

Unit 2: Dictionary methods

BigSurv Text Analysis

Dr. Rochelle Terman

Department of Political Science
University of Chicago

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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

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## 1    2-faced  negative
## 2    2-faces  negative
## 3         a+   positive
## 4   abnormal  negative
## 5   abolish  negative
## 6  abominable  negative
## 7  abominably  negative
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##	word	sentiment
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## 2	abandon	fear
## 3	abandon	negative
## 4	abandon	sadness
## 5	abandoned	anger
## 6	abandoned	fear
## 7	abandoned	negative
## 8	abandoned	sadness
## 9	abandonment	anger
## 10	abandonment	fear

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 - Binary: {Positive (+1), Negative (-1)}

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

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- 6) Many many more....

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 - Output as dictionary

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

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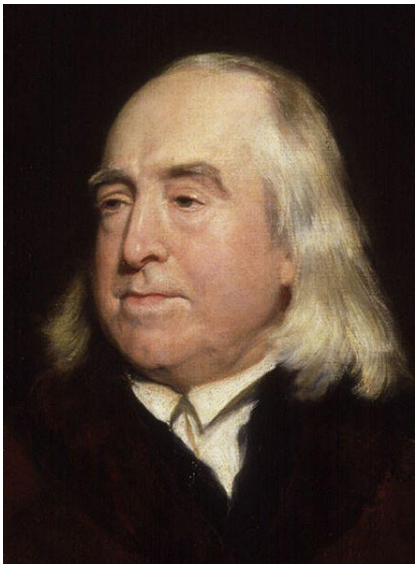
$Y_i \approx$ continuous \rightsquigarrow Classification

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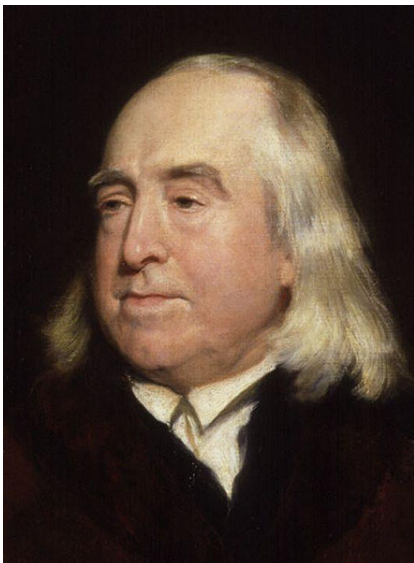
$Y_i < 0 \Rightarrow$ Negative Category

$Y_i \approx 0$ Ambiguous

Measuring Happiness

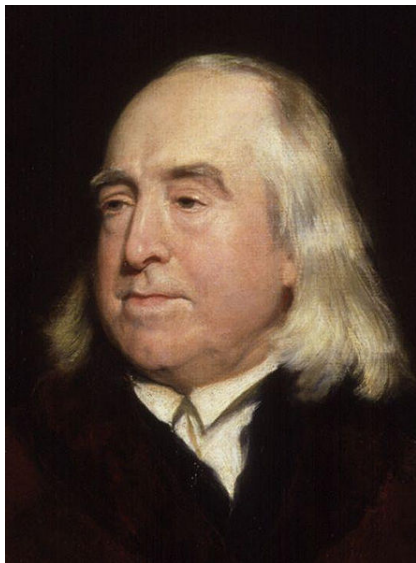


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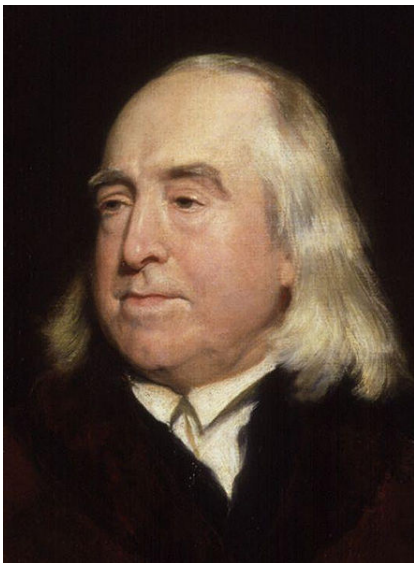
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Measuring Happiness



