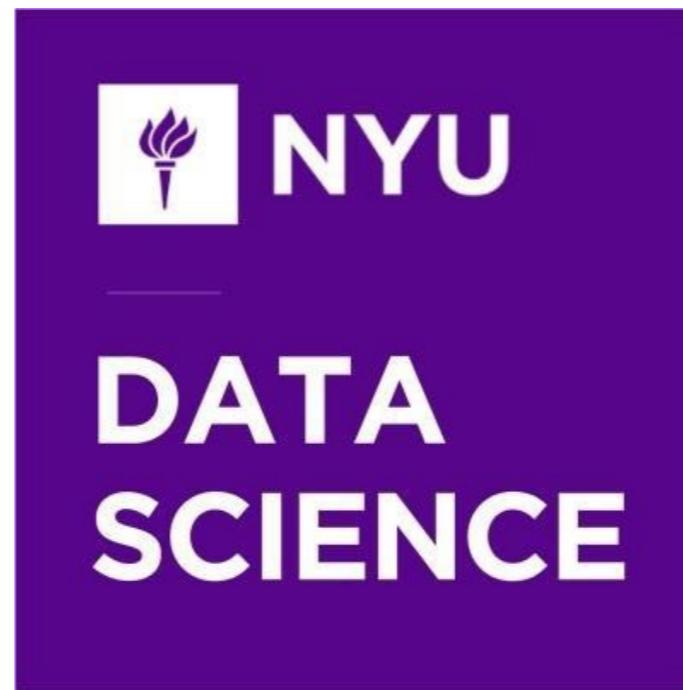


Online Social Networks and Mobility - Practical

Bruno Gonçalves
www.bgoncalves.com



Registering an Application

The screenshot shows a web browser window with the URL <https://apps.twitter.com/app/5827134/keys>. The page title is "Data Mining Tutorial". The main content area is titled "Application settings" and contains the following information:

Setting	Value
API key	[Redacted]
API secret	[Redacted]
Access level	Read-only (modify app permissions)
Owner	bgoncalves
Owner ID	15008596

Below this is a section titled "Application actions" with buttons for "Regenerate API keys" and "Change App Permissions".

At the bottom is a section titled "Your access token" with the following information:

Setting	Value
Access token	[Redacted]
Access token secret	[Redacted]
Access level	Read-only
Owner	bgoncalves
Owner ID	15008596

A file upload input field at the bottom left contains the file "slick.bmp". A "Show All" button is located at the bottom right.

API Basics

<https://dev.twitter.com/docs>

- The `twitter` module provides the oauth interface. We just need to provide the right credentials.
- Best to keep the credentials in a `dict` and parametrize our calls with the dict key. This way we can switch between different accounts easily.
- `.Twitter(auth)` takes an `OAuth` instance as argument and returns a `Twitter` object that we can use to interact with the API
- `Twitter` methods mimic API structure
- 4 basic types of objects:
 - Tweets
 - Users
 - Entities
 - Places

Authenticating with the API

```
import twitter
from twitter_accounts import accounts

app = accounts["social"]

auth = twitter.oauth.OAuth(app["token"],
                           app["token_secret"],
                           app["api_key"],
                           app["api_secret"])

twitter_api = twitter.Twitter(auth=auth)
```

- In the remainder of this course, the `accounts` dict will live inside the `twitter_accounts.py` file
- 4 basic types of objects:
 - Tweets
 - Users
 - Entities
 - Places

Searching for Tweets

<https://dev.twitter.com/docs/api/1.1/get/search/tweets>

- `.search.tweets(query, count)`
 - `query` is the content to search for
 - `count` is the maximum number of results to return
- returns dict with a list of “`statuses`” and “`search_metadata`”

```
{u'completed_in': 0.027,
 u'count': 15,
 u'max_id': 438088492577345536,
 u'max_id_str': u'438088492577345536',
 u'next_results': u'?max_id=438088485145034752&q=soccer&include_entities=1',
 u'query': u'soccer',
 u'refresh_url': u'?since_id=438088492577345536&q=soccer&include_entities=1',
 u'since_id': 0,
 u'since_id_str': u'0'}
```

- `search_results[“search_metadata”][“next_results”]` can be used to get the next page of results

Searching for Tweets

<https://dev.twitter.com/docs/api/1.1/get/search/tweets>

```
query = "instagaram"
count = 200

search_results = twitter_api.search.tweets(q=query, count=count)

statuses = search_results["statuses"]
tweet_count = 0

while True:
    try:
        next_results = search_results["search_metadata"]["next_results"]

        args = dict(parse.parse_qsl(next_results[1:]))

        search_results = twitter_api.search.tweets(**args)
        statuses = search_results["statuses"]

        print(search_results["search_metadata"]["max_id"])

        for tweet in statuses:
            tweet_count += 1

            if tweet_count % 10000 == 0:
                print(tweet_count, file=sys.stderr)

            print(tweet["text"])
    except:
        break
```

twitter_search.py

User Timeline

https://dev.twitter.com/docs/api/1.1/get/statuses/user_timeline

- `.statuses.user_timeline()` returns a set of tweets posted by a single user
- Important options:
 - `include_rts='true'` to include retweets by this user
 - `count=200` number of tweets to return in each call
 - `trim_user='true'` to not include the user information (save bandwidth and processing time)
 - `max_id=1234` to include only tweets with an id lower than `1234`
- Returns at most `200` tweets in each call. Can get all of a users tweets (up to 3200) with multiple calls using `max_id`

User Timeline

https://dev.twitter.com/docs/api/1.1/get/statuses/user_timeline

```
import twitter
from twitter_accounts import accounts

app = accounts["social"]

auth = twitter.oauth.OAuth(app["token"],
                           app["token_secret"],
                           app["api_key"],
                           app["api_secret"])

twitter_api = twitter.Twitter(auth=auth)
screen_name = "BarackObama"

args = { "count" : 200,
         "trim_user": "true",
         "include_rts": "true"
     }

tweets = twitter_api.statuses.user_timeline(screen_name = screen_name, **args)
tweets_new = tweets

while len(tweets_new) > 0:
    max_id = tweets[-1]["id"] - 1
    tweets_new = twitter_api.statuses.user_timeline(screen_name = screen_name, max_id=max_id, **args)
    tweets += tweets_new

print("Found", len(tweets), "tweets")
```

Streaming Geocoded data

<https://dev.twitter.com/streaming/overview/request-parameters#locations>

- The Streaming api provides realtime data, subject to filters
- Use `TwitterStream` instead of `Twitter` object (`.TwitterStream(auth=twitter_api.auth)`)
- `.status.filter(track=q)` will return tweets that match the query `q` in real time
- Returns generator that you can iterate over
- `.status.filter(locations=bb)` will return tweets that occur within the bounding box `bb` in real time
 - `bb` is a comma separated pair of lon/lat coordinates.
 - `-180,-90,180,90` - World
 - `-74,40,-73,41` - NYC

Streaming Geocoded data

<https://dev.twitter.com/streaming/overview/request-parameters#locations>

```
import twitter
from twitter_accounts import accounts
import sys
import gzip

app = accounts["social"]

auth = twitter.oauth.OAuth(app["token"],
                           app["token_secret"],
                           app["api_key"],
                           app["api_secret"])

stream_api = twitter.TwitterStream(auth=auth)

query = "-74,40,-73,41" # NYC
stream_results = stream_api.statuses.filter(locations=query)
tweet_count = 0

fp = gzip.open("NYC.json.gz", "a")

for tweet in stream_results:
    try:
        tweet_count += 1
        print(tweet_count, tweet["id"])
        print(tweet, file=fp)
    except:
        pass

    if tweet_count % 10000 == 0:
        print(tweet_count, file=sys.stderr)
        break
```

Foursquare

Registering An Application

The screenshot shows a web browser window for Foursquare. The URL in the address bar is <https://foursquare.com/developers/apps>. The page has a blue header with the Foursquare logo and navigation links like 'I'm looking for...', 'Lyon, FR', and a search icon. Below the header, there's a promotional section for the app with the text 'Find great places on the go.' and a 'GET THE APP' button. The main content area is titled 'My Apps' and contains a card for an app named 'Test1'. The card includes a preview image showing a blurred interface, a link to 'More about this app...', and a 'CREATE A NEW APP' button. To the right of the app card, there are sections for 'Access Token URL' (https://foursquare.com/oauth2/access_token) and 'Authorize URL' (<https://foursquare.com/oauth2/authorize>). At the bottom, there's a 'Learn more about:' section with links to 'OAuth2 and foursquare' and 'The foursquare API'. The footer of the page includes links for 'About', 'Blog', 'Businesses', 'Cities', 'Developers', 'Help', 'Jobs', 'Cookies (Updated)', 'Privacy (Updated)', 'Terms', and 'English'. It also features a copyright notice: 'Foursquare © 2015 ♡ Lovingly made in NYC & SF'.

