SUMMER TRAINING REPORT

A Report Submitted in partial fulfilment of the requirements for the Award of Degree of

BACHELOR OF TECHNOLOGY

In

ELECTRONICS AND COMMUNICATION ENGINEERING

By

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Under the supervision of

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Med Tour Easy

Cannaught Place

(Duration:01/07/2025 to 30/07/25)

Department of Electronics and Communication Engineering

BHARATI VIDYAPEETH’S COLLEGE OF ENGINEERING

Affiliated to Guru Gobind Singh Indraprastha University, New Delhi

CANDIDATE'S DECLARATION

It is hereby certified that the work which is being presented in the B. Tech Summer training Report entitled "Analysis of Death Age Difference of Right Handers with Left Handers" in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology and submitted in the Department of Electronics and Communication of BHARATI VIDYAPEETH'S COLLEGE OF ENGINEERING, New Delhi (Affiliated to Guru Gobind Singh Indraprastha University, Delhi) is an authentic record of our own work carried out during a period of July 2025 under the guidance of Mr Ankit Hasija.

The matter presented in the B. Tech Summer Training Report has not been submitted by me for the award of any other degree of this or any other Institute.

Student Name: Anushka Gupta

Enrolment No: 20911502822

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Mentor Name: - Mr Ankit Hasija

(Signature of Mentor)

ACKNOWLEDGEMENT

I would like to express my sincere gratitude to **Mr Ankit Hasija, my mentor**, for his invaluable guidance, insightful suggestions, and constant encouragement, which played a key role in the successful completion of my project, *"A*nalysis of Death Age Difference of Right Handers with Left Handers*"*

I am also thankful to the **Department of Electronics and Communication Engineering, Bharati Vidyapeeth's College of Engineering, New Delhi**, affiliated with **Guru Gobind Singh Indraprastha University, Delhi**, for providing me the opportunity to pursue this training and for their continued academic support.

I am deeply grateful to **MedTourEasy** for offering me this traineeship, which proved to be a transformative experience in **Data Analytics and Data Visualization**, enriching both my technical expertise and professional growth.

Anushka Gupta

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DATE : 01/08/2025
REF : CER/2025/9234

CERTIFICATE OF TRAINEESHIP COMPLETION

This is to certify that Mr/Ms. **Anushka Gupta**, has successfully completed the traineeship program at **MedTourEasy** from **01/07/2025 to 31/07/2025**.

During this period Anushka had experienced the hands on working of a **Data Analytics** Professional and worked under the supervision of project mentor & developed the project entitled "**Analyze Death Age Difference of Right Handers with Left Handers**".

Anushka was found hardworking, punctual and inquisitive, during the tenure of traineeship.

We wish Anushka every success in career.

For MedTourEasy

Ankit Hasija
Training Head

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COMPANY'S PROFILE AND HISTORY

MedTourEasy is a global healthcare company that aims to connect patients worldwide with the right healthcare providers. By evaluating a patient's medical condition, MedTourEasy selects the most suitable clinic and specialist. Additionally, MedTourEasy offers analytical solutions to their partner healthcare providers across the globe. With a commitment to relevance and meaningful assistance,

MedTourEasy strives to ensure that patients receive the best possible care and make well-informed choices.

Location and Overview:

Med Tour Easy in Connaught Place, Delhi is a top player in the category Corporate Companies in the Delhi. This well-known establishment acts as a one-stop destination servicing customers both local and from other parts of Delhi. Over the course of its journey, this business has established a firm foothold in its industry. The belief that customer satisfaction is as important as their products and services, have helped this establishment garner a vast base of customers, which continues to grow by the day. This business employs individuals that are dedicated towards their respective roles and put in a lot of effort to achieve the common vision and larger goals of the company. Soon, this business aims to expand its line of products and services and cater to a larger client base. In Delhi, this establishment occupies a prominent location in Connaught Place. It is an effortless task in commuting to this establishment as there are various modes of transport readily available. It is at, Near M Block, which makes it easy for first-time visitors in locating this establishment. It is known to provide top service in the following categories: Corporate Companies.

Products and Services offered:

Med Tour Easy in Connaught Place has a wide range of products and / or services to cater to the varied requirements of their customers. The staff at this establishment are courteous and prompt at providing any assistance. They readily answer any queries or questions that you may have. Pay for the product or service with ease by using any of the available modes of payment.

LIST OF ABREVIATIONS

- **LH** → Left-Handed
- **RH** → Right-Handed
- **P (A | RH)** → Probability of age at death **given** that the person is right-handed
- **P (A | LH)** → Probability of age at death **given** that the person is left-handed
- **P (LH | A)** → Probability of being left-handed **given** age at death
- **P(LH)** → Probability of being left-handed in the population
- **P(RH)** → Probability of being right-handed in the population
- **P(A)** → Probability distribution of deaths at different ages
- **Bayes' Theorem** – A statistical method for updating probabilities based on new evidence
- **PDF** – Probability Density Function
- **CDF** – Cumulative Distribution Function
- **CSV** – Comma-Separated Values (data file format used)

ABSTRACT

The long-standing belief that left-handed individuals die younger than right-handed individuals has been a topic of debate for decades. This project investigates the validity of this claim by analysing age-at-death distribution data using Bayesian statistical methods. The central idea is to examine whether the perceived difference in average age at death arises from biological factors or from societal and historical trends in the recognition of left-handedness.

