Group No

Group Member Names:

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1. Problem Statement

Students are expected to identify a classification / regression problem of your choice. You have to detail the problem under this heading which basically addresses the following questions.

1. What is the problem that you are trying to solve?
2. What kind of prediction (classification / regression) task are you performing?

ENSURE THAT YOU ARE USING NUMERICAL / CATEGORICAL DATA only.

DO NOT use images or textual data.

Score: 1 Mark in total (0.5 mark each)

```
!head -n 10 ./StudentsPerformance.csv
```

```
"gender","race/ethnicity","parental level of education","lunch","test preparation course","ma
"female","group B","bachelor's degree","standard","none","72","72","74"
"female","group C","some college","standard","completed","69","90","88"
"female","group B","master's degree","standard","none","90","95","93"
"male","group A","associate's degree","free/reduced","none","47","57","44"
"male","group C","some college","standard","none","76","78","75"
"female","group B","associate's degree","standard","none","71","83","78"
"female","group B","some college","standard","completed","88","95","92"
"male","group B","some college","free/reduced","none","40","43","39"
"male","group D","high school","free/reduced","completed","64","64","67"
```

Student Performance Prediction

In this problem, we are trying to predict the scores of students in three tests given information regarding their demographic information, academic attributes and their preparedness for the tests. The intention here is to figure out the performance beforehand and use that as a pre-emptive measure to bolster the student's aptitude in places where he needs help. Since the scores are continuous in nature, we are going to model this as a regression problem. As we have three test scores to predict, we will have 3 outputs and we have 5 attributes/features.

2. Data Acquisition

For the problem identified by you, students have to find the data source themselves from any data source.

2.1 Download the data directly

Since we're downloading data from kaggle, we will use the kaggle API to fetch the data. For that we will need to install the kaggle library and set our credentials in order to use it. Follow these steps in order to authenticate and create a new API Token to use the kaggle python library for downloading the dataset.

```
!pip install -q kaggle
```

```
# Take a look at your credentials file
# !cat ~/.kaggle/kaggle.json
```

```
# Protect your authentication file against accidental overwriting by only allowing read ac
# !chmod +400 ~/.kaggle/kaggle.json
```

```
# Download the dataset from kaggle
# !kaggle datasets download -d spscientist/students-performance-in-exams
```

```
# Unip the downloaded dataset and delete the zip
# !unzip -q students-performance-in-exams.zip
# !rm students-performance-in-exams.zip
```

2.2 Code for converting the above downloaded data into a form suitable for DL

The data is in the form of a csv file and can be conveniently used for building our deep learning regression model

2.3 Write your observations from the above.

1. Size of the dataset
2. What type of data attributes are there?

Score: 2 Mark

```
# Get the size of the dataset
!ls -alth StudentsPerformance.csv
```

```
-rw-rw-r-- 1 vinayak vinayak 71K Oct 11  2019 StudentsPerformance.csv
```

```
# Number of records in the dataset
!cat StudentsPerformance.csv| wc -l
```

```
1001
```

```
# Peek at the header and first row of the dataset
!head -n 2 StudentsPerformance.csv
```

```
"gender","race/ethnicity","parental level of education","lunch","test preparation course","ma
"female","group B","bachelor's degree","standard","none","72","72","74"
```

```
<b>Size of dataset</b>
```

Disk Space occupied: 71KB

Total Number of records: 1000

```
<b>Attribute information is as follows</b>
```

Attribute Name	Description	Attribute Type
Gender	Gender of the subject	Nominal
Race/Ethnicity	Race to which the subject belongs(masked)	Nominal
Parental Level of Education	Extent of education	Ordinal
Lunch	Kind of lunch opted for	Nominal
Test Prep Course	Whether or not preparation for the test is done	Ordinal
Math Score	Marks obtained in math	Numeric
Reading Score	Marks obtained in reading	Numeric
Writing Score	Marks obtained in writing	Numeric

3. Data Preparation

Perform the data prepracessing that is required for the data that you have downloaded.