Registering An Application

- with this code we can now request an **auth_token** which will allow us to authenticate with the Foursquare API

```
access_token = client.oauth.get_token('CODE')
```

- This will return the OAuth2 access_token that we can then use directly.

```
import foursquare
from foursquare_accounts import accounts

app = accounts["tutorial"]

client = foursquare.Foursquare(client_id=app["client_id"],
                               client_secret=app["client_secret"])

client.set_access_token(app["access_token"])
```

- Much simpler and intuitive
- Less prone to mistakes
- Automatically takes care of all the dirty details

Venues

<https://developer.foursquare.com/overview/venues.html>

- `.venues(venue_id)`

Returns a venue object

```
[u'rating',
 u'reasons',
 u'likes',
 u'mayor',
 u'createdAt',
 u'verified',
 u'id',
 u'shortUrl',
 u'pageUpdates',
 u'location',
 u'tips',
 u'listed',
 u'canonicalUrl',
 u'tags',
 u'photos',
 u'attributes',
 u'stats',
 u'dislike',
 u'hereNow',
 u'categories',
 u'name',
 u'like',
 u'phrases',
 u'specials',
 u'contact',
 u'popular',
 u'timeZone']
```

- `.venues.similar(venue_id)`

Returns a list of similar venues (abbreviated)

- `.venues.search({"query":query, "near":location})`

Searches for places matching the `query`

("pizza", "Eiffel Tower", etc) near `location` ("Paris", etc).

```
[u'count',
 u'groups',
 u'summary']
```

Similar Venues

<https://developer.foursquare.com/overview/venues.html>

```
import foursquare
from foursquare_accounts import accounts

app = accounts["tutorial"]

client = foursquare.Foursquare(client_id=app["client_id"],
                                client_secret=app["client_secret"])

client.set_access_token(app["access_token"])

venue_id = "43695300f964a5208c291fe3"
venue = client.venues(venue_id)
similar = client.venues.similar(venue_id)

print("Similar venues to", venue["venue"]["name"], "(", venue["venue"]["hereNow"]["summary"], ")")

for venue in similar["similarVenues"]["items"]:
    print(venue["name"])
```

foursquare_venues.py

Venue Search

<https://developer.foursquare.com/overview/venues.html>

```
import foursquare
from foursquare_accounts import accounts

app = accounts["tutorial"]

client = foursquare.Foursquare(client_id=app["client_id"],
                               client_secret=app["client_secret"])

client.set_access_token(app["access_token"])

results = client.venues.search({"query": "candy", "ll": "45.507297, -73.565469"})

for result in results["venues"]:
    print(result["name"])
```

Population Density, v4: Gridded x

Bruno

sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density

NASA EARTH DATA Data Discovery DAACs Community Science Disciplines

SOCIOECONOMIC DATA AND APPLICATIONS CENTER (SEDAC)
A Data Center in NASA's Earth Observing System Data and Information System (EOSDIS) — Hosted by CIESIN at Columbia University

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Gridded Population of the World (GPW), v4

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Collection Overview

Methods

Data Sets (8)

*Population Density, v4
(2000, 2005, 2010,
2015, 2020)*

Show All...

Map Gallery (27)

Map Services (26)

Citations

FAQs

What's New in GPWv4?

Documentation

What is UN-adjusted

Set Overview **Data Download** Maps Map Services Documentation Metadata

Purpose:

To provide estimates of population density for the years 2000, 2005, 2010, 2015, and 2020, based on counts consistent with national censuses and population registers, as raster data to facilitate data integration.

Abstract:

Gridded Population of the World, Version 4 (GPWv4)
Population Density consists of estimates of human population density based on counts consistent with national censuses and population registers, for the years 2000, 2005, 2010, 2015, and 2020. A proportional allocation gridding algorithm, utilizing approximately 12.5 million national and sub-national administrative units, is used to assign population values to 30 arc-second (~1 km) grid cells. The population density grids are created by dividing the population count grids by the land area grids. The pixel values represent persons per square kilometer.

GPWv4: Population Density - 2000

1 of 5 < >

Recommended Citation(s)*:

ASCII Grid

- Perhaps the simplest raster file

- ASCII text based

- A small header

```
ncols          246
nrows          119
xllcorner     -126.50000000000
yllcorner      22.750000000000
cellsize       0.250000000000
NODATA_value   -9999
```

- Followed by rows of numbers

- Very convenient to Read and Write

ASCII Grid

```
import numpy as np
import matplotlib.pyplot as plt

def map_points(xllcorner, yllcorner, cellsize, nrows, x, y):
    x = int((x-xllcorner)/cellsize)
    y = (nrows-1)-int((y-yllcorner)/cellsize)

    return x, y

fp = open("US_pop.asc")
ncols, count = fp.readline().split()
ncols = int(count)
nrows, count = fp.readline().split()
nrows = int(count)
xllcorner, value = fp.readline().split()
xllcorner = float(value)
yllcorner, value = fp.readline().split()
yllcorner = float(value)
cellsize, value = fp.readline().split()
cellsize = float(value)

NODATA_value, value = fp.readline().split()
NODATA_value = float(value)

data = []
for line in fp:
    fields = line.strip().split()
    data.append([float(field) for field in fields])

data = np.array(data)
data[data==NODATA_value] = 0

x = -74.243251
y = 40.730503

coord_x, coord_y = map_points(xllcorner, yllcorner, cellsize, nrows, x, y)
print(data[coord_y, coord_x])
```

ASCII Grid

```
import numpy as np
import matplotlib.pyplot as plt

def map_points(xllcorner, yllcorner, cellsize, nrows, x, y):
    x = int((x-xllcorner)/cellsize)
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yllcorner = float(value)
cellsize, value = fp.readline().split()
cellsize = float(value)

NODATA_value, value = fp.readline().split()
NODATA_value = float(value)

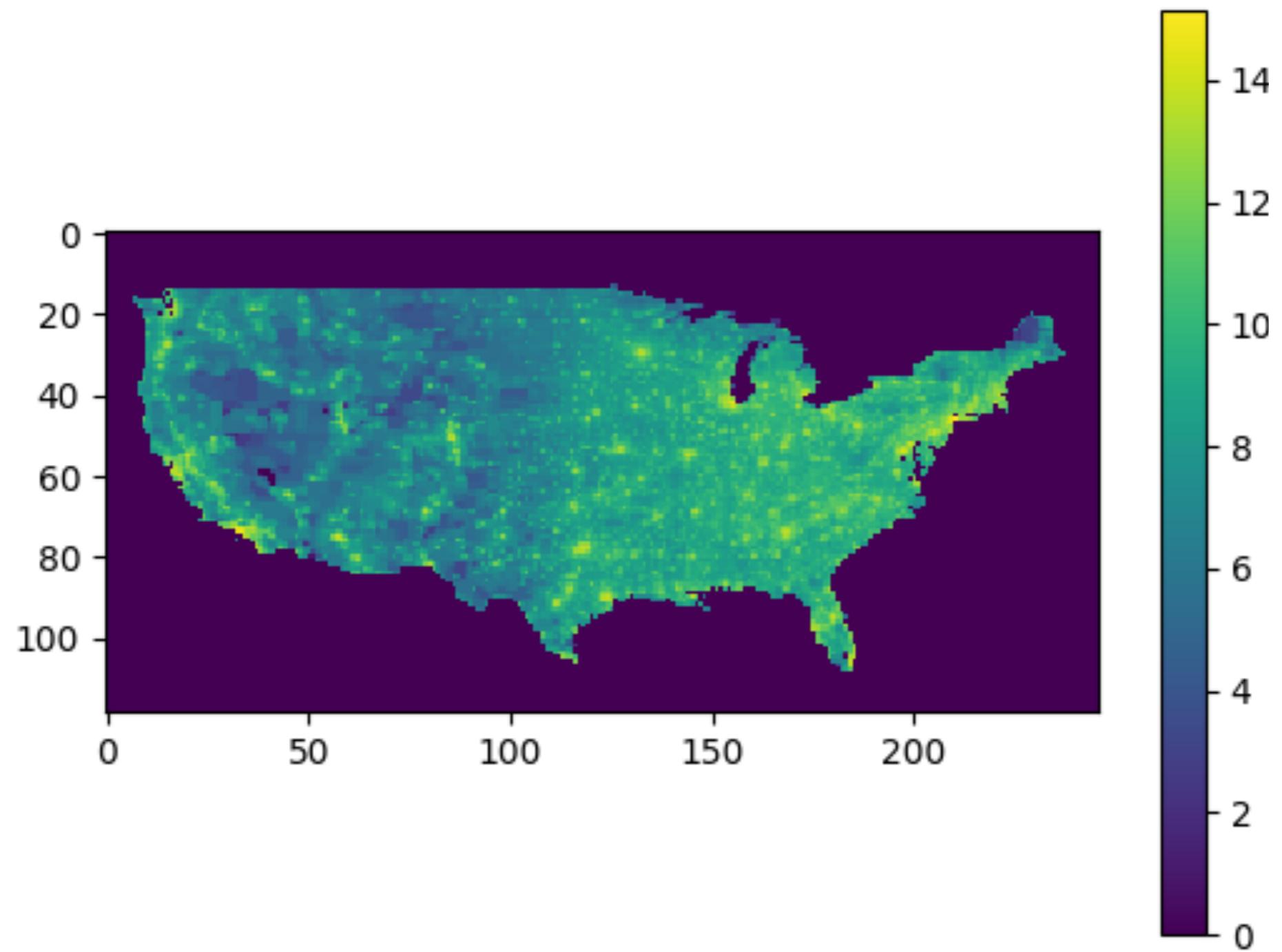
data = []
for line in fp:
    fields = line.strip().split()
    data.append([float(field) for field in fields])

data = np.array(data)
data[data==NODATA_value] = 0

x = -74.243251
y = 40.730503

coord_x, coord_y = map_points(xllcorner, yllcorner, cellsize, nrows, x, y)
print(data[coord_y, coord_x])
```

