

```
In [1]: import os
os.environ['AWS_ACCESS_KEY_ID'] = "*****"
os.environ['AWS_SECRET_ACCESS_KEY'] = "*****"
```

```
In [2]: from pyspark.sql import SparkSession
import os
import pandas as pd
from sklearn.preprocessing import MinMaxScaler

spark = (SparkSession.builder
        .appName("quant-etl")
        .master("local[*]")
        .config("spark.driver.memory", "10g")
        .config("spark.sql.execution.arrow.pyspark.enabled", "true")
        .config("spark.databricks.delta.schema.autoMerge.enabled", "true")
        .config("spark.sql.debug.maxToStringFields", 1000)
        .config(
            "spark.jars.packages",
            "io.delta:delta-core_2.12:2.4.0,"
            "org.apache.hadoop:hadoop-aws:3.3.4,"
            "com.amazonaws:aws-java-sdk-bundle:1.12.670"
        )
        .config("spark.sql.extensions", "io.delta.sql.DeltaSparkSessionExtension")
        .config("spark.sql.catalog.spark_catalog", "org.apache.spark.sql.delta.catalog.DeltaCatalog")
        .config("spark.hadoop.fs.s3a.access.key", os.getenv("AWS_ACCESS_KEY_ID"))
        .config("spark.hadoop.fs.s3a.secret.key", os.getenv("AWS_SECRET_ACCESS_KEY"))
        .config("spark.hadoop.fs.s3a.endpoint", "s3.amazonaws.com")
        .config("spark.sql.warehouse.dir", "s3a://quantdata-warehouse")
        .getOrCreate())
```

24/03/04 21:20:55 WARN Utils: Your hostname, Mohammads-MacBook-Pro.local resolves to a loopback address: 127.0.0.1; using 192.168.1.102 instead (on interface en0)

24/03/04 21:20:55 WARN Utils: Set SPARK_LOCAL_IP if you need to bind to another address

:: loading settings :: url = jar:file:/Users/mohammadshbaita/miniforge3/lib/python3.9/site-packages/pyspark/jars/ivy-2.5.1.jar!/org/apache/ivy/core/settings/ivysettings.xml

```

Ivy Default Cache set to: /Users/mohammadshbaita/.ivy2/cache
The jars for the packages stored in: /Users/mohammadshbaita/.ivy2/jars
io.delta#delta-core_2.12 added as a dependency
org.apache.hadoop#hadoop-aws added as a dependency
com.amazonaws#aws-java-sdk-bundle added as a dependency
:: resolving dependencies :: org.apache.spark#spark-submit-parent-0d2e933f-
82ae-44bc-ab93-f1a90ca08607;1.0
   confs: [default]
   found io.delta#delta-core_2.12;2.4.0 in central
   found io.delta#delta-storage;2.4.0 in central
   found org.antlr#antlr4-runtime;4.9.3 in central
   found org.apache.hadoop#hadoop-aws;3.3.4 in central
   found org.wildfly.openssl#wildfly-openssl;1.0.7.Final in central
   found com.amazonaws#aws-java-sdk-bundle;1.12.670 in central
:: resolution report :: resolve 536ms :: artifacts dl 14ms
   :: modules in use:
   com.amazonaws#aws-java-sdk-bundle;1.12.670 from central in [default]
t]
   io.delta#delta-core_2.12;2.4.0 from central in [default]
   io.delta#delta-storage;2.4.0 from central in [default]
   org.antlr#antlr4-runtime;4.9.3 from central in [default]
   org.apache.hadoop#hadoop-aws;3.3.4 from central in [default]
   org.wildfly.openssl#wildfly-openssl;1.0.7.Final from central in [de
fault]
   :: evicted modules:
   com.amazonaws#aws-java-sdk-bundle;1.12.262 by [com.amazonaws#aws-ja
va-sdk-bundle;1.12.670] in [default]
-----
--
|               |               modules               || artifacts
|               | number| search|dwnlded|evicted|| number|dwnlde
d|
-----
--
|               | 7   | 0   | 0   | 1   || 6   | 0
|
-----
--
:: retrieving :: org.apache.spark#spark-submit-parent-0d2e933f-82ae-44bc-ab
93-f1a90ca08607
   confs: [default]
   0 artifacts copied, 6 already retrieved (0kB/10ms)
24/03/04 21:20:56 WARN NativeCodeLoader: Unable to load native-hadoop libra
ry for your platform... using builtin-java classes where applicable
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLo
gLevel(newLevel).

```

Load the three tables from our warehouse (ad_details, district, property_type)

```

In [31]: ad_table = spark.read.format("delta").load(f"s3a://quantdata-warehouse/ad_de
district_table = spark.read.format("delta").load(f"s3a://quantdata-warehouse
property_type_table = spark.read.format("delta").load(f"s3a://quantdata-ware

```

Part Two

1. Calculate the average rate increase in rent prices when switching from a 2-Bedroom Apartment to a 3-bedroom Apartment in Riyadh for both families and singles.
2. Calculate the average duration it takes to close a post and mention the parameters that affect this duration. Also, mention the district with the shortest duration it takes to close a post with property type of villa.
3. Provide the correlation matrix for the effects on prices after normalization for both rents and sales, and comment on the most price affecting parameters.
4. Give a sales price valuation of rental properties (convert rental properties to sales properties) based on 6% ROI (Return on Investment) then estimate the meter price distribution per property type and district and comment on the result.
5. Add any general insights you find during your work on the data

Data Preprocessing

Hot Encoders

```
In [34]: def encode_swimming_pool(value):  
    if value == 'مسبح':  
        return 1  
    else:  
        return 0  
  
def encode_is_closed(value):  
    if value == 'مغلق':  
        return 0  
    else:  
        return 1  
  
def encode_is_commercial(value):  
    if value == 'تجاري':  
        return 0  
    elif value == 'سكني':  
        return 1  
    elif value == 'كلاهما':  
        return 2  
    else:  
        return 3  
  
def encode_is_driver_room_exist(value):
```

```
    if value == 'غرفة سائق':
        return 1
    else:
        return 0

def encode_is_duplex(value):
    if value == 'دوبلكس':
        return 1
    else:
        return 0

def encode_is_couple(value):
    if value == 'عزاب':
        return 0
    else:
        return 1

def encode_is_furnished(value):
    if value == 'مؤثثة':
        return 1
    else:
        return 0

def encode_is_maid_room_exist(value):

    if value == 'غرفة خادمة':
        return 1
    else:
        return 0

def encode_is_owner(value):
    if value == 'مالك':
        return 1
    else:
        return 0

def encode_is_rent_type(value):
    if value == 'سنوي':
        return 0
    elif value == 'يومي':
        return 1
    elif value == 'شهري':
        return 2
    else:
        return 3

def encode_is_street_direction(value):
    if value == 'شرق':
        return 0
    elif value == 'شوارع 3':
        return 1
    elif value == 'جنوب غربي':
        return 2
    elif value == 'جنوب':
        return 3
    elif value == 'جنوب غربي':
```

```

        return 4
    elif value == 'شمال':
        return 5
    elif value == 'غرب':
        return 6
    elif value == 'شمال غربي':
        return 7
    elif value == 'شوارع 4':
        return 8
    elif value == 'جنوب شرقي':
        return 9
    elif value == 'شمال شرقي':
        return 10
    else:
        return 11

def encode_is_rent_or_sale(value):
    if value == 'للإيجار':
        return 1
    elif value == 'للبيع':
        return 0
    elif value == 'SALE':
        return 0
    elif value == 'RENT':
        return 1
    else:
        return 2

def encode_is_paid(value):
    if value == 'مجاني':
        return 0
    elif value == 'مدفوع':
        return 1
    else:
        return 2

