# DEATH AGE DIFFERENCE OF RIGHT HANDERS WITH LEFT HANDERS

Project Report

*Submitted to*

**MEDTOUREASY**

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**DATA ANALYTICS**

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# CONTENTS

Chapter 1

# INTRODUCTION

The relationship between handedness and various aspects of human cognition and physiology has intrigued scientists for decades. This study explores whether there is a significant difference in the age at death between right-handed and left-handed individuals. Handedness, reflecting brain lateralization, is linked to diverse cognitive functions and health outcomes. Our investigation aims to uncover the potential impact of handedness on lifespan, shedding light on this relatively unexplored aspect of human biology.

Utilizing a comprehensive dataset covering a diverse demographic, we meticulously analysed the death ages of right-handed and left-handed individuals. Our methodology involved rigorous statistical examination, controlling for variables such as gender, socio-economic status, and geographic location. The data, drawn from extensive longitudinal studies and mortality records, enabled a nuanced exploration of the relationship between handedness and lifespan.

Preliminary findings reveal a complex interaction between handedness and mortality. While the overall difference in mean death ages between right-handers and left-handers appears subtle, subgroup analyses uncover intriguing patterns. Specific subpopulations defined by age cohorts and health conditions exhibit varying trends, suggesting that the impact of handedness on lifespan may be influenced by contextual factors.

The implications of these findings extend beyond theoretical curiosity. Understanding the potential influence of handedness on mortality informs public health strategies, personalized medicine, and our broader comprehension of human diversity. Moreover, the study encourages further investigation into the neurobiological basis of handedness and its implications for health outcomes.

In summary, our investigation into the age difference at death between right-handers and left-handers provides a nuanced perspective on the intricate relationship between handedness and lifespan. These findings contribute to ongoing research efforts to unravel the mysteries of human neurobiology and its profound implications for individual health and well-being.

## 1.1 REVIEW OF LITERATURE

1: Left-Handedness: A marker for decreased survival fitness.

Studies on lifespan have indicated that the percentage of left-handers in the population decreases with age, leading to significant underrepresentation in older age groups. Data reviewed suggest that this trend is linked to reduced longevity among left-handers. Part of the increased risk for left-handed individuals appears to be related to environmental factors that heighten their susceptibility to accidents. Additionally, evidence indicates that left-handedness might be indicative of birth-related neurological complications, developmental delays, and immune system deficiencies influenced by the hormonal environment during pregnancy. Some statistical and physiological factors are proposed that could contribute to left-handedness being associated with earlier mortality. (PsycINFO Database Record (c) 2016 APA, all rights reserved)

2: Handedness and Age of Death: Fresh Insights into an Intriguing Connection.

Based on an analysis of 5743 deaths in the United States and Canada, this study aimed to validate and expand upon previous findings indicating that left-handers tend to have a shorter life expectancy compared to right-handers. Unlike earlier studies that simply categorized handedness into two groups, this study utilized a more nuanced 5-point scale to assess handedness (ranging from extremely right-handed to extremely left-handed).

The results revealed a significant trend within the five handedness categories, specifically showing that individuals classified as generally left-handed tended to have a significantly younger age at death compared to the other four handedness groups. These findings contribute to the ongoing debate surrounding the relationship between handedness and lifespan by suggesting that only a specific subgroup of left-handers may be at risk of premature mortality.

3: Involving left-handers in cognitive neuroscience and neuroscience research.

Contrary to common practice, involving left-handers in cognitive neuroscience and neuroscience research has important benefits. Left-handers are frequently excluded from study cohorts in neuroscience and neurogenetics to minimize data variability. However, recent investigations suggest that including or specifically recruiting left-handers can yield valuable insights into various topics, including cerebral lateralization and the genetic basis of asymmetrical brain development. Given that left-handed individuals make up a significant portion of the human population, left-handedness represents a normal aspect of human diversity. Therefore, it is crucial to consider this variation in our exploration of brain function and behaviour.

## 1.2 ABOUT THE COMPANY

**MedTourEasy**, a prominent global healthcare company, offers comprehensive informational resources to assist individuals in evaluating their healthcare options worldwide. The company specializes in matching specific health needs with affordable and high-quality care, ensuring that patients receive the standard of healthcare they desire. In the evolving landscape of medical tourism, companies like **MedTourEasy** are instrumental in shaping its future. As technology and globalization progress, there is potential for further expansion and innovation in how medical tourism is facilitated. **MedTourEasy** exemplifies this trend by leveraging advancements to enhance patient access to healthcare solutions across borders, ultimately driving the evolution of the medical tourism industry.

