互评作业1: 数据探索性分析与数据预处理

程序所在代码仓库地址：Github

1.要求

1.1. 问题描述

本次作业中，自行选择2个数据集进行探索性分析与预处理。

1.2. 数据集

可选数据集包括：

- GitHub Dataset
- MovieLens 10M Dataset
- Alzheimer Disease and Healthy Aging Data in US
- Movies Dataset from Pirated Sites
- VitalDB
- Tweet Sentiment's Impact on Stock Returns

1.3. 数据分析要求

1.3.1 数据摘要和可视化

- 数据摘要
    - 标称属性，给出每个可能取值的频数
    - 数值属性，给出5数概括及缺失值的个数
- 数据可视化
    - 使用直方图、盒图等检查数据分布及离群点

1.3.2 数据缺失的处理

观察数据集中缺失数据，分析其缺失的原因。分别使用下列四种策略对缺失值进行处理:

- 将缺失部分剔除
- 用最高频率值来填补缺失值
- 通过属性的相关关系来填补缺失值
- 通过数据对象之间的相似性来填补缺失值

注意：在处理后完成，要对比新旧数据集的差异。

1.4 提交内容

- 分析过程报告（PDF格式）
- 程序所在代码仓库地址（使用Github或码云），仓库中应包含完整的处理数据的代码和使用说明
- 所选择的数据集在仓库的README文件中说明
- 相关的数据文件不要上传到代码仓库中

建议：使用Jupyter Notebook将分析报告和代码组织在一起，使用Notebook的导出功能将报告导出为PDF格式的文件上传到乐学。

2 GitHub Dataset

数据集为github dataset

In [ ]:
```
import os
import requests
import pandas as pd
import matplotlib.pyplot as plt
from scipy import stats
from sklearn.impute import KNNImputer
from sklearn.metrics.pairwise import euclidean_distances
import numpy as np
```

2.1 加载数据集

In [ ]:
```
def check_dataset(dataset_path):

    if not os.path.exists(dataset_path):
        print("[!] dataset not exist")
    else:
        print("[!] dataset already exists")


github_data_path = '../data/github_dataset/archive'
check_dataset(github_data_path)

df = pd.read_csv(github_data_path + "/github_dataset.csv")
print("[!] load dataset")

df.head()
```

```
[!] dataset already exists
[!] load dataset
```

Out[ ]:

	repositories	stars_count	forks_count	issues_count	pull_reques
0	octocat/Hello-World	0	0	612	3
1	EddieHubCommunity/support	271	150	536	
2	ethereum/aleth	0	0	313	[illegible]
3	localstack/localstack	0	0	290	[illegible]
4	education/classroom	0	589	202	[illegible]

In [ ]:
```
print("columns:\n",df.columns, "\n")
print(df.info())
```

```
columns:
 Index(['repositories', 'stars_count', 'forks_count', 'issues_count',
       'pull_requests', 'contributors', 'language'],
      dtype='object')

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1052 entries, 0 to 1051
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   repositories   1052 non-null   object
 1   stars_count    1052 non-null   int64 
 2   forks_count    1052 non-null   int64 
 3   issues_count   1052 non-null   int64 
 4   pull_requests  1052 non-null   int64 
 5   contributors   1052 non-null   int64 
 6   language       907 non-null    object
dtypes: int64(5), object(2)
memory usage: 57.7+ KB
None
```

2.2.1 数据摘要

In [ ]:
```
print('属性类别数:', len(df.columns))
print('总行数:', len(df), "\n")
```

```
属性类别数: 7
总行数: 1052
```

对于标称属性，给出每个可能取值的频数

In [ ]:
```
def nominal_frequency(data, nominal_attrs):
    frequencies = {}
    for col in nominal_attrs:
        frequencies[col] = data[col].value_counts()
    return frequencies

nominal_attributes = nominal_attributes = ['repositories', 'language']
nominal_frequencies = nominal_frequency(df, nominal_attributes)


for attr, freq in nominal_frequencies.items():
    print(f"Attribute: {attr}")
    print(freq)
    print("\n")
```

```
Attribute: repositories
kameshsampath/ansible-role-rosa-demos          2
aloisdeniel/bluff                              2
antoniaandreou/github-slideshow                2
jgthms/bulma-start                             2
artkirienko/hlds-docker-dproto                 2
                                              ..
WhiteHouse/CIOmanagement                       1
0xCaso/defillama-telegram-bot                  1
ethereum/blake2b-py                            1
openfoodfacts/folksonomy_mobile_experiment     1
gamemann/All_PropHealth                        1
Name: repositories, Length: 972, dtype: int64


Attribute: language
JavaScript          253
Python              155
HTML                 72
Java                 44
CSS                  37
TypeScript           37
Dart                 36
C++                  29
Jupyter Notebook     29
Ruby                 28
C                    26
Shell                25
PHP                  16
Go                   15
Rust                 10
Swift                10
C#                    8
Objective-C           8
Kotlin                7
Makefile              6
Jinja                 5
SCSS                  4
CoffeeScript          3
Perl                  3
Dockerfile            3
Solidity              3
AutoHotkey            3
Hack                  2
Pawn                  2
CodeQL                2
PowerShell            2
Assembly              2
Vim Script            2
Vue                   2
Elixir                2
Gherkin               1
QMake                 1
CMake                 1
Oz                    1
Cuda                  1
QML                   1
ActionScript          1
Roff                  1
HCL                   1
```

```
R                   1
PureBasic           1
Smarty              1
Less                1
Svelte              1
Haskell             1
SourcePawn          1
Name: language, dtype: int64
```

对于数值属性，给出5数概括及缺失值的个数

In [ ]:

```
def numeric_summary(data, numeric_attrs):
    summary = {}
    for col in numeric_attrs:
        summary[col] = {
            'min': data[col].min(),
            'q1': data[col].quantile(0.25),
            'median': data[col].median(),
            'q3': data[col].quantile(0.75),
            'max': data[col].max(),
            'missing_values': data[col].isnull().sum()
        }
    return summary

numeric_attributes = ['stars_count', 'forks_count', 'issues_count', 'pull


numeric_summaries = numeric_summary(df, numeric_attributes)
for attr, summary in numeric_summaries.items():
    print(f"Attribute: {attr}")
    print("Min:", summary['min'])
    print("Q1:", summary['q1'])
    print("Median:", summary['median'])
    print("Q3:", summary['q3'])
    print("Max:", summary['max'])
    print("Missing Values:", summary['missing_values'])
    print("\n")
```

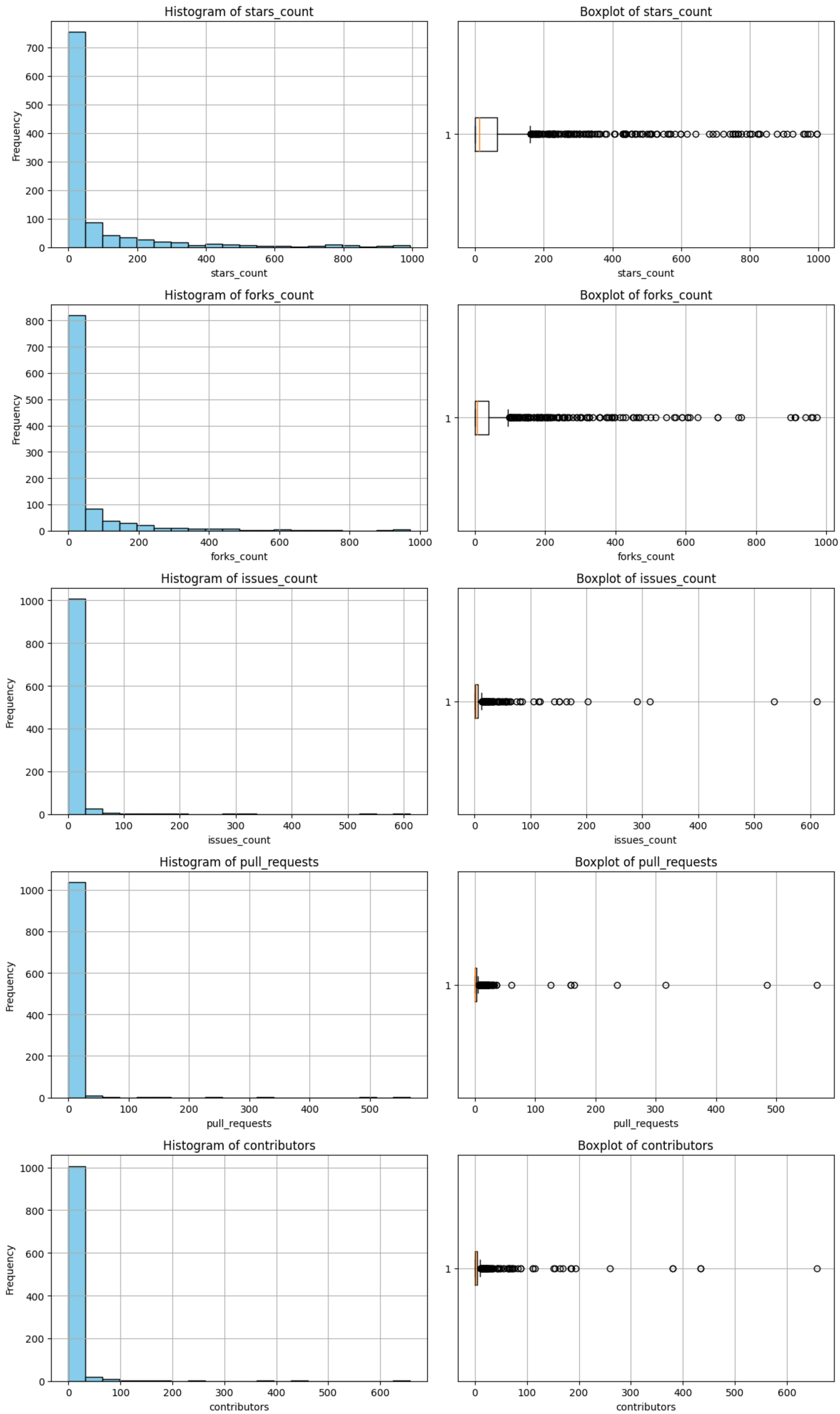
```
Attribute: stars_count
Min: 0
Q1: 1.0
Median: 12.0
Q3: 65.25
Max: 995
Missing Values: 0


Attribute: forks_count
Min: 0
Q1: 1.0
Median: 6.0
Q3: 38.25
Max: 973
Missing Values: 0


Attribute: issues_count
Min: 1
Q1: 1.0
Median: 2.0
Q3: 6.0
Max: 612
Missing Values: 0


Attribute: pull_requests
Min: 0
Q1: 0.0
Median: 0.0
Q3: 2.0
Max: 567
Missing Values: 0


Attribute: contributors
Min: 0
Q1: 0.0
Median: 2.0
Q3: 4.0
Max: 658
Missing Values: 0
```

2.2.2 数据可视化

使用直方图、盒图等检查数据分布及离群点

In [ ]:
```
fig, axs = plt.subplots(len(numeric_attributes), 2, figsize=(12, 20))

for i, attr in enumerate(numeric_attributes):
    axs[i, 0].hist(df[attr].dropna(), bins=20, color='skyblue', edgecolor
    axs[i, 0].set_title(f'Histogram of {attr}')
    axs[i, 0].set_xlabel(attr)
    axs[i, 0].set_ylabel('Frequency')
    axs[i, 0].grid(True)
```

