simplistic word-morph game to study how people learn and adapt new navigational strategies. However, path selection and the impact individual characteristics have on said selection have not been studied in-depth.

In this work, we build upon this existing body research by creating a network-based game called Synonymous. First, we provide the network the game is build upon and its associated properties. Afterwards, we use the network properties to analyze the paths the participants traversed when playing the game and we provide the results.

The foundation of Synonymous is a large complex network of English words. Within the network, words are connected when they are synonyms, e.g., **angry** and **mad** are connected but **angry** and **support** are not. When playing Synonymous the participants are given a *start word* and an *end word*. The goal of the game is to find the end word by traversing the network of synonyms, starting from the start word. A step from one word to another can only be taken when the words are connected, thus when they are synonyms. The participant should choose the synonym that they think will bring them closer to their end word, i.e. a word that is most likely to be a synonyms of, or has synonyms that are more likely to be a synonym of the end word.

Analyzing node properties of the individual steps along the paths provided us with valuable insights about path selection. Furthermore, the participants provided us with data about their personal characteristics, like their age, gender and level of education, allowing us to identify how personal characteristics may have an impact on the way we people navigate information spaces. Moreover, analyzing the network of synonyms itself provided us with useful insights about the structure of the network and the properties of the words within it. For example, the relation between the number of synonyms a word has and its perceived simplicity.

We found that people tend to choose words with a high number of synonyms when starting the game. When nearing to the end word, they tend choose more specific words with a lower degree. Humans also tend to choose simpler words more often than harder words. Furthermore, we observed that females exclusive chose simpler words with higher degrees. Finally, we found that the self-proclaimed level of English fluency is no indicator for how quickly participants completed the game.

This thesis is structured as follows: Section 2 discusses the previous work this thesis builds upon and Section 3 explains the Synonymous game and how we set up the experiments. In Section 4 the network and the network properties are analyzed and in Section 5 the results from the experiments are provided and discussed. Finally, in Section 6 we summarize our results and provide the scope for further research.

2 Related Work

In this section, we will cover the state-of-the-art work in the field of understanding complex network navigation. We will discuss the previous work upon which our research builds with the goal of giving the reader more insight about the context in which our work exists.

When discussing networks such as social or information networks, one almost exclusively talks about *complex networks*. We define a complex network as a set of nodes and links with non-trivial topological properties and they often occur in networks representing real systems, such as social or information networks. A study by Watts and Strogatz [5] showed that most real-world networks are *small world* networks. Small world networks have small average path lengths between any two nodes within the network, that is, any node within the network is reachable in only a few steps. Nodes in small-world networks also tend to form tight-knit groups, or clusters, where there are many interconnections. This is seen in social networks where friends of friends are often also friends, resulting in locally dense connections. A famous experiment by Milgram [6] verified the existence of the aforementioned small distances. Participants were asked to send a letter to an unknown recipient that did not live close by. They had to send the letter to an acquaintance, one they thought would get the letter closer to the intended unknown recipient. They found that any two people on earth are only, on average, separated by six steps. This phenomenon is called *six degrees of separation*, where any two nodes within a small world network have a shortest path length of 6, on average [7]. The results of study were reproduced in 2003 in a similar study using emails [8]. Furthermore, Kleinberg [9] noted that humans are able to find these short paths even though they know very little about the target node or the network. Simsek and Jensen [10] identify two network characteristics that can guide navigation; homophily and degree. Homophily describes the tendency of attributes of connected nodes to be correlated and degree describes the presence of high-degree nodes within the network, also known as hubs. When linking this back to the real-world experiment by Milgram [6], people tend to know people who work in similar fields or live in the same city (homophily) and those people tend to know someone with a broad network (high-degree). A 2012 study by West and Leskovec [2] asked participants to navigate from one Wikipedia article page to another along a chain of hyperlinks on the Wikipedia articles they visited, a game called the *Wikipedia Game*. They found that people tend to navigate through high-degree hubs in the early stages, while they search for contextual similarities in later stages. In 2014, Takes and Kosters [3] identified measurements for the difficulty of a path in the Wikipedia Game when looking at both local and global difficulty measures. For local difficulty measures they found that the outdegree of the starting article does not appear to play a very significant role, whereas the indegree of the goal article is of great influence to the difficulty of finding a certain path. Furthermore, for global difficulty measures they found the distance between the starting and goal article to be a good measure of difficulty. When studying the same Wikipedia Game, Zhu and Kartész [11] found that people navigate to the target article using two routes; geographical routes where they navigate through articles related to countries or cities, and occupational routes where they navigate through articles related to similar occupations like science, art or sports.

Iyengar et al. [4] created a simple word game that presents a well-defined navigation problem in a complex network: Given two words of the same length, the participants were asked to find a sequence of words such that each next word in the sequence differs only one letter from the previous word. They concluded that when people must navigate a network without any geographical information, nor any notion of meaningful homophily between the nodes that they navigate through *landmarks*. Such landmarks are shown to have a central position in complex networks which leads to a direct correlation between such a structure and human navigation. Individual characteristics have also shown to impact network navigation. Zhu, Yassari and Kertész [12] concluded that age negatively impacts knowledge space navigation, while multilingualism enhances it. Furthermore, they concluded that under time pressure male participants outperformed female participants, an effect not observed without time pressure.

3 Synomymous game design

In this section, we will discuss the development process of the Synonymous game and the dataset that was used to during the process. Moreover, we introduce the database tables that store the participants data and the data from the played games. Finally, we will provide an example of what a game of Synonymous looks like for the participants.

3.1 Developing a network-based game

Synonymous is developed in Visual Studio [13] and uses the ASP.NET Core framework by Microsoft [14]. The dataset is stored in an SQL-database and is managed using Microsoft SQL Server Management Studio [15]. First, the development direction was that of an actual application (an executable file). However, after completing the first prototype it became clear that such an executable file would be hard to distribute, and thus hard to gather data with. Therefore, we switched to the ASP.NET Core framework which allows for web-development in Microsoft's C# programming language [16].

3.2 Synonymous dataset & data gathering

The SQL-database consists of four tables that are depicted in Figure 1. The *Synonyms* table is used to store the words and their synonyms. Every synonym of a word is in turn a foreign key to a word itself, with its own synonyms. This table is the foundation of the Synonymous network. The *Definitions* table stores all definitions for a word. The *Users* table is used to store data that the participants enter before playing Synonymous. They are asked to provide their gender, age, country of birth and their highest level of education. Furthermore, we asked the participants to truthfully give an indication of their level of English fluency, ranging from very bad to excellent. The *Games* table is used to store real-time data about the games being played. The start, current and end word, the time it took and the path taken to complete the game are all stored here.

The biggest part of the experiment was conducted in a controlled environment, namely the classrooms of Universities. Professors were asked to give their students some time to play the game, providing no specific instruction besides entering their personal details truthfully. A small part of the experiment was conducted uncontrolled: We shared the game with friends and family who could register themselves and play, and potentially share the game with other people.

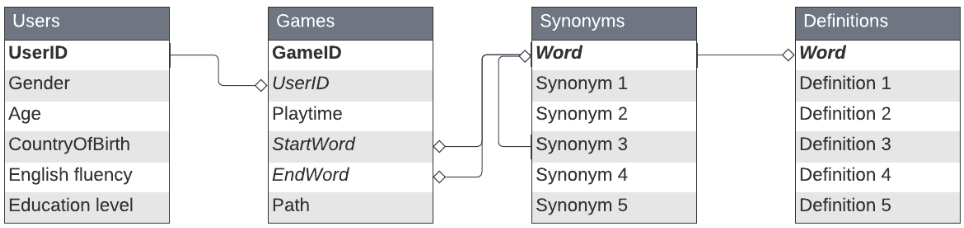

Figure 1: Data structure for the Synonymous dataset.

3.3 Playing Synonymous

As stated in Section 1, the goal while playing Synonymous is to navigate through a network of synonyms in order to reach the *end word* from a *start word*. A step from one word to another can only be taken if the words are connected (i.e. neighbors), meaning they are synonyms. Because of this the game only displays the words that are synonyms to your current word, and you can select one to 'move' to that word. An example game is depicted in Figure 2, with the start word **channel** and the end word **repair**. When the game starts, the synonyms of **channel** are displayed and one can be chosen. If the participant is unsure what the definitions of a word are, the word can be hovered to reveal multiple definitions (shown by hovering **pipe** in Figure 2). The synonym **pipe** is selected and the game is moved to a next screen, where the synonyms of **pipe** are shown (Figure 3). This process continues with the goal of finding a word that is a synonym of the end word **repair**. This is achieved in Figure reffig:end when **patch** is selected, in turn revealing the word **repair** (Figure 4). When the end word is selected the participant is shown their completion time, how many games they have completed and their fastest completion time so far. Finally, they are offered to play another round of Synonymous.

