Report from Analysis : Everest_Casualties_Analysis

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1. Selecting a Unique Dataset

Objective:

The primary goal is to load the dataset into a Python environment and perform an initial examination to understand its structure and quality. This sets the foundation for all subsequent data cleaning and analysis tasks.

Overview of the Dataset:

The dataset is titled **"Mount Everest Deaths"** and contains records related to fatalities on Mount Everest. Upon loading, the following columns were identified:

- **no.**: An identifier or serial number for each record.
- **name**: The name of the individual.
- **date**: The date of the incident.
- **age**: The age of the individual at the time of death.
- **expedition**: The name of the expedition the individual was part of.
- **nationality**: The nationality of the individual.
- **cause_of_death**: The reason for the individual's death.
- **location**: The place on Mount Everest where the incident occurred.

Actions Performed:

1. **Dataset Loading**:
   The dataset was successfully loaded using the Pandas library (pd.read_csv()), allowing for efficient data manipulation and exploration.
2. **Preview of the Dataset**:
   The head() function was used to view the first few rows, offering a snapshot of the data.
3. **Summary Information**:
   - **Column Names and Data Types**: The info() function provided details on column data types and the number of non-null values.
   - **Missing Values**: The isnull().sum() function was employed to identify columns with missing data.
4. **Initial Observations**:
   - The dataset contains both numerical and categorical columns.
   - Missing values were identified in several columns, including age and cause_of_death.
   - The column names were inconsistent, with some having spaces or special characters (e.g., no. and cause_of_death).

Outcome:

code:

```
import pandas as pd
# Load the dataset
file_path = 'D:/mount_everest_deaths.csv'
data = pd.read_csv(file_path)

# Display the first few rows to inspect the dataset
data.head() # Dataset preview
```

Output:

	No.	Name	Date	Age	Expedition	Nationality	Cause of death	Location
0	1	Dorje	June 7, 1922	NaN	1922 British Mount Everest Expedition	Nepal	Avalanche	Below North Col
1	2	Lhakpa	June 7, 1922	NaN	1922 British Mount Everest Expedition	Nepal	Avalanche	Below North Col
2	3	Norbu	June 7, 1922	NaN	1922 British Mount Everest Expedition	Nepal	Avalanche	Below North Col
3	4	Pasang	June 7, 1922	NaN	1922 British Mount Everest Expedition	Nepal	Avalanche	Below North Col
4	5	Pema	June 7, 1922	NaN	1922 British Mount Everest Expedition	Nepal	Avalanche	Below North Col

code:

```
data.info() # Dataset Info
```

output:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 310 entries, 0 to 309
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   No.             310 non-null    int64  
 1   Name            310 non-null    object 
 2   Date            310 non-null    object 
 3   Age             160 non-null    float64
 4   Expedition      271 non-null    object 
 5   Nationality     309 non-null    object 
 6   Cause of death  296 non-null    object 
 7   Location        291 non-null    object 
dtypes: float64(1), int64(1), object(6)
memory usage: 19.5+ KB
```

2. Cleaning The Dataset using Pandas and Numpy

The dataset under consideration records the details of fatalities on Mount Everest. It contains information about individuals, their expeditions, and other related details such as age, cause of death, and location. The dataset required cleaning to ensure it is ready for further preprocessing, exploratory data analysis (EDA), and modeling.

Steps Taken in Data Cleaning

1. Handling Missing Values

The dataset contained missing values in several columns:

- **Age**: Missing values in this column were filled with the median age **(38.0).** This approach minimizes the effect of outliers and ensures a balanced distribution.
- **Expedition**: Missing entries were replaced with the placeholder "Unknown Expedition" to ensure completeness.
- **Cause of Death**: Missing entries were replaced with the placeholder "Unknown Cause" to maintain data consistency.
- **Location**: Missing entries were replaced with "Unknown Location" to retain important spatial information without introducing biases.

2. Date Conversion

The **Date** column, originally in string format, was converted to a proper `datetime` format. This conversion facilitates easier analysis of temporal patterns, such as trends over the years.

3. Duplicate Removal

The dataset was checked for duplicate rows. While no duplicates were found, the process ensures data integrity.

4. Critical Null Checks

Columns critical for analysis, such as **Name** and **Date**, were verified to ensure no missing values existed. Rows with such critical data missing were removed if necessary.

5. Data Type Corrections

- The **Date** column was transformed into a `datetime` object.
- Numeric fields, such as **Age**, were retained as `float64` for flexibility in statistical analysis.

Post-Cleaning Dataset Overview

- **Number of Entries**: 310 rows
- **Columns**: 8 (No., Name, Date, Age, Expedition, Nationality, Cause of Death, Location)
- **Data Completeness**: No missing values remain.
- **Data Consistency**: All column values align with their intended data types.

code:

```
import pandas as pd
 import numpy as np

# Convert 'Date' to datetime format
data['Date'] = pd.to_datetime(data['Date'], errors='coerce')

# Handle missing values
data['Age'] = data['Age'].fillna(data['Age'].median())  # Replace NaN in 'Age' with the median age
data['Expedition'] = data['Expedition'].fillna('Unknown Expedition')  # Fill missing expeditions
data['Cause of death'] = data['Cause of death'].fillna('Unknown Cause')  # Fill missing causes
data['Location'] = data['Location'].fillna('Unknown Location')  # Fill missing locations

# Drop any rows where critical columns like 'Name' or 'Date' might be missing (none in this case)
data = data.dropna(subset=['Name', 'Date'])

# Check for and remove duplicates
data = data.drop_duplicates()

# Final cleaned dataset overview
data.info()
data
```

output:

```
<class 'pandas.core.frame.DataFrame'>
Index: 309 entries, 0 to 309
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   No.             309 non-null    int64
 1   Name            309 non-null    object
 2   Date            309 non-null    datetime64[ns]
 3   Age             309 non-null    float64
 4   Expedition      309 non-null    object
 5   Nationality     308 non-null    object
 6   Cause of death  309 non-null    object
 7   Location        309 non-null    object
dtypes: datetime64[ns](1), float64(1), int64(1), object(5)
memory usage: 21.7+ KB
```

1-100 309 rows × 8 columns

	No.	Name	Date	Age	Expedition	Nationality	Cause of death	Location
0	1	Dorje	1922-06-07	38.0	1922 British Mount Everest Expedition	Nepal	Avalanche	Below North Col
1	2	Lhakpa	1922-06-07	38.0	1922 British Mount Everest Expedition	Nepal	Avalanche	Below North Col
2	3	Norbu	1922-06-07	38.0	1922 British Mount Everest Expedition	Nepal	Avalanche	Below North Col
3	4	Pasang	1922-06-07	38.0	1922 British Mount Everest Expedition	Nepal	Avalanche	Below North Col
4	5	Pema	1922-06-07	38.0	1922 British Mount Everest Expedition	Nepal	Avalanche	Below North Col
5	6	Sange	1922-06-07	38.0	1922 British Mount Everest Expedition	Nepal	Avalanche	Below North Col
6	7	Temba	1922-06-07	38.0	1922 British Mount Everest Expedition	Nepal	Avalanche	Below North Col
7	8	Man Bahadur	1924-05-13	38.0	1924 British Mount Everest Expedition	Nepal	Pneumonia	Above Rongbuk B.C.
8	9	Lance-Naik Shamsherpun	1924-05-17	38.0	1924 British Mount Everest Expedition	Nepal	Brain hemorrhage	Above Rongbuk B.C.
9	10	Andrew Irvine	1924-06-09	22.0	1924 British Mount Everest Expedition	United Kingdom	Unknown. Body never found	N.E. Ridge

3. Preprocess The Columns using Pandas and Numpy

Objective:

The main goal of data preprocessing is to prepare raw data for further **Exploratory Data Analysis (EDA)** and machine learning models. Preprocessing ensures the data is cleaned, consistent, and in the right format for analysis. This report outlines the steps taken to preprocess the dataset to improve its quality and structure.

Dataset Overview:

The dataset consists of information related to individuals' climbing expeditions, including features such as **Age**, **Nationality**, **Cause of Death**, and **Location**. The dataset also contains temporal features like **Date** for extracting insights about the expeditions over time.

1. Standardization of Text Columns

Text data often contain inconsistencies like extra spaces, different capitalizations, and special characters. Standardizing these columns helps ensure consistency across the dataset:

- **Trimming Whitespaces**: Leading and trailing spaces were removed from all string fields to ensure uniformity.
- **Capitalization**: All text in the **Name**, **Expedition**, **Nationality**, **Cause of Death**, and **Location** columns were standardized to title case (first letter capitalized) for consistency.

2. Feature Extraction from Date

The **Date** column was transformed to a **datetime** format to allow easier manipulation. Several features were extracted from this column:

- **Year**: Extracted the year of the expedition.
- **Month**: Extracted the month to identify possible seasonal patterns.
- **Day of the Week**: Extracted the day of the week to determine if certain days influence the outcomes of expeditions.
- **Day**: Extracted the specific day of the month for more detailed time-based analysis.
- **Quarter**: The quarter (1-4) was derived to explore potential seasonal trends or correlations.

After extracting the temporal features, the **Date** column was removed as it was no longer needed.

3. Handling Numerical Data

Numerical columns, such as **Age**, may contain outliers or skewed distributions. The following steps were applied:

- **Normalization of Age**: The **Age** column was normalized using **Min-Max Scaling**, which scales the values between 0 and 1. This ensures that the feature is on the same scale as other numerical features, which is especially important for machine learning algorithms that are sensitive to feature scaling.
- **Outlier Handling**: Outliers in the **Age** column were detected using the **Interquartile Range (IQR)** method. The outliers were identified as values that fall outside the lower and upper bounds (1.5 * IQR from the first and third quartiles). These outliers were replaced by the median of **Age** to avoid skewing the analysis.

4. Categorical Feature Encoding

Machine learning models often require categorical variables to be encoded into numerical form. The following encoding methods were used:

- **Age Grouping**: The **Age** column was divided into **Age Groups** with categories such as 'Young', 'Middle-Aged', 'Elderly', and 'Very Elderly'. This grouping simplifies the analysis of age-related patterns.

5. Reorganization of Columns

After preprocessing, the dataset's columns were rearranged to enhance readability:

- **Key Features**: The first columns include **Name**, **Year**, **Month**, **DayOfWeek**, **Age**, and **Nationality**, as these are the most important features for analysis.
- **Encoded Features**: One-hot encoded features, such as **Cause of Death**, **Location**, and **Age Group**, were placed after the key features.

This reorganization makes the dataset more structured and easier to analyze.

6. Final Dataset Overview

The final preprocessed dataset includes the following features:

- **Numerical Features**: Age (normalized), Year, Month, DayOfWeek, etc.
- **Categorical Features**: One-hot encoded **Cause of Death**, **Location**, and **Age Group**.

Outcome: *code:*

```
import pandas as pd
import numpy as np

# 1. Drop rows with missing values
data.dropna(inplace=True)

# 2. Standardize text columns
text_columns = ['Name', 'Expedition', 'Nationality', 'Cause of death',
'Location']
for col in text_columns:
    data[col] = data[col].str.strip().str.title()  # Remove
leading/trailing spaces and capitalize

