Machine Learning Using AWS SageMaker

Classification Models using Sleep Data from Kaggle: https://www.kaggle.com/datasets/uom190346a/sleep-health-and-lifestyle-dataset/data.

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Dependencies

In [2]:
```
import pandas as pd
import numpy as np
import os
import io
from io import StringIO
import tarfile
import matplotlib.pyplot as plt
import seaborn as sns
import joblib
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler, FunctionTra
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
```

In [ ]:
```
#pip install boto3
```

In [ ]:
```
#pip install -U sagemaker
```

In [ ]:
```
#pip install --upgrade s3fs
```

In [50]:
```
import sagemaker
import boto3
from sagemaker.sklearn.model import SKLearnModel
from sagemaker.predictor import Predictor
from sagemaker.serializers import CSVSerializer
from sagemaker.deserializers import CSVDeserializer
from sagemaker.deserializers import JSONDeserializer
```

The following S3 Bucket path "s3_path" is where my csv file is currently being stored (copy the S3 URL).

In [4]:
```
s3_path = "s3://sagemaker-studio-296632356656-77qw9lvy0ee/SleepHealth.csv"
sleep_data = pd.read_csv(s3_path)
```

In [ ]:
```
#sleep_data.head()
```

Exploratory Data Analysis

Sleep Disorder categories -> None, Sleep Apnea, Insomnia. It seems Jupyter read files in a different way than Google Colab. The two models were created using Colab (to avoid using SageMaker costs etc).

In [5]:
```
sleep_data["Sleep Disorder"] = sleep_data["Sleep Disorder"].fillna("None")
sleep_data.head()
```

Out[5]:

	Person ID	Gender	Age	Occupation	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	BMI Category	Pre
0	1	Male	27	Software Engineer	6.1	6	42	6	Overweight	1
1	2	Male	28	Doctor	6.2	6	60	8	Normal	1
2	3	Male	28	Doctor	6.2	6	60	8	Normal	1
3	4	Male	28	Sales Representative	5.9	4	30	8	Obese	1
4	5	Male	28	Sales Representative	5.9	4	30	8	Obese	1

In [6]:
```
print(sleep_data["Gender"].value_counts())
```

```
Gender
Male      189
Female    185
Name: count, dtype: int64
```

In [7]:
```
print(sleep_data["Occupation"].value_counts())
```

```
Occupation
Nurse                   73
Doctor                  71
Engineer                63
Lawyer                  47
Teacher                 40
Accountant              37
Salesperson             32
Software Engineer        4
Scientist                4
Sales Representative     2
Manager                  1
Name: count, dtype: int64
```

I don't really know why the dataset creator has Normal and Normal Weight categories. I will just make them one category instead of having 2.

In [8]:
```
sleep_data["BMI Category"] = sleep_data["BMI Category"].replace("Normal Weig
print(sleep_data["BMI Category"].value_counts())
```

```
BMI Category
Normal        216
Overweight    148
Obese          10
Name: count, dtype: int64
```

In [9]:
```
print(sleep_data["Sleep Disorder"].value_counts())
```

```
Sleep Disorder
None           219
Sleep Apnea     78
Insomnia        77
Name: count, dtype: int64
```

In [10]:
```
sleep_data.isnull().sum()
```

Out[10]:
```
Person ID                  0
Gender                     0
Age                        0
Occupation                 0
Sleep Duration             0
Quality of Sleep           0
Physical Activity Level    0
Stress Level               0
BMI Category               0
Blood Pressure             0
Heart Rate                 0
Daily Steps                0
Sleep Disorder             0
dtype: int64
```

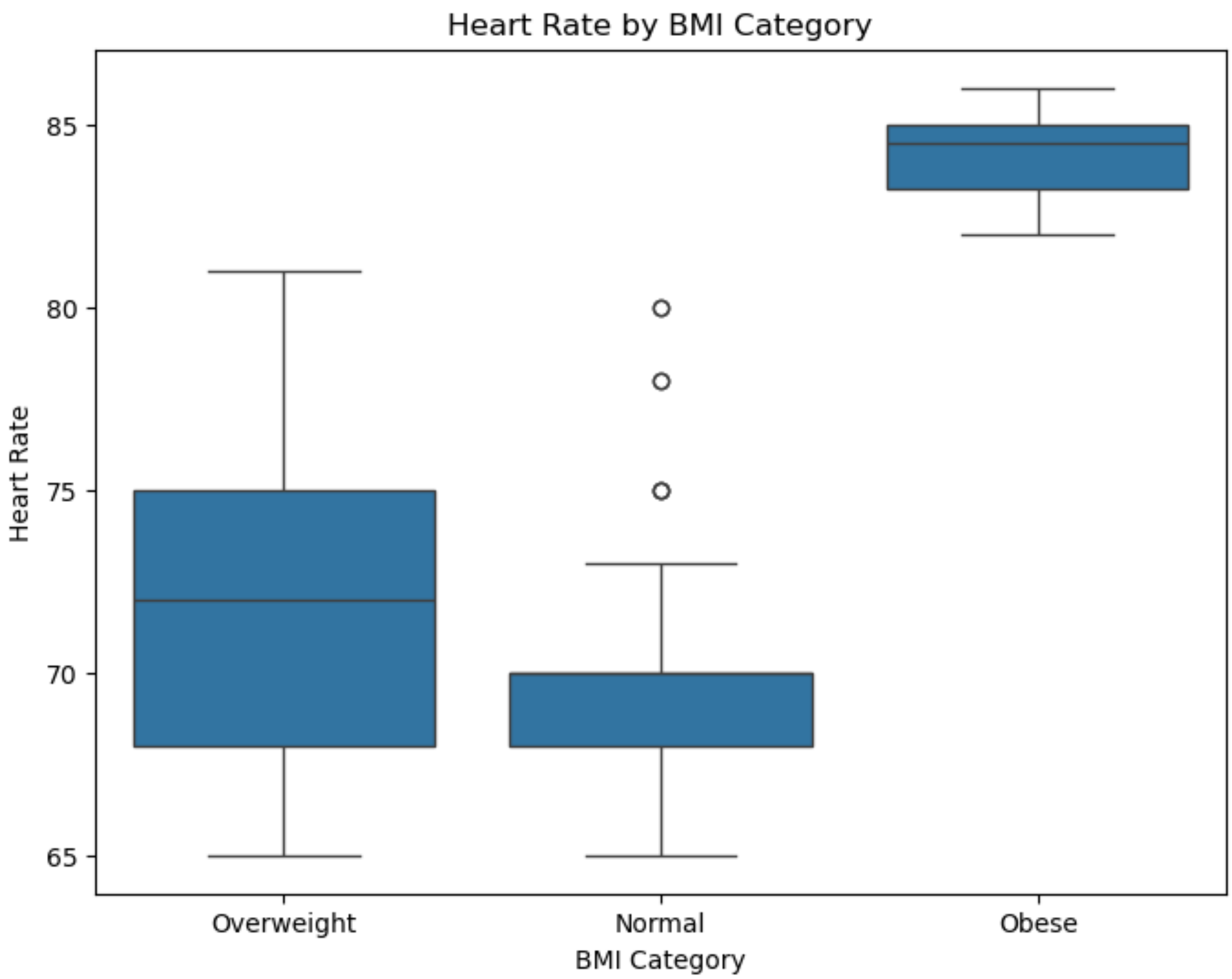
In [11]:
```
duplicates = sleep_data.duplicated().sum()
print("Number of duplicates in sleep data: ", duplicates)
```

```
Number of duplicates in sleep data:  0
```

