2.4 filtered vocab

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1 2.4 Filter vocabulary

This notebook looks at feature importance using word frequencies in comparison to classification features. + Remove terms that are only digits. + Keep words that appear in < 10% of non-transfused documents, AND also change by more than 30% between the 2 groups (non transfused - transfused) + or are only in the transfused group + Inner Join with the vocabulary from 2.3 + save as all_filtered_features.csv

```
[1]: import pandas as pd
  import os
  import re
  import sys

import numpy as np
  from datetime import datetime
  from sklearn.feature_extraction.text import CountVectorizer

import psycopg2
  from sqlalchemy import create_engine

%matplotlib inline
```

```
POSTGRES_CONNECT = os.environ.get("POSTGRES_CONNECT")
POSTGRES_ENGINE = os.environ.get("POSTGRES_ENGINE")

conn = psycopg2.connect(POSTGRES_CONNECT)
engine = create_engine(POSTGRES_ENGINE)

cur = conn.cursor();
cur.execute("""SET_search_path = mimiciii;""")
```

```
[3]: path ="./"
```

1.0.1 Read in Notes

```
[4]: mimic_transfused_notes = pd.read_sql("""select * from mimiciii.

→transfused_notes_unique""", engine)

mimic_ctrl_notes = pd.read_sql("""select * from mimiciii.ctrl_notes_unique""", 

→engine)
```

1.0.2 Vectorize Dataframe A

FILTER: only keep words present in <10% of documents and words that are not just digits

```
[5]: def get_words_a(df):
    # count vectorize
    vect = CountVectorizer(lowercase=True, strip_accents=None, analyzer = 
    'word', max_df = 0.1)
    vect_dat = vect.fit_transform(df['text'])
    vocab = vect.get_feature_names()
    return vect_dat, vocab
```

```
[9]: def filter_sparse(dtm, vocab, filtered_vocab):
    # get index of terms we want to keep
    # this is slow, just give it some time (~20min?)
    vocab_idx = [vocab.index(k) for k in filtered_vocab]

# handle sparse matrix
sorted_dtm = dtm.sorted_indices()
# filter the document term matrix
filtered_dtm = sorted_dtm.T[vocab_idx]

return filtered_dtm
```

```
[13]: def wrapper_a(df):
    vect, vocabulary = get_words_a(df)
    filtered_vocabulary = no_ints(vocabulary)
```

```
filtered_vect = filter_sparse(vect, vocabulary, filtered_vocabulary)
          return filtered_vect, filtered_vocabulary
[14]: ctrl_vect, ctrl_vocab = wrapper_a(mimic_ctrl_notes)
     removed 99806
[15]: # to save
      with open(path + 'ctrl_vect.pickle', 'wb') as picklefile:
          pickle.dump(ctrl_vect, picklefile)
      with open(path + 'ctrl_vocab.pickle', 'wb') as picklefile:
          pickle.dump(ctrl_vocab, picklefile)
[16]: #to load
      with open(path1 + path2 + 'ctrl_vocab.pickle','rb') as f:
          ctrl_vocab=pickle.load(f)
      with open(path1 + path2 + 'ctrl_vect.pickle', 'rb') as f:
          ctrl_vect=pickle.load(f)
     1.1 then vectorize dataframe B (transfused) data using the vocabulary from A
          (control)
[17]: def get_words_b(df, vocab_in):
          # count vectorize
          vect = CountVectorizer(lowercase=True, strip_accents=None, analyzer = ∪
       →'word', vocabulary = vocab_in)
          vect_dat = vect.fit_transform(df['text'])
          vocab_out = vect.get_feature_names()
          # transpose to match filtered
          sorted dtm = vect dat.sorted indices()
          transposed_dtm = sorted_dtm.T
          return transposed_dtm, vocab_out
[18]: xf_vect, xf_vocab = get_words_b(mimic_transfused_notes, ctrl_vocab)
[19]: # to save
      with open(path1 + path2 + 'xf_vect.pickle', 'wb') as picklefile:
```

with open(path1 + path2 + 'xf_vocab.pickle', 'wb') as picklefile:

pickle.dump(xf_vect, picklefile)

pickle.dump(xf_vocab, picklefile)

```
[4]: #to load
with open(path1 + path2 + 'xf_vocab.pickle','rb') as f:
    xf_vocab=pickle.load(f)

with open(path1 + path2 + 'xf_vect.pickle','rb') as f:
    xf_vect=pickle.load(f)
```

