Gathering and preprocessing

In [5]:
```
import pandas as pd
import os
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime, timedelta
import colorsys

pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

Combine the data

In [9]:
```
files = [file for file in os.listdir("./LGA_data") if file.endswith(".xls")]
all_files = pd.DataFrame()

for file in files:
    df = pd.read_excel("./LGA_data/" + file)
    all_files = pd.concat([all_files, df])
```

```
/var/folders/1c/xdsm7htj4334pn2n9vx5kz900000gn/T/ipykernel_35213/912865602.py:6: F
utureWarning: The behavior of DataFrame concatenation with empty or all-NA entries
is deprecated. In a future version, this will no longer exclude empty or all-NA co
lumns when determining the result dtypes. To retain the old behavior, exclude the
relevant entries before the concat operation.
  all_files = pd.concat([all_files, df])
```

Clean the data

In [10]:
```
num_rows = all_files.shape[0]
print("Number of rows before cleaning:", num_rows)
all_files.dropna(subset=['Street Display'], inplace=True)
num_rows = all_files.shape[0]
print("Number of rows after dropping NAs:", num_rows)
all_files.drop_duplicates(inplace=True)
num_rows = all_files.shape[0]
print("Number of rows after dropping duplicates:", num_rows)
# Find the indices of the rows with sale price equal to 0
indices_to_drop = all_files[all_files['Sale Price'] == 0].index
# Drop the rows from the dataset
all_files.drop(indices_to_drop, inplace=True)
num_rows = all_files.shape[0]
print("Number of rows after dropping obs with sales price = 0:", num_rows)
```

```
Number of rows before cleaning: 874193
Number of rows after dropping NAs: 873680
Number of rows after dropping duplicates: 873610
Number of rows after dropping obs with sales price = 0: 526056
```

In [11]:
```
all_files = all_files.reset_index(drop=True)
df = all_files
```

```
# df.to_csv('alldata.csv', index=False)
```

Check the data

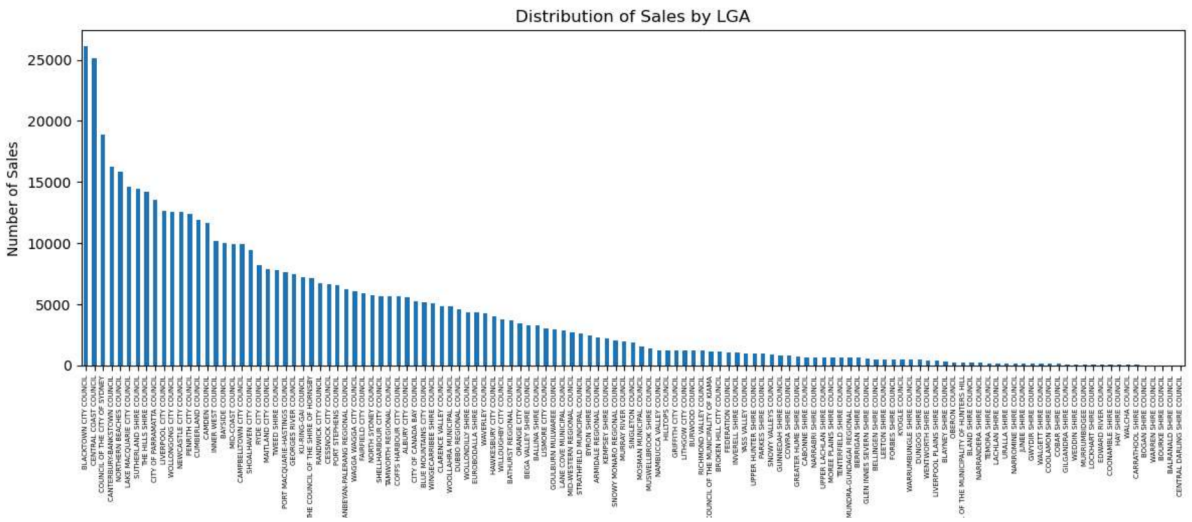
In [ ]:

```
# Check if all LGAs have sale data from 1/7/2018 to 1/7/2023
# oldest_sale_dates = df.groupby('LGA')['Sale Date'].min()
# print(oldest_sale_dates)
# oldest_sale_dates.to_csv('oldest_sale_dates.csv')
```

When downloading the data, I noticed that there would be a maximum of 10,000 observations downloaded for each LGA. I want to investigate whether there is a gap of sales data in those LGAs from 01/07/2018 to 01/07/2023. I will need to download more data for these LGAs. Below I find at what date I should re-download data.

In [ ]:

```
# Group the data by LGA and count the number of sales
sales_count_by_lga = df['LGA'].value_counts()

# Plot the distribution graph
plt.figure(figsize=(12, 6))  # Adjust the figure size as needed
sales_count_by_lga.plot(kind='bar')
plt.xlabel('LGA')
plt.ylabel('Number of Sales')
plt.title('Distribution of Sales by LGA')
plt.xticks(rotation=90, fontsize=5)  # Rotate x-axis labels if needed
plt.tight_layout()  # Adjust the layout
plt.show()

# Filter LGAs with 10,000 sales
lgas_with_10000_sales = sales_count_by_lga[sales_count_by_lga == 10000]

# Print the names of LGAs with 10,000 sales
print("LGAs with 10,000 sales, latest sale dates, and Street Display:")
for lga in lgas_with_10000_sales.index:
    lga_data = df[df['LGA'] == lga]
    latest_sale_date = lga_data['Sale Date'].max()
    latest_sale_street_display = lga_data.loc[lga_data['Sale Date'] == latest_sa
    print(f"LGA: {lga}, Latest Sale Date: {latest_sale_date}, Street Display: {l
```



LGAs with 10,000 sales, latest sale dates, and Street Display:

In [ ]:
```
# lga_specific_sales = df[df['LGA'] == 'RYDE CITY COUNCIL']
# lga_specific_sales.head(30)
```

Now I'll check to see if the data looks right and makes sense

In [12]:
```
df.columns
```

Out[12]:
```
Index(['Disclaimer', 'Building Name', 'Street Display',
       'Alternate Street Display', 'Other', 'Unit', 'Number', 'Street Name',
       'Locality', 'Postcode', 'Alt. Street', 'Alt. Locality',
       'Legal Description', 'Volume/Folio', 'Vendor Names', 'Vendor Address',
       'Purchaser Names', 'Purchaser Address', 'Volume Folio', 'Parish',
       'Office Name', 'Agent Name', 'First Price', 'Change %', 'Last Price',
       'Change %.1', 'Days To Sell', 'Sale Price', 'Sale Date',
       'Settlement Date', 'Sale Type', 'Area', 'Building Area', 'Bedrooms',
       'Bathrooms', 'Car Parks', 'Property Type', 'Land Use', 'Zoning',
       'Main Rooms', 'Build Year', 'Building Style', 'Storeys', 'Wall Type',
       'Roof Type', 'Improvements', 'Hundred', 'Sale Category',
       'Document Status', 'Parties Related Flag', 'Parties Related',
       'Valuation Date', 'Valuation Amount', 'LGA', 'Dealing Number',
       'Government Number', 'Parent Government Number', 'PDS ID', 'Sale ID',
       'Load Date', 'Property ID'],
      dtype='object')
```

In [13]:
```
df.dtypes
```

Out[13]:
```
Disclaimer                  object
Building Name               object
Street Display              object
Alternate Street Display   float64
Other                      float64
Unit                       float64
Number                      object
Street Name                 object
Locality                    object
Postcode                   float64
Alt. Street                float64
Alt. Locality              float64
Legal Description           object
Volume/Folio               float64
Vendor Names                object
Vendor Address              object
Purchaser Names             object
Purchaser Address           object
Volume Folio               float64
Parish                     float64
Office Name                 object
Agent Name                  object
First Price                 object
Change %                   float64
Last Price                  object
Change %.1                 float64
```

```
Days To Sell                      float64
Sale Price                        float64
Sale Date                  datetime64[ns]
Settlement Date            datetime64[ns]
Sale Type                          object
Area                              float64
Building Area                     float64
Bedrooms                          float64
Bathrooms                         float64
Car Parks                         float64
Property Type                      object
Land Use                           object
Zoning                             object
Main Rooms                        float64
Build Year                        float64
Building Style                     object
Storeys                           float64
Wall Type                          object
Roof Type                          object
Improvements                      float64
Hundred                           float64
Sale Category                      object
Document Status                   float64
Parties Related Flag              float64
Parties Related                   float64
Valuation Date             datetime64[ns]
Valuation Amount                  float64
LGA                                object
Dealing Number                     object
Government Number                  object
Parent Government Number          float64
PDS ID                            float64
Sale ID                           float64
Load Date                  datetime64[ns]
Property ID                       float64
dtype: object
```

In [14]:

```
# Calculate summary statistics for numeric columns
summary_stats = df[['Sale Price', 'Area', 'Bedrooms', 'Bathrooms', 'Car Parks']]

