Part A – Exploratory Data Analysis

1.Load and explore the dataset.

In [5]:
```
from pathlib import Path
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# Render plots inline in Jupyter
%matplotlib inline

# Paths (put your data files under ./data/)
DATA_DIR = Path("data")
CSV_PATH = DATA_DIR / "zomato_df_final_data.csv"

# Basic checks
assert CSV_PATH.exists(), f"CSV not found: {CSV_PATH}"

# Load CSV
df = pd.read_csv(CSV_PATH, low_memory=False)

# Quick peek
print(f"Shape: {df.shape}")
display(df.head(5))
display(df.columns)
```

```
Shape: (10500, 17)
```

	address	cost	cuisine	lat	link	
0	371A Pitt Street, CBD, Sydney	50.0	['Hot Pot', 'Korean BBQ', 'BBQ', 'Korean']	-33.876059	https://www.zomato.com/sydney/sydney-madang-cbd	151.2
1	Shop 7A, 2 Huntley Street, Alexandria, Sydney	80.0	['Cafe', 'Coffee and Tea', 'Salad', 'Poké']	-33.910999	https://www.zomato.com/sydney/the-grounds-of-a...	151.1
2	Level G, The Darling at the Star, 80 Pyrmont ...	120.0	['Japanese']	-33.867971	https://www.zomato.com/sydney/sokyo-pyrmont	151.1
3	Sydney Opera House, Bennelong Point, Circular...	270.0	['Modern Australian']	-33.856784	https://www.zomato.com/sydney/bennelong-restau...	151.2
4	20 Campbell Street, Chinatown, Sydney	55.0	['Thai', 'Salad']	-33.879035	https://www.zomato.com/sydney/chat-thai-chinatown	151.2

```
Index(['address', 'cost', 'cuisine', 'lat', 'link', 'lng', 'phone',
       'rating_number', 'rating_text', 'subzone', 'title', 'type', 'votes',
```

In [6]:

```
# 1) shape
print(f"Rows: {df.shape[0]}, Cols: {df.shape[1]}")

# 2) dtypes
display(df.dtypes)

# 3) missing values
missing = (
    df.isna().sum()
    .to_frame("missing_count")
    .assign(missing_pct=lambda x: (x["missing_count"]/len(df)*100).round(2))
    .sort_values("missing_count", ascending=False)
)
display(missing.head(10))

# 4) numeric describe
num_cols = df.select_dtypes(include=[np.number]).columns.tolist()
display(df[num_cols].describe().T)
```

```
Rows: 10500, Cols: 17
address           object
cost             float64
cuisine           object
lat              float64
link              object
lng              float64
phone             object
rating_number    float64
rating_text       object
subzone           object
title             object
type              object
votes            float64
groupon             bool
color             object
cost_2           float64
cuisine_color     object
dtype: object
```

	missing_count	missing_pct
rating_number	3316	31.58
votes	3316	31.58
rating_text	3316	31.58
cost_2	346	3.30
cost	346	3.30
lng	192	1.83
lat	192	1.83
type	48	0.46
address	0	0.00
phone	0	0.00

	count	mean	std	min	25%	50%	
cost	10154.0	51.153240	27.799485	8.000000	30.000000	45.000000	60.00
lat	10308.0	-32.921377	8.263449	-37.858473	-33.899094	-33.872741	-33.8
lng	10308.0	148.067359	26.695402	-123.270371	151.061061	151.172468	151.20
rating_number	7184.0	3.283672	0.454580	1.800000	3.000000	3.300000	3.60
votes	7184.0	83.581013	175.117966	4.000000	12.000000	32.000000	87.00

Insights:

- Substantial missing in target variables (`rating_number` , `rating_text`) means we may need to drop or impute carefully.
- Cost distribution is right-skewed; most restaurants between 30–60, but some very high outliers.
- Votes distribution is very skewed: a few restaurants have thousands of votes, most have few.

2. Answer the following with plots/graphs, and description

How many unique cuisines are served?

In [7]:
```
import ast

# Parse cuisine strings into lists
def parse_cuisine(x):
    if pd.isna(x):
        return []
    try:
        parsed = ast.literal_eval(x)
        if isinstance(parsed, list):
            return [str(i).strip() for i in parsed if str(i).strip()]
    except Exception:
        return [s.strip() for s in x.split(",") if s.strip()]
    return []

df["cuisine_list"] = df["cuisine"].apply(parse_cuisine)

# Count unique cuisines
all_cuisines = set(c for sublist in df["cuisine_list"] for c in sublist)
print(f"Number of unique cuisines: {len(all_cuisines)}")
```

