```
#| default_exp models.nhits
```

```
#| hide
%load_ext autoreload
%autoreload 2
```

NHITS

Long-horizon forecasting is challenging because of the *volatility* of the predictions and the *computational complexity*. To solve this problem we created the Neural Hierarchical Interpolation for Time Series (NHITS). `NHITS` builds upon `NBEATS` and specializes its partial outputs in the different frequencies of the time series through hierarchical interpolation and multi-rate input processing. On the long-horizon forecasting task `NHITS` improved accuracy by 25% on AAAI's best paper award the `Informer`, while being 50x faster.

The model is composed of several MLPs with ReLU non-linearities. Blocks are connected via doubly residual stacking principle with the backcast $\tilde{\mathbf{y}}_{t-L:t,l}$ and forecast $\hat{\mathbf{y}}_{t+1:t+H,l}$ outputs of the l-th block. Multi-rate input pooling, hierarchical interpolation and backcast residual connections together induce the specialization of the additive predictions in different signal bands, reducing memory footprint and computational time, thus improving the architecture parsimony and accuracy.

References

-Boris N. Oreshkin, Dmitri Carpov, Nicolas Chapados, Yoshua Bengio (2019). "N-BEATS: Neural basis expansion analysis for interpretable time series forecasting".
-Cristian Challu, Kin G. Olivares, Boris N. Oreshkin, Federico Garza, Max Mergenthaler-Canseco, Artur Dubrawski (2023). "NHITS: Neural Hierarchical Interpolation for Time Series Forecasting". Accepted at the Thirty-Seventh AAAI Conference on Artificial Intelligence.
-Zhou, H.; Zhang, S.; Peng, J.; Zhang, S.; Li, J.; Xiong, H.; and Zhang, W. (2020). "Informer: Beyond Efficient Transformer for Long Sequence Time-Series Forecasting". Association for the Advancement of Artificial Intelligence Conference 2021 (AAAI 2021).

Figure 1. Neural Hierarchical Interpolation for Time Series (NHITS).

```
!pip install neuralforecast
```

```
!pip install nbdev
```

```
#| hide
import os
os.environ["PYTORCH_ENABLE_MPS_FALLBACK"] = "1"
os.environ["CUDA_VISIBLE_DEVICES"] = "0"
```

```
#| export
from typing import Tuple, Optional

import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F

from neuralforecast.losses.pytorch import MAE
from neuralforecast.common._base_windows import BaseWindows
```

```
#| hide
from fastcore.test import test_eq
from nbdev.showdoc import show_doc
from neuralforecast.utils import generate_series
```

```
#| hide
import logging
import warnings

logging.getLogger("pytorch_lightning").setLevel(logging.ERROR)
warnings.filterwarnings("ignore")

import matplotlib.pyplot as plt

#plt.rcParams["axes.grid"]=True
plt.rcParams['font.family'] = 'serif'
#plt.rcParams["figure.figsize"] = (4,2)
```

Define a PyTorch module called "_IdentityBasis" that performs interpolation on input tensors to produce a forecast based on specified backcast and forecast sizes, using different interpolation modes, and returns the backcast and forecast tensors as output.

```
#| export
class _IdentityBasis(nn.Module):
    def __init__(self, backcast_size: int, forecast_size: int,
                 interpolation_mode: str, out_features: int=1):
        super().__init__()
        assert (interpolation_mode in ['linear','nearest']) or ('cubic' in interpolation_mode)
        self.forecast_size = forecast_size
        self.backcast_size = backcast_size
        self.interpolation_mode = interpolation_mode
        self.out_features = out_features

    def forward(self, theta: torch.Tensor) -> Tuple[torch.Tensor, torch.Tensor]:

        backcast = theta[:, :self.backcast_size]
        knots = theta[:, self.backcast_size:]

        # Interpolation is performed on default dim=-1 := H
        knots = knots.reshape(len(knots), self.out_features, -1)
        if self.interpolation_mode in ['nearest', 'linear']:
            #knots = knots[:,None,:]
            forecast = F.interpolate(knots, size=self.forecast_size, mode=self.interpolation_mode)
            #forecast = forecast[:,0,:]
        elif 'cubic' in self.interpolation_mode:
            if self.out_features>1:
                raise Exception('Cubic interpolation not available with multiple outputs.')
            batch_size = len(backcast)
            knots = knots[:,None,:,:]
            forecast = torch.zeros((len(knots), self.forecast_size)).to(knots.device)
            n_batches = int(np.ceil(len(knots)/batch_size))
            for i in range(n_batches):
                forecast_i = F.interpolate(knots[i*batch_size:(i+1)*batch_size],
                                           size=self.forecast_size, mode='bicubic')
                forecast[i*batch_size:(i+1)*batch_size] += forecast_i[:,0,0,:] # [B,None,H,H] -> [B,H]
            forecast = forecast[:,None,:] # [B,H] -> [B,None,H]

        # [B,Q,H] -> [B,H,Q]
        forecast = forecast.permute(0, 2, 1)
        return backcast, forecast
```