```

```

In [35]: ad_table['has_swimming_pool'] = ad_table['has_swimming_pool'].apply(encode_s
ad_table['is_closed'] = ad_table['is_closed'].apply(encode_is_closed)
ad_table['residential_or_commercial'] = ad_table['residential_or_commercial']
ad_table['driver_room'] = ad_table['driver_room'].apply(encode_is_driver_roo
ad_table['is_duplex'] = ad_table['is_duplex'].apply(encode_is_duplex)
ad_table['families_or_singles'] = ad_table['families_or_singles'].apply(enco
ad_table['is_furnished'] = ad_table['is_furnished'].apply(encode_is_furnishe
ad_table['maid_room'] = ad_table['maid_room'].apply(encode_is_maid_room_exis
ad_table['advertiser_type'] = ad_table['advertiser_type'].apply(encode_is_ow
ad_table['rent_type'] = ad_table['rent_type'].apply(encode_is_rent_type)
ad_table['street_direction'] = ad_table['street_direction'].apply(encode_is_
ad_table['purpose'] = ad_table['purpose'].apply(encode_is_rent_or_sale)
ad_table['is_paid'] = ad_table['is_paid'].apply(encode_is_paid)

```

```

In [36]: ad_table["rent_type"].unique()

```

```

Out[36]: array([0, 3, 2, 1])

```

```
In [37]: ad_table['purpose'].unique()
```

```
Out[37]: array([1, 0])
```

Change Data Types

```
In [66]: ad_table['price'] = pd.to_numeric(ad_table['price'], errors='coerce')
ad_table['number_of_bedrooms'] = pd.to_numeric(ad_table['number_of_bedrooms'], errors='coerce')
ad_table['number_of_apartments'] = pd.to_numeric(ad_table['number_of_apartments'], errors='coerce')
ad_table['floor'] = pd.to_numeric(ad_table['floor'], downcast='integer', errors='coerce')
ad_table['number_of_kitchens'] = pd.to_numeric(ad_table['number_of_kitchens'], errors='coerce')
ad_table['has_swimming_pool'] = pd.to_numeric(ad_table['has_swimming_pool'], errors='coerce')
ad_table['is_closed'] = pd.to_numeric(ad_table['is_closed'], downcast='integer', errors='coerce')
ad_table['residential_or_commercial'] = pd.to_numeric(ad_table['residential_or_commercial'], errors='coerce')
ad_table['driver_room'] = pd.to_numeric(ad_table['driver_room'], downcast='integer', errors='coerce')
ad_table['is_duplex'] = pd.to_numeric(ad_table['is_duplex'], downcast='integer', errors='coerce')
ad_table['families_or_singles'] = pd.to_numeric(ad_table['families_or_singles'], errors='coerce')
ad_table['is_furnished'] = pd.to_numeric(ad_table['is_furnished'], downcast='integer', errors='coerce')
ad_table['maid_room'] = pd.to_numeric(ad_table['maid_room'], downcast='integer', errors='coerce')
ad_table['advertiser_type'] = pd.to_numeric(ad_table['advertiser_type'], downcast='integer', errors='coerce')
ad_table['street_direction'] = pd.to_numeric(ad_table['street_direction'], downcast='integer', errors='coerce')
ad_table['purpose'] = pd.to_numeric(ad_table['purpose'], downcast='integer', errors='coerce')
ad_table['is_paid'] = pd.to_numeric(ad_table['is_paid'], downcast='integer', errors='coerce')
ad_table['created_at'] = pd.to_datetime(ad_table['created_at'], errors='coerce')
ad_table['updated_at'] = pd.to_datetime(ad_table['updated_at'], errors='coerce')
```

=====

Average Rate Increase

Calculate the average rate increase in rent prices when switching from a 2-Bedroom Apartment to a 3-bedroom Apartment in Riyadh for both families and singles.

=====

Filter district table for Riyadh

```
In [67]: riyadh_district_ids = district_table[(district_table['city_name_en'] == 'Riyadh')]
riyadh_ads = ad_table[ad_table['district_id'].isin(riyadh_district_ids)]
```

Filter only the apartment porperty type

```
In [68]: property_type_ids = property_type_table[(property_type_table['property_type'] == 'Apartment')]
apartment_ads = ad_table[ad_table['property_type_id'].isin(property_type_ids)]
len(apartment_ads.index)
```

```
Out[68]: 24850
```

```
In [85]: apartment_ads.columns
```

```
Out[85]: Index(['id', 'district_id', 'property_type_id', 'district_name_en',
               'property_type', 'property_age_less_than', 'number_of_apartments',
               'number_of_bedrooms', 'floor', 'number_of_kitchens', 'is_closed',
               'residential_or_commercial', 'driver_room', 'is_duplex',
               'families_or_singles', 'is_furnished', 'halls_Num', 'maid_room',
               'price_per_meter', 'advertiser_type', 'has_swimming_pool', 'is_pai
               d',
               'price', 'purpose', 'rent_type', 'rooms_num', 'space',
               'street_direction', 'street_width_range', 'toilets_num', 'latitude',
               'longitude', 'property_age_range', 'created_at', 'updated_at',
               'data_source'],
               dtype='object')
```

Filter on rent type = Monthly, purpose = For Rent and is not furnished

```
In [86]: rent_ads = apartment_ads[(apartment_ads['purpose'] == 1) & (apartment_ads['r
len(rent_ads.index)
```

```
Out[86]: 730
```

