

## **Problem Set - 6**

Please read all of the guidelines carefully before submitting the problem set. (Unless specified) each question is **20 points** and there are **100 points** in total.

**Due date: Friday, April 1, 11:59 PM. Late submissions will be accepted with a penalty! (10% reduction per day – no submissions accepted two days after the deadline.)**

## **Grading**

**Your answers will be evaluated based on the following criteria:**

- **Completeness:** Your answers will be checked for completeness. Specifically, for a question that requires several steps of thinking / writing / coding, we expect you to complete the full range of steps to answer the question. The range of steps that needs to be completed will be determined by the course material and the specific nature of the question.
- **Correctness:** Your answers will be checked for correctness. For your answer to be correct, you need to have the correct answer, correct implementation, and the correct result. 'Correct' means that you follow the steps suggested by the assignment and your instructor and obtain the expected result without making any theoretical / mathematical / coding mistakes. 'Correctness' is not a binary term, there may be varying degrees of correctness; and, your grade will be evaluated based on how different your answer is from the expected result.
- **Format:** An indispensable part of every assignment is the format. To make sure that your assignment can be read and processed easily, we expect you to follow the guidelines set by the instructor. These guidelines may include specific requirements about text-based answers, code files, and datasets.
- **Academic Honesty:** We assign that your submission fulfills the academic honesty expectations set by the instructor and put forward in the syllabus. Specifically, when expected, you need to produce work within the limits defined in the syllabus – some of the assignments may require you to work individually, and some others in a team. For more information, please read the syllabus.

## **Guidelines – Before You Start**

- 1) **You should complete the problem set on your own.** Discussing ideas is fine; but, sharing answers and sharing code will be considered as plagiarism.
- 2) You will be using the **Python** programming language. You need to write your codes in an empty **.ipynb** file.
- 3) Make sure that you provide many comments to describe your code and the variables that you created.
- 4) Please use **LaTeX** or **MS Word** to submit your written responses (hand-written responses will not be graded).
- 5) For some of the coding exercises, you may need to do a little bit of **"Googling"** or review the documentation.

## **Deliverables:**

- 1) The code of the problem set in **.ipynb** format (one file)

2) Short answers written with **LaTeX** or **MS Word** and exported in **.pdf** format (one file)

### **What is Moral Machine Experiment?**

Moral Machine is an online platform, developed by Iyad Rahwan's *Scalable Cooperation* group at the Massachusetts Institute of Technology, that generates moral dilemmas and collects information on the decisions that people make between two destructive outcomes. The platform is the brain child of Iyad Rahwan and social psychologists Azim Shariff and Jean-François Bonnefon, who conceived of the idea ahead of the publication of their article about the ethics of self-driving cars.



The presented scenarios are often variations of the trolley problem, and the information collected would be used for further research regarding the decisions that machine intelligence must make in the future. For example, as artificial intelligence plays an increasingly significant role in autonomous driving technology, research projects like Moral Machine help to find solutions for challenging life-and-death decisions that will face self-driving vehicles.

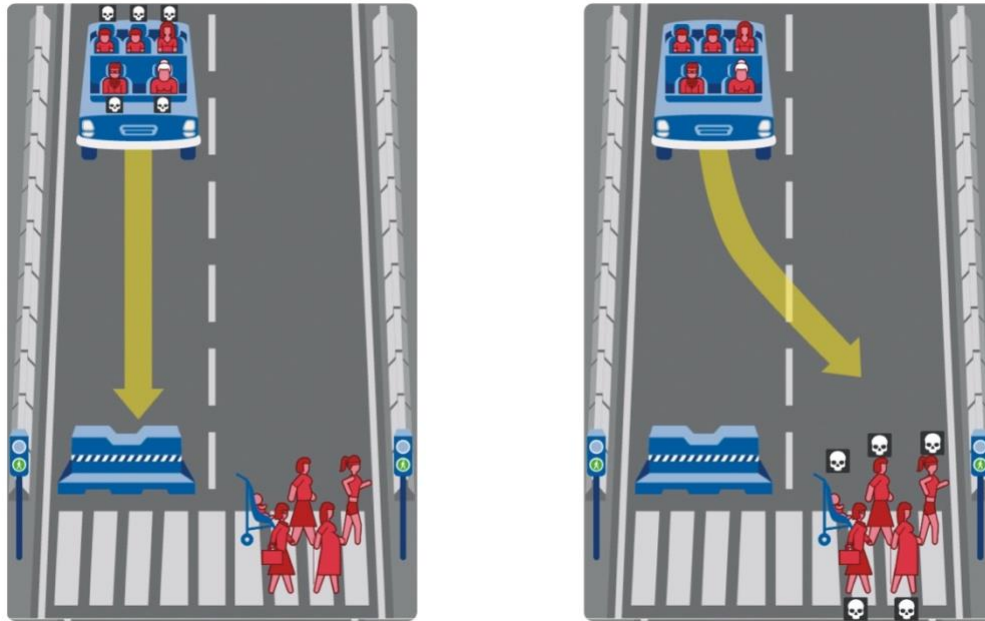
Analysis of the data collected through Moral Machine showed broad differences in relative preferences among different countries, and correlations between these preferences and various national metrics.