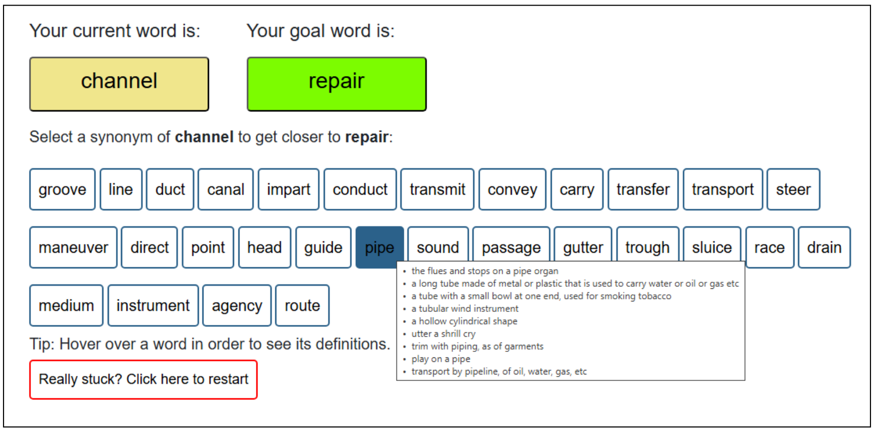

Figure 2: Start screen of the Synonymous game.

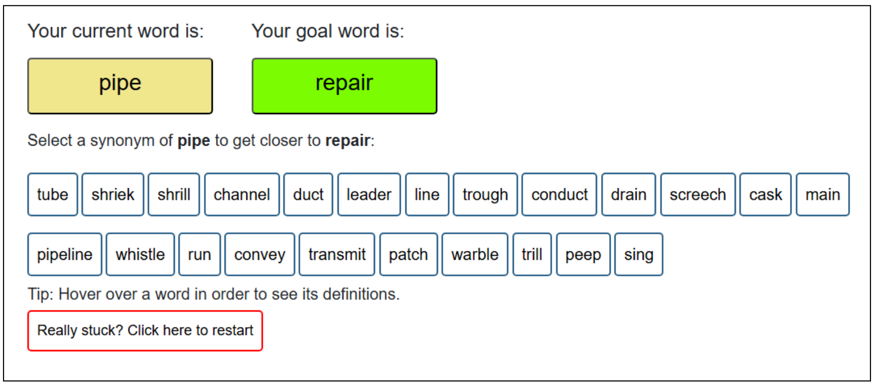

Figure 3: The next screen after selecting the synonym **pipe**.

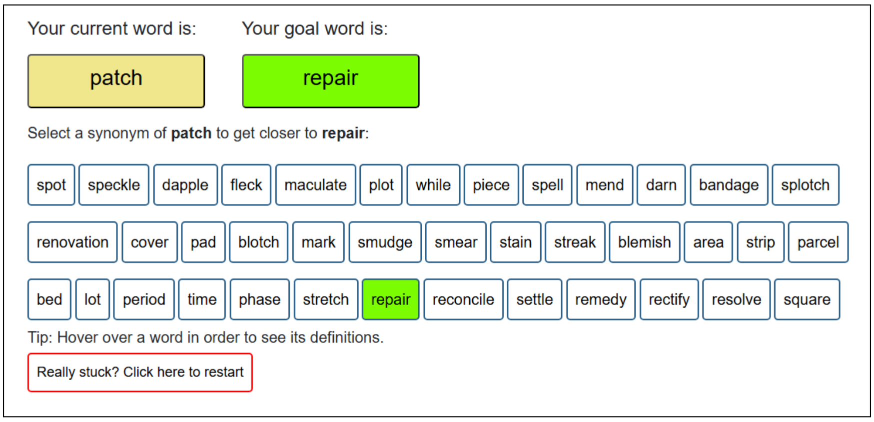

Figure 4: The screen after selecting a synonym to the *end word*.

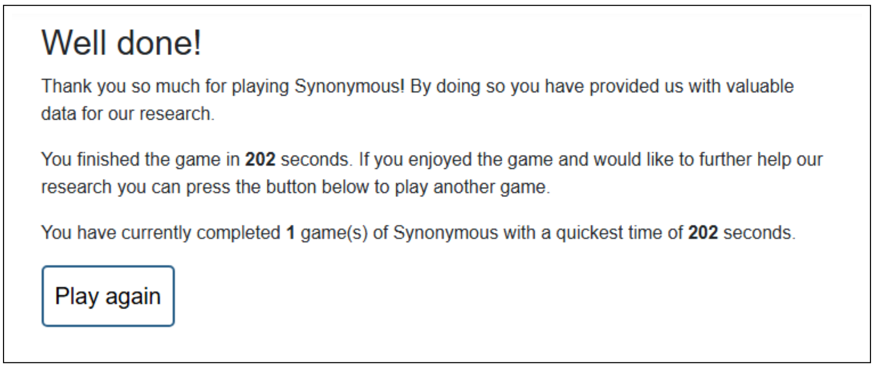

Figure 5: Completion screen after finishing a Synonymous game.

4 Network analysis of the Synonymous dataset

Network analysis has provided useful insights to understand various different types of complex networks, including different types of social networks [17, 18], social media networks [19, 20], collaboration networks [21, 22], bank transaction networks [23], terrorist networks [24], criminal networks [25] and dark networks [26, 27]. In this section, we will analyze the dataset that is the foundation of the Synonymous game. We will first provide preliminaries to provide sufficient background knowledge about networks and their properties. Next, we will analyze the Synonymous dataset and discuss the results.

4.1 Preliminaries: Network properties

A network graph is an ordered pair $G = (V, E)$ composed of a set vertices V and a set of edges E, which are the links between two distinct vertices in V. The *degree* of a node is defined by the number of edges connected to it. The neighborhood of node u is defined as the set of nodes that u shares an edge with. The degree centrality is the first basic property to analyze in a network [28]. A *path* between nodes u and v (with $u, v \in V$) is a sequence of nodes $(u, x_1, ..., x_{k-1}, v)$. A path can also be represented using the traversed edges $(e_1, e_2, ..., e_k)$ with $e_1 = (u, x_1)$ and $e_k = (x_{k-1}, v)$. The length of a path is defined by the number of edges in the path. A path between two nodes is called a *shortest path* if all other paths between between them are of greater or equal length. The length of a shortest path between nodes u and v is also known as the *distance*, denoted as $d(u, v)$. The *clustering coefficient* of a node in a graph measures how connected the node's neighbors are to each other [29]. It is the ratio of the number of actual connections between a node's neighbors to the number of possible connections between them.

Centrality functions are real-valued functions that assign numbers or rankings to nodes within a graph corresponding to their network position [30, 31]. The higher the centrality value, the more central the node. The first centrality measure used in this thesis is *closeness*. The closeness centrality of a node is the average length of the shortest path between the node and all other nodes in the graph [32, 33]. Thus, the closer to the node is to all the other nodes, the more central it is. The closeness centrality $C_C(v)$ of a node v is given by:

$$C_C(v) = \frac{n-1}{\sum_{u \neq v} d(v, u)}$$

where n is $|V|$.

The second centrality measure is *betweenness*. The betweenness centrality of a node is a quantification of how many times the node acts as a bridge along the shortest path between two other nodes [34]. The betweenness centrality $C_B(v)$ of a node v is given by the formula:

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

where:

- σ_{st} is the total number of shortest paths from node s to node t,
- $\sigma_{st}(v)$ is the number of those shortest paths that pass through node v,
- $u, s, t \in V$

pagerank is a measurement that ranks nodes in a graph based on the importance of its neighbors [35]. A node's importance is determined by the number and quality of incoming edges from other nodes, with higher-ranked nodes passing more influence.

The *k-core* of a graph is a subgraph in which every node has at least k connections (degree) to other nodes within the subgraph. It is obtained by recursively removing all nodes with fewer than k edges until no such nodes remain [36]. The k-core number of a node is the largest k-core subgraph the node belongs to. It tells how central a node is in the given network [37].

Furthermore, we estimated the simplicity of a word in our network. A frequency list of the one million most commonly used words within a corpus was composed by Hermit Dave [38] and every word in the Synonymous network received a *simplicity score* based on their ranking in this list. The 36 words that were not contained in the list received a simplicity score of 0. Due to the high variation in frequency scores of the words the simplicity scores are normalized in a Gaussian-like manner.

