

COS30018 – Intelligent System

Option B: Stock Price Prediction

Report v0.4

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Summary function to create DL models	2
Summary experiments of different configuration of DL models and model training	2

Summary function to create DL models

```
def create_model(sequence_length, n_features, units=256, cell=LSTM, n_layers=2, dropout=0.3,
                 loss="mean_absolute_error", optimizer="rmsprop", bidirectional=False):
    model = Sequential()
    for i in range(n_layers):
        if i == 0:
            # first layer
            if bidirectional:
                model.add(Bidirectional(cell(units, return_sequences=True), batch_input_shape=(None, sequence_length, n_features)))
            else:
                model.add(cell(units, return_sequences=True, batch_input_shape=(None, sequence_length, n_features)))
        elif i == n_layers - 1:
            # last layer
            if bidirectional:
                model.add(Bidirectional(cell(units, return_sequences=False)))
            else:
                model.add(cell(units, return_sequences=False))
        else:
            # hidden layers
            if bidirectional:
                model.add(Bidirectional(cell(units, return_sequences=True)))
            else:
                model.add(cell(units, return_sequences=True))
        # add dropout after each layer
        model.add(Dropout(dropout))
    model.add(Dense(1, activation="linear"))
    model.compile(loss=loss, metrics=["mean_absolute_error"], optimizer=optimizer)
    return model
```

✓ 0.0s

After creating model at putting input and output into sequence data (Sequential) I create for loop depending on the number layers we want to add, inside that there are three layers inside with choice of whether include bidirectional or simple layer. At the end of the loop, add the Dropout layer into sequential model. After the loop, add Dense layer with unit and linear activation, then compile the model with same loss and metrics, and use optimiser that we want (like adam). Finally, return model in overall function.

Summary experiments of different configuration of DL models and model training

```

LAYER_NAME = LSTM

N_SIZE = 256

N_LAYERS = 3

BATCH_SIZE = 64

EPOCHS = 100

DATE_NOW = time.strftime("%Y-%m-%d")

LOSS='huber_loss'

OPTIMIZER='adam'

N_FEATURES = ["adjclose", "volume", "open", "high", "low"]

# whether to use bidirectional RNNs
BIDIRECTIONAL = False

# 40% dropout
DROPOUT = 0.4

# When to shuffle the dataset
shuffle_str = f"sh-{int(SHUFFLE)}"

# When to scale the dataset
scale_str = f"sc-{int(SCALE)}"

# Whether to split the dataset by date
SPLIT_BY_DATE_str = f"sbd-{int(SPLIT_BY_DATE)}"

# save model name, and make it unique as possible
model_name = f"{DATE_NOW}_{TICKER}-{shuffle_str}-{scale_str}-{SPLIT_BY_DATE_str}-{LAYER_NAME.__name__}-seq-{N_STEPS}-step-{LOOKUP_STEP}-layers-{N_LAYERS}-units-{N_SIZE}-epoch-{EPOCHS}"

if BIDIRECTIONAL:
    model_name += "-b"

✓ 0.0s

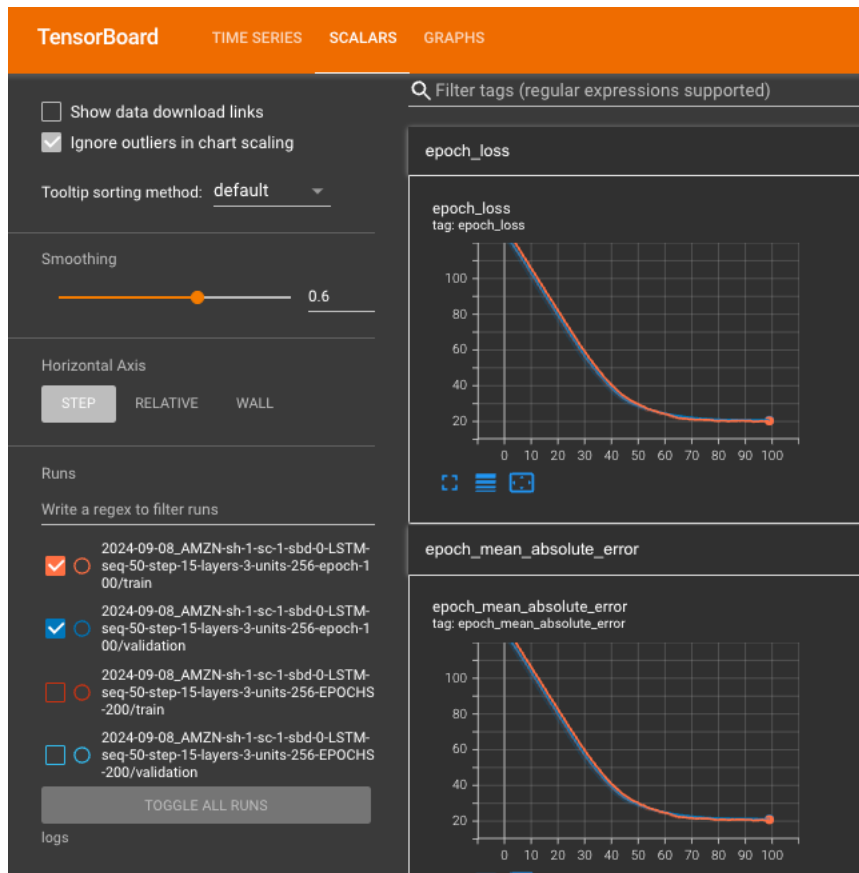
```

