ECE/CS 498DS Spring 2021
Mini Project 1: Safety Analysis of Unmanned Vehicles

As we discussed in class, artificial intelligence (AI)-driven technologies are being integrated into many activities that we take for granted. For example, the continued development and commercial deployment of unmanned vehicles promise a global revolution of the transportation infrastructure. In this project, you will investigate two types of unmanned vehicles: 1) Autonomous Vehicles (AVs) running on the road; and 2) Unmanned Aerial Vehicles (UAVs) flying in the airspace. By analyzing their failure records, you will derive insights about their safety and common causes of failure. Such insights are instrumental in making unmanned vehicles more reliable and safer for use in the society.

In this project, you will study the failure records of AVs and UAVs using fundamental concepts from probability and statistics and relating them to data. The concepts you will learn and apply include the following

1. Handling datasets (Importing, extracting and summarizing features)
2. Basic statistical analysis of the dataset
3. Probabilistic Analysis of the data using concepts from ECE 313 (e.g., Probability, Conditional Probability, Total Probability)
4. Use Bayesian inference to derive posterior probabilities
5. Create and performance inference with a Bayesian Network

Part 1: Autonomous vehicles

Background:
First, we will explore failures and disengagements in Autonomous Vehicles (AVs) being tested on public roads in California. The dataset you will be using however, while derived from the California Department of Motor Vehicles (DMV) database, **has been sufficiently altered to be manageable for this project. As such, the results of the analysis you perform will not directly represent the California study.** The analysis will use statistical and probabilistic approaches to evaluate how well the AI-driven decision and control of AVs works under a variety of conditions and developing insights into why/how they disengage.

Autonomous Vehicles are complex systems that use artificial intelligence (AI) and machine learning (ML) to integrate mechanical, electronic and computing technologies to make real-time driving decisions. Several states in the USA (e.g. California, Texas, Nevada, Pennsylvania, and Florida) and other parts of the world (e.g. China [1]) have already started field-testing AVs on public roads. As AVs have started interacting more directly with humans on public roads, the safety and resilience of AVs is a significant concern (Uber's [2] fatal accident, Tesla's [3] autopilot flaw) and must be thoroughly evaluated through analysis of data obtained during field-testing.

The California DMV mandates that all manufacturers testing AVs on public roads file annual reports detailing disengagements and accidents. A **disengagement** occurs when a failure in the AV system causes control of the vehicle to switch from software to the human driver.

Dataset description:

In a real-world setting, the data required for analysis might be spread across multiple sources. That is the case in our analysis too. Below is a description of the raw files in which the data is available and the data fields in the file. As mentioned previously, the data has been derived from California DMV, but has been sufficiently modified. Identicality to a known AV manufacturer is purely coincidental.

mp1_av_disengagement.csv
This file lists the details of each disengagement that happened in AV testing.

Column Name	Explanation
Month	Month and year when the disengagement happened
Car	ID of the AV
Location	Where the car was when the disengagement happened

Weather	Weather conditions when the disengagement happened
TypeOfTrigger	Whether the disengagement was automatic (decision taken by AV) or manual (decision taken by human driver)
ReactionTime	Time taken, in seconds, by the human driver to take control of the car after an automatic trigger. NOTE: ReactionTime is not given for manual disengagements since it does not involve a trigger by the AV.
Cause	Reason for the disengagement

mp1_av_totalmiles.csv

This file contains the total number of miles driven and other summary statistics by month.

Column Name	**Explanation**
Month	Month and year of AV testing
Car	ID of the AV
Miles driven	Total number of miles driven by the AV during the given month
Total number of disengagements	Number of disengagements during the given month
Number of automatic disengagements	Number of disengagements where the AV decided to give control to the human driver
Number of manual disengagements	Number of times the human driver decided to take control of the AV

Task 0 – Getting to know the analysis environment (5 points)

Before any analysis can be done on a given dataset, you will need to know how to import, handle and do some basic data manipulation programmatically. This task is designed to help you get accustomed to the data analysis environment. In doing so, you will also summarize some of the key performance metrics for evaluating the safety of AVs. Complete the following tasks using Python Jupyter Notebook. **Throughout this MP we recommend using Pandas data frame for data analysis; however, this is not required.**

1. Import the csv data into Jupyter Notebook. (1 point)

2. Summarize the following information: (1 point)
    a. Total number of AV disengagements over the entire duration of available data
    b. Number of unique months that have recorded AV disengagements
    c. For each column in the AV disengagement data, list the number of missing values (shown as NaN).

