demo_dkf

December 2, 2021

1 Structured Deep Kalman Filter (DKF)

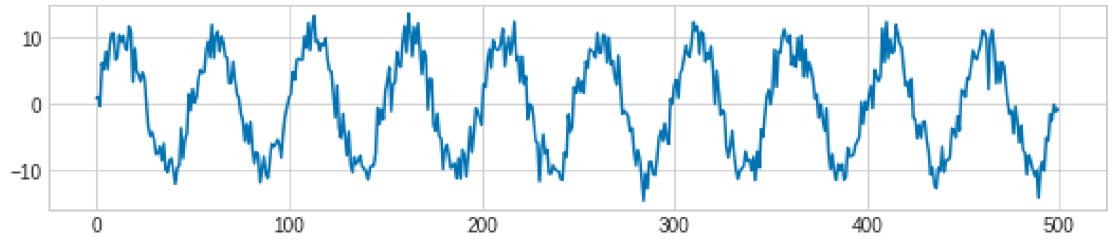
1.1 References

- https://github.com/DanieleGammelli/DeepKalmanFilter
- Pyro and Pixyz

[ ]:
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn import preprocessing
```

[ ]:
```
plt.style.use('seaborn-colorblind')
plt.style.use('seaborn-whitegrid')
```

[ ]:
```
seq_len = 500

# Generating sample data
data = np.sin(np.linspace(0, 20*np.pi, seq_len))
data += np.random.normal(0, 0.2, size=seq_len)
data *= 10

plt.figure(figsize=(10, 2))
plt.plot(data)
plt.show()
```



[ ]:
```
def split_data(data, val_len, test_len):
    assert val_len > 0
```

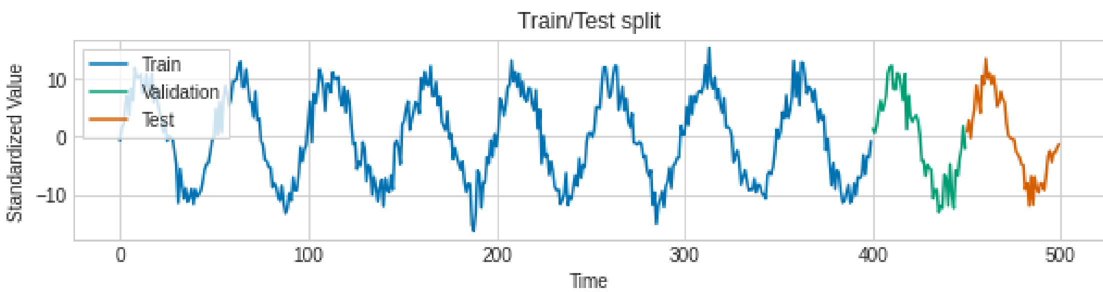
```
    assert test_len > 0
    # Split lengths
    train_value = {
        'T': data.shape[0] - val_len - test_len,
        'T_val': val_len,
        'T_test': test_len,
    }

    y = data.copy().reshape((-1, 1)) if data.ndim == 1 else data.copy()
    y_train, y_val, y_test = np.split(data, [-val_len-test_len, -test_len])
    if y_train.ndim == 1: y_train = y_train.reshape((-1, 1))
    if y_val.ndim == 1: y_val = y_val.reshape((-1, 1))
    if y_test.ndim == 1: y_test = y_test.reshape((-1, 1))
    return y, y_train, y_val, y_test, train_value

def standardize_data(y, y_train, y_val, y_test):
    scaler = preprocessing.StandardScaler()
    y_train_sc = scaler.fit_transform(y_train.reshape(-1,1))
    y_val_sc = scaler.transform(y_val.reshape(-1,1))
    y_test_sc = scaler.transform(y_test.reshape(-1,1))
    y_sc = scaler.transform(y.reshape(-1,1))

    return y_sc, y_train_sc, y_val_sc, y_test_sc, scaler

def transform_to_torch_tensor(y, y_train, y_val, y_test, y_sc, y_train_sc,␣
 ↪y_val_sc, y_test_sc, train_value):
    T = train_value['T']
    T_val = train_value['T_val']
    T_test = train_value['T_test']

    y_train_sc = torch.FloatTensor(y_train_sc).reshape(1, T, y_train_sc.
 ↪shape[1])
    y_val_sc = torch.FloatTensor(y_val_sc).reshape(1, T_val, y_test_sc.shape[1])
    y_test_sc = torch.FloatTensor(y_test_sc).reshape(1, T_test, y_test_sc.
 ↪shape[1])
    y_sc = torch.FloatTensor(y_sc).reshape(1, y_sc.shape[0], y_sc.shape[1])
    y_train = torch.FloatTensor(y_train).reshape(1, T, y_train.shape[1])
    y_val = torch.FloatTensor(y_val).reshape(1, T_val, y_val.shape[1])
    y_test = torch.FloatTensor(y_test).reshape(1, T_test, y_test.shape[1])
    y = torch.FloatTensor(y).reshape(1, y.shape[0], y.shape[1])

    return y, y_train, y_val, y_test, y_sc, y_train_sc, y_val_sc, y_test_sc
```

[ ]:
```
y, y_train, y_val, y_test, train_value = split_data(data, 50, 50)
y_sc, y_train_sc, y_val_sc, y_test_sc, scaler = standardize_data(y, y_train,␣
 ↪y_val, y_test)
(y_tensor, y_train_tensor, y_val_tensor, y_test_tensor,
```

