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Analysis of recall performance for news headlines across variables: word count, readability, polarity and subjectivity

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Abstract

In recent years, global events, escalating geopolitical tensions, and other major international issues have arisen, and we often find ourselves searching for information on these events in the digital world. Large news platforms continue to play a central role in informing and shaping opinions. However, there is ever-growing evidence that people only read headlines when navigating news platforms, which, in turn, are known to use manifold techniques to attract and retain consumers' attention. Moreover, scientific studies suggest that simpler, more readable language and negative sentiments in headlines increase consumption rates, whereas positive sentiments have the opposite effect. There is contradicting evidence regarding the influence of word count, with some studies claiming it has an effect, while others do not.

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This paper investigates recall for online news headlines by showing participants a set of seen headlines and then putting their memory to the test by showing these again jumbled with new articles as a means of assessing whether the variables of headline length, positive or negative emotions, i.e. polarity, readability and subjectivity, among others, influence successful recall time and accuracy. The results indicate that readability has a significant influence on reaction time. After constructing a model, both word count and reaction time significantly predict reaction time. Regarding recall accuracy, no significant influence of the variables was found, and none of them predict accuracy significantly. An additional finding is that participants responded more quickly when giving incorrect responses, and this difference is statistically significant. However, when studying if participants responded faster when looking at previously seen and unseen headlines, no significant difference was found.

Keywords: news headlines, word count, readability, polarity, subjectivity, reaction time, recall accuracy.

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Introduction

We are constantly being bombarded with information about events around the globe and this pervades our lives. Therefore, we often resort to big media outlets for news and information and these, in turn, sway our view of the world. We can also discern emerging trends indicative of a new technology shift. For instance, people increasingly turn to short news videos, which are typically defined as lasting for a few minutes or less. Across countries, two-thirds (66%) said that they access short news videos at least once a week, with higher levels being detected outside the US and Western Europe. However, the use of news outlets and social media platforms to find information are interconnected as between 52% and 82% of people in a recent survey, depending on the specific location, reported obtaining information from social media platforms and other news outlets, mainly because platforms host content from news outlets. Thus, online news platforms remain crucial in shaping public opinion and this study will focus on them.

at just the headline or a few lines, which makes headlines particularly interesting to research. Of course, many studies regarding headlines have been conducted, but they have primarily focused on headline attention and click-through rates (CTR), which measures the percentage of users who click on a headline after viewing it. A notable gap in the literature is thus the limited research on how headlines are recalled. This study aims to address this gap by exploring the factors that influence headline recall. To do so, I will scrape BBC News headlines and analyze them using various Python libraries. These headlines will then be presented to participants, and their accuracy and reaction times will be measured to assess their recall.

Regarding the storage and retrieval of the headlines, Baddeley's theory of working memory suggests that working memory is a space where we temporarily hold and use information before it can be transferred to long-term memory. This theory includes a central executive, which directs attention and cognitive resources, and two “slave systems”: the visuospatial sketchpad to retain visual and spatial images and the phonological loop to maintain verbal information (Baddeley, 1992). This theory is highly relevant because it explains how participants might store the headlines.

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According to Treisman's Feature Integration Theory, people process basic features without attention, but attention is required to correctly bind these features together (Anderson, 2020). Therefore, participants will need to invest attention to the headlines to extract features from headlines.

Participants could potentially store headlines’ meaning in many ways. For instance, they might hold the information as an abstract meaning, similar to amodal systems or they might store them in one modality and have the capacity to move it to a different modality, similar to modal systems (Wajnerman Paz, 2019). Other recent investigations suggest that the brain employs a combination of modal and amodal representations (Michel, 2021). People do not tend to focus on the exact wording in memory tasks, unless cued to do so, but rather they focus on a more abstract meaning that encapsulates the presented text (Anderson, 2020). Therefore, participants will most likely store some form of meaning instead of the exact wording.

A recent scientific breakthrough has been the discovery that every negative word, on average, increases the CTR of that headline by 2.3% and that every positive word decreases the CTR by 1.0% (Robertson et al., 2023). This is consistent with negativity bias, a phenomenon in which negative events, emotions, or stimuli have a greater psychological impact on individuals than positive or neutral ones of the same intensity (Rozin & Royzman, 2001). All of this suggests that the emotional nature of the words contained within a headline alters our behavior when reading articles. It seems like a worthwhile endeavor to see if these results extrapolate to headline recall and retrieval, with the hypothesis that negative emotions enhance recall while positive emotions hinder it.

