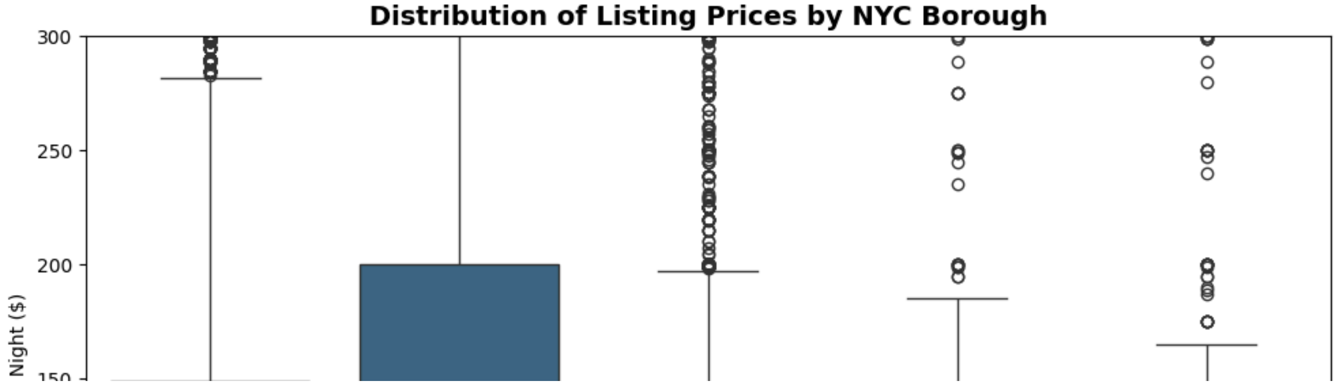
```
 dataset using kagglehub
glehub

 latest version
glehub.dataset_download("dgomonov/new-york-city-airbnb-open-data")
h to dataset files:", path)

ecessary libraries
das as pd
py as np
plotlib.pyplot as plt
born as sns
rn.preprocessing import MinMaxScaler
rn.ensemble import RandomForestRegressor
rn.cluster import KMeans
rn.metrics import silhouette_score


 dataset from the kagglehub download path
set file is typically named 'AB_NYC_2019.csv' within the downloaded directory
 os.path.join(path, "AB_NYC_2019.csv")
ad_csv(csv_path)

e preprocessing steps mentioned (example)
 rows where 'last_review' or 'reviews_per_month' is NaN
 df.dropna(subset=['last_review', 'reviews_per_month']).copy()
ng 'last_review' to datetime and creating 'days_since_last_review'
last_review'] = pd.to_datetime(df_clean['last_review'])
days_since_last_review'] = (pd.to_datetime('2019-12-31') - df_clean['last_review']).dt.days
 extreme price outliers
 df_clean[df_clean['price'] <= 1000]

taset loaded successfully with {len(df_clean)} rows after preprocessing")
```

