Athena 2.0: Contextualized Dialogue Management for an Alexa Prize SocialBot

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Abstract

Athena 2.0 is an Alexa Prize SocialBot that has been a finalist in the last two Alexa Prize Grand Challenges. One reason for Athena’s success is its novel dialogue management strategy, which allows it to dynamically construct dialogues and responses from component modules, leading to novel conversations with every interaction. Here we describe Athena’s system design and performance in the Alexa Prize during the 20/21 competition. A live demo of Athena as well as video recordings will provoke discussion on the state of the art in conversational AI.

1 Introduction

There has been tremendous progress over the last 10 years on conversational AI, and a number of practical systems have been deployed. The Alexa Prize competition seeks to stimulate research and development on conversational AI for open-domain topic-oriented dialogue (Fang et al., 2018; Liang et al., 2020; Finch et al., 2020; Harrison et al., 2020; Pichl et al., 2020; Curry et al., 2018). However, the longstanding tension between hand-scripting the dialogue interaction, and producing systems that scale to new domains and types of interaction still remains (Eric and Manning, 2017; Cervone et al., 2019) Neural end-to-end spoken dialogue systems are not yet at a point where they perform well in interactions with real users (Paranjape et al., 2020; Gopalakrishnan et al., 2020; Dinan et al., 2019).

Athena’s dialogue management architecture aims to be scalable and dynamic, by supporting many different interactions for every topic, and by constructing system utterances by concatenating multiple dialogue acts that achieve different purposes (Stent, 2000). A key aspect of Athena is the existence of multiple Response Generators (RGs) for each topic, which can be flexibly interleaved during a particular interaction, as illustrated in Figure 1. This approach contrasts with the commonly used approach of handcrafting conversation flowgraphs for each topic, a static directed graph where the nodes are the system utterances, and outgoing edges are represent possible user replies. This approach has not changed for over 20 years (Seneff et al., 1998; Glass and Weinstein, 2001; Buntschuh et al., 1998), and its strengths and limitations are well known. Flow-graphs are hand constructed and thus do not scale well. However, each system response can assume a fixed prior context, which allows it to support fluent and coherent dialogues with sufficient handcrafting.

In contrast, the ability of Athena’s Dialogue Manager (DM) to interleave RGs allows Athena to dynamically construct conversations that never follow the same path. However, this more flexible approach requires RGs to pay the overhead cost of continuously adapting to the current context, as described in Section 3. By eschewing a graph-based representation of dialogue state, Athena’s DM is flexible enough to use RG responses in contexts that were not planned out prior to the conversation starting, and that do not need to follow rigid guidelines. We believe this modular dialogue management approach promises to scale to deeper and richer conversations, while at the same time allow new conversational topics to be easily added to and integrated into the system.

2 Athena Architecture and Overview

Figure 2 details Athena’s architecture. Athena is built using the Cobot framework provided by Amazon (Khatri et al., 2018). It runs as an on-demand application that is initiated by an “Alexa, let’s chat” user request to any Alexa-enabled device, such as

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1In accordance with the Alexa Prize rules on user privacy, these conversations are between team members and Athena.
an Amazon Echo or the Alexa app installed on a phone. During the Alexa Prize, Athena participates in about 9K conversations a week. The Cobot framework provides support for automatically scaling to large volumes of user traffic.

The inputs to Athena are the ASR hypotheses for a user’s turn from Amazon, and a conversation ID that is used to retrieve the conversation history and state information from a back-end database. The ASR hypothesis is fed into a natural language understanding (NLU) pipeline that produces a set of NLU features for the user utterance and conversation context. The NLU consists of Cobot’s module for topic classification, and Athena modules for utterance segmentation, dialogue act tagging, named entity recognition and linking, and coreference resolution (Harrison et al., 2020; Patil et al., 2021). The right-hand side of Figure 2 indicates how Athena’s RGs use knowledge bases and fun facts databases organized by topic and named entity. Athena uses the Wikidata Knowledge Graph to aid in Named Entity Resolution and for Knowledge-Graph based RGs. These are essential for creating an intelligent and versatile conversational agent (Fang et al., 2018; Chen et al., 2018).

Based on the NLU features and conversation context, the Dialogue Manager (DM) calls specific Response Generators (RGs) to populate a response pool. The DM then applies a trained neural response ranker to select from the response pool generated by the RGs. Finally, Athena’s responses are spoken by Amazon’s text-to-speech service.

