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User Engagement Analysis For Restaurant Success

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ABSTRACT :

In a competitive market like the restaurant industry, understanding the factors that influence business success is crucial for stakeholders. Utilizing the Yelp dataset, this project aims to investigate the relationship between user engagement (reviews, tips, and check-ins) and business success metrics (review count, ratings) for restaurants.

Problem Statement :

Understanding the factors that influence business success is crucial for stakeholders in the restaurant industry. This project aims to investigate the relationship between user engagement (reviews, tips, and check-ins) and business success metrics (review count, ratings) for restaurants using the Yelp dataset.

Research Objectives :

1. **Quantify the correlation between user engagement (reviews, tips, check-ins) and review count/average star rating:** This will help us determine if restaurants with higher user engagement experience a corresponding increase in reviews and ratings.
2. **Analyze the impact of sentiment on review count and average star rating:** We will investigate if positive sentiment in reviews and tips translates to higher star ratings and potentially influences the total number of reviews left.
3. **Time trends in User Engagement:** We will explore if consistent user engagement over time is a stronger indicator of long-term success compared to sporadic bursts of activity.

Hypothesis Testing :

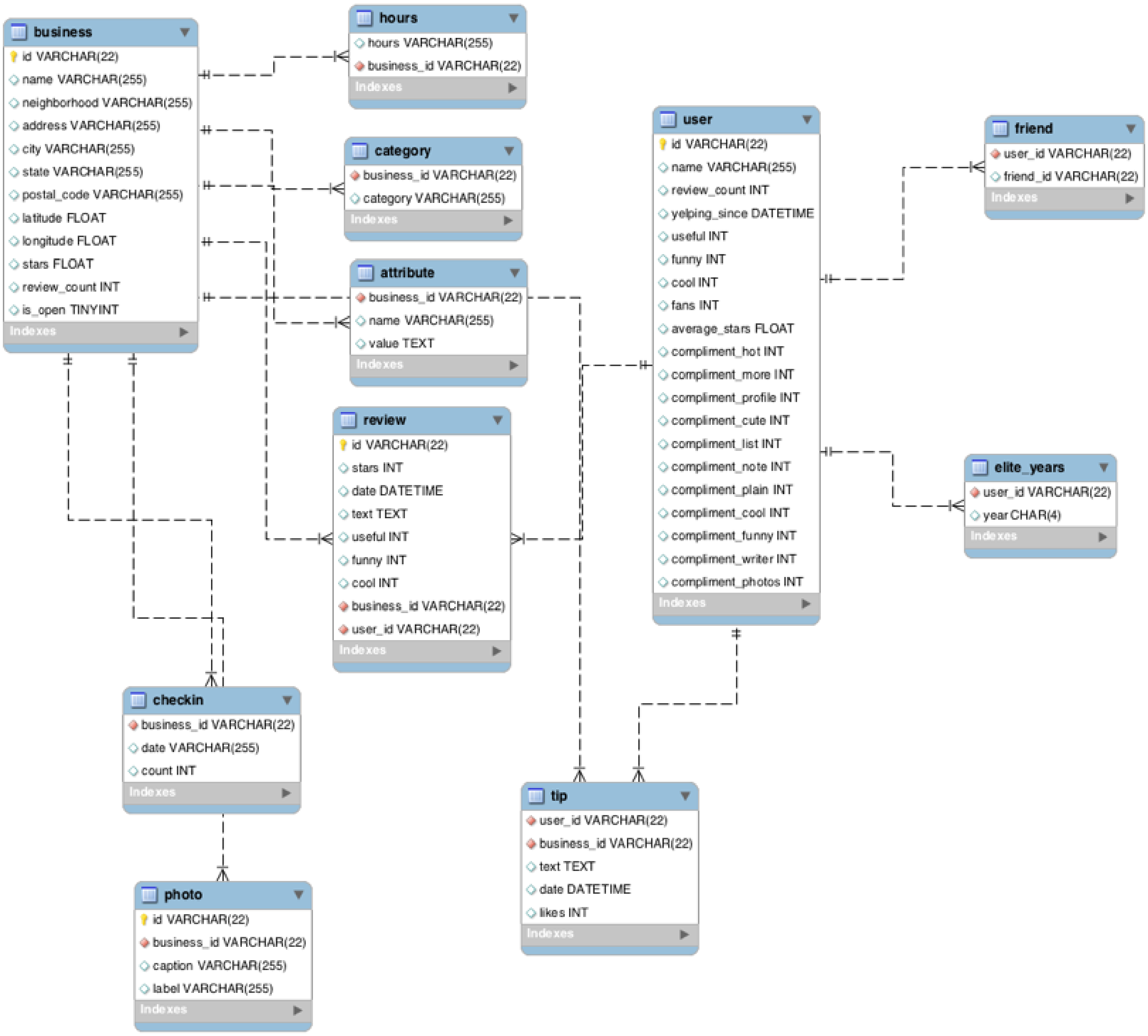
- Higher levels of user engagement (more reviews, tips, and check-ins) correlate with higher review counts and ratings for restaurants.
- Positive sentiment expressed in reviews and tips contributes to higher overall ratings and review counts for restaurants.
- Consistent engagement over time is positively associated with sustained business success for restaurants.

Importing Libraries :

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
import numpy as np
```

```
import sqlite3
import folium
import pandas as pd
from geopy.geocoders import Nominatim
from matplotlib.colors import LinearSegmentedColormap
from IPython.display import display
import warnings
warnings.filterwarnings('ignore')
```

Database Connection



- This dataset is a subset of Yelp and has information about businesses across 8 metropolitan areas in the USA and Canada.
- The original data is shared by Yelp as JSON files.
- The five JSON files are business, review, user, tip and checkin.
- The JSON files are stored in the database for easy retrieval of data.

```
# creating database connection
conn = sqlite3.connect('yelp.db')
# tables in the database
tables = pd.read_sql_query("SELECT name FROM sqlite_master WHERE type='table'",conn)
tables
    name
```

```
0  business
1    review
2      user
3       tip
4   checkin
# explore what type of data available in the tables
for table in tables['name']:
    print('-'*50,f'{table}','-'*50)
    display(pd.read_sql_query(f"select * from {table} limit 5",conn))
-------------------------------------------------- business --------------------------------------------------
              business_id                       name  \
0  Pns2l4eNsfO8kk83dixA6A  Abby Rappoport, LAC, CMQ
1  mpf3x-BjTdTEA3yCZrAYPw              The UPS Store
2  tUFrWirKiKi_TAnsVWINQQ                     Target
3  MTSW4McQd7CbVtyjqoe9mw         St Honore Pastries
4  mWMc6_wTdE0EUBKIGXDVfA  Perkiomen Valley Brewery

                           address           city state postal_code  \
0          1616 Chapala St, Ste 2  Santa Barbara    CA       93101
1  87 Grasso Plaza Shopping Center         Affton    MO       63123
2             5255 E Broadway Blvd         Tucson    AZ       85711
3                      935 Race St   Philadelphia    PA       19107
4                    101 Walnut St     Green Lane    PA       18054

    latitude   longitude  stars  review_count  is_open  \
0  34.426679 -119.711197    5.0             7        0
1  38.551126  -90.335695    3.0            15        1
2  32.223236 -110.880452    3.5            22        0
3  39.955505  -75.155564    4.0            80        1
4  40.338183  -75.471659    4.5            13        1

