Problem 1: PCA, decision trees, logistic regression. [16 **points**]
As an engineer focused on advancing electric vehicle design, you are tasked with evaluating the suitability of various materials for use as chassis of the vehicle. Given a dataset of mechanical properties from different materials you aim to develop a predictive model that determines whether a material is suitable for the chassis[1]. The dataset has 1500 samples and 15 features. The labels are 1: appropriate, 0: inappropriate.

1. You notice that several samples are missing values for features 2, 5, 10. State two approaches to address the missing values. (2 points)

   Solution:

   - *Mean/Median Imputation:* Replace the missing values in each feature with the mean or the median of the non-missing values in that feature.

     $$\hat{x}_i = \text{mean}(X) \quad \text{or} \quad \hat{x}_i = \text{median}(X)$$

   - *K-Nearest Neighbors (KNN) Imputation:* Estimate missing values based on the values of the nearest neighbors (samples with similar feature values).

     $$\hat{x}_i = \frac{1}{k} \sum_{j \in \text{neighbors}} x_j$$

   - *Deletion:* Remove samples that have missing values.
   - *Regression Imputation:* Use a predictive model to estimate missing values based on the other features.

2. You suspect some of the features are correlated. Hence, you perform a dimensionality reduction. Let $X \in \mathbb{R}^{1500 \times 15}$ denote the normalized data, prior to dimensionality reduction.

   (a) How do you determine the first 2 principal components, $v_1, v_2 \in \mathbb{R}^{15}$, of X? (2 points)
   Solution: We calculated the first two principal components of $X^T X$, namely the two eigenvectors associated with the two largest eigenvalues of $X^T X$.

   (b) Write the equation for projecting the data on the space spanned by v_1, v_2. (2 points)
   Solution:

   $$X \left[\frac{v_1}{\|v_1\|}, \frac{v_2}{\|v_2\|} \right].$$

Now, we consider the reduced dimensional dataset $A \in \mathbb{R}^{1500 \times 2}$. Denote the features by a_1, a_2. We aim to develop a decision tree for determining the suitability of a given material as a chassis. Let us use 1200 samples for training and the remainder for test. From this 1200 samples, 50 had label 1.

3. Suppose the second feature has values in the set $\{-3, -2, -1, 0, 1, 2, 3\}$. To compute the best value for making a split in a node using this feature, for which candidate values you need to compute and compare the gini indices? (1 point)

   Solution: We calculated the Gini index for each value in the set $\{-2.5, -1.5, 0.5, 1.5, 2.5\}$ and split the data using the value with the lowest Gini index.

[1] The problem is inspired by the following paper.

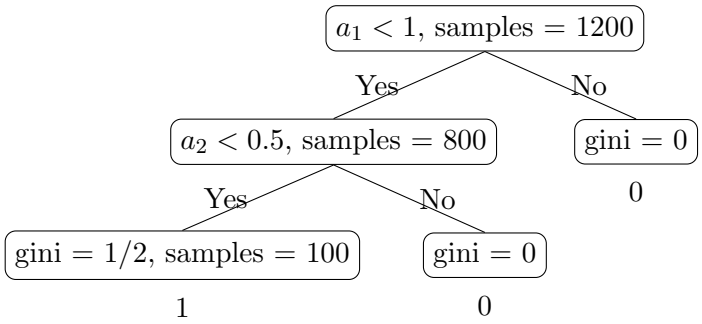
4. The optimized tree is as follows. What is the false positive rate, that is, the ratio between false positives and the total number of negatives (true label 0) ? (2 points)

   Solution: We first calculate the number of false positives. Since the Gini index for the node with prediction 1 is given as

