A Survey of Predictive Text

Joshua Leppo[1]

[1]Computer Science, Penn State Harrisburg, Penn State University, 777 West Harrisburg Pike, Middletown, 17057, PA, USA.

Abstract

Text prediction and generation have a multitude of practical applications. It can help users type faster with less errors. It can assist with text translation and text compression or summary. Just as there are many practical applications, there are many more potential solutions. In this paper, we will see various solutions to the problem of text generation and get a sense of how they have evolved over the years. We see in the early years how a probabilistic approach was a useful tool in text prediction, and how, with advances in technology, that gave way to neural networks in more recent years. We review several papers from various time periods beginning in the early 2000's up to 2020. The field of text prediction is as diverse as it is interesting.

Keywords: Text Prediction, Text Generation, NLP, CNN, RNN, LSTM, n-gram

Github Repo: https://github.com/jzl6309/NLP_Paper_Review.git

1 Introduction

Natural Language Processing (NLP) is a field within machine learning that deals with human language. While there are many subfields within NLP, in this literature survey, we will review text prediction within the text processing field. A computer's ability to recognize text patterns and make meaningful and useful predictions about which characters or words might come next has a variety of practical applications.

Text predictions can be used to speed up the time it takes to respond to emails or write letters. It can lead to decreased spelling and grammatical errors. It can assist with the translation from one language to another. These abilities

can benefit business by increasing productivity and efficiency. Individuals with cognitive or motor impairments will benefit from needing less keystrokes to complete their writing as well as minimizing errors. There are a number of practical applications that have an even greater number of benefits. Research on NLP text prediction methods is required to ensure efficient, useful text predictions.

In this literature survey, we will explore twelve papers ranging from 2005 up to and including 2023. There are three papers from 2020 to current, three papers from 2015 to 2019, three papers from 2010 to 2014 and three papers written before 2010. This should provide a range of views and methods on the topic of text prediction, covering almost twenty years of research.

We begin with methods outlined in early papers written before 2010. The first paper begins with one of the earliest methods of generating text, n-grams. The n-gram model is a probabilistic model that uses basic probability to predict the most likely next word given a previous set of words. The second paper we review also uses n-grams but within the specific context of providing single word predictions to assist users in typing faster. This is especially useful to user with cognitive or physical disabilities that making typing a difficult and time-consuming activity. The final paper in this category to review continues with a probabilistic approach to word prediction with a focus on "confused" words. The model is built as a classification model that uses probabilistic feature extraction techniques to classify confused words to make more accurate work predictions.

In the next section of the paper, we review papers written between 2010 and 2014. Here, we are introduced to new approaches and more sophisticated language models. The first paper we review how grammar can be used with parallel corpora to create either a translation model or a text compression model. In the next paper, we return to n-grams and see how it can benefit Sindhi word prediction. The final paper to review in this section provides our introduction to neural networks with a look at generating text with Recurrent Neural Networks (RNN).

We continue our review with papers between 2015 and 2019. The first paper in this section uses data mining techniques and compares probabilistic approaches like Naïve Bayes and Decision Tree models. The second paper in this section gives us our first look at Convolutional Neural Networks (CNN). They use a CNN with an attention mechanism to predict medical codes given medical notes. The last paper to review in this section uses inverse reinforcement learning built with a long short term memory (LSTM) model to train a text generation model.

Finally, we look at papers written since 2020. The first paper in this section use text generation to generate adversarial texts to improve on existing NLP models. They use both CNN and multilayer perceptron (MLP) models to train an adversarial text generator that successfully fool classification models. The next paper in this section we review uses an LSTM model with a context extraction feature that allows the model to generate text semantically similar

words based on a given input. The final paper we review presents methods of pretraining federated text models to improve speed and performance in federated learning models.

2 Papers Before 2010

In this section, we review [1], which predicts sentence completion using an n-gram model with beam search. [2] focuses on single word predictions and a user interface for efficient use of the model. In [3], word disambiguation is approached using a classification system rather than a straight forward prediction model.

2.1 Predicting Sentences using N-Gram Language Models

In [1], the authors address the problem of text prediction using an N-Gram language model shown in the following equation:

$$\text{argmax} \prod_{j=1}^{T} P(w_{t+j} | w_{t+j-N+1}, \ldots, w_{t+j-1})$$

The Viterbi principle is used to simplify the problem and improve efficiency. The model attempts to address the issue of predicting subsequent words given some beginning sentence fragment. This feature has the ability to greatly increase productivity in menial repetitive tasks, such as answering emails or entering command line commands in a terminal. The full algorithm is seen below.

Since the purpose is to improve productivity, the model quantifies improvement by considering only perfect predictions. Consider a text prediction for an email draft. If the user accepts the prediction, but still needs to go back to make corrections, then the prediction did not improve efficiency. For this reason, the results only consider a good prediction one in which the prediction was accepted in its entirety and not corrected.

They use an instance-based method of text prediction as their base line and compare that to the performance of their model. They use a diverse corpus of emails, weather reports and recipes. Evaluation is based primarily on two components. They look at precision, which is the ratio of accepted predictions, and they look at recall, which is a ratio that essentially quantifies the number of keystrokes saved by the accepted prediction. Ultimately, their research shows increased precision and recall where training documents have less diversity. For example, service center emails achieved much higher keystroke savings than recipes. However, in all situations, their model provides some benefit in improved efficiency and productivity.

