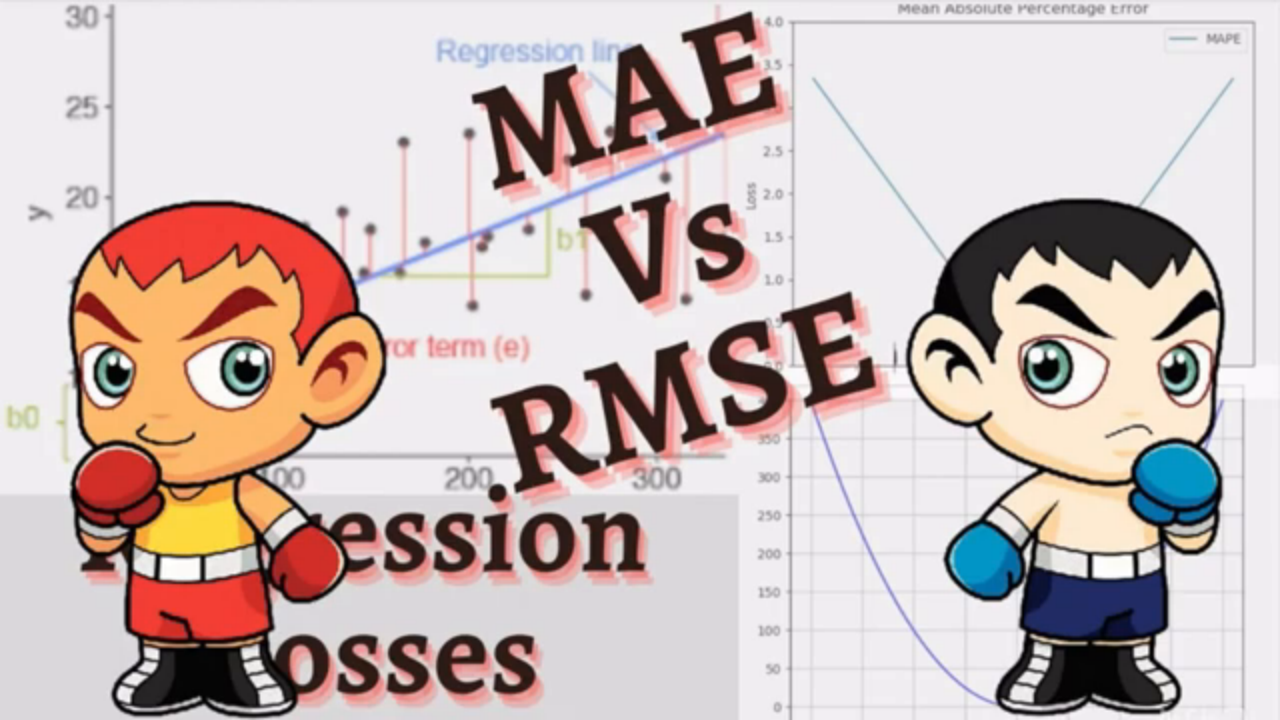
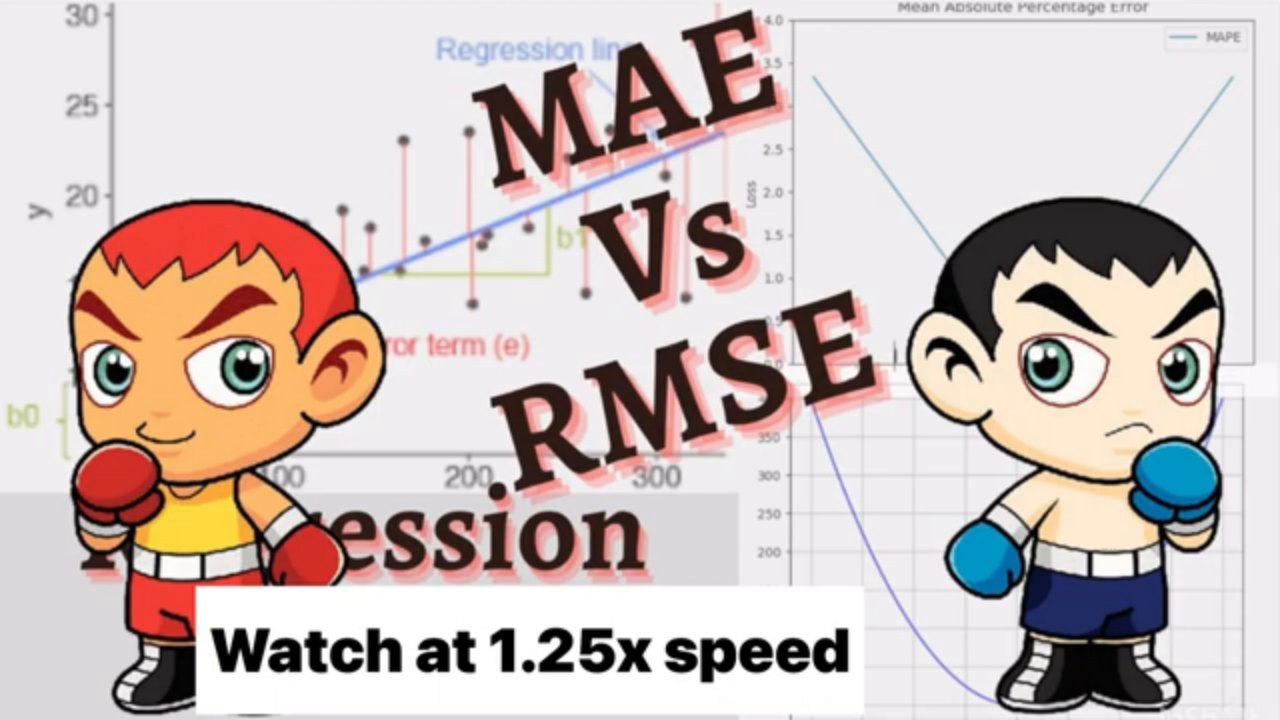
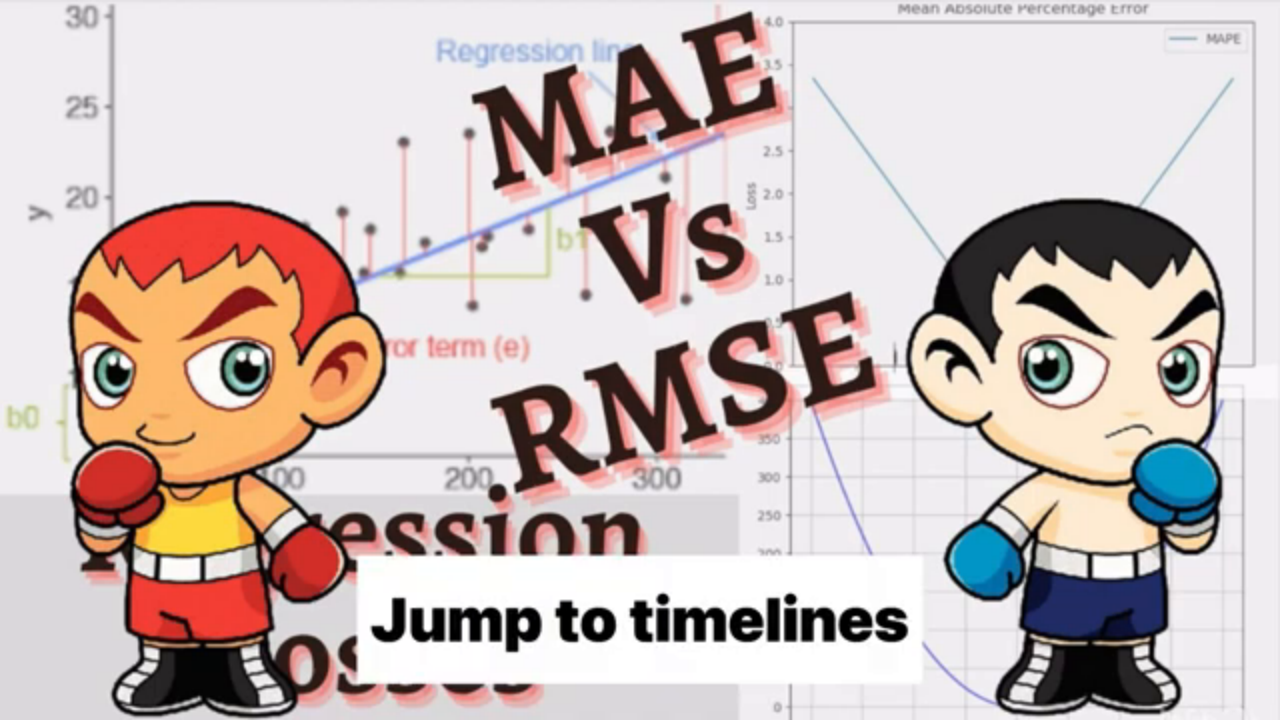
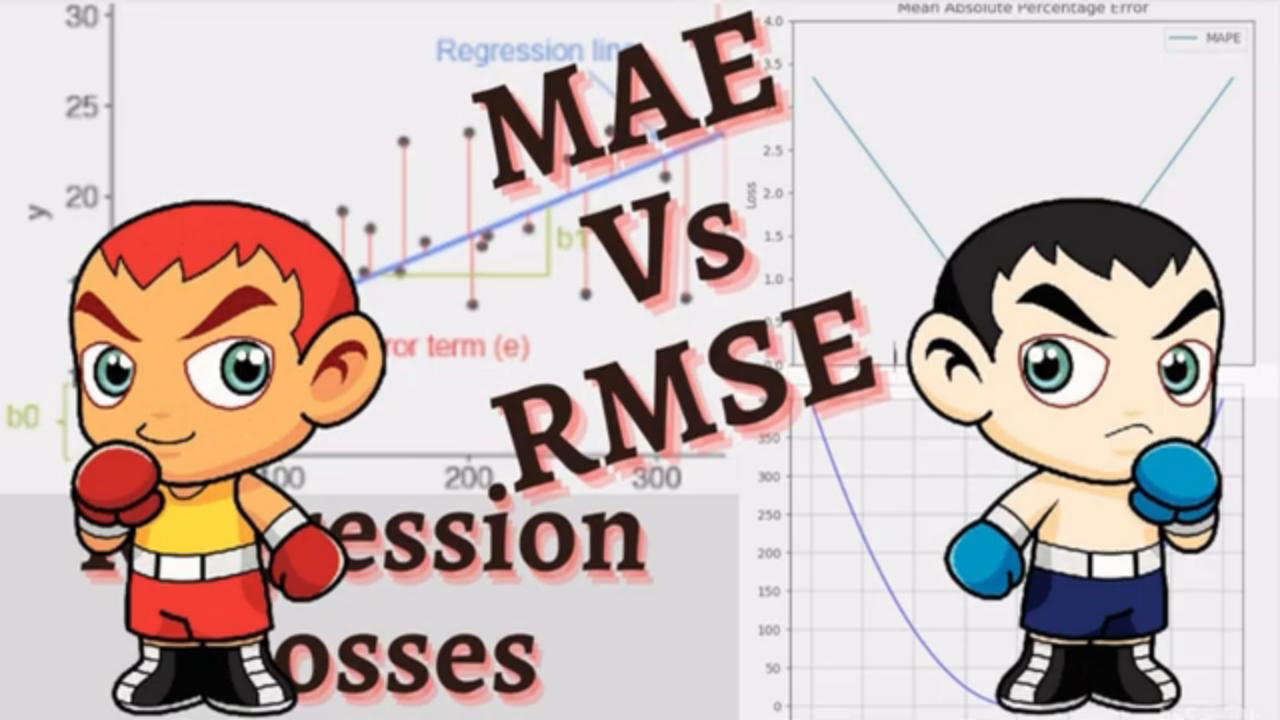