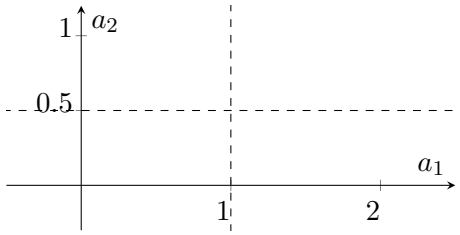
$$\frac{1}{2} = 1 - p_1^2 - p_2^2 = 2p_1(1 - p_1),$$

   where p_1 is the probability of being negative (e.g., labeled as 0) among all the 100 samples. By solving the above equation, we obtain $p_1 = \frac{1}{2}$. Therefore, the number of false positives is $100 \times \frac{1}{2} = 50$. Since there are 1150 negative samples in total, we calculate the false positive rate as

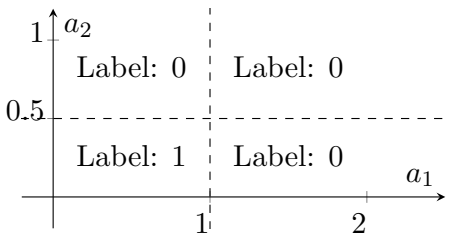
$$\textbf{False positive rate} = \frac{\text{False positives}}{\text{All negatives}} = \frac{50}{1100 + 50} = \frac{1}{23}.$$



5. For the regions shown in the graph below, put the label, $\{0, 1\}$ based on the prediction of the above decision tree. (2 points)

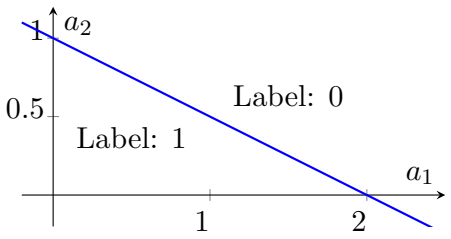


   Solution:



6. Next, rather than using a decision tree, you decide to do the classification with logistic regression. The optimization of logistic loss results in the line $a_2 = -\frac{1}{2}a_1 + 1$. Draw the line on the graph and determine the labels according to the logistic regression predictor. (3 points)

   Solution:



7. The training and test accuracy of the two methods are given below. What would be the probability of error on an unseen data point for each of the two methods? (2 points)

	training set accuracy	test set accuracy
decision tree	0.96	0.92
logistic regression	0.93	0.94

Solution: For the decision tree, the expected error is 0.08 (8%). For the logistic regression, the expected error is 0.06 (6%).

Problem 2: k-means, Naive Bayes and linear regression. [16 **points**]
The starting class of mechanical engineering in university X is very large, and being an international university, many students have moved from abroad. To make friends, the students have found *app-F*. They log into this app through their Instagram account, and the app uses their historical data to categorize them and then recommends potential friends as students in the same category.

1. Suppose the app has used historical data of its past $N = 4000$ users, extracting 5 features from the samples, and then has used k-means to categorize people. For $k = 3$, let $\mu_i \in \mathbb{R}^5$, $i = 1, 2, 3$, be the means. For a new student with feature vector $x^i \in \mathbb{R}^5$ how could we use the clusters to design a 1-nearest-neighbor (1-NN) classifier with Euclidean distance metric? (1 point)

   Solution: Given some metric $d : \mathbb{R}^5 \times \mathbb{R}^5 \to \mathbb{R}_+$, the 1-nearest-neighbor classifier is given by $\hat{y}(x) = \arg\min_{i\in[k]} d(x, \mu_i)$ (1-NN with respect to means) or by $\hat{y}(x) = \arg\min_{i\in[k]} d(x^{j^*(x)}, \mu_i)$, where $j^*(x)$ is the index of the nearest neighbor of x (1-NN with respect to data).

2. The above nearest neighbor classifier can act poorly. So, the app decides to design a Naive Bayes classifier. The number of data points in the three categories A, B, C, were $1500, 300, 2200$, respectively. What is the prior probability of category A? (1 point)

   Solution: The prior probability of category A can be computed as

$$P(y = A) = \frac{\#\text{data points in class } A}{N} = 1500/4000 = 3/8 = 0.375.$$

3. For data points in category A the mean of feature 1 is 11.5 and its standard deviation is 2.34. Write the likelihood of feature 1 given category A, assuming Gaussian distribution. (2 points)