3.1 Apply techiniques

- to remove duplicate data
- to impute or remove missing data
- to remove data inconsistencies

IF ANY

```
!pip install -q seaborn pandas numpy matplotlib
```

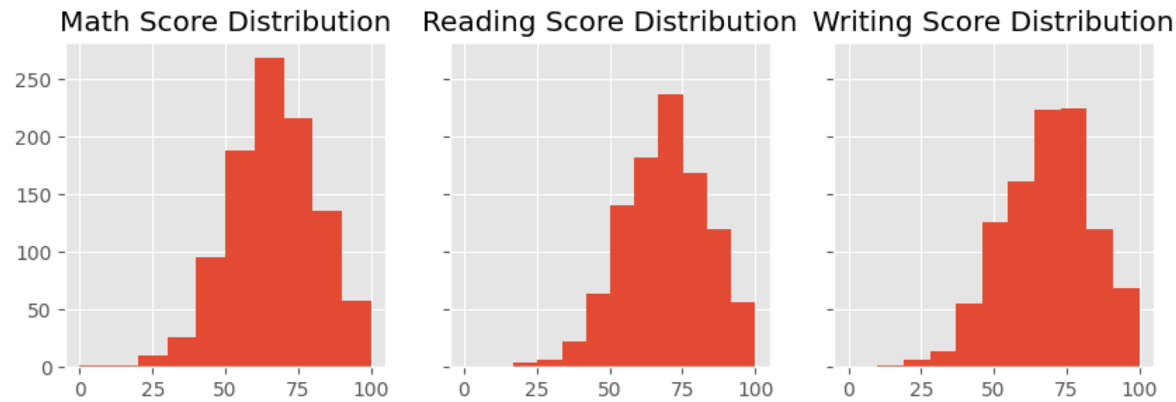
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
plt.style.use("ggplot")
import seaborn as sns
%matplotlib inline

# Read the data into a dataframe
df = pd.read_csv("StudentsPerformance.csv")
df.head(2)
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	rea
0	female	group B	bachelor's degree	standard	none	72	72
1	female	group C	some college	standard	completed	69	90

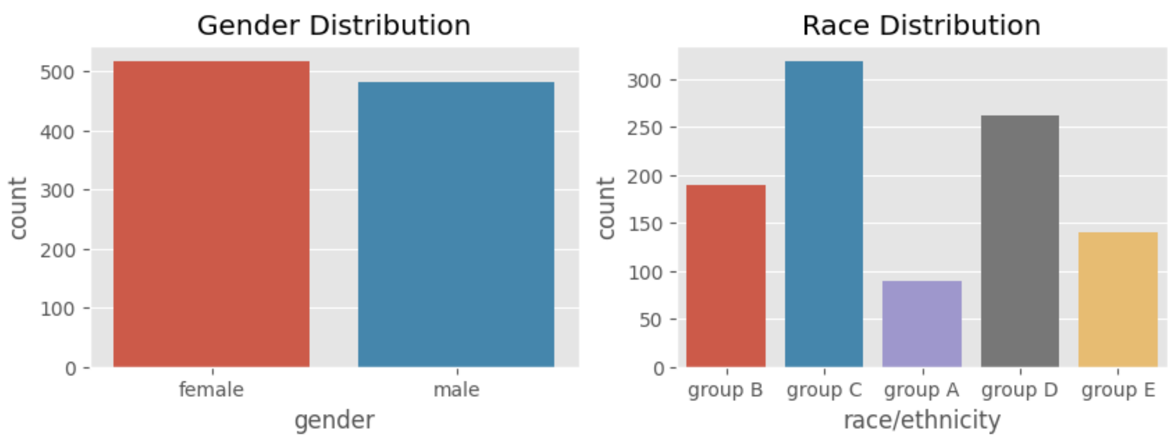
```
# Peek at all the column names
print(f"Dataset columns\n{df.columns.tolist()}")
```

```
Dataset columns
['gender', 'race/ethnicity', 'parental level of education', 'lunch', 'test preparation cours
```

