ECE/CS 498DS Spring 2020
Mini Project 1: Autonomous Vehicle Safety Analysis

As we discussed in class, artificial intelligence (AI)-driven technologies are being integrated into many activities that we take for granted. This project explores 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.

In this project, you will study disengagement data from AV manufactures and analyze the current state of AV safety. 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, Bayes formula)
4. Create a Naive Bayes model to classify data based on features (e.g., weather conditions) in the dataset

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

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.

2. Summarize the following information
    a. Total number of AV disengagements over the entire duration of available data
    b. Number of unique months that have recorded AV disengagements
    c. List of unique locations of AV disengagements
    d. Number of unique causes for AV disengagements
    e. Which columns in the datasets (if any) have missing values? How many missing values do these column(s) have? (NAs (not valid entries) commonly occur in real world datasets…)

3. Plot a pie chart for the causes of AV disengagement. Based on the pie-chart, list the top 2 leading causes of disengagement?

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

Task 1 – Basic Analysis of AV Disengagements

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. What do the following distributions signify about samples drawn from it
    a. Gaussian distribution
    b. Exponential distribution
    c. Weibull distribution

2. 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?

3. Compute the average reaction time
   a. For the entire duration of the dataset
   b. For the entire duration of the dataset differentiated by the location of disengagement

4. 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? Perform a hypothesis testing at a 0.05 significance level.

5. 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?

<u>Task 2 – Probabilistic Analysis of AV Disengagement</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 on maximum number of disengagements in a mile allows us to treat the occurrence of a disengagement in a mile as a random variable with a _________________ distribution.
b. Based on the above assumptions, calculate the probability of disengagement per mile on a cloudy day.
c. Based on the above assumptions, calculate the probability of disengagement per mile on a clear day.
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.
e. How likely is it that in 12000 miles, there are 150 or more disengagements under cloudy conditions? [Hint: Think of an appropriate approximation that makes the computation feasible/easier.]

2. Answer the following question about hypothesis testing:
   a. What does the normal distribution represent in the hypothesis testing?
   b. Does rejecting the null hypothesis mean accepting the alternative hypothesis? Explain your answer.

3. 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? [Hint: Use a Z-test for testing this hypothesis].

4. What's the conditional probability that the reaction time is: (Hint, there might be multiple conditions to consider.)
   a. Greater than 0.6s given that the weather was cloudy? Reaction time is measured only in cases where there was an automatic disengagement.
   b. Greater than 0.9s given the weather was clear? Reaction time is measured only in cases where there was an automatic disengagement.

5. 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 0.6s under cloudy conditions and, (ii) a reaction time greater than 0.9s under clear conditions. Find the probability of an accident per mile involving an AV disengagement. [Hint: Use the theorem of total probability to express the probability of an accident per mile as a sum of the conditional probabilities calculated in the previous questions in this task].

6. The probability of a human driver causing a car accident is $2x10^{-6}$ [4]. How do AVs compare to human drivers? Justify your conclusion and explain its consequences.

7. 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?

Task 3 - Using the Naive Bayes Model

Sometimes, it might be difficult to pinpoint the cause of an AV failure when an accident or disengagement occurs. This situation might arise when the monitoring system does not detect the problem, or the logged data gets corrupted. However, with enough correct data about previous disengagements and their causes, we can predict the cause of the latest unknown disengagement. One way to solve this problem is to train a Naive Bayes classifier based on features in existing data and then feed features of the unknown disengagement to predict the cause. The usual way of doing that is to split the available data into a *training* dataset, which is used to build the Naïve Bayes ML model, and a *test* dataset, which is used to evaluate the model. You should be able to interpret the results, and validity of the assumptions that go into using Naïve Bayes model.

1. Though there are 10 different causes for disengagement, they can be grouped into the following 3 classes – (i) Controller, (ii) Perception System, and (iii) Computer System. The mapping from Disengagement Cause to Class is given in the table below. You will use these 3 classes as the labels in the NB model. Modify your pandas data frame to include a ‘Class’ column.

	Disengagement Cause	Class
1	Incorrect behavior prediction of others	Controller
2	Recklessly behaving agent	Controller
3	Unwanted Driver Discomfort	Controller
4	Adverse road surface conditions	Perception System
5	Emergency Vehicle	Perception System
6	Position Estimation Failure	Perception System
7	Incorrect Traffic Light Detection	Perception System
8	System Tuning and Calibration	Computer System
9	Hardware Fault	Computer System
10	Software Froze	Computer System

2. Split the data randomly into training and testing (80-20 split). Use the fields ‘Location’, ‘Weather’, and ‘TypeOfTrigger’ as features and use ‘Class’ as assigned in the previous question as the label.

3. Using the training dataset, create a NB model to identify the cause of disengagement based on the features ‘Location’, ‘Weather’, and ‘TypeOfTrigger’. **Show the conditional probability tables from the training dataset.**

4. Using the model to predict the cause of the disengagement for the test dataset. Compute the accuracy achieved by your model.

5. To get a better estimate of the model performance, perform cross-validation. Repeat sub-questions 2, 3 and 4 five times for different splits of training and test data, and report the average accuracy.

6. Is the NB model doing better than chance? Explain.

7. What are the assumptions in NB in the context of this problem? Are the assumptions realistic? Explain.

8. Based on your answer to part 7, comment on whether any improvements can be gained in classification accuracy. If yes, how?

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.

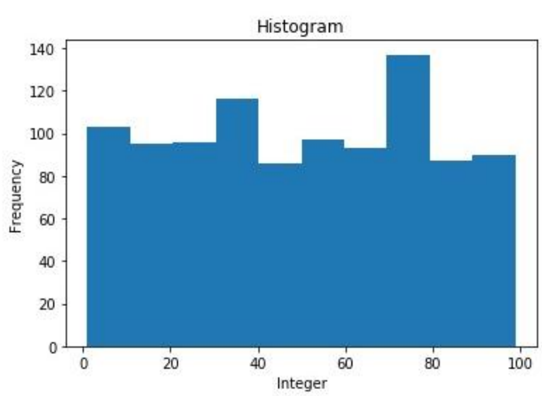
Task 0

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 130 points)

- Task 0 - 5 points
- Task 1 - 10 points
- Task 2 - 48 points
- Task 3 - 37 points
- ipynb formatting – 10 points
- Presentation – 20 points

Due Dates/ Timeline

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

- Checkpoint: **February 6th, 2020 @ 11:59 PM**
  - Jupyter Notebook with completed code for Tasks 0 and 1
  - PDF of slides with answers for questions from Tasks 0 and 1 (we will provide template for these slides)
- Final Submission: **February 20th, 2020 @ 11:59 PM**
  - Jupyter Notebook with completed code for Tasks 0-3
  - PDF of slides with answer for questions from Tasks 0-3 (we will provide templates for these slides)
- 10-Minute Presentations: **TBD**
  - Date and times of these presentations will be announced on Piazza and in-class during the coming weeks.
  - Your group will present the slide deck turned in at the final submission
  - See “MP1 Presentation Details” section below for additional information

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.

MP1 Presentation Details

You need to present your findings from MP1 to the TAs/instructor.

- The presentation will be held outside normal class/lecture hours
- Each group will sign up for a 10 minute timeslot that will consist of ~8 minutes for presenting and ~2 minutes for questions
- We will provide template slides for the presentation
- The restriction on time will be strictly followed – **you will be asked to stop if you exceed the time limit**
- Don’t be late on the day of the presentation; a team not being able to present for a missing/late member will be penalized

Please post your questions on Piazza or contact the instructors. Hope you enjoy this exploration of AV log 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