AD VALOREM REVENUE AND SCHOOL QUALITY:

PREDICTING SCHOOL PERFORMANCE IN OKLAHOMA PUBLIC SCHOOLS USING NEURAL NETWORKS, PCA AND REGRESSION

Tom Curran

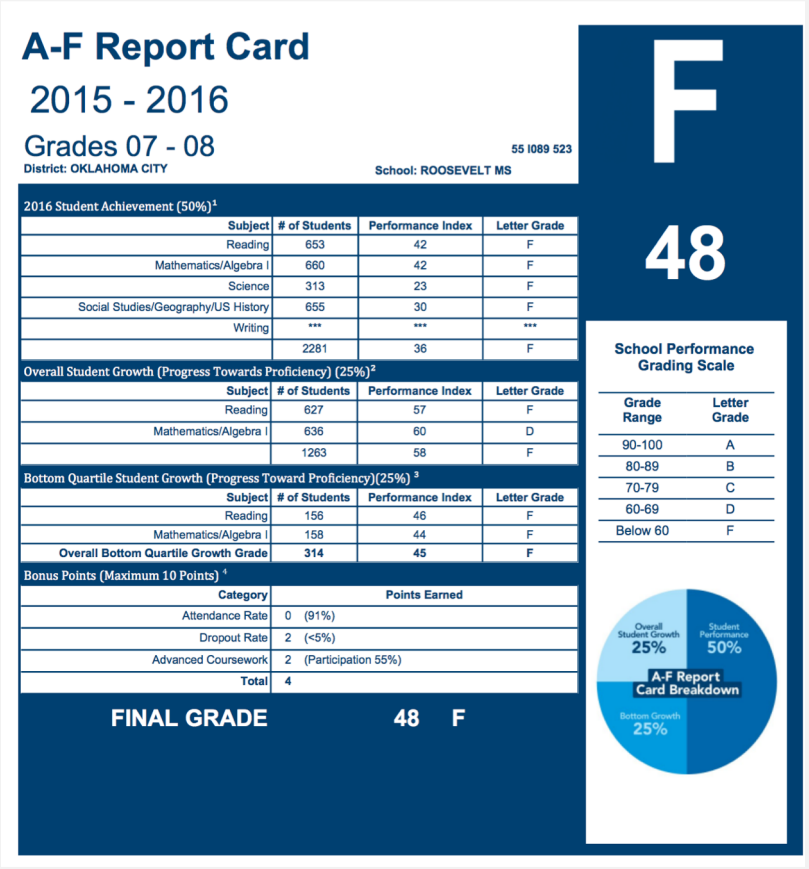
MACSS Project Proposal

April 4, 2018

RESEARCH QUESTION:

- **Is a school district's ad valorem revenue the primary driver of school quality in Oklahoma?**

- Oklahoma school quality is measured in through a statewide evaluation tool called the A – F Report card
- Schools are issued a letter grade at the end of each academic year to judge their academic performance on end of year state subject tests
- A-F Letter grade is based entirely on test performance and does not account for socio-economic factors



A-F Report Card

2015 - 2016

Grades 07 - 08

55 I089 523

District: OKLAHOMA CITY

School: ROOSEVELT MS

2016 Student Achievement (50%)[1]

Subject	# of Students	Performance Index	Letter Grade
Reading	653	42	F
Mathematics/Algebra I	660	42	F
Science	313	23	F
Social Studies/Geography/US History	655	30	F
Writing	***	***	***
	2281	36	F

Overall Student Growth (Progress Towards Proficiency) (25%)[2]

Subject	# of Students	Performance Index	Letter Grade
Reading	627	57	F
Mathematics/Algebra I	636	60	D
	1263	58	F

Bottom Quartile Student Growth (Progress Toward Proficiency)(25%)[3]

Subject	# of Students	Performance Index	Letter Grade
Reading	156	46	F
Mathematics/Algebra I	158	44	F
Overall Bottom Quartile Growth Grade	**314**	**45**	**F**

Bonus Points (Maximum 10 Points)[4]

Category	Points Earned
Attendance Rate	0 (91%)
Dropout Rate	2 (<5%)
Advanced Coursework	2 (Participation 55%)
Total	4

FINAL GRADE 48 F

F

48

School Performance Grading Scale

Grade Range	Letter Grade
90-100	A
80-89	B
70-79	C
60-69	D
Below 60	F

RESEARCH SUPPORTS CONVENTIONAL WISDOM

- **More money means more and better teachers:**
  - "Students of less effective teachers experienced reading achievement gains of one third of a standard deviation less than that of students with effective teachers. In mathematics the differences was slightly less than one half a standard deviation." (Stronge et al 2008)
- **More money means smaller class sizes, even when quality teachers are not available**
  - *Class Size Reduction and Student Achievement: The Potential Tradeoff between Teacher Quality and Class Size* (Jepsen et al 2007)

RESEARCH ALSO DISPROVES CONVENTIONAL WISDOM:

- **School quality and outcomes of students is not related to student teacher ratio or spending:**
  - "…studies find that, on balance, improving school resources such as the pupil-teacher ratio or per pupil spending do not improve students performance on standardized achievement tests" (Eide et al 1997)
  - *The Effects of Class Size on Student Achievement: New Evidence from Population Variation* (Hoxby 2008)
- **A students performance is not related to school quality but more reliant on parents and family:**
  - "Most previous research on effects of school has concluded that the effect of school or teacher quality on academic achievement is less than that of family background or other characteristics" (Heyneman et al 1983)
- **School quality doesn't matter at all:**
  - *Does School Quality Matter? Evidence From The National Longitudinal Survey of Youth* (Betts 1995)

GOALS & CONTRIBUTION OF RESEARCH:

- **Goals**:
  - Understand how different economic and sociological factors interact with each other to influence school quality
  - Create predictive model for school quality using Oklahoma's existing A-F Framework
  - Employ model to create and enhance existing policy levers

- **Research Contribution:**
  - Very little school quality program evaluation literature employs neural networks
  - Using neural networks and other theoretical approaches means model is not constrained to a subject domain
  - Captures the complex interactions of variables that eludes other predictive or explanatory models
  - Brings together diverse but related data sets to develop a more robust models

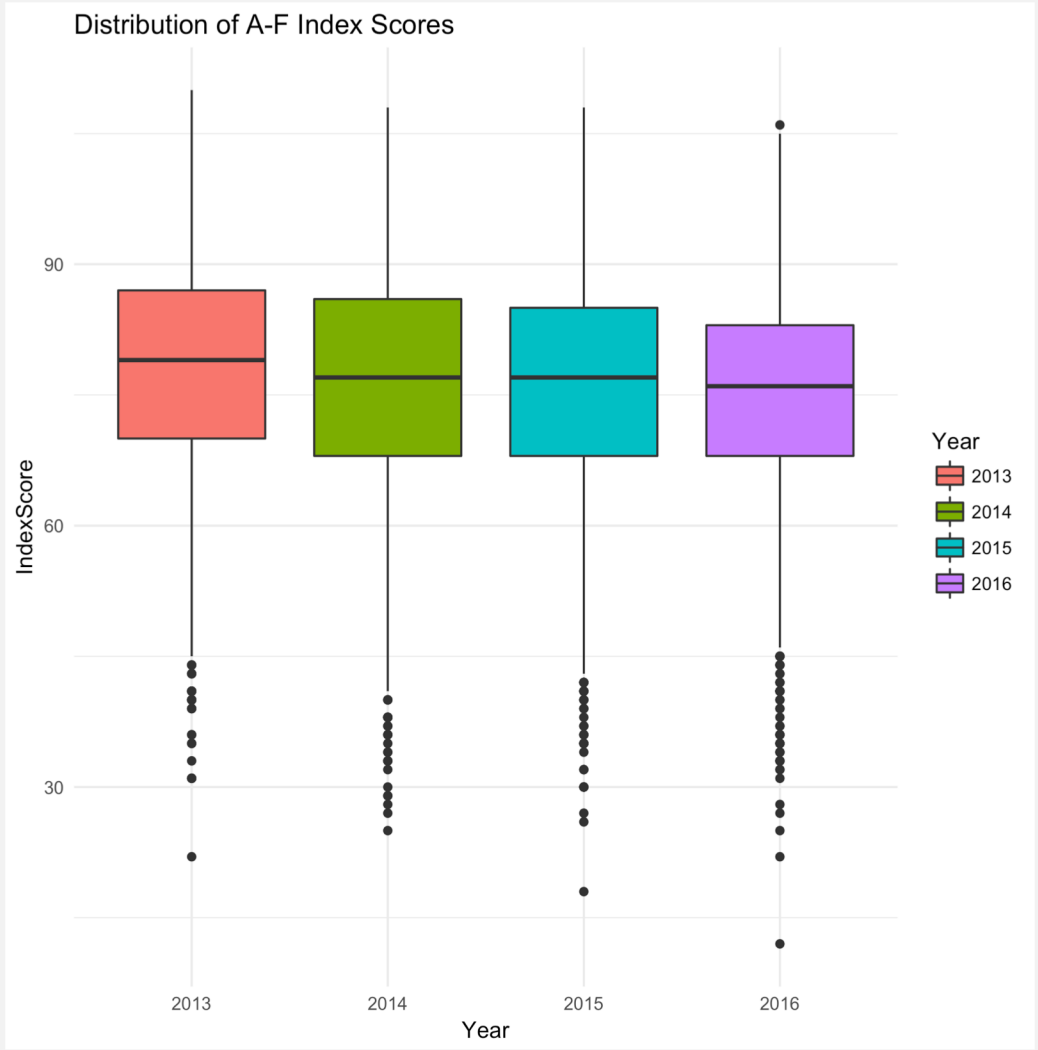
WHY THIS PROJECT IS INTERESTING

- Oklahoma is ranked #39 in education
- What's the Matter with Oklahoma – Economist Article from January 30th 2018
- Budget Crisis forces 4 day school week
- As of April 2, 2018 Teachers in Oklahoma are on strike – similar to West Virginia
- Ad Valorem Taxes make up a large percentage of school district's revenue
- Lots of economic activity in Oklahoma
  - Scott Pruitt, former AG of Oklahoma, opened Oklahoma to fracking for oil and gas causing a surge in revenues for Oklahoma counties and added land valuation
  - Google building server farms in Oklahoma (Minco County)

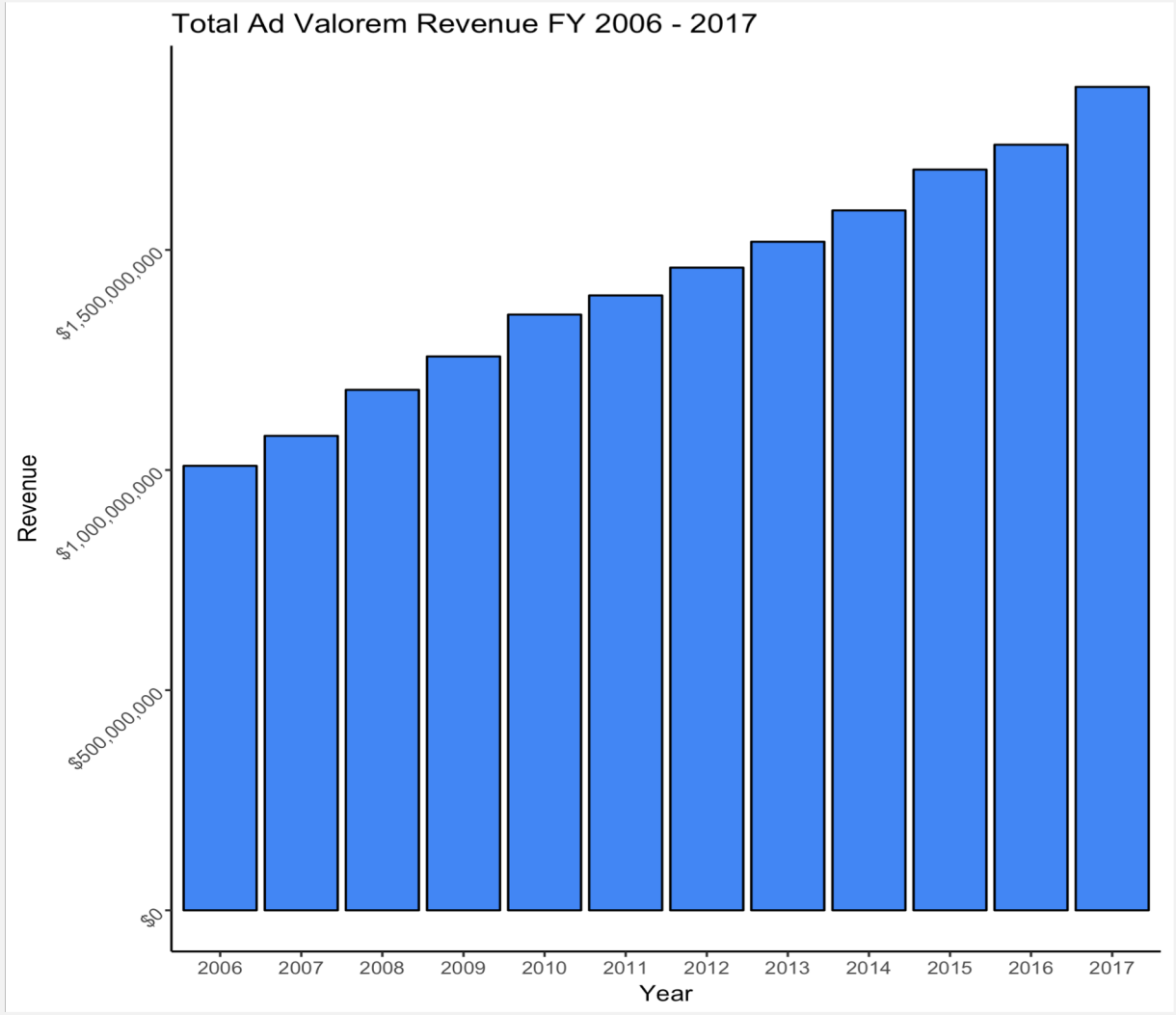
DATA AND SOURCES

- Oklahoma has a robust reporting index that offers rich variety of data source:
  - **Office of Educational Quality and Accountability District and School Profile Reports**
    - Reports will provide basis for non financial dimensions to analysis
    - Included Data:
      - ADM, ADA, % Attending College, Average ACT Score, Suspension Rates, Average Income, Average Property Value, % of parents attending Parent Teacher Conference, juvenile arrests, Free and Reduced Lunch
  - **Oklahoma Cost Accounting System District Revenue Summary Reports:**
    - Detailed break down of state and federal incomes for school budgets
    - Will act as the main source of calculating ad valorem revenue as well as any other revenue source
    - Data available from 2006 to 2017
  - **Oklahoma A-F Reporting Index:**
    - Contains A-F Index Scores and inputs into A-F Score for 2013 - 2016

SOURCE: OKSDE A-F REPORT INDEX



SOURCE: OCAS DISTRICT REVENUE SUMMARY REPORT



THEORY & METHODS:

- Use three different methods to test model:
  - **Linear Regression**
    - Predict A-F Index Score using linear model
  - **Principal Component Analysis (PCA)**
    - Dimensionality Reduction combined with Regression methods
  - **Artificial Neural Network**
    - Capture hidden layers, non-linear relationships and interaction effects that illustrates the complexity that goes into measuring school quality.

- Using these theories and methods I will evaluate the performance to see which one provides the most accurate prediction of school quality

COMPUTATIONAL TOOLS:

- **MySQL**
  - Use database hosted by the Oklahoma Public School Resource Center to aggregate and manage necessary data

- **Python**
  - Data Cleaning and Management – SQLAlchemy, Pandas, Numpy
  - Multinomial Logistic Regression – Scikit learn LogisticRegression()
  - Principal Component Analysis – Scikit Learn Decomposition()
  - Artificial Neural Network – Tensor Flow, PyTorch

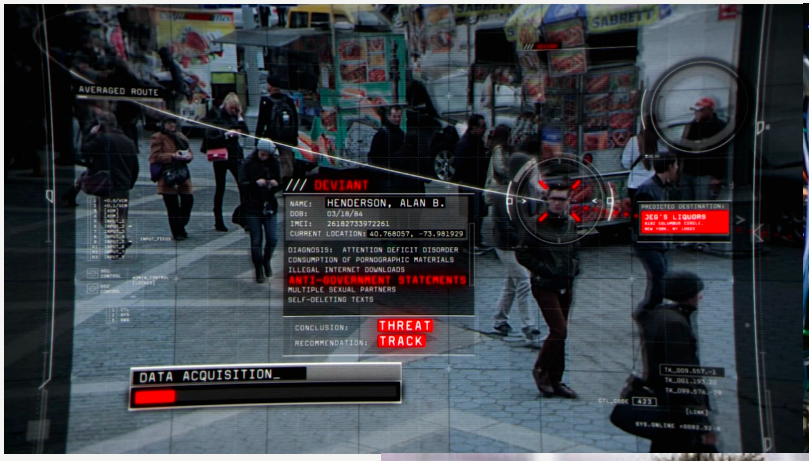
PREDICT CRIME

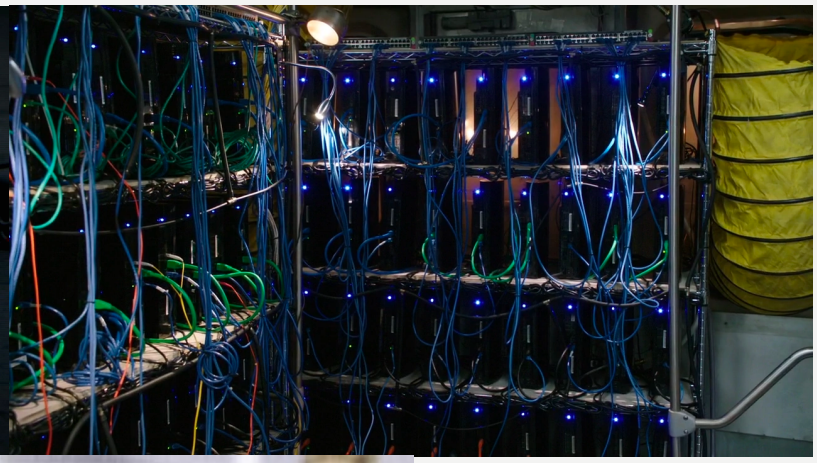
USING SPATIAL AND TEMPORAL APPROACH

A COMPARISON STUDY BETWEEN CHICAGO AND SEATTLE

Yangyang Dai

RESEARCH BACKGROUND AND IDEAS





A crime will happen!!!

When ??
Where ??

AVAILABLE STUDIES AND RESOURCES

- Example studies:
- Predict London crime rates, predict crime types in Denver, Los Angeles and etc.
- Eg. A. Bogomolov, B. Lepri, J. Staiano, N. Oliver, F. Pianesi and A. Pentland, 'Once Upon a Crime: Towards Crime Prediction from Demographics and Mobile Data', CoRR, vol. 14092983, 2014.
- Methods overview:
  - SVM: using this method is still slow and computationally expensive
  - Fuzzy time series: works well on binary data, but not so much on more levels
  - Artificial neural network (ANN): relatively accurate, but takes a long time in training phases
  - Unsupervised method by using multivariate time series based on parametric Minkowski model and dynamic time wrapping (DTW), however, this method is difficult to handle a missing value in order to get more accurate results
  - Bayesian Network: it may lead to some deviation during conducted the experiment, so the more factors unrelated to the geography should be considered to improve the accuracy of the model.
  - decision tree: eg, the result of crime cases has been classified into two classes such as neutral and danger. However, this method does not work well on all type of datasets.
  - logistic regression: the limitation of this approach is difficult to identify the probability of burglary activity and specific locations.

AVAILABLE STUDIES AND RESOURCES

- **Contribution** and **focuses:**
- mid-west vs. west coast
- the newly developed vs. Early developed
- Crime city vs. civilized city

CRIME DATA

- Mid-West
  - With relatively long history, early-developed
  - infamous for the crime, gangs

- Chicago crime – 2001 to present
- extracted from the Chicago Police Department's CLEAR (Citizen Law Enforcement Analysis and Reporting) system
- 22 attributes (id, date, block, x, y coordinate etc.), 6.57M instances of crimes
- https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-present/ijzp-q8t2

ID	Case Numb	Date	Block	IUCR	Primary Type	Description	Locati
11267718	JB201047	03/26/2018 11:55:00 PM	066XX S WESTERN AVE	0860	THEFT	RETAIL THEFT	GAS ST
11267724	JB201048	03/26/2018 11:45:00 PM	007XX S WELLS ST	1330	CRIMINAL TRESPASS	TO LAND	CONST
11267725	JB201049	03/26/2018 11:45:00 PM	117XX S THROOP ST	0910	MOTOR VEHICLE THEFT	AUTOMOBILE	STREET
11267755	JB201053	03/26/2018 11:40:00 PM	064XX W IRVING PARK RD	1330	CRIMINAL TRESPASS	TO LAND	GROCE
11267705	JB201038	03/26/2018 11:35:00 PM	068XX S ASHLAND AVE	502P	OTHER OFFENSE	FALSE/STOLEN/ALTERED TRP	STREET
11267737	JB201040	03/26/2018 11:30:00 PM	031XX S KEELER AVE	0326	ROBBERY	AGGRAVATED VEHICULAR HIJACKING	STREET
11267784	JB201062	03/26/2018 11:30:00 PM	040XX W MAYPOLE AVE	031A	ROBBERY	ARMED: HANDGUN	STREET
11267753	JB201044	03/26/2018 11:19:00 PM	039XX W 63RD ST	1812	NARCOTICS	POSS: CANNABIS MORE THAN 30GMS	STREET
11267813	JB201046	03/26/2018 11:15:00 PM	003XX W 109TH PL	0486	BATTERY	DOMESTIC BATTERY SIMPLE	RESIDE
11268448	JB202026	03/26/2018 11:15:00 PM	007XX W 47TH ST	1320	CRIMINAL DAMAGE	TO VEHICLE	STREET
11267714	JB201023	03/26/2018 11:10:00 PM	071XX S ASHLAND AVE	0320	ROBBERY	STRONGARM - NO WEAPON	STREET
11267792	JB201032	03/26/2018 11:08:00 PM	077XX S CORNELL AVE	1310	CRIMINAL DAMAGE	TO PROPERTY	RESIDE
11267701	JB201028	03/26/2018 11:05:00 PM	033XX W WARNER AVE	1320	CRIMINAL DAMAGE	TO VEHICLE	STREET
11268384	JB201839	03/26/2018 11:05:00 PM	056XX S WABASH AVE	0620	BURGLARY	UNLAWFUL ENTRY	APARTM

CRIME DATA

West coast
- Newly developed, tech-oriented

- Seattle crime – 2010 to 2017
- all the Police responses to 9-1-1 calls within the city
- 19 attributes, 1.47M instances
- https://data.seattle.gov/Public-Safety/Seattle-Police-Department-911-Incident-Response/3k2p-39jp?category=Public-Safety&view_name=Seattle-Police-Department-911-Incident-Response

Hundred Block Location	District/Sec	Zone/B	Census Tr	Longitude	Latitude	Incident Location
3 AV S / S WASHINGTON ST	K	K3	9200.2014	-122.330271593	47.600875809	(47.600875809°, -122.330271593°)
20XX BLOCK OF 15 AV W	Q	Q1	5802.2003	-122.37613941	47.636336049	(47.636336049°, -122.37613941°)
6 AV / YESLER WY	K	K3	9200.1002	-122.326350868	47.601708802	(47.601708802°, -122.326350868°)
86XX BLOCK OF 24 AV SW	F	F2	11401.2005	-122.363172642	47.525585666	(47.525585666°, -122.363172642°)
135XX BLOCK OF 23 AV NE	L	L1	200.6017	-122.304248161	47.727498035	(47.727498035°, -122.304248161°)
63XX BLOCK OF 29 AV SW	F	F1	10700.4001	-122.369833395	47.546493546	(47.546493546°, -122.369833395°)
MARTIN LUTHER KING JR WY S / S GENESEE ST	R	R2	10001.3006	-122.295370641	47.563805602	(47.563805602°, -122.295370641°)
CALIFORNIA AV SW / SW ALASKA ST	W	W2	10500.4003	-122.386778535	47.561104368	(47.561104368°, -122.386778535°)
24XX BLOCK OF AURORA AV N	Q	Q2	6000.2045	-122.346642846	47.641419741	(47.641419741°, -122.346642846°)
43XX BLOCK OF S FERDINAND ST	R	R3	10300.1002	-122.278843236	47.558197565	(47.558197565°, -122.278843236°)
68XX BLOCK OF 30 AV NE	U	U3	3800.1004	-122.29516869	47.678505415	(47.678505415°, -122.29516869°)
1XX BLOCK OF NW 81 ST	J	J2	2900.1014	-122.359311741	47.687664142	(47.687664142°, -122.359311741°)
26XX BLOCK OF S DEARBORN ST	G	G3	8900.4011	-122.298174668	47.595534943	(47.595534943°, -122.298174668°)
30XX BLOCK OF E UNION ST	C	C3	8800.1000	-122.293157653	47.612937729	(47.612937729°, -122.293157653°)

METHODS – FRAMEWORK

- Ideas:
- Build models using Chicago and Seattle crime data, train and test the two models, and predict the crime in each two cities
- Compare the temporal and spatial crime distributions
- Understand the differences and similarities between two cities
  - Crime distribution over the 12 months, Weekly distribution, daily distribution
  - Location or neighborhood differences (apart, street, sidewalk, school…)
  - Crime type differences

METHODS – DATA PREPARATION

- Data cleaning: missing values
- Data reduction: eg. possible dimension reduction
- Data integration: eg. unify attribute naming, adopt military time system
- Data Transformation and Discretization:
  - create crime_type, crime_time variables, group into smaller subsets if too many, into hour intervals

METHODS – MODELS AND ANALYSIS

- **Apriori Algorithm**
  - to find all possible crime frequent patterns regardless of the committed crime type
  - come up with a list of all crime hotspots along with its related frequent time
- **Naïve Bayesian Classifier**
  - assumes the independent effect between attribute value
  - sklearn
  - Multinomial Näive Bayes, crime type prediction
- **Decision Tree Classifier**
  - sklearn
  - entropy function for the information gain to measure the quality of the split

Evaluation:

- prediction accuracy
- Running time

POTENTIAL RESULTS

- Spatial and temporal hot spots in Chicago and Seattle
- Comparison of crime patterns
- Predicted Crime type in a given location within a give period of time

- Questions?

