Survival of Gentrification / Depreciation in Restaurants

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1 Abstract

2 Introduction

Yelp Dataset Papers:

(**???????????**)

Zillow Dataset Papers:

Has previously been combined with the yelp dataset **?**.

Our goal is to use the correlation of two time-series:

1. The monthly median rent, as tracked by Zillow Rental Data. 2. The median restaurant review rating (stars) for each restaurant in a neighborhood.

Zillow rental data can be used to detect appreciating, and depreciating neighborhoods.

As rents rise in a given neighborhood, which types of businesses fare / worse better in the reviews? As rents fall in a given neighborhood, which types of business fare / worse better in the reviews?

We hope to present concrete suggestions to restaurant owners to improve the survivability of their businesses in times of strong appreciation / depreciation in the housing market.

3 Data

3.1 Yelp Academic Dataset

The Yelp Academic Dataset contains five files:

1) `yelp_academic_dataset_business.json`

2) `yelp_academic_dataset_review.json`

3) `yelp_academic_dataset_user.json`

4) `yelp_academic_dataset_checkin.json`

The Yelp Dataset Business file includes

3.2 Zillow Public Dataset

The Zillow Public Dataset (hereafter Zillow dataset) contains many files.

Zillow divides homes into geographic "neighborhoods" with well defined boundaries. The Zillow Home Value Index (ZHVI) is Zillow's best estimate of median home price in a neighborhood. ZHVI is reported on a monthly basis for 6,958 neighborhoods across the US.

Median rental price for studio, one, two, three, four and five or more bedroom apartments are reported for a smaller set of about 300 neighborhoods.

The Zillow neighborhood boundaries `http://www.zillow.com/howto/api/neighborhood-boundaries.htm`

Each Zillow neighborhood has geographic boundaries, defined in an associated ESRI arcGIS shape file. Boundary information `http://www.zillowgroup.com/news/7000-neighborhood-boundary-` Released in 2008

ZHVI methodology. `http://www.zillow.com/research/zhvi-methodology-6032/` (**?**)

4 Methods

4.1 Combination of Datasets

Each Yelp business is tagged with a geographic (latitude, longitude) coordinate. In this section, we describe how we sort each Yelp business into its appropriate Zillow neighborhood.

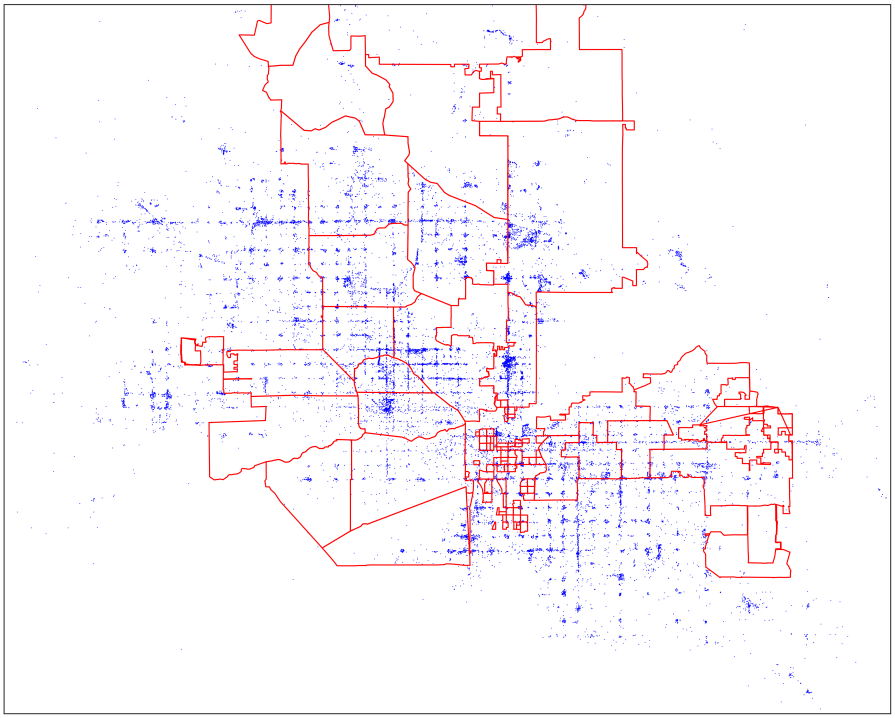

Figure 1: Yelp Businesses (points in blue) and Zillow neighborhood boundaries (lines in red) for the Phoenix, AZ metro area. In §**??**, we describe how we sort each Yelp Business into its appropriate Zillow neighborhood.

