Effective Representation to Capture Collaboration Behaviors between Explainer and User

Arjun Akula, Song-Chun Zhu
UCLA
aakula@ucla.edu, sczhu@stat.ucla.edu

Abstract
An explainable AI (XAI) model aims to provide transparency (in the form of justification, explanation, etc) for its predictions or actions made by it. Recently, there has been a lot of focus on building XAI models, especially to provide explanations for understanding and interpreting the predictions made by deep learning models. At UCLA, we propose a generic framework to interact with an XAI model in natural language.

1 Introduction
Most work on XAI typically focuses on black-box models and generating explanations about their performance in terms of, e.g., feature visualization and attribution (Sundararajan et al., 2017; Ramprasaath et al., 2016; Zeiler and Fergus, 2014). However, solely generating explanations, regardless of their type (visualization or attribution) and utility, is not sufficient for increasing understandability and predictability. Current works on XAI generate explanations about their performance in terms of, e.g., feature visualization and attention maps (Sundararajan et al., 2017; Ramprasaath et al., 2016; Zeiler and Fergus, 2014; Smilkov et al., 2017; Kim et al., 2014; Zhang et al., 2018). However, solely generating explanations, regardless of their type (visualization or attention maps) and utility, is not sufficient for increasing understandability and predictability (Jain and Wallace, 2019).

In our UCLA lab, our focus is on the Explainer module. Explainer takes a natural language question from the user and identifies the intention behind it. Explainer is also responsible for controlling the dialog flow with the user. Explainable performer provides the important evidences that are necessary to answer user’s question. Atomic Performer assists Explainable performer in identifying the evidences. Explainer uses this evidence to generate most acceptable and convincing explanation. We control the dialog flow inside the Explainer using discourse model called Rhetorical Structure Theory (RST). In general, RST would be an efficient and simplest way to track contextual information. Since explanations are context-dependent, we believe that RST would be the right model to capture contextual information in the Explainer (Akula and Zhu, 2019a; Akula et al., 2020a; Akula and Zhu, 2019b; Akula et al., 2021c,d,b).

Given a user’s question, we first identify the dialog act of the question. We then identify the question type (contrast type) and explanation type as mentioned in the next section. Based on the explanation type, we generate the explanation and present it to the user (Akula et al., 2013, 2018, 2021a; Gupta et al., 2016; Akula et al., 2019b; Akula, 2021; Akula et al., 2019a, 2020b).

Questions posed by the user to obtain explanations from an XAI model are typically contrastive in nature. For example, questions such as "Why do the model think the people are in sitting posture?", "Why do you think two persons are sitting instead of one?", need contrastive explanations. In order to generate a convincing explanation, XAI model needs to understand the implicit contrast that it presupposes (Agarwal et al., 2018; Akula et al., 2019c; Akula, 2015; Palakurthi et al., 2015; Agarwal et al., 2017; Dasgupta et al., 2014).

Explainer’s knowledge using the question types such as NOT-X, NOT-X1-BUT-X2, NOT-X-BUT-Y. Question types such as DO-X, DO-NOT-X and DO-X-NOT-Y are used by the user as intervention techniques. We now propose the following seven types of explanation types that are motivated from an algorithmic approach rather than on theoretical grounds.

1. Direct Explanation: Explaining based on detection scores
2. Part-based Explanation: Explaining based on the evidences of detected parts for the concept asked
3. Causal Explanation, Temporal Explanation: Explaining based on the constraints from the spatiotemporal surround

4. Common-sense Explanation: Explaining based on the common-sense knowledge of the concept domain

5. Counter-factual Explanation: Explaining based on the evidences provided for the counter-factual questions asked by the Ex-plainer

6. Discourse Entailment based Explanation: Explaining based on the discourse relations among various objects/frames in the concept/videos (Akula et al., 2020c; R Akula et al., 2019; Pulijala et al., 2013; Gupta et al., 2012).

2 Explainable AI models using Discourse relations

Given a document (or a paragraph), discourse relation tell us how two segments (or sentences) in the document are logically connected with each other. To be more specific, discourse relations (often represented as a tree) tell us what is the function of each segment of the document, plausible reason for the presence of a segment, role of each segment w.r.t other segments, etc. In a nutshell, it provides explanation of the coherence of document/text.

In this work, we aim to propose the idea of the discourse phenomenon for videos. The intuition behind this is simple: any video can be mapped to a document (or a group of sentences). And discourse can be used to explain coherence of any document. Therefore we can use discourse to explain coherence of a video. We believe that obtaining discourse cues from videos would help us in generating better context-sensitive explanations.

