

INTERVIEW: A Large-Scale Open-Source Corpus of Media Dialog

Bodhisattwa Prasad Majumder*, Shuyang Li*, Jianmo Ni, Julian McAuley

Computer Science and Engineering

University of California, San Diego

{bmajumde, sh1008, jin018, jmcauley}@ucsd.edu

Abstract

Existing conversational datasets consist either of written proxies for dialog or small-scale transcriptions of natural speech. We introduce INTERVIEW: a large-scale (105K conversations) media dialog dataset collected from news interview transcripts. Compared to existing large-scale proxies for conversational data, language models trained on our dataset exhibit better zero-shot out-of-domain performance on existing spoken dialog datasets, demonstrating its usefulness in modeling real-world conversations. INTERVIEW contains speaker role annotations for each turn, facilitating the development of engaging, responsive dialog systems. In fact, experiments on two dialog tasks show that leveraging such labels improves performance over strong speaker-agnostic baselines, and enabling models to generate more specific and inquisitive responses in interview-style conversations.

1 Introduction

Large repositories of textual communications (e.g. forum and microblog posts) have gained recent popularity as proxies for dialog (Galley et al., 2019; Ritter et al., 2010; Lowe et al., 2015). However, conversations in these settings differ from natural dialog: turns may be sparsely scattered over a large temporal span, contain distinct syntax and vocabulary (Maity et al., 2016), and differ greatly in formality and focus (Li et al., 2017). In this paper, we investigate how appropriate such data is for modeling natural dialog, and introduce INTERVIEW, a new high-quality large-scale open-domain conversational dataset grounded in interview settings with annotations for specific speaker roles.

We compare the performance of state-of-the-art language models fine-tuned on INTERVIEW and

Dataset	Spoken	# Dialogs	# Turns	# Words
Reddit	✗	147 M	–	1,800.0 M
DailyDialog	✗	13,118	102,979	1.4 M
CALLHOME	✓	120	22,214	0.3 M
INTERVIEW 2P	✓	23,714	454,739	21.7 M
INTERVIEW	✓	105,848	3,199,856	126.7 M

Table 1: Comparative dialog dataset statistics, including two-party (2P) and full INTERVIEW dataset

other popular conversational datasets, demonstrating that INTERVIEW contains more complex dialog and better models the characteristics of natural spoken conversations. Our dataset is an order of magnitude larger than existing high-quality natural dialog datasets and contains speaker role annotations for each turn, facilitating the development of conversational agents and assistive systems for settings involving specific speaker roles, such as doctor-patient interviews or hosted talk shows.

In particular, we explore the tasks of *role modeling in media dialog* and *role change detection* on INTERVIEW and find that leveraging role information can enable more nuanced, on-topic and natural dialog generation, as well as improve role change classification performance.

In summary, we present INTERVIEW, the first large-scale open-domain media dialog dataset. We explore two tasks for which it serves as a promising benchmark dataset: speaker role modeling and speaker change detection. We build simple yet strong models to show quantitatively that role labels from INTERVIEW improve performance on such tasks. INTERVIEW’s scale, spoken origins, role diversity, and complex utterances make it a better source for grounded open-domain conversations.

2 Related Works

Broadly speaking, dialog and conversation datasets can be classified as constrained (goal-oriented)

* denotes equal contribution

or open-domain, written or spoken, and scripted or spontaneous (Serban et al., 2018). In the realm of written dialog, the closest proxy to natural dialog comes in the form of role-play-style (Bernsen et al., 1998) conversations, featuring two agents instructed to participate in a constrained conversation. This setup has seen recent usage to construct goal-oriented (Byrne et al., 2019; Budzianowski et al., 2018) and grounded conversations (Dinan et al., 2019; Gopalakrishnan et al., 2019). These datasets are expensive to collect at scale and are heavily constrained/guided by the instructions given to participants. Several initiatives have recorded and manually transcribed natural conversations occurring in the course of normal life, resulting in small, high-quality natural dialog datasets (Canavan et al., 1997; Godfrey et al., 1992; Renals et al., 2007; Morgan et al., 2001). We explore an alternative venue for collecting a large-scale dataset of natural dialog: conversations and interviews on public radio.

