In [1]:

```
#| default_exp models.autoformer
```

Autoformer

The Autoformer model tackles the challenge of finding reliable dependencies on intricate temporal patterns of long-horizon forecasting.

The architecture has the following distinctive features:

- In-built progressive decomposition in trend and seasonal compontents based on a moving average filter.
- Auto-Correlation mechanism that discovers the period-based dependencies by calculating the autocorrelation and aggregating similar sub-series based on the periodicity.
- Classic encoder-decoder proposed by Vaswani et al. (2017) with a multi-head attention mechanism.

The Autoformer model utilizes a three-component approach to define its embedding:

- It employs encoded autoregressive features obtained from a convolution network.
- Absolute positional embeddings obtained from calendar features are utilized.

References

- Wu, Haixu, Jiehui Xu, Jianmin Wang, and Mingsheng Long. "Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting"

Figure 1. Autoformer Architecture.

In [20]:

```
#| export
import math
import numpy as np
from typing import Optional

import torch
import torch.nn as nn
import torch.nn.functional as F

from neuralforecast.common._modules import DataEmbedding
from neuralforecast.common._base_windows import BaseWindows

from neuralforecast.losses.pytorch import MAE
```

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In [21]:
```
#| hide
from fastcore.test import test_eq
from nbdev.showdoc import show_doc
```

1. Auxiliary Functions

In [22]:
```
#| export
class AutoCorrelation(nn.Module):
    """
    AutoCorrelation Mechanism with the following two phases:
    (1) period-based dependencies discovery
    (2) time delay aggregation
    This block can replace the self-attention family mechanism seamlessly.
    """
    def __init__(self, mask_flag=True, factor=1, scale=None, attention_dropo
        super(AutoCorrelation, self).__init__()
        self.factor = factor
        self.scale = scale
        self.mask_flag = mask_flag
        self.output_attention = output_attention
        self.dropout = nn.Dropout(attention_dropout)

    def time_delay_agg_training(self, values, corr):
        """
        SpeedUp version of Autocorrelation (a batch-normalization style desi
        This is for the training phase.
        """
        head = values.shape[1]
        channel = values.shape[2]
        length = values.shape[3]
        # find top k
        top_k = int(self.factor * math.log(length))
        mean_value = torch.mean(torch.mean(corr, dim=1), dim=1)
        index = torch.topk(torch.mean(mean_value, dim=0), top_k, dim=-1)[1]
        weights = torch.stack([mean_value[:, index[i]] for i in range(top_k)
        # update corr
        tmp_corr = torch.softmax(weights, dim=-1)
        # aggregation
        tmp_values = values
        delays_agg = torch.zeros_like(values, dtype=torch.float, device=valu
        for i in range(top_k):
            pattern = torch.roll(tmp_values, -int(index[i]), -1)
            delays_agg = delays_agg + pattern * \
                         (tmp_corr[:, i].unsqueeze(1).unsqueeze(1).unsqueeze
        return delays_agg

    def time_delay_agg_inference(self, values, corr):
        """
        SpeedUp version of Autocorrelation (a batch-normalization style desi
        This is for the inference phase.
        """
        batch = values.shape[0]
        head = values.shape[1]
        channel = values.shape[2]
```

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```
        length = values.shape[3]
        # index init
        init_index = torch.arange(length, device=values.device).unsqueeze(0)
        # find top k
        top_k = int(self.factor * math.log(length))
        mean_value = torch.mean(torch.mean(corr, dim=1), dim=1)
        weights = torch.topk(mean_value, top_k, dim=-1)[0]
        delay = torch.topk(mean_value, top_k, dim=-1)[1]
        # update corr
        tmp_corr = torch.softmax(weights, dim=-1)
        # aggregation
        tmp_values = values.repeat(1, 1, 1, 2)
        delays_agg = torch.zeros_like(values, dtype=torch.float, device=valu
        for i in range(top_k):
            tmp_delay = init_index + delay[:, i].unsqueeze(1).unsqueeze(1).u
            pattern = torch.gather(tmp_values, dim=-1, index=tmp_delay)
            delays_agg = delays_agg + pattern * \
                         (tmp_corr[:, i].unsqueeze(1).unsqueeze(1).unsqueeze
        return delays_agg

    def time_delay_agg_full(self, values, corr):
        """
        Standard version of Autocorrelation
        """
        batch = values.shape[0]
        head = values.shape[1]
        channel = values.shape[2]
        length = values.shape[3]
        # index init
        init_index = torch.arange(length, device=values.device).unsqueeze(0)
        # find top k
        top_k = int(self.factor * math.log(length))
        weights = torch.topk(corr, top_k, dim=-1)[0]
        delay = torch.topk(corr, top_k, dim=-1)[1]
        # update corr
        tmp_corr = torch.softmax(weights, dim=-1)
        # aggregation
        tmp_values = values.repeat(1, 1, 1, 2)
        delays_agg = torch.zeros_like(values, dtype=torch.float, device=valu
        for i in range(top_k):
            tmp_delay = init_index + delay[..., i].unsqueeze(-1)
            pattern = torch.gather(tmp_values, dim=-1, index=tmp_delay)
            delays_agg = delays_agg + pattern * (tmp_corr[..., i].unsqueeze(
        return delays_agg

    def forward(self, queries, keys, values, attn_mask):
        B, L, H, E = queries.shape
        _, S, _, D = values.shape
        if L > S:
            zeros = torch.zeros_like(queries[:, :(L - S), :], dtype=torch.fl
            values = torch.cat([values, zeros], dim=1)
            keys = torch.cat([keys, zeros], dim=1)
        else:
            values = values[:, :L, :, :]
            keys = keys[:, :L, :, :]
```

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```
        # period-based dependencies
        q_fft = torch.fft.rfft(queries.permute(0, 2, 3, 1).contiguous(), dim
        k_fft = torch.fft.rfft(keys.permute(0, 2, 3, 1).contiguous(), dim=-1
        res = q_fft * torch.conj(k_fft)
        corr = torch.fft.irfft(res, dim=-1)

        # time delay agg
        if self.training:
            V = self.time_delay_agg_training(values.permute(0, 2, 3, 1).cont
        else:
            V = self.time_delay_agg_inference(values.permute(0, 2, 3, 1).cor

        if self.output_attention:
            return (V.contiguous(), corr.permute(0, 3, 1, 2))
        else:
            return (V.contiguous(), None)


class AutoCorrelationLayer(nn.Module):
    def __init__(self, correlation, hidden_size, n_head, d_keys=None,
                 d_values=None):
        super(AutoCorrelationLayer, self).__init__()

        d_keys = d_keys or (hidden_size // n_head)
        d_values = d_values or (hidden_size // n_head)

        self.inner_correlation = correlation
        self.query_projection = nn.Linear(hidden_size, d_keys * n_head)
        self.key_projection = nn.Linear(hidden_size, d_keys * n_head)
        self.value_projection = nn.Linear(hidden_size, d_values * n_head)
        self.out_projection = nn.Linear(d_values * n_head, hidden_size)
        self.n_head = n_head

    def forward(self, queries, keys, values, attn_mask):
        B, L, _ = queries.shape
        _, S, _ = keys.shape
        H = self.n_head

        queries = self.query_projection(queries).view(B, L, H, -1)
        keys = self.key_projection(keys).view(B, S, H, -1)
        values = self.value_projection(values).view(B, S, H, -1)

        out, attn = self.inner_correlation(
            queries,
            keys,
            values,
            attn_mask
        )
        out = out.view(B, L, -1)

        return self.out_projection(out), attn


class LayerNorm(nn.Module):
    """
    Special designed layernorm for the seasonal part
```

