POLI176: Text as Data*
Summer II, Tu/Th 11am-1:50pm
Yin Yuan

Class Information

Time: Tu/Th 11am-1:50pm
Zoom Link: https://ucsd.zoom.us/j/95694462805 kechang@ucsd.edu

Instructor Information

Yin Yuan
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TAs Information

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Office Hours: TBD

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Course Overview

In the digital age, a large part of human knowledge, communications and activities are recorded in the form of text that is publicly accessible in large quantities. Wikipedia, political party's manifestos, politicians' press releases, newspapers, social media posts...these new forms of data open up opportunities to explore new questions about and measure human behaviors in a way not possible before.

This course focuses on implementation of common tools of automated text analysis. We focus on two broad tasks: classification (categorizing texts into pre-specified “bins”) and scaling (arranging or scoring texts along a continuum). Within each type of task, the tools are introduced following different stages of inquiry. First, a general question is proposed which directs us to collect texts from particular sources. The collected raw texts are then preprocessed and represented in a form amenable to further statistical analyses. Next, we want to get to know our data better through exploratory analyses. In social science researches, this stage facilitates hypotheses formation. With the help of unsupervised machine learning techniques, we discover interesting ways to organize and categorize our data that inform us of questions and hypotheses that have never occurred to us. Third, inspired by our exploration, we create specific measures using texts often with the help of supervised machine learning techniques. Finally, we use these measures to test hypotheses and make causal claims that explain social phenomena or inform decisions.

This course is application oriented. While we do not delve deeply into the mathematical details behind techniques and algorithms, we do not treat them completely as black box and will help you understand their inner workings on an intuitive level.

Course Structure

Each lecture consists of two parts. In the first half of the lecture we explain how certain text analytical tools work and look at how social scientists have used them to answer interesting questions. The second half of the lecture focuses on implementation of these tools in R. We will pose coding challenges and pause for you to work them out in groups before going through solutions together.

*The development of this course is influenced by Molly Roberts, Justin Grimmer, Brandon Stewart and Arthur Spirling.
Prerequisites

The primary programming language of this course is R. Although a quick refresher of R might be given, you are highly encouraged to familiarize yourself with common data structures in R (vector, matrices, data frames, lists), conditional statement, for loop, function, the apply family, etc. This introduction to R (https://thomasleeper.com/Rcourse/Intro2R/Intro2R.pdf) covers most of the basics. Datacamp (www.datacamp.com) offers “Introduction to R” and “Intermediate R” that together take about 10 hours to complete. You can refer to these resources or other online resources (e.g. Codeacademy, Coursera) if R is completely new to you.

Problem Sets

There will be three problem sets throughout the course (please see course outline below for specific due dates). Each problem set will be posted a week prior to the due date. The problem sets are designed to be a “learning-by-doing” process where you can practice what you learned in class with real world problems.

Note: All deadlines in this course are at 11:59pm on that date.

Final Project and Memos

You will submit a report for your final project (12-15 pages, double-spaced, 12pt, tables and figures included) on September 5th (Saturday).

However, you will not complete the final project in one setting. Throughout the course, you will write three memos (1-2 pages, double-spaced, 12pt) for your final project. In each memo, you will answer to a prompt that guides you in thinking about how the methods discussed in class can help you explore the questions you are interested in.

Grading

The course grade is determined by the following components:

<table>
<thead>
<tr>
<th>Component</th>
<th>Percentage</th>
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<tbody>
<tr>
<td>Three Problem Sets</td>
<td>15%×3 = 45%</td>
</tr>
<tr>
<td>Three Memos</td>
<td>5%×3 = 15%</td>
</tr>
<tr>
<td>Final Project</td>
<td>40%</td>
</tr>
</tbody>
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Grade Scale

Final letter grades will be assigned according to the following scale:

<table>
<thead>
<tr>
<th>Grade</th>
<th>Percentage</th>
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<tbody>
<tr>
<td>A/A+</td>
<td>93 – 96/97+</td>
</tr>
<tr>
<td>A–</td>
<td>90 – 92</td>
</tr>
<tr>
<td>B+</td>
<td>87 – 89</td>
</tr>
<tr>
<td>B</td>
<td>83 – 86</td>
</tr>
<tr>
<td>B–</td>
<td>80 – 82</td>
</tr>
<tr>
<td>C+</td>
<td>77 – 79</td>
</tr>
<tr>
<td>C</td>
<td>73 – 76</td>
</tr>
<tr>
<td>C–</td>
<td>70 – 72</td>
</tr>
<tr>
<td>D</td>
<td>60 – 69</td>
</tr>
<tr>
<td>F</td>
<td>0 – 59</td>
</tr>
</tbody>
</table>
Please note: students taking Pass/Not Pass as grading option must achieve a C– (i.e. 70) for a Pass.