                                          categories
0  Doctors, Traditional Chinese Medicine, Naturop...
1  Shipping Centers, Local Services, Notaries, Ma...
2  Department Stores, Shopping, Fashion, Home & G...
3  Restaurants, Food, Bubble Tea, Coffee & Tea, B...
4                          Brewpubs, Breweries, Food
-------------------------------------------------- review --------------------------------------------------
                review_id                 user_id             business_id  \
0  KU_O5udG6zpxOg-VcAEodg  mh_-eMZ6K5RLWhZyISBhwA  XQfwVwDr-v0ZS3_CbbE5Xw
1  BiTunyQ73aT9WBnpR9DZGw  OyoGAe7OKpv6SyGZT5g77Q  7ATYjTIgM3jUlt4UM3IypQ
2  saUsX_uimxRlCVr67Z4Jig  8g_iMtfSiwikVnbP2etR0A  YjUWPpI6HXG530lwP-fb2A
3  AqPFMleE6RsU23_auESxiA  _7bHUi9Uuf5__HHc_Q8guQ  kxX2SOes4o-D3ZQBkiMRfA
4  Sx8TMOWLNuJBWer-0pcmoA  bcjbaE6dDog4jkNY91ncLQ  e4Vwtrqf-wpJfwesgvdgxQ

   stars  useful  funny  cool  \
0    3.0       0      0     0
1    5.0       1      0     1
2    3.0       0      0     0
3    5.0       1      0     1
4    4.0       1      0     1

                                                text                 date
0  If you decide to eat here, just be aware it is...  2018-07-07 22:09:11
1  I've taken a lot of spin classes over the year...  2012-01-03 15:28:18
2  Family diner. Had the buffet. Eclectic assortm...  2014-02-05 20:30:30
3  Wow!  Yummy, different,  delicious.   Our favo...  2015-01-04 00:01:03
4  Cute interior and owner (?) gave us tour of up...  2017-01-14 20:54:15
-------------------------------------------------- user --------------------------------------------------
                  user_id    name  review_count        yelping_since  useful  \
```

```
0  qVc8ODYU5SZjKXVBgXdI7w  Walker       585  2007-01-25 16:47:26    7217
1  j14WgRoU_-2ZE1aw1dXrJg  Daniel      4333  2009-01-25 04:35:42   43091
2  2WnXYQFK0hXEoTxPtV2zvg   Steph       665  2008-07-25 10:41:00    2086
3  SZDeASXq7o05mMNLshsdIA    Gwen       224  2005-11-29 04:38:33     512
4  hA5lMy-EnncsH4JoR-hFGQ   Karen        79  2007-01-05 19:40:59      29

   funny   cool                                      elite  \
0   1259   5994                                       2007
1  13066  27281  2009,2010,2011,2012,2013,2014,2015,2016,2017,2...
2   1010   1003                      2009,2010,2011,2012,2013
3    330    299                                2009,2010,2011
4     15      7

                                             friends  fans  ...  \
0  NSCy54eWehBJyZdG2iE84w, pe42u7DcCH2QmI81NX-8qA...   267  ...
1  ueRPE0CX75ePGMqOFVj6IQ, 52oH4DrRvzzl8wh5UXyU0A...  3138  ...
2  LuO3Bn4f3rlhyHIaNfTlnA, j9B4XdHUhDfTKVecyWQgyA...    52  ...
3  enx1vVPnfdNUdPho6PH_wg, 4wOcvMLtU6a9Lslggq74Vg...    28  ...
4  PBK4q9KEEBHhFvSXCUirIw, 3FWPpM7KU1gXeOM_ZbYMbA...     1  ...

   compliment_more  compliment_profile  compliment_cute  compliment_list  \
0               65                  55               56               18
1              264                 184              157              251
2               13                  10               17                3
3                4                   1                6                2
4                1                   0                0                0

   compliment_note  compliment_plain  compliment_cool  compliment_funny  \
0              232               844              467               467
1             1847              7054             3131              3131
2               66                96              119               119
3               12                16               26                26
4                1                 1                0                 0

   compliment_writer  compliment_photos
0                239                180
1               1521               1946
2                 35                 18
3                 10                  9
4                  0                  0

[5 rows x 22 columns]
-------------------------------------------------- tip --------------------------------------------------
                  user_id             business_id  \
0  AGNUgVwnZUey3gcPCJ76iw  3uLgwr0qeCNMjKenHJwPGQ
1  NBN4MgHP9D3cw--SnauTkA  QoezRbYQncpRqyrLH6Iqjg
2  -copOvldyKh1qr-vzkDEvw  MYoRNLb5chwjQe3c_k37Gg
3  FjMQVZjSqY8syIO-53KFKw  hV-bABTK-glh5wj31ps_Jw
4  ld0AperBXk1h6UbqmM80zw  _uN0OudeJ3Zl_tf6nxg5ww

                                                text                 date  \
0                       Avengers time with the ladies.  2012-05-18 02:17:21
1  They have lots of good deserts and tasty cuban...  2013-02-05 18:35:10
2              It's open even when you think it isn't  2013-08-18 00:56:08
3                          Very decent fried chicken  2017-06-27 23:05:38
4             Appetizers.. platter special for lunch  2012-10-06 19:43:09

   compliment_count
0                 0
1                 0
```

```
2             0
3             0
4             0
------------------------------------------------- checkin -------------------------------------------------
          business_id                                  date
0  ---kPU91CF4Lq2-WlRu9Lw  2020-03-13 21:10:56, 2020-06-02 22:18:06, 2020...
1  --0iUa4sNDFiZFrAdIWhZQ  2010-09-13 21:43:09, 2011-05-04 23:08:15, 2011...
2  --30_8IhuyMHbSOcNWd6DQ         2013-06-14 23:29:17, 2014-08-13 23:20:22
3  --7PUidqRWpRSpXebiyxTg  2011-02-15 17:12:00, 2011-07-28 02:46:10, 2012...
4  --7jw19RH9JKXgFohspgQw  2014-04-21 20:42:11, 2014-04-28 21:04:46, 2014...
```

Data Analysis

```
# total business count
pd.read_sql_query("select count(*) from business ",conn)
  count(*)
0   150346
# restaurants business that are open
business_id = pd.read_sql_query("select business_id, review_count from business WHERE LOWER(categories) LIKE '%restaurant%' and is_open = 1",conn)
business_id
               business_id  review_count
0     MTSW4McQd7CbVtyjqoe9mw           80
1     CF33F8-E6oudUQ46HnavjQ            6
2     bBDDEgkFA1Otx9Lfe7BZUQ           10
3     eEOYSgkmpB90uNA7lDOMRA           10
4     il_Ro8jwPlHresjw9EGmBg           28
...                      ...          ...
34999  w_4xUt-1AyY2ZwKtnjW0Xg          998
35000  l9eLGG9ZKpLJzboZq-9LRQ           11
35001  cM6V90ExQD6KMSU3rRB5ZA           33
35002  WnT9NIzQgLlILjPT0kEcsQ           35
35003  2O2K6SXPWv56amqxCECd4w           14

[35004 rows x 2 columns]
```

- Out of 150k businesses, 35k are restaurants business and are open.