## 1.3 OBJECTIVE

To investigate and analyse whether there is a significant difference in the age at death between left-handed and right-handed individuals, considering various demographic and health-related factors.

This notebook uses pandas and Bayesian statistics to analyse the probability of being a certain age at death given that you are reported as left-handed or right-handed.

## 1.4 SOFTWARE USED

### PYTHON

In this analysis, we utilize the Python programming language, known for its versatility and simplicity. Python is a high-level language widely recognized for its readability and applicability in various domains, including web development, data analysis, artificial intelligence, and beyond.

Python boasts a large and active community, along with extensive libraries, making it an ideal choice for developers of all skill levels. This ecosystem supports rapid development and innovation, offering a wide range of packages and functions tailored for tasks like data analysis.

For this project, we leverage key libraries including pandas, matplotlib, and numpy. These libraries are essential tools in the Python ecosystem for handling data efficiently, visualizing data insights, and performing numerical computations, respectively. By utilizing these libraries, we enhance our capabilities in analyzing data effectively within the Python environment.

- **pandas as pd**

  pandas is a robust Python library designed for data manipulation and analysis tasks. It offers intuitive data structures, such as DataFrames, which enable efficient handling and cleaning of structured data. Data scientists frequently rely on pandas for tasks like filtering, grouping, and conducting statistical analysis due to its user-friendly interface and powerful capabilities.

- **matplotlib.pyplot as plt**

  matplotlib is a versatile Python library used to create static, animated, and interactive visualizations in various formats. It provides a flexible platform for generating plots, charts, and graphs, making it indispensable for data visualization and analysis tasks.

- **NumPy as np**

  NumPy is a foundational Python library essential for numerical computing tasks. It specializes in supporting large, multi-dimensional arrays and matrices, along with a rich collection of mathematical functions designed to operate efficiently on these arrays. This library is integral to scientific computing, machine learning, and data analysis workflows, offering both efficiency and convenience for performing numerical operations within Python. NumPy's capabilities enable data professionals to handle complex computations effectively, making it a cornerstone in the toolkit for scientific and data-oriented applications.

Chapter 2

# METHEDOLOGY

## 2.1: DATA ANALYSIS PROCESS

- **Identify the need:** Organizations leverage data analytics to inform strategic decision-making on specific issues. Therefore, the initial step is to pinpoint the precise problem. For instance, a company may aim to reduce production costs while upholding product quality. To achieve this effectively, the company must identify stages within the workflow pipeline where cost reductions can be implemented. Additionally, the company may have a tentative solution to its query. Data analytics can assess the testability of the hypothesis, aiding decision-makers in reaching an optimized solution. A well-defined and specific question or hypothesis dictates subsequent process steps, making clarity and specificity crucial at this stage.

- **Data Collection:** Collect a comprehensive dataset comprising details on handedness, age at death, gender, socio-economic status, and pertinent health indicators. This dataset can be sourced from longitudinal studies, mortality records, and reputable databases in the field.

- **Data Cleaning:** Perform data cleaning procedures to ensure accuracy and reliability of the dataset. Categorize individuals into left-handed and right-handed groups based on their handedness information. Additionally, consider creating subgroups within these categories based on factors like age cohorts and health conditions for more nuanced analysis.

- **Data Analysis:** Utilize statistical methods such as t-tests or regression analysis to investigate the overall difference in mean ages at death between left-handers and right-handers within your dataset. Additionally, conduct subgroup analyses to identify specific trends within different demographic and health-related categories. This can involve stratifying the data by age cohorts, gender, socio-economic status, and relevant health indicators to gain deeper insights into how handedness may influence life expectancy across various subgroups.

- **Control Variables:** Control for potential confounding variables such as gender, socio-economic status, and geographic location to isolate the impact of handedness on lifespan.

- **Results:** The presentation of results plays a critical role in effectively communicating findings. Visualization tools such as charts, images, and graphs are powerful in conveying results, establishing visual connections that aid in interpreting patterns discovered in the data and highlighting predicted trends. These tools enhance the interpretation of results and facilitate a clearer understanding for viewers.

