cafe_feedback_exploration

November 19, 2025

1 Cafe Feedback Exploration & Walkthrough

This notebook captures the thinking, data processing steps, and exploratory visuals that underpin the Streamlit dashboard.

1.1 Walkthrough & Process

- **Goal**: surface hard (ratings, spend) and soft (comments) signals for cafe locations, and deliver actionable insights.
- **Steps taken**: inspect raw schema -> normalise Location strings -> parse/clean ratings and currency -> coerce timestamps -> derive calendar fields -> profile distributions for each column -> build visuals.
- **Why this matters**: the raw file contains stray spaces in locations and timestamp-like strings in Transaction Value; without cleaning, filters and spend averages become misleading. Keeping cleaning documented here keeps the dashboard uncluttered.
- **How to refresh**: rerun this notebook on new drops; cleaned outputs and charts will stay in sync with the app.

1.2 Quick explanation of data processing

- Drop empty Unnamed columns; coerce Rating to numeric.
- Strip/collapse whitespace in Location to merge duplicates (e.g., Albany -> Albany).
- Parse Transaction Value as currency, strip $/commas, and discard impossible spends (<=0 or >) to remove timestamp artefacts.
- Parse Transaction Date and Time as day-first datetime; derive Date and DayName for trend views.
- Persist these steps so dashboard filters and aggregates stay realistic.

[48]:
```
import re
from pathlib import Path

import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns

sns.set_theme()

DATA_FILE = Path("Sample data - Cafe - Sample data 2400 records.csv")
raw_df = pd.read_csv(DATA_FILE)
```

```
raw_df.head()
```

[48]:
```
              Location  Rating  \
0               Domain       5
1               Timaru       5
2           Upper Hutt       5
3   Wellington central       4
4            Henderson       5

                                             Comment  \
0  Awesome, friendly staff, they all are smiling …
1                                        The service
2  The staff are fabulous and neither is too much…
3            More dairy + gluten free food options.
4           Friendly welcoming staff always smiling

  Transaction Date and Time Transaction Value feedback_id Unnamed: 6  \
0     19/10/2024 6:03:00 AM            $19.50     4974583        NaN
1     19/10/2024 6:09:00 AM            $19.17     4974584        NaN
2     19/10/2024 6:13:00 AM            $10.60     4974586        NaN
3     19/10/2024 6:21:00 AM             $4.00     4974587        NaN
4     19/10/2024 6:43:00 AM             $5.50     4974591        NaN

   Unnamed: 7
0         NaN
1         NaN
2         NaN
3         NaN
4         NaN
```

1.3 Raw exploration before cleaning

- Visualise raw values first to spot anomalies that drive cleaning decisions.

