TURNING TWEETS INTO KNOWLEDGE

An Introduction to Text Analytics

Twitter

- Twitter is a social networking and communication website founded in 2006
- Users share and send messages that can be no longer than 140 characters long
- One of the Top 10 most-visited sites on the internet
- Initial Public Offering in 2013
- Valuation ~$31 billion

Impact of Twitter

- Use by protestors across the world
- Natural disaster notification, tracking of diseases
- Celebrities, politicians, and companies connect with fans and customers
- Everyone is watching!

2013 AP Twitter Hack

- The Associated Press is a major news agency that distributes news stories to other news agencies
- In April 2013 someone tweeted the above message from the main AP verified Twitter account
- S&P500 stock index fell 1% in seconds, but the White House rapidly clarified

Understanding People

- Many companies maintain online presences
- Managing public perception in age of instant communication essential
- Reacting to changing sentiment, identifying offensive posts, determining topics of interest…
- How can we use analytics to address this?

Using Text as Data

- Until now, our data has typically been
  - Structured
  - Numerical
  - Categorical

- Tweets are
  - Loosely structured
  - Textual
  - Poor spelling, non-traditional grammar
  - Multilingual

Text Analytics

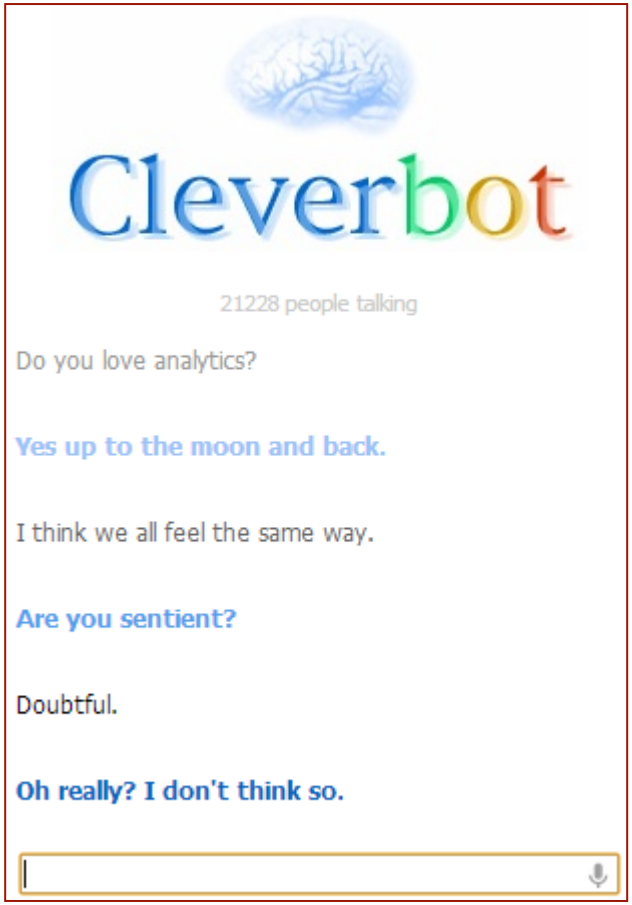
- We have discussed why people care about textual data, but how do we handle it?
- Humans can't keep up with Internet-scale volumes of data
  - ~500 million tweets per day!
- Even at a small scale, the cost and time required may be prohibitive

How Can Computers Help?

- Computers need to understand text
- This field is called **Natural Language Processing**
- The goal is to understand and derive meaning from human language
- In 1950, Alan Turing proposes a test of machine intelligence: passes if it can take part in a real-time conversation and cannot be distinguished from a human

History of Natural Language Processing

- Some progress: "chatterbots" like ELIZA
- Initial focus on understanding grammar
- Focus shifting now towards statistical, machine learning techniques that learn from large bodies of text
- Modern "artificial intelligences": Apple's Siri and Google Now



Why is it Hard?

- Computers need to understand text
- Ambiguity:
  - "I put my **bag** in the **car**. **It** is **large and blue**"
  - "**It**" = **bag**? "**It**" = **car**?
- Context:
  - Homonyms, metaphors
  - Sarcasm
- In this lecture, we'll see how we can build analytics models using text as our data

Sentiment Mining - Apple

- **Apple** is a computer company known for its laptops, phones, tablets, and personal media players
- Large numbers of fans, large number of "haters"
- Apple wants to monitor how people feel about them over time, and how people receive new announcements.
- **Challenge: Can we correctly classify tweets as being negative, positive, or neither about Apple?**

Creating the Dataset

- Twitter data is publically available
  - Scrape website, or
  - Use special interface for programmers (API)
  - Sender of tweet may be useful, but we will ignore
- Need to construct the outcome variable for tweets
  - Thousands of tweets
  - Two people may disagree over the correct classification
  - One option is to use **Amazon Mechanical Turk**