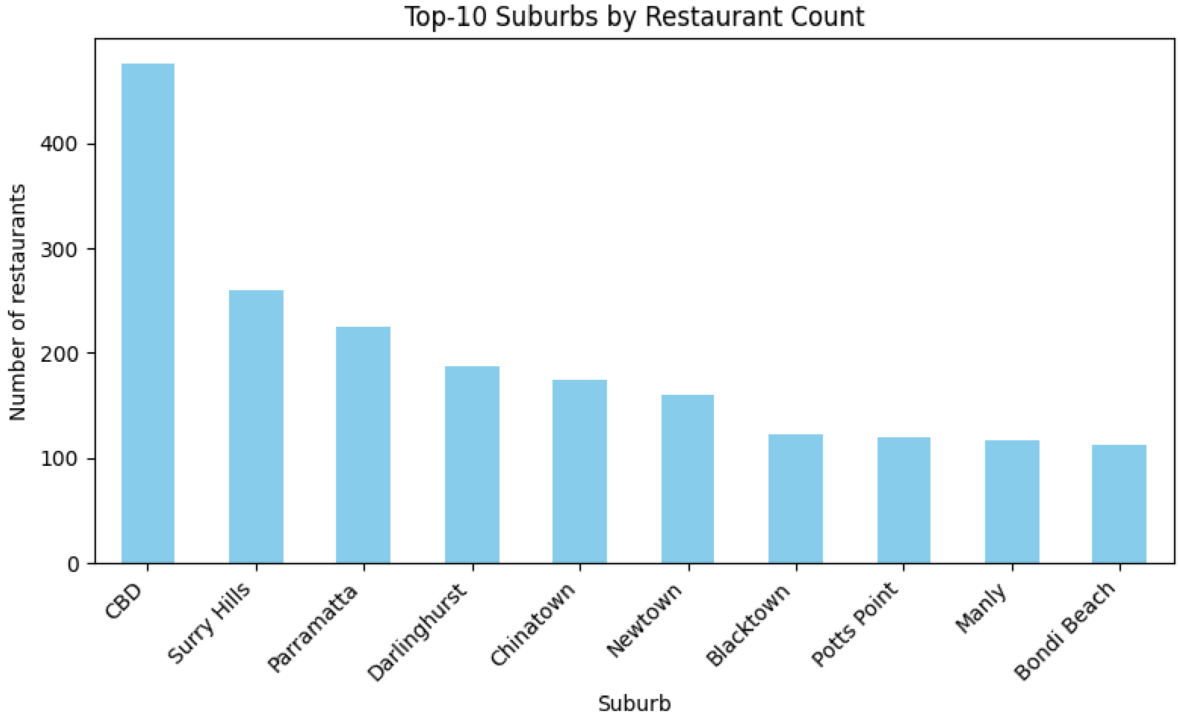
```
Number of unique cuisines: 134
```

- The dataset contains **134 unique cuisines**.

In [8]:
```
# Top 3 suburbs by restaurant count
top3 = df["subzone"].value_counts().head(3)
print("Top 3 suburbs:\n", top3)

# Plot Top 10 suburbs
top10 = df["subzone"].value_counts().head(10)

plt.figure(figsize=(8,5))
top10.plot(kind="bar", color="skyblue")
```

```
plt.title("Top-10 Suburbs by Restaurant Count")
plt.xlabel("Suburb")
plt.ylabel("Number of restaurants")
plt.xticks(rotation=45, ha="right")
plt.tight_layout()
plt.show()
```

```
Top 3 suburbs:
 subzone
CBD             476
Surry Hills     260
Parramatta      225
Name: count, dtype: int64
```



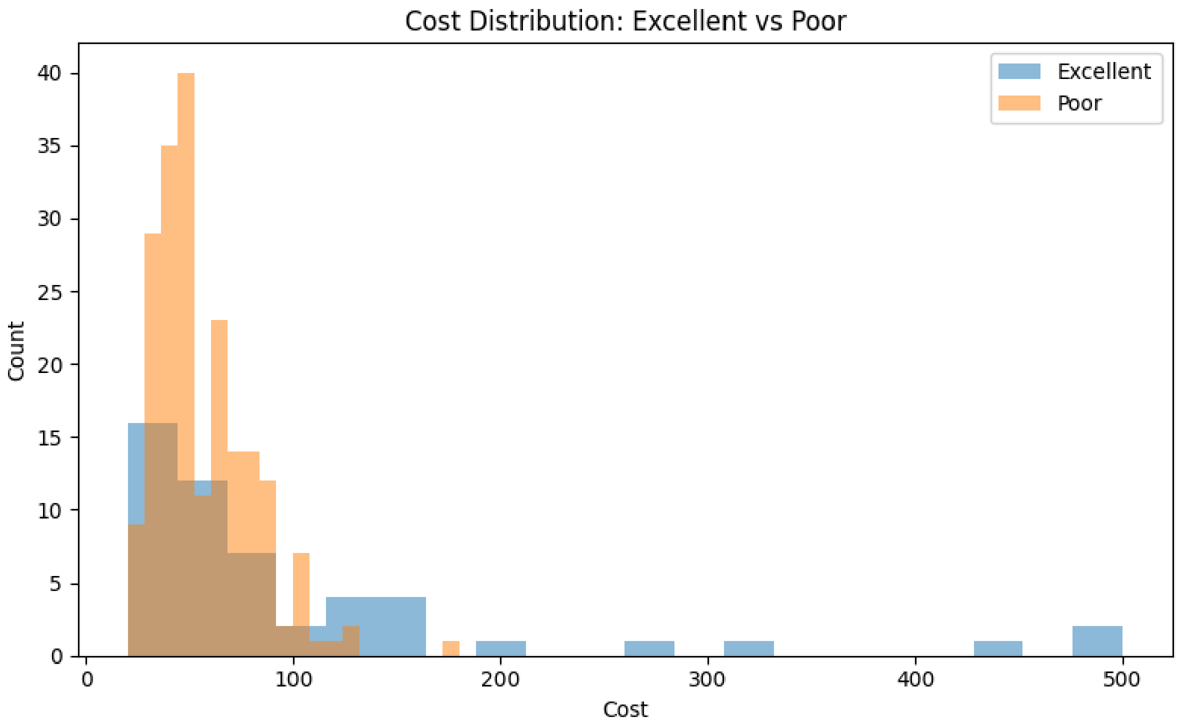
- The top 3 suburbs are:
  1. CBD (476 restaurants)
  2. Surry Hills (260 restaurants)
  3. Parramatta (225 restaurants)

The bar chart below shows the distribution for the top-10 suburbs.

