01_using_pretrained_vectors

September 29, 2021

0.1 Imports & Settings

[1]:

```
import warnings
warnings.filterwarnings('ignore')
```

[2]:

```
from time import time
from collections import Counter
from pathlib import Path
import pandas as pd
import numpy as np
from numpy.linalg import norm
from scipy.spatial.distance import cdist, cosine

import matplotlib.pyplot as plt
from matplotlib.ticker import FuncFormatter
import seaborn as sns

from gensim.models import Word2Vec, KeyedVectors
from gensim.scripts.glove2word2vec import glove2word2vec

from sklearn.decomposition import IncrementalPCA
```

[3]:

```
sns.set_style('white')
```

[4]:

```
analogies_path = Path('data', 'analogies-en.txt')
```

0.2 Convert GloVE Vectors to gensim format

The various GloVE vectors are available here. Download link for the wikipedia version. Unzip and store in `data/glove`.

[5]:

```
glove_path = Path('..', 'data', 'glove')
```

0.2.1 WikiPedia

[6]:
```
glove_wiki_file= glove_path / 'glove.6B.300d.txt'
word2vec_wiki_file = glove_path / 'glove.wiki.gensim.txt'
```

[7]:
```
glove2word2vec(glove_input_file=glove_wiki_file,␣
 ↪word2vec_output_file=word2vec_wiki_file)
```

[7]:
```
(400000, 300)
```

0.2.2 Twitter Data

[8]:
```
glove_twitter_file= glove_path / 'glove.twitter.27B.200d.txt'
word2vec_twitter_file = glove_path / 'glove.twitter.gensim.txt'
```

[9]:
```
glove2word2vec(glove_input_file=glove_twitter_file,␣
 ↪word2vec_output_file=word2vec_twitter_file)
```

[9]:
```
(1193514, 200)
```

0.2.3 Common Crawl

[10]:
```
glove_crawl_file= glove_path / 'glove.840B.300d.txt'
word2vec_crawl_file = glove_path / 'glove.crawl.gensim.txt'
```

[11]:
```
glove2word2vec(glove_input_file=glove_crawl_file,␣
 ↪word2vec_output_file=word2vec_crawl_file)
```

[11]:
```
(2196017, 300)
```

0.3 Evaluate embeddings

[33]:
```
results_path = Path('results', 'glove')
```

[12]:
```
def eval_analogies(file_name, vocab=30000):
    model = KeyedVectors.load_word2vec_format(file_name, binary=False)
    accuracy = model.wv.accuracy(analogies_path,
                                 restrict_vocab=vocab,
                                 case_insensitive=True)
    return (pd.DataFrame([[c['section'],
                           len(c['correct']),
                           len(c['incorrect'])] for c in accuracy],
                         columns=['category', 'correct', 'incorrect'])
            .assign(samples=lambda x: x.correct.add(x.incorrect))
            .assign(average=lambda x: x.correct.div(x.samples))
            .drop(['correct', 'incorrect'], axis=1))
```

[13]:

```
result = eval_analogies(word2vec_twitter_file, vocab=100000)
```

0.3.1 twitter result

[14]:

```
twitter_result = eval_analogies(word2vec_twitter_file, vocab=100000)
twitter_result.to_csv(glove_path / 'accuracy_twitter.csv', index=False)
twitter_result
```

[14]:

```
                      category  samples   average
0      capital-common-countries      462  0.701299
1                 capital-world      930  0.690323
2                 city-in-state     3644  0.350714
3                      currency      268  0.018657
4                        family      342  0.824561
5     gram1-adjective-to-adverb      650  0.143077
6                gram2-opposite      342  0.365497
7             gram3-comparative     1260  0.757937
8             gram4-superlative      930  0.686022
9      gram5-present-participle      702  0.750712
10  gram6-nationality-adjective      870  0.750575
11             gram7-past-tense     1190  0.576471
12                 gram8-plural     1122  0.811052
13           gram9-plural-verbs      600  0.655000
14                        total    13312  0.564228
```