```
# What is the descriptive stats for review count and star rating for businesses?
pd.read_sql_query(f"""SELECT
 AVG(review_count) AS average_review_count,
 MIN(review_count) AS min_review_count,
 MAX(review_count) AS max_review_count,
 (SELECT review_count FROM business ORDER BY review_count LIMIT 1 OFFSET (SELECT COUNT(*) FROM business) / 2) AS median_review_count,

 AVG(stars) AS average_star_rating,
 MIN(stars) AS min_star_rating,
 MAX(stars) AS max_star_rating,
 (SELECT stars FROM business ORDER BY stars LIMIT 1 OFFSET (SELECT COUNT(*) FROM business) / 2) AS median_star_rating

FROM business
WHERE business_id IN {tuple(business_id['business_id'])};

""",conn).transpose()
                               0
average_review_count   104.097789
min_review_count         5.000000
max_review_count      7568.000000
median_review_count     15.000000
average_star_rating      3.523969
min_star_rating          1.000000
```

```
max_star_rating         5.000000
median_star_rating      3.500000
```

- Analyzing the median and maximum review count revealed a significant number of restaurants with much higher review counts compared to others. This could skew further analysis.
- To address this, we decided to remove restaurants with outlier review counts.
- We will implement to identify and remove outliers using the Interquartile Range (IQR) method.

```
# function for removing outliers using interquartile range
def remove_outliers(df, col):
  q1 = df[col].quantile(0.25)
  q3 = df[col].quantile(0.75)
  iqr = q3 - q1
  lower_bound = q1 - 1.5 * iqr
  upper_bound = q3 + 1.5 * iqr
  df = df[(df[col] >= lower_bound) & (df[col] <= upper_bound)]
  return df

business_id = remove_outliers(business_id,'review_count')
# check for the outliers removed
pd.read_sql_query(f"""SELECT
  AVG(review_count) AS average_review_count,
  MIN(review_count) AS min_review_count,
  MAX(review_count) AS max_review_count,
  (SELECT review_count FROM business ORDER BY review_count LIMIT 1 OFFSET (SELECT COUNT(*) FROM business) / 2) AS
median_review_count,

  AVG(stars) AS average_star_rating,
  MIN(stars) AS min_star_rating,
  MAX(stars) AS max_star_rating,
  (SELECT stars FROM business ORDER BY stars LIMIT 1 OFFSET (SELECT COUNT(*) FROM business) / 2) AS median_star_rating

FROM business
WHERE business_id IN {tuple(business_id['business_id'])};

""",conn).transpose()
                              0
average_review_count   55.975426
min_review_count        5.000000
max_review_count      248.000000
median_review_count    15.000000
average_star_rating     3.477281
min_star_rating         1.000000
max_star_rating         5.000000
median_star_rating      3.500000
```

After removing outliers, now we are getting average review count as 55 for the restaurants business.

```
# Which restaurants have the highest number of reviews?
pd.read_sql_query(f"""SELECT name, SUM(review_count) as review_count, AVG(stars) AS avg_rating
FROM business
WHERE business_id IN {tuple(business_id['business_id'])}
GROUP BY name
ORDER BY review_count DESC
LIMIT 10;""",conn)
                    name  review_count  avg_rating
0             McDonald's         16490    1.868702
1  Chipotle Mexican Grill         9071    2.381757
2              Taco Bell          8017    2.141813
3            Chick-fil-A          7687    3.377419
4            First Watch          6761    3.875000
5            Panera Bread          6613    2.661905
6      Buffalo Wild Wings          6483    2.344828
```

```
7         Domino's Pizza         6091    2.290210
8              Wendy's         5930    2.030159
9              Chili's         5744    2.514706
# Which restaurants have the highest raing?
pd.read_sql_query(f"""SELECT name, SUM(review_count) as review_count, AVG(stars) AS avg_rating
FROM business
WHERE business_id IN {tuple(business_id['business_id'])}
GROUP BY name
ORDER BY avg_rating DESC
LIMIT 10;
""",conn)
                            name  review_count  avg_rating
0                         ā café           48         5.0
1                 two birds cafe           77         5.0
2  the brewers cabinet production           13         5.0
3             taqueria la cañada           17         5.0
4                       la bamba           44         5.0
5                 la 5th av tacos          24         5.0
6  el sabor mexican and chinese food       21         5.0
7         eat.drink.Om...YOGA CAFE          7         5.0
8          d4 Tabletop Gaming Cafe          8         5.0
9          cabbage vegetarian cafe         12         5.0
```

- No Direct Correlation: Higher ratings do not guarantee a higher review count, and vice versa.
- Review count reflects user engagement but not necessarily overall customer satisfaction or business performance.
- Success in the restaurant business is not solely determined by ratings or review counts.

```
# Do restaurants with higher engagement tend to have higher ratings?
review_count_df = pd.read_sql_query(f"""SELECT total.avg_rating as rating,
AVG(total.review_count) as avg_review_count,
AVG(total.checkin_count) as avg_checkin_count,
AVG(total.tip_count) as avg_tip_count
FROM
(SELECT
   b.business_id,
   SUM(b.review_count) AS review_count,
   AVG(b.stars) AS avg_rating,
   SUM(LENGTH(cc.date) - LENGTH(REPLACE(cc.date, ',', '')) + 1) AS checkin_count,
   SUM(tip.tip_count) as tip_count
FROM
   business b
LEFT JOIN
   checkin cc ON b.business_id = cc.business_id
LEFT JOIN
   (select business_id, count(business_id) as tip_count from tip GROUP BY business_id ORDER BY tip_count) as tip on b.business_id =
tip.business_id
WHERE b.business_id IN {tuple(business_id['business_id'])}
GROUP BY
   b.business_id) as total

GROUP BY total.avg_rating

""",conn)
display(review_count_df)

colors = ['#FFF1E5','#F8862C", "#CB754B"]
custom_cmap = LinearSegmentedColormap.from_list("mycmap", colors)
sns.heatmap(review_count_df.corr(), cmap = custom_cmap, annot = True, linewidths=0.5, linecolor = 'black')