```
y_sc, y_train_sc, y_val_sc, y_test_sc) = transform_to_torch_tensor(
   y, y_train, y_val, y_test, y_sc, y_train_sc, y_val_sc, y_test_sc,␣
 ↪train_value)

y_train.shape, y_val.shape, y_test.shape
```

[ ]: ((400, 1), (50, 1), (50, 1))

[ ]:
```
plt.figure(figsize=(10, 2))
plt.plot(np.arange(len(y_train)), y_train, label='Train')
plt.plot(np.arange(len(y_train), len(y_train)+len(y_val)), y_val,␣
 ↪label='Validation')
plt.plot(np.arange(len(y_train)+len(y_val),␣
 ↪len(y_train)+len(y_val)+len(y_test)), y_test, label='Test')
plt.legend(frameon=True, fancybox=False, loc='upper left')
plt.title('Train/Test split')
plt.xlabel('Time')
plt.ylabel('Standardized Value')
plt.show()
```



[ ]:
```
def plot_predictions(y_train, y_val, y_test, y_pred, y_025, y_975, train_value):

    T = train_value['T']
    T_val = train_value['T_val']
    T_test = train_value['T_test']
    T_pred = T + T_val + T_test

    x_train = np.arange(T)
    x_val = np.arange(T, T+T_val)
    x_test = np.arange(T+T_val, T_pred)
    x_pred = np.arange(T_pred)

    plt.figure(figsize=(10, 2))

    # Data
```

```python
    plt.scatter(x_train, y_train, label='Train', color='k', s=5)
    plt.scatter(x_val, y_val, label='Val', color='c', s=5)
    plt.scatter(x_test, y_test, label='Test', color='b', s=5)
    # Predictions
    plt.plot(x_pred, y_pred, label='Prediction', color='r')
    plt.fill_between(x_pred, y_025, y_975, alpha=0.2, facecolor='r')
    # Windows
    plt.vlines([T, T+T_val], -10000, 10000, linestyles=':', color='k')
    plt.ylim(min([y_train.min(), y_val.min(), y_test.min(), y_pred.min()]) - 2,
             max([y_train.max(), y_val.max(), y_test.max(), y_pred.max()]) + 2)

    plt.legend(frameon=True, fancybox=False)
    plt.xlabel('Time')
    plt.ylabel('Value')
```

[ ]:
```python
import torch
import torch.nn as nn
import pyro
import pyro.distributions as dist
import pyro.poutine as poutine
from pyro.infer import SVI, Trace_ELBO
```

[ ]:
```python
class Emitter(nn.Module):
    """
    Parameterizes the bernoulli observation likelihood `p(x_t | z_t)`
    """

    def __init__(self, input_dim, z_dim, emission_dim):
        super(Emitter, self).__init__()
        # initialize the three linear transformations used in the neural network
        self.lin_z_to_hidden = nn.Linear(z_dim, emission_dim)
        self.lin_hidden_to_hidden = nn.Linear(emission_dim, emission_dim)
        self.lin_hidden_to_input_loc = nn.Linear(emission_dim, input_dim)
        # initialize the two non-linearities used in the neural network
        self.relu = nn.ReLU()

    def forward(self, z_t):
        """
        Given the latent z at a particular time step t we return the vector of
        probabilities `ps` that parameterizes the bernoulli distribution␣
↪`p(x_t|z_t)`
        """
#         print("Emis_Zt, ", z_t.shape)
        h1 = self.relu(self.lin_z_to_hidden(z_t))
        h2 = self.relu(self.lin_hidden_to_hidden(h1))
        mu = self.lin_hidden_to_input_loc(h2)
#         print("Emis_MU, ", mu.shape)
```

```
        return mu
```

[ ]:
```
class GatedTransition(nn.Module):
    """
    Parameterizes the gaussian latent transition probability `p(z_t | z_{t-1})`
    See section 5 in the reference for comparison.
    """

    def __init__(self, z_dim, transition_dim):
        super(GatedTransition, self).__init__()
        # initialize the six linear transformations used in the neural network
        self.lin_gate_z_to_hidden = nn.Linear(z_dim, transition_dim)
        self.lin_gate_hidden_to_z = nn.Linear(transition_dim, z_dim)
        self.lin_proposed_mean_z_to_hidden = nn.Linear(z_dim, transition_dim)
        self.lin_proposed_mean_hidden_to_z = nn.Linear(transition_dim, z_dim)
        self.lin_sig = nn.Linear(z_dim, z_dim)
        self.lin_z_to_loc = nn.Linear(z_dim, z_dim)
        # modify the default initialization of lin_z_to_loc
        # so that it's starts out as the identity function
        self.lin_z_to_loc.weight.data = torch.eye(z_dim)
        self.lin_z_to_loc.bias.data = torch.zeros(z_dim)
        # initialize the three non-linearities used in the neural network
        self.relu = nn.ReLU()
        self.softplus = nn.Softplus()
        #self.batchnorm = nn.BatchNorm1d(num_features=transition_dim)

