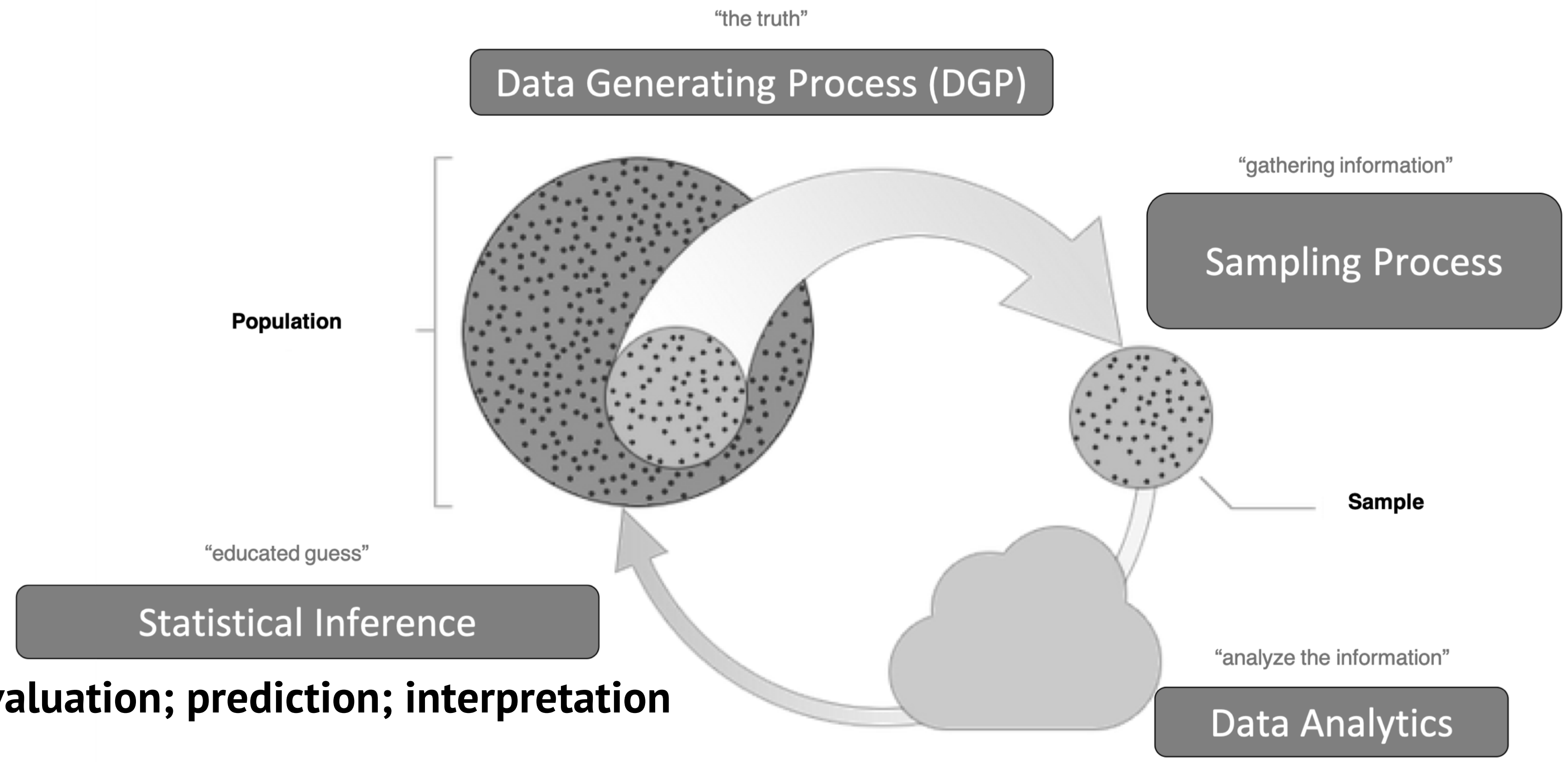
URP 6931. Introduction to Urban Analytics

Lecture 06: Network representation with nodes and edges

Instructor: Shenhao Wang
Assistant Professor, Director of Urban AI Lab
Department of Urban and Regional Planning
University of Florida

Review lecture 03-05

Regression: recovering $E[Y|X]$



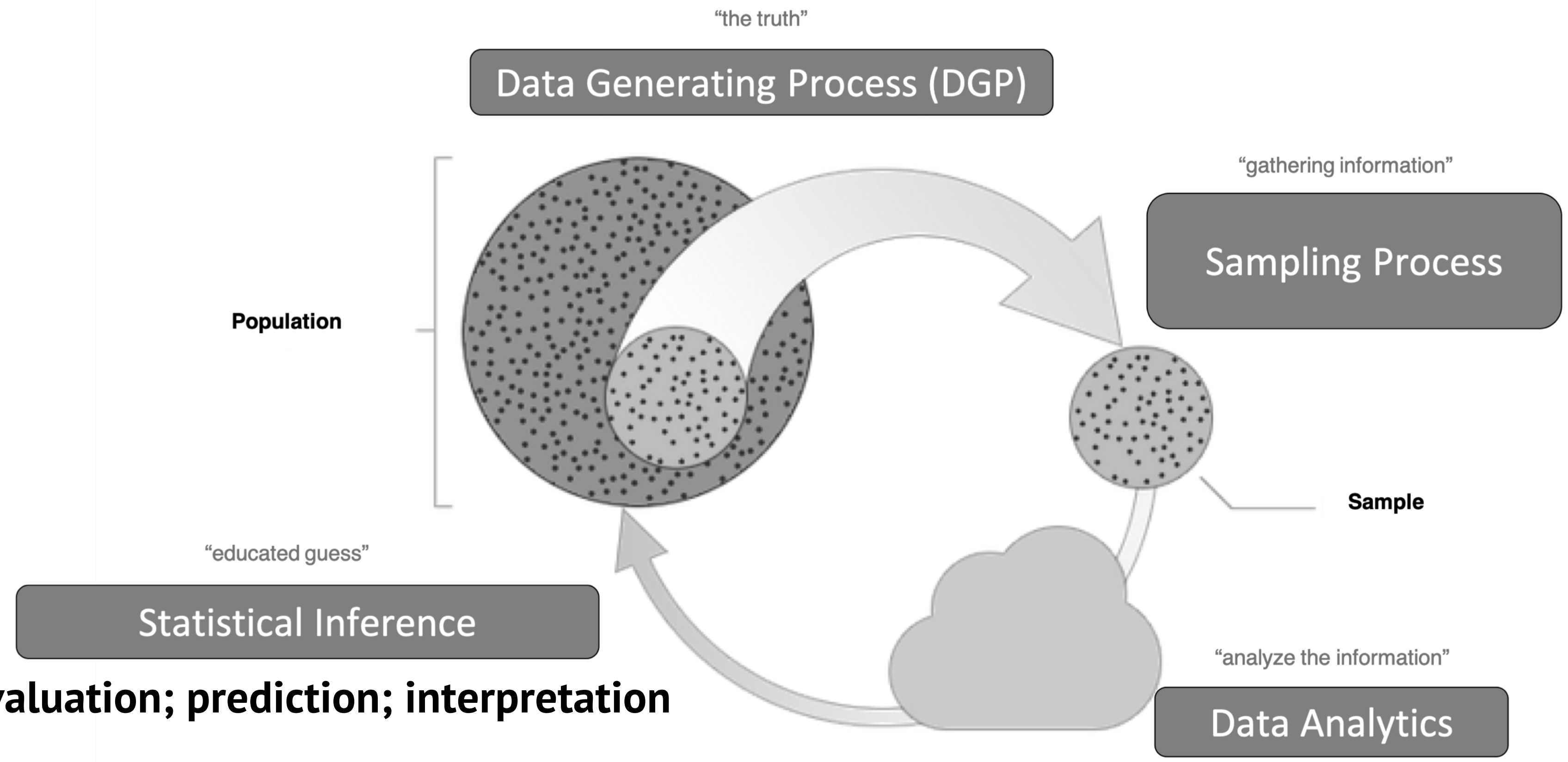
Data: i.i.d.
Y: continuous
Y: {0, 1}

Evaluation; prediction; interpretation

Regression: $\widehat{E}[Y|X] = \sigma(\widehat{\beta}_0 + \widehat{\beta}_1 x_{1i} + \widehat{\beta}_2 x_{2i} + \cdots + \widehat{\beta}_k x_{ki})$
Estimation/Training/Learning: OLS & MLE

Preview lecture 06

Regression: recovering $E[Y|X]$



Data: ~~i.i.d.~~
Graph: (X, A)

Evaluation; prediction; interpretation

Regression: $\hat{E}[Y|X] = \sigma(\hat{\beta}_0 + \hat{\beta}_1 x_{1i} + \hat{\beta}_2 x_{2i} + \cdots + \hat{\beta}_k x_{ki})$
Estimation/Training/Learning: OLS & MLE

Outline

1
Graph examples and representation: nodes and edges

2
What are the nodes and node features? Census and hierarchical spatial units

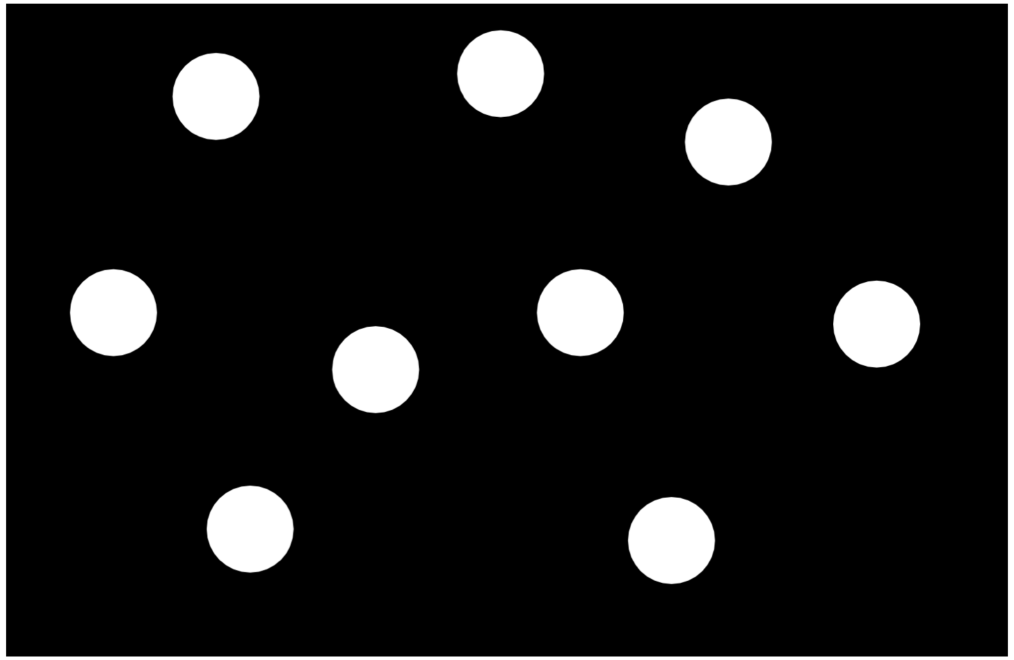
3
What are the edges and edge features? Flexibility in defining edges

4
Graph metrics and power-law distribution

5
GIS as visualization for network analysis

Graph representation

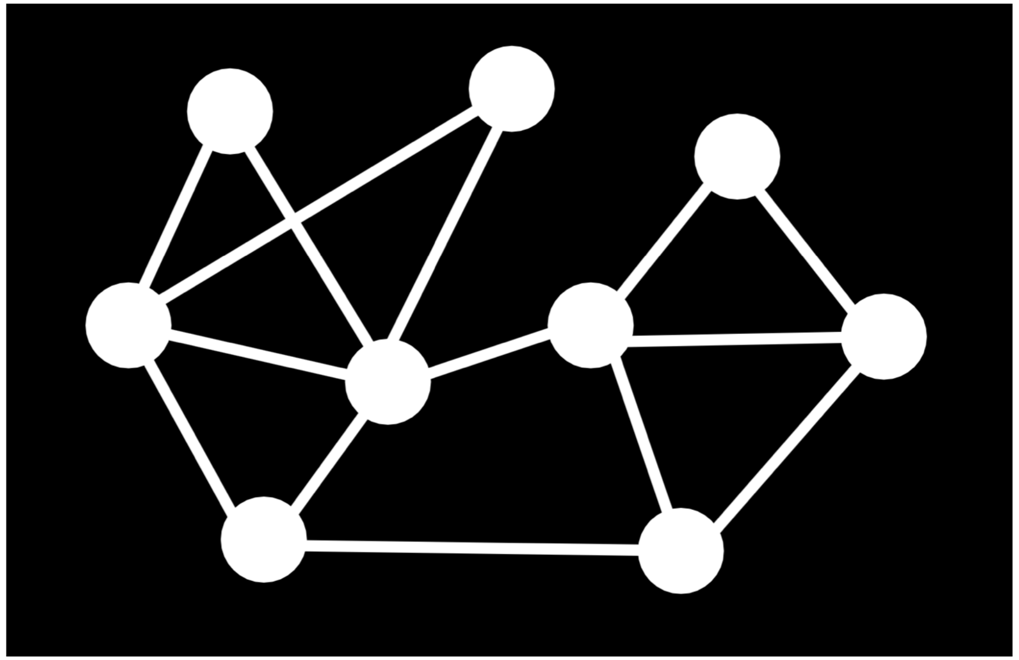
Nodes



OLD

(1) nodes & (2) node features

Graph = nodes + edges

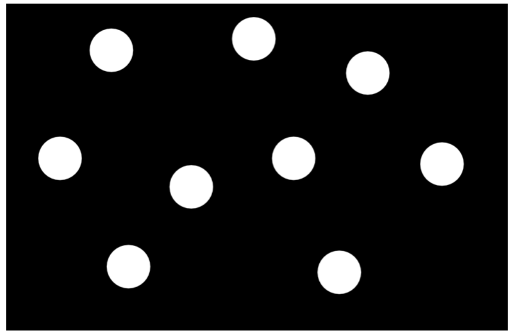


NEW

(3) edges and (4) edge features

Generalize i.i.d. data to graphs

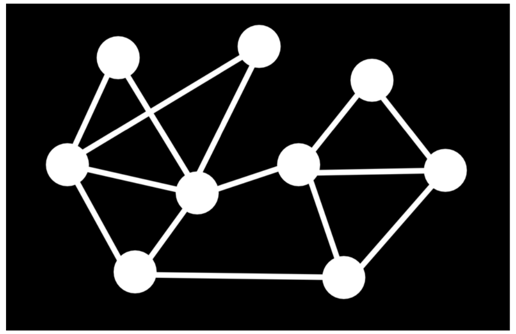
Nodes



About nodes and node features

- We already learnt nodes because i.i.d. data can be seen as nodes. E.g., individuals or census tracts.
- We also learnt node features because node features simply represent the variables of the nodes (e.g. individuals or census tracts).
- Here we only change the terminology from data points to nodes, and from variables to features.

Graph (nodes + edges)

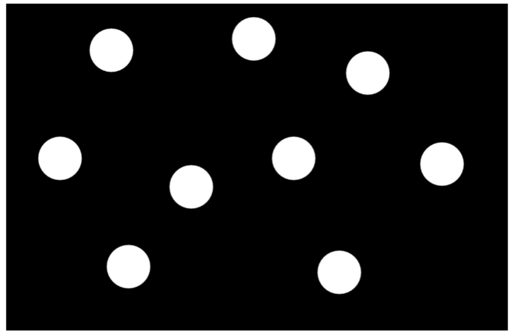


About edges and edge features

- Edges that connect the nodes are the new things in today's lecture.
- Edges describe the relationship between the nodes.
- Edges can be defined in a very flexible manner.

Two constant questions in your mind…

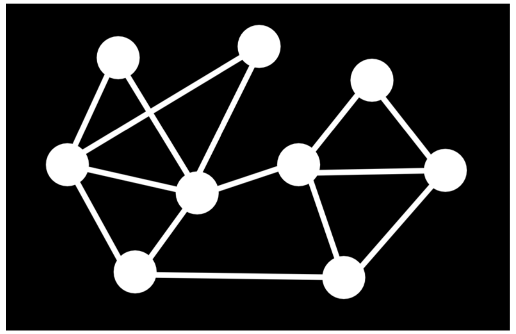
Nodes



Leading Question:

What are the nodes and node features?

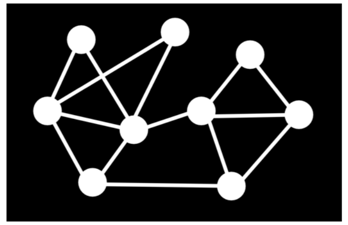
Graph (nodes + edges)



Leading Question:

What are the edges and edge features?