Experiment with the first one in details:

- Layer name: LSTM
- Size number: 256
- Layer number: 3
- Batch size: 64
- Epochs: 100
- LOSS: huber_loss
- Optimizer: adam
- Bidirectional: False
- Dropout: 0.4

✓ 5m 29.3s

Training takes 5 minutes 29 seconds



The graph show the curve line from 0 to 80 before decrease slightly till 100

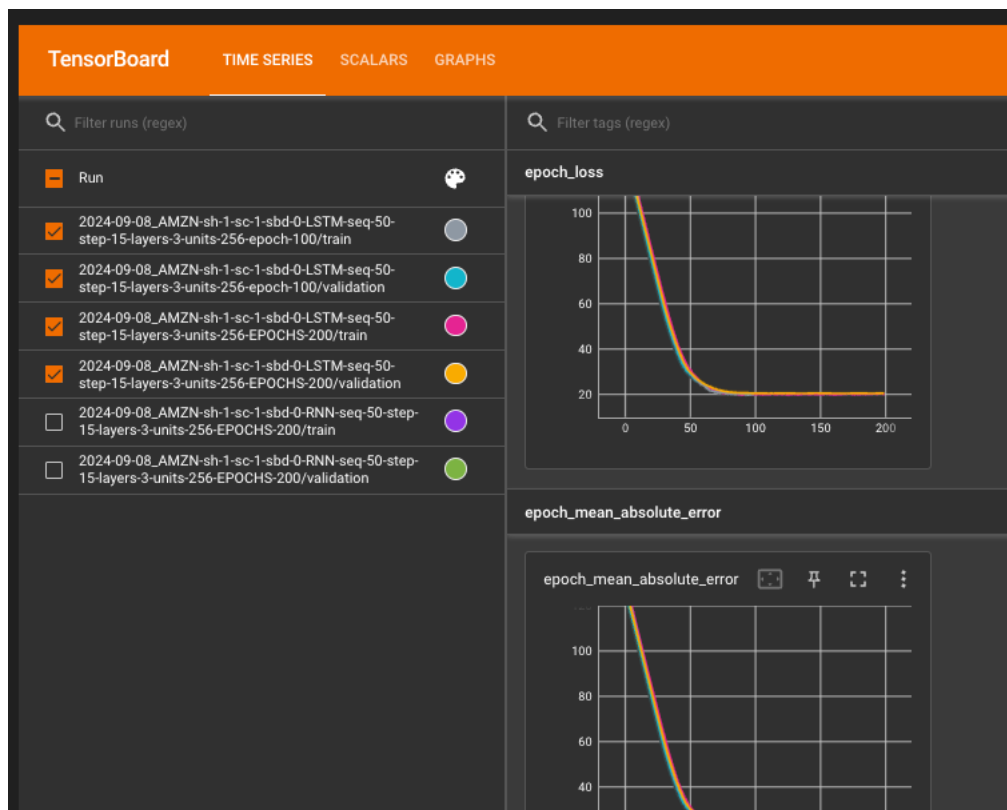
```
EPOCHS = 200

# save model name, and make it unique as possible
model_name = f"{DATE_NOW}_{TICKER}-{shuffle_str}-{scale_str}-{SPLIT_BY_DATE_str}-{LAYER_NAME.__name__}-seq-{N_STEPS}-step-{LOOKUP_STEP}-layers-{N_LAYERS}-units-{N_SIZE}-EPOCHS-{EPOCHS}"
✓ 0.0s
```