In [12]:
```
sleep_data.info()
```

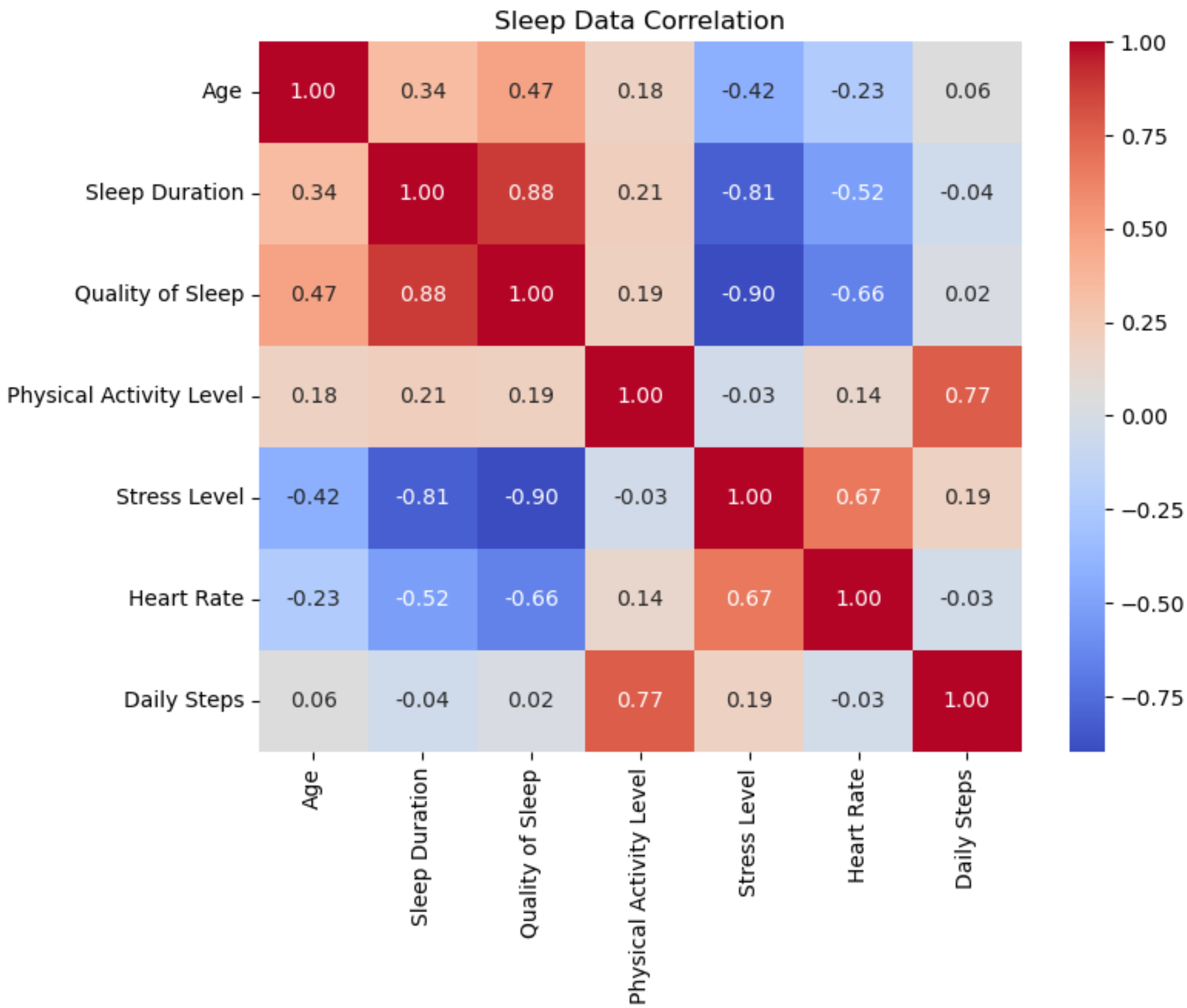
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 374 entries, 0 to 373
Data columns (total 13 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Person ID                374 non-null    int64  
 1   Gender                   374 non-null    object 
 2   Age                      374 non-null    int64  
 3   Occupation               374 non-null    object 
 4   Sleep Duration           374 non-null    float64
 5   Quality of Sleep         374 non-null    int64  
 6   Physical Activity Level  374 non-null    int64  
 7   Stress Level             374 non-null    int64  
 8   BMI Category             374 non-null    object 
 9   Blood Pressure           374 non-null    object 
 10  Heart Rate               374 non-null    int64  
 11  Daily Steps              374 non-null    int64  
 12  Sleep Disorder           374 non-null    object 
dtypes: float64(1), int64(7), object(5)
memory usage: 38.1+ KB
```

In [13]:
```
plt.figure(figsize=(8, 6))
sns.boxplot(data = sleep_data, x = "BMI Category", y = "Heart Rate")
plt.title("Heart Rate by BMI Category")
plt.show()
```



The above boxplot shows the distributions of heart rates across the three BMI categories as shown below. As we all know the horizontal line within the box shows the median heart rate for each BMI category. There are also some outliers that might indicate that the data points might be usually high or low. The "Normal" category's box is shorter, suggesting less variability in heart rate. The “Obese” category shows that the median heart rate is higher than Normal category, showing more variability among people within this group (wider IQR). The “Overweight” category seemes to indicate a wider IQR, suggesting more variability compares to the "Normal Category".

In [14]:
```
numerical_cols = ["Age", "Sleep Duration", "Quality of Sleep", "Physical Act
plt.figure(figsize=(8, 6))
sns.heatmap(sleep_data[numerical_cols].corr(), annot=True, fmt=".2f", cmap='
plt.title("Sleep Data Correlation")
plt.show()
```

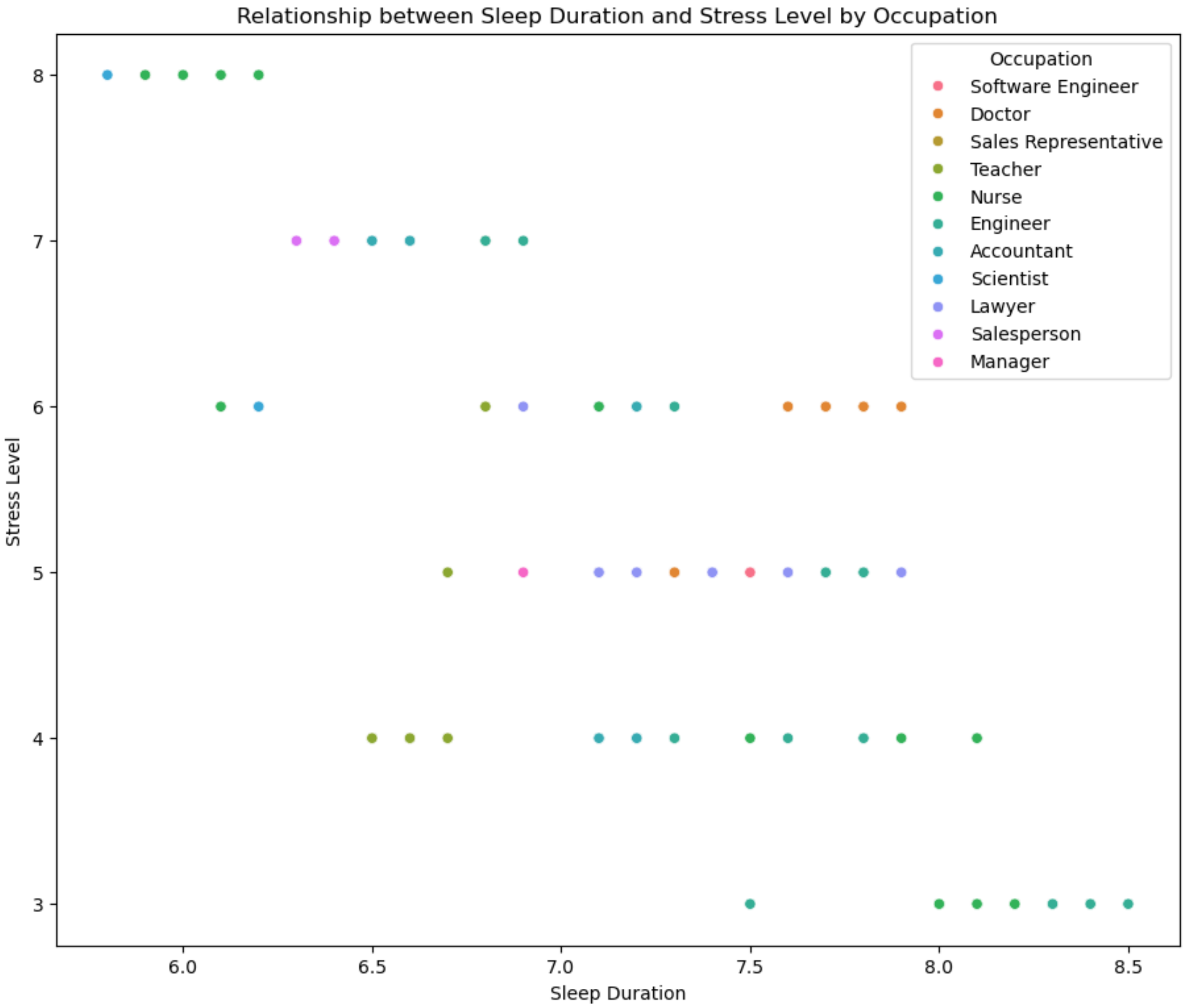


The above heat map shows the following:

- Strong positive correlation between Quality of Sleep and Sleep Duration (0.88).
- Strong negative correlation between Stress Level and Sleep Duration (-0.81) and Quality of Sleep (-0.90). Stress Levels may be associated with bad and shorter sleep.
- Strong positive correlation between Daily Steps and Physical Activity Level (0.77). This is something common because more physical activity is generally associated with a higher number of steps taken daily.
- Positive correlation of (0.67) between Stress Level and Heart Rate, indicating that higher stress levels are associated with higher heart rates.

In [15]:
```
plt.figure(figsize=(11, 9))
sns.scatterplot(data=sleep_data, x = "Sleep Duration", y = "Stress Level", h
plt.title("Relationship between Sleep Duration and Stress Level by Occupatic
```

Out[15]: Text(0.5, 1.0, 'Relationship between Sleep Duration and Stress Level by Occ upation')



In [16]:
```
sleep_data.describe()
```

Out[16]:

	Person ID	Age	Sleep Duration	Quality of Sleep	Physical Activity Level	Stress Level	Heart Ra
count	374.000000	374.000000	374.000000	374.000000	374.000000	374.000000	374.00000
mean	187.500000	42.184492	7.132086	7.312834	59.171123	5.385027	70.1657
std	108.108742	8.673133	0.795657	1.196956	20.830804	1.774526	4.1356
min	1.000000	27.000000	5.800000	4.000000	30.000000	3.000000	65.00000
25%	94.250000	35.250000	6.400000	6.000000	45.000000	4.000000	68.00000
50%	187.500000	43.000000	7.200000	7.000000	60.000000	5.000000	70.00000
75%	280.750000	50.000000	7.800000	8.000000	75.000000	7.000000	72.00000
max	374.000000	59.000000	8.500000	9.000000	90.000000	8.000000	86.00000

Model Implementation

The data shows it is a mix of numerical and categorical variables. It is a clean dataset with no null values and no duplicates. Since I was getting really used to work with TensorFlow (Keras), for this project I will be working with Scikit-Learn and apply everything I learnt from the Applied Machine Learning course from Professor James Shanahan.

I am going to be implementing many steps from the Sklearn library such as preprocessing steps, pipelines, transformers, feature engineering etc. Also, I tried to understand how to read blood pressure numbers and I came across an article that explains how to read those numbers. It seems the number on the top is the “systolic blood pressure” and the second number that goes under systolic is the “diastolic blood pressure”.

Systolic blood pressure (the first number) – indicates how much pressure your blood is exerting against your artery walls when the heart contracts. This tend to be the most “important” number due to being a major risk factor for cardiovascular disease for people over 50. Diastolic blood pressure (the second number) – indicates how much pressure your blood is exerting against your artery walls while the heart muscle is resting between contractions. So, knowing this I will try and split these two numbers into two new columns to see if I can get a much better performance off these models.

All techniques and structures were taken from my notes and homeworks from -> Applied Machine Learning course by Professor James Shannahan. Additionally, lets train_test_split the data using the same default configuration I've used during the applied machine learning course.

Model 1: Logistic Regression

This is a logistic regression model created to predict the likelyhood of someone having a Sleep Disorder (None, Insomnia, Sleep Apnea). This can be considered a multiclassification task.

In [17]:
```
X = sleep_data.drop(["Sleep Disorder"], axis=1)  # Feature variables, also c
y = sleep_data["Sleep Disorder"]  # Target variable
```

In [18]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test
```

