TU_PRACUJE_DEMO_DKF_MV_FROM_PDF_TEST

August 27, 2023

1 Orignalny kod

[3]:
```
import pandas as pd
import torch
import torch.nn as nn
from torch.distributions import MultivariateNormal
import pandas as pd
import numpy as np
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
import matplotlib.pyplot as plt
import numpy as np
from sklearn import preprocessing
import torch
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import scale
from sklearn.metrics.pairwise import haversine_distances
from math import radians
```

[4]:
```
class GatedTransition(nn.Module):
    def __init__(self, z_dim, hid_dim):
        super(GatedTransition, self).__init__()
        self.gate = nn.Sequential(nn.Linear(z_dim, hid_dim),
            nn.ReLU(),
            nn.Linear(hid_dim, z_dim),
            nn.Sigmoid())
        self.proposed_mean = nn.Sequential(nn.Linear(z_dim, hid_dim),
            nn.ReLU(),
            nn.Linear(hid_dim, z_dim))
        self.z_to_mu = nn.Linear(z_dim, z_dim)
        # modify the default initialization of z_to_mu
        # so that it starts out as the identity function
        self.z_to_mu.weight.data = torch.eye(z_dim)
        self.z_to_mu.bias.data = torch.zeros(z_dim)
        self.z_to_logvar = nn.Linear(z_dim, z_dim)
        self.relu = nn.ReLU()
```

```python
    def forward(self, z_t_1):
        #
        gate = self.gate(z_t_1)
        proposed_mean = self.proposed_mean(z_t_1)
        mu = (1 - gate) * self.z_to_mu(z_t_1) + gate * proposed_mean
        logvar = self.z_to_logvar(self.relu(proposed_mean))
        # sampling
        eps = torch.randn(z_t_1.size())
        z_t = mu + eps * torch.exp(.5 * logvar)
        return z_t, mu, logvar
```

[5]:
```python
class Combiner(nn.Module):
    # PostNet
    def __init__(self, z_dim, hid_dim):
        super(Combiner, self).__init__()
        self.z_dim = z_dim
        self.z_to_hidden = nn.Linear(z_dim, hid_dim)
        self.hidden_to_mu = nn.Linear(hid_dim, z_dim)
        self.hidden_to_logvar = nn.Linear(hid_dim, z_dim)
        self.tanh = nn.Tanh()
    def forward(self, z_t_1, h_rnn):
        # combine the rnn hidden state with a transformed version of z_t_1
        h_combined = 0.5 * (self.tanh(self.z_to_hidden(z_t_1)) + h_rnn)
        # use the combined hidden state
        # to compute the mean used to sample z_t
        mu = self.hidden_to_mu(h_combined)
        # use the combined hidden state
        # to compute the scale used to sample z_t
        logvar = self.hidden_to_logvar(h_combined)
        eps = torch.randn(z_t_1.size())
        z_t = mu + eps * torch.exp(.5 * logvar)
        return z_t, mu, logvar
```

[6]:
```python
class Emitter(nn.Module):
    def __init__(self, z_dim, hid_dim, input_dim) -> None:
        super().__init__()
        self.input_dim = input_dim
        self.z_to_hidden = nn.Linear(z_dim, hid_dim)
        self.hidden_to_hidden = nn.Linear(hid_dim, hid_dim)
        self.hidden_to_input_mu = nn.Linear(hid_dim, input_dim)
        self.logvar = nn.Parameter(torch.ones(input_dim))
        self.relu = nn.ReLU()
    def forward(self, z_t):
        h1 = self.relu(self.z_to_hidden(z_t))
        h2 = self.relu(self.hidden_to_hidden(h1))
        mu = self.hidden_to_input_mu(h2)
        # return mu # x_t
```

```
        eps = torch.randn(z_t.size(0), self.input_dim)
        x_t = mu + eps * torch.exp(.5 * self.logvar)
        return x_t, mu, self.logvar
```

[7]:
```
class DKF(nn.Module):
    # Structured Inference Networks
    # Current version ignores backward RNN outputs
    def __init__(self, input_dim, z_dim=50, trans_dim=30, emission_dim=30,
            rnn_dim=100, num_rnn_layers=1) -> None:

        super().__init__()
        self.input_dim = input_dim
        self.z_dim = z_dim
        self.trans_dim = trans_dim
        self.emission_dim = emission_dim
        self.rnn_dim = rnn_dim
        self.num_rnn_layers = num_rnn_layers
        self.trans = GatedTransition(z_dim, trans_dim)
        self.emitter = Emitter(z_dim, emission_dim, input_dim)
        self.combiner = Combiner(z_dim, rnn_dim)
        self.z_0 = nn.Parameter(torch.zeros(z_dim))
        self.z_q_0 = nn.Parameter(torch.zeros(z_dim))
        self.h_0 = nn.Parameter(torch.zeros(1, 1, rnn_dim))
        # corresponding learning 'l' in the original code
        self.rnn = nn.RNN(input_size=input_dim,
            hidden_size=rnn_dim,
            nonlinearity="relu",
            batch_first=True,
            bidirectional=False,
            num_layers=num_rnn_layers)

    def kl_div(self, mu1, logvar1, mu2=None, logvar2=None):
        if mu2 is None:
            mu2 = torch.zeros(1, device=mu1.device)
        if logvar2 is None:
            logvar2 = torch.zeros(1, device=mu1.device)
        return torch.sum(0.5 * (
            logvar2 - logvar1 + (torch.exp(logvar1) + (mu1 - mu2).pow(2))
            / torch.exp(logvar2) - torch.ones(1, device=mu1.device)
        ), 1)

    def infer(self, x):
        batch_size, T_max, x_dim = x.size()
        h_0 = self.h_0.expand(1, batch_size, self.rnn_dim).contiguous()
        rnn_out, h_n = self.rnn(x, h_0)
        z_prev = self.z_q_0.expand(batch_size, self.z_q_0.size(0))
        kl_states = torch.zeros((batch_size, T_max))
```

```python
        rec_losses = torch.zeros((batch_size, T_max))
        for t in range(T_max):
            # p(z_t|z_{t-1})
            z_prior, z_prior_mu, z_prior_logvar = self.trans(z_prev)
            # q(z_t|z_{t-1},x_{t:T})
            z_t, z_mu, z_logvar = self.combiner(z_prev, rnn_out[:, t])
            # p(x_t|z_t)
            x_t, x_mu, x_logvar = self.emitter(z_t)
            # compute loss
            kl_states[:, t] = self.kl_div(
                z_mu, z_logvar, z_prior_mu, z_prior_logvar)
            rec_losses[:, t] = nn.MSELoss(reduction='none')(
                x_t.contiguous().view(-1),
                # x_mu.contiguous().view(-1),
                x[:, t].contiguous().view(-1)
            ).view(batch_size, -1).mean(dim=1)
            z_prev = z_t
        return rec_losses.mean(), kl_states.mean()

    def filter(self, x, num_sample=100):
        # Outputs
        x_hat = torch.zeros(x.size())
        x_025 = torch.zeros(x.size())
        x_975 = torch.zeros(x.size())
        # predictions
        batch_size, T_max, x_dim = x.size()
        assert batch_size == 1
        z_prev = self.z_0.expand(num_sample, self.z_0.size(0))
        h_0 = self.h_0.expand(1, 1, self.rnn_dim).contiguous()
        rnn_out, _ = self.rnn(x, h_0)
        rnn_out = rnn_out.expand(num_sample,
            rnn_out.size(1), rnn_out.size(2))
        for t in range(T_max):
            # z_t: (num_sample, z_dim)
            z_t, z_mu, z_logvar = self.combiner(z_prev, rnn_out[:, t])
            x_t, x_mu, x_logvar = self.emitter(z_t)
            # x_hat[:, t] = x_mu
            x_covar = torch.diag(torch.sqrt(torch.exp(.5 * x_logvar)))
            x_samples = MultivariateNormal(
                x_mu, covariance_matrix=x_covar).sample()
            # # sampling z_t and computing quantiles
            # x_samples = MultivariateNormal(
            #   loc=x_mu, covariance_matrix=x_covar).sample_n(num_sample)
            x_hat[:, t] = x_samples.mean(0)
            x_025[:, t] = x_samples.quantile(0.025, 0)
            x_975[:, t] = x_samples.quantile(0.975, 0)
            # x_hat[:, t] = x_t.mean(0)
```

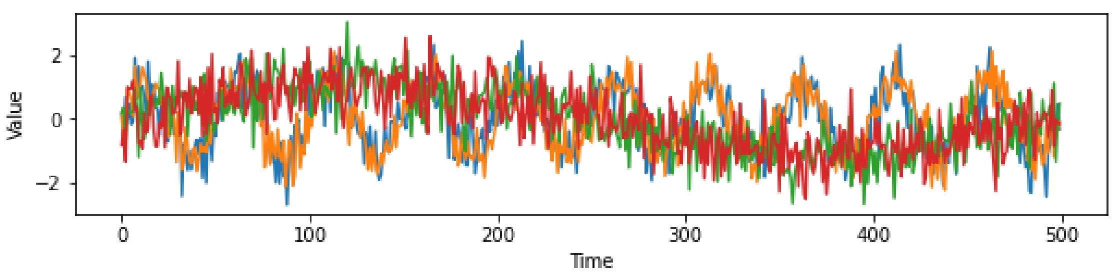
```
            # x_025[:, t] = x_t.quantile(0.025, 0)
            # x_975[:, t] = x_t.quantile(0.975, 0)
            z_prev = z_t
            # z_prev = z_mu
        return x_hat, x_025, x_975

    def predict(self, x, pred_steps=1, num_sample=100):
        """ x should contain the prediction period
        """
        # Outputs
        x_hat = torch.zeros(x.size()) # predictions
        x_025 = torch.zeros(x.size())
        x_975 = torch.zeros(x.size())
        batch_size, T_max, x_dim = x.size()
        assert batch_size == 1
        z_prev = self.z_0.expand(num_sample, self.z_0.size(0))
        h_0 = self.h_0.expand(1, 1, self.rnn_dim).contiguous()
        rnn_out, _ = self.rnn(x[:, :T_max-pred_steps], h_0)
        rnn_out = rnn_out.expand(num_sample,
            rnn_out.size(1), rnn_out.size(2))
        for t in range(T_max - pred_steps):
            # z_t: (num_sample, z_dim)
            z_t, z_mu, z_logvar = self.combiner(z_prev, rnn_out[:, t])
            x_t, x_mu, x_logvar = self.emitter(z_t)
            x_covar = torch.diag(torch.sqrt(torch.exp(.5 * x_logvar)))
            x_samples = MultivariateNormal(
                x_mu, covariance_matrix=x_covar).sample()
            x_hat[:, t] = x_samples.mean(0)
            x_025[:, t] = x_samples.quantile(0.025, 0)
            x_975[:, t] = x_samples.quantile(0.975, 0)
            z_prev = z_mu
        for t in range(T_max - pred_steps, T_max):
            rnn_out, _ = self.rnn(x[:, :t], h_0)
            rnn_out = rnn_out.expand(
                num_sample, rnn_out.size(1), rnn_out.size(2))
            z_t_1, z_mu, z_logvar = self.combiner(z_prev, rnn_out[:, -1])
            z_t, z_mu, z_logvar = self.trans(z_t_1)
            x_t, x_mu, x_logvar = self.emitter(z_t)
            x_covar = torch.diag(torch.sqrt(torch.exp(.5 * x_logvar)))
            x_samples = MultivariateNormal(
                x_mu, covariance_matrix=x_covar).sample()
            x_hat[:, t] = x_samples.mean(0)
            x_025[:, t] = x_samples.quantile(0.025, 0)
            x_975[:, t] = x_samples.quantile(0.975, 0)
        return x_hat, x_025, x_975

    def train_step(self, x, annealing_factor = 0.1):
```

```
        self.train()
        # self.rnn.train()
        rec_loss, kl_loss = self.infer(x)
        total_loss = rec_loss + annealing_factor * kl_loss
        self.optimizer.zero_grad()
        total_loss.backward()
        # nn.utils.clip_grad_norm_(self.parameters(), 5.)
        self.optimizer.step()
        return rec_loss.item(), kl_loss.item(), total_loss.item()

    def validation_step(self, x, annealing_factor=0.1):
        self.eval()
        rec_loss, kl_loss = self.infer(x)
        total_loss = rec_loss + annealing_factor * kl_loss
        return rec_loss.item(), kl_loss.item(), total_loss.item()

    def fit(self, x, x_val=None, num_epochs=100, annealing_factor=0.1,
            verbose_step=1, eval_step=1, check_point_path=None,
            patience=20, learning_rate=0.01):

        self.optimizer = torch.optim.Adam(
            self.parameters(), lr=learning_rate)

        losses = []
        kl_losses = []
        rec_losses = []
        val_losses = []
        val_kl_losses = []
        val_rec_losses = []
        parameter_values = []


        stats_dict = {}

        for index, param in enumerate(self.parameters()):
            stats_dict['mean_var_median' + str(index)] = []





        for epoch in range(num_epochs):
            for index, param in enumerate(self.parameters()):
                param_value = param.detach().numpy()
                stats_dict['mean_var_median' + str(index)].append([np.
↪mean(param_value), np.var(param_value), np.median(param_value)])
```

```python
            try:
                res = self.train_step(x, annealing_factor=annealing_factor)
                losses.append(res[2])
                kl_losses.append(res[1])
                rec_losses.append(res[0])

                if epoch % verbose_step == verbose_step - 1:
                    message = f'Epoch= {epoch+1}/{num_epochs}, '
                    message += f'loss= {res[2]:.3f}, '
                    message += f'mse= {res[0]:.3f}, '
                    message += f'kld= {res[1]:.3f}'
                    if (epoch % 10 == 0):
                        print(message)

                if x_val is not None:
                    val_res = self.validation_step(x_val, annealing_factor)
                    val_losses.append(val_res[2])
                    val_kl_losses.append(val_res[1])
                    val_rec_losses.append(val_res[0])

                if epoch % eval_step == eval_step - 1 and x_val is not None:
                    message = f'\tval_loss= {val_res[2]:.3f}, '
                    message += f'val_mse= {val_res[0]:.3f}, '
                    message += f'val_kld= {val_res[1]:.3f}'
                    if (epoch % 10 == 0):
                        print(message)

            except KeyboardInterrupt:
                break

        history = {'loss': losses,
                   'kl_loss': kl_losses,
                   'rec_loss': rec_losses}

        if x_val is not None:
            history.update({'val_loss': val_losses,
                            'val_kl_loss': val_kl_losses,
                            'rec_loss': rec_losses})


        return history, stats_dict

    def save_model(self, filename):
        """ dkf.pth """
        torch.save(self.to('cpu').state_dict(), filename)

    def load_model(self, filename):
```

```
        self.load_state_dict(torch.load(filename))

    def get_config(self):
        return {
            'input_dim': self.input_dim,
            'z_dim': self.z_dim,
            'trans_dim': self.trans_dim,
            'emission_dim': self.emission_dim,
            'rnn_dim': self.rnn_dim,
            'num_rnn_layers': self.num_rnn_layers
        }
```

[8]:
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import scale
# import warnings
# warnings.filterwarnings('ignore')
T = 500 # sequence length
observations = 2*np.sin(np.linspace(0, 20*np.pi, T))
interventions = 2*np.sin(np.linspace(0, 2*np.pi, T))
data = np.vstack([observations, observations*1.2, interventions,
  interventions*0.85]).T
data += np.random.randn(*data.shape)
# data[:, 2:] = preprocessing.minmax_scale(data[:, 2:])
data = scale(data)

plt.figure(figsize=(10, 2))
plt.plot(data)
plt.xlabel('Time')
plt.ylabel('Value')
plt.show()
```



[9]:
```
x = torch.FloatTensor(data).reshape(1, *data.shape)
x_train = torch.FloatTensor(data[:400]).reshape(1, 400, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[400:450]).reshape(1, 50, data.shape[1])
```

```
#print(x_val)
```

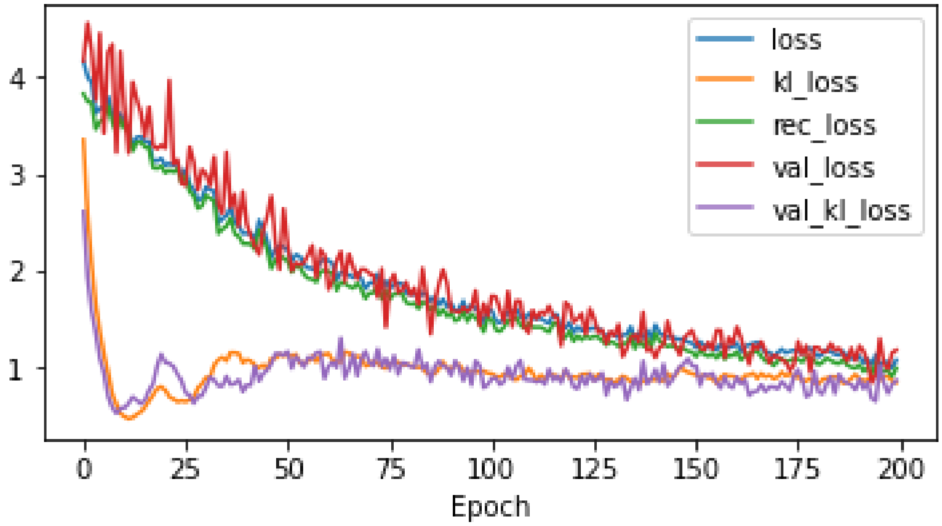
[10]:
```
dkf = DKF(input_dim=4, z_dim=20, rnn_dim=20, trans_dim=20, emission_dim=20)
```

[11]:
```
history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
↪annealing_factor=0.1)
```

```
Epoch= 1/200, loss= 4.163, mse= 3.828, kld= 3.354
        val_loss= 4.171, val_mse= 3.910, val_kld= 2.609
Epoch= 11/200, loss= 3.523, mse= 3.474, kld= 0.493
        val_loss= 3.676, val_mse= 3.618, val_kld= 0.583
Epoch= 21/200, loss= 3.090, mse= 3.014, kld= 0.764
        val_loss= 3.270, val_mse= 3.165, val_kld= 1.053
Epoch= 31/200, loss= 2.867, mse= 2.778, kld= 0.894
        val_loss= 3.000, val_mse= 2.921, val_kld= 0.797
Epoch= 41/200, loss= 2.388, mse= 2.280, kld= 1.079
        val_loss= 2.478, val_mse= 2.396, val_kld= 0.818
Epoch= 51/200, loss= 2.212, mse= 2.098, kld= 1.132
        val_loss= 2.259, val_mse= 2.143, val_kld= 1.164
Epoch= 61/200, loss= 2.107, mse= 1.992, kld= 1.144
        val_loss= 1.807, val_mse= 1.705, val_kld= 1.012
Epoch= 71/200, loss= 1.871, mse= 1.768, kld= 1.028
        val_loss= 1.971, val_mse= 1.865, val_kld= 1.054
Epoch= 81/200, loss= 1.755, mse= 1.653, kld= 1.022
        val_loss= 1.747, val_mse= 1.646, val_kld= 1.011
Epoch= 91/200, loss= 1.662, mse= 1.562, kld= 0.992
        val_loss= 1.585, val_mse= 1.493, val_kld= 0.917
Epoch= 101/200, loss= 1.586, mse= 1.493, kld= 0.934
        val_loss= 1.738, val_mse= 1.650, val_kld= 0.885
Epoch= 111/200, loss= 1.508, mse= 1.414, kld= 0.940
        val_loss= 1.591, val_mse= 1.505, val_kld= 0.865
Epoch= 121/200, loss= 1.361, mse= 1.270, kld= 0.903
        val_loss= 1.468, val_mse= 1.389, val_kld= 0.797
Epoch= 131/200, loss= 1.336, mse= 1.253, kld= 0.837
        val_loss= 1.328, val_mse= 1.248, val_kld= 0.798
Epoch= 141/200, loss= 1.441, mse= 1.354, kld= 0.871
        val_loss= 1.100, val_mse= 1.003, val_kld= 0.976
Epoch= 151/200, loss= 1.203, mse= 1.110, kld= 0.921
        val_loss= 1.265, val_mse= 1.164, val_kld= 1.014
Epoch= 161/200, loss= 1.250, mse= 1.161, kld= 0.894
        val_loss= 1.418, val_mse= 1.328, val_kld= 0.898
Epoch= 171/200, loss= 1.153, mse= 1.064, kld= 0.899
        val_loss= 1.110, val_mse= 1.032, val_kld= 0.778
Epoch= 181/200, loss= 1.111, mse= 1.029, kld= 0.828
        val_loss= 1.202, val_mse= 1.128, val_kld= 0.745
Epoch= 191/200, loss= 1.116, mse= 1.028, kld= 0.882
        val_loss= 1.221, val_mse= 1.133, val_kld= 0.882
```

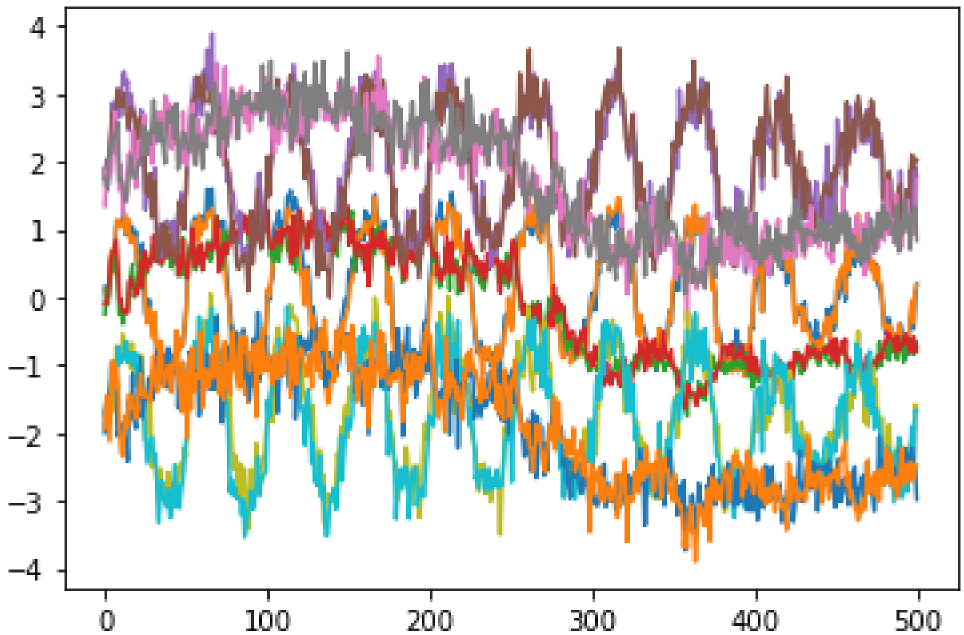
[12]:
```python
pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

[12]: <AxesSubplot:xlabel='Epoch'>

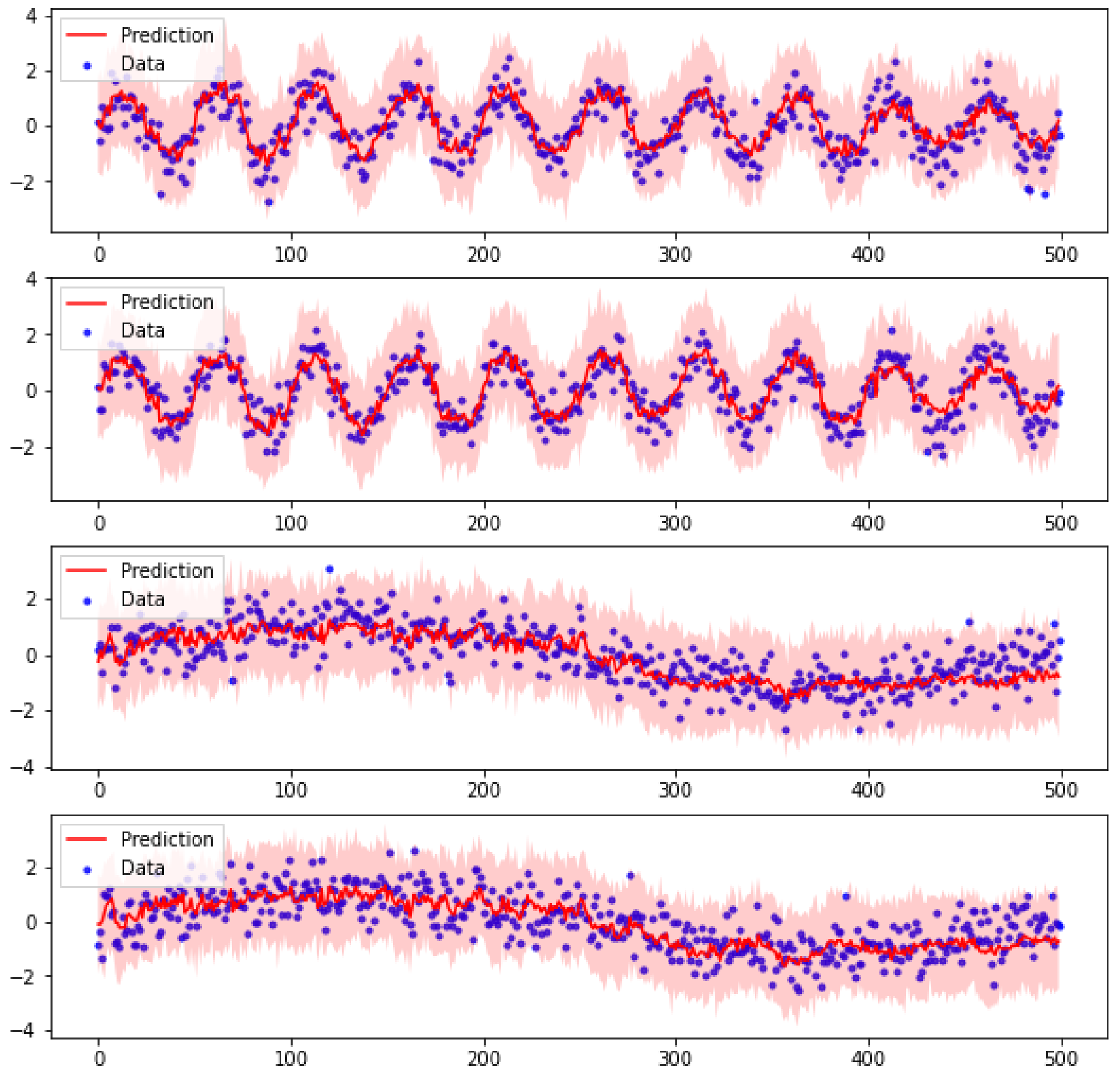


[13]:
```python
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 100)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

[13]:
```
[<matplotlib.lines.Line2D at 0x7f9bfc4815e0>,
 <matplotlib.lines.Line2D at 0x7f9bfc4816d0>,
 <matplotlib.lines.Line2D at 0x7f9bfc4c5ca0>,
 <matplotlib.lines.Line2D at 0x7f9bfc481820>]
```

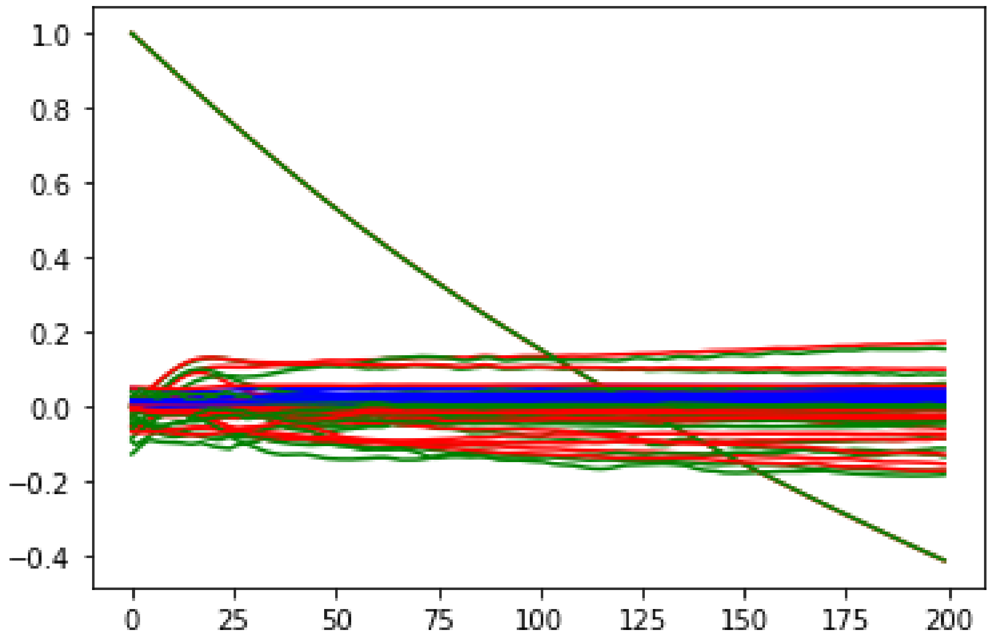



```
[14]: fig, ax = plt.subplots(4, figsize=(10, 10))

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
                     facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```



[15]:
```
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'
```

```
    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],
 ↪label = stat, c = colour)



plt.show()
```



[ ]:

```

```

2 Moja praca

2.1 Wczytanie danych

[16]:

```
import matplotlib.pyplot as plt
import numpy as np
from sklearn import preprocessing
import torch
```

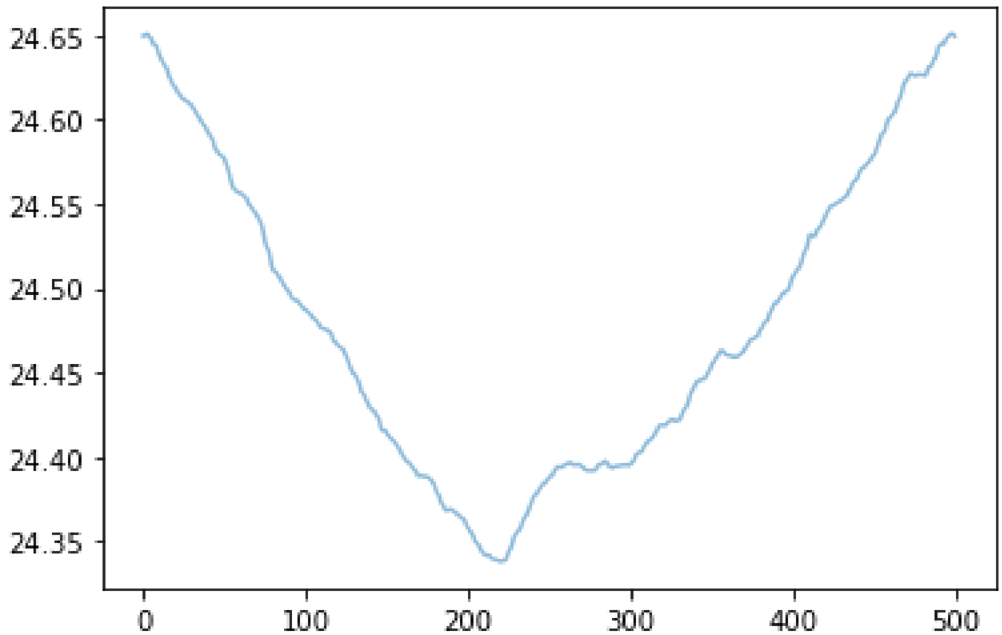
[17]:

```
#FIRST on 10 000 workouts - train 9000, test 1000
data_endo = []
i = 0
#with gzip.open('endomondoHR.json.gz') as f:
```

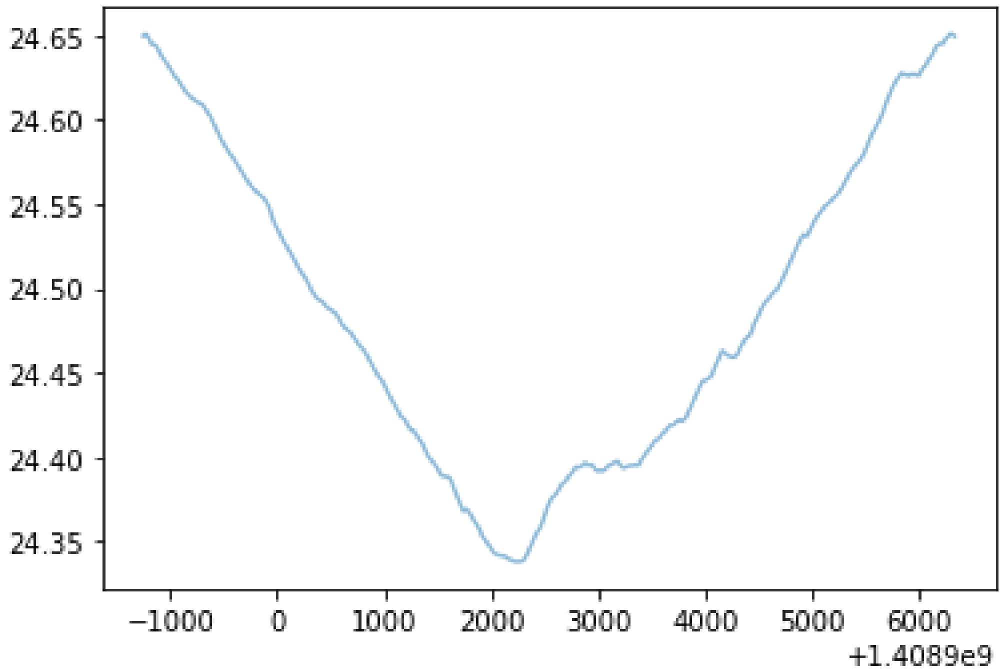
```
with open('endomondoHR_proper.json') as f:
    for l in f:
        i += 1
        #print(i)
        data_endo.append(eval(l))
        if i == 10000:
            break
        #print(data[0])
```

2.2 Wstępne wykresy

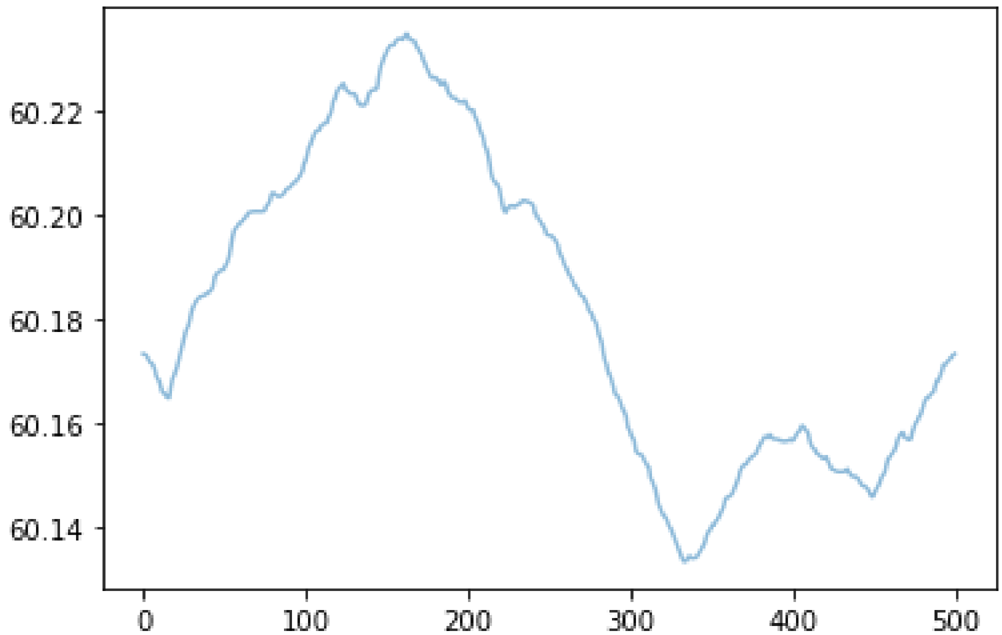
[18]:
```
# Plot ithmeasurement x longitude



#print(data_endo[0].keys())
y=np.asarray(data_endo[0]['longitude'])
z=np.asarray(data_endo[0]['latitude'])
x =[]
#print(len(x))
data_t = []
for i in range(len(y)):
    x.append(i)
    data_t.append((x[i], y[i]))
#print(data_t)
data_t = np.asarray(data_t)
#colors = np.random.rand(N)
#area = (30 * np.random.rand(N))**2  # 0 to 15 point radii

plt.plot(x, y, alpha=0.5)
plt.show()
#print(y.shape)
```



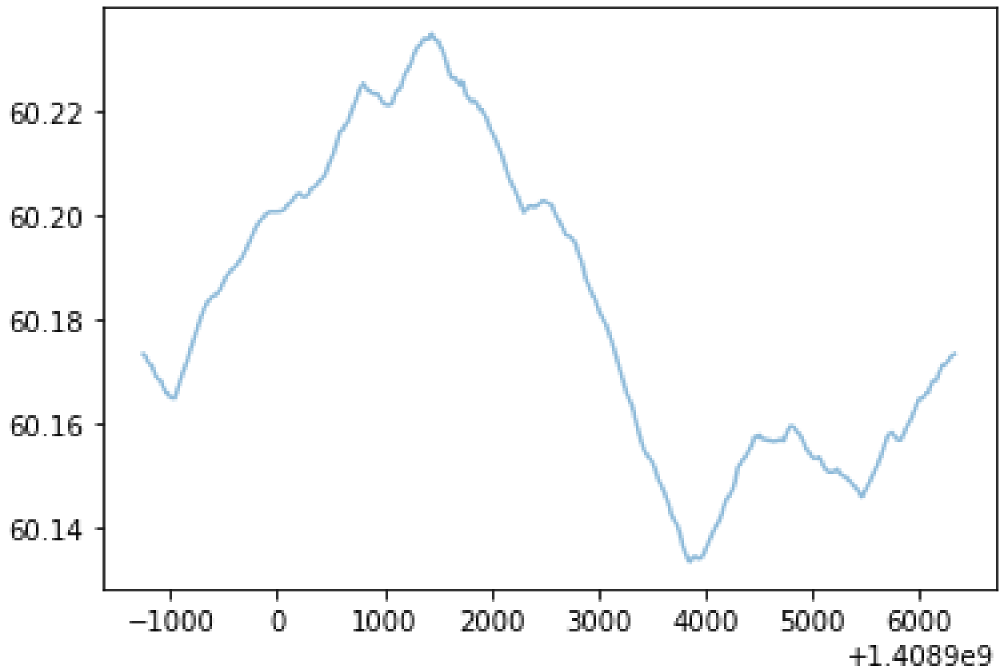
[19]:
```
# Plot timestamp x longitude


#print(data_endo[0].keys())
y=np.asarray(data_endo[0]['longitude'])
z=np.asarray(data_endo[0]['latitude'])
x =[]
#print(len(x))
data_t = []
for i in range(len(y)):
    x.append(i)
    data_t.append((x[i], y[i]))
#print(data_t)
data_t = np.asarray(data_t)
#colors = np.random.rand(N)
#area = (30 * np.random.rand(N))**2  # 0 to 15 point radii



x = np.asarray(data_endo[0]['timestamp'])


plt.plot(x, y, alpha=0.5)
plt.show()
#print(y.shape)
```



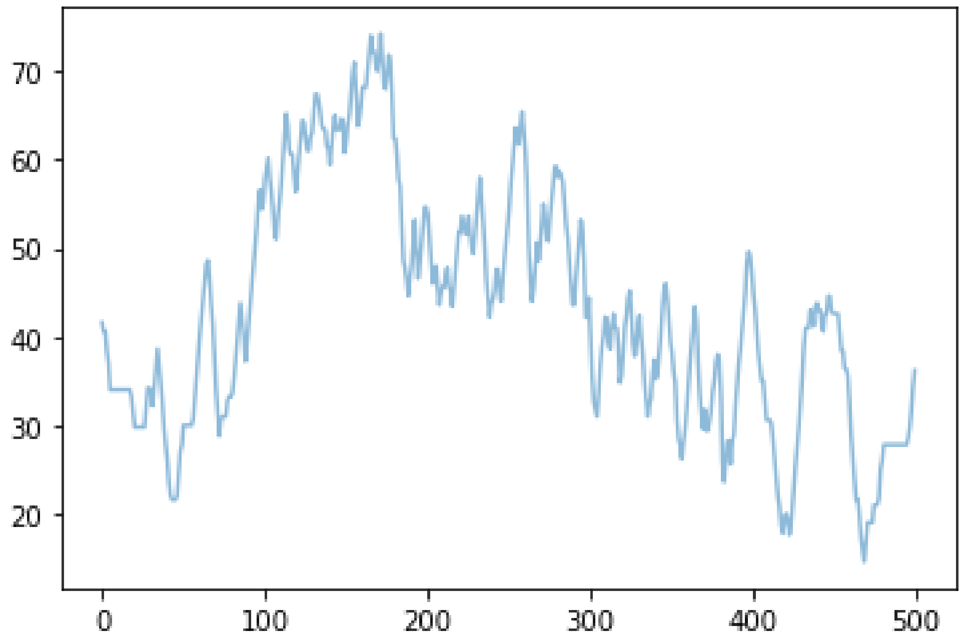
[20]:
```
# Plot ithmeasurement x latitude



#print(data_endo[0].keys())
y=np.asarray(data_endo[0]['latitude'])
z=np.asarray(data_endo[0]['latitude'])
x =[]
#print(len(x))
data_t = []
for i in range(len(y)):
    x.append(i)
    data_t.append((x[i], y[i]))
#print(data_t)
data_t = np.asarray(data_t)
#colors = np.random.rand(N)
#area = (30 * np.random.rand(N))**2  # 0 to 15 point radii

plt.plot(x, y, alpha=0.5)
plt.show()
#print(y.shape)
```