A bit math about graph representation



Graph: nodes and edges

$$G = (V, E)$$

Node and edge representations

$$(X, A)$$

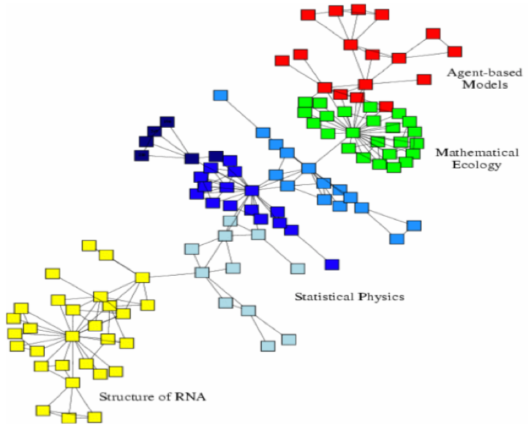
The adjacency matrix is the key component to define the graph. Adjacency matrix of size $N * N$ (where N is the number of nodes) with

$$A_{ij} = \begin{cases} 1, \text{if } (i,j) \in E \\ 0, otherwise \end{cases}$$

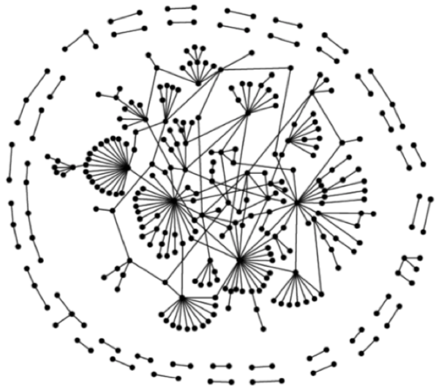
- [**Whiteboard**.] What does the adjacency matrix look like?
- When edges have weights, A_{ij} is non-binary and becomes W_{ij}. We shall treat A_{ij} and W_{ij} as two types of edge features. However, we only discuss the simplest case A_{ij}, which represents undirected graph with binary edge variables.

Many data have the graph structure.
What are the nodes and edges?

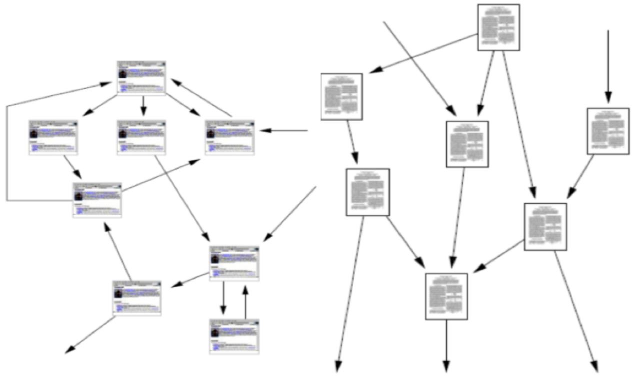
Social networks



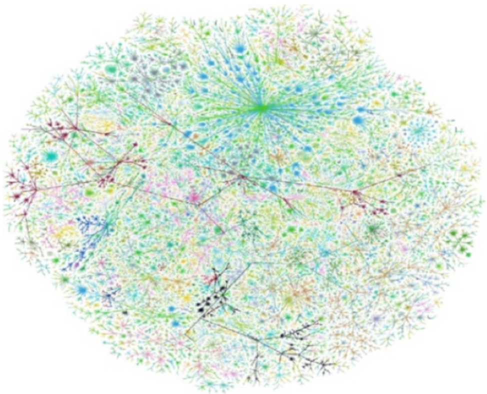
Research topic networks



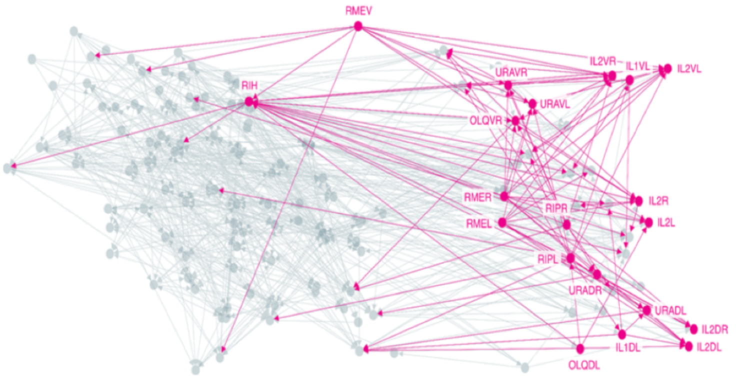
Communication networks



Information networks:
Web & citations

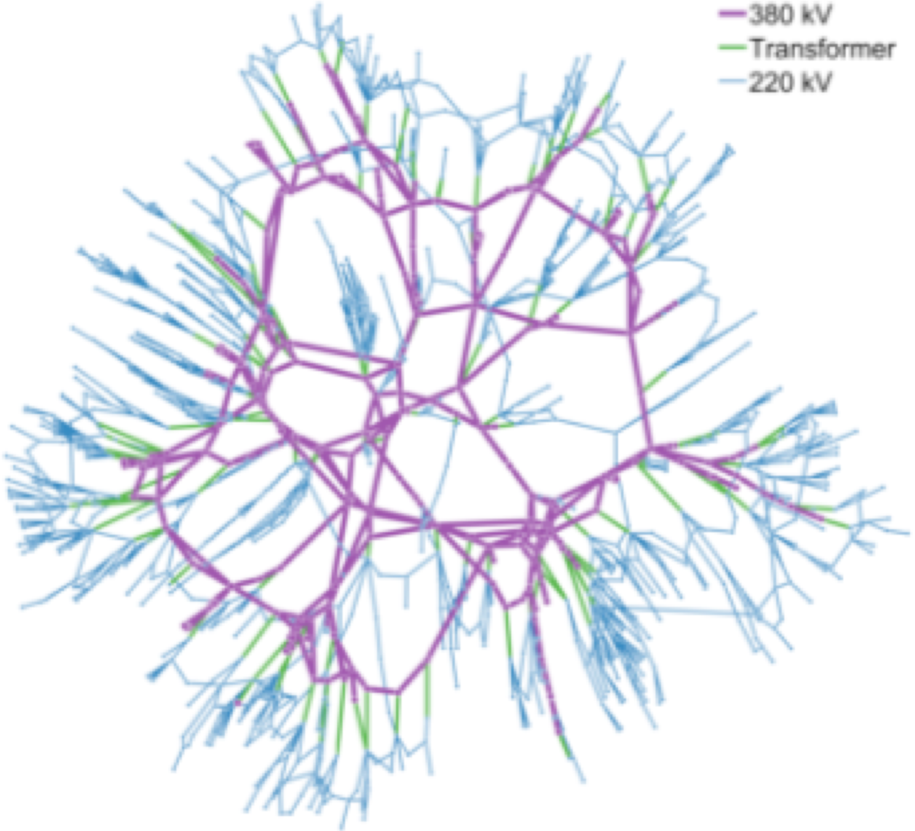


Internet

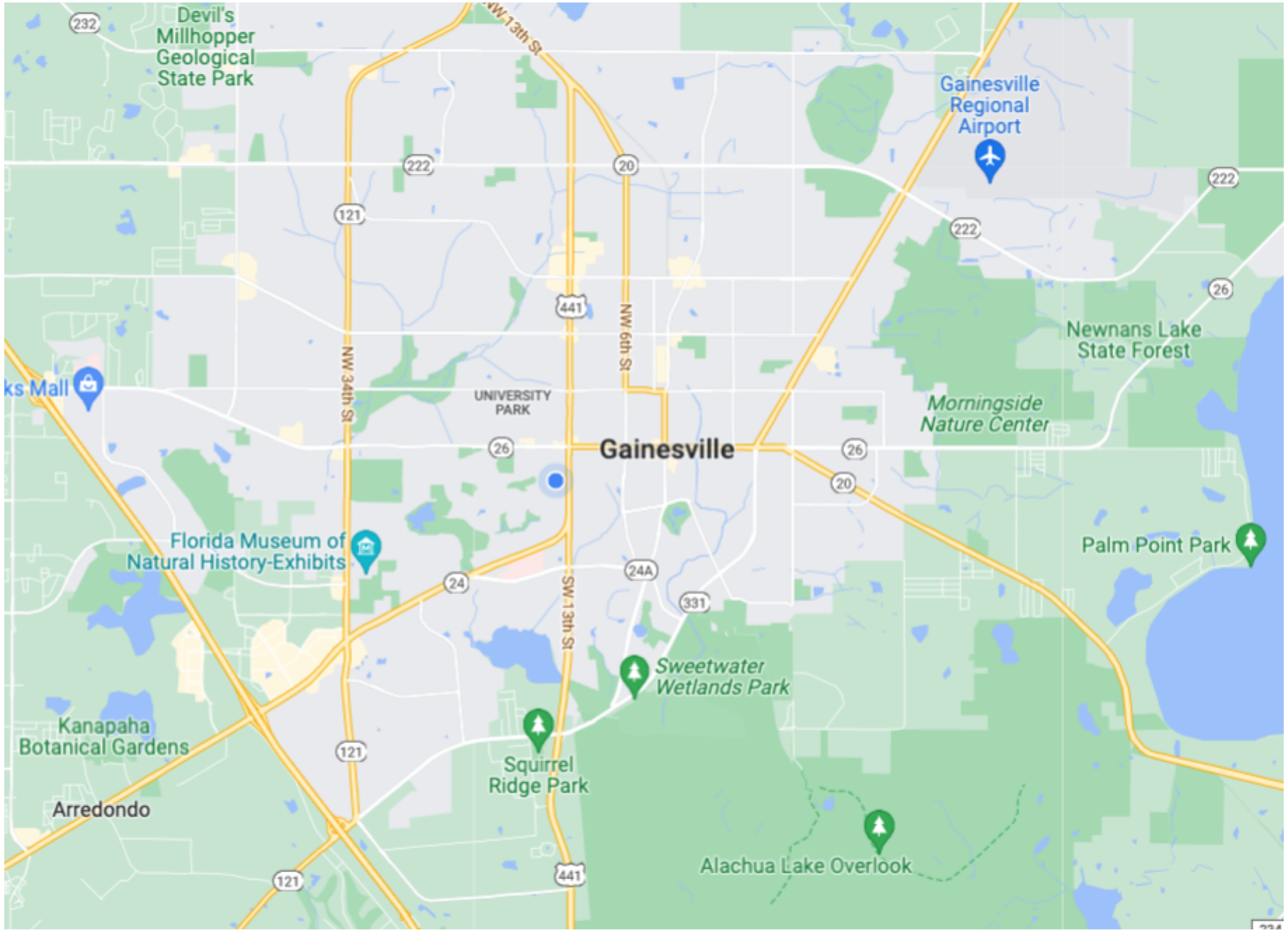


Networks of neurons

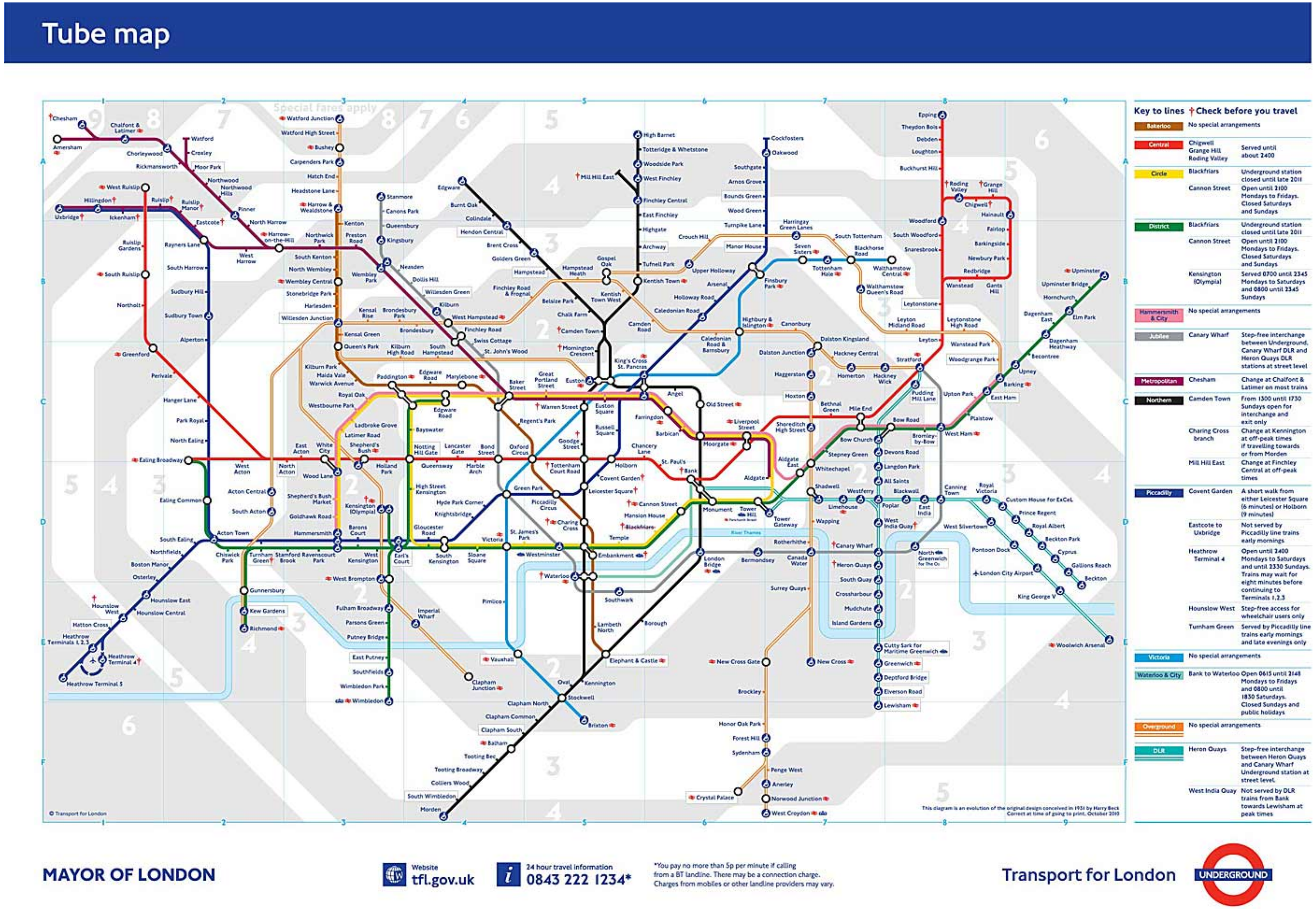
Urban network example 1: electrical & power networks
What are the nodes and edges?



Urban network example 2: road networks
What are the nodes and edges?



Urban network example 3: transit networks
What are the nodes and edges?



Part 2. What are the nodes and node features? census data and hierarchical spatial units

- A bit detour into a general introduction into census (ACS)
- Hierarchical spatial units – what are the nodes?

American Community Survey (ACS)

- A bit history - American Community Survey (ACS) replaces the traditional census since 2005.
- It has the yearly sampling in the form of a huge and rolling survey that is continually refreshed.
- ACS includes nearly 3 million addresses per year. It is around 2.5% sample of the total US households. In a five-year cycle, it accounts for about 12.5% of the total households.
- ACS is a nationwide and continuous survey.

Census data is of high quality

- Census is the only source for demographic data with a wide geographic scope.
- Census is the most reliable and detailed information for describing local areas, e.g., neighborhoods, cities, and counties.
- Census is the most consistent source of time series demographic data available.
- U.S. Congressional representatives are apportioned based on census counts. Federal funding for schools, employment services, highway assistance, housing construction, hospital services, assisted living programs, etc. are all distributed based on census figures.

Variables in ACS (Census)

Variables includes:

Social characteristics
- Marital status
- Place of birth
- Education
- Ancestry
- Residence
- Language
- etc.

Economic characteristics
- Labor force status
- Place of work
- Journey to work
- etc.

Housing unit characteristics
- Units in structure
- Number of rooms
- Number of bedrooms
- Year structure built
- Year moved into unit
- Vehicles
- Etc.

Financial characteristics of housing
- Value of home
- Monthly rent
- Shelter costs

ACS data is released every year as 1-year, 3-year, and 5-year estimate.