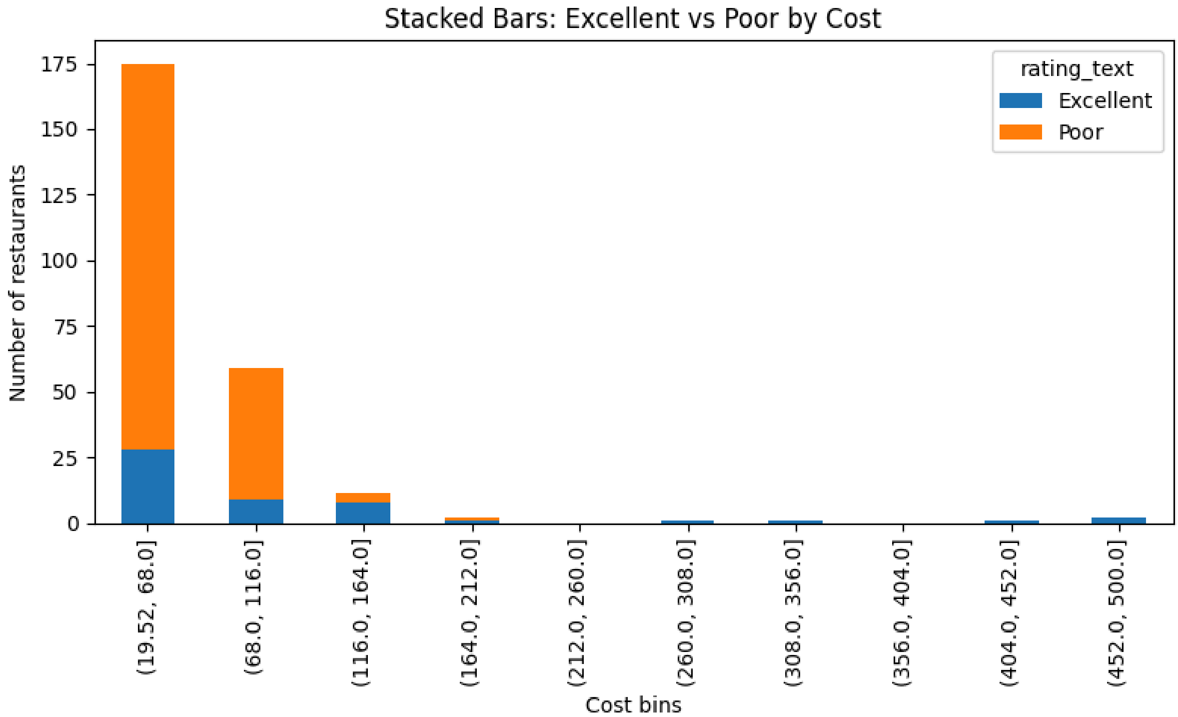
Are restaurants with“Excellent”ratings more expensive than those with“Poor”ratings?

In [9]:
```
# Filter Excellent vs Poor
sub = df[df["rating_text"].isin(["Excellent", "Poor"])].dropna(subset=["cos

# Histogram comparison
plt.figure(figsize=(8,5))
plt.hist(sub[sub["rating_text"]=="Excellent"]["cost"], bins=20, alpha=0.5, 
plt.hist(sub[sub["rating_text"]=="Poor"]["cost"], bins=20, alpha=0.5, label=
plt.title("Cost Distribution: Excellent vs Poor")
plt.xlabel("Cost")
plt.ylabel("Count")
plt.legend()
plt.tight_layout()
plt.show()
```

```
# Stacked bars by cost bins
cost_bins = pd.cut(sub["cost"], bins=10)
stacked = sub.groupby([cost_bins,"rating_text"]).size().unstack(fill_value=(

stacked.plot(kind="bar", stacked=True, figsize=(8,5), title="Stacked Bars: [
plt.xlabel("Cost bins")
plt.ylabel("Number of restaurants")
plt.tight_layout()
plt.show()

# Compare mean/median
print(sub.groupby("rating_text")["cost"].agg(["count","median","mean"]))
```




```
C:\Users\AkeyT\AppData\Local\Temp\ipykernel_2100\2432569108.py:17: FutureWa
rning:

The default of observed=False is deprecated and will be changed to True in
a future version of pandas. Pass observed=False to retain current behavior
or observed=True to adopt the future default and silence this warning.
```




```
             count  median        mean
rating_text
Excellent       51    60.0  101.666667
Poor           201    50.0   55.845771
```

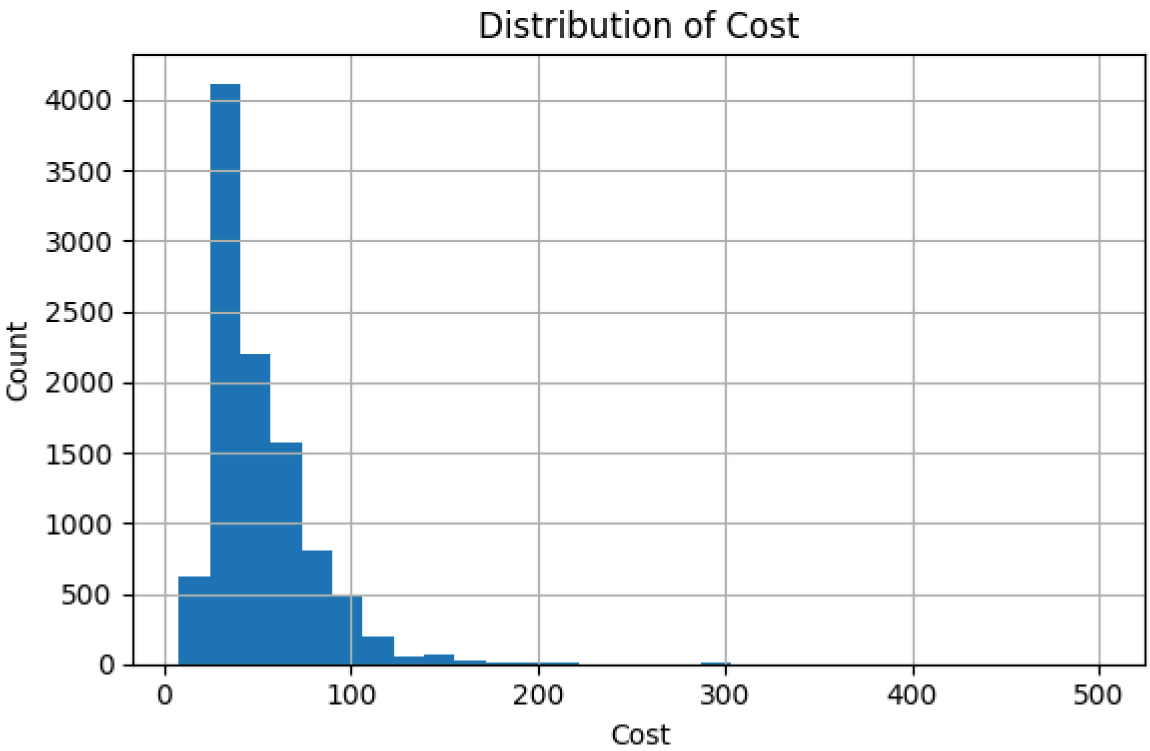
- Median cost for Excellent restaurants: 60
- Median cost for Poor restaurants: 50
- Mean cost for Excellent restaurants: 101.7
- Mean cost for Poor restaurants: 55.8