Finally, *community detection* is crucial in real-world networks because it helps uncover the structure and function of complex systems. Communities are groups of nodes in a network that are more densely connected to each other than to the rest of the network [39]. To partition the network into communities we used the Leiden community detection algorithm by Traag et al. [40]. The algorithm guarantees that communities are well connected and is partly based on the Louvain algorithm [41]. When partitioning a network into communities a *modularity score* is assigned to the partitions. This score is a measure of the strength of division in a network, it quantifies how well nodes within the same community are connected compared to nodes in different communities [42]. A negative modularity score indicates the division is worse than random, and a modularity score close to 1 suggest highly distinct and densely connected communities with minimal cross-community links. A score between 0.3 and 0.7 is considered "good" in many practical contexts because it strikes a balance between meaningful community structure and the inherent limitations of real-world networks.

4.2 Network analysis

The following section uses the aforementioned definitions to analyze the Synonymous dataset.

4.2.1 Network properties

The fundamental network of Synonymous has 7836 nodes and 87371 edges and every node represents an English word. The network is a connected graph, meaning for every pair of nodes there is a path of vertices that connects them.

The distribution of the shortest path lengths is shown in Figure 6. All shortest paths are of length equal to or shorter than 6, confirming it is a small world network. The degree distribution is depicted in Figure 7 and follows the distribution we expected, many words having a relatively low degree, with little words having a very high degree.

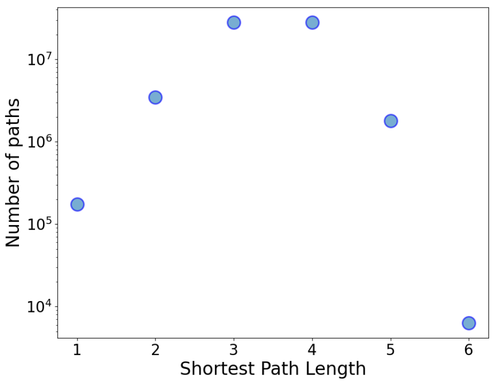

Figure 6: Shortest Path distribution.

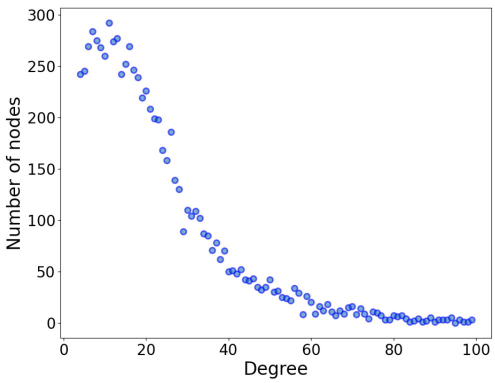

Figure 7: Degree distribution.

The distribution of the closeness centrality is depicted in Figure 8 and follows a normal distribution. More words have an average closeness centrality and are thus relatively close to all other words, whereas fewer words have a low or high closeness centrality and are further away from or closer to all other words, respectively. The distribution for the betweenness centrality is shown in Figure 9 and follow an exponentially decreasing distribution. This implies that many words only occur on a few shortest paths, where as few words occur on many of shortest paths.

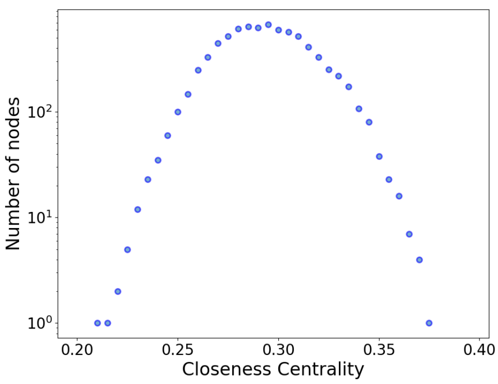

Figure 8: Closeness centrality distribution.

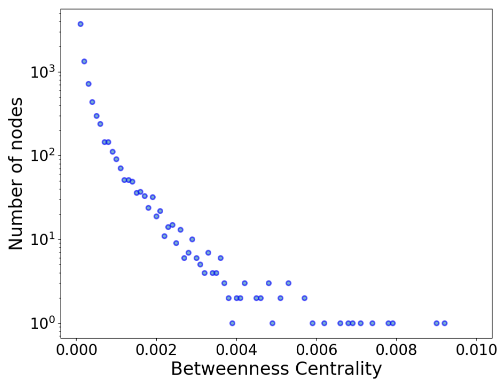

Figure 9: Betweenness centrality distribution.

Figure 10 shows the distribution of clustering coefficient. The number of nodes with high clustering coefficient increases until the clustering coefficient nears 1. This implies that our network is highly clustered, which is to be expected with a network of synonyms. This is due to the high likelihood of neighboring nodes of a word also being synonyms of each other, due to the high similarity in meaning. The pagerank distribution is shown in Figure 11 and follows a Lognormal distribution.

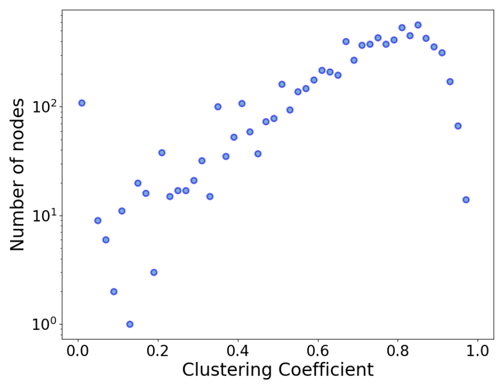

Figure 10: Clustering coefficient distribution.

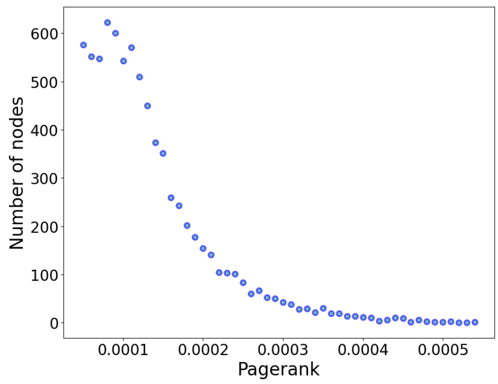

Figure 11: Pagerank distribution.

The distribution for the k-core number is shown in Figure 12. The members of size k steadily increases until $k = 14$, where the members rise to 1968 when $k = 16$. Cores sizes $k = 17$ and $k = 18$ have no member, but $k = 19$ and $k = 20$ do. The distribution of the simplicity score is depicted in Figure 13 and follows the tail-end of a normal distribution. Few words have a high simplicity score, whereas many have a low simplicity score.

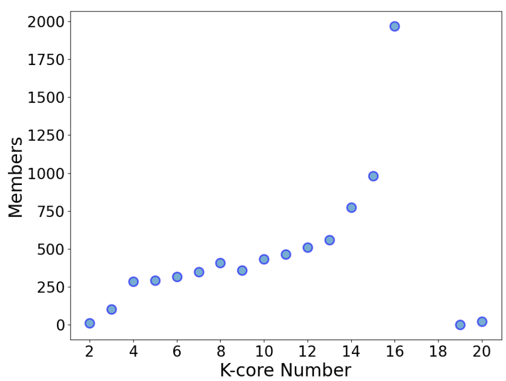

Figure 12: k-core Distribution.

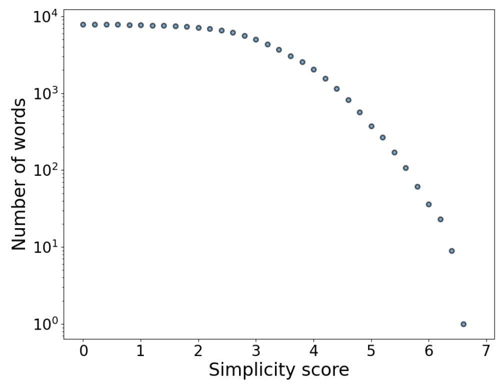

Figure 13: Simplicity score distribution.

4.2.2 Linguistic properties

Because the nodes in the graph represent English words they have linguistic properties, such as what *part of speech* it belongs to. Parts of speech are the fundamental categories of words in grammar, such as nouns, verbs, adjectives, adverbs. The parts of speech distribution is depicted in Figure 14. Nouns make up 65.8% of the words, verbs make up 20.3%, adjectives make up 13.4% and the remaining 0.6% are adverbs.

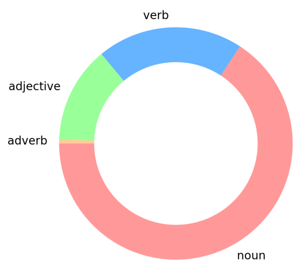

Figure 14: Part of Speech distribution.