    def forward(self, z_t_1):
        """
        Given the latent `z_{t-1}` corresponding to the time step t-1
        we return the mean and scale vectors that parameterize the
        (diagonal) gaussian distribution `p(z_t | z_{t-1})`
        """
        # compute the gating function
        _gate = self.relu(self.lin_gate_z_to_hidden(z_t_1))
#          _gate = self.batchnorm(_gate)
        gate = torch.sigmoid(self.lin_gate_hidden_to_z(_gate))
        # compute the 'proposed mean'
        _proposed_mean = self.relu(self.lin_proposed_mean_z_to_hidden(z_t_1))
        proposed_mean = self.lin_proposed_mean_hidden_to_z(_proposed_mean)
        # assemble the actual mean used to sample z_t, which mixes a linear␣
↪transformation
        # of z_{t-1} with the proposed mean modulated by the gating function
        loc = (1 - gate) * self.lin_z_to_loc(z_t_1) + gate * proposed_mean
        # compute the scale used to sample z_t, using the proposed mean from
        # above as input the softplus ensures that scale is positive
        scale = self.softplus(self.lin_sig(self.relu(proposed_mean)))
        # return loc, scale which can be fed into Normal
```

```
        return loc, scale
```

```
[ ]: class Combiner(nn.Module):
         """
         Parameterizes `q(z_t | z_{t-1}, x_{t:T})`, which is the basic building block
         of the guide (i.e. the variational distribution). The dependence on `x_{t:
     ↪T}` is
         through the hidden state of the RNN (see the PyTorch module `rnn` below)
         """

         def __init__(self, z_dim, rnn_dim):
             super(Combiner, self).__init__()
             # initialize the three linear transformations used in the neural network
             self.lin_z_to_hidden = nn.Linear(z_dim, rnn_dim)
             self.lin_hidden_to_loc = nn.Linear(rnn_dim, z_dim)
             self.lin_hidden_to_scale = nn.Linear(rnn_dim, z_dim)
             # initialize the two non-linearities used in the neural network
             self.tanh = nn.Tanh()
             self.softplus = nn.Softplus()

         def forward(self, z_t_1, h_rnn):
             """
             Given the latent z at at a particular time step t-1 as well as the␣
     ↪hidden
             state of the RNN `h(x_{t:T})` we return the mean and scale vectors that
             parameterize the (diagonal) gaussian distribution `q(z_t | z_{t-1},␣
     ↪x_{t:T})`
             """
             # combine the rnn hidden state with a transformed version of z_t_1
             h_combined = 0.5 * (self.tanh(self.lin_z_to_hidden(z_t_1)) + h_rnn)
             # use the combined hidden state to compute the mean used to sample z_t
             loc = self.lin_hidden_to_loc(h_combined)
             # use the combined hidden state to compute the scale used to sample z_t
             scale = self.softplus(self.lin_hidden_to_scale(h_combined))
             # return loc, scale which can be fed into Normal
             return loc, scale
```

```
[ ]: class DKF(nn.Module):
         """
         This PyTorch Module encapsulates the model as well as the
         variational distribution (the guide) for the Deep Markov Model
         """

         def __init__(self, input_dim=1, z_dim=10, emission_dim=30,
                      transition_dim=30, rnn_dim=10, num_layers=1,
                      auto_scale=False, use_cuda=False, annealing_factor=1.0):
```

```
        super(DKF, self).__init__()

        # instantiate PyTorch modules used in the model and guide below
        self.emitter  = Emitter(input_dim, z_dim, emission_dim)
        self.trans    = GatedTransition(z_dim, transition_dim)
        self.combiner = Combiner(z_dim, rnn_dim)

        self.rnn = nn.RNN(input_size=input_dim,
                          hidden_size=rnn_dim,
                          nonlinearity="relu",
                          batch_first=True,
                          bidirectional=False,
                          num_layers=num_layers)

        # define a (trainable) parameters z_0 and z_q_0 that help define the␣
↪probability
        # distributions p(z_1) and q(z_1)
        # (since for t = 1 there are no previous latents to condition on)
        self.z_0 = nn.Parameter(torch.zeros(z_dim))
        self.z_q_0 = nn.Parameter(torch.zeros(z_dim))
        self.sigma = nn.Parameter(torch.ones(input_dim)*0.3)
        # define a (trainable) parameter for the initial hidden state of the rnn
        self.h_0 = nn.Parameter(torch.zeros(1, 1, rnn_dim))

        self.use_cuda = use_cuda
        self.annealing_factor = annealing_factor
        self.scaler = preprocessing.StandardScaler() if auto_scale else None
        # if on gpu cuda-ize all PyTorch (sub)modules
        if use_cuda: self.cuda()

    # the model p(x_{1:T} | z_{1:T}) p(z_{1:T})
    def model(self, sequence=None):
        # get batch_size
        batch_size = len(sequence)
#         print("batch_size", batch_size)
        # this is the number of time steps we need to process in the mini-batch
        T_max = len(sequence[0]) if isinstance(sequence, list) else sequence.
↪size(1)

        # register all PyTorch (sub)modules with pyro
        # this needs to happen in both the model and guide
        pyro.module("dkf", self)

        # set z_prev = z_0 to setup the recursive conditioning in p(z_t |␣
↪z_{t-1})
        z_prev = self.z_0.expand(batch_size, self.z_0.size(0))
#         print("z_prev ", z_prev.shape)
```

