Understanding Human Reading Comprehension with Brain Signals

Ziyi Ye
yeziyi1998@gmail.com
BNRist, DCST, Tsinghua University
Beijing, China

Xiaohui Xie
xiexh_thu@163.com
BNRist, DCST, Tsinghua University
Beijing, China

Yiqun Liu
yiqunliu@tsinghua.edu.cn
BNRist, DCST, Tsinghua University
Beijing, China

Zhihong Wang
wangzhh629@mail.tsinghua.edu.cn
BNRist, DCST, Tsinghua University
Beijing, China

Xuesong Chen
chenxuesong1128@163.com
BNRist, DCST, Tsinghua University
Beijing, China

Min Zhang
z-m@tsinghua.edu.cn
BNRist, DCST, Tsinghua University
Beijing, China

Shaoping Ma
msp@tsinghua.edu.cn
BNRist, DCST, Tsinghua University
Beijing, China

ABSTRACT

Reading comprehension is a complex cognitive process involving many human brain activities. Plenty of works have studied the reading patterns and attention allocation mechanisms in the reading process. However, little is known about what happens in human brain during reading comprehension and how we can utilize this information as implicit feedback to facilitate information acquisition performance. With the advances in brain imaging techniques such as electroencephalogram (EEG), it is possible to collect high-precision brain signals in almost real time.

With neuroimaging techniques, we carefully design a lab-based user study to investigate brain activities during reading comprehension. Our findings show that neural responses vary with different types of contents, i.e., contents that can satisfy users’ information needs and contents that cannot. We suggest that various cognitive activities, e.g., cognitive loading, semantic-thematic understanding, and inferential processing, at the micro-time scale during reading comprehension underpin these neural responses. Inspired by these detectable differences in cognitive activities, we construct supervised learning models based on EEG features for two reading comprehension tasks: answer sentence classification and answer extraction. Results show that it is feasible to improve their performance with brain signals. These findings imply that brain signals are valuable feedback for enhancing human-computer interactions during reading comprehension.

1 INTRODUCTION

Human reading comprehension is a complex cognitive process involved in many search processes, e.g., information seeking and relevance judgement. In that regard, understanding reading comprehension is beneficial for a more proactive Information Retrieval (IR) system, such as inferring search intent [15], designing search interface [48], and constructing ranking models [33]. Prior studies have investigated the behavioral patterns and attention allocation mechanisms of human reading process utilizing explicit feedback [32], mouse movement [35], and eye-tracking [3, 32]. However, these methods can’t straightforwardly uncover the real brain activities and underlying psychological factors during reading comprehension. Hence, the question of “What is the nature of reading comprehension in IR scenarios?” remains an open problem.

Recently, the rapid developments of neuroimaging technology (e.g., EEG and functional magnetic resonance imaging (fMRI)) make it feasible to explore brain activities in IR scenarios. Extensive studies have applied neurological devices to explore the emergence of Information Need (IN) [43] and relevance judgment procedure [1, 41]. These studies constitute an important step in unraveling these cognitive processes in IR scenarios and provide findings that can not be obtained by previous techniques like eye-tracking. Nonetheless, few works have thoroughly investigated the cognitive processes during the information seeking task in reading comprehension, i.e., neural responses when users locate key information for their IN. In this paper, key information refers to answers and semantic-related spans (examples are shown in Table 1).

Furthermore, the differences in neural activities imply that brain signals can be utilized as valuable feedback. Previous studies have used brain signals to predict realization of IN [42] and perceived relevance [11, 17, 27] in IR tasks. However, brain signals have rarely been applied to detect the reading and answer seeking states of users, i.e., whether users have found useful section (answer sentence classification) and whether users have located the answer span (answer extraction). Detecting and understanding these states is helpful for the design of proactive IR systems.

CCS CONCEPTS

- Information systems → Information retrieval; Users and interactive retrieval.

KEYWORDS

Reading Comprehension, Answer Extraction, Relevance Prediction, Brain Signals, EEG
In this paper, we aim to interpret the cognitive processes during reading comprehension and explore the effectiveness of brain signals to complete reading comprehension tasks, raising the following research questions:

- **RQ1**: Are there any detectable differences in brain activities when users find key information during reading comprehension? If yes,
- **RQ2**: Is it possible to construct a prediction model for answer sentence classification with the differences? And,
- **RQ3**: Is it possible to separate potential answer words from other contents with the differences?

To shed light on these research questions, we conduct a lab-based user study to investigate reading comprehension in the context of question answering. In this user study, a EEG device is applied to collect brain activities, which are later examined with event related potential (ERP) analysis, a typical method in neuroscience [38]. Based on the analysis, we find brain activities vary with different types of contents. Notably, we find that the particular ERP component N400, which is associated with "expectedness"[19, 29], differs in answer words, semantic-related words, and ordinary words (The definition of ERP components, e.g., N100 and N400, can be found in Section 3.5.1). Answer words contribute to larger P600, which may be caused by two typical cognitive activities: semantic-thematic understanding and inferential processing. The findings in brain activities illustrate that reading comprehension has a neural basis. Furthermore, we construct models based on brain signals to complete two reading comprehension tasks: answer sentence classification and answer extraction. Experimental results show that EEG signals can be used in these tasks, with a significant improvement of 14.5% in answer sentence classification (in terms of mean average precision (MAP)) and 30.1% in answer extraction (in terms of Area under the ROC curve (AUC)) compared to random baseline, respectively. To summarize, main contributions are as follows:

- We carry out a lab-based user study to demonstrate the significant differences between the cognitive responses to key information and ordinary information during reading comprehension. We speculate these differences imply cognitive phenomena, including cognitive loading, semantic understanding, and inferential processing.
- We construct EEG-based models to complete answer sentence classification and answer extraction tasks. To our best knowledge, we are the first to perform answer sentence classification and answer extraction tasks with brain signals.
- We conduct extensive experiments to deal with different settings, i.e., 10-fold cross validation on questions (CVOQ) and leave-one-participant-out (LOPO), for unseen questions and unseen users, respectively. The experimental results illustrate that EEG data can be used as valuable implicit feedback for better human-computer interactions.

