Assignment1

September 22, 2017

1 Introduction

This notebook examines hip-hop lyrics as a political genre, specifically mentions of 2016 primary presidential candidates and their shifting hip-hop narrative . The idea is inspired from the raw data behind the story "Hip-Hop Is Turning On Donald Trump", by FiveThirtyEight. The dataset and full story can be accessed here: https://github.com/fivethirtyeight/data/tree/master/hip-hop-candidate-lyrics

Major sections include - 1. Descriptive statistics, Exploratory data analysis 2. Sentiment analysis on lyrics -comparing multiple sentiment lexicons 3. Candidate mentions - Sentiment over time -Linear regressions over presidency and interaction of sentiment mentions over time 4. Candidate mentions - Themes/Subjects over time -Linear regressions over presidency and interaction of thematic mentions over time

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        %matplotlib inline
        pd.set_option('display.max_columns', None)

In [2]: df = pd.read_csv('genius_hip_hop_lyrics.csv', index_col=0)
        df.head()

Out[2]:          candidate              song        artist sentiment      theme  \
        id
        1   Mike Huckabee  None Shall Pass    Aesop Rock   neutral        NaN
        2   Mike Huckabee        Wellstone     Soul Khan  negative        NaN
        3        Jeb Bush              Awe    Dez & Nobs   neutral        NaN
        4        Jeb Bush        The Truth      Diabolic  negative  political
        5        Jeb Bush        Money Man  Gorilla Zoe  negative   personal

            album_release_date                                               line
        id
        1                 2011  Wither by the watering hole, Border patrol / W...
        2                 2012  Might find the door but never touch the key / ...
        3                 2006         I heard Jeb Bush looking for a (inaudible)
        4                 2006  What you heard before ain't as big of a lesson...
        5                 2007  I'm comin back from Florida / Wit Jeb Bush and...
```

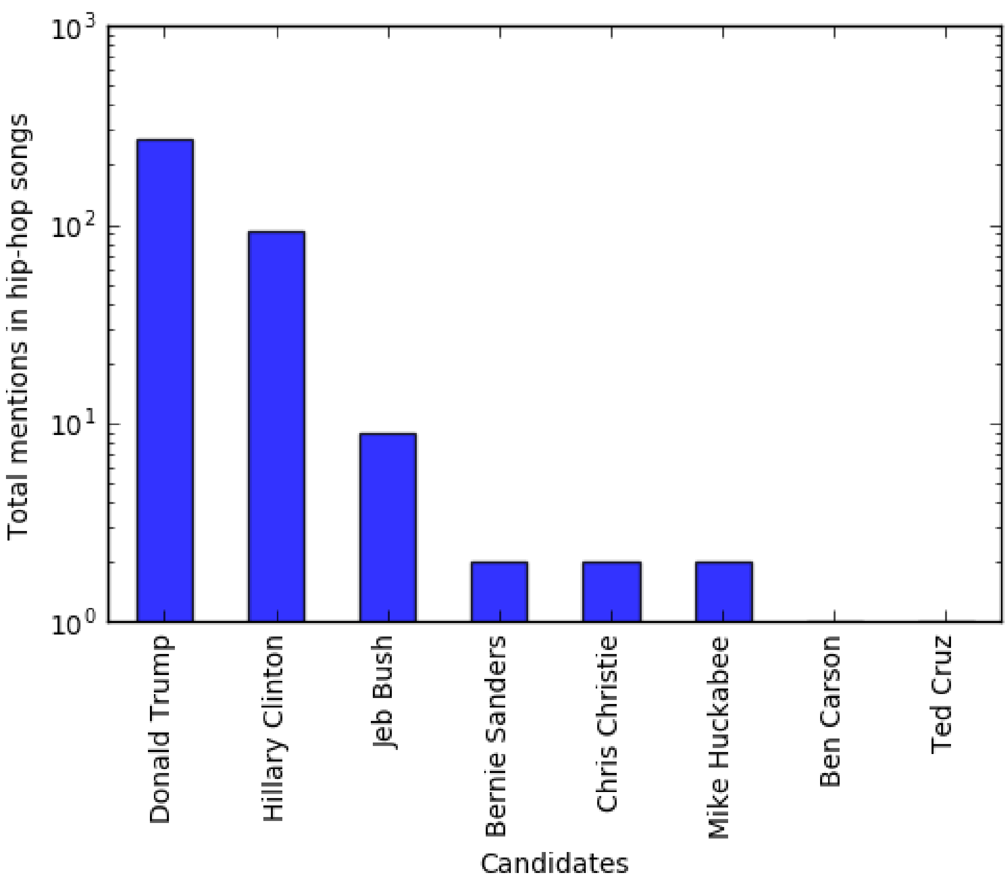
```
                                                  url
id
1   http://genius.com/Aesop-rock-none-shall-pass-l...
2          http://genius.com/Soul-khan-wellstone-lyrics
3             http://genius.com/Dez-and-nobs-awe-lyrics
4           http://genius.com/Diabolic-the-truth-lyrics
5       http://genius.com/Gorilla-zoe-money-man-lyrics
```

