Jurassic is (almost) All You Need: Few-Shot Meaning-to-Text Generation for Open-Domain Dialogue

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Abstract One challenge with open-domain dialogue systems is the need to produce truthful, high-quality responses on any topic. We aim to improve the quality and coverage of Athena, an Alexa Prize dialogue system. We experiment with few-shot prompt-based learning, comparing GPT-Neo to Jurassic-1, for the movies, music, TV, sports, and video game domains, both within and cross-domain, with different prompt set sizes (2, 3, 10), formats, and meaning representations consisting of either sets of WikiData KG triples, or dialogue acts. Our evaluation uses BLEURT and human metrics, and shows that with 10-shot prompting, Athena-Jurassic’s performance is significantly better for coherence and semantic accuracy. Experiments with 2-shot cross-domain prompts results in a huge performance drop for Athena-GPT-Neo, whose semantic accuracy falls to 0.41, and whose untrue hallucination rate increases to 12%. Experiments with dialogue acts for video games show that with 10-shot prompting, both models learn to control dialogue acts, but Athena-Jurassic has significantly higher coherence, and only 4% untrue hallucinations. Our results suggest that Athena-Jurassic produces high enough quality outputs to be useful in live systems with real users. To our knowledge, these are the first results demonstrating that few-shot semantic prompt-based learning can create NLGs that generalize to new domains, and produce high-quality, semantically-controlled, conversational responses directly from meaning representations.

1 Introduction

One challenge with open-domain dialogue systems is the need to respond to users’ utterances on any topic with high-quality responses. To handle this challenge, a common approach is to use an ensemble of response generators (RGs) and then train a ranker to select from a pool of possible responses [8, 40, 16, 32, 6, 10, 11]. The ensemble of RGs can use a variety of generation techniques. One type of RG generates responses directly from the dialogue context, using a pre-trained model
such as GPT-2 that is possibly tuned on additional conversational data, such as Topical Chat or Empathetic Dialogues\cite{Li2020}. Knowledge-Grounded response generation is a variant of this approach, where knowledge in the form of text is available during generation to control the utterance content and veracity\cite{Reed2021}. Template-Based RGs are also quite common, where templates are hand-written and then populated with values from a database or knowledge graph (KG).

We are primarily interested in Meaning-to-Text (M2T) NLG engines, where the desired meaning is specified and the NLG engine produces one or more utterances that express that meaning. These can be trained with parallel corpora of meaning representations (MRs) and reference utterances \cite{Yao2020,Reed2020,Choi2020,Choi2020a}, or can be trained by tuning a large language model with a domain specific training set \cite{Sennrich2016,Shah2019,Shah2019a,Shah2019b}. These M2T engines are most often used for task-oriented responses on specific (sets of) topics, such as restaurants, sports, movies, hotels, laptops, TVs, and video games \cite{Reed2020,Choi2020,Choi2020a,Shah2019}.

Recent work on language models as few-shot learners \cite{Brown2020} suggests a novel paradigm for creating a M2T NLG engine with prompt-based learning, where prompts are provided that condition the language model to produce a certain type of output. In our case, these conditioning prompts consist of pairs of meaning representations and their corresponding output. Our aim in this paper is to investigate how prompt-based learning can improve the quality and the coverage of the M2T RGs in Athena, a dialogue system that has been a finalist in the Alexa Prize for the last two years \cite{Li2019,Reed2020}.

There are two types of M2T RGs in Athena. One set are template-based whose MRs are sets of triples from the WikiData Knowledge-Graph (KG-RGs). These KG-RGs cover the movies, sports, music, and TV topics. One advantage of using WikiData is the automatic updates to its knowledge by its editors. Another benefit is the ability to traverse the KG to new relations or entities, to say more things about a topic in a dialogue \cite{Li2019a}. A third benefit is that Athena represents named entities as KG triples, allowing flexible control over their generation.

A1: Do you have a favorite musician?
U1: yeah, Taylor Swift.
A2: Ok, Taylor Swift. Wow! Taylor Swift is very prolific! She has 114 songs, that’s a lot!
(Taylor Swift, numTracks, 114)
U2: yeah, that is a lot
A3: I like Taylor Swift’s song, 22. It came out in 2013. Do you like that song?
(Taylor Swift, song, 22), (22, date, 2013)
U3: yeah, it’s a good one.
A4: Right? This is interesting, Taylor Swift sings the song Bad Blood with Kendrick Lamar, want to hear more about Kendrick Lamar?
(Bad Blood, performer, Taylor Swift), (Bad Blood, performer, Kendrick Lamar)
U4: not really
A5: One of my favorite musicians is P!nk. Isn’t this interesting, P!nk won a Grammy Award for Best Pop Collaboration with Vocals. Do you want to hear more?
(P!nk, award, Grammy Award for Best Pop Collaboration with Vocals)

Fig. 1 A conversation about music between Athena (A) and a user (U). The music KG-RG interweaves template-based utterances based on KG triples with other template-based utterances. Response segments generated using the KG triples are highlighted in orange. For each segment, the KG triples used by the RG as the input MR are shown below the response.
entities and pronouns with their Wikidata IDs, providing a direct link to the KG.