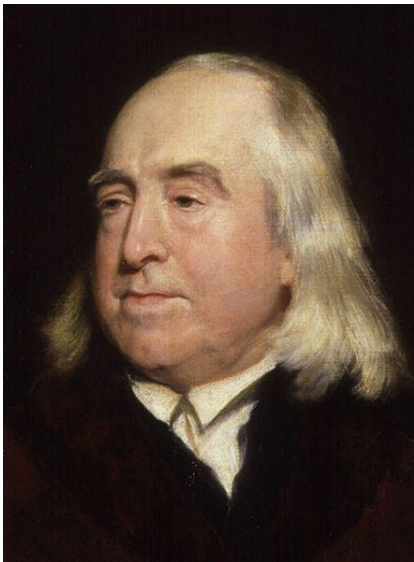
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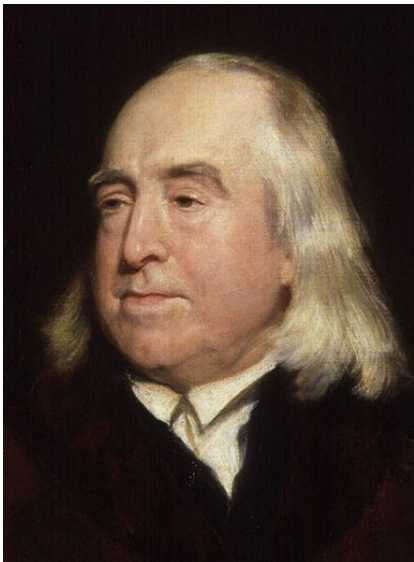
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$$\text{Happiness}_i = \frac{\sum_{p=1}^P \theta_p X_{ip}}{\sum_{p=1}^P X_{ip}}$$

Lyrics for Michael Jackson's Billie Jean

"She was more like a beauty queen
from a movie scene.
:
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
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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

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

$$\begin{aligned} \Rightarrow v_{\text{Billie Jean}} &= 7.1 \\ \text{-----} \\ v_{\text{Thriller}} &= 6.3 \\ v_{\text{Michael Jackson}} &= 6.4 \end{aligned}$$

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Happiest Song on Thriller?

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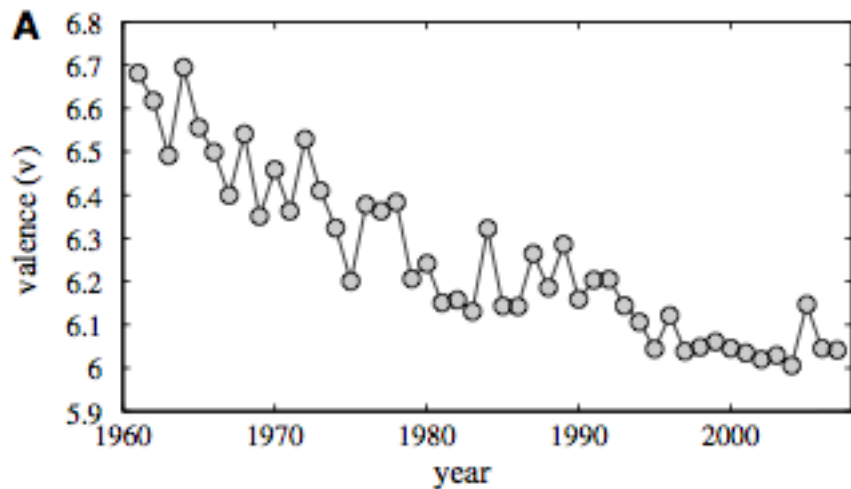
$$v_{\text{text}} = \frac{\sum_k v_k f_k}{\sum_k f_k}$$

$$\begin{aligned} \rightarrow v_{\text{Billie Jean}} &= 7.1 \\ \text{-----} \\ v_{\text{Thriller}} &= 6.3 \\ v_{\text{Michael Jackson}} &= 6.4 \end{aligned}$$

