Hands-on

Day 1: Comparing Representations

https://colab.research.google.com/drive/1JBW5pQ3-HxilyiJuZMREG8uBzzkQwuPS?usp=sharing

SemEval 2020 Task 1 Corpora

```
from languagechange.benchmark import SemEval2020Task1
```

```
semeval_en = SemEval2020Task1('EN')
```

```
corpus1 = semeval_en.corpus1_token
corpus2 = semeval_en.corpus2_token
```

```
corpus1 = semeval_en.corpus1_lemma
corpus2 = semeval_en.corpus2_lemma
```

Choose your corpus

```
import urllib.request

with open('brown_nolines.txt','w+') as g:
     url = 'http://www.sls.hawaii.edu/bley-vroman/brown_nolines.txt'
     for line in urllib.request.urlopen(url):
          g.write(line.decode('utf-8'))


from languagechange.corpora import LinebyLineCorpus

brown_corpus = LinebyLineCorpus('brown_nolines.txt', name='Brown Corpus', is_tokenized=False,
is_sentence_tokenized=True)
```

Static Embeddings

```
from languagechange.models.representation.staticimport StaticModel, CountModel, PPMI, SVD

# CORPUS 1
count_encoder1 = CountModel(corpus1, window_size=10, savepath='count_matrix1')
count_encoder1.encode()
PPMI_encoder1 = PPMI(count_encoder1, shifting_parameter=5, smoothing_parameter=0.75,
savepath='ppmi_matrix1')
PPMI_encoder1.encode()
svd_encoder1 = SVD(PPMI_encoder1, dimensionality=100, gamma=1.0, savepath='svd_count_matrix1')
svd_encoder1.encode()
svd_encoder1.load()
```

Extract Embeddings

```
encoder = svd_encoder1

def most_similar_idxs(word_idx, M, k):
    sims = np.dot(M[word_idx],M.T)
    return np.flip(np.argsort(sims))[:k]

M = np.asarray(encoder.matrix().todense())
M = preprocessing.normalize(M)
idx2word = encoder.row2word()
word2idx = {idx2word[i]:i for i in idx2word}

idx_word = word2idx['plane_nn']
idxs = most_similar_idxs(idx_word, M, 10)

vectors = M[idxs]
words = [idx2word[i] for i in idxs]
print(words)
```