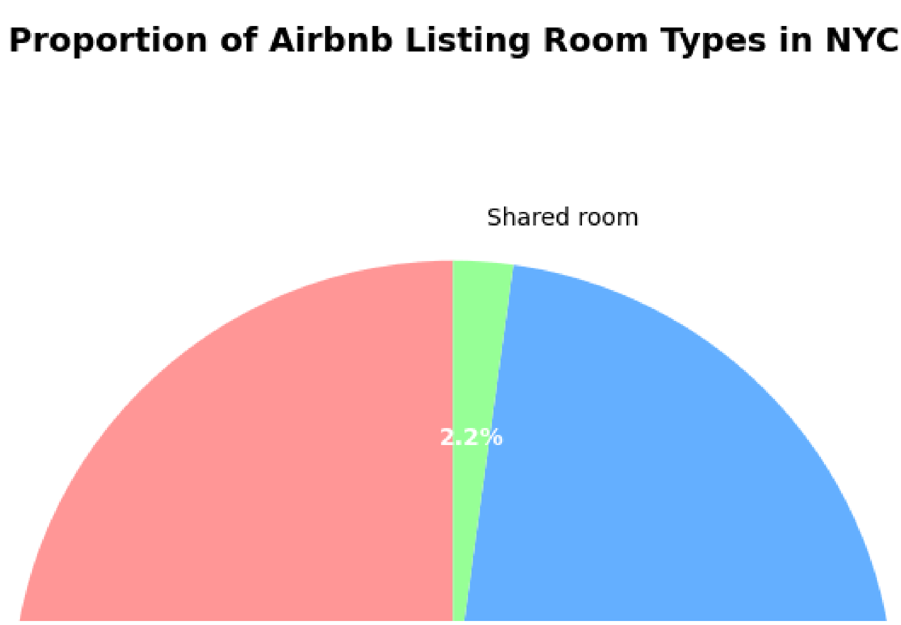
```
Using Colab cache for faster access to the 'new-york-city-airbnb-open-data' data
Path to dataset files: /kaggle/input/new-york-city-airbnb-open-data
Dataset loaded successfully with 38736 rows after preprocessing
```

```
# Set the style
plt.style.use('default')
fig, ax = plt.subplots(figsize=(10, 6))

# Create the boxplot
sns.boxplot(data=df_clean, x='neighbourhood_group', y='price', ax=ax, palette='viridis')
# Set the title and labels
ax.set_title('Distribution of Listing Prices by NYC Borough', fontsize=14, fontweight='bold
ax.set_xlabel('Neighbourhood Group (Borough)')
ax.set_ylabel('Price per Night ($)')
# Set y-axis limit to focus on the main distribution
ax.set_ylim(0, 300)

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

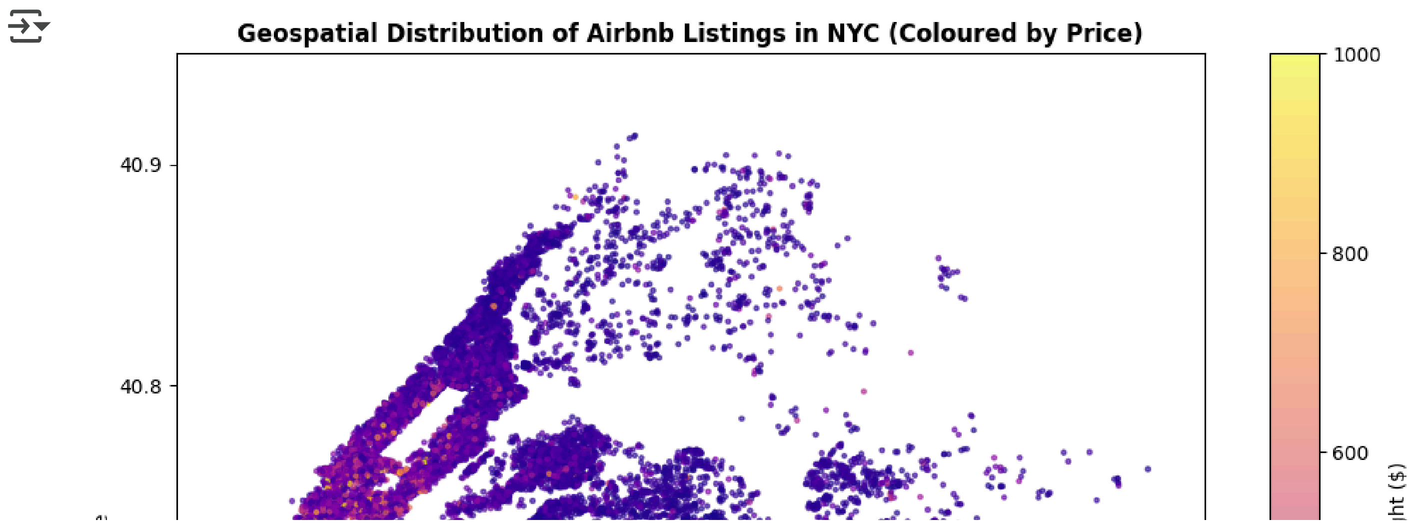
```
/tmp/ipython-input-85374419.py:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v

  sns.boxplot(data=df_clean, x='neighbourhood_group', y='price', ax=ax, palette=
```



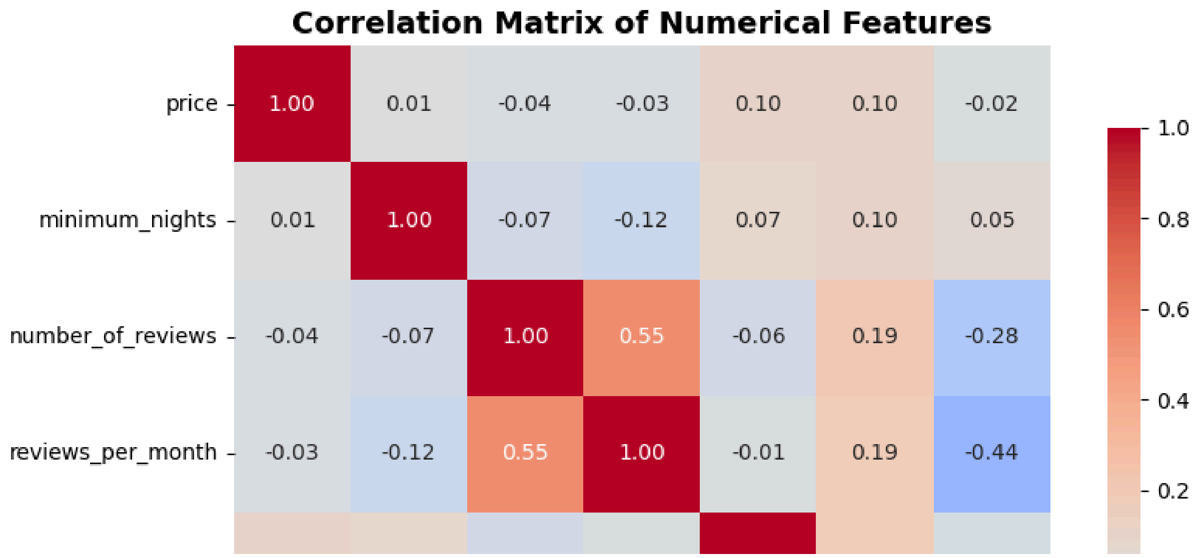

