

1. Significant earthquakes since 2150 B.C.

1.1 读取数据并计算死亡总数最多的20个国家，最后再打印

```
In [8]: import pandas as pd
file_name = 'earthquakes-2024-10-25_14-33-37_+0800.tsv'

# 读取 TSV 文件
Sig_Eqs = pd.read_csv(file_name, sep='\t')
```

```
In [9]: # 计算每个国家的死亡总数
deaths_by_country = Sig_Eqs['Location Name'].value_counts()

# 打印死亡总数最多的20个国家
print(deaths_by_country.head(20))
```

Location Name	
CHINA: YUNNAN PROVINCE	68
RUSSIA: KURIL ISLANDS	53
TURKEY	47
CHINA: SICHUAN PROVINCE	46
BALKANS NW: CROATIA	34
VANUATU ISLANDS	34
SOLOMON ISLANDS	34
PERU	27
SWITZERLAND	27
CHINA: GANSU PROVINCE	27
MEXICO: OAXACA	26
TAIWAN	25
ITALY: N	25
ITALY: CENTRAL	24
CHILE: NORTHERN	24
INDONESIA: BANDA SEA	24
GREECE: CRETE	23
TURKEY: ANTAKYA (ANTIOCH)	22
NEW CALEDONIA: LOYALTY ISLANDS	22
JAPAN: SANRIKU	22

Name: count, dtype: int64

1.2 导入 `matplotlib.pyplot`，再过滤震级大于3.0的地震，从原始的 `Sig_Eqs` DataFrame 中筛选出 `Mag`（震级）大于3.0的地震事件，存储在新的 DataFrame `Ms` 中。确保 'Year' 列是 `datetime` 类型，确保所有数据都能被正确处理。获取年份并计数，从 `Ms` DataFrame 的 `Year` 列中提取年份，并使用 `value_counts()` 方法统计每个年份的地震次数。 `sort_index()` 方法确保结果按照年份排序。最后绘制时间序列图。

```
In [10]: import matplotlib.pyplot as plt
# 过滤 Ms 列震级大于3.0的地震
Ms = Sig_Eqs[Sig_Eqs['Mag'] > 3.]
# 确保 'Year' 列是 datetime 类型

Ms['Year'] = pd.to_datetime(Ms['Year'], errors='coerce')
annual_eq_counts = Ms['Year'].dt.year.value_counts().sort_index()

# 绘制时间序列
```

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```
plt.plot(annual_eq_counts.index, annual_eq_counts.values, marker='o')
plt.title('Annual Earthquake Counts with Mag > 3.0')
plt.xlabel('Year')
plt.ylabel('Number of Earthquakes')
plt.grid(True)
plt.show()
```

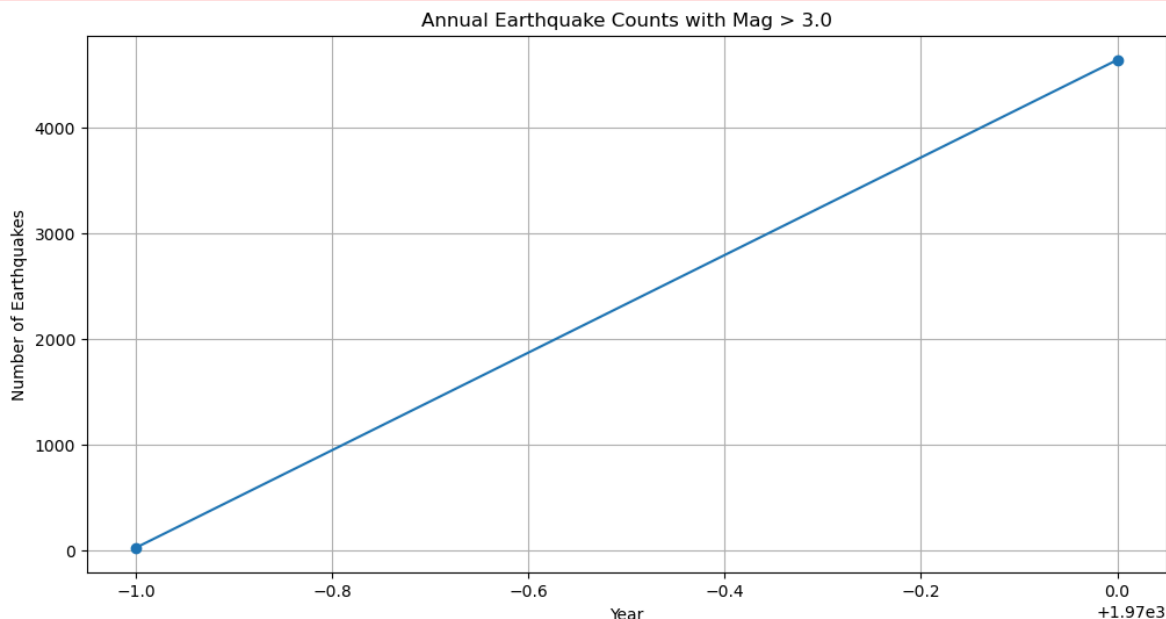
C:\Users\HONOR\AppData\Local\Temp\ipykernel_287116\978098864.py:9: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
Ms['Year'] = pd.to_datetime(Ms['Year'], errors='coerce')
```



原因分析：地震级数大于三级的地震总数增加可能与地球板块活动增强、地震活跃期的到来、地震活动增强现象、地震活动的空间尺度和时间尺度变化等因素有关。这些因素共同作用，可能导致我们观测到的大于三级的地震总数有所增加。

1.3定义函数 `CountEq_LargestEq`，筛选出该国家的所有地震数据，计算并返回该国家的地震总数。找出该国家最大的地震事件，并返回其日期和地点。应用函数并存储结果。将结果转换为 DataFrame。最后排序和打印结果，根据地震总数降序排列

`results_df`，打印排序后的 DataFrame，显示每个国家的地震总数、最大地震的日期和地点。

In [24]: `import pandas as pd`

```
def CountEq_LargestEq(country):
    # 筛选特定国家的地震数据
    country_eqs = Sig_Eqs[Sig_Eqs['Location Name'] == country]

    # 计算地震总数
    total_eqs = len(country_eqs)

    # 寻找最大地震
```

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```
# 检查是否有任何非 NA 值
```

```
        if country_eqs['Mag'].notna().any():
            max_eq_index = country_eqs['Mag'].idxmax()
            max_eq = country_eqs.loc[max_eq_index]
            largest_eq_date = max_eq['Year']
            largest_eq_location = max_eq['Location Name']
        else:
            largest_eq_date = None
            largest_eq_location = None
    else:
        largest_eq_date = None
        largest_eq_location = None

    return total_eqs, largest_eq_date, largest_eq_location

# 应用函数并打印结果
countries = Sig_Eqs['Location Name'].unique()
results = {country: CountEq_LargestEq(country) for country in countries}

# 将结果转换为 DataFrame
results_df = pd.DataFrame(results).T
results_df.columns = ['Total Earthquakes', 'Largest Earthquake Date', 'Largest E