Second experiment with different Epochs, others keep the same, reducing to 200 epochs

[56] ✓ 11m 3.6s

Training takes 11 minutes 3 seconds



The graph shows the time series in 200 epoches, with decreasing significantly from 0 to more than 50, before stabilising till the end.

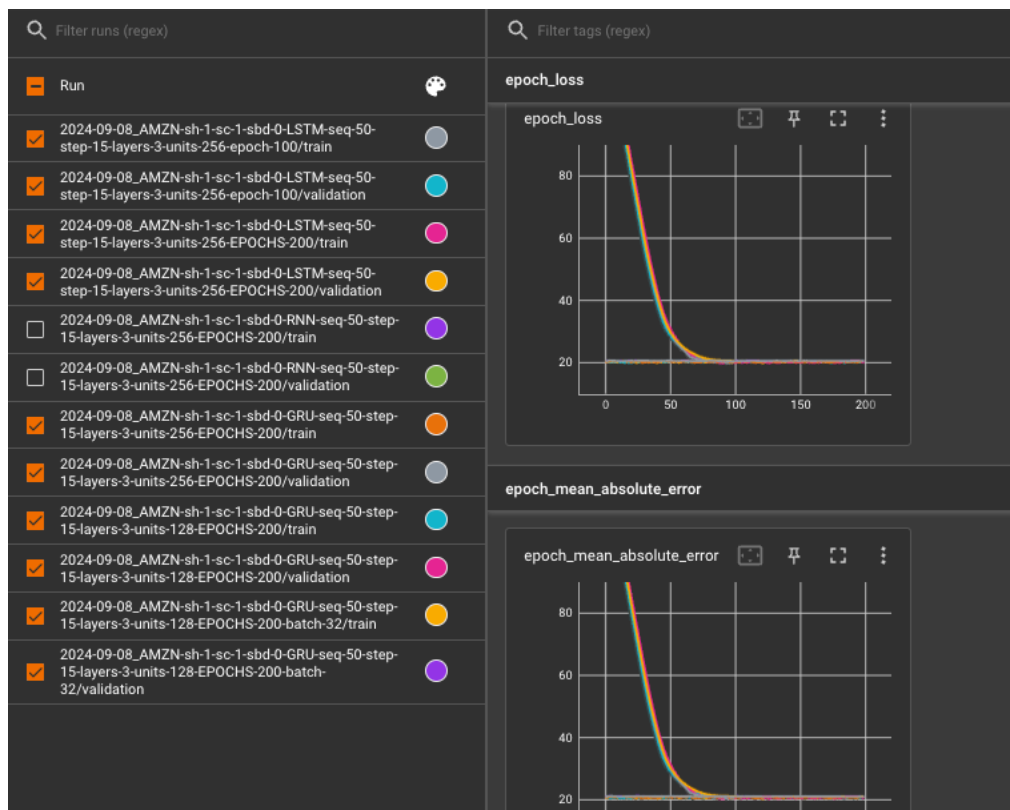
```
LAYER_NAME = GRU

# save model name, and make it unique as possible
model_name = f"{DATE_NOW}_{TICKER}-{shuffle_str}-{scale_str}-{SPLIT_BY_DATE_str}-{LAYER_NAME}_{name__}-seq-{N_STEPS}-step-{LOOKUP_STEP}-layers-{N_LAYERS}-units-{N_SIZE}-EPOCHS-{EPOCHS}"
```

Third experiment with different layer name, use GRU layer name

```
[60] ✓ 10m 49.7s
```