4.2.3 Communities

The partitioning of the Synonymous network using the Leiden algorithm is visualized in Figure 15. The partitioning has a modularity score of 0.5, which is a good score for a real-world complex network. Moreover, we used the linguistic properties to identify the basis for the partition to provide us with insights and allow for further analysis. However, we found no relation between the linguistic properties of the words and the partitions. All but one of the communities has close to the same distribution of parts of speech as the entire graph. The average word length over all communities averages between 6.03 and 7.03 with no outliers, and the same is true for the simplicity scores, which is between 3.3 and 3.5. However, average values of non-linguistic properties, such as the closeness and betweenness centrality, do differ between communities. This is to be expected when some communities lay in the center of the graph and other communities lay on the periphery.

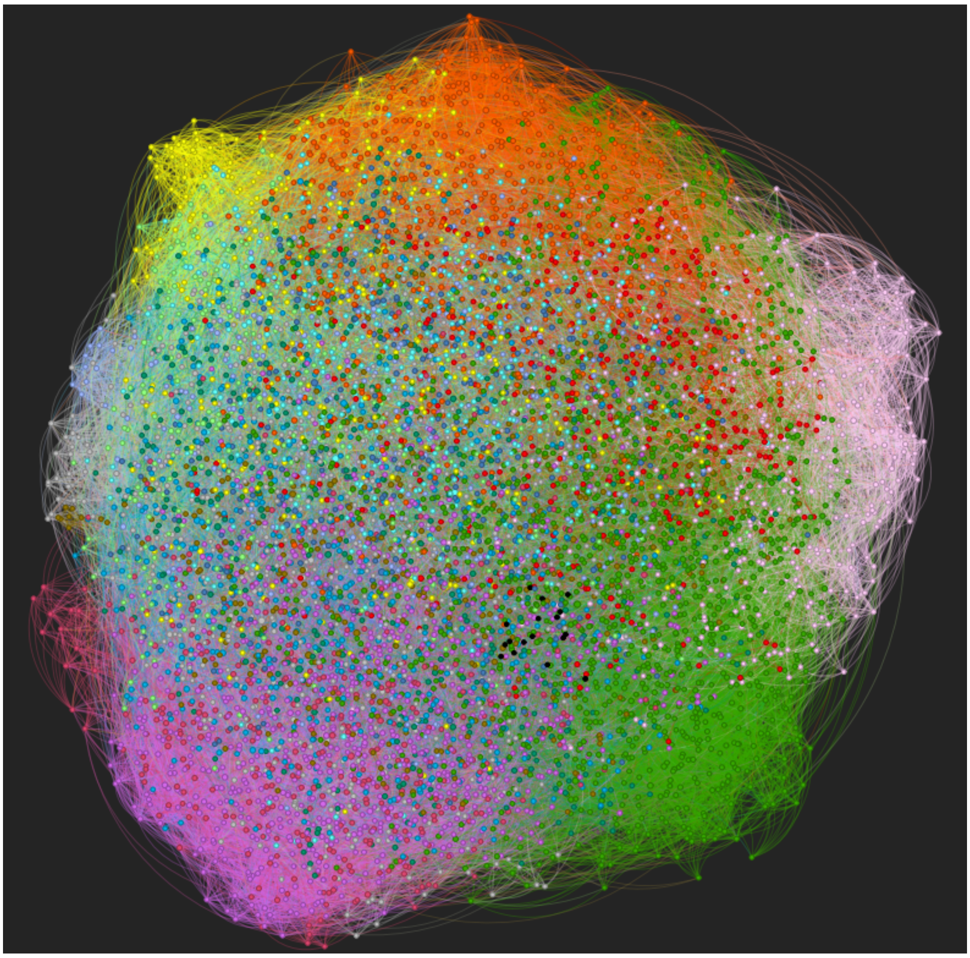

Figure 15: Community partitioning using the Leiden algorithm for G.

5 Results and Discussion

The following section analyzes the data collected while participants played Synonymous. For each game we recorded every step, as well as the completion time and whether or not the participant managed to complete the game. First, we look at relationship between how often a word is chosen and the node properties of that word. Next, we will look at the paths the participants chose to complete the games and finally, we take a look at whether individual differences have an impact on path selection. Table 1 shows the statistics for the recorded games. Participants that completed at least one game of Synonymous are referred to as successful participants in the table.

Total games played	1,179
Total games finished	175
Total participants	165
Successful participants	62

Table 1: Gathered user and game statistics.

5.1 Word simplicity analysis

We first look at correlation between the simplicity score and the other properties introduced in Section 4.2.1 and the results are depicted in the figures below. The degree of the word increases as the simplicity score increases (Figure 16) and this shows that simpler words tend to have more synonyms. The correlation between the clustering coefficient and the simplicity score is less obvious. However, words with a simplicity score over 5 nearly exclusively have a high clustering coefficient (Figure 17). A clear correlation between closeness centrality and the simplicity can be observed (Figure 18) and the same is true for the pagerank (Figure 19). The betweenness centrality also grows with the simplicity score but it does so exponentially (Figure 20).

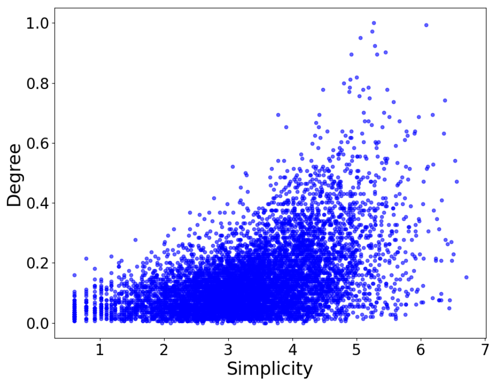

Figure 16: Degree vs. Simplicity score.

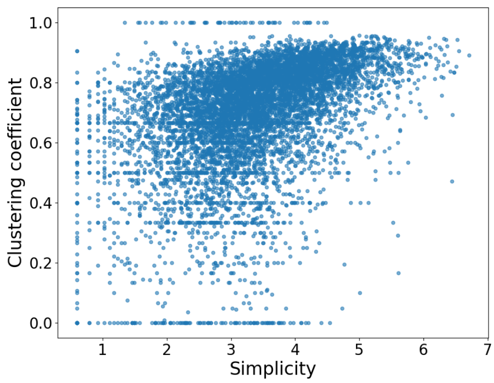

Figure 17: Clustering vs. Simplicity score.

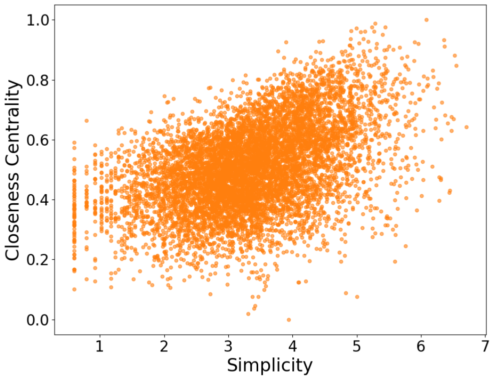

Figure 18: Closeness vs. Simplicity score.

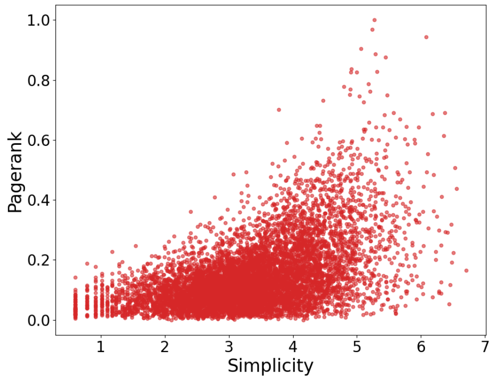

Figure 19: Pagerank vs. Simplicity score.

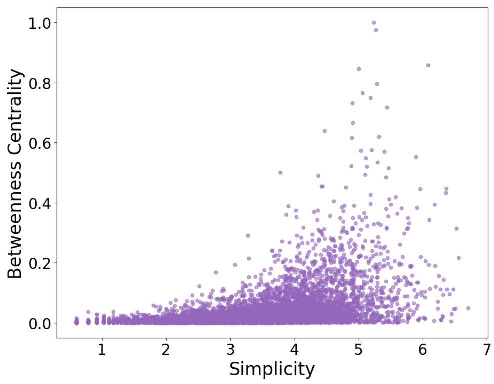

Figure 20: Betweenness vs. Simplicity score.

