

MeanCache: User-Centric Semantic Cache for Large Language Model Based Web Services



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Introduction

Services like ChatGPT revolutionize web search but incur high costs due to billions of parameters; caching repeated queries (31%) could reduce costs.

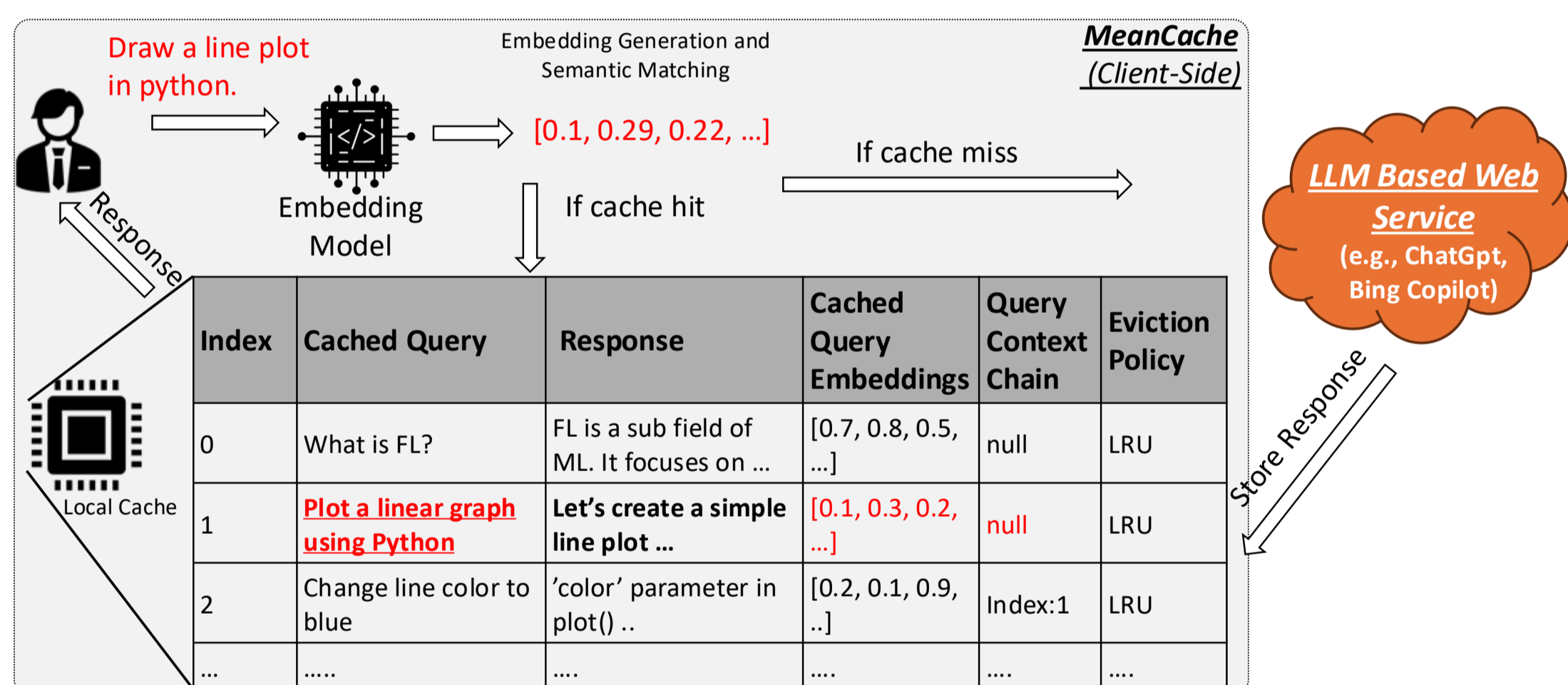
Problem Statement

- Existing caching methods rely on keyword matching, failing to capture semantic similarities.
- High false hit rates, especially with contextual queries (GPTCache [2]).
- Centralized caches raise privacy concerns.

