Unit 2: Dictionary methods

IPM Text Analysis

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University of Chicago

July 2018


Thriller
25
THE WORLD'S BIGGEST
SELLING ALBUM
OF ALL TIME
Michael Jackson

Today: Measuring expressed sentiment in documents
Goal: Classify (measure) sentiment in texts
Method: Dictionary methods

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Game Plan:

1) Dictionaries
2) Applying dictionaries to text to measure sentiment
3) Applications, interpretation, and pitfalls

Key Terms:

- Dictionary
- Sentiment analysis
- Word weights

Dictionaries

- Dictionaries are lists of words belonging to a category.

Dictionaries

```
## 1      2-faced  negative
## 2      2-faces  negative
## 3           a+  positive
## 4     abnormal  negative
## 5      abolish  negative
## 6   abominable  negative
## 7   abominably  negative
## 8    abominate  negative
## 9  abomination  negative
## 10       abort  negative
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##  2    abandon      fear
##  3    abandon  negative
##  4    abandon   sadness
##  5  abandoned     anger
##  6  abandoned      fear
##  7  abandoned  negative
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- Word weights / scores
  - Binary: $\{$Positive $(+1)$, Negative (-1)$\}$

Dictionaries

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## 1      abandon   -2
## 2    abandoned   -2
## 3     abandons   -2
## 4     abducted   -2
## 5    abduction   -2
## 6   abductions   -2
## 7        abhor   -3
## 8     abhorred   -3
## 9    abhorrent   -3
## 10      abhors   -3
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- Non-sentiment dictionaries: Words about sports, food, places...

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      - Output as dictionary

Applying Dictionaries to Documents

- Vector of word counts: $\boldsymbol{X}_i = (X_{i1}, X_{i2}, \ldots, X_{iP})$, $i = (1, \ldots, N)$

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$Y_i \approx 0$ Ambiguous

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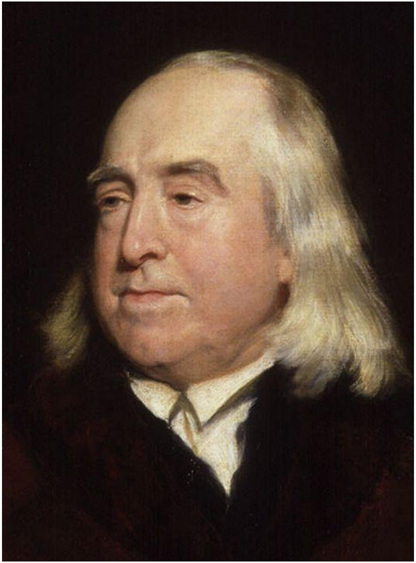

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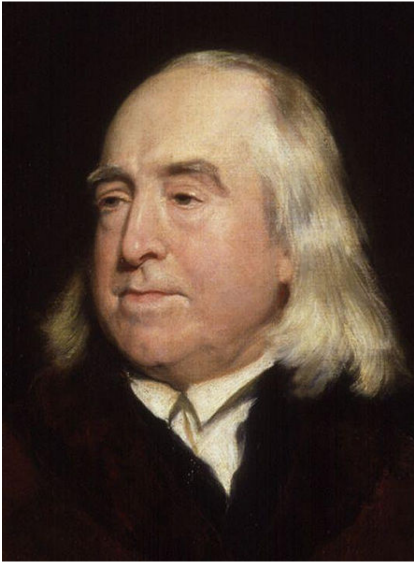

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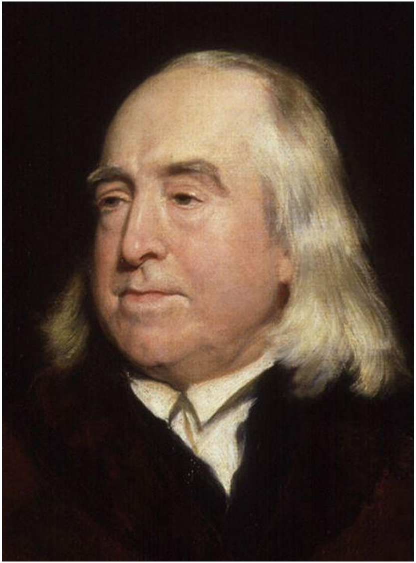

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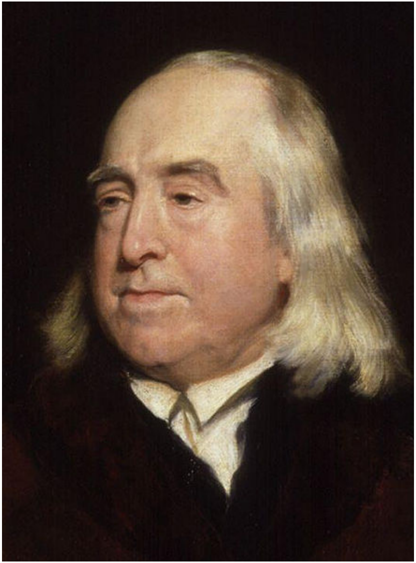

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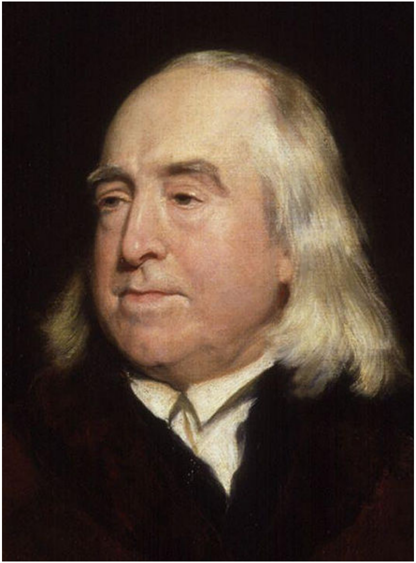

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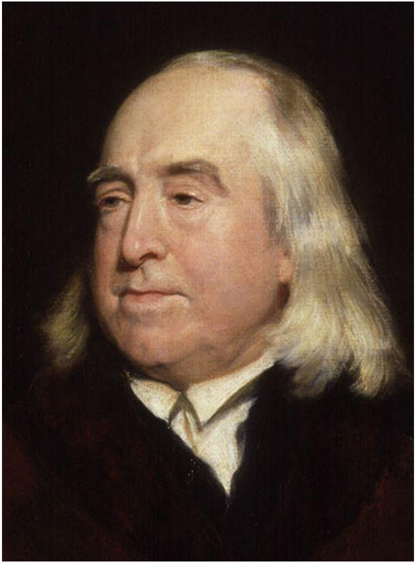

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Use Dictionary Methods

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$$\text{Happiness}_i = \frac{\sum_{p=1}^{P} \theta_p X_{ip}}{\sum_{p=1}^{P} X_{ip}}$$