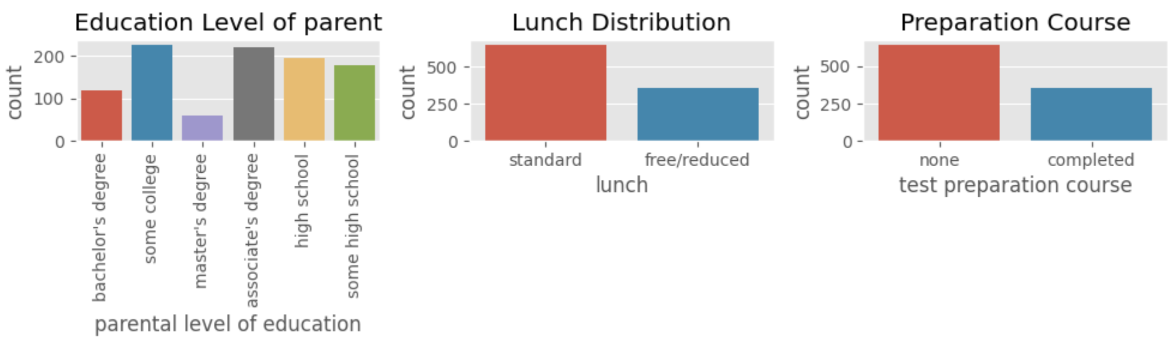
```
fig, ax = plt.subplots(1, 3, figsize = (10,3), sharex = True, sharey = True)
ax[0].hist(df["math score"]); ax[0].set_title(f"Math Score Distribution")
ax[1].hist(df["reading score"]); ax[1].set_title(f"Reading Score Distribution")
ax[2].hist(df["writing score"]); ax[2].set_title(f"Writing Score Distribution");
```




```
fig, ax = plt.subplots(1, 2, figsize = (10,3))
sns.countplot(x = df["gender"], ax = ax[0]); ax[0].set_title("Gender Distribution")
sns.countplot(x = df["race/ethnicity"], ax = ax[1]); ax[1].set_title("Race Distribution");
```




```
fig, ax = plt.subplots(1, 3, figsize = (10,3))

sns.countplot(x = df["parental level of education"], ax = ax[0]); ax[0].set_title("Educati
sns.countplot(x = df["lunch"], ax = ax[1]); ax[1].set_title("Lunch Distribution")
sns.countplot(x = df["test preparation course"], ax = ax[2]); ax[2].set_title("Preparation
fig.tight_layout();
```



- `Gender`, `Lunch Distribution` and `Preparation Course` are binary variables with a very slight imbalance in their levels (in the latter 2)
- `Parent's education` is a six level ordinal variable with a relatively small number of parents having bachelor's or master's degree
- `Race` is also an imbalanced distribution with five levels (Masked).

It seems like the scores are near normal distributed with a slight left skew.

```
df.isnull().sum()
```

```
gender                         0
race/ethnicity                 0
parental level of education    0
lunch                          0
test preparation course        0
math score                     0
reading score                  0
writing score                  0
dtype: int64
```

None of the columns in the dataset are missing. So, we don't need to impute anything or substitute for any record across any feature in the dataset.

```
df.duplicated().sum()
```

```
0
```

None of the records seem to be duplicated. All rows are unique instances. Hence keep the records as is.

3.2 Encode categorical data

```
!pip install -q scikit-learn
```

- The binary attributes are all nominal in nature and can be simply encoded in a `1/0` fashion.
- `Race` is a nominal attribute which could be one-hot-encoded
- `Parent's education` is an ordinal attribute and can be label encoded.

```
for col, level in [("gender", "male"), ("lunch", "standard"), ("test preparation course",
    df[col] = df[col].apply(lambda x: 0. if x == level else 1.)
df.head(2)
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	readir
0	1.0	group B	bachelor's degree	0.0	0.0	72	72
1	1.0	group C	some college	0.0	1.0	69	90

```
df["parental level of education"].unique()
```

```
array(["bachelor's degree", 'some college', "master's degree",
       "associate's degree", 'high school', 'some high school'],
      dtype=object)
```

```
education_order = {"high school": 0, "some high school": 0, "some college": 1,
                   "associate's degree": 2, "bachelor's degree": 3, "master's degree": 4}
df["parental level of education"] = df["parental level of education"].apply(lambda x: educ
df.head(2)
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	readin
0	1.0	group B	3	0.0	0.0	72	72
1	1.0	group C	1	0.0	1.0	69	90