Input: N-gram language model, initial sentence fragment $w_1, \ldots, w_t$, beam width k, confidence threshold θ.

1. Viterbi initialization:
   Let $\delta_{t,-N}(w_{t-N+1}, \ldots, w_t | w_{t-N+1}, \ldots, w_t) = 1$;
   let $s = -N + 1$;
   $beam(s - 1) = \{\delta_{t,-N}(w_{t-N+1}, \ldots, w_t | w_{t-N+1}, \ldots, w_t)\}$.

2. **Do** Viterbi recursion **until** break:

   (a) **For** all $\delta_{t,s-1}(w'_0, \ldots, w'_{N-1} | \ldots)$ in $beam(s - 1)$, **for** all w_N in vocabulary, store $\delta_{t,s}(w'_1, \ldots, w'_N | \ldots)$ (Equation 9) in $beam(s)$ and calculate $\Psi_{t,s}(w'_1, \ldots, w'_N | \ldots)$ (Equation 12).

   (b) **If** $\text{argmax}_{w_N} \max_{w'_1, \ldots, w'_{N-1}} \delta_{t,s}(w'_1, \ldots, w'_N | \ldots) = period$ **then** break.

   (c) **If** $\max \delta_{t,s}(w'_1, \ldots, w'_N | w_{t-N+1}, \ldots, w_t) < \theta$ **then** decrement s; break.

   (d) Prune all but the best k elements in $beam(s)$.

   (e) Increment s.

3. **Let** $T = s + N$. Collect words by path backtracking:
   $(w^*_{t+T-N+1}, \ldots, w^*_{t+T}) = \text{argmax}\, \delta_{t,T-N}(w'_1, \ldots, w'_N | ...)$.
   For $s = T - N \ldots 1$:
   $w^*_{t+s} = \Psi_{t,s}(w^*_{t+s+1}, \ldots, w^*_{t+s+N} | w_{t-N+1}, \ldots, w_t)$.

Return $w^*_{t+1}, \ldots, w^*_{t+T}$.

2.2 Advances in NLP applied to Word Prediction

The approach in [2] focuses on individual word prediction rather than sentence completion. Word prediction greatly benefits individuals with cognitive or motor disabilities by greatly reducing the amount of time it takes to write and reducing the amount of potential errors due to misspellings. They developed a method that includes both statistical analysis as well as rule-based features called FastType.

FastType is a user interface designed to decrease necessary keystrokes while improving spelling. The authors improve on the original FastType by implementing DonKey, which is simply an improved interface with an improved underlying language model to improve predictions. Predictions are improved by adding POS n-gram models and Tagged Word n-gram models together in their model. The DonKey user interface simply provides a ranked list of suggestions based on the typed characters. The user can choose a word from the list by clicking a button that corresponds to the word or by using a mouse or other pointing device.

The system is evaluated using three metrics, the ratio of keystrokes saved, the number of keystrokes until the correct word appears in the list and the amount of time that is saved by using the system instead of typing the full word out. They tested using list lengths of 5, 10 and 20. While there was some variation between the list length, the keystrokes saved ratio was between about 46% and 55%, increasing with list length. Keystrokes until completion ranged from 2.55 to 2.06, decreasing with list length. The amount of time saved was about 25% to 29%, increasing with list length. In all areas, their improvements to the language model and their improvements to the user interface produced improved results when compared with current benchmarks at their time.

2.3 A Learning-Classification Based Approach for Word Prediction

In this paper, [3] looks at word prediction as a classification problem. They use machine learning methods with feature extraction techniques that are developed from Mutual Information and Chi-Square techniques. This model is able to produce candidate words from a given context and then classify them to predict the most likely next word.

Given a corpus text, multiple sets of "confusion" words, or words that are often confused, are extracted along with some number of words preceding them. The features they extract are not just the preceding words but are words that are more helpful in telling one confused word from another, which is largely what sets their model apart from other similar feature extraction language models. These features are selected using Mutual Information and Chi-Square techniques and are arranged into feature vectors.

The vectors are used to train the classifier using Support Vector Machines (SVM). Each confused word is used as a class to train the classifier. This is done for each set of confused words, so that they each have a classifier model. Predictions are made by considering the given context and classifying it to the most likely confused word.

The evaluation of the model was done using Naïve Bayes as the baseline and a number of different datasets taken from various websites and databases. They used three confusion sets comprised of various confused words used extensively in word prediction research. The Bayesian approach outperformed their method in only one of the datasets and only by about 1%. The other three datasets saw increases over the Bayesian approach by as much as 7%. Overall,

their approach is able to produce high accuracy while considering only small amounts of context.

