Module4_HD_vectors_ngrams_ToDo

September 29, 2021

[1]:
```
##Load modules and libraries
import numpy as np
import os.path
import string
import matplotlib
import matplotlib.pyplot as plt

# For my hw1 code
SEED = 1234
RNG = np.random.default_rng(SEED)
import time
```

1 Function to generate Item memory for symbols

[2]:
```
def makeItemMemory(dimension):
    alphabet = list(string.ascii_lowercase+' ') # set of used symbols
    HDdic = {}
    for symb in alphabet:
        HDdic[symb] = 2*np.random.randint(low=0, high=2, size=dimension)-1 #␣
 ↪assign a random bipolar HD vector
    return HDdic
```

2 Parameters

[3]:
```
langLabels = ['pol', 'ces', 'slk', 'slv', 'bul', 'ron', 'ita',  'por',   ␣
 ↪'spa',   'fra', 'eng', 'deu',  'nld', 'dan', 'swe', 'fin', 'hun', 'est',␣
 ↪'lav', 'lit', 'ell'] # Names of training files for different languages
langFull = ['Polish', 'Czech', 'Slovak', 'Slovene','Bulgarian', 'Romanian',␣
 ↪'Italian',  'Portuguese',   'Spanish',   'French', 'English', 'German',␣
 ↪'Dutch', 'Danish', 'Swedish', 'Finnish', 'Hungarian', 'Estonian', 'Latvian',␣
 ↪'Lithuanian',   'Greek'] # Full names of languages

dimension = 1024 # Dimensionality for high-dimensional vectors
n=3 # size of n-gram
```

```
dataSizeLimit=20000 # number symbols to consider for each language. If set to 0␣
↪then take full dataset
```

3 Initialize profile vectors

[4]:
```
def initProfiles(dimension: int = dimension, langLabels: list = langLabels):
    HDProfiles = {}
    for lang in langLabels:
        HDProfiles[lang] = np.zeros(dimension) # initialize profile vectors
    return HDProfiles
```

4 Function to form an HD vector for a given n-gram

[5]:
```
######################
#Function from my HW1
#####################
def bind(vector1: np.array, vector2: np.array) -> np.array:
    bound_vector = vector1 * vector2
    return bound_vector

def permutation(vector1: np.array) -> np.array:
    #Using roll for consistent permutation
    permuted_vector = np.roll(vector1, 1)
    return permuted_vector

def makengramHD(seq: str, HDdic: dict, dimension: int = dimension) -> np.array:
    n=len(seq)
    HDgram=np.ones(dimension) # initialize n-gram's HD vector to all ones

    #ToDo use binding and permutation operations to create n-gram's HD vector
    for letter in seq:
        letter_embedding = HDdic[letter]
        HDgram = bind(
                        letter_embedding,
                        permutation(
                                        HDgram
                                    )
                    )

    return HDgram
```

5 Construct HD vectors representing n-gram statistics for each language

[6]:
```
def construct_hdvec(dimension: int = dimension, n: int = n, langLabels: list =␣
↪langLabels) -> dict:
    HDdic=makeItemMemory(dimension) # make item memory for the set of used␣
↪symbols (26 letters  + space)
    HDProfiles=initProfiles(dimension,langLabels) # initialize profile HD␣
↪vectors

    #For each language
    for lang in langLabels:
        #print (lang)
        data_file_name=os.path.abspath(os.path.join('training_texts', lang +'.
↪txt')) # get training data

        with open(data_file_name, 'r') as f:
            langdData = f.read() # read file
        f.close()

        # if training data should be trimmed
        if dataSizeLimit>0 and len(langdData)>dataSizeLimit:
            langdData=langdData[0:dataSizeLimit]

        #Construct profile HD vectors
        start = time.time()
        for i in range(0,len(langdData)-n+1):
            seq=langdData[i:i+n] # pick the current n-gram
            HDgram=makengramHD(seq,HDdic, dimension) # get n-gram's HD vector
            HDProfiles[lang] += HDgram # update profile HD vector
#          print(f"Language {lang} took {time.time()- start} sec")

    return HDProfiles
```

