Data Science for the Public Good Discussion & Coding

2019 Midwest Big Data Summer School Aaron D. Schroeder, PhD Social Decision Analytics Division Bioinformatics Institute, University of Virginia



We study policy-focused problems



P&G

MITRE

Local / State Government

Arlington County, Virginia Fairfax County, Virginia State Higher Education Council of Virginia Virginia Department of Emergency Management

Federal Statistical Agencies

U.S. Census Bureau Housing and Urban Development National Science Foundation National Center for Science & Engineering Statistics

Department of Defense

U.S. Army Research Institute Defense Manpower Data Center Minerva Research Initiative

Industry MITRE Corporation Procter & Gamble



• <u>SDAD Web Page</u>





Our Data Science Framework

Problem Identification: Relevant Theories & Working Hypotheses ADMINISTRATIVE DATA: Local, State, & Federal **DATA SOURCES DESIGNED DATA** Discovery, Inventory, **OPPORTUNISTIC DATA FLOWS** & Acquisition **PROCEDURAL DATA DATA INGESTION & GOVERNANCE** DATA DATA DATA DATA PROFILING PREPERATION LINKAGE **EXPLORATION** Data Structure, Ontology, Cleaning, Characterization, Selection & Data Quality, Transformation, Summarization, Provences & Alignment, Visualization Restructuring Meta Data Entity Resolution FITNESS-FOR-USE-ASSESSMENT **Statistical Modeling and Data Analyses**

Keller, S.A., S. Shipp, G. Korkmaz, E. Molfino, J. Goldstein, V. Lancaster, B. Pires, D. Higdon, D. Chen, and A. Schroeder. 2018. "Harnessing the Power of Data to Support Community-Based Research." WIREs Computational Statistics. e1426.

Keller, S.A., G. Korkmaz, M. Orr, A. Schroeder, S. Shipp. 2017. "<u>The Evolution of Data Quality: Understanding the Transdisciplinary Origins of Data Quality</u> <u>Concepts and Approaches</u>." Annual Review of Statistics and Its Applications 2017. 4:5.1-5.24.



Continuous Process of Engagment



S. Keller, V. Lancaster, S. Shipp. (2017). <u>Building Capacity for Data-Driven Governance:</u> <u>Creating a New Foundation for Democracy</u>. *Statistics and Public Policy*, September.



Observations from Our Work Thus Far

Issues that have arisen and repeat from our community engagements thus far:

- Locating and describing a population within a community
- Estimating a statistic and a measure of its variability to evaluate its usefulness for the purpose at hand
- Forecasting future needs
- Evaluating a program, policy, or standard operating procedure

Research challenges that are emerging through our work:

- Formalization and automation of Data
 Science Framework
- Data integration, analysis, and linkage across multiple levels of data support
- Data and corresponding estimation redistribution across multiple geographies
- Composite indices development and alignment with issues



Data Science for the Public Good (DSPG)

- Experiential learning program through which participants learn everything they need to know to get started working as a data scientist in policy-oriented positions
- Creating Public Good-Oriented Data Scientists, or "Policy Scientists"
- Learning not just how to do the work, but also how to work across disciplines on problem-solving teams
- For the graduate fellows, also learning how to run these teams, managing both up an down
- All started when asked to teach "Research Methods" for Masters of Public Administration students



Data Science for the Public Good (DSPG)





RESIDENTIAL SMOKE ALARM NEED IN ARLINGTON COUNTY







Harsimrat Pandher (VT), David Park (VT), Daniel Wilkin (VT), Joseph Kim (VT) Claire Kelling (PSU) with Gizem Korkmaz and Stephanie Shipp (SDAL) Sponsor: Gary Anderson, The National Center for Science & Engineering Statistics



ANALYZING THE ECONOMIC IMPACT AND SOCIAL INTEGRATION OF REFUGEES IN ROANOKE, VIRGINIA

Claire Kelling (PSU), Kyle Morgan (VT), Craig Morton (VT), Hannah Brinkley (VT), Adrienne Rogers (VT) with Mark Orr, Stephanie Shipp, and Bianica Pires (SDAL)

A STUDY ON WMATA BUS FARE EVASION



PROFILE OF NEW KENT, VA

David Park, Joseph Kim, David Hinkle, Lata Kodali (Virginia Tech) with D. Sponsor: Carl Frick, Virginia Corporate Extension (VCE) representative.

CREATING SYNTHETIC DATA FOR VIRGINIA LONGITUDINAL DATA SYSTEM

Sponsor: Tod Massa (SCHEV – State Council for Higher Education in Virginia)

DEFINING AND MEASURING EQUITY IN ALEXANDRIA, VA

PROFILING ARMY BASES 🧕

Cool: identify publicly available data sources (e.g., Census and BLS data) to create social, demographic, economic and other quantifable profiles of Army bases and ther surrounding areas, identify relevant variable for use in statistical models. Soorassr: Crea Ruark: Andrew Slauchter: US Army Research institute for Behavioral & Social: Science Research



DSPG Experience Goals

Engage in meaningful research focused on real-world problems and addresses social policy

Work in partnership with government sponsors and policy makers

Learn essential tools for scientific and statistical computing, including R, Python, Databases, GIS, and other software tools as needed for projects Learn the entire Data Science for Policy process, from stakeholder engagement and problem definition to the delivery of policy impacting analyses, tools and data products

Work on truly multi-disciplinary project teams comprising diverse levels of experience (students, post-docs, researchers, and federal leaders) and a broad range of academic perspectives (data science, statistics, economics, sociology, psychology, geography, and others)

> Directly interact with policy leaders and government agencies through field trips and regular policy events on Capitol Hill and the surrounding area

Engage with leading policy practitioners and researchers through SDAD's Visiting Scholar program, which includes economists, statisticians, and other social science researchers with diverse public and private sector experience



DSPG Annual Symposium, Speaker Series



THE UNIVERSITY OF VIRGINIA'S Biocomplexity Institute, Darden School of Business, and Data Science Institute in partnership with the Northern Virginia Technology Council announce the Data Science for the Public Good (DSPG) Forum, an opportunity for civic engagement through two Forum events, including a Distinguished Speaker Series and Annual Symposium. These events will bring together key public and private stakeholders to discuss how "doing data science" can support evidence-based policymaking and innovation to enhance the quality of life where we all live, learn, work, and play.