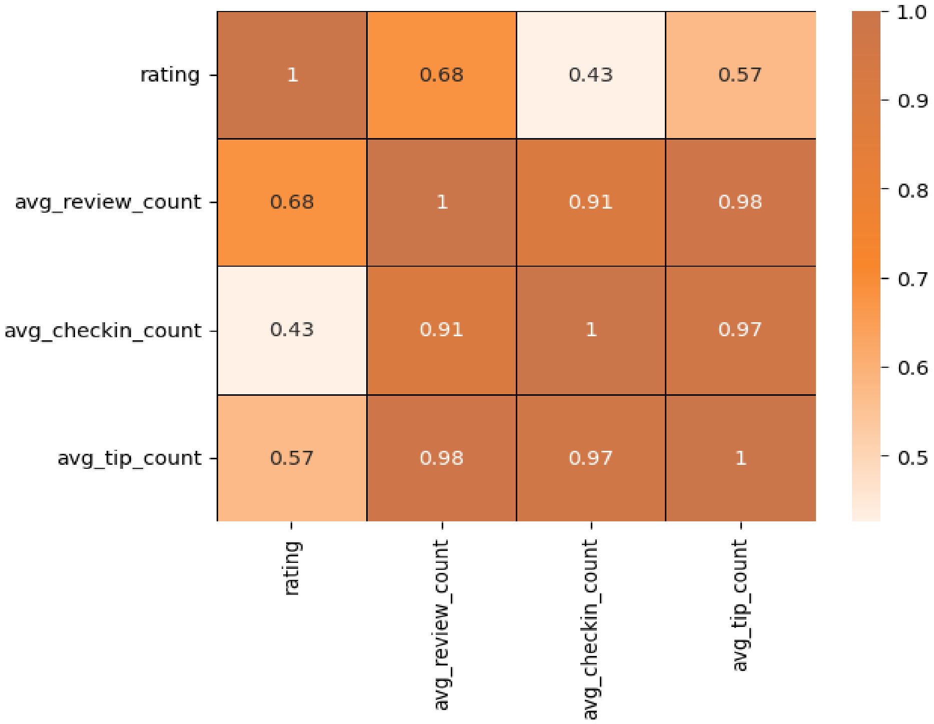
plt.figure(figsize=(15,5))
plt.title('AVG Engagement based on Rating\n\n')
plt.yticks([])
```

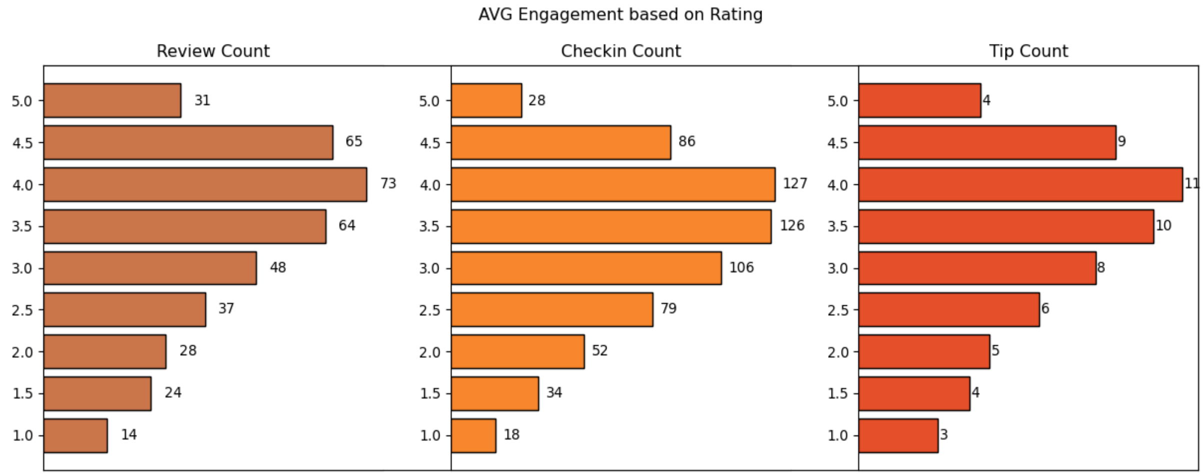
```
plt.xticks([])
plt.subplot(1,3,1)
plt.title('Review Count')
plt.barh(review_count_df['rating'].astype('str'), review_count_df['avg_review_count'], edgecolor = 'k', color = '#CB754B')
plt.gca().spines['right'].set_visible(False)
for i, value in enumerate(review_count_df['avg_review_count']):
    plt.text(value+3, i, str(round(value)), color='black', va='center')

plt.xticks([])
plt.subplot(1,3,2)
plt.title('Checkin Count')
plt.barh(review_count_df['rating'].astype('str'), review_count_df['avg_checkin_count'], edgecolor = 'k', color = '#F8862C')
plt.gca().spines['right'].set_visible(False)
for i, value in enumerate(review_count_df['avg_checkin_count']):
    plt.text(value+3, i, str(round(value)), color='black', va='center')

plt.xticks([])
plt.subplot(1,3,3)
plt.title('Tip Count')
plt.barh(review_count_df['rating'].astype('str'), review_count_df['avg_tip_count'], edgecolor = 'k',color='#E54F29')
for i, value in enumerate(review_count_df['avg_tip_count']):
    plt.text(value+0.05, i, str(round(value)), color='black', va='center')
plt.xticks([])
plt.show()
```

	rating	avg_review_count	avg_checkin_count	avg_tip_count
0	1.0	14.365079	17.518072	2.781513
1	1.5	24.358459	34.480969	3.884654
2	2.0	27.759629	52.386515	4.581058
3	2.5	36.631037	79.349429	6.325225
4	3.0	48.054998	105.970405	8.301950
5	3.5	63.730125	125.781702	10.320786
6	4.0	73.136954	127.139075	11.329362
7	4.5	65.282554	86.177605	8.995201
8	5.0	31.127979	27.545113	4.269082





- Data shows a general increase in average review, check-in, and tip counts as ratings improve from 1 to 4 stars.
- Restaurants rated 4 stars exhibit the highest engagement across reviews, check-ins, and tips, suggesting a peak in user interaction.
- Interestingly, engagement metrics (reviews, check-ins, tips) dip for restaurants rated 4.5 and significantly more at 5 stars.
- The drop in engagement at 5.0 stars might suggest either a saturation point where fewer customers feel compelled to add their reviews, or a selectivity where only a small, satisfied audience frequents these establishments.

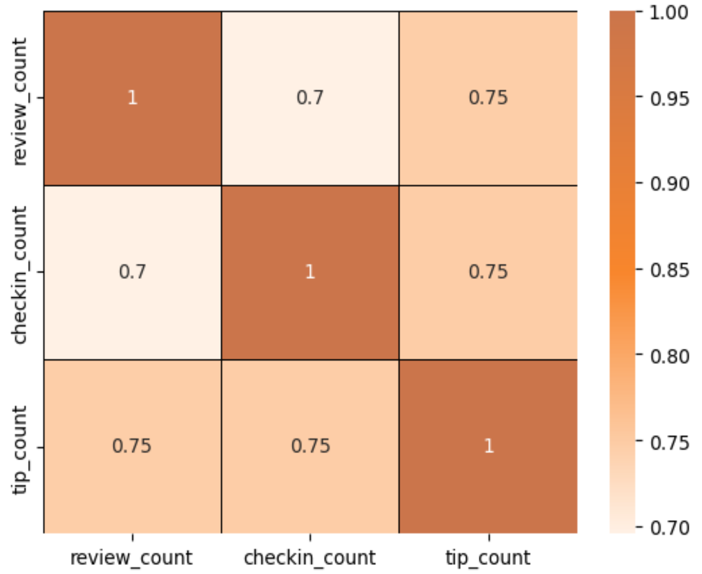
```
# Is there a correlation between the number of reviews, tips, and check-ins for a business?
engagement_df = pd.read_sql_query(f"""SELECT
    b.business_id,
    SUM(b.review_count) AS review_count,
    AVG(b.stars) AS avg_rating,
    SUM(LENGTH(cc.date) - LENGTH(REPLACE(cc.date, ',', '')) + 1) AS checkin_count,
    SUM(tip.tip_count) as tip_count,
    (CASE WHEN b.stars >= 3.5 THEN 'High-Rated' ELSE 'Low-Rated' END)  as rating_category
FROM
    business b
LEFT JOIN
    checkin cc ON b.business_id = cc.business_id
LEFT JOIN
    (select business_id, count(business_id) as tip_count from tip GROUP BY business_id ORDER BY tip_count) as tip on b.business_id =
tip.business_id
WHERE b.business_id IN {tuple(business_id['business_id'])}
GROUP BY
    b.business_id
ORDER BY
    review_count DESC,
    checkin_count DESC;
""",conn).dropna()