Another relevant study found that more readable headlines with a simpler linguistic style were associated with higher CTRs, although word count was not a significant factor (Shulman et al., 2024). In the current study, readability will be measured with the Flesch Reading Ease metric, which takes sentence length and average number of syllables per word into account, under the hypothesis that greater readability enhances headline recall. According to another study, word count in financial news headlines influences readers' behavior. Specifically, long headlines initially attract attention but cause readers to shift their focus away from them very quickly (She & Zhang, 2019). Another goal, therefore, is to ascertain whether word count has an influence on headline recall, with the hypothesis that shorter headlines are more easily remembered and retrieved.

Subjectivity, gramatically, can be manifest in the presence of question or exclamation marks, the use of specific pronouns and verbs and wording styles (Vis, 2011). While headline emotionality has been extensively studied, subjectivity remains underexplored. This experiment will analyze subjectivity focusing on expressions indicative of opinions or facts. The hypothesis is that more subjective headlines will be better remembered and recalled than objective ones.

Hypotheses

This paper aims to determine the influence of emotional tone, readability, word count and subjectivity on headline recall. The hypotheses are as follows:

In relation to headlines' emotional tones, I hypothesize that:

- **H1.1:** More negative headlines will be recalled with greater accuracy than more positive headlines.
- **H1.2:** More negative headlines will be recalled faster than more positive headlines.

In relation to headlines’ readability scores, I hypothesize that:

- **H2.1:** Headlines with greater readability will be recalled with greater accuracy, as opposed to headlines with lower readability.
- **H2.2:** Headlines with greater readability will be recalled faster, as opposed to headlines with lower readability.

In relation to headlines’ word counts, I hypothesize that:

- **H3.1:** Shorter headlines will be recalled with greater accuracy compared to longer headlines.
- **H3.2:** Shorter headlines will be recalled faster compared to longer headlines.

In relation to headlines’ subjectivity scores, I hypothesize that:

- **H4.1:** More subjective headlines will be recalled with greater accuracy relative to more objective headlines.
- **H4.2:** More subjective headlines will be recalled faster relative to more objective headlines.

Pertaining to the nature of participants’ responses, I hypothesize that:

- **H5:** Participants will respond more quickly when providing correct responses, as compared to incorrect responses.

Concerning participants' exposure to the headlines, I hypothesize that:

- **H6:** Participants will respond more quickly to seen headlines than to unseen headlines.

Methods

The experiment required participants to be recruited to collect data and subsequently perform analyses to test the above-mentioned hypotheses. All participants volunteered to participate in this study.

Participants

24 participants were recruited for this experiment. The participants were all students from the Cognitive Science degree at Aarhus University. All participants were made fully aware of the implications, the objective and potential benefits and risks of the experiment. They knew exactly the data that would be collected and were assured that personal information, such as age, nationality or gender, would not be collected to not put their identities at risk. Randomized 6-digit identifiers were used to differentiate between participants while maintaining

anonymization. They were told that the experiment was voluntary, that they could withdraw their consent and data at any time, during or after the experiment, and all data would be anonymized. All of this was done at the start of the experiment. As a result, we can safely say that informed consent was given.

Materials

24 news headlines were chosen from the BBC News website, which were then grouped into three groups of eight headlines each.

Procedure

The PsychoPy software (v2024.2.1post4) (Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Richard Hochenberger, Sogo, H., … Jonas Kristoffer Lindelov. (2019)) platform, which runs on Python, was used for both the headline scraping and presentation to participants. BBC headlines were used in this experiment due to their great coverage of events in English, global authority, reach across the globe and consistent linguistic features, controlling for regional dialects.

The experimenter selected 24 headlines from the BBC News website to scrape using the Python library *BeautifulSoup* (Richardson, L. (2007)) and split them into 3 groups of 8 headline URLs. The headlines were analyzed. The *TextStat* package was used to calculate the word count (discrete) and readability (continuous, usually 0 to 100, Flesch Reading Ease) and the *TextBlob* (Loria, S. (2018)) package was used to get the polarity (continuous, -1 to 1) and subjectivity (continuous, 0 to 1) of each headline.

