Visual World Paradigm

A classical visual world study showing how people predict upcoming words with the help of Gazepoint eye tracker

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Abstract

The study presented in this paper explores the dynamics of predictive language processing through the visual world paradigm (VWP), a widely employed method in cognitive psychology. The primary objective of the research is to unwind how individuals anticipate or predict forthcoming words during the unfolding of the spoken instructions. The Gazepoint GP3 eye tracker is leveraged for precise gaze pattern analysis. The investigation delves into the impact of competitor words on gaze patterns, to study the cognitive mechanisms underlying real-time language comprehension. Our experiment uses a collection of competitor words sharing phonetic or semantic similarities with the target, and validates the hypothesis that the existence of such competitors leads to an increased number of fixations on them, reflecting the participants' evolving predictions of the upcoming word.

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Chapter 1

Introduction

1.1 Visual World Paradigm

The visual world paradigm is an experimental framework that investigates language processing by monitoring participants' eye movements while they interact with visual stimuli. Introduced by psychologists Richard Cooper and Thomas P. McDermott in the late 1990s, this paradigm have been continuosly refined and expanded, adapting it to different research questions and using advancements in eye-tracking technology to gain deeper insights into real-time language comprehension and visual attention processes. Through this framework the researchers try to simulate the integration of spoken language and visual information as they naturally occur in everyday situations so that we can draw inferences on the attention focus on specific objects in their visual display over time.

1.2 Objective of our project

Our research question is:

Does the presence of similar-sounding words influence our tendency to focus on those words apart from the target word as the word unfolds?

Our project is to study the nature of spoken word recognition as the word unfolds. We try to investigate the visual world paradigm by using the participants' eye movements which serve as an index of their ongoing language processing and interpretation. We dive deeper in trying to understand how the participants predict the upcoming word in a spoken instruction and how the cognitive mechanism's underlying real-time language comprehension influence their gaze patterns.

We aim to explore two fundamental conclusions concerning spoken word recognition and the underlying models, based upon the established research in this domain:

- Spoken word recognition is dynamic in nature which suggests that listeners continuously update and refine their interpretations as more information becomes available. It is not a discrete process rather it is a continuous process that unfolds over time which means that listeners don't just process words in isolation. As the speech or the spoken word unfolds, listeners use contextual cues, phonetic information, and their linguistic knowledge to build and revise their understanding of the spoken input.
- Spoken word recognition models like the *Cohort model* (Marslen-Wilson,1987 [5]; Marslen-Wilson & Welsh, 1978 [4]), *Shortlist model* (Norris, 1994 [8]), *TRACE model* (McClelland & Elman, 1986 [7]) etc., make assumptions that multiple candidates compete for recognition during the unfolding of the spoken word. For example in the cohort model, the authors propose that when a word is heard, it triggers some potential words (a 'cohort') that share the initial sounds. For instance, when 'beaker' is heard, both 'beaker' and 'beetle' become active choices. As speech unfolds, mismatched sounds cause activation of irrelevant words (like 'beetle' in this case) to decrease. Eventually, the correct word is chosen when there is enough evidence to support it.

Paul D.Allopenna, James S. Magnuson and Michael K. Tanenhaus in their paper "Tracking the Time Course of Spoken Word Recognition Using Eye Movements: Evidence for Continuous Mapping Models" [1] investigated a similar structure of the experiment to validate the above conclusions. One of the experiment was replicated by us to validate the hypothesis i.e., the results (see Figure 1.1) in the form of probability of fixations over time. This was the reference paper for our project, which we will be referring to throughout the report.

In the graph shown in Figure 1.1 we have the probability of fixation on four words over time. The four words are:

1. **Referent** *(e.g., beaker)*: This is the target word, which is investigated for recognition.
2. **Cohort** *(e.g., beetle)*: Cohort is a similar sounding word to the target word. It shares the same initial phoneme with the target word. For example, the words *beetle* or *beagle* can be the cohort for the word *beaker*.
3. **Rhyme** *(e.g., speaker)*: Rhyme is the word which rhymes with the target word. For example, *speaker* can be the rhyme for the word *beaker* and *handle* can be the rhyme for the word *candle*.
4. **Unrelated** *(e.g., carriage)*: This is a word which is totally unrelated to the target word. For example, the words *carriage* and *sandwich* are totally unrelated to the word *beaker*. So these can be the unrelated words for the word *beaker*.

The figure is plotted against time, the x-axis represents the time in milliseconds and the y-axis represents the probability of fixation on each of the four words. The figure is plotted for the full competitor condition (see conditions in Section 3.4). The word offset is at around 375 ms i.e. the average duration of the auditory stimulus. The figure shows that the participants fixate on the cohort word more than the other words in the beginning. This is because the cohort word shares the same initial phoneme with the target word. The participant also attends to the rhyme word as it rhymes with the target word. The participants fixate on the target word after the word

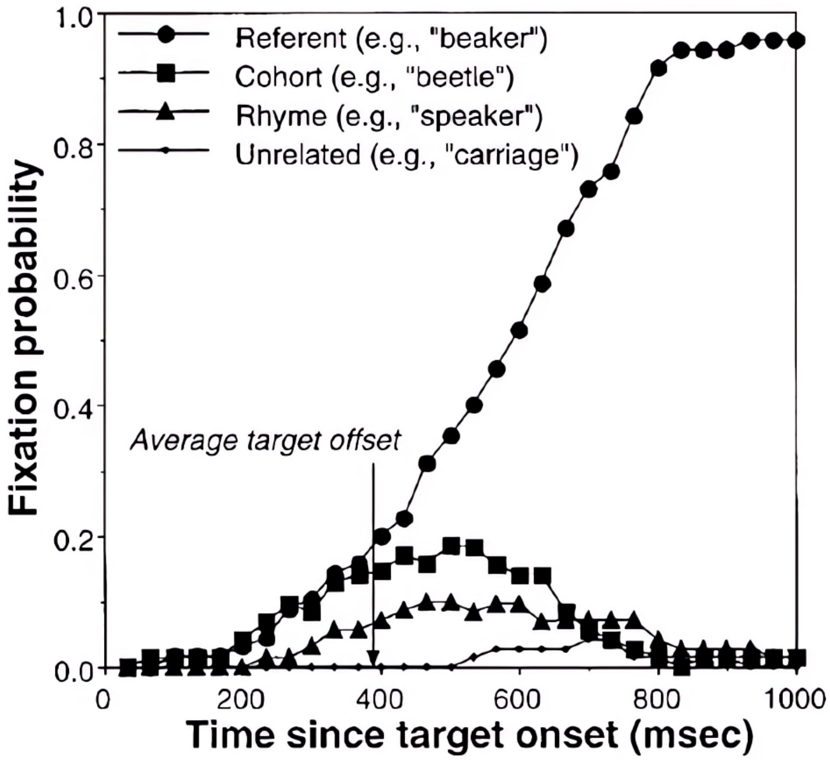


Figure 1.1: Probability of fixating on each item type over time in the full competitor condition

offset. The figure also shows that the participants fixate on the unrelated word the least. This is because the unrelated word is totally indepedent of the target word and thus the participants do not fixate on it.

With reference to the sample words used in the figure, at the start of the trial, the participants hear [bi], which could be the beginning of *beaker* but also could be the beginning of *beetle*. So during the first 200 ms the participants start fixating at both of those words, more than they look at the others. After some time as they hear the [k] i.e. now they are hearing [bik], thus they discard their choice of *beetle* and stop fixating at it. But by the time they have heard the whole word *beaker*, they might realize that *beaker* rhymes with *speaker* and get confused about if they heard *speaker* at the first place. For the last word *carriage*, the pronunciation is totally unrelated to the target *beaker*, so there is very less probability of the participant actually fixating at the unrelated word [9].

Through this project we try to replicate the results obtained by the authors in the reference paper [1] and validate it through our eye tracking experiment.

Chapter 2

Experiment Design

2.1 Software and Hardware

- **Software**: The experiment is designed in OpenSesame[6] which is a graphical experiment building software to create experiments for psychology, neuroscience, and experimental economics. Eye trackers can be integrated with OpenSesame to record the eye movements of the participants, which is finally used to analyze the data. It is available on Windows, Mac OS and Linux.
- **Language**: Python was used along with the OpenSesame GUI to create the experiment. Libraries like Pandas, Numpy, Matplotlib were used to analyze the data. `PsychoPy` was used as the backend for OpenSesame. Other options available for backends are PyGame, Expyriment, etc.
- **Eye Tracker**: The experiment is conducted using the GazePoint GP3 eye tracker. It is a binocular eye tracker that can record at 150 Hz. The eye tracker is connected to the computer and the participants are seated at a distance of around 60 cm from the screen. The experiment was conducted in a dimly lit laboratory setup to avoid any external light source that might interfere with the eye tracking. The GazePoint API [2] is referred for the anaylsis of the eye tracking data.

2.2 Structure of the Stimulus

The experiment is designed to test the participants' ability to predict the upcoming word in a spoken instruction. The experiment is designed in such a way that the participants are presented with a visual display of four objects in a grid and they are instructed to click on the object that matches the spoken instruction.

A trial in the experiment corresponds to one spoken instruction and its response.

The following Figure 2.1 shows the user interface presented to the participants for each trial:

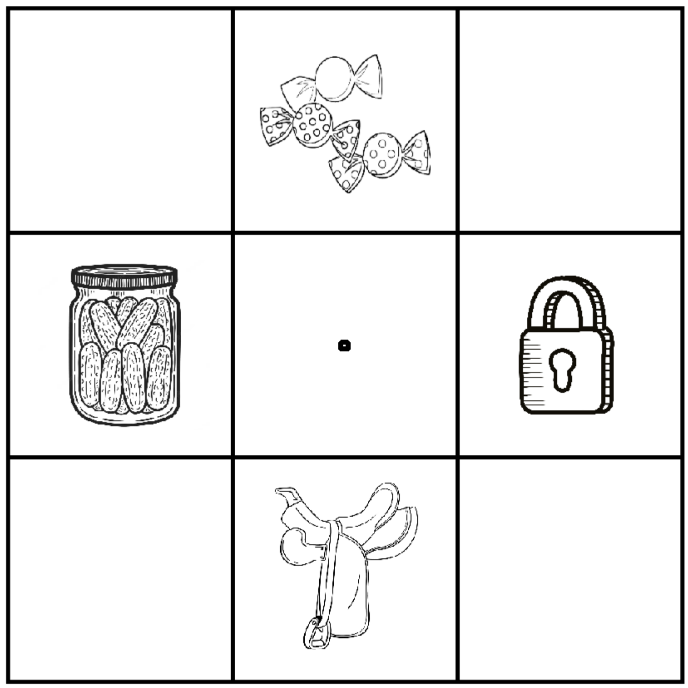


Figure 2.1: User Interface of one trial

In each trial, we have a 3x3 grid structure with four objects in it. Each trial has four stimuli displayed. The four stimuli are a combination of referent, cohort, rhyme and unrelated words. All or atleast two of the combinations are present in each trial according to the condition set (full competitor, rhyme competitor, unrelated competitor, etc.), which will be referred in the @sec-conditions. The stimulus used are only line drawings of the objects, to remove ambiguity in the visual display. The dot in the center of the grid is the fixation point for the participants.

2.3 Design of the Experiment

The experiment follows the following structure in OpenSesame:

1. **Introduction to the experiment**: It contains some preliminary instructions for the participants to understand the experiment. It also mentions that each progression will require a mouse click. The foreground color is set to black and the background color is set to white throughout the experiment. Figure 2.2 shows the introduction to the experiment.

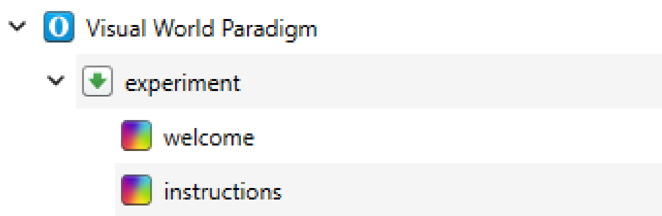


Figure 2.2: Introduction section of the OpenSesame experiment

2. **Initialization of variables**: The position variables (top, bottom, left and right) are initialized and are used to set the position of the objects in the grid. The `pygaze` module is also intialized to record the eye movements of the participants.

