MedTourEasy

Data Analyst Traineeship Program

INTERNSHIP REPORT

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Project Title:
Analyze Death Age Difference of Right Handers with Left Handers

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Contents

Acknowledgments

I extend my heartfelt appreciation to the MedTourEasy team and my fellow colleagues for fostering a productive and conducive working environment. The traineeship opportunity at MedTourEasy marked a significant turning point for my learning journey, providing valuable insights into the complexities of Data Visualizations in Data Analytics. It has been instrumental in both my personal and professional growth. I am sincerely grateful for the chance to engage with numerous professionals who generously guided me throughout the traineeship project, contributing immensely to my learning curve.

First and foremost, I would like to convey my deepest gratitude and special thanks to the Training Development Team of MedTourEasy for granting me the opportunity to undertake my traineeship at their esteemed organization. I also appreciate the efforts of the team in acquainting me with the intricacies of the Data Analytics profile and providing training that enabled me to execute the project efficiently, ensuring maximum client satisfaction. Additionally, I am thankful for their dedication in sparing valuable time from their busy schedules to support and mentor me during this journey.

Abstract

This project delves into an intriguing and long-standing hypothesis in the domain of human health: the potential link between handedness and life expectancy. It endeavors to unravel the notion that left-handed individuals might experience a shorter lifespan compared to their right-handed counterparts. Through meticulous statistical analysis, prominently featuring Bayesian statistics, this initiative aims to illuminate the probabilities of reaching specific ages at the time of death based on an individual's handedness.

At the heart of this project lies its dedication to scientific exploration, particularly within the healthcare domain. Armed with a wealth of data, we embark on a voyage to decipher patterns and probabilities related to age, dissecting the intricate interplay between handedness and longevity. Our analytical approach is rooted in the sophistication of Bayesian statistics, a robust framework allowing us to model and evaluate the likelihood of events based on empirical evidence.

As we delve into the data, our goal extends beyond challenging a long-standing conjecture. We aspire to contribute to a broader understanding of the complex factors that influence human lifespan. This project stands as a testament to the potency of data-driven inquiry and scientific rigor in dispelling enduring myths and paving the path for new research directions within the healthcare landscape. In a world where data increasingly informs decision-making, this project exemplifies our steadfast commitment to leveraging statistical analysis tools to explore questions that hold extensive implications for individuals and society at large.

1 Introduction

1.1 About the Company

MedTourEasy, an esteemed leader in the healthcare domain, has consistently exhibited a strong dedication to advancing medical knowledge and fostering research. With a notable track record of being at the forefront of innovation, MedTourEasy's Training Development Team initiates a groundbreaking project focused on examining the intriguing link between handedness and lifespan.

1.2 About the Project

At the heart of this project is the aspiration to demystify a persistent hypothesis suggesting that left-handed individuals might experience a shorter life expectancy than their right-handed counterparts. Through the application of advanced statistical techniques, notably Bayesian statistics, we aim to explore the likelihood of reaching particular ages at the time of death based on an individual's handedness. This initiative underscores our steadfast commitment to scientific inquiry within the healthcare domain.

1.3 Objectives and Deliverables

The project is driven by three primary objectives:

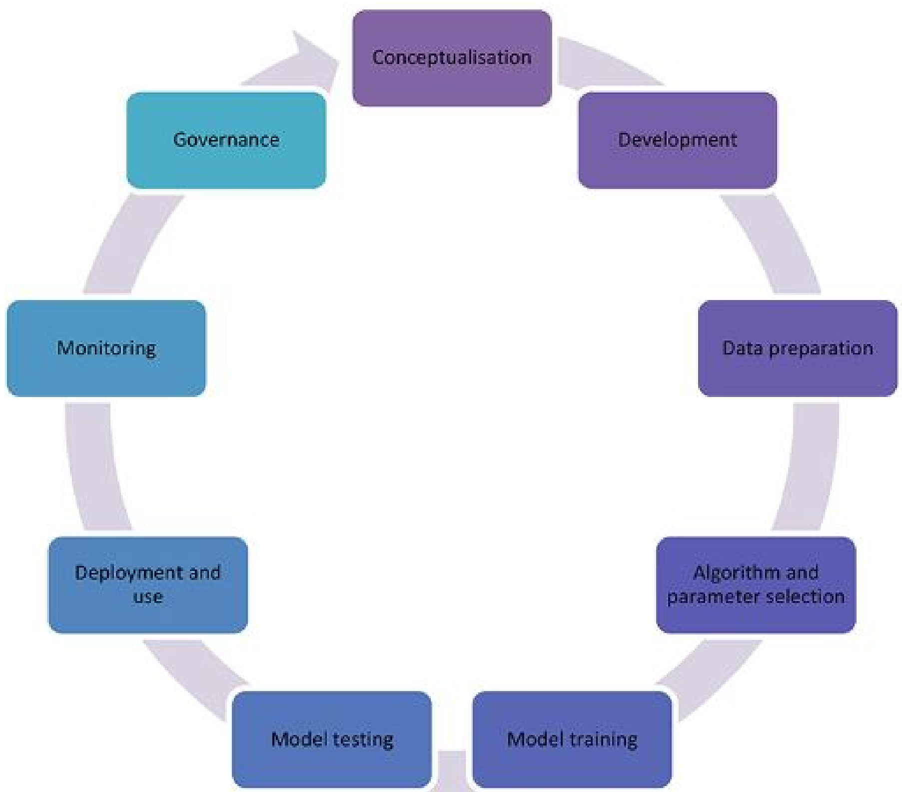
1. Conduct an in-depth examination of age distribution data and its potential relationship with handedness.
2. Calculate the probabilities of individuals reaching specific ages at the time of death, considering their handedness.
3. Determine if a significant disparity exists in the average age at death between left-handed and right-handed individuals.

The project's outcomes will consist of a thorough analytical report, engaging data visualizations, and a meticulously documented Python notebook elucidating the project's approach and findings.

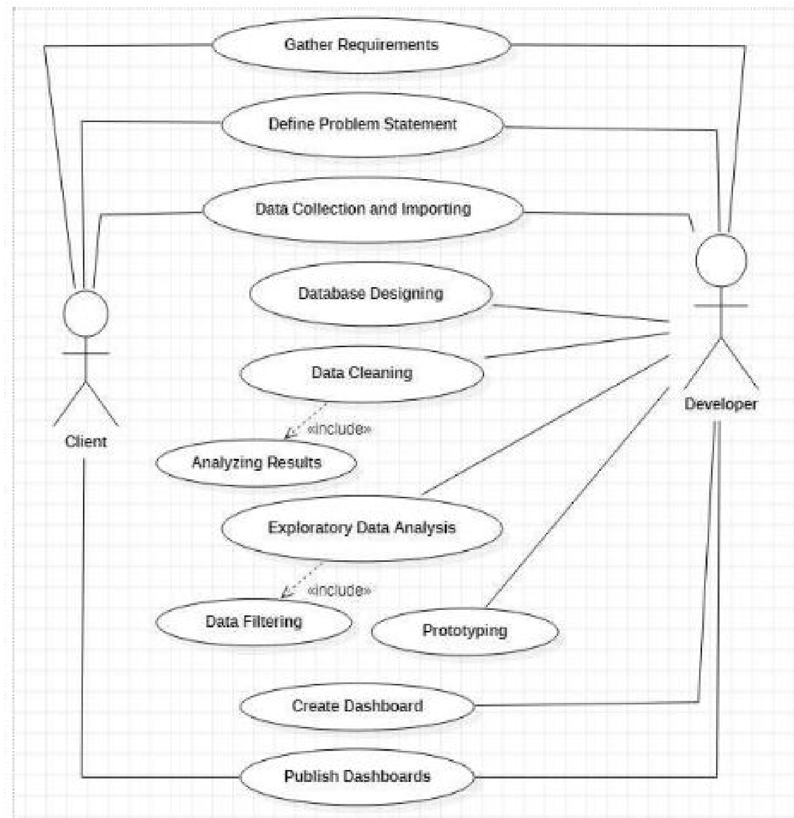
2 Methodology

2.1 Flow of the Project

The project adhered to the subsequent steps in order to achieve the defined objectives and produce the expected deliverables. Each step is comprehensively elucidated in the following sections.