Each group concerned different events: Donald Trump’s victory in the 2024 US presidential election, escalation in the Middle East and North Korean missiles and troops in the war in Ukraine. The group segmentation strategy aimed to prevent participants from feeling overwhelmed by memorizing too many headlines at once, and by grouping headlines pertaining to the same event together it was ensured that there would be minimal contextual differences between headlines of the same group. Each group featured headlines with varying length and readability, emotionality and subjectivity scores to include all combinations and reduce potential biases during presentation. However, the groups will not be analyzed separately; instead, all 24 headlines will be treated as a single dataset. This approach provides a comprehensive analysis of how the variables affect headline recall.

Participants were presented with an experiment window using the PsychoPy framework, an open-source Python package. The experiment commenced when an introductory message was shown, stating that they were to be shown news headlines. Then they had to give their consent to continue. The options were the following: to view the conditions, to give their consent (this would take them to the experiment) or to deny their consent (this would abort the experiment). If the conditions were accepted, they had to press ‘space’ to start. This would take them to the three rounds of headline recalling in a randomized order. In each round, they were instructed to memorize upcoming articles. They were then shown four news headlines in sequence, for 3 seconds each, followed by a 5-second interlude, where they were asked “Have you seen the following headlines?” and were told to press ‘Y’ (yes) if they had seen an article or ‘N’ (no) if they had not. After that, they had to say whether they had seen each headline in that group by pressing one of those two keys. All the processes in the experiment, including round order, the shown headlines of each group and their order, and the order of the 8 headlines of each group in the recall phase, were randomized to offset potential order biases. Once they had completed the three rounds, they were shown a goodbye message.

All the data gathered was contained within one data frame, with 24 rows per participant and the following columns: participant identification, headline, response (correct or incorrect), whether the headline had been initially shown (shown or not shown) and the independent variables from the previous analysis, which are number of words, readability, polarity and subjectivity.

Analysis

For the following analyses, the programming language R (v.4.4.1) (R Core Team (2024)) was used. The *tidyverse (*Wickham H, Averick M, Bryan J, Chang W, McGowan LD, François R, Grolemund G, Hayes A, Henry L, Hester J, Kuhn M, Pedersen TL, Miller E, Bache SM, Müller K, Ooms J, Robinson D, Seidel DP, Spinu V, Takahashi K, Vaughan D, Wilke C, Woo K, Yutani H (2019)), a collection of diverse R packages, was employed throughout because of its useful features, such as pipes. The *read_delim* function from the *readr* (Wickham H, Hester J, Bryan J (2024)) package was used to import the csv file with participants' data. The *select* function from the *dplyr* (Wickham H, François R, Henry L, Müller K, Vaughan D (2023)) package was used to remove unwanted columns. The *pastecs* (Grosjean P, Ibanez F (2024)) package was used repeatedly to carry out statistical analyses.

The *ggplot2* (H. Wickham, 2016) package was used in many instances to plot data, specifically, the *geom_histogram* function was used. The *lme4* (Douglas Bates, Martin Maechler, Ben Bolker, Steve Walker (2015)) package was used to construct mixed-effects models: the *lmer* function was used with reaction time as the dependent variable and the *glmer* function with accuracy as the dependent variable to build a Generalized Linear Mixed Model (GLMM) and a Generalized Linear Model (GLM).

Analysis of reaction time

The reaction time variable without any transformations was not normally distributed, therefore I proceeded to transform reaction time to try to make it normal. I tried logarithmic and inverse transformations to no avail. However, after that, I used an inverse power transformation and it made reaction time normally distributed. This is the inverse power transformation I used:

$$\frac{1}{(reaction\ time)^{0.2}} \quad \text{or} \quad \frac{1}{\sqrt[5]{reaction\ time}}$$

I employed Pearson's correlation four times between transformed reaction time and the independent variables. Then I checked if the independent variables were normal.

