Evaluating Performance of a Regressor

Regression Model produces numeric output.

How much is my home worth?

How many passengers are going to travel by air this year?

To find out how good the model predictions are, we need to check predictions against previously unseen samples that were not used for training. Usually, 30% of the available samples are reserved for testing while remaining 70% of samples are used for training.

By comparing predicted values against known results in test data, we can assess overall model performance

Common Techniques for evaluating performance:

- Visually observe using Plots
- Residual Histograms
- Evaluate with Metrics like Root Mean Square Error (RMSE)

While Plots are good for humans to visually observe the results, we often need a single metric that can indicate quality of a model. This can be useful for programmatically identifying which model is performing better (for example: using automatic model tuning to select the best performing model)

Reference:
https://docs.aws.amazon.com/machine-learning/latest/dg/evaluating-model-accuracy.html
RMSE:
https://en.wikipedia.org/wiki/Root-mean-square_deviation
Mean Absolute Error:
https://en.wikipedia.org/wiki/Mean_absolute_error

Allowing Dave's re-typing of the code

In [25]:

```
do_code_of_dave = False

## Quick and Reckless, starting
!date +'%s_%Y%m%dT%H%M%S'
```

```
1689633685_20230717T224125
```

In [2]:

```
if not do_code_of_dave:
    import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
```

In [3]:
```
if not do_code_of_dave:
    from sklearn.metrics import mean_squared_error, mean_absolute_error
```

Dave's re-typing of the code

In [19]:
```
!date +'%s_%Y%m%dT%H%M%S'
```

```
1689631362_20230717T220242
```

In [20]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error, mean_absolute_error

#  Do we not need:
#+    %matplotlib inline
#+ on AWS Jupyter, or did I somehow delete it when
#+ things were wonky the first time I came to the
#+ notebook?

do_need_magic = False
if do_need_magic:
    %matplotlib inline
```

Air Passengers Data

Columns

- Passengers = Actual Number of passengers who traveled by air
- Model1_Prediction = Number of Passengers predicted by model 1
- Model2_Prediction = Number of Passengers predicted by model 2
- Model3_Prediction = Number of Passengers predicted by model 3
- Model4_Prediction = Number of Passengers predicted by model 4

We are going to compare performance of these four models

World Bank Air Traffic Passengers Dataset:
https://data.worldbank.org/indicator/NY.GDP.MKTP.CD
https://data.worldbank.org/indicator/SP.POP.TOTL

In [9]:
```
if not do_code_of_dave:
    models = ['Model 1','Model 2', 'Model 3', 'Model 4']
    df_air = pd.read_csv('airpassengers_sample.csv',index_col=0)
```

In [10]:
```
if not do_code_of_dave:
    df_air
```

Dave's re-typing of the code

In [11]:
```
models = ['Model 1', 'Model 2', 'Model 3', 'Model 4']
df_air = pd.read_csv('airpassengers_sample.csv', index_col=0)
```

In [12]:
```
df_air
```

Out[12]:

	GDP	Population	Passengers	Model1_Prediction	Model2_Prediction	Model3_Prediction	M
Year							
2008	14.72	304.09	701.78	710	701	850	
2009	14.42	306.77	679.42	650	670	450	
2010	14.96	309.34	720.50	700	715	1000	
2011	15.52	311.64	730.80	750	735	550	
2012	16.16	313.99	736.70	769	740	700	
2013	16.69	316.23	743.17	800	740	900	
2014	17.43	318.62	762.71	745	760	1100	
2015	18.12	321.04	798.22	780	790	1200	
2016	18.62	323.41	824.04	800	825	1500	
2017	19.39	325.72	849.40	875	855	1600	

Plot Data

Compare performance visually

In [15]:
```
if not do_code_of_dave:
    plt.figure(figsize=(10,10))