# 按照地震总数降序排列
results_df = results_df.sort_values(by='Total Earthquakes', ascending=False)

# 打印结果
print(results_df)
```

Total Earthquakes \	
CHINA: YUNNAN PROVINCE	68
RUSSIA: KURIL ISLANDS	53
TURKEY	47
CHINA: SICHUAN PROVINCE	46
SOLOMON ISLANDS	34
...	...
INDONESIA: SUMATERA: BREUEH ISLAND	1.0
URUGUAY: COLOGNE	1.0
CHINA: BOHAI GULF	1
NEW ZEALAND: SOUTH ISLAND: AMURI DISTRICT	1
NaN	0.0
Largest Earthquake Date \	
CHINA: YUNNAN PROVINCE	1833.0
RUSSIA: KURIL ISLANDS	1963.0
TURKEY	1944.0
CHINA: SICHUAN PROVINCE	2008.0
SOLOMON ISLANDS	1977.0
...	...
INDONESIA: SUMATERA: BREUEH ISLAND	NaN
URUGUAY: COLOGNE	NaN
CHINA: BOHAI GULF	1888.0
NEW ZEALAND: SOUTH ISLAND: AMURI DISTRICT	1888.0
NaN	NaN
Largest Earthquake Loc	
ation	
CHINA: YUNNAN PROVINCE	CHINA: YUNNAN PRO
VINCE	
RUSSIA: KURIL ISLANDS	RUSSIA: KURIL IS
LANDS	
TURKEY	T
URKEY	
CHINA: SICHUAN PROVINCE	CHINA: SICHUAN PRO
VINCE	
SOLOMON ISLANDS	SOLOMON IS
LANDS	
...	
...	
INDONESIA: SUMATERA: BREUEH ISLAND	
NaN	
URUGUAY: COLOGNE	
NaN	
CHINA: BOHAI GULF	CHINA: BOHAI
GULF	
NEW ZEALAND: SOUTH ISLAND: AMURI DISTRICT	NEW ZEALAND: SOUTH ISLAND: AMURI DIS
TRICT	
NaN	
NaN	
[3996 rows x 3 columns]	

In []:

2. Air temperature in Shenzhen during the past 25 years

首先导入库和数据，再进行数据处理，转换为日期格式，重采样和计算平均值，最后绘制图表。

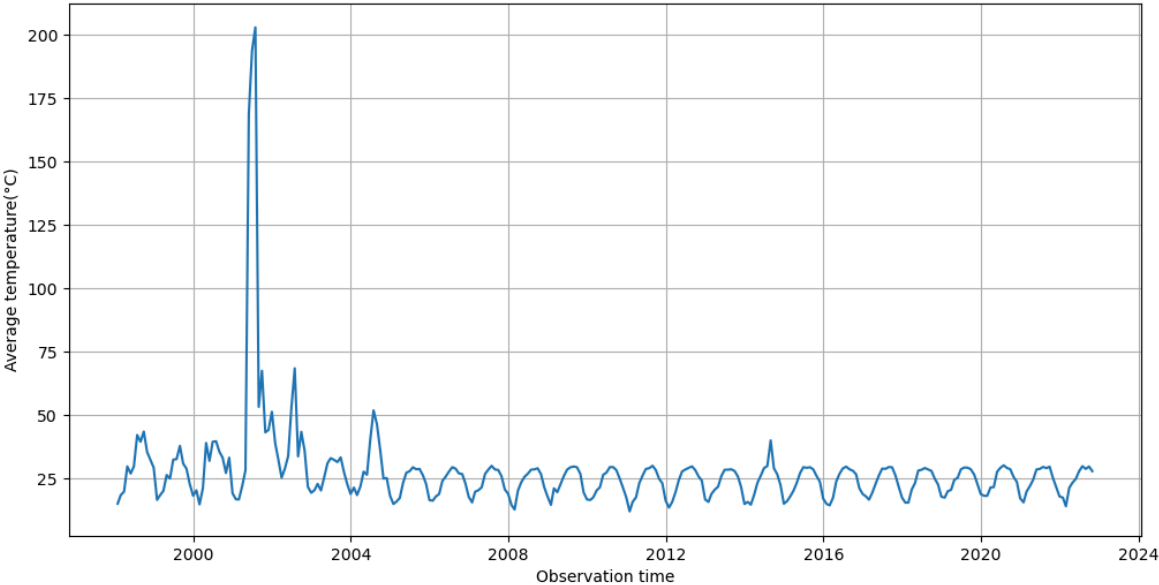
```
In [57]: import pandas as pd
import matplotlib.pyplot as plt
data = pd.read_csv('Baoan_Weather_1998_2022.csv', low_memory=False)

# 数据清理
data['TMP'] = data['TMP'].replace('+9999', pd.NA) # 替换缺失值
data['TMP'] = data['TMP'].str.split(',', expand=True)[0] # 仅保留温度部分
data['TMP'] = pd.to_numeric(data['TMP'], errors='coerce') # 转换为浮点数

# 将DATE列转为日期格式
data['DATE'] = pd.to_datetime(data['DATE'])

monthly_avg_temp = data.resample('ME', on='DATE')['TMP'].mean() / 10

# 绘图
plt.figure(figsize=(12, 6))
plt.plot(monthly_avg_temp.index, monthly_avg_temp.values)
plt.xlabel('Observation time')
plt.ylabel('Average temperature(°C)')
plt.grid()
plt.show()
```



趋势分析：图中曲线趋势显示了月平均气温随观测时间的变化，从2000年到2020年，气温变化呈现出周期性的波动，可能受到季节性因素的影响，同时整体上可能显示出长期的温度上升趋势，这可能与全球气候变暖的趋势相吻合。

```
In [ ]:
```

3. Global collection of hurricanes

导入库，读取数据

```
In [62]: import pandas as pd
Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js
# 读取CSV文件，设置low_memory=False以尝试更准确地推断数据类型
```

```
df = pd.read_csv('ibtracs.ALL.list.v04r00.csv',
                 usecols=range(17),
                 skiprows=[1, 2],
                 parse_dates=['ISO_TIME'],
                 na_values=['NOT_NAMED', 'NAME'],
                 low_memory=False)

# 显示前几行数据以检查加载是否正确
df.head()
```

Out[62]:

	SID	SEASON	NUMBER	BASIN	SUBBASIN	NAME	ISO_TIME	NAT
0	1842298N11080	1842	1	NI	BB	NaN	1842-10-25 06:00:00	
1	1842298N11080	1842	1	NI	BB	NaN	1842-10-25 09:00:00	
2	1842298N11080	1842	1	NI	BB	NaN	1842-10-25 12:00:00	
3	1842298N11080	1842	1	NI	BB	NaN	1842-10-25 15:00:00	
4	1842298N11080	1842	1	NI	AS	NaN	1842-10-25 18:00:00	

筛选10个风速最大的

```
In [63]: # 筛选出有风速和名称的数据
df_filtered = df[['NAME', 'WMO_WIND']].dropna()