3 Dialogue Management

A Dialogue Manager (DM) for open-domain conversation faces a particularly challenging task due to the universe of possible valid responses at each point of a conversation. While goal-oriented dialogues have a clear task completion objective which the DM can optimize when making decisions (Walker et al., 2001, 1997; Walker, 2000), the DM for open-domain dialogues does not have an obvious way to measure the appropriateness of possible candidate responses.

Athena’s DM architecture can be decomposed into a number of sub-components, corresponding to phases of dialogue management, oriented as a pipeline. The DM sub-modules in Figure 3 are described in more detail in Harrison et al. (2020).

The Topic Manager in Figure 3 is responsible for classifying user utterances into topics, and the implementation of the DM’s topic hierarchy. The topic hierarchy is a partially ordered list of topics in order of predicted “goodness” learned from past conversations, using a scoring function that combines user ratings and the number of turns per topic.
per conversation, as described in Section 5. The topic hierarchy is a parameter for system-initiative topic initiations as well as suggesting topics for users to initiate. This makes it extremely easy to change which topics are promoted at any time, e.g., for collecting more data on a particular topic. It can also be personalized for each user. For example, if when asked about weekend activities, the user describes playing in a baseball league, we can prioritize talking about sports. This information persists across conversations. If the user is also an avid painter, but our system did not get a chance to discuss painting in the previous conversation, we will prioritize it when the user returns.

The interface between the DM and the RGs in Figure 3, is a contract-based approach. The DM passes a set of response conditions to the RGs, which the RGs must meet for their response to be considered. This approach allows Athena to have many RG types (see Section 4).

The Response Ranker is based on a BERT-based ranker fine-tuned on hand-annotated Alexa Prize conversation data (Wolf et al., 2019; Devlin et al., 2018). The current tuning set size is ~10K utterances. Annotation involves ranking candidate responses within a context of five turns. We have repeatedly annotated additional data and retrained our response ranker, which is useful when, for example, new RGs are added to Athena.

4 Response Generation

Athena uses four types of RGs: Flow-RGs, Knowledge-Graph RGs, Entity-Based Indexing RGs, and Neural NLG RGs.

4.1 Flow-RG

Flow-RG is a framework that we developed with the objective of creating robust and modular flow-based RGs. This is still the most reliable way to provide the DM with a pool of possible responses at each turn of the dialogue, even though such flows have to be handcrafted. Flow-based RGs exhibit context-awareness and fluency superior to other RG types, such as retrieval-based or neural. This RG design naturally has a rather limited support for user initiative, which we make up for with other RGs in Athena, and by ensuring the responses from different RGs get smoothly interwoven across multiple turns, as well as within a single turn.

An RG defined in this framework has three components. First, a flow graph consisting of nodes specifying the responses, and edges determining which node of the flow to move on to given the current user utterance and dialogue state. Flow-RG enforces each next turn in the flow graph to be conditioned on the dialogue act(s) of the user utterance, while other features of the utterance – such as its sentiment, or the presence of a named entity or a particular keyword – are deemed secondary and
are optional in branching conditions.\textsuperscript{2} This reduces the chance of Athena’s subsequent response ignoring the user’s intent, which can be anything from expressing an opinion, to requesting information, to merely acknowledging Athena’s response in the previous turn. The second component comprises response segment templates, while the third component is a set of callback functions that generate more context-dependent response segments.

A flow graph can be broken down into smaller miniflows that are independent and can possibly be executed in an arbitrary order. Each RG then typically handles a single topic, with multiple miniflows being responsible for different subtopics. An example of multiple miniflows forming a cohesive dialogue can be seen in Appendix A.

**Response Composition.** The response in each turn is assembled from one or more segments specified in the corresponding node. Each segment is defined either (1) in the form of a set of templates, or (2) as a callback function that returns a set of templates. While both offer an easy way to use paraphrases for increased diversity of the responses, the latter is more robust in that it can use the previous context and more of the NLU information about the user utterance. Figure 4 shows the process of a response being assembled from three segments, two of which are different types of callback function: one fills a template slot with a value from the associated knowledge source, while the other initiates a new miniflow and composes the response text recursively, which ultimately corresponds to the last segment in the example.

When composing a response, each segment’s final set of texts is sampled from, and all of them are concatenated. This is repeated until up to five different response candidates are composed. These are eventually all returned to the DM, which picks one of them that is not too similar to any of Athena’s previous responses.

