

# Imports and Data Load

```
In [1]: import pickle
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from keras import models
from keras import layers
from keras import optimizers
from keras import regularizers
from keras.models import load_model
from keras.callbacks import ModelCheckpoint

from sklearn.feature_extraction.text import TfidfVectorizer

from Functions import *
```

```
In [2]: # Printing Errors
def errors(model,error_func,X_tr,X_te,y_tr,y_te,squared=False):
    train_error = error_func(y_tr,model.predict(X_tr))
    test_error = error_func(y_te,model.predict(X_te))
    if squared:
        train_error = train_error**.5
        test_error = test_error**.5
    print("Train Error:",round(train_error))
    print("Test Error:",round(test_error))
```

```
In [3]: df = pickle.load(open(r"Data\players_cleaned_df.pickle","rb"))
```

## Base Model

### Train Test Validation Split

- Using 80% of the data to train

```
In [4]: X = df['title']
y = df['views']
X_train_pre, X_test_pre, y_train, y_test = train_test_split(X,y,test_size=150,random_state=4521)
X_train_f_pre,X_val_pre,y_train_f,y_val = train_test_split(X_train_pre,y_train,test_size=100,random_state=4521)
```

### TF IDF Vectorizing

```
In [5]: tf = TfidfVectorizer(preprocessor=splitter, lowercase=False)
fit_tf = tf.fit(X_train_f_pre)
```

```
In [6]: X_train_f = tf.transform(X_train_f_pre).todense()
```

```
X_val = tf.transform(X_val_pre).todense()
X_test = tf.transform(X_test_pre).todense()
```

# Modeling

## Loss on RMSE

```
In [7]: # Building Model
model_mse = models.Sequential()
model_mse.add(layers.Dense(units=100,activation='relu',input_shape=(X_train_f.shape[1],)))
model_mse.add(layers.Dense(units=50,activation='relu'))
model_mse.add(layers.Dropout(rate=0.3))
model_mse.add(layers.Dense(units=50,activation='relu'))
model_mse.add(layers.Dropout(rate=0.3))
model_mse.add(layers.Dense(units=1,activation='linear'))

# Compilation Step
model_mse.compile(optimizer='adam',
                  loss='mse',
                  metrics=['mse'])

In [8]: # Callbacks to save best model and weights
mse_callback = ModelCheckpoint(r'Data/model_mse.h5',monitor='val_mse',mode='min',save_best_only=True)

In [9]: # Training Step
history_mse = model_mse.fit(X_train_f, y_train_f, batch_size=5,epochs=50,validation_data=(X_val,y_val),
                           callbacks=[mse_callback])
```

```
Epoch 1/50
201/201 [=====] - 0s 2ms/step - loss: 22864877568.0000 - mse: 22864877568.0000 - val_loss: 22608545792.0000 - val_mse: 22608545792.0000
Epoch 2/50
201/201 [=====] - 0s 1ms/step - loss: 21012891648.0000 - mse: 21012891648.0000 - val_loss: 17454555136.0000 - val_mse: 17454555136.0000
Epoch 3/50
201/201 [=====] - 0s 1ms/step - loss: 14194554880.0000 - mse: 14194554880.0000 - val_loss: 11084909568.0000 - val_mse: 11084909568.0000
Epoch 4/50
201/201 [=====] - 0s 1ms/step - loss: 11371836416.0000 - mse: 11371836416.0000 - val_loss: 10426193920.0000 - val_mse: 10426193920.0000
Epoch 5/50
201/201 [=====] - 0s 1ms/step - loss: 10849937408.0000 - mse: 10849937408.0000 - val_loss: 10297724928.0000 - val_mse: 10297724928.0000
Epoch 6/50
201/201 [=====] - 0s 2ms/step - loss: 10489520128.0000 - mse: 10489520128.0000 - val_loss: 10192214016.0000 - val_mse: 10192214016.0000
Epoch 7/50
201/201 [=====] - 0s 1ms/step - loss: 10188888064.0000 - mse: 10188888064.0000 - val_loss: 10096762880.0000 - val_mse: 10096762880.0000
Epoch 8/50
201/201 [=====] - 0s 1ms/step - loss: 10152669184.0000 - mse: 10152669184.0000 - val_loss: 10010775552.0000 - val_mse: 10010775552.0000
Epoch 9/50
201/201 [=====] - 0s 1ms/step - loss: 10008129536.0000 - mse: 10008129536.0000 - val_loss: 9987360768.0000 - val_mse: 9987360768.0000
Epoch 10/50
201/201 [=====] - 0s 1ms/step - loss: 9552846848.0000 - mse: 9552847872.0000 - val_loss: 9956941824.0000 - val_mse: 9956941824.0000
Epoch 11/50
201/201 [=====] - 0s 1ms/step - loss: 9161172992.0000 - mse: 9161172992.0000 - val_loss: 9869966336.0000 - val_mse: 9869966336.0000
Epoch 12/50
201/201 [=====] - 0s 806us/step - loss: 9258063872.0000 - mse: 9258063872.0000 - val_loss: 9872061440.0000 - val_mse: 9872061440.0000
Epoch 13/50
201/201 [=====] - 0s 1ms/step - loss: 9315786752.0000 - mse: 9315786752.0000 - val_loss: 9854706688.0000 - val_mse: 9854706688.0000
Epoch 14/50
201/201 [=====] - 0s 833us/step - loss: 8742283264.0000 - mse: 8742283264.0000 - val_loss: 9880892416.0000 - val_mse: 9880892416.0000
Epoch 15/50
201/201 [=====] - 0s 811us/step - loss: 8788494336.0000 - mse: 8788495360.0000 - val_loss: 9911536640.0000 - val_mse: 9911536640.0000
Epoch 16/50
201/201 [=====] - 0s 866us/step - loss: 8809339904.0000 - mse: 8809339904.0000 - val_loss: 9928307712.0000 - val_mse: 9928307712.0000
```