   Solution: The likelihood feature 1 given category A is given by

$$\begin{aligned} p(x_1|y = A) &= \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_1 - \mu)^2}{2\sigma^2}\right) \\ &= \frac{1}{\sqrt{2\pi} \cdot 2.34} \exp\left(-\frac{(x_1 - 11.5)^2}{2 \cdot 2.34^2}\right) \approx 0.17 \cdot \exp\left(-\frac{(x_1 - 11.5)^2}{10.95}\right). \end{aligned}$$

4. Feature 2 takes values in $\{0, 1\}$. In category A, 1000 samples have value of 1 for their feature 2. Write the probability of feature 2 being equal to 1 given category A. (2 points)

   Solution: The probability of feature 2 being equal to 1 given A is

$$P(x_2 = 1|y = A) = 1000/1500 = 2/3.$$

5. Using the first two features and the Naive Bayes assumption, complete the expression for the probability of a student with feature $x^{\text{test}} = (13, 0)^\top$ to belong to category A, using Parts 3 and 4 results. (2 points).

$$P(y^{\text{test}} = A|x^{\text{test}}) = \frac{\cdots\cdots\cdots}{p(x^{\text{test}})}$$

   Solution:

$$\begin{aligned} P(y^{\text{test}} = A|x^{\text{test}}) &= \frac{P(y^{\text{test}} = A)p(x_1^{\text{test}} = 13|y^{\text{test}} = A)P(x_2^{\text{test}} = 0|y^{\text{test}} = A)}{p(x^{\text{test}})} \\ &= \frac{0.375 \times 0.17 \times \exp\left(-1.5^2/10.95\right) \times 1/3}{p(x^{\text{test}})}. \end{aligned}$$

In the campus orientation week, the students listened to a talk from the recent Nobel laureate highlighting the dangers of AI in reducing diversity in our societies[2]. Several students wisely deleted their app, and opted for a new approach to find friends. Namely, by attending their classes, and sitting next to a random student each time. Luckily, the teacher finally has a reasonable number of students to study the potential correlation between class attendance and grades.

6. Let x denote the number of class hours attended, and y denote the grade of a student. For $N = 200$ students, the covariance matrix D of the above features and the mean vector μ is given below. Write the formula for the correlation between x and y and compute it. (2 points)

$$D = \begin{pmatrix} 9 & 5 \\ 5 & 4 \end{pmatrix}, \qquad \mu = \begin{pmatrix} 24 \\ 63 \end{pmatrix}$$

Solution: Let $\mu = [\mu_x, \mu_y]^\top$ and $D = \begin{bmatrix} D_{x,x} & D_{x,y} \\ D_{y,x} & D_{y,y}. \end{bmatrix}$ and define the empirical covariance and standard deviation as

$$\hat{\sigma}_z = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x^i - \mu_x)^2}, \quad z \in \{x, y\},$$
$$\widehat{\mathrm{Cov}}(x, y) = \frac{1}{N}\sum_{i=1}^{N}(x^i - \mu_x)(y^i - \mu_y).$$

We have $\widehat{\mathrm{Cov}}(x, y) = D_{x,y} = 5$, $\hat{\sigma}_x = \sqrt{D_{x,x}} = 3$, and $\hat{\sigma}_y = \sqrt{D_{y,y}} = 2$. The empirical correlation is given by

$$\widehat{\mathrm{Corr}}(x, y) = \widehat{\mathrm{Cov}}(x, y)/(\hat{\sigma}_x \hat{\sigma}_y) = 5/6.$$

The teacher subtracts the mean of the features from each student data point (x^i, y^i), and then releases the resulting N data pairs, anonymized (hiding identities of students).

7. Student S wants to use the above to fit a linear regression and then decide how many hours to attend lecture to get a desired grade. To this end, she considers fitting a line without an offset, $y = wx$, to the released data. Write the mean-square-loss she needs to optimize. (1 point)

Solution: The mean-square loss is given by $L(w) = \frac{1}{N}\sum_{i=1}^{N}(y^i - wx^i)^2$.

