Yelp Dataset Investigation

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Data Analytics and Visualization

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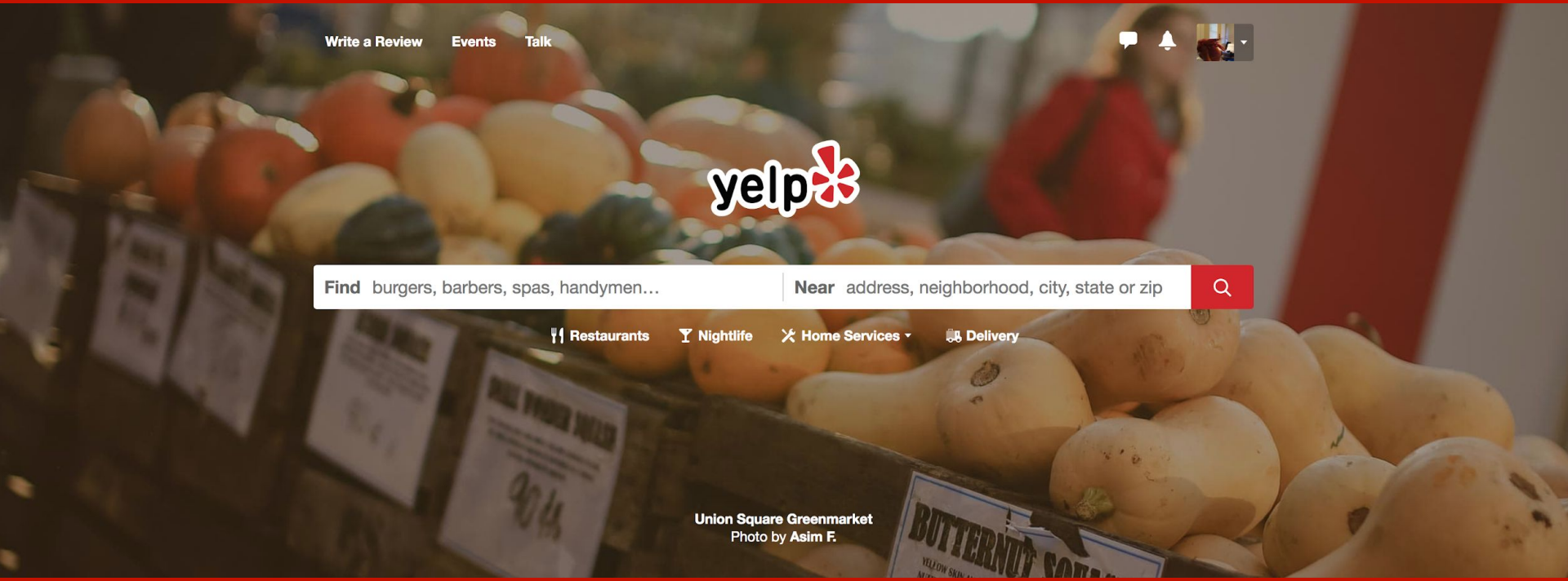

Write a Review
Events
Talk
yelp
Find burgers, barbers, spas, handymen…
Near address, neighborhood, city, state or zip
Restaurants
Nightlife
Home Services
Delivery
Union Square Greenmarket
Photo by Asim F.

Ramen Tatsu-Ya Claimed

1121 reviews Details

$$ · Ramen Edit

Write a Review Add Photo Share Bookmark

1234 S Lamar Blvd Edit
Austin, TX 78704
Bouldin Creek, South Lamar District, 78704 (South Austin)
Get Directions
(512) 893-5561
ramen-tatsuya.com
Message the business
Send to your Phone

See all 1359

"I get the og (veggie when it's offered on Sunday's) with a **spicy bomb** and it is amazing!" in 73 reviews

"In total, We ordered the **Tonkotsu Original**, the Tsukemen w/ extra chashu, Gyoza and the Gotcha Matcha dessert." in 38 reviews

Today **11:00 am - 10:00 pm**
Closed now

Full menu

$$$$ Price range **$11-30**

Yelp Dataset Challenge

Discover what insights lie hidden in our data.

What is the dataset challenge?

The challenge is a chance for students to conduct research or analysis on our data and share their discoveries with us. Whether you're trying to figure out how food trends start or identify the impact of different connections from the local graph, you'll have a chance to win cash prizes for your work! See some of the past winners and hundreds of academic papers written using the dataset.

The Dataset

5,200,000 reviews

174,000 businesses

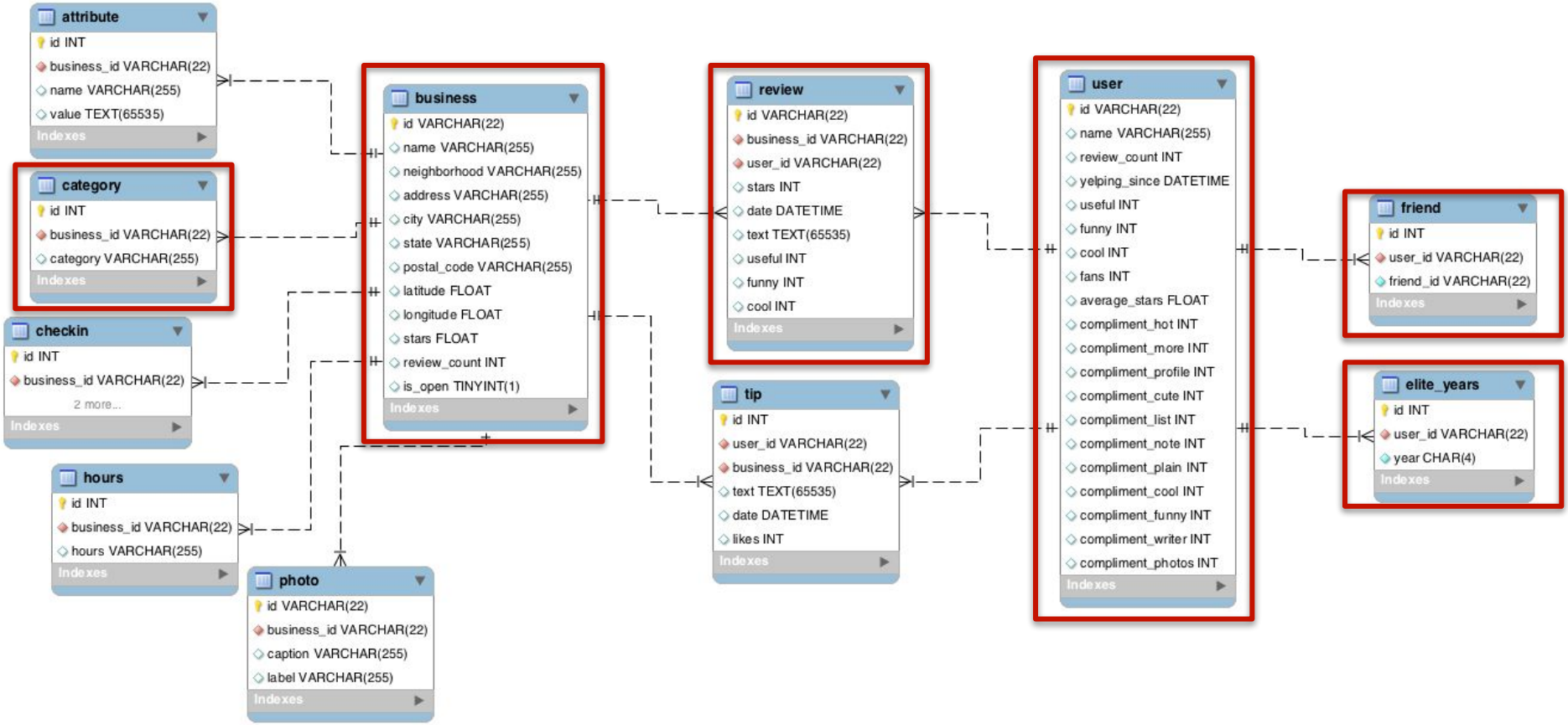
11 metropolitan areas

1,100,000 tips by 1,300,000 users
Over 1.2 million business attributes like hours, parking, availability, and ambience
Aggregated check-ins over time for each of the 174,000 businesses

Project Goals

- Drive toward Yelp’s KPIs
- Sharpen SQL DBA skills
- Explore Tableau
- Create business-driven, dynamic dashboards (all-time and periodic roll-ups)

yelp Dataset



SQL and Tableau performance issues

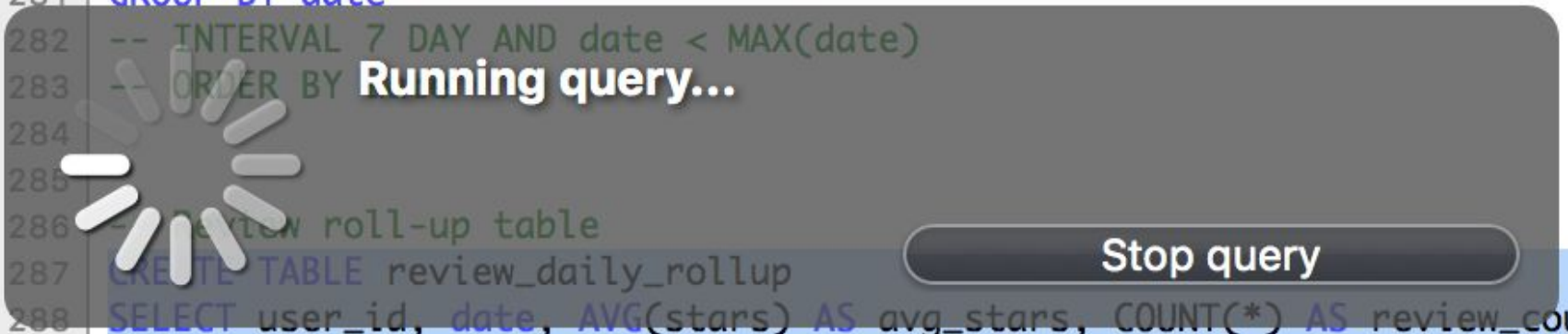
- 7.5 GB
- 1.3 million user rows
- 5.2 million review rows
- Tableau is slow, so:
  - Forget joins
  - Create custom pre-aggregated tables in MySQL and visualize
  - Utilize extracts

```sql
USE yelp_db;

-- Aggregated table with friend counts
CREATE TABLE user_copy as SELECT
    user.*,
    COALESCE(friend.friend_count,
    0) friend_count,
    IF(elite.user_id is null,
    0,
    1) elite_status
FROM
    user as user
LEFT JOIN
    (
        SELECT
            user_id,
            count(*) friend_count
        FROM
            friend
        GROUP BY
            1
    ) friend
        ON friend.user_id = user.id
LEFT JOIN
    (
        SELECT
            DISTINCT    user_id
        FROM
            elite_years
    ) elite
        ON friend.user_id = elite.user_id;


-- Per-day review roll-up table

CREATE TABLE review_daily_rollup SELECT
    user_id,
    date,
    AVG(stars) AS avg_stars,
    COUNT(*) AS review_count
FROM
    review
GROUP BY
    date,
    user_id
ORDER BY
    date DESC;
```

Optimizations

- Created custom pre-agged tables
- Connected MySQL database to Tableau
- Plus:
    - Flag columns (0/1)
    - Self-joins (*Categories*)
    - Daily/weekly rollup tables based on aggregations

```
280 WHERE date >= MAX(date)
281 GROUP BY date
282 -- INTERVAL 7 DAY AND date < MAX(date)
283 -- ORDER BY
284
285
286 -- Review roll-up table
287 CREATE TABLE review_daily_rollup
288 SELECT user_id, date, AVG(stars) AS avg_stars, COUNT(*) AS review_count
289 FROM review
```



