Decompositional Semantics for Improved Language Models

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B.Tech - M.Tech Dual Degree

Thesis Defense

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June 15, 2015

Outline

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Introduction to Decompositional Semantics

Decompositional Semantics is a way to describe a language entity word/paragraph/document by a constrained representation that identifies the most relevant representation conveying the semantics of the whole.

For example, a document can be broken into aspects such as its tf-idf representation, distributed semantics vector, etc.

Introduction to Decompositional Semantics

Why need Decompositional Semantics?

- It is language independent

- It decomposes language entity into various aspects that are latent in its meaning

- All aspects are important in their own ways

Introduction to Decompositional Semantics

Decompositional Semantics in Sentiment Analysis domain,

- A set of documents $D = \{d_1, \ldots, d_{|D|}\}$

- A set of aspects $A = \{a_1, \ldots, a_{|M|}\}$

- Training data for n ($n < |D|$) documents, $\mathcal{T} = \{l_{d_1}, \ldots, l_{d_n}\}$

Example :

Documents	tf-idf	Word Vector Average	Document Vector	BOW
d_1	0	0	1	0
d_2	0	1	1	0
d_3	1	0	0	1
d_4	×	×	×	×
d_5	1	1	1	1

Using $\mathcal{T}$, D and A, the supervised classifier $\mathcal{C}$ learns a representation to predict sentiments of individual documents.

Problem Statement

Better Language Representation

- To highlight the vitality of Decompositional Semantics in language representation
- To use Distributional Semantics for under resourced languages such as Hindi
- To demonstrate the effect of various parameters on language representation

Contribution of this thesis

Hindi

- Better representation of Hindi text using Distributional semantics
- Achieved state-of-the-art results for sentiment analysis on product and movie review corpus

Paper accepted in regICON'15

New Corpus

- Released a corpus of 700 Hindi movie reviews
- Largest corpus in Hindi in reviews domain

English

- Proposed a more generic representation of English text
- Achieved state-of-the-art results for sentiment analysis on IMDB movie reviews and Amazon electronics reviews

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Background on Language Representation

Bag of Words(BOW) Model

- Document d_i represented by $v_{d_i} \in \mathbb{R}^{|V|}$

- Each element in v_{d_i} denotes presence/absence of each word

- Drawbacks:

  - High-dimensionality

  - Ignores word ordering

  - Ignores word context

  - Very sparse

  - No relative importance to words

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Term Frequency-Inverse Document Frequency(tf-idf) Model

- Document d_i represented by $v_{d_i} \in \mathbb{R}^{|V|}$

- Each element in v_{d_i} is the product of term frequency and inverse document frequency: $tfidf(t, d) = tf(t, d) \times \log(\frac{\|D\|}{df(t)})$

- Gives weights to terms which are less frequent and hence important

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Background on Language Representation

Distributed Representation of Words(Mikolov et al., 2013b)

- Each word $w_i \in V$ is represented using a vector $v_{w_i} \in \mathbb{R}^k$

- The vocabulary V can be represented by a matrix $V \in \mathbb{R}^{k \times |V|}$

- Vectors (v_{w_i}) should encode the semantics of the words in vocabulary

- Drawbacks:

  - Ignores exact word ordering

  - Cannot represent documents as vectors without composition

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- Each document $d_i \in D$ is represented using a vector $v_{d_i} \in \mathbb{R}^k$

- The set D can be represented by a matrix $D \in \mathbb{R}^{k \times |D|}$

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- Comments:

    - Can represent documents

    - Ignores contribution of individual word while building document vectors

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Background on Sentiment Analysis

- Pang et al.(2004) obtained 87.2% accuracy on a dataset that discarded objective sentences and used text categorization techniques on the subjective sentences

- Socher et al.(2013) used recursive neural network over sentiment treebank for sentiment classification

- Le and Mikolov (2014) use document vector model and obtained 92.6% accuracy on IMDB movie review dataset