3. **Trial Loop Items**: This loop runs the experiment for 36 trials. The trial loop contains the following sequence of events:

   - **Fixation Cross**: A fixation cross is displayed at the center of the screen. It is a black dot on a white background which is displayed to ensure that the participants are looking at the center of the screen before the spoken instruction is played. It is displayed using the sketchpad item in OpenSesame.

   - **Stimulus**:

     1. The visual stimuli for each trial are loaded from the `stimuli.csv` file. The csv file contains information about the four objects that are displayed in the grid. It contains the following information:
        - **Stimulus**: The name of the objects that are displayed in the grid.
        - **Type**: The type of the object. The type can be referent, cohort, rhyme or unrelated. The type of the object is used to determine the condition of the trial.
        - **Condition**: The condition of the trial.
        - **Target**: The target object which is spoken in the audio instruction.

        You can find the stimuli.csv file here.
     2. We also have accompanying audio stimuli for each trial. The audio is digitally recorded in the following format:
        - **Instruction**: 'Fixate on the [object]' that the participants have to click on.

        You can find the audio stimuli here. Each response is captured with a mouse click. The mouse click is recorded and logged using the `mouse_click_response` item in OpenSesame.

   - **Logging**: The onset and offset of the fixation instruction and the stimulus (both audio and visual) are logged for each trial. We also log the position of the mouse click and the target object along with its position (top, right, bottom, left) that the participants clicked on (see Section 6.2.1).

   - **Gaze Contingency**: Two centre fixation audio prompts which state *'Fixate at the* *center'* and '*Now fixate at the center*', mark the beginning and the end of one trial. These are played to ensure that the participants are looking at the center of the screen before the stimulus instruction is played. This is implemented by introducing a delay of 1.1s after the prompt.

4. **End of Experiment**: The experiment ends with a thank you message for the participants.

The timeline of one trial is shown in Figure 2.3 .

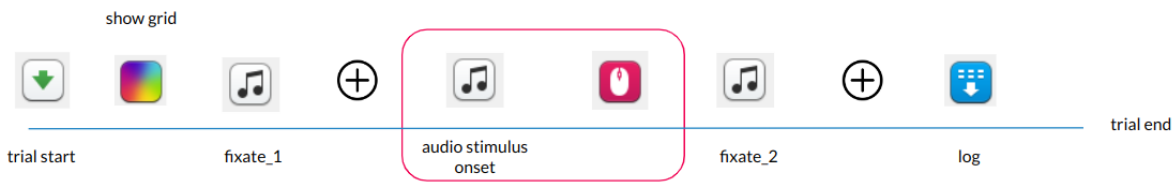


Figure 2.3: Timeline of a trial

2.4 Logic of the experiment

1. Stimuli are chosen as per the different pairs of sets included in the reference paper [1].
    - For e.g., One criteria of choosing these words are based on frequency per million words in the Kucera and Francis, 1967, corpus [3] .
2. A fixation at any point on the screen indicates that the participant is paying attention to it. Thus, we record the fixations throughout the experiment to deduce the attention of the pariticipant when we instruct them to fixate at a certain point of the canvas.
3. Noting timestamps of the samples is essential. Our experiment is designed to record how a participant attends to the stimuli and how they respond to the spoken instruction while the instruction is unfolding. Thus we record the timestamps of the samples to understand the chronology of the fixation events.
4. Fixations at the centre of the screen mark the start and end of a trial. This is to make sure we don't overlap the data of two trials while recording the data since each participant will have different response times and thus a fixed duration for each trial based on a timeout will not be feasible.

Chapter 3

Stimulus Design and Preprocessing

3.1 Visual Stimuli

For our study, we required uncomplicated and easily comprehensible stimuli to ensure easy understanding for the participants. Therefore, we opted for line drawing images as our chosen type of images. We sourced these stimuli with a Creative Commons License BY-SA, obtaining them from online platforms. In cases where certain line drawings were not directly accessible, we employed an edge detection algorithm within the GIMP software to create the desired line drawing stimuli. Each individual stimulus measures 256 x 256 pixels and is saved in PNG format. The Figure 3.1 illustrates an example of the stimuli used in our experiment.

Figure 3.1: Line Drawing of the Pickle Stimuli

We selected similar stimuli as the reference paper for our experiment. The experiment uses eight *referent - cohort - rhyme - unrelated* sets which are listed below:

1. beaker, beetle, speaker, dolphin
2. carrot, carriage, parrot, nickel
3. candle, candy, handle, dollar
4. pickle, picture, nickel, speaker
5. casket, castle, basket,nickel

6. paddle, padlock, saddle, dollar
7. dollar, dolphin, collar, beaker
8. sandal, sandwich, candle, parrot

3.2 Auditory Stimuli

As outlined in the referenced paper, during the course of the experiment, the examiner verbally provided instructions to each participant for every trial, such as 'click on the [beaker]' However, this approach could potentially consume a significant amount of time and introduce errors, as the duration taken by the examiner to vocalize the stimulus name and instructions might differ for various participants. To prevent potential errors stemming from variations in the examiner's delivery speed, (digital) synthetic audio stimuli were generated that audibly articulated both the stimulus names and the associated actions to be performed. To facilitate this process, the website acoust.io was employed to create the audio stimuli. The below listed configuration was used to ensure the uniformity of the generated audio stimuli:

1. Voice Profile: DAVIS
2. Playback speed: 0.8x
3. Sampling rate: 48Hz (relevant for use with `psychoPy` backend in OpenSesame)

3.3 Stimuli Preprocessing

The stimuli collected needed to be preprocessed before they could be used in the experiment. The preprocessing steps are as follows:

1. Resizing the line drawings into 256 x 256 pixels. The OpenCV library was used to read and resize the images.

```
img = cv2.resize(img, size)
```

2. Converting the audio files to `.wav` format. The audio files were generated in `.mp3` format (see Section 3.2). The `.mp3` files were converted to `.wav` format using the `ffmpeg` library.

```
for file in $DIRPATH/*.mp3; do
    filename=$(basename "$file")
    filename="${filename%.*}"
    ffmpeg -i $file $OUTDIR/$filename.wav
done
```

3. A trailing silence after each audio was observed in the generated audio stimuli which could affect the response time of the participants. The silence was removed using the `pydub` library.

```
def detect_leading_silence(sound, silence_threshold, chunk_size=10):
    trim_ms = 0 # ms
    while sound[trim_ms:trim_ms+chunk_size].dBFS < silence_threshold:
```

```
        trim_ms += chunk_size
    return trim_ms
```

The function analyzes an audio snippet to find the duration of the silence at the end of the signal. It iterates over chunks of the audio and measures the volume (dBFS) in each chunk until the volume is below the provided silence threshold. The accumulated time of detected silence is then returned as the result and then removed using the `sound[trim_ms:]` function, spectifying the start and the end trim duration.

4. The sampling rate of all the audio samples was also made equal to work with the `PsychoPy` backend. The sampling rate was changed to 48Hz.

3.4 Conditions

During each trial, participants were presented with four line drawings on a computer screen. They were instructed to click on one of the objects using a computer mouse. The four combination sets of stimuli types were as follows:

1. Full Competitor Set: This set included a referent, a cohort, a rhyme, and an unrelated object (e.g., beaker, beetle, speaker, and carriage).
2. Cohort Competitor Set: This set consisted of a referent, a cohort, and two unrelated objects (e.g., beaker, beetle, parrot, and carriage).
3. Rhyme Competitor Set: This set comprised a referent, a rhyme, and two unrelated objects (e.g., beaker, speaker, dolphin, and carriage).
4. Unrelated Set: In this set, there was one referent and three unrelated objects (e.g., beaker, dolphin, parrot, and nickel).

The illustration shown in Figure 3.2 depicts the four different types of competitor sets.

For each type of competitor set, different elements could be designated as the *target* for the trial. This determined the specific kind of lexical competition that could arise. For instance, within the full competitor set, the referent could be the target (resulting in cohort and rhyme competition), the cohort (leading to cohort competition with the referent), the rhyme (leading to rhyme competition with the referent), or the unrelated object (which was meant to eliminate all form of competition).

Within each competitor set, every item was utilized as the target an equal number of times. The number of trials was kept the same for all conditions i.e., 3 in our case. The various conditions, their frequencies, and the specific targets associated with them are mentioned in detail in Figure 3.3.

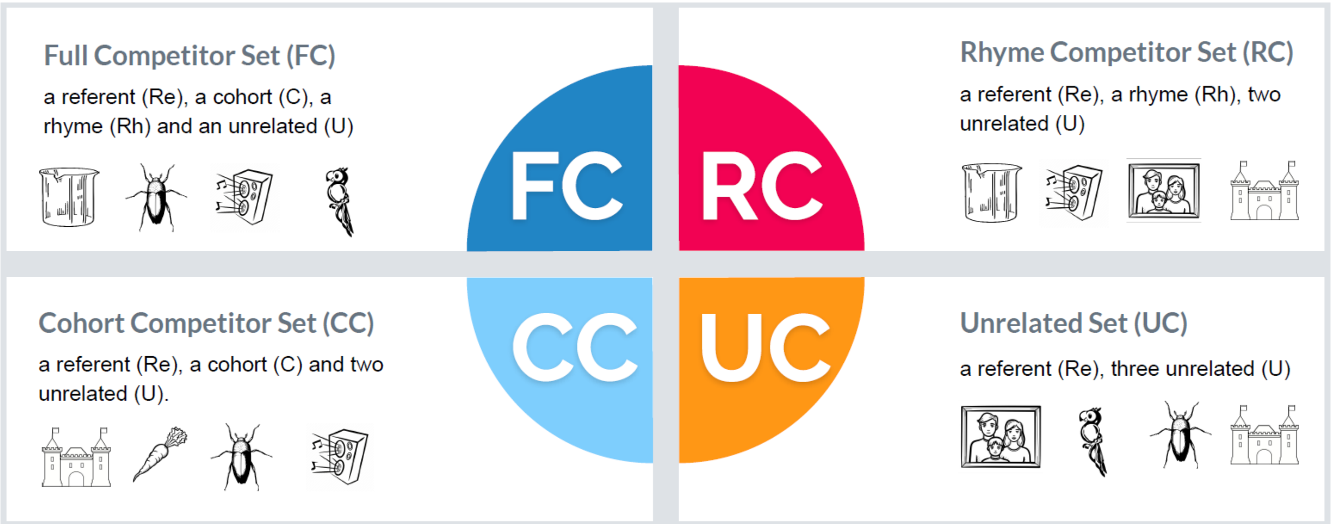


Figure 3.2: Conditions

Condition No	Trials (how many examples of such)	Conditions		
		Competitor Set	Target	Distractors
1	3	FC	Re	C, Rh, U
2	3	FC	C	Re, Rh, U
3	3	FC	Rh	Re, C, U
4	3	FC	U	Re, C, Rh
5	3	CC	Re	C, U, U
6	3	CC	C	Re, U, U
7	3	CC	U	Re, C, U
8	3	RC	Re	Rh, U, U
9	3	RC	Rh	Re, U, U
10	3	RC	U	Re, Rh, U
11	3	UC	Re	U, U, U
12	3	UC	U	Re, U, U

Figure 3.3: Condition Table

3.5 Randomization

In addition to making sure all items appeared equally as often as targets (in order to preclude frequency-based strategies by participants), the overall frequency of each stimulus was also controlled. A randomization alogirthm was implemented that made sure following 3 randomizations were achieved.

1. **Order Randomization**: The order of the trials are randomized across participants.
2. **Stimuli Distribution**: Each stimuli is shown approx. equal number of times.
3. **Target Distribution**: Each stimuli is chosen as the target an approx. equal number of times.
4. **Position Randomization**: The position of the stimuli in the grid box is randomized across trials.