### 2 RELATED WORK

#### 2.1 Reading Comprehension

Reading comprehension is a cognitive process for acquiring information in text-based search scenarios, which involves vision processing, semantic understanding, and information gaining [8]. In the field of IR, reading comprehension is an essential process in many tasks such as relevance estimation, question answering, and search engine result page (SERP) inspection. Many prior works study users’ reading patterns and attention allocation in IR scenarios with eye-tracking devices. Gwizdka [15] investigates the reading behavior with eye movements and indicate that text document processing depends on relevance and perceived relevance. Li et al. [32] study the attention distribution during passage-level reading comprehension with eye movements and explicit feedback. Then a two-stage reading model is further processed with their findings.

Moreover, existing works investigate implicit feedback during reading comprehension, which can be used to detect users’ satisfaction, model search context, and inspire machine models. For example, Liu et al. [35] utilize mouse movements to study the SERP inspecting process and predict users’ satisfaction of Web page. Cole et al. [6] show that eye movement patterns during reading comprehension could infer users’ pre-knowledge for better modeling search context. Zheng et al. [58] extract features derived from human reading behavior patterns with eye movements to improve performance in the machine reading comprehension task.

Although neuroscience technology is widely used to study the cognitive process of reading behavior in general domain (e.g., linguistics), these studies are focused on word recognition [20, 44] and syntactic analysis [13, 45]. Little research literature concentrates on studying reading comprehension in IR domain, which is associated with information seeking. Hence, we try to uncover the psychological factors when people perceive key information and understand human reading comprehension from a neuroscience perspective.

#### 2.2 Neuroscience & IR

There is a growing number of researches using neuroimaging techniques to study IR-related tasks. These works mainly focus on studying the fundamental concepts in IR (e.g., IN and relevance) and leveraging brain signals as implicit feedback. In terms of IN, Moshfeghi et al. [43] use fMRI to examine the neural processes involved in how IN emerges. They reveal that a distributed network of brain regions commonly associates with activities related to the IN. Besides IN, previous works delve into using brain signals to understand relevance from a neuroscience perspective better. In particular, fMRI devices with the higher spatial resolution are adopted to identify which brain regions are activated [40], while EEG devices with the higher time resolution to find out when relevance judgment is happening [1].

As implicit feedback, brain signals are widely used in emotion recognition [5, 57], device controlling [34, 39], and state monitoring [36]. In IR scenario, previous studies have demonstrated the effectiveness of brain signals for IR tasks: predicting realization of INs and relevance. Moshfeghi et al. [42] propose generalized and personalized methods to predict the realization of INs using fMRI features. Moreover, Kauppi et al. [25] conduct a feasibility study on predicting the relevance of visual objects with Magnetoencephalography (MEG)-based classifiers. For textual information relevance, Eugster et al. [11] use short-term EEG signals and support vector machines (SVM) to predict term-relevance within given topic and achieve an improvement of 8.30% in accuracy.
compared to random baseline. They further build an intent model based on the predicted relevance to recommend information [10]. Moreover, Gwizdka et al. [17] apply eye movements and long-term EEG signals to the assessment of text relevance. Their classification model with EEG features shows an improvement of 20% in AUC compared with random baseline. Different from short-term EEG signals, long-term EEG signals reflect more on mental state [14] but can hardly relate to the semantic understanding of specific contents. Hence, it might be less useful if users maintain the same level of concentration when reading different types of contents.

What we add on top of these works is that we use neuroimaging techniques to investigate reading comprehension. Our findings uncover the brain activities when people locate key information during reading and answer seeking process. Moreover, real-time brain signals are captured to perform reading comprehension tasks, aiming to detect people’s reading and answer seeking states automatically. Different from previous work, we perform a sentence-level task (answer sentence classification) by integrating short-term EEG signals and determining the specific location of answer words in a sentence context (answer extraction). Results show the feasibility of constructing a better human-computer interaction system with brain signals.

3 USER STUDY

In this paper, we conduct an empirical user study to investigate brain activities associated with reading comprehension. Participants are recruited to perform several reading comprehension tasks. Each trial includes a factoid question and the following sentence with graded relevance described in Section 3.2.1. Under a controlled user study setup in the prevention of potentially confusing effects, EEG data is recorded during the reading process. In the following, we introduce the experimental design and analysis methods in detail.

3.1 Participants

We recruit 21 college students aged from 18 to 27 (M$^1 = 22.10$, SD$^2 = 2.07$). Among them, there are 11 males and 10 females, who mainly major in computer science, physics, arts, and engineering. All the participants are native Chinese speakers mastering college-level Chinese reading and writing skills. And they admit that they are right-handed and do not suffer from any neurological disease. The number of participants are similar to previous user studies (e.g., 23 participants in [47] and 20 participants in [1]). It takes about two hours to complete the whole task for each participant, including 40 minutes for preparation, 50 minutes for the main task, and 15 minutes for the questionnaire procedure. Each participant is paid US$30 after they complete all the tasks.

3.2 Task preparation

In this section, we describe the preparation work before the user study. Specifically, we introduce how we construct the reading comprehension dataset for the user study and how we obtain the golden standard annotation for the following analysis. The details about the pilot study are also provided.

Table 1: Example of user study tasks. The wavy lines and underlines indicate the answer words and the semantic-related words, respectively.

| Question                                      | Perfectly relevant                                      | Relevant                                          | Irrelevant                                      |
|-----------------------------------------------|--------------------------------------------------------|---------------------------------------------------|--------------------------------------------------|
| What is the largest mammal in the world?     | The blue whale is the largest animal in the world, reaching an adult volume of 33 meters. | The largest animal in the world in terms of superficial area is the Arctic chardonnay jellyfish. | It is estimated that there are about 10 billion capillaries in human body. |

3.2.1 Dataset. For our user study, we first sample real-world questions from the WebQA [31], a factoid Q/A dataset, whose questions are open-domain with a close-ended answer, and most of them are collected from a large community question answering (Q/A) website Baidu Zhidao. We use this dataset for the following reasons: (1) It is one of the largest Chinese Q/A datasets. (2) It provides human annotation for correct answers and corresponding evidence.