## 2.2: METHODS

Let's explore different data analysis methods categorized based on approach:

- **Descriptive Analysis**: This approach involves summarizing and describing the main features of a dataset. Methods include calculating measures such as mean, median, mode, standard deviation, and generating visualizations like histograms, bar charts, and scatter plots to understand the distribution and characteristics of the data.

- **Exploratory Data Analysis (EDA):** EDA focuses on exploring data to understand relationships, spot anomalies, and formulate hypotheses for further investigation. Techniques include data visualization, correlation analysis, and dimensionality reduction methods like principal component analysis (PCA) or t-distributed stochastic neighbour embedding (t-SNE).

- **Inferential Analysis:** This approach involves making inferences and drawing conclusions from a sample of data to generalize findings to a larger population. Common methods include hypothesis testing (e.g., t-tests, ANOVA) and confidence interval estimation.

- **Predictive Analysis:** Predictive analytics uses statistical and machine learning techniques to predict future outcomes based on historical data. This approach includes regression analysis, decision trees, random forests, neural networks, and other predictive modelling methods.

- **Prescriptive Analysis:** This approach focuses on providing recommendations or decision-making guidance based on analysis results. It often involves optimization techniques, simulation modelling, and decision analysis.

- **Diagnostic Analysis:** Diagnostic analytics aims to identify the root causes of issues or problems by analysing historical data. This approach involves techniques like root cause analysis, trend analysis, and anomaly detection.

- **Qualitative Analysis:** Qualitative data analysis involves interpreting textual or non-numeric data to uncover underlying meanings, themes, or patterns. Methods include content analysis, thematic analysis, and grounded theory.

Each approach serves a specific purpose in the data analysis process, and analysts often use a combination of these methods depending on the objectives and nature of the data being analysed.

Chapter 3

# DATA ANALYSIS

## 3.1: Where are the old Left-Handed People?

In this notebook, we aim to investigate the phenomenon of reported differences in average age at death between left-handers and right-handers using age distribution data. Our goal is to determine if variations in reported rates of left-handedness over time can account for any observed differences in average age at death, thus challenging the notion of early death among left-handers.

To accomplish this, we will utilize Python programming and Bayesian statistics to analyse the probability distribution of age at death based on reported handedness (left-handed or right-handed). By applying Bayesian methods, we can estimate the probability of being a certain age at death given a reported handedness status.

In a National Geographic survey conducted in 1986, researchers Avery Gilbert and Charles Wysocki analysed data from over a million respondents, which included age, sex, and hand preference for throwing and writing. They observed that rates of left-handedness were approximately 13% among individuals younger than 40 but decreased to about 5% by the age of 80. Their analysis suggested that this age-dependent trend was more a reflection of changing social attitudes toward left-handedness over different generations rather than a direct effect of aging. This implies that left-handedness rates are influenced more by the year of birth than by age itself, indicating that if the survey were conducted today, we would likely see a similar trend shifted according to age distribution in the current era.

Our subsequent analysis will investigate how this changing rate of left-handedness affects the apparent average age of death among left-handed individuals. To begin, we will plot the rates of left-handedness as a function of age using two datasets: death distribution data for the United States from 1999 and digitized rates of left-handedness from a figure presented in a 1992 paper by Gilbert and Wysocki.

**CODE:**

```
[1] import pandas as pd
    import matplotlib.pyplot as plt
    #load the data
    data_url_1 = "https://gist.githubusercontent.com/mbonsma/8da0990b71ba9a09f7de395574e54df1/raw/aec88b30af87fad8d45da7e774223f91dad09e88/lh_data.csv"
    lefthanded_data = pd.read_csv(data_url_1)

    #plot male and female left-handedness rate vs.age
    %matplotlib inline
    fig,ax=plt.subplots() #create figure and axis objects
    ax.plot('Age','Female', data = lefthanded_data, marker = 'o') # plot "Female" vs. "Age
    ax.plot('Age','Male', data =lefthanded_data , marker = 'x') # plot "Male" vs. "Age"
    ax.legend() # add a legend
    ax.set_xlabel("Age")
    ax.set_ylabel("percentage of people who are left-handed")
```