Two bedrooms and three bedrooms for families and singles

```
In [70]: two_bedroom_families = rent_ads[(rent_ads['number_of_bedrooms'] == 2) & (ren
three_bedroom_families = rent_ads[(rent_ads['number_of_bedrooms'] == 3) & (r

two_bedroom_singles = rent_ads[(rent_ads['number_of_bedrooms'] == 2) & (rent
three_bedroom_singles = rent_ads[(rent_ads['number_of_bedrooms'] == 3) & (re

(print(f"number of records for two_bedroom_families: {len(two_bedroom_famili
      f"number of records for three_bedroom_families: {len(three_bedroom_fam
      f"number of records for two_bedroom_singles: {len(two_bedroom_singles.
      f"number of records for three_bedroom_singles: {len(three_bedroom_sing
)
```

```
number of records for two_bedroom_families: 92
number of records for three_bedroom_families: 201
number of records for two_bedroom_singles: 67
number of records for three_bedroom_singles: 21
```

```
In [163... two_bedroom_families.to_csv("two_bedroom_families.csv")
three_bedroom_families.to_csv("three_bedroom_families.csv")
two_bedroom_singles.to_csv("two_bedroom_singles.csv")
three_bedroom_singles.to_csv("three_bedroom_singles.csv")
```

```
In [77]: df_zero_or_below = three_bedroom_singles[three_bedroom_singles['price'] <= 0
# three_bedroom_families['price'].isna().sum()
# two_bedroom_singles['price'].isna().sum()
# three_bedroom_singles['price'].isna().sum()
df_zero_or_below
```

```
Out[77]:   id  district_id  property_type_id  district_name_en  property_type  property_age_less_than
```

0 rows x 36 columns

Calculate average prices

```
In [78]: avg_price_two_bedroom_families = two_bedroom_families['price'].mean()
avg_price_three_bedroom_families = three_bedroom_families['price'].mean()
avg_price_two_bedroom_singles = two_bedroom_singles['price'].mean()
avg_price_three_bedroom_singles = three_bedroom_singles['price'].mean()
(print(f"avg_price_two_bedroom_families: {avg_price_two_bedroom_families}\n"
      f"avg_price_three_bedroom_families: {avg_price_three_bedroom_families}\n"
      f"two_bedroom_singles: {avg_price_two_bedroom_singles}\n"
      f"three_bedroom_singles: {avg_price_three_bedroom_singles}\n")
)

avg_price_two_bedroom_families: 120204.6171875
avg_price_three_bedroom_families: 58250572.0
two_bedroom_singles: 13007.4482421875
three_bedroom_singles: 23981276.0
```

Calculate rate increase

```
In [79]: rate_increase_families = ((avg_price_three_bedroom_families - avg_price_two_
rate_increase_singles = ((avg_price_three_bedroom_singles - avg_price_two_be
```

Calculate the average rate increase in rent prices when switching from a 2-Bedroom Apartment to a 3-bedroom Apartment in Riyadh for both families and singles.

```
In [80]: rate_increase_families, rate_increase_singles
```

```
Out[80]: (48359.51232910156, 184265.72265625)
```

The above data indicates that there is a problem in it

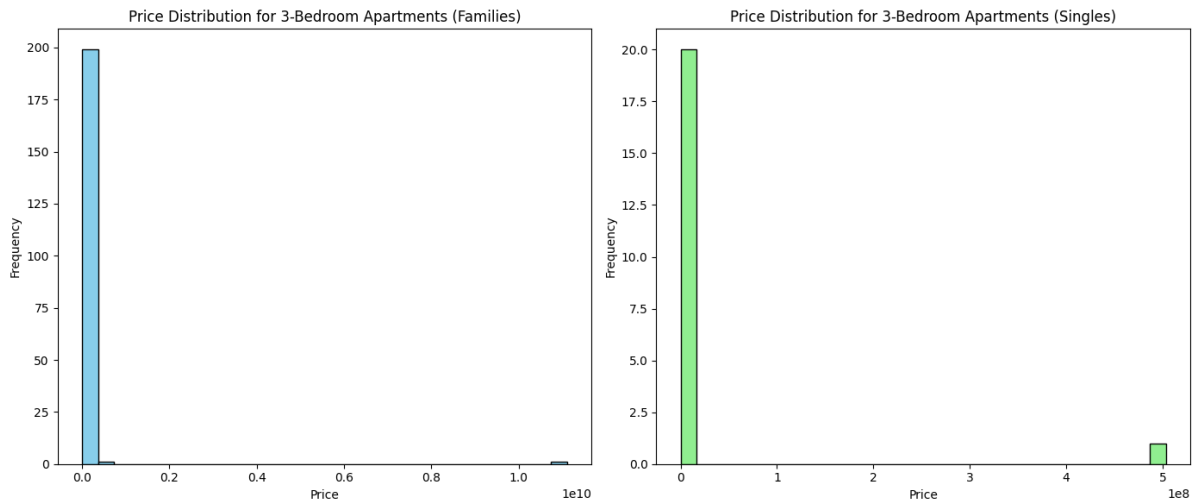
Step 1: Analyze and Visualize Price Distributions (Code Provided Above)

```
In [164]: fig, ax = plt.subplots(1, 2, figsize=(14, 6))

# Distribution of prices for 3-bedroom families apartments
ax[0].hist(three_bedroom_families['price'], bins=30, color='skyblue', edgeco
ax[0].set_title('Price Distribution for 3-Bedroom Apartments (Families)')
ax[0].set_xlabel('Price')
ax[0].set_ylabel('Frequency')

# Distribution of prices for 3-bedroom singles apartments
ax[1].hist(three_bedroom_singles['price'], bins=30, color='lightgreen', edge
ax[1].set_title('Price Distribution for 3-Bedroom Apartments (Singles)')
ax[1].set_xlabel('Price')
ax[1].set_ylabel('Frequency')

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

Function to remove outliers

```
In [166... def remove_outliers(df, column_name):
    """
    Remove outliers from a dataframe based on the column specified.
    Outliers are defined as values more than 3 standard deviations from the
    """
    mean = df[column_name].mean()
    std_dev = df[column_name].std()
    cutoff = std_dev * 3
    lower_bound = mean - cutoff
    upper_bound = mean + cutoff

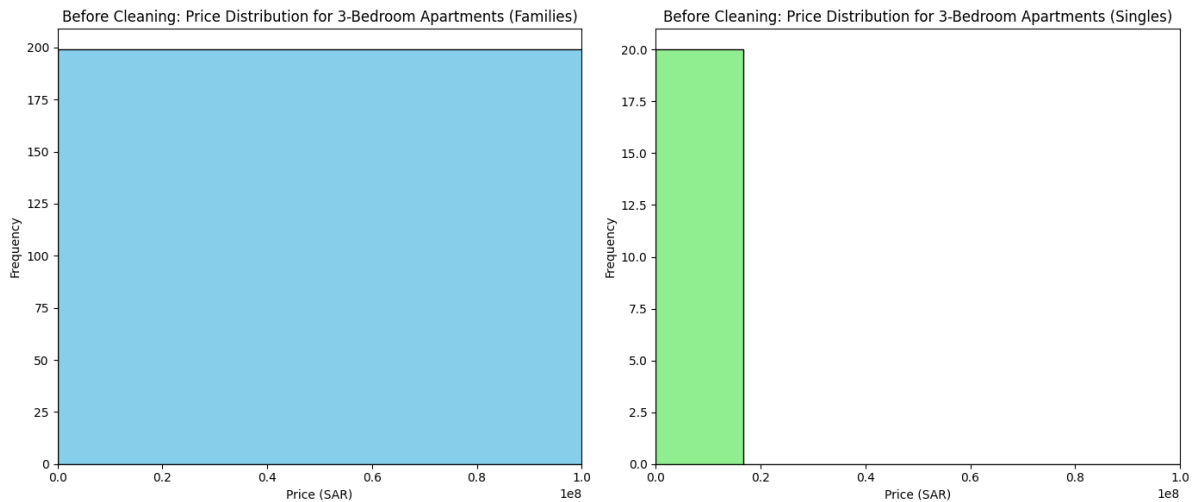
    # Filter out the outliers
    cleaned_df = df[(df[column_name] >= lower_bound) & (df[column_name] <= u
    return cleaned_df
```