Business Tables

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Business Dashboard

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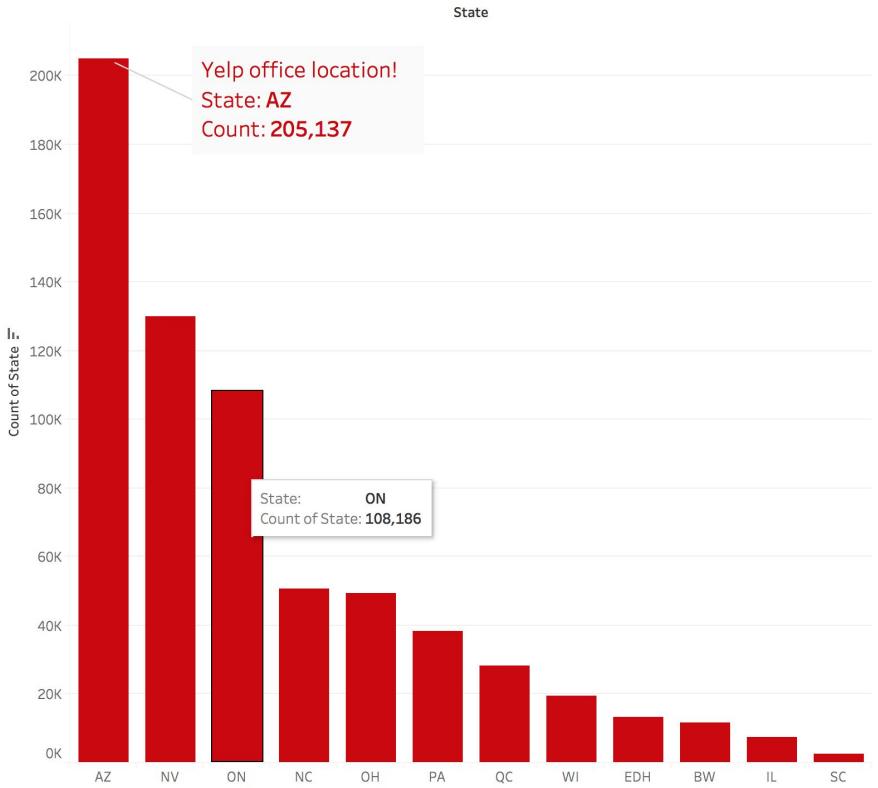
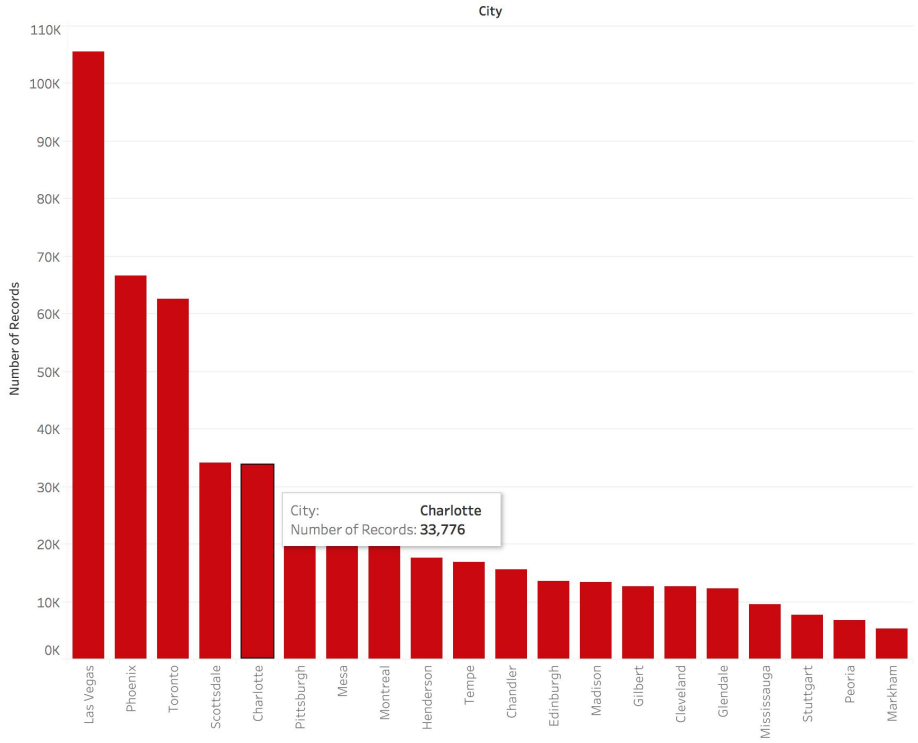
Most Businesses by State



Most Businesses by City



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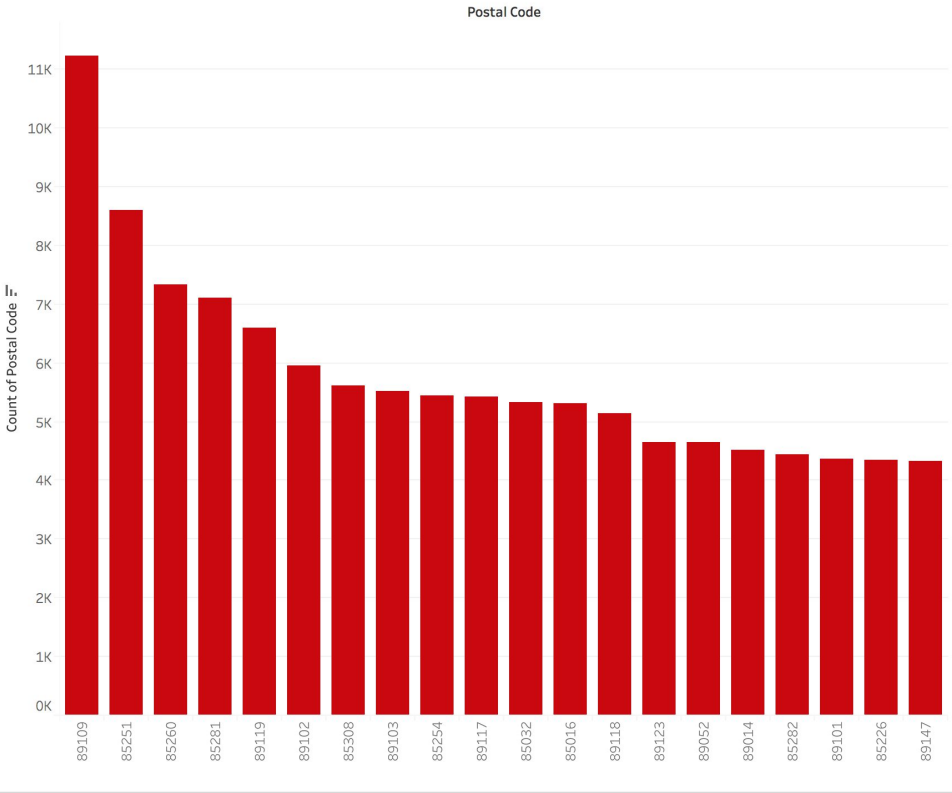
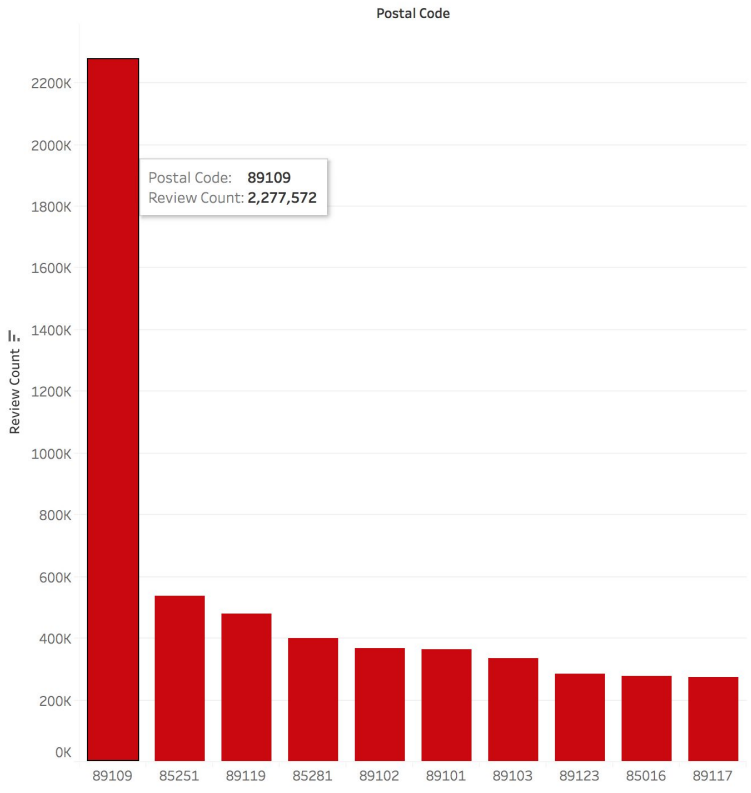
Most Businesses by Postal Code



Most Reviews by Postal Code



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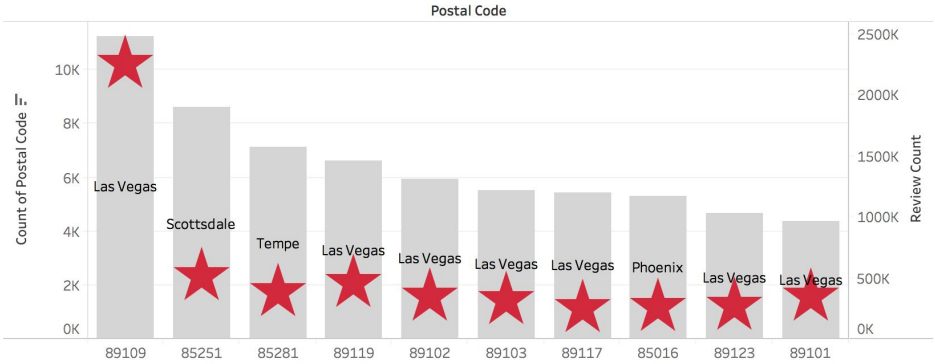
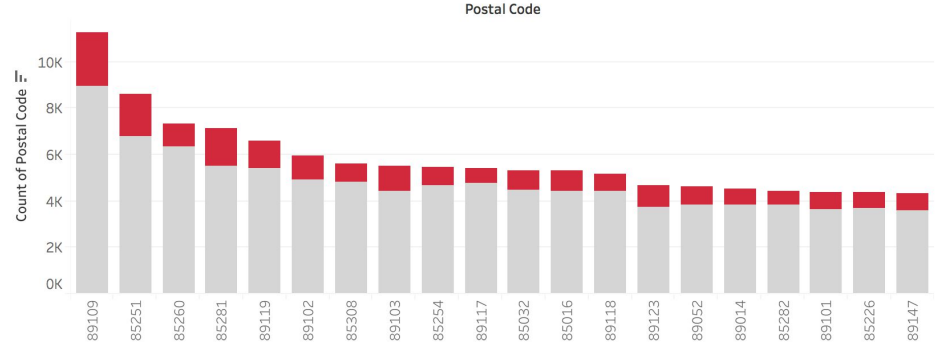
Business dashboard

Top 10 Most Businesses by Postal Code - Review Count/City



Top 20 Most Businesses by Postal Code - Open/Closed



Measure Names
- Count of Postal Code
- Review Count

Postal Code
- (All)
- ☑
- 1511
- 1528
- 1530
- 1531
- 1636
- 2100
- 7912
- 8967
- 02224
- 05440
- 05452
- 06618
- 06632
- 07141
- 08054
- 09544
- 10173
- 12200
- 12919
- 12923
- 12958
- 12979
- 15003
- 15009
- 15012

Limit
Top 20 by COUNT([Postal Code])

Is Open
- 0
- 1

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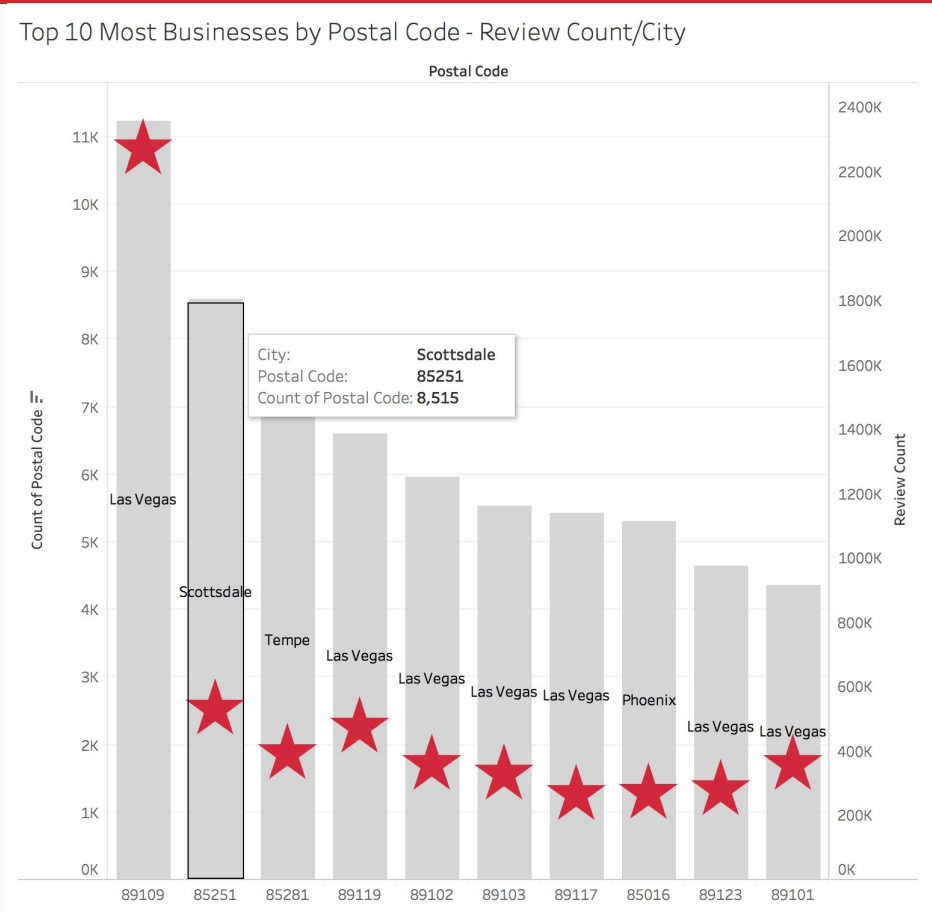
Review count doesn't exactly pace with business presence