3 Papers Between 2010 and 2014

In this section, we will review papers between 2010 and 2014 that offer a variety of aproaches to text generation and/or text prediction. In [4], we look at using synchronous context-free grammar (SCFG) to assist in text-to-text bilingual translation. In [5], we are shown how n-grams with smoothing offer a powerful tool in word prediction with homographic words that occur in great numbers in certain languages. Finally, in [6], we are introduced to Recurrent Neural Networks (RNNs) as a powerful tool in text generation and are shown a variation that allows for reasonable performance allowing one to train large datasets using the model.

3.1 Learning Sentential Paraphrases from Bilingual Parallel Corpora for Text-to-Text Generation

In this paper, [4] research methods to generate paraphrases from bilingual parallel corpora. Key uses for this technique include language translation as well as text compression. Analysis is done on the types of paraphrases and on the sort of transformations they are able to complete with them. They also introduce methods for how one could alter their models to fit it to other text-to-text generation problems. As a result, they are able to show how their model is suitable for a number of text generative tasks while producing excellent results when compared to other methods at that time.

They use a syntactically informed synchronous context-free grammar (SCFG) in their model. The grammar is a 5-tuple and is defined as follows:

$$\mathcal{G} = \langle \mathcal{N}, \mathcal{T}_S, \mathcal{T}_T, \mathcal{R}, S \rangle,$$

where $\mathcal{N}$ is a set of nonterminal symbols, $\mathcal{T}_\mathcal{S}$ and $\mathcal{T}_\mathcal{T}$ are the source and target language vocabularies, $\mathcal{R}$ is a set of rules and $\mathcal{S} \in \mathcal{N}$ is the root symbol. The rule in $\mathcal{R}$ take the form:

$$C \to \langle \gamma, \alpha, \sim, w \rangle,$$

where the rule's left hand side $\mathcal{C} \in \mathcal{N}$ is a nonterminal, $\gamma \in (\mathcal{N} \bigcup \mathcal{T}_\mathcal{S})^*$ and $\alpha \in (\mathcal{N} \bigcup \mathcal{T}_\mathcal{T})^*$ are strings of terminal and nonterminal symbols with an equal number of nonterminals $c_{NT}(\gamma) = c_{NT}(\alpha)$ and

$$\sim: \{1 \dots c_{NT}(\gamma)\} \to \{1 \dots c_{NT}(\alpha)\}$$

constitutes a one-to-one correspondency function between the nonterminal in α and γ.

In translation, the bitext is parsed and aligned, and this grammar is used with extraction methods to generate rules used for translation. Weights are assigned to the rules and trained iteratively using a number of features. These can include "phrase translation probabilities, word-for-word lexical translation probabilities, a 'rule application penalty', and a language model probability." Then, an input sentence is translated by using the grammar and the CKY algorithm to find the derivation with the highest probability.

In paraphrasing, they simply make minor adjustments to the translation rules of the grammar and use lexical and phrasal probability features. They are basically accomplishing paraphrasing by creating an English to English translation. This methods allows for a number of text-to-text applications including text simplification, compression, query expansion.

Their method was compared to state-of-the-art approaches at their time. They also used human judges to review their output. Judges were asked to consider grammar and meaning. When reviewing compressed (paraphrased) sentences, were grammatically correct while still maintaining their original meaning. Their results were promising showing that their compression methods did comparable or better than other approaches.

3.2 Probabilistic Analysis of Sindhi Word Prediction using N-Grams

We return to n-gram modeling in this paper where [5] use bigram, trigram and 4-gram models with Laplace smoothing within the context of Sindhi word prediction. They capitalize on the probabilistic approach of n-grams in order to distinguish between homographic words which occur regularly in the Sindhi language. Due to the morphological ambiguity created from the lack of diacritics in most application of written text, the information contained in n-gram modeling is well suited for word prediction in this language. Results are based mainly on perplexity however, comparative studies on other languages with morphological structure are also looked at.

The n-gram model is based on the probability of a word given it's preceding word, $P(w_n|w_{n-1})$. However, this bigram model can be generalized to n-gram as follows:

$$P(w_n|w_1^{n-1}) \approx P(w_n|w_{n-N+1}^{n-1})$$

Smoothing is used by adding one to any zero probability bigrams in the model as follows:

$$C_i^* = (C_i + 1)\frac{N}{N+V}$$

They use a back-off technique where if a 4-gram is not present, they look for a trigram and use that probability. If that is not present, then they look for a bigram and use that probability. They use number of media to build their corpus including books, newspapers, internet etc... An algorithm is used to

tokenize the Sindhi words. Bigram, trigram and 4-gram models are created and stored in three separate databases before adding the smoothing.

Results were promising for all models but show that 4-gram is best suited for the Sindhi language. The perplexity of the 4-gram model was 69.07, which is almost half of the bigram model at 109.89. Since Sindhi is orthographically similar to other languages like Arabic, Urdu or Persian, [5] provides strong evidence that probabilistic analysis will also be useful for those as well.

3.3 Generating Text with Recurrent Neural Networks

In [6], Recurrent Neural Networks (RNNs) are used to make next character predictions based on the previous sequence of characters. The approach used makes use of the Hessian-Free optimizer (HF) to simplify training. A slight change to the standard RNN architecture is made to improve performance by using multiplicative connections "which allow the current input character to determine the transition matrix from one hidden state vector to the next."