Figure 3.4 shows the number of stimuli appearances in the 36 trials and 4 stimuli are displayed in each trial. Since a total of 23 stimuli were chosen for the experiment, each stimulus could get 36*4/23 = 6.26 i.e. either 6 or 7 appearances.

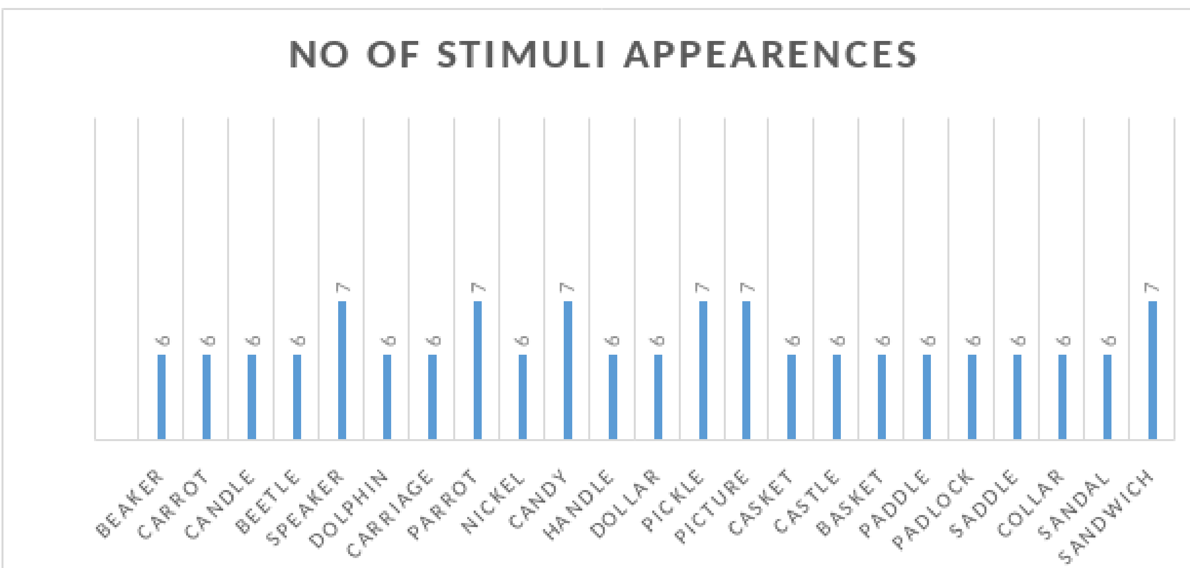


Figure 3.4: Plot of the number of stimuli appearances

Figure 3.5 shows the number of target appearances in 36 trials. Since there were 23 stimuli, each stimulus could get 36/23 = 1.565 i.e. either 1 or 2 apppearances as a target.

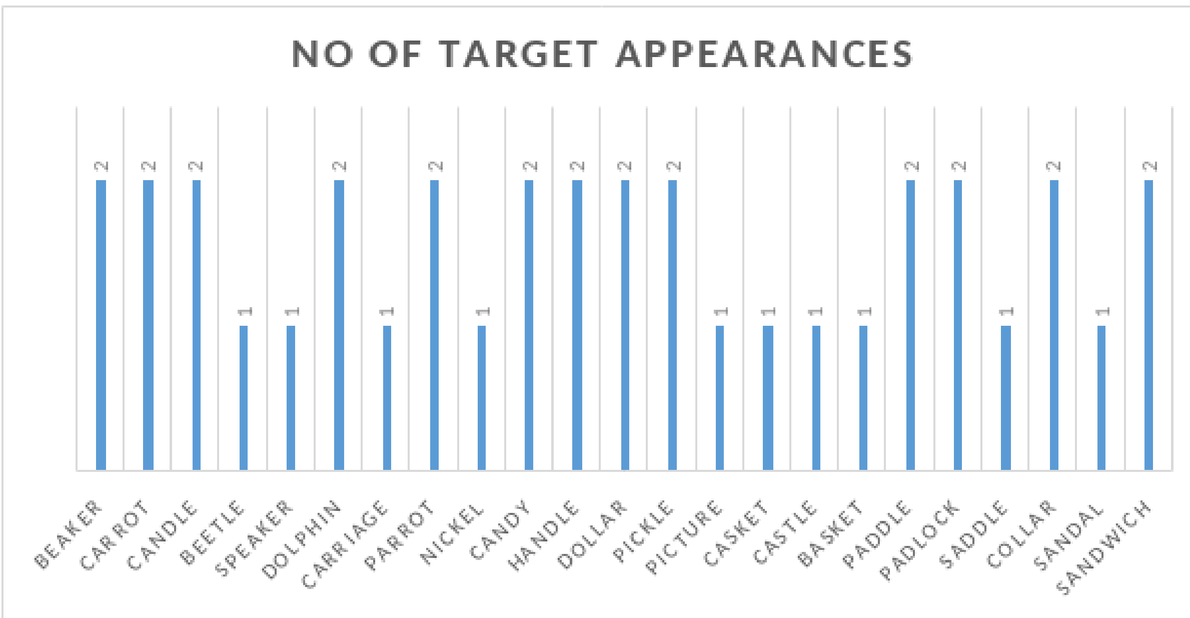


Figure 3.5: Plot of the number of target appearances

Chapter 4

Experiment Organization

The experiment was carried out within a laboratory setting, where each session included only examiners and a single participant. Overall, 15 participants took part in the experiment. Participants received a meeting invitation in which they were asked about their availability. Important details regarding the experiment were shared, while the specific nature of the experiment remained undisclosed. Clear guidelines, including a PDF with directions to the laboratory's location were provided, outlining the do's and don'ts for the day of the experiment. The examiners were responsible for the smooth execution of the experiment and thus we followed these guidelines before the experiment.

Upon the arrival of participants at the laboratory on the designated experiment day, introductory details about the data collection protocol were adhered to in accordance with the procedure. We narrated the preliminary information to each participants before starting the experiment. Additionally, participants were requested to review and sign the consent form to confirm their agreement. To minimize interruptions during the experiment, participants were instructed to either turn off their phones or set them to silent mode.

Before commencing the experiment, participants were acquainted with the stimuli. Visual aids, in the form of pictures on a sheet, were employed for this purpose. Each participant was then guided to audibly identify and name the objects depicted in the images until they accurately named them. This preparation process ensured that participants were thoroughly prepared for the upcoming experiment.

The experiment utilized the GazePoint GP3 eye tracker as its primary tool for data collection. At the outset, participants' eye calibration was meticulously carried out using the calibration software. Particular attention was given to ensure the accuracy of the calibration process. In instances where accuracy was compromised, recalibration was promptly administered to maintain data quality.

To facilitate the experiment, a setup with two distinct monitor screens was prepared. One screen was under the control of the participant, while the other was managed by the examiner. The sequence of events commenced with the examiner launching the experiment on the OpenGaze platform through their control. Subsequently, control was seamlessly transitioned to the participant for their active involvement.

To assist the participants during the experiment, text-based instructions were presented on the screens. These instructions provided guidance and clarity, enhancing the participants' ability to engage effectively with the task at hand.

During the course of the experiment, audio messages were introduced as additional cues. These audio cues were intentionally played at a significant volume through external speakers. Their purpose was to draw the participants' attention to the center of the screen prior to the presentation of audio stimuli. This protocol enabled the precise tracking of the commencement and conclusion of each trial.

The experiment encompassed a total of 36 trials, contributing to an overall runtime of approximately 8 to 9 minutes. This condensed timeframe was deliberate, aimed at maintaining participants' focus and engagement throughout the session.

When considering the overall experience of each participant, it is to be noted that the entire process, from the preliminary pre-experiment information briefing to the subsequent post-experiment discussion sessions, spanned a total duration of approximately 18 minutes.

Following each experiment session, participants received a debriefing outlining the central objective of our study, and their valuable feedback was carefully recorded. As a token of appreciation, a small energy bar was provided to each participant.

After the experiment, the examiners made sure the post-experiment guidelines were followed.

Chapter 5

Quality Control

Upon gathering data from all participants but prior to delving into data analysis, the step of quality control was essential. This step aimed to ascertain uniform data quality across the collected dataset, aligning with the criteria outlined in the referenced paper. Accordingly, trials that failed to meet the following three criteria were excluded from the subsequent analyses.

1. During a trial, the calibration deteriorated to such an extent that it was not possible to label fixations.
2. The participant did not maintain fixation on the cross until the appropriate instruction began.
3. The participant never fixated on or selected the correct target.

In accordance with these criteria, data from 3 participants were excluded due to quality concerns. To facilitate thorough analysis, data logs were incorporated, documenting the commencement of auditory stimuli as `LOG_AUDIO_TARGET_START` and extending up to the conclusion marked by the mouse click response as `CLICK_RESPONSE_END`. This approach aided in identifying trial durations and associating data with specific trials.

Subsequently, these logged details were cross-verified, ensuring their presence for each trial. If any logs were missing, adjustments to the sampling rate were made to uphold data integrity.

5.1 Managing Coordinate Systems

OpenSesame/Opengaze use different coordinate systems, to have a proper analysis of our collected data, coordinates needed to be converted to a common coordinate system. This section is expanded on further in Section 6.2.3.

5.2 Fixation Plots (Spatial view)

For data analysis and examination, fixation graphs were generated. A graph depicting FPOGX against FPOGY was created, including solely the samples where FPOGV equalled 1, this precaution was taken to exclusively utilize valid fixation samples.

Subsequently, a grid box representing the stimuli was incorporated, with corresponding labels for each stimuli box. Additionally, legends were introduced to the graph, encompassing information such as the condition number, target, and selected stimuli. Figure 5.1 and Figure 5.2, show the fixation plot of two trials of one of the participant.

