SURVEY OF NATURAL ANSWER GENERATION: FACTOID TO FULL-LENGTH ANSWER

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ABSTRACT

In Question Answering domain, to present the user with a more conversational experience the task of generation of "full length answer" from factoid answer becomes very important. In recent years, the task of Question Answering over passages (reading comprehension) has evolved into a very active research area. A reading comprehension system extracts a span of text, consisting of named entities etc., which serve as the answer to a given question (known as "factoid answer"). However, these spans of text would result in an unnatural reading experience to user in a systems like chatbots and speech assistants. Usually, dialogue systems solve this issue by using template-based language generation. These systems, though adequate for a domain-specific task, are too restrictive and predefined for a domain-independent system. This report talks about the existing approaches used to solve the above task of natural answering.

1 Introduction

Factoid question answering (QA) is the task of extracting answers for a question from a given passage. These answers are usually short spans of text, such as named entities, dates, etc. Modern factoid QA systems which use machine comprehension datasets, predict the answer span from relevant documents using encoder-decoder architectures with co-attention. Conversely, knowledge-base (KB) oriented QA systems retrieve relevant facts using structured queries or neural representation of the question. Formulating the retrieved factoid answer into a full-length natural sentence is, hence, a natural extension and post-processing step of any QA system. A simple approach for this task might be to use hand-crafted rules to restructure the question into a declarative statement. However, such rule based approaches fail when the extracted answer span, contains words from the question or when there are multiple independent clauses and the system has to choose words specific to the question to formulate the answer. This leads to unnatural repetition of words in the full-length answer or grammatically incorrect sentence formulation. On the other hand, neural-network based approaches in modern dialogue systems use end-to end encoder-decoder architectures to convert an abstract dialogue action into natural language utterances. Such modern task-oriented dialogue systems usually learn to map dialogue histories to system response. Non-task oriented dialogue systems such as generative systems can formulate responses not present in the training data but lacks the capability to incorporate factual information without external knowledge bases.

2 Motivation

Applications like task-oriented conversational agents or chatbots often rely on QA systems to return factually correct responses to queries, but need to generate Natural Language Responses. Current QA systems usually return an answer span in the available context, or a Knowledge Base fact triplet (Subject, Predicate, Object). Using existing state-of-the art QA systems to generate full length natural responses is a natural extension of such systems. Exploration of hybrid neural approaches using abstractive & extractive techniques simultaneously and rule based systems using constituency and dependency parse of the question. Unlike conversational chat-bots designed to mimic human conversation without the need to be factually correct, or task-oriented dialogue systems which place the retrieved answer in a predefined template, our system automatically generates accurate full-length answers, thereby, enhancing the system's usage in these situations. This system can be used in any such task-specific scenarios where natural answers are desired, by a hybrid system which combines template based answer with the neural based response which are not restricted to a limited set of templates.

3 Problem Statement

Generate a response template (Natural answer) i.e generate a full length answer given a question and its factoid answer as input. Example :-

- Sample Input:
  - Question : When were the normans in normandy?
  - Factoid Answer : 10th and 11th centuries
- Output: Any 1 of the 2 below
  - During the **10th and 11th centuries** , the normans were in normandy.
  - The normans were in normandy during the **10th and 11th centuries**.

Question *: Who was the duke in the battle of hastings ?*
Factoid answer *: william the conqueror*
Target *: [The duke in the battle of hastings was william the conqueror. , William the conqueror was the duke in the battle of hastings.]*

There has been a lot of interest recently in QA and task-oriented dialogue systems. End-to-end memory networks use a language modelling architecture which learns query embeddings in addition to input and output memory representations from source sequences and predicts an answer. Rule based systems such as ((Weston et al., 2015)) sets up a variety of tasks for inferring and answering the question. Some improvement on the memory networks is based handles out-of-vocabulary (OOV) words by inserting special words into the vocabulary for each knowledge base entity types. These systems are dependent on templates or special heuristics to reproduce facts. We demonstrate through our baseline model that generating template-like sentences from factual input can be achieved with limited success. Recent works on KB-based end-to-end QA systems such as (Yin et al., 2016), (He et al., 2017), (Liu et al., 2018) generate full-length answers with neural pointer networks (Gulcehre et al., 2016) after retrieving facts from a knowledge base (KB). Dialogue systems such as (Lian et al., 2019) (Liu et al., 2018) extract information from knowledge bases to formulate a response. Systems such as (Fu and Feng, 2018) uses KB based key-value memory after extracting information from documents or external KBs. However, these systems are restricted to only information modeled by the KB or slot-value memory. Our system, is generic and can be used with any knowledge source, structured such as a knowledge base or free form such as machine-comprehension dataset. Since our system doesn't use any additional relational information as modelled in a KB, it is invariant to the type of dataset. The pointer generator network, introduced in (See et al., 2017), is a generative summarization model that can copy out-of-vocabulary (OOV) words from a source sequence. Our work is inspired from the ability of this network to accurately reproduce information from source. To the best of our knowledge, there is no existing QA data-set which addresses the task directly. However, Knowledge-based QA dataset such as (Yin et al., 2016) creates a knowledgebase from Chinese websites and extracts questionanswer pairs from Chinese communityQA webpage. The system built over this dataset, is able to generate natural answers to simple questions. The recently released CoQA dataset (Reddy et al., 2019) is an abstractive conversational question answering dataset through which the system generates free-form answers from the whole conversational history using the aforementioned pointergenerator network. While the CoQA challenge extracts free-form text from the passages, our system incorporates the structure of the question to give a full-length sentence as answer to the given query.

4 Introduction of Recent Summarization and Machine Translation techniques used in Neural Natural Answer Generation

Recently due to the success of neural networks, various newer approaches using deep neural networks are getting proposed. Along with summarization, Machine Translation(MT) is also getting discussed. In machine translation, input text presented in one language is converted to another language. Like summarization, machine translation also makes use of language interpretation and generation modules. One of the groundbreaking approaches of MT is presented in section 2.1.1 proposed by (Bahdanau et al., 2016). On top of the basic idea presented in the approach of Neural Machine Translation(NMT), various other approaches were proposed, summarization using sequence-to-sequence RNN is one of them. Recurring Neural Network(RNN) is an advanced form of feedforward neural network, where the neuron is used to train recursively in a single pass of training and such multiple passes can be used to train the model. Enhancements are made to the Sequenceto-Sequence(S2S) models by adding the notion of attention. Attention allows the model to search for a specific location to learn from. Neural Attention Model for Sentence Summarization as explained in section 2.1.2 is one of such models. Finally, we describe pointer-generator network model (See et al., 2017) in section 2.2 for text summarization, which enhances attention model by probabilistically choosing between generation and extraction.

4.1 Basic Neural Machine Translation (NMT)

Jointly Learning to Align and Translate is an approach to the neural machine translation, where input available in one language is translated to target language. The Natural language Generation (NLG) as can be used to perform task of translation. In this section, we describe the translation using deep neural network approach. The notion of alignment captures the mapping between word generated as part of the output and the words present in the source sentence whereas translation has usual meaning of converting from source language to target language. Traditional NMT approaches haven't captured the alignment part and they were working at phrase level, whereas (Bahdanau et al., 2016) works at sentence level meaning that at a time single sentence gets translated to the target sentence.