#  Ensure 'Date' column is in datetime format and extract features
data['Date'] = pd.to_datetime(data['Date'], errors='coerce')
data['Year'] = data['Date'].dt.year  # Extract Year
data['Month'] = data['Date'].dt.month  # Extract Month
data['DayOfWeek'] = data['Date'].dt.dayofweek  # Extract Day of the week
(0=Monday, 6=Sunday)

#  Handle outliers in 'Age' using IQR (Create a new column 'Age_Cleaned')
Q1 = data['Age'].quantile(0.25)  # First quartile
Q3 = data['Age'].quantile(0.75)  # Third quartile
IQR = Q3 - Q1  # Interquartile range
lower_bound = Q1 - 1.5 * IQR  # Lower bound
upper_bound = Q3 + 1.5 * IQR  # Upper bound

# Create a new column with outlier-handled values
age_median = data['Age'].median()
data['Age_Cleaned'] = np.where((data['Age'] < lower_bound) | (data['Age'] >
upper_bound), age_median, data['Age'])

#  Normalize the 'Age_Cleaned' column
data['Age_Normalized'] = (data['Age_Cleaned'] - data['Age_Cleaned'].min())
/ (data['Age_Cleaned'].max() - data['Age_Cleaned'].min())

# Create age groups based on the 'Age_Cleaned' column
bins = [0, 25, 50, 75, 100]  # Age ranges
labels = ['Young', 'Middle-Aged', 'Elderly', 'Very Elderly']  # Age group
labels
data['Age_Group'] = pd.cut(data['Age_Cleaned'], bins=bins, labels=labels,
include_lowest=True)

# Reorganize columns
columns_order = ['Name', 'Date', 'Year', 'Month', 'DayOfWeek', 'Age',
'Age_Cleaned', 'Age_Normalized', 'Nationality'] + \
                [col for col in data.columns if col not in ['Name', 'Date',
'Year', 'Month', 'DayOfWeek', 'Age', 'Age_Cleaned', 'Age_Normalized',
'Nationality']]
data = data[columns_order]

# Preview the processed dataset
print("\nProcessed Dataset Preview:")
data.head()
```

output:

1-100 308 rows × 14 columns

	Name	Date	Year	Month	DayOfWeek	Age	Age_Cleaned	Age_Normalized	Nationality	No.	Expedition
0	Dorje	1922-06-07	1922	6	2	38.0	38.0	0.50	Nepal	1	1922 British Mount Everest Expedition
1	Lhakpa	1922-06-07	1922	6	2	38.0	38.0	0.50	Nepal	2	1922 British Mount Everest Expedition
2	Norbu	1922-06-07	1922	6	2	38.0	38.0	0.50	Nepal	3	1922 British Mount Everest Expedition
3	Pasang	1922-06-07	1922	6	2	38.0	38.0	0.50	Nepal	4	1922 British Mount Everest Expedition
4	Pema	1922-06-07	1922	6	2	38.0	38.0	0.50	Nepal	5	1922 British Mount Everest Expedition
5	Sange	1922-06-07	1922	6	2	38.0	38.0	0.50	Nepal	6	1922 British Mount Everest Expedition
6	Temba	1922-06-07	1922	6	2	38.0	38.0	0.50	Nepal	7	1922 British Mount Everest Expedition
7	Man Bahadur	1924-05-13	1924	5	1	38.0	38.0	0.50	Nepal	8	1924 British Mount Everest Expedition
8	Lance-Naik Shamsherpun	1924-05-17	1924	5	5	38.0	38.0	0.50	Nepal	9	1924 British Mount Everest Expedition
9	Andrew Irvine	1924-06-09	1924	6	0	22.0	38.0	0.50	United Kingdom	10	1924 British Mount Everest Expedition
10	George Mallory	1924-06-09	1924	6	0	37.0	37.0	0.25	United Kingdom	11	1924 British Mount Everest Expedition
11	Maurice Wilson	1934-05-31	1934	5	3	36.0	36.0	0.00	United Kingdom	12	Solo Expedition
12	Dorje Mingma	1952-10-31	1952	10	4	38.0	38.0	0.50	Nepal	13	Swiss Expedition
13	Wang Ji	1960-04-11	1960	4	0	38.0	38.0	0.50	China	14	Chinese Expedition Northern Slope
14	Shao Shi-Ching	1960-04-29	1960	4	4	38.0	38.0	0.50	China	15	Chinese Expedition Northern Slope
15	Nawang Tshering	1962-04-28	1962	4	5	38.0	38.0	0.50	Nepal	16	Chinese Expedition Northern Slope
16	Jake Breitenbach	1963-03-23	1963	3	5	27.0	38.0	0.50	United States	17	Norman Dyhrenfurth'S American Mount Everes
17	Ma Gao-Shu	1966-05-01	1966	5	6	38.0	38.0	0.50	China	18	Chinese Everest Expedition
18	Phu Dorjee Sherpa	1969-10-18	1969	10	5	38.0	38.0	0.50	Nepal	19	Japanese Everest Expedition
19	Nima Dorje	1970-04-05	1970	4	6	38.0	38.0	0.50	Nepal	20	Japanese Skiing Expedition
20	Kunga Norbu	1970-04-05	1970	4	6	38.0	38.0	0.50	Nepal	21	Japanese Skiing Expedition
21	Mima Norbu	1970-04-05	1970	4	6	38.0	38.0	0.50	Nepal	22	Japanese Skiing Expedition
22	Pasang	1970-04-05	1970	4	6	38.0	38.0	0.50	Nepal	23	Japanese Skiing Expedition
23	Kami Tshering	1970-04-05	1970	4	6	38.0	38.0	0.50	Nepal	24	Japanese Skiing Expedition
24	Kyak Tsering	1970-04-09	1970	4	3	36.0	36.0	0.00	Nepal	25	Japanese Skiing Expedition
25	Kiyoshi Narita	1970-04-21	1970	4	1	38.0	38.0	0.50	Japan	26	Japanese Skiing Expedition
26	Harsh Vardhan	1971-04-18	1971	4	6	31.0	38.0	0.50	India	27	International Expedition Of 1971
27	Tony Tighe	1972-11-16	1972	11	3	38.0	38.0	0.50	Australia	28	Mt. Qomolangma Expedition
28	Jangbu	1973-10-12	1973	10	4	38.0	38.0	0.50	Nepal	29	Unknown Expedition
29	Gérard Devouassoux	1974-09-09	1974	9	0	38.0	38.0	0.50	France	30	French West Ridge Direct Expedition
30	Pemba Dorje	1974-09-09	1974	9	0	38.0	38.0	0.50	Nepal	31	French West Ridge Direct Expedition
31	Lhakpa	1974-09-09	1974	9	0	38.0	38.0	0.50	Nepal	32	French West Ridge Direct Expedition
32	Nawang Lutuk	1974-09-09	1974	9	0	38.0	38.0	0.50	Nepal	33	French West Ridge Direct Expedition
33	Nima Wangchu	1974-09-09	1974	9	0	38.0	38.0	0.50	Nepal	34	French West Ridge Direct Expedition
34	Sanu Wongal	1974-09-09	1974	9	0	38.0	38.0	0.50	Nepal	35	French West Ridge Direct Expedition
35	Wu Zhuong Yue	1975-05-04	1975	5	6	38.0	38.0	0.50	China	36	Unknown Expedition
37	Mick Burke	1975-09-26	1975	9	4	34.0	38.0	0.50	United Kingdom	38	Bonington'S 1975 Everest Expedition
38	Terry Thompson	1976-04-10	1976	4	5	38.0	38.0	0.50	United Kingdom	39	British-Nepal Army Everest Expedition
39	Dawa Nuru	1978-04-18	1978	4	1	38.0	38.0	0.50	Nepal	40	Unknown Expedition
40	Shi Ming-Ji	1978-04-18	1978	4	1	38.0	38.0	0.50	China	41	Chinese Iranian Expedition
41	Ang Phu	1979-05-16	1979	5	2	38.0	38.0	0.50	Nepal	42	Yugoslavian Expedition
42	Ray Genet	1979-10-02	1979	10	1	48.0	38.0	0.50	United States	43	Gerhard Schmatz German Expedition Or 1979
43	Hannelore Schmatz	1979-10-02	1979	10	1	39.0	39.0	0.75	Germany	44	Gerhard Schmatz German Expedition Or 1979
44	Wang Hong-Bao	1979-10-12	1979	10	4	38.0	38.0	0.50	China	45	Japanese Alpine Club Reconnaissance Expedi
45	Lou Lan	1979-10-12	1979	10	4	38.0	38.0	0.50	China	46	Japanese Alpine Club Reconnaissance Expedi
46	Nima Thaxi	1979-10-12	1979	10	4	38.0	38.0	0.50	China	47	Japanese Alpine Club Reconnaissance Expedi

4. Exploratory Data Analysis (EDA) on the Data using Seaborn

This report summarizes the findings of the exploratory data analysis (EDA) performed on the dataset related to Mount Everest incidents. The EDA utilized various visualizations and statistical summaries to uncover patterns and insights.

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1. Age Distribution

- **Objective:** Analyze the age distribution of individuals in the dataset.
  - A **histogram** and **density plot** revealed the most common age ranges.
  - A **box plot** highlighted the presence of outliers in the age column.
  - Age distribution showed a significant concentration in certain age groups, likely tied to typical climber demographics.

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2. Age Group Analysis

- **Objective:** Group individuals into categories based on age and examine their distribution.
  - A **FacetGrid histogram** showed variations in the count of individuals across age groups.
  - Age groups such as "Young" and "Middle-Aged" had the highest representation.

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3. Cause of Death

- **Objective:** Identify the most common causes of death.
  - A **bar plot** displayed the top 10 causes of death.
  - A **stem plot** highlighted the count of fatalities for these causes.
  - A **pie chart** visualized the proportional distribution of each cause.

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4. Nationality Distribution

- **Objective:** Explore the distribution of nationalities in the dataset.
  - A **bar plot** showed Nepalese climbers had the highest representation, potentially due to their roles as guides or local climbers.
  - A **pie chart** confirmed the dominance of a few nationalities in the dataset.

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5. Incidents Over Time

- **Objective:** Examine the temporal trends in fatalities.
  - A **line plot** of fatalities over years revealed peaks, likely tied to specific disasters or seasons.
  - A **cumulative count plot** highlighted a steady increase in incidents over time.

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6. Cause of Death by Month

- **Objective:** Investigate the seasonality of incidents.
  - A **heatmap** of causes of death by month identified certain months (e.g., April, May) as particularly dangerous, aligning with climbing seasons.

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7. Relationship Between Age and Year

- **Objective:** Explore how age correlates with the year of incidents.
  - A **scatter plot** showed no strong trend but highlighted individual clusters.

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8. Expedition and Age Analysis

- **Objective:** Analyze participation and age in expeditions.
  - A **count plot** for expeditions revealed the most common expeditions in the dataset.
  - A **bar plot** and **scatter plot** further connected age with expedition participation.

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9. Distribution by Cause of Death

- **Objective:** Investigate how causes of death vary across individuals.
  - A **violin plot** displayed the age distribution for each cause of death, highlighting variations in age ranges for different causes.

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10. Temporal Patterns

- **Objective:** Understand how incidents changed over decades or years.
  - A **line plot** and **cumulative plot** confirmed the increasing trend in fatalities, particularly after significant events like avalanches or earthquakes.

Outcome:

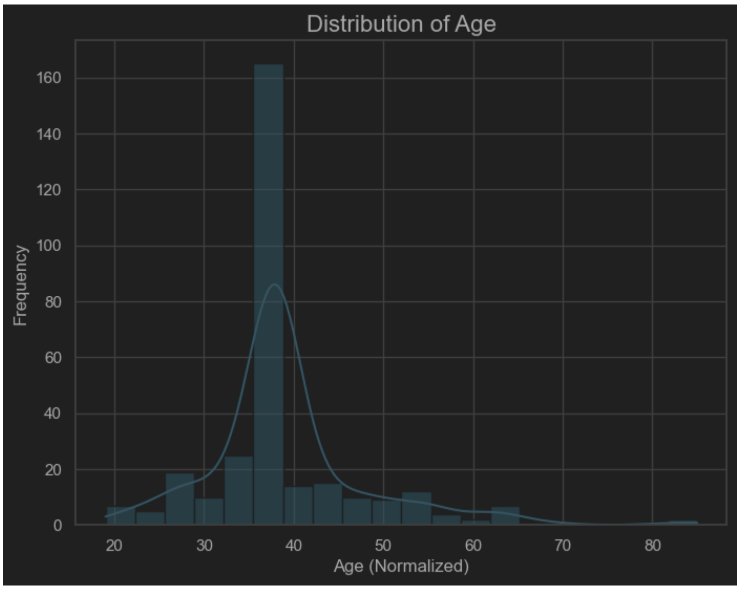
code:

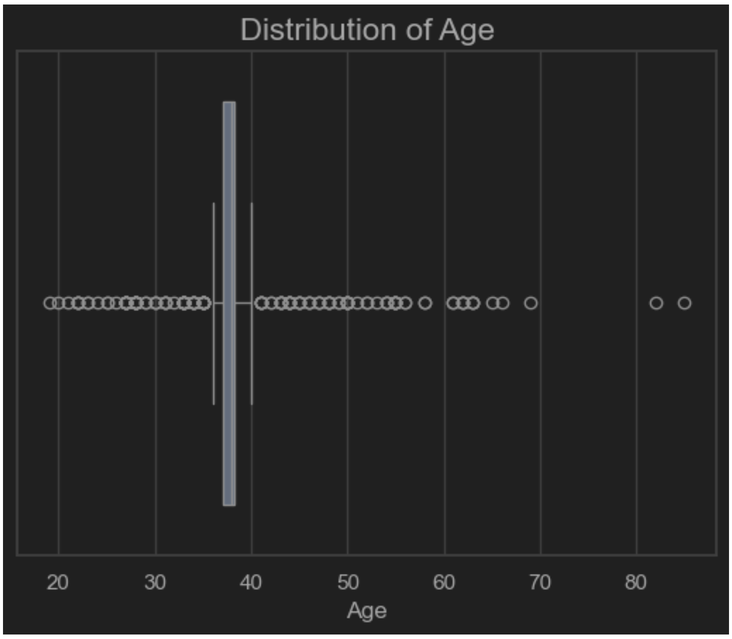
```
import seaborn as sns
import matplotlib.pyplot as plt
# age bar
plt.figure(figsize=(8, 6))
sns.histplot(data['Age'], kde=True, bins=20, color='skyblue')
plt.title('Distribution of Age', fontsize=16)
plt.xlabel('Age (Normalized)', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.show()

