An End-to-End ML System for Personalized Conversational Voice Models in Walmart E-Commerce

Rahul Radhakrishnan Iyer∗
Walmart Labs
Sunnyvale, CA
Praveenkumar Kanumala
Walmart Labs
Sunnyvale, CA
Stephen Guo
Walmart Labs
Sunnyvale, CA
Kannan Achan
Walmart Labs
Sunnyvale, CA

Abstract
Searching for and making decisions about products is becoming increasingly easier in the e-commerce space, thanks to the evolution of recommender systems. Personalization and recommender systems have gone hand-in-hand to help customers fulfill their shopping needs and improve their experiences in the process. With the growing adoption of conversational platforms for shopping, it has become important to build personalized models at scale to handle the large influx of data and perform inference in real-time. In this work, we present an end-to-end machine learning system for personalized conversational voice commerce. We include components for implicit feedback to the model, model training, evaluation on update, and a real-time inference engine. Our system personalizes voice shopping for Walmart Grocery customers and is currently available via Google Assistant, Siri and Google Home devices.

1 Introduction
There has been a growing need for shopping ease, especially in the e-commerce domain. With the advent of virtual assistants in the marketplace, users have started taking different avenues to obtain their everyday needs. It has been estimated that over 16% of smart speaker owners shop monthly by voice and over 21% of the consumers have engaged in voice shopping. With increasing adoption of conversational platforms, it has become paramount to personalize and cater the shopping experiences to the users’ needs.

Conversational search and recommendation are relatively new research topics, but the basic concepts date back to some of the most early works in the community. For example, Croft and Thompson [3] designed IIR (Intelligent Intermediary for Information Retrieval) – an expert intermediary system that takes activities to communicate with the user during a search session similar to what is done by a human intermediary; Belkin et al [1] designed the MERIT system – an interactive information retrieval system that used script-based conversational interaction for effective search. Radlinski and Craswell [26] proposed a theoretical framework for conversational search, which described some basic design philosophies for conversational search systems. Kenter and de Rijke [19] formalized conversational search as a machine reading task for question answering.

Yang et al [29, 30] conducted next question prediction and response ranking in conversations. Spina and Trippas et al studied the ways of presenting search results over speech-only channels [27] and transcribing the spoken search recordings [28] to support conversational search. Christakopoulou et al [2] proposed an interactive recommendation protocol that collects like/dislike feedback from users to refine the recommendations. Recently, several approaches involving natural language processing [7, 9–12, 14, 15, 17, 18], machine learning [5, 13, 16, 21, 22], deep learning [6, 20] and numerical optimizations [4, 8, 23–25] have also been used in the visual and language domains.

In this work, we present an end-to-end machine learning system for conversational voice models, particularly addressing conversational search, with a capability of real-time update. We have currently deployed several models for different conversational tasks using common feature sets: however, we focus on the specific use-case of search ranking. Our approach differs from existing prior works in the following ways

• We propose an end-to-end machine learning system for conversational voice models, including a seamless deployment system and real-time update of the models
• We include an implicit feedback system to personalize the voice shopping experience
• Our system has the ability to perform real-time inference with reduced latency
• We use a common feature store for different models deployed through the system
• Testing on held-out data before updating and pushing model to model store

*Corresponding Author: rahul.iyer@walmartlabs.com
2 Overview of End-to-End ML System

In this section, we provide a high level overview of the End-to-End ML system as illustrated in Figure 1. This system is comprised of 3 main components and each individual component is described below.

2.1 Model Training and Evaluation

We build feature sets from different sources using Hive/Spark Jobs. This is then stored in a distributed data store, which is used for both offline model training and Real-Time online (model) inference. The trained model is evaluated on a held-out standard dataset and pushed into the Model Store if performance is sufficient on evaluation metrics.

2.2 Real-time Inference with Deployment

This component consists of a set of pipelines, which are responsible for pulling the latest model from the model store, packaging into a docker image, and then pushing the custom image into the internal Docker Registry. The responsibility of the other pipeline is to take the latest image and deploy into the Real-Time inference system. The Real-Time inference system consists of an inference wrapper API, such as Flask, and TensorFlow Serving. The inference wrapper API connects to the feature store for a real-time fetch and call the TensorFlow Serving API with these features.

2.3 Feedback System

The Feedback system collects the click stream data and ATC data from clients, which is then stored on Hadoop. This feedback data is used in model training and updates.