```
        # we enclose all the sample statements in the model in a plate.
        # this marks that each datapoint is conditionally independent of the␣
↪others
        with pyro.plate("data", batch_size):
            mus = torch.zeros((batch_size, T_max, 1))
            sigmas = torch.zeros((batch_size, T_max, 1))
            # sample the latents z and observed x's one time step at a time
            for t in range(1, T_max + 1):
                # the next chunk of code samples z_t ~ p(z_t | z_{t-1})
                # note that (both here and elsewhere) we use poutine.scale to␣
↪take care
                # of KL annealing. we use the mask() method to deal with␣
↪raggedness
                # in the observed data (i.e. different sequences in the␣
↪mini-batch
                # have different lengths)

                # first compute the parameters of the diagonal gaussian␣
↪distribution p(z_t | z_{t-1})
                z_loc, z_scale = self.trans(z_prev)

                # then sample z_t according to dist.Normal(z_loc, z_scale)
                # note that we use the reshape method so that the univariate␣
↪Normal distribution
                # is treated as a multivariate Normal distribution with a␣
↪diagonal covariance.
                with poutine.scale(scale=self.annealing_factor):
                    z_t = pyro.sample("z_%d" % t, dist.Normal(z_loc, z_scale).
↪to_event(1))
                # print("z_t, ", z_t.shape)
                # compute the probabilities that parameterize the bernoulli␣
↪likelihood
                emission_mu_t = self.emitter(z_t)
                # print("Mus, ", mus[:, t-1].shape)
                # print("Emis, ", emission_mu_t.shape)

                mus[:,t-1,:] = emission_mu_t
                # the next statement instructs pyro to observe x_t according to␣
↪the
                # bernoulli distribution p(x_t|z_t)
                if isinstance(sequence, list):
                    pyro.sample("obs_y_%d" % t,
                                dist.Normal(loc=emission_mu_t, scale=self.sigma).
↪to_event(1), obs=None)
                else:
                    pyro.sample("obs_y_%d" % t,
```

```
                                dist.Normal(loc=emission_mu_t, scale=self.
↪sigma).to_event(1), obs=sequence[:, t-1, :].view(-1))
                # the latent sampled at this time step will be conditioned upon
                # in the next time step so keep track of it
                z_prev = z_t
            return mus

    def guide(self, sequence=None):
        # get batch_size
        batch_size = len(sequence)
        # this is the number of time steps we need to process in the mini-batch
        T_max = len(sequence[0]) if isinstance(sequence, list) else sequence.
↪size(1)
        # register all PyTorch (sub)modules with pyro
        pyro.module("dkf", self)
        # if on gpu we need the fully broadcast view of the rnn initial state
        # to be in contiguous gpu memory
        h_0_contig = self.h_0.expand(1, batch_size, self.rnn.hidden_size).
↪contiguous()
        # push the observed x's through the rnn;
        # rnn_output contains the hidden state at each time step
        rnn_output, rnn_hidden_state = self.rnn(sequence, h_0_contig)

        # reverse rnn_output to get initial ordering
#         rnn_output = torch.flip(rnn_output[:, :, :], dims=[1])

        # set z_prev = z_q_0 to setup the recursive conditioning in q(z_t |...)
        z_prev = self.z_q_0.expand(batch_size, self.z_q_0.size(0))

        # we enclose all the sample statements in the guide in a plate.
        # this marks that each datapoint is conditionally independent of the␣
↪others.
        with pyro.plate("data", batch_size):
            # sample the latents z one time step at a time
            for t in range(1, T_max + 1):
                # the next two lines assemble the distribution q(z_t | z_{t-1},␣
↪x_{t:T})
                z_loc, z_scale = self.combiner(z_prev, rnn_output[:, t - 1, :])

                z_dist = dist.Normal(z_loc, z_scale)
                assert z_dist.event_shape == ()
                assert z_dist.batch_shape == (batch_size, self.z_q_0.size(0))
                # sample z_t from the distribution z_dist
                with pyro.poutine.scale(scale=self.annealing_factor):
                # ".to_event(1)" indicates latent dimensions are independent
                    z_t = pyro.sample("z_%d" % t, z_dist.to_event(1))
```

```
                # the latent sampled at this time step will be conditioned upon␣
↪in the next time step
                # so keep track of it
                z_prev = z_t

        def predict(self, ):
            return

        def forecast(self, forecast_steps, data=None):
            return
```

```
[ ]: # Parameter initialization
pyro.clear_param_store()

# Model instance
dkf = DKF(z_dim=20, rnn_dim=50, emission_dim=30, transition_dim=30,␣
 ↪annealing_factor=0.1)

optimizer = pyro.optim.PyroOptim(torch.optim.Adam, {'lr': 0.001})
svi = SVI(dkf.model, dkf.guide, optimizer, loss=Trace_ELBO())
```

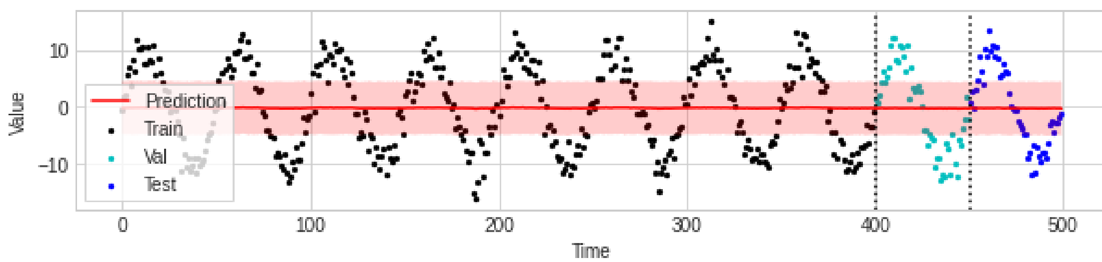
```
[ ]: # Learning config
num_samples = 10000
num_epochs = 300
log_interval = 5
eval_interval = 5 * log_interval