MeanCache: Our Solution

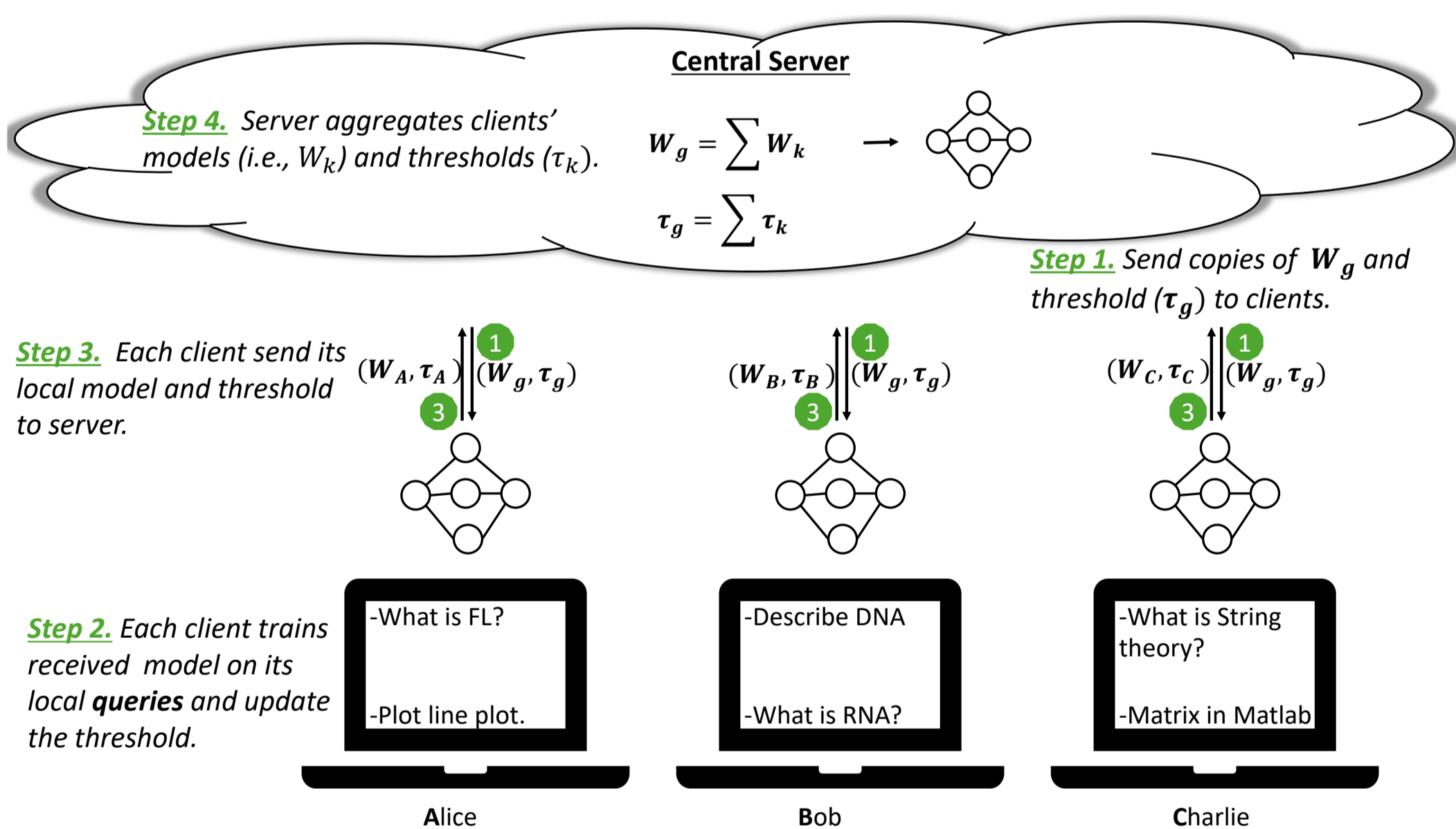
- User-Centric:** Local user's cache to preserve privacy and reduce server load.
- Federated Learning:** Collaborative training of smaller embedding models without the need to share user data.
- Context Awareness:** Encodes context chains to handle contextual queries.
- Embedding Compression:** Applies PCA to reduce embedding dimensions, saving storage and speeding up searches.

“Draw a line plot in Python” is a duplicate query. MeanCache [1] retrieves a semantically matched response from the user's cache (Index-1 Response).

