Exploring Context, Attention and Audio Features for Audio Visual Scene-Aware Dialog

Shachi H Kumar  Eda Okur  Saurav Sahay  Jonathan Huang  Lama Nachman
Intel Labs, Anticipatory Computing Lab, USA
{shachi.h.kumar, eda.okur, saurav.sahay, jonathan.huang, lama.nachman}@intel.com

1. Introduction

We are witnessing a confluence of vision, speech and dialog system technologies that are enabling the IVAs to learn audio-visual groundings of utterances and have conversations with users about the objects, activities and events surrounding them. Recent progress in visual grounding techniques [2, 4] and Audio Understanding [5] are enabling machines to understand shared semantic concepts and listen to the various sensory events in the environment. With audio and visual grounding methods [13, 7], end-to-end multimodal SDS [13] are trained to meaningfully communicate with us in natural language about the real dynamic audio-visual sensory world around us. In this work, we explore the role of ‘topics’ as the context of the conversation along with multimodal attention into such an end-to-end audio-visual scene-aware dialog system architecture. We also incorporate an end-to-end audio classification ConvNet, AclNet, into our models. We develop and test our approaches on the Audio Visual Scene-Aware Dialog (AVSD) dataset [1] released as a part of the DSTC7. We present the analysis of our experiments and show that some of our model variations outperform the baseline system [6] released for AVSD.

2. Model Description

In this section, we describe the main architecture explorations of our work as shown in Figure 1.

**Topic Model Explorations:** Topics form a very important source of context in a dialog. We train Latent Dirichlet Allocation (LDA [3]) and Guided LDA [9] models on questions, answers, QA pairs, captions and history and incorporate the topic distributions as features or use them to learn topic embeddings. Since we are interested in identifying specific topics (e.g., entertainment, cooking, cleaning), we use Guided LDA to generate topics based on seedwords.

**Attention Explorations:** We explore several configurations of the model where at every step, the decoder attends to the dialog history representations and AV features to selectively focus on relevant parts of the dialog history and audio/video. This helps create a combination of the dialog history and multimodal context that is richer than the single context vectors of the individual modalities.

**Audio Feature Explorations:** We used an end-to-end audio classification ConvNet, called AclNet [8]. AclNet takes raw, amplitude-normalized 44.1 kHz audio samples as input, and produces classification output without the need to compute spectral features. AclNet is trained using the ESC-50 [12] corpus, a dataset of 50 classes of environmental sounds organized in 5 semantic categories (animals, interior/domestic, exterior/urban, human, natural landscapes).

3. Dataset

We use the dialog dataset [11] consisting of conversations between two people about a video (from Charades human action dataset [14]), which was released as part of the AVSD challenge at DSTC7. We use the official-training (7659 dialogs) and prototype-validation sets (732 dialogs) to train, and prototype-test set (733 dialogs) to evaluate our models.

4. Experiments and Results

**Topic Experiments:** We use separate topic models trained on questions, answers, QA pairs, captions and history to generate topics for samples from each category. Table 1 compares the baseline model with the addition of StandardLDA and GuidedLDA topic distributions as features to the decoder, as well as by learning topic embeddings. In general, GuidedLDA models perform better than StandardLDA, and GuidedLDA + GloVe [11] is our best performing model.

|                  | Bleu1 | Bleu2 | Bleu3 | Bleu4 | Meteor | Rouge | CIDEr |
|------------------|-------|-------|-------|-------|--------|-------|-------|
| Baseline         | 0.273 | 0.173 | 0.118 | 0.084 | 0.117  | 0.291 | 0.766 |
| StandardLDA      | 0.255 | 0.164 | 0.113 | 0.082 | 0.114  | 0.285 | 0.772 |
| GuidedLDA        | 0.265 | 0.170 | 0.117 | 0.084 | 0.118  | 0.293 | 0.812 |
| GuidedLDA+all    | 0.272 | 0.173 | 0.118 | 0.085 | 0.119  | 0.293 | 0.793 |
| GuidedLDA+GloVe  | 0.275 | 0.175 | 0.119 | 0.085 | 0.121  | 0.293 | 0.797 |
| Topic-embeddings | 0.257 | 0.165 | 0.114 | 0.083 | 0.115  | 0.287 | 0.772 |
| HLSTM-with-topics| 0.260 | 0.166 | 0.115 | 0.084 | 0.117  | 0.290 | 0.797 |

Table 1. Topic Experiments

---

1Further details can be found in the full-paper version of this work [10].
Audio Experiments: Table 2 shows the comparison of the baseline B (without audio features), and B+VGGish (provided as a part of the AVSD task) and B+AclNet features. We analyse the effects of audio features on the overall dataset as well as specifically on audio-related dialogs. From Table 2, we observe that B+AclNet performs the best both on overall dataset and audio-related dialogs.