5.2 Word selection analysis

Of the 7836 words in the Synonymous network only 5285 words were used after 175 games were completed. Depending on how many times the word was used it received a *usage count*, while words that were not used received a usage score of zero. The relation between the usage of a word and the simplicity score is depicted in Figure 21 a correlation can be seen, indicating that humans tend to choose simpler words more often than harder words. Though, this does not imply that the most used words strictly have a high simplicity score. Table 2 ranks the 20 most used words against their simplicity rank. The simplicity rank indicates how they rank among the other 7836 words based on their simplicity. More than half of the words in the table rank among the top 5% to 7% of the simplest words. However, there are exceptions like the 5th most used word **objurgate**, which has a simplicity rank in the bottom 2% of the simplest words.

This observation is different to what Iyengar et al. [4] found as they observed no correlation between the most frequently used words in their experiment and their simplicity. However, this might be due to the differences in game structures.

Usage rank	Word	Usage count	Simplicity rank
1	support	26	571
2	recognition	22	2424
3	cover	22	470
4	end	21	163
5	objurgate	20	7698
6	separate	20	1077
7	control	19	317
8	break	19	241
9	rough	18	922
10	collapse	18	2408
11	whack	18	219
12	start	18	150
13	mark	18	482
14	cut	17	232
15	reveal	17	1487
16	terminate	17	3089
17	hold	17	143
18	acknowledge	17	2365
19	finish	16	393
20	modify	16	4359

Table 2: Comparing word usage and word simplicity.

Moreover, we look at the correlation between the usage of a word with the other properties discussed in Section 4.2. A higher clustering coefficient also seems to indicate a higher usage score (Figure 26). The same holds true for the closeness centrality of a word; words that get used more often tend to have higher closeness centrality (Figure 24). However, the opposite is true for the relation between the the betweenness centrality and the usage (Figure 23), the usage of a word seems to negatively correlated. The relation between the pagerank and the usage score is similar to that of the degree. Both do generally increase when the usage score increases, however, when looking at Figure 25 and 22 this correlation is not really evident. The similarity of degree and pagerank can also be observed in Figure 16 and 19, concluding that both properties follow the same laws. A study on this phenomenon by Litvak et al. [43] supports this notion. They found that the tail distributions of pagerank and indegree differ only by a multiplicative constant.

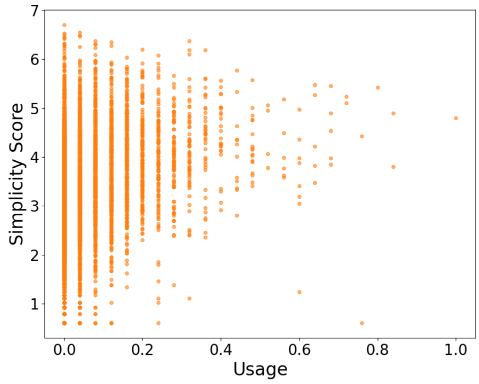

Figure 21: Simplicity score vs. Usage.

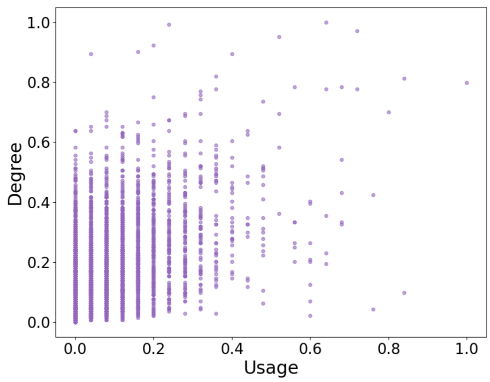

Figure 22: Degree vs. Usage.

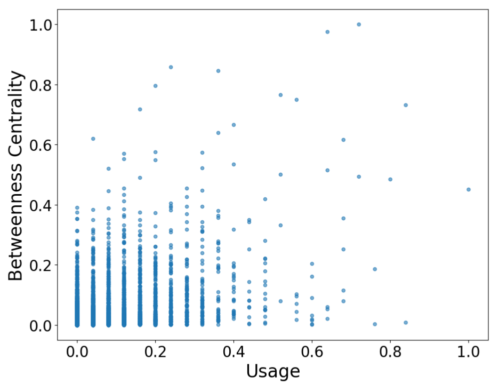

Figure 23: Betweenness vs. Usage.

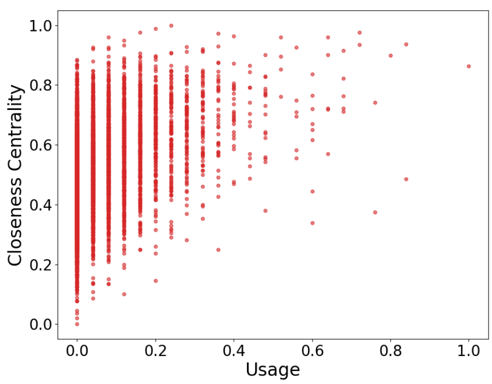

Figure 24: Closeness vs. Usage.

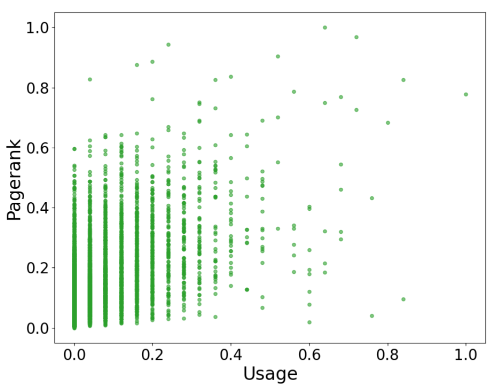

Figure 25: Pagerank vs. Usage.

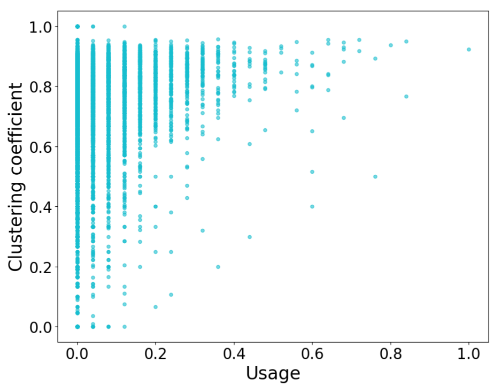

Figure 26: Clustering vs. Usage.

5.3 Path selection analysis

Looking at the paths participants chose to navigate the network provides valuable insight into human navigation. For every completed game, we compared the actual path length taken by users with the shortest path between the start word and end word. The results are depicted in Figure 27 and show us that for paths of length 2 and 3 some participants found the shortest paths. However, no participants found the shortest path when the game required a minimum of 4 or 5 steps to be taken. The chances of selecting the correct step once, twice or three times in a row are far more likely than selecting the correct step 4 or 5 times in a row. Games with a shortest path length of 1 should always end after one step, after all the participant can directly select the end word. Though, some outliers finished in 3 steps by first going to another synonym, then going back and finally selecting the end word.

We can also observe that the maximum path length taken by users for the games of shortest path length 4 and 5 is comparatively lower. One reason is that there were less games played with paths with a shortest distance of 5 as the nodes are selected uniformly at random. As seen in the distribution in Figure 6, fewer shortest paths of length 5 exist. Another reason might be that the paths with a higher shortest distance are on periphery of the network and if the participants reach the corresponding community, they might find the actual word. However, an in-depth analysis is required to better understand this phenomenon.

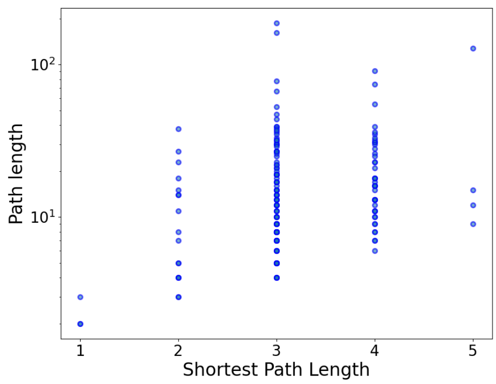

Figure 27: Shortest possible path compared to taken path length.

In order to study the patterns humans use to navigate complex networks, we analyze every individual step taken by participants in a game. Analyzing individual steps gives insight into navigational preferences, e.g., whether humans prefer to move from high degree nodes to low degree nodes and do they start by with selecting simpler words or directly choose for harder words. The results can be observed in Figures 28 through 33. The figures show the average value per step over every game, for games with a path length up to 70. We omitted the games with path length greater than 70 due to the low quantity of games.