```
In [3]: # List of 2016 primary candidates
        df.candidate.unique()
```

```
Out[3]: array(['Mike Huckabee', 'Jeb Bush', 'Ben Carson', 'Chris Christie',
               'Ted Cruz', 'Hillary Clinton', 'Bernie Sanders', 'Donald Trump'], dt
```

```
In [4]: # Get number of mentions for each candidate
        ax = df['candidate'].value_counts().plot(kind="bar",logy=True, alpha=0.8)
        ax.set_xlabel("Candidates")
        ax.set_ylabel("Total mentions in hip-hop songs")
```

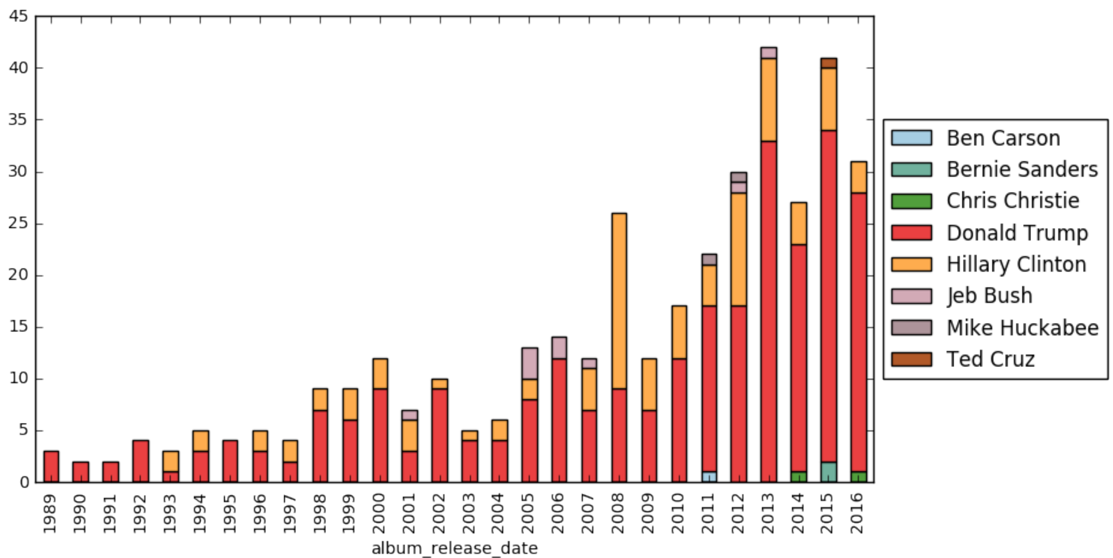
```
Out[4]: <matplotlib.text.Text at 0x112a8f3d0>
```



1.0.1 Temporal analysis of every mention of 2016 primary candidates in hip-hop songs

```
In [5]: df.groupby(['album_release_date', 'candidate']).size().unstack().plot(kind=
```

```
Out[5]: <matplotlib.legend.Legend at 0x11289e950>
```



Trump's prominence and longevity as a figure in hip-hop is staggering. He and his brand have been referenced in a total of 266 songs dating back to 1989.

1.1 Sentiment analysis on lyrics -comparing multiple sentiment lexicons

To see whether the hip-hop narratives around the candidates were changing in the run-up to the 2016 election, the dataset includes sentiment annotations for every reference as positive, negative or neutral. First, let's test how well different sentiment lexicons work on hip-hop lyrics taking the human annotations as ground truth.

```
In [6]: from nltk.corpus import opinion_lexicon
```

```
In [7]: opinion_lexicon.positive()
```

```
Out[7]: [u'a+', u'abound', u'abounds', u'abundance', ...]
```

```
In [8]: opinion_lexicon.negative()
```

```
Out[8]: [u'2-faced', u'2-faces', u'abnormal', u'abolish', ...]
```

```
In [9]: #White space tokenize
        df.loc[4]['line'].split(' ')
```

```
Out[9]: ['What',
         'you',
         'heard',
         'before',
         "ain't",
         'as',
         'big',
         'of',
         'a',
         'lesson',
         '/',
         'As',
         'George',
         'and',
         'Jeb',
         'Bush',
         'rigging',
         'elections']
```

```
In [10]: # white space tokenization seems to work fine. Function call to the inters
         def count_words_sets(text,lex_list):
             assert(type(lex_list) == list)
             tokens = set([token.lower() for token in text.split(' ')])
             return [len(tokens.intersection(lex)) for lex in lex_list]
```

```
In [11]: neg_set = set(opinion_lexicon.negative())
         pos_set = set(opinion_lexicon.positive())
```

```
In [12]: counts = [count_words_sets(text,[pos_set,neg_set]) for text in df['line']]
```

```
In [13]: df = df.assign(pos_words = [count[0] for count in counts])
         df = df.assign(neg_words = [count[1] for count in counts])
```

```
In [14]: df.head()
```

```
Out[14]:         candidate               song       artist sentiment      theme  \
         id
         1   Mike Huckabee  None Shall Pass   Aesop Rock   neutral        NaN
         2   Mike Huckabee        Wellstone    Soul Khan  negative        NaN
         3        Jeb Bush              Awe   Dez & Nobs   neutral        NaN
         4        Jeb Bush        The Truth     Diabolic  negative  political
         5        Jeb Bush        Money Man  Gorilla Zoe  negative   personal

             album_release_date                                              line
         id
         1                 2011  Wither by the watering hole, Border patrol / W...
         2                 2012  Might find the door but never touch the key / ...
         3                 2006         I heard Jeb Bush looking for a (inaudible)
         4                 2006  What you heard before ain't as big of a lesson...
```

```
5                   2007  I'm comin back from Florida / Wit Jeb Bush and...