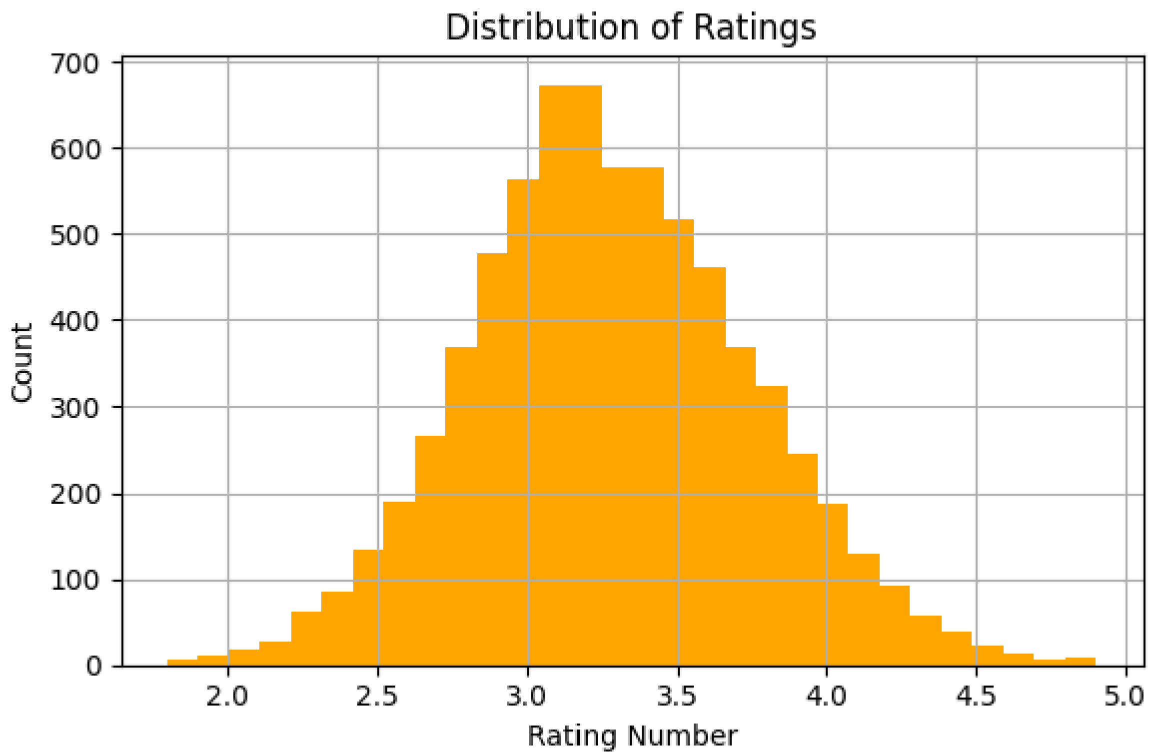
From both the histograms and the stacked bars, we observe that Excellent restaurants tend to have higher costs than Poor restaurants. This supports the idea that restaurants with Excellent ratings are generally more expensive.

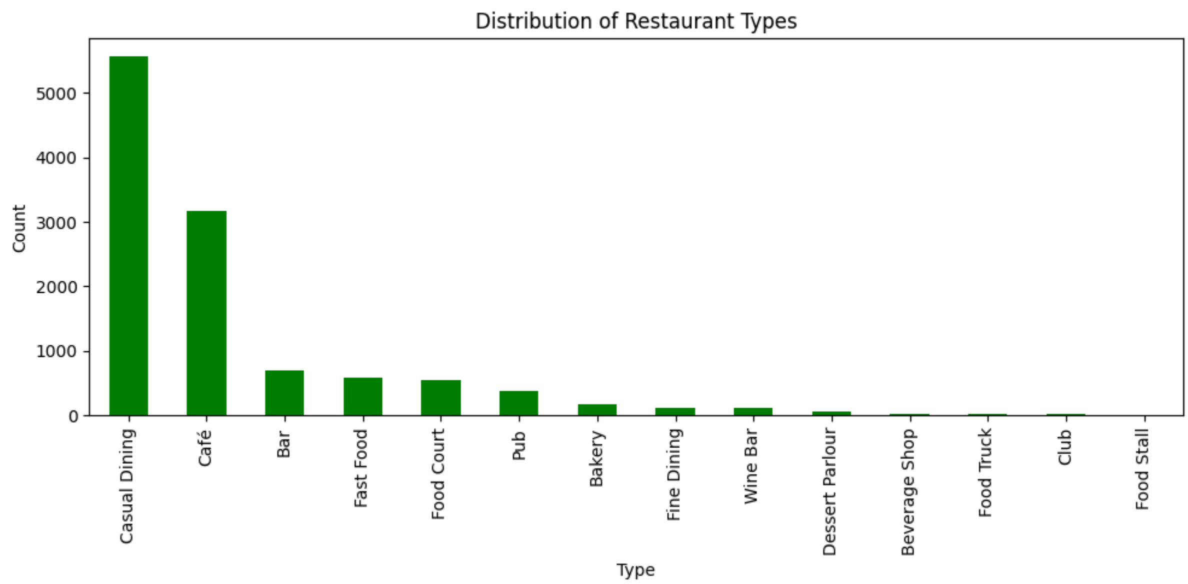
3.Explore key variables.