6 Compute cosine similarities between profile HD vectors

[7]:
```
from typing import Tuple
def get_cossim(HDProfiles: dict, langLabels: list = langLabels, langFull: list␣
↪= langFull) -> Tuple[np.array, list]:

    Languages=[] # full names of the lanuages in the right order
    keys=list(HDProfiles.keys()) # order of lanuages in the dictionary
    for key in keys:
        ind=langLabels.index(key)
        Languages.append(langFull[ind])
    # Get profiles HD vector into an array
    profiles=np.array(list(HDProfiles.values()))

    #ToDo calculate cosine similarity between HD vectors in "profiles"
    from sklearn.metrics.pairwise import cosine_similarity #Using because its␣
↪probably faster, have my code in comments in case this is not allowed
    cos_sim = cosine_similarity(profiles)

    # rows = profiles.shape[0]
    # cos_sim = np.zeros((rows,rows))
    # for i in range(rows):
    #     for j in range(rows):
    #         cos_sim[i][j] = np.dot(rows[i], rows[i]) / (np.linalg.
↪norm(rows[i]) * np.linalg.norm(rows[j]))
    return cos_sim, Languages
```

7 Visualize cosine similarities

[8]:
```
def plot(cos_sim: np.array,
         languages: list,
         title: str) -> matplotlib.pyplot.figure:

    plt.rcParams.update({'font.size': 9})

    fig, ax = plt.subplots(dpi=300)
    im = ax.imshow(cos_sim, cmap="inferno",vmin=0, vmax=1)

    #ToDo visualize cosine similarity between language profiles
    plt.xticks(np.arange(0, len(langLabels)), langLabels, rotation =45)
    plt.yticks(np.arange(0, len(langLabels)), langLabels)

    ax.set_title(title)
    fig.tight_layout()
    return fig
```

[9]:
```
def run_experiment(dimension: int = dimension, n: int = n,
                   title: str="Cosine similarity between language profiles") ->␣
↪matplotlib.pyplot.figure:

    HDProfiles = construct_hdvec(dimension, n)
    cos_sim, languages = get_cossim(HDProfiles)
    plt_fig = plot(cos_sim, languages, title)
    plt.show()
```

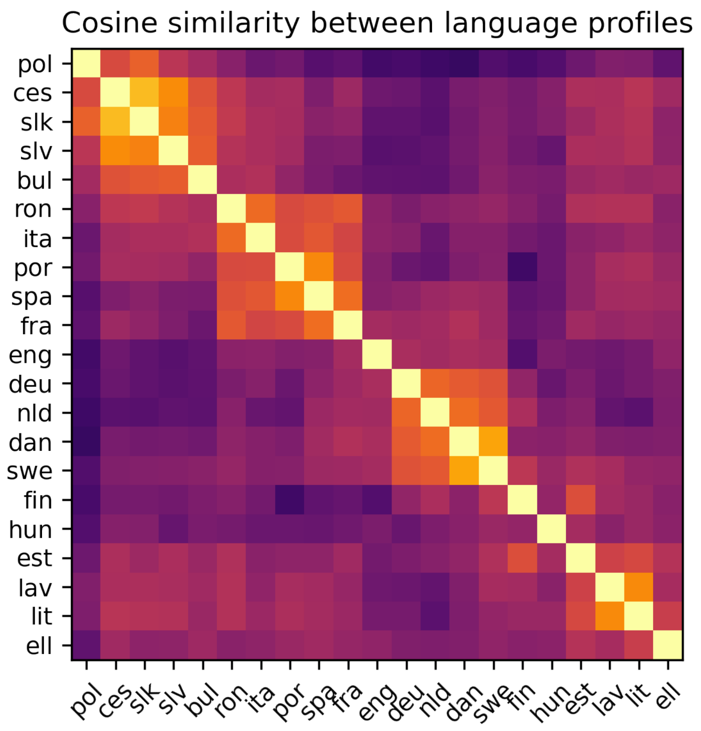
7.1 Question 1

Visualize the cosine similarities between languages' profile HD vectors (for example, by showing a heatmap of pairwise similarities). Are your results qualitatively similar to Figure 1 in "Language Geometry Using Random Indexing"?

