Rajeev_Trendy_Names

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1 Determine "TRENDY" names

- There are several ways one could find "trendy" names, i.e. ones that rise quickly from obscurity to popularity, then fade quickly. One could look at percentage changes, but others have already done this, and one would have to use a second algorithm to distinguish truly popular names
- This method is borrowed from peak analysis in chemistry chromatography; it weighs the results in favour of the most popular names with the sharpest peaks. The names with the lowest ratio of maximum popularity (normalized frequency, i.e. peak height) to peak width a a certain percentage (e.g. 10%) of peak height are the most "spiky".

1.0.1 Load dataframes; run this before every subsequent section

```
In [7]: save_path = "rajeev_data/trendy_names" # files created by this notebook will be saved
        import time
        import os
        if not os.path.isdir(save_path): # creates path if it does not exist
            os.makedirs(save_path)
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        %run Rajeev_download_process_files.py
        last_year = years.year.max()
Data already downloaded.
Data already extracted.
Processing.
Tail of dataframe 'yob':
Tail of dataframe 'names':
Tail of dataframe 'years':
Tail of dataframe 'yob1900':
```

```
Tail of dataframe 'names1900': Tail of dataframe 'years1900':
```

1.0.2 Find largest ratios of peak height to width at 10 percent height for 1000 most popular names of each sex

Low-popularity names are not included because their low signal-to-noise ratio would create false positives

```
In [8]: # create dataframes of most popular names
        top_cutoff = 1000 #consider only this number of most popular names of each sex;
                          #it saves calculation time and does not change final result
        peak_height_cutoff = 0.1 # ten percent of peak height
        ###
        start = time.time()
        dfnamesm = names[names.sex == 'M']
        dfnamesf = names[names.sex == 'F']
        dfnamesm = dfnamesm.sort_values(by='pct_sum', ascending=False)
        dfnamesf = dfnamesf.sort_values(by='pct_sum', ascending=False)
        dfnamesm = dfnamesm[:top_cutoff]
        dfnamesf = dfnamesf[:top_cutoff]
        # create dataframe of peak analyses
        dfresult = pd.DataFrame()
        print("Countdown F, then M to zero: ",)
        sx = 'F'
        print(sx,)
        total = len(dfnamesf)
        for nm in list(dfnamesf.name):
            total -= 1
            if total % 100 == 0: print(total,)
            df = yob[(yob.name == nm) & (yob.sex == sx)]
           pct_sum = names[(names.name == nm) & (names.sex == sx)].pct_sum.iloc[0]
            year_count = names[(names.name == nm) & (names.sex == sx)].year_count.iloc[0]
           year_min = names[(names.name == nm) & (names.sex == sx)].year_min.iloc[0]
            year_max = names[(names.name == nm) & (names.sex == sx)].year_max.iloc[0]
           pct_max = df.pct.max()
            df = df.sort_values(by='year')
```