```python
# Calculate the value counts for room_type
room_type_counts = df_clean['room_type'].value_counts()

# Create the pie chart
plt.figure(figsize=(8, 8))
wedges, texts, autotexts = plt.pie(room_type_counts.values,
                                   labels=room_type_counts.index,
                                   autopct='%1.1f%%',
                                   startangle=90,
                                   colors=['#ff9999','#66b3ff','#99ff99'])
# Style the percentages inside the wedges
for autotext in autotexts:
    autotext.set_color('white')
    autotext.set_fontweight('bold')
# Ensure the pie is drawn as a circle
plt.axis('equal')
plt.title('Proportion of Airbnb Listing Room Types in NYC', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()
```



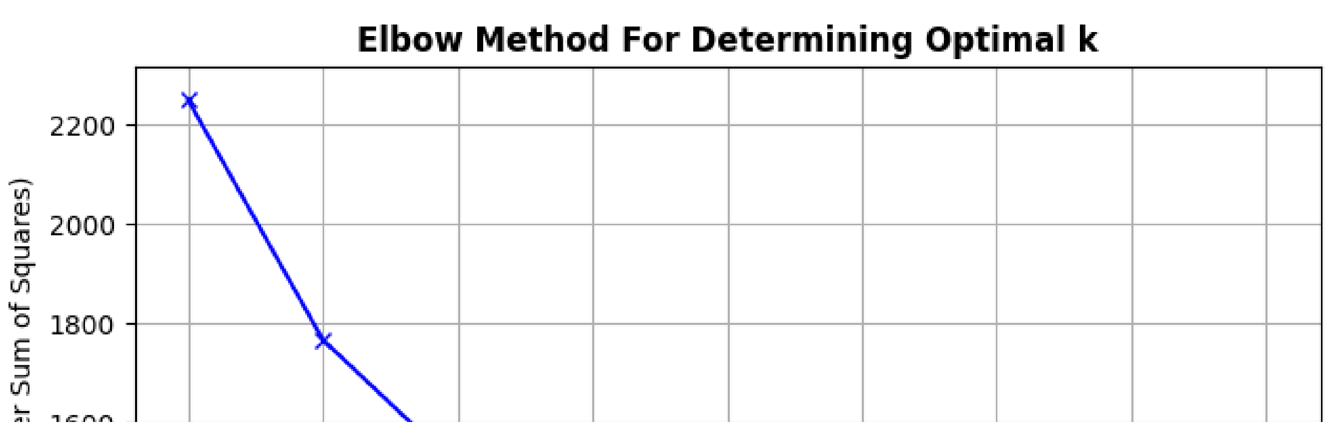
```
plt.figure(figsize=(10, 8))
# Create a scatter plot, colouring points by price
scatter = plt.scatter(df_clean['longitude'],
                      df_clean['latitude'],
                      c=df_clean['price'],
                      cmap='plasma',
                      alpha=0.6,
                      s=5) # s controls the size of the points
# Add a colorbar
cbar = plt.colorbar(scatter)
cbar.set_label('Price per Night ($)')
# Add titles and labels
plt.title('Geospatial Distribution of Airbnb Listings in NYC (Coloured by Price)', fontsize
plt.xlabel('Longitude')
plt.ylabel('Latitude')
# Optional: Add a rough outline of NYC
plt.xlim(-74.05, -73.7)
plt.ylim(40.5, 40.95)

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




```
# Select a subset of numerical features for correlation
numerical_features = ['price', 'minimum_nights', 'number_of_reviews', 'reviews_per_month',
corr_matrix = df_clean[numerical_features].corr()

# Create the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix,
            annot=True, # Puts the correlation value in each cell
            cmap='coolwarm', # Red-Blue colour scheme
            center=0, # Centers the colormap at 0
            square=True,
            fmt='.2f', # Format annotations to 2 decimal places
            cbar_kws={"shrink": .8})
plt.title('Correlation Matrix of Numerical Features', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()
```