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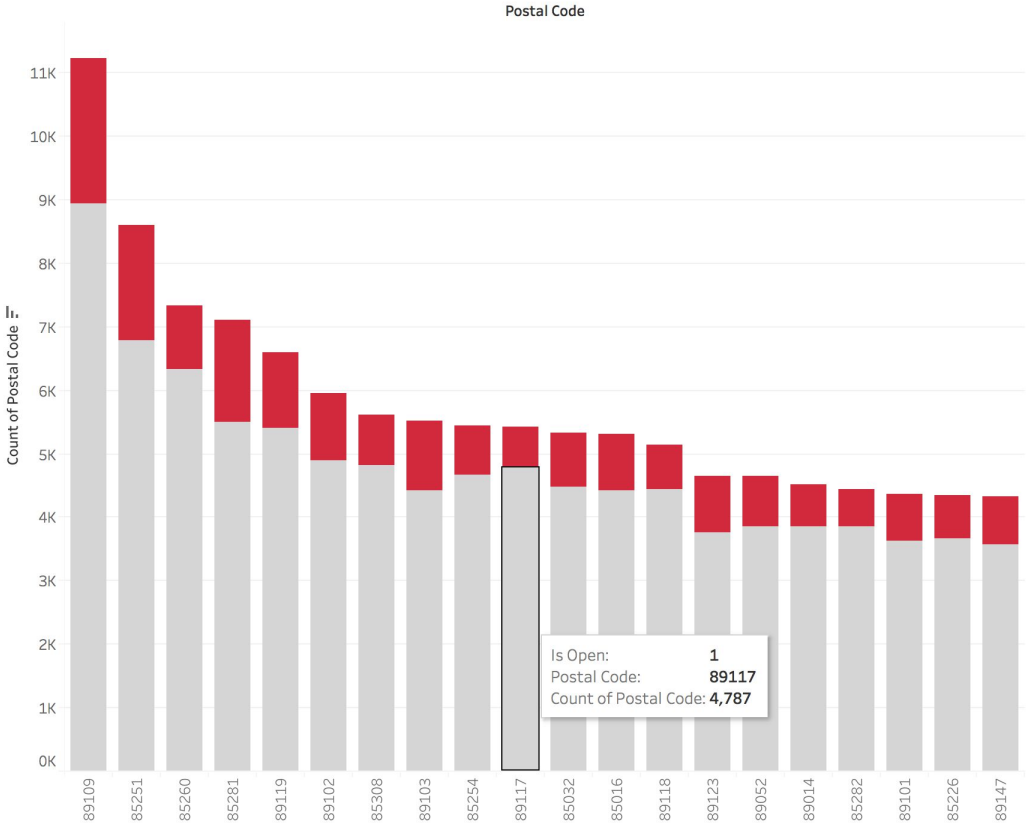
Top 20 Most Businesses by Postal Code - Open/Closed



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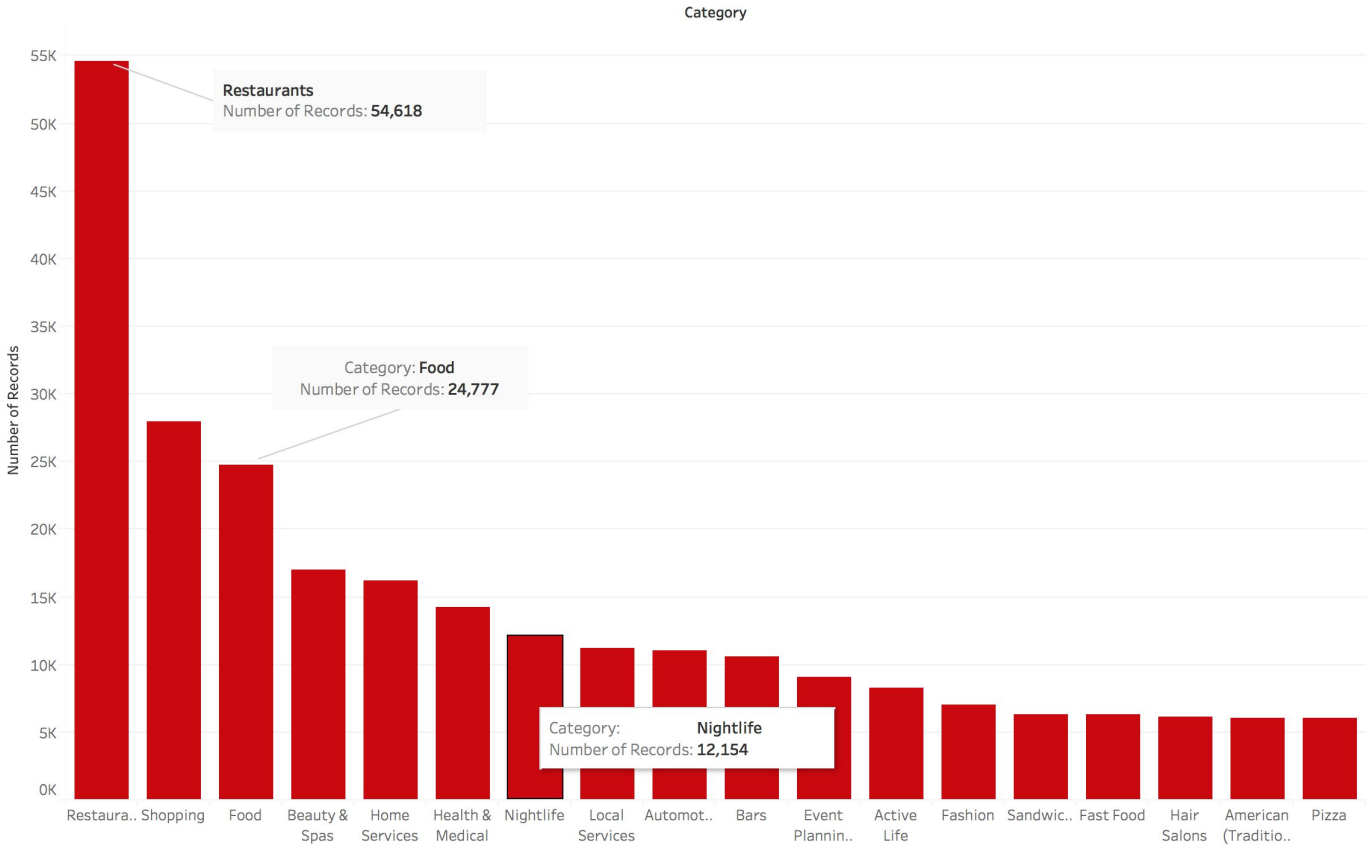
Category Frequency



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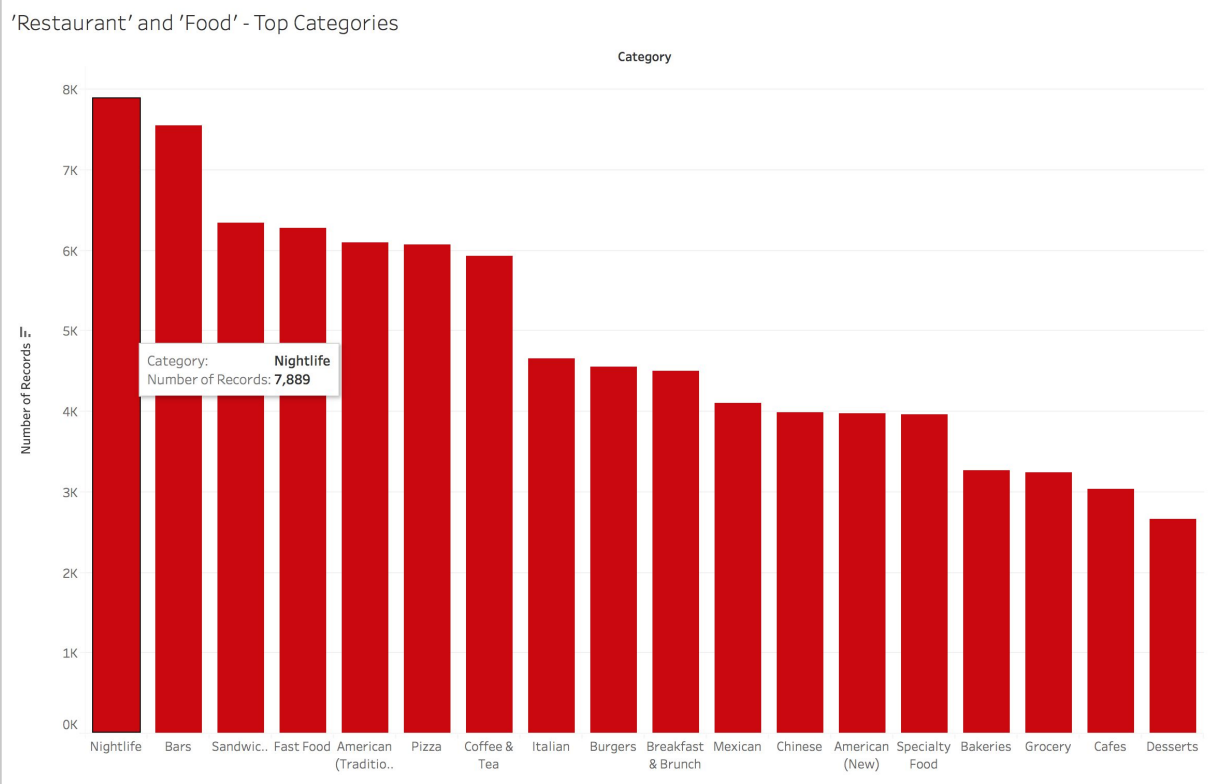
Within Restaurants and Food, top categories are:

- Nightlife
- Bars
- Sandwiches
- Fast Food
- American (Traditional)



Review Tables

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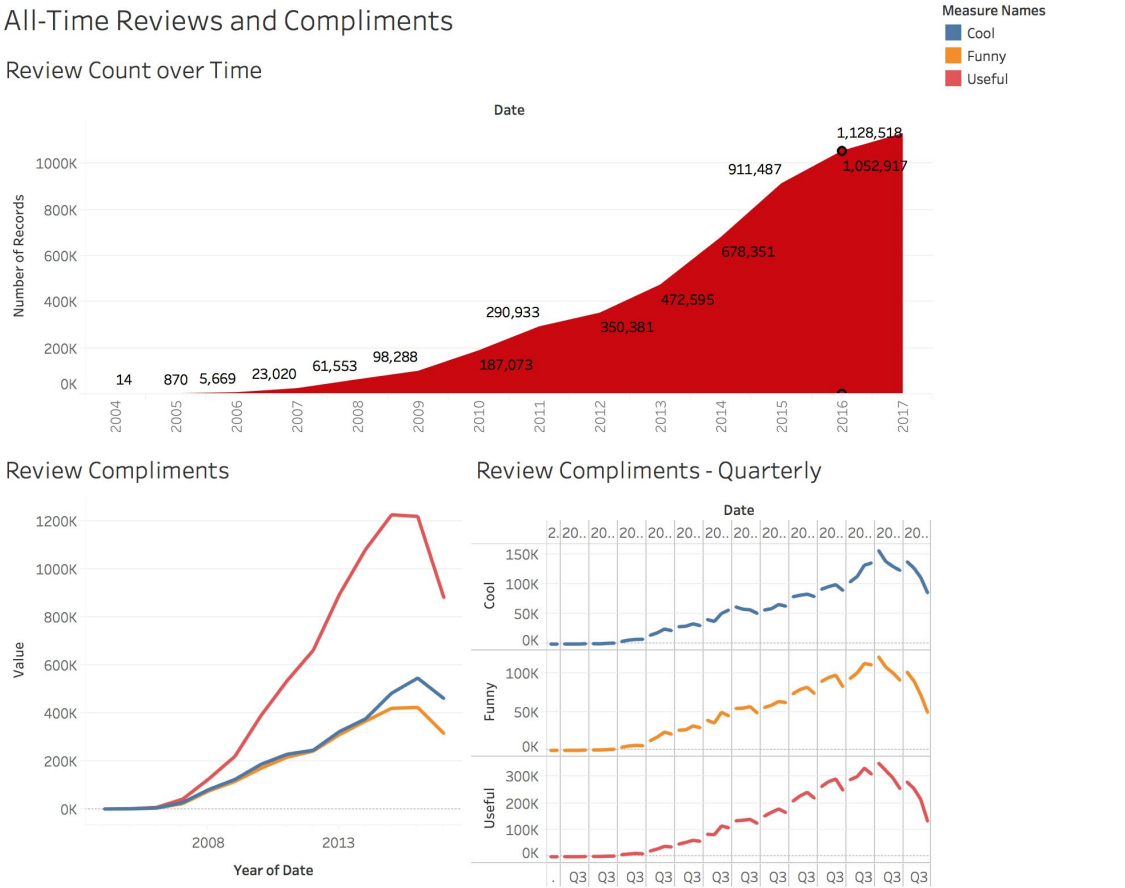
Overall Reviews Dashboard



