

Implementing **Housing Analytics** locally

Georgia Smart Webinar. May 9, 2019

Dr. Omar Isaac Asensio
Assistant Professor, School of Public Policy
Georgia Institute of Technology

Overview

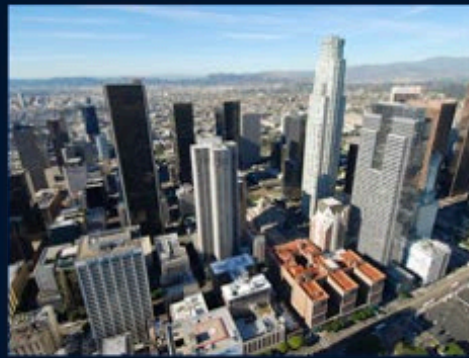
- Research overview: smart data housing analytics (**open data versus analytics**)
- Albany, GA
- Some considerations on implementing effective data transitions and cultural change around big data

About the speaker

Randomized Policy Experiments



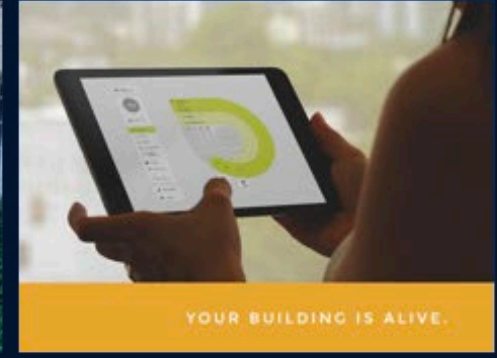
Energy Conservation
Randomized Controlled
Trials (RCTs)



Smart Grid and Energy
Efficiency Program
Evaluation



Machine Learning and
Real-time Intelligence in
Sustainable Transportation
Infrastructure



Civic Data Science and
Urban Sustainability &
Computational and Statistical
Models

Social and Behavioral Dimensions of Energy Use

SCIENTIFIC
AMERICAN

NBC NEWS

THE ECONOMIC TIMES

The
Washington Post

YAHOO!
News

Utility
DIVE

CBS
RADIO

Los Angeles Times

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The Objective

1. Through the Georgia Smart program, Georgia tech has partnered with the City of Albany
2. To build a housing data inventory to better manage housing investments and address issues of **neighborhood blight**

Housing Analytics and Data Visualization Initiative

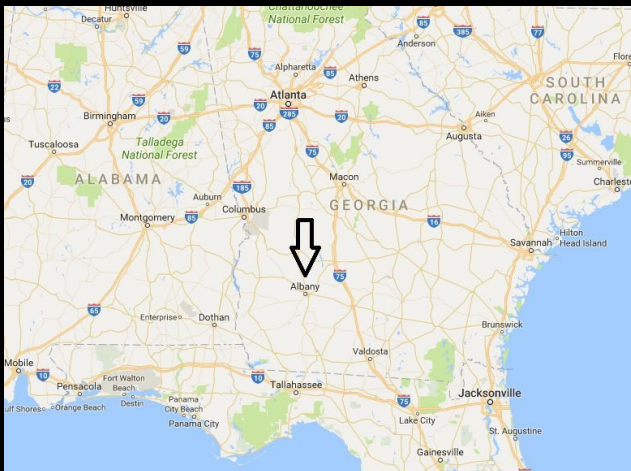
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Proposal Lead
City of Albany, GA

In Collaboration With
The Department of Community & Economic Development (DCED)
Dougherty County, GA
Albany Georgia Initiative for Community Housing (GICH)
Fight Albany Blight (FAB)
Albany Works! (New Community Partner)
Dr. Omar I. Asensio (Georgia Tech)

Albany, GA



Ray Charles Memorial

A community in South Georgia,
“Big city amenities, small town feel.”

Population: ~73,000

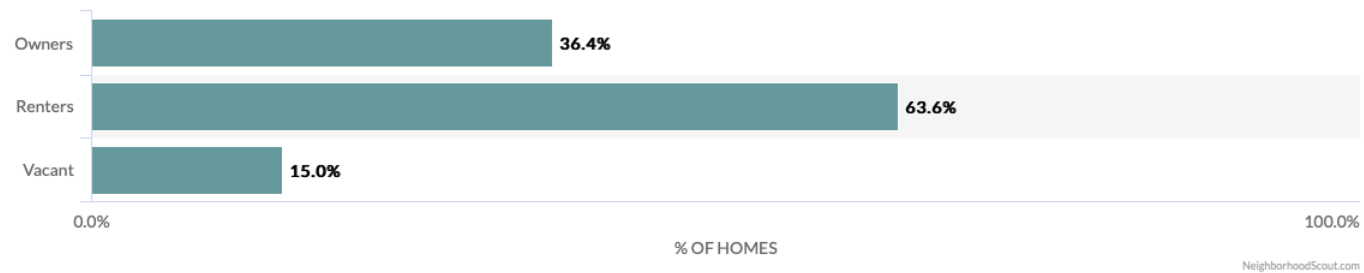
Why housing?

