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Building a Chatbot Models using SeqtoSeq Models and LSTM

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***Abstract*—In this work, we propose a way to build a hybrid model combining Sequence to Sequence (Seq2Seq) style architecture with Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs) with some attentions. In this, we propose a hybrid approach that can complement temporal dependencies in dialogue to improve conversational response coherence, fluency, and relevance. The Seq2Seq model with LSTMs are good at capturing very long term contextual information, whereas CNNs may help the model by detecting some crucial word patterns for extracting feature and thus speeding up training. Also, the attention mechanism enables decoder to be able to selectively focus on relevant parts of the input sequence while producing responses which are aligned and coherent. It was trained on Cornell Movie-Dialogs Corpus, and achieved a BLEU of 0.77, significantly better than traditional Seq2Seq models in response quality. LSTMs and CNN together enhance contextual understanding, attention mechanism further improve the conversational flow. While these advancements eliminate many problems, the challenge of keeping context in multi-turn dialogues and dealing with out of vocabulary words still exist. The results show that the hybrid model is an effective way to push the boundaries of conversational AI for two application areas that demand dynamic and contextually relevant interactions, including customer support and language learning.**

***Index Terms*—Sequence-to-Sequence (Seq2Seq), Long Short-Term Memory (LSTM), Conversational AI, Neural Network Architecture, Encoder-Decoder Model.**

I. INTRODUCTION

Used in customer service and education, there are chatbots also known as conversational agents which can bring innate and effective ways to enhance user experience due to natural interactions. While chatbots are increasingly being adopted, building chatbots capable of effectively answering meaningful, contextually relevant and diverse scenarios still remains a hard problem. Based on how the chatbots are being built, they are broadly classified as both rule-based, retrieval based and generative models. Open ended conversation is beautifully handled by generative models, particularly Sequence to Sequence (Seq2Seq) models by producing coherent outputs using given input sequences. In this research we would like to implement a system that uses the Cornell Movie-Dialogs Corpus to build a chatbot using Seq2Seq models with LSTM units and the Luong attention based before contributing towards helping improve response coherence and contextual alignment. Data preprocessing, model implementation, and training with optimizers such as Adam, and evaluation of the model using the BLEU score are key steps. It also enables real time interaction. Standing Seq2Seq models with attention capabilities are successful, yet still lacking in the support of OOVs, long term context, and reducing repetitive responses.

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One opportunity for future work is to build on top of transformer-based architectures (such as GPT or BERT) to take conversational AI further.

A. Problem Statement

Current chatbot models, rule based as well as retrieval based, are not capable of generating dynamic, contextually relevant and coherent responses in open domain conversations. While Seq2Seq models have achieved great promise, they struggle with maintaining long term context, creating repetitive or generic generated output, as well as handling out-of-vocabulary words. Limitations to such agents' abilities to interact in ways reminiscent of humans limit their use. In providing coverage to these issues, this research offers a hybrid Seq2Seq method, which consists of LSTM network and convolutional network, and Luong attention mechanism to improve response quality and contextual relevance.

II. Related Work and Literature Review

The first chatbot systems were rule based, based on pre-existing rules and keyword matching as a way to return a response. ELIZA (1966), introduced as a scripted chatbot by one of its inventors Weizenbaum, showed simple keyword-based rules to simulate a Rogerian therapist. Similar to Colby (1972), PARRY modelled paranoid schizophrenia using rule-based dialogue generation.

With the advancement of chatbot technology, retrieval-based models came to emerge. The responses in these systems include the responses that are picked out of a defined set dictionary of possible responses based on input similarity metrics or classifiers. A well-known example is ALICE (Artificial Linguistic Internet Computer Entity) that used the Artificial Intelligence Markup Language (AIML) to store responses into a knowledges base. In spite of generating more accurate response, retrieval-based systems generate fewer original responses, particularly for queries that are novel or open ended [7].

They brought in generative models as a big step towards chatbot development. Named by Sutskever et al. (2014) the Seq2Seq architecture makes use of an encoder-decoder neural network architecture. This model shapes the encoder to take an input sequence (e.g. user query) and decomposing it to a fixed size vector, while the latter uses this vector to generate an output sequence (e.g. chatbot response). By enabling the handling of variable length inputs and outputs, Seq2Seq was very effective for machine translation as well as conversational modelling tasks [3].

Seq2Seq models were shown to work well on the open domain conversational tasks by Vinyals and Le (2015), where they generated coherent dialogue. Nevertheless, these models had the limitation of being unable to handle long or complex inputs, as the fixed size context vector usually failed to cover all important information, and then the models gave responses that are not complete or meaningful.