# 将风速转换为数值类型，以便进行排序
df_filtered['WMO_WIND'] = pd.to_numeric(df_filtered['WMO_WIND'], errors='coerce')

# 按风速降序排序，并取前10个
top_10_hurricanes = df_filtered.sort_values(by='WMO_WIND', ascending=False).head()

# 打印结果
print(top_10_hurricanes)
```

	NAME	WMO_WIND
665954	PATRICIA	185.0
665952	PATRICIA	180.0
665956	PATRICIA	180.0
427636	ALLEN	165.0
482074	GILBERT	160.0
605746	WILMA	160.0
689332	DORIAN	160.0
689333	DORIAN	160.0
552459	LINDA	160.0
427634	ALLEN	155.0

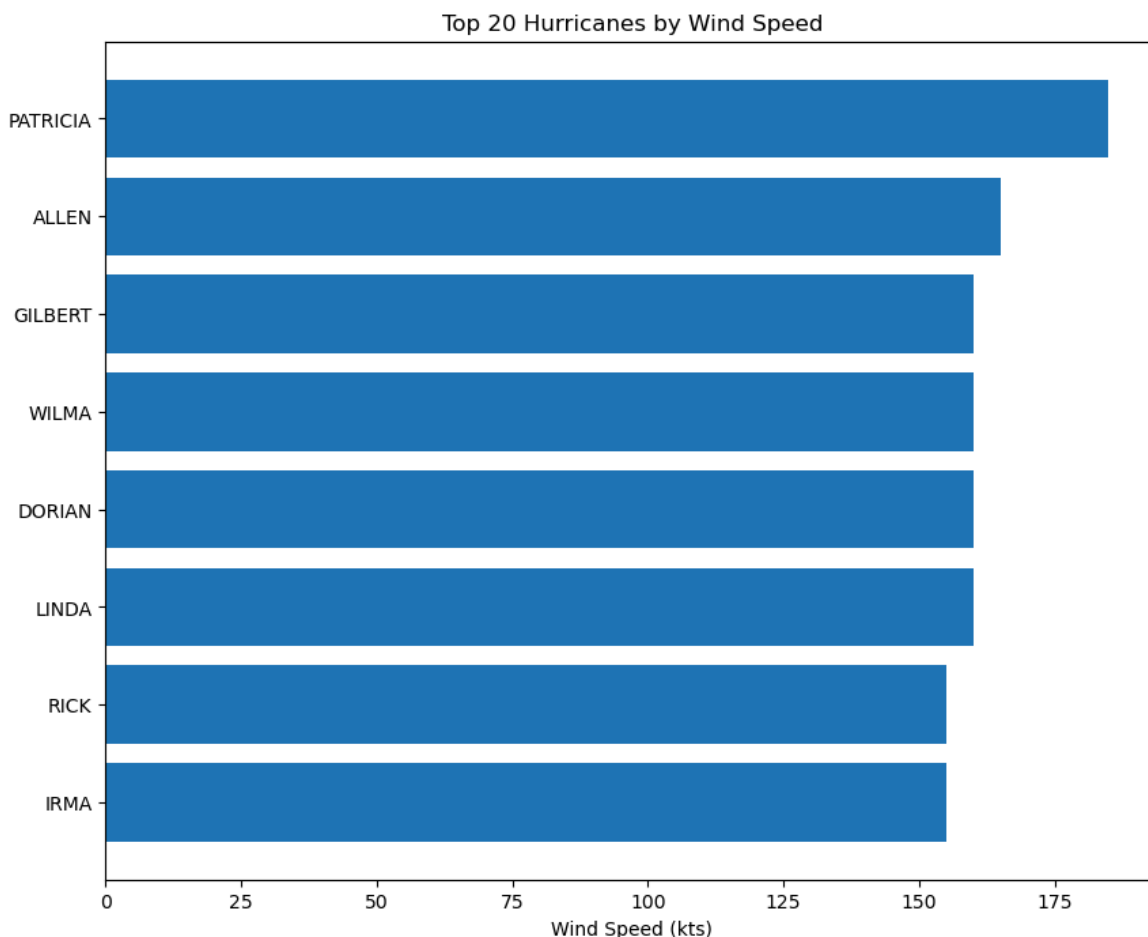
先对df_filtered 的DataFrame进行处理，将风速列 WMO_WIND 转换为数值类型，然后按风速降序排序并选取前20个飓风，最后绘制一个水平条形图来展示这些飓风的名称和对应的风速，其中最大的飓风显示在图表的顶部。

```
In [64]: import matplotlib.pyplot as plt

# 继续使用df_filtered
df_filtered['WMO_WIND'] = pd.to_numeric(df_filtered['WMO_WIND'], errors='coerce')

# 按风速降序排序，并取前20个
top_20_hurricanes = df_filtered.sort_values(by='WMO_WIND', ascending=False).head(20)

# 绘制条形图
plt.figure(figsize=(10, 8))
plt.barh(top_20_hurricanes['NAME'], top_20_hurricanes['WMO_WIND'])
plt.xlabel('Wind Speed (kts)')
plt.title('Top 20 Hurricanes by Wind Speed')
plt.gca().invert_yaxis() # 反转y轴，使得最大的飓风在顶部
plt.show()
```



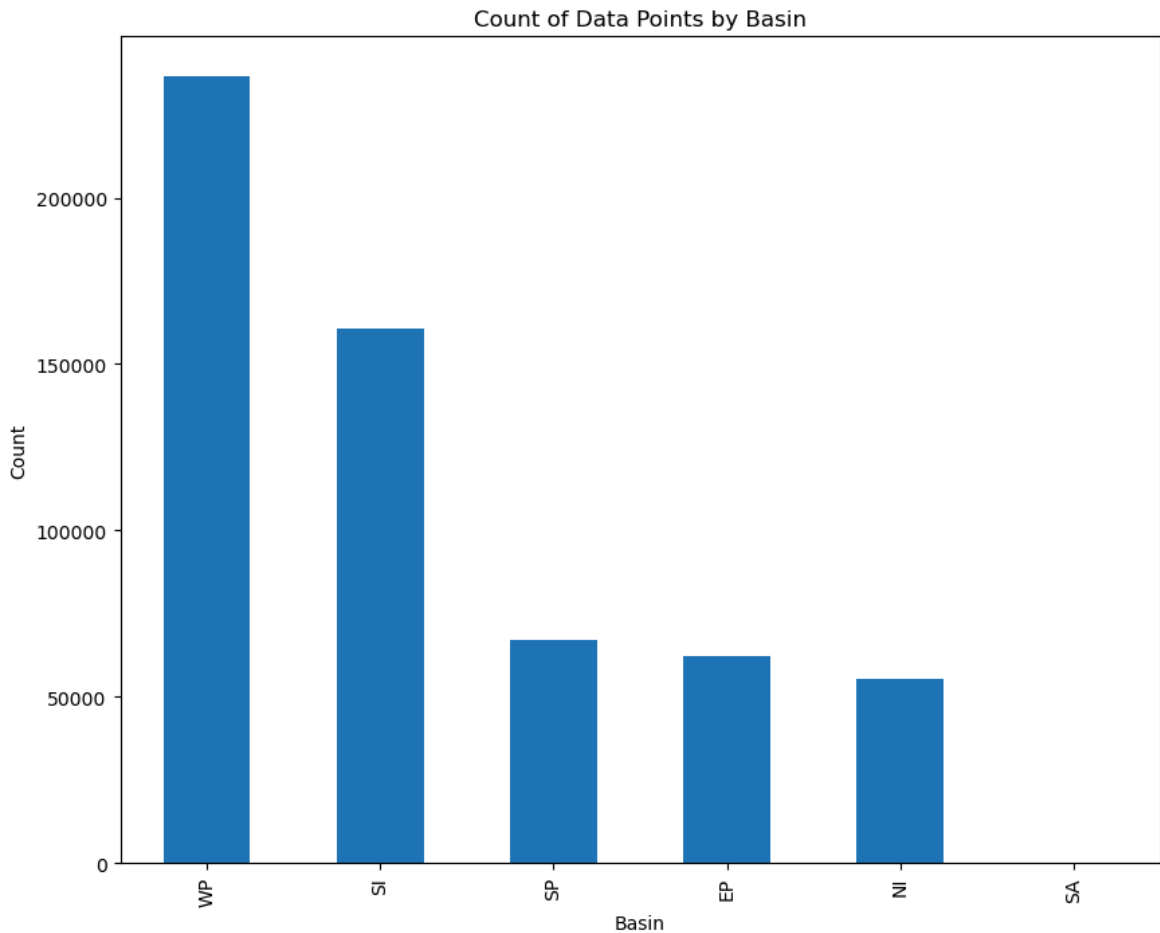
统计DataFrame df 中每个洗消槽的数据点数量，并通过绘制条形图来可视化这些统计结果，其中X轴表示洗消槽，Y轴表示对应的数据点数量，图表标题为“按洗消槽分类的数据点数量统计”。