MAE
Vs
RMSE
Regression losses
Regression line
Mean Absolute Percentage Error
MAPE
Loss


MAE
Vs
RMSE
Watch at 1.25x speed


MAE
Vs
RMSE
Jump to timelines


MAE
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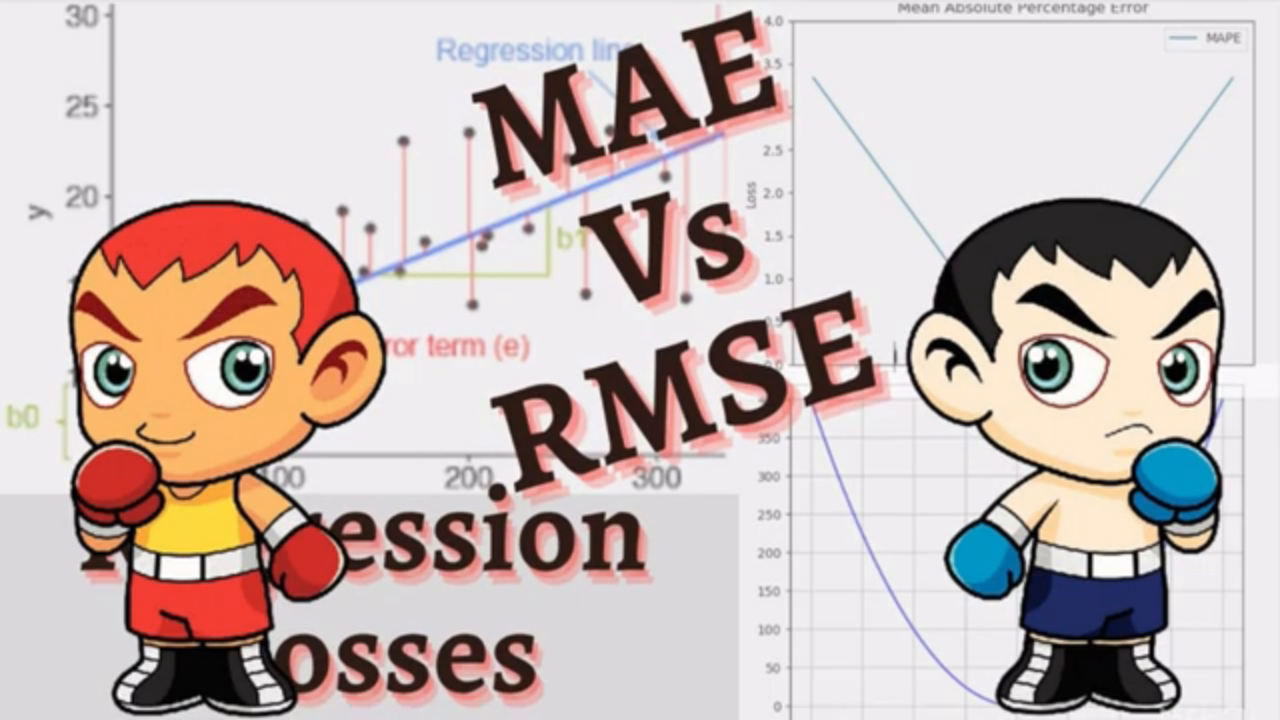
y
b0
b1
or term (e)
30
25
20
200
300
4.0
3.5
2.5
2.0
1.5
1.0
350
300
250
200
150
100
50
0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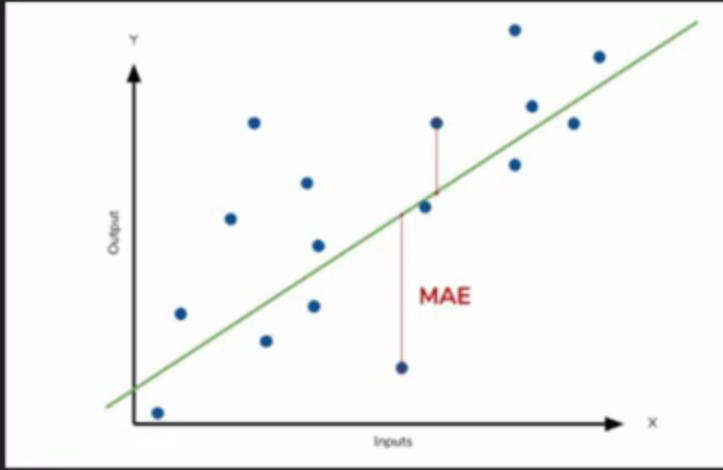
MAE (Mean Absolute Error)