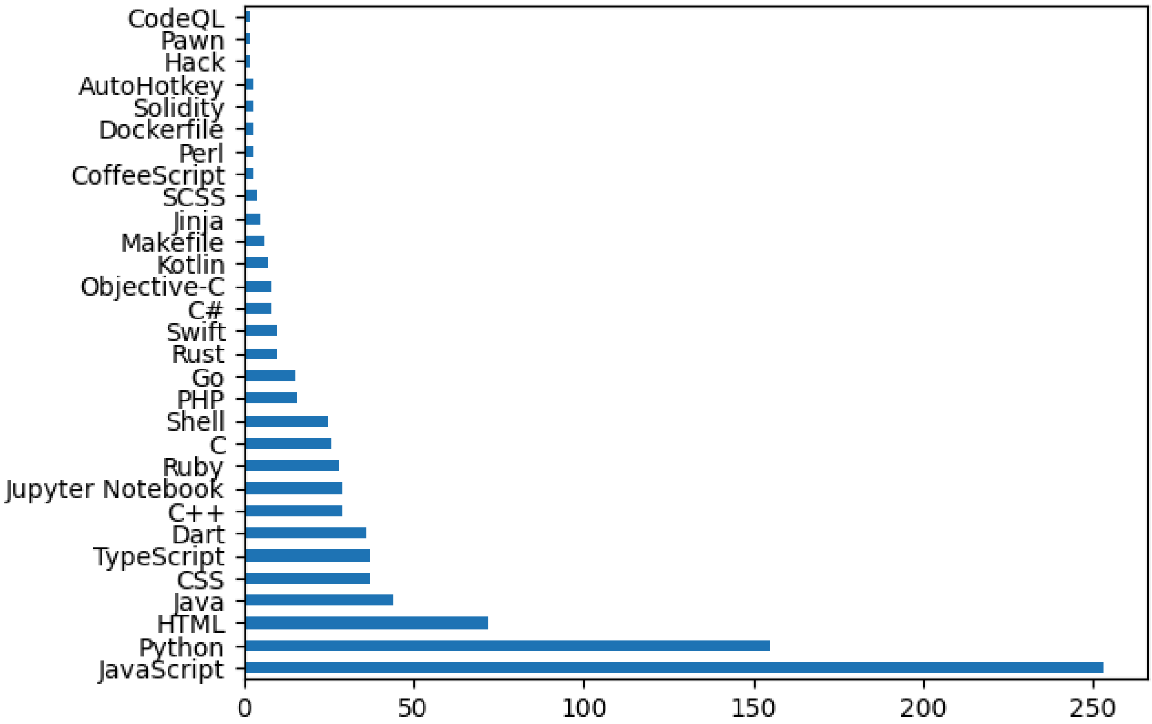
```
    axs[i, 1].boxplot(df[attr].dropna(), vert=False)
    axs[i, 1].set_title(f'Boxplot of {attr}')
    axs[i, 1].set_xlabel(attr)
    axs[i, 1].grid(True)

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


Histogram of stars_count
Frequency
stars_count
Boxplot of stars_count
stars_count
Histogram of forks_count
Frequency
forks_count
Boxplot of forks_count
forks_count
Histogram of issues_count
Frequency
issues_count
Boxplot of issues_count
issues_count
Histogram of pull_requests
Frequency
pull_requests
Boxplot of pull_requests
pull_requests
Histogram of contributors
Frequency
contributors
Boxplot of contributors
contributors

以"language"属性为例，绘制直方图检查数据分布，可以看出出现频率最高的为JavaScript

In [ ]:
```
df["language"].value_counts().head(30).plot.barh()
```

Out[ ]: <AxesSubplot:>



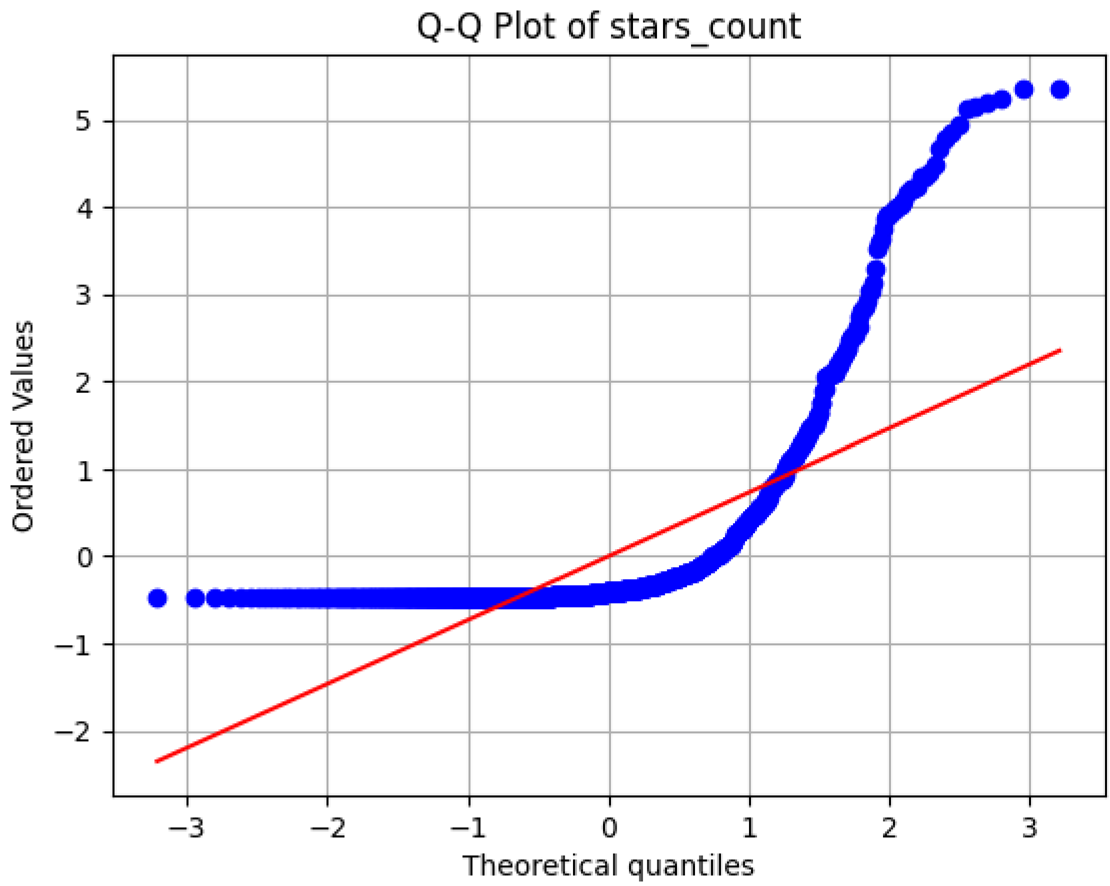
绘制Q-Q图并检查数据分布和离群点。

使用Shapiro-Wilk 检验数据是否符合正态分布，如果 p-value 大于 0.05，则表示数据符合正态分布。

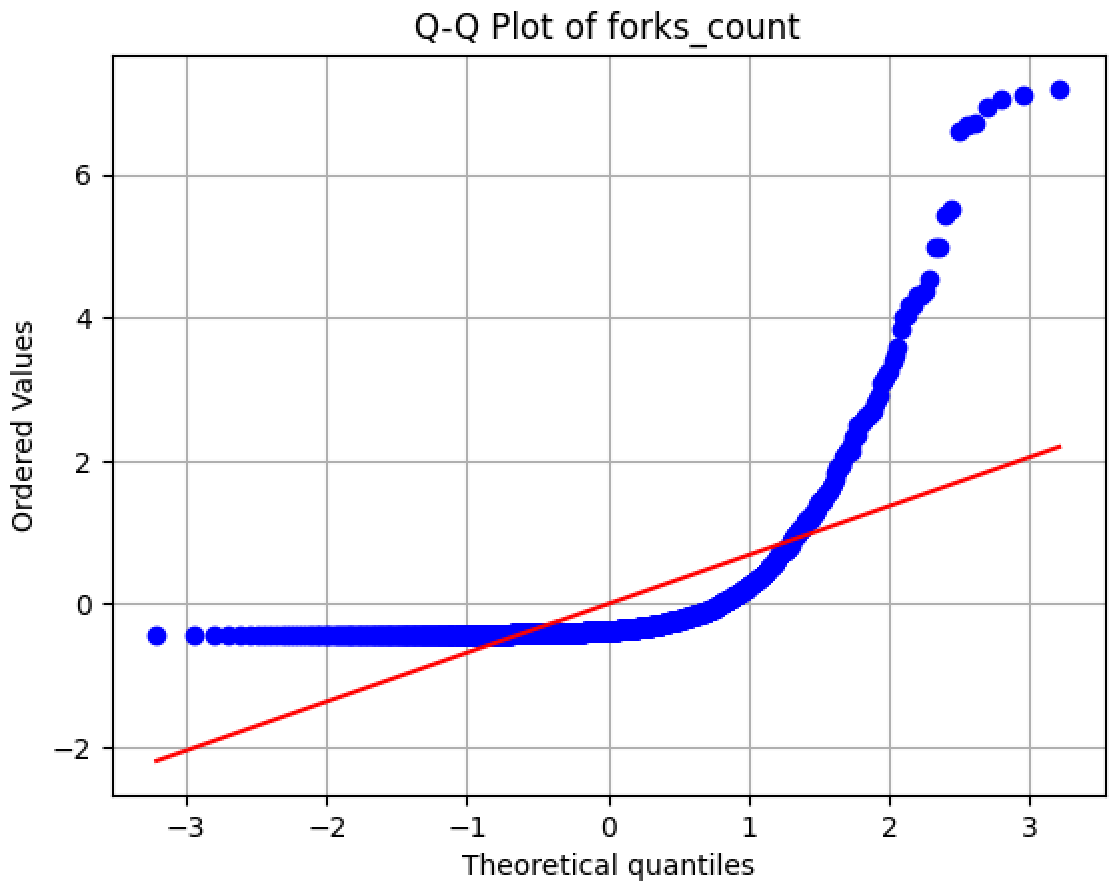
根据图表和数据可知，该数据集中所有数值属性都不符合正态分布且都存在离群点。

In [ ]:
```
for attr in numeric_attributes:
    data = df[attr].dropna()

    z_scores = (data - data.mean()) / data.std()

    stats.probplot(z_scores, dist="norm", plot=plt)
    plt.title(f'Q-Q Plot of {attr}')
    plt.xlabel('Theoretical quantiles')
    plt.ylabel('Ordered Values')
    plt.grid(True)
    plt.show()

    # 判断离群点是否符合正态分布
    print(f"Attribute: {attr}")

    outliers = z_scores[(z_scores > 3) | (z_scores < -3)]
    if len(outliers) > 0:
        print("There are outliers.")
    else:
        print("There are no outliers.")
    print("Normality Test (Shapiro-Wilk):")
```

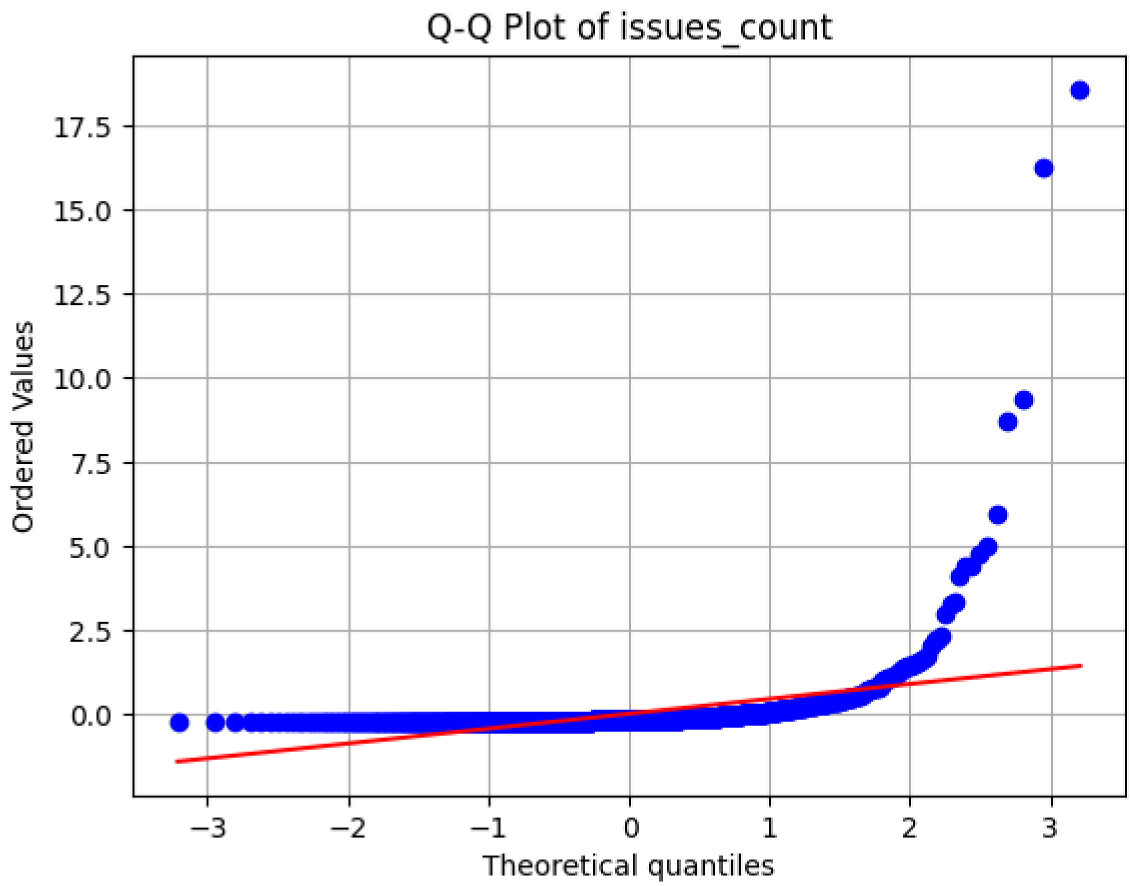
```
    _, p_value = stats.shapiro(data)
    if p_value > 0.05:
        print("The data is normally distributed.")
    else:
        print("The data is not normally distributed.")
    print("\n")
```



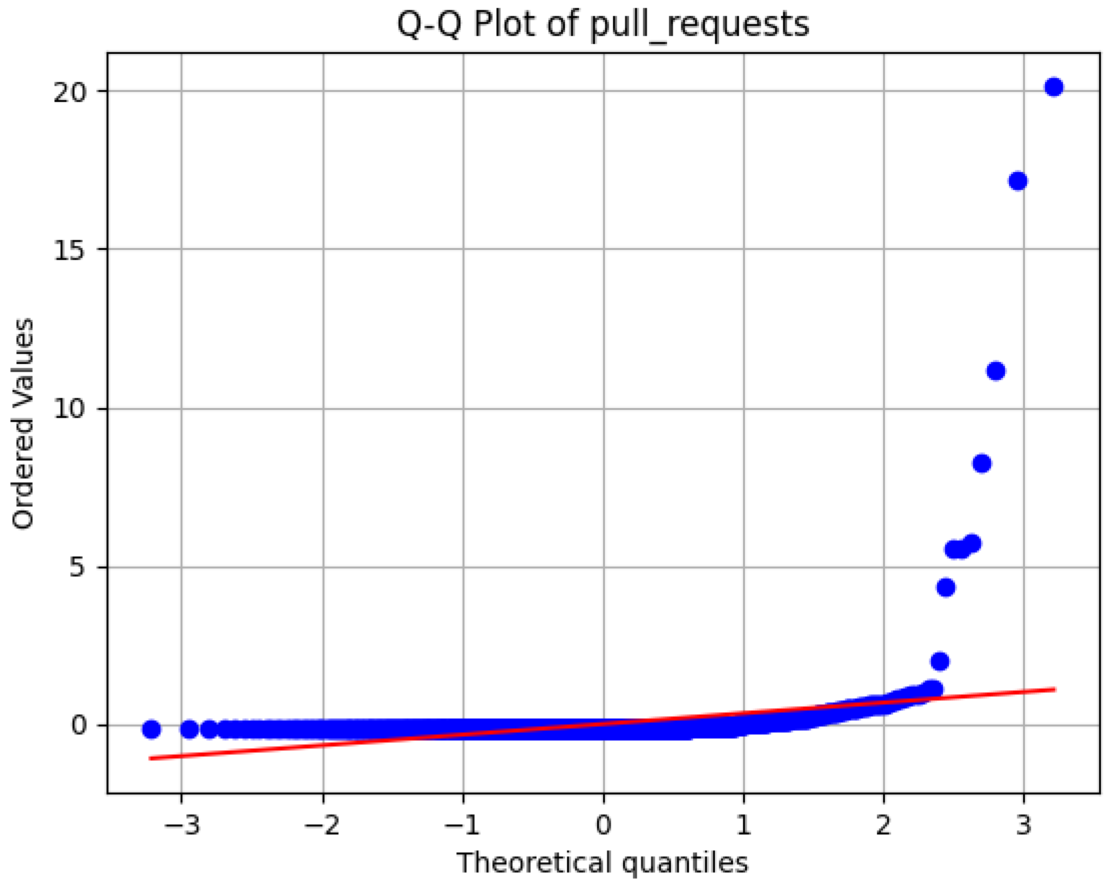

```
Attribute: stars_count
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```



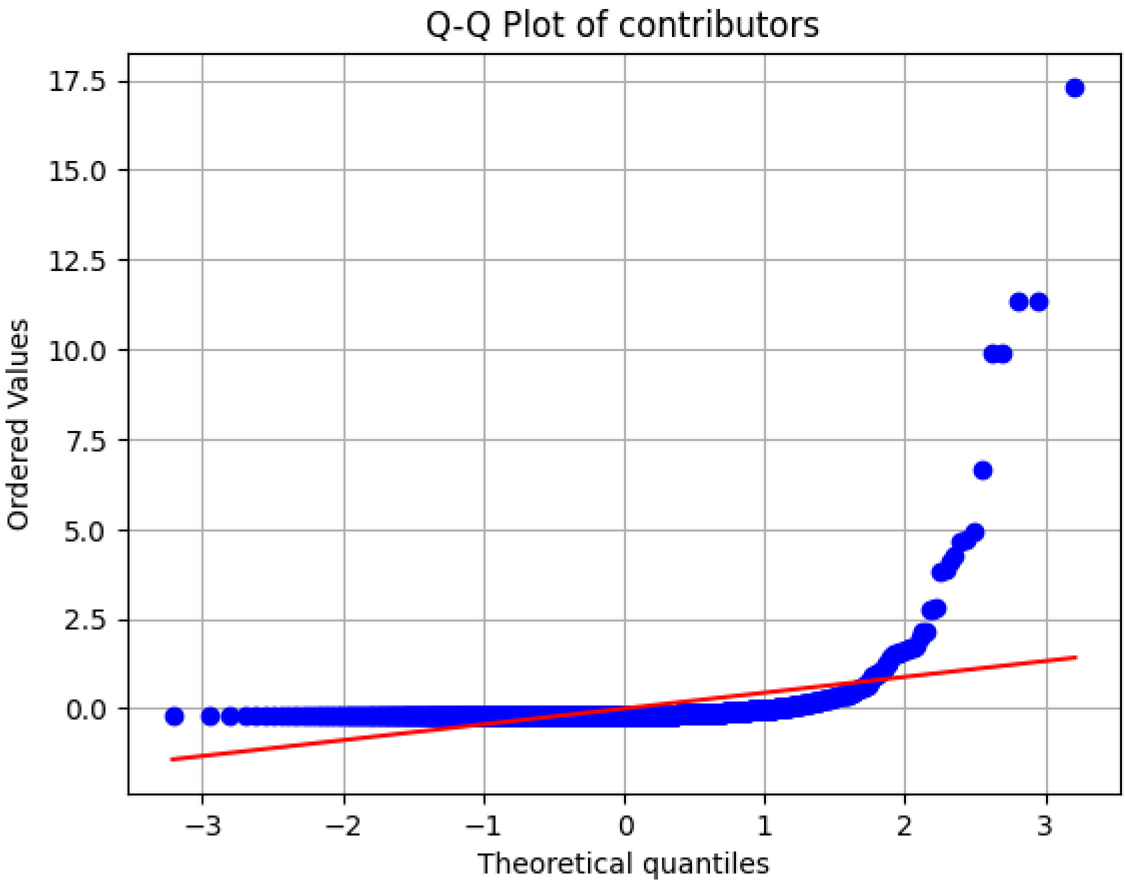

```
Attribute: forks_count
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```