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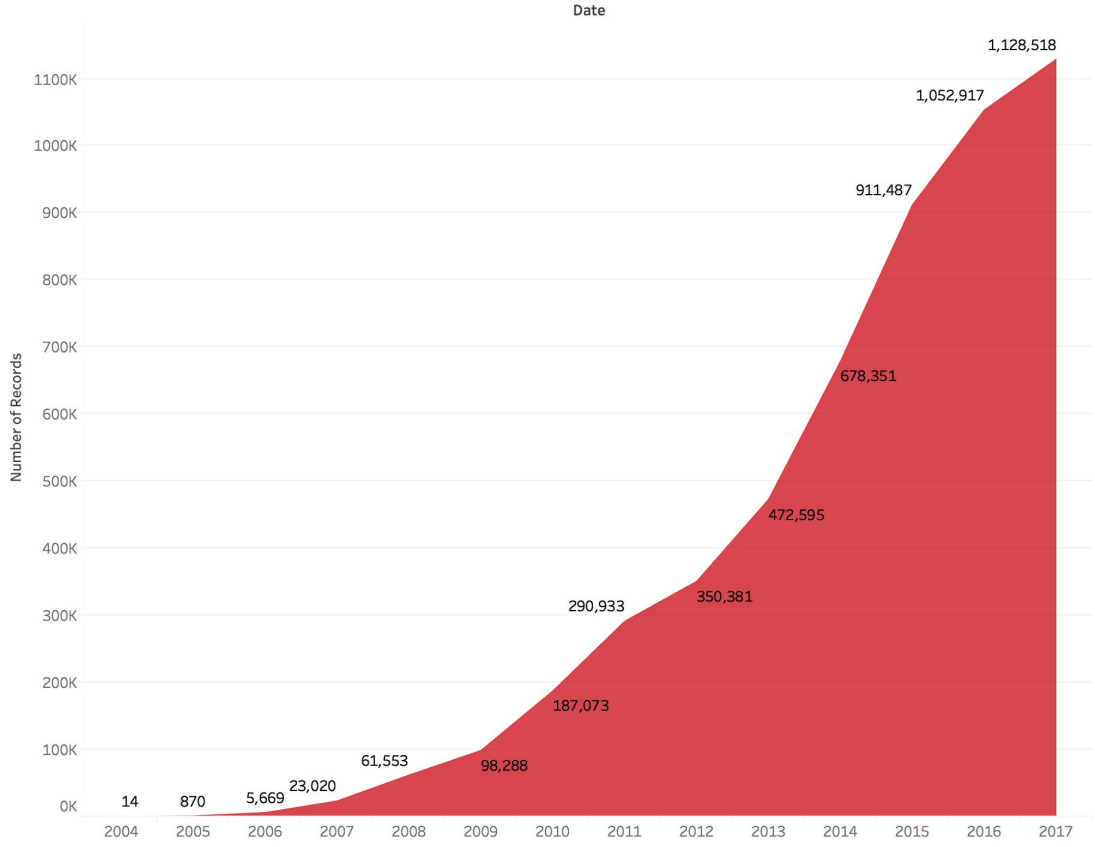
Review Count over Time



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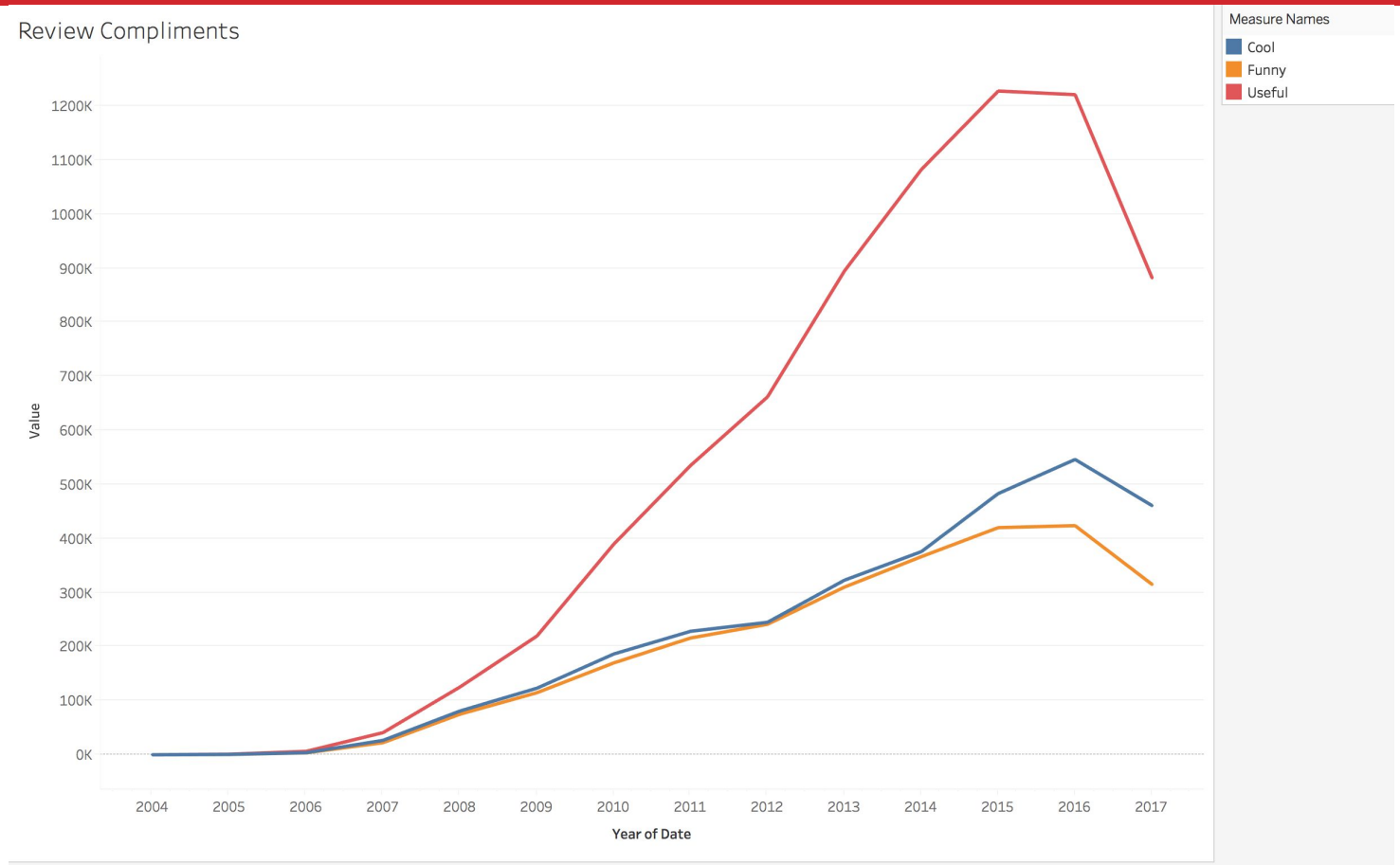

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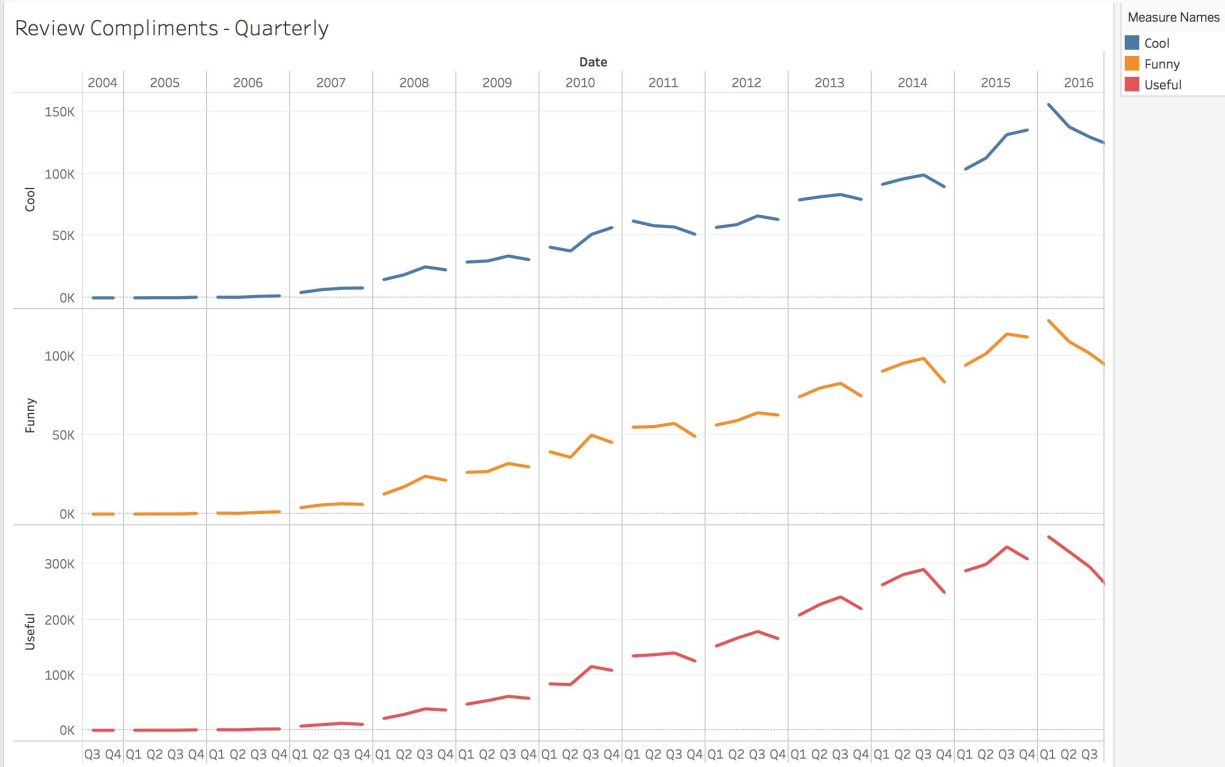
Mysterious dip in compliments in 2016. Is review count affected?



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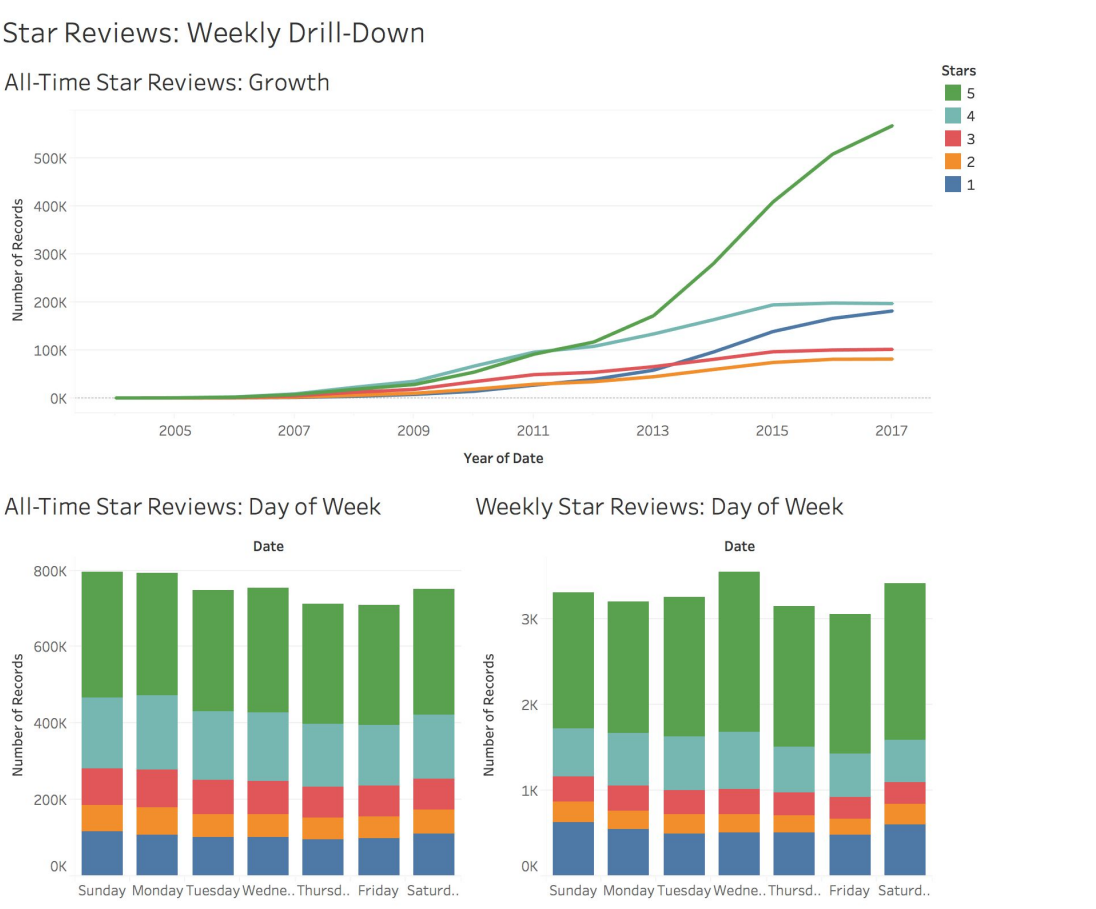
Stars Dashboard