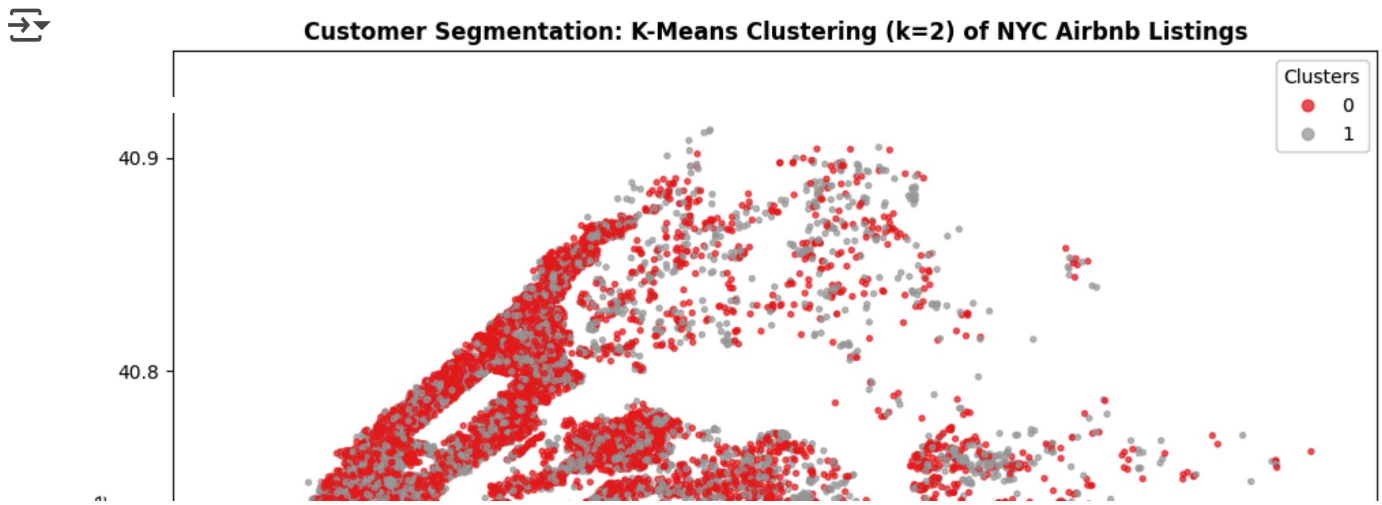



```
# 1. Select and scale features for clustering
cluster_features = ['price', 'availability_365', 'latitude', 'longitude']
X_cluster = df_clean[cluster_features].copy()
scaler = MinMaxScaler()
X_cluster_scaled = scaler.fit_transform(X_cluster)

# 2. Calculate inertia for a range of k values
inertias = []
K = range(2, 11)
for k in K:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(X_cluster_scaled)
    inertias.append(kmeans.inertia_)

# 3. Plot the Elbow Method graph
plt.figure(figsize=(8, 5))
plt.plot(K, inertias, 'bx-')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia (Within-Cluster Sum of Squares)')
plt.title('Elbow Method For Determining Optimal k', fontweight='bold')
plt.xticks(K)
plt.grid(True)
plt.show()
```




```
# Perform K-Means with the chosen k (e.g., k=2)
kmeans = KMeans(n_clusters=2, random_state=42, n_init=10)
df_clean['cluster'] = kmeans.fit_predict(X_cluster_scaled)
```

```
# Plot the results
plt.figure(figsize=(10, 8))
scatter = plt.scatter(df_clean['longitude'],
                     df_clean['latitude'],
                     c=df_clean['cluster'],
                     cmap='Set1', # Good distinct colours for clusters
                     alpha=0.7,
                     s=8)
# Add a legend for the clusters
legend1 = plt.legend(*scatter.legend_elements(), title="Clusters", loc='upper right')
plt.gca().add_artist(legend1)
# Add titles and labels
plt.title('Customer Segmentation: K-Means Clustering (k=2) of NYC Airbnb Listings', fontsiz
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.xlim(-74.05, -73.7)
plt.ylim(40.5, 40.95)

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

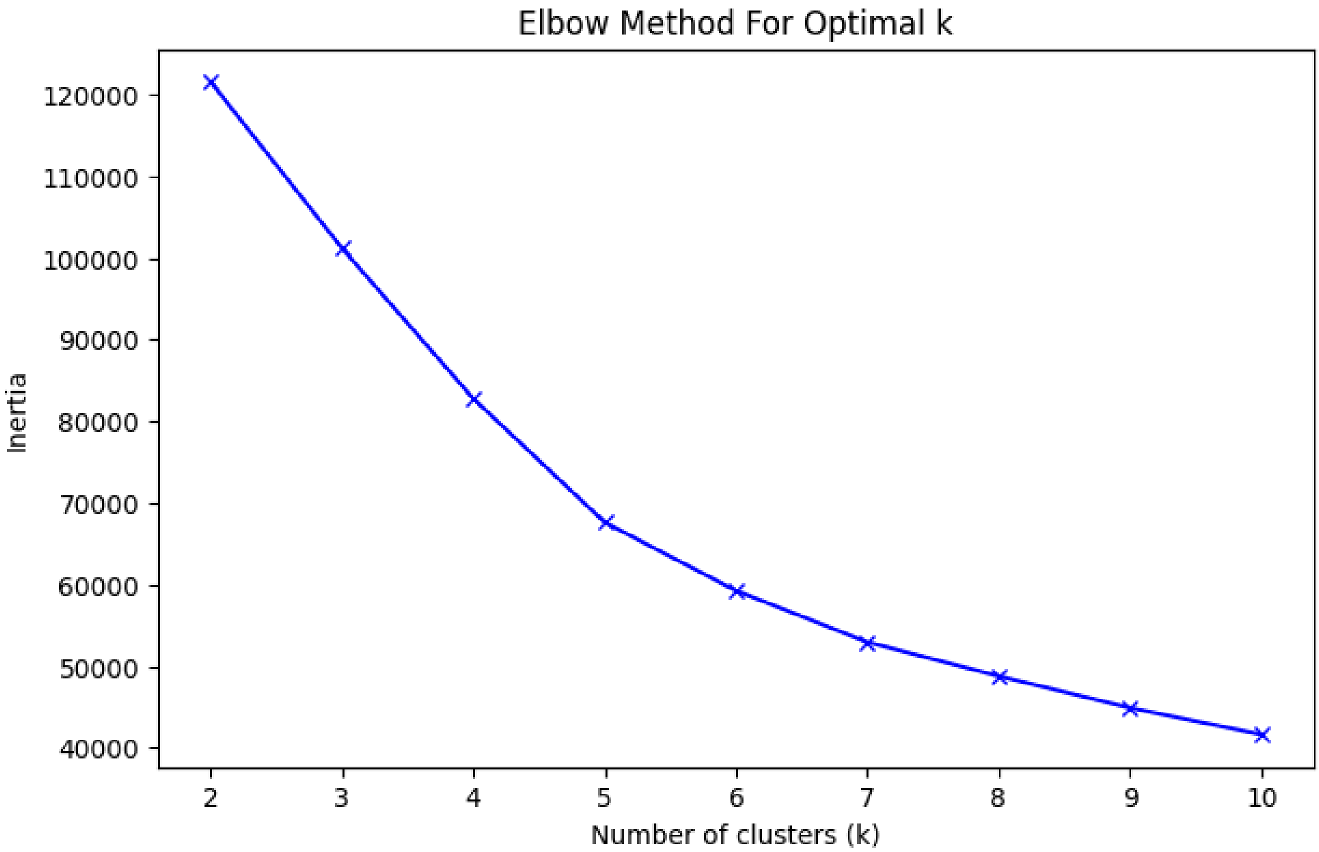