Define a PyTorch module called "NHITSBlock" that represents a neural network block, which takes various inputs, performs pooling and MLP operations, and returns a backcast and forecast using a specified basis function, with support for different activation functions and pooling modes.

```
#| exporti
ACTIVATIONS = ['ReLU',
               'Softplus',
               'Tanh',
               'SELU',
               'LeakyReLU',
               'PReLU',
               'Sigmoid']

POOLING = ['MaxPool1d',
           'AvgPool1d']

class NHITSBlock(nn.Module):
    """
    NHITS block which takes a basis function as an argument.
    """
    def __init__(self,
                 input_size: int,
                 h: int,
                 n_theta: int,
                 mlp_units: list,
                 basis: nn.Module,
                 futr_input_size: int,
                 hist_input_size: int,
                 stat_input_size: int,
                 n_pool_kernel_size: int,
                 pooling_mode: str,
                 dropout_prob: float,
```

```
                 activation: str):
        super().__init__()

        pooled_hist_size = int(np.ceil(input_size/n_pool_kernel_size))
        pooled_futr_size = int(np.ceil((input_size+h)/n_pool_kernel_size))

        input_size = pooled_hist_size + \
                     hist_input_size * pooled_hist_size + \
                     futr_input_size * pooled_futr_size + stat_input_size

        self.dropout_prob = dropout_prob
        self.futr_input_size = futr_input_size
        self.hist_input_size = hist_input_size
        self.stat_input_size = stat_input_size

        assert activation in ACTIVATIONS, f'{activation} is not in {ACTIVATIONS}'
        assert pooling_mode in POOLING, f'{pooling_mode} is not in {POOLING}'

        activ = getattr(nn, activation)()

        self.pooling_layer = getattr(nn, pooling_mode)(kernel_size=n_pool_kernel_size,
                                                       stride=n_pool_kernel_size, ceil_mode=True)

        # Block MLPs
        hidden_layers = [nn.Linear(in_features=input_size,
                                   out_features=mlp_units[0][0])]
        for layer in mlp_units:
            hidden_layers.append(nn.Linear(in_features=layer[0],
                                           out_features=layer[1]))
            hidden_layers.append(activ)

            if self.dropout_prob>0:
                #raise NotImplementedError('dropout')
                hidden_layers.append(nn.Dropout(p=self.dropout_prob))

        output_layer = [nn.Linear(in_features=mlp_units[-1][1], out_features=n_theta)]
        layers = hidden_layers + output_layer
        self.layers = nn.Sequential(*layers)
        self.basis = basis

    def forward(self, insample_y: torch.Tensor, futr_exog: torch.Tensor,
                hist_exog: torch.Tensor, stat_exog: torch.Tensor) -> Tuple[torch.Tensor, torch.Tensor]:

        # Pooling
        # Pool1d needs 3D input, (B,C,L), adding C dimension
        insample_y = insample_y.unsqueeze(1)
        insample_y = self.pooling_layer(insample_y)
        insample_y = insample_y.squeeze(1)

        # Flatten MLP inputs [B, L+H, C] -> [B, (L+H)*C]
        # Contatenate [ Y_t, | X_{t-L},..., X_{t} | F_{t-L},..., F_{t+H} | S ]
        batch_size = len(insample_y)
        if self.hist_input_size > 0:
            hist_exog = hist_exog.permute(0,2,1) # [B, L, C] -> [B, C, L]
            hist_exog = self.pooling_layer(hist_exog)
            hist_exog = hist_exog.permute(0,2,1) # [B, C, L] -> [B, L, C]
            insample_y = torch.cat(( insample_y, hist_exog.reshape(batch_size,-1) ), dim=1)

        if self.futr_input_size > 0:
            futr_exog = futr_exog.permute(0,2,1) # [B, L, C] -> [B, C, L]
            futr_exog = self.pooling_layer(futr_exog)
            futr_exog = futr_exog.permute(0,2,1) # [B, C, L] -> [B, L, C]
            insample_y = torch.cat(( insample_y, futr_exog.reshape(batch_size,-1) ), dim=1)

        if self.stat_input_size > 0:
            insample_y = torch.cat(( insample_y, stat_exog.reshape(batch_size,-1) ), dim=1)

        # Compute local projection weights and projection
        theta = self.layers(insample_y)
        backcast, forecast = self.basis(theta)
        return backcast, forecast
```

Define a class called "NHITS" that inherits from a base class "BaseWindows" and is used for time series forecasting. It constructs a neural network model with multiple blocks, each containing an "NHITSBlock" module. The model takes various input data, performs forecasting using a stack of blocks, and returns the forecasted values. The architecture of the model is highly configurable, allowing for customization of parameters such as the number of blocks, layer sizes, and activation functions, and it supports various options for handling time series data, including pooling and downsampling.

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

    The Neural Hierarchical Interpolation for Time Series (NHITS), is an MLP-based deep
    neural architecture with backward and forward residual links. NHITS tackles volatility and
    memory complexity challenges, by locally specializing its sequential predictions into
    the signals frequencies with hierarchical interpolation and pooling.