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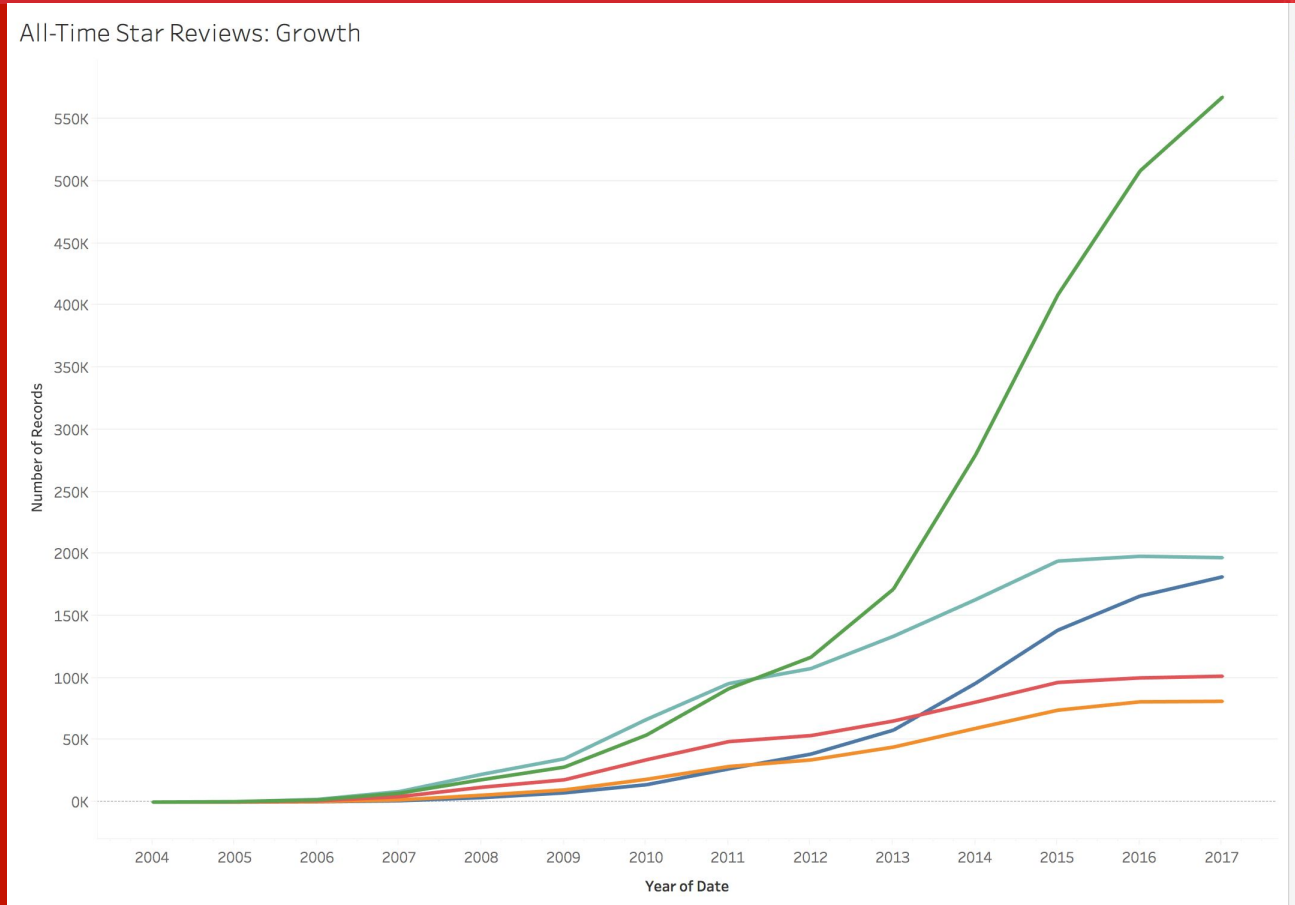
Most reviews?

5 STARS!



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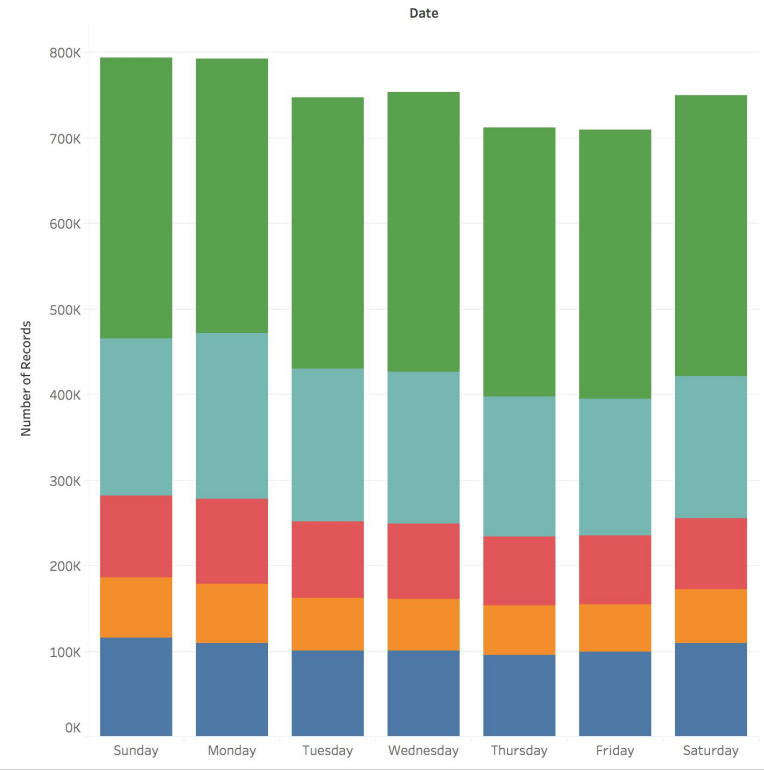
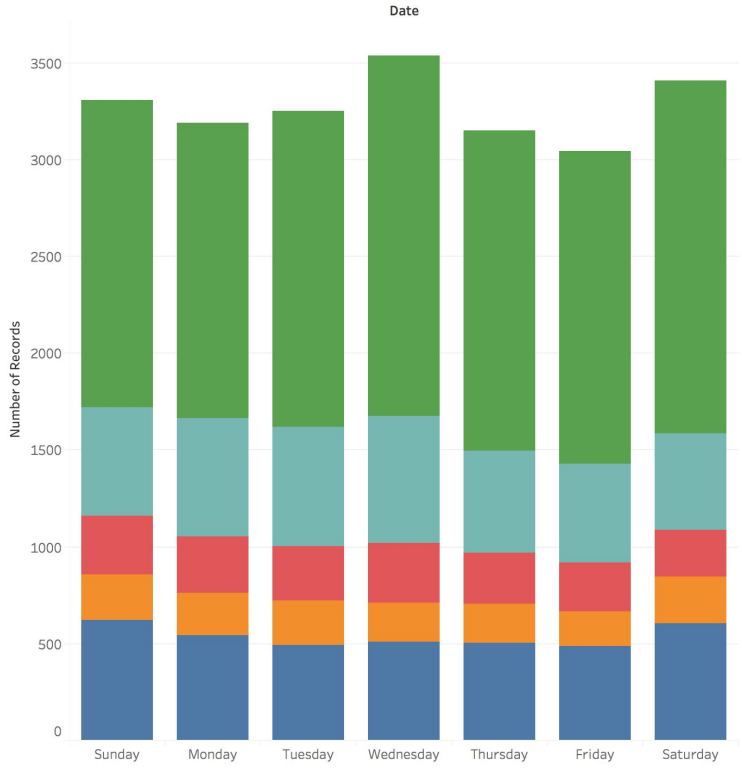
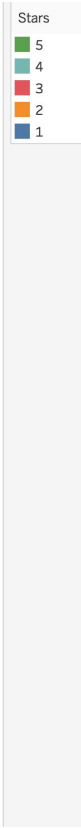
All-Time Star Reviews: Day of Week



Weekly Star Reviews: Day of Week





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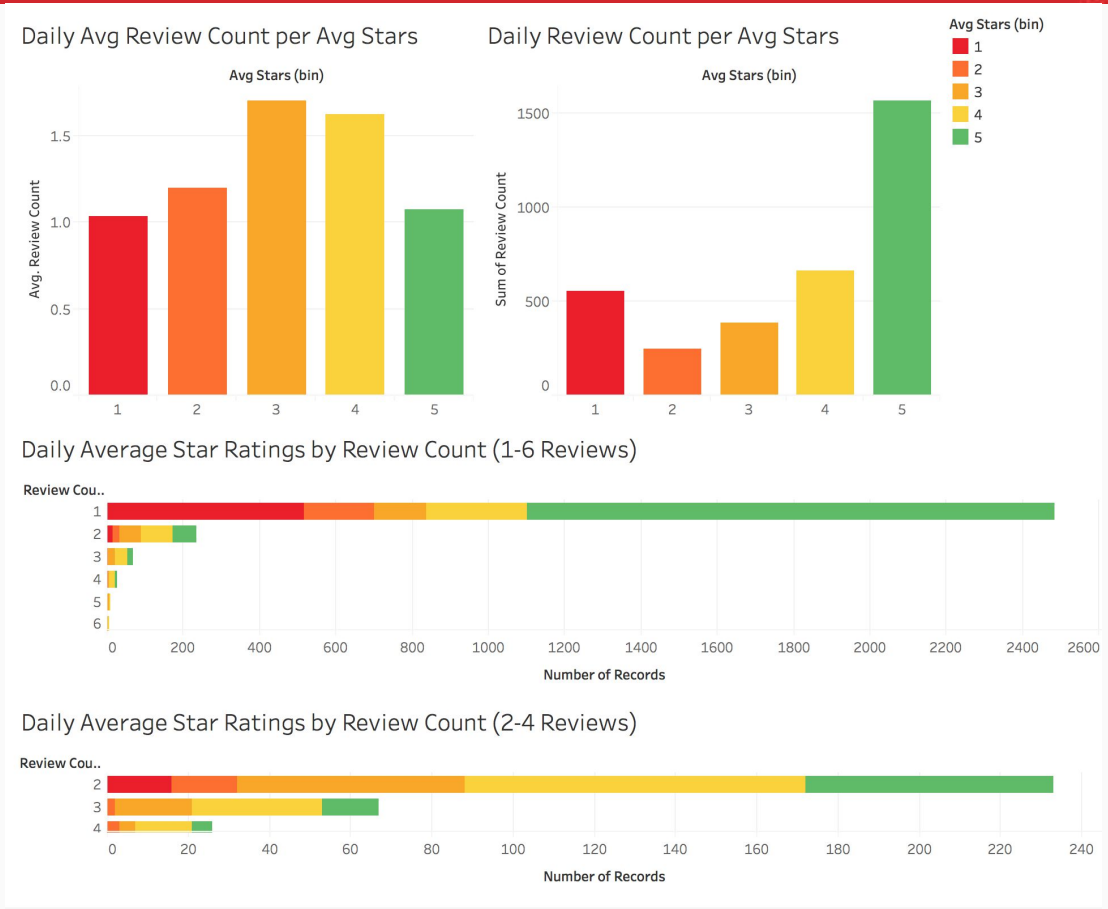
Weekly Stars-Reviews Dashboard



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Users who averaged 3 stars left the most reviews

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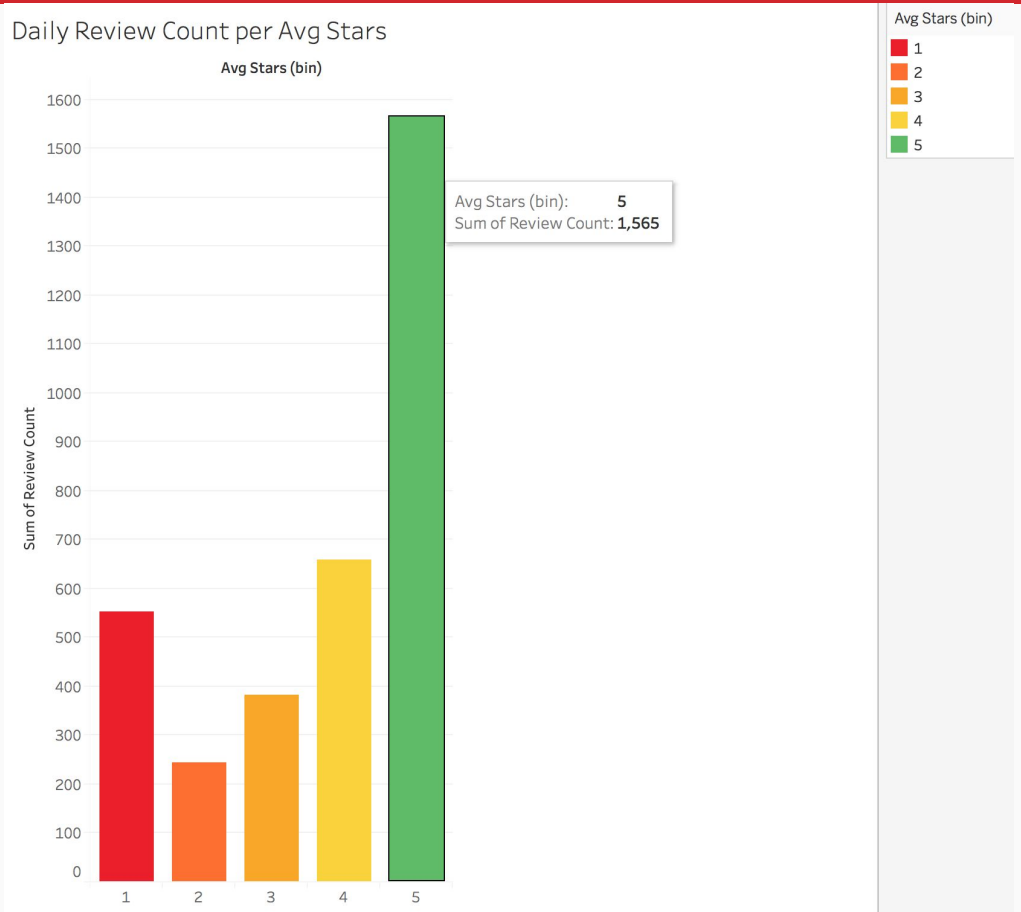
Most reviews?