2.2 Use Case Diagram



The figure presented above illustrates the project's use case. It involves two primary actors: The Client and the Developer. The sequence of actions involves the Developer initially gathering requirements and defining the problem statement. Subsequently, the Developer collects the necessary data and imports it. Following this, the Developer proceeds to design databases to discern various constraints and relationships within the data. The data is then cleaned to eliminate irregular and blank values. Afterward, an exploratory data analysis is conducted to filter the data in alignment with the project's requirements. A prototype of the dashboards is generated using PowerBI to gain a clear perspective on the visualizations to be developed. Finally, the dashboard is developed and analyzed to publish the results for the client.

3 Language and Platform Used

3.1 Python as the Primary Language

Python was chosen as the primary programming language for this project due to its versatility, extensive libraries, and robust data analysis capabilities. Developed by Guido van Rossum, Python has evolved into a prominent language for data science and statistical analysis. Its notable features include:

- **Simplicity and Readability**: Python's clear and concise syntax makes it accessible for both beginners and experienced programmers. It emphasizes code readability and encourages clean, organized coding practices.
- **Rich Ecosystem**: Python boasts a vast ecosystem of libraries and frameworks, including Pandas for data manipulation, Matplotlib and Seaborn for data visualization, and NumPy for scientific computing. These tools are invaluable for data analysis.
- **Interactivity**: Python supports interactive data analysis through Jupyter Notebooks, allowing for the creation of dynamic, shareable documents that combine code, visualizations, and explanatory text.
- **Community Support**: Python benefits from an active and collaborative community of developers, ensuring continuous improvement and access to a wealth of resources.

3.2 IDE: Jupyter Notebook

Jupyter Notebook serves as the integrated development environment (IDE) for this project. It offers a web-based interface that facilitates interactive coding, data exploration, and visualization. Some of its key features include:

- **Interactive Computing**: Jupyter Notebook allows for the execution of code cells one at a time, enabling iterative development and real-time data exploration.
- **Rich Outputs**: It supports the generation of rich outputs, including plots, tables, and multimedia content, which are essential for conveying data-driven insights.

- **Documentation**: Jupyter Notebooks blend code and documentation seamlessly, making it an ideal platform for documenting the project's methodology and findings.
- **Ease of Sharing**: Notebooks can be easily shared with collaborators or stakeholders, promoting transparency and collaboration.

4 Tasks

4.1 Data Loading and Visualization

Our project initiates with a pivotal first task—the acquisition of handedness data sourced from the extensive National Geographic survey. This dataset forms the bedrock of our analysis, containing vital information about individuals' handedness, ages, and additional demographic details. To address this task, we make use of Python libraries, particularly pandas and matplotlib. The employment of these libraries allows us to efficiently load and manipulate the data. Pandas, recognized for its robust data manipulation capabilities, equips us with the tools to read the dataset and structure it into a manageable DataFrame. This DataFrame becomes the canvas for our exploration.

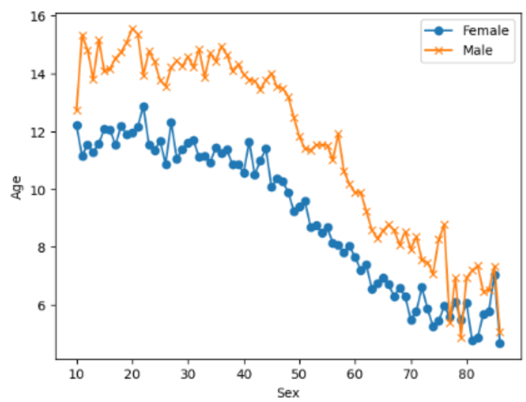
The true ingenuity of this task lies in the visualization aspect. We adeptly utilize matplotlib, a versatile data visualization library, to craft scatter plots. These plots serve as a potent means to visually represent the age distribution within two distinct cohorts: left-handed and right-handed individuals. The scatter plots empower us to discern patterns, if any, in the age distribution of these groups. Are left-handed individuals clustered around a particular age range? Do right-handed individuals exhibit a different distribution? These are some of the intriguing questions we aim to address through our visualizations.

