```
#####Remove the comment and install the following libraries
#!pip install pytorch-forecastingimport numpy as np
import pandas as pd
import torch
import torch.nn as nn

import lightning.pytorch as pl
from lightning.pytorch.callbacks import EarlyStopping,
LearningRateMonitor
from lightning.pytorch.loggers import TensorBoardLogger

from pytorch_forecasting import Baseline, TemporalFusionTransformer,
TimeSeriesDataSet
from pytorch_forecasting.data import GroupNormalizer
from pytorch_forecasting.metrics import SMAPE, PoissonLoss,
QuantileLoss, MAE
from pytorch_forecasting.data.encoders import NaNLabelEncoder

import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

data= pd.read_excel("/kaggle/input/airqualityuci/AirQualityUCI.xlsx")

data.head()

        Date      Time  CO(GT)  PT08.S1(CO)  NMHC(GT)   C6H6(GT)  \
0 2004-03-10  18:00:00     2.6      1360.00       150  11.881723
1 2004-03-10  19:00:00     2.0      1292.25       112   9.397165
2 2004-03-10  20:00:00     2.2      1402.00        88   8.997817
3 2004-03-10  21:00:00     2.2      1375.50        80   9.228796
4 2004-03-10  22:00:00     1.6      1272.25        51   6.518224

   PT08.S2(NMHC)  NOx(GT)  PT08.S3(NOx)  NO2(GT)  PT08.S4(NO2)
PT08.S5(O3)  \
0        1045.50    166.0       1056.25    113.0       1692.00
1267.50
1         954.75    103.0       1173.75     92.0       1558.75
972.25
2         939.25    131.0       1140.00    114.0       1554.50
1074.00
3         948.25    172.0       1092.00    122.0       1583.75
1203.25
4         835.50    131.0       1205.00    116.0       1490.00
1110.00

       T         RH        AH
0  13.60  48.875001  0.757754
1  13.30  47.700000  0.725487
```

```
2  11.90  53.975000  0.750239
3  11.00  60.000000  0.786713
4  11.15  59.575001  0.788794
```

```python
x=data.isnull().sum()
x
```

```
Date             0
Time             0
CO(GT)           0
PT08.S1(CO)      0
NMHC(GT)         0
C6H6(GT)         0
PT08.S2(NMHC)    0
NOx(GT)          0
PT08.S3(NOx)     0
NO2(GT)          0
PT08.S4(NO2)     0
PT08.S5(O3)      0
T                0
RH               0
AH               0
dtype: int64
```

Continuos Feature Report

```python
numeric_features= data.select_dtypes(include=[np.number])
def build_continuous_features_report(data_df):

    """Build tabular report for continuous features"""

    stats = {
        "Count": len,
        "Miss %": lambda df: df.isna().sum() / len(df) * 100,
        "Card.": lambda df: df.nunique(),
        "Min": lambda df: df.min(),
        "1st Qrt.": lambda df: df.quantile(0.25),
        "Mean": lambda df: df.mean(),
        "Median": lambda df: df.median(),
        "3rd Qrt": lambda df: df.quantile(0.75),
        "Max": lambda df: df.max(),
        "Std. Dev.": lambda df: df.std(),
    }

    contin_feat_names = data_df.select_dtypes("number").columns
    continuous_data_df = data_df[contin_feat_names]

    report_df = pd.DataFrame(index=contin_feat_names,
columns=stats.keys())
```

```python
    for stat_name, fn in stats.items():
        # NOTE: ignore warnings for empty features
        with warnings.catch_warnings():
            warnings.simplefilter("ignore", category=RuntimeWarning)
            report_df[stat_name] = fn(continuous_data_df)

    return report_df

build_continuous_features_report(data)
```

```
               Count  Miss %  Card.    Min      1st Qrt.  
Mean  \
CO(GT)          9357     0.0     97 -200.0      0.600000    -34.207524

PT08.S1(CO)     9357     0.0   3246 -200.0    921.000000   1048.869652

NMHC(GT)        9357     0.0    430 -200.0   -200.000000   -159.090093

C6H6(GT)        9357     0.0   3773 -200.0      4.004958      1.865576

PT08.S2(NMHC)   9357     0.0   3773 -200.0    711.000000    894.475963

NOx(GT)         9357     0.0   2467 -200.0     50.000000    168.604200

PT08.S3(NOx)    9357     0.0   3519 -200.0    637.000000    794.872333

NO2(GT)         9357     0.0   1420 -200.0     53.000000     58.135898

PT08.S4(NO2)    9357     0.0   4408 -200.0   1184.750000   1391.363266

PT08.S5(O3)     9357     0.0   4679 -200.0    699.750000    974.951534

T               9357     0.0   3368 -200.0     10.950000      9.776600

RH              9357     0.0   4903 -200.0     34.050000     39.483611

AH              9357     0.0   8988 -200.0      0.692275     -6.837604


                    Median      3rd Qrt          Max    Std. Dev.
CO(GT)            1.500000     2.600000    11.900000    77.657170
PT08.S1(CO)    1052.500000  1221.250000  2039.750000   329.817015
NMHC(GT)       -200.000000  -200.000000  1189.000000   139.789093
C6H6(GT)          7.886653    13.636091    63.741476    41.380154
PT08.S2(NMHC)   894.500000  1104.750000  2214.000000   342.315902
NOx(GT)         141.000000   284.200000  1479.000000   257.424561
PT08.S3(NOx)    794.250000   960.250000  2682.750000   321.977031
NO2(GT)          96.000000   133.000000   339.700000   126.931428
PT08.S4(NO2)   1445.500000  1662.000000  2775.000000   467.192382
PT08.S5(O3)     942.000000  1255.250000  2522.750000   456.922728
T                17.200000    24.075000    44.600000    43.203438
```

```
RH                  48.550000    61.875000    88.725000   51.215645
AH                   0.976823     1.296223     2.231036   38.976670
```

Exploratory Data Analysis(EDA)

```
import pandas as pd

# Define the data for the table
df = {
    'Variable Name': ['Date', 'Time', 'CO(GT)', 'PT08.S1(CO)',
'NMHC(GT)', 'C6H6(GT)', 'PT08.S2(NMHC)', 'NOx(GT)', 'PT08.S3(NOx)',
'NO2(GT)'],
    'Role': ['Feature', 'Feature', 'Feature', 'Feature', 'Feature',
'Feature', 'Feature', 'Feature', 'Feature', 'Feature'],
    'Type': ['Date', 'Categorical', 'Integer', 'Categorical',
'Integer', 'Continuous', 'Categorical', 'Integer', 'Categorical',
'Integer'],
    'Description': [
        'Date of the measurement',
        'Time of the measurement',
        'True hourly averaged concentration of CO in mg/m³ (reference
analyzer)',
        'Hourly averaged sensor response (nominal CO targeted)',
        'True hourly averaged overall Non-Methanic HydroCarbons
concentration in microg/m³ (reference analyzer)',
        'True hourly averaged Benzene concentration in microg/m³
(reference analyzer)',
        'Hourly averaged sensor response (nominal NMHC targeted)',
        'True hourly averaged NOx concentration in ppb (reference
analyzer)',
        'Hourly averaged sensor response (nominal NOx targeted)',
        'True hourly averaged NO2 concentration in microg/m³
(reference analyzer)'
    ],
    'Units': ['N/A', 'N/A', 'mg/m³', 'N/A', 'microg/m³', 'microg/m³',
'N/A', 'ppb', 'N/A', 'microg/m³']
}


df_description = pd.DataFrame(df)


print(df_description)
```