7.1.1 Answer

Yes, we can see the clustering between the Slavic languages, Romanic languages, Uralic languages.

[10]:
```
run_experiment()
```



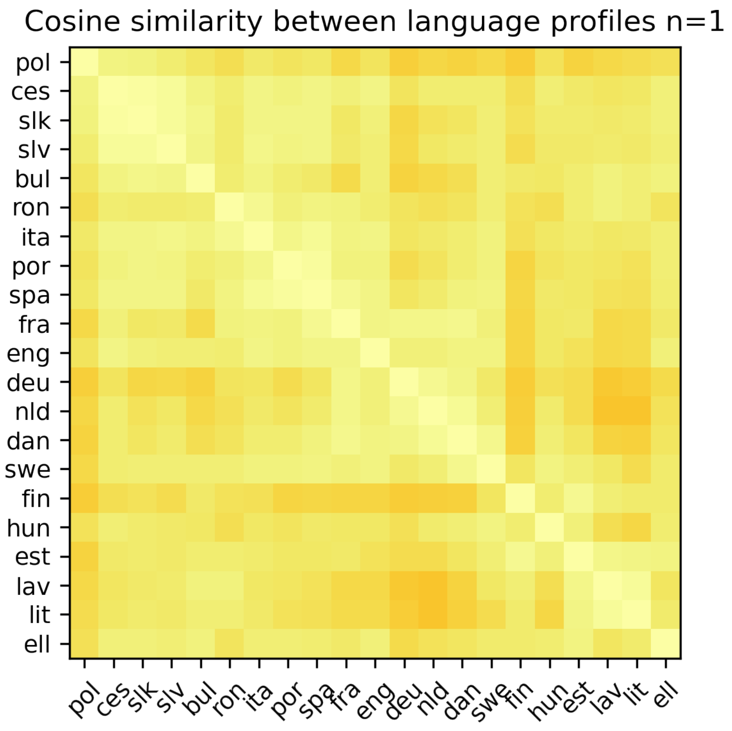
7.2 Question 2

By default, the size of n-grams is set to 3. How does your visualization change if you change the value of n? What happens to cosine similarities when n is either too small or too large?

