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HERALD COLLEGE KATHMANDU

Artificial Intelligence and Machine Learning.

6CS012

QUESTION AND ANSWER

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1 Long Question: Answer any 1

(5 pt.) You are a Data Scientist at eSewa, Nepal's leading digital payment platform.

- Identify two high - impact areas where unsupervised learning could add significant business value.
- For each area:
  - Define the problem clearly (e.g., customer behavior clustering, fraud pattern detaction).
  - Propose a specific unsupervised learning approach (e.g., clustering, anomaly detaction, dimensionality reduction) and recommend one or more algorithms (e.g., K-Means, DBSCAN, Autoencoders).
  - Briefly explain how the outputs from these models can be integrated into eSewa's products or services to drive business decisions.

Answer:

As a Data Scientist at eSewa, Nepal's leading digital payment platform, I believe that unsupervised learning could be quite useful. The two most high impact areas that could significant business value are:

1. Customer Behavior Clustering:
   eSewa has a wide variety of users from student paying tuition to businesses making large transactions. However, these users behave differently like some are too much active, some are inactive, some are price-sensitive and some are loyals. So , here using clustering techniques like K-Means Clustering, DBSCAN and Gaussian Mixture Models (GMM), we can group users based on their app usage, transaction types, and frequency of payments. Y understanding these groups, eSewa can :
   - Develop customized features for different types of user.
   - Personalize marketing and offere targeted promotions.
   - Improve customer support by prioritizing high-value users
   - Identify and prevent users likely to leave.

2. Fraud Detection Pattern :
   Since digital payments are vulnerable to fraud, detecting unusual avtivity is critical. Usign unsupervised anomaly detection techniques like Autoencoders and Isolation Forests, along with other similar techniques, we can automatically identify questionable transactions that, for instance, involve sending or transferring a large sum. Which will help:
   - To trigger real-time fraud alerts
   - To improve platform security
   - To build user trust by reducing fraudulent activity

The outputs from the models can be used in internal dasboards for monitoring , sent it to marketing teams for smarter marketing promotions, and linked to real-time alert systems to prevent fraud as it happens.

Overall, unsupervised learning enables eSewa to make smarter decisions faster, improve customer satisfaction and increase platform security

2 Short Question: Pick one from each category.

2.1 Overfitting: Answer any 1.

(2.5 pt.) In the context of machine learning:

- Define and differentiate between overfitting and underfitting.
- Explain why both are problematic for model performance.
- Illustrate your explanation with simple examples (e.g., overfitting a training dataset, underfitting a complex pattern).

Answer:

Overfitting and Underfitting can be defined as a situation that happens when a model learns the training data too well and perform very well in training data but poorly perform on unseen or new data, because it has memorized instead of generalized whereas Underfitting happens when a model doesn't capture the patterns in the data and performs poorly on both training sets because it hasn't learned enough from the data.

In machine learning, both overfitting and underfitting are common issues that affect model performance as:

- Overfitting leads to high variance which indicates the model is too sensitive to training data. For example: A decision tree that perfectly classifies training data, including noise, but performs badly on test data.

- Underfitting leads to high bias which indicates the model is too simple and misses key patterns. For example: A linear model trying to predict a complex pattern but failing to make accurate predictions.

  For balancing these kind of models,
  i) We can use Dropout which randomly turns off some neurons during training so the model doesn't rely too much on specific parts. `
  ii) We can use Data Augmentation which expands the training data by rotating, flipping, or altering images which will help the model learn general features.
  iii) We can apply regularization , cross-validation, and choose the right model complexity to balance learning.

2.2 Neural Network Architecture: Answer any 1.

(2.5 pt.) Difference between CNN and RNN:

- Explain the fundamental differences between a Convolutional Neural Network (CNN) and a Recurrent Neural Network (RNN).
  - Provide examples of scenarios where one would be more suitable than the other (e.g., image recognition vs. time-series prediction).
- Briefly discuss common challenges faced during the training of deep learning models (e.g., vanishing gradients, overfitting).
  - Provide possible solutions or techniques to address these challenges (e.g., batch normalization, early stopping).

Answer:

CNN (Convolution Neural Network) and RNN (Recurrent Neural Network) are both deep learning architectures but are designed for different tasks to perform.

S.N.	CNN	RNN
1)	CNNs are best suited for image and spatial data. They use filters to detect visual patterns such as edges, textures, and shapes. Pooling layers help reduce dimensionality, making CNNs efficient and robust to position changes.	RNNs are designed for sequential or time-dependent data. They have memory (hidden states) that allow them to retain past information, making them ideal for understanding context in sequences.
2)	Example: CNNs are used in tasks like image classification (e.g., recognizing dogs vs cats), facial recognition or object detection	Example: RNNs are used in language modelling, sentiment analysis, speech recognition, and time- series forecasting (e.g. predicting stock prices)

Common challenges faced during the training of deep learning models are:

- Vanishing Gradients:
  In deep networks, especially RNNs, gradients can become extremely small during back propagation, making it hard for earlier layers to learn.

  Solutions: Use advanced architectures like LSTM or GRU, which are designed to remember long-term dependencies.

- Overfitting:
  When a model performs well on training data but poorly on unseen data, it has memorized rather than generalized.

Solutions: Dropout, Early Stopping and Batch Normalization