On Approximately Searching for Similar Word Embeddings

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NGT is available on website
(glue codes for comparing algorithms coming soon)
http://research-lab.yahoo.co.jp/software/ngt/

Introduction

Background

- Searching for the (*k*-nearest) similar word embeddings is one of the most basic operation in NLP applications,
  e.g., extracting synonyms, inferring the meanings of polysemous words, aligning words in two sentences in different languages, solving analogical questions, and searching for documents related to a query
- Gorman and Curran (ACL 2006) reported that SASH (tree-based method) performed the best for count-based embeddings

Purpose

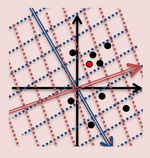
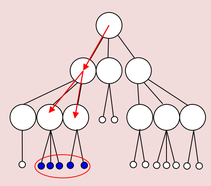
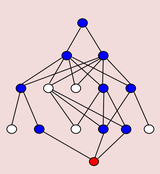
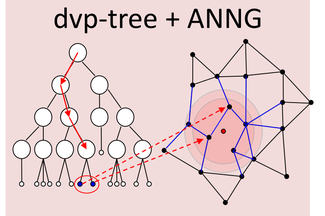
- Address how to **quickly** and **accurately** find similar embeddings

Contributions

- Focus on neural word embeddings (dense vectors) learned by a recently developed skip-gram model [Mikolov+, 2013]
- Show that a graph-based search method (NGT) clearly performs better than SASH from different aspects
- Report the useful facts
  - Normalizing vectors can achieve an effective search with cosine similarity
  - Search performance is more strongly related to a learning model of embeddings than its training data
  - Distribution shape of embeddings is a key factor relating to the search performance
  - Final performance of a target application can be far different from the search performance

Similarity Search Algorithms

- Three types of **metric-based** indexing are generally used in **approximate** similarity search as below:
- **Hash-based** indexing is a method to reduce the dimensionality of high-dimensional space by using some hash functions
  - Basically designed for *radius search*, not *k*-nearest search
- **Tree-based** indexing is used to recursively divide the entire search space into hierarchical subspaces
  - Descending from the root node to the leaf nodes in the tree structure and scanning only neighbors belonging to the subspaces
- **Graph-based** indexing is a method to find nearest neighbors by using a approximate neighborhood graph
  - Traversing neighbors on the graph from a certain node
- Compared search algorithms (available online) as below:

LSH (Hash-based)	FLANN (Tree-based)	SASH (Tree-based)	NGT (Graph-based)
	k-means tree 	M-Tree 	dvp-tree + ANNG 

- LSH: Locality-Sensitive Hashing and Implementation (E2LSH), [Andoni, 2004]
- FLANN: Fast Library for Approximate Nearest Neighbors, [Muja+, 2008-2013]
- SASH: Spatial Approximation Sample Hierarchy, [Houle+, 2005-2013]
- NGT: Neighborhood Graph and Tree for indexing, [Iwasaki, 2015-2016]

Experiments

Task Settings

- Search for *k*-nearest neighbor embeddings close to a given vector in a test set after indexing with a training set
  - 1K embeddings are extracted as a test set by random sampling
- Plot the average precision versus its computation time (log-scale) by changing the parameter for precision of each method

Basic Settings

- Distance Function : Normalized distance
- Dimension : 200-dimensional word embeddings
- Top@*k* : Top-10 nearest neighbors
- Data Size (for indexing): 2 million words
- Data Source (for training): English Wikipedia in February 2015
- Model : Skip-gram model with hierarchical softmax (word2vec)
- Task : Search task

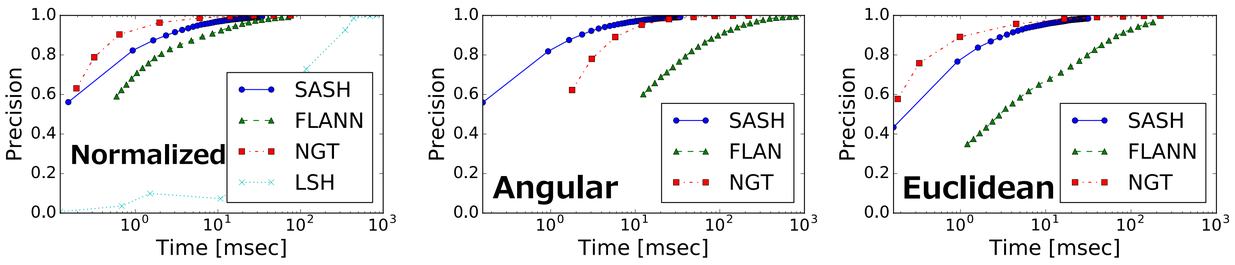
◆ Change Distance Function

- Precision versus computation time of Normalized, Angular and Euclidean distances

Normalized: $d^{norm}(x,y) = d^{euc}(\frac{x}{\|x\|}, \frac{y}{\|y\|})$ Angular: $d^{angle}(x,y) = \arccos(\cos(x,y))$ Euclidean: $d^{euc}(x,y) = \|x-y\|$

d^{norm} and d^{angle} yield the same results as cosine distance $d^{cos}(x,y) = 1 - \cos(x,y)$
(d^{cos} can not be used for indexing since the triangle inequality is not satisfied)

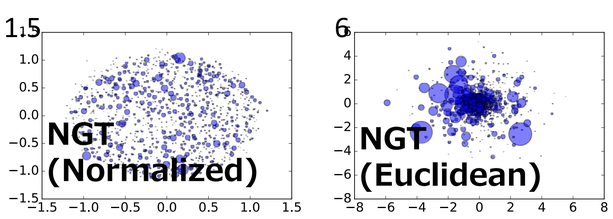
Fact: $N_k(x, d^{norm}) = N_k(x, d^{angle}) = N_k(x, d^{cos})$, where $N_k(x,d)$ is *k*-NNs of *x* by *d*



- **NGT (Normalized) performed the best for cosine similarity**
- SASH (Angular) performed relatively well, but the indexing time with the angular distance is larger than the Euclidean distance
- "Normalized" performed generally better than "Euclidean"
- *Why is "Normalized" faster than "Euclidean"?*

Normalization can align embeddings so as to divide the entire search space more efficiently.