- **Background:** There are three basic steps in any type of encoder-decoder model. For each step, various parameters need to be learnt. Method of learning parameter is highly dependent on the objective function that the model tries to learn.
  - **Encoder State:** Model encodes input sequence in a suitable format, in case of NMT each word in input sentence is represented using fixed length vector which is also called as the embedding of the word. Embedding can be seen as a representation of word the in the continuous space. Word2Vec, Golve are two widely used embedding techniques.
  - **Hidden State:** This is a black box step, where encoded input is transformed to produce output of same length as the input. Simply length of vector produced by hidden state is same as the length of the column of embedding matrix. Number of hidden steps varies as per the suggested model.
  - **Decoder State:** Decoder step reverses the process done by the encoder step and generat word on the basis of its embedding.

4.2 Neural Attention model of summarization

It is also called as Attention Based Summarization(ABS) (Rush et al., 2015). It tries to make use of the linguistic structure for generation of summaries, for that it captures the attention in input sequence to produce correct output. This is an extension to the model presented in section 2.1.1 and successor of this model is presented in section 2.2. The approach presented in the paper (Rush et al., 2015) is of abstractive sentence summarization which takes sentence as input and converts it into a condensed form. This approach can be further extended to produce summary of documents. The approach proposed makes use of basic feedforward neural networks and generates probability distribution over output sequence. Encoder takes input words and already generated words as input and transforms this using feature matrix.To train the model negative log likelihood objective function is used and to generate the summary sentence. In decoder beam search algorithm is proposed, as complicity of greedy algorithm is exponential in terms of the window.

5 Pointer-Generator Network

Recent summarization approaches discussed so far tries to generate the summaries irrespective of correctness of factual data and without considering novelty of information in produced summary. Abstractive summarization proposed in this paper (See et al., 2017) tries to overcome these shortcomings along with handling of OOVs. The author discusses three approaches (1)Baseline model (section 2.2.1) (2)Pointer generator model (section 2.2.2)

5.1 Baseline Sequence-to-Sequence Attention model

This section discusses the baseline Sequence-to-Sequence Attention model for Abstractive Summarization . Proposed baseline uses single bidirectional LSTM as encoder and single layer unidirectional LSTM as decoder. This baseline model is depicted in figure 1 from which it gets clear that the word beat gets generate based on present context of sentence. Let encoder hidden states be h_i and decoder hidden states be s_i then attention distribution at time-step t can be formulated as shown in equation 2.1 and 2.2 where $v, W_h, W_s$and b_a are learnable parameters.

$$e_i^t = v^T tanh(W_h h_i + W_s s^t + b_a) \tag{1}$$

$$a_t = softmax(e_t) \tag{2}$$

Attention can be considered as the location to produce next word from. Attention is used to get weighted sum of hidden state which represents overall hidden state h. This hidden state along with hidden state of decoder then used to probability distribution P_v over all words in vocabulary.

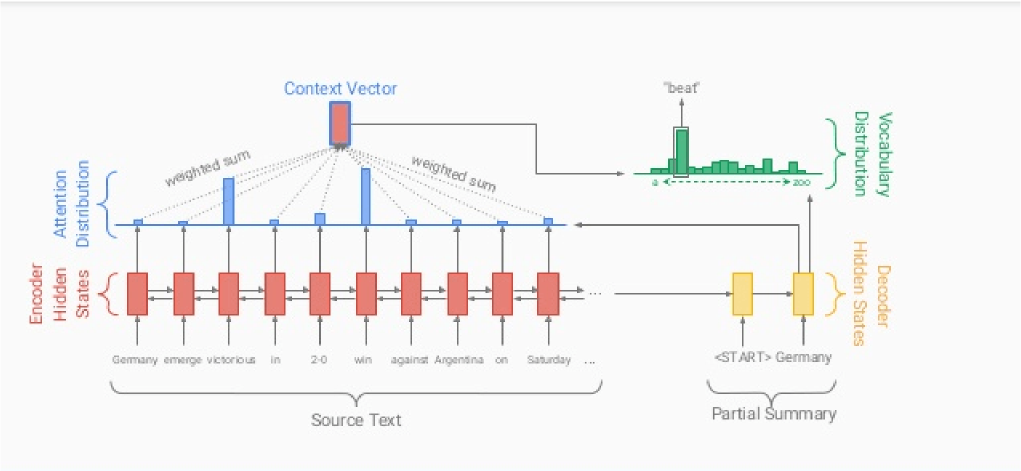


Figure 1: Baseline Sequence-to-Sequence Attention model for Abstractive Summarization (See et al., 2017)

5.2 Pointer-Generator Network

This is hybrid model which combines the baseline model and the model of pointer network proposed in Vinyals et al., 2015. Pointer generation model tries to handle OOVs either by copying from input text or by generating from decoder vocabulary. Figure 2 describes use of working of pointer-generator model.

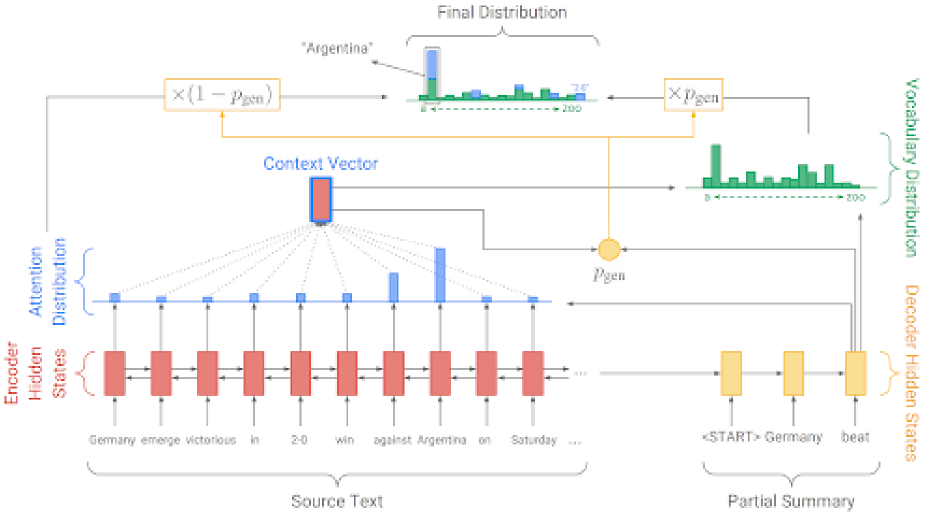


Figure 2: Pointer-Generator Model for Abstractive Text Summarization (See et al., 2017)

The proposed model switch is modelled as continuous variable between range [0, 1]. The authors call this is a soft switch and a function is used to decide between generation and pointer mechanism. The notion of extended vocabulary which is a combination of vocabulary and all words appearing in the input text. When w happens to be OOV, P_v becomes zero and in case of non-appearance in source document, attention term becomes zero. Negative log-likelihood is used as loss function to train the model and learn the parametes.

6 Transformer based Natural Language Generation for Question Answering (Akermi et al. (2020))

The work presented in Pal et al. (2019) and Akermi et al. (2020) tried to tackle this task of Natural Answer Generation for QA by proposing a supervised approach and unsupervised approach respectively. In Pal et al. (2019) the model was trained on a small data set whose questions/answers pairs were extracted from machine comprehension data-sets and augmented manually which make generalization and capturing variation very limited. In Akermi et al. (2020) they have used syntactic parser to form rules to get fragments useful for the formation of natural answer. They assume that only one word could be missing and it should be located before the factoid answer within the identified structure. This assumption cannot be generalized and can lead to incomplete answers with grammatical errors.
The work in Akermi et al. (2020) used Cutting edge transformers Language models to solve this task. Also to predict this missing word, they use BERT as the generation model (GM) for its ability to capture bidirectionally the context of a given word within a sentence. Their assumption was that one word could be missing and that it is located before the short answer within the identified structure, as it could be the case for a missing article (the, a, etc.) or a preposition (in, at, etc.) for example.

