Brain-Computer Interface for Search

Ziyi Ye
University of Copenhagen & Tsinghua University

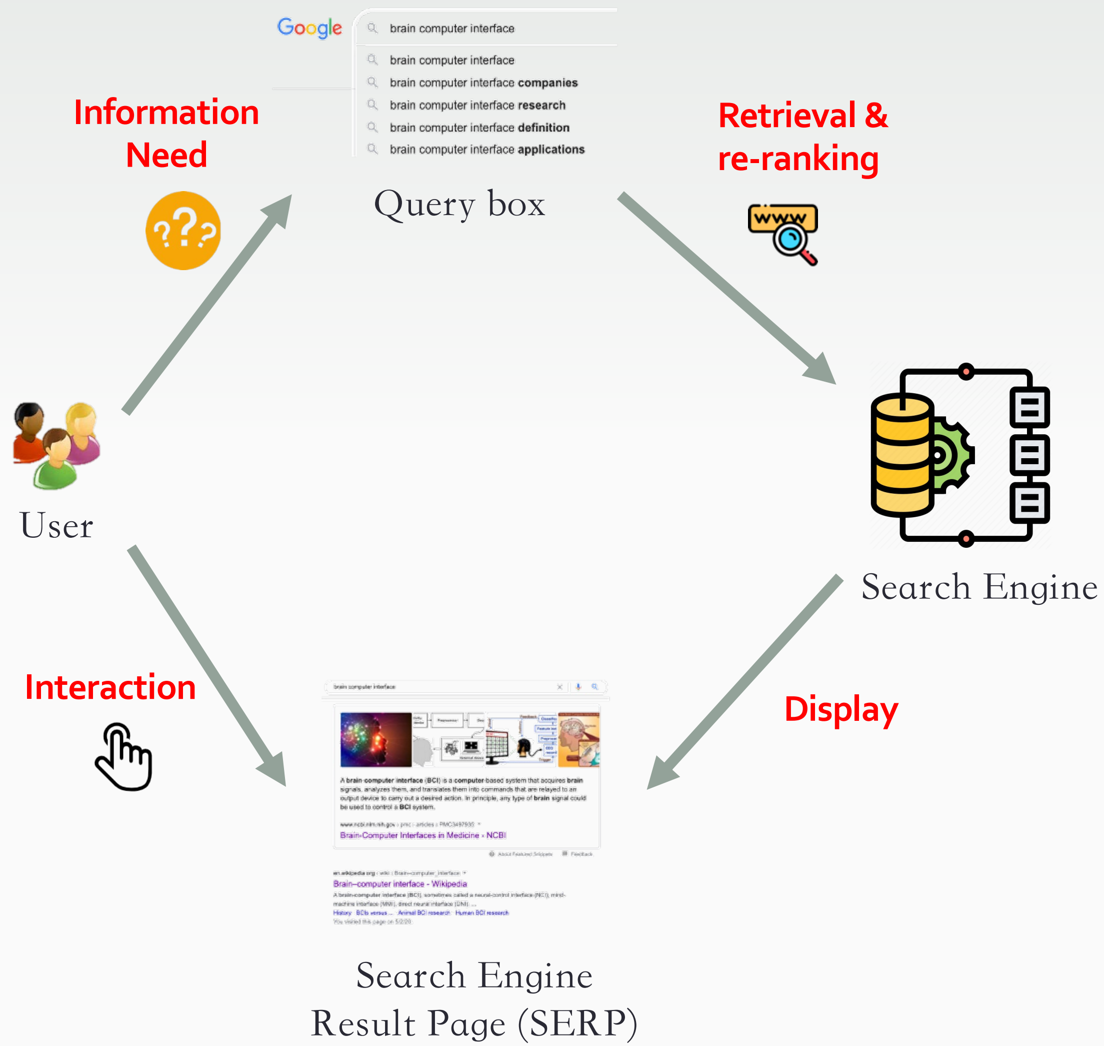
Introduction to myself

- Name: Ziyi Ye
- Position: Guest PhD student
- Adviser and group (here):
  - Christina and Tuukka; IRLab
- Adviser and group (home university):
  - Yiqun Liu; THUIR