T = len(y_train)
T_pred = len(y_val) + len(y_test)

for epoch in range(num_epochs):
    try:
        # single batch
        loss = svi.step(y_train_sc) / y_train_sc.size(1)
        val_loss = svi.evaluate_loss(y_val_sc) / y_val_sc.size(1)

        if epoch % log_interval == log_interval - 1:
            print('Epoch {}/{}, loss= {:.3f}, val_loss= {:.3f}, sigma= {:.3f}'.
 ↪format(
                epoch+1, num_epochs, loss, val_loss, torch.exp(dkf.sigma).
 ↪item()))

        if epoch % eval_interval == eval_interval - 1:
            # define initial hidden state
            h_0_contig = dkf.h_0.expand(1, 1, dkf.rnn.hidden_size).contiguous()

            # define num_latent samples
```

```
            num_latent_samples = 10000

            # Expand z_prev to have dimensions (num_latent_samples, latent_size)
            z_prev = dkf.z_0.expand(num_latent_samples, dkf.z_0.size(0))

            # book-keeping
            z_samples = []
            z_scales = [[], []]
            y_samples = []
            y_mean = []
            y_025 = []
            y_975 = []

            # Train Predictions
            rnn_output, rnn_hidden_state = dkf.rnn(y_sc[:, :T, :].float(),␣
↪h_0_contig)

            # reverse rnn_output to get initial ordering
            #             rnn_output = torch.flip(rnn_output[:, :, :], dims=[1])

            rnn_output = rnn_output.expand(num_latent_samples, rnn_output.
↪size(1), rnn_output.size(2))

            for t in range(T):
                # compute mean and variance of z_t
                z_loc, z_scale = dkf.combiner(z_prev, rnn_output[:, t, :])
                z_scales[0].append(z_scale.norm(dim=1).mean().item())
                z_scales[1].append(z_scale.norm(dim=1).std().item())
                # sample from z_t distribution
                z_t = dist.Normal(loc=z_loc, scale=z_scale).to_event(1).
↪sample(sample_shape=[1]).reshape(z_prev.shape)
                if t != T-1:
                    z_samples.append(z_t)

                # compute mean of y_t
                y_loc = dkf.emitter(z_t).view(num_latent_samples, y_sc.size(2))

                # sample from y_t distribution
                y_t = dist.Normal(loc=y_loc, scale=dkf.sigma).to_event(1).
↪sample(sample_shape=[1]).view(num_latent_samples, y_sc.size(2)).detach().
↪numpy()
                y_samples.append(y_t)

                # store z_t for next computation
                if t != T-1:
                    z_prev = z_samples[-1]
```

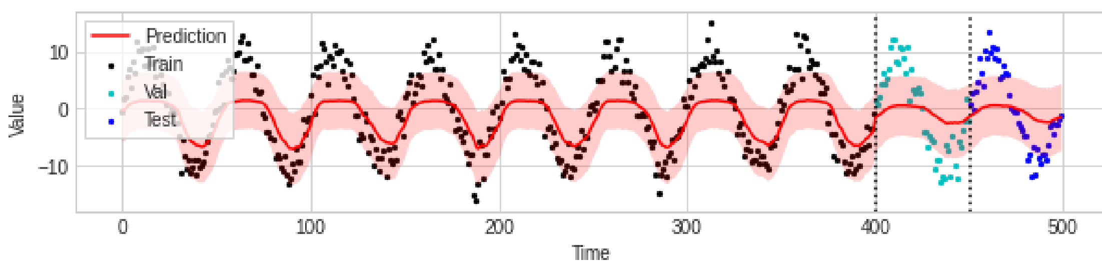
```
                # store predictions and CI
                y_mean.append(np.mean(y_t, axis=0))
                y_025.append(np.quantile(a=y_t, q=0.025, axis=0))
                y_975.append(np.quantile(a=y_t, q=0.975, axis=0))

            # Test Predictions
            for t in range(T, T + T_pred):
                rnn_output, rnn_hidden_state = dkf.rnn(y_sc[:, :t, :].float(),␣
↪h_0_contig)

                rnn_output = rnn_output.expand(num_latent_samples, rnn_output.
↪size(1), rnn_output.size(2))

                # compute mean and variance of z_t_1
                z_loc, z_scale = dkf.combiner(z_samples[-1], rnn_output[:, -1, :
↪])
                z_scales[0].append(z_scale.norm(dim=1).mean().item())
                z_scales[1].append(z_scale.norm(dim=1).std().item())

                # sample from z_t_1 distribution
                z_t_1 = dist.Normal(loc=z_loc, scale=z_scale).to_event(1).
↪sample(sample_shape=[1]).reshape(z_prev.shape)
                z_samples.append(z_t_1)