#box age distrubation
sns.boxplot(x=data['Age'])
plt.title('Distribution of Age', fontsize=16)

# age density
sns.kdeplot(data['Age'], fill=True)
plt.title('Age Density', fontsize=16)

#  Dependency Plots
sns.pairplot(data, hue='Cause of death', palette='tab10')
plt.show()

# age-group
g = sns.FacetGrid(data, col='Age_Group')
g.map(sns.histplot, 'Age')

# pie-chart cause of death
cause=data['Cause of death'].apply(lambda x: x[0:25])
cause1=cause.value_counts()
print(cause1)
plt.figure(figsize=(6,6), dpi=80)
plt.pie(cause1,
labels=cause1.index.tolist(),counterclock=False,startangle=0)
plt.axis('equal')
plt.title('Cause of death', fontsize=20)
plt.show()

# expedition Bar Graph
plt.figure(figsize=(20,7))
sns.countplot(x="Expedition", data=data)
plt.title("Expedition Bar Graph")
plt.xticks(rotation=90)
plt.show()

# person bar graph
plt.figure(figsize=(20,7))
sns.countplot(x="Age", data=data)
plt.title('Person Age Bar Graph')
plt.xticks(rotation=90)
plt.show()


#bar Graph Nationality
fig = plt.figure(figsize=(12,6))
```

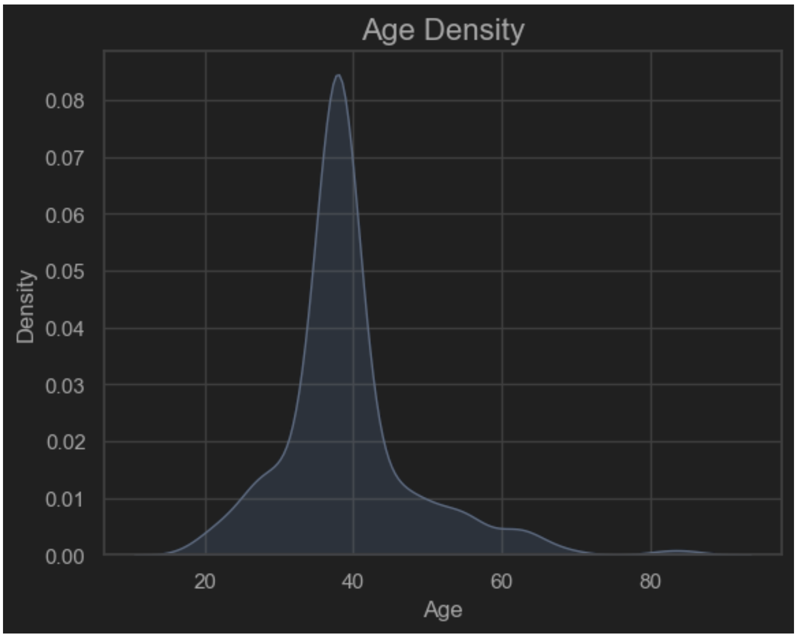
```
sns.barplot(x=data['Nationality'].value_counts().index,y=data['Nationality'
].value_counts().values,palette=color,edgecolor='#000080')
plt.xlabel('Nationality',weight='bold')
plt.tick_params(axis='x',labelsize=10,rotation=90)
plt.tick_params(labelleft=False,left=False)
plt.title('Nepal Nationality more deaths in mount-everest-climbing')
plt.suptitle('Nationality
Distripution',weight='bold',fontname='monospace',fontsize=20)

# nationality pie-chart
nation=data['Nationality']
nation1=nation.value_counts()
plt.figure(figsize=(6,6), dpi=80)
plt.pie(nation1,
labels=nation1.index.tolist(),counterclock=False,startangle=0)
plt.axis('equal')
plt.title('Nationality', fontsize=20)
plt.show()

# age vs year scatter plot
plt.figure(figsize=(10, 6))
sns.scatterplot(data=data, x='Age', y='Year', color='blue', alpha=0.7)
plt.title('Scatter Plot of Age vs. Year', fontsize=16)
plt.xlabel('Age', fontsize=12)
plt.ylabel('Year', fontsize=12)
plt.grid(alpha=0.3)
plt.show()

# BarPlot
sns.barplot(x=data['Cause of death'].value_counts().head(10).index,
            y=data['Cause of death'].value_counts().head(10).values)
plt.xticks(rotation=90)
plt.title('Cause of Death', fontsize=16)

# Nationality Bar
nationality_age_mean =
data.groupby('Nationality')['Age'].mean().sort_values(ascending=False)
sns.barplot(x=nationality_age_mean.index, y=nationality_age_mean.values)
plt.xticks(rotation=90)
plt.title('Nationality', fontsize=16)

# violin Plot
sns.violinplot(data=data, x='Cause of death', y='Age', palette='muted')
plt.title('Age Distribution by Cause of Death')
plt.xticks(rotation=45)
plt.show()

#top 10 cause of death
top_causes = data['Cause of death'].value_counts().head(10)
plt.stem(top_causes.index, top_causes.values)
plt.title('Top 10 Causes of Death')
plt.xlabel('Cause of Death')
plt.ylabel('Count')
plt.xticks(rotation=90)
plt.show()



# Line - Number of Incident Over Years
data['Year'].value_counts().sort_index().plot(kind='line', marker='o')
plt.title('Number of Incidents Over Years')
```

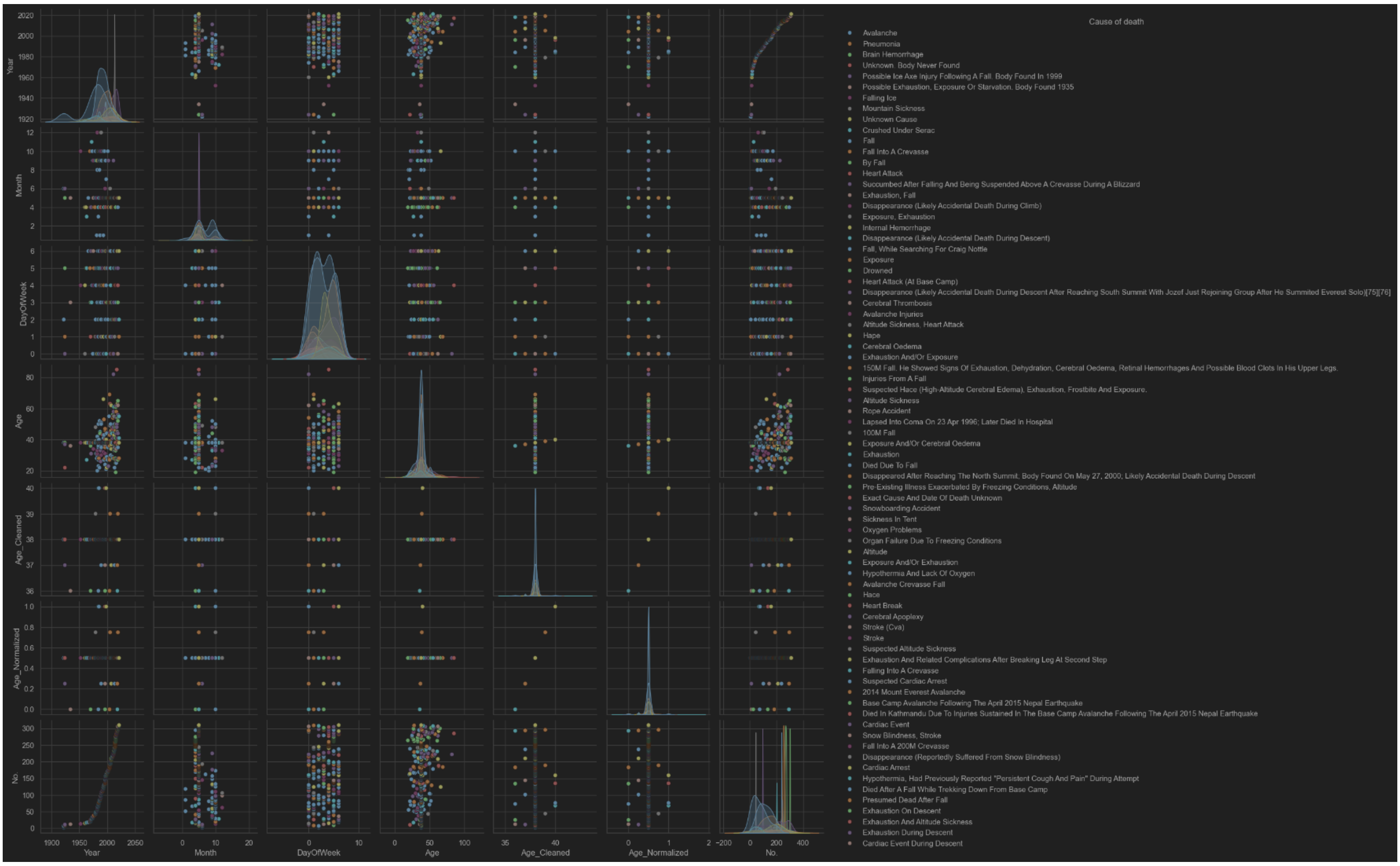
```
plt.xlabel('Year')
plt.ylabel('Count')
plt.show()