WHY HAVE THE CHINESE BECOME MORE TOLERATE ON PUPPY LOVE SINCE LATE 2000S: A FUNCTIONAL ANALYSIS

YILUN DAI

RESEARCH QUESTION: INTRODUCTION

- The Chinese Definition of puppy love: 早恋 (zao lian, early love), most commonly refer to dating and having a love relationship before college
- Puppy love has been a taboo from 1950s to early 2000s
- However, there has been an increasing tolerance on puppy love since late 2000s
- Why are Chinese people changing their opinion?

RESEARCH QUESTION: PAST LITERATURE

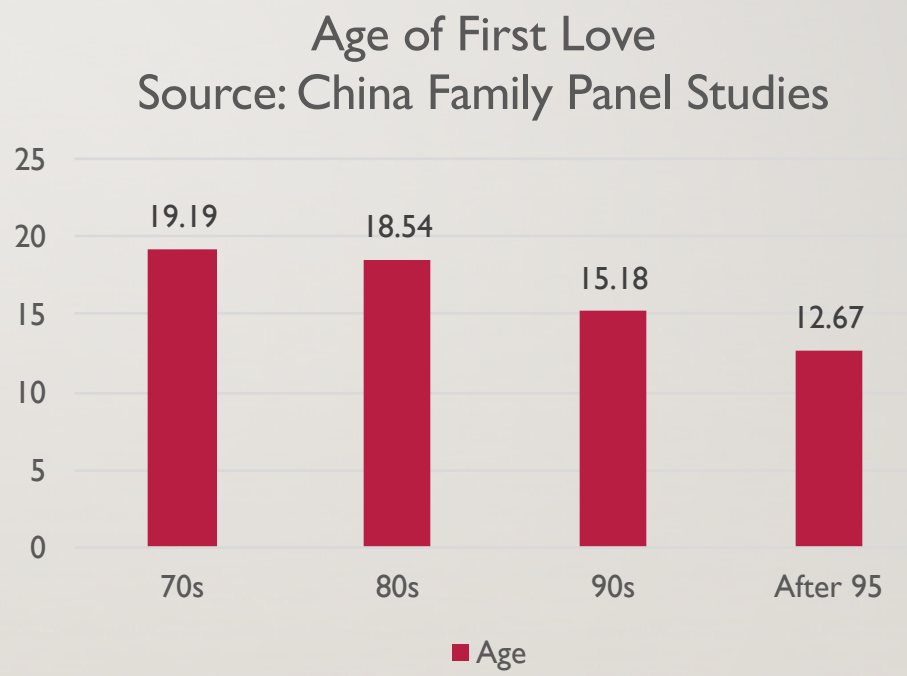
- Shen, Y. (2015). Too young to date! The origins of zaolian (early love) as a social problem in 20th-century China. History Of Science, 53(1), 86.
  - Provided structural explanation for this taboo in 20th century
  - Purpose: to prevent early marriage, early birth and school drop-outs
  - Qualitative analysis on political documents
- Wang, J. (2013, August 31). Puppy love no longer taboo [Electronic version]. *Shanghai Daily*
  - Gave cultural explanations on the change: many parents themselves experienced puppy love and controlling parents, and therefore are more understanding

RESEARCH QUESTION: THIS PROJECT

- Will provide functional and structural explanation on the recent change in attitude towards puppy love
- Will use computational methods and quantitative analysis

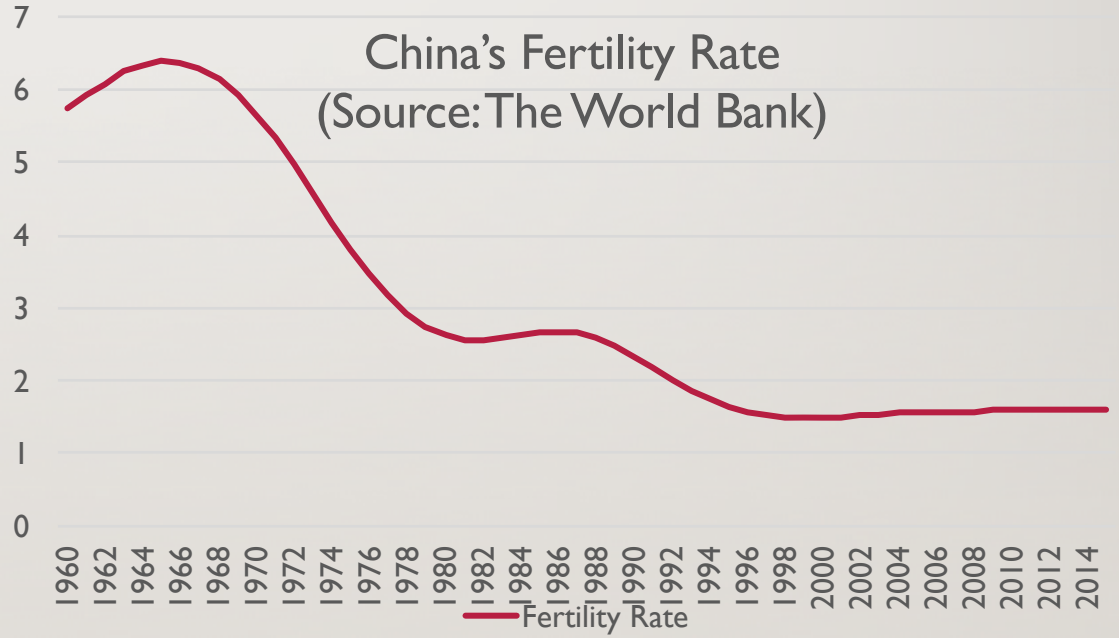
DATA USED

- Love relationships and marital status statistics from China Family Panel Studies (PKU and i.baihe.com, 2015)
- Movie and TV series data from Douban
- Chinese Fertility rate and marriage rate statistics from the World Bank
- Study abroad statistics: National Bureau of Statistics of China



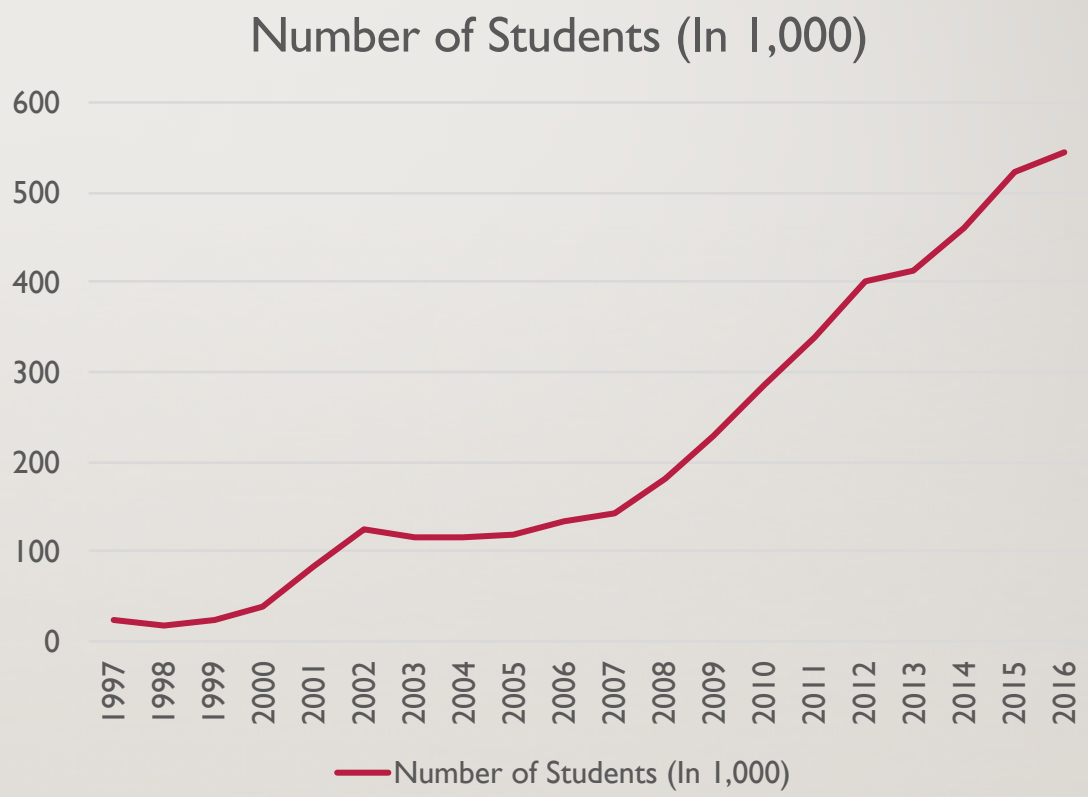
DATA USED: FERTILITY RATE

- Plunging fertility rate since 1990
- One Child Policy became effective in 1980s not 90s
- little change even after the "second child policy"



DATA USED: NUMBER OF STUDENTS STUDYING ABROAD

- Form of education is diversifying
- College Entrance Exam (Gaokao) is no longer the only way to higher education
- Score is no longer the one and only standard for "good student"



METHODS AND TOOLS

- Web crawling: fetching TV series data from Douban
  - Tool: Beautifulsoup in Python
- Digital Survey on first love age, opinions on marriage, and childbirth
- Time Series Analysis: constructing VAR models with exogenous variables and conduct Granger Causality test
  - Tool: R studio

THEORIES USED:

- VAR model with exogenous variables (Christopher Sims, 1980):
  - A multivariate time series process that includes both exogenous and endogenous variables
  - $Y(t) = \sum_{j=1}^{p} A_{11,j} X(t-j) + \sum_{j=1}^{p} A_{12,j} Y(t-j) + E_1(t)$
- Granger Causality:
  - "If a signal X_1 "Granger causes" a signal X_2, then past values of X_1 should contain information that helps predict X_2 above and beyond the information contained in past values of X_2 alone" (Anil Seth, 2007). Theory developed by Clive Granger in 1960s.
  - $X_1(t) = \sum_{j=1}^{p} A_{11,j} X_1(t-j) + \sum_{j=1}^{p} A_{12,j} X_2(t-j) + E_1(t)$
  - $X_2(t) = \sum_{j=1}^{p} A_{21,j} X_1(t-j) + \sum_{j=1}^{p} A_{22,j} X_2(t-j) + E_2(t)$

HYPOTHETICAL RESULT

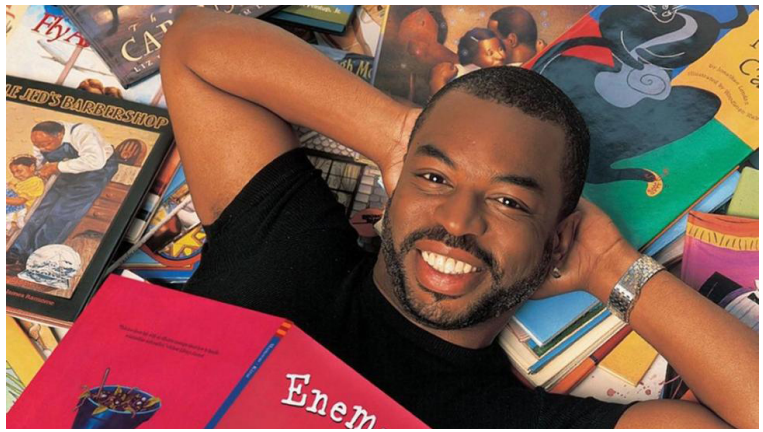
- The number of TV series that have puppy love contents is increasing
- The declining fertility rate and marriage rate, and the increasing number of students studying abroad granger cause the increasing tolerance of puppy love in China

Take a Look!: Investigating the Relative Contributions of Children's Books and Child-Directed Speech

Joseph Denby

Perspectives on Computational Research

April 4, 2018



How do we learn language?

or, more specifically,

From where do children glean English language rules/use and what does each source contribute respectively?

Background

- Extensive work on child-directed speech (CDS)
  - Aspects of CDS predict vocabulary skill (Rowe 2008; Rowe 2012)
  - CDS linguistic construction differs markedly from standard speech (Cameron-Faulkner et al., 2001)
- Recent work investigates children's books as important source
  - e.g., Whitehurst et al., 1988; Montag et al., 2015; Montag et al., 2017

Setup / Objective

- Caregiver speech and picture books are two prominent sources of linguistic input for children
- Research has historically neglected the latter
- Important to assess their relative (unique?) contributions

Montag et al.(2015), 2

What language-learning data might early picture books provide that everyday conversations do not?

Objective

Question(s) for this project:

Are there substantive differences in the content of child-directed speech and age-appropriate children's books? If so, what?

Procedure

- Exploratory Content Analysis on Speech and Text Corpora
  1. Relative POS usage across time
  2. Average sentence complexity (using tree parsing)
  3. Lexical diversity through type-token ratio (TTR)
  4. ...etc.

Corpora – Language Development Project (LDP)

- UChicago-based initiative to document parent-child interactions with a socioeconomically-diverse sample ($n = 102$)
- Ecological check-ins between ages 14 - 58 months at four month intervals
- Analysis draws from transcripts of caregiver speech

	subject	age	p_chat
0	22	1	play with Mommy's hand . no . no, no, no . nop...
1	22	2	what are you crawling for ? stand up . what ...
2	22	3	you want to show her how you do a head+stand ?...
3	22	4	how do flowers taste ? yeah . do you eat flow...
4	22	5	what ? you brought it down because you said...
5	22	6	do do do . &xxx get the foot book ? where is ...
6	22	7	right ? are you a mysterious girl ? no on...

Corpora – Books

Montag, J. L., Jones, M. N., & Smith, L. B. (2015). The words children hear: Picture books and the statistics for language learning. Psychological Science, 26, 1489-1496.

Alexander and the Terrible, Horrible, No Good, Very Bad Day by Judith Viorst
Angelina Ice Skates by Katharine Holabird
Are You My Mother? by P. D. Eastman
Arnie the Doughnut by Laurie Keller
Arthur Writes a Story by Marc Brown
A Bad Case of Stripes by David Shannon
Bark, George by Jules Feiffer
Bear Wants More by Karma Wilson
The Berenstain Bears and the Green-Eyed Monster by Stan Berenstain and Jan Berenstain
The Berenstain Bears Forget Their Manners by Stan Berenstain and Jan Berenstain
Blueberries for Sal by Robert McCloskey
Bread and Jam for Frances by Russell Hoban
Brown Bear, Brown Bear, What Do You See? by Bill Martin, Jr.
Bunny Party by Rosemary Wells
Caps for Sale by Esphyr Slobodkina
The Carrot Seed by Ruth Krauss
The Cat in the Hat by Dr. Seuss
Charlie and the New Baby by Ree Drummond
Chicka Chicka 1-2-3 by Bill Martin, Jr., Michael Sampson, and Lois Ehlert
Chicka Chicka Boom Boom by Bill Martin, Jr., and John Archambault
Chrysanthemum by Kevin Henkes
How Do Dinosaurs Say Good Night? by Jane Yolen and Mark Teague
How to Train a Train by Jason Carter Eaton
If You Give a Moose a Muffin by Laura Joffe Numeroff
If You Give a Mouse a Cookie by Laura Joffe Numeroff
I'm a Big Sister by Joanna Cole
The Keeping Quilt by Patricia Polacco
Knuffle Bunny by Mo Willems
Ladybug Girl at the Beach by David Soman and Jacky Davis
Lilly's Purple Plastic Purse by Kevin Henkes
Little Blue Truck Leads the Way by Alice Schertle
The Little Engine That Could by Watty Piper
The Little House by Virginia Lee Burton
Llama Llama Home With Mama by Anna Dewdney
Llama Llama Red Pajama by Anna Dewdney
The Lorax by Dr. Seuss
Love You Forever by Sheila McGraw
Madeline by Ludwig Bemelmans
Maisy Goes Camping by Lucy Cousins
Maisy Goes to the Library by Lucy Cousins
Make Way for Ducklings by Robert McCloskey
Mike Mulligan and His Steam Shovel by Virginia Lee Burton
Miss Rumphius by Barbara Cooney
The Napping House by Audrey Wood
No, David! by David Shannon
Oh, the Places You'll Go by Dr. Seuss

Projections

- Replicate previous work showing that books exhibit higher TTR (with different speech corpus)
- Uncover meaningful distinctions between syntactic make-up of books vs. speech
  - Hopefully highlight specific benefits of children's books (and speech)

Thank you!

Questions?

Subsidies and Secession Demands: Text Analysis of Regional Parliaments in Spain and the United Kingdom 1999-2017

By
Dan Gamarnik

Research Question

- Why do secessionist demands happen in rich, relatively affluent, non-deprived, democratic (RRANDD) minority regions?
  - Specifically demands by *government officials* in ethnic minority, regional governments.
  - Not protests or violence.
- Use computational text analysis of regional parliaments for secessionist demands of Spain (Catalonia, Basque Country) and the UK (Scotland, Wales)

Literature Review

- Previous ethnic conflict literature has trouble addressing why RRANDD regions make demands.
- Relative deprivation theory (Horowitz 1981; Gurr 1970):
  - Ethnic groups rebel when they are poorer than the rest, discriminated against or under state violence
  - None of this is true in RRANDD regions
- Relational Materialist theory:
  - Robert Hale (2008) argues regions secede when economically they will be better off
  - Estimates show that in all regions they will be the same or worse off if they were independent.

Literature Review (cont).

- Globalization theory (Hopkins 2014):
  - Argues that regions threaten to secede because of economic integration and increased austerity (ie spending cuts)
  - But cannot explain why some regions try to secede and others do not in the same country.
- No theory has fully explained this phenomenon yet.

Theory

- Secession is result of elite and public discontent *specific* to each region.
  - Conventional story: funding cuts lead to anger among public.
  - Fiscal appeasement theory suggests that funding is actually *co-opting* officials from seceeding and thus funding cuts is ending co-optation.
- Many factors can be analyzed in a model for this.

Model

- $Y_{Demands} = B0 + B1_{SecessionPolls} + B2_{NationalistVote} + B3_{RegionalFunding} + \varepsilon$

Model (cont).

- Also considering doing an instrumental variable for when central government tax revenue
  - Based on logic of bargaining (Putnam 1988) it assumes that regional officials not demand it if the government doesn't have funding to give them.
  - But, if it is co-optation, (and they want their own state) then they will not reduce demands.
    - If goal is to start their own country, not funding.

Research Design

- Use computational text analysis on minorty parliament speeches in Spain and the UK
  - Looks at *local* parliaments of each region.
  - Use “secessionist” regions (Catalonia, Scotland) that had referendums for it
  - Also use “control” minority regions which did not have secessionist referendums (Basque Country, Wales).

Research Design (cont).

- Text analysis will look for secessionist stem words like “secession” and “independence” in both the majority and regional minority language (English/Spanish, Catalan/Gaelic/Welsh)
- This is the *dependent* variable
- Will use a word count of these phrases by month from 1999 to 2017.
  - N = 228
- These are proxies for number of demands made in these parliaments
- Because demand phrases are rare events I will use a poisson regression.

Conclusion

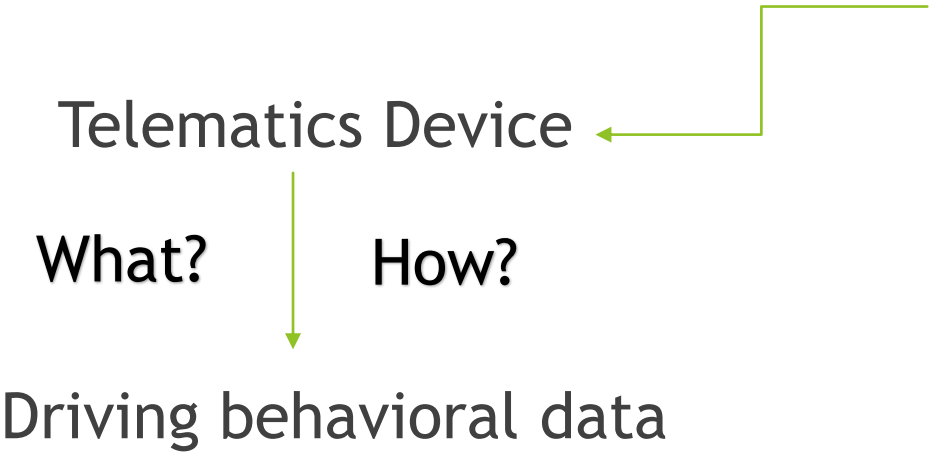
- I will use text analysis and instrumental variables to measure secessionist demands in RRANDD regions of Europe.
- It will use parliamentary speeches and test various ways for how funding might affect secessionist demands.

Using Telematics and Insurance Data to Predict Accident Risk: Evidence from Beijing

Kanyao Han

Research Question

How can we improve accident risk prediction in this digital era?



Traditional method in Insurance Industry

Customer Records → Logistic regression (or other regression)

Demographic features: Gender, Age, Job…

Vehicle features: Price, Type, Equipment…

Self-report driving mileage

Previous claim record

$$log(\frac{P(y_i = 1|d_{ij}, v_{ik}, m_i, c_i)}{1 - P(y_i = 1|d_{ij}, v_{ik}, m_i, c_i)}) = \alpha + \sum_{j=1}^{J} \beta_j d_{ij} + \sum_{k=1}^{K} \gamma_k v_{ik} + \delta m_i + \eta c_i + \epsilon_i$$

Traditional Method: Drawbacks

- Actual user ≠ customer in insurance record (like family car).
- Demographic features are not usually good indicators (Jin, Deng & Jiang, 2018) .
- Self-reported records, such as annual driving mileage(White, 1976) , are usually not exactly same as the actual ones.

A solution: combining telematics data and traditional insurance data.

Data! Data! Data!

- A confidential car insurance dataset from insurance company: 150,000 observations

can be merged by vehicle id number

- A confidential telematics dataset from telematics company (10,000 cars over 3 months):

  In-vehicle sensor data: acceleration, hard brake, actual mileage…

  GPS data: averagely each car contains over 10,000 GPS observation

An example of GPS data structure of a car

For ethical and confidential reason, I don't display some identifiable variables.

VIN <chr>	lon <chr>	lat <chr>	time <S3: POSIXct>
Confidentiality	116.365120	39.953669	2016-01-01 09:50:06
	116.364989	39.953702	2016-01-01 09:50:39
	116.364955	39.953041	2016-01-01 09:50:51
	116.364960	39.952391	2016-01-01 09:51:03
	116.365124	39.951912	2016-01-01 09:51:16
	116.365120	39.951150	2016-01-01 09:51:26
	116.365201	39.950516	2016-01-01 09:51:35
	116.365211	39.949626	2016-01-01 09:52:10
	116.365295	39.948980	2016-01-01 09:52:19
	116.365168	39.948152	2016-01-01 09:52:40

1–10 of 22,573 rows

Previous 1 2 3 4 5 6 … 100 Next

Extracting data from GPS (Some examples)

- Actual demographic features

  Where the car owner live → Economic status

- Driving behavior

  Night driving, urban driving, etc.