[49]:
```
# Raw distributions prior to cleaning
raw_location_counts = raw_df["Location"].value_counts()
print("Locations")
display(raw_location_counts)

# Duplicate locations due to extra spaces
normalized_locations = raw_df.assign(
    NormalizedLocation=raw_df["Location"].astype(str).str.strip()
)
dup_location_table = (
    normalized_locations.groupby("NormalizedLocation", dropna=False)
    .agg(
        sample_raw=("Location", "first"),
```

```
        occurrences=("Location", "size"),
        unique_raw_variants=("Location", "nunique"),
    )
    .reset_index()
    .rename(
        columns={
            "NormalizedLocation": "Location (duplicate)",
            "sample_raw": "Raw location sample",
            "occurrences": "Occurrences",
            "unique_raw_variants": "Unique raw variants",
        }
    )
)
dup_location_table = (
    dup_location_table[dup_location_table["Unique raw variants"] > 1]
    .sort_values("Occurrences", ascending=False)
    .drop(columns="Unique raw variants")
)
print("\nDuplicated location table:")
display(dup_location_table)

# Transaction Value: non-currency patterns
raw_txn_strings = raw_df["Transaction Value"]
print("\nExamples of transaction values containing non-currency patterns:")
display(raw_txn_strings[raw_txn_strings.str.contains("/", na=True)])

# Transaction Value: numeric outliers
raw_txn_numeric = pd.to_numeric(
    raw_txn_strings.str.replace("[^0-9.]", "", regex=True), errors="coerce"
)
anomaly_upper_threshold = 500
anomaly_lower_threshold = 0
anomalies = raw_txn_numeric[
    (raw_txn_numeric > anomaly_upper_threshold) | (raw_txn_numeric <=␣
 ↪anomaly_lower_threshold)
].sort_values(ascending=False)
print(f"{len(anomalies)} raw transaction values are outside the expected range␣
 ↪[0, {anomaly_upper_threshold}]")
display(anomalies)


# Ratings: value counts and out-of-range/missing
rating_raw = raw_df['Rating']
print('Rating value counts (raw):')
display(rating_raw.value_counts(dropna=False))
rating_numeric = pd.to_numeric(rating_raw, errors='coerce')
```

```
rating_anomalies = rating_raw[(rating_numeric.isna()) | (rating_numeric < 1) |␣
↪(rating_numeric > 5)]
print(f"{len(rating_anomalies)} ratings are missing or outside 1-5")
display(rating_anomalies)

# Transaction Date and Time: non-parsable examples
raw_dates = raw_df["Transaction Date and Time"]
standard_format = "%d/%m/%Y %I:%M:%S %p"
parsed_dates = pd.to_datetime(raw_dates, format=standard_format,␣
↪errors="coerce")
bad_dates = raw_dates[parsed_dates.isna()]
print(f"{len(bad_dates)} transaction datetime values could not be parsed")
display(bad_dates)

# feedback_id: blanks, non-numeric, duplicates
feedback_raw = raw_df['feedback_id'].astype(str).str.strip()
bad_feedback = feedback_raw[(feedback_raw == '') | (~feedback_raw.str.
↪match(r'^\d+$'))]
print(f"{len(bad_feedback)} feedback_id values are non-numeric")
display(bad_feedback)
dup_feedback = feedback_raw[feedback_raw.duplicated(keep=False)]
print(f"{len(dup_feedback)} feedback_id values are duplicates")
display(dup_feedback)

# Blank unnamed columns
cols_to_display = raw_df.columns[6:9]
print(f"Inspecting columns (6th & 7th): {cols_to_display.tolist()}")
preview_cols = (
    raw_df[cols_to_display]
    .astype("object")
    .sort_values(by=cols_to_display.tolist(), ascending=False)
    .head(10)
)
display(preview_cols)
```

```
Locations

Location
Wanganui           54
Rangiora           51
Palmerston Nth     48
Palmerston Nth     47
Kapiti             47
                   ..
Whakatane          15
Henderson          12
Pukekohe           11
Lincoln Road        7
```

```
Queen Street        2
Name: count, Length: 75, dtype: int64

Duplicated location table:

   Location (duplicate) Raw location sample  Occurrences
40       Palmerston Nth     Palmerston Nth            95
22         Invercargill      Invercargill             77
34               Nelson             Nelson            77
5                Botany             Botany            63
51              Rotorua             Rotorua           60
0                Albany            Albany             55
44             Pukekohe           Pukekohe            49
20            Henderson           Henderson           38

Examples of transaction values containing non-currency patterns:

509    20/10/2020 8:24:00 AM
Name: Transaction Value, dtype: object

92 raw transaction values are outside the expected range [0, 500]

509     2.010202e+12
2362    2.410201e+11
1986    2.310201e+11
1556    2.210201e+11
1249    2.210201e+11
            …
2269    0.000000e+00
2293    0.000000e+00
2340    0.000000e+00
2367    0.000000e+00
2393    0.000000e+00
Name: Transaction Value, Length: 92, dtype: float64

Rating value counts (raw):

Rating
5    1980
4     335
3      68
2      16
1       8
Name: count, dtype: int64

0 ratings are missing or outside 1-5

Series([], Name: Rating, dtype: int64)

5 transaction datetime values could not be parsed
```

```
509                          WEB
1249    kim.wise@auckland.ac.nz
1556        robsued47@gmail.com
1986         tkmolloy@gmail.com
2362          lynn.m@xtra.co.nz
Name: Transaction Date and Time, dtype: object
```

```
5 feedback_id values are non-numeric
```

```
509        16.1
1249    WJZPJCF
1556    NFTUTGH
1986    MTKPDCF
2362    MFFPYCF
Name: feedback_id, dtype: object
```

```
0 feedback_id values are duplicates
```

```
Series([], Name: feedback_id, dtype: object)
```

```
Inspecting columns (6th & 7th): ['Unnamed: 6', 'Unnamed: 7']
```

```
     Unnamed: 6 Unnamed: 7
509     DEPLHCF  4975742.0
2362    4979455        NaN
1986    4978775        NaN
1556    4977933        NaN
1249    4977334        NaN
0           NaN        NaN
1           NaN        NaN
2           NaN        NaN
3           NaN        NaN
4           NaN        NaN
```

Raw-data findings: - Locations appear multiple times due to extra space (e.g., Albany vs Albany). - Transaction Value includes timestamp-like strings (e.g., 20/10/2020 8:24:00 AM) and extreme magnitudes (e.g., 241020120707.0) that would inflate spend if unfiltered. - Transaction Date and Time has entries that are not datetime. - feedback_id includes non-numeric strings that should be cleaned. - 2 unnamed columns are almost entirely blank and can be removed. - These observed issues motivate the cleaning rules applied below.

