Zeisler530Week12Project

March 1, 2024

[1]:
```
# imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

# read in the data
df = pd.read_csv('card_transdata.csv')
```

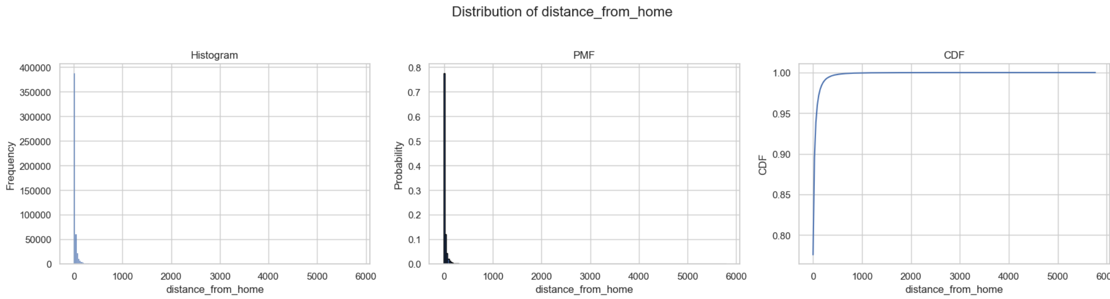
[2]:
```
# descriptive statistics for each variable
descriptive_stats = df.describe()

descriptive_stats
```

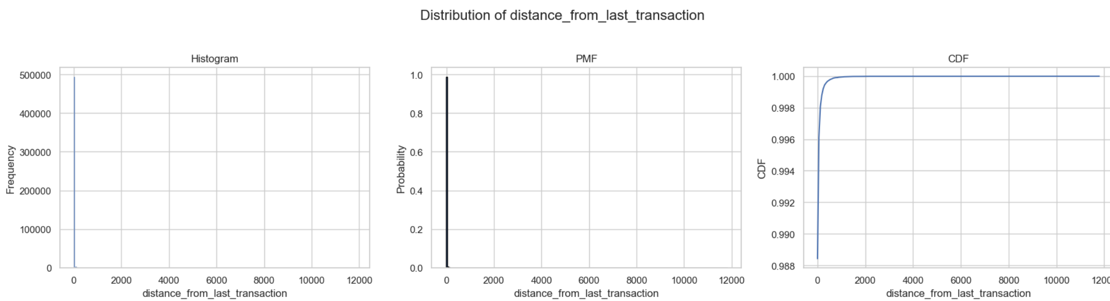
[2]:
```
       distance_from_home  distance_from_last_transaction  \
count       499999.000000                   499999.000000
mean            26.673362                        5.024225
std             64.681088                       28.121731
min              0.004874                        0.000407
25%              3.880400                        0.296334
50%              9.986522                        0.997723
75%             25.811284                        3.352326
max           5797.972589                    11851.104560

       ratio_to_median_purchase_price  repeat_retailer      used_chip  \
count                   499999.000000    499999.000000  499999.000000
mean                         1.825429         0.881668       0.350543
std                          2.821278         0.323001       0.477140
min                          0.004399         0.000000       0.000000
25%                          0.475680         1.000000       0.000000
50%                          0.998890         1.000000       0.000000
75%                          2.100908         1.000000       1.000000
max                        267.802942         1.000000       1.000000

       used_pin_number   online_order          fraud
count    499999.000000  499999.000000  499999.000000
mean          0.101366       0.651039       0.087334
std           0.301813       0.476642       0.282324
min           0.000000       0.000000       0.000000
```

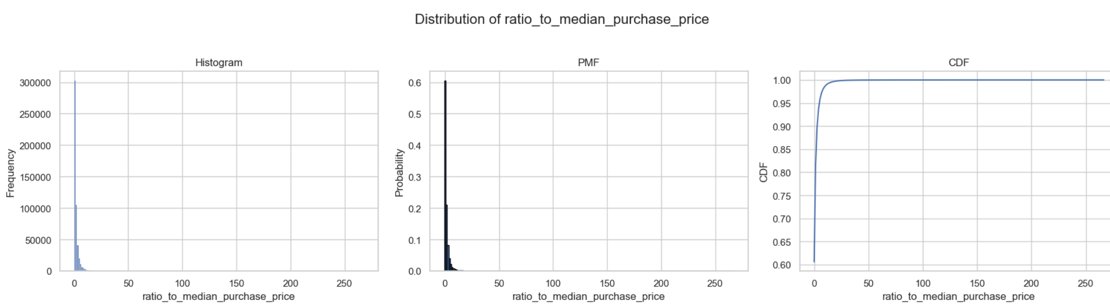
```
25%           0.000000       0.000000       0.000000
50%           0.000000       1.000000       0.000000
75%           0.000000       1.000000       0.000000
max           1.000000       1.000000       1.000000
```