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```
    """
    def __init__(self, channels):
        super(LayerNorm, self).__init__()
        self.layernorm = nn.LayerNorm(channels)

    def forward(self, x):
        x_hat = self.layernorm(x)
        bias = torch.mean(x_hat, dim=1).unsqueeze(1).repeat(1, x.shape[1], 1
        return x_hat - bias


class MovingAvg(nn.Module):
    """
    Moving average block to highlight the trend of time series
    """
    def __init__(self, kernel_size, stride):
        super(MovingAvg, self).__init__()
        self.kernel_size = kernel_size
        self.avg = nn.AvgPool1d(kernel_size=kernel_size, stride=stride, padd

    def forward(self, x):
        # padding on the both ends of time series
        front = x[:, 0:1, :].repeat(1, (self.kernel_size - 1) // 2, 1)
        end = x[:, -1:, :].repeat(1, (self.kernel_size - 1) // 2, 1)
        x = torch.cat([front, x, end], dim=1)
        x = self.avg(x.permute(0, 2, 1))
        x = x.permute(0, 2, 1)
        return x


class SeriesDecomp(nn.Module):
    """
    Series decomposition block
    """
    def __init__(self, kernel_size):
        super(SeriesDecomp, self).__init__()
        self.MovingAvg = MovingAvg(kernel_size, stride=1)

    def forward(self, x):
        moving_mean = self.MovingAvg(x)
        res = x - moving_mean
        return res, moving_mean


class EncoderLayer(nn.Module):
    """
    Autoformer encoder layer with the progressive decomposition architecture
    """
    def __init__(self, attention, hidden_size, conv_hidden_size=None, Moving
        super(EncoderLayer, self).__init__()
        conv_hidden_size = conv_hidden_size or 4 * hidden_size
        self.attention = attention
        self.conv1 = nn.Conv1d(in_channels=hidden_size, out_channels=conv_hi
        self.conv2 = nn.Conv1d(in_channels=conv_hidden_size, out_channels=hi
        self.decomp1 = SeriesDecomp(MovingAvg)
        self.decomp2 = SeriesDecomp(MovingAvg)
```

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```
        self.dropout = nn.Dropout(dropout)
        self.activation = F.relu if activation == "relu" else F.gelu

    def forward(self, x, attn_mask=None):
        new_x, attn = self.attention(
            x, x, x,
            attn_mask=attn_mask
        )
        x = x + self.dropout(new_x)
        x, _ = self.decomp1(x)
        y = x
        y = self.dropout(self.activation(self.conv1(y.transpose(-1, 1))))
        y = self.dropout(self.conv2(y).transpose(-1, 1))
        res, _ = self.decomp2(x + y)
        return res, attn


class Encoder(nn.Module):
    """
    Autoformer encoder
    """
    def __init__(self, attn_layers, conv_layers=None, norm_layer=None):
        super(Encoder, self).__init__()
        self.attn_layers = nn.ModuleList(attn_layers)
        self.conv_layers = nn.ModuleList(conv_layers) if conv_layers is not
        self.norm = norm_layer

    def forward(self, x, attn_mask=None):
        attns = []
        if self.conv_layers is not None:
            for attn_layer, conv_layer in zip(self.attn_layers, self.conv_la
                x, attn = attn_layer(x, attn_mask=attn_mask)
                x = conv_layer(x)
                attns.append(attn)
            x, attn = self.attn_layers[-1](x)
            attns.append(attn)
        else:
            for attn_layer in self.attn_layers:
                x, attn = attn_layer(x, attn_mask=attn_mask)
                attns.append(attn)

        if self.norm is not None:
            x = self.norm(x)

        return x, attns


class DecoderLayer(nn.Module):
    """
    Autoformer decoder layer with the progressive decomposition architecture
    """
    def __init__(self, self_attention, cross_attention, hidden_size, c_out,
                 MovingAvg=25, dropout=0.1, activation="relu"):
        super(DecoderLayer, self).__init__()
        conv_hidden_size = conv_hidden_size or 4 * hidden_size
        self.self_attention = self_attention
```

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```python
        self.cross_attention = cross_attention
        self.conv1 = nn.Conv1d(in_channels=hidden_size, out_channels=conv_hi
        self.conv2 = nn.Conv1d(in_channels=conv_hidden_size, out_channels=hi
        self.decomp1 = SeriesDecomp(MovingAvg)
        self.decomp2 = SeriesDecomp(MovingAvg)
        self.decomp3 = SeriesDecomp(MovingAvg)
        self.dropout = nn.Dropout(dropout)
        self.projection = nn.Conv1d(in_channels=hidden_size, out_channels=c_
                                    padding_mode='circular', bias=False)
        self.activation = F.relu if activation == "relu" else F.gelu

    def forward(self, x, cross, x_mask=None, cross_mask=None):
        x = x + self.dropout(self.self_attention(
            x, x, x,
            attn_mask=x_mask
        )[0])
        x, trend1 = self.decomp1(x)
        x = x + self.dropout(self.cross_attention(
            x, cross, cross,
            attn_mask=cross_mask
        )[0])
        x, trend2 = self.decomp2(x)
        y = x
        y = self.dropout(self.activation(self.conv1(y.transpose(-1, 1))))
        y = self.dropout(self.conv2(y).transpose(-1, 1))
        x, trend3 = self.decomp3(x + y)

        residual_trend = trend1 + trend2 + trend3
        residual_trend = self.projection(residual_trend.permute(0, 2, 1)).tr
        return x, residual_trend


class Decoder(nn.Module):
    """
    Autoformer decoder
    """
    def __init__(self, layers, norm_layer=None, projection=None):
        super(Decoder, self).__init__()
        self.layers = nn.ModuleList(layers)
        self.norm = norm_layer
        self.projection = projection

    def forward(self, x, cross, x_mask=None, cross_mask=None, trend=None):
        for layer in self.layers:
            x, residual_trend = layer(x, cross, x_mask=x_mask, cross_mask=cr
            trend = trend + residual_trend

        if self.norm is not None:
            x = self.norm(x)

        if self.projection is not None:
            x = self.projection(x)
        return x, trend
```

3. Autoformer

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In [23]:

```
#| export
class Autoformer(BaseWindows):
    """ Autoformer

    The Autoformer model tackles the challenge of finding reliable dependenc

    The architecture has the following distinctive features:
    - In-built progressive decomposition in trend and seasonal compontents b
    - Auto-Correlation mechanism that discovers the period-based dependencie
    calculating the autocorrelation and aggregating similar sub-series based
    - Classic encoder-decoder proposed by Vaswani et al. (2017) with a multi

    The Autoformer model utilizes a three-component approach to define its e
    - It employs encoded autoregressive features obtained from a convolution
    - Absolute positional embeddings obtained from calendar features are uti

    *Parameters:*<br>
    `h`: int, forecast horizon.<br>
    `input_size`: int, maximum sequence length for truncated train backpropa
    `futr_exog_list`: str list, future exogenous columns.<br>
    `hist_exog_list`: str list, historic exogenous columns.<br>
    `stat_exog_list`: str list, static exogenous columns.<br>
    `exclude_insample_y`: bool=False, the model skips the autoregressive fea
        `decoder_input_size_multiplier`: float = 0.5, .<br>
    `hidden_size`: int=128, units of embeddings and encoders.<br>
    `n_head`: int=4, controls number of multi-head's attention.<br>
    `dropout`: float (0, 1), dropout throughout Autoformer architecture.<br>
        `factor`: int=3, Probsparse attention factor.<br>
        `conv_hidden_size`: int=32, channels of the convolutional encoder.<b
        `activation`: str=`GELU`, activation from ['ReLU', 'Softplus', 'Tanh
    `encoder_layers`: int=2, number of layers for the TCN encoder.<br>
    `decoder_layers`: int=1, number of layers for the MLP decoder.<br>
    `distil`: bool = True, wether the Autoformer decoder uses bottlenecks.<b
    `loss`: PyTorch module, instantiated train loss class from [losses colle
    `max_steps`: int=1000, maximum number of training steps.<br>
    `learning_rate`: float=1e-3, Learning rate between (0, 1).<br>
    `num_lr_decays`: int=-1, Number of learning rate decays, evenly distribu
    `early_stop_patience_steps`: int=-1, Number of validation iterations bef
    `val_check_steps`: int=100, Number of training steps between every valid
    `batch_size`: int=32, number of different series in each batch.<br>
    `valid_batch_size`: int=None, number of different series in each validat
    `windows_batch_size`: int=1024, number of windows to sample in each trai
    `inference_windows_batch_size`: int=1024, number of windows to sample in
    `start_padding_enabled`: bool=False, if True, the model will pad the tim
    `scaler_type`: str='robust', type of scaler for temporal inputs normaliz
    `random_seed`: int=1, random_seed for pytorch initializer and numpy gene
    `num_workers_loader`: int=os.cpu_count(), workers to be used by `TimeSer
    `drop_last_loader`: bool=False, if True `TimeSeriesDataLoader` drops las
    `alias`: str, optional,  Custom name of the model.<br>
    `**trainer_kwargs`: int,  keyword trainer arguments inherited from [PyTo

        *References*<br>
        - [Wu, Haixu, Jiehui Xu, Jianmin Wang, and Mingsheng Long. "Autoform
    """
              ss attributes
```

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```
    SAMPLING_TYPE = 'windows'

    def __init__(self,
                 h: int,
                 input_size: int,
                 stat_exog_list = None,
                 hist_exog_list = None,
                 futr_exog_list = None,
                 exclude_insample_y = False,
                 decoder_input_size_multiplier: float = 0.5,
                 hidden_size: int = 128,
                 dropout: float = 0.05,
                 factor: int = 3,
                 n_head: int = 4,
                 conv_hidden_size: int = 32,
                 activation: str = 'gelu',
                 encoder_layers: int = 2,
                 decoder_layers: int = 1,
                 MovingAvg_window: int = 25,
                 loss = MAE(),
                 valid_loss = None,
                 max_steps: int = 5000,
                 learning_rate: float = 1e-4,
                 num_lr_decays: int = -1,
                 early_stop_patience_steps: int =-1,
                 val_check_steps: int = 100,
                 batch_size: int = 32,
                 valid_batch_size: Optional[int] = None,
                 windows_batch_size = 1024,
                 inference_windows_batch_size = 1024,
                 start_padding_enabled = False,
                 step_size: int = 1,
                 scaler_type: str = 'identity',
                 random_seed: int = 1,
                 num_workers_loader: int = 0,
                 drop_last_loader: bool = False,
                 **trainer_kwargs):
        super(Autoformer, self).__init__(h=h,
                                          input_size=input_size,
                                          hist_exog_list=hist_exog_list,
                                          stat_exog_list=stat_exog_list,
                                          futr_exog_list = futr_exog_list,
                                          exclude_insample_y = exclude_insample
                                          loss=loss,
                                          valid_loss=valid_loss,
                                          max_steps=max_steps,
                                          learning_rate=learning_rate,
                                          num_lr_decays=num_lr_decays,
                                          early_stop_patience_steps=early_stop_
                                          val_check_steps=val_check_steps,
                                          batch_size=batch_size,
                                          windows_batch_size=windows_batch_size
                                          valid_batch_size=valid_batch_size,
                                          inference_windows_batch_size=inferenc
                                          start_padding_enabled = start_padding
                                          step_size=step_size,
```

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```
                                        scaler_type=scaler_type,
                                        num_workers_loader=num_workers_loader
                                        drop_last_loader=drop_last_loader,
                                        random_seed=random_seed,
                                        **trainer_kwargs)

        # Architecture
        self.futr_input_size = len(self.futr_exog_list)
        self.hist_input_size = len(self.hist_exog_list)
        self.stat_input_size = len(self.stat_exog_list)

        if self.stat_input_size > 0:
            raise Exception('Autoformer does not support static variables ye

        if self.hist_input_size > 0:
            raise Exception('Autoformer does not support historical variable

        self.label_len = int(np.ceil(input_size * decoder_input_size_multipl
        if (self.label_len >= input_size) or (self.label_len <= 0):
            raise Exception(f'Check decoder_input_size_multiplier={decoder_i

        if activation not in ['relu', 'gelu']:
            raise Exception(f'Check activation={activation}')

        self.c_out = self.loss.outputsize_multiplier
        self.output_attention = False
        self.enc_in = 1
        self.dec_in = 1

        # Decomposition
        self.decomp = SeriesDecomp(MovingAvg_window)

        # Embedding
        self.enc_embedding = DataEmbedding(c_in=self.enc_in,
                                            exog_input_size=self.hist_input_s
                                            hidden_size=hidden_size,
                                            pos_embedding=False,
                                            dropout=dropout)
        self.dec_embedding = DataEmbedding(self.dec_in,
                                            exog_input_size=self.hist_input_s
                                            hidden_size=hidden_size,
                                            pos_embedding=False,
                                            dropout=dropout)