RENT & OWNERSHIP



AVERAGE MARKET RENT:
\$815 / per month

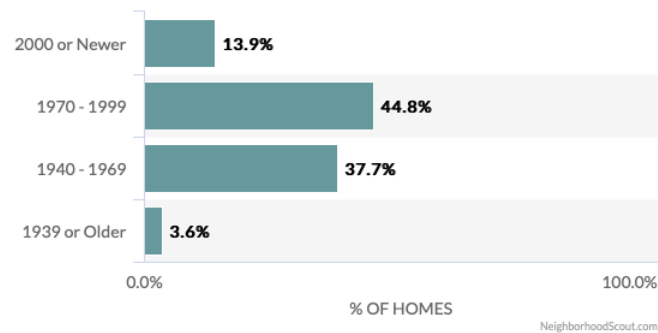
HOMEOWNERSHIP RATE



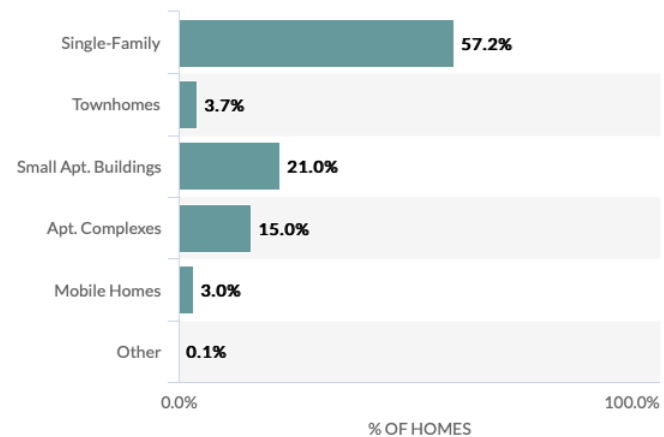
HOUSING MARKET DETAILS



AGE OF HOMES



TYPES OF HOMES

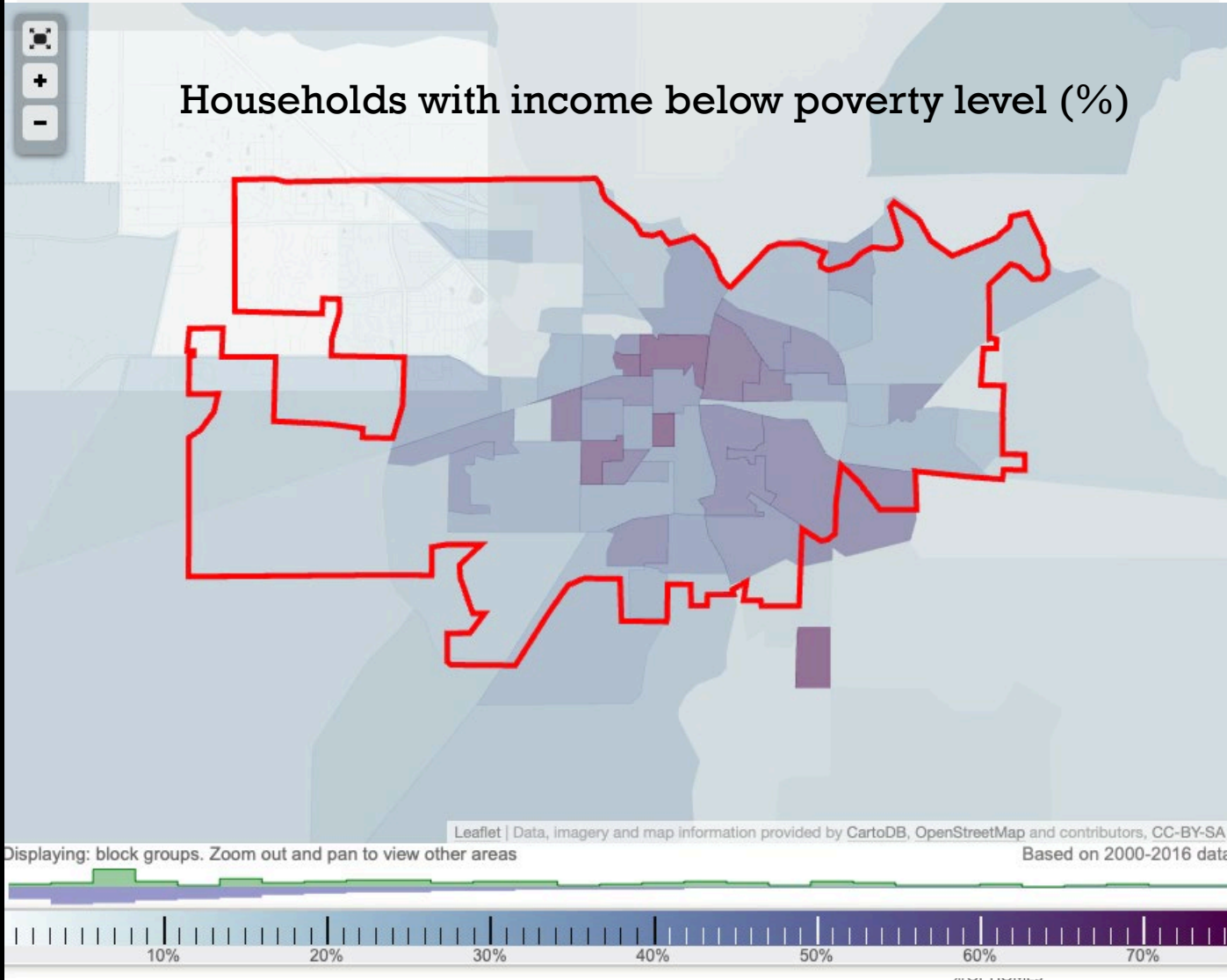


Why housing?

RENT & OWNERSHIP



Households with income below poverty level (%)



The Challenge

1. Important city data is typically siloed across various information systems and city departments
2. To increase transparency, many governments are moving towards open data, but users have diverse interests in the usage of the data and requirements for data presentation