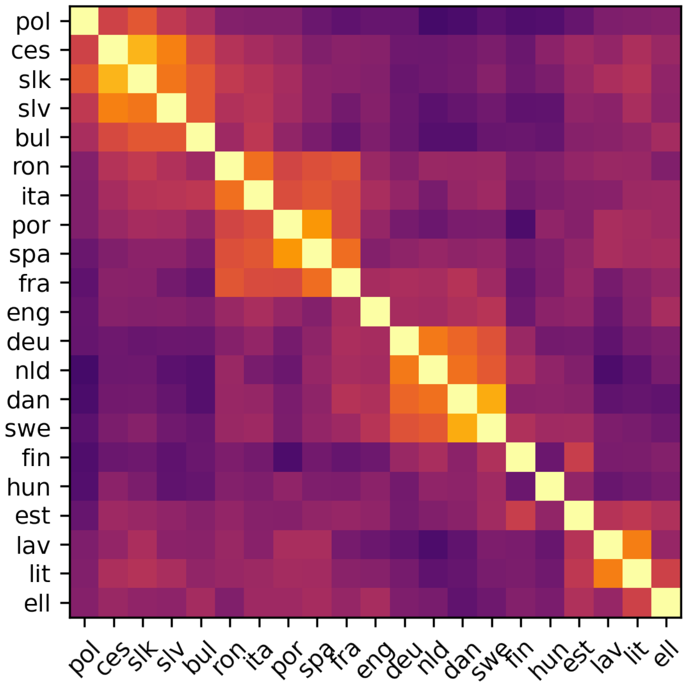
7.2.1 Answer

N of 3 seems optimal. If n is too small, every language is very similar to each other. This is because we are simply adding random vectors (there are no permutations applied, which are needed to create the notion of a sequence) to create our langauge embedding. While random vectors are orthogonal, this means that there non-zero bits (in the simple binary setting) are in non-overlapping regions. Thus, we essentially create vectors of 1s (in the binary case) when doing letter-grams. This idea extends to the case of bipolar vectors (following Pentti's paper from lec1). If n is too big, the cos similarity matrix becomes too sparse. I think is because we are comparing frequencies of larger substrings which occur less in our text corpus (especially given my data limit of 20k).

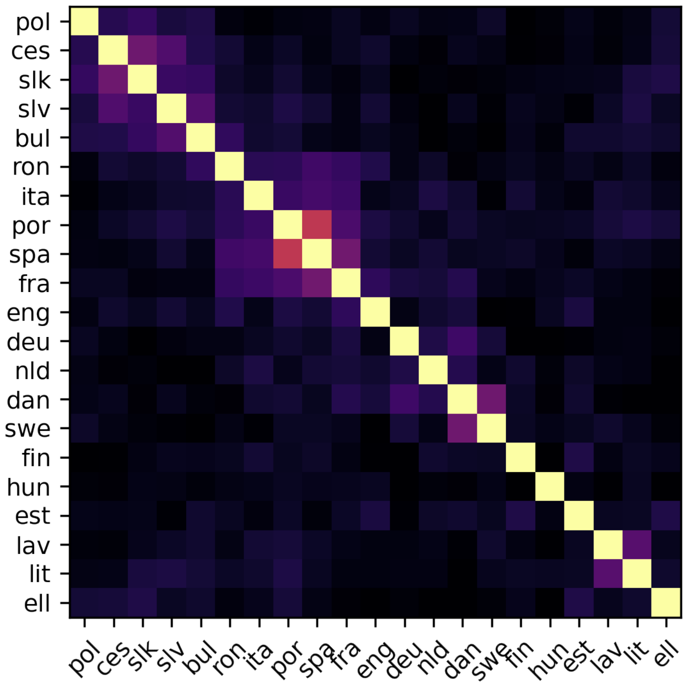
```
[11]: for n_i in [1, 3, 5,7]:
          run_experiment(n=n_i, title=f"Cosine similarity between language profiles␣
       ↪n={n_i}")
```