LET THE CONVERSATIONS BEGIN REGISTER NOW •

DISTINGUISHED SPEAKER SERIES

Former Governor of Maryland Martin O'Malley kicks off the series with his talk, Smart Government: The Data, the Map, and the Method.

-

DATE: June 14, 2019 | TALK AND Q&A SESSION: 4:00pm - 5:00pm | RECEPTION: 5:00pm - 6:30pm

ANNUAL SYMPOSIUM

The 4th Annual Symposium celebrates the Biocomplexity Institute's 2019 DSPG Young Scholars and their research. Keynote speakers include: Phil Bourne, Director of the University of Virginia's Data Science Institute and Acting Dean of the School of Data Science; Ron Jarmin, Deputy Director and Chief Operating Officer of the U.S. Census Bureau.

DATE: August 9, 2019 | TIME: 1:00pm - 4:30pm

LOCATION OF EVENTS: University of Virginia Darden School of Business Sands Family Grounds, 1100 Wilson Blvd., 30th Floor, Arlington, VA 22209.

REGISTRATION for these events and more information about the Data Science for the Public Good Forum is available at biocomplexity.virginia.edu/events.



Data Science for the Public Good Forum



The University of Virginia's Biocomplexity Institute, Darden School of Business, and Data Science Institute in partnership with the Northern Virginia Technology Council announce the Data Science for the Public Good Forum, an opportunity for civic engagement, comprised of a Distinguished Speaker Series and Annual Symposium.

The Data Science for the Public Good (DSPG) Forum builds on the Biocomplexity Institute's highly successful and distinctive DSPG research platform that leverages cutting-edge public policy analytics and unprecedented data access, and serves as an honest broker to identify, visualize, and understand the full complement of interests that affect the public good.

As central programs of the Forum, the Distinguished Speaker Series and Annual Symposium will bring together key public and private stakeholders to discuss how "doing data science" can support evidence-based policymaking and innovation to enhance the quality of life where we all live, learn, work, and play,

We can't wait to begin these important conversations with you!

DATA SCIENCE FOR THE PUBLIC GOOD DISTINGUISHED SPEAKER SERIES

June 14, 2019



The former Governor of Maryland, Martin O'Malley, will be our inaugural speaker and kick off the Data Science for the Public Good Distinguished Speaker Series with his talk. Smart Government: The Data, the Map, and the Method.

Date: June 14, 2019

Talk and O&A Session: 4:00-5:00pm Reception: 5:00-6:30pm

Location: University of Virginia Darden School of Business Sands Family Grounds 1100 Wilson Boulevard, 30th Floor Arlington, VA 22209

Register for the Distinguished Speaker Series.

DATA SCIENCE FOR THE PUBLIC GOOD ANNUAL SYMPOSIUM

August 9, 2019



In its fourth year, the Data Science for the Public Good Annual Symposium will celebrate the Biocomplexity Institute's 2019 Young Scholars and their research. Speakers will include Phil Bourne, Director of the University of Virginia's Data Science Institute and Acting Dean of the School of Data Science, and Ron Jarmin, Deputy Director and Chief Operating Officer of the U.S. Census Bureau.

Date: August 9, 2019

Symposium: 1:00-4:30pm





DSPG Syllabus

• DSPG 2019 Program Schedule





Projects - WMATA

- **Problem:** WMATA loses approximately 10-20 million dollars a year due to bus fare evasion on its 1300-1500 daily trips
- **Research Goal:** Provide insights into the problem of bus fare evasion that can be used to guide fare
- evasion interventions
- Analysis Plan: Using WMATA administrative data locate where fare evaders live and American Community Survey
- to tell their story at the census
- block group level





General Observations about Fare Evasion

- Widespread national and international problem
- Typically estimated using observer surveys and not using administrative data
 - Observer surveys include: high costs, missed assignments, difficulty processing large passenger volumes, data interpretation issues, data entry and analysis costs, and potential data collection inconsistencies between observers
- The fare evasion estimates from surveys do not include an estimate of the variability



WMATA Administrative Data Sources

Data Sources for the first week of May (5/1 - 5/7/2017)

- Bus Stops (10,988 observations): Contains the stop ID, stop name, latitude, and longitude
- Automated Person Counter (APC): Contains front & back door entries and exits for a bus, route, trip number and bus stop
- Farebox: Contains cash & SmarTrip transactions for a bus, trip number, & bus stop
- Data Issues: Imprecise latitude and longitude coordinates, missing or mislabeled bus routes and stop IDs in Farebox and APC data, missing trip numbers in Farebox data

Data	Uncleaned	Cleaned	Monday - Friday
APC	3,793,655	3,791,332	3,105,623
Farebox	2,729,668	2,060,055	1,751,335



Fare Evasion in Evenings 2-8 pm



- Locations to add money to SmartTrip cards in DC
- Could this contribute to fare evasion?



Economic Vulnerability Index

Composite economic vulnerability index by **census block groups** with bus stops in the seven WMATA jurisdictions

The composite index was constructed using ACS (2015) variables:

- % households in poverty (Federal)
- % households with no vehicle
- % households qualifying for SNAP
- % households with housing burden > 50%



Insights for Potential Interventions

• Not all economically vulnerable Census Block Groups have high numbers of fare evaders, but all Census Block Groups with a high numbers of fare evaders are economically vulnerable.



Cautionary Tale: Need Accurate Estimates for Policy Implementation and Evaluation

To test hypotheses or experiments for interventions, need to know how accurately fare evasion can be estimated - what effect sizes can be measured!



So Much Learning!





