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, 5] and cross-lingual document classification [4]. 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 [7], which is not commonly used in visualizing word embeddings, such as;

- Overlap of words when zoomed out.
- A counter-intuitive features of a t-SNE visualization (e.g., "cluster sizes mean nothing"[1])
- There are many other alternatives to visualize word embeddings than commonly used t-SNE (e.g., UMAP [6] or *k*-Nearest Neighbor graph), but no thorough comparison conducted.

Figure **??** shows an example of *k*-nearest neighbor graph and Figure **??** shows an example of visualization using t-SNE.
Also, many researchers decided to visualize embeddings in the 3D space, like Tensorboard (Figure 1) [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.

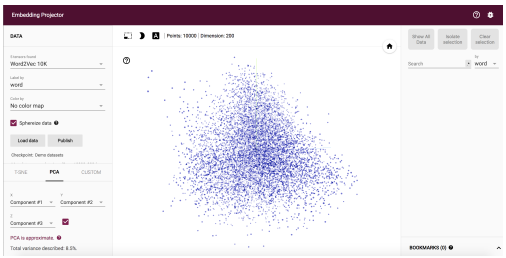

Figure 1: The visualizaiton of word embeddings using Tensorboard.

2 Description of the Project

Figure 2 shows the output of our visualization.

Figure 2: The visualizaiton of word embeddings using clustered network and emojis.

Our approach for constructing the visualization is as follows:

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

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

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.

2.2 Interaction

Users can click on emojis to “drill-down” [3] the cluster and look into which words are 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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