        # Encoder
        self.encoder = Encoder(
            [
                EncoderLayer(
                    AutoCorrelationLayer(
                        AutoCorrelation(False, factor,
                                        attention_dropout=dropout,
                                        output_attention=self.output_attention
                        hidden_size, n_head),
                    hidden_size=hidden_size,
                    conv_hidden_size=conv_hidden_size,
                    MovingAvg=MovingAvg_window,
```

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```
                    dropout=dropout,
                    activation=activation
                ) for l in range(encoder_layers)
            ],
            norm_layer=LayerNorm(hidden_size)
        )
        # Decoder
        self.decoder = Decoder(
            [
                DecoderLayer(
                    AutoCorrelationLayer(
                        AutoCorrelation(True, factor, attention_dropout=drop
                        hidden_size, n_head),
                    AutoCorrelationLayer(
                        AutoCorrelation(False, factor, attention_dropout=dro
                        hidden_size, n_head),
                    hidden_size=hidden_size,
                    c_out=self.c_out,
                    conv_hidden_size=conv_hidden_size,
                    MovingAvg=MovingAvg_window,
                    dropout=dropout,
                    activation=activation,
                )
                for l in range(decoder_layers)
            ],
            norm_layer=LayerNorm(hidden_size),
            projection=nn.Linear(hidden_size, self.c_out, bias=True)
        )

    def forward(self, windows_batch):
        # Parse windows_batch
        insample_y    = windows_batch['insample_y']
        #insample_mask = windows_batch['insample_mask']
        #hist_exog     = windows_batch['hist_exog']
        #stat_exog     = windows_batch['stat_exog']
        futr_exog     = windows_batch['futr_exog']

        # Parse inputs
        insample_y = insample_y.unsqueeze(-1) # [Ws,L,1]
        if self.futr_input_size > 0:
            x_mark_enc = futr_exog[:,:self.input_size,:]
            x_mark_dec = futr_exog[:,-(self.label_len+self.h):,:]
        else:
            x_mark_enc = None
            x_mark_dec = None

        x_dec = torch.zeros(size=(len(insample_y),self.h,1)).to(insample_y.d
        x_dec = torch.cat([insample_y[:,-self.label_len:,:], x_dec], dim=1)

        # decomp init
        mean = torch.mean(insample_y, dim=1).unsqueeze(1).repeat(1, self.h,
        zeros = torch.zeros([x_dec.shape[0], self.h, x_dec.shape[2]], device
        seasonal_init, trend_init = self.decomp(insample_y)
        # decoder input
        trend_init = torch.cat([trend_init[:, -self.label_len:, :], mean], d
        seasonal_init = torch.cat([seasonal_init[:, -self.label_len:, :], ze
```

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```
        # enc
        enc_out = self.enc_embedding(insample_y, x_mark_enc)
        enc_out, attns = self.encoder(enc_out, attn_mask=None)
        # dec
        dec_out = self.dec_embedding(seasonal_init, x_mark_dec)
        seasonal_part, trend_part = self.decoder(dec_out, enc_out, x_mask=No
                                                 trend=trend_init)
        # final
        dec_out = trend_part + seasonal_part

        forecast = self.loss.domain_map(dec_out[:, -self.h:])
        return forecast
```

In [24]:
```
show_doc(Autoformer)
```

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Out[24]:

Autoformer

```
 Autoformer (h:int, input_size:int, stat_exog_list=None,
             hist_exog_list=None, futr_exog_list=None,
             exclude_insample_y=False,
             decoder_input_size_multiplier:float=0.5, hidd
en_size:int=128,
             dropout:float=0.05, factor:int=3, n_head:int=
4,
             conv_hidden_size:int=32, activation:str='gel
u',
             encoder_layers:int=2, decoder_layers:int=1,
             MovingAvg_window:int=25, loss=MAE(), valid_lo
ss=None,
             max_steps:int=5000, learning_rate:float=0.000
1,
             num_lr_decays:int=-1, early_stop_patience_ste
ps:int=-1,
             val_check_steps:int=100, batch_size:int=32,
             valid_batch_size:Optional[int]=None, windows_
batch_size=1024,
             inference_windows_batch_size=1024,
             start_padding_enabled=False, step_size:int=1,
             scaler_type:str='identity', random_seed:int=
1,
             num_workers_loader:int=0, drop_last_loader:bo
ol=False,
             **trainer_kwargs)
```

Autoformer

The Autoformer model tackles the challenge of finding reliable dependencies on intricate temporal patterns of long-horizon forecasting.

The architecture has the following distinctive features:

- In-built progressive decomposition in trend and seasonal compontents based on a moving average filter.
- Auto-Correlation mechanism that discovers the period-based dependencies by calculating the autocorrelation and aggregating similar sub-series based on the periodicity.

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- Classic encoder-decoder proposed by Vaswani et al. (2017) with a multi-head attention mechanism.

The Autoformer model utilizes a three-component approach to define its embedding:

- It employs encoded autoregressive features obtained from a convolution network.
- Absolute positional embeddings obtained from calendar features are utilized.

Parameters:
`h` : int, forecast horizon.
`input_size` : int, maximum sequence length for truncated train backpropagation. Default -1 uses all history.
`futr_exog_list` : str list, future exogenous columns.
`hist_exog_list` : str list, historic exogenous columns.
`stat_exog_list` : str list, static exogenous columns.
`exclude_insample_y` : bool=False, the model skips the autoregressive features y[t-input_size:t] if True.
`decoder_input_size_multiplier` : float = 0.5, .
`hidden_size` : int=128, units of embeddings and encoders.
`n_head` : int=4, controls number of multi-head's attention.
`dropout` : float (0, 1), dropout throughout Autoformer architecture.
`factor` : int=3, Probsparse attention factor.
`conv_hidden_size` : int=32, channels of the convolutional encoder.
`activation` : str=`GELU`, activation from ['ReLU', 'Softplus', 'Tanh', 'SELU', 'LeakyReLU', 'PReLU', 'Sigmoid', 'GELU'].
`encoder_layers` : int=2, number of layers for the TCN encoder.
`decoder_layers` : int=1, number of layers for the MLP decoder.
`distil` : bool = True, wether the Autoformer decoder uses bottlenecks.
`loss` : PyTorch module, instantiated train loss class from losses collection.
`max_steps` : int=1000, maximum number of training steps.
`learning_rate` : float=1e-3, Learning rate between (0, 1).
`num_lr_decays` : int=-1, Number of learning rate decays, evenly distributed across max_steps.
`early_stop_patience_steps` : int=-1, Number of validation iterations before early stopping.
`val_check_steps` : int=100, Number of training steps between every validation loss check.
`batch_size` : int=32, number of different series in each batch.
`valid_batch_size` : int=None, number of different series in each validation and test batch, if None uses batch_size.
`windows_batch_size` : int=1024, number of windows to sample in each training

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batch, default uses all.

`inference_windows_batch_size`: int=1024, number of windows to sample in each inference batch.

`start_padding_enabled`: bool=False, if True, the model will pad the time series with zeros at the beginning, by input size.

`scaler_type`: str='robust', type of scaler for temporal inputs normalization see temporal scalers.

`random_seed`: int=1, random_seed for pytorch initializer and numpy generators.

`num_workers_loader`: int=os.cpu_count(), workers to be used by `TimeSeriesDataLoader`.

`drop_last_loader`: bool=False, if True `TimeSeriesDataLoader` drops last non-full batch.

`alias`: str, optional, Custom name of the model.

`**trainer_kwargs`: int, keyword trainer arguments inherited from PyTorch Lighning's trainer.