Background on Sentiment Analysis

There has been limited work on sentiment analysis in Hindi

- Joshi et al.(2010) used In-language sentiment analysis, Machine Translation and Resource Based Sentiment Analysis to achieve 78.1% accuracy

- Mukherjee et al.(2012) presented the inclusion of discourse markers in a BOW model to improve the sentiment classification accuracy by 2-4%

- Mittal et al.(2013) incorporate hand-coded rules dealing with negation and discourse relations achieving 80.2% accuracy

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Hindi Product and Movie Review Corpus

- Product Review dataset (LTG, IIIT Hyderabad) contains 350 Positive reviews and 350 Negative reviews

- Movie Review dataset (CFILT, IIT Bombay) contains 127 Positive reviews and 125 Negative reviews

- Each review is around 1-2 sentences long and the sentences are mainly focused on sentiment, either positive or negative.

700-Movie Review Corpus

- We collected Hindi movie reviews from websites such as Dainik Jagran and Navbharat Times

- The movie reviews are longer than the previous corpus and contains subjects other than sentiment

Overall	
Positive Reviews	356
Negative Reviews	341
Total Reviews	697
29.7 sentences per document	
494.6 words per document	

Table 1 : Statistics of Movie Reviews from Jagran and Navbharat

English Corpus

IMDB Movie Reviews

- Contains 25,000 positive and 25,000 negative reviews for training purpose
- It also contains an additional 50,000 unlabeled documents for unsupervised learning

Amazon Product Reviews

- There are 3 review datasets: Watches, Electronics and MP3 each of size 30.8MB, 728.4MB and 27.7MB respectively
- Electronics dataset consists of 1,241,778 reviews, Watches Dataset consists of 68,356 reviews and MP3 Dataset consists of 31,000 reviews
- Datasets are split into 80-20 ratio for training and testing

Wikipedia

Hindi

Hindi Wikipedia text dump (approx. 290MB) containing around 24M words with 724K words in the vocabulary.

English

English Wikipedia text dump (approx. 20.3GB) contains around 3.5B words with 7.8M words in the vocabulary.

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3 **Datasets**

4 **Method and Experiments**

5 **Results**

6 **Conclusion and Future Work**

7 **Appendix**

Distributed Word Representation

Skipgram

- Each current word acts as an input to a log-linear classifier with continuous projection layer, and predict words within a certain range before and after the current word

- The objective is to maximize the probability of the context given a word:

$$p(c|w; \theta) = \frac{\exp^{v_c \cdot v_w}}{\sum_{c' \in C} \exp^{v_c \cdot v_w}}$$

- v_c and $v_w \in R^d$ are vector representations for context c and word w respectively. C is the set of all available contexts. The parameters θ are v_{c_i}, v_{w_i} for $w \in V$, $c \in C$, $i \in 1, ..., d$

Distributed Word Representation

- Weights between the input layer and the output layer can be represented by a $V \times N$ matrix **W**

- Each row of **W** is the N-dimension vector representation v_w of the associated word of the input layer

- Given a word, assuming $x_k = 1$ and $x_{k'} = 0$ for $k' \neq k$, then
$$h = x^T W = W_{(k,.)} := v_{w_I}$$
$$u_j = v'^T_{w_j}.h$$

- v_{w_I} is the vector representation of the input word w_I and u_j is the score of each word in the vocabulary

- There is a different weight matrix **W'**$=\{w'_{ij}\}$ which is a $N \times V$ matrix between hidden and output layer

- Softmax function is used to predict probabilities and Stochastic Gradient Descent is used to update the parameters of the model

Distributed Document Representation

Motivation

- Drawbacks in BOW like sparsity, high-dimensionality, inability to encode context information and consider word ordering
- Composition models alone cannot represent documents (Blacoe and Lapata, 2012)
- Recursive Tensor Neural Networks (Socher et al.,2013) are computationally expensive and cannot be composed into document vectors when there are multiple sentences due to parsing issues
- Presence of similarity measures to deal with synonyms or semantically similar documents

Distributed Document Representation

- Every document is now mapped to a unique vector and id, represented by a matrix D

- Word vector matrix W is shared across all documents and contexts are now separately sampled for each document

- The only difference in this model is that h is now constructed with both W and D.