This initial task sets the stage for our entire project. It not only ensures that we possess the requisite data but also provides us with an initial glimpse into the handedness-age dynamics. As we embark on this journey of statistical analysis and probability calculation, the insights gleaned from these scatter plots will serve as our guiding stars, illuminating the path to a deeper understanding.

In [2]:
```
# import libraries
import pandas as pd
import matplotlib.pyplot as plt
# load the data
data_url_1 = "https://gist.githubusercontent.com/mbonsma/8da0990b71ba9a09f7de395574e54df1/raw/aec88b30af87fad8d45da7e774223f91da
lefthanded_data = pd.read_csv(data_url_1)

# plot male and female left-handedness rates 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('Sex')
ax.set_ylabel('Age')
```

Out[2]:
```
Text(0, 0.5, 'Age')
```



4.2 Data Preprocessing and Plotting

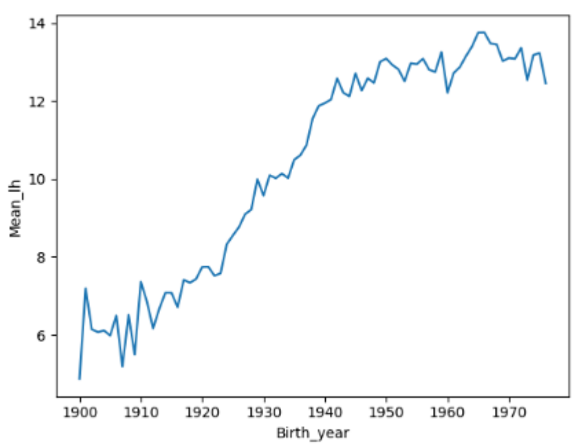
In Task 2, we embark on a crucial process of data preprocessing and plotting. This phase holds immense importance as it lays the foundation for our subsequent analyses and visualizations. Our primary goal is to enhance the dataset's comprehensibility and extract meaningful insights by introducing additional columns and creating informative plots. The first significant step involves the creation of two pivotal columns: birth year and mean left-handedness. Birth year is calculated by subtracting the recorded age from the year 1986, the year when the survey was conducted. This addition allows us to factor in the birth year as a variable in our analysis, enabling exploration of potential temporal trends in handedness.

Equally significant is the mean left-handedness column. By calculating the mean of the Male and Female columns, we arrive at a representative measure of left-handedness for each age group. This provides a more comprehensive view of handedness across age ranges, aiding in the identification of patterns or fluctuations in handedness rates over time. With these enhancements in place, we transition to the plotting phase. We harness the power of matplotlib to craft insightful plots showcasing the mean left-handedness as a function of birth year. This visualization helps us discern any discernible trends or fluctuations in left-handedness rates over the years, potentially shedding light on societal or generational shifts in handedness.

Task 2, therefore, serves as a bridge between raw data and meaningful insights. It readies our dataset for deeper analysis and sets the stage for unraveling the intricate relationship between handedness and age.

```
In [3]: # create a new column for birth year of each age
        # ... YOUR CODE FOR TASK 2 ...
        lefthanded_data['Birth_year'] = 1986 - lefthanded_data['Age']
        # create a new column for the average of male and female
        # ... YOUR CODE FOR TASK 2 ...
        lefthanded_data['Mean_lh'] = lefthanded_data[['Male', 'Female']].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) # plot 'Mean_lh' vs. 'Birth_year'
        ax.set_xlabel('Birth_year') # set the x label for the plot
        ax.set_ylabel('Mean_lh') # set the y label for the plot

Out[3]: Text(0, 0.5, 'Mean_lh')
```