    **Parameters:**<br>
    `h`: int, Forecast horizon. <br>
    `input_size`: int, autorregresive inputs size, y=[1,2,3,4] input_size=2 -> y_[t-2:t]=[1,2].<br>
    `stat_exog_list`: str list, static exogenous columns.<br>
    `hist_exog_list`: str list, historic exogenous columns.<br>
    `futr_exog_list`: str list, future exogenous columns.<br>
    `exclude_insample_y`: bool=False, the model skips the autoregressive features y[t-input_size:t] if True.<br>
    `activation`: str, activation from ['ReLU', 'Softplus', 'Tanh', 'SELU', 'LeakyReLU', 'PReLU', 'Sigmoid'].<br>
    `stack_types`: List[str], stacks list in the form N * ['identity'], to be deprecated in favor of `n_stacks`. Note that len(stack_type
    `n_blocks`: List[int], Number of blocks for each stack. Note that len(n_blocks) = len(stack_types).<br>
    `mlp_units`: List[List[int]], Structure of hidden layers for each stack type. Each internal list should contain the number of units o
    `n_freq_downsample`: List[int], list with the stack's coefficients (inverse expressivity ratios). Note that len(stack_types)=len(n_fr
    `interpolation_mode`: str='linear', interpolation basis from ['linear', 'nearest', 'cubic'].<br>
    `n_pool_kernel_size`: List[int], list with the size of the windows to take a max/avg over. Note that len(stack_types)=len(n_freq_down
    `pooling_mode`: str, input pooling module from ['MaxPool1d', 'AvgPool1d'].<br>
    `dropout_prob_theta`: float, Float between (0, 1). Dropout for NHITS basis.<br>
    `loss`: PyTorch module, instantiated train loss class from [losses collection](https://nixtla.github.io/neuralforecast/losses.pytorch
    `valid_loss`: PyTorch module=`loss`, instantiated valid loss class from [losses collection](https://nixtla.github.io/neuralforecast/l
    `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 distributed across max_steps.<br>
    `early_stop_patience_steps`: int=-1, Number of validation iterations before early stopping.<br>
    `val_check_steps`: int=100, Number of training steps between every validation loss check.<br>
    `batch_size`: int=32, number of different series in each batch.<br>
    `valid_batch_size`: int=None, number of different series in each validation and test batch, if None uses batch_size.<br>
    `windows_batch_size`: int=1024, number of windows to sample in each training batch, default uses all.<br>
    `inference_windows_batch_size`: int=-1, number of windows to sample in each inference batch, -1 uses all.<br>
    `start_padding_enabled`: bool=False, if True, the model will pad the time series with zeros at the beginning, by input size.<br>
    `step_size`: int=1, step size between each window of temporal data.<br>
    `scaler_type`: str='identity', type of scaler for temporal inputs normalization see [temporal scalers](https://nixtla.github.io/neura
    `random_seed`: int, random_seed for pytorch initializer and numpy generators.<br>
    `num_workers_loader`: int=os.cpu_count(), workers to be used by `TimeSeriesDataLoader`.<br>
    `drop_last_loader`: bool=False, if True `TimeSeriesDataLoader` drops last non-full batch.<br>
    `alias`: str, optional,  Custom name of the model.<br>
    `**trainer_kwargs`: int,  keyword trainer arguments inherited from [PyTorch Lighning's trainer](https://pytorch-lightning.readthedocs

    **References:**<br>
    -[Cristian Challu, Kin G. Olivares, Boris N. Oreshkin, Federico Garza,
    Max Mergenthaler-Canseco, Artur Dubrawski (2023). "NHITS: Neural Hierarchical Interpolation for Time Series Forecasting".
    Accepted at the Thirty-Seventh AAAI Conference on Artificial Intelligence.](https://arxiv.org/abs/2201.12886)
    """
    # Class attributes
    SAMPLING_TYPE = 'windows'

    def __init__(self,
                 h,
                 input_size,
                 futr_exog_list = None,
                 hist_exog_list = None,
                 stat_exog_list = None,
                 exclude_insample_y = False,
                 stack_types: list = ['identity', 'identity', 'identity'],
                 n_blocks: list = [1, 1, 1],
                 mlp_units: list = 3 * [[512, 512]],
                 n_pool_kernel_size: list = [2, 2, 1],
                 n_freq_downsample: list = [4, 2, 1],
                 pooling_mode: str = 'MaxPool1d',
                 interpolation_mode: str = 'linear',
                 dropout_prob_theta = 0.,
                 activation = 'ReLU',
                 loss = MAE(),
                 valid_loss = None,
                 max_steps: int = 1000,
                 learning_rate: float = 1e-3,
                 num_lr_decays: int = 3,
                 early_stop_patience_steps: int =-1,
                 val_check_steps: int = 100,
                 batch_size: int = 32,
```

```
                 valid_batch_size: Optional[int] = None,
                 windows_batch_size: int = 1024,
                 inference_windows_batch_size: int = -1,
                 start_padding_enabled = False,
                 step_size: int = 1,
                 scaler_type: str = 'identity',
                 random_seed: int = 1,
                 num_workers_loader = 0,
                 drop_last_loader = False,
                 **trainer_kwargs):