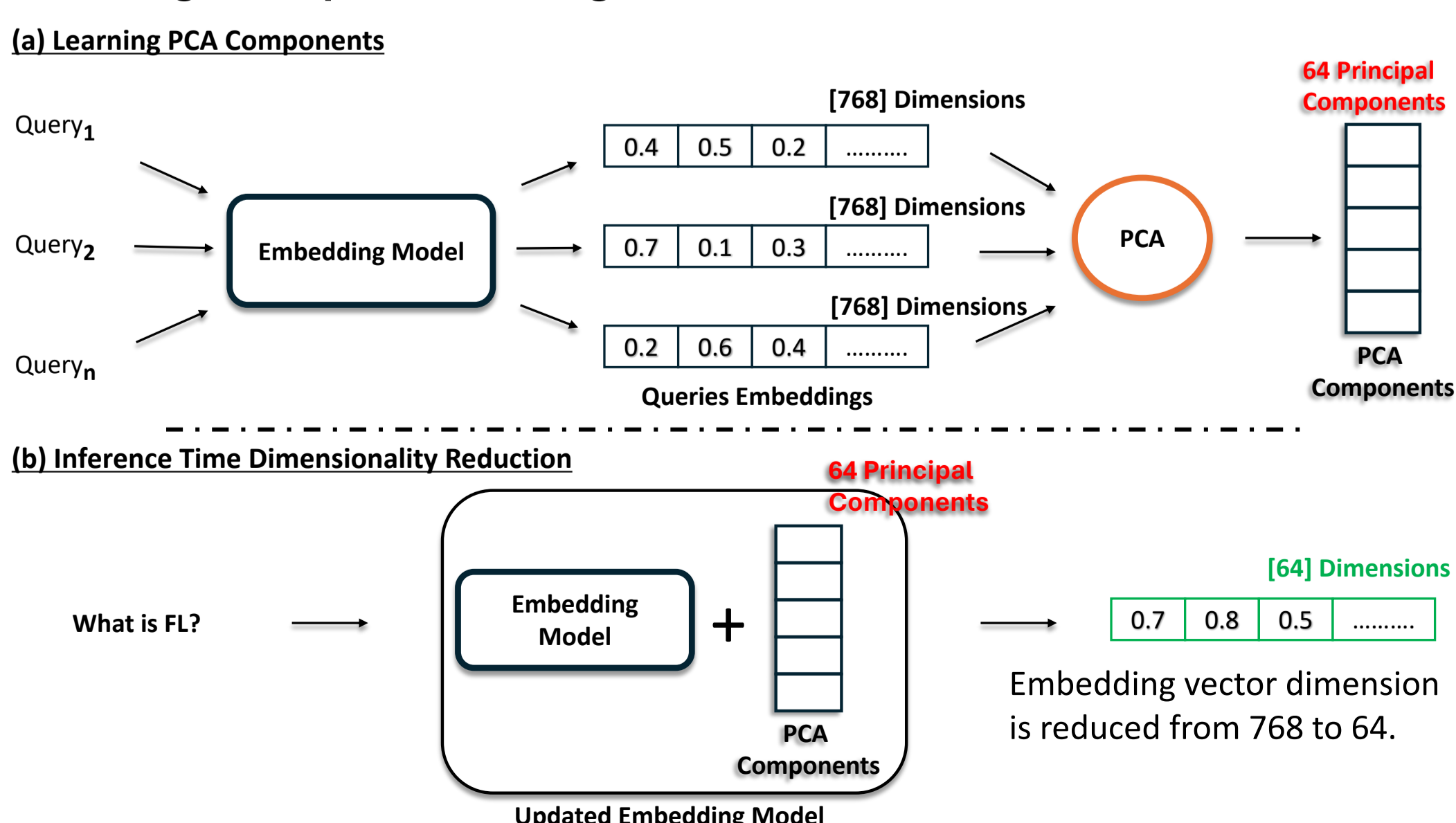


Use of Federated Learning and PCA in MeanCache

Privacy-Preserving Embedding Model FL Training in MeanCache.



Embeddings Compression using PCA in MeanCache.



Results - Comparison with Baseline

| Metrics | Standalone Queries | | | Contextual Queries | |
|-----------|--------------------|-------------------|--------------------|--------------------|-------------|
| | GPTCache | MeanCache (MPNet) | MeanCache (Albert) | GPTCache | MeanCache |
| F score | 0.56 | 0.73 | 0.68 | 0.67 | 0.93 |
| Precision | 0.52 | 0.72 | 0.66 | 0.66 | 0.98 |
| Recall | 0.85 | 0.78 | 0.77 | 0.71 | 0.79 |
| Accuracy | 0.72 | 0.85 | 0.81 | 0.61 | 0.86 |

Table 1. MeanCache outperforms GPTCache on both standalone and contextual queries.