Projects – Operation FireSafe



Issue: Fire Department wants to improve the efficiency of their Operation FireSafe program

Out of 5,623 visits to single family homes only 1,799 had an adequate number of working smoke detectors

Goal: Construct models to predict for each single family home the probability it has adequate smoke detectors



The DATA

- Household Level (Administrative Data): Operation FireSafe data for the 5,623 single family homes visited
- Household Level (Administrative Data): Real estate tax assessments for 60,343 single family homes including tenure, home age, value, size, and number of bedrooms
- Household Level (Opportunity Data): Geocoded the single family home locations
- Census Tract Block Group Level (Designed Data):
- 5-year 2015 American Community Survey household level demographic and socioeconomic data



Model to Predict Regions in the County in Need of Smoke Alarms

- Bayesian logistic regression model with conditionally autoregressive spatial effects¹
- Identify the predictors of housing units in need of a smoke alarm installation or battery replacement $Y_i \sim \text{Bernoulli}(p_i)$

$$\log\left(rac{p_i}{1-p_i}
ight) = \mu_i + \phi_i \qquad egin{array}{cc} \mu_i = \mathbf{X}_i^T oldsymbol{eta} & oldsymbol{eta} \sim N(\mathbf{0}, \mathbf{I}_{1000}) \end{array}$$

$$\phi_i | \phi_{-i}, \mathbf{W}, \tau^2, \rho \sim N\left(\frac{\rho \sum_{k=1}^K w_{ik} \phi_k}{\rho \sum_{k=1}^K w_{ik} + 1 - \rho}, \frac{\tau^2}{\rho \sum_{k=1}^K w_{ik} + 1 - \rho}\right)$$

- Response Y_i =1 if household *i* needs a smoke alarm intervention.
- The spatial component is given by the weighted neighborhood matrix W, where
 - $w_{ij} = 1$ if households *i* and *j* are in the same block group
 - $w_{ij} = 0.5$ if households *i* and *j* are in neighboring block groups

• $w_{ij} = 0$ otherwise

¹Leroux B, Lei X, Breslow N (1999). Estimation of disease rates in small areas: a new mixed model for spatial dependence. *Statistical Models in Epidemiology, the Environment and Clinical Trials*. Springer-Verlag: New York.

Evaluating Predictive Performance

- Metrics
 - **Precision**: When the model suggests the home has a smoke alarm, what percentage of these homes actually have it?
 - **Recall**: What percentage of homes with alarms is the model catching?
- When $p_i < t$ for threshold t, the **model predicts** that household i needs a smoke alarm intervention
 - We find the value of t that maximizes precision and recall
- Models are trained using repeated holdout samples of 10%, 15% and 20% of the observations
 - For each holdout sample, the model is fit and predicted probabilities are assigned to the holdout samples
- 2015 Operation FireSafe data used to estimate the performance of 2016 data
 - Then both years were used to make final predictions for 2017
- Predictions made at the household level and aggregated to Census block groups



Probability of Having a Smoke Alarm

Bayesian logistic regression model with conditionally autoregressive spatial effects





Findings

Predictors of smoke detector need

At the household level:

- Home value (-)
- Age of home (+)

At the neighborhood level:

- Median income (-)
- Percent living alone (+)
- Percent family households (-)

ACFD used a list of vulnerable neighborhoods predicted to target their visits for 2017



Projects – Arlington Restaurant Initiative Measuring the Impact of Alcohol-Related Crime Reduction Strategies for Restaurants and Nightlife in Arlington

• Arlington County features some of the most unique restaurants and nightlife destinations in the Washington D.C. metro region. Areas such as Clarendon, however, with a large number of restaurants have become a difficult issue for police to manage due to alcohol-related crimes such as malicious wounding, sexual assault, public intoxication, assault on police, DUI, disorderly conduct, and rape.



Projects – Arlington Restaurant Initiative Measuring the Impact of Alcohol-Related Crime Reduction Strategies for Restaurants and Nightlife in Arlington

• Arlington County Police Department (ACPD) launched the Arlington Restaurant Initiative (ARI) that focuses on best practices for restaurants and nightlife to reduce the risk of alcohol-related disorder. The initiative grew out of the Clarendon Detail, the creation of a team of patrol officers using overtime to control pedestrian and road traffic, and to ensure that intoxicated patrons are protected from harm.



Projects – Arlington Restaurant Initiative Measuring the Impact of Alcohol-Related Crime Reduction Strategies for Restaurants and Nightlife in Arlington

- Objective: Evaluate effectiveness (social and economic impact) of ARI in Clarendon to help ACPD sustain and support program funding.
- Need a justifiable funding model that goes beyond counting arrest



Projects – Arlington Restaurant Initiative

≡ Menu ARI Overview

leatmap



Clarendon has over 40 restaurants (pinned in blue circles) with ABC (Alcohol and Beverage Control) licenses and an average of 5,500 patrons per weekend night. Each year, approximately 580,000 patrons visit Clarendon between 21:00 and 03:00, especially during holidays and special "drinking" events. Alcoholrelated crime counts in Clarendon on Friday, Saturday, and Sunday between 21:00 and 03:00 for 2015-2017 are given in yellow and green circles.



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	id	description 🕴	location 🍦	latitude 🕴	longitude 🍦	start 🕴	end 🕴	year 🔶	month 🕴	day_of_week 🍦
	1 2018- 0531000	7 DUI	S WALTER REED DR / 18TH ST S	38.85299031	-77.08812649	2018-05- 31T00:43:00Z	2018-05- 31T00:43:00Z	2018	5	Thursday
	2 2018- 05280152	DUI 3+ OFFENSE OR 2 2+ FELONY OFFENSE	1XX N GLEBE RD	38.87262371	-77.10374707	2018-05- 28T16:51:00Z	2018-05- 28T16:51:00Z	2018	5	Monday
	3 2018- 0528005	7 DUI	N LYNN ST / LEE HWY	38.89716894	-77.06996344	2018-05- 28T05:00:00Z	2018-05- 28T05:00:00Z	2018	5	Monday
	4 2018- 05270039	ÐUI	ARLINGTON BLVD / N COLUMBUS ST	38.86547337	-77.11670666	2018-05- 27T04:04:00Z	2018-05- 27T04:04:00Z	2018	5	Sunday
	5 2018- 05260260		XX 8468436440000000	38.84758519	-77.08140523	2018-05- 26T23:40:00Z	2018-05- 26T23:40:00Z	2018	5	Saturday
	6 2018- 05260243	3 DUI	13TH ST S / S GEORGE MASON DR	38.85768855	-77.09867447	2018-05- 26T22:37:00Z	2018-05- 26T22:37:00Z	2018	5	Saturday
	7 2018- 05260178	B DUI	23XX 25TH ST S	38.84887425	-77.07555001	2018-05- 26T17:15:00Z	2018-05- 26T17:30:00Z	2018	5	Saturday
	8 2018- 05260025	5 DUI	25XX S WALTER REED DR	38.84614347	-77.10075429	2018-05- 26T01:30:00Z	2018-05- 26T01:30:00Z	2018	5	Saturday
	9 2018- 05250034	4 DUI	N HIGHLAND ST / 9TH RD N	38.88215652	-77.09260151	2018-05- 25T03:08:00Z	2018-05- 25T03:08:00Z	2018	5	Friday
	10 2018- 0525002	5 DUI	10TH ST N / FAIRFAX DR	38.88351863	-77.09836161	2018-05- 25T02:04:00Z	2018-05- 25T02:06:00Z	2018	5	Friday