2 compare

```
[28]: def compare_freq(matrix_a, vocab_a, label_a, matrix_b, vocab_b, label_b,
       →threshold=0.3):
          ^{\prime\prime\prime} calc the sum of each term (matrix should be transposed after_{\!\sqcup}
       \neg vectorization)
          calc percentage of change between a and b
          filter out <threshold% change'''
          sum_a = matrix_a.sum(axis=1)
          sum_b = matrix_b.sum(axis=1)
          both= pd.DataFrame(sum_a, index=vocab_a, columns=[label_a])
          both[label_b] = sum_b
          # combine
          both['percent_change'] = (both[label_b].map(int) - both[label_a].map(int)) /
       → both[label_a].map(int)
          # FILTER keep words that changed more than or eq to %threshold
          both = both[both['percent_change'] >= threshold]
          return both
```

3 get new words

```
[26]: # vectorize the full dataset to get words that are new for the transfused when under the compared to ctrl)

def get_new_word_freqs(df_a, label_a, df_b, label_b):

# count vectorize a

vect_a = CountVectorizer(lowercase=True, strip_accents=None, analyzer = under the count vectorizer(lowercase=True) word')

vect_dat_a = vect_a.fit_transform(df_a['text'])
```

```
vocab_a = vect_a.get_feature_names()
   # count vectorize b
  vect_b = CountVectorizer(lowercase=True, strip_accents=None, analyzer = __
vect dat b = vect b.fit transform(df b['text'])
  vocab_b = vect_b.get_feature_names()
   # compare
  newwords = list(set(vocab_b) - set(vocab_a))
  # FILTER out digits and empty strings
  newwords_filtered = [x for x in newwords if not x.isdigit()]
  print('removed ' + str(len(newwords)-len(newwords_filtered)))
  filtered_vect = filter_sparse(vect_dat_b, vocab_b, newwords_filtered)
  sum_b = filtered_vect.sum(axis=1)
  sum_df = pd.DataFrame(sum_b, index=newwords_filtered, columns=[label_b])
  sum_df[label_a] = 0
  return sum df
```

- 3.0.1 get words that appear in < 10% of control-documents, that also change by more than 30% from non-transfused to transfused
- 3.0.2 OR new in transfused documents

```
[33]: newwords_df = get_new_word_freqs( mimic_ctrl_notes, 'ctrl', □

→mimic_transfused_notes, 'xf')

newwords_df.head()
```

removed 15283

```
[33]: xf ctrl
bfmw 1 0
qnoontime 1 0
dicline 1 0
apprpo 1 0
smoul 1 0
```

```
[34]: newwords_df.sort_values('xf',ascending=False).head(50)
```

```
[34]: xf ctrl
4uffp 144 0
percreta 91 0
1urbc 89 0
closures 83 0
```

	00	•
accreta	80	0
normocarb	75 68	0
prbcx1		
40ppm	63 50	0
pcells	58	0
defibritide	57	0
prbcx2	56	0
haps	55	0
trisodium	55	0
txn	54	0
refeed	47	0
esmark	43	0
400mcgs	43	0
cisaturcurium	41	0
3uffp	41	0
cytogam	40	0
cvhd	40	0
debranching	39	0
rectocolectomy	39	0
colure	37	0
cvvhf	37	0
acineterbacter	37	0
acidiotic	36	0
meshing	36	0
1ffp	36	0
octeretide	36	0
gastrrectomy	36	0
fusarium	35	0
sqcjojqj	35	0
dncjojqj	34	0
nasoduodenal	34	0
x1uprbcs	33	0
cvvdh	33	0
dialys	32	0
рссо	32	0
2un	31	0
recirc	31	0
angioembolization	30	0
coagulator	30	0
faschiotomy	30	0
methergine	30	0
iuprbc	30	0
nsiad	30	0
Oportex	30	0
23st	29	0
rotarest	29	0
TOTALEST	23	U

[32]: newwords_df.sort_values('ctrl',ascending=False).head(50)