**Interweaving with Other RGs.** Every topic in Athena has a corresponding Flow-RG, and most topics also have one or two other RGs that can interact with its Flow-RG to dynamically construct a topical sub-dialogue. In line with the DM’s way of response building, the final response in Flow-RG is split into three parts: an opener, a body, and a hand-off. This response structure is particularly useful for creating seamless transitions whether it is between miniflows, or between two RGs. To this end, Flow-RG sets the response from an ending miniflow as the opener (typically, some form of acknowledgement of the user’s response, or a short answer), and the body and hand-off parts are reserved for the intro response provided by a new miniflow. The same mechanism is used for certain transitions from Flow-RG to a different RG, mainly: 1) when the flow’s content is exhausted, and transitions thus to a fallback response chosen by the DM that initiates a new topic, and 2) when a leaf node of the miniflow is reached, and the DM decides to switch to a different RG on the same topic. The latter is utilized in the DM’s interweaving strategy, wherein a flow-based RG takes turns with an entity-centric or fun fact-based RG in han-
dling a subdialogue on the same topic.

Flow-RG makes it possible for a flow to resume after a few turns handled by a different RG on the same topic. The flow can simply begin a new miniflow, if there is at least one miniflow that has not yet been visited. Resumption is also possible in the middle of a miniflow, which allows a different RG to chime in for up to two turns (such as EVI answering an on-topic factual question that the flow has no answer prepared for), and then have the miniflow pick up where it left off.

4.2 Knowledge Graph-Based RGs

The goal of the Knowledge Graph-based RGs (KG RGs) is to create deep knowledge-grounded conversations, where Athena always has more to say, by traversing relations in the Wikidata knowledge graph. Athena has four KG RGs covering movies, music, sports and TV, with conversations anchored around KG nodes (named entities). Each topic attempts to continue the conversation by either responding with a fact about an entity in context, or by selecting an entity from a set of fallback entities. When the system has either run out of facts on a particular entity, or has been on the same entity for a number of turns above a threshold, the RG attempts to traverse one or more relation edges, to a related entity, to continue the conversation. An example for the TV KG RG is in Figure 1.

4.3 Entity-Based Indexing RGs

Entity-Based Indexing RGs are topical retrieval-based generators where the focus of the response is on “fun facts” for entities in a topic. Table 2 indicates how many fun facts these RGs have for each topic, and provides examples.

4.4 Neural NLG RGs

We have also developed and experimented with several different neural NLGs, including neural...
### Table 2: Fun facts for popular entity-based RG topics.

| Topic     | #Facts | Example                                                                                                                                                       |
|-----------|--------|--------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Animals   | 90     | I read this surprising fact about koalas. The fingerprints of a koala are so indistinguishable from humans that they have on occasion been confused at a crime scene. Imagine having your fingerprints confused with a koala, how strange! |
| Comic Books | 26     | Batman and Robin are the best superhero sidekick team. Once, after Batman and Robin rescued it from a slaughterhouse, DC comics included a Bat-cow.                        |
| Harry Potter | 21     | Fred and George Weasley were such tricksters. When Fred and George Weasley bewitched snowballs to hit Professor Quirrell’s turban, they were unwittingly hitting Voldemort in the face. |
| Movies    | 34     | One of my favorite movie series of all time are the James Bond movies. Before signing on as James Bond, Daniel Craig wasn’t sure he wanted to play the role.            |
| Music     | 31     | I like to think that when music is played, it makes everyone happier, even animals. Researchers at the University of Leicester found that cows produce 3% more milk when they listen to relaxing music. |
| Nature    | 15     | I like learning more about nature. It’s actually really dark in the Amazon Forest! The forest is so thick that only 1% of sunlight can make it through.               |
| Video Games | 20     | Here’s a fact I discovered recently about World of Warcraft. A lot of famous people played World of Warcraft, including Vin Diesel, Mila Kunis and even Robin Williams. Isn’t that cool?! |

NLGs that generate from meaning representations and are thus topic specific (Juraska et al., 2019; Harrison et al., 2019; Oraby et al., 2019).

We also developed a neural NLG that we call Discourse-Driven NRG (DD-NRG) that generates directly from the conversation context and can be used for any topic (Rajasekaran, 2020; Tosh, 2020). We also systematically tested two topic-agnostic neural NLGs provided by Amazon, the PD-NRG (Hedayatnia et al., 2020) and a model called Topical-NRG that was trained on the Alexa Prize conversations of all finalists in the 19/20 competition. We found that it was difficult to control the quality of the neural RG outputs and guarantee their coherence, so we only deployed them to collect experimental data for short periods. We are currently experimenting with methods for controllable generation for these RGs (Reed et al., 2020; Harrison et al., 2019; Juraska and Walker, 2021).