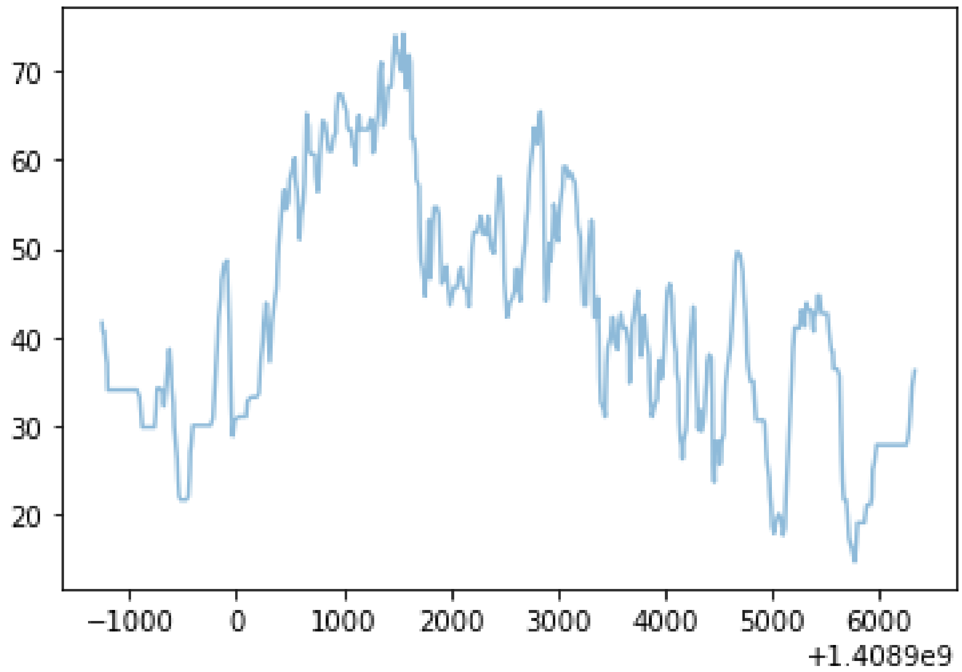
[21]:
```
# Plot timestamp x latitude


#print(data_endo[0].keys())
y=np.asarray(data_endo[0]['latitude'])
z=np.asarray(data_endo[0]['latitude'])
x =[]
#print(len(x))
data_t = []
for i in range(len(y)):
    x.append(i)
    data_t.append((x[i], y[i]))
#print(data_t)
data_t = np.asarray(data_t)
#colors = np.random.rand(N)
#area = (30 * np.random.rand(N))**2  # 0 to 15 point radii



x = np.asarray(data_endo[0]['timestamp'])


plt.plot(x, y, alpha=0.5)
plt.show()
#print(y.shape)
```



[22]:
```
# Plot ithmeasurement x altitude

#print(data_endo[0].keys())
y=np.asarray(data_endo[0]['altitude'])
z=np.asarray(data_endo[0]['latitude'])
x =[]
#print(len(x))
data_t = []
for i in range(len(y)):
    x.append(i)
    data_t.append((x[i], y[i]))
#print(data_t)
data_t = np.asarray(data_t)
#colors = np.random.rand(N)
#area = (30 * np.random.rand(N))**2  # 0 to 15 point radii

plt.plot(x, y, alpha=0.5)
plt.show()
#print(y.shape)
```



[23]:
```
# Plot timestamp x altitude


#print(data_endo[0].keys())
y=np.asarray(data_endo[0]['altitude'])
z=np.asarray(data_endo[0]['latitude'])
x =[]
#print(len(x))
data_t = []
for i in range(len(y)):
    x.append(i)
    data_t.append((x[i], y[i]))
#print(data_t)
data_t = np.asarray(data_t)
#colors = np.random.rand(N)
#area = (30 * np.random.rand(N))**2  # 0 to 15 point radii



x = np.asarray(data_endo[0]['timestamp'])


plt.plot(x, y, alpha=0.5)
plt.show()
#print(y.shape)
```



[24]:
```
####OK wykresy sie zgadzaja
```

[25]:
```
###TERAZ TRENUJEMY DLA 1 WORKOUTU LONGITUDE,TRAIN TO PIERWSZE 450 A VAL TO␣
 ↪KOLEJNE 50
```

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

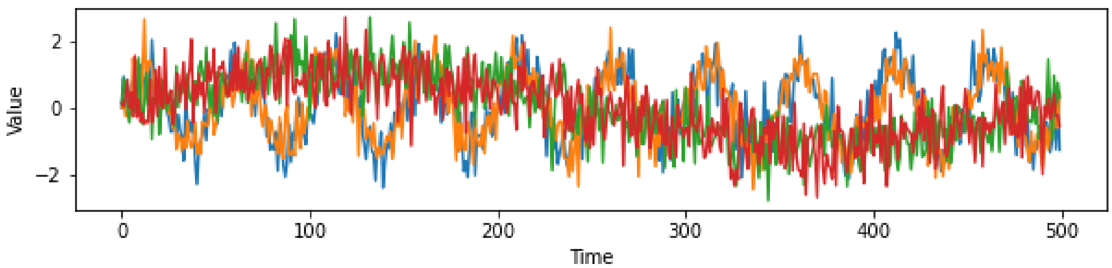
[ ]:

[ ]:

[ ]:

[24]:
```
#### ITHMEASUREMENT vs LONGITUDE
```

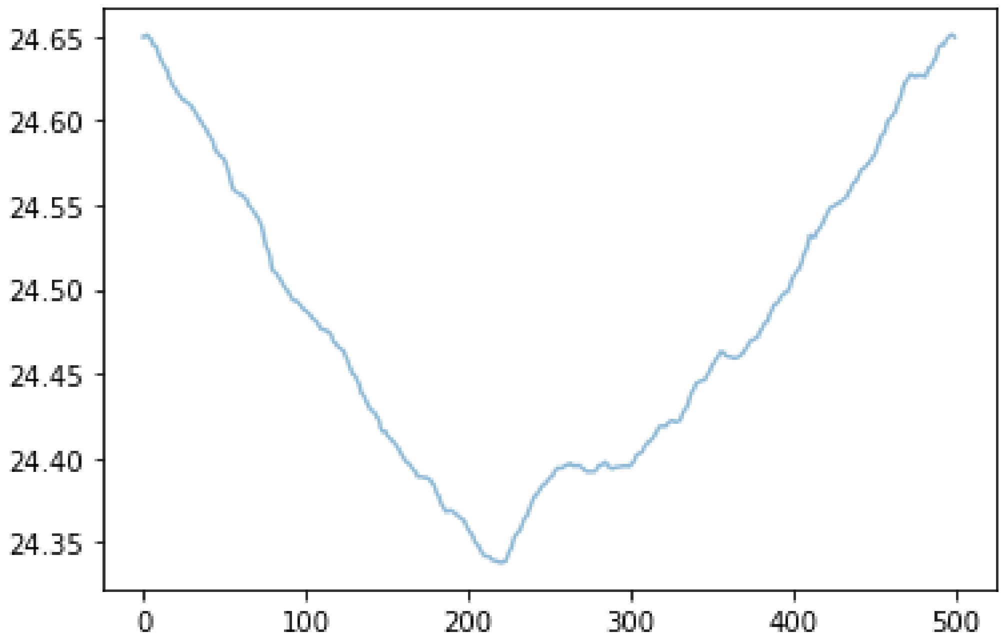
[25]:
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import scale
# import warnings
# warnings.filterwarnings('ignore')
T = 500 # sequence length
observations = 2*np.sin(np.linspace(0, 20*np.pi, T))
interventions = 2*np.sin(np.linspace(0, 2*np.pi, T))
data = np.vstack([observations, observations*1.2, interventions,
  interventions*0.85]).T
data += np.random.randn(*data.shape)
# data[:, 2:] = preprocessing.minmax_scale(data[:, 2:])
data = scale(data)

plt.figure(figsize=(10, 2))
plt.plot(data)
plt.xlabel('Time')
plt.ylabel('Value')
plt.show()
```



[26]:
```
x = torch.FloatTensor(data).reshape(1, *data.shape)
#print(x)
x_train = torch.FloatTensor(data[:400]).reshape(1, 400, data.shape[1])
#print(x_train)
x_val = torch.FloatTensor(data[400:450]).reshape(1, 50, data.shape[1])
#print(x_val)
#print(data.shape[1])
```

[27]:
```
# Plot ithmeasurement x longitude



#print(data_endo[0].keys())
y=np.asarray(data_endo[0]['longitude'])
z=np.asarray(data_endo[0]['latitude'])
x =[]
```

```
#print(len(x))
data_t = []
for i in range(len(y)):
    x.append(i)
    data_t.append((x[i], y[i]))
#print(data_t)
data_t = np.asarray(data_t)
#colors = np.random.rand(N)
#area = (30 * np.random.rand(N))**2  # 0 to 15 point radii

plt.plot(x, y, alpha=0.5)
plt.show()
#print(y.shape)
```



2.3 Trenowane dla 1 treningu po longitude

[32]:
```
#x = torch.FloatTensor(data).reshape(1, *data.shape)
#x_train = torch.FloatTensor(data[:400]).reshape(1, 400, data.shape[1])
#x_val   = torch.FloatTensor(data[400:450]).reshape(1, 50, data.shape[1])

y_data = torch.FloatTensor(y).reshape(1, 500, 1)
#print(y_data)
y_train = torch.FloatTensor(y[:450]).reshape(1, 450, 1)
#print(y_train)
```

```
y_val = torch.FloatTensor(y[450:500]).reshape(1, 50, 1)
#print(y_val)
```

[33]:
```
dkf = DKF(input_dim=1, z_dim=5, rnn_dim=5, trans_dim=5, emission_dim=5)
```

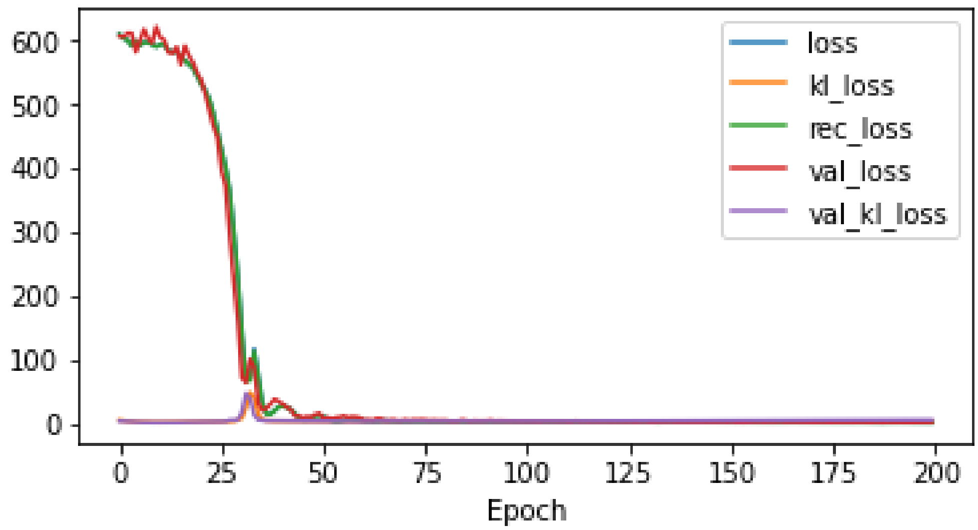
[34]:
```
history, param_dict = dkf.fit(y_train, y_val, num_epochs=200,␣
 ↪annealing_factor=0.1)
```

```
Epoch= 1/200, loss= 609.565, mse= 609.060, kld= 5.051
        val_loss= 606.549, val_mse= 606.194, val_kld= 3.551
Epoch= 11/200, loss= 593.252, mse= 593.116, kld= 1.361
        val_loss= 604.587, val_mse= 604.445, val_kld= 1.420
Epoch= 21/200, loss= 531.615, mse= 531.407, kld= 2.080
        val_loss= 538.189, val_mse= 537.962, val_kld= 2.266
Epoch= 31/200, loss= 140.203, mse= 139.373, kld= 8.300
        val_loss= 71.422, val_mse= 69.680, val_kld= 17.418
Epoch= 41/200, loss= 27.100, mse= 26.725, kld= 3.756
        val_loss= 29.652, val_mse= 29.257, val_kld= 3.949
Epoch= 51/200, loss= 10.490, mse= 10.204, kld= 2.854
        val_loss= 7.213, val_mse= 6.887, val_kld= 3.264
Epoch= 61/200, loss= 4.125, mse= 3.914, kld= 2.111
        val_loss= 4.940, val_mse= 4.675, val_kld= 2.653
Epoch= 71/200, loss= 2.446, mse= 2.200, kld= 2.452
        val_loss= 5.792, val_mse= 5.489, val_kld= 3.034
Epoch= 81/200, loss= 2.836, mse= 2.590, kld= 2.462
        val_loss= 4.688, val_mse= 4.369, val_kld= 3.189
Epoch= 91/200, loss= 2.146, mse= 1.928, kld= 2.181
        val_loss= 3.903, val_mse= 3.601, val_kld= 3.027
Epoch= 101/200, loss= 2.034, mse= 1.828, kld= 2.066
        val_loss= 2.874, val_mse= 2.570, val_kld= 3.036
Epoch= 111/200, loss= 1.874, mse= 1.667, kld= 2.067
        val_loss= 2.132, val_mse= 1.804, val_kld= 3.283
Epoch= 121/200, loss= 1.639, mse= 1.437, kld= 2.021
        val_loss= 2.426, val_mse= 2.088, val_kld= 3.382
Epoch= 131/200, loss= 1.725, mse= 1.518, kld= 2.063
        val_loss= 1.794, val_mse= 1.424, val_kld= 3.703
Epoch= 141/200, loss= 1.833, mse= 1.630, kld= 2.037
        val_loss= 1.508, val_mse= 1.116, val_kld= 3.925
Epoch= 151/200, loss= 1.498, mse= 1.297, kld= 2.008
        val_loss= 2.418, val_mse= 2.003, val_kld= 4.151
Epoch= 161/200, loss= 1.422, mse= 1.223, kld= 1.991
        val_loss= 1.811, val_mse= 1.368, val_kld= 4.438
Epoch= 171/200, loss= 1.443, mse= 1.238, kld= 2.051
        val_loss= 1.588, val_mse= 1.109, val_kld= 4.797
Epoch= 181/200, loss= 1.492, mse= 1.292, kld= 1.992
        val_loss= 1.521, val_mse= 1.023, val_kld= 4.983
Epoch= 191/200, loss= 1.165, mse= 0.969, kld= 1.959
```

val_loss= 1.833, val_mse= 1.307, val_kld= 5.260

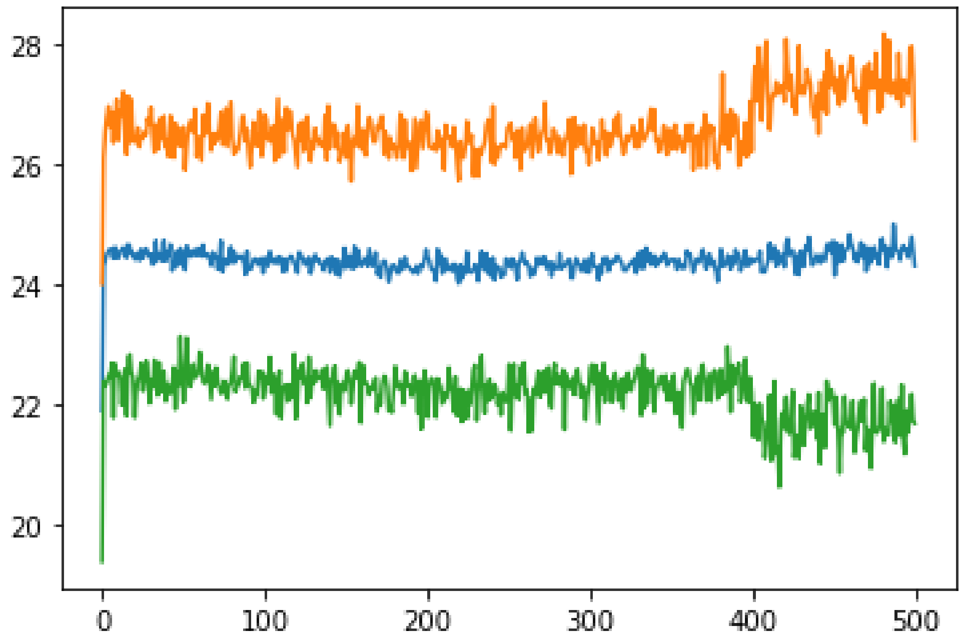
[35]:
```
pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

[35]: <AxesSubplot:xlabel='Epoch'>

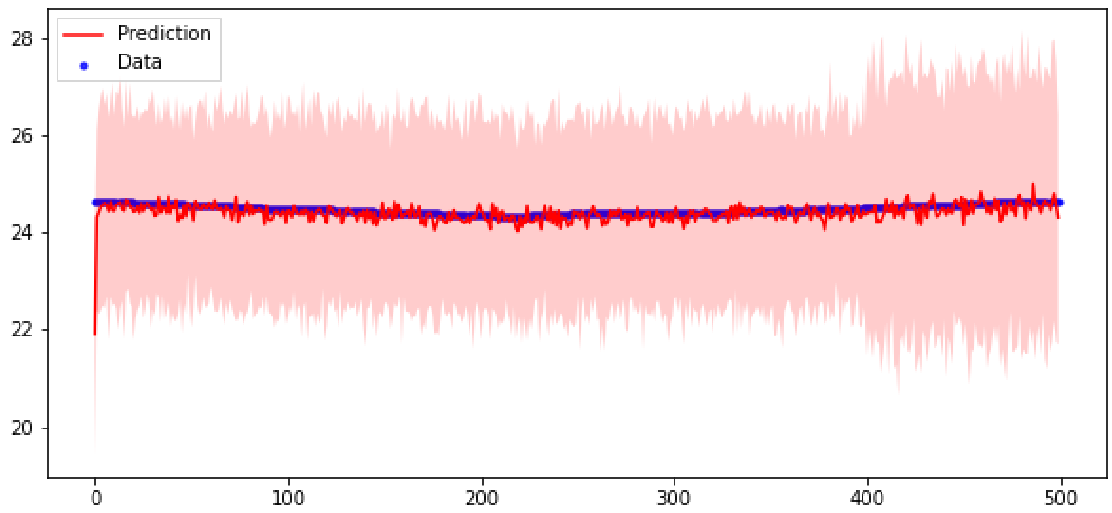


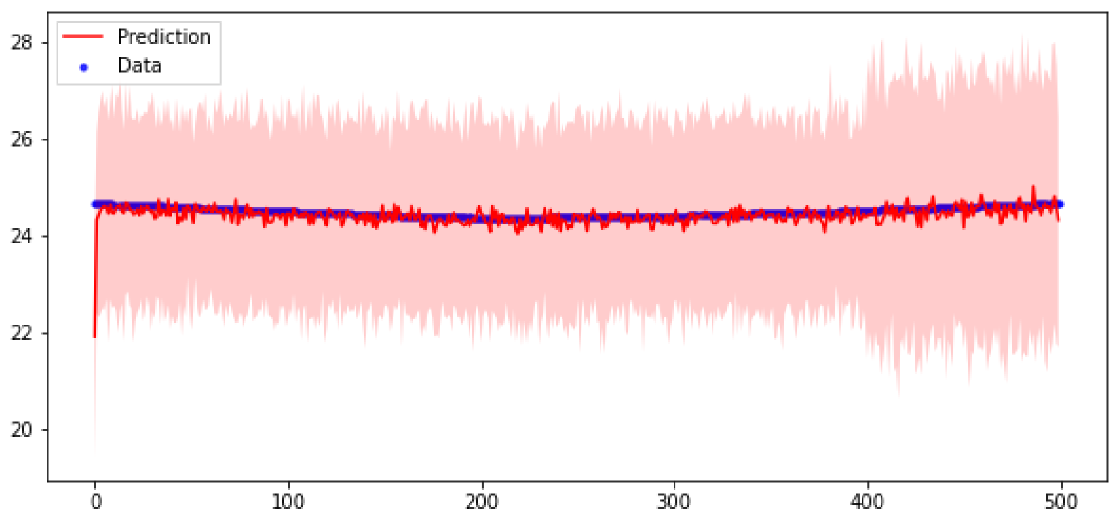
[36]:
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(y_data, 100)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

[36]: [<matplotlib.lines.Line2D at 0x7f1bcc2ae250>]



[37]:
```
fig, ax = plt.subplots(2, figsize=(10, 10))

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(y.shape[0]),
        y[:], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, 0], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, 0], x_975[:, 0],
                     facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```





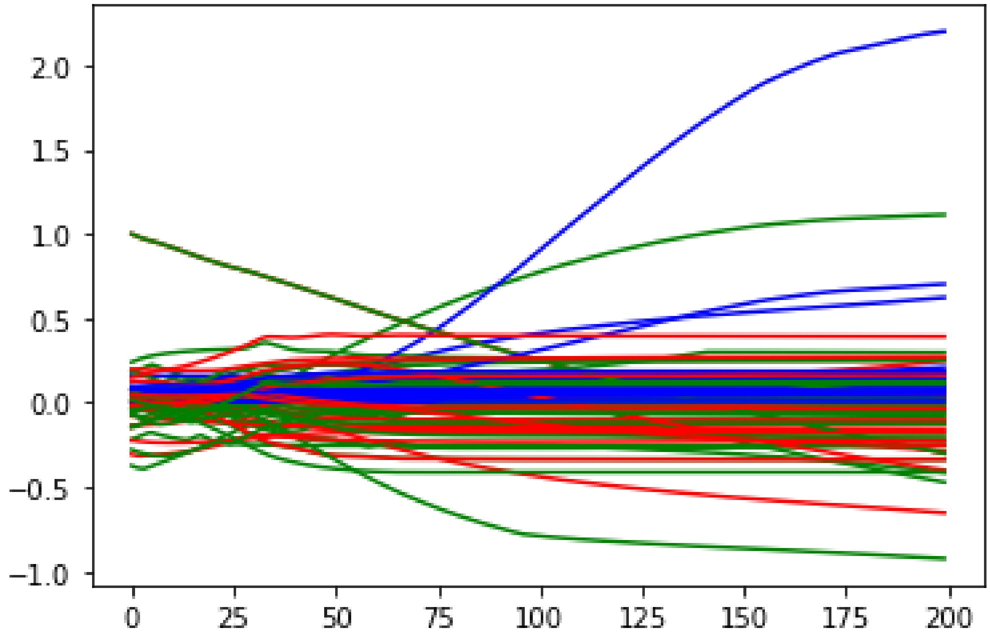
[38]:
```
mse_values = mean_squared_error(y_data[0], x_hat)
r_squared_values = r2_score(y_data[0], x_hat)
mae_values = mean_absolute_error(y_data[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

```
# Print the DataFrame
print(df)

mse_values = mean_squared_error(y_data[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(y_data[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(y_data[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)

print(x_hat.shape)
```

```
              MSE  R-squared       MAE
Average  0.035344  -3.183149  0.118508
              MSE  R-squared       MAE
sample1  0.035344  -3.183149  0.118508
(500, 1)
```

[39]:
```
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'

    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],␣
 ↪label = stat, c = colour)
```

```
plt.show()
```



[40]:
```
#####################################################################################
```

[ ]:
```
```

[ ]:
```
```

[ ]:
```
```

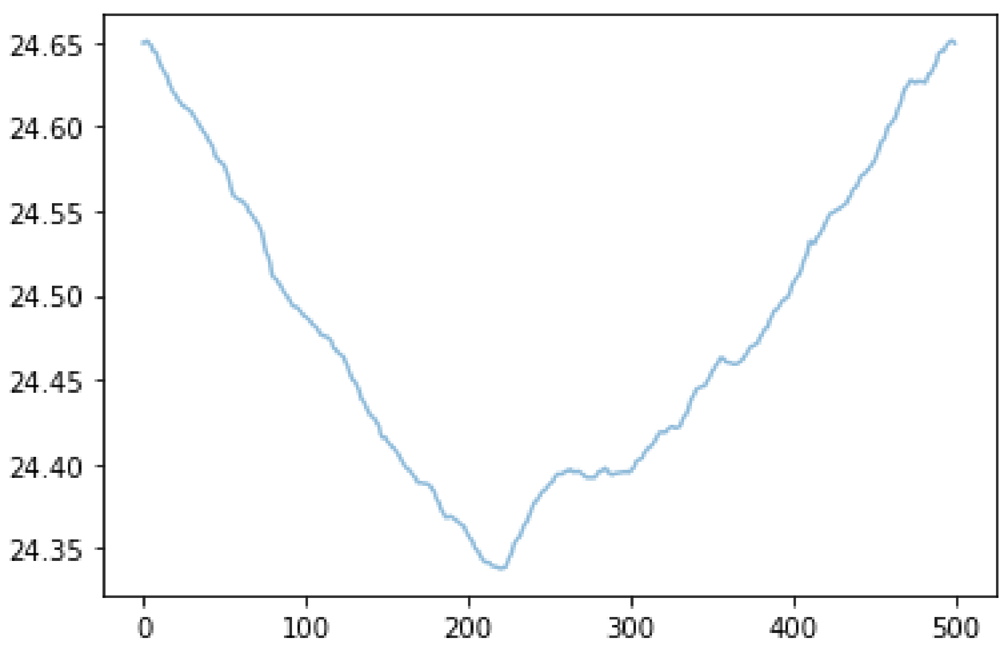
[ ]:
```
```

[41]:
```
#####################################################################################
```

[42]:
```
#TUTAJ TRENUJEMY DKF'a dla 1szego WORKOUTU 3 na RAZ LON LAT ALT
```

[43]:
```
# Plot ithmeasurement x longitude


#print(data_endo[0].keys())
y=np.asarray(data_endo[0]['longitude'])
z=np.asarray(data_endo[0]['latitude'])
x =[]
#print(len(x))
```

```python
data_t = []
for i in range(len(y)):
    x.append(i)
    data_t.append((x[i], y[i]))
#print(data_t)
data_t = np.asarray(data_t)
#colors = np.random.rand(N)
#area = (30 * np.random.rand(N))**2  # 0 to 15 point radii

plt.plot(x, y, alpha=0.5)
plt.show()
#print(y.shape)





first_workout_data = np.vstack([np.asarray(data_endo[0]['longitude']), np.
 ↪asarray(data_endo[0]['latitude']), np.asarray(data_endo[0]['altitude'])]).T
print(first_workout_data.shape)
```




```
(500, 3)
```

2.4 Trenowane dla pierwszego treningu po longitude, latitude i altitude

[44]:
```
x = torch.FloatTensor(first_workout_data).reshape(1, *first_workout_data.shape)
#print(x)
x_train = torch.FloatTensor(first_workout_data[:450]).reshape(1, 450,␣
 ↪first_workout_data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(first_workout_data[450:500]).reshape(1, 50,␣
 ↪first_workout_data.shape[1])
#print(x_val)
```

[45]:
```
dkf = DKF(input_dim=3, z_dim=15, rnn_dim=15, trans_dim=15, emission_dim=15)
```

[46]:
```
history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
 ↪annealing_factor=0.1)
```

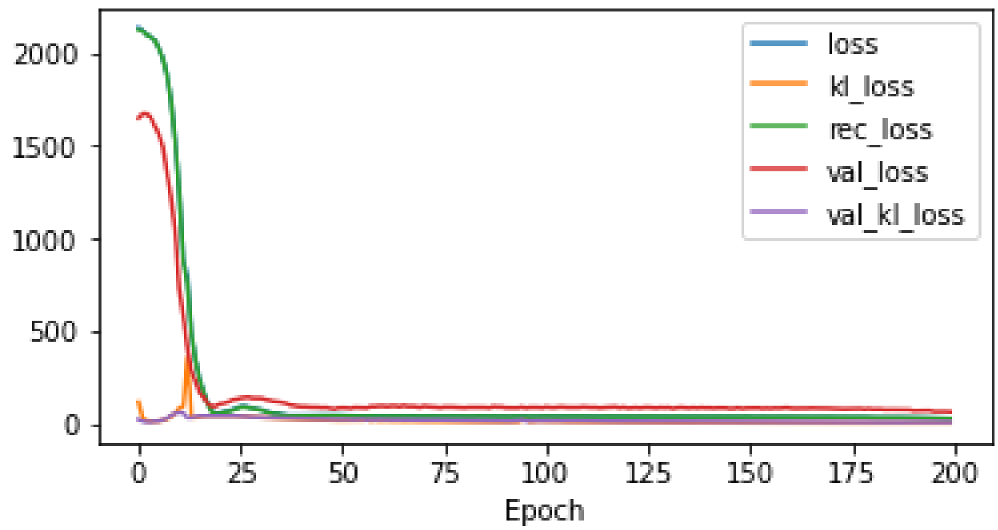
```
Epoch= 1/200, loss= 2137.991, mse= 2126.206, kld= 117.855
        val_loss= 1648.675, val_mse= 1646.222, val_kld= 24.528
Epoch= 11/200, loss= 1256.645, mse= 1248.165, kld= 84.806
        val_loss= 728.850, val_mse= 722.706, val_kld= 61.433
Epoch= 21/200, loss= 59.002, mse= 54.734, kld= 42.677
        val_loss= 107.794, val_mse= 103.569, val_kld= 42.250
Epoch= 31/200, loss= 77.736, mse= 74.301, kld= 34.354
        val_loss= 136.987, val_mse= 133.483, val_kld= 35.035
Epoch= 41/200, loss= 43.736, mse= 41.256, kld= 24.799
        val_loss= 91.683, val_mse= 88.787, val_kld= 28.960
Epoch= 51/200, loss= 45.020, mse= 43.201, kld= 18.186
        val_loss= 86.446, val_mse= 83.956, val_kld= 24.898
Epoch= 61/200, loss= 41.355, mse= 39.687, kld= 16.675
        val_loss= 95.323, val_mse= 93.070, val_kld= 22.526
Epoch= 71/200, loss= 40.994, mse= 39.573, kld= 14.206
        val_loss= 95.193, val_mse= 93.190, val_kld= 20.035
Epoch= 81/200, loss= 40.424, mse= 39.185, kld= 12.389
        val_loss= 86.212, val_mse= 84.338, val_kld= 18.746
Epoch= 91/200, loss= 39.880, mse= 38.849, kld= 10.304
        val_loss= 86.576, val_mse= 85.028, val_kld= 15.477
Epoch= 101/200, loss= 40.115, mse= 38.701, kld= 14.132
        val_loss= 90.962, val_mse= 89.284, val_kld= 16.775
Epoch= 111/200, loss= 38.335, mse= 37.316, kld= 10.192
        val_loss= 89.185, val_mse= 87.628, val_kld= 15.570
Epoch= 121/200, loss= 39.168, mse= 38.350, kld= 8.179
        val_loss= 84.703, val_mse= 83.295, val_kld= 14.080
Epoch= 131/200, loss= 37.826, mse= 37.119, kld= 7.070
        val_loss= 88.044, val_mse= 86.865, val_kld= 11.782
Epoch= 141/200, loss= 37.961, mse= 37.330, kld= 6.304
        val_loss= 86.310, val_mse= 85.118, val_kld= 11.918
Epoch= 151/200, loss= 37.146, mse= 36.573, kld= 5.730
```

```
        val_loss= 85.025, val_mse= 83.942, val_kld= 10.834
Epoch= 161/200, loss= 37.018, mse= 36.515, kld= 5.030
        val_loss= 83.682, val_mse= 82.735, val_kld= 9.479
Epoch= 171/200, loss= 35.749, mse= 35.266, kld= 4.832
        val_loss= 81.685, val_mse= 80.835, val_kld= 8.502
Epoch= 181/200, loss= 34.765, mse= 34.291, kld= 4.739
        val_loss= 78.164, val_mse= 77.261, val_kld= 9.033
Epoch= 191/200, loss= 33.127, mse= 32.648, kld= 4.789
        val_loss= 70.886, val_mse= 70.003, val_kld= 8.835
```

[47]:

```
pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

[47]: <AxesSubplot:xlabel='Epoch'>

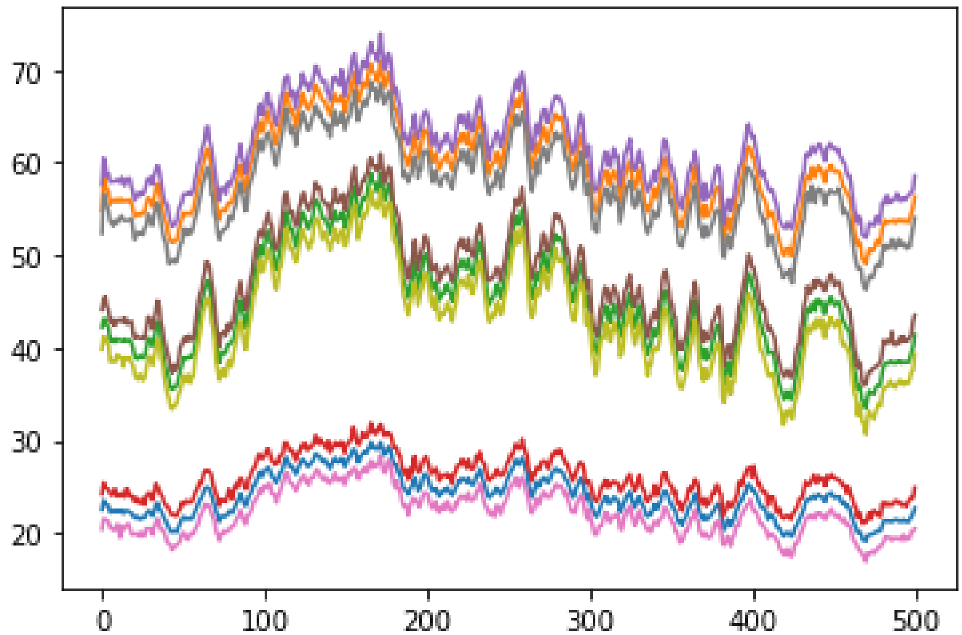


[48]:

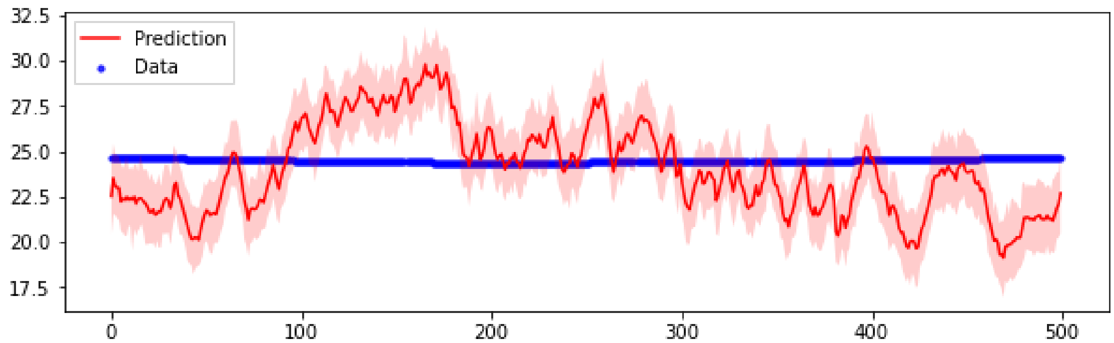
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 100)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

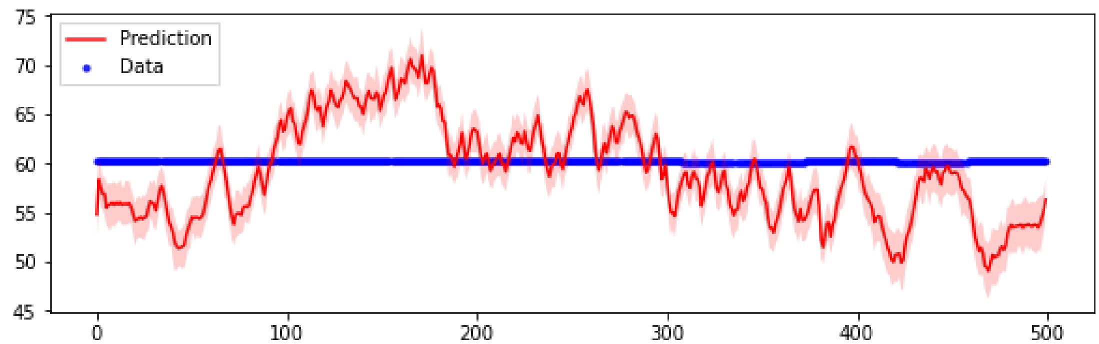
[48]:

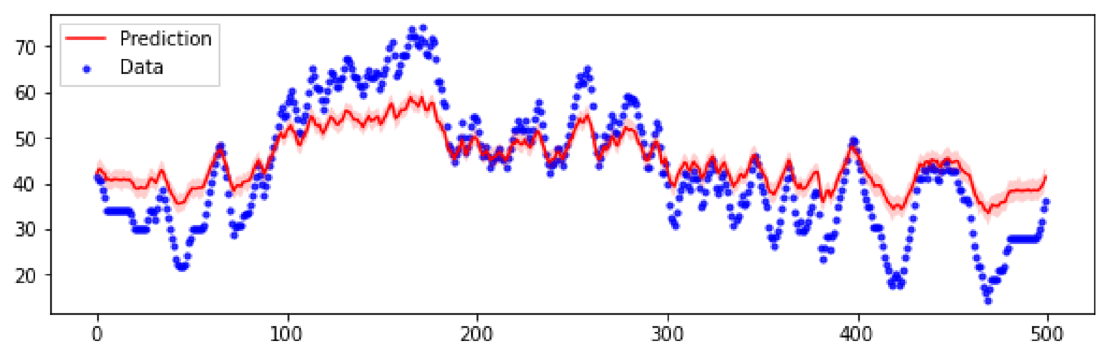
```
[<matplotlib.lines.Line2D at 0x7f1bcc32fb50>,
 <matplotlib.lines.Line2D at 0x7f1bcc32f730>,
 <matplotlib.lines.Line2D at 0x7f1bcc32f670>]
```



[49]:
```
fig, ax = plt.subplots(3, figsize=(10, 10))

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(first_workout_data.shape[0]),
        first_workout_data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
                    facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```







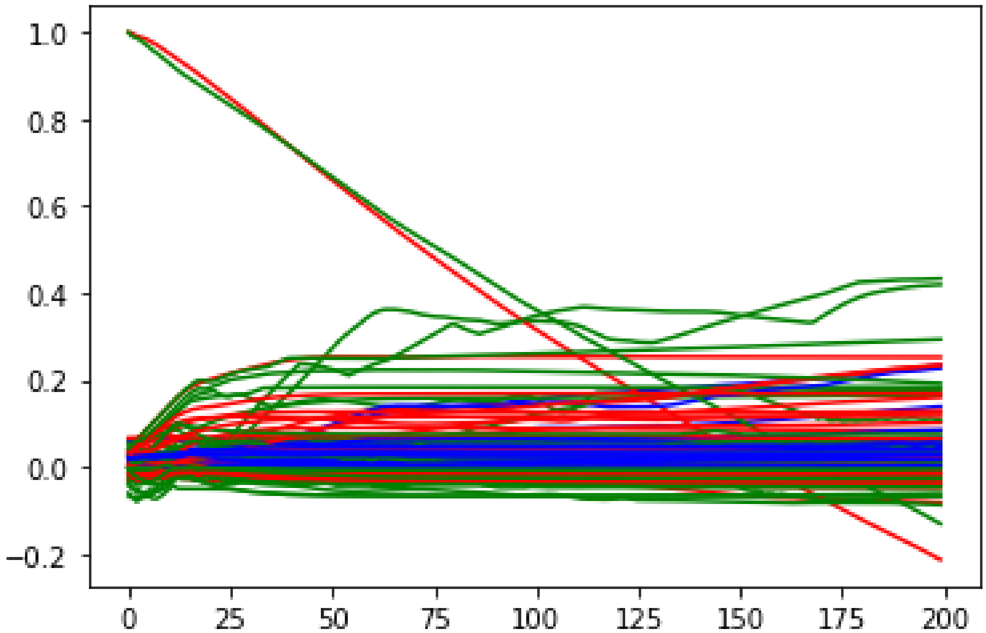
[50]:
```python
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

```python
# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
               MSE    R-squared       MAE
Average  30.811045 -9595.493595  4.282147
               MSE     R-squared       MAE
sample1   6.431111   -760.156997  2.136508
sample2  25.136131 -28026.988624  4.201183
sample3  60.865898      0.664835  6.508749
```

[51]:
```python
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'

    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],␣
↪label = stat, c = colour)
```

