Small training example demonstrating the visualizations

In this notebook we show few small networks that learn the available data. The goal is to "beat" the Zero predictor and that required few iterations on manual hyperparameter search. It is possible to find better models but no computing power was invested on this sample.

Note that the Delay based networks have few orders of magnitude fewer parameters than those presented in the paper. Also, except dropping learning rate there are no fancy callbacks.

In [1]:

```
%load_ext autoreload
%autoreload 2
import matplotlib
import matplotlib.pyplot as plt
from matplotlib import cm
import numpy as np
import pandas as pd
from pathlib import Path

import torch
from fastai.data.transforms import TfmdLists, DataLoaders
import fastai.learner
import fastai.callback.schedule
import fastai.callback.tracker
import fastai.basics
import fastai.losses


import network_definitions
```

In [2]:

```
data_load_path = Path("../data_sample")
train_data = np.load(data_load_path / "train_samples.npy")
valid_data = np.load(data_load_path / "valid_samples.npy")
train_samples = list(train_data)  # to match the requirements of fastai.TfmdLis
valid_samples = list(valid_data)

sample_length = train_data[0].shape[0]
# Settings to match the paper experiments. Except the number of columns, all the
future_length = 30
past_length = sample_length - future_length
no_features = train_data[0].shape[1]
known_column_indexes = list(range(no_features))  # [0, 1, 2, 3]
command_indexes = [2]
target_indexes = [3]
feature_groups = [(0, 1, 3)]
average_range = 0.2
batch_size = 32

feature_itemizer = network_definitions.FeatureItemizer(future_length, known_colu
                                         command_indexes, target_indexes, featu
tls_train = TfmdLists(train_samples, [feature_itemizer])
tls_valid = TfmdLists(valid_samples, [feature_itemizer])
data_dloader = DataLoaders.from_dsets(tls_train, tls_valid, bs=batch_size, drop_
print(f"Data volumes: Train: {len(train_samples)}, Validation: {len(valid_sample
```

```
Data volumes: Train: 7255, Validation: 1073
```

In [3]:
```
def get_SAffAffGau():
    model = network_definitions.ConstructDelayNet(no_features, len(command_index
                                                  filter_low_classname="AffineTra
                                                  aggregator_low_expansion=0.2, a
                                                  temporal_contractor_classname='
                                                  filter_high_classname="GaussFil
                                                  aggregator_high_expansion=0.5,
    return model

def get_SLogAffGau():
    model = network_definitions.ConstructDelayNet(no_features, len(command_index
                                                  filter_low_classname="LogGauss'
                                                  aggregator_low_expansion=0.2, a
                                                  temporal_contractor_classname='
                                                  filter_high_classname="GaussFil
                                                  aggregator_high_expansion=0.5,
    return model

def get_AttA1():
    model = network_definitions.ICCP_Wrap_AttentionModel(no_features, len(comman
                                                          hidden_size=8, num_laye
    return model

def instantiate_learner(model, data_loader):
    learner = fastai.learner.Learner(data_loader, model, loss_func=fastai.losses
                      cbs=[fastai.callback.tracker.ReduceLROnPlateau(patience=10,
                           fastai.callback.tracker.EarlyStoppingCallback(patience
                           fastai.callback.tracker.SaveModelCallback(fname="best_
                           fastai.callback.tracker.TerminateOnNaNCallback(),
                            ],)
    return learner

def evaluate_learner(crt_learner, samples):
    raw_preds, raw_targets = crt_learner.get_preds()
    eval_itemset_arr = np.array(samples)
    feature_itemizer = crt_learner.dls[0].fs[0]
    future_temp_pred_transf = network_definitions.decode_predictions_from_the_ne
    future_temp_target_transf = network_definitions.decode_predictions_from_the_
    mae = np.average(np.abs(future_temp_target_transf[:, -future_length:] - futu
    mae_wrt_to_time = np.average(np.abs(future_temp_target_transf[:, -future_len
    return mae, mae_wrt_to_time, future_temp_pred_transf, future_temp_target_tra
```

In [4]:
```
model_names = []
learners = []
global_lr_rate = 1e-3
global_no_max_epochs = 50
```