yrcutstart = 0

```
yrcutend= 0
    pctcut_sum = 0
    for idx, row in df.iterrows():
        currpct =df.pct[idx]
        curryr = df.year[idx]
        if currpct >= peak_height_cutoff*pct_max:
            pctcut_sum += currpct
            if yrcutstart == 0:
                yrcutstart = curryr
            yrcutend = curryr
    tail_front = yrcutstart - year_min
    tail_end = year_max - yrcutend
    yrcutspan = yrcutend-yrcutstart
    yrcutratio = 1.0*yrcutspan/year_count
    spikiness = pct_max / yrcutspan
    dfresult = dfresult.append(pd.DataFrame({'name':[nm],
                     'sex':[sx],
                     'year_count': [year_count],
                     'year_min':[year_min],
                     'year_max':[year_max],
                     'pct_max':[pct_max],
                     'pct_sum':[pct_sum],
                     'yrcutstart':[yrcutstart],
                     'yrcutend': [yrcutend],
                     'yrcutspan':[yrcutspan],
                     'yrcutratio':[yrcutratio],
                     'pctcut_sum':[pctcut_sum],
                     'tail_front':[tail_front],
                     'tail_end':[tail_end],
                     'spikiness':[spikiness] }))
sx = 'M'
print(sx,)
total = len(dfnamesm)
for nm in list(dfnamesm.name):
   total -= 1
    if total % 100 == 0: print(total,)
    df = yob[(yob.name == nm) & (yob.sex == sx)]
    pct_sum = names[(names.name == nm) & (names.sex == sx)].pct_sum.iloc[0]
    year_count = names[(names.name == nm) & (names.sex == sx)].year_count.iloc[0]
    year_min = names[(names.name == nm) & (names.sex == sx)].year_min.iloc[0]
    year_max = names[(names.name == nm) & (names.sex == sx)].year_max.iloc[0]
   pct_max = df.pct.max()
```

```
df = df.sort_values(by='year')
    yrcutstart = 0
    yrcutend= 0
    pctcut_sum = 0
    for idx, row in df.iterrows():
        currpct =df.pct[idx]
        curryr = df.year[idx]
        if currpct >= peak_height_cutoff*pct_max:
            pctcut_sum += currpct
            if yrcutstart == 0:
                yrcutstart = curryr
            yrcutend = curryr
    tail_front = yrcutstart - year_min
    tail_end = year_max - yrcutend
    yrcutspan = yrcutend-yrcutstart
    yrcutratio = 1.0*yrcutspan/year_count
    spikiness = pct_max / yrcutspan
    dfresult = dfresult.append(pd.DataFrame({'name':[nm],
                     'sex':[sx],
                     'year_count':[year_count],
                     'year_min':[year_min],
                     'year_max':[year_max],
                     'pct_max':[pct_max],
                     'pct_sum':[pct_sum],
                     'yrcutstart':[yrcutstart],
                     'yrcutend':[yrcutend],
                     'yrcutspan':[yrcutspan],
                     'yrcutratio':[yrcutratio],
                     'pctcut_sum':[pctcut_sum],
                     'tail_front':[tail_front],
                     'tail_end':[tail_end],
                     'spikiness':[spikiness] }))
picklepath = save_path + 'trendiness_'+ str(int(100*peak_height_cutoff))+'.pickle'
csvpath = save_path + 'trendiness_'+ str(int(100*peak_height_cutoff))+'.csv'
dfresult = dfresult[(dfresult.tail_end != 0 ) & (dfresult.tail_front != 0)] # remove n
df.reset_index(drop=True, inplace=True)
dfresult.to_pickle(picklepath)
dfresult.to_csv(csvpath)
print('\nFiles saved.')
```

```
Countdown F, then M to zero:
F
900
800
700
600
500
400
300
200
100
0
М
900
800
700
600
500
400
300
200
100
0
```

Files saved.

In [9]: print(dfresult(sex == 'F').sort_values(by='spikiness', ascending=False).reset