Now let's one hot encode the categorical column for race. We shall drop the first race to avoid redundancy

```
from sklearn.preprocessing import OneHotEncoder
ohe = OneHotEncoder(drop = "first")
df_encoded = pd.DataFrame(ohe.fit_transform(df[["race/ethnicity"]]).toarray(), columns = o
```

```
df_processed = pd.concat([df, df_encoded], axis = 1)
```

```
df_processed
```

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	reac
0	1.0	group B	3	0.0	0.0	72	72
1	1.0	group C	1	0.0	1.0	69	90
2	1.0	group B	4	0.0	0.0	90	95
3	0.0	group A	2	1.0	0.0	47	57
4	0.0	group C	1	0.0	0.0	76	78
...	...	...	...	...	...	...	...
995	1.0	group E	4	0.0	1.0	88	99
996	0.0	group C	0	1.0	0.0	62	55
997	1.0	group C	0	1.0	1.0	59	71

	gender	race/ethnicity	parental level of education	lunch	test preparation course	math score	rea
998	1.0	group D	1	0.0	1.0	68	78
999	1.0	group D	1	1.0	0.0	77	86

```
df_processed.drop(["race/ethnicity"], inplace = True, axis = 1)
```

3.3 Normalize the data

Out targets are numerical. We shall normalize them to lie in the range of 0-1.

Since we've seen that the range of marks is from 0 to 100, we shall simply divide by 100 to bring the data in 0-1 range.

```
df.columns
```

```
Index(['gender', 'race/ethnicity', 'parental level of education', 'lunch',
       'test preparation course', 'math score', 'reading score',
       'writing score'],
      dtype='object')
```

```
for col in ["math score", "reading score", "writing score"]:
    df_processed[col] = df_processed[col] / 100
df_processed.head(2)
```

	gender	parental level of education	lunch	test preparation course	math score	reading score	writing
0	1.0	3	0.0	0.0	0.72	0.72	0.74
1	1.0	1	0.0	1.0	0.69	0.90	0.88

We could also normalize the parental level of education to lie between 0-1 so it would be easier for the network when learning

```
df_processed["parental level of education"] = df_processed["parental level of education"]
```

3.4 Feature Engineering

if any

```
# In this problem, there doesn't seem to be much scope for feature engineering
df_processed.head(2)
```

	gender	parental level of education	lunch	test preparation course	math score	reading score	writing
0	1.0	0.75	0.0	0.0	0.72	0.72	0.74
1	1.0	0.25	0.0	1.0	0.69	0.90	0.88

3.5 Identify the target variables.

- Separate the data front the target such that the dataset is in the form of (X,y) or (Features, Label)
- Discretize / Encode the target variable or perform one-hot encoding on the target or any other as and if required.

```
target_variables = ["math score", "reading score", "writing score"]
attribute_variables = [x for x in df_processed.columns.tolist() if x not in target_variabl

X = df_processed[attribute_variables].values
y = df_processed[target_variables].values
```

```
# Have a look at the X and y variables
X, y
```

```
(array([[1.  , 0.75, 0.  , ..., 0.  , 0.  , 0.  ],
        [1.  , 0.25, 0.  , ..., 1.  , 0.  , 0.  ],
        [1.  , 1.  , 0.  , ..., 0.  , 0.  , 0.  ],
        ...,
        [1.  , 0.  , 1.  , ..., 1.  , 0.  , 0.  ],
        [1.  , 0.25, 0.  , ..., 0.  , 1.  , 0.  ],
        [1.  , 0.25, 1.  , ..., 0.  , 1.  , 0.  ]]),
 array([[0.72, 0.72, 0.74],
        [0.69, 0.9 , 0.88],
        [0.9 , 0.95, 0.93],
        ...,
        [0.59, 0.71, 0.65],
        [0.68, 0.78, 0.77],
        [0.77, 0.86, 0.86]]))
```

```
# Inspect the shape of both these arrays
X.shape, y.shape
```

```
((1000, 8), (1000, 3))
```

3.6 Split the data into training set and testing set

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 42, test_size = 0
```

```
X_train.shape, y_train.shape
```

```
((800, 8), (800, 3))
```

```
X_test.shape, y_test.shape
```

```
((200, 8), (200, 3))
```

```
# Make sure that the train and test set sizes are 80% and 20% of the entire data respectiv
assert X_train.shape[0] == len(X) * 0.8
assert X_test.shape[0] == len(X) * 0.2
```

3.7 Report

Mention the method adopted and justify why the method was used * to remove duplicate data, if present * to impute or remove missing data, if present * to remove data inconsistencies, if present * to encode categorical data * the normalization technique used

If the any of the above are not present, then also add in the report below.

Report the size of the training dataset and testing dataset

Score: 3 Marks

```
<b>Data Deduplication</b><br>
<span>None, the data had no duplicates</span><br>
<b>Missing Data Imputation</b><br>
<span>None of the instances had a single attibute missing.</span><br>
<b>Data Inconsistency</b><br>
<span>Provided data seemed consistent.</span><br>
<b>Categorical Data Encoding</b><br>
<ul>
    <li>The binary attributes are all nominal in nature and can be simply encoded in a `1/0`
    <li>`Race` is a nominal attribute which is one-hot-encoded</li>
    <li>`Parent's education` is an ordinal attribute and is label encoded.</li>
</ul>
<b>Normalization Technique Used</b><br>
<span>Division by a hundred. Since we knew the range of data to begin with.</span><br>
<b>Dataset Sizes</b><br>
<span>Train: 800  | Test: 200</span>
```

4. Deep Neural Network Architecture

4.1 Design the architecture that you will be using to solve the prediction problem identified.

- Add dense layers, specifying the number of units in each layer and the activation function used in the layer.

```
#!pip install tensorflow
```

```
import tensorflow as tf
from tensorflow.keras import layers
from tensorflow.keras.regularizers import l1
```

```
2022-12-03 21:46:21.969016: I tensorflow/core/platform/cpu_feature_guard.cc:193] This Tensor
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
2022-12-03 21:46:22.265398: W tensorflow/compiler/xla/stream_executor/platform/default/dso_l
2022-12-03 21:46:22.265419: I tensorflow/compiler/xla/stream_executor/cuda/cudart_stub.cc:29
2022-12-03 21:46:22.875893: W tensorflow/compiler/xla/stream_executor/platform/default/dso_l
2022-12-03 21:46:22.875979: W tensorflow/compiler/xla/stream_executor/platform/default/dso_l
2022-12-03 21:46:22.875988: W tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT W
```

```
X_train.shape
```

```
(800, 8)
```

```
model = tf.keras.Sequential([ layers.Input(X_train.shape[-1],),
                              layers.Dense(64, activation='relu', kernel_regularizer = l1(
                              layers.BatchNormalization(), layers.Dropout(.1),
                              layers.Dense(32, activation = 'relu'),
                              layers.Dense(3, activation = 'linear')])
```

```
2022-12-03 21:46:23.706042: I tensorflow/compiler/xla/stream_executor/cuda/cuda_gpu_executor
2022-12-03 21:46:23.707153: W tensorflow/compiler/xla/stream_executor/platform/default/dso_lo
2022-12-03 21:46:23.707373: W tensorflow/compiler/xla/stream_executor/platform/default/dso_lo
2022-12-03 21:46:23.707582: W tensorflow/compiler/xla/stream_executor/platform/default/dso_lo
2022-12-03 21:46:23.712396: W tensorflow/compiler/xla/stream_executor/platform/default/dso_lo
2022-12-03 21:46:23.712630: W tensorflow/compiler/xla/stream_executor/platform/default/dso_lo
2022-12-03 21:46:23.712847: W tensorflow/compiler/xla/stream_executor/platform/default/dso_lo
2022-12-03 21:46:23.712888: W tensorflow/core/common_runtime/gpu/gpu_device.cc:1934] Cannot d
Skipping registering GPU devices...
2022-12-03 21:46:23.713632: I tensorflow/core/platform/cpu_feature_guard.cc:193] This Tensor
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 64)                576

 batch_normalization (BatchN  (None, 64)               256
 ormalization)

 dropout (Dropout)           (None, 64)                0

 dense_1 (Dense)             (None, 32)                2080
```

```
 dense_2 (Dense)             (None, 3)                 99

=================================================================
Total params: 3,011
Trainable params: 2,883
Non-trainable params: 128
_________________________________________________________________
```

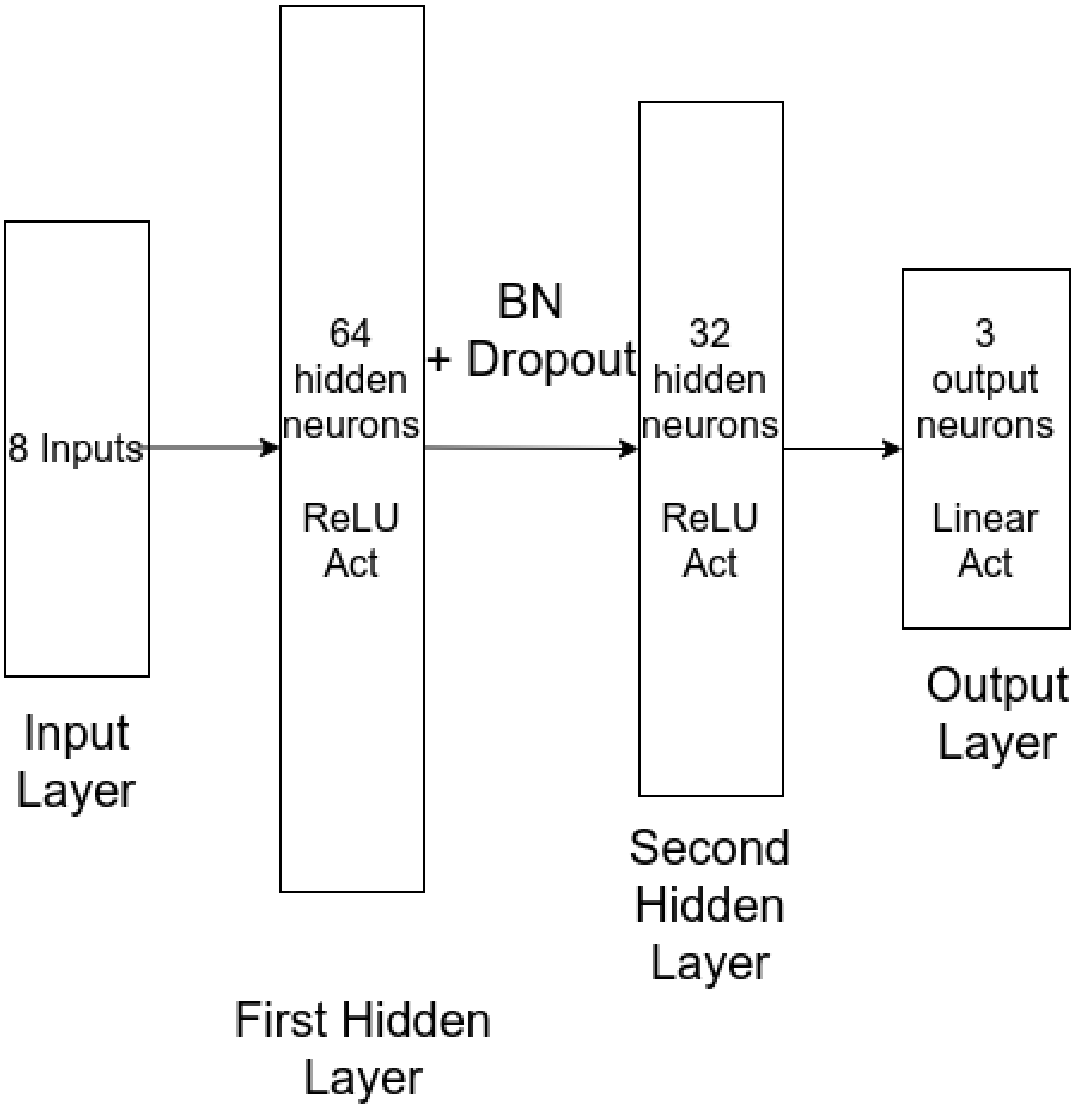
4.2 Report

Report the following and provide justification for the same.

- Number of layers
- Number of units in each layer
- Activation function used in each hidden layer
- Activation function used in the output layer
- Total number of trainable parameters

Score: 4 Marks

We have defined a two layer model as follows



Number of layers
Our architecture is as defined above: 1 input, 2 hidden and 1 output layer
Number of units in each layer

Input layer - 8 neurons
First Hidden Layer - 64 neurons
Batch Normalization Layer - 64 neurons
Dropout with p = 10%
Second Hidden Layer - 64 neurons
Output Layer - 3 neurons

Activation function in hidden layers
<span>In both hidden layers, ReLU is used as activation. It is easy to implement, differentia
Activation function in output layer
<span>Linear Activation function is used in the output layer. The output although constrained
Total number of trainable parameters

5. Training the model

5.1 Configure the training

Configure the model for training, by using appropriate optimizers and regularizations

```
from sklearn.metrics import mean_squared_error
from functools import partial

def RMSE(y_true, y_pred):
    return tf.py_function(partial(mean_squared_error, squared=False), (y_true, y_pred), tf
```

```
from tensorflow.keras.optimizers import SGD, Adam

def train_model(optim, lr, bs, eps):

    # Define the model architecture
    model = tf.keras.Sequential([ layers.Input(X_train.shape[-1],),
                                  layers.Dense(64, activation='relu', kernel_regularizer = l1(
                                  layers.BatchNormalization(), layers.Dropout(.1),
                                  layers.Dense(32, activation = 'relu'),
                                  layers.Dense(3, activation = 'linear')])

    # Define optimizer, learning rate and metric
    if optim == "SGD":
        model.compile(optimizer=SGD(learning_rate = lr),
                      loss=tf.keras.losses.MeanSquaredError(),
                      metrics=[RMSE])
    else:
        model.compile(optimizer=Adam(learning_rate = lr),
                      loss=tf.keras.losses.MeanSquaredError(),
                      metrics=[RMSE])
```

```
    # Train the model
    history = model.fit(x = X_train, y = y_train, validation_data = (X_test, y_test), epoc
    return model, history
```

5.2 Train the model

```
from itertools import product
optims = ["SGD", "Adam"]; learning_rates = [5e-2, 1e-3]; epochs = [20,40]; batch_sizes = [
hyperparam_combinations = list(product(optims, learning_rates, epochs, batch_sizes))
print(f"Total hyperparam combinations:\n{hyperparam_combinations}")
```

```
Total hyperparam combinations:
[('SGD', 0.05, 20, 8), ('SGD', 0.05, 20, 32), ('SGD', 0.05, 20, 64), ('SGD', 0.05, 40, 8), (
```

```
models = []
for optim, lr, eps, bs in hyperparam_combinations:
    print(f"\n============================ Beginning trial with hyperparams: OPTIMIZER: {o
    model = train_model(optim, lr, bs, eps)
    models.append(model)
```

```
============================ Beginning trial with hyperparams: OPTIMIZER: SGD, LEARNING RATE

Epoch 1/20
```

```
final_metrics = []
best_hyperparam = None; lowest_loss = 10000; idx = -1
for mdl, history in models:
    final_metrics.append(history.history["val_RMSE"][-1])

for i, (hparam, metric) in enumerate(zip(hyperparam_combinations, final_metrics)):
    print(f"Optimizer: {hparam[0]:>5}| LR: {hparam[1]:.4f}| Epochs: {hparam[2]}| Batch Siz

    if lowest_loss > metric:
        lowest_loss = metric
        best_hyperparam = hparam
        idx = i
```

```python
print(f"\nBest Combination: {best_hyperparam}| Corresponding Validation RMSE: {lowest_loss
```

Justify your choice of optimizers and regulizations used and the hyperparameters tuned

Score: 4 Marks