ASCII Grid



US Flight dataset

https://www.transtats.bts.gov/databases.asp?Mode_ID=1&Mode_Desc=Aviation&Subject_ID2=0

The screenshot shows the Bureau of Transportation Statistics (BTS) website. At the top, there's a navigation bar with links for 'Explore Topics and Geography', 'Browse Statistical Products and Data', 'Learn About BTS and Our Work', and 'Newsroom'. Below the navigation is a search bar with a magnifying glass icon. The main content area features a title 'Bureau of Transportation Statistics' and a sub-section titled 'Data Library: Aviation'. This section lists various databases with their descriptions and profile links. On the left side, there's a sidebar with links for 'Resources' (Database Directory, Glossary, Upcoming Releases), 'Data Finder' (By Mode: Aviation, Maritime, Highway, Transit, Rail, Pipeline, Bike/Pedestrian, Other), and 'By Subject' (Safety, Freight Transport, Passenger Travel, Infrastructure). The URL in the browser bar is https://www.transtats.bts.gov/databases.asp?Mode_ID=1&Mode_Desc=Aviation&Subject_ID2=0.

OST-R > BTS



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Data Finder

By Mode

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Maritime

Highway

Transit

Rail

Pipeline

Bike/Pedestrian

Other

By Subject

Safety

Freight Transport

Passenger Travel

Infrastructure

Data Library: Aviation

Databases	Summary Tables	Glossary	Filter Subject	All Subjects	Go
				<<Prev Rows 1 to 15 of 26 Next>>	

Database Name	Description	Profile
Air Carrier Financial Reports (Form 41 Financial Data)	Form 41 Financial Schedule consists of financial information on large U.S. certified air carriers--includes balance sheet, cash flow, employment, income statement, fuel cost and consumption, aircraft operating expenses, and operating expenses. Note: Numbers presented on B1, B11 Balance Sheet and P11, P12 Statement of Operations now follow the format of common public financial documents. This format reverses signs from the accounting format in which numbers appeared prior to 10/18/2006 (Examples).	Profile
Air Carrier Statistics (Form 41 Traffic)- U.S. Carriers	Monthly data reported by certificated U.S. air carriers on passengers, freight and mail transported. Also includes aircraft type, service class, available capacity and seats, and aircraft hours ramp-to-ramp and airborne.	Profile
Air Carrier Statistics (Form 41 Traffic)- All Carriers	Monthly data reported by certificated U.S. and foreign air carriers on passengers, freight and mail transported. Also includes aircraft type, service class, available capacity and seats, and aircraft hours ramp-to-ramp and airborne.	Profile
Air Carrier Summary Data (Form 41 and 298C Summary Data)	Summary data of the non-stop segment and on-flight market data reported by air carriers on Form 41 and Form 298C	Profile
Airline On-Time Performance Data	Monthly data reported by US certified air carriers that account for at least one percent of domestic scheduled passenger revenues--includes scheduled and actual arrival and departure times for flights.	Profile
Airline Origin and Destination Survey (DB1B)	Origin and Destination Survey (DB1B) is a 10% sample of airline tickets from reporting carriers. Data includes origin, destination and other itinerary details of passengers transported.	Profile
American Travel Survey (ATS) 1995	National data on the nature and characteristics of long-distance personal travel, from a household survey conducted by BTS about every five years.	Profile

US Flight dataset

bit.ly/BTS_Airports

RITA | BTS | Transtats Bruno

Secure https://www.transtats.bts.gov/FieldInfo.asp?Field_Desc=Origin%20Airport%2C%20Airport%20ID.%20An%20identification%20number%20as... 5

United States Department of Transportation

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Bureau of Transportation Statistics

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OST-R > BTS

Air Carriers : T-100 Domestic Market (All Carriers)

Field: Origin Airport, Airport ID. An identification number assigned by US DOT to identify a unique airport. Use this field for airport analysis across a range of years because an airport can change its airport code and airport codes can be reused.

Format results for printing Download Lookup Table Databases Data Tables Table Contents

<<Prev Rows : 1 - 100 of 1974 Next>>

Code	Description
10001	Afognak Lake, AK: Afognak Lake Airport
10003	Granite Mountain, AK: Bear Creek Mining Strip
10004	Lik, AK: Lik Mining Camp
10005	Little Squaw, AK: Little Squaw Airport
10006	Kizhuyak, AK: Kizhuyak Bay
10008	Elizabeth Island, AK: Elizabeth Island Airport
10009	Homer, AK: Augustin Island
10010	Hudson, NY: Columbia County
10011	Peach Springs, AZ: Grand Canyon West
10012	Blairstown, NJ: Blairstown Airport
10013	Crosbyton, TX: Crosbyton Municipal
10014	Fairbanks/Ft. Wainwright, AK: Blair Lake
10015	Deadmans Bay, AK: Deadmans Bay Airport
10016	Halio Bay, AK: Halio Bay Airport
10017	Red Lake, AK: Red Lake Airport
10020	Selawik, AK: Poland Norton Memorial

US Airports

```
import googlemaps
from google_accounts import accounts

app = accounts["torino"]
gmaps = googlemaps.Client(key=app["api_key"])

line_count = 0
for line in open("flights/L_AIRPORT_ID.csv"):
    fields = line.strip()[:-1].split(',')

    line_count += 1

    if line_count > 1:
        try:
            airport_id = fields[0]
            airport_name = ", ".join(fields[2:])

            geocode_result = gmaps.geocode(airport_name)

            print(airport_id[1:-1], geocode_result[0]["geometry"]["location"]["lat"], \
                  geocode_result[0]["geometry"]["location"]["lng"])
        except:
            pass
```