```
In [65]: # 计算每个洗消槽的数据点数量
basin_counts = df['BASIN'].value_counts()

plt.figure(figsize=(10, 8))
```

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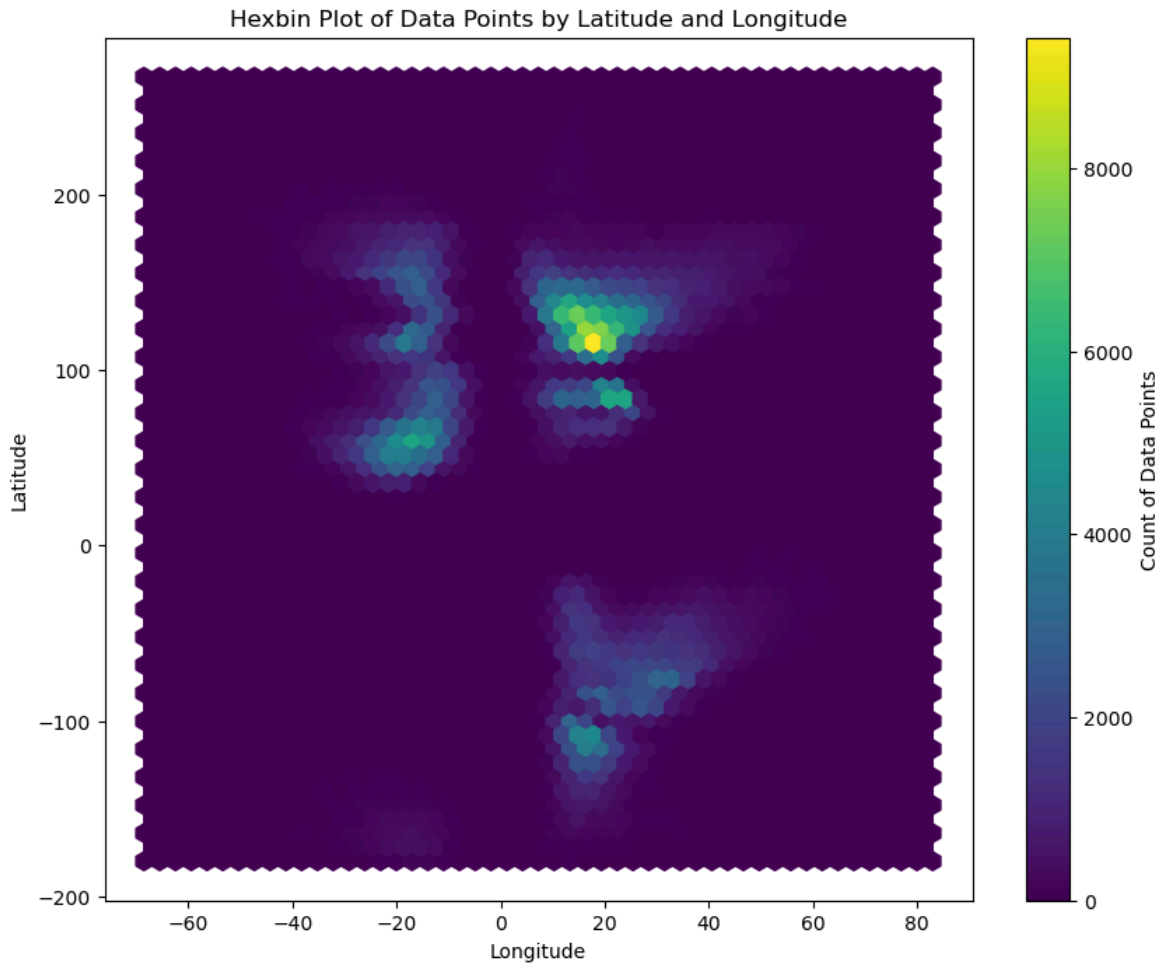
```
basin_counts.plot(kind='bar')
plt.xlabel('Basin')
plt.ylabel('Count')
plt.title('Count of Data Points by Basin')
plt.show()
```



先清理DataFrame df，移除缺少纬度（LAT）和经度（LON）数据的行，然后使用 hexbin函数绘制一个六边形分箱图，以展示数据点在地理坐标系中的分布密度。图中的X轴表示经度，Y轴表示纬度，颜色深浅表示数据点的密度，同时包含一个颜色条以解释颜色与数据点数量的关系，图表标题为“按纬度和经度分箱的数据点分布图”。

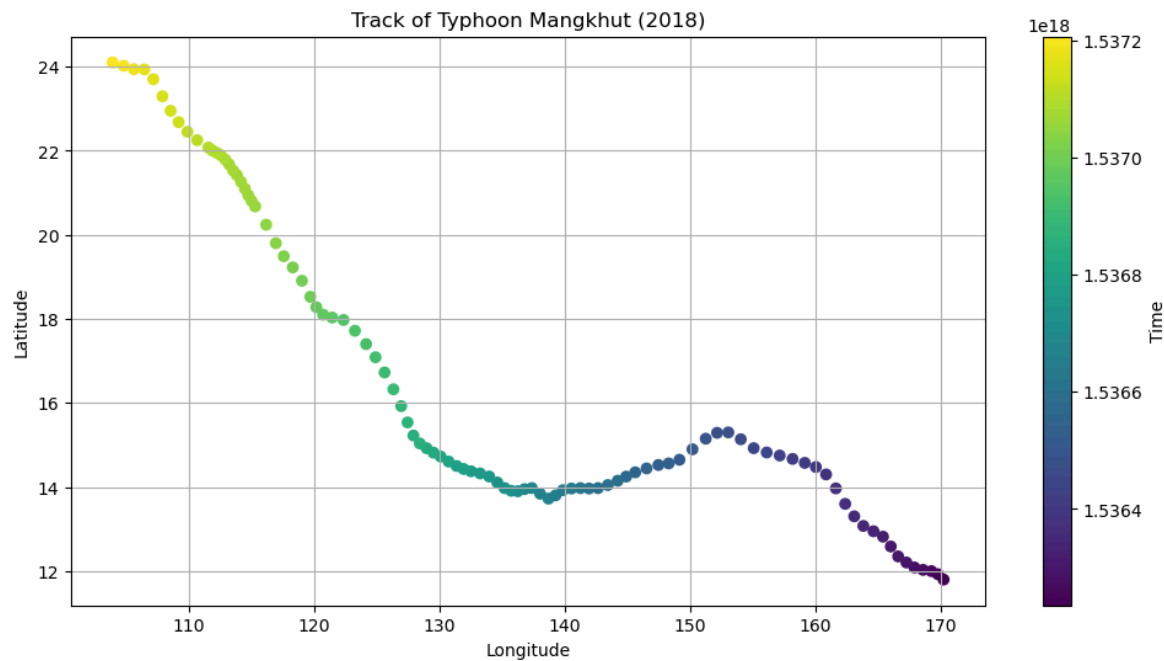
```
In [66]: # 确保纬度和经度列存在且没有缺失值
df = df.dropna(subset=['LAT', 'LON'])