In [10]:
```
# Distribution of cost
df["cost"].dropna().hist(bins=30, figsize=(6,4))
plt.title("Distribution of Cost")
plt.xlabel("Cost")
plt.ylabel("Count")
plt.tight_layout()
plt.show()

# Distribution of rating_number
df["rating_number"].dropna().hist(bins=30, figsize=(6,4), color="orange")
plt.title("Distribution of Ratings")
plt.xlabel("Rating Number")
plt.ylabel("Count")
plt.tight_layout()
plt.show()

# Distribution of restaurant types
import ast
from collections import Counter

# Parse type field (some are like "['Casual Dining']", need to convert to li
```

```
def parse_type(x):
    if pd.isna(x):
        return []
    try:
        parsed = ast.literal_eval(x)
        if isinstance(parsed, list):
            return [str(i).strip() for i in parsed if str(i).strip()]
    except Exception:
        return [str(x).strip()]
    return []

df["type_list"] = df["type"].apply(parse_type)

# Flatten list of all types
all_types = [t for sublist in df["type_list"] for t in sublist]
type_counts = Counter(all_types)

# Convert to DataFrame
type_counts_df = pd.DataFrame(type_counts.most_common(), columns=["type","co

# Plot all types
plt.figure(figsize=(10,5))
type_counts_df.plot(kind="bar", x="type", y="count", legend=False, ax=plt.ge
plt.title("Distribution of Restaurant Types")
plt.xlabel("Type")
plt.ylabel("Count")
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



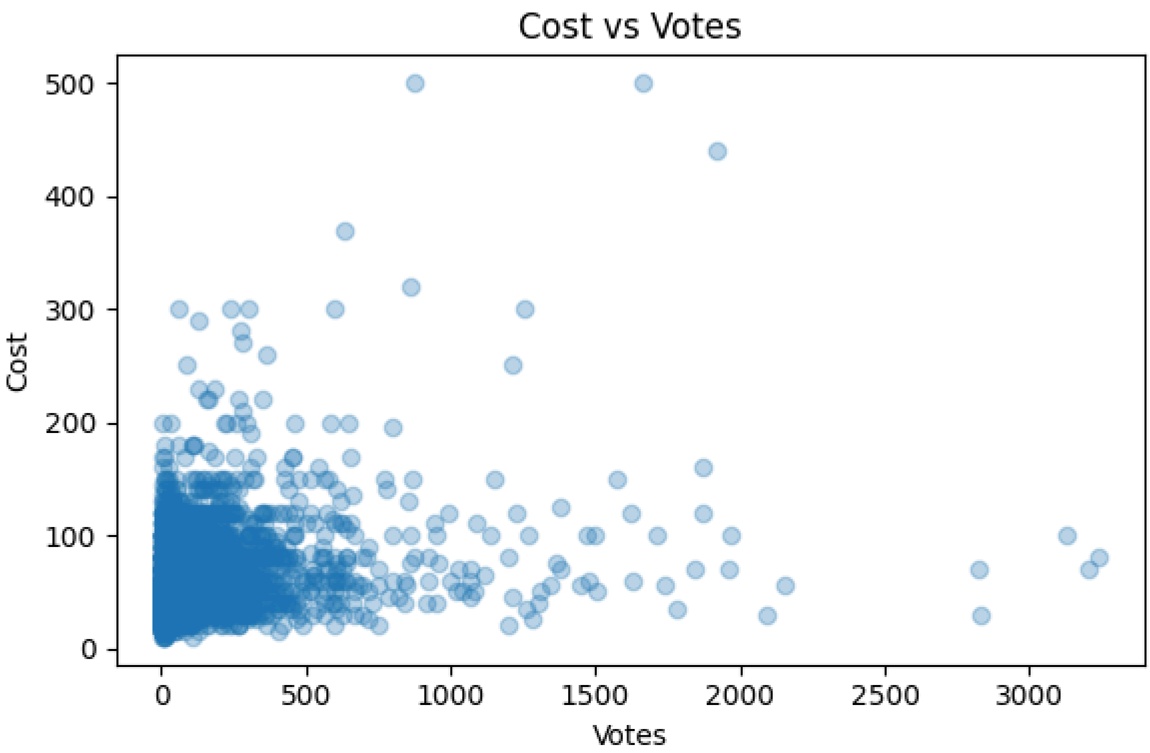


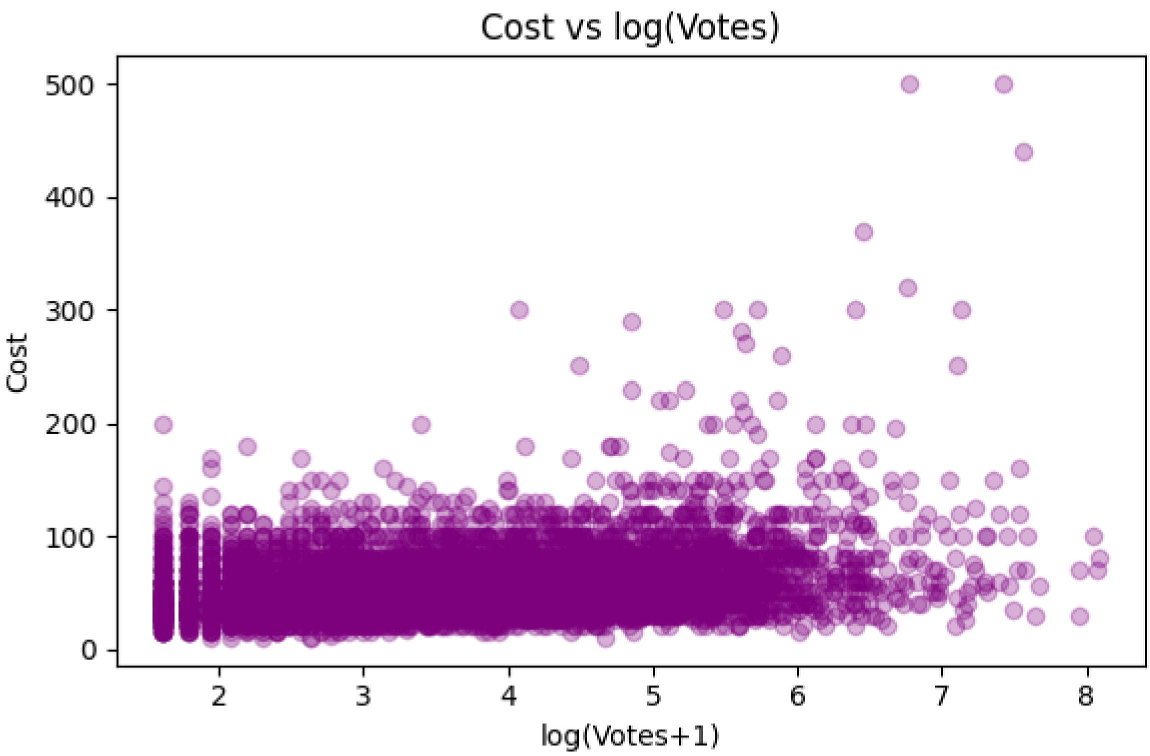


- **Cost**: The distribution is highly right-skewed. Most restaurants have costs between 20 and 80, but some outliers reach up to 500.
- **Ratings**: Ratings are concentrated between 3.0 and 3.5, showing a near-normal distribution. Very few restaurants are rated below 2.0 or above 4.5.
- **Restaurant types**: The most common categories are Casual Dining (>5000) and Café (~3200), followed by smaller groups such as Bar, Fast Food, and Food Court.

In [11]:
```
from scipy.stats import pearsonr
import numpy as np
import matplotlib.pyplot as plt