Semantic Composition

The Principle of Compositionality is that meaning of a complex expression is determined by the meaning of its constituents and the rules which guide this combination. It is also known as Frege's Principle. For example,

The movie is funny and the screenplay is good

In the above sentence, consider the word vectors are represented by $w(x)$ and the sentence vector as $S(x)$. Hence,

$$S(x) = c_1 w_1(x) \Theta c_2 w_2(x) \Theta c_3 w_3(x) \Theta c_4 w_4(x) \ldots \Theta c_k w_k(x) \qquad (1)$$

where Θ can be any operation(e.g., addition, multiplication) and c_is are constants.

Semantic Composition

- We describe two approaches to incorporate graded weighting into word vectors for building document vectors.

- Let v_{w_i} be the vector representation of the ith word. Then document vector v_{d_i} for i^{th} document is:

$$v_{d_i} = \begin{cases} 0 & w_k \in stopwords \\ \sum_{w_k \in d_i} v_{w_k} & w_k \notin stopwords \end{cases}$$

The above equation is 0-1 step-function which ignores contribution of all stop words.

- Another schema which incorporates idf weight is:

$$v_{d_i} = \begin{cases} 0 & idf(w_k, d_i) \leq \delta \\ \sum_{w_k \in d_i} idf(w_k, d_i).v_{w_k} & otherwise \end{cases}$$

where δ is a pre-defined threshold below which the word has no importance and above which the idf terms gives importance to that particular word.

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Semantic Composition

Composition	Accuracy
Multiplication	50.30
Average	88.42
Weighted Average	**89.56**

Table 2 : Results of Vector Composition with different Operations

Method	Weight	Accuracy(1)	Accuracy(2)
0-1 Weighting	0	93.84	93.06
	1	**93.91**	**93.18**
Graded idf Weighting	2	**93.89**	93.17
	2.5	93.87	93.16
	2.8	93.86	93.16
	3	93.86	**93.22**
	4	93.83	93.12

Table 3 : Results on IMDB Movie Reviews(Composite Document Vector);Accuracy(2) is when we exclude tf-idf features
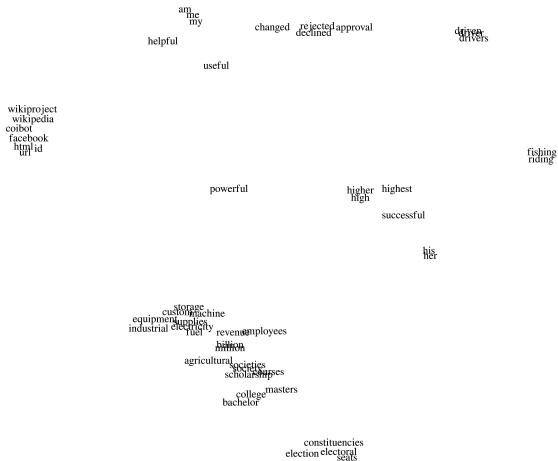
Effect of Context Size

Figure 1 : High Dimensional representation of Wiki Text with Context Size 5

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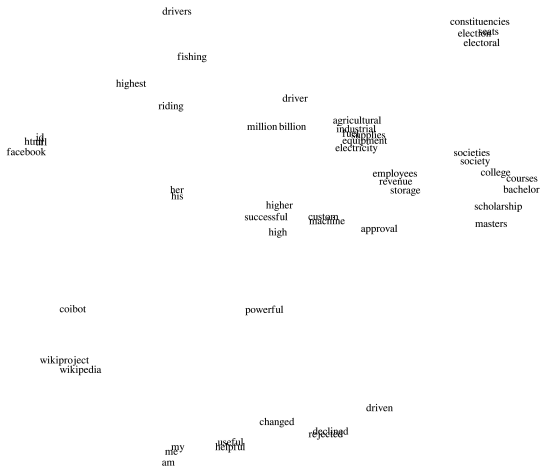0000
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Effect of Context Size