# 绘制hexbin图
plt.figure(figsize=(10, 8))
plt.hexbin(df['LAT'], df['LON'], gridsize=50, cmap='viridis')
plt.colorbar(label='Count of Data Points')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Hexbin Plot of Data Points by Latitude and Longitude')
plt.show()
```

先筛选出2018年台风“山竹” (Mangkhut) 的数据，并绘制其路径的散点图。图中以经度为x轴，纬度为y轴，散点的颜色表示不同时间点，使用颜色条来标记时间，图表标题为“2018年台风山竹的路径”。同时，图中添加了网格线以便于观察。

```
In [67]: # 筛选出2018年的台风山竹 (Mangkhut) 的数据
mangosteen = df[(df['ISO_TIME'].dt.year == 2018) & (df['NAME'] == 'MANGKHUT')]
# 绘制散点图，以经度为x轴，纬度为y轴
plt.figure(figsize=(12, 6))
plt.scatter(mangosteen['LON'], mangosteen['LAT'], c=mangosteen['ISO_TIME'], cmap=
plt.colorbar(label='Time')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Track of Typhoon Mangkhut (2018)')
plt.grid(True)
plt.show()
```



先读取数据，并进行了初步的数据筛选，保留了1970年以后在西太平洋（WP）和东太平洋（EP）盆地发生的台风记录，最后展示筛选后数据的前几行。

```
In [68]: import pandas as pd

# 读取CSV文件
df = pd.read_csv('ibtracs.ALL.list.v04r00.csv',
                 usecols=range(17),
                 skiprows=[1, 2],
                 parse_dates=['ISO_TIME'],
                 na_values=['NOT_NAMED', 'NAME'],
                 low_memory=False)

# 过滤条件：1970年以后，且盆地为WP或EP
filtered_df = df[(df['ISO_TIME'].dt.year >= 1970) & (df['BASIN'].isin(['WP', 'EP'])]
filtered_df.head()
```

Out[68]:

	SID	SEASON	NUMBER	BASIN	SUBBASIN	NAME	ISO_TIME
350393	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 00:00:00
350394	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 03:00:00
350395	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 06:00:00
350396	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 09:00:00
350397	1970050N07151	1970	22	WP	MM	NANCY	1970-02-19 12:00:00

检查并确保ISO_TIME列中的所有数据都是有效的日期时间格式，将非日期时间格式的字符串转换为NaT。然后，代码删除了所有包含NaT值的行，并提取了日期部分。最后，代码统计了每天的数据点数量，并绘制了一个条形图来展示每天的数据点计数，X轴为日期，Y轴为数据点数量，图表标题为“每日数据点计数”。

```
In [5]: import pandas as pd
import matplotlib.pyplot as plt

# 读取CSV文件
df = pd.read_csv('ibtracs.ALL.list.v04r00.csv',
                 usecols=range(17),
                 skiprows=[1, 2],
                 parse_dates=['ISO_TIME'],
                 na_values=['NOT_NAMED', 'NAME'],
                 low_memory=False)

# 过滤条件：1970年以后，且盆地为WP或EP
filtered_df = df[(df['ISO_TIME'].dt.year >= 1970) & (df['BASIN'].isin(['WP', 'EP'])]
# 首先检查 'ISO_TIME' 列中是否有空值或非日期时间格式的字符串
print(filtered_df['ISO_TIME'].head())

# 尝试转换 'ISO_TIME' 列到 datetime 类型，指定 errors='coerce' 以处理错误
filtered_df['ISO_TIME'] = pd.to_datetime(filtered_df['ISO_TIME'], errors='coerce')

# 检查转换后的结果，看是否有 NaT 值
print(filtered_df['ISO_TIME'].head())

# 如果有 NaT 值，选择填充它们或从 DataFrame 中删除这些行
filtered_df = filtered_df.dropna(subset=['ISO_TIME'])

filtered_df['DATE'] = filtered_df['ISO_TIME'].dt.date

# 继续数据处理
daily_counts = filtered_df['DATE'].value_counts().sort_index()

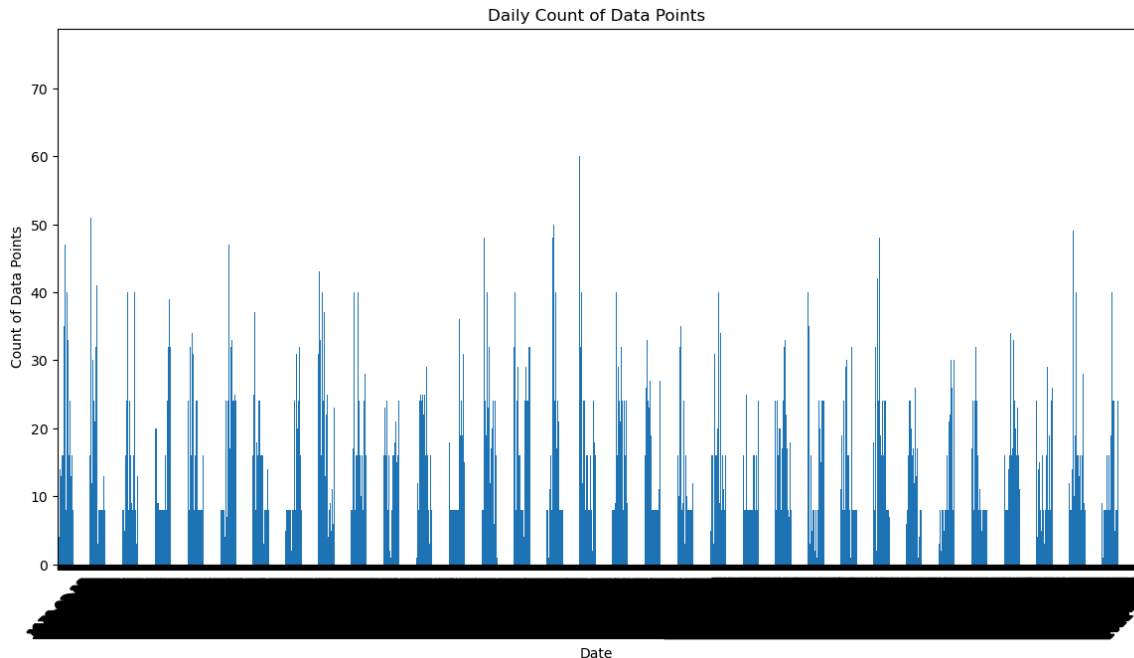
# 绘制条形图
plt.figure(figsize=(14, 7))
daily_counts.plot(kind='bar')
plt.xlabel('Date')
plt.ylabel('Count of Data Points')
plt.title('Daily Count of Data Points')
plt.xticks(rotation=45) # 旋转 x 轴标签以提高可读性
plt.show()

350393    1970-02-19 00:00:00
350394    1970-02-19 03:00:00
350395    1970-02-19 06:00:00
350396    1970-02-19 09:00:00
350397    1970-02-19 12:00:00
Name: ISO_TIME, dtype: datetime64[ns]
350393    1970-02-19 00:00:00
350394    1970-02-19 03:00:00
350395    1970-02-19 06:00:00
350396    1970-02-19 09:00:00
350397    1970-02-19 12:00:00
Name: ISO_TIME, dtype: datetime64[ns]
```

C:\Users\HONOR\AppData\Local\Temp\ipykernel_295484\89350123.py:18: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
filtered_df['ISO_TIME'] = pd.to_datetime(filtered_df['ISO_TIME'], errors='coerce')
```