        # Inherit BaseWindows class
        super(NHITS, self).__init__(h=h,
                                    input_size=input_size,
                                    futr_exog_list=futr_exog_list,
                                    hist_exog_list=hist_exog_list,
                                    stat_exog_list=stat_exog_list,
                                    exclude_insample_y = exclude_insample_y,
                                    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_patience_steps,
                                    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=inference_windows_batch_size,
                                    start_padding_enabled=start_padding_enabled,
                                    step_size=step_size,
                                    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)

        blocks = self.create_stack(h=h,
                                   input_size=input_size,
                                   stack_types=stack_types,
                                   futr_input_size=self.futr_input_size,
                                   hist_input_size=self.hist_input_size,
                                   stat_input_size=self.stat_input_size,
                                   n_blocks=n_blocks,
                                   mlp_units=mlp_units,
                                   n_pool_kernel_size=n_pool_kernel_size,
                                   n_freq_downsample=n_freq_downsample,
                                   pooling_mode=pooling_mode,
                                   interpolation_mode=interpolation_mode,
                                   dropout_prob_theta=dropout_prob_theta,
                                   activation=activation)
        self.blocks = torch.nn.ModuleList(blocks)

    def create_stack(self,
                     h,
                     input_size,
                     stack_types,
                     n_blocks,
                     mlp_units,
                     n_pool_kernel_size,
                     n_freq_downsample,
                     pooling_mode,
                     interpolation_mode,
                     dropout_prob_theta,
                     activation,
                     futr_input_size, hist_input_size, stat_input_size):

        block_list = []
        for i in range(len(stack_types)):
            for block_id in range(n_blocks[i]):

                assert stack_types[i] == 'identity', f'Block type {stack_types[i]} not found!'

                n_theta = (input_size + self.loss.outputsize_multiplier*max(h//n_freq_downsample[i], 1) )
                basis = _IdentityBasis(backcast_size=input_size, forecast_size=h,
                                       out_features=self.loss.outputsize_multiplier,
                                       interpolation_mode=interpolation_mode)
```

```
            nbeats_block = NHITSBlock(h=h,
                                      input_size=input_size,
                                      futr_input_size=futr_input_size,
                                      hist_input_size=hist_input_size,
                                      stat_input_size=stat_input_size,
                                      n_theta=n_theta,
                                      mlp_units=mlp_units,
                                      n_pool_kernel_size=n_pool_kernel_size[i],
                                      pooling_mode=pooling_mode,
                                      basis=basis,
                                      dropout_prob=dropout_prob_theta,
                                      activation=activation)

            # Select type of evaluation and apply it to all layers of block
            block_list.append(nbeats_block)

        return block_list

    def forward(self, windows_batch):

        # Parse windows_batch
        insample_y    = windows_batch['insample_y']
        insample_mask = windows_batch['insample_mask']
        futr_exog     = windows_batch['futr_exog']
        hist_exog     = windows_batch['hist_exog']
        stat_exog     = windows_batch['stat_exog']

        # insample
        residuals = insample_y.flip(dims=(-1,)) #backcast init
        insample_mask = insample_mask.flip(dims=(-1,))

        forecast = insample_y[:, -1:, None] # Level with Naive1
        block_forecasts = [ forecast.repeat(1, self.h, 1) ]
        for i, block in enumerate(self.blocks):
            backcast, block_forecast = block(insample_y=residuals, futr_exog=futr_exog,
                                             hist_exog=hist_exog, stat_exog=stat_exog)
            residuals = (residuals - backcast) * insample_mask
            forecast = forecast + block_forecast

            if self.decompose_forecast:
                block_forecasts.append(block_forecast)

        # Adapting output's domain
        forecast = self.loss.domain_map(forecast)

        if self.decompose_forecast:
            # (n_batch, n_blocks, h, output_size)
            block_forecasts = torch.stack(block_forecasts)
            block_forecasts = block_forecasts.permute(1,0,2,3)
            block_forecasts = block_forecasts.squeeze(-1) # univariate output
            return block_forecasts
        else:
            return forecast

show_doc(NHITS)
```

NHITS

```
NHITS (h, input_size, futr_exog_list=None, hist_exog_list=None,
       stat_exog_list=None, exclude_insample_y=False,
       stack_types:list=['identity', 'identity', 'identity'],
       n_blocks:list=[1, 1, 1], mlp_units:list=[[512, 512], [512, 512],
       [512, 512]], n_pool_kernel_size:list=[2, 2, 1],
       n_freq_downsample:list=[4, 2, 1], pooling_mode:str='MaxPool1d',
       interpolation_mode:str='linear', dropout_prob_theta=0.0,
       activation='ReLU', loss=MAE(), valid_loss=None,
       max_steps:int=1000, learning_rate:float=0.001,
       num_lr_decays:int=3, early_stop_patience_steps:int=-1,
       val_check_steps:int=100, batch_size:int=32,
       valid_batch_size:Optional[int]=None, windows_batch_size:int=1024,
       inference_windows_batch_size:int=-1, start_padding_enabled=False,
       step_size:int=1, scaler_type:str='identity', random_seed:int=1,
       num_workers_loader=0, drop_last_loader=False, **trainer_kwargs)
```

NHITS

The Neural Hierarchical Interpolation for Time Series (NHITS), is an MLP-based deep neural architecture with backward and forward residual links. NHITS tackles volatility and memory complexity challenges, by locally specializing its sequential predictions into the signals frequencies with hierarchical interpolation and pooling.

Parameters:
h: int, Forecast horizon.
`input_size`: int, autorregresive inputs size, y=[1,2,3,4] input_size=2 -> y_[t-2:t]=[1,2].
`stat_exog_list`: str list, static exogenous columns.
`hist_exog_list`: str list, historic exogenous columns.
`futr_exog_list`: str list, future exogenous columns.
`exclude_insample_y`: bool=False, the model skips the autoregressive features y[t-input_size:t] if True.
`activation`: str, activation from ['ReLU', 'Softplus', 'Tanh', 'SELU', 'LeakyReLU', 'PReLU', 'Sigmoid'].
`stack_types`: List[str], stacks list in the form N * ['identity'], to be deprecated in favor of `n_stacks`. Note that len(stack_types)=len(n_freq_downsample)=len(n_pool_kernel_size).
`n_blocks`: List[int], Number of blocks for each stack. Note that len(n_blocks) = len(stack_types).
`mlp_units`: List[List[int]], Structure of hidden layers for each stack type. Each internal list should contain the number of units of each hidden layer. Note that len(n_hidden) = len(stack_types).
`n_freq_downsample`: List[int], list with the stack's coefficients (inverse expressivity ratios). Note that len(stack_types)=len(n_freq_downsample)=len(n_pool_kernel_size).