The multiplicative RNN, dubbed MRNN by the authors, did comparatively well against other character predicting methods but what stood out most interesting was it's ability to generate text with high-level linguistic structure and grammatical structure. The standard RNN with input vectors $(x_1, ..., x_T)$, hidden states $(h_1, ..., h_T)$ and outputs $(o_1, ..., o_T)$ is iterates from $t = 1$ to T as follows:

$$h_t = tanh(W_{hx}x_t + W_{hh}h_{t-1} + b_h)$$
$$o_t = W_{oh}h_t + b_0)$$

Where W_{hx} is the input-to-hidden weight matrix, Whh is the hidden-to-output weight matrix and b_h and b_0 are biases. Exploding and vanishing gradient is managed through the use of the HF optimizer, which is shown to work well for their application. The "MRNN computes the hidden state sequence $(h_1, ..., h_T)$, an additional 'factor state sequence' $(f_1, ..., f_T)$ and output sequence $(o_1, ..., o_T)$ by iterating the equations:"

$$f_t = diag(W_{fx}x_t) \cdot W_{fh}h_{t-1}$$
$$h_t = tanh(W_{hf}f_t + W_{hx}x_t)$$
$$o_t = W_{oh}h_t + b_0$$

Figure 1 is taken directly from the paper and provides a detailed explanation of the network. The difficulty with this approach is with the product of weights in gradient descent that can result is artificially high derivatives. However, the HF optimizer offers the solution to this problem as a 2nd order method that is particularly good at dealing with those kinds of issues.

The MRNN is trained along side standard RNN as well as a few other current state-of-the-art language modelers on three different datasets. The datasets used were a cleaned up dump of Wikipedia, a collection of articles from the New York Times and a corpus of machine learning papers downloaded

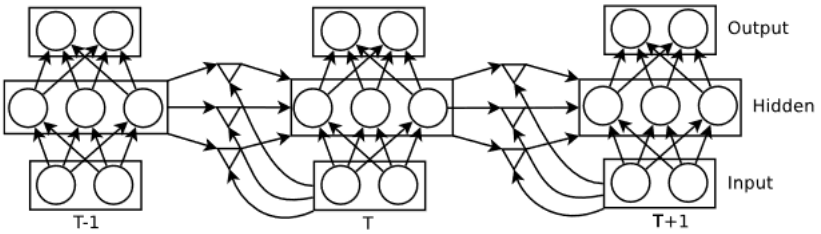

Fig. 1: "The Multiplicative Recurrent Neural Network 'gates' the recurrent weight matrix with the input symbol. Each triangle symbol represents a factor that applies a learned linear filter at each of its two input vertices. The product of the outputs of these two linear filters is then sent, via weighted connections, to all the units connected to the third vertex of the triangle. Consequently every input can synthesize its own hidden-to-hidden weight matrix by determining the gains on all of the factors, each of which represents a rank one hidden-to-hidden weight matrix defined by the outer-product of its incoming and outgoing weight-vectors to the hidden units. The synthesized weight matrices share 'structure' because they are all formed by blending the same set of rank one matrices. In contrast, an unconstrained tensor model ensures that each input has a completely separate weight matrix."

and converted to text. The results were promising showing that the MRNN did perform comparatively to the other methods placing slightly better the one while slightly less than the other when comparing performance using bits per character (bpc). The author's also produce various text generated by the three different models to show MRNN's ability to "learn" information about the input corpus. For example, when using the Wikipedia model and prompted with a list of countries, the MRNN model recognizes the input is a list and generates text accordingly.

[6] propose a novel approach to RNNs that solve computational difficulties the made use of model virtual impractical at the time. Using their MRRN approach, they were able to manage performance and train large datasets comparatively well consider other current methods. Further, they were able to show the raw power of RNN models in their ability to learn from the input and model their corpus with a high level of accuracy

3.4 Results 1

Using n-gram language models to predict and generate sentences is largely dependent on the input dataset the model is trained on. Using a dataset comprised of the works of Shakespeare, I was able to successfully implement a functional model using n-grams with laplace smoothing that generates text with the distinct flavour and voice of Shakespearean plays. As stated in [1], sentence prediction usefulness requires a diverse set of documents that are

"thematically related." This allows the model to be focused to the type of text generation that is required.

3.5 Results 2

I was able to build an RNN model and train it using the Shakespearean texts. Due to time constraints and limited system resources, I kept the model small and was only able to train for 5 epochs. However, results were still surprisingly good. See the sample output below.

```
Generated Text:
And so heardering oath thy masters, and you sir, how good?

BAPTISTA:
Alast you remember mine by the charantless
Tall mine excress, the rume conceive The coldon
A jest, away in mine own leaving bass.
Spoke's away of a clouds such a
sweet man, little Claudio, birth
How wound I lively my meant aponting gream our hand?

GRUMIO:
At, he smiles of fair Katharine,
Post dost like my kingly head, this is the lass! a man a lenttener,
stall's not conseating a fool, a
Tater, while and in rest.

LUCENTIO:
Horte good: you are gone.

Crown:
Nesty much: he may shail, now thank you again.
```

4 Papers Between 2015 and 2019

This section explores data mining to predict user entries in user entry forms in [7]. In [8], a convolutional neural network (CNN) using an attention mechanism is used to predict medical codes given medical notes. Finally, text generation is approached using inverse reinforcement learning (IRL) model in [9]. Also, results for the IRL using the synthetic oracle dataset are given at the end of the section.

