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**Module Code & Module Title**

**6CS012 – Artificial Intelligence and Machine Learning**

**Assignment III – 6CS012 (AI & ML)**

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Ans: Being a Data Scientist at eSewa, which is Nepal's biggest digital wallet, I would mainly concentrate on implementing unsupervised learning in these two major aspects:

# 1. Clustering Customer Behaviors

## Problem Statement:

Users behave differently. Some people go ahead and recharge their phones daily; some others use eSewa to make payments for buying things online; some others just do not use the platform at all in the first place.In order to better service these users, I would like to apply clustering methods in order to first group users by similar behaviors.

## Unsupervised Learning Method:

In this case, I would use Clustering, which does not require labels. With clustering, we can provide a method for finding patterns by clustering similar users together without trying to define them via modeling.

## Algorithms:

## K-Means.

K-means works by clustering to ‘k’ clusters which surround centroids (which are center points). K-means is best used in instances when you are familiar with the types of users we wish to cluster, i.e., 4 segments: heavy users; casual users; occasional users; inactive users.

## DBSCAN (Density-Based Spatial Clustering of Applications with Noise).

DBSCAN doesn't need to know the number of clusters to find. It clusters users based on estimating how tightly packed clusters their respective data points are. It can classify users even if some have patterns of very different behaviors or have some random rates of usage.

## Business Application and Integration:

The data set of group users can be used to either:

* Facilitating targeted promotions (i.e., cash backs for users who pay utility bills).
* Creating different dashboards for different types of users; or
* Increasing user engagement by sending notifications

# 2. Fraud Pattern Detection

## Problem Definition:

Since fraudulent transactions differ, their detection has not been too easy for them to have fixed rules. This means that fraud cannot be labeled beforehand in all cases; hence unsupervised learning must be used.

## Unsupervised Learning Method:

Anyways, Anomaly Detection can be used, which would learn the norm and flag any kind of anomaly.

## Algorithms:

## Autoencoder:

This is a particular type of neural network that attempts to recreate the input. If it does a bad job, that input is considered to be unusual. Such networks are very useful in fraud detection where a transaction doesn't behave like the norm.

## Isolation Forest:

This algorithm isolates strange points very fast. It splits the data randomly: the fewer splits it takes to isolate a data point, the more likely it is an anomaly.

## Dimensionality Reduction (support methods):

Before attempting anomaly detection, one can reduce the large transaction data to a few key features using algorithms like PCA (Principal Component Analysis).

## Business Integration:

* Flagging suspicious transactions and temporarily block them on eSewa.
* Using the score given by models to let humans prioritize investigation on those cases.
* Building trust by detecting frauds proactively.

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Ans: In machine learning, overfitting and underfitting are two major issues that affect how well a model performs.

* **Overfitting** happens when a model learns the training data too perfectly, including minor details and noise. While it performs very well on the training data, it fails to give accurate results on new or unseen data. Suppose we train a model in eSewa to identify loyal users, but the model memorizes every specific transaction rather than general patterns. When a new user behaves slightly differently, the model misclassifies them.
* **Underfitting** on the other hand occurs when a model is too simple to learn the real relationships in the data. It performs poorly even on the training data. Suppose we build a fraud detection system in eSewa that only looks at transaction amounts. Fraud is more complex than just amount, so this simple model misses many actual fraud cases because it cannot understand deeper patterns.

Both overfitting and underfitting lead to poor model performance in real-world applications as we discussed in esewa above.

* **Overfitting** creates a model that performs very well on training data but fails on new or unseen data because it has memorized details rather than learned general patterns.
* **Underfitting** creates a model that cannot even learn from the training data properly because it is too simple or not trained well enough.

As a result, neither model can make reliable predictions — overfitting fails to generalize, and underfitting fails to learn. A good model must strike a balance between the two to make useful predictions on new data. I hope I’ve properly included the illustrations and the term differences of overfitting and underfitting in my explanation above.

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Ans: **Convolutional Neural Networks (CNNs)** and Rec**urrent Neural Networks (RNNs)** are two important types of deep learning models used for different purposes based on the nature of the data.

**CNN**s are best suited for handling image data. They work by detecting local patterns in images, such as edges, textures, and colors, through the use of filters (also called kernels). These filters scan over the input image and help the model learn to recognize objects or features. **CNN**s are commonly used in image classification, face recognition, and document scanning.

In the case of eSewa, **CNN**s may be utilized during the user identity verification for KYC procedures; in other words, **CNN**-based systems could scan and check user-supplied documents like citizenship cards or profile photos to ascertain the image conforms to the required format and quality.

On the contrary, **RNN**s are made for dealing with sequential data where the order of information is important. **RNN**s can remember inputs from the past in order to inform time-series prediction, text analysis, and behavior pattern analysis.

At eSewa, **RNN**s can be used to analyze and predict user transaction behavior. For instance, based on past payment history, the system could attempt to predict what service a user is likely to use next: paying electricity bills at the start of the month, for example.

The challenges arise in training because of the following:

* **Disappearing Gradients:** The early layers in deep networks stop learning because the derivatives of the equations become so small. **LSTM** (Long Short-Term Memory) and **GRU** (Gated Recurrent Unit) are improved forms of **RNN**s which can take care of this.
* **Overfitting:** For that matter deep models can also learn the training data instead of learning from the data. Early stopping analyzes the model performance with a validation dataset while training the model. Once the model’s performance improves, the training is stopped early, before fitting over the training dataset (overfitting). For example with the esewa, if the model is being trained to make decisions for users (e.g., recharge, utility payment, fund transfers), we can stop the training process when the model has learned the general patterns of the usage and not specific user behavior that does not generalize to others. Dropout randomly “drops” (removes) some of neuron during the model training. This leads to the model not depending as heavily on certain paths or features, which helps produce better generalization. Assume we are building a deep model to detect fraud, dropout means the model cannot depend too much on a few common types or patterns of transactions, but instead learns a wider pattern of risky behaviour.

In all of the answers above, I’ve mentioned the examples of esewa as it’ll be more easier to understand as we are using it in our daily life and is a real world example.