ADDITIONAL MODELS

Importing the necessary libraries

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```
data = pd.read_csv("/content/cleaned_data.csv")
```

```
data
```

	job_title	salary	pay_period	work_type	location	experience_level	sponsored	currency	skills	company_name
0	Sales Manager	88336.222112	2	1	Santa Clarita, CA	5	0	USD	SALE, BD	CargoLogin.
1	Model Risk Auditor	88336.222112	3	0	New York, NY	5	0	USD	ACCT, FIN	Employvision Inc.
2	NY Studio Assistant	88336.222112	2	1	New York, NY	5	1	USD	DSGN, ART, IT	Ken Fulk Inc
3	Office Associate	42000.000000	2	1	Albany, GA	5	1	USD	ADM	Sunnyland Farms
4	Education Manager	88336.222112	2	1	United States	5	0	USD	EDU, TRNG	Paradigm Senior Services
...	...	...	...	...	...	...	...	...	...	...
14338	Sanitation Technician	88336.222112	1	4	West Columbia, SC	2	0	USD	ENG, IT	Aspire Bakeries
14339	Unit Secretary	88336.222112	2	1	Teaneck, NJ	2	0	USD	ADM	Holy Name Medical Center
14340	Radiology Aide, Perdiem	88336.222112	1	4	Teaneck, NJ	2	0	USD	HCPR	Holy Name Medical Center
										Columbia

```
df = data[['salary','pay_period','work_type','experience_level','sponsored','company_size','category_ComplexOnsiteApply','category_OffsiteApply','category_SimpleOnsiteApply']]
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14343 entries, 0 to 14342
Data columns (total 9 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   salary                       14343 non-null  float64
 1   pay_period                   14343 non-null  int64
 2   work_type                    14343 non-null  int64
 3   experience_level             14343 non-null  int64
 4   sponsored                    14343 non-null  int64
 5   company_size                 14343 non-null  float64
 6   category_ComplexOnsiteApply  14343 non-null  int64
 7   category_OffsiteApply        14343 non-null  int64
 8   category_SimpleOnsiteApply   14343 non-null  int64
dtypes: float64(2), int64(7)
memory usage: 1008.6 KB
```

Below 3 features "experience_level", "pay_period", and "work_type" are choosen as independent variables and "salary" is choosen as our target variable or dependent variable

```
X = df[['experience_level','pay_period','work_type']] # Feature
y = df['salary']                                     # Target Variable
```

Split the data into training, validation and testing sets using sklearn train_test_split

```
from sklearn.model_selection import train_test_split
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.2, random_state=42)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, random_state=42)
```

With the help of sklearn train_test_split we splitted the dataset into two parst train set and test set. So, total 14343 rows are splitted into three sets where 11474 in train set, 1434 rows into validation set and remaining 1435 in test set.

```
X_train.shape
```

```
(11474, 3)
```

```
X_val.shape
```

```
(1434, 3)
```

```
X_test.shape
```

```
(1435, 3)
```

```
y_train.shape
```

```
(11474,)
```

Scaling the data

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_val = scaler.fit_transform(X_val)
X_test = scaler.transform(X_test)
```

```
y_train = scaler.fit_transform(y_train.values.reshape(-1, 1))
y_val = scaler.transform(y_val.values.reshape(-1, 1))
y_test = scaler.transform(y_test.values.reshape(-1, 1))
```

Scaling is done using StandardScaler which is z-score. Scaling is one of the important process in Ml applications to perform so that the model has higher acccuracy.

```
X_train
```

```
array([[ 0.77935155, -0.03795617, -0.13485794],
       [ 0.77935155, -0.03795617, -0.13485794],
       [ 0.77935155, -0.03795617, -0.13485794],
       ...,
       [ 0.77935155, -0.03795617, -0.13485794],
       [ 0.77935155, -0.03795617, -0.13485794],
       [-0.90026522, -0.03795617, -0.13485794]])
```

```
X_val
```

```
array([[ 0.72847308, -0.04287203, -0.14191681],
       [ 0.72847308, -2.23853257,  3.21262237],
       [-0.98966902, -0.04287203, -0.14191681],
       ...,
       [-2.13509708, -2.23853257,  3.21262237],
       [-2.13509708, -0.04287203, -0.14191681],
       [ 0.72847308, -0.04287203, -0.14191681]])
```

```
X_test
```

```
array([[ 0.72847308, -0.04287203, -0.14191681],
       [ 0.72847308, -0.04287203, -0.14191681],
       [-2.13509708, -0.04287203, -0.14191681],
       ...,
       [ 0.72847308,  2.1527885 , -1.26009654],
       [ 0.72847308, -0.04287203, -0.14191681],
       [ 0.72847308, -0.04287203, -0.14191681]])
```

```
y_train
```

```
array([[-0.01236833],
       [-0.01236833],
       [-0.01236833],
       ...,
       [-0.01236833],
       [ 0.93892532],
       [-0.01236833]])
```

```
y_val
```

```
array([[ 3.00119977],
       [-0.01236833],
       [-0.01236833],
       ...,
       [-0.01236833],
       [-0.11062506],
       [ 0.97943428]])
```

```
y_test
```

```
array([[-0.01236833],
       [-0.01236833],
       [ 1.04305011],
       ...,
       [-0.01236833],
       [-0.01236833],
       [-0.01236833]])
```