Amazon Mechanical Turk

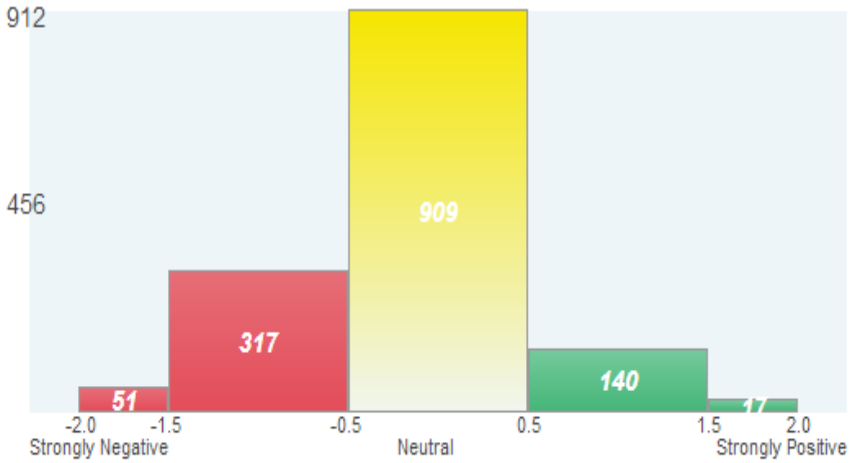
- Break tasks down into small components and distribute online
- People can sign up to perform the tasks for a fee
  - Pay workers, e.g. $0.02 per classified tweet
  - Amazon MTurk serves as a broker, takes small cut
- Many tasks require human intelligence, but may be time consuming or require building otherwise unneeded capacity

Our Human Intelligence Task

- Actual question we used:

Judge the sentiment expressed by the following item toward the software company "Apple"

- Workers could pick from
  - Strongly Negative (-2)
  - Negative (-1)
  - Neutral (0)
  - Positive (+1)
  - Strongly Positive (+2)



- Five workers labeled each tweet

Our Human Intelligence Task

- For each tweet, we take the average of the five scores.
  - "LOVE U @APPLE" (1.8)
  - "@apple @twitter Happy Programmers' Day folks!" (0.4)
  - "So disappointed in @Apple Sold me a Macbook Air that WONT run my apps. So I have to drive hours to return it. They wont let me ship it." (-1.4)
- We have labels, but how do we build independent variables from the text of a tweet?

A Bag of Words

- Fully understanding text is difficult
- Simpler approach:

  Count the number of times each words appears

- "This course is great. I would recommend this course to my friends."

THIS	COURSE	GREAT	…	WOULD	FRIENDS
2	2	1	…	1	1

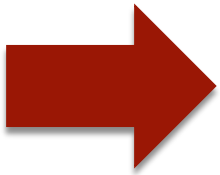
A Simple but Effective Approach

- One feature for each word - a simple approach, but effective
- Used as a baseline in text analytics projects and natural language processing
- Not the whole story though - preprocessing can dramatically improve performance!

Cleaning Up Irregularities

- Text data often has many inconsistencies that will cause algorithms trouble
- Computers are very literal by default – Apple, APPLE, and ApPLe will all be counted separately.
- Change all words to either lower-case or upper-case

Apple	APPLE	ApPLe
apple	apple	apple

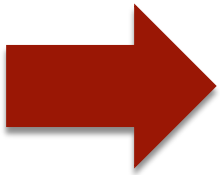


apple
3

Cleaning Up Irregularities

- Punctuation also causes problems – basic approach is to remove everything that isn't a,b,…,z
- Sometimes punctuation **is** meaningful
  - Twitter: **@apple** is a message to Apple, **#apple** is about Apple
  - Web addresses: **www.website.com/somepage.html**
- Should tailor approach to the specific problem

@Apple	APPLE!	--apple--
apple	apple	apple



apple
3

Removing Unhelpful Terms

- Many words are frequently used but are only meaningful in a sentence - **"stop words"**
  - Examples: *the, is, at, which*…
  - Unlikely to improve machine learning prediction quality
  - Remove to reduce size of data

- Two words at a time?
  - "The Who" ➔ " "
  - "Take That" ➔ "Take"

Stemming

- Do we need to draw a distinction between the following words?

  argue argued argues arguing

- Could all be represented by a common **stem**, **argu**

- Algorithmic process of performing this reduction is called **stemming**

- Many ways to approach the problem

Stemming

- Could build a **database of words** and their stems
  - **Pro**: handles exceptions
  - **Con**: won't handle new words, bad for the Internet!
- Can write a **rule-based** algorithm
  - e.g. if word ends in "ed", "ing", or "ly", remove it
  - **Pro**: handles new/unknown words well
  - **Con**: many exceptions, misses words like **child** and **children** (but would get other plurals: **dog** and **dogs**)

Stemming

- The second option is widely popular
  - "**Porter Stemmer**" by Martin Porter in 1980, still used!
  - Stemmers have been written for many languages
- Other options include machine learning (train algorithms to recognize the roots of words) and combinations of the above

Real example from data:

"by far the best customer care service I have ever received"

→ *"by far the best custom care servic I have ever receiv"*

Sentiment Analysis Today

- Over 7,000 research articles have been written on this topic
- Hundreds of start-ups are developing sentiment analysis solutions
- Many websites perform real-time analysis of tweets
  - "tweetfeel" shows trends given any term
  - "The Stock Sonar" shows sentiment and stock prices

Text Analytics in General

- Selecting the specific features that are relevant in the application
- Applying problem specific knowledge can get better results
  - Meaning of symbols
  - Features like number of words

The Analytics Edge

- Analytical sentiment analysis can replace more labor-intensive methods like polling
- Text analytics can deal with the massive amounts of unstructured data being generated on the internet
- Computers are becoming more and more capable of interacting with humans and performing human tasks
- In the next lecture, we'll discuss IBM Watson, an impressive feat in the area of Text Analytics