    # Plot Actual versus predictions by each model
    # We are going to draw 4 plots in a 2 x 2 grid
    # 221 = 2 rows, 2 columns, 1st sub plot
    # 222 = 2 rows, 2 columns, 2nd sub plot
    # and so forth

    # Model 1
    plt.subplot(221)
    plt.plot(df_air['Passengers'], label='Actual')
    plt.plot(df_air['Model1_Prediction'],label='Model 1')
    plt.xlabel('Year')
    plt.ylabel('Passengers (Millions)')
    plt.legend()

    # Model 2
    plt.subplot(222)
    plt.plot(df_air['Passengers'], label='Actual')
    plt.plot(df_air['Model2_Prediction'],label='Model 2')
    plt.xlabel('Year')
```

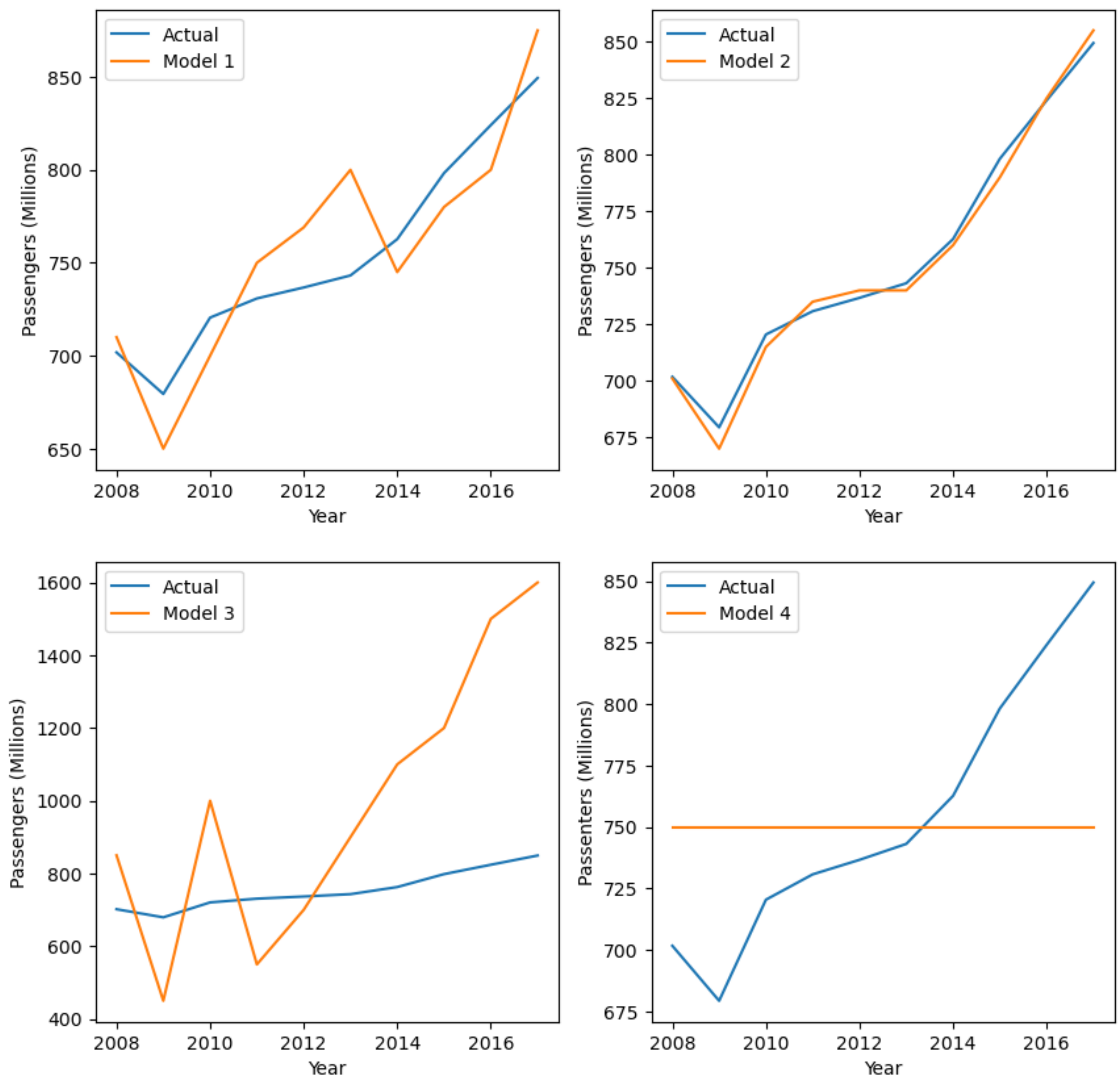
```
    plt.ylabel('Passengers (Millions)')
    plt.legend()

