Metadata

Course: DS 5001 Module: 07 Homework

Topic: PCA

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Instructions

In this week's code exercise, you will apply PCA to a new corpus, a collection of gothic g and detective d novels from English literature. Using the tables novels-LIB.csv and novels-CORPUS.csv found in /data/novelsand the notebook from this week (MO7_01_PCA.ipynb) as well as previous relevant notebooks, perform the following tasks:

- 1. Import the LIB and CORPUS tables from the provided CSV files.
- The index OHCO for CORPUS is ['book_id','chapter_id','para_num','sent_num','token_num']
- The index for LIB is 'book_id'.
- 1. Extract a VOCAB table and add max_pos as a feature.
- 2. Compute TFIDF and VOCAB['dfidf'] for the CORPUS using the following parameters:
- bag = ['book_id', 'chap_id']
- tf_method = 'max'
- idf_method = 'standard'
- 1. Create a DOC table from the TFIDF index in which each row represents a bag, i.e. a chapter. In other words, it should have ['book_id', 'chap_id'] as its index. This table should have information from the LIB table added to it, so that each chapter is identified with an author, title, and genre. These data will appear in your visualizations. For example, in a scatter plot of documents in the first two principle components, you will want to know the book and chapter of each data point.
- 2. Create a reduced version of the TFIDF table with only the top 1000 nouns (i.e. NN and NNS) in descending order of DFIDF.
- Do not "collapse" table -- keep the index as (book_id, chap_id).
- 1. Write a function that computes PCA from a given document-term count matrix (this included weighted counts, such a tfidf). It should return three dataframes: LOADINGS (the term-component matrix), DCM (the document-component matrix), COMPINF (the component information table). Give it the following parameters:
- X # The input matrix
- k # The number of components to generate

- norm_docs # True or False
- center_by_mean # True of False
- center_by_variance # True or False
- 1. Compute PCA from the feature-reduced TFIDF table using your function. Use the following parameter values:
- X = TFIDF_REDUCED Or whatever you called your reduced TFIDF table
- k=10
- norm_docs = True
- center_by_mean = False
- center_by_variance = False
- 1. Visualize your results using scatter plots and box plots.

When you have finished these tasks, answer the questions listed below.

Questions

$\mathbf{Q}\mathbf{1}$

Looking at the documents plotted against the first principle component (PC), which genre has the more narrow range, i.e. distance between the minimum and maximum values? This can be seen using a box plot.

Answer: Detective d

$\mathbf{Q2}$

Looking at the documents plotted against the first PC, which author has the highest absolute value, in terms of both mean and range? In other words, which author is farthest from 0? Again, the box plots of each author are useful here.

Answer: Radcliffe.

$\mathbf{Q3}$

In the third PC, which author has, by far, the maximum range?

Answer: Radcliffe.

$\mathbf{Q4}$

Looking at the loadings for the second PC, how would you characterize the opposition, based on the top three words at each pole?

Answer: family or indoors vs world or outdoors

There are many possible answers here. To be correct, but show evidence of interpreting the words found at each pole.

Q_5

Recompute the principle components with center_by_variance set to True. This will change the words that appear at the extremes of the first PC. Does this change your interpretation in the previous question?

Answer: Yes. The words are sufficiently different in meaning to warrant a change in interpretation.

Solution

Set Up

Config

```
data_home = "../../repo/lessons/data"
local_lib = "../../repo/lessons/data"
data_prefix = 'novels'
OHCO = ['book_id', 'chap_id', 'para_num', 'sent_num', 'token_num']
bag = OHCO[:2] # chapter
max_terms = 1000
tf_method = 'max'
global_term_sig = 'dfidf'
n_comps = 10
center_by_mean=False
center_by_variance=False
```

Imports

```
import pandas as pd
import numpy as np
from scipy.linalg import norm, eigh
from sklearn.decomposition import PCA
import plotly_express as px
```

Prepare the Data

Get LIB

```
book_id
secretadversary d christie
styles d christie
moonstone d collins
```

```
adventures d doyle baskervilles d doyle
```