ACS provides single-year and multiyear estimates:

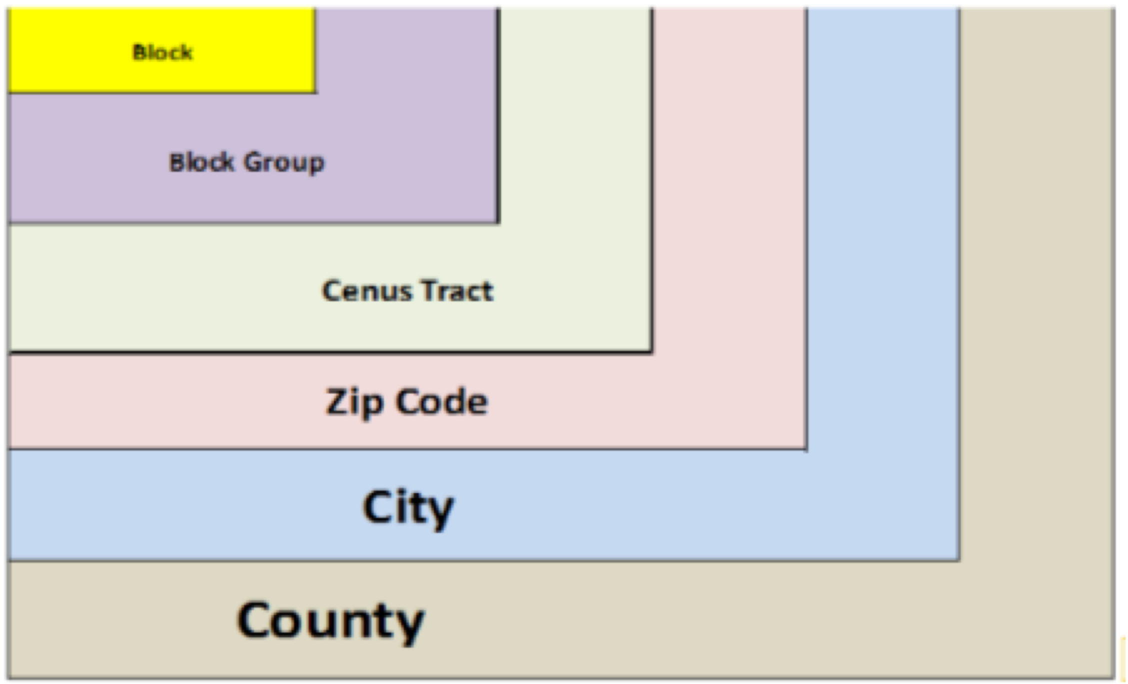
- Single-year = information is collected over 12-month period
- 3-year = information is collected over 1 36-month period
- 5-year = information is collected of a 60-month period

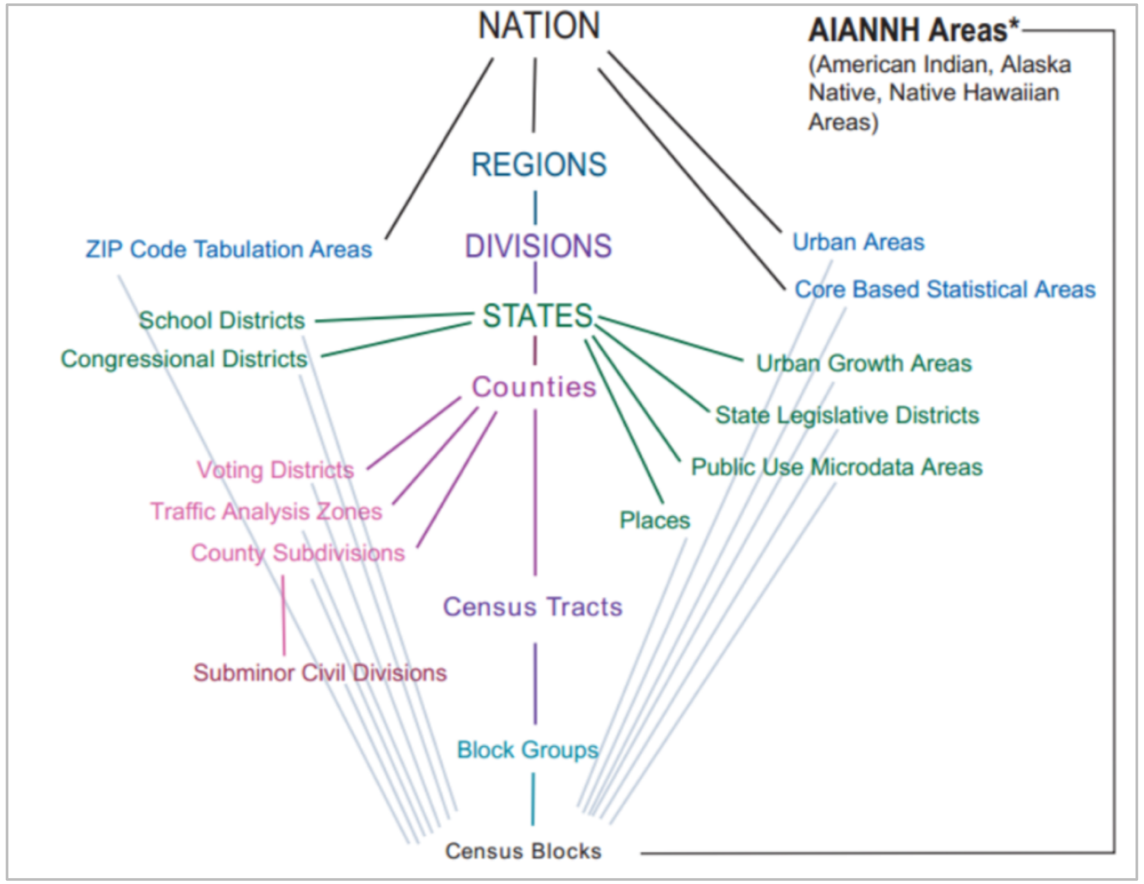
Distinguishing features of ACS 1-year, 3-year, and 5-year estimates

1-year estimates	3-year estimates	5-year estimates
12 months of collected data	36 months of collected data	60 months of collected data
Data for areas with populations of 65,000+	Data for areas with populations of 20,000+	Data for all areas
Smallest sample size	Larger sample size than 1-year	Largest sample size
Less reliable than 3-year or 5-year	More reliable than 1-year; less reliable than 5-year	Most reliable
Most current data	Less current than 1-year estimates; more current than 5-year	Least current
Best used when	**Best used when**	**Best used when**
Currency is more important than precision Analyzing large populations	More precise than 1-year, more current than 5-year Analyzing smaller populations Examining smaller geographies because 1-year estimates are not available	Precision is more important than currency Analyzing very small populations Examining tracts and other smaller geographies because 1-year estimates are not available

Census geography: a hierarchical spatial structure

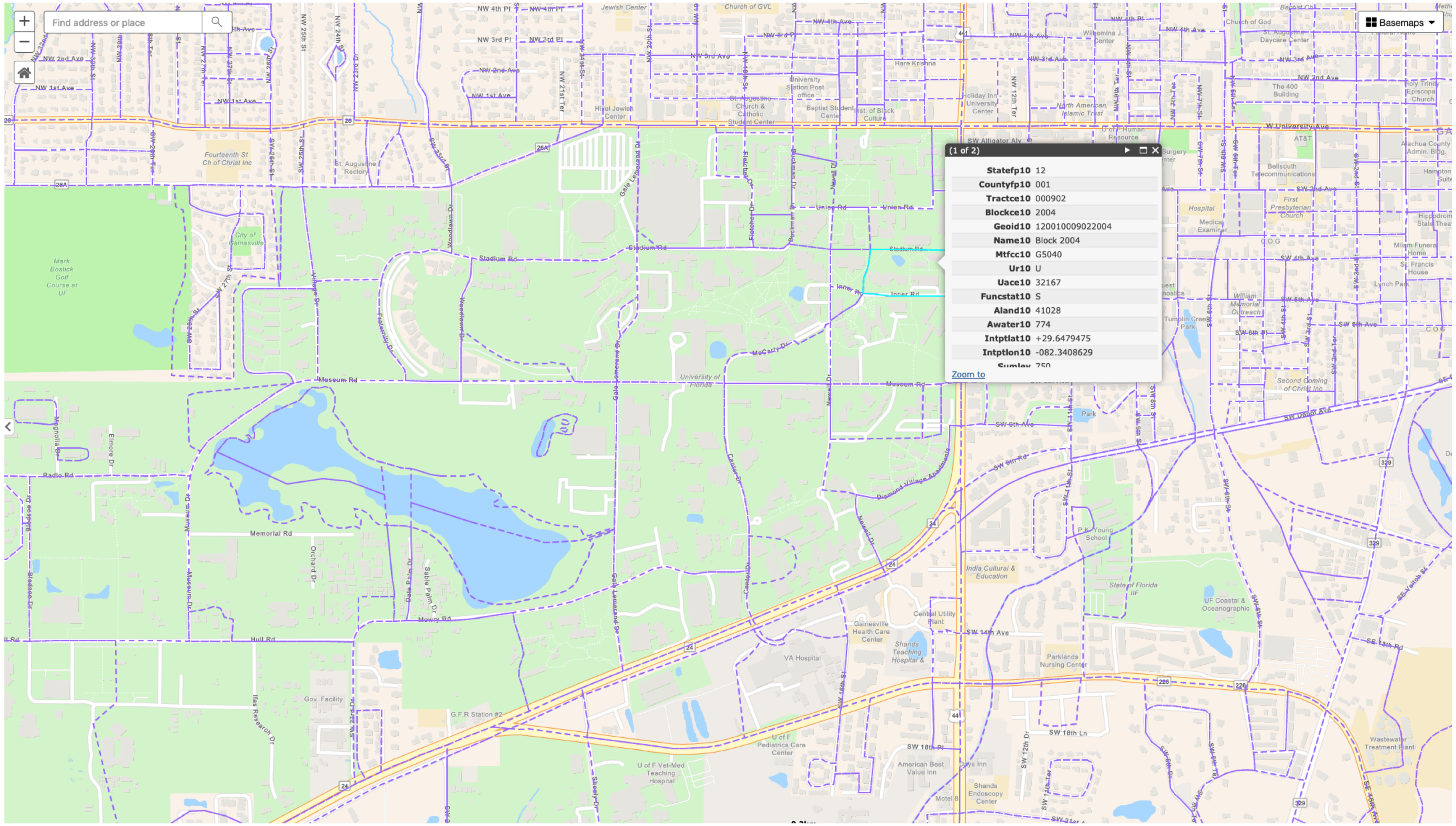
- The spatial units include a hierarchical structure: nation – regions – divisions – states – counties – census tracts – block groups – census blocks.
- Census blocks are the most basic unit in census. However, since census blocks have a very high spatial resolution, the use of the census blocks could trigger privacy concerns. We commonly work on the spatial level of census tracts.

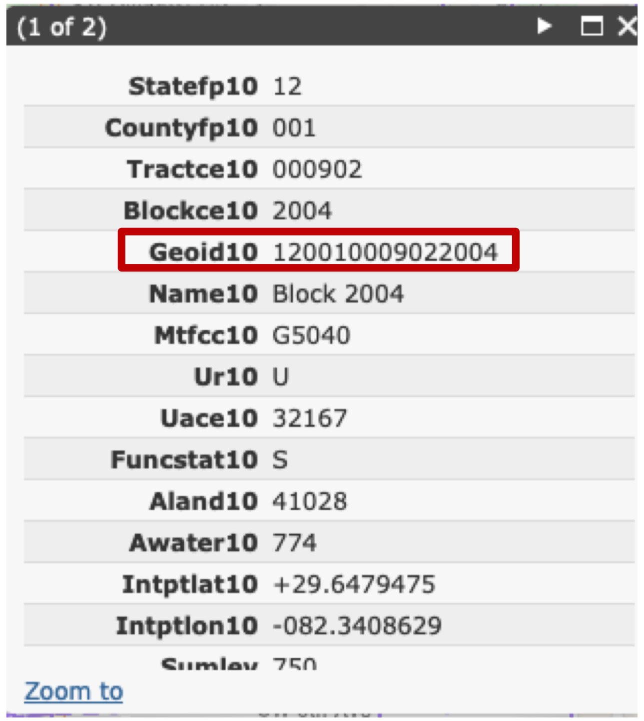




Federal Information Processing Series (FIPS) codes represent the hierarchical spatial structure

What is the FIPS code for our department on the UF campus?



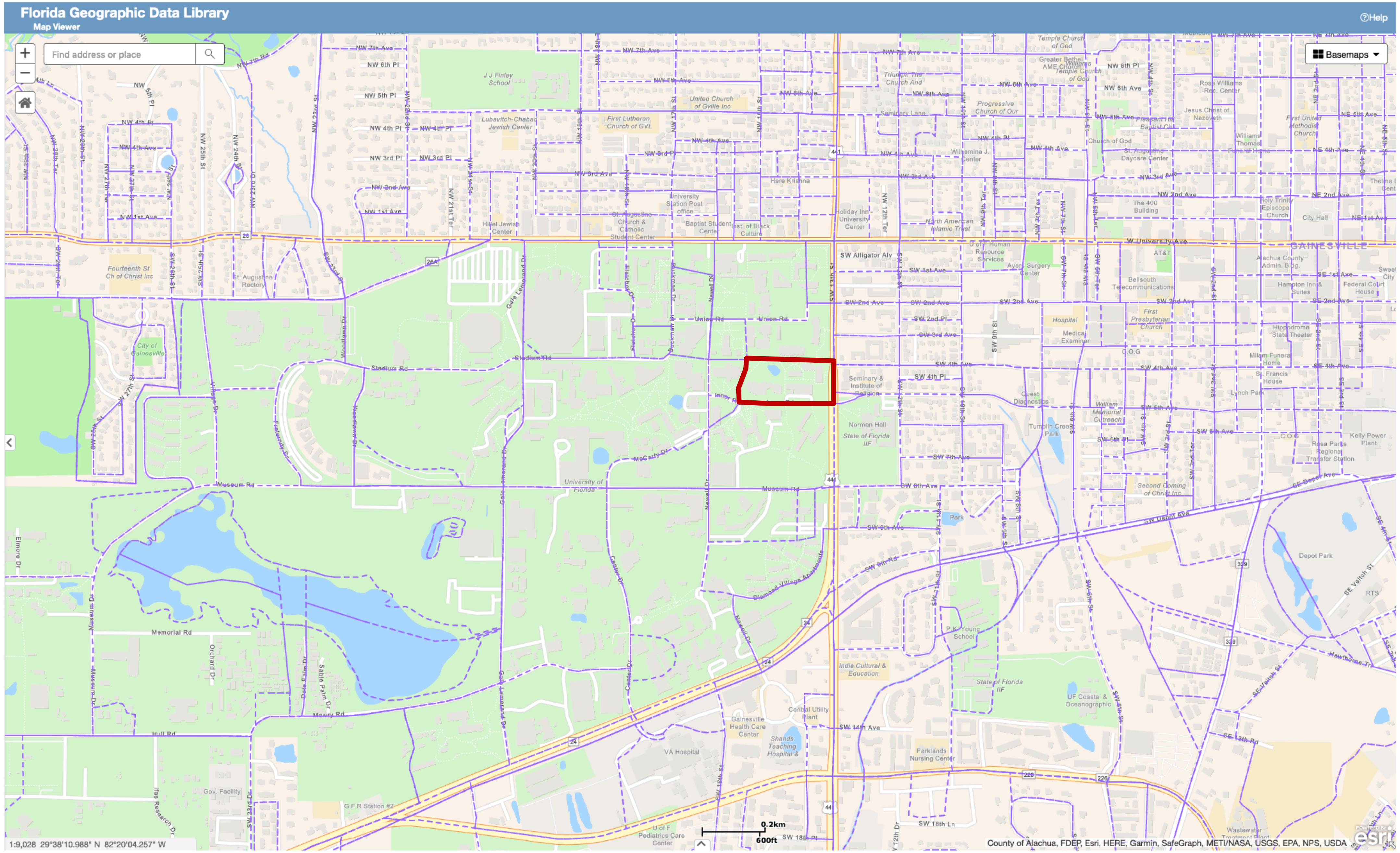


Our GEOID: 120010009022004

(1 of 2)

Statefp10	12
Countyfp10	001
Tractce10	000902
Blockce10	2004
Geoid10	120010009022004
Name10	Block 2004
Mtfcc10	G5040
Ur10	U
Uace10	32167
Funcstat10	S
Aland10	41028
Awater10	774
Intptlat10	+29.6479475
Intptlon10	-082.3408629
Sumlev	750

Zoom to



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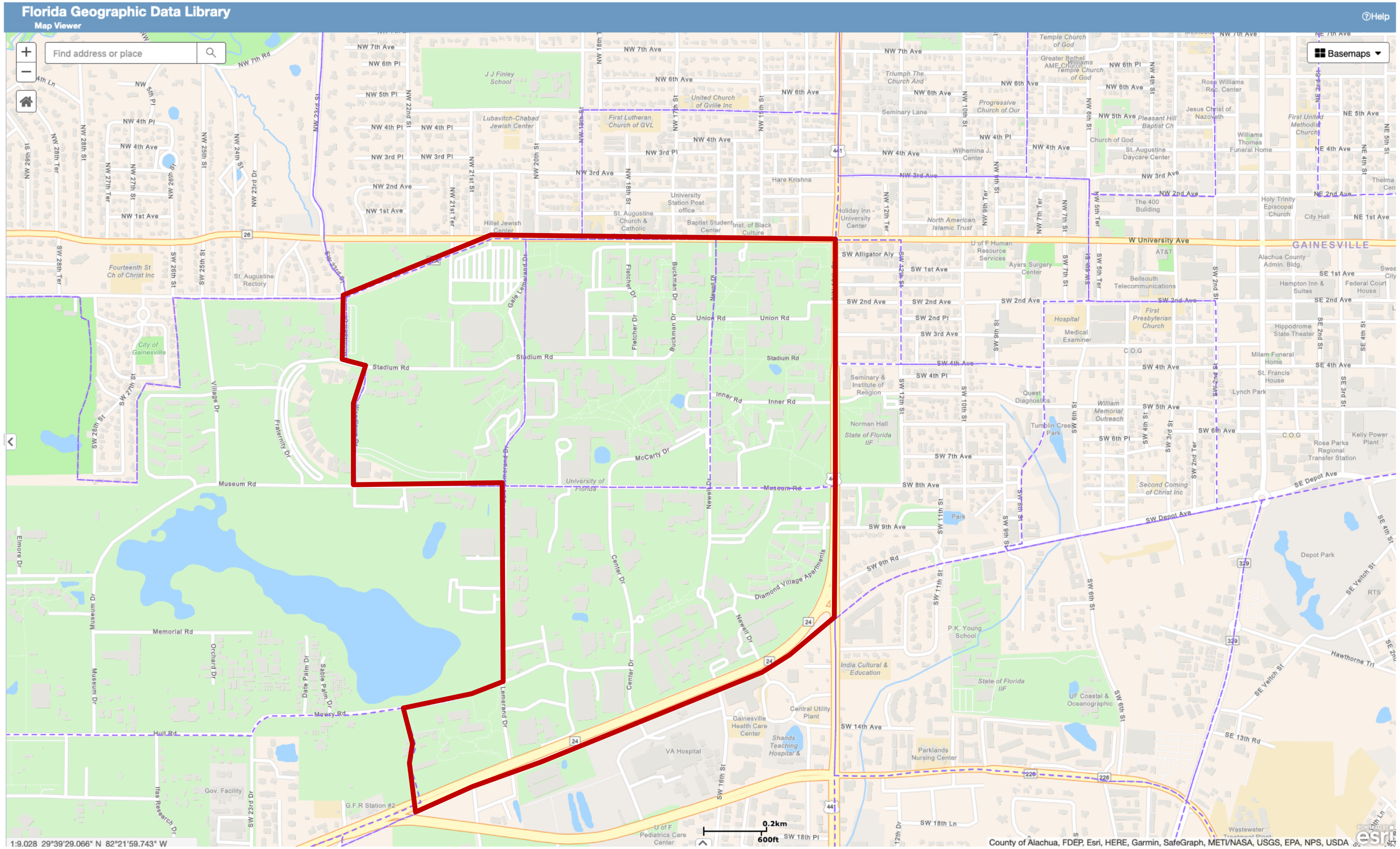

