Going Beyond T-SNE: Exposing whatlies in Text Embeddings

Vincent D. Warmerdam  
Rasa  
Schönhauser Allee 175  
10119 Berlin  
v.warmerdam@rasa.com

Thomas Kober  
Rasa  
Schönhauser Allee 175  
10119 Berlin  
t.kober@rasa.com

Rachael Tatman  
Rasa  
Schönhauser Allee 175  
10119 Berlin  
r.tatman@rasa.com

Abstract

We introduce whatlies, an open source toolkit for visually inspecting word and sentence embeddings. The project offers a unified and extensible API with current support for a range of popular embedding backends including spaCy, tfhub, huggingface transformers, gensim, fastText and BytePair embeddings. The package combines a domain specific language for vector arithmetic with visualisation tools that make exploring word embeddings more intuitive and concise. It offers support for many popular dimensionality reduction techniques as well as many interactive visualisations that can either be statically exported or shared via Jupyter notebooks. The project documentation is available from https://rasahq.github.io/whatlies/.

1 Introduction

The use of pre-trained word embeddings (Mikolov et al., 2013a; Pennington et al., 2014) or language model based sentence encoders (Peters et al., 2018; Devlin et al., 2019) has become a ubiquitous part of NLP pipelines and end-user applications in both industry and academia. At the same time, a growing body of work has established that pre-trained embeddings codify the underlying biases of the text corpora they were trained on (Bolukbasi et al., 2016; Garg et al., 2018; Brunet et al., 2019). Hence, practitioners need tools to help select which set of embeddings to use for a particular project, detect potential need for debiasing and evaluate the debiased embeddings. Simplified visualisations of the latent semantic space provide an accessible way to achieve this.

Therefore we created whatlies, a toolkit offering a programmatic interface that supports vector arithmetic on a set of embeddings and visualising the space after any operations have been carried out. For example, Figure 1 shows an example of how representations for queen, king, man, and woman can be projected along the axes \(v_{\text{queen}} - v_{\text{king}}\) and \(v_{\text{man}}\) projected away from \(v_{\text{queen}} - v_{\text{king}}\). Both the vector arithmetic and the visualisation were done using the whatlies. The support for arithmetic expressions is integral in whatlies because it leads to more meaningful visualisations and concise code.

Figure 1: Projections of \(w_{\text{king}}\), \(w_{\text{queen}}\), \(w_{\text{man}}\), \(w_{\text{queen}} - w_{\text{king}}\) and \(w_{\text{man}}\) projected away from \(v_{\text{queen}} - v_{\text{king}}\). Both the vector arithmetic and the visualisation were done using the whatlies. The support for arithmetic expressions is integral in whatlies because it leads to more meaningful visualisations and concise code.

\(^{1}\text{https://projector.tensorflow.org/}\)
jector, parallax and whatlies is that the first two provide a non-extensible browser-based interface, whereas whatlies provides a programmatic one. Therefore whatlies can be more easily extended to any specific practical need and cover individual use-cases. The goal of whatlies is to offer a set of tools that can be used from a Jupyter notebook with a range of visualisation capabilities that goes beyond the commonly used static T-SNE (van der Maaten and Hinton, 2008) plots. whatlies can be installed via pip, the code is available from https://github.com/RasaHQ/whatlies2 and the documentation is hosted at https://rasahq.github.io/whatlies/.