Ziyi Ye
叶子逸
Ph.D. 2020-

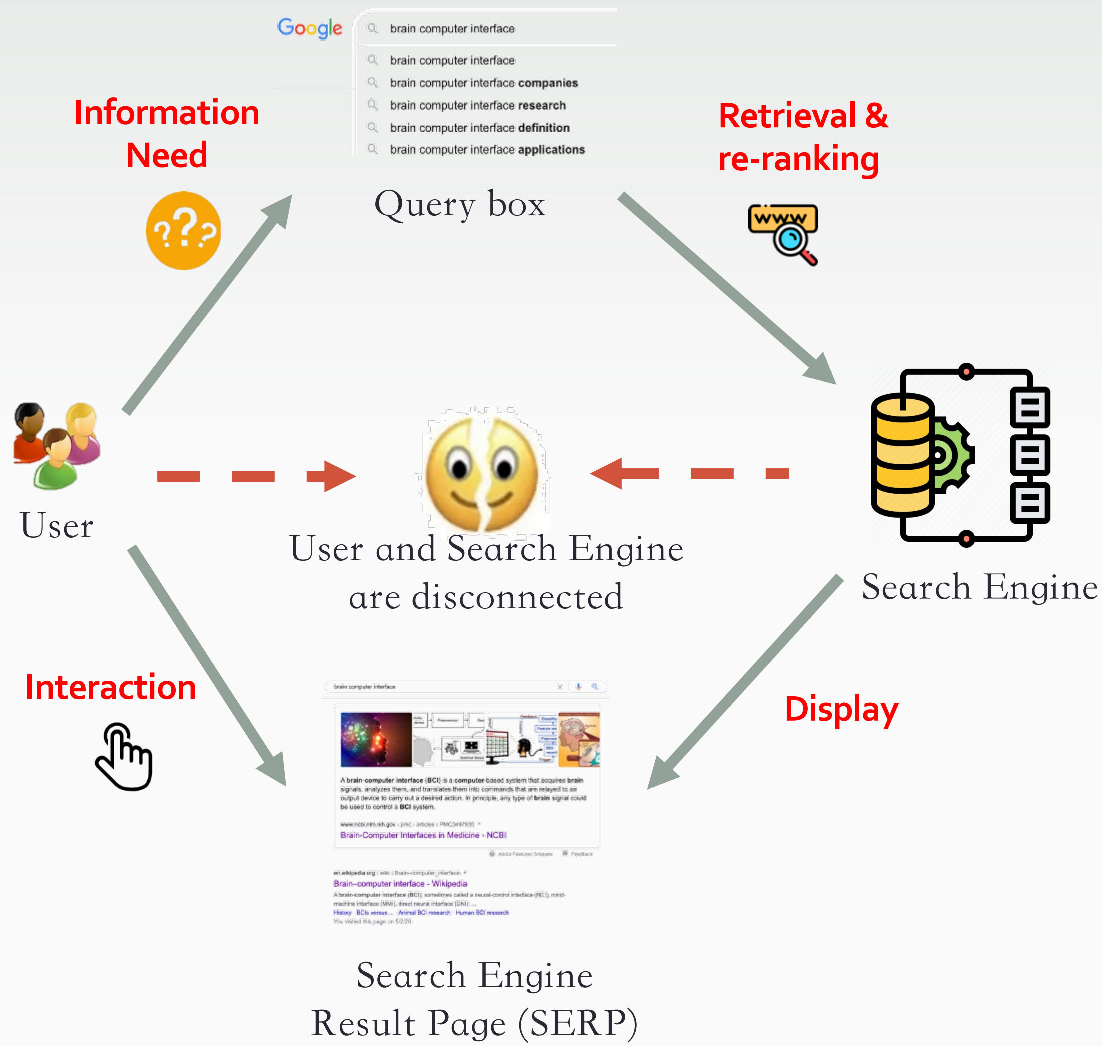
Background

- Current search paradigm



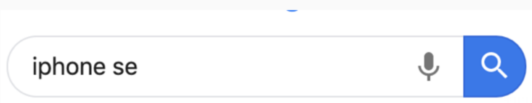
Background

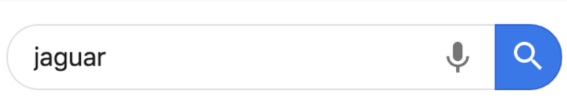
- Current search paradigm



Challenges 1

- The input query is:
  - Short (2-3 words in English, 6-7 characters in Chinese)
  - Users' intents are unspecific
  - Queries can be ambiguous
  - Sometimes it is hard to formulate a good query





Is *iPhone SE* a good choice

JAGUAR

What is this? How can I search about it?

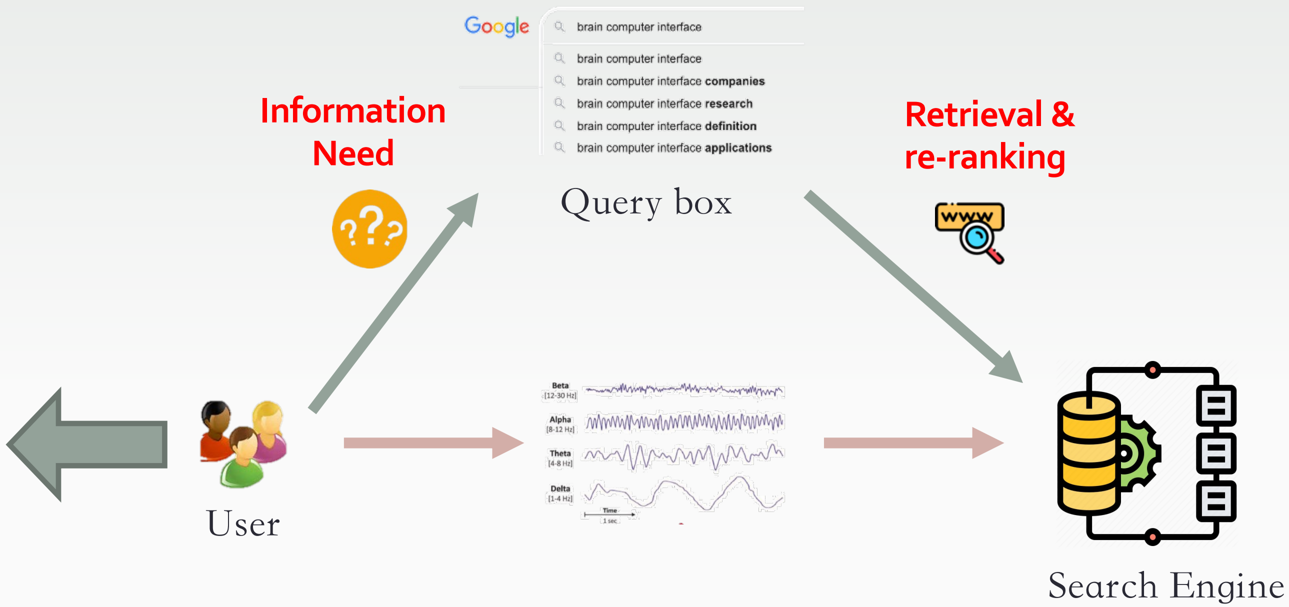
Where to buy an *iPhone SE*

Challenges 2

- Users are reluctant to give satisfaction feedback after search
- Current solution:
  - Use user behavior (click/dwell time/…) as implicit feedback
    - Not very accurate for an individual user ☹
  - Cranfield evaluation based on relevance annotation
    - Not a real-time feedback from the genuine user ☹
    - Additional cost for hiring annotators ☹