Figure 1 provides a conversation with the Music KG-RG that shows how the knowledge triples from WikiData are realized with templates. The other RG, for the video games topic, is based on the Viggo corpus. This is a parallel corpus of MRs and crowd-sourced realizations. An conversation with the Viggo RG is below in Figure 3.

Both of these RGs require substantial human effort. The KG-RGs require two steps: (1) sets of interesting and frequently populated KG relations must be selected by hand and, (2) templates must be hand-written to realize them. This means that they currently cover a limited set of relations, ones that are populated frequently enough to make writing templates worthwhile. As previous work on dialogue generation has shown, even combinations of existing relations typically require multiple additional templates to be written. The existing KG-RG entities and relations are in Table 1, as well as novel KG-RG relations and entities that we experiment with below with 2-shot prompting.

| Topic  | Entities                          | Relations                  |
|--------|----------------------------------|----------------------------|
| Movies | Movies Actors Directors Awards*  | cast voice Cast spouse children Num genre award director* work* |
|        |                                   | date* screenWriter* producer* |
| Music  | Musicians Bands Awards* Songs*   | performer (song and album) numTracks genre award memberOf |
|        | Albums*                          | instrument label date* show* work* |
| Sports | Athletes Sports Awards*          | team position participant (tournament, leagues) spouse |
|        |                                  | children Num award height date* work* ranking* duration* |
|        |                                  | reviewScoreBy* disciplineCompetedIn* numMatches* numAwards* draftedBy* draftPicknum* startTime* |
| TV     | Shows Assessment* characterRole* | cast role creator director genre award characterRole* |
|        |                                  | narrativeLocation* mainSubject* assessment* |
|        |                                  | assessmentOutcome* hasPart* occupation* derivativeWork* |
|        |                                  | startTime* endTime* filmingLocation* setInPeriod* |
|        |                                  | numSeasons* numEpisodes* |

Table 1 The KG topics, entities and relations in the Athena-KG-synthetic corpus. A * indicates novel entities and relations that are tested in Section 4.

The neural Viggo RG required constructing dialogue acts and meaning representations, populating their content with information from IGDB, crowd-sourcing responses, and cleaning the resulting corpus, in order to experiment with methods for improving the fluency and semantic accuracy responses. Thus the ability to reliably generate high-quality responses directly from MRs via neural NLGs would transform the use of M2T NLGs in dialogue systems.

We utilize Athena’s current RGs to create prompt and test sets for two new neural Meaning-to-Text RGs, Athena-GPT-Neo and Athena-Jurassic. We conduct few-shot prompt-based learning experiments, where we systematically vary within and cross-domain prompts, different prompt set sizes (2, 3, 10), prompt formats, and in accordance with the Alexa Prize rules, the shared conversations in Figure 1 and Figure 3 are between Athena and our team, or UCSC undergraduates, rather than real users.
| Topic | Example |
|-------|---------|
| Movies | (Wonder Woman, director, Patty Jenkins)  
I believe I read that Wonder Woman is directed by Patty Jenkins. Sometimes a director’s unique voice really comes through in their work. Do you think that happened in this case? |
| Music | (Rihanna, record label, Def Jam Records)  
Here’s another musician who worked for the same label Def Jam Records, called Rihanna. Want to hear about them? |
| Sports | (Lebron James, member of sports team, Los Angeles Lakers), (Lebron James, position played on team/specialty, power forward)  
Lebron James has played on many famous teams such as the Los Angeles Lakers, and played many positions like power forward. |
| TV | (Lost, genre, paranormal television program), (Lost, genre, drama television)  
Lost is considered both a paranormal television program and a drama television. What’s your opinion of paranormal television programs or drama television shows? |

Fig. 2 Sets of KG triples used as meaning representations, and the corresponding utterances. Dialogue Act types are not represented in the MRs but note that some KG triples are realized with multiple dialogue acts, combining statements, opinions and questions.

and type of meaning representations. We expect that these NLGs to generalize beyond their conditioning data \([33, 15, 3, 31]\). We evaluate the results using both BLEURT and human evaluation. Our results show that, with 10-shot conditioning, both Athena-GPT-Neo and Athena-Jurassic generally produce coherent outputs, but that for within-domain experiments, Athena-Jurassic’s performance is significantly better for the human evaluation metrics of coherence and semantic accuracy. Experiments with 2-shot prompts on completely novel MRs results in a huge performance drop for Athena-GPT-Neo, whose semantic accuracy falls to 0.41, and untrue hallucination rate increases to 12%. Experiments with the Viggo video games corpus shows that, with 10-shot prompts, both Athena-GPT-Neo and Athena-Jurassic can learn to control the dialogue acts realized, but Athena-Jurassic has significantly higher coherence, mainly because Athena-GPT-Neo produces some redundant and repetitive utterances. Athena-GPT-Neo also produces untrue hallucinations in 12% of the video game outputs. We use the human evaluation to examine whether the BLEURT scores are meaningful with results showing that BLEURT scores have a very good correlation with semantic accuracy, but not with coherence, or other human metrics. Our results suggest that Athena-Jurassic can reliably produce outputs that are high enough quality to be used in live systems with real users. To our knowledge, this is the first paper to show that few-shot prompt-based learning can create NLGs that generalize to new domains, and produce high-quality, semantically-controlled, conversational responses directly from MRs and KG triples.