[50]:
```
# Cleaning helpers
def parse_transaction(val):
    if pd.isna(val):
        return None
    s = str(val).strip()
    m = re.search(r"-?\$?\s*([0-9]{1,3}(?:,[0-9]{3})*|[0-9]+)(?:\.[0-9]{1,2})?
↪", s)
    if not m:
        return None
    try:
```

```
        v = float(re.sub(r"[,$]", "", m.group()))
    except ValueError:
        return None
    if v <= 0 or v > 500:
        return None
    return v

df = raw_df.copy()
df = df.loc[:, ~df.columns.str.contains("^Unnamed")]
df["Location"] = df["Location"].astype(str).str.strip().str.replace(r"\s+", "␣
 ↪", regex=True)
df["Rating"] = pd.to_numeric(df["Rating"], errors="coerce")
df["Transaction Value"] = df["Transaction Value"].apply(parse_transaction)
df["Transaction Date and Time"] = pd.to_datetime(df["Transaction Date and␣
 ↪Time"], dayfirst=True, errors="coerce")
df["Date"] = df["Transaction Date and Time"].dt.date
df["DayName"] = df["Transaction Date and Time"].dt.day_name()
df.dropna(subset=["Rating", "Transaction Value"], inplace=True)
df.head()
```

[50]:

```
             Location  Rating  \
0              Domain       5
1              Timaru       5
2          Upper Hutt       5
3  Wellington central       4
4           Henderson       5

                                            Comment  \
0  Awesome, friendly staff, they all are smiling …
1                                       The service
2  The staff are fabulous and neither is too much…
3              More dairy + gluten free food options.
4             Friendly welcoming staff always smiling

  Transaction Date and Time  Transaction Value feedback_id        Date  \
0       2024-10-19 06:03:00              19.50     4974583  2024-10-19
1       2024-10-19 06:09:00              19.17     4974584  2024-10-19
2       2024-10-19 06:13:00              10.60     4974586  2024-10-19
3       2024-10-19 06:21:00               4.00     4974587  2024-10-19
4       2024-10-19 06:43:00               5.50     4974591  2024-10-19

    DayName
0  Saturday
1  Saturday
2  Saturday
3  Saturday
4  Saturday
```

1.4 Categorical distributions (all categories printed)

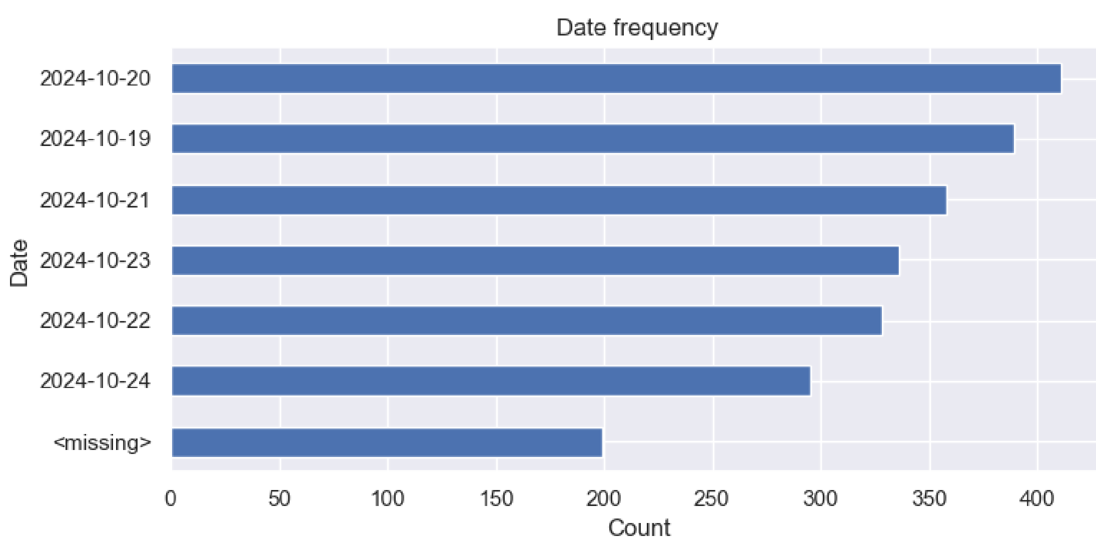
For each categorical-like column, the full value counts are displayed. Plots are shown when the category count is manageable.