More precisely, we manually sample 155 questions that cover topics including science, history, sports, and art. We generate three sentences for each question from this dataset and manually annotate each sentence with a relevance label. Specifically, we select the ground truth sentence from the dataset, the top sentence retrieved by BM25 but doesn’t contain answer spans, and a randomly selected sentence as candidate sentences of perfectly relevant, relevant, and irrelevant, respectively. Further annotation is applied to check and adjust their relevance labels in Section 3.2.2 with the definitions of the relevance levels given below:

- **Perfectly relevant**: The sentence is dedicated to the question so we can get the exact answer to the question. It is worth being a top result in a search engine.
- **Relevant**: The sentence provides some information relevant to the question. It is semantic relevant, but its contribution to solving the question may be minimal.
- **Irrelevant**: The sentence does not provide any useful information about the question, and it is semantic irrelevant.

These definitions are modified from the definitions in TREC 2019 deep learning track [7] with four relevance levels. We merge the relevance level of highly relevant and relevant into relevant in our definition to simplify task settings. Some of the sentences are manually modified to reduce the length and resolve grammar problems. Finally, the average question length is 8.7 (SD = 4.0), the average sentence length is 9.8 (SD = 3.0). Examples of sentences with different relevance levels are provided in Table 1. All the data will be open to the public after the double-blind review process.

Following the above steps, we obtain a dataset consists of 155 questions and 465 sentences (each question has three corresponding sentences). During the user study, participants will see a random sentence among the three sentences for a given question.

---

$^1$Mean value.

$^2$Standard deviation.

https://zhidao.baidu.com/
3.2 Procedure

This user study adheres to the ethical procedures for the protection of human participants in research and is approved by anonymized.

Table 2: Word-level basic statistics for user study dataset.

| Word-level | answer | semantic-related | ordinary |
|------------|--------|------------------|----------|
| No. (%)    | 188 (5.6%) | 904 (27.0%) | 2259 (67.4%) |

Table 3: Sentence-level basic statistics for user study dataset.

| Sentence-level | perfectly relevant | relevant | irrelevant |
|----------------|---------------------|---------|-----------|
| No. (%)        | 157 (33.8%) | 152 (32.7%) | 156 (33.6%) |

Figure 1: Structure of the main task. First, a question is presented on the screen, and the participants can press the space key to skip after reading. Then, a fixation cross and the words in the sentence are presented automatically in temporal sequence. Third, an ordinary test (90% probability) or a special test (10% probability) is presented, and the participants should press a key to answer. The process is repeated for all 150 questions divided into six groups in the main task and five questions in the training step. Participants can rest for a while between groups.

The procedure of the user study, which consists of 6 stages, is illustrated in Table 4. We detail each step in the following.

Stage 1-4. Participants fill in an entry questionnaire to report demographic information, such as age and gender. After a brief introduction to our user study, participants are asked to sign an informed consent about security and privacy protection. All participants are notified that they can withdraw at any time and receive partial payment according to their degree of completion. Then they read user study instructions about the main procedure of the user study. Prior to the main task, participants undergo a training step with five questions, which resembles the main task. The training step ensures that participants are familiar with the procedure of the main task. During the training step, they can ask any questions about the procedure or repeat training if required. For a trial in the main task and the training step, each participant is instructed to complete a key-pressing task, either the J-key (using the right hand) or the F-key (using the left hand), on a QWERTY keyboard.

Stage 5. Figure 1 illustrates the procedure of each trial in the main task. The main task contains 150 trials in total and is divided into six groups, each containing 25 trials. The trials follow the same order of steps, i.e., S1 to S4 shown in Figure 1: (S1) Participants view a factoid question randomly selected from the dataset. Once they fully understand the question, they can press the space key and enter the second step. (S2) A fixation cross is presented on the screen center to catch participants’ attention and indicate the location of the following sentence presentation. The fixation cross
will be presented for 1,000 milliseconds. (S3) A sentence randomly selected from three candidates will be presented word by word, and each word will be shown for 750 milliseconds. The sequential presentation of words is a typical approach applied in natural sentence processing ERP studies [28]. The setting of reading pace is based on previous studies about carry-over of stimulus-evoked [9] and appropriately adjust in the pilot study. During this sentence reading procedure, participants are asked to reduce body movement and frequent blinks to avoid noise. (S4) Participants take a binary decision test about the question and the sentence. Two kinds of tests are randomly given. The ordinary test is “Can this sentence answer the previous question?” and the special test is a binary factual judgment involving the sentence. The ordinary test is to confirm that participants have read the question carefully and are able to judge the relationship between the given question and the sentence. While the special test is to ensure that, even if the participants can make the judgment of ordinary test beforehand, they should read the total sentence as well. The probability for each kind of test is determined according to the pilot study. The final setting is 90% probability for the ordinary test and 10% probability for the special test. Finally, after the participants press the key (“J-key refers to “Yes” and F-key refers to “No”) to pass the test, the next trial starts.

While the special test is to ensure that, even if the participants can make the judgment of ordinary test beforehand, they should read the total sentence as well. The probability for each kind of test is determined according to the pilot study. The final setting is 90% probability for the ordinary test and 10% probability for the special test. Finally, after the participants press the key (“J-key refers to “Yes” and F-key refers to “No”) to pass the test, the next trial starts.

For each group, researchers will check the test accuracy is above 80% and ensure that the participants are performing tasks carefully. For the ordinary test, researchers will determine time points of different steps based on previous studies about carry-over of stimulus-evoked [9] and appropriate adjustments in the pilot study. During this sentence presentation, participants are asked to reduce body movement and frequent blinks to avoid noise. While the special test is a binary factual judgment involving the sentence. The ordinary test is to confirm that participants have read the question carefully and are able to judge the relationship between the given question and the sentence. While the special test is to ensure that, even if the participants can make the judgment of ordinary test beforehand, they should read the total sentence as well. The probability for each kind of test is determined according to the pilot study. The final setting is 90% probability for the ordinary test and 10% probability for the special test. Finally, after the participants press the key (“J-key refers to “Yes” and F-key refers to “No”) to pass the test, the next trial starts.

**Stage 6.** After completing the main task, they should fill in a post-questionnaire about the familiarity of given questions during the main task.