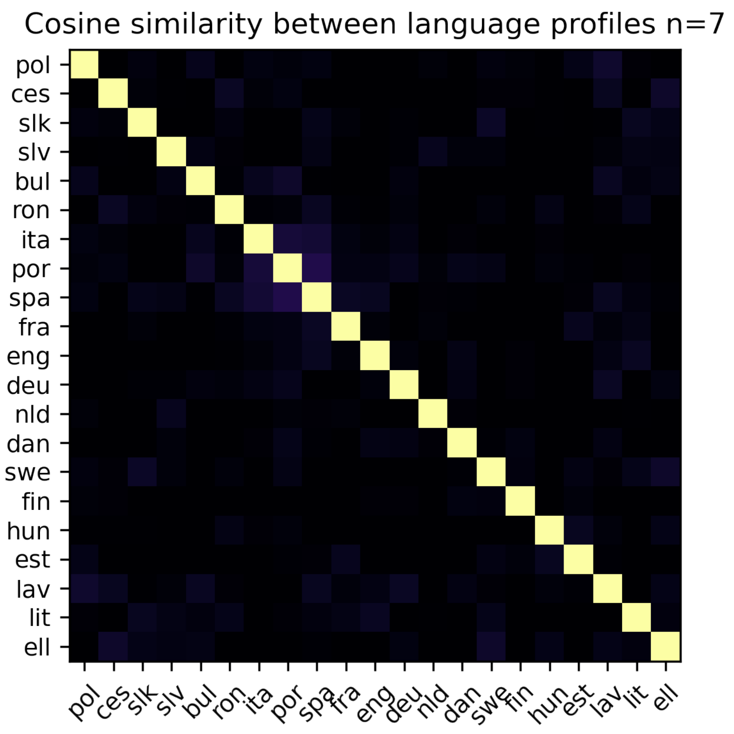


Cosine similarity between language profiles n=3



Cosine similarity between language profiles n=5





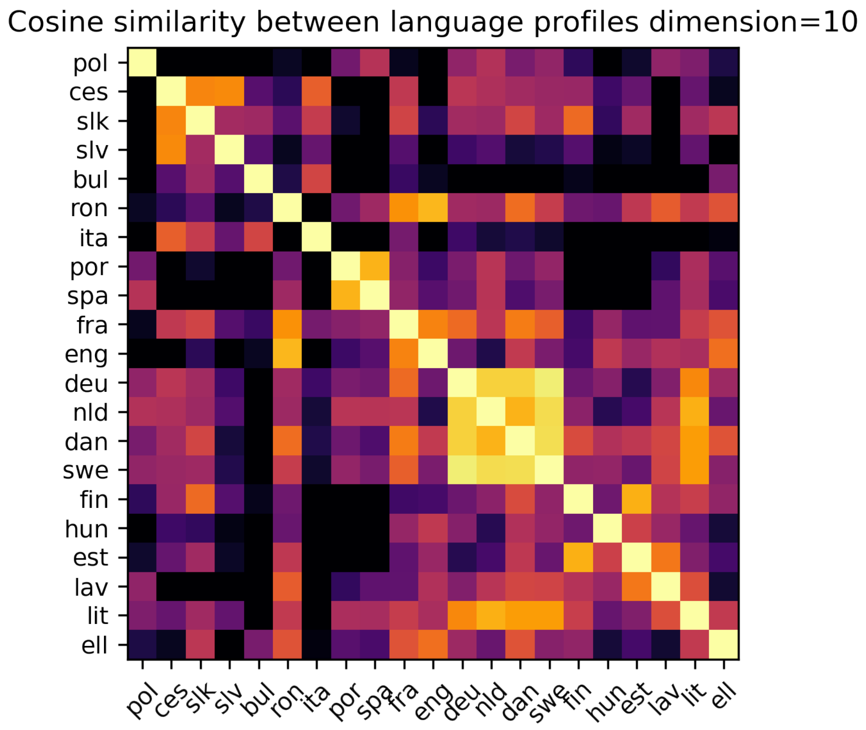
7.3 Question 3

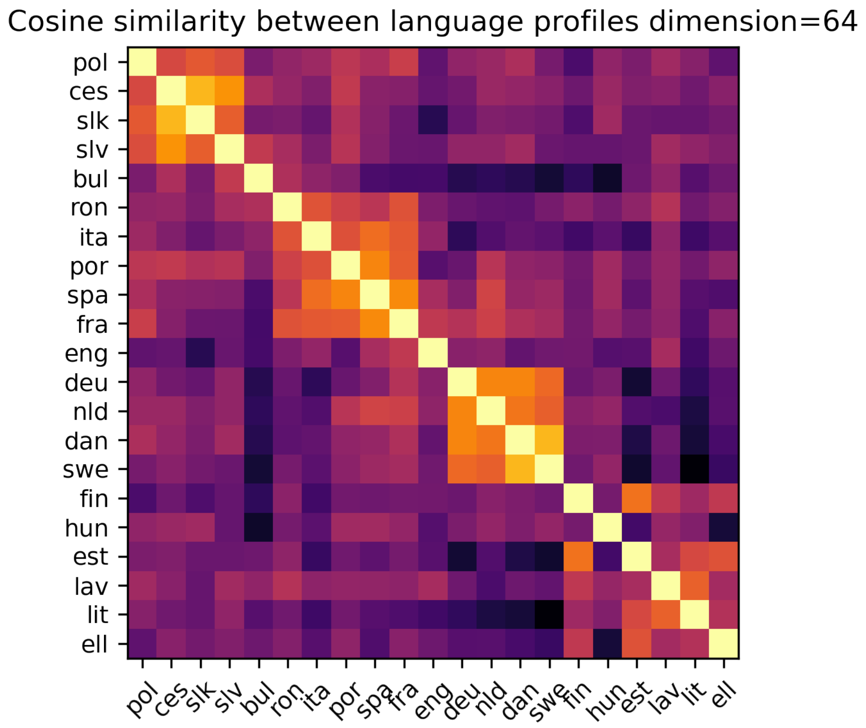
By default, the dimensionality of HD vectors is set to 1,024. Is this dimensionality enough to visualize the similarity between languages' n-gram statistics? What happens if the dimensionality of HD vectors is reduced dramatically?