The US Defense Advanced Research Projects Agency (DARPA) has undertaken efforts to collect broadcast and informal conversation from public and private sources including messaging boards, SMS (DARPA, 2011), and broadcast newswire content (Strassel, 2004; Cohen, 2007). However, it proves difficult to adopt these datasets as widely available benchmarks on dialog modeling tasks, as they come with a substantial cost (\$100-\$1000 per dataset/year, covering up to a hundred hours of transcribed conversation). In this vein, we contribute an open-access large-scale corpus of cleanly annotated broadcast media dialog.

Weizman (2008) explores the patterns and discourse within media dialog and contrast the associated speaker role dynamics with spontaneous natural conversation. The author manually annotates and investigates 24 hours of Israeli news television programs. We see an opportunity for the investigation of speaker dynamics and significance of speaker roles at scale with our dataset.

Dialog modeling of open-domain chit-chat predicts one turn of dialog from one or many context turn(s). Structured approaches for dialog modeling build on hierarchical RNNs (Sordoni et al., 2015a; Serban et al., 2016; Sankar and Ravi, 2019), with recent work employing a simple concatenation of dialog history in a transformer-based architecture (Zhang et al., 2019). We draw inspiration from recent works in dialog generation that model speakers via persistent ‘personas,’ whose representations

Model	INTERVIEW	DailyDialog	CALLHOME
GPT2	35.20	57.19	137.21
FT-INTERVIEW	<u>17.77</u>	32.85	51.40
FT-DailyDialog	50.05	<u>11.63</u>	82.67
FT-CALLHOME	32.10	33.30	<u>28.19</u>

Table 2: Zero-shot BPE perplexity for GPT2-based models. **Bold** denotes best *out-of-domain* performance.

are learned from a set of grounding facts (Zhang et al., 2018) or other non-conversational metadata (Luan et al., 2017). Our approach eschews external grounding and learns speaker embeddings via dialog modeling, similar to Li et al. (2016). We, however, propose to learn speaker embeddings for different *roles* and capture role-dependent lexical profiles in conversation.

3 INTERVIEW Dataset¹

We collect a novel dataset of 105K multi-party interview transcripts for 7 programs on National Public Radio (NPR)² over 20 years (1999–2019), total of 10k hours. These transcripts contain a total of 3M turns comprising 7.5M sentences (127M words) from 184K speakers, of which 287 are hosts. To investigate role-play in media dialog, we curate a subset, **INTERVIEW 2P**, with **two roles**: a *host* and a *guest*, comprising 23K two-party conversations encompassing 455K turns, with 1.24M sentences and 21.7M words.

In these two-party conversations, each speaker takes an average of nine turns per dialog. Guests tend to speak longer on their turns, with 1.6x as many sentences spoken and 2x as many words per turn, and also use a more diverse vocabulary (1.6x size). Meanwhile, hosts ask five times as many questions as guests, with 40% of their dialog turns containing questions. When asking questions, hosts and guests use interrogative forms (See et al., 2019) at the same rate (65%). We note that the *host* and *guest* roles have differing discourse patterns, which support the notion of **role modeling**.

Comparison with Other Datasets To assess how well INTERVIEW represents open-domain dialog, we look to two datasets in widespread usage: DailyDialog (Li et al., 2017), 13K short dialogs written to simulate simple conversations from daily life; and CALLHOME (Canavan et al., 1997), tran-

¹<https://www.kaggle.com/shuyangli94/interview-npr-media-dialog-transcripts>

²<https://www.npr.org/>

scriptions from 120 half-hour casual telephone conversations. We measure the language modeling performance of a pre-trained transformer model—117M-parameter GPT2 (Radford et al., 2019)—both in its original form and versions fine-tuned (FT) on the training splits for INTERVIEW, DailyDialog, and CALLHOME. We evaluated the zero-shot performance of these models on the test splits of these datasets, with perplexities shown in Table 2.

While models fine-tuned on the training set performed best on each dataset as expected, we observe that **1)** models trained on other datasets obtain relatively poor zero-shot performance on INTERVIEW; and **2)** the model trained on INTERVIEW achieved the best out-of-domain performance on DailyDialog and CALLHOME by large margins. This suggests that language models trained on INTERVIEW can learn patterns characteristic of natural open-domain dialog in both simple daily conversation and informal long spoken exchanges. We also investigate DialoGPT, a model pre-trained on 147M Reddit threads as a proxy for dialog (Zhang et al., 2019). Our results show that while Reddit threads can be used to emulate conversation, they may not resemble natural speech; DialoGPT posts by far the worst zero-shot modeling performance across all test datasets (>500 perplexity)—inferior to zero-shot GPT2. These experiments confirm that INTERVIEW, a dataset of real, complex conversations, is useful for modeling patterns in natural spoken dialog. We show statistics for INTERVIEW compared to other dialog datasets in Table 1.

