U23AI118

Lab 2 : Analyzing NYC Dataset

```python
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```python
df = pd.read_csv('yellow_tripdata_sample.csv')
print("Shape = ", df.shape)
print("Columns:", df.columns.tolist()) # tolist gives proper structure
print("Initial row", df.head())
```

```
Shape =  (995, 19)
Columns: ['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime', 'passenger_count', 't
Initial row    VendorID tpep_pickup_datetime tpep_dropoff_datetime  passenger_count  \
0         2  2024-01-01 00:57:55   2024-01-01 01:17:43              1.0
1         1  2024-01-01 00:03:00   2024-01-01 00:09:36              1.0
2         1  2024-01-01 00:17:06   2024-01-01 00:35:01              1.0
3         1  2024-01-01 00:36:38   2024-01-01 00:44:56              1.0
4         1  2024-01-01 00:46:51   2024-01-01 00:52:57              1.0

   trip_distance  RatecodeID store_and_fwd_flag  PULocationID  DOLocationID  \
0           1.72         1.0                  N           186            79
1           1.80         1.0                  N           140           236
2           4.70         1.0                  N           236            79
3           1.40         1.0                  N            79           211
4           0.80         1.0                  N           211           148

   payment_type  fare_amount  extra  mta_tax  tip_amount  tolls_amount  \
0             2         17.7    1.0      0.5        0.00           0.0
1             1         10.0    3.5      0.5        3.75           0.0
2             1         23.3    3.5      0.5        3.00           0.0
3             1         10.0    3.5      0.5        2.00           0.0
4             1          7.9    3.5      0.5        3.20           0.0

   improvement_surcharge  total_amount  congestion_surcharge  Airport_fee
0                    1.0         22.70                   2.5          0.0
1                    1.0         18.75                   2.5          0.0
2                    1.0         31.30                   2.5          0.0
3                    1.0         17.00                   2.5          0.0
4                    1.0         16.10                   2.5          0.0
```

```python
# Analysing before Data Cleaning
print("Info :",df.info())
print("Missing Values :")
```

```
print(df.isnull().sum())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 995 entries, 0 to 994
Data columns (total 19 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   VendorID               995 non-null    int64
 1   tpep_pickup_datetime   995 non-null    object
 2   tpep_dropoff_datetime  995 non-null    object
 3   passenger_count        995 non-null    float64
 4   trip_distance          995 non-null    float64
 5   RatecodeID             995 non-null    float64
 6   store_and_fwd_flag     995 non-null    object
 7   PULocationID           995 non-null    int64
 8   DOLocationID           995 non-null    int64
 9   payment_type           995 non-null    int64
 10  fare_amount            995 non-null    float64
 11  extra                  995 non-null    float64
 12  mta_tax                995 non-null    float64
 13  tip_amount             995 non-null    float64
 14  tolls_amount           995 non-null    float64
 15  improvement_surcharge  995 non-null    float64
 16  total_amount           995 non-null    float64
 17  congestion_surcharge   995 non-null    float64
 18  Airport_fee            995 non-null    float64
dtypes: float64(12), int64(4), object(3)
memory usage: 147.8+ KB
Info : None
Missing Values :
VendorID                 0
tpep_pickup_datetime     0
tpep_dropoff_datetime    0
passenger_count          0
trip_distance            0
RatecodeID               0
store_and_fwd_flag       0
PULocationID             0
DOLocationID             0
payment_type             0
fare_amount              0
extra                    0
mta_tax                  0
tip_amount               0
tolls_amount             0
improvement_surcharge    0
```

```
total_amount             0
congestion_surcharge     0
Airport_fee              0
dtype: int64
```

```
df_clean = df.copy()

# Filter out invalid values
df_clean = df_clean[
    (df_clean['passenger_count'] > 0) &
    (df_clean['passenger_count'] <= 8) &
    (df_clean['trip_distance'] > 0) &
    (df_clean['trip_distance'] <= 100) &
    (df_clean['fare_amount'] > 0) &
    (df_clean['fare_amount'] <= 500) &
    (df_clean['total_amount'] > 0) &
    (df_clean['total_amount'] <= 500) &
    (df_clean['tip_amount'] >= 0) &
    (df_clean['tip_amount'] <= 100) &
    (df_clean['extra'] >= 0)
]

print(f"Original dataset size: {len(df)}")
print(f"Cleaned dataset size: {len(df_clean)}")
print(f"Removed {len(df) - len(df_clean)} rows ({((len(df) - len(df_clean))/len(df)*100):.2f
```

```
Original dataset size: 995
Cleaned dataset size: 968
Removed 27 rows (2.71%)
```

```
df.describe()
```

```
         VendorID  passenger_count  trip_distance  RatecodeID  PULocationID  \
count  995.000000       995.000000     995.000000  995.000000    995.000000
mean     1.703518         1.581910       2.890472    1.138693    165.323618
std      0.456936         0.911625       3.125268    3.126260     67.808656
min      1.000000         0.000000       0.000000    1.000000      4.000000
25%      1.000000         1.000000       1.125000    1.000000    114.000000
50%      2.000000         1.000000       1.960000    1.000000    161.000000
75%      2.000000         2.000000       3.400000    1.000000    236.000000
max      2.000000         6.000000      23.900000   99.000000    265.000000

       DOLocationID  payment_type  fare_amount       extra     mta_tax  \
count    995.000000    995.000000   995.000000  995.000000  995.000000
mean     163.204020      1.228141    18.278593    1.741457    0.491960
std       73.059288      0.486448    14.916422    1.255742    0.077276
min        4.000000      1.000000   -47.800000   -1.000000   -0.500000
25%      107.000000      1.000000     9.300000    1.000000    0.500000
```