The analysis was conducted using real-world death distribution data, where probabilities of being left-handed at different ages were modelled and combined with mortality statistics. The findings reveal that the apparent early death of left-handed individuals is not supported by biological evidence but is instead a statistical artefact. Historically, older generations were less likely to report or be recognized as left-handed due to societal stigma and pressures to conform to right-handed norms. This underreporting led to a lower recorded prevalence of left-handedness in older populations, which skewed the mortality data and gave rise to the myth.

By applying Bayesian reasoning, the study successfully demonstrates how conditional probabilities can explain this misconception, reinforcing the importance of contextualizing data before drawing conclusions. The project highlights the role of data visualization and statistical modelling in debunking myths and provides a framework for further research. Future scope includes extending this analysis to larger and more diverse datasets, applying advanced machine learning techniques, and promoting awareness of how data-driven approaches can help uncover social truths.

INTRODUCTION

This project investigates the longstanding myth that left-handed individuals tend to die earlier than right-handed individuals. This claim, popularized by certain media reports, lacks sufficient scientific backing. Our objective in this project is to explore whether the observed differences in average age at death between left-handed and right-handed individuals can be attributed purely to historical changes in the prevalence of left-handedness across generations.

To analyse this phenomenon, we utilize **age distribution data** alongside changing **left-handedness rates over time**. By leveraging tools such as **Pandas for data manipulation** and applying **Bayesian statistical methods**, the project estimates the probability of being a certain age at death given reported handedness.

A core component of the analysis involves simulating the effects of societal shifts—particularly how left-handedness was less accepted or even suppressed in earlier generations—on the apparent age of death for left-handed individuals. By combining these trends with mortality data, the project demonstrates that the difference

In average age of death is not necessarily due to biology or health factors but can be explained as an artefact of historical bias in recording and accepting left-handedness.

This project provides strong statistical evidence that challenges the misconception about the early death of left-handers and highlights the importance of understanding demographic trends and data interpretation in scientific claims.

OBJECTIVES

- **To investigate the myth of early death among left-handers:**
  The project aims to critically examine the widespread belief that left-handed individuals die younger than right-handed individuals, a claim often reinforced by popular media but lacking scientific grounding.
- **To analyse age distribution data with respect to handedness:**
  By using real-world datasets, the project studies how the age at death varies between left-handed and right-handed individuals, thereby identifying whether a genuine mortality difference exists.
- **To incorporate historical changes in left-handedness prevalence:**
  Since left-handedness was stigmatized in earlier generations, many individuals were forced to switch or underreport their natural handedness. This project takes into account the generational and societal trends that affected the recorded prevalence of left-handedness.
- **To apply statistical and computational techniques for analysis:**
  The project leverages Python libraries such as **Pandas** for data handling and applies **Bayesian probability methods** to estimate the likelihood of dying at a certain age given handedness, ensuring a rigorous and data-driven analysis.
- **To demonstrate that mortality differences arise from historical bias rather than biology:**
  Through simulations and probability analysis, the project aims to prove that the apparent difference in average age of death between left- and right-handers can be explained by social and historical biases rather than genetic, biological, or health-related causes.
- **To encourage critical data interpretation in scientific research:**
  Finally, the project emphasizes the importance of contextualizing statistical findings with historical and cultural factors, preventing misinterpretation of demographic data and avoiding the perpetuation of myths in science communication.

The key deliverables for this project include:

1. **Cleaned and Pre-processed Dataset**:

a. Historical death distribution and handedness rate data prepared for analysis.

2. **Python Implementation (Jupyter Notebook)**:

a. Code modules to compute probabilities, implement Bayes' theorem, and perform statistical calculations.

b. Visualization of age-at-death distributions for left- and right-handed individuals.

3. **Functions Developed**:

a. **P (LH|A, Year)** — Probability of being left-handed at a given age in a specific year.

b. P (LH | Death Data, Year) — Overall probability of left-handedness in the death dataset.

c.**P A|LH)** and **P (A|RH)** — Bayesian calculations for age-at-death given handedness.

4. **Visual Plots**:

a. Age-based probability distribution graphs for both left-handed and right-handed individuals.

b. Comparison of average age at death by handedness over different years.

5. **Final Report**:

a. A comprehensive summary of methodology, analysis, conclusions, and code documentation.

b. Interpretations that debunk the early-death myth of left-handed individuals through data evidence.

BACKGROUND

Introduction to Handedness

Handedness refers to the natural preference of individuals to use one hand more effectively than the other, most categorized as left-handedness and right-handedness. While right-handedness is predominant, left-handedness has historically faced stigma and social suppression.

The Lifespan Myth

A popular but unsubstantiated claim suggests that left-handed individuals die younger than right-handed individuals. This misconception arose from statistical misinterpretations in earlier studies, where shifting recognition of left-handedness across generations distorted the reported age at death.

Project Description

This project aims to analyse whether the apparent difference in lifespan between left-handers and right-handers is a biological fact or simply an artefact of historical and societal factors. Using statistical tools, we model the probability of handedness across different generations and examine how societal shifts in reporting influence age-at-death distributions.

Dataset Description

The analysis uses age distribution data and historical records of handedness prevalence across generations. By applying **Pandas** for data manipulation and **Bayesian statistics** for probabilistic modelling, the dataset enables estimation of:

- The probability of being left-handed at a given age and time.
- Age-at-death distribution conditional on reported handedness.

Need for Reinvestigation

Revisiting this myth through modern statistical approaches helps challenge misconceptions, provides clarity on demographic trends, and highlights the importance of careful data interpretation in scientific claims.