[32]:		ctrl	xf
	degranulation	183	0
	ghb	167	0
	gbl	98	0
	achondroplasia	92	0
	melas	65	0
	hajdu	65	0
	ifedsfq	61	0
	hypereosinophilic	52	0
	rickham	51	0
	hq	40	0
	lice	38	0
	rufinamide	37	0
	qwl	37	0
	ycjojqj	35	0
	ocjojqj	35	0
	53yf	33	0
	gastrocrom	32	0
	cactus	32	0
	intralipid	30	0
	duchenne	28	0
	flatbush	28	0
	breakable	28	0
	6ng	27	0
	quadrantanopsia	27	0
	lhm	26	0
	coilinganesthesia	26	0
	mcds	26	0
	klcjojqj	25	0
	qwcjojqj	24	0
	viewscope	23	0
	sfq	23	0
	bornewood	23	0
	mango	22	0
	baycove	22	0
	agraphia	22	0
	ketostix	21	0
	chyli	21	0
	dofetelide	21	0
	uconn	20	0
	deac4	19	0
	nasah	18	0
	chanmber	17	0
	ifedp	17	0
	arrhythimia	17	0

```
springhouse
                           17
                                0
      dyslexia
                           17
      dyh
                           17
      ictally
                           17
      stetting
                                0
                           17
      decarboxylase
                           17
[35]: newwords_df.to_csv(path1 + 'newwords.csv')
[54]: newwords_df.reset_index(inplace=True)
      percent_df.reset_index(inplace=True)
      # removing any overlap
      newwords filtered =newwords df[~newwords_df['index'].isin(percent_df['index'])]
      # combining new words with words from pre/post meeting frequency threshold
      allfreq = pd.concat([percent_df, newwords_filtered], axis = 0, sort = True)
      # filling empty 'pre' counts with O
      allfreq['ctrl'].fillna(0, inplace = True)
      allfreq.rename(columns = {'index': 'vocab'}, inplace = True)
      allfreq['percent_change'] = allfreq.percent_change*100
[55]: # spot check pfi
      allfreq[allfreq['vocab'] == '4uffp']
[55]:
              ctrl vocab percent_change
                                            xf
      111550
                 0 4uffp
                                      {\tt NaN}
                                           144
[56]: allfreq[allfreq['vocab'] == 'prbcs']
[56]:
             ctrl vocab percent_change
                                             xf
      40554
              876 prbcs
                             1625.799087 15118
     3.1 Comparing to Classification Features
[59]: | features = pd.read_csv(path + 'final_classification_features.csv')
      features.drop(columns= 'Unnamed: 0', inplace = True)
[60]: features.head()
[60]:
            vocab NB_total_hadmids NB_total_count_freq NB_ratio LR_12_coef \
      0
             rvad
                               22.0
                                                   380.0 0.748991
                                                                            NaN
      1
                               23.0
                                                   421.0 0.759843
             apml
                                                                            NaN
```

```
11.0
                                                                                                                                                                        80.0 0.782175
                      3
                                                                                                                                                                                                                                                  NaN
                                  accreta
                      4
                                            4923
                                                                                                        4.0
                                                                                                                                                                        70.0 0.784472
                                                                                                                                                                                                                                                  NaN
                               LR_12_total_count_freq LR_12_total_hadmids LR_11_coef
                                                                                                                                                                                                                    chi2_pval_p_05
                      0
                                                                                           NaN
                                                                                                                                                              NaN
                                                                                                                                                                                                    NaN
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                                                                                           NaN
                                                                                                                                                              NaN
                                                                                                                                                                                                                        4.257674e-119
                      1
                                                                                                                                                                                                    NaN
                      2
                                                                                           NaN
                                                                                                                                                              NaN
                                                                                                                                                                                                    NaN
                                                                                                                                                                                                                           1.452410e-27
                      3
                                                                                            NaN
                                                                                                                                                              NaN
                                                                                                                                                                                                    NaN
                                                                                                                                                                                                                           1.977585e-24
                      4
                                                                                                                                                                                                                           1.399844e-20
                                                                                            NaN
                                                                                                                                                              NaN
                                                                                                                                                                                                    {\tt NaN}
                    Taking intersection of classification features and frequency threshold words
  [61]:
                   feats = features.merge(allfreq, on = 'vocab', how = 'inner')
  [62]:
                     feats.shape
  [62]: (41664, 12)
  [63]:
                    feats.isnull().sum()
  [63]: vocab
                                                                                                                     0
                     NB_total_hadmids
                                                                                                         36945
                      NB_total_count_freq
                                                                                                         36945
                     NB_ratio
                                                                                                         36945
                     LR_12_coef
                                                                                                         39183
                     LR_12_total_count_freq
                                                                                                        39183
                     LR_12_total_hadmids
                                                                                                        39183
                     LR_11_coef
                                                                                                         39280
                      chi2_pval_p_05
                                                                                                               115
                      ctrl
                                                                                                                     0
                     percent_change
                                                                                                         12625
                                                                                                                     0
                      dtype: int64
      []: feats.

→drop(columns=['NB_total_hadmids','NB_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_total_count_freq','LR_12_t
                      feats.rename(columns={'ctrl':'freq_control','xf':
                         →'freq_transfused'},inplace=True)
                      feats.head()
[104]: feats.to_csv(path +'all_filtered_features.csv')
```

91.0 0.769518

NaN

2 percreta

6.0