    # Model 3
    plt.subplot(223)
    plt.plot(df_air['Passengers'], label='Actual')
    plt.plot(df_air['Model3_Prediction'],label='Model 3')
    plt.xlabel('Year')
    plt.ylabel('Passengers (Millions)')
    plt.legend()

    # Model 4
    plt.subplot(224)
    plt.plot(df_air['Passengers'], label='Actual')
    plt.plot(df_air['Model4_Prediction'],label='Model 4')
    plt.xlabel('Year')
    plt.ylabel('Passengers (Millions)')
    plt.legend()

    plt.show()
```

Dave's re-typing of the code

In [24]:

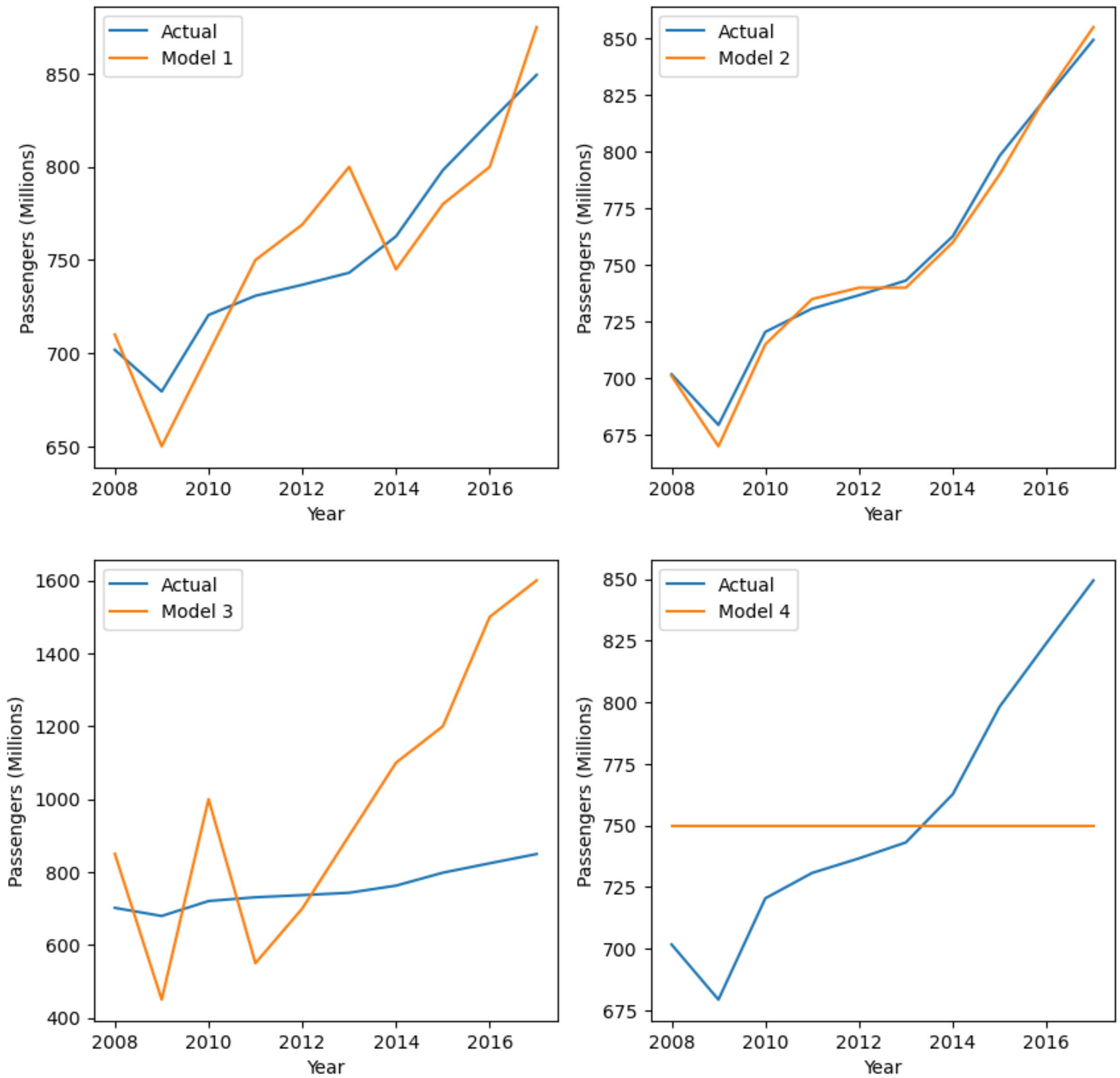
```
plt.figure(figsize=(10,10))