```
Attribute: issues_count
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```




```
Attribute: pull_requests
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```




```
Attribute: contributors
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```

2.3 数据缺失的处理

根据结果可知，只有"language"属性有缺失数据。

观察数据集中缺失数据，分析其缺失的原因。分别使用下列四种策略对缺失值进行处理:

- 将缺失部分剔除
- 用最高频率值来填补缺失值
- 通过属性的相关关系来填补缺失值
- 通过数据对象之间的相似性来填补缺失值

注意：在处理后完成，要对比新旧数据集的差异。

In [ ]:
```
def check_missing_data(data, numeric_attrs, nominal_attrs):
    missing_data = {}

    for attr in numeric_attrs:
        missing_count = data[attr].isnull().sum()
        if missing_count > 0:
            missing_data[attr] = missing_count
            print(f"Attribute: {attr}, Missing Count: {missing_count}")
        else:
            print(f"Attribute: {attr} don't have missing data")
```

```
    for attr in nominal_attrs:
        missing_count = data[attr].isnull().sum()
        if missing_count > 0:
            missing_data[attr] = missing_count
            print(f"Attribute: {attr}, Missing Count: {missing_count}")
        else:
            print(f"Attribute: {attr} don't have missing data")

    return missing_data

missing_data = check_missing_data(df, numeric_attributes, nominal_attribu
```

```
Attribute: stars_count don't have missing data
Attribute: forks_count don't have missing data
Attribute: issues_count don't have missing data
Attribute: pull_requests don't have missing data
Attribute: contributors don't have missing data
Attribute: repositories don't have missing data
Attribute: language, Missing Count: 145
```

2.3.1 将缺失部分剔除

使用将缺失部分剔除策略对缺失值进行处理，在处理后完成，对比新旧数据集的差异。

In [ ]:
```
def remove_missing_data(data, attribute):
    new_data = data.copy()

    new_data = new_data.dropna(subset=[attribute])

    return new_data

missing_attribute = 'language'
new_df = remove_missing_data(df, missing_attribute)
df.head()
```

Out[ ]:

	repositories	stars_count	forks_count	issues_count	pull_reques
0	octocat/Hello-World	0	0	612	3
1	EddieHubCommunity/support	271	150	536	
2	ethereum/aleth	0	0	313	1
3	localstack/localstack	0	0	290	3
4	education/classroom	0	589	202	2

In [ ]:
```
new_df.head()
```

Out[ ]:

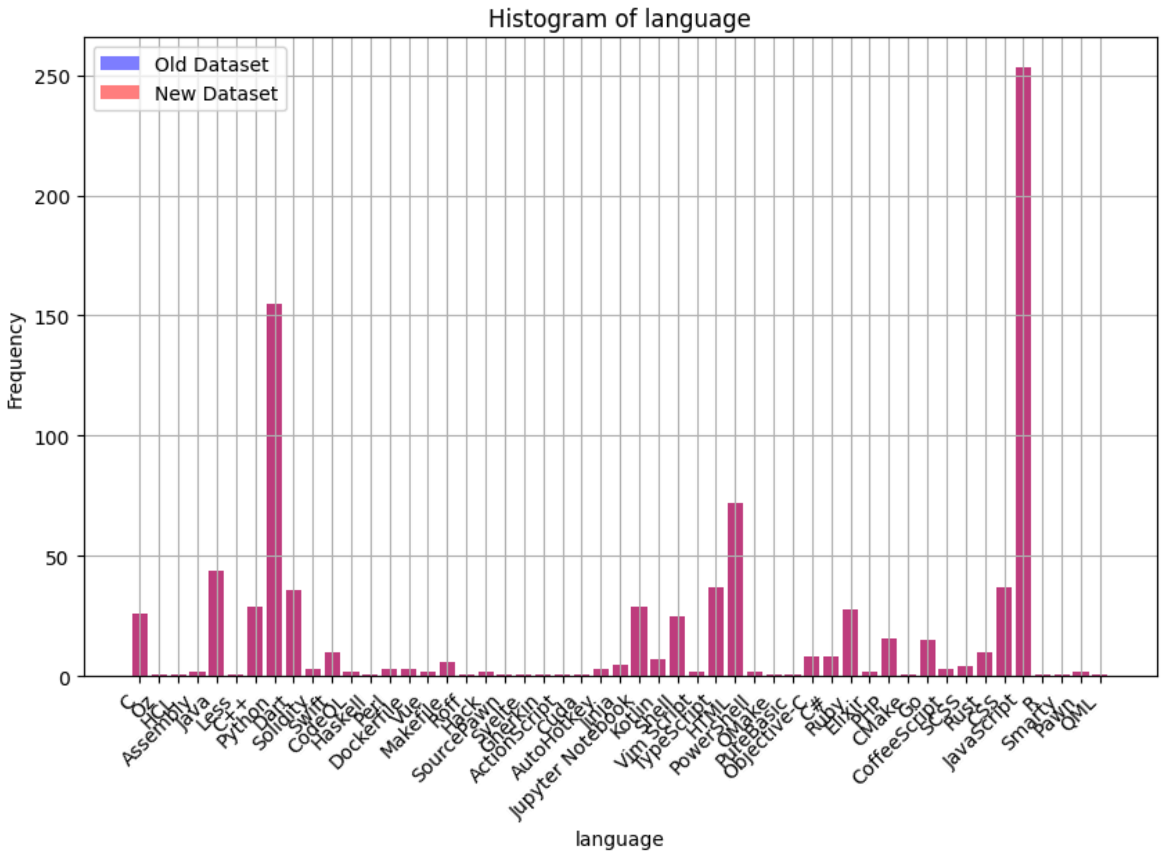
	repositories	stars_count	forks_count	issues_count	pull_requests	con
2	ethereum/aleth	0	0	313	27	
3	localstack/localstack	0	0	290	30	
4	education/classroom	0	589	202	22	
5	shobhit97/open-gpstracker	0	0	172	0	
6	donnemartin/system-design-primer	0	0	164	164	

对比删除前后数据集中记录条数，使用柱状图直观的比较前后差异。

In [ ]:

```python
print(f"\nNumber of rows in old dataset: {len(df)}")
print(f"Number of rows in new dataset: {len(new_df)}")

def compare_histograms(old_data, new_data, attribute):

    old_counts = old_data[attribute].value_counts()
    new_counts = new_data[attribute].value_counts()
    all_values = list(set(old_counts.index) | set(new_counts.index))

    plt.figure(figsize=(10, 6))
    plt.bar(all_values, old_counts.reindex(all_values, fill_value=0), col
    plt.bar(all_values, new_counts.reindex(all_values, fill_value=0), col
    plt.title(f'Histogram of {attribute}')
    plt.xlabel(attribute)
    plt.ylabel('Frequency')
    plt.xticks(rotation=45, ha='right')
    plt.legend()
    plt.grid(True)
    plt.show()

compare_histograms(df, new_df, 'language')
```

```
Number of rows in old dataset: 1052
Number of rows in new dataset: 907
```



In [ ]:
```
new_df.isna().sum()
```

Out[ ]:
```
repositories     0
stars_count      0
forks_count      0
issues_count     0
pull_requests    0
contributors     0
language         0
dtype: int64
```

2.3.2 用最高频率值来填补

使用最高频率值来填补缺失值策略对缺失值进行处理，在处理后完成，对比新旧数据集的差异。

最高频率值为JavaScript

In [ ]:
```
def fill_missing_with_mode(data, attribute):
    new_data = data.copy()

    mode_value = new_data[attribute].mode()[0]
    print(f'{mode_value} is the language with the highest frequency.\n')

    new_data[attribute].fillna(mode_value, inplace=True)

    return new_data

new_df = fill_missing_with_mode(df, missing_attribute)
```

```
JavaScript is the language with the highest frequency.
```

In [ ]:
```
df.head()
```

Out[ ]:

	repositories	stars_count	forks_count	issues_count	pull_reques
0	octocat/Hello-World	0	0	612	3
1	EddieHubCommunity/support	271	150	536	
2	ethereum/aleth	0	0	313	[illegible]
3	localstack/localstack	0	0	290	[illegible]
4	education/classroom	0	589	202	[illegible]

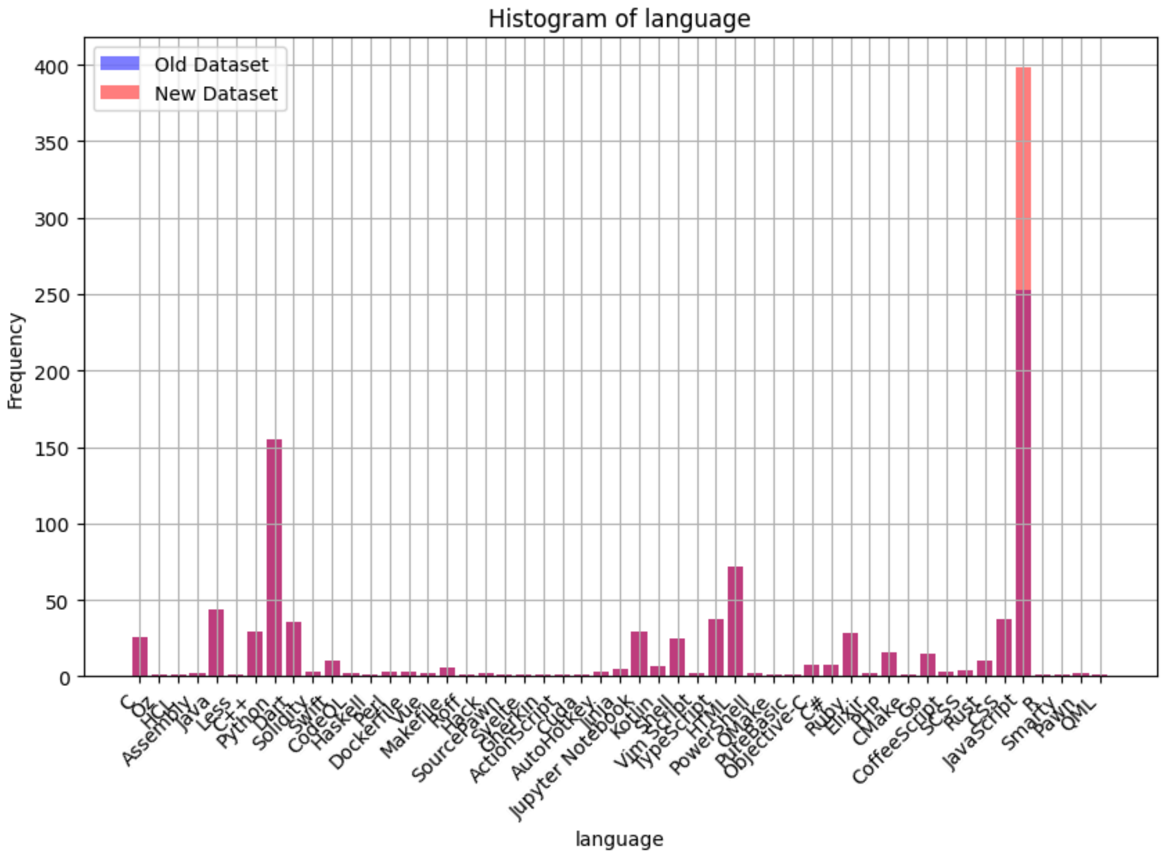
In [ ]:
```
new_df.head()
```

Out[ ]:

	repositories	stars_count	forks_count	issues_count	pull_reques
0	octocat/Hello-World	0	0	612	3
1	EddieHubCommunity/support	271	150	536	
2	ethereum/aleth	0	0	313	[illegible]
3	localstack/localstack	0	0	290	[illegible]
4	education/classroom	0	589	202	[illegible]

In [ ]:
```
print(f"\nNumber of rows in old dataset: {len(df)}")
print(f"Number of rows in new dataset: {len(new_df)}")

print("\nDifferences between old and new datasets:")
print((df[missing_attribute] != new_df[missing_attribute]).sum())

compare_histograms(df, new_df, 'language')
```

```
Number of rows in old dataset: 1052
Number of rows in new dataset: 1052

Differences between old and new datasets:
145
```



2.3.3 通过属性的相关关系来填补

通过属性的相关关系来填补缺失值策略对缺失值进行处理，在处理后完成，对比新旧数据集的差异。

由于该数据集中只有"language"和"repositories"两个属性为标称值，所以使用"repositories"来填补缺失值。

In [ ]:
```
def fill_missing_with_related_attribute(data, missing_attribute, related_
    new_data = data.copy()

    # 计算相关属性的众数值
    related_mode_value = new_data[related_attribute].mode()[0]

    new_data[missing_attribute].fillna(related_mode_value, inplace=True)

    return new_data

related_attribute = 'repositories'


new_df = fill_missing_with_related_attribute(df, missing_attribute, relat
df.head()
```

Out[ ]:

	repositories	stars_count	forks_count	issues_count	pull_reques
0	octocat/Hello-World	0	0	612	3
1	EddieHubCommunity/support	271	150	536	
2	ethereum/aleth	0	0	313	2
3	localstack/localstack	0	0	290	3
4	education/classroom	0	589	202	2

In [ ]:

```python
new_df.head()
```

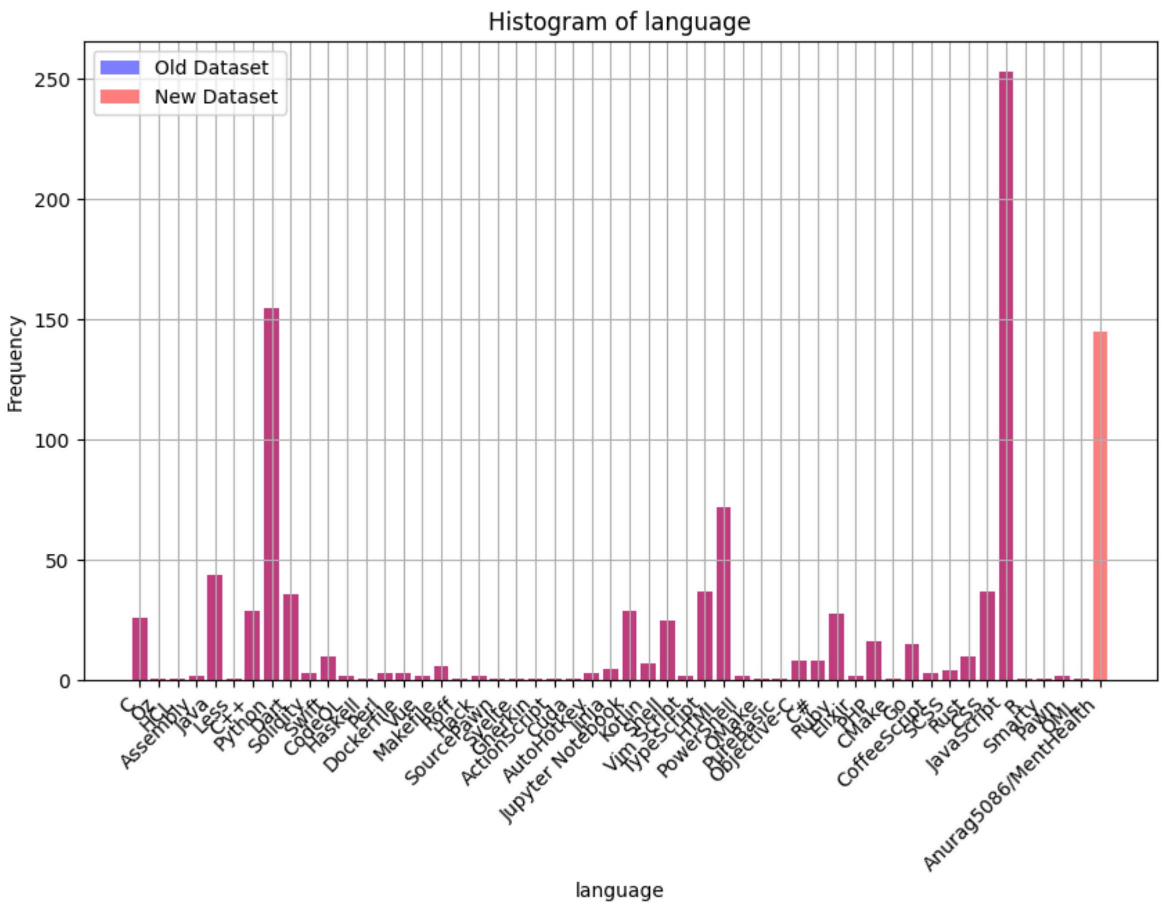
Out[ ]:

	repositories	stars_count	forks_count	issues_count	pull_reques
0	octocat/Hello-World	0	0	612	3
1	EddieHubCommunity/support	271	150	536	
2	ethereum/aleth	0	0	313	2
3	localstack/localstack	0	0	290	3
4	education/classroom	0	589	202	2