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j|$$



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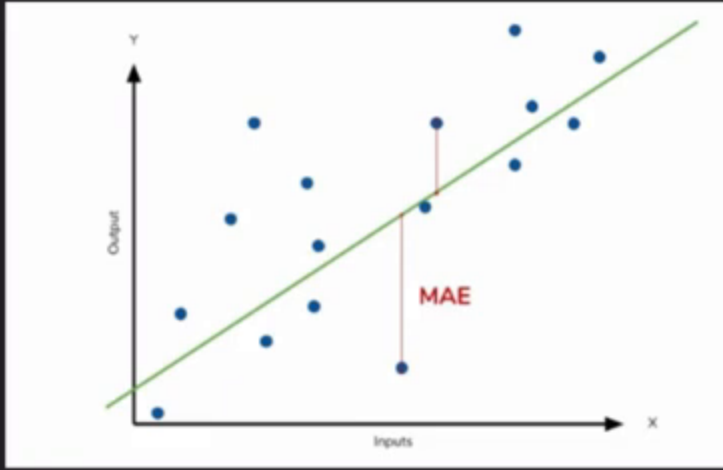

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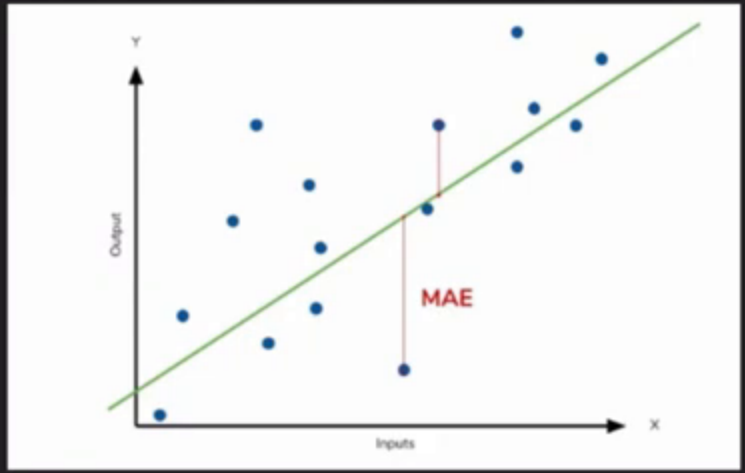

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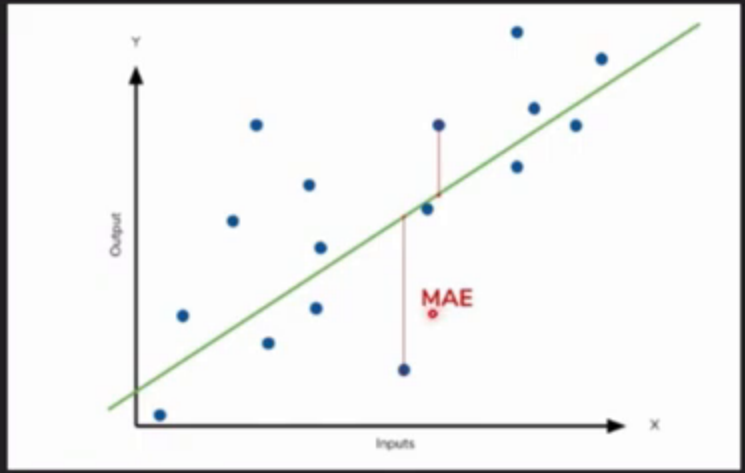

MSE (Mean Squared Error)

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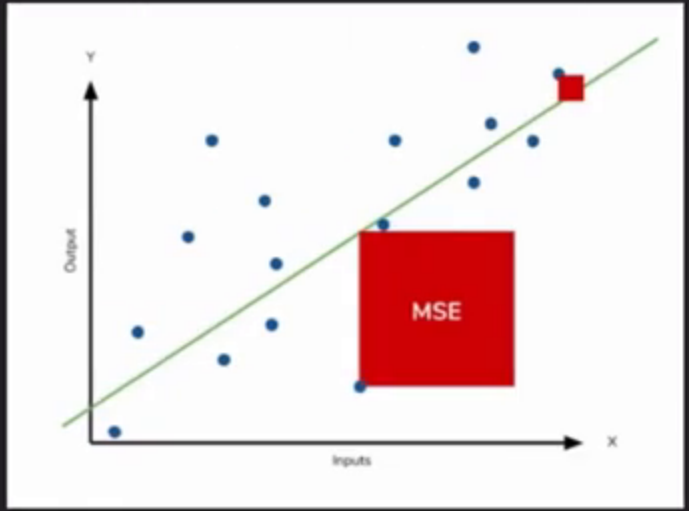
The square of the difference between actual and predicted



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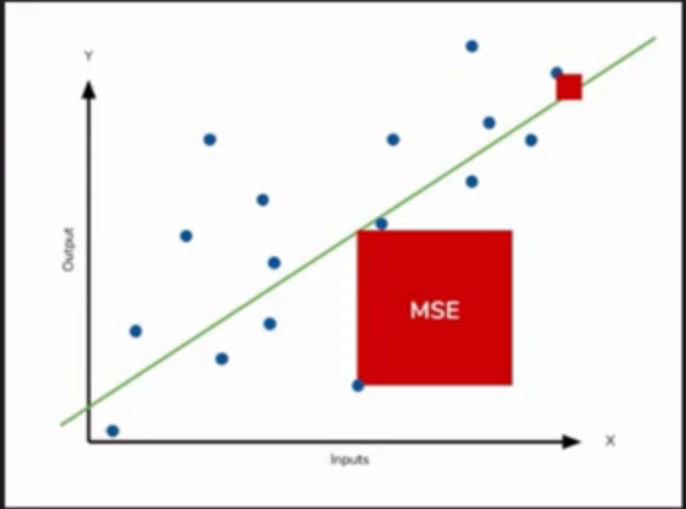

RMSE (Root Mean Squared Error)

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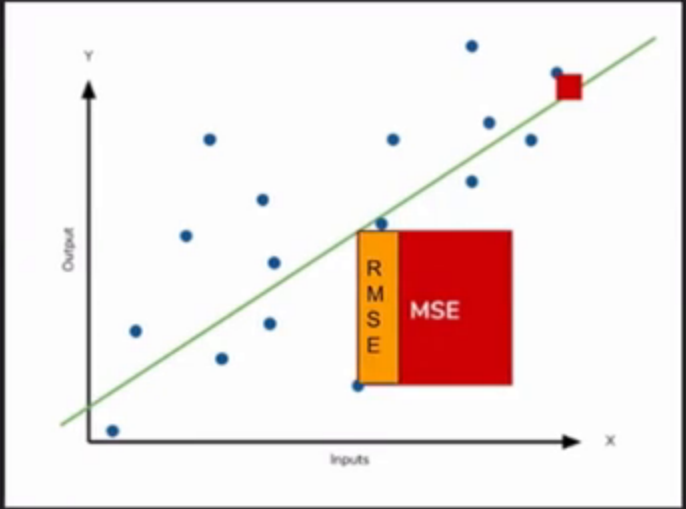