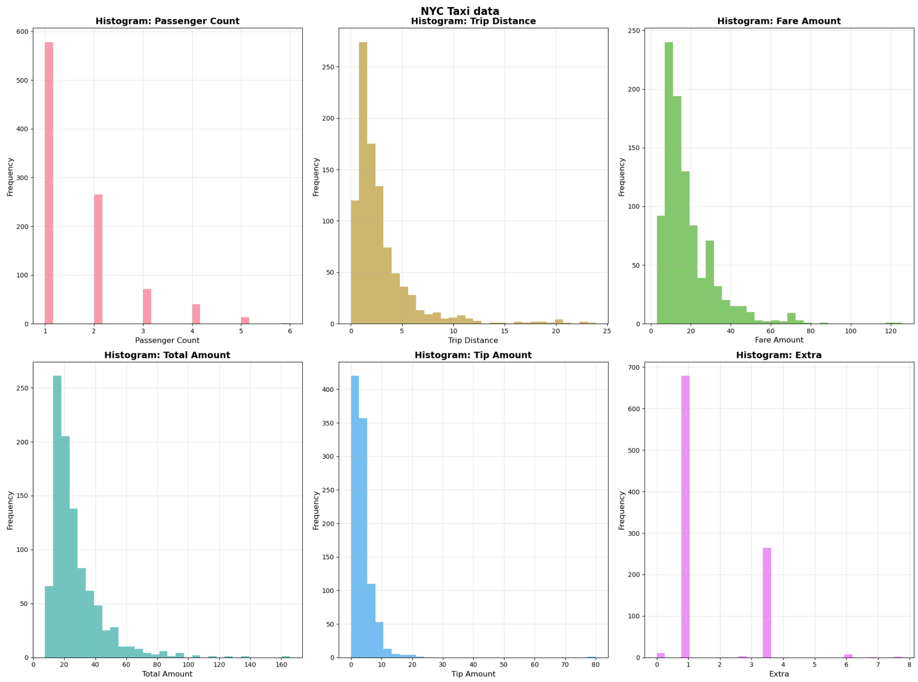
```
50%      162.000000      1.000000    14.200000    1.000000    0.500000
75%      236.000000      1.000000    22.600000    3.500000    0.500000
max      265.000000      4.000000   180.000000    7.750000    0.500000

       tip_amount  tolls_amount  improvement_surcharge  total_amount  \
count  995.000000    995.000000             995.000000    995.000000
mean     3.483146      0.197357               0.988945     26.847538
std      4.195507      1.180907               0.144929     18.092018
min      0.000000      0.000000              -1.000000    -52.800000
25%      0.000000      0.000000               1.000000     16.320000
50%      3.000000      0.000000               1.000000     22.200000
75%      4.820000      0.000000               1.000000     31.770000
max     80.000000     12.750000               1.000000    217.200000

       congestion_surcharge  Airport_fee
count            995.000000   995.000000
mean               2.326633     0.052764
std                0.673846     0.309523
min               -2.500000    -1.750000
25%                2.500000     0.000000
50%                2.500000     0.000000
75%                2.500000     0.000000
max                2.500000     1.750000
```

```python
numerical_cols = ['passenger_count', 'trip_distance', 'fare_amount', 'total_amount', 'tip_am
def descriptive_stats(data,column):     #Description of data function
    stats_dict = {
        'mean' : data[column].mean(),
        'median': data[column].median(),
        'mode': data[column].mode().iloc[0] if not data[column].mode().empty else np.nan,
        'min': data[column].min(),
        'max': data[column].max(),
        'std': data[column].std(),
        'variance': data[column].var(),
        'skew': data[column].skew(),
        'kurtosis': data[column].kurtosis()
    }
    return stats_dict
stats_summary = {}
for col in numerical_cols:
    stats_summary[col] = descriptive_stats(df_clean ,  col )

stats_df = pd.DataFrame(stats_summary).round(4)   # pd.Datafram() - Converting into tabular

stats_df
```

```
          passenger_count  trip_distance  fare_amount  total_amount  \
```

```
mean              1.6033         2.9154      18.4021       27.0301
median            1.0000         1.9800      14.2000       22.2000
mode              1.0000         0.9000       6.5000       16.3200
min               1.0000         0.0100       3.0000        7.6000
max               6.0000        23.9000     125.5000      165.6400
std               0.9037         3.1103      13.5733       16.4536
variance          0.8166         9.6739     184.2334      270.7200
skew              1.7247         3.3208       2.5125        2.6814
kurtosis          2.8847        14.2673      10.2395       11.5664

          tip_amount   extra
mean          3.4819  1.7371
median        3.0000  1.0000
mode          0.0000  1.0000
min           0.0000  0.0000
max          80.0000  7.7500
std           4.0774  1.2323
variance     16.6254  1.5186
skew          7.6468  1.2739
kurtosis    129.1305  0.9350
```