The following example illustrates the different steps of the approach proposed in Akermi et al. (2020):

Question: When did princess Diana die?

1. Question parsing and answer extraction using state of art machine comprehension system: short answer = August 31, 1997
2. Chunking the question into text fragments using the UDPipe based dependency analysis: Q=When, did die, princess Diana
3. Removing question marker fragment (when) and updating the verb tense and form using a rule-based approach that we have defined: Q=died, princess Diana
4. Adding the short answer: Q=died; princess Diana; August 31, 1997
5. Generating the set of possible answer structures S: S=died princess Diana August 31, 1997; . August 31, 1997 died princess Diana; . princess Diana died August 31, 1997; . . . .
6. Evaluating the different answer structures using a LM: Best Structure = princess Diana died August 31, 1997
7. Generating possible missing word for structure with BERT: Princess Diana died [missing word] August 31, 1997 (missing word = on)

Answer: Princess Diana died on August 31, 1997.

7 Modified Pointer Generator Approach

In this chapter we will study about the modified Pointer Generator Approach used to solve the task of converting factoid answer to a full length answer proposed by (Pal et al., 2019) . We will discuss about the architecture details of the approach and discuss how exactly pointer generator is used to solve this task. We will also discuss some results of this approach and talk about error analysis of this model towards the end of this chapter

7.1 Architecture

The problem of generating full-length answer from the question and the factoid answer was framed into a Neural Machine Translation (NMT) task using two approaches. We built a model based on the pointer-generator architecture described in (See et al., 2017) except we use two encoders on the source side to encode question and factoid answer separately as shown in Figure 3. Let the question be represented by words $Q = q_1, q_2, ..., q_n$. Let the factoid answer be represented by words $A = a_1, a_2, a_3, ..., a_m$. The question and answer sequence are encoded using two 3-layered bidirectional LSTMs which share weights. This produces two sequences of hidden states

$$h_Q^t = BILSTM(h_Q^{t-1}, q_t) \tag{3}$$

$$h_A^t = BILSTM(h_A^{t-1}, a_t) \tag{4}$$

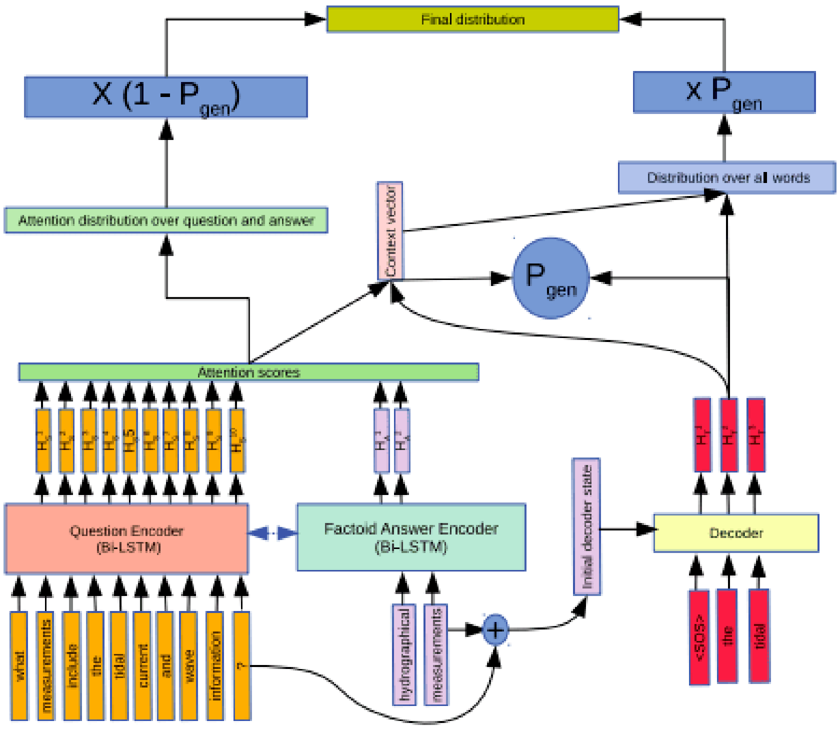


Figure 3: The 2 encoder pointer generator uses the question and factoid answer as input to generate a full-length answer in an end-to-end learning environment.

Figure 3: Modified Pointer Generator Architecture (Pal et al., 2019)

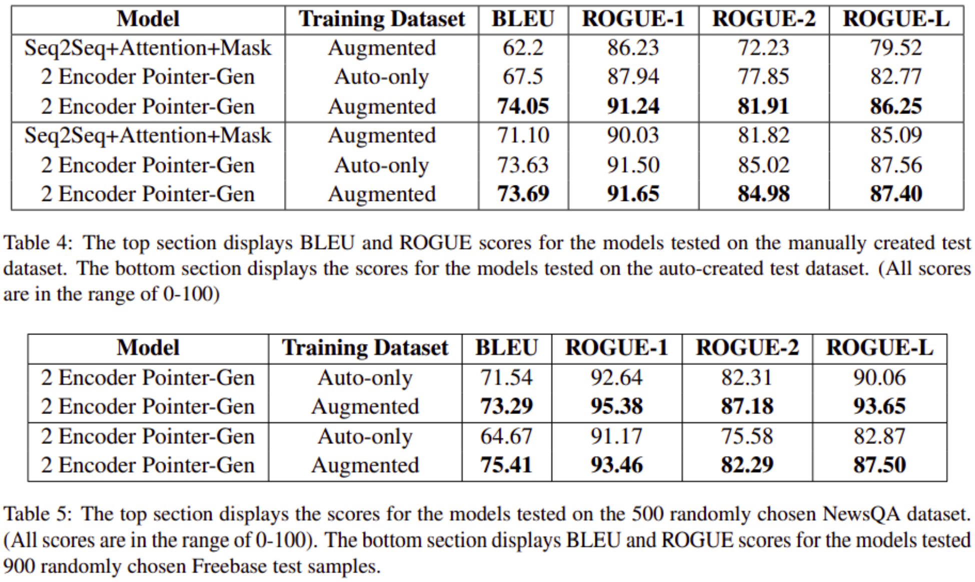
We choose to encode the source sequences separately, since there is no syntactic connection between the question and the factoid answer. We then stack together the encoded hidden states of the 2 encoders to produce a single list of source hidden states, $h_S = [h_Q; h_A]$. The decoder is initialized with the combined final states of the two encoders as

$$h_T^0 = h_A^m + h_Q^n \tag{5}$$

The challenge to correctly reproduce factual information in the full-length answer led us to use copy attention from the pointer generator network as described in (See et al., 2017). The copy distribution, using an extended vocabulary comprising of source words, will capture the probability of replicating words from either the question or answer, whereas the global attention distribution has the ability to generate new words from the vocabulary. The final probability of predicting a word is as follows:

$$P(W_{final}) = p_g P_{gen} + (1 - P_g) P_{copy} \tag{6}$$

Above is the final probability of generating a word . For out-of-vocabulary words which are present only in the source and for w belongs to V , only P_{copy} is used predict the word. These words are usually factual information from the question or answer, such as dates and named entities and hence needs to be copied exactly as it appears in the source sequences. Prepositions, conjunctions and other placeholders, such as $at, between, in,$ which help in combining the question and answer sequences are usually in-vocab words not present in the source are predicted with P_{gen}. For in-vocabulary words which are present in the source, the final probability of predicting the word uses both the terms of above equation.