### 3.4 Apparatus

Our study uses a laptop computer with a 17-inch monitor with a resolution of 1,600 × 900. A 40 electrodes Scan NuAmps Express system (Compumedics Ltd., VIC, Australia) and a 37-channel Quick-Cap (Compumedical NeuroScan) are deployed to capture the participants’ EEG data. Thirty electrodes (Fp1, Fp2, F7, F3, Fz, F4, F8, FT7, FC3, Cz, FC4, FT8, T3, C3, Cz, C4, T4, TP7, C3, Pz, CP4, TP8, T5, P3, P4, T6, O1, Oz, and O2) are arranged according to the international 10-20 systems [23]. Two reference electrodes (A1 and A2) are placed on both mastoid bones. Four eye channels are placed vertically above the right eye (VEOU), vertically below the right eye (VEOL), horizontally on the outside of the left eye (HEOL), and horizontally on the outside of the right eye (HEOR). The impedance of the electrodes is calibrated under 10 kΩ in the preparation step, while the sampling rate is set at 1,000 Hz. All the computations and data pre-processing are performed using the Curry V8.3 (Neuroscan, TX), a widely used commercial source localization software package.

### 3.5 ERP analysis methods

#### 3.5.1 Introduction to ERP

ERP is voltage generated in the brain structures in response to specific events or stimuli [2]. It usually refers to the brief EEG data epoch, which is less than 1,000 ms after the experimentially designed stimuli. ERP analysis has been widely used in neuroscience, psychology, and computational linguistics [37]. ERP components are evoked amplitudes in different time windows, including N100, N400 (negative wave in 100 ms, 400 ms), and P200, P600 (positive wave in 200 ms, 600ms). Previous studies have revealed the detectable ERP components are associated with neural activity with respect to both sensory and cognitive processes. The average waveform change between ERP components is also widely studied, such as the change from N100 component to P200 component [49].

#### 3.5.2 Data pre-processing

EEG data commonly contains noise sources related to power line noise, eye blinks, body movement, etc. For better ERP analysis, EEG data should be pre-processed according to standard procedures.

First, the EEG data is re-referencing to average mastoids (A1 and A2), which is a commonly used re-referencing scheme. Second, baseline correlation for each electrode is applied to the EEG data to remove fluctuations in the signal. Third, a low-pass filter of 30 Hz and a high-pass filter of 0.5 Hz are applied to preserve the EEG frequency band. Fourth, artifact reduction is applied to remove components associated with ocular, cardiac, and muscular artifacts. We perform a parametric noise covariance model [21] to remove those artifacts. Moreover, epochs (brief EEG segment, 1,000ms in our experimental settings) with an absolute maximum voltage over the threshold 100 μV are marked as bad. Channels are dropped manually according to the invalid epoch rate. Fifth, the EEG data is down-sample to 500 Hz for the following analysis. Finally, interested epochs are extracted according to the triggers (time points to locate interested EEG data, see in Section 3.3), and baseline corrected using the pre-stimulus period -200-0 ms. ERPs are averaged across the same type of words for further analysis.

#### 3.5.3 Time window and Region of interest (ROI)

Time windows and ROI are supposed to be determined for further ERP components analysis. To distinguish ERP components, time windows are split in our analysis. Lehmann and Skrandies [30] propose a method to determine components of evoked scalp potentials in terms of times of occurrence (latency) and location on the scalp (topography), which is one of the most established measures in ERP mapping. The Global Field Power (GFP) is calculated between 0-750 ms, and we determine time segments according to the power distribution. As a result, the determined time segments are 60-120 ms for N100, 120-320 ms for P200 component, 320-520 ms for N400 components, and 520-750 ms for P600 component, respectively. As an early component, N100 is a pre-attentive potential which does not involve semantic understanding of textual content [38, 54]. Hence we only discuss findings in P200, N400, and P600 components in this article.

Different areas of the brain have different functions, e.g., parietal is associated with logistics and mathematical thinking. In the field of IR, frontal, parietal, and r-temporal are implied to be related to relevance judgments [40]. In that regard, it is necessary to identify ROI. In particular, a permutation T-test is applied on sensor data in a fixed time window for each ERP component. Then ROI is identified based on the active sensors as well as their spatial distribution. Electrodes are assigned to seven brain areas according to their spatial distribution: prefrontal (FP1, FP2), frontal (F7, F3, Fz, F4, F8), central (C3, Cz, C4, FC3, FC4), parietal (CPz, CP3, CP4, Pz, P3, P4), l-temporal (FT7, T3, TP7, T5), r-temporal (FT8, T4, TP8, T6), and occipital (O1, O2, Oz). The selected ROIs for each time window are shown in 5.
We have tried to combine the effect of sentence relevance and find words: answer words, semantic-related words, and ordinary words. A post-questionnaire is used to collect the users’ perceived familiarity level on the topics of all the questions, with a five-point Likert scale (Highly familiar, Somewhat familiar, Neither familiar nor unfamiliar, Somewhat unfamiliar, Totally unfamiliar). It reveals that no matter how familiar the user is, the reading process will evoke similar patterns in the brain.

The behavioral responses are analyzed in terms of the accuracy rate and the reaction time of the binary decision test. The average accuracy rate of users is 89.24% (SD=7.31%), indicating that most users devote enough attention as we expected. Specifically, the accuracy rate is 97.93% for perfectly relevant, 92.03% for relevant, and 89.98% for irrelevant, while the reaction time is 1.00s for perfectly relevant, 1.29s for relevant, and 1.39s for irrelevant. These results indicate that behavioral responses are different accordingly, considering the graded relevance of sentences. Therefore, we can speculate that neurological factors exist behind these differences, which is essential to study.

### 3.5.4 Statistical Methods

In order to test the difference of ERP components between different types of words, we applied repeated measures ANOVA. The independent variable is the three types of words: answer words, semantic-related words, and ordinary words. Examples of different types of words can be found in Table 1. The dependent variable is the mean signal in a given time window and ROI. We have tried to combine the effect of sentence relevance and find the results of ERP analysis are similar. Thus they are not reported in our study. Before the multi-group comparison, Shapiro-Wilk’s test is applied to check the normality of data. To check the feasibility of repeated measures ANOVA, each condition’s sphericity assumption is verified using the Mauchly’s test. Then the Greenhouse-Geisser method is applied when the sphericity is not met. Finally, we apply post hoc Bonferroni tests to conduct pair-wise comparisons between groups.

| Time window | ROI       | Multicomparison          | ANOVA p   |
|-------------|-----------|--------------------------|-----------|
| 120-320ms   | frontal   | A>S*                     | *         |
|             | parietal  | A>O*                     | *         |
| 320-520ms   | central   | A>S*,A>O**               | **        |
|             | r-temporal| A>O**                    | *         |
|             | parietal  | A>S*,A>O**               | **        |
| 520-750ms   | central   | A>S**, A>O**             | **        |
|             | l-temporal| A>S**, A>O*, S>O*        | **        |
|             | parietal  | A>S*, A>O**              | **        |

### 4 STATISTICAL ANALYSIS

Questionnaire and behavioral response analyses are provided in this section. Besides, to investigate the brain activities and psychological factors of reading comprehension, we perform statistical analysis based on collected brain signals (RQ1). Furthermore, explanations and discussions from a neuroscience perspective are given to understand our findings.