3. Plot a pie chart for the causes of AV disengagement. Based on the pie-chart, list the top 3 leading causes of disengagement? (1 point)

4. Visualize the trend of disengagement/mile over time with monthly granularity. How would you describe the trend? Are AV's maturing over time? (2 points)

Task 1 – Basic Analysis of AV Disengagements (8 points)

Once you are comfortable handling the data, you can start doing some meaningful analysis. In this task, you will be fitting probability distributions to the data and interpreting the distributions. You will also understand how interpretation of the distribution provides us with insights about the data.

Complete the following tasks

1. If the AV suddenly disengages, there may not be enough time for the human to react. It is also possible, that the human is not sufficiently attentive while in the AV because of reliance on the technology. To understand the human alertness level, we measure the reaction time of the human driver in the field. Plot the probability distribution of reaction times. Does this distribution fit any known distributions (Gaussian, Weibull, Exponential)? What does the fit distribution signify? (2 points)

2. Compute the average reaction time: (2 points)

a. For the entire duration of the dataset
b. For the entire duration of the dataset differentiated by the location of disengagement

3. It is known that the mean reaction time for humans in non-AV cars is 1.09 seconds [4]. Is the mean reaction time for humans in AV cars different from non-AV cars? To be conservative, first perform a hypothesis testing at 0.03 significance level. Next, perform a hypothesis testing at 0.05 significance level, what can you conclude on how the significance level affects our conclusion? (2 points)

4. Plot the probability distribution of disengagements/mile with monthly granularity. Does this distribution fit any known distributions (Gaussian, Weibull, Exponential)? What does the distribution that fits signify? (2 points)

<u>Task 2 – Probabilistic Analysis of AV Disengagement (36 points)</u>

Humans adapt to the lighting and weather conditions while driving. Given that AV technology uses sensors like camera and LiDAR whose performance may vary under different lighting and weather conditions, it becomes paramount to understand if AVs are able to cope with the change in the environment (sensor performance). The dataset provided to you has disengagement measurements under different weather conditions which can help us understand the same.

Given below are some assumptions that you will need to do the analysis for this task.

1. There can be at most one disengagement in a mile
2. A day can be either clear or cloudy, but not both. The probability of a day being clear in California is 72% [5].
3. The AV is equally likely to drive on a cloudy day as on a clear day.

The above assumptions should be enough. However, in case you need to make more assumptions, consult the instructors or make a post on Piazza. The instructors will respond as quickly as possible.

1. Based on the above assumptions, answer the following questions on basic probability.
   a. The assumption of at most one disengagement per mile allows us to treat the occurrence of a disengagement in a mile as a random variable with a _________________ distribution. (1 point)
   b. Based on the above assumptions, calculate the probability of disengagement per mile on a cloudy day. (2 points)

c. Based on the above assumptions, calculate the probability of disengagement per mile on a clear day. (2 points)
d. Similarly, calculate the probability of an automatic disengagement per mile on a cloudy day, and the probability of an automatic disengagement per mile on a clear day. (4 points)
e. How likely is it that in 10000 miles, there are 100 or more disengagements under cloudy conditions? (4 points)

2. At a 0.05 significance level, test the following hypothesis: The AV has more disengagements (*automatic* and *manual*) on cloudy days than clear days. Based on the result of the hypothesis test, what can you conclude about the impact of weather conditions on AV safety? (4 points)

3. What's the conditional probability that the reaction time is: (Hint, there might be multiple conditions to consider)
   a. Greater than 0.4s given that the weather was cloudy? Reaction time is measured only in cases where there was an automatic disengagement. (3 points)
   b. Greater than 0.7s given that the weather was clear? Reaction time is measured only in cases where there was an automatic disengagement. (2 points)

4. A study found that an **automatic AV disengagement** will result in an accident if the human driver is *slow* in reacting. Following reactions are considered slow: (i) a reaction time greater than 0.4s under cloudy conditions and, (ii) a reaction time greater than 0.7s under clear conditions. Find the probability of an accident per mile due to automatic AV disengagement and slow reaction. (6 points)

5. The probability of a human driver causing a car accident is 2×10^{-6} [4]. How do the accident rates of AV obtained from the previous question compare to that of human drivers? Justify your conclusion and explain its consequences. (3 points)

6. The hypothesis test you performed in this task is an example of a *parametric test* that assumes that the observed data is distributed similarly to some other well-known distribution (such as a normal distribution). However, sometimes, we need to compare two distributions of data that don't follow any such well-known distributions. Perform a two-sample Kolmogorov-Smirnov test (using the ks_2samp package from Scipy) to compare the following two distributions: (1) **distribution of disengagement reaction time when the weather is cloudy** and (2) **distribution of disengagement reaction time when the weather is clear**. What are your null and alternative hypotheses? Assuming a significance level threshold of 0.1, what can you conclude

from the test results about the impact of weather conditions on disengagement reaction time? (5 points)

Part 2: Unmanned Aerial Vehicles (UAVs)

Background

The experience obtained in analyzing AV safety is applicable to a wide range of cyber-physical systems. In this task, we will investigate the UAV accident data extracted from multi-national databases, including NASA, the FAA's Aviation Safety Reporting System (ASRS), Australian Transport Safety Bureau (ATSB), and UK Air Accident Investigation Branch (AAIB). The data have been substantially altered to be manageable for this project. Two datasets used for this task are explained below.