engagement_df = remove_outliers(engagement_df,'checkin_count')
display(engagement_df)
sns.heatmap(engagement_df[['review_count','checkin_count','tip_count']].corr(), cmap = custom_cmap, annot = True, linewidths=0.5, linecolor =
'black')
```

	business_id	review_count	avg_rating	checkin_count \
14	30OhTA38fp8xuqW4O2D6Eg	248	4.0	296.0
15	Aw9Tldxcg5ifodzn0R2O6g	248	4.0	252.0
16	9iSoPNBV54dj6L0rxO4RWw	248	3.5	219.0
17	HI1zbZuujFH9yPBKP1GH6g	248	4.5	214.0
18	7dbUShu3yTUVNhTrdnF0FQ	248	4.0	166.0
...	...	...	...	...
31389	v2xhzKIW-1bySJw5UPy8Jw	5	2.5	1.0
31392	wp_fwjX8JJC85F-sgb7ASg	5	5.0	1.0
31393	x3eNFvMD1LaqpBnJSD6A9Q	5	3.0	1.0
31397	yeJAs2OrnRRhsbywHPGMeQ	5	5.0	1.0
31398	z00F0RSAGimvSU9IrTevOw	5	1.0	1.0

```
      tip_count rating_category
14         14.0      High-Rated
15         18.0      High-Rated
16          7.0      High-Rated
17         21.0      High-Rated
18         16.0      High-Rated
...         ...             ...
31389       1.0       Low-Rated
31392       1.0      High-Rated
31393       1.0       Low-Rated
31397       3.0      High-Rated
31398       1.0       Low-Rated

[25473 rows x 6 columns]
<Axes: >
```




```
# Is there a difference in the user engagement (reviews, tips, and check-ins) between high-rated and low-rated businesses?
engagement_df.groupby('rating_category')[['review_count', 'checkin_count', 'tip_count']].mean()
                 review_count  checkin_count  tip_count
rating_category
High-Rated          63.099378       80.71859   8.069794
Low-Rated           37.152862       64.84321   5.456341
```

- The dataset shows a strong positive correlation among review counts, check-in counts, and tip counts.
- These correlations suggest that user engagement across different platforms (reviews, tips, and check-ins) is interlinked; higher activity in one area tends to be associated with higher activity in others.
- Businesses should focus on strategies that boost all types of user engagement, as increases in one type of engagement are likely to drive increases in others, enhancing overall visibility and interaction with customers.

```
# function to calculate the success score based on the avg rating and total review count
def calculate_success_metric(df):
    success_score = []
    for index, row in df.iterrows():
        score = row['avg_rating'] * np.log(row['review_count'] + 1)
        success_score.append(score)
    return success_score
# How do the success metrics (review_count or avg_rating) of restaurants vary across different states and cities?

city_df = pd.read_sql_query(f"""SELECT state,city, latitude, longitude, AVG(stars) AS avg_rating, SUM(review_count) as review_count,
COUNT(*) as restaurant_count
FROM business
WHERE business_id IN {tuple(business_id['business_id'])}
```

```
GROUP BY state, city
ORDER BY review_count DESC
limit 10;""",conn)


city_df['success_score'] = calculate_success_metric(city_df)
display(city_df)
# Create a base map
m = folium.Map(location=[city_df['latitude'].mean(), city_df['longitude'].mean()], zoom_start=4)

# Define a color scale
color_scale = folium.LinearColormap(colors=['green', 'yellow', '#E54F29'],
                                    vmin=city_df['success_score'].min(),
                                    vmax=city_df['success_score'].max())

# Add markers to the map
for index, row in city_df.iterrows():
    folium.CircleMarker(
        location=[row['latitude'], row['longitude']],
        radius=5,
        color=color_scale(row['success_score']),
        fill=True,
        fill_color=color_scale(row['success_score']),
        fill_opacity=0.7,
        popup=f"Success Score: {row['success_score']}"
    ).add_to(m)

# Add color scale to the map
m.add_child(color_scale)
```

```
  state          city   latitude   longitude  avg_rating  review_count  \
0    PA  Philadelphia  39.955505  -75.155564    3.532156        175487
1    FL         Tampa  27.890814  -82.502346    3.571429        104376
2    IN  Indianapolis  39.637133  -86.127217    3.412111         92639
3    AZ        Tucson  32.338572 -111.010760    3.386187         91613
4    TN     Nashville  36.208102  -86.768170    3.493590         87070
5    LA   New Orleans  29.963974  -90.042604    3.693676         69239
6    MO   Saint Louis  38.583223  -90.407187    3.414303         51490
7    NV          Reno  39.476518 -119.784037    3.479626         48393
8    AB      Edmonton  53.436403 -113.604288    3.509379         45916
9    ID         Boise  43.611192 -116.206275    3.558824         36104

   restaurant_count  success_score
0              3001      42.651934
1              1715      41.270588
2              1701      39.022521
3              1419      38.688341
4              1404      39.737764
5              1012      41.167252
6               811      37.042331
7               589      37.535187
8              1546      37.671748
9               561      37.346958
<folium.folium.Map at 0x156514e50>
```

- Philadelphia emerges as the top city with the highest success score, indicating a combination of high ratings and active user engagement.
- Following Philadelphia, Tampa, Indianapolis, and Tucson rank among the top cities with significant success scores, suggesting thriving restaurant scenes in these areas.
- The success metrics vary significantly across different states and cities, highlighting regional differences in dining preferences, culinary scenes, and customer engagement levels.

- Identifying cities with high success scores presents opportunities for restaurant chains to expand or invest further, while areas with lower scores may require targeted efforts to improve ratings and increase user engagement.

```
# Are there any patterns in user engagement over time for successful businesses compared to less successful ones?
#  Are there any seasonal trends in the user engagement for restaurants?

high_rated_engagement = pd.read_sql_query(f"""
SELECT review.month_year, review.review_count, tip.tip_count FROM
(SELECT strftime('%m-%Y', date) AS month_year, COUNT(*) AS review_count
FROM review
WHERE business_id IN {tuple(business_id['business_id'])} and stars >= 3.5
GROUP BY month_year
ORDER BY month_year) as review
JOIN
(SELECT AVG(b.stars), strftime('%m-%Y', tip.date) AS month_year, COUNT(*) AS tip_count
FROM tip
JOIN business as b
on tip.business_id = b.business_id
WHERE tip.business_id IN {tuple(business_id['business_id'])} and b.stars >= 3.5
GROUP BY month_year
ORDER BY month_year) as tip

on review.month_year = tip.month_year
;""",conn)

low_rated_engagement = pd.read_sql_query(f"""
SELECT review.month_year, review.review_count, tip.tip_count FROM
(SELECT strftime('%m-%Y', date) AS month_year, COUNT(*) AS review_count
FROM review
WHERE business_id IN {tuple(business_id['business_id'])} and stars < 3.5
GROUP BY month_year
ORDER BY month_year) as review
JOIN
(SELECT AVG(b.stars), strftime('%m-%Y', tip.date) AS month_year, COUNT(*) AS tip_count
FROM tip
JOIN business as b
on tip.business_id = b.business_id
WHERE tip.business_id IN {tuple(business_id['business_id'])} and b.stars < 3.5
GROUP BY month_year
ORDER BY month_year) as tip

on review.month_year = tip.month_year
;""",conn)

time_rating = pd.read_sql_query(f"""SELECT strftime('%m-%Y', date) AS month_year, AVG(stars) as avg_rating
FROM review
WHERE business_id IN {tuple(business_id['business_id'])}
GROUP BY month_year
ORDER BY month_year
;""",conn)
time_rating['month_year'] = pd.to_datetime(time_rating['month_year'])
time_rating.sort_values('month_year',inplace = True)
time_rating = time_rating[time_rating['month_year']>'2017']