2 Datasets

We use two datasets for prompt-based learning for Athena’s response generators. One is based on Athena’s KG RGs for the domains of music, movies, sports, and TV.
Figure 2 provides KG triples (entity, relation, entity) and responses produced by the current KG-RGs. Each response is designed to continue the conversation with one or more statements, opinions, and/or question dialogue acts about an entity. However, the MRs represent the triples and do not explicitly represent dialogue acts. Some responses are based on traversing the KG links to a related entity, and introducing that entity, as illustrated in the music example about Rihanna, where the record label Def Jam Records is used to link two music artists. A music conversation was given in Figure 1 above. Both existing and novel KG-RG entities and relations are in Table 1.

To use prompt-based learning to create new KG-RGs, we create a new corpus, Athena-KG-Synthetic, of sets of knowledge triples and their template-based responses. We select five template categories and their paraphrases from the movies RG, two from music, three from sports, and two from TV. We query WikiData for thousands of KG triples to populate the templates and then split the resulting dataset into ~32K train, 3558 development, and a test set of 100 instances for each template category.

The second dataset is the Viggo dataset. The Viggo RG combines responses generated from templates with those generated from meaning representations, as shown in Figure 3. The set of dialogue acts (DAs) are carefully constructed to be conversational and engage the user, rather than being purely informative. We directly use the ViGGO corpus’s training, development and test sets. Each corpus instance uses one of Viggo’s 9 dialogue acts such as verify attribute, request explanation, or recommend. Most DAs are compatible with many combinations of content slots, using 14 video game attributes, yielding hundreds of response types. Figure 4 shows four DAs with various slot combinations.

Viggo and the Athena-KG-Synthetic corpus are available from nlds.soe.ucsc.edu.
confirm(name=[Hellblade: Senua's Sacrifice], release_year=2017, developer=[Ninja Theory])

Oh, do you mean the 2017 game from Ninja Theory, Hellblade: Senua's Sacrifice?

suggest(name=[Half-Life 2], genres=[shooter], player_perspective=[first person])

Do you also enjoy playing first-person shooters, such as Half-Life 2?

give_opinion(name=[SpellForce 3], rating=[poor], genres=[real-time strategy, role-playing], player_perspective=[bird view])

I think that SpellForce 3 is one of the worst games I’ve ever played. Trying to combine the real-time strategy and role-playing genres just doesn’t work, and the bird's eye view makes it near impossible to play.

verify_attribute(name=[Little Big Adventure], rating=[average], has_multiplayer=[no], platforms=[PlayStation])

I recall that you were not that fond of Little Big Adventure. Does single-player gaming on the PlayStation quickly get boring for you?

Fig. 4 Viggo structured MRs (gray rows) and the corresponding reference utterances (with slot mentions in bold). Dialogue Act types are indicated in italics at the beginning of the MRs.

3 Experimental Setup

We utilize the models GPT-Neo and Jurassic-1 jumbo [1, 25]. GPT-Neo is a transformer-based language model that has 1.7 billion parameters. It was created as an open-sourced alternative to GPT-3. Similarly to previous GPT-2 and GPT-3 models, GPT-Neo predicts the next word given the previous words in the text. The team from EleutherAI generated an open source training set, The Pile [12], comparable to that used for GPT models. The Pile is 825GB with data from 22 diverse sources, such as academic sources (Arxiv, PubMed), Github, and Wikipedia. GPT-Neo has a vocabulary size of ~50K tokens. The EleutherAI team provides three models (125M, 1.3B, 2.7B), which were trained as masked auto-regressive models using cross-entropy loss. When compared to the closest GPT-3 model (GPT-3 Ada), GPT-Neo 2.7B had better performance on all linguistic and scientific reasoning benchmarks (Hellaswag, Piqa, Winogrande, MathQA, PubMedQA). We use GPT-Neo 1.3B, which has promising performance for its size.

Jurassic-1 is also an auto-regressive transformer-based language model, that achieves state of the art performance on a set of common sense and QA zero-shot and few-shot tasks [25, 48, 38]. AI2 Labs has released two versions, J1-large with 7.5B parameters and J1-jumbo with 178B parameters. Jurassic-1 is pre-trained with 300B tokens taken from publicly available resources, and has a larger vocabulary than other similar models with

3 Experiments with GPT-2-small showed that models tuned with the ~32K train did not generalize to unseen relations within the tuning domain, such as from the director to the screenwriter relation, nor did these models generalize across domains.

| PROMPT | confirm = yes | name = Tony Hawk’s Pro Skater 3 | release_year = 2001 | genres = sport |
|--------|---------------|-------------------------------|--------------------|----------------|
| SENTENCE | Gotcha! So you’re referring to the Tony Hawk’s Pro Skater 3 sports game, which was released in 2001? |
250K tokens. Jurassic-1 has a larger vocabulary by including n-gram phrases as tokens along with the standard unigram and subword tokens. Jurassic-1’s architecture attempts to optimize the Jurassic’s depth-width tradeoff [24, 25]. The paper claims that Jurassic-1 can predict text from a broader set of domains than GPT-3, and is superior to GPT-3 in few-shot settings, due to its ability to fit more examples into a prompt. We use temperature = 0.7 to promote interesting and varied output: the effect of temperature is illustrated in Figure [6] by the multiple outputs.