### Table 3: Athena’s performance during the semi-finals and the finals for rating, length and duration.

|                  | Ratings |       | Turns |       | Time |       |
|------------------|---------|-------|-------|-------|------|-------|
|                  | Mean    | Median| Mean  | Median| Mean | Median|
| Semifinals       | 3.62    | 4.0   | 17    | 24    | 2.46 |       |
| Finals           | 3.71    | 4.0   | 18    | 24    | 2.01 |       |

5 Evaluation and Analysis

The two criteria that are specified in the Alexa Prize Grand Challenge that systems aim to optimize are length of conversation and user ratings. The Grand Prize will go to a system that achieves conversations of at least 20 minutes with average ratings of 4.0 on a scale of 1 to 5.³

Over the 4 years our team has been in the competition, we have found that interactions with users are vulnerable to noise due to the competition setup (Bowden et al., 2019a,b; Harrison et al., 2020). Users often get into the Alexa Prize skill by accident leading to many conversations of only 1 or 2 turns (Shalyminov et al., 2018). Surprisingly, even for single turn conversations, some users still provide ratings. To improve our analysis of system performance, we remove these very short conversations from the data. Table 3 show the ratings, lengths in turns, and durations, during the semi-finals and the finals. On June 25th, before entering the finals, the average rating across all the systems in the semi-finals was 3.41 and the median duration was 2.12.

³https://www.amazon.science/academic-engagements/alexa-prize-socialbot-grand-challenge-4-finalists-announced
versations from January to June are in Figure 6. The purple and red bars indicate proportions of the topic that occur in conversations with ratings of 4 and 5 respectively. This suggests that the highest performing topics include animals, comic books, Harry Potter, hobbies, and video games, and that only a few topics are actually performing poorly, such as dinosaurs, news and sports.

However, presence in a conversation is a rather imprecise indicator of topic quality. In order to better understand the contribution of each topic to Athena’s overall ratings, we developed a novel scoring function that aims to optimize topic selection over the prizes’ user ratings and conversation duration criteria. Thus, our scoring function gives credit based on the number of utterances in a conversation that are contributed by each topic in the conversation. The number of utterances is multiplied by the conversation rating and summed for each topic over all rated conversations. This sum is then normalized to produce its Z-score. The plot shown in Figure 7 indicates for each topic, how many standard deviations its performance is above or below the Athena’s mean performance for two weeks in June, 2021. This plot indicates that the topics that contribute most to long dialogues that are more highly rated include movies, animals, video games, music and hobbies, all of which are 1 or more standard deviations above the mean in performance. Walker et al. (2021) discusses the impact of topic selection and dialogue behaviors on user ratings and conversation length.

We also investigated the impact of personalization on the dialogue manager with an A/B study run over 22 days. The A system has the fully personalized dialogue manager, while B utilizes our previously existing heuristic topic selection strategy. We selected conversations of 6 turns or more to allow personalization to have an effect and also filter out conversations that never perform topic promotion; thus, we only inspect conversations that differ due to the topic selection strategy. After filtering, personalization occurred in roughly 25% of conversations. Our results, shown in Table 4, indicate a statistically significant increase in both user rating and conversation length.

|               | personalized | heuristic | p-value |
|---------------|--------------|-----------|---------|
| convs         | 1066         | 614       |         |
| rating        | 4.02         | 3.85      | .007    |
| length        | 38.07        | 35.07     | .016    |

Table 4: Personalized topic selection vs. heuristic topic selection over 22 days.

6 Conclusion

This paper describes Athena, and its design and performance in the Alexa Prize Grand Challenge 4. Our system demonstration will illustrate both the strengths and the weaknesses of Athena and provide the basis for discussion about the state of the art of open-domain conversational AI.

Acknowledgements

We would like to thank Christian Benavidez, Yaqing Cao, James Graupera, Colin Harmon, Venkatesh Nagubandi, Meltem Ozcan, Diego Pedro, Navya Rao, Stephanie Rich, Jasiel Rivera-Trinadad and Aditya Tarde for helping with fun facts, Wikidata queries and prosody markup.