5 STARS!



User Tables

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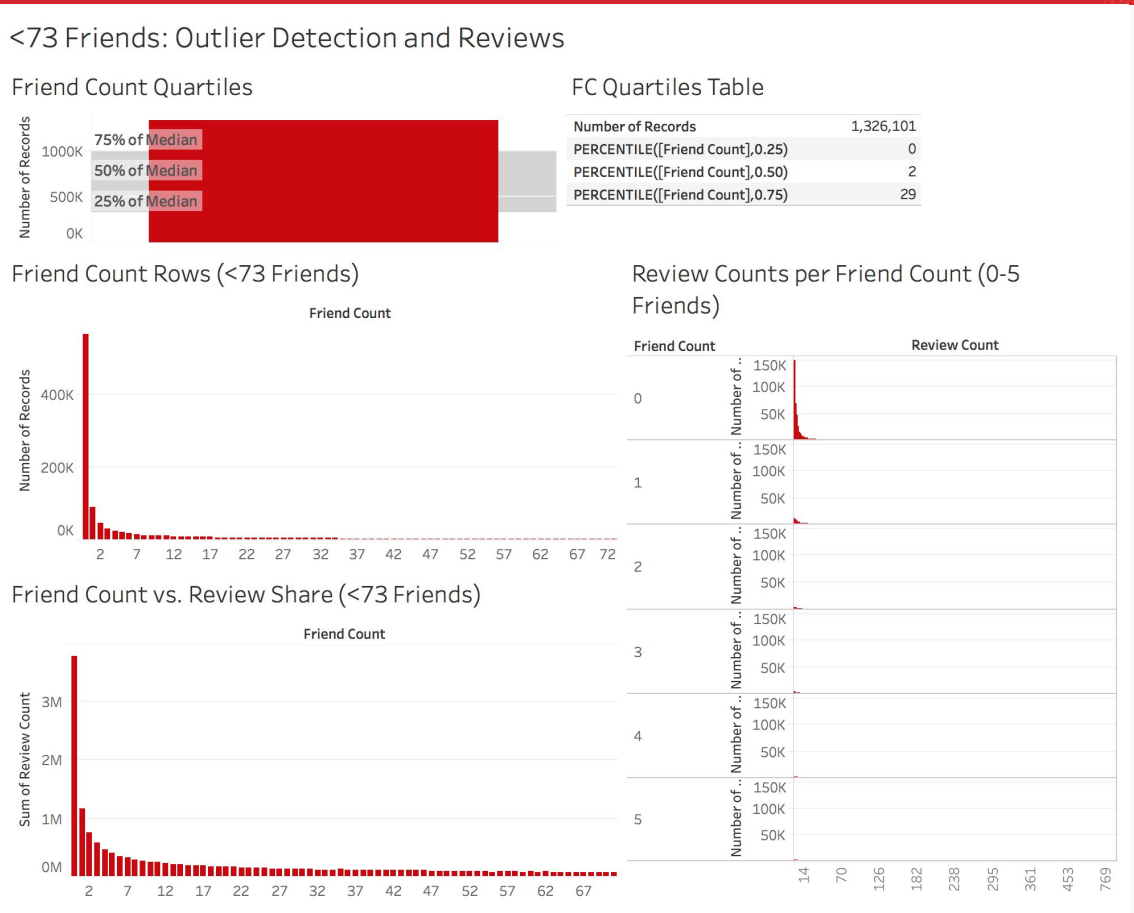
<73 Friends Dashboard



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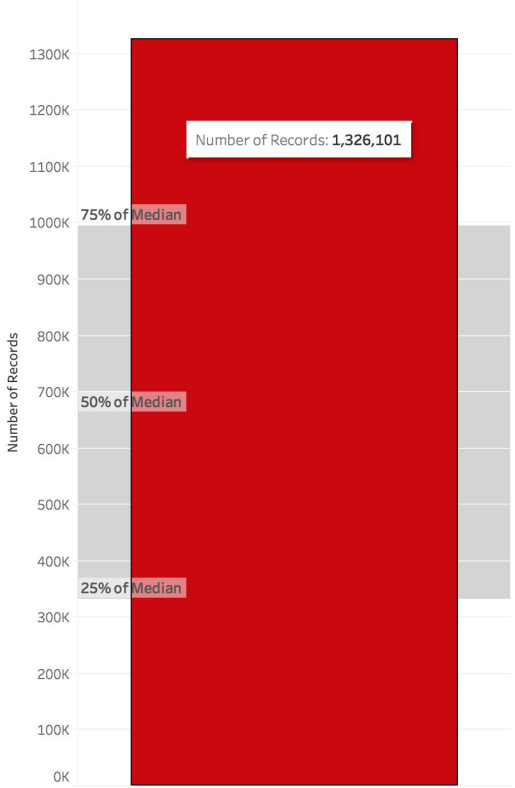
Friend Count Quartiles



Friend Count Quartiles Table

Number of Records	1,326,101
PERCENTILE([Friend Count],0.25)	0
PERCENTILE([Friend Count],0.50)	2
PERCENTILE([Friend Count],0.75)	29

Interquartile Range = 29 - 0 = 29

Outlier fences = 1.5*IQR

→ Greater than 72 friends

Understanding user behavior

- Most users have zero friends
- Median friend count is 2
- Most reviews come from zero-friend users
- Outliers with a shocking number of friends (>72) are responsible for some 15-20% of all reviews
  - Yelp as a social media platform?
  - Spammers?
  - Bots?

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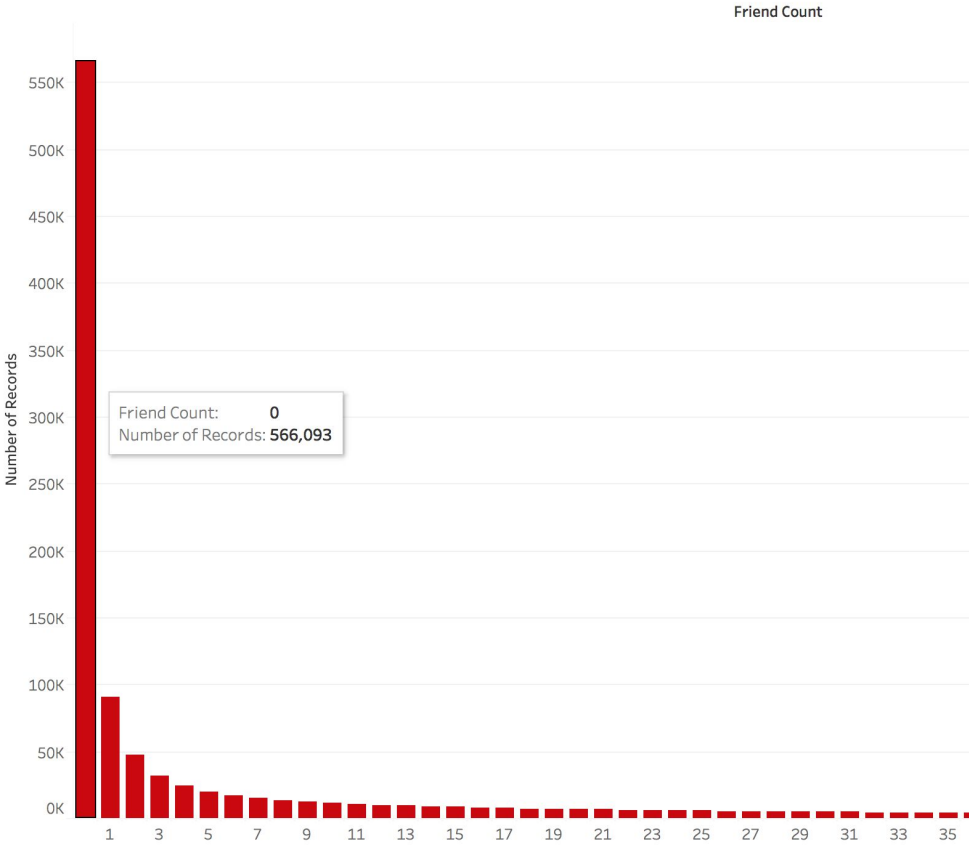
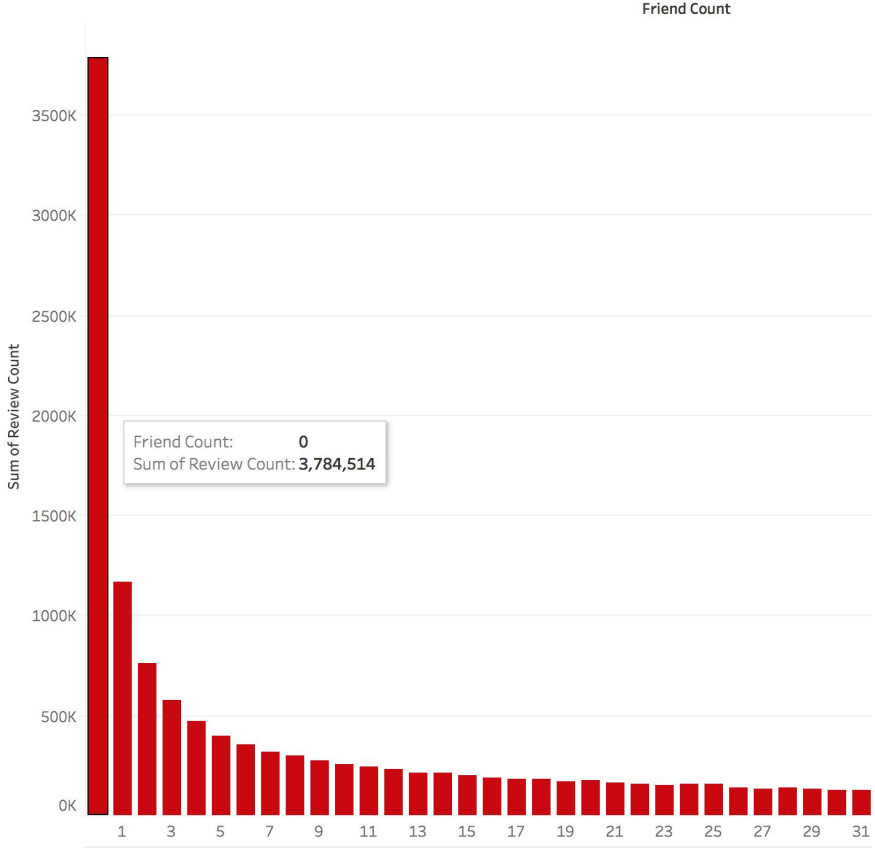
Friend Count Rows (<73 Friends)



Friend Count vs. Review Share (<73 Friends)



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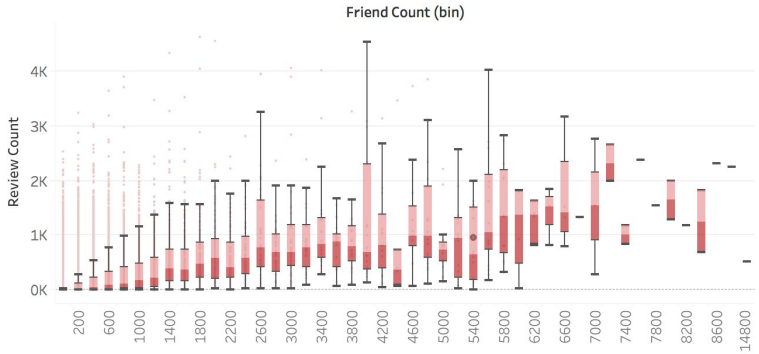
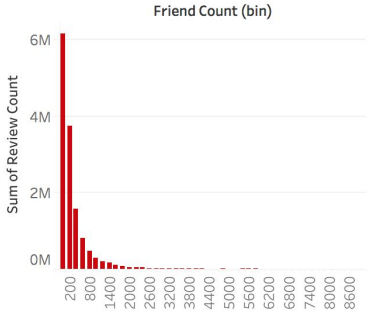
>72 Friends (Outliers) Dashboard

> 72 Friends: Networkers, Bad Actors, Bots?

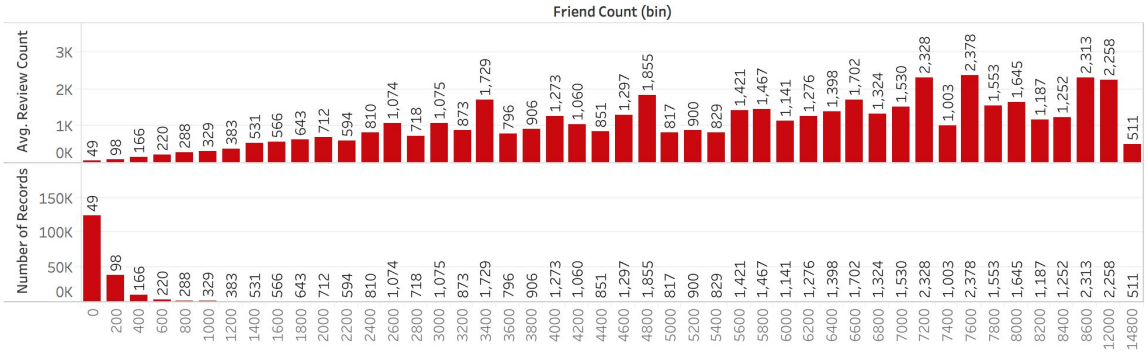
Binned Boxplots: <5k Reviews



Power Users: Friend Count vs. Review Share (> 72)



Power Users: Friend Count vs. Reviews (> 72)