                # run transition network forward
                z_t_loc, z_t_scale = dkf.trans(z_t_1)

                z_t = dist.Normal(loc=z_t_loc, scale=z_t_scale).to_event(1).
↪sample(sample_shape=[1]).reshape(z_prev.shape)

                # compute mean of y_t
                y_loc = dkf.emitter(z_t).view(num_latent_samples, y_sc.size(2))

                # sample from y_t distribution
                y_t = dist.Normal(loc=y_loc, scale=dkf.sigma).to_event(1).
↪sample(sample_shape=[1]).view(num_latent_samples, y_sc.size(2)).detach().
↪numpy()
                y_samples.append(y_t)

                # store predictions and CI
                y_mean.append(np.mean(y_t, axis=0))
                y_025.append(np.quantile(a=y_t, q=0.025, axis=0))
                y_975.append(np.quantile(a=y_t, q=0.975, axis=0))

            # compute predictions
            # y_pred = np.array(y_mean)
```

```python
            # y_025 = np.array(y_025)
            # y_975 = np.array(y_975)
            y_pred = scaler.inverse_transform(np.array(y_mean))
            y_025 = scaler.inverse_transform(np.array(y_025))
            y_975 = scaler.inverse_transform(np.array(y_975))

            plot_predictions(y_train, y_val, y_test,
                 y_pred, y_025[:, 0], y_975[:, 0], train_value)
            plt.show()

    except KeyboardInterrupt:
        break
```

```
Epoch 5/300, loss= 5.477, val_loss= 5.488, sigma= 1.357
Epoch 10/300, loss= 5.241, val_loss= 5.334, sigma= 1.363
Epoch 15/300, loss= 5.032, val_loss= 4.972, sigma= 1.370
Epoch 20/300, loss= 4.877, val_loss= 4.950, sigma= 1.377
Epoch 25/300, loss= 4.730, val_loss= 4.812, sigma= 1.383
```

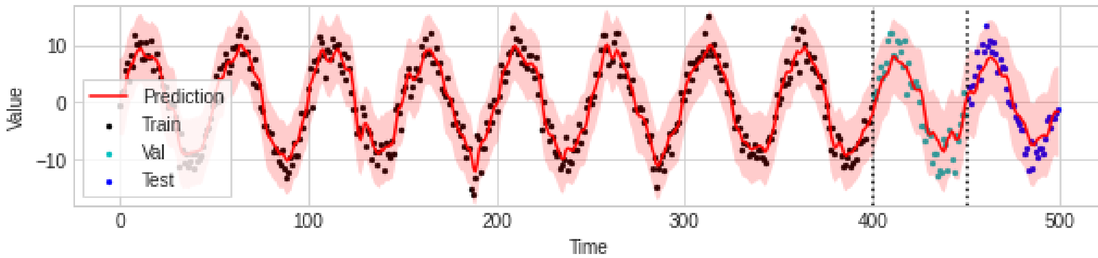



```
Epoch 30/300, loss= 4.463, val_loss= 4.601, sigma= 1.390
Epoch 35/300, loss= 4.303, val_loss= 4.174, sigma= 1.396
Epoch 40/300, loss= 3.891, val_loss= 3.978, sigma= 1.402
Epoch 45/300, loss= 3.214, val_loss= 3.346, sigma= 1.408
Epoch 50/300, loss= 2.576, val_loss= 2.647, sigma= 1.413
```

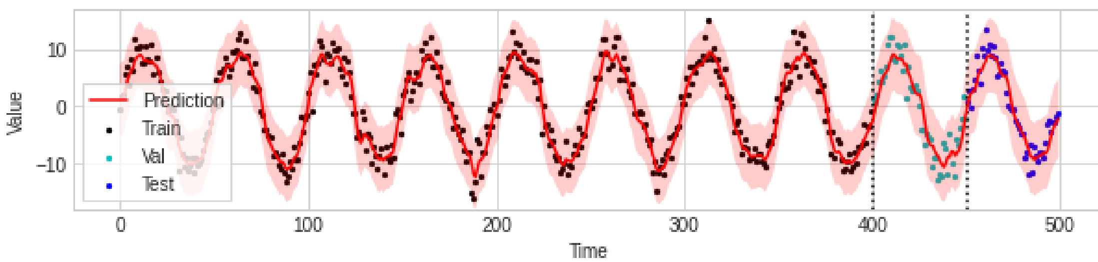