```
*References*<br>
- [Wu, Haixu, Jiehui Xu, Jianmin Wang, and Mingsheng Long. "Autoform
er: Decomposition transformers with auto-correlation for long-term s
eries forecasting"](https://proceedings.neurips.cc/paper/2021/hash/b
cc0d400288793e8bdcd7c19a8ac0c2b-Abstract.html)<br>
```

In [6]:
```
show_doc(Autoformer.fit, name='Autoformer.fit')
```

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Out[6]:

Autoformer.fit

> ```
> Autoformer.fit (dataset, val_size=0, test_size=0, random_
> seed=None)
> ```

Fit.

The `fit` method, optimizes the neural network's weights using the initialization parameters (`learning_rate`, `windows_batch_size`, ...) and the `loss` function as defined during the initialization. Within `fit` we use a PyTorch Lightning `Trainer` that inherits the initialization's `self.trainer_kwargs`, to customize its inputs, see PL's trainer arguments.

The method is designed to be compatible with SKLearn-like classes and in particular to be compatible with the StatsForecast library.

By default the `model` is not saving training checkpoints to protect disk memory, to get them change `enable_checkpointing=True` in `__init__`.

Parameters:
`dataset`: NeuralForecast's `TimeSeriesDataset`, see documentation.
`val_size`: int, validation size for temporal cross-validation.
`random_seed`: int=None, random_seed for pytorch initializer and numpy generators, overwrites model.**init**'s.
`test_size`: int, test size for temporal cross-validation.

In [8]:
```
show_doc(Autoformer.predict, name='Autoformer.predict')
```

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Out[8]:

Autoformer.predict

> ```
> Autoformer.predict (dataset, test_size=None, step_size=1,
>                      random_seed=None, **data_module_kwarg
> s)
> ```

Predict.

Neural network prediction with PL's `Trainer` execution of `predict_step`.

Parameters:
`dataset`: NeuralForecast's `TimeSeriesDataset`, see documentation.
`test_size`: int=None, test size for temporal cross-validation.
`step_size`: int=1, Step size between each window.
`random_seed`: int=None, random_seed for pytorch initializer and numpy generators, overwrites model.**init**'s.
`**data_module_kwargs`: PL's TimeSeriesDataModule args, see documentation.

Usage Example

In [9]:

```
#| eval: false
import numpy as np
import pandas as pd
import pytorch_lightning as pl
import matplotlib.pyplot as plt

from neuralforecast import NeuralForecast
from neuralforecast.models import MLP
from neuralforecast.losses.pytorch import MQLoss, DistributionLoss
from neuralforecast.tsdataset import TimeSeriesDataset
from neuralforecast.utils import AirPassengers, AirPassengersPanel, AirPasse

AirPassengersPanel, calendar_cols = augment_calendar_df(df=AirPassengersPane

Y_train_df = AirPassengersPanel[AirPassengersPanel.ds<AirPassengersPanel['ds
Y_test_df = AirPassengersPanel[AirPassengersPanel.ds>=AirPassengersPanel['ds

model = Autoformer(h=12,
                 input_size=24,
                 hidden_size = 16,
                 conv_hidden_size = 32,
                 n_head=2,
                 loss=MAE(),
                 futr_exog_list=calendar_cols,
                 scaler_type='robust',
                 learning_rate=1e-3,
                 max_steps=300,
                 val_check_steps=50,
```

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```
                  early_stop_patience_steps=2)

nf = NeuralForecast(
    models=[model],
    freq='M'
)
nf.fit(df=Y_train_df, static_df=AirPassengersStatic, val_size=12)
forecasts = nf.predict(futr_df=Y_test_df)

Y_hat_df = forecasts.reset_index(drop=False).drop(columns=['unique_id','ds']
plot_df = pd.concat([Y_test_df, Y_hat_df], axis=1)
plot_df = pd.concat([Y_train_df, plot_df])

if model.loss.is_distribution_output:
    plot_df = plot_df[plot_df.unique_id=='Airline1'].drop('unique_id', axis=
    plt.plot(plot_df['ds'], plot_df['y'], c='black', label='True')
    plt.plot(plot_df['ds'], plot_df['Autoformer-median'], c='blue', label='m
    plt.fill_between(x=plot_df['ds'][-12:],
                     y1=plot_df['Autoformer-lo-90'][-12:].values,
                     y2=plot_df['Autoformer-hi-90'][-12:].values,
                     alpha=0.4, label='level 90')
    plt.grid()
    plt.legend()
    plt.plot()
else:
    plot_df = plot_df[plot_df.unique_id=='Airline1'].drop('unique_id', axis=
    plt.plot(plot_df['ds'], plot_df['y'], c='black', label='True')
    plt.plot(plot_df['ds'], plot_df['Autoformer'], c='blue', label='Forecast
    plt.legend()
    plt.grid()
```

```
Seed set to 1
2023-11-02 00:51:42.424894: I tensorflow/core/util/port.cc:111] oneDNN custo
m operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn t
hem off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2023-11-02 00:51:42.515256: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could n
ot find cuda drivers on your machine, GPU will not be used.
2023-11-02 00:51:42.837663: E tensorflow/compiler/xla/stream_executor/cuda/c
uda_dnn.cc:9342] Unable to register cuDNN factory: Attempting to register fa
ctory for plugin cuDNN when one has already been registered
2023-11-02 00:51:42.837728: E tensorflow/compiler/xla/stream_executor/cuda/c
uda_fft.cc:609] Unable to register cuFFT factory: Attempting to register fac
tory for plugin cuFFT when one has already been registered
2023-11-02 00:51:42.839420: E tensorflow/compiler/xla/stream_executor/cuda/c
uda_blas.cc:1518] Unable to register cuBLAS factory: Attempting to register
factory for plugin cuBLAS when one has already been registered
2023-11-02 00:51:42.970876: I tensorflow/core/platform/cpu_feature_guard.cc:
182] This TensorFlow binary is optimized to use available CPU instructions i
n performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operation
s, rebuild TensorFlow with the appropriate compiler flags.
2023-11-02 00:51:44.751923: W tensorflow/compiler/tf2tensorrt/utils/py_util
s.cc:38] TF-TRT Warning: Could not find TensorRT
Sanity Checking: |
| 0/2 [00:00…
```