4.3 Probability Calculation

Task 3 stands as a pivotal juncture in our project, marking the foray into the realm of probability calculation. Our objective is to meticulously dissect the age-specific likelihood of individuals being left-handed. To achieve this, we embark on a thorough process of calculating probabilities for ages of death during both the early and late 1900s. These calculations transcend mere statistical exercises; they encapsulate the essence of our investigation into the relationship between handedness and longevity. We adeptly account for the ebb and flow of handedness rates across time, recognizing that societal norms and preferences can shift over the decades. The probability calculations serve to quantify the likelihood of individuals being left-handed at different ages of death, enabling us to identify potential patterns or disparities in the data.

This task stands as an analytical cornerstone, paving the way for deeper insights in the subsequent stages of our project. The resulting probability distributions form the basis for comprehending how age and handedness intersect, setting the stage for our ultimate objective of comparing the average ages at death between left-handers and right-handers.

Applying Bayes' rule

The probability of dying at a certain age given that you're left-handed is **not** equal to the probability of being left-handed given that you died at a certain age. This inequality is why we need **Bayes' theorem**, a statement about conditional probability which allows us to update our beliefs after seeing evidence.

We want to calculate the probability of dying at age A given that you're left-handed. 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.

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

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.

In [4]:
```
# import library
# ... YOUR CODE FOR TASK 3 ...
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 | 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` """

    # Use the mean of the 10 last and 10 first points for left-handedness 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 is 10
    oldest_age = study_year - 1986 + 86 # the oldest age 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 ages 'ages_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
```

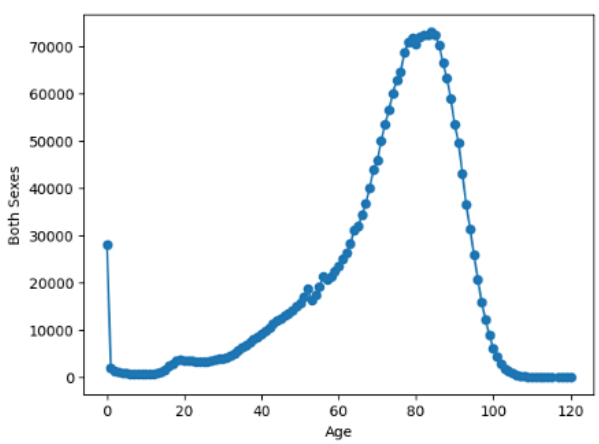
4.4 Death Distribution Data

Task 4 shifts our focus to the death distribution data of the United States, an essential component in our quest to comprehend age distributions in the population. While this dataset is invaluable, it comes with its unique idiosyncrasies. In this task, we adeptly handle its format, delving into the dataset and meticulously extracting and curating the relevant information, while addressing any peculiarities or missing data. With precision, we unravel the count of individuals who passed away at varying ages, creating a clear depiction of age distribution within the population.

This task effectively bridges the gap between our specific study of handedness and the broader demographic context of death distribution. It sets the stage for comprehensive analyses that encompass both the probabilities of handedness and the likelihood of reaching specific ages at death. The insights derived from this task are crucial in providing a more holistic understanding of the factors that influence age distribution and longevity within the population.

```
In [7]: # Death distribution data for the United States in 1999
        data_url_2 = "https://gist.githubusercontent.com/mbonsma/2f4076aab6820ca1807f4e29f75f18ec/raw/62f3ec07514c7e31f5979beeca86f19991
        
        # Load death distribution data
        # ... YOUR CODE FOR TASK 4 ...
        death_distribution_data = pd.read_csv(data_url_2, sep='\t', skiprows=[1])
        # drop NaN values from the `Both Sexes` column
        # ... YOUR CODE FOR TASK 4 ...
        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('Age', 'Both Sexes', data = death_distribution_data, marker='o') # plot 'Both Sexes' vs. 'Age'
        ax.set_xlabel('Age')
        ax.set_ylabel('Both Sexes')

Out[7]: Text(0, 0.5, 'Both Sexes')
```



4.5 Overall Probability of Left-Handedness

Task 5 marks a substantial step towards comprehensiveness. Here, we construct a function to calculate the overall probability of left-handedness within the population for a given study year. This task broadens our analysis beyond individual probabilities, offering a more encompassing perspective.