首先在DataFrame `filtered_df` 中添加一个新的列 `DAY_OF_YEAR`, 用于存储 `ISO_TIME` 列中每个日期对应的一年中的第几天。然后, 它计算了一年中的每一天的平均数据点数, 方法是统计 `DAY_OF_YEAR` 列中每个唯一值的出现次数, 并将这些计数除以总的唯一值数量, 从而得到每天的平均数据点数。最后, 它展示这个气候学数据的前10行。

```
In [59]: # 计算一年中的第几天
filtered_df.loc[:, 'DAY_OF_YEAR'] = filtered_df['ISO_TIME'].dt.dayofyear
# 计算气候学: 一年中每一天的平均数据点数
climatology = filtered_df['DAY_OF_YEAR'].value_counts().sort_index() / len(filtered_df)
climatology.head(10)
```

```
Out[59]: DAY_OF_YEAR
1      0.226776
2      0.196721
3      0.202186
4      0.254098
5      0.286885
6      0.330601
7      0.308743
8      0.396175
9      0.377049
10     0.374317
Name: count, dtype: float64
```

首先计算 `filtered_df` 中每个日期对应的一年中的第几天, 并将结果存储在新列 `DAY_OF_YEAR` 中。然后, 它通过将每个 `DAY_OF_YEAR` 对应的日期计数与之前计算的气候学平均值 `climatology` 进行比较, 来计算日计数距平。距平是通过从每个日期的计数中减去相应的气候学平均值来得到的。最后, 它展示这些距平值的前10行。

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```
In [15]: # 计算日计数距平
filtered_df.loc[:, 'DAY_OF_YEAR'] = filtered_df['ISO_TIME'].dt.dayofyear
anomalies = filtered_df.groupby('DAY_OF_YEAR')['DATE'].count() - climatology
anomalies.head(10)
```

```
-----
NameError                                Traceback (most recent call last)
Cell In[15], line 2
      1 # 计算日计数距平
----> 2 filtered_df.loc[:, 'DAY_OF_YEAR'] = filtered_df['ISO_TIME'].dt.dayofyear
      3 anomalies = filtered_df.groupby('DAY_OF_YEAR')['DATE'].count() - climatology
      4 anomalies.head(10)

NameError: name 'filtered_df' is not defined
```

首先创建了一个包含日期和随机飓风活动数据的示例DataFrame，然后使用Pandas的resample函数将数据重新采样为年分辨率，并绘制了年飓风活动图。接着，它计算了年活动的平均值和标准差，定义了活动值超过平均值2个标准差的年份为异常年份，并打印出这些异常年份。这个过程可以帮助识别飓风活动异常的年份。

```
In [40]: import pandas as pd
import numpy as np # 导入 NumPy 库
import matplotlib.pyplot as plt

# 这里我们使用一个示例DataFrame来模拟
data = {
    'date': pd.date_range(start='1842-10-25', periods=100, freq='D'),
    'activity': np.random.randint(0, 100, size=100) # 随机生成一些活动数据
}
df = pd.DataFrame(data)
df.set_index('date', inplace=True)

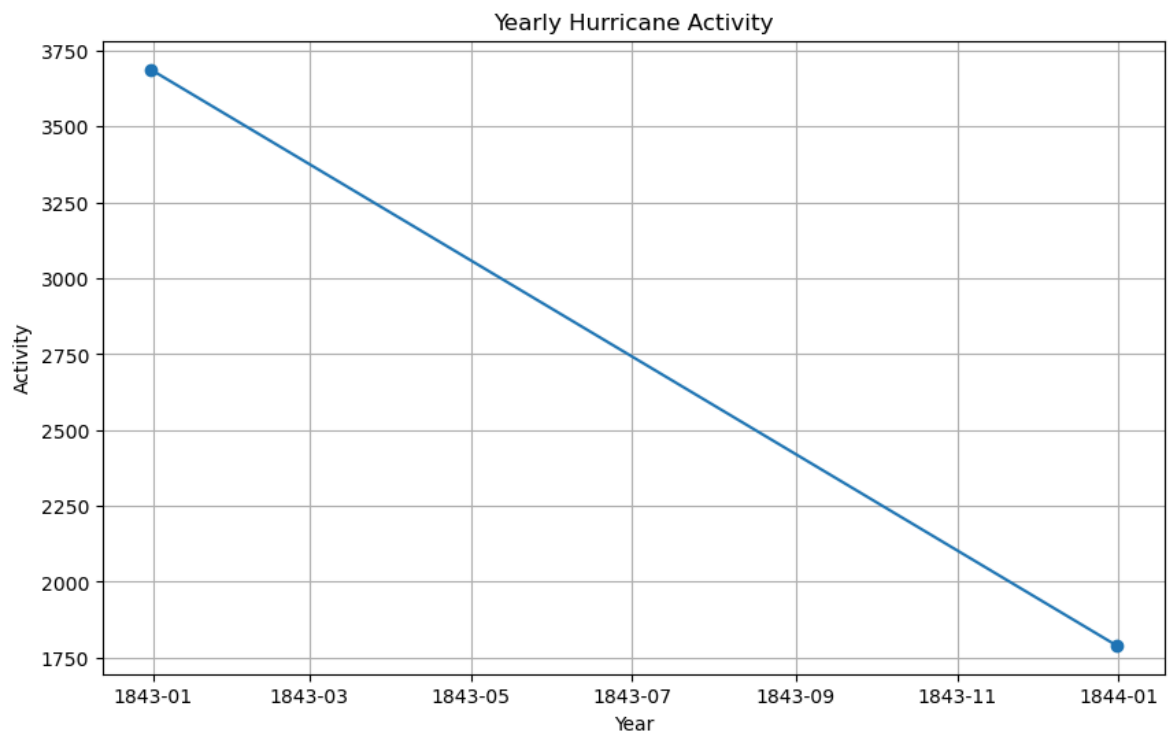
# 重新采样到年分辨率
yearly_activity = df.resample('YE').sum()

# 绘制重新采样后的数据
plt.figure(figsize=(10, 6))
plt.plot(yearly_activity.index, yearly_activity['activity'], marker='o')
plt.title('Yearly Hurricane Activity')
plt.xlabel('Year')
plt.ylabel('Activity')
plt.grid(True)
plt.show()

# 识别异常年份，这里简单地定义异常为活动值超过平均值的2个标准差
mean_activity = yearly_activity['activity'].mean()
std_activity = yearly_activity['activity'].std()
threshold = mean_activity + 2 * std_activity

# 找出超过阈值的年份
anomalous_years = yearly_activity[yearly_activity['activity'] > threshold].index

print(f"Anomalous hurricane activity years: {anomalous_years.tolist()}")
```



Anomalous hurricane activity years: []

In []:

4. Explore a data set

读取数据，并清理缺失值

```
In [24]: import pandas as pd
```

```
In [25]: # 加载数据集
df = pd.read_csv('Marine_CSV_sample .csv')