4.1 Predicting user entries by using data mining algorithms

A number of applications for text prediction have been discussed so far. Here, [7] tests data mining with a number of methods to make data entry systems easier and more user-friendly. Naive Bayes, Rule Induction, K-NN and Decision Tree methods are tested for high predictive accuracy in an effort to make Government decision system more efficient and easier to use.

The dataset used was taken from the Government decision system of the Palestinian Ministers Council. Data mining preparation and preprocessing

was performed on the dataset to prepare it. The methods used were Replace Missing Values, Select Attributes, and Filter Examples. After preprossing, association rules are set up using two methods, FP-Growth and Create Association Rules. Once the dataset was ready, it is used to create classification models that will predict certain entries in the system based on the user initial entries, i.e., as they input data at the beginning of the form, it makes suggestions about entries in other areas of the form. The data was ran through the four models noted earlier. The equation for Naive Bayes classification is given below as it performed best.

$$y = argmax_y P(y) \prod_{i=1}^{n} P(x_i|y)$$

While results showed Naive Bayes outperforming the other methods with K-NN coming in second, accuracy overall stayed somewhat low at a max of 68.41%. The author's noted the large number of class's and the varying number of possible inputs to the system. Overall, the process and methods show promise as another strong method for making text predictions that ultimately make system usage easier and an end user's use of it more user-friendly.

4.2 Explainable Prediction of Medical Codes from Clinical Text

Assigning proper medical codes can be a challenging task due to the large volume of available codes and the fact that the medical texts are doctor's notes, which tend to have non-standard abbreviations, irrelevant information and even misspellings. In this paper, [8] propose a convolutional neural network (CNN) that uses attention to predict medical codes given medical text as input. The datasets used are two versions of MIMIC, which are text discharge summaries from intensive care unit stays. They call their method Convolutional Attention for Multi-Label classification (CAML). The attention mechanism allows the model to provide explanations for the predictions by assigning importance values to n-grams from the input.

Medical code predictions are modeled as a multi-label text classification problem. The attention mechanism is used to choose the parts of the text that are the most likely for each of the possible medical codes. A sigmoid activation function is used to transform the output into a probability. The model's architecture is shown in figure 2.

The model is evaluated using a number of methods including baselines of a one-dimensional CNN, bag-of-words (BOW) logistic regression and bidirectional gated recurrent unit (Bi-GRU). Various parameters are tuned using an optimization package. Metrics used for evaluation include area under the ROC curve (AUC), F1 and precision 8. They use micro and macro metrics for AUC and F1 where they treat each text/code pair as an individual prediction, or they average the per-label metrics. Prediction results are also provided to

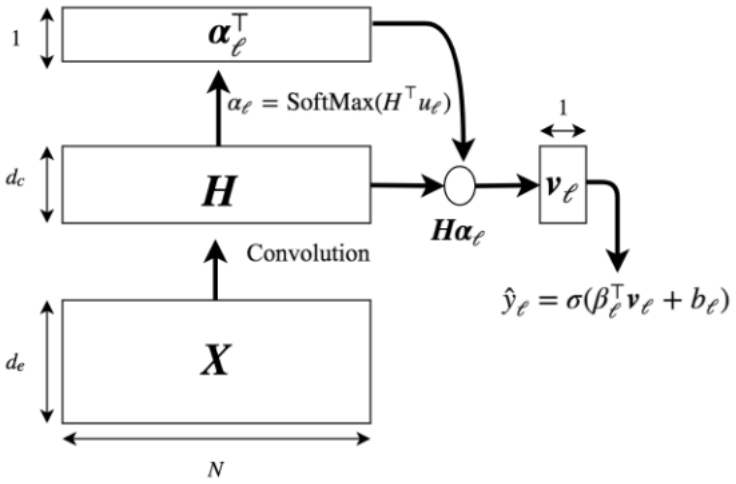

Fig. 2: CAML Architecture

physicians to provide feedback on the predicted codes as well as how informative the k-grams were that were used by the attention mechanism to make the prediction.

Final results show CAML producing better results in all of the metrics for all but one of the datasets that were tested. Their approach offers a strong model able to predict useful medical codes. Further, the model contains an attention mechanism that is able to provide explanation to why a particular prediction was made. Because of these feature, the model could be a strong building block on which future automated medical coding could be built.

4.3 Toward Diverse Text Generation with Inverse Reinforcement Learning

In this paper, [9] approach text prediction using inverse reinforcement learning (IRL). The model trains a reward function and an optimal policy alternating back and forth. Training this way allows the model to generate instant rewards at each step creating more dense reward signals. The generation policy works by sampling one word at a time to create sequences of text. The benefits of this approach is that it creates high quality diverse text.