4 Tasks and Experiments

We additionally explore two tasks that are facilitated by speaker role annotations in INTERVIEW: 1) generating appropriate responses for a specific role given a conversation history (speaker role modeling); and 2) predicting whether a new speaker will interject on the next sentence of a conversation. These tasks are crucial components to building fluent and role-specific dialog systems, for settings such as healthcare and customer service.

4.1 Task 1: Role Modeling

We generate a response conditioned on the **host** speaker role, to specifically model how an interview host speaks and inquires, contrary to speaker-agnostic dialog settings (Sordoni et al., 2015b; Shang et al., 2015). Individual guests appear sparsely and their utterances heavily rely on ex-

ternal world knowledge. Thus, we model host responses, which are generally aimed towards moderating the conversation via follow-up questions and acknowledgements. Role-specific generation like this can benefit the development of assistive technologies and role-dependent dialog systems.

We approach speaker role modeling conditional language modeling task: generating the next response $T_{t,\mathbf{h}}$ for host \mathbf{h} with the highest likelihood given a trace of prior utterances $T_{1\dots t,g}$ and $T_{1\dots t-1,\mathbf{h}}$. We use a transformer decoder to generate tokens $T_{1\dots t}$ from inputs $T_{0\dots t-1}$, but calculate loss only across the target sequence (gold host response). We mimic the input schema for DialoGPT, concatenating all historical turns with separator tokens, appending the host target response.

Conditioning on Speakers To condition on a speaker role, we prepend each utterance in the dialog history with a role-specific speaker ID. *Hosts* each have one ID, while *guests* share a single ID, allowing us to model idiosyncrasies and interviewing patterns for individual hosts:

$$P(T_{t,\mathbf{h}}|T_{1\dots t,g}, T_{1\dots t-1,\mathbf{h}}, \mathbf{h}).$$

These role-specific speaker IDs are modeled by a speaker embedding layer of the same dimensions as the transformer hidden state, injected into the transformer input layer. We fine-tune GPT2 (**Speaker GPT2**) and DialoGPT (**Speaker DialoGPT**) on our dataset with speaker embeddings. We also fine-tune (FT) DialoGPT and GPT2 on INTERVIEW without speaker information as strong speaker-agnostic baselines for host response generation.

For training and evaluation, we provide our model with up to 512 tokens of non-truncated historical turns. We use an 80-10-10 train/dev/test split with unique conversations in each split.

We use GPT2-small (Transformer with 12 layers, 768 hidden size, 12 heads, and 117M parameters) as the base architecture for all of our models. We perform BPE tokenization with the GPT2Tokenizer³. We use the RAdam optimizer (Liu et al., 2019) with a learning rate of $10^{-6} \times \text{batch size} \times \text{no. of GPUs}$ to utilize linear scaling in multi-GPU training. Our models are trained to convergence on 8 NVIDIA Tesla V100 GPUs, with a batch size of 5 per GPU. We use teacher-forcing to calculate perplexity for all train/dev/test splits. We

³https://huggingface.co/transformers/model_doc/gpt2.html

Model	BPE PPL	BLEU-1	BLEU-4	# Words	Q Rate (%)	NPO (%)	HMA	MRR
Gold	–	–	–	29.3	55.1	37.17	–	–
FT DialoGPT	20.4	11.79	0.29	19.9	53.1	45.28	0.1000	0.2930
FT GPT2	17.4	11.00	0.29	18.2	52.9	45.54	0.1000	0.2930
Speaker DialoGPT	15.3	12.23	0.42	20.8	56.4	47.02	0.3174	0.4662
Speaker GPT2	17.3	12.04	0.30	21.3	59.4	47.37	0.3344	0.4810

Table 3: Metrics on generated host responses on test set. NPO = Noun-phrase overlap with dialog history, HMA = Host Matching Accuracy, MRR = Mean Reciprocal Rank.

Context	SCOTT SIMON: Airstrikes by Syria and the Russian allies have been exacting a high cost in civilian lives [...] Panos Mourtzis is the U.N.’s humanitarian coordinator for Syria[...] GUEST: [...] within Idlib itself, it’s [...] the area where many people had fled from [...] GUEST: What we are calling for is [...] the protection of the children, the women, the families, the civilians who are living in this area. SCOTT SIMON:
Gold	And there have also been strikes from the rebel side.
FT GPT2	What do you see in the future for the U.N.?
Speaker DialoGPT	Mr. Mourtzis, [...] we have seen reports that there is a large number of people who live in the area, and they have been killed or wounded in the fighting, and that there are people who live in areas that are being targeted . What do you see as the biggest threat, the biggest danger, of the people that live in Idlib ?