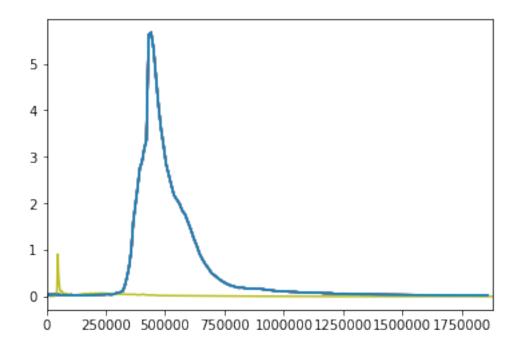
	index	name	pct_max	x pct_sum	n pctcu	t_sum sex	spikiness	tail_end	\
0	0	Linda	5.66670	2 86.555278	78.1	25872 F	0.182797	47	
1	0	Brittany	2.05000	1 19.963709	18.4	03812 F	0.120588	16	
2	0	Debra	2.58557	1 29.137515	5 26.7	80622 F	0.117526	44	
3	0	Shirley	4.03951	6 53.522958	3 46.6	10027 F	0.112209	59	
4	0	Ashley	3.15563	2 47.449055	5 44.5	45735 F	0.105188	6	
5	0	Jennifer	4.30112	0 88.448228	82.4	79855 F	0.104905	14	
6	0	Deborah	2.81590	0 40.420231	1 36.5	84367 F	0.104293	42	
7	0	Lisa	3.41434	0 55.329716	52.2	14487 F	0.100422	27	
8	0	Jessica	3.22122	0 60.657733	3 57.3	55505 F	0.092035	10	
9	0	Betty	3.39635	8 84.950758	3 76.3	00854 F	0.069313	57	
	tail_f	ront year	c_count	year_max ye	ear_min	yrcutend	yrcutratio	\	
0		58	137	2016	1880	1969	0.226277		
1		20	54	2016	1963	2000	0.314815		
2		36	102	2016	1914	1972	0.215686		
3		41	136	2016	1880	1957	0.264706		
4		63	78	2016	1917	2010	0.384615		
5		45	99	2016	1916	2002	0.414141		

```
67
6
                        137
                                  2016
                                             1880
                                                        1974
                                                                 0.197080
7
            69
                        113
                                  2016
                                             1886
                                                        1989
                                                                 0.300885
8
            91
                        137
                                  2016
                                             1880
                                                        2006
                                                                 0.255474
9
            30
                        137
                                  2016
                                             1880
                                                        1959
                                                                 0.357664
   yrcutspan
               yrcutstart
0
          31
                      1938
           17
1
                      1983
2
          22
                     1950
3
          36
                      1921
4
          30
                     1980
5
          41
                     1961
6
          27
                      1947
7
          34
                      1955
8
           35
                      1971
9
           49
                      1910
In [10]: print(dfresult[dfresult.sex == 'M'].sort_values(by='spikiness', ascending=False).rese
   index
                                                                          tail_end
              name
                                   pct_sum pctcut_sum sex
                                                              spikiness
                     pct_max
0
       0
             Dewey
                    0.908795
                                  5.135351
                                               2.104963
                                                               0.151466
                                                                                113
                                                                                  7
       0
                                 58.825162
1
             Jason
                    3.481697
                                              54.843751
                                                               0.084919
2
       0
                                                                                121
            Grover
                    0.712437
                                 6.551928
                                               3.901046
                                                               0.059370
3
       0
              Mark
                   2.754202
                                 74.030527
                                              65.988047
                                                               0.051966
                                                                                 17
4
       0
                    2.026481
                                 51.795390
                                              48.723030
                                                               0.038971
                                                                                 31
              Gary
                                                           Μ
5
                                                                                  7
       0
            Brian
                    2.290481
                                 63.852754
                                              61.003633
                                                               0.038822
                                                           Μ
6
       0
            Larry
                    1.909725
                                 49.613461
                                              44.996293
                                                               0.037446
                                                                                 34
7
       0
             Scott
                    1.747625
                                 42.881843
                                              39.137994
                                                               0.037184
                                                                                 19
8
       0
                                106.781089
                                                                                 33
            Donald
                    2.945288
                                             100.561545
                                                               0.036362
9
          Woodrow 0.455162
                                                               0.035012
                                  4.011130
                                               2.757148
                                                                                 92
   tail_front
                year_count
                             year_max
                                        year_min
                                                   yrcutend
                                                              yrcutratio
0
                                  2016
                                             1887
                                                        1903
                                                                 0.046154
            10
                        130
            88
                        137
1
                                  2016
                                             1880
                                                        2009
                                                                 0.299270
2
            3
                        137
                                  2016
                                                        1895
                                             1880
                                                                 0.087591
3
            66
                        137
                                  2016
                                                        1999
                                                                 0.386861
                                             1880
4
            53
                        135
                                  2016
                                             1880
                                                        1985
                                                                 0.385185
5
            41
                        107
                                  2016
                                                                 0.551402
                                             1909
                                                        2009
6
            51
                        137
                                  2016
                                             1880
                                                        1982
                                                                 0.372263
7
            70
                        137
                                  2016
                                             1880
                                                        1997
                                                                 0.343066
8
            22
                        137
                                  2016
                                             1880
                                                        1983
                                                                 0.591241
9
            11
                        113
                                  2016
                                             1900
                                                        1924
                                                                 0.115044
   yrcutspan yrcutstart
0
            6
                      1897
           41
1
                      1968
           12
                      1883
```

3	53	1946
4	52	1933
5	59	1950
6	51	1931
7	47	1950
8	81	1902
9	13	1911

1.1 Plot Female and Male names with highest spikiness

Female Name="Linda" and max spikiness



Male Name="Dewey" and max spikiness