Get CORPUS

```
CORPUS = pd.read_csv(f'{data_home}/{data_prefix}/{data_prefix}-CORPUS.csv').set_index(OHCO)
CORPUS.head()
```

| | | | | | pos | term_str |
|-----------------|---------|----------|----------|-----------|-----|-------------|
| book_id | chap_id | para_num | sent_num | token_num | | |
| secretadversary | 1 | 0 | 1 | 0 | DT | the |
| | | | | 1 | NNP | young |
| | | | | 2 | NNP | adventurers |
| | | | | 3 | NNP | ltd |
| | | 1 | 0 | 0 | JJ | tommy |

Extract VOCAB

```
VOCAB = CORPUS.term_str.value_counts().to_frame('n').sort_index()
VOCAB.index.name = 'term_str'
VOCAB['max_pos'] = CORPUS.value_counts(['term_str','pos']).unstack().idxmax(1)
NOUNS = VOCAB[VOCAB.max_pos.isin(['NN','NNS'])]
```

Create BOW

```
BOW = CORPUS.groupby(bag+['term_str']).term_str.count().to_frame('n')
BOW
```

| | | | n |
|--------------------|------------------|-----------|-----|
| book_id | ${\tt chap_id}$ | term_str | |
| ${\tt adventures}$ | 1 | a | 225 |
| | | abandoned | 1 |
| | | abhorrent | 1 |
| | | able | 3 |
| | | about | 9 |
| | | | |
| usher | 1 | yet | 22 |
| | | you | 9 |
| | | your | 2 |
| | | youth | 1 |
| | | zigzag | 2 |

[377222 rows x 1 columns]

```
Create DTM
DTM = BOW.n.unstack(fill_value=0)
Create TFIDF
VOCAB['df'] = DTM.astype('bool').sum()
VOCAB['idf'] = np.log2(len(DTM) / VOCAB.df)
TFIDF = (DTM.T / DTM.T.max()).T * VOCAB.idf
 # TFIDF
Create DFIDF
VOCAB['dfidf'] = VOCAB.df * VOCAB.idf
VOCAB.dfidf
term_str
                                                             0.000000
aback
                                                      46.368028
                                                             8.321928
abaft
                                                        98.408049
abandon
abandoned 124.513524
                                                            20.210897
                                                            8.321928
æt
ætat
                                                            8.321928
                                                        14.643856
ça
émeutes
                                                               8.321928
Name: dfidf, Length: 27396, dtype: float64
VIDX = VOCAB[VOCAB.max_pos.isin(['NN','NNS'])].sort_values('dfidf', ascending=False).head(max_pos.isin(['NN','NNS']))].sort_values('dfidf', ascending=False).head('max_pos.isin(['NN','NNS']))].sort_values('dfidf', ascending).head('max_pos.isin(['NN','NNS']))].sort_values('dfidf', ascending).head('max_pos.isin(['NN','NNS']))].sort_values('dfidf', ascending).head('max_pos.isin(['NN','NNS']))].sort_values('dfidf', ascending).head('max_pos.isin(['NN','NNS']))].sort_values('dfidf', ascending).head('max_pos.isin(['NN','NNS']))].sort_values('dfidf', ascending).head('max_pos.isin(['NN','NNS']))].sort_values('dfidf', ascending).head('max_pos.isin(['NN','NNS']))].sort_values('dfidf', ascending).head('max_pos.isin(['NN','NNS']))].sort_values('dfidf', ascending).head('max_pos.isin(['NN','NNS']))].sort_values('dfidf', ascending).head('max_pos.isin(['NN','NNS']))].sort_values('max_pos.isin(['NN','NNS']))].sort_values('max_pos.isin(['NN','NNS']))].head('max_pos.isin(['NN','NNS']))].sort_values('max_pos.isin(['NN','NNS']))].sort_values('max_pos.isin(['NN','NNS']))].sort_values('max_pos.isin(['NN','NNS']))].sort_values('max_pos.isin(['NN','NNS']))].sort_values('max_pos.isin(['NN','NNS']))].sort_values('max_pos.isin(['NN','NNS']))].sort_values('max_pos.isin(['NN','NNS']))].sort_values('max_pos.isin(['NN','NNS']))].sort_values('max_pos.isin(['NN','NNS']))].sort_values('max_pos.isin(['NN','N
Compute PCA
 # norm?
```