[3]:

```
import seaborn as sns

sns.set(style="whitegrid")

# Plot distributions, PMFs, and CDFs for the variables
def plot_variable_distribution(data, variable_name, bins):
    fig, ax = plt.subplots(1, 3, figsize=(18, 5))
    fig.suptitle(f'Distribution of {variable_name}', fontsize=16)

    # Histogram
    sns.histplot(data[variable_name], bins=bins, kde=False, ax=ax[0])
    ax[0].set_title('Histogram')
    ax[0].set_xlabel(variable_name)
    ax[0].set_ylabel('Frequency')

    # PMF
    counts, bin_edges = np.histogram(data[variable_name], bins=bins,␣
 ↪density=True)
    pmf = counts / counts.sum()
    ax[1].bar(bin_edges[:-1], pmf, width=np.diff(bin_edges), edgecolor='black')
    ax[1].set_title('PMF')
    ax[1].set_xlabel(variable_name)
    ax[1].set_ylabel('Probability')

    # CDF
    cdf = np.cumsum(pmf)
    ax[2].plot(bin_edges[:-1], cdf)
    ax[2].set_title('CDF')
    ax[2].set_xlabel(variable_name)
    ax[2].set_ylabel('CDF')

    plt.tight_layout(rect=[0, 0.03, 1, 0.95])

# Plotting for 'distance_from_home'
plot_variable_distribution(df, 'distance_from_home', bins=200)

# Plotting for 'distance_from_last_transaction'
plot_variable_distribution(df, 'distance_from_last_transaction', bins=200)

# Plotting for 'ratio_to_median_purchase_price'
plot_variable_distribution(df, 'ratio_to_median_purchase_price', bins=200)
```