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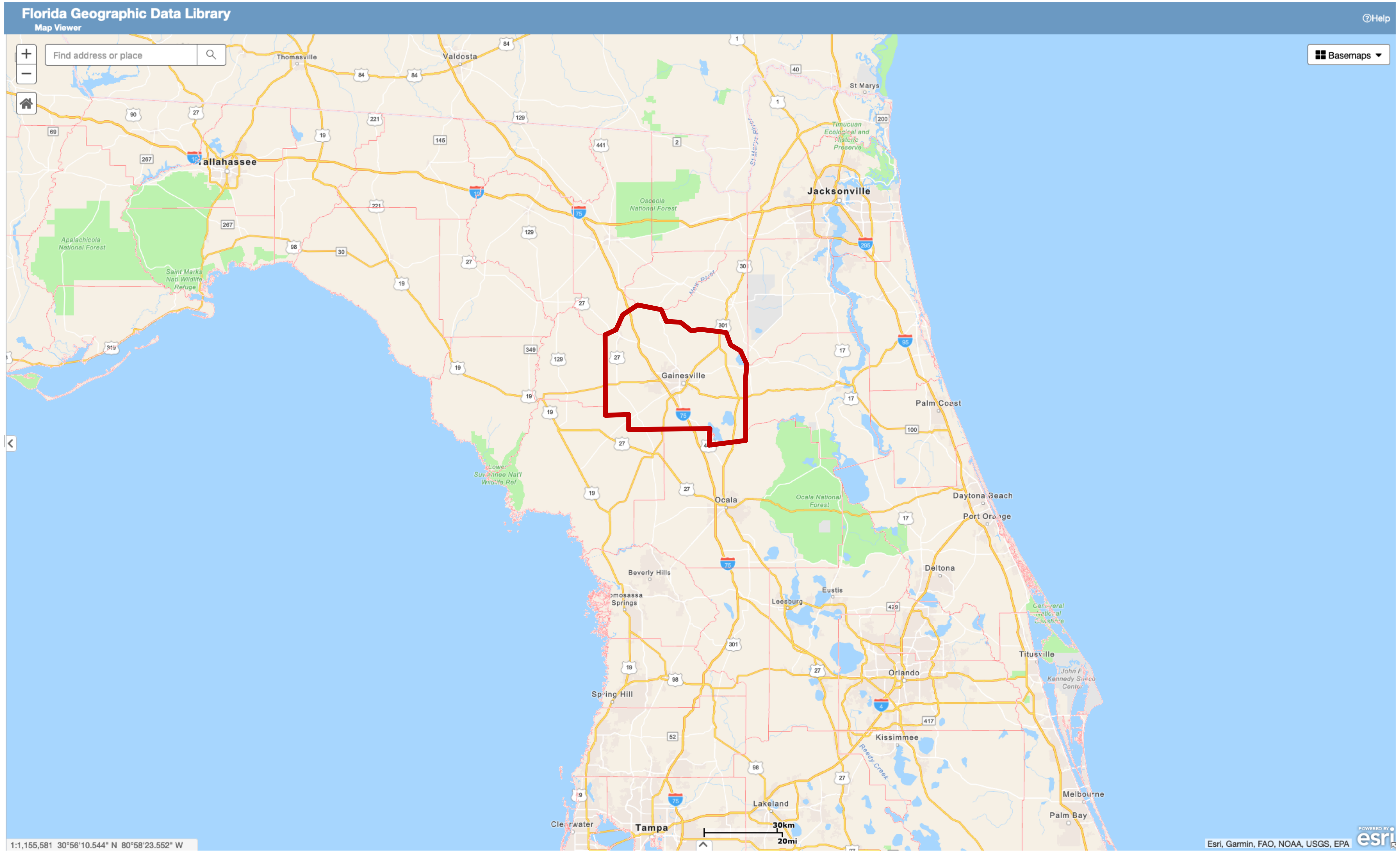

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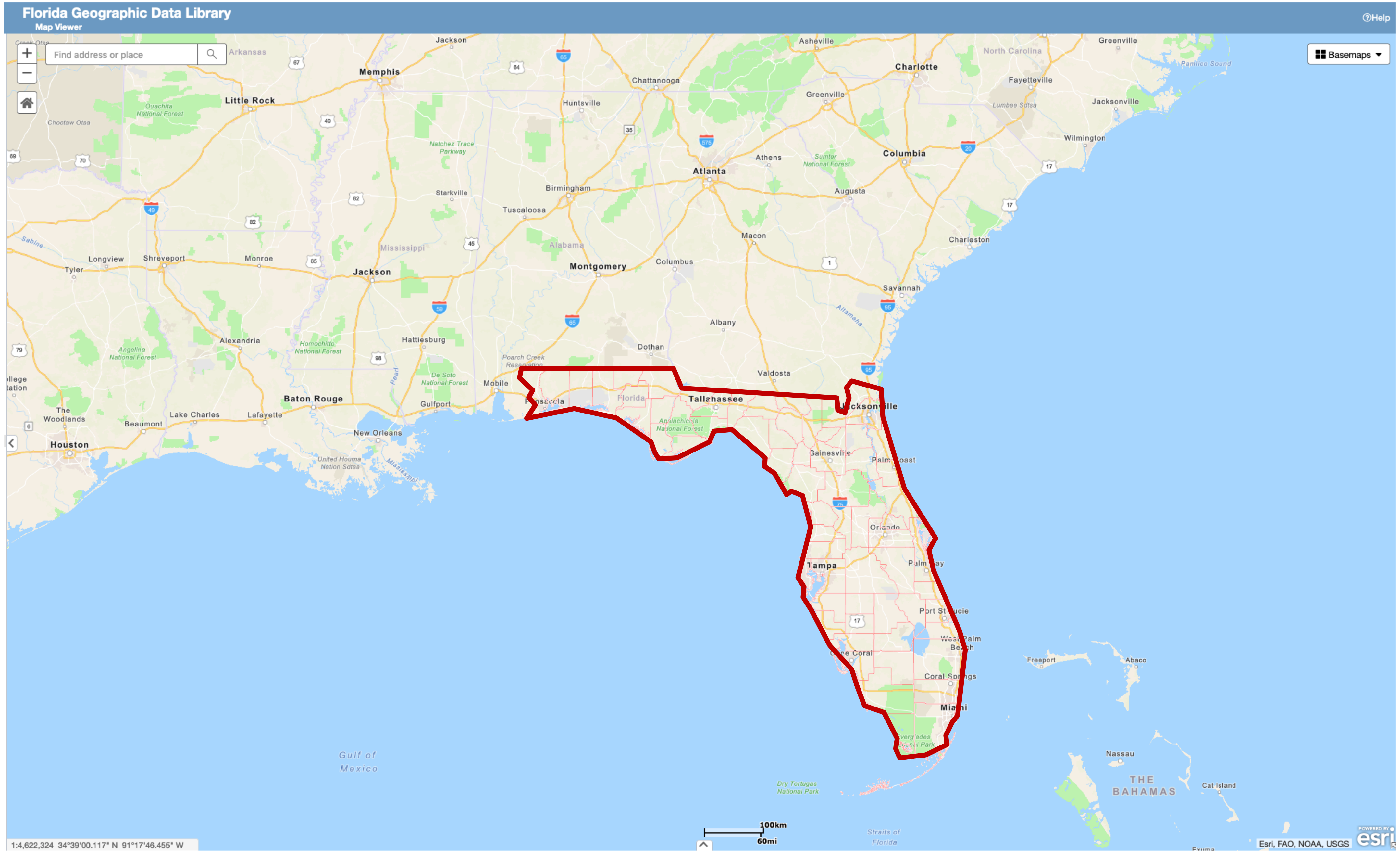
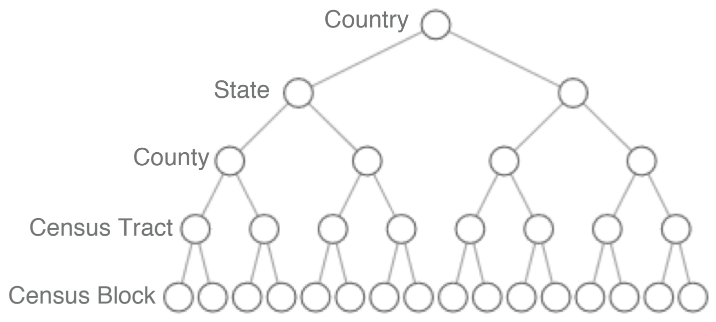
Zoom to



The hierarchical spatial structure is captured in this GEOID

Our GEOID: 12 001 000902 2004

State | County | Census Tract | Census Block

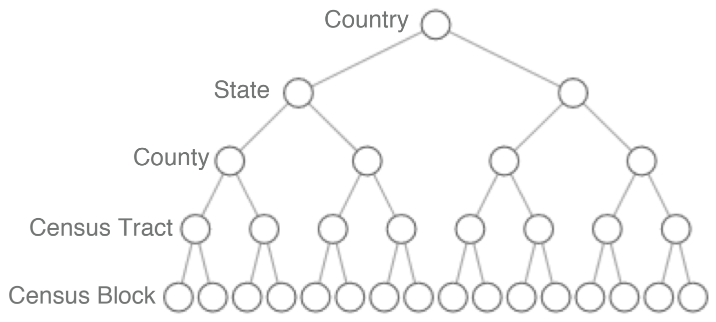


Notes

- Implicitly this GEOID indicates a tree structure.
- The tree structure has multiple levels, and each level uses consistent spatial units.
- Hierarchical representation is critical for DL, which we will discuss in Module 3.

Question: How is this hierarchical spatial structure related to urban network analysis (e.g. nodes and edges)?

Our GEOID: 12 001 000902 2004



About nodes

- **What are the nodes?** (1) Any horizontal level as nodes, e.g., census block, census tracts, counties, or states; (2) nodes across different levels; (3) the whole tree structure. Option 1 is most common in urban applications, and options 2&3 are common in methodological articles.
- **What are the node features?** The socioeconomic variables of the spatial units
- We shall always remember people as another possibility of nodes.
- The choice of spatial units has an impact on your analytical result. i.e., modifiable areal unit problem (MAUP)

About edges

- The hierarchical spatial structure essentially describes a relationship on edges, or more precisely, the network communities.

Modifiable Areal Unit Problem (MAUP)

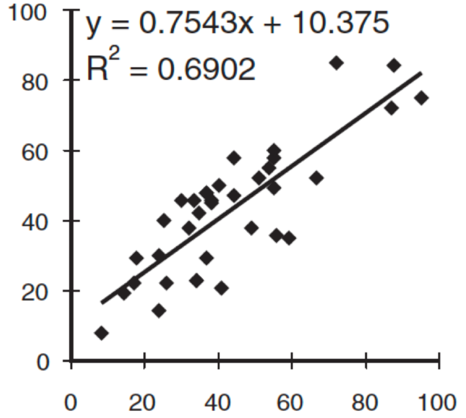
- Regression results vary with the spatial resolution.
- Essentially it is about our leading question – what are the nodes?
- There is no optimal strategy in choosing the spatial resolution. Most of the time, it depends on your data and research question.
- However, there are multiscale modeling techniques from ML/DL communities, which can partially solve this issue. This approach is not explored much in urban applications

Independent variable

87	95	72	37	44	24
40	55	55	38	88	34
41	30	26	35	38	24
14	56	37	34	8	18
49	44	51	67	17	37
55	25	33	32	59	54

Dependent variable

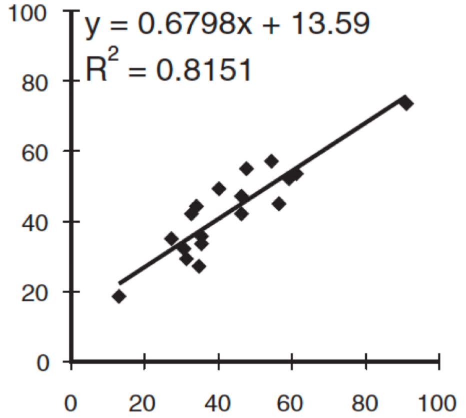
72	75	85	29	58	30
50	60	49	46	84	23
21	46	22	42	45	14
19	36	48	23	8	29
38	47	52	52	22	48
58	40	46	38	35	55



Aggregation scheme 1

91	54.5	34
47.5	46.5	61
35.5	30.5	31
35	35.5	13
46.5	59	27
40	32.5	56.5

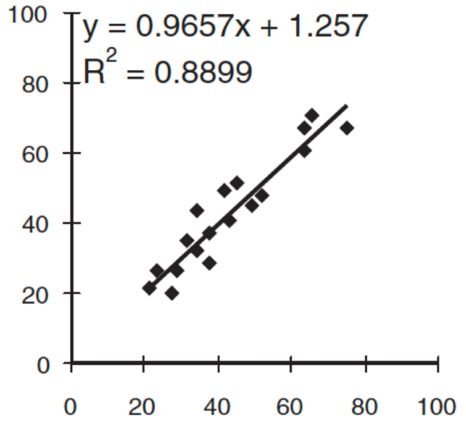
73.5	57	44
55	47.5	53.5
33.5	32	29.5
27.5	35.5	18.5
42.5	52	35
49	42	45



Aggregation scheme 2

63.5	75	63.5	37.5	66	29
27.5	43	31.5	34.5	23	21
52	34.5	42	49.5	38	45.5

61	67.5	67	37.5	71	26.5
20	41	35	32.5	26.5	21.5
48	43.5	49	45	28.5	51.5



Part 3. What are the edges and edge features?

- Intuition about the edges, which describe the closeness/similarity (or reversely distance/dissimilarity) between nodes.
- Eight options of defining edges in a naïve example
- Flexibility in defining edges.

Intuitively, edges describe the closeness/similarity of nodes

Social network (e.g. Facebook)

- Nodes: people;
- edges: friends between person A and person B.

Communication network (e.g. phone calls)

- Nodes: people;
- edges: phone call from person A to person B.

Internet

- Nodes: webpages;
- edges: link from website A to website B.

Citation network

- Nodes: papers;
- Edges: references from paper A to paper B

Urban applications

- Nodes: spatial units.
- Edges: land use similarities, human visitations, proximity, etc.

How to define edges in urban applications?

closeness/similarity

Notes

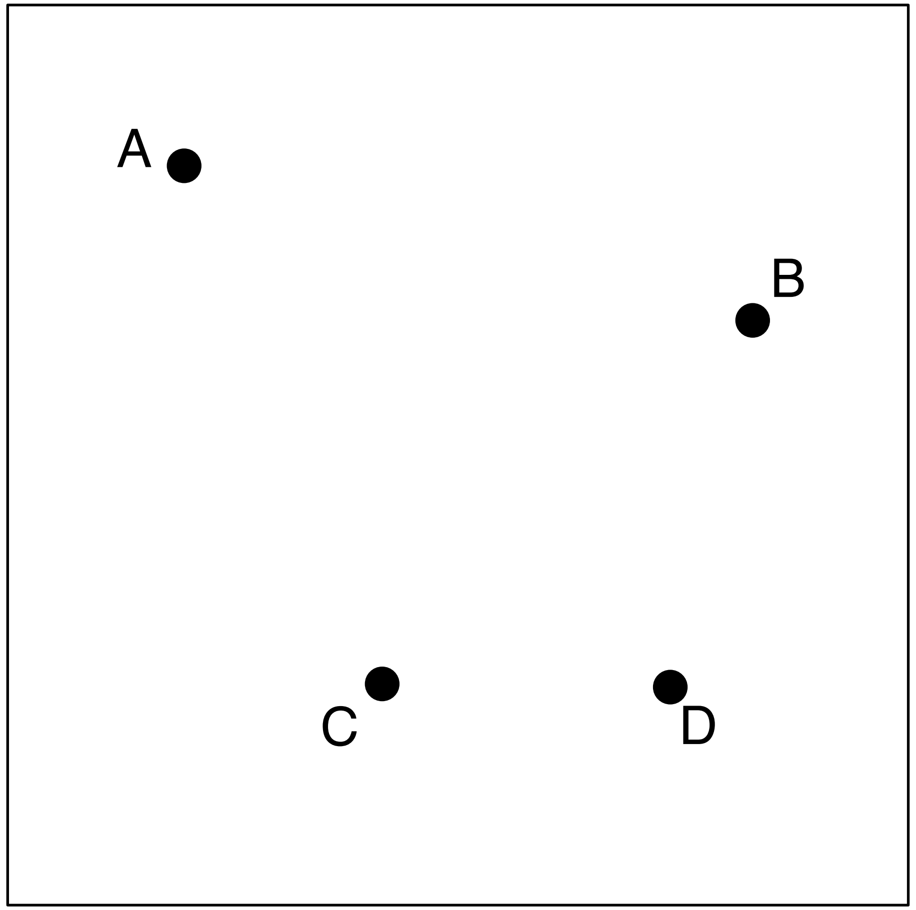
- A general view about closeness/similarity (or distance/dissimilarity) is critical.
- Edges exist when the two nodes are “close”
- Urban examples
  - Land use similarities
  - Human visitations
  - Spatial proximity, etc.