XGBoost

XGBoost is an ensemble learning technique that generates a final prediction that is both robust and accurate by combining the predictions of several weak models, usually decision trees.

XGBoost is a flexible machine learning model that excels at both classification and regression tasks and is well-known for its strong handling of missing data and resistance to outliers

References:

https://xgboost.readthedocs.io/en/stable/python/python_intro.html

https://arxiv.org/abs/1603.02754


```
# Importing the XGBRegressor from xgboost
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score

# Creating the model
xgb_model = XGBRegressor(objective='reg:squarederror',
                      colsample_bytree=0.3,
                      learning_rate=0.1,
                      max_depth=5,
                      alpha=10,
                      n_estimators=100,
                      random_state=42)

# Training the model which is called fitting
xgb_model.fit(X_train, y_train)
```

```
                          XGBRegressor
XGBRegressor(alpha=10, base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=0.3, device=None, early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None, feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=0.1, max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=5, max_leaves=None,
             min_child_weight=None, missing=nan, monotone_constraints=None,
             multi_strategy=None, n_estimators=100, n_jobs=None,
             num_parallel_tree=None, ...)
```

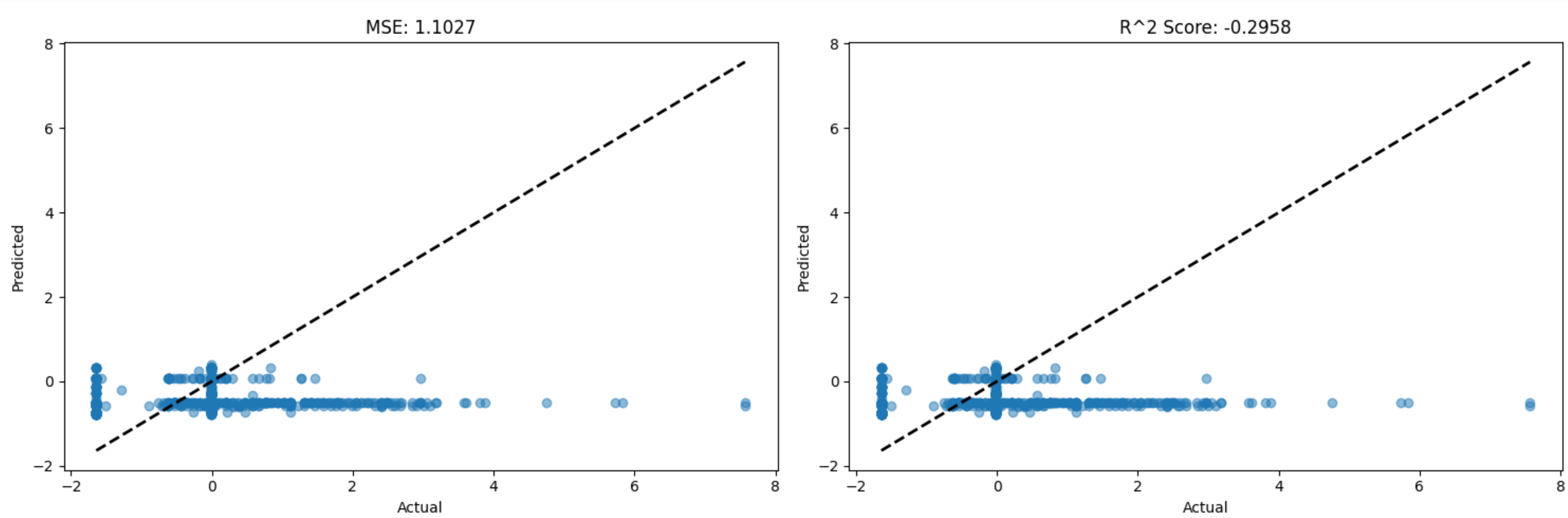
```
# predicting on the test set
y_pred_xgb = xgb_model.predict(X_test)
```

```
#Mean Squared Error and R^2 Score values
mse_xgb = mean_squared_error(y_test, y_pred_xgb)
print("MSE for XGBoost:", mse_xgb)

r2_xgb = r2_score(y_test, y_pred_xgb)
print("R^2 Score for XGBoost:", r2_xgb)
```

```
MSE for XGBoost: 1.1026548089454695
R^2 Score for XGBoost: -0.2958400350749928
```

```
#plot
plt.scatter(y_test, y_pred_xgb, alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='--', linewidth=2)
plt.xlabel('Actual Salary')
plt.ylabel('Predicted Salary')
plt.title('Actual vs. Predicted Salary')
plt.show()
```


```
# Plotting the evaluation metrics using plt library
fig, axs = plt.subplots(1, 2, figsize=(15, 5))

# Mean Squared Error (MSE)
axs[0].scatter(y_test, y_pred_xgb, alpha=0.5)
axs[0].plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], 'k--', lw=2)
axs[0].set_title(f'MSE: {mse_xgb:.4f}')
axs[0].set_xlabel('Actual')
axs[0].set_ylabel('Predicted')

# R^2 Score
axs[1].scatter(y_test, y_pred_xgb, alpha=0.5)
axs[1].plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], 'k--', lw=2)
axs[1].set_title(f'R^2 Score: {r2_xgb:.4f}')
axs[1].set_xlabel('Actual')
axs[1].set_ylabel('Predicted')

plt.tight_layout()
plt.show()
```