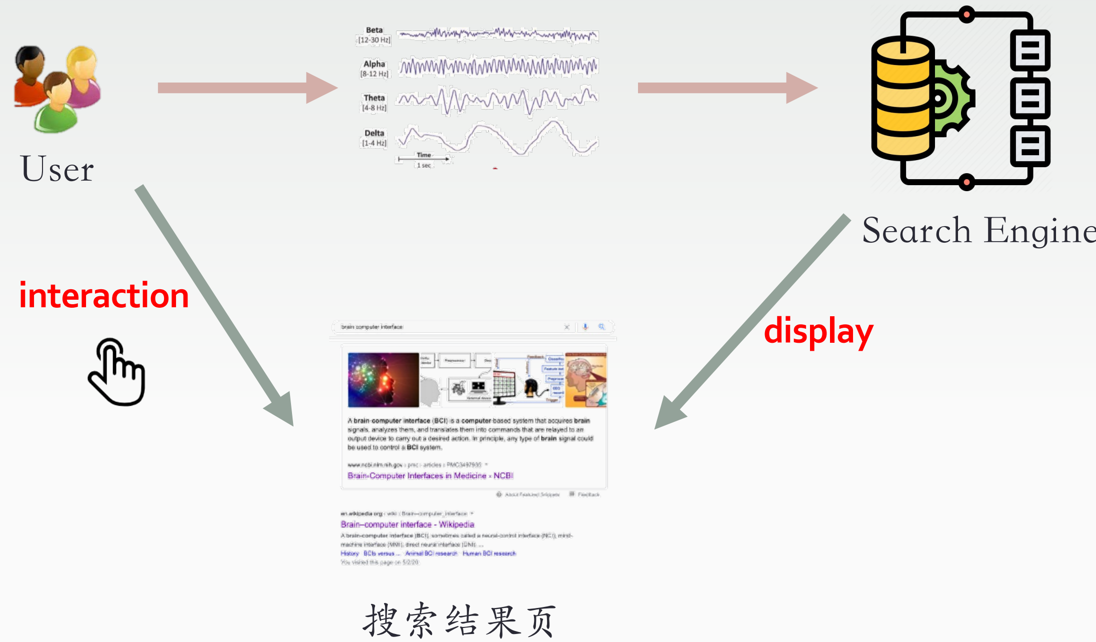
How BCI Can Help?

Challenges 1: Understanding information need



BCI can provide a clearer description of user's intent and information need to the search engine

How BCI Can Help?



Challenges 2: Modeling user feedback

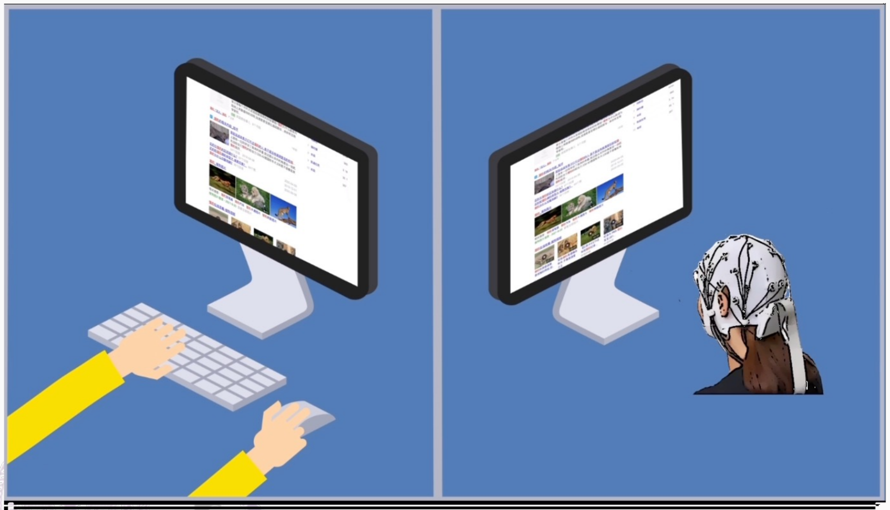
BCI can provide almost real-time satisfaction feedback

Is BCI for Search even possible?

- The definition of BCIs
  - Active BCIs
    - Control external devices through conscious brain activity
    - Whether we can control search engine with BCIs?
  - Passive BCIs
    - Read user cognitive state changes without user control
    - Whether Passive BCIs can help understand user's information need and modeling user feedback?

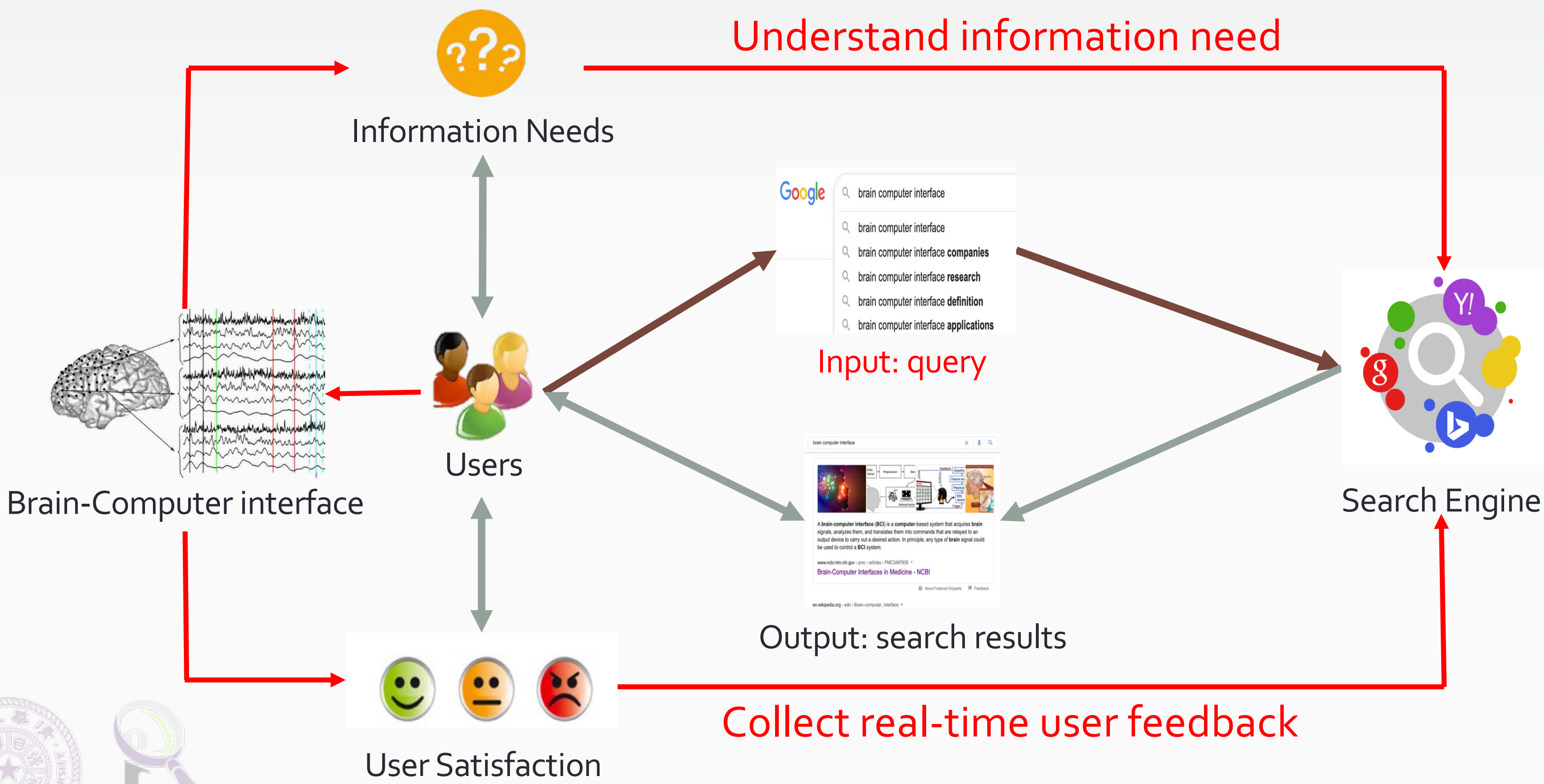
Is BCI for Search even possible?