2 What lies in whatlies — Usage and Examples

Embedding backends. The current version of whatlies supports word-level as well as sentence-level embeddings in any human language that is supported by the following libraries:

- BytePair embeddings (Sennrich et al., 2016) via the BPemb project (Heinzerling and Strube, 2018)
- fastText (Bojanowski et al., 2017)
- gensim (ˇReh˚u˚ek and Sojka, 2010)
- huggingface (Wolf et al., 2019)
- sense2vec (Trask et al., 2015); via spaCy
- spaCy3
- tfhub4

Embeddings are loaded via a unified API:

```python
from whatlies.language import \
SpacyLanguage, FasttextLanguage, \
TFHubLanguage, HFTransformersLanguage

# spaCy
lang_sp = SpacyLanguage('en_core_web_md')
emb_king = lang_sp['king']
emb_queen = lang_sp['queen']

# fastText
ft = 'cc.en.300.bin'
lang_ft = FasttextLanguage(ft)
emb_ft = lang_ft['pizza']

# TF-Hub
tf_hub = 'https://tfhub.dev/google/

model = tf_hub + 'nnlm-en-dim50/2'
lang_tf = TFHubLanguage(model)
emb_tf = lang_tf['whatlies is awesome']

# Huggingface
bert = 'bert-base-cased'
lang_hf = HFTransformersLanguage(bert)
emb_hf = lang['whatlies rocks']
```

In order to retrieve a sentence representation for word-level embeddings such as fastText, whatlies returns the summed representation of the individual word vectors. For pre-trained encoders such as BERT (Devlin et al., 2019) or ConveRT (Henderson et al., 2019), whatlies uses its internal [CLS] token for representing a sentence.

Similarity Retrieval. The library also supports retrieving similar items on the basis of a number of commonly used distance/similarity metrics such as cosine or Euclidean distance:

```python
from whatlies.language import \
SpacyLanguage

lang = SpacyLanguage('en_core_web_md')
lang.score_similar("man", n=5,
metric='cosine')
[(Emb[man], 0.0),
 (Emb[woman], 0.2598254680633545),
 (Emb[guy], 0.2932106256849854),
 (Emb[boy], 0.2954298257827759),
 (Emb[he], 0.3168887495994568)]

# NB: Results are cosine _distances_
```

Vector Arithmetic. Support of arithmetic expressions on embeddings is integral in any whatlies functions. For example the code for creating Figure 1 from the Introduction highlights that it does not make a difference whether the plotting functionality is invoked on an embedding itself or on a representation derived from an arithmetic operation:

```python
import matplotlib.pylab as plt
from whatlies import Embedding

man = Embedding("man", [0.5, 0.1])
woman = Embedding("woman", [0.5, 0.6])
king = Embedding("king", [0.7, 0.33])
queen = Embedding("queen", [0.7, 0.9])

man.plot(kind="arrow", color="blue")
woman.plot(kind="arrow", color="red")
king.plot(kind="arrow", color="blue")
queen.plot(kind="arrow", color="red")

diff = (queen - king)

orth = (man | (queen - king))
diff.plot(color="pink", show_ops=True)

orth.plot(color="pink", show_ops=True)
```

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2 Community PRs are greatly appreciated ©.
3 https://spacy.io/
4 https://www.tensorflow.org/hub

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This feature allows users to construct custom queries and use it e.g. in combination with the similarity retrieval functionality. For example, we can validate the widely circulated analogy of Mikolov et al. (2013b) on spaCy’s medium English model in only 4 lines of code (including imports):

\[
 w_{\text{queen}} \approx w_{\text{king}} - w_{\text{man}} + w_{\text{woman}}
\]

```python
from whatlies.language import SpacyLanguage
lang = SpacyLanguage('en_core_web_md')
> e = lang['king'] - lang['man'] + lang['woman']
> lang.score_similar(e, n=5, metric='cosine')
[(Emb[king], 0.19757413864135742),
 (Emb[queen], 0.2119154930114746),
 (Emb[prince], 0.35989218950271606),
 (Emb[princes], 0.37914562225341797),
 (Emb[kings], 0.37914562225341797)]
```

Excluding the query word \textit{king} \textsuperscript{5}, the analogy returns the anticipated result: \textit{queen}.