Epoch 17/50  
201/201 [=====] - 0s 871us/step - loss: 8456592384.0000 - mse: 8456592384.0000 - val\_loss: 9974156288.0000 - val\_mse: 9974156288.0000  
Epoch 18/50  
201/201 [=====] - 0s 786us/step - loss: 8088896000.0000 - mse: 8088896000.0000 - val\_loss: 10027202560.0000 - val\_mse: 10027202560.0000  
Epoch 19/50  
201/201 [=====] - 0s 791us/step - loss: 7946066432.0000 - mse: 7946066432.0000 - val\_loss: 10075773952.0000 - val\_mse: 10075773952.0000  
Epoch 20/50  
201/201 [=====] - 0s 784us/step - loss: 8402590720.0000 - mse: 8402591232.0000 - val\_loss: 9986622464.0000 - val\_mse: 9986622464.0000  
Epoch 21/50  
201/201 [=====] - 0s 794us/step - loss: 7432691712.0000 - mse: 7432691712.0000 - val\_loss: 10104501248.0000 - val\_mse: 10104501248.0000  
Epoch 22/50  
201/201 [=====] - 0s 811us/step - loss: 7418897408.0000 - mse: 7418897408.0000 - val\_loss: 10254196736.0000 - val\_mse: 10254196736.0000  
Epoch 23/50  
201/201 [=====] - 0s 806us/step - loss: 7511144960.0000 - mse: 7511144960.0000 - val\_loss: 10359079936.0000 - val\_mse: 10359079936.0000  
Epoch 24/50  
201/201 [=====] - 0s 811us/step - loss: 7054074368.0000 - mse: 7054074368.0000 - val\_loss: 10450403328.0000 - val\_mse: 10450403328.0000  
Epoch 25/50  
201/201 [=====] - 0s 851us/step - loss: 6811890688.0000 - mse: 6811890688.0000 - val\_loss: 10523816960.0000 - val\_mse: 10523816960.0000  
Epoch 26/50  
201/201 [=====] - 0s 776us/step - loss: 6609806848.0000 - mse: 6609806848.0000 - val\_loss: 10584741888.0000 - val\_mse: 10584741888.0000  
Epoch 27/50  
201/201 [=====] - 0s 915us/step - loss: 6278964224.0000 - mse: 6278964224.0000 - val\_loss: 10814289920.0000 - val\_mse: 10814290944.0000  
Epoch 28/50  
201/201 [=====] - 0s 803us/step - loss: 6228643840.0000 - mse: 6228643840.0000 - val\_loss: 10831601664.0000 - val\_mse: 10831601664.0000  
Epoch 29/50  
201/201 [=====] - 0s 826us/step - loss: 6382892544.0000 - mse: 6382893056.0000 - val\_loss: 10973137920.0000 - val\_mse: 10973137920.0000  
Epoch 30/50  
201/201 [=====] - 0s 794us/step - loss: 6168603136.0000 - mse: 6168603136.0000 - val\_loss: 11144339456.0000 - val\_mse: 11144339456.0000  
Epoch 31/50  
201/201 [=====] - 0s 826us/step - loss: 5850513920.0000 - mse: 5850513920.0000 - val\_loss: 11192217600.0000 - val\_mse: 11192217600.0000  
Epoch 32/50  
201/201 [=====] - 0s 791us/step - loss: 5858704896.0000 - mse: 5858704896.0000 - val\_loss: 11398353920.0000 - val\_mse: 11398353920.0000  
Epoch 33/50  
201/201 [=====] - 0s 786us/step - loss: 5905655808.0000 - mse: 5905655808.0000 - val\_loss: 11580657664.0000 - val\_mse: 11580657664.0000  
Epoch 34/50  
201/201 [=====] - 0s 858us/step - loss: 5691936768.0000 - mse: 5691936768.0000 - val\_loss: 11785588736.0000 - val\_mse: 11785588736.0000  
Epoch 35/50  
201/201 [=====] - 0s 796us/step - loss: 5059318272.0000 - mse: 5059318784.0000 - val\_loss: 11862248448.0000 - val\_mse: 11862248448.0000  
Epoch 36/50  
201/201 [=====] - 0s 803us/step - loss: 5471619072.0000 - mse: 5471619072.0000 - val\_loss: 12058333184.0000 - val\_mse: 12058332160.0000  
Epoch 37/50  
201/201 [=====] - 0s 818us/step - loss: 5588750336.0000 - mse: 5588750336.0000 - val\_loss: 12300024832.0000 - val\_mse: 12300024832.0000  
Epoch 38/50  
201/201 [=====] - 0s 789us/step - loss: 5049052672.0000 - mse: 5049052672.0000 - val\_loss: 12417171456.0000 - val\_mse: 12417171456.0000  
Epoch 39/50  
201/201 [=====] - 0s 784us/step - loss: 5125270016.0000 - mse: 5125270016.0000 - val\_loss: 12548323328.0000 - val\_mse: 12548323328.0000  
Epoch 40/50  
201/201 [=====] - 0s 851us/step - loss: 4869039616.0000 - mse: 4869039616.0000 - val\_loss: 12732727296.0000 - val\_mse: 12732727296.0000  
Epoch 41/50  
201/201 [=====] - 0s 831us/step - loss: 4914767872.0000 - mse: 4914767872.0000 - val\_loss: 12838292480.0000 - val\_mse: 12838292480.0000  
Epoch 42/50  
201/201 [=====] - 0s 866us/step - loss: 4585613312.0000 - mse: 4585613312.0000 - val\_loss: 12899891200.0000 - val\_mse: 12899891200.0000  
Epoch 43/50  
201/201 [=====] - 0s 808us/step - loss: 4261107200.0000 - mse: 4261107456.0000 - val\_loss: 13349902336.0000 - val\_mse: 13349902336.0000  
Epoch 44/50  
201/201 [=====] - 0s 779us/step - loss: 4801070080.0000 - mse: 4801070080.0000 - val\_loss: 13468987392.0000 - val\_mse: 13468987392.0000  
Epoch 45/50  
201/201 [=====] - 0s 791us/step - loss: 4417151488.0000 - mse: 4417151488.0000 - val\_loss: 13740407808.0000 - val\_mse: 13740407808.0000  
Epoch 46/50  
201/201 [=====] - 0s 789us/step - loss: 4595155968.0000 - mse: 4595155968.0000 - val\_loss: 13663938560.0000 - val\_mse: 13663938560.0000  
Epoch 47/50  
201/201 [=====] - 0s 791us/step - loss: 4085115648.0000 - mse: 4085115648.0000 - val\_loss: 14013236224.0000 - val\_mse: 14013236224.0000  
Epoch 48/50  
201/201 [=====] - 0s 794us/step - loss: 4431241728.0000 - mse: 4431241728.0000 - val\_loss: 14421834752.0000 - val\_mse: 14421834752.0000

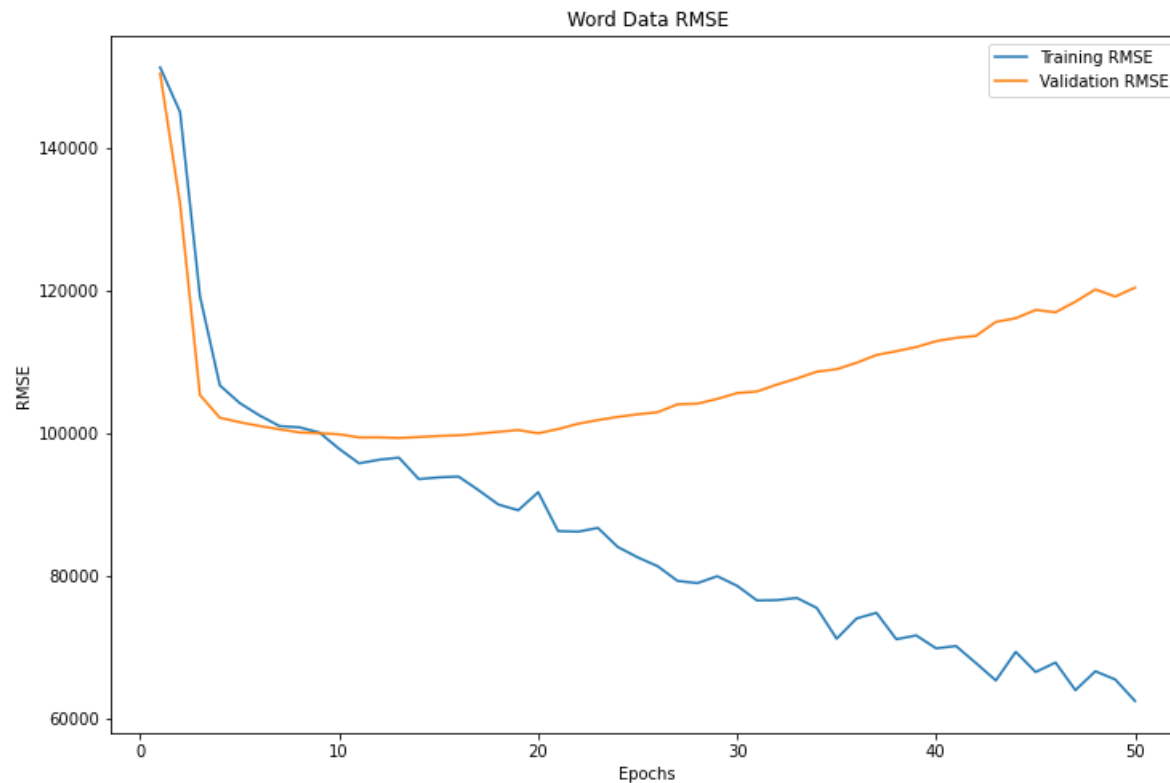
```
Epoch 49/50
201/201 [=====] - 0s 786us/step - loss: 4279117312.0000 - mse: 4279117568.0000 - val_loss: 14184458240.0000 - val_mse: 14184458240.0000
Epoch 50/50
201/201 [=====] - 0s 774us/step - loss: 3892425728.0000 - mse: 3892425984.0000 - val_loss: 14483440640.0000 - val_mse: 14483440640.0000
```

```
In [10]: # Plotting Loss
fig, ax = plt.subplots(figsize=(12, 8))

model_dict = history_mse.history

rmse_values = np.sqrt(model_dict['mse'])
val_rmse_values = np.sqrt(model_dict['val_mse'])

epochs = range(1, len(rmse_values) + 1)
ax.plot(epochs, rmse_values, label='Training RMSE')
ax.plot(epochs, val_rmse_values, label='Validation RMSE')
plt.legend()
plt.title('Word Data RMSE')
plt.xlabel('Epochs')
plt.ylabel('RMSE')
plt.show()
```