After that, I ran Kendall's correlation four times because of my non-normal independent variables and the presence of ties in my data. Then I constructed a model with transformed reaction time and the four independent variables*:*

$$transformed\ RT\ \sim\ word\ count + readability + polarity + subjectivity$$

Due to issues with the assumptions, I chose a mixed-effects model, instead, using *lmer*. This is the model I constructed:

$$transformed\ RT \sim word\ count + readability + polarity + subjectivity + (1|ID)$$

Analysis of recall accuracy

My data frame contained a column that indicated whether the response given in each case was correct or incorrect. I transformed this column, so that correct equated to 1 and incorrect to 0, making this a binary dependent variable. I ran Point-Biserial correlations between accuracy and the four variables. However, as the latter were not normal, I ran Kendall's correlation. I also built two models with accuracy and the four independent variables, with a binomial family specification, but I had difficulties with the assumptions in both cases. These are the models:

$$accuracy \sim word\ count + readability + polarity + subjectivity + (1|ID)$$

$$accuracy \sim word\ count + readability + polarity + subjectivity$$

Analysis of correct and incorrect responses

In this section, I created a data frame with the mean reaction times of each participant for both their correct and incorrect responses. This data frame had one row per participant and one column with correct responses and another with incorrect responses. I subtracted the mean reaction time of the incorrect responses from the correct responses to obtain the difference in reaction times. I removed data points more than 3 standard deviations away from the mean. Finally, I conducted a one-sample t-test with the difference in reaction times and a mu = 0 specification.

Analysis of seen and unseen headlines

In this part, I also created a data frame with the mean reaction times of each participant for both their seen and unseen headlines. This data frame had one row per participant and one column with seen headlines and another with unseen headlines. I subtracted the mean reaction time of the unseen headlines from that of the seen headlines to obtain the difference in reaction times. I also removed data points more than 3 standard deviations away from the mean. Finally, I conducted a one-sample t-test with the difference in reaction times and a mu = 0 specification.

Results

Results of the reaction time analysis

The results of the Kendall correlation tests indicate that there is not a significant correlation between the transformed reaction time and word count ($\tau = -0.045$, $p = 0.13$), polarity ($\tau = -0.0098$, $p = 0.74$) and subjectivity ($\tau = -0.027$, $p = 0.36$).

However, according to the results, there is a significant correlation between the transformed reaction time and readability ($\tau = 0.066$, $p = 0.021$).

Figure 1 – Scatter plot with a regression line showing the relationship between non-transformed reaction time and readability.

Furthermore, a mixed-effects model was constructed to examine the relationship between the transformed reaction time and word count, readability, polarity, and subjectivity, with a random intercept for ID to account for individual differences as participants registered multiple responses. The model yields a significant relationship in the cases of word count ($\beta = -0.0056$, $SE = 0.0026$, $t = -2.13$, $p = 0.033$) and readability ($\beta = 0.0084$, $SE = 0.0032$, $t = 2.59$, $p = 0.0098$). The intercept is also highly significant ($\beta = 0.87$, $SE = 0.0076$, $t = 114.78$, $p < 0.001$). However, this does not apply to polarity ($\beta = 0.0023$, $SE = 0.0026$, $t = 0.91$, $p = 0.36$) and subjectivity ($\beta = 0.0033$, $SE = 0.0032$, $t = 1.04$, $p = 0.29$). The random effects indicate that there is a small variance in intercepts across individuals (Variance = 0.0012, Std. Dev. = 0.035), with a residual variance for reaction time being somewhat larger (Variance = 0.0037, Std. Dev. = 0.061).

Figure 2 – Scatter plot with a regression line showing the relationship between non-transformed reaction time and word count.

Results of the recall accuracy analysis

The results of the Kendall correlation tests indicate that there is not a significant correlation between the binary accuracy variable and word count ($\tau = 0.0089$, $p = 0.8$), readability ($\tau = -0.018$, $p = 0.6$), polarity ($\tau = -0.049$, $p = 0.19$) and subjectivity ($\tau = -0.0083$, $p = 0.82$).