```
plt.show()
```



[ ]:
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```

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```

[ ]:
```
#TERAZ DKF DLA LONGITUDE DLA 3 PIERWSZYCH WORKOUTOW
```

2.5 Trenowane dla 3 pierwszych treningow po longitude

[52]:
```
longitude_three_data = np.vstack([np.asarray(data_endo[0]['longitude']), np.
 ↪asarray(data_endo[1]['longitude']), np.asarray(data_endo[2]['longitude'])]).T
#print(first_workout_data.shape)
```

[53]:
```
x = torch.FloatTensor(longitude_three_data).reshape(1, *longitude_three_data.
 ↪shape)
#print(x)
```

```
x_train = torch.FloatTensor(longitude_three_data[:450]).reshape(1, 450,␣
↪longitude_three_data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(longitude_three_data[450:500]).reshape(1, 50,␣
↪longitude_three_data.shape[1])
#print(x_val)
```

[54]:
```
dkf = DKF(input_dim=3, z_dim=15, rnn_dim=15, trans_dim=15, emission_dim=15)
```

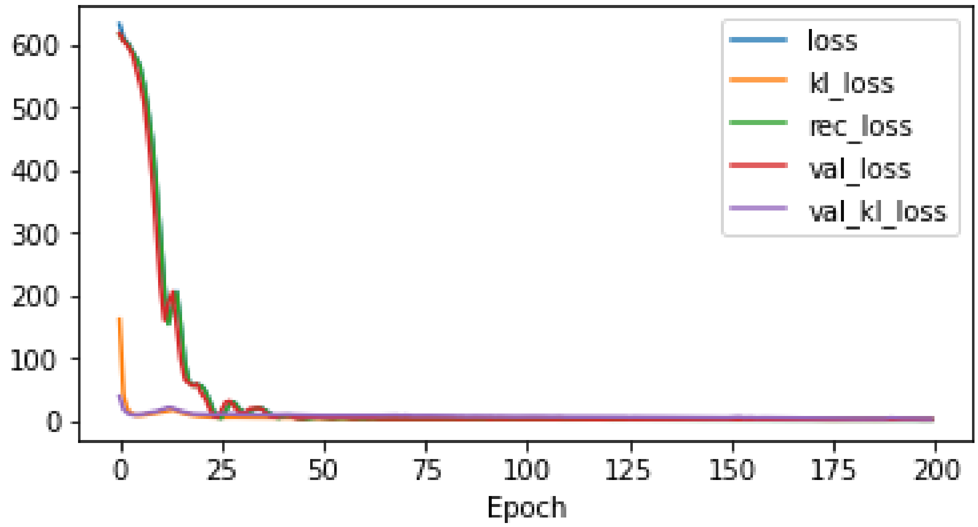
[55]:
```
history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
↪annealing_factor=0.1)
```

```
Epoch= 1/200, loss= 633.595, mse= 617.423, kld= 161.721
        val_loss= 618.901, val_mse= 615.115, val_kld= 37.855
Epoch= 11/200, loss= 297.543, mse= 296.320, kld= 12.231
        val_loss= 217.358, val_mse= 215.741, val_kld= 16.168
Epoch= 21/200, loss= 55.305, mse= 54.663, kld= 6.426
        val_loss= 43.157, val_mse= 42.225, val_kld= 9.317
Epoch= 31/200, loss= 14.258, mse= 13.761, kld= 4.968
        val_loss= 11.982, val_mse= 11.076, val_kld= 9.056
Epoch= 41/200, loss= 6.076, mse= 5.571, kld= 5.051
        val_loss= 7.917, val_mse= 6.979, val_kld= 9.378
Epoch= 51/200, loss= 4.762, mse= 4.434, kld= 3.280
        val_loss= 4.390, val_mse= 3.630, val_kld= 7.596
Epoch= 61/200, loss= 2.693, mse= 2.396, kld= 2.963
        val_loss= 3.893, val_mse= 3.126, val_kld= 7.674
Epoch= 71/200, loss= 2.195, mse= 1.921, kld= 2.737
        val_loss= 2.698, val_mse= 1.877, val_kld= 8.218
Epoch= 81/200, loss= 1.911, mse= 1.678, kld= 2.330
        val_loss= 2.650, val_mse= 1.922, val_kld= 7.274
Epoch= 91/200, loss= 1.654, mse= 1.430, kld= 2.243
        val_loss= 1.976, val_mse= 1.309, val_kld= 6.669
Epoch= 101/200, loss= 1.544, mse= 1.360, kld= 1.843
        val_loss= 1.835, val_mse= 1.208, val_kld= 6.263
Epoch= 111/200, loss= 1.433, mse= 1.246, kld= 1.874
        val_loss= 2.130, val_mse= 1.538, val_kld= 5.918
Epoch= 121/200, loss= 1.388, mse= 1.191, kld= 1.976
        val_loss= 1.805, val_mse= 1.223, val_kld= 5.820
Epoch= 131/200, loss= 1.247, mse= 1.079, kld= 1.680
        val_loss= 1.876, val_mse= 1.347, val_kld= 5.287
Epoch= 141/200, loss= 1.234, mse= 1.086, kld= 1.488
        val_loss= 1.456, val_mse= 0.997, val_kld= 4.590
Epoch= 151/200, loss= 1.090, mse= 0.944, kld= 1.457
        val_loss= 1.440, val_mse= 0.964, val_kld= 4.761
Epoch= 161/200, loss= 1.103, mse= 0.933, kld= 1.704
        val_loss= 1.182, val_mse= 0.825, val_kld= 3.569
Epoch= 171/200, loss= 0.993, mse= 0.871, kld= 1.213
```

```
        val_loss= 1.206, val_mse= 0.896, val_kld= 3.100
Epoch= 181/200, loss= 0.985, mse= 0.871, kld= 1.144
        val_loss= 1.048, val_mse= 0.805, val_kld= 2.426
Epoch= 191/200, loss= 1.044, mse= 0.791, kld= 2.535
        val_loss= 1.196, val_mse= 0.848, val_kld= 3.479
```

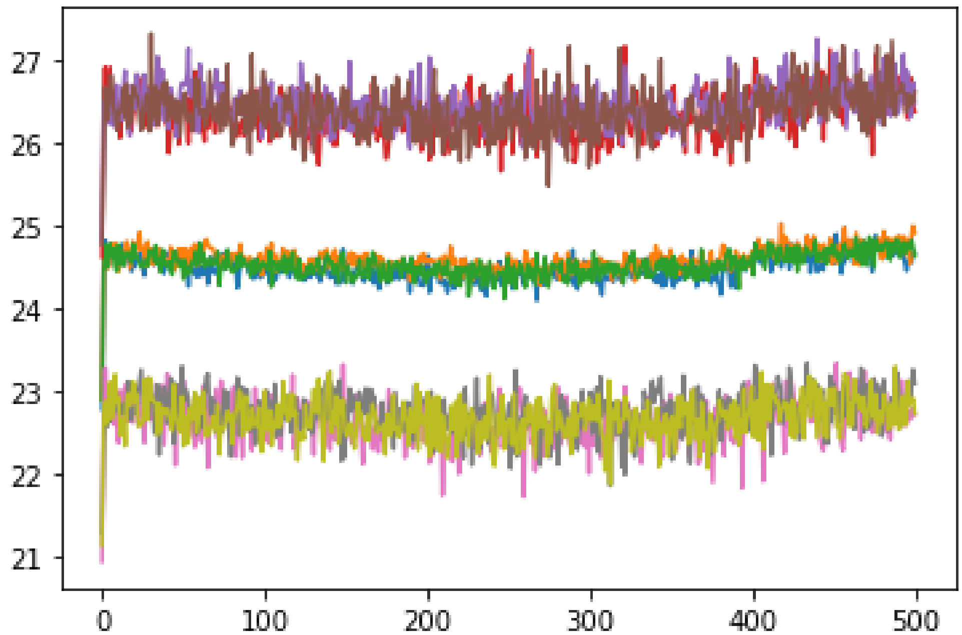
[56]:
```
pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

[56]:
```
<AxesSubplot:xlabel='Epoch'>
```



[57]:
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 100)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

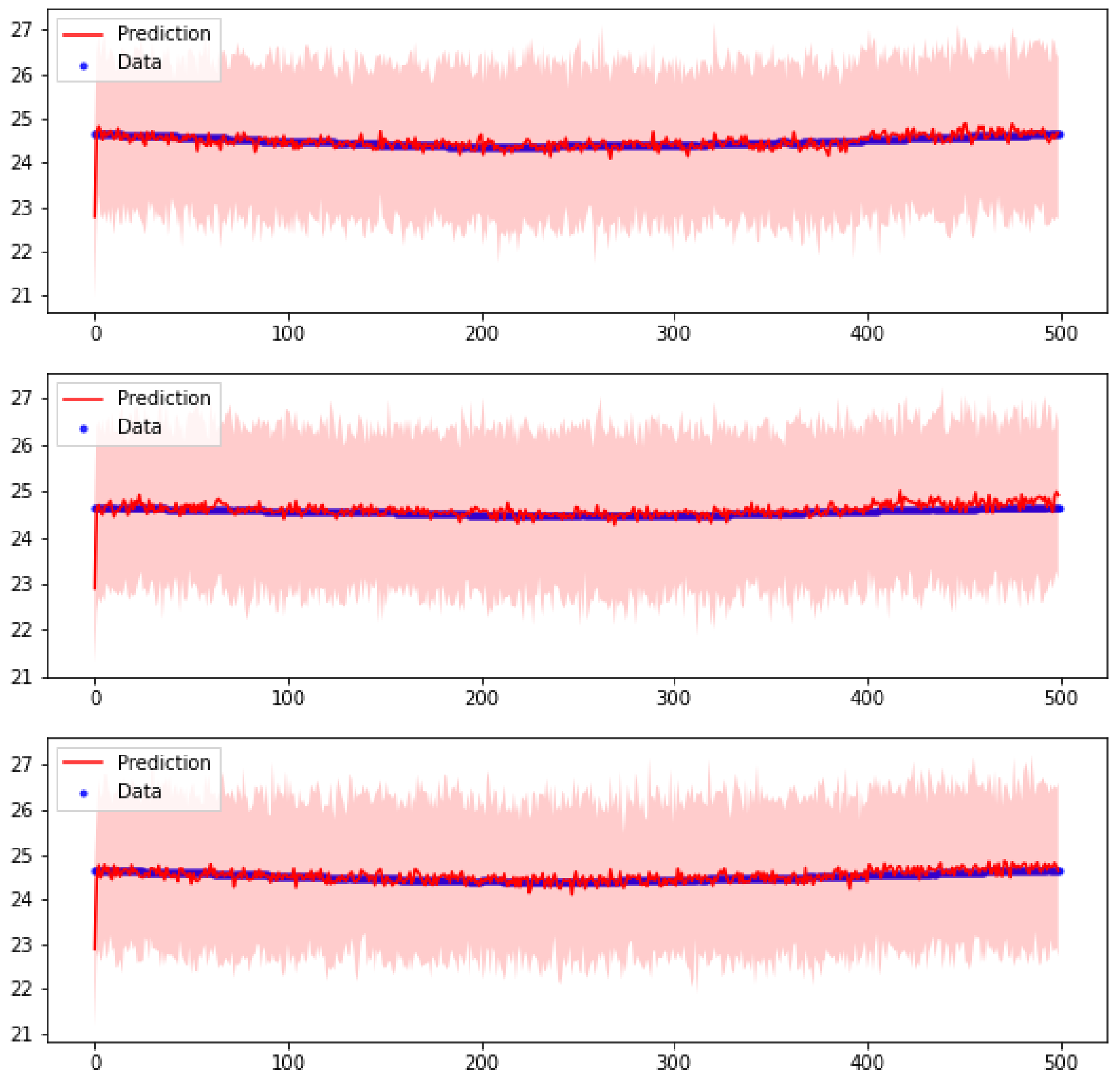
[57]:
```
[<matplotlib.lines.Line2D at 0x7f1bcc2ab820>,
 <matplotlib.lines.Line2D at 0x7f1bcc2ab370>,
 <matplotlib.lines.Line2D at 0x7f1bcc2f4820>]
```



[58]:
```
fig, ax = plt.subplots(3, figsize=(10, 10))

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(longitude_three_data.shape[0]),
        longitude_three_data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
                    facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```



[59]:
```
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

```python
# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
              MSE  R-squared       MAE
Average  0.017611  -2.137534  0.087514
              MSE  R-squared       MAE
sample1  0.017798  -1.106433  0.084893
sample2  0.017971  -3.747880  0.089084
sample3  0.017065  -1.558291  0.088566
```

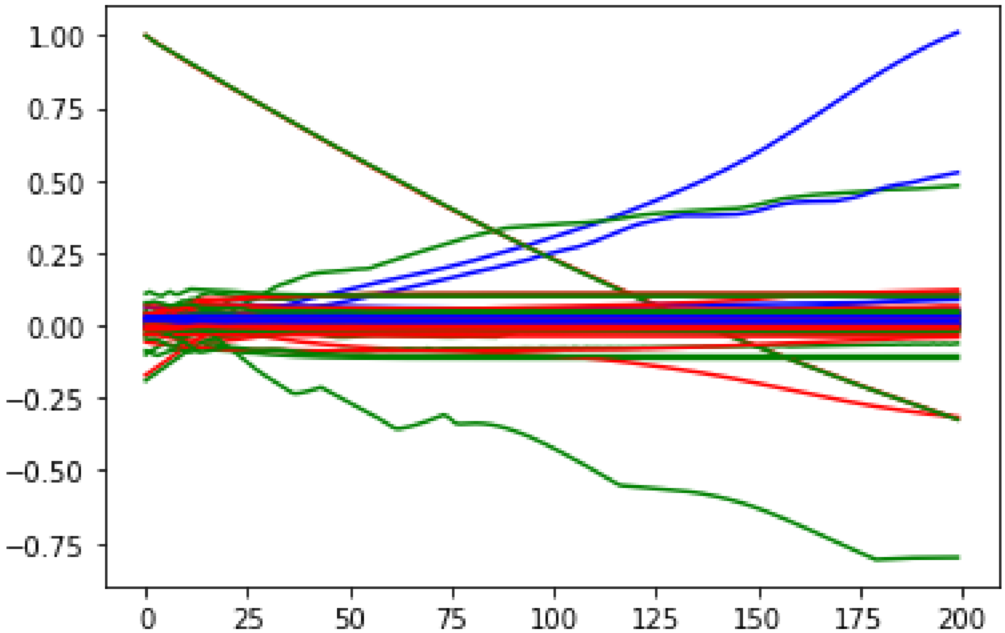
[60]:

```python
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'

    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],␣
 ↪label = stat, c = colour)
```

```
plt.show()
```



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[ ]:
```
#TUTAJ DKF PO ALTITUDE DLA 5 WORKOUTOW
```

2.6 Trenowane dla 5 pierwszych treningow po altitude

[61]:
```
data = np.vstack([np.asarray(data_endo[0]['altitude']), np.
 ↪asarray(data_endo[1]['altitude']),
                  np.asarray(data_endo[2]['altitude']), np.
 ↪asarray(data_endo[3]['altitude']),
                  np.asarray(data_endo[4]['altitude'])]).T
#print(data.shape)
```

[62]:
```
x = torch.FloatTensor(data).reshape(1, *data.shape)
#print(x)
x_train = torch.FloatTensor(data[:450]).reshape(1, 450, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[450:500]).reshape(1, 50, data.shape[1])
#print(x_val)
```

[63]:
```
dkf = DKF(input_dim=5, z_dim=25, rnn_dim=25, trans_dim=25, emission_dim=25)
```

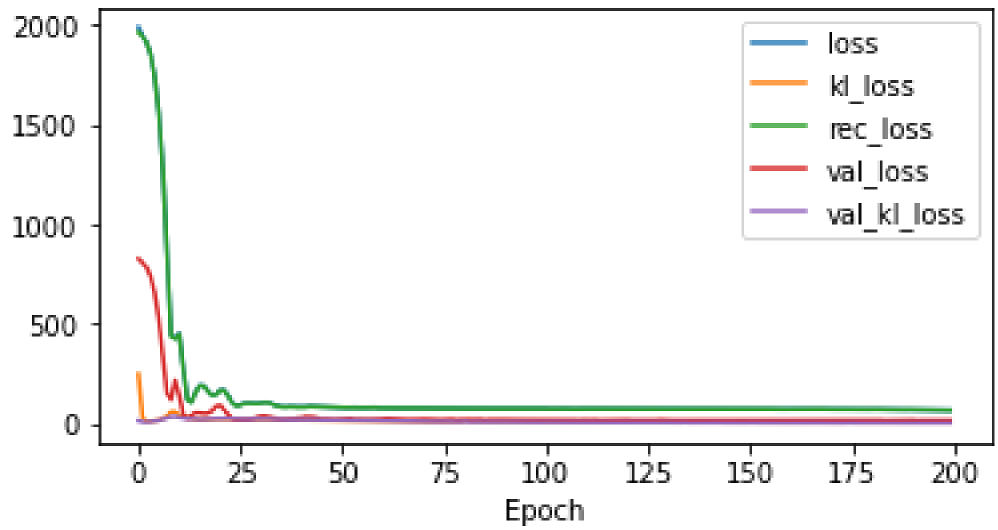
[64]:
```
history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
↪annealing_factor=0.1)
```

```
Epoch= 1/200, loss= 1989.756, mse= 1964.765, kld= 249.905
        val_loss= 828.705, val_mse= 827.090, val_kld= 16.153
Epoch= 11/200, loss= 453.677, mse= 449.086, kld= 45.911
        val_loss= 144.426, val_mse= 141.169, val_kld= 32.564
Epoch= 21/200, loss= 168.490, mse= 165.855, kld= 26.354
        val_loss= 92.657, val_mse= 89.861, val_kld= 27.963
Epoch= 31/200, loss= 105.231, mse= 102.795, kld= 24.359
        val_loss= 38.923, val_mse= 36.388, val_kld= 25.351
Epoch= 41/200, loss= 85.490, mse= 83.526, kld= 19.633
        val_loss= 31.391, val_mse= 29.146, val_kld= 22.449
Epoch= 51/200, loss= 80.925, mse= 79.280, kld= 16.445
        val_loss= 23.711, val_mse= 21.704, val_kld= 20.065
Epoch= 61/200, loss= 79.985, mse= 78.460, kld= 15.250
        val_loss= 25.174, val_mse= 23.573, val_kld= 16.011
Epoch= 71/200, loss= 79.053, mse= 77.857, kld= 11.961
        val_loss= 24.048, val_mse= 22.808, val_kld= 12.402
Epoch= 81/200, loss= 77.559, mse= 76.207, kld= 13.528
        val_loss= 21.416, val_mse= 20.224, val_kld= 11.925
Epoch= 91/200, loss= 77.166, mse= 76.126, kld= 10.399
        val_loss= 21.815, val_mse= 20.882, val_kld= 9.336
Epoch= 101/200, loss= 77.333, mse= 76.423, kld= 9.100
        val_loss= 20.532, val_mse= 19.728, val_kld= 8.040
Epoch= 111/200, loss= 76.322, mse= 75.535, kld= 7.880
        val_loss= 20.102, val_mse= 19.324, val_kld= 7.775
Epoch= 121/200, loss= 75.310, mse= 74.577, kld= 7.333
        val_loss= 20.675, val_mse= 19.973, val_kld= 7.021
Epoch= 131/200, loss= 75.595, mse= 74.880, kld= 7.141
        val_loss= 19.203, val_mse= 18.468, val_kld= 7.342
Epoch= 141/200, loss= 75.708, mse= 74.929, kld= 7.786
        val_loss= 19.996, val_mse= 19.385, val_kld= 6.116
Epoch= 151/200, loss= 75.103, mse= 74.445, kld= 6.579
        val_loss= 19.126, val_mse= 18.444, val_kld= 6.815
Epoch= 161/200, loss= 74.344, mse= 73.694, kld= 6.506
        val_loss= 18.527, val_mse= 17.942, val_kld= 5.843
Epoch= 171/200, loss= 73.857, mse= 73.232, kld= 6.250
```

```
        val_loss= 18.349, val_mse= 17.738, val_kld= 6.107
Epoch= 181/200, loss= 73.783, mse= 73.120, kld= 6.626
        val_loss= 18.749, val_mse= 18.190, val_kld= 5.587
Epoch= 191/200, loss= 71.784, mse= 71.110, kld= 6.737
        val_loss= 19.643, val_mse= 19.003, val_kld= 6.397
```

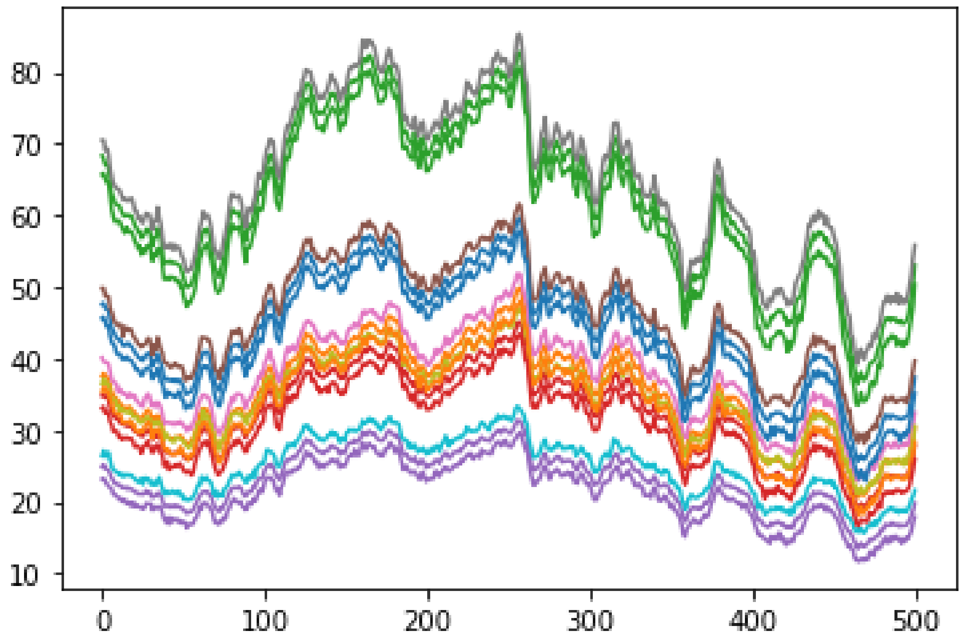
[65]:
```python
pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

[65]:
```
<AxesSubplot:xlabel='Epoch'>
```



[66]:
```python
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 100)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

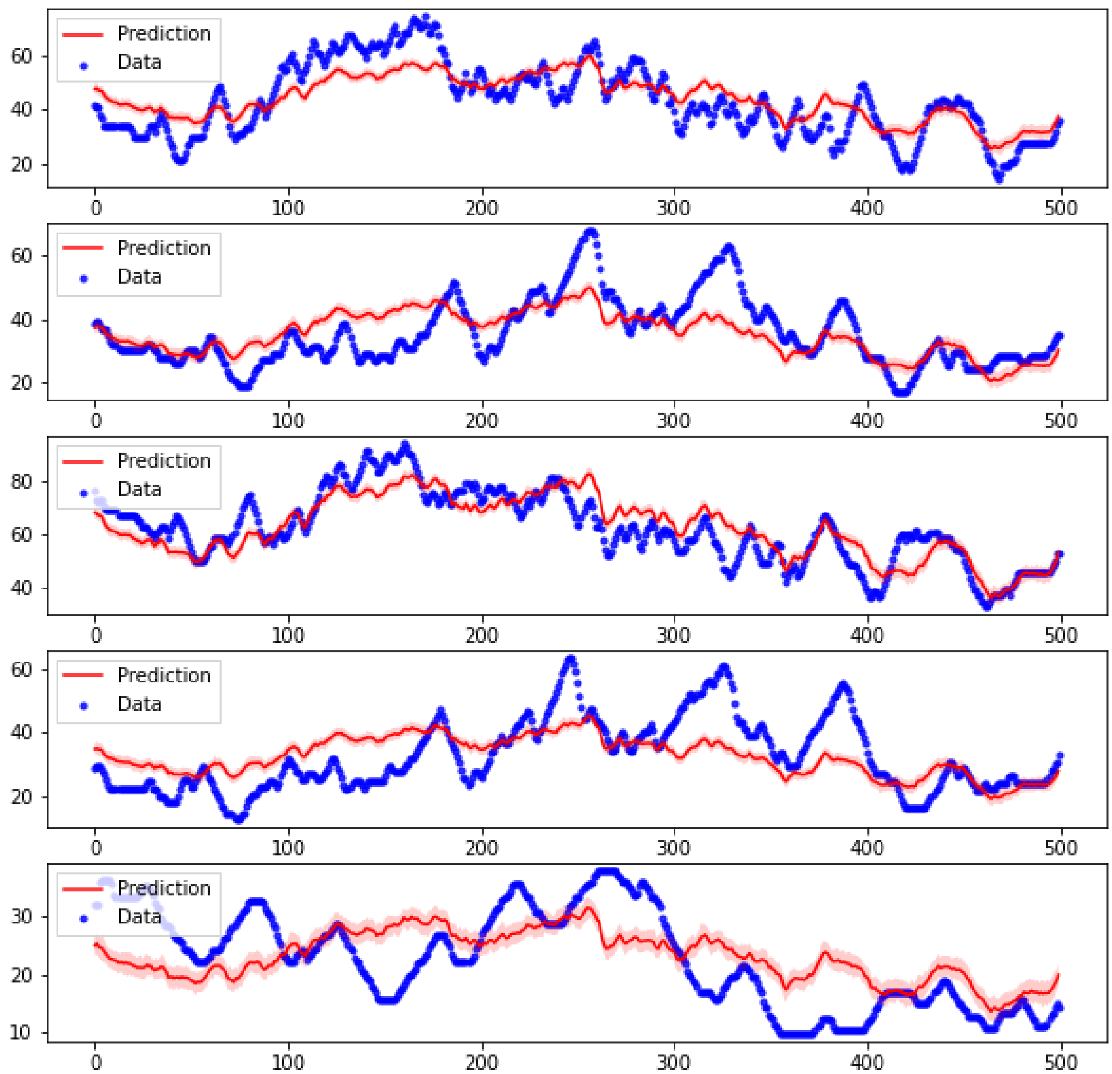
[66]:
```
[<matplotlib.lines.Line2D at 0x7f1b79398940>,
 <matplotlib.lines.Line2D at 0x7f1b793ffc40>,
 <matplotlib.lines.Line2D at 0x7f1b793ff970>,
 <matplotlib.lines.Line2D at 0x7f1b793ffd30>,
 <matplotlib.lines.Line2D at 0x7f1b793fff70>]
```



[67]:
```
fig, ax = plt.subplots(5, figsize=(10, 10))

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
                     facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```



[68]:
```
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

```python
# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

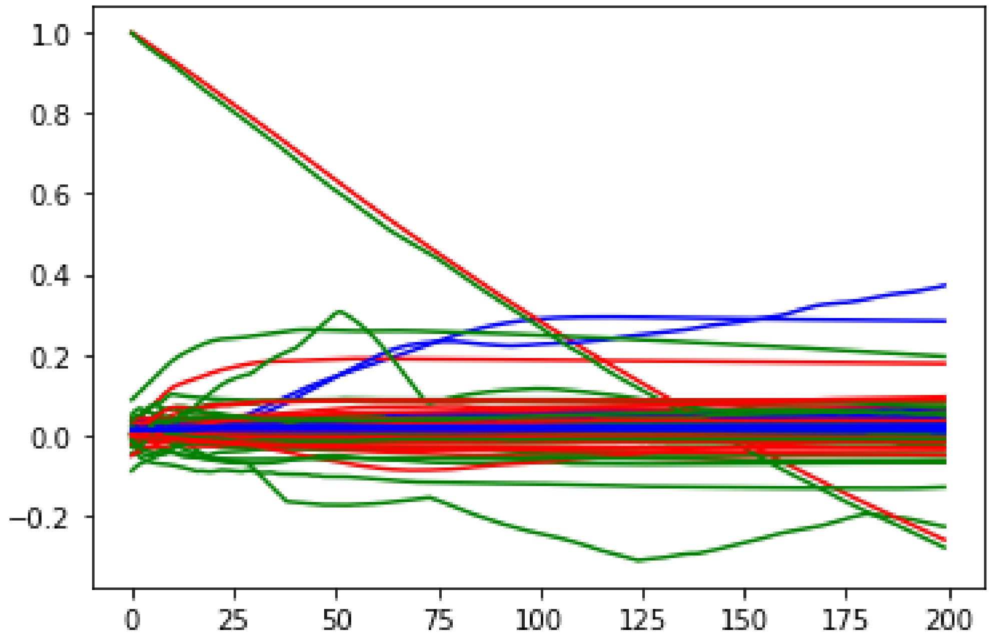
```
               MSE  R-squared       MAE
Average  62.864613   0.478931  6.402478
               MSE  R-squared       MAE
sample1  63.101223   0.652526  6.758931
sample2  59.574207   0.446659  5.932997
sample3  51.535629   0.705010  5.830832
sample4  89.060036   0.316807  7.526007
sample5  51.051968   0.273654  5.963626
```

[69]:
```python
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'

    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],
 ↪label = stat, c = colour)
```

```
plt.show()
```



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[ ]:

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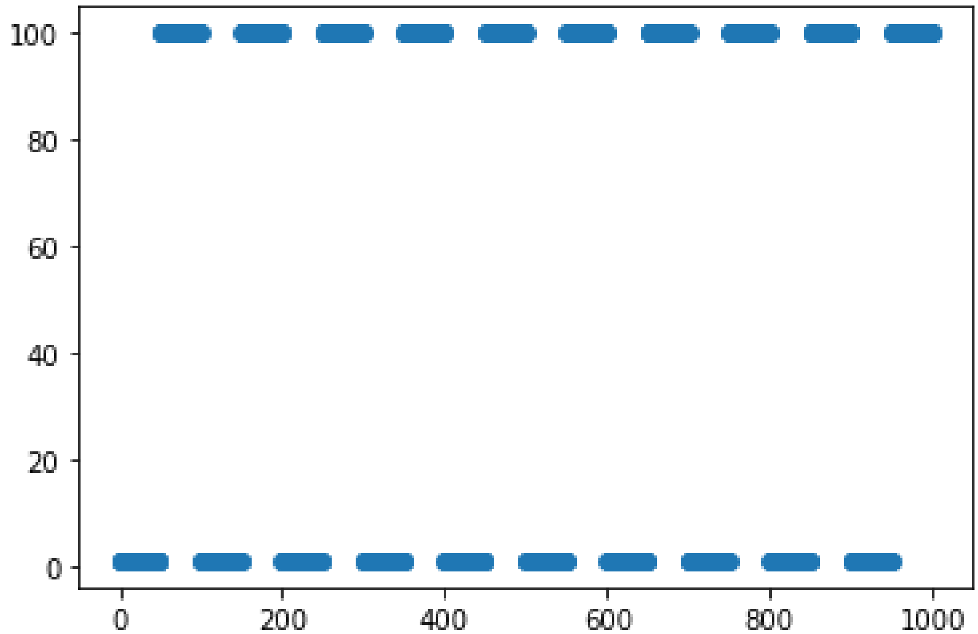
```
###############################################################################################
```

[ ]:
```
#Preparing test synthetic datasets - each 1000 measurements
```

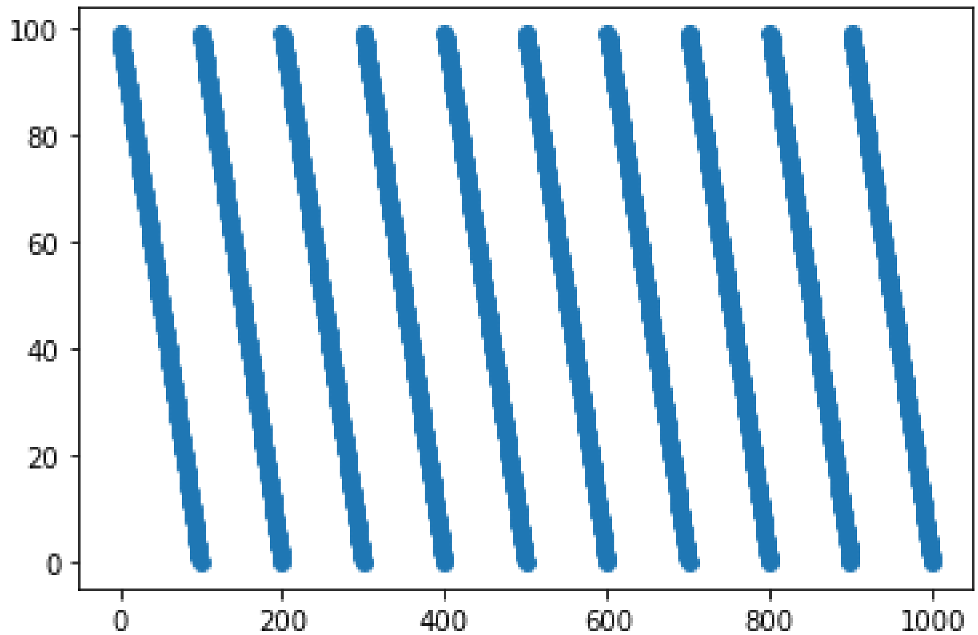
3 Przygotowanie danych syntetycznych

[70]:
```
#Dataset 1 - binary a bunch of 1's then a bunch of 100's
data_bin = []
while len(data_bin)<1000:
```

```
    data_bin.extend([1 for i in range(50)])
    data_bin.extend([100 for i in range(50)])
data_bin = np.asarray(data_bin[:1000])
#print(data_bin)
plt.scatter(range(len(data_bin)),data_bin)
plt.show()
```

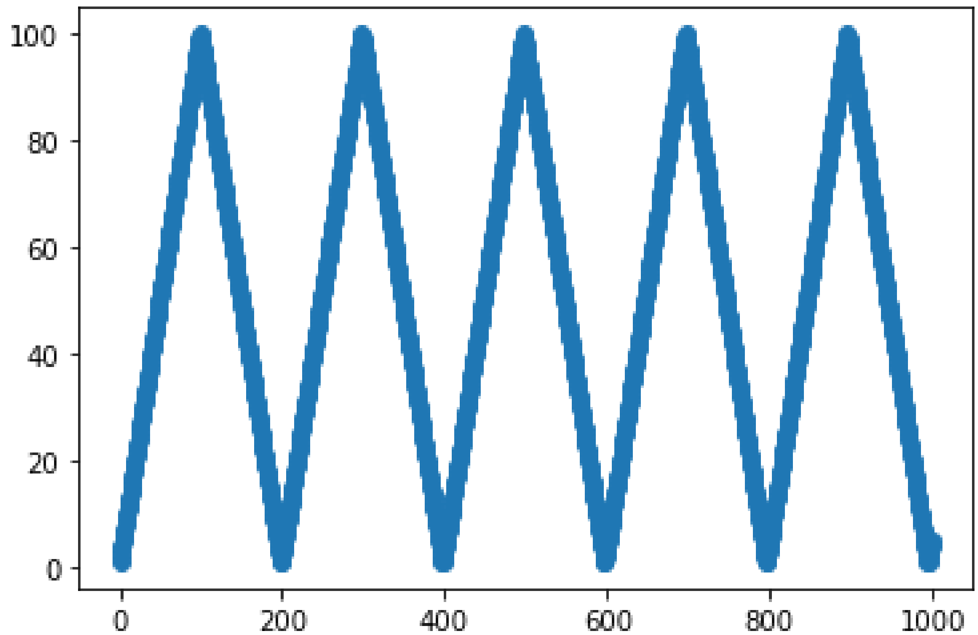


[71]:
```
#Dataset 2 - Decreasing from 100 to 1 in a loop
data_spike = []
while len(data_spike)<1000:
    data_spike.extend([-i + 100 for i in range(1, 101)])

data_spike = np.asarray(data_spike[:1000])
#print(data_spike)
plt.scatter(range(len(data_spike)), data_spike)
plt.show()
```

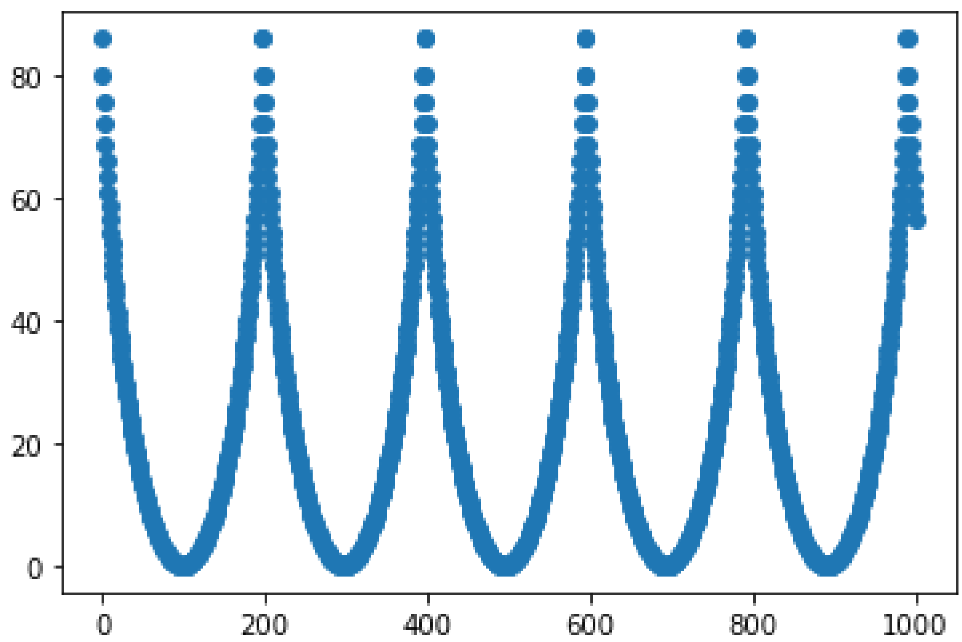


[72]:
```
#Dataset 3 - Growing from 1 to 100 then from 100 to 1
```

[73]:
```
data_alt = []
while len(data_alt)<1000:
    data_alt.extend([i for i in range(1,100)])
    data_alt.extend([i for i in range(100,0,-1)])

data_alt = np.asarray(data_alt[:1000])
#print(data_alt)
plt.scatter(range(len(data_alt)), data_alt)
plt.show()
```



[74]:
```
#Dataset 4 - Lower half of a circle
data_circle = []
while len(data_circle)<1000:
    data_circle.extend([-np.sqrt(100 ** 2 - i ** 2) + 100 for i in␣
 ↪range(99,0,-1)])
    data_circle.extend([-np.sqrt(100 ** 2 - i ** 2) + 100 for i in␣
 ↪range(1,100)])

data_circle = np.asarray(data_circle[:1000])
#print(data_circle)
#print(len(data_circle))
plt.scatter(range(len(data_circle)), data_circle)
plt.show()
```



[75]:
```
data = np.vstack([data_bin, data_spike, data_alt, data_circle]).T
#print(data.shape)
```

[76]:
```
data = np.vstack([data_bin, data_spike, data_alt, data_circle]).T
#print(data.shape)

x = torch.FloatTensor(data).reshape(1, *data.shape)
#print(x)
x_train = torch.FloatTensor(data[:600]).reshape(1, 600, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[600:800]).reshape(1, 200, data.shape[1])
#print(x_val)
```

3.1 Trenowanie dla danych syntetycznych

[77]:
```
dkf = DKF(input_dim=4, z_dim=20, rnn_dim=20, trans_dim=20, emission_dim=20)
```

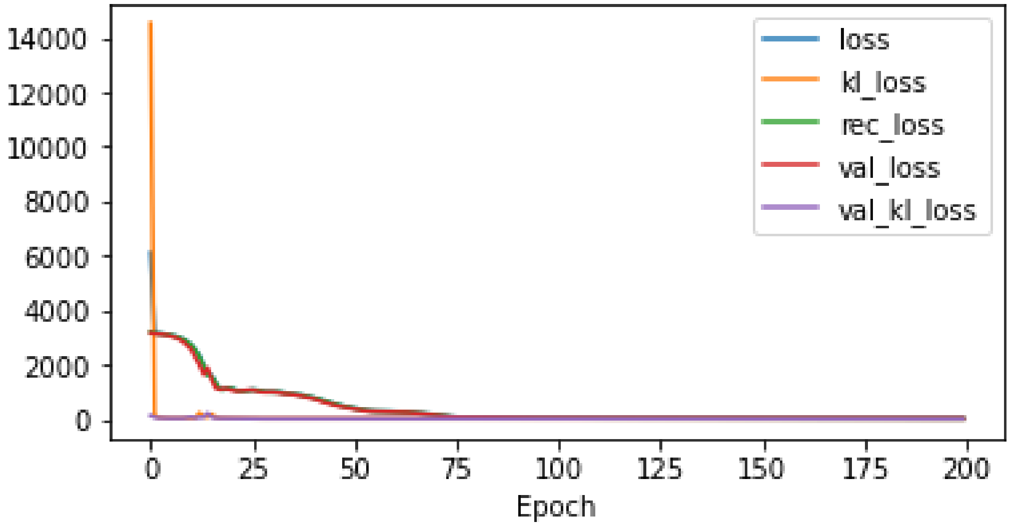
[78]:
```
history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
 ↪annealing_factor=0.2)
```

```
Epoch= 1/200, loss= 6117.203, mse= 3209.053, kld= 14540.748
        val_loss= 3176.538, val_mse= 3148.563, val_kld= 139.872
Epoch= 11/200, loss= 2726.004, mse= 2717.518, kld= 42.432
        val_loss= 2561.604, val_mse= 2546.139, val_kld= 77.321
Epoch= 21/200, loss= 1129.696, mse= 1122.428, kld= 36.343
```