In [ ]:

```python
print("\nDifferences between old and new datasets:")
print((df[missing_attribute] != new_df[missing_attribute]).sum())

compare_histograms(df, new_df, 'language')
```

```
Differences between old and new datasets:
145
```



2.3.4 通过数据对象之间的相似性来填补

通过数据对象之间的相似性来填补缺失值策略对缺失值进行处理，在处理后完成，对比新旧数据集的差异。

对于每一条缺失数据，计算其与非缺失记录的欧式距离衡量相似度，使用最相似的记录来填补缺失值。

In [ ]:
```
def fill_missing_language(data, missing_attribute, numeric_attributes):

    new_data = data.copy()

    missing_language_records = new_data[new_data[missing_attribute].isna(

    non_missing_language_records = new_data.dropna(subset=[missing_attrib

    filled_data = new_data.copy()

    for index, row in missing_language_records.iterrows():
        missing_numeric_values = row[numeric_attributes].values.reshape(1

        distances = euclidean_distances(missing_numeric_values, non_missi

        most_similar_index = np.argmin(distances)
        filled_language_value = non_missing_language_records.iloc[most_si

        filled_data.at[index, missing_attribute] = filled_language_value

    return filled_data

new_df = filled_df = fill_missing_language(df, missing_attribute, numeric
df.head()
```

Out[ ]:

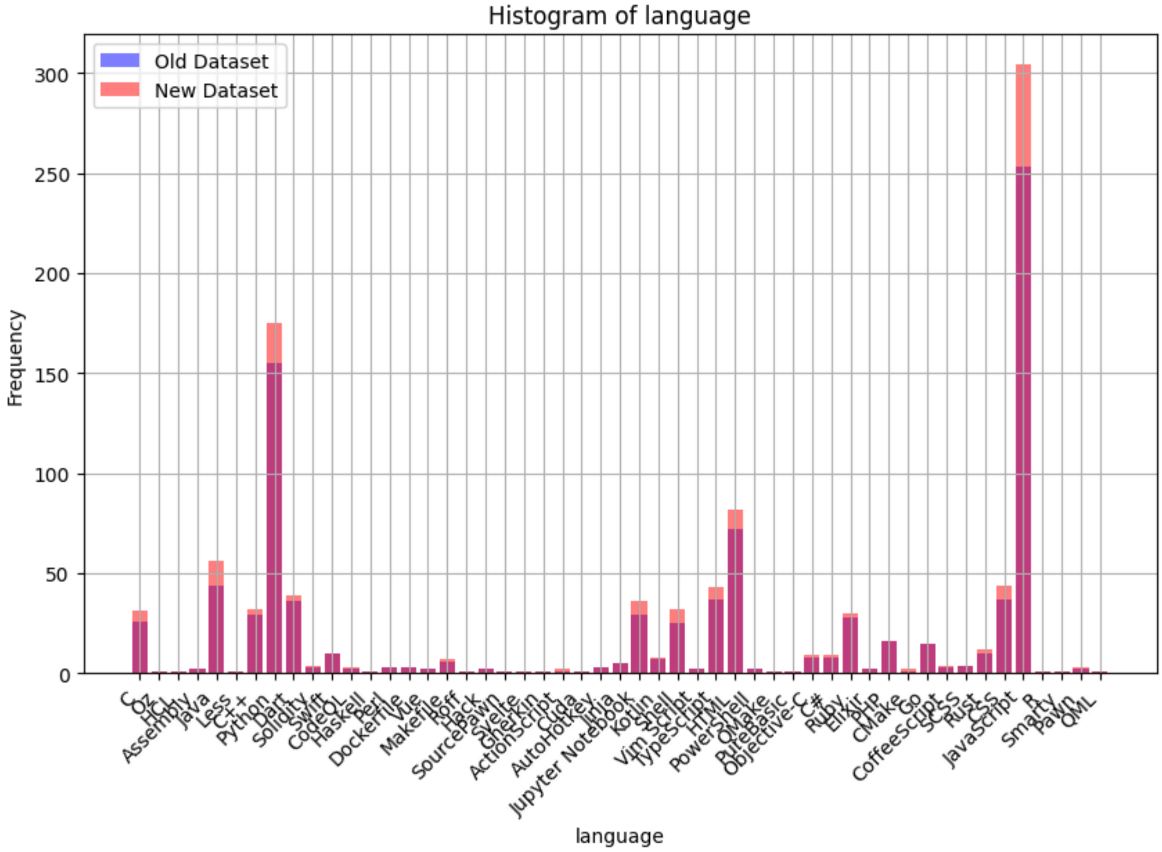
	repositories	stars_count	forks_count	issues_count	pull_reques
0	octocat/Hello-World	0	0	612	3
1	EddieHubCommunity/support	271	150	536	
2	ethereum/aleth	0	0	313	1
3	localstack/localstack	0	0	290	3
4	education/classroom	0	589	202	2

In [ ]:
```
new_df.head()
```

Out[ ]:

	repositories	stars_count	forks_count	issues_count	pull_reques
0	octocat/Hello-World	0	0	612	3
1	EddieHubCommunity/support	271	150	536	
2	ethereum/aleth	0	0	313	1
3	localstack/localstack	0	0	290	3
4	education/classroom	0	589	202	2

In [ ]:
```
compare_histograms(df, new_df, 'language')
```



3 Tweet Sentiment's Impact on Stock Returns

数据集为Tweet Sentiment's Impact on Stock Returns

3.1 加载数据集

In [ ]:
```
def check_dataset(dataset_path):

    if not os.path.exists(dataset_path):
        print("[!] dataset not exist")
    else:
        print("[!] dataset already exists")


github_data_path = '../data/TSISR/archive'
check_dataset(github_data_path)

df = pd.read_csv(github_data_path + "/reduced_dataset-release.csv")
print("[!] load dataset")

df.head()
```

```
[!] dataset already exists
[!] load dataset
```

```
/Users/zhangyunhe/anaconda3/envs/ML/lib/python3.7/site-packages/IPython/co
re/interactiveshell.py:3553: DtypeWarning: Columns (13) have mixed types.S
pecify dtype option on import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

Out[ ]:

	Unnamed: 0	TWEET	STOCK	DATE	LAST_PRICE	1_DAY_RETUR
0	0	RT @robertoglezcano: @amazon #Patents Show Fl...	NaN	NaN	NaN	Na
1	NaN	Amazon	31/01/2017	823.48	0.008379	0.01492
2	1	@FAME95FM1 Jamaicans make money with @Payoneer...	PayPal	31/01/2017	39.780000	0.0020
3	2	@CBSi Jamaicans make money with @Payoneer @Pay...	PayPal	31/01/2017	39.780000	0.0020
4	3	@Hitz92fm Jamaicans make money with @Payoneer ...	PayPal	31/01/2017	39.780000	0.0020

In [ ]:

```
print("columns:\n",df.columns, "\n")
print(df.info())
```

```
columns:
 Index(['Unnamed: 0', 'TWEET', 'STOCK', 'DATE', 'LAST_PRICE', '1_DAY_RETUR
N',
       '2_DAY_RETURN', '3_DAY_RETURN', '7_DAY_RETURN', 'PX_VOLUME',
       'VOLATILITY_10D', 'VOLATILITY_30D', 'LSTM_POLARITY',
       'TEXTBLOB_POLARITY', 'MENTION'],
      dtype='object')

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 143282 entries, 0 to 143281
Data columns (total 15 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         124761 non-null  object
 1   TWEET              143279 non-null  object
 2   STOCK              85176 non-null   object
 3   DATE               85176 non-null   object
 4   LAST_PRICE         85176 non-null   float64
 5   1_DAY_RETURN       85176 non-null   float64
 6   2_DAY_RETURN       85176 non-null   float64
 7   3_DAY_RETURN       85176 non-null   float64
 8   7_DAY_RETURN       85176 non-null   float64
 9   PX_VOLUME          85176 non-null   float64
 10  VOLATILITY_10D     85171 non-null   float64
 11  VOLATILITY_30D     85165 non-null   float64
 12  LSTM_POLARITY      85175 non-null   object
 13  TEXTBLOB_POLARITY  45594 non-null   object
 14  MENTION            27073 non-null   object
dtypes: float64(8), object(7)
memory usage: 16.4+ MB
None
```

3.2.1 数据摘要

In [ ]:
```
print('属性类别数:', len(df.columns))
print('总行数:', len(df), "\n")
```

```
属性类别数: 15
总行数: 143282
```

对于标称属性，给出每个可能取值的频数

In [ ]:
```
def nominal_frequency(data, nominal_attrs):
    frequencies = {}
    for col in nominal_attrs:
        frequencies[col] = data[col].value_counts()
    return frequencies

nominal_attributes = nominal_attributes = ['Unnamed: 0', 'TWEET', 'STOCK'
nominal_frequencies = nominal_frequency(df, nominal_attributes)


for attr, freq in nominal_frequencies.items():
    print(f"Attribute: {attr}")
    print(freq)
    print("\n")
```

```
Attribute: Unnamed: 0
Nike       8224
eBay       7022
Reuters    3618
Netflix    3548
Apple      2117
           ...
28392         1
28391         1
28390         1
28389         1
862071        1
Name: Unnamed: 0, Length: 85278, dtype: int64


Attribute: TWEET
eBay
3726
04/09/2018
3467
05/09/2018
2525
Reuters
2093
06/09/2018
1880

...
@Lynxii @nextofficial It’s called Sunday trading law love, look it up and
stop acting so entitled\r\r
1
@Ryanair This lady shouldn’t have been moved from her seat. The racist sho
uld have been removed from the plane. A c… https://t.co/5TdJ1OGgCU
1
Absolutely disgusting of @Ryanair to enable this vile racist. They moved t
he lady! They should have kicked that man… https://t.co/XmHLtUdMLJ
1
@marklovegrove @MarieBYates @Ryanair @_SJPeace_ The right thing to do is a
lways going to be uncomfortable.  Stop ra… https://t.co/snAkktnaCu
1
RT @Google: With hands-free ordering from your Google Assistant, it's a br
ew-tiful #NationalCoffeeDay. Just say "Hey Google, talk to @Starb…\r
1
Name: TWEET, Length: 61030, dtype: int64


Attribute: STOCK
Nike       3797
79.6       2710
Reuters    2482
Apple      2238
eBay       2063
           ...
37.52         1
1201.26       1
413.5         1
108.25        1
81.86         1
Name: STOCK, Length: 2696, dtype: int64
```

```
Attribute: DATE
0.0                        10518
0.03266331658291468         2710
04/09/2018                  1837
-0.004004004004004097       1800
13/09/2018                  1602
                           ...
184.88                         1
4036.7                         1
65.48                          1
0.007709251101321586           1
0.0025851776043666237          1
Name: DATE, Length: 4260, dtype: int64


Attribute: LSTM_POLARITY
1                          14805
-1                         12268
0.0                        10050
@Nike                       8165
@eBay                       7288
                           ...
0.07826704545454545            1
-0.025568181818181827          1
0.3145454545454546             1
-0.08750000000000001           1
-0.4833333333333333            1
Name: LSTM_POLARITY, Length: 997, dtype: int64


Attribute: TEXTBLOB_POLARITY
0.0                        7878
0.0                        6589
@eBay                      4058
@Reuters                   2301
@netflix                   1546
                           ...
0.1787878787878788            1
0.13125                       1
0.170995670995671             1
0.2348484848484849            1
-0.038690476190476206         1
Name: TEXTBLOB_POLARITY, Length: 1406, dtype: int64


Attribute: MENTION
@Nike                3787
@Reuters             2655
@Apple               2181
@eBay                2174
@netflix             1952
                     ...
@vodafone               4
@21CF                   4
@bancosantander         4
@CarrefourGroup         2
@cardinalhealth         2
Name: MENTION, Length: 100, dtype: int64
```

对于数值属性，给出5数概括及缺失值的个数

In [ ]:
```
def numeric_summary(data, numeric_attrs):
    summary = {}
    for col in numeric_attrs:
        summary[col] = {
            'min': data[col].min(),
            'q1': data[col].quantile(0.25),
            'median': data[col].median(),
            'q3': data[col].quantile(0.75),
            'max': data[col].max(),
            'missing_values': data[col].isnull().sum()
        }
    return summary

numeric_attributes = ['LAST_PRICE', '1_DAY_RETURN','2_DAY_RETURN', '3_DAY


numeric_summaries = numeric_summary(df, numeric_attributes)
for attr, summary in numeric_summaries.items():
    print(f"Attribute: {attr}")
    print("Min:", summary['min'])
    print("Q1:", summary['q1'])
    print("Median:", summary['median'])
    print("Q3:", summary['q3'])
    print("Max:", summary['max'])
    print("Missing Values:", summary['missing_values'])
    print("\n")
```

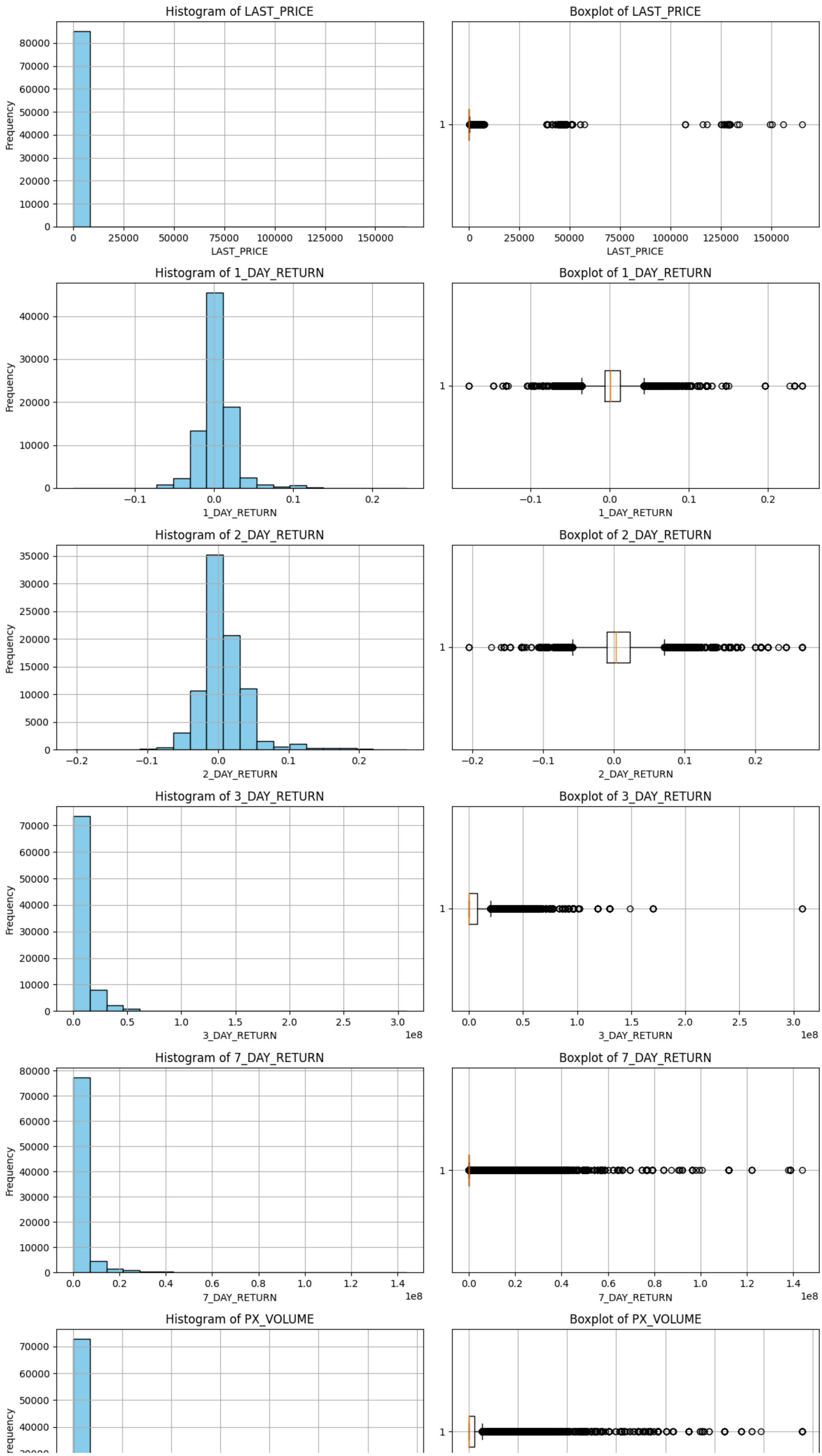
```
Attribute: LAST_PRICE
Min: -0.1735537190082644
Q1: -0.0004139072847681
Median: 0.0099706744868034
Q3: 49.9725
Max: 165500.0
Missing Values: 58106