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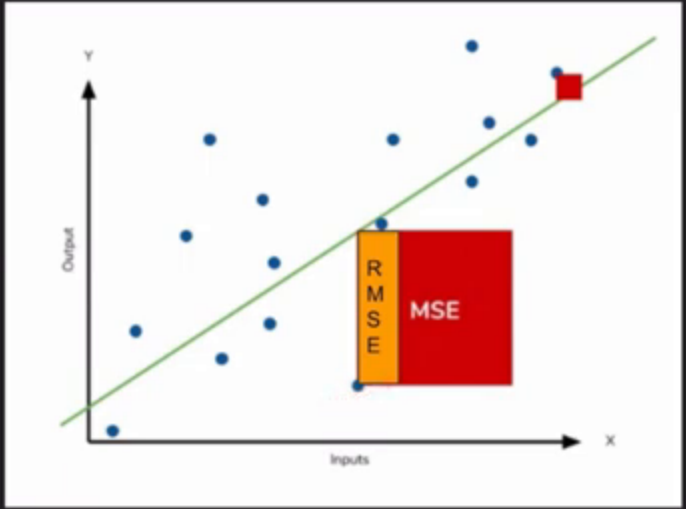

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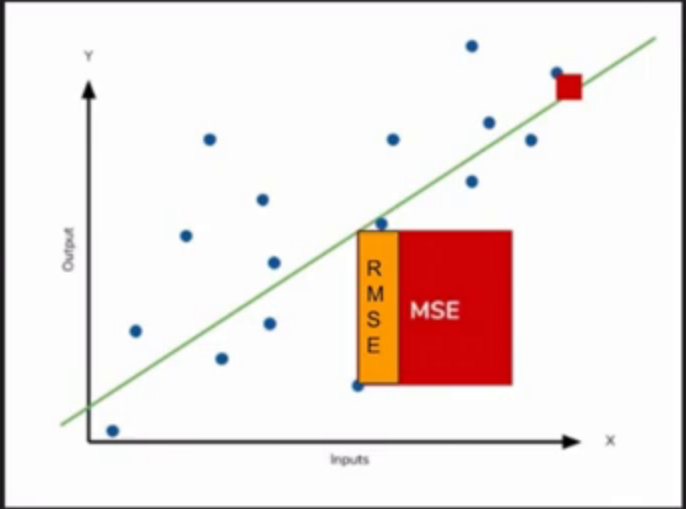

Similarities

- Distance based metrics
- Negatively oriented scores - lower values are better
- Range - 0 to ∞
- Mean or Average prediction across whole dataset

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Differences

- MSE or RMSE gives high weightage to large errors
- MAE treats all errors the same way
- MAE <= RMSE
- MAE is easily interpretable
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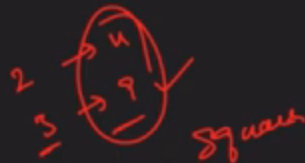

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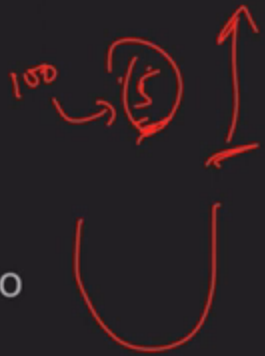

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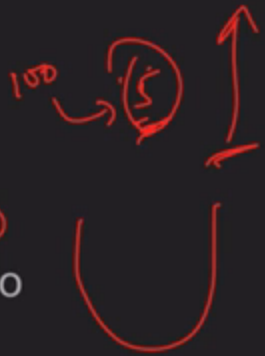

```
[ ] import numpy as np
    import seaborn as sns
    import matplotlib.pyplot as plt
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Definitions of MAE, MSE, RMSE

[ ] 1 cell hidden

Create random sample data

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Helper function for creating noisy data and plotting the charts

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+ Code + Text

Connect Editing

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Connected to
Python 3 Google Compute Engine backend

RAM: 0.81 GB/12.68 GB Disk: 22.54 GB/107.72 GB

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Definitions of MAE, MSE, RMSE

```
[ ] def mae(data, ref):
        mae = 0
        c = 0
        for i in data:
          mae += abs(i-ref)
          c += 1
        return mae / c

    def mse(data, ref):
        mse = 0
        c = 0
        for i in data:
          mse += (i-ref)**2
          c += 1
        return mse / c

    def rmse(data, ref):
        return (mse(data, ref))**(1/2)
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Create random sample data

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[ ] num_sets = 1000
    num_points = 1000

    # Generates x sets with y data points each
    data = np.random.normal(100, 20, (num_sets, num_points))
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Helper function for creating noisy data and plotting the charts

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Helper function for creating noisy data and plotting the charts

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[ ] def evaluate_metrics(data, num_outliers, amplitude_outliers):

        # Sample random "num_ouliers" points for each set
        noise = np.random.uniform(0, num_points, (num_sets, num_outliers))

        # Lists to keep the metrics for all original sets
        mae_original = []
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+ Code + Text

RAM Disk

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        # For each observation set, evaluates all three distances to the mean of the set
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[ ]  mse_original = []
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     # Lists to keep the metrics for all noisy sets
     mae_noisy = []
     mse_noisy = []
     rmse_noisy = []

     # For each observation set, evaluates all three distances to the mean of the set
     for i in range(data.shape[0]):
         # Recovers the observations
         observations = data[i]
         # Create a noisy verion of the data with the randomly-chosen outliers
         outliers = [int(i) for i in noise[i]]
         observations_noisy = []
         c  = 0
         for x in observations:
             if c in outliers:
                 observations_noisy.append(x * amplitude_outliers)
             else:
                 observations_noisy.append(x)
             c += 1

         # Calculates the mean value of the set.
         # It is important to use the mean of the original set in both cases, to prevent it from shifting and altering the resu
         set_mean = np.mean(observations)

         # Evaluate the metrics
         mae_original.append(mae(observations, set_mean))
         mse_original.append(mse(observations, set_mean))
         rmse_original.append(rmse(observations, set_mean))
         mae_noisy.append(mae(observations_noisy, set_mean))
         mse_noisy.append(mse(observations_noisy, set_mean))
```

```
[ ]                observations_noisy.append(x)
            c += 1

        # Calculates the mean value of the set.
        # It is important to use the mean of the original set in both cases, to prevent it from shifting and altering the resu
        set_mean = np.mean(observations)

        # Evaluate the metrics
        mae_original.append(mae(observations, set_mean))
        mse_original.append(mse(observations, set_mean))
        rmse_original.append(rmse(observations, set_mean))
        mae_noisy.append(mae(observations_noisy, set_mean))
        mse_noisy.append(mse(observations_noisy, set_mean))
        rmse_noisy.append(rmse(observations_noisy, set_mean))

    # Plots all
    plt.figure(figsize=(12, 4))
    ax1 = plt.subplot(1, 3, 1)
    ax2 = plt.subplot(1, 3, 2)
    ax3 = plt.subplot(1, 3, 3)
    sns.histplot(mae_original, ax = ax1, color = 'maroon', kde = True, fill = False)
    sns.histplot(mae_noisy, ax = ax1, color = 'r', kde = True)
    sns.histplot(rmse_original, ax = ax2, color = 'darkgreen', kde = True, fill = False)
    sns.histplot(rmse_noisy, ax = ax2, color = 'g', kde = True)
    sns.histplot(mse_original, ax = ax3, color = 'darkblue', kde = True, fill = False)
    sns.histplot(mse_noisy, ax = ax3, color = 'b', kde = True)
    ax1.legend(["Original", "Noisy"], loc = 'lower right')
    ax2.legend(["Original", "Noisy"], loc = 'lower right')
    ax3.legend(["Original", "Noisy"], loc = 'lower right')
    ax1.set_title("MAE")
    ax2.set_title("RMSE")
```

+ Code + Text

RAM Disk

Editing

```
[ ]                observations_noisy.append(x)
            c += 1

        # Calculates the mean value of the set.
        # It is important to use the mean of the original set in both cases, to prevent it from shifting and altering the resu
        set_mean = np.mean(observations)

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        mse_original.append(mse(observations, set_mean))
        rmse_original.append(rmse(observations, set_mean))
        mae_noisy.append(mae(observations_noisy, set_mean))
        mse_noisy.append(mse(observations_noisy, set_mean))
        rmse_noisy.append(rmse(observations_noisy, set_mean))