Dataset description

mp1_uav_accidents.csv

This file lists the details of accidents that happened in UAV deployment.

Column Name	Explanation
Year	Year and month when the accident happened.
Month	
Altitude	The altitude (unit: ft) UAV flew at when the accident happened.
Phase_of_Flight	The flight phase (takeoff, cruise, or landing) of UAVs when the accident happened.
Precipitation	Rainy (including all kinds of precipitation) or Dry.
WindSpeed	Wind speed (unit: mph) when the accident happened
Mission	The mission that UAV is conducting when the accident happened
RootCause	Reason for the accident.
TimeBeforeAccident	Time before the accident (unit: minutes) during this flight

mp1_uav_totalhours.csv

This file contains the total flight hour of all registered UAVs by month.

Column Name	Explanation
Year	Year and month when the accident happened.
Month	
Total Flight Hours	Total flight hours (unit: hours) during the given month reported by all the registered UAVs.

Task 3 – Failure data analysis for UAVs (36 points)

The experience from analyzing AVs is generalizable to a variety of systems, such as UAVs. When a UAV meets an accident, it is important to identify the cause of the accident so that one can fix the problem. In this task, you will use a novel metric to measure UAV safety and use it to understand how safety is influenced by environmental factors. Further, you will diagnose the cause of a UAV accident based on observations and investigate how your conclusions change based on the environmental factor.

1. Visualize the trend of accident per flight hour over time with monthly granularity. How would you describe the trend? What can you conclude about UAVs technology based on trend? (2 points)

2. As included in the given dataset, the *time before accident* is a metric to evaluate the resilience of UAVs. (3 points)

    a. A longer time before accident suggests that a UAV is _______ (more/less) prone to failure.
    b. Plot the distribution of time before accident. Which of the following three distributions best fits the data distribution: Gaussian, Poisson, Exponential? What does the fit distribution signify?

3. When operated outdoors, UAVs are exposed to a variety of weather conditions which might lead to safety issues. Here, you will investigate the effect of weather on UAV safety using correlation analysis with Pearson's correlation coefficient. (5 points)

    a. Create a scatter plot on flight time before accidents vs wind strength. Put wind strength on the horizontal axis and flight time on the vertical axis. Does wind speed have an effect on time before accident?
    b. What is the range of values of Pearson's correlation coefficient? What does a correlation value of 0 imply?
    c. Calculate the Pearson's correlation coefficient between wind speed and flight time before accidents. What does the value tell you about the relationship between wind speed and flight time?

4. To further evaluate how drastic the effect of wind speed is on UAVs safety, one can estimate the effect separately for high and low wind speeds. To start the analysis, convert the wind speed into a binary variable (High/Low) using a threshold at 10 mph. (i.e., wind speed > 10 mph is considered High, and wind speed <= 10 mph is considered Low) (8 points)

    a. Plot box plots to visualize the *time before accident* in high wind speed and Low wind speed separately.
    b. Compute the average time before accident for the entire duration of the dataset for each wind speed (high or low).

c. Does high wind speed make UAVs more prone to failure? Test this hypothesis using a z-test at a 0.05 significance level. (Hint: compare the mean)
d. Is z-test an appropriate test for the hypothesis in *part c*? Please justify your answer.
e. What is the difference in mean time before accident for high and low wind speeds?
f. Name two other statistical tests for comparing the means of two distributions. Specify in brief under what conditions should they be used (One sentence for each statistical test. You may browse the internet to answer this question.)

5. Next, you will investigate how to diagnose the cause of a UAV failure based on new observations. For the subparts *a, b, and c*, assume that the wind speed is **Low***.* (8 points)
    a. A UAV had an accident in its take-off phase. What is the posterior probability that the root cause of the accident was "Sensors & Mechanical Components"?
    b. Suppose that the accident in part *a* was minor and did not harm the UAV. Right after the first accident pilots attempted to fly the UAV again. An accident occurred during take-off in the second attempt too. Based on this additional evidence, what is the posterior probability that the root cause of accident was "Sensors & Mechanical Components"?
    c. Assume such attempts (with failures on takeoff) are successively repeated for many times. Will this posterior probability converge to a certain value? If yes, what is that value?
    d. How do your conclusions in *part a*, and b change if the wind speed was high?