#### 4.1 Questionnaire and Behavioral Response

A post-questionnaire is used to collect the users’ perceived familiarity level on the topics of all the questions, with a five-point Likert scale (Highly familiar, Somewhat familiar, Neither familiar nor unfamiliar, Somewhat unfamiliar, Totally unfamiliar). The Highly familiar level indicates that users know the answer previously, while the Totally unfamiliar level indicates that the users know nothing about the question’s background. About one-third of questions are reported familiar to the users (Highly familiar: 21.07%, Somewhat familiar: 16.85%) and another one-third unfamiliar to the users (Somewhat unfamiliar: 26.9%, Totally unfamiliar: 3.78%). The rest of them are reported to be Neither familiar nor unfamiliar (31.4%). ERP analysis shows no significant difference in our study across different familiarity levels. (three groups: Highly familiar and Somewhat familiar; Somewhat unfamiliar and Totally unfamiliar; Neither familiar nor unfamiliar).

320-520ms. The grand-averaged N400 component waveforms in the 320-520ms time window after the word stimulus onset are examined, showing significant differences in central (F[2,40] = 12.57, p < 0.001)
Figure 3: Condition-wise topographies averaged across time windows for three word types and possible potential mental phenomena. A, B, C, D, E, and F refer to frontal, central, parietal, l-temporal, r-temporal, and electrode T6, respectively. The lower and upper bounds are ±3 μV for 120–320 ms time window, and ±3 μV for other time windows.

520–750 ms. The P600 waveforms evoked by the stimulus are grand-averaged on the 520–750 ms window, which show significant effect in central (F[2, 40] = 17.45, p < 0.001), l-temporal (F[2, 40] = 15.87, p < 0.001), and parietal (F[2, 40] = 20.27, p < 0.001). The Bonferroni’s test reveals that the mean positivity of answer words in P600 is significantly larger than that of semantic-related words (p < 0.05) and ordinary words (p < 0.001). Besides, the mean negativity of the semantic-related words is significantly smaller than that of ordinary words (p < 0.05) in electrodes T4 and T6.

N400 is well-known to be associated with the message-level representation on the processing of upcoming words [19, 29]. The higher “expectedness” of a word in the current semantic context usually leads to a smaller N400 negativity. Our statistical analysis suggests that the N400 negativity of answer words in N400 is significantly smaller than that of semantic-related words (p < 0.05) and ordinary words (p < 0.001). The Bonferroni’s test reveals that the mean negativity of semantic-related words is again smaller than that of ordinary words. The finding of “expectedness” is consistent with previous finding of cognitive loading in Section 4.2 since words of higher “expectedness” may need less cognitive resource. Additionally, our findings also imply that semantic-related words have higher “expectedness” than ordinary words.

50 ms. The P600 waveforms evoked by the stimulus are grand-averaged on the 520–750 ms window, which show significant effect in central (F[2, 40] = 17.45, p < 0.001), l-temporal (F[2, 40] = 15.87, p < 0.001), and parietal (F[2, 40] = 20.27, p < 0.001). The Bonferroni’s test reveals that the mean positivity of answer words in P600 is significantly larger than that of semantic-related words (p < 0.001) and ordinary words (p < 0.001) in central. Besides, the mean negativity of the semantic-related words is significantly smaller than that of ordinary words in l-temporal (p < 0.01).

P600 is well-known to be related to syntactic analysis, however recent studies reveal that it is also associated with semantic-thematic anomalous [52] and inferential processing [4]. In IR scenario, Eugster et al. [10] show relevant words would elicit higher P600 amplitudes. Pinkosova et al. [47] indicate that the link between higher relevance and P600 amplitude might come from discourse memory in the brain. In our study, sentences have no problem at the syntactic level after we check manually. Thus, we speculate that the differences among different contents may be caused by semantic-thematic anomalous and inferential processing. Both of these aspects are also related to discourse memory, as Pinkosova et al. [47] indicate.

More specifically, it is interesting to find that P600 is the highest in answer words, followed by ordinary words, while lowest in semantic-related words, especially in l-temporal (related to language recognition). For answer words, it is obvious that inferential processing is initiated in human’s brain, causing significantly higher P600. Similarly, semantic-related words may also relate to inferential processing, but to a less extent. Both types of words have a minimal relationship with semantic-thematic anomalous since they are semantically correct. Nevertheless, for ordinary words, semantic-thematic anomalous becomes dominant compared to semantic-related words since it is less helpful for semantic-thematic understanding. Thus ordinary words result in a relatively high P600 amplitude. Generally speaking, it is most likely that semantic-related words would cost relatively low discourse memory. However, the interesting phenomenon and its underlying neurological explanations need further exploration by more strictly designed experiments.

Answer to RQ1. To conclude, the ERP analysis across time windows shows that neural differences exist between processing key information and ordinary information during reading comprehension. Figure 3 present a summary of condition-wise topographies and possible mental phenomena according to the significant findings. These differences in ERP components can help us understand how humans carry out reading comprehension tasks. Studies in P200 and N400 components reveal that locating the answer words is usually associated with higher “expectedness” in the reading comprehension process. Besides, the P600 effect might be explained by a mixture of semantic-thematic anomalous and inferential processing. Our interesting findings in P600 effect provide evidence to later periods of semantic understanding in reading comprehension. Moreover, these findings also encourage us that the implicit feedback collected with EEG devices can be used to detect users’ reading and answer seeking states during reading comprehension.