Question: Is Boston “closer” to New Hampshire or San Francisco?

How to create the edges?
Define adjacency matrix with some sense of closeness/similarity

Example:

- Four nodes: A, B, C, and D. e.g. centroids of four census tracts (or any spatial unit).
- We know their Euclidean distances
  - AB: 22
  - AC: 21
  - AD: 25
  - BC: 21
  - BD: 16
  - CD: 9



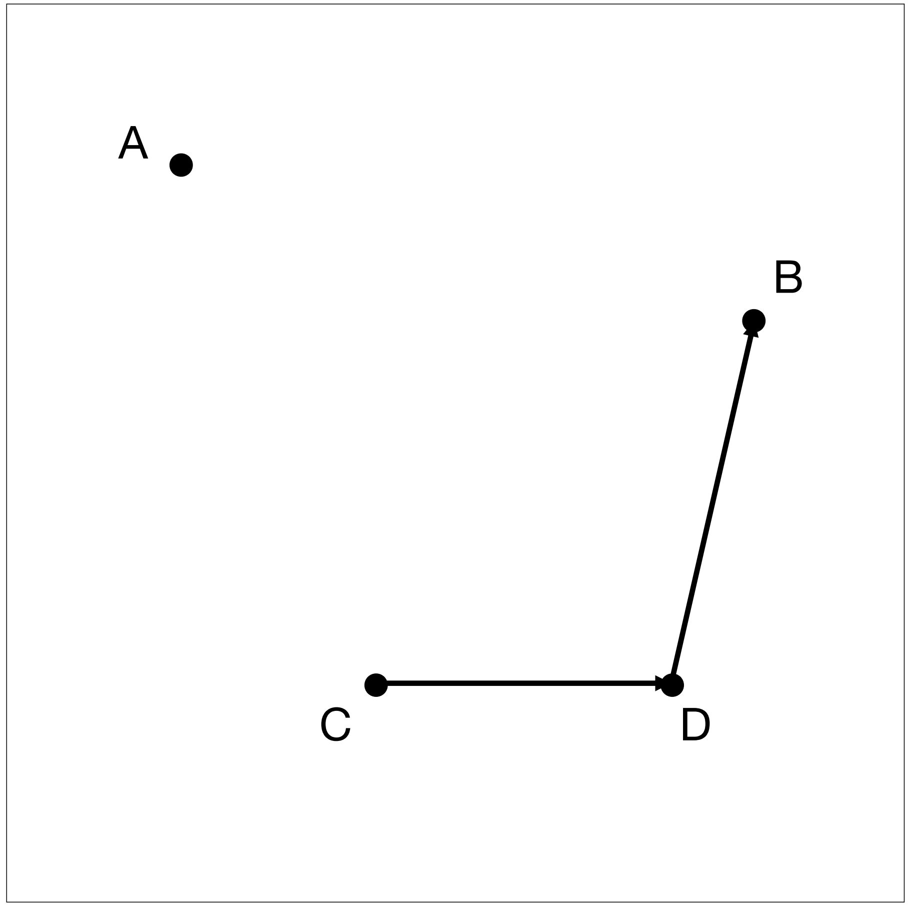
How to create the edges?
Define adjacency matrix with some sense of closeness/similarity

Option 1

- Use a threshold with a fixed distance to define the adjacency matrix. E.g. $\delta = 18$.
- Row and column index: A, B, C, D.

$A_{d\leq 18} =$

	A	B	C	D
A	*	0	0	0
B	0	*	0	1
C	0	0	*	1
D	0	1	1	*



AB: 22
AC: 21
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CD: 9

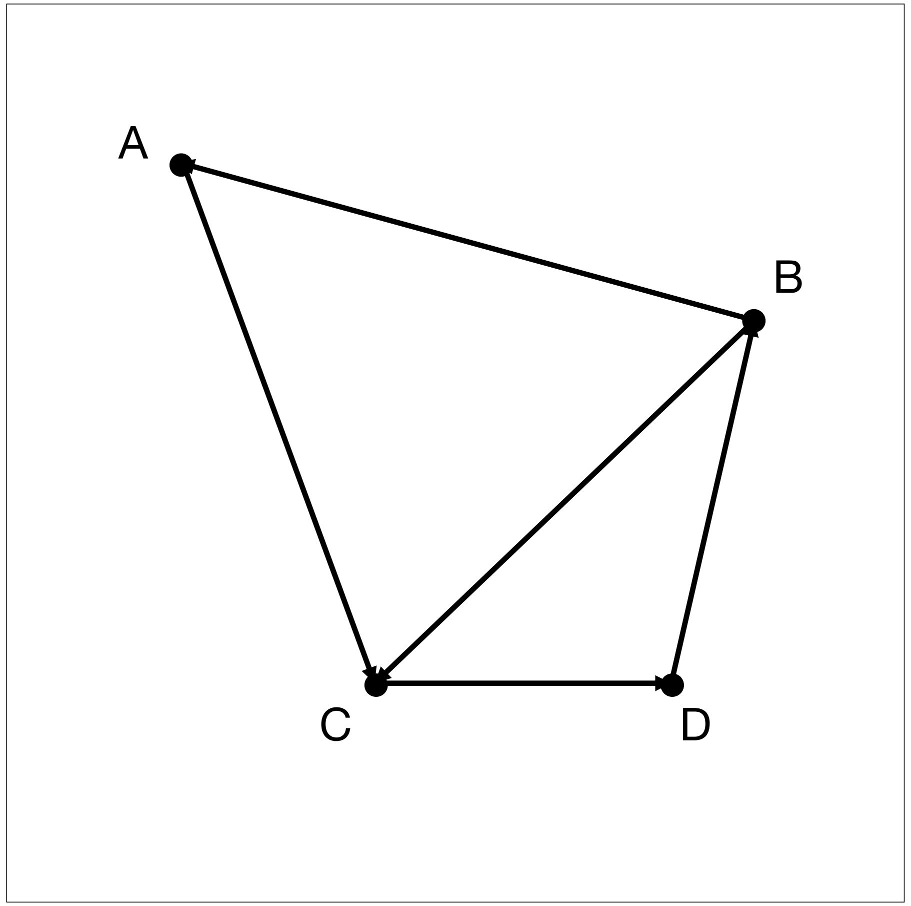
How to create the edges?
Define adjacency matrix with some sense of closeness/similarity

Option 2

- Use a threshold with a fixed distance to define the adjacency matrix. E.g. $\delta = 23$.
- Row and column index: A, B, C, D.

$A_{d \leq 23} =$

	A	B	C	D
A	*	1	1	0
B	1	*	1	1
C	1	1	*	1
D	0	1	1	*



AB: 22
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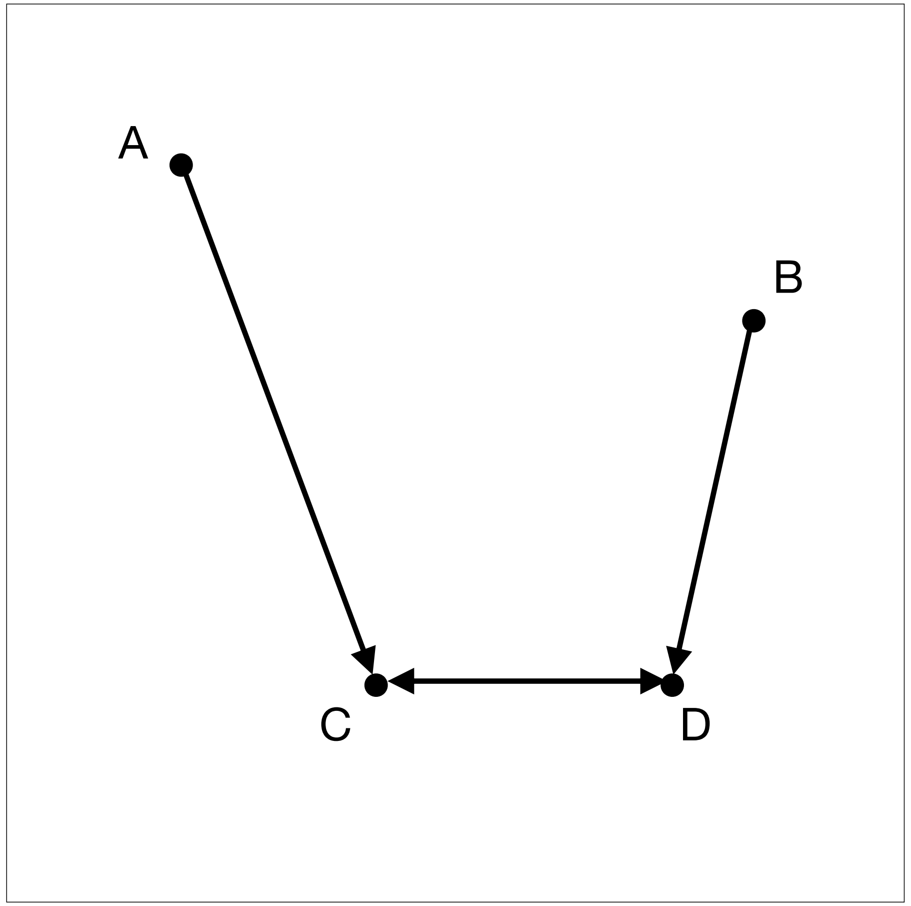
How to create the edges?
Define adjacency matrix with some sense of closeness/similarity

Option 3

- Find the K nearest neighbors of each node ($K = 1$)
- Row and column index: A, B, C, D.
- The adjacency matrix is asymmetric because we are implicitly working on a directed graph.
- This matrix is row normalized because the sum of each row equals to one.

$A_{k=1} =$

	A	B	C	D
A	*	0	1	0
B	0	*	0	1
C	0	0	*	1
D	0	0	1	*



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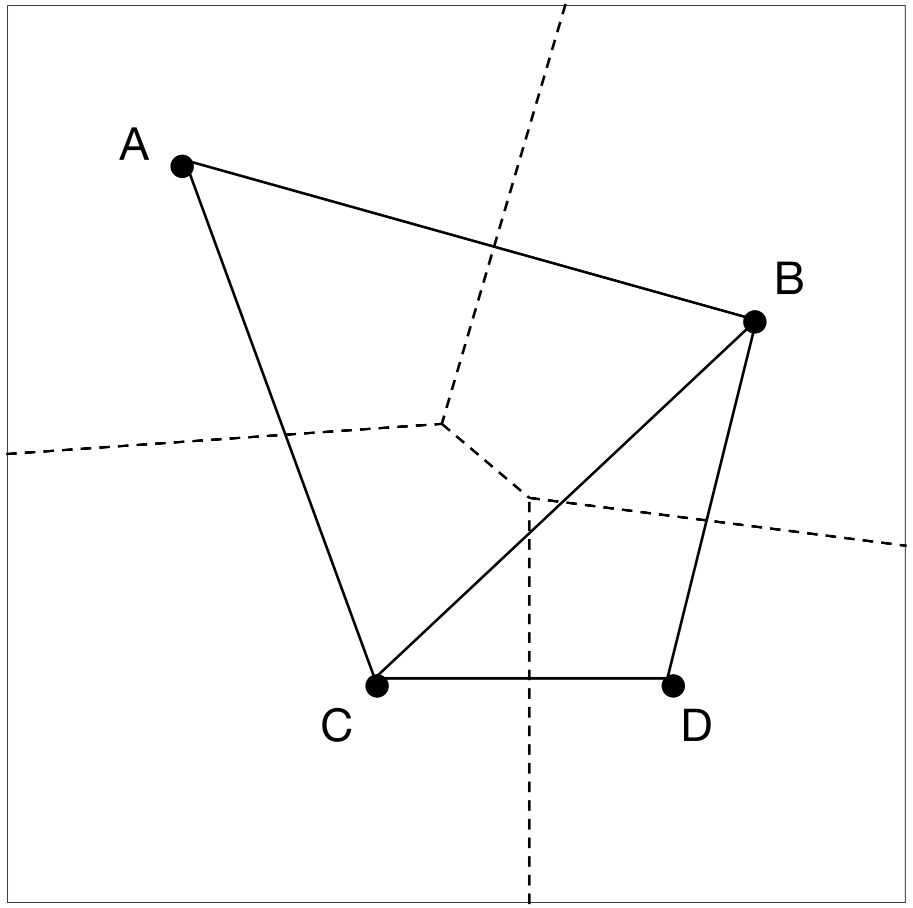
How to create the edges?
Define adjacency matrix with some sense of closeness/similarity

Option 4

- Suppose that each node represents a parcel. Define the adjacency if two parcels have a shared boundary.

$A =$

	A	B	C	D
A	*	1	1	0
B	1	*	1	1
C	1	1	*	1
D	0	1	1	*



AB: 22
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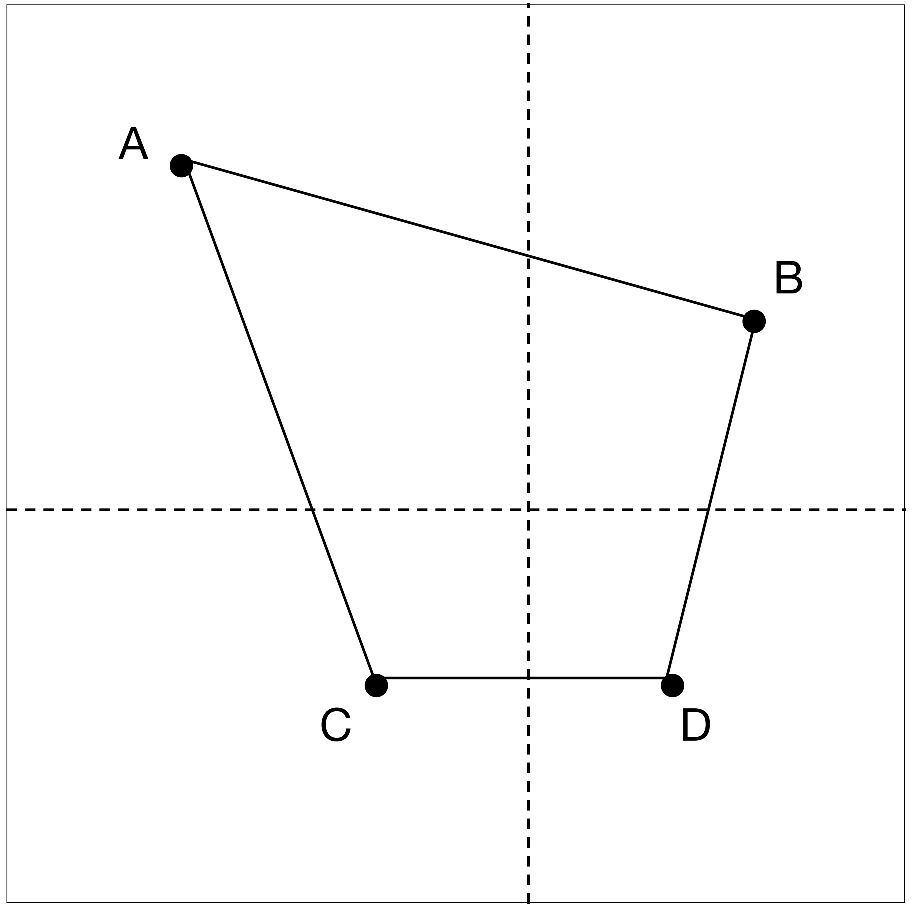
How to create the edges?
Define adjacency matrix with some sense of closeness/similarity

Option 5

- Suppose that each node represents a parcel but the boundaries are orthogonal.
- Define the adjacency if two parcels have a shared boundary.
- It is also called “Rook’s Case”