Distance Matrix

```
from geopy import distance

airports = {}

for line in open("airport_gps.dat"):
    fields = line.strip().split()

    airport_id = int(fields[0])
    lat = float(fields[1])
    lon = float(fields[2])

    airports[airport_id] = (lat, lon)

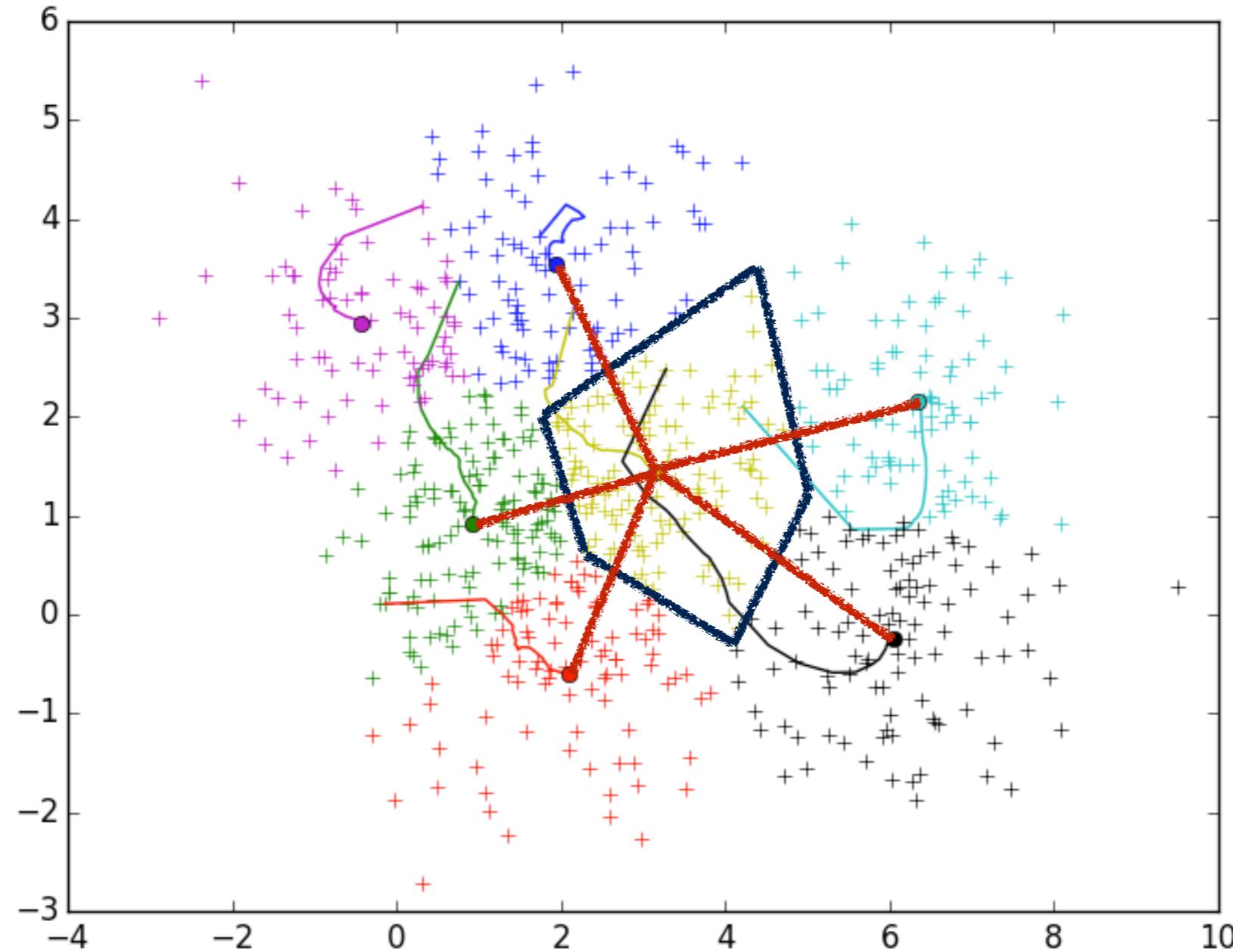
airport_list = airports.keys()

for airport_i in airport_list:
    for airport_j in airport_list:
        try:
            if airport_i != airport_j:
                dist = distance.distance(airports[airport_i], airports[airport_j]).km

                if dist < 20:
                    print(airport_i, airport_j, dist)
        except:
            pass
```

K-Means: Structure

Voronoi Tesselation



Voronoi cells

```
pop, xllcorner, yllcorner, cellsize = load_asc('US_pop.asc')
airports = load_airports('airport_gps.dat')
coords = np.array(list(airports.values()))
nrows = pop.shape[0]
ncols = pop.shape[1]

seeds = []

for i in range(coords.shape[0]):
    x, y = map_points(xllcorner, yllcorner, cellsize, nrows, coords[i][1], coords[i][0])

    if x <0 or x>= ncols:
        continue

    if y <0 or y >= nrows:
        continue

    if pop[y, x] > 0:
        seeds.append((x,y))

seeds = np.array(seeds)

positions = np.zeros((nrows*ncols, 2), dtype='int')

count = 0
for i in range(nrows):
    for j in range(ncols):
        positions[count][0] = j
        positions[count][1] = i
        count += 1
```