  Familiarity with the road (how often a driver/drivers driving in one area/road)

- Driving environment

  Various road conditions in which a driver/drivers driving the car (I also have some types of road conditions data).

Method: Spatial data aggregation

Modeling

- Response:

  Self-reported claim in insurance data ⟹ Accident or not

  Claim amount ⟹ Accident loss

- Features:

  Traditional features in insurance data

  Driving behavior in in-vehicle sensor data

  Demography, behavior and environment in GPS data

Model Selection

In data-driven research, there is no golden standard for model selection. Trying different algorithm and parameter.

- Classification (self-reported claim):

  Neural network often performs other algorithm in accident prediction (Paefgen et al. , 2013)

- Regression (claim amount):

  Lasso and elastic net are frequently used when there is dozens of features.

So what?

- For insurance company: improving pricing strategy based on telematics data

- For telematics company: risk scoring service based on both classification and regression

- For academics: most similar research are just based on in-vehicle sensor data. The driving behavior and environment information extracted from GPS data have not been given enough attention. It has large potential for prediction.

Is Coffee Shop an Indicator of Gentrification and Crime?

JIE HENG

Gentrification and Crime

- What is gentrification:

  "The process by which higher income households displace lower income [households] of a neighborhood, changing the essential character and flavor of that neighborhood"

  Kennedy, Maureen and Paul Leonard. 2001. "Dealing with Neighborhood Change: A Primer on Gentrification and Policy Changes." Discussion Paper Prepared for the Brookings Institution Center on Urban and Metropolitan Policy.

- Criminological theory and the association between gentrification and crime:
  - Broken windows thesis
  - Civic communities perspective, Routine activities theory, Defended communities thesis, Social disorganization
  - Gentrification starts, crime rates goes down

Gentrification and Crime

- How to identify gentrification:
  - “Coffee shop capture a more subtle cultural process of neighborhood change that might not be captured by such census indicators.”--- Richard Lloyd

- Papachristos, Smith & Fugiero. 2011. “More Coffee, Less Crime? The Relationship between Gentrification and Neighborhood Crime Rates in Chicago, 1991 to 2005”
  - Chicago is a racially segregated city
  - Asian neighborhood

Gentrification and Crime

- How to identify gentrification:
  - “Coffee shop capture a more subtle cultural process of neighborhood change that might not be captured by such census indicators.”--- Richard Lloyd

- Papachristos, Smith & Fugiero. 2011. “More Coffee, Less Crime? The Relationship between Gentrification and Neighborhood Crime Rates in Chicago, 1991 to 2005”
  - Chicago is a racially segregated city
  - Asian neighborhood

Research Questions:

1. Is there a relation between the number of coffee shops and crime associated with gentrification in a city with high ethno-racial diversity (New York)?
2. Whether the number of coffee shops of neighborhoods and other features of neighborhoods(race, income) are associated with crimes(murder, robbery)?

Data

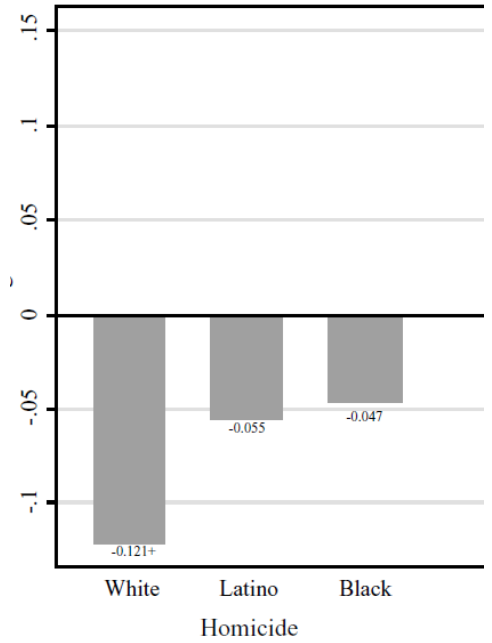
- The number of Coffee shops in NY:
  - Sidewalk Café Licenses and Applications
  - Legally Operating Businesses
  - Grand Street BID Business Directory
- Income, population, education, race, housing built
  - census
- Crime data:
  - NYPD Complaint Data to Current

Methods

Independent variables

- Education(bachelor degree)
- Gentrifiers(move to the neiborghood),
- New housing built in 5 years
- Log of mean family income,
- Percent of population that is Black, White, Hispanic, Asian, foreign born,
- the average number of coffee shop.

Dependent variable: count of crime



Maps-- observation

PCA/factor analysis

Compare models to predict crime

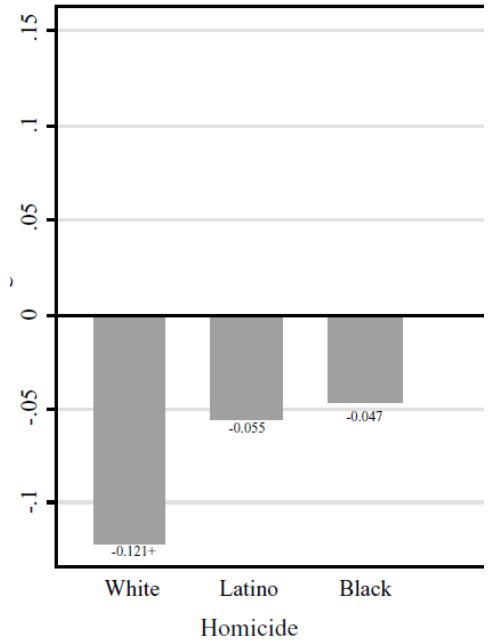
Crime type & coffee shops

Methods

Independent variables

- Education(bachelor degree)
- Gentrifiers(move to the neiborghood),
- New housing built in 5 years
- Log of mean family income,
- Percent of population that is Black, White, Hispanic, Asian, foreign born,
- the average number of coffee shop.

Dependent variable: count of crime



Maps-- observation

PCA/factor analysis

Compare models to predict crime

Crime type & coffee shops

Challenges

1. Data cleaning
2. Divide the crime data to neighborhoods according to the GPS coordinates

Thank you

THE AESTHETICS OF KNOWLEDGE CONSUMPTION:

[A Study of Textual and Graphical Forms in Online Science Communication]

Project Proposal

Leoson Hoay

RESEARCH QUESTION

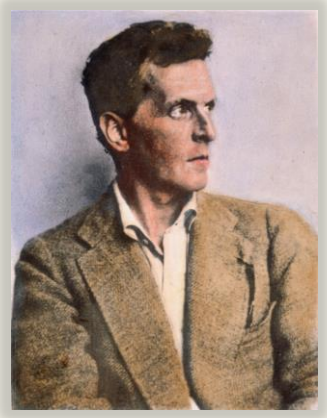
- Can **aesthetic measures** of science web articles predict the **readership** and **reader linger time** of the publication/website that the articles belong to? (Observational)

...and/or:

- Can aesthetic measures on web articles predict readers' **ratings of scientific content/websites**, and their **interest in the aforementioned content?** (Survey/Experimental)

FOUNDATIONS

- "Ethics and Aesthetics are one."/"Knowledge is in the end based on acknowledgement." – Ludwig Wittgenstein (1914 - 1916, 1953)
  - ***Value* and Aesthetics are inextricable** (Gombrich, 1960)
  - *Build on previous studies in HCI (Human-Computer Interaction) and knowledge aesthetics*
- **Defining and Quantifying "Aesthetics"**
  - "Formal notions" relating a reader to the content
    - **Form** and Function
  - **Text Aesthetics**: Semantic Consistency (Tang, Qin and Liu, 2015)
  - **Layout Aesthetics**: HCI/UX Literature – Pixel Fields, Screen Balance, Entropy, Complexity, Gestalt Unity, Edge Density, etc. (Machado et. al 2015, Rigau et. al 2007, Ngo et. al 2000 and others)



BITS AND PIECES

- **Text Aesthetics**: Semantic Consistency
- **Layout Aesthetics (6 measures):** (+Color Distribution, +Edge Density)**:**

$$M_D(r) = 1 - avg_{1i<jr}\{NID(i,j)\}$$

Kolmogorov Complexity

$$(x_c, y_c) = \left(\frac{\sum_i a_i x_i}{\sum_i a_i}, \frac{\sum_i a_i y_i}{\sum_i a_i}\right)$$

Screen Equilibrium

$$M_I(r) = \frac{I(X_l, \hat{Y}_r)}{H(X_l)}$$

Shannon Entropy

$$sqm = (p, d)$$

Screen Sequence

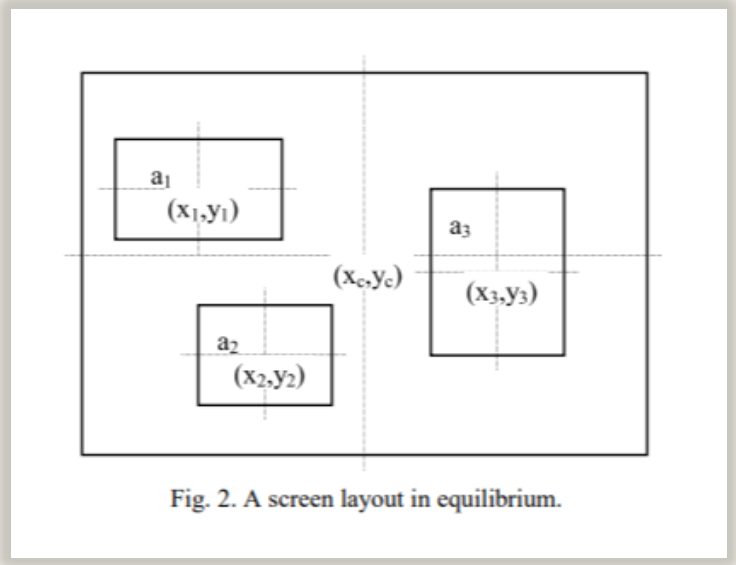


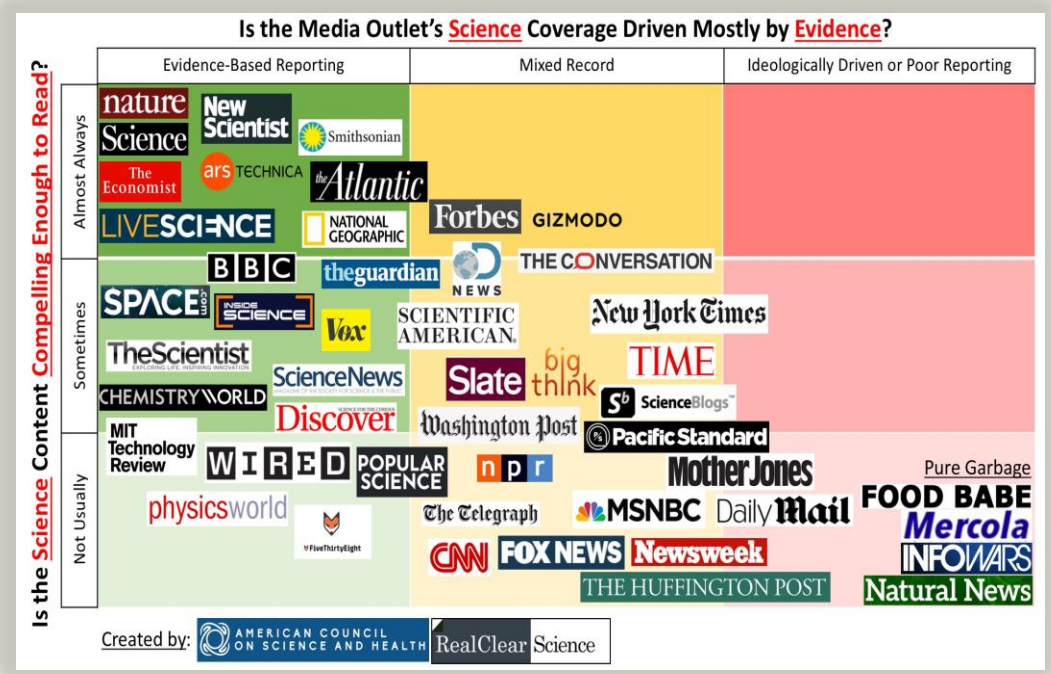
Fig. 2. A screen layout in equilibrium.

Gravitational model of screen equilibrium (Ngo and others 2000, 2002)

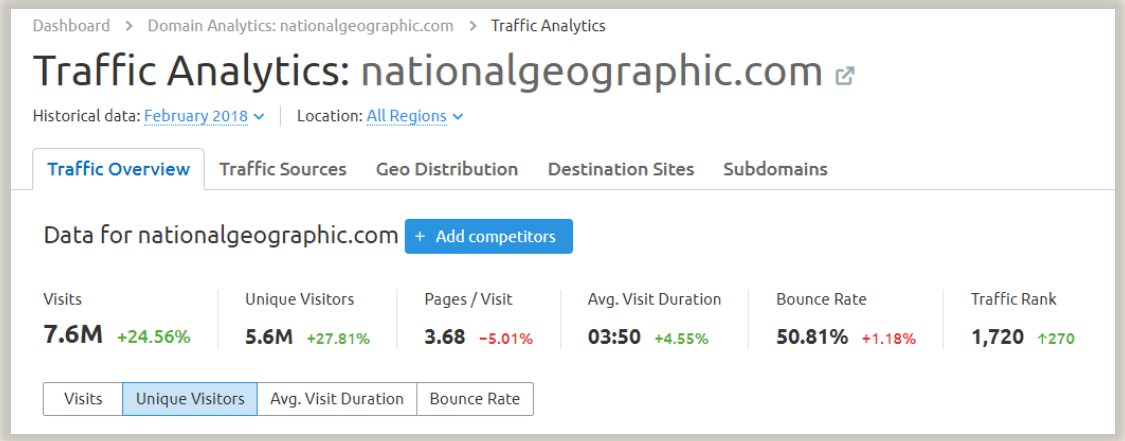
DATA SOURCE(S)

- Aesthetics: Science Website Article Layouts and Text Content
  - *Popular American web publications – National Geographic, BBC Earth, Nature, WIRED, New Scientist, etc. (Include global publications?)*
  - *Layouts: **PhantomJS** to scrape screenshots of article pages*
- Readership, Linger Time: Website Metrics
  - *Domain Data*
  - ***Estimated Data (SimilarWeb, SEMRush)***

DATA SOURCES



American Council on Science and Health, RealClearScience (2017)

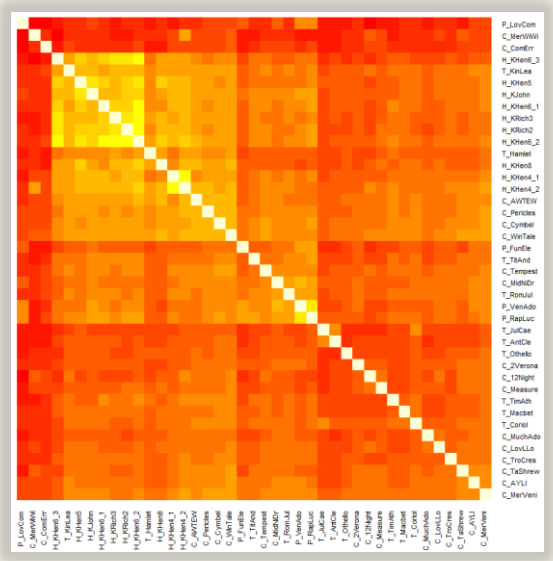


SEMRush.com

33 articles x 30 publications = 990 data points

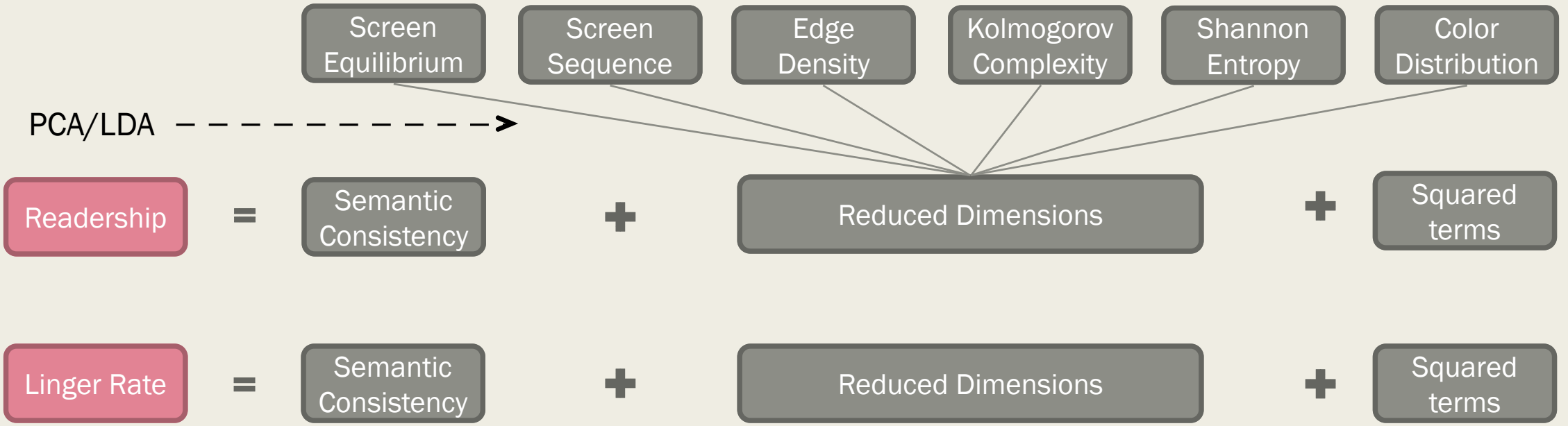
METHODS

- **Article Text Consistency:** Gensim + Doc2Vec/Word2Vec
  - ***Trained vector space of documents*** *from each individual science media outlet used to calculate individual article similarity*
  - ***'Document Congruence'*** *for each science article formulated as the inverse of the document distance from the vector space*
  - *Other models: Cosine Similarity, WMD (Word Mover's Distance)*
- **Article Webpage Aesthetics:**
  - ***EBImage*** *in R for pixel analysis,* ***scikit-image*** *for clustering,* ***OCRopus*** *for layout analysis,* ***OpenCV*** *for almost everything else*



METHODS

- Supervised Learning



EXPECTED FINDINGS

- Model should be able to predict readership relatively well, maybe not as well for linger rate
  - *While observing that higher aesthetic scores are usually correlated with higher readership and longer visit duration*
  - ***Expected Challenges:*** *Unknown requirements for n-power (larger dataset may be needed), extreme non-linearity, inaccuracies in traffic estimation*

- Survey/Experimental: Aesthetic scores based on HCI and UI principles should predict readers' ratings of content/websites and initial interest level well

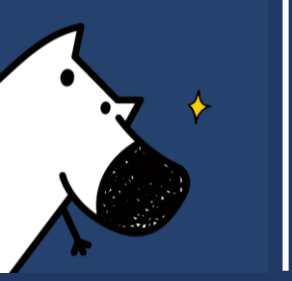
Virtue alone cannot save the world. Only actions will.

VIRTUE ALONE CANNOT SAVE THE WORLD. *ONLY ACTIONS WILL*.

Knowledge

Presentation/Representation

This presentation was presented at:
Saieh 247, The University of Chicago
Chicago, Illinois
United States of America
Earth
The Solar System
The Milky Way
The Local Group
Virgo Supercluster
The Known Universe



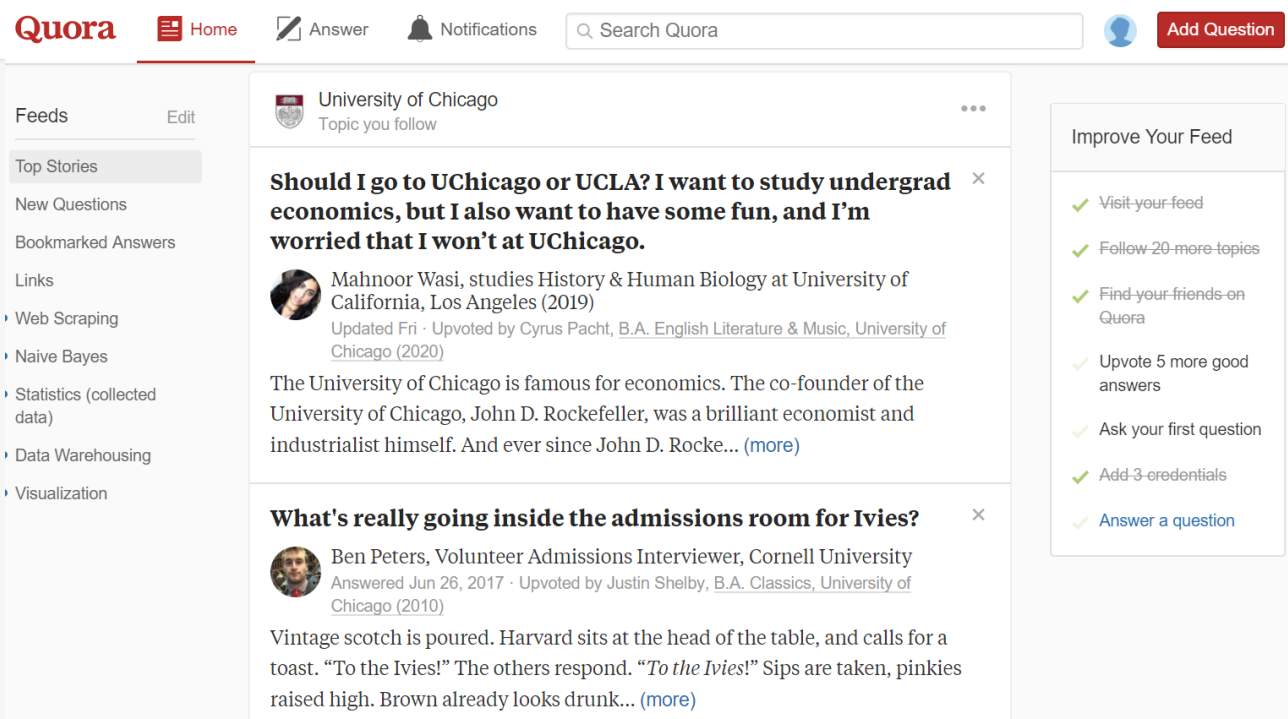
User Behavior in Q&A community: an analysis of Zhihu

Andi Liao

2018/04/04

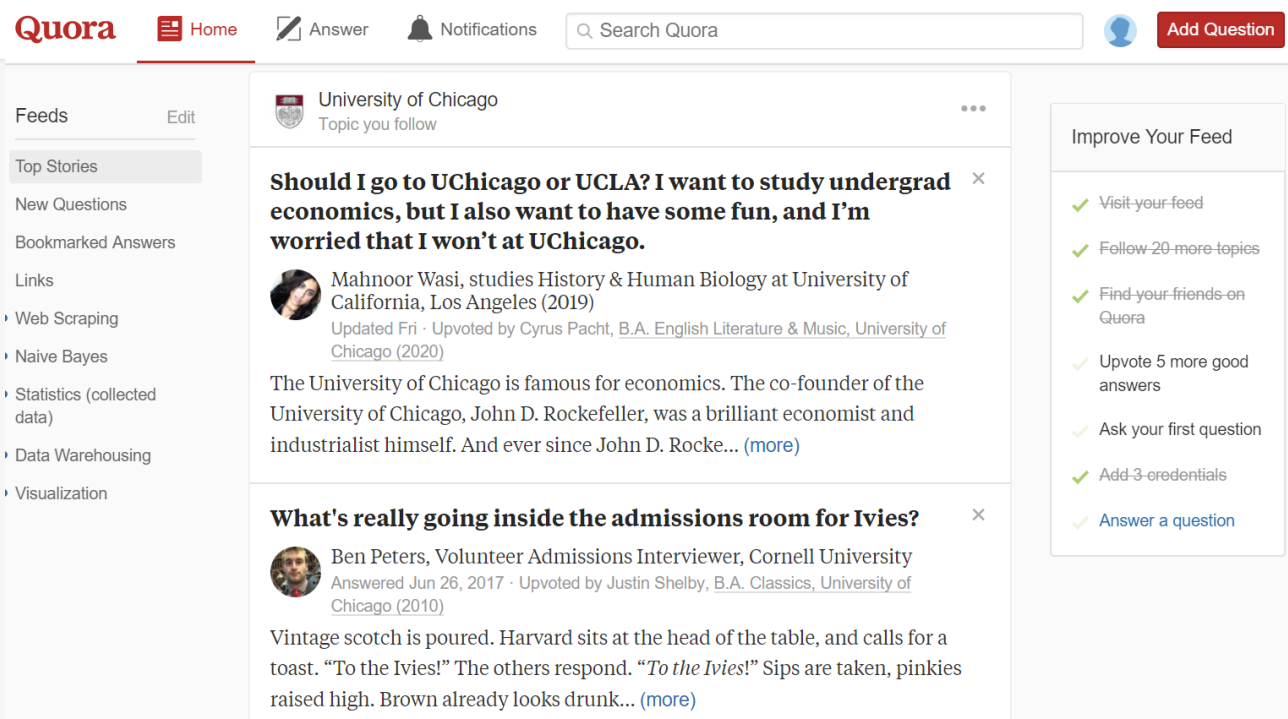
Brief Intro to Zhihu

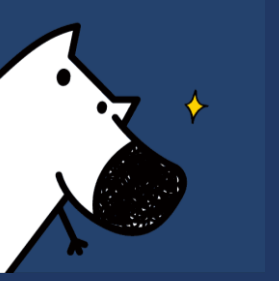
- Similar with Quora
  - Q&A Community - Follower & Following, Upvotes & Downvotes
  - User Interface - Navigate Bar, Topics
  - Recommend System - Feed, Invitation