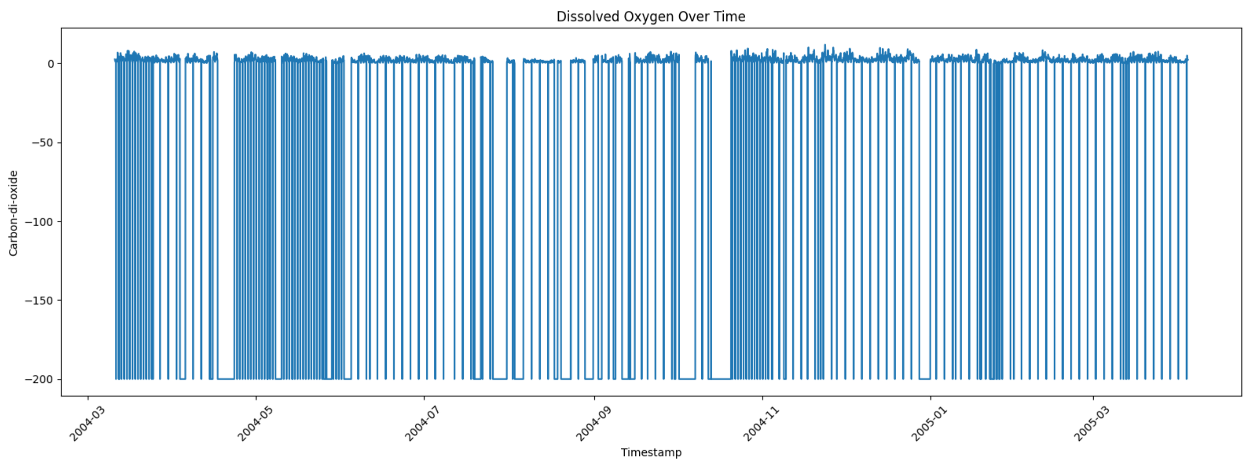
```
   Variable Name     Role         Type  \
0           Date  Feature         Date
1           Time  Feature  Categorical
2         CO(GT)  Feature      Integer
```

```
3    PT08.S1(CO)  Feature  Categorical
4       NMHC(GT)  Feature      Integer
5       C6H6(GT)  Feature   Continuous
6  PT08.S2(NMHC)  Feature  Categorical
7        NOx(GT)  Feature      Integer
8   PT08.S3(NOx)  Feature  Categorical
9        NO2(GT)  Feature      Integer

                                         Description      Units
0                            Date of the measurement        N/A
1                            Time of the measurement        N/A
2  True hourly averaged concentration of CO in mg...      mg/m³
3  Hourly averaged sensor response (nominal CO ta...        N/A
4  True hourly averaged overall Non-Methanic Hydr...  microg/m³
5  True hourly averaged Benzene concentration in ...  microg/m³
6  Hourly averaged sensor response (nominal NMHC ...        N/A
7  True hourly averaged NOx concentration in ppb ...        ppb
8  Hourly averaged sensor response (nominal NOx t...        N/A
9  True hourly averaged NO2 concentration in micr...  microg/m³
```

```
data['datetime'] = pd.to_datetime(data['Date'].astype(str) + ' ' +
data['Time'].astype(str))

#data.set_index('datetime',inplace=True)
data.drop(['Date','Time'],axis = 1,inplace = True)

data.head()
```

```
   CO(GT)  PT08.S1(CO)  NMHC(GT)   C6H6(GT)  PT08.S2(NMHC)  NOx(GT)  \
0     2.6      1360.00       150  11.881723        1045.50    166.0
1     2.0      1292.25       112   9.397165         954.75    103.0
2     2.2      1402.00        88   8.997817         939.25    131.0
3     2.2      1375.50        80   9.228796         948.25    172.0
4     1.6      1272.25        51   6.518224         835.50    131.0

   PT08.S3(NOx)  NO2(GT)  PT08.S4(NO2)  PT08.S5(O3)      T         RH
\
0       1056.25    113.0       1692.00      1267.50  13.60  48.875001

1       1173.75     92.0       1558.75       972.25  13.30  47.700000

2       1140.00    114.0       1554.50      1074.00  11.90  53.975000

3       1092.00    122.0       1583.75      1203.25  11.00  60.000000

4       1205.00    116.0       1490.00      1110.00  11.15  59.575001


         AH            datetime
0  0.757754 2004-03-10 18:00:00
1  0.725487 2004-03-10 19:00:00
```

```
2   0.750239 2004-03-10 20:00:00
3   0.786713 2004-03-10 21:00:00
4   0.788794 2004-03-10 22:00:00

plt.figure(figsize=(16, 6))  # Adjust the size as needed
linestyle='-', color='blue'
plt.plot(data['datetime'], data['CO(GT)'] )
plt.title('Dissolved Oxygen Over Time')
plt.xlabel('Timestamp')
plt.ylabel('Carbon-di-oxide')
plt.xticks(rotation=45)  # Rotate the x-axis labels for better
readability
plt.tight_layout()  # Adjust layout to not cut off labels
plt.show()
```




```
count_negative_200 = len(data[data['CO(GT)'] == -200])
count_negative_200

1683
```

From the above plot we can see that th

```
total_counts = numeric_features.count()
negative_value_counts = (numeric_features < 0).sum()

percentage_negative = (negative_value_counts / total_counts) * 100

results_df = pd.DataFrame({
    'Total_Count': total_counts,
    'Negative_Count': negative_value_counts,
    'Percentage_Negative': percentage_negative
})

print("Number of negative values in each numeric column:")
print(results_df)
```

```
Number of negative values in each numeric column:
                Total_Count  Negative_Count  Percentage_Negative
CO(GT)                 9357            1683            17.986534
PT08.S1(CO)            9357             366             3.911510
NMHC(GT)               9357            8443            90.231912
C6H6(GT)               9357             366             3.911510
PT08.S2(NMHC)          9357             366             3.911510
NOx(GT)                9357            1639            17.516298
PT08.S3(NOx)           9357             366             3.911510
NO2(GT)                9357            1642            17.548360
PT08.S4(NO2)           9357             366             3.911510
PT08.S5(O3)            9357             366             3.911510
T                      9357             380             4.061131
RH                     9357             366             3.911510
AH                     9357             366             3.911510
```

```
negative_values = data[data['CO(GT)'] < 0]
print('The precentage of CO2 having negative
value',len(negative_values)/len(data['CO(GT)'])*100)
```

```
The precentage of CO2 having negative value 17.986534145559474
```

```
total_counts = numeric_features.count()
negative_value_counts = (numeric_features < 0).sum()

percentage_negative = (negative_value_counts / total_counts) * 100

results_df = pd.DataFrame({
    'Total_Count': total_counts,
    'Negative_Count': negative_value_counts,
    'Percentage_Negative': percentage_negative
})

print("Number of negative values in each numeric column:")
print(results_df)
```

```
Number of negative values in each numeric column:
                Total_Count  Negative_Count  Percentage_Negative
CO(GT)                 9357            1683            17.986534
PT08.S1(CO)            9357             366             3.911510
NMHC(GT)               9357            8443            90.231912
C6H6(GT)               9357             366             3.911510
PT08.S2(NMHC)          9357             366             3.911510
NOx(GT)                9357            1639            17.516298
PT08.S3(NOx)           9357             366             3.911510
NO2(GT)                9357            1642            17.548360
PT08.S4(NO2)           9357             366             3.911510
PT08.S5(O3)            9357             366             3.911510
T                      9357             380             4.061131
```

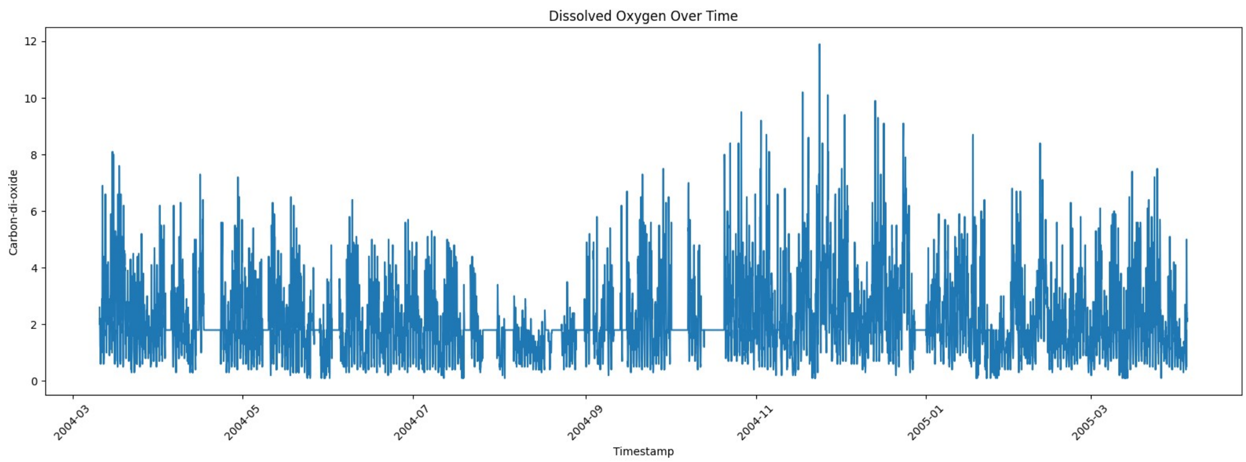
```
RH                     9357            366              3.911510
AH                     9357            366              3.911510
```

Data Prepartion and Feature Engineering

```
# Dropped NMHC(GT) because it has 90.231912% negative values. Parti
data.drop(['NMHC(GT)'],axis = 1,inplace = True)
numeric_features = data.select_dtypes(include=[np.number])

# Replacing the nagtive values with Nan
numeric_features = numeric_features.mask(numeric_features < 0)

# Impute NaN values with median
numeric_features = numeric_features.fillna(numeric_features.median())

# Update 'data' DataFrame with imputed values
data[numeric_features.columns] = numeric_features


total_counts = numeric_features.count()
negative_value_counts = (numeric_features < 0).sum()


percentage_negative = (negative_value_counts / total_counts) * 100


results_df = pd.DataFrame({
    'Total_Count': total_counts,
    'Negative_Count': negative_value_counts,
    'Percentage_Negative': percentage_negative
})

print("Number of negative values in each numeric column after
processing:")
print(results_df)
```

```
Number of negative values in each numeric column after processing:
               Total_Count  Negative_Count  Percentage_Negative
CO(GT)                9357               0                  0.0
PT08.S1(CO)           9357               0                  0.0
C6H6(GT)              9357               0                  0.0
PT08.S2(NMHC)         9357               0                  0.0
NOx(GT)               9357               0                  0.0
PT08.S3(NOx)          9357               0                  0.0
NO2(GT)               9357               0                  0.0
PT08.S4(NO2)          9357               0                  0.0
PT08.S5(O3)           9357               0                  0.0
T                     9357               0                  0.0
RH                    9357               0                  0.0
AH                    9357               0                  0.0
```

```
plt.figure(figsize=(16, 6))
plt.plot(data['datetime'], data['CO(GT)'] )
plt.title('Dissolved Oxygen Over Time')
plt.xlabel('Timestamp')
plt.ylabel('Carbon-di-oxide')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```




```
data.isnull().sum()

data.head()

   CO(GT)  PT08.S1(CO)   C6H6(GT)  PT08.S2(NMHC)  NOx(GT)
PT08.S3(NOx)  \
0     2.6      1360.00  11.881723        1045.50    166.0
1056.25
1     2.0      1292.25   9.397165         954.75    103.0
1173.75
2     2.2      1402.00   8.997817         939.25    131.0
1140.00
3     2.2      1375.50   9.228796         948.25    172.0
1092.00
4     1.6      1272.25   6.518224         835.50    131.0
1205.00

   NO2(GT)  PT08.S4(NO2)  PT08.S5(O3)      T         RH        AH  \
0    113.0       1692.00      1267.50  13.60  48.875001  0.757754
1     92.0       1558.75       972.25  13.30  47.700000  0.725487
2    114.0       1554.50      1074.00  11.90  53.975000  0.750239
3    122.0       1583.75      1203.25  11.00  60.000000  0.786713
4    116.0       1490.00      1110.00  11.15  59.575001  0.788794

             datetime
0 2004-03-10 18:00:00
```

```
1 2004-03-10 19:00:00
2 2004-03-10 20:00:00
3 2004-03-10 21:00:00
4 2004-03-10 22:00:00
```

Since the objective is calulating 24- hour future value therefore, we wiil shift the our target varaibles by future 24 values so that the model learns to predict future values.The temporal order will reamin the same also other feautures will also remain the same as it will the model to learn how the current features relate to the future target values.