8. Derive the gradient of the loss function with respect to the line slope $w \in \mathbb{R}$. (1 point)

Solution: The gradient is given by

$$\nabla L(w) = \frac{2}{N}\sum_{i=1}^{N}(wx^i - y^i)x^i = 2\left(w\underbrace{\frac{1}{N}\sum_{i=1}^{N}(x^i)^2}_{D_{x,x}} - \underbrace{\frac{1}{N}\sum_{i=1}^{N}x^i y^i}_{D_{x,y}}\right) = 2(wD_{x,x} - D_{x,y}),$$

where we used that the data has been centered i.e. $x^i \leftarrow x^i - \mu_x$ and $y^i \leftarrow y^i - \mu_y$.

[2]Listen to the talk here.

9. Compute the w that optimizes the loss based on the information in matrix D. (2 points)

   Solution: We need to look for a stationary point w with $\nabla L(w) = 2(wD_{x,x} - D_{x,y}) = 0$. Rearranging terms yields $w = D_{x,y}/D_{x,x} = 5/9$.

10. Given the feature means μ in part 6, use the above model to determine how many lecture hours student S should attend to have an expected grade of 83. (2 points)

    Solution: We identified the linear relationship $(83 - \mu_y)/w = x - \mu_x$. Rearranging terms yields $x = (83 - \mu_y)/w + \mu_x = 20/5 \cdot 9 + 24 = 60$. Hence, according to the linear regression model, the student should attend 60 hours of classes.

    Note: ideally, the student should have divided the data to a training and test sets. Furthermore, we don't recommend using this approach as it can only give an "expected" grade.

Problem 3, Convolutional neural networks, train and test performance. [18 **points**]
Landmines are responsible for death of thousands of people per year, most of them civilians, and there are still over 100 million landmines buried in earth[3]. Committed to use your engineering degree for a meaningful cause, you have joined a startup that uses drones equipped with infrared camera to locate buried landmines [4]. Now you will use your AI course to locate landmines from camera images.

Let us consider a grayscale image of size 256×256.

1. For training data, your analyze 1200 images obtained from landmines with known locations. You have labeled an image 1 if there indeed exists a landmine in the region captured by the image and 0 otherwise. Of these 1200 images, 40 had a landmine. What would be the accuracy of any classifier that labels all images as 0? Should one be satisfied with this classifier? (2 points)

   Solution: The accuracy is

   $$\frac{\#\text{Correct predictions}}{\#\text{Predictions}} = 1160/1200 \approx 0.97.$$

   Although the accuracy is high, we shouldn't be satisfied with the classifier, as its false negative rate (FNR) is

   $$\text{FNR} = \frac{\text{FN}}{\text{FN} + \text{TP}} = \frac{40}{40+0} = 1,$$

   meaning that it won't detect any landmines.

We aim to design an automated method for detecting landmines from stream of camera images.

2. Our aim is to first reduce the noise in the image and then detect the edges. To this end, which of the two filters below should be applied first to the image? Justify your answer. (2 points)

   $$A = \begin{pmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{pmatrix}, \qquad B = \begin{pmatrix} 0.055 & 0.11 & 0.055 \\ 0.11 & 0.23 & 0.11 \\ 0.055 & 0.11 & 0.055 \end{pmatrix}.$$

   Solution: Filter A is Laplacian filter which is detecting edges and B a Gaussian filter which helps to reduce noise. So, we first apply filter B and then A.

3. After the above convolutions (without padding), you use 1000 of data points for training a logistic regression classifier. To this point, you flatten the images, and use them as input to the classifier. How many parameters need to be determined to define this classifier? (2 points)

   Solution: Given the input dimension 256×256 and the filter size $F = 3$, the image height and width after the first convolution are $W_1 = H_1 = W_{\text{in}} - F + 1 = 254$ and after the second convolution $W_2 = H_2 = W_2 - F + 1 = 252$. Therefore, we need $252 \times 252 + 1 = 63'505$ parameters for the logistic regression.