JNIVERSITY VIRGINIA



VERSITY IRGINIA



*JNIVERSITY 9VIRGINIA

New Data Sources for VCE Community Profiles

Project Background

- VCE District Planning includes an process of Community Profiling
- SDAL is currently working with VCE to develop a Dashboard that will allow for a deeper level of analysis than is currently conducted, including:
 - Location (Place)-Level Data (Places of Worship, SNAP Providers, Social Service Locations)
 - Sub-County-Level Data (Block Groups, Water Districts, School Boundaries)
 - **Tools** for quick descriptive analysis (Maps, Time-Series, Scatterplots





New Data Sources for VCE Community Profiles

Health

Project Goal(s) / Research Questions

- County Discover possible sub-county data sources for use by VCE in creating OBJACK GROUP School District community profiles, including: Map Level Data
 - **Radon Levels**
 - **Active Coal Mine Locations**
 - Water Quality (Rivers)
 - Water Quality (Treatment Plants)
 - **Soil Status Quality**
 - **Crop Coverage**
- Profile discovered data sources quality, structure, provenance and metadata
- Determine necessary transformations for data re-purposing and overall data source fitness to support VCE goals
- Incorporate new data into dashboard; create new dashboard tools





New Data Sources for VCE Community Profiles




Fairfax Youth Partnership

Describing Populations and Forecasting Future Needs

- Issue: Characterize the factors that describe depression and obesity in youth
- Goal: This type of understanding will allow Fairfax County to implement policies targeted to address youth behaviors
- Approach: Identify access to food and physical activity options, e.g. grocery stores, restaurants, farmers markets, community gardens, parks, and more





The DATA

Household Level

- Geocoded the household locations
- Supervisor districts

Places of Interest

- Food, parks and recreation centers
- Transportation routes and modalities
- Clinics

Census Tract Block Group Level

 5-year 2015 American Community Survey - household level measures of economic vulnerability

School Level

- Locations and boundaries
- Fairfax County Youth Survey, 2010 2015



Youth Reporting Depressive Symptoms

Percentage of Students Who Felt Sad or Hopeless in the Past Year





Source: Fairfax County Youth Survey, 2010 - 2015



Distance to Healthy and Unhealthy Foods based on Location of Housing Units

Supervisor Districts in Fairfax County, Virginia



Students Reporting Depressive Symptoms and Location of Mental Health Providers



% of Students reporting depressive symptoms on youth survey -those who felt so sad or hopeless almost everyday for two weeks or more in a row during the past 12 months

Point are locations of Mental Health Providers - reported from Psychology Today and

SAMHSA



Distance to Healthy and Unhealthy Foods based on Location of Housing Units

Supervisor Districts in Fairfax County, Virginia



Box Plots: Minutes per Week of Physical Activity



2016 2016

2016 Fairfax Youth Survey: H3, PC

Factors That Might Affect Obesity



Response Variable

- 1 No Physical Activity
- 2 5+ Days of Physical Activity
- 3 5+ Servings ofFruit andVegetables
- 4 1+sugary drink per day
- 5 Unhealthy weight loss
- 6 Food Insecurity



Statistical Geographic Data Redistribution Data science innovations to develop *sub-county* data-driven insights

- Synthetic population technology Creating socioeconomic profiles of Supervisor Districts and High School Attendance Areas by statistically aligning American Community Survey data to these new geographic boundaries
- Geocoding housing units, both owned and rented based on tax assessment records and the reconstruction of rental units from files provided by Fairfax demographer
- New sources of data obtained from local administrative data and webscraping, with a focus on access to food and physical activity
- Vulnerability Composite Indicators integrating data
- Exploring the data using visualization tools





Examples of **place data:**

- All restaurants
- Fast Food restaurants
- Farmer's Markets
- Community Gardens
- Recreation Centers
- SNAP Retailers

• Parks

Direct aggregation based on location of housing units

Geocoding owner-occupied local housing stock In general, adding rental units can be a challenge and may require imputation





Re-distribution of data based on Synthetic Populations

- Use American Community Survey (ACS) summaries and PUMS microdata to impute synthetic person data for all people in area of interest
- Re-weight synthetic data according to ACS tables to simultaneously match the relevant distributions, to Census Tracts or Block Groups
 - Age, income, race, and poverty in this case
- Aggregate synthetic person data to compute summaries, and margins of error, over the new geographic boundaries



Sub-county Vulnerability Indicators



Based on a statistical combination of the percentage of Households with:

- housing burdens > 50% of Household income
- no vehicle
- receiving Supplemental Nutrition Assistance Program (SNAP)
- in poverty



Fairfax Profiles by Supervisor Districts

Dashed lines = Average; Supervisor Districts arranged by Vulnerability Index from high to low



Repurposing Administrative Data for Statistical Purposes

National Academy of Sciences Workshop on Data Privacy for Employment Data, Jun 6 2017

> Aaron D. Schroeder, Ph.D. Senior Data Research Scientist Social & Decision Analytics Lab Biocomplexity Institute of Virginia Tech