**Multilingual Support.** whatlies supports any human language that is available from its current list of supported embedding backends. This allows us to check the royal analogy from above in languages other than English. The code snippet below shows the results for Spanish and Dutch, using pre-trained fastText embeddings\textsuperscript{6}.

```python
from whatlies.language import FasttextLanguage
es = FasttextLanguage('cc.es.300.bin')
nl = FasttextLanguage('cc.nl.300.bin')
emb_es = es['rey'] - es['hombre'] + es['mujer']
emb_nl = nl['koning'] - nl['man'] + nl['vrouw']
es.score_similar(emb_es, n=5, metric='cosine')
[(Emb[rey], 0.04499000310897827),
 (Emb[monarca], 0.24673408269882202),
 (Emb[Rey], 0.2799408435821533),
 (Emb[reina], 0.2993239760398865),
 (Emb[prncipe], 0.3025314211845398)]
nl.score_similar(emb_nl, n=5, metric='cosine')
[(Emb[koning], 0.48337286710739136),
 (Emb[koningen], 0.5858825445175171),
 (Emb[koningin], 0.6115483045578003),
 (Emb[Koning], 0.6155665676156616),
 (Emb[kroonprins], 0.658723771572113)]
```

\textsuperscript{5}As appears to be standard practice in word analogy evaluation (Levy and Goldberg, 2014).

\textsuperscript{6}The embeddings are available from https://fasttext.cc/docs/en/crawl-vectors.html.

While for Spanish, the correct answer \textit{reina} is only at rank 3 (excluding \textit{rey} from the list), the second ranked \textit{monarca} (female form of \textit{monarch}) is getting close. For Dutch, the correct answer \textit{koningin} is at rank 2, surpassed only by \textit{koningen} (plural of \textit{king}). Another interesting observation is that the cosine distances — even of the query words — vary wildly in the embeddings for the two languages.

**Sets of Embeddings.** In the previous examples we have typically only retrieved single embeddings. However, whatlies also supports the notion of an “Embedding Set”, that can hold any number of embeddings:

```python
from whatlies.language import SpacyLanguage
lang = SpacyLanguage('en_core_web_lg')
words = ['prince', 'princess', 'nurse', 'doctor', 'man', 'woman', 'sentences also embed']
# NB: 'sentences also embed' will be represented as the sum of the 3 individual words.
emb = lang[words]
```

It is often more useful to analyse a set of embeddings at once, rather than many individual ones. Therefore, any arithmetic operations that can be applied to single embeddings, can also be applied to all of the embeddings in a given set.

The \texttt{emb} variable in the previous code example represents an EmbeddingSet. These are collections of embeddings which can be simpler to analyse than many individual variables. Users can, for example, apply vector arithmetic to the entire EmbeddingSet.

```python
new_emb = emb | (emb['man'] - emb['woman'])
```

**Visualisation Tools.** Any visualisations in whatlies are most useful when performed on EmbeddingSets. They offer a variety of methods for plotting, such as the distance map in Figure 2:

```python
words = ['man', 'woman', 'king', 'queen', 'red', 'green', 'yellow']
emb = lang[words]
emb.plot_distance(metric='cosine')
```

whatlies also offers interactive visualisations using “Altair” as a plotting backend\textsuperscript{7}:

\textsuperscript{7}Examples of the interactive visualisations can be seen on the project’s github page: https://github.com/RasaHQ/whatlies
Figure 2: Pairwise distances for a set of words using cosine distance.

```python
emb.plot_interactive(x_axis="man", y_axis="yellow", show_axis_point=True)
```

The above code snippet projects every vector in the `EmbeddingSet` onto the vectors on the specified axes. This creates the values we can use for 2D visualisations. For example, given that `man` is on the x-axis the value for ‘yellow’ on that axis will be:

\[
v(yellow \rightarrow man) = \frac{w_{yellow} \cdot w_{man}}{w_{man} \cdot w_{man}}
\]

which results in Figure 3.

Figure 3: Plotting example terms along the axes `man` vs. `yellow`.