Model	Training Dataset	BLEU	ROGUE-1	ROGUE-2	ROGUE-L
Seq2Seq+Attention+Mask	Augmented	62.2	86.23	72.23	79.52
2 Encoder Pointer-Gen	Auto-only	67.5	87.94	77.85	82.77
2 Encoder Pointer-Gen	Augmented	**74.05**	**91.24**	**81.91**	**86.25**
Seq2Seq+Attention+Mask	Augmented	71.10	90.03	81.82	85.09
2 Encoder Pointer-Gen	Auto-only	73.63	91.50	85.02	87.56
2 Encoder Pointer-Gen	Augmented	**73.69**	**91.65**	**84.98**	**87.40**

Table 4: The top section displays BLEU and ROGUE scores for the models tested on the manually created test dataset. The bottom section displays the scores for the models tested on the auto-created test dataset. (All scores are in the range of 0-100)

Model	Training Dataset	BLEU	ROGUE-1	ROGUE-2	ROGUE-L
2 Encoder Pointer-Gen	Auto-only	71.54	92.64	82.31	90.06
2 Encoder Pointer-Gen	Augmented	**73.29**	**95.38**	**87.18**	**93.65**
2 Encoder Pointer-Gen	Auto-only	64.67	91.17	75.58	82.87
2 Encoder Pointer-Gen	Augmented	**75.41**	**93.46**	**82.29**	**87.50**

Table 5: The top section displays the scores for the models tested on the 500 randomly chosen NewsQA dataset. (All scores are in the range of 0-100). The bottom section displays BLEU and ROGUE scores for the models tested 900 randomly chosen Freebase test samples.

Figure 4: Results of Modified Pointer Generator Approach (Pal et al., 2019)

7.2 Results

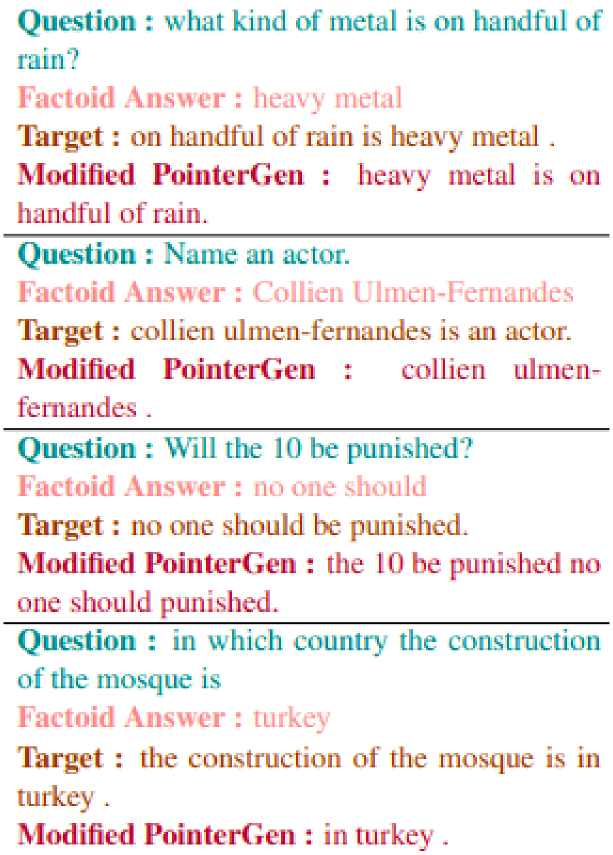
In this section, we will illustrate the results of the Modified Pointer Generator Approach on the open domain dataset and other test datasets created from other question answering dataset like Freebase and NewsQA which is used to check cross dataset accuracy of the model.
For that a test dataset is created having 900 examples from NewsQA and 500 examples from Freebase test samples.
Above figure contains 2 tables, the first table top section displays BLEU and ROGUE scores for the models tested on the manually created test dataset. The bottom section displays the scores for the models tested on the auto-created test dataset.
The second table top section displays the scores for the models tested on the 500 randomly chosen NewsQA dataset. The bottom section displays BLEU and ROGUE scores for the models tested 900 randomly chosen Freebase test samples. (All scores are in the range of 0-100)

7.3 Limitations and Error Analysis

The main limitation of this approach are stated in below points. Not all failure cases were of below type but for maximum cases these were the failure outputs. Also from the figure below we can see some examples wherein these failure cases are described in some detail. Also there were other failure cases as well wherein the model just output the question itself which may be due to model becomes biased towards adding more part from the question than the factoid answer which results in complete copying of the question in some examples cases. Below are the main types of failure cases stated

- Incoherent sentence due to failure in reasoning
- Outputs only the factoid answer
- Outputs clausal answers
- Failure to incorporate morphological variations

In the above figure, Example 1 is from the Freebase dataset where the system confuses between the subject and the object. Example 2 is from Freebase not present in the training and validation data. Example 3 is from NewsQA dataset where the system fails to understand the semantics. Example 4 id from NewsQA dataset where the system fails to generate the complete full-length answer
In short this model doesn't give good results even for very straight forward example cases present in our dataset and



Question : what kind of metal is on handful of rain?
Factoid Answer : heavy metal
Target : on handful of rain is heavy metal .
Modified PointerGen : heavy metal is on handful of rain.

Question : Name an actor.
Factoid Answer : Collien Ulmen-Fernandes
Target : collien ulmen-fernandes is an actor.
Modified PointerGen : collien ulmen-fernandes .

Question : Will the 10 be punished?
Factoid Answer : no one should
Target : no one should be punished.
Modified PointerGen : the 10 be punished no one should punished.

Question : in which country the construction of the mosque is
Factoid Answer : turkey
Target : the construction of the mosque is in turkey .
Modified PointerGen : in turkey .

Figure 5: Failure cases of the Modified Pointer Generator Approach (Pal et al., 2019)

so using it for general case queries would not be very beneficial as for many cases we will not get the expected target answer.

8 Dialog GPT-2 Approach

This chapter will describe about our second approach about the finetuning the DialoGPT model on the dataset discussed in previous chapter. We will disuss about how the DialoGPT model was finetuned how the input to the model was changed to solve the task of Natural Answer Generation. Then we will discuss about different experiments completed and discuss results of the experiment giving the best results. Also we will talk about some error analysis at the end of this section about this model and analyse why this models fails to give good results.

9 Brief introduction of DialoGPT model

DIALOGPT (dialogue generative pre-trained transformer) (Zhang et al., 2020) is a tunable gigawordscale neural network model for generation of conversational reponses, trained on Reddit data. Trained on 147M conversation-like exchanges extracted from Reddit comment chains over a period spanning from 2005 through 2017, DialoGPT extends the Hugging Face PyTorch transformer to attain a performance close to human both in terms of automatic and human evaluation in single-turn dialogue settings. The pre-trained model and training pipeline are publicly released to facilitate research into neural response generation and the development of more intelligent opendomain dialogue systems. DIALOGPT extends GPT-2 (Zhang et al., 2020) to address the challenges of conversational neural response generation. Neural response generation is a subcategory of text-generation that shares the objective of generating natural-looking text (distinct from any training instance) that is relevant to the prompt. Modelling conversations, however, presents distinct challenges in that human dialogue, which encapsulates the possibly competing goals of two participants, is intrinsically more diverse in the range of potential responses Like GPT-2, DIALOGPT is formulated as an autoregressive (AR) language model, and uses the multi-layer transformer as model architecture. Unlike GPT-2, however, DIALOGPT is trained

Model	BLEU	ROUGE-1	ROUGE-L
DGPT finetuned on 13k manual data (8 epochs)	40.13	70.61	67.01
DGPT finetuned on 15k manual+auto (3 epochs)	33.77	59.27	53.68
Modified Pointer Generator	73.29	95.38	93.65

Table 1: DGPT Model results on 420 examples from NewsQA dataset

Model	BLEU	ROUGE-1	ROUGE-L
DGPT finetuned on 13k manual data (8 epochs)	33.23	66.51	60.35
Modified Pointer Generator	74.05	91.24	86.25

Table 2: DGPT Model results on 3200 examples from manually annotated test dataset

on large-scale dialogue pairs/sessions extracted from Reddit discussion chains. Our assumption is that this should enable DIALOGPT to capture the joint distribution of P(Target, Source) in conversational flow with finer granularity. In practice, this is what we observe: sentences generated by DIALOGPT are diverse and contain information specific to the source prompt, analogous what GPT-2 generates for continuous text.