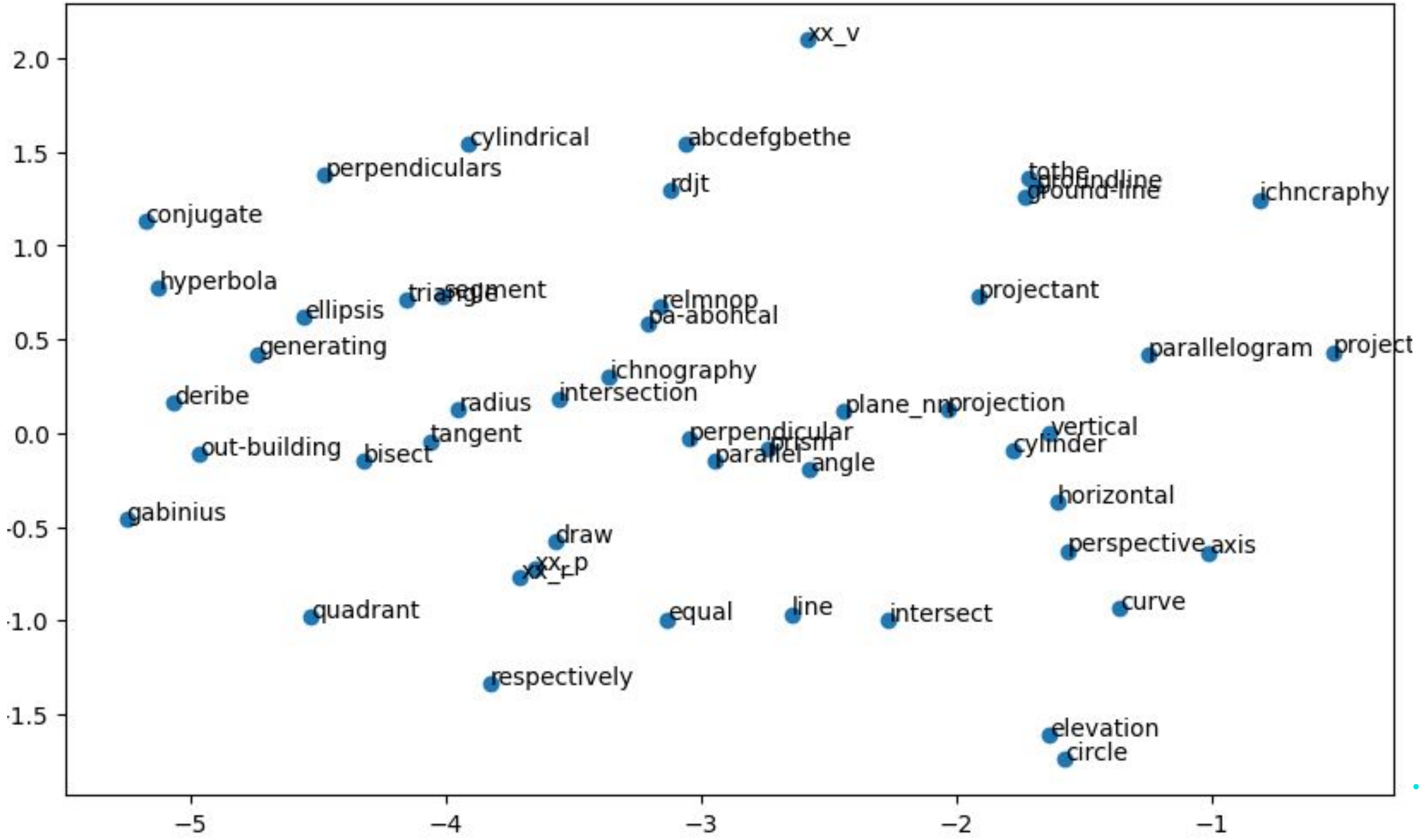
```
'plane_nn', 'projection', 'parallel',
'perpendicular', 'angle',
'ichnography', 'projectant',
'intersection', 'vertical', 'prism'
```