5 EXPERIMENTS AND DISCUSSIONS

To explore the reading and answer seeking process, we conduct two experimental tasks, i.e., answer sentence classification and answer extraction, based on the EEG data collected in our user study. The answer sentence classification task is arranged to predict the answer sentence (i.e., perfectly relevant) to a given question (RQ2). The answer extraction task is intended to extract the answer word from the answer sentence (RQ3). These tasks are crucial in the study of machine reading comprehension [31, 51, 55]. Note that we aim to demonstrate the effectiveness and interpretability of EEG signals as implicit feedback. Investigation on how to combine brain signals and content information is left as future work.

5.1 Features

Previous works in EEG feature engineering contain two major types of EEG features, i.e., Frequency-band-based features (FBFs) and Event-related-potential-based features (ERPFs). On the one hand,
FBFs capture frequency information during the whole time window. Frequency information in different bands is associated with attentiveness (delta [18] and beta [26]), cognitive performance (theta and alpha [26]), and semantic violation (gamma [46]). Previous works have shown the effectiveness of FBFs for relevance prediction [10, 11]. On the other hand, ERPFs capture the time domain information within a specific short window when users receive a stimulation. Previous works in brain–computer interface (BCI) systems have shown the effectiveness of ERP components, such as N170 and P300, in terms of online target detection [56]. In the field of IR, ERPFs are shown to be associated with relevance judgments [11, 22] and decision making in information seeking [12]. Analyses in Section 4.2 also show the potential correlation between ERPs and the information seeking process during reading comprehension. For the above reason, FBFs and ERPFs are extracted in our study.

Concretely speaking, we include EEG features from three brain regions (central, r-temporal, and parietal). The reason is that these regions have significant differences in cognitive responses across different types of words, as shown in Section 4.2. For FBFs, average band power and differential entropy are calculated from the frequency bands of delta (0.5-4Hz), theta (4-8Hz), alpha (8-13Hz), and beta (13-30Hz). For ERPFs, five time points are evenly sampled from P200 (120-320ms), N400 (320-520ms), and P600 (520-750ms), respectively.

As a result, the representation for each word is a 69-dimensional vector (2×4 FBFs×3 regions, 5×3ERPFs×3 regions) that contains information from EEG data.

Table 6: Experimental result of answer extraction (LOPO strategy). \( p\)-value indicates significantly better AUC than the baseline (with two-tailed pairwise t-test).

| Model | Mean AUC | \( p\)-value | Improvement |
|-------|----------|--------------|-------------|
| baseline | 0.500 | – | – |
| SVM | 0.569 | 6e-3 | 13.8% |
| GBDT | 0.577 | 7e-5 | 15.4% |
| LR | 0.584 | 1e-4 | 16.8% |
| CRF | 0.651 | 2e-15 | 30.2% |

5.2 Experimental Settings

Given word-level EEG features, the answer extraction task is designed as a binary classification problem to estimate the probability of a word being the answer. Three supervised learning models—logistic regression (LR), support vector machines (SVM), and gradient boosting decision tree (GBDT)—are devised to solve the classification task. What’s more, we propose linear-chain Conditional Random Field (CRF) and cast the binary classification problem as a sequence tagging task to predict the label of each word in its sentence-level context. This is to our knowledge the first time that CRF has been applied to EEG-based answer extraction while prior work was applied to text-based answer extraction. In our experiment, it’s important to note that each word in a sentence is not appropriate.

For the answer sentence classification task, we consider perfectly relevant sentences as positive examples. Then, the answer sentence classification task is regarded as a classification problem of estimating the probability that a sentence being perfectly relevant. And it can also be treated as a ranking problem when ranking the corresponding sentences of a question accordingly. Four supervised learning models are applied in the experiments, i.e., LR, SVM, GBDT, and recurrent neural network (RNN). The baseline is a random model, of which the procedure is the same as described in the answer extraction task. For the LR, SVM, and GBDT, the probability that a sentence being positive is computed based on the predicted answer probability of each word in the answer extraction task. More specifically, the score \( S \) of a sentence can be written as:

\[
S = \frac{\max(W_1, ..., W_n) + \text{mean}(W_1, ..., W_n) + \text{median}(W_1, ..., W_n)}{3}
\]

Where \( W_i \) represents the score (predicted probability) of the \( i\)-th word in the given sentence, \( n \) refers to the number of words in this sentence. According to Eq. 1, the score of a sentence is the average of the max/median/mean values of words’ score in the sentence. This method integrates word-level information to the sentence-level, which is similar to Zheng et al. [58] in the attention estimation task with eye-tracking features. For the RNN model, EEG features of each word in a sentence are fed into the network, and the final hidden layer is connected to a fully connected layer to obtain the probability distribution. Then the sentence-level relevance labels are utilized to calculate the loss. Note that CRF is not suitable in the answer sentence classification task since it estimates words’ score in the sentence context. Thus aggregating the words’ score in a sentence is not appropriate.

We perform two training strategies in our experiments to deal with unseen questions and unseen users: CVOQ and LOPO, respectively. The CVOQ strategy partitions the questions and their corresponding sentences into ten folds, then uses the rest folds for training when validating each fold. The LOPO strategy learns a supervised model using the remaining participants’ data when validating each participant. As for evaluation metrics, keeping with prior work [50, 55], we use AUC for both answer extraction and answer sentence classification and MAP for answer sentence classification since it can also be treated as a ranking problem.

5.3 Results and Discussions

5.3.1 Answer extraction. The results of two training strategies (CVOQ and LOPO) in answer extraction are similar. Therefore, we only show observations from LOPO strategy in Table 6. Generally, it can be seen that all the models based on the EEG features are significantly better than the baseline. Among them, the CRF model improves the most (30.2% in AUC compared to the baseline) since it combines sequence information. The results demonstrate the feasibility of using EEG data to locate answer words and monitor users’ answer seeking process.

The classification AUC for each individual based on LOPO strategy is presented in Figure 4. Previous works have demonstrated the "BCI illiteracy" [53], which means that about 15 – 30% participants are unable to achieve successful feedback in BCI systems. Thus there exist some participants that may not achieve promising
results (e.g., participant 15 for LR model) for natural physical reasons. When considering the result of the best 70% participants, the AUC achieves 0.682 and 0.618 for CRF and LR, respectively.

To investigate the influence of EEG features and sequence information, we conduct an ablation study on CRF, including CRF\E and CRF\S. CRF\E masks and replaces EEG features with word position alternatively while CRF\S shuffles the word sequence to mask the sequence information. Results are presented in Table 7. Note that CRF\E achieves better results than the baseline since it can learn the distribution probability of answer words in the sequence. However, CRF is significantly better than CRF\E, which suggests that EEG features can provide information in addition to the distribution probability of answer words. As for sequence information, there also exist significant reductions in AUC when sequence information is lost. It implies that sequence information can facilitate the EEG-based model.

