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Review on Text Generation Models

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Abstract: The generation of natural language text from the given data has become common today. The text generation system find out the required information to must include in the output. The automatic text generation system has variety of applications. The researchers found that in the 192 countries in the private colleges and university college 56.7 million students are studying. The number of students in the world is increasing. And all students should have a proper Text Books. The number of Text Books production is limited and it is not sufficient to satisfy the student's requirements. The text books as per the syllabus make students to learn easy. Here we are attempt to develop a Text Book generator software. The software is to get a pdf formatted Text Book as per their syllabus. In which the syllabus of our subjects are given as the input to the system, and generate a text document by collecting the information using web crawling method from the trusted educational websites. The generated text document is summarized to get a precise and crisp summary with the required data.

Keywords: Educational Websites, Summary, Text Book Generator, Web Crawling

I. INTRODUCTION

The generation of natural language text from the given data has become common today. Its use has become more ubiquitous. The input to the natural language generation system can be in many forms such as tables, dataset of records etc. The text generation system has wide variety of application such as to generate the product description, weather forecasting, generating cooking recipes etc. In this paper we are attempting a research on the automatic text generation to apply on the field of education to solve a problem that is the numbers of students who are studying in private and government colleges under the university are very large. So that they will face a big problem is that they do not get proper study material as per their syllabus. For producing a large number of Text Books play a crucial role in the current scenario. The number of Text Books produced is limited and it is not sufficient to satisfy the requirements of students. So they depend on GOOGLE or other educational websites for study. So here we are attempt to overcome this problem by trying to develop software for the creation of a textbook. Mainly it contains two parts: text generation and text summarization. The main idea of this to generate text from the different data set and gather it to the text document and finally it summarizes to get the short and crisp summary in pdf format output. In which the syllabus of our subjects are given as the input to the system in the form of an image. And the technique OCR is used to recognize each character that are present in the given input image. After that the result of the OCR will transfer into the text generation module. The text generation module will collect data from a variety of datasets that are present on the web using web crawler. A web crawler is a mechanism that is used to access different data pages from the Internet. When the web crawler collects the web pages from the web the URL of each page should be copied. And this is used for further reference. All the downloaded pages are transferred into the text summarization module to get the crisp and short summary. In this paper we are attempting to study and compare the different automatic text generation systems.

II. LITERATURE SURVEY

In [1], it generates a natural language summary based on the information in an RNN. It contains an order planning method for table- to- text generation, and also contains a linking mechanism and copying mechanism. The linking mechanism provide the relationship between different fields in the table and enable the neural network for plan which of them is first and which is next. Then the copy mechanism is used to cope with rare words. For generating the summary it takes table as the input and generate natural language summary based on the information contained in the RNN. Mainly it contains three components: an encoder, dispatcher and a decoder. The encoder will capture the information in the table. The dispatcher plans what to generate next. After encoding the information in the table the RNN is used to decode the natural language summary and it predicts the target words in the sentence. It contains a visualization analysis to understand the order planning mechanism. Here use a neural encoder for representing the information in the table. First split the contents in each field into separate words and transform this table into a large sequence. The RNN used in this method has a Long Shot Term Memory (LSTM) units. It used to read the contents in the table and also used to read the field name. For representing the words and fields use different or separate matrices. The dispatcher used here is an attention mechanism.

The content based attention is based on the content representation. For generating the text calculates the attention weights based on the encoded vector and contents in the table. And also contains a link based attention which distinguishes the relationships between the fields in the table.

In [2], it contains a sequence to sequence technique for model the table content and structure by using the local and global addressing scheme. Local addressing is used to determine which particular word in the table should be focused while generating the description. And global addressing is used to determine which particular word in the table should be focused more for generating the summary. It contains an encoder- decoder framework using the long short term memory. It first encodes the field values in the table and the LSTM decoder is used to generate natural language summary of the table. This decoding phase will contains a novel dual attention mechanism, which consist of two parts: word level attention and field level attention. Word level attention is for local addressing and field level attention is for global addressing. The experiments on WIKIBIO data set provide substantial improvement over the baselines. In the case of local addressing, the table which are used here contains a set of fields. The local addressing is used to encode each record in the table. The encoder which used here is a LSTM encoder which identifies the dependencies between different words that are included in the table. For building a connection between different words in the table word level attention and dual attention mechanism is used. The global addressing is used to represent the inner record information in the table. For enabling the global addressing field level attention mechanisms are used here. The table structure is encoded for table representation and also contains a novel field gating LSTM which used to embedding the field into the cell memory of LSTM unit. Then the table information are reduced and the information in the table are unimportant which are not used for generating the description. Basically dual attention mechanism is used to generate the description from the table.