```
show_doc(NHITS.fit, name='NHITS.fit')
```

NHITS.fit

```
NHITS.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.

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

```
show_doc(NHITS.predict, name='NHITS.predict')
```

NHITS.predict

```
NHITS.predict (dataset, test_size=None, step_size=1, random_seed=None,
               **data_module_kwargs)
```

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](#).

```
#| hide
import logging
import warnings
logging.getLogger("pytorch_lightning").setLevel(logging.ERROR)
warnings.filterwarnings("ignore")
```

This code splits a time series dataset into training and test sets, fits an NHITS forecasting model on the training data, and plots the combined actual and predicted values.

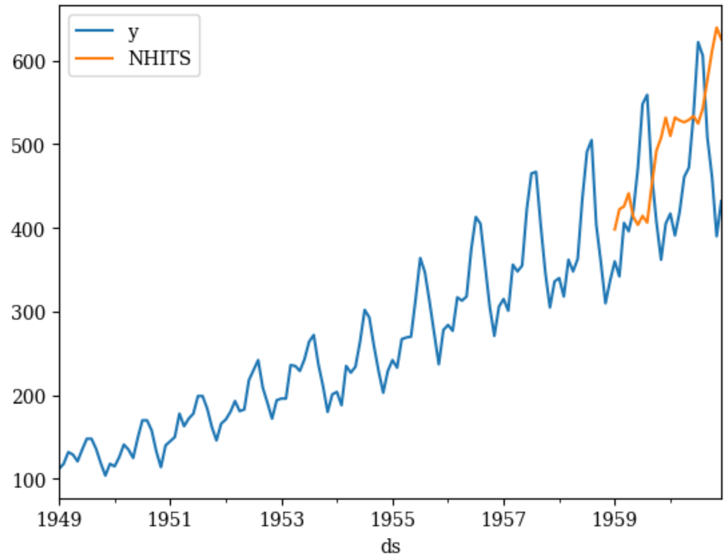
```
#| hide
import pandas as pd
import matplotlib.pyplot as plt

import pytorch_lightning as pl

from neuralforecast.utils import AirPassengersDF as Y_df
from neuralforecast.tsdataset import TimeSeriesDataset, TimeSeriesLoader

Y_train_df = Y_df[Y_df.ds<Y_df['ds'].values[-24]] # 132 train
Y_test_df = Y_df[Y_df.ds>=Y_df['ds'].values[-24]] # 12 test

dataset, *_ = TimeSeriesDataset.from_df(df = Y_train_df)
model = NHITS(h=24,
              input_size=24*2,
              max_steps=1,
              windows_batch_size=None,
              n_freq_downsample=[12,4,1],
              pooling_mode='MaxPool1d')
model.fit(dataset=dataset)
y_hat = model.predict(dataset=dataset)
Y_test_df['NHITS'] = y_hat

pd.concat([Y_train_df, Y_test_df]).drop('unique_id', axis=1).set_index('ds').plot()
```

```
INFO:lightning_fabric.utilities.seed:Seed set to 1
```

Epoch 0: 100% 1/1 [00:00<00:00, 1.47it/s, v_num=81, train_loss_step=57.80, train_loss_epoch=57.80]

Predicting DataLoader 0: 100% 1/1 [00:00<00:00, 41.63it/s]

```
<Axes: xlabel='ds'>
```



The code first decomposes the model's forecast into different components. It then creates a 5-subplot figure for visualization. The first subplot displays the true and forecasted values, while the subsequent subplots show the components of the forecast, such as the level and various stack outputs.

```
#| hide
# qualitative decomposition evaluation
y_hat = model.decompose(dataset=dataset)

fig, ax = plt.subplots(5, 1, figsize=(10, 15))

ax[0].plot(Y_test_df['y'].values, label='True', color="#9C9DB2", linewidth=4)
ax[0].plot(y_hat.sum(axis=1).flatten(), label='Forecast', color="#7B3841")
ax[0].legend(prop={'size': 20})
for label in (ax[0].get_xticklabels() + ax[0].get_yticklabels()):
    label.set_fontsize(18)
ax[0].set_ylabel('y', fontsize=20)
```

```
ax[1].plot(y_hat[0,0], label='level', color="#7B3841")
ax[1].set_ylabel('Level', fontsize=20)

ax[2].plot(y_hat[0,1], label='stack1', color="#7B3841")
ax[2].set_ylabel('Stack 1', fontsize=20)

ax[3].plot(y_hat[0,2], label='stack2', color="#D9AE9E")
ax[3].set_ylabel('Stack 2', fontsize=20)

ax[4].plot(y_hat[0,3], label='stack3', color="#D9AE9E")
ax[4].set_ylabel('Stack 3', fontsize=20)

ax[4].set_xlabel('Prediction \u03C4 \u2208 {t+1,..., t+H}', fontsize=20)
```