                                                     url  pos_words  neg_word
id
1   http://genius.com/Aesop-rock-none-shall-pass-l...          0
2        http://genius.com/Soul-khan-wellstone-lyrics          1
3           http://genius.com/Dez-and-nobs-awe-lyrics          0
4         http://genius.com/Diabolic-the-truth-lyrics          0
5      http://genius.com/Gorilla-zoe-money-man-lyrics          0
```

```
In [15]: preds = []
         for index,row in df.iterrows():
             if row['pos_words'] < row['neg_words']:
                 preds.append('negative')
             elif row['pos_words'] > row['neg_words']:
                 preds.append('positive')
             else:
                 preds.append('neutral')
         df['predicted_sentiment'] = preds
         #df.head()
```

Classifier performance -

```
In [16]: #Baseline performance by majority class
         df['sentiment'].value_counts()

Out[16]: positive    178
         neutral     128
         negative     71
         Name: sentiment, dtype: int64
```

Baseline accuracy by predicting majority class would be 178/377 = 0.472

```
In [17]: acc=(df['predicted_sentiment']==df['sentiment']).mean()
         print('Accuracy on nltk opinion lexicon: %.4f'%acc)

Accuracy on nltk opinion lexicon: 0.5385
```

Let's try a domain specific sentiment lexicon. SocialSent at Stanford University provides Community-specific sentiment lexicons for the 250 largest subreddit communities from reddit.com. We pick the sentiment lexicon for r/Music which is a subreddit dedicated to discussions on music. Lexicon available at: https://nlp.stanford.edu/projects/socialsent/

```
In [18]: music_senti_lexicon = pd.read_csv('Music.tsv',sep='\t',header=None,names=[
         music_senti_lexicon.head()

Out[18]:        token  meansenti  stdsenti
         0  nickleback      -5.93      1.08
```

```
1      dislike      -5.87      0.83
2        creed      -5.75      1.07
3   nickelback      -5.54      1.07
4       hating      -5.48      1.26
```

```
In [19]: #function to label sentiment based on word counts
         def label_domain_sentiment(row):
             if row['meansenti'] < 0:
                 return 'negative'
             elif row['meansenti'] > 0:
                 return 'positive'
```

```
In [20]: music_senti_lexicon['senti'] = music_senti_lexicon.apply (lambda row: labe
         music_senti_lexicon.head()
         music_senti_lexicon['senti'].value_counts()
```

```
Out[20]: positive    2711
         negative    2240
         Name: senti, dtype: int64
```

```
In [21]: positive_lexicon = set(music_senti_lexicon.loc[music_senti_lexicon['senti'
         negative_lexicon = set(music_senti_lexicon.loc[music_senti_lexicon['senti'
         len(positive_lexicon), len(negative_lexicon)
```

```
Out[21]: (2711, 2240)
```

```
In [22]: counts1 = [count_words_sets(text,[positive_lexicon,negative_lexicon]) for
```

```
In [23]: df = df.assign(pos_words_music = [count[0] for count in counts1])
         df = df.assign(neg_words_music = [count[1] for count in counts1])
         #df.head()
```

```
In [24]: preds_music = []
         for index,row in df.iterrows():
             if row['pos_words_music'] < row['neg_words_music']:
                 preds_music.append('negative')
             elif row['pos_words_music'] > row['neg_words_music']:
                 preds_music.append('positive')
             else:
                 preds_music.append('neutral')
         df['predicted_sentiment_music'] = preds_music
```

```
In [25]: df.head()
```

```
Out[25]:         candidate              song       artist sentiment      theme  \
         id
         1   Mike Huckabee  None Shall Pass   Aesop Rock   neutral        NaN
         2   Mike Huckabee        Wellstone    Soul Khan  negative        NaN
         3        Jeb Bush              Awe   Dez & Nobs   neutral        NaN
```

```
4        Jeb Bush        The Truth     Diabolic  negative  political
5        Jeb Bush        Money Man  Gorilla Zoe  negative   personal

    album_release_date                                                line
id
1                 2011  Wither by the watering hole, Border patrol / W...
2                 2012  Might find the door but never touch the key / ...
3                 2006         I heard Jeb Bush looking for a (inaudible)
4                 2006  What you heard before ain't as big of a lesson...
5                 2007  I'm comin back from Florida / Wit Jeb Bush and...