Figure 2 : High Dimensional representation of Wiki Text with Context Size 10

Effect of Context Size

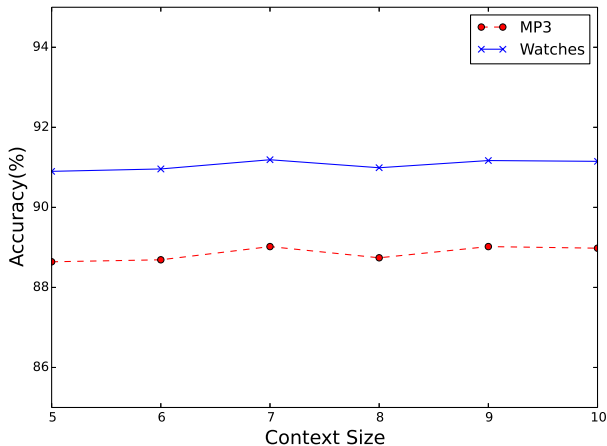Figure 3 : Variation of Accuracy with Different Context Size on Watches and MP3 Datasets

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SkipGram or CBOW?
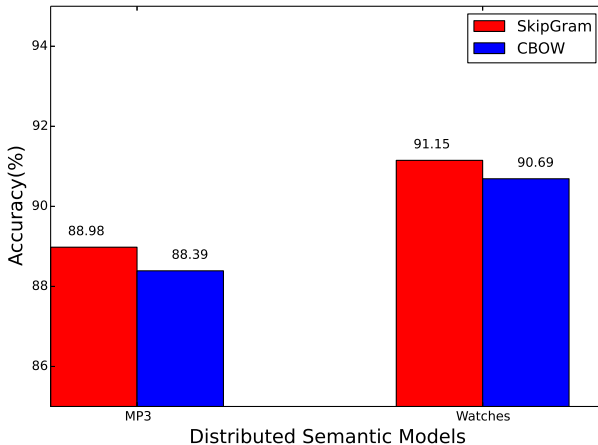
Figure 4 : Variation of Accuracy with skipgram and cbow on Watches and MP3 Datasets.

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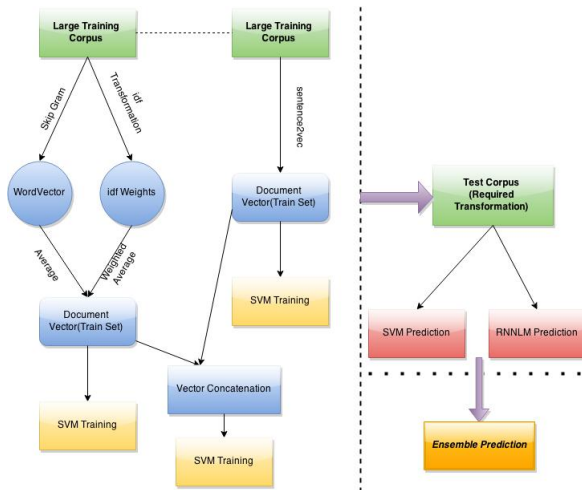0000
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Work Flow

Figure 5 : Work Flow

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Result on English Dataset

Method	IMDB	Amazon	Hindi
RNNLM (Baseline)	86.45	90.03	78.84
Paragraph Vector(Le and Mikolov,2014)	92.58	91.30	74.57
Averaged Vector	88.42	88.52	79.62
Weighted Average Vector	89.56	88.63	85.90
Composite Document Vector	93.91	92.17	90.30

Table 4 : Comparison of accuracies on 3 Datasets(IMDB, Amazon Electronics Review and Hindi Movie Reviews(IITB)) for various types of document composition models. The state of the art for these tasks are: IMDB: 92.58%; Amazon:85.90%, Hindi:79.0%.