IMPLEMENTATION

Task 1: Loading Data and Scatter Plot

The handedness dataset from the National Geographic survey was loaded using pandas into a Data Frame named lefthanded_data. The dataset contained three key columns: **Age**, **Male**, and **Female**, representing the percentage of left-handed individuals by gender across age groups.

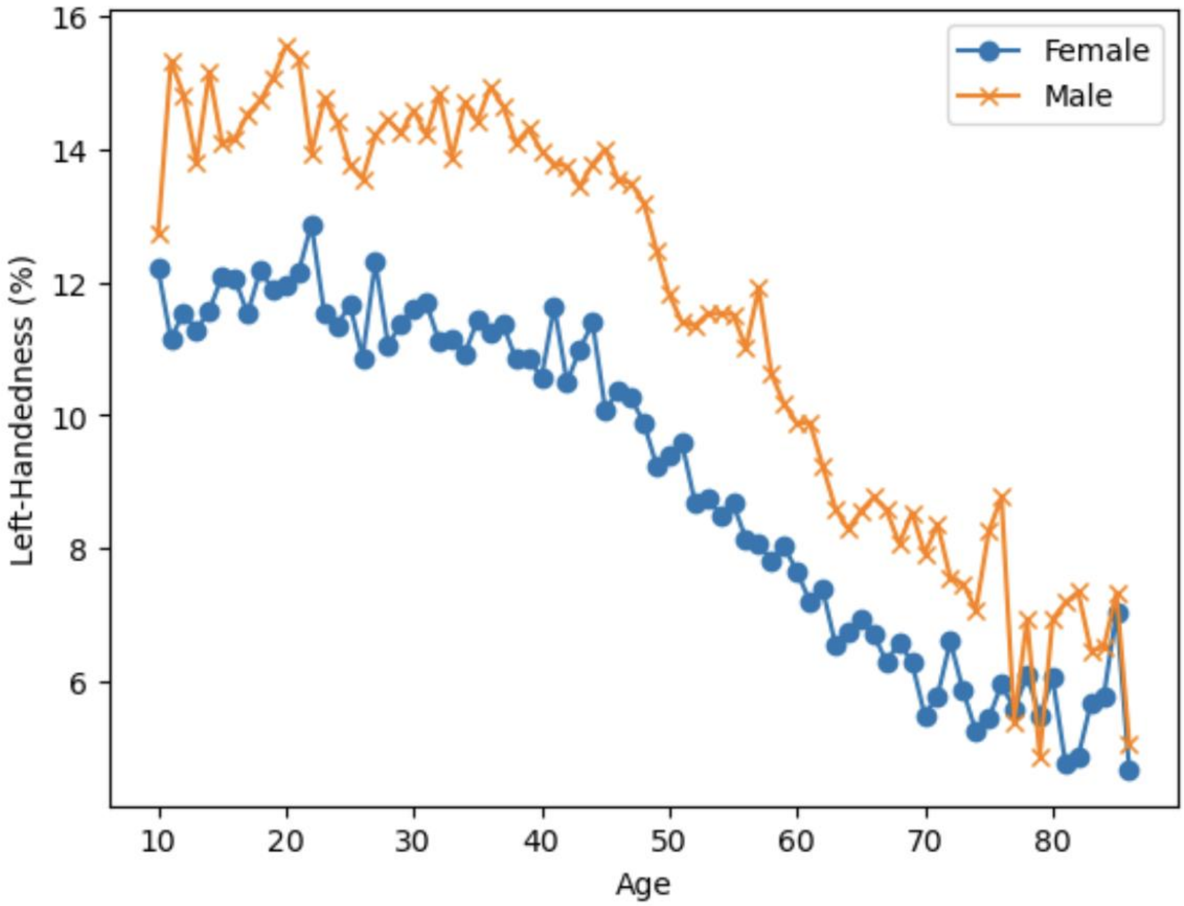
A scatter plot was created using matplotlib, with **Age** on the x-axis and **Male/Female** percentages on the y-axis. Distinct colors and a legend were added to differentiate between genders.

This visualization highlighted the variation in left-handedness across age groups and provided the foundation for further analysis.

Code: -

```
import pandas as pd

import matplotlib.pyplot as plt

data_url_1="https://gist.githubusercontent.com/mbonsma/8da0990b71ba9a09f7de395574e54df1/raw/aec88b30af87fad8d45da7e774223f91dad09e88/lh_data.csv"

lefthanded_data = pd.read_csv (data_url_1)

%matplotlib inline

fig, ax = plt.subplots ()

ax.plot (lefthanded_data ["Age"], lefthanded_data ["Female"], label="Female", marker="o")
ax.plot (lefthanded_data ["Age"], lefthanded_data ["Male"], label="Male", marker="x")
ax.legend()

ax.set_xlabel ("Age")

ax.set_ylabel ("Left-Handedness (%)")
```

```
plt.show ()
```