- Active BCI for controlling the search engine
  - Accuracy of letter inputting -> 0.77 action inputting -> almost 1.0
  - Time to input an action or letter: 0.4-1.8s
  - Approximately 5s from inputting the query to enter destination Web page



Is BCI for Search even possible?

- Passive BCIs to understand search process & boost information access performance

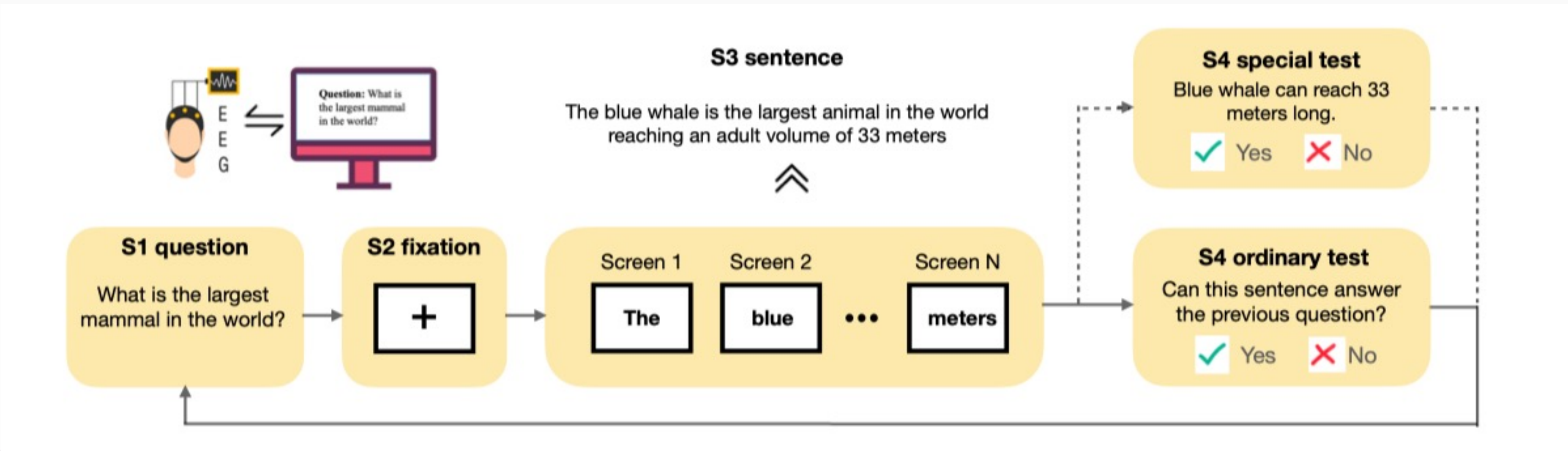


BMI helps build better cognitive model

- Understanding information need and relevance judgment
  - EEG-based User study

21 participants

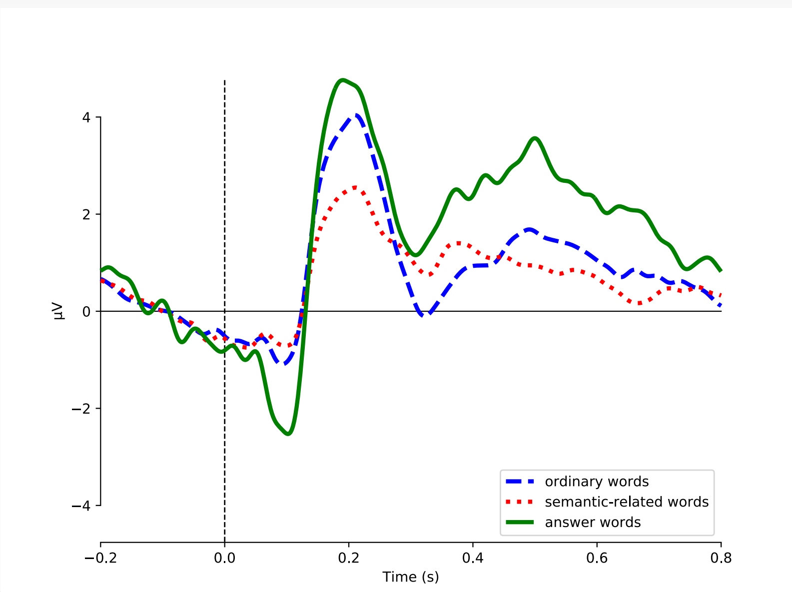
1. Entry questionnaire → 2. Informed consent → 3. Training step → 4. Main task → 5. Post-task questionnaire