A logistic regression model was used, with the dependent variable accuracy and the four independent variables. The results show that only the intercept is significant ($\beta = 2.08$, $SE = 0.13$, $z = 15.39$, $p < 0.001$). However, none of the predictors are statistically significant, with the following values: word count ($\beta = -0.13$, $SE = 0.12$, $z = -1.06$, $p = 0.28$), readability ($\beta = 0.06$, $SE = 0.17$, $z = 0.34$, $p = 0.73$), polarity ($\beta = -0.18$, $SE = 0.13$, $z = -1.33$, $p = 0.18$) and subjectivity ($\beta = 0.04$, $SE = 0.17$, $z = 0.22$, $p = 0.82$). The results of this model are unreliable because the assumption of homoscedasticity is violated.

Results of the correct and incorrect responses' analysis

A one-sample t-test was conducted to determine whether the difference in reaction time for correct and incorrect responses is significantly different from zero. The results reveal a significant difference in the mean reaction time difference, $t(22) = 3.36$, $p = 0.0028$. The 95% confidence interval for the mean difference is [0.0091, 0.038], and the sample mean of the reaction time difference is approximately 0.024.

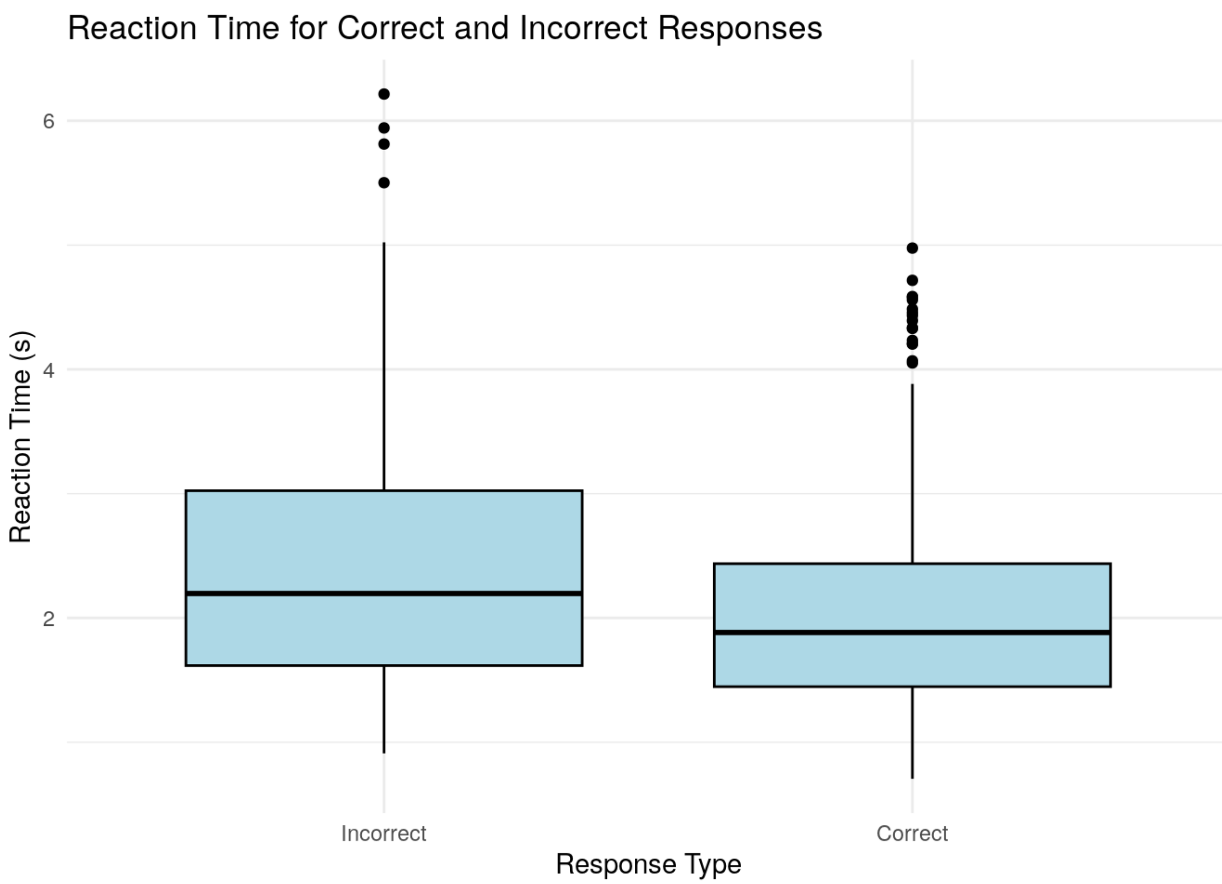

Figure 3 – Box plot showing the difference in the means between participants' correct and incorrect responses.