```
import kagglehub
import os

# Download latest version
path = kagglehub.dataset_download("dgomonov/new-york-city-airbnb-open-data")
print("Path to dataset files:", path)

# Track 1: Classical ML - Price Prediction & Clustering
print("=== TRACK 1: Classical Machine Learning ===\n")

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import r2_score, mean_squared_error
```

```
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# Load and prep data - MODIFIED TO USE KAGGLEHUB PATH
# First, let's check what files are in the downloaded directory
print("Files in downloaded directory:", os.listdir(path))

# Find the CSV file (it might have a different name)
csv_files = [f for f in os.listdir(path) if f.endswith('.csv')]
if csv_files:
    csv_path = os.path.join(path, csv_files[0])
    print(f"Using CSV file: {csv_path}")
    df = pd.read_csv(csv_path)
else:
    # If no CSV files found, try the most common name
    try:
        csv_path = os.path.join(path, "AB_NYC_2019.csv")
        df = pd.read_csv(csv_path)
        print("Using AB_NYC_2019.csv")
    except FileNotFoundError:
        # If that doesn't work, try listing all files to see what's available
        all_files = os.listdir(path)
        print("Available files:", all_files)
        raise FileNotFoundError("Could not find CSV file in the downloaded dataset")

df_clean = df.dropna(subset=['last_review', 'reviews_per_month']).copy()
df_clean = df_clean[df_clean['price'] <= 1000]
df_clean['last_review'] = pd.to_datetime(df_clean['last_review'])
df_clean['days_since_last_review'] = (pd.to_datetime('2019-12-31') - df_clean['last_review'

# Define features and target
X = df_clean[['neighbourhood_group', 'room_type', 'latitude', 'longitude',
              'minimum_nights', 'number_of_reviews', 'reviews_per_month',
              'calculated_host_listings_count', 'availability_365',
              'days_since_last_review']]
y = df_clean['price']

# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Preprocessing: Encode categoricals, scale numericals
numeric_features = ['latitude', 'longitude', 'minimum_nights', 'number_of_reviews',
                   'reviews_per_month', 'calculated_host_listings_count',
                   'availability_365', 'days_since_last_review']
categorical_features = ['neighbourhood_group', 'room_type']

preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numeric_features),
        ('cat', OneHotEncoder(handle_unknown='ignore'), categorical_features)
    ])

# Train and evaluate models
models = {
    "Linear Regression": LinearRegression(),
    "Random Forest": RandomForestRegressor(n_estimators=100, random_state=42),
    "Gradient Boosting": GradientBoostingRegressor(random_state=42)
}

results = {}
```

```python
for name, model in models.items():
    pipeline = Pipeline(steps=[('preprocessor', preprocessor),
                              ('regressor', model)])
    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)
    r2 = r2_score(y_test, y_pred)
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    results[name] = {'R2': r2, 'RMSE': rmse}
    print(f"{name}: R² = {r2:.3f}, RMSE = {rmse:.3f}")

# Clustering Analysis
cluster_features = ['price', 'availability_365', 'latitude', 'longitude']
X_cluster = df_clean[cluster_features].copy()
scaler = StandardScaler()
X_cluster_scaled = scaler.fit_transform(X_cluster)

# Find optimal k using Elbow Method
inertias = []
k_range = range(2, 11)
for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    kmeans.fit(X_cluster_scaled)
    inertias.append(kmeans.inertia_)

plt.figure(figsize=(8, 5))
plt.plot(k_range, inertias, 'bx-')
plt.xlabel('Number of clusters (k)')
plt.ylabel('Inertia')
plt.title('Elbow Method For Optimal k')
plt.show()