# Prepare data
pair = df[["cost","votes"]].dropna().copy()
pair["log_votes"] = np.log1p(pair["votes"])  # log transform to reduce skew

# Scatter: cost vs votes
plt.figure(figsize=(6,4))
```

```python
plt.scatter(pair["votes"], pair["cost"], alpha=0.3)
plt.title("Cost vs Votes")
plt.xlabel("Votes")
plt.ylabel("Cost")
plt.tight_layout()
plt.show()

# Scatter: cost vs log(votes)
plt.figure(figsize=(6,4))
plt.scatter(pair["log_votes"], pair["cost"], alpha=0.3, color="purple")
plt.title("Cost vs log(Votes)")
plt.xlabel("log(Votes+1)")
plt.ylabel("Cost")
plt.tight_layout()
plt.show()

# Pearson correlation
r1, p1 = pearsonr(pair["cost"], pair["votes"])
r2, p2 = pearsonr(pair["cost"], pair["log_votes"])
print(f"Pearson r(cost, votes) = {r1:.3f}  (p={p1:.3g})")
print(f"Pearson r(cost, log(votes)) = {r2:.3f}  (p={p2:.3g})")
```






```
Pearson r(cost, votes) = 0.270  (p=9.91e-119)
Pearson r(cost, log(votes)) = 0.303  (p=2.58e-150)
```

Correlation:

- Pearson r(cost, votes) = 0.270 ($p < 0.001$)
- Pearson r(cost, log(votes)) = 0.303 ($p < 0.001$)
- Interpretation: higher-cost restaurants tend to attract more votes, but the relationship is only moderate.

- **Observation**:
  - Sydney's dining scene is clearly shaped by casual restaurants and cafés — these two categories make up the majority of venues.
  - Most places are quite affordable, but there's a small group of very expensive ones pulling the cost range up to 500.
  - Ratings mostly sit in the middle to high range, which suggests people rarely give extremely low scores.
  - The number of votes is very uneven: a handful of popular restaurants get thousands of votes, while most others only get a few.

4.Geospatial Analysis.

In [12]:
```
import geopandas as gpd
from pathlib import Path

GEOJSON_PATH = Path("data/sydney.geojson")

gdf = gpd.read_file(GEOJSON_PATH)
display(gdf.head(2))
print(list(gdf.columns))
```

	SSC_CODE	SSC_NAME	CONF_VALUE	SQKM	geometry
0	10001	Abbotsbury	Very good	4.984673	POLYGON ((150.85118 -33.87069, 150.85104 -33.8...
1	10002	Abbotsford (NSW)	Very good	1.017855	POLYGON ((151.12593 -33.84578, 151.12678 -33.8...

['SSC_CODE', 'SSC_NAME', 'CONF_VALUE', 'SQKM', 'geometry']

In [13]:

```
# Paths
GEOJSON_PATH = Path("data/sydney.geojson")

# Read polygons
gdf = gpd.read_file(GEOJSON_PATH)

# Parse cuisine_list if not present
def parse_cuisine(x):
    if pd.isna(x): return []
    try:
        v = ast.literal_eval(str(x))
        if isinstance(v, list):
            return [str(i).strip() for i in v if str(i).strip()]
    except Exception:
        return [s.strip() for s in str(x).split(",") if s.strip()]
    return []

if "cuisine_list" not in df.columns:
    df["cuisine_list"] = df["cuisine"].apply(parse_cuisine)

# Use SSC_NAME as suburb name, normalise to join with df['subzone']
NAME_COL = "SSC_NAME"

def norm(s):
    if pd.isna(s): return ""
    return str(s).upper().strip()

gdf["SUBURB_NORM"] = gdf[NAME_COL].apply(norm)
df["SUBURB_NORM"]  = df["subzone"].apply(norm)

# Counts per suburb
suburb_total = (df.groupby("SUBURB_NORM")
                  .size()
                  .rename("rest_count")
                  .reset_index())

# Choose a cuisine to map (edit here if needed)
target_cuisine = "Chinese"

has_target = df["cuisine_list"].apply(
    lambda xs: any(c.strip().lower() == target_cuisine.lower() for c in xs)
)
suburb_cuisine = (df.loc[has_target]
                    .groupby("SUBURB_NORM")
                    .size()
                    .rename(f"{target_cuisine}_count")
                    .reset_index())

# Join back to polygons
count_col = f"{target_cuisine}_count"
gj = (gdf.merge(suburb_total, on="SUBURB_NORM", how="left")
         .merge(suburb_cuisine, on="SUBURB_NORM", how="left"))