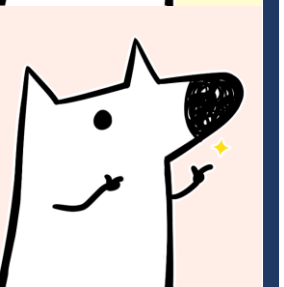
Brief Intro to Zhihu

- Difference with Quora:
  - User Identity - Any Name
  - Upvote - Agree
  - Top Writer - Centered



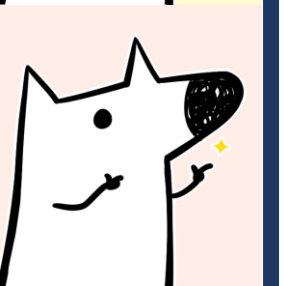


Research Question

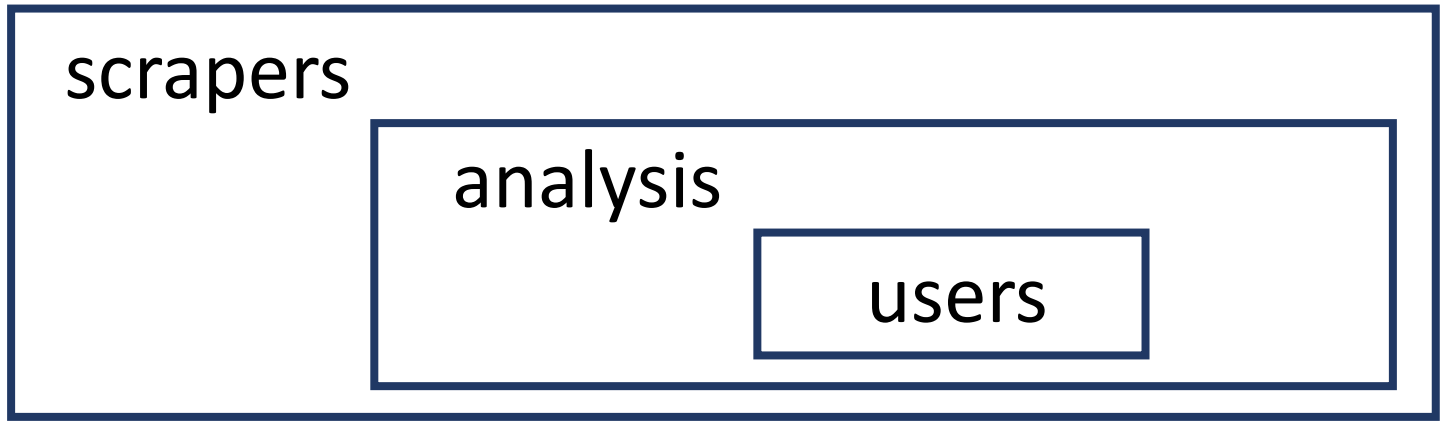


- User Behavior & Interaction in Zhihu Community
  - Clustering:
    - Is it possible to cluster users based on data of their activities?
  - Prediction:
    - Is it possible to predict a new user to be a top writer based on data of his activities?

Why It Matters?

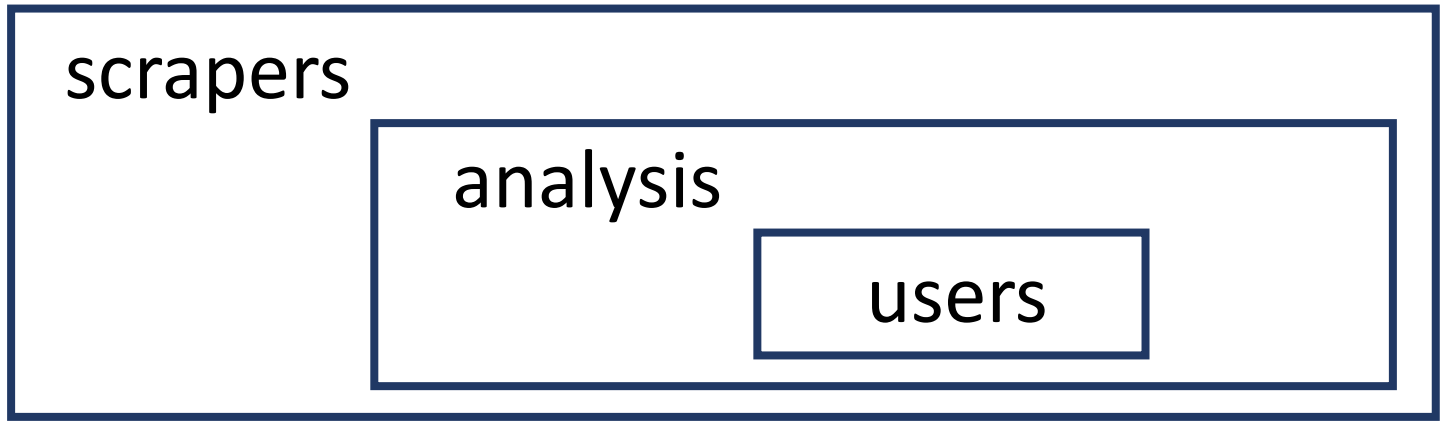


- Mixture: knowledge sharing + social
  - Venmo: Finance + Social
  - Weibo: Nickname + Comment
- Many scrapers, but few analysis focused on users in depth



Why It Matters?

- Mixture: knowledge sharing + social
  - Venmo: Finance + Social
  - Weibo: Nickname + Comment
- Many scrapers, but few analysis focused on users in depth

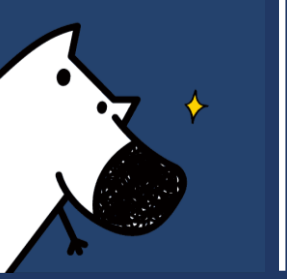


Data Source

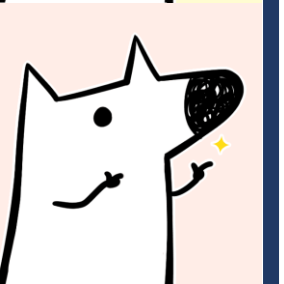
- Scraper: https://github.com/MatrixSeven/ZhihuSpider - Java
  - Backup: https://github.com/7sDream/zhihu-oauth - Python unofficial API

- Data form: Mysql database

Follower	User	User Information
user_name	user_id	company, job
follower_name	index_url	education
update_time	token	answer, question
…	…	…



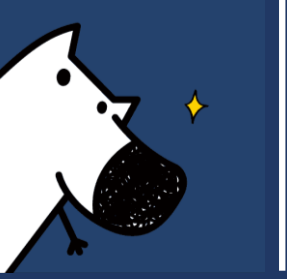
Possible Theory



- Social and Interaction Graph
  - Degree-distribution: following, follower
  - Clustering coefficient: similarity
  - Reciprocity and balance: symmetric relationship
  - Assortativity: tend to connect similar nodes in the network
  - Tie Strength: interaction frequency

- Reference:

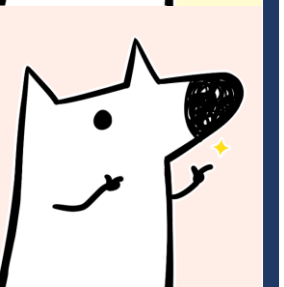
  - Zhang, X., Tang, S., Zhao, Y., Wang, G., Zheng, H., & Zhao, B. Y. (2017). Cold Hard E-Cash: Friends and Vendors in the Venmo Digital Payments System. In *ICWSM* (pp. 387-396).
  - Wang, T., Chen, Y., Wang, Y., Wang, B., Wang, G., Li, X., ... & Zhao, B. Y. (2016). The power of comments: fostering social interactions in microblog networks. *Frontiers of Computer Science*, *10*(5), 889-907.
  - Wang, G., Gill, K., Mohanlal, M., Zheng, H., & Zhao, B. Y. (2013, May). Wisdom in the social crowd: an analysis of quora. In Proceedings of the 22nd international conference on World Wide Web (pp. 1341-1352). ACM.

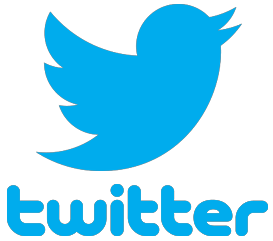


Method & Tool

- Clustering & Prediction
  - K-mean++ clustering
  - Random forest classifiers
- Challenge
  - Supervised learning methods without labels
  - Categorical variables exist
- Reference
  - Patil, S., & Lee, K. (2016). Detecting experts on Quora: by their activity, quality of answers, linguistic characteristics and temporal behaviors. Social network analysis and mining, 6(1), 5.

Expectation





Non-Social

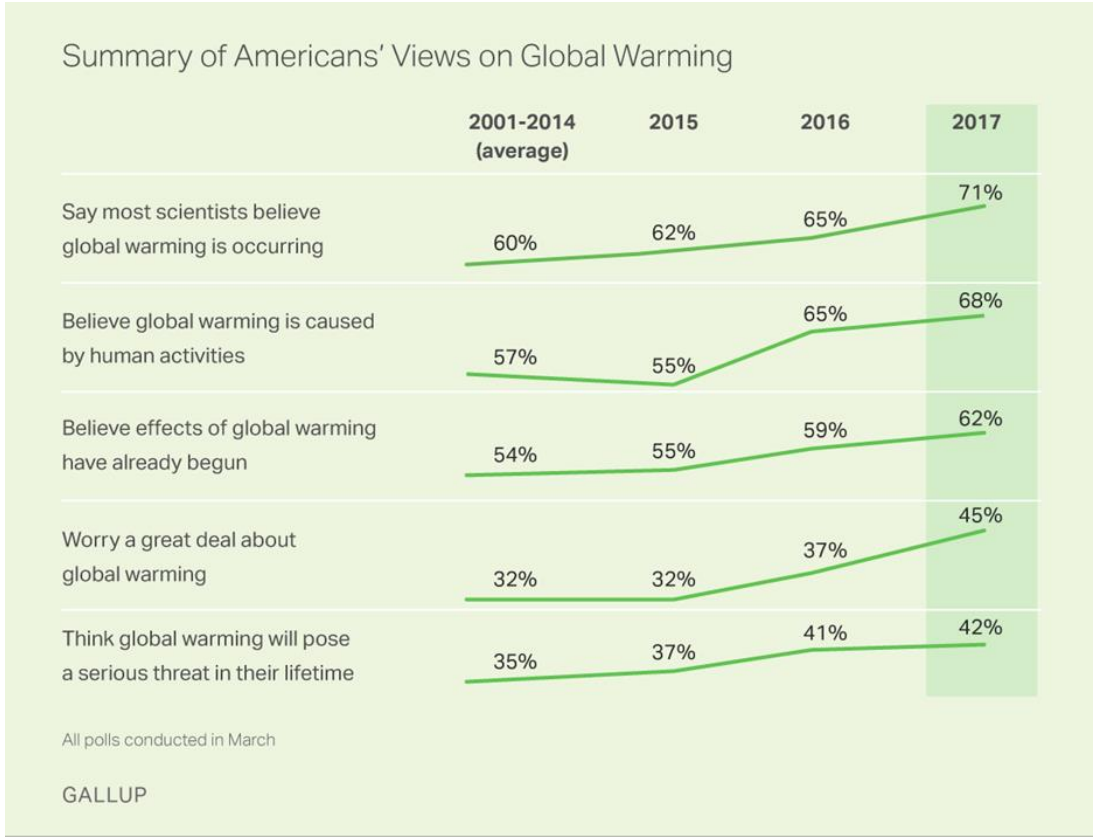
Social

How Abnormal Temperatures Affect Climate Change Attitudes and Behaviors

Kris Nichols

The Threat of Climate Change

- Polls indicate that Americans are increasingly concerned about climate change.
- Why is there a disconnect between the personal danger a person feels from climate change and the existential danger of climate change?



(Leiserowitz, Maibach, Roser-Renouf, Feinberg, & Rosenthal, 2015; Saad, 2017)

Perceived Low Risk of Personal Harm

- Research has indicated a number of potential cognitive biases that may be contributing to this such as skepticism in science, an identity protection mechanism, framing effects, and cognitive dissonance.

- To further investigate how individuals react when personally confronted with the effects of climate change, researchers have begun to investigate how individuals climate change attitudes may fluctuate with abnormal weather.

(Brooks, Oxley, Vedlitz, Zahran, Lindsey, 2014; Poortinga, Spence, Whitmarsh, Capstick, & Pidgeon, 2011; Nerlich, Koteyko, & Brown, 2009; Spence, & Pidgeon, 2010)

Potential Problems in the Literature

- Methodological:
  - Non-response bias in national survey
  - Lack of precision in instruments
  - Observer-expectancy bias
- Content
  - What does concern really indicate?
    - Particularly in the face of proposed identity-protection mechanisms
  - Lack of insight into mechanisms
  - Introduces schism between behavior and attitudes.
    - Is a person who answers “Not Concerned” on a survey, but googles “climate change debunked” shortly after taking it really not concerned?

Proposed Project

- Investigate how abnormal temperatures affect number of Google searches for climate change cross Democratic, Republican, and swing states may alter climate change behavior as measured by Google search data.

  - Allow for greater clarity as to potential mechanisms
  - Allow for comparison between conservative and liberal states
  - Allow for greater ability to interpret concern

Google Search Data

- Arguably, Google search data at its best is data that represents true, unaltered behavior and motivation.
- If someone is concerned about climate change we should see higher activity for climate change Google searches.
- Those who are looking to affirm their disbelief in climate change will also be visible with this data.

Table 1
Signal-to-noise ratio in Google search terms.

Term	Underlying variable	t-Stat	R^2
God	Percent believe in god	8.45	0.65
Gun	Percent own gun	8.94	0.62
African American(s)	Percent Black	13.15	0.78
Hispanic	Percent Hispanic	8.71	0.61
Jewish	Percent Jewish	17.08	0.86

Notes: The t-stat and R^2 are from a regression with the normalized search volume of the word(s) in the first column as the independent variable and measures of the value in the second column as the dependent variable. The normalized search volume for all terms is from 2004 to 2007. All data are at the state level. Percent Black and Percent Hispanic are from the American Community Survey, for 2008; the Jewish population is from 2002, gun ownership from 2001, and belief in God from 2007. Jewish data are missing one observation (South Dakota); belief in God data are missing for 10 states. The data for belief in God, percent Jewish, and percent owning guns can be found at http://pewforum.org/how-religious-is-your-state-.aspx, http://www.jewishvirtuallibrary.org/jsource/US-Israel/usjewpop.html, and http://www.washingtonpost.com/wp-srv/health/interactives/guns/ownership.html, respectively.

Other Data

- I would also like to include the effect of ***media*** as a parameter in this project.
- No study to date has investigated the role of media in proliferating fears about climate change in the context of abnormal weather and this could be an important motivator of people's fears – or the lack thereof.
- This parameter will likely be realized through the scraping of articles on climate change and running sentiment analysis on these articles.

Model: ARIMA Models

- ARIMA models attempt to describe the movements in a stationary time series as a function of what are called "autoregressive and moving average" parameters
- AR: Autoregressive part of the model
    - Forecast the variable of interest using a linear combination of past values of the variable
- MA: Moving Average part of the model
    - A moving average model uses past forecast errors in a regression-like model
- I: Integrated or “Differencing”
    - Subtracting previous values d times
- ARIMAX
    - Allows for covariates

Proposed Models

- I will utilize three competing models for this project:
  - A Seasonal ARIMA model which maps Google searches for climate change onto a seasonal series.
  - A Seasonal ARIMAX model while will use Google searches for climate change “debunked” or other disproval terms as a covariate.
  - Finally, a Seasonal ARIMAX model which will use the media parameter as a covariate with the Google data to measure how the effect of media fits into this model.
- The ARIMA methodology will allow for analysis over a period of time while allowing for the flexibility of “Seasons” which capture the cyclic volatility of some seasons containing more abnormal weather than otbers.

Hypotheses

- Predict that regardless of political party, that states with high amounts of abnormal weather will have significantly more general Google searches regarding climate change and global warming.

- Furthermore, I predict that when Google searches for “climate change not real” or “global warming not real” are included in analyses that these data will control for the majority of variation in Republican states.

- This study will suggest a cognitive dissonance mechanism by which participants initially Google “climate change not real” to soothe their dissonance.

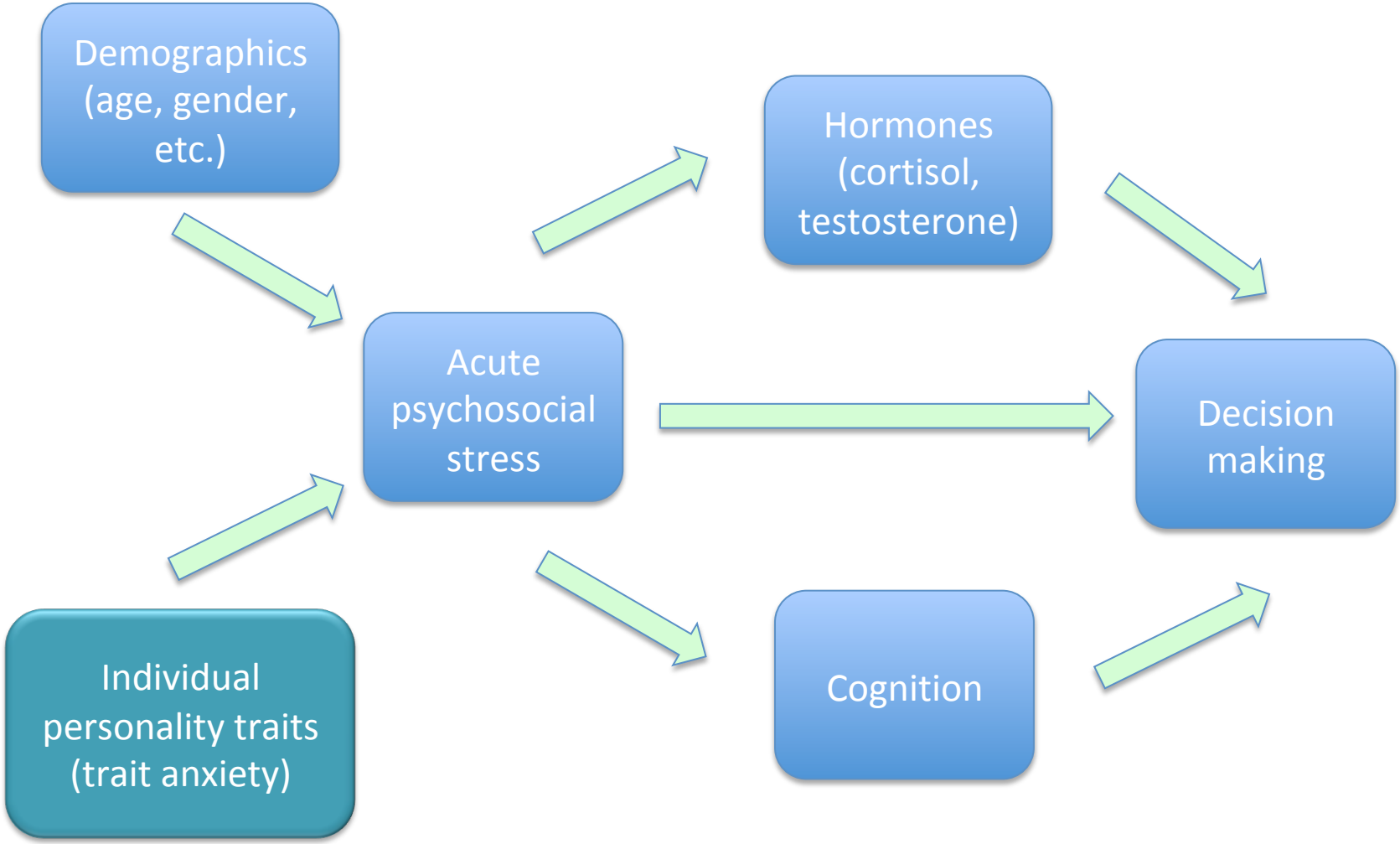
A digital survey investigation of the construct validity of the Trait Anxiety Inventory in the UChicago community

Nora Nickels

Perspectives of Computational Research

Spring 2018

Background


Demographics (age, gender, etc.)
Hormones (cortisol, testosterone)
Acute psychosocial stress
Decision making
Individual personality traits (trait anxiety)
Cognition

Research Question

- In my study, to save money/time, some of these trait questionnaires are taken outside of the lab.

- RQ: How strong is the construct validity of the Trait Anxiety Inventory in my dissertation research population; specifically, does setting, time of day, and mood relate to trait anxiety responses of UChicago community members when the T.A.I. is completed outside of a controlled laboratory setting?

What do we know?

- The State-Trait Anxiety Inventory
  - Long standing, frequently used, sensitive, valid (Spielberger, 1989; Chapman & Cox, 1977)
  - Retest correlations show reliability (Spielberger et al, 1983)

- Benefits of online questionnaire vs. in person questionnaire (Murthy, 2008)

What don’t we know?

- Risks of digital questionnaire
  - In person, have more environmental control
- Is the trait anxiety inventory susceptible to this risk?
  - Extraneous effects of mood, time of day, and setting
- Stability of responses of specific UChicago student population
  - Stressful environment

Model / Theory

- In person vs. digital survey distribution
- If the TAI measures trait anxiety as a stable trait, then **trait anxiety scores** should not by statistically significantly related to **setting factors** that are not stable, such as:
  - Time of day
  - Mood
  - Setting (where the survey was taken)

Methods

- Qualtrics survey (digitally administered)
  - Administer the TAI
  - Administer post-survey questions:
    - Time of day
    - Setting
    - Mood
- Qualtrics
  - Software that enables users to collect and analyze data online
  - Benefits of digital design

Methods

- Recruitment:
  - Goal: To test questionnaire validity within UChicago sample
  - Population: UChicago community
  - Sampling frame: UChicago community members accessible via listservs, Martketplace, Facebook
  - Sample: actual respondents of recruitment
  - Target: 200 respondents

Analyses

- Descriptive statistics:
  - Distribution of anxiety scores
- Regression model:
  - Exogenous variables:
    - Setting, time of day, mood
  - Endogenous variable:
    - Trait anxiety score

Connection to research question: If extraneous factors of setting do not negatively affect questionnaire responses, we should see no relationship between the extraneous / exogenous variables and anxiety scores.

Questions?

References:

Chapman, C. R., and Cox, G. B. (1977). Determinants of anxiety in elective surgery patients. In C. D. Spielberger and I. G. Sarason (Eds.), Stress and anxiety (Vol. 4, pp. 269–290). Washington, DC: Hemisphere/Wiley

Murthy, D. (2008). Digital ethnography: An examination of the use of new technologies for social research. Sociology, 42(5), 837-855.