Perform training on all networks

In [5]:
```
SAffAffGau_learner = instantiate_learner(get_SAffAffGau(), data_dloader)
SAffAffGau_learner.fit_one_cycle(global_no_max_epochs, global_lr_rate)
model_names.append("SAffAffGau")
learners.append(SAffAffGau_learner)
```

epoch	train_loss	valid_loss	time
0	0.229754	0.215578	00:09

epoch	train_loss	valid_loss	time
1	0.169978	0.161708	00:08
2	0.090535	0.083229	00:08
3	0.020491	0.015789	00:08
4	0.009193	0.008843	00:08
5	0.007192	0.007676	00:08
6	0.007126	0.007225	00:08
7	0.007160	0.007236	00:08
8	0.007025	0.007290	00:08
9	0.006608	0.007282	00:08
10	0.006528	0.007503	00:08
11	0.006530	0.007005	00:08
12	0.006234	0.006922	00:08
13	0.006031	0.007465	00:09
14	0.006140	0.006910	00:08
15	0.005954	0.007177	00:08
16	0.005787	0.006455	00:08
17	0.005907	0.006117	00:08
18	0.005656	0.005758	00:08
19	0.005439	0.006351	00:08
20	0.005509	0.005868	00:08
21	0.005598	0.005533	00:09
22	0.005216	0.005581	00:08
23	0.005182	0.005684	00:08
24	0.005229	0.005430	00:08
25	0.005277	0.005764	00:09
26	0.005409	0.005424	00:08
27	0.004980	0.005275	00:09
28	0.005130	0.005288	00:09
29	0.004973	0.005634	00:08
30	0.005221	0.005202	00:08
31	0.004991	0.005165	00:08
32	0.004662	0.005331	00:08
33	0.005033	0.005159	00:08
34	0.005133	0.005230	00:08
35	0.005036	0.005339	00:08
36	0.004869	0.005249	00:09

epoch	train_loss	valid_loss	time
37	0.004864	0.005459	00:08
38	0.005123	0.005177	00:08
39	0.004945	0.005279	00:08
40	0.005067	0.005164	00:09
41	0.005146	0.005134	00:09
42	0.004929	0.005210	00:08
43	0.004737	0.005165	00:08
44	0.004954	0.005044	00:08
45	0.004992	0.005094	00:08
46	0.004925	0.005185	00:08
47	0.004751	0.005131	00:08
48	0.005085	0.005122	00:08
49	0.004979	0.005093	00:08

```
Better model found at epoch 0 with valid_loss value: 0.21557800471782684.
Better model found at epoch 1 with valid_loss value: 0.1617080420255661.
Better model found at epoch 2 with valid_loss value: 0.0832289382815361.
Better model found at epoch 3 with valid_loss value: 0.01578901708126068.
Better model found at epoch 4 with valid_loss value: 0.008842738345265388.
Better model found at epoch 5 with valid_loss value: 0.007675706408917904.
Better model found at epoch 6 with valid_loss value: 0.007225068286061287.
Better model found at epoch 11 with valid_loss value: 0.007004912942647934.
Better model found at epoch 12 with valid_loss value: 0.00692222872748971.
Better model found at epoch 14 with valid_loss value: 0.006909816525876522.
Better model found at epoch 16 with valid_loss value: 0.0064553311094641685.
Better model found at epoch 17 with valid_loss value: 0.0061165159568190575.
Better model found at epoch 18 with valid_loss value: 0.005758226383477449.
Better model found at epoch 21 with valid_loss value: 0.005533043760806322.
Better model found at epoch 24 with valid_loss value: 0.005429862067103386.
Better model found at epoch 26 with valid_loss value: 0.005424467381089926.
Better model found at epoch 27 with valid_loss value: 0.005275101400911808.
Better model found at epoch 30 with valid_loss value: 0.005202378612011671.
Better model found at epoch 31 with valid_loss value: 0.00516463490203023.
Better model found at epoch 33 with valid_loss value: 0.005158796440809965.
Better model found at epoch 41 with valid_loss value: 0.005133894272148609.
Better model found at epoch 44 with valid_loss value: 0.005043629556894302.
```