To perform this sorting, we employ a two-step approach. In the first step, we test every Yelp business for inclusion in the bounding box of every Zillow neighborhood. In the second step, we test every Yelp business for polygon inclusion in the neighborhoods which bounding boxes it lies within. We use this two-step approach because the first step can rule out all but two or three of the

We introduce the concept of the bounding box which we will define as the smallest range of latitudes and longitudes that include the whole neighborhood polygon. We test each Yelp business for inclusion in the set of 6,958 bounding boxes. In Fig. **??**, we see a randomly selected Yelp business, displayed as a red point. We see that this business is included in the bounding boxes of two Zillow neighborhoods.

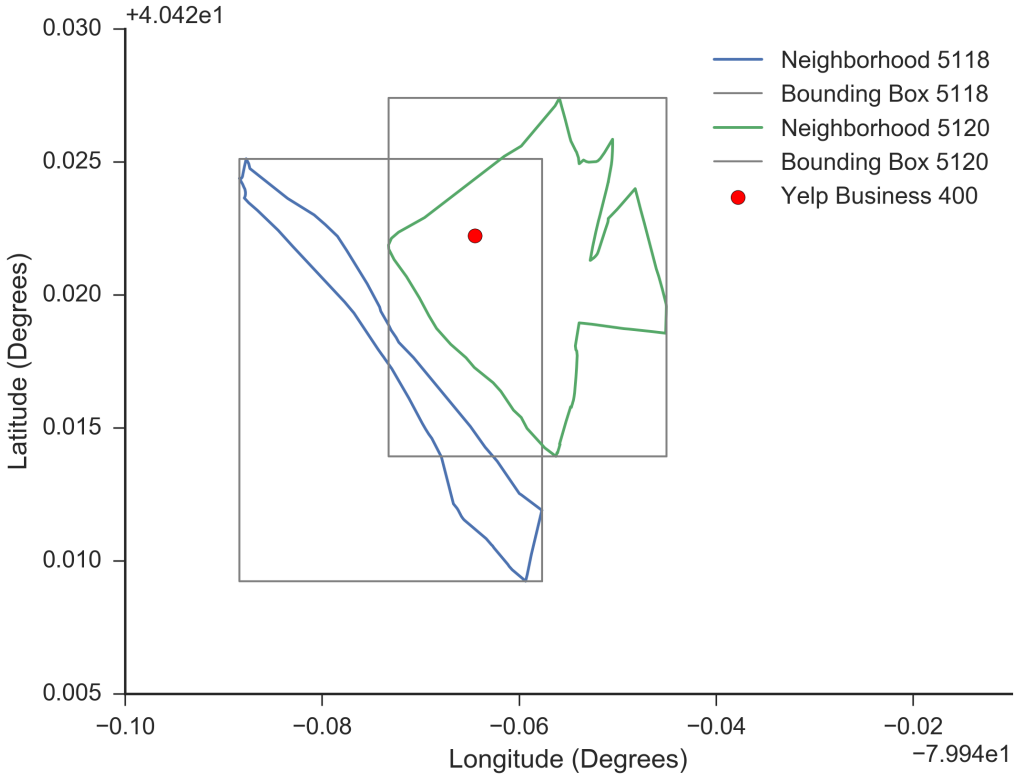

Figure 2: Example of neighborhood and neighborhood bounding box inclusion method. Yelp business 400 (the red point) is included in the bounding boxes of two Zillow neighborhoods. It is only included in one neighborhood polygon, however.

We then test for point-in-polygon inclusion using an implementation of a ray-casting method in `Python` (**?**). For each Yelp business, we only test the Zillow neighborhoods whose bounding boxes it lies within.

