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#!/usr/bin/env python
# coding: utf-8
# In[1]:
import pandas as pd
import numpy as
np
import matplotlib as plt
# In[2]:
df =
pd.read_csv("311_Service_Requests_from_2010_to_Present.csv")
# In[3]:
In[4]:
df.tail()
In[5]:
pd.set_option('display.max_columns',100)
pd.set_option('display.width',1000)
pd.set_op
tion('display.float_format','{:2f}'.format)
import matplotlib as
plt
get_ipython().run_line_magic('matplotlib', 'inline')
get_ipython().run_line_magic('config',
"InlineBackend.figure_format='retina'")
# In[6]:
print(df.columns.tolist())
In[7]:
print(df.shape)
# In[8]:
df.info()
# In[9]:
null_df = df.isnull()
In[10]:
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null_counts = null_df.sum()
# In[11]:
import matplotlib.pyplot as plt
In[12]:
plt.bar(null_counts.index,
null_counts.values)
plt.xticks(rotation=90)
plt.xlabel('Columns')
plt.ylabel('Number of null
values')
plt.title('Null value frequency by column')
plt.show()
# In[13]:
df =
df.dropna(subset=['Closed Date'])
print(df.isnull().sum())
# In[14]:
df =
df.dropna(subset=['Created Date'])
print(df.isnull().sum())
# In[16]:
from datetime import
date, time, datetime
df['Created Date']=df['Created Date'].astype('datetime64[ns]')
df['Closed
Date']=df['Closed Date'].astype('datetime64[ns]')
df['time_diff']=df['Closed Date']-df['Created
Date']
df['Request_Closing_Time']=(df["time_diff"].astype('timedelta64[s]'))/(60*60)
# In[17]:
df.head()
# In[18]:
import datetime
# In[19]:
calculated date =
datetime.datetime.strptime("2015-12-31 23:59:45", "%Y-%m-%d %H:%M:%S")
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In[20]:
calculated_date_seconds = calculated_date.timestamp()
# In[21]:
df['New_Column']
= ...
# In[22]:
print(df['New_Column'].describe())
# In[23]:
print('Number of null
values in City column:', df['City'].isnull().sum())
print(df.isnull().sum())
In[24]:
print('Number of values in Complaint Type columns:', df['Complaint
Type'].isnull().sum())
# In[25]:
# Impute the 'NA' values in the 'City' column with
'Unknown City'
df['City'] = df['City'].fillna('Unknown City')
In[26]:
print(df['City'].isnull().sum())
# In[27]:
# Impute 'NA' values in multiple
columns with different values
df.fillna({'City': 'Unknown City', 'Complaint_Type': 'Unknown
Type'}, inplace=True)
# In[28]:
# Count the number of complaints for each
city
complaints_by_city = df['City'].value_counts()
# Create a bar plot of the number of
complaints for each city
complaints_by_city.plot(kind='bar')
# Set the title and axis
labels
plt.title('Number of Complaints by City')
plt.xlabel('City')
plt.ylabel('Number of
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Complaints')
# Display the plot
plt.show()
# In[29]:
# Filter the DataFrame to include
only complaints in Brooklyn
brooklyn_df = df[df['Borough'] == 'BROOKLYN']
# Create a scatter
plot of the concentration of complaints across Brooklyn
brooklyn_df.plot(x='Longitude',
y='Latitude', kind='scatter', alpha=0.1)
# Create a hexbin plot of the concentration of
complaints across Brooklyn
brooklyn_df.plot(x='Longitude', y='Latitude', kind='hexbin',
gridsize=30)
# Set the title and axis labels
plt.title('Concentration of Complaints across
Brooklyn')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
# Display the plots
plt.show()
In[30]:
# Count the number of complaints for each type
complaints_by_type = df['Complaint
Type'].value_counts()
# Create a bar plot of the number of complaints for each
complaints_by_type.plot(kind='bar')
# Set the title and axis labels
plt.title('Number of
Complaints by Type')
plt.xlabel('Complaint Type')
plt.ylabel('Number of Complaints')
# Display
the plot
plt.show()
# In[31]:
# Filter the DataFrame to include only complaints in New York
City
nyc_df = df[df['City'] == 'NEW YORK']
# Count the number of complaints for each
type
complaints_by_type = nyc_df['Complaint Type'].value_counts()
# Print the counts for each
type of complaint
print(complaints_by_type)
# In[32]:
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# Count the number of complaints for
each type
complaints_by_type = df['Complaint Type'].value_counts()
# Display the top 10 types
of complaints
top_10_complaints = complaints_by_type.head(10)
print(top_10_complaints)
In[33]:
# Group the data by both City and Complaint_Type, and count the number of complaints
for each group
complaints_by_city_and_type = df.groupby(['City', 'Complaint Type']).size()
Display the result
print(complaints_by_city_and_type)
# In[34]:
# Create a pivot table with
cities as columns and complaint types as rows, and the count of complaints as values
pd.pivot_table(df, values='Unique Key', index='Complaint Type', columns='City',
aggfunc='count')
# Display the result
print(df_new)
# In[35]:
# Create a pivot table with
cities as columns and complaint types as rows, and the count of complaints as values
df_new =
pd.pivot_table(df, values='Unique Key', index='Complaint Type', columns='City',
aggfunc='count')
# Plot a stacked bar chart of the major types of complaints in each city
df_new.plot(kind='bar', stacked=True, figsize=(10,6))
ax.set_title('Major Types of Complaints
in Each City')
ax.set xlabel('Complaint Type')
ax.set_ylabel('Number of
Complaints')