These plots are fully interactive. It is possible to click and drag in order to navigate through the embedding space and zoom in and out. These plots can be hosted on a website but they can also be exported to `png/svg` for publication. It is furthermore possible to apply any vector arithmetic operations for these plots, resulting in Figure 4:

```python
e = emb["man"] - emb["woman"]
emb.plot_interactive(x_axis=e, y_axis="yellow", show_axis_point=True)
```

Figure 4: Plotting example terms along the transformed `man - woman` axis and the `yellow` axis.

**Transformations.** `whatlies` also supports several techniques for dimensionality reduction of `EmbeddingSet`s prior to plotting. This is demonstrated in Figure 5 below.

```python
from whatlies.transformers import Pca
from whatlies.transformers import Umap

p1 = (emb.transform(Pca(2)).plot_interactive("pca_0", "pca_1"))
p2 = (emb.transform(Umap(2)).plot_interactive("umap_0", "umap_1"))
p1 | p2
```

Figure 5: Demonstration of PCA and UMAP transformations.

Transformations in `whatlies` are slightly different than for example scikit-learn transformations because in addition to dimensionality reduction, the transformation can also add embeddings.
that represent each principal component to the EmbeddingSet object. As a result, they can be referred to as axes for creating visualisations as seen in Figure 5.

Scikit-Learn Integration. To facilitate quick exploration of different word embeddings we have also made our library compatible with scikit-learn (Pedregosa et al., 2011). The Rasa library uses numpy (Oliphant, 2006) to represent the numerical vectors associated to the input text. This means that it is possible to use the whatlies embedding backends as feature extractors in scikit-learn pipelines, as the code snippet below shows:

```python
from whatlies.language import \
BytePairLanguage
from sklearn.pipeline import Pipeline

pipe = Pipeline([
    ('embed', BytePairLanguage('en')),
    ('model', LogisticRegression())
])

X = ['i really like this post',
     'thanks for that comment',
     'i enjoy this friendly forum',
     'this is a bad post',
     'i dislike this article',
     'this is not well written']

y = np.array([1, 1, 1, 0, 0, 0])

pipe.fit(X, y).predict(X)
```

This feature enables fast exploration of many different word embedding algorithms.

3 A Tale of two Use-cases

Visualising Bias. One use-case of whatlies is to gain insight into bias-related issues in an embedding space. Because the library readily supports vector arithmetic it is possible to create an EmbeddingSet holding pairs of representations:

```python
lang = SpacyLanguage("en_core_web_lg")
emb_of_pairs = EmbeddingSet(
    (lang['nurse'] - lang['doctor']),
    (lang['nurse'] - lang['surgeon']),
    (lang['woman'] - lang['man']),
)
```

Subsequently, the new EmbeddingSet can be visualised as a distance map as in Figure 6, revealing a number of spurious correlations that suggest a gender bias in the embedding space.

```python
emb_of_pairs.plot_distance(metric="cosine")
```

Visualising issues in the embedding space like this creates an effective way to communicate potential risks of using embeddings in production to non-technical stakeholders.

![Figure 6: Distance map for visualising bias. If there was no bias then we would expect 'she-he' to have a distance near 1.0 compared to 'nurse-physician'. The figure shows this is not the case.](image)

It is possible to apply the debiasing technique introduced by Bolukbasi et al. (2016) in order to approximately remove the direction corresponding to gender. The code snippet below achieves this by, again, using the arithmetic notation.

```python
lang = SpacyLanguage("en_core_web_lg")
emb = lang[words]
axis = EmbeddingSet(
    (lang['man'] - lang['woman']),
    (lang['king'] - lang['queen']),
    (lang['father'] - lang['mother']))
    ).average()
emb_debias = emb | axis
```

Figure 7 shows the result of applying the debiasing technique, highlighting that some of the spurious correlations have indeed been removed.