```
        val_loss= 1065.781, val_mse= 1058.985, val_kld= 33.979
Epoch= 31/200, loss= 1001.916, mse= 996.810, kld= 25.527
        val_loss= 1006.467, val_mse= 1001.305, val_kld= 25.809
Epoch= 41/200, loss= 791.160, mse= 785.361, kld= 28.995
        val_loss= 752.302, val_mse= 746.351, val_kld= 29.751
Epoch= 51/200, loss= 407.302, mse= 401.078, kld= 31.123
        val_loss= 378.340, val_mse= 372.099, val_kld= 31.207
Epoch= 61/200, loss= 277.994, mse= 272.483, kld= 27.557
        val_loss= 267.741, val_mse= 262.279, val_kld= 27.311
Epoch= 71/200, loss= 164.073, mse= 159.104, kld= 24.845
        val_loss= 144.851, val_mse= 139.818, val_kld= 25.165
Epoch= 81/200, loss= 69.784, mse= 64.926, kld= 24.292
        val_loss= 69.351, val_mse= 64.329, val_kld= 25.108
Epoch= 91/200, loss= 42.974, mse= 38.248, kld= 23.631
        val_loss= 44.168, val_mse= 39.423, val_kld= 23.723
Epoch= 101/200, loss= 36.204, mse= 31.942, kld= 21.310
        val_loss= 35.288, val_mse= 30.912, val_kld= 21.882
Epoch= 111/200, loss= 33.979, mse= 29.832, kld= 20.737
        val_loss= 34.520, val_mse= 30.261, val_kld= 21.294
Epoch= 121/200, loss= 31.563, mse= 27.613, kld= 19.749
        val_loss= 32.191, val_mse= 28.145, val_kld= 20.227
Epoch= 131/200, loss= 30.670, mse= 26.892, kld= 18.890
        val_loss= 31.900, val_mse= 28.021, val_kld= 19.395
Epoch= 141/200, loss= 29.904, mse= 26.133, kld= 18.855
        val_loss= 31.808, val_mse= 27.957, val_kld= 19.257
Epoch= 151/200, loss= 29.405, mse= 25.781, kld= 18.120
        val_loss= 30.633, val_mse= 26.949, val_kld= 18.420
Epoch= 161/200, loss= 28.401, mse= 24.829, kld= 17.862
        val_loss= 29.498, val_mse= 25.896, val_kld= 18.010
Epoch= 171/200, loss= 27.657, mse= 24.129, kld= 17.642
        val_loss= 28.655, val_mse= 25.115, val_kld= 17.699
Epoch= 181/200, loss= 26.929, mse= 23.515, kld= 17.070
        val_loss= 27.474, val_mse= 23.985, val_kld= 17.445
Epoch= 191/200, loss= 25.957, mse= 22.576, kld= 16.904
        val_loss= 26.087, val_mse= 22.509, val_kld= 17.889
```

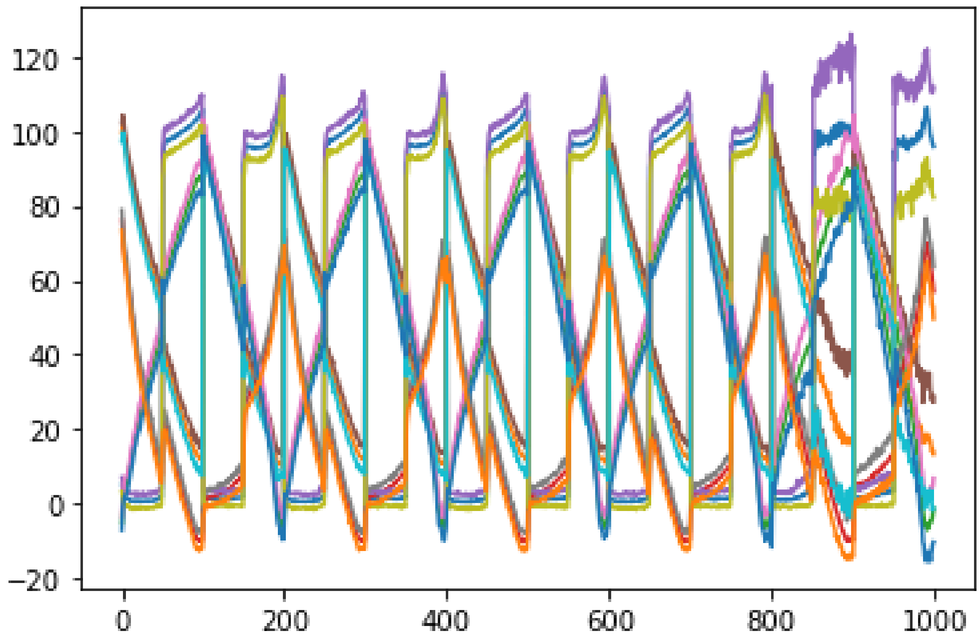
[79]:
```
pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

[79]: <AxesSubplot:xlabel='Epoch'>

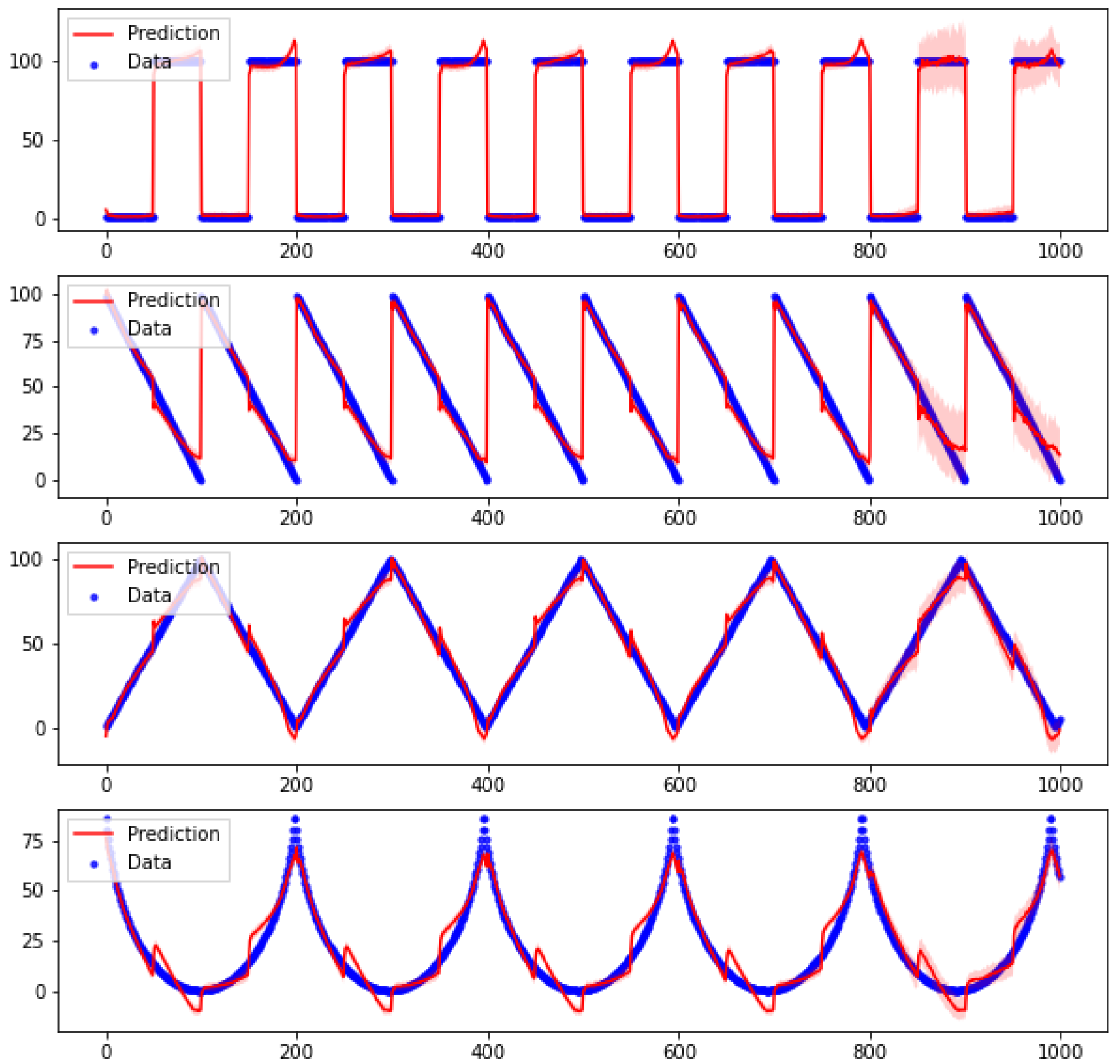


[80]:
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 200)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

[80]:
```
[<matplotlib.lines.Line2D at 0x7f1b7939c6a0>,
 <matplotlib.lines.Line2D at 0x7f1bcc120f10>,
 <matplotlib.lines.Line2D at 0x7f1bcc0d4430>,
 <matplotlib.lines.Line2D at 0x7f1bcc120850>]
```



[81]:
```
fig, ax = plt.subplots(4, figsize=(10, 10))

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
                     facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```



[82]:

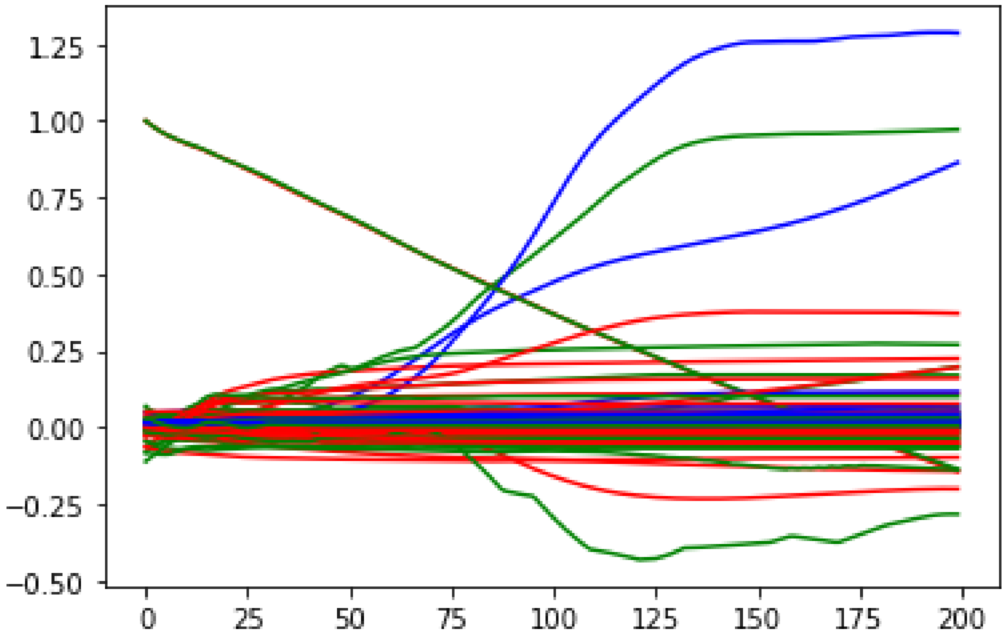
```
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

```python
# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
               MSE  R-squared       MAE
Average  32.974434   0.962559  3.374494
               MSE  R-squared       MAE
sample1  45.461315   0.981446  2.230901
sample2  31.859379   0.961765  3.216502
sample3  21.515621   0.974142  3.607184
sample4  33.061409   0.932885  4.443388
```

[83]:
```python
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'

    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],␣
↪label = stat, c = colour)
```

```
plt.show()
```



[ ]:
```
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```

[ ]:

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[ ]:

4 Przesuniecie i normalizacja danych

4.1 Trenowanie dla pierwszych 5 treningow po przesunieciu w plaszczyznie longitude x latitude

[106]:
```
#5 Workoutow, gdzie zbijamy longitude i latitude w przesuniecie



def translation(i):
```

```
    lon = np.asarray(data_endo[i]['longitude'])
    lat = np.asarray(data_endo[i]['latitude'])
    tra = np.sqrt(np.power(lon, 2) + np.power(lat,2))
    return tra

data = np.vstack( [translation(i) for i in range(5)]).T
#print(data.shape)
```

[107]:
```
x = torch.FloatTensor(data).reshape(1, *data.shape)
#print(x)
x_train = torch.FloatTensor(data[:400]).reshape(1, 400, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[400:450]).reshape(1, 50, data.shape[1])
#print(x_val)
```

[108]:
```
dkf = DKF(input_dim=5, z_dim=25, rnn_dim=25, trans_dim=25, emission_dim=25)
```

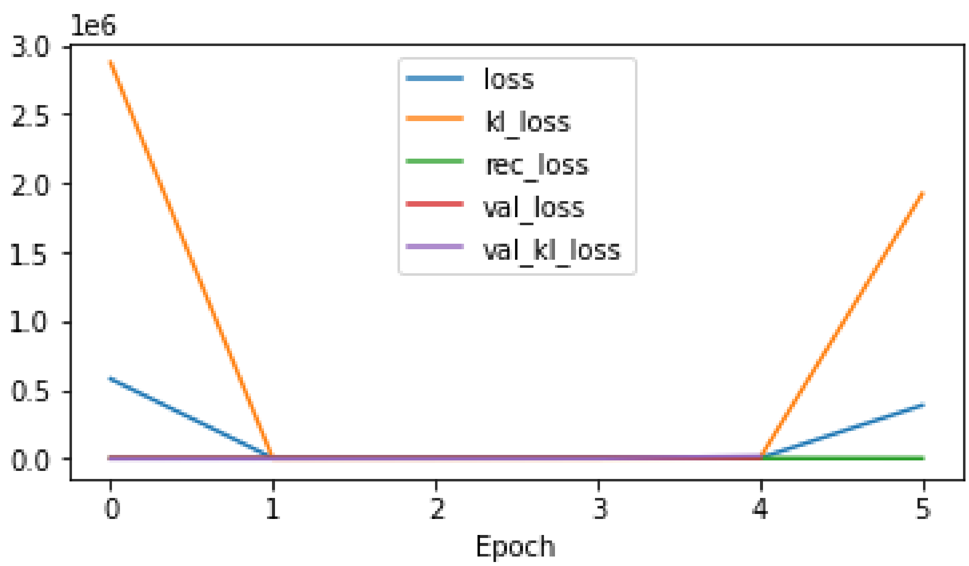
[109]:
```
history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
↪annealing_factor=0.2)
```

```
Epoch= 1/200, loss= 140797165568.000, mse= 4160.956, kld= 703985811456.000
        val_loss= 4271.971, val_mse= 4129.419, val_kld= 712.758
Epoch= 11/200, loss= 2776.105, mse= 2768.228, kld= 39.387
        val_loss= 2384.907, val_mse= 2376.591, val_kld= 41.581
Epoch= 21/200, loss= 962.078, mse= 954.502, kld= 37.880
        val_loss= 724.822, val_mse= 716.839, val_kld= 39.914
Epoch= 31/200, loss= 406.484, mse= 398.960, kld= 37.621
        val_loss= 384.169, val_mse= 375.953, val_kld= 41.080
Epoch= 41/200, loss= 219.039, mse= 212.142, kld= 34.486
        val_loss= 282.330, val_mse= 274.514, val_kld= 39.078
Epoch= 51/200, loss= 141.682, mse= 135.451, kld= 31.155
        val_loss= 113.614, val_mse= 106.862, val_kld= 33.761
Epoch= 61/200, loss= 74.510, mse= 68.847, kld= 28.317
        val_loss= 79.173, val_mse= 72.741, val_kld= 32.162
Epoch= 71/200, loss= 61.444, mse= 56.144, kld= 26.499
        val_loss= 59.801, val_mse= 53.687, val_kld= 30.570
Epoch= 81/200, loss= 46.203, mse= 41.145, kld= 25.288
        val_loss= 44.855, val_mse= 39.192, val_kld= 28.316
Epoch= 91/200, loss= 34.409, mse= 29.580, kld= 24.140
        val_loss= 38.490, val_mse= 32.932, val_kld= 27.791
Epoch= 101/200, loss= 27.530, mse= 22.832, kld= 23.487
        val_loss= 33.358, val_mse= 28.011, val_kld= 26.736
Epoch= 111/200, loss= 25.789, mse= 21.226, kld= 22.815
        val_loss= 25.253, val_mse= 19.853, val_kld= 26.996
Epoch= 121/200, loss= 20.004, mse= 15.585, kld= 22.094
        val_loss= 21.489, val_mse= 16.495, val_kld= 24.967
Epoch= 131/200, loss= 18.226, mse= 13.895, kld= 21.658
```

```
        val_loss= 19.201, val_mse= 14.283, val_kld= 24.588
Epoch= 141/200, loss= 18.597, mse= 14.261, kld= 21.679
        val_loss= 20.346, val_mse= 15.508, val_kld= 24.190
Epoch= 151/200, loss= 16.884, mse= 12.630, kld= 21.267
        val_loss= 21.443, val_mse= 16.456, val_kld= 24.932
Epoch= 161/200, loss= 15.364, mse= 11.279, kld= 20.427
        val_loss= 15.373, val_mse= 10.437, val_kld= 24.681
Epoch= 171/200, loss= 14.884, mse= 10.853, kld= 20.157
        val_loss= 17.531, val_mse= 12.840, val_kld= 23.453
Epoch= 181/200, loss= 13.758, mse= 9.801, kld= 19.783
        val_loss= 16.255, val_mse= 11.530, val_kld= 23.627
Epoch= 191/200, loss= 14.248, mse= 10.348, kld= 19.499
        val_loss= 11.850, val_mse= 7.322, val_kld= 22.642
```

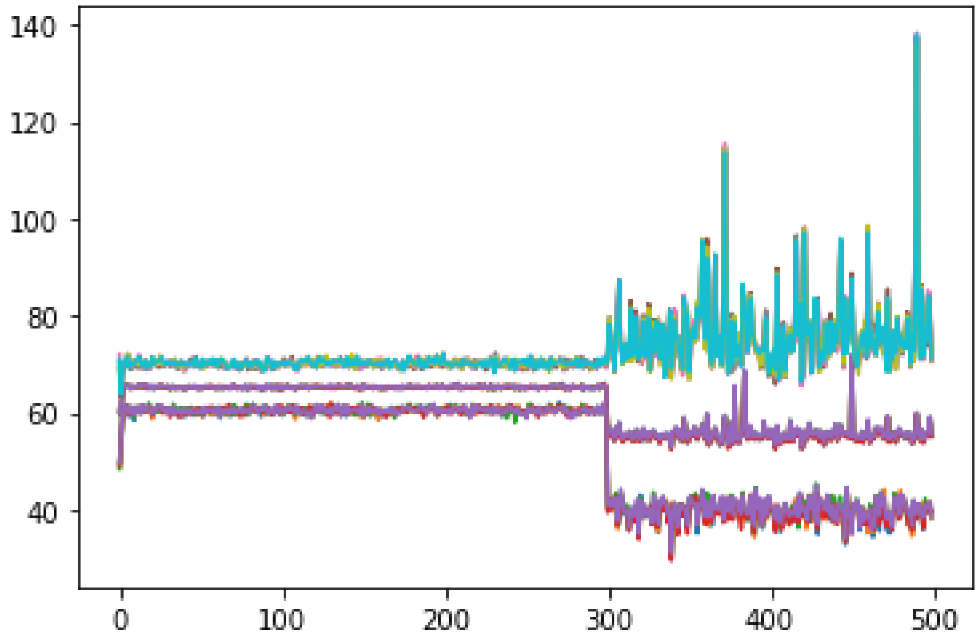
[88]:
```
pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

[88]: <AxesSubplot:xlabel='Epoch'>

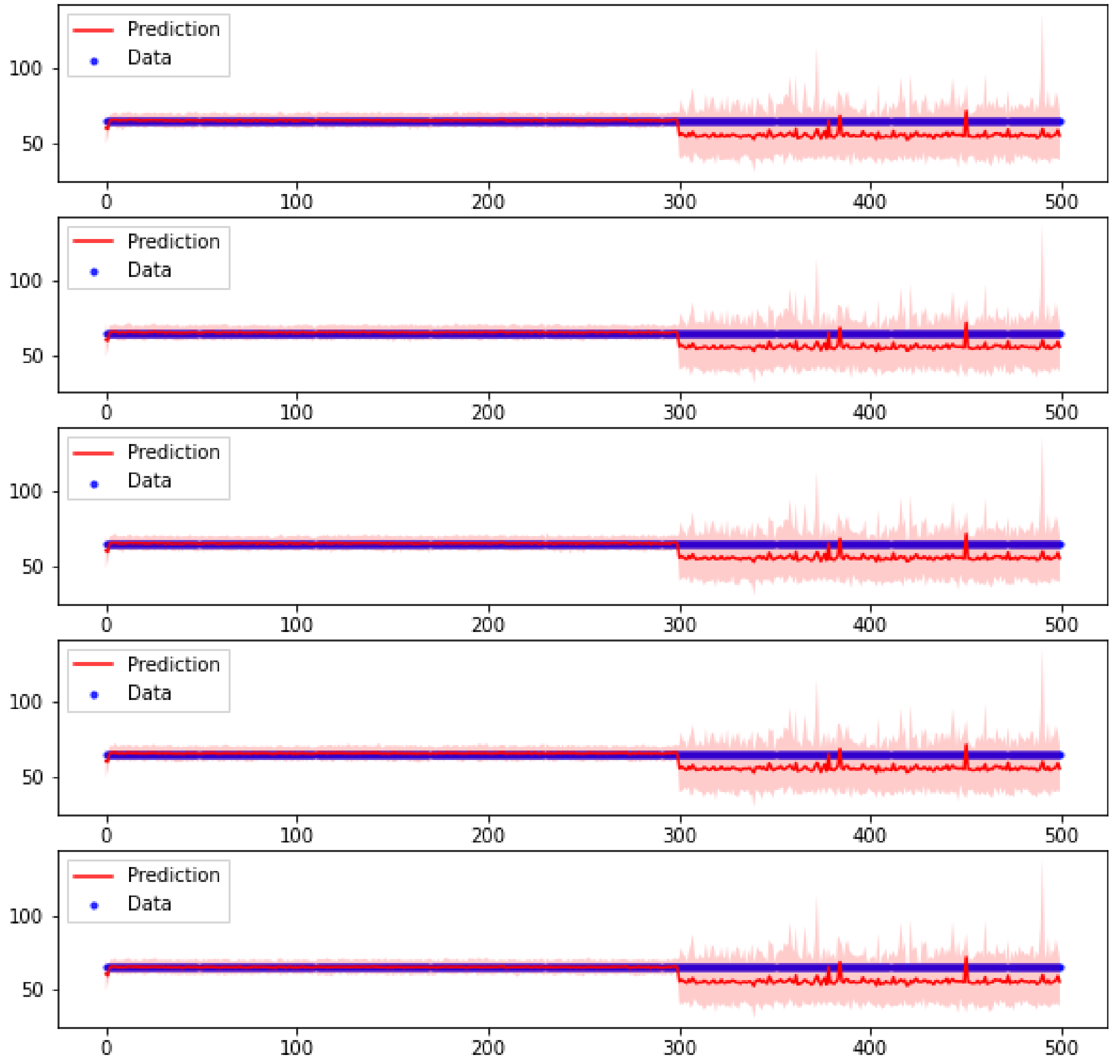


[110]:
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 200)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

[110]: [<matplotlib.lines.Line2D at 0x7f1bcc04d1c0>,
 <matplotlib.lines.Line2D at 0x7f1b7921f430>,
 <matplotlib.lines.Line2D at 0x7f1b7921fb20>,
 <matplotlib.lines.Line2D at 0x7f1b7921f4f0>,
 <matplotlib.lines.Line2D at 0x7f1b7921f850>]



[111]:
```
fig, ax = plt.subplots(5, figsize=(10, 10))

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
                     facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```



[112]:

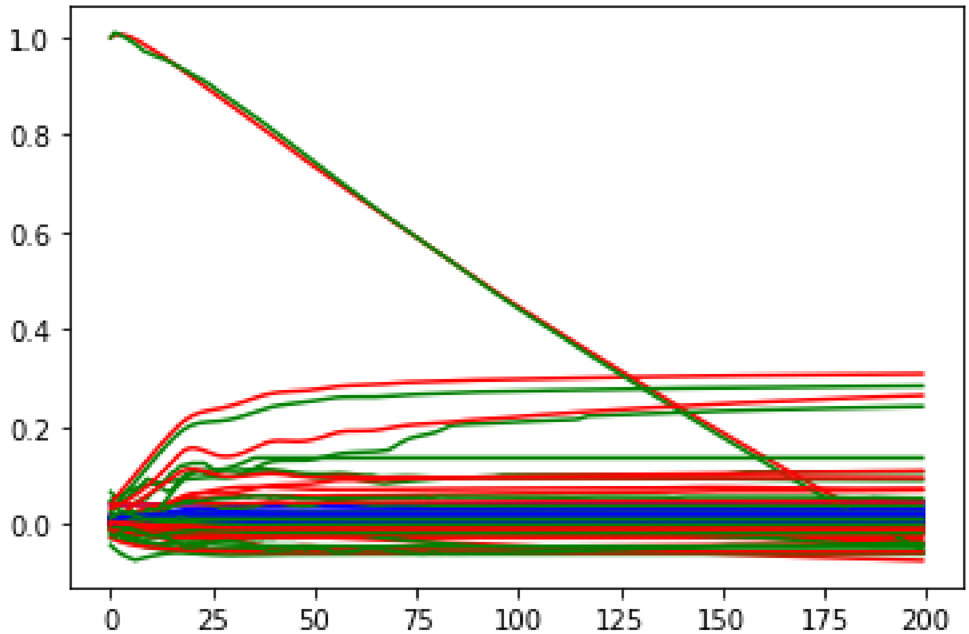
```
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

```
# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
               MSE     R-squared       MAE
Average  36.923252 -50194.284252  3.995948
               MSE     R-squared       MAE
sample1  38.253452 -31364.757568  4.044456
sample2  37.217949 -55978.252240  4.001642
sample3  35.177475 -26092.323091  3.924832
sample4  38.462711 -59397.750429  4.093288
sample5  35.504665 -78138.337931  3.915524
```

[113]:
```
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'

    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],␣
 ↪label = stat, c = colour)
```

```
plt.show()
```



[114]:
```
##########################################################################################
```

4.2 Trenowane dla znormalizowanych latitude i longitude

[115]:
```
#Normalizacja dla 2D - latitude i longitude



def NormalizeData(data):
    return 100*(data - np.min(data)) / (np.max(data) - np.min(data))

norm_long = NormalizeData(np.asarray(data_endo[0]['longitude']))
norm_lat  = NormalizeData(np.asarray(data_endo[0]['latitude']))
#norm_alt  = NormalizeData(np.asarray(data_endo[0]['altitude']))

data = np.vstack([norm_long, norm_lat]).T
#print(data.shape)
```

[116]:
```
x = torch.FloatTensor(data).reshape(1, *data.shape)
#print(x)
x_train = torch.FloatTensor(data[:400]).reshape(1, 400, data.shape[1])
```

```
#print(x_train)
x_val    = torch.FloatTensor(data[400:450]).reshape(1, 50, data.shape[1])
#print(x_val)
```

[117]:
```
dkf = DKF(input_dim=2, z_dim=10, rnn_dim=10, trans_dim=10, emission_dim=10)
```

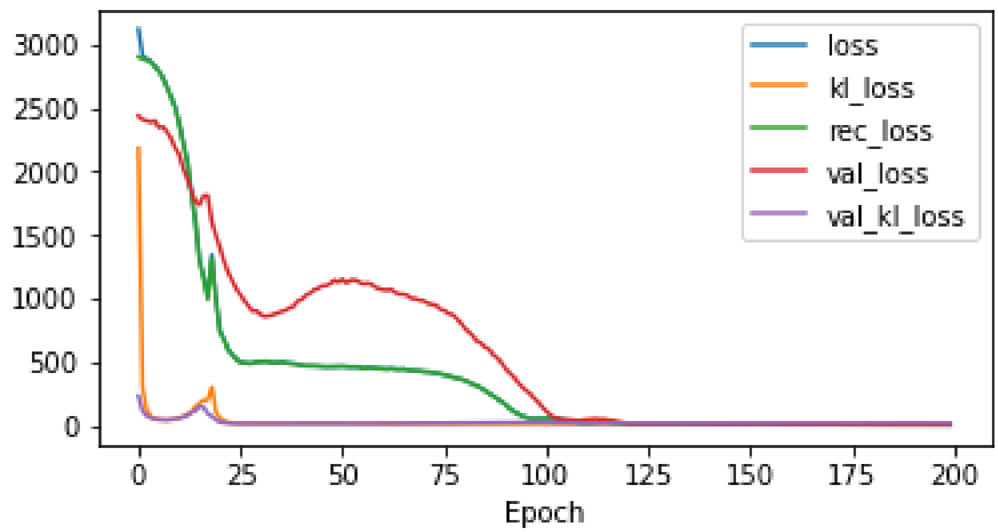
[118]:
```
history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
 ↪annealing_factor=0.1)
```

```
Epoch= 1/200, loss= 3118.313, mse= 2900.149, kld= 2181.634
        val_loss= 2433.552, val_mse= 2410.444, val_kld= 231.078
Epoch= 11/200, loss= 2375.828, mse= 2370.026, kld= 58.024
        val_loss= 2133.090, val_mse= 2127.643, val_kld= 54.472
Epoch= 21/200, loss= 741.790, mse= 736.640, kld= 51.499
        val_loss= 1397.663, val_mse= 1395.062, val_kld= 26.011
Epoch= 31/200, loss= 499.875, mse= 498.668, kld= 12.074
        val_loss= 870.232, val_mse= 868.908, val_kld= 13.237
Epoch= 41/200, loss= 471.822, mse= 470.358, kld= 14.644
        val_loss= 990.632, val_mse= 989.151, val_kld= 14.807
Epoch= 51/200, loss= 463.410, mse= 462.054, kld= 13.556
        val_loss= 1149.186, val_mse= 1147.773, val_kld= 14.126
Epoch= 61/200, loss= 444.632, mse= 443.428, kld= 12.042
        val_loss= 1066.610, val_mse= 1065.274, val_kld= 13.366
Epoch= 71/200, loss= 420.887, mse= 419.742, kld= 11.455
        val_loss= 979.144, val_mse= 977.626, val_kld= 15.172
Epoch= 81/200, loss= 353.634, mse= 352.455, kld= 11.789
        val_loss= 763.583, val_mse= 761.679, val_kld= 19.036
Epoch= 91/200, loss= 162.450, mse= 161.184, kld= 12.662
        val_loss= 445.200, val_mse= 442.775, val_kld= 24.251
Epoch= 101/200, loss= 53.118, mse= 51.837, kld= 12.812
        val_loss= 111.112, val_mse= 108.957, val_kld= 21.549
Epoch= 111/200, loss= 18.537, mse= 17.362, kld= 11.756
        val_loss= 44.310, val_mse= 42.645, val_kld= 16.647
Epoch= 121/200, loss= 13.688, mse= 12.537, kld= 11.513
        val_loss= 13.214, val_mse= 11.484, val_kld= 17.297
Epoch= 131/200, loss= 10.990, mse= 9.851, kld= 11.393
        val_loss= 12.633, val_mse= 10.927, val_kld= 17.057
Epoch= 141/200, loss= 8.296, mse= 7.171, kld= 11.249
        val_loss= 9.923, val_mse= 8.270, val_kld= 16.533
Epoch= 151/200, loss= 7.696, mse= 6.585, kld= 11.110
        val_loss= 8.518, val_mse= 6.879, val_kld= 16.395
Epoch= 161/200, loss= 6.245, mse= 5.132, kld= 11.137
        val_loss= 6.301, val_mse= 4.657, val_kld= 16.441
Epoch= 171/200, loss= 5.121, mse= 4.008, kld= 11.135
        val_loss= 6.247, val_mse= 4.616, val_kld= 16.315
Epoch= 181/200, loss= 4.705, mse= 3.590, kld= 11.157
        val_loss= 5.778, val_mse= 4.114, val_kld= 16.635
```

```
Epoch= 191/200, loss= 4.578, mse= 3.464, kld= 11.136
        val_loss= 5.322, val_mse= 3.632, val_kld= 16.904
```

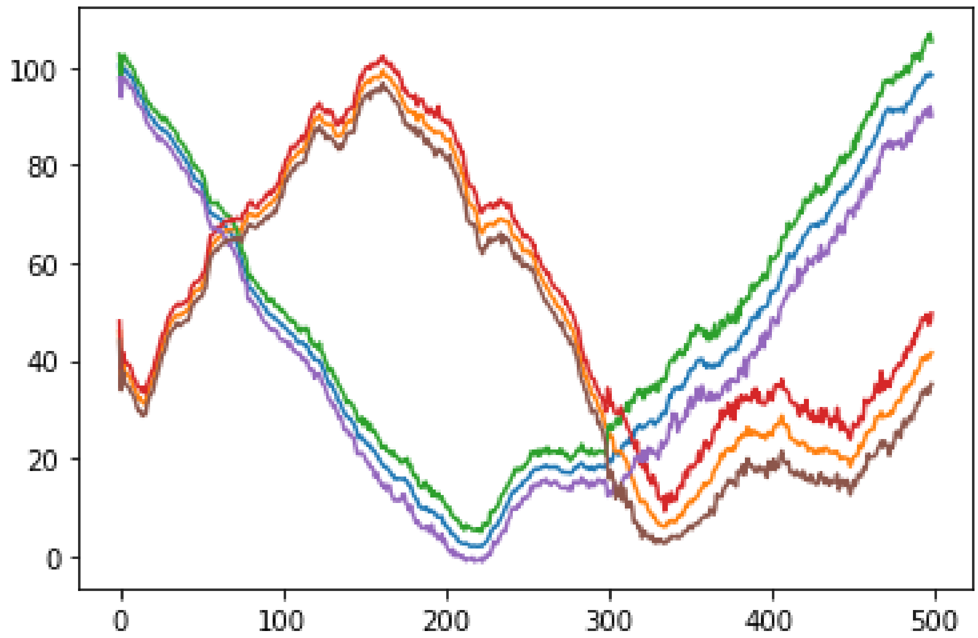
[119]:
```
pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

[119]:
```
<AxesSubplot:xlabel='Epoch'>
```

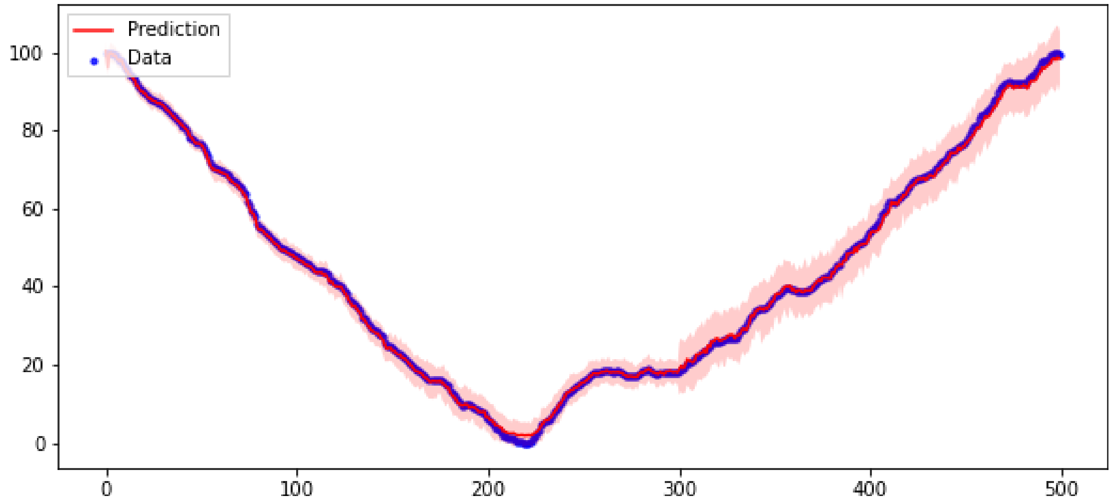


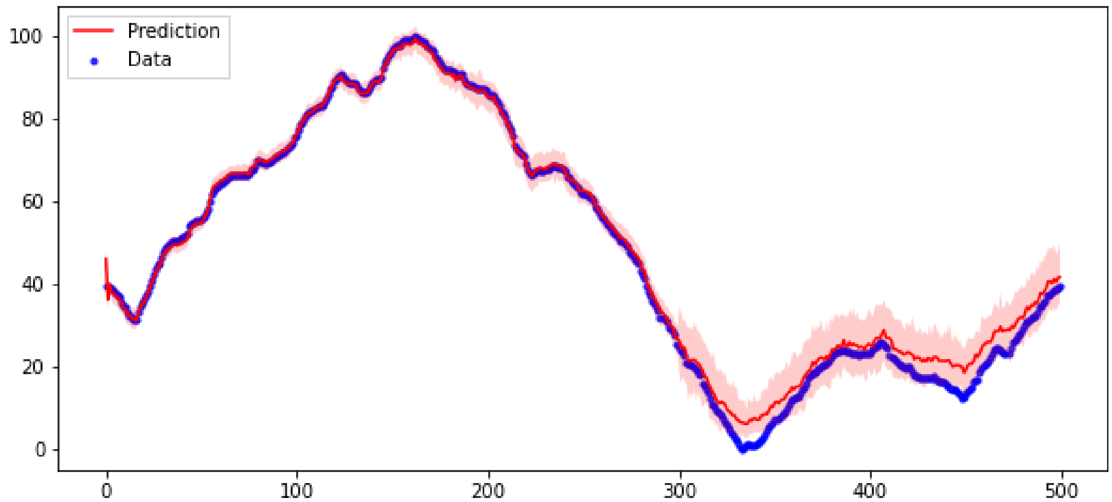
[120]:
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 200)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

[120]:
```
[<matplotlib.lines.Line2D at 0x7f1b7902ab80>,
 <matplotlib.lines.Line2D at 0x7f1b7902a070>]
```



[121]:
```
fig, ax = plt.subplots(2, figsize=(10, 10))

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
                     facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```





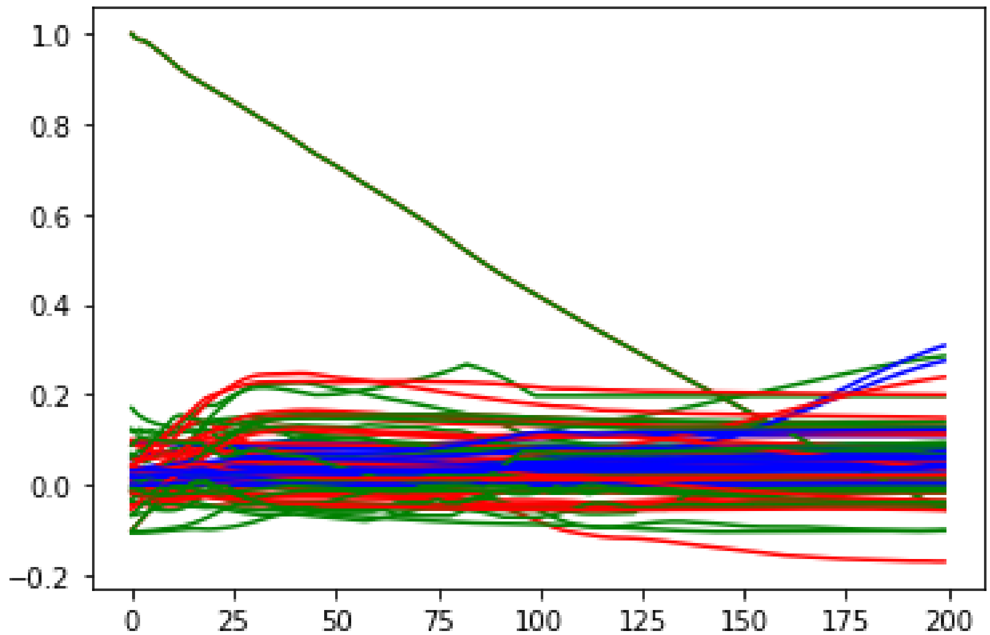
[122]:

```
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

```
# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
              MSE  R-squared      MAE
Average  3.458408   0.996028  1.16509
              MSE  R-squared       MAE
sample1  0.630599   0.999268  0.571248
sample2  6.286216   0.992789  1.758933
```

[123]:
```
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'

    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],␣
 ↪label = stat, c = colour)



plt.show()
```




```
[ ]: #Normalizacja dla 3D - latitude, longitude i altitude
```

4.3 Trenowanie dla znormalizowanych danych latitude, longitude, altitude

```
[124]: def NormalizeData(data):
           return 100*(data - np.min(data)) / (np.max(data) - np.min(data))

       norm_long = NormalizeData(np.asarray(data_endo[0]['longitude']))
       norm_lat  = NormalizeData(np.asarray(data_endo[0]['latitude']))
       norm_alt  = NormalizeData(np.asarray(data_endo[0]['altitude']))

       data = np.vstack([norm_long, norm_lat, norm_alt]).T
       #print(data.shape)
```