We have two large datasets (Section [2]), but we focus on GPT-Neo and Jurassic-1 few-shot (2, 3, 10) experiments, for two prompt formats, since format matters for Jurassic-1 [25]. In the QA format in Figure [5], the prompt instances consist of input MRs marked as the prompt and the response marked as sentence. The S2S format in the top of Figure [6] simply separates the MR and text into two lines, with an empty line separating test instances. In Figure [6] the 2-shot conditioning prompts are from the music and movies domains, and the test item is from the restaurant domain. We generate multiple outputs, shown in italics, to illustrate the effect of temperature. All of the outputs are natural and coherent. Only the last output, Babbo restaurant is rated outstanding. I heard they serve great food, fails to realize all the MR attributes, missing eatType=bistro and food=French.

The 2-shot experiments are intended to create a challenging task for testing the models’ ability to generalize. In addition to 2-shot conditioning with the two examples in Figure [6], the test set consists of novel hand-crafted MRs that are currently not in Athena, which in some cases also use rare relations. The goal is to test how well the models do at realizing responses directly from the WikiData KG, without any domain-specific or relation-specific conditioning. Table [6] illustrates a good case of generalization to the restaurant domain. Table [7] shows examples of the novel MRs used in the test set.
indicates with a * those entities and relations corresponding to the novel MRs in our test set, and example novel MRs for each topic domain are in Figure 7.

For evaluation metrics, we use BLEURT along with human evaluation for the following metrics: (1) coherence: makes sense and is natural; (2) semantic accuracy: triples realized divided by total triples for the KG RGs and attributes realized divided by total attributes for Viggo; (3) good hallucinations: additional true information, not specified in the MR, is added to the utterance from the LM’s own knowledge; (4) bad hallucinations: additional false information is added to the utterance from the LM’s own knowledge; (5) dialogue act accuracy: whether the output utterance matches the dialogue act specified for Viggo, exemplified in the outputs in Figure 4; (6) whether a question is added to the end of the response, that was not specified in the MR or by the dialogue act, as seen in the 2nd example output in Figure 6. Remember that no dialogue acts are specified by the MRs for the Athena KG-RGs, but that some of the Viggo dialogue acts, such as suggest typically are realized as questions or include a question. For the 2-shot experiments with the novel MRs, there are no reference utterances and BLEURT scores cannot be calculated, so we use the human evaluation metrics.

It is important to note that BLEURT scores by themselves are not intended to mean anything: they are only useful for comparing models [39]. In addition, BLEURT, like other n-gram scoring metrics, doesn’t account for stylistic variation which is often desirable [29, 17]. Also, previous work shows that the correlation of BLEURT to human ratings of naturalness varies across conversational domains [47]. However, that work was based on crowd-sourced open-domain dialogues where both sides of the dialogue were produced by humans. Here it might be expected that BLEURT would be a good predictor of semantic accuracy. Therefore we use BLEURT as first indicator of a model’s performance and use BLEURT scores to decide whether to perform human evaluation on a model’s output. Then we examine whether the BLEURT scores are highly correlated with the human metrics for coherence and semantic accuracy.

4 Experimental Results

We report results for all the KG-RG topics and for Viggo, with both GPT-Neo and Jurassic-1. The models were also conditioned and tested for both the QA format in Figure 5 and the S2S format in Figure 6. For the KG-RG topics, we also experiment with all possible cross-domain combinations of conditioning and test.

Few-Shot Knowledge-Graph Response Generation. For each topic (movies, music, sports, TV), we randomly select ten instances for conditioning and 50 for testing (200 total). We tune Jurassic-1 and GPT-Neo with each conditioning set and then test each model on all four topics (test on 200) to examine both within and cross-domain few-shot performance. Table 2 provides the BLEURT results for both Athena-GPT-Neo and Athena-Jurassic and for both S2S and QA formats. Rows indicate the conditioning domain, while columns indicate test domains. The diagonal of each subtable reports within-domain performance. The average BLEURT scores over all topics for
Table 2 BLEURT scores for testing within and across domain for Athena-Jurassic and Athena GPT-Neo. Prompt inputs in either S2S or QA format, conditioning on 10 instances of each topic.