Table 4: Sample generated responses. **Bold** emphasizes specificity and topicality.

avoid modeling salutations and sign-offs (which tend to be formulaic, speaker-independent, and specific to the radio station) by restricting the target turns to those with at least three prior turns and two following turns of conversation, resulting in a target training set of 87K host-only turns and 11K host-only turns for dev and test.

We decode the host response via top- k sampling (Radford et al., 2019) with $k = 5$. Results across all models on the test set are in Table 3.

Performance Speaker-conditioned models generate utterances closer to gold length than speaker-agnostic baselines, with significantly lower perplexity and higher BLEU scores. This indicates that including speaker information promotes the generation of higher fidelity responses. Our speaker models, especially Speaker GPT2, produce the most inquisitive responses (59.4% question-asking rate).

In an interview setting, it is also important for host utterances to be *related* to the conversation at hand. We evaluate the content similarity between generated responses and the dialog history. We show that our speaker-conditioned models generate responses with the most noun-phrases⁴ / topical references. These also overlap the most with topics in the dialog history, indicating topical relatedness. We note that gold responses include more noun phrases with lower historical overlap, possibly due to hosts bringing up new topics.

⁴detected via <https://spacy.io/>

Speaker Role Ranking To measure the conditioning effect of speaker role profiles on host response generation, we generate a dialog turn with the gold host profile and a dialog history. We then compute the likelihood of generating that response conditioned on the same context but with the gold and nine *randomly sampled* hosts. As in Majumder et al. (2019), we rank the likelihoods for each host and report the host matching accuracy (HMA)—proportion where the gold host is highest ranked—and Mean Reciprocal Rank (MMR) (Radev et al., 2002) of the gold host. Our speaker-conditioned models achieve much higher HMA and MRR compared to strong speaker-agnostic baselines, indicating significant conditioning on host profiles.

Qualitative Analysis Our models additionally exhibit several qualitative properties of high-quality and fluent conversation. We present a sample generation in Table 4 (additional samples in the **Appendix**) that is indicative of broad trends across the test set. None of the models are able to introduce novel information (like Gold), but our speaker-conditioned models produce markedly better inquisitive responses. While GPT2 generates a natural-sounding short question with little relevance to the topic at hand, our Speaker DialoGPT model paraphrases previous turns and refers to existing entities to ask a substantial and coherent question. We further performed a **human evaluation** on a Likert scale to assess subjective dialog qual-

ity, with human raters preferring speaker model responses to speaker-agnostic models 62.5% of the time across 150 pairwise comparisons.

4.2 Task 2: Role Change Detection

We also investigate role change detection as a binary classification task for two-party dialogs. As a single turn of dialog may consist of multiple sentences, we aim to use a series of historical sentences and their speakers to classify whether a role change will occur in the *next sentence of dialog*. In contrast to previous textual speaker change detection tasks (Meng et al., 2017), we do not provide the target sentence for which we are predicting the role change. This setting is more realistic for a real-time assistive dialog system and online prediction in general.

We fine-tune BERT (Devlin et al., 2019) to encode the dialog history, classifying speaker changes with a linear layer over the [CLS] representation. To understand the role of contextual speaker information in this task, we investigate representing the dialog history with and without speaker labels for each turn. This is a difficult task on our dataset, as BERT obtains a 63.2 F1 score without speaker information, struggling to predict role changes substantially better than random. While the task remains difficult, the classifier benefits from the inclusion of speaker labels, learning speaker embeddings and achieving a 66.1 F1 score. We see the potential for further research toward learning speaker representations to predict role changes and infer the structure of dialogs.

5 Conclusion

We contribute a large-scale media dialog dataset that can act as a benchmark for complex open-domain, role-dependent grounded dialog. We present baseline model for role-conditioned dialog generation and show that they benefit from speaker information when added. **In future work**, we aim to perform temporal analyses of trends and biases within INTERVIEW and take advantage of the news setting to investigate external knowledge grounding in long natural conversations. These directions could potentially lead to more coherent free-form and assistive dialog systems.