## Best Results

```
In [11]: best_mse = load_model(r'Data/model_mse.h5')
errors(best_mse, mean_squared_error, X_train_f, X_test, y_train_f, y_test, squared=True)
```

```
Train Error: 92474
Test Error: 80133
```

```
In [42]: print("Average Views: ", round(y_train_f.mean()))
```

Average Views: 107394

## Loss on MAE

```
In [12]: # Building Model
model_mae = models.Sequential()
model_mae.add(layers.Dense(units=100,activation='relu',input_shape=(X_train_f.shape[1],)))
model_mae.add(layers.Dense(units=50,activation='relu'))
model_mae.add(layers.Dropout(rate=0.3))
model_mae.add(layers.Dense(units=50,activation='relu'))
model_mae.add(layers.Dropout(rate=0.3))
model_mae.add(layers.Dense(units=1,activation='linear'))

# Compilation Step
model_mae.compile(optimizer='adam',
                  loss='mae',
                  metrics=['mae'])
```

```
In [13]: # Callbacks to save best model and weights
mae_callback = ModelCheckpoint(r'Data/model_mae.h5',monitor='val_mae',mode='min',save_best_only=True)
```

```
In [14]: # Training Step
history_mae = model_mae.fit(X_train_f, y_train_f, batch_size=5,epochs=50,validation_data=(X_val,y_val),
                           callbacks=[mae_callback])
```

```
Epoch 1/50
201/201 [=====] - 0s 2ms/step - loss: 107011.4453 - mae: 107011.4453 - val_loss: 104764.5234 - val_mae: 104764.5234
Epoch 2/50
201/201 [=====] - 0s 1ms/step - loss: 86345.1406 - mae: 86345.1406 - val_loss: 57888.5391 - val_mae: 57888.5391
Epoch 3/50
201/201 [=====] - 0s 1ms/step - loss: 54574.5352 - mae: 54574.5352 - val_loss: 51394.2266 - val_mae: 51394.2266
Epoch 4/50
201/201 [=====] - 0s 1ms/step - loss: 51534.9492 - mae: 51534.9492 - val_loss: 50059.7500 - val_mae: 50059.7500
Epoch 5/50
201/201 [=====] - 0s 2ms/step - loss: 49361.3359 - mae: 49361.3359 - val_loss: 48721.4688 - val_mae: 48721.4688
Epoch 6/50
201/201 [=====] - 0s 1ms/step - loss: 47231.3672 - mae: 47231.3672 - val_loss: 48354.5039 - val_mae: 48354.5039
Epoch 7/50
201/201 [=====] - 0s 2ms/step - loss: 46755.5898 - mae: 46755.5898 - val_loss: 47161.7891 - val_mae: 47161.7891
Epoch 8/50
201/201 [=====] - 0s 1ms/step - loss: 45464.2852 - mae: 45464.2852 - val_loss: 47056.0781 - val_mae: 47056.0781
Epoch 9/50
201/201 [=====] - 0s 1ms/step - loss: 44402.3125 - mae: 44402.3125 - val_loss: 46692.6992 - val_mae: 46692.6992
Epoch 10/50
201/201 [=====] - 0s 788us/step - loss: 43394.0508 - mae: 43394.0508 - val_loss: 46802.6250 - val_mae: 46802.6250
Epoch 11/50
201/201 [=====] - 0s 1ms/step - loss: 41698.8281 - mae: 41698.8281 - val_loss: 46638.0117 - val_mae: 46638.0117
Epoch 12/50
201/201 [=====] - 0s 793us/step - loss: 40573.7734 - mae: 40573.7734 - val_loss: 47569.9062 - val_mae: 47569.9062
Epoch 13/50
201/201 [=====] - 0s 853us/step - loss: 39210.9609 - mae: 39210.9609 - val_loss: 47104.0469 - val_mae: 47104.0469
Epoch 14/50
201/201 [=====] - 0s 813us/step - loss: 37762.3828 - mae: 37762.3828 - val_loss: 48053.7969 - val_mae: 48053.7969
Epoch 15/50
201/201 [=====] - 0s 786us/step - loss: 38326.9922 - mae: 38326.9922 - val_loss: 47839.0742 - val_mae: 47839.0742
Epoch 16/50
201/201 [=====] - 0s 781us/step - loss: 37075.1992 - mae: 37075.1992 - val_loss: 48363.8164 - val_mae: 48363.8164
Epoch 17/50
201/201 [=====] - 0s 789us/step - loss: 36390.5547 - mae: 36390.5547 - val_loss: 48390.9609 - val_mae: 48390.9609
```

Epoch 18/50  
201/201 [=====] - 0s 794us/step - loss: 36131.7969 - mae: 36131.7969 - val\_loss: 48962.1289 - val\_mae: 48962.1289  
Epoch 19/50  
201/201 [=====] - 0s 806us/step - loss: 35132.2578 - mae: 35132.2617 - val\_loss: 48851.9844 - val\_mae: 48851.9844  
Epoch 20/50  
201/201 [=====] - 0s 781us/step - loss: 35110.4102 - mae: 35110.4102 - val\_loss: 48773.9219 - val\_mae: 48773.9219  
Epoch 21/50  
201/201 [=====] - 0s 794us/step - loss: 33489.8125 - mae: 33489.8125 - val\_loss: 48902.8086 - val\_mae: 48902.8086  
Epoch 22/50  
201/201 [=====] - 0s 769us/step - loss: 34056.5625 - mae: 34056.5625 - val\_loss: 49159.5781 - val\_mae: 49159.5781  
Epoch 23/50  
201/201 [=====] - 0s 799us/step - loss: 33200.8945 - mae: 33200.8906 - val\_loss: 49952.7031 - val\_mae: 49952.7031  
Epoch 24/50  
201/201 [=====] - 0s 801us/step - loss: 33130.9297 - mae: 33130.9297 - val\_loss: 49907.0547 - val\_mae: 49907.0547  
Epoch 25/50  
201/201 [=====] - 0s 774us/step - loss: 32135.2695 - mae: 32135.2695 - val\_loss: 49784.7109 - val\_mae: 49784.7109  
Epoch 26/50  
201/201 [=====] - 0s 774us/step - loss: 31463.3008 - mae: 31463.3008 - val\_loss: 50212.3008 - val\_mae: 50212.3008  
Epoch 27/50  
201/201 [=====] - 0s 806us/step - loss: 31575.9102 - mae: 31575.9102 - val\_loss: 50355.8945 - val\_mae: 50355.8945  
Epoch 28/50  
201/201 [=====] - 0s 821us/step - loss: 31666.7969 - mae: 31666.7969 - val\_loss: 51314.6367 - val\_mae: 51314.6367  
Epoch 29/50  
201/201 [=====] - 0s 771us/step - loss: 30925.7598 - mae: 30925.7598 - val\_loss: 51230.0469 - val\_mae: 51230.0469  
Epoch 30/50  
201/201 [=====] - 0s 781us/step - loss: 30831.8984 - mae: 30831.8984 - val\_loss: 51784.1719 - val\_mae: 51784.1719  
Epoch 31/50  
201/201 [=====] - 0s 789us/step - loss: 30097.2676 - mae: 30097.2676 - val\_loss: 51212.1797 - val\_mae: 51212.1797  
Epoch 32/50  
201/201 [=====] - 0s 784us/step - loss: 29891.1953 - mae: 29891.1914 - val\_loss: 51281.8164 - val\_mae: 51281.8164  
Epoch 33/50  
201/201 [=====] - 0s 789us/step - loss: 29686.7871 - mae: 29686.7871 - val\_loss: 51840.7812 - val\_mae: 51840.7812  
Epoch 34/50  
201/201 [=====] - 0s 836us/step - loss: 29048.4629 - mae: 29048.4629 - val\_loss: 51725.4258 - val\_mae: 51725.4258  
Epoch 35/50  
201/201 [=====] - 0s 774us/step - loss: 28326.9355 - mae: 28326.9355 - val\_loss: 53296.2695 - val\_mae: 53296.2695  
Epoch 36/50  
201/201 [=====] - 0s 789us/step - loss: 28548.0176 - mae: 28548.0176 - val\_loss: 52490.6953 - val\_mae: 52490.6953  
Epoch 37/50  
201/201 [=====] - 0s 813us/step - loss: 28404.0000 - mae: 28404.0000 - val\_loss: 52686.0586 - val\_mae: 52686.0586  
Epoch 38/50  
201/201 [=====] - 0s 776us/step - loss: 28144.8262 - mae: 28144.8262 - val\_loss: 53218.9062 - val\_mae: 53218.9062  
Epoch 39/50  
201/201 [=====] - 0s 801us/step - loss: 27857.2793 - mae: 27857.2793 - val\_loss: 53390.2734 - val\_mae: 53390.2734  
Epoch 40/50  
201/201 [=====] - 0s 858us/step - loss: 28127.9512 - mae: 28127.9512 - val\_loss: 53219.7383 - val\_mae: 53219.7383  
Epoch 41/50  
201/201 [=====] - 0s 779us/step - loss: 28088.2812 - mae: 28088.2812 - val\_loss: 53781.9453 - val\_mae: 53781.9453  
Epoch 42/50  
201/201 [=====] - 0s 799us/step - loss: 28166.3809 - mae: 28166.3809 - val\_loss: 54238.2617 - val\_mae: 54238.2617  
Epoch 43/50  
201/201 [=====] - 0s 781us/step - loss: 27677.0371 - mae: 27677.0371 - val\_loss: 54818.6562 - val\_mae: 54818.6562  
Epoch 44/50  
201/201 [=====] - 0s 915us/step - loss: 27511.9082 - mae: 27511.9082 - val\_loss: 54264.6445 - val\_mae: 54264.6445  
Epoch 45/50  
201/201 [=====] - 0s 786us/step - loss: 27040.6895 - mae: 27040.6895 - val\_loss: 55468.1133 - val\_mae: 55468.1133  
Epoch 46/50  
201/201 [=====] - 0s 806us/step - loss: 26729.5742 - mae: 26729.5742 - val\_loss: 56815.9336 - val\_mae: 56815.9336  
Epoch 47/50  
201/201 [=====] - 0s 771us/step - loss: 25381.4980 - mae: 25381.4980 - val\_loss: 55713.6484 - val\_mae: 55713.6484  
Epoch 48/50  
201/201 [=====] - 0s 781us/step - loss: 25906.0332 - mae: 25906.0332 - val\_loss: 55635.4062 - val\_mae: 55635.4062  
Epoch 49/50  
201/201 [=====] - 0s 801us/step - loss: 25913.2793 - mae: 25913.2793 - val\_loss: 56609.4805 - val\_mae: 56609.4805