[51]:
```
categorical_cols = []
numeric_cols = []

for col in df.columns:
    if pd.api.types.is_numeric_dtype(df[col]):
        numeric_cols.append(col)
    elif pd.api.types.is_datetime64_any_dtype(df[col]):
        categorical_cols.append(col)
    else:
        categorical_cols.append(col)

for col in categorical_cols:
    print(f"\n==== {col} (categorical-like) ====")
    vc = df[col].fillna("<missing>").value_counts()
    display(vc)
    if 1 < len(vc) <= 30:
        vc.sort_values().plot(kind="barh", title=f"{col} frequency",␣
 ↪figsize=(8, max(4, len(vc) * 0.25)))
        plt.xlabel("Count")
        plt.tight_layout()
        plt.show()
```

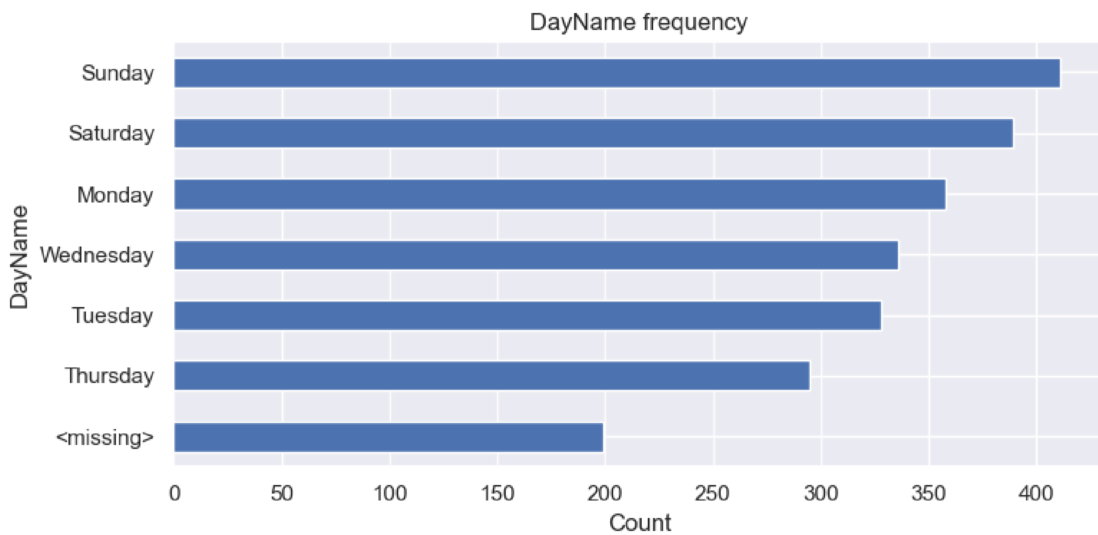
```
==== Location (categorical-like) ====

Location
Palmerston Nth    92
Invercargill      76
Nelson            75
Botany            62
Rotorua           59
                  ..
Williams Drive    16
Rosebank Road     15
Whakatane         14
Lincoln Road       7
Queen Street       1
Name: count, Length: 67, dtype: int64


==== Comment (categorical-like) ====

Comment
```

```
Great service                                                                    ␣
↪                                                                                ␣
↪                                            14
Friendly staff                                                                   ␣
↪                                                                                ␣
↪                                            13
Good service                                                                     ␣
↪                                                                                ␣
↪                                             9
Service                                                                          ␣
↪                                                                                ␣
↪                                             8
Friendly service                                                                 ␣
↪                                                                                ␣
↪                                             8
                                                                                 ␣
↪                                                                                ␣
↪                                            ..
The Muffin was very tasty.                                                       ␣
↪                                                                                ␣
↪                                             1
love the friendly staff at the Nelson shop, they're really awesome!              ␣
↪                                                                                ␣
↪                                             1
Engagement with the wait staff was warmer and friendly.                          ␣
↪                                                                                ␣
↪                                             1
Rob and the team are so lovely they welcomed me with a big smile and by name . I␣
↪go there all the time and they know what coffee I like and it have ready for␣
↪me by the time I get up to the counter .     1
Always clean with good selection of food. Fantastic coffee with friendly␣
↪personal service.                                                               ␣
↪                                                    1
Name: count, Length: 2185, dtype: int64


==== Transaction Date and Time (categorical-like) ====

Transaction Date and Time
<missing>              199
2024-10-24 09:28:00      7
2024-10-19 08:50:00      6
2024-10-21 09:27:00      6
2024-10-19 09:44:00      6
                      …
2024-10-24 11:13:00      1
2024-10-24 09:19:00      1
2024-10-23 08:57:00      1
```

```
2024-10-22 10:22:00      1
2024-10-24 10:14:00      1
Name: count, Length: 1260, dtype: int64


==== feedback_id (categorical-like) ====

feedback_id
4979626    1
4974583    1
4974584    1
4974586    1
4974587    1
          ..
4974621    1
4974622    1
4974623    1
4974625    1
4974626    1
Name: count, Length: 2316, dtype: int64


==== Date (categorical-like) ====

Date
2024-10-20    411
2024-10-19    389
2024-10-21    358
2024-10-23    336
2024-10-22    328
2024-10-24    295
<missing>     199
Name: count, dtype: int64
```



```
==== DayName (categorical-like) ====

DayName
Sunday       411
Saturday     389
Monday       358
Wednesday    336
Tuesday      328
Thursday     295
<missing>    199
Name: count, dtype: int64
```