4. You observe that the false negative rates are higher than the false positive rates of your classifier. To try to remedy this, would you choose $\tau \in (0,1)$ or $\tau > 1$ below? Justify. (2 points)
   $L(w,b) = \frac{1}{N}\sum_{i=1}^{N} y^i \log(1+e^{-z_i}) + \boxed{\tau}(1-y^i)\log(1+e^{z_i})$.

   Solution: The loss term $y^i \log(1+e^{-z_i})$ penalizes false negatives, as it is large if $y^i = 1$ and $z^i < 0$. To increase its weight relative to $(1-y^i)\log(1+e^{z_i})$, which penalizes false positives, we choose $\tau \in (0,1)$.

[3] See the United Nations report here.
[4] Inspired by the following article.

5. Now, your classifier seems to overfit to the training data. Propose a modification in the cost above that has the potential to reduce this overfit. (1 point)

   Solution: We can add L1 or L2 regularization to the loss. That is, we add the regularization term $\lambda\|w\|_1$ or $\lambda\|w\|_2^2$, where $\lambda > 0$, to the above logistic loss.

Instead of following the steps 2-5 above, you decide to design a convolutional neural network (CNN).

6. You apply 3 convolution filters in the first layer of your CNN (without padding), with each filter having a size of 5×5. How many weights and biases need to be determined to define these filters? (2 points)

   Solution: The number of paramaters is

   $$\#\text{ parameters} = (F^2 \cdot C_{\text{in}} \cdot C_{\text{out}}) + C_{\text{out}} = 75 + 3 = 78,$$

   where

   - F = Kernel Size = 5
   - C_{in} = Number of Input Channels = 1
   - C_{out} = Number of Output Channels (Filters) = 3.

7. Next, you pass the 3 matrices obtained after the convolution step above through a hyperbolic tangent (tanh) nonlinearity. What would be the range of values of each entry of the resulting 3 matrices? (1 point)

   Solution: After the tanh activation, the matrix entries will take values in $[-1, 1]$.

8. In the third step, you do a max pooling with stride of 4. What is the size of each of the 3 output matrices? (1 point)

   Solution: After the convolutional layer, the matrices will have size $W_1 = H_1 = W_{\text{in}} - F + 1 = 256 - 5 + 1 = 252$. Therefore, after the max pooling step, the matrices have height and width $252/4 = 63$.

9. Finally, you flatten the image and use it as an input to a logistic regression classifier. How many weights and biases need to be determined for this last layer? (2 points)

   Solution: The flattened image is a vector of length $63 \times 63 \times 3 = 11'907$, so we need $63 \times 63 \times 3 + 1 = 11'908$ parameters for the logistic regression classifier.

10. You find that the training accuracy is 99.9% but the test accuracy is 90%. Is the approach overfitting or underfitting? (1 point)

    Solution: As the model performs much worse on the test set, it is overfitting to the training data.

11. Your colleague thinks that your neural network is too simple. Is it likely that making the network deeper fix the above discrepancy? Justify your answer. (1 point)

    Solution: No, as the neural network is already overfitting, increasing the model complexity by making the network deeper would likely lead to even more problems with overfitting.

12. Your other colleague thinks that stochastic gradient descent has not been able to find the optimal set of parameters. Is this likely based on the above training and test accuracies? (1 point)

    Solution: No, the high training accuracy suggests that the training loss was minimized successfully.

Problem 4, Reinforcement learning. [20 **points**]
Lithium-ion batteries are crucial in power systems, electric vehicles, and consumer electronics. However, developing an optimal charging scheme for them is challenging. We will use reinforcement learning to this end[5]. Let $x \in \mathbb{R}^4$ denote the state of the battery dynamics (capturing voltages at different locations and the state of charge of the battery) and $u \in \mathbb{R}$ denote the input, which is the current applied to the battery. The discretized dynamics are given by:

$$x(t+1) = f(x(t), u(t), w(t)),$$

where $w(t)$ is the uncertainty, sampled from the uniform distribution on the interval $[0, 1]$. Furthermore, $f : \mathbb{R}^4 \times \mathbb{R} \times \mathbb{R} \to \mathbb{R}^4$ is unknown but we have a simulator that can evaluate it at any x, u, w.

