## MIMIC-III - NLP

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#### **DESCRIPTION**

This presentation compares the ability of three libraries/models to recognize and extract named entities from medical notes and visualize them through tSNE plots. The medical notes from MIMIC-III are filtered down to include only notes from patients with Neuromyelitis Optica Spectrum Disorder or NMOSD (ICD Code: 3410).

- Entities were extracted using Spacy, Scispacy, and blueBERT.
- For the Spacy and Scispacy models, Spacy's Displacy function visualized recognized entities, and gensim was used to create word2vecs.
- For each model tSNE plots were created using matplotlib and sklearn for both GloVe 50D (a pretrained model) and the medical notes for the NMOSD patients.

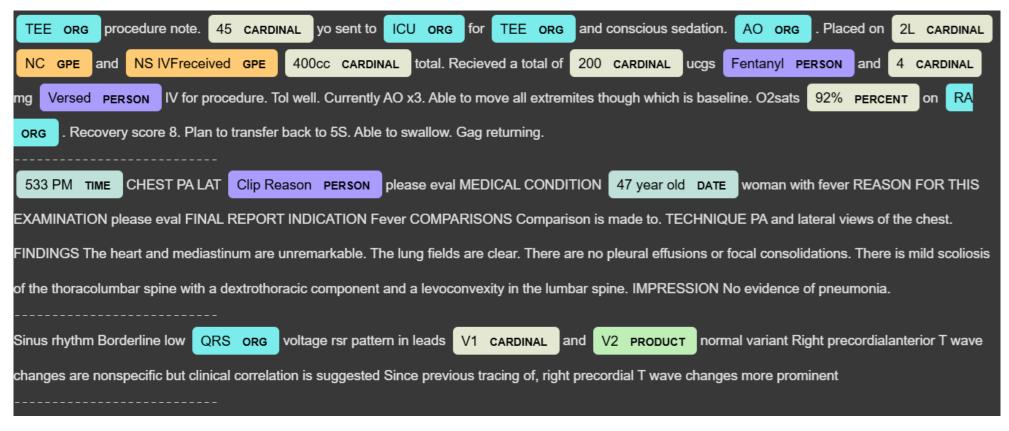
Note: This dataset is only limited to patients admitted to one hospital, the Beth Israel Deaconess Medical Center in Boston, Massachusetts.

#### **PREPROCESSING**

- To get the medical notes for the NMOSD patients, a query was sent to the noteevents table to get the text and was joined with the diagnoses\_icd table for patients with the 3410 icd9 code.
- Rows are filtered to only contain unique text (duplicate medical notes are removed) to save computation time.
- The text is cleaned by removing excess whitespace and uncommon characters. The stamps on the radiology notes are also filtered out using latex.



#### SPACY ENTITY VISUALIZATION



We can see that this doesn't recognize many medical entities or misclassifies them.