In [3], it is used to generate natural language summary from the structured data for the address specific characteristics of the problem. It proposes a neural component to address ‘stays on’ and ‘never look back’ behaviour while decoding. And it introduces a dataset for French and German and it gives the state of the art result on the dataset. It gives an improved performance on the target domain.

In [4], it generates a model for the natural language sentence which describes the region of a particular table. It maps each rows in the table to particular vectors and then generates the natural language sentence. If the table contains rare words then a flexible copying mechanism is used to replicate those rare words from the table to the output sequence. Mainly the table to text generation has three challenges: what was the good representation of a table, how to generate natural language sentences automatically, how to use the low frequency words in the table. In this paper it uses a neural network model which takes each row from the table and generates a natural language which describes that particular row. It describes an encoder-decoder framework. The encoder part represents each row in a vector and decoder part for generating rare words from the table it uses a copying mechanism. GRU based RNN is the backbone of the decoder. In the attention mechanism while generating a word the decoder use the important information from the given table. For increase the relevance between the sentence and the table use this information into decoder, global and local. Basically the encoder-decoder approach is used to generate the sentence which describes the entire rows in the table.

In [5], the content selection determines which data is produced to the output system. Here for learning the content selection rules it uses an efficient method. This model allows capturing the dependencies between the items to be inputted. In the case of concept- to-text generation, the content selection is the major task. In this paper for learning the content-selection component a data-driven method is proposed. In the case of a database each entities in the database has a type and for each type there will be a set of attributes associated with it. Also each entry has a label and which specifies that whether that entry is included in the generated text or not. A learning algorithm is provided for the database entities during the training process. To select the database entities is the main aim of the content selection component. The content selection component takes every entity in the database in isolation. Then formulate the content to be selected. In the case of isolation some of the entities of the database are to be selected than the others. By considering the entity attribute values the individual preference scores are calculated. For discovering the links automatically uses a corpus-driven method. Also by using the generate-and-prune approach induces the important links. This paper mainly describes about the data-driven method for automatic content selection.

In [6], it presents a robust generation system which is used for content selection and surface realization. Here the end-to-end generation process is divided into a sequence of local decisions, arranged hierarchically and each trained discriminatively. Also it has three domains: robocup, technical weather forecasts and common weather forecast. For combining both the content selection and surface realization a powerful generation system is used. Also improving the performance feature-based design is additionally used. The main advantage of this approach is the ability to use the global features. By measuring the BLEU score we can evaluate the surface realization. Also by measuring the F1 score we can evaluate the macro content selection. Then conduct a human evaluation by using the Amazon Mechanical Turk. To capture some properties of the domain the feature-based approach is straightforward to the domain specific features. This was one of the advantages of feature-based approach.

In [7], it mainly describes the generation framework that was used to create five versions of a weather forecast generator. The used generation framework combines the probabilistic generation methodology with a comprehensive model. This generator was evaluated by using or measuring the output quality. This paper mainly summarizes the pcRU framework. The pcRU is a language generation framework. By applying the transformations to the representations the NGL systems to be composed the generation rules. The main aim of this approach is by using the NLG method it is used to reducing the development time and increasing the reusability of systems and components. Finally it improves the development time, produces better output and it is computationally more efficient. By compared to the n-gram-based generate-and-select NLG it reduce the computational expense and also improves the generated language quality. This was the aim of this approach. The structured probabilistic model makes the informed decisions during the generation phase.

In [8], it automatically produces an output in the form of text from the non-linguistic input. In this paper it deals with an unsupervised domain-independent fashion for capture the content selection here we will use a joint model. Content selection means that what to say and surface realization mean that how to say. For describing the inherent structure of the input here uses a probabilistic context-free grammar. Here the grammar can be represented as a weighted hyper graph. And for finding the best derivation tree for the given input recast generation are used. For finding the best derivation by using the hyper graphs framework we formulate the input as a PCFG. At the decoding time this model takes the k best derivations.

In [9], this paper introduces a neural model that scales large and rich domains. It generates biographical sentences from the Wikipedia from the tables. This paper describes a conditional neural language model for the generation of text. This model mixes a fixed number of vocabularies with the copy actions by extending this model. Then from the input database to the produced output sentence transfer the words. Depending on the data fields this paper allows the model to embed the words. Both the local and global conditioning are improves this model. This paper mainly focused for generating only the first sentence.

In [10] this paper presents a platform Data2Text Studio for automated text generate from the input which is structured data. This will improve outputted generated text. Using this Data2Text generation technology which produce a text from the structured data and the output is efficiently describe the input data in the generated text. The generated text can be used in the many applications. The architecture of the Data2Text Studio consist mainly three components which are model training, model revision and text generation. . The platform is equipped with a semi-HMMs model which extract automatically the high quality templates and corresponding trigger conditions from parallel data and it can support learning for how can use the some specific phrase in some particular situations.