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    sns.histplot(mae_noisy, ax = ax1, color = 'r', kde = True)
    sns.histplot(rmse_original, ax = ax2, color = 'darkgreen', kde = True, fill = False)
    sns.histplot(rmse_noisy, ax = ax2, color = 'g', kde = True)
    sns.histplot(mse_original, ax = ax3, color = 'darkblue', kde = True, fill = False)
    sns.histplot(mse_noisy, ax = ax3, color = 'b', kde = True)
    ax1.legend(["Original", "Noisy"], loc = 'lower right')
    ax2.legend(["Original", "Noisy"], loc = 'lower right')
    ax3.legend(["Original", "Noisy"], loc = 'lower right')
    ax1.set_title("MAE")
    ax2.set_title("RMSE")
```

```
[ ]         # Evaluate the metrics
            mae_original.append(mae(observations, set_mean))
            mse_original.append(mse(observations, set_mean))
            rmse_original.append(rmse(observations, set_mean))
            mae_noisy.append(mae(observations_noisy, set_mean))
            mse_noisy.append(mse(observations_noisy, set_mean))
            rmse_noisy.append(rmse(observations_noisy, set_mean))

        # Plots all
        plt.figure(figsize=(12, 4))
        ax1 = plt.subplot(1, 3, 1)
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        sns.histplot(mae_original, ax = ax1, color = 'maroon', kde = True, fill = False)
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        sns.histplot(rmse_original, ax = ax2, color = 'darkgreen', kde = True, fill = False)
        sns.histplot(rmse_noisy, ax = ax2, color = 'g', kde = True)
        sns.histplot(mse_original, ax = ax3, color = 'darkblue', kde = True, fill = False)
        sns.histplot(mse_noisy, ax = ax3, color = 'b', kde = True)
        ax1.legend(["Original", "Noisy"], loc = 'lower right')
        ax2.legend(["Original", "Noisy"], loc = 'lower right')
        ax3.legend(["Original", "Noisy"], loc = 'lower right')
        ax1.set_title("MAE")
        ax2.set_title("RMSE")
        ax3.set_title("MSE")
        plt.tight_layout()
```

+ Code + Text

RAM Disk

Editing

```
[4]  ax3.legend(["Original", "Noisy"], loc = "lower right")
     ax1.set_title("MAE")
     ax2.set_title("RMSE")
     ax3.set_title("MSE")
     plt.tight_layout()
```

evaluate

+ Code + Text

RAM Disk

Editing

```
[4]     ax3.legend(["Original", "Noisy"], loc = "lower right")
        ax1.set_title("MAE")
        ax2.set_title("RMSE")
        ax3.set_title("MSE")
        plt.tight_layout()
```

```
evaluate_metrics(data, num_outliers=0)
```

s here

+ Code + Text

RAM Disk

Editing

```
[4]     ax3.legend(["Original", "Noisy"], loc = "lower right")
        ax1.set_title("MAE")
        ax2.set_title("RMSE")
        ax3.set_title("MSE")
        plt.tight_layout()
```

```
evaluate_metrics(data, num_outliers=0, amplitude_outliers=0)
```

+ Code + Text

RAM Disk

Editing

```
[4]     ax3.legend(["Original", "Noisy"], loc = "lower right")
        ax1.set_title("MAE")
        ax2.set_title("RMSE")
        ax3.set_title("MSE")
        plt.tight_layout()
```

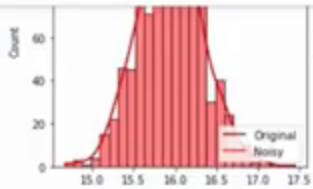
```
evaluate_metrics(data, num_outliers=0, amplitude_outliers=1)
```

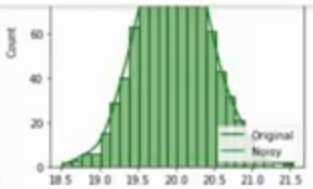
+ Code + Text

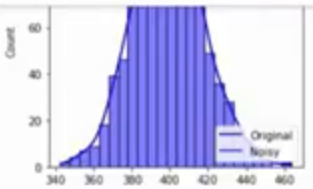
RAM Disk

Editing

[5]







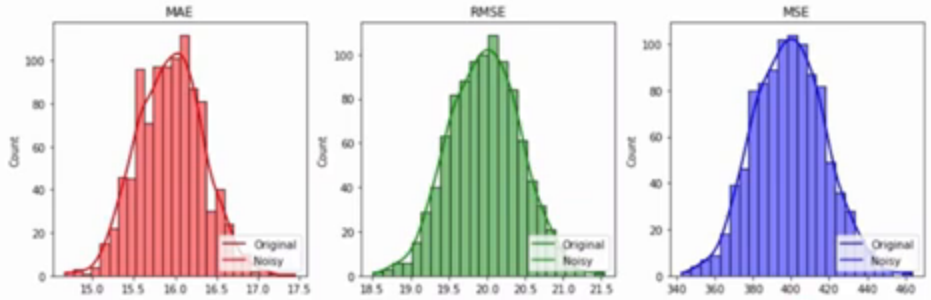
+ Code + Text

RAM Disk

Editing

```
[4]     ax3.set_title("MSE")
        plt.tight_layout()
```

```
[5] evaluate_metrics(data, num_outliers=0, amplitude_outliers=1)
```



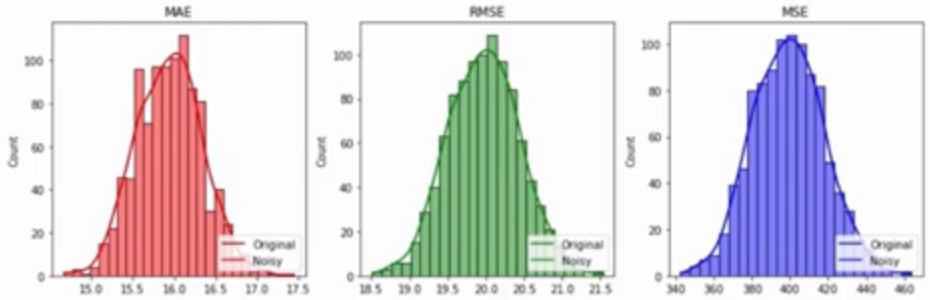
+ Code + Text

RAM Disk

Editing

```
[4]     ax3.set_title("MSE")
        plt.tight_layout()
```

```
[5] evaluate_metrics(data, num_outliers=0, amplitude_outliers=1)
```



+ Code + Text

RAM Disk

Editing

```
[4]     ax3.set_title("MSE")
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```

```
[5] evaluate_metrics(data, num_outliers=0, amplitude_outliers=1)
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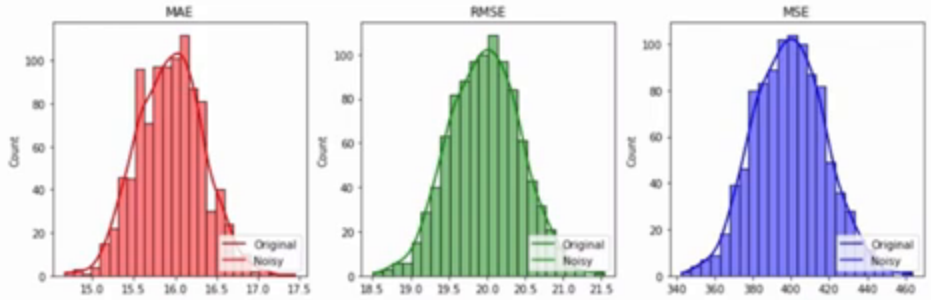

+ Code + Text

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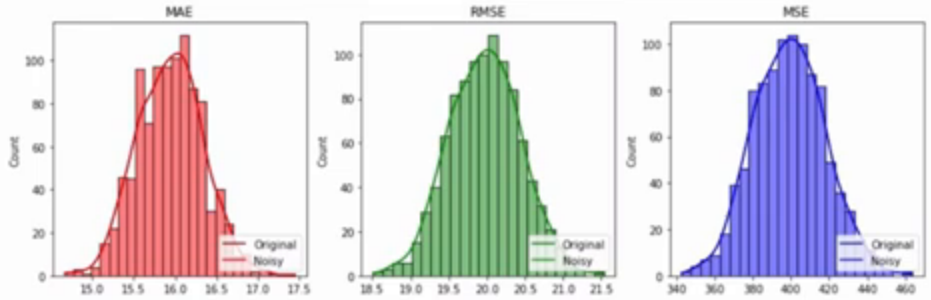
Editing