                                           url  pos_words  neg_word
id
1   http://genius.com/Aesop-rock-none-shall-pass-l...          0
2        http://genius.com/Soul-khan-wellstone-lyrics          1
3           http://genius.com/Dez-and-nobs-awe-lyrics          0
4         http://genius.com/Diabolic-the-truth-lyrics          0
5      http://genius.com/Gorilla-zoe-money-man-lyrics          0

   predicted_sentiment  pos_words_music  neg_words_music  \
id
1              neutral                2                2
2              neutral                2                7
3              neutral                0                3
4              neutral                3                5
5              neutral                5                2

   predicted_sentiment_music
id
1                    neutral
2                   negative
3                   negative
4                   negative
5                   positive
```

In [26]:
```python
acc=(df['predicted_sentiment_music']==df['sentiment']).mean()
print('Accuracy on r/music sentiment lexicon: %.4f'%acc)
```

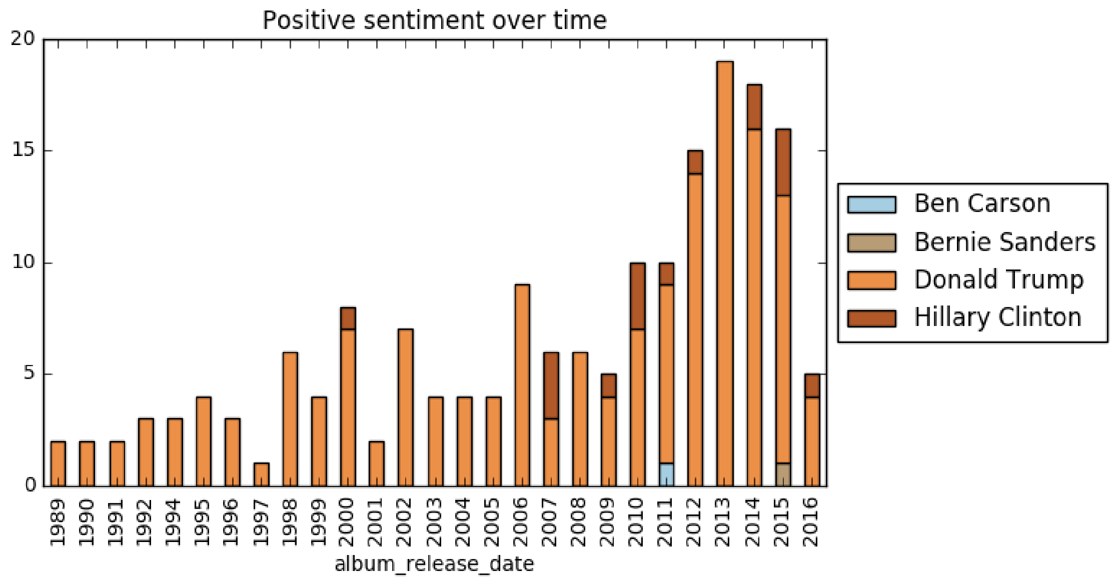
```
Accuracy on r/music sentiment lexicon: 0.2971
```

Domain specific sentiment lexicon is performing much worse. Why? The lines from lyrics seem to be have more general english tokens. Whereas, the r/music lexicon has very specific tokens, trained on discussions on music. It performs poorly when applied to a different domain, here - hip-hop lyrics.

1.2 Candidate mentions, by sentiment over time

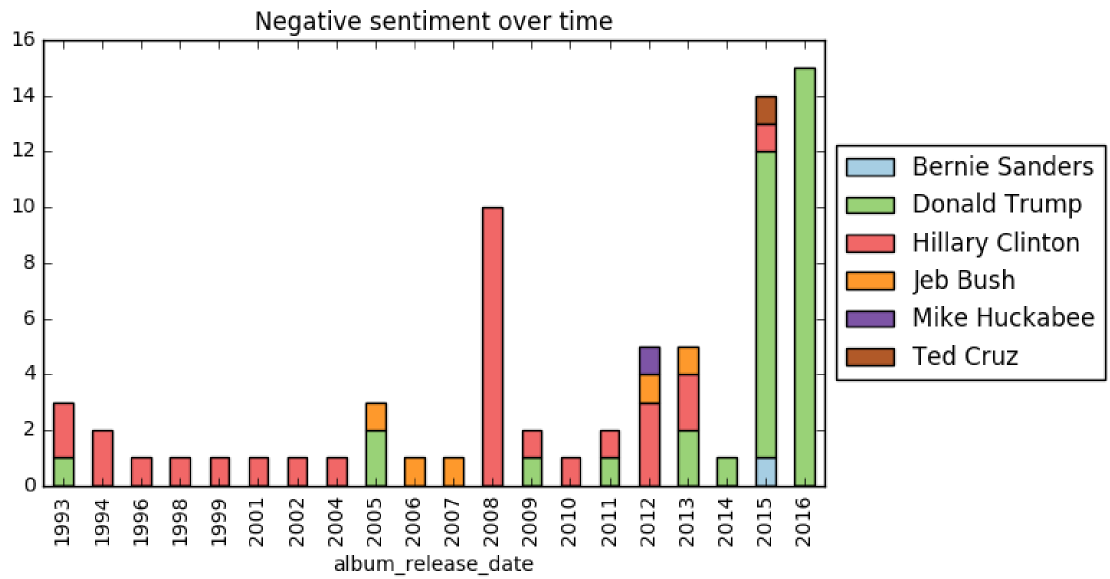
In [27]:
```
sentiment_over_time = df.groupby(['album_release_date', 'sentiment','candi
posdf = sentiment_over_time[sentiment_over_time.sentiment == 'positive']
posdf.pivot_table(index='album_release_date', columns='candidate', values=
plt.title('Positive sentiment over time')
```

Out[27]: <matplotlib.text.Text at 0x11ab53150>

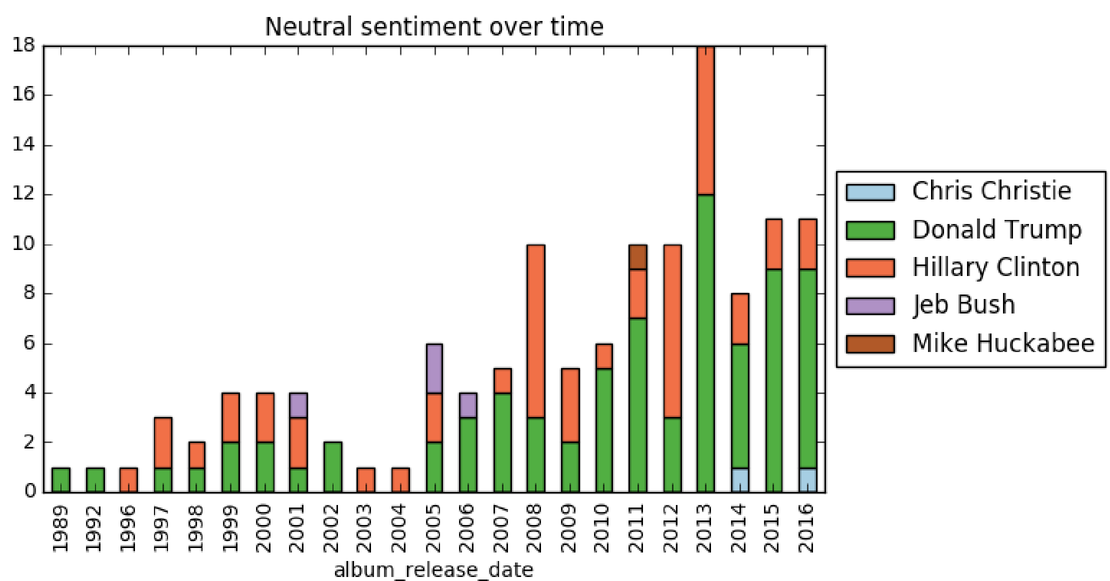


In [28]:
```
negdf = sentiment_over_time[sentiment_over_time.sentiment == 'negative']
negdf.pivot_table(index='album_release_date', columns='candidate', values=
plt.title('Negative sentiment over time')
```

Out[28]: <matplotlib.text.Text at 0x11aedbed0>