```
## Shifitng the target feature to 24 rows ahead
data['CO(GT)'] = data['CO(GT)'].shift(-24)

## The missing value for shifitng the rows are imputed by median
data['CO(GT)'] = data['CO(GT)'].fillna(data['CO(GT)'].median())

data['datetime'] = pd.to_datetime(data['datetime'])

# Creating 'day', 'month', and 'hour' features from the datetime
column
data['day'] = data['datetime'].dt.day.astype(str)
data['month'] = data['datetime'].dt.month.astype(str)
data['hour'] = data['datetime'].dt.hour.astype(str)
data['time_idx'] = range(len(data))

data.head()

   CO(GT)  PT08.S1(CO)   C6H6(GT)  PT08.S2(NMHC)  NOx(GT)
PT08.S3(NOx)  \
0     4.8      1360.00  11.881723        1045.50    166.0
1056.25
1     6.9      1292.25   9.397165         954.75    103.0
1173.75
2     6.1      1402.00   8.997817         939.25    131.0
1140.00
3     3.9      1375.50   9.228796         948.25    172.0
1092.00
4     1.5      1272.25   6.518224         835.50    131.0
1205.00

   NO2(GT)  PT08.S4(NO2)  PT08.S5(O3)      T         RH        AH  \
0    113.0       1692.00      1267.50  13.60  48.875001  0.757754
1     92.0       1558.75       972.25  13.30  47.700000  0.725487
2    114.0       1554.50      1074.00  11.90  53.975000  0.750239
3    122.0       1583.75      1203.25  11.00  60.000000  0.786713
4    116.0       1490.00      1110.00  11.15  59.575001  0.788794

             datetime day month hour  time_idx
0 2004-03-10 18:00:00  10     3   18         0
1 2004-03-10 19:00:00  10     3   19         1
```

```
2 2004-03-10 20:00:00  10     3   20         2
3 2004-03-10 21:00:00  10     3   21         3
4 2004-03-10 22:00:00  10     3   22         4
```

Modelling

Splititng the dataset

```
data.columns = [col.replace('.', '_') for col in data.columns]
total_rows = len(data)

# Spliting 70% for training and the remaining 30% for testing
train_end = int(total_rows * 0.7)
train_data = data.iloc[:train_end]
test_data = data.iloc[train_end:]

# Now,again 80% of the training data for actual training and 20% for
validation

validation_cutoff = int(len(train_data) * 0.8)

# Spliting the training data into training and validation sets
train_actual = train_data.iloc[:validation_cutoff]
validation_data = train_data.iloc[validation_cutoff:]
print("Training Data Shape:", train_actual.shape)
print("Validation Data Shape:", validation_data.shape)
print("Testing Data Shape:", test_data.shape)
```

```
Training Data Shape: (5239, 17)
Validation Data Shape: (1310, 17)
Testing Data Shape: (2808, 17)
```

```
data.head()
```

```
   CO(GT)  PT08_S1(CO)   C6H6(GT)  PT08_S2(NMHC)  NOx(GT)
PT08_S3(NOx)  \
0     4.8      1360.00  11.881723        1045.50    166.0
1056.25
1     6.9      1292.25   9.397165         954.75    103.0
1173.75
2     6.1      1402.00   8.997817         939.25    131.0
1140.00
3     3.9      1375.50   9.228796         948.25    172.0
1092.00
4     1.5      1272.25   6.518224         835.50    131.0
1205.00

   NO2(GT)  PT08_S4(NO2)  PT08_S5(O3)      T         RH        AH  \
0    113.0       1692.00      1267.50  13.60  48.875001  0.757754
```

```
1     92.0       1558.75       972.25  13.30  47.700000  0.725487
2    114.0       1554.50      1074.00  11.90  53.975000  0.750239
3    122.0       1583.75      1203.25  11.00  60.000000  0.786713
4    116.0       1490.00      1110.00  11.15  59.575001  0.788794

             datetime day month hour  time_idx
0 2004-03-10 18:00:00  10     3   18         0
1 2004-03-10 19:00:00  10     3   19         1
2 2004-03-10 20:00:00  10     3   20         2
3 2004-03-10 21:00:00  10     3   21         3
4 2004-03-10 22:00:00  10     3   22         4

max_prediction_length = 24
max_encoder_length = 24

train_actual['group'] = 0

training = TimeSeriesDataSet(
    train_actual,
    time_idx="time_idx",
    target="CO(GT)",
    group_ids=["group"],  # Single time series
    min_encoder_length=max_encoder_length // 2,
    max_encoder_length=max_encoder_length,
    min_prediction_length=1,
    max_prediction_length=max_prediction_length,
    static_categoricals=[],  # No static categoricals in the dataset
    static_reals=[],  # No static reals the dataset
    time_varying_known_categoricals=["day", "month", "hour"],  # Time-
related features
    time_varying_known_reals=["time_idx"],  # Known reals including
time index
    time_varying_unknown_categoricals=[],
    time_varying_unknown_reals=[
        'PT08_S1(CO)', 'C6H6(GT)', 'PT08_S2(NMHC)', 'NOx(GT)',
       'PT08_S3(NOx)', 'NO2(GT)', 'PT08_S4(NO2)', 'PT08_S5(O3)', 'T',
'RH', 'AH'
    ],
    target_normalizer=GroupNormalizer(groups=["group"],
transformation="softplus"),
    add_relative_time_idx=True,
    add_target_scales=True,
    add_encoder_length=True,
    categorical_encoders={
        "day": NaNLabelEncoder(add_nan=True),
        "month": NaNLabelEncoder(add_nan=True),
        "hour": NaNLabelEncoder(add_nan=True)
    }
)
```

```
# Dataloaders for model
batch_size = 64
train_dataloader = training.to_dataloader(train=True,
batch_size=batch_size, num_workers= 0 )
validation_data['group'] = 0
validation = TimeSeriesDataSet.from_dataset(training, validation_data,
predict=True, stop_randomization=True)
val_dataloader = validation.to_dataloader(train=False,
batch_size=batch_size * 10, num_workers= 0)
```

Baseline Model

```
baseline_predictions = Baseline().predict(val_dataloader,
return_y=True)
MAE()(baseline_predictions.output, baseline_predictions.y)
```

```
INFO: Trainer will use only 1 of 2 GPUs because it is running inside
an interactive / notebook environment. You may try to set
`Trainer(devices=2)` but please note that multi-GPU inside interactive
/ notebook environments is considered experimental and unstable. Your
mileage may vary.
INFO: GPU available: True (cuda), used: True
INFO: TPU available: False, using: 0 TPU cores
INFO: HPU available: False, using: 0 HPUs
2024-08-22 14:53:15.088430: E
external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261] Unable
to register cuDNN factory: Attempting to register factory for plugin
cuDNN when one has already been registered
2024-08-22 14:53:15.088498: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607] Unable to
register cuFFT factory: Attempting to register factory for plugin
cuFFT when one has already been registered
2024-08-22 14:53:15.090211: E
external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1515] Unable
to register cuBLAS factory: Attempting to register factory for plugin
cuBLAS when one has already been registered
INFO: LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0,1]

tensor(0.9250, device='cuda:0')
```

Opimal Learning Rate

```
pl.seed_everything(42)

# GPU if available
device = "cuda" if torch.cuda.is_available() else "cpu"


trainer = pl.Trainer(
```

```
    accelerator=device,
    gradient_clip_val=0.1,
)