Spielberger, C. D. (1989). State–Trait Anxiety Inventory: a comprehensive bibliography. Palo Alto, CA: Consulting Psychologists Press

Spielberger, C. D., Vagg, P. R., Barker, L. R., Donham, G. W. & Westberry, L. G. (1980). The factor structure of the State–Trait Anxiety Inventory. In I. G. Sarason and C. D. Spielberger (Eds.), Stress and anxiety (Vol. 7, pp. 95–109). New York: Hemisphere/Wiley

PREDICTING COLLEGE RETENTION RATES: AN APPLICATION OF THE CRITICAL MASS THEORY

Kevin Sun

Wednesday, April 4, 2018

MA Computational Social Science

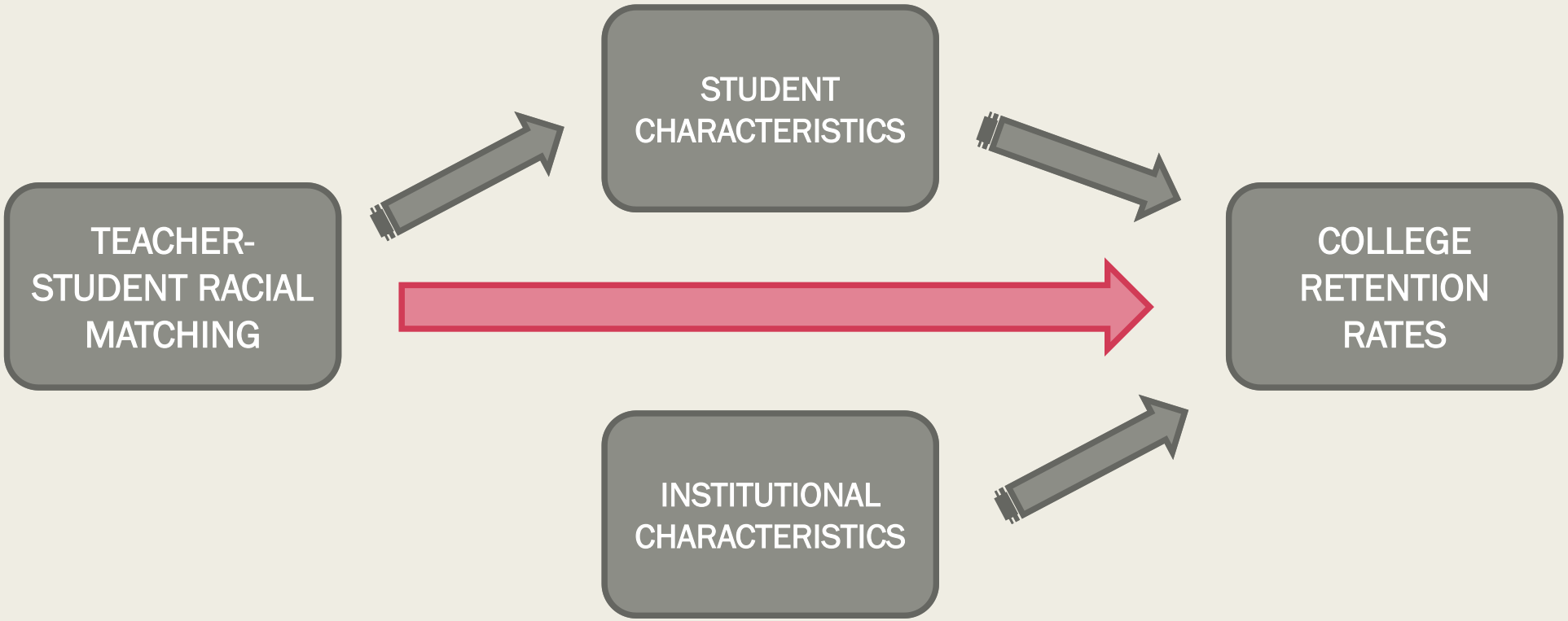
Research Proposal

RESEARCH QUESTION:

To what extent can college retention-rates be predicted by bureaucratic representation at the K-12 level?

- College retention: students who return to college their second year
- Bureaucratic representation: Teachers & administrators sharing demographic similarities with students

THE LAY OF THE LAND:



THE LITERATURE: On Retention

- High School Achievement (Astin, Korn, Green 1987)
- Integration into academic and social community (Tinto 1975, 1987)
- Demographic Traits (Astin 1975; St. John, Hu, Simmons, Musoba 2001)
- Psychological Traits (Trapmann, Hell, Hirn, Schuler 2007; Oswald, Schmitt, Kim, Ramsay, Gillepsie 2004)

THE LITERATURE: Racial Matching

- Assessment of student behavior & disciplinary outcomes (Bates & Glick 2013; Lindsay & Hart 2017)
- Expectation of student potential (Gershenson, Holt, Papageorge 2016; McGrady and Reynolds 2012; Dee 2005)
- Representation of non-white students in gifted programs (Grissom, Rodriguez, Kern 2017)
- Math & reading achievement (Dee 2004; Clotfelter, Ladd, and Vigdor 2007)
- Student perception of non-white teachers (Cherng & Halpin 2016)

THE DATA:

- **Teacher & Administration Demographics:** Chicago Public Schools
  - *Individual teachers at each school*
    - Impute race/ethnicity of each teacher
    - *NamSor*
    - *ethnicolr*
- **Other Demographics & School-Level Data:** Chicago Public Schools
- **College Attendance & Persistence Rates:** National Student Clearinghouse

METHODS & MODELS

$$Retention = \beta_0 + \beta_1(BureacraticRepresentation) + \beta_2(DemographicControls)$$

METHODS & MODELS

- OLS
- Decision Tree
- Random Forest

ANTICIPATED CHALLENGES & EXTENSIONS:

- Imputing race based on names
- Analysis on every school district in the U.S.
- Ideal: student-teacher racial matching
- Hypothesis: A “critical mass” of teachers/administrators of color at a school will be associated with higher college retention/persistence levels in that school’s graduates

DECODING CENSORSHIP ON RUSSIAN SOCIAL MEDIA USING FACEBOOK AND VK

ALEXANDER TYAN

MACSS 32000

RESEARCH QUESTION

WHAT ARE THE CENSORSHIP CRITERIA FOR SOCIAL MEDIA POSTS IN RUSSIA?

BACKGROUND AND MOTIVATION

- VK.COM
  - MOST VISITED IN RUSSIA (BY TRAFFIC) (SIMILARWEB, 2018)
  - SECOND MOST VISITED SOCIAL NETWORK GLOBALLY (BY TRAFFIC) (SIMILARWEB, 2017)
  - USED BY 40% OF RUSSIANS (LEVADA CENTER, 2017)
  - USED BY 53% OF 18-24 YEAR-OLDS (IBID)
- SOCIAL MEDIA TRENDS
  - GROWING AUDIENCE, DRIVEN BY 18-25 YEAR-OLDS (IBID)
  - 10% GROWTH IN THE LAST 4 YEARS (IBID)

More background and motivation

- Ex. 2011 duma election protests
- VK penetration increases chances of protest and number of protesters (Enikolopov et al, 2015)
- Social media helps overcome collective action problems (ibid)
- Social media disseminate protest information (ibid; White and McAllister, 2013)
- Governments may use different criteria for censorship (King et al, 2013, 2017)

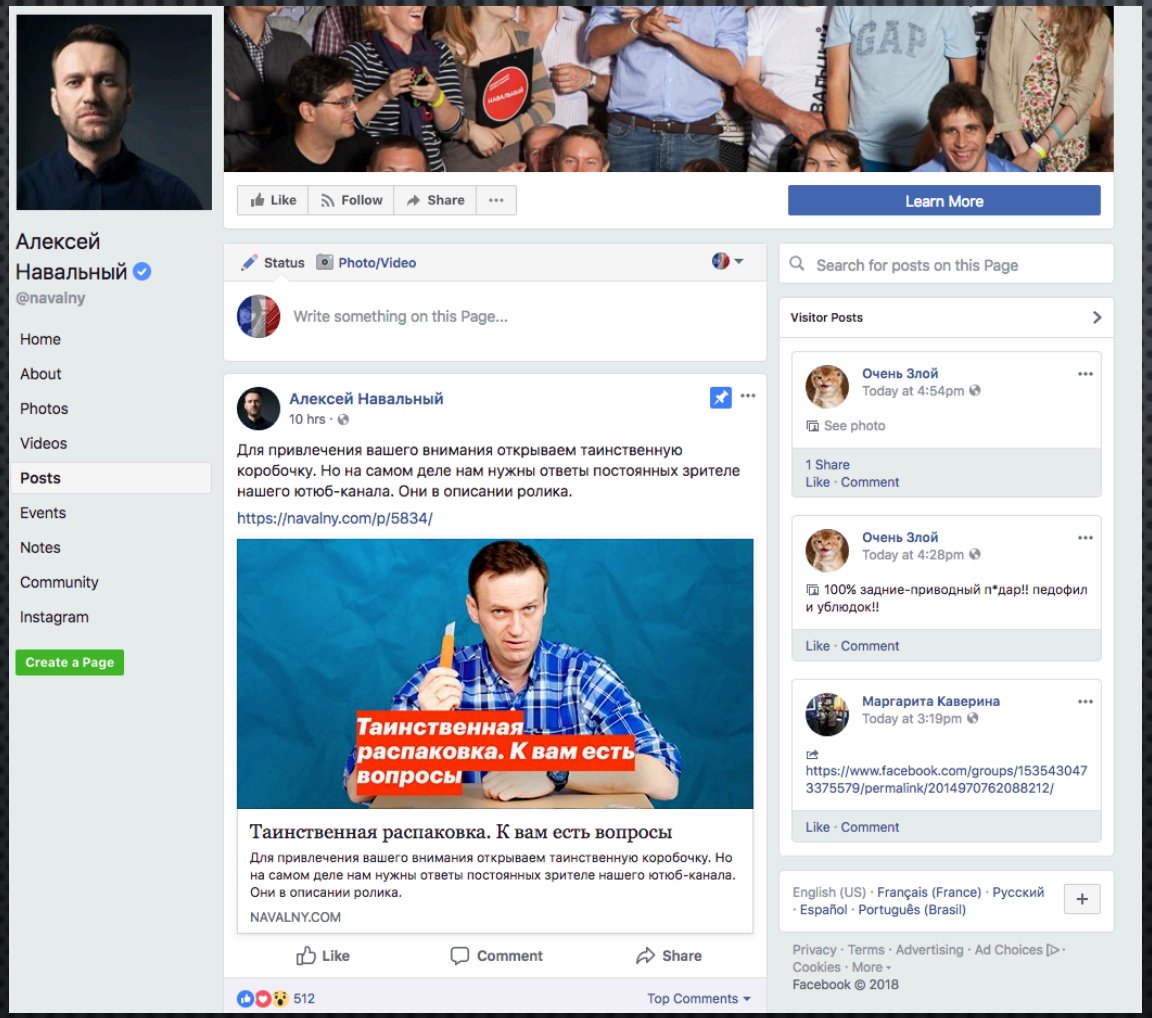
More background and motivation

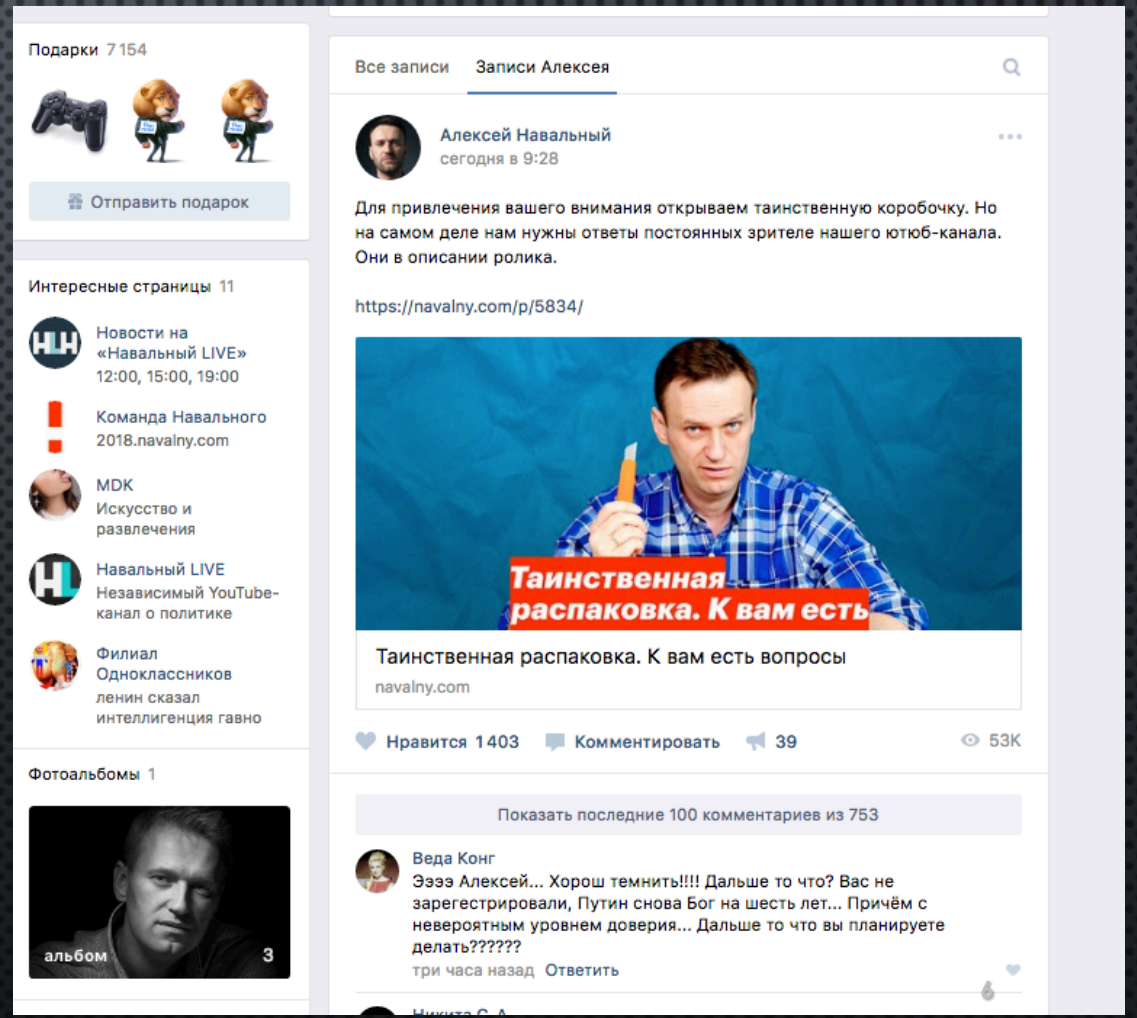
- Ex. 2011 duma election protests
- VK penetration increases chances of protest and number of protesters (Enikolopov et al, 2015)
- Social media helps overcome collective action problems (ibid)
- Social media disseminate protest information (ibid; White and McAllister, 2013)
- Governments may use different criteria for censorship (King et al, 2013, 2017)

Contribution

- General contribution to understanding of online protest mobilization
- Establish methodology to track the evolution of censorship in Russia
- Fill the gap in systematic knowledge of online censorship in Russia

RESEARCH DESIGN AND MODEL





Research Design and Model

- API/Webscraping of Alexey Navalny VK and Facebook posts (Public)
- NLP Analysis (Topic Modelling?) and Classification:
- Post Attributes (text content, types of posts) ~ probability of censorship

Anticipated Limitations and Challenges

- External Validity
- Confounding Variables and Other Sources of Censorship
- Technical Hurdles

Anticipated Limitations and Challenges

- External Validity
- Confounding Variables and Other Sources of Censorship
- Technical Hurdles

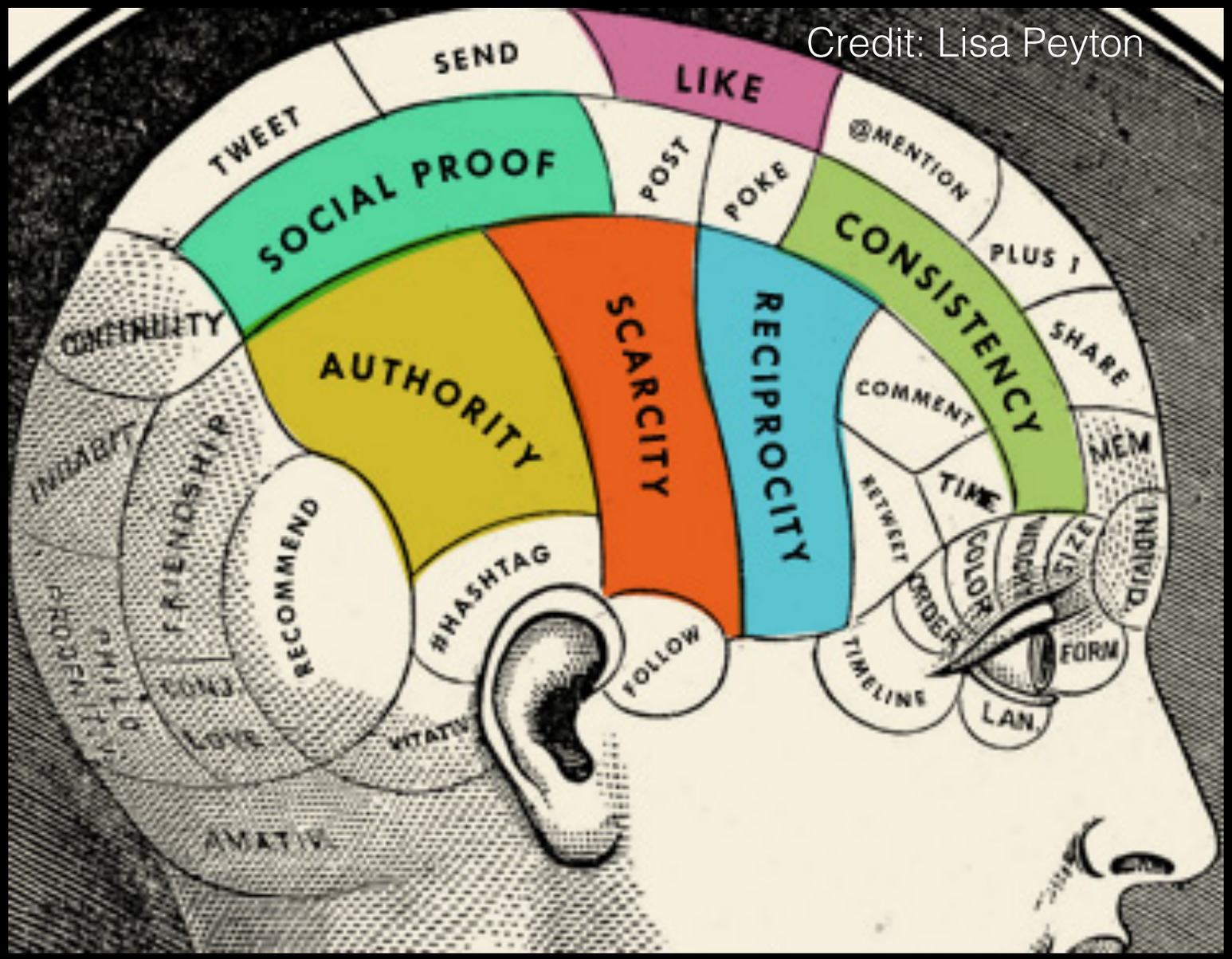
Anticipated Limitations and Challenges

- External Validity
- Confounding Variables and Other Sources of Censorship
- Technical Hurdles

Sumer Vaid

(Social) Media Psychology

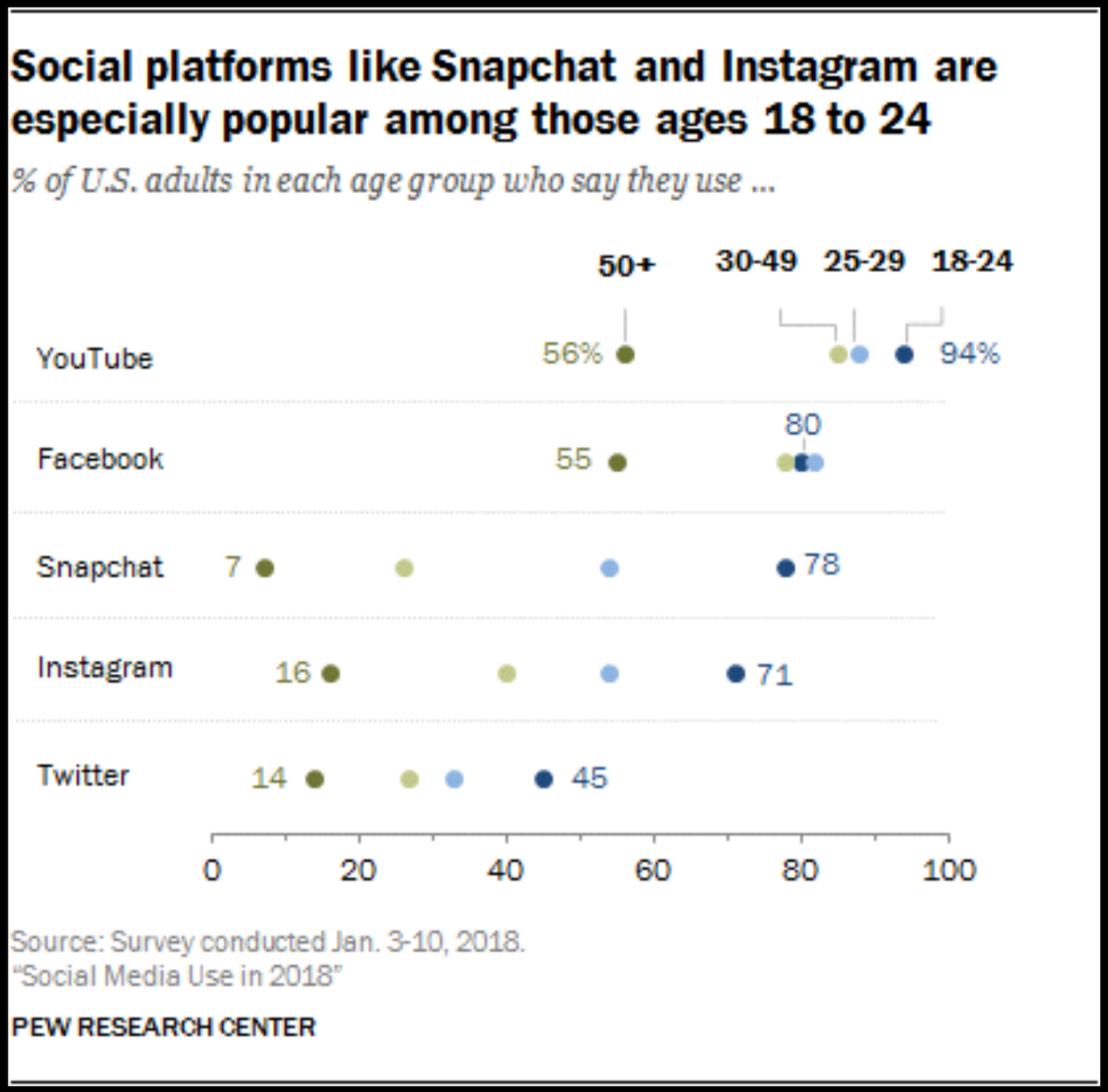
Predicting frequency of social media use from personality traits