Usage Example

```
!pip install pytorch-lightning
!pip install neuralforecast
```

We have executed the code for a total of six times, each with different combinations of pooling techniques and interpolation modes. Specifically, we ran the code three times using max pooling and three times using average pooling. For each pooling method, we applied one of the following interpolation modes: Linear, Cubic, and Nearest.

1. Max Pooling with Linear Interpolation
2. Max Pooling with Cubic Interpolation
3. Max Pooling with Nearest Interpolation
4. Average Pooling with Linear Interpolation
5. Average Pooling with Cubic Interpolation
6. Average Pooling with Nearest Interpolation

1. Max Pooling with Linear Interpolation

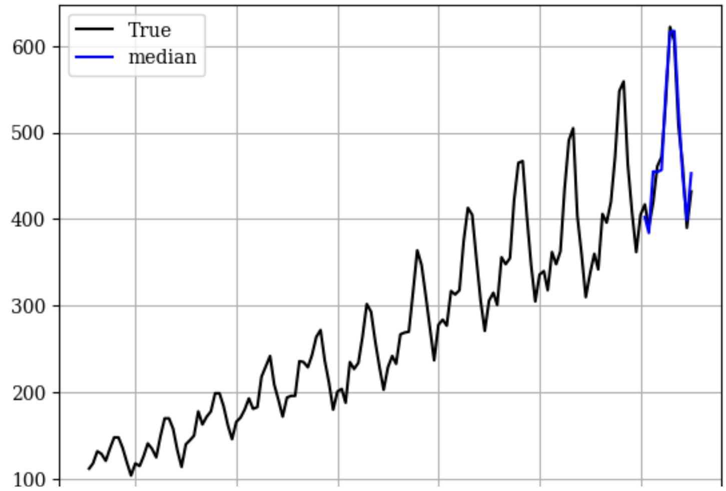
```
#| eval: false
import numpy as np
import pandas as pd
import pytorch_lightning as pl
import matplotlib.pyplot as plt

from neuralforecast import NeuralForecast
from neuralforecast.models import NHITS
from neuralforecast.losses.pytorch import DistributionLoss, HuberLoss, MAE
from neuralforecast.tsdataset import TimeSeriesDataset
from neuralforecast.utils import AirPassengers, AirPassengersPanel, AirPassengersStatic

#AirPassengersPanel['y'] = 1 * (AirPassengersPanel['trend'] % 12) < 2
Y_train_df = AirPassengersPanel[AirPassengersPanel.ds<AirPassengersPanel['ds'].values[-12]].reset_index(drop=True) # 132 train
Y_test_df = AirPassengersPanel[AirPassengersPanel.ds>=AirPassengersPanel['ds'].values[-12]].reset_index(drop=True) # 12 test

model = NHITS(h=12,
              input_size=24,
              #loss=DistributionLoss(distribution='StudentT', level=[80, 90], return_params=True),
              loss=HuberLoss(delta=0.5),
              valid_loss=MAE(),
              stat_exog_list=['airline1'],
              scaler_type='robust',
              max_steps=200,
              early_stop_patience_steps=2,
              val_check_steps=10,
              learning_rate=1e-3,
              pooling_mode='MaxPool1d',
              interpolation_mode="linear")

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

# Plot quantile predictions
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])

plot_df = plot_df[plot_df.unique_id=='Airline1'].drop('unique_id', axis=1)
plt.plot(plot_df['ds'], plot_df['y'], c='black', label='True')
plt.plot(plot_df['ds'], plot_df['NHITS'], c='blue', label='median')
# plt.plot(plot_df['ds'], plot_df['NHITS-median'], c='blue', label='median')
# plt.fill_between(x=plot_df['ds'][-12:],
#                  y1=plot_df['NHITS-lo-90'][-12:].values,
#                  y2=plot_df['NHITS-hi-90'][-12:].values,
#                  alpha=0.4, label='level 90')
plt.legend()
plt.grid()
plt.plot()
```

```
INFO:lightning_fabric.utilities.seed:Seed set to 1
```

Epoch 29: 100% 1/1 [00:00<00:00, 1.85it/s, v_num=108, train_loss_step=0.0876, train_loss_epoch=0.0876, valid_loss=38.30]

Predicting DataLoader 0: 100% 1/1 [00:00<00:00, 50.70it/s]

```
[]
```




```
y_true = Y_test_df.y.values
y_hat = Y_hat_df['NHITS'].values
```

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

Max_linear_mae = mae(y_hat, y_true)
Max_linear_mse = mse(y_hat, y_true)
print('Max linear MAE: ', Max_linear_mae)
print('Max linear MSE: ', Max_linear_mse)
```

```
Max linear MAE:  14.198963165283203
Max linear MSE:  270.21525646672427
```

2. Max Pooling with Cubic Interpolation