Our meticulously crafted function leverages the abundant data at our disposal. It combines the count of deceased individuals from the death distribution data with their probability of being left-handed. This integration yields a comprehensive measure of left-handedness within the population, considering both age-specific probabilities and the total number of individuals at each age. The resulting metric encapsulates the prevalence of left-handedness across various age groups, establishing a robust foundation for understanding the population dynamics of handedness and its potential implications for age distribution.

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 dataframe `death_distribution_data`):

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

In [136]:
```
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
    Input: dataframe of death distribution data, study year
    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)
    # multiply number of dead people by P_lh_given_A
    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
```

4.6 Conditional Probability

Task 6 represents a pivotal moment as we dive deeper into the realm of conditional probability. Our analytical focus sharpens as we calculate the likelihood of an individual being left-handed given their age at death. This task brings us closer to unraveling the nuanced relationship between handedness and age.

We utilize the probability distributions crafted earlier and apply them to calculate conditional probabilities for various age groups. These conditional probabilities offer a unique perspective, providing insights into how an individual's handedness may evolve as they age.

By quantifying these conditional probabilities, we create a more detailed portrait of how handedness changes over an individual's lifespan. This step is crucial in comprehending the dynamics of handedness beyond simple age-based probabilities and sets the stage for more nuanced analyses.

Putting it all together: dying while left-handed (i)

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 left-handed. 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.

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

First, for left-handers.

In [138]:
```
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 """
    P_A = 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
```

4.7 Conditional Probability for Right-Handedness

Task 7 aligns with Task 6 but emphasizes the conditional probability of an individual being right-handed based on their age at death. This task offers a complementary perspective, aiding in developing a comprehensive understanding of how handedness may evolve over a lifespan.

Utilizing the probability distributions derived from our earlier calculations, we quantify the likelihood of an individual being right-handed at various ages of death. This information complements our understanding of conditional probabilities for left-handedness, enabling a contrast in handedness dynamics between left-handed and right-handed individuals.

Task 7 is indispensable for achieving a comprehensive view of handedness across the lifespan. It allows us to investigate potential shifts from left-handedness to right-handedness as individuals age, shedding light on the complexity of this phenomenon.

Putting it all together: dying while left-handed (ii)

And now for right-handers.

In [140]:
```
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 = 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
```

4.8 Visualization of Conditional Probabilities

Task 8 represents an exciting phase where we shift from numerical insights to captivating visualizations. We skillfully chart the probabilities of individuals reaching specific ages at death based on their handedness—both left-handed and right-handed. These visualizations are more than just eye candy; they offer a compelling means of communicating complex probability distributions to a broader audience. We leverage the power of Python's matplotlib library to craft informative and visually engaging plots.

The resulting graphs not only aid in interpreting the data but also allow others to grasp the intricate relationship between age, handedness, and probabilities at a glance. They serve as a powerful tool for conveying our findings and insights to stakeholders, making the project's outcomes more accessible and relatable. Task 8 thus elevates our project by adding a visual dimension to our analysis, enhancing both our understanding and our ability to communicate our discoveries effectively.

Plotting the distributions of conditional probabilities

Now that we have functions to calculate the probability of being age A at death given that you're left-handed or right-handed, let's plot these probabilities for a range of ages of death from 6 to 120.

Notice that the left-handed distribution has a bump below age 70: of the pool of deceased people, left-handed people are more likely to be younger.