4.2 Description of Combined Dataset

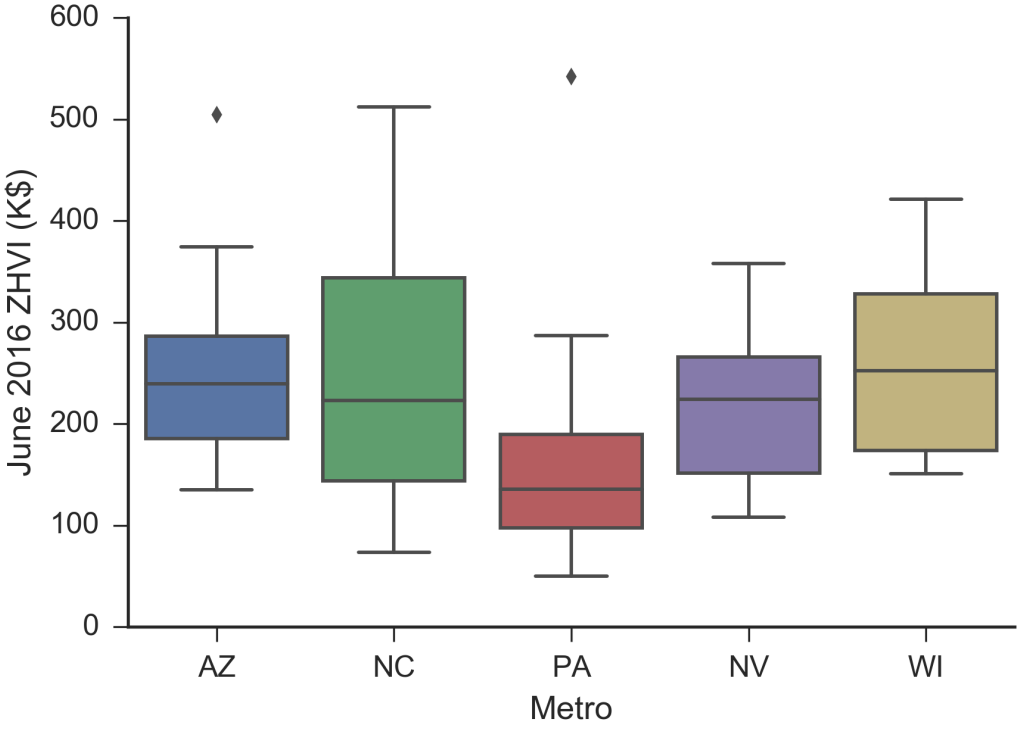

Figure 3:

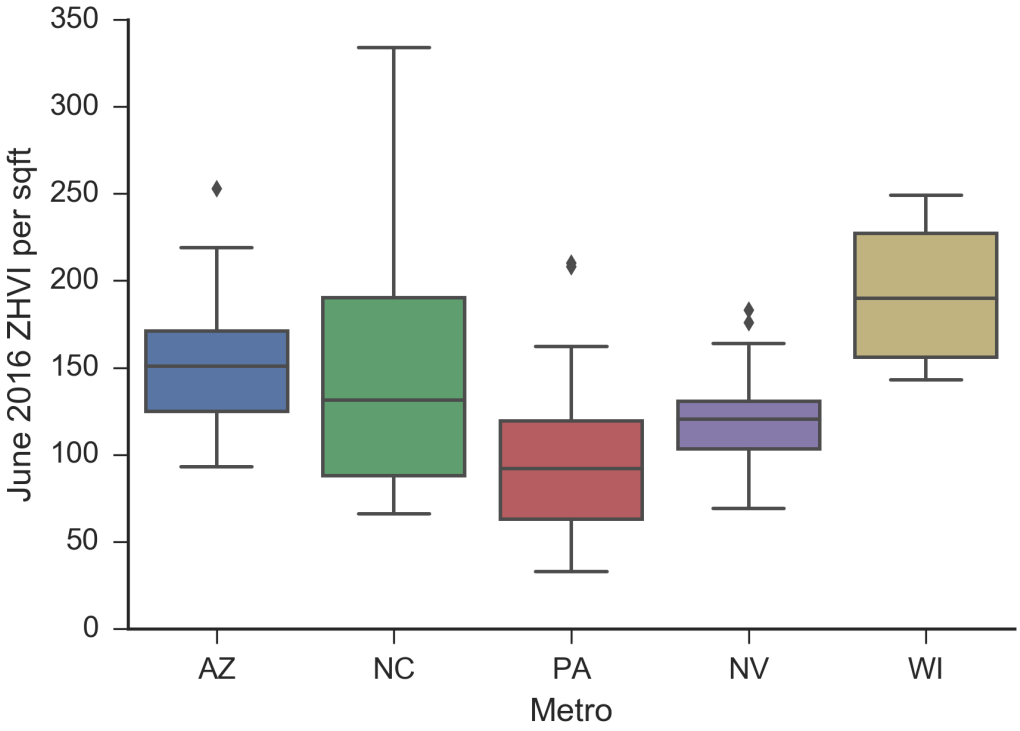
350
300
250
200
150
100
50
0
June 2016 ZHVI per sqft
AZ
NC
PA
NV
WI
Metro