# TemporalFusionTransformer model
tft = TemporalFusionTransformer.from_dataset(
    training,
    learning_rate=0.03,  # This can be adjusted later with the found
optimal learning rate
    hidden_size=8,
    attention_head_size=1,
    dropout=0.1,
    hidden_continuous_size=8,
    loss=QuantileLoss(),
    optimizer="Ranger",
)

print(f"Number of parameters in network: {tft.size()/1e3:.1f}k")
```

```
INFO: Seed set to 42
INFO: Trainer will use only 1 of 2 GPUs because it is running inside
an interactive / notebook environment. You may try to set
`Trainer(devices=2)` but please note that multi-GPU inside interactive
/ notebook environments is considered experimental and unstable. Your
mileage may vary.
INFO: GPU available: True (cuda), used: True
INFO: TPU available: False, using: 0 TPU cores
INFO: HPU available: False, using: 0 HPUs
```

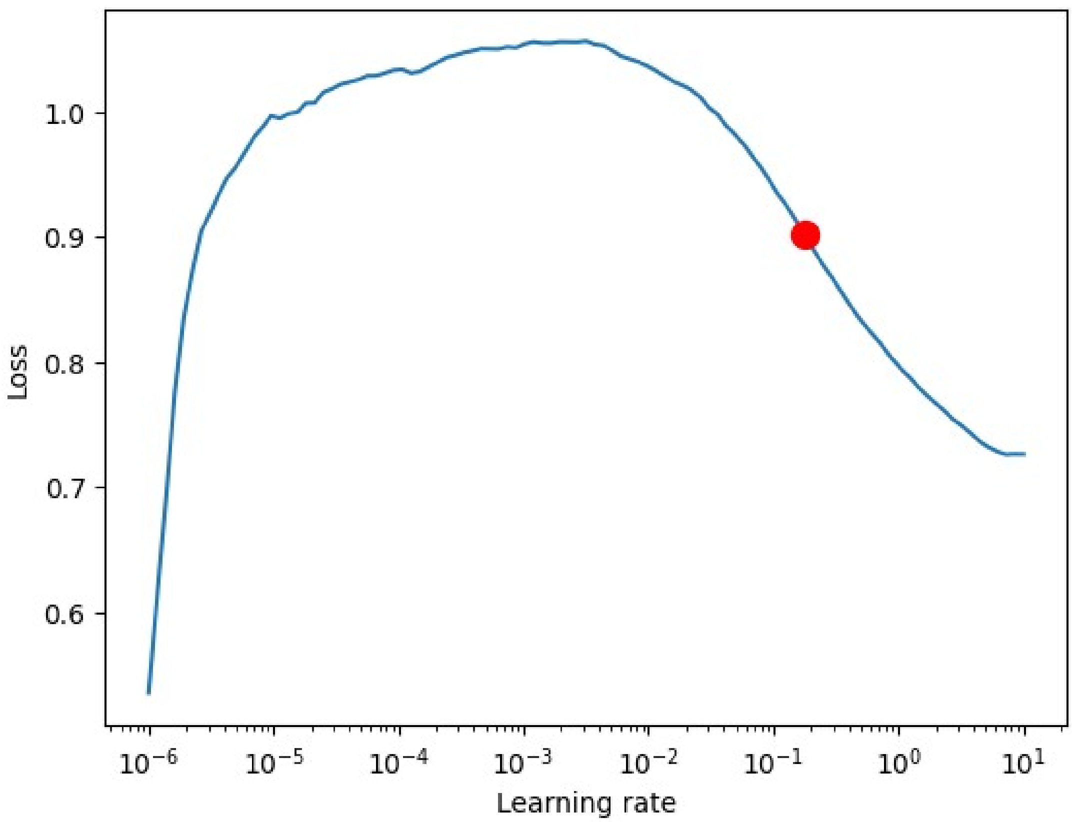
```
Number of parameters in network: 12.2k
```

```
#from lightning.pytorch.tuner import Tuner
from lightning.pytorch.tuner import Tuner

res = Tuner(trainer).lr_find(
    tft,
    train_dataloaders=train_dataloader,
    val_dataloaders=val_dataloader,
    max_lr=10.0,
    min_lr=1e-6,
)

print(f"suggested learning rate: {res.suggestion()}")
fig =  res.plot(show=True, suggest=True)
fig.show()
```

```
INFO: LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0,1]
```


{"model_id":"df12f657a1964441897d18be4eb1f4d3","version_major":2,"vers
ion_minor":0}

```
INFO: `Trainer.fit` stopped: `max_steps=100` reached.
INFO: Learning rate set to 0.17782794100389226
INFO: Restoring states from the checkpoint path at
/kaggle/working/.lr_find_19ee2ec8-24e2-4a15-ba6b-f2e5cf7cc080.ckpt
INFO: Restored all states from the checkpoint at
/kaggle/working/.lr_find_19ee2ec8-24e2-4a15-ba6b-f2e5cf7cc080.ckpt

suggested learning rate: 0.17782794100389226
```




```
early_stop_callback = EarlyStopping(monitor="val_loss", min_delta=1e-
4, patience=10, verbose=False, mode="min")
lr_logger = LearningRateMonitor()  # log the learning rate
logger = TensorBoardLogger("lightning_logs")  # logging results to a
tensorboard

trainer = pl.Trainer(
    max_epochs=50,
    accelerator=device,
    enable_model_summary=True,
    gradient_clip_val=0.1,
    limit_train_batches=50,
    # fast_dev_run=True,
    callbacks=[lr_logger, early_stop_callback],
```

```
    logger=logger,
)

tft = TemporalFusionTransformer.from_dataset(
    training,
    learning_rate=0.2,
    hidden_size=16,
    attention_head_size=2,
    dropout=0.1,
    hidden_continuous_size=8,
    loss=QuantileLoss(),
    log_interval=10,
    optimizer="Ranger",
    reduce_on_plateau_patience=4,
)
print(f"Number of parameters in network: {tft.size()/1e3:.1f}k")
```

```
INFO: Trainer will use only 1 of 2 GPUs because it is running inside
an interactive / notebook environment. You may try to set
`Trainer(devices=2)` but please note that multi-GPU inside interactive
/ notebook environments is considered experimental and unstable. Your
mileage may vary.
INFO: GPU available: True (cuda), used: True
INFO: TPU available: False, using: 0 TPU cores
INFO: HPU available: False, using: 0 HPUs
```

```
Number of parameters in network: 28.2k
```

```
trainer.fit(
    tft,
    train_dataloaders=train_dataloader,
    val_dataloaders=val_dataloader,
)
```

```
INFO: LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0,1]
INFO:
   | Name                               | Type
| Params | Mode
----------------------------------------------------------------------
--------------------------
0  | loss                               | QuantileLoss
| 0      | train
1  | logging_metrics                    | ModuleList
| 0      | train
2  | input_embeddings                   | MultiEmbedding
| 647    | train
3  | prescalers                         | ModuleDict
| 256    | train
4  | static_variable_selection          | VariableSelectionNetwork
| 1.7 K  | train
```

```
5  | encoder_variable_selection         | VariableSelectionNetwork
| 10.3 K | train
6  | decoder_variable_selection         | VariableSelectionNetwork
| 1.6 K  | train
7  | static_context_variable_selection  | GatedResidualNetwork
| 1.1 K  | train
8  | static_context_initial_hidden_lstm | GatedResidualNetwork
| 1.1 K  | train
9  | static_context_initial_cell_lstm   | GatedResidualNetwork
| 1.1 K  | train
10 | static_context_enrichment          | GatedResidualNetwork
| 1.1 K  | train
11 | lstm_encoder                       | LSTM
| 2.2 K  | train
12 | lstm_decoder                       | LSTM
| 2.2 K  | train
13 | post_lstm_gate_encoder             | GatedLinearUnit
| 544    | train
14 | post_lstm_add_norm_encoder         | AddNorm
| 32     | train
15 | static_enrichment                  | GatedResidualNetwork
| 1.4 K  | train
16 | multihead_attn                     |
InterpretableMultiHeadAttention | 808    | train
17 | post_attn_gate_norm                | GateAddNorm
| 576    | train
18 | pos_wise_ff                        | GatedResidualNetwork
| 1.1 K  | train
19 | pre_output_gate_norm               | GateAddNorm
| 576    | train
20 | output_layer                       | Linear
| 119    | train
----------------------------------------------------------------------
--------------------------
28.2 K    Trainable params
0         Non-trainable params
28.2 K    Total params
0.113     Total estimated model params size (MB)
452       Modules in train mode
0         Modules in eval mode
```

{"model_id":"a03adb07baf644ac9f53af09d0159d0e","version_major":2,"version_minor":0}

{"model_id":"36da665875eb48bb87d458dfa4deb1a1","version_major":2,"version_minor":0}

{"model_id":"dd3bacebaf0242c19f32bb6141784355","version_major":2,"version_minor":0}

```
{"model_id":"1fc36e6c1b324e34a30ce4318f4080d5","version_major":2,"version_minor":0}

{"model_id":"42bc0506c664477d8d764301e7de4d36","version_major":2,"version_minor":0}

{"model_id":"e97e07280b5245e59fe5434904de30bb","version_major":2,"version_minor":0}

{"model_id":"c19c669581a74b28af146e47dd09747e","version_major":2,"version_minor":0}

{"model_id":"8d48a41c5ec845cba58ed60f4017e55c","version_major":2,"version_minor":0}

{"model_id":"caa422d168ab431e995c146251eeacdc","version_major":2,"version_minor":0}

{"model_id":"95a4e865a52a49fbbfe4c36a8e9c537c","version_major":2,"version_minor":0}

{"model_id":"ec8dd19851af458e8296ab64dd6a11bd","version_major":2,"version_minor":0}

{"model_id":"a9e544aa3b144e5aa1392212f12f1093","version_major":2,"version_minor":0}

{"model_id":"28420082944b4e6c8b82f0f244a4111c","version_major":2,"version_minor":0}

{"model_id":"0d2884caf66941c4af9d0728b208ec60","version_major":2,"version_minor":0}
```


Hyperparameter Tuning

```
# import optuna
# #from pytorch_forecasting.models.temporal_fusion_transformer.tuning import optimize_hyperparameters
# # study
# study = optimize_hyperparameters(
#     train_dataloader,
#     val_dataloader,
#     model_path="optuna_test",
#     n_trials=200,
#     max_epochs=50,
#     gradient_clip_val_range=(0.01, 1.0),
#     hidden_size_range=(8, 128),
#     hidden_continuous_size_range=(8, 128),
#     attention_head_size_range=(1, 4),
#     learning_rate_range=(0.001, 0.1),
#     dropout_range=(0.1, 0.3),
```

```
#     trainer_kwargs=dict(limit_train_batches=30),
#     reduce_on_plateau_patience=4,
#     use_learning_rate_finder=False,  # use Optuna to find ideal
learning rate or use in-built learning rate finder
# )