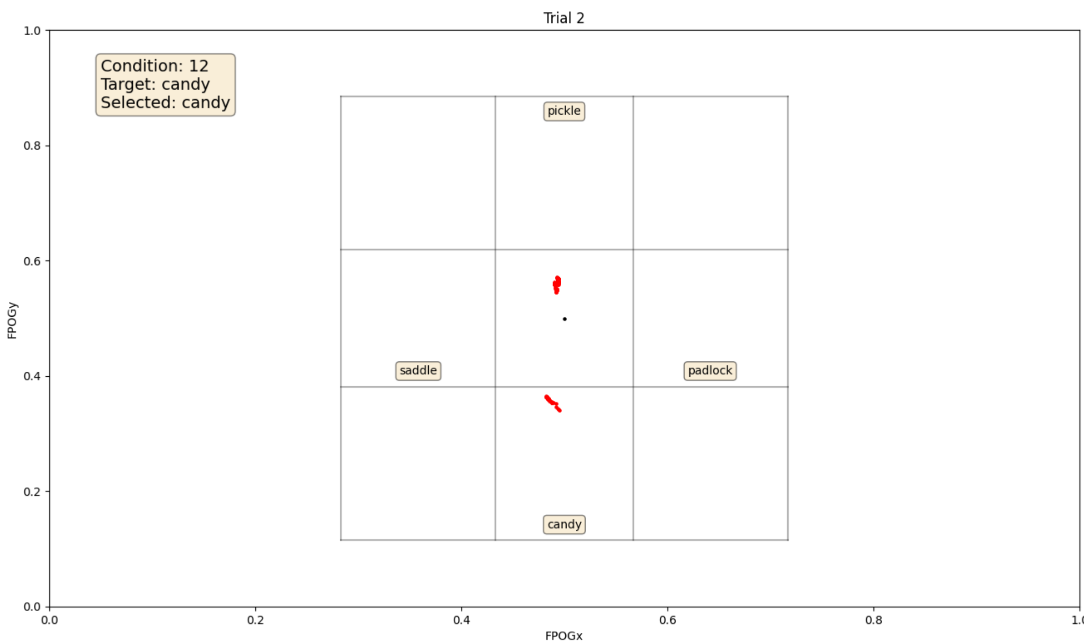


Figure 5.1: Fixation plot of trial 2 of a participant

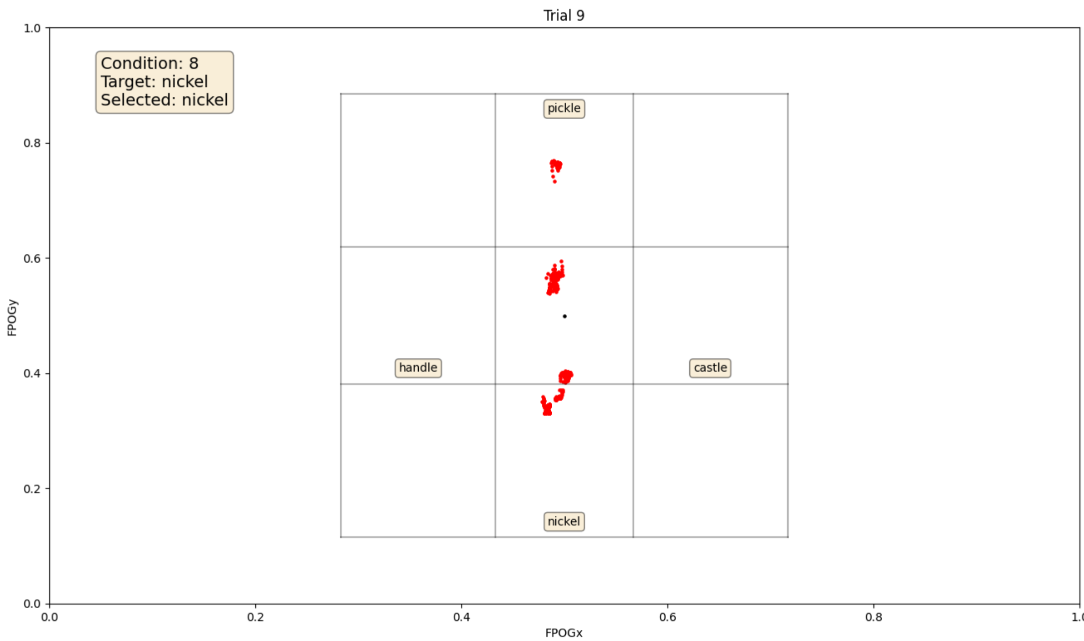


Figure 5.2: Fixation plot of trial 9 of a participant

Chapter 6

Preprocessing and Analysis

The objective of this section is to describe the preprocessing steps that were performed on the raw data obtained from the eyetracker experiments and the analysis that was performed on the preprocessed data. The analysis was performed in order to answer the research questions posed in the introduction section. The procedure described in the reference paper was followed for the analysis.

6.1 Organizing the raw data into trial-wise data

The basic unit of analysis in the visual world paradigm experiment is a trial. A trial is a single instance of the experiment. The first task was to organize the raw data into trial-wise data. Here the raw data was present in the .tsv files. Each file contained the data for a single participant. The data was read into a pandas dataframe named `df_interest` and then the columns that were not required were dropped. The columns, `TIME`, `BPOGX`, `BPOGY`, `FPOGD`, `FPOGX`, `FPOGY`, `FPOGV` and `USER` were relevant for our analysis so these were the columns remaining in the dataframe.

> **i** Note:
>
> The `FPOGV` column indicated whether the fixation was valid or not. This was determined by the fixation detection algorithm of the GP3 eyetracker.

In order to organize the entries of the dataframe into trials, the rows corresponding to the start and end of the trials needed to be identified. After acquiring the indices of the corresponding rows, the dataframe was split into multiple dataframes, each corresponding to a single trial.

```
# get the indices of the rows where the user column contains the phrase 'START_TRIAL'
start_indices = df_interest[df_interest["USER"].str.contains("START_TRIAL")].index

# get the indices of the rows where the user column contains the phrase 'FINAL_FIXATION_END'
end_indices = df_interest[df_interest["USER"].str.contains("FINAL_FIXATION_END")].index
```

```
# split the dataframe based on the start and end indices
df_list = [
    df_interest.iloc[start_indices[i] : end_indices[i]]
    for i in range(len(start_indices))
]
```

At this point, the dataframes corresponding to the individual trials were ready. Our analysis is mainly concerned with the gaze data from the point of onset of the audio stimulus up till the point at which the participant clicks on a stimulus. So, the dataframes were further sliced to retain only the data from the specified interval. In order to perform this, the `USER` column was used. The rows corresponding to the start of the audio stimulus and the end of the click response were identified by the strings `LOG_AUDIO_TARGET_START` and `CLICK_RESPONSE_END` respectively. The rows between these two specified row indices were sliced and the resulting dataframes were stored in a list named `audio_df_list`. The dataframe corresponding to one trial is shown in Figure 6.1.

```
# extract the row index where the user column contains the phrase 'LOG_AUDIO_TARGET_START'
audio_start_index = selected_df[
    selected_df["USER"].str.contains("LOG_AUDIO_TARGET_START")
].index[0]
# extract the row index where the user column contains the phrase 'LOG_AUDIO_TARGET_END'
audio_end_index = selected_df[
    selected_df["USER"].str.contains("CLICK_RESPONSE_END")
].index[0]
# split the dataframe based on the audio start and end indices
# store the split dataframe in a list
audio_df_list.append(selected_df.iloc[audio_start_index : audio_end_index + 1])
```

	TIME	BPOGX	BPOGY	FPOGD	FPOGX	FPOGY	FPOGV	USER	trial_number
0	57.91305	0.50808	0.47709	1.74694	0.49711	0.46464	1	LOG_AUDIO_TARGET_START	0
1	57.92954	0.50812	0.48550	1.76344	0.49731	0.46505	1		0
2	57.94503	0.50679	0.45819	1.77892	0.49725	0.46476	1		0
3	57.96120	0.50044	0.46452	1.79509	0.49716	0.46428	1		0
4	57.97736	0.50029	0.45900	1.81125	0.49707	0.46367	1		0
...	...	...	...	...	...	...	...	...	...
3621	469.25360	0.48646	0.25336	0.25867	0.50388	0.22997	1		35
3622	469.26984	0.48670	0.26408	0.27490	0.50293	0.23186	1		35
3623	469.28601	0.51019	0.27612	0.29108	0.50331	0.23419	1		35
3624	469.30215	0.49822	0.27407	0.30722	0.50305	0.23619	1		35
3625	469.31839	0.49828	0.26523	0.32346	0.50283	0.23757	1	CLICK_RESPONSE_END	35

Figure 6.1: Dataframe containing the gaze data from the point of onset of the audio stimulus up till the point at which the participant clicks on a stimulus.

6.2 Extracting trial information

6.2.1 Exploring the logs in the .tsv files

The logs present in the `.tsv` files are important for our analysis. Apart from containing the data recordings from the experiments, they also contain the information about the individual trials. In the text block below, the logs for a sample trial are shown.

```
START_EXP
START_TRIAL: 0 T: SADDLE.PNG R: PICKLE.PNG B: PADLOCK.PNG L: CANDY.PNG
FIXATE_CENTER_AUDIO_ONSET, COND: 12 TARGET: CANDY
CENTRE_GAZE_START
INSTRUCTION_TO_CLICK_ONSET
LOG_AUDIO_TARGET_START
LOG_AUDIO_TARGET_END
CLICK_RESPONSE_END
FINAL_FIXATION_START, SELECTED: CANDY.PNG
FINAL_FIXATION_END
….
….
….
….
STOP_EXP
```

The logs are in the form of a sequence of events. Each log event is a line in the log file. Out of these log events, the following ones are relevant for our analysis:

- `START_TRIAL: 0 T: SADDLE.PNG R: PICKLE.PNG B: PADLOCK.PNG L: CANDY.PNG` : This line contains the information about the trial. The trial number is 0. The images on the left, right, top and bottom of the target image are `SADDLE.PNG`, `PICKLE.PNG`, `PADLOCK.PNG` and `CANDY.PNG` respectively.
- `FIXATE_CENTER_AUDIO_ONSET, COND: 12 TARGET: CANDY`: Other than indicating the onset of the audio for fixation, this line also contains the target word and the condition number. In this case, the target word is `CANDY` and the condition number is 12.
- `FINAL_FIXATION_START, SELECTED: CANDY.PNG`: This line indicates the onset of the final fixation on the target image and the stimulus that was selected. The participant selected the image `CANDY.PNG` as the target image.

Following the slicing procedure mentioned the previous section, the indices of the rows corresponding to these three log events are retrieved.

```python
# get all rows whose indices are stored in start_indices
# will be used to extract the position of the stimuli
trial_strings = df_interest.iloc[start_indices]["USER"].reset_index(drop=True)


# get the indices of rows that contain the phrase 'FIXATE_CENTER_AUDIO_ONSET'
```

```
target_row_indices = df_interest[
    df_interest["USER"].str.contains("FIXATE_CENTER_AUDIO_ONSET")
].index
target_rows = df_interest.iloc[target_row_indices].reset_index(drop=True)["USER"]

# get the indices of rows that contain the phrase 'FINAL_FIXATION_START'
fixation_row_indices = df_interest[
    df_interest["USER"].str.contains("FINAL_FIXATION_START")
].index
fixation_rows = df_interest.iloc[fixation_row_indices].reset_index(drop=True)["USER"]
```

6.2.2 Applying regex on the log event strings

The retrieved data were all of the datatype string so regex was used to extract the data points of interest. This consisted of the name of the stimulus at the top, bottom, left and right positions of the grid, the target word, the condition number and the selected stimulus. The extracted data were stored in a python dictionary named `stimuli_loc_dict` with appropriate keys.

```
# use regex to extract the number afer 'COND:'
cond_numbers = [re.findall(r"COND: (\d+)", row)[0] for row in target_rows]
# use regex to extract the word after 'TARGET:'
target_words = [re.findall(r"TARGET: (\w+)", row)[0] for row in target_rows]
# use regex to extract the word after 'SELECTED: '
selected_words = [re.findall(r"SELECTED: (\w+)", row)[0] for row in fixation_rows]

# use regex to extract the image names at the top, bottom, right and left positions
top_stimuli = [
    re.findall(r"T: (\w+)", trial_string)[0] for trial_string in trial_strings
]
bottom_stimuli = [
    re.findall(r"B: (\w+)", trial_string)[0] for trial_string in trial_strings
]
right_stimuli = [
    re.findall(r"R: (\w+)", trial_string)[0] for trial_string in trial_strings
]
left_stimuli = [
    re.findall(r"\sL: (\w+)", trial_string)[0] for trial_string in trial_strings
]
```

6.2.3 Dealing with multiple coordinate systems

The gaze data contained in `audio_df_list` provided the coordinates where the participant was fixating at a given timestamp but for our task we needed to know which stimulus the participant was fixating at. The coordinates of the grid boxes were noted from the OpenSesame experiment UI. But one issue with this data is that these coordinates had the origin at the center of the screen whereas the gaze data had the origin at the top left corner of the screen. So, the coordinates of the grid boxes were converted to the coordinate system of the gaze data and then scaled to the range [0, 1][1]. The functions `shift_coordinate_system` and `shift_coordinate_system_single` were defined for this purpose. The function `shift_coordinate_system` accepted a dictionary of coordinates while the function `shift_coordinate_system_single` accepted a single set of coordinates (tuple). The functions returned the shifted coordinates.

```
# shift the origin from (0, 0) to (-960, 540)
# perform the same on outer_points and inner_points
def shift_coordinate_system(coord_dict):
    for key, value in coord_dict.items():
        coord_dict[key] = (value[0] + 960, -1 * value[1] + 540)

        # scale to [0, 1]
        coord_dict[key] = (coord_dict[key][0] / 1920, coord_dict[key][1] / 1080)
    return coord_dict

def shift_coordinate_system_single(coord):
    coord = (coord[0] + 960, -1 * coord[1] + 540)
    coord = (coord[0] / 1920, coord[1] / 1080)
    return coord
```

The gaze data acquired from the GP3 eye tracker follows a different coordinate system. The origin of the gaze data coordinate system is at the top left corner of the screen. Additionally, the y-axis is inverted, meaning that the y-coordinate increases as the participant looks down. In order to convert the gaze data to the cartesian coordinate system and to enable comparison with the transformed OpenSesame UI coordinates, the function `shift_coordinate_system_top_left_to_bottom_left` was defined. The scaled version of the cartesian coordinates was chosen in order to enable use with plotting libraries such as *matplotlib* and *seaborn*.

```
def shift_coordinate_system_top_left_to_bottom_left(x, y):
    return (x, -1 * y + 1)
```

> **Note:**
>
> The GP3 gaze data coordinates are in the range `[0, 1]` so no scaling is required.