References

- Niels Ole Bernsen, Hans Dybkjær, and Laila Dybkjær. 1998. *Designing interactive speech systems - from first ideas to user testing*. Springer.
- Pawel Budzianowski, Tsung-Hsien Wen, Bo-Hsiang Tseng, Iñigo Casanueva, Stefan Ultes, Osman Ramadan, and Milica Gasic. 2018. *Multiwoz - A large-scale multi-domain wizard-of-oz dataset for task-oriented dialogue modelling*. In *EMNLP*.
- Bill Byrne, Karthik Krishnamoorthi, Chinnadhurai Sankar, Arvind Neelakantan, Ben Goodrich, Daniel Duckworth, Semih Yavuz, Amit Dubey, Kyu-Young Kim, and Andy Cedilnik. 2019. *Taskmaster-1: Toward a realistic and diverse dialog dataset*. In *EMNLP*.
- Alexandra Canavan, David Graff, and George Zipperlen. 1997. *Callhome american english speech*. *Linguistic Data Consortium*.
- Jordan Cohen. 2007. *The gale project: A description and an update*. In *2007 IEEE Workshop on Automatic Speech Recognition & Understanding (ASRU)*, pages 237–237. IEEE.
- DARPA. 2011. *Broad Agency Announcement: I2O Broad Operational Language Translation (BOLT)*. DARPA-BAA-11-40.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. *BERT: pre-training of deep bidirectional transformers for language understanding*. In *NAACL-HLT*.
- Emily Dinan, Stephen Roller, Kurt Shuster, Angela Fan, Michael Auli, and Jason Weston. 2019. *Wizard of wikipedia: Knowledge-powered conversational agents*. In *ICLR*.
- Michel Galley, Chris Brockett, Xiang Gao, Jianfeng Gao, and Bill Dolan. 2019. *Grounded response generation task at dstc7*.
- John J Godfrey, Edward C Holliman, and Jane McDaniel. 1992. *Switchboard: Telephone speech corpus for research and development*. In *ICASSP*, volume 1. IEEE.
- Karthik Gopalakrishnan, Behnam Hedayatnia, Qinqiang Chen, Anna Gottardi, Sanjeev Kwatra, Anu Venkatesh, Raefer Gabriel, and Dilek Hakkani-Tr. 2019. *Topical-Chat: Towards Knowledge-Grounded Open-Domain Conversations*. In *Inter-speech*.
- Jiwei Li, Michel Galley, Chris Brockett, Georgios P. Spithourakis, Jianfeng Gao, and William B. Dolan. 2016. *A persona-based neural conversation model*. In *ACL*.
- Yanran Li, Hui Su, Xiaoyu Shen, Wenjie Li, Ziqiang Cao, and Shuzi Niu. 2017. *Dailydialog: A manually labelled multi-turn dialogue dataset*. In *IJCNLP*.
- Liyuan Liu, Haoming Jiang, Pengcheng He, Weizhu Chen, Xiaodong Liu, Jianfeng Gao, and Jiawei Han. 2019. *On the variance of the adaptive learning rate and beyond*. *CoRR*, abs/1908.03265.