The generated text sequence is given as $s_{1:T}$. The probability of generating the text sequence is given by:

$$q_\theta(x_{1:T}) = \prod_{t=1}^{T-1} \pi_\theta(a_t = x_{t+1} | s_t = x_{1:t})$$

There are two steps to the IRL model. Train the reward function, and then, train the optimal policy that maximizes the reward to generate text. Figure 3 shows an illustration of the model.

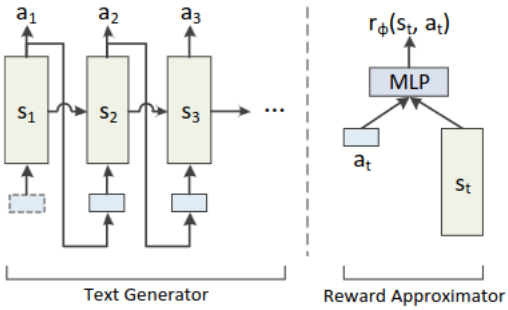

Fig. 3: Illustration of the model

The reward function is given by:

$$\mathcal{J}_r(\phi) = \frac{1}{N}\sum_{n=1}^{N} \log p_\phi(\tau_n) = \frac{1}{N}\sum_{n=1}^{N} R_\phi(\tau_n) - \log Z$$

where τ_n denotes the n^{th} sample in the training set. The text generator is modeled after a long short term memory (LSTM) network. Training follows the same steps outlined previously where the model iteratively updates the reward based on the token, then, generates a token based on that reward and then repeats.

The model is trained on three datasets. They use the synthetic oracle dataset, COCO image captions dataset and IMDB movie reviews dataset. The models are evaluated differently for each of the datasets. The synthetic oracle dataset is evaluated using the average negative log-likelihood (NLL). When compared to state-of-the-art maximum likelihood estimation (MLE) models, the IRL model has a lower NLL score, which indicates a higher quality of the generated text sequences. The COCO image captions dataset is evaluated using a number of differnt BLEU metrics. In most areas, the IRL outperformed the MLE models. The exception being the BLEU metric which seeks to measure the precision of the generator. One MLE model did outperform the IRL model. This is believed to be due to the fact that the leading MLE model has a tendency to repeat safe text sequences while the IRL model produces more diverse texts. Finally, The IMDB move reviews dataset is evaluated using the same BLEU metrics as the COCO dataset. However, it is also evaluated by humans where sentences are asked to score them, and the scores are averaged out for the sentences. In either case, their model outperformed the others by producing high quality diverse text sequences.

This paper approaches text generation using the inverse reinforcement learning (IRL) model where reward and token generation are updated at each step of training. The model is trained on a diverse set of datasets and is evaluated using a number of metrics including human opinion. In most areas, the model outperforms current state-of-the-art models. The model's success is in it's ability to generate texts that are diverse and high quality.

4.4 Results

Figure 4 shows output of the IRL model as it trains. Due to time constraints, I was unable to train the model for the number of epochs that were trained for the paper.

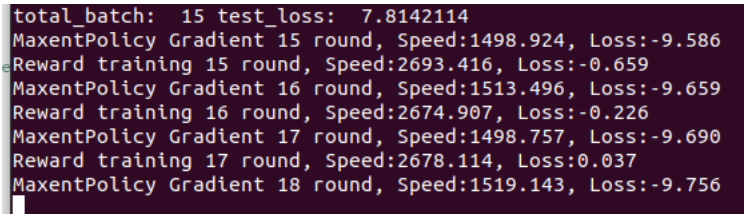

Fig. 4: Running output of IRL Model as it trains the reward and optimal policy iteratively.

5 Papers Since 2020

In this section we conclude with three additional papers on text generation. [10] provides an approach to adversarial text generation that improves other text based models. [11] uses a context extraction method in conjunction with an LSTM model to generate text with semantic similarities to the given input. Finally, [12] improves on federated learning models by using pretrainig methods.

5.1 CAT-Gen: Improving Robustness in NLP Models via Controlled Adversarial Text Generation

In this paper, [10] work to improve NLP models through the generation of better adversarial texts that are more diverse and fluent than other approaches. The adversarial text generation is constrained to certain controllable attributes that allow the generated text to be semantically similar to the input text. The model is called the Controlled Adversarial Text Generation (CAT-Gen), which makes changes to the controlled attributes to generate the adversarial text.

The model has three stages, pre-training, change of attribute and optimizing for attacks. The encoder and decoder are pre-trained using teacher-forcing. Cross entropy loss is used between the input and output of each token. The

attribute classifier is also pre-trained and a separate dataset. Then, the pre-trained attribute classifier is used to train the decoder to create output with changed attributes. Finally, the model searches the attribute space to find attributes that generate strong text that could be successful in their attacks. This is done by choosing an attribute that maximizes cross entropy loss. The model uses convolutional neural network (CNN) for attributes and labels. It used multilayer preceptron (MLP) for the projector. The model's archetecture is shown in figure 5.