0.3.2 wiki result

[15]:

```
wiki_result = eval_analogies(word2vec_wiki_file, vocab=100000)
wiki_result.to_csv(glove_path / 'accuracy_wiki.csv', index=False)
wiki_result
```

[15]:

```
                      category  samples   average
0      capital-common-countries      506  0.948617
1                 capital-world     8372  0.964644
2                 city-in-state     4242  0.599953
3                      currency      752  0.174202
4                        family      506  0.881423
5     gram1-adjective-to-adverb      992  0.225806
6                gram2-opposite      756  0.285714
7             gram3-comparative     1332  0.882132
8             gram4-superlative     1056  0.746212
9      gram5-present-participle     1056  0.699811
10  gram6-nationality-adjective     1640  0.925000
11             gram7-past-tense     1560  0.611538
12                 gram8-plural     1332  0.780781
13           gram9-plural-verbs      870  0.585057
14                        total    24972  0.754445
```

0.3.3 Common Crawl result

[16]:

```
crawl_result = eval_analogies(word2vec_crawl_file, vocab=100000)
crawl_result.to_csv(glove_path / 'accuracy_crawl.csv', index=False)
crawl_result
```

[16]:

```
                       category  samples   average
0       capital-common-countries      506  0.946640
1                  capital-world     4290  0.917483
2                  city-in-state     4242  0.706742
3                       currency      206  0.184466
4                         family      420  0.978571
5      gram1-adjective-to-adverb      992  0.388105
6                 gram2-opposite      702  0.363248
7              gram3-comparative     1332  0.876877
8              gram4-superlative     1122  0.919786
9       gram5-present-participle     1056  0.827652
10  gram6-nationality-adjective     1406  0.948791
11               gram7-past-tense     1560  0.621154
12                   gram8-plural     1332  0.864114
13             gram9-plural-verbs      870  0.672414
14                          total    20036  0.779347
```

0.3.4 Combine & compare results

[17]:

```
cat_dict = {'capital-common-countries':'Capitals',
            'capital-world':'Capitals RoW',
            'city-in-state':'City-State',
            'currency':'Currency',
            'family':'Famliy',
            'gram1-adjective-to-adverb':'Adj-Adverb',
            'gram2-opposite':'Opposite',
            'gram3-comparative':'Comparative',
            'gram4-superlative':'Superlative',
            'gram5-present-participle':'Pres. Part.',
            'gram6-nationality-adjective':'Nationality',
            'gram7-past-tense':'Past Tense',
            'gram8-plural':'Plural',
            'gram9-plural-verbs':'Plural Verbs',
            'total':'Total'}
```

[18]:

```
accuracy = (twitter_result.assign(glove='Twitter')
            .append(wiki_result.assign(glove='Wiki'))
            .append(crawl_result.assign(glove='Crawl')))
```

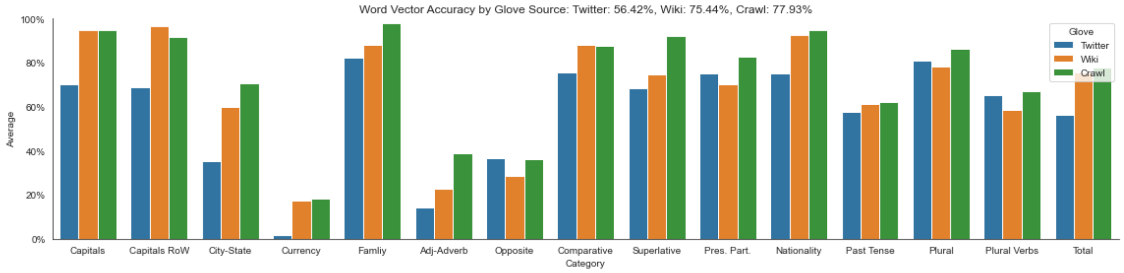
[19]:

```
accuracy.category = accuracy.category.replace(cat_dict)
accuracy = accuracy.rename(columns=str.capitalize)
```