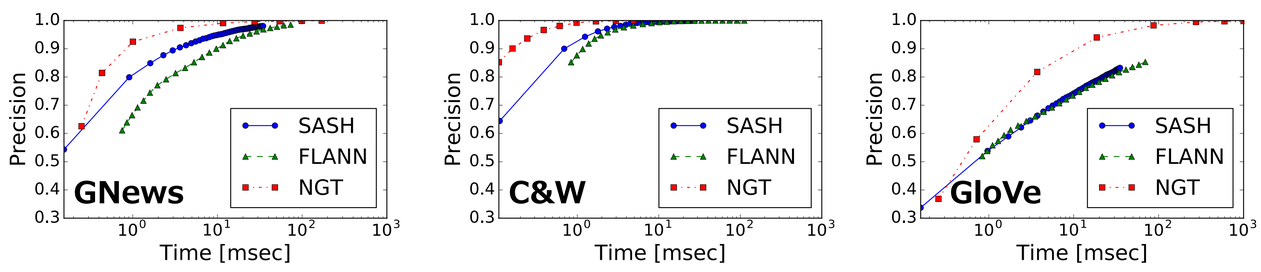
- 2D visualization 1K test embeddings by MDS (the radius of each circle represents the search time by NGT)



◆ Change Data Source and Model

- Precision versus computation time of GNews, C&W and GloVe embeddings

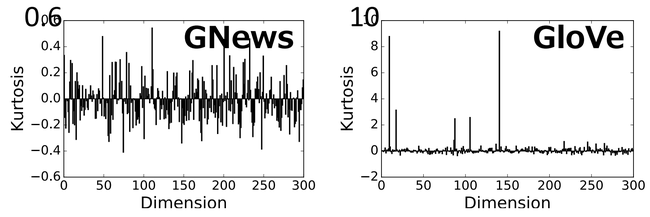
- GNews: 300 dim, 2M words, Google News dataset, skip-gram, [Mikolov+, 2013]
- C&W: 200 dim, 300K words, RCV1 corpus, DNN, [Collobert&Weston 2008]
- GloVe: 300 dim, 2M words, Common Crawl corpora, GloVe, [Pennington+ 2014]



- NGT performed the best when changing data source and model
- GNews and Wikipedia (skip-gram) had almost the same tendency
- **Performance can be affected by learning models**
- *Why is "GloVe" so slow?*

"GloVe" has several high kurtosis (tailedness) peaks, which means the large variations of nearest neighbor distances can harm efficient indexing.

- Visualize kurtosis of each dimension



$K(X) = \mu_4/\mu_3 - 3$, $\mu_n = E[(X - E[X])^n]$

◆ Change Task

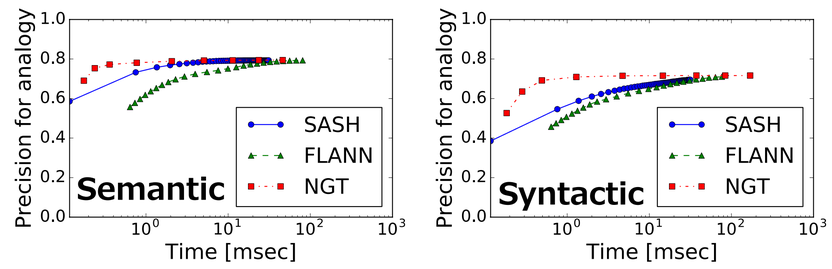
- Precision versus computation time of semantic/syntactic analogy task

- Semantic: find vec('Japan') by vec('Berlin') − vec('Germany') + vec('Tokyo')
- Syntactic: find vec('better') by vec('bad') − vec('worse') + vec('good')

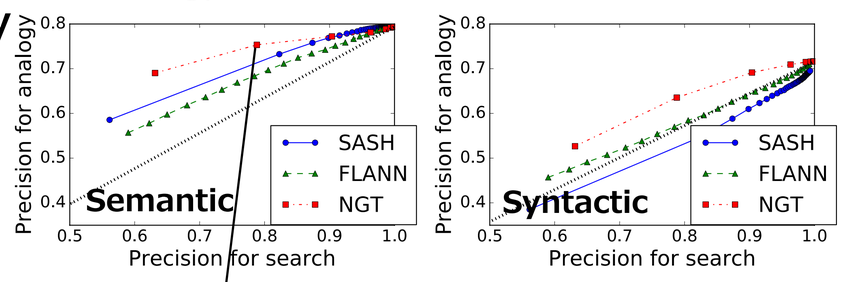
- NGT performed the best for analogy task
- *How is search task related to analogy task?*

Analogy precision can be far different from estimated precision by search task.

- Might be sufficient for another task even if the precision of search task is not so good



- Analogy tasks versus search task



When the search precision by NGT is 0.8, the analogy precision 0.75 is unexpectedly high, although its naïve estimation (black dot) is 0.64

◆ Change Dimension, Top@k, Data Size

- NGT performed the best (Please see the details in our paper)

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