Epoch 50/50

201/201 [=====] - 0s 771us/step - loss: 26062.0176 - mae: 26062.0176 - val\_loss: 56917.1914 - val\_mae: 56917.1914

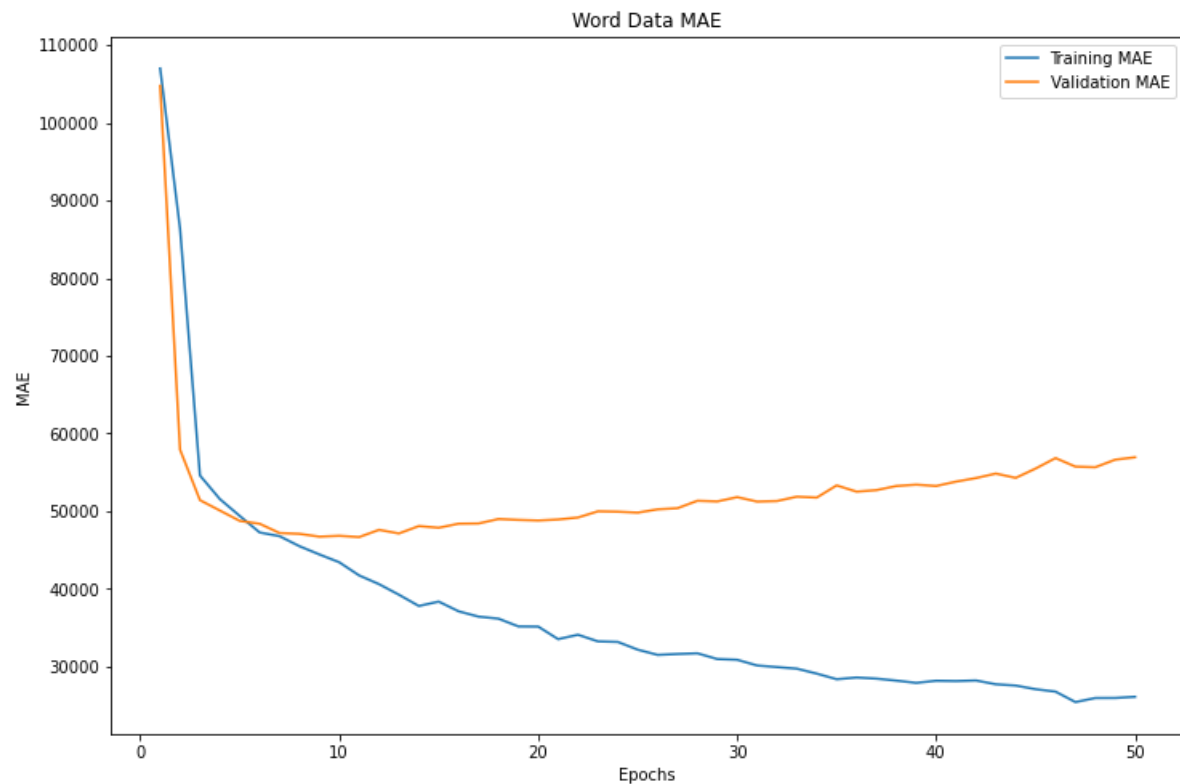
In [15]:

```
# Plotting Loss
fig, ax = plt.subplots(figsize=(12, 8))

model_dict = history_mae.history

mae_values = model_dict['mae']
val_mae_values = model_dict['val_mae']

epochs = range(1, len(mae_values) + 1)
ax.plot(epochs, mae_values, label='Training MAE')
ax.plot(epochs, val_mae_values, label='Validation MAE')
plt.legend()
plt.title('Word Data MAE')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.show()
```



## Best Results

In [16]:

```
best_mae = load_model(r'Data/model_mae.h5')
errors(best_mae, mean_absolute_error, X_train_f, X_test, y_train_f, y_test, squared=False)
```

Train Error: 38081

Test Error: 46656

# Model After Removing Outliers

## Outlier Removal using IQR along with Train Test Validation Split

```
In [17]: round(y_train.describe(),2)
```

```
Out[17]: count      1102.00  
mean      107397.09  
std       106641.20  
min        8088.00  
25%       54421.00  
50%       81922.00  
75%      127335.75  
max      1783323.00  
Name: views, dtype: float64
```

```
In [18]: iqr_df = pickle.load(open(r"Data\players_cleaned_df.pickle","rb"))
```

```
In [19]: X_iqr = iqr_df[['title']]  
y_iqr = iqr_df[['views']]  
  
X_train_iqr_pre,X_test_iqr_pre,y_train_iqr,y_test_iqr = train_test_split(X_iqr,y_iqr,test_size=150,random_state=4521)
```

```
In [20]: # Obtaining Lower and Upper Limits using IQR  
q25 = y_train_iqr['views'].describe()['25%']  
q75 = y_train_iqr['views'].describe()['75%']  
iqr = q75-q25  
low_lim = q25-1.5*iqr  
upp_lim = q75+1.5*iqr
```

```
In [21]: # Resetting Index to use to help filtering out Locations of outliers  
X_train_iqr_pre.reset_index(inplace=True)  
X_test_iqr_pre.reset_index(inplace=True)  
y_train_iqr.reset_index(inplace=True)  
y_test_iqr.reset_index(inplace=True)
```

```
In [22]: # Finding Indexes within range  
train_keep_in = y_train_iqr['views'].index[(low_lim < y_train_iqr['views']) & (y_train_iqr['views'] < upp_lim)]  
test_keep_in = y_test_iqr['views'].index[(low_lim < y_test_iqr['views']) & (y_test_iqr['views'] < upp_lim)]
```

```
In [23]: # New Train and Test data after removing outliers based on train  
X_train_iqrf_pre = X_train_iqr_pre.iloc[train_keep_in].drop('index',axis=1)['title']  
y_train_iqrf = np.array(y_train_iqr.iloc[train_keep_in].drop('index',axis=1))  
X_test_iqrf_pre = X_test_iqr_pre.iloc[test_keep_in].drop('index',axis=1)['title']  
y_test_iqrf = np.array(y_test_iqr.iloc[test_keep_in].drop('index',axis=1))
```

```
In [24]: # Validation Split  
X_train_val_iqr_pre,X_val_iqr_pre,y_train_val_iqr,y_val_iqr = train_test_split(X_train_iqrf_pre,  
                                                                              y_train_iqrf,  
                                                                              test_size=100,random_state=4521)
```