```
#AirPassengersPanel['y'] = 1 * (AirPassengersPanel['trend'] % 12) < 2
Y_train_df = AirPassengersPanel[AirPassengersPanel.ds<AirPassengersPanel['ds'].values[-12]].reset_index(drop=True) # 132 train
Y_test_df = AirPassengersPanel[AirPassengersPanel.ds>=AirPassengersPanel['ds'].values[-12]].reset_index(drop=True) # 12 test
```

```
model = NHITS(h=12,
              input_size=24,
              #loss=DistributionLoss(distribution='StudentT', level=[80, 90], return_params=True),
              loss=HuberLoss(delta=0.5),
              valid_loss=MAE(),
              stat_exog_list=['airline1'],
              scaler_type='robust',
              max_steps=200,
              early_stop_patience_steps=2,
              val_check_steps=10,
              learning_rate=1e-3,
              pooling_mode='MaxPool1d',
              interpolation_mode='cubic')

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

# Plot quantile predictions
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])

plot_df = plot_df[plot_df.unique_id=='Airline1'].drop('unique_id', axis=1)
```

```
INFO:lightning_fabric.utilities.seed:Seed set to 1
```

Epoch 29: 100% 1/1 [00:00<00:00, 1.58it/s, v_num=110, train_loss_step=0.0834, train_loss_epoch=0.0834, valid_loss=38.00]

Predicting DataLoader 0: 100% 1/1 [00:00<00:00, 58.15it/s]

```
y_true = Y_test_df.y.values
y_hat = Y_hat_df['NHITS'].values
```

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

Max_cubic_mae = mae(y_hat, y_true)
Max_cubic_mse = mse(y_hat, y_true)
print('Max cubic MAE: ', Max_cubic_mae)
print('Max cubic MSE: ', Max_cubic_mse)
```

```
Max cubic MAE:  12.6770871480306
Max cubic MSE:  252.47157817384382
```

3. Max Pooling with Nearest Interpolation

```
#AirPassengersPanel['y'] = 1 * (AirPassengersPanel['trend'] % 12) < 2
Y_train_df = AirPassengersPanel[AirPassengersPanel.ds<AirPassengersPanel['ds'].values[-12]].reset_index(drop=True) # 132 train
Y_test_df = AirPassengersPanel[AirPassengersPanel.ds>=AirPassengersPanel['ds'].values[-12]].reset_index(drop=True) # 12 test
```

```
model = NHITS(h=12,
              input_size=24,
              #loss=DistributionLoss(distribution='StudentT', level=[80, 90], return_params=True),
              loss=HuberLoss(delta=0.5),
              valid_loss=MAE(),
              stat_exog_list=['airline1'],
              scaler_type='robust',
              max_steps=200,
              early_stop_patience_steps=2,
              val_check_steps=10,
              learning_rate=1e-3,
              pooling_mode='MaxPool1d',
              interpolation_mode='nearest')

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

# Plot quantile predictions
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])

plot_df = plot_df[plot_df.unique_id=='Airline1'].drop('unique_id', axis=1)
```

```
INFO:lightning_fabric.utilities.seed:Seed set to 1
```

Epoch 29: 100% 1/1 [00:00<00:00, 2.54it/s, v_num=112, train_loss_step=0.0831, train_loss_epoch=0.0831, valid_loss=39.20]

Predicting DataLoader 0: 100% 1/1 [00:00<00:00, 53.04it/s]

```
y_true = Y_test_df.y.values
y_hat = Y_hat_df['NHITS'].values
```

```
from neuralforecast.losses.numpy import mae, mse
Max_nearest_mae = mae(y_hat, y_true)
Max_nearest_mse = mse(y_hat, y_true)

print('Max nearest MAE: ', Max_nearest_mae)
print('Max nearest MSE: ', Max_nearest_mse)
```

```
Max nearest MAE:  13.812933603922525
Max nearest MSE:  295.4155105924777
```

4. Average Pooling with Linear Interpolation

```
#AirPassengersPanel['y'] = 1 * (AirPassengersPanel['trend'] % 12) < 2
Y_train_df = AirPassengersPanel[AirPassengersPanel.ds<AirPassengersPanel['ds'].values[-12]].reset_index(drop=True) # 132 train
Y_test_df = AirPassengersPanel[AirPassengersPanel.ds>=AirPassengersPanel['ds'].values[-12]].reset_index(drop=True) # 12 test
```

```
model = NHITS(h=12,
              input_size=24,
              #loss=DistributionLoss(distribution='StudentT', level=[80, 90], return_params=True),
              loss=HuberLoss(delta=0.5),
              valid_loss=MAE(),
              stat_exog_list=['airline1'],
```

```
              scaler_type='robust',
              max_steps=200,
              early_stop_patience_steps=2,
              val_check_steps=10,
              learning_rate=1e-3,
              pooling_mode='AvgPool1d',
              interpolation_mode='linear')

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

# Plot quantile predictions
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])

plot_df = plot_df[plot_df.unique_id=='Airline1'].drop('unique_id', axis=1)
```

```
INFO:lightning_fabric.utilities.seed:Seed set to 1
```