[38]:
```
accuracy.to_csv(results_path / 'accuracy.csv', index=False)
```

[39]:
```
accuracy = pd.read_csv(results_path / 'accuracy.csv')
```

[40]:
```
fig, ax = plt.subplots(figsize=(16, 4))
sns.barplot(x='Category', y='Average', hue='Glove', data=accuracy, ax=ax)
ax.set_title(f'Word Vector Accuracy by Glove Source: Twitter: {0.564228:.2%},␣
 ↪Wiki: {0.75444:.2%}, Crawl: {0.779347:.2%}')
ax.set_ylim(0,1)
ax.yaxis.set_major_formatter(FuncFormatter(lambda y, _: '{:.0%}'.format(y)))
sns.despine()
fig.tight_layout()
fig.savefig(results_path / 'glove_accuracy', dpi=300);
```



0.4 Visualize Embeddings

0.4.1 Load GloVe Wiki Vectors

[22]:
```
model = KeyedVectors.load_word2vec_format(word2vec_wiki_file, binary=False)
```

[23]:
```
accuracy = model.accuracy(questions=str(analogies_path), restrict_vocab=100000)
```

[24]:
```
vectors = model.vectors[:100000]
vectors /= norm(vectors, axis=1).reshape(-1, 1)
vectors.shape
```

[24]:
```
(100000, 300)
```

[25]:
```
words = model.index2word[:100000]
word2id = {w:i for i, w in enumerate(words)}
```

0.4.2 Project Embedding into 2D

[26]:
```
pca = IncrementalPCA(n_components=2)

vectors2D = pca.fit_transform(vectors)
pd.Series(pca.explained_variance_ratio_).mul(100)
```

[26]:
```
0    2.604632
1    1.293812
dtype: float64
```

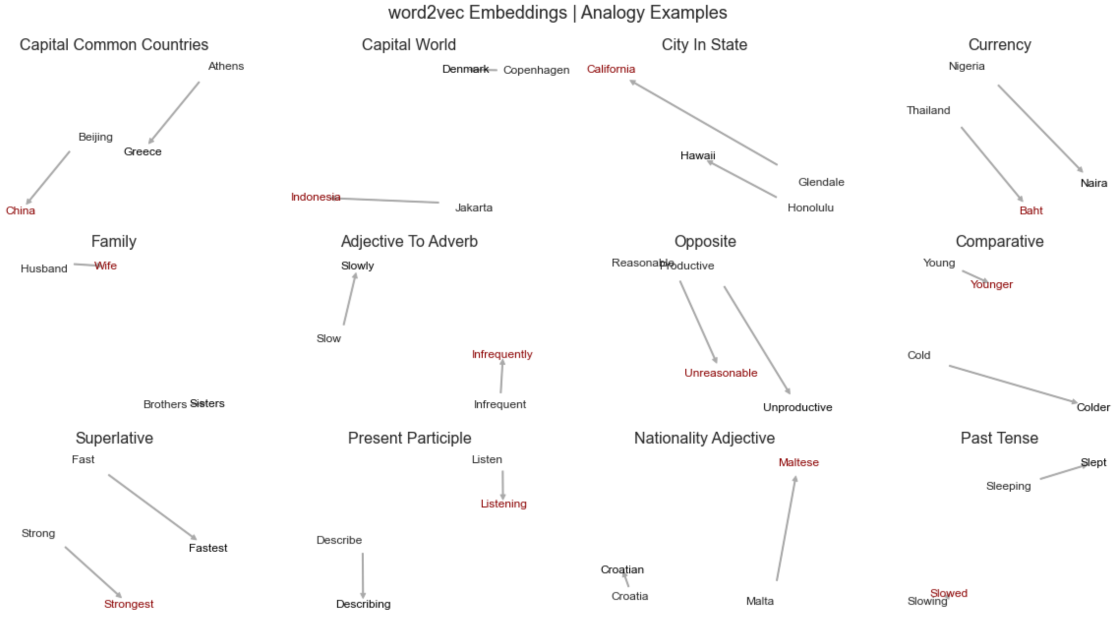
0.4.3 Plot Analogy Examples

[27]:
```
results = pd.DataFrame()
correct = incorrect = 0
for section in accuracy:
    correct += len(section['correct'])
    incorrect += len(section['incorrect'])
    df = pd.DataFrame(section['correct']).apply(lambda x: x.str.lower()).
 ↪assign(section=section['section'])
    results = pd.concat([results, df])
```