Every Repurposing Is a New "Investigation"

- Locating the Data Repurposing Discussion
- Overview of the SDAD "Investigative Process" for Repurposing Data
- Recommendations for Research-Enabling Standards for Integrated Administrative Data Systems to Aid Future Investigations



Data Repurposing Locating the Discussion







CLD3 - Data Science Processes & Platforms for Evidence-Based





Data Science Processes & Platforms for Evidence-Based Policy



Community Discovery Process

- Facilitate preliminary problem identification & hypothesis generation starts with critical communityleader-defined issues and good *contextual assessment*
 - THIS SHOULD TAKE A LONG TIME
 - Biggest BANG for the BUCK for facilitated sessions is here
- Conduct data management system status discovery to ascertain methods and technologies currently employed
- Determine data storage and management capacity requirements of the entire process
- Conduct data analytics capabilities assessment are they going to use a statistical model you build? Or do they just need better counts?
- Conduct data discovery and inventory process to identify potential data sources related to the specific issue areas

Deploy data connection technologies as required by an already established data access plan to enable the IVERSITY data transfer and management

Community Discovery Process Situation Analysis & Hypothesis Generation: Context, Stakeholders, Joint-Visioning

Example: Implementation Environment of the Virginia Longitudinal Data System

- Multiple levels of statutory law
- Multiple implementations of regulatory law at each level of statutory law
- Most conservative interpretation of regulatory law becomes de facto standard

"No one person , inside or outside a government agency, should be able to create a set of identified linked data records between partner agencies"

- Has a direct and significant effect on the potential success of the technical approach chosen – A Centralized, Hierarchical Data Warehouse will likely Fail!
- Easy to see, if you look for it!



• Learn the Language! e.g. Virginia Towns





Data Discovery & Inventory

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mmu	Data Agreements						
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The first step preliminary inventory

- identify which sources are worthy of a deeper screening
- includes 6 questions and a qualitative evaluation of purpose, data collection method, timeliness, selectivity, accessibility, and description

- 1. Are the data collected opinion-based, (e.g., people's attitudes, preferences, etc.)?
- 2. Are the data collection recurring, (i.e., must be collected at least annually)?
- 3. Are there data available for 2013?
- 4. Geographic granularity

For Education

- Are the data collected at least the school level?
- Can the data be linked to other education/workforce datasets, (e.g., K-12, higher education, workforce)?
- If this is a state dataset, how do they define school districts within this state?
- If applicable, what types of schools does it cover, (e.g., public, private, charter)?

For Housing

- Are the data collected at the property or housing unit level?

Additional Screening Information

Purpose:

- What is the purpose of the organization collecting the data, (e.g., the Virginia Department of Education (VDOE) coordinates education for the state and makes policy recommendations)?
- Why are the data collected and how does the organization use the data, (e.g., VDOE collects the data for administrative purposes to assess student and school progress and to inform school policies)?
- Who else uses these data, (e.g., businesses, policy-makers, citizens, researchers)?
- Who do they sell the data to, (e.g., Zillow for individual homeowners, CoreLogic for multiple uses, business for economic development, Chief Economists at trade associations)?

Method:

- What is the data collection method, (e.g., paper questionnaire, operator entry, online survey, interview, sensors, algorithms for creating datasets from twitter feeds)?
- What is the type of data collected, (e.g., designed collection, intentional observation, administrative data, digital data)?
- If designed, who created the questions, (e.g., government, researchers, private business)?
- What are the raw sources of the collected data prior to any aggregation, (e.g., self-report, third party)?

Description:

- What is the general topic of the data, (e.g., student learning, housing quality)?
- What are the earliest and latest dates for which data are available, (e.g., 1995-2005)?

Timeliness:

- Are the data collected and available periodically, (e.g, every year or decade)?
- How soon after a reference period ends can a data source be prepared and provided, (e.g., one year)?

Selectivity:

- What is the universe (e.g., population) that the data represents (e.g., students who attended public school in Virginia in 1995)?

*

Accessibility:

- How are the data accessed, (e.g., API, downloaded csv, txt, etc.)?
 - * Are they open data?
 - * Any legal, regulatory, or administrative restrictions on accessing the data source?
 - * Cost? Is it one-time or annual or project-based payment?
- Describe any gaps/concerns you see with this dataset

Does this dataset appear to meet for the needs for the Census Bureau study? Yes/No

Data Discovery & Inventory

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- Conducted on a selected subset from inventory
- Much deeper dive
- Output is a subset of data sets selected for acquisition and initial analysis of their fitness for analysis

Description/Features

- What is the temporal nature of the data: longitudinal, time-series, or one time point?
- Are the data geospatial? If Yes, at what level, (e.g. census tracts, coordinates)?

Metadata

- Is there information available to assess the transparency and soundness of the methods to gather the data for our purposes, (*i.e., supplementing the census*)?
- Is there a description of each variable in the source along with their valid values?
- Are there unique IDs for unique elements that can be used for linking data?
- Is there a data dictionary or codebook?

Selectivity

- What unit is represented at the record level of the data source, (e.g., person, household, family, housing unit, property)?
- Does this universe match the stated intentions for the data collection? If not, what has been included or excluded and why (e.g., do the data exclude certain individuals due to the way the data are collected)?
- What is the sampling technique used (if applicable, e.g., convenience, snowball, random)?
- What is the coverage, (e.g. response rate)?

Stability/Coherence

- Were there any changes to the universe of data being captured (including geographical areas covered) and if so what were they, (e.g., changed the geographical boundaries of census tracts)?
- Were there any changes in the data capture method and if so what were they, (e.g., revised questions, data collection mode, classification categories, algorithms for social media data)?
- Were there any changes in the sources of data and if so what were they, (e.g., data were reported by teachers in 2010 and reported by principals in 2011; used Current Population Survey in 2011 and American Community Survey in 2012)?