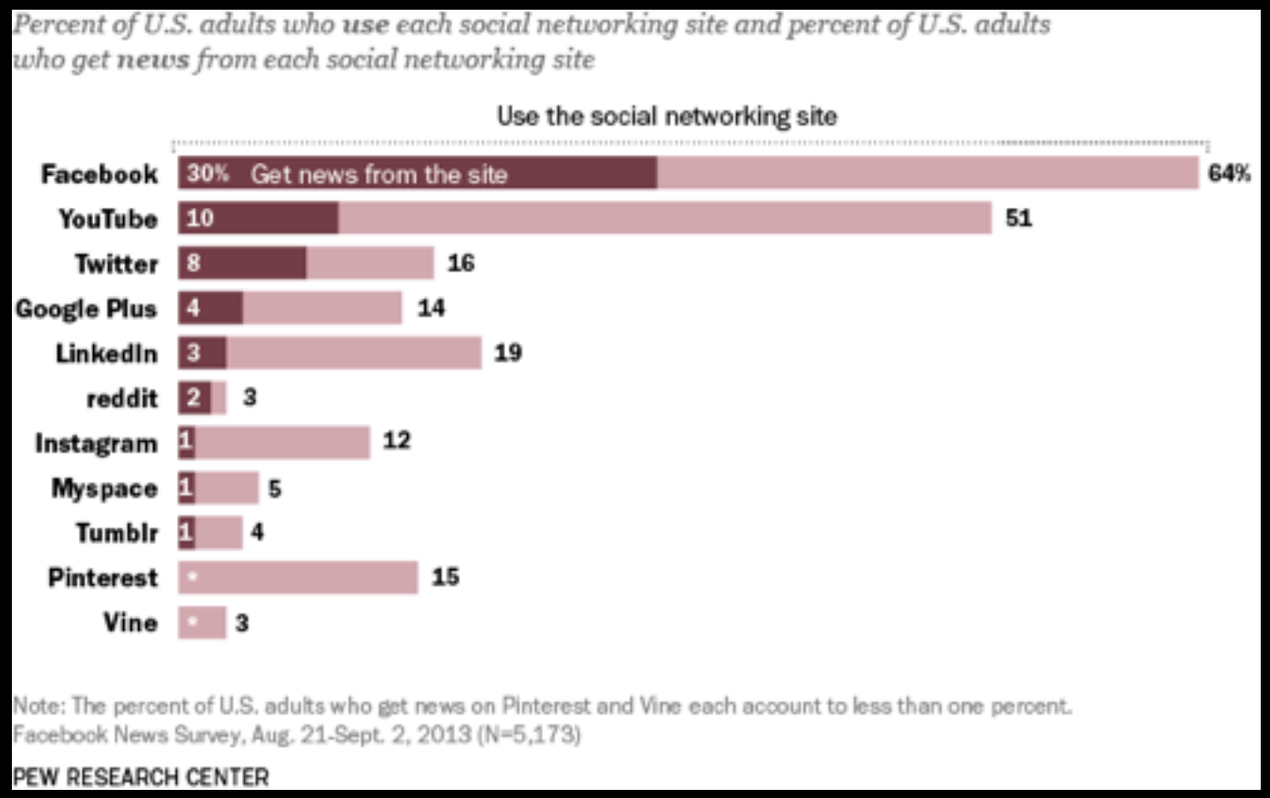


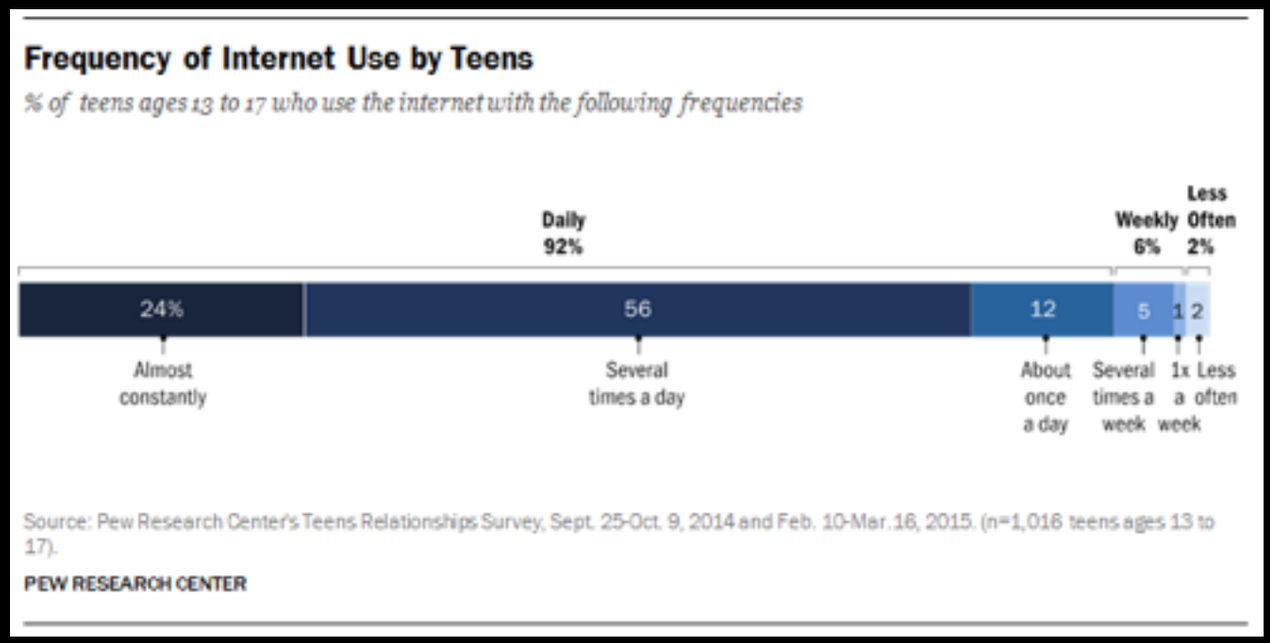
Media psychologists study the interplay between media and behavior.

(Social) Media Psychology

Social media usage is a diverse phenomenon.







(Social) Media Psychology

Social media usage is a diverse phenomenon.

Substantial 'reciprocity' across major social media platforms

% of __ users who also ...

	Use Twitter	Use Instagram	Use Facebook	Use Snapchat	Use YouTube	Use WhatsApp	Use Pinterest	Use LinkedIn
Twitter	–	73%	90%	54%	95%	35%	49%	50%
Instagram	50	–	91	60	95	35	47	41
Facebook	32	47	–	35	87	27	37	33
Snapchat	48	77	89	–	95	33	44	37
YouTube	31	45	81	35	–	28	36	32
WhatsApp	38	55	85	40	92	–	33	40
Pinterest	41	56	89	41	92	25	–	42
LinkedIn	47	57	90	40	94	35	49	–

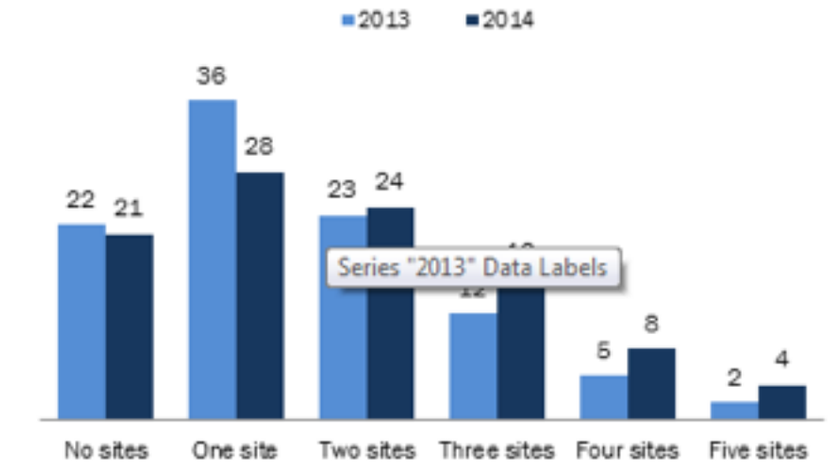
Source: Survey conducted Jan. 3-10, 2018.
"Social Media Use in 2018"

PEW RESEARCH CENTER

90% of LinkedIn users also use Facebook

More people use multiple sites

% of internet users who use the following number of social networking sites (sites measured include: Facebook, Twitter, Instagram, Pinterest and LinkedIn), 2013 vs. 2014



Pew Research Center's Internet Project September Combined Omnibus Survey, September 11-14 & September 18-21, 2014. N=1,597.

PEW RESEARCH CENTER

Why do different people use different kinds of social media platforms in different ways?

Let's use psychology to understand the origins of diversity in social media usage.

How do different kinds of people use different kinds of social media platforms in different ways?

Personality Differences

Demographic Differences

How can individual and personality differences explain patterns of social media usage?

Past Research

Demographic Survey + Personality Survey + Social Media Use Survey

A tale of two sites: Twitter vs. Facebook and the personality predictors of social media usage

David John Hughes [a,*], Moss Rowe [a,b], Mark Batey [a], Andrew Lee [a]

[a] *Psychometrics at Work Research Group, Manchester Business School East, The University of Manchester, United Kingdom*
[b] *Department of Psychology, University of Bath, United Kingdom*

Table 4
Model summaries and fit statistics for latent variable regression models.

Model	*R*	*β*	X^2	*df*	CFI
Twitter Info					
A: Sociability	10.1	−.318**	5.245	5	1.000
B: Sociability &	17.5	−.284**	25.896	18	.990
Need for Cognition &		.273**			
C: Sociability &	**20.8**	**−.313****	**29.419**	**23**	**.992**
Need for Cognition		**.219****			
Age		**.192***			
Twitter Social					
D:Conscientiousness	8.5	−.291**	n/a	0	n/a
E:Conscientiousness &	**12.3**	**−.248****	**18.271**	**7**	**.975**
Openness		**.201****			
F:Conscientiousness &	10.1	−.238**	11.640	12	1.00
Sociability		.158*			
Facebook Info					
G: Sociability	11.8	.343**	9.660	5	.995
H: Sociability &	13.8	.332**	43.396	18	.979
Need for cognition		−1.42*			
I: Sociability &	**15.8**	**.335****	**47.053**	**23**	**.981**
Need for Cognition &		**−.119***			
Age		**−.145***			
Facebook Social					
J: Sociability	2.4	.156**	3.945	5	1.000
K: Sociability &	4.8	.161**	19.75	18	.998
Neuroticism		.153*			
L: Sociability &	**9.4**	**.162****	**22.867**	**23**	**1.000**
Neuroticism &		**.119***			
Age		**−.219****			

Note: All factor indicator loadings are >0.7.
* $p < .05$.
** $p < .001$.

Past Research

Demographic Survey + Personality Survey + Social Media Use Survey

Who interacts on the Web?: The intersection of users' personality and social media use

Teresa Correa *, Amber Willard Hinsley, Homero Gil de Zúñiga

Center for Journalism & Communication Research, School of Journalism, University of Texas at Austin, USA

Table 4
Regression on social media use by age.

	Young adults (18–29)				Adults (30 and older)			
	Model 1		Model 2		Model 1		Model 2	
	Beta	*p* value	Beta	*p* value	Beta	*p* value	Beta	*p* value
Gender	.05	.63	.12	.001	−.05	.13	−.03	.4
Race	−.26	.01	−.23	.10	−.09	.01	−.12	.001
Education	.01	.93	.08	.8	−.02	.57	−.03	.4
Income	−.05	.66	−.10	.000	.02	.55	.03	.52
Life satisfaction	.004	.97	.000	.50	−.09	.01	−.08	.05
R^2	6.9%				2%			
Extraversion			.31	.005			.14	.000
Emotional stability			−.15	.18			−.15	.004
Openness			.06	.56			.08	.03
R^2			18.4%				6%	

What about other social media platforms, other personality traits and cross-platform usage?

Nearly 56% of all American internet users use more than one social media platform (Pew, 2015)

Present Research I

What personality differences, specifically for adolescents, predict social media usage?

Does personality predict usage of social media applications other than Facebook and Twitter?

What about personality traits other than the big five? Do these also predict social media usage?

What about personality traits other than the big five? Do these also predict social media usage?

Can we predict cross-platform social media usage from personality data?

Computation I

1540 students (mean age=18.83) from UT Austin, enrolled in an online class, completed the survey as a part of the class. Two sub-samples from Fall 16 and Spring 2017 were collapsed to create one large dataset.

Big-Five Inventory
Dirty Dozen Measure of the Dark Triad
Attachment Style-Questionnaire
CES-Depression Questionnaire
Social Connectedness Questionnaire
Rosenberg Self-Esteem Questionnaire
Demographics
Individual Differences
11 Social Media Use Items

We expect that a users' personality traits (especially the big-five inventory) will be able to predict social media usage, even after accounting for the variance explained by demographic variables.

Computation II

1540 students (mean age=18.83) from UT Austin, enrolled in an online class, completed the survey as a part of the class. Two sub-samples from Fall 16 and Spring 2017 were collapsed to create one large dataset.

Big-Five Inventory
Dirty Dozen Measure of the Dark Triad
Attachment Style-Questionnaire
CES-Depression Questionnaire
Social Connectedness Questionnaire
Rosenberg Self-Esteem Questionnaire
Demographics
Individual Differences
11 Social Media Use Items

We expect that a users' personality traits (especially the big-five inventory) will be able to predict social media usage, even after accounting for the variance explained by demographic variables.

Computation

Study 1

1. Use stepwise and hierarchical regression techniques to model individual social media use items as the exogenous variable and personality traits as the endogenous variable.

2. Explore better modeling strategies for social media use variables from personality data.

Study 2

1. Run Principal Component Analysis on social media use variables to shed light on underlying structure in cross-platform social media usage.

2. Use stepwise and hierarchical regression techniques to model factor scores from step 1 as exogenous variables, with personality and demographic information as endogenous variables.

RESTAURANT ATTRIBUTES AND HOW THEY AFFECT YELP RATINGS

MACS 30200

Fangfang Wan

Why it's interesting?

- We can see what makes a restaurant highly rated – valuable for restaurant owners
- We can see if a rating is fair in our own perspective – valuable for guests

yelp

Find tacos, cheap dinner, Max's | Near Chicago, IL

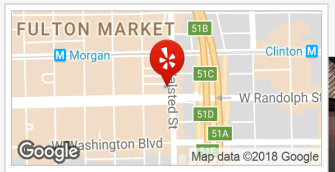
Restaurants | Nightlife | Home Services | Write a Review | Even

Au Cheval

Claimed

4874 reviews | Details

$$ · Bars, Burgers, American (Traditional) | Edit



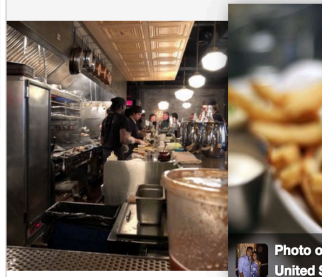
800 W Randolph St
Chicago, IL 60607
b/t Green St & Halsted St
West Loop, Near West Side
Edit

Get Directions

Clinton-Green and 1 more station

auchevalchicago.com

Send to your Phone



"You have to get it "au cheval" style with a **fried egg** and bacon (which was more lil pork belly)." in 592 reviews

$2 Fried Egg

Michelle E.

Chicago, IL

3 friends

11 reviews

20 photos

Share review

Embed review

Compliment

Send message

Follow Michelle E.

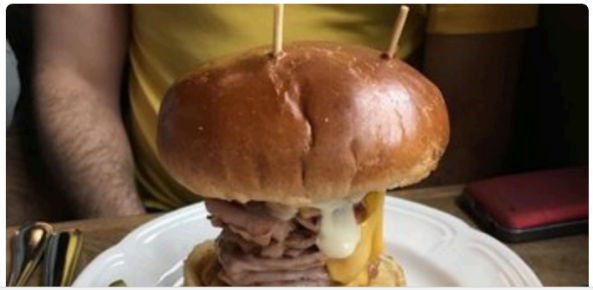
3/31/2018

I have heard about the legend of these burgers for years. Finally pulled the trigger and went for lunch. The line was no joke. I had heard about the wait, but was hoping that maybe today it would be shorter; it was a 1 hr and 15 minute wait. However you can see your spot in line and wait via an app of you would like.

The waitstaff was quick to take our order. Everything arrived quickly. I got the single cheeseburger with egg and bacon along with the friends with Mornay and aioli sauces to split with my mothers. It was plenty of food and the cheeseburger was stacked high with the bacon and the egg. This is definitely a napkin meal as I had on to my cheeseburger to prevent the toppings from sliding out.

All the items I ordered were super good. The fries with the aioli were great. The Mornay sauce I could have done without. The pickles on the cheeseburger, and the side pickle, were all very good. Loved how the red onions on it were chopped super fine- just enough to add flavor with the fear of biting into a huge chunk.

If I am ever just craving the cheeseburger and fries, may try one of the Small Cheval restaurants. But I would miss the aioli...



Contribution

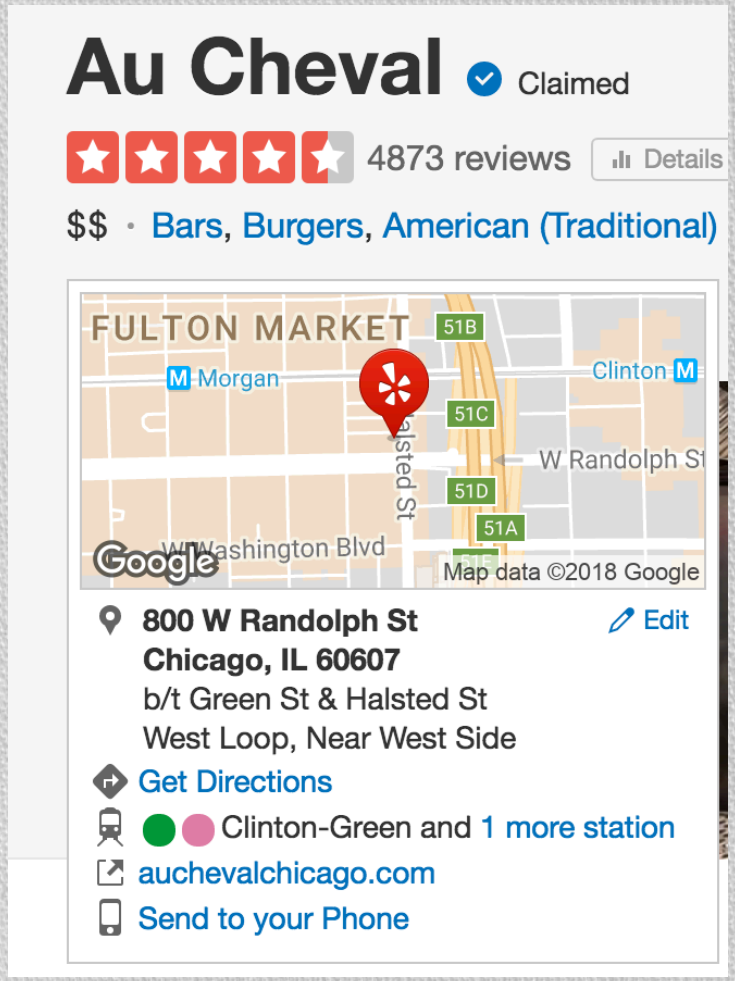
- Add evidence to business researches
- Provide guidance on how to improve Yelp rating for restaurants, and then revenue (Luca, 2016)

Literature Review

- Luca, M. (2016). Reviews, reputation, and revenue: The case of Yelp.com
- Byers, J. W., Mitzenmacher, M., & Zervas, G. (2012, June). The groupon effect on yelp ratings: a root cause analysis. In *Proceedings of the 13th ACM conference on electronic commerce* (pp. 248-265). ACM.

Data

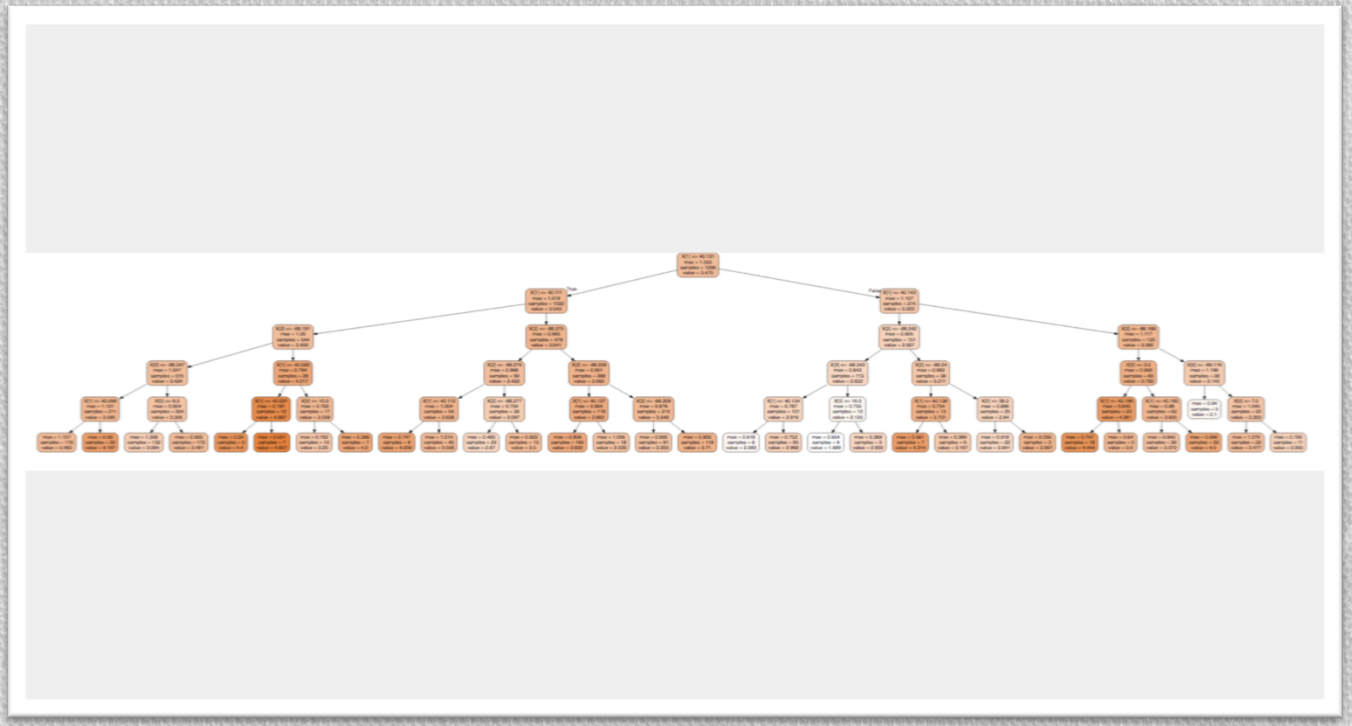
- Web scraping from Yelp html.



More business info

Takes Reservations **No**
Delivery **No**
Take-out **No**
Accepts Credit Cards **Yes**
Accepts Apple Pay **No**
Accepts Android Pay **No**
Good For **Dinner**
Parking **Valet, Street**
Bike Parking **Yes**
Good for Kids **No**
Good for Groups **No**
Attire **Casual**
Ambience **Trendy**
Noise Level **Loud**
Music **Background**
Good For Dancing **No**
Alcohol **Full Bar**
Best Nights **Mon, Tue, Wed**
Outdoor Seating **No**
Wi-Fi **No**
Has TV **No**
Drive-Thru **No**
Caters **No**
Has Pool Table **No**
Gender Neutral Restrooms **Yes**

Data Plot (all businesses in IL as an example. Data from https://www.kaggle.com/yelp-dataset/yelp-dataset/data)



Theory

Not exactly a theory in strict sense –

How do restaurant owners' behaviors affect Yelp rating?

Byers, J. W., Mitzenmacher, M., & Zervas, G. (2012, June). The groupon effect on yelp ratings: a root cause analysis. In *Proceedings of the 13th ACM conference on electronic commerce* (pp. 248-265). ACM.

Model and Tentative results

- Model:
  - Decision tree
  - Linear regression
  - X: attributes of a restaurant (price level, parking, accept Apple Pay, etc.) y: Yelp rating of a restaurant
- Tentative results:
  - Restaurants that offer parking, with higher price level, offer alcohol, etc. may have higher Yelp ratings.

Computational tools

- Computational methods: Mainly Python
  - Linear Regression
  - Tree-based methods
  - Web scraping

Thank you!

Neighborhood Disadvantage and High School Dropout

MACS30200 Lerong Wang

Research Question

- **To what extent do neighborhood disadvantages affect high school dropout rates**
- Use NYC data
- Neighborhood disadvantage: poverty rate, unemployment rate, crime rate...
- Control individual characteristics such as race and gender

Motivation

Neighborhood Effect: The neighborhood effect is an economic and social science concept that posits that neighborhoods have either a direct or indirect effect on individual behaviors.

Why studying high school dropout is important?

- Dropping out from high school is associated with negative employment and life outcomes
- Dropout status has also been linked with poor health, including poor mental health
- Possible policy implications for reducing dropout rates

Previous Work

- Donnelly, Louis. Neighborhood disadvantage and school dropout. Retrieved from https://doi.org/doi:10.7282/T37S7QRD
- Vartanian, Thomas P., and Philip M. Gleason. “Do Neighborhood Conditions Affect High School Dropout and College Graduation Rates?” *The Journal of Socio-Economics*, vol. 28, no. 1, 1999, pp. 21–41., doi:10.1016/s1053-5357(99)00011-6.
- “Poverty and High School Dropouts.” *American Psychological Association*, American Psychological Association, www.apa.org/pi/ses/resources/indicator/2013/05/poverty-dropouts.aspx.