For every property there seems to be a minimum halfway through the game, especially for the degree an closeness centrality. This is consistent with the notion of *center-strategicness* introduced by Iyengar et al. [4]. They found that a strategy with one minimum was superior than strategies with more minima. However, this minimum is likely not due to strategic decisions but rather because most participants have reached their end word by step 30. This is confirmed by the fact that only 29 of the 175 completed games have a path length over 30.

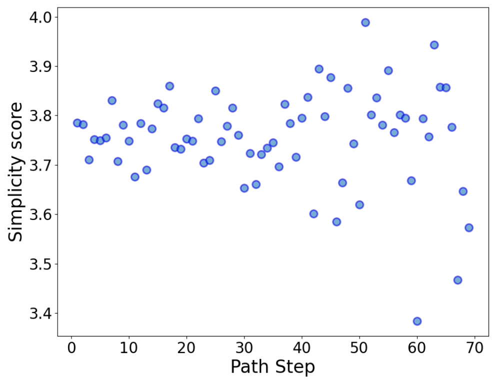

Figure 28: Simplicity score per step.

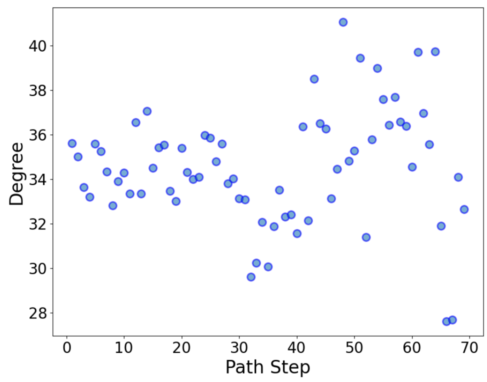

Figure 29: Degree per step.

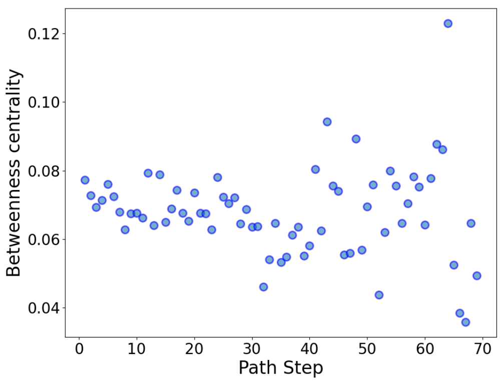

Figure 30: Betweenness centrality per step.

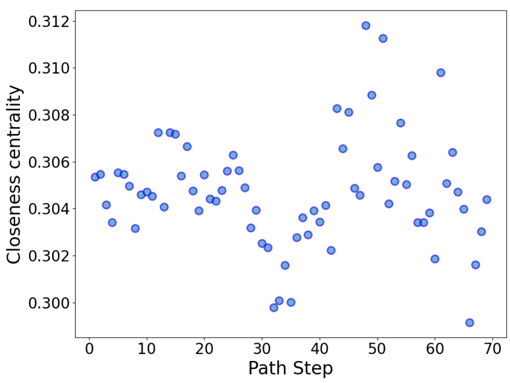

Figure 31: Closeness centrality per step.

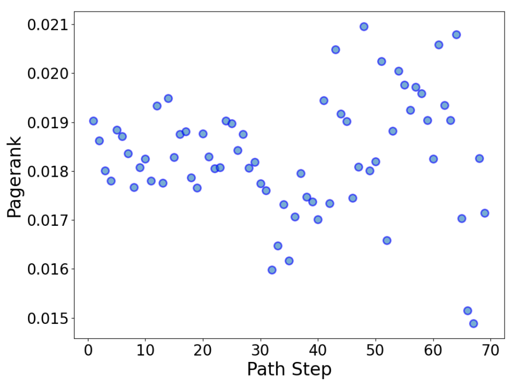

Figure 32: Pagerank per step.

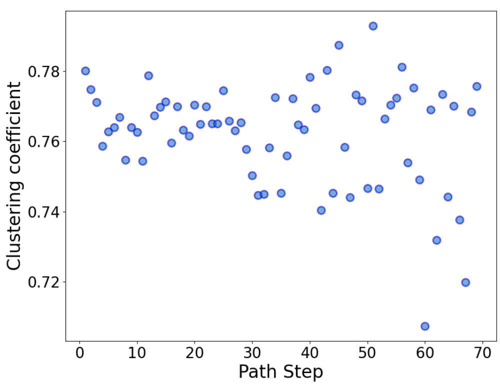

Figure 33: Clustering per step.

Moreover, a game that finishes after 5 steps requires a different strategy to a game that finishes after 30. To make a fairer comparison, figures 34 through 39 show the average value per step for games with an exact path length 30. When observing the figures it is evident that all properties see a drop in value when nearing the end of a game. The study by West and Leskovec [2] found that humans tend to navigate through high-degree hubs in the early stages, while they search for contextual similarities in later stages. The paths taken to complete a game of Synonymous seem to follow a similar trend.

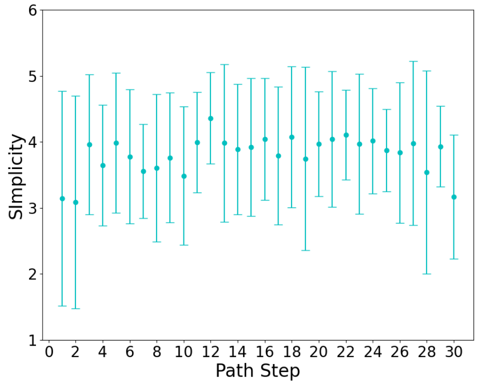

Figure 34: Simplicity for game length 30.

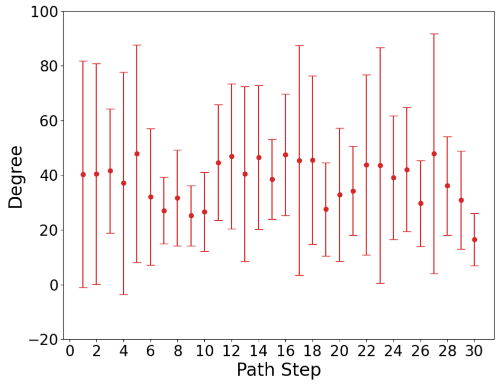

Figure 35: Degree for game length 30.

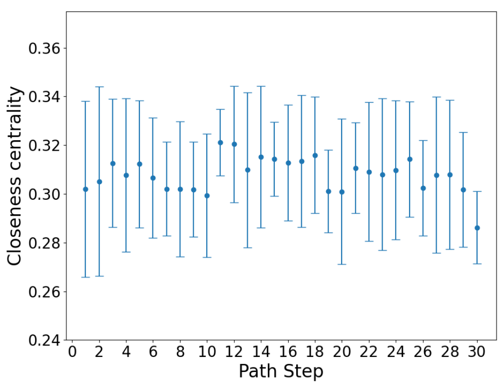

Figure 36: Closeness for game length 30.

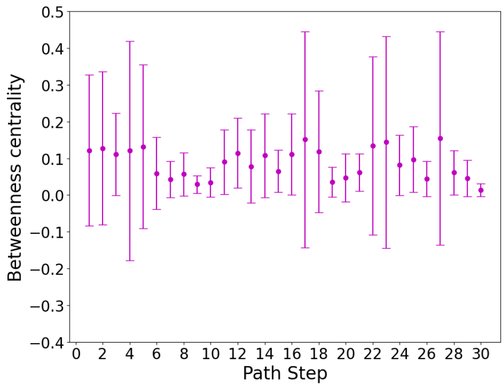

Figure 37: Betweenness for game length 30.

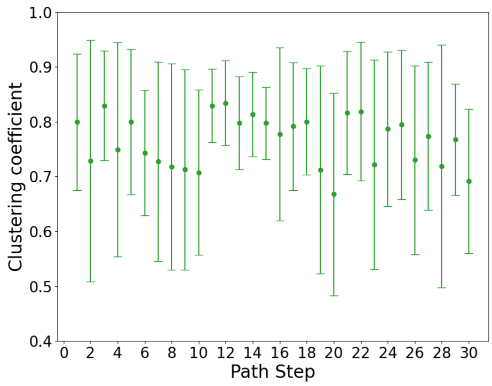

Figure 38: Clustering for game length 30.

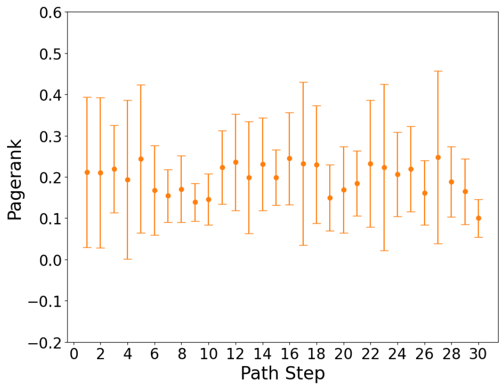

Figure 39: Pagerank for game length 30.