## Refitting TFIDF Vectorizer

```
In [25]: tf_o = TfidfVectorizer(preprocessor=splitter, lowercase=False)
```



```
fit_tf_o = tf_o.fit(X_train_val_iqr_pre)
```

```
In [26]: X_train_val_iqr = tf_o.transform(X_train_val_iqr_pre).todense()  
X_val_iqr = tf_o.transform(X_val_iqr_pre).todense()  
X_test_iqrf = tf_o.transform(X_test_iqrf_pre).todense()
```

## Modeling P2

### Loss on RMSE

```
In [27]: # Building Model  
model_mse_iqr = models.Sequential()  
model_mse_iqr.add(layers.Dense(units=100,activation='relu',input_shape=(X_train_val_iqr.shape[1],)))  
model_mse_iqr.add(layers.Dense(units=50,activation='relu'))  
model_mse_iqr.add(layers.Dropout(rate=0.3))  
model_mse_iqr.add(layers.Dense(units=50,activation='relu'))  
model_mse_iqr.add(layers.Dropout(rate=0.3))  
model_mse_iqr.add(layers.Dense(units=1,activation='linear'))  
  
# Compilation Step  
model_mse_iqr.compile(optimizer='adam',  
                      loss='mse',  
                      metrics=['mse'])
```

```
In [28]: # Callbacks to save best model and weights  
mse_iqr_callback = ModelCheckpoint(r'Data/model_mse_iqr.h5',monitor='val_mse',mode='min',save_best_only=True)
```

```
In [29]: # Training Step  
history_mse_iqr = model_mse_iqr.fit(X_train_val_iqr, y_train_val_iqr,  
                                   batch_size=5,epochs=50,  
                                   validation_data=(X_val_iqr,y_val_iqr),  
                                   callbacks=[mse_iqr_callback])
```

```
Epoch 1/50  
186/186 [=====] - 0s 2ms/step - loss: 9669542912.0000 - mse: 9669542912.0000 - val_loss: 9165594624.0000 - val_mse: 9165594624.0000  
Epoch 2/50  
186/186 [=====] - 0s 1ms/step - loss: 7269039104.0000 - mse: 7269039104.0000 - val_loss: 3394633728.0000 - val_mse: 3394632960.0000  
Epoch 3/50  
186/186 [=====] - 0s 1ms/step - loss: 2552547840.0000 - mse: 2552547840.0000 - val_loss: 1484074368.0000 - val_mse: 1484074368.0000  
Epoch 4/50  
186/186 [=====] - 0s 2ms/step - loss: 1995598592.0000 - mse: 1995598592.0000 - val_loss: 1413213696.0000 - val_mse: 1413213568.0000  
Epoch 5/50  
186/186 [=====] - 0s 2ms/step - loss: 1826328704.0000 - mse: 1826328704.0000 - val_loss: 1373378560.0000 - val_mse: 1373378560.0000  
Epoch 6/50  
186/186 [=====] - 0s 1ms/step - loss: 1632627328.0000 - mse: 1632627328.0000 - val_loss: 1364385280.0000 - val_mse: 1364385280.0000  
Epoch 7/50  
186/186 [=====] - 0s 1ms/step - loss: 1577581184.0000 - mse: 1577581184.0000 - val_loss: 1343427712.0000 - val_mse: 1343427712.0000  
Epoch 8/50  
186/186 [=====] - 0s 806us/step - loss: 1432932608.0000 - mse: 1432932608.0000 - val_loss: 1349921152.0000 - val_mse: 1349921152.0000  
Epoch 9/50  
186/186 [=====] - 0s 820us/step - loss: 1408477952.0000 - mse: 1408477952.0000 - val_loss: 1374935808.0000 - val_mse: 1374935808.0000  
Epoch 10/50  
186/186 [=====] - 0s 817us/step - loss: 1323601536.0000 - mse: 1323601536.0000 - val_loss: 1365176960.0000 - val_mse: 1365176960.0000  
Epoch 11/50  
186/186 [=====] - 0s 817us/step - loss: 1275370240.0000 - mse: 1275370240.0000 - val_loss: 1371182976.0000 - val_mse: 1371182976.0000  
Epoch 12/50  
186/186 [=====] - 0s 823us/step - loss: 1101467904.0000 - mse: 1101467904.0000 - val_loss: 1421867264.0000 - val_mse: 1421867264.0000  
Epoch 13/50  
186/186 [=====] - 0s 820us/step - loss: 1169893120.0000 - mse: 1169893120.0000 - val_loss: 1437480576.0000 - val_mse: 1437480576.0000
```