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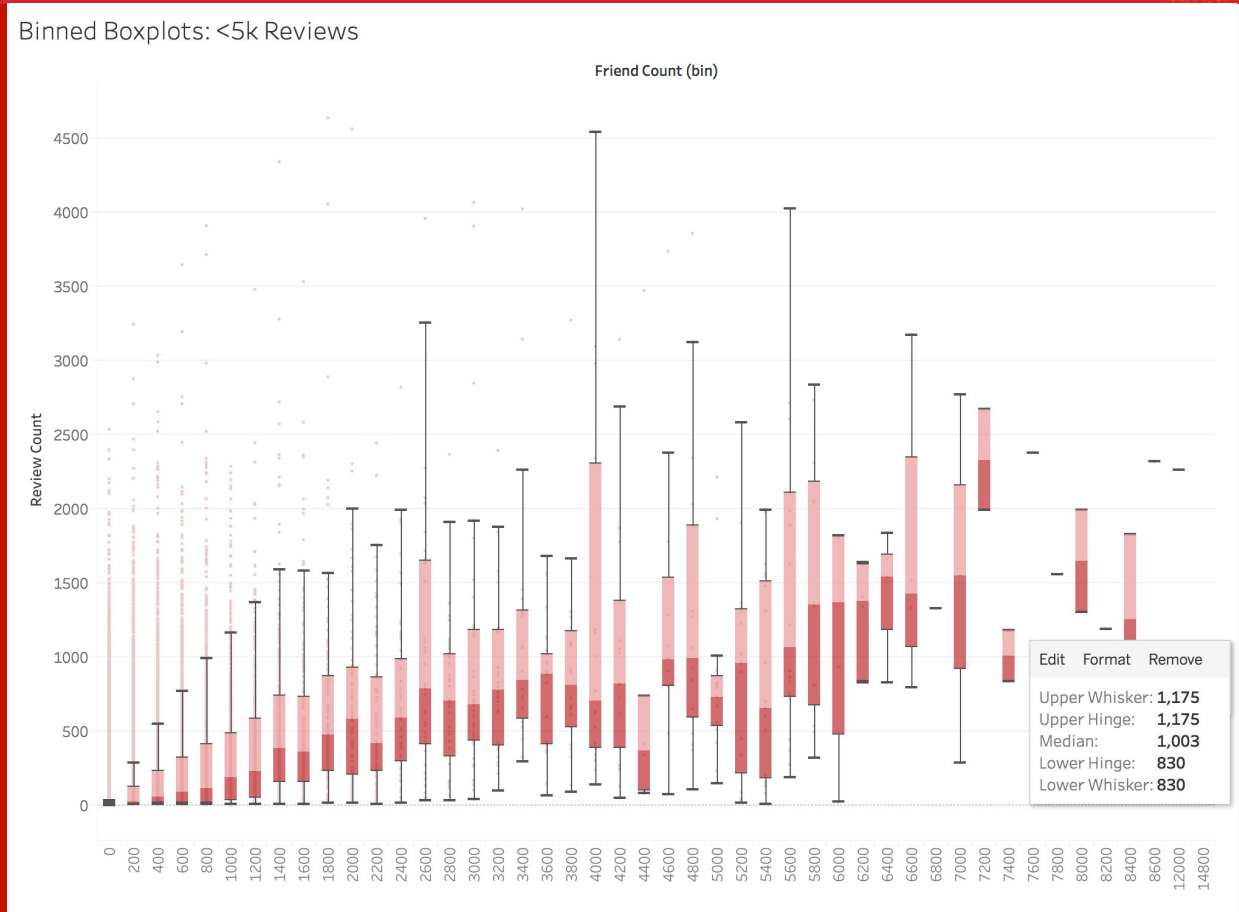
Big buckets: 200 users



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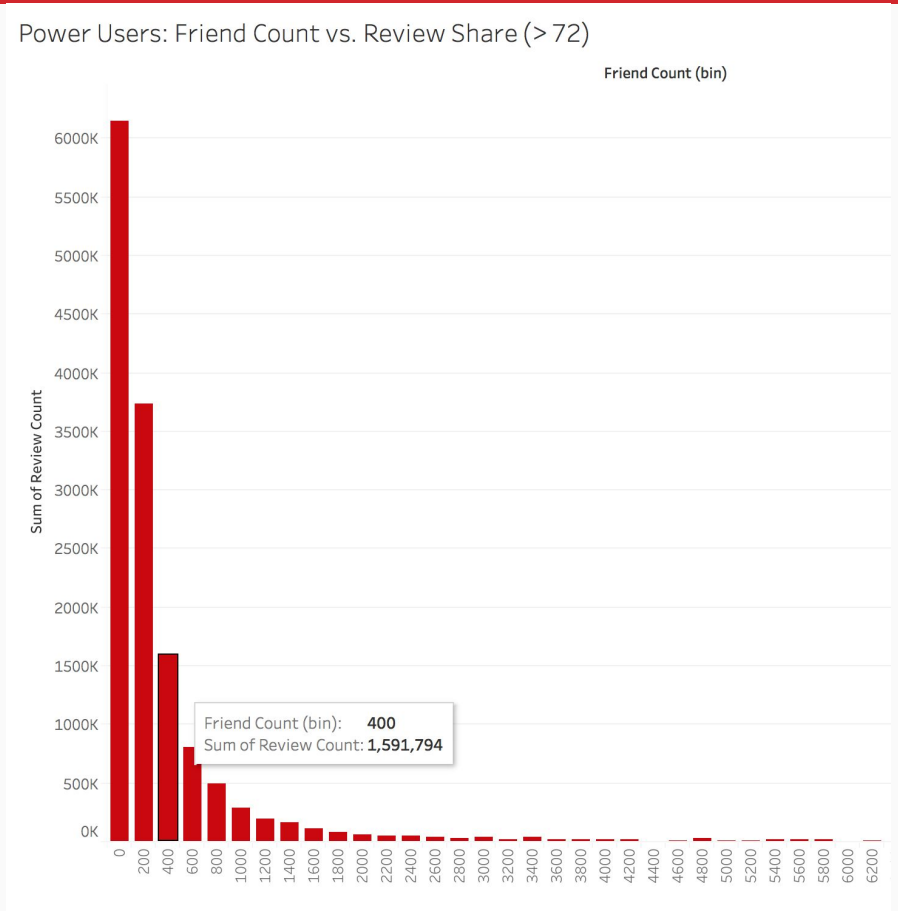
Low-friend buckets produce the majority of reviews, but *outlier high-friend users account for a significant portion of reviews*



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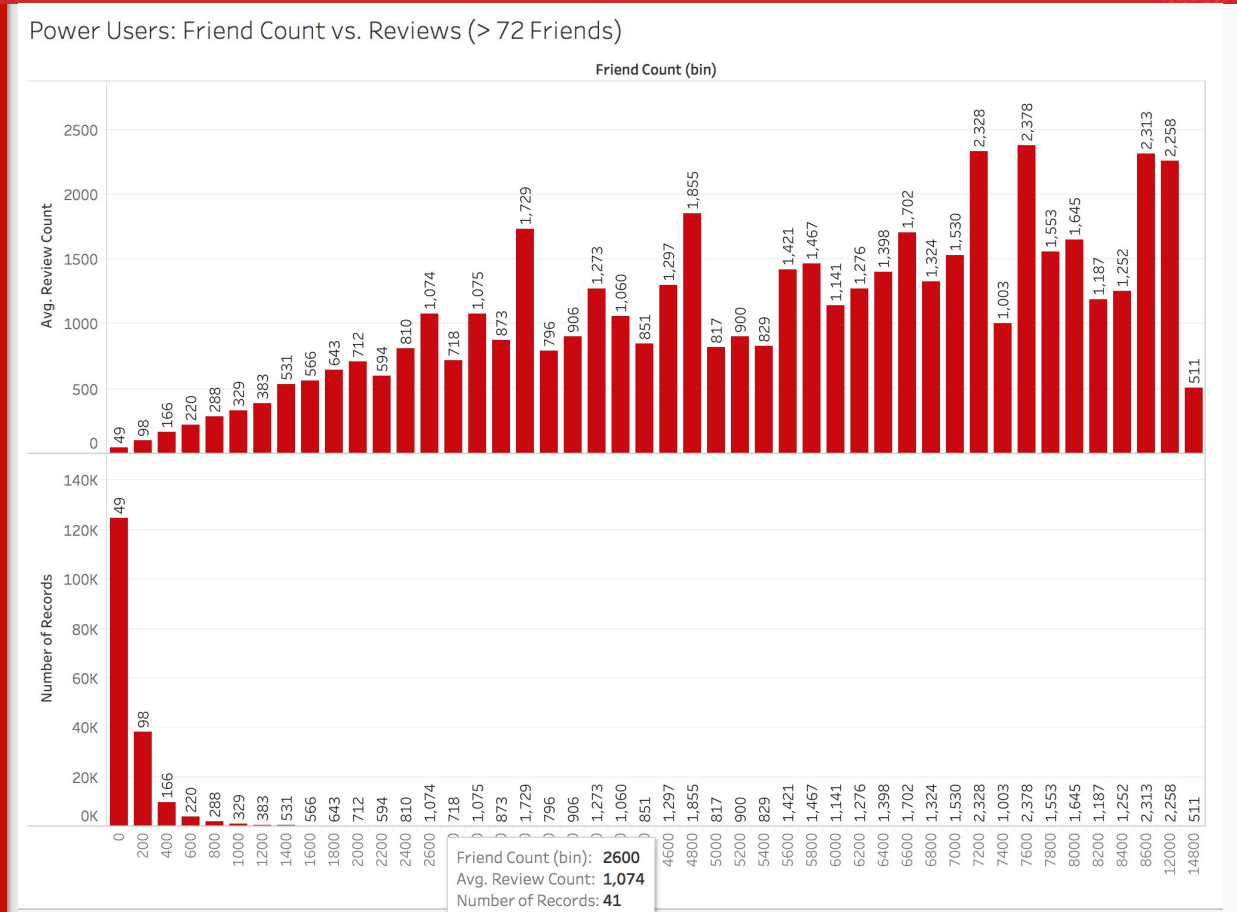
A prolific few



Extra time, extra Yelp

- Even better pre-agged tables; more interesting pivots
- Move to Postgres
- Chi-Square test of independence on average stars by weekday (TabPy)
- Automate top city dashboards (users, review activity, businesses)
- Business category vs. review count
- Descriptive → predictive analytics

Extra time, extra Yelp

- Map and analyze lat/long of users' reviewed businesses
- Where are trendsetters going before it's popular?
  - What is a 'trendsetter'? What is 'popular'?
  - Review/check-in throughput
- Reviews: NLP, text analysis, prediction modeling
  - Review stars
  - Compliments
  - Dubious accounts
- Image analysis

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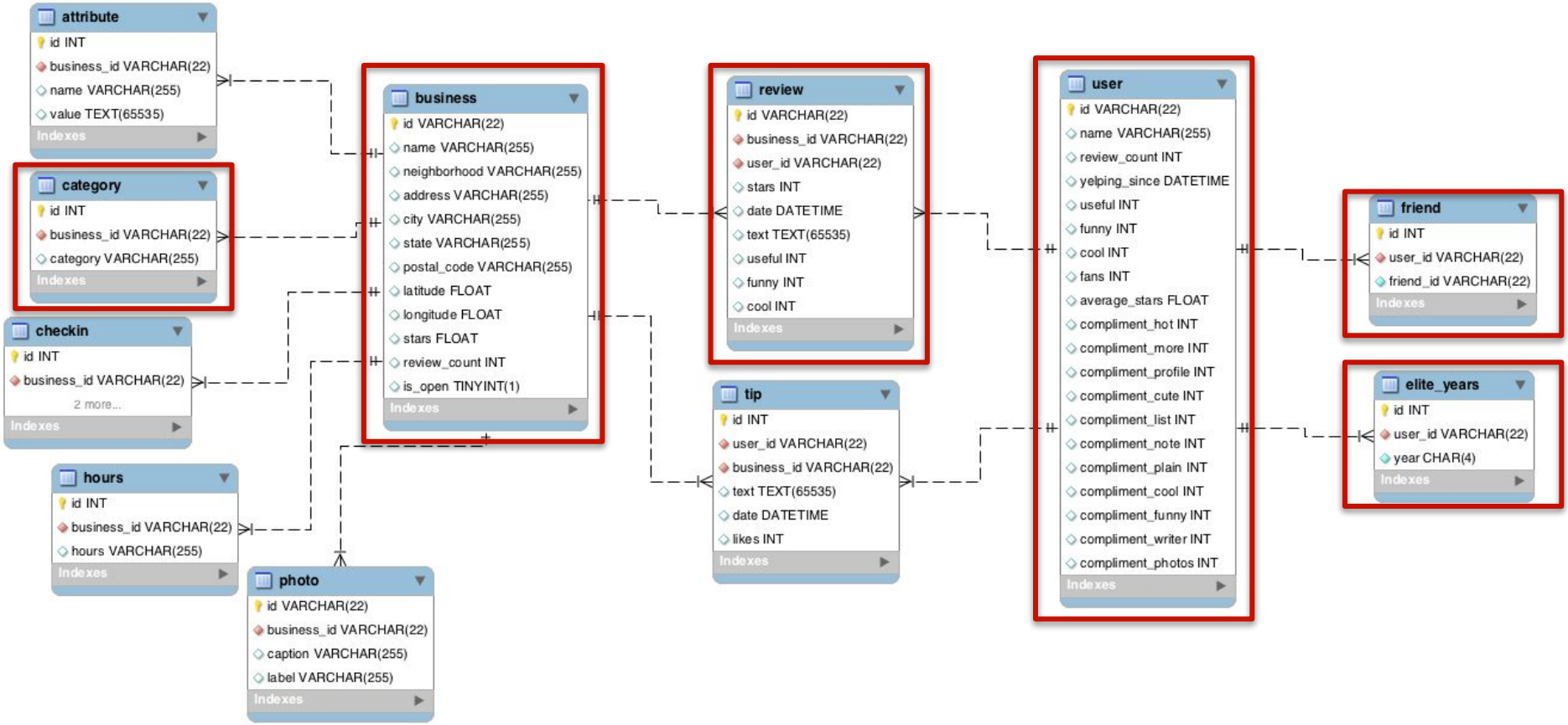