Attribute: 1_DAY_RETURN
Min: -0.1778512396694214
Q1: -0.0059891383423284
Median: 0.0011188839589404
Q3: 0.0136032611184903
Max: 0.24363885871119
Missing Values: 58106


Attribute: 2_DAY_RETURN
Min: -0.2049586776859504
Q1: -0.009847977204623175
Median: 0.0031618281115262
Q3: 0.022653721682847825
Max: 0.2671133119720361
Missing Values: 58106


Attribute: 3_DAY_RETURN
Min: -0.1778512396694214
Q1: 0.0
Median: 0.0374371859296482
Q3: 7943443.0
Max: 308106768.0
Missing Values: 58106


Attribute: 7_DAY_RETURN
Min: -0.2049586776859504
Q1: 0.0338680926916221
Median: 20.517
Q3: 52.668
Max: 143947510.0
Missing Values: 58106


Attribute: PX_VOLUME
Min: 1.0
Q1: 17.152
Median: 24.07800000000001
Q3: 2628128.0
Max: 169803668.0
Missing Values: 58106


Attribute: VOLATILITY_10D
Min: -1.0
Q1: 1.0
Median: 9.482
Q3: 20.289
Max: 124.137
```

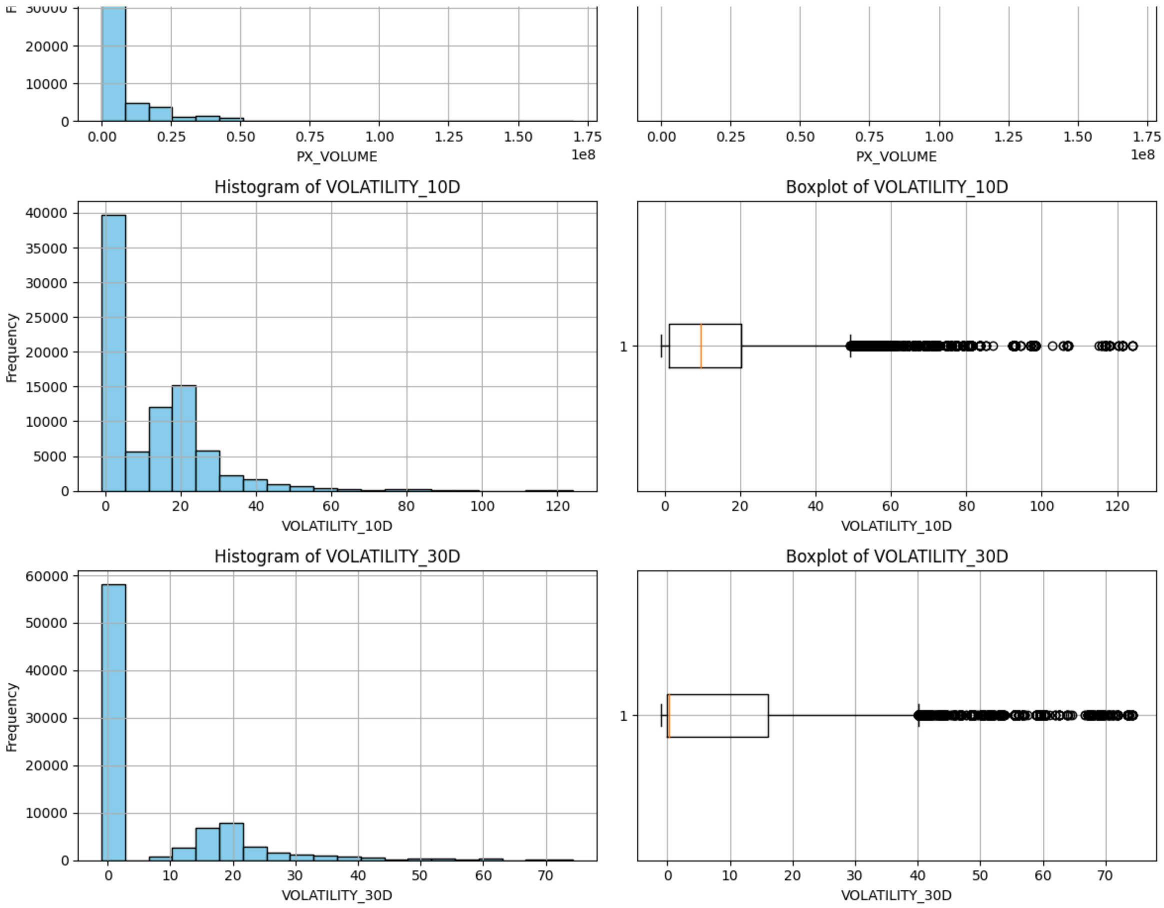
```
Missing Values: 58111


Attribute: VOLATILITY_30D
Min: -1.0
Q1: 0.0
Median: 0.3
Q3: 16.026
Max: 74.355
Missing Values: 58117
```

3.2.2 数据可视化

使用直方图、盒图等检查数据分布及离群点

In [ ]:
```
fig, axs = plt.subplots(len(numeric_attributes), 2, figsize=(12, 30))

for i, attr in enumerate(numeric_attributes):
    axs[i, 0].hist(df[attr].dropna(), bins=20, color='skyblue', edgecolor
    axs[i, 0].set_title(f'Histogram of {attr}')
    axs[i, 0].set_xlabel(attr)
    axs[i, 0].set_ylabel('Frequency')
    axs[i, 0].grid(True)

    axs[i, 1].boxplot(df[attr].dropna(), vert=False)
    axs[i, 1].set_title(f'Boxplot of {attr}')
    axs[i, 1].set_xlabel(attr)
    axs[i, 1].grid(True)

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

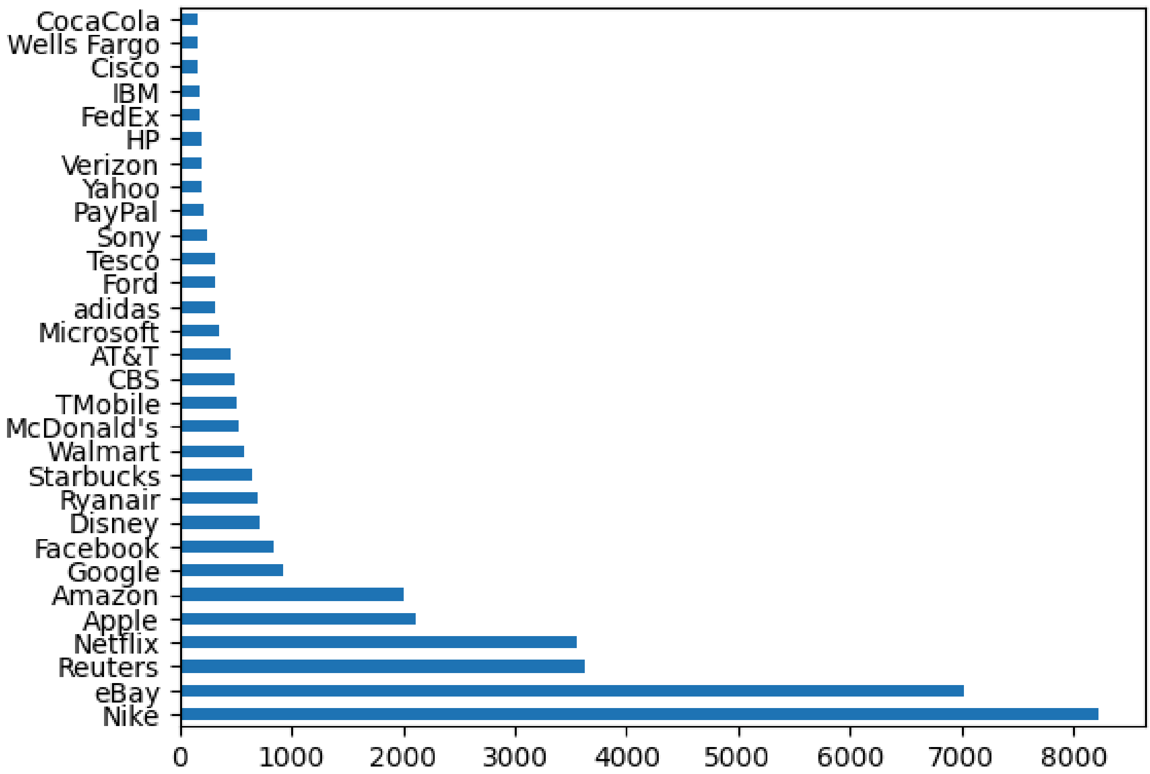

Histogram of LAST_PRICE
Frequency
LAST_PRICE
Boxplot of LAST_PRICE
LAST_PRICE
Histogram of 1_DAY_RETURN
Frequency
1_DAY_RETURN
Boxplot of 1_DAY_RETURN
1_DAY_RETURN
Histogram of 2_DAY_RETURN
Frequency
2_DAY_RETURN
Boxplot of 2_DAY_RETURN
2_DAY_RETURN
Histogram of 3_DAY_RETURN
Frequency
3_DAY_RETURN
1e8
Boxplot of 3_DAY_RETURN
3_DAY_RETURN
1e8
Histogram of 7_DAY_RETURN
Frequency
7_DAY_RETURN
1e8
Boxplot of 7_DAY_RETURN
7_DAY_RETURN
1e8
Histogram of PX_VOLUME
Boxplot of PX_VOLUME



以"Unnamed: 0"和"STOCK"属性为例，绘制直方图检查数据分布

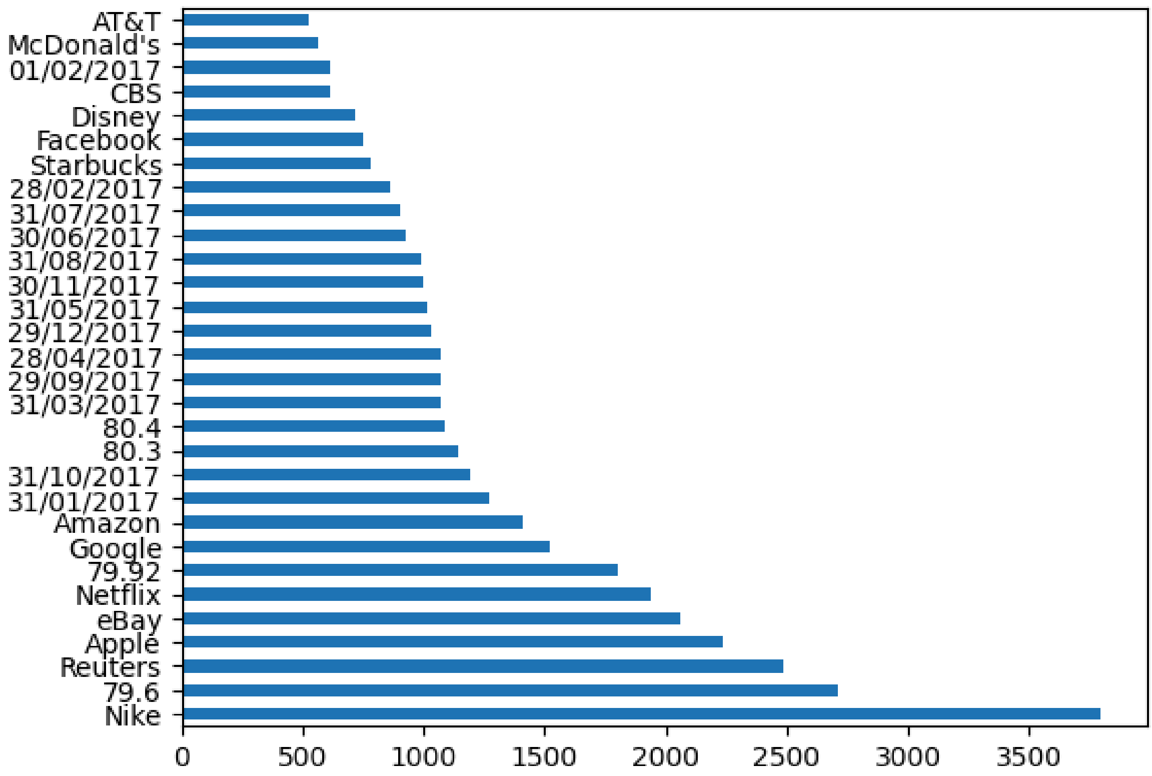
In [ ]:
```
df["Unnamed: 0"].value_counts().head(30).plot.barh()
```