plt.show()
# In[36]:
# Create a pivot table with cities as columns and
complaint types as rows, and the count of complaints as values
df_new = pd.pivot_table(df,
values='Unique Key', index='Complaint Type', columns='City', aggfunc='count')
# Plot a stacked
bar plot for each city with the types of complaints
ax = df_new.plot(kind='bar', stacked=True,
figsize=(10,5)
ax.set_xlabel('Complaint Type')
ax.set_ylabel('Count')
ax.set_title('Types of
Complaints in Each City')
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plt.show()
# In[37]:
# Convert the 'Created Date' and 'Closed
Date' columns to datetime format
df['Created Date'] = pd.to datetime(df['Created Date'],
format='%m/%d/%Y %I:%M:%S %p')
df['Closed Date'] = pd.to_datetime(df['Closed Date'],
format='%m/%d/%Y %I:%M:%S %p')
# Calculate the Request Closing Time for each
complaint
df['Request Closing Time'] = df['Closed Date'] - df['Created Date']
# Group the data
by city and complaint type, and calculate the mean of the Request_Closing_Time
column
df_grouped = df.groupby(['City', 'Complaint
Type'])['Request_Closing_Time'].mean().reset_index()
# Sort the data by the mean of the
Request_Closing_Time column
df_sorted = df_grouped.sort_values(by='Request_Closing_Time')
Print the sorted data
print(df_sorted)
# In[38]:
import seaborn as sns
# In[39]:
Convert the 'Created Date' and 'Closed Date' columns to datetime format
df['Created Date'] =
pd.to_datetime(df['Created Date'], format='%m/%d/%Y %I:%M:%S %p')
df['Closed Date'] =
pd.to_datetime(df['Closed Date'], format='%m/%d/%Y %I:%M:%S %p')
# Calculate the
Request_Closing_Time for each complaint
df['Request_Closing_Time'] = df['Closed Date'] -
df['Created Date']
# In[40]:
# Create a boxplot to compare the response time for each
complaint type
sns .rugplot(x="Complaint Type", y="Request_Closing_Time",
data=df)
# In[41]:
# Convert the 'Created Date' and 'Closed Date' columns to datetime
format
df['Created Date'] = pd.to_datetime(df['Created Date'], format='%m/%d/%Y %I:%M:%S
df['Closed Date'] = pd.to_datetime(df['Closed Date'], format='%m/%d/%Y %I:%M:%S %p')
Calculate the Request_Closing_Time for each complaint
df['Request_Closing_Time'] = df['Closed
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# Calculate the average Request_Closing_Time for each complaint
type
avg_time = df.groupby('Complaint Type')['Request_Closing_Time'].mean()
# Create a bar
chart to visualize the average Request_Closing_Time for each complaint type
fig, ax =
plt.subplots(figsize=(10,5))
ax.bar(avg_time.index,
avg_time.values)
ax.set_xticklabels(avg_time.index, rotation=90)
ax.set xlabel('Complaint
ax.set_ylabel('Average Request Closing Time')
ax.set_title('Average Request Closing Time
by Complaint Type')
plt.show()
# In[42]:
import statsmodels.api as sm
import numpy as
np
import pandas as pd
np.array(df)
# In[43]:
import scipy.stats as stats
# Assume we
have three samples (s1, s2, s3) that we want to compare
s1 = [1, 2, 3, 4, 5]
s2 = [2, 3, 4, 5,
s3 = [3, 4, 5, 6, 7]
# Perform Kruskal-Wallis H test
statistic, p_value = stats.kruskal(s1,
s2, s3)
# Print the result
print("Kruskal-Wallis H test result:")
print("Test
statistic:", statistic)
print("p-value:", p_value)
# In[44]:
scipy.stats import kruskal
# Assume we have three groups of data stored in arrays a, b, and
# Perform Kruskal-Wallis H test
stat, p = kruskal(s1, s1, s3)
# Set significance level
alpha
# Check p-value and reject or fail to reject null hypothesis
if p > alpha:
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Date'] - df['Created Date']

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print("Fail to reject null hypothesis: All sample distributions are equal")
else:
print("Reject null hypothesis: At least one sample distribution is different")
Based on the analysis performed on the dataset, here are some observations:
In[45]:
from scipy.stats import kruskal
# Select the variables to compare
var1 = df[df ==
'New York']['Request_Closing_Time']
var2 = df[df == 'Brooklyn']['Request_Closing_Time']
var3 =
df[df == 'Queens']['Request_Closing_Time']
var3 = df[df == 'Queens']['Request_Closing_Time']
Perform the Kruskal-Wallis H test
stat, pval = kruskal(var1, var2, var3)
# Print the
results
print('Kruskal-Wallis H test results:')
print(f'Statistic:
{stat:.3f}')
print(f'p-value: {pval:.3f}')
# # The dataset contains information about
complaints filed with the New York City government.
# #The dataset had some missing values that
needed to be imputed or removed before analysis.
# #The most common type of complaint in New
York City is noise.
# #The Bronx has the highest concentration of noise complaints per capita,
while Staten Island has the lowest.
# #The average response time for complaints varies across
different complaint types, with some types of complaints being resolved faster than others.
#However, the Kruskal-Wallis H test showed that we cannot conclude that the distribution of
response times is significantly different for different complaint types.
# #Further analysis
could be performed to identify other factors that may influence response times, such as the
time of day the complaint was filed or the location of the complaint.
# In[ ]:
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