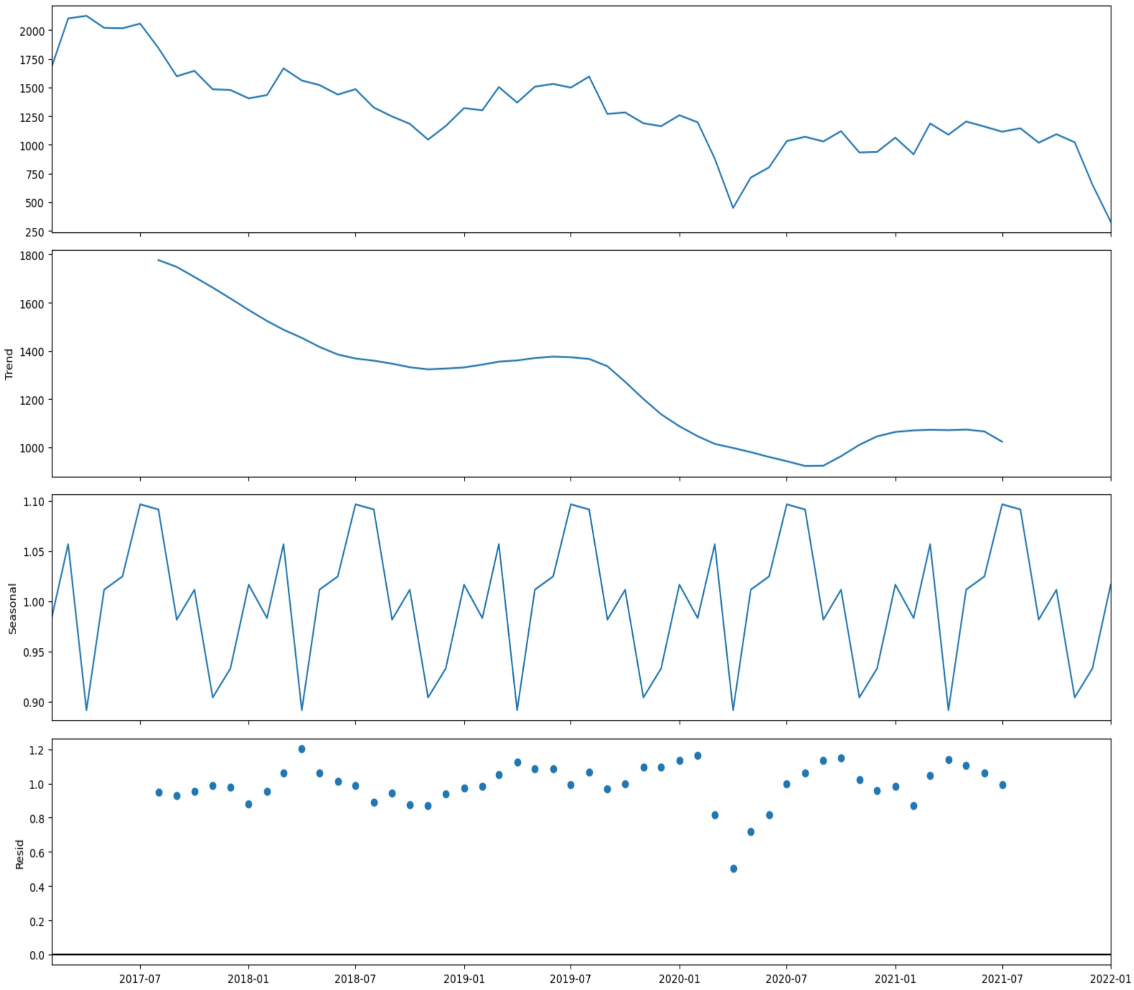
high_rated_engagement['month_year'] = pd.to_datetime(high_rated_engagement['month_year'])
high_rated_engagement.sort_values('month_year',inplace = True)
high_rated_engagement = high_rated_engagement[high_rated_engagement['month_year']>'2017']

low_rated_engagement['month_year'] = pd.to_datetime(low_rated_engagement['month_year'])
low_rated_engagement.sort_values('month_year',inplace = True)
low_rated_engagement = low_rated_engagement[low_rated_engagement['month_year']>'2017']
```

```
high_rated_engagement['avg_rating'] = time_rating['avg_rating'].values

plt.figure(figsize = (15,8))
plt.subplot(3,1,1)
plt.title('Tip Engagement Over Time')
plt.plot(high_rated_engagement['month_year'],high_rated_engagement['tip_count'], label = 'High Rated', color = '#E54F29')
plt.plot(low_rated_engagement['month_year'],low_rated_engagement['tip_count'], label = 'low Rated',color = '#F8862C')
plt.legend()
plt.subplot(3,1,2)
plt.title('Review Engagement Over Time')
plt.plot(high_rated_engagement['month_year'],high_rated_engagement['review_count'], label = 'High Rated', color = '#E54F29')
plt.plot(low_rated_engagement['month_year'],low_rated_engagement['review_count'],  label = 'Low Rated', color = '#F8862C')
plt.legend()
plt.subplot(3,1,3)
plt.title('Avg Rating Over Time')
plt.plot(time_rating['month_year'],time_rating['avg_rating'], color = '#E54F29')
plt.tight_layout()
plt.show()
```


```
tip_high_rated = high_rated_engagement[['month_year','tip_count']].set_index('month_year')
review_high_rated = high_rated_engagement[['month_year','review_count']].set_index('month_year')
rating_df = time_rating[['month_year','avg_rating']].set_index('month_year')
from statsmodels.tsa.seasonal import seasonal_decompose
multiplicative_decomposition = seasonal_decompose(tip_high_rated,
                                     model='multiplicative', period = 12)
plt.rcParams.update({'figure.figsize': (16,12)})
multiplicative_decomposition.plot()
plt.show()
```