Out[ ]: <AxesSubplot:>



In [ ]:
```
df["STOCK"].value_counts().head(30).plot.barh()
```

Out[ ]: <AxesSubplot:>



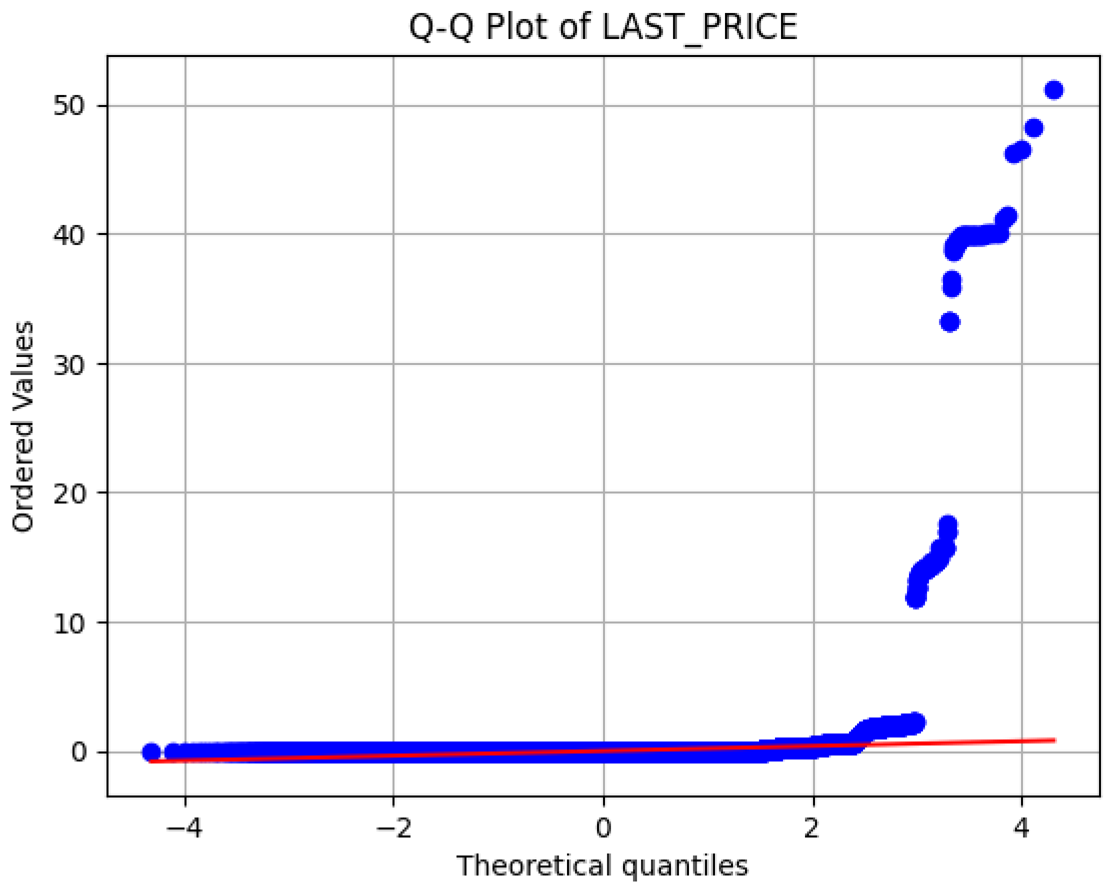
绘制Q-Q图并检查数据分布和离群点

使用Shapiro-Wilk 检验数据是否符合正态分布，如果 p-value 大于 0.05，则表示数据符合正态分布。

根据图表和数据可知，该数据集中所有数值属性都不符合正态分布且都存在离群点

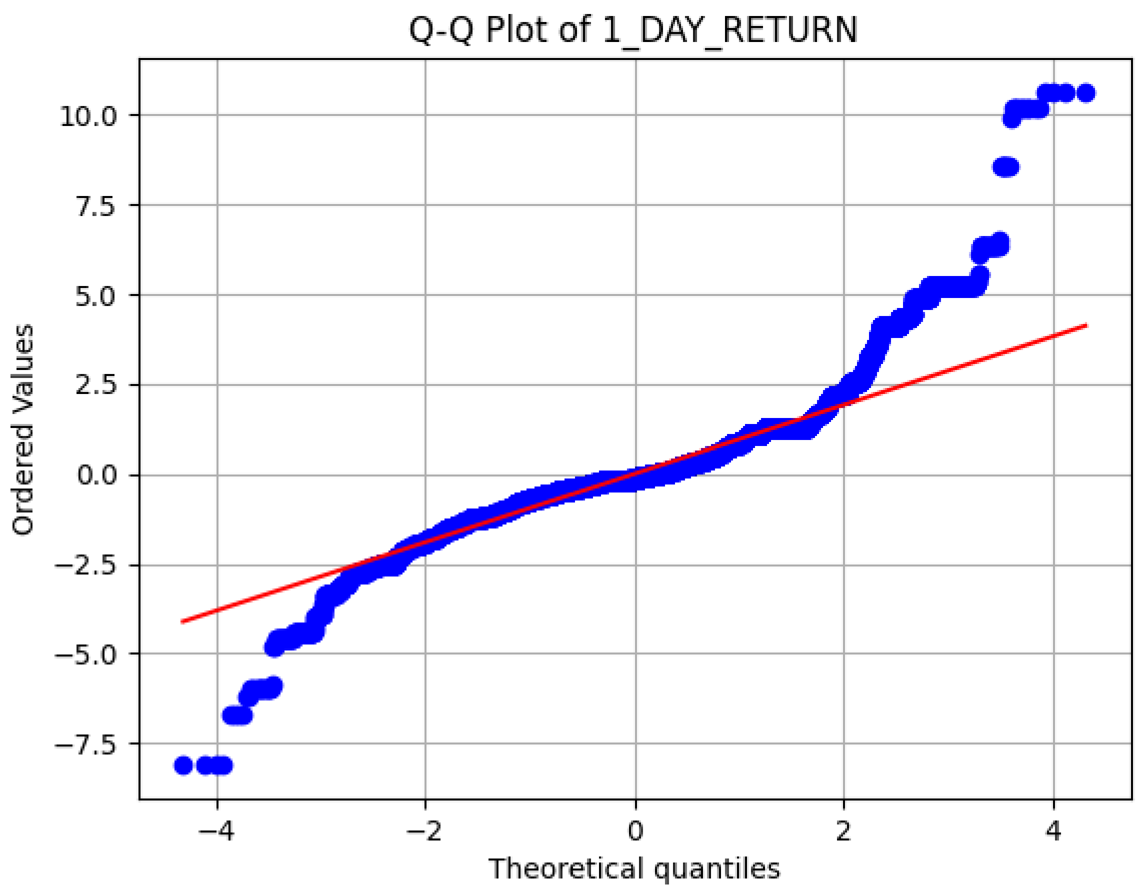
In [ ]:
```
for attr in numeric_attributes:
    data = df[attr].dropna()

    z_scores = (data - data.mean()) / data.std()

    stats.probplot(z_scores, dist="norm", plot=plt)
    plt.title(f'Q-Q Plot of {attr}')
    plt.xlabel('Theoretical quantiles')
    plt.ylabel('Ordered Values')
    plt.grid(True)
    plt.show()

    # 判断离群点是否符合正态分布
    print(f"Attribute: {attr}")

    outliers = z_scores[(z_scores > 3) | (z_scores < -3)]
    if len(outliers) > 0:
        print("There are outliers.")
    else:
        print("There are no outliers.")
    print("Normality Test (Shapiro-Wilk):")
    _, p_value = stats.shapiro(data)
    if p_value > 0.05:
        print("The data is normally distributed.")
    else:
```

```
        print("The data is not normally distributed.")
    print("\n")
```

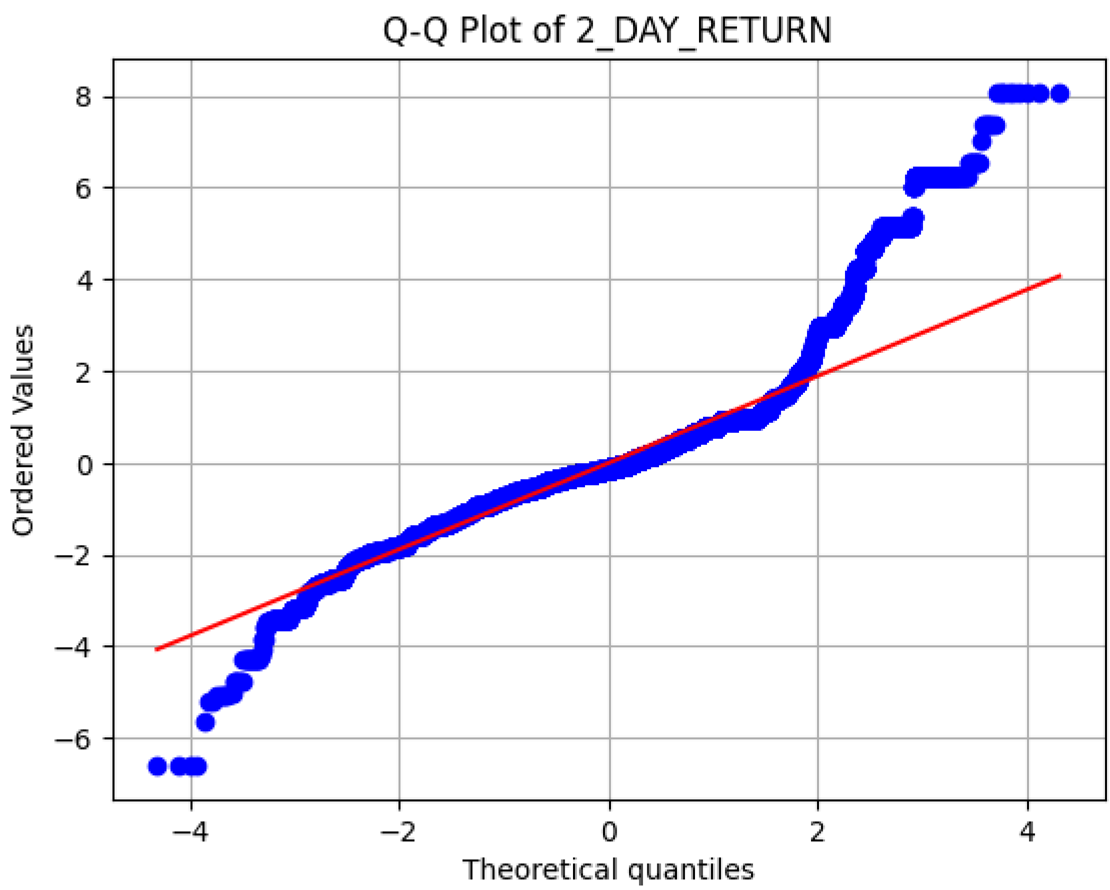



```
Attribute: LAST_PRICE
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```

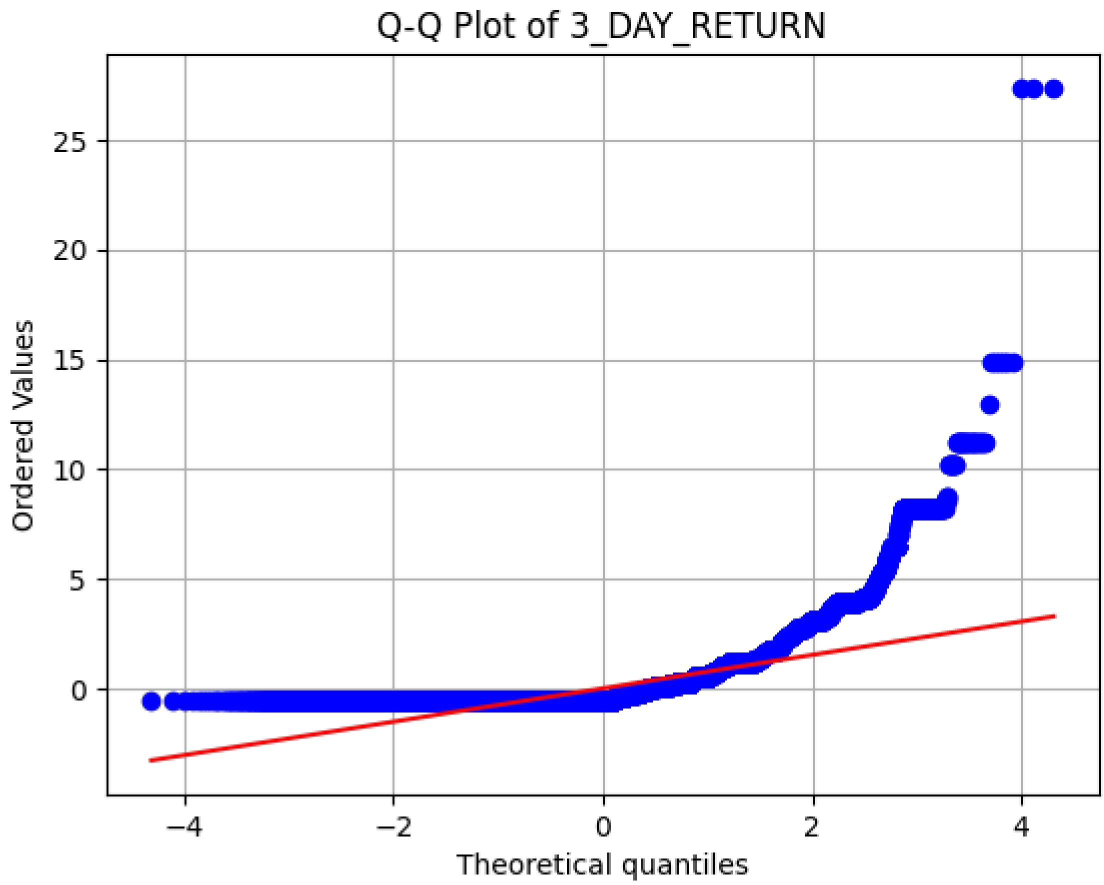
```
/Users/zhangyunhe/anaconda3/envs/ML/lib/python3.7/site-packages/scipy/stat
s/morestats.py:1760: UserWarning: p-value may not be accurate for N > 500
0.
  warnings.warn("p-value may not be accurate for N > 5000.")
```



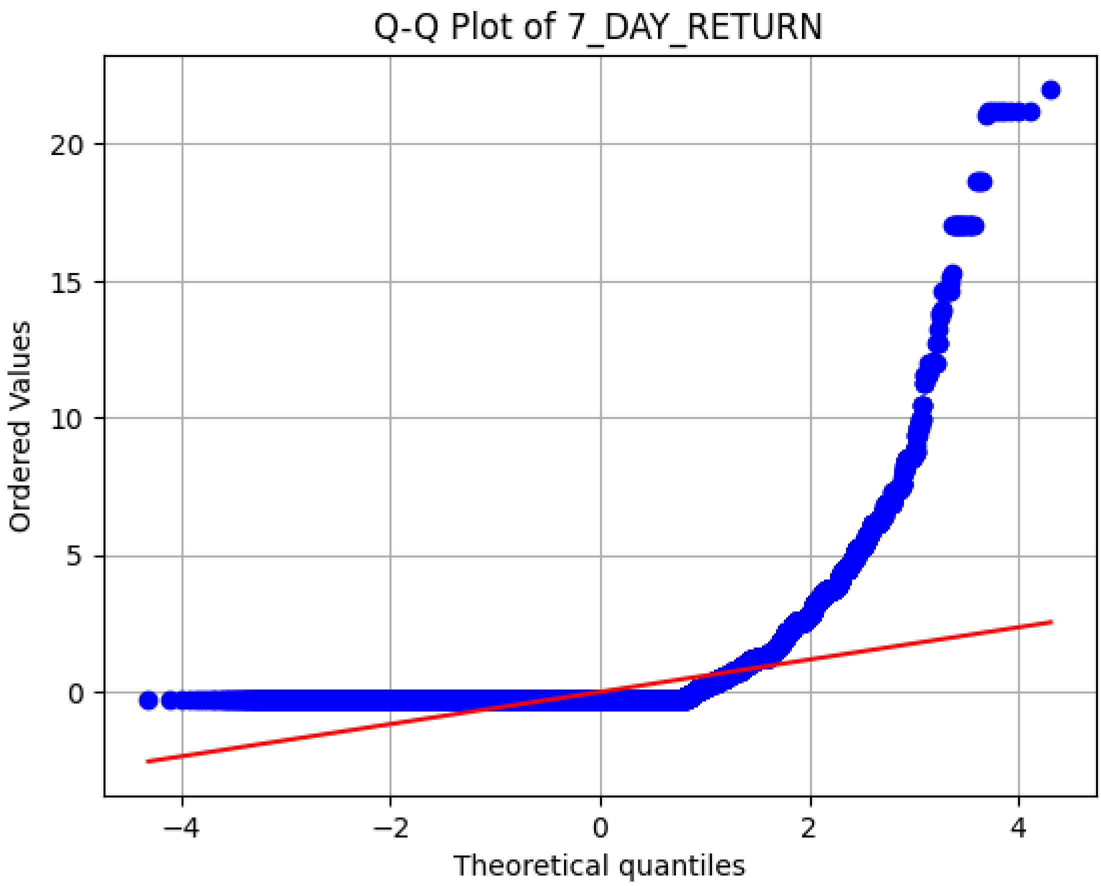