Extreme Machine Learning Model (ELM)

One class of models based on neural networks are Extreme Learning Machines. Unlike conventional neural networks, they have a single hidden layer and fixed, randomly assigned weights between the input and hidden layer. ELMs are renowned for being easy to use and having quick training periods.

References

https://www.sciencedirect.com/science/article/pii/S1877050916310157

https://github.com/diogocampospy/pyrenn

```
#Importing MLPRegressor from sklearn neural networks
from sklearn.neural_network import MLPRegressor
```

```
#Creating the model
elm_model = MLPRegressor(hidden_layer_sizes=(10,),activation='logistic',max_iter=1000,random_state=42)

#Training the model
elm_model.fit(X_train,y_train)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:1623: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the sh
  y = column_or_1d(y, warn=True)
```

```
MLPRegressor
MLPRegressor(activation='logistic', hidden_layer_sizes=(10,), max_iter=1000,
             random_state=42)
```

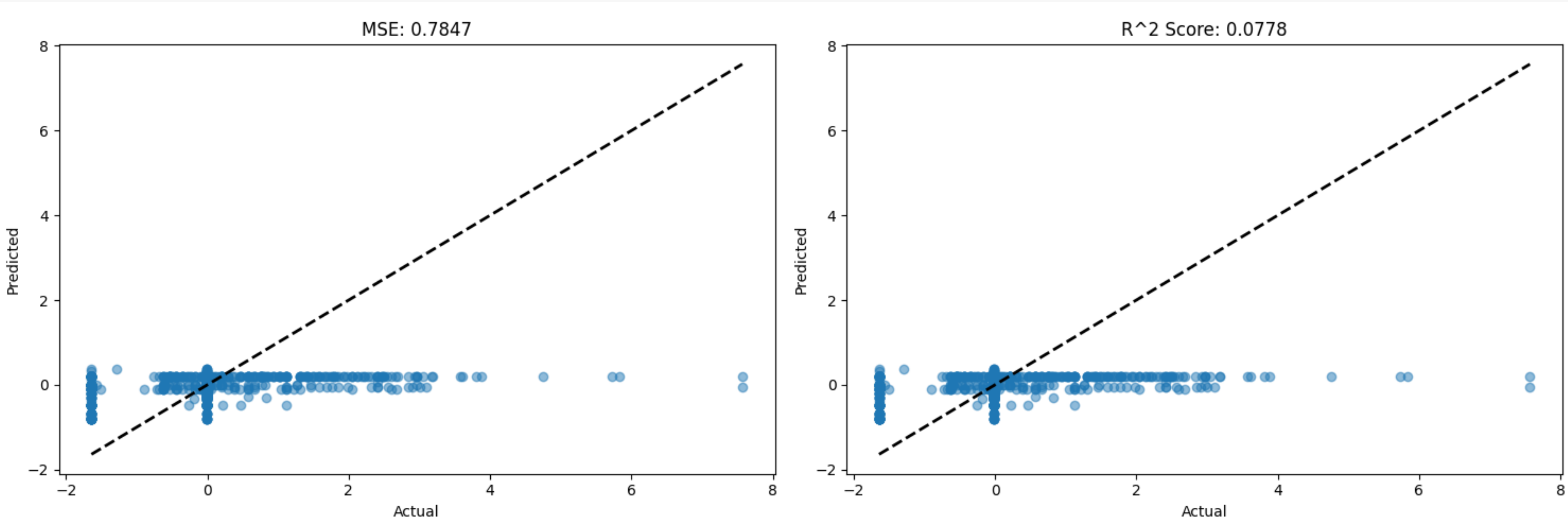
```
#Predicting on test set
y_pred_elm = elm_model.predict(X_test)
```

```
#Mean Squared Error and R^2 Score values
mse_elm = mean_squared_error(y_test, y_pred_elm)
print("MSE for XGBoost:", mse_elm)

r2_elm = r2_score(y_test, y_pred_elm)
print("R^2 Score for XGBoost:", r2_elm)
```

```
MSE for XGBoost: 0.784694782579755
R^2 Score for XGBoost: 0.07782661778460531
```

```
#plot
plt.scatter(y_test, y_pred_elm, alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='--', linewidth=2)
plt.xlabel('Actual Salary')
plt.ylabel('Predicted Salary')
plt.title('Actual vs. Predicted Salary')
plt.show()
```


```
# Plotting the evaluation metrics using plt library
fig, axs = plt.subplots(1, 2, figsize=(15, 5))

# Mean Squared Error (MSE)
axs[0].scatter(y_test, y_pred_elm, alpha=0.5)
axs[0].plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], 'k--', lw=2)
axs[0].set_title(f'MSE: {mse_elm:.4f}')
axs[0].set_xlabel('Actual')
axs[0].set_ylabel('Predicted')

# R^2 Score
axs[1].scatter(y_test, y_pred_elm, alpha=0.5)
axs[1].plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], 'k--', lw=2)
axs[1].set_title(f'R^2 Score: {r2_elm:.4f}')
axs[1].set_xlabel('Actual')
axs[1].set_ylabel('Predicted')

plt.tight_layout()
plt.show()
```



Basic Deep Learning Model with Two Layers

An input layer, a hidden layer, and an output layer make up the two layers of a basic neural network architecture represented by this model. Despite being straightforward, it can identify non-linear relationships in the data. Important design decisions that affect the model's performance are the quantity of neurons in the hidden layer and the activation functions that are employed.

Refrences

https://www.tensorflow.org/tutorials

https://www.deeplearningbook.org/

```
# Importing the Sequential and Dense models from tensorflow
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

```
#Creating the model
model = Sequential()

#Adding the two layers to the model
model.add(Dense(units=64, activation='relu', input_dim=X_train.shape[1]))
model.add(Dense(units=1, activation='linear'))
```

```
# Compiling the model using adam optimizer
model.compile(optimizer='adam', loss='mean_squared_error')
```

```
# Train the model
history = model.fit(X_train, y_train, epochs=50, batch_size=32, validation_data=(X_test, y_test))
```