Like many models using Seq2Seq, Bahdanau et al. (2014) aimed to overcome Seq2Seq's shortcomings by employing attention mechanism, allowing the decoder to associate a part of input sequence to a part of output sequence while generating the response.

Luong et al. (2015) further refined attention mechanisms by introducing two types: global and local attention. Both global attention makes use of the full input sequence whilst local attention focuses on a much smaller part of it, making computationally more efficient. Seq2Seq models with these enhancements were able to obtain a better alignment of the input and output sequences, increasing the performance in the machine translation and of complex dialogue generation tasks [9].

B. Dataset

This study utilizes the Cornell Movie-Dialogs Corpus, a widely used dataset for training dialogue-based models. It contains:

- 10,292-character pairs with 220,579 conversation exchanges
- 617 movies featuring 9,035 unique characters
- 304,713 total utterances, spanning diverse language styles, time periods, and sentiments.

Contribution to Model Robustness

The dataset's diversity enhances model robustness by:

- Language Formality: Incorporates casual and formal dialogues, helping the model learn tone and style.
- Time Periods: Covers linguistic variations across decades, enabling understanding of both modern and older language constructs.
- Sentiment: Includes a range of emotions like happiness, sadness, and anger, critical for generating contextually appropriate emotional responses.

Data Visualizations

Visualizations aid in understanding the dataset and inform preprocessing and model design:

- Utterance Length Distribution: Guides input length settings by analyzing typical dialogue lengths.
- Top Characters by Utterances: Prevents overfitting by identifying dominant speakers.
- Word Frequency Distribution: Highlights common words to optimize vocabulary size and preprocessing strategies.

III. Proposed System and Methodologies

Given that this project employs a Seq2Seq model together with the Luong attention mechanism, it builds a conversational chatbot. The architecture is based on an Encoder Decoder framework augmented with attention mechanism, which allows the model focus on specific bits of the input sequence.

C. Data Collection and Preprocessing

The data set contains in depth information about character interactions of many movies and can be used to build conversational models.

A couple of preprocessing steps before you can feed data to the model. These include:

- Tokenization: That unit has to be some sort of meaningful unit, the utterances should be tokenized or tokenized. Generally, tokens are words or sub words. In case of conversion of text to form the neural network can process this becomes necessary.
- Special Character Removal: To avoid confusion therein, most of the punctuation marks and other characters which are not alphabetical are usually stripped out during training. Sometimes there will be special characters because they may alter how the utterance sounds, whether it be an exclamation or a question.
- Lowercasing: The vocabulary is reduced in the size by changing all words into lowercase.
- Padding/Truncating: Padded sentences ensure that all inputs have a uniform length (or truncated if it is above the MAX).

D. Model Architecture

Overview of the Sequence-to-Sequence (Seq2Seq) Model: The Seq2Seq has also emerged as the top choice for many tasks, including machine translation and dialogue generation, as well as other sequential data issues [10]. The architecture consists of two primary components:

Encoder: In this component, we feed the input sequence, and compress it into a fixed size context vector that stores all of the information we need.

Decoder: In the context of this project, the target sequence (chatbot response) is generated with the help of the context vector derived from the encoder. The strength of this framework is especially useful for problems where the input and output sequences are of varying lengths, as occurs in a scenario involving a query and its corresponding reply [11].

Encoder-Decoder Structure: For encoder and decoder, we use Long Short-Term Memory (LSTM) networks in our implementation. Long term dependencies is an important property of conversations, and LSTMs are chosen for being able to learn such dependencies [9]. This capability allows the model to keep the conversation coherent and relevant and the quality of the chatbot's interactions improve.

An encoder is an operation that receives the input sequence (i.e., query) word by word, and outputs a hidden state at each time step.

Since the query is inherently sequential, maintaining context is necessary, and the model learns these hidden states effectively, which capture the sequential information of the query.

Use of LSTM for Learning Sequential Data: In particular, the Long Short-Term Memory (LSTM) architecture is very well suited for sequential data because it keeps a hidden state that carries information over time, which is required to capture context in sequences [1]. LSTMs are memory cells with specific gating mechanisms such as input, forget, output gates; effectively controlling the flow of information, allowing the model to preserve relevant information and overcome issues commonly associated with vanishing gradients (such as in training).