- Ryan Lowe, Nissan Pow, Iulian Serban, and Joelle Pineau. 2015. *The ubuntu dialogue corpus: A large dataset for research in unstructured multi-turn dialogue systems*. In *SIGDIAL*.
- Yi Luan, Chris Brockett, Bill Dolan, Jianfeng Gao, and Michel Galley. 2017. *Multi-task learning for speaker-role adaptation in neural conversation models*. In *IJCNLP*.
- Suman Kalyan Maity, Anshrit E. Chaudhary, Shraman Kumar, Animesh Mukherjee, Chaitanya Sarada, Abhijeet Patil, and Akash Mondal. 2016. *Wassup? LOL : Characterizing out-of-vocabulary words in twitter*. In *CSCW*.
- Bodhisattwa Prasad Majumder, Shuyang Li, Jianmo Ni, and Julian McAuley. 2019. *Generating personalized recipes from historical user preferences*. In *EMNLP*, pages 5975–5981.
- Zhao Meng, Lili Mou, and Zhi Jin. 2017. *Hierarchical RNN with static sentence-level attention for text-based speaker change detection*. In *CIKM*.
- Nelson Morgan, Don Baron, Jane Edwards, Daniel P. W. Ellis, David Gelbart, Adam Janin, Thilo Pfau, Elizabeth Shriberg, and Andreas Stolcke. 2001. *The meeting project at ICSI*. In *HLT*.
- Dragomir R. Radev, Hong Qi, Harris Wu, and Weiguo Fan. 2002. *Evaluating web-based question answering systems*. In *LREC*.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. *Language models are unsupervised multitask learners*. *OpenAI Blog*, 1(8).
- Steve Renals, Thomas Hain, and Hervé Bourlard. 2007. *Recognition and understanding of meetings the ami and amida projects*. In *ASRU*, pages 238–247. IEEE.
- Alan Ritter, Colin Cherry, and Bill Dolan. 2010. *Unsupervised modeling of twitter conversations*. In *HLT*.
- Chinnadhurai Sankar and Sujith Ravi. 2019. *Deep reinforcement learning for modeling chit-chat dialog with discrete attributes*. *CoRR*, abs/1907.02848.
- Abigail See, Stephen Roller, Douwe Kiela, and Jason Weston. 2019. *What makes a good conversation? how controllable attributes affect human judgments*. In *NAACL-HLT*.
- Iulian Vlad Serban, Ryan Lowe, Peter Henderson, Laurent Charlin, and Joelle Pineau. 2018. *A survey of available corpora for building data-driven dialogue systems: The journal version*. *D&D*, 9(1).
- Iulian Vlad Serban, Alessandro Sordoni, Yoshua Bengio, Aaron C. Courville, and Joelle Pineau. 2016. *Building end-to-end dialogue systems using generative hierarchical neural network models*. In *AAAI*.
- Lifeng Shang, Zhengdong Lu, and Hang Li. 2015. *Neural responding machine for short-text conversation*. In *ACL*.
- Alessandro Sordoni, Yoshua Bengio, Hossein Vahabi, Christina Lioma, Jakob Grue Simonsen, and Jian-Yun Nie. 2015a. *A hierarchical recurrent encoder-decoder for generative context-aware query suggestion*. In *CIKM*.
- Alessandro Sordoni, Michel Galley, Michael Auli, Chris Brockett, Yangfeng Ji, Margaret Mitchell, Jian-Yun Nie, Jianfeng Gao, and Bill Dolan. 2015b. *A neural network approach to context-sensitive generation of conversational responses*. In *NAACL-HLT*.
- Stephanie M Strassel. 2004. *Linguistic resources for effective, affordable, reusable speech-to-text*. In *LREC*.
- Elda Weizman. 2008. *Positioning in media dialogue: Negotiating roles in the news interview*, volume 3. John Benjamins Publishing.
- Saizheng Zhang, Emily Dinan, Jack Urbanek, Arthur Szlam, Douwe Kiela, and Jason Weston. 2018. *Personalizing dialogue agents: I have a dog, do you have pets too?* In *ACL*.
- Yizhe Zhang, Siqi Sun, Michel Galley, Yen-Chun Chen, Chris Brockett, Xiang Gao, Jianfeng Gao, Jingjing Liu, and Bill Dolan. 2019. *Dialogpt: Large-scale generative pre-training for conversational response generation*. *CoRR*, abs/1911.00536.

A Generated Examples

See the following tables for sample dialog histories and generated host responses from each of our baseline and speaker-conditioned dialog models.