Accuracy

- Are there any known sources of error, (e.g., missing records, missing values, duplications, erroneous inclusions)?
- Describe any quality control checks performed by the data's owner, (e.g., deleted duplicates, checked for recording errors)

Accessibility

- Are any records or fields collected, but not included in data source, such as for confidentiality reasons, (e.g., does not include any student files in which there are less the 5 students in a category)?
- Is there a subset of variables and/or data that must be obtained through a separate process, (e.g. state level data openly available, but one must apply to get census tract)?
- If yes, is there a separate legal, regulatory, or administrative restrictions on accessing the data source?
- Cost? Is it a one time, annual, or project-based payment?

Privacy and security

- Was consent given by participant? If so, how was consent given, (e.g., online form, in-person discussion)?
- Are there legal limitations or restrictions on the use of the data, (e.g., Family Educational Rights and Privacy Act -FERPA)?
- What confidentiality policies are in place, (e.g., cannot share data outside of requesting institution; does not include personally identifiable information)?

Research

- What research has been done with this dataset, (e.g., impact of policies, predictors of student success, housing stock inventory assessment)?
- Include any links to research if provided.
- List any other data use notes provided by the supplier.



Data Management Process & Platform

- Establish type and method of data transfer
 - pushed to or pulled into the cooperative platform?
 - staying where it is and being dynamically queried in a federated manner as needed?
- Establish the best transfer protocol(s) to use given the types and method of transfer
 - e.g. SFTP, secure Dropbox, secured REST API, VT SAFR-Data Adapter for secure federated queries
 - Establish designed collection systems (e.g. behavioral experiments)
- Establish data marshaling processes
 - system mediation logic, data pipeline and data transformation, transfer schedule, and data provenance maintenance
- Establish secure data storage procedures
 - e.g. each project being stored on a new projectdedicated encrypted partition, original data being

stored as non-removable and non-editable





Data Information Process & Platform

- The Lexicon: an inventory of and history of changes to:
 - every available data field in every available data source
 - the structure of their storage
 - possible values and meanings of the information
 - possible transformations of each set of field values from one data source to another another data source
 - methods of data source access
 - matching algorithms and how they are to be used in conjunction with possible field value transformations
- Provides fundamental functions for the operation of the framework and is a **requirement** that the data information be collected from all partner communities
- Enables removal of much complexity required for high quality data linkage
 - i.e. No enforcing data standardization schemes on data partners









Data Analytics Process

- Data Fitness Analysis (Data Re-Purposing)
 - Modeling is a function of the research question (the use) – drives all data actions
 - Fitness assessment is about fitness of the data for the model
 - Fitness is a function of the model, data quality needs of the model, and data coverage (representativeness) needs of the model
 - When using multiple data sources, fitness will need to assess linking across data sources
 - Fitness must characterize information content in the results
 - Accuracy and precision





Data Analytics Process

- Data Fitness Analysis
 - Data Profiling
 - Structure
 - Quality
 - Provenance & Metadata
 - Data Preparation
 - Data Linkage

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- Data Exploration
- Data Analysis & Hypothesis Testing
- Creation of Community Data Tools





Repurposing Data for Statistical Purposes

Data Fitness Analysis: Profiling Structure, Quality, Metadata & Provenance

Missing Variables

values in column headers instead of variable names

e.g. Value-ranges being used as column headers (0-9|10-19|20-29|...)

Combined Variables

more than one variable represented in a attribute (column) value e.g. An attribute combining gender and age (m25, f32,...)

e.g. An attribute combining gender and age (m25, i

Multiple Observation Directions

variables in both columns and rows

e.g. A dataset with an element(column) for each day of the month (horizontal) and an element(column) for 'month' (vertical)

note. the messiest and can be dealt with multiple ways according to the needs of the specific analysis

Combined Observation Unit Types

more than one observation unit type per table

e.g. A table containing both individual demographic data and a periodic measurement like weekly attendance where demographic data and weekly attendance are separate observational units and need to be in separate datasets.

Divided Observation Unit Type

observation unit type is split among multiple tables

e.g. Individual demographic information split among several datasets; for example, separate tables for gender, ethnicity, and surname.







Repurposing Data for Statistical Purposes

Data Fitness Analysis: Profiling Structure, Quality, Metadata & Provenance Combined Observation Unit Types

Current Structure of Williamsburg MLS Data

_										
	List Number	Agency Name	Agency Phone	Agency Email	Listing Agent	Listing Agent Phone	Listing Agent Email	Co-Listing Agent	Property Type	Card Format
	Book Section	Selling Agency	Selling Agency Phone	Selling Agency Email	Selling Agent	Selling Agent Phone	Selling Agent Email	Co-Selling Agent	End Date	book_sec
	Listing Date	Sold Date	Under Cont. Date	Fall-thru Date	Status	Status Change	Withdraw Date	Cancel Date	Contingent	Cont. Remarks
	Orig. List Price	Price	Sold Price	high_price	Low Price	assessed_val	Partial Tax Assmnt	financing	Area	Relocation
	St. #	box_nbr	St. Dir.	Street Name	Address 2	streetdirsuffix	Street Suffix	carrier_route	City	State
	county	country	Zip Code	geo_county	Taxes	geo_lat	geo_lon	Est. Fin. SqFt	sqft1	sqft2
	sqft3	sqft4	Year Built	2+ Bdroms on 1st Flr	Realtor.com Type	lot_size	Total Acres	Condo Level	sell_broker_comm	Variable Commission
	stories	Total Rooms	Total Bedrooms	total_bath	Baths - Full	Baths - Half	baths_3_4	Garage Type	garage_stall	Water Frontage
	Zoning	taxes	Tax Year	Subdivision	Public Remarks	Agent Remarks	Parcel ID	Legal Description	Directions	Foreclosure
	Owner Phone	Owner Name	Neighborhood	mod_timestamp	Ltd Service Agent	Occupied By	Owner/Agent	Mster Bdrm 1st Floor	SqFt Source	Listing Type
	# Stories	# Fireplaces	Golf Frontage	IDX Y/N	Supplement Attached	Seller Concession(s)	Special Assmnts	Туре	Rollback Taxes	userdefined16
	SellingBroker Incent	Ownership	Describe Concession	How Sold	Selling Broker Comp	userdefined22	Assessed Value	Est.Unfinished Sq Ft	Tax Rate	Garage Bays
	userdefined27	userdefined28	userdefined29	userdefined30	Est. Closing Date	userdefined32	userdefined33	Lot Description	Short/CompromiseSale	userdefined36
	userdefined37	userdefined38	userdefined39	userdefined40	userdefined41	userdefined42	userdefined43	userdefined44	userdefined45	userdefined46
	userdefined47	userdefined48	userdefined49	userdefined50	userdefined51	userdefined52	userdefined53	userdefined54	userdefined55	userdefined56
-	Photo URL	Days on Market	Rooms	Features						