Epoch 29: 100% 1/1 [00:00<00:00, 1.79it/s, v_num=106, train_loss_step=0.0823, train_loss_epoch=0.0823, valid_loss=39.70]

Predicting DataLoader 0: 100% 1/1 [00:00<00:00, 48.47it/s]

```
y_true = Y_test_df.y.values
y_hat = Y_hat_df['NHITS'].values
```

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

Avg_linear_mae = mae(y_hat, y_true)
Avg_linear_mse = mse(y_hat, y_true)

print('AvgPool linear MAE: ', Avg_linear_mae)
print('AvgPool linear MSE: ', Avg_linear_mse)
```

```
AvgPool linear MAE:  14.644779205322266
AvgPool linear MSE:  309.45152617249795
```

5. Average Pooling with Cubic Interpolation

```
#AirPassengersPanel['y'] = 1 * (AirPassengersPanel['trend'] % 12) < 2
Y_train_df = AirPassengersPanel[AirPassengersPanel.ds<AirPassengersPanel['ds'].values[-12]].reset_index(drop=True) # 132 train
Y_test_df = AirPassengersPanel[AirPassengersPanel.ds>=AirPassengersPanel['ds'].values[-12]].reset_index(drop=True) # 12 test
```

```
model = NHITS(h=12,
              input_size=24,
              #loss=DistributionLoss(distribution='StudentT', level=[80, 90], return_params=True),
              loss=HuberLoss(delta=0.5),
              valid_loss=MAE(),
              stat_exog_list=['airline1'],
              scaler_type='robust',
              max_steps=200,
              early_stop_patience_steps=2,
              val_check_steps=10,
              learning_rate=1e-3,
              interpolation_mode='cubic',
              pooling_mode='AvgPool1d')

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

# Plot quantile predictions
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])

plot_df = plot_df[plot_df.unique_id=='Airline1'].drop('unique_id', axis=1)
```

```
INFO:lightning_fabric.utilities.seed:Seed set to 1
```

Epoch 29: 100% 1/1 [00:00<00:00, 1.43it/s, v_num=102, train_loss_step=0.0784, train_loss_epoch=0.0784, valid_loss=39.10]

Predicting DataLoader 0: 100% 1/1 [00:00<00:00, 54.58it/s]

```
y_true = Y_test_df.y.values
y_hat = Y_hat_df['NHITS'].values
```

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

Avg_cubic_mae = mae(y_hat, y_true)
Avg_cubic_mse = mse(y_hat, y_true)

print('AvgPool cubic MAE: ', Avg_cubic_mae)
print('AvgPool cubic MSE: ', Avg_cubic_mse)
```

```
AvgPool cubic MAE:  14.273418426513672
AvgPool cubic MSE:  318.5927762616969
```

6. Average Pooling with Nearest Interpolation

```
#AirPassengersPanel['y'] = 1 * (AirPassengersPanel['trend'] % 12) < 2
Y_train_df = AirPassengersPanel[AirPassengersPanel.ds<AirPassengersPanel['ds'].values[-12]].reset_index(drop=True) # 132 train
Y_test_df = AirPassengersPanel[AirPassengersPanel.ds>=AirPassengersPanel['ds'].values[-12]].reset_index(drop=True) # 12 test
```

```
model = NHITS(h=12,
              input_size=24,
              #loss=DistributionLoss(distribution='StudentT', level=[80, 90], return_params=True),
              loss=HuberLoss(delta=0.5),
              valid_loss=MAE(),
              stat_exog_list=['airline1'],
              scaler_type='robust',
              max_steps=200,
              early_stop_patience_steps=2,
              val_check_steps=10,
              learning_rate=1e-3,
              interpolation_mode='nearest',
              pooling_mode='AvgPool1d')

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

# Plot quantile predictions
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])

plot_df = plot_df[plot_df.unique_id=='Airline1'].drop('unique_id', axis=1)
```

```
INFO:lightning_fabric.utilities.seed:Seed set to 1
Epoch 29: 100%    1/1 [00:00<00:00, 1.56it/s, v_num=100, train_loss_step=0.0827, train_loss_epoch=0.0827, valid_loss=42.20]

Predicting DataLoader 0: 100%    1/1 [00:00<00:00, 33.58it/s]
```

```
y_true = Y_test_df.y.values
y_hat = Y_hat_df['NHITS'].values
```

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

Avg_nearest_mae = mae(y_hat, y_true)
Avg_nearest_mse = mse(y_hat, y_true)

print('AvgPool nearest MAE: ', Avg_nearest_mae)
print('AvgPool nearest MSE: ', Avg_nearest_mse)
```

```
AvgPool nearest MAE:  13.42660903930664
AvgPool nearest MSE:  286.05055224790704
```

```
data = {
    "MaxPool: mae": [Max_linear_mae, Max_cubic_mae, Max_nearest_mae],
    "MaxPool: mse": [Max_linear_mse, Max_cubic_mse, Max_nearest_mse],
    "AvgPool mae": [Avg_linear_mae, Avg_cubic_mae, Avg_nearest_mae],
    "AvgPool: mse": [Avg_linear_mse, Avg_cubic_mse, Avg_nearest_mse]
}

# Define the row names
rows = ["linear", "cubic", "nearest"]

# Create the DataFrame
df = pd.DataFrame(data, index=rows)

# Print the DataFrame
print(df)
```