Context	<p>SCOTT SIMON: Airstrikes by Syria and the Russian allies have been exacting a high cost in civilian lives and could trigger yet another wave of refugees if they can find a place to go.</p> <p>SCOTT SIMON: Panos Moutzis is the U.N.'s humanitarian coordinator for Syria and joins us now. Mr. Moutzis, thanks so much for being with us.</p> <p>GUEST: Thank you for calling me.</p> <p>SCOTT SIMON: What do you hear from people on the ground in and around Idlib?</p> <p>GUEST: People on the ground are really panicking. Women, children, families have been, on a daily basis for the last four months, been in an area where there's been bombing, airstrikes, ground offensives that has really made their life impossible. More than 400,000 had to run to safety within the governorate in an area where 3 million people are living. We've had more than a hundred incidents of health clinics, schools, water distribution points, a market that received a direct strike, which was really - has tolled, so far, more than 500 deaths and a total panic where one sees entire villages and towns deserted, people running to safety.</p> <p>GUEST: So our biggest concern is really the protection of civilians. The basic rule of war - that residential areas, civilians should be respected and protected - it is violated at this point in the Idlib area. And that's really something that is not acceptable.</p> <p>SCOTT SIMON: We should remind people, in fact, a direct intentional attack on civilians is a war crime, isn't it?</p> <p>GUEST: It is. If it's proven that it's intentional, it is.</p> <p>GUEST: And, of course, we have humanitarian assistance programs on the ground providing lifesaving assistance to the thousands of people who are escaping, going into safety. The worry is, first of all, within Idlib itself, it's a governorate with 3 million people living. This is the area where many people had fled from throughout the country. So there's a displacement that is happening on the doorstep of Turkey with 3 million people inside. And it has, also, all the elements to create further regional destabilization should this escalation continue.</p> <p>GUEST: What we are calling for is a cessation of hostilities. There must be a peaceful way forward, a way which - a solution that does not involve residential areas being bombed, a solution that is not military and that - a solution that ensures the protection of the children, the women, the families, the civilians who are living in this area.</p> <p>SCOTT SIMON:</p>
Gold	And there have also been strikes from the rebel side.
FT DialoGPT	Mr. Moutzis, I want you to tell me about some of the people who are in these areas that you're talking to. I know that you're a refugee yourself, but you've also been involved in fighting in the north and the south of Syria . How are they dealing with these attacks in Syria?
FT GPT2	What do you see in the future for the U.N.?
Speaker GPT2	Well, that's what you've been talking about, right?
Speaker DialoGPT	Mr. Moutzis, we should note that this is a very small group that has, you know, a very small number of members. And we have seen reports that there is a large number of people who live in the area, and they have been killed or wounded in the fighting, and that there are people who live in areas that are being targeted . What do you see as the biggest threat, the biggest danger, of the people that live in Idlib ?

Table 5: Sample generated response on Syrian air strikes. **Bold** emphasizes specificity and topicality. **Red** denotes factually incorrect or inconsistent segments.

Context	<p>GUEST: And it's unclear to me even at this point if he had the authority to launch that special operations team or whether someone outside that chain of command and Department of Defense or Southern Command, or pardon me, in Special Operations Command, you know, overruled that. And it's never become obvious to me what that chain of command was. And it seemed to me that would be one of the first questions the congressional people are asking - doing the inquiries should've been asking.</p> <p>NEAL CONAN: So in other words, had the ambassador, the head of mission, been alive, he would've been in control? But once he was dead, there was nobody in control.</p> <p>GUEST: Well, that's one issue, but the second issue is whether or not that special operations team was under the mission's control. If it wasn't, that decision was made in Washington. And then in that case, all right, who made that decision and why did they make that decision, and where did that come from based - above at the desk on Washington and so forth. And those questions have never been answered or is, as far as I can tell, in the current congressional testimony, haven't even been asked. They seem to be dancing around who's to blame rather than to try to figure out exactly what happened. That really is - that's disturbing if we're going to try to do lessons learned on this thing.</p> <p>NEAL CONAN: The other agency that was involved and, speaking of dancing around, is the Central Intelligence Agency.</p> <p>GUEST: Well, the Central Intelligence Agency was and, you know, theoretically they also were under the control of the mission. But that's - again, and that's why the senior agency thing becomes so muddled, were they or were they not, and also that special operations team, I don't think, was a working for the CIA. I think they were, you know, DOD asset that obviously was operating in support of the mission there on the ground. So who was in-charge remains a question. Obviously, the deputy from his testimony didn't think he had the power to do that, nor was the special operations commander on the ground able to take independent action apparently without going back to D.C.</p> <p>NEAL CONAN: And...</p> <p>GUEST: So that really raises some questions that we really ought to get to before the next one of these things pops up.</p> <p>NEAL CONAN:</p>
Gold	There was also confusion. Ordinarily there would have been military aircraft - Air Force planes on call on behalf of the - to support operations, if the mission called, but they were too far away.
FT DialoGPT	Well, you know, the CIA, you're saying, has the agency been able to determine what went wrong in the past? Is it clear that that's been done?
FT GPT2	We've heard a lot of talk in recent weeks about the importance of a strong national security strategy. What's that strategy? Is there a sense that the United States is at risk if we don't get it?
Speaker GPT2	Well, that's NPR senior correspondent James Bamford speaking with us from New York.
Speaker DialoGPT	But the question that's being asked now is: Is there a way in which the CIA is going to be able to do that without the special counsel or the FBI or the president, and without the president's approval or the president's permission?

Table 6: Sample generated response. **Bold** emphasizes specificity and topicality.