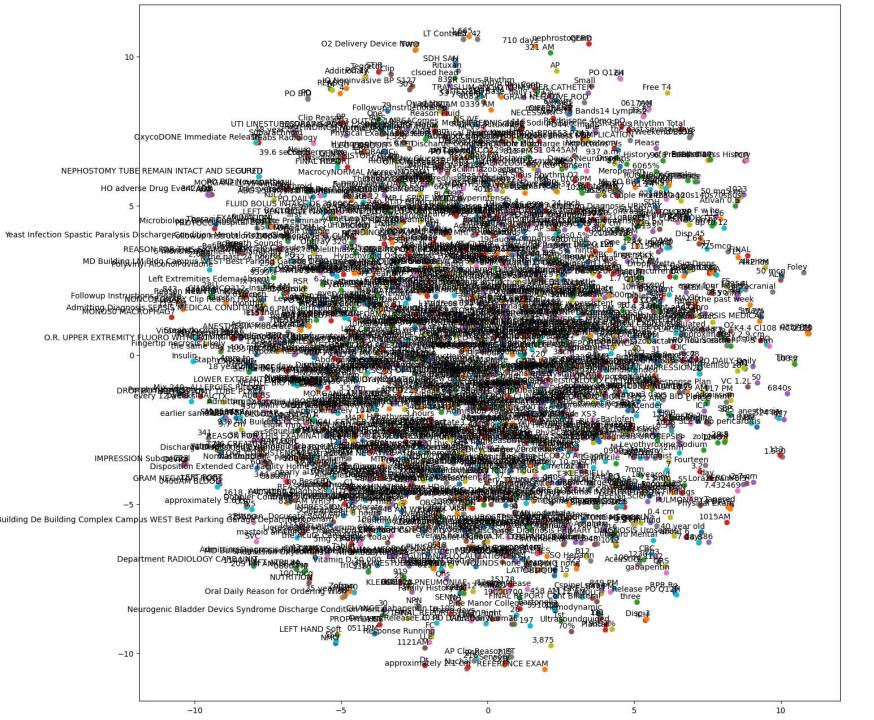
#### SPACY WORD2VEC

The word2vec does not strongly map similar entities to diverticulitis.

```
7.9646967e-03, 9.7369244e-03, 2.2322494e-03, -1.9185887e-04,
-2.1456373e-03, 7.9063070e-04, 5.0655100e-03, -8.1803100e-03,
3.2964419e-03, 6.9003613e-03, 4.8365938e-03, 4.9708998e-03,
2.7084881e-03, -9.0624178e-03, -3.6999600e-03, 7.5932681e-03,
5.1846472e-03, -5.3115557e-03, 1.4378357e-03, 2.3279563e-03,
-4.8689158e-03, -4.6908404e-03, 1.1710131e-03, 3.8234696e-03,
9.5103923e-03, -6.8599689e-03, -5.3088400e-03, 5.2709496e-03,
8.8702748e-03, 9.3907611e-03, 6.0181660e-03, 1.6135850e-03,
5.2177846e-03, -7.7261948e-03, -5.9987400e-03, 1.1794148e-04,
3.1815395e-03, 4.2114435e-03, 7.3190173e-03, 2.7855113e-03,
9.8167490e-03, 2.4591100e-03, -1.4726407e-03, -7.6487820e-05,
6.6566565e-03, -5.5224048e-03, -9.4300946e-03, -6.6872020e-03,
-7.4649178e-03, 1.5948660e-03, -2.1997862e-03, -8.5103353e-03,
4.8395633e-03, -9.5864395e-03, -1.1666270e-03, 1.9909346e-03,
-5.8462759e-03, -6.0708686e-03, 4.8035355e-03, -2.3023332e-03,
5.5653458e-03, -4.7132988e-03, -9.8666791e-03, 5.3380257e-03,
5.8715898e-03, -9.5486576e-03, 2.3364690e-03, 1.3866995e-03,
6.8748058e-03, -8.8529084e-03, 9.2356559e-03, 6.6955318e-03,
-1.5590680e-04, 8.7511018e-03, -5.1983115e-03, -2.8004721e-03,
```

```
# Find most similiar words to 'diverticulitis'
model_spacy.wv.similar_by_word('diverticulitis')

[('PO BID 11', 0.337181955575943),
  ('1500', 0.3282739520072937),
  ('20 99%RA', 0.2829912602901459),
  ('30cchr', 0.28291019797325134),
  ('Intrathecal', 0.28091850876808167),
  ('225', 0.2789475619792938),
  ('BILLING DIAGNOSIS ICU CARE GLYCEMIC CONTROL RISS', 0.
  ('Results Labs', 0.24722597002983093),
  ('0641PM', 0.24681124091148376),
  ('Home', 0.2464621365070343)]
```

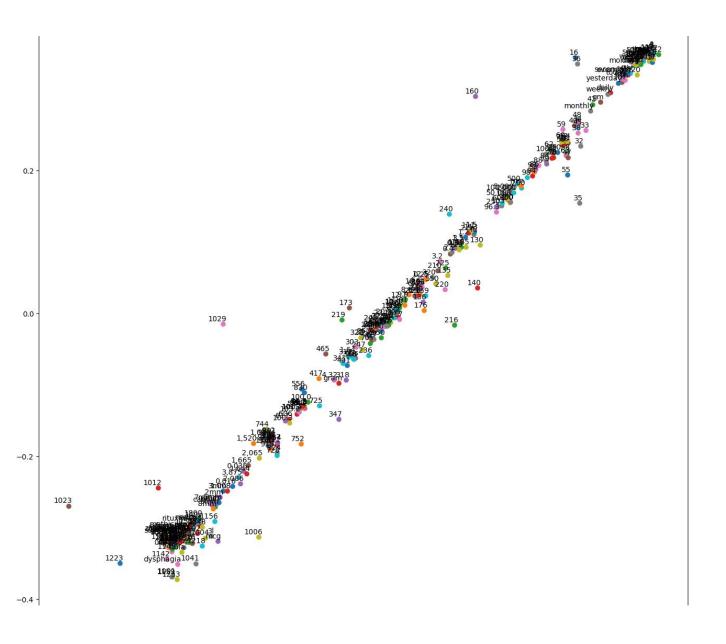


## SPACY TSNE PLOT

This Spacy tSNE plot does not seem to clearly map the similarity of the entities.