Extract Embeddings

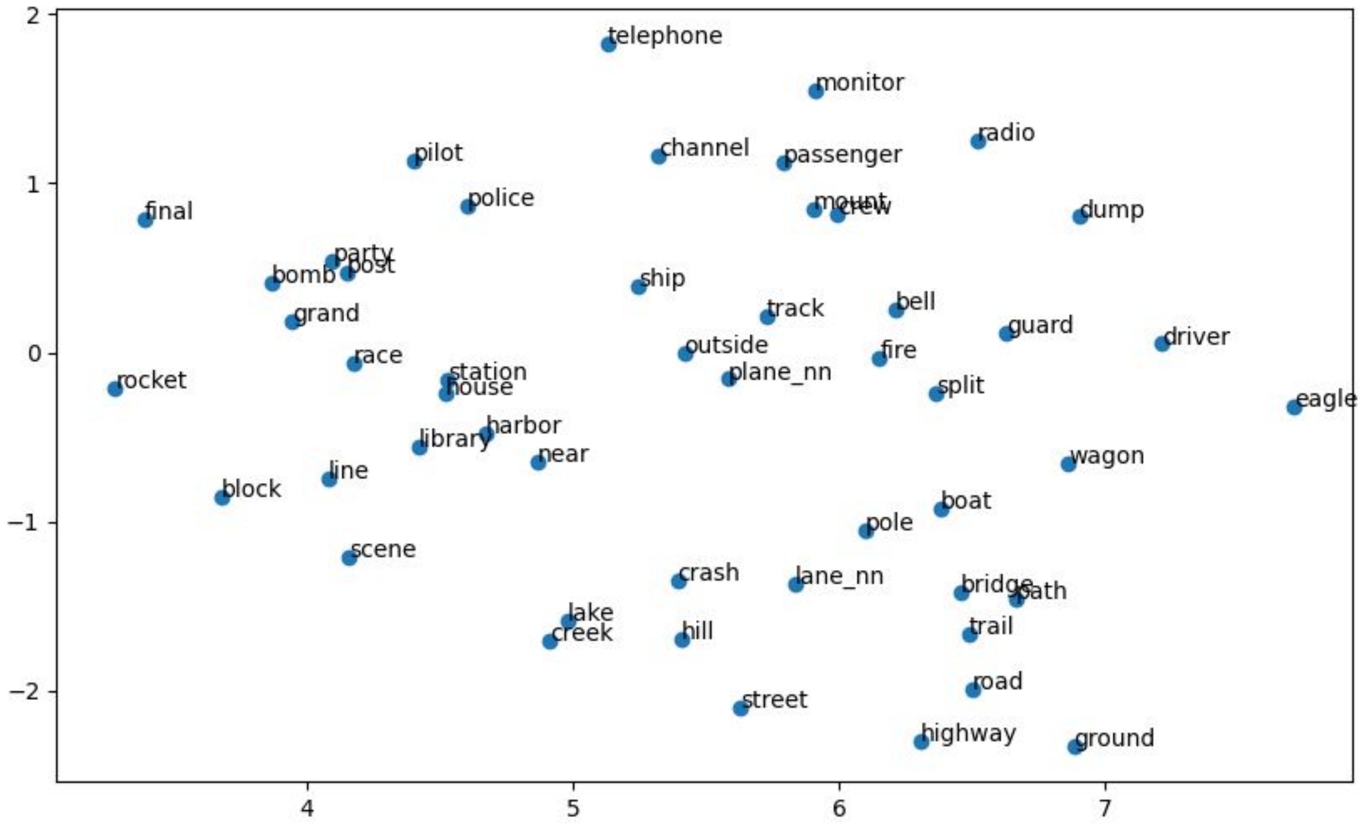
```
encoder = svd_encoder2

def most_similar_idxs(word_idx, M, k):
   sims = np.dot(M[word_idx],M.T)
   return np.flip(np.argsort(sims))[:k]

M = np.asarray(encoder.matrix().todense())
M = preprocessing.normalize(M)
idx2word = encoder.row2word()
word2idx = {idx2word[i]:i for i in idx2word}

idx_word = word2idx['plane_nn']
idxs = most_similar_idxs(idx_word, M, 10)

vectors = M[idxs]
words = [idx2word[i] for i in idxs]
print(words)
```

```
'plane_nn', 'ship', 'track', 'station',
'boat', 'outside', 'harbor', 'lane_nn',
'road', 'mount',
```

PPMI-SVD Embeddings (Corpus 1)



PPMI-SVD Embeddings (Corpus 2)



Align Static Embeddings

```
from sklearn.metrics.pairwise import cosine_similarity

plane1, plane2 = np.asarray(svd_encoder1['plane_nn']), np.asarray(svd_encoder2['plane_nn'])
will1, will2 = np.asarray(svd_encoder1['will']), np.asarray(svd_encoder2['will'])

print('plane1-plane2 similarity', cosine_similarity(plane1, plane2)[0][0])
print('will1-will2 similarity', cosine_similarity(will1, will2)[0][0])
```

```
plane1-plane2 similarity 0.17147865696062017
will1-will2 similarity 0.15674904444597207
```

Align Static Embeddings

```
from languagechange.models.representation.alignment import OrthogonalProcrustes

alignment = OrthogonalProcrustes('aligned1','aligned2')
alignment.align(svd_encoder1, svd_encoder2)

aligned1 = StaticModel('aligned1')
aligned2 = StaticModel('aligned2')
aligned1.load()
aligned2.load()
```

