ANN PRACTICAL

FOR CLASSIFICATION

Tensorflow → library for Deep learning by Google

keras → API on top of Tensorflow

Important; we can use either Tensorflow / Pytorch.

STEP I; Setting up Environment

Bash → conda create -p venv python == 3.13
conda activate venv
pip install -r requirements.txt
install ipykernell

PREPROCESSING

1. Remove unnecessary columns
2. use Label Encoder → Binary Categories
3. use OHE for → Multi Categories

Imp- If we use label Encoder on Multi class, it will assign a=1, b=2, c=0; which will mean for DL b > a & c, so OHE is preffered.

4. Save Encoders in pickle file.
5. Split the Data into train_test
6. Scale the Data (Standard Scaler)
   → Save this also as pickle

VVImp In Tensorflow, we call ANN as sequential Model

Useful parameters; steps

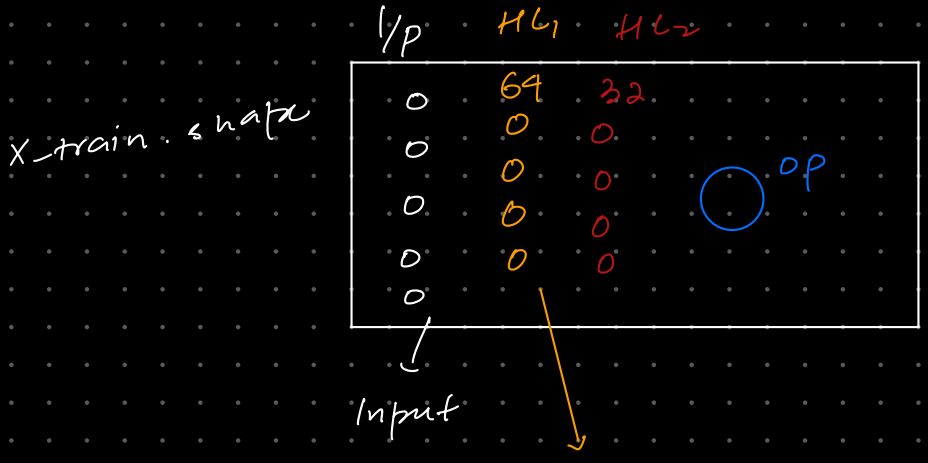
1. sequential
2. Dense ——→ 64 means 64 Neuron
3. Activation fn → Sigmoid, softmax → O/p
   Relu, Tanh → Hidden
4. Optimizers →

5. Loss → GD, SGD

6. Evaluation Metrics

7. Training → Logs → folders
↓
Tensorboard

Libraries → tensorflow.keras.models import Sequential ← ANN
tensorflow.keras.layers import Dense → Nodes
tensorflow.keras.callbacks import EarlyStopping
TensorBoard
↳ logs



Nodes I can setup with Dense

Build ANN Model

```
# Build ANN Model
model = Sequential()
model.add(Dense(64, activation='relu', input_shape=(X_train_scaled.shape[1],))) ## 1st Input layer connected to 64 neurons - HL1
model.add(Dense(32, activation='relu')) # no shaoe needed here as it is a hidden layer - Hidden layer with 32 neurons - HL2
model.add(Dense(1, activation='sigmoid')) # Output layer with 1 neuron for binary classification
```

→ Setup Optimizer, Loss function, metrics

```
# compile the model with optimizer, loss function and metrics
from tensorflow.keras.optimizers import Adam
model.compile(optimizer=Adam(learning_rate=0.01), loss='binary_crossentropy', metrics=['accuracy'])
```

→ setup Tensorboard & Earlystopping

- ✅ **TensorBoard**: For **real-time monitoring** of training (loss, accuracy, etc.)
- ✅ **EarlyStopping**: To **automatically stop training** when performance stops improving (prevents overfitting and saves time) → stops when model reaches convergence

→ mention epochs

```
# Set up the tensorboard callback
log_dir = "logs/fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard_callback = TensorBoard(log_dir=log_dir, histogram_freq=1)

# Set up early stopping
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)
```