```
In [167... # Initial visualization of price distributions for 3-bedroom apartments
fig, ax = plt.subplots(1, 2, figsize=(14, 6))

# 3-bedroom families apartments before cleaning
ax[0].hist(three_bedroom_families['price'], bins=30, color='skyblue', edgeco
ax[0].set_title('Before Cleaning: Price Distribution for 3-Bedroom Apartment
ax[0].set_xlabel('Price (SAR)')
ax[0].set_ylabel('Frequency')
ax[0].set_xlim([0, 100000000]) # Adjust based on your data to improve reada

# 3-bedroom singles apartments before cleaning
ax[1].hist(three_bedroom_singles['price'], bins=30, color='lightgreen', edge
ax[1].set_title('Before Cleaning: Price Distribution for 3-Bedroom Apartment
ax[1].set_xlabel('Price (SAR)')
ax[1].set_ylabel('Frequency')
ax[1].set_xlim([0, 100000000]) # Adjust based on your data to improve reada

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



Before Cleaning (Families and Singles): These histograms show the original price distributions for 3-bedroom apartments, catering to families and singles. The wide range of prices, especially with some extremely high values, indicates the presence of outliers that could significantly affect the average price calculations.

Remove outliers from the 3-bedroom datasets

```
In [168... three_bedroom_families_cleaned = remove_outliers(three_bedroom_families, 'price')
three_bedroom_singles_cleaned = remove_outliers(three_bedroom_singles, 'price')
```

Visualization of price distributions after removing outliers

```
In [169... fig, ax = plt.subplots(2, 2, figsize=(14, 12), sharex=True)

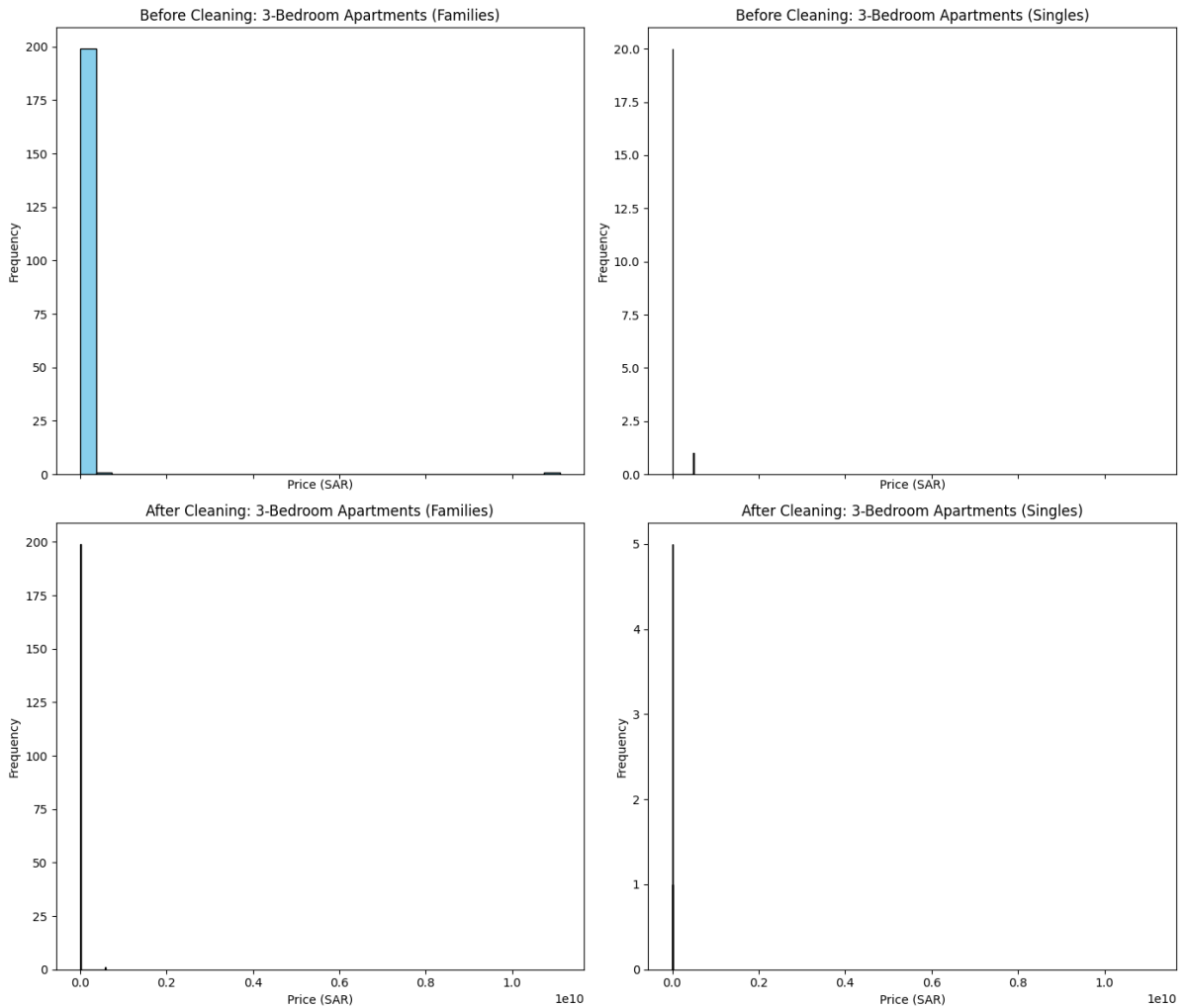
# Before cleaning - families
ax[0, 0].hist(three_bedroom_families['price'], bins=30, color='skyblue', edgecolor='black')
ax[0, 0].set_title('Before Cleaning: 3-Bedroom Apartments (Families)')
ax[0, 0].set_xlabel('Price (SAR)')
ax[0, 0].set_ylabel('Frequency')

# After cleaning - families
ax[1, 0].hist(three_bedroom_families_cleaned['price'], bins=30, color='skyblue', edgecolor='black')
ax[1, 0].set_title('After Cleaning: 3-Bedroom Apartments (Families)')
ax[1, 0].set_xlabel('Price (SAR)')
ax[1, 0].set_ylabel('Frequency')

# Before cleaning - singles
ax[0, 1].hist(three_bedroom_singles['price'], bins=30, color='lightgreen', edgecolor='black')
ax[0, 1].set_title('Before Cleaning: 3-Bedroom Apartments (Singles)')
ax[0, 1].set_xlabel('Price (SAR)')
ax[0, 1].set_ylabel('Frequency')

# After cleaning - singles
ax[1, 1].hist(three_bedroom_singles_cleaned['price'], bins=30, color='lightgreen', edgecolor='black')
ax[1, 1].set_title('After Cleaning: 3-Bedroom Apartments (Singles)')
ax[1, 1].set_xlabel('Price (SAR)')
ax[1, 1].set_ylabel('Frequency')
```