[28]:
```
def find_most_similar_analogy(v):
    """Find analogy that most similar in 2D"""
    v1 = vectors2D[v[1]] - vectors2D[v[0]]
    v2 = vectors2D[v[3]] - vectors2D[v[2]]
    idx, most_similar = None, np.inf

    for i in range(len(v1)):
        similarity = cosine(v1[i], v2[i])
        if similarity < most_similar:
            idx = i
            most_similar = similarity
    return idx
```

[29]:
```
def get_plot_lims(coordinates):
    xlim, ylim = coordinates.agg(['min', 'max']).T.values
    xrange, yrange = (xlim[1] - xlim[0]) * .1, (ylim[1] - ylim[0]) * .1
    xlim[0], xlim[1] = xlim[0] - xrange, xlim[1] + xrange
    ylim[0], ylim[1] = ylim[0] - yrange, ylim[1] + yrange
    return xlim, ylim
```

[34]:
```
fig, axes = plt.subplots(nrows=3, ncols=4, figsize=(16, 9))
axes = axes.flatten()
fc = ec = 'darkgrey'
for s, (section, result) in enumerate(results.groupby('section')):
    if s > 11:
        break

    df = result.drop('section', axis=1).apply(lambda x: x.map(word2id))
    most_similar_idx = find_most_similar_analogy(df)

    best_analogy = result.iloc[most_similar_idx, :4].tolist()

    analogy_idx = [words.index(word) for word in best_analogy]
    best_analogy = [a.capitalize() for a in best_analogy]

    coords = pd.DataFrame(vectors2D[analogy_idx])  # xy array

    xlim, ylim = get_plot_lims(coords)
    axes[s].set_xlim(xlim)
    axes[s].set_ylim(ylim)

    for i in [0, 2]:
        axes[s].annotate(s=best_analogy[i], xy=coords.iloc[i+1], xytext=coords.
 ↪iloc[i],
                         arrowprops=dict(width=1,headwidth=5, headlength=5,
                                         fc=fc, ec=ec, shrink=.1),
                         fontsize=12)

        axes[s].annotate(best_analogy[i+1], xy=coords.iloc[i+1],
                         xytext=coords.iloc[i+1],
                         va='center', ha='center',
                         fontsize=12, color='darkred' if i == 2 else 'k');

    axes[s].axis('off')
    title = ' '.join([s.capitalize()
                      for s in section.split('-') if not s.startswith('gram')])
    axes[s].set_title(title, fontsize=16)

fig.suptitle('word2vec Embeddings | Analogy Examples', fontsize=18)
fig.tight_layout()
fig.subplots_adjust(top=.9);
```


word2vec Embeddings | Analogy Examples
Capital Common Countries
Athens
Beijing
Greece
China
Capital World
Denmark
Copenhagen
Indonesia
Jakarta
City In State
California
Hawaii
Glendale
Honolulu
Currency
Nigeria
Thailand
Naira
Baht
Family
Husband
Wife
Brothers
Sisters
Adjective To Adverb
Slowly
Slow
Infrequently
Infrequent
Opposite
Reasonable
Productive
Unreasonable
Unproductive
Comparative
Young
Younger
Cold
Colder
Superlative
Fast
Strong
Fastest
Strongest
Present Participle
Listen
Listening
Describe
Describing
Nationality Adjective
Maltese
Croatian
Croatia
Malta
Past Tense
Slept
Sleeping
Slowed
Slowing

```
[ ]:
```