In [11] this paper presents a statistical framework that produces a text description from the attributes of the product as the input to the system. It is used to generate a product description from the product attributes. To generate the product description a system needs to aware of the relative importance of the attributes in the input which is given to the system. By using the statistical frame work the system has the advantages those are coherent with facts, fluency and it is highly automated. For deciding what to say and how to say for the generation of product description from the product attribute data the proposed structured information and template information are helpful.

In [12] this paper presents a system that generates the natural language text using semantic data as input. The main task of this system is to find out the right information to include in the generated text which is the output of the Natural Language Generation (NLG) is known as content selection and it is very highly domain independent. That means the new rules have to be developed for each new domain and this is done by manually so that it is very difficult task. So that in this paper presented a method for learning the content selection rules for text generation in different domains. His methodology how that the data available from the internet for various domain is using here. In this experiment they are using three methods that are exact matching, statistical selection and rule induction to get the rule from the indirect observations from the data. The content selection has the significance importance in the acceptance of the generated text by the final user.

In [13] this paper presents a data - driven method for the concept to text generation. That means automatically creating text output from the non-linguistic input. They defined a probabilistic context-free grammar that describes the structure of the input and represent it as a weighted hyper graph. The non-linguistic input means such as databases of records, logic form and expert system knowledge bases. The method data driven approach to text generation is simple, flexible and it is also a domain independent method. In this method the key concept is to reduce the content selection and surface realization into a common parsing problem. They define the probabilistic context free grammar PCFG that capture the structure of the input databases and it correspondence to natural language. For generation they first learn the weight of the PCFG by maximizing the joint likelihood of the model. By finding the best derivation tree in the hyper graph the generation of text is performed. The improvement to the system by using discriminative reranking. In this method typically create a list of n-best candidates from a generative model and reranking with arbitrary features. This model result has significantly higher fluency and semantic correctness. It has the flexibility to incorporate to additional, more elaborate features.

In [14] this paper, Artificial intelligence are interested in text generation for a long time but heat produced lower levels of activities. Now AI understood that this text generation is essential and it is needed for uses. Text generation with penman has some merits as it is portable, reusable and embedded in many of the system. Penman make sure to generate multi paragraph in English language there are for modules in penman knowledge acquisition module providing an area of knowledge connecting with what is all about the goal in communication. Text planning module is an arrangements to make attention towards readers on the basis of which portion to be presented and knowledge in the content. The sentence generation module for representing the output in English language is defined with proper grammar.

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In [15] The inventions in the category of text generations have paved for a drastic grammatical system in English. This paper includes augmentations of a vivid kind of precedents in the systematic outlay. Nigel who is encoded in the computer program emphasizes on the text control purposes.

In [16] this paper, RNN use storing and updating the list of items is discussed at formal of text string for modelling the global quality of being logical and consistent. Two models- language model having a remark interjected in a conversation for the adjusting to make generation of output by dynamic. That encourages reference of agenda items and assessment on cooking recipes and dialogue system responses in demonstration at high coherence with great improvement in semantic coverage of agenda. Checklist consist of different levels at its high level RNN language model for encoding and its main goal is for bag-of-words and produce an output in the form of token. Vector is represented as a soft checklist that performs according to agenda during its generation and updating every time.

In [17] this paper, Recent Empirical approaches are used without any ordering. Generation of text from database and a system having capable of being end to end generation, which contain ordering as well as content selection. Operations are performed in document levels and mostly by set of grammar rules and these rules are used for planning the content. There comes near or nearer 2 ways for develop approach. One is to form a tree where documents are nodes on the relationship between database records and this comes near or nearer inspiration from rhetorical structure theory. Other one has a combination of tree structure.

In [18] this paper proposes an entity-centric neural architecture for data-to-text generation. In this model creates an entity specific representation which is dynamically updated. The output text is generated based on the data which given as the input and entity memory representations using the hierarchical attention at each step. This model generates a descriptive text with a decoder argument with a memory cell and a processor for the each entity. It generates text using hierarchical attention over the input table and entity memory. This model generates the output text which is coherent, concise and factually correct by the human evaluation.

In [19], it deals with from the annotated data how to take the decisions for ordering the word and word choice in the generated natural language. Here the system contains mainly four trainable systems for the generation of natural language. It can be done in the travel domain called the NLG. For expressing the concept uses a lookup table, which is used to store the most frequent phrases and is also used for comparison purposes. Here NLG1 is the lookup table. For finding the most probability word NLG1 and NLG2 are used with respect to the maximum entropy probability model. From this NLG2 is used to predict the words from left-to-right and NLG3 are used to predict the words which are in the dependency tree order. And the final domain NLG4 is implemented in a dialogue strategy. In which the order of the word is modified dynamically. So basically from the annotated data the NLG system is used to represent the practicality of learning the decisions for ordering the word and word choice. At the runtime we are reordering the words for reflecting the dialogue sate. Then it will make a conversational system which speaks more naturally.