Lyrics for
Michael Jackson's Billie Jean

"She was more like a beauty queen
from a movie scene.
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And mother always told me,
be careful who you love.
And be careful of what you do
'cause the lie becomes the truth.
Billie Jean is not my lover,
She's just a girl who claims
that I am the one.
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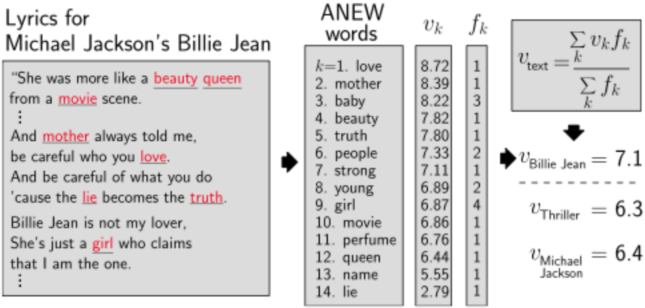
ANEW words	v_k	f_k
k=1. love	8.72	1
2. mother	8.39	1
3. baby	8.22	3
4. beauty	7.82	1
5. truth	7.80	1
6. people	7.33	2
7. strong	7.11	1
8. young	6.89	2
9. girl	6.87	4
10. movie	6.86	1
11. perfume	6.76	1
12. queen	6.44	1
13. name	5.55	1
14. lie	2.79	1

$$v_{\text{text}} = \frac{\sum_k v_k f_k}{\sum_k f_k}$$

$$v_{\text{Billie Jean}} = 7.1$$

$$v_{\text{Thriller}} = 6.3$$

$$v_{\text{Michael Jackson}} = 6.4$$



Happiest Song on Thriller?

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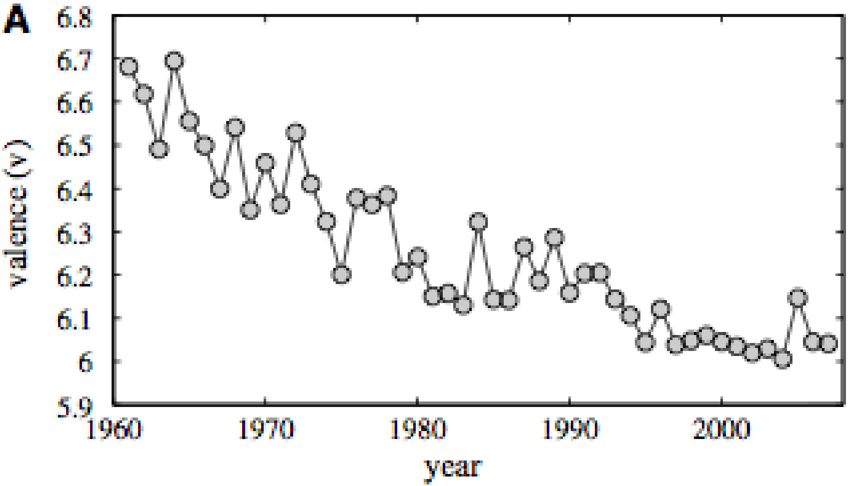

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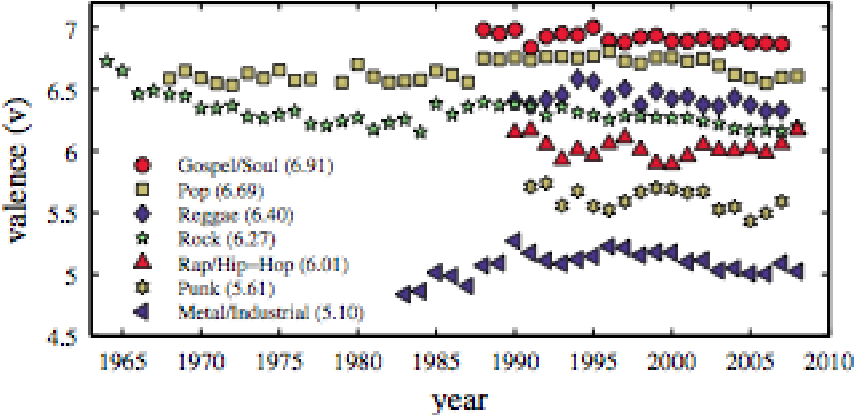
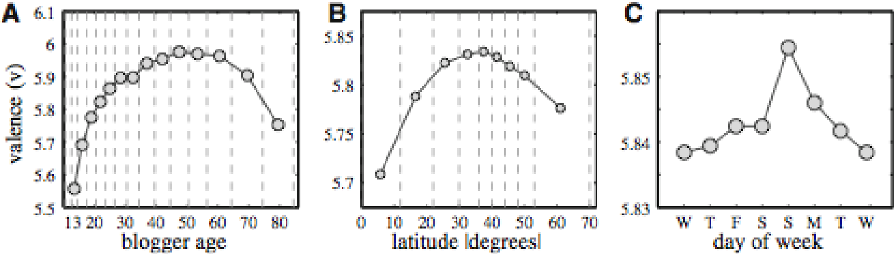
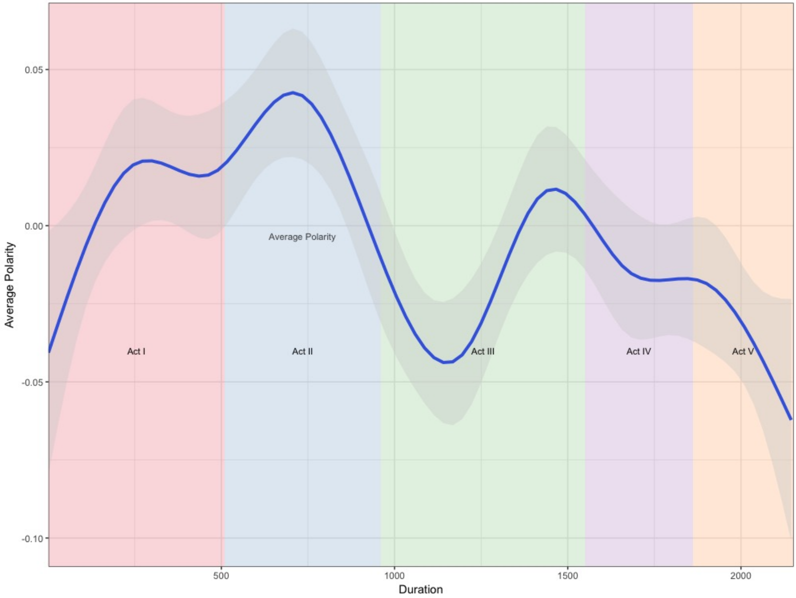


Happiness in Society



Visualizing Plots: Romeo & Juliet



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Context Matters

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R Code!
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