

Automatic Generation of Elementary Level Mathematical Questions

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DECLARATION

I declare that this is my own work and this dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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ABSTRACT

Mathematical Word Problems (MWP) play a vital role in mathematics education. An MWP is a combination of not only the numerical quantities, units, and variables, but also textual content. Therefore, in order to understand a particular MWP, a student requires knowledge in mathematics as well as in literacy. This makes it difficult to solve MWPs when compared with other types of mathematics problems. Therefore, students require a large number of similar questions to practice. On the other hand, the composition of numerical quantities, units, and mathematical operations impel the problems to possess specific constraints. Therefore, due to the inherent nature of MWPs, tutors find it difficult to produce a lot of similar yet creative questions. Therefore, there is a timely requirement of a platform that can automatically generate accurate and constraint-wise satisfied MWPs.

Due to the template-based nature of existing approaches for automatically generating MWPs, they tend to limit the creativity and novelty of the generated MWPs. Regarding the generation of MWPs in multiple languages, language-specific morphological and syntactic features paves way for extra constraints. Existing template-oriented techniques for MWP generation cannot identify constraints that are language-dependant, especially in morphologically rich yet low resource languages such as Sinhala and Tamil.

Utilizing deep neural language generation mechanisms, we deliver a solution for the aforementioned restrictions. This thesis elaborates an approach by which a Long Short Term Memory (LSTM) network which can generate simple MWPs while fulfilling above-mentioned constraints. The methodology inputs a blend of character embeddings, word embeddings, and Part of Speech (POS) tag embeddings to the LSTM network and the attention is produced for units and numerical values. We used our model to generate MWPS in three languages, English, Sinhala, and Tamil. Irrespective of the language, the model was capable of generating single and multi sentenced MWPs with an average BLEU score of more than 20%.

Keywords: Multi-lingual Mathematical Word Problem generation; Natural Language Generation; Neural Networks; Embeddings;

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LIST OF ABBREVIATIONS

MWP	Mathematical Word Problem
RNN	Recurrent Neural Network
LSTM	Long Short Memory Network
CL-LSTM	Character Level Long Short Memory Network
WL-LSTM	Word Level Long Short Memory Network
RL	Reinforcement Learning
GAN	Generative Adversarial Network
MLE	Maximum Likelihood Estimation
OOV	Out-Of-Vocabulary