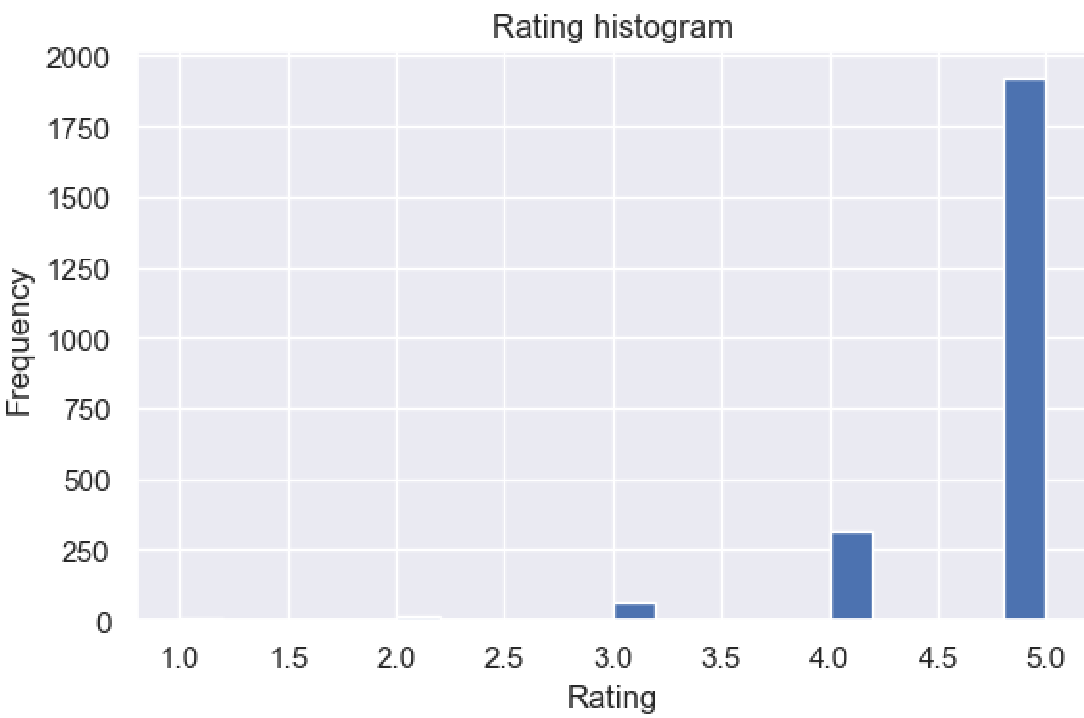
1.5 Numeric distributions

Descriptive stats and histograms for each numeric-like column.