My Contributions

- Prior research emphasizes on poverty and socio-economic status
- I will take more environmental determinants into account
- Model comparison

Data

- High School Dropout Rate: NYC Department of Education Graduation Outcomes
- Neighborhood Disadvantage: American Community Survey
- Neighborhood Disadvantage: www.nyc.gov

New York City Department of Education

Graduation Rate Report

District Graduation Rate

All Students

				Cohort	Total Grads		Total Regents			Advanced Regents			Regents without Advanced			Local			Still Enrolled		Dropout		SACC (IEP Diploma)	
District	Category	Cohort Year	Cohort	#	#	% of cohort	#	% of cohort	% of grads	#	% of cohort	% of grads	#	% of cohort	% of grads	#	% of cohort	% of grads	#	% of cohort	#	% of cohort	#	% of cohort
1	All Students	2013	4 year August	1043	639	61.3	608	58.3	95.1	215	20.6	33.6	393	37.7	61.5	31	3.0	4.9	258	24.7	121	11.6	7	0.7
1	All Students	2012	4 year August	1069	652	61.0	641	60.0	98.3	229	21.4	35.1	412	38.5	63.2	11	1.0	1.7	258	24.1	148	13.8	7	0.7
1	All Students	2011	4 year August	1128	665	59.0	635	56.3	95.5	166	14.7	25.0	469	41.6	70.5	30	2.7	4.5	303	26.9	143	12.7	10	0.9
1	All Students	2010	4 year August	1104	590	53.4	564	51.1	95.6	127	11.5	21.5	437	39.6	74.1	26	2.4	4.4	308	27.9	197	17.8	2	0.2
1	All Students	2009	4 year August	1080	597	55.3	569	52.7	95.3	154	14.3	25.8	415	38.4	69.5	28	2.6	4.7	283	26.2	189	17.5	2	0.2
1	All Students	2008	4 year August	1128	685	60.7	661	58.6	96.5	187	16.6	27.3	474	42.0	69.2	24	2.1	3.5	246	21.8	172	15.2	12	1.1
1	All Students	2007	4 year August	1069	646	60.4	559	52.3	86.5	155	14.5	24.0	404	37.8	62.5	87	8.1	13.5	244	22.8	147	13.8	15	1.4
1	All Students	2006	4 year August	905	563	62.2	498	55.0	88.5	126	13.9	22.4	372	41.1	66.1	65	7.2	11.5	211	23.3	102	11.3	15	1.7
1	All Students	2005	4 year August	886	560	63.2	430	48.5	76.8	115	13.0	20.5	315	35.6	56.3	130	14.7	23.2	217	24.5	86	9.7	7	0.8
1	All Students	2013	4 year June	1043	613	58.8	588	56.4	95.9	211	20.2	34.4	377	36.1	61.5	25	2.4	4.1	284	27.2	121	11.6	7	0.7
1	All Students	2012	4 year June	1069	629	58.8	617	57.7	98.1	228	21.3	36.2	389	36.4	61.8	12	1.1	1.9	281	26.3	148	13.8	7	0.7
1	All Students	2011	4 year June	1128	649	57.5	622	55.1	95.8	166	14.7	25.6	456	40.4	70.3	27	2.4	4.2	319	28.3	143	12.7	10	0.9
1	All Students	2010	4 year June	1104	564	51.1	543	49.2	96.3	127	11.5	22.5	416	37.7	73.8	21	1.9	3.7	334	30.3	197	17.8	2	0.2
1	All Students	2009	4 year June	1080	569	52.7	544	50.4	95.6	153	14.2	26.9	391	36.2	68.7	25	2.3	4.4	311	28.8	189	17.5	2	0.2
1	All Students	2008	4 year June	1128	639	56.6	620	55.0	97.0	184	16.3	28.8	436	38.7	68.2	19	1.7	3.0	290	25.7	173	15.3	13	1.2
1	All Students	2007	4 year June	1069	608	56.9	535	50.0	88.0	153	14.3	25.2	382	35.7	62.8	73	6.8	12.0	280	26.2	148	13.8	16	1.5
1	All Students	2006	4 year June	905	549	60.7	493	54.5	89.8	125	13.8	22.8	368	40.7	67.0	56	6.2	10.2	225	24.9	102	11.3	15	1.7
1	All Students	2005	4 year June	886	522	58.9	419	47.3	80.3	113	12.8	21.6	306	34.5	58.6	103	11.6	19.7	255	28.8	86	9.7	7	0.8
1	All Students	2004	4 year June	756	470	62.2	347	45.9	73.8	111	14.7	23.6	236	31.2	50.2	123	16.3	26.2	213	28.2	68	9.0	3	0.4
1	All Students	2003	4 year June	603	328	54.4	285	47.3	86.9	60	10.0	18.3	225	37.3	68.6	43	7.1	13.1	209	34.7	60	10.0	5	0.8
1	All Students	2002	4 year June	381	212	55.6	185	48.6	87.3	18	4.7	8.5	167	43.8	78.8	27	7.1	12.7	130	34.1	28	7.3	5	1.3
1	All Students	2001	4 year June	376	252	67.0	205	54.5	81.3	19	5.1	7.5	186	49.5	73.8	47	12.5	18.7	58	15.4	54	14.4	11	2.9
1	All Students	2012	5 year August	1082	753	69.6	727	67.2	96.5	231	21.3	30.7	496	45.8	65.9	26	2.4	3.5	128	11.8	187	17.3	9	0.8

NOTES | All | ELL | SWD | Ethnicity | Gender | Ever_ELL | +

Methods

- Spatial analysis to analyze the pattern of high school dropout rates in NYC: Local spatial autocorrelation using Geoda
- Linear Regression
- Random Forest/Tree-based Method in Python

Thank you!

- Questions?

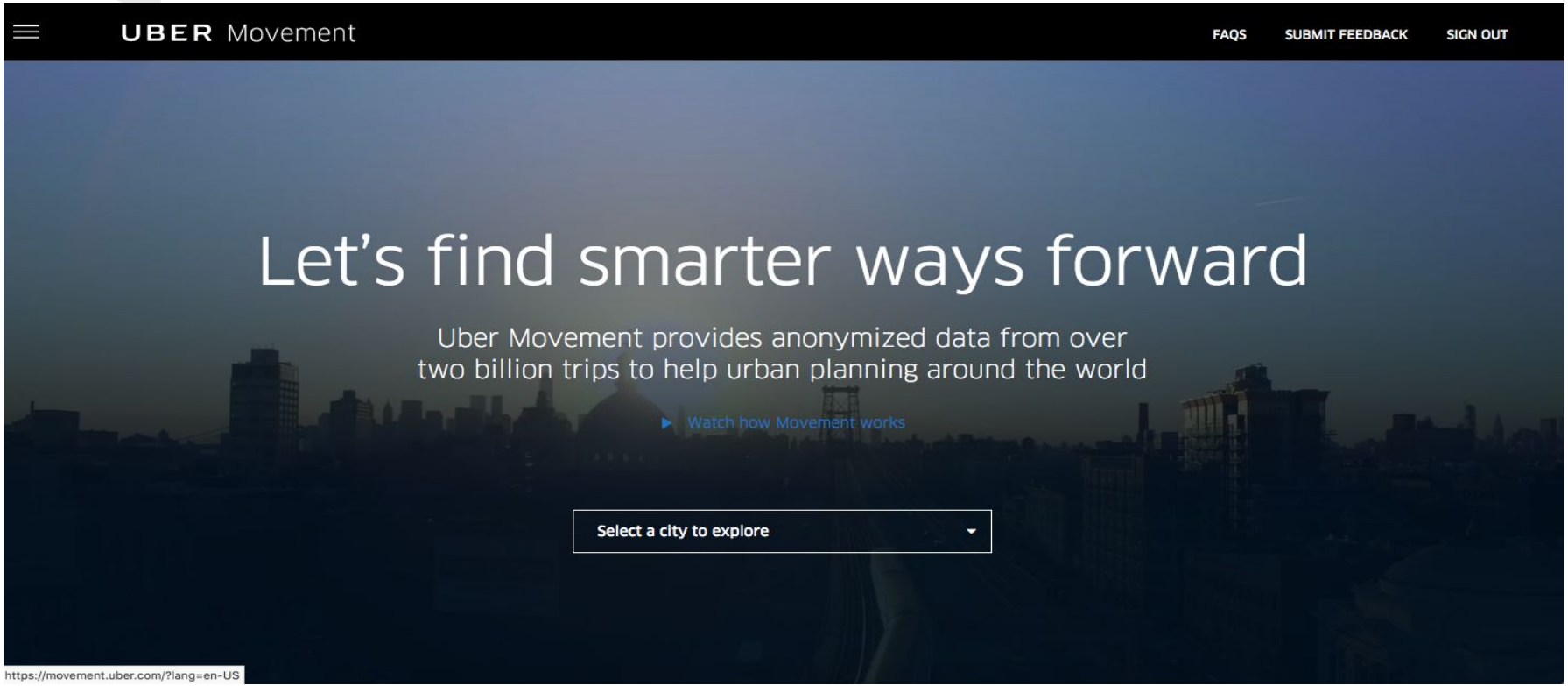
MACSS Project Proposal

Laurence Warner

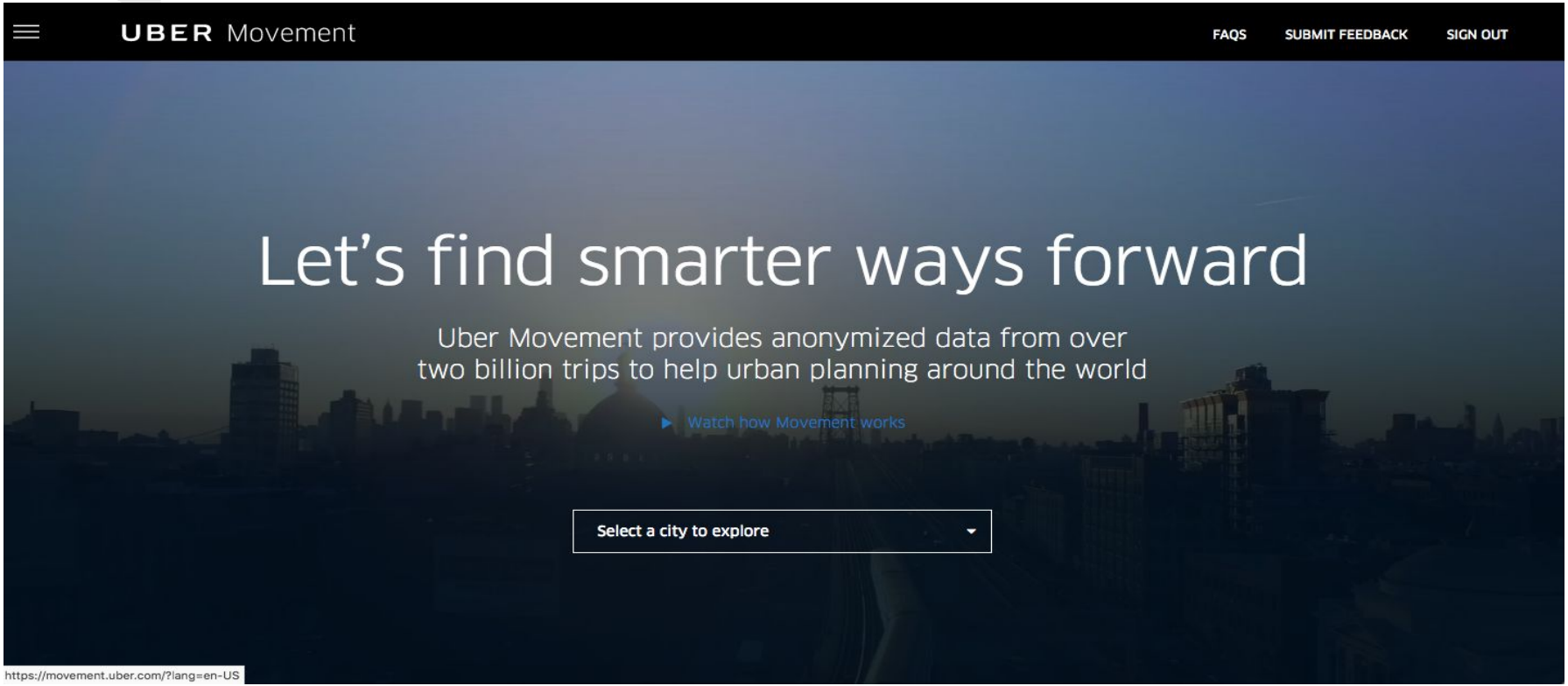
Research Question

Which special events cause the greatest changes in traffic flows in major US cities?

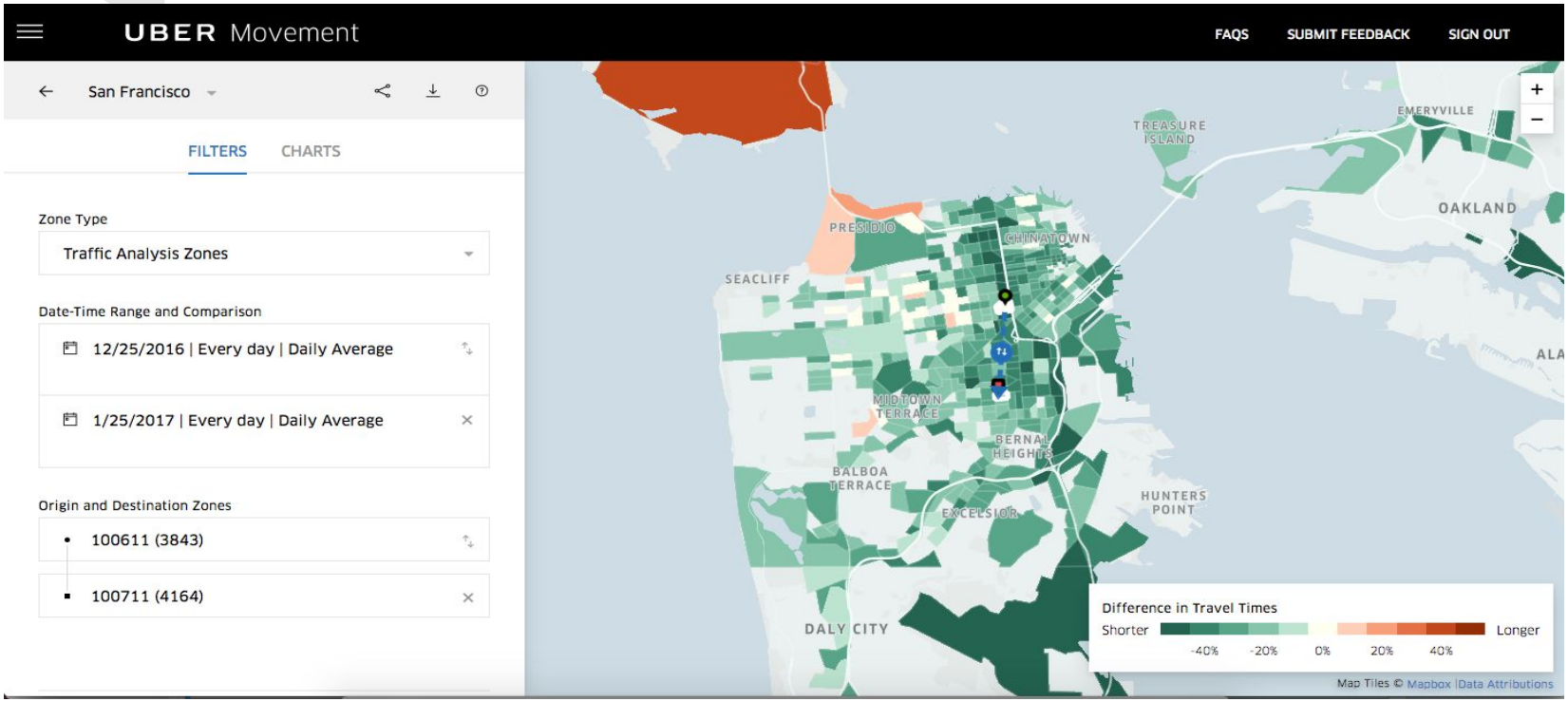
Data


UBER Movement
FAQS
SUBMIT FEEDBACK
SIGN OUT
Let's find smarter ways forward
Uber Movement provides anonymized data from over two billion trips to help urban planning around the world
Watch how Movement works
Select a city to explore
https://movement.uber.com/?lang=en-US

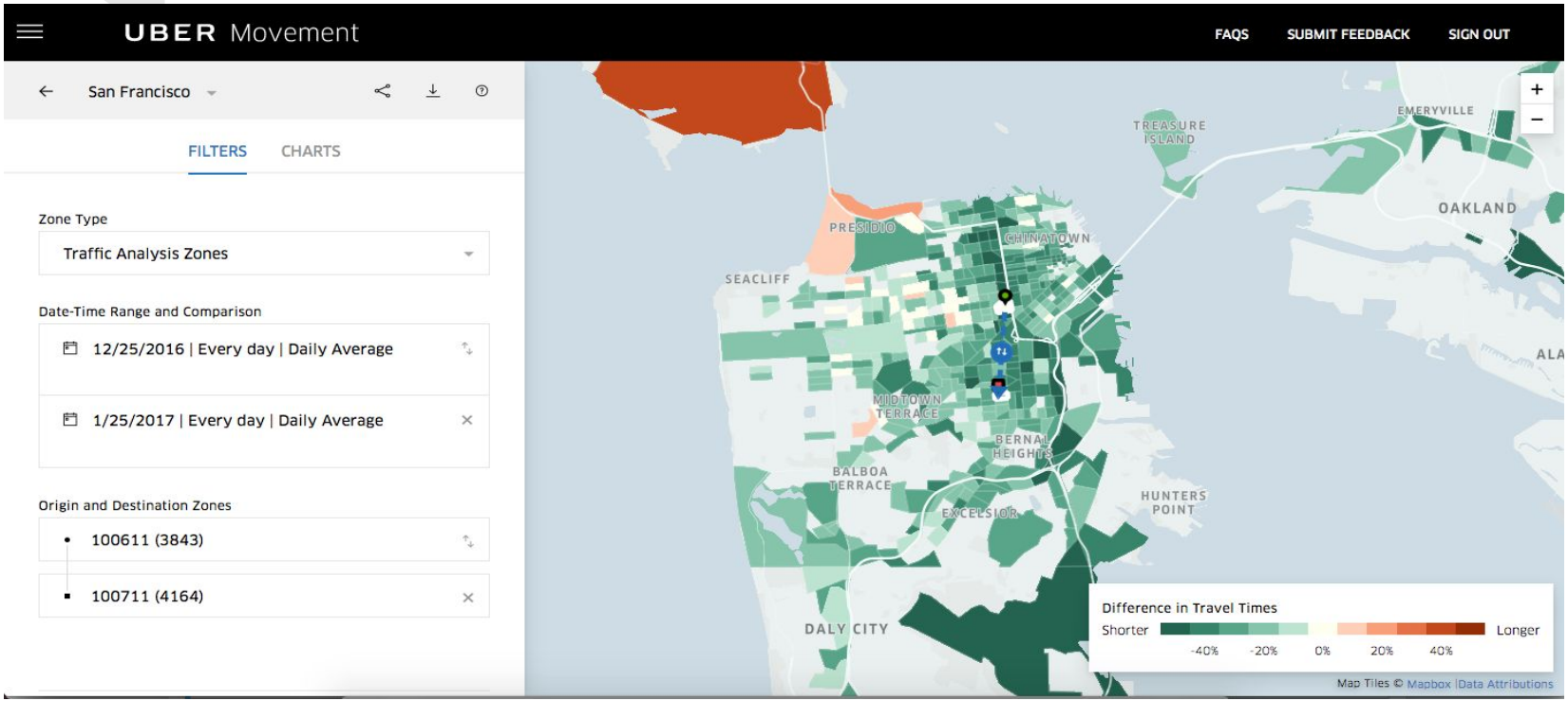
Data


UBER Movement
FAQS
SUBMIT FEEDBACK
SIGN OUT
Let's find smarter ways forward
Uber Movement provides anonymized data from over two billion trips to help urban planning around the world
Watch how Movement works
Select a city to explore
https://movement.uber.com/?lang=en-US