# with open("test_study.pkl", "wb") as fout:
#     pickle.dump(study, fout)

# print(study.best_trial.params)

import pickle
import random


# Hyperparameter tuning using random search
def random_search_tuning(num_trials, hyperparameter_ranges):
    best_params = None
    best_loss = float("inf")

    for _ in range(num_trials):

        params = {
            "hidden_size":
random.randint(hyperparameter_ranges["hidden_size"][0],
hyperparameter_ranges["hidden_size"][1]),
            "hidden_continuous_size":
random.randint(hyperparameter_ranges["hidden_continuous_size"][0],
hyperparameter_ranges["hidden_continuous_size"][1]),
            "attention_head_size":
random.randint(hyperparameter_ranges["attention_head_size"][0],
hyperparameter_ranges["attention_head_size"][1]),
            "learning_rate":
random.uniform(hyperparameter_ranges["learning_rate"][0],
hyperparameter_ranges["learning_rate"][1]),
            "dropout": random.uniform(hyperparameter_ranges["dropout"]
[0], hyperparameter_ranges["dropout"][1]),
            "gradient_clip_val":
random.uniform(hyperparameter_ranges["gradient_clip_val"][0],
hyperparameter_ranges["gradient_clip_val"][1]),
        }


        tft = TemporalFusionTransformer.from_dataset(
            training,
            hidden_size=params["hidden_size"],
            attention_head_size=params["attention_head_size"],
            dropout=params["dropout"],
            hidden_continuous_size=params["hidden_continuous_size"],
```

```
            learning_rate=params["learning_rate"],
            loss=QuantileLoss(),
            log_interval=10,
            optimizer="Ranger",
            reduce_on_plateau_patience=4,
        )

        #  trainer
        trainer = pl.Trainer(
            max_epochs=10,
            accelerator= device,
            gradient_clip_val=params["gradient_clip_val"],  # gradient
clipping happens here in the Trainer
            callbacks=[LearningRateMonitor(),
EarlyStopping(monitor="val_loss", patience=4)],
            logger=TensorBoardLogger("logs",
name="tft_random_search"),
            limit_train_batches=50,
        )

        # model training
        trainer.fit(
            tft,
            train_dataloaders=train_dataloader,
            val_dataloaders=val_dataloader,
        )


        val_loss = trainer.callback_metrics["val_loss"].item()


        if val_loss < best_loss:
            best_loss = val_loss
            best_params = params

    return best_params, best_loss

# hyperparameter ranges
hyperparameter_ranges = {
    "hidden_size": (8, 128),
    "hidden_continuous_size": (8, 128),
    "attention_head_size": (1, 4),
    "learning_rate": (0.001, 0.1),
    "dropout": (0.1, 0.3),
    "gradient_clip_val": (0.01, 1.0)
}

# Perform random search tuning
best_params, best_loss = random_search_tuning(num_trials= 3,
hyperparameter_ranges=hyperparameter_ranges)
```

```python
# Print the best hyperparameters
print("Best Hyperparameters:", best_params)
print("Best Validation Loss:", best_loss)

# Save the best hyperparameters
with open("best_params.pkl", "wb") as fout:
    pickle.dump(best_params, fout)
```

```
INFO: Trainer will use only 1 of 2 GPUs because it is running inside
an interactive / notebook environment. You may try to set
`Trainer(devices=2)` but please note that multi-GPU inside interactive
/ notebook environments is considered experimental and unstable. Your
mileage may vary.
INFO: GPU available: True (cuda), used: True
INFO: TPU available: False, using: 0 TPU cores
INFO: HPU available: False, using: 0 HPUs
INFO: LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0,1]
INFO:
   | Name                               | Type
| Params | Mode
----------------------------------------------------------------------
--------------------------
0  | loss                               | QuantileLoss
| 0      | train
1  | logging_metrics                    | ModuleList
| 0      | train
2  | input_embeddings                   | MultiEmbedding
| 647    | train
3  | prescalers                         | ModuleDict
| 704    | train
4  | static_variable_selection          | VariableSelectionNetwork
| 17.0 K | train
5  | encoder_variable_selection         | VariableSelectionNetwork
| 80.9 K | train
6  | decoder_variable_selection         | VariableSelectionNetwork
| 12.9 K | train
7  | static_context_variable_selection  | GatedResidualNetwork
| 32.2 K | train
8  | static_context_initial_hidden_lstm | GatedResidualNetwork
| 32.2 K | train
9  | static_context_initial_cell_lstm   | GatedResidualNetwork
| 32.2 K | train
10 | static_context_enrichment          | GatedResidualNetwork
| 32.2 K | train
11 | lstm_encoder                       | LSTM
| 64.1 K | train
12 | lstm_decoder                       | LSTM
| 64.1 K | train
13 | post_lstm_gate_encoder             | GatedLinearUnit
```

```
| 16.0 K | train
14 | post_lstm_add_norm_encoder         | AddNorm
| 178    | train
15 | static_enrichment                  | GatedResidualNetwork
| 40.1 K | train
16 | multihead_attn                     |
InterpretableMultiHeadAttention | 32.0 K | train
17 | post_attn_gate_norm                | GateAddNorm
| 16.2 K | train
18 | pos_wise_ff                        | GatedResidualNetwork
| 32.2 K | train
19 | pre_output_gate_norm               | GateAddNorm
| 16.2 K | train
20 | output_layer                       | Linear
| 630    | train
----------------------------------------------------------------------
--------------------------
521 K     Trainable params
0         Non-trainable params
521 K     Total params
2.088     Total estimated model params size (MB)
450       Modules in train mode
0         Modules in eval mode
```

{"model_id":"b88c6aada5f34d6c94e9fa64013c2982","version_major":2,"version_minor":0}

{"model_id":"2688f6a25374496cba1568d0e9df063b","version_major":2,"version_minor":0}

{"model_id":"0b63a7d20c884b14bbfd65d2cd9bfbf2","version_major":2,"version_minor":0}

{"model_id":"1098a41670ea44d7b034c5128c24d012","version_major":2,"version_minor":0}

{"model_id":"b4071dc3ab584f30b72221395ae3c0ac","version_major":2,"version_minor":0}

{"model_id":"1b0b95a0d4fa43178fa6dc796f81e1ce","version_major":2,"version_minor":0}

{"model_id":"51292871eaa34aa985738b23f89317fc","version_major":2,"version_minor":0}

{"model_id":"e2356ad6d3d340c697c0483afd86f217","version_major":2,"version_minor":0}

{"model_id":"4c46d27b59c741b9ae51d71957856bc5","version_major":2,"version_minor":0}

```
INFO: Trainer will use only 1 of 2 GPUs because it is running inside
an interactive / notebook environment. You may try to set
`Trainer(devices=2)` but please note that multi-GPU inside interactive
/ notebook environments is considered experimental and unstable. Your
mileage may vary.
INFO: GPU available: True (cuda), used: True
INFO: TPU available: False, using: 0 TPU cores
INFO: HPU available: False, using: 0 HPUs
INFO: LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0,1]
INFO:
   | Name                               | Type
| Params | Mode
----------------------------------------------------------------------
--------------------------
0  | loss                               | QuantileLoss
| 0      | train
1  | logging_metrics                    | ModuleList
| 0      | train
2  | input_embeddings                   | MultiEmbedding
| 647    | train
3  | prescalers                         | ModuleDict
| 3.0 K  | train
4  | static_variable_selection          | VariableSelectionNetwork
| 11.9 K | train
5  | encoder_variable_selection         | VariableSelectionNetwork
| 69.2 K | train
6  | decoder_variable_selection         | VariableSelectionNetwork
| 8.8 K  | train
7  | static_context_variable_selection  | GatedResidualNetwork
| 1.9 K  | train
8  | static_context_initial_hidden_lstm | GatedResidualNetwork
| 1.9 K  | train
9  | static_context_initial_cell_lstm   | GatedResidualNetwork
| 1.9 K  | train
10 | static_context_enrichment          | GatedResidualNetwork
| 1.9 K  | train
11 | lstm_encoder                       | LSTM
| 3.7 K  | train
12 | lstm_decoder                       | LSTM
| 3.7 K  | train
13 | post_lstm_gate_encoder             | GatedLinearUnit
| 924    | train
14 | post_lstm_add_norm_encoder         | AddNorm
| 42     | train
15 | static_enrichment                  | GatedResidualNetwork
| 2.3 K  | train
16 | multihead_attn                     |
InterpretableMultiHeadAttention | 1.8 K  | train
17 | post_attn_gate_norm                | GateAddNorm
| 966    | train
```

```
18 | pos_wise_ff                        | GatedResidualNetwork
| 1.9 K  | train
19 | pre_output_gate_norm               | GateAddNorm
| 966    | train
20 | output_layer                       | Linear
| 154    | train
----------------------------------------------------------------------
--------------------------
114 K     Trainable params
0         Non-trainable params
114 K     Total params
0.457     Total estimated model params size (MB)
450       Modules in train mode
0         Modules in eval mode
```


{"model_id":"57eaec947718475dba551bdffe771c41","version_major":2,"version_minor":0}

{"model_id":"a3b4c44a17fe4019bd7b41e5d108ade9","version_major":2,"version_minor":0}

{"model_id":"3ebcbc71650749639fbc2a04da6d67a9","version_major":2,"version_minor":0}

{"model_id":"477f03b3735a46418627b9c3994e7478","version_major":2,"version_minor":0}

{"model_id":"2961c6b7e2f2473d8b5e76794587bec6","version_major":2,"version_minor":0}

{"model_id":"ab294ec1c1b24c8f9669de415c96a2cb","version_major":2,"version_minor":0}

{"model_id":"56b4d750810146c9953d6925b865421d","version_major":2,"version_minor":0}

{"model_id":"bbcc7a0d5bbd45aab54126fcd34fa5b7","version_major":2,"version_minor":0}