Define Function

```
def get_pca(TFIDF,
            k=10,
            norm_docs=True,
            norm_level=2,
            center_by_mean=True,
            center_by_variance=False):
    if TFIDF.isna().sum().sum():
        TFIDF = TFIDF.fillna(0)
```

```
TFIDF = TFIDF.apply(lambda x: x / norm(x), 1).fillna(0)
    if center_by_mean:
       TFIDF = TFIDF - TFIDF.mean()
    if center_by_variance:
       TFIDF = TFIDF / TFIDF.std()
   COV = TFIDF.cov()
    eig_vals, eig_vecs = eigh(COV)
   EIG VEC = pd.DataFrame(eig vecs, index=COV.index, columns=COV.index)
   EIG_VAL = pd.DataFrame(eig_vals, index=COV.index, columns=['eig_val'])
   EIG_VAL.index.name = 'term_str'
    EIG_IDX = EIG_VAL.eig_val.sort_values(ascending=False).head(k)
    COMPS = EIG_VEC[EIG_IDX.index].T
    COMPS.index = [i for i in range(COMPS.shape[0])]
    COMPS.index.name = 'pc_id'
    LOADINGS = COMPS.T
   DCM = TFIDF.dot(LOADINGS)
    COMPINF = pd.DataFrame(index=COMPS.index)
    for i in range(k):
        for j in [0, 1]:
            top_terms = ' '.join(LOADINGS.sort_values(i, ascending=bool(j)).head(5).index.to
            COMPINF.loc[i, j] = top_terms
    COMPINF = COMPINF.rename(columns={0:'pos', 1:'neg'})
    COMPINF['eig_val'] = EIG_IDX.reset_index(drop=True).to_frame()
    COMPINF['exp_var'] = COMPINF.eig_val / COMPINF.eig_val.sum()
    return LOADINGS, DCM, COMPINF
LOADINGS, DCM, COMPINF = get_pca(TFIDF[VIDX], norm_docs=True, norm_level=2, center_by_mean=0
LOADINGS
                      0
                                1
                                                    3
                                                                        5 \
pc_id
term str
              0.019484 0.016559 -0.007586 -0.003938 -0.017489 0.025233
yours
```

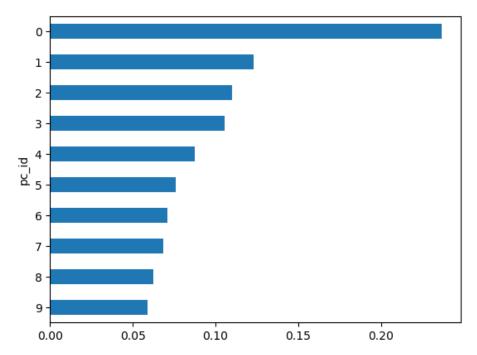
if norm_docs:

```
-0.009054 0.007702 -0.010562 -0.019532 -0.012423 0.016606
reply
            -0.001659 0.001893 -0.033437 0.018477 -0.008462
order
                                                           0.032114
            0.027110
curiosity
            -0.001513 -0.001008  0.018553 -0.013331 -0.008593
memory
                                                           0.014673
. . .
                  . . .
                                    . . .
                                              . . .
                                                       . . .
                           . . .
             0.024363 - 0.008369 - 0.005117 - 0.002852 - 0.010479
lad
                                                           0.006415
            -0.031909 -0.017446 -0.019341 -0.019341
enquiry
                                                 0.011217
                                                           0.005914
             0.032418 -0.031064 -0.030680 0.022937
                                                  0.006646 0.019362
bag
investigation 0.023187 0.013508 -0.017991 -0.006847 0.057409 -0.003030
inclination
            -0.016683 0.027050 0.002015 0.006067 -0.007924 -0.004001
                             7
                    6
                                      8
                                               9
pc_id
term_str
             0.003145 -0.008342 0.007351 0.005823
yours
reply
            -0.011956 0.013342 0.026030 0.002001
order
             0.010416 -0.015883 -0.018002 -0.000714
             curiosity
memory
            -0.033355 0.016084 -0.016580 0.017187
. . .
lad
             0.030052 -0.001212 -0.036436
                                         0.032535
             enquiry
            -0.089170 -0.056387 0.036524 0.037134
bag
investigation -0.016042 0.013304 -0.047208 -0.016968
             inclination
[1000 rows x 10 columns]
COMPINE
                                        pos \
pc_id
0
                  thats youre shes cab lawyer
1
          brother engagement father sister son
2
           chateau cottage woods sea mountains
3
             blood whilst child sleep monster
4
               chateau cab dog inquiry letter
5
             chateau convent bed coffee crime
6
                 cab brother castle son horse
7
            aunt evidence murderer cab murder
8
      aunt brother acquaintance engagement box
9
              castle box chateau river whilst
                                            eig_val
                                                     exp_var
                                      neg
pc_id
        chateau castle chamber woods convent 0.042644
0
                                                    0.236543
            mountains woods sea rocks whilst 0.022226
1
                                                    0.123285
```