Align Static Embeddings

```
from sklearn.metrics.pairwise import cosine_similarity

plane1, plane2 = np.asarray(aligned1['plane_nn']), np.asarray(aligned2['plane_nn'])
will1, will2 = np.asarray(aligned1['will']), np.asarray(aligned2['will'])

print('plane1-plane2 similarity', cosine_similarity(plane1, plane2)[0][0])
print('will1-will2 similarity', cosine_similarity(will1, will2)[0][0])
```

```
plane1-plane2 similarity 0.20925707400117863
will1-will2 similarity 0.26262717664099955
```

Contextualized Embeddings

```python
from languagechange.models.representation.contextualized import BERT

target_words = list(semeval_en.binary_task.keys())
print([str(t) for t in target_words])

bert = BERT('bert-base-uncased', device='cuda')

usages = corpus1.search(target_words)

vectors = bert.encode(usages['graft_nn'])
print(vectors.shape)
```

XL-LEXEME

```python
from languagechange.models.representation.contextualized import XL_LEXEME

model = XL_LEXEME(device='cuda')

vectors = model.encode(usages['graft_nn'])
print(vectors.shape)
```

Exercise

Explore different words you think have changed (plane, graft, cell, gay, mouse).

Use different meaning representation models (count, PPMI, contextualized).

Report your findings qualitatively

Build your own visualization!

Challenge: Build your own visualization of Semantic Change

1. Choose a model: static embeddings, contextualized embeddings or XL-LEXEME
2. Choose a corpus
3. Choose a word that changed its meaning over time
4. Extract the embeddings
5. Plot the embeddings to show the semantic change

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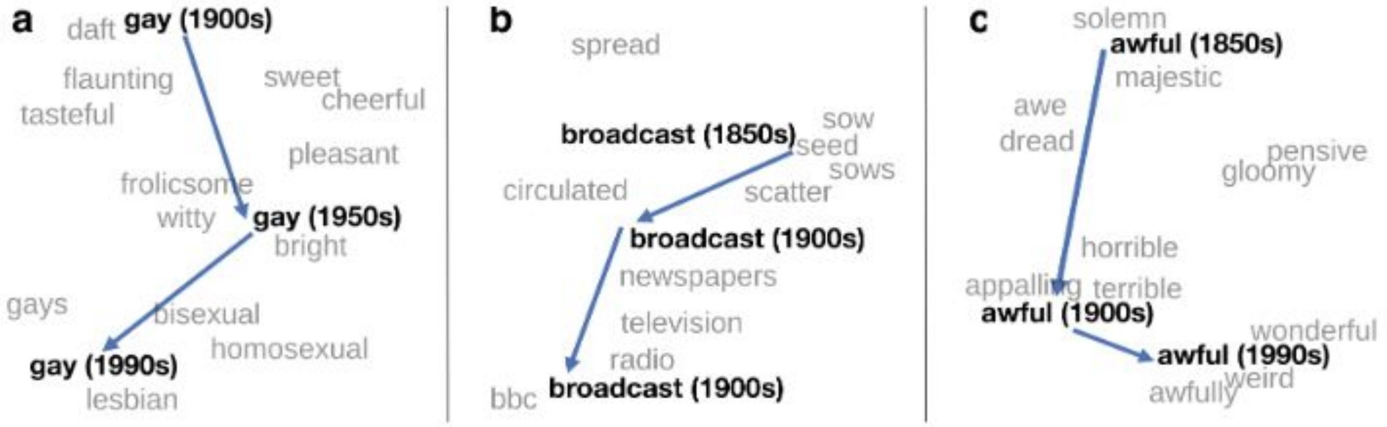
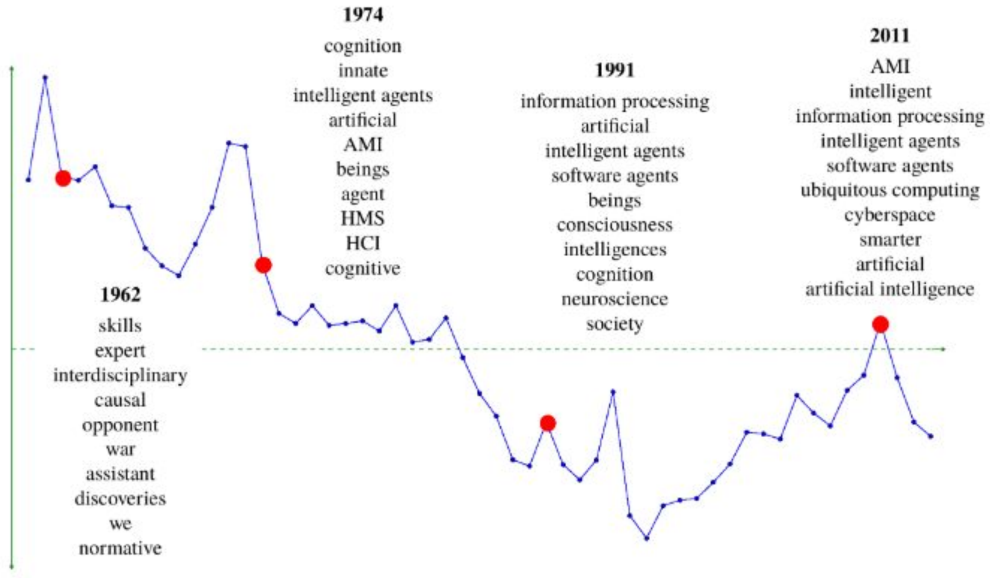
Previous visualizations (1)