Ruko zara sabr karo till 5 epochs

→ Train the Model file

```
history = model.fit(X_train_scaled, y_train,
                    validation_data=(X_test_scaled, y_test),
                    epochs=100,
                    callbacks=[tensorboard_callback, early_stopping])
```

✓ 16.5s

```
Epoch 1/100
250/250 [==============================] - 2s 7ms/step - loss: 0.5535 - accuracy: 0.7806 - val_loss: 0.5473 - val_accuracy: 0.8030
Epoch 2/100
250/250 [==============================] - 1s 6ms/step - loss: 1.2733 - accuracy: 0.7465 - val_loss: 1.9880 - val_accuracy: 0.6815
Epoch 3/100
250/250 [==============================] - 1s 6ms/step - loss: 2.8616 - accuracy: 0.7368 - val_loss: 3.8312 - val_accuracy: 0.7565
Epoch 4/100
250/250 [==============================] - 1s 6ms/step - loss: 3.3271 - accuracy: 0.7303 - val_loss: 17.8678 - val_accuracy: 0.6560
Epoch 5/100
250/250 [==============================] - 1s 6ms/step - loss: 6.7133 - accuracy: 0.7289 - val_loss: 3.3616 - val_accuracy: 0.8045
Epoch 6/100
250/250 [==============================] - 1s 6ms/step - loss: 8.6875 - accuracy: 0.7306 - val_loss: 9.0012 - val_accuracy: 0.7670
Epoch 7/100
250/250 [==============================] - 1s 6ms/step - loss: 13.4958 - accuracy: 0.7394 - val_loss: 7.7190 - val_accuracy: 0.7380
Epoch 8/100
250/250 [==============================] - 1s 6ms/step - loss: 24.6641 - accuracy: 0.7144 - val_loss: 17.9428 - val_accuracy: 0.7920
Epoch 9/100
250/250 [==============================] - 1s 6ms/step - loss: 18.2670 - accuracy: 0.7521 - val_loss: 6.6817 - val_accuracy: 0.8015
Epoch 10/100
250/250 [==============================] - 1s 6ms/step - loss: 19.5793 - accuracy: 0.7377 - val_loss: 43.4841 - val_accuracy: 0.6100
Epoch 11/100
250/250 [==============================] - 1s 6ms/step - loss: 25.3717 - accuracy: 0.7340 - val_loss: 17.2696 - val_accuracy: 0.7635
```

→ Save model as .h5

```
# Save model file   as .h5 is compatible with Keras
model.save('customer_churn_model.h5')
```

→ Monitor logs in Tensorboard.

```
# Load TensorBoard Extension
%load_ext tensorboard

# Launch TensorBoard
%tensorboard --logdir logs/fit
```

Finally Get Predictions

→ Import pkl files & .h5 file

→ Get prediction → Ready for production.

→ Create app.py which runs all the trained models

For Regression

```python
### Load the trained model, scaler pickle,onehot
model=load_model('customer_churn_model.h5')

## load the encoder and scaler
with open('ohe_geo.pkl','rb') as file:
    label_encoder_geo=pickle.load(file)

with open('label_encoder_gender.pkl', 'rb') as file:
    label_encoder_gender = pickle.load(file)

with open('scaler.pkl', 'rb') as file:
    scaler = pickle.load(file)
```

In [65]:
```python
## PRedict churn
prediction=model.predict(input_scaled)
prediction
```

```
WARNING:tensorflow:5 out of the last 5 calls to <function Model.make_predict_function.<locals>.predict_function at 0x33227f560> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for  more details.
WARNING:tensorflow:5 out of the last 5 calls to <function Model.make_predict_function.<locals>.predict_function at 0x33227f560> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for  more details.
1/1 [==============================] - 0s 37ms/step
```

Out[65]:
```
array([[0.01600381]], dtype=float32)
```

In [66]:
```python
prediction_proba = prediction[0][0]
```

In [67]:
```python
prediction_proba
```

Out[67]:
```
0.016003806
```

In [68]:
```python
if prediction_proba > 0.5:
    print('The customer is likely to churn.')
else:
    print('The customer is not likely to churn.')
```

```
The customer is not likely to churn.
```