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



After Cleaning (Families and Singles): After removing outliers (defined as prices more than 3 standard deviations from the mean), these histograms present the cleaned price distributions. The distributions are now more concentrated, indicating a removal of extreme values. This cleaning process should lead to more representative average price calculations.

Recalculate the average prices without outliers

```
In [170...] avg_price_three_bedroom_families_cleaned = three_bedroom_families_cleaned['p
avg_price_three_bedroom_singles_cleaned = three_bedroom_singles_cleaned['pri

print(f"Average price for a 3-bedroom apartment for families (cleaned): {avg_
print(f"Average price for a 3-bedroom apartment for singles (cleaned): {avg_

Average price for a 3-bedroom apartment for families (cleaned): 2986318.75
SAR
Average price for a 3-bedroom apartment for singles (cleaned): 5840.00 SAR
```

```
In [171...] # Recalculate the average prices without outliers
rate_increase_families = ((avg_price_three_bedroom_families_cleaned - avg_pr
rate_increase_singles = ((avg_price_three_bedroom_singles_cleaned - avg_pric
```

```
In [172... rate_increase_families, rate_increase_singles
```

```
Out[172]: (2384.36279296875, -55.102646350860596)
```

These rates suggest a substantial increase in rent prices for families when moving from a 2-bedroom to a 3-bedroom apartment, while indicating a decrease for singles. However, the negative rate for singles seems counterintuitive since it implies that moving to a larger apartment would, on average, cost less, which is generally not expected in real estate markets.

=====

2. Calculate the average duration it takes to close a post and mention the parameters that affect this duration. Also, mention the district with the shortest duration it takes to close a post with property type of villa.

=====

I will consider the difference between updated and created date without checking is_closed it the duration to close the post

Step 1: Calculate Duration to Close a Post

```
In [115... ad_table['created_at'] = pd.to_datetime(ad_table['created_at'])
ad_table['updated_at'] = pd.to_datetime(ad_table['updated_at'])
ad_table['closing_duration'] = (ad_table['updated_at'] - ad_table['created_a
```

Step 2: Identify Parameters Affecting Duration

```
In [114... ad_table.columns
```

```
Out[114]: Index(['id', 'district_id', 'property_type_id', 'district_name_en',
                'property_type', 'property_age_less_than', 'number_of_apartments',
                'number_of_bedrooms', 'floor', 'number_of_kitchens', 'is_closed',
                'residential_or_commercial', 'driver_room', 'is_duplex',
                'families_or_singles', 'is_furnished', 'halls_Num', 'maid_room',
                'price_per_meter', 'advertiser_type', 'has_swimming_pool', 'is_pai
d',
                'price', 'purpose', 'rent_type', 'rooms_num', 'space',
                'street_direction', 'street_width_range', 'toilets_num', 'latitud
e',
                'longitude', 'property_age_range', 'created_at', 'updated_at',
                'data_source', 'closing_duration'],
                dtype='object')
```

```
In [127... # This step involves statistical analysis. As a simple approach, you can sta
correlations = ad_table[['closing_duration', 'price', 'number_of_bedrooms', '
correlations
```

```
Out[127]:
```

	closing_duration	price	number_of_bedrooms	is_furnished	has
closing_duration	1.000000	-0.004561	-0.049748	-0.013467	
price	-0.004561	1.000000	-0.004130	0.007733	
number_of_bedrooms	-0.049748	-0.004130	1.000000	0.099894	
is_furnished	-0.013467	0.007733	0.099894	1.000000	
has_swimming_pool	0.046696	-0.000483	0.221229	0.117984	
maid_room	0.062801	-0.004159	0.534709	0.114554	
driver_room	0.068518	-0.003818	0.490236	0.097253	

Step 3: Find the District with the Shortest Duration for Villas

Step 3.a identify villas from property_type_table

```
In [128... #property_type_table["property_type"].unique
```

```
In [129... villa_type_ids = property_type_table[(property_type_table['property_type'] .s
```

Step 3.b Group by district_id and calculate average closing_duration

```
In [130... villa_ads = ad_table[ad_table['property_type_id'].isin(villa_type_ids)]
avg_duration_by_district = villa_ads.groupby('district_id')['closing_duratio
```

Step 3.c Find the district with the shortest duration

```
In [131... shortest_duration_district = avg_duration_by_district.loc[avg_duration_by_di
```

Step 3.e Get district details

```
In [132... district_details = district_table[district_table['district_id'] == shortest_
```

Output

```
In [133... average_duration = ad_table['closing_duration'].mean()
print(f"Average closing duration: {average_duration} days")
print("Correlation with other parameters:\n", correlations)
print(f"District with shortest closing duration for villas: {district_detail
```

Average closing duration: 50.11803646396776 days

Correlation with other parameters:

	closing_duration	price	number_of_bedrooms	\
closing_duration	1.000000	-0.004561	-0.049748	
price	-0.004561	1.000000	-0.004130	
number_of_bedrooms	-0.049748	-0.004130	1.000000	
is_furnished	-0.013467	0.007733	0.099894	
has_swimming_pool	0.046696	-0.000483	0.221229	
maid_room	0.062801	-0.004159	0.534709	
driver_room	0.068518	-0.003818	0.490236	

	is_furnished	has_swimming_pool	maid_room	driver_room
closing_duration	-0.013467	0.046696	0.062801	0.068518
price	0.007733	-0.000483	-0.004159	-0.003818
number_of_bedrooms	0.099894	0.221229	0.534709	0.490236
is_furnished	1.000000	0.117984	0.114554	0.097253
has_swimming_pool	0.117984	1.000000	0.334912	0.352679
maid_room	0.114554	0.334912	1.000000	0.788474
driver_room	0.097253	0.352679	0.788474	1.000000

District with shortest closing duration for villas: Siyah (ID: 159844990f032677bdc2c66b26191c62ebb6ffab80747a56e7e63702c4352d29)

=====

3. Provide the correlation matrix for the effects on prices after normalization for both rents and sales, and comment on the most price affecting parameters.