# Fill NaNs for plotting
```

```
gj[["rest_count", count_col]] = gj[["rest_count", count_col]].fillna(0)

display(gj[[NAME_COL, "SUBURB_NORM", "rest_count", count_col]].head(10))
```

	SSC_NAME	SUBURB_NORM	rest_count	Chinese_count
0	Abbotsbury	ABBOTSBURY	0.0	0.0
1	Abbotsford (NSW)	ABBOTSFORD (NSW)	0.0	0.0
2	Acacia Gardens	ACACIA GARDENS	0.0	0.0
3	Airds	AIRDS	0.0	0.0
4	Alexandria	ALEXANDRIA	70.0	2.0
5	Alfords Point	ALFORDS POINT	0.0	0.0
6	Allambie Heights	ALLAMBIE HEIGHTS	0.0	0.0
7	Allawah	ALLAWAH	0.0	0.0
8	Annandale (NSW)	ANNANDALE (NSW)	0.0	0.0
9	Arncliffe	ARNCLIFFE	34.0	3.0

In [14]:

```
# How many suburbs matched (non-zero restaurants)?
matched = (gj["rest_count"] > 0).sum()
total = len(gj)
print(f"Matched suburbs with restaurants: {matched}/{total}")

import re

def clean_name(s):
    if pd.isna(s):
        return ""
    s = str(s).upper().strip()
    # remove anything in brackets, e.g., "SURRY HILLS (NSW)" -> "SURRY HILLS
    s = re.sub(r"\(.*?\)", "", s)
    # collapse multiple spaces
    s = re.sub(r"\s+", " ", s)
    return s.strip()

# Apply cleaning
gdf["SUBURB_CLEAN"] = gdf["SSC_NAME"].apply(clean_name)
df["SUBURB_CLEAN"]  = df["subzone"].apply(clean_name)

# Recalculate counts
suburb_total = (df.groupby("SUBURB_CLEAN")
                  .size()
                  .rename("rest_count")
                  .reset_index())

target_cuisine = "Chinese"
has_target = df["cuisine_list"].apply(
    lambda xs: any(c.strip().lower() == target_cuisine.lower() for c in xs)
)
suburb_cuisine = (df.loc[has_target]
                    .groupby("SUBURB_CLEAN")
                    .size()
                    .rename(f"{target_cuisine}_count")
                    .reset_index())

# Join back
count_col = f"{target_cuisine}_count"
gj = (gdf.merge(suburb_total, on="SUBURB_CLEAN", how="left")
```

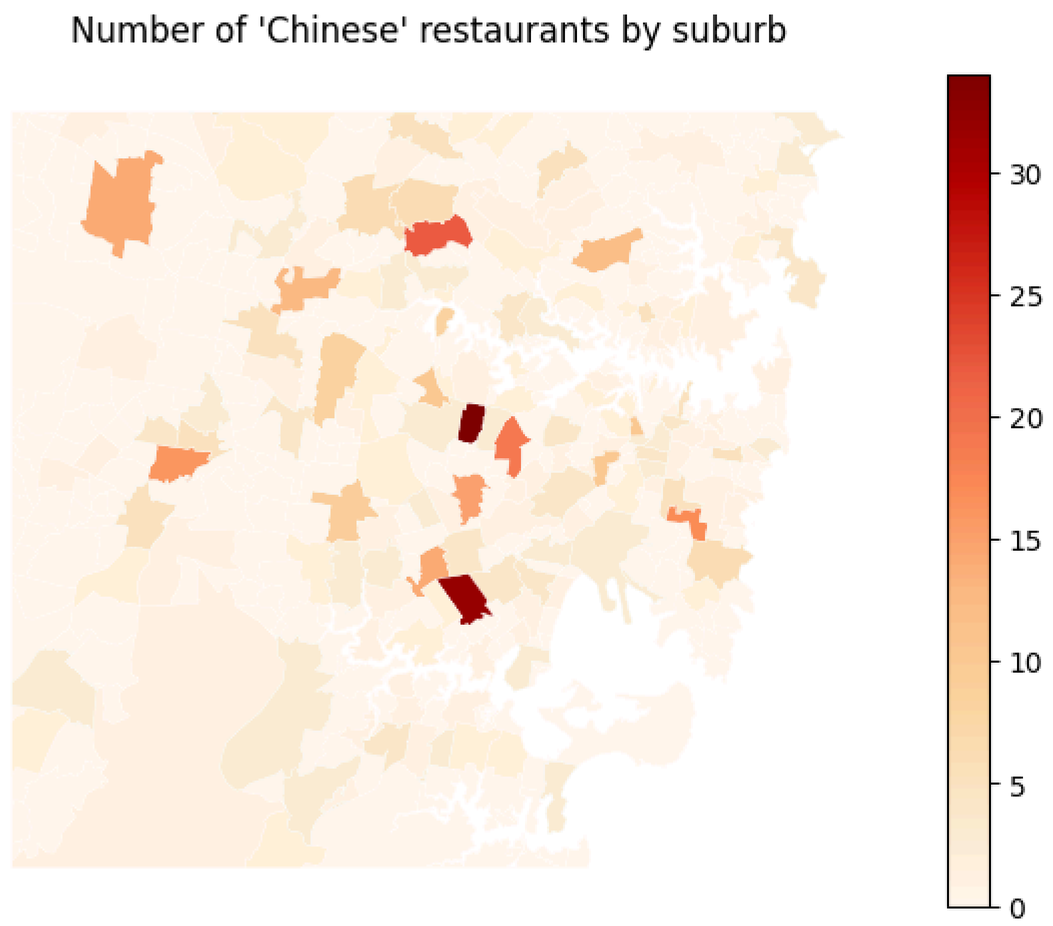
```
        .merge(suburb_cuisine, on="SUBURB_CLEAN", how="left"))
gj[["rest_count", count_col]] = gj[["rest_count", count_col]].fillna(0)

# Check match rate again
matched = (gj["rest_count"] > 0).sum()
total = len(gj)
print(f"Matched suburbs with restaurants: {matched}/{total}")
```

```
Matched suburbs with restaurants: 157/494
Matched suburbs with restaurants: 216/494
```

In [15]:

```
import matplotlib.pyplot as plt

# choose the column for plotting
count_col = f"{target_cuisine}_count"

plt.figure(figsize=(8,8))
ax = gj.plot(
    column=count_col,
    cmap="OrRd",
    legend=True,
    linewidth=0.2,
    edgecolor="white",
    missing_kwds={"color":"lightgrey", "label":"No data"}
)
ax.set_title(f"Number of '{target_cuisine}' restaurants by suburb", pad=12)
ax.set_axis_off()
plt.tight_layout()
plt.show()
```

<Figure size 800x800 with 0 Axes>

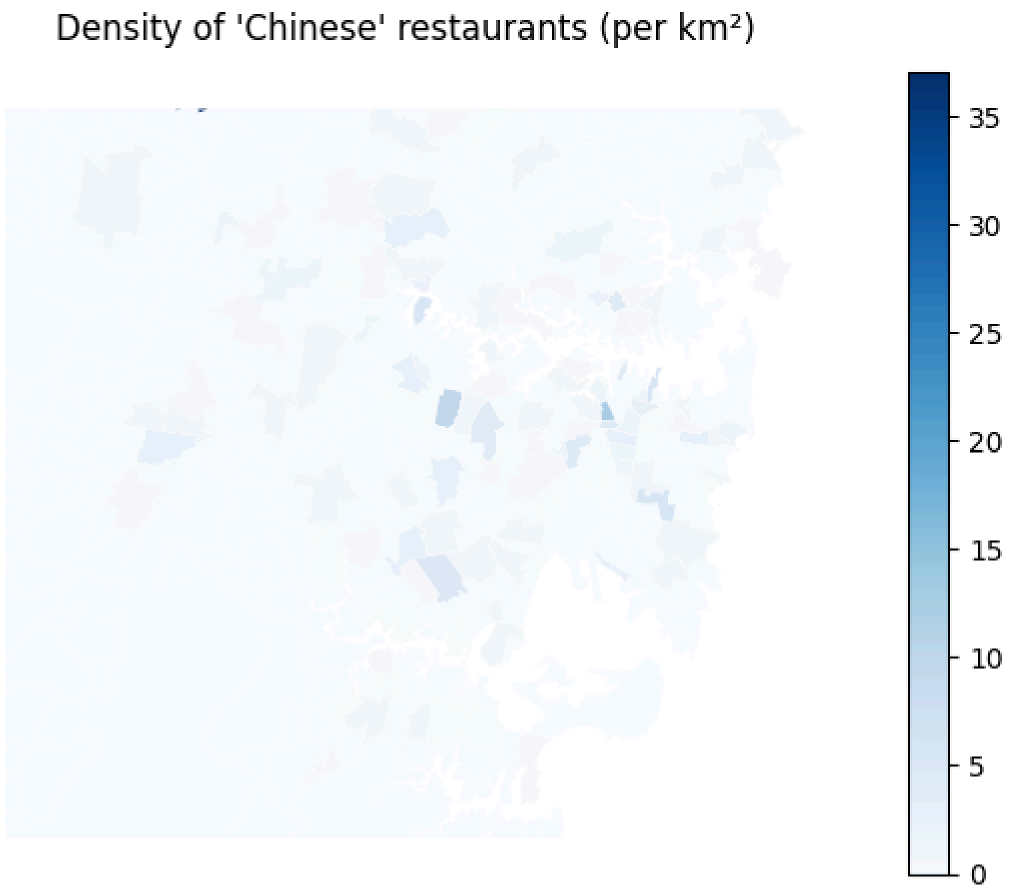


In [16]:

```
# Project to metric CRS to compute area (EPSG:3857 for quick demo)
gj_m = gj.to_crs(epsg=3857)
gj_m["area_km2"] = gj_m.geometry.area / 1e6
```

```
gj_m["cuisine_density"] = gj_m[count_col] / gj_m["area_km2"].replace({0: np

plt.figure(figsize=(8,8))
ax = gj_m.plot(
    column="cuisine_density",
    cmap="Blues",
    legend=True,
    linewidth=0.2,
    edgecolor="white",
    missing_kwds={"color":"lightgrey", "label":"No data"}
)
ax.set_title(f"Density of '{target_cuisine}' restaurants (per km²)", pad=12
ax.set_axis_off()
plt.tight_layout()
plt.show()
```

```
<Figure size 800x800 with 0 Axes>
```



Geospatial Analysis

We used the provided `sydney.geojson` file together with the `geopandas` library to merge restaurant records with suburb polygons.

- After name cleaning, **216 out of 494 suburbs (~44%)** were successfully matched, improving from the initial 157 matches.
- The choropleth below colors each suburb by the **number of Chinese restaurants** recorded. Darker red suburbs (such as the CBD and surrounding areas) clearly emerge as hotspots.
- We also produced a density map (restaurants per km²). This shows that while most suburbs appear light due to their large areas and relatively few restaurants, a few small suburbs stand out with high concentrations, confirming real cuisine clusters.

Limitations:

- Not all suburbs matched due to naming inconsistencies, leaving some polygons in grey.
- The analysis may underestimate total counts, but the main clusters are still clearly visible.
- Counting is done per listed cuisine, so a multi-cuisine restaurant contributes to more than one category.

5.Interactive Visualisation.

In [23]:
```
import pandas as pd
import numpy as np
import plotly.express as px
import plotly.io as pio

# Force Plotly to render in the default web browser
pio.renderers.default = "browser"

# Load dataset
df = pd.read_csv("data/zomato_df_final_data.csv")

# Prepare data
pair = df[["cost","votes"]].dropna().copy()
pair["log_votes"] = np.log1p(pair["votes"])  # log transform to reduce skew

# Interactive scatter: cost vs votes
fig1 = px.scatter(
    pair,
    x="votes",
    y="cost",
    title="Interactive Scatter: Cost vs Votes",
    labels={"votes": "Votes", "cost": "Cost"},
    hover_data=["votes", "cost"]
)
fig1.show()

# Interactive scatter: cost vs log(votes)
fig2 = px.scatter(
    pair,
    x="log_votes",
    y="cost",
    title="Interactive Scatter: Cost vs log(Votes)",
    labels={"log_votes": "log(Votes+1)", "cost": "Cost"},
    hover_data=["log_votes", "cost"]
)
fig2.show()
```