```
Epoch 4/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9388 - val_loss: 0.7760
Epoch 5/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9381 - val_loss: 0.7722
Epoch 6/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9377 - val_loss: 0.7713
Epoch 7/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9372 - val_loss: 0.7731
Epoch 8/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9365 - val_loss: 0.7707
Epoch 9/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9366 - val_loss: 0.7743
Epoch 10/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9355 - val_loss: 0.7819
Epoch 11/50
359/359 [==============================] - 1s 3ms/step - loss: 0.9373 - val_loss: 0.7733
Epoch 12/50
359/359 [==============================] - 1s 3ms/step - loss: 0.9364 - val_loss: 0.7737
Epoch 13/50
359/359 [==============================] - 1s 3ms/step - loss: 0.9351 - val_loss: 0.7769
Epoch 14/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9352 - val_loss: 0.7733
Epoch 15/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9356 - val_loss: 0.7764
Epoch 16/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9340 - val_loss: 0.7711
Epoch 17/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9345 - val_loss: 0.7696
Epoch 18/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9342 - val_loss: 0.7718
Epoch 19/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9328 - val_loss: 0.7788
Epoch 20/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9326 - val_loss: 0.7689
Epoch 21/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9321 - val_loss: 0.7702
Epoch 22/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9310 - val_loss: 0.7660
Epoch 23/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9306 - val_loss: 0.7652
Epoch 24/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9305 - val_loss: 0.7669
Epoch 25/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9288 - val_loss: 0.7694
Epoch 26/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9288 - val_loss: 0.7671
Epoch 27/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9276 - val_loss: 0.7721
Epoch 28/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9286 - val_loss: 0.7630
Epoch 29/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9264 - val_loss: 0.7688
Epoch 30/50
359/359 [==============================] - 1s 3ms/step - loss: 0.9268 - val_loss: 0.7611
Epoch 31/50
359/359 [==============================] - 1s 2ms/step - loss: 0.9254 - val_loss: 0.7648
Epoch 32/50
359/359 [==============================] - 1s 3ms/step - loss: 0.9260 - val_loss: 0.7648
Epoch 33/50
```

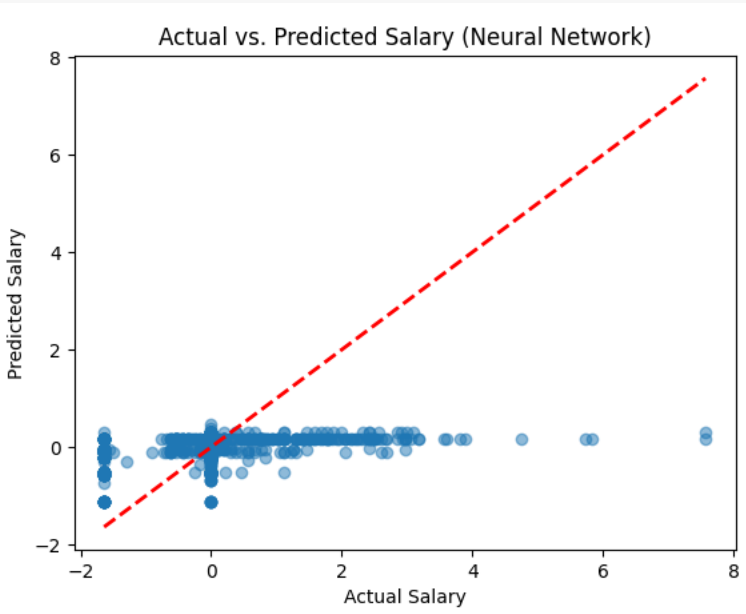
```
# Make predictions on the test data
y_pred_deep = model.predict(X_test)
```

```
45/45 [==============================] - 0s 1ms/step
```

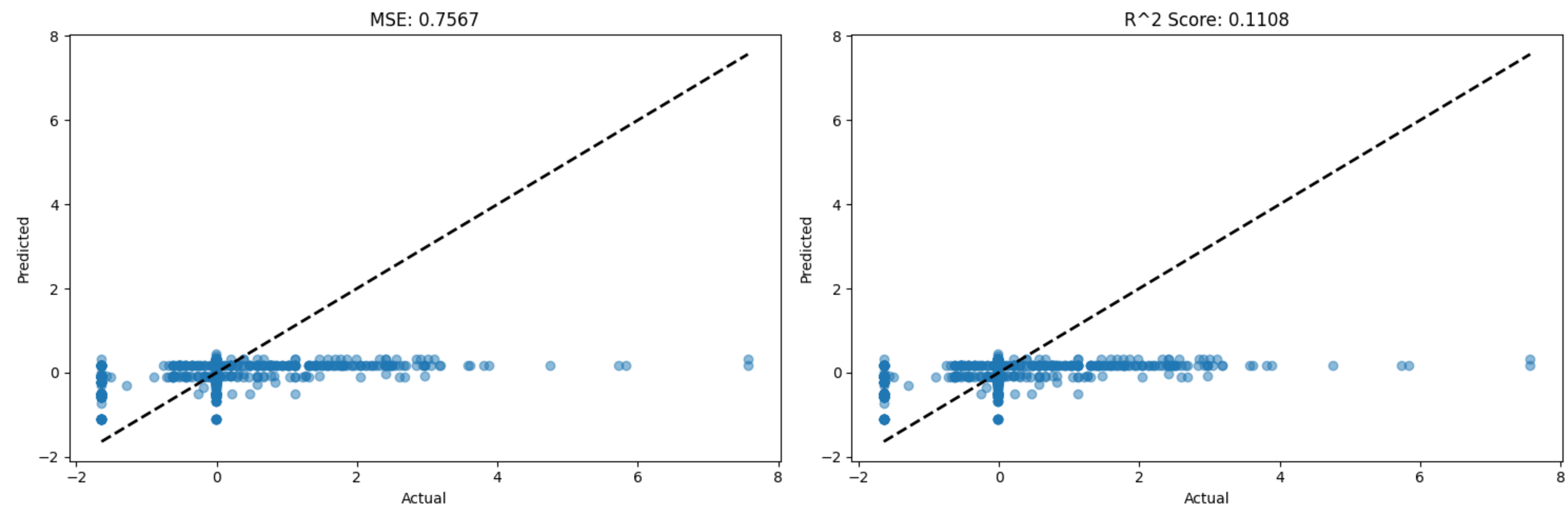
```
#Mean Squared Error and R^2 Score values
mse_deep = mean_squared_error(y_test, y_pred_deep)
print(f'Mean Squared Error: {mse_deep}')