Some very bad graphs

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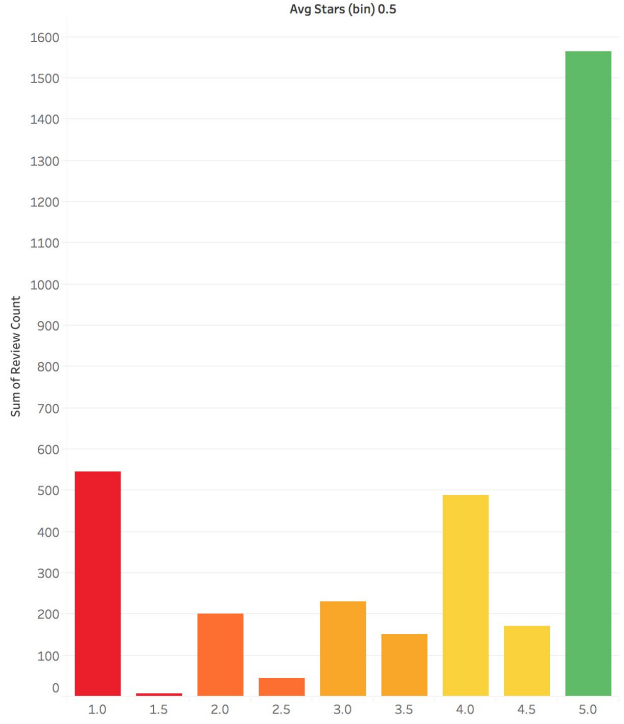
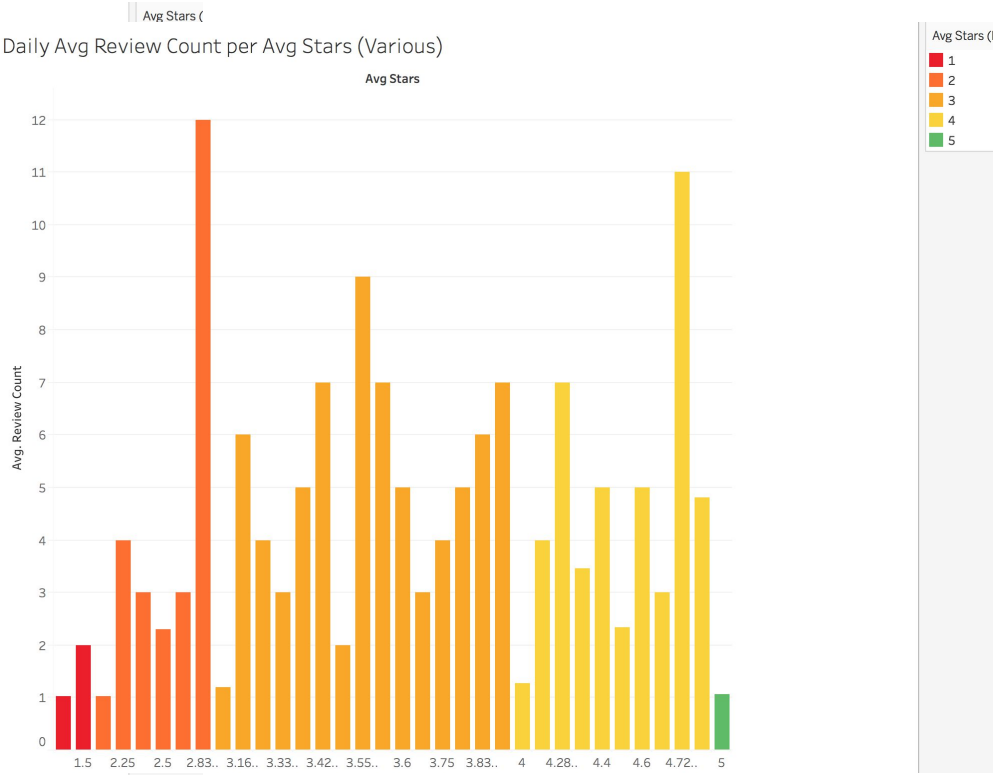
Misleading bins

Daily Reviews per Avg Stars (0.5 Bins)



Too many bins

Daily Avg Review Count per Avg Stars (Various)



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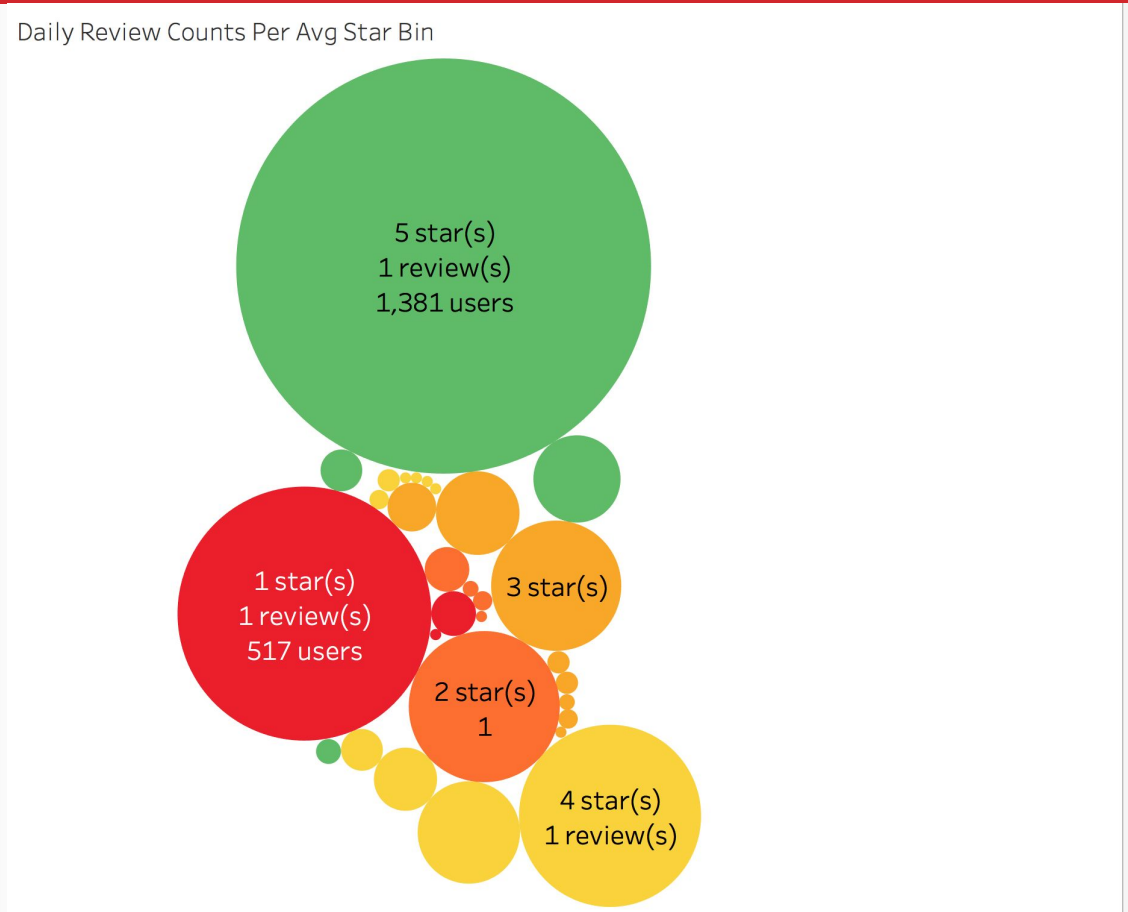
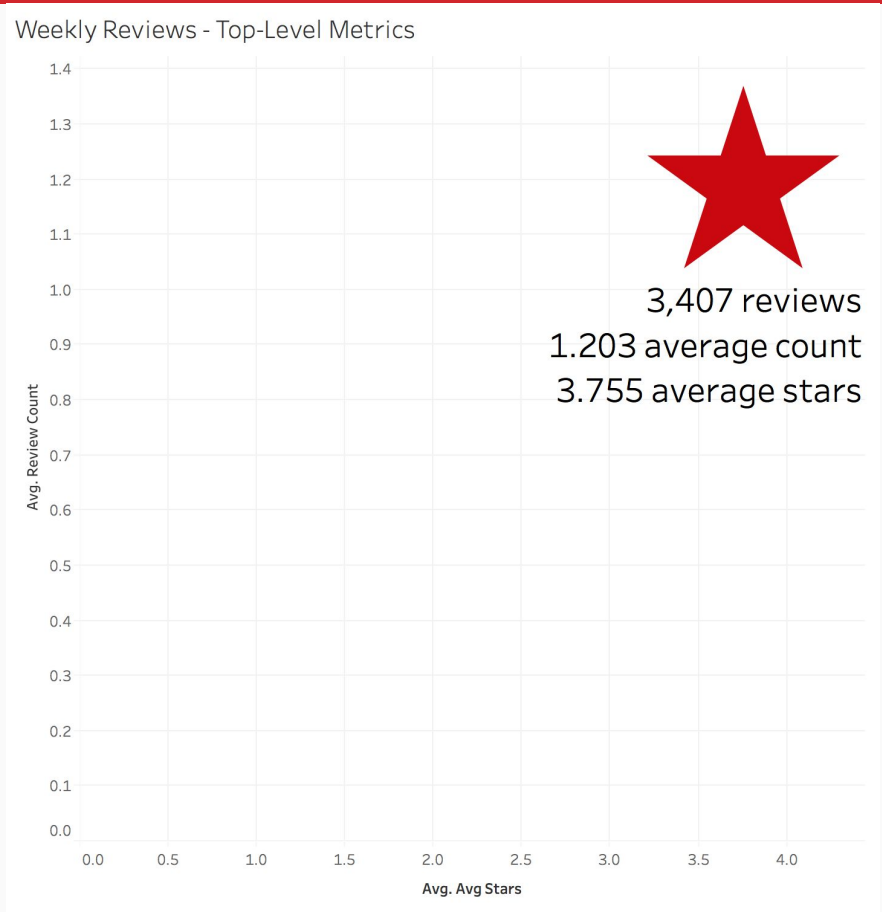
Not helpful



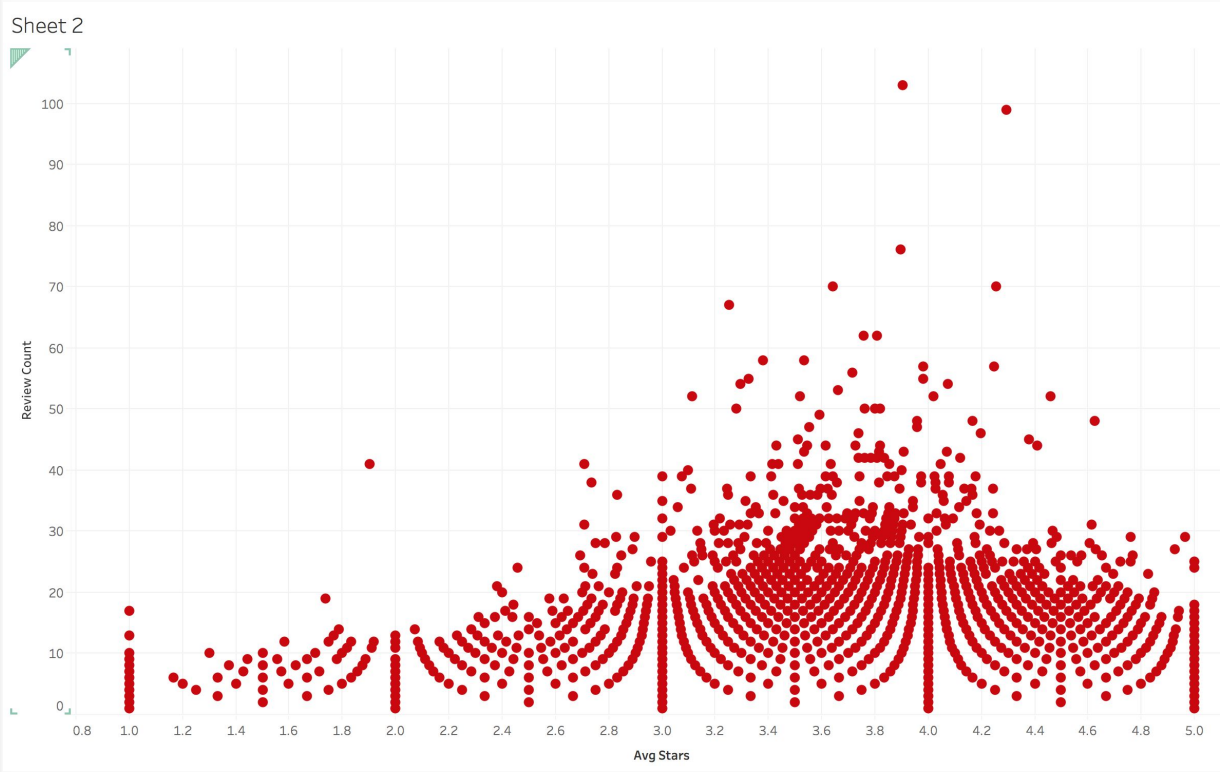
yelp Dataset

The self-congratulatory one-dot scatterplot



yelp Dataset

Rorschach?



yelp Write a Review

Questions?

Woohoo! As good as it gets!

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Want to work with me?

linkedin.com/in/caelanosullivan

github.com/caelanosullivan