9.1 Architecture of DIALOGPT model

DIALOGPT model was trained on the basis of the GPT-2 (Budzianowski and Vulić, 2019), (Radford et al., 2018) architecture.The GPT-2 transformer model adopts the generic transformer language model (Vaswani et al., 2017) and leverages a stack of masked multi-head self attention layers to train on massive web-text data. The text generated either from scratch or based on a user-specific prompt is realistic-looking. The success of GPT-2 demonstrates that a transformer language model is able to characterize human language data distributions at a fine-grained level, presumably due to large large model capacity and superior efficiency. This model inherits from GPT-2 (Radford et al., 2018), a 12-to-48 layer transformer with layer normalization, a initialization scheme that accounts for model depth that we modified, and byte pair encodings for the tokenizer. We follow the OpenAI GPT-2 to model a multiturn dialogue session as a long text and frame the generation task as language modeling. First concatenate all dialog turns within a dialogue session into a long text ended by the end-of-text token. Then the conditional probability of response generation given dialogue is written as product of series of conditional probabilities.

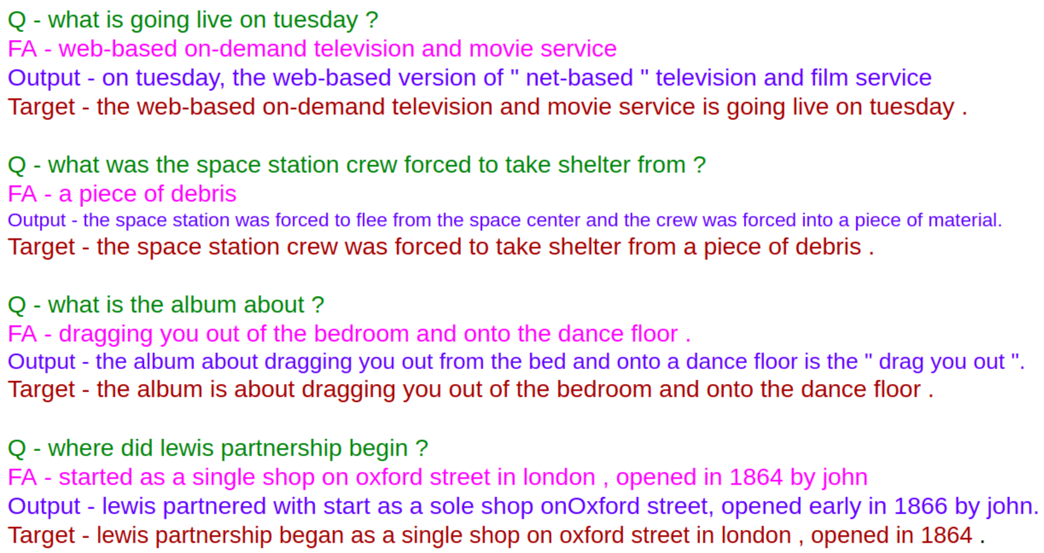
9.2 Experiments

Handling models like GPT-2 and DIALOGPT which are trained on huge corpus of data is very difficult. Finetuning these models is even more difficult as these models require a very available memory to run on the machine. We were able to run all our experiments on Google Collab as on CFILT servers memory available was less. Hence in collab due to frequent session disconnection in between we managed to run few experiments that too decreasing the amount of data used for fine tuning. We tried different combinations of data for finetuning like combining manual annotated data with the auto annotated examples etc. But finally best results were achieved when only the manually annotated data was used to finetune the DIALOGPT model. Using the 13000 manually annotated and finetuning it for 8 epochs gave the best results on 420 examples of NewsQA dataset. Finetuning was done without changing the hyperparameters given in DialoGPT2 paper.

- **How the input was provided in finetuning the DGPT model?**
  Normally DIALOGPT models are used to make conversational chatbots and their finetuning is also done for making conversational agent where the input is the question asked and all the previous dialogues are kept as series of context and are passed as input to the model for training. Here in our task since all our questions are independent we have passed the input as question and the factoid answer as context and response as the GOLD standard answer that we have. Here instead of a series of conversations passed as context normally in our case we only give the factoid answer as a context to the model.

9.3 Results and model Output

In the above 2 tables we have evaluated finetuned DGPT model and compared the ROUGE and BLEU scores of this model with the modified pointer generator approach. Here we see that there has been a significant difference in all the 3 scores between the DGPT model and the Modified Pointer Generator approach. Scores on the output of DGPT model is very less. In the next section we will discuss some reasons why scores are very less in DGPT model.



Q - what is going live on tuesday ?
FA - web-based on-demand television and movie service
Output - on tuesday, the web-based version of " net-based " television and film service
Target - the web-based on-demand television and movie service is going live on tuesday .

Q - what was the space station crew forced to take shelter from ?
FA - a piece of debris
Output - the space station was forced to flee from the space center and the crew was forced into a piece of material.
Target - the space station crew was forced to take shelter from a piece of debris .

Q - what is the album about ?
FA - dragging you out of the bedroom and onto the dance floor .
Output - the album about dragging you out from the bed and onto a dance floor is the " drag you out ".
Target - the album is about dragging you out of the bedroom and onto the dance floor .

Q - where did lewis partnership begin ?
FA - started as a single shop on oxford street in london , opened in 1864 by john
Output - lewis partnered with start as a sole shop onOxford street, opened early in 1866 by john.
Target - lewis partnership began as a single shop on oxford street in london , opened in 1864 .

Figure 6: DGPT model sample output examples

Here we also discuss some of the output predictions on some examples by the DGPT model so that we get some idea of the model behaviour and how the answers are predicted.

9.4 Model Limitations and Error Analysis

Problem of adding unwanted things in the final answers which doesn't have any mention in the question and the factoid answer is the main shortcoming of this model. There are instances where there is repetition of some words in the answer and in some cases Factoid answer is not present in the final answer Mismatch in the questions having some numerical data or year is mentioned The model has some errors copying the proper nouns as given in the questions. The final answer has that names but with changed spelling. (eg:- elizabeth -> elizabetha; alexander -> alexandrick).
In the above figure also it is evident that many unwanted things are added in the output from the DGPT model as compared to the GOLD standard which are not present in both the question as well as the factoid answer. In the first example we can see web-based changes to "net-based" movie becomes film in the DGPT output. In the second example space station becomes space centre the complete answer structure is semantically wrong, the last part is making wrong sense. In the third example the term "drag you out" is unwanted and is added at the end of the answer even when the factoid answer was copied in the output before, this shows that there are changes of repetition that occurs in the model output. In the fourth example we can see mismatch in the year mentioned in the factoid answer. In DGPT model output 1866 is given whereas actually the year given in the answer is 1864.
So by analysing above examples we can conclude that DGPT model is not able to copy fact, numbers present in the question or the factoid answer. Also DGPT model has high bias of generating related things in the natural answer that is why BLEU and ROUGE scores decrease as GOLD standard doesn't related words into account.