# Apply K-Means with k=2
kmeans = KMeans(n_clusters=2, random_state=42, n_init=10)
clusters = kmeans.fit_predict(X_cluster_scaled)
df_clean['cluster'] = clusters

# Analyze clusters
cluster_profile = df_clean.groupby('cluster')[['price', 'availability_365']].mean()
print("\nCluster Profiles:")
print(cluster_profile)

# Visualize clusters geographically
plt.figure(figsize=(10, 6))
scatter = plt.scatter(df_clean['longitude'], df_clean['latitude'],
                     c=df_clean['cluster'], cmap='viridis', alpha=0.6, s=10)
plt.colorbar(scatter)
plt.title('Geographic Distribution of Clusters')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()

print("\n--- Track 1 Complete ---")
```

```
Using Colab cache for faster access to the 'new-york-city-airbnb-open-data' data
Path to dataset files: /kaggle/input/new-york-city-airbnb-open-data
=== TRACK 1: Classical Machine Learning ===

Files in downloaded directory: ['AB_NYC_2019.csv', 'New_York_City_.png']
Using CSV file: /kaggle/input/new-york-city-airbnb-open-data/AB_NYC_2019.csv
Linear Regression: R² = 0.349, RMSE = 82.937
Random Forest: R² = 0.453, RMSE = 76.047
Gradient Boosting: R² = 0.446, RMSE = 76.524
```




```
Cluster Profiles:
              price  availability_365
cluster
0        158.615624        275.069974
1        123.681225         28.717173
```

```
import kagglehub
import os

# Download latest version
path = kagglehub.dataset_download("dgomonov/new-york-city-airbnb-open-data")
print("Path to dataset files:", path)

# Track 2: Deep Learning - Image & Text Analysis
print("=== TRACK 2: Deep Learning ===\n")

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
```

```
from tensorflow.keras.applications import VGG16
from tensorflow.keras.preprocessing import image
from tensorflow.keras.applications.vgg16 import preprocess_input
from tensorflow.keras.models import Model, Sequential
from tensorflow.keras.layers import Dense, concatenate, Input, Dropout, GlobalAveragePoolin
from tensorflow.keras.optimizers import Adam
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

# Load the dataset from kagglehub path
csv_files = [f for f in os.listdir(path) if f.endswith('.csv')]
if csv_files:
    csv_path = os.path.join(path, csv_files[0])
    print(f"Using CSV file: {csv_path}")
    df = pd.read_csv(csv_path)
else:
    csv_path = os.path.join(path, "AB_NYC_2019.csv")
    df = pd.read_csv(csv_path)

# Basic preprocessing
df_clean = df.dropna(subset=['last_review', 'reviews_per_month']).copy()
df_clean = df_clean[df_clean['price'] <= 1000]
df_clean['last_review'] = pd.to_datetime(df_clean['last_review'])
df_clean['days_since_last_review'] = (pd.to_datetime('2019-12-31') - df_clean['last_review'

print(f"Dataset loaded with {len(df_clean)} rows")

# 1. Text Feature Extraction
print("Extracting text features from listing names...")
tfidf = TfidfVectorizer(max_features=500, stop_words='english')
text_features = tfidf.fit_transform(df_clean['name'].fillna('')).toarray()
print(f"Text features shape: {text_features.shape}")

# 2. Structured Data Features
print("Preparing structured data features...")
structured_features = df_clean[['latitude', 'longitude', 'minimum_nights',
                               'number_of_reviews', 'reviews_per_month',
                               'calculated_host_listings_count', 'availability_365',
                               'days_since_last_review']].values

# Scale structured features
scaler = StandardScaler()
structured_features_scaled = scaler.fit_transform(structured_features)

# 3. Combine text and structured features
combined_features = np.concatenate([text_features, structured_features_scaled], axis=1)
print(f"Combined features shape: {combined_features.shape}")

# 4. Target variable
y = df_clean['price'].values

# 5. Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    combined_features, y, test_size=0.2, random_state=42
)

# 6. Build and train a deep learning model
print("Building deep learning model...")
model = Sequential([
```

```
    Dense(256, activation='relu', input_shape=(X_train.shape[1],)),
    Dropout(0.3),
    Dense(128, activation='relu'),
    Dropout(0.3),
    Dense(64, activation='relu'),
    Dense(1, activation='linear')  # Regression output
])

model.compile(
    optimizer=Adam(learning_rate=0.001),
    loss='mse',
    metrics=['mae']
)

print("Model summary:")
model.summary()

# Train the model
print("Training model...")
history = model.fit(
    X_train, y_train,
    validation_split=0.2,
    epochs=20,
    batch_size=32,
    verbose=1
)

# Evaluate the model
test_loss, test_mae = model.evaluate(X_test, y_test, verbose=0)
print(f"\nTest MAE: ${test_mae:.2f}")
print(f"Test Loss (MSE): {test_loss:.2f}")