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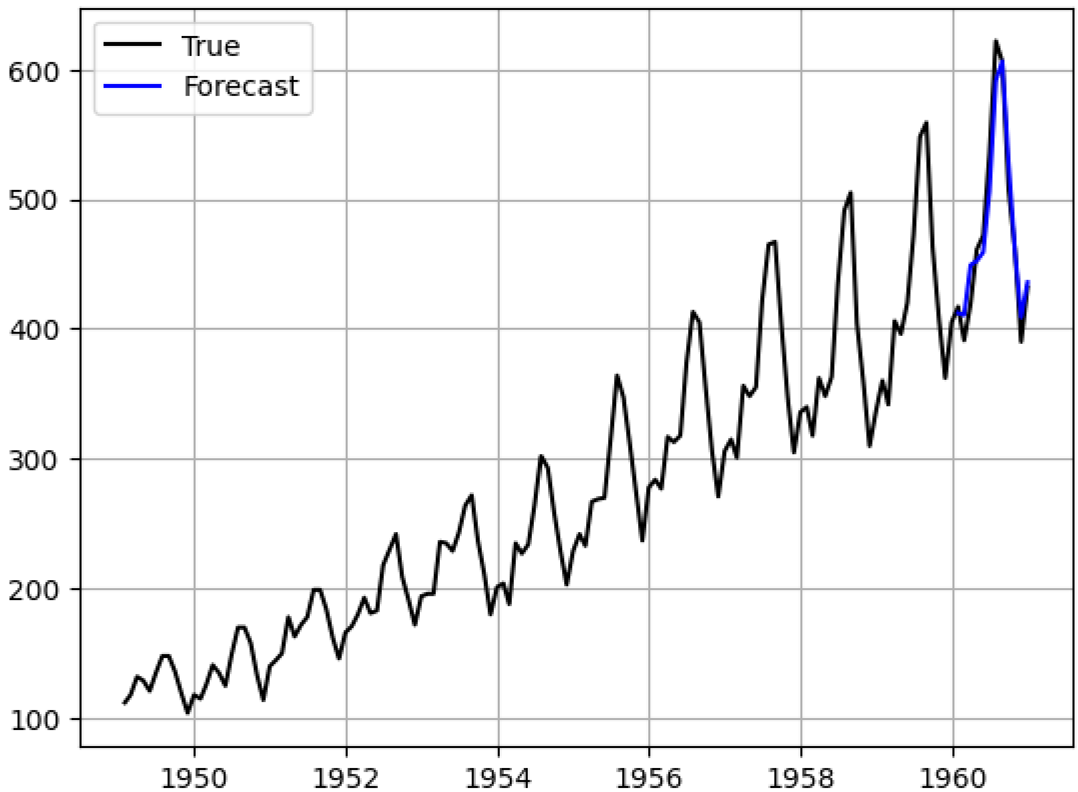
```
Training: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Predicting: |
| 0/? [00:00…
```



In [18]:
```
y_true = Y_test_df.y.values
y_hat = Y_hat_df['Autoformer'].values

from neuralforecast.losses.numpy import mae, mse

print('MAE: ', mae(y_hat, y_true))
print('MSE: ', mse(y_hat, y_true))
```

```
MAE:  15.130399068196615
MSE:  349.1350725169759
```

Autoformer Implementation

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Exchange rate

In [19]:
```
import pandas as pd
from neuralforecast import NeuralForecast

Y_df = pd.read_csv("raw_data/df_Exchange.csv")

Y_df['ds'] = pd.to_datetime(Y_df['ds'])

# For this excercise we are going to take 20% of the DataSet
n_time = len(Y_df.ds.unique())
val_size = int(.1 * n_time)
test_size = int(.2 * n_time)

Y_df.groupby('unique_id').head(2)
```

Out[19]:

	unique_id	ds	y
0	0	1990-01-01	0.606785
1	0	1990-01-02	0.570900
7588	1	1990-01-01	-0.361671
7589	1	1990-01-02	-0.367639
15176	2	1990-01-01	0.735367
15177	2	1990-01-02	0.729629
22764	3	1990-01-01	-1.164373
22765	3	1990-01-02	-1.170907
30352	4	1990-01-01	2.851890
30353	4	1990-01-02	2.851890
37940	5	1990-01-01	-1.861369
37941	5	1990-01-02	-1.838665
45528	6	1990-01-01	-1.820047
45529	6	1990-01-02	-1.847258
53116	OT	1990-01-01	-0.124081
53117	OT	1990-01-02	-0.113588

In [25]:
```
horizon = 96

model = Autoformer(h=horizon,
                input_size = horizon,
                max_steps=100,
                val_check_steps=10,
                batch_size = 8,
                hidden_size = 32,
                windows_batch_size = 256,
```

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```
                 early_stop_patience_steps=2)

nf = NeuralForecast(
    models=[model],
    freq='D'
)

Y_hat_df = nf.cross_validation(df=Y_df,
                               val_size=val_size,
                               test_size=test_size,
                               n_windows=None)
```

```
Seed set to 1
Sanity Checking: |
| 0/? [00:00…
Training: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Predicting: |
| 0/? [00:00…
```

In [27]:
```
Y_hat_df.head()
```

Out[27]:

	unique_id	ds	cutoff	Autoformer	y
0	0	2006-08-16	2006-08-15	3.044964	2.948076
1	0	2006-08-17	2006-08-15	3.030476	3.049320
2	0	2006-08-18	2006-08-15	3.028900	3.064168
3	0	2006-08-19	2006-08-15	3.050043	3.005783
4	0	2006-08-20	2006-08-15	3.117382	3.010031

In [28]:
```
Y_hat_df.to_csv('results/Exchange_rate/autoformer.csv')
```

In [26]:
```
from neuralforecast.losses.numpy import mae, mse

print('MAE: ', mae(Y_hat_df['y'], Y_hat_df['Autoformer']))
print('MSE: ', mse(Y_hat_df['y'], Y_hat_df['Autoformer']))
```

```
MAE:  0.29645489153468074
MSE:  0.161861597390966
```

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Weather

In [11]:
```
import pandas as pd
from neuralforecast import NeuralForecast

Y_df = pd.read_csv("raw_data/df_Weather.csv")

Y_df['ds'] = pd.to_datetime(Y_df['ds'])

# For this excercise we are going to take 20% of the DataSet
n_time = len(Y_df.ds.unique())
val_size = int(.1 * n_time)
test_size = int(.2 * n_time)