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A Appendix

| A: I’d like to hear your ideas on this. If you could choose one food to live on for your entire life, which food would it be? Why? |
| U: I think nachos |

| A: That’s an interesting answer! If I was a human, I would eat Sweet potatoes. Sweet potatoes are a really nutritious food. You can eat them in a variety of ways like baked, fries, or twice baked. Anyway, that’s my thoughts on the matter. |
| U: I like the beach more |

| A: Okay. I was curious about your opinion on this. If you had the option, would you rather spend time in the mountains, or, at the beach |
| U: I like the beach more |

| A: Choosing the beach is a good choice! If I was a human, I would spend time at the ocean - I would walk on the beach, search for shells, and relax in the sun. Anyhow, that’s where my minds at, let’s move forward. |

Table 5: Two examples of Athena’s attempt to increase topical depth by asking different types of playful questions. We crowdsourced 2.5k playful questions, which were then curated for quality. All of this content was also updated to match Athena’s self-aware personality, e.g., If I was human. “A” denotes Athena and “U” the user turns.
A: But most people seem to find dinosaurs really interesting. There are dinosaur movies and whole floors of natural history museums dedicated to dinosaurs. Personally, I find it fascinating that modern birds are descended from a particular family of dinosaurs.

U: hella cool

A: Definitely. I was surprised to hear how much work went into creating the movie Land Before Time. Over 600 background paintings were made for the film. The artists had to create a believable environment in which there was almost no foliage. Most paintings depicted beautiful but barren wastelands.

U: surprising

A: Right? My favorite dinosaur is the Tyrannosaurus Rex. It’s huge and ferocious, but the little arms make it somewhat adorable. What about you? What’s your favorite dinosaur?

U: i’m not sure i have to say a t. rex

A: Okay. There are lots of movies about dinosaurs. One of the most famous dinosaur movies is Jurassic Park, old but classic. Are there any dinosaur movies that you love?

U: i have to say jurassic park because that’s the only one i’ve seen

A: Awesome! That one is well known! I seem to remember people saying the dinosaurs were very vivid

U: i never knew that

A: yeah, I love to collect these fun facts! But anyways, I’m interested in your opinion. Would you rather ride on the back of a pterodactyl or brontosaurus as your primary means of transportation?

U: i have to say brontosaurus and i hate heights

A: Choosing a Brontosaurus you say, great pick! I would rather ride a pterodactyl so I could experience flight as well as move around more efficiently. Riding a brontosaurus would be thrilling because of their size but less practical than a pterodactyl. So, okay. Do you know why dinosaurs are extinct?

U: yeah cause i’m eat your head it right

A: Ah nice, you must be super smart. Let me tell you what I heard. The mass extinction of dinosaurs is a scientific mystery, but most hypotheses include an extraterrestrial impact or a massive bout of volcanism. What do you think happened?

U: i’d say aliens

A: I’d like to hear your ideas on this. Let’s say you are trapped on Jurassic World alone with the dinosaurs, what would you do to survive?

U: i’m not sure i just say find sheltering something and start there

A: It’s a hard question! I would try to become closer to the younger dinosaurs so that they would grow up with me and feel more comfortable with me. I would also try to help them by finding food and shelter for them. At any rate, Dinosaurs had a lot of different ways to attack other dinosaurs and to defend themselves. To help fight meat eaters such as the Allosaurus or Spinosaurus, many plant eaters had natural weapons at their disposal.

Table 6: An example conversation about Dinosaurs, one of our more niche topics. We use a variety of different miniflows to increase our topical depth. “A” denotes Athena and “U” the user turns.

A: One thing that really interests me is people’s hobbies. Can you give me some info about swimming?

U: it’s pretty fun

A: Right? Sounds totally tubular. Why do you like swimming?

U: it’s because i can kind of just feel like i can move around and do a lot of stuff i can’t do on land

A: Cool! How did you first get started with swimming?

U: i took swimming lessons

A: I realize you might be totally in love with swimming, but I’m curious. Is there any part of the hobby you don’t like?

U: tough lessons

A: Well swimming sounds interesting, thanks for telling me all about your hobby. A lot of people have cool hobbies, but what about me? What kind of hobby do you think I would like?

U: maybe writing

A: Alright. Why do you think writing is a good fit for me?

U: because you like expressing yourself seems like

A: Ok. I see. Do you need any special equipment or skills to get into writing?

U: just paper and pen and imagination

A: I see. Thank you for recommending writing to me, I’ll try to find out more about the hobby in the future!

Table 7: An example of Athena engaging the user about their hobby, swimming, which we previously learned about in the Introduction RG. “A” denotes Athena and “U” the user turns.