Epoch 14/50  
186/186 [=====] - 0s 812us/step - loss: 1065137152.0000 - mse: 1065137152.0000 - val\_loss: 1413002752.0000 - val\_mse: 1413002752.0000  
Epoch 15/50  
186/186 [=====] - 0s 828us/step - loss: 980213952.0000 - mse: 980213952.0000 - val\_loss: 1427142400.0000 - val\_mse: 1427142400.0000  
Epoch 16/50  
186/186 [=====] - 0s 814us/step - loss: 980904960.0000 - mse: 980904960.0000 - val\_loss: 1538939904.0000 - val\_mse: 1538939904.0000  
Epoch 17/50  
186/186 [=====] - 0s 858us/step - loss: 915076672.0000 - mse: 915076672.0000 - val\_loss: 1474715520.0000 - val\_mse: 1474715520.0000  
Epoch 18/50  
186/186 [=====] - 0s 828us/step - loss: 867639296.0000 - mse: 867639296.0000 - val\_loss: 1534741376.0000 - val\_mse: 1534741376.0000  
Epoch 19/50  
186/186 [=====] - 0s 858us/step - loss: 772372864.0000 - mse: 772372864.0000 - val\_loss: 1641467904.0000 - val\_mse: 1641467904.0000  
Epoch 20/50  
186/186 [=====] - 0s 804us/step - loss: 777818496.0000 - mse: 777818496.0000 - val\_loss: 1646414720.0000 - val\_mse: 1646414720.0000  
Epoch 21/50  
186/186 [=====] - 0s 815us/step - loss: 729658624.0000 - mse: 729658624.0000 - val\_loss: 1613557632.0000 - val\_mse: 1613557632.0000  
Epoch 22/50  
186/186 [=====] - 0s 815us/step - loss: 752312576.0000 - mse: 752312576.0000 - val\_loss: 1646134912.0000 - val\_mse: 1646134912.0000  
Epoch 23/50  
186/186 [=====] - 0s 806us/step - loss: 692163648.0000 - mse: 692163648.0000 - val\_loss: 1705949696.0000 - val\_mse: 1705949696.0000  
Epoch 24/50  
186/186 [=====] - 0s 841us/step - loss: 666294784.0000 - mse: 666294784.0000 - val\_loss: 1709229568.0000 - val\_mse: 1709229568.0000  
Epoch 25/50  
186/186 [=====] - 0s 809us/step - loss: 679875392.0000 - mse: 679875392.0000 - val\_loss: 1811406336.0000 - val\_mse: 1811406336.0000  
Epoch 26/50  
186/186 [=====] - 0s 874us/step - loss: 602394944.0000 - mse: 602394944.0000 - val\_loss: 1835742464.0000 - val\_mse: 1835742464.0000  
Epoch 27/50  
186/186 [=====] - 0s 815us/step - loss: 622894592.0000 - mse: 622894592.0000 - val\_loss: 1847775104.0000 - val\_mse: 1847775104.0000  
Epoch 28/50  
186/186 [=====] - 0s 852us/step - loss: 587455168.0000 - mse: 587455168.0000 - val\_loss: 1817292416.0000 - val\_mse: 1817292416.0000  
Epoch 29/50  
186/186 [=====] - 0s 817us/step - loss: 647716608.0000 - mse: 647716608.0000 - val\_loss: 1854676224.0000 - val\_mse: 1854676224.0000  
Epoch 30/50  
186/186 [=====] - 0s 836us/step - loss: 538372416.0000 - mse: 538372416.0000 - val\_loss: 1903652096.0000 - val\_mse: 1903652096.0000  
Epoch 31/50  
186/186 [=====] - 0s 823us/step - loss: 519506688.0000 - mse: 519506688.0000 - val\_loss: 1971063296.0000 - val\_mse: 1971063296.0000  
Epoch 32/50  
186/186 [=====] - 0s 809us/step - loss: 530193280.0000 - mse: 530193280.0000 - val\_loss: 1905033984.0000 - val\_mse: 1905033984.0000  
Epoch 33/50  
186/186 [=====] - 0s 863us/step - loss: 510174496.0000 - mse: 510174496.0000 - val\_loss: 1936756736.0000 - val\_mse: 1936756736.0000  
Epoch 34/50  
186/186 [=====] - 0s 820us/step - loss: 577728960.0000 - mse: 577728960.0000 - val\_loss: 1962839040.0000 - val\_mse: 1962839040.0000  
Epoch 35/50  
186/186 [=====] - 0s 806us/step - loss: 550592960.0000 - mse: 550592960.0000 - val\_loss: 1960493568.0000 - val\_mse: 1960493568.0000  
Epoch 36/50  
186/186 [=====] - 0s 812us/step - loss: 497770528.0000 - mse: 497770528.0000 - val\_loss: 2009859840.0000 - val\_mse: 2009859840.0000  
Epoch 37/50  
186/186 [=====] - 0s 868us/step - loss: 500594720.0000 - mse: 500594720.0000 - val\_loss: 2078542592.0000 - val\_mse: 2078542592.0000  
Epoch 38/50  
186/186 [=====] - 0s 804us/step - loss: 473274528.0000 - mse: 473274528.0000 - val\_loss: 2013526272.0000 - val\_mse: 2013526272.0000  
Epoch 39/50  
186/186 [=====] - 0s 820us/step - loss: 488786848.0000 - mse: 488786848.0000 - val\_loss: 2041867904.0000 - val\_mse: 2041867904.0000  
Epoch 40/50  
186/186 [=====] - 0s 858us/step - loss: 498232736.0000 - mse: 498232736.0000 - val\_loss: 2082082432.0000 - val\_mse: 2082082432.0000  
Epoch 41/50  
186/186 [=====] - 0s 815us/step - loss: 477123616.0000 - mse: 477123616.0000 - val\_loss: 2001896192.0000 - val\_mse: 2001896192.0000  
Epoch 42/50  
186/186 [=====] - 0s 828us/step - loss: 458445664.0000 - mse: 458445664.0000 - val\_loss: 2157771264.0000 - val\_mse: 2157771264.0000  
Epoch 43/50  
186/186 [=====] - 0s 831us/step - loss: 474575968.0000 - mse: 474575968.0000 - val\_loss: 2125895936.0000 - val\_mse: 2125895936.0000  
Epoch 44/50  
186/186 [=====] - 0s 874us/step - loss: 473503616.0000 - mse: 473503616.0000 - val\_loss: 2193018624.0000 - val\_mse: 2193018624.0000  
Epoch 45/50  
186/186 [=====] - 0s 839us/step - loss: 451639328.0000 - mse: 451639328.0000 - val\_loss: 2191993344.0000 - val\_mse: 2191993344.0000

```

Epoch 46/50
186/186 [=====] - 0s 812us/step - loss: 463224000.0000 - mse: 463224000.0000 - val_loss: 2232480000.0000 - val_mse: 2232480000.0000
Epoch 47/50
186/186 [=====] - 0s 860us/step - loss: 413991616.0000 - mse: 413991616.0000 - val_loss: 2160750848.0000 - val_mse: 2160750848.0000
Epoch 48/50
186/186 [=====] - 0s 809us/step - loss: 446111456.0000 - mse: 446111456.0000 - val_loss: 2331602176.0000 - val_mse: 2331602176.0000
Epoch 49/50
186/186 [=====] - 0s 806us/step - loss: 430186208.0000 - mse: 430186208.0000 - val_loss: 2244182528.0000 - val_mse: 2244182528.0000
Epoch 50/50
186/186 [=====] - 0s 817us/step - loss: 393826528.0000 - mse: 393826528.0000 - val_loss: 2161483008.0000 - val_mse: 2161483008.0000

```

In [30]:

```

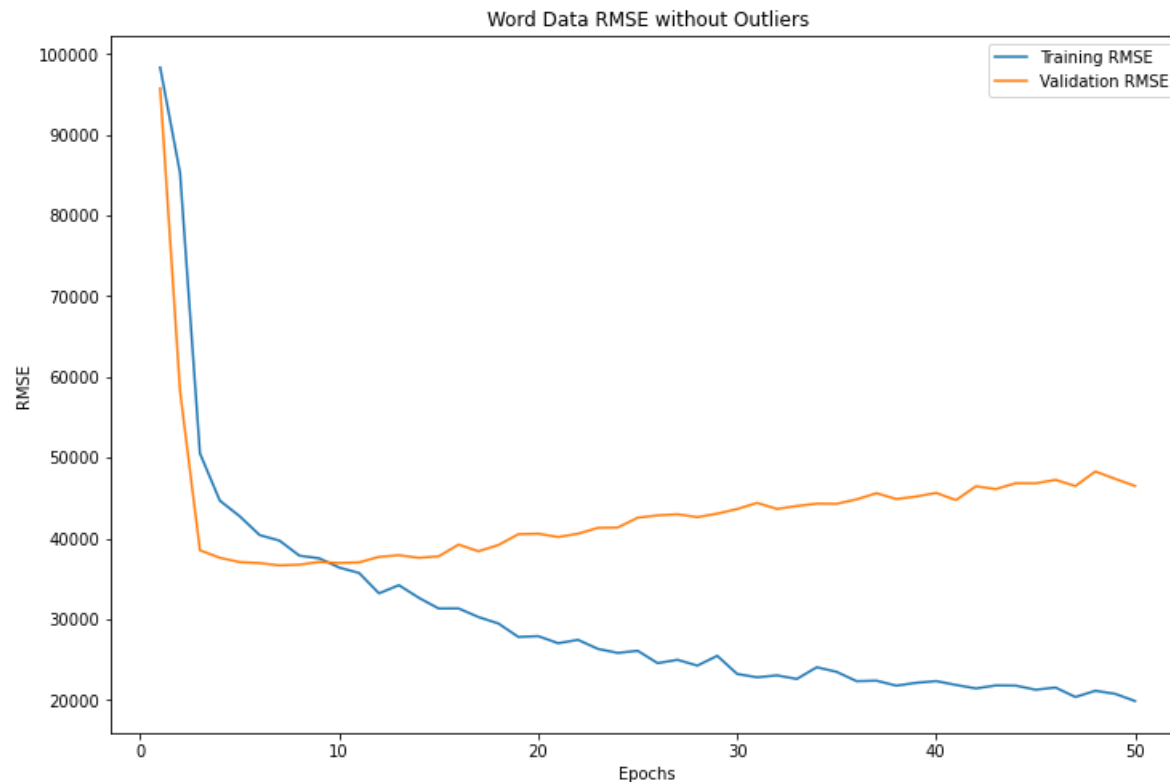
# Plotting Loss
fig, ax = plt.subplots(figsize=(12, 8))

model_dict = history_mse_iqr.history

rmse_values = np.sqrt(model_dict['mse'])
val_rmse_values = np.sqrt(model_dict['val_mse'])

epochs = range(1, len(rmse_values) + 1)
ax.plot(epochs, rmse_values, label='Training RMSE')
ax.plot(epochs, val_rmse_values, label='Validation RMSE')
plt.legend()
plt.title('Word Data RMSE without Outliers')
plt.xlabel('Epochs')
plt.ylabel('RMSE')
plt.show()