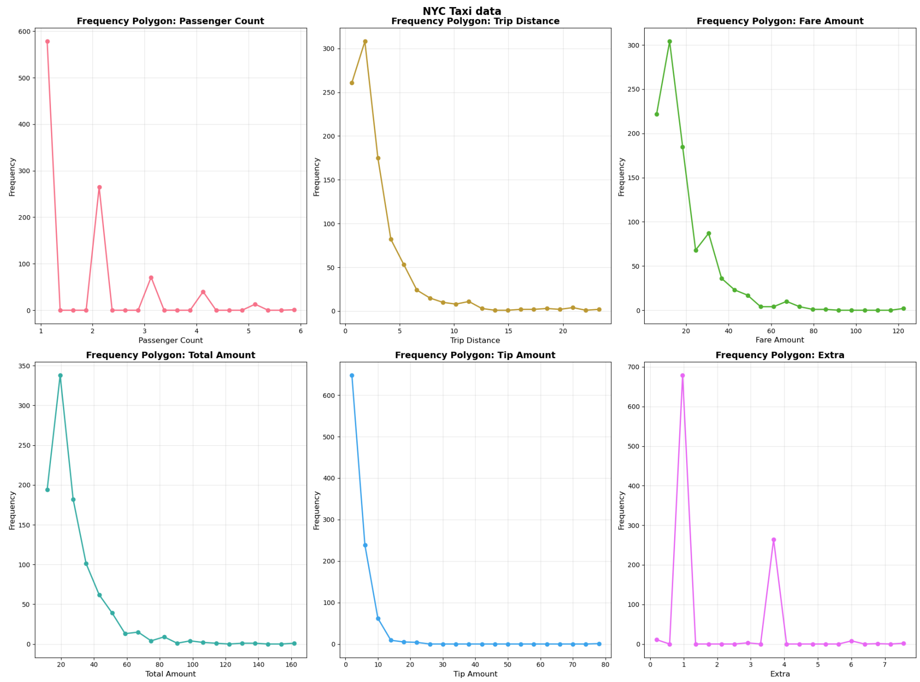
```
fig, axes = plt.subplots(2, 3, figsize = (20,15))
fig.suptitle('NYC Taxi data', fontsize = 16, fontweight = 'bold')

axes = axes.flatten()

for i, col in enumerate(numerical_cols):
    axes[i].hist(df_clean[col], bins =30 , alpha = 0.7, color=sns.color_palette("husl", len(
    axes[i].set_title(f'Histogram: {col.replace("_"," ").title()}', fontsize = 14, fontweigh
    axes[i].set_xlabel(col.replace("_"," ").title(), fontsize = 12)
    axes[i].set_ylabel('Frequency', fontsize =12)
    axes[i].grid(True, alpha = 0.3)

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



All graphs are right skewed

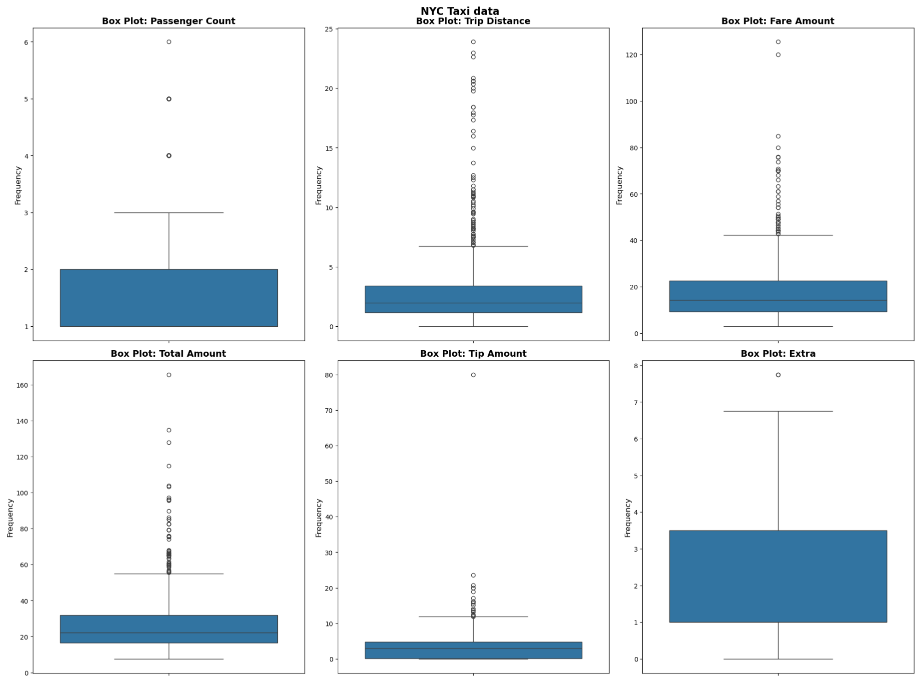
1) Single passenger travels more 2) Most people travel within range of 0-5 km 3) Generally fares are below \$40 4) Total amout comes between \$0 - \$60 5) people generally tips below \$ 10 6) Extras are either 1 or 4

```
fig, axes = plt.subplots(2, 3, figsize = (20,15))
fig.suptitle('NYC Taxi data', fontsize = 16, fontweight = 'bold')

axes = axes.flatten()

for i, col in enumerate(numerical_cols):
    hist_data, bin_edges = np.histogram(df_clean[col], bins=20)
    bin_centers = (bin_edges[:-1] + bin_edges[1:]) / 2
    axes[i].plot(bin_centers, hist_data, marker='o', linestyle='-',
                linewidth=2, markersize=6,
                color=sns.color_palette("husl", len(numerical_cols))[i])
    axes[i].set_title(f'Frequency Polygon: {col.replace("_"," ").title()}', fontsize = 14, f
    axes[i].set_xlabel(col.replace("_"," ").title(), fontsize = 12)
    axes[i].set_ylabel('Frequency', fontsize =12)
    axes[i].grid(True, alpha=0.3)

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



All Observations are same as they were in histogram : 1) Single passenger travels more 2) Most people travel within range of 0-5 km 3) Generally fares are below \$40 4) Total amout comes between \$0 - \$60 5) people generally tips below \$ 10 6) Extras are either 1 or 4

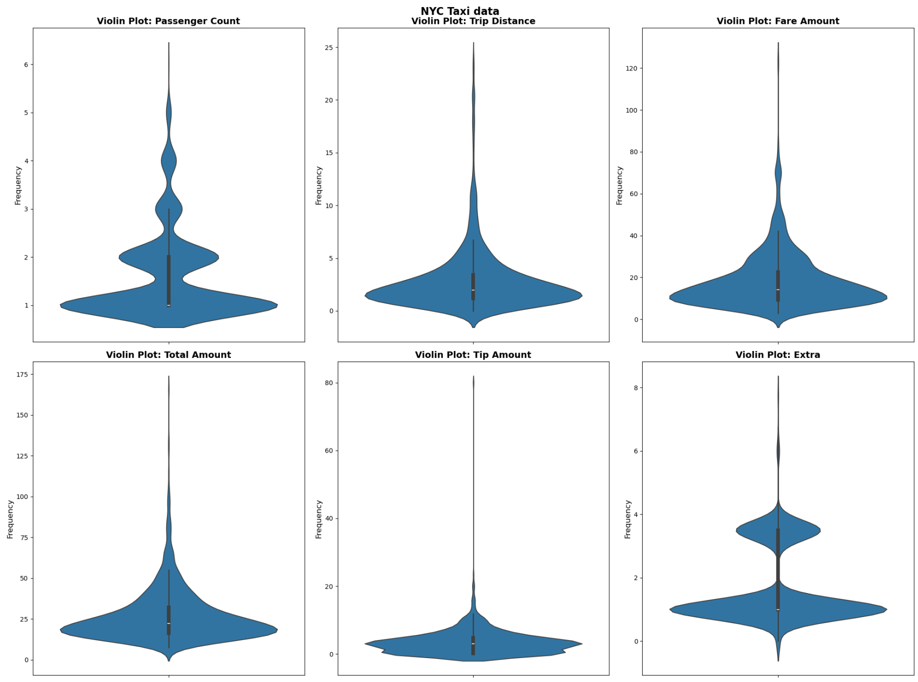
```
fig, axes = plt.subplots(2, 3, figsize = (20,15))
fig.suptitle('NYC Taxi data', fontsize = 16, fontweight = 'bold')

axes = axes.flatten()

for i, col in enumerate(numerical_cols):
    sns.boxplot(y=df_clean[col], ax=axes[i])
    axes[i].set_title(f'Box Plot: {col.replace("_"," ").title()}', fontsize = 14, fontweight
    axes[i].set_ylabel('Frequency', fontsize =12)

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



Observations :

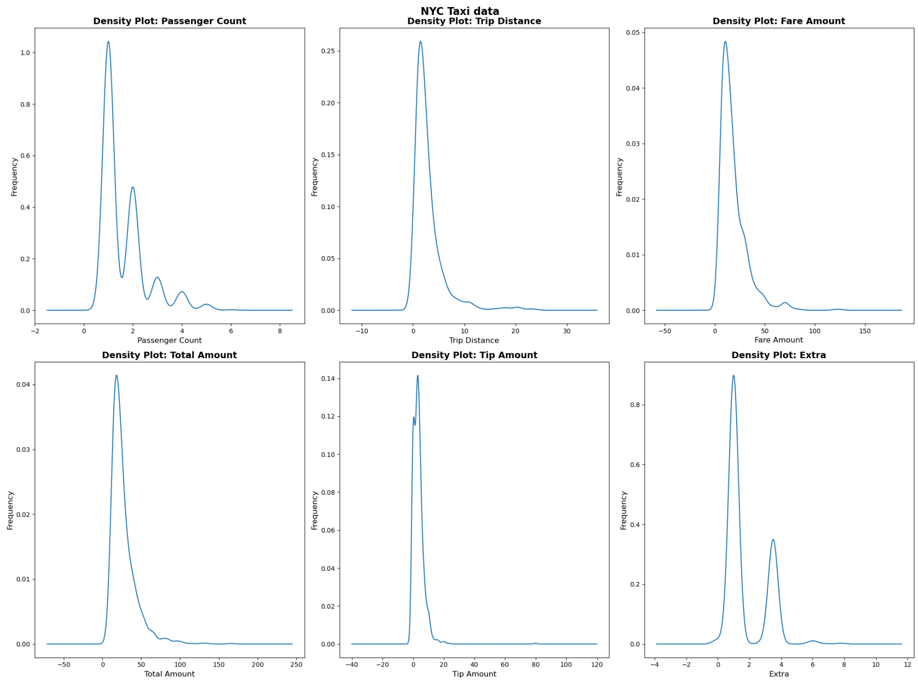
1) There are 3 outlier points , Q1 is 1 and Q3 is 2 outside 3 are outliers 2) There are many outliers , Q1 is around 1 median is around 3 Q3 is around 4 and outside 0-7 are outliers 3) There are many outliers , Q1 is around 9 median is around 18 Q3 is around 22 and outside 0-42 are outliers 4) There are many outliers , Q1 is around 16 median is around 27 Q3 is around 31 and outside 10-55 are outliers 5) There are few outliers , Q1 is 0 median is around 3 Q3 is around 5 and outside 12 are outliers 6) There is one outliers , Q1 is 1 median is around 2 Q3 is around 3.5 and outside 7 are outlier