# Category Portion
data['Cause of
death'].value_counts(normalize=True).plot.pie(autopct='%1.1f%%',
figsize=(8, 8))
plt.title('Proportion of Causes of Death')
plt.show()

# Heatmape of cause of death by month
pivot_table = data.pivot_table(index='Cause of death', columns='Month',
aggfunc='size', fill_value=0)
sns.heatmap(pivot_table, cmap='YlGnBu')
plt.title('Heatmap of Causes of Death by Month')
plt.xlabel('Month')
plt.ylabel('Cause of Death')
plt.show()

# fatalities over time
data['Cumulative_Count'] = data.groupby('Year').cumcount() + 1
sns.lineplot(x='Year', y='Cumulative_Count', data=data, marker='o')
plt.title('Cumulative Fatalities Over Time')
plt.show()
```

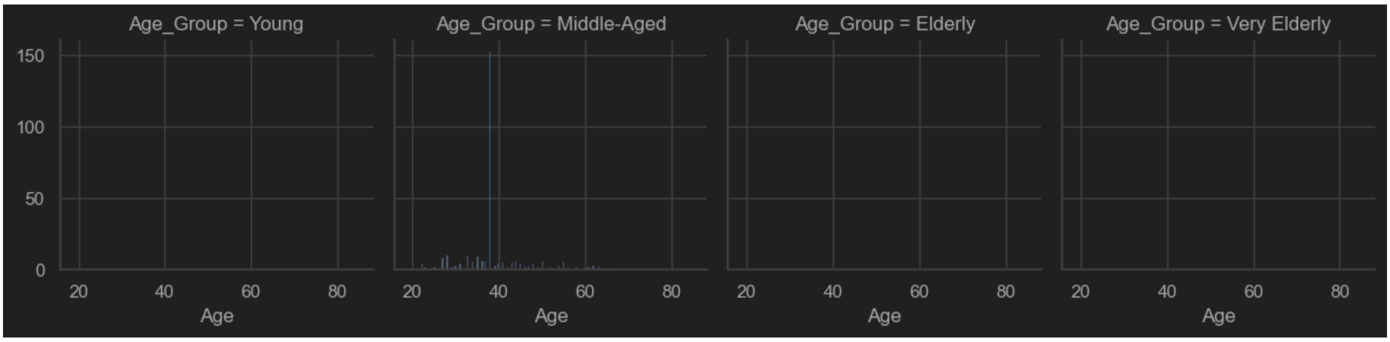
output:

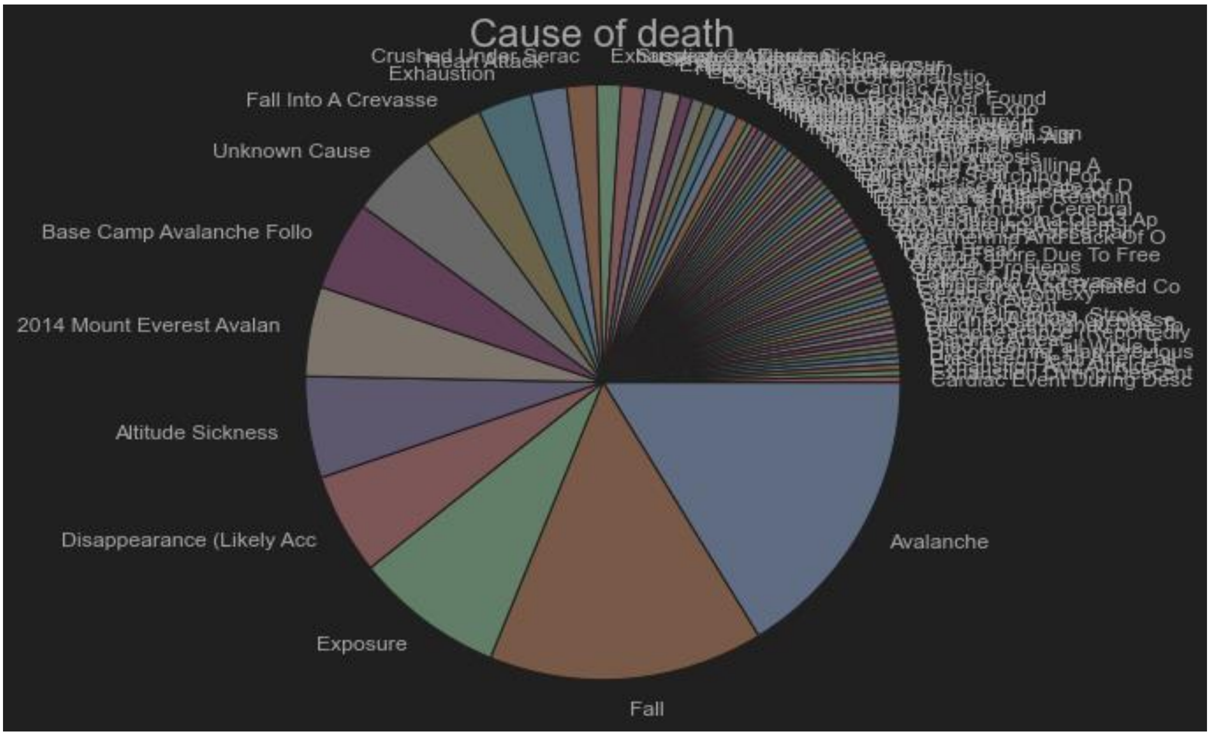

Distribution of Age
Frequency
0
20
40
60
80
100
120
140
160
20
30
40
50
60
70
80
Age (Normalized)

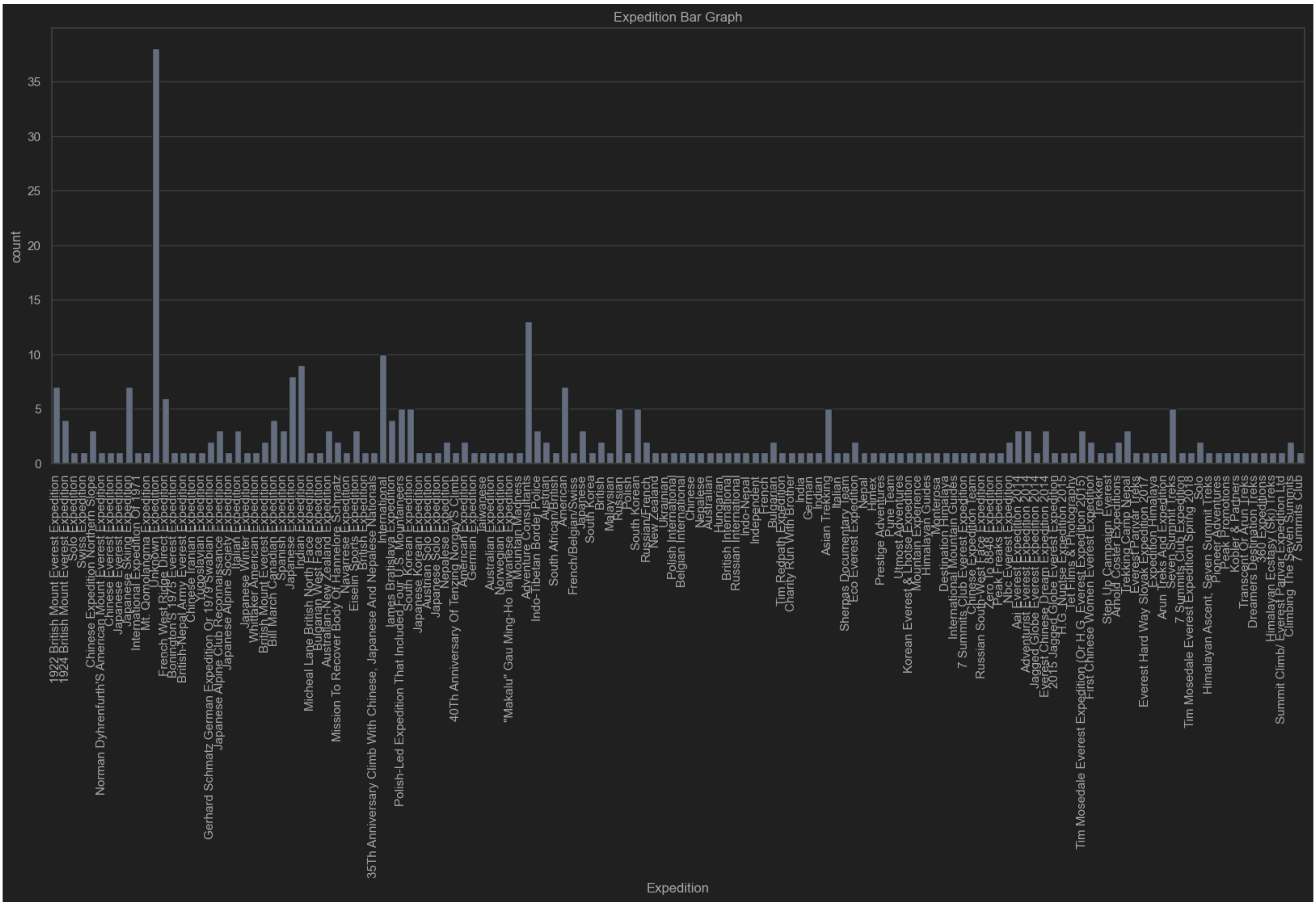

Distribution of Age
20
30
40
50
60
70
80
Age

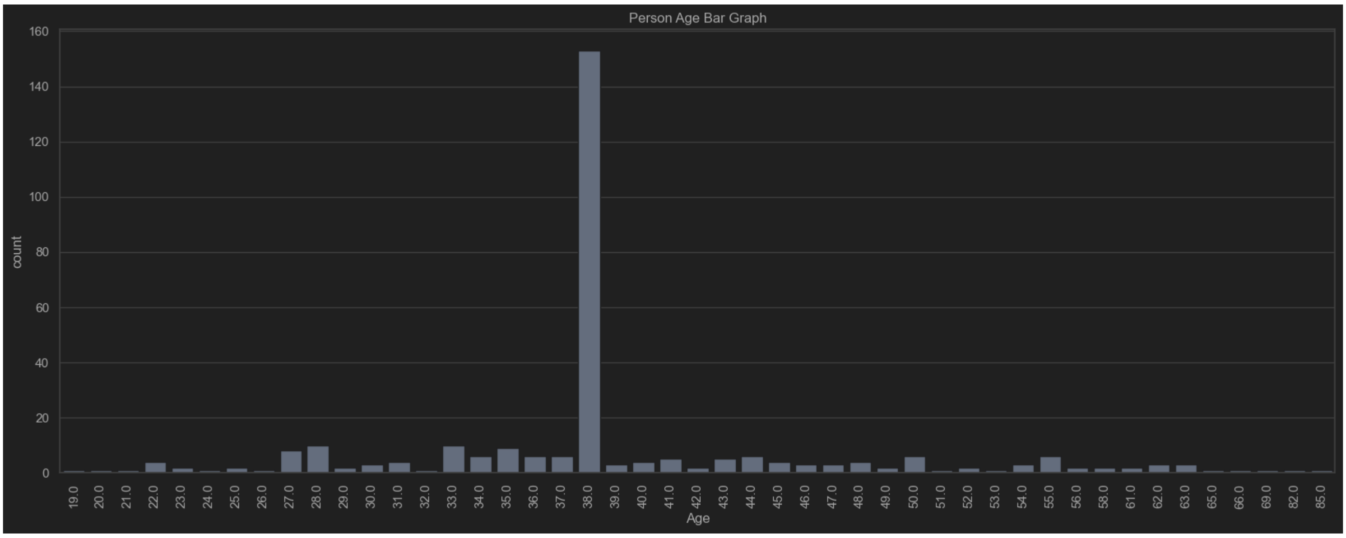

Age Density
Density
0.00
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
20
40
60
80
Age

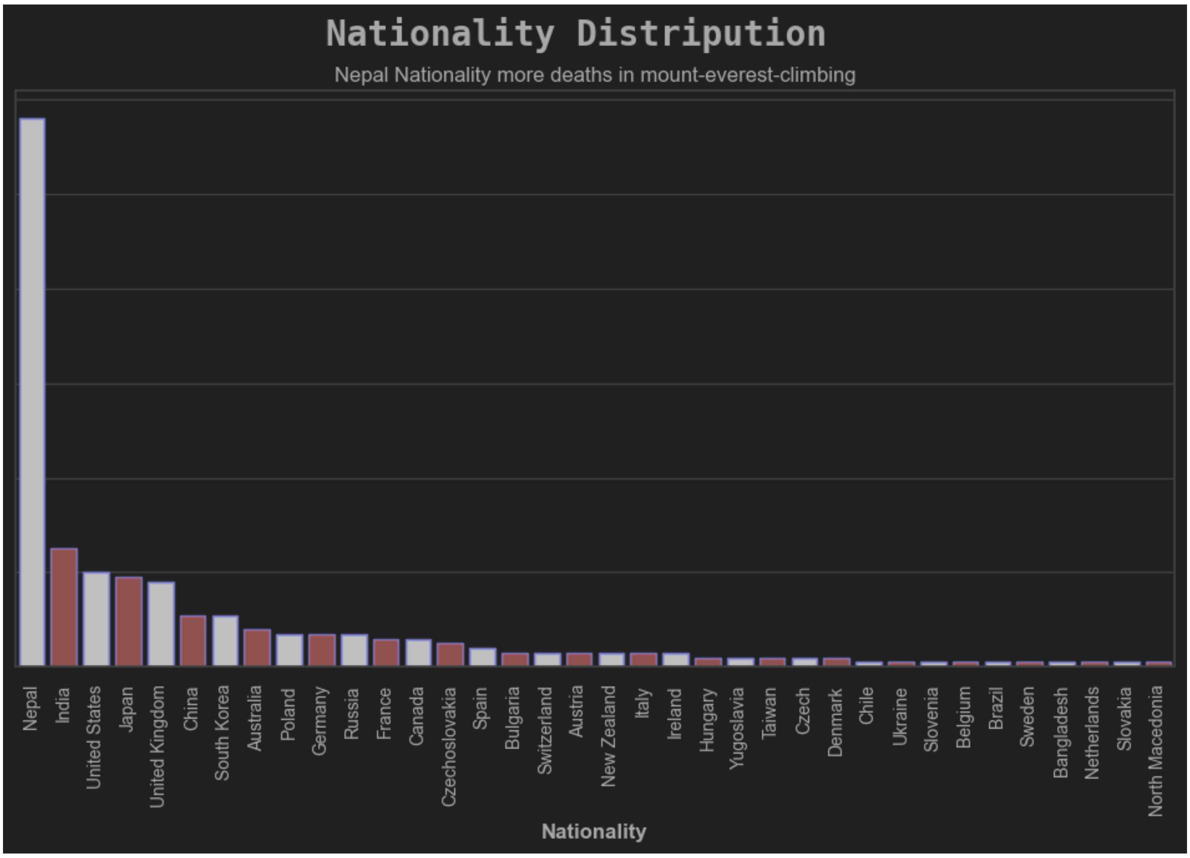

Year
Month
DayOfWeek
Age
Age_Cleaned
Age_Normalized
No.
Cause of death
Avalanche
Pneumonia
Brain Hemorrhage
Unknown. Body Never Found
Possible Ice Axe Injury Following A Fall. Body Found In 1999
Possible Exhaustion, Exposure Or Starvation. Body Found 1935
Falling Ice
Mountain Sickness
Unknown Cause
Crushed Under Serac
Fall
Fall Into A Crevasse
By Fall
Heart Attack
Succumbed After Falling And Being Suspended Above A Crevasse During A Blizzard
Exhaustion, Fall
Disappearance (Likely Accidental Death During Climb)
Exposure, Exhaustion
Internal Hemorrhage
Disappearance (Likely Accidental Death During Descent)
Fall, While Searching For Craig Nottle
Exposure
Drowned
Heart Attack (At Base Camp)
Disappearance (Likely Accidental Death During Descent After Reaching South Summit With Jozef Just Rejoining Group After He Summited Everest Solo)[75][76]
Cerebral Thrombosis
Avalanche Injuries
Altitude Sickness, Heart Attack
Hape
Cerebral Oedema
Exhaustion And/Or Exposure
150M Fall. He Showed Signs Of Exhaustion, Dehydration, Cerebral Oedema, Retinal Hemorrhages And Possible Blood Clots In His Upper Legs.
Injuries From A Fall
Suspected Hace (High-Altitude Cerebral Edema), Exhaustion, Frostbite And Exposure.
Altitude Sickness
Rope Accident
Lapsed Into Coma On 23 Apr 1996; Later Died In Hospital
100M Fall
Exposure And/Or Cerebral Oedema
Exhaustion
Died Due To Fall
Disappeared After Reaching The North Summit; Body Found On May 27, 2000; Likely Accidental Death During Descent
Pre-Existing Illness Exacerbated By Freezing Conditions, Altitude
Exact Cause And Date Of Death Unknown
Snowboarding Accident
Sickness In Tent
Oxygen Problems
Organ Failure Due To Freezing Conditions
Altitude
Exposure And/Or Exhaustion
Hypothermia And Lack Of Oxygen
