**Loss Function** Definition: A mathematical function that quantifies the difference between predicted and true values. Regression: Mean Squared Error (MSE), Mean Absolute Error (MAE). Classification: Cross-Entropy Loss, Hinge Loss. Predicted Guides model optimization during training by minimizing the error. Gradient Descent: Common optimization technique using the derivative of the loss function Negative Confusion Matrix **Definition**: A table summarizing the performance of a classification model. Actual Components: True/False +ves/-ves [(T or F)(P or N]) - Correctly/Incorrectly predicted positive/negative instances. Accuracy: (TP+TN)/(TP+TN+FP+FN) Derived Metrics: **Precision**: TP/(TP+FP) – How many positive predictions were correct. Recall (Sensitivity): TP/(TP+FN) - How many actual positives were correctly predicted. F1 Score: Harmonic mean of precision and recall: 2 (Precision Recall)/(Precision+Recall). **ROC and AUC** ROC Curve ROC Curve: Graphical plot of True Positive Rate (Recall) vs. False Positive Rate. True/False Positive Rate: (TP or FP)/(TP+FN) AUC (Area Under Curve): Measures the ability of the model to distinguish between classes. Ranges from 0.5 (random guessing) to 1.0 (perfect model). Represents the probability that a randomly chosen positive instance ranks higher than a randomly chosen negative one. 0 **Logistic Regression**  $\textbf{Definition:} \ A \ \text{statistical model for binary classification using a sigmoid function to output probabilities.} \qquad \textbf{Equation:} \ \sigma(z) = 1/(1 + e^{-z}), \ \text{where} \ z = \beta 0 + \beta 1x 1 + \cdots + \beta nx n$ • Loss Function: Cross-Entropy Loss. Regularization: L1 (Lasso): Promotes sparsity in features. L2 (Ridge): Penalizes large coefficients to prevent overfitting. Principal Component Analysis (PCA) Definition: Dimensionality reduction technique that transforms data into principal components, capturing maximum variance. Steps: 1. Standardize data. 2. Compute covariance matrix. 3. Perform eigendecomposition to get eigenvectors (directions) and eigenvalues (variance explained). 4. Select top components based on explained variance. Use Case: Reducing noise and computational complexity in high-dimensional data. Naive Bayes (NB) Definition: Probabilistic classifier based on Bayes' theorem, assuming independence among predictors. Bayes' Theorem:  $P(A|B)=P(B|A) \cdot P(A) / P(B)$ . Strengths: Fast, simple, effective for text classification Variants: Gaussian NB: For continuous data. Bernoulli NB: For binary data. Multinomial NB: For discrete counts. **Definition**: A tree-structured algorithm for classification or regression. Decision Tree (DT) Key Concepts: Splits data recursively based on feature thresholds. Criteria: Gini Impurity, Entropy. Limitations: Prone to overfitting (solved using pruning or ensembles). Advantages: Interpretability, non-parametric. k-Nearest Neighbors (kNN) Definition: Instance-based algorithm that assigns a class based on the majority vote of k nearest neighbors. Key Steps: 1. Compute distance (e.g., Euclidean, Manhattan). 2. Identify k nearest neighbors. 3. Predict based on majority class (classification) or average (regression). Challenges: Sensitive to outliers, computationally expensive for large datasets. Support Vector Machine (SVM) **Definition**: A model that finds the hyperplane best separating data points of different classes. Margin: Distance between the hyperplane and nearest data points. Kernel Trick: Transforms data into higher dimensions to find a linear separator. Types: Linear, Polynomial, RBF (Gaussian). Key Concepts: Loss Function: Hinge Loss. Strengths: Effective in high-dimensional spaces, robust to outliers. Definition: Computational models inspired by biological neural networks, capable of approximating complex functions. **Neural Network (NN)** Components: Input Layer: Features. **Hidden Layers**: Nonlinear transformations. **Output Layer**: Predictions. Activation Functions: Sigmoid, ReLU, Tanh. Training: Forward Propagation: Predicts output. Backward Propagation: Optimizes weights using gradients of the loss function. Use Case: Handles non-linear, high-dimensional data well. SHAP (SHapley Additive exPlanations) **Definition**: A framework for interpreting predictions by attributing feature contributions based on Shapley values. Key Concepts: Shapley Value: From game theory, measures the contribution of a feature by considering all permutations. Additive Explanation: Breaks predictions into individual contributions. Advantages: Model-agnostic; Provides insights into feature importance and interaction. Use Case: Enhances trust and understanding in black-box models. What is a key difference between classical regressions (CR) and ML methods? Ans: CR typically tests if features are statistically significant while ML does not typically do so. Reason: Classical regressions focus on feature significance (hypothesis testing), whereas ML methods prioritize prediction accuracy. In a ML prediction, the recall is 2/3, precision is 3/4, number of TP's is 1/5 of number of TN's. What is accuracy? From the question, TP = 1/5 TN  $\rightarrow$  accuracy comes out to be 75.67% 1. Recall = TP/(TP+FN)=2/3 2. Precision = TP/(TP+FP)=3/4 Which of the following is an ensemble effect? Ans: Building cost estimation based on estimates submitted by a dozen established building corporations. Reason: Ensemble methods combine multiple predictions (like averaging) from several models, similar to combining estimates here. A simple DT predicting a target numerical value with conditions (Feature 3 > 5.6, Feature 1 > 0.7, Feature 4 <= 1.2). What is the predicted value? Sample of 10 Firms with target values  $Y_i$ Feature 1 <= 0.7? Following the decision tree: **Feature 3 > 5.6**  $\rightarrow$  **Yes** branch; **Feature 1 > 0.7**  $\rightarrow$  **No** branch. Terminal node values are: 0.15, 0.05. The **predicted value** is the average of these two values: (0.15+0.05)/2=0.10.  $\text{Minimizing objective function using L1 regularization term} \quad \sum_{k=1}^{n} \left( Y_k - \sum_{j=0}^{p} b_j X_{jk} \right)^2 + \alpha \sum_{j=0}^{p} \left| b_j \right| \text{ is Lasson for the property of the property of$ Feature 3 <= 5.6? Reason: The L1 norm (sum of absolute values) is characteristic of Lasso regression, which encourages sparsity in feature coefficients. In an SVM classification, what is the perpendicular distance between parallel planes x+2y+z=5 and x+2y+z=7? The formula for the perpendicular distance between two parallel planes ax+by+cz=d1 and ax+by+cz=d2 is: dist = |d2-d1|/sqrt(a^2+b^2+c^2) Here: a=1, b=2, c=1, d1=5, d2=7. Substituting into the formula yields 2/sqrt(6). In running the Neural Network (NN), how can you improve accuracy while reducing loss? Increasing epochs improves training (but risks overfitting); Decreasing batch size allows more granular updates; Increasing the number of layers can enhance model complexity. In logistic regression, prediction of class with label Y=1 is done through? Ans: Fitting Expected Value of Y given the features. Reason: Logistic regression models the probability that Y=1 given the features using a sigmoid function. PCA transforms original features into features with what property?