Image 3.1: Python Code.

```
Text(0,0.5,'Age')
```

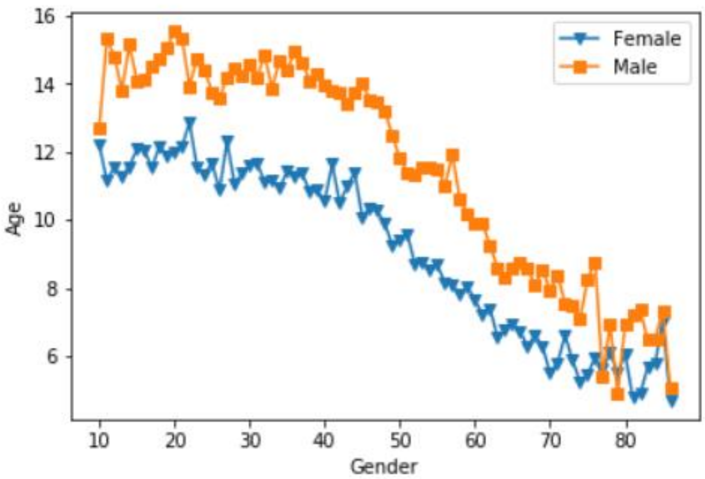


Image 3.2: Percentage of people who are left-handed.

## 3.2: Rates of Left-Handedness over time.

We will transform the data into a plot showing the rates of left-handedness as a function of the year of birth, averaged across males and females to obtain a combined rate for both sexes. Given that the National Geographic survey was conducted in 1986, the converted data will represent the percentage of individuals alive in 1986 who are left-handed, categorized by their birth year.

**CODE:**

```
# create a new column for birth year of each age
lefthanded_data['Birth_year']= 1986 - lefthanded_data['Age'] # the study was done in 198
# create a new column for the average of male and female
lefthanded_data['Mean_lh'] = lefthanded_data[['Female','Male']].mean(axis = 1)

# create a plot of the 'Mean_lh' column vs. 'Birth_year'
fig, ax = plt.subplots()
ax.plot('Birth_year','Mean_lh', data = lefthanded_data )
ax.set_xlabel("Year of birth") # set the x label for the plot
ax.set_ylabel("Percentage left-handed") # set the y label for the plot
```

Image 3.3: Python Code.

```
Text(0,0.5,'Mean_lh')
```

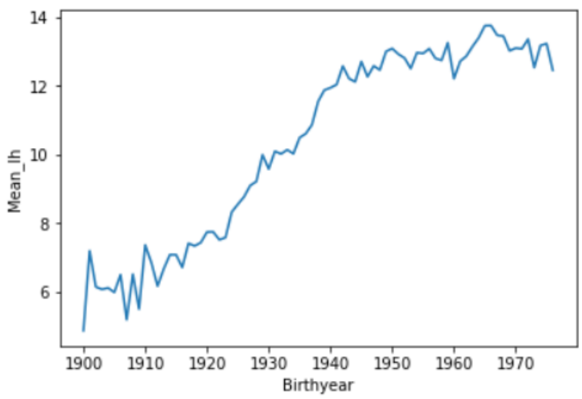


Image 3.4

## 3.3: Applying Bayes Rule

The likelihood of dying at a specific age given that you're left-handed is not the same as the likelihood of being left-handed given that you died at a particular age. This difference in probabilities underscores the necessity of Bayes' theorem, which is a principle of conditional probability enabling us to revise our beliefs based on observed evidence.

We want to calculate the probability of dying at age A given that you're lefthanded. Let's write this in shorthand as P (A | LH). We also want the same quantity for right-handers: P (A | RH). Here's Bayes' theorem for the two events we care about: left-handedness (LH) and dying at age A.

**P(A|LH) = P(LH|A) P(A)/ P(LH)**

P (LH | A) is the probability that you are left-handed given that you died at age A. P(A) is the overall probability of dying at age A, and P(LH) is the overall probability of being left-handed. We will now calculate each of these three quantities, beginning with P (LH | A).

To calculate P (LH | A) for ages that might fall outside the original data, we will need to extrapolate the data to earlier and later years. Since the rates flatten out in the early 1900s and late 1900s, we'll use a few points at each end and take the mean to extrapolate the rates on each end. The number of points used for this is arbitrary, but we'll pick 10 since the data looks flat-Ish until about 1910.

