Data Mining I
Text Mining

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Outline

1. What is Text Mining?
2. Text Preprocessing
3. Feature Creation
4. Feature Selection
5. Pattern Discovery
6. Processing Text from Social Media
Motivation for Text Mining

Approximately 90% of the world’s data is held in unstructured formats.

(source: Oracle Corporation)

- Web pages
- Emails
- Technical documents
- Corporate documents
- Books
- Digital libraries
- Customer complaint letters
The extraction of implicit, previously unknown and potentially useful information from a large amount of textual resources.

Text Mining

- Data Mining
- Information Retrieval
- Statistics
- Web Mining
- Computational Linguistics & NLP
Search Versus Discovery

Structured Data

Search/Query (Goal-oriented)

- Query Processing
- Information Retrieval

Text

Discovery (Opportunistic)

- Data Mining
- Text Mining
Some Text Mining Applications

• Classification of news stories or web pages
• Email and news filtering / Spam detection
• Sentiment analysis
• Clustering documents or web pages
• Query suggestion / auto complete
• Gain insights about relations between people, places or organizations described in a document corpus
Examples
Examples

Hey, got your SMS. I’m on Facebook and there’s a deal for the Coho Winery.

Do you want to go for dinner?
Examples
The Text Mining Process

1. Text Preprocessing
   - Syntactic/Semantic analysis

2. Feature Generation
   - e.g., Bag of words

3. Feature Selection
   - Reduce large number of features

4. Data Mining
   - Clustering
   - Classification
   - Association Analysis
Text Preprocessing

1. Tokenization
2. Stopword Removal
3. Stemming
Syntactic / Linguistic Text Analysis

- **Simple Syntactic Analysis**
  - Text Cleanup (remove punctuation, HTML tags, …)
  - Normalize case
  - Tokenization (break text into single words or n-grams)

- **Advanced Linguistic Analysis**
  - Word Sense Disambiguation
    - Determine which sense a word is having.
    - Normalize synonyms (United States, USA, US)
    - Normalize pronouns ("he" → "Barack Obama")
  - Part Of Speech (POS) tagging
    - Parse sentences according to grammar
    - Determine function of each term
    - e.g. “John (noun) gave (verb) the (det) ball (noun)"
Synonym Normalization

• Usually using catalogs
  – such as WordNet

• Example for a large-scale catalog
  – Wikipedia Surface Forms

• Normalized forms: titles of Wikipedia pages
  – e.g., “United States Armed Forces”

• Other forms: anchor texts of links to that page
  – “The music of Nine Inch Nails has reportedly been used by the U.S. military as music torture to break down the resolve of detainees.”

Extracted normalization pattern:
“U.S. military” → “United States Armed Forces”
Synonym Normalization

• Catalogs work great for common knowledge
  – not so well for special domains
• Possible remedy: string similarity
• Example: edit distance
  – Notion: the minimum number of edits needed to transform one string into the other
  – Allowed edit operations:
    • insert a character into the string
    • delete a character from the string
    • replace one character with a different character
• Examples:
  – levenshtein('John Smith', 'John K. Smith ') = 3 (3 inserts)
  – levenshtein('John Smith', 'Jack Smith') = 3 (3 substitutions)
Jaro Distance

• Measures the dissimilarity of two strings
• Developed for name comparison in the U.S. Census
• Optimized for comparing person names
• Based on the number of common characters within a specific distance
• Example:

Prof._John_Doe

Dr._John_Doe
n-gram Based Similarity

- Measures the similarity of two strings
- split string into set of trigrams:
  - e.g., “similarity” becomes “sim”, “imi”, “mil”, “ila”, “lar”, ..,
- measure overlap of trigrams
  - e.g., Jaccard: \(|\text{common trigrams}| / |\text{all trigrams}|\)

- Example: clustering similar product offers on eBay
- “iPhone5 Apple” vs. “Apple iPhone 5”
  - Jaccard: 7/15 = 0.47
POS Tagging

• Task
  – determining word classes and syntactic functions
  – finding the structure of a sentence

POS Tagging

- Sometimes, multiple results are possible
  - language is ambiguous!

Charniak: Statistical techniques for natural language parsing (1997)
POS Tagging

• Supervised approach
  – Use an annotated corpus of text
  – i.e., a set of sentences with human-created POS tags

• Note: words may have different functions in different contexts (particularly in English)
  – I move (VERB) to Mannheim next year.
  – He made a clever move (NOUN).

• Naive Algorithm by Charniak (1997)
  – Use the most common tag for each word
  – Assign NOUN to every unknown word
  – Result: 90% accuracy, using a training corpus of 300,000 words
POS Tagging

• Simple algorithm for key phrase extraction
  – e.g., annotation of text corpora

• Use all NP of the form ADJ+NOUN*

• Example sentence:
  – *Text mining refers to the process of deriving high-quality information from text.*

• Key phrases:
  – *text mining* (NOUN+NOUN)
  – *process* (NOUN)
  – *high-quality information* (ADJ NOUN NOUN)
  – *text* (NOUN)
Stop Words Removal

- Many of the most frequently used words in English are likely to be useless for text mining

- These words are called *stop words*
  - examples: the, of, and, to, an, is, that, ...
  - typically text contains about 400 to 500 different stop words
  - for an application, an additional domain specific stop words list may be constructed

- Why should we remove stop words?
  - Reduce data set size
    - stop words account for 20-30% of total word counts
  - Improve efficiency and effectiveness
  - stop words may confuse the mining algorithm
    - just like irrelevant features in standard data mining
More Examples of Stopwords

a about above across after again against all almost alone along already also although always am among an and another any anybody anyone anything anywhere are area areas aren’t around as ask asked asking asks at away b back backed backing backs be became because become becomes been before began behind being beings below best better between big both but by c came can cannot can’t case cases certain certainly clear clearly come could couldn’t d did didn’t differ different differently do does doesn’t doing done don’t down downeddowning downs during e each early either end ended ending ends enough even evenly ever every everybody everyone everything everywhere f face faces fact facts far felt few find finds first for four from fully further furthered furthering furthers g gave general generally get gets give given gives go going good goods got great greater greatest group grouped grouping groups h had hadn’t has hasn’t have haven’t having he he’d he’ll her here here’s hers herself he’s high higher highest him himself his how however how’s i i’d if i’ll i’m important in interest interested interesting interests into is isn’t it its it’s itself i’ve j just k keep keeps kind knew know known knows l large largely last later latest least least least let lets let’s like likely long longer longest m made make making man many may me member members men might more most mostly mr mrs much must mustn’t my myself n necessary need needed needing needs never new newer newest next no nobody non noone nor not nothing now nowhere number numbers o of off often old older oldest on once one only open opened opening opens or order ordered ordering orders other others ought our ours ourselves out over own p part parted parting parts per perhaps place places point pointed pointing points possible present presented presenting presents problem problems put puts q quite r rather really right room rooms s said same saw say says second seconds see seem seemed seeming seems sees several shallshan’t she she’d she’ll she’s should shouldn’t show showed showing shows side sides since small smaller smallest so some somebody someone something somewhere state states still such sure t take taken than that that’s the their theirs them themselves then there therefore there’s these they they’d they’ll they’re they’ve thing things think thinks this those though thought thoughts three through thus to today together too took toward turn turned turning turns two u under until up upon us use used uses v very w want wanted wanting wants was wasn’t way ways we we’d well we’ll wells went were we’re weren’t we’ve what’s when when’s where where’s whether which while who whole whom who’s whose why why’s will with within without won’t work worked working works would wouldn’t x y year years yes yet you you’d you’ll
Stopword Removal

• Note: words may have different functions in different contexts
  – *He can* (AUX VERB) *read*.
  – *The can* (NOUN) *will rust*.

• After removing stopwords naively
  – “can” is removed
  – We cannot find out that the text is about cans
  – We cannot query for texts about cans
  – etc.
POS Tagging Revisited

• Improvement over naïve algorithm
  – respect *transition probabilities*

<table>
<thead>
<tr>
<th>The</th>
<th>can</th>
<th>will</th>
<th>rust</th>
</tr>
</thead>
<tbody>
<tr>
<td>det</td>
<td>modal-verb</td>
<td>modal-verb</td>
<td>noun</td>
</tr>
<tr>
<td>noun</td>
<td>noun</td>
<td>verb</td>
<td>verb</td>
</tr>
</tbody>
</table>

• Improves accuracy to 96-97%
• Upper limit: 98%

Charniak: Statistical techniques for natural language parsing (1997)
Stemming

- Techniques to find out the root/stem of a word.
  - Words: User, users, used, using → Stem: use
  - Words: Engineering, engineered → Stem: engineer

- Usefulness for Text Mining
  - improve effectiveness text mining methods
    - matching similar words
  - reduce term vector size
    - combing words with same roots may reduce indexing size as much as 40-50%
Lookup-based Stemming

- Create a lookup table with all inflected forms
  - e.g. WordNet, Wiktionary

- Example:

<table>
<thead>
<tr>
<th>Base Form</th>
<th>Inflected Forms</th>
</tr>
</thead>
<tbody>
<tr>
<td>move</td>
<td>moves, moved, moving</td>
</tr>
<tr>
<td>go</td>
<td>goes, went, gone, going</td>
</tr>
<tr>
<td>apple</td>
<td>apples</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>
Rule-based Stemming

• remove endings
  – if a word ends with a consonant other than s, followed by an s, then delete s (puts → put)
  – if a word ends in es, drop the s (uses → use)
  – if a word ends in ing, delete the ing unless the remaining word consists only of one letter or of th (reading → read)
  – If a word ends with ed, preceded by a consonant, delete the ed unless this leaves only a single letter (founded → found)
  – ...

• transform words
  – if a word ends with “ies” but not “eies” or “aies” then “ies” → “y” (flies → fly)
  – ...

Stemming Comparison

- **Lookup tables**
  - are accurate
  - exceptions are handled easily (e.g., *went* → *go*)
  - consume much space, in particular for highly inflected languages

- **Rule-based stemming**
  - low space consumption
  - works for emerging words without update (e.g., *iPads* → *iPad*)
  - prone to overstemming errors, e.g.
    - *sling* → *sl*
    - *sled* → *sl*
Preprocessing Operators in RapidMiner

• To use these operators, you need to install the Text Processing Extension first
Feature Generation

Text Preprocessing

Text Transformation (Feature Generation)

Feature Selection

Data Mining / Pattern Discovery

Interpretation / Evaluation
## Term-Document Matrix

| Term       | A  | B  | C  | D  | E  | F  | G  | H  | I  | J  | K  | L  | M  | N  | O  | P  | Q  | R  | S  | T  | Σ  |
|------------|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| oil        | 5  | 12 | 2  | 1  | 1  | 7  | 3  | 3  | 5  | 9  | 5  | 4  | 5  | 4  | 3  | 4  | 5  | 3  | 3  | 1  | 85 |
| price      | 5  | 6  | 2  | 2  | 0  | 8  | 1  | 2  | 2  | 10 | 5  | 1  | 5  | 2  | 0  | 3  | 3  | 3  | 3  | 0  | 63 |
| opec       | 0  | 15 | 0  | 0  | 0  | 8  | 1  | 2  | 2  | 6  | 5  | 2  | 2  | 4  | 0  | 0  | 0  | 0  | 0  | 0  | 47 |
| mln        | 0  | 4  | 0  | 0  | 2  | 4  | 1  | 0  | 0  | 3  | 9  | 0  | 0  | 0  | 0  | 3  | 3  | 0  | 0  | 2  | 31 |
| market     | 2  | 5  | 0  | 0  | 0  | 3  | 0  | 2  | 0  | 10 | 1  | 2  | 2  | 0  | 0  | 0  | 0  | 0  | 3  | 0  | 30 |
| barrel     | 2  | 0  | 1  | 1  | 0  | 4  | 0  | 0  | 1  | 3  | 3  | 0  | 1  | 1  | 0  | 3  | 3  | 1  | 0  | 2  | 26 |
| bpd        | 0  | 4  | 0  | 0  | 0  | 7  | 0  | 0  | 0  | 2  | 8  | 0  | 0  | 2  | 0  | 0  | 0  | 0  | 0  | 0  | 23 |
| dlsr       | 2  | 0  | 1  | 2  | 2  | 2  | 1  | 0  | 0  | 4  | 2  | 0  | 0  | 0  | 1  | 1  | 5  | 0  | 0  | 23 |
| crude      | 2  | 0  | 2  | 3  | 0  | 2  | 0  | 0  | 0  | 5  | 2  | 0  | 2  | 0  | 0  | 2  | 0  | 1  | 0  | 21 |
| saudi      | 0  | 0  | 0  | 0  | 0  | 0  | 1  | 0  | 0  | 5  | 7  | 1  | 4  | 0  | 0  | 0  | 0  | 0  | 0  | 18 |
| kuwait     | 0  | 0  | 0  | 0  | 0  | 10 | 0  | 1  | 0  | 3  | 0  | 1  | 0  | 2  | 0  | 0  | 0  | 0  | 0  | 17 |
| offici     | 0  | 0  | 0  | 0  | 0  | 5  | 1  | 1  | 0  | 1  | 4  | 3  | 1  | 0  | 0  | 0  | 0  | 1  | 0  | 17 |
| meet       | 0  | 0  | 0  | 0  | 0  | 3  | 0  | 1  | 1  | 0  | 1  | 0  | 2  | 0  | 0  | 0  | 0  | 0  | 0  | 14 |
| pct        | 0  | 0  | 0  | 0  | 0  | 2  | 0  | 2  | 2  | 2  | 1  | 0  | 0  | 1  | 0  | 0  | 1  | 1  | 0  | 14 |
| product    | 1  | 6  | 0  | 0  | 0  | 1  | 0  | 0  | 0  | 4  | 0  | 0  | 2  | 0  | 0  | 0  | 0  | 1  | 0  | 13 |
| accord     | 0  | 0  | 0  | 0  | 0  | 5  | 0  | 0  | 0  | 5  | 1  | 0  | 2  | 0  | 0  | 0  | 0  | 0  | 4  | 12 |
| futur      | 0  | 0  | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 1  | 1  | 0  | 0  | 12 |
| minist     | 0  | 0  | 0  | 0  | 0  | 3  | 0  | 0  | 1  | 3  | 1 | 2  | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 12 |
| govern     | 0  | 0  | 0  | 0  | 0  | 0  | 5  | 0  | 0  | 6  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 11 |
| month      | 0  | 1  | 0  | 0  | 0  | 2  | 0  | 2  | 0  | 1  | 0  | 5  | 0  | 0  | 0  | 0  | 0  | 0  | 11 |
| report     | 0  | 1  | 0  | 0  | 0  | 1  | 8  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 11 |
| sheikh     | 0  | 0  | 0  | 0  | 0  | 3  | 0  | 0  | 5  | 2  | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0  | 11 |
| industri   | 0  | 2  | 0  | 0  | 0  | 1  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 1  | 2  | 0  | 1  | 0  | 10 |
| produc     | 0  | 0  | 0  | 0  | 0  | 4  | 1  | 1  | 0  | 3  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 10 |
| quota      | 0  | 2  | 0  | 0  | 0  | 4  | 0  | 0  | 0  | 1  | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 0  | 10 |
| reserv     | 0  | 0  | 0  | 0  | 3  | 0  | 0  | 0  | 1  | 0  | 0  | 0  | 0  | 0  | 3  | 3  | 0  | 0  | 0  | 10 |
| world      | 0  | 1  | 0  | 0  | 0  | 1  | 3  | 0  | 1  | 1  | 0  | 0  | 0  | 0  | 0  | 0  | 1  | 0  | 1  | 10 |

Σ | 48 | 204 | 34 | 39 | 46 | 219 | 219 | 73 | 161 | 180 | 208 | 57 | 61 | 54 | 56 | 68 | 89 | 44 | 147 | 32 | 2039
Feature Generation

• Document is treated as a bag of words (or terms)
  – each word or term becomes a feature
  – order of words/terms is ignored

• Each document is represented by a vector.
• Different techniques for vector creation:
  – Binary Term Occurrence: Boolean attributes describe whether or not a term appears in the document
  – Term Occurrence: Number of occurrences of a term in the document (problematic if documents have different length)
  – Terms frequency: Attributes represent the frequency in which a term appears in the document (Number of occurrences / Number of words in document)
  – TF-IDF: see next slide
The TF-IDF Term Weighting Scheme

• The TF-IDF weight (term frequency–inverse document frequency) evaluates how important a word is to a corpus of documents

• TF: Term Frequency (see previous slide)
• IDF: Inverse Document Frequency
• N: total number of docs in corpus
• df$_i$: the number of docs in which ti appears

• Gives more weight to rare words
• Give less weight to common words (domain-specific “stopwords”)

\[ idf_i = \log \frac{N}{df_i} \]

\[ w_{ij} = tf_{ij} \times idf_i. \]
Feature Selection

- Not all features help!
- Learners have difficulty with high dimensional data
Pruning Document Vectors in RapidMiner

• Prune methods
  – Specify if and how too frequent or too infrequent words should be ignored

• Different options:
  – *Percentual*: ignore words that appear in less / more than this percentage of all documents
  – *Absolute*: ignore words that appear in less / more than that many documents
  – *By Rank*: Specifies how many percent of the most infrequent / infrequent words are ignored
• POS tags may help with feature selection
  – sometimes, certain classes of words may be discarded
  – e.g., modal verbs
  – e.g., adjectives
    • texts about red and blue cars are similar
    • texts about red and blue trousers are similar
Named Entity Recognition and Linking

• Named Entity Recognition (NER):
  – identifying persons, places, organizations, …

• Example:
  – “Stock quote of Apple Inc. expected to exceed $600.”
    → “Stock quote of <ORGANIZATION>Apple Inc.</ORGANIZATION> expected to exceed <AMOUNT>$600</AMOUNT>.”

• The classes of NER may be useful features
  – the exact amount of money does not matter
  – useful to know that any amount is mentioned
Named Entity Recognition and Linking

- Named Entity Linking
  - Identify named entities in a knowledge base
  - e.g., Link to Wikipedia

- May be used to create additional features
  - e.g., Wikipedia categories
    - Categories: *Mobile phone manufacturers, Technology companies of the United States*, ...
Named Entity Recognition and Linking

- Example: RapidMiner Linked Open Data Extension
  - Can use DBpedia
    (a structured subset of Wikipedia)
  - Named Entity Linking with DBpedia Spotlight
    - uses Wikipedia surface forms
    - plus contextual disambiguation
  - Feature extraction: e.g., all types of the identified entities
Named Entity Recognition and Linking

• Example set of texts:
  – “Again crash on I90”
  – “Accident on I90”

• Model:
  – type=Road → indicates traffic accident

• Applying the model:
  – “Two cars crashed on I51” → indicates traffic accident

• Note:
  – The feature “I90” alone is not as useful!
Pattern Discovery

- Clustering
- Classification
- Association Analysis
Text Mining: Clustering Definition

- Given a set of documents and a similarity measure among documents

- find clusters such that:
  - documents in one cluster are more similar to one another
  - documents in separate clusters are less similar to one another

- Question: Which similarity measures are a good choice for comparing document vectors?
Jaccard Coefficient

- **Asymmetric binary attributes**: If one of the states is more important or more valuable than the other.
  - By convention, state 1 represents the more important state
  - 1 is typically the rare or infrequent state
  - Example: Binary Term Occurences

- **Jaccard coefficient** is a popular measure

\[
\text{dist}(x_i, x_j) = \frac{M_{11}}{M_{01} + M_{10} + M_{11}}
\]

Number of 11 matches / number of not-both-zero attributes values
Jaccard Coefficient

• Sample document set:
  – d1 = “Saturn is the gas planet with rings.”
  – d2 = “Jupiter is the largest gas planet.”
  – d3 = “Saturn is the Roman god of sowing.”

• Documents as vectors:
  – Vector structure:
    (Saturn, is, the, gas, planet, with, rings, Jupiter, largest, Roman, god, of sowing)
    d1: 111111100000
    d2: 0111100110000
    d3: 111000000111

• \( \text{sim}(d_1,d_2) = 0.44 \)
• \( \text{sim}(d_1,d_3) = 0.27 \)
• \( \text{sim}(d_2,d_3) = 0.18 \)
Cosine Similarity

- Often used for computing the similarity of documents
  If d1 and d2 are two document vectors, then

\[
\cos(d_1, d_2) = \frac{d_1 \cdot d_2}{\|d_1\| \|d_2\|}
\]

where \( \cdot \) indicates vector dot product and \( \|d\| \) is the length of vector d.

- Example:
  - \(d_1 = 3 2 0 5 0 0 0 2 0 0\)
  - \(d_2 = 1 0 0 0 0 0 0 1 0 2\)
  - \(d_1 \cdot d_2 = 3*1 + 2*0 + 0*0 + 5*0 + 0*0 + 0*0 + 0*0 + 2*1 + 0*0 + 0*2 = 5\)
  - \(\|d_1\| = (3*3 + 2*2 + 0*0 + 5*5 + 0*0 + 0*0 + 0*0 + 2*1 + 0*0 + 0*2)^{0.5} = (42)^{0.5} = 6.481\)
  - \(\|d_2\| = (1*1 + 0*0 + 0*0 + 0*0 + 0*0 + 0*0 + 0*0 + 1*1 + 0*0 + 2*2)^{0.5} = (6)^{0.5} = 2.245\)
  - \(\cos(d_1, d_2) = 0.3150\)
Cosine Similarity and TF-IDF

• A commonly used combination for text clustering
• Each document is represented by vectors of TF-IDF weights

• Sample document set:
  – “Saturn is the gas planet with rings.”
  – “Jupiter is the largest gas planet.”
  – “Saturn is the Roman god of sowing.”

• First document as TF-IDF vector:
  – \((\frac{1}{7} \log(3/2), \frac{1}{7} \log(3/3), \frac{1}{7} \log(3/3), ..., 0, 0, 0, ...)\)
Cosine Similarity and TF-IDF

- Sample document set:
  - \(d_1 = \text{“Saturn is the gas planet with rings.”} \)
  - \(d_2 = \text{“Jupiter is the largest gas planet.”} \)
  - \(d_3 = \text{“Saturn is the Roman god of sowing.”} \)

- Documents as vectors:
  - Vector structure:
    (Saturn, is, the, gas, planet, with, rings, Jupiter, largest, Roman, god, of sowing)
  - \(d_1 = (0.03, 0, 0, 0.03, 0.03, 0.07, 0.07, 0, 0, 0, 0, 0) \)
  - \(d_2 = (0, 0, 0.03, 0.03, 0, 0, 0.08, 0.08, 0, 0, 0, 0) \)
  - \(d_3 = (0.03, 0, 0, 0, 0, 0, 0, 0, 0.07, 0.07, 0.07, 0.07) \)

- \(\text{sim}(d_1,d_2) = 0.13\)
- \(\text{sim}(d_1,d_3) = 0.05\)
- \(\text{sim}(d_2,d_3) = 0.0\)
Text Mining: Classification Definition

• Given: A collection of labeled documents (training set)
• Find: Model for the class (as a function of the values of the features)
• Goal: Previously unseen documents should be assigned a class as accurately as possible (test set)
• Classification methods commonly used for text
  – Naive Bayes
  – Support Vector Machines
  – (but kNN and Decision Trees may also work)
Text Mining: Sentiment Analysis

• A specific classification task
• Given: a text
• Target: a class of sentiments
  – e.g., positive, neutral, negative
  – e.g., sad, happy, angry, surprised

• Can be implemented as supervised classification task
  – requires training data
  – i.e., pairs like <text;sentiment>
Text Mining: Sentiment Analysis

• Labeling data for sentiment analysis
  – is expensive
  – like every data labeling task

• Example public data sets for labeling: reviews

  173 of 213 people found the following review helpful
  🌟🌟🌟🌟🌟 Listen Closer
  Trent Reznor should just release an album with a new title, new artwork, and new song titles. But instead of actual new material, it should all just be the songs from The Downward Spiral.

  It can be called There You Go, ****heads.

  After all, it's what everyone wants.

  I remember the day I bought The Downward Spiral. My first thought after...
  Read the full review ›
  Published 1 month ago by Philip Atherton

  Vs.
  19 of 21 people found the following review helpful
  🌟🌟🌟🌟🌟 Good, But Not Their Best
  Its funny how immediately after an established band that's been around for a while comes out with a new album all the fan-boys give reviews saying it's the greatest thing ever. I am a Nine Inch Nails fan too and have all their albums, so I'd thought I'd give my review which I hope is a little more fair.

  It's an electronic based album with some guitar, bass,...
  Read the full review ›
  Published 1 month ago by JKat

• e.g., uclassify: trained on 40,000 Amazon reviews, ~80% accuracy
Preprocessing for Sentiment Analysis

• Recap – we started our processing with:
  Simple Syntactic Analysis
  – Text Cleanup (remove punctuation, HTML tags, …)
  – Normalize case
  – …

• Suitable for some text processing tasks

• However, reasonable features for sentiment analysis might include
  – punctuation: use of “!” “?” “?!”
  – smileys (usually encoded using interpunctuation: ;-))
  – use of visual markup, where available (red color, bold face, …)
  – amount of capitalization (“screaming”)
Sentiment Analysis for Aspects

• Example product review:
  – “The image quality is good, but the zoom sucks.”

• Putting the pieces together:
  – POS tagging
  – Keyphrase extraction
  – Marking sentiment words

\[
\begin{align*}
\text{The image quality} & \text{ is good} \\
\text{but} & \\
\text{the zoom} & \text{sucks.}
\end{align*}
\]
Some Text Classification Tricks

• Finding selective words
  – weight words according to their correlation with label
  – select Top-K words with highest correlation

• Sentiment Analysis
  – use external dictionary of opinion words
  – Bing Liu’s List
    http://www.cs.uic.edu/~liub/FBS/opinion-lexicon-English.rar
  – restrict word list to these words
Text Classification: Identifying Fake Reviews

- Useful features (besides text):
  - length of review
  - use of positive sentiment words (e.g., SentiWordNet)
  - ...

- However, text classification alone only yields a low accuracy

Other ways to go:
  - include other reviews of the same reviewer, find typical patterns
  - review frequency
  - typical rating behavior
  - similarity of product description and review
  - ...
Query Completion Revisited
Query Completion Revisited

• How to refine a query?
  – Terms that frequently co-occur with the terms entered (corpus: documents)
  – Terms that are frequently searched together with the terms entered (corpus: query logs)

• Given some terms entered: t1, t2
  – look for t3 so that t1, t2, t3 is a frequent pattern

• Approach: use a corpus of texts
  – represent them as binary vectors
  – look for frequent patterns (see previous lecture)
Auto-complete Revisited

- Method: sequential pattern mining
  - find frequent *sequences* that start with a given root
  - see lecture Data Mining II
Auto-complete Revisited

- Google hosts a corpus of frequent patterns
- mined from Google books
- see http://books.google.com/ngrams/
Processing Text from Social Media

• An interesting source of knowledge
  – e.g., market research
  – e.g., opinion mining

• However, challenging to process with standard methods

• Example (a real tweet):
  – “ikr smh he asked fir yo last name so he can add u on fb lololol”
Processing Text from Social Media

• Respect special characters
  – e.g., hashtags and user mentions
  – may be treated separately

• Normalizing
  – unfolding abbreviations (“2mor0” → “tomorrow”)
  – replacing slang words with standard English
  – spelling corrections
Processing Text from Social Media

• POS Tagging
  – the POS tagger by Charniak was trained on news texts
  – will work very poorly on social media data
  – there are specialized POS taggers trained on Twitter data

• Named Entity Recognition
  – often relies on capitalized words
    • “The document was signed by the US congress.”
    • The document was signed by us.”
  – there are particular NER tools for social media
Summary

• Main task: Preprocessing of text in order be able to apply well known Data Mining algorithms

• There are lots of alternative preprocessing techniques

• Text Mining is tricky, but “ok”-ish results are easily achieved

• Additional resources:
  – Paper: Hotho et al: A Brief Survey of Text Mining
  – GATE: Feature rich open-source text processing toolkit
  – Video Series: Text Mining with RapidMiner by Vancouver Data

• If you want more
  – visit Simone Paolo Ponzetto's Lectures on Text Analytics and Web Search and Information Retrieval
Questions?