5.3.2 Answer sentence classification. The pair-wise t-test illustrates that there is no significant difference between the performance of two strategies: LOPO and CVOQ. Therefore, we only present observations from CVOQ strategy in Table 8. All of our EEG-based models are significantly better than the baseline, with a maximum improvement of 14.5% (RNN) in terms of MAP. Generally, these results demonstrate the possibility of using EEG data to help classify answer sentences. As for the performance in different relevance levels, our classification AUC of perfectly relevant and relevant sentences (0.638 for RNN) is lower than that of perfectly relevant and irrelevant sentences (0.671 for RNN), which suggests that semantic-related sentences are more difficult to be distinguished.

Note that RNN model integrates sequence information and utilizes sentence-level labels directly. In contrast, the other models only leverage word-level information and labels. Despite their huge differences from the RNN model, they are also effective in our task. It suggests that word-level EEG signals may contain serial information. Further research is required to explore this phenomenon and construct a more effective EEG-based model.

Answer to RQ2 & RQ3. Experimental results in Section 5.3.2 and Section 5.3.1 suggest that EEG signals can be leveraged to classify answer sentence and extract the answer words. Both of these tasks are essential in reading comprehension to detect human reading and answer seeking states. On the one hand, our work shows that brain signals can be utilized to detect whether and where users find answers, which is rarely studied. On the other hand, this paper is among the first to use word-level EEG features to classify answer sentence and construct feasible EEG-based models. Moreover, we apply two different strategies, CVOQ and LOPO, to investigate the EEG-based models’ performance in unseen questions setting and unseen users setting. Results illustrate that brain signals can be useful and robust feedback in different settings.

6 CONCLUSION

In this paper, we have studied brain activities under a reading comprehension scenario. We have investigated the cognitive responses when users locate different text contents, including answer span contents, semantic-related contents, and other ordinary contents. Our analysis contributes to a better understanding of reading comprehension. Insightful findings include: (1) There are detectable differences in neural activities between contents that can satisfy the information need and contents that can not. These differences are related to cognitive loading, “expectiveness”, inferential processing, and other aspects. Specifically, manifestations in regard to answer words start as a change in cognitive loading (P200) and follow with elicitations in ERP components related to semantic understanding and inferential processing (N400 and P600). Semantic-related words have higher “expectedness” and might demand less discourse memory effort. (2) We have demonstrated that EEG signals can be useful to detect users’ reading and answer seeking state. To our best knowledge, this is the first work utilizing brain signals for two reading comprehension tasks: answer sentence classification and answer extraction. (3) Experimental results show that EEG signals can deal with both the unseen questions and the unseen users. Therefore, brain signals can be used as valuable and interpretable implicit feedback during reading comprehension.
However, our study is limited to a lab-based sentence-level reading comprehension scenario under our experimental paradigm. The limitations may guide future works such as: (1) It is meaningful to collect brain signals during information seeking and acquisition in a real-life setting and construct brain signals enhanced information system. (2) Utilizing brain signals in a passage-level scenario to facilitate the construction of computational reading models and neural ranking models may be another essential direction.

REFERENCES

[1] Marco Allegretti, Yashar Moshfeghi, Maria Hadjigeorgieva, Frank E Pollick, Joren M Jose, and Gabriella Pasi. 2015. When relevance judgment is happening? An EEG-based study. In Proceedings of the 38th international acm sigir conference on research and development in information retrieval. 719–722.

[2] DHR Blackwood and WJ Muir. 1990. Cognitive brain potentials and their application. The British Journal of Psychiatry 157, 59 (1990), 96–101.

[3] Valeria Bolotova, Vladislav Blinov, Yukun Zheng, W Bruce Croft, Falk Scholer, and Mark Sanderson. 2020. Do People and Neural Nets Pay Attention to the Same Words: Studying Eye-tracking Data for Non-factoid QA Evaluation. In Proceedings of the 29th ACM International Conference on Information & Knowledge Management. 85–94.

[4] Petra Burkhart. 2006. Inferential bridging relations reveal distinct neural mechanisms. Evidence from event-related brain potentials. Brain and Language 98, 2 (2006), 159–168.

[5] Guillaume Chanel, Joel JM Kierkels, Mohammad Soleymani, and Thierry Pun. 2009. Short-term emotion assessment in a recall paradigm. International Journal of Human-Computer Studies 67, 8 (2009), 607–627.

[6] Michael J Cole, Jacek Gwizdka, Chang Liu, Nicholas J Betkin, and Xiangmin Zhang. 2013. Inferring user knowledge level from eye movement patterns. Information Processing & Management 49, 5 (2013), 1075–1098.

[7] Nick Crawford, Bhaskar Mitra, Emine Yilmaz, Daniel Campos, and Ellen M Voorhees. 2020. Of the trec 2019 deep learning track. arXiv preprint arXiv:2003.07820 (2020).

[8] Robert G Crowder and Richard K Wagner. 1992. The psychology of reading: An introduction. Oxford University Press.

[9] Olaf Dimigen, Werner Sommer, Annette Hohlfeld, Arthur M Jacobs, and Reinhold Thalía Harmony, Thalía Fernández, Juan Silva, Jorge Bernal, Lourdes Díaz-Comas, Manuel JA Eugster, Tuukka Ruotsalo, Michiel M Spapé, Oswald Barral, Niklas Thalía Fernández, and Juan Silva. 2019. Towards brain-activity-controlled information retrieval: Decrypting visual relevance from EEG signals. NeuralImage 112 (2015), 258–296.

[10] Wolfgang Klimesch. 1999. EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain research reviews 29, 2-3 (1999), 169–195.

[11] Bianchetti Koolstra, Christian Mühl, and Ioannis Patras. 2009. EEG analysis for implicit tagging of video data. In 2009 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops. IEEE, 1–6.

[12] Marta Kutas and Steven A Fililyard. 1980. Reading between the lines: Event-related brain potentials during natural sentence processing. Brain and Language 11, 2 (1980), 354–373.