[1]The scaling is performed with regard to the resolution of a screen resolution of 1920x1080. Hence, a maximum value of 1 along height and width correspond to 1080 and 1920 respectively.

6.3 Fixation plots

The preprocessing steps described in the previous sections are performed on the recorded data, it is possible to plot the fixations of the participants (See Section 5.2). Such plots allow us visualize the fixations of the participants and identify any outliers. The plot elements can be classified into two groups:

1. Overlay elements: These elements are plotted in order to provide reference for the position of the grid and indicate the stimulus image in each grid box element. The condition number and the target word are also displayed in the plot. The function `draw_grid` is used to draw the grid.

```
def draw_grid(inn, out, ax):
    # draw line from A to B
    ax.plot(
        [out["A"][0], out["B"][0]], [out["A"][1], out["B"][1]], color="black", alpha=0.3
    )
    # draw line from B to C
    ax.plot(
        [out["B"][0], out["C"][0]], [out["B"][1], out["C"][1]], color="black", alpha=0.3
    )
    # draw line from C to D
    ...
    ...
    # create a tiny circle at the center
    ax.scatter(inn["M"][0], inn["M"][1], color="black", s=5)
```

The text elements are plotted using `matplotlib.pyplot.text()` function. See example:

```
# top stimuli
ax.text(
    0.5,
    0.8685,
    stimuli_dict[i][0].lower(),
    transform=ax.transAxes,
    fontsize=10,
    verticalalignment="top",
    bbox=props,
    ha="center",
)
```

2. Fixation elements: These elements are plotted in order to indicate the fixations of the participants. As indicated in the code block below, the matplotlib `scatter` function is used.

```
# new_fpog_x and new_fpog_y are the x and y coordinates of the fixations
ax.scatter(new_fpog_x, new_fpog_y, color='red', s=5)
```

ℹ Note:

The fixation plots can be generated by running the script `create_fixation_plots.py` in the `/src` directory.

6.4 Deduce location of fixations

Using the coordinates of the edges of the grid boxes, it is possible to deduce the location of the fixations. The gridbox has four boxes that where a stimulus can be placed. The coordinates of the fixations and the coordinates of the stimulus boxes are converted to the scaled cartesian coordinate system. The function `check_if_within_rect` accepts the x and y coordinates of the fixation and the coordinates of the stimulus box and returns a boolean value indicating whether the fixation is within the stimulus box. The function `check_if_within_rect` is called for each stimulus box and the stimulus box for which the function returns `True` is the stimulus box where the participant was fixating.

```
def get_rect(x, y):
    if check_if_within_rect(x, y, top_rect):
        return 'top'
    elif check_if_within_rect(x, y, right_rect):
        return 'right'
    elif check_if_within_rect(x, y, bottom_rect):
        return 'bottom'
    elif check_if_within_rect(x, y, left_rect):
        return 'left'
    elif check_if_within_rect(x, y, centre_rect):
        return 'centre'
    else:
        return 'outside'
```

The function `get_rect` is applied to each row of the dataframe using the `df.apply` function. The resulting column is named `rect` (see Figure 6.2). At the point, for each data point, we know at which stimulus box the participant was fixating.

```
# use df.apply to apply the get_rect function to each row
audio_df_valid_fixation["rect"] = audio_df_valid_fixation.apply(
    lambda row: get_rect(row["FPOGX"], row["FPOGY"]), axis=1
)
```

	TIME	BPOGX	BPOGY	FPOGD	FPOGX	FPOGY	FPOGV	USER	trial_number	rect
0	57.91305	0.50808	0.47709	1.74694	0.49711	0.46464	1	LOG_AUDIO_TARGET_START	0	centre
1	57.92954	0.50812	0.48550	1.76344	0.49731	0.46505	1		0	centre
2	57.94503	0.50679	0.45819	1.77892	0.49725	0.46476	1		0	centre
3	57.96120	0.50044	0.46452	1.79509	0.49716	0.46428	1		0	centre
4	57.97736	0.50029	0.45900	1.81125	0.49707	0.46367	1		0	centre
...	...	...	...	...	...	...	...	...	...	...
3248	469.25360	0.48646	0.25336	0.25867	0.50388	0.22997	1		35	top
3249	469.26984	0.48670	0.26408	0.27490	0.50293	0.23186	1		35	top
3250	469.28601	0.51019	0.27612	0.29108	0.50331	0.23419	1		35	top
3251	469.30215	0.49822	0.27407	0.30722	0.50305	0.23619	1		35	top
3252	469.31839	0.49828	0.26523	0.32346	0.50283	0.23757	1	CLICK_RESPONSE_END	35	top

Figure 6.2: The `rect` column (highlighted) indicates the stimulus box where the participant was fixating.

6.5 Mapping stimulus location to stimulus type

The analysis plot is concerned with the stimulus type rather than the stimulus location. The fixations have already been mapped to the stimulus location so by using the data available in the csv log file it was possible to map the stimulus location to the stimulus type for each trial. The csv logfile contains the following columns, *referent, cohort, rhyme, distractor, target, trial number* and *condition number*. Each row indicates the names of the stimulus that was assigned the role of referent, cohort, rhyme, etc., for a given trial.

The csv log file was read into a pandas dataframe named `logger_df`. This dataframe has 36 rows, each corresponding to a trial. The information available in this dataframe can be combined with that available in the dictionary `stimuli_loc_dict` to map the stimulus location (top, right, bottom, left) to the stimulus type. The columns `top`, `right`, `bottom` and `left` were added to the dataframe `logger_df` and the values were populated using the dictionary `stimuli_loc_dict`.

```
# add the data from the stimuli_loc_dict to the logger_df
logger_df["top"] = [
    stimuli_loc_dict[idx][0].lower() for idx in logger_df["count_trial_sequence"]
]
logger_df["right"] = [
    stimuli_loc_dict[idx][1].lower() for idx in logger_df["count_trial_sequence"]
]
logger_df["bottom"] = [
    stimuli_loc_dict[idx][2].lower() for idx in logger_df["count_trial_sequence"]
]
logger_df["left"] = [
    stimuli_loc_dict[idx][3].lower() for idx in logger_df["count_trial_sequence"]
]
```

	referant	cohort	rhyme	distractor	target	count_trial_sequence	condition	top	right	bottom	left
0	dollar	basket	collar	handle	dollar	0	8	collar	handle	dollar	basket
1	saddle	padlock	pickle	candy	candy	1	12	pickle	padlock	candy	saddle
2	dollar	dolphin	collar	castle	collar	2	3	castle	dolphin	collar	dollar
3	paddle	padlock	saddle	candy	candy	3	4	padlock	saddle	paddle	candy
4	dolphin	speaker	candy	paddle	paddle	4	12	dolphin	speaker	candy	paddle
5	beaker	beetle	speaker	castle	beaker	5	1	castle	beaker	beetle	speaker
6	parrot	padlock	collar	saddle	saddle	6	7	parrot	collar	saddle	padlock
7	basket	parrot	casket	sandal	basket	7	8	basket	parrot	casket	sandal
8	castle	casket	dolphin	handle	casket	8	6	dolphin	handle	casket	castle
9	picture	pickle	candle	basket	pickle	9	6	candle	pickle	basket	picture

Figure 6.3: The newly added columns `top`, `right`, `bottom` and `left` (highlighted in red) contain the names of the stimuli at the top, right, bottom and left positions of the grid respectively for each trial. The values of these columns were determined using `stimuli_loc_dict` dictionary and the existing columns of `logger_df` (highlighted in blue).

These new columns were filled by the names of the stimuli but we are interested in the stimulus type. The next step was to add additional columns to the `logger_df` dataframe that contained the type of stimuli. The columns `top_type`, `right_type`, `bottom_type` and `left_type` were added to the `logger_df` dataframe. The values of these columns were populated by checking if the stimulus name was the same as the name of the referent, distractor, rhyme or cohort. The code block below shows how the contents of the `logger_df` were utilized to fill the columns `top_type`, `right_type`, `bottom_type` and `left_type`.

```
# create columns 'top_type', 'right_type', 'bottom_type', 'left_type' and
# populate them with the type of stimuli by checking if the stimuli is
# a referent, distractor, rhyme or cohort
logger_df['top_type'] = logger_df.apply(lambda row: 'referent'
        if row['top'] == row['referent'] else 'distractor'
        if row['top'] == row['distractor'] else 'rhyme'
        if row['top'] == row['rhyme'] else 'cohort'
        if row['top'] == row['cohort'] else 'NA', axis=1)
...
...
logger_df['left_type'] = logger_df.apply(lambda row: 'referent'
        if row['left'] == row['referent'] else 'distractor'
        if row['left'] == row['distractor'] else 'rhyme'
        if row['left'] == row['rhyme'] else 'cohort'
        if row['left'] == row['cohort'] else 'NA', axis=1)
```

Now every fixation could be mapped to a stimulus type i.e. whether the participant was fixating on the referent, distractor, rhyme or cohort. Although all required data for the mapping was available, the mapping was actually performed by the function `get_seen_stimuli_type` that loops through the rows of the `logger_df` dataframe and returns the stimulus type that the participant was fixating on. This function modified the `seen` column of the `audio_df_valid_fixation` dataframe so that it now contained the stimulus type that the participant was fixating on.

6.6 Issue of unequal entries per trial

The task of the final analysis plot is to visualize the proportion of fixations on the each stimulus type across trials and all participants. In order to create the plot, each trial must have equal number of data points. But the number of data points per trial is not equal, the number is dependent on the number of **valid** fixations made by the participant.

This issue is evident from the following plots:

6.6.1 Plotting the number of fixations per trial for one participant

This is done to visualize the number of fixations per trial for one participant. See Figure 6.4.

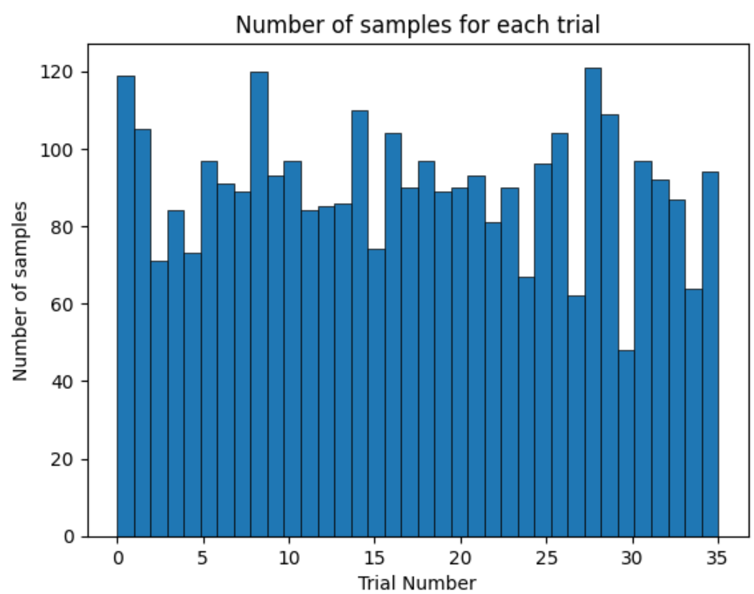


Figure 6.4: Plotting the number of fixations per trial for one participant

It is evident from the plot that the number of fixations per trial is not equal.