Avalanche Crevasse Fall
Hace
Heart Break
Cerebral Apoplexy
Stroke (Cva)
Stroke
Suspected Altitude Sickness
Exhaustion And Related Complications After Breaking Leg At Second Step
Falling Into A Crevasse
Suspected Cardiac Arrest
2014 Mount Everest Avalanche
Base Camp Avalanche Following The April 2015 Nepal Earthquake
Died In Kathmandu Due To Injuries Sustained In The Base Camp Avalanche Following The April 2015 Nepal Earthquake
Cardiac Event
Snow Blindness, Stroke
Fall Into A 200M Crevasse
Disappearance (Reportedly Suffered From Snow Blindness)
Cardiac Arrest
Hypothermia, Had Previously Reported "Persistent Cough And Pain" During Attempt
Died After A Fall While Trekking Down From Base Camp
Presumed Dead After Fall
Exhaustion On Descent
Exhaustion And Altitude Sickness
Exhaustion During Descent
Cardiac Event During Descent

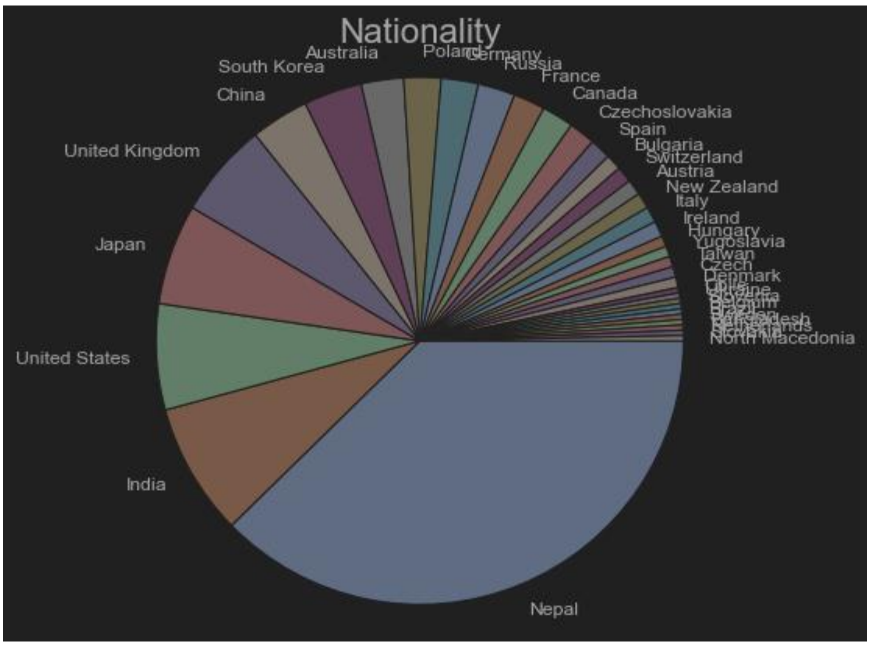

Age_Group = Young
Age_Group = Middle-Aged
Age_Group = Elderly
Age_Group = Very Elderly
150
100
50
0
20
40
60
80
Age

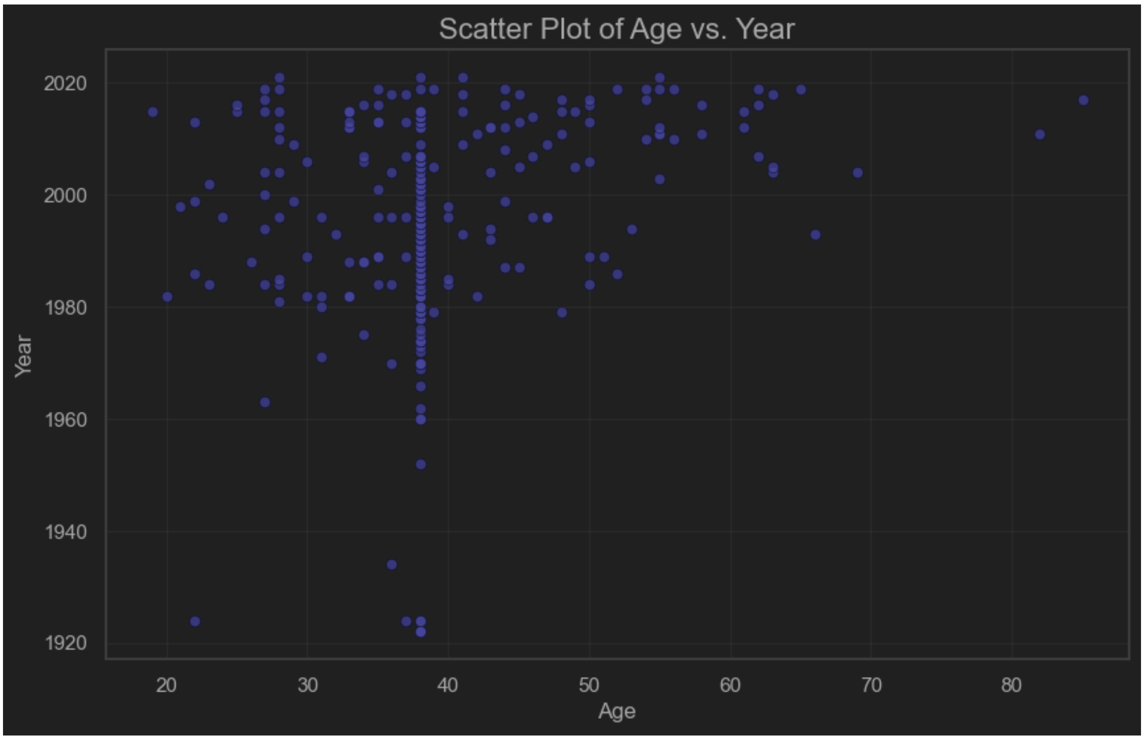

Cause of death
Crushed Under Serac
Heart Attack
Exhaustion
Fall Into A Crevasse
Unknown Cause
Base Camp Avalanche Follo
2014 Mount Everest Avalan
Altitude Sickness
Disappearance (Likely Acc
Exposure
Fall
Avalanche
Cardiac Event During Desc

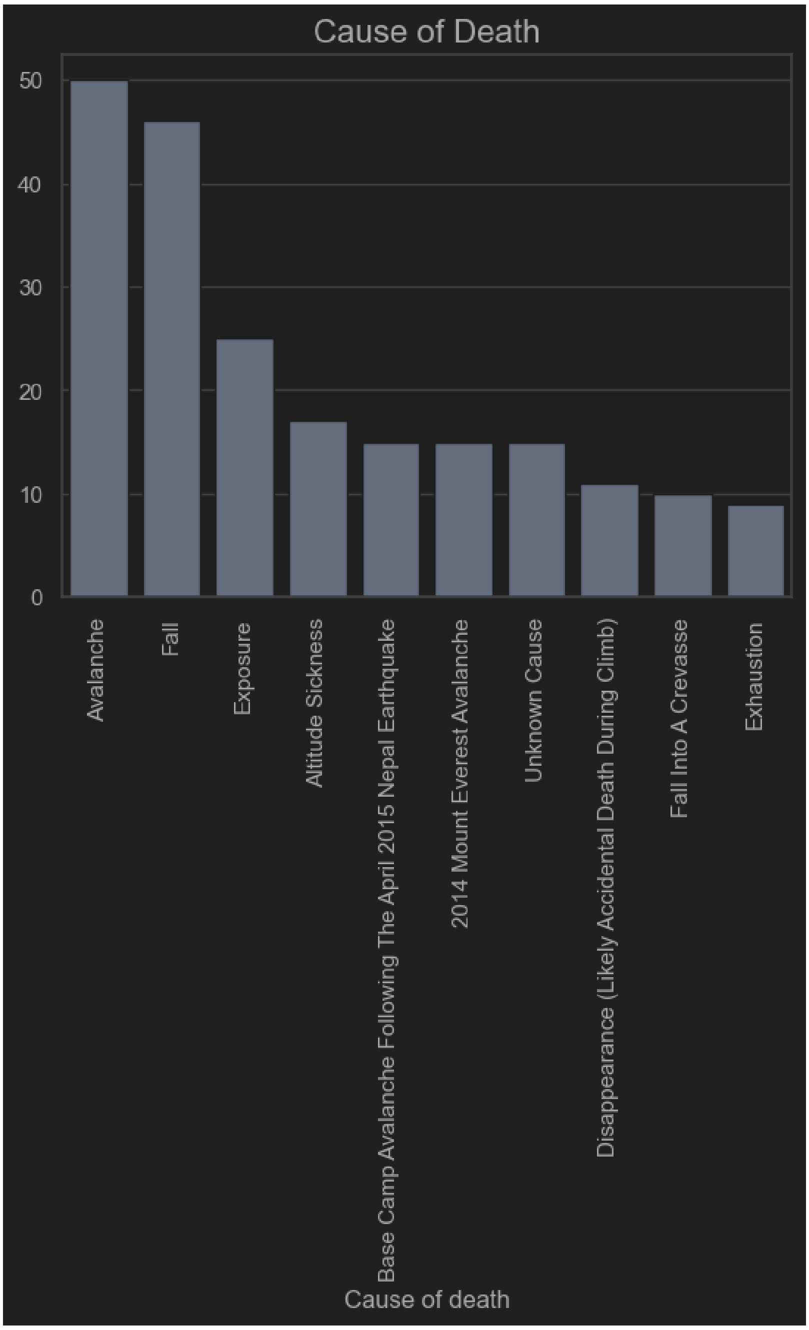

Expedition Bar Graph
count
Expedition
0
5
10
15
20
25
30
35

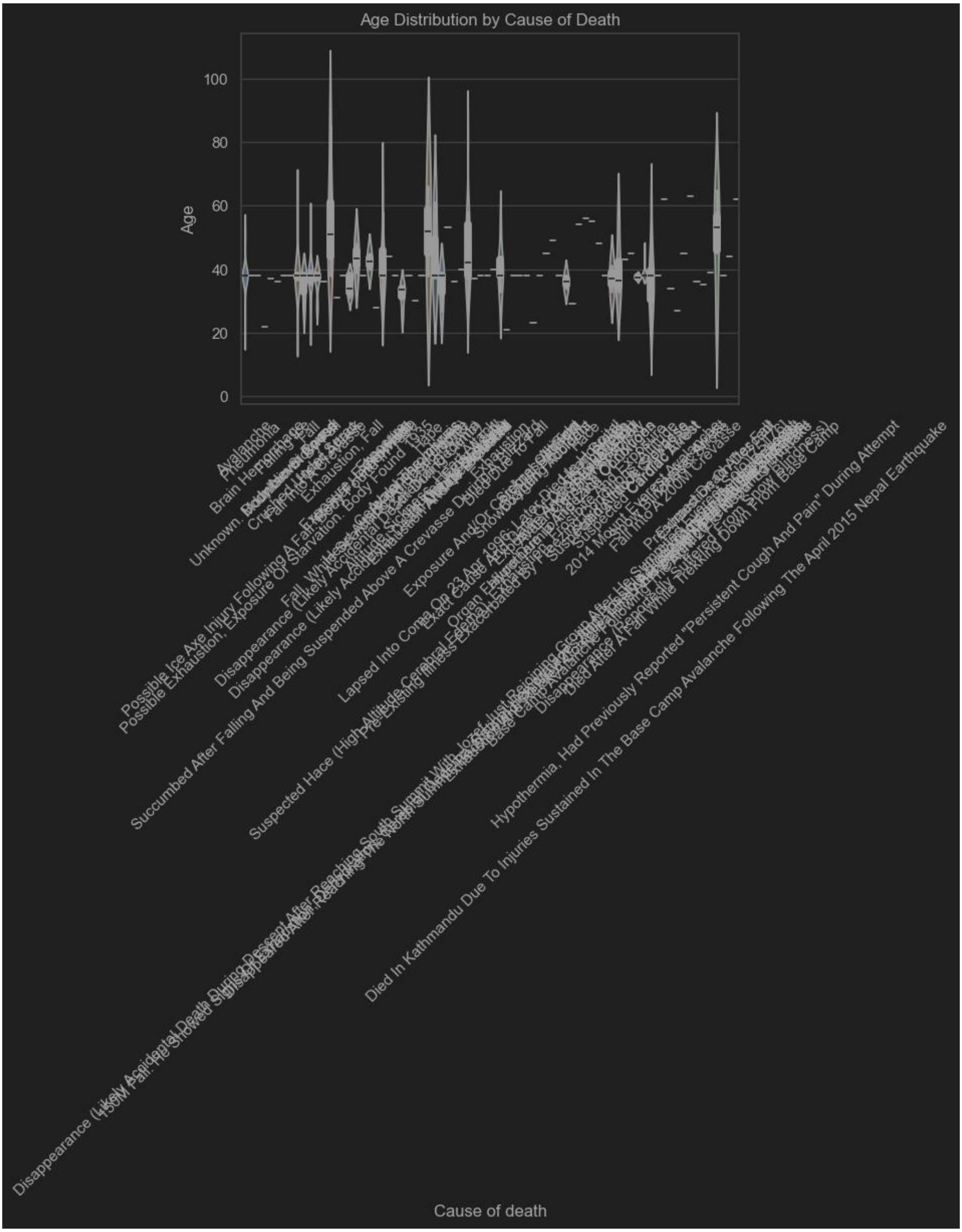

Person Age Bar Graph
count
160
140
120
100
80
60
40
20
0
19.0 20.0 21.0 22.0 23.0 24.0 25.0 26.0 27.0 28.0 29.0 30.0 31.0 32.0 33.0 34.0 35.0 36.0 37.0 38.0 39.0 40.0 41.0 42.0 43.0 44.0 45.0 46.0 47.0 48.0 49.0 50.0 51.0 52.0 53.0 54.0 55.0 56.0 58.0 61.0 62.0 63.0 65.0 66.0 69.0 82.0 85.0
Age


Nationality Distripution
Nepal Nationality more deaths in mount-everest-climbing
Nepal
India
United States
Japan
United Kingdom
China
South Korea
Australia
Poland
Germany
Russia
France
Canada
Czechoslovakia
Spain
Bulgaria
Switzerland
Austria
New Zealand
Italy
Ireland
Hungary
Yugoslavia
Taiwan
Czech
Denmark
Chile
Ukraine
Slovenia
Belgium
Brazil
Sweden
Bangladesh
Netherlands
Slovakia
North Macedonia
Nationality

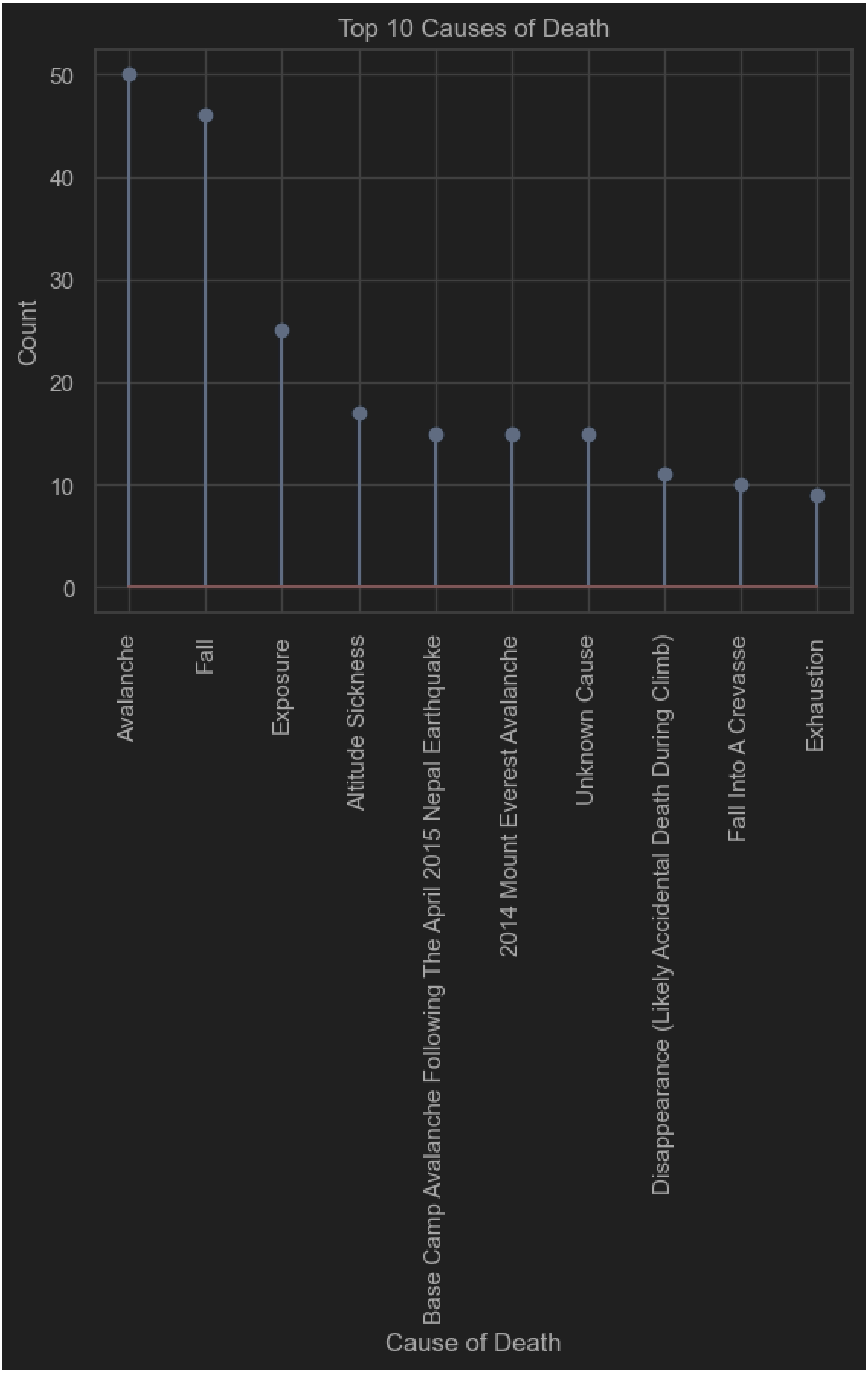

Nationality
South Korea
Australia
Poland
Germany
Russia
France
Canada
Czechoslovakia
Spain
Bulgaria
Switzerland
Austria
New Zealand
Italy
Ireland
Hungary
Yugoslavia
Taiwan
Czech
Denmark
North Macedonia
China
United Kingdom
Japan
United States
India
Nepal

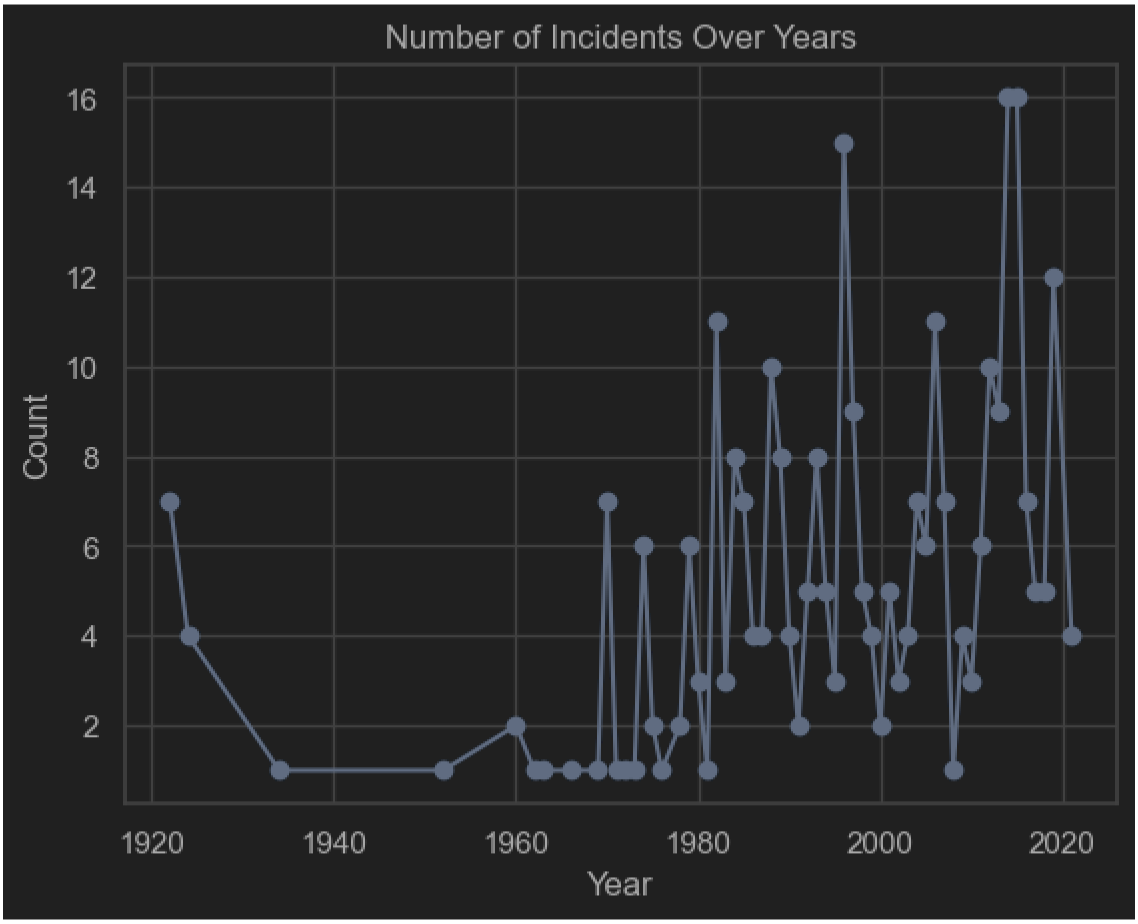

Scatter Plot of Age vs. Year
Year
2020
2000
1980
1960
1940
1920
20
30
40
50
60
70
80
Age


Cause of Death
50
40
30
20
10
0
Avalanche
Fall
Exposure
Altitude Sickness
Base Camp Avalanche Following The April 2015 Nepal Earthquake
2014 Mount Everest Avalanche
Unknown Cause
Disappearance (Likely Accidental Death During Climb)
Fall Into A Crevasse
Exhaustion
Cause of death