Attention Experiments: Table 3 shows that the configuration where decoder attends to all of the sentence-LSTM output states performs better than the baseline. In order to compare the results based on semantic meaningfulness, we performed quantitative analysis on dialogs that contained binary answer in the ground truth. We evaluate our models on their ability to predict these binary answers correctly and present this analysis in Figure 2 which shows once again that the configuration where decoder attends to all of the sentence-LSTM output states performs best on binary answer evaluation.

5. Conclusion

In this paper, we present some explorations and techniques for contextual and multimodal end-to-end audiovisual scene aware dialog system. We incorporate context of the dialog in the form of topics, we use various attention mechanisms to enable the decoder to focus on relevant parts of the dialog history and audio/video features, and incorporate audio features from an end-to-end audio classification architecture, AclNet. We validate our approaches on the AVSD dataset and show that these techniques give better performance compared to the baseline.
References

[1] Huda AlAmri, Vincent Cartillier, Raphael Gontijo Lopes, Abhishek Das, Jue Wang, Irfan Essa, Dhruv Batra, Devi Parikh, Anoop Cherian, Tim K. Marks, and Chiori Hori. Audio visual scene-aware dialog (AVSD) challenge at DSTC7. CoRR, abs/1806.00525, 2018.

[2] S. Antol, A. Agrawal, J. Lu, M. Mitchell, D. Batra, C. L. Zitnick, and D. Parikh. Vqa: Visual question answering. In 2015 IEEE International Conference on Computer Vision (ICCV), pages 2425–2433, Dec 2015.

[3] David M Blei, Andrew Y Ng, and Michael I Jordan. Latent dirichlet allocation. Journal of machine Learning research, 3(Jan):993–1022, 2003.

[4] Abhishek Das, Satwik Kottur, Khushi Gupta, Avi Singh, Deshraj Yadav, Jose M. F. Moura, Devi Parikh, and Dhruv Batra. Visual dialog. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Jul 2017.

[5] Shawn Hershey, Sourish Chaudhuri, Daniel PW Ellis, Jort F Gemmeke, Aren Jansen, R Channing Moore, Manoj Plakal, Devin Platt, Rif A Saurous, Bryan Seybold, et al. Cnn architectures for large-scale audio classification. In Acoustics, Speech and Signal Processing (ICASSP), 2017 IEEE International Conference. IEEE, 2017.

[6] Chiori Hori, Huda AlAmri, Jue Wang, Gordon Wichern, Takaaki Hori, Anoop Cherian, Tim K. Marks, Vincent Cartillier, Raphael Gontijo Lopes, Abhishek Das, Irfan Essa, Dhruv Batra, and Devi Parikh. End-to-end audio visual scene-aware dialog using multimodal attention-based video features. CoRR, abs/1806.08409, 2018.

[7] Chiori Hori, Takaaki Hori, Teng-Yok Lee, Ziming Zhang, Bret Harsham, John R. Hershey, Tim K. Marks, and Kazuhiko Sumi. Attention-based multimodal fusion for video description. 2017 IEEE International Conference on Computer Vision (ICCV), Oct 2017.

[8] Jonathan J Huang and Juan Jose Alvarado Leanos. Acnet: Efficient end-to-end audio classification cnn. arXiv preprint arXiv:1811.06669, 2018.

[9] Jagadeesh Jagarlamudi, Hal Daumé III, and Raghavendra Udupa. Incorporating lexical priors into topic models. In Walter Daelemans, Mirella Lapata, and Lluís Márquez, editors, EACL 2012. 13th Conference of the European Chapter of the Association for Computational Linguistics. The Association for Computer Linguistics, 2012.

[10] Shachi H Kumar, Eda Okur, Saurav Sahay, Juan Jose Alvarado Leanos, Jonathan Huang, and Lama Nachman. Context, attention and audio feature explorations for audio visual scene-aware dialog. In DSTC7 Workshop at AAAI 2019, arXiv:1812.08407, 2019.

[11] Jeffrey Pennington, Richard Socher, and Christopher D. Manning. Glove: Global vectors for word representation. In Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543, 2014.

[12] Karol J. Piczak. ESC: Dataset for Environmental Sound Classification. In Proceedings of the 23rd Annual ACM Conference on Multimedia, pages 1015–1018. ACM Press, 2015.

[13] Iulian Vlad Serban, Alessandro Sordoni, Yoshua Bengio, Aaron C Courville, and Joelle Pineau. Building end-to-end dialogue systems using generative hierarchical network models. In AAAI, volume 16, pages 3776–3784, 2016.

[14] Gunnar A. Sigurdsson, Güll Varol, Xiaolong Wang, Ali Farhadi, Ivan Laptev, and Abhinav Gupta. Hollywood in homes: Crowdsourcing data collection for activity understanding. In Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling, editors, Computer Vision - ECCV 2016 - 14th European Conference, Proceedings, 2016.

[15] Haoran Yu, Jiang Wang, Zhiheng Huang, Yi Yang, and Wei Xu. Video paragraph captioning using hierarchical recurrent neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4584–4593, 2016.