```
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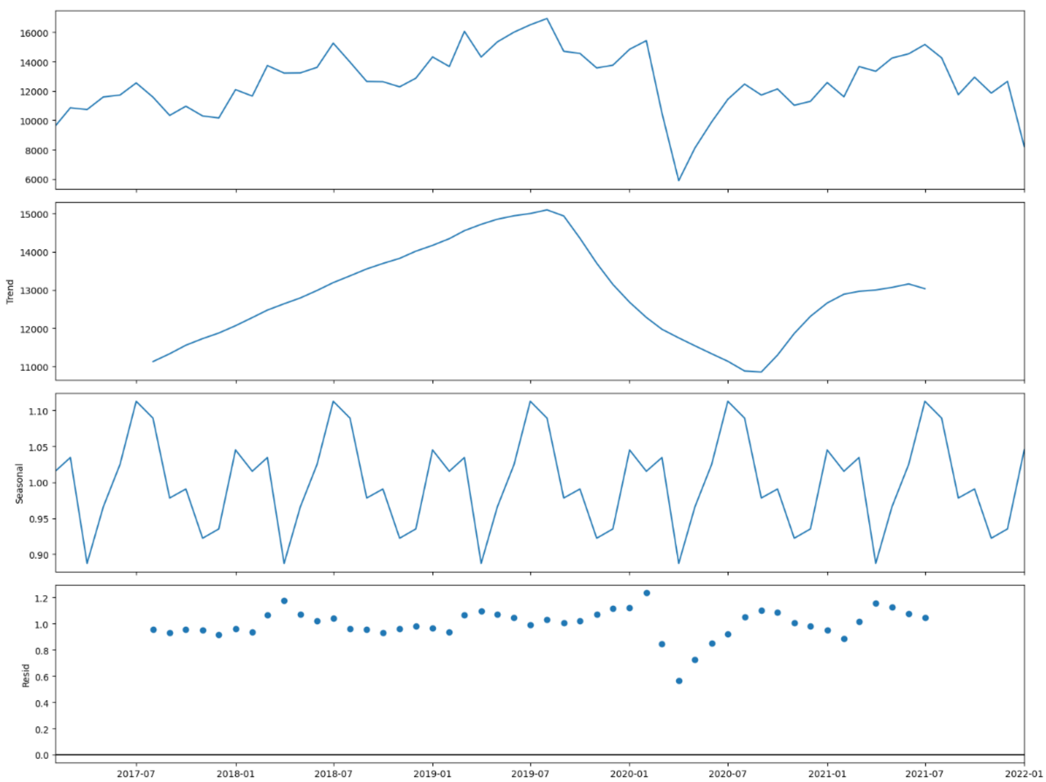


- Successful businesses, particularly those with higher ratings (above 3.5), exhibit consistent and possibly increasing user engagement over time.
- High rated restaurants maintain a steady or growing level of user engagement over time, reflecting ongoing customer interest and satisfaction.
- Tip count is showing a downward trend whereas review count is showing an upward trend with time.
- Year starting and year ending from around November and March is highly engaging and seasonal.

```
# How does the sentiment of reviews and tips (useful, funny, cool) correlate with the success metrics of restaurants?
sentiment_df = pd.read_sql_query(f"""SELECT b.business_id, AVG(b.stars) as avg_rating, SUM(b.review_count) as review_count,
SUM(s.useful_count) as useful_count,
SUM(s.funny_count) as funny_count,
SUM(s.cool_count) as cool_count
FROM
(SELECT business_id,
   SUM(useful) as useful_count,
   SUM(funny) as funny_count,
   SUM(cool) as cool_count
FROM
   review
GROUP BY business_id) as s
JOIN business as b on b.business_id = s.business_id

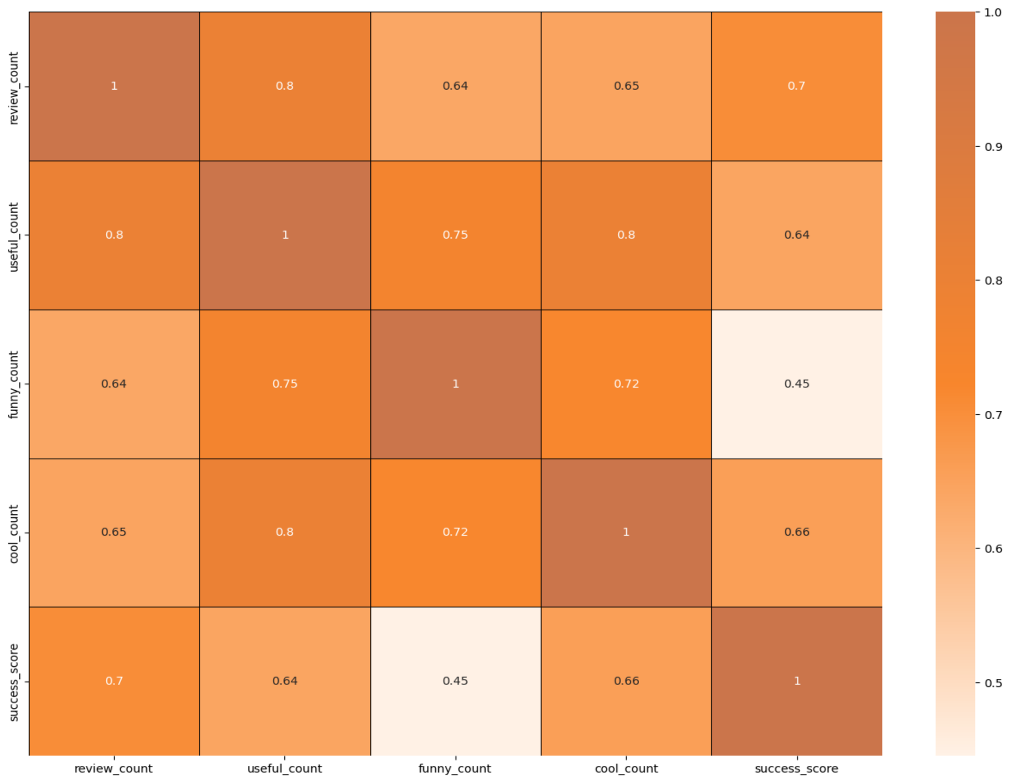
WHERE b.business_id IN {tuple(business_id['business_id'])}
GROUP BY b.business_id
ORDER BY review_count""",conn)

sentiment_df = remove_outliers(sentiment_df,'review_count')
sentiment_df = remove_outliers(sentiment_df,'useful_count')
sentiment_df = remove_outliers(sentiment_df,'funny_count')
sentiment_df = remove_outliers(sentiment_df,'cool_count')

sentiment_df['success_score'] = calculate_success_metric(sentiment_df)

sns.heatmap(sentiment_df.iloc[:,2:].corr(), cmap = custom_cmap, annot = True, linewidths=0.5, linecolor = 'black')

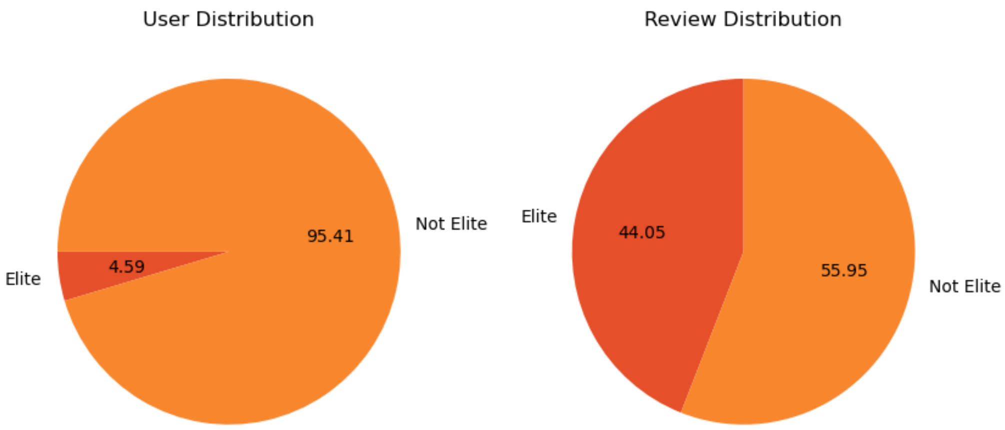
plt.show()
```