# Plot Actual versus Predictions by each model
# We will draw 4 plots in a 2 x 2 grid
#DWB# Nice review for me
# 221 = 2 rows, 2 columns, 1st sub plot
#DWB# That will be top-left, but what about the others?
# 222 = 2 rows, 2 columns, 2nd sub plot
#DWB# That ends up being ___ in the upper-right
# and so forth
#DWB# I'm doing the so forth
#DWB# 223 = 2 rows, 2 columns, 3rd sub plot
#DWB# That ends up being ___ in the lower-left
#DWB# 224 = 2 rows, 2 columns, 4th sub plot
#DWB# That ends up being ___ in the lower-right

# Model 1: in upper-left as expected
plt.subplot(221)
plt.plot(df_air['Passengers'], label='Actual')
plt.plot(df_air['Model1_Prediction'], label="Model 1")
plt.xlabel('Year')
plt.ylabel('Passengers (Millions)')
plt.legend()

# Model 2: in upper-right
plt.subplot(222)
plt.plot(df_air['Passengers'], label='Actual')
plt.plot(df_air['Model2_Prediction'], label="Model 2")
plt.xlabel('Year')
plt.ylabel('Passengers (Millions)')
plt.legend()
```

```
# Model 3: in lower-left
plt.subplot(223)
plt.plot(df_air['Passengers'], label='Actual')
plt.plot(df_air['Model3_Prediction'], label='Model 3')
plt.xlabel('Year')
plt.ylabel('Passengers (Millions)')
plt.legend()

# Model 4: in lower-right
plt.subplot(224)
plt.plot(df_air['Passengers'], label='Actual')
plt.plot(df_air['Model4_Prediction'], label='Model 4')
plt.xlabel('Year')
plt.ylabel('Passenters (Millions)')
plt.legend()

plt.show()
```



In [26]:
```
if not do_code_of_dave:
    # Same plot as above...more concise code
    plt.figure(figsize=(10,10))
```

```
    for idx, model in enumerate(models):
        plt.subplot(2,2,idx+1)
        plt.plot(df_air['Passengers'], label='Actual')
        plt.plot(df_air[model.replace(' ','') + '_Prediction'],
                 label=model)
        plt.xlabel('Year')
        plt.ylabel('Passengers (Millions)')
        plt.legend()
```



Dave's re-typing of the code

In [ ]:
```
## I was thinking of doing this myself as I went through typing the code
## Same plot as above ... more concise code
#plt.figure(figsize=(10,10))
#
#for idx, model in enumerate(models):
#    plt.subplot(2,2,idx+1)
#    plt.plot(df_air['Passengers'], label='Actual')
#
```