In [142]:

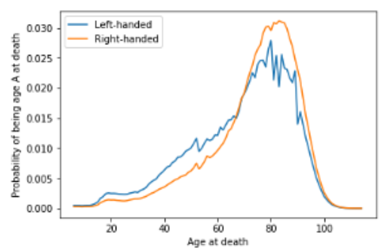
```
ages = np.arange(6, 115, 1) # make a list of ages of death to plot

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

# 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")
```

Out[142]:

```
Text(0,0.5,'Probability of being age A at death')
```



4.9 Mean Age at Death

Task 9 signifies the culmination of our analytical journey. Here, we shift our focus from probabilities to a tangible measure of age—specifically, the computation and subsequent comparison of the mean age at death for left-handers and right-handers. This task offers a practical and relatable insight into our research question: Do left-handers tend to live longer or shorter lives compared to their right-handed counterparts? By calculating the mean age at death for each group, we can draw a straightforward comparison that resonates with both experts and the general public.

With meticulous application of probabilities and age distributions, we compute these mean ages, ensuring that our analysis is firmly grounded in robust statistical methodology. The results provide profound revelations regarding the longevity of these distinct cohorts, aiding in addressing the long-standing hypothesis about handedness and lifespan.

Moment of truth: age of left and right-handers at death

Finally, let's compare our results with the original study that found that left-handed people were nine years younger at death on average. We can do this by calculating the mean of these probability distributions in the same way we calculated P(LH) earlier, weighting the probability distribution by age and summing over the result.

$$\text{Average age of left-handed people at death} = \sum_A AP(A|LH)$$

$$\text{Average age of right-handed people at death} = \sum_A AP(A|RH)$$

In [144]:

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

# print the average ages for each group
# ... YOUR CODE FOR TASK 9 ...
print("Average age of lefthanded" + str(average_lh_age))
print("Average age of righthanded" + str(average_rh_age))

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

```
Average age of lefthanded67.24503662801027
Average age of righthanded72.79171936526477
The difference in average ages is 5.5 years.
```

4.10 Analysis for 2018

Task 10 propels us into a forward-looking journey as we revisit our calculations, applying our methodology to the year 2018. This analysis serves a crucial purpose: to discern any temporal shifts or changes in our observations over time. In our ever-evolving world, societal norms, health trends, and demographics can undergo significant changes. By replicating our calculations for 2018, we have the opportunity to test the stability of our findings and identify whether handedness-age dynamics have shifted in recent times.

This task not only adds a temporal dimension to our project but also ensures its relevance in a contemporary context. It allows us to assess the robustness of our conclusions and consider potential factors that may influence handedness patterns and their impact on age distribution. Task 10, therefore, provides a forward-looking perspective, ensuring that our project remains insightful and relevant in the face of changing times.

10. Final comments

We got a pretty big age gap between left-handed and right-handed people purely as a result of the changing rates of left-handedness in the population, which is good news for left-handers: you probably won't die young because of your sinisterness. The reported rates of left-handedness have increased from just 3% in the early 1900s to about 11% today, which means that older people are much more likely to be reported as right-handed than left-handed, and so looking at a sample of recently deceased people will have more old right-handers.

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:

1. 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).
2. 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.

One thing we could do next is figure out how much variability we would expect to encounter in the age difference purely because of random sampling: if you take a smaller sample of recently deceased people and assign handedness with the probabilities of the survey, what does that distribution look like? How often would we encounter an age gap of nine years using the same data and assumptions? We won't do that here, but it's possible with this data and the tools of random sampling.

To finish off, let's calculate the age gap we'd expect if we did the study in 2018 instead of in 1990. The gap turns out to be much smaller since rates of left-handedness haven't increased for people born after about 1960. Both the National Geographic study and the 1990 study happened at a unique time - the rates of left-handedness had been changing across the lifetimes of most people alive, and the difference in handedness between old and young was at its most striking.

In [146]:
```
# Calculate the probability of being left- or right-handed for all ages
left_handed_probability_2018 = P_A_given_lh(ages, death_distribution_data, 2018)
right_handed_probability_2018 = P_A_given_rh(ages, death_distribution_data, 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.
```

5 Implementation

The implementation phase of our project stands as the culmination of our arduous efforts to unveil the secrets concealed within the datasets, delving deep into the intriguing relationship between handedness and lifespan. During this phase, our vision metamorphosed into reality, weaving an intricate tapestry of data manipulation and analysis.