```



Best Results

```
In [31]: best_mse_iqr = load_model(r'Data/model_mse_iqr.h5')
errors(best_mse_iqr,mean_squared_error,X_train_val_iqr,X_test_iqrf,
       y_train_val_iqr,y_test_iqrf,squared=True)
```

Train Error: 35893  
Test Error: 40412

## Loss on MAE

```
In [32]: # Building Model
model_mae_iqr = models.Sequential()
model_mae_iqr.add(layers.Dense(units=100,activation='relu',input_shape=(X_train_val_iqr.shape[1],)))
model_mae_iqr.add(layers.Dense(units=50,activation='relu'))
model_mae_iqr.add(layers.Dropout(rate=0.3))
model_mae_iqr.add(layers.Dense(units=50,activation='relu'))
model_mae_iqr.add(layers.Dropout(rate=0.3))
model_mae_iqr.add(layers.Dense(units=1,activation='linear'))

# Compilation Step
model_mae_iqr.compile(optimizer='adam',
                      loss='mae',
                      metrics=['mae'])
```

```
In [33]: # Callbacks to save best model and weights
mae_iqr_callback = ModelCheckpoint(r'Data/model_mae_iqr.h5',monitor='val_mae',mode='min',save_best_only=True)
```

```
In [34]: # Training Step
history_mae_iqr = model_mae_iqr.fit(np.array(X_train_val_iqr), y_train_val_iqr,
                                   batch_size=5,epochs=50,
                                   validation_data=(np.array(X_val_iqr),y_val_iqr),
                                   callbacks=[mae_iqr_callback])
```

Epoch 1/50  
134/186 [=====>.....] - ETA: 0s - loss: 89491.8750 - mae: 89491.8750WARNING:tensorflow:Callbacks method `on\_test\_batch\_end` is slow compared to the batch time (batch time: 0.0000s vs `on\_test\_batch\_end` time: 0.0005s). Check your callbacks.  
186/186 [=====] - 0s 2ms/step - loss: 86495.9922 - mae: 86495.9922 - val\_loss: 87916.8516 - val\_mae: 87916.8516  
Epoch 2/50  
186/186 [=====] - 0s 2ms/step - loss: 75556.8203 - mae: 75556.8203 - val\_loss: 55836.1133 - val\_mae: 55836.1133  
Epoch 3/50  
186/186 [=====] - 0s 2ms/step - loss: 41165.7852 - mae: 41165.7852 - val\_loss: 29477.8281 - val\_mae: 29477.8301  
Epoch 4/50  
186/186 [=====] - 0s 2ms/step - loss: 34673.3906 - mae: 34673.3906 - val\_loss: 28654.9004 - val\_mae: 28654.9004  
Epoch 5/50  
186/186 [=====] - 0s 2ms/step - loss: 32903.0664 - mae: 32903.0664 - val\_loss: 27799.8301 - val\_mae: 27799.8301  
Epoch 6/50  
186/186 [=====] - 0s 1ms/step - loss: 31716.4629 - mae: 31716.4629 - val\_loss: 27242.5273 - val\_mae: 27242.5273  
Epoch 7/50  
186/186 [=====] - 0s 1ms/step - loss: 30412.2520 - mae: 30412.2520 - val\_loss: 27105.2617 - val\_mae: 27105.2617  
Epoch 8/50  
186/186 [=====] - 0s 1ms/step - loss: 29767.8965 - mae: 29767.8965 - val\_loss: 26994.0156 - val\_mae: 26994.0156  
Epoch 9/50  
186/186 [=====] - 0s 1ms/step - loss: 28266.7305 - mae: 28266.7305 - val\_loss: 26533.8516 - val\_mae: 26533.8516  
Epoch 10/50  
186/186 [=====] - 0s 811us/step - loss: 27163.7559 - mae: 27163.7559 - val\_loss: 26768.1641 - val\_mae: 26768.1641  
Epoch 11/50  
186/186 [=====] - 0s 817us/step - loss: 26788.7832 - mae: 26788.7832 - val\_loss: 27010.9316 - val\_mae: 27010.9297  
Epoch 12/50  
186/186 [=====] - 0s 876us/step - loss: 25233.3105 - mae: 25233.3105 - val\_loss: 27389.0918 - val\_mae: 27389.0918  
Epoch 13/50  
186/186 [=====] - 0s 812us/step - loss: 25205.2305 - mae: 25205.2305 - val\_loss: 26945.5293 - val\_mae: 26945.5293

Epoch 14/50  
186/186 [=====] - 0s 815us/step - loss: 24738.4336 - mae: 24738.4336 - val\_loss: 27086.1328 - val\_mae: 27086.1328  
Epoch 15/50  
186/186 [=====] - 0s 817us/step - loss: 23294.9863 - mae: 23294.9863 - val\_loss: 27241.1504 - val\_mae: 27241.1504  
Epoch 16/50  
186/186 [=====] - 0s 820us/step - loss: 23065.3164 - mae: 23065.3164 - val\_loss: 27260.5195 - val\_mae: 27260.5195  
Epoch 17/50  
186/186 [=====] - 0s 809us/step - loss: 22793.9727 - mae: 22793.9727 - val\_loss: 27271.8496 - val\_mae: 27271.8496  
Epoch 18/50  
186/186 [=====] - 0s 817us/step - loss: 21638.5547 - mae: 21638.5547 - val\_loss: 27532.5742 - val\_mae: 27532.5742  
Epoch 19/50  
186/186 [=====] - 0s 804us/step - loss: 22342.0059 - mae: 22342.0039 - val\_loss: 27817.6094 - val\_mae: 27817.6094  
Epoch 20/50  
186/186 [=====] - 0s 850us/step - loss: 21037.4785 - mae: 21037.4785 - val\_loss: 27671.8828 - val\_mae: 27671.8828  
Epoch 21/50  
186/186 [=====] - 0s 817us/step - loss: 21365.1348 - mae: 21365.1348 - val\_loss: 27770.2344 - val\_mae: 27770.2383  
Epoch 22/50  
186/186 [=====] - 0s 825us/step - loss: 19859.0137 - mae: 19859.0137 - val\_loss: 28176.1074 - val\_mae: 28176.1055  
Epoch 23/50  
186/186 [=====] - 0s 809us/step - loss: 21059.2949 - mae: 21059.2949 - val\_loss: 28398.5547 - val\_mae: 28398.5547  
Epoch 24/50  
186/186 [=====] - 0s 828us/step - loss: 19408.8301 - mae: 19408.8301 - val\_loss: 28226.6523 - val\_mae: 28226.6523  
Epoch 25/50  
186/186 [=====] - 0s 976us/step - loss: 19569.7266 - mae: 19569.7266 - val\_loss: 28681.8945 - val\_mae: 28681.8945  
Epoch 26/50  
186/186 [=====] - 0s 831us/step - loss: 18772.6777 - mae: 18772.6777 - val\_loss: 28145.8477 - val\_mae: 28145.8477  
Epoch 27/50  
186/186 [=====] - 0s 817us/step - loss: 19046.9082 - mae: 19046.9082 - val\_loss: 28068.9902 - val\_mae: 28068.9922  
Epoch 28/50  
186/186 [=====] - 0s 815us/step - loss: 18778.9336 - mae: 18778.9336 - val\_loss: 28422.7441 - val\_mae: 28422.7441  
Epoch 29/50  
186/186 [=====] - 0s 809us/step - loss: 18951.2930 - mae: 18951.2930 - val\_loss: 28446.5176 - val\_mae: 28446.5156  
Epoch 30/50  
186/186 [=====] - 0s 874us/step - loss: 18560.9082 - mae: 18560.9082 - val\_loss: 28598.6328 - val\_mae: 28598.6328  
Epoch 31/50  
186/186 [=====] - 0s 839us/step - loss: 18157.3438 - mae: 18157.3438 - val\_loss: 28514.8496 - val\_mae: 28514.8496  
Epoch 32/50  
186/186 [=====] - 0s 820us/step - loss: 18591.2559 - mae: 18591.2559 - val\_loss: 29269.2051 - val\_mae: 29269.2031  
Epoch 33/50  
186/186 [=====] - 0s 809us/step - loss: 18403.0645 - mae: 18403.0645 - val\_loss: 28725.0352 - val\_mae: 28725.0352  
Epoch 34/50  
186/186 [=====] - 0s 844us/step - loss: 18139.2754 - mae: 18139.2754 - val\_loss: 28906.2246 - val\_mae: 28906.2246  
Epoch 35/50  
186/186 [=====] - 0s 809us/step - loss: 17508.7285 - mae: 17508.7285 - val\_loss: 28925.7422 - val\_mae: 28925.7422  
Epoch 36/50  
186/186 [=====] - 0s 804us/step - loss: 17176.2285 - mae: 17176.2285 - val\_loss: 29122.6133 - val\_mae: 29122.6133  
Epoch 37/50  
186/186 [=====] - 0s 866us/step - loss: 17728.2148 - mae: 17728.2148 - val\_loss: 29094.0078 - val\_mae: 29094.0078  
Epoch 38/50  
186/186 [=====] - 0s 815us/step - loss: 16826.3574 - mae: 16826.3574 - val\_loss: 29487.0996 - val\_mae: 29487.0996  
Epoch 39/50  
186/186 [=====] - 0s 815us/step - loss: 17087.8320 - mae: 17087.8320 - val\_loss: 29396.5156 - val\_mae: 29396.5176  
Epoch 40/50  
186/186 [=====] - 0s 796us/step - loss: 17459.8066 - mae: 17459.8066 - val\_loss: 29743.4844 - val\_mae: 29743.4844  
Epoch 41/50  
186/186 [=====] - 0s 828us/step - loss: 16873.1328 - mae: 16873.1328 - val\_loss: 29724.2500 - val\_mae: 29724.2500  
Epoch 42/50  
186/186 [=====] - 0s 825us/step - loss: 16402.9355 - mae: 16402.9355 - val\_loss: 29783.7871 - val\_mae: 29783.7871  
Epoch 43/50  
186/186 [=====] - 0s 812us/step - loss: 17332.8125 - mae: 17332.8125 - val\_loss: 29893.6133 - val\_mae: 29893.6133  
Epoch 44/50  
186/186 [=====] - 0s 903us/step - loss: 16457.3066 - mae: 16457.3066 - val\_loss: 30233.7148 - val\_mae: 30233.7148  
Epoch 45/50  
186/186 [=====] - 0s 849us/step - loss: 16912.3750 - mae: 16912.3750 - val\_loss: 30385.6172 - val\_mae: 30385.6172