We are trying to learn the mapping from videos to its corresponding discourse representation (i.e. discourse tree) using end-to-end learning models. There are quite a few methods in the literature that try to map video/image to text. Also, there are few approaches that aim to extract hierarchical structure from the videos using unsupervised methods. However none of these approaches try to understand the discourse phenomenon in the videos.

We are currently working on two different approaches to learn the mapping from videos to its discourse representation. In the first approach, we map input videos to a sequence of vectors. We flatten the output discourse trees to a paragraph and then we use hierarchical RNN (two-levels). Basically the first level RNN captures intra-sentence dependencies and the second level RNN captures inter-sentence dependencies. In the second approach, we would like to use multi-task learning i.e. a combination of unsupervised and supervised methods. We plan on using Variational Auto-encoder as an unsupervised method and hierarchical RNN as a supervised method.

We plan on using TACoS-MultiLevel dataset: It contains 185 long videos (6 minutes on average) filmed in an indoor environment. Descriptions are manually annotated for each video. The videos are closed-domain, containing different actors, fine-grained activities, and small interacting objects in daily cooking scenarios. There are about 280 sentences in each video description on an average. Moreover, to obtain the discourse trees for the above dataset, we can use an off-the-shelf discourse tagger (like RST tagger) to map the video descriptions to discourse trees.

We believe that an And-Or graph (AOG) representation is efficient to capture the underlying evidences used by the XAI model in making a prediction. We aim to show that the AOG representation facilitates the XAI model in generating context based explanations. We are working on building a rule-based algorithm to predict the most appropriate explanation type for a given user question. We plan to evaluate our approach on two explanation datasets: Visual Question Answering Explanation dataset (VQA-X) and Action Explanation dataset (ACT-X). We believe that the proposed question and explanation categories are sufficient enough to represent all the variations of questions and explanations in the datasets. We also plan on demonstrating that AOG representation is the key in generating most appropriate explanation for a given user question.

We plan to evaluate the effectiveness of our explanation interface and the dialogue. Extending principles identified in [Kulesza 2015], we will apply different evaluation metrics based on the following evaluation criteria (Smilkov et al., 2017; Sundararajan et al., 2017; Zeiler and Fergus, 2014; Kim et al., 2014; Zhang et al., 2018):

1. Correctness in recognizing the type of intents of users’ explanation requests. Different types of intention will require different types of ex-
2. Relevancy of explanations. The provided explanation needs to satisfy the user’s intention. Accuracy will be used to measure the relevancy. We will also measure the generated explanations (e.g., language) with the ground-truth explanations using metrics such as METEOR and CIDEr [Hendricks 2016].

3. Fidelity to the interpretable model’s behaviors. This metric estimates how well X-pg matches STC-pg. Standard costs or similarity of matching graphs will be used for estimating fidelity. Low fidelity between the two parse graphs may be justified in some cases, e.g., when the Explainer has to summarize fragments in the STC-pg and hence avoid overwhelming the User with detailed explanations.

References

Shivali Agarwal, Vishalaksh Aggarwal, Arjun R Akula, Gargi Banerjee Dasgupta, and Giriprasad Sridhara. 2017. Automatic problem extraction and analysis from unstructured text in it tickets. *IBM Journal of Research and Development*, 61(1):4–41.

Shivali Agarwal, Arjun R Akula, Gaargi B Dasgupta, Shripad J Nadgowda, and Tapan K Nayak. 2018. Structured representation and classification of noisy and unstructured tickets in service delivery. US Patent 10,095,779.

Arjun Akula, Spandana Gella, Keze Wang, Song-chun Zhu, and Siva Reddy. 2021a. Mind the context: The impact of contextualization in neural module networks for grounding visual referring expressions. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 6398–6416.

Arjun Akula, Varun Jampani, Soravit Changpinyo, and Song-Chun Zhu. 2021b. Robust visual reasoning via language guided neural module networks. *Advances in Neural Information Processing Systems*, 34.

Arjun Akula, Rajeev Sangal, and Radhika Mamidi. 2013. A novel approach towards incorporating context processing capabilities in nildb system. In *Proceedings of the sixth international joint conference on natural language processing*, pages 1216–1222.

Arjun R Akula. 2015. A novel approach towards building a generic, portable and contextual nildb system. *International Institute of Information Technology Hyderabad*.
Arjun R Akula, Gargi B Dasgupta, Vijay Ekambaram, and Ramasuri Narayanan. 2021d. Measuring effective utilization of a service practitioner for ticket resolution via a wearable device. US Patent 10,929,264.

Arjun R. Akula, Spandana Gella, Yasen Al-Onaizan, Song-Chun Zhu, and Siva Reddy. 2020a. Words aren’t enough, their order matters: On the robustness of grounding visual referring expressions. In ACL.

