Text Data Mining:
Predictive and Exploratory Analysis of Text

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August 21, 2013
Introductions

• Hello, my name is ______.
• However, I’d rather be called ______. (optional)
• I’m in the ______ program.
• I’m taking this course because I’d like to learn how to ______.
What is Text Data Mining?

- The science and practice of building and evaluating computer programs that automatically detect or discover interesting and useful things in collections of natural language text.
Related Fields

- **Machine Learning**: developing computer programs that improve their performance with “experience”
- **Data Mining**: developing methods that discover patterns within large structured datasets
- **Statistics**: developing methods for the interpretation of data in reaching conclusions with a certain degree of confidence
Text Data Mining in this Course

• Predictive Analysis of Text
  ‣ developing computer programs that automatically recognize or detect a particular concept within a span of text

• Exploratory Analysis of Text:
  ‣ developing computer programs that automatically discover interesting and useful patterns or trends in text collections
Predictive Analysis: The Big Picture
Predictive Analysis
example: recognizing triangles
We could imagine writing a “triangle detector” by hand:
- if shape has three sides, then shape = triangle.
- otherwise, shape = other

Alternatively, we could use supervised machine learning!
Predictive Analysis
example: recognizing triangles

training

machine learning algorithm

labeled examples

model

testing

new, unlabeled examples

model

predictions
Predictive Analysis

basic ingredients

1. **Training data:** a set of examples of the concept we want to automatically recognize

2. **Representation:** a set of features that we believe are useful in recognizing the desired concept

3. **Learning algorithm:** a computer program that uses the training data to learn a predictive model of the concept
Predictive Analysis
basic ingredients

4. **Model**: a function that describes a predictive relationship between feature values and the presence/absence of the concept

5. **Test data**: a set of previously unseen examples used to estimate the model’s effectiveness

6. **Performance metrics**: a set of statistics used to measure the predictive effectiveness of the model
Predictive Analysis
representation: features
Predictive Analysis

representation: features

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Predictive Analysis
example: recognizing triangles

training

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Predictive Analysis
example: recognizing triangles

**Training**

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**Model**

**Testing**

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Predictive Analysis
basic ingredients: the focus in this course

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Training data + Representation
what could possibly go wrong?
**Training data + Representation**

**what could possibly go wrong?**

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## Training data + Representation
what could possibly go wrong?

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1. bad feature representation!
Training data + Representation
what could possibly go wrong?
Training data + Representation
what could possibly go wrong?

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## Training data + Representation

What could possibly go wrong?

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2. bad data + misleading features
Training data + Representation
what could possibly go wrong?
### Training data + Representation

**what could possibly go wrong?**

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3. bad training data!
Evaluating a Model
example: recognizing triangles

1. Make predictions on data that is “unlabeled”
   - we know what the true labels are, but the model doesn’t “see” or use these labels

2. Evaluate based on some metric that compares the model’s predicted labels with the known true labels

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Evaluating a Model
example: recognizing triangles

- Many evaluation metrics can be generated from a contingency table

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- What number(s) do we want to maximize?
- What number(s) do we want to minimize?
Evaluating a Model
example: recognizing triangles

- **True positives (A):** number of triangles correctly predicted as triangles
- **False positives (B):** number of “other” incorrectly predicted as triangles
- **False negatives (C):** number of triangles incorrectly predicted as “other”
- **True negatives (D):** number of “other” correctly predicted as “other”
Evaluating a Model
your first metric: accuracy

- **Accuracy**: percentage of predictions that are correct (i.e., true positives and true negatives)

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• **Accuracy**: percentage of predictions that are correct (i.e., true positives and true negatives)

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\frac{(A + D)}{(A + B + C + D)}
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Evaluating a Model
your first metric: accuracy

- **Accuracy**: percentage of predictions that are correct (i.e., true positives and true negatives)

- What is the accuracy of this model?
Evaluating a Model
your first metric: accuracy

- **Accuracy**: percentage of predictions that are correct (i.e., true positives and true negatives)

- What is the accuracy of this model?
Evaluating a Model
what could possibly go wrong?