castle aunt chamber apartment lamp 0.019867 0.110199

```
3
               chateau thats aunt youre shes 0.019055 0.105694
4
                thats youre shes guess youve 0.015809
                                                        0.087692
5
          mountains castle rocks aunt horses 0.013682
                                                        0.075895
6
                                                        0.070817
            aunt whilst sleep aunts mistress 0.012767
7
               chateau sleep whilst lady bed 0.012347
                                                        0.068490
8
      cottage mistress servants lady convent 0.011256
                                                        0.062436
9
                 candle lamp walls bosom bed 0.010628 0.058949
```

COMPINF.exp_var.sort_values().plot.barh();



Create DOC

DOC = pd.DataFrame(index=TFIDF.index).join(LIB)
DOC

| | | genre_id | author_id |
|--------------------|---------|----------|-----------|
| book_id | chap_id | | |
| ${\tt adventures}$ | 1 | d | doyle |
| | 2 | d | doyle |
| | 3 | d | doyle |
| | 4 | d | doyle |
| | 5 | d | doyle |
| | | | |
| udolpho | 54 | g | radcliffe |

[320 rows x 2 columns]

 $\label'] = DOC.apply(lambda x: f''\{x.author_id.title()\} \{x.name[0].title()\} Ch\{x.name[1]\} DOC$

| | | genre_id | author_id | label |
|------------|---------|----------|-----------|--------------------------|
| book_id | chap_id | | | |
| adventures | 1 | d | doyle | Doyle Adventures Ch1-d |
| | 2 | d | doyle | Doyle Adventures Ch2-d |
| | 3 | d | doyle | Doyle Adventures Ch3-d |
| | 4 | d | doyle | Doyle Adventures Ch4-d |
| | 5 | d | doyle | Doyle Adventures Ch5-d |
| | | | | • • • |
| udolpho | 54 | g | radcliffe | Radcliffe Udolpho Ch54-g |
| | 55 | g | radcliffe | Radcliffe Udolpho Ch55-g |
| | 56 | g | radcliffe | Radcliffe Udolpho Ch56-g |
| | 57 | g | radcliffe | Radcliffe Udolpho Ch57-g |
| usher | 1 | g | poe | Poe Usher Ch1-g |

[320 rows x 3 columns]

Visualize

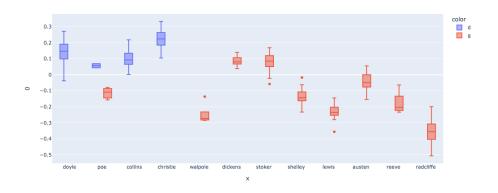
Docs PC0 Genre

px.box(DCM, x=DOC.genre_id, y=0, height=500, color=DOC.genre_id)