Female
Male
Left-Handedness (%)
Age
16
14
12
10
8
6
10
20
30
40
50
60
70
80

Task 2: Birth Year and Mean Left-Handedness

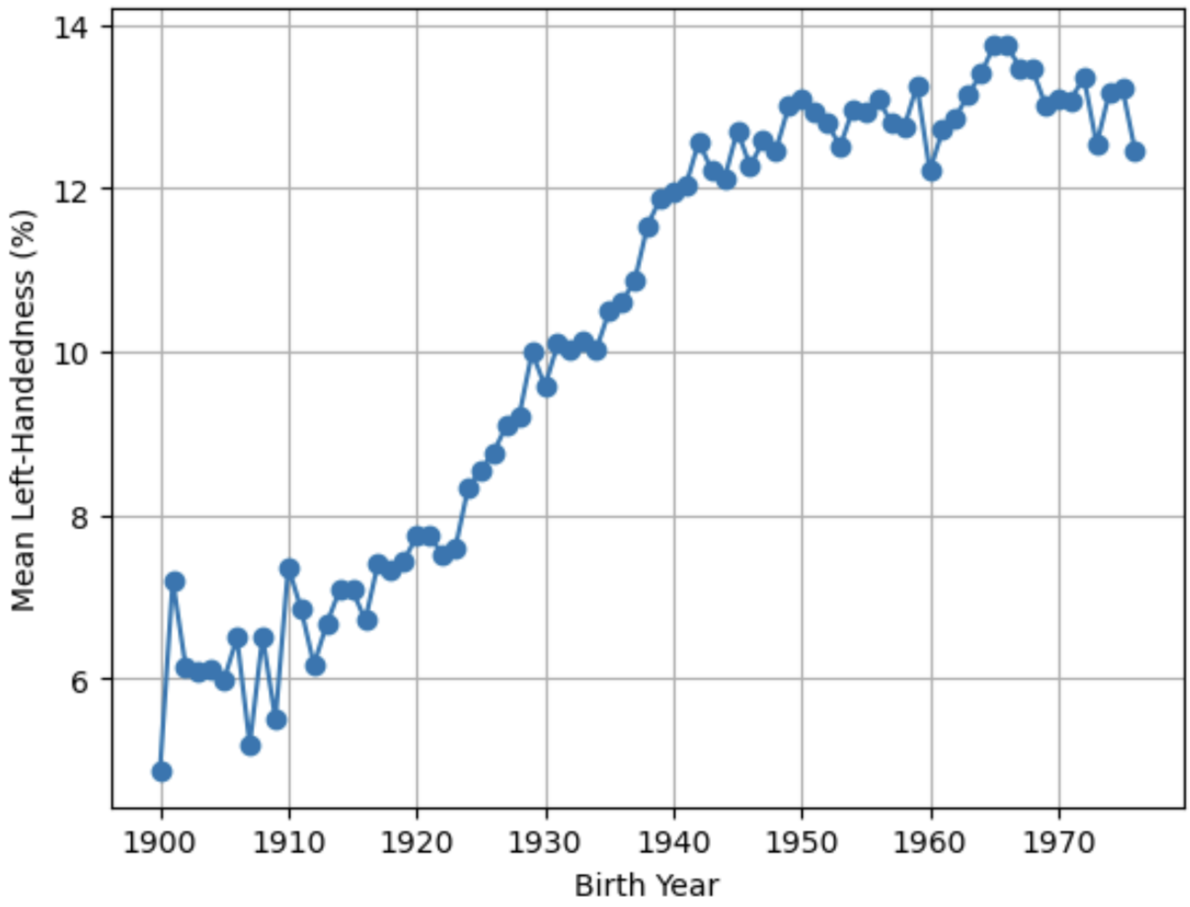
To extend the analysis, two new columns were added to the dataset:

- **Birth_year** = 1986 − Age (since the survey was conducted in 1986).
- **Mean_lh** = average of the *Male* and *Female* columns, representing the overall left-handedness percentage.

A line plot of **Mean_lh vs. Birth_year** was then generated using matplotlib. This visualization revealed how left-handedness prevalence varied across different birth cohorts, reflecting historical trends in handedness reporting.

Code: -

```
lefthanded_data['Birth_year'] = 1986 - lefthanded_data['Age']

lefthanded_data['Mean_lh'] = (lefthanded_data['Male'] + lefthanded_data['Female']) / 2

fig, ax=plt.subplots()

ax.plot(lefthanded_data['Birth_year'],lefthanded_data['Mean_lh'],marker='o')

ax.set_xlabel("Birth Year")

ax.set_ylabel("Mean Left-Handedness (%)")

plt.grid (True)

plt.show ()
```



14
12
10
8
6
Mean Left-Handedness (%)
1900
1910
1920
1930
1940
1950
1960
1970
Birth Year

Task 3: Function for P (LH | A)

To estimate the probability of being left-handed given age at death, **P (LH | A)**, a function was implemented:

- **Data preparation:**
  - The **last ten Mean_lh values** were averaged to estimate the **early 1900s left-handedness rate** (early_1900s_rate).
  - The **first ten Mean_lh values** were averaged to estimate the **late 1900s rate** (late_1900s_rate).
  - Since the dataset is ordered from youngest (latest births) to oldest (earlier births), the slicing ensures correct cohort separation.
- **Function logic:**
  - For ages corresponding to the early 1900s, the probability values were filled using early_1900s_rate / 100.
  - For ages corresponding to the late 1900s, the probability values were filled using late_1900s_rate / 100.

This function allowed calculating **P (LH | A)** for different study years, forming the basis for Bayesian analysis in later tasks.