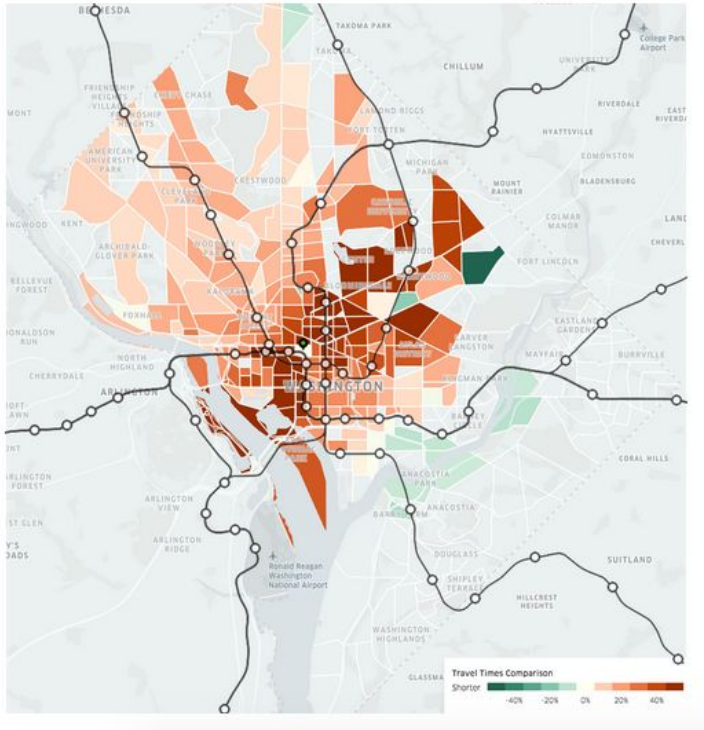
Public Holidays



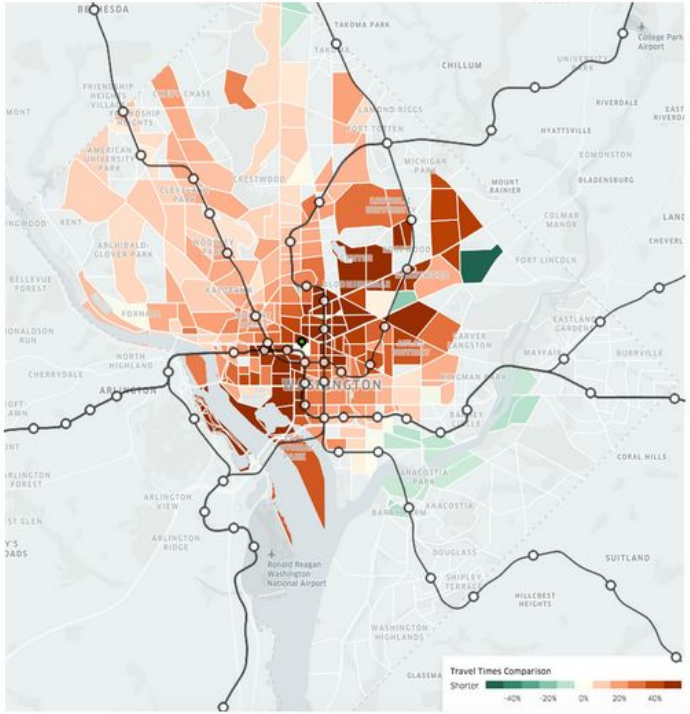
Public Holidays



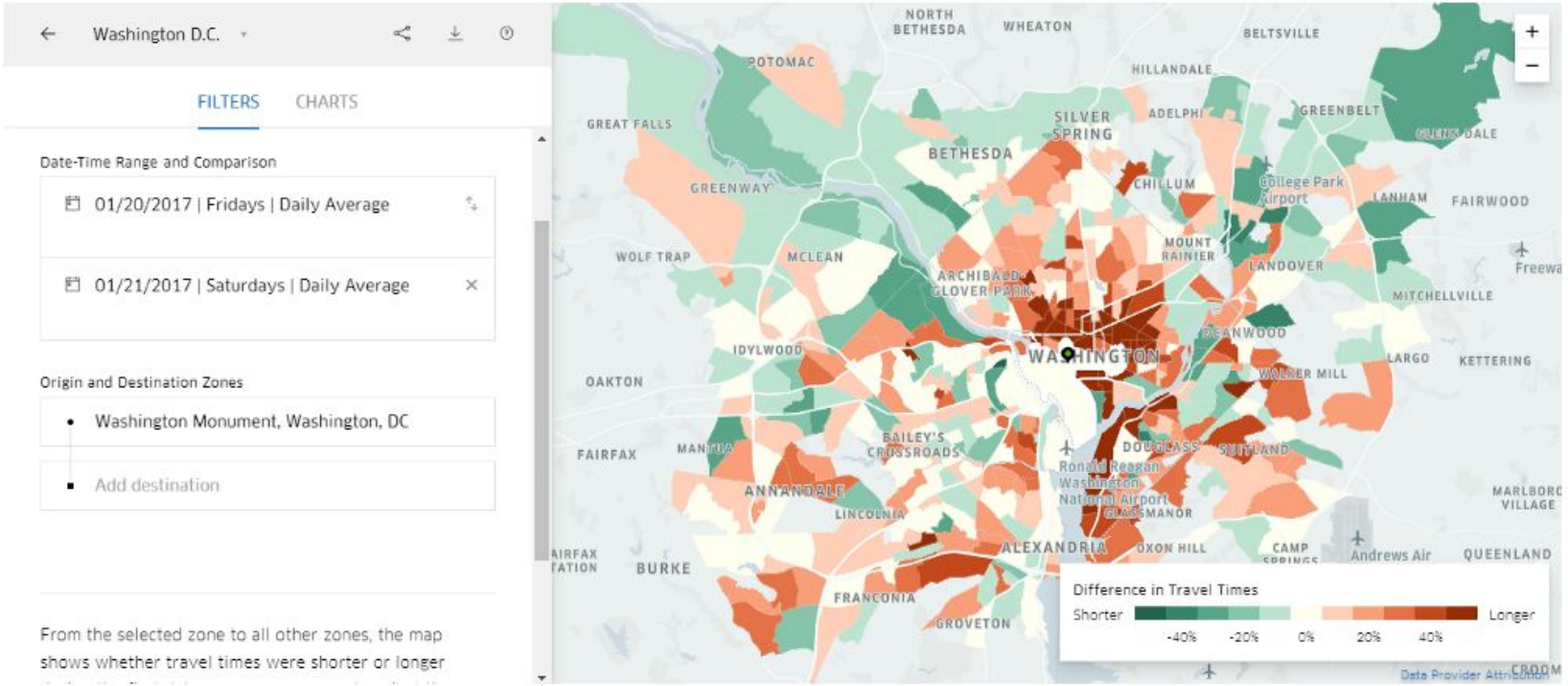
Transport problems



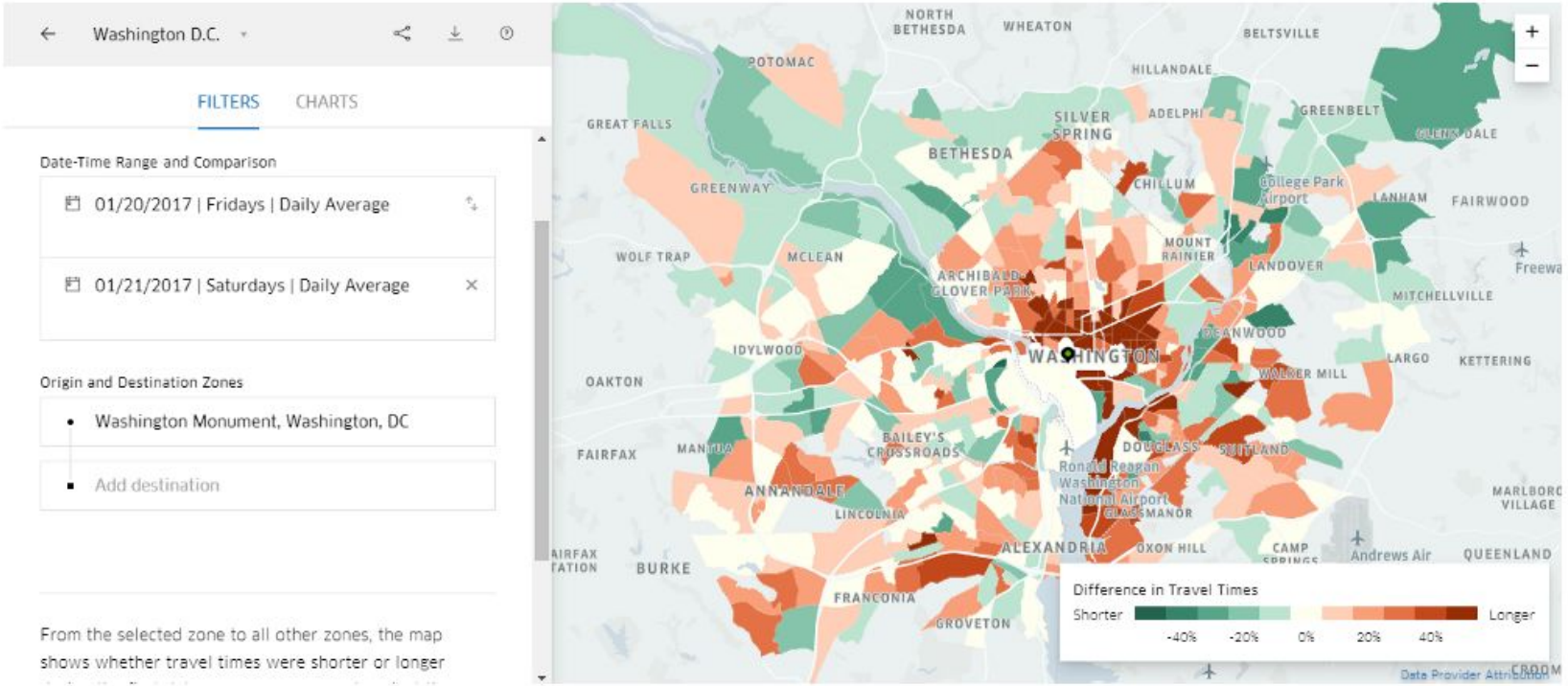
Transport problems



Special Events



Special Events



Understanding The Ideological Stances of Chinese Opinion Leaders:

A Story told by Social Media Data

Yinxian Zhang

Department of Sociology

Research Question One

1. How to measure Chinese opinion leaders' ideological preferences?

- ~~Party Affiliation~~
- ~~Polls/Vote~~
- ~~Survey~~

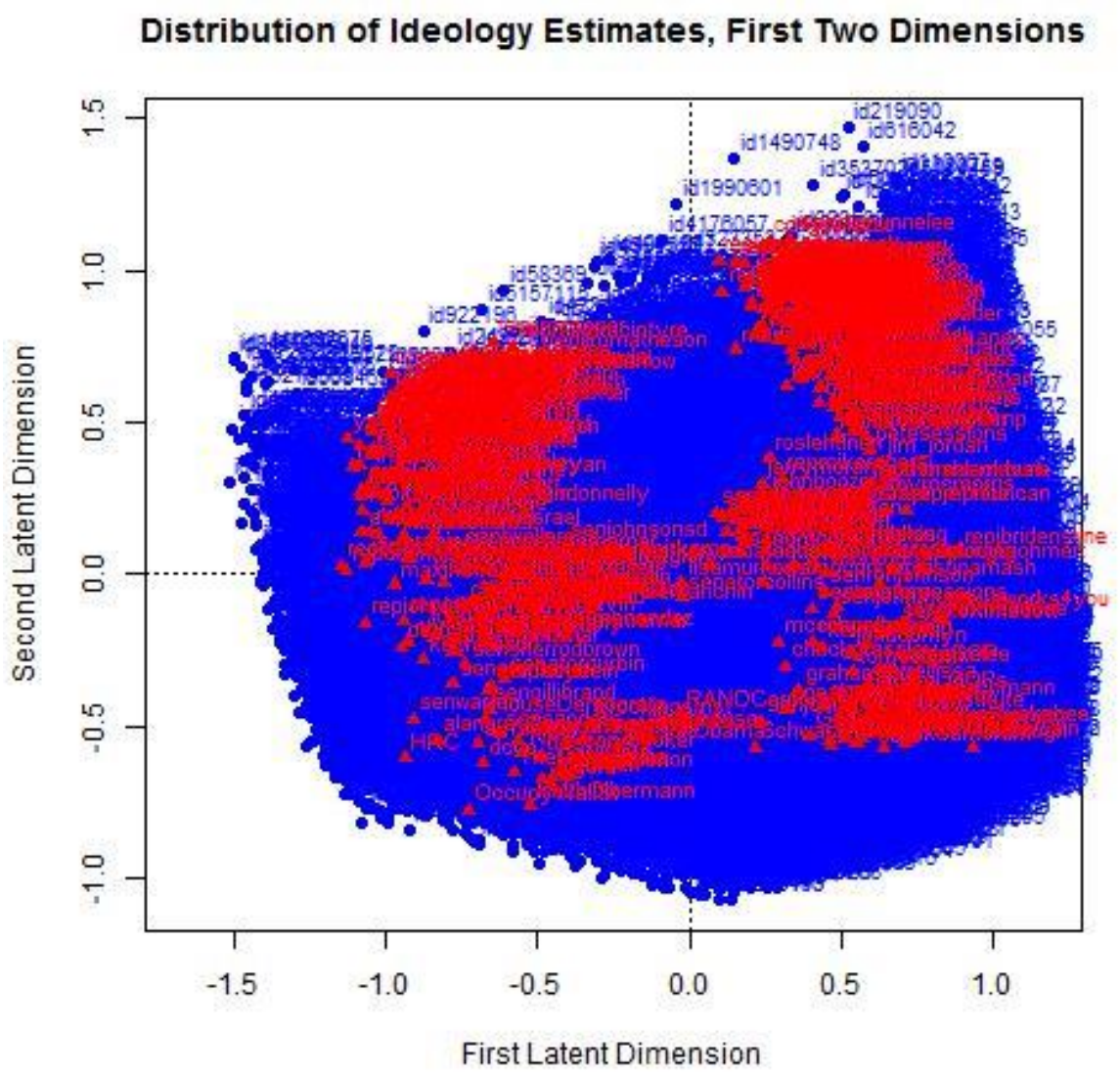
Research Question One

1. How to measure Chinese opinion leaders' ideological preferences?

Method

$$p\left(Y_{ij}=1 \mid \alpha_i, \beta_j, d_{ij}\right) = \text{Logit}\left(\alpha_i + \beta_j - d_{ij}\right),$$

α_i : the "out degree" of an ordinary user *i;*
β_j: the "in degree" of an opinion leader *j.*
d: the distance between i and j in the ideological space



Barberá, P., Jost, J. T., Nagler, J., Tucker, J. A., & Bonneau, R. (2015). Tweeting From Left to Right: Is Online Political Communication More Than an Echo Chamber? *Psychological Science,* doi: 10.1177/0956797615594620.

Research Question Two

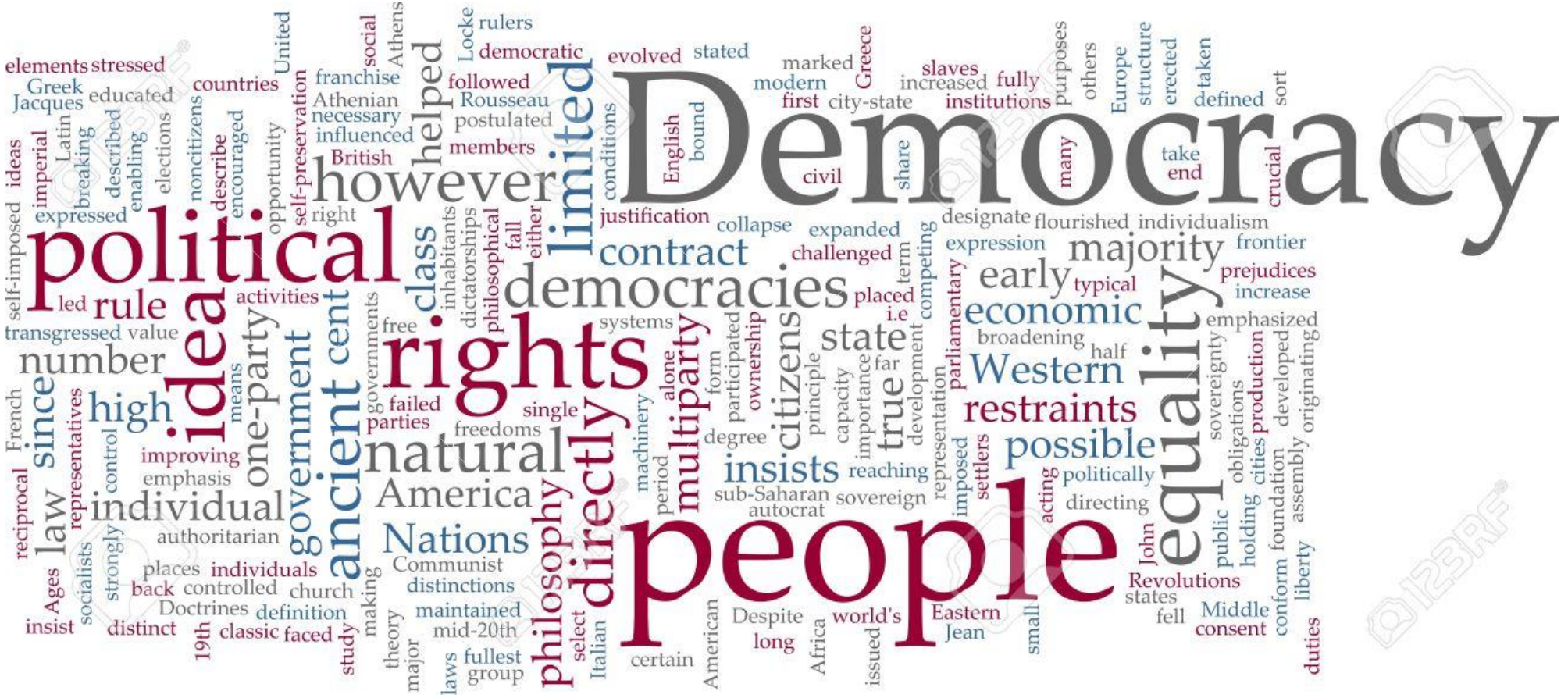
2. How to make sense of the ideological clustering?

- It is also a validation of the original estimation.

** Note that the connotations of the political “left” and “right” are very different in China from what they mean in western societies.

Research Question Two

What opinion leaders talk about when they talk about "democracy"?



Method

Social media posts mentioning “Democracy/民主”

< 140 characters short texts

- Topic detection: LDA? v.s. Hierarchical clustering
- Word embedding: W2V model
- Qualitative reading

Data

- 2.7 billion posts produced by over 170 million active users in 2013 on Weibo, plus their user profiles (following relationships), obtained via APIs.
- 228 opinion leaders identified. [e.g. Ren Zhiqiang(任志强), Sun Liping(孙立平), Wuyue Sanren(五岳散人), Zuoyeben(作业本), Sima Nan(司马南), Hu Xijin(胡锡进), Dai Xu(戴旭), Cai Xiaoxin(蔡小心)…]

Data

- 2.7 billion posts produced by over 170 million active users in 2013 on Weibo, plus their user profiles (following relationships), obtained via APIs.
- 228 opinion leaders identified. (Zhang, Yinxian, Jiajun Liu and Jirong Wen. *forthcoming*. "Nationalism on Weibo". *The China Quarterly*.)

	Mean	SD	Min	Max
Follower count	2272875	4904651	24799	3.45e+07
Following count	1385.25	895.45	0	3685
Friends count	1143.53	791.16	0	3623
2013 post count	443.21	434.70	30	3092

- IRB approved.

Expected outcomes

- 1. Getting ideological positions (and clustering) of Chinese opinion leaders.
  - Easy to extend to ordinary people.
  - One of the pioneering studies to measure ideological preferences of Chinese people using observational data.

- 2. Interpreting the ideological stances of different opinion leader clusters.
  - Understanding the specific connotations of "democracy" in the Chinese context.
  - What are people's opinions towards democracy? → joining in the scholarly efforts to explain the (lack of) democratization process in China.

Actor, Culture or Structure?

A Predictive Model on News Article Popularity

Weiwei Zheng

Introduction

What influences News Popularity?

- Agenda Setting vs. Agenda Building

  Media *influences what we think.*

  Transfer of the media agenda is a reciprocal process.

  -- Rogers, Dearing, 1988

- **Audience** takes an active role in virtual sphere during the process of information diffusion. **Human autonomy matters**.
- News popularity can be predicted by **crowd** manipulation.

  -- D. Horne and Adali, 2017

Introduction

What shapes human behavior?

- "Duality of structure" : social practice, which is the principal unit of investigation, has both a **structural** and an **agency**-component.

-- Anthony Giddens

- **Culture** is an important mechanism.
- “A critical site of social action and intervention, where power relations are both established and potentially unsettled. ”

-- Stuart Hall

- Headline negativity, subjectivity and overall sentiment influence news popularity.

-- Reis, Julio, etc., 2015

Research Questions

Goal: To build a predictive model on news popularity

- Can active participants/opinion leaders, news content, and network structure altogether predict the popularity of online news article?
- Hypothesis: Yes.

Significance of the Topic:

1) Touch on the relationship between network structure and info diffusion (ameliorate communication strategy online).
2) Look into the mechanism and process of developing online public opinion.

Informal Model

Dependent Variable – News popularity

an aggregate of communication effect and public opinion

Predictive Variables – three dimensions

- Structure

  Audience Network Attributes
- Agency

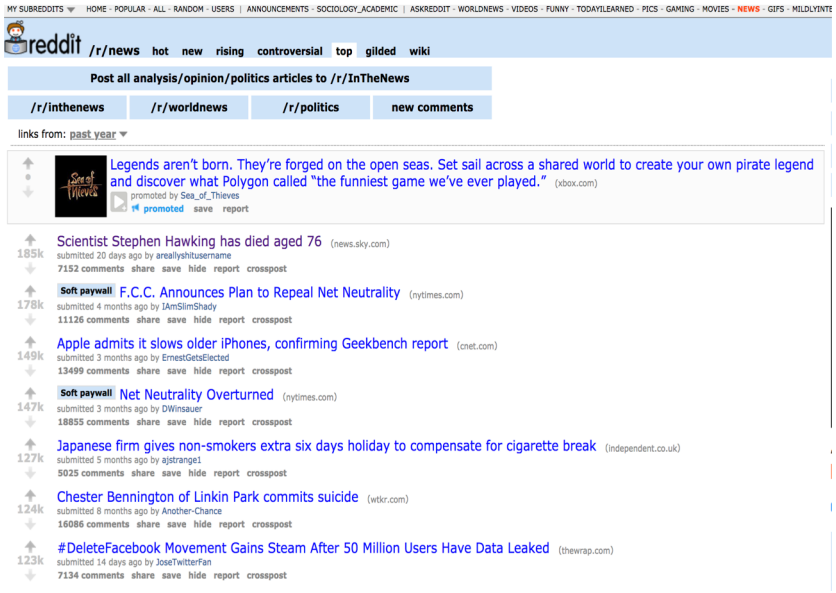
  Opinion Leaders (number of actors of different roles)
- Culture

  News articles' content, sentiment, media agency

Confounders – Date of published, total time of view

Data Sources

- Reddit *an American social news aggregation, web content rating, and discussion website.*
- API: Praw
- /r/news, /r/worldnews (top section)



Data Sources

- News Articles

  All urls in /r/news (worldnews) top section

  head title, content, word count

- API: Newspaper3k (supports NLTK)

"All the News That's Fit to Print"

The New York Times

Late Edition

Today, clouds, afternoon rain, breezy, high 56. Tonight, a bit of rain early, some clearing, low 45. Tomorrow, a late-day shower, high 59. Weather map is on Page 18.

VOL. CLXII . . No. 56,092 NEW YORK, SUNDAY, MARCH 31, 2013 $5.00

As OSHA Emphasizes Safety, Long-Term Health Risks Fester

Toxic Factory Fumes Test Agency's Powers

By IAN URBINA

TAYLORSVILLE, N.C. — Sheri Farley walks with a limp. The only job she could hold would be one where she does not have to stand or sit longer than 20 minutes, otherwise pain screams down her spine and up her legs.

"Damaged goods," Ms. Farley describes herself, recalling how she recently overheard a child whispering to her mother about whether the "crippled lady" was a meth addict.

For about five years, Ms. Farley, 45, stood alongside about a dozen other workers, spray gun in hand, gluing together foam cushions for chairs and couches sold under brand names like Broyhill, Ralph Lauren and Thomasville. Fumes from the glue formed a yellowish fog inside the plant, and Ms. Farley's doctors say that breathing them in eventually ate away at her nerve endings, resulting in what she and her co-workers call "dead foot."

A chemical she handled — known as n-propyl bromide, or nPB — is also used by tens of thousands of workers in auto body shops, dry cleaners and high-tech electronics manufacturing plants across the nation. Medical researchers, government officials and even chemical companies that once manufactured nPB have warned for over a decade that it causes neurological damage and infertility when inhaled at low levels over long periods, but its use has grown 15-fold in the past six years.

Such hazards demonstrate the difficulty, despite decades of effort, of ensuring that Americans can breathe clean air on the job. Even as worker after worker fell ill, records from the Occupational Safety and Health Administration show that managers at Rosale Comfort Seating, where Ms. Farley was employed, repeatedly exposed gluers to nPB levels that exceeded levels federal officials considered safe, failed to provide respirators and turned off fans meant to vent fumes.

SHORT OF MONEY, EGYPT SEES CRISIS ON FUEL AND FOOD

ECONOMIC FEARS DEEPEN

Government Is Pressed to Increase Taxes and Cut Subsidies

By DAVID D. KIRKPATRICK

QALYUBEYA, Egypt — A fuel shortage has helped send food prices soaring. Electricity is blacking out even before the summer. And gas-line gunfights have killed at least five people and wounded dozens over the past two weeks.

The root of the crisis, economists say, is that Egypt is running out of the hard currency it needs for fuel imports. The shortage is raising questions about Egypt's ability to keep importing wheat that is essential to subsidized bread supplies, stirring fears of an economic catastrophe at a time when the government is already struggling to quell vio-

The Boston Globe

SUNDAY, APRIL 9, 2017

DEPORTATIONS TO BEGIN

President Trump calls for tripling of ICE force; riots continue

Curfews extended in multiple cities

PRESIDENT TRUMP has set in motion one of his most controversial campaign promises, calling on Congress to fund a "massive deportation force" by tripling the number of federal Immigration and Customs Enforcement agents.

The president made the announcement in a nationally televised address last night from the Old Post Office building in Washington, D.C., now a Trump International Hotel. In a surprise move after the speech, Trump invited Attorney General Chris Christie to stand right next to him at the podium to field questions. "Too_side_eye for Christie this time," tweeted Fox News Channel reporter Megyn Kelly, who was covering the speech from a sports bar near Rockefeller Center because she has been placed on a White House blacklist.

Although Trump reiterated his promise to eject some 11.3 million illegal workers on a two-year timetable — "so fast that your head will spin" — he also promised to "do it humanely." He did not immediately offer details but said he intends to flesh out the policy with special adviser George Papado-

Markets sink as trade war looms

WORLDWIDE STOCKS plunged again Friday, completing the worst month on record as trade wars with both China and Mexico seem imminent.

Markets from the Dow to the FTSE to the Nikkei have sunk on speculation that China is dumping some of its US Treasury holdings after the Trump administration announced tariffs as high as 45 percent for all Chinese imports and 35 percent for some Mexican goods.

"I don't mind trade wars when we're losing $58 billion a year," the president said last year. But Chinese officials have made it no secret that they will not let tariffs go unanswered.

Methods

Data Processing

- API: Networkx, NLTK
- Average clustering, transitivity, centrality, connectivity, etc.
- Algorithm to differentiate different types of users
- Text Classification (Bayes Classifiers, SVM, sentiment)
- Topic Modeling (Generative Models and LDA)

Sample size

- now 1,000 top news/worldnews and several hundred comment trees for each)

Model Selection

- Machine Learning: lasso regression, principal component regression, spline

Few Points to Mention

Algorithm Confounding Issues

- Probably only top news can be scrapped

(Reddit limits number of objects to be returned by Praw within 1000)

- Unpredictable size of comment data
- Data sources, sample size and methods are subject to change

Measurement Issues

1) unable to measure the impact from the offline world
2) silent participants are filtered
3) unable to study the interaction between different dimensions

Citations

Buntain, Cody, and Jennifer Golbeck. "Identifying social roles in reddit using network structure." In *Proceedings of the 23rd International Conference on World Wide Web*, pp. 615-620. ACM, 2014.

Horne, Benjamin D., and Sibel Adali. "The impact of crowds on news engagement: A reddit case study." *arXiv preprint arXiv:1703.10570* (2017).

Lippmann, Walter. *Public opinion*. Routledge, 2017.

Mrogers, Everett, and James Wdearing. "Agenda-setting research: Where has it been, where is it going?." *Annals of the International Communication Association* 11, no. 1 (1988): 555-594.

Reis, Julio, Fabrıcio Benevenuto, P. Vaz de Melo, Raquel Prates, Haewoon Kwak, and Jisun An. "Breaking the news: First impressions matter on online news." In *Proceedings of the 9th International AAAI Conference on Web-Blogs and Social Media*. 2015.

Zaman, Tauhid, Emily B. Fox, and Eric T. Bradlow. "A Bayesian approach for predicting the popularity of tweets." *The Annals of Applied Statistics* 8, no. 3 (2014): 1583-1611.