### **Explanation for Data Collection**

Before you start, it will be helpful to take a look the following:

- The *Nature* article on Moral Machine Experiment
- The Moral Machine web page: <http://moralmachine.mit.edu/>

The “Moral Machine Experiment” is about making decisions in a potential accident situation. The ultimate goal is to implement some ethical rules into the algorithms of self-driving cars. An example:



In a potential accident situation, a self-driving car may have **some passengers** or may have **no passengers at all**. Thus, if a human is going to die, the self-driving car will *first* need to decide between three choices:

- 1) Pedestrians vs. Pedestrians (No passengers in the self-driving car)
- 2) Pedestrians Ahead vs. Passengers
- 3) Passengers vs. Pedestrians on Other Lane

After that, the self-driving car evaluates the legal complications. Again, there are three choices:

- 1) No crossing (No traffic light)
- 2) Legal crossing ahead (Green light)
- 3) Illegal crossing ahead (Red light)

After that, the self-driving car evaluates what type of people there are in the environment. And the people can be in three different places:

- 1) In the self-driving car
- 2) On lane crossing ahead
- 3) On other lane crossing

Here is a complete list of the type of people and animals who can get killed in a car accident according to the *Moral Machine Experiment*<sup>1</sup>:

- 1) Man
- 2) Woman
- 3) Boy
- 4) Girl
- 5) Elderly Man
- 6) Elderly Woman
- 7) Large Man
- 8) Large Woman
- 9) Male Executive
- 10) Female Executive
- 11) Male Doctor
- 12) Female Doctor
- 13) Male Athlete
- 14) Female Athlete
- 15) Pregnant Woman
- 16) Homeless Person
- 17) Criminal
- 18) Baby
- 19) Dog
- 20) Cat



### **Lab - Coding**

In this assignment, you will be working with moral machine experiment dataset.

This dataset provides information on hundreds of accident scenarios. The data has been provided in the assignment folder (**moral\_machine\_data.xlsx**). Open the .xlsx file and take a look at it before starting.

Color legend:

**Records**

**Demographics**

**Description of the accident situation**

**Your ethical decision**

**The results of your decision**

Column names [colors below match the description above]:

record\_no

<sup>1</sup> Keep in mind that the *Moral Machine Experiment* is a simplistic representation of the real world.

age, gender, grown\_up\_in\_US, grown\_up\_in\_a\_foreign\_country, city\_of\_origin, state\_of\_origin, region\_of\_origin, country\_of\_origin, no\_of\_sisters, no\_of\_brothers, intended\_or\_declared\_major\_1, intended\_or\_declared\_major\_2, intended\_or\_declared\_minor\_1, intended\_or\_declared\_minor\_2

pedestrians\_vs\_pedestrians, pedestrians\_ahead\_vs\_passengers, passengers\_vs\_pedestrians\_on\_other\_lane, no\_crossing, legal\_crossing\_ahead, illegal\_crossing\_ahead, legal\_crossing\_on\_other\_lane, illegal\_crossing\_on\_other\_lane, passengers\_in\_the\_self\_driving\_car, pedestrians\_on\_lane\_crossing\_ahead, pedestrians\_on\_other\_lane\_crossing

passengers\_in\_the\_car, pedestrians\_on\_lane\_ahead, pedestrians\_on\_other\_lane