```
In [29]: neudf = sentiment_over_time[sentiment_over_time.sentiment == 'neutral']
         neudf.pivot_table(index='album_release_date', columns='candidate', values=
         plt.title('Neutral sentiment over time')

Out[29]: <matplotlib.text.Text at 0x11b5d3c90>
```



Things start to look a little different for Trump in 2015. Before 2015, Trump had received only eight negative references in total; over the last year and a half, however, that number almost quadrupled in 2015. This is a reflection of a chance in his public persona from being a business tycoon to a politician (now making controversial statements around race, immigration etc). Hillary has a sweeping negative sentiment in 2008, from all the hip-hop lyrics during that year. This could be a reflection of the racial politics associated with her during the 2008 elections. Let's see if the polarity of mentions in hip-hop songs are predictive of presidency of the candidate.

In [30]:
```
#Adding column for candidates who won the presidency
elected_presidents =  ['Donald Trump']
def label_president(row):
    if row['candidate'] == 'Donald Trump':
        return 1
    else:
        return 0
sentiment_over_time['presidency'] = sentiment_over_time.apply (lambda row:
sentiment_over_time.head(10)
```

Out[30]:
```
   album_release_date sentiment        candidate  mentions  presidency
0                1989   neutral     Donald Trump         1           1
1                1989  positive     Donald Trump         2           1
2                1990  positive     Donald Trump         2           1
3                1991  positive     Donald Trump         2           1
4                1992   neutral     Donald Trump         1           1
5                1992  positive     Donald Trump         3           1
6                1993  negative     Donald Trump         1           1
7                1993  negative  Hillary Clinton         2           0
8                1994  negative  Hillary Clinton         2           0
9                1994  positive     Donald Trump         3           1
```

In [31]:
```
import statsmodels.formula.api as sm
result = sm.ols(formula= 'presidency ~ album_release_date',data=sentiment_
result.summary2()
```

Out[31]:
```
<class 'statsmodels.iolib.summary2.Summary'>
"""
                  Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.028
Dependent Variable: presidency       AIC:                165.1265
Date:               2017-09-22 16:33 BIC:                170.5989
No. Observations:   114              Log-Likelihood:     -80.563
Df Model:           1                F-statistic:        4.217
Df Residuals:       112              Prob (F-statistic): 0.0423
R-squared:          0.036            Scale:              0.24493
------------------------------------------------------------------
                   Coef.  Std.Err.    t    P>|t|   [0.025  0.975]
------------------------------------------------------------------
Intercept         26.4633  12.6518  2.0917 0.0387  1.3954 51.5311
album_release_date -0.0130   0.0063 -2.0535 0.0423 -0.0254 -0.0005
------------------------------------------------------------------
```