Context	<p>SCOTT SIMON: You could find Jim Dunne slinking around Death Valley in peak heat, perched on a tree limb in Milford, Mich., or shooting through chain-link fences and barbed wire in Arizona. Jim Dunne is credited with maybe inventing the art and business of automotive spy photography. He died this week at the age of 87.</p> <p>SCOTT SIMON: Michelle Krebs, his friend and director of automotive relations for AutoTrader.com, joins us from studios of WDET in Detroit. Thanks so much for being with us.</p> <p>GUEST: Oh, well, thank you for letting me talk about Jim.</p> <p>SCOTT SIMON: Well, how did he get into this line of business - spy photography in the auto industry?</p> <p>GUEST: Well, like many of us, it was a lot of things that came together. He was in reconnaissance in the Army in the '50s. He got his degree in industrial engineering here at Wayne State University. And then he had seven kids he had to put through college.</p> <p>GUEST: And so he invented this thing called spy photography. He realized that he needed a competitive edge against different magazines. He was at Popular Science and then Popular Mechanics. And he thought maybe taking pictures of these cars that the automakers don't want me to take pictures of would be a business.</p> <p>SCOTT SIMON: What are some of the things he'd do to gain access, as they say these days?</p> <p>GUEST: Well, one of the amazing ones was that he would dress up with a short-sleeved white shirt, a skinny black tie, a pocket protector and a (laughter) - and a clipboard and just march into the Chrysler plant, where he knew that they had secret models hidden inside - out in the back part of the plant. And he could take pictures of them there.</p> <p>SCOTT SIMON:</p>
Gold	Oh, my gosh. And people fell for that 'cause he was so convincing.
FT DialoGPT	And how did this man become an icon?
FT GPT2	And he did that.
Speaker GPT2	So he would have to be in a car dealership to get ahold of that stuff, right? I mean, what would he have to show me?
Speaker DialoGPT	And what was it like to be a spy photographer at the time?

Table 7: Sample generated response on auto spy photography. **Bold** emphasizes specificity and topicality.

Context	<p>GUEST: We have a plant in Kentucky and Taiwan and Japan. And yes, we make large sheets of this glass, and then we put it into crates, and then we ship it to companies called finishers, most of them are in China, and those are the companies that actually cut the glass into the pieces, drill holes, polish, et cetera, into the shapes of the parts that go onto the devices.</p> <p>IRA FLATOW: Why can't you - I'm sorry, why can't you make it the shape itself beforehand?</p> <p>GUEST: Well, it's much cheaper, more effective, to make these large sheets of glass and then cut it later, as opposed to trying to mold - or mold from molten glass into a small part.</p> <p>IRA FLATOW: It's not having to do with maybe the glass being too tough or brittle to work with at that point?</p> <p>GUEST: No, that's a good question, but we - the chemical strengthening process actually happens after our immediate customers have cut the parts down to the size, the shape of the parts.</p> <p>IRA FLATOW: There's a famous story in Walter Isaacson's biography of Steve Jobs that says he actually came down at one point and demanded that Corning make him some glass for his - any truth to that?</p> <p>GUEST: Well, the story, we certainly, we don't comment in detail about the relationship with different customers, but the story is there in the book, and it's true.</p> <p>IRA FLATOW: Is there other kinds of products, now that you've discovered how popular and ubiquitous the Gorilla Glass could be - any other places we might see it showing up?</p> <p>GUEST: It's a really exciting time for us, Ira, to - it's only five years in, and it's been a tremendous success story for the company. Handsets really have taken off. We're at a point now where almost half of all handsets in the world made are smartphones with some type of touch capability.</p> <p>GUEST: And then I'm sure you know of tablet computers, are very exciting, have grown quite magnificently in the last few years. And the market is starting to think about expanding touch interfaces with the different devices. If you think about your laptop computer, for example, or monitors or tabletops, even the front of a refrigerator, there's a lot more applications out there, we feel.</p> <p>GUEST: We feel that touch and the interface of touch is only going to grow.</p> <p>IRA FLATOW:</p>
Gold	Do you have to design and engineer the glass specifically to be touched as a utility?
FT DialoGPT	I have to ask you, you know, I think you mentioned that you have been working on this for a very long time.
FT GPT2	I'm thinking of the iPad, for example.
Speaker GPT2	So if the Gorilla Glass has been in the news , I mean, you have a lot of people in the world looking at it and saying, well, we want to make it thinner. But we don't have the power to make it thinner.
Speaker DialoGPT	You're saying that the market is growing?

Table 8: Sample generated response. **Bold** emphasizes specificity and topicality. **Red** denotes factually incorrect or inconsistent segments.