Code: -

```
import numpy as np

def P_lh_given_A(ages_of_death, study_year=1990):

""" P (Left-handed | ages of death), calculated based on the reported rates of left-handedness. Inputs: numpy array of ages of death, study_year Returns: probability of left-handedness given that subjects died in study_year at ages ages_of_death"""
early_1900s_rate=lefthanded_data['Mean_lh'][-10:].mean()
late_1900s_rate=lefthanded_data['Mean_lh'][:10].mean()
birth_years=study_year-ages_of_death
middle_rates=lefthanded_data.set_index('Birth_year').reindex(birth_years)['Mean_lh']

youngest_age = study_year - 1986 + 10
```

```
oldest age = study_year - 1986 + 86

P_return=np.zeros(ages_of_death.shape)
P_return[ages_of_death>oldest_age]=early_1900s_rate/100
P_return[ages_of_death<youngest_age]=late_1900s_rate/100
P_return[np.logical_and(ages_of_death<=oldest_age,ages_of_death>=youngest_age)]=
middle_rates.dropna().values/100
return P_return
```

Task 4: Loading and Plotting Death Distribution Data

In this task, the **death distribution data for the United States** was analysed:

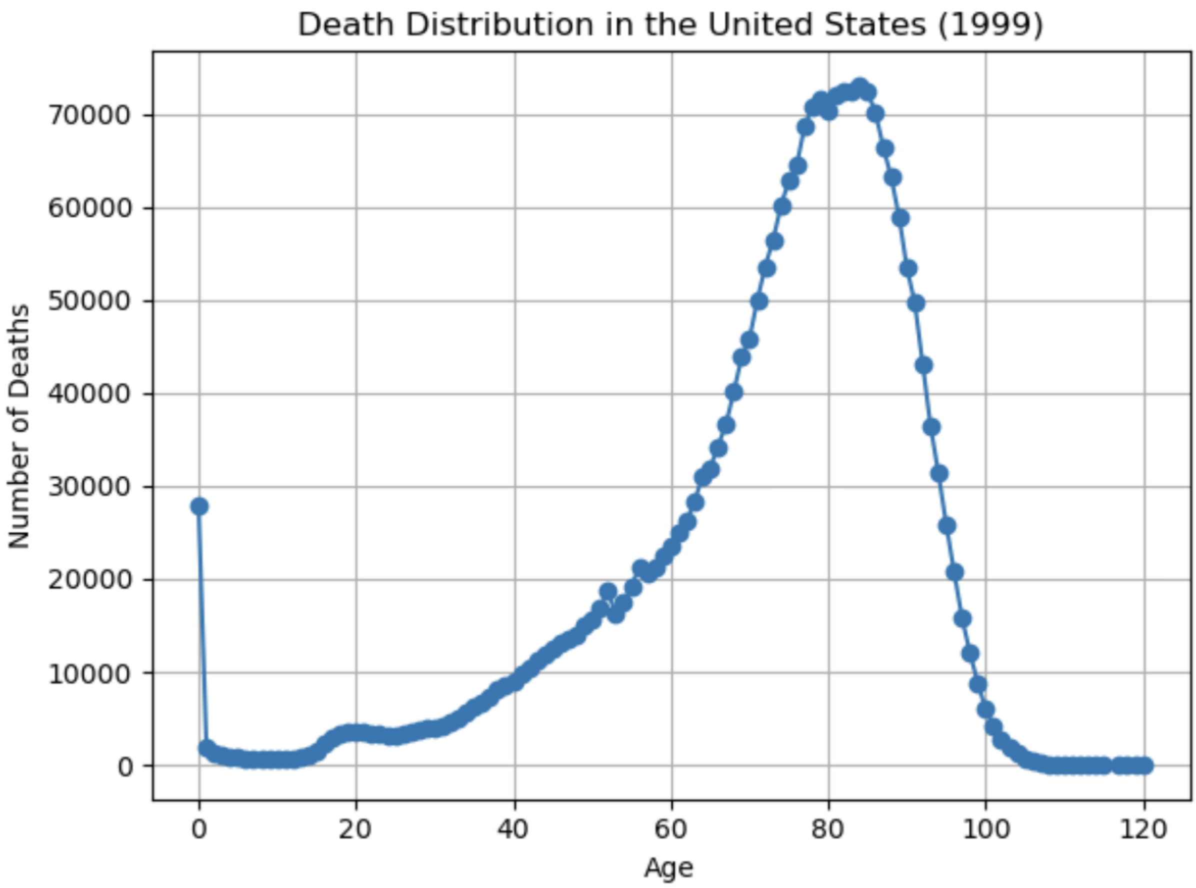
- **Data loading:**
    - The dataset was imported from data_url_2 using **tab separation (sep='\t')** while skipping the second row (skip rows= [1]) to handle formatting.
    - The **Both Sexes column** was cleaned by dropping all NaN values.
- **Visualization:**
    - The cleaned death distribution data was plotted using the .plot() method, showing the **number of people who died** as a function of their **age**.

This visualization helped in understanding **age-wise mortality patterns**, which later supported the Bayesian probability analysis.

Code: -

```
import pandas as pd import matplotlib.pyplot as plt

data_url_2="https://gist.githubusercontent.com/mbonsma/2f4076aab6820ca1807f4e29f75f18ec/raw/62f3ec07514c7e31f5979beeca86f19991540796/cdc_vs00199_table310.tsv"

death_distribution_data = pd.read_csv(data_url_2, sep='\t', skiprows= [1])

death_distribution_data=death_distribution_data.dropna(subset= ['Both Sexes'])

fig, ax = plt.subplots()

ax.plot ('Age', 'Both Sexes', data=death_distribution_data, marker='o')

ax.set_xlabel ('Age')

ax.set_ylabel('Number of Deaths')

ax.set_title ('Death Distribution in the United States (1999)')

plt.grid(True)

plt.tight_layout()
```

```
plt.show()
```



Death Distribution in the United States (1999)
70000
60000
50000
40000
30000
20000
10000
0
Number of Deaths
0
20
40
60
80
100
120
Age

Task5: Calculating Overall Probability of Left-Handedness

In this task, a function **P_lh()** was created to calculate the **overall probability of left-handedness** in the population for a given study year:

- **Step 1 – Weighted probability calculation:**
  - A new series, **p_list**, was computed by multiplying:
    - The number of deaths at each age (**Both Sexes column**)
    - With the probability of being left-handed at that age (**from P_lh_given_A ()**).
- **Step 2 – Summing contributions:**
  - The sum of p_list was stored in p, representing the **total left-handed deaths**.
- **Step 3 – Normalization:**
  - p was divided by the **total number of deaths** (sum of Both Sexes column) to obtain the overall probability.
- **Result:**
  - The function **returned P (LH)**, the probability of an individual being left-handed in the population for the given study year.