Arjun R Akula, Spandana Gella, Yasen Al-Onaizan, Song-Chun Zhu, and Siva Reddy. 2020b. Words aren’t enough, their order matters: On the robustness of grounding visual referring expressions. arXiv preprint arXiv:2005.01655.

Arjun R Akula, Changsong Liu, Sari Saba-Sadiya, Hongjing Lu, Sinisa Todorovic, Joyce Y Chai, and Song-Chun Zhu. 2019a. X-tom: Explaining with theory-of-mind for gaining justified human trust. arXiv preprint arXiv:1909.06907.

Arjun R Akula, Changsong Liu, Sinisa Todorovic, Joyce Y Chai, and Song-Chun Zhu. 2019b. Explainable ai as collaborative task solving. In CVPR Workshops, pages 91–94.

Arjun R Akula, Sinisa Todorovic, Joyce Y Chai, and Song-Chun Zhu. 2019c. Natural language interaction with explainable ai models. In CVPR Workshops, pages 87–90.

Arjun R. Akula, Shuai Wang, and Song-Chun Zhu. 2020c. Cocox: Generating conceptual and counterfactual explanations via fault-lines. In The Thirty-Fourth AAAI Conference on Artificial Intelligence, AAAI 2020, The Thirty-Second Innovative Applications of Artificial Intelligence Conference, EAAI 2020, The Tenth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2020, New York, NY, USA, February 7-12, 2020, pages 2594–2601. AAAI Press.

Arjun R. Akula and Song-Chun Zhu. 2019a. Visual discourse parsing. CVPR 2019 Workshop on Language and Vision, arXiv:1903.02252.

Arjun R Akula and Song-Chun Zhu. 2019b. Visual discourse parsing. ArXiv preprint, abs/1903.02252.

Arjun Reddy Akula. 2021. Gaining Justified Human Trust by Improving Explainability in Vision and Language Reasoning Models. Ph.D. thesis, UCLA.

Gargi B Dasgupta, Tapan K Nayak, Arjun R Akula, Shivali Agarwal, and Shripad J Nadgowda. 2014. Towards auto-remediation in services delivery: Context-based classification of noisy and unstructured tickets. In International Conference on Service-Oriented Computing, pages 478–485. Springer.

Abhijeet Gupta, Arjun Akula, Deepak Malladi, Puneeth Kukkadapu, Vinay Ainaovolu, and Rajeev Sangal. 2012. A novel approach towards building a portable nlidb system using the computational paninian grammar framework. In 2012 International Conference on Asian Language Processing, pages 93–96. IEEE.

Abhirut Gupta, Arjun Akula, Gargi Dasgupta, Pooja Aggarwal, and Prateeti Mohapatra. 2016. Desire: Deep semantic understanding and retrieval for technical support services. In International Conference on Service-Oriented Computing, pages 207–210. Springer.

Sarthak Jain and Byron C. Wallace. 2019. Attention is not explanation. Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL).

Been Kim, Cynthia Rudin, and Julie A Shah. 2014. The bayesian case model: A generative approach for case-based reasoning and prototype classification. In Advances in Neural Information Processing Systems, pages 1952–1960.

Ashish Palakurthi, SM Ruthu, Arjun Akula, and Radhika Mamidi. 2015. Classification of attributes in a natural language query into different sql clauses. In Proceedings of the International Conference Recent Advances in Natural Language Processing, pages 497–506.

Vasu Pulijala, Arjun R Akula, and Azeemuddin Syed. 2013. A web-based virtual laboratory for electromagnetic theory. In 2013 IEEE Fifth International Conference on Technology for Education (I4e 2013), pages 13–18. IEEE.

Arjun R Akula, Sinisa Todorovic, Joyce Y Chai, and Song-Chun Zhu. 2019. Natural language interaction with explainable ai models. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pages 87–90.

RS Ramprasaath, D Abhishek, V Ramakrishna, C Michael, P Devi, and B Dhruv. 2016. Grad-cam: Why did you say that? visual explanations from deep networks via gradient-based localization. CVPR 2016.

Daniel Smilkov, Nikhil Thorat, Been Kim, Fernanda Viégas, and Martin Wattenberg. 2017. Smoothgrad: removing noise by adding noise. arXiv preprint arXiv:1706.03825.

Mukund Sundararajan, Ankur Taly, and Qi Qi Yan. 2017. Axiomatic attribution for deep networks. 34th International Conference on Machine Learning.

Matthew D Zeiler and Rob Fergus. 2014. Visualizing and understanding convolutional networks. In European conference on computer vision, pages 818–833. Springer.
Quanshi Zhang, Ying Nian Wu, and Song-Chun Zhu. 2018. Interpretable convolutional neural networks. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 8827–8836.