As expected, the within-domain results (highlighted in yellow) show that the models perform best when prompts are from their own domain. The best results for in-domain conditioning are for sports, with an average BLEURT score of 0.23 for the S2S format for Jurassic, and 0.26 for the S2S format for GPT-Neo, as well as a 0.21 for the QA format for GPT-Neo. The within-domain performance for the TV domain is also good, with a score of 0.22 for the QA format for GPT-Neo, and a score of 0.17 for Jurassic for the S2S format. Interestingly, sometimes a specific topic’s prompts perform as well or better for another topic than its own (highlighted in turquoise), e.g., GPT-NEO S2S conditioned with TV prompts performs better on movies than TV, and Jurassic QA, when conditioned with music prompts, performs better for TV. This could arise because two domains are similar (TV and movies) or because one domain is easier, e.g., the averages across the columns of each section suggest that TV is easier.

The averages also clearly indicate that, for Jurassic, the S2S format works better, with large differences across all topic columns and topic diagonals, and an overall S2S of -0.34 compared to QA of -0.47 (p < .01). For GPT-Neo, the overall differences between S2S (-0.33) and QA (-0.37) are not significant, and the story is more complex because GPT-Neo QA works well for both TV (0.22) and sports (0.21). The differences between S2S and QA are not significant for TV or movies, but GPT-Neo S2S is significantly better than GPT-Neo QA for music and sports.

A comparison of BLEURT scores for S2S for Jurassic vs. GPT-Neo for each topic, shows that GPT-Neo is significantly better for Movies (p = .007), Jurassic is significantly better for music (p = .005), GPT-Neo shows a trend to be better for TV (p = .07) and there are no differences for Sports (p = .87). However, a paired t-test comparing BLEURT scores across all topics for both GPT-Neo and Jurassic shows that the overall differences are not significant.
Since the overall differences for GPT-Neo S2S are not significantly different than GPT-Neo QA, we focus the human evaluation on comparing Athena-Jurassic to Athena-GPT-NEO for the S2S format. This will allow us to directly compare the human metrics for the two models while the prompt format is fixed. We restrict the annotation to the within-domain testing. We sampled 30 of the 50 test examples for each topic (240 examples). Three experts familiar with Athena labeled each output for coherence, semantic accuracy, good and bad extra information (hallucinations), and whether a question was added to the end of the response (remember that no dialogue acts were specified in the Athena-KG MRs). We also counted the number of words in each output to measure some aspects of the style of the outputs.

Table 3 presents the results for the human metrics, showing that the average coherence (Coher) for Athena-GPT-Neo is significantly lower than Athena-Jurassic (p = .002), as well as the semantic accuracy (SemAcc) (p = .002). Athena-GPT-Neo hallucinates much more (total 33%) than Athena-Jurassic (total 18%). Although 22% of Athena-GPT-Neo’s hallucinations are good, 11% of the utterances include at least one bad hallucination, in addition to failing to realize the semantic triples included in the MRs.

Both models frequently add questions, which can be considered as either a feature or a bug. They are usually quite natural, but the Athena KG MRs do not specify dialogue acts. Thus, there is no way to control whether the questions appear or not. The models use a similar number of words. Still, given the low semantic accuracy of Athena-GPT-Neo, many words in the GPT-Neo outputs must be due to hallucinations.

The human evaluation suggests large differences between Athena-GPT-Neo and Athena-Jurassic in terms of the quality of the output, but there were no significant differences in overall BLEURT scores between GPT-Neo S2S and Jurassic S2S. We therefore test whether BLEURT scores are meaningful proxies for the human metrics of coherence and semantic accuracy, finding that the correlation across all the topics, for each model indicate that BLEURT scores do correlate with semantic accuracy, with a correlation of 0.65 for Athena-GPT-Neo, and 0.46 for Athena-GPT-Jurassic. Coherence is not correlated with BLEURT, with correlations of .02 for Athena-GPT-Neo and -0.05 for Athena-Jurassic.
| ID | Topic | Input MR                                                                 | Output                                                                 |
|----|-------|--------------------------------------------------------------------------|------------------------------------------------------------------------|
| M1 | Movies| (Peter Capaldi, award, BAFTA Award for Best Short Film), (BAFTA Award for Best Short Film, show, 47th British Academy Film Awards), (BAFTA Award for Best Short Film, work, Franz Kafka’s It’s a Wonderful Life) | I think it’s really great when a talented actor wins an award. do you think Peter Capaldi deserved to win a BAFTA Award for Best Short Film in 1980, for Franz Kafka’s It’s a Wonderful Life? |
| M2 | Music| (Kellie Pickler, song, Red High Heels), (Red High Heels, genre, country music) | Kellie Pickler is a country singer, and she’s also a rapper. Do you know her songs? |
| M3 | TV   | (Saturday Night Live, award, Primetime Emmy Award for Outstanding Variety Sketch Series), (Saturday Night Live, date, 2019) | Saturday Night Live won a Primetime Emmy Award for Outstanding Variety Sketch Series in 2019. How does the fact that it got this award affect your opinion of the show? |
| M4 | Sports| (Len Ford, member of sports team, Los Angeles Dons), (Len Ford, position played on team, end) | Did you know that Len Ford has played as a part of famous teams, such as the Los Angeles Dons, and played positions such as end. |