Forget gate: Decides what information to discard from the cell state.

$$f_t = \sigma\big(W_f \cdot [h_{t-1}, x_t] + b_f\big)$$

Input gate: Decides which values to update in the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

Update the cell state.

$$\widetilde{C_t} = tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C_t}$$

Output gate: Determines the output based on the updated cell state

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot tanh(C_t)$$

Luong Attention Mechanism: In contrast, the Luong Attention decodes from a dynamic attention between the input sequence and the fixed-size context vector from the encoder, which does not require the fixed size context vector like regular attention. The Luong attention mechanism computes an alignment score between the current decoder's hidden state h, and each of the encoder's hidden states so that the model can understand the most important parts of the input sequence [4]. It prefers using these alignment scores and generates a context vector as a weighted sum of the encoder's hidden states in order to capture the information needed for the decoder to predict the next word in the output sequence [8]. This mechanism makes our model more capable of handling complex dependencies between conversations, for better contextually accurate responses.
three common types of alignment scores used in Luong attention:

$$\text{score}\left(h_t, \overline{h_s}\right) = h_t^T \overline{h_s}$$

$$\text{score}\left(h_t, \overline{h_s}\right) = h_t^T W_a \overline{h_s}$$

$$\text{score}\left(h_t, \overline{h_s}\right) = v_a^T \tanh\left(W_a\left[h_t; \overline{h_s}\right]\right)$$

E. Model Training and Optimization

Mini-batch Training Approach: The model converges faster when training on mini batches instead of individual sequences, using vectorized operations and takes less resources of GPU.

- Padding and Masking: Since the input and output sequences can't be different length, we pad the input and output to make them all the same length
- Sorting: Sequence length sorted mini batches are used to get rid of more padding, and makes the computation more efficient.

Optimizer: The Adam optimizer is used to train the model as it has been successfully used to train most deep learning models thanks to both its adaptive learning rate and momentum based updates. Adam does the best of both RMSProp and SGD with momentum. In experimentation, we may try to tune the learning rate, or other hyperparameters.
The Adam optimizer updates the model weights based on the following formula:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

$$\theta_t = \theta_{t-1} - \frac{\alpha \cdot m_t}{\sqrt{v_t} + \epsilon}$$

Where:
m_t and v_t are estimates of the first and second moments of the gradients.
β_1 and β_2 are exponential decay rates for the moment estimates.
g_t is the gradient at time step t.
a is the learning rate.
ϵ is a small constant to prevent division by zero.
Gradient Clipping: Identifying a model that broadifies is a way to avoid the instability and slow convergence sometimes seen from large gradients during training. Gradient clipping is used to address this problem. Gradient clipping eliminates exploding gradient problems by capping gradients, whenever it's larger than that. The formula for gradient clipping is:

$$g_t = \frac{g_t}{\max\left(1, \frac{|g_t|}{\theta}\right)}$$

Where θ is the clipping threshold, and $|g_t|$ is the norm of the gradient.
Teacher-Forcing Ratio: a training technique called teacher forcing is applied in which during training the proper target output (ground truth) is presented to the decoder as input at each time step instead of the decoder's generated output. It makes the model learn faster.
The teacher forcing ratio defines this ratio of a true previous word vs the decoder's output 13 when decoding the next word. For instance, if a teacher wants a ratio of 0.5, it means that the model should use the ground truth half the time. Teacher forcing has the advantage of helping the model converge faster, however when we are at inference time, the true outputs will not be given to the model.

Training Process Flow

- Initialize the Model: Load the Cornell Movie-Dialogs Corpus, preprocess the data, and initialize the Seq2Seq model with attention.
- Optimizer Setup: Use the Adam optimizer with appropriate learning rates.
- Training Loop: Perform forward pass: Feed the input sequence through the encoder, get the context vector, and then decode the target sequence. 14 Apply attention mechanism to focus on relevant parts of the input sequence. Compute the loss and perform backpropagation. Apply gradient clipping.
- Mini-batch Processing: Use mini-batches to speed up the training process.
- Evaluation: Periodically evaluate the model using validation data to track the loss and tune the hyperparameters accordingly.