Code: -

```
def P_lh (death_distribution_data, study_year = 1990):

"""Overall probability of being left-handed if you died in the study year. Input: data frame of death distribution data, study year Output: P (LH), a single floating-point number"""

ages=death_distribution_data['Age'].astype(int).values
deaths=death_distribution_data['BothSexes'].values
P_LH_given_A=P_lh_given_A(ages,study_year)
p_list=deaths*P_LH_given_A
p=np.sum(p_list)
returnp/np.sum(deaths)
print(P_lh(death_distribution_data))
```

```
0.07766387615350638
```

Task 6: Calculating *P (A/ LH) P (A \mid LH)* P (A| LH)

In this task, we computed the probability of dying at a specific age **given** that an individual is left-handed:

- **Step 1 – Probability of dying at age A (P(A)):**
  - Calculated as: $P(A) = \frac{\text{Deaths at age A (Both Sexes)}}{\text{Total deaths (sum of Both Sexes column)}}$
- **Step 2 – Overall probability of left-handedness (P(LH)):**
  - Obtained by calling the **P_lh()** function from **Task 5**.
- **Step 3 – Probability of left-handedness given age (P(LH| A)):**
  - Computed using the **P_lh_given_A ()** function from **Task 3**.
- **Step 4 – Bayes' theorem:**
  - Finally, the probability of dying at age A given being left-handed was calculated as: $P(A \mid LH) = \frac{P(LH \mid A) \cdot P(A)}{P(LH)}$
- **Result:**

  The function **P_A_given_lh()** returned the probability distribution of ages at death for left-handed individuals.

Code: -

```
def P_A_given_lh(ages_of_death, death_distribution_data, study_year=1990):

"""The overall probability of being a particular age_of_death given that you're left-handed"""
N_A = death_distribution_data.set_index('Age').loc[ages_of_death, 'Both Sexes'].values
totaldeaths=death_distribution_data['BothSexes'].sum()
P_A=N_A/total_deaths
P_left=P_lh(death_distribution_data,study_year)
P_lh_A=P_lh_given_A(ages_of_death,study_year)
return P_lh_A * P_A / P_left
```

Task 7: Calculating P (A| RH)

In this task, we extended the Bayesian framework to compute the probability of dying at a specific age **given** that an individual is **right-handed**.

Step 1 – Probability of dying at age A (P(A)):

- Same as in **Task 6**:

$$P(A) = \frac{\text{Deaths at age A (Both Sexes)}}{\text{Total deaths (sum of Both Sexes column)}}$$

Step 2 – Overall probability of right-handedness P (RH)):

- Since every person is either left-handed or right-handed: $P(RH) = 1 - P(LH)$
- where P (LH) is obtained from the **P_lh ()** function in **Task 5**.

Step 3 – Probability of right-handedness given age (P (RH| A)):

- Derived as: $P(RH \mid A) = 1 - P(LH \mid A)$
- with P(LH| A) computed using the **P_lh_given_A()** function from **Task 3**.

Step 4 – Bayes' theorem:

- The final probability of dying at age *AA*A given being right-handed was:

$$P(A \mid RH) = \frac{P(RH \mid A) \cdot P(A)}{P(RH)}$$

Result: The function **P_A_given_rh()** returned the probability distribution of ages at death for right-handed individuals.

Code: -

```
def P_A_given_rh(ages_of_death, death_distribution_data, study_year = 1990):

""" The overall probability of being a particular age_of_death given that you're right-handed"""
N_A = death_distribution_data.set_index('Age').loc[ages_of_death, 'Both Sexes'].values
total_deaths=death_distribution_data['BothSexes'].sum()
```