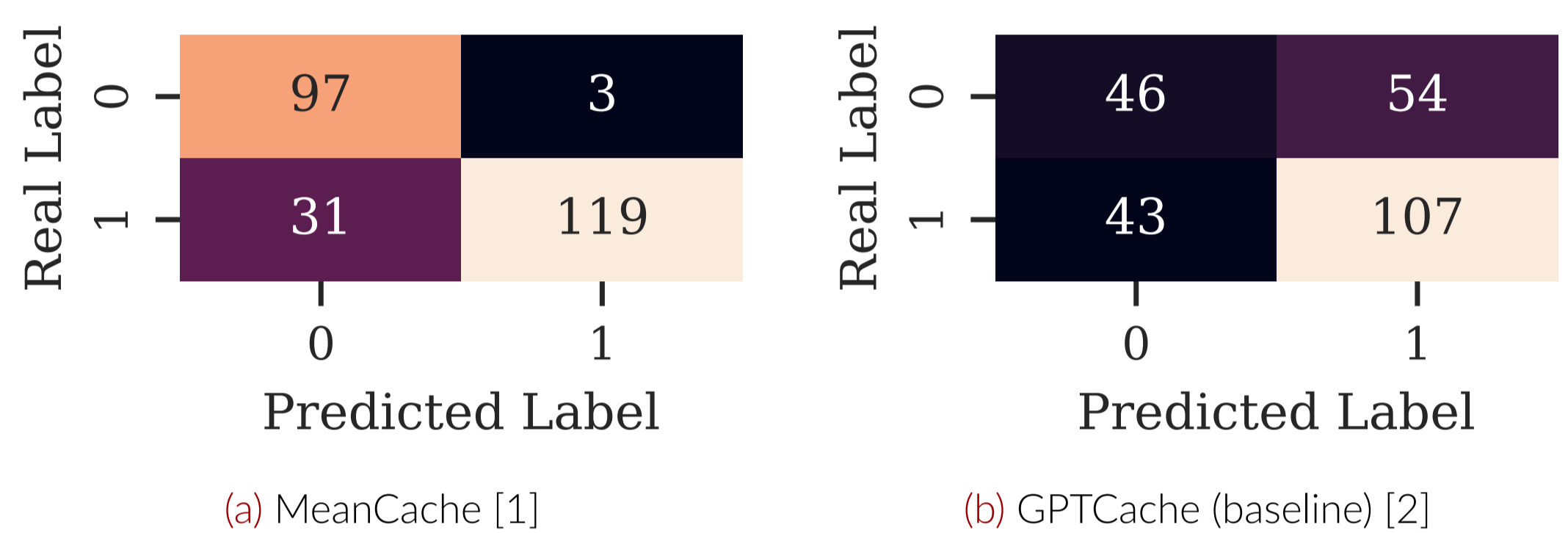


Figure 1. MeanCache only reports three false hits compared to 54 false hits by GPTCache. False hits are undesirable as they require the user to resend the query to the LLM service to obtain the correct response.

Conclusion

- MeanCache effectively reduces LLM inference costs by caching semantically similar queries locally.
- MeanCache ensures user privacy through federated learning and local caching.
- MeanCache outperforms the baseline (GPTCache), especially in handling contextual queries.

Future Work

- Multimodal Caching:** Expand MeanCache to support multimodal caching, including vision and audio data.
- Embedding Quantization:** Investigate quantization of embeddings to significantly speed up semantic caching and reduce memory and disk usage.
- Optimizing Query Caching:** Assess caching benefits for different queries to optimize cache (e.g., excluding time-sensitive, grammatical, and long queries.)
- Eviction Policy:** Investigate optimal eviction policies for semantic caching.
- Benchmarking:** Create diverse benchmark dataset to evaluate semantic caching across domains (e.g., medical, software engineering).

MeanCache Key Features and Evaluation Highlights

- Privacy-Preserving:** No user data stored on central servers.
- Scalable:** Efficient local caching and federated model training.
- Contextual Queries:** Only 3 false hits vs. 54 by GPTCache.
- High Accuracy:** MeanCache surpasses baseline for contextual queries with 25% higher F-score and 32% better precision.
- Storage & Speed:** Embedding compression reduces storage by 83% and speeds up matching by 11%.

References

- [1] Gill, Waris, et al. “MeanCache: User-Centric Semantic Cache for Large Language Model Based Web Services.” arXiv preprint arXiv:2403.02694 (2024).
- [2] Bang, Fu. “GPTCache: An open-source semantic cache for LLM applications enabling faster answers and cost savings.” Proceedings of the 3rd Workshop for Natural Language Processing Open Source Software (NLP-OSS 2023). 2023.