# WORD EMBEDDING AND ITS APPLICATIONS FOR TELUGU LANGUAGE

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## PREFACE

Word embedding methods are used to represent words in a numerical way. The machine learning or deeplearning algorithms process the text data. The machines cannot understand the text data, it understands only numbers so we need to convert the text data to numerical form by using word embeddings techniques. Representing a word using vocabulary. Next map vocabulary to vectors. Onehot vectors are a quick and easy way to represent words as vectors of real-valued numbers. In perspective of the word embeddings technology. bv using are represented in syntactic form only. Whereas by using the predictive based embeddings, the words are represented in semantic form. In perspective of languages, the Indian subcontinent consists of a number of separate linguistic communities each of which share a common language and culture 22 major languages have been given constitutional recognition. We want to try this technology in the Telugu language, we want to build and test the different word embedding model on different machine learning(ML) algorithms. We tested two embedding model on 3 Machine learning algorithms for Telugu language. The main challenge is with the aggloramatives and inflections. In Teluguthere are so many inflections. Telugu is a highly inflected as well as morphologically rich language. A slight modification in a word can change its form to express a completely different meaning from the original one. Using the application data set by comparing the two embedding models with Machine learning algorithms Word2vector model works well compared to One hot encoding model.

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