```
[4]     ax3.set_title("MSE")
        plt.tight_layout()
```

```
[5] evaluate_metrics(data, num_outliers=0, amplitude_outliers=1)
```



+ Code + Text

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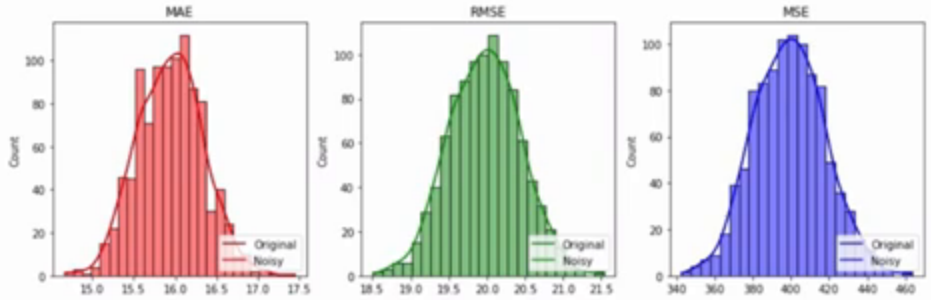
Editing

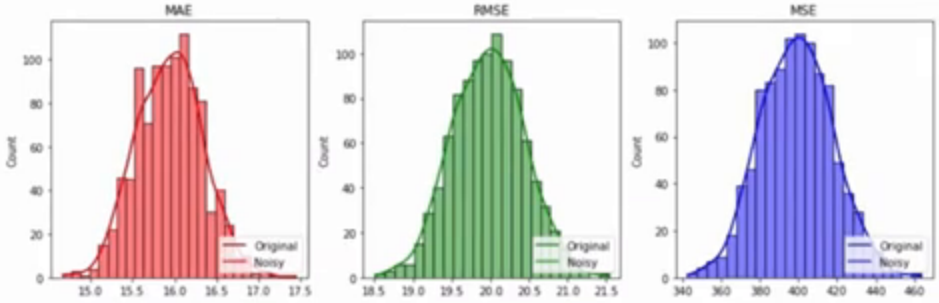
```
[4]     ax3.set_title("MSE")
        plt.tight_layout()
```

```
[5] evaluate_metrics(data, num_outliers=0, amplitude_outliers=1)
```



```
[4]  ax3.set_title("MSE")
     plt.tight_layout()
```

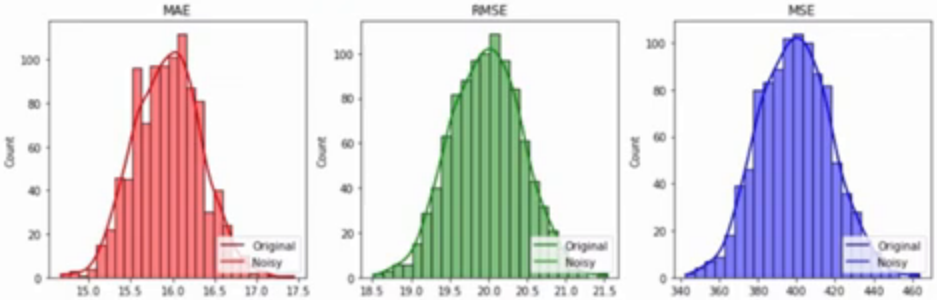
```
[5]  evaluate_metrics(data, num_outliers=0, amplitude_outliers=1)
```




```
evaluate_metrics(data, num_outliers=0, amplitude_outliers=1)
```

```
    ax3.set_title("MSE")
    plt.tight_layout()
```

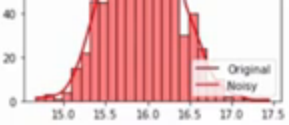
```
[5] evaluate_metrics(data, num_outliers=0, amplitude_outliers=1)
```

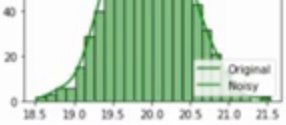


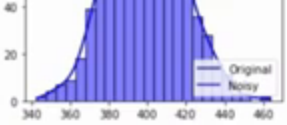

```
evaluate_metrics(data, num_outliers=2, amplitude_outliers=2)
```

4s completed at 10:49 AM

[5]



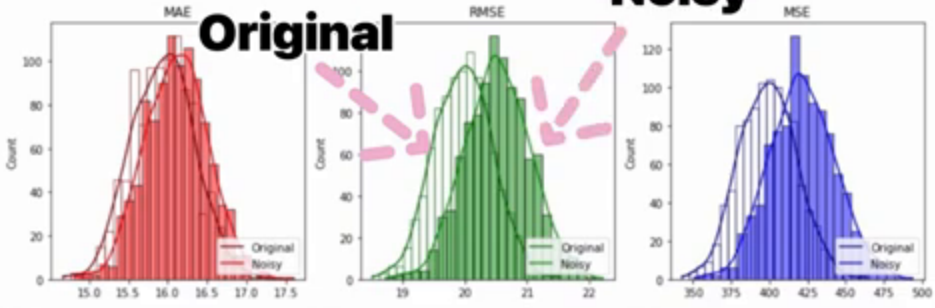





```
evaluate_metrics(data, num_outliers=2, amplitude_outliers=2)
```

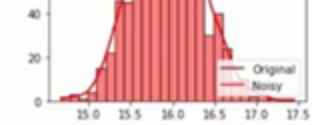
Original

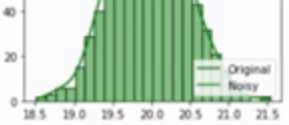
Noisy

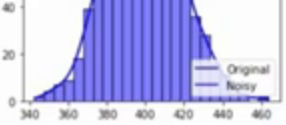


[ ]

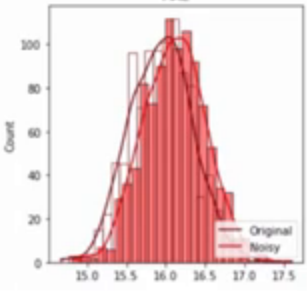
4s completed at 10:53 AM

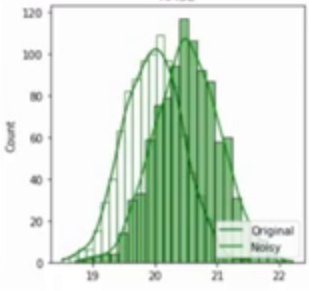


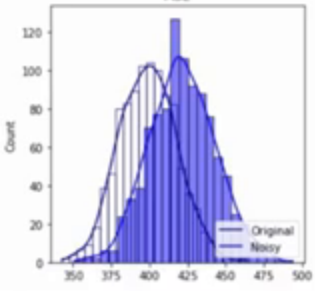




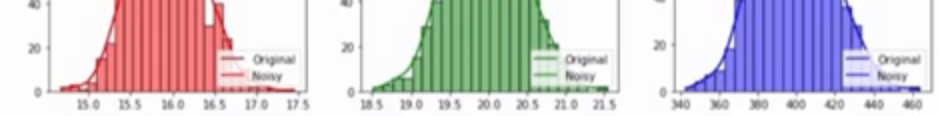