```
INFO: Trainer will use only 1 of 2 GPUs because it is running inside
an interactive / notebook environment. You may try to set
`Trainer(devices=2)` but please note that multi-GPU inside interactive
/ notebook environments is considered experimental and unstable. Your
mileage may vary.
INFO: GPU available: True (cuda), used: True
INFO: TPU available: False, using: 0 TPU cores
INFO: HPU available: False, using: 0 HPUs
INFO: LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0,1]
INFO:
   | Name                               | Type
| Params | Mode
```

```
----------------------------------------------------------------------
--------------------------
0  | loss                               | QuantileLoss
| 0      | train
1  | logging_metrics                    | ModuleList
| 0      | train
2  | input_embeddings                   | MultiEmbedding
| 647    | train
3  | prescalers                         | ModuleDict
| 2.3 K  | train
4  | static_variable_selection          | VariableSelectionNetwork
| 22.4 K | train
5  | encoder_variable_selection         | VariableSelectionNetwork
| 111 K  | train
6  | decoder_variable_selection         | VariableSelectionNetwork
| 16.0 K | train
7  | static_context_variable_selection  | GatedResidualNetwork
| 5.7 K  | train
8  | static_context_initial_hidden_lstm | GatedResidualNetwork
| 5.7 K  | train
9  | static_context_initial_cell_lstm   | GatedResidualNetwork
| 5.7 K  | train
10 | static_context_enrichment          | GatedResidualNetwork
| 5.7 K  | train
11 | lstm_encoder                       | LSTM
| 11.2 K | train
12 | lstm_decoder                       | LSTM
| 11.2 K | train
13 | post_lstm_gate_encoder             | GatedLinearUnit
| 2.8 K  | train
14 | post_lstm_add_norm_encoder         | AddNorm
| 74     | train
15 | static_enrichment                  | GatedResidualNetwork
| 7.1 K  | train
16 | multihead_attn                     |
InterpretableMultiHeadAttention | 5.6 K  | train
17 | post_attn_gate_norm                | GateAddNorm
| 2.9 K  | train
18 | pos_wise_ff                        | GatedResidualNetwork
| 5.7 K  | train
19 | pre_output_gate_norm               | GateAddNorm
| 2.9 K  | train
20 | output_layer                       | Linear
| 266    | train
----------------------------------------------------------------------
--------------------------
222 K     Trainable params
0         Non-trainable params
222 K     Total params
```

```
0.891     Total estimated model params size (MB)
450       Modules in train mode
0         Modules in eval mode
```


{"model_id":"29574955e95b4b9a941819fc0a1ef6ae","version_major":2,"version_minor":0}

{"model_id":"b659440a103148aaaa6cc44f98f93cfa","version_major":2,"version_minor":0}

{"model_id":"0d1bcf73ce354c48b58302e2ffcb8531","version_major":2,"version_minor":0}

{"model_id":"d18fec3af0594eae8e97d33c7e0630d3","version_major":2,"version_minor":0}

{"model_id":"0a9cd464ac72453697a91bfcc43d7eed","version_major":2,"version_minor":0}

{"model_id":"9b56a0af502d4dbea6bd7795822b4ed1","version_major":2,"version_minor":0}

{"model_id":"2d9eee4cf150402cb7ceee53714164f0","version_major":2,"version_minor":0}

{"model_id":"186bfef146284439a9a4360286578783","version_major":2,"version_minor":0}


```
Best Hyperparameters: {'hidden_size': 21, 'hidden_continuous_size':
94, 'attention_head_size': 1, 'learning_rate': 0.05945875873245493,
'dropout': 0.10635653589635673, 'gradient_clip_val':
0.10275828746297652}
Best Validation Loss: 0.3436449468135834
```

```
best_model_path = trainer.checkpoint_callback.best_model_path
best_tft =
TemporalFusionTransformer.load_from_checkpoint(best_model_path)
```

```
# mean absolute error on validation set
predictions = best_tft.predict(val_dataloader, return_y=True,
trainer_kwargs=dict(accelerator= device))
MAE()(predictions.output, predictions.y)
```

```
INFO: GPU available: True (cuda), used: False
INFO: TPU available: False, using: 0 TPU cores
INFO: HPU available: False, using: 0 HPUs
```

```
tensor(1.1578)
```

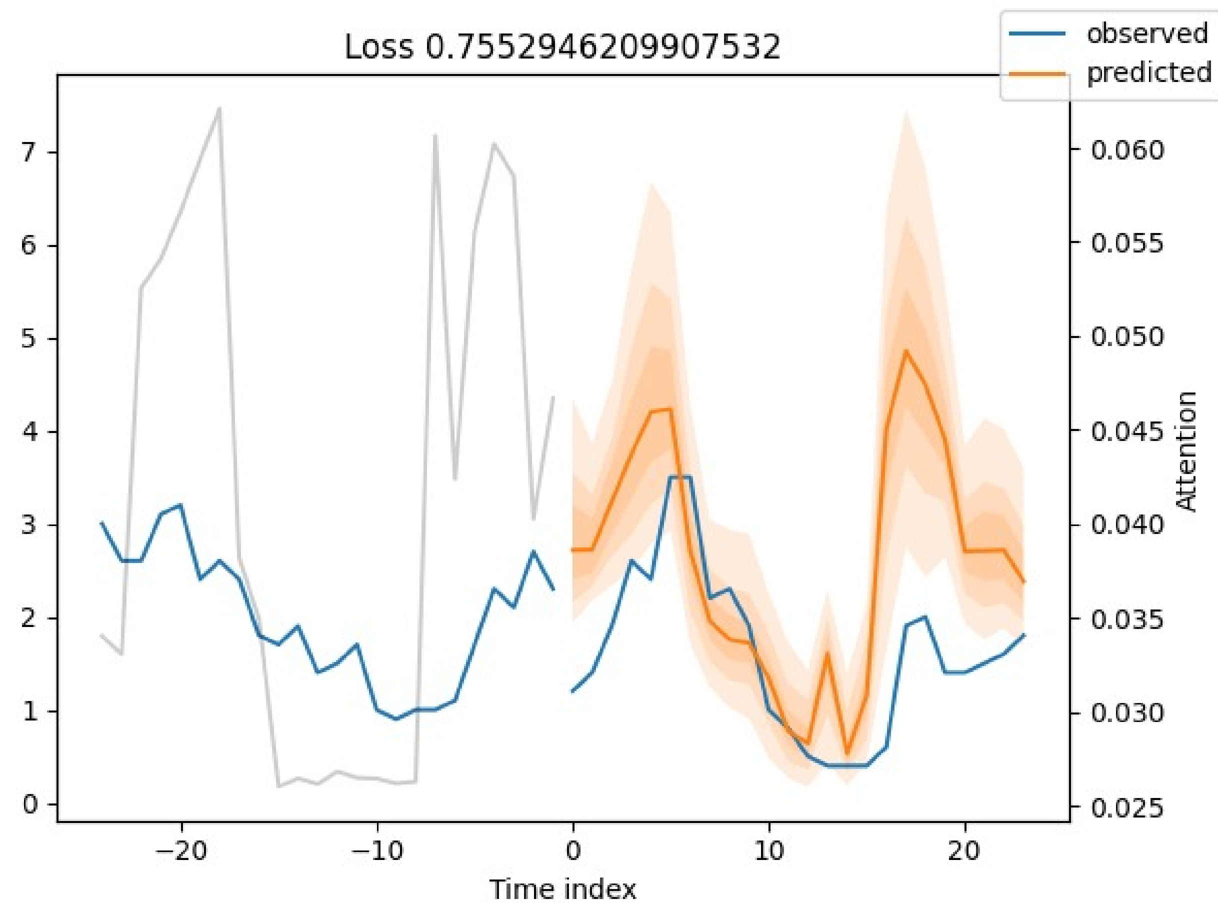
```
raw_predictions = best_tft.predict(val_dataloader, mode="raw",
return_x=True)
```

```
INFO: Trainer will use only 1 of 2 GPUs because it is running inside
an interactive / notebook environment. You may try to set
`Trainer(devices=2)` but please note that multi-GPU inside interactive
/ notebook environments is considered experimental and unstable. Your
mileage may vary.
INFO: GPU available: True (cuda), used: True
INFO: TPU available: False, using: 0 TPU cores
INFO: HPU available: False, using: 0 HPUs
INFO: LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0,1]
```

