Visualizing Low-Dimensional Word Embeddings with Emoji Annotations

Yoshinari Fujinuma*
Department of Computer Science
University of Colorado Boulder

Shantanu Karnwal†
Department of Computer Science
University of Colorado Boulder

Abstract

Word embeddings are quite a buzz in today's time in the lingusitics community, mainly because of their excellent performance in NLP applications like machine translation, topic modelling, question answering, etc. But when we try to look at the visualizations of these embeddings, we don't seem to get any sort of take-home knowledge from that. We propose 2D visualizations of these embeddings by using a clustering algorithm, and to have these clusters express their semantic information in a more understandable way, we annotate these clusters with emojis.

1 Introduction

Word embeddings, especially cross-lingual embeddings, has been successful in multiple NLP applications such as machine translation [2, 8] and cross-lingual document classification [7]. But one area where there has not been very specific research is discovering the meanings of the embeddings themselves.

One way to efficiently convey this semantic information about embeddings is to enable an efficient interaction between humans and the visualizations of these embeddings. However, there have been a lot of problems in the current visualizations of these embeddings. For example, there are potential problems of naively displaying the word embeddings projected onto 2D space using t-SNE [11], which is not commonly used in visualizing word embeddings, such as;

- Overlap of words when zoomed out (Figure 1).
- A counter-intuitive features of a t-SNE visualization (e.g., "cluster sizes mean nothing"[1])

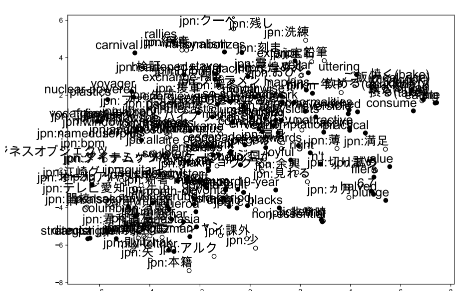

Figure 1: An example of a visualizaiton of word embeddings using t-SNE. Visualization of around 200 words causes clutter and makes humans hard to extract useful information.

*e-mail: Yoshinari.Fujinuma@colorado.edu
†e-mail: Shantanu.Karnwal@colorado.edu

[1]https://distill.pub/2016/misread-tsne/

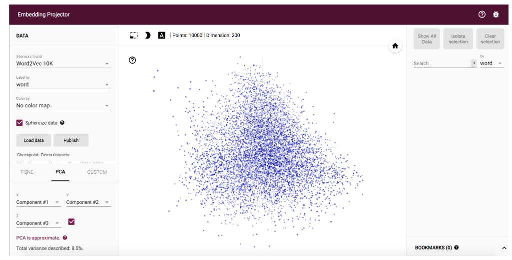

Figure 2: The visualizaiton of word embeddings using Tensorboard.

Also, many researchers decided to visualize embeddings in the 3D space, like Tensorboard (Figure 2) [1], but it ends up looking like a large cluttered collection of points. A visualization like that is just useful if the goal is to just play around with the click-and-drag interaction, but in the end, there is no semantic information being conveyed.

The ultimate goal of any good visualization is to convey the user about everything the data represents, and not what the data is like. Therefore, we think that semantics is a crucial aspect of any good visualization. So when we decided to carry on this project, the key question we asked ourselves was - How can we represent word embeddings efficiently in a 2D design space by keeping the clutter on the design space as minimum as possible?

Therefore using this motivation, we carry forward this project, and accomplished the following:

- Used a 2D design space to visualize the entire word2vec embedding space.
- Kept the clutter minimized by having an efficient k-means clustering algorithm implemented on the cosine similarities of these word vectors.
- Convey the semantic information of every single cluster by annotating them with Emojis, because of their excellent way of conveying semantic information with just a single character.

2 Description of the Project

Our goal for this project is to visualize word embeddings by avoiding the clutters caused by too many data points. Our core idea for the approach is to collapse the data points into clusters and annotate with emoji to summarize the cluster. Figure 3 shows the example output of our visualization.

Our approach for constructing the visualization is as follows:

1. Train a word embedding using a raw corpus.
2. Run k-means [9] and obtain clusters
3. Assign an emoji to each cluster
4. Visualize using D3.js

For the number of clusters k, we empirically set $k = \{40, 50\}$.

Figure 3: The visualization of word embeddings using clustered network and emojis.

Figure 4: An example of expanding clusters after clicking on emojis.