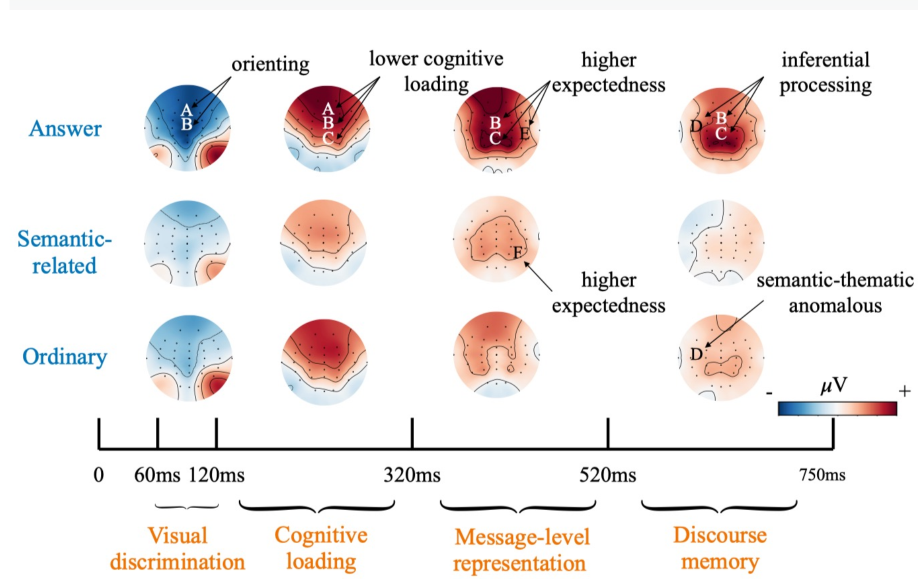


Ye et al. “Towards a Better Understanding of Human Reading Comprehension with Brain Signals.” theWebConf 2022

BMI helps build better cognitive model

- Understanding information relevance judgment
  - Detectable differences exists in brain activities when users find key information and read normal contents.
  - ERP analyses reveal various cognitive activities, e.g., semantic-thematic understanding and inferential processing.





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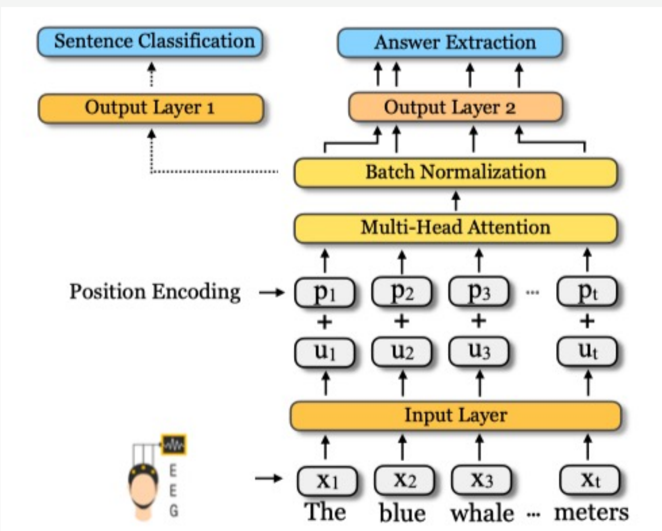
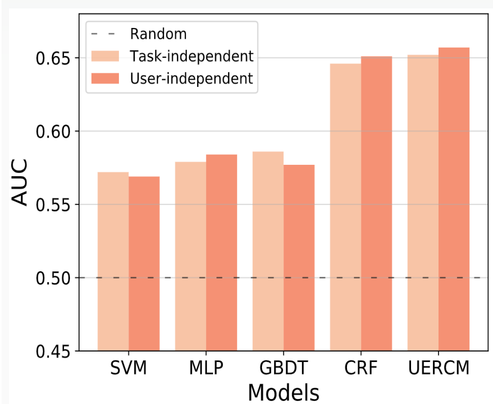
BMI helps build better cognitive model

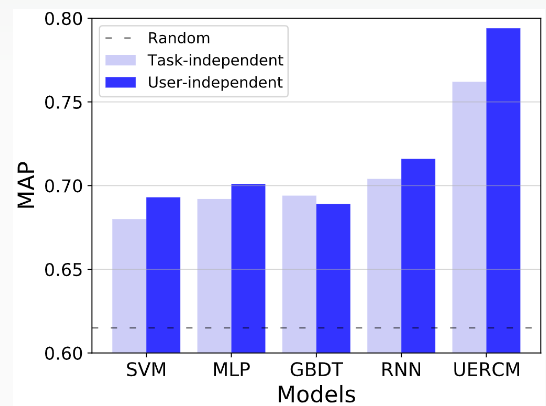
- Understanding human relevance judgment
  - EEG signals can be useful feedbacks in reading comprehension tasks: answer extraction and answer sentence classification.



The UERCM framework.



Answer extraction.



Answer sentence classification.

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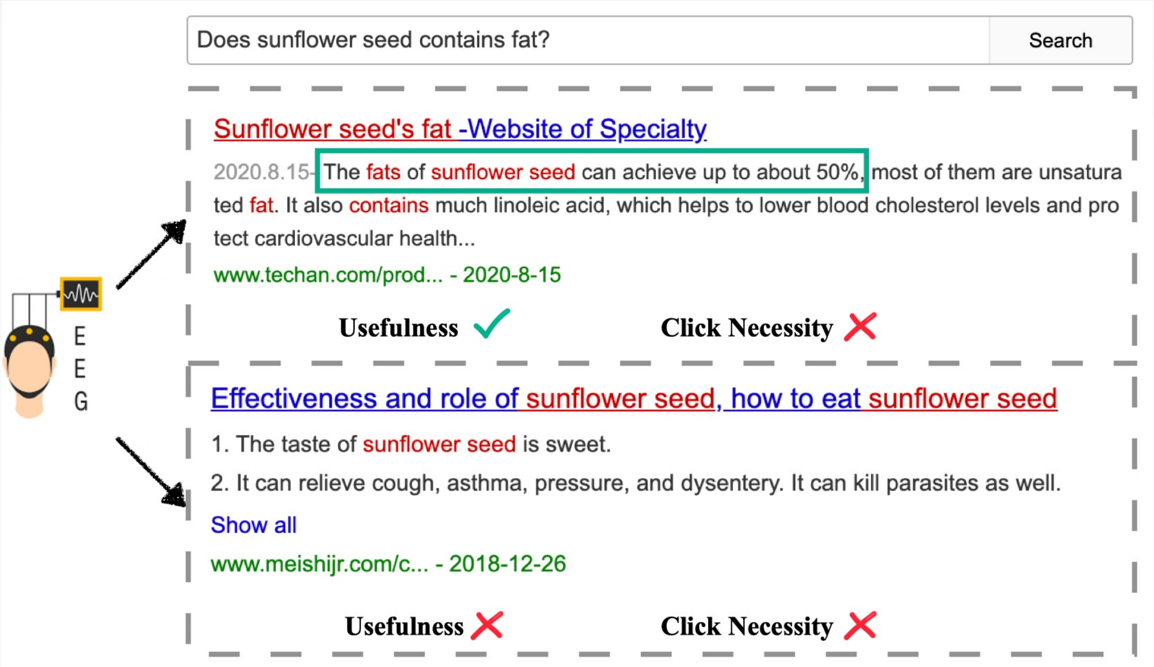
BMI helps challenging IR problems