Result on English Dataset

Method	Accuracy
Maas et al.(2011)	88.89
NBSVM-bi (Wang & Manning, 2012)	91.22
NBSVM-uni (Wang & Manning, 2012)	88.29
SVM-uni (Wang & Manning, 2012)	89.16
Paragraph Vector (Le and Mikolov(2014))	92.58
WordVector+Wiki(Our Method)	88.60
Weigted WordVector+Tfldf(Our Method)	89.56
Weighted WordVector+Tfldf+Document Vector	**93.91**
Ensemble of Enhanced Document Vector and RNNLM	94.19

Table 5 : Results on IMDB Movie Review Dataset

Result on English Dataset

Method	Accuracy
WordVector Averaging	88.42
Weighted WordVector Average	89.56
Weigted WordVector Averaging+Wiki	88.60
Weigted WordVector Averaging+TfIdf	90.67
WordVector Averaging+Document Vector	93.18
WordVector Averaging+Wiki+Document Vector	93.18
WordVector Averaging+Document Vector+RNNLM	93.70
WordVector Averaging+Wiki+Document Vector+RNNLM	93.57
WordVector Averaging+TfIdf+Document Vector	93.91
WordVector Averaging+Wiki+Document Vector+TfIdf	93.55
WordVector Averaging+TfIdf+Document Vector+RNNLM	**94.19**

Table 6 : Comparison of results on IMDB Movie Review Dataset with Various Features
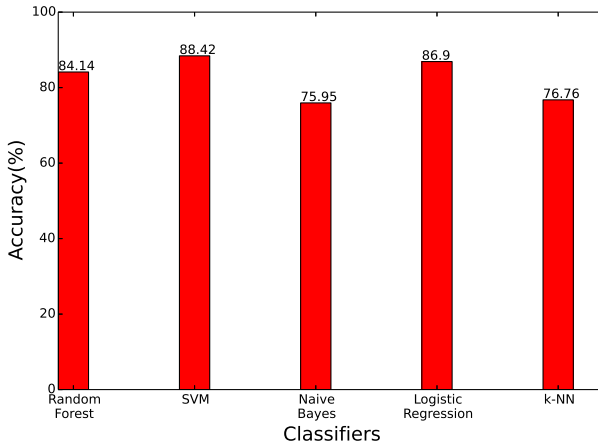
Result on English Dataset

Figure 6 : Accuracies of Different Classifiers with Average Word Vectors on IMDB Dataset.

Result on English Dataset

Features	Accuracy
Dredze et al.(2008)	85.90
Max Entropy	83.79
WordVector Averaging (Our Method)	89.41
Composite Document Vector(Our Method)	92.17
Composite Document Vector+RNNLM	**92.91**

Table 7 : Results on Amazon Electronics Review Dataset

Result on Hindi Dataset

Features	Accuracy(1)	Accuracy(2)
WordVector Averaging	78.0	79.62
WordVector+tf-idf	90.73	89.52
WordVector+tf-idf without stop words	91.14	89.97
Weighted WordVector	89.71	85.90
Weighted WordVector+tf-idf	**92.89**	**90.30**

Table 8 : Accuracies for Product Review and Movie Review Datasets.

Result on Hindi Dataset

Experiment	Features	Accuracy
Subjective Lexicon (Bakliwal et al.(2012))	Simple Scoring	79.03
Hindi-SWN Baseline (Arora et al.(2013))	Adjective and Adverb presence	69.30
Word Vector with SVM (Our method)	tf-idf with word vector	91.14
Weighted Word Vector with SVM (Our method)	tf-idf+weighted word vector	**92.89**

Table 9 : Comparison of Approaches: Product Review Dataset

Experiment	Features	Accuracy
In language using SVM (Joshi et al.(2010))	tf-idf	78.14
MT Based using SVM (Joshi et al.(2010))	tf-idf	65.96
Improved Hindi-SWN (Bakliwal et al.(2012))	Adjective and Adverb presence	79.0
WordVector Averaging	word vector	78.0
Word Vector with SVM (Our method)	tf-idf; word vector	89.97
Weighted Word Vector with SVM (Our method)	tf-idf+weighted word vector	**90.30**