```
fig, axes = plt.subplots(2, 3, figsize = (20,15))
fig.suptitle('NYC Taxi data', fontsize = 16, fontweight = 'bold')

axes = axes.flatten()

for i, col in enumerate(numerical_cols):
    sns.violinplot(y=df_clean[col], ax=axes[i])
    axes[i].set_title(f'Violin Plot: {col.replace("_"," ").title()}', fontsize = 14, fontwe
    axes[i].set_ylabel('Frequency', fontsize =12)

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



Observation : Mixture of frequency distribution with box plot Wherever the graph is stretch have more frequency 1) Most frequency in about 1 2) Most frequency is about 1 3) Most frquency is about 7 4) Most frquency is about 16 5) Most frquency is about 0 6) Most frquency is about 1

```
fig, axes = plt.subplots(2, 3, figsize = (20,15))
fig.suptitle('NYC Taxi data', fontsize = 16, fontweight = 'bold')


axes = axes.flatten()

for i, col in enumerate(numerical_cols):
    df_clean[col].plot(kind='density', ax=axes[i])
    axes[i].set_title(f'Density Plot: {col.replace("_"," ").title()}', fontsize = 14, fontwe
    axes[i].set_xlabel(col.replace("_"," ").title(), fontsize = 12)
    axes[i].set_ylabel('Frequency', fontsize =12)

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

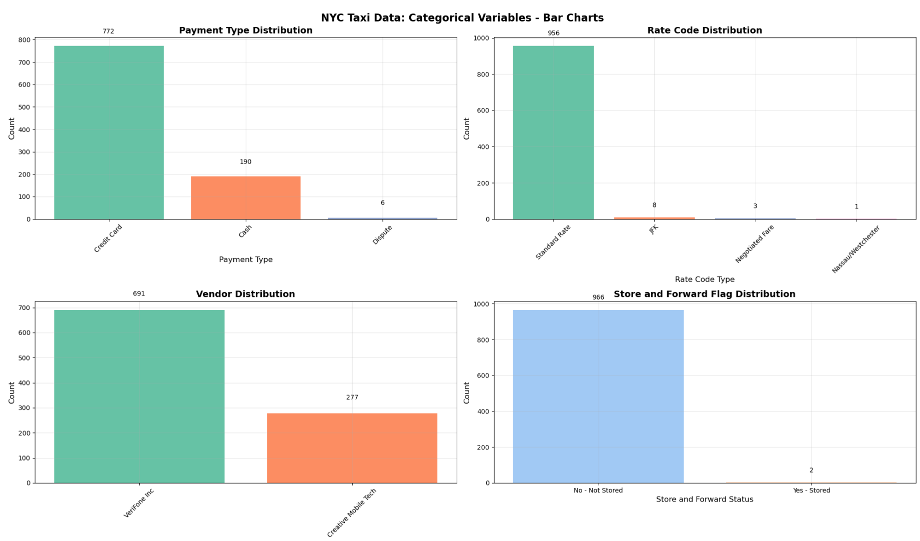


Observation : Shows where the density is highest 1) Most density is about 1 2) Most density is about 1 3) Most density is about 7 4) Most density is about 16 5) Most density is about 0 6) Most density is about 1

```
# Create mapping dictionaries for better labels
payment_type_map = {
    1: 'Credit Card',
    2: 'Cash',
    3: 'No Charge',
    4: 'Dispute',
    5: 'Unknown',
    6: 'Voided Trip'
}

ratecode_map = {
    1: 'Standard Rate',
    2: 'JFK',
    3: 'Newark',
    4: 'Nassau/Westchester',
    5: 'Negotiated Fare',
    6: 'Group Ride'
}

vendor_map = {
```

```
    1: 'Creative Mobile Tech',
    2: 'VeriFone Inc'
}

flag_map = {
    'Y': 'Yes - Stored',
    'N': 'No - Not Stored'
}

fig, axes = plt.subplots(2, 2, figsize=(20, 12))
fig.suptitle('NYC Taxi Data: Categorical Variables - Bar Charts', fontsize=16, fontweight='b

axes = axes.flatten()