3. **Open data alone is often insufficient** to paint a picture of how well our policies and programs are working

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Actual number: now estimated to be **150+ million records across 21 city departments**; with real-time automated data updates such as utilities, crime, or disaster recovery data.

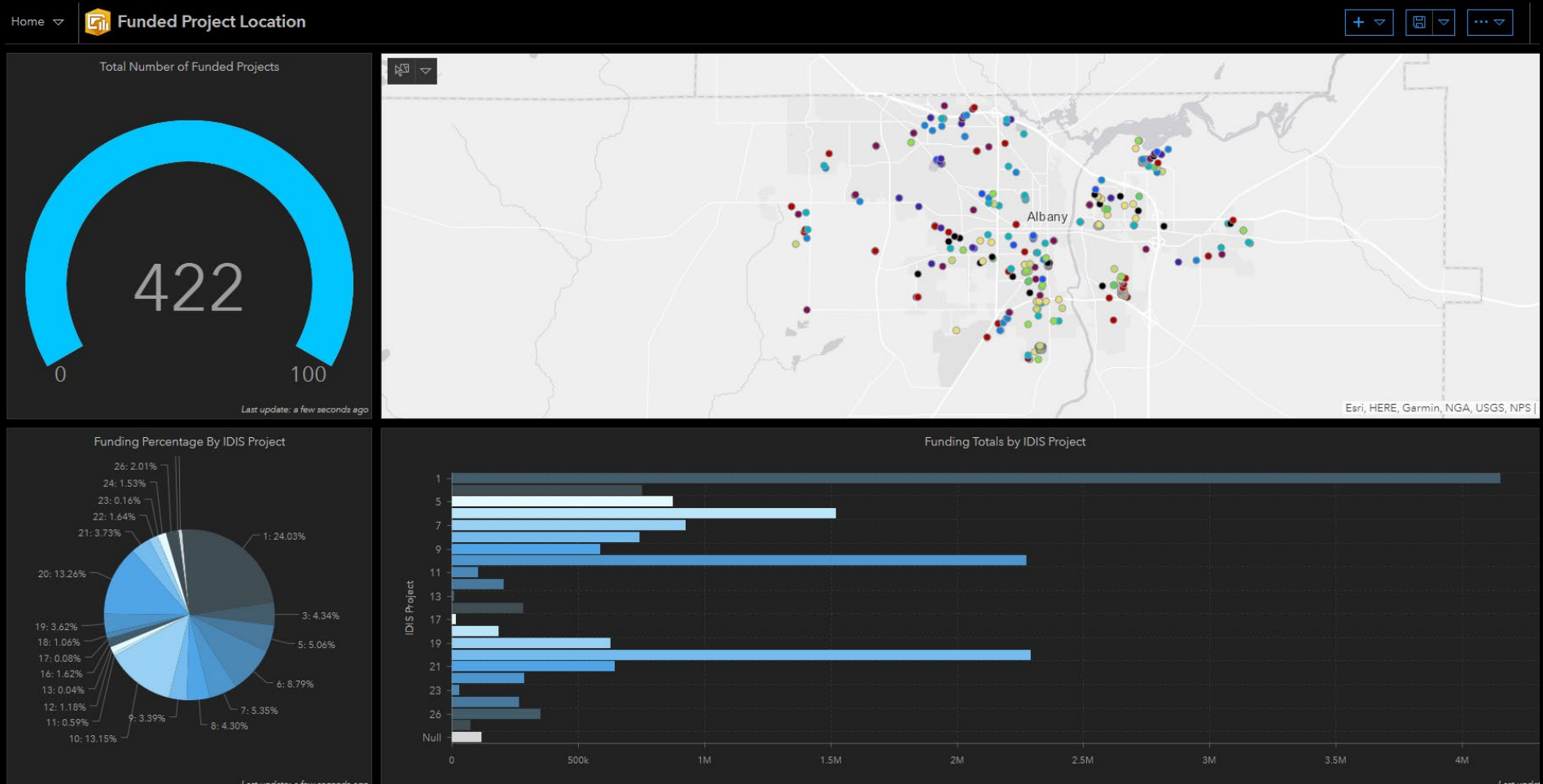
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Share a **known pattern** in your data set
using numbers or a simple visualization.