```
for idx in range(10):  # plot 10 examples
    best_tft.plot_prediction(raw_predictions.x,
raw_predictions.output, idx=idx, add_loss_to_title=True)
```

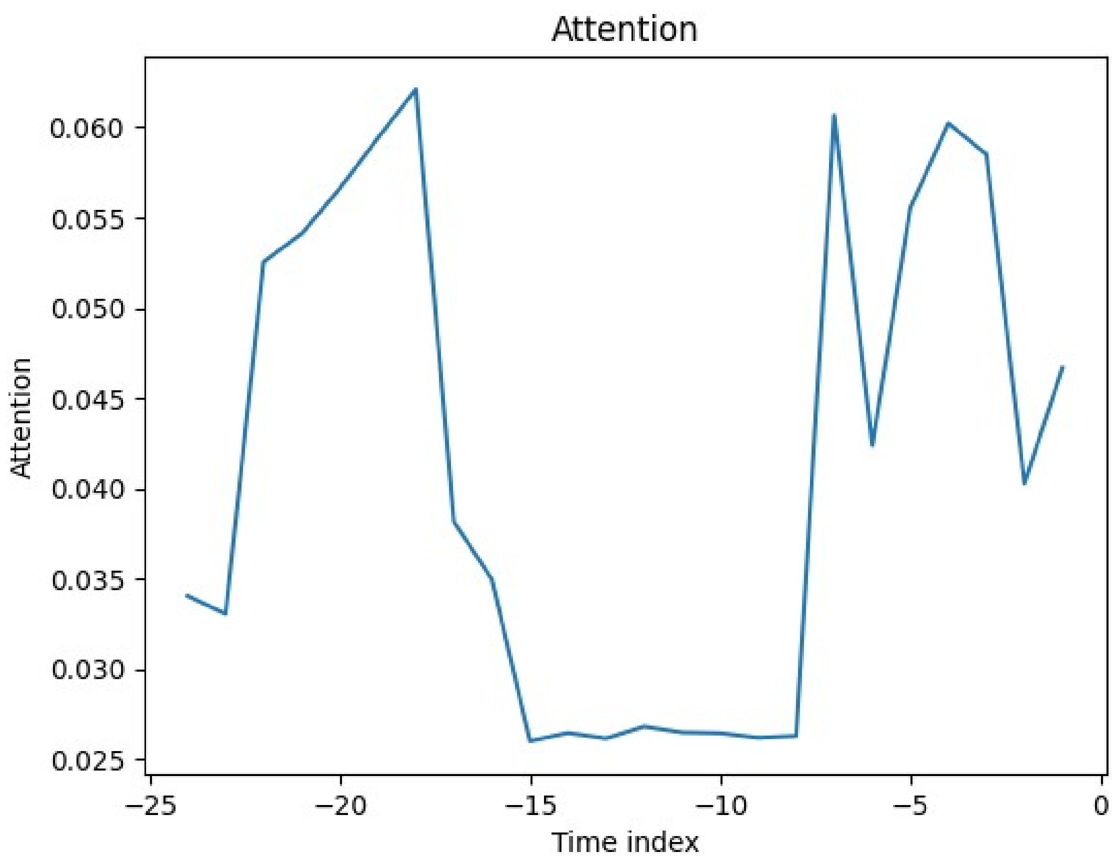
```
----------------------------------------------------------------------
-----
IndexError                                Traceback (most recent call
last)
Cell In[45], line 2
      1 for idx in range(10):  # plot 10 examples
----> 2     best_tft.plot_prediction(raw_predictions.x,
raw_predictions.output, idx=idx, add_loss_to_title=True)

File
/opt/conda/lib/python3.10/site-packages/pytorch_forecasting/models/
temporal_fusion_transformer/__init__.py:711, in
TemporalFusionTransformer.plot_prediction(self, x, out, idx,
plot_attention, add_loss_to_title, show_future_observed, ax, **kwargs)
    694 """
    695 Plot actuals vs prediction and attention
    696
   (...)
    707     plt.Figure: matplotlib figure
    708 """
    710 # plot prediction as normal
--> 711 fig = super().plot_prediction(
    712     x,
    713     out,
    714     idx=idx,
    715     add_loss_to_title=add_loss_to_title,
    716     show_future_observed=show_future_observed,
    717     ax=ax,
    718     **kwargs,
    719 )
    721 # add attention on secondary axis
    722 if plot_attention:

File
/opt/conda/lib/python3.10/site-packages/pytorch_forecasting/models/
base_model.py:999, in BaseModel.plot_prediction(self, x, out, idx,
```

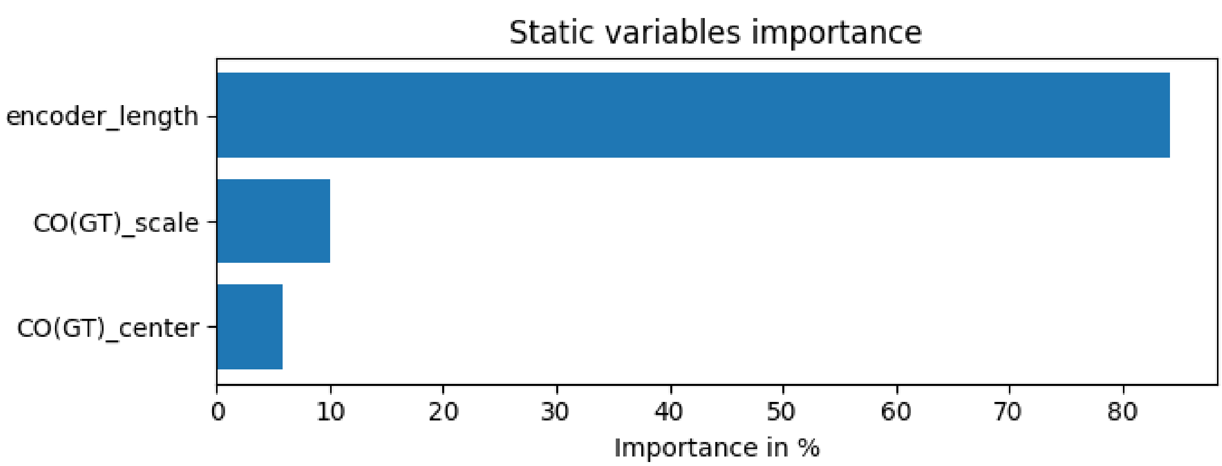
```
add_loss_to_title, show_future_observed, ax, quantiles_kwargs,
prediction_kwargs)
    995 figs = []
    996 for y_raw, y_hat, y_quantile, encoder_target, decoder_target
in zip(
    997     y_raws, y_hats, y_quantiles, encoder_targets,
decoder_targets
    998 ):
--> 999     y_all = torch.cat([encoder_target[idx],
decoder_target[idx]])
   1000     max_encoder_length = x["encoder_lengths"].max()
   1001     y = torch.cat(
   1002         (
   1003             y_all[: x["encoder_lengths"][idx]],
   1004             y_all[max_encoder_length : (max_encoder_length +
x["decoder_lengths"][idx])],
   1005         ),
   1006     )

IndexError: index 1 is out of bounds for dimension 0 with size 1
```

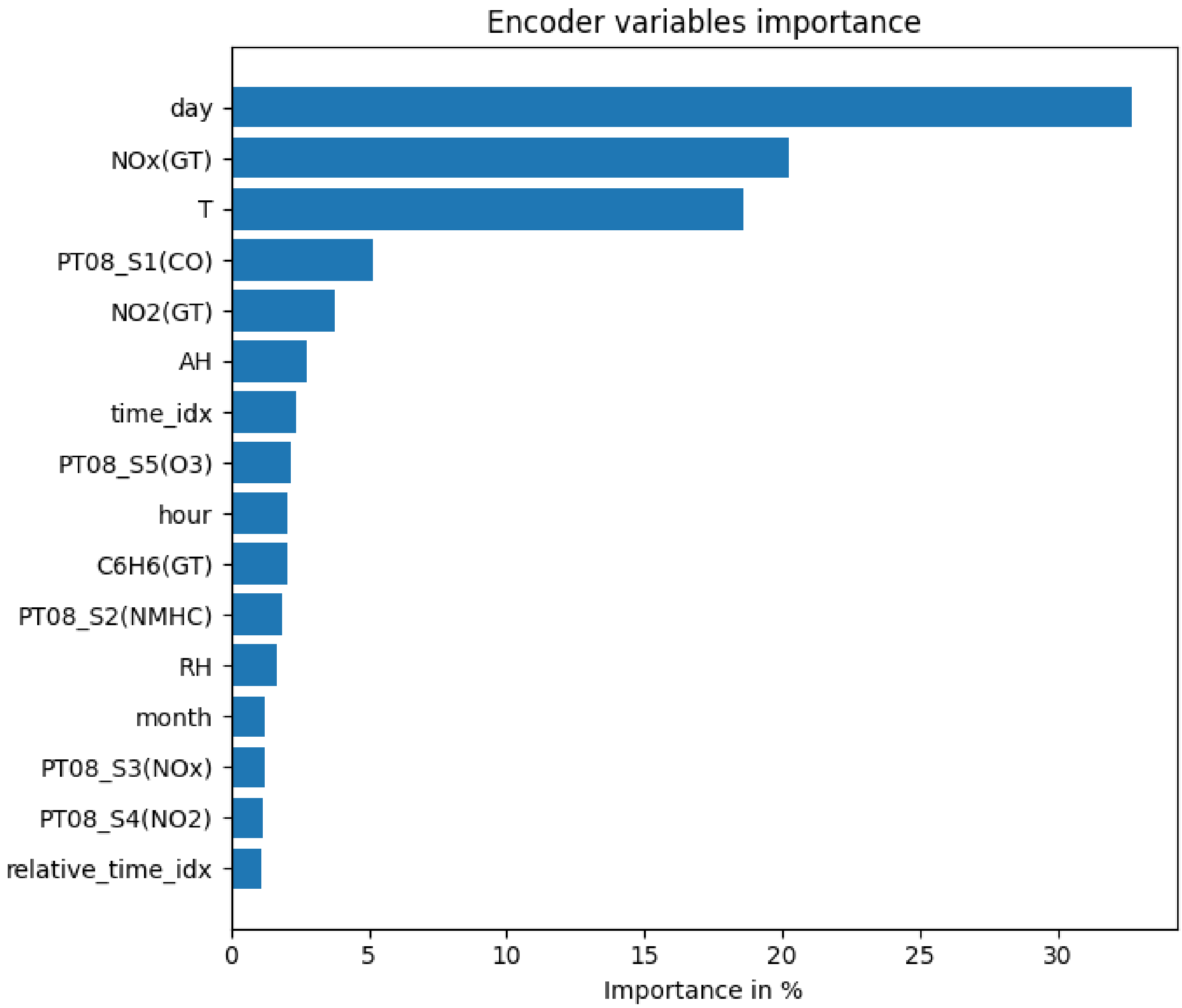


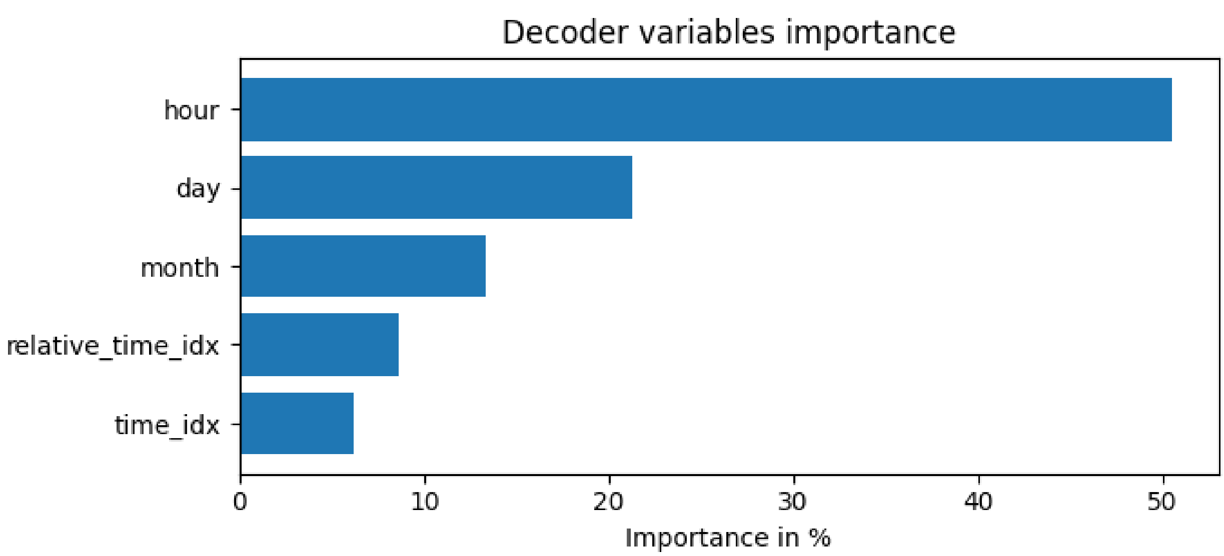
```
interpretation = tft.interpret_output(raw_predictions.output,
reduction="sum")
tft.plot_interpretation(interpretation)
```