10 Rule Based Approach

In this chapter, we will discuss the rule based approach to generate natural answers. We will first discuss about how this approach came to our mind, then we will discuss the algorithm. Then we will discuss results and model output using this approach and compare the results from previous approaches. Lastly we will discuss some error analysis of this approach.

10.1 Ideation

This approach came into our mind when we manually saw a large number of test examples and from that we were able to find a pattern in the full length answers. Then we came up with the idea of implementing the rule based approach which will use the sentence structure of the question at its core to generate a full length target answer. Initially we started with a very basic algorithm where we just replaced the WH words with the factoid answer and give the answer as it is without structuring but it had numerous failure examples. Then after seeing the failure examples of the above algorithm we were able to find a pattern related to the position of auxiliary verb and the main verb and then using this idea we were able to improve upon the failure cases we had in the above rule based approach. With this improvements many failure cases became exactly correct or very close to the target answer in the test dataset. So this is how this approach was formulated based on analysing the test examples and using the parse tree of the questions we were able to implement this approach.

10.2 Approach

There are 2 versions which will be discussed in this section wherein the second version is an improvement over the first version.
In the First version of our Rule based approach we just replaced the WH word present in the question with the factoid answer. In this method first we will find the position of the WH word present in the question then replace that word with given factoid answer to give a natural answer. Remember that we have not changed the question structure only there is a replacement of on word with the factoid answer. The WH word was found by using the POS tags output of the given question. AllenNLP constituency parser output was used to get POS tags of every word of the question. If the tag is "WP" or "WRB" then we replace that word with Factoid answer. Some examples are stated below for better understanding of the approach:-

Question *: What is the capital of India?*
Factoid answer *: Delhi*
Rule Based Output v1 *: Delhi is the capital of India*
Target answer *: Delhi is the capital of India*

Question *: what was the space station crew forced to take shelter from?*
Factoid answer *: a piece of debris*
Rule Based Output v1 *: a piece of debris was the space station crew forced to take shelter from*
Target answer *: the space station crew was forced to take shelter from a piece of debris*

In the second version, we modify the above approach based on the position of AUX VERB and MAIN VERB present in the question. We formulate the algorithm as to solve the problem of ordering of natural answer i.e answer followed by question or question followed by answer. So, we look if the main verb and auxiliary verb are together then factoid answer is replaced with WH part same as done in first version and if not then we have to add factoid answer in the end. In the latter case we start our answer from the word after the auxiliary verb, then after all the words before the main verb is copied we add the auxiliary word present in the question then we copy the part of from the question from the MAIN VERB to the end and then at the end we add the factoid answer. In other words we use dependency parse tree to get AUX and VERB tag and check if they are together and added this condition to the existing rule based model if they are together we follow first version. If AUX and VERB tag are not together then we add factoid answer at the end of the question. If question does not have verb in it then we add all words after auxiliary word in the answer, then add auxiliary verb and finally the factoid answer is added at the end. Some sample example output using second version is stated below:-

Question *: What is the capital of India?*
Factoid answer *: Delhi*
Rule Based Output v2 *: the capital of India is Delhi*
Target answer *: Delhi is the capital of India*

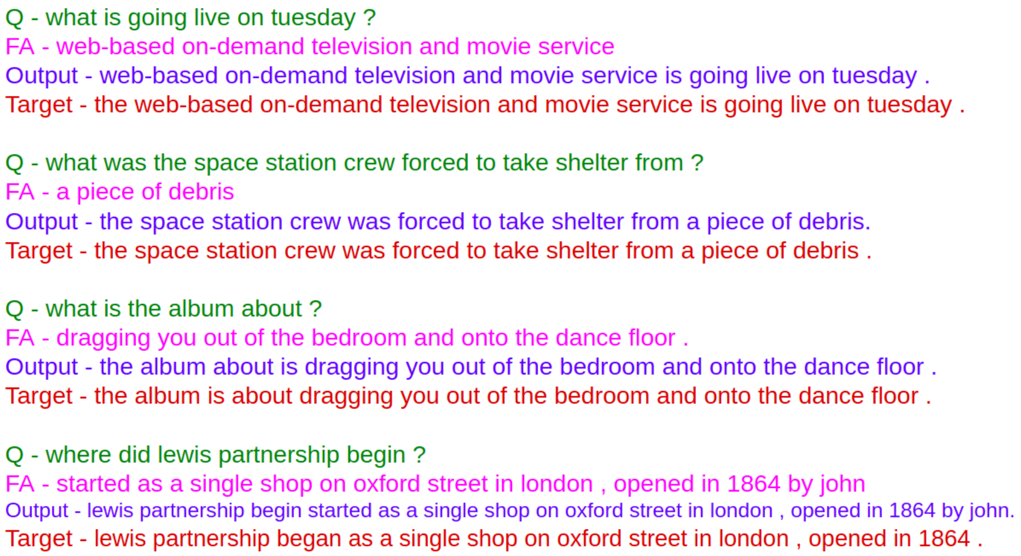
Question *: what was the space station crew forced to take shelter from?*
Factoid answer *: a piece of debris*
Rule Based Output v2 *: the space station crew was forced to take shelter from a piece of debris*
Target answer *: the space station crew was forced to take shelter from a piece of debris*

10.3 Results and Model Output

In the below table we have evaluated and compared the scores of all the models with rule based approach discussed above(R-1 means ROUGE-1 and R-L means ROUGE-L). We can see a significant rise in ROUGE-L score which means that higher order n-grams are matching the GOLD standard but there has been a decrease of BLEU scores which points at lower n grams are not getting matched which may be due to restructuring of the question done hence there is a chance

Model	BLEU	R-1	R-L
DGPT finetuned 13k manual data (8 epochs)	40.13	70.61	67.01
Rule based approach v2	63.51	90.35	83.33
Rule based approach v1	69.59	89.166	72.177
Modified Pointer Generator	73.29	95.38	93.65

Table 3: Rule Based Model results on 420 examples from NewsQA dataset



Q - what is going live on tuesday ?
FA - web-based on-demand television and movie service
Output - web-based on-demand television and movie service is going live on tuesday .
Target - the web-based on-demand television and movie service is going live on tuesday .

Q - what was the space station crew forced to take shelter from ?
FA - a piece of debris
Output - the space station crew was forced to take shelter from a piece of debris.
Target - the space station crew was forced to take shelter from a piece of debris .

Q - what is the album about ?
FA - dragging you out of the bedroom and onto the dance floor .
Output - the album about is dragging you out of the bedroom and onto the dance floor .
Target - the album is about dragging you out of the bedroom and onto the dance floor .

Q - where did lewis partnership begin ?
FA - started as a single shop on oxford street in london , opened in 1864 by john
Output - lewis partnership begin started as a single shop on oxford street in london , opened in 1864 by john.
Target - lewis partnership began as a single shop on oxford street in london , opened in 1864 .

Figure 7: Rule Based v2 model sample output examples

of some mistakes about handling all the TAGS in writing the algorithm. Also there are questions without the normal structure like question starting from auxiliary verb Eg. Can you help me in today's homework? etc. in the dataset which would decrease the scores.