Voronoi cells

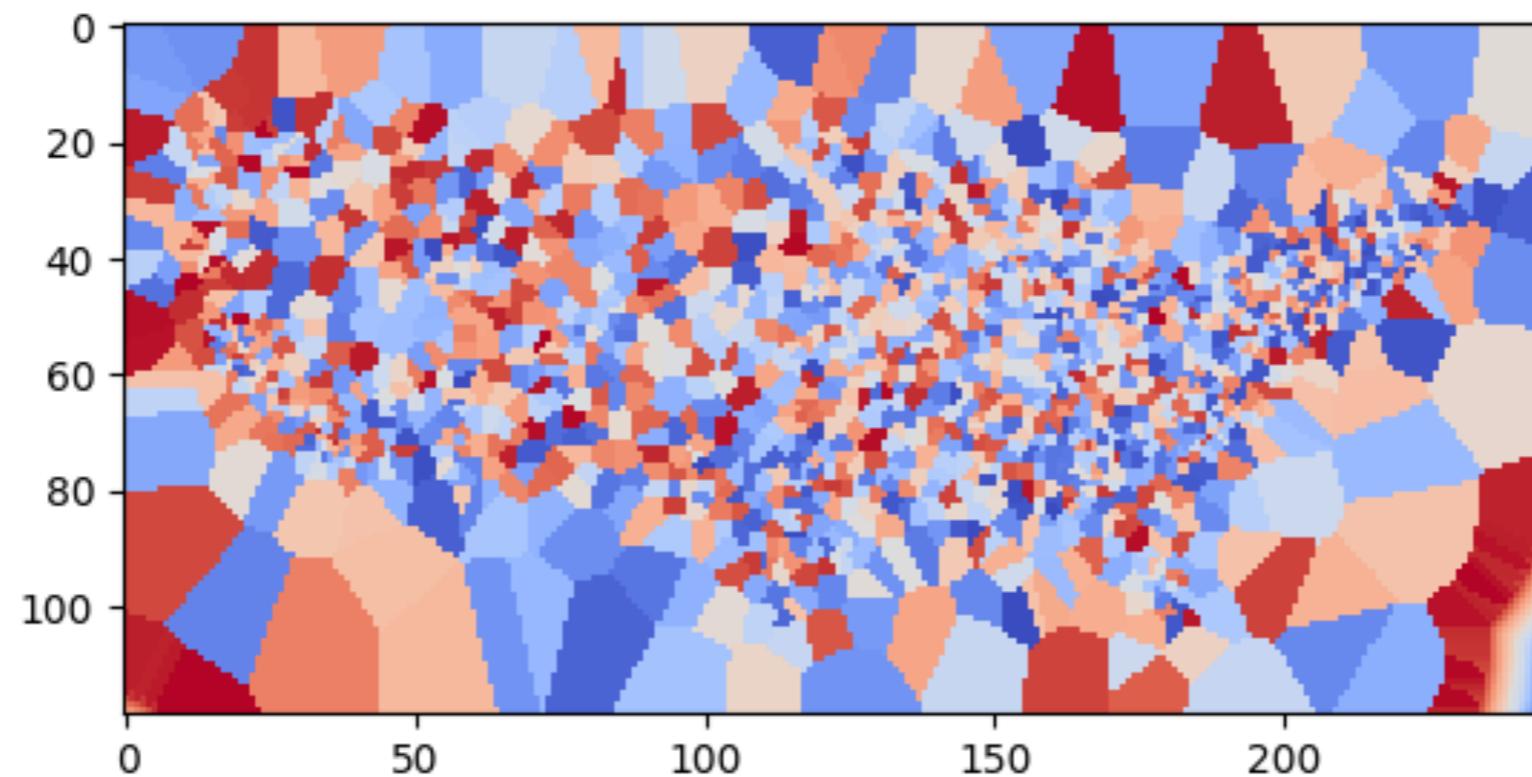
```
kmeans = KMeans(n_clusters=seeds.shape[0], init=seeds, n_init=1, max_iter=1)
kmeans.fit(positions)

basins = np.zeros((nrows, ncols), dtype='int')

for i in range(len(kmeans.labels_)):
    basins[positions[i][1]][positions[i][0]] = kmeans.labels_[i]

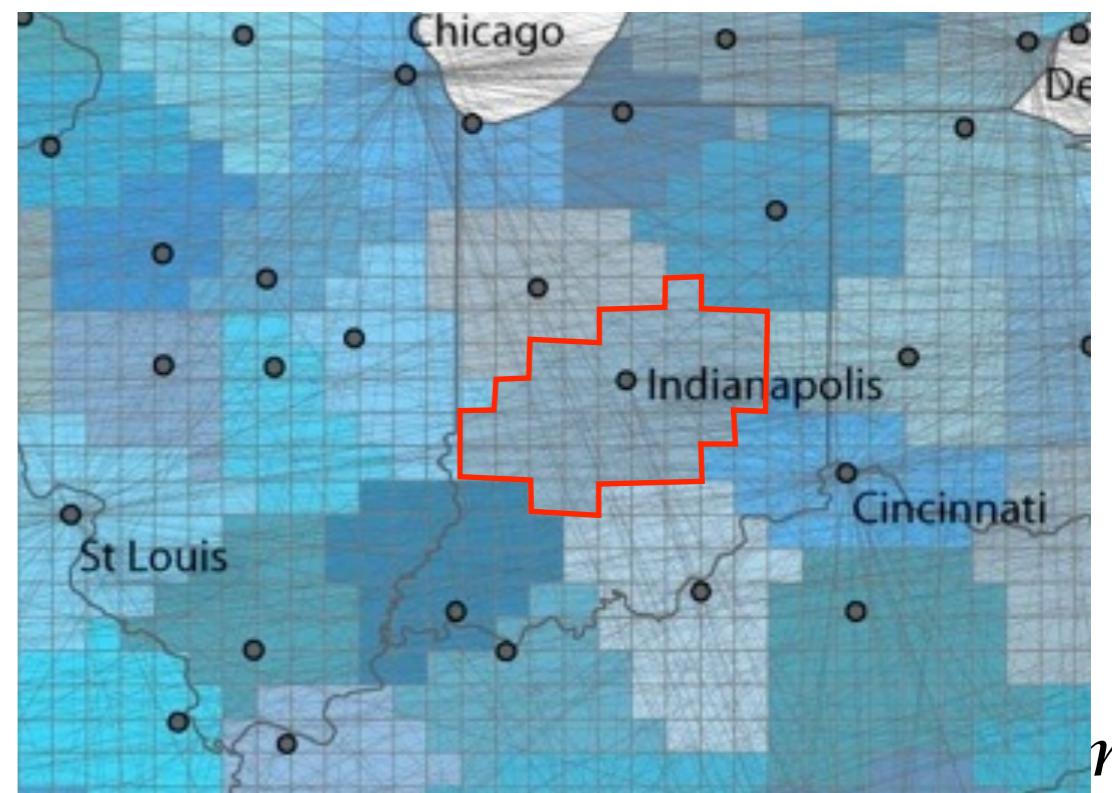
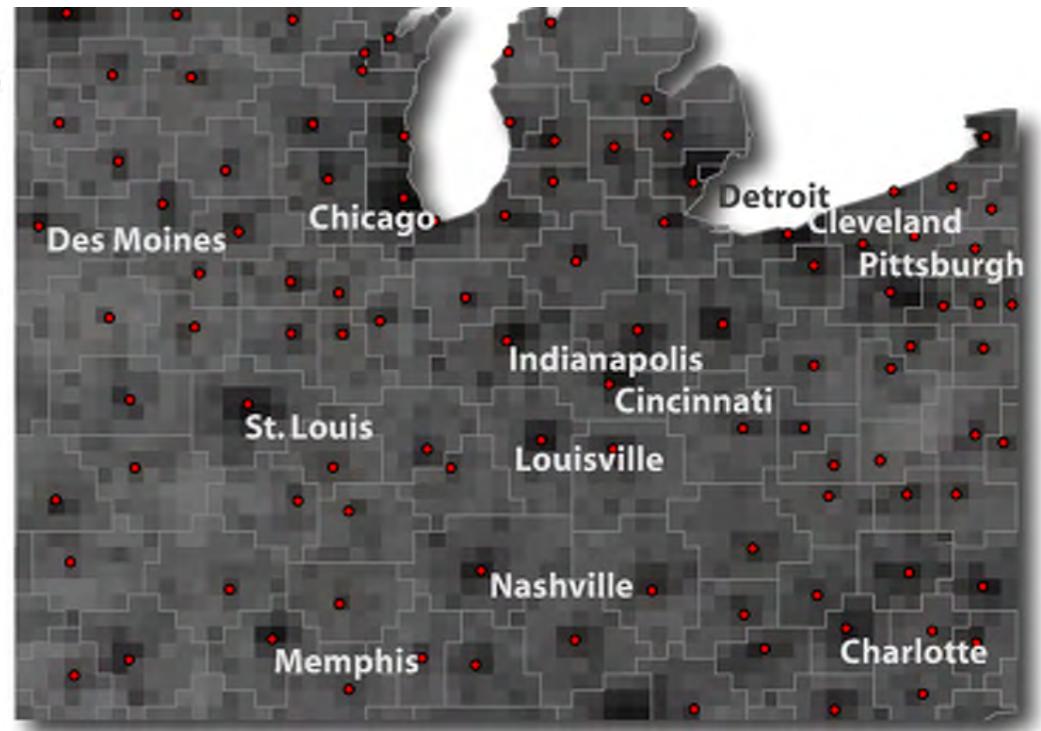
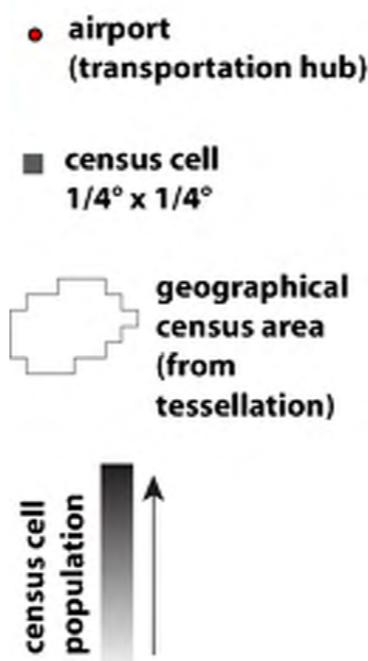
plt.imshow(basins, cmap=cm.coolwarm)
plt.savefig('basins.png')
```

Voronoi cells



Population Distribution

PNAS 106, 21484 (2009)

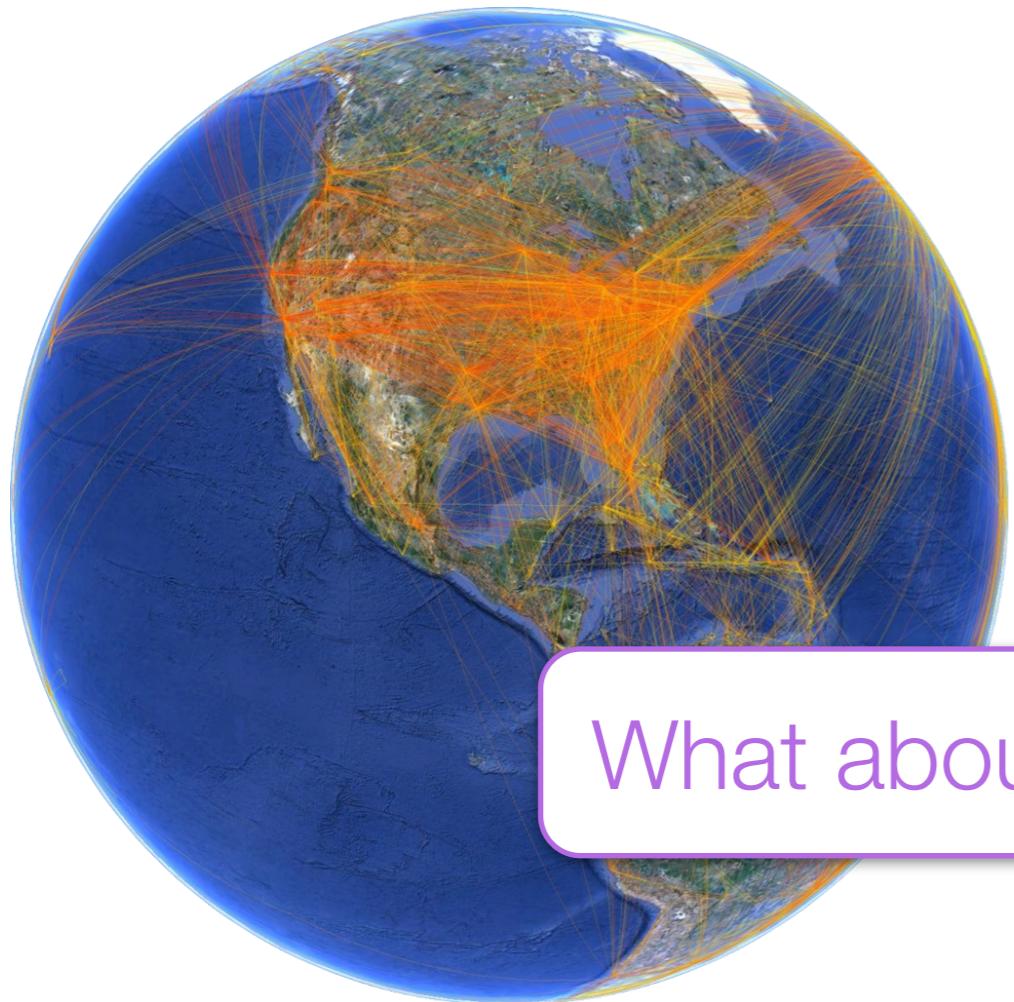


Complete IATA and OAG databases:

3362 airports worldwide
220 countries

Long Range Mobility

PNAS 106, 21484 (2009)



$$P_{jl} = \frac{w_{jl}}{N_j} \Delta t$$

- Probability that any individual in class X travel from $j \rightarrow l$

What about Short Range Mobility?

w
population

Complete IATA and OAG databases:

3362 airports worldwide

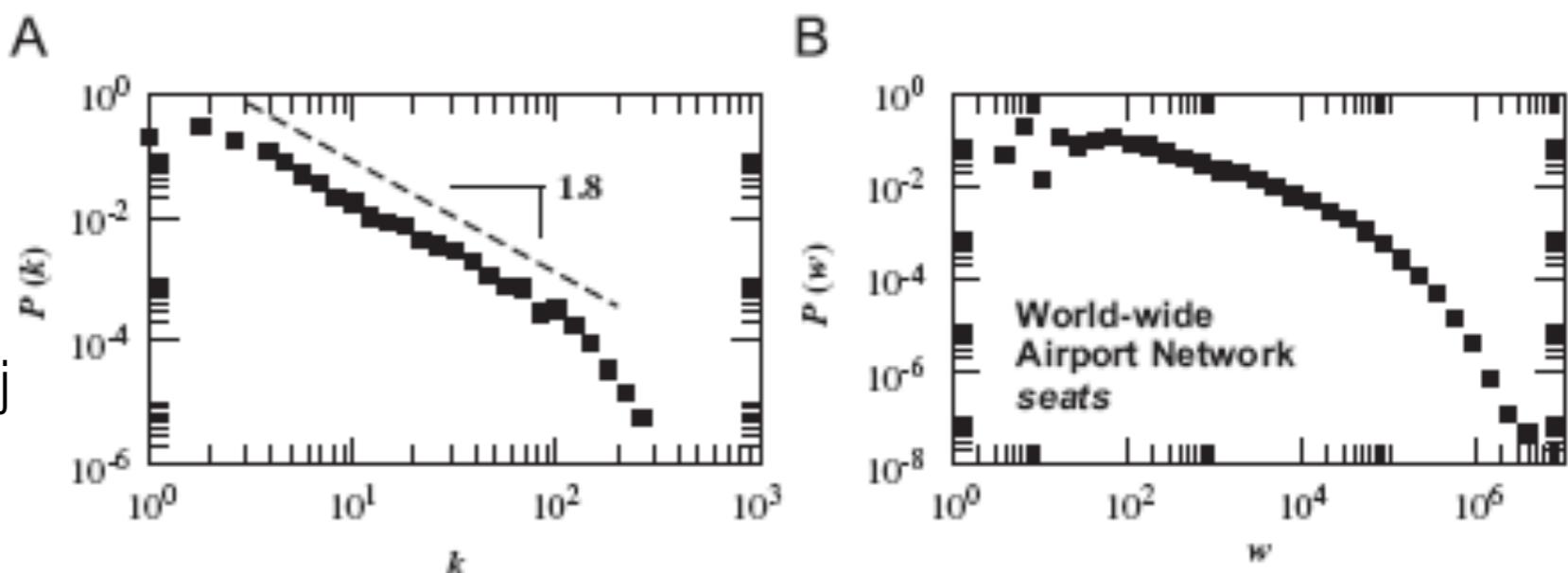
220 countries

> 20,000 connections

w_{ij} #passengers on connection i-j

>99% total traffic

@bgoncalves



Gravity-Law of Commuting

PNAS 106, 21484 (2009)

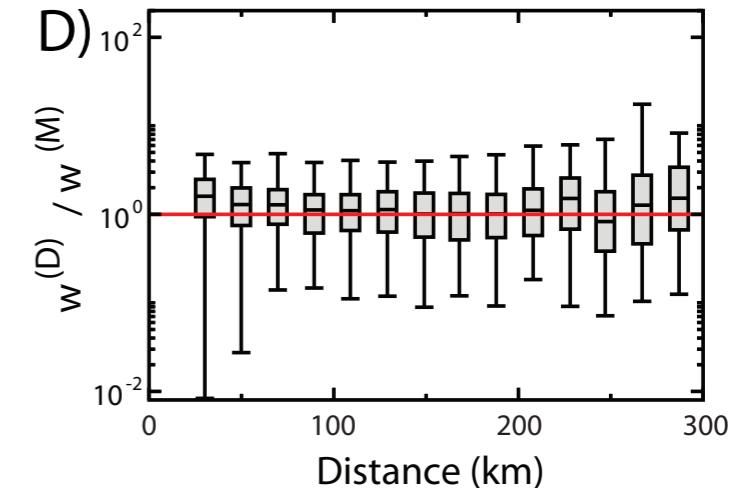
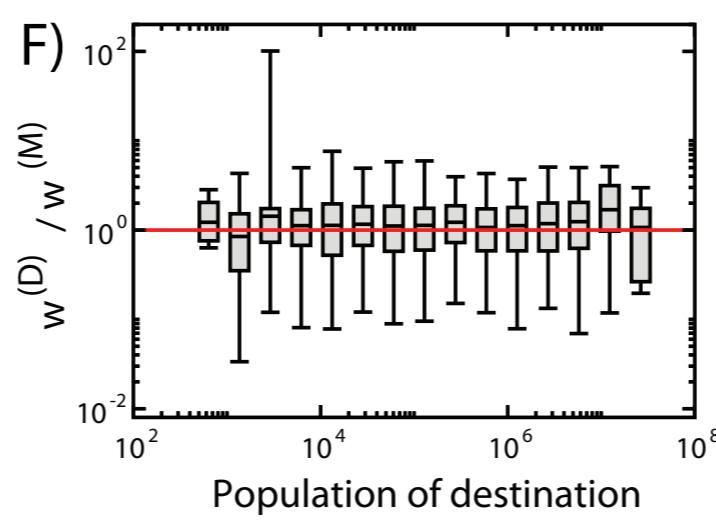
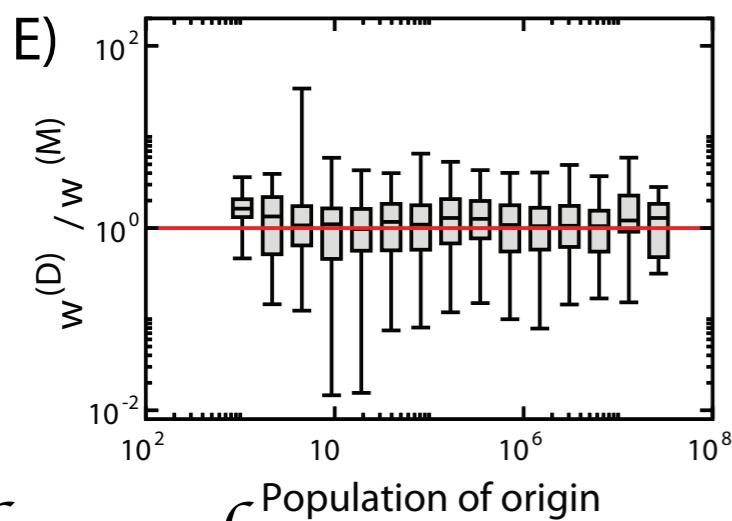
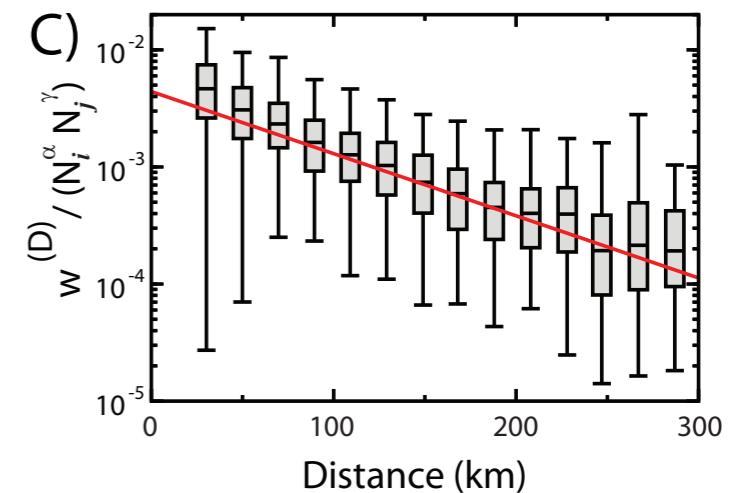
Table 1

Commuting networks in each continent. Number of countries (N), number of administrative units (V) and inter-links between them (E) are summarized.