man\_no\_of\_passengers\_died, man\_no\_of\_pedestrians\_on\_lane\_ahead\_died, man\_no\_of\_pedestrians\_on\_other\_lane\_died, man\_no\_of\_passengers\_saved, man\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, man\_no\_of\_pedestrians\_on\_other\_lane\_saved, woman\_no\_of\_passengers\_died, woman\_no\_of\_pedestrians\_on\_lane\_ahead\_died, woman\_no\_of\_pedestrians\_on\_other\_lane\_died, woman\_no\_of\_passengers\_saved, woman\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, woman\_no\_of\_pedestrians\_on\_other\_lane\_saved, boy\_no\_of\_passengers\_died, boy\_no\_of\_pedestrians\_on\_lane\_ahead\_died, boy\_no\_of\_pedestrians\_on\_other\_lane\_died, boy\_no\_of\_passengers\_saved, boy\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, boy\_no\_of\_pedestrians\_on\_other\_lane\_saved, girl\_no\_of\_passengers\_died, girl\_no\_of\_pedestrians\_on\_lane\_ahead\_died, girl\_no\_of\_pedestrians\_on\_other\_lane\_died, girl\_no\_of\_passengers\_saved, girl\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, girl\_no\_of\_pedestrians\_on\_other\_lane\_saved, elderly\_man\_no\_of\_passengers\_died, elderly\_man\_no\_of\_pedestrians\_on\_lane\_ahead\_died, elderly\_man\_no\_of\_pedestrians\_on\_other\_lane\_died, elderly\_man\_no\_of\_passengers\_saved, elderly\_man\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, elderly\_man\_no\_of\_pedestrians\_on\_other\_lane\_saved, elderly\_woman\_no\_of\_passengers\_died, elderly\_woman\_no\_of\_pedestrians\_on\_lane\_ahead\_died, elderly\_woman\_no\_of\_pedestrians\_on\_other\_lane\_died, elderly\_woman\_no\_of\_passengers\_saved, elderly\_woman\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, elderly\_woman\_no\_of\_pedestrians\_on\_other\_lane\_saved, large\_man\_no\_of\_passengers\_died, large\_man\_no\_of\_pedestrians\_on\_lane\_ahead\_died, large\_man\_no\_of\_pedestrians\_on\_other\_lane\_died, large\_man\_no\_of\_passengers\_saved, large\_man\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, large\_man\_no\_of\_pedestrians\_on\_other\_lane\_saved, large\_woman\_no\_of\_passengers\_died, large\_woman\_no\_of\_pedestrians\_on\_lane\_ahead\_died, large\_woman\_no\_of\_pedestrians\_on\_other\_lane\_died, large\_woman\_no\_of\_passengers\_saved, large\_woman\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, large\_woman\_no\_of\_pedestrians\_on\_other\_lane\_saved, male\_executive\_no\_of\_passengers\_died, male\_executive\_no\_of\_pedestrians\_on\_lane\_ahead\_died, male\_executive\_no\_of\_pedestrians\_on\_other\_lane\_died, male\_executive\_no\_of\_passengers\_saved, male\_executive\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, male\_executive\_no\_of\_pedestrians\_on\_other\_lane\_saved, female\_executive\_no\_of\_passengers\_died, female\_executive\_no\_of\_pedestrians\_on\_lane\_ahead\_died, female\_executive\_no\_of\_pedestrians\_on\_other\_lane\_died, female\_executive\_no\_of\_passengers\_saved, female\_executive\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, female\_executive\_no\_of\_pedestrians\_on\_other\_lane\_saved, male\_doctor\_no\_of\_passengers\_died, male\_doctor\_no\_of\_pedestrians\_on\_lane\_ahead\_died, male\_doctor\_no\_of\_pedestrians\_on\_other\_lane\_died, male\_doctor\_no\_of\_passengers\_saved, male\_doctor\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, male\_doctor\_no\_of\_pedestrians\_on\_other\_lane\_saved, female\_doctor\_no\_of\_passengers\_died, female\_doctor\_no\_of\_pedestrians\_on\_lane\_ahead\_died, female\_doctor\_no\_of\_pedestrians\_on\_other\_lane\_died, female\_doctor\_no\_of\_passengers\_saved, female\_doctor\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, female\_doctor\_no\_of\_pedestrians\_on\_other\_lane\_saved, male\_athlete\_no\_of\_passengers\_died, male\_athlete\_no\_of\_pedestrians\_on\_lane\_ahead\_died, male\_athlete\_no\_of\_pedestrians\_on\_other\_lane\_died, male\_athlete\_no\_of\_passengers\_saved, male\_athlete\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, male\_athlete\_no\_of\_pedestrians\_on\_other\_lane\_saved, female\_athlete\_no\_of\_passengers\_died, female\_athlete\_no\_of\_pedestrians\_on\_lane\_ahead\_died, female\_athlete\_no\_of\_pedestrians\_on\_other\_lane\_died, female\_athlete\_no\_of\_passengers\_saved, female\_athlete\_no\_of\_pedestrians\_on\_lane\_ahead\_saved, female\_athlete\_no\_of\_pedestrians\_on\_other\_lane\_saved