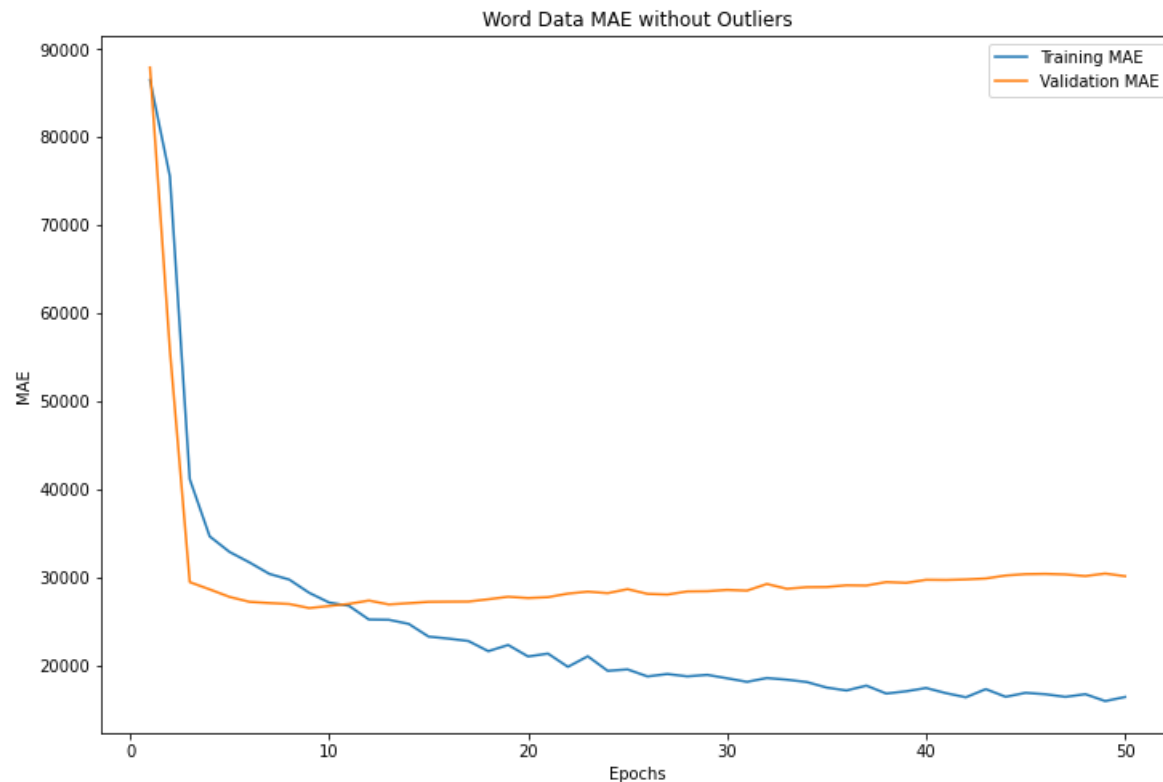
```
Epoch 46/50
186/186 [=====] - 0s 941us/step - loss: 16748.1934 - mae: 16748.1934 - val_loss: 30417.8770 - val_mae: 30417.8770
Epoch 47/50
186/186 [=====] - 0s 922us/step - loss: 16450.7539 - mae: 16450.7539 - val_loss: 30353.2422 - val_mae: 30353.2422
Epoch 48/50
186/186 [=====] - 0s 895us/step - loss: 16759.8359 - mae: 16759.8359 - val_loss: 30165.8379 - val_mae: 30165.8379
Epoch 49/50
186/186 [=====] - 0s 839us/step - loss: 15972.7998 - mae: 15972.7998 - val_loss: 30454.1875 - val_mae: 30454.1875
Epoch 50/50
186/186 [=====] - 0s 898us/step - loss: 16437.9219 - mae: 16437.9219 - val_loss: 30153.0918 - val_mae: 30153.0918
```

```
In [35]: # Plotting Loss
fig, ax = plt.subplots(figsize=(12, 8))

model_dict = history_mae_iqr.history

mae_values = model_dict['mae']
val_mae_values = model_dict['val_mae']

epochs = range(1, len(mae_values) + 1)
ax.plot(epochs, mae_values, label='Training MAE')
ax.plot(epochs, val_mae_values, label='Validation MAE')
plt.legend()
plt.title('Word Data MAE without Outliers')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.show()
```



Best Results

```
In [36]: best_mae_iqr = load_model(r'Data/model_mae_iqr.h5')
errors(best_mae_iqr,mean_absolute_error,X_train_val_iqr,X_test_iqrf,
       y_train_val_iqr,y_test_iqrf,squared=False)
```

Train Error: 24838

Test Error: 30935

## Findings

- Loss on MAE produced the lowest error overall
- Removing outliers improved model performance

## Final Stats

```
In [37]: y_test_preds = best_mae_iqr.predict(np.array(X_test_iqrf))
y_train_preds = best_mae_iqr.predict(np.array(X_train_val_iqr))
```

```
In [45]: print("Average Views:",round(y_train_val_iqr.mean()))
print("Train MAE:",round(mean_absolute_error(y_train_val_iqr,y_train_preds)))
print("Test MAE:",round(mean_absolute_error(y_test_iqrf,y_test_preds)))
```

Average Views: 86653

Train MAE: 24838

Test MAE: 30935

## Exporting MAE Model without Outliers

```
In [39]: best_mae_iqr.save(r'Data\model.h5')
best_mae_iqr.save_weights(r'Data\model_weights.h5')
```