

## WEEK 6:

### EXERCISE 1:

[https://keras.io/examples/structured\\_data/wide\\_deep\\_cross\\_networks/](https://keras.io/examples/structured_data/wide_deep_cross_networks/)

Use the Covertypes dataset from the UCI Machine Learning Repository. The task is to predict forest cover type from cartographic variables.

Create two representations of the input features: sparse and dense:

1. In the **sparse** representation, the categorical features are encoded with one-hot encoding using the **CategoryEncoding** layer. This representation can be useful for the model to *memorize* particular feature values to make certain predictions.
2. In the **dense** representation, the categorical features are encoded with low-dimensional embeddings using the **Embedding** layer. This representation helps the model to *generalize* well to unseen feature combinations.

Split the data into training (85%) and validation (15%) sets.

Model 1 :

Create a multi-layer feed-forward network, where the categorical features are one-hot encoded.

learning\_rate = 0.001

dropout\_rate = 0.1

batch\_size = 265

num\_epochs = 50

hidden\_units = [32, 32]

Model 2:

Create a Wide & Deep model where the wide part of the model is a linear model, while the deep part of the model is a multi-layer feed-forward network. Use the sparse representation of the input features in the wide part of the model and the dense representation of the input features for the deep part of the model.

Model 3:

Create a Deep & Cross model. The deep part of this model is the same as the deep part created in the previous experiment. The key idea of the cross part is to apply explicit feature crossing in an efficient way, where the degree of cross features grows with layer depth.

Compare the loss and accuracy of the three models.

## **EXERCISE 2:**

Use the google stock price dataset available in Kaggle.

<https://www.kaggle.com/datasets/medharawat/google-stock-price>

Using a training set of 50 time steps, build a Simple RNN model vs a LSTM model, both with 4 layers. Compare their accuracy using an mean square error.

Plot the actual vs predicted values using the test data for the year 2017.