=====

In [134... `ad_table.columns`

```
Out[134]: Index(['id', 'district_id', 'property_type_id', 'district_name_en',
                'property_type', 'property_age_less_than', 'number_of_apartments',
                'number_of_bedrooms', 'floor', 'number_of_kitchens', 'is_closed',
                'residential_or_commercial', 'driver_room', 'is_duplex',
                'families_or_singles', 'is_furnished', 'halls_Num', 'maid_room',
                'price_per_meter', 'advertiser_type', 'has_swimming_pool', 'is_pai
d',
                'price', 'purpose', 'rent_type', 'rooms_num', 'space',
                'street_direction', 'street_width_range', 'toilets_num', 'latitud
e',
                'longitude', 'property_age_range', 'created_at', 'updated_at',
                'data_source', 'closing_duration'],
                dtype='object')
```

```
In [136... # Assuming 'ad_table' contains your data, including both rent and sale price
# and a 'for_sale_or_rent' column to differentiate between sale (e.g., value

# Step 1: Normalize the price data
scaler = MinMaxScaler()
ad_table['normalized_price'] = scaler.fit_transform(ad_table[['price']])

# Step 2: Select relevant parameters (assuming these columns exist in your data)
parameters = ['number_of_bedrooms', 'space', 'toilets_num', 'property_age_range']

# Step 3: Calculate the correlation matrix
correlation_matrix = ad_table[parameters].corr()

# Display the correlation matrix
print(correlation_matrix)
```

	number_of_bedrooms	space	normalized_price	\
number_of_bedrooms	1.000000	-0.011265	-0.004130	
space	-0.011265	1.000000	0.207093	
normalized_price	-0.004130	0.207093	1.000000	
has_swimming_pool	0.221229	0.012604	-0.000483	
maid_room	0.534709	-0.003503	-0.004159	
driver_room	0.490236	-0.002513	-0.003818	

	has_swimming_pool	maid_room	driver_room
number_of_bedrooms	0.221229	0.534709	0.490236
space	0.012604	-0.003503	-0.002513
normalized_price	-0.000483	-0.004159	-0.003818
has_swimming_pool	1.000000	0.334912	0.352679
maid_room	0.334912	1.000000	0.788474
driver_room	0.352679	0.788474	1.000000

=====

4. Give a sales price valuation of rental properties (convert rental properties to sales properties) based on 6% ROI (Return on Investment) then estimate the meter price distribution per property type and district and comment on the result.

=====

RENT_TYPE :-> Yearly = 0, Daily = 1, Monthly = 2

PURPOSE :-> SALE = 0 RENT = 1

1. Filter for rental properties (purpose = 1 for rent)

```
In [138... rentals = ad_table[ad_table['purpose'] == 1]
```

2. Convert rental price to annual basis

Daily to yearly: Multiply by 365 Monthly to yearly: Multiply by 12 Yearly remains the same

```
In [139... rentals['annual_rent'] = rentals.apply(  
    lambda x: x['price'] * 365 if x['rent_type'] == 1 else (x['price'] * 12  
    axis=1  
)
```

```
/var/folders/fw/2jnc1knn08g378bkr2zksm5h0000gn/T/ipykernel_10323/325415596  
9.py:1: 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/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy  
rentals['annual_rent'] = rentals.apply(
```

3. Calculate sales price valuation based on 6% ROI

```
In [140... rentals['sales_price_valuation'] = rentals['annual_rent'] / 0.06
```

```
/var/folders/fw/2jnc1knn08g378bkr2zksm5h0000gn/T/ipykernel_10323/201328349  
1.py:1: 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/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy  
rentals['sales_price_valuation'] = rentals['annual_rent'] / 0.06
```

4. Calculate price per meter

```
In [141... rentals['price_per_meter'] = rentals['sales_price_valuation'] / rentals['spa
```

```
/var/folders/fw/2jnc1knn08g378bkr2zksm5h0000gn/T/ipykernel_10323/267291610  
9.py:1: 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/stable/user\_guide/indexing.html#returning-a-view-versus-a-copy  
rentals['price_per_meter'] = rentals['sales_price_valuation'] / rentals  
['space']
```


5. Group by property type and district, and calculate descriptive statistics for price per meter

```
In [142... grouped_data = rentals.groupby(['property_type', 'district_name_en'])['price
```

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

		count	mean	std \
property_type	district_name_en			
أرض	Ad Dar Al Baida	2.0	2.644231e+03	7.932288e+02
	Al Aqiq	5.0	5.134377e+03	3.281292e+03
	Al Faiha	2.0	1.482143e+03	1.271109e+03
	Al Faisaliyah	4.0	3.165412e+03	2.125569e+03
	Al Ghnamiyah	5.0	1.960140e+03	2.005449e+03
...
استراحة	As Sulai	31.0	1.105599e+04	3.538762e+04
	Ash Sharq	88.0	1.415873e+04	8.636449e+04
	Ash Shifa	5.0	3.457204e+04	6.481482e+04
	Badr	13.0	4.058979e+03	7.243406e+03
	Banban	29.0	5.993984e+07	3.227551e+08

		min	25%	50% \
property_type	district_name_en			
أرض	Ad Dar Al Baida	2083.333333	2363.782051	2644.230769
	Al Aqiq	1632.653061	2052.545156	5566.666667
	Al Faiha	583.333333	1032.738095	1482.142857
	Al Faisaliyah	1129.943503	1556.263050	2932.518116
	Al Ghnamiyah	250.000000	583.333333	666.666667
...
استراحة	As Sulai	1083.333333	1483.333333	3205.128205
	Ash Sharq	16.666667	1833.333333	2443.438914
	Ash Shifa	202.777778	250.000000	7407.407407
	Badr	137.254902	1555.555556	2166.666667
	Banban	92.592593	1703.333333	2380.952381

		75%	max
property_type	district_name_en		
أرض	Ad Dar Al Baida	2924.679487	3.205128e+03
	Al Aqiq	7160.759040	9.259259e+03
	Al Faiha	1931.547619	2.380952e+03
	Al Faisaliyah	4541.666667	5.666667e+03
	Al Ghnamiyah	4150.000000	4.150702e+03
...
استراحة	As Sulai	5107.142857	2.000000e+05
	Ash Sharq	3645.833333	8.111111e+05
	Ash Shifa	15000.000000	1.500000e+05
	Badr	2823.529412	2.800000e+04
	Banban	10428.571429	1.738095e+09

[100 rows x 8 columns]

```
In [146... cleaned_grouped_data.to_csv("cleaned_grouped_data.csv")
```

Highest and Lowest Average Price per Meter

```
In [148... highest_avg = cleaned_grouped_data.sort_values(by='mean', ascending=False).h
lowest_avg = cleaned_grouped_data.sort_values(by='mean', ascending=True).hea
```

Highest and Lowest Standard Deviation

```
In [149... highest_std = cleaned_grouped_data.sort_values(by='std', ascending=False).h
lowest_std = cleaned_grouped_data.sort_values(by='std', ascending=True).head
```