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### Questions

- 1) **[20 points]** Please do the following:
  - a. **[10 points]** Code the PCA algorithm from scratch. (Note: Your code should be able to process any  $m \times n$  dataset). (Note: Set `random.seed(265)` before you start).
  - b. **[10 points]** **Test your algorithm** on the columns that denote 'the results of your decision' (more information can be found in the data dictionary above). (Note: Set number of dimensions to 2).
- 2) **[20 points]** Using the two principal components you obtained in **Q1**, create five scatterplots for the following five columns by using the `visualization_code.py` file in the assignment folder. Cluster labels will be determined by the unique values in columns of the dataset (you don't need to run a separate clustering algorithm, but you will need to create class labels for some of the observations in the columns below) (example: USA = Cluster 0, India = Cluster 1 etc.):
  - a. **[3 points]** *age*
  - b. **[3 points]** *gender*
  - c. **[3 points]** *grown\_up\_in\_US*
  - d. **[3 points]** *country\_of\_origin*
  - e. **[3 points]** *no\_of\_siblings* (you will need to create a new column by doing: *no\_of\_sisters* + *no\_of\_brothers*)
  - f. **[5 points]** Interpret the visuals you obtained above in around 200 words. Specifically: Do you see any patterns? Which column do you think creates the best clustering pattern?
- 3) **[20 points]** Repeat **Q2**, this time using spectral embedding for dimensionality reduction. Please answer the following:
  - a. **[10 points]** What is spectral embedding? Please do some online research and explain how spectral embedding works in around 200 words.

- b. **[10 points]** Using the `SpectralEmbedding` module of `sklearn`<sup>2</sup>, create the same set of five graphs (**1 point** each). Interpret the results in around 150 words (**5 points**). Specifically: Do you see any patterns? Which column do you think creates the best clustering pattern? And: Are the results better than PCA?
- 4) **[20 points]** Repeat **Q2**, this time using T-SNE for dimensionality reduction. Please answer the following:
- a. **[10 points]** What is T-SNE? Please do some online research and explain how T-SNE works in around 200 words.
- b. **[10 points]** Using the `TSNE` module of `sklearn`<sup>3</sup>, create the same set of five graphs (**1 point** each). Interpret the results 150 words (**5 points**). Specifically: Do you see any patterns? Which column do you think creates the best clustering pattern? And: Compare the results to PCA and Spectral Embedding. Are the results any better?
- 5) **[20 points]** Finally, create a correlation matrix<sup>4</sup> that looks at the correlations between all of the numerical and numerically coded variables in your dataset (excluding the string variables) and also the six new dimension reduction columns you created in **Q2**, **Q3**, and **Q4**. Please do the following:
- a. **[10 points]** Create the correlation matrix.
- b. **[10 points]** Interpret the results in around 250 words. Specifically, answer the following: Are there any variables that are strongly correlated? (i) Are there any variables from the original dataset that are strongly correlated with the dimension reduction variables? (ii) Do you think there are any variables in the original dataset that are strongly represented by the dimension reduction variables? (iii)



**One set of ethical guidelines for all types of cars?**

<sup>2</sup> <https://scikit-learn.org/stable/modules/generated/sklearn.manifold.SpectralEmbedding.html#:~:text=Spectral%20embedding%20for%20non%2Dlinear,eigenvectors%20for%20each%20data%20point>

<sup>3</sup> <https://scikit-learn.org/stable/modules/generated/sklearn.manifold.TSNE.html#sklearn.manifold.TSNE>

<sup>4</sup> Here is an example: [https://seaborn.pydata.org/examples/many\\_pairwise\\_correlations.html](https://seaborn.pydata.org/examples/many_pairwise_correlations.html)