```
Omnibus:                 0.164        Durbin-Watson:           3.021
Prob(Omnibus):           0.921        Jarque-Bera (JB):        16.445
Skew:                    0.088        Prob(JB):                0.000
Kurtosis:                1.148        Condition No.:           547575
==================================================================
* The condition number is large (5e+05). This might indicate
strong multicollinearity or other numerical problems.
"""
```

Although the p-value looks statistically significant, p < alpha (0.05) the R^2 is bad. The model is not a good fit over hip hop album releases but seems better than chance.

```
In [32]: result = sm.ols(formula= 'presidency ~ C(sentiment) + mentions',data=senti
         result.summary2()
```

```
Out[32]: <class 'statsmodels.iolib.summary2.Summary'>
"""
                   Results: Ordinary least squares
=====================================================================
Model:                 OLS                 Adj. R-squared:     0.224
Dependent Variable:    presidency          AIC:                141.3849
Date:                  2017-09-22 16:33    BIC:                152.3297
No. Observations:      114                 Log-Likelihood:     -66.692
Df Model:              3                   F-statistic:        11.86
Df Residuals:          110                 Prob (F-statistic): 8.62e-07
R-squared:             0.244               Scale:              0.19552
---------------------------------------------------------------------
                         Coef.  Std.Err.   t    P>|t|   [0.025 0.975]
---------------------------------------------------------------------
Intercept                0.1422   0.0842 1.6885 0.0942 -0.0247 0.3090
C(sentiment)[T.neutral]  0.1583   0.1034 1.5309 0.1287 -0.0466 0.3633
C(sentiment)[T.positive] 0.3313   0.1109 2.9866 0.0035  0.1115 0.5512
mentions                 0.0506   0.0122 4.1429 0.0001  0.0264 0.0748
---------------------------------------------------------------------
Omnibus:                  61.241        Durbin-Watson:           2.502
Prob(Omnibus):            0.000         Jarque-Bera (JB):        9.311
Skew:                     0.289         Prob(JB):                0.010
Kurtosis:                 1.725         Condition No.:           18
=====================================================================

"""
```

This model has a much better R^2 and the coefficients are more interpretable. The p-values for positive polarity and mentions are significant at $p < 0.05$. The coefficients for positive polarity weigh higher towards a presidency.

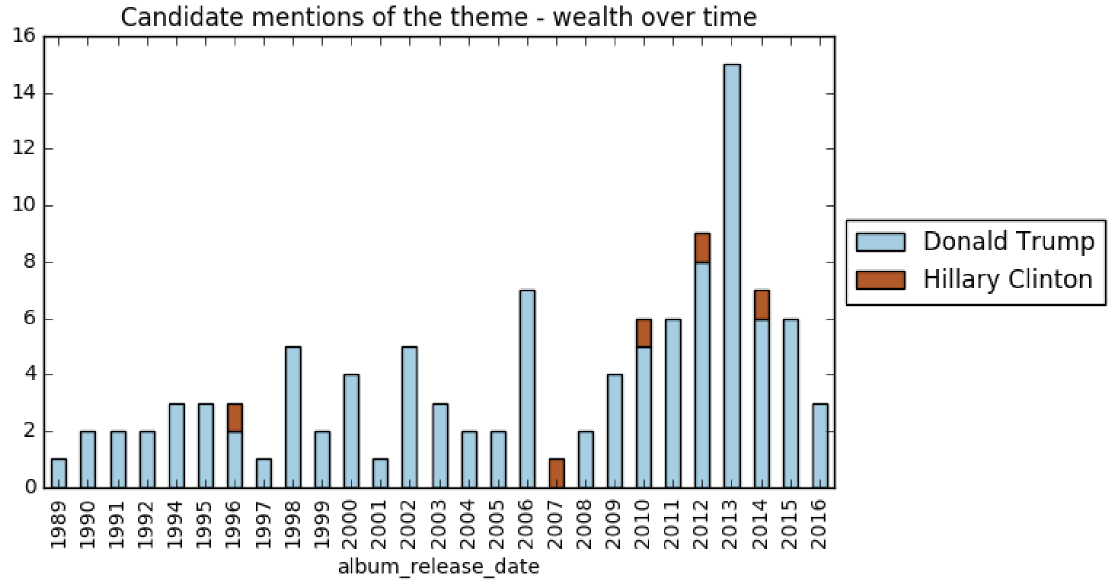
1.3 Candidate mentions - Themes/Subjects over time

```
In [33]: subject_over_time = df.groupby(['album_release_date', 'theme','candidate']
         subject_over_time.theme.values
```