1. Given an initial condition $x(0) \in \mathbb{R}^4$, and an input $u(0), u(1)$ write the steps for generating a sample trajectory $x(1), x(2) \in \mathbb{R}^4$. (2 points)

   Solution: For the first step, we sample $w(0)$ from a uniform distribution over the interval $[0, 1]$. Given the initial state $x(0)$, the initial input $u(0)$, and the noise $w(0)$, we evaluate $x(1) = f(x(0), u(0), w(0))$ from the simulator.

   For the second step, we sample $w(1)$ from a uniform distribution over the interval $[0, 1]$. Given $x(1)$, $u(1)$, and $w(1)$, we evaluate $x(2) = f(x(1), u(1), w(1))$ from the simulator.

Our goal is to ensure x_4, the battery charge, reaches a desired level x_d as fast as possible, while not damaging the battery. To this end, we design a reward, which consists of a unit penalty for every time step taken while $x_4(t)$ has not reached x_d and a term that penalizes the voltage x_1 going beyond a threshold $\bar{V}$: $\max(x_1(t) - \bar{V}, 0)$ while x_d has not been reached. The discount factor is $\gamma \in (0, 1)$.

2. Fill in the expression for the reward of a trajectory that takes T steps to reach x_d. (1 point)
   $J(x(0), \cdots, x(T), u(0), \cdots, u(T-1)) = \mathbb{E} \sum_{t=0}^{T}$ _____.
   Solution:

$$J(x(0), \cdots, x(T), u(0), \cdots, u(T-1)) = \mathbb{E} \sum_{t=0}^{T} -\gamma^t (\mathbf{1}_{x_4(t)!=x_d} + \max(x_1(t) - \bar{V}, 0))$$

3. Write the expression for the discounted cumulative reward of the following trajectory: (2 points)
   $\{x(t)\}_{t=0}^{10}$ reaches x_d at time step 10 with x_1 being one unit above $\bar{V}$ at step 5.
   Solution: Given the formula in question 2, we calculate the reward for the first trajectory as

$$-\left(\sum_{t=0}^{9} \gamma^t + \gamma^5\right).$$

Now, we want to design a control policy $\pi_\theta : \mathbb{R}^4 \to \mathbb{R}$, where θ is a policy parameter, to minimize the cost given in Part 2 of this problem.

4. How many parameters should be determined in each of the following policy classes: (3 points)
   (a) a linear policy with $u = \theta^T x$.
   (b) a neural network policy of 2 hidden layers, with 10 neurons in each depth.

   Solution: For the linear policy, we need 4 parameters. For a neural network policy, we need $(4 * 10 + 10) + (10 * 10 + 10) + (10 * 1 + 1) = 171$ parameters.

[5]Inspired by the following article, where we significantly simplified the model (from 61 dimensions to 4 dimensions).

5. Consider the linear policy in Part 4(a) above with addition of noise from a Gaussian distribution with zero mean and constant variance. Let us denote the corresponding probability density function of the policy by $\pi_\theta(u|x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(u-\theta^T x)^2}{2\sigma^2}}$. Determine $\nabla_\theta \log \pi_\theta(u|x)$. (2 points)

Solution:

$$\nabla_\theta \log \pi_\theta(u|x) = \nabla_\theta \log \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(u-\theta^T x)^2}{2\sigma^2}} = -\nabla_\theta \frac{(u-\theta^T x)^2}{2\sigma^2} = \frac{(u-\theta^T x)x}{\sigma^2}.$$

6. Describe an approach for sampling N trajectories of length T and explain how to estimate $J(\pi_\theta)$ using these sampled trajectories. (2 point)

Solution: We sample N trajectories with a truncated horizon of T as follows: for each trajectory i, at time step t, we sample $u^i(t-1)$ from $\pi_{\theta_s}(\cdot|x^i(t-1))$ and $w^i(t-1)$ from the uniform distribution on the interval $[0,1]$. We then evaluate $x^i(t)$ from the simulator, given $x^i(t-1)$, $u^i(t-1)$, and $w^i(t-1)$. Finally, we estimate the reward as

$$\hat{J}(\pi_{\theta_s}) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{t=0}^{T} \gamma^t \left(\mathbf{1}_{x_4^i(t)\neq x_d} + \max(x_1^i(t) - \bar{V}, 0)\right).$$