Training takes 10 minutes 49 seconds



The graph shows

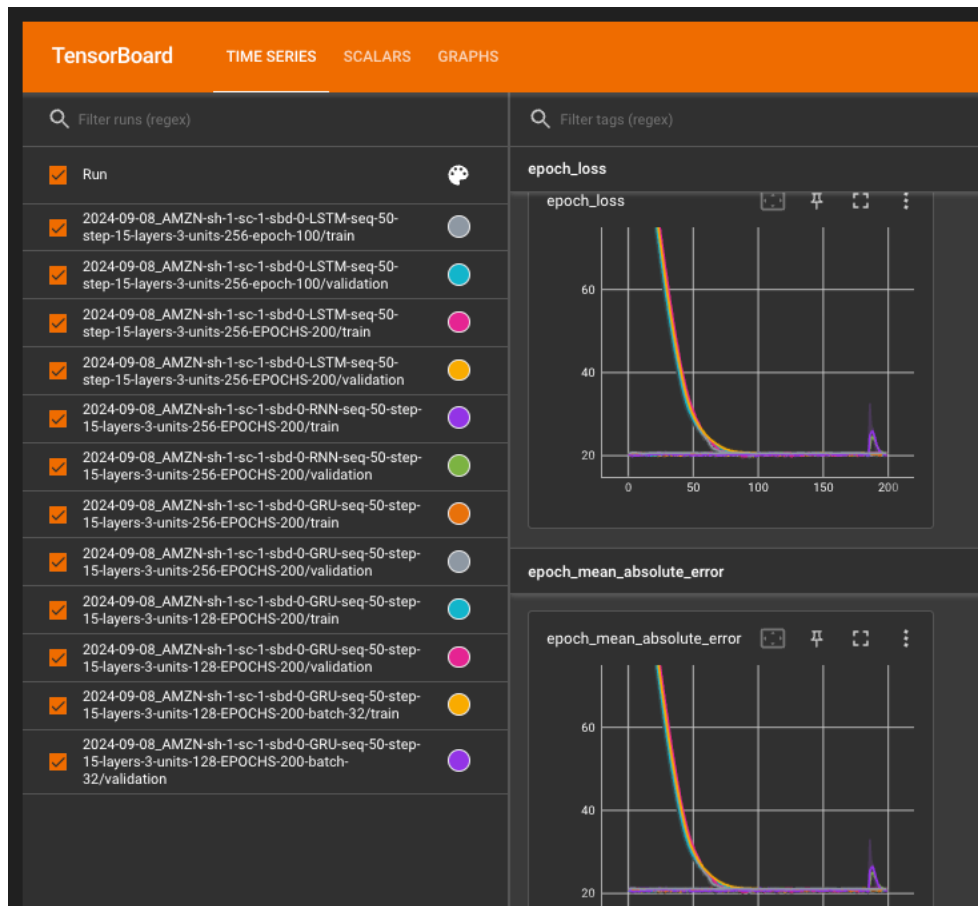
```
LAYER_NAME = RNN

# save model name, and make it unique as possible
model_name = f"({DATE_NOW}_{TICKER})-({shuffle_str})-({scale_str})-({SPLIT_BY_DATE_str})-({LAYER_NAME}_{name__})-seq-({N_STEPS})-step-({LOOKUP_STEP})-layers-({N_LAYERS})-units-({N_SIZE})-EPOCHS-({EPOCHS})"
```

Fourth experiment with different layer name, use RNN layer name

```
[58] ✓ 11m 43.2s
```

Training takes 11 minutes 43 seconds



The epoch loss and mean_absolute_error shows decreasing substantially from 0 to more than 50, before stabilizing till the end.