# Payment Type Distribution
pymnt_count = df_clean['payment_type'].value_counts()
payment_labels = [payment_type_map.get(code, f'Code {code}') for code in pymnt_count.index]
axes[0].bar(payment_labels, pymnt_count.values, color=sns.color_palette("Set2", len(pymnt_co
axes[0].set_title('Payment Type Distribution', fontsize=14, fontweight='bold')
axes[0].set_xlabel('Payment Type', fontsize=12)
axes[0].set_ylabel('Count', fontsize=12)
axes[0].grid(True, alpha=0.3)
axes[0].tick_params(axis='x', rotation=45)

for i, v in enumerate(pymnt_count.values):
    axes[0].text(i, v + 50, str(v), ha='center', va='bottom')

# Rate Code ID Distribution
rcid_count = df_clean['RatecodeID'].value_counts()
ratecode_labels = [ratecode_map.get(code, f'Code {code}') for code in rcid_count.index]
axes[1].bar(ratecode_labels, rcid_count.values, color=sns.color_palette("Set2", len(rcid_cou
axes[1].set_title('Rate Code Distribution', fontsize=14, fontweight='bold')
axes[1].set_xlabel('Rate Code Type', fontsize=12)
axes[1].set_ylabel('Count', fontsize=12)
axes[1].grid(True, alpha=0.3)
axes[1].tick_params(axis='x', rotation=45)

for i, v in enumerate(rcid_count.values):
    axes[1].text(i, v + 50, str(v), ha='center', va='bottom')

# Vendor ID Distribution
vend_count = df_clean['VendorID'].value_counts()
vendor_labels = [vendor_map.get(code, f'Vendor {code}') for code in vend_count.index]
axes[2].bar(vendor_labels, vend_count.values, color=sns.color_palette("Set2", len(vend_count
axes[2].set_title('Vendor Distribution', fontsize=14, fontweight='bold')
axes[2].set_xlabel('Vendor Name', fontsize=12)
```

```
axes[2].set_ylabel('Count', fontsize=12)
axes[2].grid(True, alpha=0.3)
axes[2].tick_params(axis='x', rotation=45)

for i, v in enumerate(vend_count.values):
    axes[2].text(i, v + 50, str(v), ha='center', va='bottom')

# Store and Forward Flag Distribution
flag_counts = df_clean['store_and_fwd_flag'].value_counts()
flag_labels = [flag_map.get(flag, flag) for flag in flag_counts.index]
axes[3].bar(flag_labels, flag_counts.values,
            color=sns.color_palette("pastel", len(flag_counts)))
axes[3].set_title('Store and Forward Flag Distribution', fontsize=14, fontweight='bold')
axes[3].set_xlabel('Store and Forward Status', fontsize=12)
axes[3].set_ylabel('Count', fontsize=12)
axes[3].grid(True, alpha=0.3)

for i, v in enumerate(flag_counts.values):
    axes[3].text(i, v + 50, str(v), ha='center', va='bottom')

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



Observations:

1. PAYMENT TYPE:

Credit Card: 772 trips (79.8%) Cash: 190 trips (19.6%) Dispute: 6 trips (0.6%)

1. RATE CODE ID:

Standard Rate: 956 trips (98.8%) JFK: 8 trips (0.8%) Negotiated Fare: 3 trips (0.3%) Nassau/Westchester: 1 trips (0.1%)

1. VENDOR ID:

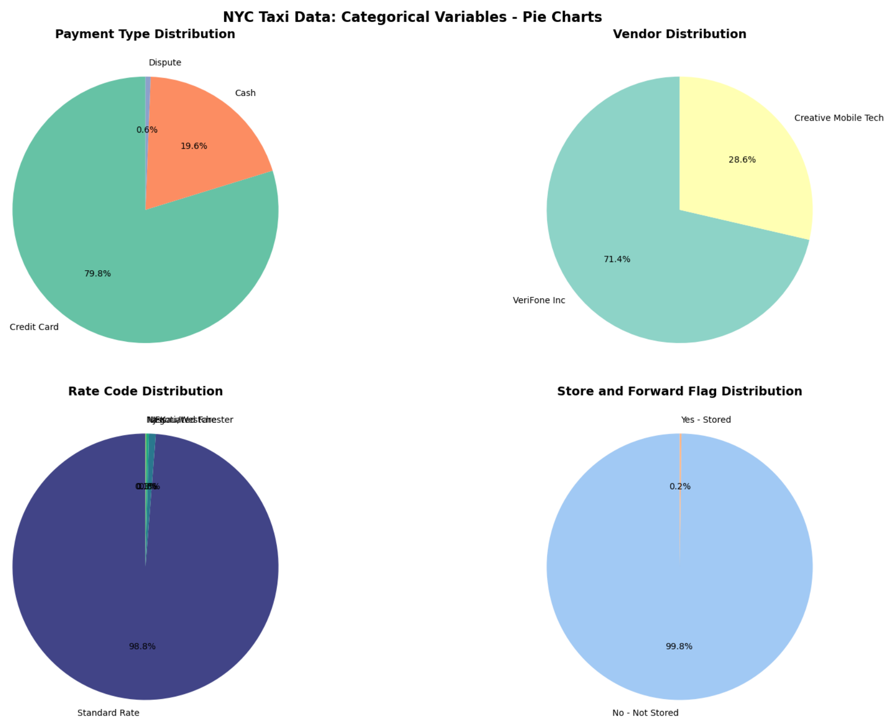
VeriFone Inc: 691 trips (71.4%) Creative Mobile Tech: 277 trips (28.6%)