6.6.2 Comparing the trial durations for each condition number

The trials corresponding to each condition number posed a different task to the participant. The duration of the trials for each condition number was compared to see if the condition number had any effect on the number of fixations. See Figure 6.5.

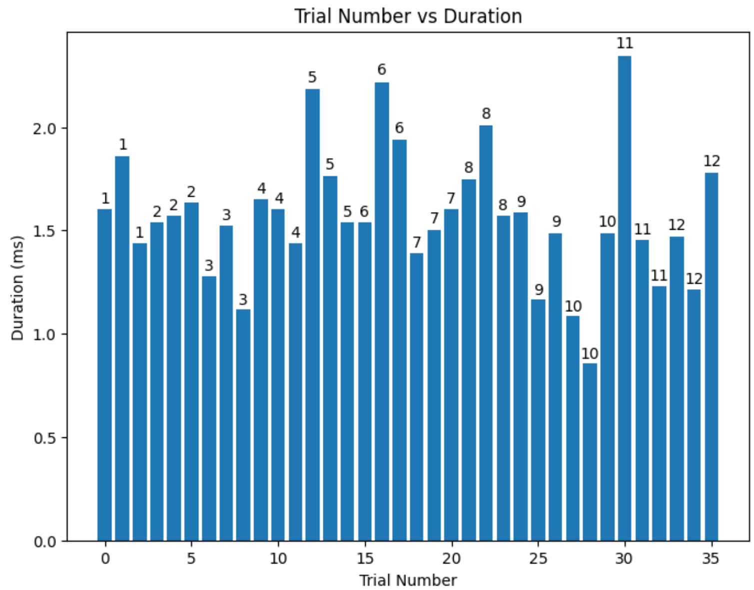


Figure 6.5: Comparing the trial durations for each condition number. Condition numbers are indicated above the bars.

It is evident from the plot that the duration of the trials for each condition number does not vary significantly. For the same condition number, the duration of the trials varies slightly. This is due to the fact that the participants were allowed to take their time to respond to the audio stimulus. Overall, there is no trend showing that some condition numbers have longer trials than others.

6.6.3 Solution: Binning the data

The data points were binned in order to ensure that each trial had equal number of data points. The binning was performed on the basis of time. An overall trial duration `avg_duration` was calculated and it was split into `N` equal parts. `N` is a user-defined parameter, it was chosen as `80` in our analysis. The data points were then binned into these parts.

```
avg_duration = 1.6
print("Average duration is set to {} s".format(avg_duration))

# divide the avg duration into N equal parts
N = 80
duration_thresholds = np.linspace(0, avg_duration, N, endpoint=True)
```

The `duration_thresholds` array contains the time thresholds for each bin.

> **Note:**
>
> The overall trial duration was calculated by averaging the trial duration across all trials and across all participants.

For determining the duration of each trial, the timestamp of the first fixation and the last fixation were used. The difference between these two timestamps was calculated and this was the duration of the trial. This duration was also used in the previous Section 6.6 to compare the trial durations for each condition number.

```
first_fixation_time = []
last_fixation_time = []
for idx, row in logger_df.iterrows():
    trial_df = audio_df_valid_fixation[audio_df_valid_fixation['trial_number'] == idx]
    first_fixation_time.append(trial_df['TIME'].min())
    last_fixation_time.append(trial_df['TIME'].max())

logger_df['first_fixation_time'] = first_fixation_time
logger_df['last_fixation_time'] = last_fixation_time

logger_df['duration'] = logger_df['last_fixation_time'] - logger_df['first_fixation_time']
```

After the bin thresholds were determined, the data points were binned into these thresholds. One of the most important column of the `logger_df` dataframe was the `seen` column that contained the name of the type of stimulus that was fixated on by the participant. During binning, the `seen` column values of entries belonging to the same bin are replaced by a single value. The value is determined by the following rules:

- First, the values `centre` and `outside` are replaced by `NA` (empty string).
- If the bin contains no values, the seen value is set to `NA`.
- If the bin contains only one value, the seen value is set to that value.
- If the bin contains more than one value, the seen value is set to the value that occurs the most number of times in the bin.

> **Note:**
>
> See `get_relevant_rect_value()` function in source code for implementation details.

A new dataframe `count_df` was created to store the binned data. The columns of this dataframe were `trial_number`, `condition_number`, `start_time`, `end_time`, `bin_start`, `bin_end`, `real_val_count`, `val_count` and `seen`.

- `trial_number` and `condition_number` were copied from the `logger_df` dataframe.
- `start_time` and `end_time` were the timestamps of the first and last fixation respectively belonging to the bin.

	trial_number	condition	start_time	end_time	bin_start	bin_end	real_val_count	val_count	seen
0	0	8	57.913050	57.932882	0.000000	0.019832	2	1	
1	0	8	57.932882	57.952714	0.019832	0.039664	1	1	
2	0	8	57.952714	57.972546	0.039664	0.059496	1	1	
3	0	8	57.972546	57.992378	0.059496	0.079328	1	1	
4	0	8	57.992378	58.012210	0.079328	0.099160	2	1	
...	...	...	...	...	...	...	...	...	...
2839	35	4	469.184581	469.204413	1.467571	1.487403	1	1	top
2840	35	4	469.204413	469.224245	1.487403	1.507235	2	1	top
2841	35	4	469.224245	469.244077	1.507235	1.527067	1	1	top
2842	35	4	469.244077	469.263909	1.527067	1.546899	1	1	top
2843	35	4	469.263909	469.283741	1.546899	1.566731	1	1	top

Figure 6.6: The `count_df` dataframe contains the binned data. The highlighted columns `bin_start`, `bin_end` indicate the start and end time of the bin.

- `bin_start` and `bin_end` were the start and end time of the bin.
- `real_val_count` was the number of data points in the bin.
- `val_count` was the effective number of data points in the bin. This was the number of data points in the bin after calling the `get_relevant_rect_value()` function.
- `seen` was the value of the `seen` column after calling the `get_relevant_rect_value()` function.

6.7 Implementing the conditions of competitor sets

The condition numbers of the four different types of competitor sets are as follows:

```
full_competitor_sets_cond = [1, 2, 3, 4]
cohort_competitor_sets_cond = [5, 6, 7]
rhyme_competitor_sets_cond = [8, 9, 10]
distractor_competitor_sets_cond = [11, 12]
```

As per the conditions (see Section 3.4), the instances of `rhyme` in the `seen` column were replaced by `distractor` for the trials with condition numbers belonging to the cohort competitor sets.

```
count_df.loc[
    count_df["condition"].isin(cohort_competitor_sets_cond), "seen"
] = count_df["seen"].apply(lambda x: "distractor" if x == "rhyme" else x)
```

Similarly, the conditions for rhyme competitor sets and distractor competitor sets were implemented.

6.8 Prepare data for plotting

6.8.1 One hot encoding

The calculation of fixation probabilities was made simpler by the one hot encoding of the `seen` column. This was done using the `pd.get_dummies()` function. The resulting dataframe was named `one_hot_count_df`. As a result of the one-hot encoding, the `seen` column was replaced by the columns `seen_cohort`, `seen_distractor`, `seen_referent` and `seen_rhyme`. The values of these columns were either 0 or 1. The value 1 indicated that the participant was fixating on the stimulus type indicated by the column name. The value 0 indicated that the participant was not fixating on the stimulus type indicated by the column name.

> **Note:**
>
> `pd.get_dummies()` adds columns of type `boolean`. The columns were converted to type `int` using the `astype()` function.

```
# one hot encode the 'seen' column
one_hot_count_df = pd.get_dummies(count_df, columns=['seen'])
```

Several of the trials acted as filler trials. These trials were not relevant for our analysis so they were removed from the dataframe.

```
# remove the rows that are not relevant for the final analysis
one_hot_count_df = one_hot_count_df[one_hot_count_df['condition'] != 2]
...
one_hot_count_df = one_hot_count_df[one_hot_count_df['condition'] != 12]
```

The groupby function was then used to group the rows by the columns `bin_start`, `bin_end` and calculate the fixation counts for each bin (See Figure 6.7). The `sum()` function was used to calculate the fixation counts. The resulting dataframe was named `grouped_time_bins_df`.

6.8.2 Implementing the conditions of the analysis plot

The final plot consisted of curves for the referent, cohort, rhyme and distractor stimuli. As per the specification of the analysis plot, the plot for the referent stimuli was created using the fixation data from three competitor sets (full competitor set, cohort competitor set and rhyme competitor set). The plot for the cohort stimuli was created using the data only from the full competitor sets and the cohort competitor sets and the plot for the rhyme stimuli was created using data only from the full competitor sets and the rhyme competitor sets.

In order to implement these requirements, the dataframe `one_hot_count_df` was sliced to form three different dataframes, each corresponding to the three competitor sets. The dataframes were named `full_competitor_sets_df`, `cohort_competitor_sets_df` and `rhyme_competitor_sets_df`. The dataframe `full_competitor_sets_df` contained the data from the full competitor sets. The

bin_start	bin_end	real_val_count	val_count	seen_cohort	seen_distractor	seen_referant	seen_rhyme
0.000000	0.019832	2	1	0	0	0	0
0.019832	0.039664	1	1	0	0	0	0
0.039664	0.059496	1	1	0	0	0	0
0.059496	0.079328	1	1	0	0	0	0
0.079328	0.099160	2	1	0	0	0	0
...	...	...	...	...	...	...	...
1.467571	1.487403	1	1	0	1	0	0
1.487403	1.507235	2	1	0	1	0	0
1.507235	1.527067	1	1	0	1	0	0
1.527067	1.546899	1	1	0	1	0	0
1.546899	1.566731	1	1	0	1	0	0

Figure 6.7: Calculation of the fixation counts for each bin.

dataframe `cohort_competitor_sets_df` contained the data from the full competitor sets and the cohort competitor sets. The dataframe `rhyme_competitor_sets_df` contained the data from the full competitor sets and the rhyme competitor sets. The dataframes were created by filtering the rows of the `one_hot_count_df` dataframe based on the condition numbers of the competitor sets.

```
full_competitor_sets_df = one_hot_count_df[
    one_hot_count_df["condition"].isin(full_competitor_sets_cond)
]
...
rhyme_competitor_sets_df = one_hot_count_df[
    one_hot_count_df["condition"].isin(rhyme_competitor_sets_cond)
]
```

The dataframe `referent_calc_sets` was created by concatenating the dataframes `full_competitor_sets_df`, `cohort_competitor_sets_df` and `rhyme_competitor_sets_df`.

```
referent_calc_sets = pd.concat(
    [
        one_hot_count_df_full_competitor_sets,
        one_hot_count_df_cohort_competitor_sets,
        one_hot_count_df_rhyme_competitor_sets,
    ],
    ignore_index=True,
)
```

Similarly, the dataframes `cohort_calc_sets` and `rhyme_calc_sets` were created.

The fixation counts for these dataframes were not the same as those obtained from the `grouped_time_bins_df` dataframe. This is because the data contained in the dataframes `referent_calc_sets`, `cohort_calc_sets` and `rhyme_calc_sets` were a subset of the data contained in the `grouped_time_bins_df` dataframe, while the `grouped_time_bins_df` dataframe contained the fixation counts disregarding the conditions necessary for the analysis.