Potential Outliers based on Max and Min Values

```
In [151... potential_outliers_max = cleaned_grouped_data.sort_values(by='max', ascending=False)
potential_outliers_min = cleaned_grouped_data.sort_values(by='min', ascending=False)
```

```
In [152... print("Highest Average Price per Meter:")
print(highest_avg)
```

Highest Average Price per Meter:

		count	mean	std \
property_type	district_name_en			
استراحة	Dahhrat Namar	23.0	2.938877e+09	1.409401e+10
	Al Maizilah	25.0	3.753019e+08	1.875861e+09
محل	Al Amal	2.0	8.516669e+07	1.204438e+08
	An Nasim Ash Sharqi	23.0	8.238752e+07	3.949045e+08
	Laban	13.0	7.147974e+07	2.567302e+08
		min	25%	50%
\				
property_type	district_name_en			
استراحة	Dahhrat Namar	1481.481481	4.416667e+03	9.125000e+03
	Al Maizilah	0.888889	2.756892e+03	4.245283e+03
محل	Al Amal	41.025641	4.258336e+07	8.516669e+07
	An Nasim Ash Sharqi	67.500068	7.256944e+03	1.041667e+04
	Laban	333.333333	8.333333e+03	1.822917e+04
		75%	max	
property_type	district_name_en			
استراحة	Dahhrat Namar	1.993981e+04	6.759259e+10	
	Al Maizilah	1.169872e+04	9.379435e+09	
محل	Al Amal	1.277500e+08	1.703333e+08	
	An Nasim Ash Sharqi	2.416667e+04	1.893939e+09	
	Laban	3.431373e+04	9.259250e+08	

```
In [153... print("\nLowest Average Price per Meter:")
print(lowest_avg)
```

Lowest Average Price per Meter:

\		count	mean	std	min
property_type	district_name_en				
بيت	Qurtubah	2.0	9.333051	10.370500	2.000000
أرض	Al Muhammadiyah	2.0	84.258333	116.542983	1.850000
مستودع	Hyt	2.0	86.937500	117.939519	3.541667
استراحة	Al Uraiya Al Wusta	2.0	91.666667	106.066017	16.666667
	Al Haer	2.0	101.273148	77.749010	46.296296

		25%	50%	75%	\
property_type	district_name_en				
بيت	Qurtubah	5.666526	9.333051	12.999577	
أرض	Al Muhammadiyah	43.054167	84.258333	125.462500	
مستودع	Hyt	45.239583	86.937500	128.635417	
استراحة	Al Uraiya Al Wusta	54.166667	91.666667	129.166667	
	Al Haer	73.784722	101.273148	128.761574	

		max
property_type	district_name_en	
بيت	Qurtubah	16.666102
أرض	Al Muhammadiyah	166.666667
مستودع	Hyt	170.333333
استراحة	Al Uraiya Al Wusta	166.666667
	Al Haer	156.250000

In [154...

```
print("\nHighest Standard Deviation in Price per Meter:")
print(highest_std)
```


Highest Standard Deviation in Price per Meter:

property_type	district_name_en	count	mean	std	\
استراحة	Dahrat Namar	23.0	2.938877e+09	1.409401e+10	
	Al Maizilah	25.0	3.753019e+08	1.875861e+09	
محل	An Nasim Ash Sharqi	23.0	8.238752e+07	3.949045e+08	
استراحة	Banban	29.0	5.993984e+07	3.227551e+08	
محل	Laban	13.0	7.147974e+07	2.567302e+08	
		min	25%	50%	
\					
property_type	district_name_en				
استراحة	Dahrat Namar	1481.481481	4416.666667	9125.000000	
	Al Maizilah	0.888889	2756.892231	4245.283019	
محل	An Nasim Ash Sharqi	67.500068	7256.944444	10416.666667	
استراحة	Banban	92.592593	1703.333333	2380.952381	
محل	Laban	333.333333	8333.333333	18229.166667	
		75%	max		
property_type	district_name_en				
استراحة	Dahrat Namar	19939.814815	6.759259e+10		
	Al Maizilah	11698.717949	9.379435e+09		
محل	An Nasim Ash Sharqi	24166.666667	1.893939e+09		
استراحة	Banban	10428.571429	1.738095e+09		
محل	Laban	34313.725490	9.259250e+08		

In [156...

```
print("\nLowest Standard Deviation in Price per Meter:")
print(lowest_std)
```


Lowest Standard Deviation in Price per Meter:

		count	mean	std	min \
property_type	district_name_en				
محل	Al Mikal	2.0	15277.777778	0.0	15277.777778
استراحة	Al Faiha	4.0	16222.222222	0.0	16222.222222
مستودع	Al Yarmuk	2.0	5333.333333	0.0	5333.333333
مكتب تجاري	An Nazim	3.0	5000.000000	0.0	5000.000000
بيت	Jarir	2.0	4772.727273	0.0	4772.727273

		25%	50%	75% \
property_type	district_name_en			
محل	Al Mikal	15277.777778	15277.777778	15277.777778
استراحة	Al Faiha	16222.222222	16222.222222	16222.222222
مستودع	Al Yarmuk	5333.333333	5333.333333	5333.333333
مكتب تجاري	An Nazim	5000.000000	5000.000000	5000.000000
بيت	Jarir	4772.727273	4772.727273	4772.727273

		max
property_type	district_name_en	
محل	Al Mikal	15277.777778
استراحة	Al Faiha	16222.222222
مستودع	Al Yarmuk	5333.333333
مكتب تجاري	An Nazim	5000.000000
بيت	Jarir	4772.727273

In [157...

```
print("\nPotential Outliers with Highest Max Value:")
print(potential_outliers_max)
```

Potential Outliers with Highest Max Value:

property_type	district_name_en	count	mean	std	\
استراحة	Dahrat Namar	23.0	2.938877e+09	1.409401e+10	
	Al Maizilah	25.0	3.753019e+08	1.875861e+09	
محل	An Nasim Ash Sharqi	23.0	8.238752e+07	3.949045e+08	
استراحة	Banban	29.0	5.993984e+07	3.227551e+08	
محل	Laban	13.0	7.147974e+07	2.567302e+08	
		min	25%	50%	
\					
property_type	district_name_en				
استراحة	Dahrat Namar	1481.481481	4416.666667	9125.000000	
	Al Maizilah	0.888889	2756.892231	4245.283019	
محل	An Nasim Ash Sharqi	67.500068	7256.944444	10416.666667	
استراحة	Banban	92.592593	1703.333333	2380.952381	
محل	Laban	333.333333	8333.333333	18229.166667	
		75%	max		
property_type	district_name_en				
استراحة	Dahrat Namar	19939.814815	6.759259e+10		
	Al Maizilah	11698.717949	9.379435e+09		
محل	An Nasim Ash Sharqi	24166.666667	1.893939e+09		
استراحة	Banban	10428.571429	1.738095e+09		
محل	Laban	34313.725490	9.259250e+08		