Results of the seen and unseen headlines' analysis

A one-sample t-test was conducted to determine whether the difference in reaction time for initially seen and unseen headlines is significantly different from zero. The results show no significant difference in the mean reaction times difference, $t(23) = -0.094$, $p = 0.92$.

The 95% confidence interval for the mean difference is [-0.013, 0.012], and the sample mean of the reaction times difference is -0.00058.

Discussion

The experiment aimed to understand the influence of different factors, including word count, readability, polarity, subjectivity, when remembering online headlines, a vital component of staying informed in the contemporary era, mainly because no specific research was found that deals with headline recall in this way. Statistical tests were also conducted to observe if there is a difference between reaction times for correct and incorrect responses, and seen and unseen headlines. The headlines were gathered, then analyzed and finally all the data was collected.

The results, as a whole, indicate several different things due to the breadth of the hypotheses. First of all, it has been shown that there is a weak negative correlation between readability and transformed reaction time, meaning that as readability increases, reaction time decreases, bearing in mind that inverse reaction time was used.

In addition, by building a model, it was proven that both word count and readability significantly predict reaction time. The model showed that as word count increases, reaction time increases and as readability increases, reaction time decreases, as inverse reaction time was used. This supports hypotheses 2.2 and 3.2, and coincides with the results of past experiments which found out that more readable headlines (Shulman et al., 2024), and shorter headlines (She & Zhang, 2019), respectively, lead to increased CTRs. However, no evidence was found to suggest that there is a relationship between reaction time and polarity, and subjectivity. Consequently, hypotheses 1.2 and 4.2 are not supported empirically in this study, contradicting past research which found that headlines with negative words lead to increased CTRs (Robertson et al., 2023).

Regarding the results of the recall accuracy analysis, no evidence was found to support the hypotheses put forth initially. Because of this, hypotheses 1.1, 2.1, 3.1 and 4.1 are not supported empirically in this experiment.

Participants also registered their responses more quickly when giving their correct responses, specifically, participants took approximately 24 milliseconds less to register their correct responses than their incorrect responses. This supports hypothesis 5.

In regards to hypothesis 6, no significant difference in reaction times for previously seen and unseen headlines was found. Thus, hypothesis 6 is not supported.

Participants felt entertained whilst doing the experiment due to reduced groups of headlines to remember, the segmentation into rounds and the feedback, making it seem remarkably like a game. Despite this, I must acknowledge the possible limitations of this study to help future researchers. The lack of significant results in the some of the cases might be due to a reduced sample size, requiring more power to obtain significant results. It would also be a good idea to explore other variables that might affect recall, especially in the case of accuracy, since none of the variables were found to be significant. It would also be worthwhile to design the experiment in such a way that data collection is maximized, as this study had many ties in the independent variables.

It is vital to consider all the possible ways of recalling headlines, ranging from amodal systems to modal representations. It is also relevant to know whether participants stored the meaning as is or in an abstract manner. However, this experiment is slightly flawed in this regard, as no information on this has been collected.

Moreover, it would be interesting to perform this study using headlines from different fields and even languages to determine whether the results can be extrapolated. Knowing that there were only 24 participants and they were all students at Aarhus University, it could be good to recruit people with a greater diversity of backgrounds and from more cultures.

On the whole, the experiment sheds light on many unexplored questions related to headline recall. The findings suggest that the nature of headline recall is nuanced and many factors intervene in these processes. Some variables were found to be significant, whilst others were not.

Repository with code

The code that was used to conduct this experiment has been stored in a public repository under an MIT license in GitHub, which anybody can access. Within it, there are two Python code files, which contain the code to scrape the headlines, analyze their features and also the necessary code to present the headlines to participants, and it also contains an R file with the code used to conduct the analyses. This experiment, therefore, complies with emerging trends like the Open Science framework. The repository can be accessed using the following link: https://github.com/alexphughes/Code-experiment---Alex-Presa-Hughes.git

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