Therefore, the groupby function for calculating the sum of the fixation counts was applied to these dataframes as well. The idea was to update these stimulus fixation counts (along with the total counts) in the `grouped_time_bins_df` dataframe.

```
# groupby sum for referent_calc_sets
groupby_time_bins_df_referent = (
    referent_calc_sets.groupby(["bin_start", "bin_end"]).sum().reset_index()
)
# groupby sum for cohort_calc_sets
groupby_time_bins_df_cohort = (
    cohort_calc_sets.groupby(["bin_start", "bin_end"]).sum().reset_index()
)
# groupby sum for rhyme_calc_sets
groupby_time_bins_df_rhyme = (
    rhyme_calc_sets.groupby(["bin_start", "bin_end"]).sum().reset_index()
)
```

The columns of interest from these dataframes were extracted and updated in the `grouped_time_bins_df` dataframe. The columns of interest, the dataframes from which they were extracted and the columns that were updated in the `grouped_time_bins_df` dataframe are shown in the table below:

Column name[2]	Source dataframe	Updated column name[3]	Type[4]
`seen_referent`	`groupby_time_bins_df_referent`	`seen_referent`	S
`seen_cohort`	`groupby_time_bins_df_cohort`	`seen_cohort`	S
`seen_rhyme`	`groupby_time_bins_df_rhyme`	`seen_rhyme`	S
`val_count`	`groupby_time_bins_df_referent`	`referent_val_count`	T
`val_count`	`groupby_time_bins_df_cohort`	`cohort_val_count`	T
`val_count`	`groupby_time_bins_df_rhyme`	`rhyme_val_count`	T

The code snippets for these changes are shown below:

```
# update the stimuli fixation counts
groupby_time_bins_df['seen_referant'] = groupby_time_bins_df_referant['seen_referant'].values
groupby_time_bins_df['seen_cohort'] = groupby_time_bins_df_cohort['seen_cohort'].values
groupby_time_bins_df['seen_rhyme'] = groupby_time_bins_df_rhyme['seen_rhyme'].values

# update the total fixation counts
```

[2] in the source dataframe
[3] in `grouped_time_bins_df`
[4] S = stimulus fixation count, T = total fixation count

```
groupby_time_bins_df['referant_value_count'] = groupby_time_bins_df_referant['val_count'].values
groupby_time_bins_df['cohort_value_count'] = groupby_time_bins_df_cohort['val_count'].values
groupby_time_bins_df['rhyme_value_count'] = groupby_time_bins_df_rhyme['val_count'].values
```

6.9 Calculating the fixation probabilities

The calculation of the fixation probabilities was the simple task of dividing the stimulus fixation counts by the respective total fixation counts. The contents of the stimulus fixation count columns were updated with the fixation probabilities.

```
groupby_time_bins_df["seen_referant"] = groupby_time_bins_df.apply(
    lambda x: x["seen_referant"] / x["referant_value_count"]
    if x["referant_value_count"] != 0
    else 0,
    axis=1,
)
groupby_time_bins_df["seen_cohort"] = groupby_time_bins_df.apply(
    lambda x: x["seen_cohort"] / x["cohort_value_count"]
    if x["cohort_value_count"] != 0
    else 0,
    axis=1,
)
groupby_time_bins_df["seen_distractor"] = groupby_time_bins_df.apply(
    lambda x: x["seen_distractor"] / x["val_count"] if x["val_count"] != 0 else 0,
    axis=1,
)
```

6.10 Saving per participant data

The dataframe with the fixation probabilities were saved to a csv file. Each participant should have a separate csv file.

```
# save groupby_time_bins_df as 'intermediate_csv/sub-x.csv'
groupby_time_bins_df.to_csv(
    "intermediate_csv/sub-" + str(subject_number) + ".csv", index=False
)
```

> **Note:**
>
> Before running the script for the final analysis plot, ensure that the processing script has been run for all participants. The script for the final analysis plot only considers the data that is available in the form of csv files for its analysis.

6.11 Plot of the final analysis

The main function of the final analysis plot script is to aggregate the data from the csv files and plot the fixation probabilities for each stimulus type over time.

The csv files were read into a pandas dataframe one by one and then concatenated into a single dataframe. The resulting dataframe was named `agg_df`.

```
agg_df = pd.DataFrame()
for csv in relevant_csvs:
    filename = "sub-" + str(csv) + ".csv"
    df = pd.read_csv(csv_path + filename)

    # concat the dataframes
    agg_df = pd.concat([agg_df, df], axis=0).reset_index(drop=True)
```

The entirety of the data is then aggregated by the columns `bin_start` and `bin_end`. The time bins are the common link between the data from different participants. The data was grouped by the time bins and the mean of the fixation probabilities is calculated for each time bin. The resulting dataframe was named `agg_df_mean`.

```
# group_by bin_start and bin_end and get the mean of the other columns
agg_df_mean = agg_df.groupby(['bin_start', 'bin_end']).mean().reset_index()
```

The data after this step was ready for plotting.

```
# plot as line plots
fig, ax = plt.subplots(figsize=(10, 6))
ax.plot(
    agg_df_mean["bin_start"],
    agg_df_mean["seen_referant"],
    "ro--",
    label="referant"
)
ax.plot(
    agg_df_mean["bin_start"],
    agg_df_mean["seen_cohort"],
    "bs--",
    label="cohort"
)
ax.plot(
    agg_df_mean["bin_start"],
    agg_df_mean["seen_rhyme"],
    "g^--",
    label="rhyme"
)
```

```
ax.plot(
    agg_df_mean["bin_start"],
    agg_df_mean["seen_distractor"],
    "c.--",
    label="distractor"
)
```

A vertical dashed line was drawn at the point of average audio offset. The average audio offset was calculated by averaging the audio offset for all audio stimuli.

```
# draw a vertical line at average_audio_stimuli_offset, do not add to legend
ax.vlines(
    average_audio_stimuli_offset,
    0,
    ymax,
    colors='k',
    linestyles='dashed',
    alpha=0.5
)
# add text to the plot
ax.text(
    average_audio_stimuli_offset + 0.02,
    ymax - 0.05,
    'Average target offset',
    fontsize=10
)
```

6.12 Analysis of the obtained results

6.12.1 Validity of the analysis plots

For the final analysis of the gaze data, the fixation probabilities over time for each of the stimulus types were plotted. The plot was created by aggregating the data from all participants. Individual analysis plot consisting of fixation probabilities over time for individual participants were first created to ascertain that the data was valid. If discrepancies were found in the individual plots, the data for that participant was discarded. The data from the remaining participants was aggregated and the final analysis plot was created.

In the initial stages of the trial, all the fixation probabilities should be close to zero. This is because the participant has not yet heard the audio stimulus and hence has not yet decided which stimulus to fixate on. As the trial progresses, the fixation probabilities should increase. The fixation probabilities for the referent stimuli should increase the most. This is because the participant is expected to fixate on the referent stimuli. Moreover, the increase in the fixation probabilities should not be sudden. Sudden increase would indicate that the experiment was not conducted properly. Examples of valid analysis plots are shown in Figure 6.8.

> **Note:**
>
> The lines in the analysis plots can be identified by their markers. Refer to the legends in the plots.

See Figure 6.9 for an example of an invalid analysis plot. The fixation probabilities for the referent stimuli increase suddenly. This indicates that the experiment was not conducted properly.

After the data from all participants was aggregated, the final analysis plot was created. See Figure 6.10.

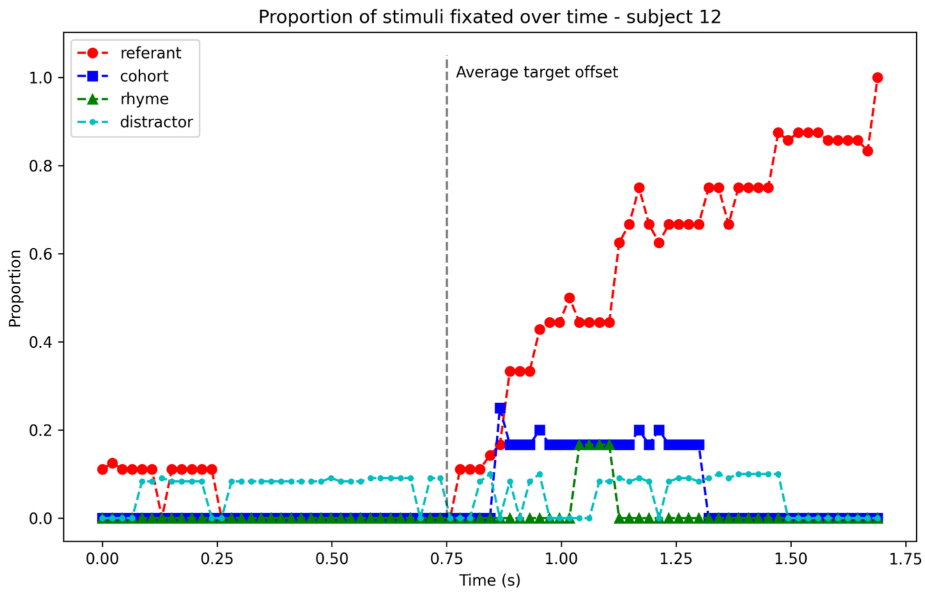
6.12.2 Inference

> **! Important:**
>
> The audio stimuli used in our experiments are longer in duration than those used in the reference paper (see Section 7.1). As a result of this, the inference events are not observed at the same time as in the reference paper. The inference events are observed at a later time in our experiments.

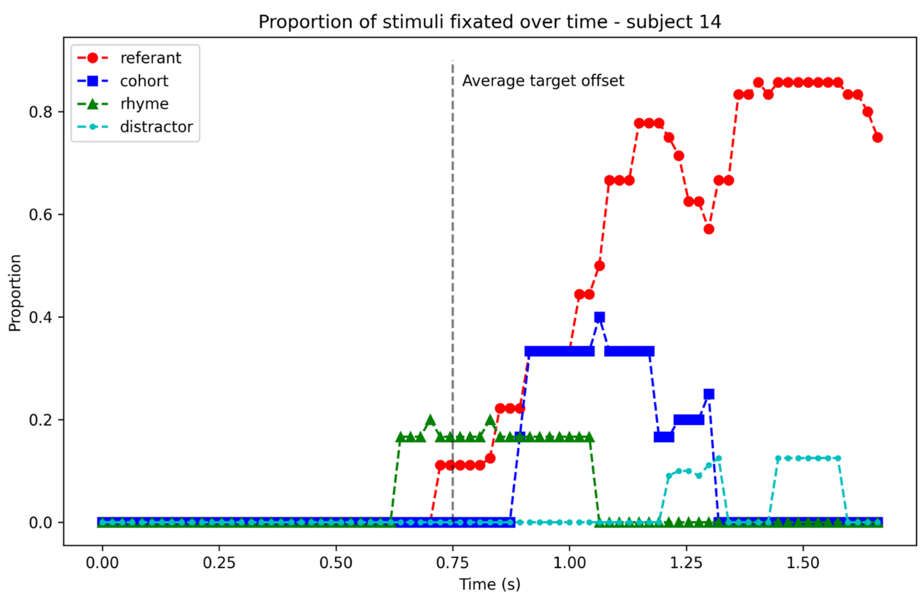
The analysis plot from the reference paper is shown in Figure 6.11 for comparison.

> **Note:**
>
> The timestamps in the following section refer to the timestamps in our analysis plot.