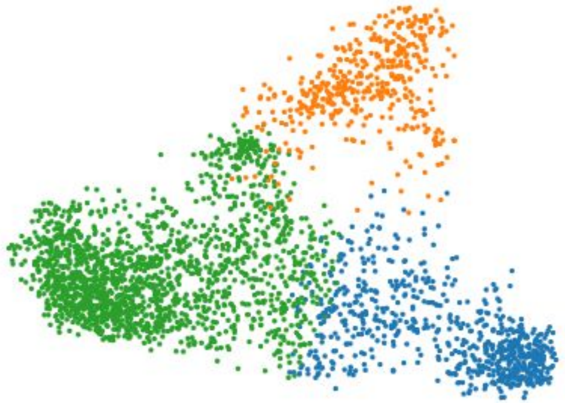
William L. Hamilton, Jure Leskovec, and Dan Jurafsky. 2016. Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1489–1501, Berlin, Germany. Association for Computational Linguistics.

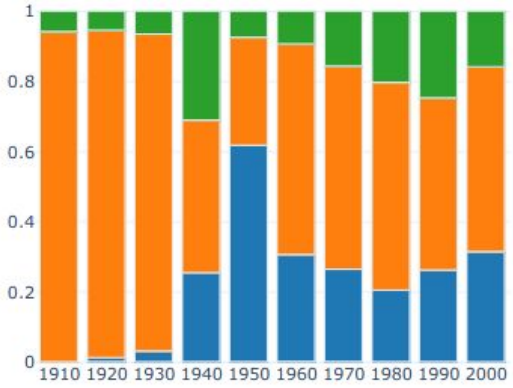
Previous visualizations (2)



Rudolph, Maja, and David Blei. "Dynamic embeddings for language evolution." In *Proceedings of the 2018 world wide web conference*, pp. 1003-1011. 2018.

Previous visualizations (3)


(a) PCA visualisation of the usage representations.



(b) Probability-based usage type distributions along time.

Mario Giulianelli, Marco Del Tredici, and Raquel Fernández. 2020. Analysing Lexical Semantic Change with Contextualised Word Representations. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 3960–3973, Online. Association for Computational Linguistics.

Show your visualization!