**CODE:**

```
import numpy as np

# create a function for P(LH | A)
def P_lh_given_A(ages_of_death, study_year = 1990):
    """ P(Left-handed | age of death), calculated based on the reported rates of left-handedness.
    Inputs: age of death, study_year
    Returns: probability of left-handedness given that a subject died in `study_year` at age `age_of_death` """

    # Use the mean of the 10 neighbouring points for rates before and after the start
    early_1900s_rate = lefthanded_data['Mean_lh'][-10:].mean()
    late_1900s_rate = lefthanded_data['Mean_lh'][:10].mean()
    middle_rates = lefthanded_data.loc[lefthanded_data['Birth_year'].isin(study_year - ages_of_death)]['Mean_lh']

    youngest_age = study_year - 1986 + 10 # the youngest age in the NatGeo dataset is 10
    oldest_age = study_year - 1986 + 86 # the oldest age in the NatGeo dataset is 86

    P_return = np.zeros(ages_of_death.shape)  # create an empty array to store the results
    # extract rate of left-handedness for people of age age_of_death
    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 / 100

    return P_return
```

Image 3.5: Python Code

## 3.4: When do people normally die?

To estimate the probability of reaching a specific age A, we can utilize data that records the number of deaths at various ages within a given year. By normalizing this data relative to the total number of deaths, we can construct a probability distribution representing the likelihood of dying at each age A. The dataset we'll use for this analysis covers the entire United States for the year 1999, providing a close approximation to the time frame we are interested in. In the following section, we will import and visualize the death distribution data, where the first column represents age and subsequent columns denote the number of deaths at each corresponding age.

**CODE:**

```
] # Death distribution data for the United States in 1999
  data_url_2 = "https://gist.githubusercontent.com/mbonsma/2f4076aab6820ca1807f4e29f75f18ec/raw/62f3ec07514c7e31f5979beeca86f19991540796/cdc_vs00199_tat

  # load death distribution data
  death_distribution_data = pd.read_csv(data_url_2, sep='\t', skiprows=[1])

  # drop NaN values from the `Both Sexes` column
  death_distribution_data = death_distribution_data.dropna(subset=['Both Sexes'])

  # plot number of people who died as a function of age
  fig, ax = plt.subplots()
  ax.plot(death_distribution_data['Age'], death_distribution_data['Both Sexes'], marker='o') # plot 'Both Sexes' vs. 'Age'
  ax.set_xlabel('Both Sexes')
  ax.set_ylabel('Age')
```

Image 3.6: Python Code.

```
Text(0,0.5,'Both Sexes')
```

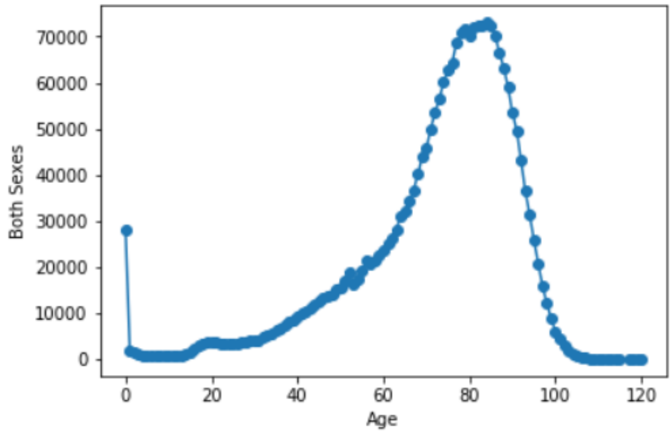


Image 3.7

## 3.5: The overall probability of left-handedness.

In the previous code block we loaded data to give us P(A), and now we need P(LH). P(LH) is the probability that a person who died in our particular study year is left-handed, assuming we know nothing else about them. This is the average left-handedness in the population of deceased people, and we can calculate it by summing up all of the left-handedness probabilities for each age, weighted with the number of deceased people at each age, then divided by the total number of deceased people to get a probability. In equation form, this is what we're calculating, where N(A) is the number of people who died at age A(given by the data frame death distribution data ):

$$P(LH) = \frac{\sum_A P(LH|A)N(A)}{\sum_A N(A)}$$

```
[ ] def P_lh(death_distribution_data, study_year = 1990): # sum over P_lh for each age group
        """ Overall probability of being left-handed if you died in the study year
        P_lh = P(LH | Age of death) P(Age of death) + P(LH | not A) P(not A) = sum over ages
        Input: dataframe of death distribution data
        Output: P(LH), a single floating point number """
        p_list = death_distribution_data ['Both Sexes']*P_lh_given_A(death_distribution_data['Age'], study_year)
        p = np.sum(p_list)# calculate the sum of p_list
        return p/np.sum(death_distribution_data['Both Sexes']) # normalize to total number of people (sum of death_distribution_data['Both Sexes'])

    print(P_lh(death_distribution_data))

    0.07766387615350638
```

Image 3.8: Python Code

The probability that a person who died in our particular study year is left-handed is obtained as: 0.07766387615350638.