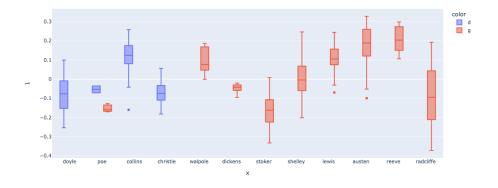
Docs PC0 Author

px.box(DCM, x=DOC.author_id, y=0, height=500, color=DOC.genre_id)



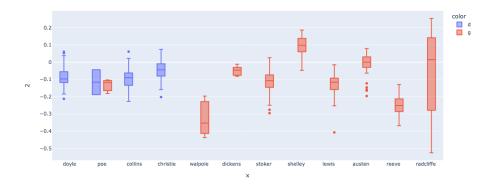
Docs PC1 Author

DCM.join(LIB.author_id).groupby('author_id').mean().idxmax()
DCM.join(LIB.author_id).groupby('author_id').mean().idxmin()
px.box(DCM, x=DOC.author_id, y=1, height=500, color=DOC.genre_id)

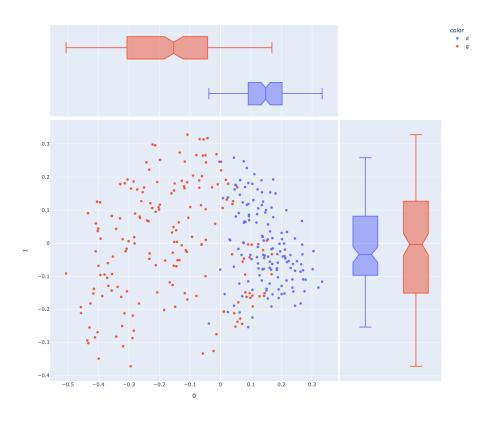


Docs PC2 Author

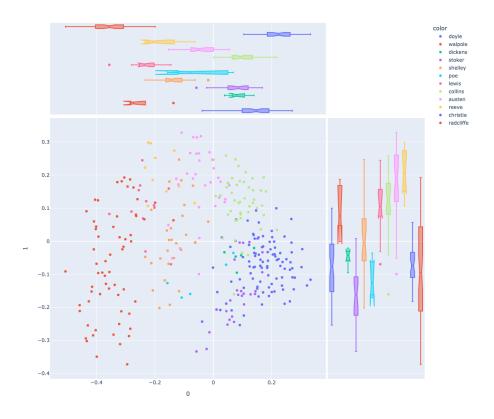
px.box(DCM, x=DOC.author_id, y=2, height=500, color=DOC.genre_id)



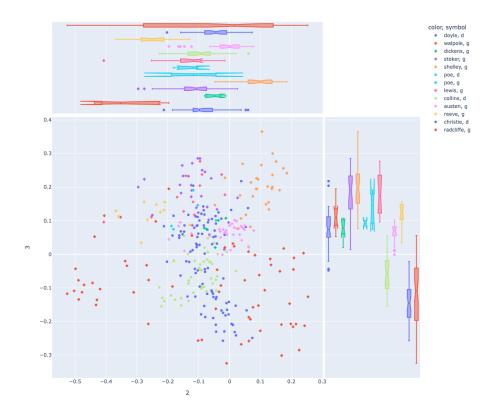
Docs PC 0 and 1 Genre



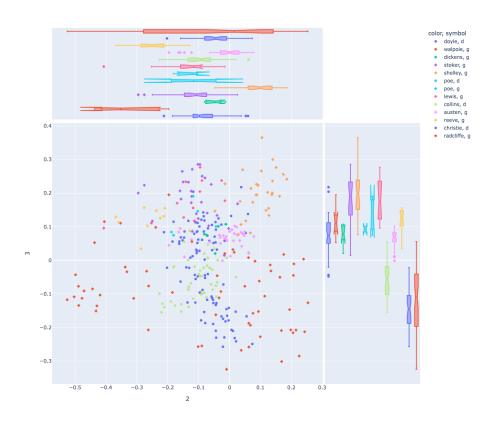
Docs PC 0 and 1 Author



Docs PC 2 and 3 Author



Docs PC 2 and 3 Author



 $\texttt{\# px.scatter_3d(DCM, 0, 1, 2, color=DOC.author_id, height=1000, hover_name=DOC.label)}$