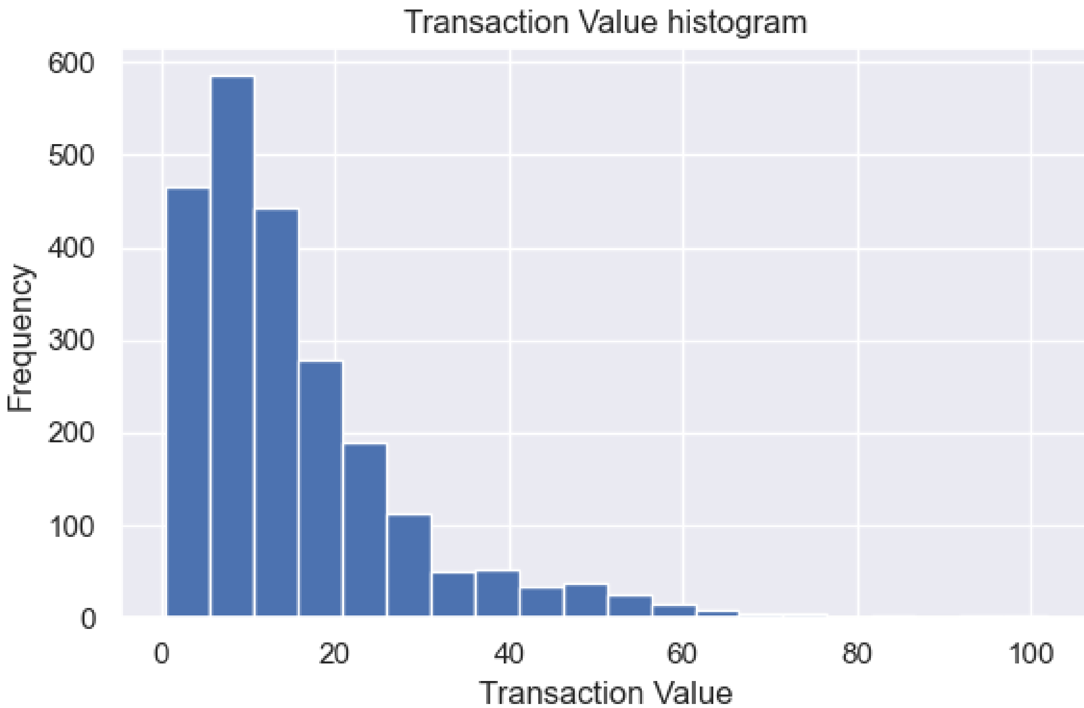
[52]:
```python
for col in numeric_cols:
    print(f"\n==== {col} (numeric-like) ====")
    series = df[col].dropna()
    display(series.describe())
    series.plot(kind="hist", bins=20, title=f"{col} histogram", figsize=(6,4))
    plt.xlabel(col)
    plt.tight_layout()
    plt.show()
```

```
==== Rating (numeric-like) ====
```

```
count    2316.000000
mean        4.779793
std         0.543445
min         1.000000
25%         5.000000
50%         5.000000
75%         5.000000
max         5.000000
Name: Rating, dtype: float64
```




```
==== Transaction Value (numeric-like) ====

count    2316.000000
mean       15.967414
std        12.962577
min         0.500000
25%         6.800000
50%        11.500000
75%        20.000000
max       102.000000
Name: Transaction Value, dtype: float64
```