**Logistics and Class Policy**

The lectures will be recorded and uploaded after class for the convenience of students in different time zones.

In general, late assignments will be deducted 2 points passing the deadline (with a 30-minute grace period) and additional 2 points for every 24 hours passing the deadline. However, we understand the challenges and struggles amid the pandemic and political events, so please reach out to us if you need an extension (prior to the due date) or if you need any help. Your health, whether physical or mental, always takes priority.

The university’s Principles of Community along with all rules and practices regarding Academic Integrity apply in this course. Although you are encouraged to work together in class on coding challenges, I expect you to work on the problem sets and final project INDEPENDENTLY. Please do not share codes or any other form of solutions to the problem sets with other students.

**Textbook and course readings**

This class does not require a main textbook. Most of the readings are recent publications on the subject matter and occasionally book chapters are picked from multiple textbooks.

For those interested, here is a list of the most recommended textbooks in machine learning and natural language processing. All of them have free electronic versions online. Some electronic copies could be accessed via UCSD library while connected to UCSD VPN.

**Machine Learning**


**Natural Language Processing**

Course Outline

Introducing Text as Data

In this section, we briefly survey the fast evolving field of automated text analysis and shows the potentials and challenges of its application in social sciences. We provide an overview of the techniques you are about to learn and the logic behind how the course is organized.

August 4: Potentials and Limits of Text as Data


Collect, Select, Preprocess and Represent Texts

In this section, we are going to learn how to collect and select text and think about the challenges that might emerge in this process (e.g. selection bias, generalizability). We will also learn how to transform raw texts into numerical form for statistical analysis and the implication of the choices we make.

August 6: Collect, Select, Preprocess and Represent Texts


Unsupervised Classification: Exploring What We Want to Measure

In this section, we will learn how to discover interesting ways to categorize and organize our text data. At this point, we still do not know what our data has to offer, and we do not have clear enough hypotheses to know what to measure or what categories we should group our texts into. We use unsupervised methods to help with hypotheses formation. In addition, we will learn how to characterize and summarize the patterns that emerge by finding distinctive words and interpreting topic model outputs.

August 11: Clustering and PCA


August 13: Distinctive Words

Memo 1 Due


Optional


August 18: Topic Models: Theory


Optional


August 20: Topic Models: Interpretation and Application

Problem Set 1 Due
Memo 2 Due


Optional


**Supervised Classification: Categorizing Texts into Known Categories**

Given the categories and organizational structures we just discovered, how do we proceed to accurately and efficiently place our texts into the right “bins”? In this section, we will learn how to turn our texts into quantitative measures (either as classifications or proportions of categories) given our hypotheses.

**August 25: Naive Bayes, SVM, Readme**

• 3.4. Hastie, Tibshirani, and Friedman. The Elements of Statistical Learning Springer


Optional


August 27: Ensemble and Validation (CONTINUE INTO DICTIONARY METHODS)

Problem Set 2 Due
Memo 3 Due


– Section 2.2 and 5.1. James, Witten, Hastie and Tibshirani. An Introduction to Statistical Learning Springer.

Optional


Arranging Texts in a Continuum: Dictionary and Scaling

Often instead of dichotomous or discrete measures, we would like to arrange our texts in a continuum. Rather than knowing a politician is a conservative or a liberal, we are more interested in quantifying where he/she is located on a left-right scale. Sometimes even the dimensions along which texts are arranged themselves are subjects of interests. Like classification tasks, we can use supervised methods to score or scale a text with a pre-defined “ruler”, or we can discover the “rulers” themselves first.

August 27 (CONTINUED): Dictionary


September 1: Scaling: Wordscore and Wordfish


Discovering Dimensions

Causal Inference, Text Network and Word Embedding

In social sciences, we often do not stop at exploratory and descriptive analyses. Our ultimate goal of discovering and creating measures is to reveal relationships between phenomena we are interested in, especially causal relationships. In other words, we would like to be able to not only predict, but also explain. Moreover, we use language to communicate, and we communicate in a social network. How could we combine the power of text analysis and social network analysis (SNA) to study patterns of communication? Finally, rapid progress in Natural Language Processing (NLP) and deep learning has enabled us to model language in a much more sophisticated way. We will look at how word embeddings represent the meaning of words by capturing the context of their appearances.

September 3: Causal Inference, Text Network and Word Embedding

Problem Set 3 Due

Optional

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Problem Set 3 Due

Optional

Optional