$A =$

	A	B	C	D
A	*	1	1	0
B	1	*	0	1
C	1	0	*	1
D	0	1	1	*



AB: 22
AC: 21
AD: 25
BC: 21
BD: 16
CD: 9

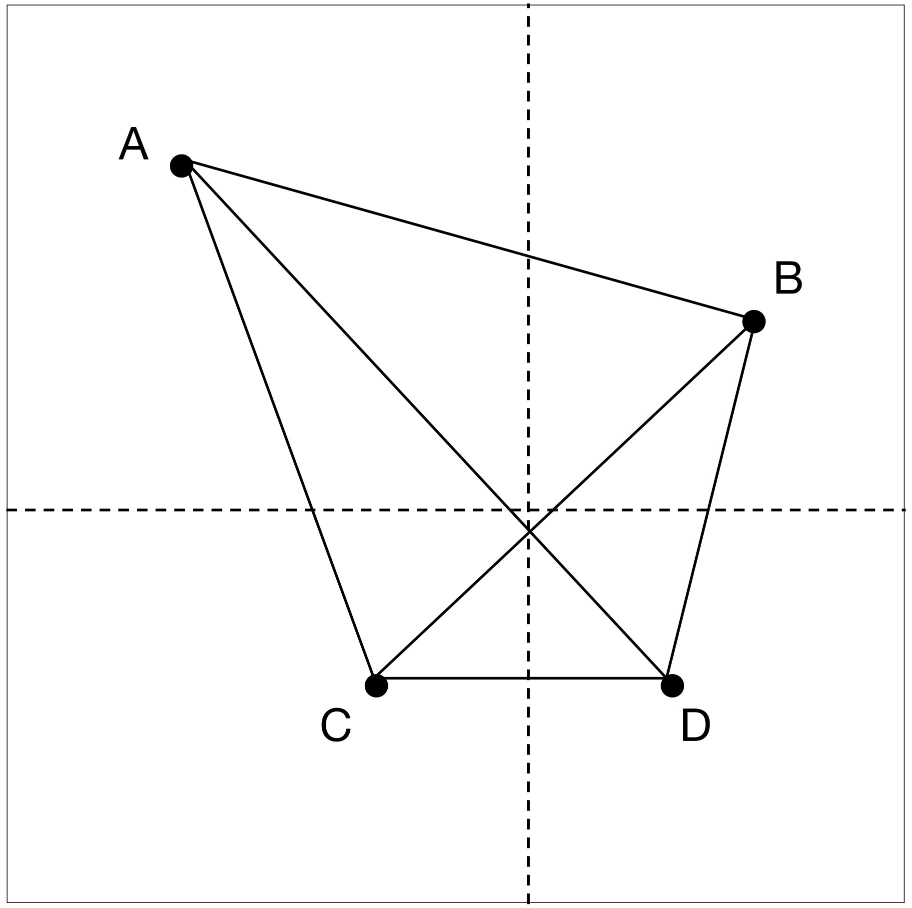
How to create the edges?
Define adjacency matrix with some sense of closeness/similarity

Option 6

- Suppose that each node represents a parcel but the boundaries are orthogonal.
- Define the adjacency if two parcels have a shared intersection.
- It is also called "Queen's Case"

$A =$

	A	B	C	D
A	*	1	1	1
B	1	*	1	1
C	1	1	*	1
D	1	1	1	*



AB: 22
AC: 21
AD: 25
BC: 21
BD: 16
CD: 9

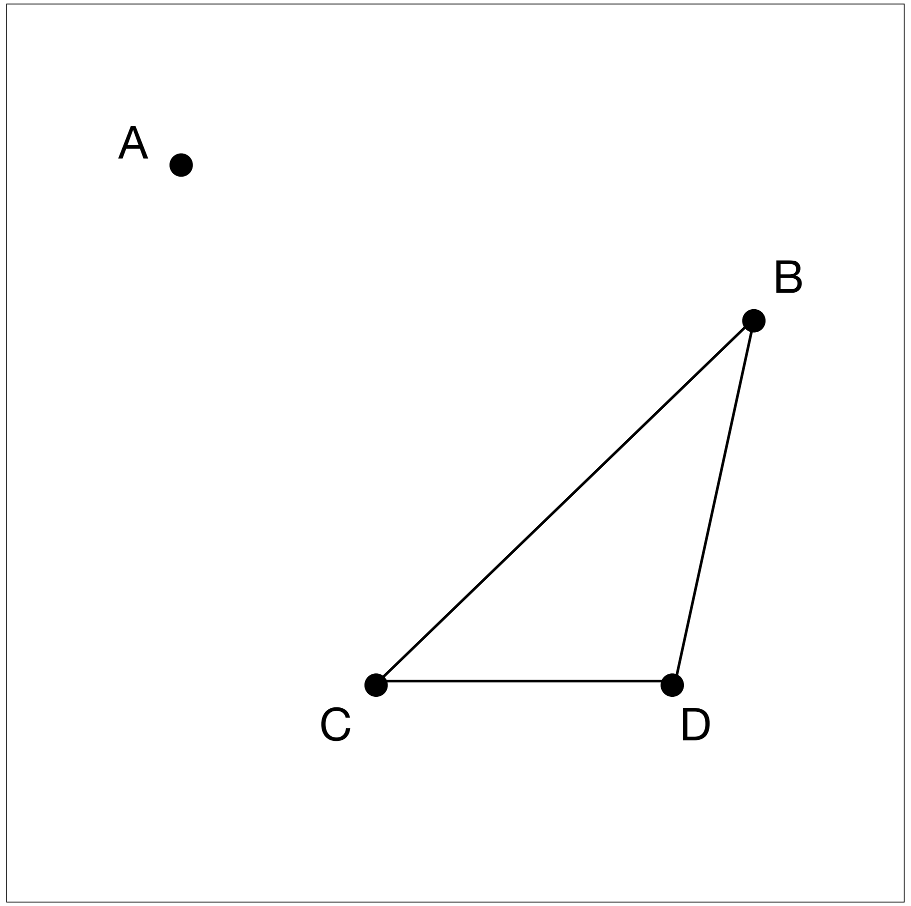
How to create the edges?
Define adjacency matrix with some sense of closeness/similarity

Option 7

- Define the similarity by node features.
- $a_{ij} = 1$, if the letter has a horizontal line of symmetry.
- I know it sounds ridiculous – but my points are (1) the flexibility of defining closeness/similarity, and (2) the possibility of using node features to define edges.

$A =$

	A	B	C	D
A	*	0	0	0
B	0	*	1	1
C	0	1	*	1
D	0	1	1	*



AB: 22
AC: 21
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BC: 21
BD: 16
CD: 9

How to create the edges?
Define adjacency matrix with some sense of closeness/similarity

Option 8

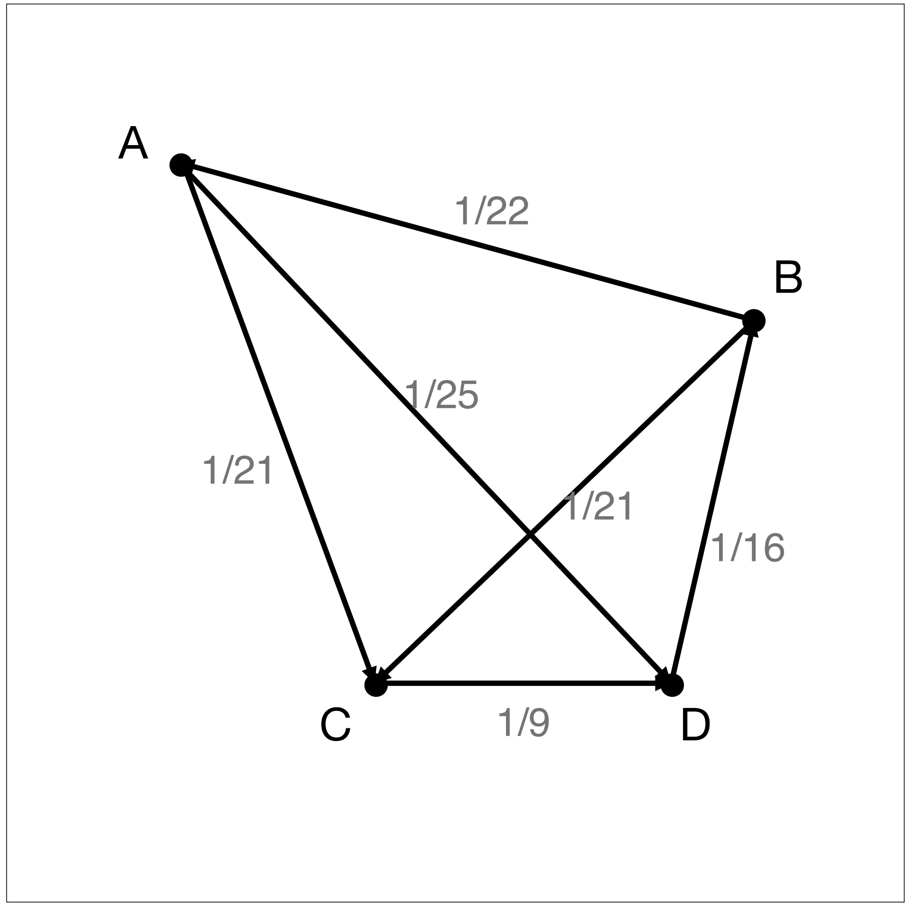
- Define the weights between nodes - larger numbers indicate more similarity. One example is

$$w_{ij} = \frac{1}{d^k}$$

- Let k = 1. But k could be any value

$W_{k=1} =$

	A	B	C	D
A	*	1/22	1/21	1/25
B	1/22	*	1/21	1/16
C	1/21	1/21	*	1/9
D	1/25	1/16	1/9	*



AB: 22
AC: 21
AD: 25
BC: 21
BD: 16
CD: 9

What are the edges and edge features?

Define the adjacency matrix with some sense of closeness/similarity

What are the edges? Use any rule you like - fixed distances, KNN, similarity between node features, etc.

What are the edge features? A_{ij} or W_{ij}

Q: Is Boston "closer" to New Hampshire or San Francisco?

A: It depends on your definition of closeness/similarity. e.g. Euclidean distance vs. socioeconomic similarity.

Q: There are so many adjacency matrices, which one should I use? The game sounds quite rigged.

A: It depends on the context. But in some cases, you can keep all the adjacency matrices. e.g., multigraphs. e.g. $A_1, A_2, A_3, \dots A_D; W_1, W_2, W_3, \dots W_D$

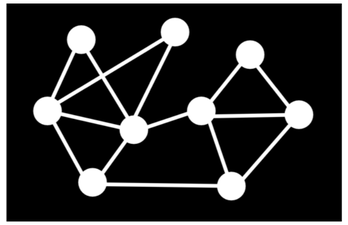
Part 4. Graph metrics and power-law distribution

- Introduce the descriptive statistics for graphs
- Delve into one metric: power-law distribution of node degrees
- Urban applications: scaling and universal law of travel
- Random vs. non-random DGPs

Metrics for graphs

Basic components of graph: nodes and edges

$$G = (V, E)$$



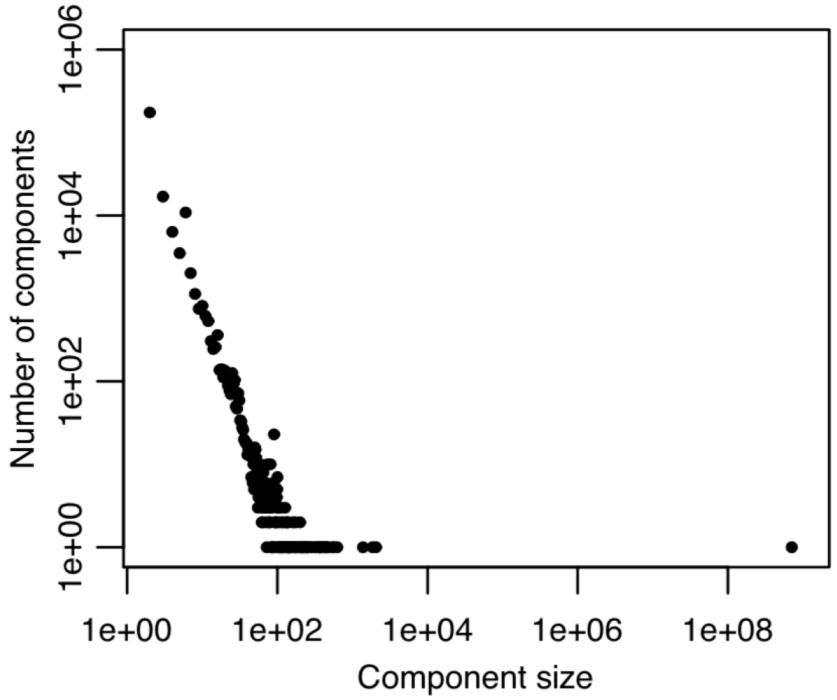
Some quantitative measures of graphs can describe the structural patterns of a graph and compare across graphs.

- Connected components
- Edge density
- Diameter and average length
- Others: centralities, clustering, homophily (skipped)
- Power-law degree distribution

Connected Components

Connected components: set of nodes that are reachable from one another.

Many networks consist of one large component and many small ones.



Component size distribution in the 2011 Facebook network on a log-log scale. Most vertices (99.91%) are in the largest component.

Edge density

The edge density is defined as

$$\rho = \frac{M}{\binom{N}{2}} = \frac{\sum_{ij} A_{ij}}{N(N-1)}, \text{ where } |V| = N, |E| = M$$

- Most graphs are sparse, i.e., $\rho \xrightarrow{N\to\infty} 0$ (the number of edges does not grow proportionally with the number of nodes)
    - e.g., friendship network: if each person has a constant number of friends c, then $\rho = \frac{CN}{\binom{N}{2}} \xrightarrow{N\to\infty} 0$
- Some graphs are dense, i.e., $\rho \xrightarrow{N\to\infty} const$

Diameter and average distance

- Let d_{ij} denote the length of the geodesic path (or shortest path) between node i and j.
- The diameter of a network is the largest distance between any two nodes in the network:

$$diameter = \max_{i,j \in V} d_{ij}$$

- The average path length is the average distance between any two nodes in the network:

$$average\ path\ length = \frac{1}{\binom{N}{2}} \sum_{i \leq j} d_{ij}$$

Small-world and six degrees of separation (average distance)

- Concept of six degrees of separation was made famous by sociologist Stanley Milgram and his study “The Small World Problem” (1967)

- In this experiment participants from a particular town were asked to get a letter to a particular person in a different town by passing it from acquaintance to acquaintance.

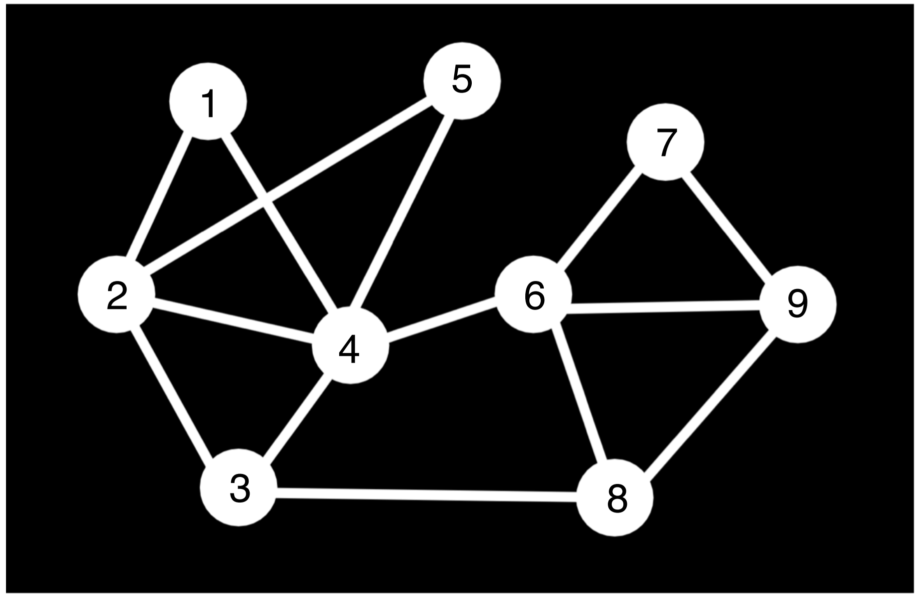
- 18 out of 96 letters made it in an average of 5.9 steps (average distance of social networks)

Power-law degree distributions

Degree of a node: # of edges incident to it.

In the graph, we have

$d_1 = 2; d_2 = 4; d_3 = 3; d_4 = 5; d_5 = 2; d_6 = 4; d_7 = 2; d_8 = 3; d_9 = 3$



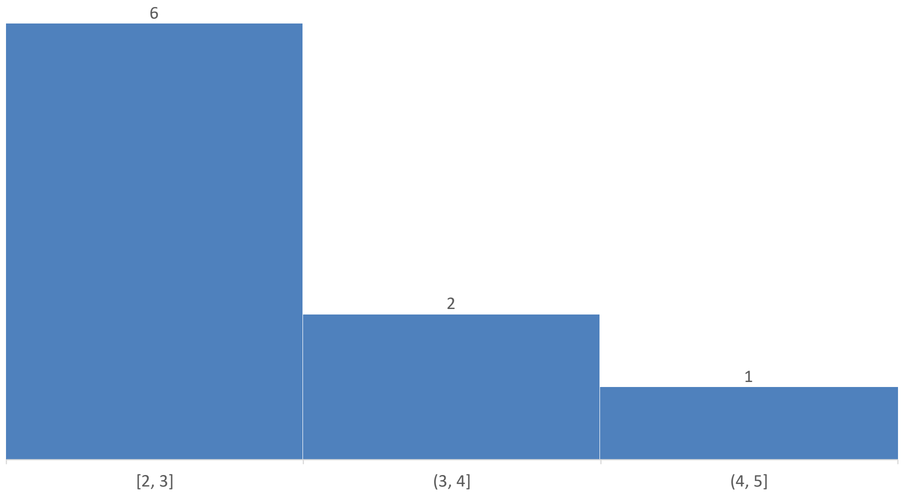
Degree distribution = Histogram

$\hat{P}(d)$: fraction of nodes with degree d.

For example in the graph above,

$$\hat{P}(d = 2) = 3/9$$

Chart Title



Degrees can be used to measure the centrality (or power) of the node. e.g. twitter network – Trump is powerful because of the large number of followers.