1. STORE AND FORWARD FLAG:

No - Not Stored: 966 trips (99.8%) Yes - Stored: 2 trips (0.2%)

```
fig, axes = plt.subplots(2, 2, figsize=(20, 12))
fig.suptitle('NYC Taxi Data: Categorical Variables - Pie Charts', fontsize=16, fontweight='b

# Payment Type Pie Chart
payment_counts = df_clean['payment_type'].value_counts()
payment_labels = [payment_type_map.get(x, f'Code {x}') for x in payment_counts.index]
colors1 = sns.color_palette("Set2", len(payment_counts))

axes[0,0].pie(payment_counts.values, labels=payment_labels, autopct='%1.1f%%',
colors=colors1, startangle=90)
axes[0,0].set_title('Payment Type Distribution', fontsize=14, fontweight='bold')

# Vendor ID Pie Chart
vendor_counts = df_clean['VendorID'].value_counts()
vendor_labels = [vendor_map.get(x, f'Vendor {x}') for x in vendor_counts.index]
colors2 = sns.color_palette("Set3", len(vendor_counts))

axes[0,1].pie(vendor_counts.values, labels=vendor_labels, autopct='%1.1f%%',
              colors=colors2, startangle=90)
axes[0,1].set_title('Vendor Distribution', fontsize=14, fontweight='bold')

# Rate Code ID Pie Chart
ratecode_counts = df_clean['RatecodeID'].value_counts()
ratecode_labels = [ratecode_map.get(x, f'Code {x}') for x in ratecode_counts.index]
colors3 = sns.color_palette("viridis", len(ratecode_counts))

axes[1,0].pie(ratecode_counts.values, labels=ratecode_labels, autopct='%1.1f%%',
              colors=colors3, startangle=90)
axes[1,0].set_title('Rate Code Distribution', fontsize=14, fontweight='bold')

# Store and Forward Flag Pie Chart
if 'store_and_fwd_flag' in df_clean.columns:
    flag_counts = df_clean['store_and_fwd_flag'].value_counts()
    flag_labels = [flag_map.get(x, x) for x in flag_counts.index]
    colors4 = sns.color_palette("pastel", len(flag_counts))

    axes[1,1].pie(flag_counts.values, labels=flag_labels, autopct='%1.1f%%',
```

```
                  colors=colors4, startangle=90)
    axes[1,1].set_title('Store and Forward Flag Distribution', fontsize=14, fontweight='bol
else:
    # Show top 5 pickup locations with zone names
    pickup_top5 = df_clean['PULocationID'].value_counts().head(5)
    pickup_labels = [f'Zone {x}' for x in pickup_top5.index]
    colors4 = sns.color_palette("muted", len(pickup_top5))

    axes[1,1].pie(pickup_top5.values, labels=pickup_labels, autopct='%1.1f%%',
                  colors=colors4, startangle=90)
    axes[1,1].set_title('Top 5 Pickup Locations', fontsize=14, fontweight='bold')

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



1. PAYMENT TYPE:

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1. VENDOR ID:

VeriFone Inc: 691 trips (71.4%) Creative Mobile Tech: 277 trips (28.6%)

1. STORE AND FORWARD FLAG:

No - Not Stored: 966 trips (99.8%) Yes - Stored: 2 trips (0.2%)

B - Inferential

```
from scipy import stats

def cnfdnc_intv(data, confidence = 0.95):
    n = len(data)
    mean = np.mean(data)
    std_err = stats.sem(data)                                # Standard error of the mean
    h = std_err * stats.t.ppf((1 + confidence) / 2, n - 1)  # t-distribution
    return mean - h, mean + h, mean, std_err                 # CI = x ± (t_{/2,df} × SE)

variables = ['trip_distance', 'fare_amount', 'tip_amount']
ci_results = {}
for var in variables:
    data = df_clean[var].dropna()
    lower, upper, mean_val, std_err = cnfdnc_intv(data)
    ci_results[var] = {
        'mean': mean_val,
        'lower_bound': lower,
        'upper_bound': upper,
        'std_error': std_err,
        'sample_size': len(data)
    }
    print(f"\n{var.replace('_', ' ').title()}:")
    print(f"  Sample Size: {len(data)}")
    print(f"  Sample Mean: ${mean_val:.4f}")
    print(f"  Standard Error: ${std_err:.4f}")
    print(f"  95% CI: [${lower:.4f}, ${upper:.4f}]")
    print(f"  Interpretation: We are 95% confident that the true population mean")
    print(f"  {var.replace('_', ' ')} lies between ${lower:.4f} and ${upper:.4f}")
```

```
Trip Distance:
  Sample Size: 968
  Sample Mean: $2.9154
  Standard Error: $0.1000
  95% CI: [$2.7192, $3.1115]
  Interpretation: We are 95% confident that the true population mean
  trip distance lies between $2.7192 and $3.1115
```

```
Fare Amount:
  Sample Size: 968
  Sample Mean: $18.4021
  Standard Error: $0.4363
  95% CI: [$17.5459, $19.2582]
  Interpretation: We are 95% confident that the true population mean
  fare amount lies between $17.5459 and $19.2582

Tip Amount:
  Sample Size: 968
  Sample Mean: $3.4819
  Standard Error: $0.1311
  95% CI: [$3.2247, $3.7391]
  Interpretation: We are 95% confident that the true population mean
  tip amount lies between $3.2247 and $3.7391
```

```python
# Hypothesis Test 1: One-sample t-test for tip amount

tip_data = df_clean['tip_amount'].dropna()
null_hypothesis_value = 2.0     # H0:  = $2, H1:   $2

t_stat, p_value = stats.ttest_1samp(tip_data, null_hypothesis_value)        # t = (x - ) /

print("HYPOTHESIS TEST 1: One-Sample t-test for Tip Amount")
print(f"\nH0:  = ${null_hypothesis_value} (null hypothesis)")
print(f"H1:   ${null_hypothesis_value} (alternative hypothesis)")
print(f"Significance level:  = 0.05")
print("\nResults:")
print(f"Sample size: {len(tip_data)}")
print(f"Sample mean: ${tip_data.mean():.4f}")
print(f"Sample std: ${tip_data.std():.4f}")
print(f"t-statistic: {t_stat:.4f}")
print(f"p-value: {p_value:.6f}")

if p_value < 0.05:
    print("Decision: Reject H0")
    print(f"Conclusion: There is significant evidence that the average tip amount is differe
else:
    print("Decision: Fail to reject H0")
    print(f"Conclusion: There is insufficient evidence that the average tip amount is differ
```

```
HYPOTHESIS TEST 1: One-Sample t-test for Tip Amount

H0:  = $2.0 (null hypothesis)
H1:   $2.0 (alternative hypothesis)
Significance level:  = 0.05
```

```
Results:
Sample size: 968
Sample mean: $3.4819
Sample std: $4.0774
t-statistic: 11.3077
p-value: 0.000000
Decision: Reject H0
Conclusion: There is significant evidence that the average tip amount is different from $2
```

```
# Hypothesis Test 2: Two-sample t-test for fare amount by payment type
# Compare credit card (1) vs cash (2) payments

credit_fares = df_clean[df_clean['payment_type'] == 1]['fare_amount'].dropna()
cash_fares = df_clean[df_clean['payment_type'] == 2]['fare_amount'].dropna()