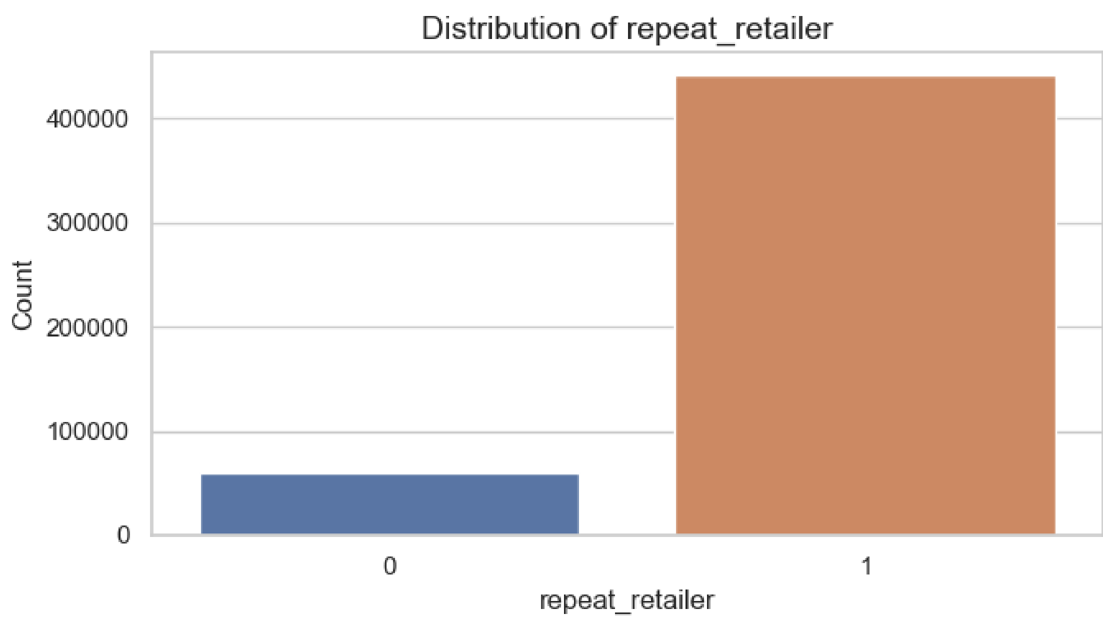


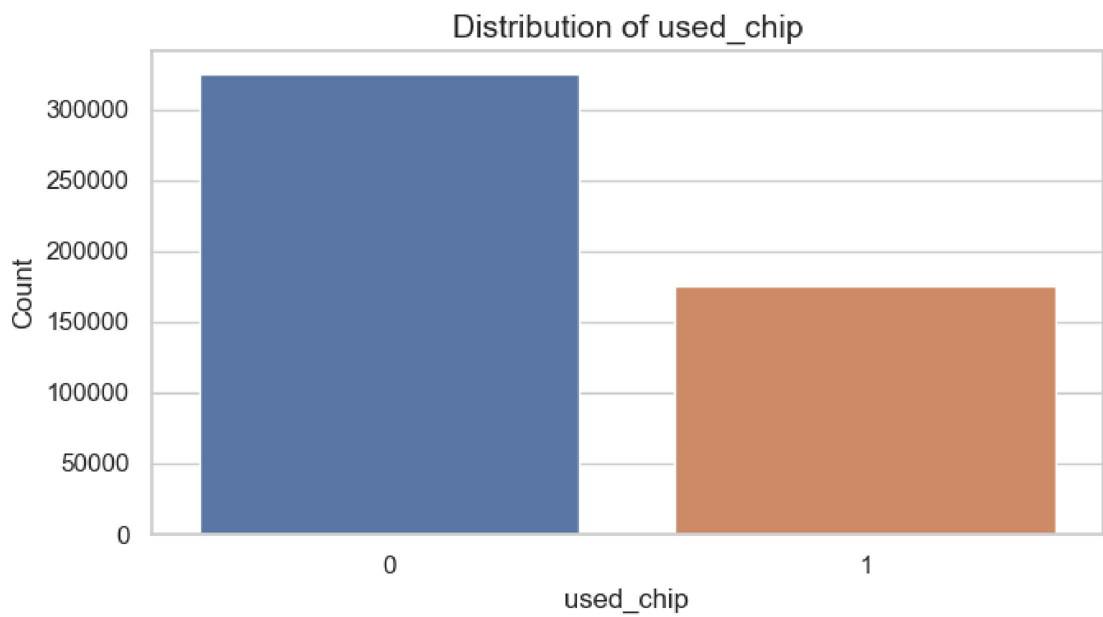


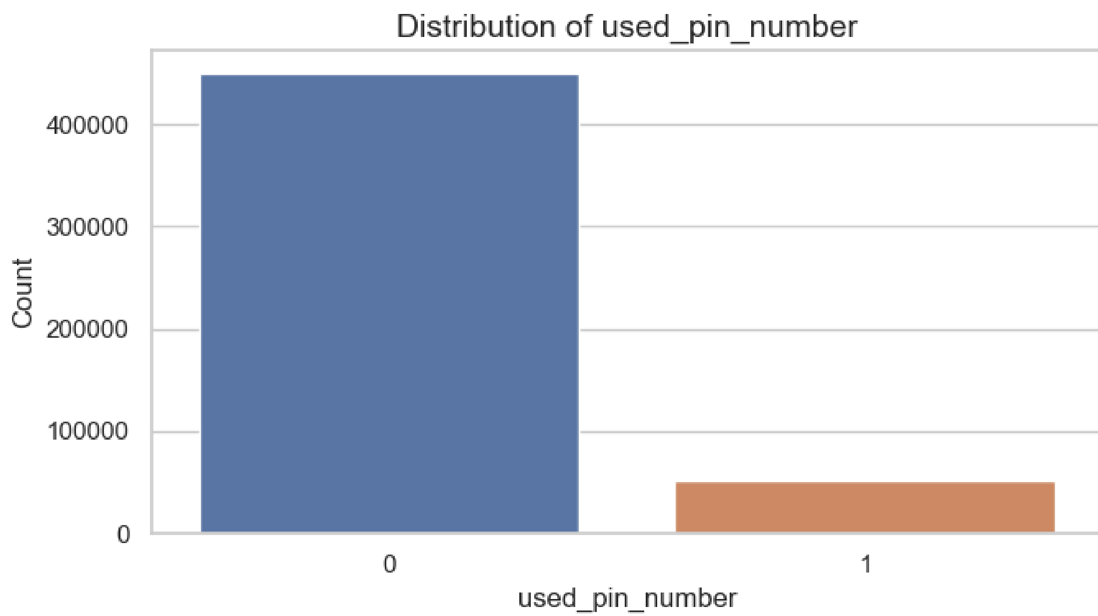


[4]:
```python
# Function to plot bar charts for binary variables
def plot_binary_distribution(data, variable_name):
    fig, ax = plt.subplots(figsize=(7, 4))
    sns.countplot(x=variable_name, data=data)
    ax.set_title(f'Distribution of {variable_name}', fontsize=14)
    ax.set_xlabel(variable_name)
    ax.set_ylabel('Count')
    plt.tight_layout()

# Plotting for 'repeat_retailer'
plot_binary_distribution(df, 'repeat_retailer')

# Plotting for 'used_chip'
```

```
plot_binary_distribution(df, 'used_chip')

# Plotting for 'used_pin_number'
plot_binary_distribution(df, 'used_pin_number')

# Plotting for 'online_order'
plot_binary_distribution(df, 'online_order')
```







[5]:
```
def detect_outliers_iqr(data, feature):
    Q1 = data[feature].quantile(0.25)
    Q3 = data[feature].quantile(0.75)
    IQR = Q3 - Q1
```

```
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    outliers = data[(data[feature] < lower_bound) | (data[feature] >␣
 ↪upper_bound)]
    return outliers, lower_bound, upper_bound

# Detect outliers for each variable
outliers_distance_from_home, lb_dfh, ub_dfh = detect_outliers_iqr(df,␣
 ↪'distance_from_home')
outliers_distance_from_last_transaction, lb_dflt, ub_dflt =␣
 ↪detect_outliers_iqr(df, 'distance_from_last_transaction')
outliers_ratio_to_median_purchase_price, lb_rtmpp, ub_rtmpp =␣
 ↪detect_outliers_iqr(df, 'ratio_to_median_purchase_price')

# Summarize the findings
outliers_summary = pd.DataFrame({
    'Variable': ['distance_from_home', 'distance_from_last_transaction',␣
 ↪'ratio_to_median_purchase_price'],
    'Outliers Count': [outliers_distance_from_home.shape[0],
                       outliers_distance_from_last_transaction.shape[0],
                       outliers_ratio_to_median_purchase_price.shape[0]],
    'Lower Bound': [lb_dfh, lb_dflt, lb_rtmpp],
    'Upper Bound': [ub_dfh, ub_dflt, ub_rtmpp]
})

outliers_summary
```