Figure 4:

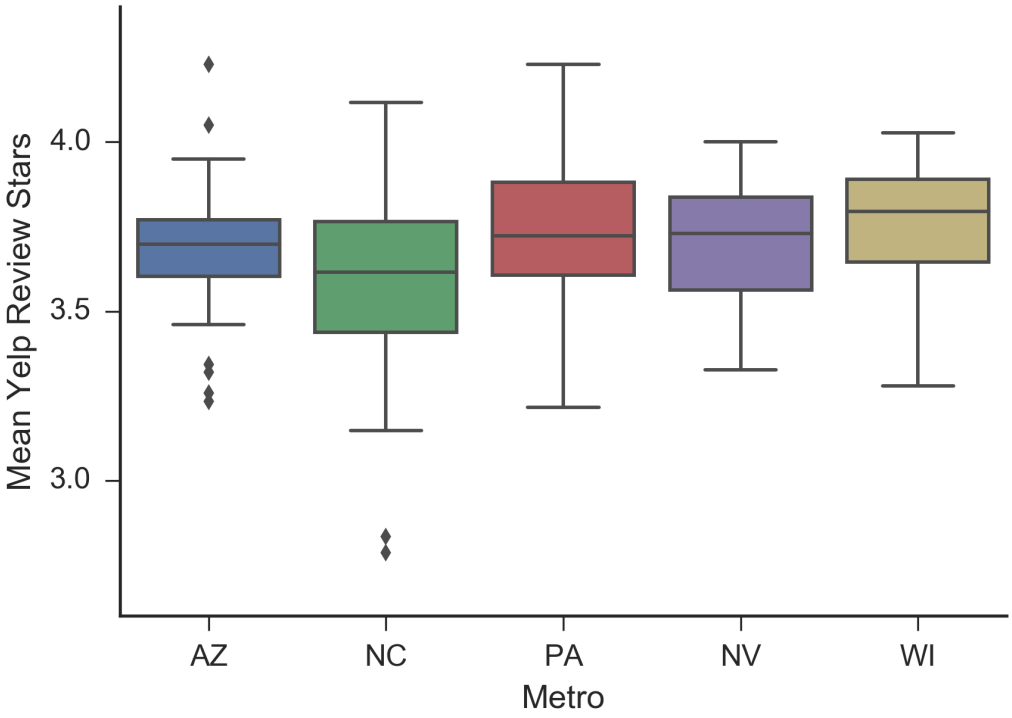

Figure 5:

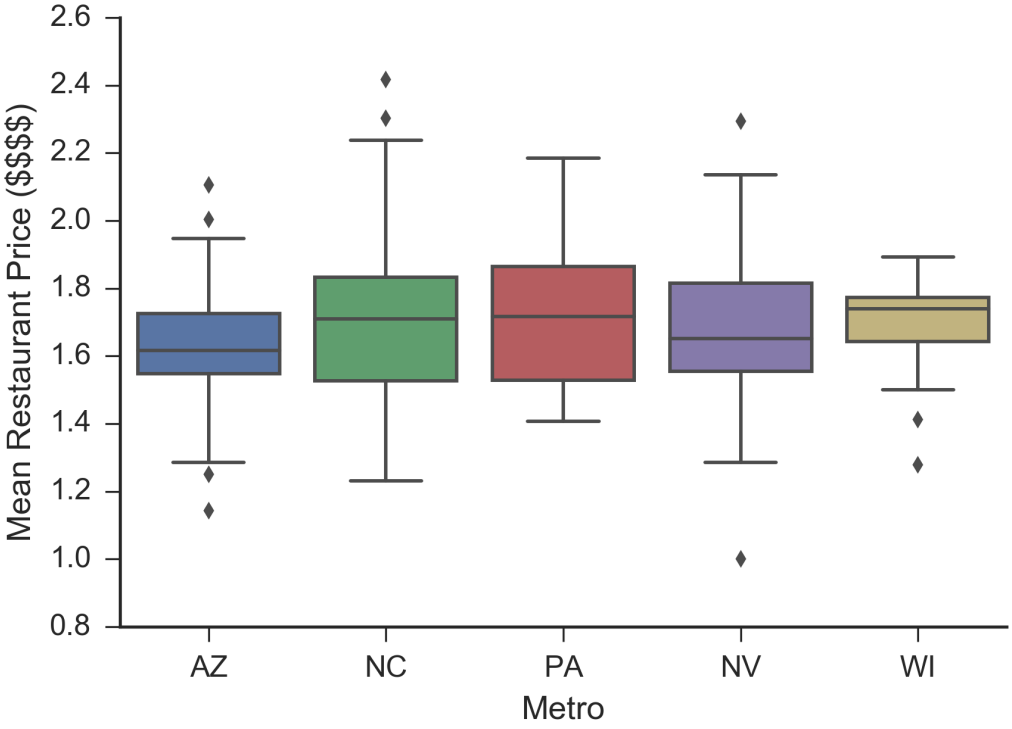

Figure 6:

The combined Zillow and Yelp Dataset contains

Metro	median (B/N)	mean (B/N)	Total B	Total N
Phoenix, AZ	116.5	467.6	19,640	42
Charlotte, NC	43.0	66.1	4,296	65
Las Vegas, NV	178.0	218.6	9,619	44
Pittsburgh, PA	43.5	94.8	2,464	26
Madison, WI	36.0	71.4	1,071	15

Table 1: min n = 20

state	median	mean	sum	len
AZ	31.609536	62.769432	2636.316160	42
NC	2.776164	3.466144	225.299334	65
NV	11.553754	22.659192	997.004433	44
PA	1.192682	1.586050	41.237288	26
WI	0.057833	0.066647	0.999710	15

Table 3: n = 20

City	median (B/N)	mean (B/N)	Total B	Total N
Charlotte	43.0	66.1	4296	65
Henderson	105.0	153.0	2907	19
Las Vegas	241.5	242.0	5809	24
Madison	36.0	71.4	1071	15
Mesa	491.5	509.5	3057	6
North Las Vegas	903.0	903.0	903	1
Phoenix	625.0	763.30	11450	15
Pittsburgh	43.5	94.8	2464	26
Scottsdale	2100.0	1531.7	4595	3
Tempe	26.5	29.9	538	18

Table 2:

4.3 Determination of Most Common Yelp Tags

Each Yelp business has user-generated tags, that allow other users to determine what genre the business is. For restaurants, common tags are "Mexican", "Chinese", etc.

4.4 Computation of Price Trend

5 Results

5.1 Statics Results

In this section, we compute static results for each neighborhood.

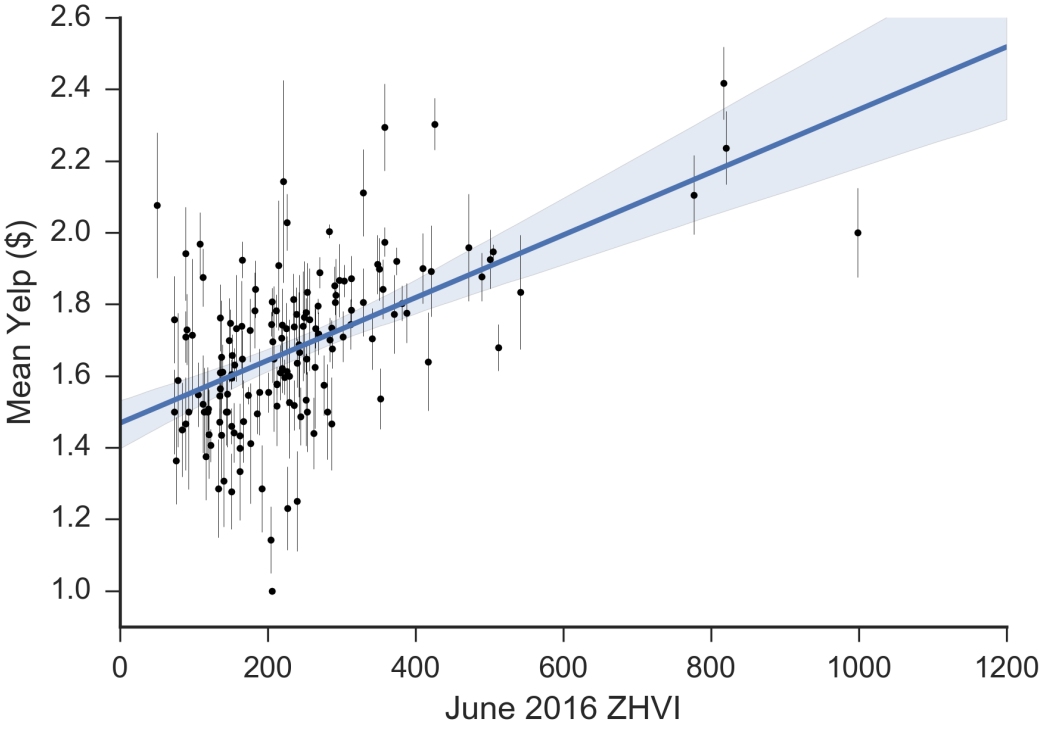
2.6
2.4
2.2
2.0
1.8
1.6
1.4
1.2
1.0
Mean Yelp ($)
0
200
400
600
800
1000
1200
June 2016 ZHVI