```
{'attention': <Figure size 640x480 with 1 Axes>,
 'static_variables': <Figure size 700x275 with 1 Axes>,
 'encoder_variables': <Figure size 700x600 with 1 Axes>,
 'decoder_variables': <Figure size 700x325 with 1 Axes>}
```






Encoder variables importance
day
NOx(GT)
T
PT08_S1(CO)
NO2(GT)
AH
time_idx
PT08_S5(O3)
hour
C6H6(GT)
PT08_S2(NMHC)
RH
month
PT08_S3(NOx)
PT08_S4(NO2)
relative_time_idx
0
5
10
15
20
25
30
Importance in %


Decoder variables importance
hour
day
month
relative_time_idx
time_idx
0
10
20
30
40
50
Importance in %

Evaluation

```
max_prediction_length = 24
max_encoder_length = 24

test_data['group'] = 0

test = TimeSeriesDataSet(
    test_data,
    time_idx="time_idx",
    target="CO(GT)",
    group_ids=["group"],  # Single time series
    min_encoder_length=max_encoder_length // 2,
    max_encoder_length=max_encoder_length,
    min_prediction_length=1,
    max_prediction_length=max_prediction_length,
    static_categoricals=[],  # No static categoricals in the dataset
    static_reals=[],  # No static reals the dataset
    time_varying_known_categoricals=["day", "month", "hour"],  # Time-
related features
    time_varying_known_reals=["time_idx"],  # Known reals including
time index
    time_varying_unknown_categoricals=[],
    time_varying_unknown_reals=[
        'PT08_S1(CO)', 'C6H6(GT)', 'PT08_S2(NMHC)', 'NOx(GT)',
       'PT08_S3(NOx)', 'NO2(GT)', 'PT08_S4(NO2)', 'PT08_S5(O3)', 'T',
'RH', 'AH'
    ],
    target_normalizer=GroupNormalizer(groups=["group"],
transformation="softplus"),
    add_relative_time_idx=True,
    add_target_scales=True,
    add_encoder_length=True,
    categorical_encoders={
        "day": NaNLabelEncoder(add_nan=True),
        "month": NaNLabelEncoder(add_nan=True),
        "hour": NaNLabelEncoder(add_nan=True)
    }
)

batch_size = 64
test_dataloader = test.to_dataloader(train=True,
batch_size=batch_size, num_workers= 0 )

predictions = tft.predict(test_dataloader, return_x=True, mode =
"raw")
```

```
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```

```
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```
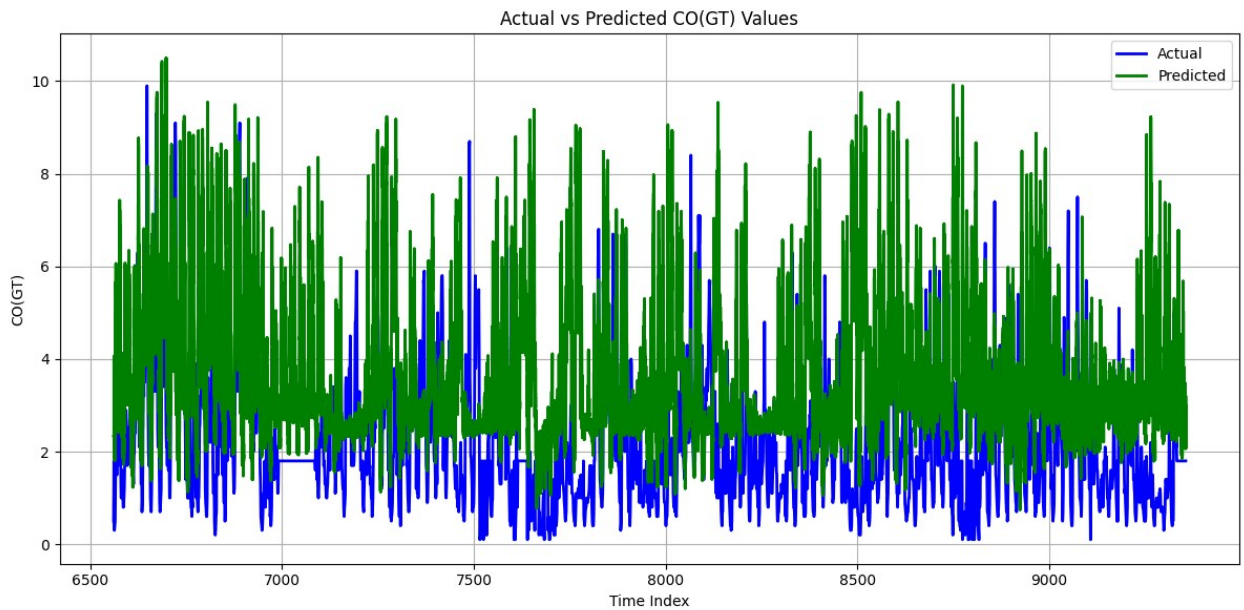

```
import matplotlib.pyplot as plt
import pandas as pd

# Extract predicted values and time indices
predicted_values = predictions.output[0][:, :,
6].cpu().numpy().flatten()
time_indices =
predictions.x['decoder_time_idx'].cpu().numpy().flatten()

# Convert to DataFrame for easier manipulation
predicted_df = pd.DataFrame({
    'time_idx': time_indices,
    'predicted': predicted_values
})

# Ensure you have the correct time_idx format in test_data
test_data_df = test_data[['time_idx', 'CO(GT)']].copy()
test_data_df['time_idx'] = test_data_df['time_idx'].astype(int)

# Merge predicted and actual values based on time_idx
merged_df = pd.merge(test_data_df, predicted_df, on='time_idx',
how='inner')

# Plot the actual vs. predicted values
plt.figure(figsize=(12, 6))

plt.plot(merged_df['time_idx'], merged_df['CO(GT)'], label='Actual',
color='blue', linewidth=2)
plt.plot(merged_df['time_idx'], merged_df['predicted'],
label='Predicted', color='green', linewidth=2)

plt.title('Actual vs Predicted CO(GT) Values')
plt.xlabel('Time Index')
plt.ylabel('CO(GT)')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```




```
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score

predicted_values = predictions.output[0][:, :,
6].cpu().numpy().flatten()
actual_values = test_data['CO(GT)'].values

# Ensure the length matches for computation
num_predictions = min(len(predicted_values), len(actual_values))
predicted_values = predicted_values[:num_predictions]
actual_values = actual_values[:num_predictions]


mae = mean_absolute_error(actual_values, predicted_values)
mse = mean_squared_error(actual_values, predicted_values)
rmse = np.sqrt(mse)
#r2 = r2_score(actual_values, predicted_values)

print(f"Mean Absolute Error (MAE): {mae:.4f}")
print(f"Mean Squared Error (MSE): {mse:.4f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.4f}")
#print(f"R-squared (R²): {r2:.4f}")
```

```
Mean Absolute Error (MAE): 1.8868
Mean Squared Error (MSE): 5.9123
Root Mean Squared Error (RMSE): 2.4315
```