In [6]:

```
SLogAffGau_learner = instantiate_learner(get_SLogAffGau(), data_dloader)
SLogAffGau_learner.fit_one_cycle(global_no_max_epochs, global_lr_rate)
model_names.append("SLogAffGau")
learners.append(SLogAffGau_learner)
```

epoch	train_loss	valid_loss	time
0	0.509574	0.500283	00:09
1	0.445961	0.420638	00:09
2	0.351695	0.318204	00:09
3	0.163822	0.101296	00:08
4	0.031649	0.034275	00:08

epoch	train_loss	valid_loss	time
5	0.015345	0.026775	00:09
6	0.010595	0.020361	00:09
7	0.008562	0.007623	00:08
8	0.007852	0.007509	00:08
9	0.007451	0.014901	00:08
10	0.007133	0.011613	00:09
11	0.007091	0.008071	00:09
12	0.006693	0.012296	00:09
13	0.006615	0.010344	00:09
14	0.006018	0.007276	00:09
15	0.006254	0.011434	00:08
16	0.006362	0.010851	00:09
17	0.006142	0.009388	00:08
18	0.006145	0.009935	00:08
19	0.005943	0.008340	00:08
20	0.005938	0.017478	00:08
21	0.005708	0.017052	00:08
22	0.005800	0.006453	00:08
23	0.005793	0.006890	00:08
24	0.005643	0.007205	00:08
25	0.005761	0.007085	00:08
26	0.005439	0.007140	00:08
27	0.005527	0.005990	00:08
28	0.005426	0.009597	00:08
29	0.005263	0.005888	00:08
30	0.005640	0.005873	00:08
31	0.005425	0.007620	00:09
32	0.005593	0.006228	00:09
33	0.005399	0.005976	00:09
34	0.005474	0.006843	00:09
35	0.005351	0.007875	00:08
36	0.005354	0.006804	00:08
37	0.005439	0.006081	00:09
38	0.005338	0.006033	00:09
39	0.005595	0.006199	00:09
40	0.005149	0.005704	00:09

epoch	train_loss	valid_loss	time
41	0.005177	0.005788	00:08
42	0.005417	0.005906	00:09
43	0.005270	0.005589	00:08
44	0.005220	0.005533	00:09
45	0.005379	0.005667	00:09
46	0.005339	0.005649	00:09
47	0.005426	0.005668	00:09
48	0.005408	0.005785	00:09
49	0.005266	0.005674	00:09

```
Better model found at epoch 0 with valid_loss value: 0.5002830028533936.
Better model found at epoch 1 with valid_loss value: 0.4206376373767853.
Better model found at epoch 2 with valid_loss value: 0.31820395588874817.
Better model found at epoch 3 with valid_loss value: 0.10129593312740326.
Better model found at epoch 4 with valid_loss value: 0.03427467495203018.
Better model found at epoch 5 with valid_loss value: 0.026774706318974495.
Better model found at epoch 6 with valid_loss value: 0.020360874012112617.
Better model found at epoch 7 with valid_loss value: 0.0076230838894844055.
Better model found at epoch 8 with valid_loss value: 0.007509196642786264.
Better model found at epoch 14 with valid_loss value: 0.007276284974068403.
Better model found at epoch 22 with valid_loss value: 0.006452830974012613.
Better model found at epoch 27 with valid_loss value: 0.0059901936911046505.
Better model found at epoch 29 with valid_loss value: 0.005888140760362148.
Better model found at epoch 30 with valid_loss value: 0.0058731501922011375.
Better model found at epoch 40 with valid_loss value: 0.005703907459974289.
Better model found at epoch 43 with valid_loss value: 0.005588890984654427.
Better model found at epoch 44 with valid_loss value: 0.005533136427402496.
```