2.1 Annotation of Clusters with Emojis

Searching for a right word to represent the cluster requires external linguistic resources e.g., WordNet and a sophisticated method e.g., hypernym prediction. However, humans associate multiple words to a given image. For example, when one looks at 🍅, the possible association of this words are "tomato", "vegetable", "food", or even "object". Therefore, we decide to use emojis to represent the clusters.

Another motivation of using emojis instead of words is the "Picture superiority effect" (e.g., [3]) i.e., humans are better remembering pictures than words. Assuming that the annotation of clusters is the most crucial component of this visualization, we use emojis to represent the clusters.

To assign an optimal emoji e_c to each cluster c with centroid vector v_c, assume we have a set of emoji and its text description t. We compute the mean word vector v_t of each word w_i in a given emoji description $t = \{w_1, w_2, ..., w_n\}$ with length n out of all set of emoji descriptions T, i.e.,

$$e_c = \mathrm{argmax}_{t \in T} \cos\_\mathrm{sim}(v_c, v_t) \tag{1}$$

where

$$v_t = \frac{\sum_{i=1}^{n} w_i}{n}. \tag{2}$$

Word vectors are trained by Skip-gram with negative sampling [10] using 1 million sentences of English news articles from Leipzig corpora collection [6]. We set the word vector dimension as 100. Emojis are obtained from dataset built by [4].

2.2 Interaction

To let the users dive deeper into further details of clusters, users can click on emojis to "drill-down" [5] the cluster and look into the nearest neighboring words in terms of the centroid in the cluster. However, even when we collapse words into each cluster, there are still overlapping words as shown in Figure 4. To solve this issue, we further made each cluster draggable and used forced layout to let users resolve the overlapping words.

3 Discussion

Outliers

Emojis are diverse

Emojis Captures Approximate Meaning

One of the successful cases of our visualization is a cluster with the spacecraft emoji 🚀 annotated. This cluster contains transportation-related words such as "c-130" and "refueling".

On the other hand, some emojis (e.g., Leo emoji) are harder to interpret what does a cluster mean. Furthermore, one emoji could have multiple descriptions (e.g., the descriptions for the leo emoji are "greek", "sign", "zodiac", "stars", "constellation", "astrology", "lion") which further requires sophisticated processing when we want to improve the quality of the visualization.

References

[1] Tensorboard: Embedding visualization — tensorflow. `https://www.tensorflow.org/versions/r1.1/get_started/embedding_viz`, 2017. Accessed: 2018-05-02.

[2] M. Artetxe, G. Labaka, E. Agirre, and K. Cho. Unsupervised neural machine translation. In *Proceedings of the International Conference on Learning Representations*, 2018.

[3] T. Curran and J. Doyle. Picture superiority doubly dissociates the erp correlates of recollection and familiarity. *Journal of Cognitive Neuroscience*, 23(5):1247–1262, 2011.

[4] B. Eisner, T. Rocktäschel, I. Augenstein, M. Bosnjak, and S. Riedel. emoji2vec: Learning emoji representations from their description. In *Proceedings of The Fourth International Workshop on Natural Language Processing for Social Media*, 2016.

[5] N. Elmqvist and J.-D. Fekete. Hierarchical aggregation for information visualization: Overview, techniques, and design guidelines. *IEEE Transactions on Visualization and Computer Graphics*, 16(3):439–454, May 2010. doi: 10.1109/TVCG.2009.84

[6] D. Goldhahn, T. Eckart, and U. Quasthoff. Building large monolingual dictionaries at the Leipzig corpora collection: From 100 to 200 languages. In *Proceedings of the Language Resources and Evaluation Conference*, 2012.

[7] A. Klementiev, I. Titov, and B. Bhattarai. Inducing crosslingual distributed representations of words. In *Proceedings of International Conference on Computational Linguistics*, 2012.

[8] G. Lample, A. Conneau, L. Denoyer, and M. Ranzato. Unsupervised machine translation using monolingual corpora only. In *Proceedings of the International Conference on Learning Representations*, 2018.

[9] S. Lloyd. Least squares quantization in pcm. *IEEE transactions on information theory*, 28(2):129–137, 1982.

[10] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean. Distributed representations of words and phrases and their compositionality. In *Proceedings of Advances in Neural Information Processing Systems*, 2013.

[11] L. Van der Maaten and G. Hinton. Visualizing high-dimensional data using t-sne. *Journal of Machine Learning Research*, 2008.