r2_deep = r2_score(y_test, y_pred_deep)
print(f'R^2 Score: {r2_deep}')
```

```
Mean Squared Error: 0.7566598483452304
R^2 Score: 0.11077327513110047
```

```
#plot
plt.scatter(y_test, y_pred_deep, alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='--', linewidth=2)
plt.xlabel('Actual Salary')
plt.ylabel('Predicted Salary')
plt.title('Actual vs. Predicted Salary (Neural Network)')
plt.show()
```



```
# Plotting the evaluation metrics using plt library
fig, axs = plt.subplots(1, 2, figsize=(15, 5))

# Mean Squared Error (MSE)
axs[0].scatter(y_test, y_pred_deep, alpha=0.5)
axs[0].plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], 'k--', lw=2)
axs[0].set_title(f'MSE: {mse_deep:.4f}')
axs[0].set_xlabel('Actual')
axs[0].set_ylabel('Predicted')

# R^2 Score
axs[1].scatter(y_test, y_pred_deep, alpha=0.5)
axs[1].plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], 'k--', lw=2)
axs[1].set_title(f'R^2 Score: {r2_deep:.4f}')
axs[1].set_xlabel('Actual')
axs[1].set_ylabel('Predicted')

plt.tight_layout()
plt.show()
```



Ensemble model containing top 3 models overall

To capitalize on the advantages of each individual model, this ensemble model combines the predictions of the top three models (Random Forest, Gradient Boosting, and Deep Learning). By combining various predictions, ensemble methods frequently lead to better generalization performance and robustness.

The top 3 models overall are Random Forest, Gradient Boosting, and ELM

```
#Importing the RandomForestRegressor from sklearn library
from sklearn.ensemble import RandomForestRegressor

# Creating the model
random_forest_model = RandomForestRegressor(n_estimators=100,
                                            max_depth = 10,
                                            min_samples_split = 10,
                                            min_samples_leaf = 4,
                                            bootstrap = True,
                                            random_state=42)

# Training the model which is called fitting
random_forest_model.fit(X_train, y_train)
```

```
<ipython-input-44-9e01c217a0ef>:13: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
  random_forest_model.fit(X_train, y_train)
```

```
RandomForestRegressor
RandomForestRegressor(max_depth=10, min_samples_leaf=4, min_samples_split=10,
                      random_state=42)
```

```
# predicting on the test set
y_pred_rf = random_forest_model.predict(X_test)
```

```
#Importing the ensemble GradientBoostingRegressor from sklearn library
from sklearn.ensemble import GradientBoostingRegressor

# Creating the model
gradient_boosting_model = GradientBoostingRegressor(n_estimators=100, random_state=42)

# Training the model which is called fitting
gradient_boosting_model.fit(X_train, y_train)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_gb.py:437: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ),
  y = column_or_1d(y, warn=True)
```

```
GradientBoostingRegressor
GradientBoostingRegressor(random_state=42)
```

```
# Predicting on the test set
y_pred_gradient_boosting = gradient_boosting_model.predict(X_test)
```

```
#Importing the KNeighborsRegressor from sklearn library
from sklearn.neighbors import KNeighborsRegressor

# Creating the model
knn_model = KNeighborsRegressor(n_neighbors=31)

# Training the model which is called fitting
knn_model.fit(X_train, y_train)
```

```
KNeighborsRegressor
KNeighborsRegressor(n_neighbors=31)
```

```
y_pred_knn = knn_model.predict(X_test)
```

Now, lets create the ensemble model using the top 3 models of the project. Using Voting Regressor we can predict the accurate salary.