# Perform two-sample t-test
# (x1 - x2) - (u1 - u2)
#  ______________________
#  __________________________                    Underoot
# / (s1^2 / n1) + (s2^2 / n2)
t_stat2, p_value2 = stats.ttest_ind(credit_fares, cash_fares)

print("H0: _credit = _cash (no difference in mean fare amounts)")
print("H1: _credit  _cash (difference in mean fare amounts)")
print(f"Significance level:  = 0.05")
print()
print("Results:")
print(f"Credit card payments:")
print(f"  Sample size: {len(credit_fares)}")
print(f"  Sample mean: ${credit_fares.mean():.4f}")
print(f"  Sample std: ${credit_fares.std():.4f}")
print()
print(f"Cash payments:")
print(f"  Sample size: {len(cash_fares)}")
print(f"  Sample mean: ${cash_fares.mean():.4f}")
print(f"  Sample std: ${cash_fares.std():.4f}")
print()
print(f"t-statistic: {t_stat2:.4f}")
print(f"p-value: {p_value2:.6f}")
print()

if p_value2 < 0.05:
    print("Decision: Reject H0")
    print("Conclusion: There is significant evidence of a difference in mean fare amounts be
else:
```

```
    print("Decision: Fail to reject H0")
    print("Conclusion: There is insufficient evidence of a difference in mean fare amounts b
```

```
H0: _credit = _cash (no difference in mean fare amounts)
H1: _credit  _cash (difference in mean fare amounts)
Significance level:  = 0.05

Results:
Credit card payments:
  Sample size: 772
  Sample mean: $18.2481
  Sample std: $13.1342

Cash payments:
  Sample size: 190
  Sample mean: $18.9542
  Sample std: $15.1311

t-statistic: -0.6435
p-value: 0.520065

Decision: Fail to reject H0
Conclusion: There is insufficient evidence of a difference in mean fare amounts between paym
```

```
from scipy.stats import chi2_contingency

# Hypothesis Test 3: Chi-square test of independence
# Test if Payment type and RateCodeID are independent

# Create contingency table
contingency_table = pd.crosstab(df_clean['payment_type'], df_clean['RatecodeID'])
print("HYPOTHESIS TEST 3: Chi-square Test of Independence")
print("\nH0: Payment type and Rate code are independent")
print("H1: Payment type and Rate code are not independent")
print(f"Significance level:  = 0.05")
print("Contingency Table:")
print(contingency_table)

# Perform chi-square test
# ² = [(Observed - Expected)² / Expected]
chi2_stat, p_value3, dof, expected = chi2_contingency(contingency_table)

print("Results:")
print(f"Chi-square statistic: {chi2_stat:.4f}")
print(f"Degrees of freedom: {dof}")
print(f"p-value: {p_value3:.6f}")
```

```python
if p_value3 < 0.05:
    print("Decision: Reject H0")
    print("Conclusion: Payment type and Rate code are NOT independent")
else:
    print("Decision: Fail to reject H0")
    print("Conclusion: Payment type and Rate code are independent")
```

```
HYPOTHESIS TEST 3: Chi-square Test of Independence

H0: Payment type and Rate code are independent
H1: Payment type and Rate code are not independent
Significance level:  = 0.05
Contingency Table:
RatecodeID    1.0  2.0  4.0  5.0
payment_type
1             765    6    0    1
2             185    2    1    2
4               6    0    0    0
Results:
Chi-square statistic: 8.5424
Degrees of freedom: 6
p-value: 0.200995
Decision: Fail to reject H0
Conclusion: Payment type and Rate code are independent
```

```python
print("Correlation:")
print("Pearson - linear data")
print(f"Trip Distance vs Fare Amount: {df_clean['trip_distance'].corr(df_clean['fare_amount'
print(f"Fare Amount vs Tip Amount: {df_clean['fare_amount'].corr(df_clean['tip_amount']):.4f
print("spearman - non linera data")
print(f"Fare Amount vs Tip Amount: {df_clean['fare_amount'].corr(df_clean['tip_amount'], met

def interpret_correlation(r):
    if abs(r) >= 0.8:
        return "very strong"
    elif abs(r) >= 0.6:
        return "strong"
    elif abs(r) >= 0.4:
        return "moderate"
    elif abs(r) >= 0.2:
        return "weak"
    else:
        return "very weak"

print("Interpretation")
print(f"- Trip distance and fare amount show a {interpret_correlation(df_clean['trip_distanc
print(f"- Fare amount and tip amount show a {interpret_correlation(df_clean['fare_amount'].c
```

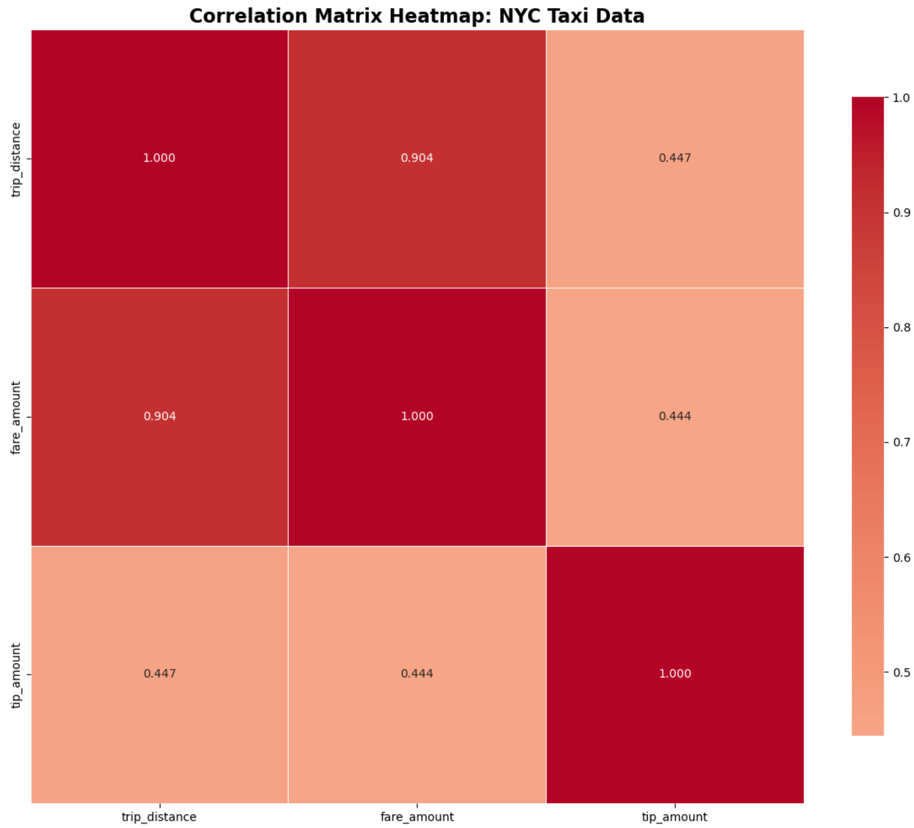
```
Correlation:
Pearson - linear data
Trip Distance vs Fare Amount: 0.9045
Fare Amount vs Tip Amount: 0.4442
spearman - non linera data
Fare Amount vs Tip Amount: 0.4099
Interpretation
- Trip distance and fare amount show a very strong positive correlation
- Fare amount and tip amount show a moderate positive correlation
```