```
evaluate_metrics(data, num_outliers=2, amplitude_outliers=2)
```



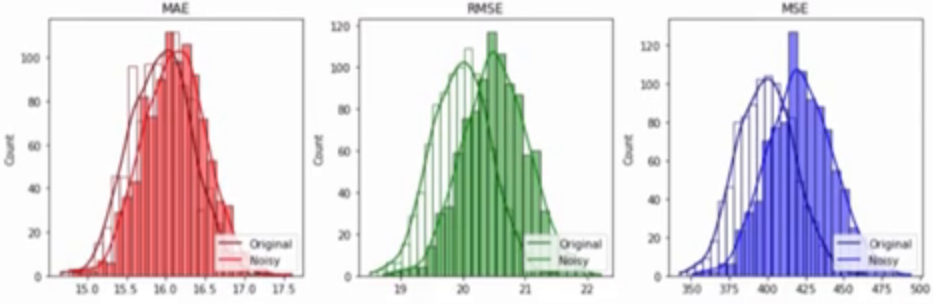





```
[ ]
```

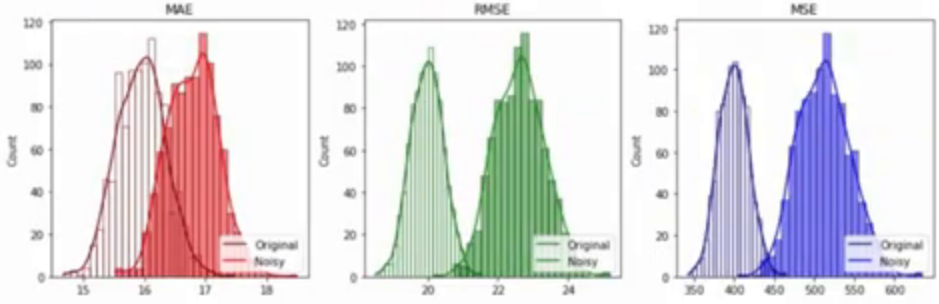



```
evaluate_metrics(data, num_outliers=2, amplitude_outliers=2)
```

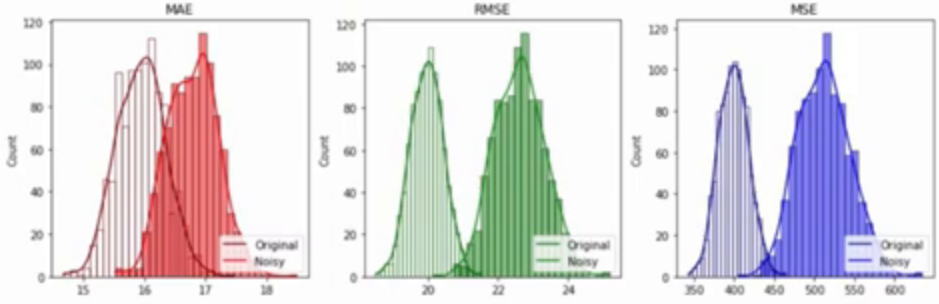



```
[ ]
```

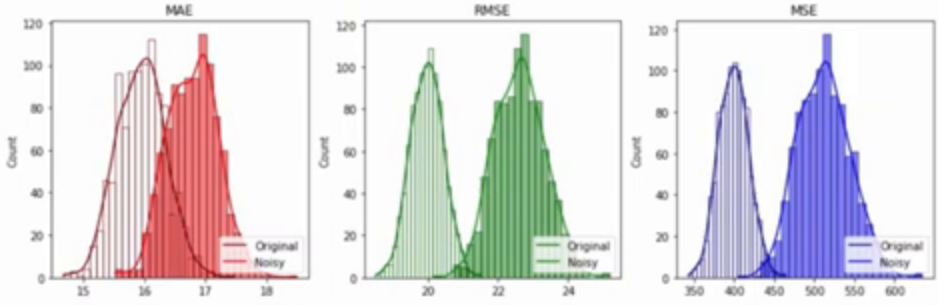
```
[7] evaluate_metrics(data, num_outliers=10, amplitude_outliers=2)
```



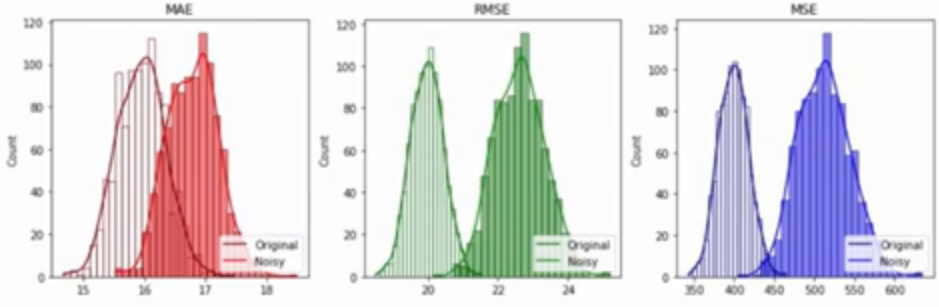
```
[7] evaluate_metrics(data, num_outliers=10, amplitude_outliers=2)
```



```
[7] evaluate_metrics(data, num_outliers=10, amplitude_outliers=2)
```

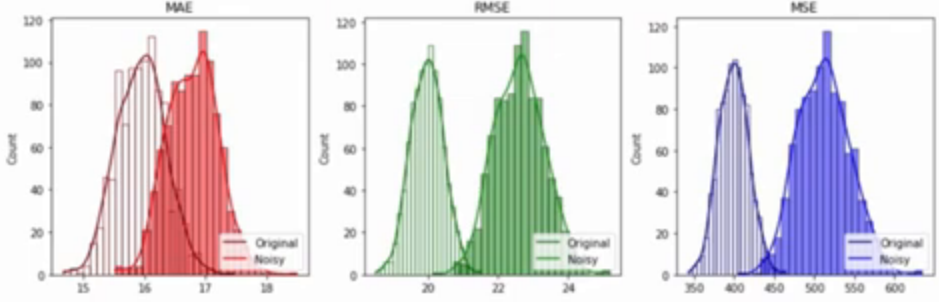


```
evaluate_metrics(data, num_outliers=10, amplitude_outliers=2)
```

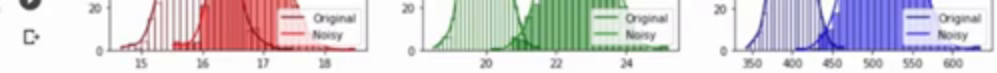



```
[ ]
```

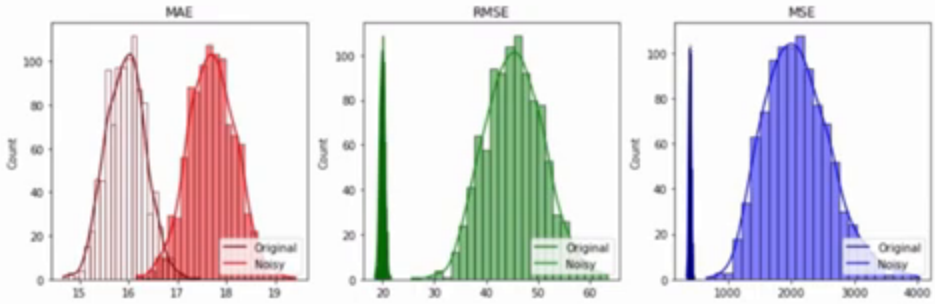
```
evaluate_metrics(data, num_outliers=10, amplitude_outliers=2)
```

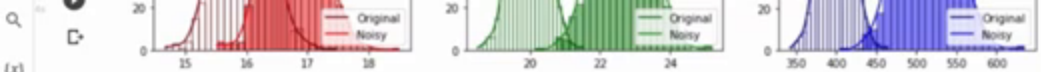



