Ques! 09

Age

Training Value 35, 28, 45, 31, 52, 29, 42, 33

Min = 28 Max = 52

Credit Score

Training Value 720, 650, 750, 600, 780, 630, 710, 640

Min = 600, Max = 780

Age, Normalise $= \frac{37-28}{52-28} = 0.375$

CreditScore, Normalise $= \frac{705-600}{780-600} = 0.5833$

Perception Calculation, $z = (w_1 \cdot x_1) + (w_2 \cdot x_2) + b$

$= (0.3 \times .375) + (0.4 \times 0.5833) + 0.1$

$= 0.4458 < .5$

Why use Normalise:

1. Faster and More stable Learning
2. Prevents One Feature from dominating
3. Help Activation function work Properly
4. Improves generalization (Better Predictions)

Ques: 10

Forward Pass

Hidden Layer Pre-Activation (z_1, z_2)

$Z_1 = (0.3 * 0.375) + (0.4 * 0.583) + 0.1 = 0.4457$

$Z_2 = (0.5 * 0.375) + (-0.2 * 0.583) - 0.1 = -0.0201$

Hidden Layer Activations (a_1, a_2) using Sigmoid

$a_1 = \sigma(0.4457) = \frac{1}{1+e^{-0.4457}} = 0.6096$

$a_2 = \sigma(-0.0201) = \frac{1}{1+e^{-(-0.0201)}} = 0.4927$

Output Layer Pre-Activation (z_o):

$Z_o = (0.6 \times 0.6096) + (-0.4 \times 0.4927) + 0.2 = 0.368$

$\hat{y} = \sigma(0.3687) = \frac{1}{1+e^{-0.3687}} = 0.5911$

Backpass

$\frac{\partial Loss}{\partial z_o} = \hat{y} - y = 0.5911 - 1 = -0.4089$

Gradient for Output Layer (W_2, b_2)

$\frac{\partial L}{\partial W_2} = \delta_o a = -0.4089 \cdot [0.6096, 0.4927]$

$= [-0.2495, -0.2015]$

$= -0.4089$

Gradient for Hidden Layer (W_1, b_1)

$\delta_{hi} = \frac{\partial L}{\partial z_o} \cdot W_2(i)\, \sigma'(z_i)$

$\sigma'(z) = \sigma(z)(1 - \sigma(z))$

$\sigma'(z_1) = 0.6096(1 - .6096) = 0.2380$

$\sigma'(z_2) = 0.4927(1 - .4927) = 0.2499$

Now Calculate

$\delta h_1 = -0.40809 \times .6 \times 0.2380 = -0.0584$

$\delta h_2 = -0.40809 \times (-0.4) \times 0.2499 = 0.0409$

Now find gradients for W_1

$$\frac{\partial L}{\partial W_1} = \begin{bmatrix} -0.0219 & 0.0153 \\ -0.0341 & 0.0239 \end{bmatrix} \qquad \frac{\partial L}{\partial b_1} = [\delta h_1, \delta h_2] = [-0.0584, 0.0409]$$

$$W_2 = [0.6 - 0.4] - 0.1 \times [-0.2495, -0.2015] = [0.6250, -0.3798]$$

$$b_2 = 0.2 - 0.1 \times (-0.40809) = 0.2409$$

$$W_1 = \begin{bmatrix} 0.3 & 0.5 \\ 0.4 & -0.2 \end{bmatrix} - 0.1 \times \begin{bmatrix} -0.0219 & 0.0153 \\ -0.0341 & 0.0239 \end{bmatrix} = \begin{bmatrix} 0.3022 & 0.4985 \\ 0.4034 & -0.2024 \end{bmatrix}$$

$$b_1 = [0.1, -0.1] - 0.1 \times [-0.0584, 0.0409] = [0.1058, -0.1041]$$

Ques no: 11

$P(\text{Low}) = \frac{4}{8} = .5$

$P(\text{high}) = \frac{4}{8} = .5$

Risk Level (Low)

Age.

$\mu = (35+45+52+42)/4 = 43.5$

$\sigma^2 = [(35-43.5)^2+(45-43.5)^2+(52-43.5)^2+(42-43.5)^2]/4 = 37.25$

Credit Score

$\mu = (720+750+780+710)/4 = 740$

$\sigma^2 = [(720-740)^2+(750-740)^2+(780-740)^2+(710-740)^2]/4 = 750$

Education

$\mu = (16+18+16)/3 = 16.67$

$\sigma^2 = [(16-16.67)^2+(18-16.67)^2+(16-16.67)^2]/3 = 0.89$

Risk Level (High)

Age.