3 Use Case: Personalized Search Re-Ranking

In this section, we describe how we utilize our system for the task of personalizing conversational voice search. The subsequent sections detail the feature sets used, modules in the architecture and model updates.

3.1 Feature Sets

We extract different feature sets from the users’ interaction behaviors and item catalog information. We utilize a cache system to store these features to use across the different models:

- User Transactional, Interaction and Household Data
- Parsed Textual Search Queries with attributes and facets
- Product attributes and facets

These feature sets are built from the different sources using Hive and Spark jobs.

3.2 Architecture

Our voice search personalization architecture consists of the following five components:

1. Data store (customer, product, query)
2. Candidate product retrieval model
3. Real-time Query parser
4. Product attribute and facet extractor
5. Tensorflow reranking model

Real-time customer engagement signals and historical transactional data are used to build a preference signal for the user, which enables us to personalize for the voice channel. The following data is stored in cache: 1) customer transactional data, 2) parsed query attributes for the top searched textual queries, 3) parsed product attributes and facets for the catalog. We utilize the feature sets stored in cache to perform the personalized ranking. The tensorflow ranker performs a similarity computation between the search query and a list of items based on the attributes/facets, and ranks them.

As soon as an update to the feature store is made, we retrain our model. It is then pushed to the model store using the pipelines described earlier if it meets the evaluation criteria.
3.3 Feedback Integration

We include a feedback loop in the system to capture explicit user preferences. If a suggestion is not accepted, the interaction behavior is used to modify the experiences accordingly.

4 Merits of the System

There are several merits to the system that we have deployed in production

• Seamlessly evaluate and update models including an implicit feedback loop
• Ability to perform real-time inference with reduced latency
• Ability to use a common feature store for different models

References

[1] Nicholas J Belkin, Colleen Cool, Adelheit Stein, and Ulrich Thiel. Cases, scripts, and information-seeking strategies: On the design of interactive information retrieval systems. Expert systems with applications, 9(3):379–395, 1995.

[2] Konstantina Christakopoulou, Filip Radlinski, and Katja Hofmann. Towards conversational recommender systems. In Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining, pages 815–824, 2016.

[3] W Bruce Croft and Roger H Thompson. I3r: A new approach to the design of document retrieval systems. Journal of the american society for information science, 38(6):389–404, 1987.

[4] Hari Prabhat Gupta, T Venkatesh, Seela Veerabhadreswara Rao, Tanima Dutta, and Rahul Radhakrishnan Iyer. Analysis of coverage under border effects in three-dimensional mobile sensor networks. IEEE Transactions on Mobile Computing, 16(9):2436–2449, 2016.

[5] Michael Honke, Rahul Iyer, and Dishant Mittal. Photorealistic style transfer for videos. arXiv preprint arXiv:1807.00273, 2018.

[6] Rahul Iyer, Yuezhang Li, Huao Li, Michael Lewis, Ramitha Sundar, and Katia Sycara. Transparency and explanation in deep reinforcement learning neural networks. In Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society, pages 144–150. ACM, 2018.

[7] Rahul Iyer, Rohit Mandrekar, Atishay Aggarwal, Pranav Chaphekar, and Gresha Bhatia. Recomob: Opinion mining for product enhancement. In 2017 International Conference on Computer Communication and Informatics (ICCCI), pages 1–5. IEEE, 2017.

[8] Rahul Iyer and Ahmed H Tewfik. Optimal ordering of observations for fast sequential detection. In 2012 Proceedings of the 20th European Signal Processing Conference (EUSIPCO), pages 126–130. IEEE, 2012.

[9] Rahul R Iyer, Katia P Sycara, and Yuezhang Li. Detecting type of persuasion: Is there structure in persuasion tactics? In CMNA@ ICAIL, pages 54–64, 2017.

[10] Rahul Radhakrishnan Iyer, Miguel Ballesteros, Chris Dyer, and Robert Frederking. Transition-based dependency parsing using perceptron learner. arXiv preprint arXiv:2001.08279, 2020.

[11] Rahul Radhakrishnan Iyer, Jing Chen, Haonan Sun, and Keyang Xu. A heterogeneous graphical model to understand user-level sentiments in social media. arXiv preprint arXiv:1912.07911, 2019.