In [158... `print("\nProperties with Lowest Min Value indicating potential outliers or o`
`print(potential_outliers_min)`

Properties with Lowest Min Value indicating potential outliers or data issues:

		count	mean	std	m
in \	property_type district_name_en				
عمارة 00	Al Uraiija	5.0	2.086621e+04	2.688352e+04	0.0000
أرض 14	An Nasim Al Gharbi	35.0	2.697102e+06	1.066860e+07	0.0000
استراحة 50	An Nasim Al Gharbi	47.0	4.487947e+04	1.397048e+05	0.0004
فيلا 7	King Abdul Aziz	32.0	7.114926e+03	1.439826e+04	0.00166
أرض 67	Ishbilyah	9.0	4.258184e+03	2.869291e+03	0.0041

		25%	50%	75%
\	property_type district_name_en			
عمارة	Al Uraiija	5442.176871	10000.000000	22222.222222
أرض	An Nasim Al Gharbi	291.666720	2272.727273	5773.907104
استراحة	An Nasim Al Gharbi	1644.444444	3111.111111	7650.000000
فيلا	King Abdul Aziz	1163.213377	3827.838828	5354.166667
أرض	Ishbilyah	3030.303030	5362.318841	5797.101449

		max
property_type	district_name_en	
عمارة	Al Uraiija	6.666667e+04
أرض	An Nasim Al Gharbi	6.083327e+07
استراحة	An Nasim Al Gharbi	6.400000e+05
فيلا	King Abdul Aziz	6.687243e+04
أرض	Ishbilyah	8.333333e+03

=====

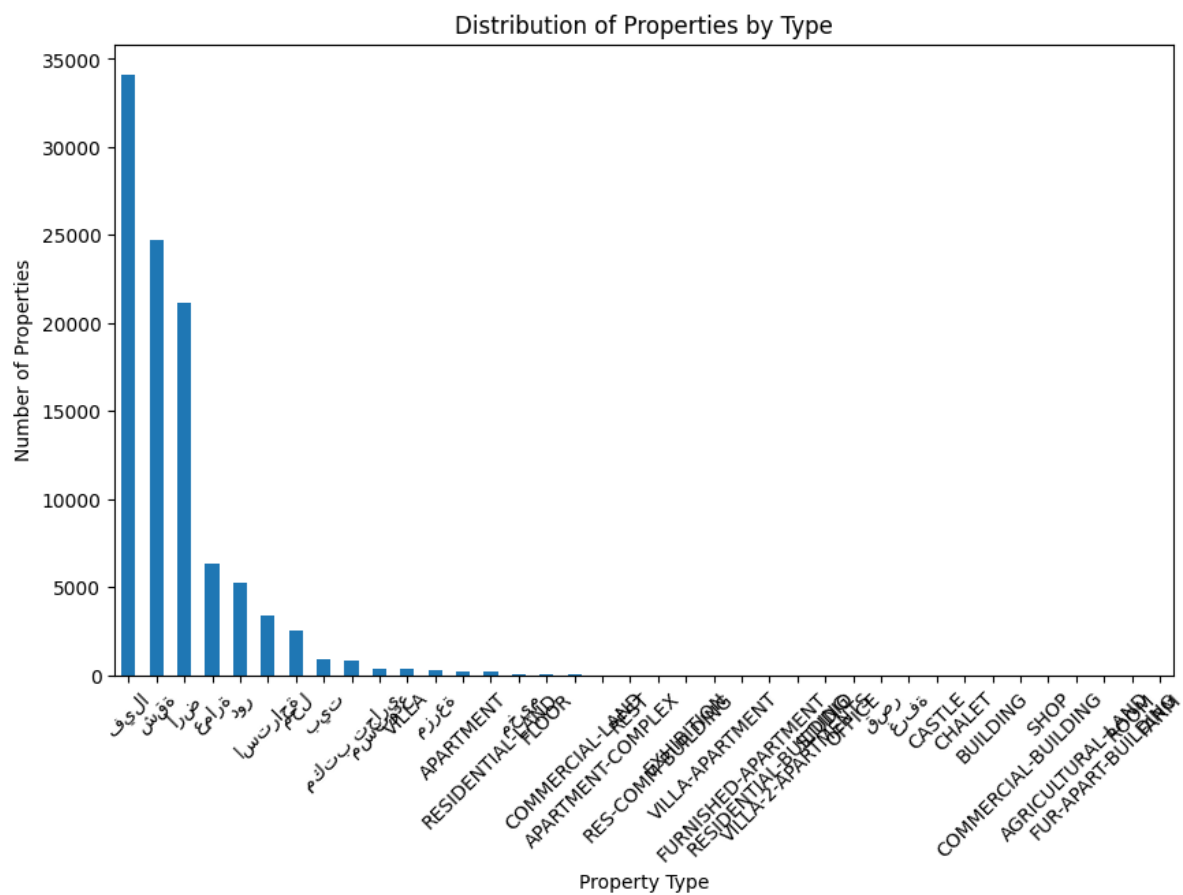
5.Add any general insights you find during your work on the data

=====

```
In [161]: # Distribution of Properties by Type
property_type_distribution = ad_table['property_type'].value_counts()

# Plotting the distribution
import matplotlib.pyplot as plt
```

```
# Output the distribution
print(property_type_distribution)
```



34123	فيلا
24675	شقة
21142	أرض
6329	عمارة
5250	دور
3397	استراحة
2555	محل
917	بيت
820	مكتب تجاري
383	مستودع
VILLA	327
289	مزرعة
APARTMENT	175
RESIDENTIAL-LAND	173
73	مخيم
FLOOR	53
COMMERCIAL-LAND	27
APARTMENT-COMPLEX	6
REST	6
RES-COMM-BUILDING	6
EXHIBITION	4
VILLA-APARTMENT	3
FURNISHED-APARTMENT	3
RESIDENTIAL-BUILDING	2
VILLA-2-APARTMENTS	2
STUDIO	2
OFFICE	2
2	قصر
2	غرفة
CASTLE	1
CHALET	1
BUILDING	1
COMMERCIAL-BUILDING	1
SHOP	1
AGRICULTURAL-LAND	1
FUR-APART-BUILDING	1
ROOM	1
FARM	1

Name: property_type, dtype: int64

Recommendations for Further Analysis:

- 1- Standardization of Property Types: Combining the counts of similarly named property types listed in both English and Arabic (e.g., VILLA and فيلا) could provide a more accurate distribution and understanding of the market.
- 2- In-depth Analysis of Niche Properties: Exploring the characteristics and pricing of less common or unique properties might uncover specific market trends or investment opportunities.
- 3- Market Segmentation: Further analysis could segment the market based on property types, identifying trends, demands, and pricing within each segment.