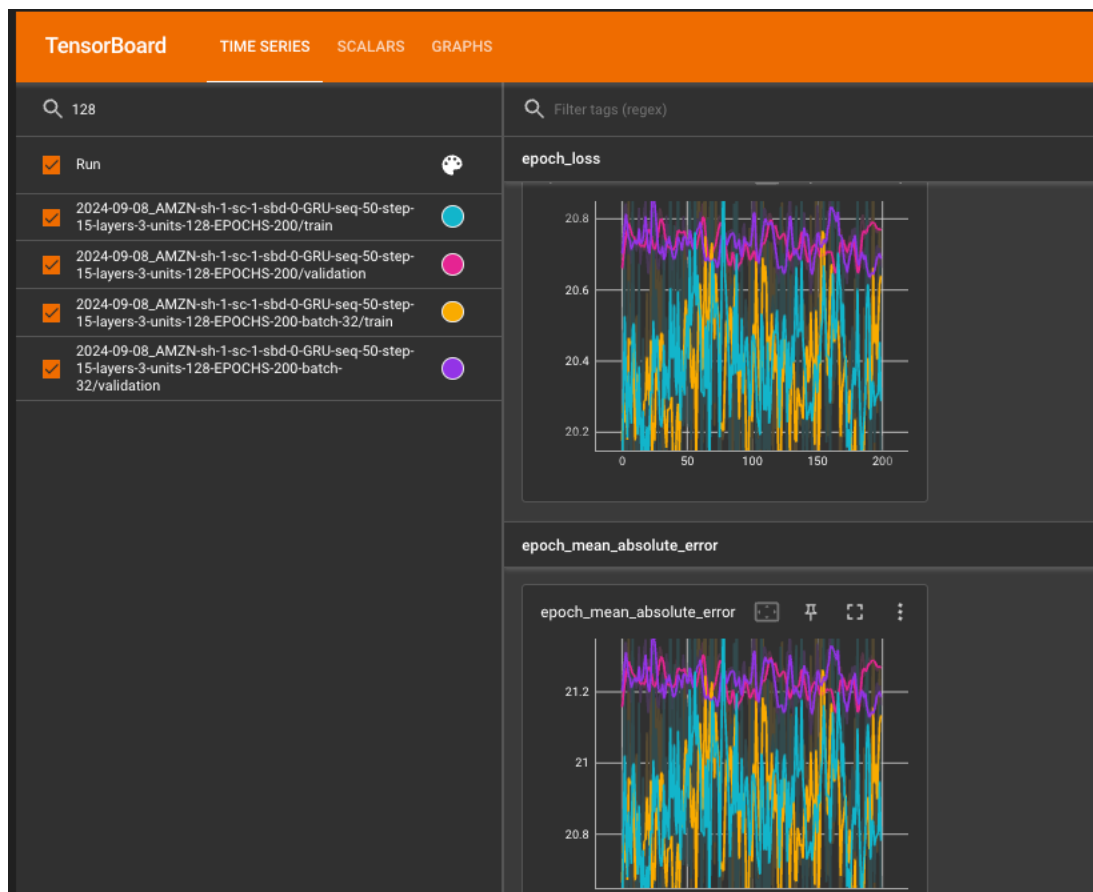
```
# layer size
N_SIZE = 128

# construct the model
model_name = f"{DATE_NOW}_{TICKER}-{shuffle_str}-{scale_str}-{SPLIT_BY_DATE_str}-{LAYER_NAME.__name__}-seq-{N_STEPS}-step-{LOOKUP_STEP}-layers-{N_LAYERS}-units-{N_SIZE}-EPOCHS-{EPOCHS}"
```

Fifth experiment with different layer size, with 128 layer size

[62] ✓ 10m 44.0s

Training takes 10 minutes 44 seconds



Timeseries at 128 size number, with fluctuation as it seen, however the validation seems always in the higher range than the others.