# 显示数据集的前几行
print(df.head())

# 清除缺失值
df = df.dropna()
```

	Identification	Latitude	Longitude	Time of Observation	\
0	D5GN6	-35.8	2.9	2015-01-12T00:00:00	
1	D5GN6	-35.9	6.9	2015-01-12T12:00:00	
2	D5GN6	-35.9	8.6	2015-01-12T18:00:00	
3	D5GN6	-35.7	11.9	2015-01-13T06:00:00	
4	D5GN6	-35.6	13.7	2015-01-13T12:00:00	

	Ice Accretion On Ship	Thickness of Ice	Accretion On Ship	\
0				
1				
2				
3				
4				

	Rate of Ice Accretion on Ship	Sea Level Pressure	\
0		29.83	
1		29.93	
2		30.02	
3		30.14	
4		30.12	

	Characteristics of Pressure	Tendency	Pressure	Tendency	...	\
0		8		0	...	
1		1		0	...	
2		1		0	...	
3		0		0	...	
4		8			...	

	Cloud Height Indicator	Cloud Height	Middle Cloud Type	High Cloud Type	\
0		5			
1		2	1	A	
2		2	0	0	
3		3	0	0	
4		5	7	A	

	Visibility	Visibility Indicator	Present Weather	Past Weather	Wind Direction	\
0	97		3	2	300	
1	97		2	2	180	
2	97		2	2	170	
3	98		1	2	140	
4	98		2	1	160	

	Wind Speed
0	139
1	165
2	154
3	118
4	123

[5 rows x 33 columns]

首先加载了一个名为 'Marine_CSV_sample.csv' 的CSV文件，并打印了数据信息以识别缺失值和数据类型。接着，检查了 'Air Temperature' 列的数据类型，并尝试将其转换为数值类型，将非数值条目转换为NaN。然后，代码清除了包含缺失值的行，并确保 'Time of Observation' 列是日期类型，将其设置为索引。最后，代码绘制了 'Air Temperature' 的时间序列图，以展示温度随时间的变化。这个过程旨在清洗和分析海洋数据中的气温信息。

```
In [12]: import pandas as pd
import matplotlib.pyplot as plt
# 加载CSV文件
df = pd.read_csv('Marine_CSV_sample.csv', low_memory=False)
```

```
print(df.info())

# 检查 'Air Temperature' 列的数据类型
print(df['Air Temperature'].dtype)

# 如果 'Air Temperature' 列不是数值类型，尝试将其转换为数值类型
# 这会把非数值的条目转换为NaN（缺失值）
df['Air Temperature'] = pd.to_numeric(df['Air Temperature'], errors='coerce')

# 再次检查数据类型，确保转换成功
print(df['Air Temperature'].dtype)

# 清除包含缺失值的行
df_cleaned = df.dropna(subset=['Air Temperature'])

# 确保时间列是日期类型
df_cleaned['Time of Observation'] = pd.to_datetime(df_cleaned['Time of Observati

# 设置时间为索引
df_cleaned.set_index('Time of Observation', inplace=True)

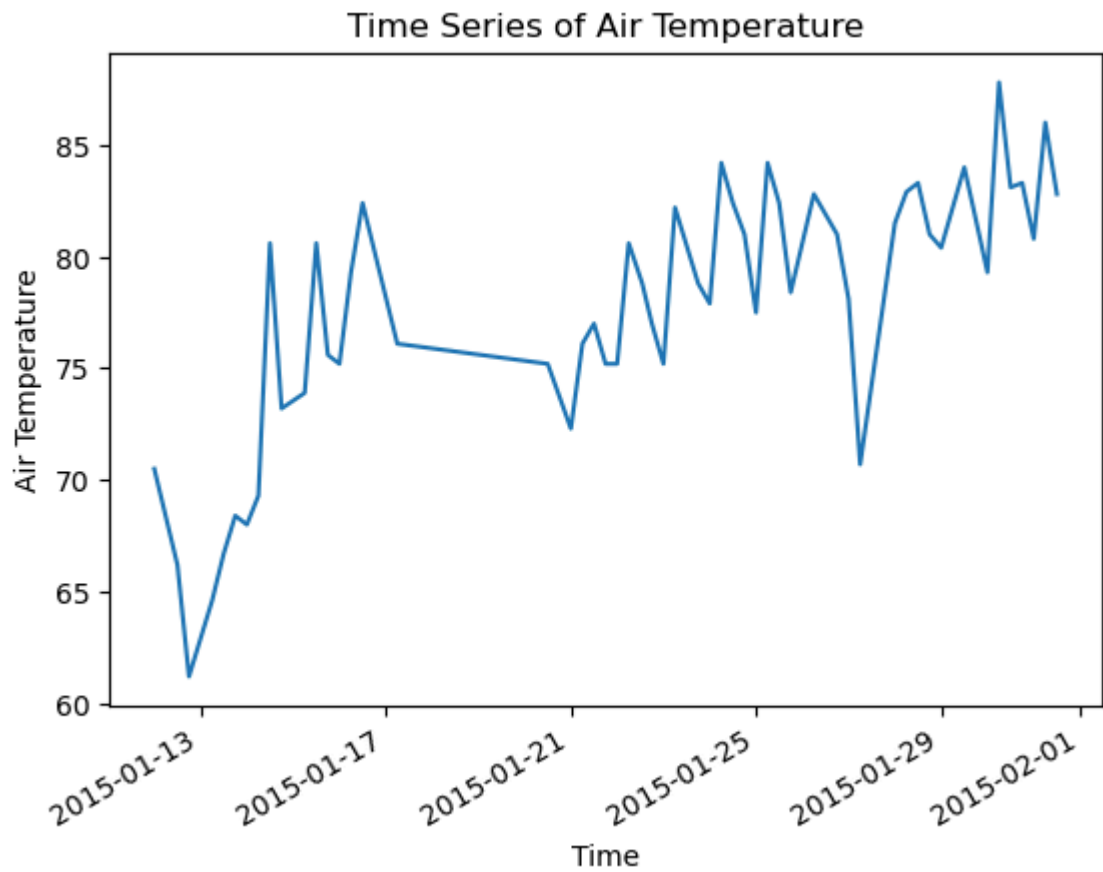
# 绘制时间序列图
df_cleaned['Air Temperature'].plot()
plt.title('Time Series of Air Temperature')
plt.xlabel('Time')
plt.ylabel('Air Temperature')
plt.show()
```



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 55 entries, 0 to 54
Data columns (total 33 columns):
#   Column                                     Non-Null Count  Dtype
---  -
0   Identification                             55 non-null     object
1   Latitude                                   55 non-null     float64
2   Longitude                                  55 non-null     float64
3   Time of Observation                         55 non-null     object
4   Ice Accretion On Ship                      55 non-null     object
5   Thickness of Ice Accretion On Ship         55 non-null     object
6   Rate of Ice Accretion on Ship              55 non-null     object
7   Sea Level Pressure                         55 non-null     object
8   Characteristics of Pressure Tendency      55 non-null     object
9   Pressure Tendency                         55 non-null     object
10  Air Temperature                           55 non-null     object
11  Wet Bulb Temperature                       55 non-null     object
12  Dew Point Temperature                     55 non-null     object
13  Sea Surface Temperature                   55 non-null     object
14  Wave Direction                            55 non-null     object
15  Wave Period                               55 non-null     object
16  Wave Height                               55 non-null     object
17  Swell Direction                           55 non-null     object
18  Swell Period                              55 non-null     object
19  Swell Height                              55 non-null     object
20  Total Cloud Amount                        55 non-null     object
21  Low Cloud Amount                          55 non-null     object
22  Low Cloud Type                            55 non-null     object
23  Cloud Height Indicator                    55 non-null     object
24  Cloud Height                              55 non-null     object
25  Middle Cloud Type                         55 non-null     object
26  High Cloud Type                           55 non-null     object
27  Visibility                                55 non-null     int64
28  Visibility Indicator                      55 non-null     object
29  Present Weather                           55 non-null     object
30  Past Weather                              55 non-null     object
31  Wind Direction                            55 non-null     int64
32  Wind Speed                                55 non-null     int64
dtypes: float64(2), int64(3), object(28)
memory usage: 14.3+ KB
None
object
float64

C:\Users\HONOR\AppData\Local\Temp\ipykernel_295268\3944193573.py:22: SettingWithC
opyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

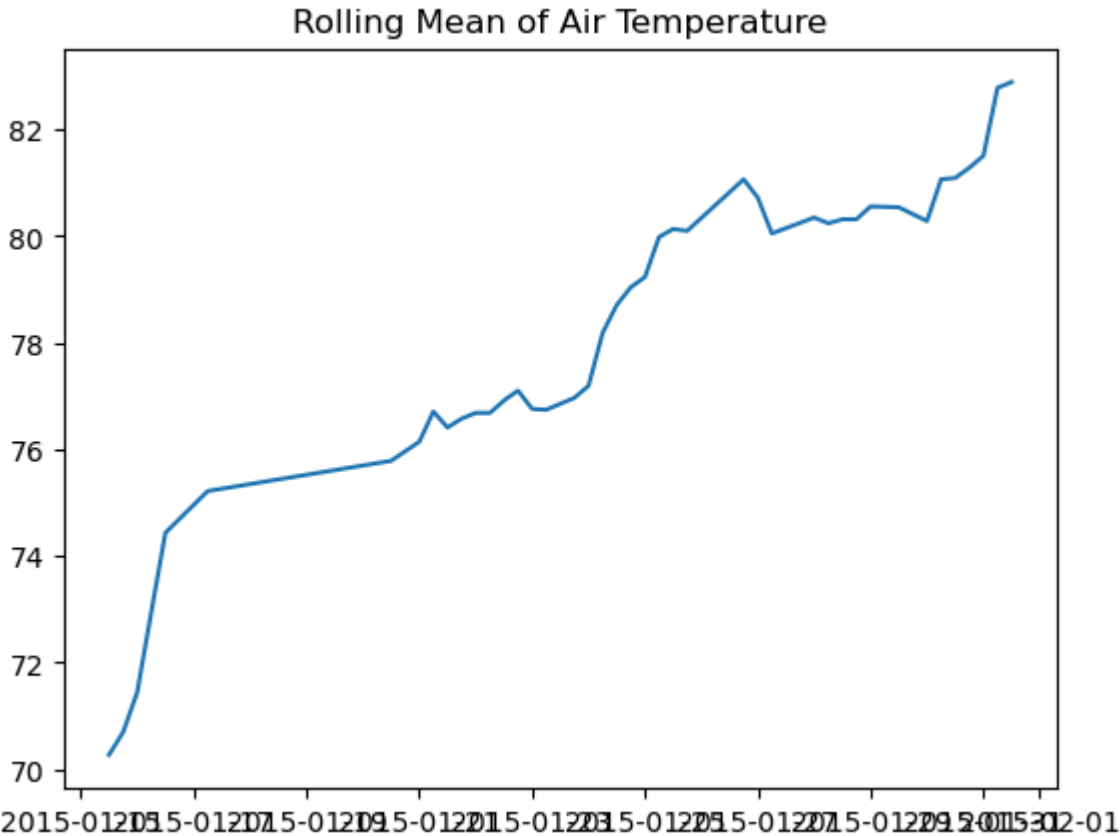
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
df_cleaned['Time of Observation'] = pd.to_datetime(df_cleaned['Time of Observat
ion'])
```