It is important to note though, that the above technique does not reliably remove all relevant bias in the embeddings and that bias is still measurably existing in the embedding space as Gonen and Goldberg (2019) have shown. This can be verified with whatlies, by plotting the neighbours of the biased and debiased space:

```python
```
Figure 7: Distance map for visualising the embedding space after the debiasing technique of Bolukbasi et al. (2016) has been applied.

```python
dist = emb.score_similar("maid", n=7)
[(Emb["maid"], 0.0),
 (Emb["maids"], 0.18290925025939941),
 (Emb["housekeeper"], 0.220336456298828),
 (Emb["maidservant"], 0.3770867586135864),
 (Emb["butler"], 0.3822709918022156),
 (Emb["mistress"], 0.3967094421386719),
 (Emb["servant"], 0.40112364292144775)]
```

```python
dist = emb_debias.score_similar("maid", n=7)
[(Emb["maid"], 0.0),
 (Emb["maids"], 0.18163418769836426),
 (Emb["housekeeper"], 0.21881639957427979),
 (Emb["maidservant"], 0.3642127513885498),
 (Emb["butler"], 0.382546067237854),
 (Emb["mistress"], 0.3955296277999878)]
```

As the output shows, the neighbourhoods of `maid` in the biased and debiased space are almost equivalent, with e.g. `mistress` still appearing relatively high-up the nearest neighbours list.

**Comparing Embedding Backends.** Another use-case for whatlies is for comparing different embeddings. For example, we wanted to analyse two different encoders for their ability to capture the intent of user utterances in a task-based dialogue system. We compared spaCy and ConveRT for their ability to embed sentences from the same intent class close together in space. Figure 8 shows that the utterances encoded with ConveRT form tighter and coherent clusters.

Figure 9 highlights the same trend with a distance map, where for spaCy there is barely any similarity between the utterances, the coherent clusters from Figure 8 are well reflected in the distance map for ConveRT.

The superiority of ConveRT in comparison to spaCy for this example is expected, though, as ConveRT is aimed at dialogue, but it is certainly useful to have a tool — whatlies — at one’s disposal with which it is possible to quickly validate this.

## 4 Roadmap

whatlies is in active development. While we cannot predict the contents of future community PRs, this is our current roadmap for future development:

- **We want to make it easier for people to research bias in word embeddings.** We will continue to investigate if there are visualisation techniques that can help spot issues and we aim to make any robust debiasing techniques available in whatlies.
- **We would like to curate labelled sets of word lists for attempting to quantify the amount of bias in a given embedding space.** Properly labelled word lists can be useful for algorithmic bias research but it might also help understand clusters. We plan to make any evaluation resources available via this package.
- **One limit of using Altair as a visualisation library is that we cannot offer interactive visualisations with many thousands of data points.** We might explore other visualisation tools for this library as well.
- **Since we’re supporting dynamic backends like BERT at the sentence level, we are aiming to also support these encoders at the word level, which requires us to specify an API for retrieving contextualised word representations within whatlies.** We are currently exploring various ways for exposing this feature and
are working with a notation that uses square brackets that can select an embedding from the context of the sentence that it resides in:

```python
text = "By whom were you built?"
lang = SpacyLanguage(mod_name)
assert lang['[bank] of the river'].vector != lang['money on the [bank]'].vector
```

At the moment we only support spaCy backends with this notation but we plan to explore this further with other embedding backends.\[^{10}\]

5 Conclusion

We have introduced whatlies, a python library for inspecting word and sentence embeddings that is very flexible due to offering a programmable interface. We currently support a variety of embedding models, including fastText, spaCy, BERT, or ConveRT. This paper has showcased its current use as well as plans for future development. The project is hosted at https://github.com/RasaHQ/whatlies and we are happy to receive community contributions that extend and improve the package.

Acknowledgements

Despite being only a few months old the project has started getting traction on github and has attracted the help of outside contributions. In particular we’d like to thank Masoud Kazemi for many contributions to the project.

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