Reason: PCA transforms features into uncorrelated (orthogonal) components. Ans: Orthogonal transformed features Which ML algorithm is most sensitive to outliers? Ans: kNN (sensitive to outliers because distance-based calculations can be skewed by extreme values) Effect of shrinking estimation: Shrinking estimation (e.g., through regularization) helps reduce overfitting, regularizes coefficients, and can indirectly perform dimension reduction. Suppose Fj's are features, and Z is the target. If  $P(F_1, F_2, \dots, F_n | Z) = \prod_{j=1}^n P(F_j | Z)$ , what is the assumption? **Ans:**  $P(F_j|Z,F_1,F_2,...,F_{j-1},F_{j+1},...,F_n)=P(F_j|Z)$ Reason: This assumption reflects conditional independence, which is fundamental in Naive Bayes classifiers. Each feature Fj is conditionally independent given the target Z The graph shows data partitioned randomly without considering timing. What could be a critical problem? Ans: Imbalanced data Reason: The graph shows two distinct distributions for Pre-Covid (yellow) and Covid-era (red) points. Random partitioning may result in an **imbalanced dataset** where one class (e.g., Covid-era) dominates, affecting the model's ability to generalize well.

Which propagation in NN uses a learning rate? Ans: Gradient Descent

Reason: Gradient descent adjusts the weights during backpropagation using the learning rate to minimize the loss function.

In ML prediction, given a target of 1.70 and SHAP values +0.85, -0.65, +0.30, what is the average predicted target?

To compute the average predicted target: Base Value=1.70 - (0.85 - 0.65 + 0.30) = 1.20