```
[125]: x = torch.FloatTensor(data).reshape(1, *data.shape)
       #print(x)
       x_train = torch.FloatTensor(data[:400]).reshape(1, 400, data.shape[1])
       #print(x_train)
       x_val   = torch.FloatTensor(data[400:450]).reshape(1, 50, data.shape[1])
       #print(x_val)
```

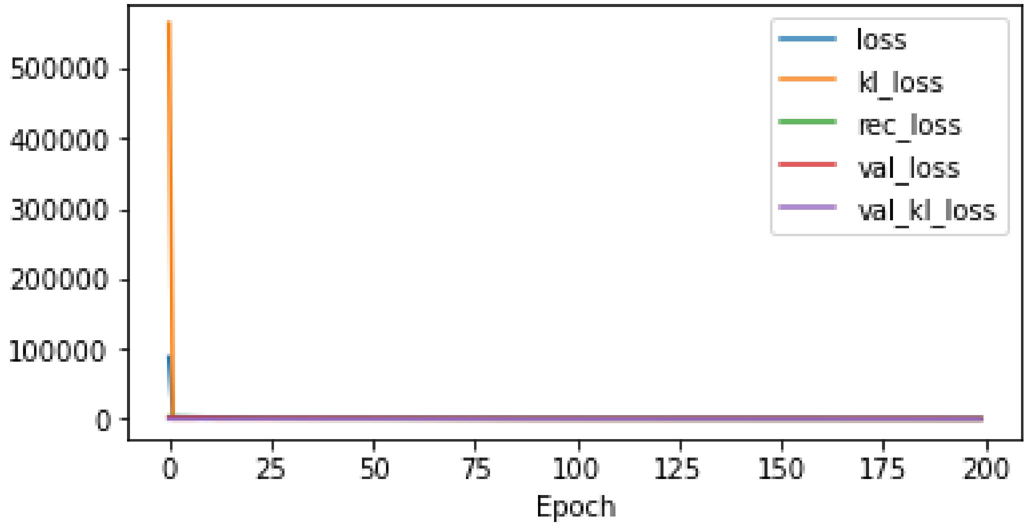
```
[126]: dkf = DKF(input_dim=3, z_dim=15, rnn_dim=15, trans_dim=15, emission_dim=15)
```

[127]:
```
history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
↪annealing_factor=0.15)
```

```
Epoch= 1/200, loss= 87677.336, mse= 3092.386, kld= 563899.688
        val_loss= 2041.264, val_mse= 2036.486, val_kld= 31.857
Epoch= 11/200, loss= 2368.847, mse= 2282.979, kld= 572.456
        val_loss= 1760.165, val_mse= 1755.875, val_kld= 28.599
Epoch= 21/200, loss= 759.383, mse= 741.362, kld= 120.144
        val_loss= 895.907, val_mse= 891.244, val_kld= 31.086
Epoch= 31/200, loss= 469.447, mse= 463.744, kld= 38.022
        val_loss= 845.622, val_mse= 841.735, val_kld= 25.917
Epoch= 41/200, loss= 424.478, mse= 419.286, kld= 34.615
        val_loss= 788.721, val_mse= 784.971, val_kld= 25.001
Epoch= 51/200, loss= 376.399, mse= 371.592, kld= 32.047
        val_loss= 750.642, val_mse= 747.125, val_kld= 23.442
Epoch= 61/200, loss= 273.757, mse= 269.003, kld= 31.690
        val_loss= 536.563, val_mse= 532.775, val_kld= 25.249
Epoch= 71/200, loss= 124.908, mse= 119.888, kld= 33.467
        val_loss= 210.081, val_mse= 205.379, val_kld= 31.349
Epoch= 81/200, loss= 104.887, mse= 100.054, kld= 32.221
        val_loss= 109.089, val_mse= 104.316, val_kld= 31.818
Epoch= 91/200, loss= 93.291, mse= 88.861, kld= 29.530
        val_loss= 105.256, val_mse= 101.150, val_kld= 27.371
Epoch= 101/200, loss= 88.247, mse= 84.103, kld= 27.627
        val_loss= 103.267, val_mse= 99.148, val_kld= 27.457
Epoch= 111/200, loss= 84.083, mse= 80.163, kld= 26.135
        val_loss= 95.637, val_mse= 91.655, val_kld= 26.546
Epoch= 121/200, loss= 80.991, mse= 77.311, kld= 24.530
        val_loss= 96.148, val_mse= 92.245, val_kld= 26.022
Epoch= 131/200, loss= 79.793, mse= 76.194, kld= 23.991
        val_loss= 108.639, val_mse= 104.646, val_kld= 26.617
Epoch= 141/200, loss= 75.538, mse= 71.947, kld= 23.938
        val_loss= 104.707, val_mse= 100.748, val_kld= 26.394
Epoch= 151/200, loss= 68.881, mse= 65.295, kld= 23.906
        val_loss= 102.606, val_mse= 98.588, val_kld= 26.788
Epoch= 161/200, loss= 56.770, mse= 53.063, kld= 24.715
        val_loss= 86.973, val_mse= 82.936, val_kld= 26.910
Epoch= 171/200, loss= 34.503, mse= 30.684, kld= 25.461
        val_loss= 44.290, val_mse= 40.312, val_kld= 26.524
Epoch= 181/200, loss= 16.781, mse= 12.822, kld= 26.395
        val_loss= 25.793, val_mse= 21.930, val_kld= 25.758
Epoch= 191/200, loss= 19.009, mse= 15.307, kld= 24.682
        val_loss= 20.759, val_mse= 17.197, val_kld= 23.744
```

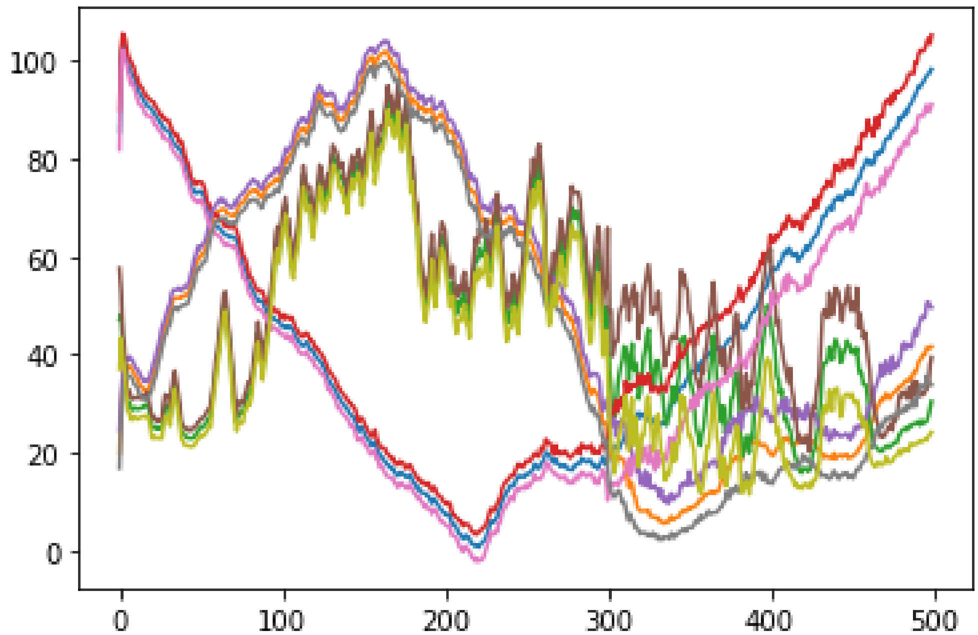
[128]:
```
pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

[128]: <AxesSubplot:xlabel='Epoch'>

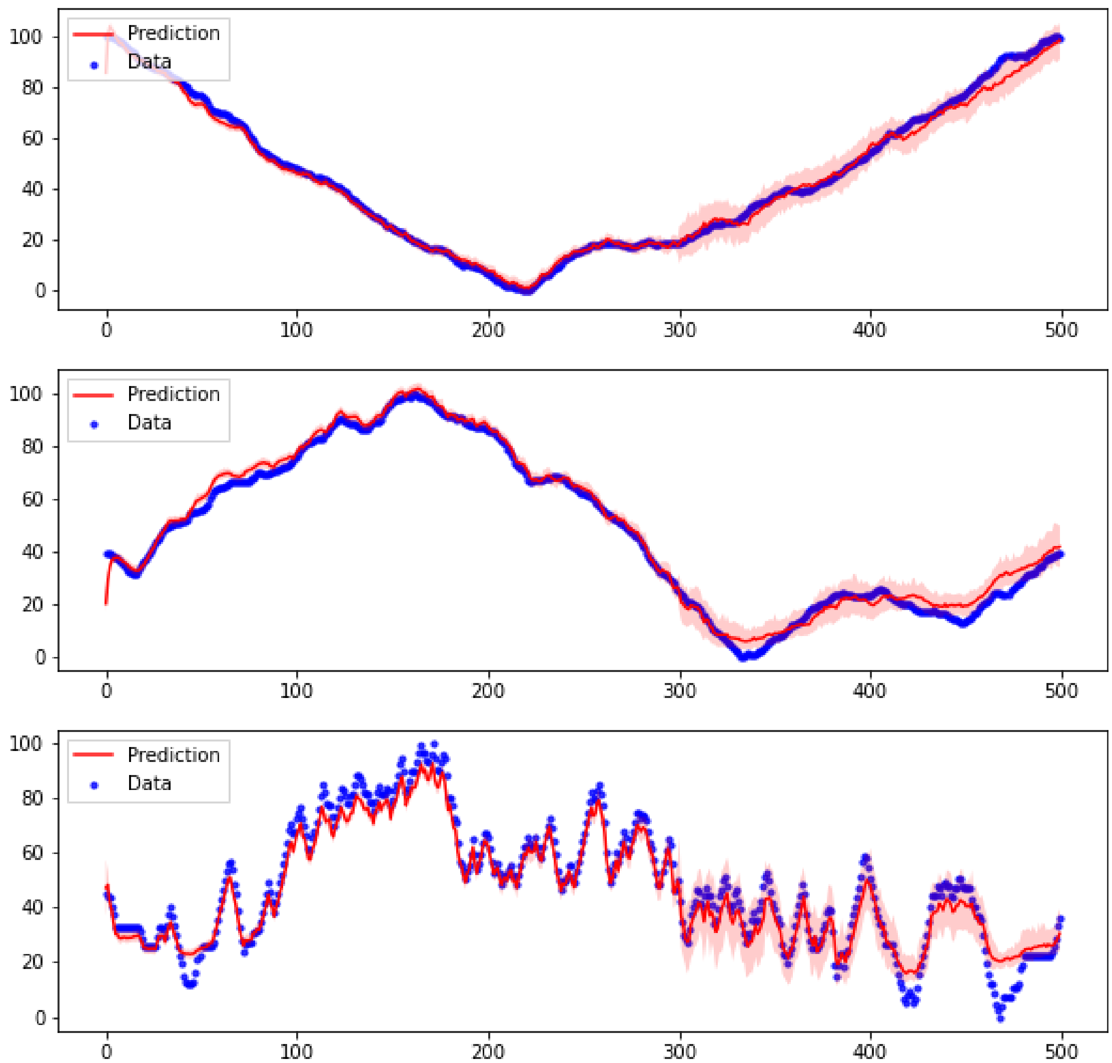


[129]:
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 200)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

[129]:
```
[<matplotlib.lines.Line2D at 0x7f1bcc084760>,
 <matplotlib.lines.Line2D at 0x7f1bcc084ca0>,
 <matplotlib.lines.Line2D at 0x7f1bcc084790>]
```



[130]:
```
fig, ax = plt.subplots(3, figsize=(10, 10))

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
                     facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```



[131]:
```
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

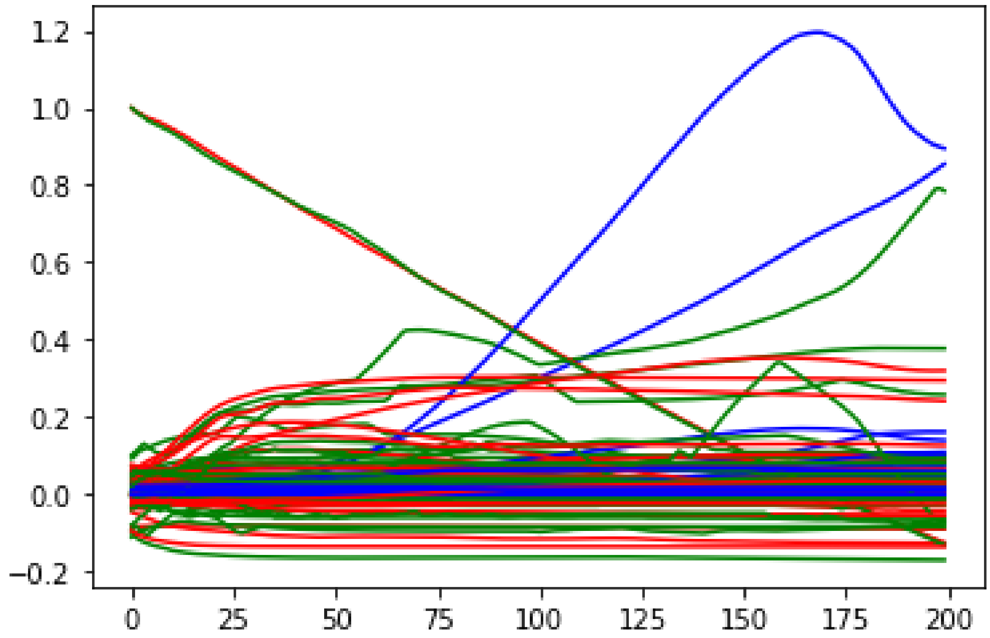
```
# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
               MSE  R-squared      MAE
Average  14.512703   0.975705  2.82244
               MSE  R-squared       MAE
sample1   6.263494   0.992725  1.794515
sample2   9.025548   0.989646  2.357442
sample3  28.249067   0.944744  4.315363
```

[132]:

```
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'

    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],␣
↪label = stat, c = colour)
```

```
plt.show()
```



[ ]:
```
################################################################################
```

[ ]:

[ ]:

[ ]:

[ ]:
```
#5 Workoutow ze znormalizowanym altitude
```

4.4 5 treningow z znormalizowanym altitude

[34]:
```
def NormalizeData(data):
    return 100*(data - np.min(data)) / (np.max(data) - np.min(data))


data = np.vstack([NormalizeData(np.asarray(data_endo[i]['altitude'])) for i in␣
 ↪range(5)]).T
print(data.shape)

print(data)
```

```
(500, 5)
[[45.30201342 41.8972332  70.95709571 31.39534884 79.28571429]
 [43.62416107 43.08300395 65.67656766 32.94573643 79.28571429]
 [43.62416107 43.08300395 64.35643564 32.94573643 79.28571429]
 …
 [28.8590604  33.59683794 27.72277228 33.72093023 16.42857143]
 [33.22147651 35.17786561 32.01320132 35.65891473 18.57142857]
 [36.24161074 35.17786561 32.01320132 39.53488372 15.71428571]]
```

[175]:
```python
x = torch.FloatTensor(data).reshape(1, *data.shape)
#print(x)
x_train = torch.FloatTensor(data[:400]).reshape(1, 400, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[400:450]).reshape(1, 50, data.shape[1])
#print(x_val)
```

[176]:
```python
dkf = DKF(input_dim=5, z_dim=25, rnn_dim=25, trans_dim=25, emission_dim=25)
```

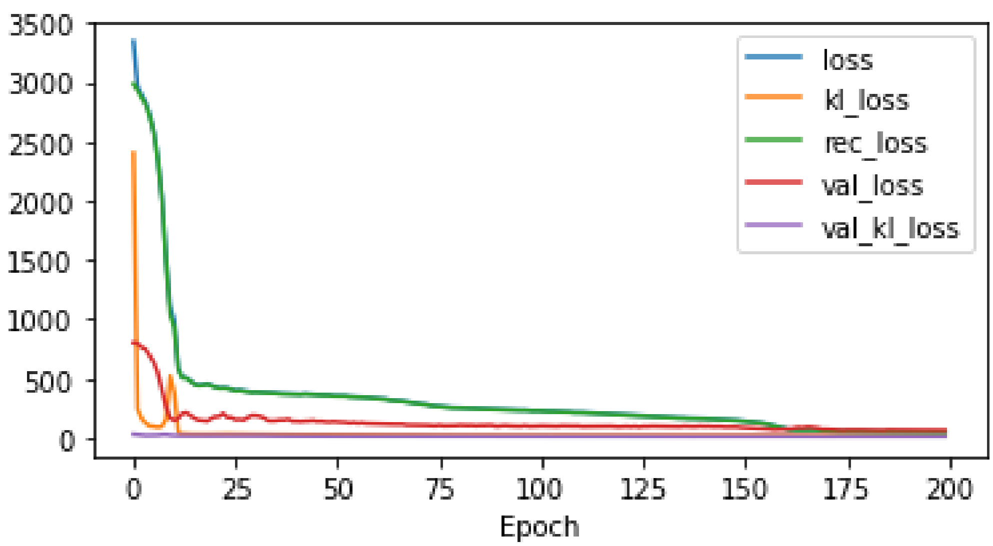
[177]:
```python
history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
↪annealing_factor=0.15)
```

```
Epoch= 1/200, loss= 3347.626, mse= 2986.764, kld= 2405.749
        val_loss= 801.293, val_mse= 796.716, val_kld= 30.512
Epoch= 11/200, loss= 991.998, mse= 934.937, kld= 380.408
        val_loss= 147.990, val_mse= 145.149, val_kld= 18.936
Epoch= 21/200, loss= 431.285, mse= 426.682, kld= 30.683
        val_loss= 177.697, val_mse= 174.658, val_kld= 20.256
Epoch= 31/200, loss= 386.801, mse= 382.360, kld= 29.608
        val_loss= 187.265, val_mse= 184.507, val_kld= 18.381
Epoch= 41/200, loss= 368.403, mse= 364.418, kld= 26.561
        val_loss= 140.761, val_mse= 138.468, val_kld= 15.286
Epoch= 51/200, loss= 354.228, mse= 350.664, kld= 23.764
        val_loss= 133.770, val_mse= 131.646, val_kld= 14.161
Epoch= 61/200, loss= 329.328, mse= 326.084, kld= 21.628
        val_loss= 119.308, val_mse= 117.353, val_kld= 13.033
Epoch= 71/200, loss= 288.281, mse= 285.122, kld= 21.059
        val_loss= 109.773, val_mse= 107.890, val_kld= 12.548
Epoch= 81/200, loss= 252.804, mse= 249.694, kld= 20.732
        val_loss= 107.644, val_mse= 105.698, val_kld= 12.978
Epoch= 91/200, loss= 239.290, mse= 236.256, kld= 20.228
        val_loss= 100.788, val_mse= 98.858, val_kld= 12.871
Epoch= 101/200, loss= 226.883, mse= 224.000, kld= 19.219
        val_loss= 101.471, val_mse= 99.653, val_kld= 12.120
Epoch= 111/200, loss= 213.632, mse= 210.699, kld= 19.550
        val_loss= 96.192, val_mse= 94.356, val_kld= 12.237
Epoch= 121/200, loss= 194.891, mse= 191.967, kld= 19.492
        val_loss= 95.960, val_mse= 94.106, val_kld= 12.361
Epoch= 131/200, loss= 174.983, mse= 172.091, kld= 19.278
```

```
        val_loss= 97.648, val_mse= 95.834, val_kld= 12.092
Epoch= 141/200, loss= 162.954, mse= 160.117, kld= 18.913
        val_loss= 96.841, val_mse= 95.036, val_kld= 12.034
Epoch= 151/200, loss= 140.628, mse= 137.720, kld= 19.385
        val_loss= 85.566, val_mse= 83.776, val_kld= 11.934
Epoch= 161/200, loss= 76.839, mse= 73.927, kld= 19.416
        val_loss= 73.940, val_mse= 72.064, val_kld= 12.501
Epoch= 171/200, loss= 60.262, mse= 57.386, kld= 19.174
        val_loss= 74.254, val_mse= 72.469, val_kld= 11.895
Epoch= 181/200, loss= 55.070, mse= 52.124, kld= 19.636
        val_loss= 65.750, val_mse= 63.886, val_kld= 12.422
Epoch= 191/200, loss= 51.462, mse= 48.657, kld= 18.701
        val_loss= 66.485, val_mse= 64.613, val_kld= 12.485
```

[178]:
```
pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

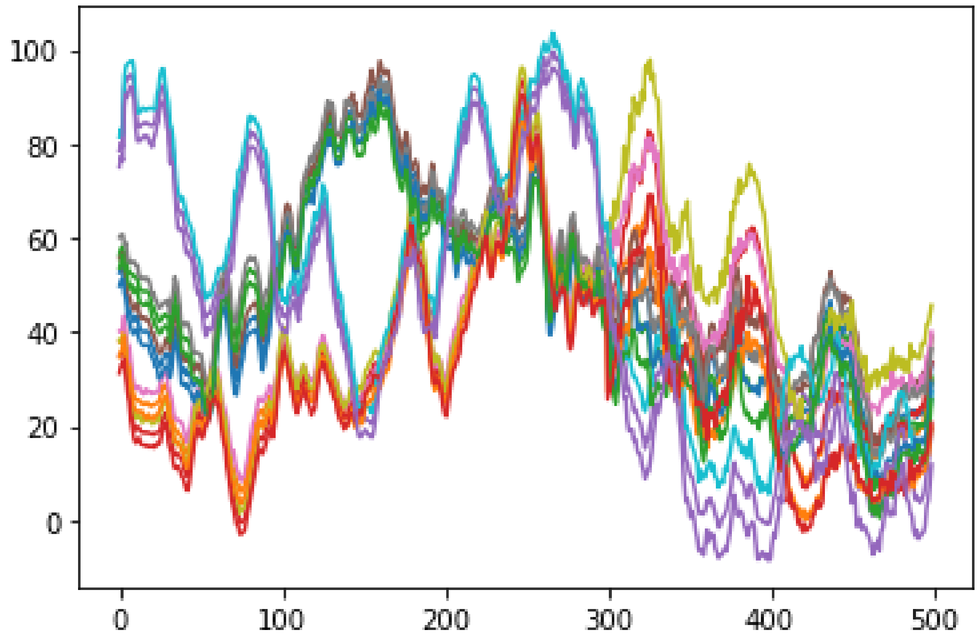
[178]: <AxesSubplot:xlabel='Epoch'>



[179]:
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 200)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

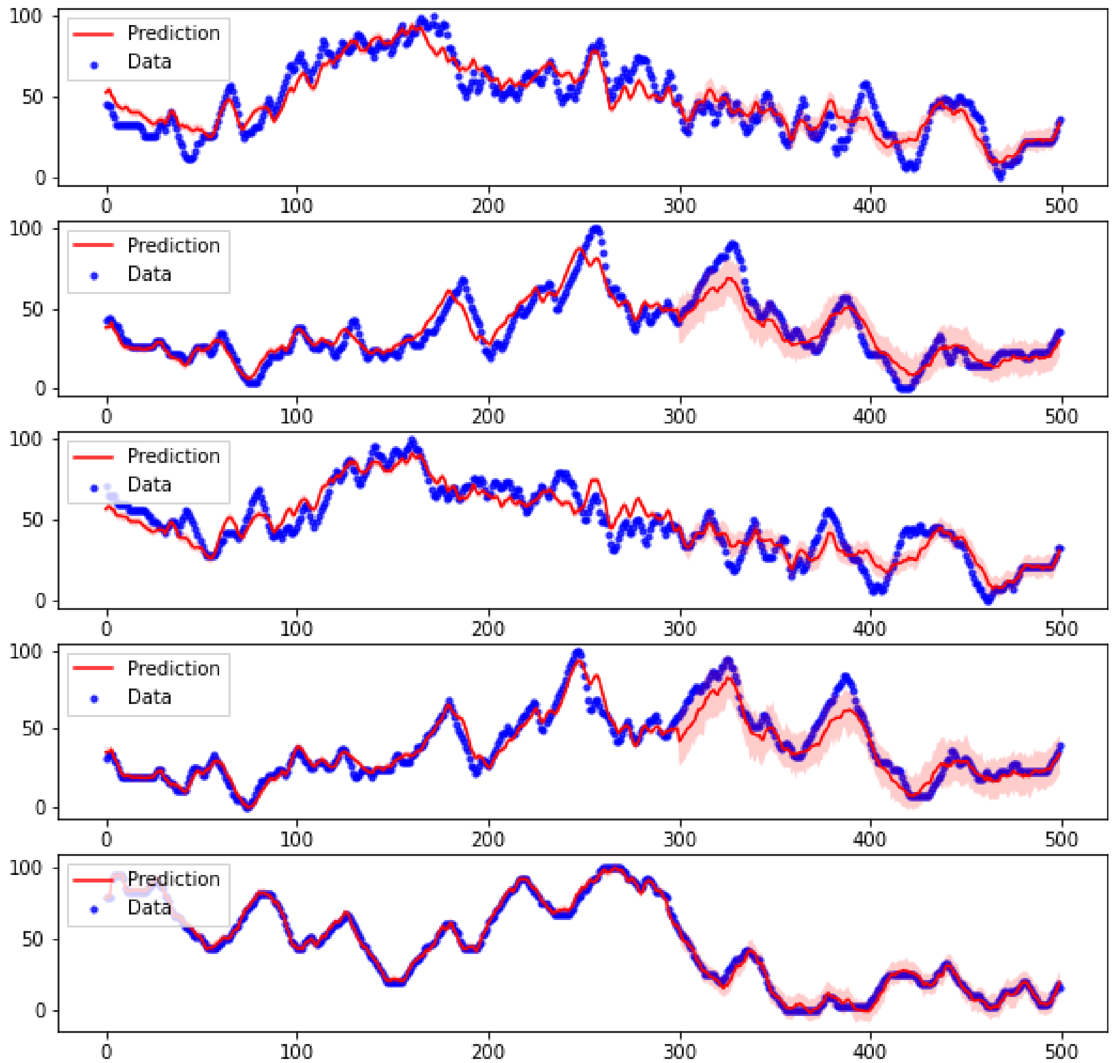
[179]:

```
[<matplotlib.lines.Line2D at 0x7f1b792b3e50>,
 <matplotlib.lines.Line2D at 0x7f1b793619d0>,
 <matplotlib.lines.Line2D at 0x7f1b79361310>,
 <matplotlib.lines.Line2D at 0x7f1b79361790>,
 <matplotlib.lines.Line2D at 0x7f1b793612e0>]
```



[180]:

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

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
                     facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```



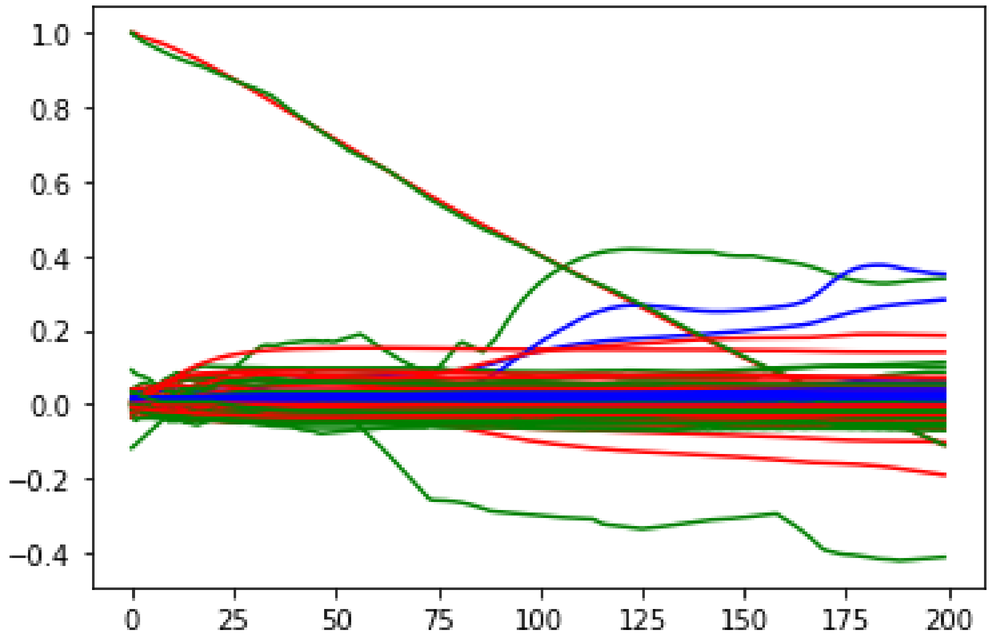
[181]:
```
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

```
# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
              MSE  R-squared       MAE
Average  52.47303   0.890493  5.317832
               MSE  R-squared       MAE
sample1  79.457825   0.844578  7.286608
sample2  55.667458   0.867615  5.790020
sample3  74.255318   0.843911  6.940994
sample4  48.043316   0.901872  4.946120
sample5   4.941264   0.994488  1.625420
```

[182]:
```
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'

    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],␣
 ↪label = stat, c = colour)
```

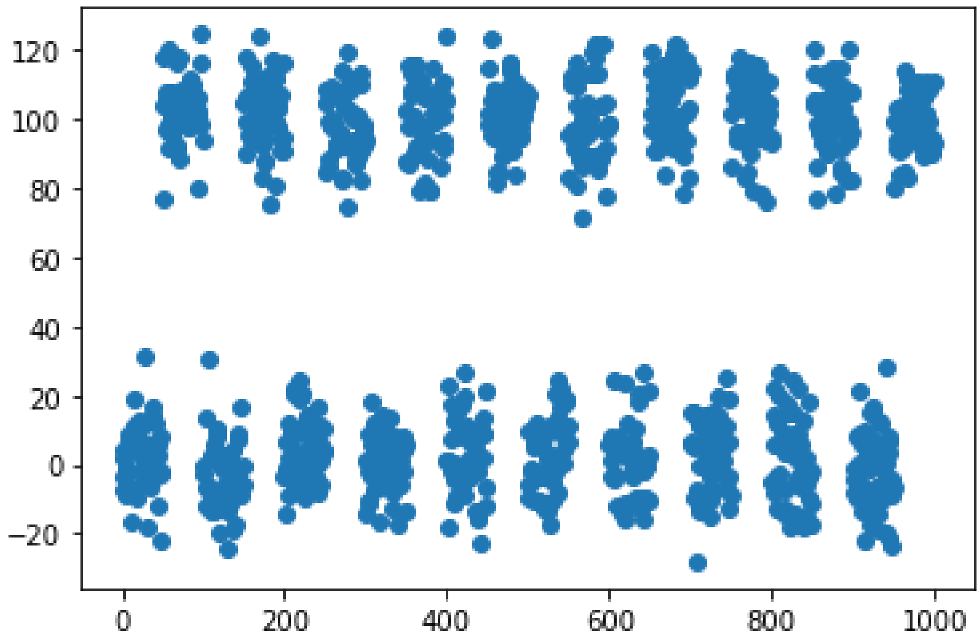
```
plt.show()
```

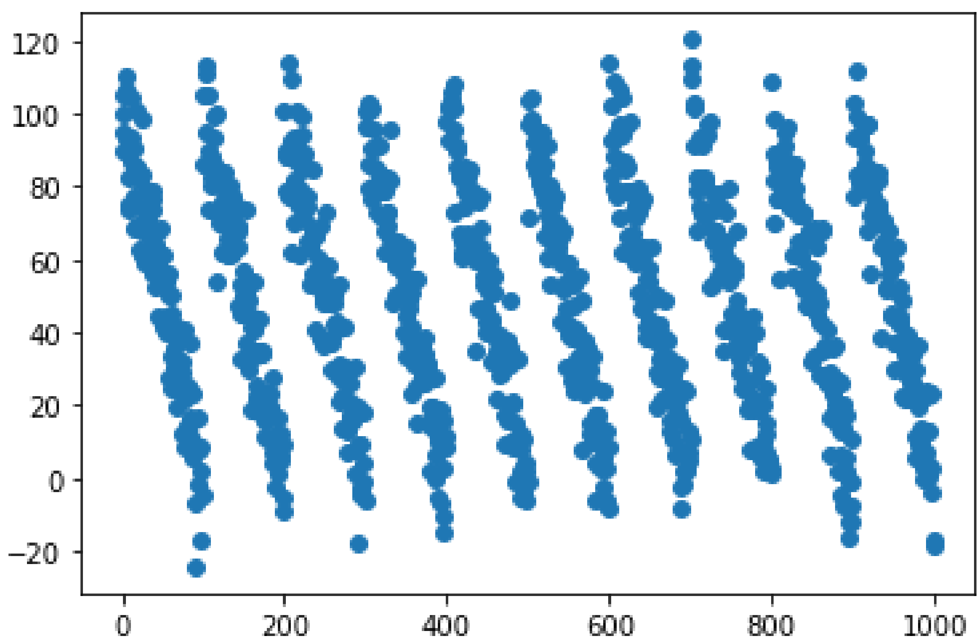


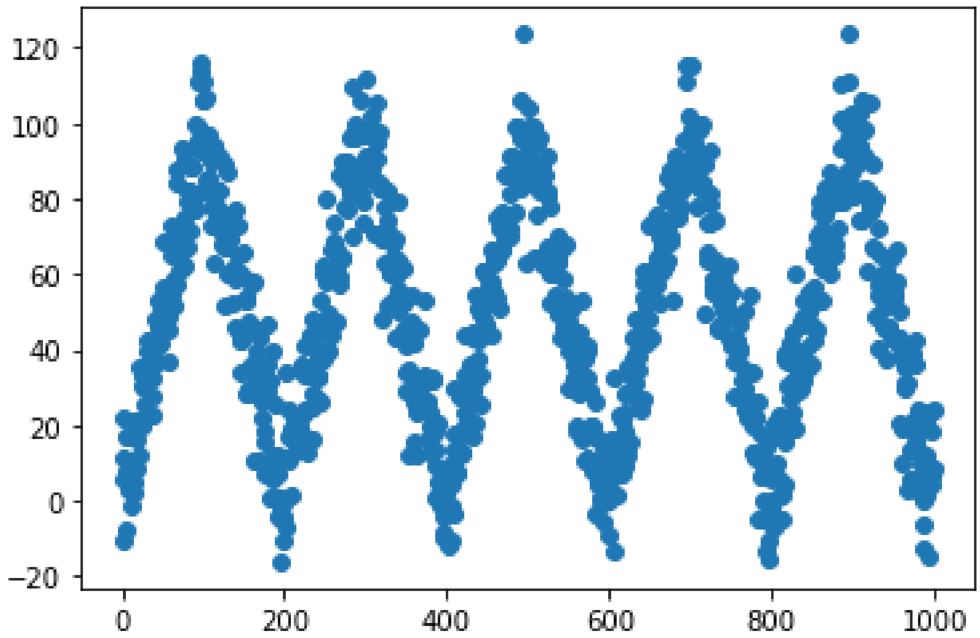
4.5 Syntetyczne zaszumione

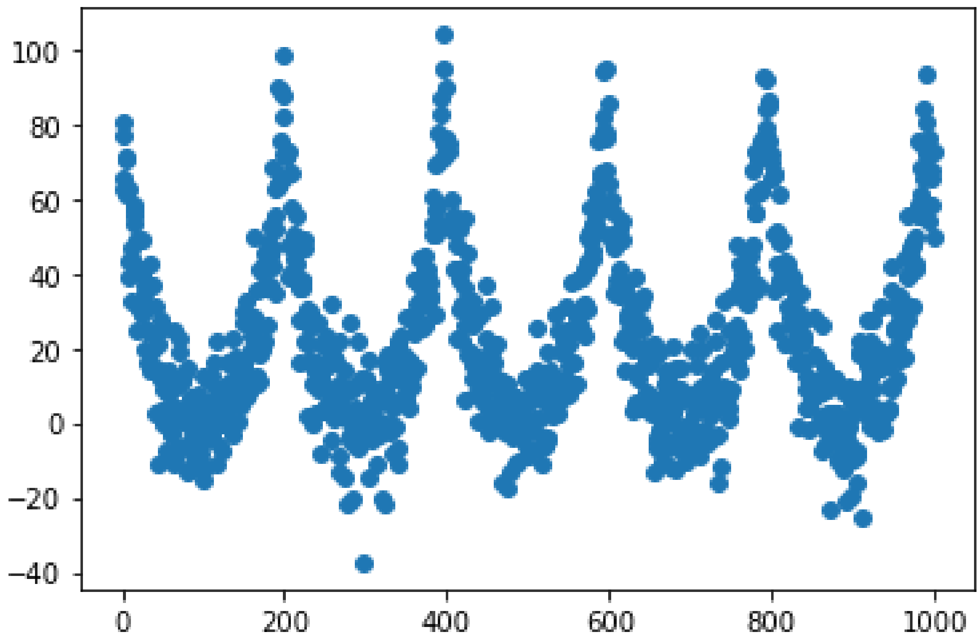
[184]:
```
#Dataset 1 - binary a bunch of 1's then a bunch of 100's
data_bin = []
while len(data_bin)<1000:
    data_bin.extend([1 for i in range(50)])
    data_bin.extend([100 for i in range(50)])
data_bin = np.asarray(data_bin[:1000])
data_bin =  data_bin + np.random.normal(0, 10, size = data_bin.shape)
#print(data_bin)
plt.scatter(range(len(data_bin)),data_bin)
plt.show()



#Dataset 2 - Decreasing from 100 to 1 in a loop
data_spike = []
while len(data_spike)<1000:
    data_spike.extend([-i + 100 for i in range(1, 101)])
```

```
data_spike = np.asarray(data_spike[:1000])
data_spike = data_spike + np.random.normal(0,10, size = data_spike.shape)
#print(data_spike)
plt.scatter(range(len(data_spike)), data_spike)
plt.show()

#Dataset 3 - Growing from 1 to 100 then from 100 to 1

data_alt = []
while len(data_alt)<1000:
    data_alt.extend([i for i in range(1,100)])
    data_alt.extend([i for i in range(100,0,-1)])

data_alt = np.asarray(data_alt[:1000])
data_alt = data_alt + np.random.normal(0, 10, size = data_alt.shape)
#print(data_alt)
plt.scatter(range(len(data_alt)), data_alt)
plt.show()

#Dataset 4 - Lower half of a circle
data_circle = []
while len(data_circle)<1000:
    data_circle.extend([-np.sqrt(100 ** 2 - i ** 2) + 100 for i in␣
 ↪range(99,0,-1)])
    data_circle.extend([-np.sqrt(100 ** 2 - i ** 2) + 100 for i in␣
 ↪range(1,100)])

data_circle = np.asarray(data_circle[:1000])
data_circle = data_circle + np.random.normal(0, 10, size = data_circle.shape)
#print(data_circle)
#print(len(data_circle))
plt.scatter(range(len(data_circle)), data_circle)
plt.show()

data = np.vstack([data_bin, data_spike, data_alt, data_circle]).T
#print(data.shape)

x = torch.FloatTensor(data).reshape(1, *data.shape)
#print(x)
x_train = torch.FloatTensor(data[:600]).reshape(1, 600, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[600:800]).reshape(1, 200, data.shape[1])
#print(x_val)
```


120
100
80
60
40
20
0
−20
0
200
400
600
800
1000


120
100
80
60
40
20
0
−20
0
200
400
600
800
1000



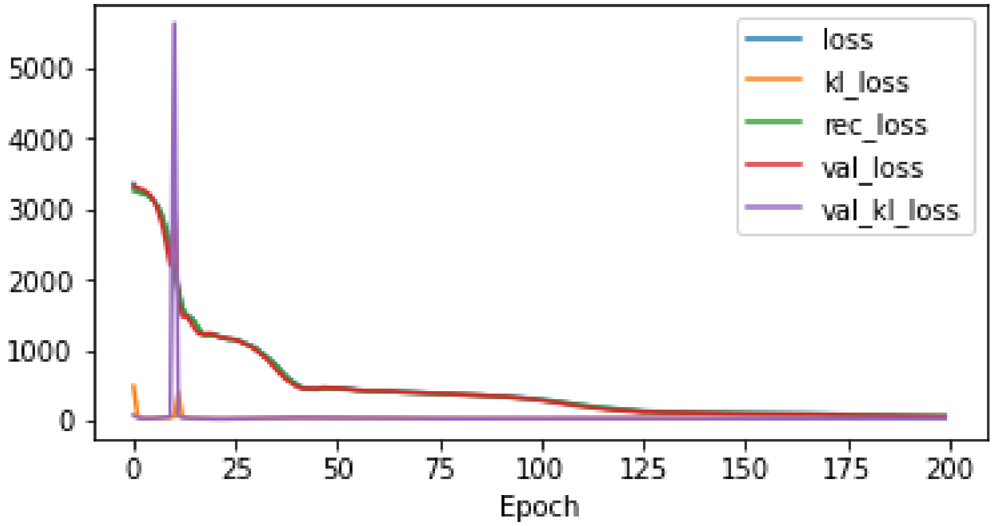


[185]:
```
## Trenowanie dla danych syntetycznych

dkf = DKF(input_dim=4, z_dim=20, rnn_dim=20, trans_dim=20, emission_dim=20)
```