In []: 进行统计检查，对Air Temperature进行了时间趋势分析和描述性统计，检查了数据类型和缺

```
In [14]: import matplotlib.pyplot as plt

# 时间趋势分析
rolling_mean = df_cleaned['Air Temperature'].rolling(window=12).mean() # 12个月
plt.plot(rolling_mean)
plt.title('Rolling Mean of Air Temperature')
plt.show()
```



```
In [27]: # 描述性统计
humidity_stats = df[['Air Temperature', 'Dew Point Temperature', 'Wet Bulb Temperature']]

# 显示描述性统计结果
display(humidity_stats)
```

	Air Temperature	Dew Point Temperature	Wet Bulb Temperature
count	55	55	55
unique	38	41	1
top	75.2	73.4	
freq	5	3	55

```
In [28]: # 数据类型检查
data_types = df[['Air Temperature', 'Dew Point Temperature', 'Wet Bulb Temperature']]

# 显示数据类型结果
display(data_types)
```

```
Air Temperature      object
Dew Point Temperature object
Wet Bulb Temperature  object
dtype: object
```

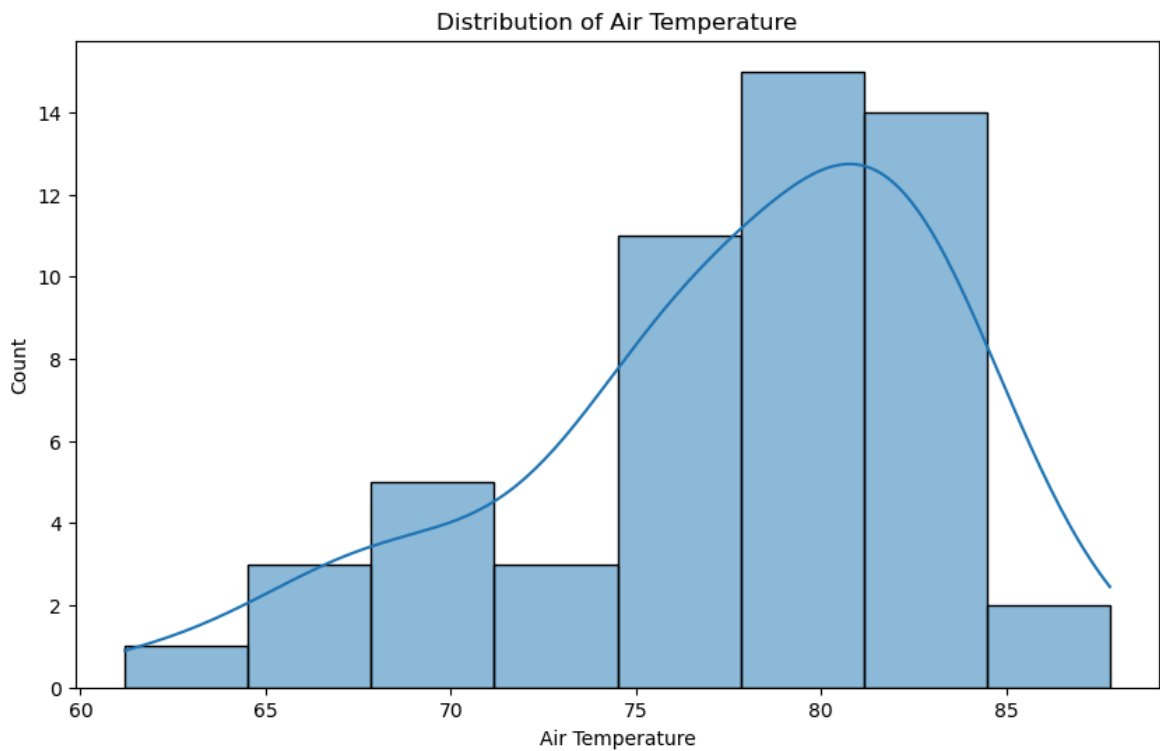
```
In [26]: # 缺失值检查
missing_values = df[['Air Temperature', 'Dew Point Temperature', 'Wet Bulb Temperature']]

# 显示缺失值结果
display(missing_values)
```

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js

```
Air Temperature      0  
Dew Point Temperature 0  
Wet Bulb Temperature 0  
dtype: int64
```

```
In [16]: import matplotlib.pyplot as plt  
import seaborn as sns  
# 分布检查: Air Temperature  
plt.figure(figsize=(10, 6))  
sns.histplot(df['Air Temperature'], kde=True)  
plt.title('Distribution of Air Temperature')  
plt.show()
```



```
In [ ]:
```

```
In [ ]:
```