In [7]:

```
AttA1_learner = instantiate_learner(get_AttA1(), data_dloader)
AttA1_learner.fit_one_cycle(min(global_no_max_epochs,10) , global_lr_rate)   # (
model_names.append("AttA1")
learners.append(AttA1_learner)
```

epoch	train_loss	valid_loss	time
0	0.009973	0.007314	00:29
1	0.007224	0.007214	00:29
2	0.006325	0.006157	00:29
3	0.005637	0.005555	00:29
4	0.005571	0.005428	00:29
5	0.005115	0.005203	00:29
6	0.005170	0.005148	00:29
7	0.004985	0.005111	00:29
8	0.004839	0.004941	00:29
9	0.004856	0.004907	00:29

```
Better model found at epoch 0 with valid_loss value: 0.007313926704227924.
Better model found at epoch 1 with valid_loss value: 0.007213677279651165.
Better model found at epoch 2 with valid_loss value: 0.006157493218779564.
```

```
Better model found at epoch 3 with valid_loss value: 0.005554764065891504.
Better model found at epoch 4 with valid_loss value: 0.0054275947622954845.
Better model found at epoch 5 with valid_loss value: 0.005202803295105696.
Better model found at epoch 6 with valid_loss value: 0.00514829158782959.
Better model found at epoch 7 with valid_loss value: 0.00511129992082715.
Better model found at epoch 8 with valid_loss value: 0.004940894898027182.
Better model found at epoch 9 with valid_loss value: 0.0049069710075855255.
```

Network summary.

In [12]:

```
for k in range(len(learners)):
    print(f"Architecture for {model_names[k]}:")
    network_definitions.print_model_weights_rec(learners[k].model, max_level=1)
```

```
Architecture for SAffAffGau:
<class 'network_definitions.ConstructDelayNet'> with 316 parameters:
      <class 'network_definitions.BankedFilters'> with 64 parameters:
      Parameters: 64
      ------------------
      <class 'network_definitions.FeatureAggregationStack'> with 92 parameters:
      Parameters: 92
      ------------------
      <class 'network_definitions.AffineTransform'> with 32 parameters:
      Parameters: 32
      ------------------
      <class 'network_definitions.BankedFilters'> with 67 parameters:
      Parameters: 67
      ------------------
      <class 'network_definitions.FeatureAggregationStack'> with 61 parameters:
      Parameters: 61
      ------------------
Parameters: 316
------------------
Architecture for SLogAffGau:
<class 'network_definitions.ConstructDelayNet'> with 340 parameters:
      <class 'network_definitions.BankedFilters'> with 64 parameters:
      Parameters: 64
      ------------------
      <class 'network_definitions.FeatureAggregationStack'> with 116 parameters:
      Parameters: 116
      ------------------
      <class 'network_definitions.AffineTransform'> with 32 parameters:
      Parameters: 32
      ------------------
      <class 'network_definitions.BankedFilters'> with 67 parameters:
      Parameters: 67
      ------------------
      <class 'network_definitions.FeatureAggregationStack'> with 61 parameters:
      Parameters: 61
      ------------------
Parameters: 340
------------------
Architecture for AttA1:
<class 'network_definitions.ICCP_Wrap_AttentionModel'> with 9155 parameters:
      <class 'network_definitions.AttentionModel'> with 9155 parameters:
      Parameters: 9155
      ------------------
Parameters: 9155
------------------
```