Y_df.groupby('unique_id').head(2)
```

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Out[11]:

	unique_id	ds	y
0	H2OC (mmol/mol)	2020-01-01 00:10:00	-0.999107
1	H2OC (mmol/mol)	2020-01-01 00:20:00	-1.008072
52695	OT	2020-01-01 00:10:00	0.044395
52696	OT	2020-01-01 00:20:00	0.044134
105390	PAR (�mol/m�/s)	2020-01-01 00:10:00	-0.679493
105391	PAR (�mol/m�/s)	2020-01-01 00:20:00	-0.679493
158085	SWDR (W/m�)	2020-01-01 00:10:00	-0.672767
158086	SWDR (W/m�)	2020-01-01 00:20:00	-0.672767
210780	T (degC)	2020-01-01 00:10:00	-1.459980
210781	T (degC)	2020-01-01 00:20:00	-1.454798
263475	Tdew (degC)	2020-01-01 00:10:00	-1.052596
263476	Tdew (degC)	2020-01-01 00:20:00	-1.069612
316170	Tlog (degC)	2020-01-01 00:10:00	-1.424132
316171	Tlog (degC)	2020-01-01 00:20:00	-1.416612
368865	Tpot (K)	2020-01-01 00:10:00	-1.607935
368866	Tpot (K)	2020-01-01 00:20:00	-1.602882
421560	VPact (mbar)	2020-01-01 00:10:00	-0.979132
421561	VPact (mbar)	2020-01-01 00:20:00	-0.990506
474255	VPdef (mbar)	2020-01-01 00:10:00	-0.838497
474256	VPdef (mbar)	2020-01-01 00:20:00	-0.828332
526950	VPmax (mbar)	2020-01-01 00:10:00	-1.141181
526951	VPmax (mbar)	2020-01-01 00:20:00	-1.138714
579645	max. PAR (�mol/m�/s)	2020-01-01 00:10:00	-0.588296
579646	max. PAR (�mol/m�/s)	2020-01-01 00:20:00	-0.588296
632340	max. wv (m/s)	2020-01-01 00:10:00	-0.832381
632341	max. wv (m/s)	2020-01-01 00:20:00	-1.125140
685035	p (mbar)	2020-01-01 00:10:00	2.114257
685036	p (mbar)	2020-01-01 00:20:00	2.099194
737730	rain (mm)	2020-01-01 00:10:00	-0.093506
737731	rain (mm)	2020-01-01 00:20:00	-0.093506
790425	raining (s)	2020-01-01 00:10:00	-0.221050
790426	raining (s)	2020-01-01 00:20:00	-0.221050
843120	rh (%)	2020-01-01 00:10:00	0.990128

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	unique_id	ds	y
843121	rh (%)	2020-01-01 00:20:00	0.942141
895815	rho (g/m**3)	2020-01-01 00:10:00	1.940406
895816	rho (g/m**3)	2020-01-01 00:20:00	1.932788
948510	sh (g/kg)	2020-01-01 00:10:00	-0.998513
948511	sh (g/kg)	2020-01-01 00:20:00	-1.009228
1001205	wd (deg)	2020-01-01 00:10:00	0.555571
1001206	wd (deg)	2020-01-01 00:20:00	0.354339
1053900	wv (m/s)	2020-01-01 00:10:00	-0.017801
1053901	wv (m/s)	2020-01-01 00:20:00	-0.029125

In [8]:

```
horizon = 96

model = Autoformer(h=horizon,
                   input_size = horizon,
                   max_steps=100,
                   val_check_steps=10,
                   batch_size = 21,
                   hidden_size = 16,
                   windows_batch_size = 256,
                   early_stop_patience_steps=2)

nf = NeuralForecast(
    models=[model],
    freq='10min'
)

Y_hat_df = nf.cross_validation(df=Y_df,
                               val_size=val_size,
                               test_size=test_size,
                               n_windows=None)
```

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```
Seed set to 1
2023-11-02 05:44:45.812388: I tensorflow/core/util/port.cc:111] oneDNN custo
m operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn t
hem off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2023-11-02 05:44:45.813943: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could n
ot find cuda drivers on your machine, GPU will not be used.
2023-11-02 05:44:45.836010: E tensorflow/compiler/xla/stream_executor/cuda/c
uda_dnn.cc:9342] Unable to register cuDNN factory: Attempting to register fa
ctory for plugin cuDNN when one has already been registered
2023-11-02 05:44:45.836041: E tensorflow/compiler/xla/stream_executor/cuda/c
uda_fft.cc:609] Unable to register cuFFT factory: Attempting to register fac
tory for plugin cuFFT when one has already been registered
2023-11-02 05:44:45.836057: E tensorflow/compiler/xla/stream_executor/cuda/c
uda_blas.cc:1518] Unable to register cuBLAS factory: Attempting to register
factory for plugin cuBLAS when one has already been registered
2023-11-02 05:44:45.841303: I tensorflow/core/platform/cpu_feature_guard.cc:
182] This TensorFlow binary is optimized to use available CPU instructions i
n performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operation
s, rebuild TensorFlow with the appropriate compiler flags.
2023-11-02 05:44:46.432899: W tensorflow/compiler/tf2tensorrt/utils/py_util
s.cc:38] TF-TRT Warning: Could not find TensorRT
Sanity Checking: |
| 0/? [00:00…
Training: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Predicting: |
| 0/? [00:00…
```

In [10]:
```
Y_hat_df.to_csv('results/Weather/Autoformer.csv')
```

In [11]:
```
from neuralforecast.losses.numpy import mae, mse
```

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```
print('MAE: ', mae(Y_hat_df['y'], Y_hat_df['Autoformer']))
print('MSE: ', mse(Y_hat_df['y'], Y_hat_df['Autoformer']))
```

```
MAE:  0.28974621539184015
MSE:  0.2305957080949505
```

Ettm2

In [7]:

```
import pandas as pd
from neuralforecast import NeuralForecast

Y_df = pd.read_csv("raw_data/df_Ettm2.csv")

Y_df['ds'] = pd.to_datetime(Y_df['ds'])

# For this excercise we are going to take 20% of the DataSet
n_time = len(Y_df.ds.unique())
val_size = int(.2 * n_time)
test_size = int(.2 * n_time)

Y_df.groupby('unique_id').head(2)
```

Out[7]:

	unique_id	ds	y
0	HUFL	2016-07-01 00:00:00	-0.041413
1	HUFL	2016-07-01 00:15:00	-0.185467
57600	HULL	2016-07-01 00:00:00	0.040104
57601	HULL	2016-07-01 00:15:00	-0.214450
115200	LUFL	2016-07-01 00:00:00	0.695804
115201	LUFL	2016-07-01 00:15:00	0.434685
172800	LULL	2016-07-01 00:00:00	0.434430
172801	LULL	2016-07-01 00:15:00	0.428168
230400	MUFL	2016-07-01 00:00:00	-0.599211
230401	MUFL	2016-07-01 00:15:00	-0.658068
288000	MULL	2016-07-01 00:00:00	-0.393536
288001	MULL	2016-07-01 00:15:00	-0.659338
345600	OT	2016-07-01 00:00:00	1.018032
345601	OT	2016-07-01 00:15:00	0.980124

In [8]:

```
horizon = 96

model = Autoformer(h=horizon,
                   input_size = horizon,
                   max_steps=100,
                   val_check_steps=10,
                   batch_size = 7,
```

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```python
                    hidden_size = 16,
                 windows_batch_size = 256,
                 early_stop_patience_steps=2)

nf = NeuralForecast(
    models=[model],
    freq='15min'
)

Y_hat_df = nf.cross_validation(df=Y_df,
                               val_size=val_size,
                               test_size=test_size,
                               n_windows=None)
```

```
Seed set to 1
2023-11-02 06:05:55.346787: I tensorflow/core/util/port.cc:111] oneDNN custo
m operations are on. You may see slightly different numerical results due to
floating-point round-off errors from different computation orders. To turn t
hem off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`.
2023-11-02 06:05:55.416697: I tensorflow/tsl/cuda/cudart_stub.cc:28] Could n
ot find cuda drivers on your machine, GPU will not be used.
2023-11-02 06:05:55.854010: E tensorflow/compiler/xla/stream_executor/cuda/c
uda_dnn.cc:9342] Unable to register cuDNN factory: Attempting to register fa
ctory for plugin cuDNN when one has already been registered
2023-11-02 06:05:55.854073: E tensorflow/compiler/xla/stream_executor/cuda/c
uda_fft.cc:609] Unable to register cuFFT factory: Attempting to register fac
tory for plugin cuFFT when one has already been registered
2023-11-02 06:05:55.856131: E tensorflow/compiler/xla/stream_executor/cuda/c
uda_blas.cc:1518] Unable to register cuBLAS factory: Attempting to register 
factory for plugin cuBLAS when one has already been registered
2023-11-02 06:05:56.039684: I tensorflow/core/platform/cpu_feature_guard.cc:
182] This TensorFlow binary is optimized to use available CPU instructions i
n performance-critical operations.
To enable the following instructions: AVX2 AVX_VNNI FMA, in other operation
s, rebuild TensorFlow with the appropriate compiler flags.
2023-11-02 06:05:58.652714: W tensorflow/compiler/tf2tensorrt/utils/py_util
s.cc:38] TF-TRT Warning: Could not find TensorRT
Sanity Checking: |
| 0/? [00:00…
Training: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
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Validation: |
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Validation: |
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Validation: |
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```

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```
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Predicting: |
| 0/? [00:00…
```

In [9]:

```
Y_hat_df.to_csv('results/Ettm2/Autoformer.csv')
```

In [11]:

```
from neuralforecast.losses.numpy import mae, mse

print('MAE: ', mae(Y_hat_df['y'], Y_hat_df['Autoformer']))
print('MSE: ', mse(Y_hat_df['y'], Y_hat_df['Autoformer']))
```

```
MAE:  0.3353140537163157
MSE:  0.2553693649575985
```

ILI

In [12]:

```
import pandas as pd
from neuralforecast import NeuralForecast

Y_df = pd.read_csv("raw_data/df_ILI.csv")

Y_df['ds'] = pd.to_datetime(Y_df['ds'])

# For this excercise we are going to take 20% of the DataSet
n_time = len(Y_df.ds.unique())
val_size = int(.1 * n_time)
test_size = int(.2 * n_time)

Y_df.groupby('unique_id').head(2)
```

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Out[12]:

	unique_id	ds	y
0	% WEIGHTED ILI	2002-01-01	-0.421499
1	% WEIGHTED ILI	2002-01-08	-0.331239
966	%UNWEIGHTED ILI	2002-01-01	-0.472442
967	%UNWEIGHTED ILI	2002-01-08	-0.429154
1932	AGE 0-4	2002-01-01	-0.981641
1933	AGE 0-4	2002-01-08	-0.934213
2898	AGE 5-24	2002-01-01	-0.692621
2899	AGE 5-24	2002-01-08	-0.676837
3864	ILITOTAL	2002-01-01	-0.819695
3865	ILITOTAL	2002-01-08	-0.796703
4830	NUM. OF PROVIDERS	2002-01-01	-1.151274
4831	NUM. OF PROVIDERS	2002-01-08	-1.088458
5796	OT	2002-01-01	-1.385709
5797	OT	2002-01-08	-1.342939

In [16]:

```
horizon = 24

model = Autoformer(h=horizon,
                input_size = horizon,
                max_steps=100,
                val_check_steps=10,
                batch_size = 7,
                hidden_size = 16,
                windows_batch_size = 256,
                early_stop_patience_steps=2)

nf = NeuralForecast(
    models=[model],
    freq='W'
)

Y_hat_df = nf.cross_validation(df=Y_df,
                               val_size=val_size,
                               test_size=test_size,
                               n_windows=None)
```

```
Seed set to 1
Sanity Checking: |
| 0/? [00:00…
Training: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Validation: |
```

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```
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Validation: |
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Validation: |
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Validation: |
| 0/? [00:00…
Validation: |
| 0/? [00:00…
Predicting: |
| 0/? [00:00…
```

In [17]:
```
Y_hat_df
```

Out[17]:

	unique_id	ds	cutoff	Autoformer	y
0	% WEIGHTED ILI	2016-10-23	2016-10-16	0.751263	NaN
1	% WEIGHTED ILI	2016-10-30	2016-10-16	0.743696	NaN
2	% WEIGHTED ILI	2016-11-06	2016-10-16	0.570308	NaN
3	% WEIGHTED ILI	2016-11-13	2016-10-16	0.405683	NaN
4	% WEIGHTED ILI	2016-11-20	2016-10-16	0.290363	NaN
...	...	...	...	...	...
28555	OT	2020-05-31	2020-01-12	4.320040	NaN
28556	OT	2020-06-07	2020-01-12	4.685857	NaN
28557	OT	2020-06-14	2020-01-12	4.701055	NaN
28558	OT	2020-06-21	2020-01-12	4.397973	NaN
28559	OT	2020-06-28	2020-01-12	2.905941	NaN

28560 rows × 5 columns

In [ ]:
```
Y_hat_df.to_csv('results/ILI/Autoformer.csv')
```

In [18]:
```
from neuralforecast.losses.numpy import mae, mse

print('MAE: ', mae(Y_hat_df['y'], Y_hat_df['Autoformer']))
print('MSE: ', mse(Y_hat_df['y'], Y_hat_df['Autoformer']))
```

```
MAE:  nan
MSE:  nan
```

In [ ]:

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