```
#
# I'm going to do 'good enough'. No more retyping, just look through code, line-by-
```

From the plots, we can observe that Model 1 and Model 2 appears to be pretty close to actuals. Model 3 plot is not matching with actuals. Model 4 is predicting a constant value

Root Mean Square Error (RMSE)

Compares Actual and Predicted values and arrives at a single metric.
Smaller RMSE value indicates better predictive quality.
Let's compute the RMSE metric for each of the models

In [27]:
```
if not do_code_of_dave:
    # RMSE
    for model in models:
        print (model)
        mse = mean_squared_error(df_air['Passengers'],
                                 df_air[model.
                                        replace(' ','') + '_Prediction'])
        print(" Mean Squared Error: {0:.2f}".format(mse))
        print(" Root Mean Square Error: {0:.2f}".format(mse**.5))
```

```
Model 1
 Mean Squared Error: 787.38
 Root Mean Square Error: 28.06
Model 2
 Mean Squared Error: 26.54
 Root Mean Square Error: 5.15
Model 3
 Mean Squared Error: 150686.81
 Root Mean Square Error: 388.18
Model 4
 Mean Squared Error: 2661.81
 Root Mean Square Error: 51.59
```

Dave's re-typing of the code

In [ ]:

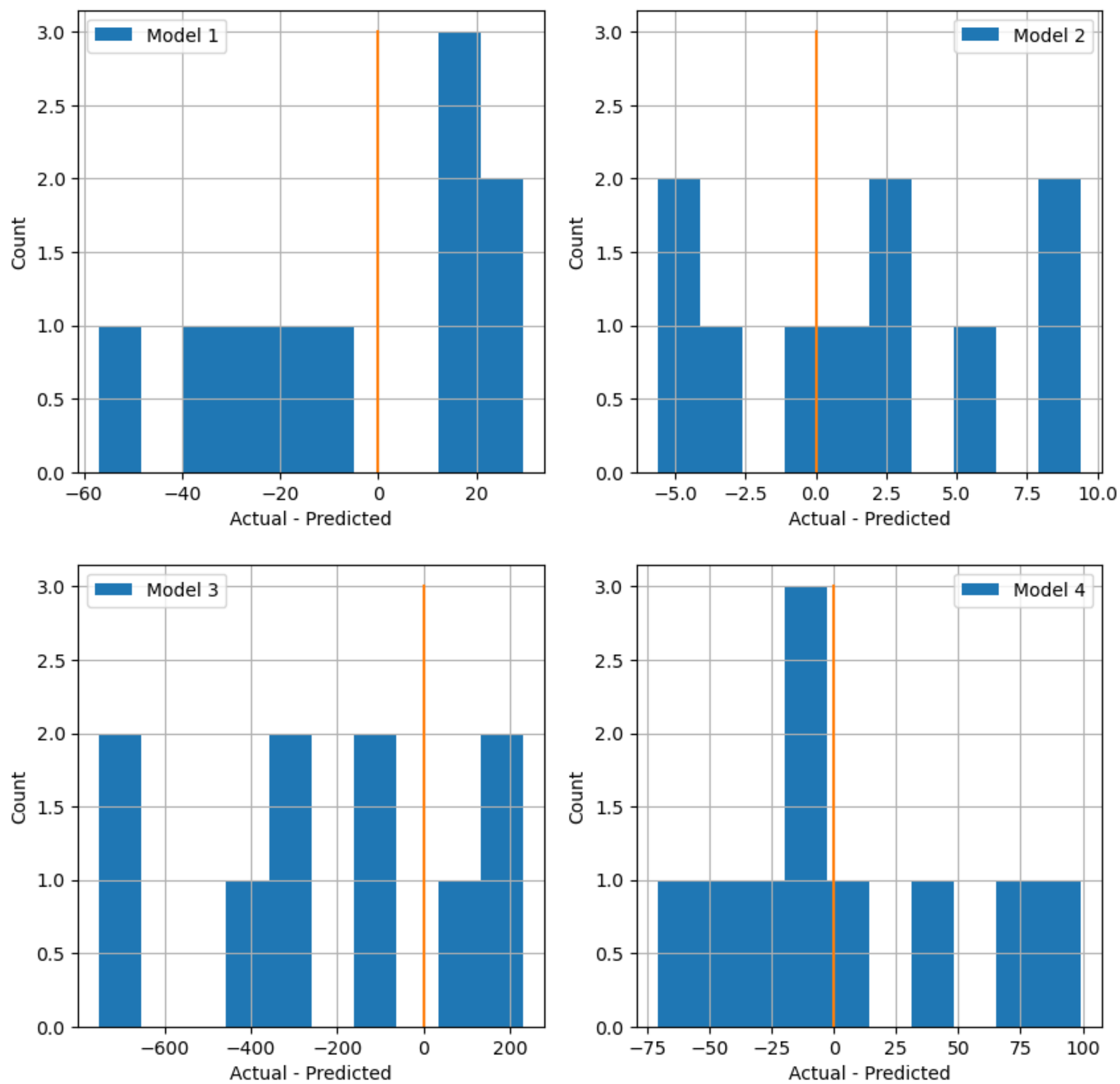
We can confirm using RMSE that Model 2 produces best outcome

Residual Histograms

"A residual for an observation in the evaluation data is the difference between the true target and the predicted target. The histogram of the residuals on the evaluation data when distributed in a bell shape and centered at zero indicates that the model makes mistakes in a random manner and does not systematically over or under predict any particular range of target values"

Reference: https://docs.aws.amazon.com/machine-learning/latest/dg/regression-model-insights.html

In [28]:
```
if not do_code_of_dave:
    plt.figure(figsize=(10,10))

