# Unit 2: Dictionary methods

FSU Summer Methods Workshop

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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

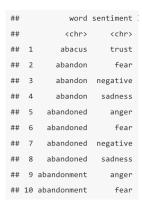
- Dictionaries are lists of words belonging to a category.

```
2-faced negative
         2-faces negative
                  positive
        abnormal
                  negative
         abolish negative
      abominable negative
       abominably negative
       abominate negative
     abomination negative
## 10
           abort negative
```

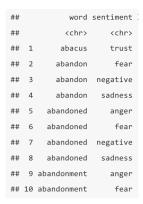
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  - Binary:  $\{Positive (+1), Negative (-1)\}$

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

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- 6) Many many more....

Three ways to create dictionaries (non-exhaustive):

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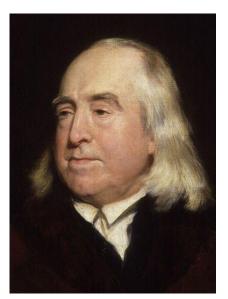
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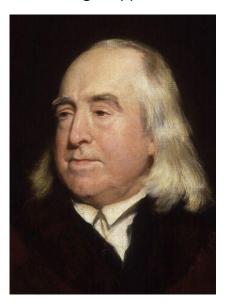
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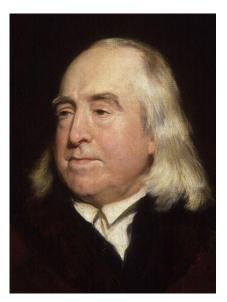
 $Y_i < 0 \Rightarrow$  Negative Category

 $Y_i \approx 0$  Ambiguous





 Quantifying Happiness: How happy is society?



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- How Happy is a Song?



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Use Dictionary Methods

Dodds and Danforth (2009): Use a dictionary method to measure happiness

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#### Lyrics for Michael Jackson's Billie Jean

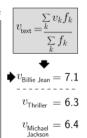
"She was more like a beauty queen from a movie scene.

I had 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,
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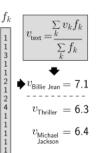


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#### ANFW $v_k$ words k=1. love 8.72 8.39 mother baby 8.22 7.82 beauty 5. truth 7.80 7.33 people 7. strong 7.11 8. young 6.89 9. girl 6.87 10. movie 6.86 6.76 perfume 6.44 12. queen 13. name 5.55 2.79 14. lie



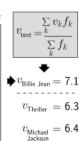
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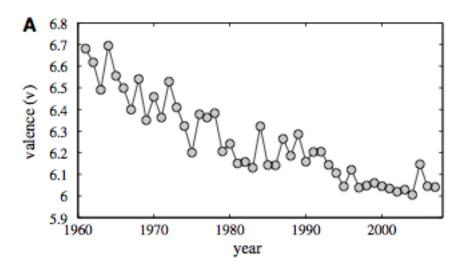
### Happiest Song on Thriller?

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

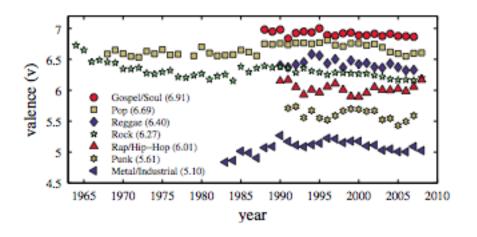
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2.79

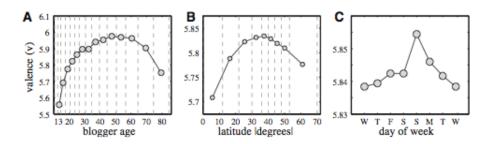
### Happiness in Society



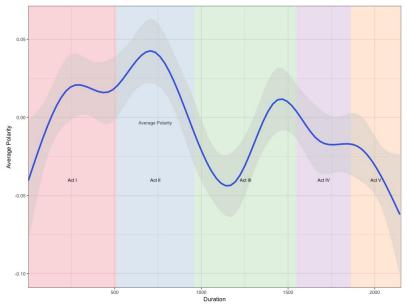
### Happiness in Society



### 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 DOING IT BEFORE. WHICH WAS PROBABLY ETHICAL, RIGHT?

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### Context Matters

R Code!