Spatial Text Labelling

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Abstract

The objective of this project is to identify and label spatial keywords in the given corpus. Instead of using any parser based method, our approach is based on word vector models. We use Google's Word2Vec in this project.

Through this project, we aim to extract the relationship between three important spatial aspects, that is, trajectors, landmarks and spatial indicators.

Given a pair of a trajector and a landmark, we try to predict a spatial indicator best describing the relationship between the two words.

Introduction

One of the major tasks in natural language processing is to talk about spatial relationships between objects. The sentence "Give me the book lying on the table" expresses information about the spatial configuration of the objects (book, table) in some space. Understanding such spatial utterances is a problem in many areas, including robotics, navigation, traffic management, and query answering systems (Tappan, 2004).

Different types of spatial roles can be assigned to different words in a sentence. We use three of them in our project:
Trajector: denotes a central object of a spatial scene.
Landmark: denotes a secondary object of a spatial scene.
Spatial Indicator: signals a spatial relation between objects.

For example, consider the sentence,
"*A lake in the forest*"
Here, *'lake'* is the trajector, *'forest'* is the landmark and *'in'* is the spatial indicator connecting the two.

A lot of work has been done earlier in this field but most of those works use a grammar based parser to find relationships among different objects. So, it becomes difficult to extend them to other languages because the parsers for other languages are not as easily available as for English. Hence, we try to use Word2Vec to obtain these relationships

Data Set

The dataset SpRL for the Spatial Role Labelling shared task at SemEval-2012 has been taken. This data is available on Github.

It contains data for static spatial relations in the form of an XML file where each child is a sentence description containing CONTENT, TRAJECTOR, LANDMARK, SPATIAL_INDICATOR and RELATION as tags.

Approach

Create Word Embeddings
Build word vocabulary by training Google's Word2Vec on sufficiently large dataset.

Train Neural Network
Train the neural network with word embeddings for trajectors and landmarks as input and embedding for spatial indicators as output.

Implementation

Firstly, we processed the dataset available to us and extracted the trajectors, landmarks and spatial indicators from each child in the XML file. In total, we had 482 different pairs of them, with 56 distinct spatial indicators. We merged prepositional phrases into a single word, for example, '*in front of*' was changed to '*in_front_of*'.

This data is then appended to the Wikipedia data and a Word2Vec model is trained using the new data. The word vector dimensions have bee taken to be 50.

A back-propagation neural network with 100 neurons in the input layer, 100 neurons in the hidden layer and 50 neurons in the output layer is built. It is trained using a pair of a trajector and a landmark word vector as input and the corresponding spatial indicator word vector as the output, with the termination condition being full epoch cycles till convergence. Of the 482 sentences, 400 have been taken in the training set and rest in the test set.

Different pairs of trajectors and landmarks are picked from the test set and tested using the neural network. The 50 dimensional word vector obtained as output is matched with the word vectors earlier obtained from Word2Vec model and the most similar word is reported as the answer.

Trajector, Landmark	Correct spatial indicator (cs)	Predicted spatial indicator (ps)	Cosine Distance between cs and ps
Sky, background	in	in	2.7186372520
Entrance, background	in	in	2.5142250183
Arch, stairs	below	on	1.7129730747
Pool, house	in	in_front_of	2.0555872556
Briefcase, chair	on	on	1.8701356229

Table 1: Results of some test cases

Results

This approach, of using word vector models instead of parsers, gives correct results for around 70% of the test cases.
As shown in Table 1, it gives an incorrect result if more than one spatial indicator can show the relationship between the given trajector and the landmark.

Conclusions

Our approach of doing spatial role labelling without using any parser based method gives good result. It is thus possible to use word vector models for this purpose.

An important advantage of using this approach in the task of spatial role labelling is that it can be easily extended to other languages like Hindi for which parsers are not readily available.

The approach fails in some cases where more than one spatial indicator seems to be valid. Of course, it would work better if the context is also taken into account rather than simply taking pairs of trajectors and landmarks. This would lead to resolve the ambiguity of more than one correct answer and will hopefully give the one as already used in the sentence.