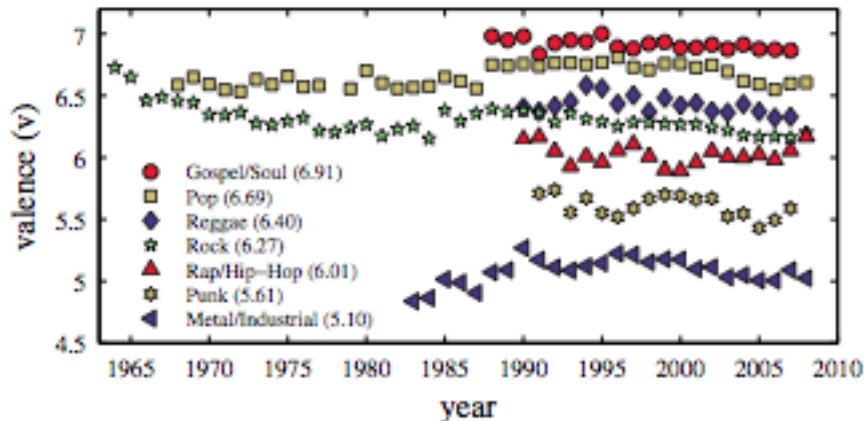
Happiest Song on Thriller?

P.Y.T. (Pretty Young Thing) (This is the right answer!)

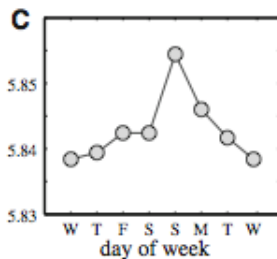
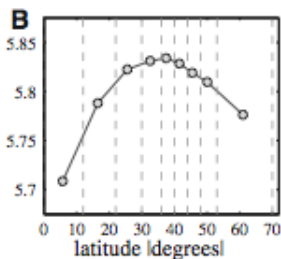
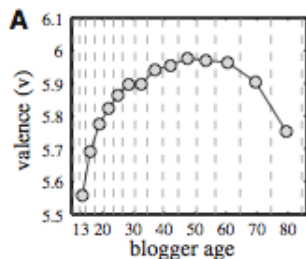
Happiness in Society



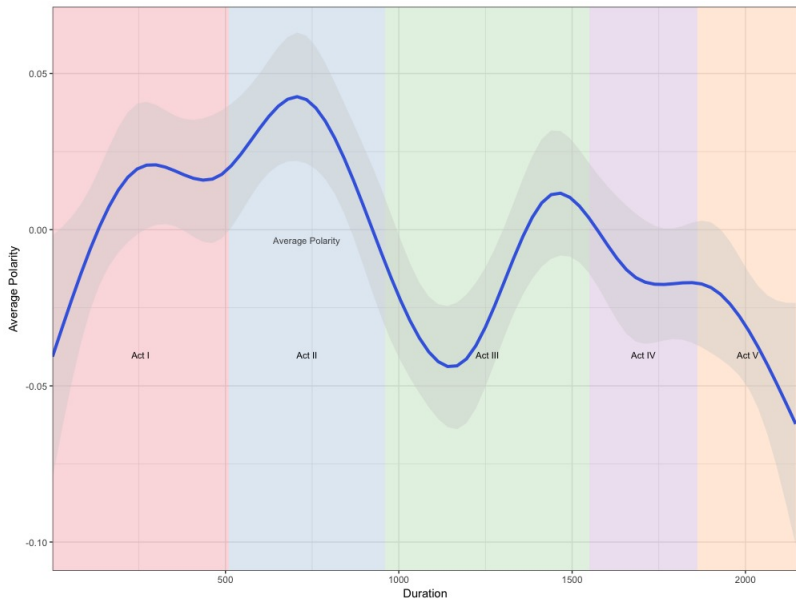
Happiness in Society



Happiness in Society



Visualizing Plots: Romeo & Juliet



Emotional Contagion on Facebook

www.pnas.org

Experimental evidence of massive-scale emotional contagion through social networks

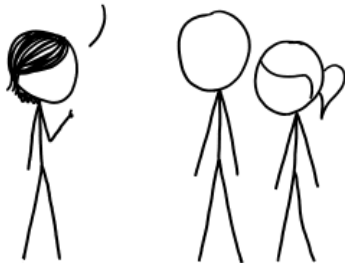
Emotional Contagion on Facebook

FACEBOOK SHOULDN'T CHOOSE WHAT
STUFF THEY SHOW US TO CONDUCT
UNETHICAL PSYCHOLOGICAL RESEARCH.

THEY SHOULD ONLY MAKE THOSE
DECISIONS BASED ON, UH...

HOWEVER THEY WERE
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WHICH WAS PROBABLY
ETHICAL, RIGHT?



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Context Matters

R Code!