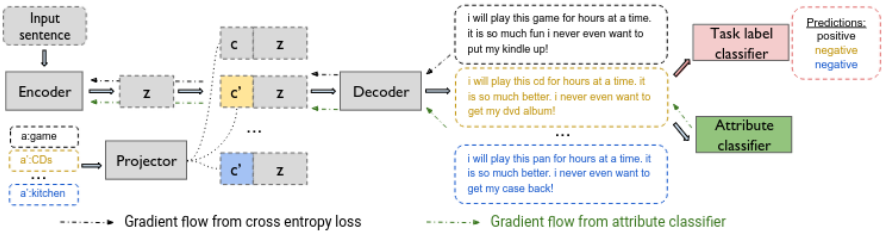

Fig. 5: Overview of the CAT-Gen model.

The model is trained using the Amazon Review dataset. The dataset is split into different training sets to train the attribute classifier and the task label classifier. The generated output maintains fluency and looks quite a lot like the original sentences. The attribute change changes a few words in the review, so they are different sentences but maintain the original sentiment. These sentences are compared to outputs of other adversarial models using BLEU-4 where CAT-Gen performed quite well. The model is also evaluated by retraining classifiers with the adversarial attacks. The CAT-Gen model is shown to improve performance better than other methods.

The controlled adversarial text generator is able to product diverse, meaningful text sequences that are both successful in their attacks as well useful in improving the attacked model. The model is evaluated using a text classifier, but the model is flexible enough to be applied to other NLP tasks by making the appropriate adjustments to the attributes. The model provides a useful tool to generate text that can in turn be used to improve other text based models.

5.2 Context Based Text-Generation Using LSTM Networks

In [11], an approach to text generation that contains context is proposed. The long short-term memory (LSTM) language model is trained with an input sequence along side a context vector. This approach allows the model to maintain the context of the given input words, so it is able to produce sentences with semantic meaning that avoid lexical ambiguity. The model is evaluated using

cosine similarity measures to gauge the semantic closeness of the generated text from the given context.

The model uses an LSTM model but also contains a method for context extraction. The extracted context, in the form of "context vectors," is fed into the LSTM model along with the input sequence at each iteration. A diagram of the model is shown below in figure 6.

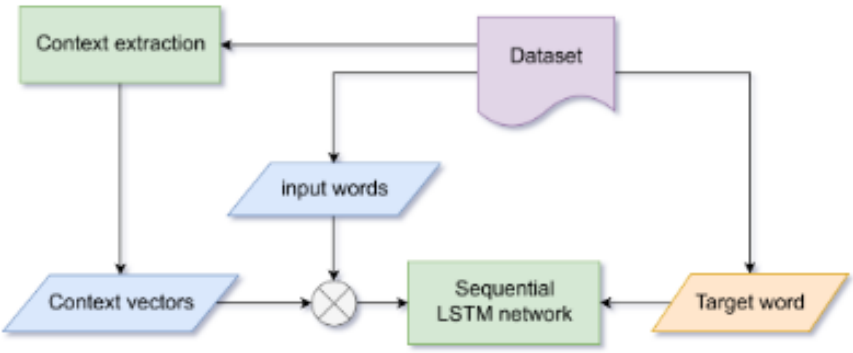

Fig. 6: LSTM model with context vector extraction

Two approaches to creating the context vectors are used. The word importance method uses term frequency-inverse document frequency (id-idf) to identify the word having the most importance. The word clustering method uses word embeddings, specifically word2vec, based on "the hypothesis that the context of a sentence is determined by a context vector present in the word vector space, such that the semantic similarity of the context vector and the accumulated sentence vector is highest." The equation to find the context vector is given below:

$$\forall s \in S, \exists c \in C \text{ s.t, } \sum_{w_i}^{w_n} \cos(s, c) \text{ is minimum,}$$

where S is a list of sentences and C is the cluster centers of the word vector space. Experiments were done using different datasets to train the word vector space. Using the same dataset (domain vector space), the context words were "localized words of action." However, using various wikipedia sources (wiki vector space) produced context words that were nouns and subjects containing broader meanings. Word vectors within the word vector space are clustered based on semantically similar words. The context vector is selected based on the cluster center having the minimum cosine distance with the sentence vectors, from which the top n words are chosen.

Since the main goal of the model is to have generated text that maintains semantic similarity, the evaluation method used is the cosine similarity measure rather than other methods that evaluate syntactic integrity. The cosine

similarity is given below:

$$\frac{1}{N} \sum_{n_i}^{n_n} m_i \cdot \cos(n_i, c)$$

Both the domain vector space and the wiki vector space context vectors were evaluated using cosine similarity. The domain vector space model outperformed the wiki vector space model.

Thus, of the methods attempted, word clustering using the same dataset used to train the language model produced the best performance. This method provides the best means of extracting context vectors from the input sentences, which can then be used to train the language model to maintain the contextual meaning of the input. Training with this additional feature provides the model a way to generate output that maintains semantic similarity with the given context.

5.3 Pretraining Federated Text Models for Next Word Prediction

Methods of transfer learning are used with federated learning in this paper to improve next word prediction models. Federated learning is form of machine learning that used distributed systems to train the model. [12] focuses on improving federated models using various forms of pretraining including pretrained word embeddings and whole model pretraining. Federated models using their pretraining approaches are compared to current federated learning baselines to show the possible improvements that can be realized using these extra features.