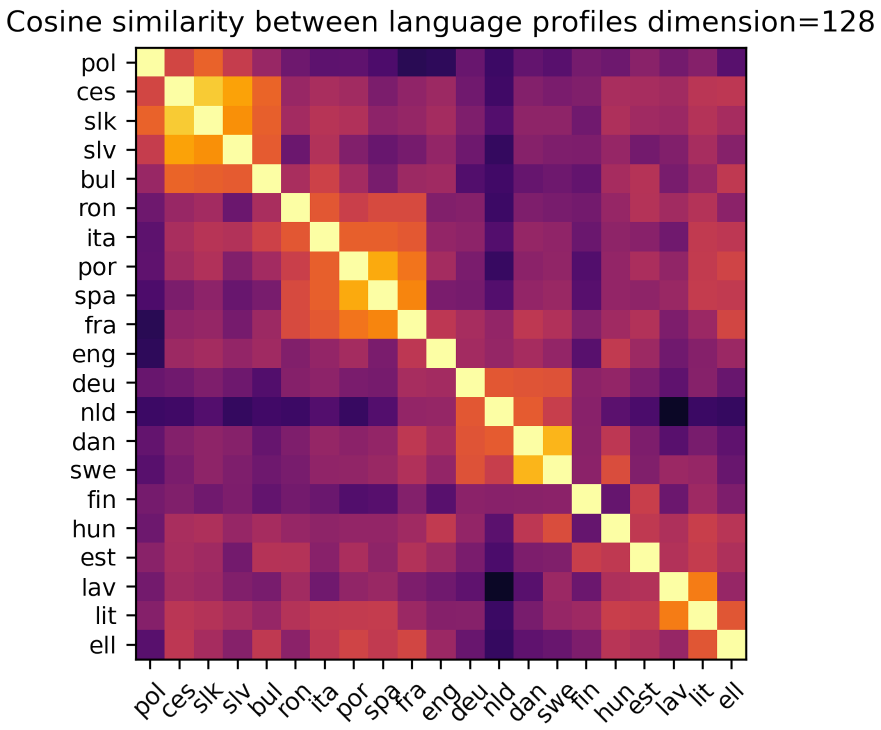
7.3.1 Answer

Yes, this dimensionality is enough. When reducing the dimensionality dramatically, we see the clustering gets worse as the matrix gets more sparse. However, some high level patterns such as similarity in Urlic languages are still seen.

```
[12]: for dim in [10, 64, 128]:
          run_experiment(dimension=dim, title=f"Cosine similarity between language␣
      ↪profiles dimension={dim}")
```


Cosine similarity between language profiles dimension=10
pol
ces
slk
slv
bul
ron
ita
por
spa
fra
eng
deu
nld
dan
swe
fin
hun
est
lav
lit
ell


Cosine similarity between language profiles dimension=64
pol
ces
slk
slv
bul
ron
ita
por
spa
fra
eng
deu
nld
dan
swe
fin
hun
est
lav
lit
ell


Cosine similarity between language profiles dimension=128
pol
ces
slk
slv
bul
ron
ita
por
spa
fra
eng
deu
nld
dan
swe
fin
hun
est
lav
lit
ell

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