Continent	N	V	E
Europe	17	65,880	4,490,650
North America	2	6986	182,255
Latin America	5	4301	102,117
Asia	4	4355	380,385
Oceania	2	746	30,679
Total	30	82,268	5,186,186

d (km)	Parameter	Estimate	Standard Error	p-value	R^2
≤ 300	α	0.46	0.01	$< 2E - 16$	0.7972
	γ	0.64	0.01	$< 2E - 16$	
	β	0.0122	0.0002	$< 2E - 16$	
> 300	α	0.35	0.06	$6.91E - 09$	0.5369
	γ	0.37	0.06	$2.12E - 09$	

$$w_{ij} = C N_i^\alpha N_j^\gamma e^{-\beta d_{ij}}$$



Short Range Mobility

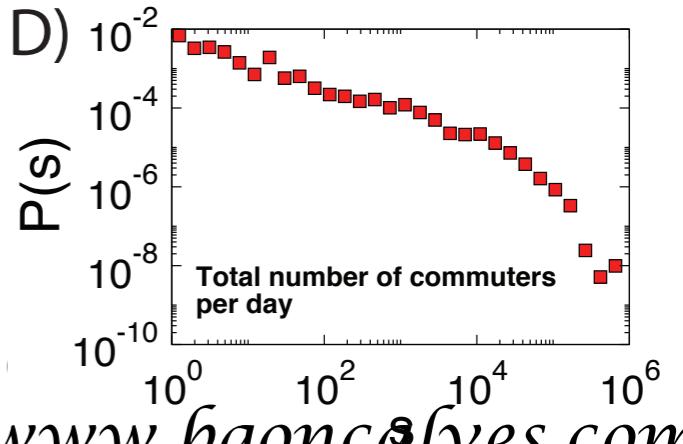
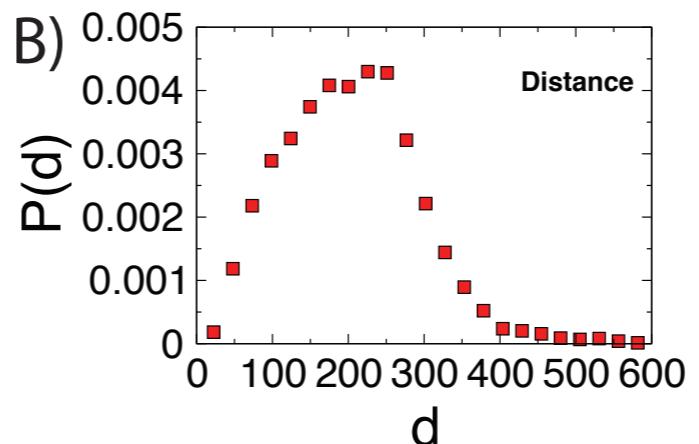
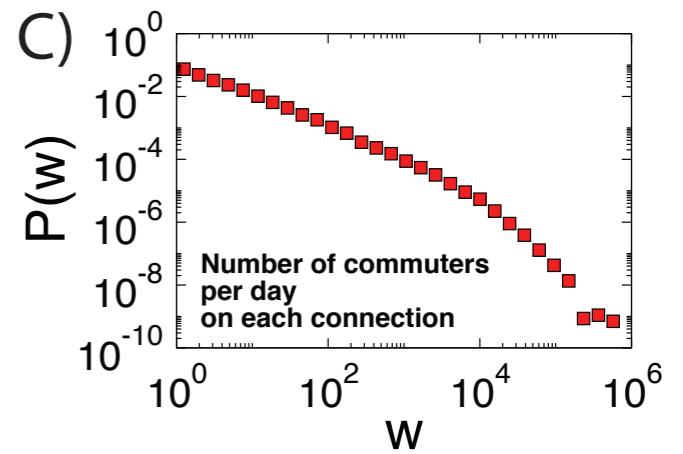
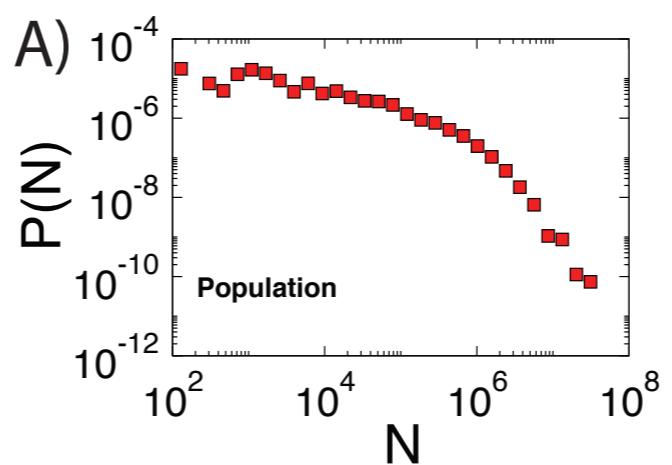
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Table 1

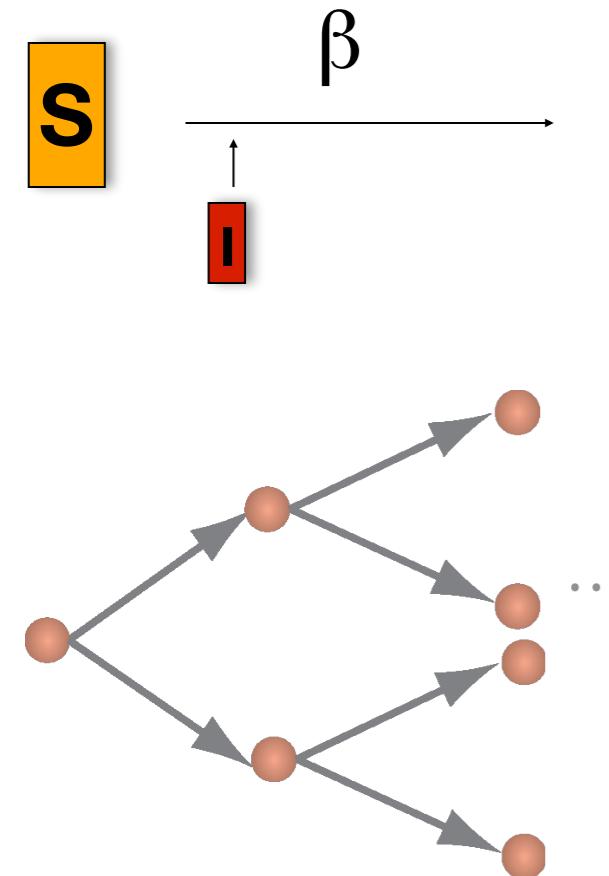
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Intra-population: The SIR model

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basic reproduction number

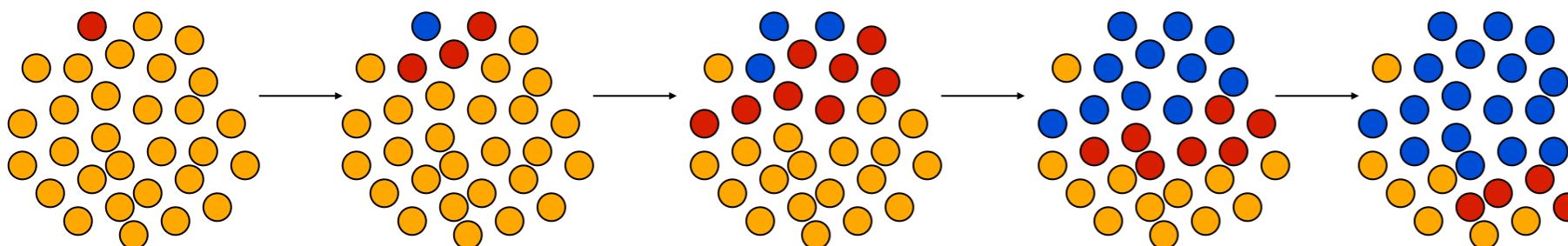
$R_0 > 1 \rightarrow$ exponential growth

Stochastic coupling terms

$$S_{j,t+\Delta t} = S_{j,t} - \text{Binom}_j(S_{j,t}, \beta \Delta t I_{j,t}/N) + \Omega_j(S)$$