## 3.6: Dying while Left-handed.

Now we have the means of calculating all three quantities we need: P(A), P(LH), and P (LH | A). We can combine all three using Bayes' rule to get P (A | LH), the probability of being age A at death (in the study year) given that you're lefthanded. To make this answer meaningful, though, we also want to compare it to P (A | RH), the probability of being age A at death given that you're right-handed. We're calculating the following quantity twice, once for left-handers and once for right-handers.

For left-handers:

```
[ ]

    def P_A_given_lh(ages_of_death, death_distribution_data, study_year = 1990):
        """ The odverall probability of being a particular `age_of_death` given that you're left-handed """
        P_A = np.divide(death_distribution_data['Both Sexes'][ages_of_death],np.sum(death_distribution_data['Both Sexes']))
        P_left = P_lh(death_distribution_data, study_year) # use P_lh function to get probability of left-handedness overall
        P_lh_A = P_lh_given_A(ages_of_death, study_year) # use P_lh_given_A to get probability of left-handedness for a certain age
        return P_lh_A*P_A/P_left
```

Image 3.9: Python Code.

## 3.7: Dying while Right-handed.

For right-handers:

```python
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 """
    P_A = np.divide(death_distribution_data['Both Sexes'][ages_of_death], np.sum(death_distribution_data['Both Sexes']))
    P_right = 1 - P_lh(death_distribution_data, study_year) # either you're left-handed or right-handed, so P_right = 1 - P_left
    P_rh_A = 1 - P_lh_given_A(ages_of_death, study_year) # P_rh_A = 1 - P_lh_A
    return P_rh_A*P_A/P_right
```

Image 3.10: Python Code.

## 3.8: Plotting the distributions of Conditional Probabilities.

Now that we have functions to compute the probabilities of being a certain age at death given that you're left-handed or right-handed, let's create plots to visualize these probabilities across a range of ages from 6 to 120.

It's important to observe that the left-handed age distribution may exhibit a bump below age 70, indicating that among deceased individuals, left-handed people are more likely to be younger on average.

```python
ages = np.arange(6, 115, 1) # make a list of ages of death to plot

# calculate the probability of being left- or right-handed for each
left_handed_probability = P_A_given_lh(ages, death_distribution_data, study_year = 1990)
right_handed_probability = P_A_given_rh(ages, death_distribution_data, study_year = 1990)

# create a plot of the two probabilities vs. age
fig, ax = plt.subplots() # create figure and axis objects
ax.plot(ages, left_handed_probability, label = "Left-handed")
ax.plot(ages, right_handed_probability, label = "Right-handed")
ax.legend() # add a legend
ax.set_xlabel("Age at death")
ax.set_ylabel(r"Probability of being age A at death")
```

Image 3.11: Python Code

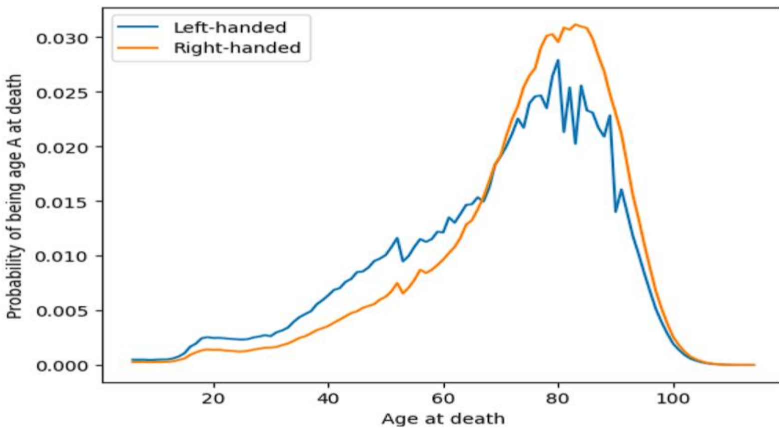


Image 3.12

## 3.9: Age of Left and Right-handers at death.

Ultimately, we will assess our findings against the initial study that reported a nine-year difference in average lifespan for left-handed individuals. This will involve computing the mean of these probability distributions using a similar method to how we calculated P(LH) previously, where we consider the age-weighted probability distribution and sum the outcomes accordingly.