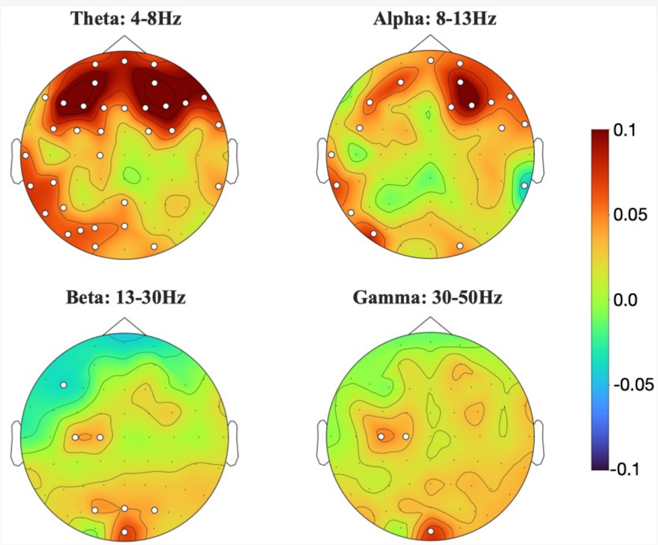
- Understanding Non-Click Result in Web Search
  - Click -> positive signal, Non-click -> negative signal ?
  - However, non-click results can also be useful considering its snippet and other components on SERP



Ye et al. “Why Don’t You Click: Understanding Non-Click Results in Web Search with Brain Signals.” SIGIR 2022

BMI helps challenging IR problems

- Significant correlations exist between band power and result usefulness
- Inspired by the correlations, we can predict non-click results' usefulness with brain signals



Model	user-independent AUC	user-independent STD	task-independent AUC	task-independent STD
DT^{cn}	0.619**	0.040	0.593**	0.080
DT^{cx}	0.664**	0.047	0.585**	0.049
DT^{bs}	0.585**	0.047	0.642	0.033
SST^{bs}	0.654**	0.043	0.655	0.037
$DT^{cn,cx}$	0.672**	0.049	0.614*	0.067
$DT^{cn,cx} + DT^{bs}$	0.687**	0.049	0.683	0.049
$DT^{cn,cx} + SST^{bs}$	**0.718**	0.040	**0.687**	0.050

M^f denotes model M using features f. cn, cx, and bs indicate content, context, and brain signals, respectively. DT and SST denotes decision tree and SST-EmotionNet, respectively.

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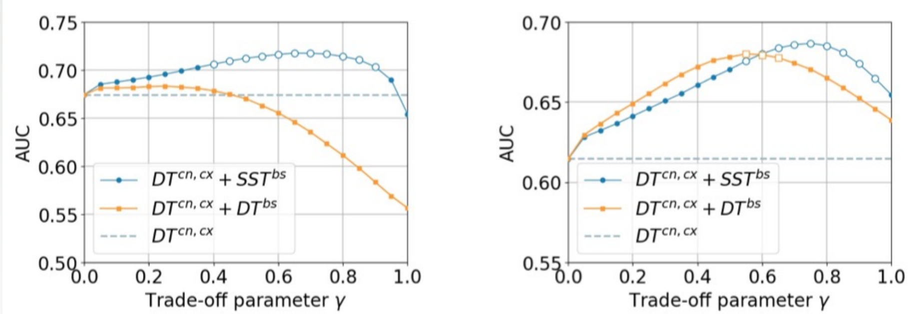
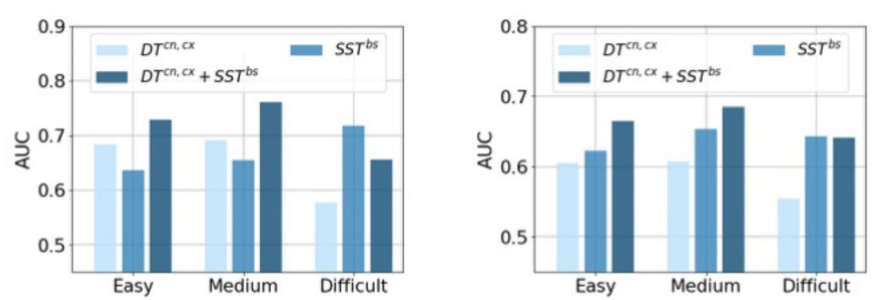
BMI helps challenging IR problems

- In-depth analyses (what’s the benefit of brain signals?)

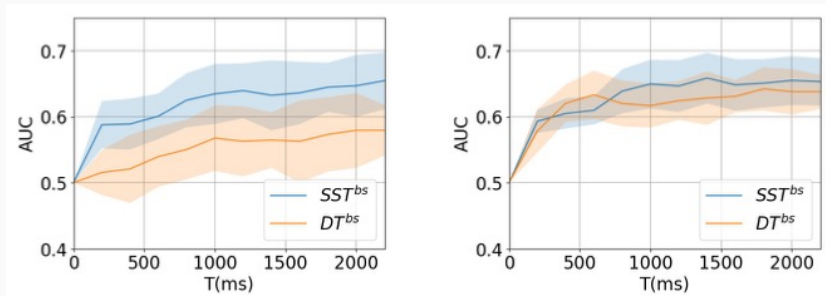


(a) User-independent. (b) Task-independent.