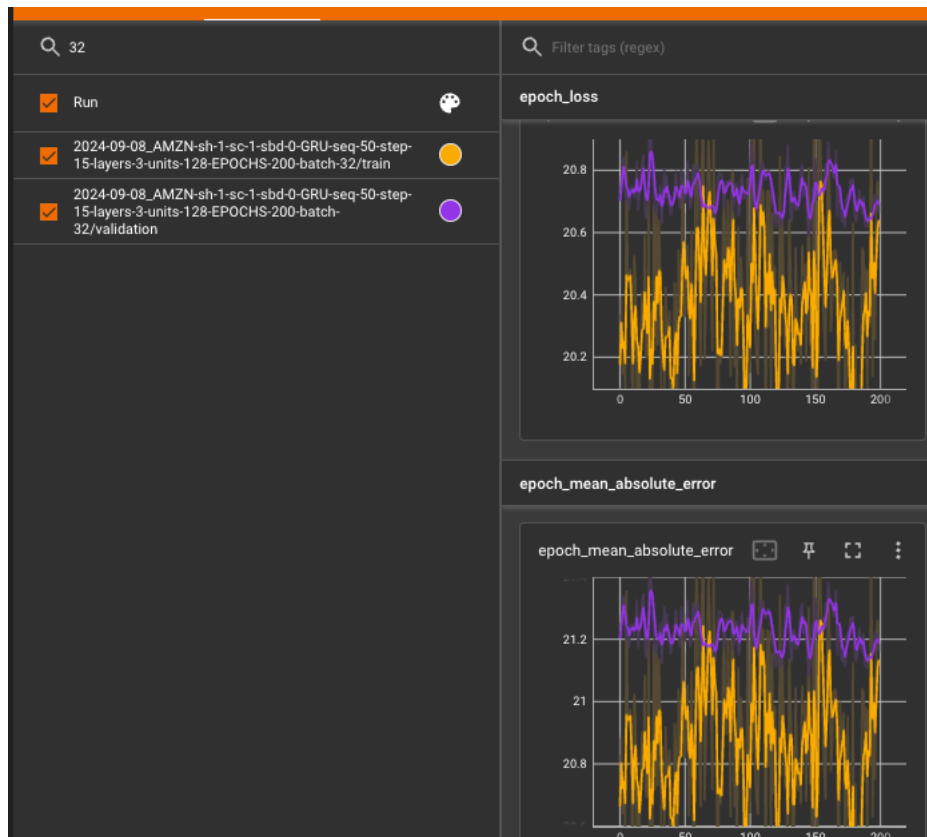
```
# Number of batch size
BATCH_SIZE = 32

# construct the model
model_name = f"{DATE_NOW}_{TICKER}-{shuffle_str}-{scale_str}-{SPLIT_BY_DATE_str}-{LAYER_NAME}_{name}_{seq}-{N_STEPS}-step-{LOOKUP_STEP}-layers-{N_LAYERS}-units-{N_SIZE}-EPOCHS-{EPOCHS}-batch-{BATCH_SIZE}"
```

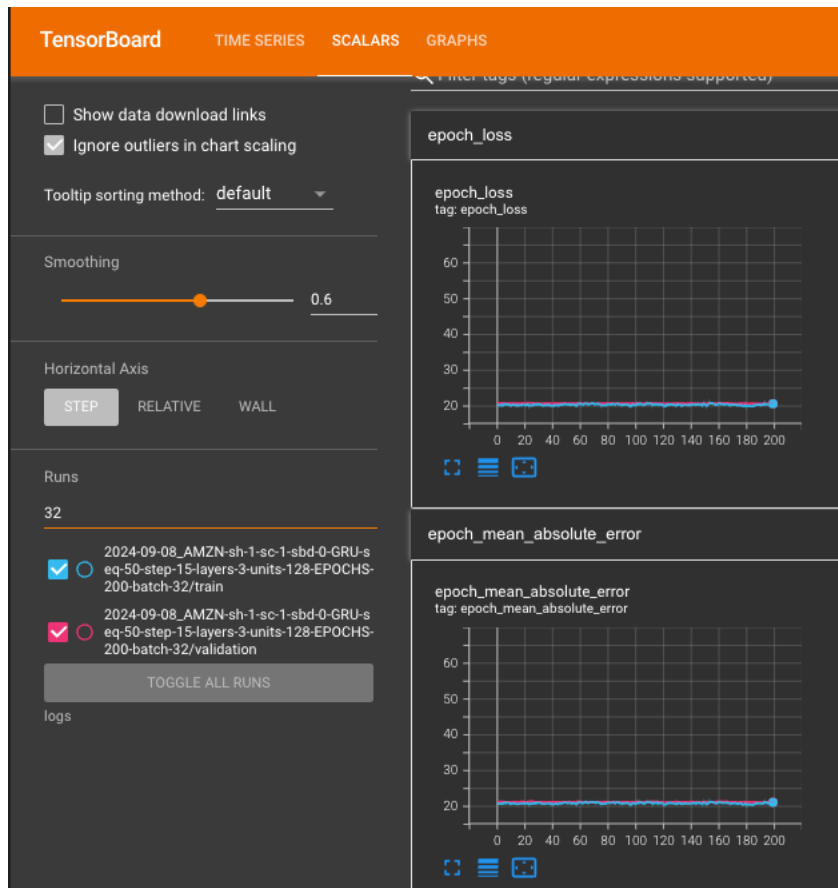
Sixth experiment with batch size, use 32 batch sizes

[64] ✓ 13m 34.7s

Training takes 13 minutes 34 seconds



Time series at training and validation at batch size 32, with fluctuation at loss and mean absolute error.



Scalars at training and validation at batch size 32, with stabilised data from 0 till 200.