```
Out[33]: array(['money', 'money', 'money', 'money', 'personal', 'personal',
               'political', 'political', 'money', 'personal', 'sexual', 'money',
               'personal', 'hotel', 'money', 'money', 'political', 'money',
               'personal', 'hotel', 'money', 'personal', 'political', 'hotel',
               'money', 'personal', 'personal', 'political', 'hotel', 'money',
               'personal', 'personal', 'hotel', 'money', 'personal', 'hotel',
               'money', 'personal', 'hotel', 'money', 'hotel', 'money', 'personal'
               'political', 'The Apprentice', 'hotel', 'money', 'personal',
               'personal', 'political', 'The Apprentice', 'hotel', 'money',
               'personal', 'political', 'The Apprentice', 'hotel', 'money',
               'personal', 'personal', 'The Apprentice', 'hotel', 'money',
               'personal', 'personal', 'political', 'hotel', 'money', 'personal',
               'political', 'political', 'The Apprentice', 'hotel', 'money',
               'money', 'personal', 'political', 'The Apprentice', 'hotel',
               'money', 'personal', 'personal', 'political', 'sexual',
               'The Apprentice', 'hotel', 'money', 'money', 'personal', 'personal'
               'political', 'political', 'The Apprentice', 'hotel', 'money',
               'personal', 'personal', 'political', 'power', 'sexual',
               'The Apprentice', 'hotel', 'money', 'money', 'personal', 'power',
               'The Apprentice', 'hotel', 'money', 'personal', 'political',
               'political', 'political', 'political', 'sexual', 'hotel', 'money',
               'personal', 'political', 'political'], dtype=object)
```

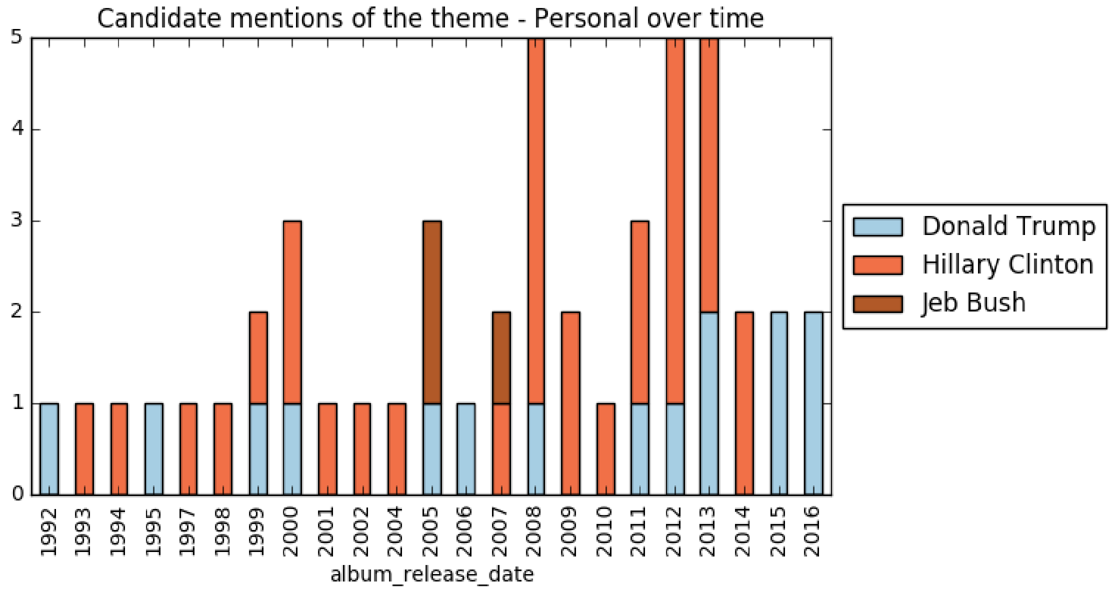
```
In [34]: wealthdf = subject_over_time[subject_over_time.theme == 'money']
         wealthdf.pivot_table(index='album_release_date', columns='candidate', valu
         plt.title("Candidate mentions of the theme - wealth over time")
```

```
Out[34]: <matplotlib.text.Text at 0x11c131210>
```



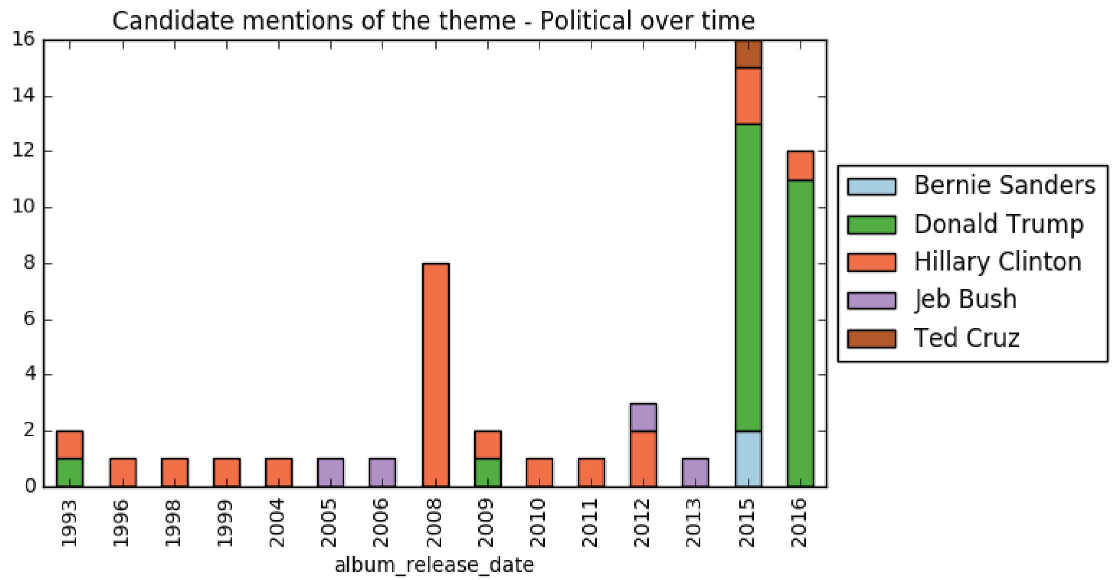
As seen above, Donald Trump's persona as a business tycoon has strongly contributed to the hip-hop narrative around him.