- In the 0 to 400 ms interval, the fixation probabilities appear to be random. This is because the participants have not yet heard the audio stimulus and hence have not yet decided which stimulus to fixate on. No specific trend is observed at this point.
- In the 400 to 800 ms interval, there is a increase in the number of fixations on the referent and the cohort stimulus.
- The curve for the referent stimulus separates from the curve for the cohort stimulus in the 800 to 1000 ms interval.
- Starting from 600 ms, the fixation probabilities for the rhyme stimulus start to increase.
- Beyond the 1000 ms mark, the referent curve starts to peak, leaving all the other competitors behind. At this point in the trial, the participant has identified the audio stimulus and has decided to fixate on the referent stimulus.
- One major deviation that was observed in our analysis plot was that the fixation probabilities for the distractor stimulus didn't decrease to around 0 towards the end of the trial. A



(a) Participant 12



(b) Participant 14

Figure 6.8: Examples of valid analysis plots

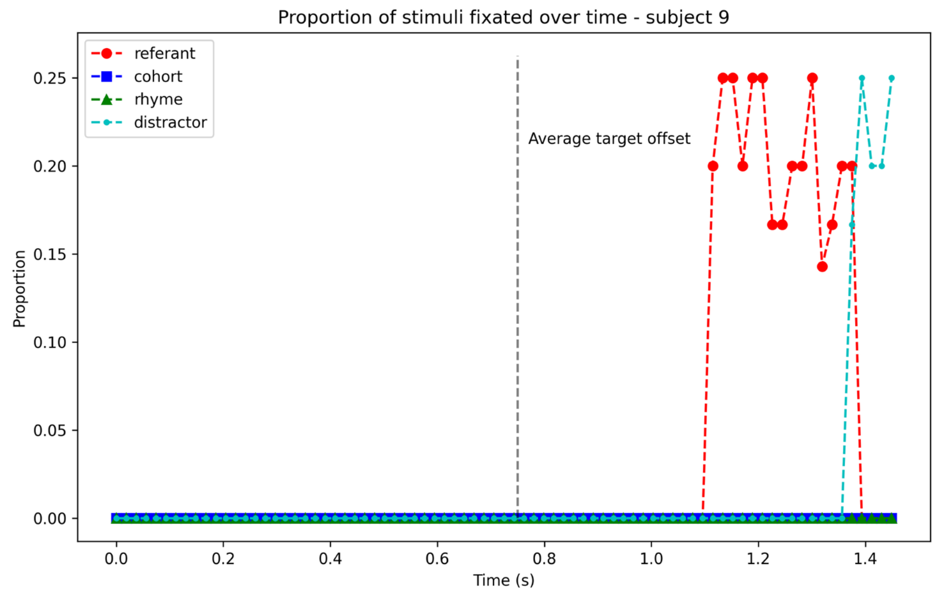


Figure 6.9: An invalid analysis plot. Obtained from the data of participant 9.

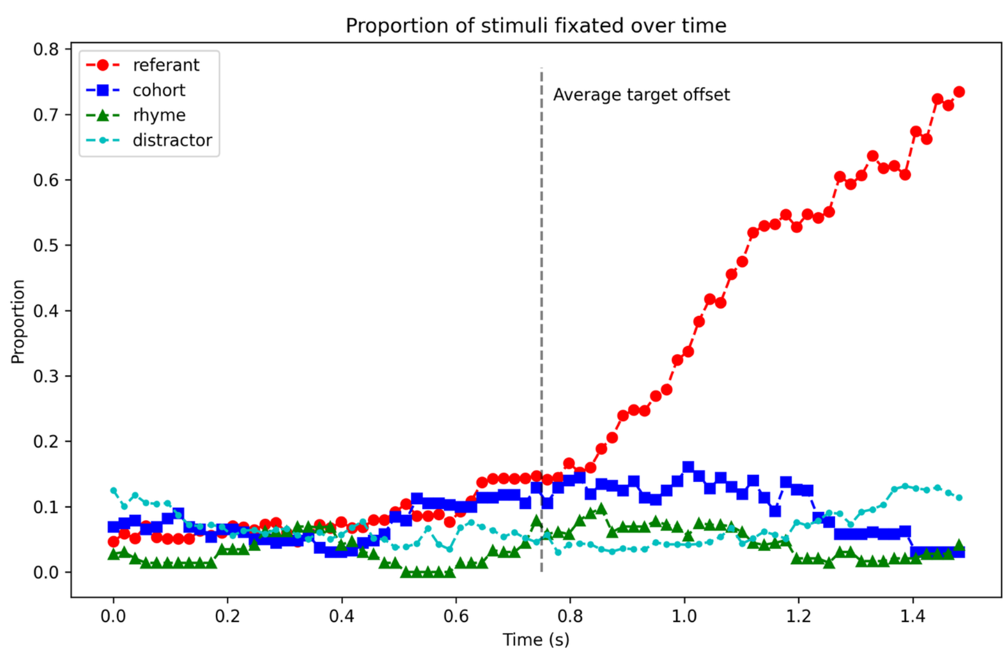


Figure 6.10: The final analysis plot.

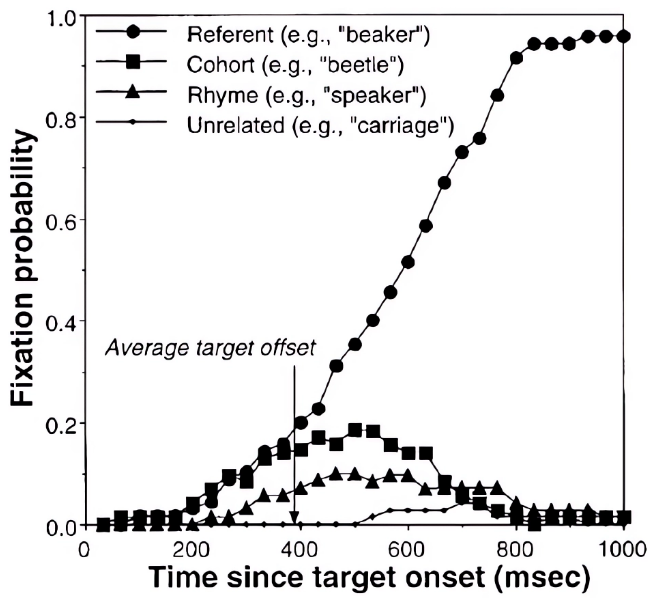


Figure 6.11: The analysis plot from the reference paper.

small peak was observed in the distractor curve at around 1400 ms. This is not observed in the reference paper.

Overall, the analysis plot obtained from our experiments is similar to the analysis plot obtained from the reference paper. The trends described in the above points are in both the plots.

Chapter 7

Challenges and Limitations

7.1 What we did not replicate from the reference paper?

1. Average duration of auditory stimulus was changed from 375 ms to 750 ms. It was done to make it more comprehensible for the participants.
   - The average duration was calculated by taking the average of the duration of all the audio stimuli. The calculation can be found here.
2. Number of trials for each participant was reduced from 96 to 36. It was done to reduce the time of the experiment and to avoid recalibration of the eye tracker in between the experiment.
3. Audio stimuli were digital (instead of analog). It was done to avoid any noise in the audio stimuli and also to have no influence of the speaker's accent on the participants.
4. Participants respond with mouse clicks instead of *drag-and-drop to the correct box* function as OpenSesame does not support drag-and-drop functionality.
5. Use of a 3x3 grid instead of 5x5 as we didin't require the additional boxes for the drag-and-drop functionality as in the reference paper.
6. No calibration functionality was added within a trial. No recalibration was performed unless the participant moved their head or eyes too much.

7.2 Challenges

1. **Balancing of trials**:
   - **Challenge**: Our stimuli had a total of *23 unique visual stimuli*, *12 different conditions* and *4 different stimuli types*. Adhering to proper randomization and balancing of trials was a challenge as we had to ensure that each participant saw the same number

of trials for each condition and also of each type and such that each stimuli object appeared an equal number of times.

- **Solution**: Although we started with a python script to generate the trials, we had to revert to manual formation of trials as the script was not able to generate balanced trials which was a primary requirement for our experiment.

2. **Random 'freezes' during experiment** :
   - **Challenge**: The experiment encountered random freezes during its run. The freezes were random and could not be reproduced. This was a major challenge as we had to restart the experiment. The most frequent freezes were found during the *gaze contingency* check, which allowed the experiment to move forward only when the participant was fixating at the center of the screen.
   - **Attempts to fix**:
     1. Replacing `While True` loop with periodic sampling

```
while True:
    gazepos = eyetracker.sample()
```

   The above code was replaced with the following code to sample the eye tracker at a fixed interval of `diff`.

```
while True:
    if clock.time() - check_timer > diff:
        gazepos = eyetracker.sample()
```

     2. Switching backend to PsychoPy: set equal sample rates of all the audio samples to make it work with the PsychoPy backend.
     3. Number of trials: reduced the number of trials to 24 from 36 to reduce the time of the experiment but the problem still persisted. This didn't help so it was reverted back to 36 trials.
   - **Solution**: Removing gaze contingent features and instead introducing a delay to ensure that the participants are fixating at the center of the screen before the spoken instruction is played. This was implemented by introducing a delay of 1.1s after the prompt.

3. **Eye tracker calibration**:
   - **Challenge**: The eye tracker calibration was a challenge as the participants were not able to calibrate with the eye tracker, due to many reasons like contact lenses, glasses, height of the participants, body posture, etc., during the experiment.
   - **Solution**: The number of participants were increased to 16 to ensure that we have atleast 12 participants with proper calibration and the timing of one full experiment was reduced to a maximum of 8 minutes to avoid recalibration in between the experiments. The participants were also given a practice trial to ensure that they are comfortable with the experiment and the eye tracker calibration.

7.3 Limitations

1. Since Visual World Paradigm is a well known experimental framework, it is possible that the participants might have been aware of the purpose of the experiment and thus were biased in their responses despite the large number of filler trials. Also, we used a relatively small set of pictures, which might have led to a learning effect i.e. the participants might have been able to predict the target word, based on the previous trials.
2. Generalizability is affected as the participants of our study only include university students of a specific age group, which does not fully represent the complexities and variations of real-world spoken word recognition scenarios. The results may not be applicable to other age groups or people with different educational backgrounds who might have more or less exposure to the field of cognitive psychology.
3. The study also may not fully address the universality of the observed effects across different languages as the original study as well as our replication is in English.

Chapter 8

Further Improvements

This projects although replicates the results of the reference paper to a great extent, there are still some improvements that can make the results and the analysis more robust and reliable. Some of the improvements are as follows:

1. More extensive study with a larger number of participants will ensure that the results are more generalizable. The study can be conducted with participants from different age groups and educational backgrounds. Also the study can be conducted in different languages to prove the universality of the observed effects.

2. The Gazepoint GP3 eye tracker can be replaced with a more advanced eye tracker like Eyelink 1000 which can record at a higher sampling rate and thus provide more accurate results. The Eyelink 1000 eye tracker allows less head movement due to its design and thus the recording of the eye movements are more accurate.

3. The experiment requires us to study the fixation behavior of the participants. Therefore, better optimized fixation detection algorithms can be used and even integrated to the open source software like OpenSesame to improve the analysis.

Chapter 9

Conclusion

In this project we attempted to investigate the dynamics of predictive language processing through the visual world paradigm. We tried to replicate the experiment conducted by Allopenna, Magnuson and Tanenhaus [1] and validate the hypothesis that the existence of similar sounding words leads to an increased number of fixations on them, reflecting the participants' evolving predictions of the upcoming word. We were able to replicate the results of the original study and thus validate the hypothesis, keeping into account the limitations of our study.

We summarize our conclusions as follows:

1. The inclusion of semantically or phonetically similar words in the spoken instructions results in a higher frequency of fixations on the visual images of the words. This phenomenon illustrates how participants are continuously adjusting their predictions for the upcoming word as they engage with the content.

2. Eye movement tracking is a reliable tool for investigating the time course of spoken word recognition and capturing the mapping process while the spoken word unfolds.

3. The results and plots obtained by us provide an empirical support for continuous and incremental mapping models of word recognition and proves that word processing is not a discrete and all-or-nothing process.

4. Our results suggest that as the spoken word unfolds over time, the listener gradually narrows down the set of candidate words based on the contextual information. This competition among candidate words occurs until a single word is identified or a clear winner emerges.

Chapter 10

Contribution Table

Table 10.1: Contributions of each team member to the project

Task	**Pritom**	**Kapil**	**Manpa**
Background Literature	o	o	x
Experiment Design	x	o	x
Stimulus Design	x	x	x
Piloting	x	x	o
Data-Recording	o	x	x
Non-Final-Talk presenting (who talks)	x	o	x
Non-Final-Talk presenting (who prepares)	x	x	x
Final-Talk Presenting (who talks)	x	x	x
Final-Talk Presenting (who prepares)	x	x	x
Data Analysis Scripts	x	o	o
Report Writing	x	x	x

- x: main contributor
- o: supporting contributor

References

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