    for idx, model in enumerate(models):
        plt.subplot(2,2,idx+1)
        residual = df_air['Passengers'] - df_air[model.replace(' ','') + '_Predicti

        plt.hist(residual,
                 label=model)
        plt.plot([0,0],[0,3])
        plt.xlabel('Actual - Predicted')
        plt.ylabel('Count')
        plt.grid()
        plt.legend()
```



Dave's re-typing of the code

In [ ]:

In [29]:
```
if not do_code_of_dave:
    # Let's print actual counts
    # How many under predictions and over predictions
    # Actual - Predicted
    # Positive Value indicates Actual is more than predicted (under estimation)
    # Negative Value indicates Actual is less than predicted (over estimation)
    # Since our test dataset has only 10 samples, it hard to find patterns.
    # But, even here, Model 3 appears to be different from other models
    # as it over predicting for larger number of samples

    for model in models:
        print (model)
        residual = df_air['Passengers'] - df_air[model.replace(' ','') + '_Predicti
        # Count number of values greater than zero and less than zero
        value_counts = (residual > 0).value_counts(sort=False)

        print(' Under Estimation: ', value_counts[True]) # difference is greater th
        print(' Over  Estimation: ',  value_counts[False]) # difference is less tha
```

```
Model 1
 Under Estimation:  5
 Over  Estimation:  5
Model 2
 Under Estimation:  6
 Over  Estimation:  4
Model 3
 Under Estimation:  3
 Over  Estimation:  7
Model 4
 Under Estimation:  4
 Over  Estimation:  6
```

Dave's re-typing of code

In [ ]:

Summary

In this example, Model 2 has the best performance followed by Model 1.
We can confirm this by visual observation using plots and by comparing RMSE metrics