One data pattern in our initial dataset is that the funds allocated for most housing projects are in impoverished portions of the city.

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What is the **biggest opportunity** you see in your data?
Who could make use of them and to what end?

The biggest opportunity in our data is simply data access. This will be a game changer in the ability of the city leaders as well as citizens to have access to data that could assist them to make better informed and data driven decisions.

What is the **biggest opportunity** you see in your data?
Who could make use of them and to what end?

I actually have two major concerns. Data accuracy and the possibility of disclosing something that is too personal for public consumption.

I wouldn't want any data that we provide to be used to intentionally or even unintentionally harm someone else.

What is the **greatest risk** you see in your data?
What wouldn't you want them to be used for?

Data Story: An example in Housing and energy consumption in LA county

Residential Per Square Foot Energy Consumption

| | Per Sq. Ft. Ranking | Cities | Population (2010) | Income | Total Usage (Residential) | Median Per Sq Ft Consumption |
|-----|---------------------|-------------------------------|-------------------|-----------|---------------------------|------------------------------|
| | 1 | Compton | 96,986 | \$44,851 | 1.6 trillion BTU | 55,058 |
| | 2 | Unincorporated Metro | 302,152 | \$38,151 | 4.1 trillion BTU | 54,958 |
| | 3 | Hidden Hills | 1,985 | \$250,001 | 163 billion BTU | 53,015 |
| | 4 | San Fernando | 23,645 | \$47,125 | 334 billion BTU | 51,956 |
| | 5 | Hawaiian Gardens | 14,860 | \$50,909 | 142 billion BTU | 50,421 |
| | 6 | Rolling Hills | 1,860 | \$219,688 | 141 billion BTU | 49,920 |
| | 7 | Burbank | 103,340 | \$67,156 | 2.5 trillion BTU | 49,920 |
| | 8 | Inglewood | 111,800 | \$44,146 | 1.9 trillion BTU | 49,693 |
| | 9 | Lynwood | 70,699 | \$44,896 | 800 billion BTU | 49,242 |
| | 10 | La Canada Flintridge | 21,405 | \$156,583 | 901 billion BTU | 48,955 |
| ... | ... | ... | ... | ... | ... | ... |
| | 84 | Lawndale | 32,769 | \$52,447 | 475 billion BTU | 36,334 |
| | 85 | Diamond Bar | 46,826 | \$88,760 | 1.2 trillion BTU | 33,440 |
| | 86 | Cudahy | 23,805 | \$41,713 | 247 billion BTU | 32,821 |
| | 87 | Walnut | 29,156 | \$97,885 | 564 billion BTU | 31,809 |
| | 88 | Bell Gardens | 42,072 | \$38,917 | 438 billion BTU | 31,316 |
| | 89 | Uninc. Santa Monica Mountains | 30,804 | \$126,594 | 536 billion BTU | 30,844 |
| | 90 | Uninc. San Fernando Valley | 3,918 | \$97,656 | 49 billion BTU | 30,132 |
| | 91 | Westlake Village | 6,022 | \$94,420 | 331 billion BTU | 27,244 |
| | 92 | Avalon | 3,569 | \$51,160 | 19 billion BTU | 12,358 |
| | 93 | Signal Hill | 11,077 | \$66,250 | 166 billion BTU | 11,361 |

