Visualizing Low-Dimensional Word Embeddings with Emoji Annotators

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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, mainly because of their 3D visualization space. We are proposing an efficient 2D visualizations of these embeddings by using efficient clustering algorithms, and to have these clusters express their semantic information in the most understandable way, we annotate these clusters with Emojis.

Index Terms: Human-centered computing—Visualization—Visualization techniques—Treemaps; Human-centered computing—Visualization—Visualization design and evaluation methods

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 [12], 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])

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?

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

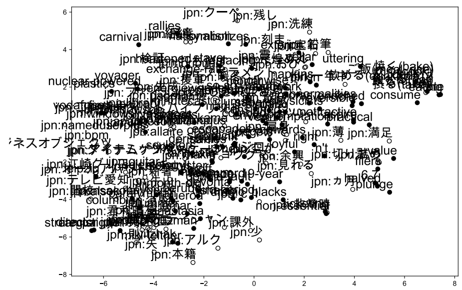

Figure 1: An example of a visualizaiton of word embeddings using t-SNE. Visualization of around 200 words causes clutter and makes humans hard to extract useful information.

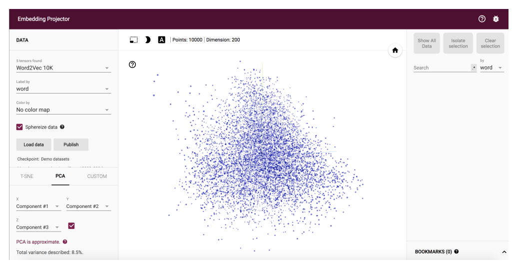

Figure 2: The visualizaiton of word embeddings using Tensorboard.

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 cluster the data points and annotate with something that correctly summerizes 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 visualizaiton of word embeddings using clustered network and emojis.

Figure 4: The visualizaiton of word embeddings using clustered network and emojis.

2.1 Annotation of Clusters with Emojis

When a human look at emoji, one connects with various possible concepts. Searching for a right word to represent the cluster requires external linguistic resources e.g., WordNet. However, images does not associate a single word. For example, when one looks at , the possible association of this words are “tomato”, “vegatable”, “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 cruicial 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.,

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

where

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

Word vectors are trained by Skip-gram with negative sampling [11] 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

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.

2.3 Force Layout

To solve the problem of overlapping texts, we also use force layout in D3.js to let the texts and emojis move and draggable.

3 Discussion

Outliers

Emojis are diverse

Emojis Captures Approximate Meaning

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