```
In [35]: personaldf = subject_over_time[subject_over_time.theme == 'personal']
         personaldf.pivot_table(index='album_release_date', columns='candidate', va
         plt.title("Candidate mentions of the theme - Personal over time")

Out[35]: <matplotlib.text.Text at 0x11c9f9210>
```



Similar to the sentiment over time, the hip-hop narrative around Hillary Clinton in 2008 seems largely around her personal life. Overall, the mentions of personal themes in the lyrics are highest for Clinton than any other candidate.

```
In [36]: politicsdf = subject_over_time[subject_over_time.theme == 'political']
         politicsdf.pivot_table(index='album_release_date', columns='candidate', va
         plt.title("Candidate mentions of the theme - Political over time")

Out[36]: <matplotlib.text.Text at 0x11cec8050>
```



Before 2015, there seem to be no political themes in the hip-hop narrative around Donald Trump. Let's check if the themes around candidate mentions in hip-hop lyrics are a predictor of presidency.

In [37]:
```
subject_over_time['presidency'] = subject_over_time.apply (lambda row: lab
subject_over_time.head()
```

Out[37]:

	album_release_date	theme	candidate	mentions	presidency
0	1989	money	Donald Trump	1	1
1	1990	money	Donald Trump	2	1
2	1991	money	Donald Trump	2	1
3	1992	money	Donald Trump	2	1
4	1992	personal	Donald Trump	1	1

In [38]:
```
result1 = sm.ols(formula='presidency ~ C(theme) + mentions + album_release
result1.summary2()
```

Out[38]:
```
<class 'statsmodels.iolib.summary2.Summary'>
"""
                   Results: Ordinary least squares
=====================================================================
Model:              OLS              Adj. R-squared:     0.448
Dependent Variable: presidency       AIC:                104.7055
Date:               2017-09-22 16:34 BIC:                129.7929
No. Observations:   120              Log-Likelihood:     -43.353
Df Model:           8                F-statistic:        13.09
Df Residuals:       111              Prob (F-statistic): 3.69e-13
R-squared:          0.485            Scale:              0.13037
---------------------------------------------------------------------
```

```
                          Coef.  Std.Err.    t    P>|t|   [0.025  0.975]
------------------------------------------------------------------------
Intercept                13.5576  10.4483  1.2976 0.1971 -7.1464 34.2616
C(theme)[T.hotel]        -0.0971   0.1448 -0.6706 0.5039 -0.3840  0.1898
C(theme)[T.money]        -0.2792   0.1409 -1.9822 0.0499 -0.5583 -0.0001
C(theme)[T.personal]     -0.6316   0.1336 -4.7260 0.0000 -0.8965 -0.3668
C(theme)[T.political]    -0.8592   0.1389 -6.1870 0.0000 -1.1344 -0.5840
C(theme)[T.power]         0.0584   0.2809  0.2081 0.8355 -0.4981  0.6150
C(theme)[T.sexual]       -0.7246   0.2140 -3.3862 0.0010 -1.1486 -0.3006
mentions                  0.0463   0.0160  2.9044 0.0044  0.0147  0.0779
album_release_date       -0.0063   0.0052 -1.2086 0.2294 -0.0166  0.0040
------------------------------------------------------------------------
Omnibus:                  3.107        Durbin-Watson:            2.243
Prob(Omnibus):            0.211        Jarque-Bera (JB):         2.834
Skew:                     0.376        Prob(JB):                 0.242
Kurtosis:                 3.026        Condition No.:            635913
========================================================================
* The condition number is large (6e+05). This might indicate
strong multicollinearity or other numerical problems.
"""
```

This appears to be a much better model. The R^2, F-statistic and $P(f - stat) << 0.01$. The p-values for money and sexual themes in hip-hop lyrics appear to be statistically significant. Let's check the correlation of residuals.

In [39]:
```python
from scipy.stats import spearmanr, pearsonr
spearmanr(subject_over_time['presidency'],result1.resid)
```

Out[39]:
```
SpearmanrResult(correlation=0.81222060273457408, pvalue=2.1539648297858562
```

correlation = 0.82 Strong evidence of correlated errors. This means that the IID assumption is likely violated, so our p-values are overconfident.

Statistically speaking then, hip-hop lyrics have no connection to the presidency.