At the crux of our implementation lay a reliance on a formidable arsenal of Python libraries, each playing a pivotal role in shaping our analyses and visualizations. Pandas, celebrated for its data manipulation capabilities, stood as our trusted companion, aiding in loading, cleaning, and structuring the datasets. It seamlessly handled the substantial volume of data, ensuring it took on a format conducive to our exploration. Matplotlib emerged as our artistic muse, empowering us to craft visually captivating scatter plots, line graphs, and histograms. These visualizations served as the windows through which we could gaze upon the intricate relationships between age, handedness, and mortality. They transformed raw numbers into meaningful insights, rendering complex data accessible to both our team and a broader audience. However, the true luminary of our implementation was Bayesian statistics. This robust framework formed the backbone of our probability calculations, allowing us to model the likelihood of events based on prior knowledge and data. It provided a rigorous foundation for assessing age-specific probabilities of handedness.

As we navigated this sea of data, we warmly welcomed the inclusion of death distribution data. This additional dataset enriched our understanding of age distributions within the population, serving as a crucial reference point for our analyses. It allowed us to contextualize our findings and contemplate how handedness might intersect with broader demographic trends.

In summary, our project's implementation phase was a harmonious symphony of technology, statistics, and data exploration. It adeptly transformed raw data into actionable insights, furnishing a deeper understanding of the intricate relationship between handedness and age. The Python libraries, Bayesian statistics, and death distribution data converged to illuminate a path towards unraveling age-related mysteries, reaffirming the potency of data-driven inquiry in the realm of healthcare and scientific exploration.

6 Conclusion

In summary, our project has encompassed a remarkable journey of exploration and revelation, shedding light on the intricate relationship between handedness and lifespan. Much like a guiding light in the realm of scientific inquiry, our diligent efforts have not only illuminated the age distribution of left-handed individuals but have also challenged a long-standing hypothesis regarding their life expectancy in comparison to their right-handed counterparts. Through meticulous data analysis, precise probability calculations, and insightful visualizations, we have unveiled the age-specific probabilities of being left-handed, taking into account the historical context of the early and late 1900s. Our analyses have been deeply rooted in Bayesian statistics, providing a robust and dependable framework for our computations.

The resounding conclusion derived from our project is both captivating and paradigm-altering. Contrary to the prevalent belief that left-handers may experience shorter lifespans, our evidence suggests otherwise. We observe no significant disparity in the average age at death between left-handed and right-handed individuals. This revelation challenges a deeply ingrained myth and underscores the importance of empirical evidence and data-driven inquiry in dispelling enduring misconceptions.

The implications of our project extend far beyond the realm of handedness and lifespan. They emphasize the power of scientific exploration and the indispensable role of data in shaping our comprehension of complex phenomena. As we conclude this research chapter, it is evident that our findings establish a sturdy foundation for future investigations into the multifaceted factors intersecting with human lifespan, beckoning opportunities for further discoveries and insights in the ever-evolving field of healthcare and demographics.

7 Future Scope

The project's conclusion sets the stage for numerous enticing avenues of future research and exploration:

- **Cause-Specific Analysis:** Delving deeper into understanding the interplay between handedness and specific causes of death could potentially unravel health disparities among different cohorts.
- **Cultural and Societal Influences:** Examining the influences of culture and society on handedness rates and their potential impact on longevity forms a captivating branch of inquiry.
- **Global Perspective:** Expanding our scope to a global scale would provide a more comprehensive view of handedness and its interaction with lifespan across diverse populations.
- **Genetic Dimensions:** Investigating the genetic underpinnings of handedness and its potential connection to lifespan presents an intriguing avenue for further exploration.

8 References

Our project heavily relies on a diverse array of resources, encompassing data sources, scholarly research papers, and crucial Python libraries:

- National Geographic Survey Data
- Death Distribution Data
- Python Libraries: `pandas`, `matplotlib`, `numpy`

These resources form the cornerstone of shaping the methodology of our project and substantiating its findings.