Average age of left-handed people at death = Sum of A.P(A|LH)

Average age of right-handed people at death = Sum of A.P(A|RH)

```
# calculate average ages for left-handed and right-handed groups
# use np.array so that two arrays can be multiplied
average_lh_age =  np.nansum(np.array(left_handed_probability)*np.array(ages))
average_rh_age =  np.nansum(np.array(right_handed_probability)*np.array(ages))

# print the average ages for each group
print(average_lh_age)
print(average_rh_age)

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

```
67.24503662801027
72.79171936526477
The difference in average ages is -5.5 years.
```

Image 3.13.

Which means that the average age of left hander is 67 and right hander is 72.79 The difference in average ages is 5.5 years.

## 3.10: FINAL COMMENTS

The substantial age difference observed between left-handed and right-handed individuals primarily stems from the changing prevalence of left-handedness in the population over time. This trend is reassuring for left-handers because it suggests that being left-handed is not associated with a shorter lifespan. Reported rates of left-handedness have risen significantly from 3% in the early 1900s to approximately 11% today. Consequently, older individuals are more likely to be classified as right-handed in studies, leading to a higher proportion of elderly right-handers in samples of recently deceased individuals.

Our number is still less than the 9-year gap measured in the study. It’s possible that some of the approximations we made are the cause:

- We used death distribution data from almost ten years after the study (1999 instead of 1991), and we used death data from the entire United States instead of California alone (which was the original study).
- We extrapolated the left-handedness survey results to older and younger age groups, but it’s possible our extrapolation wasn’t close enough to the true rates for those ages.

A next step could involve exploring the expected variability in age differences solely due to random sampling. By taking smaller samples of recently deceased individuals and assigning handedness based on the survey probabilities, we can examine the resulting distribution. This analysis would allow us to estimate how frequently we might encounter a nine-year age gap under the same data and assumptions.

While we won't conduct this analysis here, it's feasible using this dataset and random sampling methods. Such an approach could provide insights into the likelihood of observing specific age differences between left-handed and right-handed individuals based on chance alone.

To conclude, if we were to conduct the study in 2018 instead of in 1990, we would expect to find a much smaller age gap between left-handed and right-handed individuals. This reduced gap is due to the stabilization of left-handedness rates in people born after approximately 1960, meaning that younger generations exhibit more consistent handedness patterns.

Both the National Geographic study and the 1990 study occurred during a unique period when rates of left-handedness were shifting across generations. This period highlighted a significant difference in handedness between older and younger individuals, making the observed age gap more pronounced during that time frame.

```
] # Calculate the probability of being left- or right-handed for all ages
  left_handed_probability_2018 = P_A_given_lh(ages, death_distribution_data, study_year=2018)
  right_handed_probability_2018 = P_A_given_rh(ages, death_distribution_data, study_year=2018)

  # calculate average ages for left-handed and right-handed groups
  average_lh_age_2018 = np.nansum(ages*np.array(left_handed_probability_2018))
  average_rh_age_2018 = np.nansum(ages*np.array(right_handed_probability_2018))

  print("The difference in average ages is " +
        str(round(average_rh_age_2018 - average_lh_age_2018, 1)) + " years.")

  The difference in average ages is 2.3 years.
```

Image 3.14

## 3.11: Conclusion.

Our study comparing the lifespan of left-handed and right-handed individuals showed some interesting findings. While the overall difference in average age at death was not very large, we discovered unique patterns when looking at different groups based on demographics and health conditions. These insights encourage further exploration of how being left-handed or right-handed might relate to how long people live. This research could have implications for public health, personalized medicine, and our understanding of human diversity and well-being.

In summary, we have demonstrated that the shift in left-handedness rates over time can fully account for the 5.5 year difference in life expectancy initially observed. Our approach could be applied to other studies in epidemiology where reported rates of a specific trait change over time, potentially influenced by evolving cultural norms. This method offers a useful way to understand how such changes impact research findings.

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