```
Attribute: 1_DAY_RETURN
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```



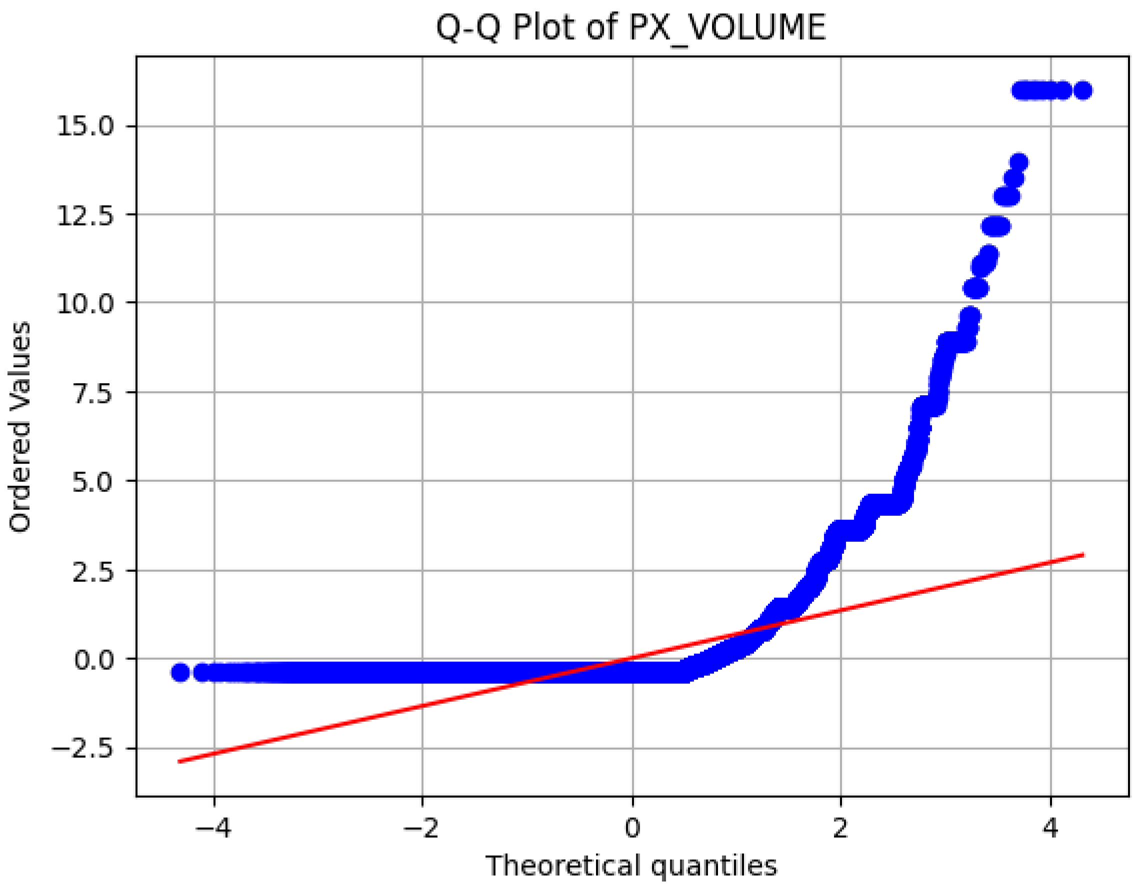
```
Attribute: 2_DAY_RETURN
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```



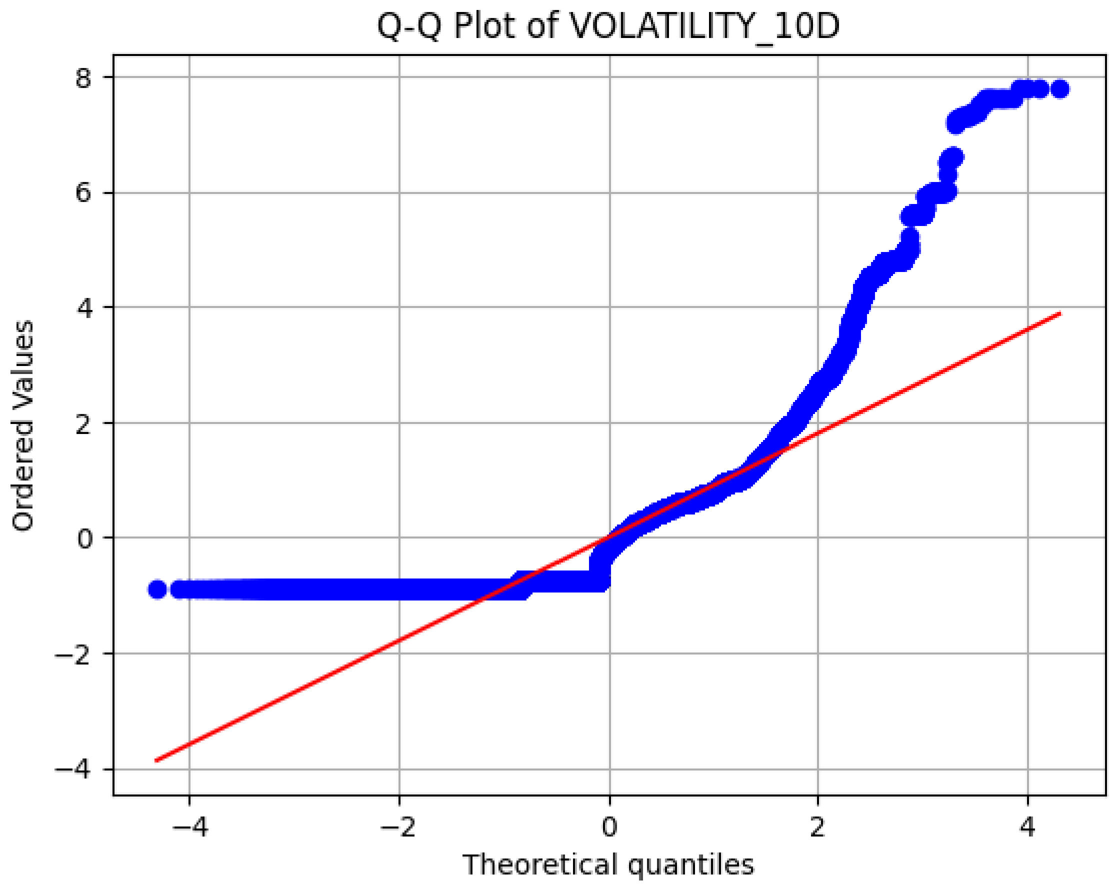

```
Attribute: 3_DAY_RETURN
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```



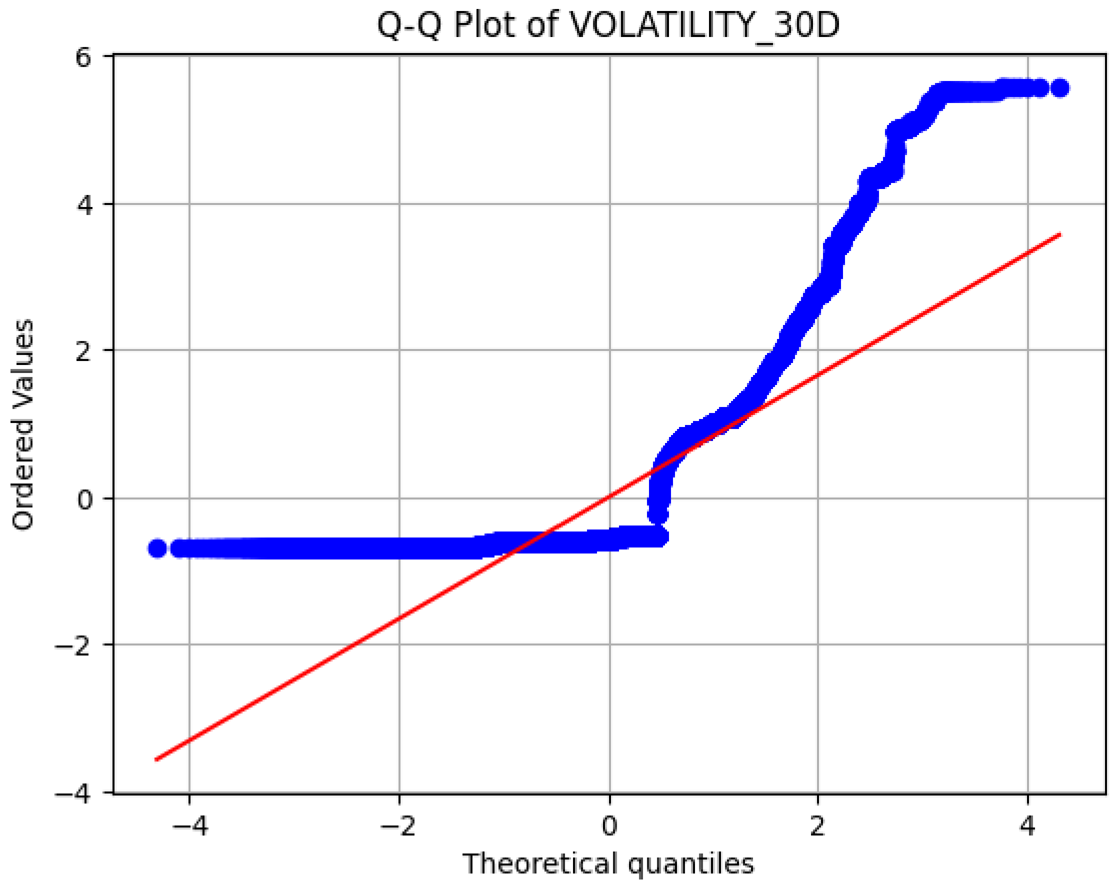

```
Attribute: 7_DAY_RETURN
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```



```
Attribute: PX_VOLUME
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```




```
Attribute: VOLATILITY_10D
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```




```
Attribute: VOLATILITY_30D
There are outliers.
Normality Test (Shapiro-Wilk):
The data is not normally distributed.
```

3.3 数据缺失的处理

观察数据集中缺失数据，分析其缺失的原因。分别使用下列四种策略对缺失值进行处理:

- 将缺失部分剔除
- 用最高频率值来填补缺失值
- 通过属性的相关关系来填补缺失值
- 通过数据对象之间的相似性来填补缺失值

注意：在处理后完成，要对比新旧数据集的差异。

In [ ]:
```
def check_missing_data(data, numeric_attrs, nominal_attrs):
    missing_data = {}

    for attr in numeric_attrs:
        missing_count = data[attr].isnull().sum()
        if missing_count > 0:
            missing_data[attr] = missing_count
            print(f"Attribute: {attr}, Missing Count: {missing_count}")
        else:
            print(f"Attribute: {attr} don't have missing data")

    for attr in nominal_attrs:
        missing_count = data[attr].isnull().sum()
```

```python
        if missing_count > 0:
            missing_data[attr] = missing_count
            print(f"Attribute: {attr}, Missing Count: {missing_count}")
        else:
            print(f"Attribute: {attr} don't have missing data")

    return missing_data

missing_data = check_missing_data(df, numeric_attributes, nominal_attribu
missing_list = [attr for attr in missing_data]

print("missing_list : ", missing_list)
```

```
Attribute: LAST_PRICE, Missing Count: 58106
Attribute: 1_DAY_RETURN, Missing Count: 58106
Attribute: 2_DAY_RETURN, Missing Count: 58106
Attribute: 3_DAY_RETURN, Missing Count: 58106
Attribute: 7_DAY_RETURN, Missing Count: 58106
Attribute: PX_VOLUME, Missing Count: 58106
Attribute: VOLATILITY_10D, Missing Count: 58111
Attribute: VOLATILITY_30D, Missing Count: 58117
Attribute: Unnamed: 0, Missing Count: 18521
Attribute: TWEET, Missing Count: 3
Attribute: STOCK, Missing Count: 58106
Attribute: DATE, Missing Count: 58106
Attribute: LSTM_POLARITY, Missing Count: 58107
Attribute: TEXTBLOB_POLARITY, Missing Count: 97688
Attribute: MENTION, Missing Count: 116209
missing_list :  ['LAST_PRICE', '1_DAY_RETURN', '2_DAY_RETURN', '3_DAY_RETU
RN', '7_DAY_RETURN', 'PX_VOLUME', 'VOLATILITY_10D', 'VOLATILITY_30D', 'Unn
amed: 0', 'TWEET', 'STOCK', 'DATE', 'LSTM_POLARITY', 'TEXTBLOB_POLARITY',
'MENTION']
```

3.3.1 将缺失部分剔除

使用将缺失部分剔除策略对缺失值进行处理，在处理后完成，对比新旧数据集的差异。

删除后新数据集仅有 27064 条记录。

In [ ]:
```python
df.isnull()
```

Out[ ]:

	Unnamed: 0	TWEET	STOCK	DATE	LAST_PRICE	1_DAY_RETURN	2_DAY_I
0	False	False	True	True	True	True	
1	True	False	False	False	False	False	
2	False	False	False	False	False	False	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	
...	...	...	...	...	...	...	
143277	False	False	True	True	True	True	
143278	True	False	False	False	False	False	
143279	False	False	False	False	False	False	
143280	False	False	True	True	True	True	
143281	True	False	False	False	False	False	

143282 rows × 15 columns

In [ ]:

```
def remove_missing_data(data, missing_list):
    new_data = data.copy()

    for attribute in missing_list:
        new_data = new_data.dropna(subset=[attribute])

    return new_data

new_df = remove_missing_data(df, missing_list)
df.head()
```

Out[ ]:

	Unnamed: 0	TWEET	STOCK	DATE	LAST_PRICE	1_DAY_RETUR
0	0	RT @robertoglezcano: @amazon #Patents Show Fl...	NaN	NaN	NaN	Na
1	NaN	Amazon	31/01/2017	823.48	0.008379	0.01492
2	1	@FAME95FM1 Jamaicans make money with @Payoneer...	PayPal	31/01/2017	39.780000	0.0020
3	2	@CBSi Jamaicans make money with @Payoneer @Pay...	PayPal	31/01/2017	39.780000	0.0020
4	3	@Hitz92fm Jamaicans make money with @Payoneer ...	PayPal	31/01/2017	39.780000	0.0020

In [ ]:

```
new_df.head()
```

Out[ ]:

	Unnamed: 0	TWEET	STOCK	DATE	LAST_PRICE	1_DAY_RETURN
2	1	@FAME95FM1 Jamaicans make money with @Payoneer...	PayPal	31/01/2017	39.78	0.002011
3	2	@CBSi Jamaicans make money with @Payoneer @Pay...	PayPal	31/01/2017	39.78	0.002011
4	3	@Hitz92fm Jamaicans make money with @Payoneer ...	PayPal	31/01/2017	39.78	0.002011
11	7	RT @nikitakhara: Thank you, @Starbucks CEO for...	Starbucks	31/01/2017	55.22	0.012314
20	12	@gawker Jamaicans make money with @Payoneer @P...	PayPal	31/01/2017	39.78	0.002011

In [ ]:
```
print(f"\nNumber of rows in old dataset: {len(df)}")
print(f"Number of rows in new dataset: {len(new_df)}")
```

```
Number of rows in old dataset: 143282
Number of rows in new dataset: 27064
```

In [ ]:
```
new_df.isnull()
```

Out[ ]:

	Unnamed: 0	TWEET	STOCK	DATE	LAST_PRICE	1_DAY_RETURN	2_DAY_I
2	False	False	False	False	False	False	
3	False	False	False	False	False	False	
4	False	False	False	False	False	False	
11	False	False	False	False	False	False	
20	False	False	False	False	False	False	
...	...	...	...	...	...	...	
143251	False	False	False	False	False	False	
143252	False	False	False	False	False	False	
143259	False	False	False	False	False	False	
143276	False	False	False	False	False	False	
143279	False	False	False	False	False	False	

27064 rows × 15 columns

In [ ]:
```
new_df.isna().sum()
```

Out[ ]:
```
Unnamed: 0           0
TWEET                0
STOCK                0
DATE                 0
LAST_PRICE           0
1_DAY_RETURN         0
2_DAY_RETURN         0
3_DAY_RETURN         0
7_DAY_RETURN         0
PX_VOLUME            0
VOLATILITY_10D       0
VOLATILITY_30D       0
LSTM_POLARITY        0
TEXTBLOB_POLARITY    0
MENTION              0
dtype: int64
```

3.3.2 用最高频率值来填补

使用最高频率值来填补缺失值策略对缺失值进行处理，在处理后完成，对比新旧数据集的差异。

In [ ]:
```
def fill_missing_with_mode(data, missing_list):
    new_data = data.copy()
```

```
    for attribute in missing_list:
        mode_value = new_data[attribute].mode()[0]
        print(f'{mode_value} is the {attribute} with the highest frequenc

        new_data[attribute].fillna(mode_value, inplace=True)

    return new_data

new_df = fill_missing_with_mode(df, missing_list)
```

```
0.0 is the LAST_PRICE with the highest frequency.