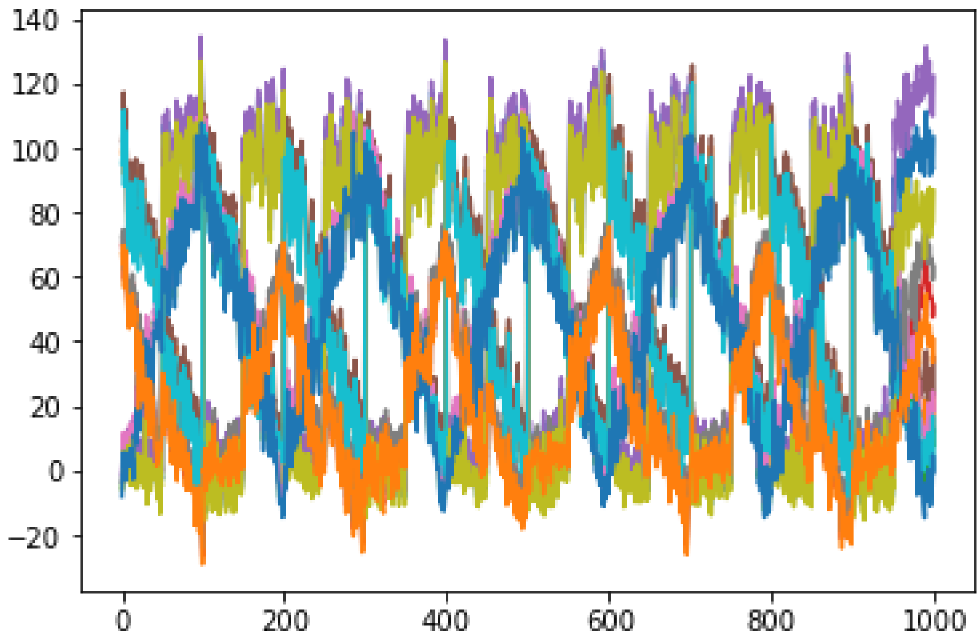
```
history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
↪annealing_factor=0.2)

pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

```
Epoch= 1/200, loss= 3358.918, mse= 3261.203, kld= 488.577
        val_loss= 3324.580, val_mse= 3309.372, val_kld= 76.041
Epoch= 11/200, loss= 2128.861, mse= 2118.391, kld= 52.348
        val_loss= 3049.993, val_mse= 1922.624, val_kld= 5636.846
Epoch= 21/200, loss= 1212.808, mse= 1208.558, kld= 21.250
        val_loss= 1205.182, val_mse= 1200.690, val_kld= 22.462
Epoch= 31/200, loss= 1027.736, mse= 1022.277, kld= 27.296
        val_loss= 990.144, val_mse= 984.481, val_kld= 28.313
Epoch= 41/200, loss= 515.483, mse= 507.947, kld= 37.679
        val_loss= 481.153, val_mse= 473.476, val_kld= 38.383
Epoch= 51/200, loss= 455.142, mse= 449.009, kld= 30.667
        val_loss= 459.377, val_mse= 453.078, val_kld= 31.494
Epoch= 61/200, loss= 414.783, mse= 409.226, kld= 27.784
        val_loss= 413.904, val_mse= 408.089, val_kld= 29.076
Epoch= 71/200, loss= 392.678, mse= 387.493, kld= 25.924
        val_loss= 394.038, val_mse= 388.589, val_kld= 27.243
Epoch= 81/200, loss= 369.300, mse= 364.314, kld= 24.930
        val_loss= 370.474, val_mse= 365.223, val_kld= 26.254
Epoch= 91/200, loss= 340.868, mse= 335.908, kld= 24.801
        val_loss= 337.425, val_mse= 332.184, val_kld= 26.205
Epoch= 101/200, loss= 297.828, mse= 292.763, kld= 25.323
        val_loss= 284.981, val_mse= 279.612, val_kld= 26.845
Epoch= 111/200, loss= 218.203, mse= 212.989, kld= 26.069
        val_loss= 194.044, val_mse= 188.451, val_kld= 27.967
Epoch= 121/200, loss= 153.277, mse= 147.871, kld= 27.027
        val_loss= 135.480, val_mse= 129.628, val_kld= 29.261
Epoch= 131/200, loss= 118.893, mse= 113.247, kld= 28.231
        val_loss= 110.174, val_mse= 104.233, val_kld= 29.708
Epoch= 141/200, loss= 107.062, mse= 101.721, kld= 26.703
        val_loss= 100.358, val_mse= 94.830, val_kld= 27.637
Epoch= 151/200, loss= 98.992, mse= 93.778, kld= 26.070
        val_loss= 90.296, val_mse= 84.910, val_kld= 26.933
Epoch= 161/200, loss= 95.743, mse= 90.652, kld= 25.458
        val_loss= 86.968, val_mse= 81.700, val_kld= 26.339
Epoch= 171/200, loss= 90.474, mse= 85.385, kld= 25.443
        val_loss= 79.886, val_mse= 74.753, val_kld= 25.665
Epoch= 181/200, loss= 74.468, mse= 69.327, kld= 25.703
        val_loss= 67.008, val_mse= 61.630, val_kld= 26.890
Epoch= 191/200, loss= 64.146, mse= 58.760, kld= 26.929
        val_loss= 62.271, val_mse= 56.784, val_kld= 27.434
```

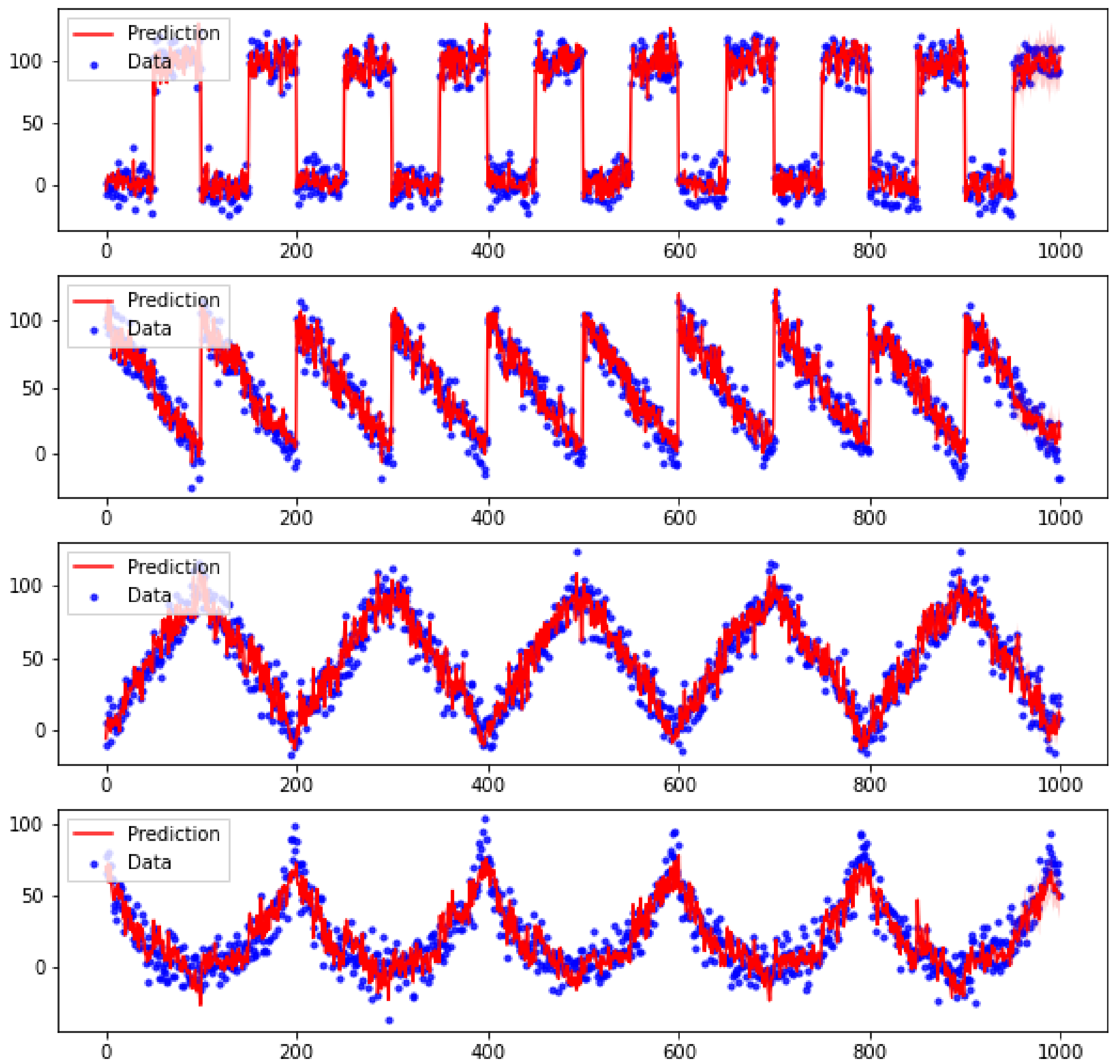
```
[185]: <AxesSubplot:xlabel='Epoch'>
```



[186]:
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 50)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)

fig, ax = plt.subplots(4, figsize=(10, 10))

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
                     facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()

#################################################################################
```



140
120
100
80
60
40
20
0
−20
0
200
400
600
800
1000



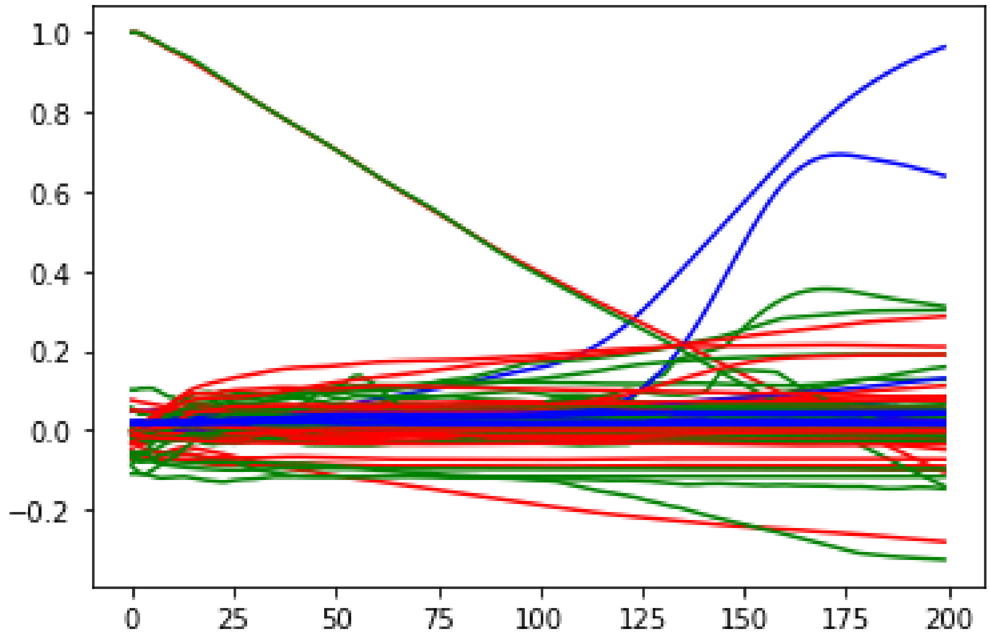
[187]:
```
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

```python
# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
               MSE  R-squared       MAE
Average  58.825966   0.930293  5.803561
               MSE  R-squared       MAE
sample1  47.724049   0.981400  5.077359
sample2  39.494244   0.958096  4.787816
sample3  49.627068   0.946506  5.516902
sample4  98.458488   0.835168  7.832165
```

[188]:
```python
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'

    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],␣
↪label = stat, c = colour)
```

```
plt.show()
```



4.6 Haversine distance

[40]:
```
def workout_to_haversine(i):
    ###Calculates haversine distance from point [0,0] in radians for a workout
    ###sklearn wants [lat,long] in radians
    ### to get distance in kilometers multiply by 6371000/1000
    lat = np.asarray(data_endo[i]['latitude'])
    lon = np.asarray(data_endo[i]['longitude'])
    coords = np.column_stack([lat, lon])
    coords_in_radians = np.radians(coords)
    zeros = np.zeros_like(coords_in_radians)
    zeros = np.radians(zeros)
    result = haversine_distances(coords_in_radians, zeros)
    result = result
    return result[:,0]
```

[190]:
```
data = np.vstack( [workout_to_haversine(i) for i in range(5)]).T
#print(data.shape)
#print(data)

x = torch.FloatTensor(data).reshape(1, *data.shape)
```

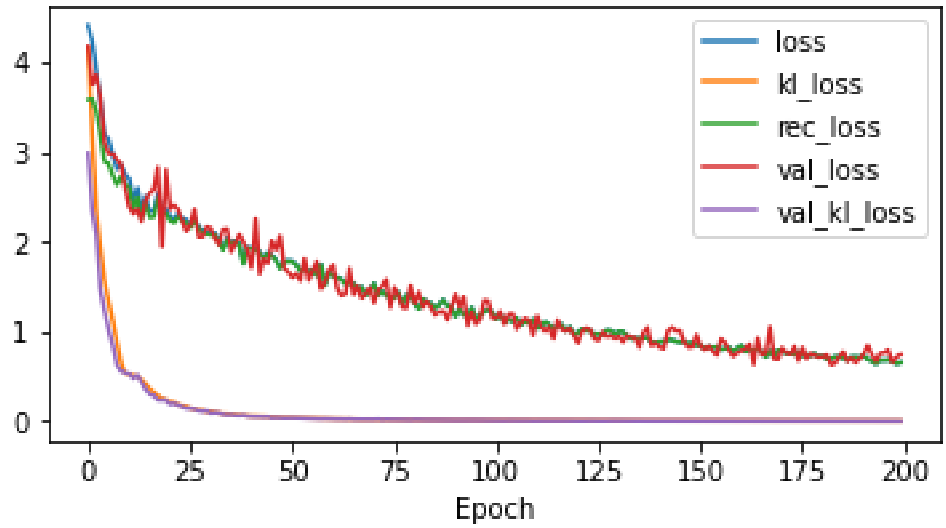
```
#print(x)
x_train = torch.FloatTensor(data[:400]).reshape(1, 400, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[400:450]).reshape(1, 50, data.shape[1])
#print(x_val)
```

[191]:
```
dkf = DKF(input_dim=5, z_dim=25, rnn_dim=25, trans_dim=25, emission_dim=25)

history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
↪annealing_factor=0.2)

pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

```
Epoch= 1/200, loss= 4.410, mse= 3.580, kld= 4.151
        val_loss= 4.179, val_mse= 3.582, val_kld= 2.989
Epoch= 11/200, loss= 2.700, mse= 2.594, kld= 0.527
        val_loss= 2.392, val_mse= 2.286, val_kld= 0.530
Epoch= 21/200, loss= 2.282, mse= 2.239, kld= 0.215
        val_loss= 2.364, val_mse= 2.326, val_kld= 0.190
Epoch= 31/200, loss= 2.099, mse= 2.077, kld= 0.111
        val_loss= 2.149, val_mse= 2.131, val_kld= 0.090
Epoch= 41/200, loss= 1.934, mse= 1.923, kld= 0.056
        val_loss= 1.712, val_mse= 1.701, val_kld= 0.054
Epoch= 51/200, loss= 1.785, mse= 1.778, kld= 0.038
        val_loss= 1.602, val_mse= 1.595, val_kld= 0.038
Epoch= 61/200, loss= 1.627, mse= 1.621, kld= 0.028
        val_loss= 1.742, val_mse= 1.737, val_kld= 0.027
Epoch= 71/200, loss= 1.539, mse= 1.534, kld= 0.021
        val_loss= 1.317, val_mse= 1.313, val_kld= 0.020
Epoch= 81/200, loss= 1.317, mse= 1.313, kld= 0.016
        val_loss= 1.314, val_mse= 1.310, val_kld= 0.018
Epoch= 91/200, loss= 1.172, mse= 1.169, kld= 0.014
        val_loss= 1.416, val_mse= 1.414, val_kld= 0.012
Epoch= 101/200, loss= 1.138, mse= 1.135, kld= 0.011
        val_loss= 1.153, val_mse= 1.151, val_kld= 0.010
Epoch= 111/200, loss= 1.038, mse= 1.036, kld= 0.010
        val_loss= 1.173, val_mse= 1.171, val_kld= 0.010
Epoch= 121/200, loss= 0.986, mse= 0.985, kld= 0.008
        val_loss= 0.871, val_mse= 0.870, val_kld= 0.008
Epoch= 131/200, loss= 1.001, mse= 1.000, kld= 0.007
        val_loss= 0.948, val_mse= 0.947, val_kld= 0.007
Epoch= 141/200, loss= 0.889, mse= 0.888, kld= 0.006
        val_loss= 0.825, val_mse= 0.824, val_kld= 0.007
Epoch= 151/200, loss= 0.845, mse= 0.844, kld= 0.005
        val_loss= 0.837, val_mse= 0.836, val_kld= 0.005
Epoch= 161/200, loss= 0.844, mse= 0.843, kld= 0.005
        val_loss= 0.787, val_mse= 0.786, val_kld= 0.005
```

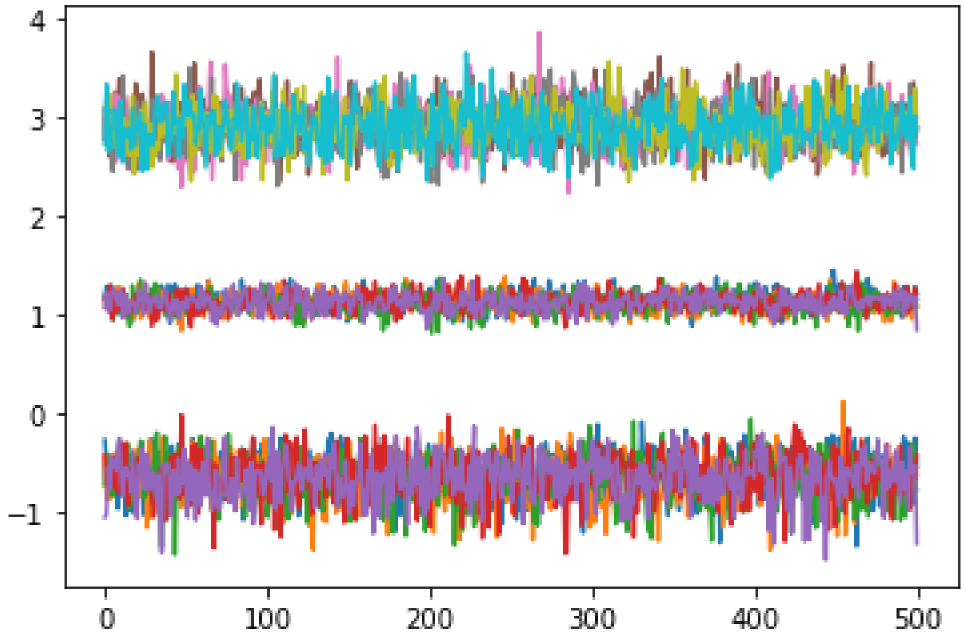
```
Epoch= 171/200, loss= 0.791, mse= 0.790, kld= 0.004
        val_loss= 0.819, val_mse= 0.819, val_kld= 0.004
Epoch= 181/200, loss= 0.728, mse= 0.727, kld= 0.004
        val_loss= 0.721, val_mse= 0.721, val_kld= 0.003
Epoch= 191/200, loss= 0.733, mse= 0.733, kld= 0.003
        val_loss= 0.750, val_mse= 0.749, val_kld= 0.004
```

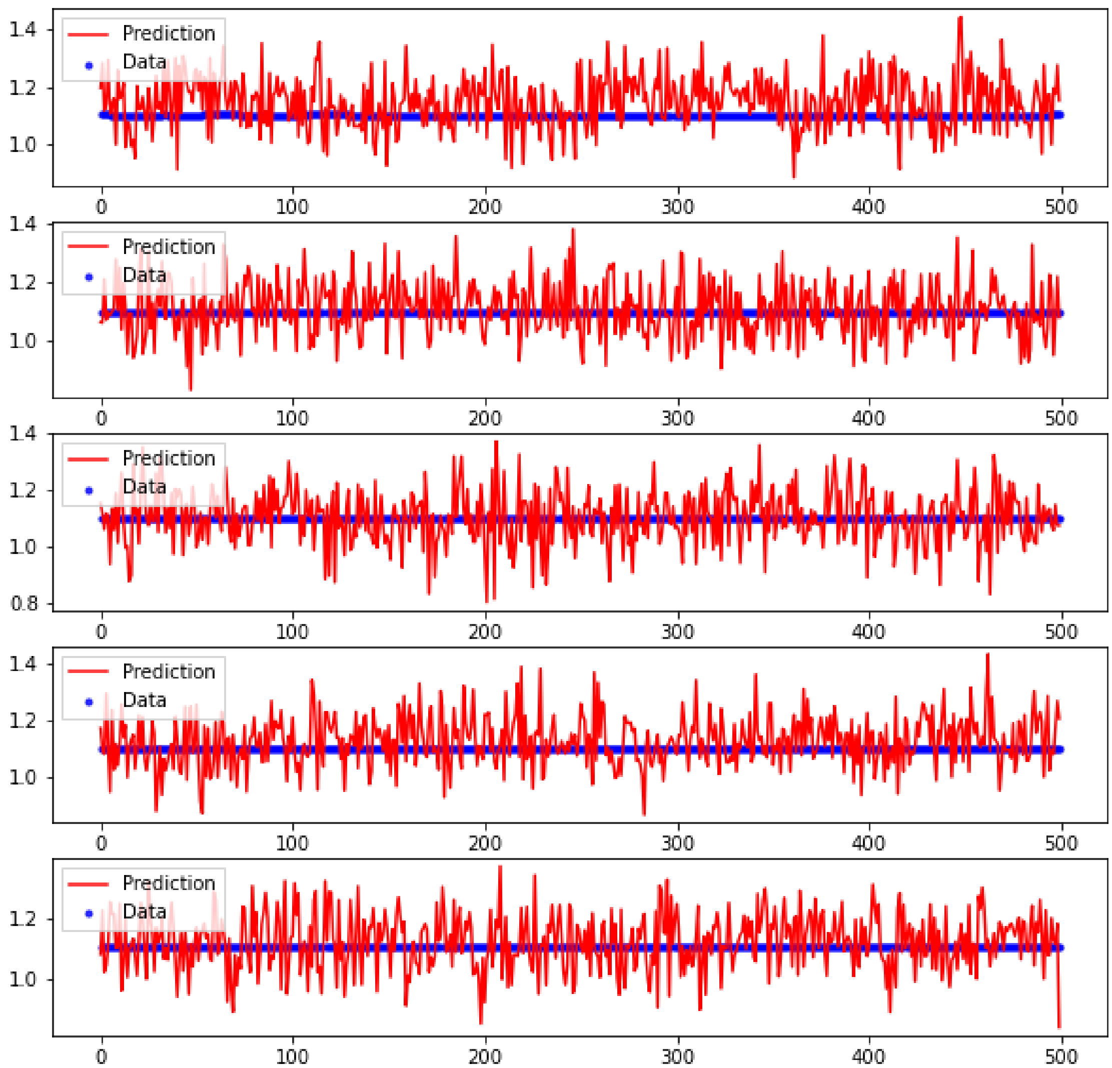
[191]: <AxesSubplot:xlabel='Epoch'>



[192]:
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 200)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)

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

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    #axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
    #                 facecolor='r', alpha=0.2)
```

```
    axi.legend(loc='upper left', fancybox=False)
plt.show()
```





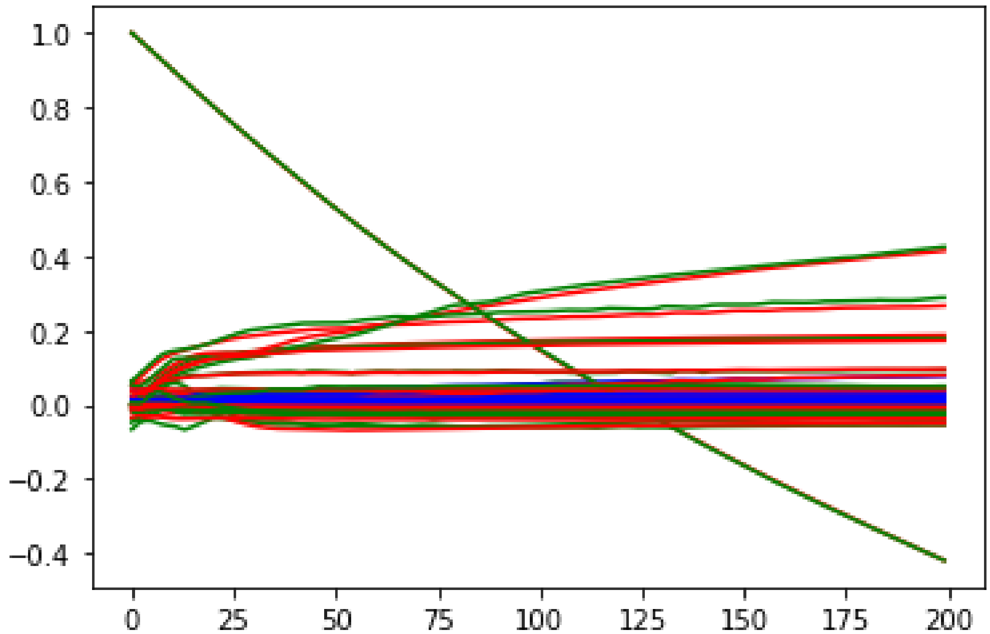
[193]:
```
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

```
# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
              MSE     R-squared       MAE
Average  0.009308 -82080.618465  0.076768
              MSE      R-squared       MAE
sample1  0.010646  -48882.357938  0.083021
sample2  0.008887  -88056.408397  0.074963
sample3  0.009471  -39887.838130  0.076926
sample4  0.008676  -87332.849371  0.072662
sample5  0.008860 -146243.638488  0.076269
```

[194]:
```
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'

    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],
 ↪label = stat, c = colour)
```

```
plt.show()
```



4.7 Haversine distance normalised to [0,100] for every workout individually

[245]:
```
data = np.vstack([NormalizeData(workout_to_haversine(i)) for i in range(5)]).T
#print(data.shape)

#print(data)

x = torch.FloatTensor(data).reshape(1, *data.shape)
print(x.shape)
x_train = torch.FloatTensor(data[:400]).reshape(1, 400, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[400:450]).reshape(1, 50, data.shape[1])
#print(x_val)
```

```
torch.Size([1, 500, 5])
```

[205]:
```
dkf = DKF(input_dim=5, z_dim=25, rnn_dim=25, trans_dim=25, emission_dim=25)

history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
 ↪annealing_factor=0.1)
```

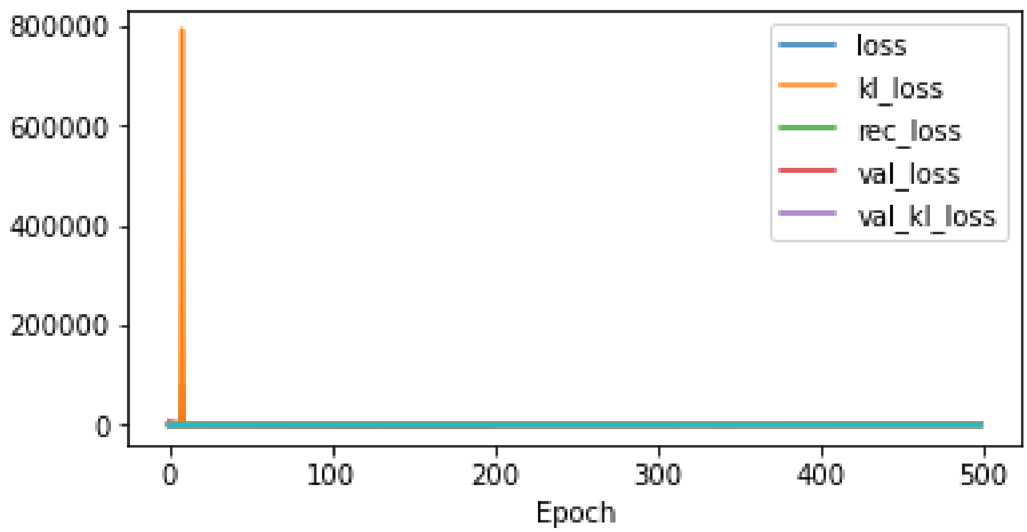
```
Epoch= 1/200, loss= 4341.791, mse= 4015.242, kld= 3265.485
        val_loss= 5940.666, val_mse= 5927.291, val_kld= 133.754
Epoch= 11/200, loss= 952.064, mse= 933.328, kld= 187.358
        val_loss= 933.971, val_mse= 918.533, val_kld= 154.382
Epoch= 21/200, loss= 728.192, mse= 724.038, kld= 41.539
        val_loss= 1349.037, val_mse= 1342.718, val_kld= 63.187
Epoch= 31/200, loss= 630.910, mse= 627.854, kld= 30.563
        val_loss= 881.972, val_mse= 876.903, val_kld= 50.699
Epoch= 41/200, loss= 617.695, mse= 614.995, kld= 27.001
        val_loss= 789.770, val_mse= 785.281, val_kld= 44.891
Epoch= 51/200, loss= 594.160, mse= 591.818, kld= 23.420
        val_loss= 772.171, val_mse= 768.216, val_kld= 39.550
Epoch= 61/200, loss= 558.315, mse= 556.170, kld= 21.455
        val_loss= 724.781, val_mse= 720.992, val_kld= 37.890
Epoch= 71/200, loss= 457.846, mse= 455.669, kld= 21.768
        val_loss= 445.924, val_mse= 441.326, val_kld= 45.987
Epoch= 81/200, loss= 220.282, mse= 217.622, kld= 26.602
        val_loss= 177.014, val_mse= 171.206, val_kld= 58.075
Epoch= 91/200, loss= 173.279, mse= 170.558, kld= 27.214
        val_loss= 158.784, val_mse= 152.867, val_kld= 59.167
Epoch= 101/200, loss= 144.138, mse= 141.703, kld= 24.352
        val_loss= 175.151, val_mse= 169.520, val_kld= 56.318
Epoch= 111/200, loss= 113.246, mse= 110.918, kld= 23.285
        val_loss= 116.356, val_mse= 110.308, val_kld= 60.485
Epoch= 121/200, loss= 65.555, mse= 63.324, kld= 22.312
        val_loss= 75.091, val_mse= 69.663, val_kld= 54.282
Epoch= 131/200, loss= 30.200, mse= 27.890, kld= 23.098
        val_loss= 27.711, val_mse= 17.897, val_kld= 98.143
Epoch= 141/200, loss= 22.810, mse= 20.636, kld= 21.736
        val_loss= 22.366, val_mse= 16.795, val_kld= 55.710
Epoch= 151/200, loss= 20.126, mse= 17.855, kld= 22.704
        val_loss= 34.236, val_mse= 13.667, val_kld= 205.682
Epoch= 161/200, loss= 19.810, mse= 17.277, kld= 25.325
        val_loss= 17.560, val_mse= 11.276, val_kld= 62.844
Epoch= 171/200, loss= 18.770, mse= 16.523, kld= 22.464
        val_loss= 17.331, val_mse= 11.854, val_kld= 54.774
Epoch= 181/200, loss= 18.525, mse= 15.838, kld= 26.870
        val_loss= 22.451, val_mse= 12.939, val_kld= 95.127
Epoch= 191/200, loss= 17.958, mse= 16.035, kld= 19.228
        val_loss= 17.581, val_mse= 12.064, val_kld= 55.173
```

[206]:
```
pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')

# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 200)
x_hat = x_hat.detach().numpy()[0]
```

```
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

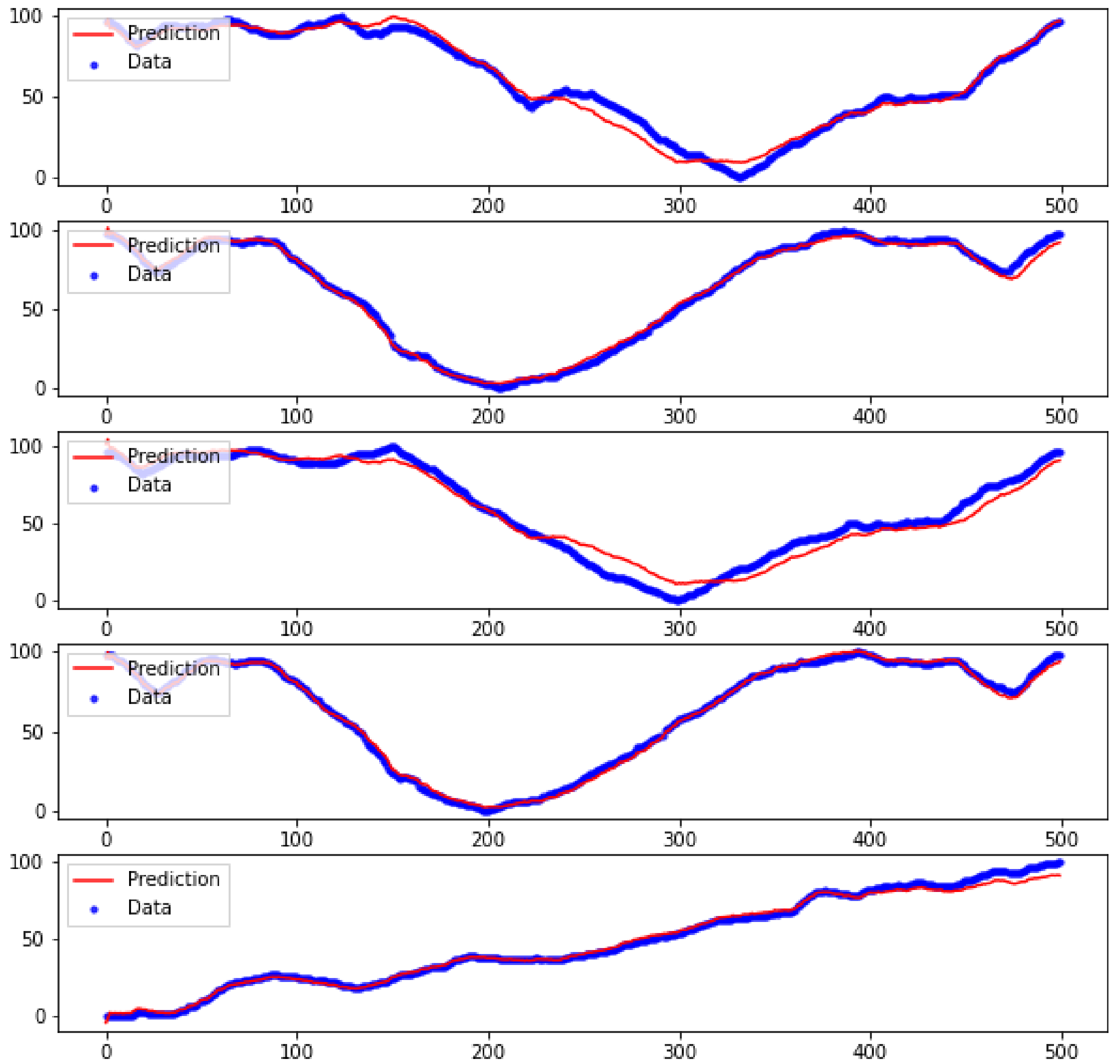
[206]:

```
[<matplotlib.lines.Line2D at 0x7f1b78e41df0>,
 <matplotlib.lines.Line2D at 0x7f1b789e74c0>,
 <matplotlib.lines.Line2D at 0x7f1b789e78b0>,
 <matplotlib.lines.Line2D at 0x7f1b789e7730>,
 <matplotlib.lines.Line2D at 0x7f1b789e74f0>]
```



[207]:

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

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    #axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
    #                 facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```



[208]:
```
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

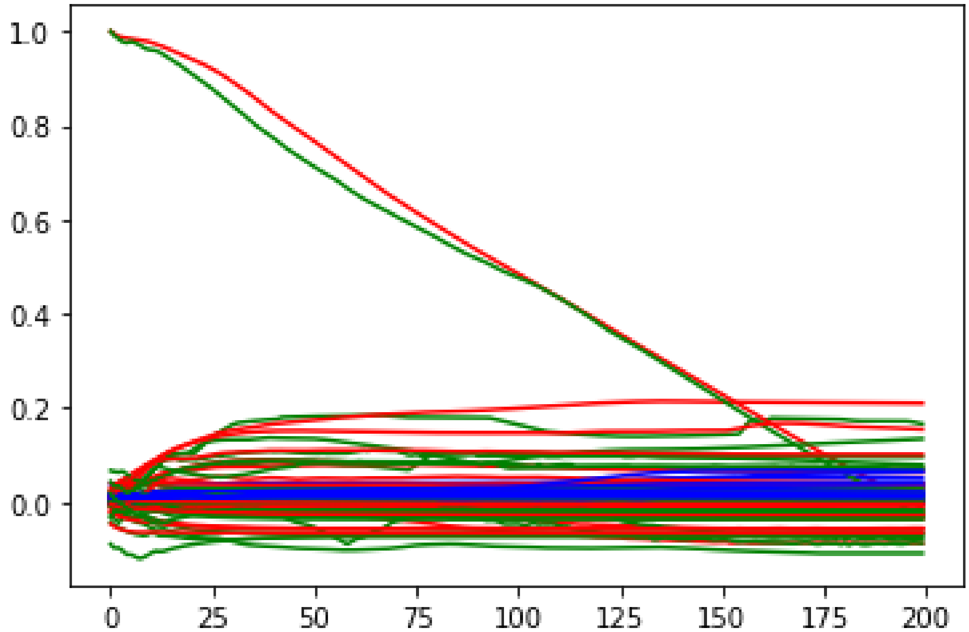
```
# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
               MSE  R-squared       MAE
Average  16.235273   0.982902  2.855905
               MSE  R-squared       MAE
sample1  20.209558   0.977223  3.442127
sample2   6.668675   0.994012  1.863886
sample3  43.467014   0.954985  5.587907
sample4   4.119992   0.996258  1.603808
sample5   6.711132   0.992033  1.781795
```

[209]:

```
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'

    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],␣
↪label = stat, c = colour)
```

```
plt.show()
```



4.8 Wodociągi Wrocławskie

[210]:
```
#i = #examples
i = 7
```

[211]:
```
df = pd.read_csv('water_consumption_profiles.csv')
```

[212]:
```
_ = df.values
```

[213]:
```
all_days = _[:,1:].T
```

[214]:
```
all_days.shape
```

[214]: (144, 651)

[215]:
```
all_days = all_days.astype('float64')
```

[216]:
```
data = all_days[:, :7]
```

[ ]:
```

```

[218]:
```
x = torch.FloatTensor(data).reshape(1, *data.shape)
#print(x)
x_train = torch.FloatTensor(data[:100]).reshape(1, 100, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[100:120]).reshape(1, 20, data.shape[1])
#print(x_val)
```

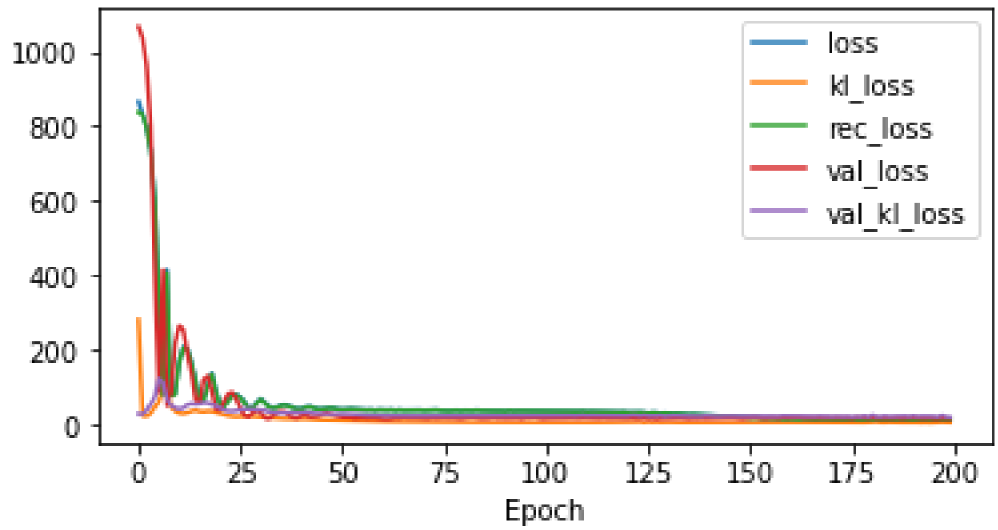
[ ]:
```

```

[219]:
```
dkf = DKF(input_dim=i, z_dim=5*i, rnn_dim=5*i, trans_dim=5*i, emission_dim=5*i)

history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
 ↪annealing_factor=0.1)

pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