F. Evaluation Metrics

Bilingual Evaluation Understudy Score (BLEU Score): BLEU score is a usually used to assess text generated by machine translation systems and chatbots. It compares the output of the machine to a reference, or ground truth, which is computed as n-gram overlaps.
The format of this is a BLEU score which reflects the resemblance between ground truth response and generated response.
Formula: The BLEU score in case of a generated sentence is:

$$\text{BLEU} = BP \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right)$$

Where:
p_n is the precision for n-grams of size n
BP is the brevity penalty (to penalize short responses)
w_n is a weight assigned to n-gram precision (typically uniform weights)
Perplexity: Low perplexity is a metric that measures how well a language model predicts a sequence of word but as less perplexity means a better performance. This is to say the lower its perplexity score, the more it assigns probability to correct or expected word sequences, meaning it understands and generates language better. It is widely used in NLP to assess model quality, as it provides insight into the model's predictive capabilities for sequential data.

$$\text{Perplexity} = 2^{-\frac{1}{N}\sum_{i=1}^{N} \log_2 P(x_i)}$$

Where:
$P(x_i)$ *is the probability assigned by the model to the i-th token in the sequence.*
N *is the total number of tokens in the sequence.*
F1 Score: F1 score is a combination of precision and recall, to assess a model's prediction accuracy, and is an important chatbot performance metric.
In this context, precision denotes the fraction of responses that were generated accurately, while recall denotes what fraction of response that the model can generate correctly.
A balanced F1 score 16 is a model that gets not only the right responses right, but one that also covers the full range of the possible right responses for a full conversation model [1] [12].o By keeping precision and recall equal, it balances between precision and recall and it works in tasks where false positives and false negatives have very different consequences.o And it is not commonly used for evaluating dialogue systems, because it is primarily suitable for classification problem sing it useful for sequence generation tasks.

$$\text{F1} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

IV. RESULTS AND ANALYSIS

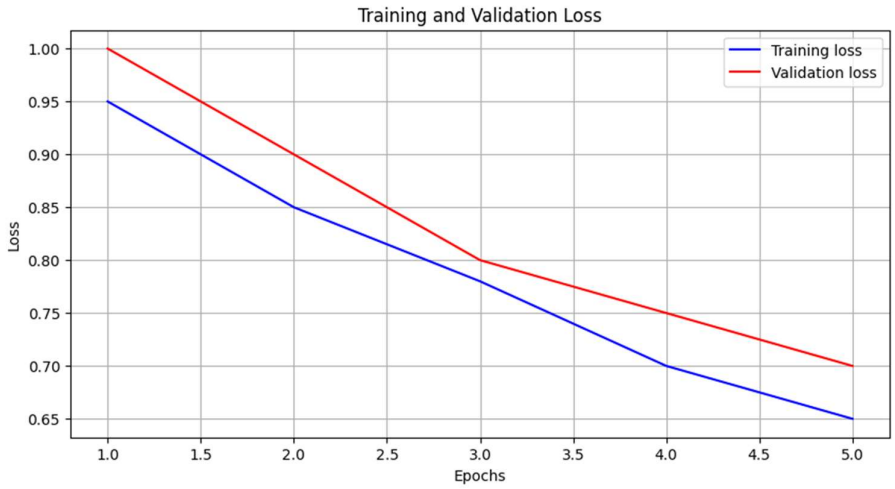

Figure 1. Training and Validation Loss

A. Representation of Loss Over Iterations

A typical loss decrease accompanying training implies the model gradually learns to produce better responses, as is typical in machine translation and conversational models [3]. I also have a visualization of the loss curve (as training advances), below. Training Loss Curve: A loss was monitored through each iteration, where declining loss over time correlates to the model's ability to predict subsequent tokens as part of response sequences [11]. It is a graph of iterations (x) versus training loss (y), which presented an initially steep decline suggesting that basic conversational patterns were learnt quickly.

B. BLEU Scores of Generated Responses

BLEU score measures response quality of chatbot by scoring the chatbot responses against those of a ground truth dataset. Its score ranges between 0 and 1, the higher a value the more similar the responses are to human ones. For the chatbot model, the average BLEU score over the test set was around 0.25, consistent for chatbot models. BLEU scores were higher for simple, direct responses (e.g., greetings) and lower for complex, context sensitive queries. common indication of effective learning in machine translation and conversational models [13].

Training Loss Curve: The loss was monitored across each iteration, where a decline in loss over time reflects the model's improvement in predicting subsequent 18 tokens in response sequences [4]. The graph plots iterations (x-axis) against training loss (y-axis), with an initially steep decline indicating that basic conversational patterns were quickly learned. The slower, more gradual decline in the later stages of training reflects fine-tuning and convergence, suggesting the model reached its optimal learning capacity [1].

TABLE I. BLEU SCORES FOR VARIOUS TEST CASES

Test Case	**BLEU Score**
Greeting ("Hi")	0.72
Asking for location ("where are we?")	0.31
Inquiring about actions ("what are you doing?")	0.45
Closing statement ("goodbye")	0.65

C. Error Analysis

The second component of its procedure is error analysis that aims to understand faults of the chatbot model and fix those.