Loadings

LOADINGS

| <pre>pc_id</pre> | 0 | 1 | 2 | 3 | 4 | 5 | \ |
|------------------|-----------|-----------|-----------|-----------|-----------|-----------|---|
| term_str | | | | | | | |
| yours | 0.019484 | 0.016559 | -0.007586 | -0.003938 | -0.017489 | 0.025233 | |
| reply | -0.009054 | 0.007702 | -0.010562 | -0.019532 | -0.012423 | 0.016606 | |
| order | -0.001659 | 0.001893 | -0.033437 | 0.018477 | -0.008462 | 0.032114 | |
| curiosity | -0.018668 | 0.012928 | -0.005848 | -0.010643 | -0.002937 | 0.027110 | |
| memory | -0.001513 | -0.001008 | 0.018553 | -0.013331 | -0.008593 | 0.014673 | |
| | | | | | | | |
| lad | 0.024363 | -0.008369 | -0.005117 | -0.002852 | -0.010479 | 0.006415 | |
| enquiry | -0.031909 | -0.017446 | -0.019341 | -0.019341 | 0.011217 | 0.005914 | |
| bag | 0.032418 | -0.031064 | -0.030680 | 0.022937 | 0.006646 | 0.019362 | |
| investigation | 0.023187 | 0.013508 | -0.017991 | -0.006847 | 0.057409 | -0.003030 | |
| inclination | -0.016683 | 0.027050 | 0.002015 | 0.006067 | -0.007924 | -0.004001 | |

| pc_id | 6 | 7 | 8 | 9 |
|---------------|-----------|-----------|-----------|-----------|
| term_str | | | | |
| yours | 0.003145 | -0.008342 | 0.007351 | 0.005823 |
| reply | -0.011956 | 0.013342 | 0.026030 | 0.002001 |
| order | 0.010416 | -0.015883 | -0.018002 | -0.000714 |
| curiosity | 0.005271 | -0.002335 | 0.007111 | -0.030269 |
| memory | -0.033355 | 0.016084 | -0.016580 | 0.017187 |
| | | | | |
| lad | 0.030052 | -0.001212 | -0.036436 | 0.032535 |
| enquiry | 0.022170 | 0.005435 | -0.008798 | 0.009281 |
| bag | -0.089170 | -0.056387 | 0.036524 | 0.037134 |
| investigation | -0.016042 | 0.013304 | -0.047208 | -0.016968 |
| inclination | 0.028011 | -0.033625 | 0.019295 | -0.014957 |

[1000 rows x 10 columns]

VOCAB.loc[VIDX]

| | n | max_pos | df | idf | dfidf |
|---------------|-----|---------|-----|----------|------------|
| term_str | | | | | |
| yours | 198 | NN | 118 | 1.439285 | 169.835635 |
| reply | 184 | NN | 118 | 1.439285 | 169.835635 |
| order | 227 | NN | 118 | 1.439285 | 169.835635 |
| curiosity | 208 | NN | 118 | 1.439285 | 169.835635 |
| memory | 208 | NN | 119 | 1.427110 | 169.826129 |
| • • • | | | | | |
| lad | 49 | NN | 35 | 3.192645 | 111.742578 |
| enquiry | 51 | NN | 35 | 3.192645 | 111.742578 |
| bag | 72 | NN | 35 | 3.192645 | 111.742578 |
| investigation | 53 | NN | 35 | 3.192645 | 111.742578 |
| inclination | 43 | NN | 35 | 3.192645 | 111.742578 |

[1000 rows x 5 columns]

Loadings PC 0 and 1 $\,$



Loadings PC 2 and 3