```
#Importing VotingRegressor from sklearn ensemble library
from sklearn.ensemble import VotingRegressor

# Creating the ensembel model with top 3 models
ensemble_model = VotingRegressor(estimators=[
    ('rf', random_forest_model),
    ('gb', gradient_boosting_model),
    ('knn', knn_model)
])
```

```
#Traing the model
ensemble_model.fit(X_train, y_train)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/ensemble/_voting.py:597: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples
  y = column_or_1d(y, warn=True)
```

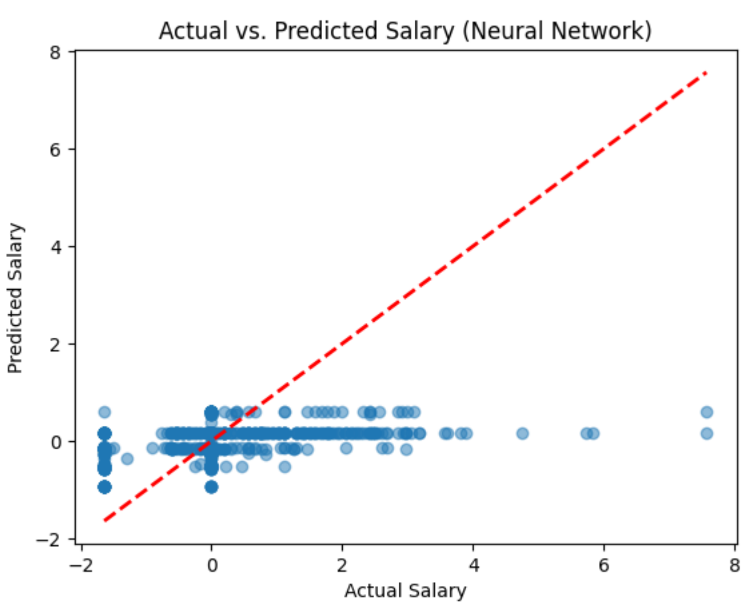
```
VotingRegressor
rf                       gb                           knn
RandomForestRegressor    GradientBoostingRegressor    KNeighborsRegressor
```

```
#Predicting on the test set
y_pred_ensemble = ensemble_model.predict(X_test)
```

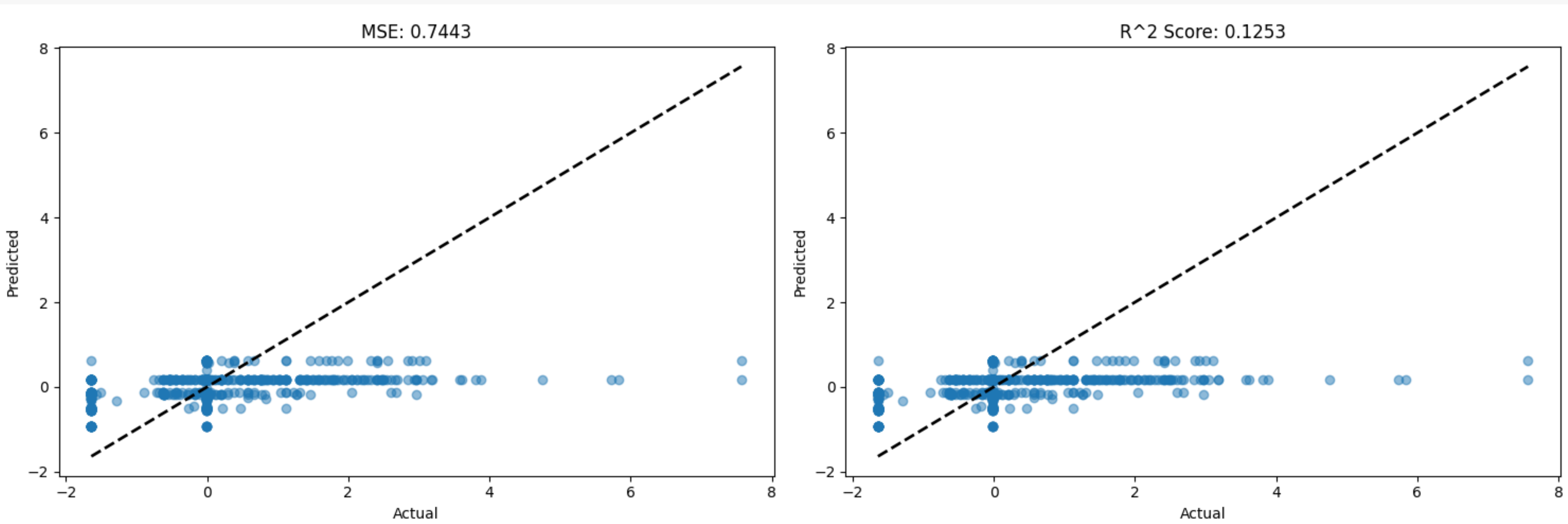
```
#Mean Squared Error and R^2 Score values
mse_ensemble = mean_squared_error(y_test, y_pred_ensemble)
print("MSE for Ensemble Model:", mse_ensemble)

r2_ensemble = r2_score(y_test, y_pred_ensemble)
print("R^2 Score for Ensemble Model:", r2_ensemble)
```