Figure 7:

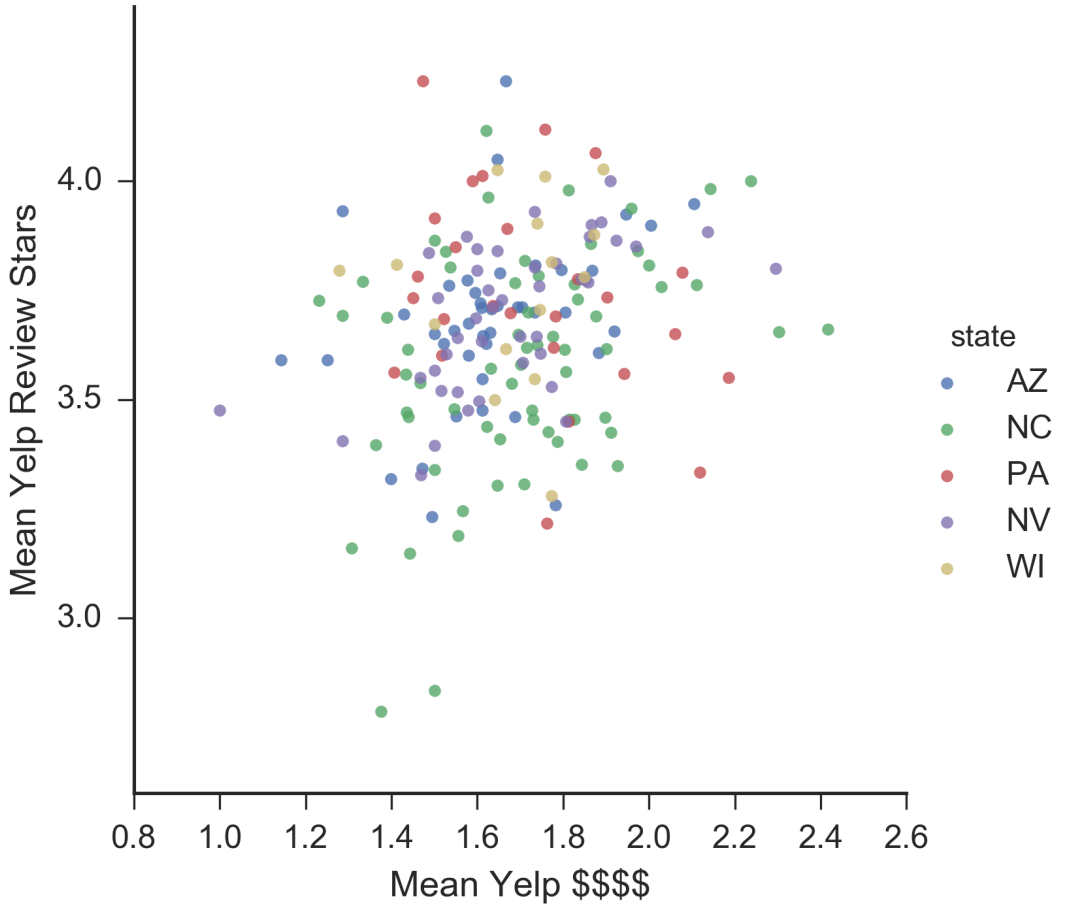

Figure 8:

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