[13] Marta Kutas and Steven A Fililyard. 1984. Brain potentials during reading reflect word expectancy and semantic association. Nature 307, 5947 (1984), 161–163.

[14] Dietrich Lehmann and Wolfgang Skrandies. 1980. Reference-free identification of components of checkerboard-evoked multichannel potential fields. Electroencephalography and clinical neurophysiology 48, 6 (1980), 609–621.

[15] Peng Li, Wei Li, Zhengyan He, Xuguang Wang, Ying Cao, Ji Zhou, and Wei Xiu. 2016. Dataset and neural recurrent sequence labeling model for open-domain factoid question answering. arXiv preprint arXiv:1607.06275 (2016).

[16] Xuangang Li, Yiqun Liu, Jiaxin Mao, Zexue He, Min Zhang, and Shaoping Ma. 2018. Understanding reading attention distribution during relevance judgment. In Proceedings of the 27th ACM International Conference on Information and Knowledge Management. 733–742.

[17] Xuangang Li, Jiaxin Mao, Chao Wang, Yiqun Liu, Min Zhang, and Shaoping Ma. 2019. Teach machine how to read: reading behavior inspired relevance estimation. In Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval. 795–804.

[18] Tiantao Liu, Leslie Goldberg, Shangkai Gao, and Bo Hong. 2010. An online brain–computer interface using non-flashing visual evoked potentials. Journal of neural engineering 7, 6 (2010), 066012.

[19] Yiqun Liu, Ye Chen, Jinhui Tang, Jiashen Sun, Min Zhang, Shaoing Ma, and Xuan Zhu. 2015. Different users, different opinions: Predicting search satisfaction with mouse movement information. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval. 493–502.

[20] Sandra K Loo and Russell A Barkley. 2005. Clinical utility of EEG in attention deficit hyperactivity disorder. Applied neurophysiology 12, 2 (2005), 64–76.

[21] Steven J Luck. 2014. An introduction to the event-related related technique. MIT press.

[22] Steven J Luck, Geoffrey F Woodman, and Edward K Vogel. 2000. Event-related potential studies of attention. Trends in cognitive sciences 4, 11 (2000), 432–440.

[23] Dennis J McFarland, William A Sarnacki, and Jonathan R Wolpaw. 2010. Electroencephalographic (EEG) control of three-dimensional movement. Journal of neural engineering 7, 3 (2010), 036007.

[24] Yashar Moshfeghi, Luisa R Pinto, Frank E Pollick, and Joren M Jose. 2013. Understanding relevance: An fMRI study. In European conference on information retrieval. Springer, 14–25.

[25] Yashar Moshfeghi and Frank E Pollick. 2018. Search process as transitions between neural states. In Proceedings of the 2018 World Wide Web Conference. 1683–1692.

[26] Yashar Moshfeghi, Peter Triantafillou, and Frank Pollick. 2019. Towards predicting a realisation of an information need based on brain signals. In The World Wide Web Conference. 1300–1309.

[27] Yashar Moshfeghi, Peter Triantafillou, and Frank Pollick. 2016. Understanding information need: An fMRI study. In Proceedings of the 9th International ACM SIGIR conference on Research and Development in Information Retrieval. 335–344.

[28] Tatsjana A Nazir, Nadia Ben-Boutayab, Nathalie Decoopdt, Avital Deutsch, and Ram Frost. 2004. Reading habits, perceptual learning, and recognition of printed
words. *Brain and language* 88, 3 (2004), 294–311.

[45] Sharlene D Newman, Toshikazu Ikuta, and Thomas Burns Jr. 2010. The effect of semantic relatedness on syntactic analysis: an fMRI study. *Brain and language* 113, 2 (2010), 51–58.

[46] Barbara Penolazzi, Alessandro Angrilli, and Remo Job. 2009. Gamma EEG activity induced by semantic violation during sentence reading. *Neuroscience Letters* 465, 1 (2009), 74–78.

[47] Zuzana Pinkosova, William J McGovern, and Yashar Moshfeghi. 2020. The cortical activity of graded relevance. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 299–308.

[48] Chen Qu, Liu Yang, W Bruce Croft, Falk Scholer, and Yongfeng Zhang. 2019. Answer interaction in non-factoid question answering systems. In *Proceedings of the 2019 Conference on Human Information Interaction and Retrieval*. 249–253.

[49] Gary E Raney. 1993. Monitoring changes in cognitive load during reading: An event-related brain potential and reaction time analysis. *Journal of Experimental Psychology: Learning, Memory, and Cognition* 19, 1 (1993), 51.

[50] Álvaro Rodrigo and Anselmo Penas. 2014. On evaluating the contribution of validation for question answering. *IEEE Transactions on Knowledge and Data Engineering* 27, 4 (2014), 1157–1161.

[51] Aliaksei Severyn and Alessandro Moschitti. 2013. Automatic feature engineering for answer selection and extraction. In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*. 458–467.

[52] Marieke Van Herten, Herman HJ Kolk, and Dorothee J Chwilla. 2005. An ERP study of P600 effects elicited by semantic anomalies. *Cognitive brain research* 22, 2 (2005), 241–255.

[53] Carmen Vidaurre and Benjamin Blankertz. 2010. Towards a cure for BCI illiteracy. *Brain topography* 23, 2 (2010), 194–198.

[54] Edward K Vogel and Steven J Luck. 2000. The visual N1 component as an index of a discrimination process. *Psychophysiology* 37, 2 (2000), 190–203.

[55] Xachen Yao, Benjamin Van Durme, Chris Callison-Burch, and Peter Clark. 2013. Answer extraction as sequence tagging with tree edit distance. In *Proceedings of the 2013 conference of the North American chapter of the association for computational linguistics: human language technologies*. 858–867.

[56] Yu Zhang, Qibin Zhao, Jing Jin, Xingyu Wang, and Andrzej Cichocki. 2012. A novel BCI based on ERP components sensitive to configural processing of human faces. *Journal of neural engineering* 9, 2 (2012), 026018.

[57] Wei-Long Zheng, Bo-Nan Dong, and Bao-Liang Lu. 2014. Multimodal recognition using EEG and eye tracking data. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 5040–5043.

[58] Yuke Zhang, Juxin Mao, Yiquan Liu, Zixin Ye, Min Zhang, and Shaoping Ma. 2019. Human behavior inspired machine reading comprehension. In *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 425–434.