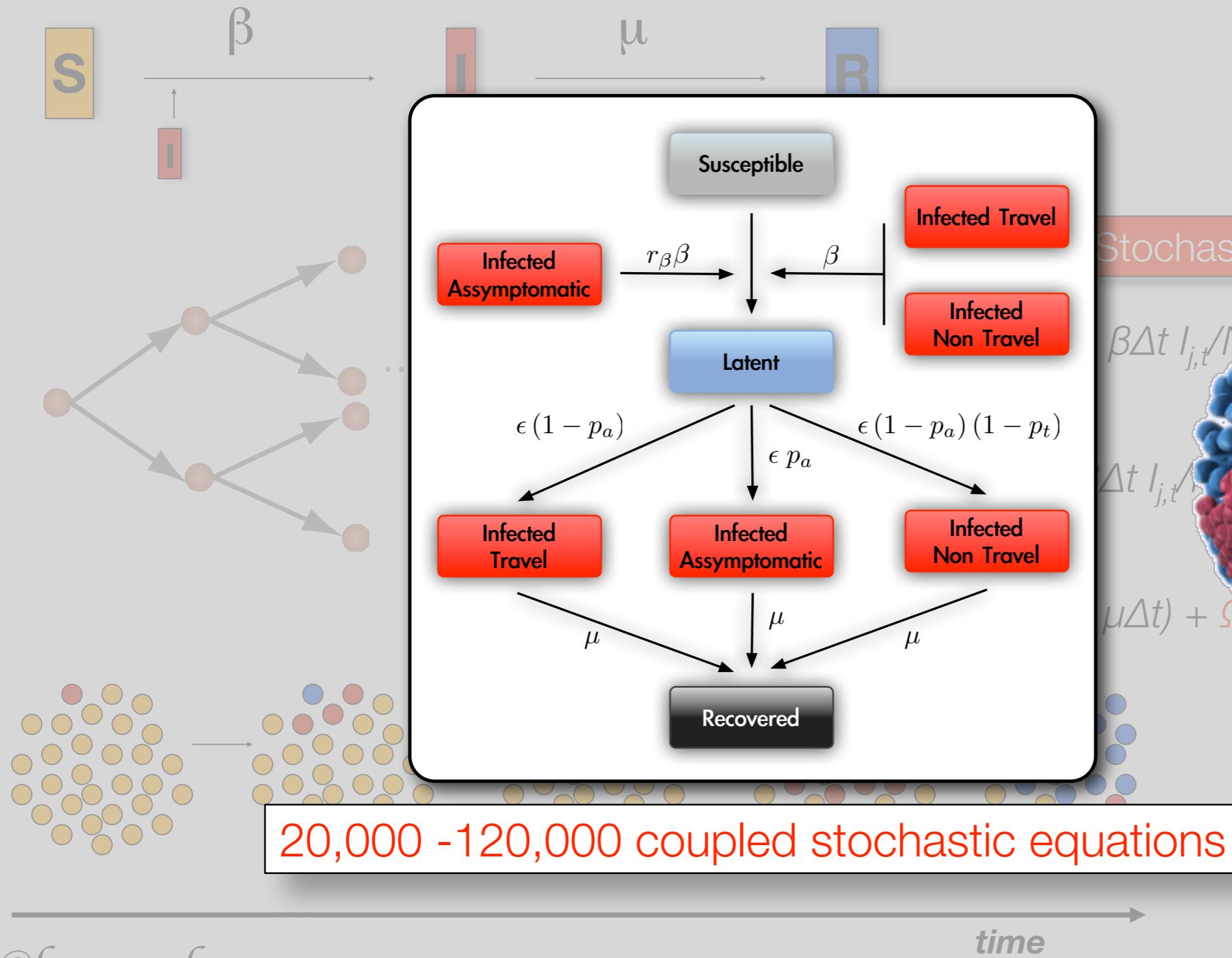
$$I_{j,t+\Delta t} = I_{j,t} + \text{Binom}_j(S_{j,t}, \beta \Delta t I_{j,t}/N) - \text{Binom}_j(I_{j,t}, \mu \Delta t) + \Omega_j(I)$$

$$R_{j,t+\Delta t} = R_{j,t} + \text{Binom}_j(I_{j,t}, \mu \Delta t) + \Omega_j(R)$$

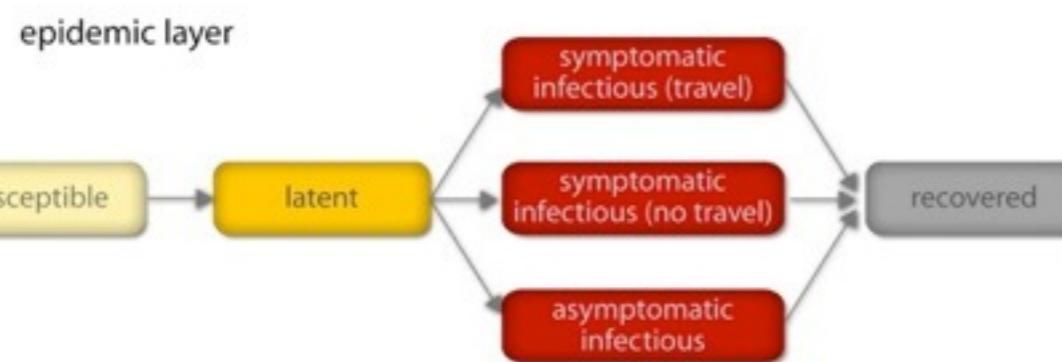
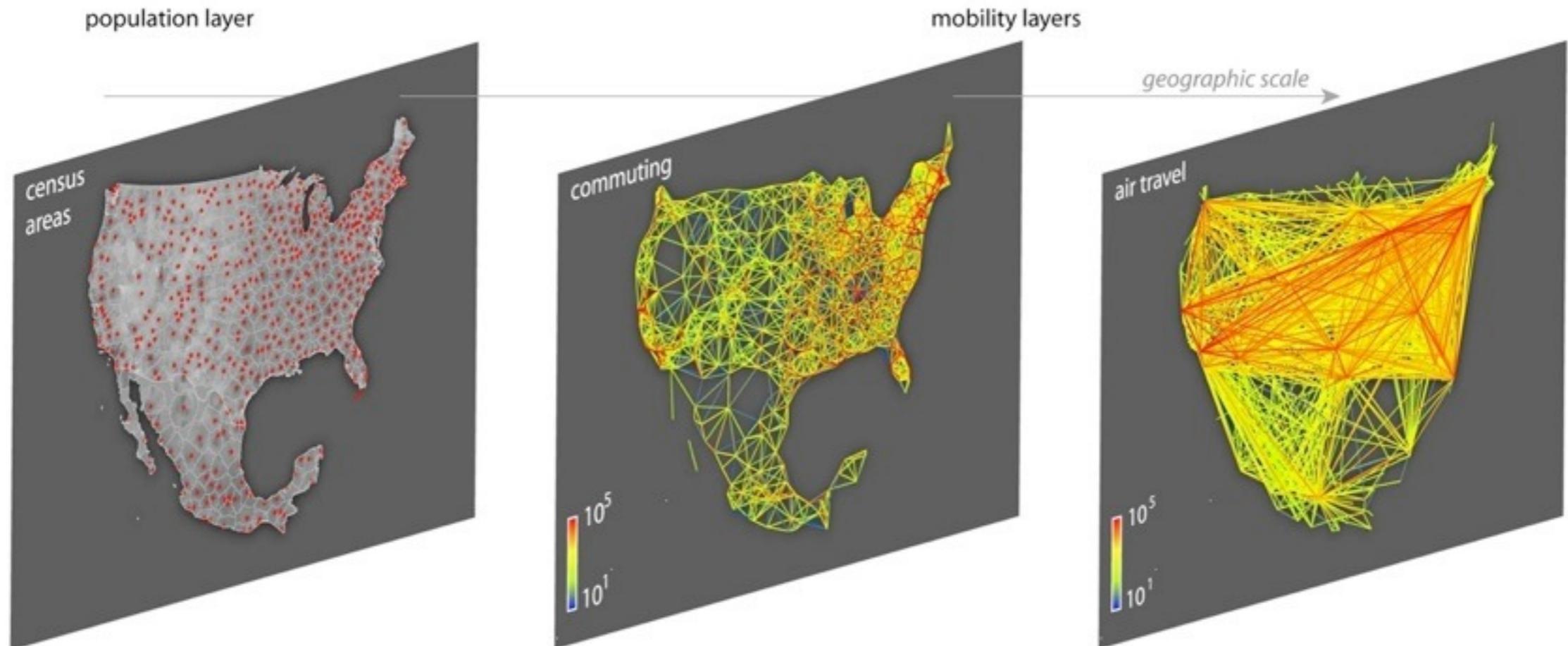


Intra-population: The SIR model

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Global Epidemic and Mobility Modeller Platform



Parameter	Value	Description
β	from R_0	transmission probability
ε^{-1}	1.9 [1.1-2.5] d	average latency period
μ^{-1}	3 [3-5] d	average infectious period
p_t	50%	probability of traveling for infectious individuals
p_a	33%	probability of being asymptomatic
r_β	50%	relative infectiousness of asymptomatic infectious individuals

Invasion Tree



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GLEaMviz
Global Epidemic and Mobility Modeler Visualization
May 5, 2009

MoBS