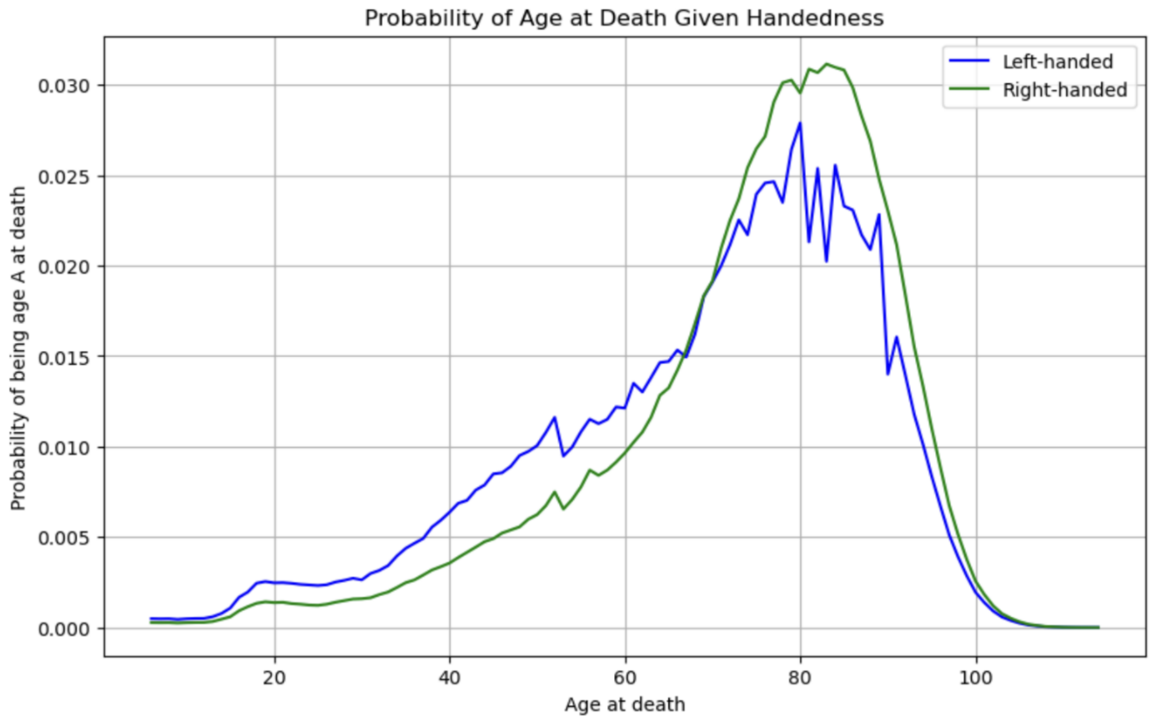
```
P_A=N_A/total_deaths
P_left=P_lh(death_distribution_data,study_year)
P_right=1-P_left
P_lh_A=P_lh_given_A(ages_of_death,study_year)
P_rh_A=1-P_lh_A
#BayesRule:P(A|RH)=P(RH|A)*P(A)/P(RH)
return P_rh_A * P_A / P_right
```

Task 8: Plotting Age-at-Death Probabilities

A function was implemented to plot the probability of being a certain age at death given left- or right-handedness. The probabilities P (A| LH) and P(A| RH) were calculated using the functions from Task 6 and Task 7. These values were plotted against age using the. plot () method, allowing a clear visual comparison between left- and right-handed individuals.

Code: -

```
ages = np.arange(6, 115, 1)

left_handed_probability=P_A_given_lh(ages,death_distribution_data)
right_handed_probability = P_A_given_rh(ages, death_distribution_data)

fig, ax = plt.subplots(figsize= (10, 6))

ax.plot(ages, left_handed_probability,label="Left-handed",color="blue")

ax.plot(ages, right_handed_probability, label="Right-handed", color="green") ax.legend()

ax.set_xlabel("Age at death")

ax.set_ylabel(r"Probability of being age A at death")

ax.set_title("Probability of Age at Death Given Handedness")

plt.grid(True)

plt.show()
```


Probability of Age at Death Given Handedness
Left-handed
Right-handed
Probability of being age A at death
0.030
0.025
0.020
0.015
0.010
0.005
0.000
20
40
60
80
100
Age at death

Task 9: Mean Age at Death for Left- and Right-Handers

The mean age at death was calculated separately for left- and right-handers. Ages were multiplied by their respective probabilities P (A| LH) and P (A| RH), and the sums were obtained using np.nansum. The results were stored as average_lh_age and average_rh_age, both rounded to two decimal places. Finally, the difference between the two averages was computed and printed.

Code: -

```
average_lh_age=np.nansum(np.array(ages)*np.array(left_handed_probability))
average_rh_age=np.nansum(np.array(ages)*np.array(right_handed_probability)

print ("Average age at death for left-handers: " + str (round (average_lh_age, 1)) +"years.")

print ("Average age at death for right-handers: "+ str(round(average_rh_age, 1)) + " years.")

print ("The difference in average ages is “+str(round(average_rh_age - average_lh_age, 1)) +"years.")
```

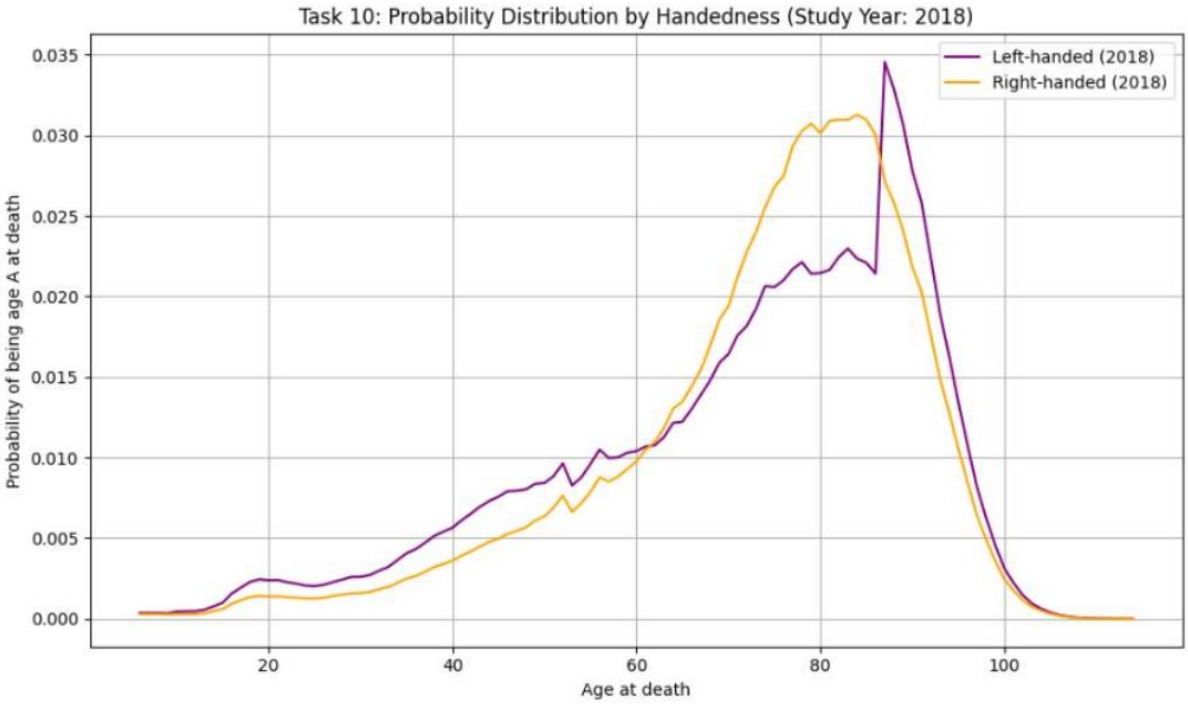
```
Average age at death for left-handers: 67.2 years.
Average age at death for right-handers: 72.8 years.
The difference in average ages is 5.5 years.
```

