Word2vec

Efficient estimation of words representation in vector space

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- 8 Precision Improvement
- Use Case

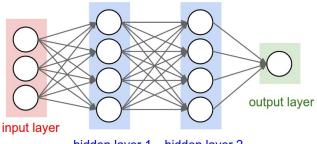
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Motivation

ML algorithms work on numerical values. To work with words, they should be converted to numbers.



hidden layer 1 hidden layer 2

Figure: Neural Network

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Possible Solution

One hot encoding

Creates new (binary) columns, indicating the presence of each possible value from the original data.

Word	Apple	Mango	Cow	Cat
Apple	1	0	0	0
Mango	0	1	0	0
Cow	0	0	1	0
Cat	0	0	0	1

Figure: One hot encoding

One hot encoding

Problem 1

As the number of words increase, the numbers of columns also increases in the table which costs more computation.

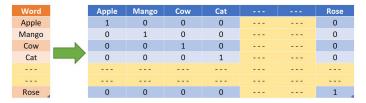


Figure: One hot encoding

One hot encoding

Problem 2

No way to find out the semantic similarities between words.

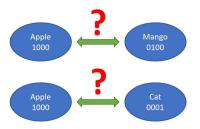


Figure: One hot encoding

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Word2vec motivation

- Relationship among the words are preserved.
- Makes the best of addition of new words in the dictionary.
- Enhanced outcomes in lots of deep learning applications.

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Functioning of Word2vec

The main goal is, the words that occur in similar context should have similar embeddings.

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Example

- Mango is a seasonal fruit.
- Orange is a seasonal fruit.

The word Mango and Orange will have similar word vector

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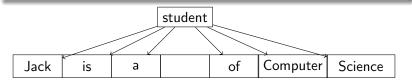
student

• Predict the context words from target

student

Jack	is	а		of	Computer	Science
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• Predict the context words from target



• Predict the target word from the context.

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Sack 15 Science

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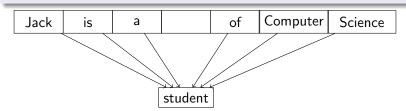
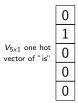
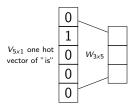
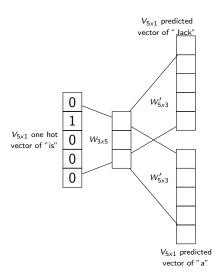


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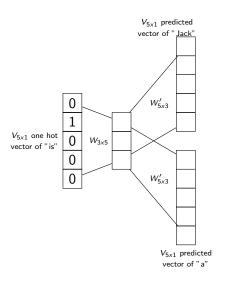
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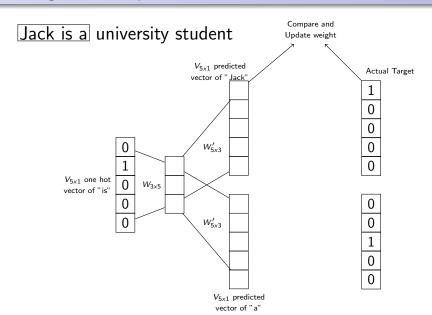


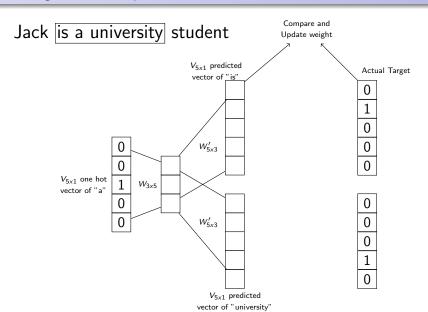




Jack is a university student







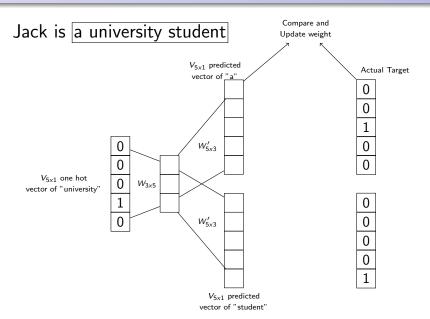
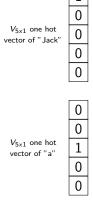


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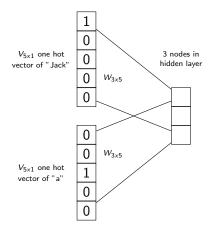
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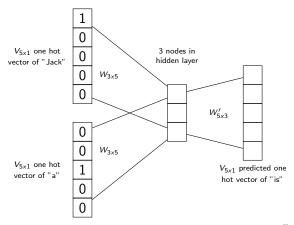
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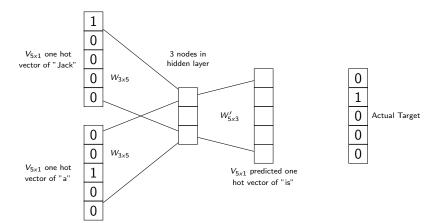
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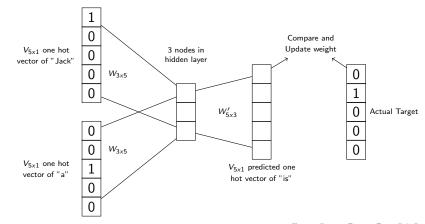


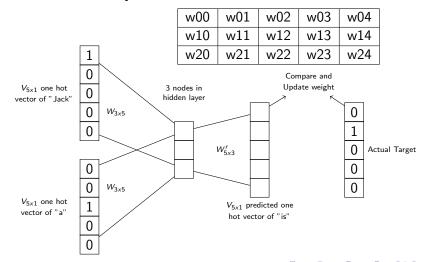
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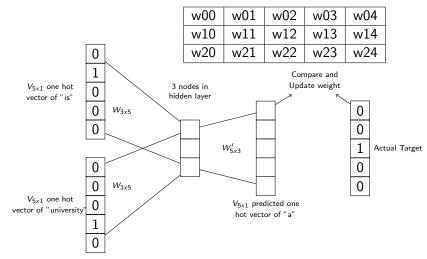












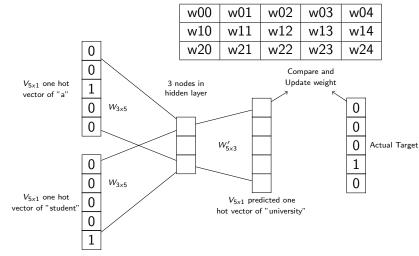


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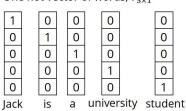
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Generating Word Vectors

Weights after training $W_{3\times5}$

w00	w01	w02	w03	w04
w10	w11	w12	w13	w14
w20	w21	w22	w23	w24

One hot vector of words, $V_{5\times1}$



Word vector for "Jack" = $W_{3\times5} \times V_{5\times1}$

w00	w01	w02	w03	w04
w10	w11	w12	w13	w14
w20	w21	w22	w23	w24

0 0 0

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- Selection of framework architecture
 - Large corpus, higher dimensions Skip gram (slower)
 - Small corpus, lower dimensions CBOW (faster)

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- Combining word2vec with Pos2vec or Glove

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Natural Language Processing

- Natural Language Processing
- Relationship between a country name and its capital name

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- Relationship between a country name and its capital name
- Analyze news headline to predict article success