# 7. Image Feature Extraction (Simulated - would require actual images)
print("\nImage processing simulation:")
print("This dataset doesn't contain actual images, but here's how it would work:")

def simulate_image_processing(listing_ids):
    """Simulate image feature extraction"""
    print(f"Would process images for {len(listing_ids)} listings")
    # In a real scenario, this would:
    # 1. Load images from paths like f"{image_dir}/{listing_id}.jpg"
    # 2. Preprocess them using VGG16/ResNet preprocessing
    # 3. Extract features using a pre-trained model
    # 4. Return feature vectors

    # Return random features for demonstration
    return np.random.rand(len(listing_ids), 512)

# Simulate image feature extraction
image_features = simulate_image_processing(df_clean['id'].head(10).tolist())
print(f"Simulated image features shape: {image_features.shape}")

# 8. Multi-modal architecture example (commented out as it requires images)
"""
print("\nMulti-modal architecture example:")
# This would combine text, structured data, and image features

# Image branch
image_input = Input(shape=(224, 224, 3))
base_model = VGG16(weights='imagenet', include_top=False, input_tensor=image_input)
```

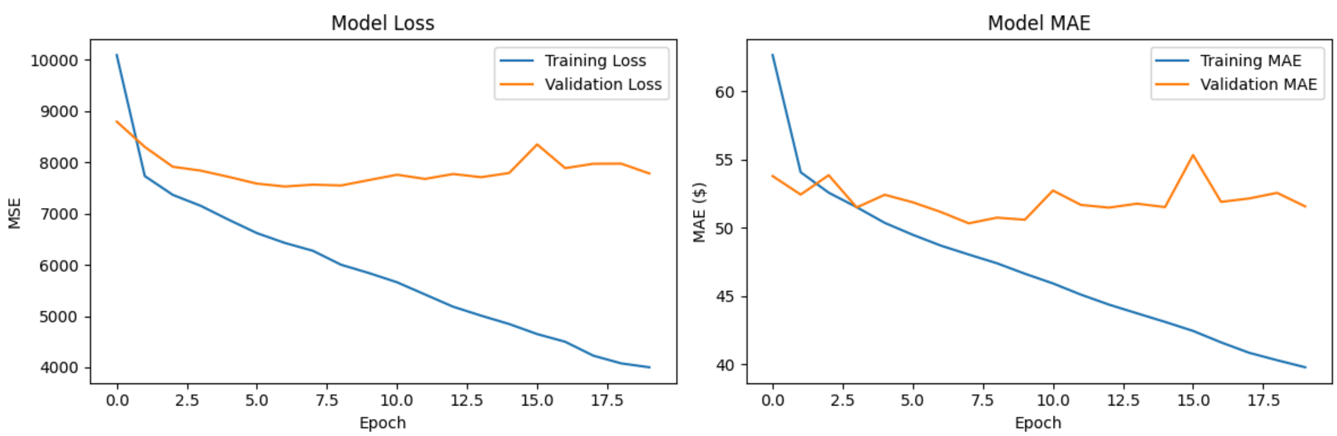
```
x = GlobalAveragePooling2D()(base_model.output)
image_branch = Model(inputs=image_input, outputs=x)

# Text + structured data branch (already prepared above)
other_features_input = Input(shape=(combined_features.shape[1],))

# Combine branches
combined = concatenate([image_branch.output, other_features_input])
x = Dense(256, activation='relu')(combined)
x = Dropout(0.4)(x)
output = Dense(1, activation='linear')(x)

multi_modal_model = Model(inputs=[image_input, other_features_input], outputs=output)
multi_modal_model.compile(optimizer=Adam(0.0005), loss='mse', metrics=['mae'])
print("Multi-modal model would be ready for training with actual images")
"""

# Plot training history
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('MSE')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history.history['mae'], label='Training MAE')
plt.plot(history.history['val_mae'], label='Validation MAE')
plt.title('Model MAE')
plt.xlabel('Epoch')
plt.ylabel('MAE ($)')
plt.legend()

plt.tight_layout()
plt.show()

# Make some predictions
sample_predictions = model.predict(X_test[:5])
print("\nSample predictions vs actual:")
for i, (pred, actual) in enumerate(zip(sample_predictions.flatten(), y_test[:5])):
    print(f"Listing {i+1}: Predicted ${pred:.2f}, Actual ${actual:.2f}, Error: ${abs(pred-a

print("\n--- Track 2 Complete ---")
```

```
Using Colab cache for faster access to the 'new-york-city-airbnb-open-data' data
Path to dataset files: /kaggle/input/new-york-city-airbnb-open-data
=== TRACK 2: Deep Learning ===

Using CSV file: /kaggle/input/new-york-city-airbnb-open-data/AB_NYC_2019.csv
Dataset loaded with 38736 rows
Extracting text features from listing names...
Text features shape: (38736, 500)
Preparing structured data features...
Combined features shape: (38736, 508)
Building deep learning model...
Model summary:
/usr/local/lib/python3.12/dist-packages/keras/src/layers/core/dense.py:93: UserW
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Model: "sequential"
```

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 256)	130,304
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32,896
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 64)	8,256
dense_3 (Dense)	(None, 1)	65