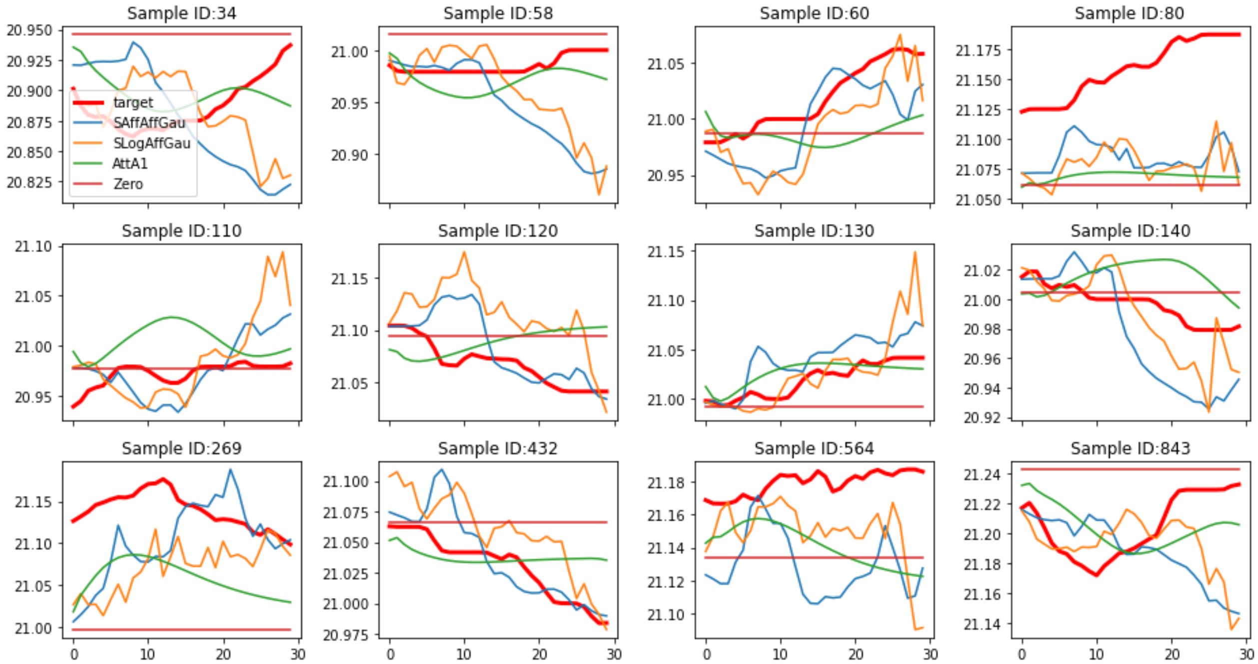
Let's do some evaluation!

In [9]:
```
maes = []
maes_timewise = []
predictions = []

for l in learners:
    mae, mae_t, scaled_preds, scaled_targets = evaluate_learner(l, valid_samples
    maes.append(mae)
    maes_timewise.append(mae_t)
    predictions.append(scaled_preds)

# Adding "zero" predictor
raw_preds, raw_targets = learners[0].get_preds()
zero_preds =  torch.zeros_like(raw_preds)
eval_itemset_arr = np.array(valid_samples)
feature_itemizer = learners[0].dls[0].fs[0]
zero_transf = network_definitions.decode_predictions_from_the_network(zero_preds
mae_zero = np.average(np.abs(scaled_targets[:, -future_length:] - zero_transf[:,
mae_zero_time = np.average(np.abs(scaled_targets[:, -future_length:] - zero_tran
model_names.append("Zero")
maes.append(mae_zero)
maes_timewise.append(mae_zero_time)
predictions.append(zero_transf)
model_names = model_names[:len(learners)+1] # just to make sure that on re-runs
for k in range(len(model_names)):
    print(f"Performance of {model_names[k]}: MAE: {maes[k]:.4}")
```

```
Performance of SAffAffGau: MAE: 0.07691
Performance of SLogAffGau: MAE: 0.08352
Performance of AttA1: MAE: 0.07397
Performance of Zero: MAE: 0.1098
```

Pretty print some results.

In [10]:
```
ids_to_plot = [34, 58, 60 , 80, 110, 120, 130, 140, 269, 432, 564, 843]
NCols = 4
NRows = int(len(ids_to_plot)/NCols) + 1 * (len(ids_to_plot) % NCols > 0)
fig, ax = plt.subplots(NRows, NCols, figsize=(13,7), sharex=True, sharey=False);
for k, sampleid in enumerate(ids_to_plot):
    gr = int(k / NCols)
    gc = int(k % NCols)
    ax[gr, gc].plot(scaled_targets[sampleid], 'r', linewidth=3, label='target')
    ax[gr, gc].set_title(f"Sample ID:{ids_to_plot[k]}")
    for i in range(len(model_names)):
        ax[gr, gc].plot(predictions[i][sampleid], label=model_names[i])

ax[0,0].legend()
fig.tight_layout()
```



Average loss with respect to the future.

One can expect that the distant future is predicted worse than near future. But how much worse? Linear? Exponentially worse?

In [11]:

```
fig, ax = plt.subplots(1, 1, figsize=(6,3), sharex=True, sharey=True);
for i in range(len(model_names)):
    ax.plot(maes_timewise[i],  label=model_names[i])
ax.legend()
fig.tight_layout()
```