# Neural-Augmented Retrieval for Open-Domain Dialogue Systems

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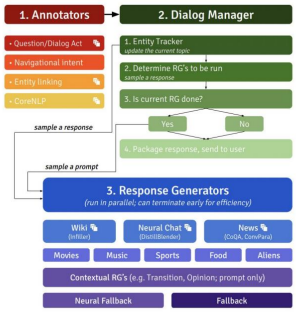
## Overview

- Progress in end-to-end deep neural dialogue agents is limited by their **knowledge** of world events and **latency** in responding to user inputs.
- Knowledge retrieval in ChirpyCardinal follows:
  - **Wikipedia entities** are identified from dialogue.
  - Entities + templates are passed to GloVe-based retrieval to return "**knowledge statements**" (KS).
  - KSs are used are used for template **infilling**.
- Challenges: GloVe-based retrieval has mixed performance, but **large retrieval models** w/ better performance based on LLMs have high latency.
- We explored:
  - Integrating **ColBERT-based retrieval** using a Faiss index to improve retrieval quality.
  - Applying alternative neural generation models for infilling, such as T5.
  - Benchmarking different **quantitative evaluation methods** for retrieved responses.
  - Integrated these models into ChirpyCardinal for end-to-end conversation

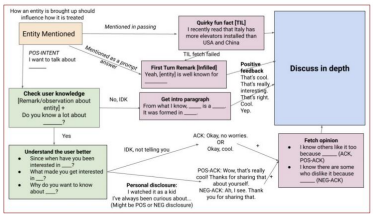
## ChirpyCardinal

- Open-source, end-to-end chatbot with foundation in multitopic, multithreaded response generators.




- This neural retrieval occurs in the Wiki response gen.

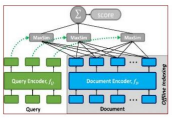
## Problem Setting



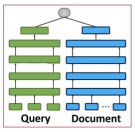

- Dataset: **May 2020 English Wikpedia Dump**
  - For GloVe search: filtered Wikipedia page corresponding to current entity.
  - For ColBERT: **21M+** passages of 180-tokens.
- Templates: **pre-created structures** ready for infilling given context.
  - Ex. Template: *I love how [[actor]] acted in [[film]], especially their <mask>.*
  - Ex. Infill: *I love how [Keanu Reaves] acted in [The Matrix], especially their ability to freeze time.*

## Task 1: Retrieval

- **ColBERT Retrieval**
  - **Data:** Faiss index of **BERT**-embedded tokenized passages.
  - **Method:** Batch **top-k** retrieval queries corresponding to different templates.




- **GloVe Retrieval**
  - **Data:** filtered sentences from entity's Wikipedia page.
  - **Method:** compute GloVe embeddings for each template, statement, then choose **top-k** pairs.




- Key difference in methods: better use of **semantic context** through BERT embeddings vs. GloVe.

## Task 1: Retrieval (cont.)

- Quan. eval. method: avg. top-k retrieval relevance.

$$AS(k) = \frac{1}{20}\sum_{i=1}^{20} s_i, \quad s_i \in \{0, \ldots, k\}$$

| Retrieval Method | AS(5) |
|---|---|
| GloVe | 2.35 ± 0.11 |
| ColBERT | 2.91 ± 0.20 |

- Add. quan. method: "adapted MRR" (aMRR).

| Retrieval Method | aMRR@5 |
|---|---|
| GloVe | 0.231 |
| ColBERT | 0.532 |

- Ablation: use sentences retrieved by ColBERT for GloVe **(Augmented GloVe)**.

| Retrieval Method | AS(5) |
|---|---|
| GloVe | 2.35 ± 0.11 |
| Augmented GloVe | 2.56 ± 0.32 |
| ColBERT | 2.91 ± 0.20 |

- ColBERT's use of semantic information makes it superior retrieval method.

## Task 2: Infilling

- **Method:** Given retrieved template + context pairs, infill the mask in the template.
- **BART** and **T5** used for conditional generation.

| | | | |
|---|---|---|---|
| 4 | **User:** i love it when the batter is crunchy<br>**Bot:** I agree! The crunch and the texture is really good. It's a shame it's hard to find a good crispy batter these days, though. [ Neural ] Did you know that fish and chips were first made in England around the 16th century? I can't believe people have been eating fish and chips for so long! [ Food ] | Fish and chips<br>Fish and chips | Food gives a DistilBlender-generated acknowledgement, followed by a scripted prompt. |
| 5 | **User:** wow that's a long time<br>**Bot:** It really is. Anyway, I'm feeling hungry now! Thanks for recommending fish and chips! [ Food ] Speaking of Fish and chips, i was reading recently and found out that fish and chips is a common take-away food in the united kingdom and numerous other countries...do you wanna talk about the United Kingdom? [ Transition ] | None<br>United Kingdom | Transition generates a transition from *Fish and chips* to *United Kingdom* to continue the conversation smoothly. |
| 6 | **User:** sure<br>**Bot:** I just learned recently that violent pirates could have been executed in the united kingdom until 1998. [ Wiki ] | United Kingdom<br>United Kingdom | User accepts the suggested entity for discussion.<br>Wiki provides an template-infilled remark about the *United Kingdom*. |
| 7 | **User:** oh that's surprising<br>**Bot:** Isn't it? Come to think of it, I did read something the other day about United Kingdom's Culture and Geography, if you're interested in talking about any of that. [ Wiki ] | United Kingdom<br>United Kingdom | Wiki suggests aspects of the *United Kingdom* to discuss. |

## Task 2: Infilling

- We again use avg. top-k retrieval relevance for evaluating quality of infilled statements.

| Retrieval+Infilling Method | AS(5) |
|---|---|
| GloVe + BART | 2.42 ± 0.13 |
| GloVe + T5 | 2.23 ± 0.08 |
| ColBERT + BART | 3.21 ± 0.19 |
| ColBERT + T5 | 2.95 ± 0.24 |

- Results emphasize the importance of the accompanying context used during infilling.

## Conclusion

- Existing neural retrieval used in ChirpyCardinal did not make full use of semantic context.
- Improved retrieval also benefits downstream infilling
- Feasibly embedded within existing framework for end-to-end neural conversation.

## Future Work

- **Broader Quantitative Evaluation:** Increase the number of people used for evaluating the quality of retrieved knowledge statements.
- **Code Optimization:** Refining the code to better leverage existing information in ChirpyCardinal will decrease latency and minimize bugs.
- **Latency Evaluation:** Further profiling of the latency of retrieval and infilling operations.

## References

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