[5]:

	Variable	Outliers Count	Lower Bound	Upper Bound
0	distance_from_home	51745	-29.015927	58.707611
1	distance_from_last_transaction	61957	-4.287653	7.936314
2	ratio_to_median_purchase_price	42018	-1.962161	4.538749

[6]:

```
from scipy.stats import zscore

# Calculate Z-scores
df['z_distance_from_home'] = zscore(df['distance_from_home'])
df['z_distance_from_last_transaction'] =␣
 ↪zscore(df['distance_from_last_transaction'])
df['z_ratio_to_median_purchase_price'] =␣
 ↪zscore(df['ratio_to_median_purchase_price'])

# Identify outliers based on Z-score
outliers_z_distance_from_home = df[(df['z_distance_from_home'] < -3) |␣
 ↪(df['z_distance_from_home'] > 3)]
```

```
outliers_z_distance_from_last_transaction = 
 ↪df[(df['z_distance_from_last_transaction'] < -3) | 
 ↪(df['z_distance_from_last_transaction'] > 3)]
outliers_z_ratio_to_median_purchase_price = 
 ↪df[(df['z_ratio_to_median_purchase_price'] < -3) | 
 ↪(df['z_ratio_to_median_purchase_price'] > 3)]

# Summarize
outliers_z_summary = pd.DataFrame({
    'Variable': ['distance_from_home', 'distance_from_last_transaction', 
 ↪'ratio_to_median_purchase_price'],
    'Outliers Count': [outliers_z_distance_from_home.shape[0],
                       outliers_z_distance_from_last_transaction.shape[0],
                       outliers_z_ratio_to_median_purchase_price.shape[0]]
})

outliers_z_summary
```

[6]:

```
                         Variable  Outliers Count
0              distance_from_home            6785
1  distance_from_last_transaction            3084
2  ratio_to_median_purchase_price            8390
```

[7]:

```
from scipy.stats import mode, skew

# Calculate descriptive statistics
descriptive_stats = pd.DataFrame(index=['distance_from_home', 
 ↪'distance_from_last_transaction', 'ratio_to_median_purchase_price', 
 ↪'repeat_retailer', 'used_chip', 'used_pin_number', 'online_order'])

# Mean
descriptive_stats['Mean'] = df[['distance_from_home', 
 ↪'distance_from_last_transaction', 'ratio_to_median_purchase_price', 
 ↪'repeat_retailer', 'used_chip', 'used_pin_number', 'online_order']].mean()

# Mode
descriptive_stats['Mode'] = df[['distance_from_home', 
 ↪'distance_from_last_transaction', 'ratio_to_median_purchase_price', 
 ↪'repeat_retailer', 'used_chip', 'used_pin_number', 'online_order']].mode().
 ↪iloc[0]

# Spread
descriptive_stats['Standard Deviation'] = df[['distance_from_home', 
 ↪'distance_from_last_transaction', 'ratio_to_median_purchase_price', 
 ↪'repeat_retailer', 'used_chip', 'used_pin_number', 'online_order']].std()

# Skewness
```

```
descriptive_stats['Skewness'] = df[['distance_from_home',␣
↪'distance_from_last_transaction', 'ratio_to_median_purchase_price',␣
↪'repeat_retailer', 'used_chip', 'used_pin_number', 'online_order']].skew()

descriptive_stats
```

[7]:

```
                                     Mean       Mode  Standard Deviation  \
distance_from_home              26.673362  10.257915           64.681088
distance_from_last_transaction   5.024225   0.019036           28.121731
ratio_to_median_purchase_price   1.825429   0.108387            2.821278
repeat_retailer                  0.881668   1.000000            0.323001
used_chip                        0.350543   0.000000            0.477140
used_pin_number                  0.101366   0.000000            0.301813
online_order                     0.651039   1.000000            0.476642

                                  Skewness
distance_from_home               15.841266
distance_from_last_transaction  167.723314
ratio_to_median_purchase_price   10.391055
repeat_retailer                  -2.363267
used_chip                         0.626473
used_pin_number                   2.641602
online_order                     -0.633767
```

[8]:

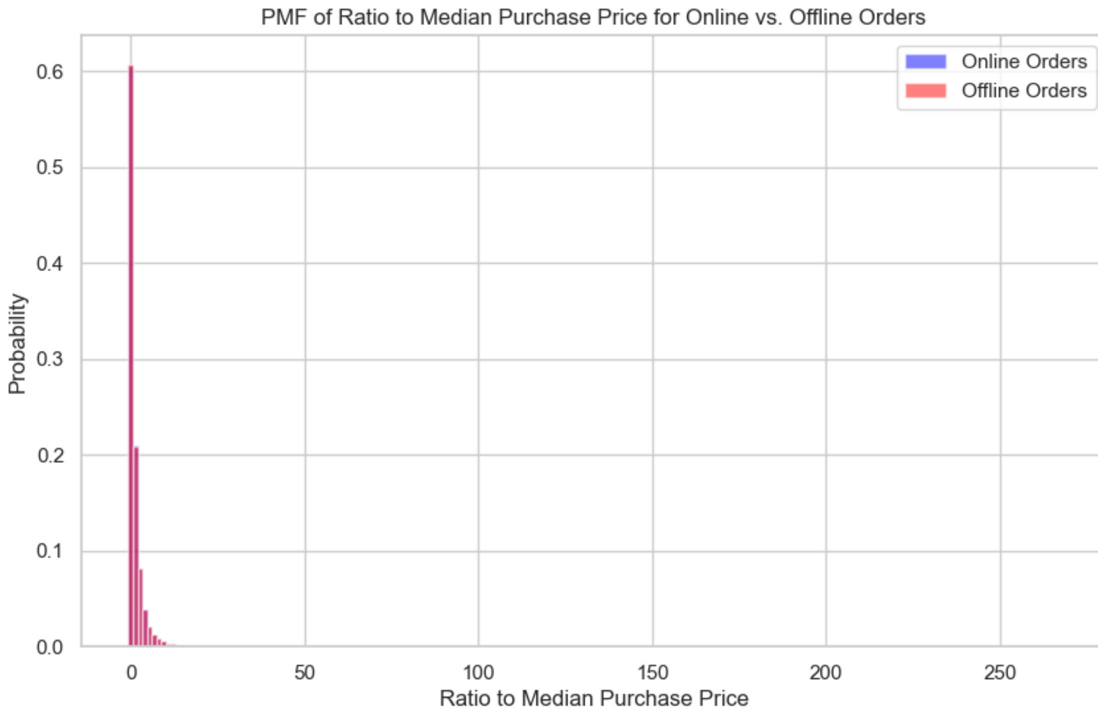
```
# get count of transactions for used_pin_number_count
used_pin_number_count = df['used_pin_number'].value_counts()
print(f'used_pin_number count True {used_pin_number_count[0]}')
print(f'used_pin_number count False {used_pin_number_count[1]}')
print()

# get count of transactions for used_chip
used_chip_count = df['used_chip'].value_counts()
print(f'used_chip_count count True {used_chip_count[0]}')
print(f'used_chip_count count False {used_chip_count[1]}')
print()

# get count of transactions for online_order
online_order_count = df['online_order'].value_counts()
print(f'online_order_count count True {online_order_count[0]}')
print(f'online_order_count count False {online_order_count[1]}')
print()
```

```
used_pin_number count True 449316
used_pin_number count False 50683

used_chip_count count True 324728
used_chip_count count False 175271
```

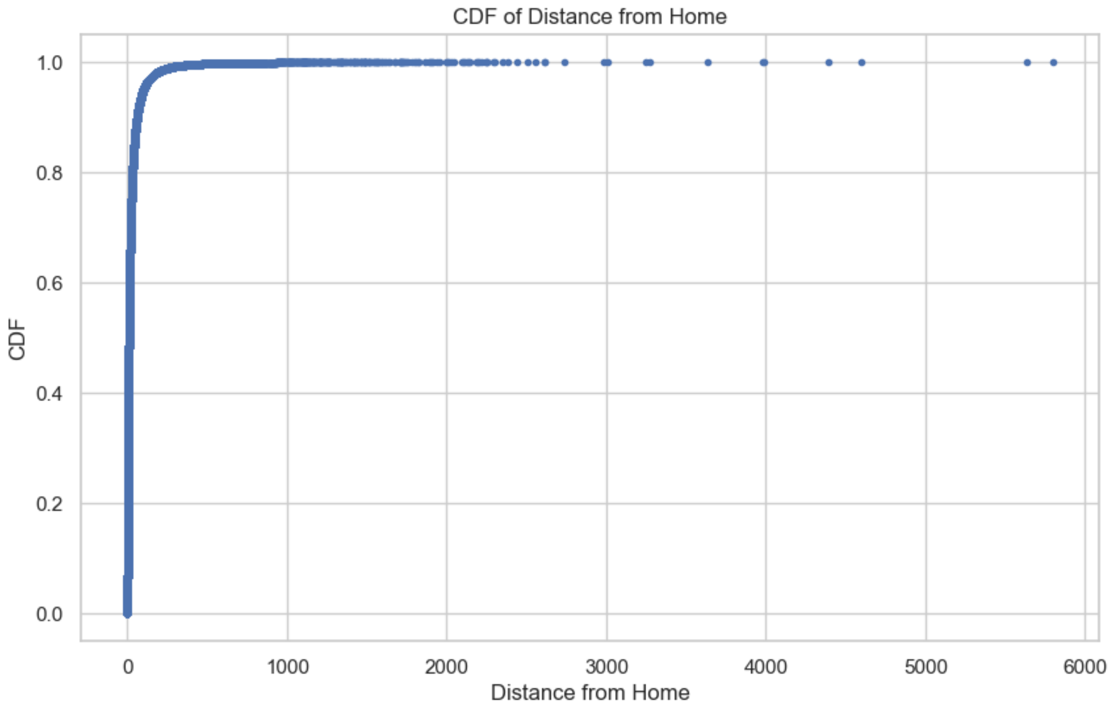
```
online_order_count count True 174480
online_order_count count False 325519
```