```
<b>Optimizer Used</b><br>
<span>SGD/Adam both were tried, they give comparitively similar performance.</span><br>
<b>Regularization Used</b>
<span>L1 Regularization with a strength of 1e-4. L1 could completely shut off an unnecessary
<b>Hyperparams Tuned</b>
<ul>
    <li><b>Optimizer</b>: Adam/ SGD</li>
    <li><b>Number of Epochs</b>: 20, 40</li>
    <li><b>Learning Rate</b>: 0.05, 0.001</li>
    <li><b>Batch Size</b>: 8, 32, 64</li>
</ul>
```

6. Test the model

Score: 2 Marks

```python
# Get the best model
mdl, history = models[idx]
```

```python
# Get the predictions for the test
predictions = mdl.predict(X_test)
```

```python
# Compute the rmses for all the three tests individually
squared_diff = (y_test - predictions) ** 2
sum_squared_diff = squared_diff.sum(axis = 0)
mean_squared_diff = sum_squared_diff / y_test.shape[0]
individual_rmses = mean_squared_diff ** 0.5

for subject, metric in zip(target_variables, individual_rmses):
    print(f"In {subject} our model is off by around {100 * metric:.2f} marks on average")
```

7. Conclusion

Plot the training and validation loss Report the testing accuracy and loss.

Report values for preformance study metrics like accuracy, precision, recall, F1 Score.

A proper comparision based on different metrics should be done and not just accuracy alone, only then the comparision becomes authentic. You may use Confusion matrix, classification report, MAE etc per the requirement of your application/problem.

Score 2 Marks

```
# Plotting the Loss and Metric curves for best model trained
fig, ax = plt.subplots(2, 2, figsize = (10,6), sharex = True, sharey = False)
ax = ax.flat

train_loss = history.history["loss"]; train_metric = history.history["RMSE"]
valid_loss = history.history["val_loss"]; valid_metric = history.history["val_RMSE"]

x = range(len(train_loss))
ax[0].plot(x, train_loss); ax[0].set_ylabel("Training Loss"); ax[0].set_title("Training Lo
ax[1].plot(x, valid_loss); ax[1].set_ylabel("Validation Loss"); ax[1].set_title("Validatio

ax[2].plot(x, train_metric); ax[2].set_xlabel("Epochs"); ax[2].set_ylabel("Training RMSE")
ax[3].plot(x, valid_metric); ax[3].set_xlabel("Epochs"); ax[3].set_ylabel("Validation RMSE
```

```
# Compute the regression metrics for the validation set
percent_error = np.abs(predictions - y_test)
mae = percent_error.mean(axis = 0)
mse = ((predictions - y_test) ** 2).mean(axis = 0)
rmse = mse ** 0.5
```

```
# Display the metrics in a dataframe
df = pd.DataFrame(np.vstack([mse, rmse, mae]))
df.index = ["MSE", "RMSE", "MAE"]
df.columns = target_variables
df
```

Since this problem is a regression problem, we are not computing metrics like accuracy, recall etc. We are only computing the Regression specific metrics and it seems like our models are off by 10-15 marks on an average in predicting the scores across the three different tests…

8. Solution

What is the solution that is proposed to solve the business problem discussed in Section 1. Also share your learnings while working through solving the problem in terms of challenges, observations, decisions made etc.

Score 2 Marks

```
<span><b>Business Solution</b>: In this project we created a model to predict the performanc
<ul>
    <li>We could form groups or pairs of students who are strong in one subject and weak in a
    <li>For those students whose scores are predicted to be too poor in a particular subject
    <li>We could understand the strength of individual candidates and provide special attenti
</ul>
<b>Challenges Faced</b>
<ul>
    <li>Exhaustive hyperparameter tuning is very difficult for neural networks. We just used
    <li>The same goes for decision of model architecture. We also tried using a single hidden
    <li> We couldn't think of any feature engineering methods by combining several features o
</ul>
<b>Future Scope</b>
<ul>
    <li>Collect/Simulate more data examples as the number of records are pretty low.</li>
    <li>Instead of plain one-hot/label encoding techniques, we could use Embeddings to repres
    <li>Doing more extensive hyperparameter tuning and training with some tricks like learnin
</ul>
```