- This is a single record with 128 fields all keyed to the variable "List Number"
- Structured this way, it is not possible to analyze property changes over time
- Pulling out a definitive list of unique properties using "Parcel ID" seems like a possibility
- However, "Parcel ID" is left blank in over 7% of entries extra work required perhaps including address, but address is not standardized

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Repurposing Data for Statistical Purposes

Data Fitness Analysis: Profiling Structure, Quality, Metadata & Provenance

Combined Observation Unit Types

Emergency Services Data Processing Example

Multiple Types of Observation on Single Page

Additionally:

Forms made available online as nested HTML Tables - each needing separate extraction







Repurposing Data for Statistical Purposes

Data Fitness Analysis: Profiling Structure, Quality, Metadata & Provenance Divided Observation Unit Types

	gender1	id	gender2
	F	43XXX13	Μ
	F	43XXX14	Μ
	М	76XXX46	F
•	F	74XXX98	Μ
	F	76XXX23	Μ
-	F	77XXX40	Μ
	М	74XXX98	F
C	М	78XXX73	F
0	F	78XXX74	Μ
0	М	77XXX84	F
0	F	79XXX87	Μ
	М	71XXX95	F
~	М	21XXX96	F
	М	71XXX54	F
C	F	71XXX55	Μ
10	F	77XXX86	Μ
	F	80XXX24	Μ
1	М	76XXX79	F





Repurposing Data for Statistical Purposes

Data Fitness Analysis: Profiling Structure, Quality, Metadata & Provenance

Completeness

percentage of elements properly populated

e.g. Testing for NULLs and empty strings where not appropriate

Value Validity

percentage of elements whose attributes possess meaningful values

e.g. A comparison constraint like {male; female} or an interval constraint like age = [0,110]

Consistency

a measure of the degree to which two or more data attributes satisfy a welldefined dependency constraint – relationship validation

e.g. Zip-code - state consistency or gender - pregnancy consistency

Uniqueness

the number of unique values taken by an attribute, or a combination of attributes in a dataset

e.g. Frequency distribution of an element

note. The more homogeneous the data values of an element, the less useful the element is for analysis

Duplication

a measure of the degree of replication of distinct observations per observation unit type

e.g. Greater than 1 registration per student per official reporting period note. Duplication occurs as a result of choice of level of aggregation


Data Fitness Analysis: Profiling Structure, Quality, Metadata & Provenance Completeness

• Seems straight-forward -- Nope

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- A set of data is complete with respect to a *given purpose* if the set contains all the relevant data for that purpose
- A common measure is the proportion of data that has values to the proportion that "should" have values.
 - Completeness is *application-specific*
 - Incorrect to simply measure number of missing field values in a record without considering which fields are necessary
 - MLS Data had MANY highly incomplete fields that were not necessary for the study at hand
- Data that are missing can be categorized as:
 - record fields not containing data
 - records not containing necessary fields
 - datasets not containing the requisite records





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Repurposing Data for Statistical Purposes

Data Fitness Analysis: Profiling Structure, Quality, Metadata & Provenance Value Validity

- Data elements with proper values have *value validity*
- The percentage of data elements whose attributes possess values within the range expected for a legitimate entry is a measure of value validity
- Checking for value validity generally comes in the form of straight-forward domain constraint rules
 - How many entries contain non-valid values for a non-empty text field representing gender?
 - < count gender where gender is not (male, female) >
 - How many entries contain non-valid values for a non-empty integer field representing age?
 - < count age where age is not between [0, 110] >





Data Fitness Analysis: Profiling Structure, Quality, Metadata & Provenance Value Validity

Pulled from current James City County MLS Data

zip code	area	subdivision	neighborhood	zoning	parcel id
23185	JCC	Governors Land	River Reach	R-4	4511000022
23188	JCC	Wellington		RESIDENT	1330800178
23188	JCC	Powhatan Secondary		RES	3741600013
23185	JCC	Kingsmill	Padgetts Ordinary	R 4	5041100213
23185	JCC	Pointe @ Jamestown		RES	4640600108
23185	JCC	Paddock Green	Paddock Green	R1	

Comparison constraint: **zoning 2015, James City County** = {A-1, R-1, R-2, R-3, R-4, R-5, R-6, R-7, R-8, LB, B-1, M-1, M-2, RT, PUD, MU, PL, EO}

- During Data Profiling issues are described, not "fixed"
- The appropriate fix depends upon the needs of the research
- It may be appropriate to simply normalize all zoning entries to the five major categories of zoning:
 Residential, Mixed Residential-Commercial, Commercial, Industrial, and Special





Data Fitness Analysis: Profiling Structure, Quality, Metadata & Provenance Consistency

- The Degree to Which Two or More Attributes Satisfy a Dependency Constraint
- Simple example
 - Location disagreements like zip and state (Record-Level)
- More complex example (Longitudinal)
 - Consistency with locally derived "truth"
 - VDOE Student Record, no definitive list of student demographics
 - Truth must be derived from multiple observations
 - Student Record has multiple observations per school year
 - Query here shows disagreement on gender for some of the observations when Student Record is matched to itself
 - select count(distinct a.internal_id) from vdoe.student_record a join vdoe.student_record b on a.internal_id = b.internal_id and a.gender <> b.gender
 - 16,310 / 2,346,058 individuals have more than one value for gender