0.0 is the 1_DAY_RETURN with the highest frequency.

0.0 is the 2_DAY_RETURN with the highest frequency.

18565837.0 is the 3_DAY_RETURN with the highest frequency.

20.517 is the 7_DAY_RETURN with the highest frequency.

20.153 is the PX_VOLUME with the highest frequency.

1.0 is the VOLATILITY_10D with the highest frequency.

0.0 is the VOLATILITY_30D with the highest frequency.

Nike is the Unnamed: 0 with the highest frequency.

eBay is the TWEET with the highest frequency.

Nike is the STOCK with the highest frequency.

0.0 is the DATE with the highest frequency.

1 is the LSTM_POLARITY with the highest frequency.

0.0 is the TEXTBLOB_POLARITY with the highest frequency.

@Nike is the MENTION with the highest frequency.
```

In [ ]:

```
df.head()
```

Out[ ]:

	Unnamed: 0	TWEET	STOCK	DATE	LAST_PRICE	1_DAY_RETUR
0	0	RT @robertoglezcano: @amazon #Patents Show Fl...	NaN	NaN	NaN	Na
1	NaN	Amazon	31/01/2017	823.48	0.008379	0.01492
2	1	@FAME95FM1 Jamaicans make money with @Payoneer...	PayPal	31/01/2017	39.780000	0.0020
3	2	@CBSi Jamaicans make money with @Payoneer @Pay...	PayPal	31/01/2017	39.780000	0.0020
4	3	@Hitz92fm Jamaicans make money with @Payoneer ...	PayPal	31/01/2017	39.780000	0.0020

In [ ]:

```
new_df.head()
```

Out[ ]:

	Unnamed: 0	TWEET	STOCK	DATE	LAST_PRICE	1_DAY_RETUR
0	0	RT @robertoglezcano: @amazon #Patents Show Fl...	Nike	0.0	0.000000	0.00000
1	Nike	Amazon	31/01/2017	823.48	0.008379	0.01492
2	1	@FAME95FM1 Jamaicans make money with @Payoneer...	PayPal	31/01/2017	39.780000	0.0020
3	2	@CBSi Jamaicans make money with @Payoneer @Pay...	PayPal	31/01/2017	39.780000	0.0020
4	3	@Hitz92fm Jamaicans make money with @Payoneer ...	PayPal	31/01/2017	39.780000	0.0020

In [ ]:

```
print(f"\nNumber of rows in old dataset: {len(df)}")
print(f"Number of rows in new dataset: {len(new_df)}")
```

```
Number of rows in old dataset: 143282
Number of rows in new dataset: 143282
```

In [ ]:

```
print("\nDifferences between old and new datasets:")
print((df[missing_list] != new_df[missing_list]).sum())
```

```
Differences between old and new datasets:
LAST_PRICE              58106
1_DAY_RETURN            58106
2_DAY_RETURN            58106
3_DAY_RETURN            58106
7_DAY_RETURN            58106
PX_VOLUME               58106
VOLATILITY_10D          58111
VOLATILITY_30D          58117
Unnamed: 0              18521
TWEET                       3
STOCK                   58106
DATE                    58106
LSTM_POLARITY           58107
TEXTBLOB_POLARITY       97688
MENTION                116209
dtype: int64
```

3.3.3 通过属性的相关关系来填补

通过属性的相关关系来填补缺失值策略对缺失值进行处理，在处理后完成，对比新旧数据集的差异。

检查数值属性的相关系数矩阵

In [ ]:
```
df.corr()
```

Out[ ]:

	LAST_PRICE	1_DAY_RETURN	2_DAY_RETURN	3_DAY_RETURN
LAST_PRICE	1.000000	-0.013310	-0.013472	-0.037885
1_DAY_RETURN	-0.013310	1.000000	0.734714	0.196885
2_DAY_RETURN	-0.013472	0.734714	1.000000	0.269247
3_DAY_RETURN	-0.037885	0.196885	0.269247	1.000000
7_DAY_RETURN	-0.022251	-0.037411	-0.063732	-0.167271
PX_VOLUME	0.016460	-0.021278	-0.026231	-0.210847
VOLATILITY_10D	0.067075	-0.051252	-0.068032	-0.435475
VOLATILITY_30D	0.099773	-0.045195	-0.039004	-0.313782

设置相关系数阈值为0.7，筛选具有相关性的数据

In [ ]:
```
correlation_matrix = df.corr()
threshold = 0.7

related_attributes = dict()
for i in range(len(correlation_matrix.columns)):
    for j in range(i):
        if abs(correlation_matrix.iloc[i, j]) > threshold:
            attribute_i = correlation_matrix.columns[i]
            attribute_j = correlation_matrix.columns[j]
            related_attributes[attribute_i] = attribute_j

print("\nAttributes with correlation greater than", threshold, ":")
```

```
for key, value in related_attributes.items():
    print(f"{key} : corelate with {value}")
```

```
Attributes with correlation greater than 0.7 :
2_DAY_RETURN : corelate with 1_DAY_RETURN
VOLATILITY_30D : corelate with VOLATILITY_10D
```

通过属性相关关系填补缺失值

In [ ]:
```
def fill_missing_with_related_attributes(data, related_attributes):
    new_data = data.copy()

    for attribute, related in related_attributes.items():

        related_mean = new_data[related].mean()
        print(f"{attribute} related with {related} , use {related_mean} f

        new_data[attribute].fillna(related_mean, inplace=True)

    return new_data

filled_df = fill_missing_with_related_attributes(df, related_attributes)
```

```
2_DAY_RETURN related with 1_DAY_RETURN , use 0.004374982086701198 fill mis
sing data

VOLATILITY_30D related with VOLATILITY_10D , use 11.883456869121542 fill m
issing data
```

In [ ]:
```
df.head()
```

Out[ ]:

	Unnamed: 0	TWEET	STOCK	DATE	LAST_PRICE	1_DAY_RETUR
0	0	RT @robertoglezcano: @amazon #Patents Show Fl...	NaN	NaN	NaN	Na
1	NaN	Amazon	31/01/2017	823.48	0.008379	0.01492
2	1	@FAME95FM1 Jamaicans make money with @Payoneer...	PayPal	31/01/2017	39.780000	0.0020
3	2	@CBSi Jamaicans make money with @Payoneer @Pay...	PayPal	31/01/2017	39.780000	0.0020
4	3	@Hitz92fm Jamaicans make money with @Payoneer ...	PayPal	31/01/2017	39.780000	0.0020

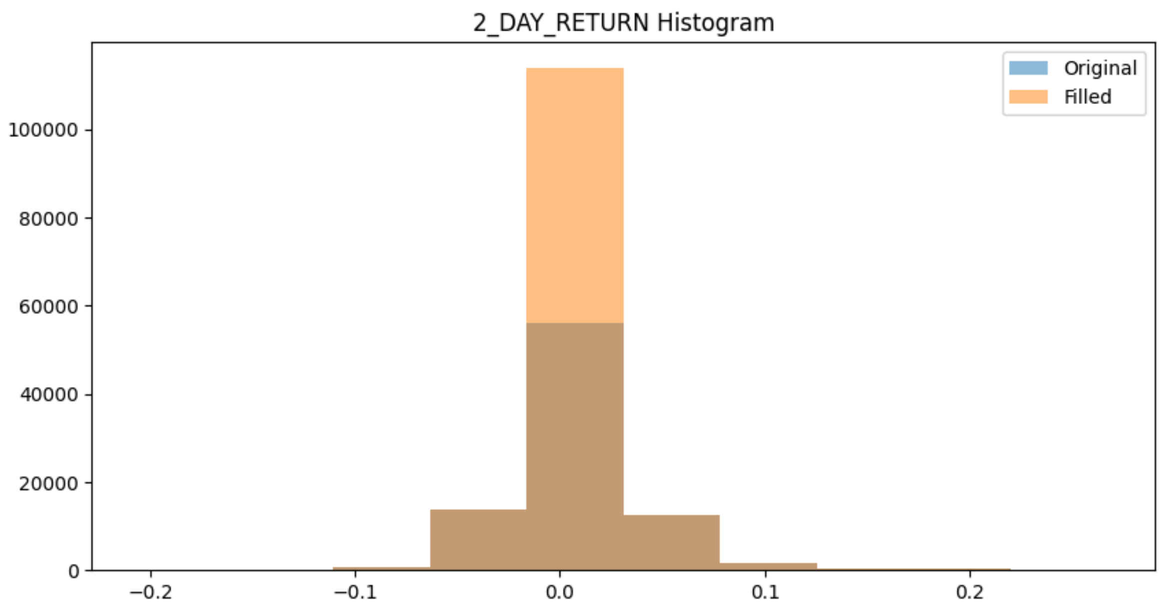
In [ ]:
```
new_df.head()
```

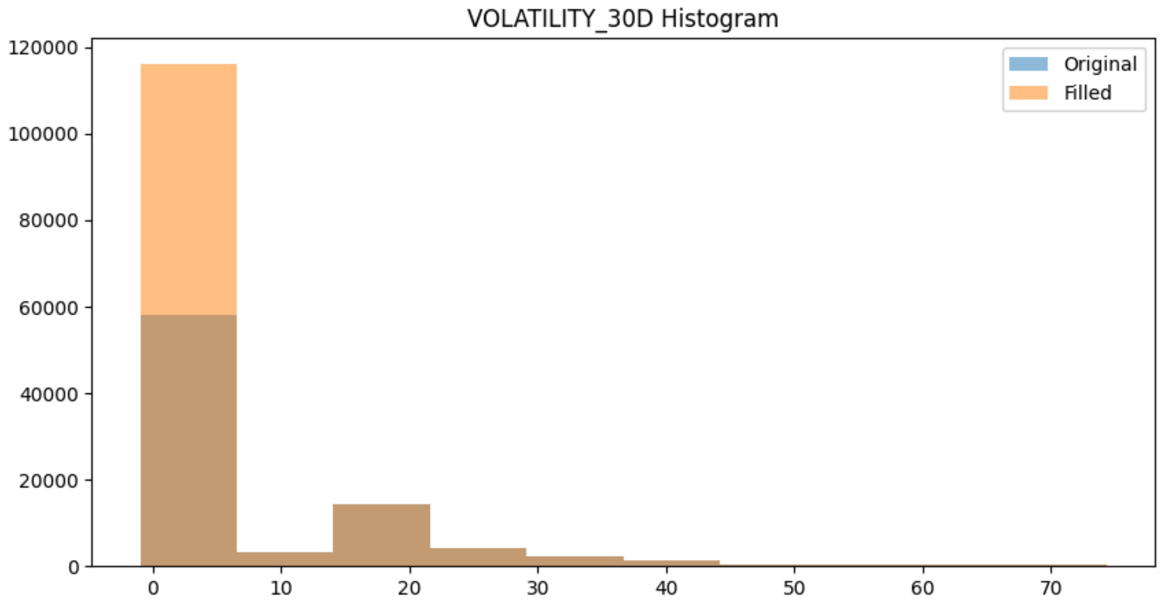
Out[ ]:

	Unnamed: 0	TWEET	STOCK	DATE	LAST_PRICE	1_DAY_RETUR
0	0	RT @robertoglezcano: @amazon #Patents Show Fl...	Nike	0.0	0.000000	0.00000
1	Nike	Amazon	31/01/2017	823.48	0.008379	0.01492
2	1	@FAME95FM1 Jamaicans make money with @Payoneer...	PayPal	31/01/2017	39.780000	0.0020
3	2	@CBSi Jamaicans make money with @Payoneer @Pay...	PayPal	31/01/2017	39.780000	0.0020
4	3	@Hitz92fm Jamaicans make money with @Payoneer ...	PayPal	31/01/2017	39.780000	0.0020

In [ ]:

```
def plot_comparison_histogram_and_boxplot(original_data, filled_data, att
    plt.figure(figsize=(10, 5))
    plt.hist(original_data[attribute], alpha=0.5, label='Original')
    plt.hist(filled_data[attribute], alpha=0.5, label='Filled')
    plt.title(f'{attribute} Histogram')
    plt.legend()

    plt.show()

plot_comparison_histogram_and_boxplot(df, new_df, "2_DAY_RETURN")
plot_comparison_histogram_and_boxplot(df, new_df, "VOLATILITY_30D")
```





3.3.4 通过数据对象之间的相似性来填补

通过数据对象之间的相似性来填补缺失值策略对缺失值进行处理，在处理后完成，对比新旧数据集的差异。

对于每一条缺失数据，使用KNN算法通过数据对象相似性来填补。

In [ ]:
```python
def fill_missing_with_knn(data, missing_attributes, k=5):
    new_data = data.copy()

    new_data = new_data.select_dtypes(include=['float64', 'int64'])

    # 对NaN值进行预处理
    new_data.fillna(new_data.mean(), inplace=True)

    sub_list = list(set(missing_attributes) & set(numeric_attributes))
    missing_data = new_data[sub_list]

    imputer = KNNImputer(n_neighbors=k)
    filled_data = imputer.fit_transform(missing_data)

    filled_df = pd.DataFrame(filled_data, columns=sub_list, index=new_dat

    new_data.update(filled_df, overwrite=True)

    return new_data

new_df = filled_df = fill_missing_with_knn(df, missing_list)
df.head()
```

Out[ ]:

	Unnamed: 0	TWEET	STOCK	DATE	LAST_PRICE	1_DAY_RETUR
0	0	RT @robertoglezcano: @amazon #Patents Show Fl...	NaN	NaN	NaN	Na
1	NaN	Amazon	31/01/2017	823.48	0.008379	0.01492
2	1	@FAME95FM1 Jamaicans make money with @Payoneer...	PayPal	31/01/2017	39.780000	0.0020
3	2	@CBSi Jamaicans make money with @Payoneer @Pay...	PayPal	31/01/2017	39.780000	0.0020
4	3	@Hitz92fm Jamaicans make money with @Payoneer ...	PayPal	31/01/2017	39.780000	0.0020

为了更直观的展示结果，此处只显示数值属性处理后的结果。

In [ ]:

```
new_df.head()
```

Out[ ]:

	LAST_PRICE	1_DAY_RETURN	2_DAY_RETURN	3_DAY_RETURN	7_DAY_RETURN
0	229.142895	0.004375	0.007293	5.891352e+06	2.020673e+06
1	0.008379	0.014924	0.014924	-1.262933e-03	3.137196e+06
2	39.780000	0.002011	0.012318	1.231775e-02	5.480141e-02
3	39.780000	0.002011	0.012318	1.231775e-02	5.480141e-02
4	39.780000	0.002011	0.012318	1.231775e-02	5.480141e-02