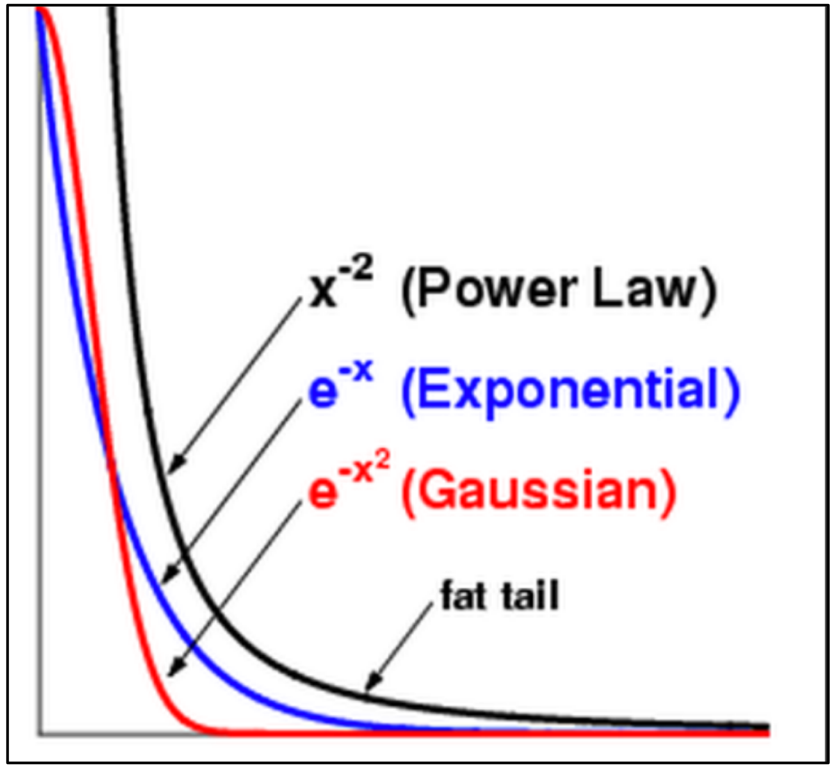
Two types of degree distributions

For large graphs, there are two types of degree distributions when d becomes very large.

1. Exponential decay: $\hat{P}(d) \sim O\left(e^{-\alpha d}\right), \alpha > 0$
2. Power-law decay: $\hat{P}(d) \sim c d^{-\gamma}, c, \gamma > 0$

Notes:

- Power-law distribution has a fat tail. Intuitively, the power-law distributions describe disproportionally powerful people, extreme natural disasters, and other rare issues, while the exponential family cannot describe such rare cases.
- Normal (Gaussian) distribution has the exponential decay.



Distribution and scales

1. Type 1 is also known as scale-dependent network.
2. Type 2 is also known as scale-free network.

Interpretation of scale-free network

Take d and d' large enough so that $\hat{P}(d) \sim cd^{-\gamma}$ and $\hat{P}(d') \sim cd'^{-\gamma}$.

Then scale the both by a factor of β, so that $d \to \beta d$, and $d' \to \beta d'$, we still have

$$\frac{\hat{P}(d)}{\hat{P}(d')} = \frac{cd^{-\gamma}}{cd'^{-\gamma}} = \frac{c(\beta d)^{-\gamma}}{c(\beta d')^{-\gamma}} = \frac{\hat{P}(\beta d)}{\hat{P}(\beta d')}$$

Notes

- Relative degree relationship between nodes does not vary with the scale of a network. e.g. social connections.
- The property of the power-law network is free of its scale.
- The property is not true for the scale-dependent network.
- Intuitively, e.g., twitter, it says that the relative power relationship between people does not vary with the scale of the network.
- In reality, many networks present this scale-free property.

Empirical results of the scale-free networks

$$\hat{P}(d) \sim c d^{-\gamma}$$

Examples

- Internet. $2.15 < \gamma < 2.3$
- Movie-actor network. $\gamma \approx 2.3$
- Citation network. $\gamma \approx 2.6$

Comments

- Fat-tail distributions have quite unstable moments (e.g., mean and variance).
- e.g. when $\gamma > 2$, $\mathrm{E}[d] < \infty$

Relating the scale-free distribution to regressions

Scale-free distribution as a univariate regression:

$$\hat{P} \sim c d^{-\gamma}$$

Taking log transformation on both sides:

$$\log \hat{P} \sim \log c - \gamma \log d$$

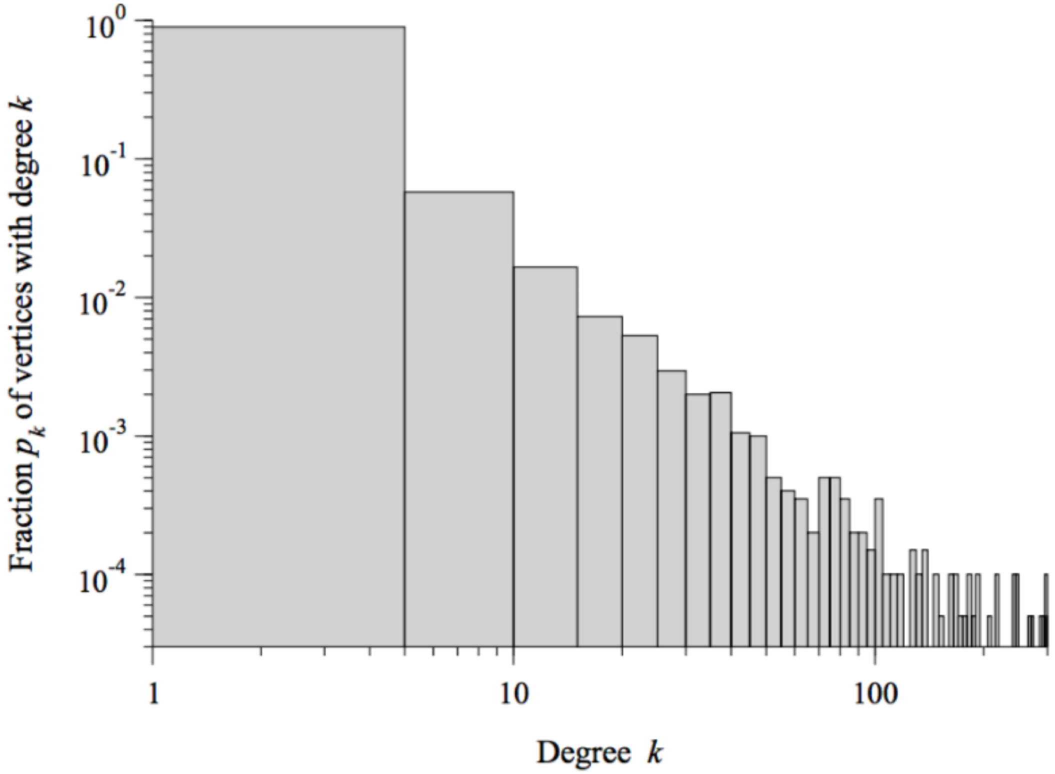
Note

- This is a univariate linear regression with $\log d$ as independent variable and $\log \hat{P}$ as dependent variable.
- If you plot $\log d$ vs. $\log \hat{P}$, you should get a straight line.
- $\hat{\beta}_0$ as $\log c$ and $\hat{\beta}_1$ as γ.

Degree distribution

Information can be captured by degree distribution

- Histogram of fraction of nodes with degree k.
- Figures from Chapter 8 in “Networks: An Introduction” by M.E.J. Newman (2010):



A fancier name: universal law of human travel

In the mobility field, people talk about the universal law of human travel, which is published on Nature & Science. This is actually the power-law distribution of human travels.

Brockmann, D., et al. (2006)

- $P(r) \sim r^{-(1+\beta)}$
- $P(t) \sim At^{-\eta}$

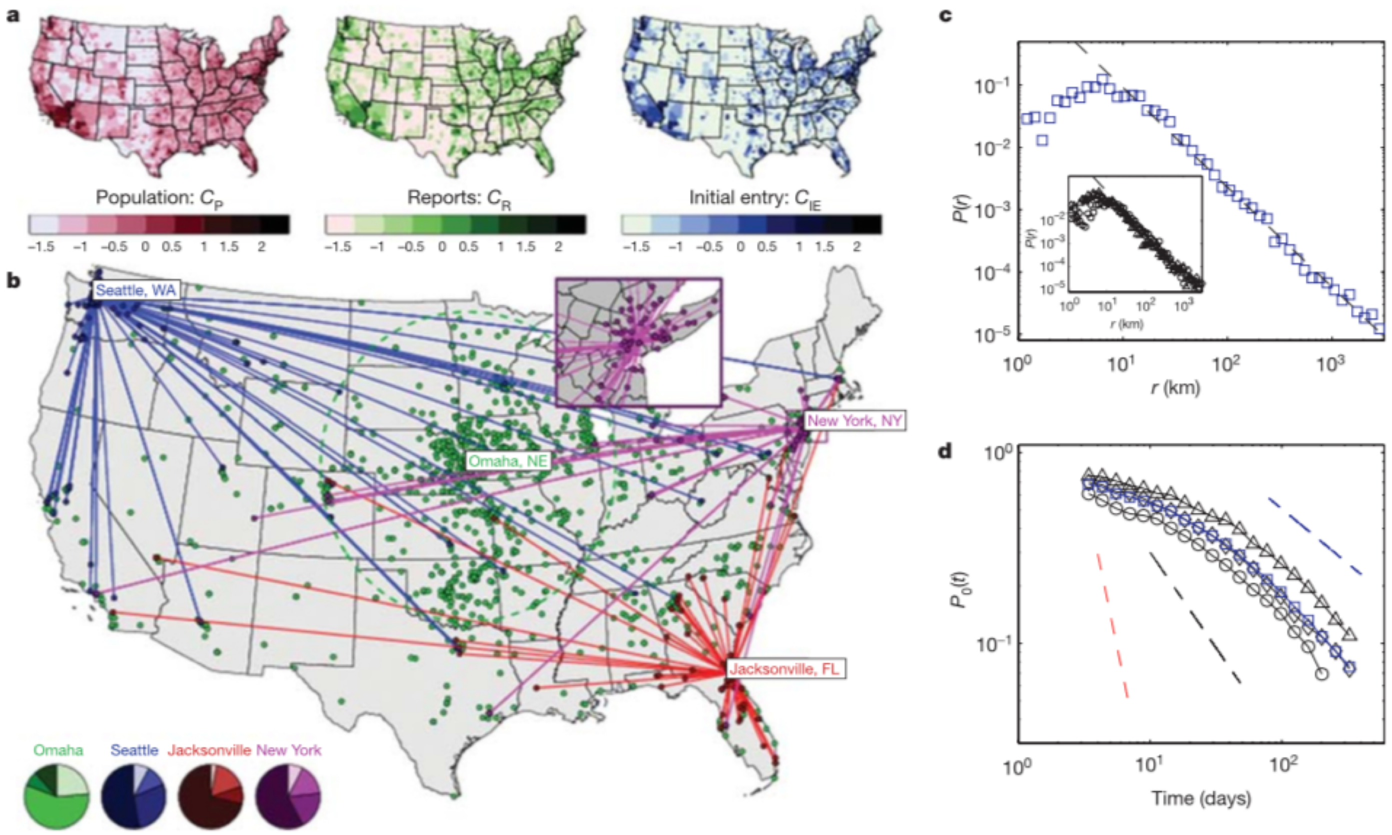
It is power-law distribution of travel distance and time.

Gonzalez, M. C., et al. (2008)

- $P(\Delta r) \sim (\Delta r + \Delta r_0)^{-\beta} \exp(-\Delta r/k)$

It combines power-law and exponential distributions to describe the travel distance.

Many follow-up works…



Brockmann, D., et al. (2006). "The scaling laws of human travel." Nature **439**(7075): 462-465;
Gonzalez, M. C., et al. (2008). "Understanding individual human mobility patterns." Nature **453**(7196): 779-782.

Questions about universal law of human travel

Brockmann, D., et al. (2006)

- $P(r) \sim r^{-(1+\beta)}$
- $P(t) \sim At^{-\eta}$

It is power-law distribution of travel distance and time.

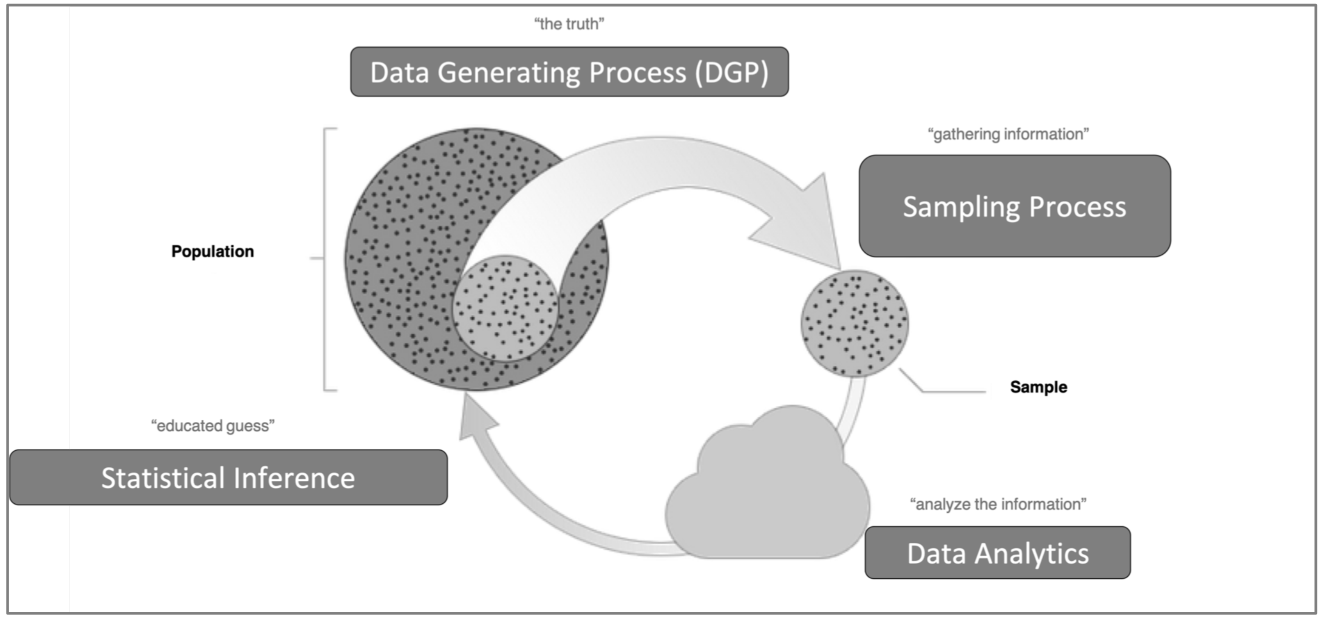
Question 1: Since the power-law distribution can be reduced to a univariate linear regression, could we criticize the “universal law” by the potential violation of A1 and A2?

Question 2: When the authors believe in the universal law, they are expecting a 100% R2. How do you think about this 100% R2?

Question 3: What about the famous $\mathrm{E} = mc^2$? It is also a univariate linear regression. If you run a simple regression and find the following form, could you become Einstein?

$$\log E = 2 \log c + \log m$$

There is no right/wrong answer because it is a conflict in belief



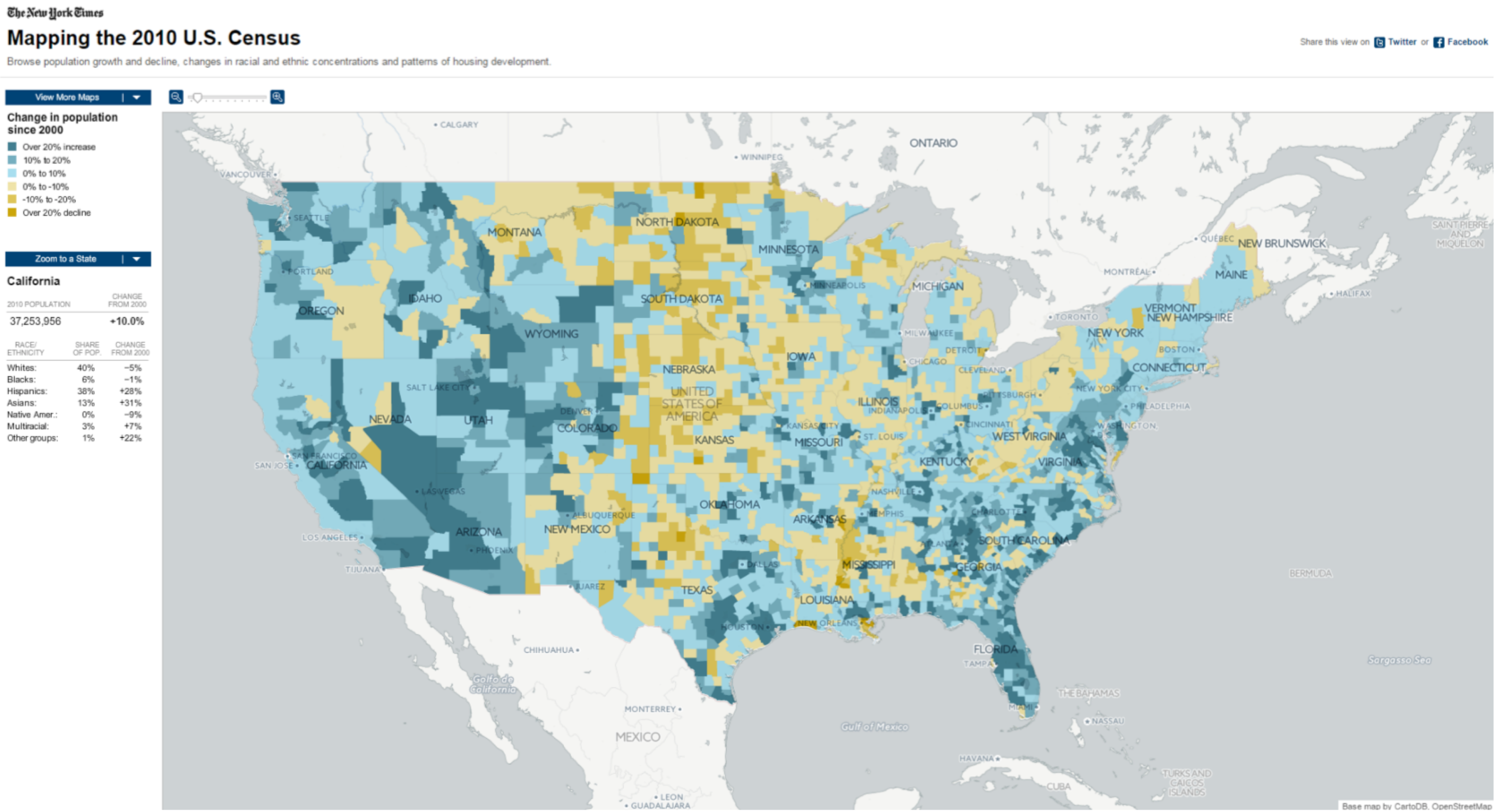
DGP: random vs. non-random

- The papers about "universal law" come from authors with physics background. Physicists (classical) believe in a deterministic truth (DGP). In this case, the maximum R2 equals to 100%.
- However, the majority of the other modeling paradigms (e.g. ML, Stat) believe in a random DGP. Under this belief, the maximum R2 is typically much lower than 100%.