The LSTM language model is used as the base model. The vanilla LSTM is trained using federated learning with the following three enhancements. They use central pretraining and federated fine-tuning. Pretrained word embeddings are used in place of random initialization. Finally, the two are combined to have centralized pretraining with pretrained word embeddings as well as federated fine-tuning. The main dataset used is from Stack Overflow posts. The vocabulary is reduced to contain only rare words. The full collection of Shakespeare is used as the dataset for pretraining.

Experiments are performed on pretraining using Shakespeare and on fine-tuning using Stack Overflow as well as pretraining and fine-tuning using Stack Overflow for both. It is shown that pretraining with a separate dataset yields greater improvement, which works well with federated training since pretraining is done centrally while fine-tuning is done separately on user devices. Various forms of pretrained word embeddings including GloVe, FastText and GPT2 are also tested with federated learning. In order to fit the word embeddings to the model, two algorithms are used. The two algorithms are given below. Pretrained word embeddings are shown to achieve comparable accuracy in less training rounds, which is a great benefit with federated training where constant communication is required.

Algorithm 1: Post-Processing Algorithm PPA(X, D)

Data: Word Embedding Matrix X, Threshold Parameter D

Result: Post-Processed Word Embedding Matrix X

/* Subtract Mean Embedding */

$X = X - \bar{X}$

/* Compute PCA Components */

$u_i = PCA(X)$ where $i = 1, 2, \ldots, D$

/* Remove Top-D Components */

for *all v in X* **do**

  $v = v - \sum_{i=1}^{D} (u_i^T \cdot v) u_i$

end for

While the pretraining methods provide some performance enhancements, there was not much improvement on accuracy. Additional research should be done using corpus that are more similar i.e., the dissimilarities between Stack Overflow posts and Shakespeare's work could impede accuracy for next word prediction models. However, the approach of using pretrained word embeddings with federated training does provide a simple way to improve performance that opens up possibilities in the field of federated learning.

5.4 Results

Sample output from test runs of the federated text model are below. Again, due to system and resource constraints, I could not run the model for long periods of time or test the various configurations. However, the model was first trained for 10 epochs without pretraining. The accuracy stayed at 0. You can see the final output in figure 7. The model was then pretrained using GPT2 word embeddings for 5 epochs and then, trained the model for 5 epochs. You can see the improvement in figure 8 even with this minimal training.

Algorithm 2: Dimensionality Reduction Algorithm PP_PCA_PP(X, N, D)

Data: Word Embedding Matrix X, New Dimension N, Threshold Parameter D
Result: Word Embedding Matrix of Reduced Dimension N: X

/* Apply Algorithm 1 (PPA) */
1 $X = PPA(X, D)$
/* Transform X Using PCA to N Dimensions */
2 $X = PCA\_Transform(X)$
/* Apply Algorithm 1 (PPA) */
3 $X = PPA(X, D)$

```
    100/Unknown - 20s 203ms/step - loss: 6.0619 - num_tokens: 124995.0000 - num_tok
ens_no_oov: 121048.0000 - num_batches: 100.0000 - num_examples: 10000.0000 - accura
cy: 0.0000e+00 - accuracy_no_oov: 0.0000e+00 - accuracy_no_oov_no_eos: 0.0000e+00
Sampling 10 new clients.
   loss: 7.354057312011719
   num_tokens: 39007
   num_tokens_no_oov: 37848
   num_batches: 199
   num_examples: 3115
   accuracy: 0.0
   accuracy_no_oov: 0.0
   accuracy_no_oov_no_eos: 0.0
```

Fig. 7: Trained 10 epochs with no pretraining.

6 Conclusion

The field of text prediction and text generation is wide a varying. The practical applications are seemingly endless from language translations to machines that can mimic human language. As advances in machine learning continue, more and more sophisticated models are created that produce more useful text predictions and generate more life-like text. With these advances the field of

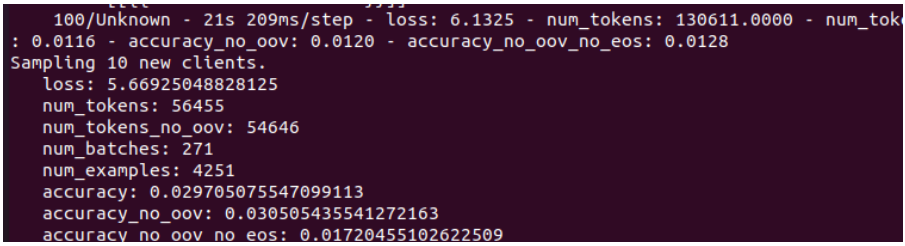

Fig. 8: Pretrained with GPT2 5 epochs. Then, trained 5 epochs.

artificial intelligence pushes closer and closer to machines that can replicate human speech or provide near perfect translations.

In this paper survey, we reviewed a number of methods of text prediction and text generation as well as a number of different applications. We reviewed probabilistic methods like Naïve Bayes and n-grams models. We also saw how more complex machine learning techniques like Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) could be used to create highly effective text generation models. There are many models that were not covered in this survey. Language models are continuously being improved and newer models are being created all the time. With new improvement, comes new areas of research and new ways the field of text prediction and text generation are making profound impacts on the world.

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