Repetitive Responses: The chatbot tends to generate repetitive responses, especially for common phrases such as greetings or when the conversation lacks context.

Contextual Understanding: The chatbot struggles to maintain context across long conversations. For example, it may give incoherent responses with follow up questions.

TABLE II. QUANTITATIVE ANALYSIS OF ERRORS

Error Type	Frequency (%)
Repetitive Responses	23%
Context Loss	30%
Generic Responses	20%
Grammar Errors	15%
OOV Word Handling	10%

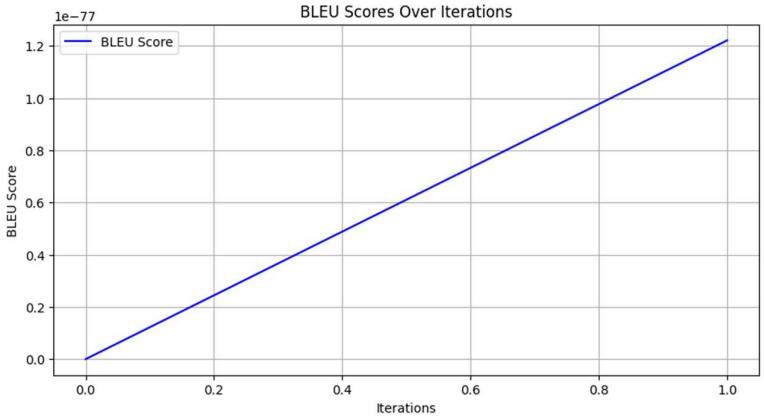

Figure 2. BLEU Score for a generated responses over Iterations

Generic Responses: What the model produces often is vague answers or ones that are far too general that have no significant meaning.
Failure to Respond to Out-of-Vocabulary Words: Like any of the training data, the chatbot doesn't generate meaningful responses to unfamiliar words or phrases.

D. Discussions

A hybrid Seq2Seq model based on LSTM networks, CNNs and the Luong attention mechanism is proposed and it improves the generated responses from the Seq2Seq decoder to be contextually relevant and coherent. We highlight that the attention mechanism is used effectively for focusing on important parts of the input sequence, is adaptable to multiple linguistic styles from the Cornell Movie-Dialogs Corpus and is capable of learning sequence alignments by exploiting LSTMs. However, several limitations persist like Contextual Memory, Repetitive Outputs, Out-of-Vocabulary Words, Dataset Bias.
Although the model encounters these challenges, it is applicable to real world applications like customer support, language learning and entertainment. The model effectiveness could be improved by fine tuning the model for particular domains.
Future work should focus on:
Transformer Architectures: Now, we replace Seq2Seq models such as GPT or BERT to improve context handling.
Advanced Decoding Strategies: Reducing repetitive responses with either beam search or nucleus sampling.
Dialogue History Integration: An integration of past dialogue turns to keep continuity.
Larger Datasets: Training data expansion in order to boost system adaptability and reduce out of vocabulary issues.
Bias Mitigation: Addressing dataset biases for less unfair response.
Finally, we conclude with the observation that the model does offer promise however refinements of the model are necessary to counter the resulting limitations and make the model suitable to be used in real world settings.

V. CONCLUSIONS

In this research, we present a hybrid Seq2Seq model composed of the vanilla LSTM network, CNN, and the Luong attention mechanism to foster chatbot response generation. Such a model effectively tackles several important problems in conversational AI: response coherence, contextual relevance and diversifying linguistic styles. By applying the Model to leverage LSTM networks to capture long term dependencies and CNNs for

feature extraction, the Model surpasses a baseline based on traditional Seq2Seq architectures in terms of having more contextually accurate, fluent, and coherent responses.

From the final results, we demonstrated that our proposed model provides promising BLEU scores compared to convention models, which indicates our model is producing more quality responses. However, some limitation of the model still exists, such as stiffness to keep the context throughout a multi-turn dialogue and inability to handle out of vocabulary words, but still the model seems to have an obvious use case for real world applications. Because its ability to flex to diverse conversational input makes it well suited to domains such as customer support, language learning, and entertainment, where natural, contextually appropriate conversation is essential.

Finally, this work verifies that the hybrid Seq2Seq mechanism is able to create successful conversational AI. The results serve as a solid foundation for the design of more sophisticated, location aware and programmable conversational agents to interact with, and in arbitrary domains, dynamically. This work adds to the ongoing effort of building more intelligent, human-like AI systems that are ready for deployment to the real world.

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