[12] Rahul Radhakrishnan Iyer, Rohan Kohli, and Shrimai Prabhumoye. Modeling product search relevance in e-commerce. arXiv preprint arXiv:2001.04980, 2020.

[13] Rahul Radhakrishnan Iyer, Sanjeev Parekh, Vikas Mohandoss, Anush Ramsurat, Bhiksha Raj, and Rita Singh. Content-based video indexing and retrieval using corrlda. arXiv preprint arXiv:1602.08581, 2016.

[14] Rahul Radhakrishnan Iyer, Yulong Pei, and Katia Sycara. Simultaneous identification of tweet purpose and position. arXiv preprint arXiv:2001.00051, 2019.

[15] Rahul Radhakrishnan Iyer and Carolyn Penstein Rose. A machine learning framework for authorship identification from texts. arXiv preprint arXiv:1912.10204, 2019.

[16] Rahul Radhakrishnan Iyer, Manish Sharma, and Vijaya Saradhi. A correspondence analysis framework for author-conference recommendations. arXiv preprint arXiv:2001.02669, 2020.

[17] Rahul Radhakrishnan Iyer and Katia Sycara. An unsupervised domain-independent framework for automated detection of persuasion tactics in text. arXiv preprint arXiv:1912.06745, 2019.

[18] Rahul Radhakrishnan Iyer, Ronghuo Zheng, Yuezhang Li, and Katia Sycara. Event outcome prediction using sentiment analysis and crowd wisdom in microblog feeds. arXiv preprint arXiv:1912.05066, 2019.
[19] Tom Kenter and Maarten de Rijke. Attentive memory networks: Efficient machine reading for conversational search. *arXiv preprint arXiv:1712.07229*, 2017.

[20] Yuezhang Li, Katia Sycara, and Rahul Iyer. Object-sensitive deep reinforcement learning. *arXiv preprint arXiv:1809.06064*, 2018.

[21] Yuezhang Li, Ronghuo Zheng, Tian Tian, Zhiting Hu, Rahul Iyer, and Katia Sycara. Joint embedding of hierarchical categories and entities for concept categorization and dataless classification. *arXiv preprint arXiv:1607.07956*, 2016.

[22] Yuezhang Li, Ronghuo Zheng, Tian Tian, Zhiting Hu, Rahul Iyer, and Katia Sycara. Joint embeddings of hierarchical categories and entities. *arXiv preprint arXiv:1605.03924*, 2016.

[23] Hai Qian, Shengwen Yang, Rahul Iyer, Xixuan Feng, Mark Wellons, and Caleb Welton. Parallel time series modeling-a case study of in-database big data analytics. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining*, pages 417–428. Springer, 2014.

[24] Rahul Radhakrishnan, Abhinoy Kumar Singh, Shovan Bhaumik, and Nutan Kumar Tomar. Multiple sparse-grid gauss–hermite filtering. *Applied Mathematical Modelling, 40*(7-8):4441–4450, 2016.

[25] Rahul Radhakrishnan, Ajay Yadav, Paresh Date, and Shovan Bhaumik. A new method for generating sigma points and weights for nonlinear filtering. *IEEE Control Systems Letters, 2*(3):519–524, 2018.

[26] Filip Radlinski and Nick Craswell. A theoretical framework for conversational search. In *Proceedings of the 2017 conference on conferencehuman information interaction and retrieval*, pages 117–126, 2017.

[27] Damiano Spina, Johanne R Trippas, Lawrence Cavedon, and Mark Sanderson. Extracting audio summaries to support effective spoken document search. *Journal of the Association for Information Science and Technology, 68*(9):2101–2115, 2017.

[28] Johanne R Trippas, Damiano Spina, Lawrence Cavedon, and Mark Sanderson. A conversational search transcription protocol and analysis. In *Proc of SIGIR 1st International Workshop on Conversational Approaches to Information Retrieval (CAIR’17), CAIR*, volume 17, 2017.

[29] Liu Yang, Minghui Qiu, Chen Qu, Jiafeng Guo, Yongfeng Zhang, W Bruce Croft, Jun Huang, and Haiqing Chen. Response ranking with deep matching networks and external knowledge in information-seeking conversation systems. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*, pages 245–254, 2018.

[30] Liu Yang, Hamed Zamani, Yongfeng Zhang, Jiafeng Guo, and W Bruce Croft. Neural matching models for question retrieval and next question prediction in conversation. *arXiv preprint arXiv:1707.05409*, 2017.