$\mu = (28+31+29+33)/4 = 30.25$

$\sigma^2 = [(28-30.25)^2+(31-30.25)^2+(29-30.25)^2+(33-30.25)^2]/4 = 3.69$

Credit Score

$\mu = (650+600+630+640)/4 = 630$

$\sigma^2 = [(650-630)^2+(600-630)^2+(630-630)^2+(640-630)^2]/4 = 325$

Education:

$\mu = (14+12+14+12)/4 = 13$

$\sigma^2 = [(14-13)^2+(12-13)^2+(14-13)^2+(12-13)^2]/4 = 1$

P(T1|Low):

Age → $x = 37$ $\quad$ $P(Age = 37 | Low) = 0.051$

CreditScore → $x = 705$ $\quad$ $P(CreditScore = 705 | Low) = 0.022$

Education → $x = 16$ $\quad$ $P(Education = 16 | Low) = 0.376$

$P(T_1 | Low) = 0.051 * 0.022 * 0.376 = 0.000422$

$P(Low | T_1) = 0.000422 \times 0.5 = 0.000211$

Age → $x = 37$ $\quad$ $P(Age = 37 | High) = 0.0002$

CreditScore → $x = 705$ $\quad$ $P(CreditScore = 705 | High) = 0.004$

Education → $x = 16$ $\quad$ $P(Education = 16 | High) = 0.004$

$P(T_1 | High) = 0.0002 \times 0.004 \times 0.004 = 0.0000000032$

$P(High | T_1) = 0.0000000032 \times 0.5 = 0.0000000016$

$P(Low | T_1) = 0.000211$

$P(High | T_1) = 0.0000000016$

T_1 is classified as: Low Risk

Ques: 12

1. Age:

* Potential Bias: The age distribution could be skew[ed], meaning some age groups are overrepresented wh[ile] others are underrepresented.
* Impact: A model trained on such data might not generalize well to age groups that are less repr[esented] leading to poor predictions for underrepresented age groups.

2. Credit Score:

* Potential Bias: If the credit score distribution is heavily skewed, the model might favor predictions based on hi[gh] credit scores. This could result in bias toward indiv[iduals] with better financial standing.
* Impact: Individuals with lower credit scores may not be adequately represented in the model, which could lead to underestimating the risk for these individuals

3. Education:

* Potential Bias: The missing values in the education colum[n] could introduce bias, especially if the missing data are not missing at random.
* Impact: A lack of diversity in the education levels or data could skew the model's understanding of how educ[ation] influences risk levels

4. Risk level:

* Potential bias: If the risk level distribution is highly imbalanced the model might be biased towards pre[dicting] "Low" risk. This could lead to poor predictions for hig[h] individuals.
* Impact: The model could underperform in predicting [high] risk individuals outcomes and focus too much on the [low] risk group

Reduce Bias

1. Resampling (for Age and Risk level)

* Method: Perform resampling to ensure a balanced distribu of age and risk levels. If certain age groups are underrepresented oversampling the underrepresented age group can help. Similarly, if the risk levels are imbalanced techniques like SMOTE can be used to balance the classes

* Justification: Resampling ensures that the model doesn't overfit to any one group, leading to better generalization across different age groups and risk levels. Balanced representation allows the model to make more accurate predictions for all groups

2. Normalization / standardization (for Credit score)

* Method: Normalize or standardize the credit score values so that the model does not give undue importance to higher scores. This could involves scalling the credit scores to fall within a specific rang or using z-score normalization to adjust for outliers.

* Justification: Credit scores can vary widely and normalizing or standardining helps reduce the effect of outliers or skewed data. This ensures that the model treats all credit scores equally, which prevents overfitting to extreme values.

3. Imputation of Missing Data (for Education)

* Method: Impute missing values in the education field using techniques like mean imputation, mode imputation or more sophisticated methods like K-nearest neighbours (KNN) imputation or multiple imputation to fill in missing education levels.

* Justification: Proper imputation ensures that missing values do not distort the data distribution. This approach helps maintain a complete dataset for all individuals, Preventing biases caused by missing data and ensuring that education level is adequately

represented in the model

4. Class Balancing (For Risk Level)

* Method: Use techniques like SMOTE or class weights to balance the representation of risk levels in the dataset. SMOTE generate synthetic data points for the underrepresented class while class weights can be adjusted so that the model penalize misclassification of underrepresented classes more heavily

* Justification: Class balancing prevents the model from being biased toward the majority class and ensures that both "Low" and "High" risk categories are learned properly. This leads to better predictions across all classes, especially the minority class.