**Fig. 8** Jurassic-1 and GPT-NEO outputs for conditioning with 10 within-domain prompts.

Figure 8 shows examples for the two S2S models for each domain when tuned on within-domain prompts, which illustrate the strengths and weaknesses between models. The Athena-GPT-Neo output for M1 was labeled a 3 for coherence. However, it leaves out the triple (BAFTA Award for Best Short Film, show, 47th British Academy Film Awards). It also includes the bad hallucination that Peter Capaldi is an actor, when in fact he wrote and directed the film. In addition, the 47th British Academy Film Awards honored the best films of 1993, so Peter Capaldi won this award in 1994, not in 1980. The semantic accuracy annotation indicates that 2/3 triples are correct, the output includes two bad hallucinations, and the output includes a question. Similarly, the GPT-Neo output for M2 shows that GPT-Neo knows that Kellie Pickler is a rapper, knowledge that was not included in the MR. This was hand-annotated as a good hallucination. However, this output fails to realize the triple (Kellie Pickler, song, Red High Heels), so semantic accuracy was 1/2 triples.

The Athena-Jurassic output for M3 was labeled as a 3 for coherence, and that it includes a question. The output correctly realizes all the triples so it was marked as semantically perfect (3/3 triples realized). The output for M4 is also labeled as a 3 for coherence. It also correctly realizes all the triples (2/2), which are realized by a Did you know question. This output would
not be annotated as including an additional question since the material in the *Did you know* question is part of the specified content in the MR.

### 2-Shot prompting on Novel Entities and Relations.

We also performed 2-shot experiments using the two prompt instances for movies and music in Figure 9. Because the realizations of each relation or sets of relations requires a template to be written for Athena’s current KG-RGs, Athena has no templates for relations that are sparsely populated. Thus, we test 80 MRs composed of entities, relations, or combinations of relations that are novel to Athena, as indicated by a * in Table 1. We only use the S2s prompt format since the results in Table 2 show that the S2S format is clearly better for Jurassic and there are no differences for GPT-Neo.

Since there are no reference utterances for the novel MRs, BLEURT scores cannot be calculated. Table 4 provides the results of the human evaluation, which indicate stark differences between Athena-GPT-Neo and Athena-Jurassic, reflecting the reduction to 2-shot prompting, and the rareness of the KG relations in the novel MRs. The novel test MRs are also harder for both types of models, but the performance of Athena-GPT-Neo declines more sharply. Compare the mean coherence of 2.58 and semantic accuracy of 0.41 for Athena-GPT-Neo in Table 4 to the mean coherence of 2.83 and semantic accuracy of 0.77 for Athena-GPT-Neo in Table 3. Then compare the mean coherence of 2.80 and semantic accuracy of 0.72 for Athena-Jurassic in Table 4 to the mean coherence of 2.96 and a semantic accuracy of 0.89 for Athena-Jurassic in Table 3. When testing with the novel MRs, Athena-GPT-Neo only adds questions 7% of the time, but Athena-Jurassic maintains a higher level and adds questions 47% of the time. When testing with the novel MRs, GPT-Neo hallucinates bad information in 12% of turns, while Jurassic only does so in 4% of turns. This supports the claim by Lieber et al. that Jurassic should generalize better [25].

Figure 10 provides novel MRs and outputs for all four topics for both Athena-GPT-Neo and Athena-Jurassic, that illustrate the differences between the models. In N1, Athena-GPT-Neo produces a coherent and semantically accurate utterance about *The Black Cauldron* that includes a bad hallucination of Stephen King as the author, when Lloyd Alexander is the author. In N2, Athena-GPT-Neo again produces a coherent utterance, but the content of that utterance doesn’t include any of the triples in the MR, only matching the name of the singer, Dua Lipa. In N3, the output is again coherent, but it fails to realize the triple (James Roday, character role, Shawn Spencer). Example N4 illustrates how GPT-Neo sometimes produces redundant or logically inconsistent outputs, where here it says the same thing about Tom Brady twice, but sometimes it repeats itself many times, e.g. *Friday Night Lights is a movie about a small town in Texas that is run by a family of criminals. The town is run by a family of criminals. ...(4 times)*. In other cases, Athena-GPT-Neo contradicts

| Model      | Coher | SemAcc | GoodH | BadH | AddQ |
|------------|-------|--------|-------|------|------|
| Athena-GPT-Neo | 2.58  | 0.41   | 15%   | 12%  | 7%   |
| Athena-Jurassic | 2.80  | 0.72   | 13%   | 4%   | 47%  |

