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## Motivation

Backtracing: Given the corpus $X$ and query $q$, retrieve the sentence that most likely caused the query.


Query $q$ (e.g., student question)

I have a question, if I project the projection again that's the same point that is $\mathrm{P}^{\wedge} 2=\mathrm{P}$. But if I keep doing such it should tell $P^{\wedge} 3=P^{\wedge} 4=P^{\wedge} n=P$, and this property holds for Identity matrix. Is my logic correct?

What did I say that triggered this student's question?
[...] The projection is the same point. So that means that if I project twice, I get the same answer as I did in the first project. So those are the two properties that tell me I'm looking at a projection matrix. [...]

- While information retrieval (IR) systems may provide answers for user queries, they do not directly assist content creators (e.g., teachers) identify segments that caused a user to ask those questions.
- Identifying the cause of a query is challenging because of $\mathbf{1}$. lack of explicit labeling, 2. large size of corpus, and 3. required domain expertise to understand both the query and corpus.
- We introduce the task of backtracing, in which systems retrieve the text segment that most likely caused a user query.


## Contributions

Task. We formalize backtracing: Retrieve the text segment that most likely caused the user query.
Benchmark. We develop a heterogeneous benchmark for backtracing: retrieving the cause of student confusion in the LECTURE setting, reader curiosity in the News Article setting, and user emotion in the Conversation setting.

Evaluations. We evaluate a suite of popular retrieval systems and show that there is room for improvement in current retrieval methods. This suggests that backtracing is not only challenging but also requires new retrieval approaches.

## Backtracing Task

Given corpus of $N$ sentences $X=\left\{x_{1}, \ldots, x_{N}\right\}$ and query $q$, backtracing selects

$$
\begin{equation*}
\hat{t}=\arg \max _{t \in 1 \ldots N} p\left(t \mid x_{1}, \ldots, x_{N}, q\right) \tag{1}
\end{equation*}
$$

where $x_{t}$ is the $t^{\text {th }}$ sentence in corpus $X$ and $p$ is a probability distribution over the corpus indices, given the corpus and the query.
This task intuitively translates to: Given a lecture transcript and student question, retrieve the lecture sentence(s) that most likely caused the student to ask that question.

## Backtracing Benchmark



Figure 1. The text context that causes the query is the green-highlighted sentence. Popular retrieval systems retrieve incorrect contexts shown in red.

Lecture. Retrieve the cause of student confusion [3] News Article. Retrieve the cause of reader curiosity [1].
Conversation. Retrieve the cause of user emotion (e.g., anger) [2].

|  | \# sentences | Lecture | News Article | Conversation |
| :---: | :---: | :---: | :---: | :---: |
| Corpus $X$ | Total | 11042 | 2125 | 8263 |
|  | Average | 525.8 | 19.0 | 12.3 |
| Query 9 | Total | 210 | 1382 | 671 |
|  | Average | 30.9 | 7.1 | 11.6 |

## Results

- The best-performing models achieve modest accuracies.

Measuring causal relevance is challenging and markedly different from existing retrieval tasks.
The methods do not generalize across domains. For instance, while a cross-encoder method performs well on the NEWS Article domain with top-3 85\% accuracy, it only manages top-3 $15 \%$ accuracy on the Conversation domain.

|  |  | $\begin{aligned} & \text { Lecture } \\ & \text { @1 } \end{aligned}$ |  | News @1 | Article ©3 | Conversation <br> @1 @3 |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Random | 0 | 2 | 6 | 21 | 11 | 31 |
|  | Edit | 4 | 8 | 7 | 18 | 1 | 16 |
|  | Bi-Encoder (Q\&A) | 23 | 37 | 48 | 71 | 1 | 32 |
|  | Bi-Encoder (all-MiniLM) | 26 | 40 | 49 | 75 | 1 | 37 |
|  | Cross-Encoder | 22 | 39 | 66 | 85 | 1 | 15 |
|  | Re-ranker | 30 | 44 | 66 | 85 | 1 | 21 |
|  | gpt-3.5-turbo-16k | 15 | N/A | 67 | N/A | 47 | N/A |
| Single-sentence | GPT2 | 21 | 34 | 43 | 64 | 3 | 46 |
| ${ }_{p\left(q \mid x_{t}\right)}$ | GPTJ | 23 | 42 | 67 | 85 | 5 | 65 |
|  | OPT 6B | 30 | 43 | 66 | 82 | 2 | 56 |
| Autoregressive | GPT2 | 11 | 16 | 9 | 18 | 5 | 54 |
| $p\left(\left.q\right\|_{x_{\leq t}}\right)$ | GPTJ | 14 | 24 | 55 | 76 | 8 | 60 |
|  | OPT 6B | 16 | 26 | 52 | 73 | 18 | 65 |
| ATE | GPT2 | 13 | 21 | 51 | 68 | 2 | 24 |
| $p(q \mid X)-p\left(q \mid X /\left\{x_{t}\right\}\right)$ | GPTJ | 8 | 18 | 67 | 79 | 3 | 18 |
|  | OPT 6B | 2 | 6 | 64 | 76 | 3 | 22 |

Table 1. Accuracy in percentage (\%). The best models in each column are bolded. For each dataset, we report the top- 1 and 3 accuracies.

More results and analysis in the paper!


References

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[^0]:    [1] Wei-Jen Ko, Te-Yuan Chen, Yiyan Huang, Greg Durrett, and Junyi Jessy Li. Inquisitive question generation for high level text comprehension. arXiv preprint arXiv:2010.01657, 2020
    2] Soujanya Poria, Navonil Majumder, Devamanyu Hazarika, Deepanway Ghosal, Rishabh Bhardwaj, Samson Yu Bai Jian, Pengfei Hong, Romila Ghosh, Abhinaba Roy, Niyati Chhaya, et al. Recognizing emotion cause in conversations. Cognitive Computation, 13:1317-1332, 2021
    [3] Rose Wang, Pawan Wirawarn, Noah Goodman, and Dorottya Demszky. Sight: A large annotated dataset on student insights gathered from higher education transcripts. In Proceedings of Innovative Use of NLP for Building Educational Applications, 2023.