- “useful, " "funny, " and "cool" are attributes associated with user reviews. They represent the feedback provided by users about the usefulness, humor, or coolness of a particular review.
- Higher counts of useful, funny, and cool reviews suggest greater user engagement and satisfaction, which are key factors contributing to a restaurant's success.

```
# Is there any difference in engagement of elite users and non elite users?
elite_df = pd.read_sql_query("""SELECT
   elite,
   COUNT(*) AS row_count,
   SUM(review_count) AS total_review_count
FROM
   (SELECT
      CASE
         WHEN elite = '' THEN 'Not Elite'
         ELSE 'Elite'
      END AS elite,
      u.review_count
   FROM
      user u) AS user_elite
GROUP BY
   elite;
""",conn)
elite_df
     elite  row_count  total_review_count
0     Elite      91198            20484441
1  Not Elite   1896699            26021235
plt.figure(figsize=(10,6))
plt.subplot(1,2,1)
plt.title('User Distribution')
plt.pie(elite_df['row_count'], labels = elite_df['elite'], autopct='%.2f', startangle = 180, colors = ['#E54F29','#F8862C'])

plt.subplot(1,2,2)
plt.title('Review Distribution')
plt.pie(elite_df['total_review_count'], labels = elite_df['elite'], autopct='%.2f', startangle = 90, colors = ['#E54F29','#F8862C'])
plt.show()
```



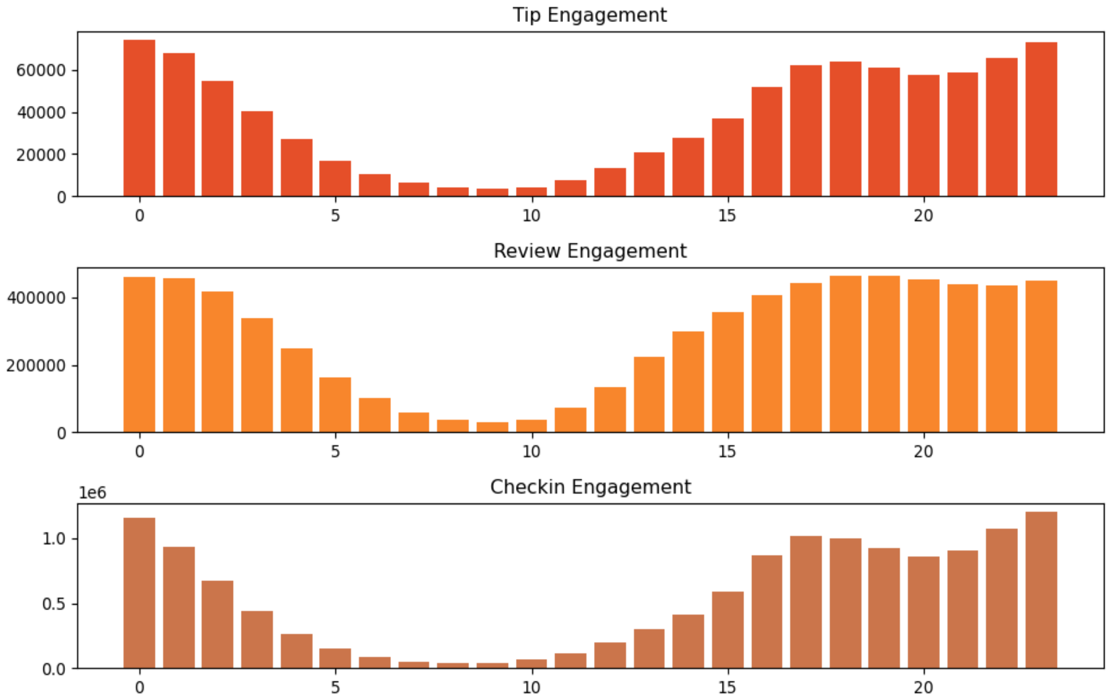
- Elite users are individuals who have been recognized and awarded the "Elite" status by Yelp for their active and high-quality contributions to the platform, such as frequent and detailed reviews, photos, and check-ins, among other criteria.
- Elite users, despite being significantly fewer in number, contribute a substantial proportion of the total review count compared to non-elite users.
- Elite users often provide detailed and insightful reviews, which can influence other users' perceptions and decisions regarding a business.
- Reviews from elite users may receive more attention and visibility on the Yelp platform due to their status, potentially leading to higher exposure for businesses.
- Establishing a positive relationship with elite users can lead to repeat visits and loyalty, as they are more likely to continue supporting businesses they have had good experiences with.

```
# What are the busiest hours for restaurants?
review_engagement = pd.read_sql_query("""SELECT
  cast (strftime('%H',date) as integer)
  as hour,
  COUNT(*) AS review_count
FROM
  review
GROUP BY
  hour;
""",conn)

tip_engagement = pd.read_sql_query("""SELECT
  cast (strftime('%H',date) as integer)
  as hour,
  COUNT(*) AS tip_count
FROM
  tip
GROUP BY
  hour;
""",conn)

checkin =  pd.read_sql_query("""SELECT date FROM checkin""",conn)
checkin_engagement = []
for i in checkin['date']:
    checkin_engagement.extend([datetime.strptime(j.strip(),"%Y-%m-%d %H:%M:%S").strftime("%H") for j in i.split(',')])

checkin_engagement = pd.DataFrame(checkin_engagement).astype('int').groupby(0)[[0]].count()
plt.figure(figsize = (10,6))
plt.subplot(3,1,1)
plt.title('Tip Engagement')
plt.bar(tip_engagement['hour'],tip_engagement['tip_count'], color = '#E54F29')
plt.subplot(3,1,2)
plt.title('Review Engagement')
plt.bar(review_engagement['hour'],review_engagement['review_count'], color = '#F8862C')
plt.subplot(3,1,3)
plt.title('Checkin Engagement')
plt.bar(checkin_engagement.index,checkin_engagement[0], color = '#CB754B')
plt.tight_layout()
plt.show()
```



- The busiest hours for restaurants, based on user engagement, span from 4 pm to 1 am.
- Knowing the peak hours allows businesses to optimize their staffing levels and resource allocation during these times to ensure efficient operations and quality service delivery.
- The concentration of user engagement during the evening and night hours suggests a higher demand for dining out during these times, potentially driven by factors such as work schedules, social gatherings, and leisure activities.

Recommendations :

- Utilizing insights from the analysis of various metrics such as user engagement, sentiment of reviews, peak hours, and the impact of elite users, businesses can make informed decisions to drive success.
- Understanding customer preferences, behavior, and satisfaction levels is paramount. Businesses should focus on delivering exceptional experiences to meet customer expectations.
- By leveraging data on peak hours and user engagement, businesses can optimize staffing levels, resource allocation, and operating hours to ensure efficiency and quality service delivery during high-demand periods.
- Positive reviews from elite users and high user engagement can boost a business's online visibility and reputation. Maintaining active engagement with customers and responding promptly to feedback is crucial for building credibility and attracting new customers.
- Collaborating with elite users and leveraging their influence can amplify promotional efforts, increase brand awareness, and drive customer acquisition. Building strong relationships with key stakeholders, including loyal customers, can further strengthen a business's position in the market.
- Businesses can adjust their operating hours or introduce special promotions to capitalize on the increased demand during peak hours.
- Less successful businesses may need to focus on strategies to enhance user engagement over time, such as improving service quality, responding to customer feedback.
- Cities with high success scores presents opportunities for restaurant chains to expand or invest further.

Acknowledgements

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