PRID: 12144689	Incident Number:1	10010848	CAD	Call Number:1108	000053		
Service:Arlingto	n County Fire Department		Date: Ja	anuary 1, 2011			
Base:Station	05		Crew 1:Pr	imary Caregiver			
Unit: Minist Shift: A Shift	(Transport)		E	EMT-P			
EMD:Not Avai Dispatched As:Fall in1	lable		Crew 2:Dr	river			
Mass Casualty:No	ury(a)		E	EMT-I	_		
Type of Svc:Scene Un	., -77.050988 ischeduled		* designates a Mode to Rec:No	ALS Provider			
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Moved Via:Stretche	Direns F		CMS Service Level:AL	nprovea LS, Level 1 Emergen	¢γ		
Outcome:Treated,	Transported by ACFD						
ef Other Type:Public Bu	rilding		Receiving: He	ospital			
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Requester: 1000000	CHICA - LOSS PREVENTION		10	525 North George Ma	son Drive		
KET. UPp.DD. UVDA	J ₁ - 77.058892		(7	703)558-5000	3698		
			Dest. GPB:38 Rec. RN:	8.888911,-77.128434 PA			
			Destination Basis:Pr	rotocol			
ast Name:	First: Citik					Times	
Address:				8		Received: 11:22:30	
ity:	ST:MD Zip:20	3748				Notified: 11:23:27	
County: Plan Sitizenshin: Unif	ted States					Dispatch: 11:23:32	
Phone:	ied states					At Ref: 11:20:55	
DOB : California	6/1000 SSN: 620-04-0040				At	Patient: 12:00:15	
Age: 44y	Sex: F Weight: 140	ð 1b			L	Leave Ref: 11:30:00	X
height: Subscriber: No					Transfer (At Rec: 12:12:00	
Race: Blac	ck, non-Hispanic				1	vailable: 12:50:00	
Barriers to Care: None	e Noted						
	territor de la	Sce	ene Information	·			
Vescription: Pt was s Num. Patients On Scen	itting in a chair in the we: 1	security office of	Macy's being tended to	by security staff			
		Chief Complaint	(Category: Fall injury)	(s))			
Laceration to R knee							
Duration: 20) Minutes						
Anatomic Location: Ex	<pre> tremity - Lower</pre>	Seco	ondary Complaint				
Hypertension							
		History	of Present Illness				
105 AOSTE a 44 YOF s	itting on a chair in the I	Macy's security off	ice holding a 4x4 on he	r right knee. Pt	is CA&OX3	w/a patent airwa	y. Visual
to close wound, then /	applied cold pack and wra	pped with cling. Pt	states that she tripped	d over an expansi	on joint	in the floor in t	he mall,
Landing on her R knee	. +PMS in the affected ex	tremity. Pt initial	ly indicated she would h	have her boy frie	nd drive	her to the hospit	al in MD,
nowever, VS reveal re. stretcher and moved h	er to the medic unit. In	does not decrease w the medic unit. est	ablished IV access via 2	be transported by 20g angiocath in	the RAC w	 Assisted pt o NS Lock. BGL=84. 	Obtained
4-lead ECG: NSR. Init	iated transport. Notified	hospital via radio	. Monitored pt's BP enro	oute to hospital.	Transpor	ted pt to VHC-Arl	ington
Medic	al History	Care was transferr	ed to continue , P/	A, w/out incident	A	llergies	
Appertension		None		None			
blained From: Palien		Neu	ırological Exam				
Level of Consciousnes	ss: Alert Loss of Cons	ciousness: No			[Glasgow Coma	Scale
Chemically Paralyze	ad: No					EVN	Tot
Neurological Preser Mental Preser	nt:Normal nt:Normal				l	Int: 4 5 6 = 1	.5
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					Femoral:	Not Checked Not	Checked
					Dorsalis:	Not Checked Not	Checked

Data Fitness Analysis: Profiling

Structure, Quality, Metadata & Provenance

Record Consistency

Emergency Services Data Processing Example

Consistency Issue: Violates time dependency constraint Leaves scene before arriving







Data Fitness Analysis: Profiling Structure, Quality, Metadata & Provenance

Observation Unit Definition

Datasets (tables) without definition and/or non-meaningful/confusing naming **Observation Unit Attributes Definition**

Attributes (columns) without definition and/or non-meaningful/confusing naming **Semantic Confusion**

Attributes with the same name but different definitions

e.g. An attribute named "Grade" can refer to both a 'score' for a test or the 'level/year'

Multiple Attribute Names

Attributes with different names but the same definition

e.g. Attributes name "Grade" and "Year" both referring to 'level/year' of schooling

Inconsistent Attribute Formats

Attributes of the same type that are formatted differently e.g. Most commonly an issue when dealing with dates and times **Data Process History**

Attributes collected at different locations, with different tools

System of Origin

Where was this data originally collected? Intermediate Storage Systems

Chain of Custody

Contact Information

Who can I contact with my questions?

Transformation

What happened to the data since collection and why?

Getting this stuff in order is a BIG part of Data Repurposing!



Data Fitness Analysis: Profiling Structure, Quality, Metadata & Provenance

Observation Unit Attributes Definition

Emergency Services Data Processing Example

Metadata needed: Time definitions unclear







Data Fitness Analysis: Profiling Structure, Quality, Metadata & Provenance

Emergency Services Data Processing Example

(Quality) Consistency Issue: Violates time dependency constraint Leaves scene before arriving

(Metadata) Metadata needed: Time definitions unclear

(Structure) Multiple Types of Observation on Single Page

Additionally:

(Structure) Forms made available online as nested HTML Tables - each needing separate extraction





Example: Consistency Quality Analysis can only be Semi-Automated







Data Science Processes for Evidence-Based Policy



Data Analytics Process

- Data Fitness Analysis
 - Data Preparation

The Data Preparation Phase includes the activities necessary to "fix" the issues of Quality, Structure, and Metadata discovered during Data Profiling – activities can include:

Cleansing

Missing Values Date Formats Nominal => numeric Outliers Inconsistent Data De-duplication Transformation Aggregation Normalization Smoothing Winsorization Feature Construction Restructuring

Data Science Processes & Platforms for Evidence-Based Policy



Data Science Processes & Platforms for Evidence-Based Policy



CLD3 - Data Science Processes & Platforms for Evidence-Based