Table 4 Human evaluation for 2-shot Novel Athena-Jurassic vs. Athena-GPT-Neo, prompted with S2S format.
| ID | Domain | Input MR | Output |
|----|--------|----------|--------|
| N1 | Movies | (The Black Cauldron, genre, film based on literature) | The Black Cauldron is a film based on the novel of the same name by Stephen King. |
| N2 | Music | (Dua Lipa, award, Grammy Award for Best New Artist), (Grammy Award for Best New Artist, show, 61st Annual Grammy Awards) | Dua Lipa is a singer-songwriter from the Philippines. She is known for her hit songs “I’m Not the One” and “I’m Not the One (Remix)”. |
| N3 | TV | (Psych, cast member, James Roday), (James Roday, character role, Shawn Spencer) | I heard James Roday starred in a good movie, called Psych. |
| N4 | Sports | (Tom Brady, award, Associated Press Athlete of the Year), (Associated Press Athlete of the Year, date, 2007) | Tom Brady is the most valuable player in the NFL. He is also the most valuable player in the NFL. |
| N5 | Movies | (Ghost Rider, producer, David S. Goyer) | Have you heard of a movie called Ghost Rider? I heard it was produced by David S. Goyer. |
| N6 | Music | (Adele, award, Grammy Award for Song of the Year), (Grammy Award for Song of the Year, show, 54th Annual Grammy Awards), (Grammy Award for Song of the Year, work, Rolling in the Deep) | Adele won an award for Song of the Year at the 54th Annual Grammy Awards. Do you like her song Rolling in the Deep? |
| N7 | TV | (Elementary, assessment, Bechdel test), (Bechdel test, assessment outcome, passes) | Elementary passes the Bechdel test because at least two of the named women talk to each other about something other than a man. |
| N8 | Sports | (Usain Bolt, record held, Men’s 100 metres world record progression), (Usain Bolt, race time, 9.58 seconds), (Usain Bolt, start time, 2009) | Usain Bolt holds the record for the men’s 100 metres. He broke the previous record, which was 9.69 seconds, at the 2009 World Championships in Berlin, Germany. |

Figure 10: Sample outputs for novel unseen relations and entities for both Jurassic-1 and GPT-Neo itself. There are no examples from Athena-Jurassic that are redundant or logically inconsistent. In future work, these categories could be added to the human metrics, even though they happen rarely.

Figure 10 also shows that Athena-Jurassic’s 2-shot outputs are remarkably good. In N5, the output is coherent, semantically correct and stylistically interesting. In N6, all three triples are realized correctly, and the last triple is embedded into a question, which seems very natural. In N7, Athena-Jurassic realizes all the content in the MR, but also produces a good hallucination, defining what the Bechdel tests actually is. In N8, Athena-Jurassic seems to know a lot about Usain Bolt: it does not actually realize the triple (Usain Bolt, race time, 9.58 seconds), but provides the race time for the previous record, and produces a good hallucination of the event that this happened at, namely the 2009 World Championships.
Few-Shot Response Generation for Viggo Video Games. We also experiment with few-shot prompt conditioning with the Viggo corpus, with a focus on the realization of dialogue acts. Athena KG MRs do not specify the dialogue act, and thus its use of questions cannot be controlled. The dialogue acts in Viggo are shown in Figure 3 and Figure 4. The Viggo experiments compare prompt conditioning with GPT-Neo and Jurassic, for both S2S and QA formats, and compares 3-shot conditioning to 10-shot conditioning per dialogue act. All experiments use a randomly selected set of 100 Viggo test items.

Table 5 provides the BLEURT scores for these prompting variations. The QA row in Table 5 for 3-shot conditioning suggests that the QA format performs better for 3-shot than the S2S format. However for 10-shot conditioning, S2S is better for both GPT-Neo and Jurassic. The BLEURT scores for Athena-Jurassic for 10-shot conditioning are clearly much better than any of the other results.

Table 6 provides the results of the human evaluation showing that Athena-GPT-Neo does better at matching the dialogue acts (DA) and achieves higher semantic accuracy (0.83) than Athena-Jurassic. However, overall the results are good for controlling dialogue acts. Table 6 also shows however that the coherence of Athena-GPT-Neo is poor compared to Athena-Jurassic. Athena-Jurassic demonstrates the knowledge that Jurassic-1 has about video games by producing far more good hallucinations (29%), while only producing 2% of bad hallucinations, as compared to the 12% of bad hallucinations by Athena-GPT-Neo.

Sample outputs for both Viggo models are shown in Figure 11. Both models produce good outputs much of the time. The low coherence of Athena-GPT-Neo primarily arises from redundancy of repeating the same information twice. Compare example V1 to example V3. Both models get the dialogue act of confirm correct. However, the Athena-Jurassic output in V3 is more varied and interesting and includes all the attributes specified in the MR. The Athena-GPT output in V1 misses out the release year attribute, and uses an odd phrasing that has got a sports genre that results in a lower coherence score. Example V2 illustrates Athena-GPT-Neo’s knowledge about video games, with a good hallucination that it is rated E for Everyone, and that means that it can be played with younger siblings. Example V4 illustrates Athena-Jurassic failing to realize some of the MR attributes, such as the availability on Steam and the full name of the game. However, the language is again very natural, e.g. that’s a huge plus for me.
| ID | Input MR                                                                                                                                                                                                 | Output                                                                                                                                                                                                 |
|----|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| V1 | confirm = yes, name = Tony Hawk’s Pro Skater 3, release_year = 2001, genres = sport                                                                                                                        | You mean the Tony Hawk’s Pro Skater 3 that has got a sport genre?                                                                                                                                       |
| V2 | give_opinion = yes, name = Might & Magic: Heroes VI, rating = average, player_perspective = bird view, platforms = PC                                                                                       | Might & Magic: Heroes VI is a solid game. I like that it has a multiplayer and, since it’s only rated E (for Everyone), I can play it with friends and younger siblings.                                    |
| V3 | confirm = yes, name = Tony Hawk’s Pro Skater 3, release_year = 2001, genres = sport                                                                                                                        | Gotcha! So you’re referring to the Tony Hawk’s Pro Skater 3 sports game, which was released in 2001?                                                                                                  |
| V4 | give_opinion = yes, name = Sid Meier’s Civilization V, rating = good, available_on_Steam = yes, has_linux_release = yes                                                                                       | 4X games can be really fun to play, and Civilization V is a pretty good example. It also happens to be available on Linux, and that’s a huge plus for me.                                                 |