5.4 Path selection with individual characteristics

The following section analyses the differences in path selection when taking individual characteristics into account. The roles that **gender**, the **level of education** and the self-proclaimed level of **English fluency** play will each be discussed in separate sections. The sample size for the following results is limited due to the low number of completed games, thus do not to draw any strong conclusions regarding these groups. The remaining individual characteristics the participants provided us with (age & country of origin) did not have enough variance to perform useful analysis.

5.4.1 Gender

The differences between genders has been a point of interest as their have been contradicting works about learning abilities of different genders. The following section will study whether gender impacts the specific path participants take. The results are shown in Figures 40 to 45 are fascinating. For every single property females, on average, choose words with higher values than males. They choose simpler words and words with a higher degree, closeness centrality, pagerank and clustering coefficient. The difference between males and females when it comes to the betweenness centrality is less significant. This is partly because there is less variance in the betweenness centrality values in the dataset, as depicted in Figure 9 in Section 4.

One notable observation is the increasing difference when the game path length increases. For example, in Figure 41 can be observed that after step 45 females exclusive chose words with an extraordinary high degree, while males did the exact opposite. As mentioned in Section 5.3, only 17% of the games ended after more than 30 steps so there is not much data to do in-depth analysis, still this difference is interesting to note nonetheless.

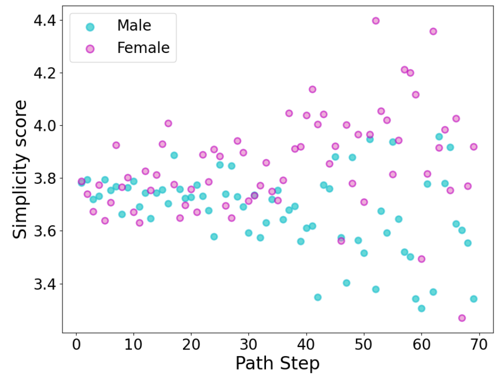

Figure 40: Simplicity score per step per gender.

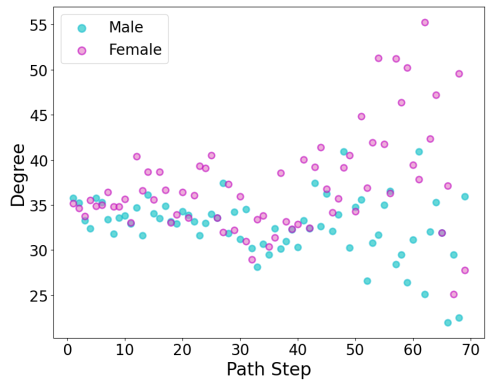

Figure 41: Degree per step per gender.

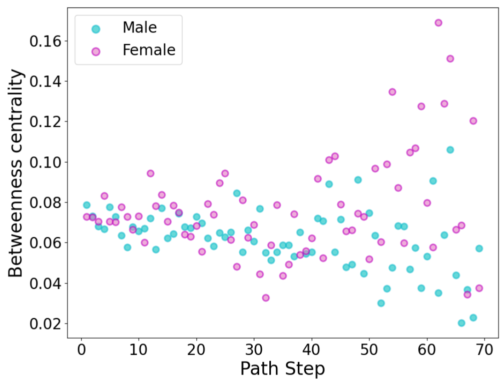

Figure 42: Betweenness centrality per step per gender.

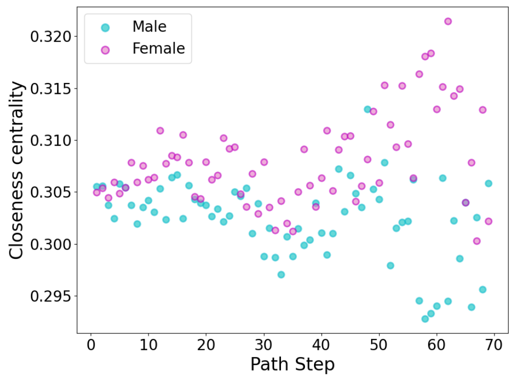

Figure 43: Closeness centrality per step per gender.

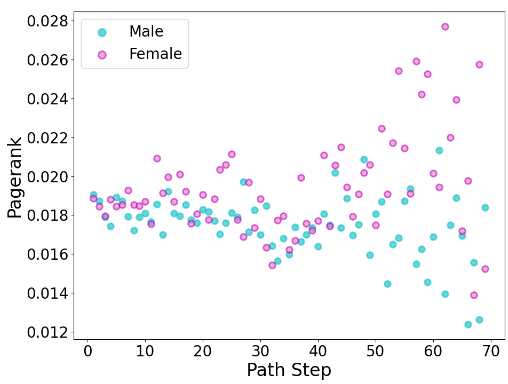

Figure 44: Pagerank per step per gender.

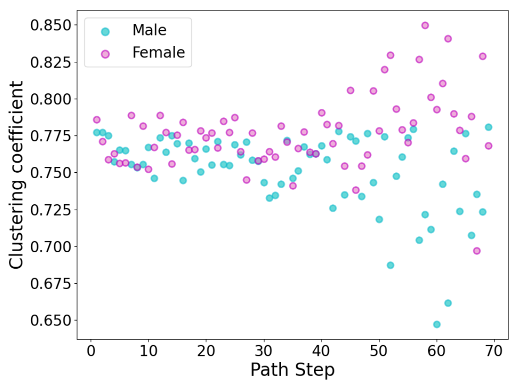

Figure 45: Clustering per step per gender.

5.4.2 Level of education

Furthermore, we look at the impact of the level of education on the specific path participants take. Due to the master group not having a single game longer than 50 steps we only analyzed games of length 50 and below. The results are shown in Figures 46 to 51 some interesting observations can be made. The first being that the bachelor group has little variance during their games of Synonymous. On average, they choose words with similar values throughout the entire game. Secondly, master students generally choose higher values for all properties compared to the middle school and bachelor groups.

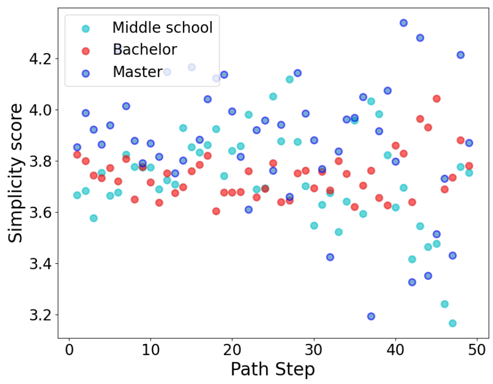

Figure 46: Simplicity score per step per level of education.

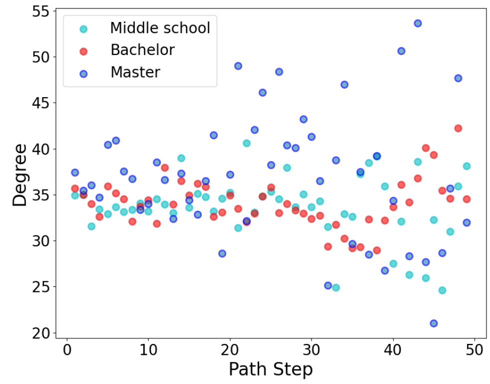

Figure 47: Degree centrality per step per level of education.

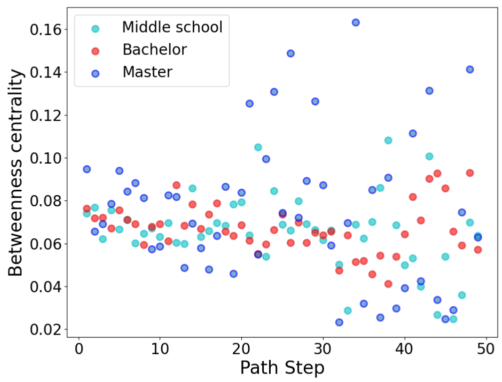

Figure 48: Betweenness centrality per step per level of education.

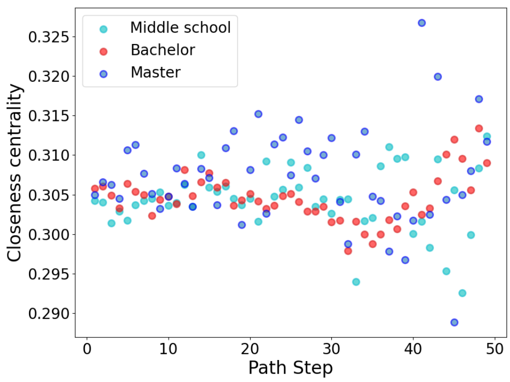

Figure 49: Closeness centrality per step per level of education.