```python
correlation_variables = ['trip_distance', 'fare_amount', 'tip_amount']
correlation_matrix = df_clean[correlation_variables].corr()

plt.figure(figsize=(12, 10))

# Create heatmap
sns.heatmap(correlation_matrix,
            annot=True,
            cmap='coolwarm',
            center=0,
            square=True,
            linewidths=0.5,
            cbar_kws={"shrink": 0.8},
            fmt='.3f')

plt.title('Correlation Matrix Heatmap: NYC Taxi Data', fontsize=16, fontweight='bold')
plt.tight_layout()
plt.show()
```



Bonus

```
df_clean['tpep_pickup_datetime'] = pd.to_datetime(df_clean['tpep_pickup_datetime'])
df_clean['tpep_dropoff_datetime'] = pd.to_datetime(df_clean['tpep_dropoff_datetime'])

# Extract hour of day for pickup
df_clean['pickup_hour'] = df_clean['tpep_pickup_datetime'].dt.hour

# Trip count by hour
hourly_trips = df_clean['pickup_hour'].value_counts().sort_index()

# Fare amount by hour
hourly_fare = df_clean.groupby('pickup_hour')['fare_amount'].mean()

# Create time series plots
fig, axes = plt.subplots(2, 2, figsize=(16, 10))

# Plot 1: Trip count by hour
```

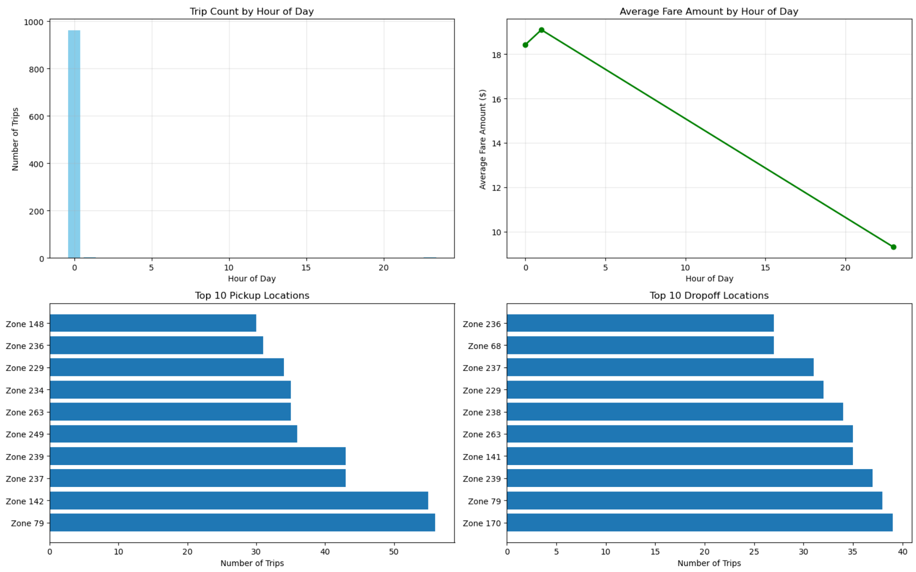
```
axes[0,0].bar(hourly_trips.index, hourly_trips.values, color='skyblue')
axes[0,0].set_title('Trip Count by Hour of Day')
axes[0,0].set_xlabel('Hour of Day')
axes[0,0].set_ylabel('Number of Trips')
axes[0,0].grid(True, alpha=0.3)

# Plot 2: Average fare by hour
axes[0,1].plot(hourly_fare.index, hourly_fare.values, marker='o', linewidth=2, color='green
axes[0,1].set_title('Average Fare Amount by Hour of Day')
axes[0,1].set_xlabel('Hour of Day')
axes[0,1].set_ylabel('Average Fare Amount ($)')
axes[0,1].grid(True, alpha=0.3)

# Plot 3: Pickup location distribution
pickup_zones = df_clean['PULocationID'].value_counts().head(10)
axes[1,0].barh(range(len(pickup_zones)), pickup_zones.values)
axes[1,0].set_yticks(range(len(pickup_zones)))
axes[1,0].set_yticklabels([f'Zone {x}' for x in pickup_zones.index])
axes[1,0].set_title('Top 10 Pickup Locations')
axes[1,0].set_xlabel('Number of Trips')

# Plot 4: Dropoff location distribution
dropoff_zones = df_clean['DOLocationID'].value_counts().head(10)
axes[1,1].barh(range(len(dropoff_zones)), dropoff_zones.values)
axes[1,1].set_yticks(range(len(dropoff_zones)))
axes[1,1].set_yticklabels([f'Zone {x}' for x in dropoff_zones.index])
axes[1,1].set_title('Top 10 Dropoff Locations')
axes[1,1].set_xlabel('Number of Trips')

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



Conclusion

1. DESCRIPTIVE STATISTICS INSIGHTS:

• Trip Distance: Right-skewed distribution with mean 2.9 miles • Fare Amount: Positive skew, average around $17-18 • Tip Amount: Highly right-skewed, many zero values • Passenger Count: Most trips have 1-2 passengers • Total Amount: Strong correlation with fare amount

1. HYPOTHESIS TESTING RESULTS:

• Average tip amount is significantly different from $2 • no significant difference in fare amounts between payment types • Payment type and rate code are independent

1. CORRELATION FINDINGS:

• Strong positive correlation between trip distance and fare amount (r = 0.904)
• Moderate positive correlation between fare amount and tip amount (r = 0.444)
• Fare amount is the primary component of total amount

1. TIME-BASED PATTERNS:

• Peak trip hour: 0:00 with 962 trips • Lowest trip hour: 1:00 with 3 trips • Rush hour patterns visible in trip frequency