10.4 Model Limitations and Error Analysis

This approach works reordering question sentence structure and copy pasting from the question and factoid answer and so if factoid answer is not factual based or is a clausal answer then this approach will fail. For eg last example of Figure 6.1 output answer had both began and started in it which is not right this is because the factoid answer contains a clause having verb part also in it, In our approach we are not checking the factoid answer structure to define our answers and hence for these examples this model will fail. Since the approach works on the question structure so if question is not properly well formed or incomplete then the answers will not be correct.

11 Post Processing Step: Grammar Correction Model

In this chapter we will describe about the post processing step in our rule based approach of natural answer generation. We will start with some introduction of the state of the art pre-trained transformer based Grammar Correction Model (GCM).

11.1 Introduction

Neural Machine Translation (NMT)-based approaches have become the preferred method for the task of GEC. In this formulation, errorful sentences correspond to the source language, and error-free sentences correspond to the target language. Recently, Transformer-based (Vaswani et al. (2017)) sequence-to-sequence (seq2seq) models have achieved state-of-the-art performance on standard GEC benchmarks. Now the focus of research has shifted more towards generating synthetic data for pretraining the Transformer-NMT-based GEC systems (Kantor et al. (2019), Grundkiewicz et al. (2019)). NMT-based GEC systems suffer from several issues which make them inconvenient for real world deployment: (i) slow inference speed, (ii) demand for large amounts of training data and (iii) interpretability and explainability; they require additional functionality to explain corrections, e.g., grammatical error type classification. Hence to deal with the aforementioned issues by simplifying the task from sequence generation to sequence tagging. We used GECToR (Omelianchuk et al. (2020)) GEC sequence tagging system that consists of three training stages: pretraining on synthetic data, fine-tuning on an errorful parallel corpus, and finally, fine-tuning on a combination of errorful and error-free parallel corpora. This model gives state of the art results on the task of Grammar Error Correction on CoNLL-2014 and BEA-2019 datasets.

11.2 Experiments and Results

We have used standard BLEU Papineni et al. (2002) (NLTK), ROUGE-1,2,L Lin (2004) (rouge-score) metrics to evaluate our system and compare our system with other approaches. We have used Tesla T4 16GB GPU to carry out the experiments. For factoid questions, we use the 2 datasets having 380 and 6768 examples, results are given in table 4 and 5 respectively. For confirmatory questions we use 166 examples dataset created and formulate a rule based approach for confirmatory questions as well. As generally confirmatory questions has a structure AUX-NP-VP so using dependency analysis we formulate our answer as NP-AUX-VP. Results of confirmatory dataset is given in table 7.

Question *: Can you tell if fridge supports quick freeze feature?*
Factoid answer *: Yes*
RB *: Yes, fridge does supports quick freeze feature.*
RB + RoBERTa *:Yes, fridge does support quick freeze feature.*

As a post processing step of all our rule based approaches i.e. for factoid questions and confirmatory questions we have used a pre-trained transformer encoder grammar error correction (GEC) given in Omelianchuk et al. (2020). This model was available with 3 cutting edge transformer encoders namely BERT, RoBERTa and XLNET. So we carried our experiments using all 3 above encoder based GEC model as a post processing step in our rule based approach; In table 4, 5, 6, 7 : "RBV2+RoBERTa" means our rule based approach with grammar correction done by RoBERTa encoder and so on.
For DialoGPT using around 13000 manually annotated and fine-tuning it for 8 epochs gave the results on 380 examples of NewsQA dataset given in table 4.
Below example gives a qualitative comparison of output from different approaches explored in this paper. It is clear that our rule based approach (RBV2) with RoBERTa based GCM (RBV2+RoBERTa) achieves higher quality of natural answers as compared to MPG. Our developed approach gives comparable results in terms of BLEU and ROUGE-1,2,L scores with MPG and reduces inference time by 85%.

Model	BLEU	R-1	R-2	R-L	Avg. time(s)
MPG Pal et al. (2019)	84.9	95.7	89.4	93.9	2.54
RBV2	79.1	96.1	85.5	93.1	0.382
RBV2+BERT	77.6	94.4	85.4	92.4	0.397
RBV2+RoBERTa	81.7	95.7	88.2	93.6	0.394
RBV2+XLNET	80.3	94.8	87.0	92.9	0.4
DialoGPT	50.3	73.4	49.3	70.0	0.908

Table 4: Results on 380 examples of NewsQA dataset

Model	BLEU	R-1	R-2	R-L	Avg. time(s)
MPG Pal et al. (2019)	75.8	94.4	87.4	91.6	2.54
RBV2	74.8	95.3	83.1	90.3	0.399
RBV2+BERT	71.5	93.9	82.4	89.5	0.411
RBV2+RoBERTa	72.1	94.0	83.1	89.8	0.411
RBV2+XLNET	71.2	93.6	82.3	89.4	0.413

Table 5: Results on 6768 examples of SqUAD dataset

Model	BLEU	ROUGE-1	ROUGE-2	ROUGE-L
MPG Pal et al. (2019)	64.1	85.7	72.5	78.8
RBV2	55.5	85.8	63.4	73.5
RBV2+BERT	54.8	81.9	60.4	71.4
RBV2+RoBERTa	55.6	82.6	61.3	72.0
RBV2+XLNET	54.8	82.0	61.1	71.7

Table 6: Results on 840 examples of Freebase dataset

Model	BLEU	R-1	R-2	R-L
RB	70.2	87.3	75.0	84.8
RB+BERT	62.7	85.5	71.6	83.4
RB+RoBERTa	66.6	84.5	73.0	84.2
RB+XLNET	67.5	86.6	74.0	84.6

Table 7: Results on 166 examples of Confirmatory questions dataset

11.3 Qualitative Analysis

Question *: where was the bus going ?*
Factoid answer *: phoenix , arizona*
MPG Pal et al. (2019) *: the bus going was at phoenix , arizona.*
RBV2 *[ours] : the bus was going phoenix , arizona.*
RBV2+RoBERTa *[ours] :The bus was going to Phoenix , Arizona.*
DialoGPT *[ours]: the bus was going to phoenix, anrizona.*

In the above example, MPG Pal et al. (2019) is making error in answer generation. Word position of was and going is interchanged and "at" is added which is wrong, correct addition should be "to".
DialoGPT has changed arizona spelling to "anrizona".
RBV2 approach does give a answer but it is not complete word "to" is missing from the answer which is added in the answer by a Grammar Error Correction (GEC) model GECToR with RoBERTa LM encoder. Omelianchuk et al. (2020). This shows the importance of using GEC as a post processing step in our rule based approach.

12 Error Analysis

This approach works reordering question sentence structure and copy pasting the factoid answer and so if factoid answer is not factual based or is a clausal answer then this approach will fail. Also the generated answers may be grammatically wrong in terms of missing a word like in, is, to etc which is corrected by the transformer based grammar correction used as a post processing step; other type of grammar error by rule based approach is incorrect position of AUX word (*e.g.* is, are etc) in the answer which is not corrected by the Omelianchuk et al. (2020) in some cases. Also for questions starting with "how many" word "many" is added in the generated answer as well, which is wrong if the factoid answer extracted is a number. Here we rely on the GCM model to do the necessary corrections and the accuracy of GCM model in correcting this is good.