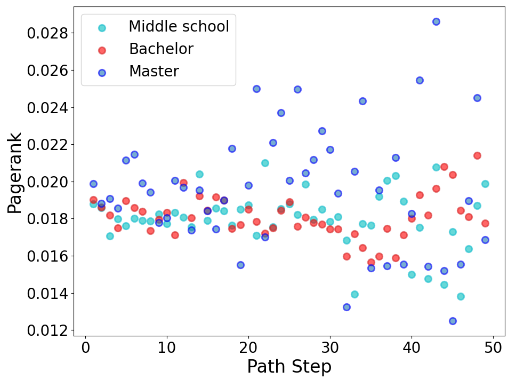

Figure 50: Pagerank per step per level of education.

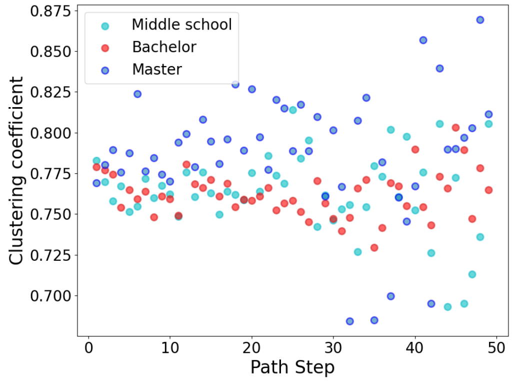

Figure 51: Clustering per step per level of education.

5.4.3 English fluency

Finally, we analyze whether the self-proclaimed level of English has an impact on the specific path participants take and the results are depicted in Figures 52 to 57. Due to the 'very good' group not having a single game longer than 47 steps we only analyzed games of length 47 and below. The 'decent' group has the most variance when choosing a word. Compared to the other four groups they choose words with the high and lowest values, without any recognizable pattern. Another notable observation is found in Figure 52. We expected the 'very bad' group to generally choose simpler words, since they would be more likely to know its definition. Yet, on average, the 'very good' and 'excellent' groups seem to choose simpler words than the 'very bad' group.

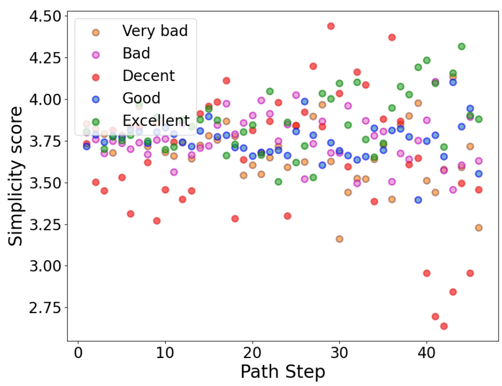

Figure 52: Simplicity score per step for English fluency.

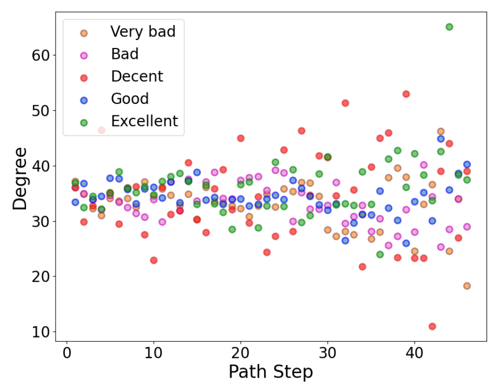

Figure 53: Degree centrality per step for English fluency.

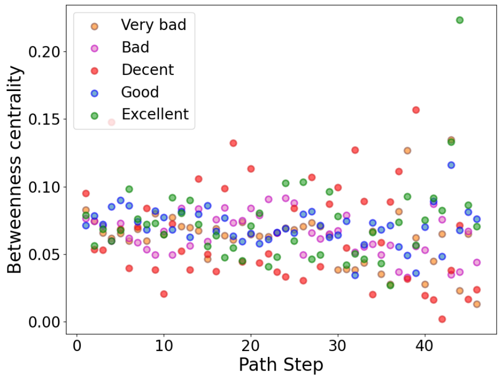

Figure 54: Betweenness centrality per step for English fluency.

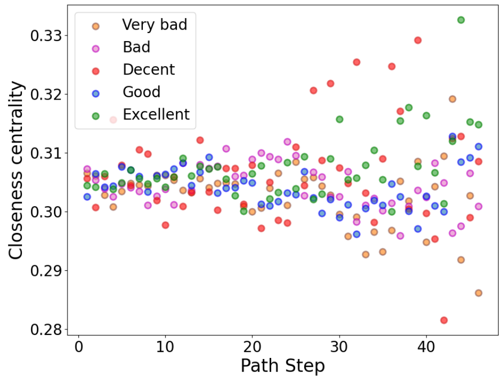

Figure 55: Closeness centrality per step for English fluency.

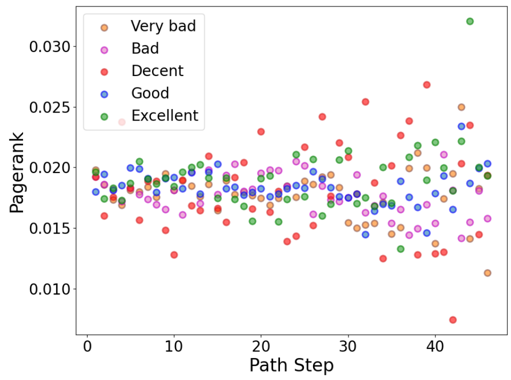

Figure 56: Pagerank per step for English fluency.

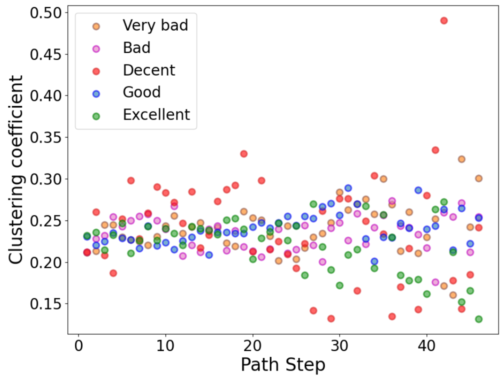

Figure 57: Clustering per step for English fluency.

6 Conclusion and Future Directions

This thesis aimed to study human path traversal and the impact of individual characteristics by means of a network-based game. The game was developed using a network of synonyms with 7836 nodes. When playing the game, participants were given a start word and were asked to navigate through the network of synonyms to reach a specified end word. With the help of this simple, yet difficult to complete game we gained a better understanding of human navigation through a digital information space and what roles personal characteristics play in path selection.

The network of synonyms is a small-world network where the longest shortest path between any pair of words has a length of 6. It is also highly clustered, another property found in small-world networks. We analyzed the relations between the properties of the words and found that the simplicity of a word has a strong correlation with the other node properties we looked at, which are the degree, pagerank, closeness and betweenness centralities and clustering coefficient.

Furthermore, while the participants played Synonymous we kept track of the path they traversed. We found people tend to choose simpler words more often than hard words. The same positive correlation can be seen between the usage of a word and its degree, closeness centrality and clustering coefficient. When looking at paths, we found that games with a shortest path length of 4 or 5 exclusively took longer than the minimal number of steps required. We also found that humans tend to go through high-degree words in the early stages of a game, while they navigate through low-degree nodes at the end.

Moreover, we found that personal characteristics could have an impact on the paths humans choose. While playing Synonymous, females exclusively choose words with higher values for all node properties than males do. This difference increases the longer a game goes on. Additionally, people with a master degree also choose higher valued words than the other levels of education. Finally, the self-proclaimed level of English fluency does not appear to have an impact on the chosen path. Though, due to the limited sample size this

While this study contributes valuable insights into the way humans navigate complex networks, several areas warrant further exploration. One avenue for future research is to gather participants with more variance in their personal characteristics. Analyzing more characteristics, e.g. age, country of birth and personal interest, can lead to the identification of key characteristics that predict navigational qualities. Furthermore, controlled experiments can be conducted with fewer participants that play more games of Synonymous. This not only offers the opportunity to study the path traversal, but also how participants learn new routes and adjust their strategies. Additionally, to further study the individual characteristics, qualitative analysis can be done by interviewing the participants. Asking questions about how they experienced the game and what strategies they used can give valuable insights. Finally, eye tracking equipment can be used to gain further knowledge about the thought process of the participants. For example, whether they analyze every available step or if they choose the first viable step they encounter.

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