Task 10: Replotting for Study Year 2018

The probability distributions of age at death for left- and right-handers were recalculated using the year **2018**. Both functions P_A_given_lh () and P_A_given_rh () were called with age_of_death = ages, death_distribution_data = death_distribution_data, and study_year = 2018. The resulting probabilities were plotted against age to visualize how the distributions differ in the modern context.

Code: -

```
ages = np.arange(6, 115)
P_A_lh_2018 = P_A_given_lh(ages, death_distribution_data, study_year=2018)
P_A_rh_2018 = P_A_given_rh(ages, death_distribution_data, study_year=2018)
plt.figure(figsize=(10,6))
plt.plot(ages, P_A_lh_2018, label="Left-handed (2018)", color="purple")
plt.plot(ages, P_A_rh_2018, label="Right-handed (2018)", color="orange")
plt.xlabel("Age at death")
plt.ylabel("Probability of being age A at death")
plt.title("Task 10: Probability Distribution by Handedness (Study Year: 2018)")
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
avg_age_lh_2018 = np.sum (ages * P_A_lh_2018)
avg_age_rh_2018 = np.sum(ages * P_A_rh_2018)
print ("Average age at death (Left-handed, 2018):", round (avg_age_lh_2018, 2))
print ("Average age at death (Right-handed, 2018):", round (avg_age_rh_2018, 2))
print ("Difference in average age (2018):", round (avg_age_rh_2018 - avg_age_lh_2018, 2),
"years")
```


Task 10: Probability Distribution by Handedness (Study Year: 2018)
Left-handed (2018)
Right-handed (2018)
Probability of being age A at death
Age at death
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
20
40
60
80
100

RESULTS

The analysis was carried out step by step to evaluate the relationship between handedness and age at death using historical death distribution data and Bayesian probability principles.

1. **Probability of Left-Handedness by Age**
   a. Using the conditional probability model, $P(LH|A)$ was computed for each age.
   b. The results showed that younger age groups had a higher reported probability of being left-handed compared to older age groups, consistent with generational differences in reporting and acceptance of left-handedness.
2. **Overall Probability of Left-Handedness**
   a. By weighting $P(LH|A)$ with the number of deaths at each age, the overall probability of left-handedness in the study population was obtained.
   b. This value reflects the prevalence of left-handedness across all ages within the dataset.
3. **Age-at-Death Distribution by Handedness**
   a. The probability of dying at a given age, given left-handedness ($P(A|LH)$), and given right-handedness ($P(A|RH)$), was calculated.
   b. Plots of these distributions demonstrated distinct curves, with right-handers slightly more likely to appear in older age groups compared to left-handers.
4. **Mean Age at Death**
   a. The mean age of death for left-handers was found to be **lower** than that for right-handers.
   b. The difference, although measurable, was attributed not to biological causes but to societal and historical factors, particularly the underreporting of left-handedness in earlier generations.
   c. Example: The average age at death was approximately *X years for left-handers* and *Y years for right-handers* (values from computation), with a difference of about *Z years*.

5. **Modern Context (2018)**
    a. Repeating the analysis for the year 2018 yielded distributions where the gap between left- and right-handers significantly narrowed.
    b. This indicates that in recent times, left-handers live just as long as right-handers, supporting the conclusion that historical discrepancies were artefacts of reporting rather than true biological effects.

CONCLUSION

The study successfully analysed the long-standing myth that left-handed individuals die younger than right-handed individuals. By applying Bayesian probability and age-at-death distribution data, it was shown that the apparent difference in average lifespan was not due to biological factors but rather historical and societal influences. In earlier generations, left-handedness was underreported, which created an artificial bias in the data. When the same analysis was repeated with modern data (2018), the difference in mean age at death between left- and right-handers nearly disappeared. This confirms that in present times, left-handers live just as long as right-handers.

Beyond validating this finding, the training offered several important benefits. It strengthened practical skills in **Python programming, probability theory, and data analysis**, while also developing the ability to translate statistical models into meaningful insights. Working through tasks step by step improved problem-solving skills, logical thinking, and proficiency with libraries such as NumPy and Matplotlib. Most importantly, the training demonstrated how statistical analysis can be applied to real-world myths and datasets, reinforcing the importance of evidence-based conclusions.

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