Incorporating conventional features and brain signals together is helpful.



(a) User-independent. (b) Task-independent.



(a) User-independent. (b) Task-independent.

Brain signal features are robust in difficult tasks.

Usefulness can be estimated in 0.8 second.

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BMI helps challenging IR problems

- We can improve the performance of search result re-ranking with the estimated usefulness.
- Personalized method (PM): re-rank with each individual's signal.
- Generalized intent modeling method (GIM): re-rank by building an intent model with the wisdom of general individuals

Model	NDCG@1	NDCG@3	NDCG@5	MRR
$BM25^{cn}$	0.407*	0.672*	0.725*	0.621*
$BERT^{cn}$	0.399*	0.691*	0.737*	0.655*
$PM^{cn,cx}$	0.446*	0.714*	0.751*	0.677*
PM^{bs}	0.457*	0.725*	0.764*	0.691
$PM^{cn,cx,bs}$	0.522*	0.752*	0.787*	0.726*
$GIM^{cn,cx}$	0.490*	0.739*	0.775*	0.709*
GIM^{bs}	0.571	0.776	0.811	0.754
$GIM^{cn,cx,bs}$	**0.591**	**0.787**	**0.814**	**0.764**

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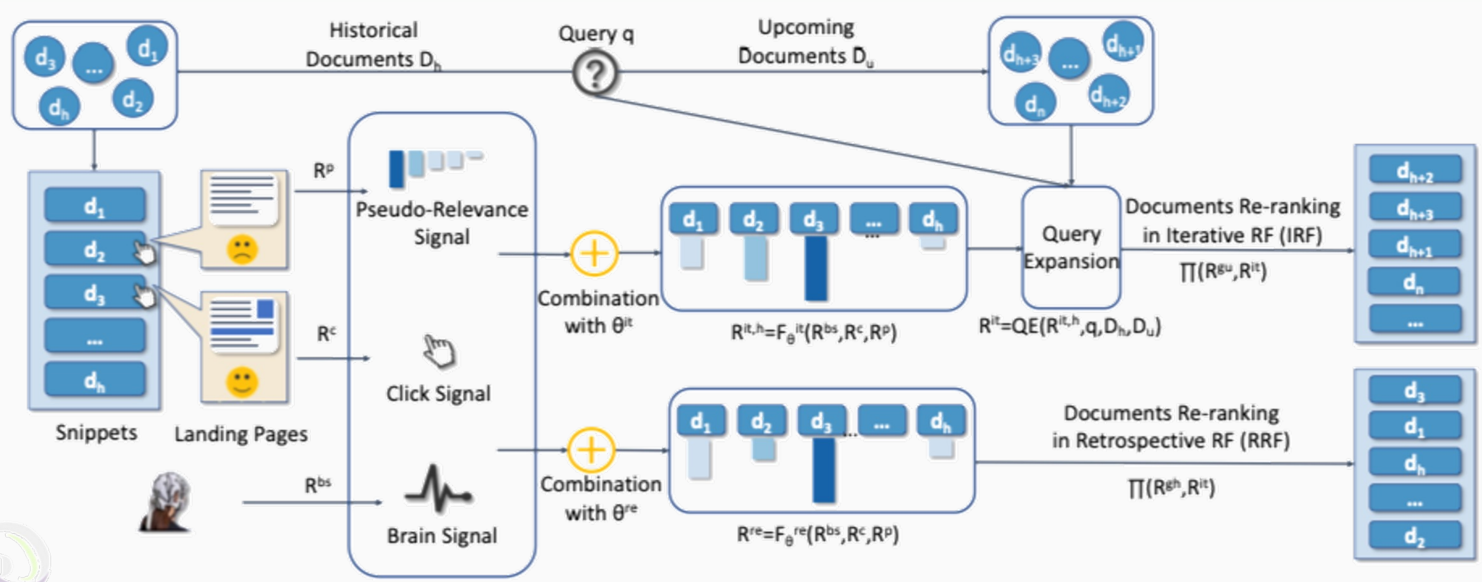
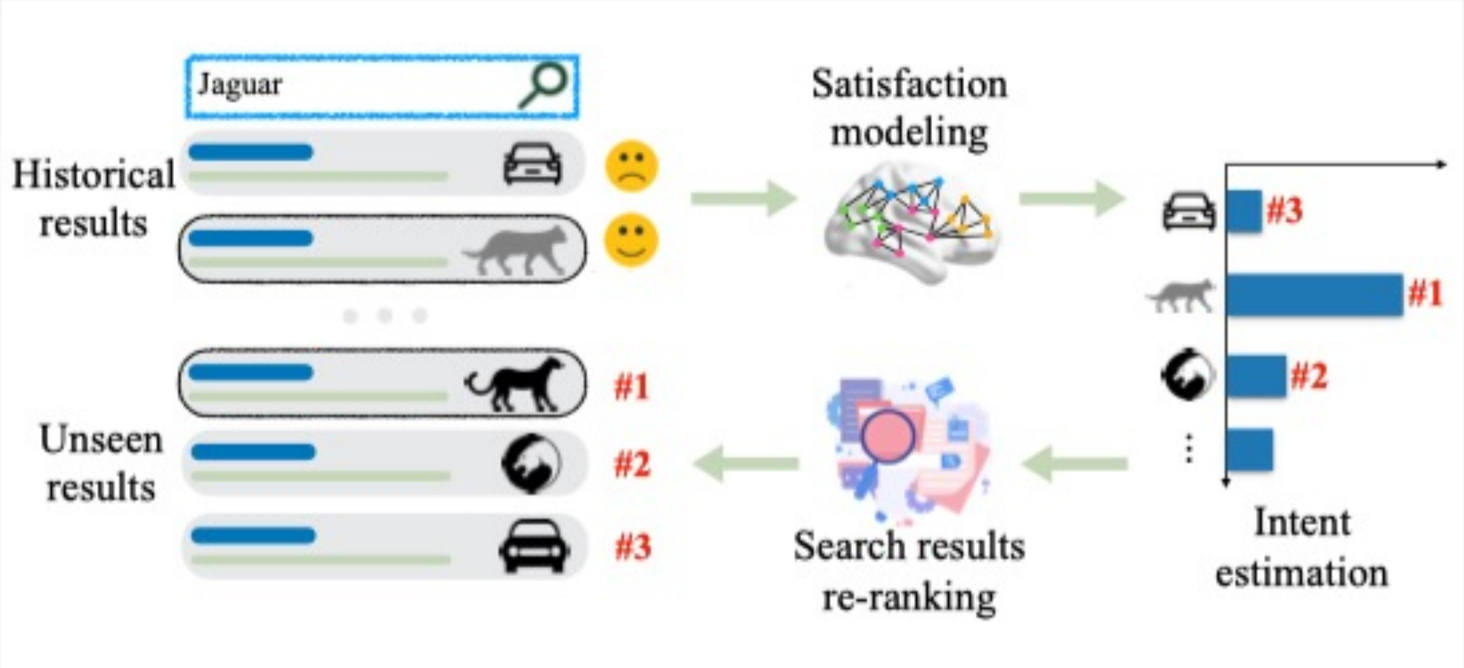
BMI helps challenging IR problems