Question *: where did lewis partnership begin?*
Factoid answer *: started as a single shop on oxford street in london, opened in 1864 by john.*
RBV2 output *: lewis partnership begin started as a single shop on oxford street in london, opened in 1864 by john.*
Target answer *: lewis partnership begin started as a single shop on oxford street in london, opened in 1864 by john.*

In the above example output answer had both begin and started in it which is not right this is because the factoid answer contains a clause having verb part also in it, In our approach we are not checking the factoid answer structure to define our answers and hence for these examples this model will fail. Since the approach works on the question structure so if question is not properly well formed or incomplete then the answers will not be correct.

13 Dataset Discription

In this chapter, we will talk about the details of the dataset we have used in this project. First we will discuss about the open domain dataset extracted from SQuAD and HarvestingQA, then some details of the LG-Soft data extracted from product manuals will be discussed.

13.1 Open Domain Dataset

We used the recently open sourced dataset made from standard machine comprehension datasets such as SQuAD (Rajpurkar et al., 2016) and HarvestingQA (Du and Cardie, 2018) to create auto-annotated data. This provide us with questions and factoid answers which we use as input to our system. For the ground-truth, we automatically extract full-length answers from the passages of these datasets by applying auto annotation technique which will be discussed below. We used 300,000 samples (question, factoid answer, full-length answer) from SQuAD and HarvestingQA. Additionally, we used manually annotated 15000 samples from SQuAD of which 2500 are used for development, 2500 for testing and rest 310000 were augmented with the auto-annotated data.

13.1.1 Auto Annotation Technique

Creating datasets for any new task is a challenge since modern systems based on neural architectures requires a large amount of data to train. To make the data creation task scalable, most of our training data is automatically generated from SQuAD and HarvestingQA. For each questionanswer pair, author of the paper (Pal et al., 2019) automatically extract the target full-length answers from corresponding passages. We iterate over the sentences in the context passage that contain the factoid answer and select the one that has the highest BLEU score with the question, given BLEUscore $>= 35\%$. Given the question-answer pair (Q, A) and the passage P, the full-length answer T is the sentence, S, in the passage:

$$T = argmaxBLEU(Q, S) \tag{7}$$

$$iffA\epsilon S\&BLEU(Q, S) >= 35\% \tag{8}$$

This method of automatically extracting samples from existing QA datasets is scalable and can be reproduced with any modern QA datasets to generate more samples to augment this autogenerated samples extracted from HarvestingQA This autogenerated data samples follow a similar question distribution as SQuaD and is biased towards what” and ”who” questions.

13.1.2 Manually Annotated Data

The auto-generated samples contain extra information in the ground-truth full-length sentences which are not aligned with the question or factoid answer. To refine our dataset to be more attuned to questions and also to capture the variability humans bring when generating new sentences, we manually annotated 15000 QA pairs, from the SQuAD dataset. We used multiple ways to answer the same question, such as in active and passive voice, to incorporate more variation to the target sentences. Apart from generating samples with the full-length answers well aligned with the question, we have also chosen complex samples from SQuAD which have long phrasal factoid answers to add more complexity to the data samples.

References

Akermi, I., Heinecke, J., and Herledan, F. (2020). Tansformer based natural language generation for question-answering. In Davis, B., Graham, Y., Kelleher, J. D., and Sripada, Y., editors, *Proceedings of the 13th International Conference on Natural Language Generation, INLG 2020, Dublin, Ireland, December 15-18, 2020*, pages 349–359. Association for Computational Linguistics.

Bahdanau, D., Cho, K., and Bengio, Y. (2016). Neural machine translation by jointly learning to align and translate.

Budzianowski, P. and Vulić, I. (2019). Hello, it’s gpt-2 – how can i help you? towards the use of pretrained language models for task-oriented dialogue systems.

Du, X. and Cardie, C. (2018). Harvesting paragraph-level question-answer pairs from Wikipedia. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1907–1917, Melbourne, Australia. Association for Computational Linguistics.

Fu, Y. and Feng, Y. (2018). Natural answer generation with heterogeneous memory. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language*

Technologies, Volume 1 (Long Papers), pages 185–195, New Orleans, Louisiana. Association for Computational Linguistics.

Grundkiewicz, R., Junczys-Dowmunt, M., and Heafield, K. (2019). Neural grammatical error correction systems with unsupervised pre-training on synthetic data. In *Proceedings of the Fourteenth Workshop on Innovative Use of NLP for Building Educational Applications*, pages 252–263, Florence, Italy. Association for Computational Linguistics.

Gulcehre, C., Ahn, S., Nallapati, R., Zhou, B., and Bengio, Y. (2016). Pointing the unknown words. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 140–149, Berlin, Germany. Association for Computational Linguistics.

He, S., Liu, C., Liu, K., and Zhao, J. (2017). Generating natural answers by incorporating copying and retrieving mechanisms in sequence-to-sequence learning. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 199–208, Vancouver, Canada. Association for Computational Linguistics.

Kantor, Y., Katz, Y., Choshen, L., Cohen-Karlik, E., Liberman, N., Toledo, A., Menczel, A., and Slonim, N. (2019). Learning to combine grammatical error corrections. In *Proceedings of the Fourteenth Workshop on Innovative Use of NLP for Building Educational Applications*, pages 139–148, Florence, Italy. Association for Computational Linguistics.

Lian, R., Xie, M., Wang, F., Peng, J., and Wu, H. (2019). Learning to select knowledge for response generation in dialog systems.

Lin, C.-Y. (2004). ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Liu, C., He, S., Liu, K., and Zhao, J. (2018). Curriculum learning for natural answer generation. In *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI-18*, pages 4223–4229. International Joint Conferences on Artificial Intelligence Organization.

Omelianchuk, K., Atrasevych, V., Chernodub, A., and Skurzhanskyi, O. (2020). GECToR – grammatical error correction: Tag, not rewrite. In *Proceedings of the Fifteenth Workshop on Innovative Use of NLP for Building Educational Applications*, pages 163–170, Seattle, WA, USA â†' Online. Association for Computational Linguistics.

Pal, V., Shrivastava, M., and Bhat, I. (2019). Answering naturally: Factoid to full length answer generation. In *Proceedings of the 2nd Workshop on New Frontiers in Summarization*, pages 1–9, Hong Kong, China. Association for Computational Linguistics.

Papineni, K., Roukos, S., Ward, T., and Zhu, W.-J. (2002). Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., and Sutskever, I. (2018). Language models are unsupervised multitask learners.

Rajpurkar, P., Zhang, J., Lopyrev, K., and Liang, P. (2016). SQuAD: 100,000+ questions for machine comprehension of text. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 2383–2392, Austin, Texas. Association for Computational Linguistics.

Reddy, S., Chen, D., and Manning, C. D. (2019). Coqa: A conversational question answering challenge.

Rush, A. M., Chopra, S., and Weston, J. (2015). A neural attention model for abstractive sentence summarization. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 379–389, Lisbon, Portugal. Association for Computational Linguistics.

See, A., Liu, P. J., and Manning, C. D. (2017). Get to the point: Summarization with pointer-generator networks. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1073–1083, Vancouver, Canada. Association for Computational Linguistics.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. (2017). Attention is all you need.

Weston, J., Bordes, A., Chopra, S., Rush, A. M., van Merriënboer, B., Joulin, A., and Mikolov, T. (2015). Towards ai-complete question answering: A set of prerequisite toy tasks.

Yin, J., Jiang, X., Lu, Z., Shang, L., Li, H., and Li, X. (2016). Neural generative question answering.

Zhang, Y., Sun, S., Galley, M., Chen, Y.-C., Brockett, C., Gao, X., Gao, J., Liu, J., and Dolan, B. (2020). DIALOGPT : Large-scale generative pre-training for conversational response generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, pages 270–278, Online. Association for Computational Linguistics.