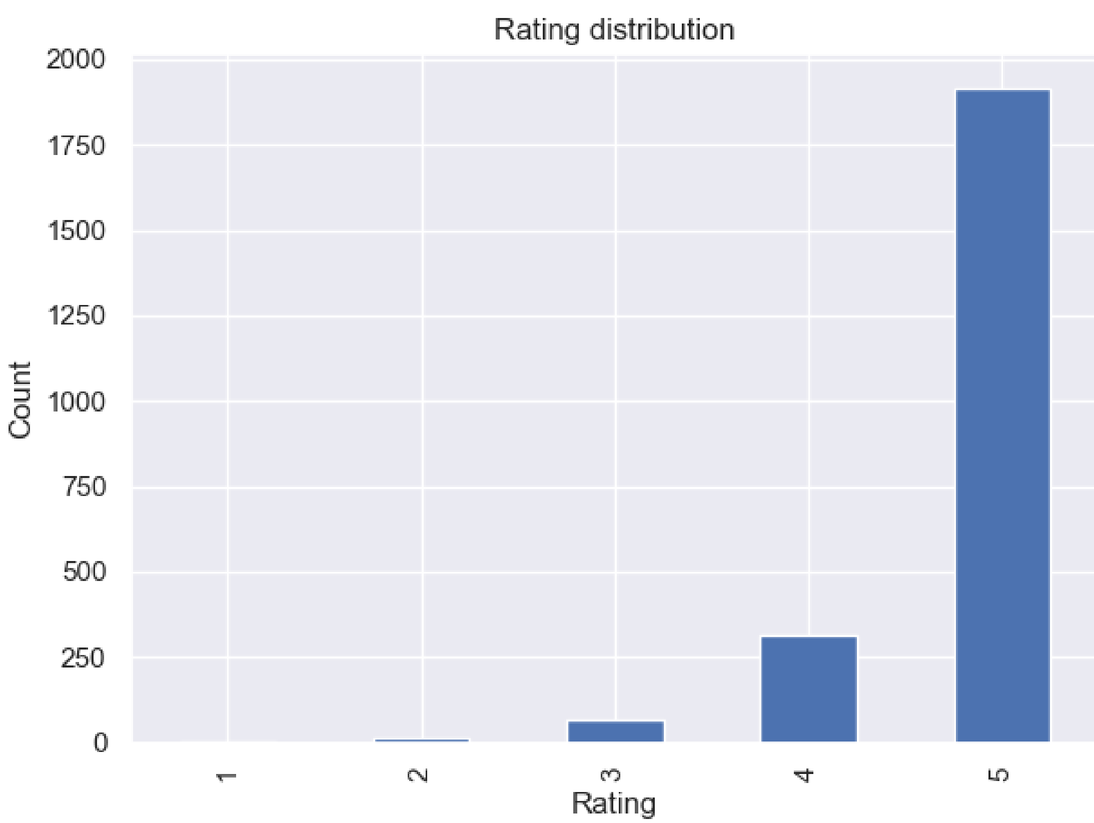


1.6 Targeted visuals

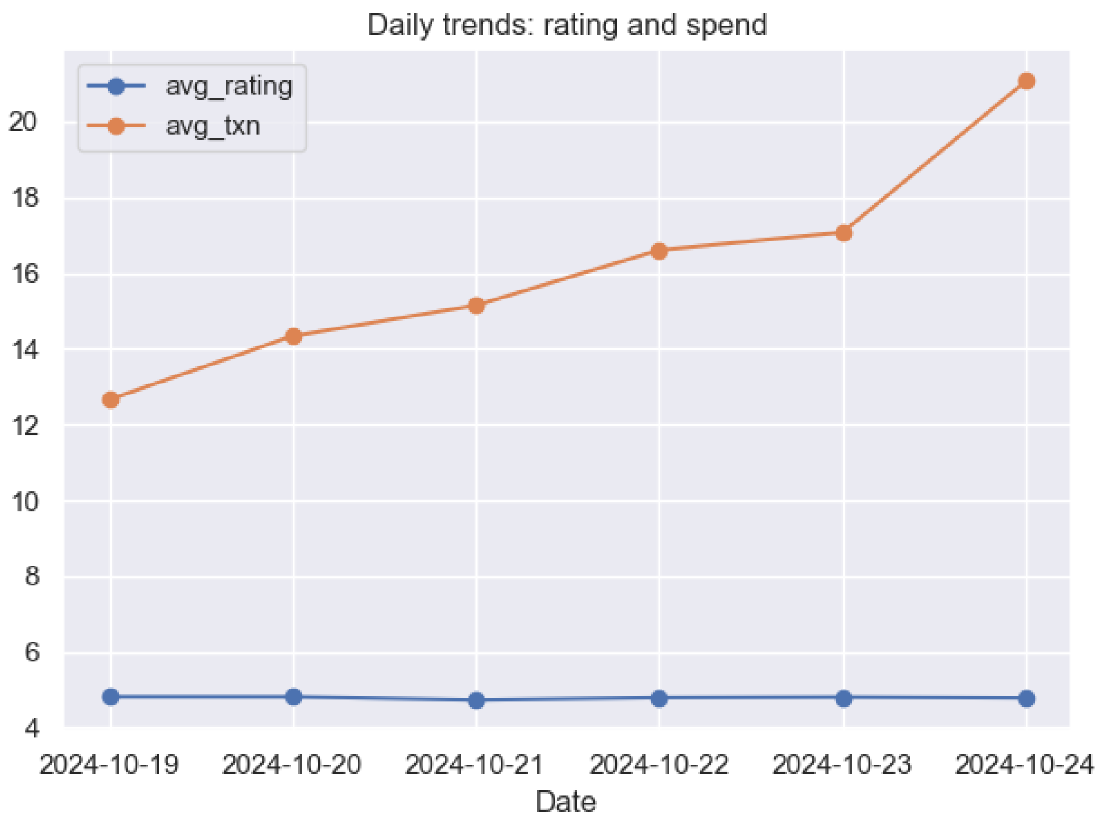
- Rating distribution and average transaction by rating
- Daily trends of rating and spend (to mirror the dashboard)
- Top comment keywords

[53]:
```
rating_counts = df["Rating"].value_counts().sort_index()
rating_counts.plot(kind="bar", title="Rating distribution", ylabel="Count",␣
↪xlabel="Rating")
plt.tight_layout()
plt.show()

avg_txn_by_rating = df.groupby("Rating")["Transaction Value"].mean()
avg_txn_by_rating.plot(kind="bar", title="Avg transaction by rating",␣
↪ylabel="$", xlabel="Rating")
plt.tight_layout()
plt.show()

daily = (
    df.groupby("Date")
    .agg(avg_rating=("Rating", "mean"), avg_txn=("Transaction Value", "mean"))
    .sort_index()
)
```