Data Story: An example in Housing and energy consumption in LA county

Residential per Capita Energy Consumption Top and Bottom 10 Residential Per Capita Cities

| | Per Capita Ranking | Cities | Population (2010) | Income | Total Usage (Residential) | Per capita consumption |
|-----|--------------------|-----------------------|-------------------|-----------|---------------------------|------------------------|
| | 1 | Malibu | 8,097 | \$115,168 | 771 billion BTU | 95 million BTU |
| | 2 | Hidden Hills | 1,985 | \$250,001 | 163 billion BTU | 82 million BTU |
| | 3 | Rolling Hills | 190,790 | \$219,688 | 141 billion BTU | 76 million BTU |
| | 4 | Westlake Village | 302,152 | \$94,419 | 331 billion BTU | 55 million BTU |
| | 5 | Beverly Hills | 211,278 | \$88,589 | 1.8 trillion BTU | 53 million BTU |
| | 6 | Calabasas | 151,745 | \$132,583 | 960 billion BTU | 50 million BTU |
| | 7 | Rolling Hills Estates | 149,746 | \$146,296 | 341 billion BTU | 49 million BTU |
| | 8 | Santa Clarita | 149,343 | \$84,375 | 9.1 trillion BTU | 49 million BTU |
| | 9 | Palos Verdes Estates | 145,438 | \$160,432 | 621 billion BTU | 46 million BTU |
| | 10 | Bradbury | 103,340 | \$124,167 | 59 billion BTU | 46 million BTU |
| ... | ... | ... | ... | ... | ... | ... |
| | 89 | South Gate | 5,591 | \$44,278 | 1.1 trillion BTU | 12 million BTU |
| | 90 | Lynwood | 11,077 | \$44,896 | 800 billion BTU | 11 million BTU |
| | 91 | Paramount | 1,985 | \$42,440 | 606 billion BTU | 11 million BTU |
| | 92 | Maywood | 13,158 | \$36,455 | 293 billion BTU | 11 million BTU |
| | 93 | Bell Gardens | 14,860 | \$38,917 | 438 billion BTU | 10 million BTU |
| | 94 | Cudahy | 1,860 | \$41,713 | 247 billion BTU | 10 million BTU |
| | 95 | Bell | 1,292 | \$38,563 | 364 billion BTU | 10 million BTU |
| | 96 | Huntington Park | 3,918 | \$39,040 | 610 billion BTU | 10 million BTU |
| | 97 | Hawaiian Gardens | 1,422 | \$50,909 | 142 billion BTU | 10 million BTU |
| | 98 | Avalon | 3,569 | \$51,160 | 19 billion BTU | 5 million BTU |

Using Analytics Dashboards for Policy and Program Evaluation

1. A Housing data inventory needs record linkage to other possible outcomes (Housing investment > Utility consumption)
2. Open Data Dashboards can be misleading and promote misinformation about performance

We often need statistical methods to uncover hidden patterns in the data

Housing starts may co-vary with redevelopment projects, so the true benefits are unclear without a reference case or baseline (counterfactual)

3. We cannot study only those housing investment projects that choose to participate e.g. self selection bias (Asensio and Delmas 2016)

Types of Data Sources for Housing Analytics

1. Curated data

Data sources under direct operational control by the City
(traditional administrative data)

2. Automated data

Data sources generated as inherent to the automatic function of a system (e.g. transit data, social data, smart meter utility data)

3. Volunteered data

Data sources collected manually or automatically (on a platform) as a result of public participation (e.g. Arc GIS Hub)

Next steps 2019-2020

- Integrate housing data with all other available city data using **ArcGIS Hub**
- **Public engagement workshops** to understand the needs of a public facing “Data Hub”
- Deploy statistical and computational methods to evaluate the performance of **20 years of housing investments in Albany**
- Summer 2019: Civic Data Science students (Chris LeDantec, Ellen Zegura)

The Research Team



Asensio Lab May 2019

Q&A