- Interpreting the value of a metric on a particular data set requires some thinking ...

- On this dataset, what would be the expected accuracy of a model that does NO learning (degenerate baseline)?
Evaluating a Model
what could possibly go wrong?

- Interpreting the value of a metric on a particular data set requires some thinking ...

- On this dataset, what would be the expected accuracy of a model that does NO learning (degenerate baseline)?
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Predictive and Exploratory Analysis of Text

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August 26, 2013
Text Data Mining in this Course

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• Exploratory Analysis of Text:
  ‣ developing computer programs that automatically discover useful patterns or trends in text collections
Exploratory Analysis: The Big Picture
Exploratory Analysis
example: clustering shapes
Exploratory Analysis

example: clustering shapes
Exploratory Analysis
example: clustering shapes

unlabeled examples

clustering algorithm
Exploratory Analysis
basic ingredients

1. **Data:** a set of examples that we want to automatically analyze in order to discover interesting trends

2. **Representation:** a set of features that we believe are useful in describing the data (i.e., its main attributes)

3. **Similarity Metric:** a measure of similarity between two examples that is based on their feature values

4. **Clustering algorithm:** an algorithm that assigns items with similar feature values to the same group
### Exploratory Analysis

representation: features

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Representation
what could possibly go wrong?
Representation

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Exploratory Analysis
basic ingredients: the focus in this course

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• Exploratory Analysis of Text:
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Predictive Analysis of Text
examples we’ll cover in class

• Topic Categorization
• Opinion Mining
• Sentiment/Affect Analysis
• Bias Detection
• Information Extraction and Relation Learning
• Text-driven Forecasting
• Temporal Summarization
Predictive Analysis of Text
example applications

- **Topic Categorization**: automatically assigning documents to a set of pre-defined topical categories
Predictive Analysis of Text

element applications

• **Opinion Mining:** automatically detecting whether a span of opinionated text expresses a *positive* or *negative* opinion about the item being judged
Opinion Mining
movie reviews

• “Great movie! It kept me on the edge of my seat the whole time. I IMAX-ed it and have no regrets.” positive

• “Waste of time! It sucked!” negative

• “This film should be brilliant. It sounds like a great plot, the actors are first grade, and the supporting cast is good as well, and Stallone is attempting to deliver a good performance. However, it can’t hold up.” negative

• “Trust me, this movie is a masterpiece .... after you’ve seen it 4+ times.”
• **Sentiment/Effect Analysis:** automatically detecting the emotional state of the author of a span of text (usually from a set of pre-defined emotional states).
Sentiment Analysis
support group posts

- “[I] also found out that the radiologist is doing the biopsy, not a breast surgeon. I am more scared now than when I…”

- “… My radiologist ‘assured’ me my scan was NOT going to be cancer...she was wrong.”

- “… My radiologist did my core biopsy. Not a problem and he did a super job of it.”

- “It's pretty standard for the radiologist to do the biopsy so I wouldn't be concerned on that score.”
Predictive Analysis of Text
example applications

• **Bias detection:** automatically detecting whether the author of a span of text favors a particular viewpoint (usually from a set of pre-defined viewpoints)
Bias Detection

• “Coming [up] next, drug addicted pregnant women no longer have anything to fear from the authorities thanks to the Supreme Court. Both sides on this in a moment.” -- Bill O’Reilly

• “Nationalizing businesses, nationalizing banks, is not a solution for the democratic party, it's the objective.” -- Rush Limbaugh

• “If you're keeping score at home, so far our war in Iraq has created a police state in that country and socialism in Spain. So, no democracies yet, but we're really getting close.” -- Jon Stewart
Information extraction: automatically detecting that a short sequence of words belongs to (or is an instance of) a particular entity type, for example:

- Person(X)
- Location(X)
- TennisPlayer(X)
- ...

Predictive Analysis of Text
example applications
Information Extraction
demo

http://www.boowa.com/
• **Relation Learning**: automatically detecting pairs of entities that share a particular relation, for example:
  
  - CEO(<person>,<company>)
  - Capital(<city>,<country>)
  - Mother(<person>,<person>)
  - ConvictedFelon(<person>,<crime>)
  - ...