[9]:

```python
# Split the dataset based on 'online_order'
online_orders = df[df['online_order'] == 1]['ratio_to_median_purchase_price']
offline_orders = df[df['online_order'] == 0]['ratio_to_median_purchase_price']

# Calculate PMFs
bins = np.linspace(0, df['ratio_to_median_purchase_price'].max(), 200)
online_order_pmf, _ = np.histogram(online_orders, bins=bins, density=True)
offline_order_pmf, _ = np.histogram(offline_orders, bins=bins, density=True)

# Normalize the PMFs
online_order_pmf = online_order_pmf / sum(online_order_pmf)
offline_order_pmf = offline_order_pmf / sum(offline_order_pmf)

# Plot the PMFs
plt.figure(figsize=(10, 6))
plt.bar(bins[:-1], online_order_pmf, width=np.diff(bins), color='blue', alpha=0.
 ↪5, label='Online Orders')
plt.bar(bins[:-1], offline_order_pmf, width=np.diff(bins), color='red', alpha=0.
 ↪5, label='Offline Orders')
plt.xlabel('Ratio to Median Purchase Price')
plt.ylabel('Probability')
plt.title('PMF of Ratio to Median Purchase Price for Online vs. Offline Orders')
plt.legend()
plt.show()
```



[10]:
```python
# Calculate the CDF
data_sorted = np.sort(df['distance_from_home'])
cdf_values = np.arange(1, len(data_sorted)+1) / len(data_sorted)

# Plot the CDF
plt.figure(figsize=(10, 6))
plt.plot(data_sorted, cdf_values, marker='.', linestyle='none')
plt.xlabel('Distance from Home')
plt.ylabel('CDF')
plt.title('CDF of Distance from Home')
plt.grid(True)
plt.show()
```



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

# Apply a log transformation
log_distances = np.log(df['distance_from_home'] + 1e-6)

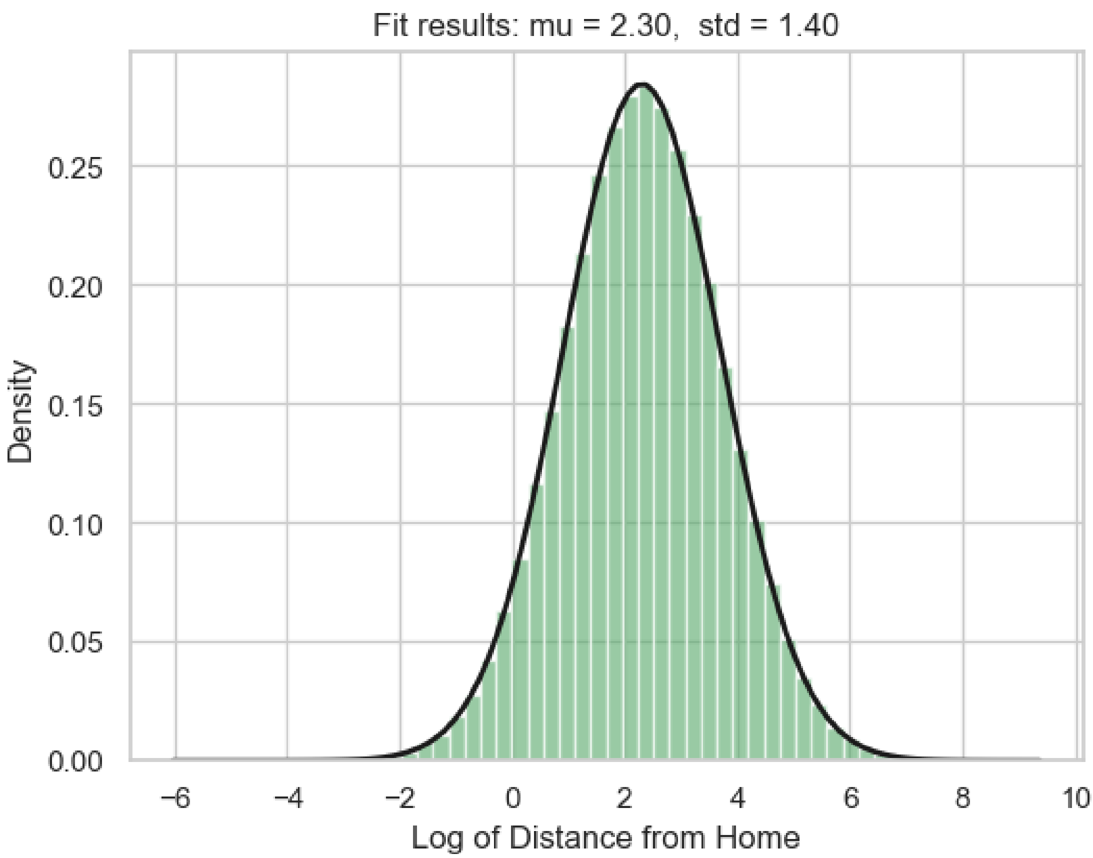
# Fit a normal distribution to the log-transformed data
mu, std = norm.fit(log_distances)