7. Given the formula for estimating the policy gradient below, how would you use the above N trajectories, Part 5 and Part 6, to compute $\hat{\nabla}_\theta J(\pi_\theta)$? (2 points)

$$\hat{\nabla}_\theta J(\pi_\theta) = \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{t=0}^{T}\gamma^t r(x^i(t), u^i(t))\right)\left(\sum_{t=0}^{T}\nabla_\theta \log \pi_\theta(u^i(t)|x^i(t))\right).$$

Solution: We plug in $-\sum_{t=0}^{T}\gamma^t \left(\mathbf{1}_{x_4^i(t)\neq x_d} + \max(x_1^i(t) - \bar{V}, 0)\right)$ for the cumulative reward of trajectory i and plug in $\sum_{t=0}^{T}\frac{(u^i(t)-\theta^T x^i(t))x^i(t)}{\sigma^2}$ for the second term above.

8. Write the stochastic gradient ascent update for θ with a learning rate of η. (2 points)

Solution:

$$\theta = \theta + \eta\hat{\nabla}_\theta J(\pi_\theta).$$

9. You initialize θ randomly and after 100 iterations of the stochastic gradient ascent, θ converges to θ_s. With a different initialization, would the algorithm converge to θ_s? Justify. (1 point)

Solution: We are performing stochastic gradient descent for a non-convex optimization problem. One reason the algorithm converges to a different θ_s is we find different local optimum given different initial conditions.

10. Now, you implement the policy π_{θ_s} on your headphone, which also has a Lithium-ion battery, by plugging and programming a variable resistor on the outlet. Unfortunately, the voltage gets out of the limit and your headphone stops working. Provide three potential reasons for why the implementation outcome is different than the simulation outcome. (3 points)
Note: this motivates the flourishing research field of safe data-driven control.

Solution:

(a) We did not enforce the voltage limit as a hard constraint but instead incorporated it into the reward design by penalizing voltages that exceed the threshold. However, this reward design may result in an optimal policy that prioritizes reaching x_d as quickly as possible, potentially increasing the risk of exceeding the voltage limit. If this policy is implemented in your headphones, the voltage may exceed the allowable threshold.

(b) A second possible reason is model mismatch, as the policy was trained in a simulated environment rather than on the real headphones. When you implemented the pre-trained policy, its performance may not have matched that observed in the simulation, potentially resulting in scenarios where the voltage exceeds the allowable threshold.

(c) A third possible reason is that the policy and dynamic are stochastic. Even if we ensure that our policy minimizes the risk of exceeding the voltage limit, the headphones will still break due to over-voltage with some probability.

Problem 5, AI Ethics. [2 **bonus points**]
You are considering working for a new startup whose goal is to bring robots to senior people's homes. There are a number of ethical issues that you reflect upon before deciding to join this company[6]. Categorize each of the 6 issues below in the three categories discussed in AI Ethics videos, namely:

A. Narrative framing; B. Social justice; C. Ethics in technology.

1. The company seeks publicity in the Swiss news and social media channels to highlight benefits of robots in old people's homes. **Solution:** A

2. The algorithms to train the robots are based on data obtained from robots interacting with old people in 2 hospitals in Canton Aargau. **Solution:** C

3. An estimated number of 1000 nurses would lose their jobs 2030 if the company becomes widely successful in Switzerland. **Solution:** B

4. Each robot costs over 30,000 CHF and thus, only a fraction of seniors can afford to have such robots. **Solution:** B

5. A select number of seniors in certain homes are consulted on whether such technology is preferred to human nurses. **Solution:** A

6. The control algorithm for navigation of robots is based on reinforcement learning and there is no clear way to interpret and understand how robots make decisions. **Solution:** C

[6]Inspired by the following article.