```
Epoch 55/300, loss= 1.788, val_loss= 1.846, sigma= 1.418
```

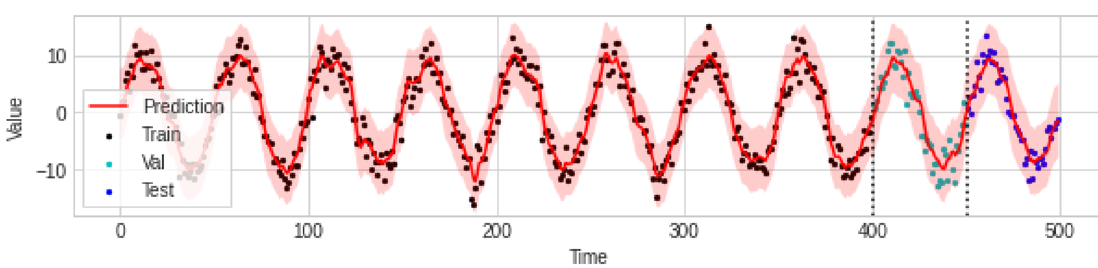
```
Epoch 60/300, loss= 1.476, val_loss= 1.300, sigma= 1.421
Epoch 65/300, loss= 0.981, val_loss= 0.871, sigma= 1.424
Epoch 70/300, loss= 0.691, val_loss= 0.626, sigma= 1.426
Epoch 75/300, loss= 0.751, val_loss= 0.657, sigma= 1.427
```



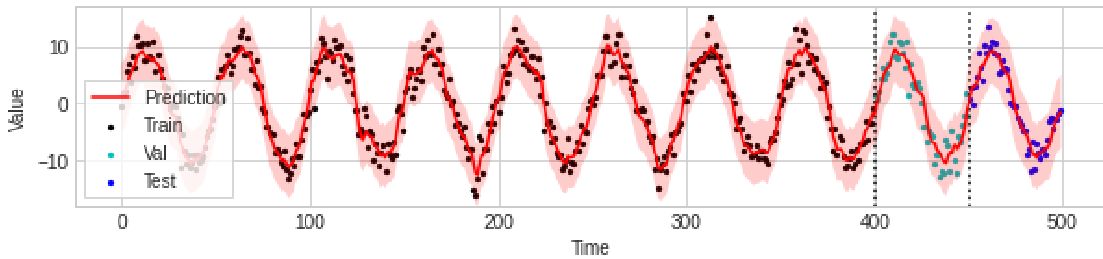

```
Epoch 80/300, loss= 0.558, val_loss= 0.550, sigma= 1.428
Epoch 85/300, loss= 0.497, val_loss= 0.545, sigma= 1.428
Epoch 90/300, loss= 0.509, val_loss= 0.544, sigma= 1.429
Epoch 95/300, loss= 0.448, val_loss= 0.568, sigma= 1.429
Epoch 100/300, loss= 0.455, val_loss= 0.599, sigma= 1.429
```



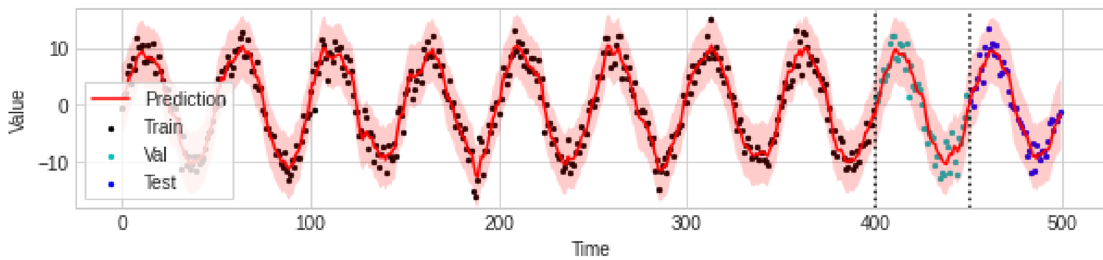

```
Epoch 105/300, loss= 0.409, val_loss= 0.475, sigma= 1.429
Epoch 110/300, loss= 0.401, val_loss= 0.444, sigma= 1.428
Epoch 115/300, loss= 0.344, val_loss= 0.328, sigma= 1.428
Epoch 120/300, loss= 0.337, val_loss= 0.551, sigma= 1.428
Epoch 125/300, loss= 0.350, val_loss= 0.483, sigma= 1.428
```



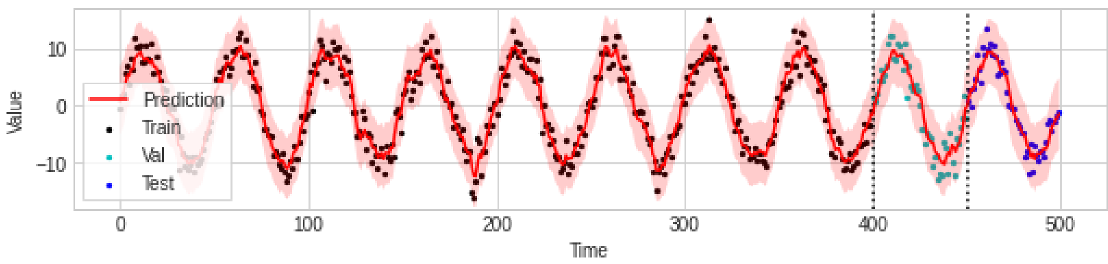
```
Epoch 130/300, loss= 0.343, val_loss= 0.467, sigma= 1.427
Epoch 135/300, loss= 0.332, val_loss= 0.356, sigma= 1.427
Epoch 140/300, loss= 0.315, val_loss= 0.338, sigma= 1.426
Epoch 145/300, loss= 0.299, val_loss= 0.454, sigma= 1.426
Epoch 150/300, loss= 0.296, val_loss= 0.391, sigma= 1.425
```



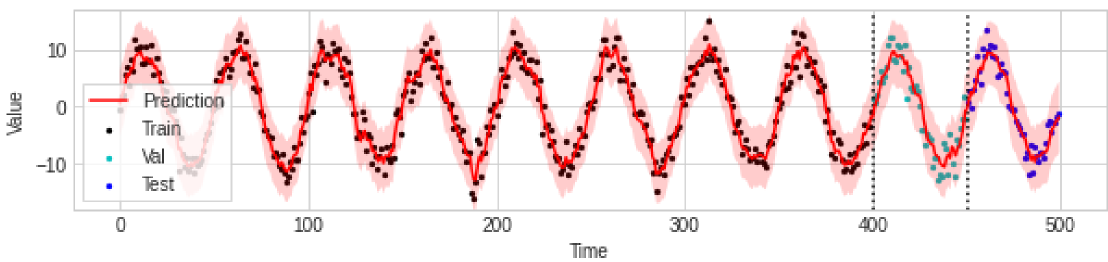