```
[ ] evaluate_metrics(data, num_outliers=0, amplitude_outliers=10)
```

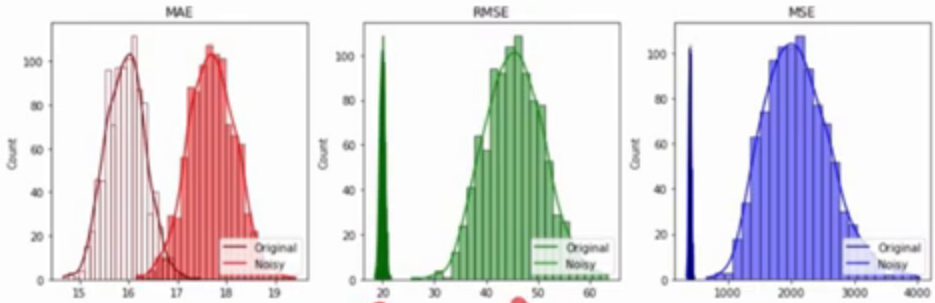


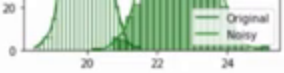

```
[8] evaluate_metrics(data, num_outliers=2, amplitude_outliers=10)
```

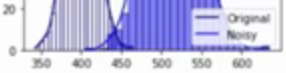





```
[8]  evaluate_metrics(data, num_outliers=2, amplitude_outliers=10)
```





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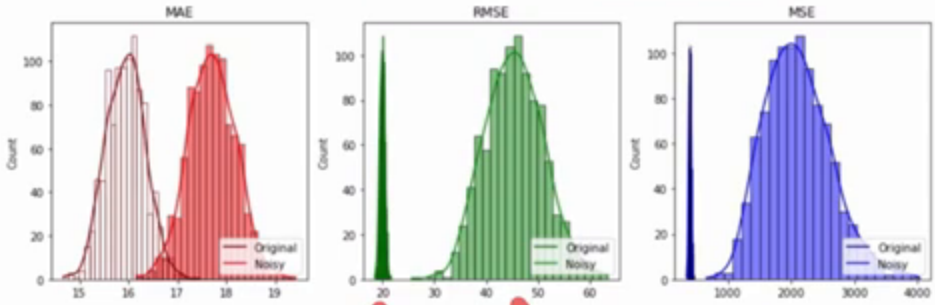


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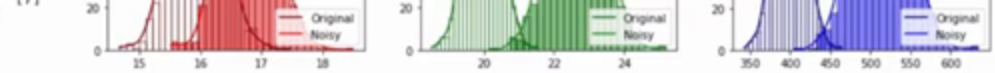


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evaluate_metrics(data, num_outliers=2, amplitude_outliers=10)
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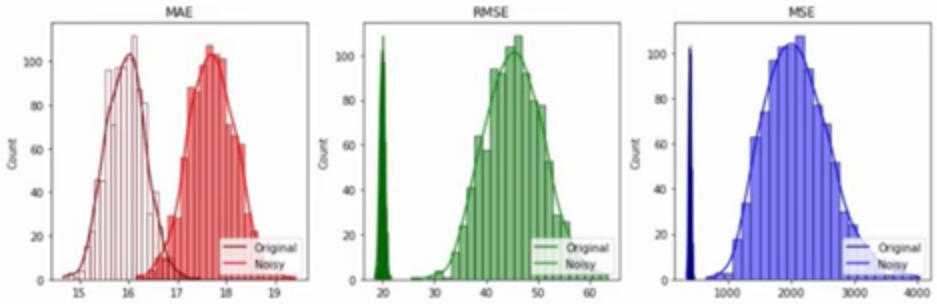


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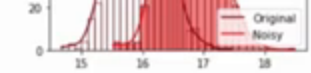

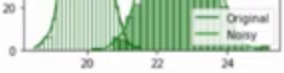

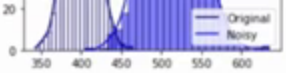


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evaluate_metrics(data, num_outliers=2, amplitude_outliers=10)
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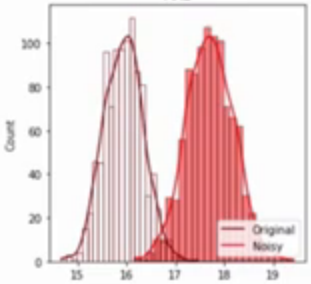

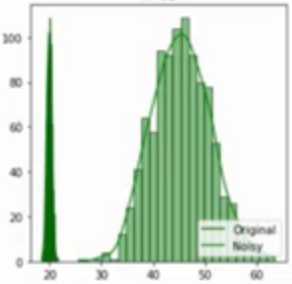

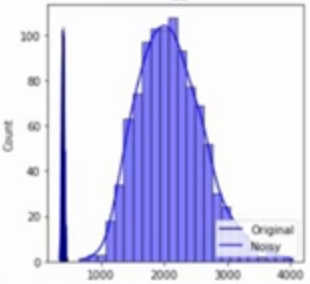


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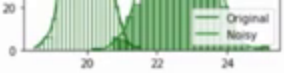

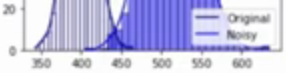


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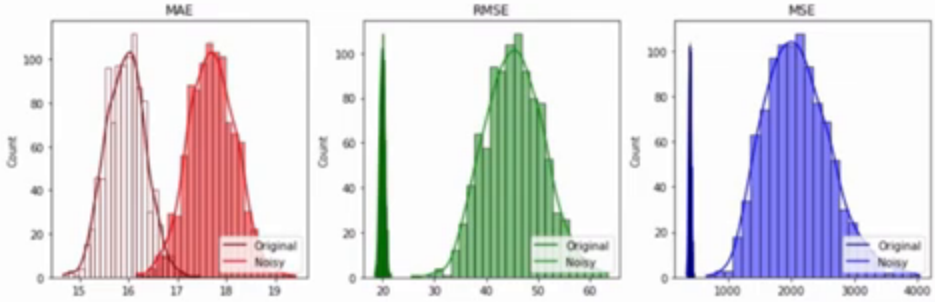


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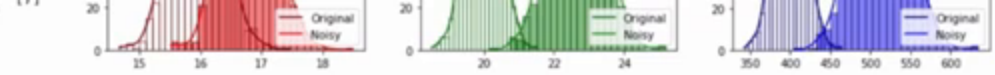


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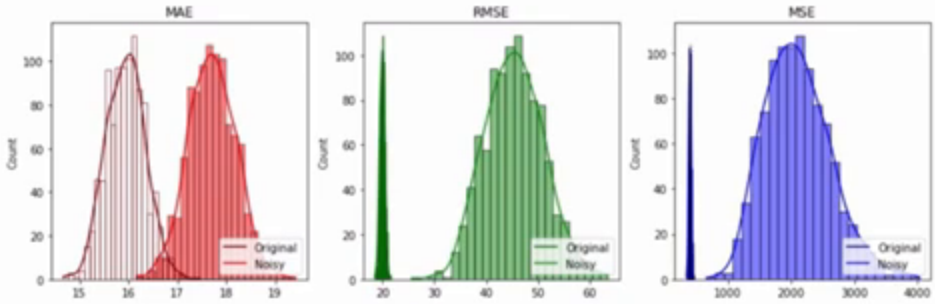


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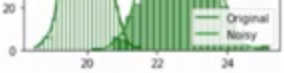

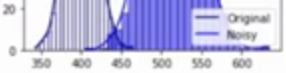


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evaluate_metrics(data, num_outliers=2, amplitude_outliers=10)
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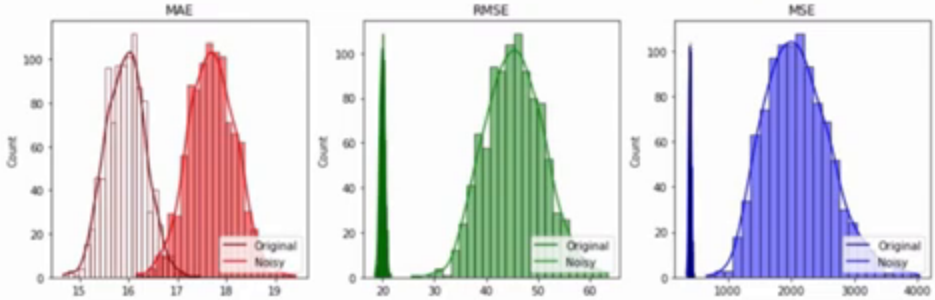


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