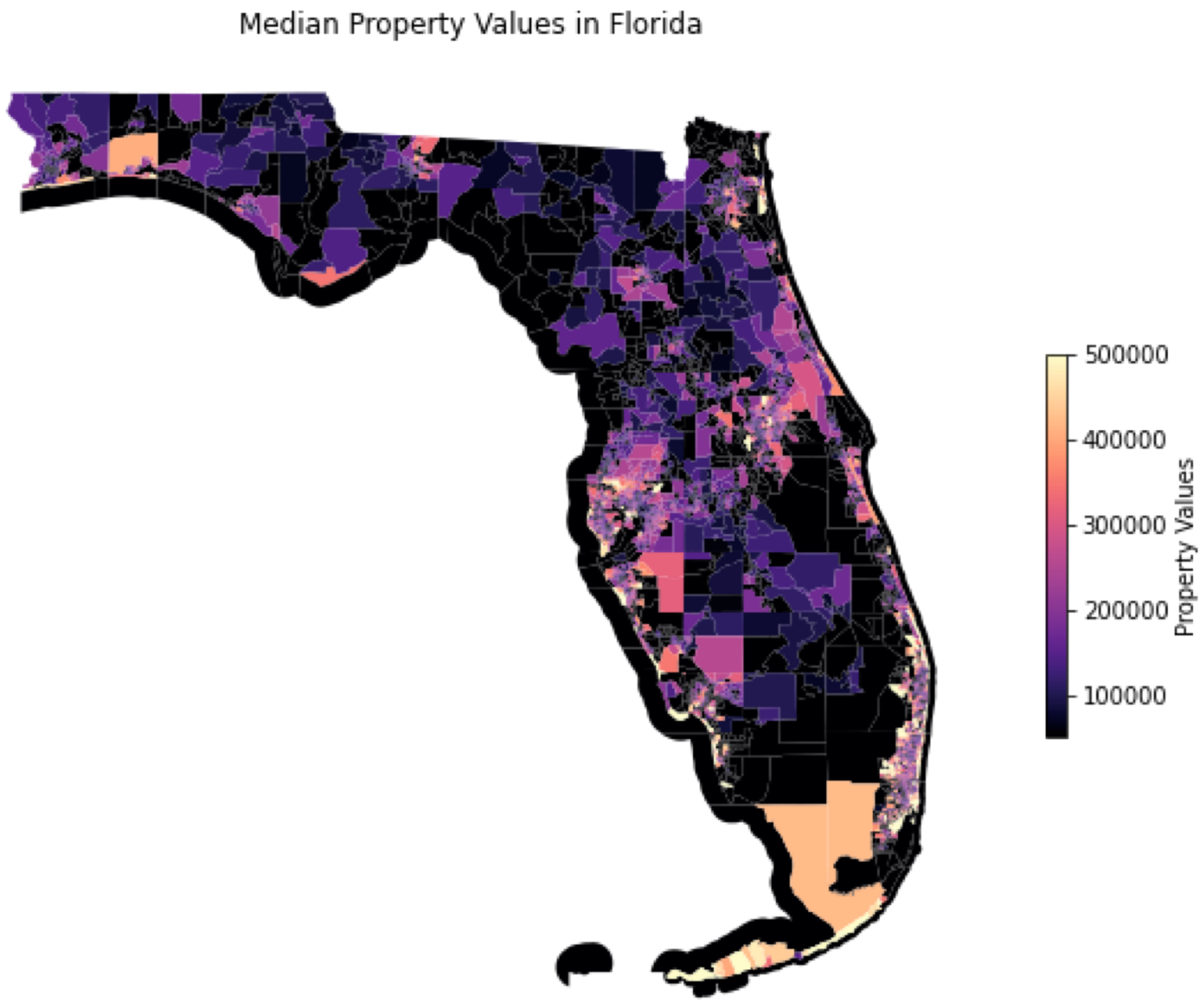
Part 5. GIS as visualization of node and edge features

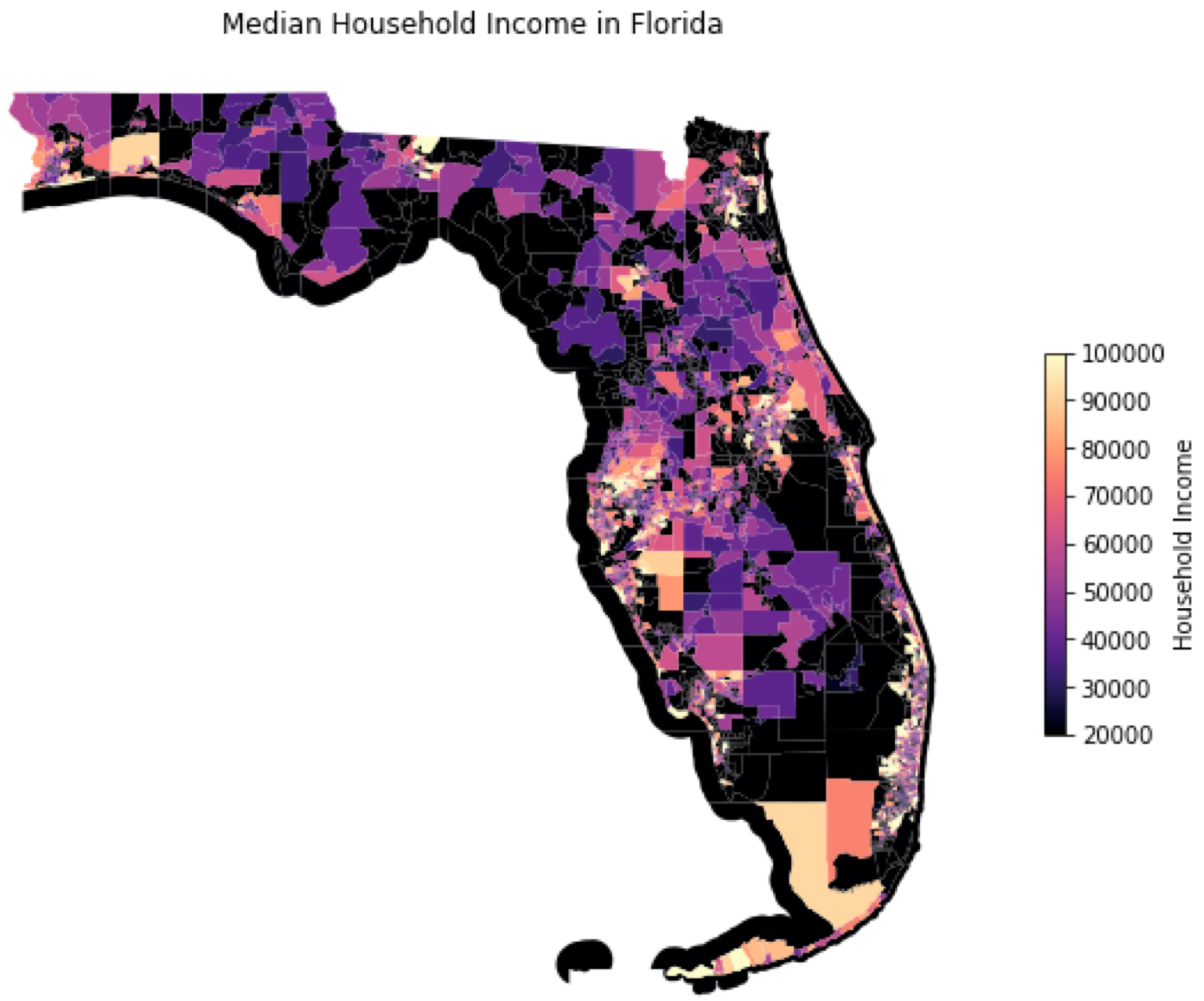
- How to think about the GIS maps? Visualizing node and edge features in a graph.
- Seek to provide a more general framework to facilitate future analysis.
- Python - GeoPandas

Visualizing the node features with counties representing the nodes

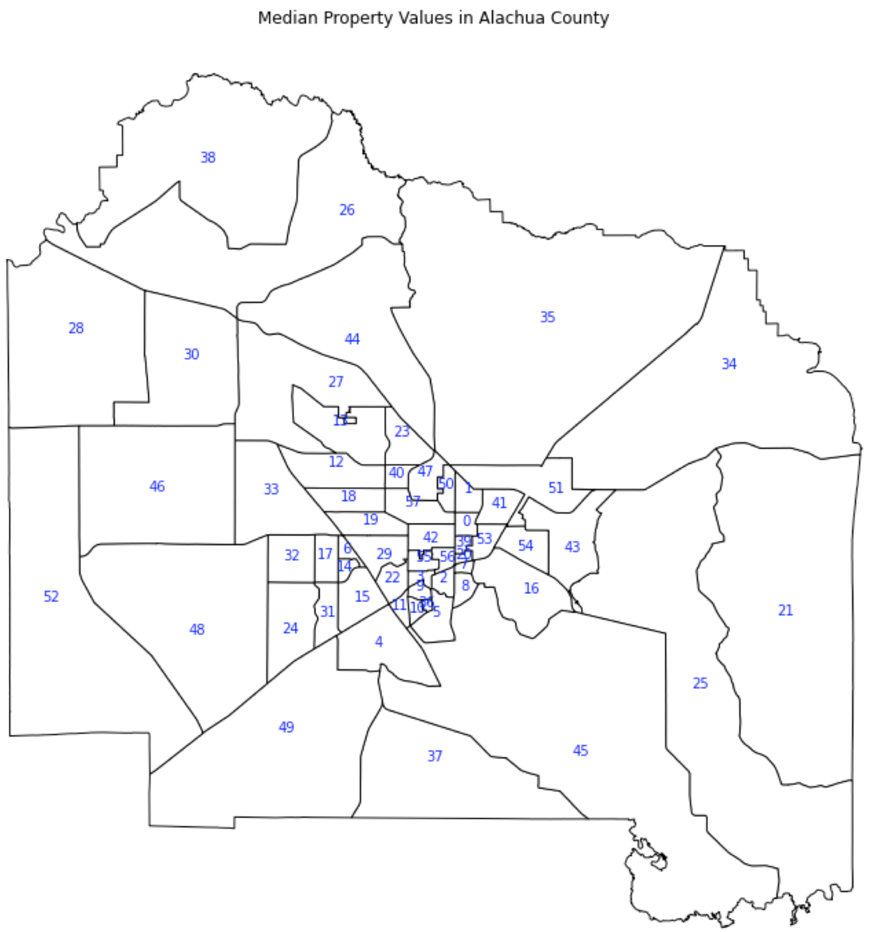


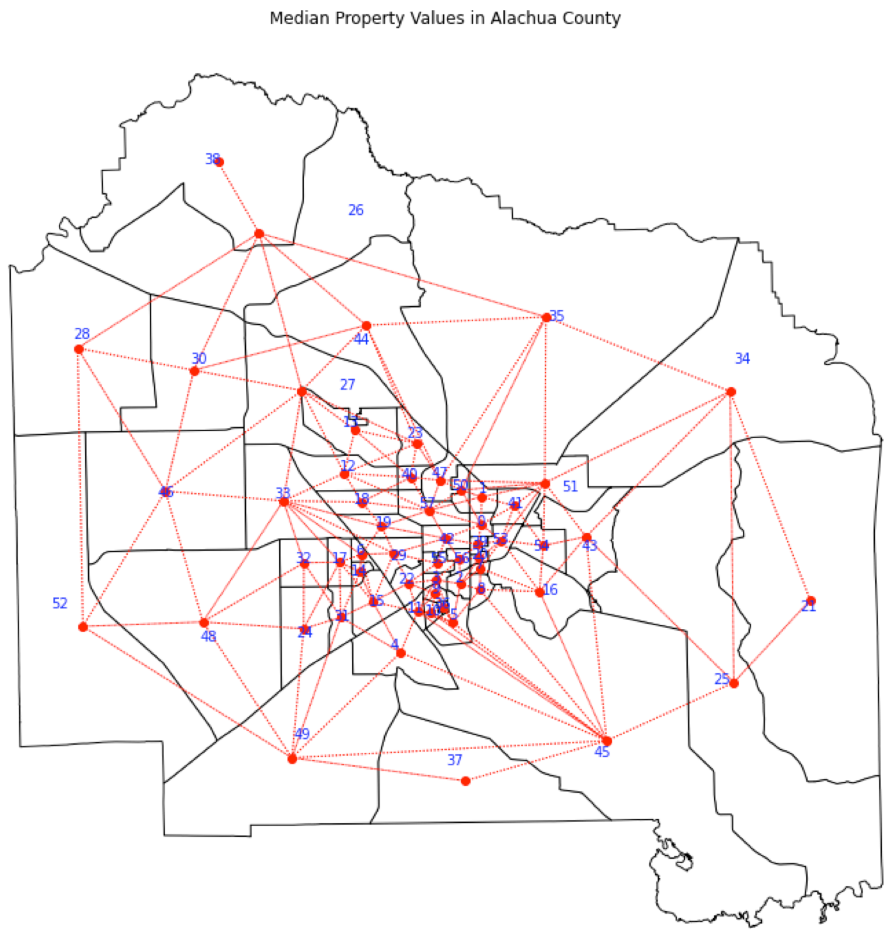
Visualizing the node features in Florida.
What are the nodes and node features?





Visualizing the nodes and edges in Alachua county
What are the edges and edge features?





Updating Syllabus

Updating syllabus

New schedule

- Module 2. Urban network analysis: Feb 21 and 28
- Module 3. ML/DL - supervised and unsupervised learning: Mar 7 and Mar 21; ANN & CNN & GNN: March 28 and April 4
- Module 4. MISC: April 11
- Module 5. Behavioral modeling: April 18

Updating timeline of the Psets

Project presentations & guest lectures

- Mid-term presentation: March 28
- Final presentation: April 25

Guest lectures

- All from MIT senior PhD students.
- Providing comparable insights for your projects
- April 4. Dingyi Zhuang: spatiotemporal prediction
- April 11. Yunhan Zheng: computational fairness
- April 18. Qingyi Wang: deep hybrid model with imagery

Week	Dates		Guest lectures	Lab sessions	Psets	Project
1	Jan 10	class overview				
2	Jan 17	review: statistics and python		Y		
Module 1: Urban statistical analysis						
3	Jan 24	univariate linear regression		Y		
4	Jan 31	multivariate linear regression		Y		
5	Feb 7	logistic regression		Y	hw 1 out	
NA	Feb 14	NA				idea due
Module 2: Urban network analysis						
6	Feb 21	urban networks: representation, centrality metrics, and GIS		Y	hw1 due	
7	Feb 28	urban networks: scaling, community, and spatial regression		Y	hw 2 out	
Module 3: Machine learning in cities						
8	Mar 7	supervised learning: classifications and regression revisited		Y		
NA	Mar 14	no class (Spring Break)				
9	Mar 21	unsupervised learning: clustering		Y	hw 3 out, hw2 due	
10	Mar 28	deep learning basics				Mid-term presentation; proposal due
11	Apr 4	deep learning with images and graphs	Yes		hw 3 due	
Module 4: MISC						
12	Apr 11	optimization, causality, and normative aspects	Yes			
Module 5: Behavioral analysis – integration of three paradigms						
13	Apr 18	deep choice models	Yes			
14	Apr 25	final presentation & course evaluation				Final presentation; report due

Note: This schedule is subject to changes.