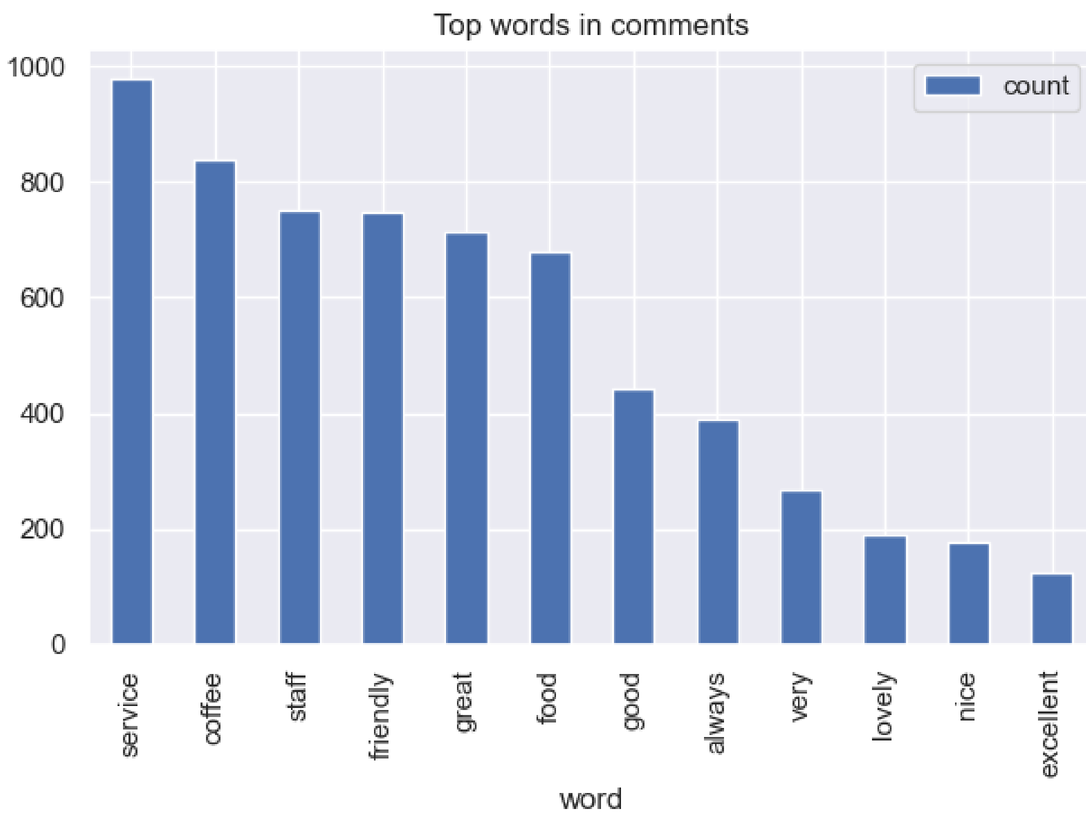
```
daily.plot(y=["avg_rating", "avg_txn"], title="Daily trends: rating and spend",␣
  ↪marker="o")
plt.tight_layout()
plt.show()

stop_words =␣
  ↪{"the","and","to","of","a","in","for","with","is","it","on","my","our","at","are","was","be
word_counts = {}
for c in df["Comment"].dropna().astype(str):
    for w in re.findall(r"[a-zA-Z']+", c.lower()):
        if w not in stop_words and len(w) > 1:
            word_counts[w] = word_counts.get(w, 0) + 1
top_words = sorted(word_counts.items(), key=lambda kv: kv[1], reverse=True)[:12]
pd.DataFrame(top_words, columns=["word", "count"]).set_index("word").
  ↪plot(kind="bar", title="Top words in comments")
plt.tight_layout()
plt.show()
```




Avg transaction by rating
$
0
5
10
15
20
1
2
3
4
5
Rating



Daily trends: rating and spend
avg_rating
avg_txn
20
18
16
14
12
10
8
6
4
2024-10-19
2024-10-20
2024-10-21
2024-10-22
2024-10-23
2024-10-24
Date



1.7 Key summaries

- Location labels need normalisation; otherwise filters show duplicates.
- Cleaning transaction values removes timestamp artefacts and keeps spend realistic (~$15 median).
- Ratings skew high while low ratings are scarce; focus on consistency and speed where comments flag issues.
- Daily trend views help spot emerging changes faster than monthly rolls.