```
 Total params: 171,521 (670.00 KB)
 Trainable params: 171,521 (670.00 KB)
 Non-trainable params: 0 (0.00 B)
Training model...
Epoch 1/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 8s 9ms/step - loss: 13700.3672 - mae: 76.3247 -
Epoch 2/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 7576.2397 - mae: 53.4341 - \
Epoch 3/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 7404.8496 - mae: 52.7862 - \
Epoch 4/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 6s 8ms/step - loss: 6983.8955 - mae: 51.5208 - \
Epoch 5/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 6818.3535 - mae: 50.4664 - \
Epoch 6/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 6s 7ms/step - loss: 6865.2710 - mae: 49.8067 - \
Epoch 7/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - loss: 6326.9604 - mae: 48.2457 - \
Epoch 8/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 6s 7ms/step - loss: 5818.0635 - mae: 47.3017 - \
Epoch 9/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 11s 8ms/step - loss: 5874.8545 - mae: 47.2077 -
Epoch 10/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 9s 6ms/step - loss: 5645.9258 - mae: 46.0405 - \
```

```
Epoch 11/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 5473.8130 - mae: 45.4200 - \
Epoch 12/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 5335.6562 - mae: 44.6936 - \
Epoch 13/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 6s 7ms/step - loss: 5035.5894 - mae: 43.9100 - \
Epoch 14/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 4932.3789 - mae: 43.2720 - \
Epoch 15/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - loss: 4737.2334 - mae: 42.4968 - \
Epoch 16/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - loss: 4360.1172 - mae: 41.3065 - \
Epoch 17/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 4318.7090 - mae: 41.0878 - \
Epoch 18/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 6s 8ms/step - loss: 4161.6958 - mae: 40.3038 - \
Epoch 19/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 5s 6ms/step - loss: 3841.6880 - mae: 39.7715 - \
Epoch 20/20
775/775 ━━━━━━━━━━━━━━━━━━━━ 5s 7ms/step - loss: 3810.4563 - mae: 39.1766 - \

Test MAE: $50.07
Test Loss (MSE): 6711.87

Image processing simulation:
This dataset doesn't contain actual images, but here's how it would work:
Would process images for 10 listings
Simulated image features shape: (10, 512)
```




```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 76ms/step

Sample predictions vs actual:
Listing 1: Predicted $166.00, Actual $200.00, Error: $34.00
Listing 2: Predicted $84.46, Actual $75.00, Error: $9.46
```

```
# Track 3: Advanced ML - Anomaly Detection
print("=== TRACK 3: Advanced Machine Learning ===\n")

from sklearn.ensemble import IsolationForest
from sklearn.svm import OneClassSVM
from sklearn.neighbors import LocalOutlierFactor
from sklearn.metrics import classification_report

# Prepare features for anomaly detection
anomaly_features = ['price', 'minimum_nights', 'number_of_reviews',
                    'calculated_host_listings_count', 'availability_365']
X_anomaly = df_clean[anomaly_features].copy()

# Handle potential infinite values
X_anomaly = X_anomaly.replace([np.inf, -np.inf], np.nan).dropna()

# Scale the features
scaler = StandardScaler()
X_anomaly_scaled = scaler.fit_transform(X_anomaly)

# 1. Isolation Forest
iso_forest = IsolationForest(contamination=0.05, random_state=42)
iso_predictions = iso_forest.fit_predict(X_anomaly_scaled)
# Convert predictions: -1 (outlier) -> 1, 1 (inlier) -> 0
iso_predictions_binary = [1 if x == -1 else 0 for x in iso_predictions]

# 2. One-Class SVM
oc_svm = OneClassSVM(nu=0.05)
svm_predictions = oc_svm.fit_predict(X_anomaly_scaled)
svm_predictions_binary = [1 if x == -1 else 0 for x in svm_predictions]

# 3. Local Outlier Factor
lof = LocalOutlierFactor(n_neighbors=20, contamination=0.05)
lof_predictions = lof.fit_predict(X_anomaly_scaled)
lof_predictions_binary = [1 if x == -1 else 0 for x in lof_predictions]

# Add predictions to dataframe for analysis
df_anomaly = df_clean.loc[X_anomaly.index].copy()
df_anomaly['iso_forest_anomaly'] = iso_predictions_binary
df_anomaly['svm_anomaly'] = svm_predictions_binary
df_anomaly['lof_anomaly'] = lof_predictions_binary

# Analyze anomalies
print("Isolation Forest detected", sum(iso_predictions_binary), "anomalies")
print("One-Class SVM detected", sum(svm_predictions_binary), "anomalies")
print("Local Outlier Factor detected", sum(lof_predictions_binary), "anomalies")

# Examine top anomalous listings
df_anomaly['total_anomaly_score'] = df_anomaly[['iso_forest_anomaly',
                                                'svm_anomaly',
                                                'lof_anomaly']].sum(axis=1)
top_anomalies = df_anomaly.nlargest(10, 'total_anomaly_score')
print("\nTop anomalous listings:")
print(top_anomalies[['name', 'neighbourhood_group', 'room_type', 'price',
                     'minimum_nights', 'total_anomaly_score']])

# Visualize anomalies in price vs. availability
plt.figure(figsize=(10, 6))
plt.scatter(df_anomaly['price'], df_anomaly['availability_365'],
```