- From helping special cases (non-clicks) to a constructing general Relevance Feedback (RF) frameworks
  - Conventional RF signals (e.g., pseudeo-relevance signals, click signals) are often biased or absent
  - Brain signals can bring additional improvement to existing RF



BMI for satisfaction modeling

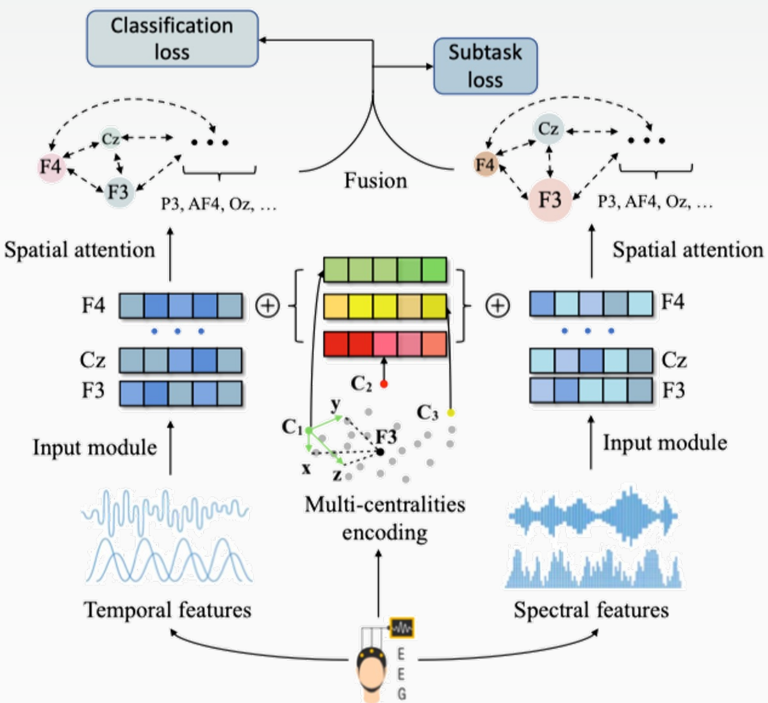
- Interactively provide satisfying information by understanding real-time user status.
  - As the search process going on, the system gets a better intent estimation of user, and then interactively adjusts its strategy



Ye et al. "Brain Topography Adaptive Satisfaction Modeling for Interactive Information Access." MM 2022

BMI for satisfaction modeling

- Decoding user satisfaction with adaptive cognitive connectives.
  - Important modules: spatial attention & multi-centralities



Model	Search-Brainwave F1	Search-Brainwave AUC	AMIGOS F1	AMIGOS AUC
Topography-invariant				
DT	0.5642*	0.5205*	0.5608*	0.6245*
MLP	0.6196*	0.5204*	0.5629*	0.6123*
SVM	0.6227*	0.5189*	0.5580*	0.5892*
CNN-based				
BENDR	0.7118*	0.7291*	0.5580*	0.5869*
EEGNet	0.7254*	0.7614*	0.6025*	0.6920*
GCN-based				
DGCNN	0.7170*	0.7374*	0.6630*	0.7663*
HetEmotionNet	0.7362*	0.7717*	0.6428*	0.7405*
RGNN	0.7440*	0.7663*	0.6694*	0.7782*
BTA (ours)	**0.7837**	**0.8278**	**0.7143**	**0.8353**

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BMI for satisfaction modeling

- **Improving Search performance with estimated user satisfaction**
  - Result re-ranking with query rewriting using a language model.

Model	NDCG@1	NDCG@5	NDCG@10	MAP@10
BM25	0.6881*	0.7397*	0.8164*	0.7333*
ULM	0.7237*	0.7620*	0.8309*	0.7687*
SLM	**0.7351**	**0.7767**	**0.8337**	**0.7741**

Overall performance.

Query	Permanent teeth
Doc1	…, online medical advice: dentist Mr.Song / ☹
Doc2	how old does a child grow its permanent teeth, … / ☺

Rewriting with pseudo feedback	Rewriting with estimated satisfaction feed back from brain
permanent, teeth, dentist, know, online, **child**, **kid**	permanent, teeth, **child**, **old**, **when**, know, **kid**

Case study.

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Thanks For Your Attention, Any Questions?

WSDM 2022

Web Search via an Efficient and Effective **Brain-Machine Interface**

WWW 2022

Towards a Better **Understanding** of Human **Reading Comprehension** with Brain Signals

SIGIR 2022

Why Don’t You Click: Understanding **Non-Click Results** in Web Search with Brain Signals

1. **Search interface controlling (WSDM2022)**:
   - Active BCIs
2. **Reading comprehension (WWW2022)**:
   - Inspirations for IR applications
3. **Satisfaction estimation (SIGIR2022)**:
   - Estimate usefulness with brain signals
   - Brain signals as “explicit feedback”

4. Topography adaptive satisfaction modeling (MM 2022)
   - Satisfaction modeling with brain topography

- **My Email: Yeziyi1998@gmail.com**
- **Papers, data, and code can be found: https://yeziyi1998.github.io/**

Thanks!