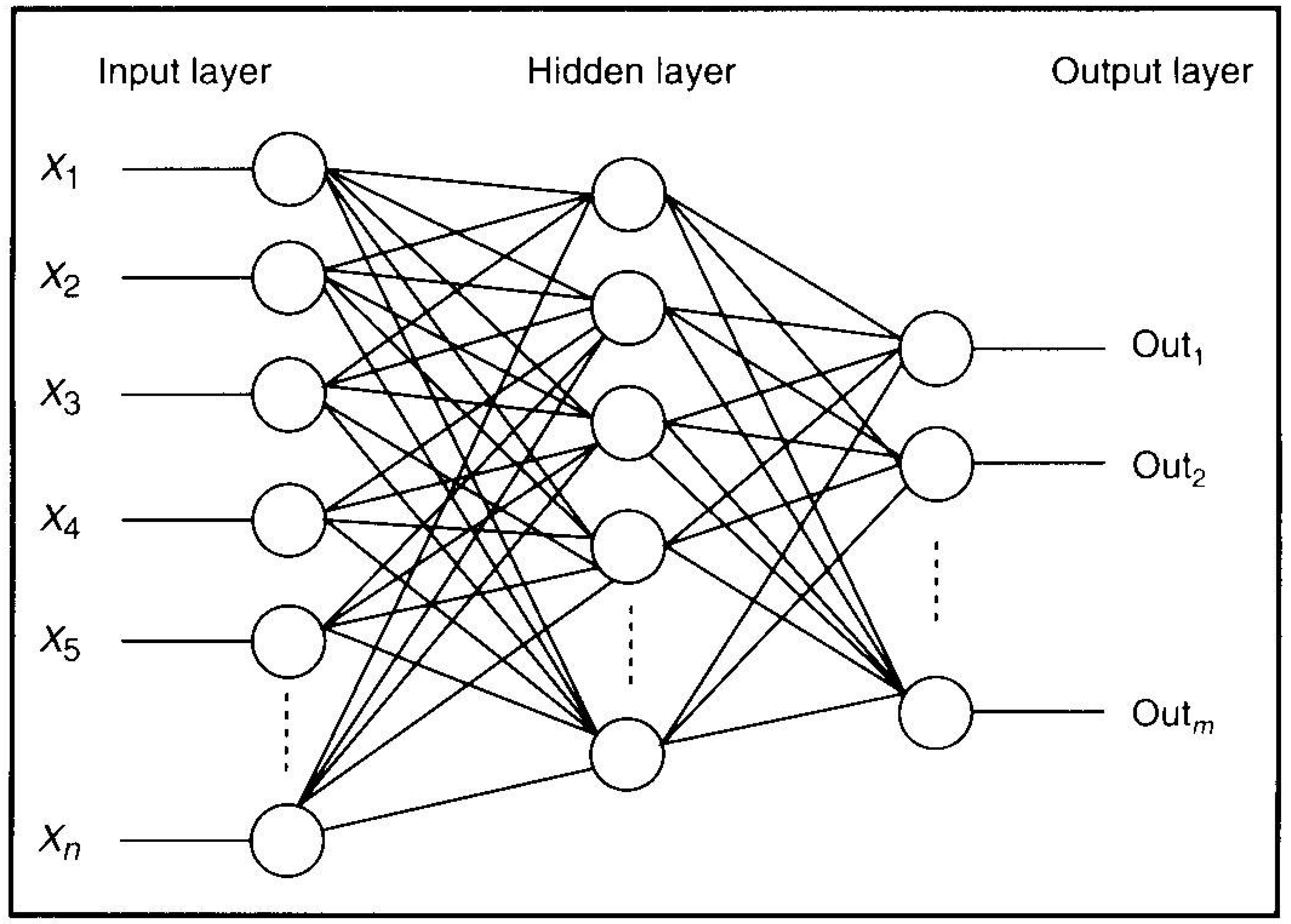

Fig. 1: Back-propagation neural network

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