Predictive Analysis of Text
example applications
Relation Learning

CEO(<person>,<company>)

Marissa Mayer Yahoo

Know Yahoo's Marissa Mayer in 11 facts - CNN.com
by John D. Sutter - in 846,411 Google+ circles - More by John D. Sutter
Jul 19, 2012 – Here's a quick guide to some of the most interesting and water-cooler-worthy facts about Marissa Mayer, who was named CEO of Yahoo on

<person>, who was named CEO of <company>
Relation Learning

CEO(<person>, <company>)

CEO(Tom LaSorda, Fisker)

CEO(Sean Connolly, Hillshire Brands)

CEO(woman, Gilt Groupe)

CEO(scottish chemist, AztraZeneca)

CEO(Bob Harrison, First Hawaiian Bank)
Predictive Analysis of Text
example applications

• **Text-based Forecasting:** monitoring incoming text (e.g., tweets) and making predictions about external, real-world events or trends, for example:
  
  ‣ a presidential candidate’s poll rating
  
  ‣ a company’s stock value change
  
  ‣ a movie’s box office earnings
  
  ‣ side-effects for a particular drug
  
  ‣ ...

Predictive Analysis of Text
example applications

- **Temporal Summarization**: monitoring incoming text (e.g., tweets) about a news event and predicting whether a sentence should be included in an on-going summary of the event.

- Updates to the summary should contain relevant, novel, and accurate information.

(Diagram from Guo et al., ECIR 2013)
Detecting other interesting properties of text: [insert your crazy idea here], for example, detecting humorous text:

- “Beauty is in the eye of the beholder” not funny
- “Beauty is in the eye of the beer holder” funny

(example from Mihalcea and Pulman, 2007)
Course Overview
Road Map
first half of the semester

• Predictive Analysis of Text
  ‣ Supervised machine learning principles
  ‣ Text representation
  ‣ Basic machine learning algorithms
  ‣ Tools for predictive analysis of text
  ‣ Experimentation and evaluation
  ‣ Labeling data and learning models with noisy labels
  ‣ Feature selection

• Exploratory Analysis of Text
  ‣ Clustering
  ‣ Outlier detection (tentative)
  ‣ Co-occurrence statistics
Road Map
second half of the semester

• Applications
  ‣ Text classification
  ‣ Opinion mining
  ‣ Sentiment analysis
  ‣ Bias detection
  ‣ Information extraction
  ‣ Relation learning
  ‣ Text-based forecasting
  ‣ Temporal Summarization

• Is there anything that you would like to learn more about?
Grading

- 40% homework
  - 10% each
- 15% midterm
- 35% term project
  - 5% proposal
  - 10% presentation
  - 20% paper
- 10% participation
Grading for Graduate Students

- H: 95-100%
- P: 80-94%
- L: 60-79%
- F: 0-59%
Grading for Undergraduate Students

- A+: 97-100%
- A: 94-96%
- A-: 90-93%
- B+: 87-89%
- B: 84-86%
- B-: 80-83%
- C+: 77-79%
- C: 74-76%
- C-: 70-73%
- D+: 67-69%
- D: 64-66%
- D-: 60-63%
- F: <= 59%
General Outline of Homework

• Given a dataset (i.e., a training and test set), run experiments where you try to predict the target class using different feature representations

• Do error analysis

• Report on what worked, what didn’t, and why!

• Answer essay questions about the assignment
  ‣ These will be associated with the course material
Homework vs. Midterm

- The homework will be more challenging than the midterm. It should be, you have more time.
Term Project

http://ils.unc.edu/courses/2013_fall/inls613_001/hw/project_description.pdf
Course Tips

- Work hard
- Do the assigned readings
- Do other readings
- Be patient and have reasonable expectations
  - you’re not supposed to understand everything we cover in class during class
- Seek help sooner rather than later
  - office hours: manning 305, T. and Th. 9:30-10:30 am
  - questions via email
- Remember the golden rule: no pain, no gain
Questions?