```
Epoch 155/300, loss= 0.309, val_loss= 0.447, sigma= 1.425
Epoch 160/300, loss= 0.296, val_loss= 0.324, sigma= 1.424
Epoch 165/300, loss= 0.285, val_loss= 0.300, sigma= 1.424
Epoch 170/300, loss= 0.266, val_loss= 0.362, sigma= 1.423
Epoch 175/300, loss= 0.285, val_loss= 0.403, sigma= 1.423
```



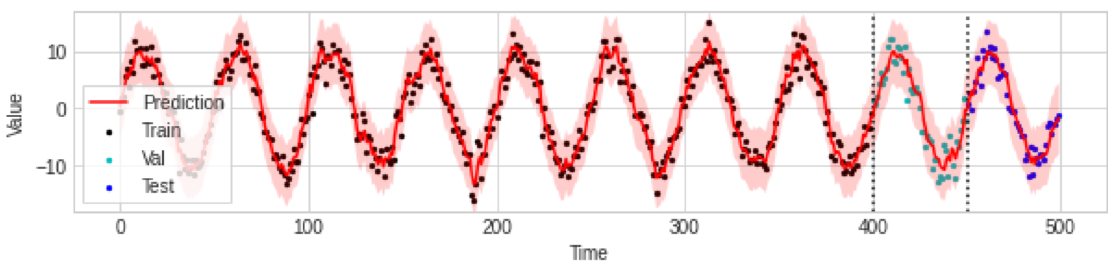

```
Epoch 180/300, loss= 0.248, val_loss= 0.418, sigma= 1.422
Epoch 185/300, loss= 0.281, val_loss= 0.272, sigma= 1.421
Epoch 190/300, loss= 0.268, val_loss= 0.341, sigma= 1.421
Epoch 195/300, loss= 0.243, val_loss= 0.317, sigma= 1.420
Epoch 200/300, loss= 0.286, val_loss= 0.346, sigma= 1.419
```



Epoch 205/300, loss= 0.224, val_loss= 0.345, sigma= 1.419
Epoch 210/300, loss= 0.233, val_loss= 0.262, sigma= 1.418
Epoch 215/300, loss= 0.233, val_loss= 0.266, sigma= 1.417
Epoch 220/300, loss= 0.240, val_loss= 0.212, sigma= 1.416
Epoch 225/300, loss= 0.232, val_loss= 0.274, sigma= 1.415

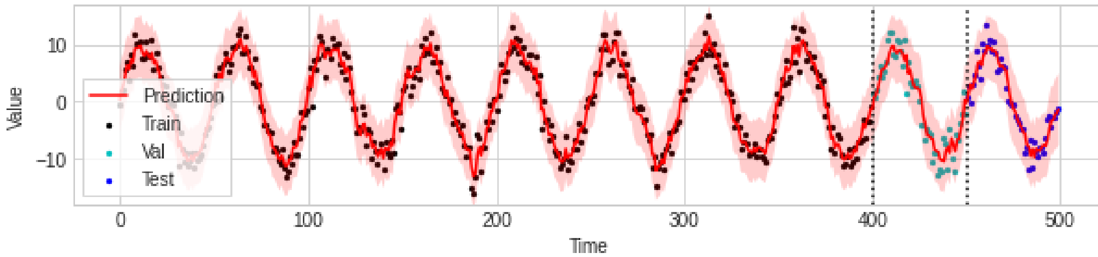


Epoch 230/300, loss= 0.214, val_loss= 0.259, sigma= 1.415
Epoch 235/300, loss= 0.200, val_loss= 0.241, sigma= 1.414
Epoch 240/300, loss= 0.185, val_loss= 0.246, sigma= 1.413
Epoch 245/300, loss= 0.220, val_loss= 0.289, sigma= 1.412
Epoch 250/300, loss= 0.220, val_loss= 0.198, sigma= 1.411



Epoch 255/300, loss= 0.217, val_loss= 0.277, sigma= 1.410
Epoch 260/300, loss= 0.178, val_loss= 0.249, sigma= 1.409
Epoch 265/300, loss= 0.191, val_loss= 0.236, sigma= 1.408

```
Epoch 270/300, loss= 0.197, val_loss= 0.239, sigma= 1.407
Epoch 275/300, loss= 0.152, val_loss= 0.235, sigma= 1.406
```




```
Epoch 280/300, loss= 0.182, val_loss= 0.234, sigma= 1.405
Epoch 285/300, loss= 0.186, val_loss= 0.266, sigma= 1.404
Epoch 290/300, loss= 0.179, val_loss= 0.261, sigma= 1.402
Epoch 295/300, loss= 0.172, val_loss= 0.245, sigma= 1.401
Epoch 300/300, loss= 0.194, val_loss= 0.172, sigma= 1.400
```