Table 10 : Comparison of Approaches: Movie Review Dataset

Odd One Out

breakfast	**cereal**	lunch	dinner
eight	seven	**owe**	nine
shopping	math	reading	science

Table 11 : Odd One Out in English

भारत	**मुम्बई**	रूस	चीन
लड़की	बेहन	**मर्द**	महिला
उद्योग	नेता	मंत्री	सरकार

Figure 7 : Odd One Out in Hindi

Similar Words

Father	France	XBOX	scratched	megabits
grandfather	Germany	XBLA	scraped	gigabits
uncle	French	Xbox360	rubbed	kilobits
mother	Greece	SmartGlass	bruised	megabit
father-in-law	Netherlands	360/PS3	cracked	terabits
brother	Scotland	XBLA	discarded	MB/s
-	-	Qubed	shoved	Tbit/s
-	-	Kinect	tripped	-

Table 12 : Top Few Similar words in English

भारत	व्यापार	ओबामा
प्रदेश	व्यवसाय	क्लिंटन
तिब्बत	पुनर्बीमा	बराक
देश	वाणिज्य	सीनेटर
आँध्रप्रदेश	बैंकिंग	राष्ट्रपति
लद्दाख	उद्योग	उम्मीदवार

Figure 8 : Top Few Similar words in Hindi

Outline

Conclusion

1. We present a unsupervised language independent model that
   - overcomes the problems of BOW models
   - gives individual importance to words as well as sentences as a whole

2. We overcome the problems of language dependent models such as Recursive Tensor Neural Network(Socher et al., 2013)

3. We release a larger and more generic dataset of Hindi movie reviews

4. We improve the state-of-the-art results on sentiment analysis
   - On the IMDB dataset, we improve by 1.6%
   - On the Amazon electronics dataset, we improve by 7.01%
   - On the Hindi product and movie reviews, we improve by 13.86% and 11.30% respectively

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Future Work

1. **Better Composition Methods**

2. Enhanced document vectors has given an indication that current representations are not sufficient to model documents and that ensembles could also prove useful in tasks such as sentiment analysis

3. Region of Importance in NLP where we filter out sentiment oriented sentences and phrases from a unfocused corpus which contains text from various domains

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Thank you!

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Ensemble of RNNLM and Enhanced Document Vectors

- We first trained a recurrent neural network and then obtained predictions on test reviews in terms of probability.
- We trained another classier(Linear SVM) using Enhanced Document Vectors and then obtained predictions on test reviews.
- We then merged these two predictions using a simple heuristic, described below, to obtain final classification.

Let $y*$ be actual output and y is the predicted output. The heuristic used is:

$$((RNNLM_{pred} - 1) * 7 + (0.5 - SVM_{pred})).y < 0 \text{ if } y* = 1$$
$$((RNNLM_{pred} - 1) * 7 + (0.5 - SVM_{pred})).y < 0 \text{ otherwise}$$

SkipGram

$h = x^T W = v_{w_i}$

v_{w_i} is the vector representation of the input word w_i

$u_j = v'^T_{w_j} \cdot h$

u_j is score of each word in vocabulary and v'_{w_j} is the $j - th$ column of matrix W'

$p(w_{c,j} = w_{O,c}|w_I) = y_{c,j} = \frac{exp(u_{c,j})}{\sum_{j'=1}^{V} exp(u_{j'})}$

where $w_{c,j}$ is the j-th word on the c-th panel of the output layer; $w_{O,c}$ is the actual c-th word in the output context words; w_I is the only input word; $y_{c,j}$ is the output of the j-th node on the c-th panel of the output layer; $u_{c,j}$ is the net input of the j-th node on the c-th panel of the output layer.

SkipGram

$u_{c,j} = u_j = {v'}_{w_j}^T . h$, for $c = 1, 2, \ldots, C$

Loss functions is:

$E = -log p(w_{O,1}, w_{O,2}, \ldots, w_{O,C} | w_I)$

$= -log \prod_{c=1}^{C} \frac{exp(u_{c,j*_c})}{\sum_{j'=1}^{V} exp(u_{j'})}$