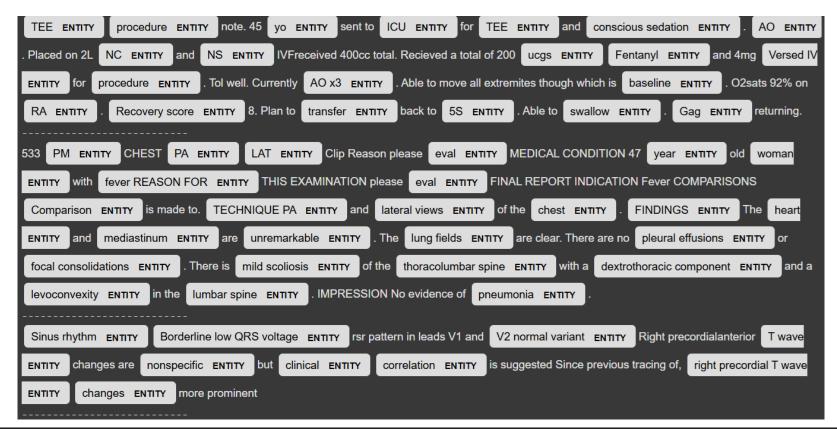
## SPACY TSNE PLOT WITH PRE-TRAINED MODEL

This plot shows a bit of an improvement in showing entity similarity.



## SCISPACY ENTITY VISUALIZATION

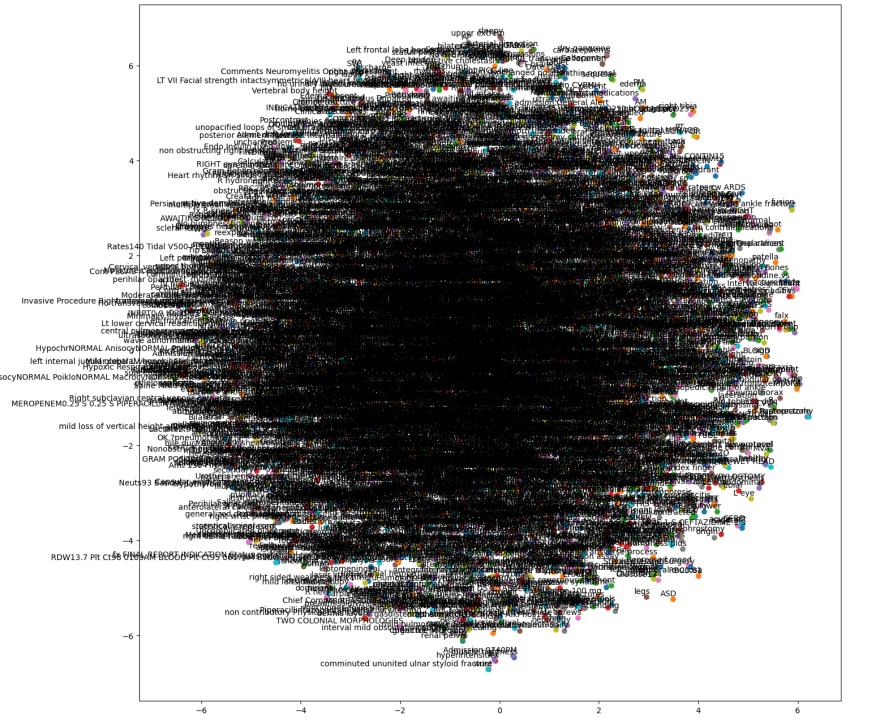
Scipacy seems to pick up a lot more entities than spacy and they seem more relevant to the medical field.



#### SCISPACY WORD2VEC

This word2vec by Scispacy seems to make a bit more sense than Spacy's however it could still improve.

```
-7.0611173e-03, -1.5227579e-03, 2.6500411e-03, 3.8315416e-03,
4.6273521e-03, -6.4738663e-03, -6.6725356e-03, -8.6745219e-03,
-9.5049599e-03, 4.6640079e-04, 4.9921954e-03, 5.1155253e-03,
-8.6483825e-03, -4.1282843e-03, 4.5276475e-03, 7.9027005e-03,
5.1184972e-03, -1.3470954e-03, -3.5143544e-03, -9.2019998e-03,
5.6368136e-03, 5.8939913e-03, 8.9649195e-03, 5.9732059e-03,
-1.0734015e-03, -7.5223846e-03, 4.5159226e-03, -8.3971135e-03,
3.8024560e-03, 3.5979334e-05, -3.9827162e-03, 3.1726509e-03,
5.2741994e-03, 9.6654259e-03, -6.7856698e-03, 2.1551482e-03,
-3.1155529e-03, -2.0836447e-03, 1.4447230e-03, 3.4121235e-03,
-1.0069066e-03, 5.7823109e-03, 7.4876416e-03, 1.6989755e-03,
-9.5217982e-03, -3.5139048e-03, -1.0162882e-03, 1.3274883e-03,
4.6040667e-03, -1.6323101e-03, -5.6531169e-03, 9.6453552e-04,
7.2515770e-03, -5.8803214e-03, 2.4550057e-03, 8.5401367e-03,
8.7210555e-03, 2.9717474e-03, -8.0181994e-03, 4.8342687e-03,
-5.8901060e-04, 6.9626104e-03, 3.1928925e-03, -3.7182108e-03,
7.4085034e-03, -9.3792444e-03, -4.0415670e-03, -8.6119082e-03,
```

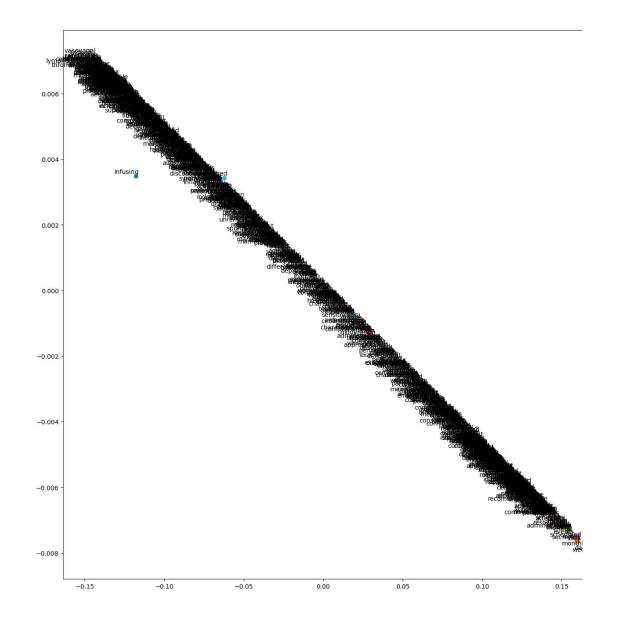


#### SISPACY TSNE PLOT

We can see from this that Scispacy was able to pick out many more entities that seem more relevant to the medical field. However, it is hard to confirm how well it does in mapping similarity between them.

# SCISPACY TSNE PLOT WITH PRE-TRAINED MODEL

We can see again that more relevant entities were picked out but is too thick to evaluate. This also shows more words compared to mainly numbers.

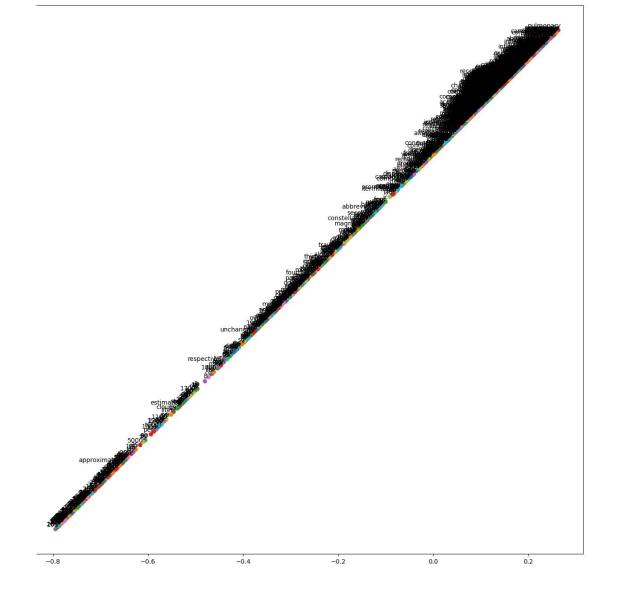


#### BLUEBERT TSNE PLOT

blueBert seemed to cluster more words more tightly and not include many entities.

### BLUEBERT TSNE PLOT WITH PRE-TRAINED MODEL

For the pre-trained model, blueBert does fairly well separating most of the words and the numbers. Words like estimate and approximate are close to numbers which makes sense.



#### CONCLUSION

- Scispacy and blueBERT outperform Spacy in medical entity recognition.
- Scispacy captures more relevant terms but struggles with similarity mapping.
- blueBERT achieves better clustering but identifies fewer entities overall.
- Future improvements include fine-tuning word embeddings on MIMIC-III data and leveraging external biomedical knowledge sources like UMLS and SNOMED-CT.