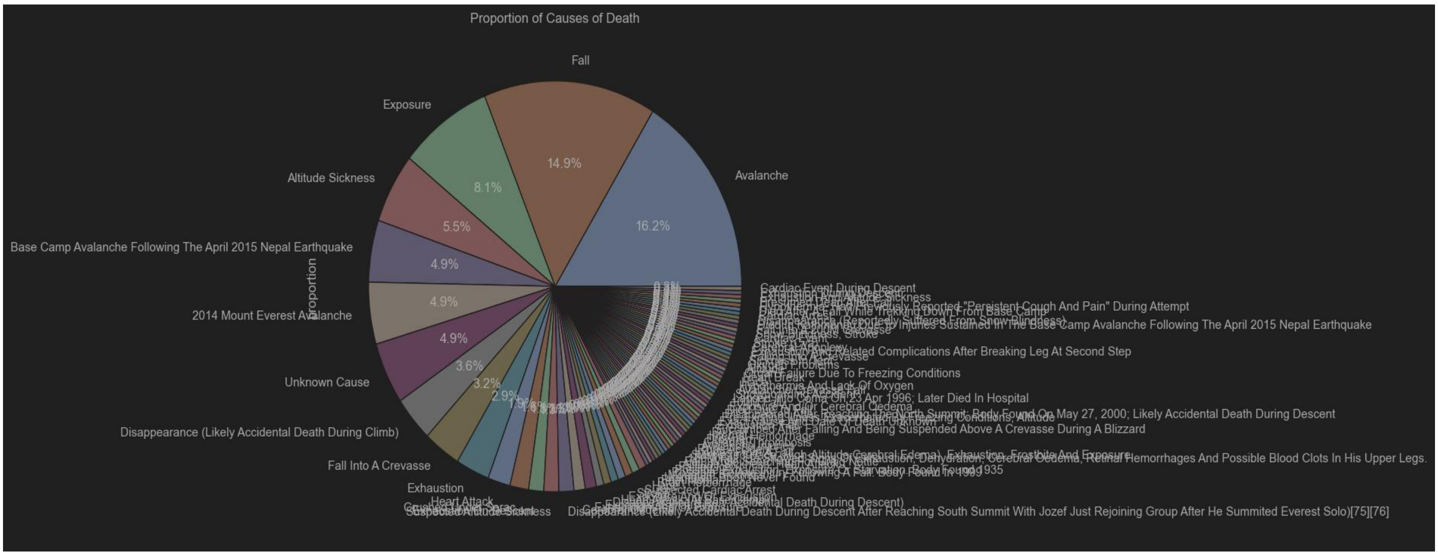


Age Distribution by Cause of Death
Age
0
20
40
60
80
100
Avalanche
Pneumonia
Brain Hemorrhage
Exhaustion, Fall
Fall Into A 200M Crevasse
Died After A Fall While Trekking Down From Base Camp
Hypothermia, Had Previously Reported "Persistent Cough And Pain" During Attempt
Died In Kathmandu Due To Injuries Sustained In The Base Camp Avalanche Following The April 2015 Nepal Earthquake
Cause of death

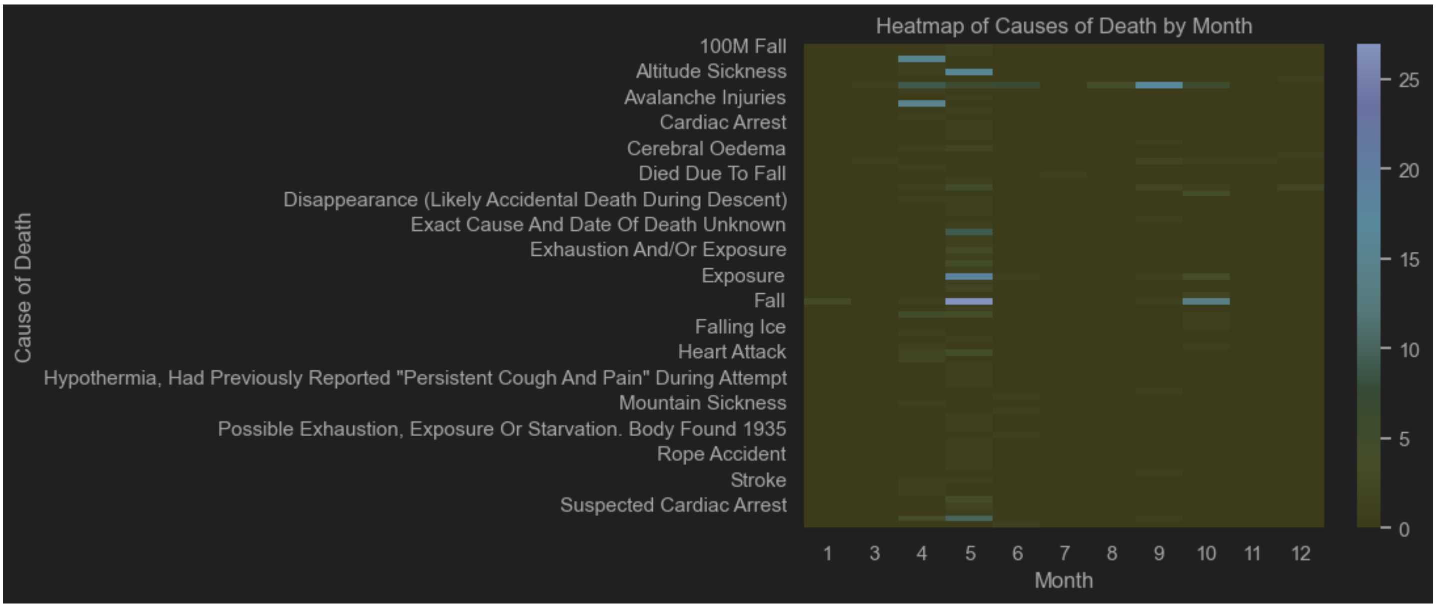

Top 10 Causes of Death
Count
0
10
20
30
40
50
Avalanche
Fall
Exposure
Altitude Sickness
Base Camp Avalanche Following The April 2015 Nepal Earthquake
2014 Mount Everest Avalanche
Unknown Cause
Disappearance (Likely Accidental Death During Climb)
Fall Into A Crevasse
Exhaustion
Cause of Death

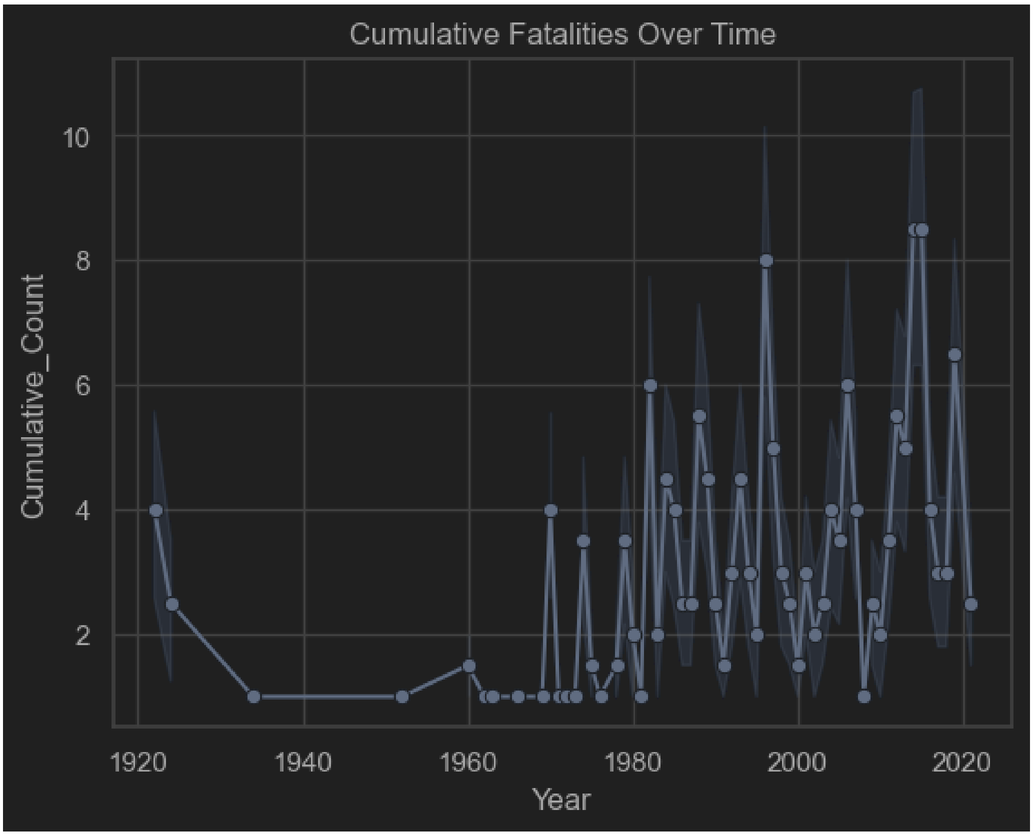


Number of Incidents Over Years
Count
Year
16
14
12
10
8
6
4
2
1920
1940
1960
1980
2000
2020



Proportion of Causes of Death
Fall
Exposure
Altitude Sickness
Base Camp Avalanche Following The April 2015 Nepal Earthquake
2014 Mount Everest Avalanche
Unknown Cause
Disappearance (Likely Accidental Death During Climb)
Fall Into A Crevasse
Exhaustion
Avalanche
16.2%
14.9%
8.1%
5.5%
4.9%
4.9%
4.9%
3.6%
3.2%
2.9%
Cardiac Event During Descent
Disappearance (Likely Accidental Death During Descent After Reaching South Summit With Jozef Just Rejoining Group After He Summited Everest Solo)[75][76]


Heatmap of Causes of Death by Month
100M Fall
Altitude Sickness
Avalanche Injuries
Cardiac Arrest
Cerebral Oedema
Died Due To Fall
Disappearance (Likely Accidental Death During Descent)
Exact Cause And Date Of Death Unknown
Exhaustion And/Or Exposure
Exposure
Fall
Falling Ice
Heart Attack
Hypothermia, Had Previously Reported "Persistent Cough And Pain" During Attempt
Mountain Sickness
Possible Exhaustion, Exposure Or Starvation. Body Found 1935
Rope Accident
Stroke
Suspected Cardiac Arrest
Cause of Death
1
3
4
5
6
7
8
9
10
11
12
Month
25
20
15
10
5
0


Cumulative Fatalities Over Time
Cumulative_Count
10
8
6
4
2
1920
1940
1960
1980
2000
2020
Year

Discussion:

The exploratory data analysis (EDA) of the Mount Everest dataset has revealed numerous trends, patterns, and actionable insights that can guide safety measures, policymaking, and operational strategies for climbers and expedition organizers. Below is a more detailed discussion, incorporating the insights gained from the analysis:

---

1. Age Distribution and Risk Factors

- **Insight:**
  - Most fatalities occur within the "Young" (18–25 years) and "Middle-Aged" (26–50 years) groups.
  - The age distribution is not uniform; the younger climbers tend to take more risks, while older climbers face physiological challenges, such as reduced oxygen efficiency at high altitudes.
  - Extreme outliers were identified but normalized for analysis, revealing robust patterns in the central age groups.
- **Discussion:**
  - Younger climbers might benefit from mandatory risk-awareness programs emphasizing cautious decision-making.
  - Older climbers could be required to undergo medical evaluations before attempting high-altitude climbs.

---

2. Nationality Trends

- **Insight:**
  - Nepalese climbers (mostly Sherpas) account for a significant proportion of fatalities. This aligns with their occupational exposure during expeditions.
  - Other nationalities follow based on expedition participation rates, reflecting global interest in Mount Everest climbs.
- **Discussion:**
  - This raises concerns about workplace safety for Sherpas, who often face the most hazardous conditions with heavy loads and repeated climbs.
  - Policy interventions, such as insurance coverage and enhanced safety gear for local guides, could reduce fatalities.

---

3. Temporal Analysis (Yearly and Monthly Trends)

- **Insight:**
  - The number of fatalities has increased over time, corresponding to growing interest in Everest expeditions.
  - April and May are peak months for incidents, coinciding with favorable weather conditions for summiting.
- **Discussion:**

- Overcrowding during peak months exacerbates risks such as avalanches, falls, and oxygen depletion.
- Introducing permit caps, staggered climb schedules, and monitoring of weather patterns could improve climber safety and reduce fatalities.

---

4. Causes of Death

- **Insight:**
  - Avalanches, falls, and altitude sickness are the top three causes of death.
  - Avalanches have been particularly devastating, especially in incidents such as the 2014 and 2015 disasters.
- **Discussion:**
  - Advanced weather forecasting systems and avalanche risk assessments are essential.
  - Investment in infrastructure, such as rope-assisted trails in avalanche-prone zones, could mitigate risks.

---

5. Expedition-Specific Risks

- **Insight:**
  - Certain expeditions have higher fatality counts, often linked to environmental hazards, poor planning, or lack of preparedness among climbers.
- **Discussion:**
  - Detailed post-expedition reports could provide valuable lessons to future climbers.
  - Certification programs for guides and climbers could ensure that only experienced individuals participate in higher-risk climbs.

---

6. Age Group and Cause of Death

- **Insight:**
  - Age influences the type of fatality risk. For example, younger climbers are more likely to die from falls, while older climbers succumb to altitude sickness and exhaustion.
- **Discussion:**
  - Expedition organizers could offer age-specific training and health monitoring.
  - Medical support systems, including high-altitude acclimatization camps, should be tailored for older participants.

---

7. Visualization Insights

- **Histograms and KDE Plots:**

- Revealed detailed age distribution with noticeable peaks around the 30–40 age range.
- Showed the concentration of incidents during certain months, emphasizing the seasonality of risks.

- **Violin and Pair Plots:**
  - Highlighted multi-dimensional relationships, such as the interplay between age, nationality, and causes of death.
- **Heatmaps:**
  - Offered granular insights into monthly variations of causes of death, showcasing patterns that could aid in seasonal risk management.
- **Scatter and Line Plots:**
  - Demonstrated the cumulative growth in fatalities and their relationship with year and expedition details.

---

8. Age vs. Year Trends

- **Insight:**
  - The scatter plot of age vs. year revealed increasing participation by younger climbers in recent years, indicating that Everest is attracting a broader demographic.
- **Discussion:**
  - Awareness campaigns about risks for first-time climbers could target this younger, less experienced demographic.
  - Providing clear guidelines on acclimatization and fitness could reduce fatalities in this group.

---

9. Cumulative Fatalities

- **Insight:**
  - The cumulative fatalities over time reflect the growing popularity of Everest expeditions, despite the increasing awareness of risks.
- **Discussion:**
  - Future policies should balance the commercial appeal of Everest with stricter safety measures to reduce this rising trend.

---

10. Insights on Expedition Peaks

- **Insight:**
  - Certain years with disaster peaks, such as 2014 (avalanche) and 2015 (earthquake), stand out in the line plot of fatalities over time.
- **Discussion:**
  - Enhanced disaster management strategies, including preemptive evacuation plans, are essential to prevent such catastrophic loss of life in the future.

Conclusion:

The exploratory data analysis (EDA) of the Mount Everest dataset provides valuable insights into the trends, patterns, and underlying factors contributing to fatalities during expeditions. Key findings include age-specific risks, seasonal trends, and the significant role of factors such as avalanches, falls, and altitude sickness. These insights highlight the need for targeted interventions, including enhanced safety measures, better preparedness, and stricter regulatory frameworks.

The analysis underscores the importance of balancing the growing commercial interest in Everest expeditions with safety and environmental sustainability. Addressing key challenges like overcrowding, occupational risks for local guides, and age-related vulnerabilities will be essential in reducing fatalities and ensuring safer climbing experiences.

Future efforts should focus on predictive modeling, improved infrastructure, and disaster management systems to mitigate risks. By leveraging data-driven insights, policymakers, climbers, and expedition organizers can work together to preserve the legacy of Mount Everest while prioritizing safety and sustainability.