6. Bayesian Network provides a more sophisticated model to infer the root cause, by describing a set of variable nodes and their casualties. In this question, you will construct a Bayesian Network to model failure scenarios of UAVs. We assume that both Precipitation (Rainy or Dry) and Wind Speed (High or Low) influence the Root Causes (for simplicity, consider the Root Cause as binary variable for this question, which is whether "Sensors & Mechanical Components" or not). Finally, the Root Causes affects which Phase of Flight (Take off, Cruise, Landing) the failure occurs in.
    a. Draw a graph for the Bayesian Network described in the question. (10 points)
    b. Count the number of parameters needed to define conditional probability distributions.
    c. Based on the number of parameters needed, derive the conditional probability table from the given dataset.
    d. According to the conditional probability table you derived, what is the probability that the root cause was "Sensors & Mechanical Components", given the day was rainy with High wind speed, and the accident happened at cruise stage.

Due Dates/ Timeline

All submissions are done on Compass2G - one submission per group. Late submission policy is applicable.

- Checkpoint: **February 8th, 2021 @ 11:59 PM**
  - Jupyter Notebook with completed code for Tasks 0 and 1 (see ipynb styling instruction below)
  - PDF of slides with answers for questions from Tasks 0 and 1 (we will provide template for these slides)
- Final Submission: **February 22nd, 2021 @ 11:59 PM**
  - Jupyter Notebook with completed code for Tasks 0-3 (see ipynb styling instructions below)
  - PDF of slides with answer for questions from Tasks 0-3 (we will provide templates for these slides)

Note that your answers to Tasks 0 and 1 will only be graded at the time of the checkpoint. Points lost for these tasks at the time of the checkpoint cannot be made up at the time of the final submission. However, in order to prevent cascading errors between tasks, you may change any incorrect answers for Tasks 0 and 1 in the Jupyter Notebook and presentation slides prior to the final submission.

ipynb Styling Guide

At the times of the checkpoint and final submission, please provide a single ipynb file, structured with a section for each task and subsections as required.

- Write your names and NetIDs of group members in the beginning.
- Explain all your work (include the code with comments)
- Write down the equations that are being used (for partial credit)
- All the charts should be appropriately formatted by showing the legend, axes labels, and chart title.
- Each question answered should include the code you used to achieve the needed charts and/or tables and an explanation/interpretation. An example template is given below.
- If you are using Google Colab, please download the project as .ipynb file and submit it.

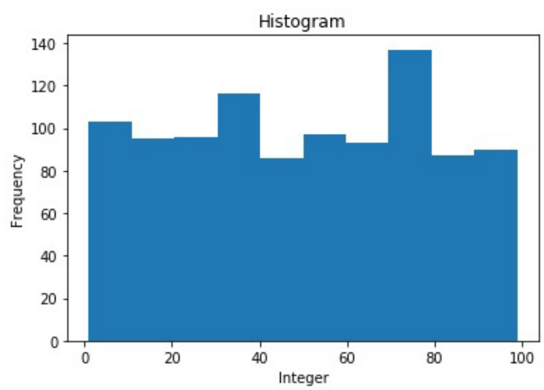
Task 0

Question 1

In [16]:
```
# Code to generate your solution
import numpy as np
import matplotlib.pyplot as plt

x = np.random.randint(1,100,1000) #Comments: Generating an array of random integers
plt.hist(x)
plt.xlabel('Integer') #Remember to label your graphs/charts and their axes.
plt.ylabel('Frequency')
plt.title("Histogram")
print('Qn 1: ')
```

Qn 1:



(Explanation to Question 1)
Based on the statistic obtained from Q1, AVs seem to be ...

Question 2

...

Grading (Total 90 points)

- Task 0 - 5 points
- Task 1 - 8 points
- Task 2 - 36 points
- Task 3 - 36 points
- ipynb formatting – 5 points

Please post your questions on Piazza or contact the instructors. Hope you enjoy this exploration of AV and UAV data!! :D

References:

1. https://www.scmp.com/magazines/post-magazine/long-reads/article/2142449/chinas-self-driving-vehicles-track-take-global
2. https://www.economist.com/the-economist-explains/2018/05/29/why-ubers-self-driving-car-killed-a-pedestrian
3. https://www.teslarati.com/tesla-research-group-autopilot-crash-demo/
4. S. S. Banerjee et al., “Hands off the wheel in autonomous vehicles? a systems perspective on over a million miles of field data,” in 2018 48th Annual IEEE/IFIP International Conf. on Dependable Systems and Networks (DSN), June 2018
5. https://www.currentresults.com/Weather/California/annual-days-of-sunshine.php