Fig. 11 Viggo outputs with 10-shot conditioning per dialogue act for QA prompt format

5 Conclusion

We used prompt-based learning to create new neural models for semantically-controlled meaning-to-text (M2T) natural language generators (NLGs) to improve the quality and the coverage of the M2T response generators in Athena, an open-domain dialogue system that has been a finalist in the Alexa Prize for the last two years [16, 28]. A major challenge for such systems is the need to produce truthful, high-quality responses on any topic. We created Athena-GPT-Neo and Athena-Jurassic using GPT-Neo [1], and Jurassic-1 [25], by experimenting with few-shot (2, 3, 10) prompt-based learning for Athena’s knowledge-graph domains of movies, music, TV, sports and with the Viggo corpus’s dialogue act-based MRs for video games. We also experimented with multiple prompt formats and with testing both within and across-domain. The ability to create NLGs that generate high-quality responses directly from MRs via few-shot prompt conditioning will greatly facilitate the use of M2T NLGs in dialogue systems. To our knowledge, these are the first results demonstrating that few-shot prompt-based learning can create M2T NLGs that generalize well to new semantic domains.

Athena-Jurassic produces high-quality, semantically-controlled, conversational responses directly from MRs and KG triples. These results confirm the choice that the Jurassic-1 creators made to use a larger vocabulary with phrasal tokens, and less depth and more width, in order to create a model that generalizes better [25, 24]. Our results show that both Athena-GPT-Neo and Athena-Jurassic generally produce coherent output with 10-shot within-domain conditioning, but that Athena-Jurassic is significantly better for both coherence and semantic accuracy. While we have not tested whether real-time response generation is possible, we believe the responses are generally of high enough quality to be used in settings with real human users,
such as the Alexa Prize [11, 28, 15]. We plan to do additional experiments with Viggo in order to improve its performance to the level required [21].

We also showed that Athena-Jurassic performs well with 2-shot conditioning, using completely novel sets of KG triples with unseen relations and entities. These novel MRs are not currently included in Athena, because the relations are rare, and creating templates for novel relations or sets of relations is typically not worth the human effort [35, 34]. For example the MR in M4 in Figure 7 describes the event of Muhammed Ali lighting the Olympic torch in 1996, a rarely populated event for the athlete entity type. Athena-Jurassic achieves a semantic accuracy of 2.72 out of 3 for MRs like this in our challenging 2-shot setting.

In experiments with the KG response generators in Athena, we found that in almost half the responses, Athena-Jurassic adds questions to the end of the response, which are typically quite natural. However the use of questions cannot be controlled because the KG-RG meaning representations do not specify dialogue acts. Thus we also experimented with few-shot conditioning for controlling dialogue acts using the MRs in the Viggo video games corpus. We showed that both Athena-GPT-Neo and Athena-Jurassic can learn to control dialogue acts with 10-shot conditioning per dialogue act. However again, Athena-Jurassic performs significantly better on the human metrics of coherence and semantic accuracy. Interestingly, often Athena-GPT-Neo successfully produces the form or syntax of the dialogue act, e.g. a verify-attribute dialogue act, while getting very few of the MR attributes correct. For example, Athena-GPT-Neo produces You said you liked Assassin’s Creed Chronicles: India. Do you think it would have been better to make it a single-player only game? when the reference utterance is So I know you said you hated Assassin’s Creed Chronicles: India. Do you think all of Climax Studios side view games are as bad?. Here, Athena-GPT-Neo only gets the name attribute correct, and misses the attributes that it is single-player, the user-rating is poor, and the developer is Climax Studios.

We also presented automatic evaluation results using BERT for cross-domain testing. Some of the BERT results are very good, and suggest that cross-domain 10-shot conditioning can also produce high quality utterances. Our results also show that BERT scores have good correlation with the human metric of semantic accuracy, but not coherence. Future work should evaluate these cross-domain results with human metrics. It would also be valuable to experiment with the large number of recently proposed automatic evaluation metrics to test whether there are better metrics than BERT for doing automatic evaluation in this task setting [19, 47]. Many recently proposed automatic metrics rely on evaluating outputs within a dialogue context, which typically is not available in M2T NLG experiments. However there are also novel reference free metrics that could be tested in this setting.

There are many other possibilities with both the WikiData knowledge graph RGs and with corpora such as Viggo for prompt-based learning and testing regimes that we have not yet experimented with or fully evaluated. We also plan to carry out future experiments on a number of other challenging problems for NLG [37, 29, 30, 17].
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