```
MSE for Ensemble Model: 0.7443307426501466
R^2 Score for Ensemble Model: 0.1252624413023703
```

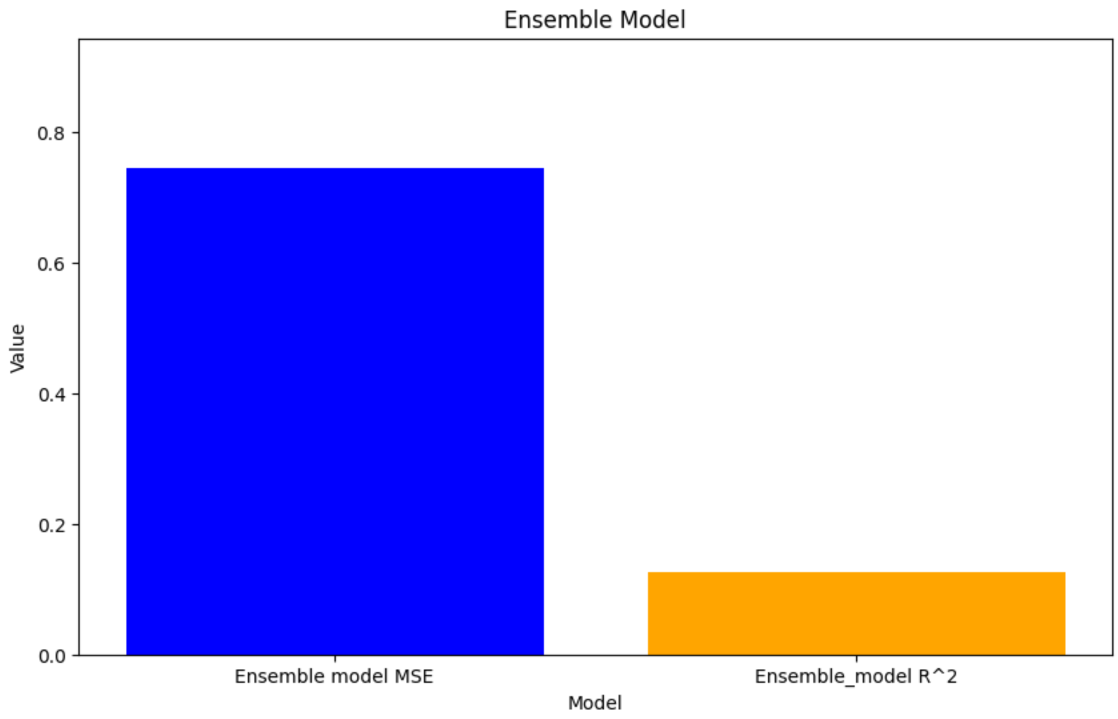
```
#plot
plt.scatter(y_test, y_pred_ensemble, alpha=0.5)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linestyle='--', linewidth=2)
plt.xlabel('Actual Salary')
plt.ylabel('Predicted Salary')
plt.title('Actual vs. Predicted Salary (Neural Network)')
plt.show()
```




```
# Plotting the evaluation metrics using plt library
fig, axs = plt.subplots(1, 2, figsize=(15, 5))

# Mean Squared Error (MSE)
axs[0].scatter(y_test, y_pred_ensemble, alpha=0.5)
axs[0].plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], 'k--', lw=2)
axs[0].set_title(f'MSE: {mse_ensemble:.4f}')
axs[0].set_xlabel('Actual')
axs[0].set_ylabel('Predicted')

# R^2 Score
axs[1].scatter(y_test, y_pred_ensemble, alpha=0.5)
axs[1].plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], 'k--', lw=2)
axs[1].set_title(f'R^2 Score: {r2_ensemble:.4f}')
axs[1].set_xlabel('Actual')
axs[1].set_ylabel('Predicted')

plt.tight_layout()
plt.show()
```



```
#List of all the models we have created
model= ['Ensemble model MSE','Ensemble_model R^2']
values = [mse_ensemble,r2_ensemble]

# Bar plot
plt.figure(figsize=(10, 6))
plt.bar(model, values, color=['blue', 'orange'])
plt.xlabel('Model')
plt.ylabel('Value')
plt.title('Ensemble Model')
plt.ylim(0, max(values) + 0.2)
plt.show()
```



Using ensemble model we got the best performance over our data. The MSE value obtained from ensemble is 0.7443 which is less than any other model but not that less compared to our top three models. This completly depends upon the selection perspective of the users in selecting best hyperparameters, selecting best models,