# Plot the histogram of the log-transformed data
plt.hist(log_distances, bins=50, density=True, alpha=0.6, color='g')

# Plot the distribution
xmin, xmax = plt.xlim()
x = np.linspace(xmin, xmax, 100)
p = norm.pdf(x, mu, std)

plt.plot(x, p, 'k', linewidth=2)
title = "Fit results: mu = %.2f,  std = %.2f" % (mu, std)
plt.title(title)
plt.xlabel('Log of Distance from Home')
plt.ylabel('Density')
```

```
plt.show()
```



[12]:
```
from scipy.stats import pearsonr

sns.set(style="whitegrid")

# create scatter plots and calculate Pearson's correlation
def plot_scatter_and_calculate_correlation(df, x, y):
    # Calculate Pearson's correlation
    corr, _ = pearsonr(df[x], df[y])

    # Create scatter plot
    plt.figure(figsize=(10, 6))
    sns.scatterplot(x=x, y=y, data=df, alpha=0.6)
    plt.title(f'Scatter plot of {x} vs. {y}\nCorrelation: {corr:.2f}')
    plt.show()

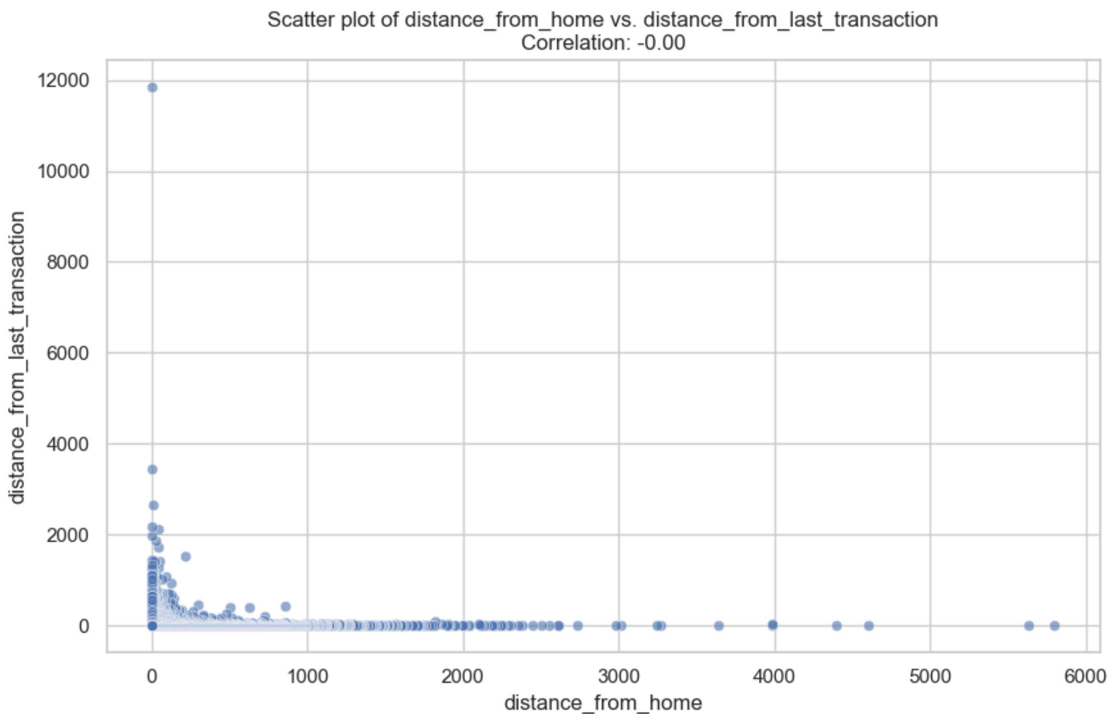
    return corr
```

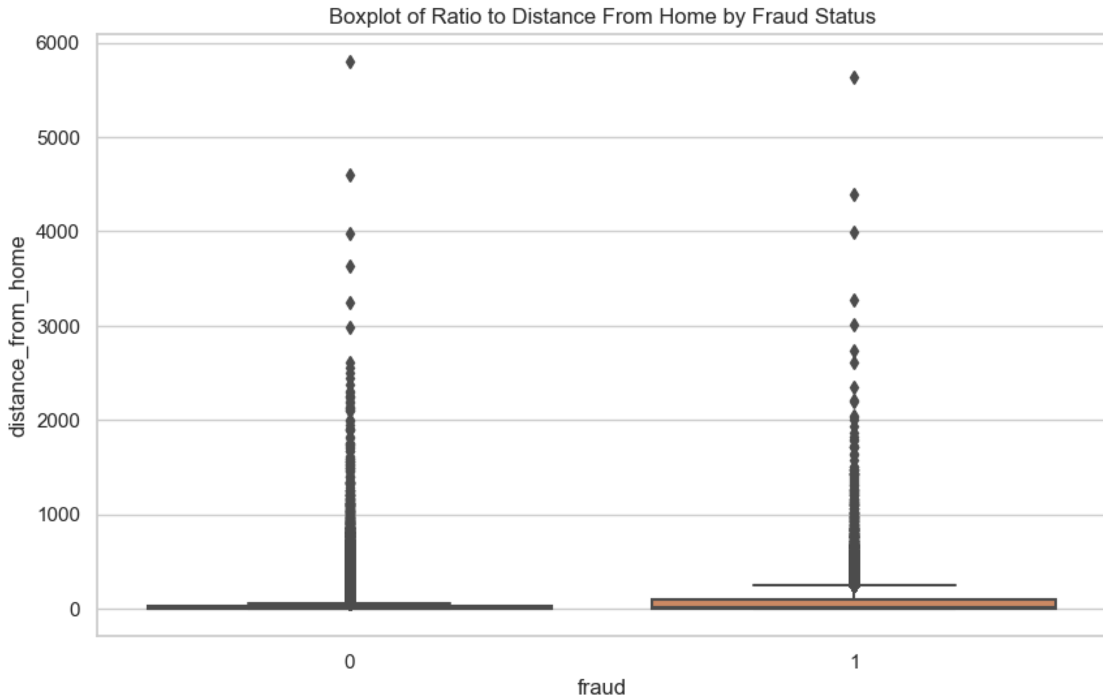
```
# Scatter plot and correlation
corr_distance = plot_scatter_and_calculate_correlation(df,␣
 ↪'distance_from_home', 'distance_from_last_transaction')