```
Epoch= 1/200, loss= 866.290, mse= 838.205, kld= 280.848
        val_loss= 1067.229, val_mse= 1064.338, val_kld= 28.914
Epoch= 11/200, loss= 169.325, mse= 166.233, kld= 30.924
        val_loss= 264.226, val_mse= 260.014, val_kld= 42.115
Epoch= 21/200, loss= 52.611, mse= 49.608, kld= 30.027
        val_loss= 38.759, val_mse= 34.283, val_kld= 44.754
Epoch= 31/200, loss= 68.499, mse= 66.442, kld= 20.570
        val_loss= 31.467, val_mse= 27.531, val_kld= 39.357
Epoch= 41/200, loss= 43.023, mse= 41.429, kld= 15.941
        val_loss= 24.426, val_mse= 21.040, val_kld= 33.862
Epoch= 51/200, loss= 40.943, mse= 39.734, kld= 12.093
        val_loss= 20.330, val_mse= 17.446, val_kld= 28.846
Epoch= 61/200, loss= 39.408, mse= 38.503, kld= 9.052
        val_loss= 15.674, val_mse= 13.235, val_kld= 24.386
Epoch= 71/200, loss= 38.137, mse= 37.384, kld= 7.524
        val_loss= 18.149, val_mse= 15.790, val_kld= 23.586
Epoch= 81/200, loss= 38.415, mse= 37.698, kld= 7.176
        val_loss= 18.241, val_mse= 15.868, val_kld= 23.732
Epoch= 91/200, loss= 36.414, mse= 35.774, kld= 6.405
        val_loss= 17.543, val_mse= 15.144, val_kld= 23.990
Epoch= 101/200, loss= 37.199, mse= 36.595, kld= 6.046
        val_loss= 17.321, val_mse= 14.842, val_kld= 24.785
Epoch= 111/200, loss= 35.242, mse= 34.646, kld= 5.961
        val_loss= 18.217, val_mse= 15.803, val_kld= 24.139
Epoch= 121/200, loss= 33.367, mse= 32.734, kld= 6.324
        val_loss= 17.538, val_mse= 15.156, val_kld= 23.820
Epoch= 131/200, loss= 30.726, mse= 30.062, kld= 6.643
        val_loss= 17.962, val_mse= 15.637, val_kld= 23.250
Epoch= 141/200, loss= 25.592, mse= 24.972, kld= 6.203
        val_loss= 17.658, val_mse= 15.334, val_kld= 23.238
Epoch= 151/200, loss= 18.814, mse= 18.196, kld= 6.176
```

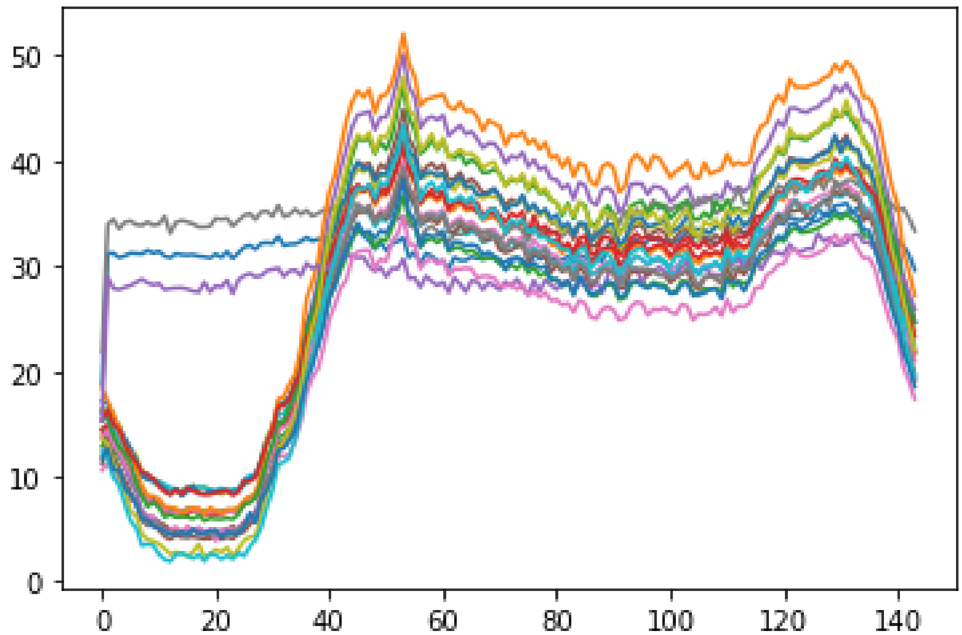
```
        val_loss= 18.630, val_mse= 16.288, val_kld= 23.415
Epoch= 161/200, loss= 16.259, mse= 15.602, kld= 6.572
        val_loss= 19.312, val_mse= 16.956, val_kld= 23.559
Epoch= 171/200, loss= 14.931, mse= 14.324, kld= 6.066
        val_loss= 18.120, val_mse= 15.967, val_kld= 21.528
Epoch= 181/200, loss= 14.257, mse= 13.605, kld= 6.516
        val_loss= 18.873, val_mse= 16.269, val_kld= 26.046
Epoch= 191/200, loss= 14.176, mse= 13.609, kld= 5.671
        val_loss= 18.446, val_mse= 16.046, val_kld= 24.000
```

[219]: <AxesSubplot:xlabel='Epoch'>

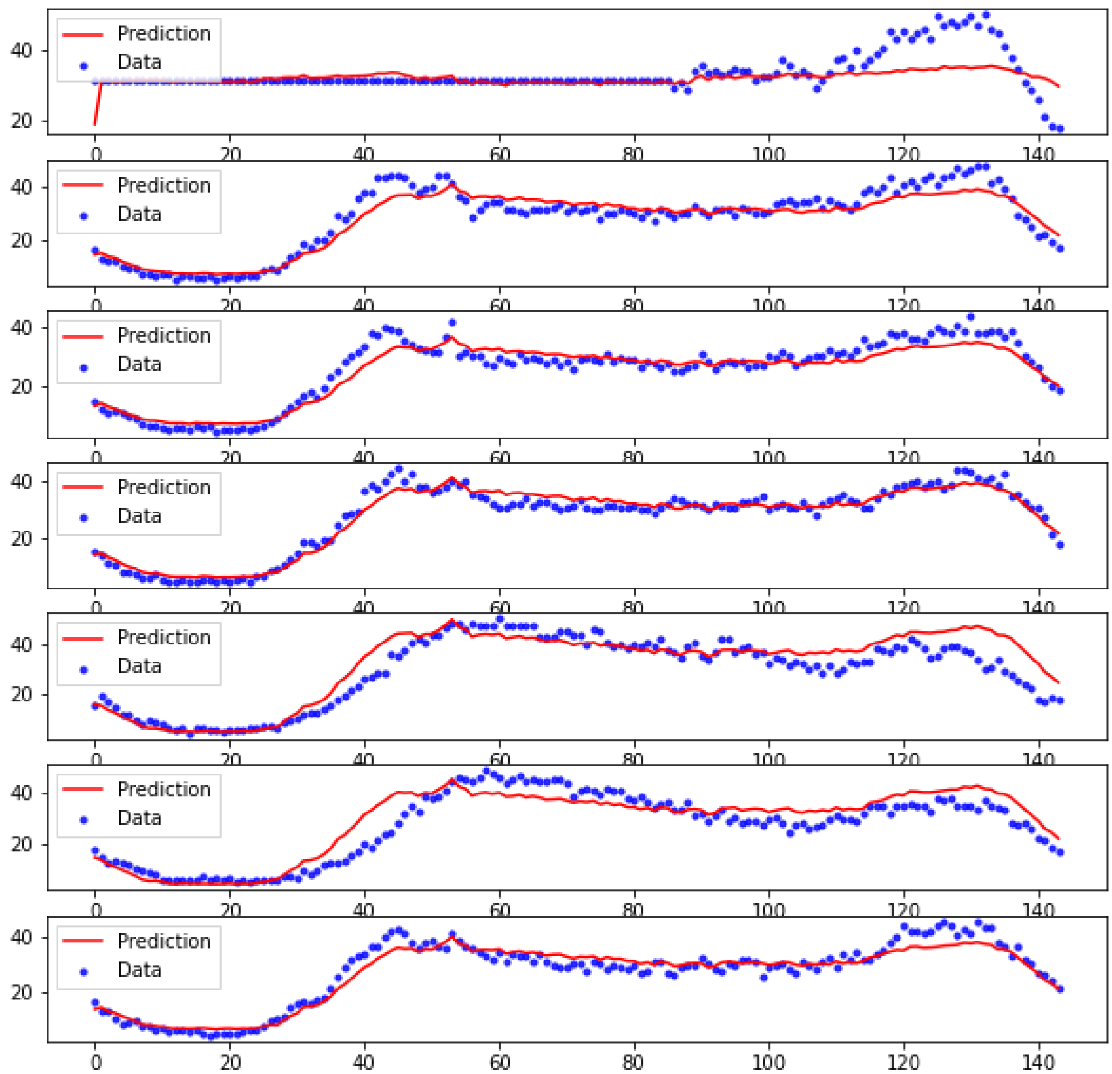


[220]:
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 50)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

[220]:
```
[<matplotlib.lines.Line2D at 0x7f1b781210d0>,
 <matplotlib.lines.Line2D at 0x7f1b781211c0>,
 <matplotlib.lines.Line2D at 0x7f1b78121280>,
 <matplotlib.lines.Line2D at 0x7f1b78121340>,
 <matplotlib.lines.Line2D at 0x7f1b78121400>,
 <matplotlib.lines.Line2D at 0x7f1b781214c0>,
 <matplotlib.lines.Line2D at 0x7f1b78121580>]
```



[221]:
```
fig, ax = plt.subplots(i, figsize=(10, 10))

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    #axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
    #                 facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```



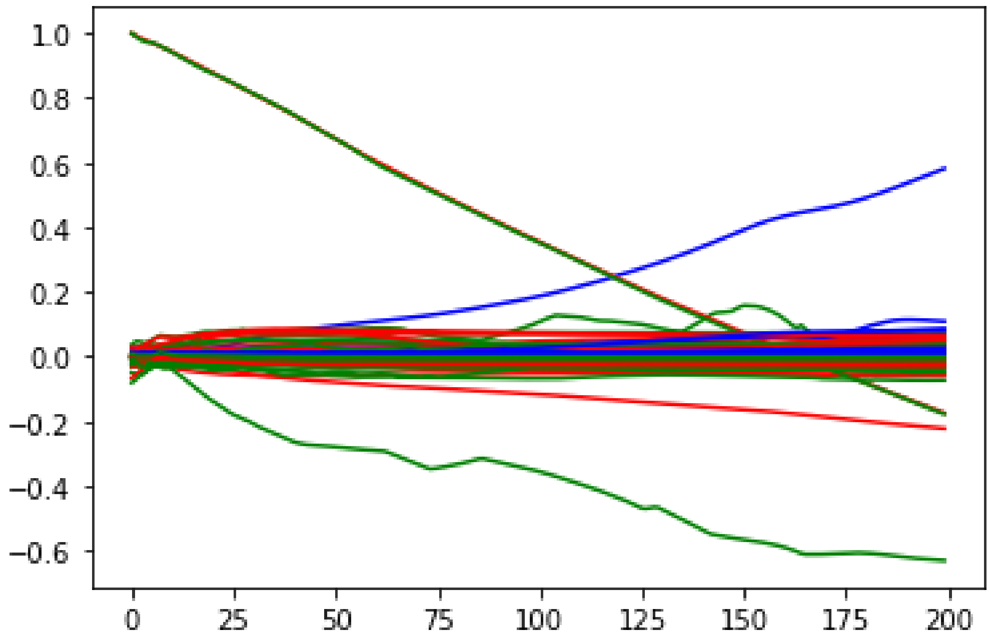
[222]:
```
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])
```

```python
# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
               MSE  R-squared       MAE
Average  19.357325   0.790829  3.219648
               MSE  R-squared       MAE
sample1  24.555601   0.229642  2.820086
sample2  16.833191   0.893629  3.302457
sample3  11.808977   0.899602  2.704458
sample4   6.952225   0.950004  2.153428
sample5  34.176804   0.823544  4.388855
sample6  30.510963   0.818955  4.627341
sample7  10.663501   0.920427  2.540912
```

[223]:
```python
for i, _ in enumerate(range(3 * len(param_dict.keys()))):

    #print(i)
    if i % 3 == 0:
        stat = "Mean"
        colour = 'r'
    elif i % 3 == 1:
        stat = "Variance"
        colour = 'b'
    else:
        stat = "Median"
        colour = 'g'
```

```
    plt.plot(np.array(param_dict['mean_var_median' + str(i % 32)])[:, i % 3],␣
↪label = stat, c = colour)



plt.show()
```



5 Sample-Normalized Deep Kalman Filter

[26]:
```
def NormalizeByRow(data):

    data = data.numpy()

    # Reshape the data into a 2-dimensional array (500 rows, 5 columns)
    reshaped_data = data.reshape(data.shape[1], data.shape[2])

    # Calculate the minimum and maximum values for each column
    min_values = np.min(reshaped_data, axis=0)
    max_values = np.max(reshaped_data, axis=0)

    # Normalize each column to the range 0 to 100
    normalized_data = ((reshaped_data - min_values) / (max_values -␣
↪min_values)) * 100
```

```
    # Reshape the normalized data back to the original shape
    normalized_data = normalized_data.reshape(1, data.shape[1], data.shape[2])
    normalized_data = torch.FloatTensor(normalized_data)

    return(normalized_data)

def DenormalizeByRow(normalized_data, original_min, original_max):
    # Convert the PyTorch tensor to a NumPy array
    normalized_data = normalized_data.numpy()

    # Reshape the normalized data into a 2-dimensional array␣
 ↪(number_of_samples, number_of_features)
    reshaped_data = normalized_data.reshape(normalized_data.shape[1],␣
 ↪normalized_data.shape[2])

    # Calculate the denormalized data using the original range
    denormalized_data = original_min + (reshaped_data / 100) * (original_max -␣
 ↪original_min)

    # Reshape the denormalized data back to the original shape
    denormalized_data = denormalized_data.reshape(1, normalized_data.shape[1],␣
 ↪normalized_data.shape[2])

    # Convert the denormalized NumPy array back to a PyTorch tensor
    denormalized_data = torch.FloatTensor(denormalized_data)

    return denormalized_data



#max_values, _ = torch.max(matrix, dim=1)
#min_values, _ = torch.min(matrix, dim=1)

#max_values = max_values.numpy()
#min_values = min_values.numpy()
```

[27]:

```
data = np.vstack([np.asarray(data_endo[0]['altitude']), np.
 ↪asarray(data_endo[1]['altitude']),
                  np.asarray(data_endo[2]['altitude']), np.
 ↪asarray(data_endo[3]['altitude']),
                  np.asarray(data_endo[4]['altitude'])]).T

x = torch.FloatTensor(data).reshape(1, *data.shape)

print(x)
```

```
y = NormalizeByRow(x)

print(y)
y = y.numpy()
print(np.max(y, axis = 1))
print(np.min(y, axis = 1))
```

```
tensor([[[41.6000, 38.4000, 76.4000, 28.6000, 32.0000],
         [40.6000, 39.0000, 73.2000, 29.4000, 32.0000],
         [40.6000, 39.0000, 72.4000, 29.4000, 32.0000],
         …,
         [31.8000, 34.2000, 50.2000, 29.8000, 14.4000],
         [34.4000, 35.0000, 52.8000, 30.8000, 15.0000],
         [36.2000, 35.0000, 52.8000, 32.8000, 14.2000]]])
tensor([[[45.3020, 41.8972, 70.9571, 31.3954, 79.2857],
         [43.6242, 43.0830, 65.6766, 32.9457, 79.2857],
         [43.6242, 43.0830, 64.3564, 32.9457, 79.2857],
         …,
         [28.8591, 33.5968, 27.7228, 33.7209, 16.4286],
         [33.2215, 35.1779, 32.0132, 35.6589, 18.5714],
         [36.2416, 35.1779, 32.0132, 39.5349, 15.7143]]])
[[100. 100. 100. 100. 100.]]
[[0. 0. 0. 0. 0.]]
```

[35]:

```
class GatedTransition(nn.Module):
    def __init__(self, z_dim, hid_dim):
        super(GatedTransition, self).__init__()
        self.gate = nn.Sequential(nn.Linear(z_dim, hid_dim),
            nn.ReLU(),
            nn.Linear(hid_dim, z_dim),
            nn.Sigmoid())
        self.proposed_mean = nn.Sequential(nn.Linear(z_dim, hid_dim),
            nn.ReLU(),
            nn.Linear(hid_dim, z_dim))
        self.z_to_mu = nn.Linear(z_dim, z_dim)
        # modify the default initialization of z_to_mu
        # so that it starts out as the identity function
        self.z_to_mu.weight.data = torch.eye(z_dim)
        self.z_to_mu.bias.data = torch.zeros(z_dim)
        self.z_to_logvar = nn.Linear(z_dim, z_dim)
        self.relu = nn.ReLU()

    def forward(self, z_t_1):
        #
        gate = self.gate(z_t_1)
        proposed_mean = self.proposed_mean(z_t_1)
```

```
        mu = (1 - gate) * self.z_to_mu(z_t_1) + gate * proposed_mean
        logvar = self.z_to_logvar(self.relu(proposed_mean))
        # sampling
        eps = torch.randn(z_t_1.size())
        z_t = mu + eps * torch.exp(.5 * logvar)
        return z_t, mu, logvar
```

[36]:
```
class Combiner(nn.Module):
    # PostNet
    def __init__(self, z_dim, hid_dim):
        super(Combiner, self).__init__()
        self.z_dim = z_dim
        self.z_to_hidden = nn.Linear(z_dim, hid_dim)
        self.hidden_to_mu = nn.Linear(hid_dim, z_dim)
        self.hidden_to_logvar = nn.Linear(hid_dim, z_dim)
        self.tanh = nn.Tanh()
    def forward(self, z_t_1, h_rnn):
        # combine the rnn hidden state with a transformed version of z_t_1
        h_combined = 0.5 * (self.tanh(self.z_to_hidden(z_t_1)) + h_rnn)
        # use the combined hidden state
        # to compute the mean used to sample z_t
        mu = self.hidden_to_mu(h_combined)
        # use the combined hidden state
        # to compute the scale used to sample z_t
        logvar = self.hidden_to_logvar(h_combined)
        eps = torch.randn(z_t_1.size())
        z_t = mu + eps * torch.exp(.5 * logvar)
        return z_t, mu, logvar
```

[37]:
```
class Emitter(nn.Module):
    def __init__(self, z_dim, hid_dim, input_dim) -> None:
        super().__init__()
        self.input_dim = input_dim
        self.z_to_hidden = nn.Linear(z_dim, hid_dim)
        self.hidden_to_hidden = nn.Linear(hid_dim, hid_dim)
        self.hidden_to_input_mu = nn.Linear(hid_dim, input_dim)
        self.logvar = nn.Parameter(torch.ones(input_dim))
        self.relu = nn.ReLU()
    def forward(self, z_t):
        h1 = self.relu(self.z_to_hidden(z_t))
        h2 = self.relu(self.hidden_to_hidden(h1))
        mu = self.hidden_to_input_mu(h2)
        # return mu # x_t
        eps = torch.randn(z_t.size(0), self.input_dim)
        x_t = mu + eps * torch.exp(.5 * self.logvar)
        return x_t, mu, self.logvar
```

[107]:
```python
class RNDKF(nn.Module):
    # Structured Inference Networks
    # Current version ignores backward RNN outputs
    def __init__(self, input_dim, z_dim=50, trans_dim=30, emission_dim=30,
            rnn_dim=100, num_rnn_layers=1) -> None:

        super().__init__()
        self.input_dim = input_dim
        self.z_dim = z_dim
        self.trans_dim = trans_dim
        self.emission_dim = emission_dim
        self.rnn_dim = rnn_dim
        self.num_rnn_layers = num_rnn_layers
        self.trans = GatedTransition(z_dim, trans_dim)
        self.emitter = Emitter(z_dim, emission_dim, input_dim)
        self.combiner = Combiner(z_dim, rnn_dim)
        self.z_0 = nn.Parameter(torch.zeros(z_dim))
        self.z_q_0 = nn.Parameter(torch.zeros(z_dim))
        self.h_0 = nn.Parameter(torch.zeros(1, 1, rnn_dim))
        # corresponding learning 'l' in the original code
        self.rnn = nn.RNN(input_size=input_dim,
            hidden_size=rnn_dim,
            nonlinearity="relu",
            batch_first=True,
            bidirectional=False,
            num_layers=num_rnn_layers)

    def kl_div(self, mu1, logvar1, mu2=None, logvar2=None):
        if mu2 is None:
            mu2 = torch.zeros(1, device=mu1.device)
        if logvar2 is None:
            logvar2 = torch.zeros(1, device=mu1.device)
        return torch.sum(0.5 * (
            logvar2 - logvar1 + (torch.exp(logvar1) + (mu1 - mu2).pow(2))
            / torch.exp(logvar2) - torch.ones(1, device=mu1.device)
        ), 1)

    def infer(self, x):
        batch_size, T_max, x_dim = x.size()
        h_0 = self.h_0.expand(1, batch_size, self.rnn_dim).contiguous()
        rnn_out, h_n = self.rnn(x, h_0)
        z_prev = self.z_q_0.expand(batch_size, self.z_q_0.size(0))
        kl_states = torch.zeros((batch_size, T_max))
        rec_losses = torch.zeros((batch_size, T_max))
        for t in range(T_max):
            # p(z_t|z_{t-1})
            z_prior, z_prior_mu, z_prior_logvar = self.trans(z_prev)
```

```python
            # q(z_t|z_{t-1},x_{t:T})
            z_t, z_mu, z_logvar = self.combiner(z_prev, rnn_out[:, t])
            # p(x_t|z_t)
            x_t, x_mu, x_logvar = self.emitter(z_t)
            # compute loss
            kl_states[:, t] = self.kl_div(
                z_mu, z_logvar, z_prior_mu, z_prior_logvar)
            rec_losses[:, t] = nn.MSELoss(reduction='none')(
                x_t.contiguous().view(-1),
                # x_mu.contiguous().view(-1),
                x[:, t].contiguous().view(-1)
            ).view(batch_size, -1).mean(dim=1)
            z_prev = z_t
        return rec_losses.mean(), kl_states.mean()

    def filter(self, x, num_sample=100):
        # Outputs
        x_hat = torch.zeros(x.size())
        x_025 = torch.zeros(x.size())
        x_975 = torch.zeros(x.size())
        # predictions
        batch_size, T_max, x_dim = x.size()
        assert batch_size == 1
        z_prev = self.z_0.expand(num_sample, self.z_0.size(0))
        h_0 = self.h_0.expand(1, 1, self.rnn_dim).contiguous()
        rnn_out, _ = self.rnn(x, h_0)
        rnn_out = rnn_out.expand(num_sample,
            rnn_out.size(1), rnn_out.size(2))
        for t in range(T_max):
            # z_t: (num_sample, z_dim)
            z_t, z_mu, z_logvar = self.combiner(z_prev, rnn_out[:, t])
            x_t, x_mu, x_logvar = self.emitter(z_t)
            # x_hat[:, t] = x_mu
            x_covar = torch.diag(torch.sqrt(torch.exp(.5 * x_logvar)))
            x_samples = MultivariateNormal(
                x_mu, covariance_matrix=x_covar).sample()
            # # sampling z_t and computing quantiles
            # x_samples = MultivariateNormal(
            #   loc=x_mu, covariance_matrix=x_covar).sample_n(num_sample)
            x_hat[:, t] = x_samples.mean(0)
            x_025[:, t] = x_samples.quantile(0.025, 0)
            x_975[:, t] = x_samples.quantile(0.975, 0)
            # x_hat[:, t] = x_t.mean(0)
            # x_025[:, t] = x_t.quantile(0.025, 0)
            # x_975[:, t] = x_t.quantile(0.975, 0)
            z_prev = z_t
            # z_prev = z_mu
```

```
        return x_hat, x_025, x_975

    def predict(self, x, pred_steps=1, num_sample=100):
        """ x should contain the prediction period
        """
        # Outputs

        max_x, _ = torch.max(x, dim=1)
        min_x, _ = torch.min(x, dim=1)

        max_x = max_x.numpy()
        min_x = min_x.numpy()

        print(max_x)
        print(min_x)

        x = NormalizeByRow(x)

        x_hat = torch.zeros(x.size()) # predictions
        x_025 = torch.zeros(x.size())
        x_975 = torch.zeros(x.size())
        batch_size, T_max, x_dim = x.size()
        assert batch_size == 1
        z_prev = self.z_0.expand(num_sample, self.z_0.size(0))
        h_0 = self.h_0.expand(1, 1, self.rnn_dim).contiguous()
        rnn_out, _ = self.rnn(x[:, :T_max-pred_steps], h_0)
        rnn_out = rnn_out.expand(num_sample,
            rnn_out.size(1), rnn_out.size(2))
        for t in range(T_max - pred_steps):
            # z_t: (num_sample, z_dim)
            z_t, z_mu, z_logvar = self.combiner(z_prev, rnn_out[:, t])
            x_t, x_mu, x_logvar = self.emitter(z_t)
            x_covar = torch.diag(torch.sqrt(torch.exp(.5 * x_logvar)))
            x_samples = MultivariateNormal(
                x_mu, covariance_matrix=x_covar).sample()
            x_hat[:, t] = x_samples.mean(0)
            x_025[:, t] = x_samples.quantile(0.025, 0)
            x_975[:, t] = x_samples.quantile(0.975, 0)
            z_prev = z_mu
        for t in range(T_max - pred_steps, T_max):
            rnn_out, _ = self.rnn(x[:, :t], h_0)
            rnn_out = rnn_out.expand(
                num_sample, rnn_out.size(1), rnn_out.size(2))
            z_t_1, z_mu, z_logvar = self.combiner(z_prev, rnn_out[:, -1])
            z_t, z_mu, z_logvar = self.trans(z_t_1)
            x_t, x_mu, x_logvar = self.emitter(z_t)
            x_covar = torch.diag(torch.sqrt(torch.exp(.5 * x_logvar)))
```

```
            x_samples = MultivariateNormal(
                x_mu, covariance_matrix=x_covar).sample()
            x_hat[:, t] = x_samples.mean(0)
            x_025[:, t] = x_samples.quantile(0.025, 0)
            x_975[:, t] = x_samples.quantile(0.975, 0)


        x_hat = DenormalizeByRow(x_hat, min_x, max_x)

        x_025 = DenormalizeByRow(x_025, min_x, max_x)

        x_975 = DenormalizeByRow(x_975, min_x, max_x)


        return x_hat, x_025, x_975

    def train_step(self, x, annealing_factor = 0.1):
        self.train()
        # self.rnn.train()
        rec_loss, kl_loss = self.infer(x)
        total_loss = rec_loss + annealing_factor * kl_loss
        self.optimizer.zero_grad()
        total_loss.backward()
        # nn.utils.clip_grad_norm_(self.parameters(), 5.)
        self.optimizer.step()
        return rec_loss.item(), kl_loss.item(), total_loss.item()

    def validation_step(self, x, annealing_factor=0.1):
        self.eval()
        rec_loss, kl_loss = self.infer(x)
        total_loss = rec_loss + annealing_factor * kl_loss
        return rec_loss.item(), kl_loss.item(), total_loss.item()

    def fit(self, x, x_val=None, num_epochs=100, annealing_factor=0.1,
            verbose_step=1, eval_step=1, check_point_path=None,
            patience=20, learning_rate=0.01):

        #print(x)
        #print(x_val)
        #print(x.shape)
        #print(x_val.shape)

        concat_x = torch.cat((x, x_val), dim = 1)

        concat_x = NormalizeByRow(concat_x)

        x = concat_x[:, :x.shape[1], :]
```

```
        x_val = concat_x[:, x.shape[1]:, :]


        #x = NormalizeByRow(x)

        #x_val = NormalizeByRow(x_val)

        self.optimizer = torch.optim.Adam(
            self.parameters(), lr=learning_rate)

        losses = []
        kl_losses = []
        rec_losses = []
        val_losses = []
        val_kl_losses = []
        val_rec_losses = []
        parameter_values = []


        stats_dict = {}

        for index, param in enumerate(self.parameters()):
            stats_dict['mean_var_median' + str(index)] = []






        for epoch in range(num_epochs):
            for index, param in enumerate(self.parameters()):
                param_value = param.detach().numpy()
                stats_dict['mean_var_median' + str(index)].append([np.
↪mean(param_value), np.var(param_value), np.median(param_value)])

            try:
                res = self.train_step(x, annealing_factor=annealing_factor)
                losses.append(res[2])
                kl_losses.append(res[1])
                rec_losses.append(res[0])

                if epoch % verbose_step == verbose_step - 1:
                    message = f'Epoch= {epoch+1}/{num_epochs}, '
                    message += f'loss= {res[2]:.3f}, '
                    message += f'mse= {res[0]:.3f}, '
                    message += f'kld= {res[1]:.3f}'
                    if (epoch % 10 == 0):
                        print(message)
```

```python
            if x_val is not None:
                val_res = self.validation_step(x_val, annealing_factor)
                val_losses.append(val_res[2])
                val_kl_losses.append(val_res[1])
                val_rec_losses.append(val_res[0])

            if epoch % eval_step == eval_step - 1 and x_val is not None:
                message = f'\tval_loss= {val_res[2]:.3f}, '
                message += f'val_mse= {val_res[0]:.3f}, '
                message += f'val_kld= {val_res[1]:.3f}'
                if (epoch % 10 == 0):
                    print(message)

        except KeyboardInterrupt:
            break

    history = {'loss': losses,
               'kl_loss': kl_losses,
               'rec_loss': rec_losses}

    if x_val is not None:
        history.update({'val_loss': val_losses,
                        'val_kl_loss': val_kl_losses,
                        'rec_loss': rec_losses})


    return history, stats_dict

def save_model(self, filename):
    """ dkf.pth """
    torch.save(self.to('cpu').state_dict(), filename)

def load_model(self, filename):
    self.load_state_dict(torch.load(filename))

def get_config(self):
    return {
        'input_dim': self.input_dim,
        'z_dim': self.z_dim,
        'trans_dim': self.trans_dim,
        'emission_dim': self.emission_dim,
        'rnn_dim': self.rnn_dim,
        'num_rnn_layers': self.num_rnn_layers
    }
```

[108]:
```
data = np.vstack([NormalizeData(workout_to_haversine(i)) for i in range(5)]).T
#print(data.shape)

#print(data)

x = torch.FloatTensor(data).reshape(1, *data.shape)
print(x.shape)
x_train = torch.FloatTensor(data[:400]).reshape(1, 400, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[400:450]).reshape(1, 50, data.shape[1])
#print(x_val)
```

```
torch.Size([1, 500, 5])
```

[109]:
```
# Create a 4 by 3 numpy array
array = np.array([[1, 2, 3],
                  [4, 5, 6],
                  [7, 8, 9],
                  [10, 11, 12]])

# Find the maximum value in each row along axis 1 (rows)
max_values = np.max(array, axis=1)

print(max_values)
x_array = x.numpy()
print(x_array.shape)
print(np.max(x_array, axis = 1))
print(np.min(x_array, axis = 1))
print(list(x_array.shape[i] for i in range(len(x_array.shape))))
print(x_array.shape[0])
```

```
[ 3  6  9 12]
(1, 500, 5)
[[100. 100. 100. 100. 100.]]
[[0. 0. 0. 0. 0.]]
[1, 500, 5]
1
```

[110]:
```
data = np.vstack([np.asarray(data_endo[0]['altitude']), np.
 ↪asarray(data_endo[1]['altitude']),
                  np.asarray(data_endo[2]['altitude']), np.
 ↪asarray(data_endo[3]['altitude']),
                  np.asarray(data_endo[4]['altitude'])]).T

x = torch.FloatTensor(data).reshape(1, *data.shape)

print(x)
```

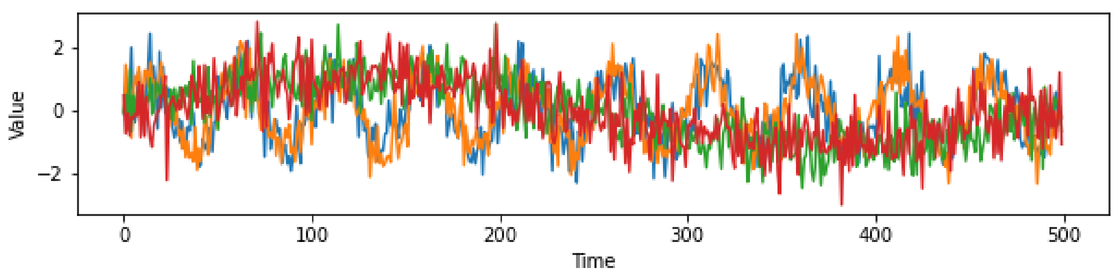
```
x_array = x.numpy()
print(np.max(x_array, axis = 1))
print(np.min(x_array, axis = 1))
```

```
tensor([[[41.6000, 38.4000, 76.4000, 28.6000, 32.0000],
         [40.6000, 39.0000, 73.2000, 29.4000, 32.0000],
         [40.6000, 39.0000, 72.4000, 29.4000, 32.0000],
         …,
         [31.8000, 34.2000, 50.2000, 29.8000, 14.4000],
         [34.4000, 35.0000, 52.8000, 30.8000, 15.0000],
         [36.2000, 35.0000, 52.8000, 32.8000, 14.2000]]])
[[74.2 67.8 94.  64.  37.8]]
[[14.6 17.2 33.4 12.4  9.8]]
```

[111]:
```
# Create a 500 by 5 matrix (replace this with your actual data)
data = np.random.rand(500, 5)

print(data)

# Calculate the minimum and maximum values for each column
min_values = np.min(data, axis=0)
max_values = np.max(data, axis=0)

# Normalize each column to the range 0 to 100
normalized_data = ((data - min_values) / (max_values - min_values)) * 100

print(normalized_data)
print(np.max(normalized_data, axis = 0))
print(np.min(normalized_data, axis = 0))
```

```
[[0.02937141 0.3199281  0.30717609 0.81927909 0.64730858]
 [0.01744385 0.95212328 0.34812517 0.09622448 0.57524033]
 [0.22026537 0.71207264 0.58740294 0.77985318 0.40450266]
 …
 [0.2783928  0.87622178 0.20625131 0.91628575 0.71523824]
 [0.63480962 0.55121823 0.26070642 0.90649128 0.63039886]
 [0.31265185 0.4270349  0.27647695 0.38161852 0.42194087]]
[[ 2.92628137 32.00393912 30.77798499 82.01770601 64.44266323]
 [ 1.73028096 95.96911066 34.89408728  9.57792894 57.14315304]
 [22.0676074  71.68091459 58.94571299 78.06779122 39.84980568]
 …
 [27.89616278 88.28943762 20.63326926 91.73639222 71.32299139]
 [63.63480125 55.40575129 26.10696582 90.75512602 62.72994448]
 [31.33138691 42.8409485  27.69218169 38.1703486  41.61605357]]
[100. 100. 100. 100. 100.]
[0. 0. 0. 0. 0.]
```

[112]:
```python
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import scale
# import warnings
# warnings.filterwarnings('ignore')
T = 500 # sequence length
observations = 2*np.sin(np.linspace(0, 20*np.pi, T))
interventions = 2*np.sin(np.linspace(0, 2*np.pi, T))
data = np.vstack([observations, observations*1.2, interventions,
  interventions*0.85]).T
data += np.random.randn(*data.shape)
# data[:, 2:] = preprocessing.minmax_scale(data[:, 2:])
data = scale(data)

plt.figure(figsize=(10, 2))
plt.plot(data)
plt.xlabel('Time')
plt.ylabel('Value')
plt.show()
```



[113]:
```python
x = torch.FloatTensor(data).reshape(1, *data.shape)
x_train = torch.FloatTensor(data[:400]).reshape(1, 400, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[400:450]).reshape(1, 50, data.shape[1])
#print(x_val)
```

[114]:
```python
dkf = RNDKF(input_dim=4, z_dim=20, rnn_dim=20, trans_dim=20, emission_dim=20)
```

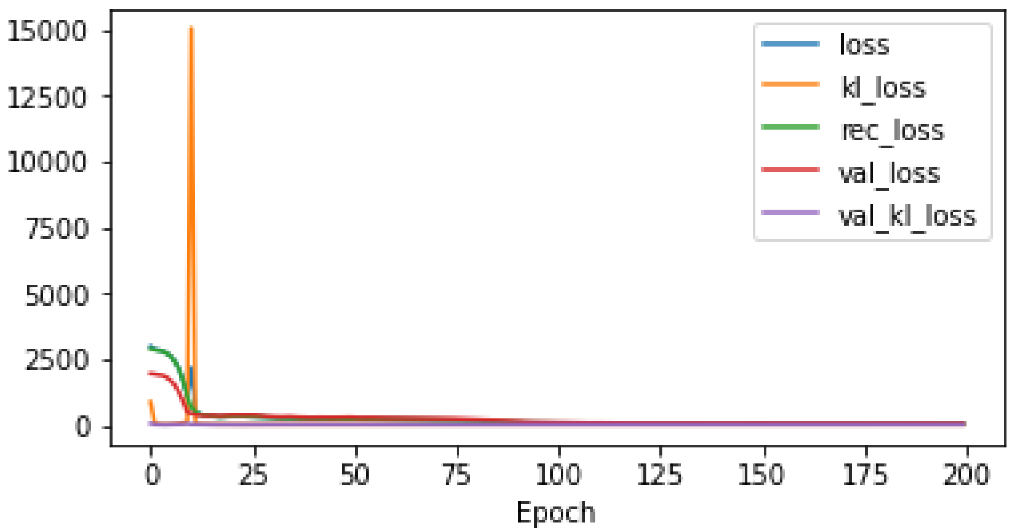
[115]:
```python
history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
↪annealing_factor=0.1)
```

```
Epoch= 1/200, loss= 2982.884, mse= 2895.622, kld= 872.619
        val_loss= 1956.585, val_mse= 1949.930, val_kld= 66.548
Epoch= 11/200, loss= 2171.065, mse= 665.464, kld= 15056.008
        val_loss= 448.582, val_mse= 445.160, val_kld= 34.221
Epoch= 21/200, loss= 349.184, mse= 346.806, kld= 23.779
```

```
        val_loss= 385.330, val_mse= 383.124, val_kld= 22.055
Epoch= 31/200, loss= 282.453, mse= 279.909, kld= 25.441
        val_loss= 328.551, val_mse= 326.063, val_kld= 24.877
Epoch= 41/200, loss= 255.664, mse= 252.620, kld= 30.437
        val_loss= 283.501, val_mse= 280.579, val_kld= 29.222
Epoch= 51/200, loss= 238.405, mse= 235.290, kld= 31.151
        val_loss= 287.336, val_mse= 284.429, val_kld= 29.065
Epoch= 61/200, loss= 226.648, mse= 223.812, kld= 28.357
        val_loss= 266.461, val_mse= 263.669, val_kld= 27.925
Epoch= 71/200, loss= 212.952, mse= 210.332, kld= 26.203
        val_loss= 252.504, val_mse= 249.874, val_kld= 26.300
Epoch= 81/200, loss= 171.735, mse= 169.209, kld= 25.259
        val_loss= 212.300, val_mse= 209.662, val_kld= 26.384
Epoch= 91/200, loss= 102.678, mse= 100.064, kld= 26.148
        val_loss= 152.581, val_mse= 149.906, val_kld= 26.755
Epoch= 101/200, loss= 86.810, mse= 84.250, kld= 25.609
        val_loss= 97.026, val_mse= 94.370, val_kld= 26.565
Epoch= 111/200, loss= 82.709, mse= 80.147, kld= 25.614
        val_loss= 92.352, val_mse= 89.692, val_kld= 26.600
Epoch= 121/200, loss= 77.772, mse= 75.154, kld= 26.185
        val_loss= 82.970, val_mse= 80.251, val_kld= 27.195
Epoch= 131/200, loss= 76.034, mse= 73.428, kld= 26.056
        val_loss= 79.127, val_mse= 76.407, val_kld= 27.195
Epoch= 141/200, loss= 74.341, mse= 71.744, kld= 25.978
        val_loss= 77.502, val_mse= 74.778, val_kld= 27.241
Epoch= 151/200, loss= 73.462, mse= 70.853, kld= 26.087
        val_loss= 78.906, val_mse= 76.213, val_kld= 26.931
Epoch= 161/200, loss= 70.988, mse= 68.372, kld= 26.165
        val_loss= 75.141, val_mse= 72.398, val_kld= 27.429
Epoch= 171/200, loss= 70.638, mse= 67.992, kld= 26.459
        val_loss= 75.860, val_mse= 73.112, val_kld= 27.483
Epoch= 181/200, loss= 68.832, mse= 66.196, kld= 26.365
        val_loss= 73.602, val_mse= 70.849, val_kld= 27.524
Epoch= 191/200, loss= 66.852, mse= 64.179, kld= 26.731
        val_loss= 69.889, val_mse= 67.178, val_kld= 27.111
```