# Print the summary statistics
print(summary_stats)
```

```
         Sale Price          Area       Bedrooms      Bathrooms      Car Parks
count  5.260560e+05  5.029530e+05  392689.000000  392470.000000  374149.000000
mean   1.096319e+06  4.918656e+04       3.159192       1.737521       1.968459
std    4.943911e+06  1.511399e+06       1.515466       1.588563       4.474361
min    1.000000e+03  7.892128e-01       0.000000       0.000000       0.000000
25%    4.710000e+05  4.201000e+02       2.000000       1.000000       1.000000
50%    7.190000e+05  6.620000e+02       3.000000       2.000000       2.000000
75%    1.125108e+06  1.112597e+03       4.000000       2.000000       2.000000
max    9.459457e+08  4.553400e+08     400.000000     815.000000    1200.000000
```

Weird that theres a property with 400 bedrooms. Same weirdness with 815 bathrooms and 1619 car parks.

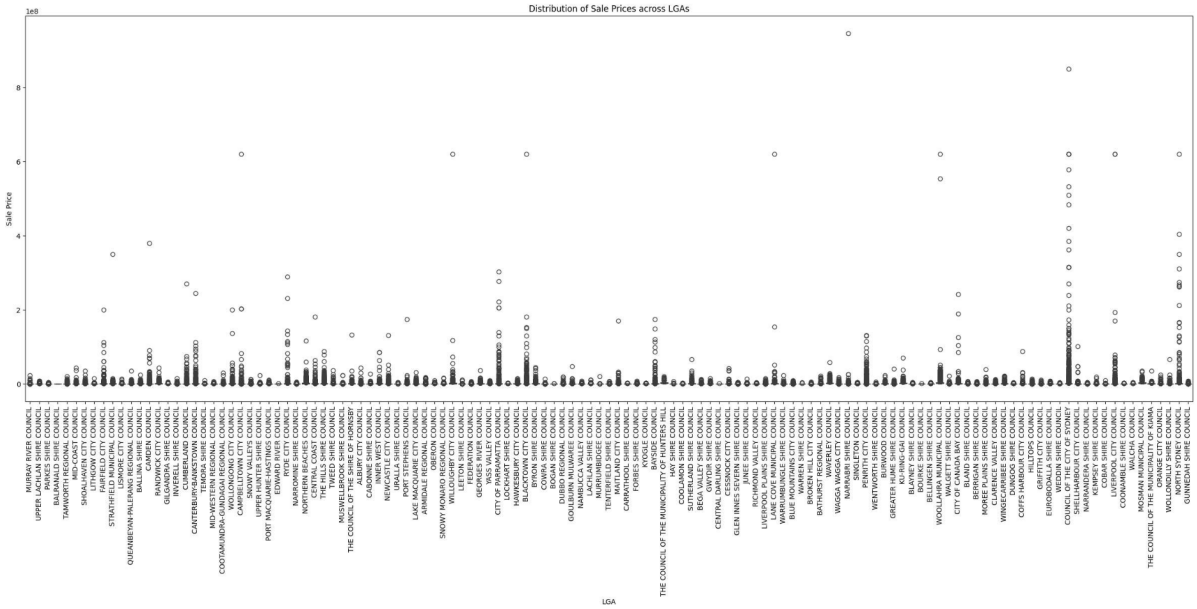
Even more weird that there's a sale for $945M.

Analysis of general descriptive statistics

Box and whisker plots

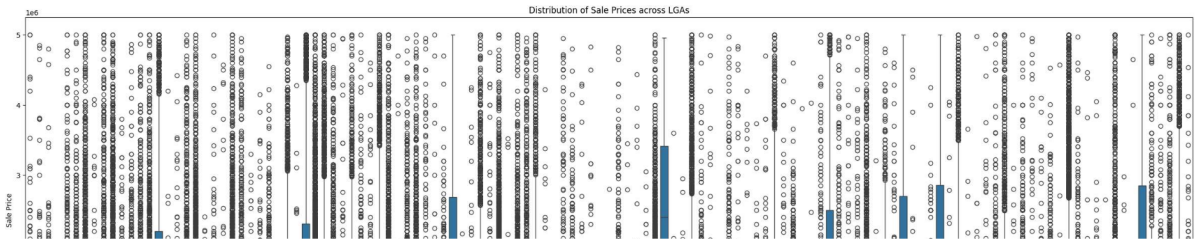
I'll use box and whisker plots to show the mean and interquartile range differences between each LGA

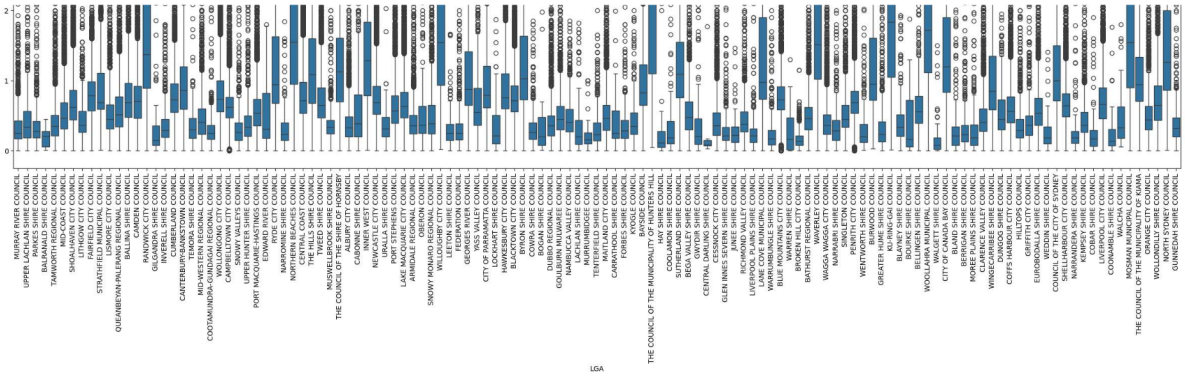
In [15]:
```
plt.figure(figsize=(30, 10))
sns.boxplot(x='LGA', y='Sale Price', data=df)
plt.xlabel('LGA')
plt.ylabel('Sale Price')
plt.title('Distribution of Sale Prices across LGAs')
plt.xticks(rotation=90)
plt.show()
```



Filtering to values below $5M to minimise outliers

In [16]:
```
df_lessthan5M = df[df['Sale Price'] <= 5000000]

plt.figure(figsize=(30, 10))
sns.boxplot(x='LGA', y='Sale Price', data=df_lessthan5M)
plt.xlabel('LGA')
plt.ylabel('Sale Price')
plt.title('Distribution of Sale Prices across LGAs')
plt.xticks(rotation=90)
plt.show()
```

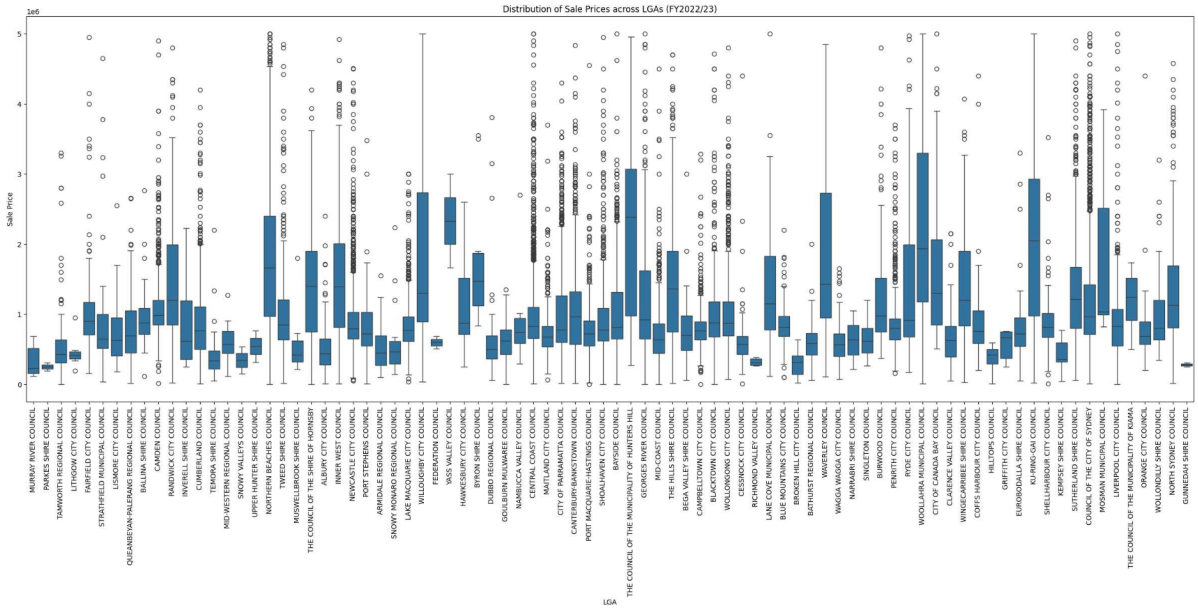




Narrowing down results to sales in the past 365 days (01/07/2022 - 01/07/2023)

In [17]:

```
# Filter the DataFrame for sales in the past year
one_year_ago = datetime.now() - timedelta(days=365)
df_oneYearAgo_lessthan5M = df_lessthan5M[df_lessthan5M['Sale Date'] >= one_year_

plt.figure(figsize=(30, 10))
sns.boxplot(x='LGA', y='Sale Price', data=df_oneYearAgo_lessthan5M)
plt.xlabel('LGA')
plt.ylabel('Sale Price')
plt.title('Distribution of Sale Prices across LGAs (FY2022/23)')
plt.xticks(rotation=90)
plt.show()
```



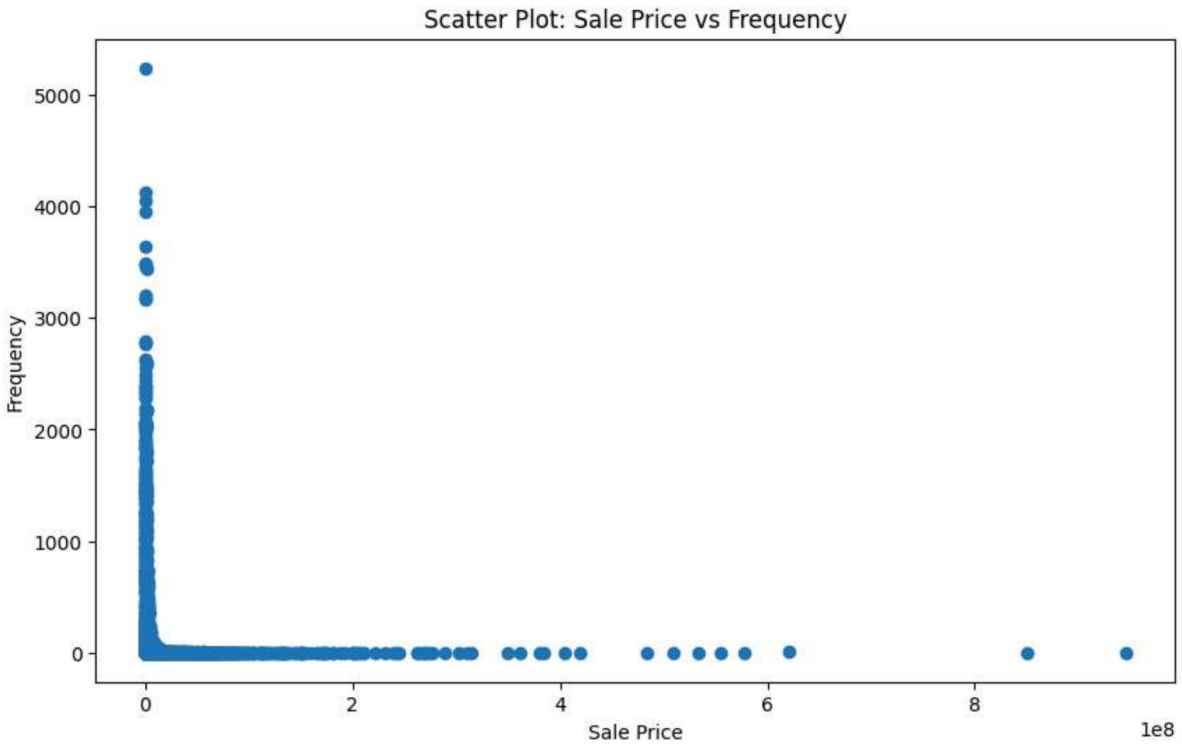
Discussion

- Wealthier LGAs often have greater interquartile ranges, whereas poorer LGAs have tight bands
- The majority of LGAs still have their sale price averages below $1M
- The lack of outliers below the interquartile range shows how tight the housing market is; there is no room to catch a bargain

Distribution plots

Distribution plots

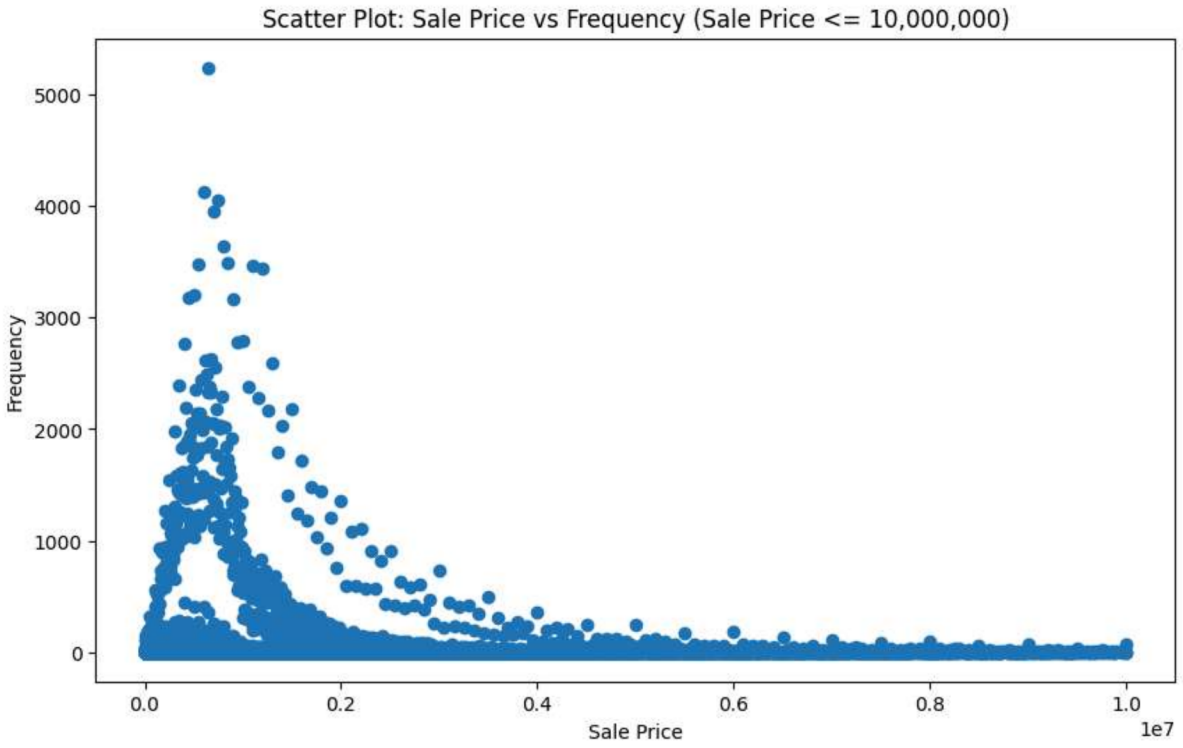
In [18]:
```
# Calculate the frequency of each sales price value
sales_price_counts = df['Sale Price'].value_counts()

# Extract the sales prices and their frequencies
sales_prices = sales_price_counts.index
frequencies = sales_price_counts.values

# Plot the scatter plot
plt.figure(figsize=(10, 6))
plt.scatter(sales_prices, frequencies)
plt.xlabel('Sale Price')
plt.ylabel('Frequency')
plt.title('Scatter Plot: Sale Price vs Frequency')
plt.show()
```



I'll need to filter the data so that the sales on the far right hand side of the above scatter plot do not heavily skew my graphs. I'll filter the results to only include sales of $10M or less as the scatter plot visually looks more interesting and is of greater relevance to normal home buyers (like myself).

In [19]:
```
# Filter the DataFrame based on the sale price condition
df_lessthan10M = df[df['Sale Price'] <= 10000000]

# Calculate the frequency of each sales price value in the filtered DataFrame
sales_price_counts = df_lessthan10M['Sale Price'].value_counts()

# Extract the sales prices and their frequencies
sales_prices = sales_price_counts.index
frequencies = sales_price_counts.values

# Plot the scatter plot
```

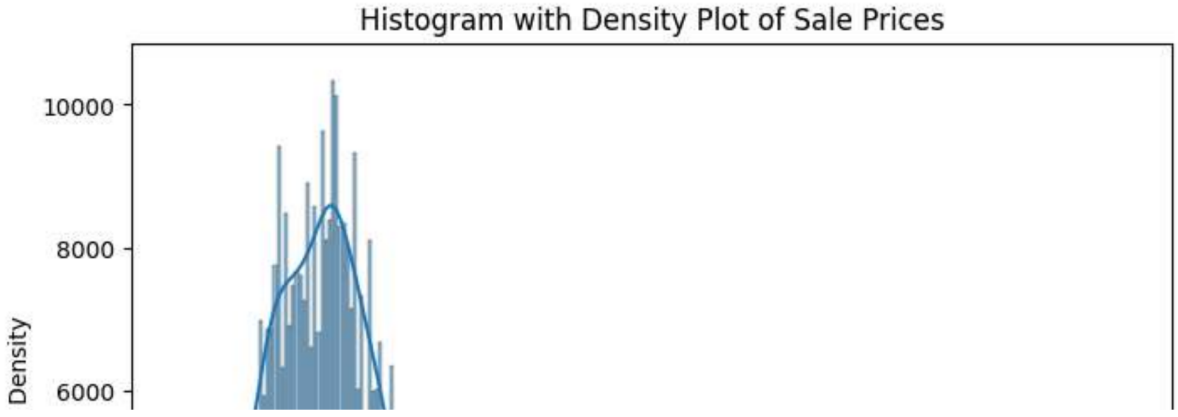
```
plt.figure(figsize=(10, 6))
plt.scatter(sales_prices, frequencies)
plt.xlabel('Sale Price')
plt.ylabel('Frequency')
plt.title('Scatter Plot: Sale Price vs Frequency (Sale Price <= 10,000,000)')
plt.show()
```

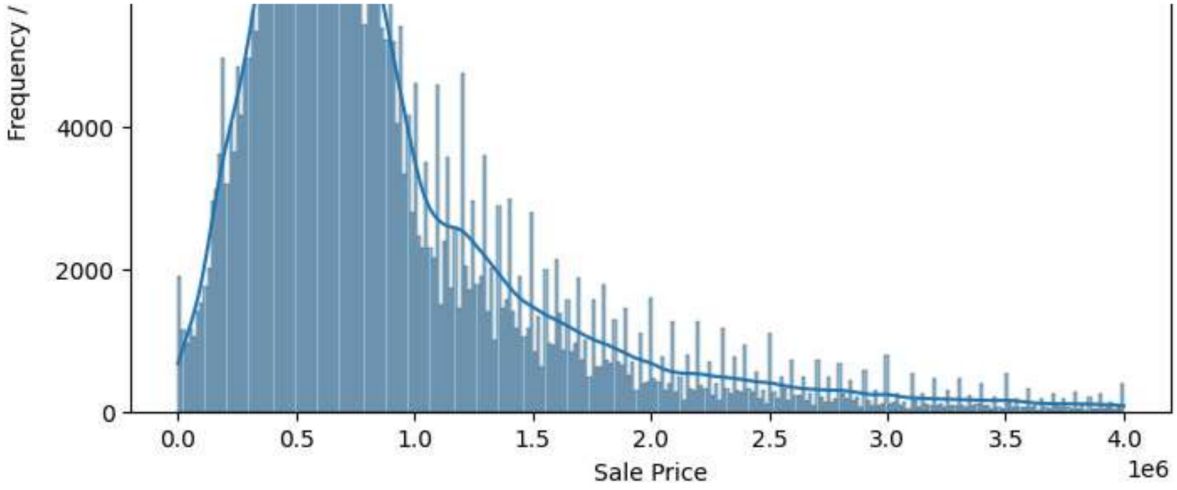


Now to plot a histogram, I will further narrow down analysis to sales upto $4M as this visually seems to be the point where there is no variation in the frequency of sale$ 4M. This gives us a much more meaningful histogram below.

In [20]:

```
df_lessthan4M = df[df['Sale Price'] <= 4000000]

plt.figure(figsize=(8, 6))
sns.histplot(df_lessthan4M['Sale Price'], kde=True)
plt.xlabel('Sale Price')
plt.ylabel('Frequency / Density')
plt.title('Histogram with Density Plot of Sale Prices')
plt.show()
```

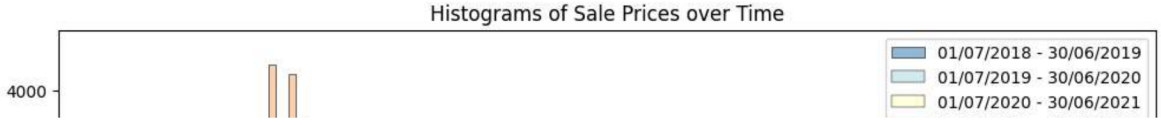


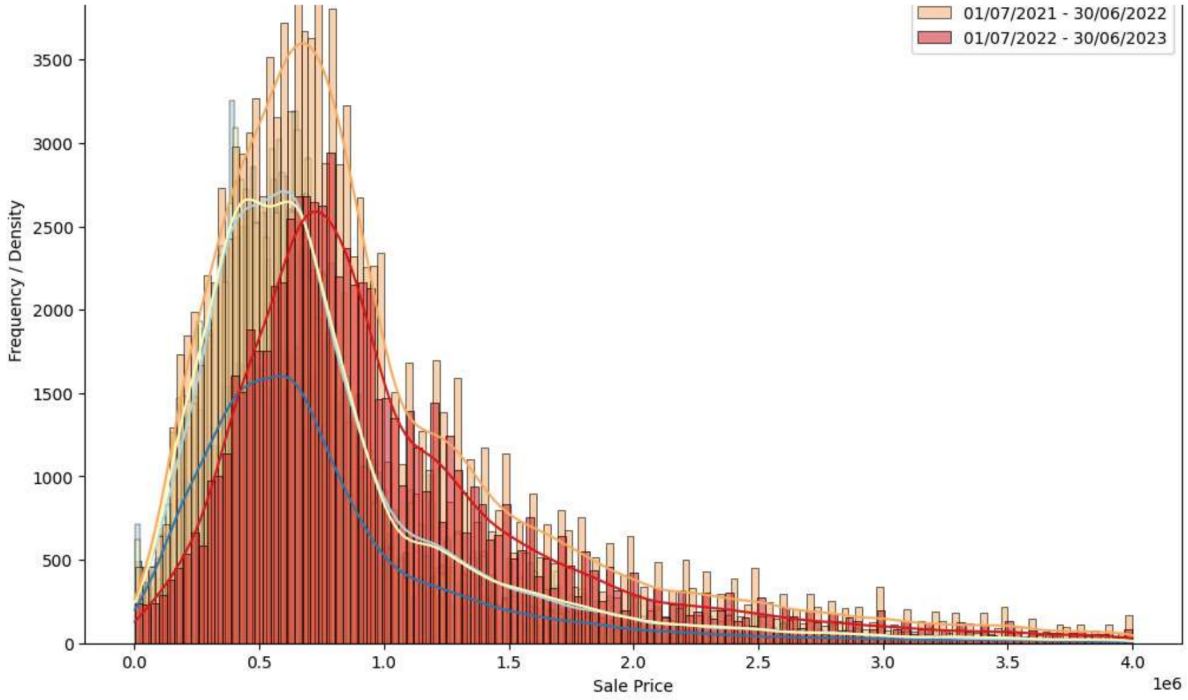


Now to plot the differences from 2018 to 2023

In [21]:

```
# Define the time periods with date ranges
time_periods = [
    '01/07/2018 - 30/06/2019',
    '01/07/2019 - 30/06/2020',
    '01/07/2020 - 30/06/2021',
    '01/07/2021 - 30/06/2022',
    '01/07/2022 - 30/06/2023'
]

colours = ['#2c7bb6', '#abd9e9', '#ffffbf', '#fdae61', '#d7191c']

# Create a list to store the filtered data for each time period
filtered_data_list_histogram = []

# Iterate over time periods
for i, time_period in enumerate(time_periods):
    # Extract start and end dates
    start_date = pd.to_datetime('01/07/2018') + pd.DateOffset(years=i)
    end_date = start_date + pd.DateOffset(years=1) - pd.DateOffset(days=1)

    # Filter the data for the specific time period
    filtered_data = df_lessthan4M[(df_lessthan4M['Sale Date'] >= start_date) & (

    filtered_data_list_histogram.append(filtered_data)

# Create the overlaid histograms
plt.figure(figsize=(12, 8))
for i, filtered_data in enumerate(filtered_data_list_histogram):
    sns.histplot(filtered_data['Sale Price'], label=time_periods[i], kde=True, a

plt.xlabel('Sale Price')
plt.ylabel('Frequency / Density')
plt.title('Histograms of Sale Prices over Time')
plt.legend()
plt.show()
```





Remember that the height of this plot is the frequency of sales.

Discussion

- $700k seems to be the average in the NSW market
- Demand for property beyond $2M seems to plateau. At this point, price is no longer an indication of demand, but rather of the intrinsic value of the home to the buyer (or at least this is how I interpret it)
- Average prices began to rise dramatically in FY2021/22 and continued to rise into FY2022/23
- Volume of sales rose from FY2018/19 to FY2019/20 dramatically, bascially stayed the same in the following year, then peaked in FY2021/22, and finally cooled down in FY2022/23 to similar levels in previous years.
- Therefore, despite the market cooling down in 2022/23, prices continued to rise. This must be explained by a lack of supply.

Analysis for property investing (02.12.2023)

In [24]:
```
df.head()
```

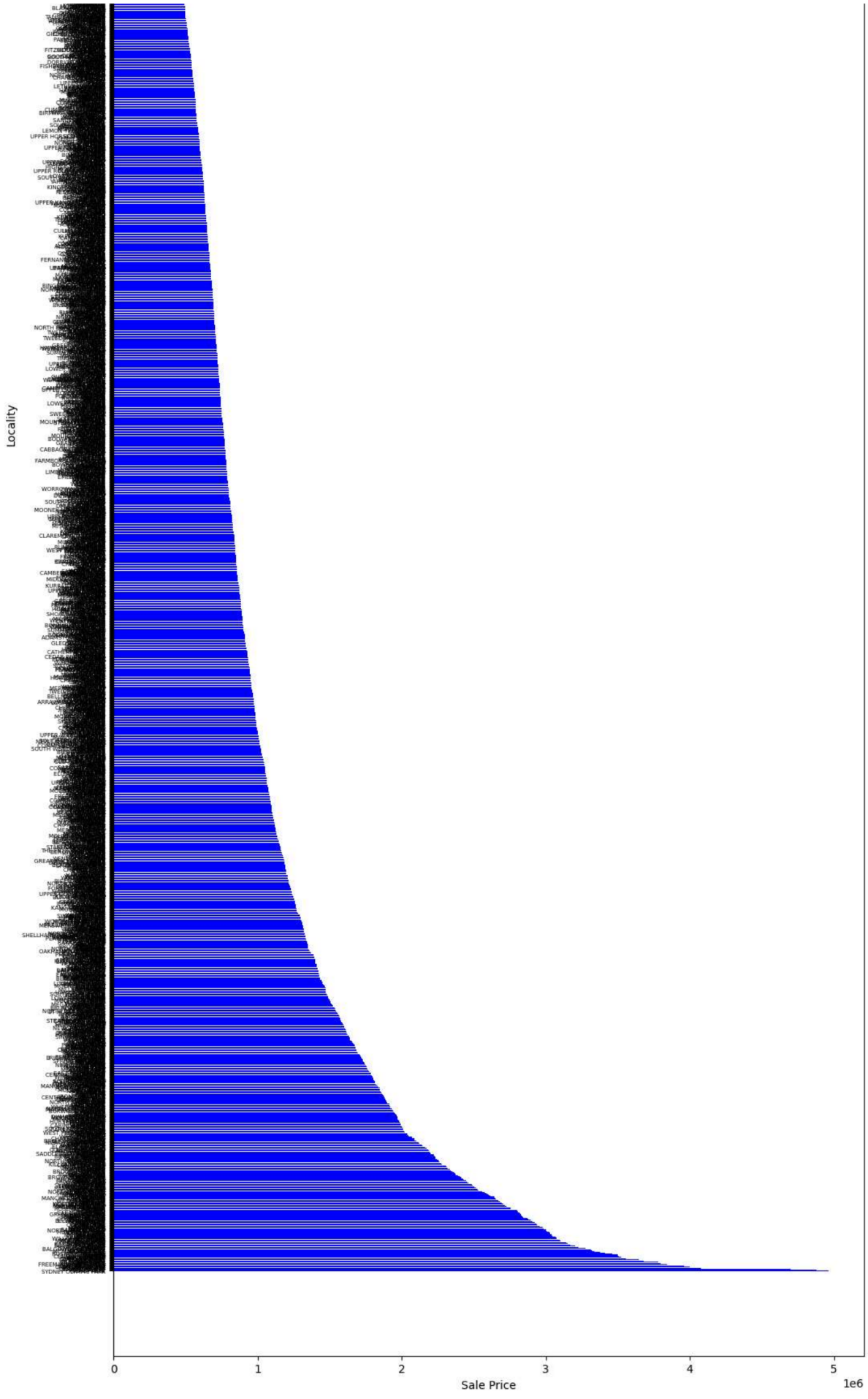
Out[24]:

	Disclaimer	Building Name	Street Display	Alternate Street Display	Other	Unit	Number	Street Name
0	NaN	NaN	24 MORAGO ST	NaN	NaN	NaN	24	MORAGO ST

1	NaN	JAKABRESUE	191 DAHWILLY RD	NaN	NaN	NaN	191	DAHWILLY RD
2	NaN	NaN	TWENTY FOUR LN	NaN	NaN	NaN	NaN	TWENTY FOUR LANE LN
3	NaN	NaN	1 MCMAHON PL	NaN	NaN	NaN	1	MCMAHON PL
4	NaN	NaN	15/314 PERRICOOTA RD	NaN	NaN	NaN	314	PERRICOOTA RD

Getting the mean and median prices of each locality for houses only

In [29]:
```
# Filter data for property type 'House' and price <= 5M
df_lessthan5M = df[df['Sale Price'] <= 5000000]
house_data = df_lessthan5M[df_lessthan5M['Property Type'] == 'House']

# Group by 'Locality' and calculate mean and median sale prices
grouped_data = house_data.groupby('Locality')['Sale Price'].agg(['mean', 'median
```


Locality
0
1
2
3
4
5
Sale Price
1e6

Filtering the data

There are way too many localities. I want to positively weight properties that are closer to the Sydney CBD. Therefore, I want to add a column that has the property's distance from the CBD.

(during this process i had immense difficulty with SSL certificate errors. It ended up working by:

1. Pip install certifi
2. /Applications/Python\ 3.11/Install\ Certificates.command)

In [61]:
```
len(df)
```

Out[61]: 526056

We'll have to request data from Noninatim 526056 times to apply a lat and long to each observation. Running the request for 5 observations took 15 seconds (3 seconds for each obs), which means it'll take **438** hours to complete for all observations.

Alternatives are:

1. *Limit the dataset and see how long it would take*

```
# Filter data for property type 'House' and price <= 5M and Sale Date = the past year
df['Sale Date'] = pd.to_datetime(df['Sale Date'])
df_lessthan5M = df[df['Sale Price'] <= 5000000]
house_data = df_lessthan5M[df_lessthan5M['Property Type'] == 'House']
most_recent_year = df['Sale Date'].dt.year.max()
house_data_recent_year = house_data[house_data['Sale Date'].dt.year == most_recent_year]
len(house_data_recent_year)
```

This still gives us 16715 obs, which would take **14** hours.

2. *Only request the lat and long of each locality, rather than its actual street address, then apply the same lat and long for all properties in the locality*

```
unique_localities = df['Locality'].unique().tolist()
print(unique_localities)
len(unique_localities)
```

This gives us 3971 localities, which would take **3.3** hours.

3. *Try and find the postcodes near sydney CBD and just pick them manually*

Postcodes in NSW are fucked – there is no interpretable way they are applied as they have been built for the purpose of postage, not location.

In [62]:
```
from geopy.distance import geodesic
from geopy.geocoders import Nominatim
```

```
from geopy.extra.rate_limiter import RateLimiter

# Create a geolocator object
geolocator = Nominatim(user_agent="NSW-property-data-analysis")


# Use the geolocator to get coordinates
location = geolocator.geocode("Sydney, Australia")
print(location.latitude, location.longitude)

# Define a function to get coordinates from an address
def get_coordinates(address):
    geocode = RateLimiter(geolocator.geocode, min_delay_seconds=1)
    location = geocode(address)
    return (location.latitude, location.longitude) if location else None

# To apply the lat and long to all obs:
# df['Coordinates'] = df['Street Display'].apply(get_coordinates)
# df.head()
```

```
-33.8698439 151.2082848
```

In [ ]:

```
# Filter data for property type 'House' and price <= 5M and Sale Date = the past
# df['Sale Date'] = pd.to_datetime(df['Sale Date'])
# df_lessthan5M = df[df['Sale Price'] <= 5000000]
# house_data = df_lessthan5M[df_lessthan5M['Property Type'] == 'House']
# most_recent_year = df['Sale Date'].dt.year.max()
# house_data_recent_year = house_data[house_data['Sale Date'].dt.year == most_re
# house_data_recent_year.head()
# len(house_data_recent_year)

# Make Locality easier for Nominatim to read
df['Locality'] = df['Locality'] + ", NSW, AUSTRALIA"

# Make a list of unique localities
unique_localities = df['Locality'].unique().tolist()
# print(unique_localities)
# len(unique_localities)

# Apply the get_coordinates function to the list of unique localities
coordinates_list = list(map(get_coordinates, unique_localities))

# Create a dictionary to map localities to coordinates
locality_coordinates_dict = dict(zip(unique_localities, coordinates_list))

# Map the coordinates back to the main DataFrame
df['Locality Coordinates'] = df['Locality'].map(locality_coordinates_dict)

df.head()
```

In [ ]:

```
df.head()
# df.info()
```

In [85]:

```
from geopy.distance import geodesic

sydney_coordinates = geolocator.geocode("Sydney, Australia")
```

```
sydney_coordinates = (sydney_coordinates.latitude, sydney_coordinates.longitude)

# Function to calculate distance
def calculate_distance(coords):
    if coords:
        return geodesic(sydney_coordinates, coords).kilometers
    else:
        return None

# Apply the calculate_distance function to the 'Coordinates' column
df['Distance to Sydney (km)'] = df['Locality Coordinates'].apply(calculate_dista

# Display or use the DataFrame with the new 'Distance to Sydney (km)' column
df.head()
```

Out[85]:

	Disclaimer	Building Name	Street Display	Alternate Street Display	Other	Unit	Number	Street Name
0	NaN	NaN	24 MORAGO ST	NaN	NaN	NaN	24	MORAGO ST
1	NaN	JAKABRESUE	191 DAHWILLY RD	NaN	NaN	NaN	191	DAHWILLY RD
2	NaN	NaN	TWENTY FOUR LN	NaN	NaN	NaN	NaN	TWENTY FOUR LANE LN
3	NaN	NaN	1 MCMAHON PL	NaN	NaN	NaN	1	MCMAHON PL
4	NaN	NaN	15/314 PERRICOOTA RD	NaN	NaN	NaN	314	PERRICOOTA RD

In [90]:

```
# Extract the first 20 unique localities
unique_localities_sample = df['Locality'].unique()[:20]

# Print the distances for the first 20 unique localities
for locality in unique_localities_sample:
    distance = df[df['Locality'] == locality]['Distance to Sydney (km)'].iloc[0]
    print(f"Locality: {locality}, Distance to Sydney: {distance} km")
```

```
Locality: MOULAMEIN, NSW, AUSTRALIA, Distance to Sydney: 672.2494515804611 km
Locality: DENILIQUIN, NSW, AUSTRALIA, Distance to Sydney: 601.2616084015729 km
Locality: MOAMA, NSW, AUSTRALIA, Distance to Sydney: 638.7688422795628 km
```

```
Locality: BUNNALOO, NSW, AUSTRALIA, Distance to Sydney: 641.833662456022 km
Locality: MATHOURA, NSW, AUSTRALIA, Distance to Sydney: 615.7587637245873 km
Locality: BARHAM, NSW, AUSTRALIA, Distance to Sydney: 676.7915426398474 km
Locality: CALDWELL, NSW, AUSTRALIA, Distance to Sydney: 643.5958491505799 km
Locality: KORALEIGH, NSW, AUSTRALIA, Distance to Sydney: 730.4218550346512 km
Locality: GONN, NSW, AUSTRALIA, Distance to Sydney: 683.9521256560512 km
Locality: WOMBOOTA, NSW, AUSTRALIA, Distance to Sydney: 645.0392460251318 km
Locality: GOODNIGHT, NSW, AUSTRALIA, Distance to Sydney: 733.3795069479451 km
Locality: WAKOOL, NSW, AUSTRALIA, Distance to Sydney: 648.8602442559296 km
Locality: MURRAY DOWNS, NSW, AUSTRALIA, Distance to Sydney: 711.0308689567172 km
Locality: BURRABOI, NSW, AUSTRALIA, Distance to Sydney: 650.4266638251733 km
Locality: SPEEWA, NSW, AUSTRALIA, Distance to Sydney: 717.0586819138582 km
Locality: TANTONAN, NSW, AUSTRALIA, Distance to Sydney: 642.2092428745092 km
Locality: KYALITE, NSW, AUSTRALIA, Distance to Sydney: 720.667687301781 km
Locality: YANGA, NSW, AUSTRALIA, Distance to Sydney: 696.630555574068 km
Locality: WAUGORAH, NSW, AUSTRALIA, Distance to Sydney: 685.3584826382369 km
Locality: TULLAKOOL, NSW, AUSTRALIA, Distance to Sydney: 663.6885839240185 km
```

Now we can filter the data where:

1. sale price is less than 5M
2. the property is a house
3. the property was sold in the recent year
4. the property is within 50km of Sydney

In [95]:

```
# Filtering properties
df['Sale Date'] = pd.to_datetime(df['Sale Date'])
df_lessthan5M = df[df['Sale Price'] <= 5000000]
house_data = df_lessthan5M[df_lessthan5M['Property Type'] == 'House']
most_recent_year = df['Sale Date'].dt.year.max()
house_data_recent_year = house_data[house_data['Sale Date'].dt.year == most_rece
localities_within_50km_of_Sydney = house_data_recent_year[house_data_recent_year
df_filtered = localities_within_50km_of_Sydney
df_filtered['Locality'] = df_filtered['Locality'].str.replace(', NSW, AUSTRALIA'


len(df_filtered)
df_filtered.head()
```

```
/var/folders/1c/xdsm7htj4334pn2n9vx5kz900000gn/T/ipykernel_35213/2582173783.py:9:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_filtered['Locality'] = df_filtered['Locality'].str.replace(', NSW, AUSTRALI
A', '')
```

Out[95]:

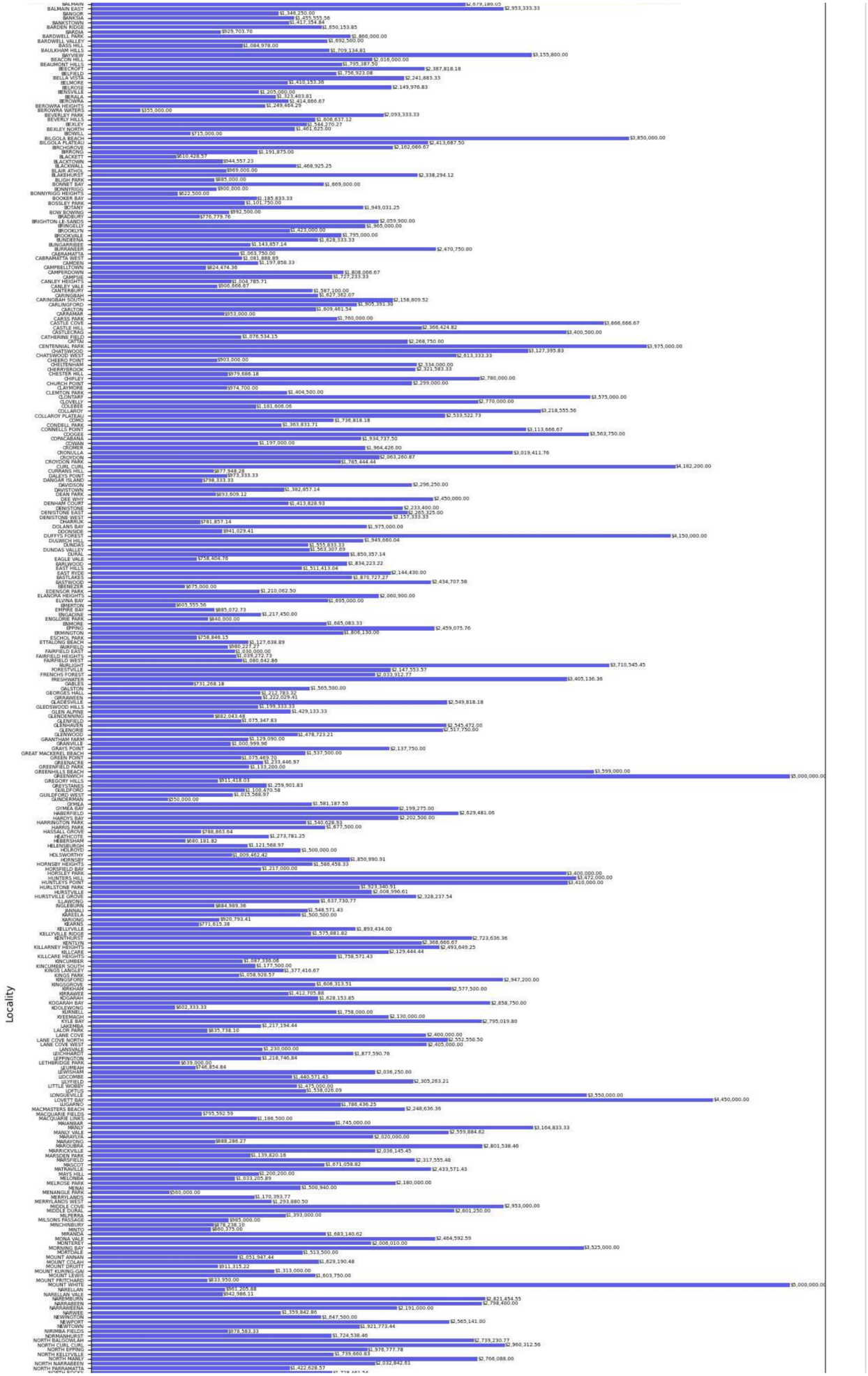
	Disclaimer	Building Name	Street Display	Alternate Street Display	Other	Unit	Number	Street
23538	NaN	NaN	77A LINDA ST	NaN	NaN	NaN	77	LIN

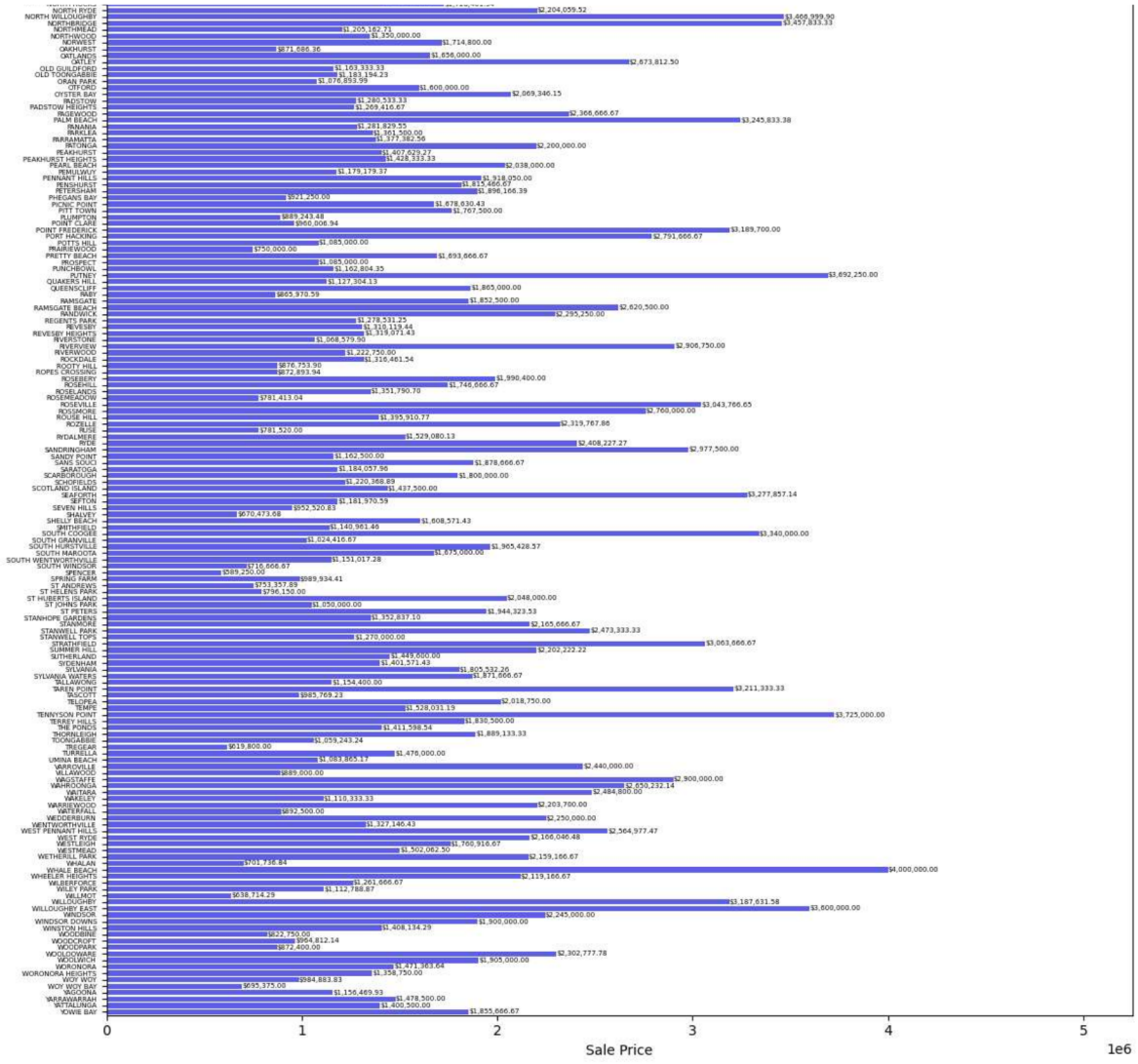
23539	NaN	NaN	166 ORCHARDLEIGH ST	NaN	NaN	NaN	166	ORCHARD
23540	NaN	NaN	12 CODRINGTON ST	NaN	NaN	NaN	12	CODRIN
23541	NaN	NaN	51 CONDELLO CRES	NaN	NaN	NaN	51	CONI
23542	NaN	NaN	125A STELLA ST	NaN	NaN	NaN	125	STEl

Analysing filtered data

In [103…

```
import matplotlib.pyplot as plt
import seaborn as sns  # Optional, but seaborn can enhance the plot aesthetics

# Group by 'Locality' and calculate mean and median for 'Sale Price'
locality_stats = df_filtered.groupby('Locality')['Sale Price'].agg(['mean', 'med

# Plotting
plt.figure(figsize=(12, 32))
bar_plot_mean = sns.barplot(x='mean', y='Locality', data=locality_stats, label='

plt.title('Mean Sale Prices by Locality')
plt.xlabel('Sale Price')
plt.ylabel('Locality')

# Rotate y-axis labels vertically and adjust font size
plt.yticks(rotation=0, fontsize=5)

# Annotate each bar with its mean sale price formatted as currency
for bar, mean_price in zip(bar_plot_mean.patches, locality_stats['mean']):
    plt.text(bar.get_width() + 500, bar.get_y() + bar.get_height() / 2, '${:,.2f

plt.legend()
plt.tight_layout()
plt.show()
```


Locality

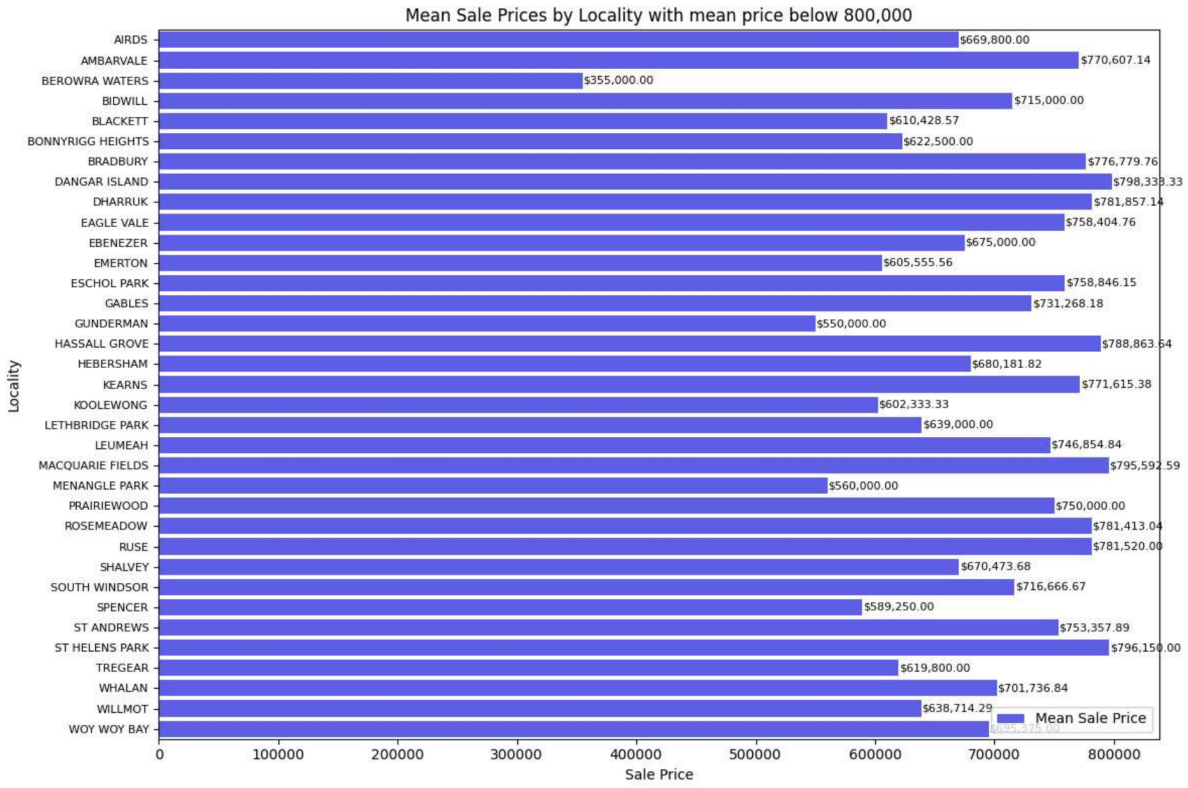


Now to further filter localities below 800k (around my max willingness to spend on an investment home)

In [109…

```
import matplotlib.pyplot as plt
import seaborn as sns  # Optional, but seaborn can enhance the plot aesthetics

# Group by 'Locality' and calculate mean and median for 'Sale Price'
locality_stats = df_filtered.groupby('Locality')['Sale Price'].agg(['mean', 'med

# Filter localities with mean price below 800,000
locality_stats = locality_stats[locality_stats['mean'] <= 800000]

# Plotting
plt.figure(figsize=(12, 8))
bar_plot_mean = sns.barplot(x='mean', y='Locality', data=locality_stats, label='

plt.title('Mean Sale Prices by Locality with mean price below 800,000')
plt.xlabel('Sale Price')
plt.ylabel('Locality')

# Rotate y-axis labels vertically and adjust font size
plt.yticks(rotation=0, fontsize=8)

# Annotate each bar with its mean sale price formatted as currency
```

```
for bar, mean_price in zip(bar_plot_mean.patches, locality_stats['mean']):
    plt.text(bar.get_width() + 500, bar.get_y() + bar.get_height() / 2, '${:,.2f

plt.legend()
plt.tight_layout()
plt.show()
```



Performing some on demand stats out of interest:

In [119…

```
# Filter DataFrame for observations with Locality equal to "ST ANDREWS"
stAndrews_observations = df_filtered[df_filtered['Locality'] == 'ST ANDREWS']

# Further filter for observations where Bedrooms >= 4
stAndrews_observations = stAndrews_observations[stAndrews_observations['Bedrooms

# Display 'Street Display', 'Sale Price', 'Sale Date', and 'Bedrooms' columns fo
print("Observations with Locality = ST ANDREWS and Bedrooms >= 4:")
print(stAndrews_observations[['Street Display', 'Sale Price', 'Sale Date', 'Bedr
```

```
Observations with Locality = ST ANDREWS and Bedrooms >= 4:
            Street Display  Sale Price  Sale Date  Bedrooms
327869         7 TUMMUL PL    770000.0 2023-01-24       3.0
327894           4 MULL PL    690000.0 2023-02-03       3.0
327983    55 STORNOWAY AVE    900000.0 2023-02-28       4.0
328011        17 LERWICK PL    775000.0 2023-03-06       3.0
328066  67 BANNOCKBURN AVE    920800.0 2023-03-20       4.0
328071    38 MIDLOTHIAN RD    820000.0 2023-03-20       3.0
328093       68 ABERDEEN RD    980000.0 2023-03-25       5.0
328153       2 BROADFORD ST    840000.0 2023-04-04       3.0
328184         5 FANNICH PL    880000.0 2023-04-11       4.0
328185  51 BANNOCKBURN AVE    760000.0 2023-04-12       3.0
328197      6 GLENEAGLES PL    675000.0 2023-04-13       3.0
```

```
328256   46 DUNCANSBY CRES    750000.0 2023-04-26       3.0
328380   47 ARDROSSAN CRES    691000.0 2023-05-20       3.0
328382        16 ELGIN AVE    790000.0 2023-05-22       3.0
328427         15 BROOM PL    927000.0 2023-06-02       4.0
328438     14 BROADFORD ST    780000.0 2023-06-05       4.0
```

In [117…

```python
# Get unique values in the 'Locality' column and sort them alphabetically
unique_localities = sorted(df_filtered['Locality'].unique())

# Print unique localities in alphabetical order
print("Unique Localities (Alphabetical Order):")
for locality in unique_localities:
    print(locality)
```

```
Unique Localities (Alphabetical Order):
ABBOTSBURY
ACACIA GARDENS
AIRDS
ALFORDS POINT
ALLAMBIE HEIGHTS
ALLAWAH
AMBARVALE
ANNANDALE
ANNANGROVE
ARCADIA
ARNCLIFFE
ARTARMON
ASHBURY
ASHFIELD
ASQUITH
AUBURN
AVALON BEACH
AVOCA BEACH
BALGOWLAH
BALGOWLAH HEIGHTS
BALMAIN
BALMAIN EAST
BANGOR
BANKSIA
BANKSTOWN
BARDEN RIDGE
BARDIA
BARDWELL PARK
BARDWELL VALLEY
BASS HILL
BAULKHAM HILLS
BAYVIEW
BEACON HILL
BEAUMONT HILLS
BEECROFT
BELFIELD
BELLA VISTA
BELMORE
BELROSE
BENSVILLE
BERALA
BEROWRA
BEROWRA HEIGHTS
BEROWRA WATERS
BEVERLEY PARK
```

```
BEVERLY HILLS
BEXLEY
BEXLEY NORTH
BIDWILL
BILGOLA BEACH
BILGOLA PLATEAU
BIRCHGROVE
BIRRONG
BLACKETT
BLACKTOWN
BLACKWALL
BLAIR ATHOL
BLAKEHURST
BLIGH PARK
BONNET BAY
BONNYRIGG
BONNYRIGG HEIGHTS
BOOKER BAY
BOSSLEY PARK
BOTANY
BOW BOWING
BRADBURY
BRIGHTON-LE-SANDS
BRINGELLY
BROOKLYN
BROOKVALE
BUNDEENA
BUNGARRIBEE
BURRANEER
CABRAMATTA
CABRAMATTA WEST
CAMDEN
CAMPBELLTOWN
CAMPERDOWN
CAMPSIE
CANLEY HEIGHTS
CANLEY VALE
CANTERBURY
CARINGBAH
CARINGBAH SOUTH
CARLINGFORD
CARLTON
CARRAMAR
CARSS PARK
CASTLE COVE
CASTLE HILL
CASTLECRAG
CATHERINE FIELD
CATTAI
CENTENNIAL PARK
CHATSWOOD
CHATSWOOD WEST
CHEERO POINT
CHELTENHAM
CHERRYBROOK
CHESTER HILL
CHIFLEY
CHURCH POINT
CLAYMORE
CLEMTON PARK
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CLONTARF
CLOVELLY
COLEBEE
COLLAROY
COLLAROY PLATEAU
COMO
CONDELL PARK
CONNELLS POINT
COOGEE
COPACABANA
COWAN
CROMER
CRONULLA
CROYDON
CROYDON PARK
CURL CURL
CURRANS HILL
DALEYS POINT
DANGAR ISLAND
DAVIDSON
DAVISTOWN
DEAN PARK
DEE WHY
DENHAM COURT
DENISTONE
DENISTONE EAST
DENISTONE WEST
DHARRUK
DOLANS BAY
DOONSIDE
DUFFYS FOREST
DULWICH HILL
DUNDAS
DUNDAS VALLEY
DURAL
EAGLE VALE
EARLWOOD
EAST HILLS
EAST RYDE
EASTLAKES
EASTWOOD
EBENEZER
EDENSOR PARK
ELANORA HEIGHTS
ELVINA BAY
EMERTON
EMPIRE BAY
ENGADINE
ENGLORIE PARK
ENMORE
EPPING
ERMINGTON
ESCHOL PARK
ETTALONG BEACH
FAIRFIELD
FAIRFIELD EAST
FAIRFIELD HEIGHTS
FAIRFIELD WEST
FAIRLIGHT
FORESTVILLE
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FRENCHS FOREST
FRESHWATER
GABLES
GALSTON
GEORGES HALL
GIRRAWEEN
GLADESVILLE
GLEDSWOOD HILLS
GLEN ALPINE
GLENDENNING
GLENFIELD
GLENHAVEN
GLENORIE
GLENWOOD
GRANTHAM FARM
GRANVILLE
GRAYS POINT
GREAT MACKEREL BEACH
GREEN POINT
GREENACRE
GREENFIELD PARK
GREENHILLS BEACH
GREENWICH
GREGORY HILLS
GREYSTANES
GUILDFORD
GUILDFORD WEST
GUNDERMAN
GYMEA
GYMEA BAY
HABERFIELD
HARDYS BAY
HARRINGTON PARK
HARRIS PARK
HASSALL GROVE
HEATHCOTE
HEBERSHAM
HELENSBURGH
HOLROYD
HOLSWORTHY
HORNSBY
HORNSBY HEIGHTS
HORSFIELD BAY
HORSLEY PARK
HUNTERS HILL
HUNTLEYS POINT
HURLSTONE PARK
HURSTVILLE
HURSTVILLE GROVE
ILLAWONG
INGLEBURN
JANNALI
KAREELA
KARIONG
KEARNS
KELLYVILLE
KELLYVILLE RIDGE
KENTHURST
KENTLYN
KILLARNEY HEIGHTS
KILLCARE
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KILLCARE HEIGHTS
KINCUMBER
KINCUMBER SOUTH
KINGS LANGLEY
KINGS PARK
KINGSFORD
KINGSGROVE
KIRKHAM
KIRRAWEE
KOGARAH
KOGARAH BAY
KOOLEWONG
KURNELL
KYEEMAGH
KYLE BAY
LAKEMBA
LALOR PARK
LANE COVE
LANE COVE NORTH
LANE COVE WEST
LANSVALE
LEICHHARDT
LEPPINGTON
LETHBRIDGE PARK
LEUMEAH
LEWISHAM
LIDCOMBE
LILYFIELD
LITTLE WOBBY
LOFTUS
LONGUEVILLE
LOVETT BAY
LUGARNO
MACMASTERS BEACH
MACQUARIE FIELDS
MACQUARIE LINKS
MAIANBAR
MANLY
MANLY VALE
MARAYLYA
MARAYONG
MAROUBRA
MARRICKVILLE
MARSDEN PARK
MARSFIELD
MASCOT
MATRAVILLE
MAYS HILL
MELONBA
MELROSE PARK
MENAI
MENANGLE PARK
MERRYLANDS
MERRYLANDS WEST
MIDDLE COVE
MIDDLE DURAL
MILPERRA
MILSONS PASSAGE
MINCHINBURY
MINTO
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MIRANDA
MONA VALE
MONTEREY
MORNING BAY
MORTDALE
MOUNT ANNAN
MOUNT COLAH
MOUNT DRUITT
MOUNT KURING-GAI
MOUNT LEWIS
MOUNT PRITCHARD
MOUNT WHITE
NARELLAN
NARELLAN VALE
NAREMBURN
NARRABEEN
NARRAWEENA
NARWEE
NEWINGTON
NEWPORT
NEWTOWN
NIRIMBA FIELDS
NORMANHURST
NORTH BALGOWLAH
NORTH CURL CURL
NORTH EPPING
NORTH KELLYVILLE
NORTH MANLY
NORTH NARRABEEN
NORTH PARRAMATTA
NORTH ROCKS
NORTH RYDE
NORTH WILLOUGHBY
NORTHBRIDGE
NORTHMEAD
NORTHWOOD
NORWEST
OAKHURST
OATLANDS
OATLEY
OLD GUILDFORD
OLD TOONGABBIE
ORAN PARK
OTFORD
OYSTER BAY
PADSTOW
PADSTOW HEIGHTS
PAGEWOOD
PALM BEACH
PANANIA
PARKLEA
PARRAMATTA
PATONGA
PEAKHURST
PEAKHURST HEIGHTS
PEARL BEACH
PEMULWUY
PENNANT HILLS
PENSHURST
PETERSHAM
PHEGANS BAY
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PHEGANS BAY
PICNIC POINT
PITT TOWN
PLUMPTON
POINT CLARE
POINT FREDERICK
PORT HACKING
POTTS HILL
PRAIRIEWOOD
PRETTY BEACH
PROSPECT
PUNCHBOWL
PUTNEY
QUAKERS HILL
QUEENSCLIFF
RABY
RAMSGATE
RAMSGATE BEACH
RANDWICK
REGENTS PARK
REVESBY
REVESBY HEIGHTS
RIVERSTONE
RIVERVIEW
RIVERWOOD
ROCKDALE
ROOTY HILL
ROPES CROSSING
ROSEBERY
ROSEHILL
ROSELANDS
ROSEMEADOW
ROSEVILLE
ROSSMORE
ROUSE HILL
ROZELLE
RUSE
RYDALMERE
RYDE
SANDRINGHAM
SANDY POINT
SANS SOUCI
SARATOGA
SCARBOROUGH
SCHOFIELDS
SCOTLAND ISLAND
SEAFORTH
SEFTON
SEVEN HILLS
SHALVEY
SHELLY BEACH
SMITHFIELD
SOUTH COOGEE
SOUTH GRANVILLE
SOUTH HURSTVILLE
SOUTH MAROOTA
SOUTH WENTWORTHVILLE
SOUTH WINDSOR
SPENCER
SPRING FARM
ST ANDREWS
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ST HELENS PARK
ST HUBERTS ISLAND
ST JOHNS PARK
ST PETERS
STANHOPE GARDENS
STANMORE
STANWELL PARK
STANWELL TOPS
STRATHFIELD
SUMMER HILL
SUTHERLAND
SYDENHAM
SYLVANIA
SYLVANIA WATERS
TALLAWONG
TAREN POINT
TASCOTT
TELOPEA
TEMPE
TENNYSON POINT
TERREY HILLS
THE PONDS
THORNLEIGH
TOONGABBIE
TREGEAR
TURRELLA
UMINA BEACH
VARROVILLE
VILLAWOOD
WAGSTAFFE
WAHROONGA
WAITARA
WAKELEY
WARRIEWOOD
WATERFALL
WEDDERBURN
WENTWORTHVILLE
WEST PENNANT HILLS
WEST RYDE
WESTLEIGH
WESTMEAD
WETHERILL PARK
WHALAN
WHALE BEACH
WHEELER HEIGHTS
WILBERFORCE
WILEY PARK
WILLMOT
WILLOUGHBY
WILLOUGHBY EAST
WINDSOR
WINDSOR DOWNS
WINSTON HILLS
WOODBINE
WOODCROFT
WOODPARK
WOOLOOWARE
WOOLWICH
WORONORA
WORONORA HEIGHTS
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WOY WOY
WOY WOY BAY
YAGOONA
YARRAWARRAH
YATTALUNGA
YOWIE BAY
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