In [20] this paper, generate answers for the question. A neural network model is used for storing the knowledge. It is impossible to store all the knowledge present in the real world. Questions are simple and factoid. Here follows sequence to sequence learning. Answers only towards the questions, an end to end format gives fluent response. Neural generative question answering model has various stages. In Interpreter question convert to a representation and store in short term memory. Enquirer takes the representation as its output and communication with long term memory and then summarization. In answers the final stage of creating answer by the interaction with generator and attention model.

In [21], for describing the content of the image this paper introduces an attention based model. This attention based model automatically learns the image content. By using a back propagations technique we can train the model which is in a deterministic manner. While generating the words in the output the model automatically fix the salient objects. Here we use a hard attention mechanism and a soft attention mechanism. These hard and soft attention mechanisms are the two image caption generators. By using the three benchmark datasets such as Flickr30k, Flickr8k and the MS COCO dataset validate the usefulness of the attention in the generation of caption. In this paper by using the BLUE and METOR metric this approach gives the state of the three benchmark datasets.

In [22], from a large or complex data the neural language generation (NLG) systems are used to generate the texts. The major difficulties that phase this system are while generating the geographic descriptions which refer the location or patterns in the given data. So for generating the geographic descriptions with involving the regions a domain of methodology is used here. The NLG systems analyse the given input data. After analysing the given input the system produces the geographic descriptions by human experts. For generating the geographic descriptions which involves the regions this paper presents a two staged approach. The first stage involves, for selecting a frame of reference it uses domain knowledge. The second phase involves by using the constraints the user select the values within that framework.

In [23] this paper presents a texygen, a branch-marking platform for text generation, in an open domain format. This always makes sure that it covers wide varieties, quality of always having the same standards, behaviour in text generation. It helps in standardization, research, improving reproductivity and reliability of its future work. There are many applications like machine translation, question answering, and information retrieval and so on. This generation process mainly makes three challenges on evaluation. First one is losing of clarity in ultimate goal or state of feeling confused because of not getting a proper understands in something to be used for. Second one, there is no need for researchers to explore the source code as publicly available 10 may the already reported experimental result to reproduce which makes

difficult full stop the third issue is its quality in the wide variety that is it makes a chance of getting a bad quality instead of producing good. Texygen already experiment And designs various evaluation methods.
In [24] this paper, we discuss about the generation of paraphrases from predicate structure using a symbol, uniform generation methodology. Here sentence generation takes as input. Some semantic representation we generate some assumption that the input is a hierarchical predicate or argument structure. Output of this process will be informed of grammatical sentence. Meaning of this output matches the original semantic input. Here we use a simple algorithm to generate sentences from predicate or argument structures. Input can be decomposed into the top predicate which is identified by using and transitive vub. Wide variety of expression is there. In order to overcome such challenges our lexicon grammatical resources play an important role in such face of generation.
In [25] this paper, generate natural language sentence bi a tree structure. Hybrid encodes meaning representation components in simple and natural way as well as natural language. The two important issue cost for the ultimate goal is to represent the meaning of natural language by a computer is essential full stop and the other one is computer should also have the ability to convert the represented meaning into human understandable natural language. Saudi goal is to produce the proper communication between the computer and human to natural language. The method used is statistical methods which contain tyre of natural language and formal meaning representation. The merits when compared with other previous approaches. By using hybrid tree it is effective for both semantic parsing as well as NLG.
In [26] this paper, we propose a new framework called LeakGAN to restore the problem for long text generation. Extensive experiment in various real life world task and synthetic data is Highly Effective in long text generation. Here formalize Hindi text generation problem as a sequential decision making process. Here we consider time step. At each time step t, the agents take the previously generated content as its current state. The process is less informative when the sentence length goes larger. To address this proposed Framework allows discriminator due to that provides additional information. The proposed paper generates long text via adversarial training.

III. CONCLUSION

Text book as per the syllabus of the subject are very important for the students. There are only limited number of text books are produced. It is not sufficient to satisfy the requirement of the large number of students. Therefore the students are facing the problem of non-availability of the text books. This proposes a solution for this problem by try to generate a pdf formatted text book from the syllabus, which is given as the input to the system. In which this paper combine the idea of web crawling, data mining, automatic extractive text summarization approaches. The system will be helping the students who are facing the non-availability of the text book as re their syllabus.

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