In [19]:
```
X_train.shape
```

Out[19]: (239, 12)

In [20]:
```
y_test.shape
```

Out[20]: (75,)

Preprocessing and Feature Engineering

In [21]:
```
num_cols = ["Age", "Sleep Duration", "Quality of Sleep", "Physical Activity
cat_cols = ["Gender", "Occupation", "BMI Category"] # categorical columns
```

The following "split_bp()" function was created with the intent of being used within the ColumnTransformer in the pipelines below to ensure the "Blood Pressure" data splitting.

Blood Pressure -> Systolic_Bp and Diastolic_Bp

However, due to how SageMaker processes data during deployment made this extremely dificult. I had no problem locally testing this scenario (I was getting the correct predictions), even creating a testing simulation worked giving all desire results. In the case of deployment endpoint, everything changes and I had to made some changes to avoid running into errors. I decided to keep the split_bp() function because it gives better results, it just part of preprocessing. Instead of being applied directly within the pipeline, the function will be applied to the X_train and X_test sets before training and testing.

In [22]:
```
def split_bp(df):
    bp_column = df["Blood Pressure"].str.split("/", n = 1, expand = True) #
    df["Systolic_BP"] = pd.to_numeric(bp_column[0]) # containing systolic va
    df["Diastolic_BP"] = pd.to_numeric(bp_column[1]) # containing diastolic
    return df.drop("Blood Pressure", axis = 1)  # dropping original "Blood P
```

In [23]:
```
#bp_transformer = FunctionTransformer(split_bp)
```

We are dealing with a mix of categorical and numerical data. I am going to be using one-hot encoding for the following columns: “Gender”, “Occupation”, and “BMI Category”. Also, I am going to be applying label encoding to the following column “Sleep Disorder” because it has levels of None, Insomnia, and Sleep Apnea. Regarding the numerical data, I will be implementing some standardization as part of the feature engineering. At the end, I will combine these scaled and encoded features into a dataframe.

Since I will me implementing regression models, I will be using standardization instead of normalization. Standardization centers data around a mean of zero and a standard deviation of one.

The Numerical and Categorical Preprocessing Pipelines:

In [24]:
```
# Preprocessing pipeline for numerical data
num_pipeline = Pipeline([
                ("imputer", SimpleImputer(strategy = "mean")),  # imputing m
                ("scaler", StandardScaler())  # scaling numerical values
])

# Preprocessing pipeline for categorical data
cat_pipeline = Pipeline([
                ("imputer", SimpleImputer(strategy = "most_frequent")),  # i
                ("onehot", OneHotEncoder(handle_unknown = "ignore"))  # one-
])
```

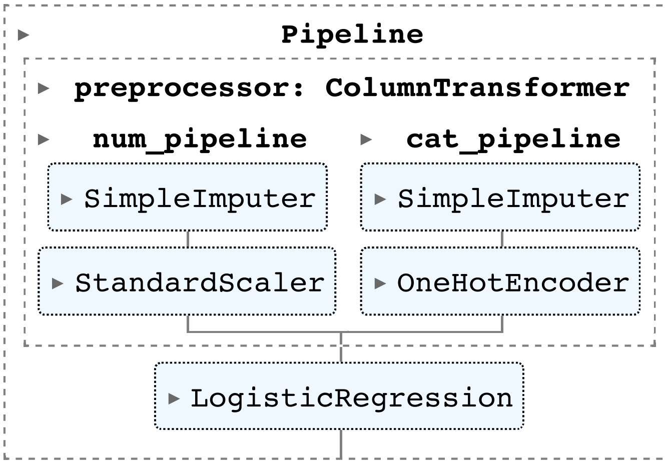
Using custome function, Transformer, and Full Pipeline:

In [ ]:
```
# Creating the preprocessor and applying bp_trasformer
#preprocessor = ColumnTransformer(transformers=[
                #("num_pipeline", num_pipeline, num_cols), # numerical
                #("cat_pipeline", cat_pipeline, cat_cols), # categorical
                #("bp_transformer", bp_transformer, ["Blood Pressure"])  # a
    #])
```

In [25]:
```
# No bp_transformer (split_bp()) wihtin the following preprocessor:
preprocessor = ColumnTransformer(transformers=[
                ("num_pipeline", num_pipeline, num_cols), # numerical
                ("cat_pipeline", cat_pipeline, cat_cols) # categorical
    ])

# Creating the full pipeline using the above preprocessor and the Logistic r
logistic_pipe = Pipeline([
            ("preprocessor", preprocessor), # preprocessor
            ("lr", LogisticRegression())  # logistic regression for model 1
])
```

In [26]:
```
logistic_pipe
```

Out[26]:



Hyperparamater Tuning

GridSearchCV - hyperparameter tuning

In [27]:
```
params = {
    "lr__C": [0.001, 0.01, 0.1, 1.0, 10.0, 100.0, 1000.0],  # regularizatior
    "lr__penalty": ["none", "l1", "l2", "elasticnet"],  # regularization - p
    "lr__solver": ["newton-cg", "lbfgs", "sag", "saga"],  # solvers appliead
}

# GridSearchCV
grid_search = GridSearchCV(logistic_pipe, param_grid = params, cv = 5, scori
```

Training

In [28]:
```
X_train_splitbp = split_bp(X_train) # this is were split_bp() is getting app
```

In [ ]:
```
grid_search.fit(X_train_splitbp, y_train)
```

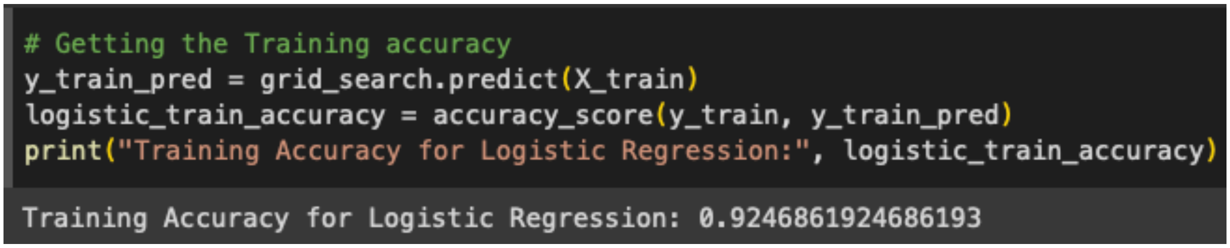
In [30]:
```
# Best hyperparameters from my gridsearchcv
print("Best hyperparameters from GridSearchCV:", grid_search.best_params_)
```

```
Best hyperparameters from GridSearchCV: {'lr__C': 0.1, 'lr__penalty': 'l2',
'lr__solver': 'newton-cg'}
```

In [31]:
```
estimator = grid_search.best_estimator_ # using this best estimator to trair
```

In [33]:
```
# Getting the Training accuracy
y_train_pred = estimator.predict(X_train_splitbp)
logistic_train_accuracy = accuracy_score(y_train, y_train_pred)
print("Training Accuracy for Logistic Regression:", logistic_train_accuracy)
```

```
Training Accuracy for Logistic Regression: 0.9037656903765691
```



```
# Getting the Training accuracy
y_train_pred = grid_search.predict(X_train)
logistic_train_accuracy = accuracy_score(y_train, y_train_pred)
print("Training Accuracy for Logistic Regression:", logistic_train_accuracy)

Training Accuracy for Logistic Regression: 0.9246861924686193
```

The above image shows a training accuracy of 0.92. This accuracy comes from training the logistic regression model using the split_bp() function in the ColumnTransformer within the preprocessing pipelines. In my case, since I took this preprocessing step out of the pipelines, my accuracy is 0.90. This is something I would normally look into, however since I don't really know about AWS SageMaker, I preffer to play it safe and just move towards deployment. The same will go into the Validation and Testing Accuracies.

Validation

In [34]:
```
X_valid_splitbp = split_bp(X_valid)
```

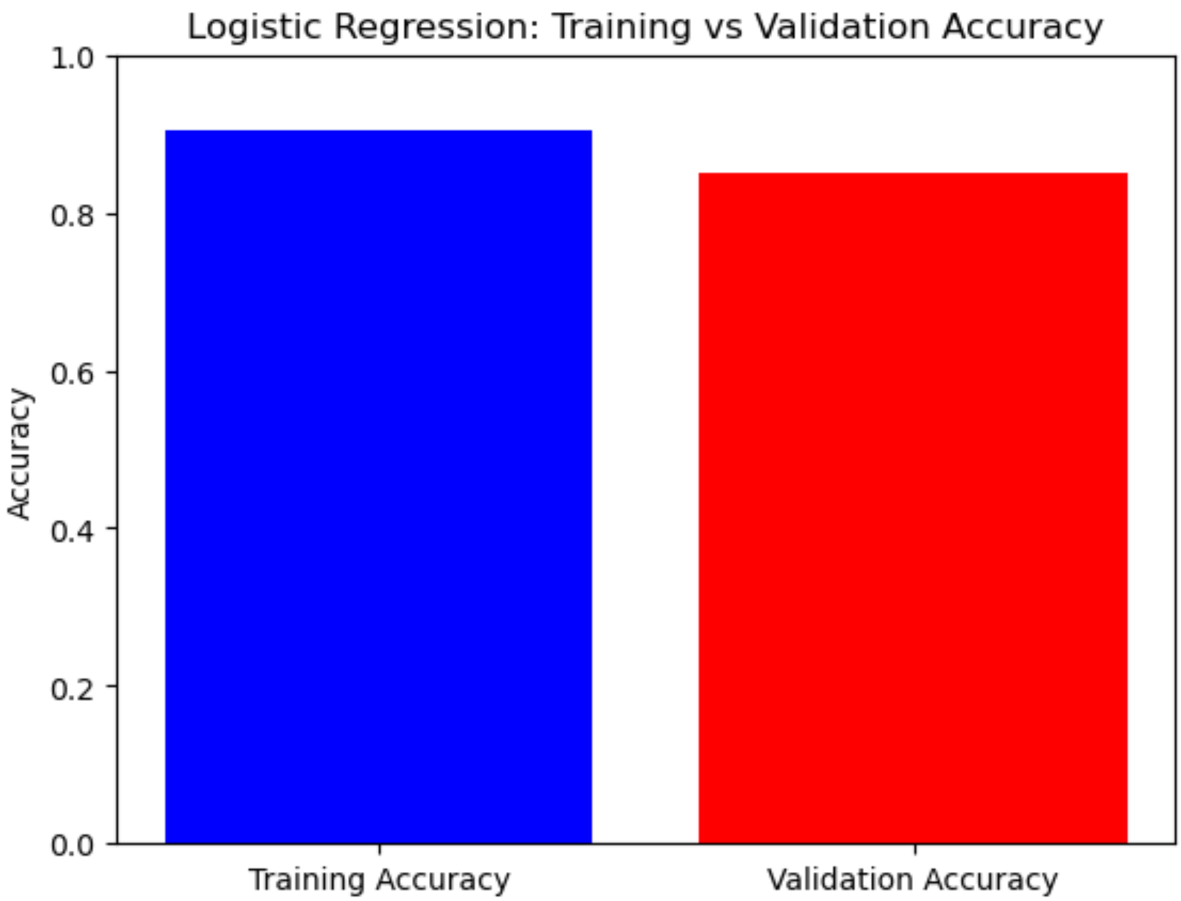
In [35]:
```
# Evaluating the Validation Accuracy
y_valid_pred = estimator.predict(X_valid_splitbp)
logistic_valid_accuracy = accuracy_score(y_valid, y_valid_pred)
print("Validation Accuracy for Logistic Regression:", logistic_valid_accurac
```

```
Validation Accuracy for Logistic Regression: 0.85
```

Training vs Validation Accuracy

The following graph will help me determine if my model might be underfitting or overfitting. The graph will compare the model's training and validation accuracies. If the training accuracy is significantly higher than the validation accuracy, it might indicate overfitting. On the other hand, if both accuracies are comparably high, it suggests that the model generalizes well. If both are low, the model might be underfitting.

In [36]:
```
acc_labels = ["Training Accuracy", "Validation Accuracy"]
acc_values = [logistic_train_accuracy, logistic_valid_accuracy]

plt.bar(acc_labels, acc_values, color=["blue", "red"])
plt.ylim([0, 1])
plt.ylabel("Accuracy")
plt.title("Logistic Regression: Training vs Validation Accuracy")
plt.show()
```



I can say it is generalizing well.

Saving the Trained Portion of Model 1

I am going to be saving the model artifacts (trained model parameters).

In [37]:
```
# Save the best estimator from the GridSearchCV
joblib.dump(grid_search.best_estimator_, "model1.joblib") # I will see this
```

Out[37]: ['model1.joblib']

AWS documentation states that SageMaker requires models to be stored as a compressed TAR File (tar.gz):

In [38]:
```
# with tarfile.open(output_filename, "w:gz") as tar:
        #tar.add(source_dir, arcname=os.path.basename(source_dir))

with tarfile.open("model1.tar.gz", "w:gz") as tar:
    tar.add("model1.joblib", arcname=os.path.basename("model1.joblib")) # S3
```

Uploading local file or directory to S3 Bucket

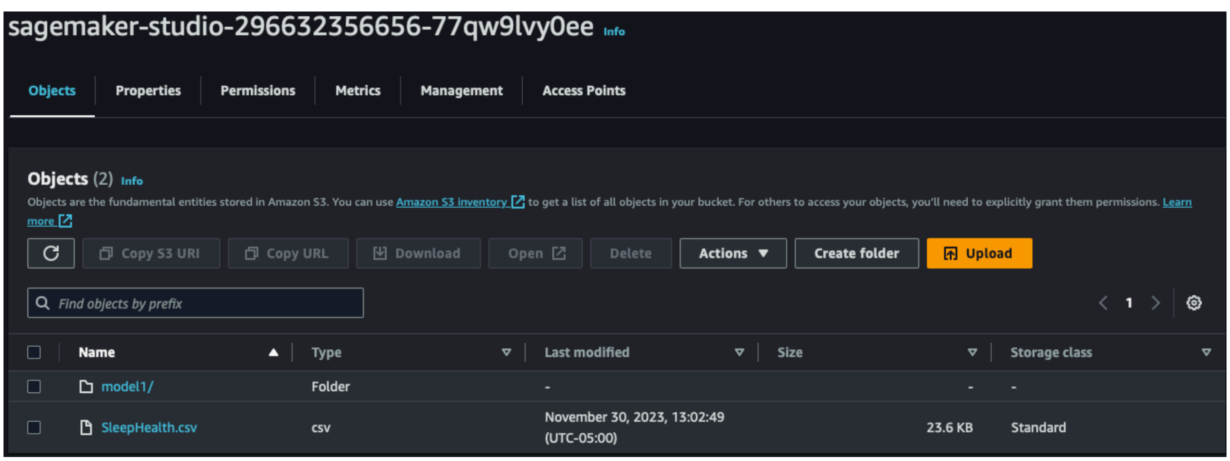
```
upload_data(path, bucket=None, key_prefix='data', callback=None, extra_args=None)
```

In [39]:
```
session = sagemaker.Session() # session
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/s
agemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-
user/.config/sagemaker/config.yaml
```

In [40]:
```
s3_bucket = "sagemaker-studio-296632356656-77qw9lvy0ee" # my s3 bucket creat
model1_prefix = "model1/logistic-regression" # model 1 is the folder that wi
model1_path = "model1.tar.gz" # path where the local model is saved

# Uploading the model to S3 Bucket
model1_upload_s3 = session.upload_data(path = model1_path, bucket = s3_bucke
print("Model uploaded to:", model1_upload_s3)
```

```
Model uploaded to: s3://sagemaker-studio-296632356656-77qw9lvy0ee/model1/lo
gistic-regression/model1.tar.gz
```



Creating SageMaker Model

Scikit Learn Model

class **sagemaker.sklearn.model.SKLearnModel**(*model_data, role=None, entry_point=None, framework_version=None, py_version='py3', image_uri=None, predictor_cls=<class 'sagemaker.sklearn.model.SKLearnPredictor'>, model_server_workers=None, **kwargs*)

In [41]:
```
role = sagemaker.get_execution_role() # role
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/s
agemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-
user/.config/sagemaker/config.yaml
```

Inference

The below code is the inference.py which is needed for the inference predictions.

- model_fn: loads the model
- input_fn: process input
- predict_fn: making predictions
- output_fn: process the output

def model_fn(model_dir): model_file = os.path.join(model_dir, "model1.joblib") # path model = joblib.load(model_file) # loading the model return model def input_fn(request_body, request_content_type): if request_content_type == "text/csv": # if text/csv format data = pd.read_csv(StringIO(request_body)) return data else: raise ValueError("Unsupported content type: " + str(request_content_type)) # else value error def predict_fn(input_data, model): prediction = model.predict(input_data) # prediction return prediction def output_fn(prediction, response_content_type): if response_content_type == "text/csv": return pd.DataFrame(prediction).to_csv(header=False, index=False) elif response_content_type == "application/json": # getting error via CloudWatch return json.dumps(prediction.tolist()) # Convert prediction to JSON to avoid error else: raise ValueError("Unsupported response content type: " + str(response_content_type)) # else value error

In [42]:
```
# Creating SKlearn Model SageMaker Version
aws_model = SKLearnModel(model_data = model1_upload_s3, # path to model 1 fi
                         role = role, # this is the SageMaker execution role
                         entry_point = "inference.py", # for model predictio
                         framework_version = "1.0-1") # getting errors: skle
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/s
agemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-
user/.config/sagemaker/config.yaml
```

Local Testing

In [43]:
```
model1 = joblib.load("model1.joblib")
```

In [44]:
```
data = split_bp(X_test) # applying the split_bp() function directly to X_tes
```

In [45]:
```
sample = data.iloc[0:10]
```

In [46]:
```
predictions = model1.predict(sample)
print(predictions)
```

```
['None' 'None' 'None' 'None' 'None' 'Insomnia' 'None' 'None' 'None' 'None']
```

Deployment

In [47]:
```
aws_predictor = aws_model.deploy(instance_type = "ml.m5.large",  # reference
                                 initial_instance_count=1)
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/s
agemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-
user/.config/sagemaker/config.yaml
-----!
```

In [48]:
```
aws_predictor.endpoint_name # getting enpoint name
```

Out[48]:
```
'sagemaker-scikit-learn-2023-12-02-00-25-28-501'
```

Checking if the endpoint is working

In [49]:
```
client = sagemaker.Session().sagemaker_client

# Describe the endpoint
response = client.describe_endpoint(EndpointName="sagemaker-scikit-learn-202

print("Endpoint Status: " + response["EndpointStatus"])
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/s
agemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-
user/.config/sagemaker/config.yaml
Endpoint Status: InService
```

Testing The Endpoint

In [51]:
```
testing_data = split_bp(X_test) # lets apply the split_bp() function to the
```

In [52]:
```
testing_sample = data.iloc[0:10] # lets pick 10
```

Content type options for Amazon SageMaker algorithm inference requests include: text/csv, application/json, and application/x-recordio-protobuf. In the case of SageMaker (SageMaker's endpoint for model predictions) we often need to send and recieve data as strings in CSV or JSON formats.

Source: https://docs.aws.amazon.com/sagemaker/latest/dg/clarify-processing-job-data-format-tabular-response.html

In [53]:
```
# Convert X_test to a csv string
csv_buffer = StringIO()
testing_sample.to_csv(csv_buffer, header=True, index=False) # to csv format
csv_string = csv_buffer.getvalue()
```

First, we need to specify how the input data should be serialized before sending it to the endpoint. Then the prediction should be deserialized once it's received back from the endpoint.

- serializer=CSVSerializer() -> Serialize data of various formats to a CSV-formatted string. This is the required format for the model endpoint to correctly process the data. I am ensuring that the input data is in csv format.
- deserializer=JSONDeserializer() -> Deserializer data to a JSON formatted string. Predictions is expected to be in JSON format. Basically, it converts the JSON formatted prediction response from the endpoint into a Python object.

In [54]:
```
endpoint_name = "sagemaker-scikit-learn-2023-12-02-00-25-28-501"  # endpoint
aws_predictor = Predictor(endpoint_name=endpoint_name, serializer=CSVSeriali

prediction = aws_predictor.predict(csv_string)
print(prediction)
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/s
agemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-
user/.config/sagemaker/config.yaml
['None', 'None', 'None', 'None', 'None', 'Insomnia', 'None', 'None', 'None'
, 'None']
```

The above predictions show that the deployed endpoint worked.

How testing went in Colab (normal ml workflow):

```
Number of correct classifications: 69
Number of misclassifications: 6
```

	Actual Label	Predicted Label	Correct Prediction
15	Insomnia	Sleep Apnea	False
40	None	Insomnia	False
43	Sleep Apnea	Insomnia	False
53	Sleep Apnea	None	False
57	Sleep Apnea	Insomnia	False
70	Insomnia	None	False

Deleting the Endpoint to avoid Costs:

In [96]:
```
#session = sagemaker.Session()
session.delete_endpoint("sagemaker-scikit-learn-2023-12-02-00-25-28-501")
```

Model 2: Choosing the Best Model

This is a multiclassficiation task to predict stress levels based on various factors such as Sleep Quality, Physical Activity, Daily Steps, and others. Stress Levels from 3 to 8 (3, 4, 5, 6, 7, 8).

In [55]:
```
X = sleep_data.drop(["Stress Level"], axis=1)  # dropping the target variabl
y = sleep_data["Stress Level"]  # target variable
```

In [56]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test
```

In [57]:
```
X_train.shape
```

Out[57]: (239, 12)

In [58]:
```
y_test.shape
```

Out[58]: (75,)

Preprocessing and Feature Engineering

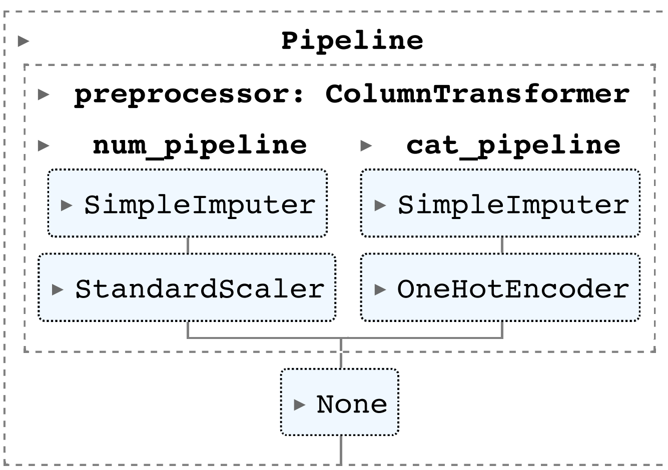
In [60]:
```
num_cols = ["Age", "Sleep Duration", "Quality of Sleep", "Physical Activity
cat_cols = ["Gender", "Occupation", "BMI Category"]  # catgeorical
```

In [61]:
```
num_pipeline = Pipeline([
                ("imputer", SimpleImputer(strategy = "mean")),  # imputing m
                ("scaler", StandardScaler())  # scaling numerical values
])

# Preprocessing pipeline for categorical data
cat_pipeline = Pipeline([
                ("imputer", SimpleImputer(strategy = "most_frequent")),  # i
                ("onehot", OneHotEncoder(handle_unknown = "ignore"))  # one-
])
```

In [62]:
```
preprocessor = ColumnTransformer(transformers=[
                ("num_pipeline", num_pipeline, num_cols), # numerical
                ("cat_pipeline", cat_pipeline, cat_cols) # categorical
    ])

# Creating the full pipeline using the above preprocessor and the Logistic r
full_pipe = Pipeline([
            ("preprocessor", preprocessor), # preprocessor
            ("classifier", None)  # None
])
```

In [63]:
```
full_pipe
```

Out[63]:



Hyperparamater Tuning

In [64]:
```
params = [
    {
        "classifier": [DecisionTreeClassifier()],
        "classifier__max_depth": [3, 5, 7],
        "classifier__min_samples_split": [10, 20],
        "classifier__min_samples_leaf": [10, 20],
    },
    {
        "classifier": [RandomForestClassifier()],
        "classifier__n_estimators": [100, 150],
        "classifier__max_features": ["auto"],
        "classifier__max_depth": [3, 5, 7],
        "classifier__min_samples_split": [10, 20],
        "classifier__min_samples_leaf": [10, 20],
    },
    {
        "classifier": [SVC()],
        "classifier__C": [1, 10],
        "classifier__kernel": ["rbf"],
        "classifier__gamma": ["scale"]
    }
]


# GridSearchCV
grid_search = GridSearchCV(full_pipe, param_grid = params, cv = 5, scoring =
```

Training

In [65]:
```
X_train_splitbp = split_bp(X_train) # this is were split_bp() is getting app
```

In [ ]:
```
grid_search.fit(X_train_splitbp, y_train)
```

In [67]:
```
# Best hyperparameters from my gridsearchcv
print("Best hyperparameters from GridSearchCV:", grid_search.best_params_)
```

```
Best hyperparameters from GridSearchCV: {'classifier': SVC(), 'classifier__
C': 10, 'classifier__gamma': 'scale', 'classifier__kernel': 'rbf'}
```

In [68]:
```
estimator = grid_search.best_estimator_ # using this best estimator to train
```

In [70]:
```
# Getting the Training accuracy
y_train_pred = estimator.predict(X_train_splitbp)
model_train_accuracy = accuracy_score(y_train, y_train_pred)
print("Training Accuracy for Best Model:", model_train_accuracy)
```

```
Training Accuracy for Best Model: 1.0
```

I know that the accuracy score for the above training is something that I should really look into. This didn't happened in Colab (I actually got 0.94 because of the split_bp() within the preprocessing pipeline). Since the main focus here is actually deploying the endpoint without any errors, I will let this slide for now. For future scenarios, this can't happen.

```
# Getting the Training accuracy
y_train_pred = best_model.predict(X_train)
model_train_accuracy = accuracy_score(y_train, y_train_pred)
print("Training Accuracy for Best Model:", model_train_accuracy)
```

```
Training Accuracy for Best Model: 0.9414225941422594
```

Validation

In [71]:

```
X_valid_splitbp = split_bp(X_valid)
```

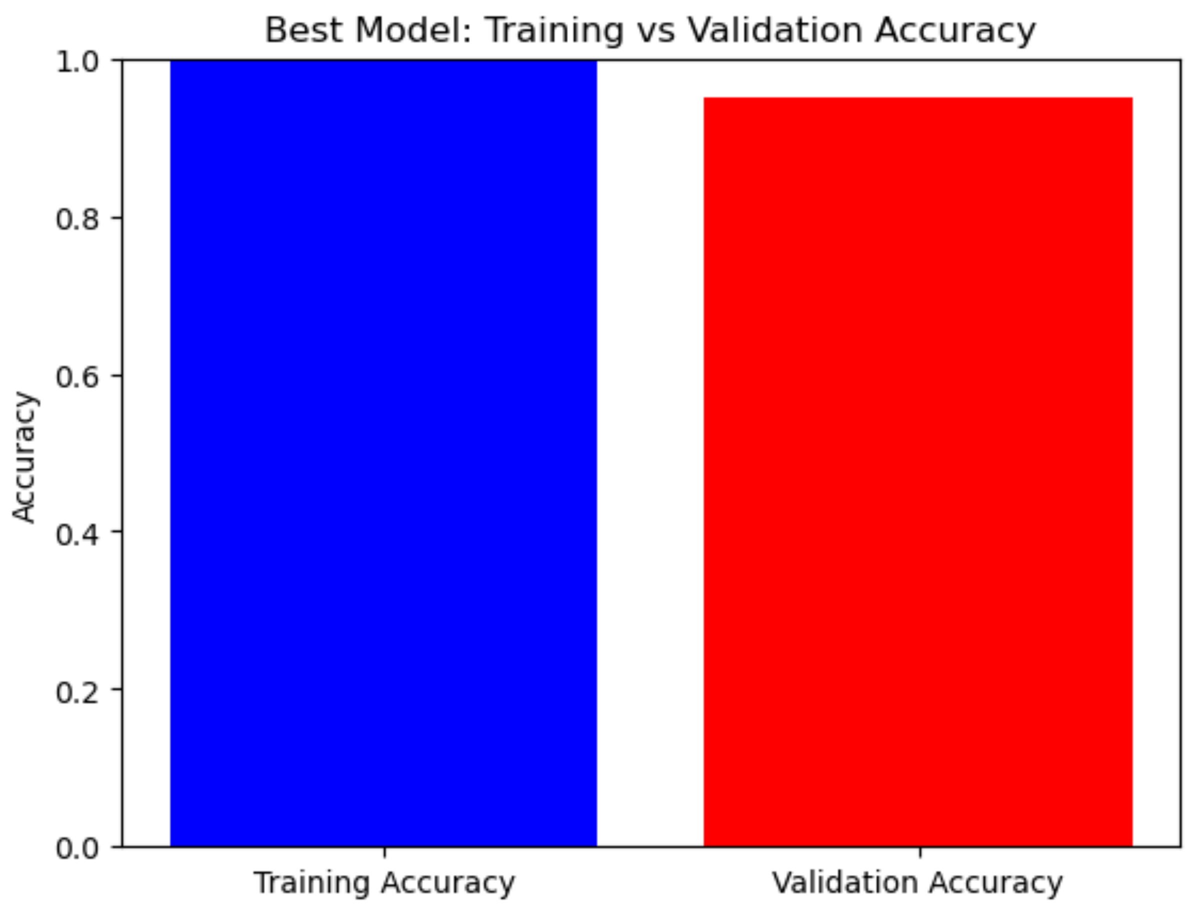
In [73]:

```
# Evaluating the Validation Accuracy
y_valid_pred = estimator.predict(X_valid_splitbp)
model_valid_accuracy = accuracy_score(y_valid, y_valid_pred)
print("Validation Accuracy for Best Model:", model_valid_accuracy)
```

```
Validation Accuracy for Best Model: 0.95
```

In [75]:

```
acc_labels = ["Training Accuracy", "Validation Accuracy"]
acc_values = [model_train_accuracy, model_valid_accuracy]

plt.bar(acc_labels, acc_values, color=["blue", "red"])
plt.ylim([0, 1])
plt.ylabel("Accuracy")
plt.title("Best Model: Training vs Validation Accuracy")
plt.show()
```



Saving the Trained Portion of Model 2

In [76]:
```
# Save the best estimator from the GridSearchCV
joblib.dump(grid_search.best_estimator_, "model2.joblib") # I will see this
```

Out[76]: ['model2.joblib']

AWS documentation states that SageMaker requires models to be stored as a compressed TAR File (tar.gz):

In [77]:
```
with tarfile.open("model2.tar.gz", "w:gz") as tar:
    tar.add("model2.joblib", arcname=os.path.basename("model2.joblib")) # S3
```

Uploading local file or directory to S3 Bucket

In [78]:
```
session = sagemaker.Session() # session
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/s
agemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-
user/.config/sagemaker/config.yaml
```

In [79]:
```
s3_bucket = "sagemaker-studio-296632356656-77qw9lvy0ee" # my s3 bucket creat
model2_prefix = "model2/classification-models" # model 1 is the folder that
model2_path = "model2.tar.gz" # path where the local model is saved

# Uploading the model to S3 Bucket
model2_upload_s3 = session.upload_data(path = model2_path, bucket = s3_bucke
print("Model uploaded to:", model2_upload_s3)
```

```
Model uploaded to: s3://sagemaker-studio-296632356656-77qw9lvy0ee/model2/cl
assification-models/model2.tar.gz
```

Name	Type	Last modified	Size	Storage class
model1/	Folder	-	-	-
model2/	Folder	-	-	-

Creating SageMaker Model

In [80]:
```
role = sagemaker.get_execution_role() # role
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/s
agemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-
user/.config/sagemaker/config.yaml
```

In [87]:
```
aws_model2 = SKLearnModel(model_data = model2_upload_s3, # path to model 1 f
                           role = role, # this is the SageMaker execution role
                           entry_point = "inference2.py", # have to change moc
                           framework_version = "1.0-1") # getting errors: skle
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/s
agemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-
user/.config/sagemaker/config.yaml
```

Local Testing

In [82]:
```
model2 = joblib.load("model2.joblib")
```

In [83]:
```
data = split_bp(X_test) # applying the split_bp() function directly to X_tes
```

In [84]:
```
sample = data.iloc[0:10]
```

In [85]:
```
predictions = model2.predict(sample)
print(predictions)
```

```
[3 8 8 3 8 7 8 4 3 5]
```

Local testing works (we can see the above stress levels), let's see if we don't run into trouble during deployment.

Deployment

In [88]:
```
aws_predictor2 = aws_model2.deploy(instance_type = "ml.m5.large",  # referen
                                    initial_instance_count=1)
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/s
agemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-
user/.config/sagemaker/config.yaml
-----!
```

In [89]:
```
aws_predictor2.endpoint_name # getting enpoint name
```

Out[89]: 'sagemaker-scikit-learn-2023-12-02-01-48-00-065'

Checking if the endpoint is working

In [90]:
```
client = sagemaker.Session().sagemaker_client

# Describe the endpoint
response = client.describe_endpoint(EndpointName="sagemaker-scikit-learn-202

print("Endpoint Status: " + response["EndpointStatus"])
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/s
agemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-
user/.config/sagemaker/config.yaml
Endpoint Status: InService
```

Testing the Endpoint

In [91]:
```
testing_data = split_bp(X_test) # lets apply the split_bp() function to the
```

In [92]:
```
testing_sample = data.iloc[0:10] # lets pick 10
```

In [93]:
```
# Convert X_test to a csv string
csv_buffer = StringIO()
testing_sample.to_csv(csv_buffer, header=True, index=False) # to csv format
csv_string = csv_buffer.getvalue()
```

In [94]:
```
endpoint_name = "sagemaker-scikit-learn-2023-12-02-01-48-00-065"  # endpoint
aws_predictor2 = Predictor(endpoint_name=endpoint_name, serializer=CSVSerial

prediction2 = aws_predictor2.predict(csv_string)
print(prediction2)
```

```
sagemaker.config INFO - Not applying SDK defaults from location: /etc/xdg/sagemaker/config.yaml
sagemaker.config INFO - Not applying SDK defaults from location: /home/ec2-user/.config/sagemaker/config.yaml
[3, 8, 8, 3, 8, 7, 8, 4, 3, 5]
```

The above predictions indicate that the deployed endpoint also worked.

Normal ML testing in Colab:

	precision	recall	f1-score	support
3	1.00	1.00	1.00	12
4	0.83	1.00	0.91	10
5	1.00	0.86	0.92	14
6	1.00	0.80	0.89	10
7	0.92	1.00	0.96	12
8	0.94	1.00	0.97	17
accuracy			0.95	75
macro avg	0.95	0.94	0.94	75
weighted avg	0.95	0.95	0.95	75

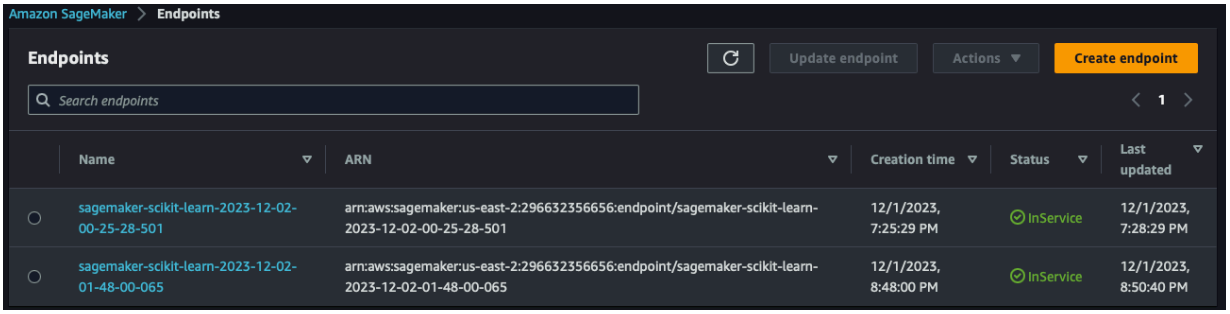
Number of correct classifications: 71
Number of misclassifications: 4

	Actual Label	Predicted Label	Correct Prediction
16	6	8	False
51	5	4	False
54	6	4	False
69	5	7	False

Deleting the Endpoint to avoid Costs:

In [95]:
```
#session = sagemaker.Session()
session.delete_endpoint("sagemaker-scikit-learn-2023-12-02-01-48-00-065")
```

My Endpoints in AWS SageMaker Console



All References:

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- isnull: https://www.geeksforgeeks.org/python-pandas-isnull-and-notnull/
- Split function: https://www.geeksforgeeks.org/python-pandas-split-strings-into-two-list-columns-using-str-split/
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- Split function: https://www.w3resource.com/pandas/series/series-str-split.php
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- Function Transformer and Pipeline creation: https://towardsdatascience.com/using-functiontransformer-and-pipeline-in-sklearn-to-predict-chardonnay-ratings-9b13fdd6c6fd
- Sklearn pipelines: https://scikit-learn.org/stable/modules/generated/sklearn.pipeline.Pipeline.html
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- ColumnTransformers: https://scikit-learn.org/stable/modules/generated/sklearn.compose.ColumnTransformer.html
- Sklearn logistic regression: https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html
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- Validation losses from GridSearchCV: https://stackoverflow.com/questions/62363657/how-can-i-plot-validation-curves-using-the-results-from-gridsearchcv
- Confusion matrix: https://scikit-learn.org/stable/modules/generated/sklearn.metrics.ConfusionMatrixDisplay.html
- using best params: https://thinkingneuron.com/how-to-find-best-hyperparameters-using-gridsearchcv-in-python/
- predicting using best estimator from GridSearchCV: https://stackoverflow.com/questions/35388647/how-to-use-gridsearchcv-output-for-a-scikit-prediction
- Resseting: https://www.w3schools.com/python/pandas/ref_df_reset_index.asp
- Lasso: https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Lasso.html
- Ridge: https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Ridge.html
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- AWS Notebook Instance: https://sagemaker-workshop.com/introduction/notebook.html
- Saving Model: https://www.analyticsvidhya.com/blog/2023/02/how-to-save-and-load-machine-learning-models-in-python-using-joblib-library/
- tarfile: https://docs.python.org/3/library/tarfile.html
- path base name: https://www.geeksforgeeks.org/python-os-path-basename-method/
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- upload_data: https://sagemaker.readthedocs.io/en/stable/session.html
- Scikit Learn Model Parameters: https://sagemaker.readthedocs.io/en/stable/sagemaker.sklearn.html
- Training ML model using Scikit Learn and SageMaker (Extremely Useful): https://medium.com/@joanisaac.biel/3-steps-to-train-a-ml-model-using-scikit-learn-and-aws-sagemaker-46aa1b7551f6
- Converting data for inference: https://docs.aws.amazon.com/sagemaker/latest/dg/cdf-inference.html
- inference.py: https://course19.fast.ai/deployment_amzn_sagemaker.html
- deploy():https://sagemaker.readthedocs.io/en/stable/api/inference/model.html
- hugginface: https://huggingface.co/docs/sagemaker/inference
- Deploy on SageMaker (Extremely useful for predictor): https://course19.fast.ai/deployment_amzn_sagemaker.html
- Predictors: https://sagemaker.readthedocs.io/en/stable/predictors.html
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- describe_endpoint: https://boto3.amazonaws.com/v1/documentation/api/latest/reference/services/sagemake
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- csv buffer: https://pythontic.com/pandas/serialization/to_csv
- serializer: https://sagemaker.readthedocs.io/en/stable/api/inference/serializers.html
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- Deployment: https://towardsdatascience.com/deploying-a-pre-trained-sklearn-model-on-amazon-sagemaker-826a2b5ac0b6
- Deployment: https://ram-vegiraju.medium.com/training-and-deploying-custom-scikit-learn-models-on-aws-sagemaker-3de6a2f669f4
- Some Endpoint and Deployment info: https://stackoverflow.com/questions/72058686/how-do-i-deploy-a-pre-trained-sklearn-model-on-aws-sagemaker-endpoint-stuck-on
- Sickit Learn SageMaker Documentation: https://sagemaker.readthedocs.io/en/stable/sagemaker.sklearn.html
- Using my own inference container: https://docs.aws.amazon.com/sagemaker/latest/dg/adapt-inference-container.html