# Boxplot of 'distance_from_home' by 'fraud'
plt.figure(figsize=(10, 6))
sns.boxplot(x='fraud', y='distance_from_home', data=df)
plt.title('Boxplot of Ratio to Distance From Home by Fraud Status')
plt.show()

corr_fraud = df['fraud'].corr(df['distance_from_home'])

corr_distance, corr_fraud
```





[12]: (-0.0009276932770463215, 0.18544141027735342)

[13]:
```
#Calculate the test statistic
def diff_of_means(data_1, data_2):
    diff = np.mean(data_1) - np.mean(data_2)
    return diff

fraudulent = df[df['fraud'] == 1]['distance_from_home']
non_fraudulent = df[df['fraud'] == 0]['distance_from_home']

observed_diff = diff_of_means(fraudulent, non_fraudulent)

def permutation_test(data_1, data_2, iters=100):
    concat_data = np.concatenate((data_1, data_2))
    perm_diffs = []

    for _ in range(iters):
        np.random.shuffle(concat_data)
        perm_fraudulent = concat_data[:len(data_1)]
        perm_non_fraudulent = concat_data[len(data_1):]
        perm_diff = diff_of_means(perm_fraudulent, perm_non_fraudulent)
        perm_diffs.append(perm_diff)

    return perm_diffs
```

```
# Run the permutation test
perm_diffs = permutation_test(fraudulent, non_fraudulent)

# Calculate the p-value
p_value = np.mean(np.array(perm_diffs) >= observed_diff)

print(f"Observed difference in means: {observed_diff}")
print(f"P-value: {p_value}")
```

```
Observed difference in means: 42.484997610698514
P-value: 0.0
```

[14]:
```
import statsmodels.api as sm

# The dependent var
y = df['fraud']

# The independent vars
X = df[['distance_from_home', 'distance_from_last_transaction',␣
↪'repeat_retailer', 'used_chip', 'used_pin_number', 'online_order']]
# X = df[['distance_from_home', 'distance_from_last_transaction']]
X = sm.add_constant(X)

# Fit the logistic regression model
model = sm.Logit(y, X)
result = model.fit()

print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.243909
         Iterations 10
                           Logit Regression Results
==============================================================================
Dep. Variable:                  fraud   No. Observations:               499999
Model:                          Logit   Df Residuals:                   499992
Method:                           MLE   Df Model:                            6
Date:                Fri, 01 Mar 2024   Pseudo R-squ.:                  0.1769
Time:                        16:56:25   Log-Likelihood:            -1.2195e+05
converged:                       True   LL-Null:                   -1.4816e+05
Covariance Type:            nonrobust   LLR p-value:                     0.000
================================================================================
==================
                                     coef    std err          z      P>|z|
[0.025      0.975]
--------------------------------------------------------------------------------
------------------
```

```
const                                -4.4085      0.028   -158.593      0.000
-4.463      -4.354
distance_from_home                    0.0086    8.2e-05    105.167      0.000
0.008       0.009
distance_from_last_transaction        0.0140      0.000     56.134      0.000
0.013       0.014
repeat_retailer                      -0.3193      0.016    -19.355      0.000
-0.352      -0.287
used_chip                            -0.5586      0.012    -46.095      0.000
-0.582      -0.535
used_pin_number                      -4.5401      0.110    -41.452      0.000
-4.755      -4.325
online_order                          2.6995      0.024    111.956      0.000
2.652       2.747
================================================================================
==================
```

[ ]:

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[ ]:

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```