[116]:
```
pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

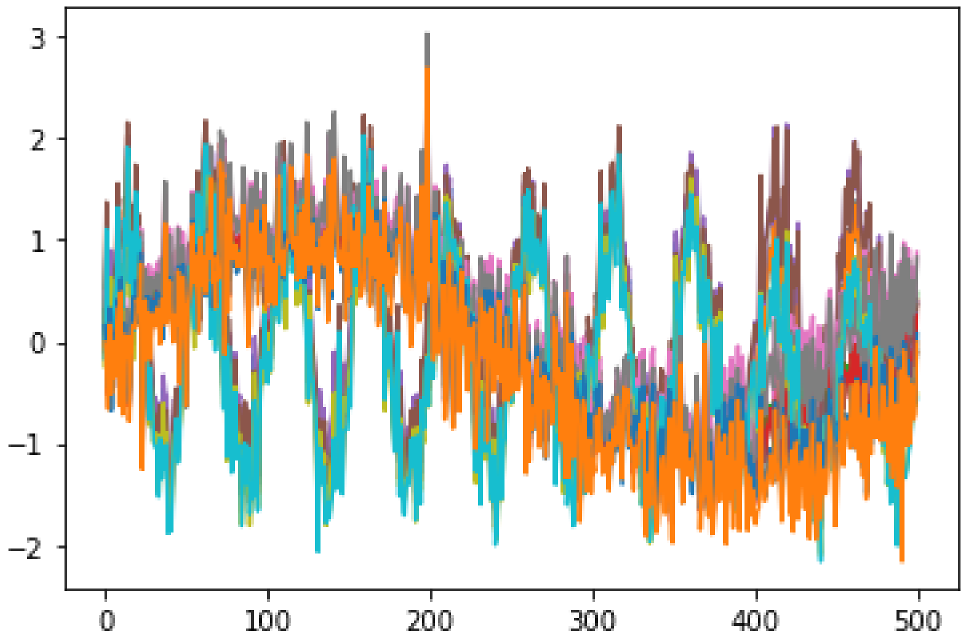
[116]:
```
<AxesSubplot:xlabel='Epoch'>
```



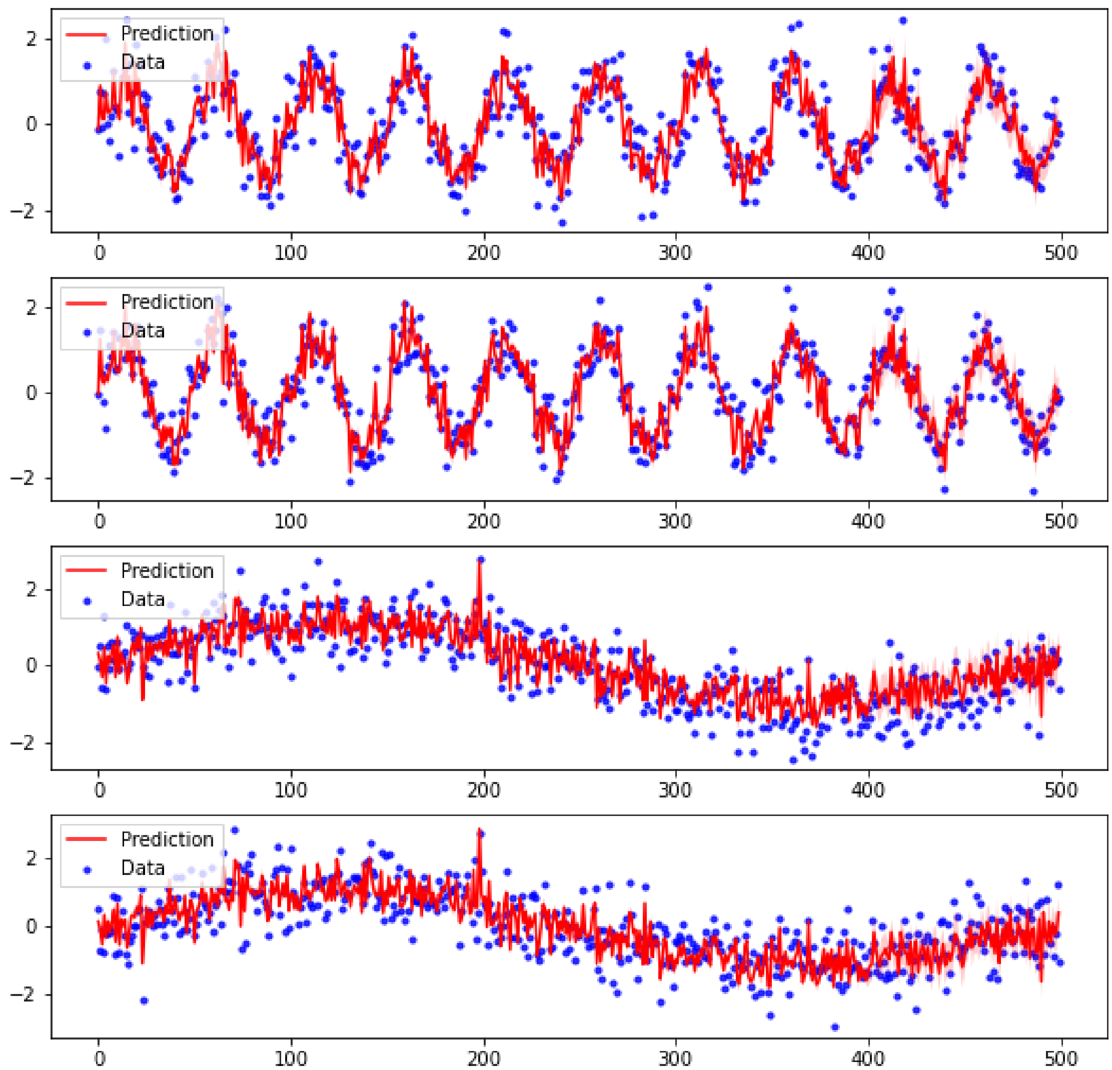
[117]:
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 100)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)
```

```
[[2.4821298 2.4622803 2.7782953 2.8465219]]
[[-2.2869356 -2.314187  -2.450089  -2.982882 ]]
torch.Size([1, 500, 4])
torch.Size([1, 500, 4])
torch.Size([1, 500, 4])
```

[117]:
```
[<matplotlib.lines.Line2D at 0x7f9ba8446100>,
 <matplotlib.lines.Line2D at 0x7f9ba84461f0>,
 <matplotlib.lines.Line2D at 0x7f9ba848c7c0>,
 <matplotlib.lines.Line2D at 0x7f9ba8446340>]
```



[118]:
```
fig, ax = plt.subplots(4, figsize=(10, 10))


#data = NormalizeData(data)

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
                     facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```




```
[ ]:
```

```
[ ]:
```

```python
[119]: def workout_to_haversine(i):
    ###Calculates haversine distance from point [0,0] in radians for a workout
    ###sklearn wants [lat,long] in radians
    ### to get distance in kilometers multiply by 6371000/1000
    lat = np.asarray(data_endo[i]['latitude'])
    lon = np.asarray(data_endo[i]['longitude'])
    coords = np.column_stack([lat, lon])
    coords_in_radians = np.radians(coords)
    zeros = np.zeros_like(coords_in_radians)
    zeros = np.radians(zeros)
```

```
    result = haversine_distances(coords_in_radians, zeros)
    result = result
    return result[:,0]
```

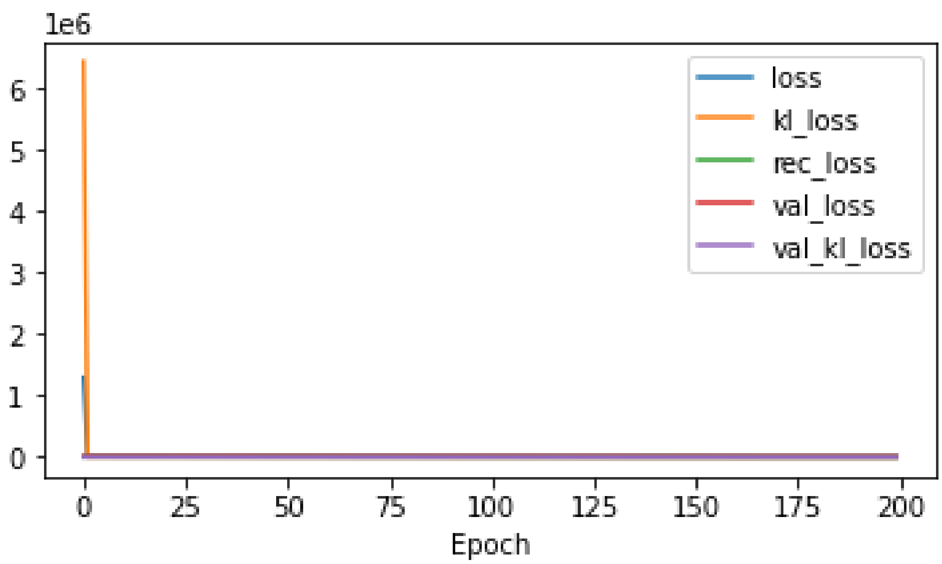
[120]:
```
data = np.vstack( [workout_to_haversine(i) for i in range(5)]).T
#print(data.shape)
#print(data)

x = torch.FloatTensor(data).reshape(1, *data.shape)
#print(x)
x_train = torch.FloatTensor(data[:400]).reshape(1, 400, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[400:450]).reshape(1, 50, data.shape[1])
#print(x_val)
```

[122]:
```
dkf = RNDKF(input_dim=5, z_dim=25, rnn_dim=25, trans_dim=25, emission_dim=25)

history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
 ↪annealing_factor=0.2)

pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')
```

```
Epoch= 1/200, loss= 1292074.875, mse= 4113.075, kld= 6439808.500
        val_loss= 6400.106, val_mse= 6343.547, val_kld= 282.795
Epoch= 11/200, loss= 1454.547, mse= 1432.065, kld= 112.410
        val_loss= 1984.734, val_mse= 1956.169, val_kld= 142.823
Epoch= 21/200, loss= 723.164, mse= 715.029, kld= 40.677
        val_loss= 1174.486, val_mse= 1160.802, val_kld= 68.422
Epoch= 31/200, loss= 606.487, mse= 598.788, kld= 38.496
        val_loss= 969.890, val_mse= 959.085, val_kld= 54.024
Epoch= 41/200, loss= 332.519, mse= 325.434, kld= 35.425
        val_loss= 410.197, val_mse= 400.222, val_kld= 49.871
Epoch= 51/200, loss= 260.372, mse= 252.045, kld= 41.631
        val_loss= 294.933, val_mse= 286.271, val_kld= 43.310
Epoch= 61/200, loss= 204.308, mse= 197.862, kld= 32.231
        val_loss= 230.228, val_mse= 221.952, val_kld= 41.378
Epoch= 71/200, loss= 166.639, mse= 160.613, kld= 30.128
        val_loss= 176.418, val_mse= 168.694, val_kld= 38.621
Epoch= 81/200, loss= 119.473, mse= 113.835, kld= 28.192
        val_loss= 157.294, val_mse= 149.619, val_kld= 38.375
Epoch= 91/200, loss= 63.734, mse= 58.323, kld= 27.053
        val_loss= 117.687, val_mse= 110.042, val_kld= 38.227
Epoch= 101/200, loss= 48.045, mse= 42.710, kld= 26.676
        val_loss= 34.997, val_mse= 27.179, val_kld= 39.092
Epoch= 111/200, loss= 38.401, mse= 32.874, kld= 27.633
        val_loss= 38.343, val_mse= 30.918, val_kld= 37.127
Epoch= 121/200, loss= 34.175, mse= 28.699, kld= 27.382
```

```
        val_loss= 34.142, val_mse= 26.182, val_kld= 39.804
Epoch= 131/200, loss= 33.222, mse= 28.196, kld= 25.131
        val_loss= 36.981, val_mse= 29.332, val_kld= 38.245
Epoch= 141/200, loss= 31.463, mse= 26.860, kld= 23.015
        val_loss= 28.934, val_mse= 21.948, val_kld= 34.930
Epoch= 151/200, loss= 28.817, mse= 24.419, kld= 21.992
        val_loss= 34.591, val_mse= 27.762, val_kld= 34.146
Epoch= 161/200, loss= 27.060, mse= 22.835, kld= 21.124
        val_loss= 33.821, val_mse= 26.658, val_kld= 35.814
Epoch= 171/200, loss= 27.223, mse= 22.857, kld= 21.829
        val_loss= 27.700, val_mse= 20.653, val_kld= 35.237
Epoch= 181/200, loss= 27.609, mse= 22.451, kld= 25.787
        val_loss= 29.714, val_mse= 22.815, val_kld= 34.498
Epoch= 191/200, loss= 25.408, mse= 21.281, kld= 20.635
        val_loss= 33.770, val_mse= 25.710, val_kld= 40.300
```

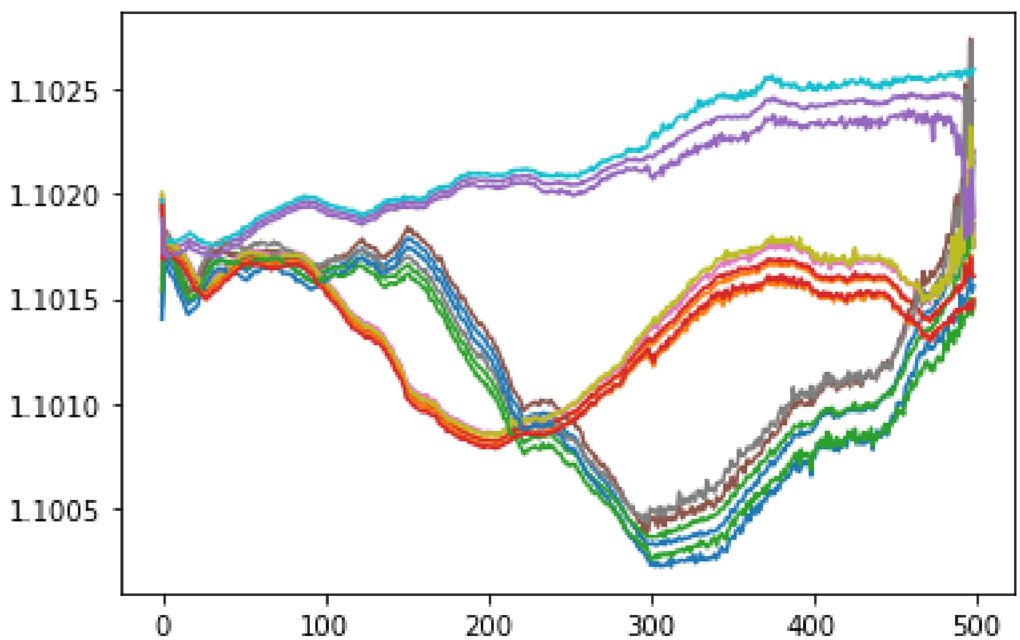
[122]: <AxesSubplot:xlabel='Epoch'>

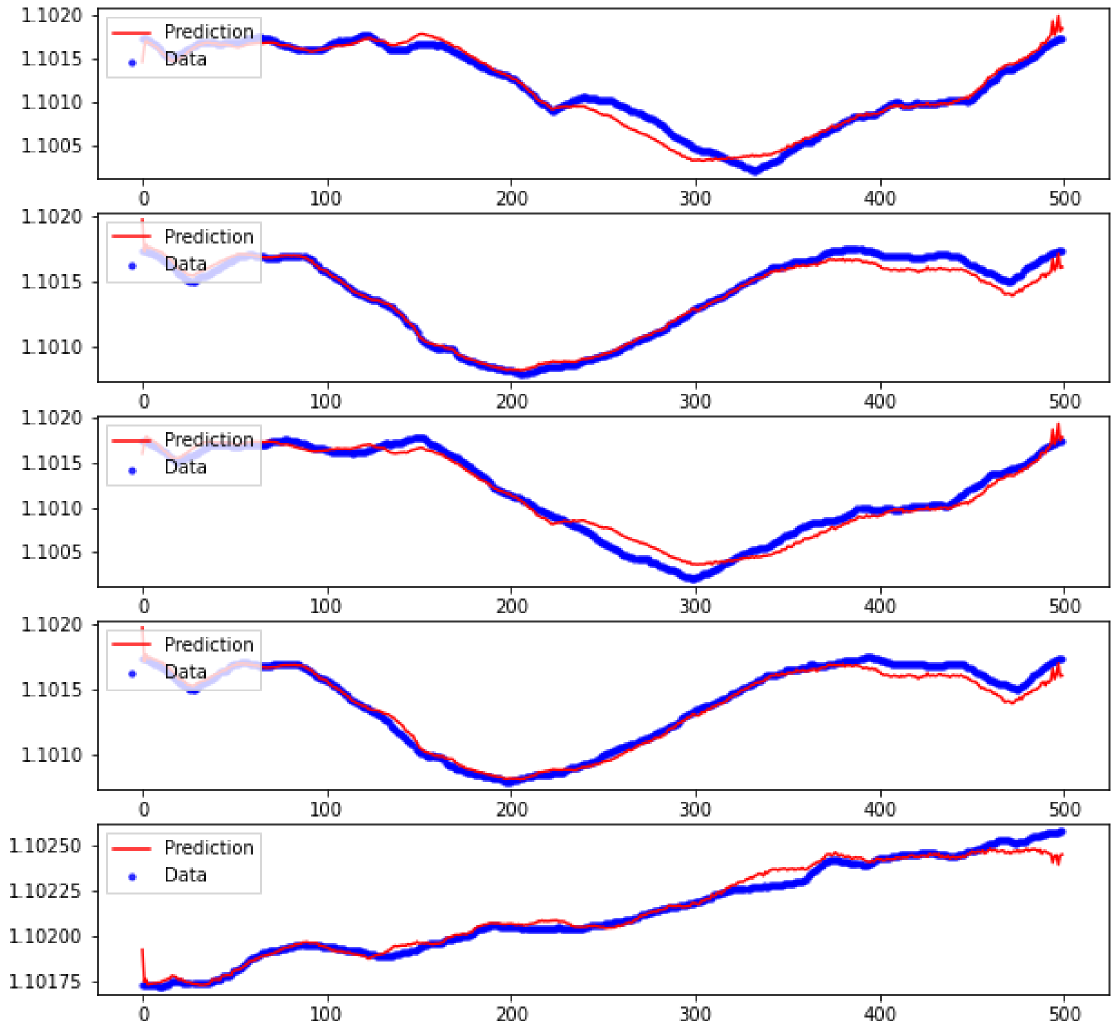


[123]:
```
# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)



x_hat, x_025, x_975 = dkf.predict(x, 200)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
```

```
plt.plot(x_975)
plt.plot(x_025)



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

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    #axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
    #                 facecolor='r', alpha=0.2)

    axi.legend(loc='upper left', fancybox=False)
plt.show()
```

```
[[1.1017815 1.1017488 1.1017824 1.1017468 1.1025736]]
[[1.1002148 1.1007968 1.1002144 1.1007969 1.1017256]]
torch.Size([1, 500, 5])
torch.Size([1, 500, 5])
torch.Size([1, 500, 5])
```





[124]:

```
mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])

# Print the DataFrame
```

```
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
                  MSE  R-squared       MAE
Average  4.540451e-09     0.9704  0.000048
                  MSE  R-squared       MAE
sample1  7.188807e-09   0.966992  0.000061
sample2  3.015378e-09   0.970123  0.000038
sample3  8.423161e-09   0.964526  0.000075
sample4  2.735537e-09   0.972464  0.000039
sample5  1.339370e-09   0.977892  0.000025
```

[ ]:

5.1 Wodociągi SNDKF

[130]:

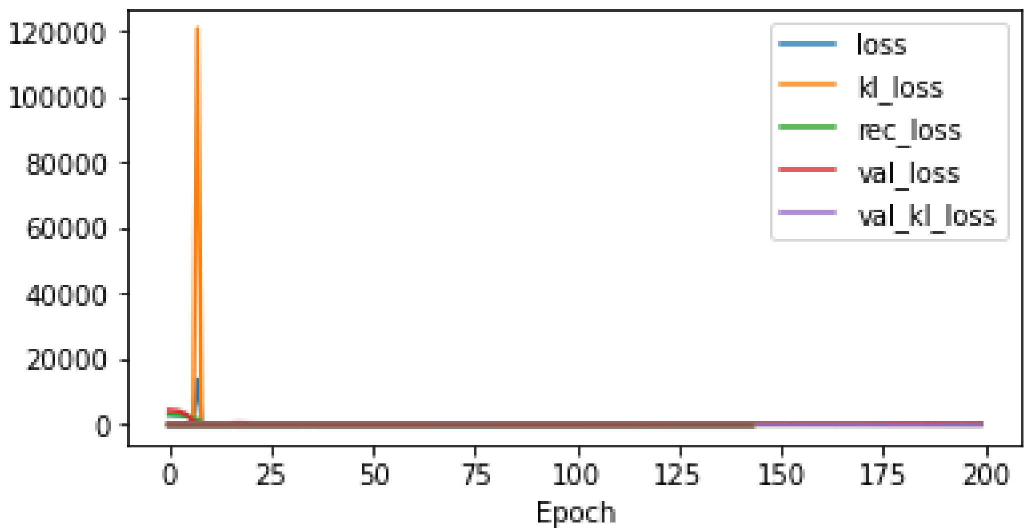
```
#i = #examples
i = 7

df = pd.read_csv('water_consumption_profiles.csv')

_ = df.values

all_days = _[:,1:].T

all_days.shape

all_days = all_days.astype('float64')
```

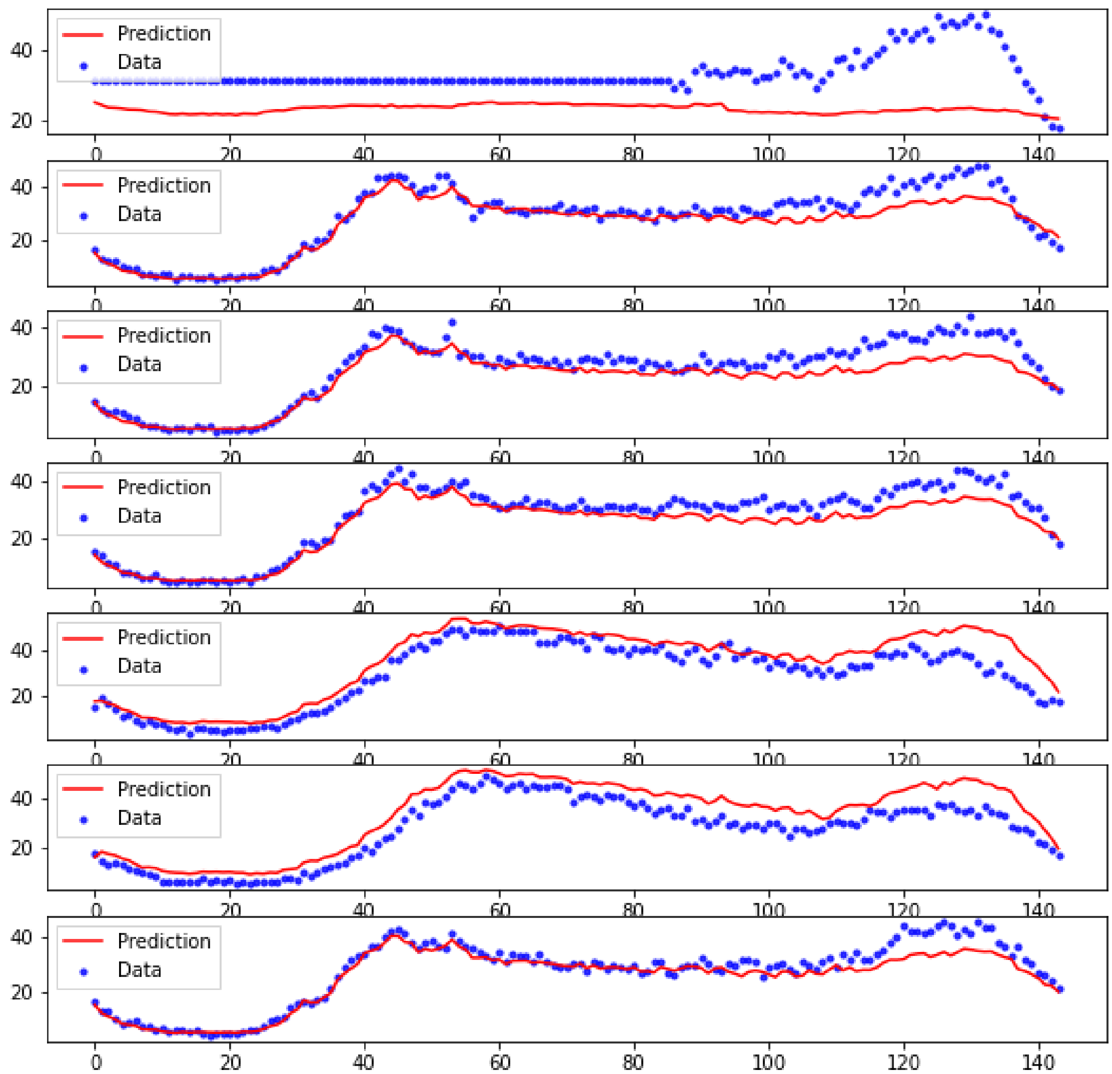
```
data = all_days[:, :7]



x = torch.FloatTensor(data).reshape(1, *data.shape)
#print(x)
x_train = torch.FloatTensor(data[:100]).reshape(1, 100, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[100:120]).reshape(1, 20, data.shape[1])
#print(x_val)






dkf = RNDKF(input_dim=i, z_dim=5*i, rnn_dim=5*i, trans_dim=5*i,␣
 ↪emission_dim=5*i)

history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
 ↪annealing_factor=0.1)

pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')


# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 50)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)


fig, ax = plt.subplots(i, figsize=(10, 10))

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    #axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
    #                 facecolor='r', alpha=0.2)
```

```python
    axi.legend(loc='upper left', fancybox=False)
plt.show()


mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])

# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
Epoch= 1/200, loss= 3126.310, mse= 3072.494, kld= 538.157
        val_loss= 4415.115, val_mse= 4406.664, val_kld= 84.511
Epoch= 11/200, loss= 264.323, mse= 256.522, kld= 78.012
        val_loss= 320.517, val_mse= 305.746, val_kld= 147.710
Epoch= 21/200, loss= 183.960, mse= 176.831, kld= 71.287
        val_loss= 524.254, val_mse= 509.496, val_kld= 147.585
Epoch= 31/200, loss= 118.478, mse= 112.019, kld= 64.598
```

```
        val_loss= 237.173, val_mse= 224.677, val_kld= 124.958
Epoch= 41/200, loss= 99.340, mse= 94.144, kld= 51.957
        val_loss= 330.789, val_mse= 319.622, val_kld= 111.669
Epoch= 51/200, loss= 98.578, mse= 93.863, kld= 47.151
        val_loss= 303.644, val_mse= 293.496, val_kld= 101.472
Epoch= 61/200, loss= 94.301, mse= 89.888, kld= 44.122
        val_loss= 286.246, val_mse= 276.507, val_kld= 97.393
Epoch= 71/200, loss= 95.705, mse= 91.834, kld= 38.702
        val_loss= 277.042, val_mse= 267.640, val_kld= 94.020
Epoch= 81/200, loss= 94.840, mse= 91.123, kld= 37.174
        val_loss= 293.153, val_mse= 284.129, val_kld= 90.242
Epoch= 91/200, loss= 92.550, mse= 89.301, kld= 32.491
        val_loss= 300.055, val_mse= 291.859, val_kld= 81.965
Epoch= 101/200, loss= 91.001, mse= 88.024, kld= 29.770
        val_loss= 288.784, val_mse= 280.600, val_kld= 81.841
Epoch= 111/200, loss= 88.449, mse= 85.583, kld= 28.659
        val_loss= 299.969, val_mse= 292.210, val_kld= 77.592
Epoch= 121/200, loss= 84.578, mse= 81.802, kld= 27.754
        val_loss= 317.132, val_mse= 309.514, val_kld= 76.179
Epoch= 131/200, loss= 83.141, mse= 80.516, kld= 26.255
        val_loss= 283.802, val_mse= 275.929, val_kld= 78.732
Epoch= 141/200, loss= 79.928, mse= 77.360, kld= 25.680
        val_loss= 228.248, val_mse= 220.139, val_kld= 81.093
Epoch= 151/200, loss= 77.730, mse= 75.115, kld= 26.150
        val_loss= 179.886, val_mse= 171.934, val_kld= 79.523
Epoch= 161/200, loss= 74.510, mse= 71.902, kld= 26.084
        val_loss= 160.131, val_mse= 152.577, val_kld= 75.539
Epoch= 171/200, loss= 65.249, mse= 62.545, kld= 27.034
        val_loss= 176.643, val_mse= 169.094, val_kld= 75.486
Epoch= 181/200, loss= 40.320, mse= 37.342, kld= 29.778
        val_loss= 271.210, val_mse= 265.183, val_kld= 60.272
Epoch= 191/200, loss= 26.639, mse= 24.196, kld= 24.423
        val_loss= 216.437, val_mse= 211.328, val_kld= 51.083
[[50.4 48.6 43.8 45.  50.4 48.6 45.6]]
[[17.4  4.2  4.2  4.8  4.2  4.8  4.2]]
torch.Size([1, 144, 7])
torch.Size([1, 144, 7])
torch.Size([1, 144, 7])
```


120000
100000
80000
60000
40000
20000
0
0
25
50
75
100
125
150
175
200
Epoch
loss
kl_loss
rec_loss
val_loss
val_kl_loss



	MSE	R-squared	MAE
Average	43.075687	0.2204	4.943866

	MSE	R-squared	MAE
sample1	140.947632	-3.421810	10.450581
sample2	20.909950	0.867868	3.297774
sample3	23.718559	0.798349	3.667260
sample4	18.296259	0.868425	3.483640
sample5	39.753922	0.794749	5.089786
sample6	44.038765	0.738684	6.049824
sample7	13.864722	0.896538	2.568191

[ ]:

[ ]:

[ ]:

```

```

5.2 5 first workouts by altitude SNDKF

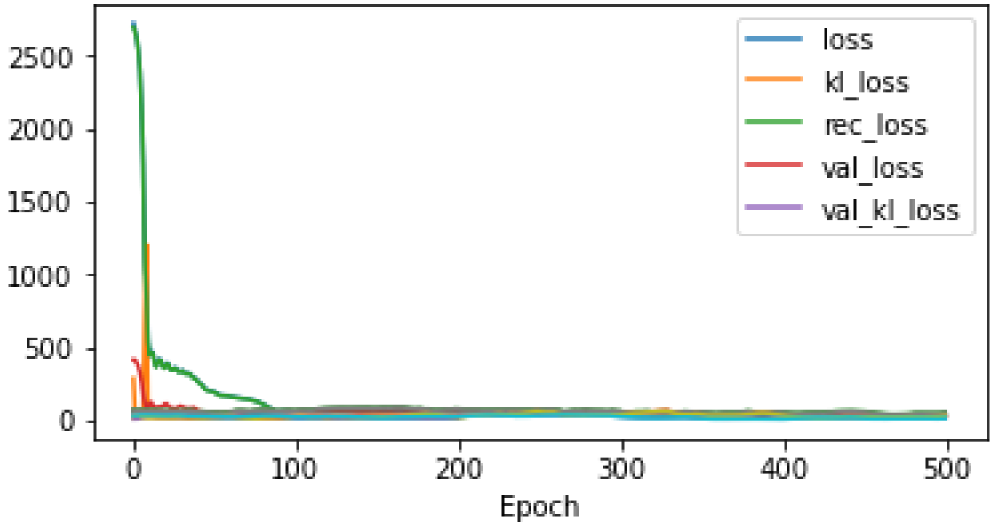
[132]:

```
data = np.vstack([np.asarray(data_endo[0]['altitude']), np.
↪asarray(data_endo[1]['altitude']),
                  np.asarray(data_endo[2]['altitude']), np.
↪asarray(data_endo[3]['altitude']),
                  np.asarray(data_endo[4]['altitude'])]).T
#print(data.shape)

x = torch.FloatTensor(data).reshape(1, *data.shape)
#print(x)
x_train = torch.FloatTensor(data[:450]).reshape(1, 450, data.shape[1])
#print(x_train)
x_val   = torch.FloatTensor(data[450:500]).reshape(1, 50, data.shape[1])
#print(x_val)

dkf = RNDKF(input_dim=5, z_dim=25, rnn_dim=25, trans_dim=25, emission_dim=25)

history, param_dict = dkf.fit(x_train, x_val, num_epochs=200,␣
↪annealing_factor=0.1)

pd.DataFrame(history).plot(figsize=(6, 3), xlabel='Epoch')

# x_hat = dkf.generate(x_train)
# x_hat, x_025, x_975 = dkf.filter(x_train)
x_hat, x_025, x_975 = dkf.predict(x, 100)
x_hat = x_hat.detach().numpy()[0]
x_025 = x_025.detach().numpy()[0]
x_975 = x_975.detach().numpy()[0]
plt.plot(x_hat)
plt.plot(x_975)
plt.plot(x_025)

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

for i, axi in enumerate(ax):
    axi.scatter(
        np.arange(data.shape[0]),
        data[:, i], s=10, alpha=0.8, label='Data', c='b')
    axi.plot(x_hat[:, i], label='Prediction', c='r')
    axi.fill_between(np.arange(x_hat.shape[0]), x_025[:, i], x_975[:, i],
                     facecolor='r', alpha=0.2)
```

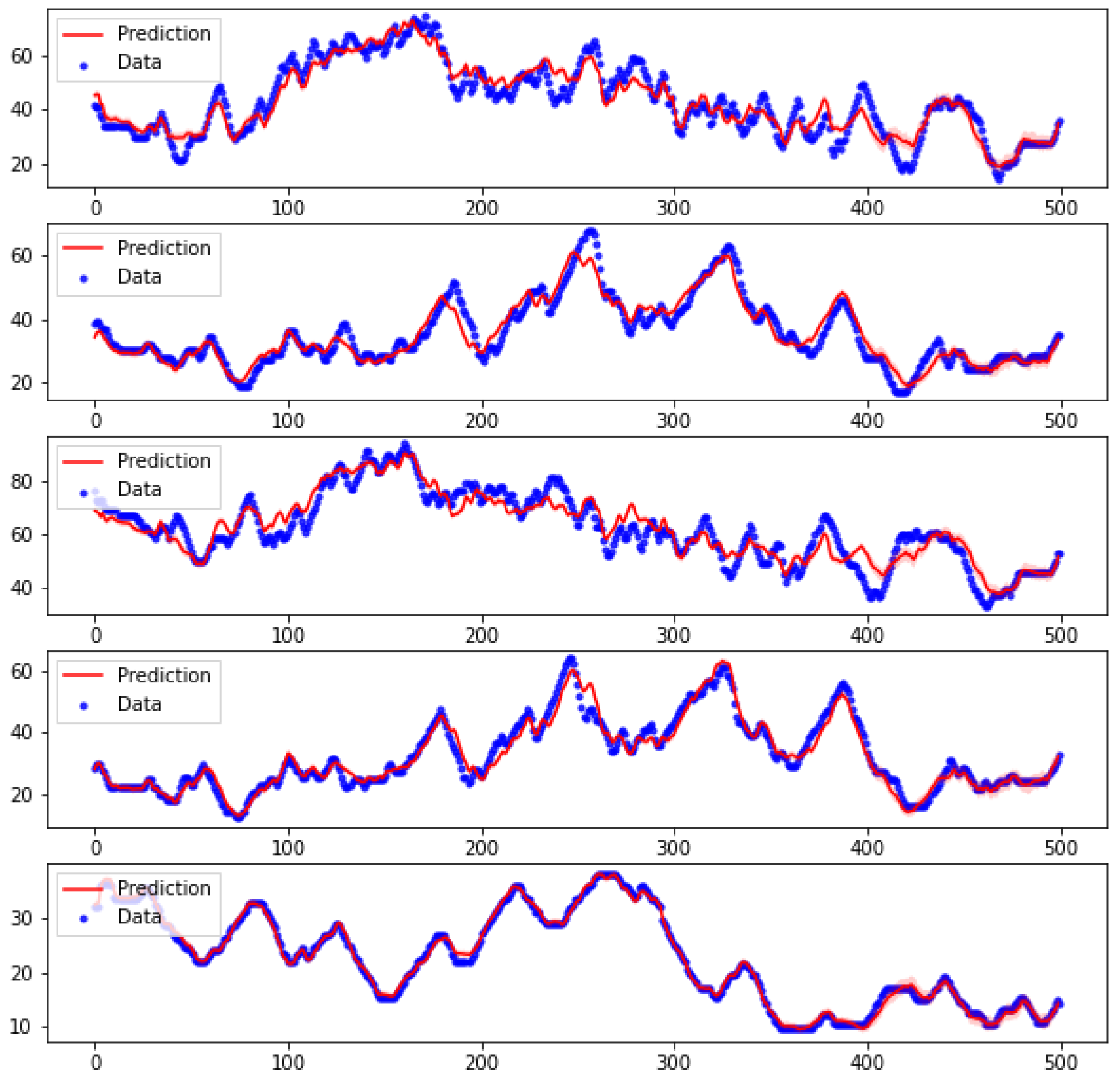
```python
    axi.legend(loc='upper left', fancybox=False)
plt.show()


mse_values = mean_squared_error(x[0], x_hat)
r_squared_values = r2_score(x[0], x_hat)
mae_values = mean_absolute_error(x[0], x_hat)

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=['Average'])

# Print the DataFrame
print(df)

mse_values = mean_squared_error(x[0], x_hat, multioutput='raw_values')
r_squared_values = r2_score(x[0], x_hat, multioutput='raw_values')
mae_values = mean_absolute_error(x[0], x_hat, multioutput='raw_values')

num_samples = x_hat.shape[1]  # Number of samples

# Create a dictionary with the evaluation metrics
data = {
    'MSE': mse_values,
    'R-squared': r_squared_values,
    'MAE': mae_values
}

# Create a DataFrame from the dictionary with appropriate column names
df = pd.DataFrame(data, index=[f"sample{i+1}" for i in range(num_samples)])

# Print the DataFrame
print(df)
```

```
Epoch= 1/200, loss= 2723.746, mse= 2695.151, kld= 285.950
        val_loss= 412.340, val_mse= 411.411, val_kld= 9.293
Epoch= 11/200, loss= 449.109, mse= 442.202, kld= 69.073
        val_loss= 117.551, val_mse= 114.303, val_kld= 32.481
Epoch= 21/200, loss= 375.882, mse= 370.567, kld= 53.154
        val_loss= 113.725, val_mse= 111.397, val_kld= 23.277
Epoch= 31/200, loss= 341.949, mse= 338.155, kld= 37.937
```

```
        val_loss= 92.765, val_mse= 90.792, val_kld= 19.729
Epoch= 41/200, loss= 261.838, mse= 258.633, kld= 32.043
        val_loss= 63.241, val_mse= 61.327, val_kld= 19.142
Epoch= 51/200, loss= 191.784, mse= 188.273, kld= 35.118
        val_loss= 52.515, val_mse= 50.492, val_kld= 20.237
Epoch= 61/200, loss= 162.849, mse= 159.988, kld= 28.608
        val_loss= 45.661, val_mse= 43.901, val_kld= 17.597
Epoch= 71/200, loss= 147.097, mse= 144.598, kld= 24.981
        val_loss= 36.539, val_mse= 34.971, val_kld= 15.684
Epoch= 81/200, loss= 110.806, mse= 108.491, kld= 23.153
        val_loss= 33.065, val_mse= 31.532, val_kld= 15.324
Epoch= 91/200, loss= 60.489, mse= 58.134, kld= 23.551
        val_loss= 20.972, val_mse= 19.291, val_kld= 16.806
Epoch= 101/200, loss= 51.685, mse= 49.374, kld= 23.115
        val_loss= 24.308, val_mse= 22.695, val_kld= 16.133
Epoch= 111/200, loss= 51.351, mse= 49.342, kld= 20.087
        val_loss= 26.518, val_mse= 24.866, val_kld= 16.515
Epoch= 121/200, loss= 48.658, mse= 46.874, kld= 17.842
        val_loss= 24.240, val_mse= 22.599, val_kld= 16.408
Epoch= 131/200, loss= 46.986, mse= 45.271, kld= 17.146
        val_loss= 22.368, val_mse= 20.799, val_kld= 15.687
Epoch= 141/200, loss= 46.690, mse= 45.072, kld= 16.180
        val_loss= 20.993, val_mse= 19.476, val_kld= 15.171
Epoch= 151/200, loss= 45.408, mse= 43.592, kld= 18.161
        val_loss= 22.372, val_mse= 20.901, val_kld= 14.709
Epoch= 161/200, loss= 44.437, mse= 42.922, kld= 15.153
        val_loss= 22.243, val_mse= 20.763, val_kld= 14.800
Epoch= 171/200, loss= 43.984, mse= 42.485, kld= 14.991
        val_loss= 23.029, val_mse= 21.581, val_kld= 14.473
Epoch= 181/200, loss= 42.368, mse= 40.951, kld= 14.174
        val_loss= 22.801, val_mse= 21.357, val_kld= 14.443
Epoch= 191/200, loss= 41.214, mse= 39.824, kld= 13.899
        val_loss= 21.853, val_mse= 20.436, val_kld= 14.168
[[74.2 67.8 94.  64.  37.8]]
[[14.6 17.2 33.4 12.4  9.8]]
torch.Size([1, 500, 5])
torch.Size([1, 500, 5])
torch.Size([1, 500, 5])
```



loss
kl_loss
rec_loss
val_loss
val_kl_loss
2500
2000
1500
1000
500
0
0
100
200
300
400
500
Epoch



	MSE	R-squared	MAE
Average	11.76773	0.923482	2.467848

	MSE	R-squared	MAE
sample1	18.407692	0.898636	3.491214
sample2	9.176114	0.914770	2.398109
sample3	23.859688	0.863427	3.962124
sample4	6.984386	0.946422	2.004938
sample5	0.410771	0.994156	0.482857

[ ]: