CNN Networks for Cambridge UK Weather Time Series

CNN models for time series analysis of Cambridge UK temperature measurements taken at the University computer lab weather station.

This notebook is being developed on Google Colab, primarily using keras/tensorflow. Initially I was most interested in short term temperature forecasts (less than 2 hours) but now mostly produce results up to 48 hours in the future for comparison with earlier baselines.

See my previous notebooks, web apps etc:

- Cambridge UK temperature forecast python notebooks
- Cambridge UK temperature forecast R models
- Bayesian optimisation of prophet temperature model
- Cambridge University Computer Laboratory weather station R shiny web app

The linked notebooks, web apps etc contain further details including:

- data description
- data cleaning and preparation
- data exploration

In particular, see the notebooks:

- cammet_baselines_2021 including persistent, simple exponential smoothing, Holt Winter's exponential smoothing and vector autoregression
- keras_mlp_fcn_resnet_time_series, which uses a streamlined version of data preparation from Tensorflow time series forecasting tutorial
- lstm_time_series with stacked LSTMs, bidirectional LSTMs and ConvLSTM1D networks

Most of the above repositories, notebooks, web apps etc were built on both less data and less thoroughly cleaned data.

```
import sys
import math
import datetime
import itertools
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from itertools import product
from sklearn.preprocessing import StandardScaler

import tensorflow as tf

# How to enable Colab GPUs https://colab.research.google.com/notebooks/gpu.ipynb
# Select the Runtime > "Change runtime type" menu to enable a GPU accelerator,
```

```
# and then re-execute this cell.
if 'google.colab' in str(get_ipython()):
    device_name = tf.test.gpu_device_name()
    if device_name != '/device:GPU:0':
        raise SystemError('GPU device not found')
    print('Found GPU at: {}'.format(device_name))
    gpu_info = !nvidia-smi
    gpu_info = '\n'.join(gpu_info)
    print(gpu_info)

# try:
#   tpu = tf.distribute.cluster_resolver.TPUClusterResolver()  # TPU detection
#   print('Running on TPU ', tpu.cluster_spec().as_dict()['worker'])
# except ValueError:
#   raise BaseException('ERROR: Not connected to a TPU runtime; please see the pre
# tf.config.experimental_connect_to_cluster(tpu)
# tf.tpu.experimental.initialize_tpu_system(tpu)
# tpu_strategy = tf.distribute.experimental.TPUStrategy(tpu)

import tensorflow.keras as keras
from keras.models import Sequential, Model, Input
from keras.layers import InputLayer, Dense, Dropout, Activation, \
                         Flatten, Reshape, LSTM, RepeatVector, Conv1D, \
                         TimeDistributed, Bidirectional, Dropout, \
                         MaxPooling1D, MaxPooling2D, Conv2D  # TODO Remove unused
from keras.layers.merge import concatenate
from keras.constraints import maxnorm
from keras import regularizers
from tensorflow.keras.optimizers import Adam
from keras.callbacks import EarlyStopping, ReduceLROnPlateau

# Reduces variance in results but won't eliminate it :-(
%env PYTHONHASHSEED=0
import random
random.seed(42)
np.random.seed(42)
tf.random.set_seed(42)

%matplotlib inline
```

```
Found GPU at: /device:GPU:0
Thu Jul  7 11:34:50 2022
+-----------------------------------------------------------------------------
| NVIDIA-SMI 460.32.03    Driver Version: 460.32.03    CUDA Version: 11.2
|-------------------------------+----------------------+----------------------
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M.
|                               |                      |               MIG M.
|===============================+======================+======================
|   0  Tesla P100-PCIE...  Off  | 00000000:00:04.0 Off |                    0
| N/A   42C    P0    33W / 250W |    375MiB / 16280MiB |      0%      Default
|                               |                      |                  N/A
+-------------------------------+----------------------+----------------------

+-----------------------------------------------------------------------------
| Processes:
```

```
|  GPU   GI   CI        PID   Type   Process name                    GPU Memory
|        ID   ID                                                     Usage
|=============================================================================
+-----------------------------------------------------------------------------
env: PYTHONHASHSEED=0
```

Import Data

The measurements are relatively noisy and there are usually several hundred missing values every year; often across multiple variables. Observations have been extensively cleaned but may still have issues. Interpolation and missing value imputation have been used to fill all missing values. See the cleaning section in the Cambridge Temperature Model repository for details. Observations start in August 2008 and end in April 2021 and occur every 30 mins.

```
if 'google.colab' in str(get_ipython()):
    data_loc = "https://github.com/makeyourownmaker/CambridgeTemperatureNotebooks/
else:
    data_loc = "../data/CamMetPrepped2021.04.26.csv"

df = pd.read_csv(data_loc, index_col=['ds'], parse_dates=['ds', 'ds.1'])
df.rename(columns={'ds.1': 'ds'}, inplace = True)
df_orig = df

print("Shape:")
print(df.shape)
print("\nInfo:")
print(df.info())
print("\nSummary stats:")
display(df.describe())
print("\nRaw data:")
display(df)
print("\n")


def plot_examples(data, x_var):
    """Plot 9 sets of observations in 3 * 3 matrix"""

    assert len(data) == 9

    cols = [col for col in data[0].columns if col != x_var]

    fig, axs = plt.subplots(3, 3, figsize = (15, 10))
    axs = axs.ravel()  # apl for the win :-)

    for i in range(9):
        for col in cols:
            axs[i].plot(data[i][x_var], data[i][col])
            axs[i].xaxis.set_tick_params(rotation = 20, labelsize = 10)

    fig.legend(cols, loc = 'upper center',  ncol = len(cols))
```

```
    return None


cols = ['ds', 'y', 'humidity', 'dew.point', # 'pressure',
        'wind.x', 'wind.y', 'day.sin', 'day.cos', 'year.sin', 'year.cos']
ex_plots = 9
hour_window = 24
starts = df.sample(n = ex_plots).index
p_data = [df.loc[starts[i]:starts[i] + datetime.timedelta(hours = hour_window), co
          for i in range(ex_plots)]
plot_examples(p_data, 'ds')
```

```
Shape:
(223250, 13)

Info:
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 223250 entries, 2008-08-01 00:30:00 to 2021-04-26 01:00:00
Data columns (total 13 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   ds                 223250 non-null  datetime64[ns]
 1   y                  223250 non-null  float64
 2   humidity           223250 non-null  float64
 3   dew.point          223250 non-null  float64
 4   pressure           223250 non-null  float64
 5   wind.speed.mean    223250 non-null  float64
 6   wind.bearing.mean  223250 non-null  float64
 7   wind.x             223250 non-null  float64
 8   wind.y             223250 non-null  float64
 9   day.sin            223250 non-null  float64
 10  day.cos            223250 non-null  float64
 11  year.sin           223250 non-null  float64
 12  year.cos           223250 non-null  float64
dtypes: datetime64[ns](1), float64(12)
memory usage: 23.8 MB
None

Summary stats:
```

	y	humidity	dew.point	pressure	wind.speed.mean	w
count	223250.000000	223250.000000	223250.000000	223250.000000	223250.000000	
mean	10.000512	78.689959	58.880634	1014.336135	4.432390	
std	6.496255	17.274417	51.630120	11.935364	4.013553	
min	-7.000000	20.000000	-100.000000	963.000000	0.000000	
25%	5.200000	68.000000	20.000000	1008.000000	1.200000	
50%	9.600000	83.000000	60.000000	1016.000000	3.500000	
75%	14.500000	92.000000	97.000000	1022.000000	6.600000	
max	36.100000	100.000000	209.000000	1051.000000	29.200000	

```
Raw data:
```

	ds	y	humidity	dew.point	pressure	wind.speed.mean	wind.be
ds							
2008-08-01 00:30:00	2008-08-01 00:30:00	19.5	65.75000	119.150000	1014.416667	1.150000	
2008-08-01 01:00:00	2008-08-01 01:00:00	19.1	49.75000	79.200000	1014.384615	1.461538	
2008-08-01 01:30:00	2008-08-01 01:30:00	19.1	66.17875	106.600000	1014.500000	1.508333	

2008-08-01 02:00:00	2008-08-01 02:00:00	19.1	58.50000	99.250000	1014.076923	1.430769
2008-08-01 02:30:00	2008-08-01 02:30:00	19.1	66.95000	121.883333	1014.416667	1.133333
...	...	...	...	...	...	...
2021-04-25 23:00:00	2021-04-25 23:00:00	3.6	61.00000	-32.000000	1028.000000	1.400000
2021-04-25 23:30:00	2021-04-25 23:30:00	3.6	64.00000	-26.000000	1028.000000	2.600000
2021-04-26 00:00:00	2021-04-26 00:00:00	3.6	58.00000	-39.000000	1028.000000	4.300000
2021-04-26 00:30:00	2021-04-26 00:30:00	3.2	62.00000	-34.000000	1027.000000	5.400000
2021-04-26 01:00:00	2021-04-26 01:00:00	3.2	62.00000	-34.000000	1027.000000	4.200000

223250 rows × 13 columns

Data augmentation with mixup

Wind velocity vectors were clustered around the 45 degree increments. Data augmentation with the mixup method is carried out to counter this clustering.

From the mixup paper: "mixup trains a neural network on convex combinations of pairs of examples and their labels".

Further details on how I apply the standard mixup technique to time series are included in the Window data section of my keras_mlp_fcn_resnet_time_series notebook.

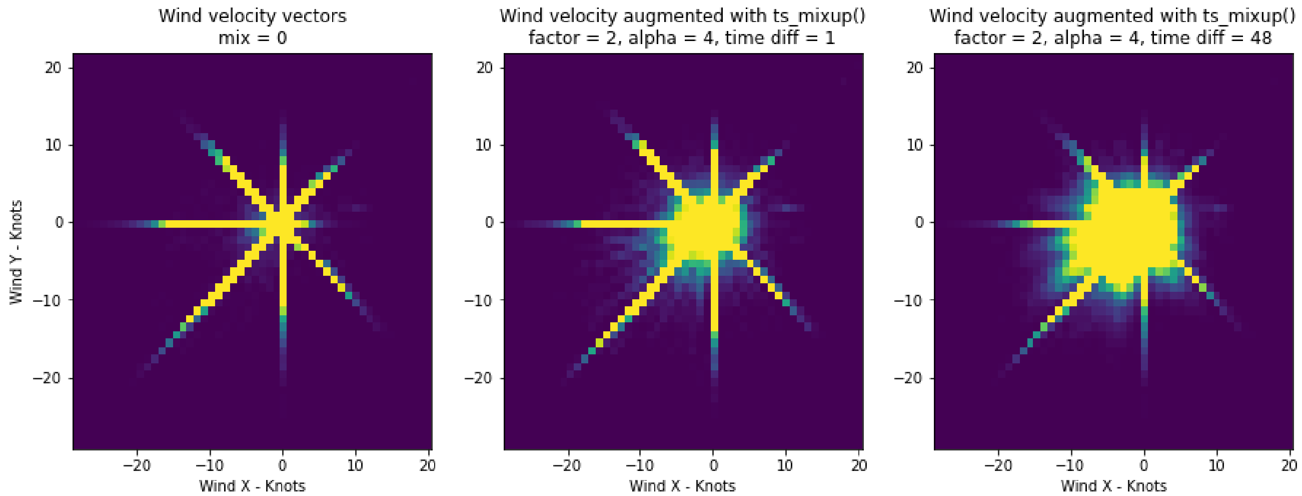
Here is a comparison of the improvement in wind velocity sparsity with standard mixup augmentation and a time series specific mixup.

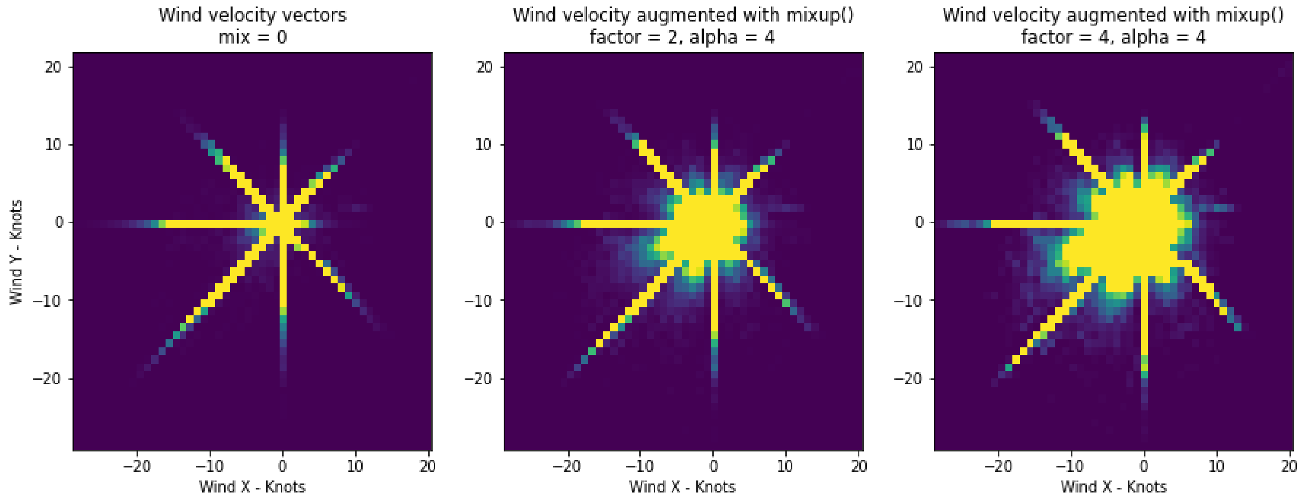
```
def mixup(data, alpha = 4.0, factor = 1):
    """Augment data with mixup method.

    Standard mixup is applied between randomly chosen observations

    Args:
      data       (pd.DataFrame):     data to run mixup on
      alpha      (float, optional): beta distribution parameter
      factor     (int, optional):   size of mixup dataset to return

    Returns:
      df (pd.DataFrame)

    Notes:
      Duplicates will be removed
      https://arxiv.org/abs/1710.09412
    """
    batch_size = len(data) - 1

    data['epoch'] = data.index.view(np.int64) // 10**9

    # random sample lambda value from beta distribution
    l   = np.random.beta(alpha, alpha, batch_size * factor)
    X_l = l.reshape(batch_size * factor, 1)

    # Get a pair of inputs and outputs
    y1  = data['y'].shift(-1).dropna()
    y1_ = pd.concat([y1] * factor)

    y2  = data['y'][0:batch_size]
    y2_ = pd.concat([y2] * factor)

    X1  = data.drop(columns='y', axis=1).shift(-1).dropna()
    X1_ = pd.concat([X1] * factor)
```

```
    X2  = data.drop(columns='y', axis=1)
    X2  = X2[0:batch_size]
    X2_ = pd.concat([X2] * factor)

    # Perform mixup
    X = X1_ * X_l + X2_ * (1 - X_l)
    y = y1_ * l   + y2_ * (1 - l)

    df = pd.DataFrame(y).join(X)
    df = data.append(df).sort_values('epoch', ascending = True)
    df = df.drop(columns='epoch', axis=1)

    df = df.drop_duplicates(keep = False)

    return df


def ts_mixup(data, alpha = 4.0, factor = 1, time_diff = 1):
    """Augment data with time series mixup method.

    Applies mixup technique to two time series separated by time_diff period.

    Args:
      data      (pd.DataFrame):    data to run mixup on
      alpha     (float, optional): beta distribution parameter
      factor    (int, optional):   size of mixup dataset to return
      time_diff (int, optional):   period between data subsets to run mixup on

    Returns:
      df (pd.DataFrame)

    Notes:
      Duplicates will be removed
      https://arxiv.org/abs/1710.09412
      Standard mixup is applied between randomly chosen observations
    """

    batch_size = len(data) - time_diff

    # Get a pair of inputs and outputs
    y1 = data['y'].shift(-time_diff).dropna()
    y2 = data['y'][0:batch_size]

    X1 = data.drop(columns='y', axis=1).shift(-time_diff).dropna()
    X2 = data.drop(columns='y', axis=1)
    X2 = X2[0:batch_size]

    df = data

    for i in range(factor):
      # random sample lambda value from beta distribution
      l   = np.random.beta(alpha, alpha, 1)
      X_l = np.repeat(l, batch_size).reshape(batch_size, 1)
```

```
      # Perform mixup
      X = X1 * X_l + X2 * (1 - X_l)
      y = y1 * l   + y2 * (1 - l)

      df_new = pd.DataFrame(y).join(X)
      idx_len = np.ceil((df.index[-1] - df.index[0]).days / 365.25)
      df_new.index = df_new.index + pd.offsets.DateOffset(years = idx_len)

      df = df.append(df_new).sort_index(ascending = True)

    df = df.drop_duplicates(keep = False)

    return df


def plot_wind_no_mixup(data, ax):
    """Plot wind vectors without mixup

    Args:
      data      (pd.DataFrame):    wind vector data to plot
      ax        (axes object):     matplotlib axes object for plot
    """

    plt1 = ax.hist2d(data['wind.x'], data['wind.y'], bins = (50, 50), vmax = 400)
    ax.set_xlabel('Wind X - Knots')
    ax.set_ylabel('Wind Y - Knots')
    ax.set_title('Wind velocity vectors\nmix = 0');


def plot_wind_with_mixup(data, ax, mix_func, mix_factor, mix_alpha = 4, mix_td = 1
    """Plot wind vectors with mixup

    Args:
      data       (pd.DataFrame):    wind vector data to plot
      ax         (axes object):     matplotlib axes object for plot
      mix_func   (function)         standard or time series mixup function
      mix_factor (int)              size of mixup dataset to return
      mix_alpha  (int, optional)    beta distribution parameter
      mix_td     (int, optional)    period between data subsets to run mixup on
    """
    title = 'Wind velocity augmented with {0:s}()\n'.format(mix_func)

    if mix_func == 'ts_mixup':
        df_mix = ts_mixup(data.loc[:, ['y', 'wind.x', 'wind.y']],
                          factor = mix_factor,
                          alpha  = mix_alpha,
                          time_diff = mix_td)
        title += 'factor = {0:d}, alpha = {1:d}, time diff = {2:d}'.format(mix_fac
    elif mix_func == 'mixup':
        df_mix = mixup(data.loc[:, ['y', 'wind.x', 'wind.y']],
                       factor = mix_factor,
                       alpha  = mix_alpha)
        title += 'factor = {0:d}, alpha = {1:d}'.format(mix_factor, mix_alpha)
```

```
    plt2 = ax.hist2d(df_mix['wind.x'], df_mix['wind.y'], bins = (50, 50), vmax =
    ax.set_xlabel('Wind X - Knots')
    ax.set_title(title);
    # plt.colorbar(plt1, ax = ax3)  # TODO fixme


fig1, (ax11, ax12, ax13) = plt.subplots(1, 3, figsize = (15, 5))
plot_wind_no_mixup(df, ax11)
plot_wind_with_mixup(df, ax12, 'ts_mixup', 2, 4, 1)
plot_wind_with_mixup(df, ax13, 'ts_mixup', 2, 4, 48)

fig2, (ax21, ax22, ax23) = plt.subplots(1, 3, figsize = (15, 5))
plot_wind_no_mixup(df, ax21)
plot_wind_with_mixup(df, ax22, 'mixup', 2)
plot_wind_with_mixup(df, ax23, 'mixup', 4)
```





Mixup improves the categorical legacy of the wind velocity data. Unfortunately, if outliers are present their influence may be reinforced. A priori it's difficult to say which mixup variant is preferable.

Split data¶

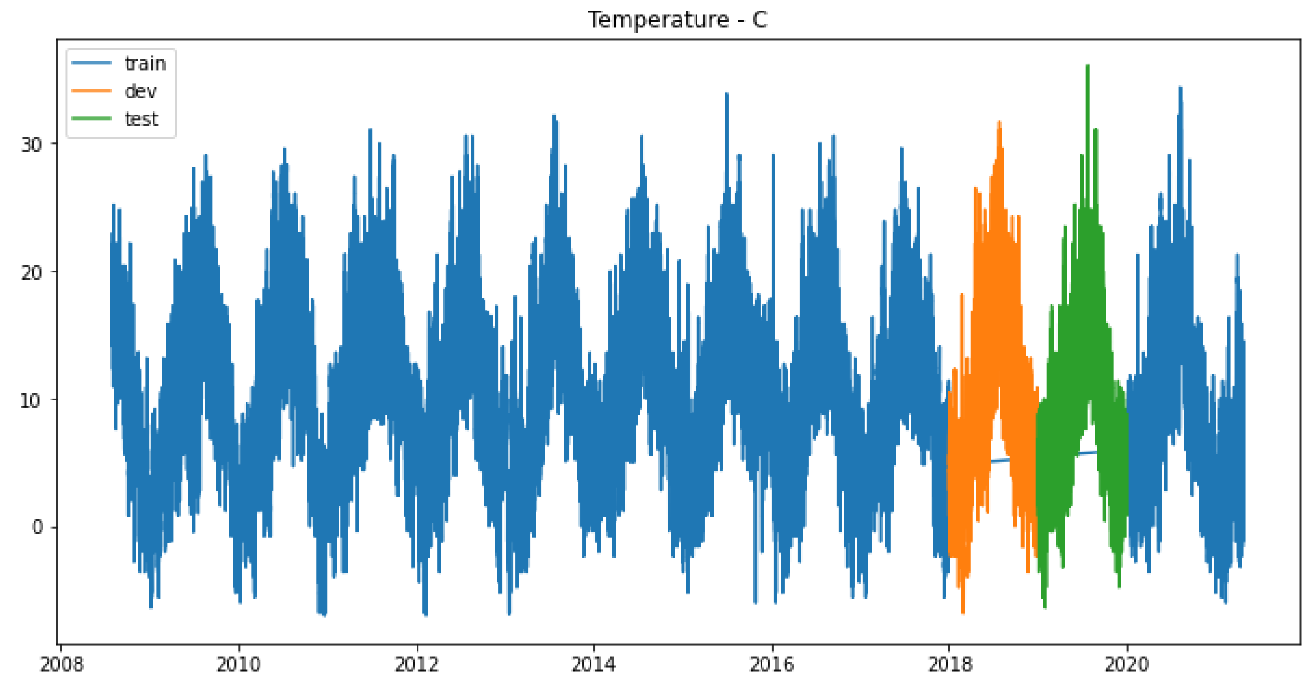
I use data from 2018 for validation, 2019 for testing and the remaining data for training. These are entirely arbitrary choices. This results in an approximate 84%, 8%, 8% split for the training, validation, and test sets respectively.

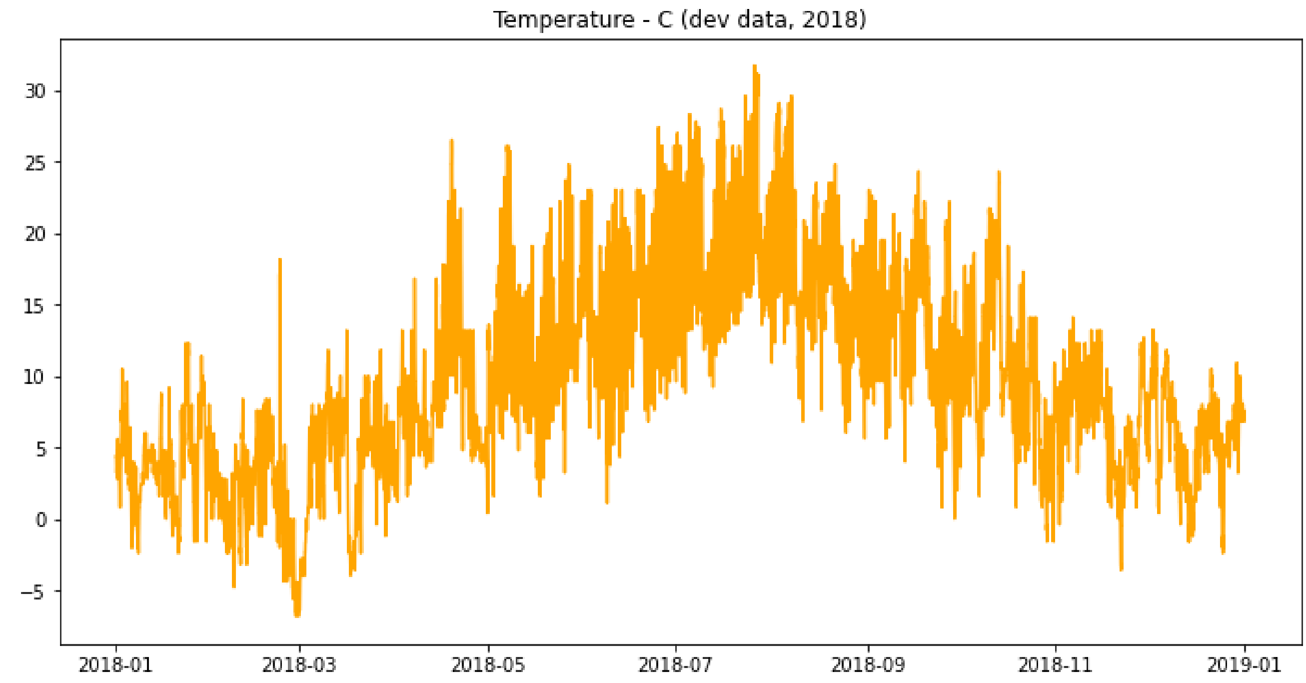
```
# keep_cols = ['y', 'humidity', 'dew.point', 'pressure', 'wind.x', 'wind.y',
#              'day.sin', 'day.cos', 'year.sin', 'year.cos', 'level', 'season1',
#              'season2']

df['year'] = df['ds'].dt.year
train_df = df.loc[(df['year'] != 2018) & (df['year'] != 2019)]
valid_df = df.loc[df['year'] == 2018]
test_df  = df.loc[df['year'] == 2019]
```

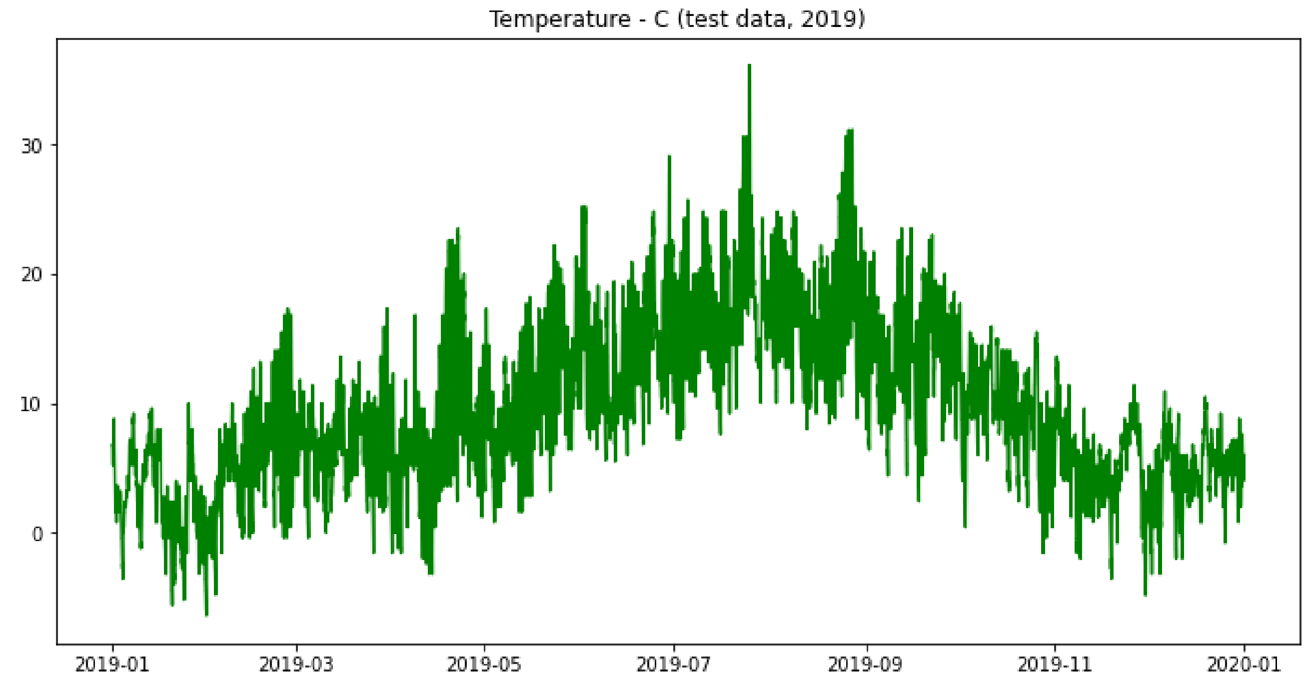
```
plt.figure(figsize = (12, 6))
plt.plot(train_df.ds, train_df.y)
plt.plot(valid_df.ds, valid_df.y)
plt.plot(test_df.ds,  test_df.y)
plt.title('Temperature - C')
plt.legend(['train', 'dev', 'test'])
plt.show()

plt.figure(figsize = (12, 6))
plt.plot(valid_df.ds, valid_df.y, color='orange')
plt.title('Temperature - C (dev data, 2018)')
plt.show()

plt.figure(figsize = (12, 6))
plt.plot(test_df.ds, test_df.y, color='green')
plt.title('Temperature - C (test data, 2019)')
plt.show()
```

```
del_cols = ['ds', 'year', 'wind.speed.mean', 'wind.bearing.mean']
train_df = train_df.drop(del_cols, axis = 1)
valid_df = valid_df.drop(del_cols, axis = 1)
test_df  = test_df.drop(del_cols,  axis = 1)
df = df.drop(del_cols, axis = 1)

# ds = {}
models = {}
models['datasets'] = {}
models['datasets']['train'] = train_df
models['datasets']['valid'] = valid_df
```

```
models['datasets']['test']  = test_df

print("df.drop shape: ", df.shape)
print("train shape:   ", train_df.shape)
print("valid shape:   ", valid_df.shape)
print("test shape:    ", test_df.shape)
```


Temperature - C
train
dev
test
30
20
10
0
2008
2010
2012
2014
2016
2018
2020


Temperature - C (dev data, 2018)
30
25
20
15
10
5
0
−5
2018-01
2018-03
2018-05
2018-07
2018-09
2018-11
2019-01


Temperature - C (test data, 2019)
30
20
10
0
2019-01
2019-03
2019-05
2019-07
2019-09
2019-11
2020-01

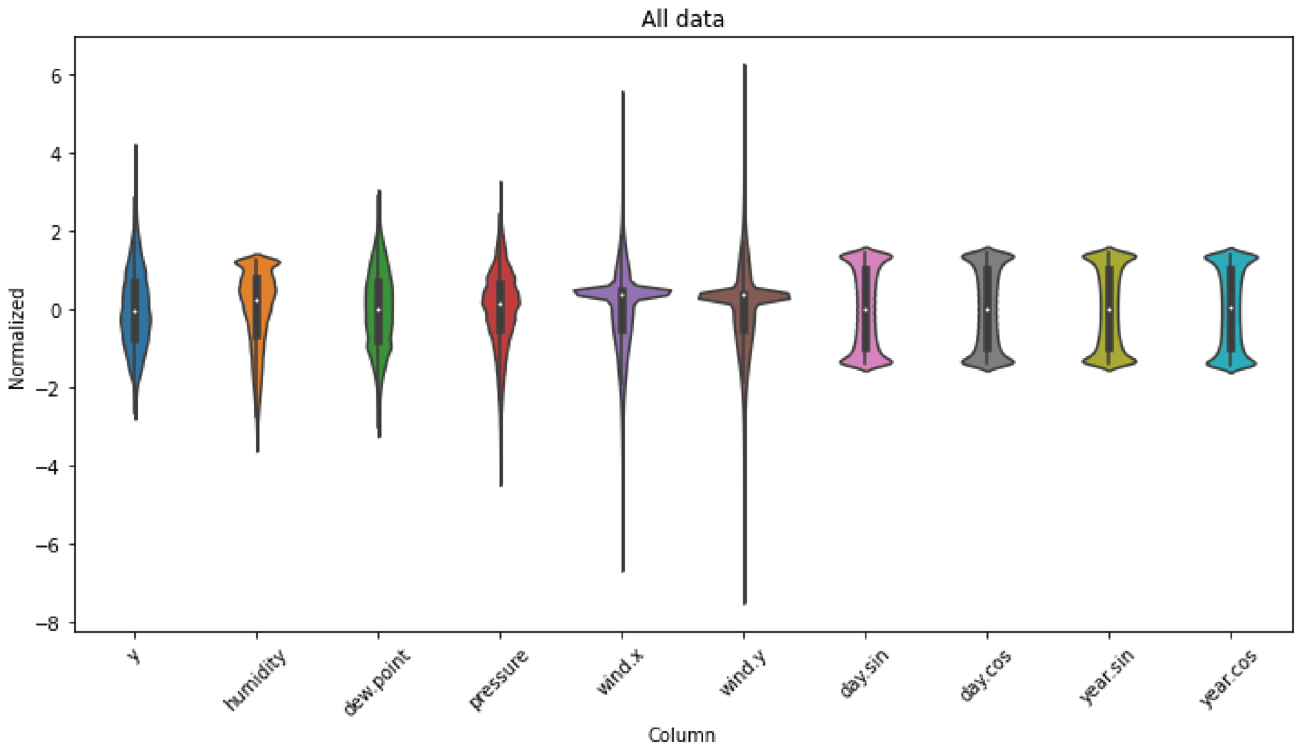
```
df.drop shape:  (223250, 10)
train shape:    (188210, 10)
valid shape:    (17520, 10)
test shape:     (17520, 10)
```

Normalise data

Features should be scaled before neural network training. Arguably, scaling should be done using moving averages to avoid accessing future values. Instead, simple standard score normalisation will be used.

The violin plot shows the distribution of features.

```
def inv_transform(scaler, data, colName, colNames):
    """An inverse scaler for use in model validation section

    For later use in plot_forecasts, plot_horizon_metrics and check_residuals

    See https://stackoverflow.com/a/62170887/100129"""

    dummy = pd.DataFrame(np.zeros((len(data), len(colNames))), columns=colNames)
    dummy[colName] = data
    dummy = pd.DataFrame(scaler.inverse_transform(dummy), columns=colNames)

    return dummy[colName].values


scaler = StandardScaler()
scaler.fit(train_df)

train_df[train_df.columns] = scaler.transform(train_df[train_df.columns] )
valid_df[valid_df.columns] = scaler.transform(valid_df[valid_df.columns] )
test_df[test_df.columns]   = scaler.transform(test_df[test_df.columns] )

df_std = scaler.transform(df)
df_std = pd.DataFrame(df_std)
df_std = df_std.melt(var_name = 'Column', value_name = 'Normalized')

plt.figure(figsize=(12, 6))
ax = sns.violinplot(x = 'Column', y = 'Normalized', data = df_std)
ax.set_xticklabels(df.keys(), rotation = 45)
ax.set_title('All data');
```



Some features have long tails but there are no glaring errors.

Window data

Models are trained using sliding windows of samples from the data.

Window parameters to consider for the tf.keras.preprocessing.timeseries_dataset_from_array function:

- sequence_length:
  - Length of the output sequences (in number of timesteps), or number of **lag** observations to use
- sequence_stride:
  - Period between successive output sequences
  - For stride s, output samples start at index data[i], data[i + s], data[i + 2 * s] etc
  - s can include an **offset** and/or 1 or more **steps ahead** to forecast
- batch_size:
  - Number of samples in each batch
- shuffle:
  - Shuffle output samples, or use chronological order

Initial values used:

- sequence_length (aka lags): 24 (corresponds to 12 hours)

- steps ahead (what to forecast):
    - 48 - 30 mins, 60 mins ... 1,410 mins and 1,440 mins
- offset (space between lags and steps ahead): 0
- batch_size: 16, 32, 64 ...
- shuffle: True for training data

The `make_dataset` function below generates tensorflow datasets for:

- Lags, steps-ahead, offset, batch size and shuffle
- Optionally multiple y columns (Not extensively tested)

Stride is used to specify offset + steps-ahead. Offset will be 0 throughout this notebook.

TODO Insert figure illustrating lags, offsets and steps-ahead.

`shuffle = True` is used with train data. `shuffle = False` is used with validation and test data so the residuals can be checked for heteroscadicity.

Throughout this notebook I use a shorthand notation to describe lags and strides. For example:

- 24l_1s_2m is 24 lags, 1 step ahead, 2 times mixup
- 24l_4s_2m is 24 lags, 4 steps ahead, 2 times mixup

See the `get_model_name` function for details of all abbreviations.

Mixup data augmentation

Data augmentation with mixup: Beyond Empirical Risk Minimization by Zhang *et al* is used to help counter the categorical legacy from the wind bearing variable. Simple 'input mixup' is used as opposed to the batch-based mixup Zhang *et al* focus on. Input mixup has the advantage that it can be used with non-neural network methods. With current settings these datasets are approximately 3 times larger but this can be varied. Three times more training data is manageable on Colab in terms of both training time and memory usage. Test and validation data is left unmodified.

I apply mixup between consecutive observations in the time series instead of the usual random observations. Applying mixup between inputs with equal temperature values will not improve performance and will increase run time.

Here are results for a multi-layer perceptron (MLP) with 24 lags, 1 step ahead, 20 epochs training on both less data and less thoroughly cleaned data.

Augmentation	Train rmse	Train mae	Valid rmse	Valid mae
No augmentation	0.0058	0.053	0.0054	0.052
Input mixup	0.0016	0.025	0.0015	0.025

See this commit for results from other architectures with and without 'input mixup'.

Setup functions for creating windowed datasets.

```
def make_dataset(dataset_params, data):
    assert dataset_params['stride'] >= dataset_params['steps_ahead']
    y_cols = dataset_params['ycols']

    total_window_size = dataset_params['lags'] + dataset_params['stride']

    data = data.drop(columns='epoch', axis = 1, errors = 'ignore')

    if dataset_params['mix_factor'] != 0:
      if dataset_params['mix_type'] == 'ts':
        data_mix = ts_mixup(data,
                            alpha     = dataset_params['mix_alpha'],
                            factor    = dataset_params['mix_factor'],
                            time_diff = dataset_params['mix_diff'])
      else:
        data_mix = mixup(data,
                         alpha  = dataset_params['mix_alpha'],
                         factor = dataset_params['mix_factor'])
    else:
      data_mix = data

    data_mix = data_mix.drop(columns='epoch', axis = 1, errors = 'ignore')
    data_np  = np.array(data_mix, dtype = np.float32)

    ds = tf.keras.preprocessing.timeseries_dataset_from_array(
              data    = data_np,
              targets = None,
              sequence_length = total_window_size,
              sequence_stride = 1,
              shuffle    = dataset_params['shuffle'],
              batch_size = dataset_params['bs'])

    col_indices = {name: i for i, name in enumerate(data.columns)}
    X_slice = slice(0, dataset_params['lags'])
    y_start = total_window_size - dataset_params['steps_ahead']
    y_slice = slice(y_start, None)


    def split_window(features):
      X = features[:, X_slice, :]
      y = features[:, y_slice, :]

      # X = tf.stack([X[:, :, col_indices[name]] for name in data.columns],
      #              axis = -1)
      y = tf.stack([y[:, :, col_indices[name]] for name in y_cols],
                   axis = -1)

      # Slicing doesn't preserve static shape info, so set the shapes manually.
      # This way the `tf.data.Datasets` are easier to inspect.
      X.set_shape([None, dataset_params['lags'],        None])
      y.set_shape([None, dataset_params['steps_ahead'], None])

      return X, y
```

```
    ds = ds.map(split_window)

    return ds


def get_model_name(models, ds_name_params):
    cols = models['datasets']['train'].loc[:, ds_name_params['xcols']].columns

    suffix = "_{0:d}l_{1:d}s".format(ds_name_params['lags'],
                                     ds_name_params['steps_ahead'])

    suffix += "_{0:d}bs".format(ds_name_params['bs'])

    if ds_name_params['feat_maps'] != 0:
      suffix += "_{0:d}fm".format(ds_name_params['feat_maps'])

    if ds_name_params['filters'] != 0:
      suffix += "_{0:d}f".format(ds_name_params['filters'])

    if ds_name_params['kern_size'] != 0 and len(ds_name_params['kern_size']) == 1:
      suffix += "_{0:d}ks".format(ds_name_params['kern_size'])

    if ds_name_params['kern_size'] != 0 and len(ds_name_params['kern_size']) > 1:
      # suffix += "_{0:d}ks".format(ds_name_params['kern_size'])
      # suffix += '_' + '-'.join(ds_name_params['kern_size']) + 'ks'
      suffix += '_' + '-'.join([str(x) for x in ds_name_params['kern_size']]) + 'k

    if ds_name_params['mix_factor'] > 0:
      suffix += "_{0:d}m".format(ds_name_params['mix_factor'])
      suffix += "_{0:d}a".format(ds_name_params['mix_alpha'])
      if ds_name_params['mix_type'] == 'ts':
        suffix += "_{0:d}td".format(ds_name_params['mix_diff'])
      if ds_name_params['mix_type'] == 'input':
        suffix += '_im'

    if 'level' in  cols and 'season1' in cols and 'season2' in cols:
      suffix += '_tbats'

    if ds_name_params['drop_out'] != 0.0:
      suffix += "_{0:.2E}do".format(ds_name_params['drop_out'])

    if ds_name_params['kern_reg'] != 0.0:
      suffix += "_{0:.2E}kr".format(ds_name_params['kern_reg'])

    if ds_name_params['recu_reg'] != 0.0:
      suffix += "_{0:.2E}rr".format(ds_name_params['recu_reg'])

    if len(ds_name_params['ycols']) > 1:
      suffix += "_{0:d}y".format(len(ds_name_params['ycols']))

    if ds_name_params['ks_feats'] > 0:
      suffix += "_{0:d}ksf".format(ds_name_params['ks_feats'])

    if ds_name_params['ks_time'] > 0:
```

```
      suffix += "_{0:d}kst".format(ds_name_params['ks_time'])

    return ds_name_params['model_type'] + suffix


def make_datasets(models, datasets_params):

    train_data = models['datasets']['train'].loc[:, datasets_params['xcols']]
    valid_data = models['datasets']['valid'].loc[:, datasets_params['xcols']]
    test_data  = models['datasets']['test'].loc[:,  datasets_params['xcols']]

    orig_mix = datasets_params['mix_factor']
    ds_train   = make_dataset(datasets_params, train_data)

    datasets_params['shuffle']    = False
    datasets_params['mix_factor'] = 0
    ds_valid   = make_dataset(datasets_params, valid_data)

    ds_test   = make_dataset(datasets_params, test_data)
    datasets_params['mix_factor'] = orig_mix

    return [ds_train, ds_valid, ds_test]


def dataset_sanity_checks(data, name):
    print(name, "batches: ", data.cardinality().numpy())
    for batch in data.take(1):
        print("\tX (batch_size, time, features): ", batch[0].shape)
        print("\ty (batch_size, time, features): ", batch[1].shape)
        print("\tX[0][0]: ", batch[0][0])
        print("\ty[0][0]: ", batch[1][0])


def plot_dataset_examples(dataset):
    fig, axs = plt.subplots(3, 3, figsize = (15, 10))
    axs = axs.ravel()
    cols = 0

    for batch in dataset.take(1):
        for i in range(9):
          x = batch[0][i].numpy()
          cols = x.shape[1]
          axs[i].plot(x)

    fig.legend(range(1, cols+1), loc = 'upper center',  ncol = cols+1);


def_cols = ['y', 'humidity', 'dew.point', 'pressure', 'wind.x', 'wind.y', \
            'day.sin', 'day.cos', 'year.sin', 'year.cos']  # def for default
```

CNN Model Building

Convolutional Neural Networks, or CNNs, use convolution kernels or filters that slide along input features to provide responses known as feature maps. CNNs assemble hierarchical patterns of increasing complexity starting with smaller and simpler patterns from their filters.

CNNs are frequently applied to analyse visual imagery. A spatial convolution can be performed over multi-variate time series observations, and a 1-dimensional temporal convolution can be applied to vector data.

TODO Include basic CNN diagram

The following are a few points I consider when building these CNN models.

Forecast horizons:

- next 24 hours - 48 steps ahead

Metrics:

- mse - mean squared error
    - mse used for loss function to avoid potential problems with infinite values from the square root function
    - rmse - root mean squared error is used for comparison with baselines
    - Huber loss may be worth exploring in the future if outliers remain an issue
- mae - median absolute error
- mape - mean absolute percentage error
    - Not used - mape fails when values, like temperature, become zero

Model enhancements:

- mixup
    - input mixup
    - trialed on final model
    - factor - 2
    - alpha - 4 (recommended in the original publication)
    - time series mixup:
        - time diff - 1, ..., 48
            - period between 2 data subsets to run mixup on

Parameters to consider optimising:

- Learning rate - use LRFinder
- Optimiser - stick with Adam
- Shuffle - true for training
- batch size - 16, 32, 64 ...
- Number of feature maps
    - 8, 16, 32 ...

- epochs
    - training shows quite fast convergence so epochs is initially kept quite low (5 or 10)

Model architectures considered:

- Conv1D followed by
    - either LSTM layer
    - or 2 Dense layers
- Multi-head
    - 3 independent Conv1D "heads" with different kernel sizes
- Conv2D
    - single Conv2D layer
        - feature extraction kernel
    - 2 stacked Conv2D layers
        - first feature extraction kernel
        - second temporal extraction kernel
    - single Conv2D layer
        - combined feature-temporal extraction kernel
- Inception-style
    - 6 inception modules with residual connections at the 3rd and 6th modules
        - where each inception module uses 3 Conv1D, MaxPooling and bottleneck layers

---

Learning rate finder

Leslie Smith was one of the first people to work on finding optimal learning rates for deep learning networks in [Cyclical Learning Rates for Training Neural Networks](). Jeremy Howard from [fast.ai]() popularised the learning rate finder used here.

Before building any models, I use a modified version of [Pavel Surmenok's Keras learning rate finder]() to get reasonably close to the optimal learning rate. It's a single small class which I add support for tensorflow datasets to, customise the graphics and add a simple summary function to.

The learning rate finder parameters may benefit from some per-architecture tuning. It's advisable to find a reasonable start_lr value by trying several values which differ by order of magnitude, i.e. 1e-3, 1e-4, 1e-5 etc. It's then worthwhile to use the learning rate finder for fine tuning.

Setup learning rate finder class for later usage:

```
from keras.callbacks import LambdaCallback
import keras.backend as K
```

```
class LRFinder:
    """
    Plots the change of the loss function of a Keras model when the learning rate
    See for details:
    https://towardsdatascience.com/estimating-optimal-learning-rate-for-a-deep-neu
    """

    def __init__(self, model):
        self.model  = model
        self.losses = []
        self.lrs    = []
        self.best_lr   = 0.001
        self.best_loss = 1e9


    def on_batch_end(self, batch, logs):
        # Log the learning rate
        lr = K.get_value(self.model.optimizer.lr)
        self.lrs.append(lr)

        # Log the loss
        loss = logs['loss']
        self.losses.append(loss)

        # Check whether the loss got too large or NaN
        if batch > 5 and (math.isnan(loss) or loss > self.best_loss * 4):
            self.model.stop_training = True
            return

        if loss < self.best_loss:
            self.best_loss = loss

        # Increase the learning rate for the next batch
        lr *= self.lr_mult
        K.set_value(self.model.optimizer.lr, lr)


    def find_ds(self, train_ds, start_lr, end_lr, batch_size=64, epochs=1, **kw_fi
        # If x_train contains data for multiple inputs, use length of the first in
        # Assumption: the first element in the list is single input; NOT a list of
        # N = x_train[0].shape[0] if isinstance(x_train, list) else x_train.shape[
        N = train_ds.cardinality().numpy()

        # Compute number of batches and LR multiplier
        num_batches = epochs * N / batch_size
        self.lr_mult = (float(end_lr) / float(start_lr)) ** (float(1) / float(num_
        # Save weights into a file
        initial_weights = self.model.get_weights()

        # Remember the original learning rate
        original_lr = K.get_value(self.model.optimizer.lr)
```

```
        # Set the initial learning rate
        K.set_value(self.model.optimizer.lr, start_lr)

        callback = LambdaCallback(on_batch_end=lambda batch, logs: self.on_batch_e

        self.model.fit(train_ds,
                       batch_size=batch_size, epochs=epochs,
                       callbacks=[callback],
                       **kw_fit)

        # Restore the weights to the state before model fitting
        self.model.set_weights(initial_weights)

        # Restore the original learning rate
        K.set_value(self.model.optimizer.lr, original_lr)


    def plot_loss(self, axs, sma, n_skip_beginning, n_skip_end, x_scale='log'):
        """
        Plot the loss.

        Parameters:
            n_skip_beginning - number of batches to skip on the left
            n_skip_end - number of batches to skip on the right
        """
        lrs = self.lrs[n_skip_beginning:-n_skip_end]
        losses = self.losses[n_skip_beginning:-n_skip_end]
        best_lr = self.get_best_lr(sma, n_skip_beginning, n_skip_end)

        axs[0].set_ylabel("loss")
        axs[0].set_xlabel("learning rate (log scale)")
        axs[0].plot(lrs, losses)
        axs[0].vlines(best_lr, np.min(losses), np.max(losses), linestyles='dashed
        axs[0].set_xscale(x_scale)


    def plot_loss_change(self, axs, sma, n_skip_beginning, n_skip_end, y_lim=None
        """
        Plot rate of change of the loss function.

        Parameters:
            axs - subplot axes
            sma - number of batches for simple moving average to smooth out the cu
            n_skip_beginning - number of batches to skip on the left
            n_skip_end - number of batches to skip on the right
            y_lim - limits for the y axis
        """
        derivatives = self.get_derivatives(sma)[n_skip_beginning:-n_skip_end]
        lrs = self.lrs[n_skip_beginning:-n_skip_end]
        best_lr = self.get_best_lr(sma, n_skip_beginning, n_skip_end)
        y_min, y_max = np.min(derivatives), np.max(derivatives)
        x_min, x_max = np.min(lrs), np.max(lrs)

        axs[1].set_ylabel("rate of loss change")
```

```
        axs[1].set_xlabel("learning rate (log scale)")
        axs[1].plot(lrs, derivatives)
        axs[1].vlines(best_lr, y_min, y_max, linestyles='dashed')
        axs[1].hlines(0, x_min, x_max, linestyles='dashed')
        axs[1].set_xscale('log')
        if y_lim == None:
            axs[1].set_ylim([y_min, y_max])
        else:
            axs[1].set_ylim(y_lim)


    def get_derivatives(self, sma):
        assert sma >= 1
        derivatives = [0] * sma
        for i in range(sma, len(self.lrs)):
            derivatives.append((self.losses[i] - self.losses[i - sma]) / sma)

        return derivatives


    def get_best_lr(self, sma, n_skip_beginning, n_skip_end):
        derivatives = self.get_derivatives(sma)
        best_der_idx = np.argmin(derivatives[n_skip_beginning:-n_skip_end])
        # print("sma:", sma)
        # print("n_skip_beginning:", n_skip_beginning)
        # print("n_skip_end:", n_skip_end)
        # print("best_der_idx:", best_der_idx)
        # print("len(derivatives):", len(derivatives))
        # print("derivatives:", derivatives)
        return self.lrs[n_skip_beginning:-n_skip_end][best_der_idx]


    def summarise_lr(self, train_ds, start_lr, end_lr, batch_size=32, epochs=1, sr
        self.find_ds(train_ds, start_lr, end_lr, batch_size, epochs)
        # print("sma:", sma)
        # print("n_skip_beginning:", n_skip_beginning)
        fig, axs = plt.subplots(1, 2, figsize = (9, 6), tight_layout = True)
        axs = axs.ravel()
        self.plot_loss(axs, sma, n_skip_beginning=n_skip_beginning, n_skip_end=5)
        self.plot_loss_change(axs, sma=sma, n_skip_beginning=n_skip_beginning, n_s
        plt.show()

        best_lr = self.get_best_lr(sma=sma, n_skip_beginning=n_skip_beginning, n_s
        print("best lr:", best_lr, "\n")

        self.best_lr = best_lr


def run_lrf(models, params):
    model_name = get_model_name(models, params)

    train_data = models[model_name]['train']
    model = models[model_name]['model']
    model.compile(loss = 'mse', metrics = ['mae'])
```

```
    lrf_inner = LRFinder(model)
    lrf_inner.summarise_lr(train_data, *params['lrf_params'])

    return lrf_inner


lrf_params = [0.000001, 10, 32, 5, 100, 25]
```

Next, define CNN and other network architectures:

- build_conv1d_lstm_model
- build_conv1d_dense_model
- build_multihead_conv1d_lstm_model
- build_multihead_conv1d_dense_model
- build_conv2d_dense_model
- build_stacked_conv2d_model
- build_conv2d_kernel2d_model
- build_inception_model

```
def get_io_shapes(data):
    for batch in data.take(1):
        in_shape  = batch[0][0].shape
        out_shape = batch[1][0].shape

    return in_shape, out_shape


def build_conv1d_lstm_model(models, params):
    model_name = get_model_name(models, params)
    data = models[model_name]['train']
    in_shape, out_shape = get_io_shapes(data)
    out_steps = out_shape[0]

    feat_maps = params['feat_maps']
    drop_out  = params['drop_out']
    kern_reg  = params['kern_reg']
    recu_reg  = params['recu_reg']
    filters   = params['filters']
    kern_size = params['kern_size']

    if len(out_shape) == 2:
      out_feats = out_shape[1]
    else:
      out_feats = 1

    cnnlstm = Sequential(name = model_name)
    cnnlstm.add(InputLayer(input_shape = in_shape))

    if drop_out != 0.0:
      cnnlstm.add(Dropout(drop_out))
```

```
    cnnlstm.add(Conv1D(filters = filters,
                       activation = 'relu',
                       kernel_size = int(kern_size)))  #, input_shape=(n_timesteps
    cnnlstm.add(MaxPooling1D(pool_size = 2))

    # Shape [batch, time, features] => [batch, feat_maps]
    cnnlstm.add(LSTM(feat_maps,
                     return_sequences = False,
                     kernel_regularizer = regularizers.l2(kern_reg),
                     recurrent_regularizer = regularizers.l2(recu_reg)))

    cnnlstm.add(Dense(feat_maps,
                      activation = 'relu',
                      kernel_regularizer = regularizers.l2(kern_reg)))

    if drop_out != 0.0:
      cnnlstm.add(Dropout(drop_out))
      # Shape => [batch, out_steps * out_feats]
      cnnlstm.add(Dense(out_steps * out_feats,
                        kernel_constraint = maxnorm(3)))
    else:
      cnnlstm.add(Dense(out_steps * out_feats))

    if len(out_shape) == 2:
      # Shape => [batch, out_steps, features].
      cnnlstm.add(Reshape([out_steps, out_feats]))

    return cnnlstm


def build_conv1d_dense_model(models, params):
    model_name = get_model_name(models, params)
    data = models[model_name]['train']
    in_shape, out_shape = get_io_shapes(data)
    out_steps = out_shape[0]

    feat_maps = params['feat_maps']
    drop_out  = params['drop_out']
    kern_reg  = params['kern_reg']
    filters   = params['filters']
    kern_size = params['kern_size']

    if len(out_shape) == 2:
      out_feats = out_shape[1]
    else:
      out_feats = 1

    cnnlstm = Sequential(name = model_name)
    cnnlstm.add(InputLayer(input_shape = in_shape))

    cnnlstm.add(Conv1D(filters = filters,
                       activation = 'relu',
                       kernel_size = int(kern_size)))  #, input_shape=(n_timesteps
```

```
    cnnlstm.add(MaxPooling1D(pool_size = 2))

    cnnlstm.add(Flatten())

    if drop_out != 0.0:
      cnnlstm.add(Dropout(drop_out))

    # Shape [batch, time, features] => [batch, feat_maps]
    cnnlstm.add(Dense(feat_maps,
                      activation = 'relu',
                      kernel_regularizer = regularizers.l2(kern_reg)))

    cnnlstm.add(Dense(int(feat_maps / 2),
                      activation = 'relu',
                      kernel_regularizer = regularizers.l2(kern_reg)))

    if drop_out != 0.0:
      cnnlstm.add(Dropout(drop_out))
      # Shape => [batch, out_steps * out_feats]
      cnnlstm.add(Dense(out_steps * out_feats,
                        kernel_constraint = maxnorm(3)))
    else:
      cnnlstm.add(Dense(out_steps * out_feats))

    if len(out_shape) == 2:
      # Shape => [batch, out_steps, features].
      cnnlstm.add(Reshape([out_steps, out_feats]))

    return cnnlstm


def build_stacked_conv1d_lstm_model(models, params):
    model_name = get_model_name(models, params)
    data = models[model_name]['train']
    in_shape, out_shape = get_io_shapes(data)
    out_steps = out_shape[0]

    feat_maps = params['feat_maps']
    drop_out  = params['drop_out']
    kern_reg  = params['kern_reg']
    recu_reg  = params['recu_reg']
    filters   = params['filters']
    kern_size = params['kern_size']

    if len(out_shape) == 2:
      out_feats = out_shape[1]
    else:
      out_feats = 1

    cnnlstm = Sequential(name = model_name)
    cnnlstm.add(InputLayer(input_shape = in_shape))

    if drop_out != 0.0:
      cnnlstm.add(Dropout(drop_out))
```

```
    cnnlstm.add(Conv1D(filters = filters,
                       kernel_size = kern_size,
                       activation = 'relu'))  #, input_shape=(n_timesteps,n_featu
    cnnlstm.add(MaxPooling1D(pool_size = 2))

    cnnlstm.add(Conv1D(filters = filters,
                       kernel_size = kern_size + 2,
                       activation = 'relu'))
    cnnlstm.add(MaxPooling1D(pool_size = 2))

    # Shape [batch, time, features] => [batch, feat_maps]
    cnnlstm.add(LSTM(feat_maps,
                     return_sequences = True,
                     kernel_regularizer = regularizers.l2(kern_reg),
                     recurrent_regularizer = regularizers.l2(recu_reg)))

    cnnlstm.add(LSTM(int(feat_maps / 2),
                     return_sequences = False,
                     kernel_regularizer = regularizers.l2(kern_reg),
                     recurrent_regularizer = regularizers.l2(recu_reg)))

    if drop_out != 0.0:
      cnnlstm.add(Dropout(drop_out))
      # Shape => [batch, out_steps * out_feats]
      cnnlstm.add(Dense(out_steps * out_feats,
                        kernel_constraint = maxnorm(3)))
    else:
      cnnlstm.add(Dense(out_steps * out_feats))

    if len(out_shape) == 2:
      # Shape => [batch, out_steps, features].
      cnnlstm.add(Reshape([out_steps, out_feats]))

    return cnnlstm


def build_multihead_conv1d_lstm_model(models, params):
    model_name = get_model_name(models, params)
    data = models[model_name]['train']
    in_shape, out_shape = get_io_shapes(data)
    out_steps = out_shape[0]

    feat_maps = params['feat_maps']
    drop_out  = params['drop_out']
    kern_reg  = params['kern_reg']
    recu_reg  = params['recu_reg']
    filters   = params['filters']
    kern_size = params['kern_size']

    if len(out_shape) == 2:
      out_feats = out_shape[1]
    else:
      out_feats = 1
```

```
    # inputs
    inputs1 = Input(shape = in_shape)

    # head 1
    conv1 = Conv1D(filters = filters,
                   kernel_size = kern_size * 2 + 1,
                   activation = 'relu')(inputs1)
    drop1 = Dropout(drop_out)(conv1)
    pool1 = MaxPooling1D(pool_size = 2)(drop1)
    flat1 = Flatten()(pool1)

      # head 2
    conv2 = Conv1D(filters = filters,
                   kernel_size = kern_size * 3 + 1,
                   activation = 'relu')(inputs1)
    drop2 = Dropout(drop_out)(conv2)
    pool2 = MaxPooling1D(pool_size = 2)(drop2)
    flat2 = Flatten()(pool2)

      # head 3
    conv3 = Conv1D(filters = filters,
                   kernel_size = kern_size * 4 + 1,
                   activation = 'relu')(inputs1)
    drop3 = Dropout(drop_out)(conv3)
    pool3 = MaxPooling1D(pool_size = 2)(drop3)
    flat3 = Flatten()(pool3)

      # merge
    merged = concatenate([flat1, flat2, flat3])
    merged_r = Reshape((-1, 1))(merged)

      # interpretation
    lstm1 = LSTM(feat_maps,
                 return_sequences = False,
                 kernel_regularizer = regularizers.l2(kern_reg),
                 recurrent_regularizer = regularizers.l2(recu_reg))(merged_r)
    outputs = Dense(out_steps * out_feats)(lstm1)

    model = Model(inputs = inputs1, outputs = outputs, name = model_name)

    return model


def build_multihead_conv1d_dense_model(models, params):
    model_name = get_model_name(models, params)
    data = models[model_name]['train']
    in_shape, out_shape = get_io_shapes(data)
    out_steps = out_shape[0]

    feat_maps = params['feat_maps']
    drop_out  = params['drop_out']
    filters   = params['filters']
    kern_size = int(params['kern_size'])  # skopt tuple conversion probs
```

```
if len(out_shape) == 2:
  out_feats = out_shape[1]
else:
  out_feats = 1

# inputs
inputs1 = Input(shape = in_shape)

# head 1
conv1 = Conv1D(filters = filters,
               kernel_size = kern_size * 2 + 1,
               activation = 'relu')(inputs1)
drop1 = Dropout(drop_out)(conv1)
pool1 = MaxPooling1D(pool_size = 2)(drop1)
flat1 = Flatten()(pool1)

  # head 2
conv2 = Conv1D(filters = filters,
               kernel_size = kern_size * 3 + 1,
               activation = 'relu')(inputs1)
drop2 = Dropout(drop_out)(conv2)
pool2 = MaxPooling1D(pool_size = 2)(drop2)
flat2 = Flatten()(pool2)

  # head 3
conv3 = Conv1D(filters = filters,
               kernel_size = kern_size * 4 + 1,
               activation = 'relu')(inputs1)
drop3 = Dropout(drop_out)(conv3)
pool3 = MaxPooling1D(pool_size = 2)(drop3)
flat3 = Flatten()(pool3)

  # merge
merged = concatenate([flat1, flat2, flat3])

  # interpretation
if drop_out != 0.0:
  dense1  = Dense(feat_maps,
                  activation = 'relu',
                  kernel_constraint = maxnorm(3))(merged)
  dense2  = Dense(int(feat_maps / 2),
                  activation = 'relu',
                  kernel_constraint = maxnorm(3))(dense1)
  outputs = Dense(out_steps * out_feats,
                  kernel_constraint = maxnorm(3))(dense2)
else:
  dense1  = Dense(feat_maps, activation = 'relu')(merged)
  dense2  = Dense(int(feat_maps / 2), activation = 'relu')(dense1)
  outputs = Dense(out_steps * out_feats)(dense2)

model = Model(inputs = inputs1, outputs = outputs, name = model_name)

return model
```

```
def build_conv2d_dense_model(models, params):
    model_name = get_model_name(models, params)
    data = models[model_name]['train']
    in_shape, out_shape = get_io_shapes(data)
    out_steps = out_shape[0]

    feat_maps = params['feat_maps']
    drop_out  = params['drop_out']
    kern_reg  = params['kern_reg']
    filters   = params['filters']
    kern_size = params['kern_size']

    if len(out_shape) == 2:
      out_feats = out_shape[1]
    else:
      out_feats = 1

    conv2d = Sequential(name = model_name)
    conv2d.add(InputLayer(input_shape = in_shape))

    if drop_out != 0.0:
      conv2d.add(Dropout(drop_out))

    conv2d.add(Reshape((in_shape[0], in_shape[1], 1)))

    conv2d.add(Conv2D(filters = filters,
                      kernel_size = (1, kern_size),
                      padding = 'same',
                      activation = 'relu'))  #, input_shape=(n_timesteps,n_feature
    conv2d.add(Flatten())

    if drop_out != 0.0:
      conv2d.add(Dropout(drop_out))

    conv2d.add(Dense(feat_maps,
                     activation = 'relu',
                     kernel_regularizer = regularizers.l2(kern_reg)))

    conv2d.add(Dense(int(feat_maps / 2),
                     activation = 'relu',
                     kernel_regularizer = regularizers.l2(kern_reg)))

    if drop_out != 0.0:
      conv2d.add(Dropout(drop_out))
      # Shape => [batch, out_steps * out_feats]
      conv2d.add(Dense(out_steps * out_feats,
                       kernel_constraint = maxnorm(3)))
    else:
      conv2d.add(Dense(out_steps * out_feats))

    if len(out_shape) == 2:
      # Shape => [batch, out_steps, features].
```

```
      conv2d.add(Reshape([out_steps, out_feats]))

    return conv2d


def build_stacked_conv2d_model(models, params):
    model_name = get_model_name(models, params)
    data = models[model_name]['train']
    in_shape, out_shape = get_io_shapes(data)
    out_steps = out_shape[0]

    feat_maps = params['feat_maps']
    drop_out  = params['drop_out']
    kern_reg  = params['kern_reg']
    filters   = params['filters']
    ks_feats  = params['ks_feats']
    ks_time   = params['ks_time']

    if len(out_shape) == 2:
      out_feats = out_shape[1]
    else:
      out_feats = 1

    s_conv2d = Sequential(name = model_name)
    s_conv2d.add(InputLayer(input_shape = in_shape))

    if drop_out != 0.0:
      s_conv2d.add(Dropout(drop_out))

    s_conv2d.add(Reshape((in_shape[0], in_shape[1], 1)))

    s_conv2d.add(Conv2D(filters = filters,
                        kernel_size = (1, ks_feats),
                        padding = 'same',
                        activation = 'relu'))  #, input_shape=(n_timesteps,n_featu

    s_conv2d.add(Conv2D(filters = filters,
                        kernel_size = (ks_time, 1),
                        padding = 'same',
                        activation = 'relu'))
    s_conv2d.add(Flatten())

    if drop_out != 0.0:
      s_conv2d.add(Dropout(drop_out))

    s_conv2d.add(Dense(feat_maps,
                       activation = 'relu',
                       kernel_regularizer = regularizers.l2(kern_reg)))

    s_conv2d.add(Dense(int(feat_maps / 2),
                       activation = 'relu',
                       kernel_regularizer = regularizers.l2(kern_reg)))

    if drop_out != 0.0:
```

```
      s_conv2d.add(Dropout(drop_out))
      # Shape => [batch, out_steps * out_feats]
      s_conv2d.add(Dense(out_steps * out_feats,
                         kernel_constraint = maxnorm(3)))
    else:
      s_conv2d.add(Dense(out_steps * out_feats))

    if len(out_shape) == 2:
      # Shape => [batch, out_steps, features].
      s_conv2d.add(Reshape([out_steps, out_feats]))

    return s_conv2d


def build_conv2d_kernel2d_model(models, params):
    model_name = get_model_name(models, params)
    data = models[model_name]['train']
    in_shape, out_shape = get_io_shapes(data)
    out_steps = out_shape[0]

    feat_maps = params['feat_maps']
    drop_out  = params['drop_out']
    kern_reg  = params['kern_reg']
    filters   = params['filters']
    ks_feats  = params['ks_feats']
    ks_time   = params['ks_time']

    if len(out_shape) == 2:
      out_feats = out_shape[1]
    else:
      out_feats = 1

    conv2dk2d = Sequential(name = model_name)
    conv2dk2d.add(InputLayer(input_shape = in_shape))

    if drop_out != 0.0:
      conv2dk2d.add(Dropout(drop_out))

    conv2dk2d.add(Reshape((in_shape[0], in_shape[1], 1)))

    conv2dk2d.add(Conv2D(filters = filters,
                        kernel_size = (ks_time, ks_feats),
                        padding = 'same',
                        activation = 'relu'))  #, input_shape=(n_timesteps,n_featu
    conv2dk2d.add(Flatten())

    if drop_out != 0.0:
      conv2dk2d.add(Dropout(drop_out))

    conv2dk2d.add(Dense(feat_maps,
                       activation = 'relu',
                       kernel_regularizer = regularizers.l2(kern_reg)))

    conv2dk2d.add(Dense(int(feat_maps / 2),
```

```
                        activation = 'relu',
                        kernel_regularizer = regularizers.l2(kern_reg)))

    if drop_out != 0.0:
      conv2dk2d.add(Dropout(drop_out))
      # Shape => [batch, out_steps * out_feats]
      conv2dk2d.add(Dense(out_steps * out_feats,
                          kernel_constraint = maxnorm(3)))
    else:
      conv2dk2d.add(Dense(out_steps * out_feats))

    if len(out_shape) == 2:
      # Shape => [batch, out_steps, features].
      conv2dk2d.add(Reshape([out_steps, out_feats]))

    return conv2dk2d


def _inception_module(params, input_tensor, stride=1, activation='linear'):

    if params['bottleneck_size'] > 0 and int(input_tensor.shape[-1]) > 1:
        input_inception = keras.layers.Conv1D(filters     = params['bottleneck_si
                                              kernel_size = 1,
                                              padding     = 'same',
                                              activation  = activation,
                                              use_bias    = False)(input_tensor)
    else:
        input_inception = input_tensor

    # kernel_size_s = [3, 5, 8, 11, 17]
    # kernel_size_s = [self.kernel_size // (2 ** i) for i in range(3)]
    kernel_size_s = params['kern_size']

    conv_list = []

    for i in range(len(kernel_size_s)):
        conv_list.append(keras.layers.Conv1D(filters     = params['filters'],
                                             kernel_size = kernel_size_s[i],
                                             strides     = stride,
                                             padding     = 'same',
                                             activation  = activation,
                                             use_bias    = False)(input_inception)

    max_pool_1 = keras.layers.MaxPool1D(pool_size = 3,
                                        strides   = stride,
                                        padding   = 'same')(input_tensor)

    conv_6 = keras.layers.Conv1D(filters     = params['filters'],
                                 kernel_size = 1,
                                 padding     = 'same',
                                 activation  = activation,
                                 use_bias    = False)(max_pool_1)

    conv_list.append(conv_6)
```

```
    x = keras.layers.Concatenate(axis = 2)(conv_list)
    x = keras.layers.BatchNormalization()(x)
    x = keras.layers.Activation(activation = 'relu')(x)

    return x


def _shortcut_layer(params, input_tensor, out_tensor):
    shortcut_y = keras.layers.Conv1D(filters     = int(out_tensor.shape[-1]),
                                     kernel_size = 1,
                                     padding     = 'same',
                                     use_bias    = False)(input_tensor)
    shortcut_y = keras.layers.BatchNormalization()(shortcut_y)

    x = keras.layers.Add()([shortcut_y, out_tensor])
    x = keras.layers.Activation('relu')(x)

    return x


def build_inception_model(models, params):
    model_name = get_model_name(models, params)
    data = models[model_name]['train']
    in_shape, out_shape = get_io_shapes(data)
    out_steps = out_shape[0]

    if len(out_shape) == 2:
      out_feats = out_shape[1]
    else:
      out_feats = 1

    input_layer = keras.layers.Input(in_shape)

    x = input_layer
    input_res = input_layer

    for d in range(params['depth']):
        x = _inception_module(params, x)

        if params['use_residual'] and d % 3 == 2:
            x = _shortcut_layer(params, input_res, x)
            input_res = x

    gap_layer = keras.layers.GlobalAveragePooling1D()(x)

    output_layer = keras.layers.Dense(out_steps * out_feats)(gap_layer)

    model = keras.models.Model(inputs  = input_layer,
                               outputs = output_layer,
                               name    = model_name)

    return model
```

```
def get_model(models, params):
    if params['model_type'] == 'conv1d_lstm':
      model = build_conv1d_lstm_model(models, params)
    elif params['model_type'] == 'conv1d_dense':
      model = build_conv1d_dense_model(models, params)
    elif params['model_type'] == 'conv2d_dense':
      model = build_conv2d_dense_model(models, params)
    elif params['model_type'] == 's_conv2d':
      model = build_stacked_conv2d_model(models, params)
    elif params['model_type'] == 'conv2dk2d':
      model = build_conv2d_kernel2d_model(models, params)
    elif params['model_type'] == 'mh_conv1d_lstm':
      model = build_multihead_conv1d_lstm_model(models, params)
    elif params['model_type'] == 'mh_conv1d_dense':
      model = build_multihead_conv1d_dense_model(models, params)
    elif params['model_type'] == 'incept':
      model = build_inception_model(models, params)

    return model


def get_default_params(model_type, steps = 48):
    params = {'xcols':        def_cols,
              'ycols':             'y',
              'lags':               48,
              'steps_ahead':     steps,
              'stride':          steps,
              'shuffle':          True,
              'bs':                 16,
              'model_type': model_type,
              'mix_type':         'ts',
              'mix_alpha':           4,
              'mix_factor':          0,
              'mix_diff':            1,
              'feat_maps':          32,
              'filters':             0,
              'kern_size':           0,
              'ks_feats':            0,
              'ks_time':             0,
              'drop_out':          0.0,
              'kern_reg':          0.0,
              'recu_reg':          0.0,
              'epochs':              5,
              'lrf_params': [0.00001, 10, 32, 5, 100, 25]}

    if params['model_type'] == 'conv1d_lstm':
      params.update({'lags': 144,
                     'bs':    32})
    elif params['model_type'] == 'conv1d_dense':
      params.update({'lags': 144,
                     'bs':    32})
    elif params['model_type'] == 'mh_conv1d_lstm':
      params.update({'lags': 144})
```

```
    elif params['model_type'] == 'mh_conv1d_dense':
      params.update({'lags': 144})
    elif params['model_type'] == 'conv2d_dense':
      params.update({'lags': 144})
    elif params['model_type'] == 's_conv2d':
      params.update({'ks_feats': 3,
                     'ks_time':  3})
    elif params['model_type'] == 'conv2dk2d':
      params.update({'ks_feats': 3,
                     'ks_time':  3})
    elif params['model_type'] == 'incept':
      params.update({'depth':            6,
                     'kern_size': [2, 4, 8],
                     'use_residual':  True,
                     'bottleneck_size': 32})

    return params


def run_model(models, params):
    model_name = get_model_name(models, params)

    h = compile_fit_validate(models, model_name, params)
    plot_history(h, model_name, params['epochs'])
    print_min_loss(h, model_name)

    return h
```

Specify some utility functions for running, plotting and summarising results:

- `plot_history`
- `plot_forecasts`
- `plot_horizon_metrics`
- `check_residuals`

For running multiple models with specified parameters:

- `random_search_params` - multiple parameters eg. lags and feature_maps
- `sweep_param` - single parameter eg. lags

and summarising performance of multiple models:

- `rank_models`
- `get_best_models`

Note that I don't use the `random_search_params` function all that much in this notebook because I prefer the scikit-optimize approach outlined in the code cell following this one.

```
def compile_fit_validate(models, model_name, params, verbose = 2):
    # Reduces variance in results but won't eliminate it :-(
    random.seed(42)
    np.random.seed(42)
```

```
    tf.random.set_seed(42)

    model = models[model_name]['model']
    train_data = models[model_name]['train']
    valid_data = models[model_name]['valid']

    model.summary()

    # opt = Adam(learning_rate = 0.001)
    opt = Adam(models[model_name]['lrf'].best_lr)

    model.compile(optimizer = opt, loss = 'mse', metrics = ['mae'])

    es = EarlyStopping(monitor = 'val_loss',
                       mode = 'min',
                       verbose = 1,
                       patience = 10,
                       restore_best_weights = True)  # return best model, not last
    lr = ReduceLROnPlateau(monitor = 'val_loss',
                           factor = 0.2,
                           patience = 5,
                           min_lr = 0.00001)

    h = model.fit(train_data, validation_data = valid_data,
                  epochs = params['epochs'], verbose = verbose, callbacks = [es, l

    return h


def plot_history(h, name, epochs = 10):
    fig, axs = plt.subplots(1, 2, figsize = (9, 6), tight_layout = True)
    axs = axs.ravel()

    if 'fm_' in name:
      name = name.replace('fm_', 'fm\n')

    axs[0].plot(h.history['loss'])
    axs[0].plot(h.history['val_loss'])
    axs[0].set_title(name + '\nloss')
    axs[0].set_xticklabels(range(1, epochs + 1))
    axs[0].set_xticks(range(0, epochs))
    axs[0].set_ylabel('loss')
    axs[0].set_xlabel('epoch')
    axs[0].legend(['train', 'valid'], loc = 'upper right')

    axs[1].plot(h.history['mae'])
    axs[1].plot(h.history['val_mae'])
    axs[1].set_title(name + '\nmae')
    axs[1].set_xticks(range(0, epochs))
    axs[1].set_xticklabels(range(1, epochs + 1))
    axs[1].set_ylabel('mae')
    axs[1].set_xlabel('epoch')
    axs[1].legend(['train', 'valid'], loc = 'upper right')
    plt.show()
```

```
    return None


def print_min_loss(h, name):
    argmin_loss     = np.argmin(np.array(h.history['loss']))
    argmin_val_loss = np.argmin(np.array(h.history['val_loss']))
    min_loss        = h.history['loss'][argmin_loss]
    min_val_loss    = h.history['val_loss'][argmin_val_loss]
    mae             = h.history['mae'][argmin_loss]
    val_mae         = h.history['val_mae'][argmin_val_loss]

    txt = "{0:s} {1:s} min loss: {2:f}\tmae: {3:f}\tepoch: {4:d}"
    print(txt.format(name, "train", min_loss,     mae,     argmin_loss + 1))
    print(txt.format(name, "valid", min_val_loss, val_mae, argmin_val_loss + 1))
    print()

    return None


def plot_forecasts(models, model_name, dataset = 'valid', subplots = 3):
    """Plot example forecasts with observations and lagged temperatures.

       First row shows near zero rmse forecasts.
       Second row shows most positive rmse forecasts.
       Third row shows most negative rmse forecasts.
    """

    # get model etc
    model   = models[model_name]['model']
    params  = models[model_name]['params']
    horizon = params['steps_ahead']
    lags    = params['lags']

    assert horizon >= 12
    assert subplots in [3, 4, 5]

    # get data
    if dataset == 'test':
      data = models[model_name]['test']
    elif dataset == 'train':
      data = models[model_name]['train']
    elif dataset == 'valid':
      data = models[model_name]['valid']
    else:
      print("Unknown dataset:", dataset)
      return None

    # make forecast
    preds = model.predict(data)
    preds = preds.reshape((preds.shape[0], preds.shape[1]))
    preds = preds[::horizon]

    obs   = np.concatenate([y for _, y in data], axis = 0)
```

```
    long_obs = obs.reshape((obs.shape[0], obs.shape[1]))
    long_obs = long_obs[::horizon]

    res = long_obs - preds  # res for residual
    res_sign = np.sign(-res.mean(axis = 1))

    err = (long_obs - preds) ** 2  # err for error
    err_row_means = err.mean(axis = 1)
    rmse_rows = res_sign * np.sqrt(err_row_means)

    # choose forecasts
    neg_rmse = np.argsort(rmse_rows)[:subplots]
    pos_rmse = np.argsort(-rmse_rows)[:subplots]
    nz_rmse  = np.argsort(np.abs(rmse_rows))[:subplots]  # nz near zero

    plot_idx = np.concatenate((nz_rmse, pos_rmse, neg_rmse))

    # plot forecasts
    fig, axs = plt.subplots(3, subplots, sharex = True, sharey = True, figsize = (
    axs = axs.ravel()

    for i in range(3 * subplots):
      lagged_obs = get_lagged_obs(long_obs, plot_idx[i] - 1, lags)
      axs[i].plot(range(-lags + 1, 1),
                  inv_transform(scaler, lagged_obs, 'y', models['datasets']['trair
                  'blue',
                  label='lagged observations')
      axs[i].plot(range(1, horizon + 1),
                  inv_transform(scaler, preds[plot_idx[i]],    'y', models['datase
                  'orange',
                  label='forecast')
      axs[i].plot(range(0, horizon),
                  inv_transform(scaler, long_obs[plot_idx[i]], 'y', models['datase
                  'green',
                  label='observations')
      sub_title = "{0:d} {1:.4f}".format(plot_idx[i], rmse_rows[plot_idx[i]])
      axs[i].title.set_text(sub_title)

    fig.suptitle(model_name + " " + dataset + "\nperiod idx, signed rmse")
    fig.text(0.5, 0.04, 'forecast horizon - half hour steps', ha='center')
    fig.text(0.04, 0.5, 'Temperature - $^\circ$C', va='center', rotation='vertical
    plt.legend(bbox_to_anchor=(1.04, 0.5), loc="center left", borderaxespad=0)
    plt.show();


def get_lagged_obs(long_obs, plot_idx, lags):
    if long_obs[plot_idx].size < lags:
      lagged_obs = np.flip(long_obs[plot_idx])
    else:
      lagged_obs = long_obs[plot_idx]

    while lagged_obs.size < lags:
      plot_idx -= 1
      lagged_obs = np.concatenate([lagged_obs, np.flip(long_obs[plot_idx])])
```

```
    if long_obs[plot_idx].size < lags:
      lagged_obs = np.flip(lagged_obs)

    return lagged_obs[-lags:]


def rmse(obs, preds):
    return np.sqrt(np.mean((obs - preds) ** 2))


def mae(obs, preds):
    return np.median(np.abs(obs - preds))


def plot_horizon_metrics(models, model_name, dataset = 'valid'):

    # get model etc
    model   = models[model_name]['model']
    params  = models[model_name]['params']
    horizon = params['steps_ahead']

    assert horizon >= 12

    # get data
    if dataset == 'test':
      data = models[model_name]['test']
    elif dataset == 'train':
      data = models[model_name]['train']
    elif dataset == 'valid':
      data = models[model_name]['valid']
    else:
      print("Unknown dataset:", dataset)
      return None

    # make forecast
    preds = model.predict(data)
    obs = np.concatenate([y for _, y in data], axis = 0)

    if len(obs.shape) == 3 and len(preds.shape) == 3:
      # multi-step, multi-feature output
      preds = preds[:, :, 0:1]
      preds = preds.reshape((preds.shape[0], preds.shape[1]))
      obs = obs[:, :, 0:1]
      obs = obs.reshape((obs.shape[0], obs.shape[1]))
    elif len(obs.shape) == 3 and len(preds.shape) == 2:
      obs = obs.reshape((obs.shape[0], obs.shape[1]))

    assert preds.shape == obs.shape

    # calculate metrics
    rmse_h, mae_h = np.zeros(horizon), np.zeros(horizon)

    for i in range(horizon):
```

```
      t_obs   = inv_transform(scaler, obs[:, i],   'y', models['datasets']['train
      t_preds = inv_transform(scaler, preds[:, i], 'y', models['datasets']['train
      rmse_h[i] = rmse(t_obs, t_preds)
      mae_h[i]  = mae(t_obs,  t_preds)

    # plot metrics for horizons
    fig, axs = plt.subplots(1, 2, figsize = (14, 7))
    fig.suptitle(model_name + " " + dataset)
    axs = axs.ravel()

    mean_val_lab = model_name + ' mean value'
    axs[0].plot(range(1, horizon+1), rmse_h, label=model_name)
    if dataset == 'test':
      var_rmse = np.array([0.39, 0.52, 0.64, 0.75, 0.86, 0.96, 1.06, 1.15, 1.23, 1
       1.45, 1.51, 1.57, 1.63, 1.68, 1.73, 1.77, 1.81, 1.85, 1.89, 1.92,
       1.96, 1.99, 2.02, 2.05, 2.08, 2.1 , 2.13, 2.15, 2.18, 2.2 , 2.22,
       2.24, 2.26, 2.28, 2.3 , 2.31, 2.33, 2.35, 2.36, 2.38, 2.39, 2.4 ,
       2.42, 2.43, 2.44, 2.45])
      axs[0].plot(range(1, horizon+1), var_rmse, label='VAR')
    else:
      axs[0].hlines(np.mean(rmse_h), xmin=1, xmax=horizon, color='yellow', linesty
    axs[0].set_xlabel("horizon - half hour steps")
    axs[0].set_ylabel("rmse")

    axs[1].plot(range(1, horizon+1), mae_h, label=model_name)
    if dataset == 'test':
      var_mae = np.array([0.39, 0.49, 0.57, 0.66, 0.74, 0.83, 0.91, 0.98, 1.05, 1.
       1.24, 1.29, 1.34, 1.39, 1.43, 1.47, 1.5 , 1.53, 1.56, 1.59, 1.62,
       1.64, 1.66, 1.68, 1.7 , 1.72, 1.73, 1.75, 1.76, 1.77, 1.78, 1.8 ,
       1.81, 1.82, 1.83, 1.83, 1.84, 1.85, 1.85, 1.86, 1.86, 1.87, 1.87,
       1.88, 1.88, 1.89, 1.89])
      axs[1].plot(range(1, horizon+1), var_mae, label='VAR')
    else:
      axs[1].hlines(np.mean(mae_h), xmin=1, xmax=horizon, color='yellow', linestyl
    axs[1].set_xlabel("horizon - half hour steps")
    axs[1].set_ylabel("mae")
    plt.legend(bbox_to_anchor=(1.04, 0.5), loc="center left", borderaxespad=0)
    plt.show()


def plot_obs_preds(obs, preds, title):
    plt.figure(figsize = (12, 8))
    plt.subplot(3, 1, 1)
    plt.scatter(x = obs, y = preds)
    y_lim = plt.ylim()
    x_lim = plt.xlim()
    plt.plot(x_lim, y_lim, 'k-', color = 'grey')
    plt.xlabel('Observations')
    plt.ylabel('Predictions')
    plt.title(title)


def plot_residuals(obs, preds, title):
    plt.subplot(3, 1, 2)
```

```
    plt.scatter(x = range(len(obs)), y = (obs - preds))
    plt.axhline(y = 0, color = 'grey')
    plt.xlabel('Position')
    plt.ylabel('Residuals')
    plt.title(title)


def plot_residuals_dist(obs, preds, title):
    data = obs - preds
    plt.subplot(3, 1, 3)
    pd.Series(data).plot(kind = 'density')
    plt.axvline(x = 0, color = 'grey')
    plt.title(title)
    plt.tight_layout()
    plt.show()


def check_residuals(models, model_name, dataset = 'valid'):
    """Plot observations against predictions, residuals and residual distribution

    Warning: The full training set will take approx. 5 mins to plot"""

    assert dataset in ['test', 'valid']

    model = models[model_name]
    data  = model[dataset]
    preds = model['model'].predict(data)
    obs   = np.concatenate([y for _, y in data], axis = 0)

    # reshape obs & preds
    label_len = obs.shape[0]
    preds_len = len(preds)
    # print("labels:", label_len)
    # print("preds:",  preds_len)
    # print("preds:",  preds.shape)
    # print("obs:",    obs.shape)
    assert label_len == preds_len

    # print("obs[0]:", obs.shape[0])
    # print("obs[1]:", obs.shape[1])
    preds_long = preds.reshape((obs.shape[0] * obs.shape[1]))
    test_long  = obs.reshape((obs.shape[0] * obs.shape[1]))

    # inverse transform using train mean & sd
    t_preds = inv_transform(scaler, preds_long, 'y', train_df.columns)
    t_obs   = inv_transform(scaler, test_long,  'y', train_df.columns)

    t_rmse = rmse(t_obs, t_preds)  # Need to treat 4 step ahead rmse & mae proper
    t_mae  =  mae(t_obs, t_preds)
    print("t rmse ", model_name, ": ",  t_rmse, sep = '')
    print("t mae ",  model_name, ":  ", t_mae,  sep = '')

    title = 'Inverse transformed data\n' + model_name
    plot_obs_preds(t_obs, t_preds, title)
```

```
    plot_residuals(t_obs, t_preds, title)
    plot_residuals_dist(t_obs, t_preds, title)
    print("\n\n")


def expand_grid(dictionary):
   return pd.DataFrame([row for row in product(*dictionary.values())],
                       columns = dictionary.keys())


def random_search_params(models, params, sweep_values, limit = 5):
    sweep_params = list(sweep_values.keys())
    assert len(sweep_params) > 1

    i = 0
    model_names = []
    sweep_df   = expand_grid(sweep_values)
    sweep_rows = sweep_df.sample(n = limit)

    for sweep_row in sweep_rows.itertuples():
      i += 1
      print("%d of %d" %(i, limit))
      print(sweep_row)
      for idx in sweep_params:
        params[idx] = getattr(sweep_row, idx)

      model_name = get_model_name(models, params)
      model_names.append(model_name)
      models[model_name] = {}
      models[model_name]['params'] = params

      ds_train, ds_valid, ds_test = make_datasets(models, params)
      models[model_name]['train'] = ds_train
      models[model_name]['valid'] = ds_valid
      models[model_name]['test']  = ds_test

      models[model_name]['model'] = get_model(models, params)
      models[model_name]['lrf']   = run_lrf(models, params)
      models[model_name]['history'] = run_model(models, params)

    summarise_history(models, model_names)

    return [models, model_names]


def sweep_param(models, params, sweep_values, verbose=False):
    sweep_params = list(sweep_values.keys())
    sweep_param  = sweep_params[0]
    assert len(sweep_params) == 1
    assert len(sweep_values[sweep_param]) >= 1

    model_names = []

    for sweep_value in sweep_values[sweep_param]:
```

```
      # params_copy = {key: value[:] for key, value in params.items()}
      params_copy = {key: value for key, value in params.items()}
      params_copy[sweep_param] = sweep_value

      if verbose == True:
        print(sweep_param, ":", sweep_value)

      model_name = get_model_name(models, params_copy)
      model_names.append(model_name)
      models[model_name] = {}
      models[model_name]['params'] = params_copy

      ds_train, ds_valid, ds_test = make_datasets(models, params_copy)
      models[model_name]['train'] = ds_train
      models[model_name]['valid'] = ds_valid
      models[model_name]['test']  = ds_test

      models[model_name]['model']   = get_model(models, params_copy)
      models[model_name]['lrf']     = run_lrf(models,   params_copy)
      models[model_name]['history'] = run_model(models, params_copy)

    summarise_history(models, model_names)

    return [models, model_names]


def check_fit(h, metric, fit_type, ignore = 1):
    badfit = 0

    h_train = h.history[metric]
    h_valid = h.history['val_' + metric]
    h_len = len(np.array(h_train))

    for i in range(ignore, h_len):
      # Disabling underfitting check for now
      # if ( fit_type == 'over'  and h_valid[i] < h_train[i] ) or \
      #    ( fit_type == 'under' and h_valid[i] > h_train[ignore] ):
      if ( fit_type == 'over'  and h_valid[i] < h_train[i] ):
        badfit += 1

    return round(badfit * 100 / (h_len - ignore), 2)


def get_history_stats(h, metric, ignore = 0):
    stats = {}

    stats['mean'] = np.mean(np.array(h.history[metric]))
    stats['std']  = np.std(np.array(h.history[metric]))

    h_argmin = np.argmin(np.array(h.history[metric]))
    h_argmax = np.argmax(np.array(h.history[metric]))
    stats['min'] = h.history[metric][h_argmin]
    stats['max'] = h.history[metric][h_argmax]
    stats['argmin'] = h_argmin
```

```
    h_len = len(np.array(h.history[metric]))
    stats['first'] = np.array(h.history[metric])[0]
    stats['last']  = np.array(h.history[metric])[h_len - 1]

    # monotonically decreasing
    stats['monod'] = np.all(np.diff(h.history[metric]) < 0)

    stats['max_eq_first'] = stats['max'] == stats['first']
    stats['min_eq_last']  = stats['min'] == stats['last']

    return stats


def summarise_history(models, model_names):

    for model_name in model_names:
      if model_name == '':
        continue

      model = models[model_name]
      model['perf'] = {}
      mod_perf = model['perf']
      mod_perf['val_loss'] = get_history_stats(model['history'], 'val_loss')
      mod_perf['val_mae']  = get_history_stats(model['history'], 'val_mae')

      mod_perf['loss'], mod_perf['mae'] = {}, {}
      mod_perf['loss']['overfit_pc']  = check_fit(model['history'], 'loss', 'over
      mod_perf['loss']['underfit_pc'] = check_fit(model['history'], 'loss', 'unde
      mod_perf['mae']['overfit_pc']   = check_fit(model['history'], 'mae',  'over
      mod_perf['mae']['underfit_pc']  = check_fit(model['history'], 'mae',  'unde

    return None


def get_all_model_names(models):
    names = []

    for name in models.keys():
      if not name in ['datasets']:
        names.append(name)

    return names


def reject_model(mod_perf, strict):
    fit_pc_lim = 0.0
    reject = False

    if mod_perf['loss']['overfit_pc']  > fit_pc_lim or \
       mod_perf['loss']['underfit_pc'] > fit_pc_lim or \
       (strict == True and mod_perf['mae']['overfit_pc']   > fit_pc_lim) or \
       (strict == True and mod_perf['mae']['underfit_pc']  > fit_pc_lim):
      reject = True
```

```
    if (strict == True and mod_perf['val_loss']['monod'] == False) or \
       (strict == True and mod_perf['val_mae']['monod']  == False):
      reject = True

    return reject


def get_best_models(models, model_names = None, strict = False):
    best_mse_mod, best_mae_mod = None, None
    low_mse, low_mae = sys.maxsize, sys.maxsize

    if model_names == None:
      model_names = get_all_model_names(models)

    for model_name in model_names:
      model = models[model_name]

      try:
        mod_perf = model['perf']
      except:
        continue

      if reject_model(mod_perf, strict):
        continue

      if mod_perf['val_loss']['min'] < low_mse:
        low_mse = mod_perf['val_loss']['min']
        best_mse_mod = model_name

      if mod_perf['val_mae']['min'] < low_mae:
        low_mae = mod_perf['val_mae']['min']
        best_mae_mod = model_name

    return ['low mse ' + str(best_mse_mod), round(low_mse, 5),
            'low mae ' + str(best_mae_mod), round(low_mae, 5)]


def plot_perf_boxplot(models, metric, model_names = None, strict = False):
    stats = []

    assert metric in ['val_loss', 'val_mae']

    if model_names == None:
      model_names = get_all_model_names(models)
      title = 'All models'
    else:
      # title = [k for k, v in locals().items() if v == 'model_names']
      title = str(len(model_names)) + ' models'

    title += ' - strict=' + str(strict)

    for model_name in model_names:
      try:
```

```
        mod_perf = models[model_name]['perf']
      except:
        continue

      if reject_model(mod_perf, strict):
        continue

      stats.append(mod_perf[metric]['min'])

    assert len(stats) > 2

    fig1, ax1 = plt.subplots()
    ax1.set_title(title + ' ' + metric)
    ax1.boxplot(stats, labels=['']);


def rank_models(models, metric, model_names = None, strict = False, limit = 5):
    stats = {}

    assert metric in ['val_loss', 'val_mae']

    if model_names == None:
      model_names = get_all_model_names(models)

    for model_name in model_names:
      try:
        mod_perf = models[model_name]['perf']
      except:
        continue

      if reject_model(mod_perf, strict):
        continue

      stats[model_name] = round(mod_perf[metric]['min'], 5)

    return sorted(stats.items(), key=lambda item: item[1])[:limit]
    # return [dict(sorted(stats.items(), key=lambda item: item[1]))][:limit]


def keep_key(d, k):
  """ models = keep_key(models, 'datasets') """
  return {k: d[k]}
```

Bayesian hyperparameter optimization

I've used the BayesianOptimization package in the past to optimise time series forecasts. It works well but doesn't have any plotting functions. It should be possible to spot irrelevant hyperparameters with the scikit-optimize plot_objective function even if the underlying gaussian processes are approximations.

The `model_fitness_1s` example function is passed to `gp_minimize` from [scikit-optimize](). The `model_fitness_1s` function should be seen as an implementation example which will be customised later for particular network architectures and parameters to optimise.

```
# !pip freeze

!pip install scikit-optimize

import skopt
from skopt import gp_minimize
from skopt.space import Real, Categorical, Integer
from skopt.plots import plot_convergence, plot_objective, plot_evaluations, \
                        plot_gaussian_process
from skopt.utils import use_named_args

print("\nskopt version:", skopt.__version__)


dim_lags = Integer(low = 4,  high = 48, name = 'lags')
dim_bs   = Integer(low = 16, high = 32, name = 'bs')
dim_fm   = Integer(low = 16, high = 32, name = 'feat_maps')
dim_drop_out = Real(low = 1e-3, high = 5e-1, prior = 'log-uniform', name = 'drop_c

bo_dims_1s = [dim_lags,
              dim_bs,
              dim_fm,
              dim_drop_out]


def create_model(params):

    model_name = get_model_name(models, params)
    models[model_name] = {}
    models[model_name]['params'] = params

    ds_train, ds_valid, ds_test = make_datasets(models, params)
    models[model_name]['train'] = ds_train
    models[model_name]['valid'] = ds_valid
    models[model_name]['test']  = ds_test

    models[model_name]['model'] = get_model(models, params)
    models[model_name]['lrf']   = run_lrf(models, params)

    return models[model_name]['model']


def get_bo_mse(params, **dims):

    params.update(**dims)

    for k, v in dims.items():
        print(k, v)
```

```
    model_names = ['']
    model_name = get_model_name(models, params)
    model_names.append(model_name)

    # skopt will re-evaluate the same point, even when gp_minimize(..., noise = 1e
    # Some problems are noisy but regardless is bad default behaviour!
    # DO NOT rebuild the model
    if not model_name in models:
      model = create_model(params)
      models[model_name]['history'] = run_model(models, params)
      summarise_history(models, model_names)

    print(model_name)
    bo_mse = models[model_name]['perf']['val_loss']['min']

    if reject_model(models[model_name]['perf'], strict = False):
      print("WARN: bad model", model_name)
      BAD_MODEL_PENALTY = 1
      bo_mse *= BAD_MODEL_PENALTY  # bad models get (arbitrarly) "higher" values

    return bo_mse


@use_named_args(dimensions = bo_dims_1s)
def model_fitness_1s(**dims):
    """This function is for illustrative purposes.
       The params values must be adapted for each optimisation task.
       Here default parameters for a single step-ahead stacked LSTM are used.
    """

    params = get_default_params('s_lstm', 1)

    return get_bo_mse(params, **dims)


def run_bo_search(bayes_opt, bo_id):

    # noise, limit but unfortunately not prevent re-evaluating the same point
    noise_level = 1e-10

    bo_search_results = gp_minimize(func = bayes_opt[bo_id]['fitness_func'],
                                    dimensions = bayes_opt[bo_id]['dims'],
                                    x0 = bayes_opt[bo_id]['init_dims'],
                                    n_calls = bayes_opt[bo_id]['calls'],
                                    acq_func = 'EI',
                                    noise = noise_level,
                                    verbose = True,
                                    random_state = 42)

    print()
    print(bo_search_results.x)
    print(bo_search_results.fun)
    print()
```

```
    plot_convergence(bo_search_results)

    plot_objective(result   = bo_search_results)
    plot_evaluations(result = bo_search_results)

    plot_bo_func_vals_dist(bo_search_results.func_vals, bo_id)

    return bo_search_results


def plot_bo_func_vals_dist(data, bo_results_id):
    """Plot skopt function values distribution using swarmplot and boxplot"""

    title = bo_results_id + ' gp_minimize function values - mse'

    fig1, ax1 = plt.subplots()
    ax1 = sns.swarmplot(y = data)
    ax1 = sns.boxplot(y = data,
                      showcaps = False,
                      boxprops = {'facecolor':'None', 'linewidth':1},
                      showfliers = False).set_title(title)
    plt.show()


hpo = {}  # hyperparameter optimisation
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-w
Collecting scikit-optimize
  Downloading scikit_optimize-0.9.0-py2.py3-none-any.whl (100 kB)
     |████████████████████████████████| 100 kB 4.6 MB/s
Collecting pyaml>=16.9
  Downloading pyaml-21.10.1-py2.py3-none-any.whl (24 kB)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-p
Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: scikit-learn>=0.20.0 in /usr/local/lib/python3.
Requirement already satisfied: PyYAML in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.
Installing collected packages: pyaml, scikit-optimize
Successfully installed pyaml-21.10.1 scikit-optimize-0.9.0

skopt version: 0.9.0
```

Conv1D-LSTM

A one-dimensional Convolutional Neural Network (CNN) is a model that has a convolutional hidden layer that operates over a 1D sequence. The CNN layers are commonly followed by a pooling layer which distills the output of the CNN layer to the most important parts.

Code for this architecture is in the `build_conv1d_lstm_model` function.

Briefly, the architecture is (omitting dropout and regularisation):

- Conv1D()
- LSTM(return_sequences=False)
- Dense(activation='relu')
- Dense()

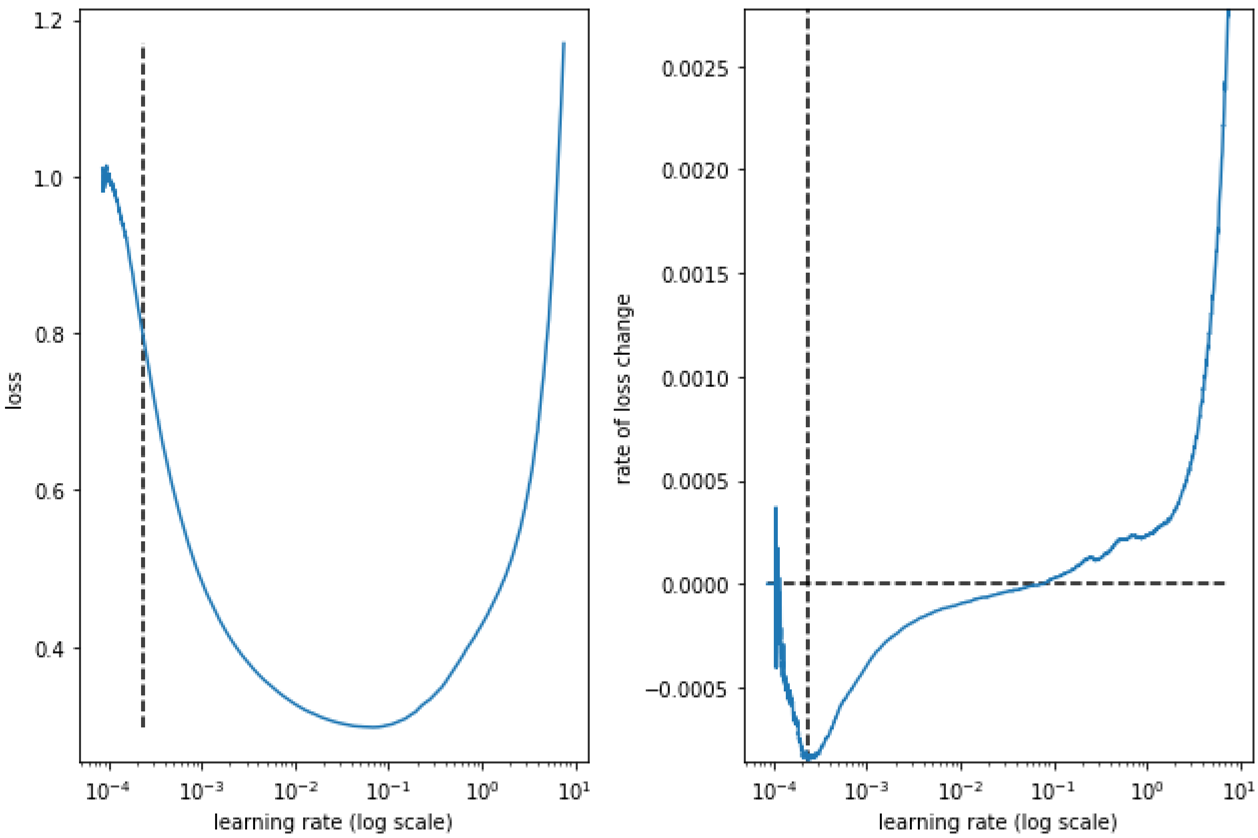
I've somewhat arbitrarily chosen to use a batch size of 32.

Optimise:

- lags
- feat_maps - LSTM feature maps
- Conv1D() filters
- Conv1D() kern_size

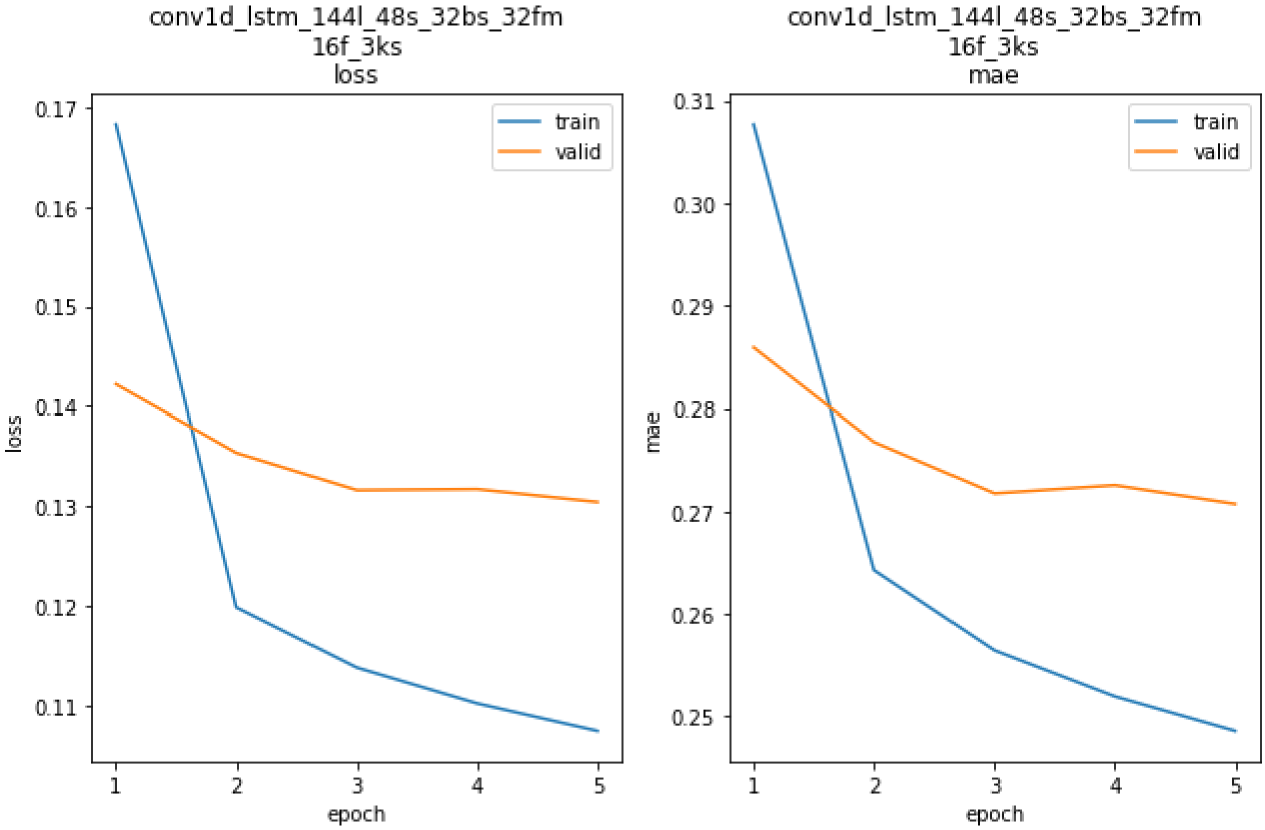
```
%%time


results_id = 'cnn1d_lstm_48s'
hpo[results_id] = {}

dim_lags      = Integer(low = 24, high = 144, name = 'lags')
dim_feat_maps = Integer(low =  8, high =  64, name = 'feat_maps')
dim_filters   = Integer(low =  4, high =  64, name = 'filters')
dim_kern_size = Integer(low =  3, high =   7, name = 'kern_size')

hpo[results_id]['dims'] = [dim_lags,
                           dim_feat_maps,
                           dim_filters,
                           dim_kern_size]
hpo[results_id]['init_dims'] = [144, 32, 16, 3]
hpo[results_id]['calls']     = 60


@use_named_args(dimensions = hpo[results_id]['dims'])
def model_fitness(**dims):
    params = get_default_params('conv1d_lstm')
    params.update({'lrf_params': [0.00008,  0.001, 32, 5, 100, 25]})

    return get_bo_mse(params, **dims)


hpo[results_id]['fitness_func'] = model_fitness
hpo[results_id]['results']      = run_bo_search(hpo, results_id)
```

```
Iteration No: 1 started. Evaluating function at provided point.
lags 144
feat_maps 32
filters 16
kern_size 3
Epoch 1/5
5876/5876 [==============================] - 77s 11ms/step - loss: 1.1906 - ma
```

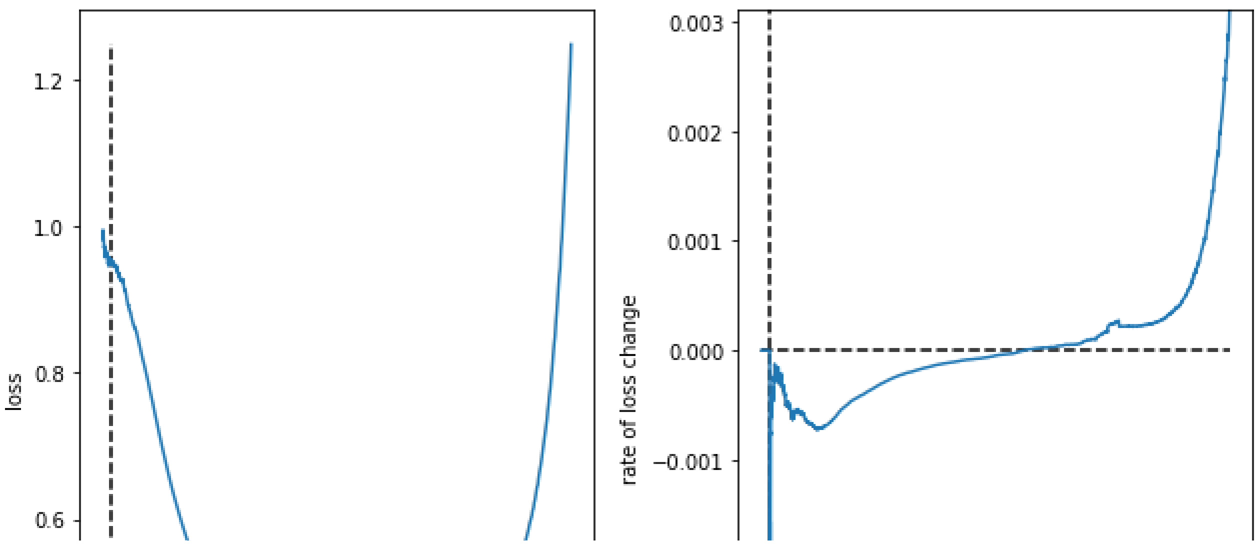


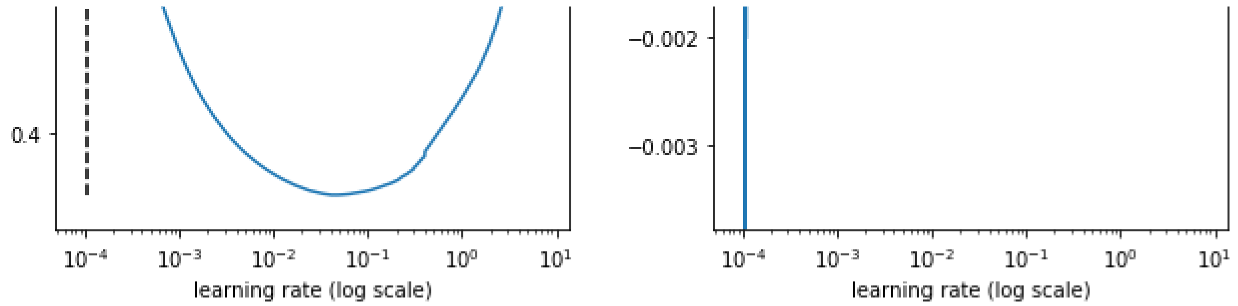

```
best lr: 0.00023779471

Model: "conv1d_lstm_144l_48s_32bs_32fm_16f_3ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 142, 16)           496

 max_pooling1d (MaxPooling1D  (None, 71, 16)           0
 )

 lstm (LSTM)                 (None, 32)                6272

 dense (Dense)               (None, 32)                1056

 dense_1 (Dense)             (None, 48)                1584

 reshape (Reshape)           (None, 48, 1)             0

=================================================================
Total params: 9,408
Trainable params: 9,408
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5876/5876 - 64s - loss: 0.1683 - mae: 0.3077 - val_loss: 0.1422 - val_mae: 0.2
Epoch 2/5
5876/5876 - 59s - loss: 0.1199 - mae: 0.2643 - val_loss: 0.1354 - val_mae: 0.2
Epoch 3/5
```

```
Epoch 3/5
5876/5876 - 60s - loss: 0.1138 - mae: 0.2564 - val_loss: 0.1316 - val_mae: 0.2
Epoch 4/5
5876/5876 - 61s - loss: 0.1102 - mae: 0.2519 - val_loss: 0.1317 - val_mae: 0.2
Epoch 5/5
5876/5876 - 57s - loss: 0.1074 - mae: 0.2486 - val_loss: 0.1304 - val_mae: 0.2
```

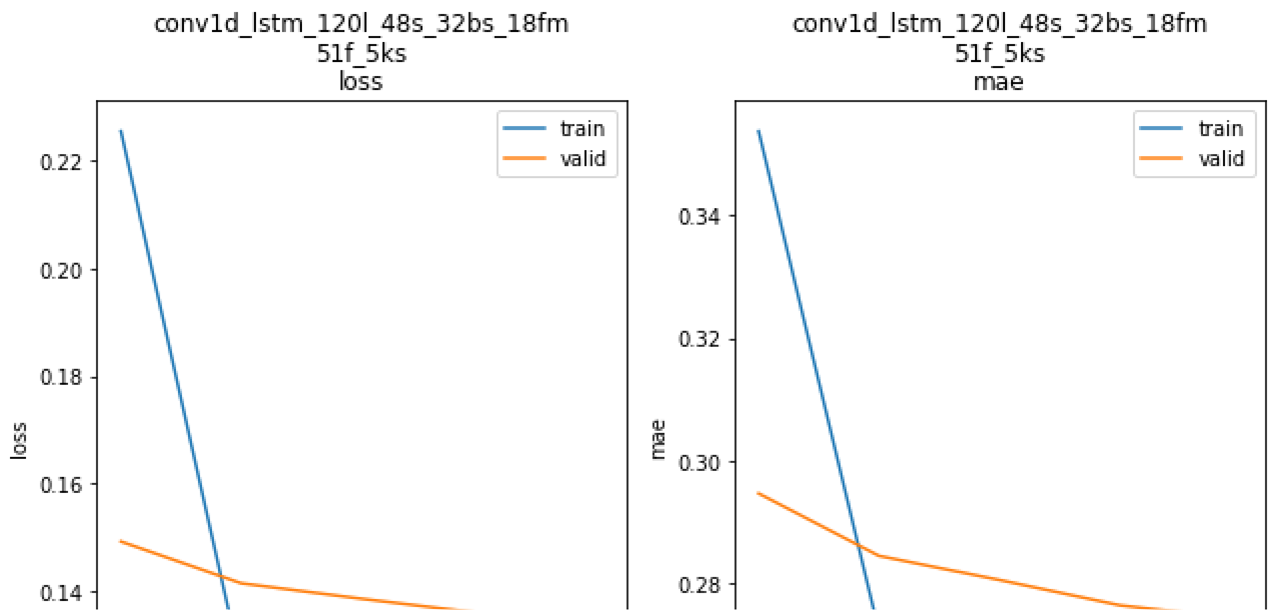


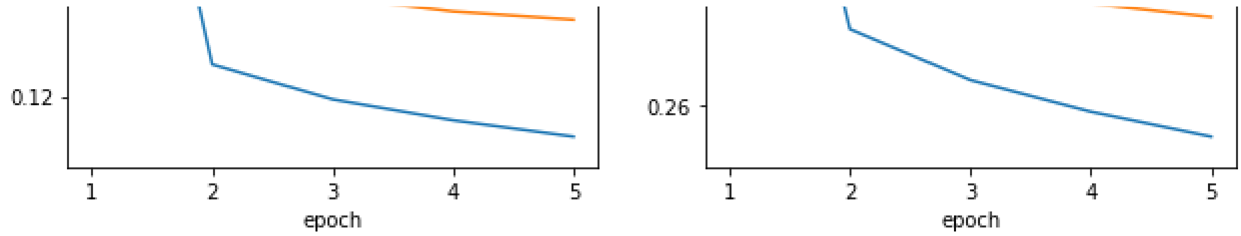

```
conv1d_lstm_144l_48s_32bs_32fm_16f_3ks train min loss: 0.107438 mae: 0.248584
conv1d_lstm_144l_48s_32bs_32fm_16f_3ks valid min loss: 0.130437 mae: 0.270731

conv1d_lstm_144l_48s_32bs_32fm_16f_3ks
Iteration No: 1 ended. Evaluation done at provided point.
Time taken: 455.3067
Function value obtained: 0.1304
Current minimum: 0.1304
Iteration No: 2 started. Evaluating function at random point.
lags 120
feat_maps 18
filters 51
kern_size 5
Epoch 1/5
5877/5877 [==============================] - 59s 10ms/step - loss: 1.2615 - ma
```



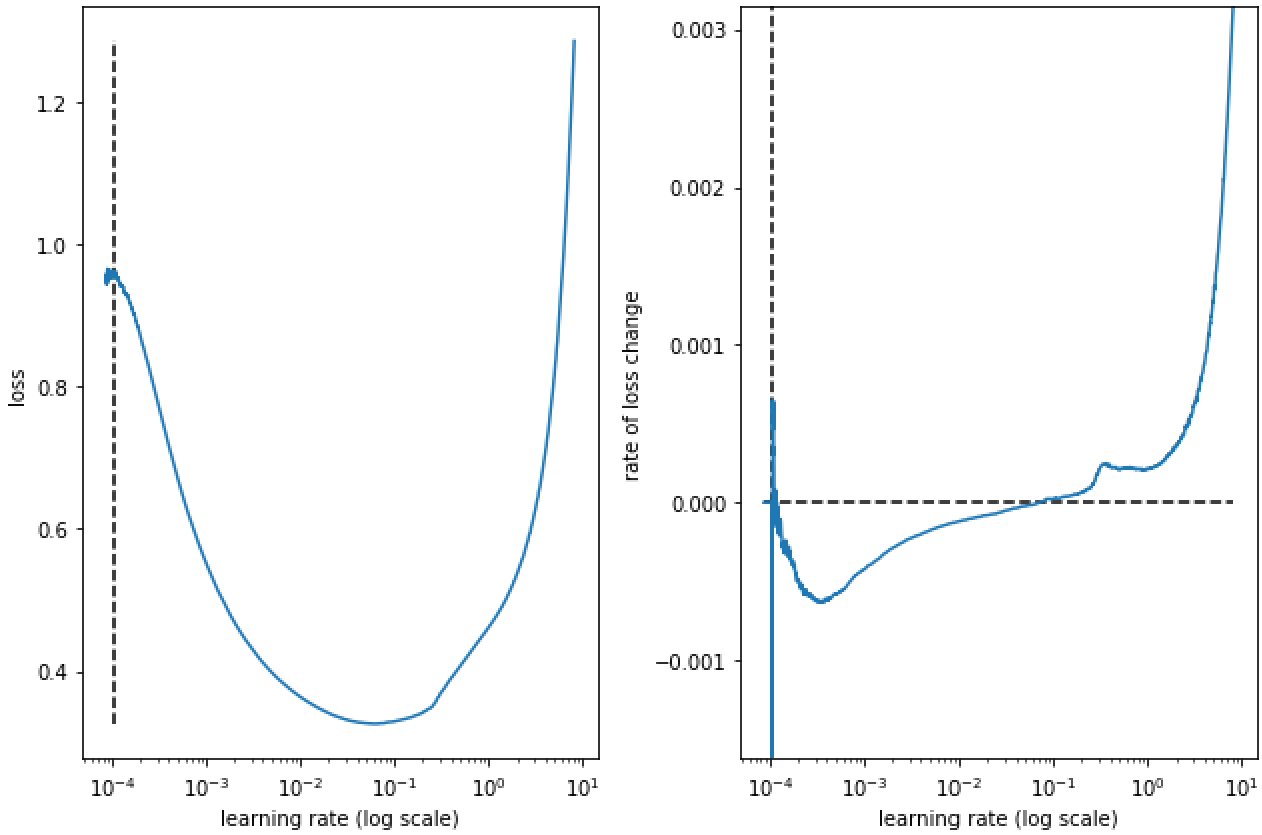



```
best lr: 0.0001053277

Model: "conv1d_lstm_120l_48s_32bs_18fm_51f_5ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_1 (Conv1D)           (None, 116, 51)           2601

 max_pooling1d_1 (MaxPooling  (None, 58, 51)           0
 1D)

 lstm_1 (LSTM)               (None, 18)                5040

 dense_2 (Dense)             (None, 18)                342

 dense_3 (Dense)             (None, 48)                912

 reshape_1 (Reshape)         (None, 48, 1)             0

=================================================================
Total params: 8,895
Trainable params: 8,895
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5877/5877 - 59s - loss: 0.2255 - mae: 0.3536 - val_loss: 0.1492 - val_mae: 0.2
Epoch 2/5
5877/5877 - 57s - loss: 0.1260 - mae: 0.2723 - val_loss: 0.1414 - val_mae: 0.2
Epoch 3/5
5877/5877 - 54s - loss: 0.1194 - mae: 0.2640 - val_loss: 0.1385 - val_mae: 0.2
Epoch 4/5
5877/5877 - 54s - loss: 0.1156 - mae: 0.2589 - val_loss: 0.1358 - val_mae: 0.2
Epoch 5/5
5877/5877 - 52s - loss: 0.1125 - mae: 0.2548 - val_loss: 0.1343 - val_mae: 0.2
```



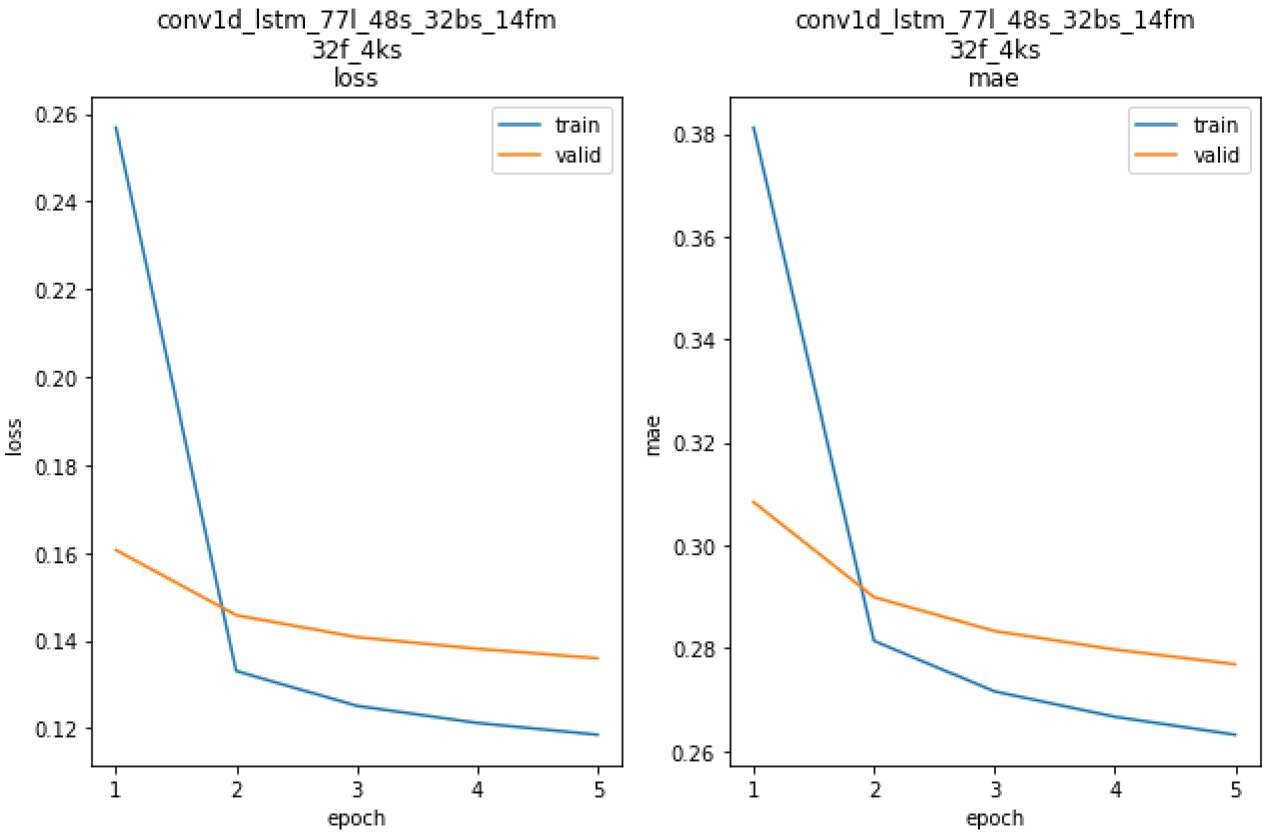



```
conv1d_lstm_120l_48s_32bs_18fm_51f_5ks train min loss: 0.112529 mae: 0.254832
conv1d_lstm_120l_48s_32bs_18fm_51f_5ks valid min loss: 0.134266 mae: 0.274278

conv1d_lstm_120l_48s_32bs_18fm_51f_5ks
Iteration No: 2 ended. Evaluation done at random point.
Time taken: 420.7501
Function value obtained: 0.1343
Current minimum: 0.1304
Iteration No: 3 started. Evaluating function at random point.
lags 77
feat_maps 14
filters 32
kern_size 4
Epoch 1/5
5878/5878 [==============================] - 54s 9ms/step - loss: 1.3057 - mae
```

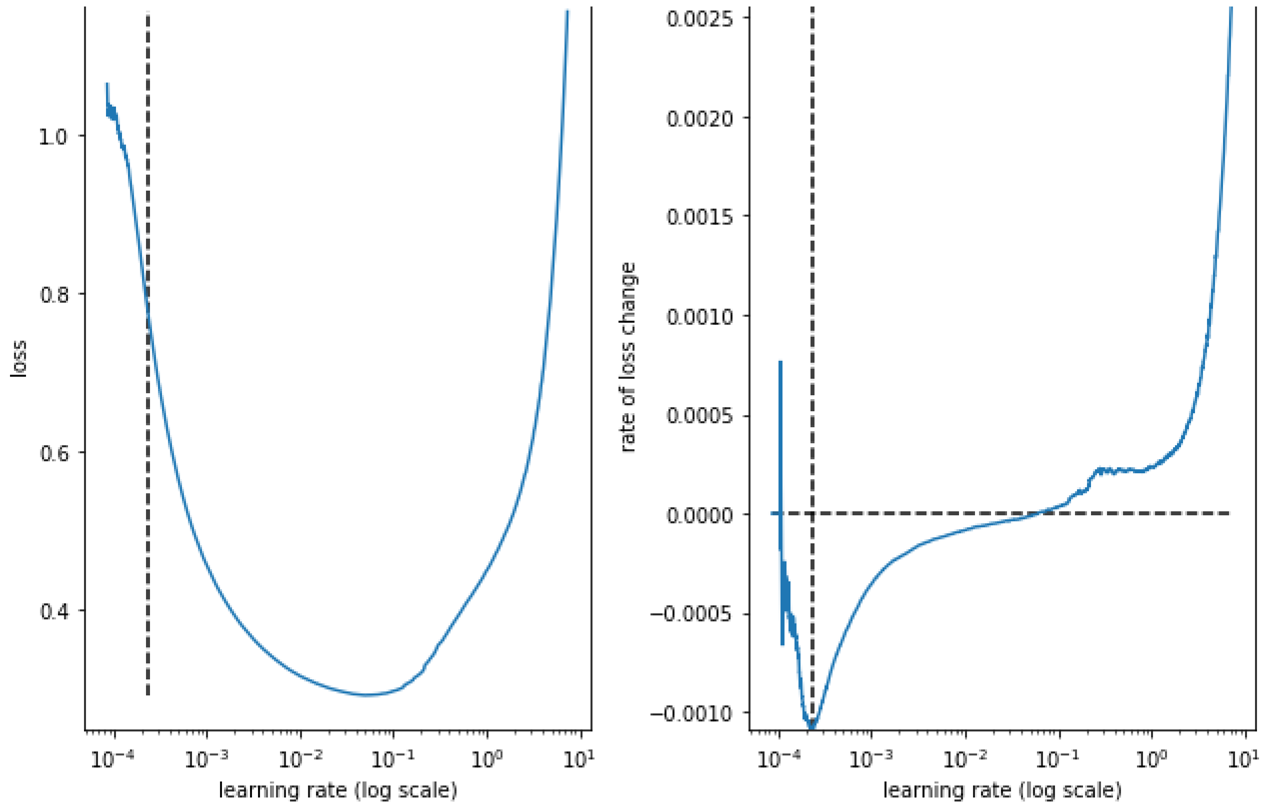



```
best lr: 0.000105322695

Model: "conv1d_lstm_77l_48s_32bs_14fm_32f_4ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_2 (Conv1D)           (None, 74, 32)            1312

 max_pooling1d_2 (MaxPooling  (None, 37, 32)           0
 1D)

 lstm_2 (LSTM)               (None, 14)                2632

 dense_4 (Dense)             (None, 14)                210
```

```
 dense_5 (Dense)             (None, 48)                720

 reshape_2 (Reshape)         (None, 48, 1)             0

=================================================================
Total params: 4,874
Trainable params: 4,874
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5878/5878 - 54s - loss: 0.2568 - mae: 0.3812 - val_loss: 0.1606 - val_mae: 0.3
Epoch 2/5
5878/5878 - 51s - loss: 0.1331 - mae: 0.2814 - val_loss: 0.1458 - val_mae: 0.2
Epoch 3/5
5878/5878 - 52s - loss: 0.1251 - mae: 0.2716 - val_loss: 0.1408 - val_mae: 0.2
Epoch 4/5
5878/5878 - 50s - loss: 0.1212 - mae: 0.2667 - val_loss: 0.1381 - val_mae: 0.2
Epoch 5/5
5878/5878 - 50s - loss: 0.1185 - mae: 0.2632 - val_loss: 0.1359 - val_mae: 0.2
```



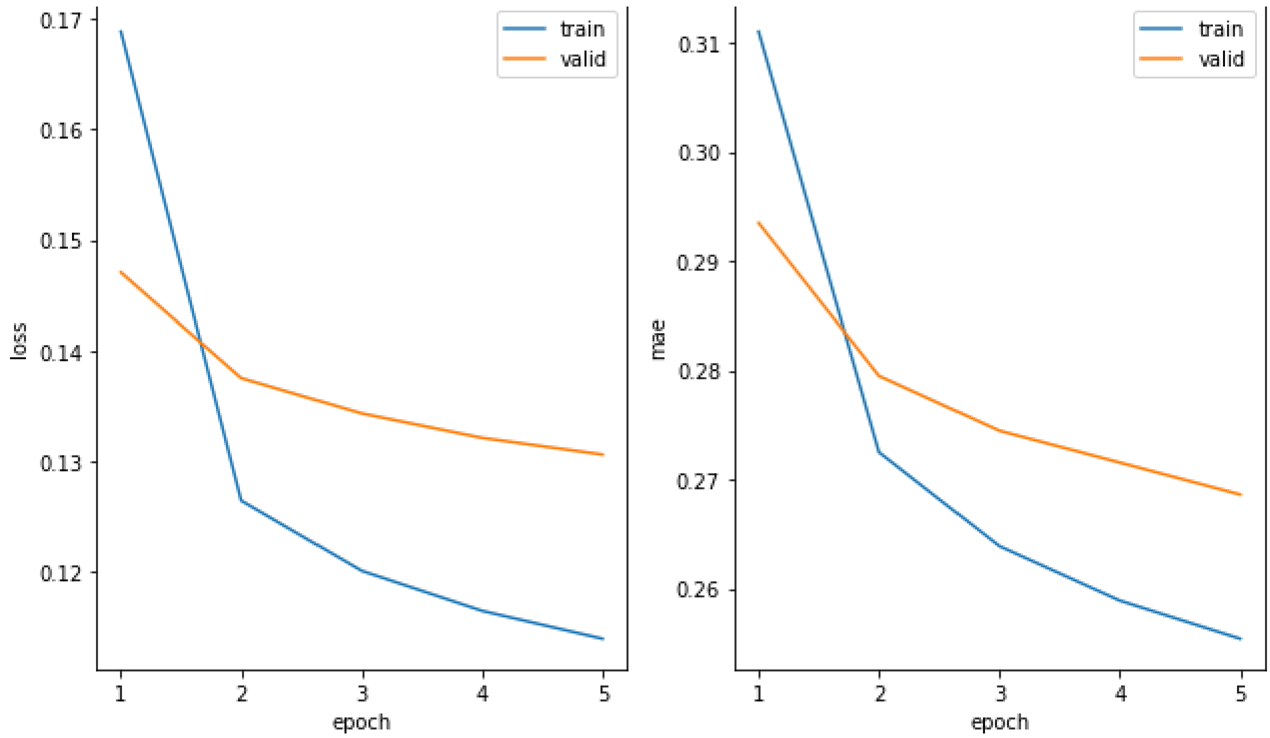

```
conv1d_lstm_77l_48s_32bs_14fm_32f_4ks train min loss: 0.118521  mae: 0.263166
conv1d_lstm_77l_48s_32bs_14fm_32f_4ks valid min loss: 0.135948  mae: 0.276882

conv1d_lstm_77l_48s_32bs_14fm_32f_4ks
Iteration No: 3 ended. Evaluation done at random point.
Time taken: 438.6643
Function value obtained: 0.1359
Current minimum: 0.1304
Iteration No: 4 started. Evaluating function at random point.
lags 41
feat_maps 44
filters 7
kern_size 6
Epoch 1/5
5879/5879 [==============================] - 54s 9ms/step - loss: 1.1707 - mae
```



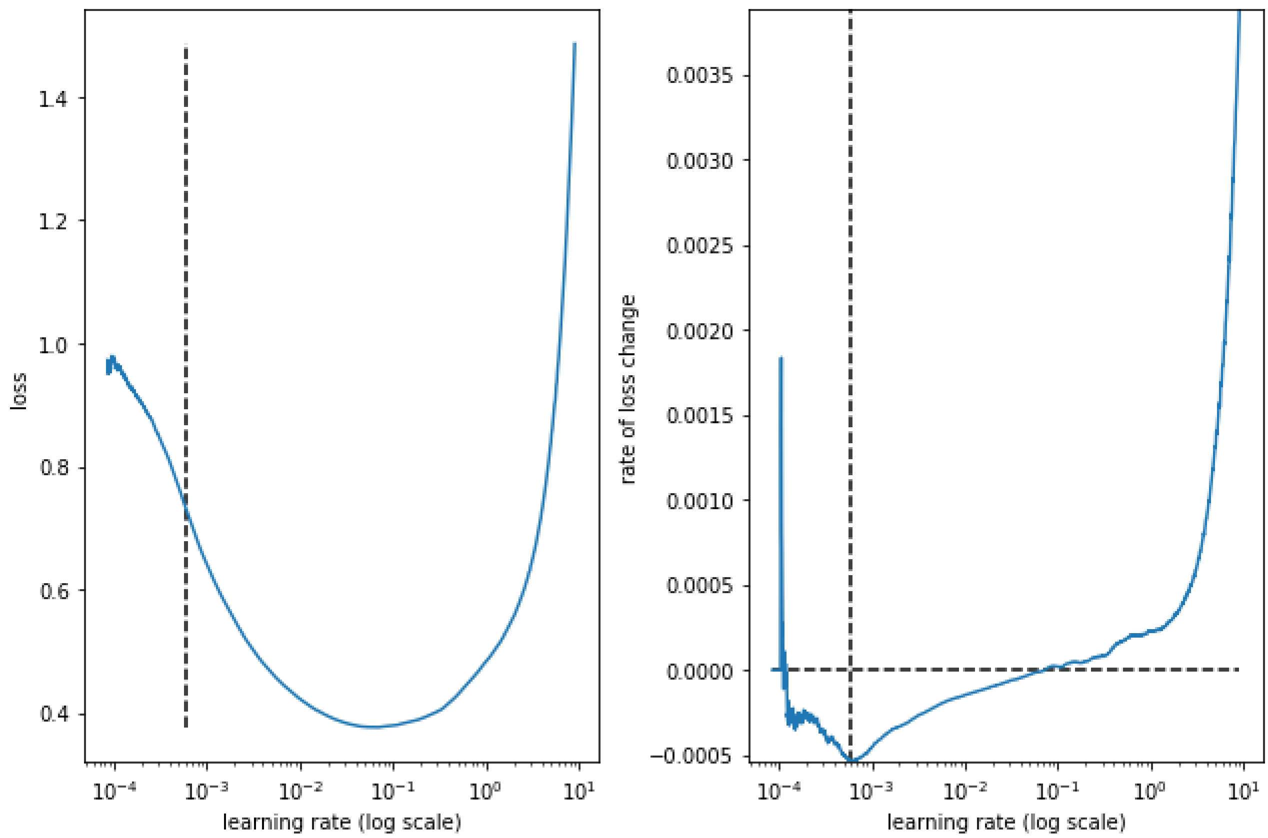

```
best lr: 0.00023185372

Model: "conv1d_lstm_41l_48s_32bs_44fm_7f_6ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_3 (Conv1D)           (None, 36, 7)             427

 max_pooling1d_3 (MaxPooling  (None, 18, 7)            0
 1D)

 lstm_3 (LSTM)               (None, 44)                9152

 dense_6 (Dense)             (None, 44)                1980

 dense_7 (Dense)             (None, 48)                2160

 reshape_3 (Reshape)         (None, 48, 1)             0

=================================================================
Total params: 13,719
Trainable params: 13,719
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5879/5879 - 50s - loss: 0.1688 - mae: 0.3110 - val_loss: 0.1471 - val_mae: 0.2
Epoch 2/5
5879/5879 - 49s - loss: 0.1264 - mae: 0.2725 - val_loss: 0.1375 - val_mae: 0.2
Epoch 3/5
5879/5879 - 47s - loss: 0.1201 - mae: 0.2639 - val_loss: 0.1343 - val_mae: 0.2
Epoch 4/5
5879/5879 - 47s - loss: 0.1165 - mae: 0.2589 - val_loss: 0.1321 - val_mae: 0.2
Epoch 5/5
5879/5879 - 49s - loss: 0.1139 - mae: 0.2554 - val_loss: 0.1306 - val_mae: 0.2
```

conv1d_lstm_41l_48s_32bs_44fm
7f_6ks
loss

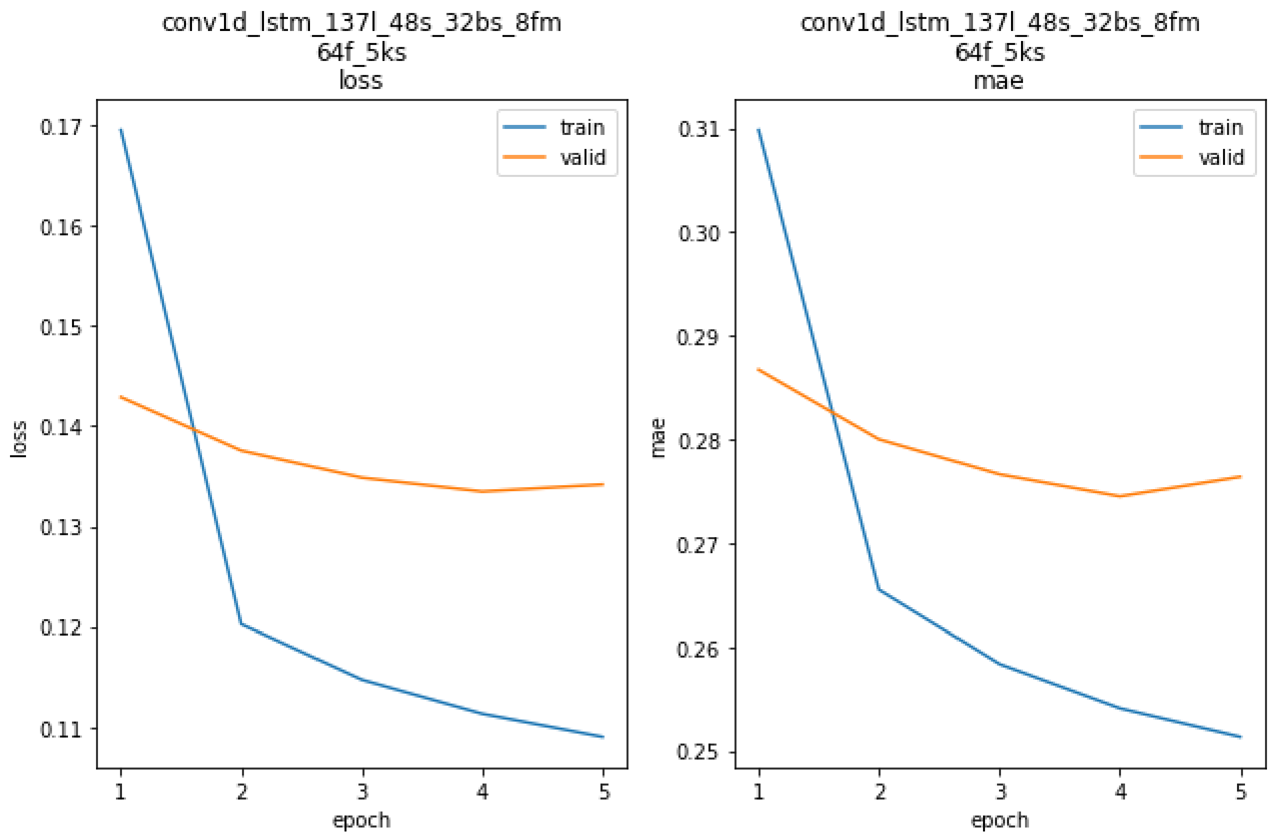
conv1d_lstm_41l_48s_32bs_44fm
7f_6ks
mae




```
conv1d_lstm_41l_48s_32bs_44fm_7f_6ks train min loss: 0.113939   mae: 0.255396
conv1d_lstm_41l_48s_32bs_44fm_7f_6ks valid min loss: 0.130608   mae: 0.268622

conv1d_lstm_41l_48s_32bs_44fm_7f_6ks
Iteration No: 4 ended. Evaluation done at random point.
Time taken: 401.3113
Function value obtained: 0.1306
Current minimum: 0.1304
Iteration No: 5 started. Evaluating function at random point.
lags 137
feat_maps 8
filters 64
kern_size 5
Epoch 1/5
5876/5876 [==============================] - 60s 10ms/step - loss: 1.5090 - ma
```

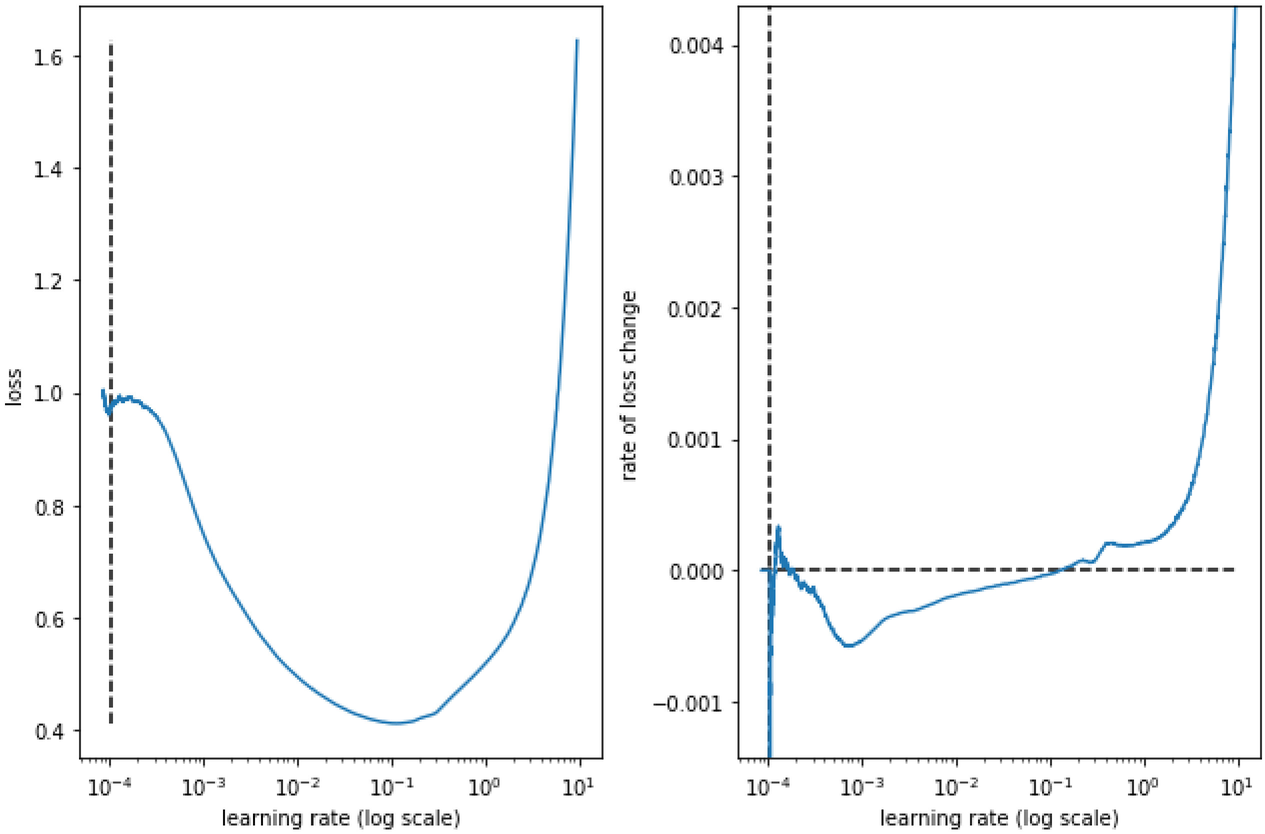


```
best lr: 0.0006042476

Model: "conv1d_lstm_137l_48s_32bs_8fm_64f_5ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_4 (Conv1D)           (None, 133, 64)           3264

 max_pooling1d_4 (MaxPooling  (None, 66, 64)           0
 1D)

 lstm_4 (LSTM)               (None, 8)                 2336

 dense_8 (Dense)             (None, 8)                 72

 dense_9 (Dense)             (None, 48)                432

 reshape_4 (Reshape)         (None, 48, 1)             0

=================================================================
Total params: 6,104
Trainable params: 6,104
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5876/5876 - 58s - loss: 0.1695 - mae: 0.3098 - val_loss: 0.1429 - val_mae: 0.2
Epoch 2/5
5876/5876 - 55s - loss: 0.1203 - mae: 0.2655 - val_loss: 0.1376 - val_mae: 0.2
Epoch 3/5
5876/5876 - 59s - loss: 0.1147 - mae: 0.2583 - val_loss: 0.1349 - val_mae: 0.2
Epoch 4/5
5876/5876 - 57s - loss: 0.1113 - mae: 0.2541 - val_loss: 0.1335 - val_mae: 0.2
Epoch 5/5
5876/5876 - 55s - loss: 0.1090 - mae: 0.2513 - val_loss: 0.1342 - val_mae: 0.2
```



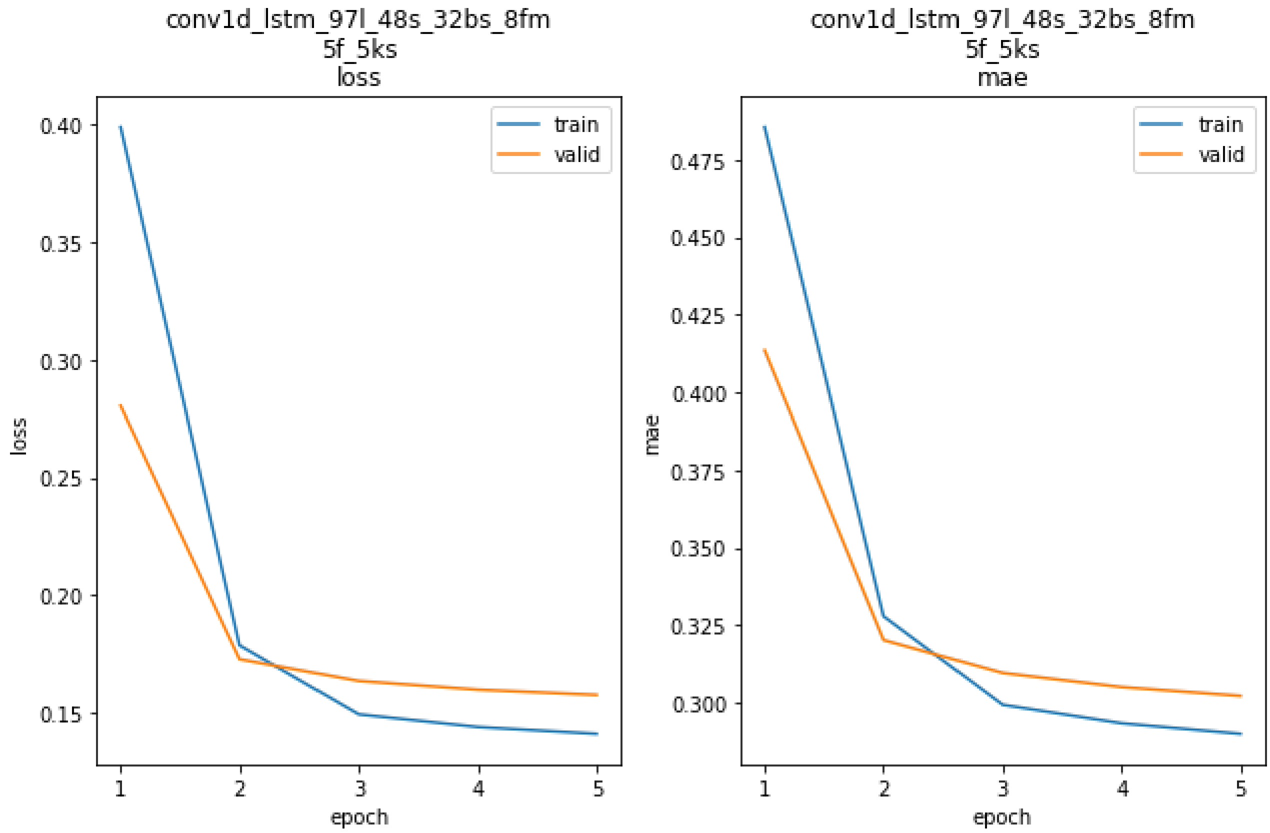

```
conv1d_lstm_137l_48s_32bs_8fm_64f_5ks train min loss: 0.109015  mae: 0.251330
conv1d_lstm_137l_48s_32bs_8fm_64f_5ks valid min loss: 0.133471  mae: 0.274498
```

```
conv1d_lstm_137l_48s_32bs_8fm_64f_5ks
Iteration No: 5 ended. Evaluation done at random point.
Time taken: 398.2453
Function value obtained: 0.1335
Current minimum: 0.1304
Iteration No: 6 started. Evaluating function at random point.
lags 97
feat_maps 8
filters 5
kern_size 5
Epoch 1/5
5878/5878 [==============================] - 59s 10ms/step - loss: 1.6504 - ma
```

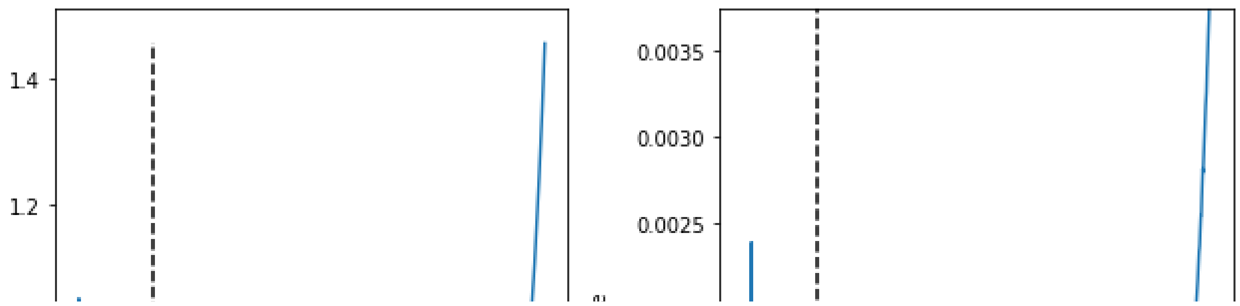


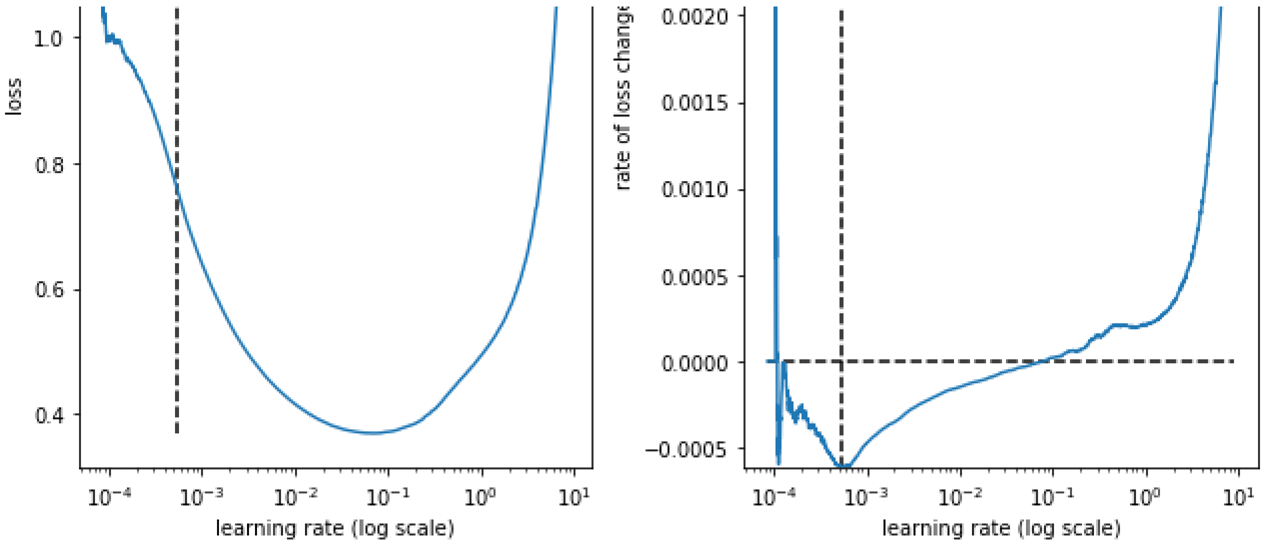

```
best lr: 0.00010619521

Model: "conv1d_lstm_97l_48s_32bs_8fm_5f_5ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_5 (Conv1D)           (None, 93, 5)             255

 max_pooling1d_5 (MaxPooling  (None, 46, 5)            0
 1D)

 lstm_5 (LSTM)               (None, 8)                 448

 dense_10 (Dense)            (None, 8)                 72

 dense_11 (Dense)            (None, 48)                432

 reshape_5 (Reshape)         (None, 48, 1)             0

=================================================================
Total params: 1,207
Trainable params: 1,207
Non-trainable params: 0
```

```
Epoch 1/5
5878/5878 - 54s - loss: 0.3989 - mae: 0.4855 - val_loss: 0.2805 - val_mae: 0.4
Epoch 2/5
5878/5878 - 54s - loss: 0.1788 - mae: 0.3279 - val_loss: 0.1729 - val_mae: 0.3
Epoch 3/5
5878/5878 - 54s - loss: 0.1495 - mae: 0.2993 - val_loss: 0.1637 - val_mae: 0.3
Epoch 4/5
5878/5878 - 52s - loss: 0.1441 - mae: 0.2933 - val_loss: 0.1600 - val_mae: 0.3
Epoch 5/5
5878/5878 - 52s - loss: 0.1412 - mae: 0.2899 - val_loss: 0.1578 - val_mae: 0.3
```

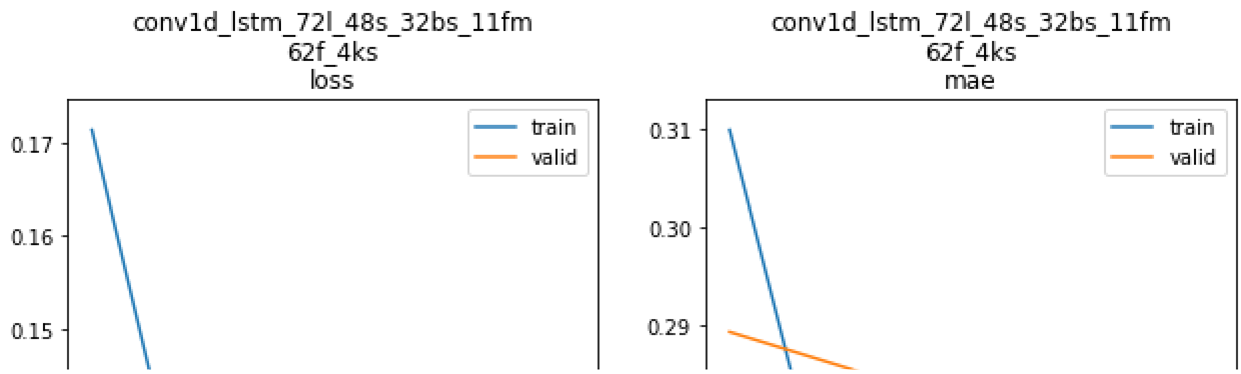


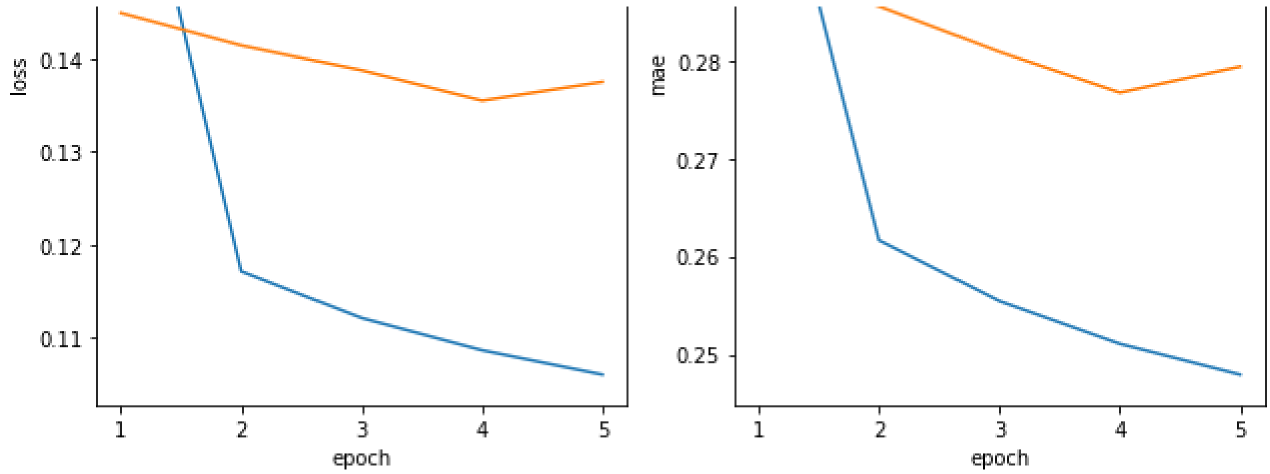

```
conv1d_lstm_97l_48s_32bs_8fm_5f_5ks train min loss: 0.141190    mae: 0.289943
conv1d_lstm_97l_48s_32bs_8fm_5f_5ks valid min loss: 0.157766    mae: 0.302214

conv1d_lstm_97l_48s_32bs_8fm_5f_5ks
WARN: bad model conv1d_lstm_97l_48s_32bs_8fm_5f_5ks
Iteration No: 6 ended. Evaluation done at random point.
Time taken: 413.2034
Function value obtained: 0.1578
Current minimum: 0.1304
Iteration No: 7 started. Evaluating function at random point.
lags 72
feat_maps 11
filters 62
kern_size 4
Epoch 1/5
5878/5878 [==============================] - 58s 9ms/step - loss: 1.4818 - mae
```



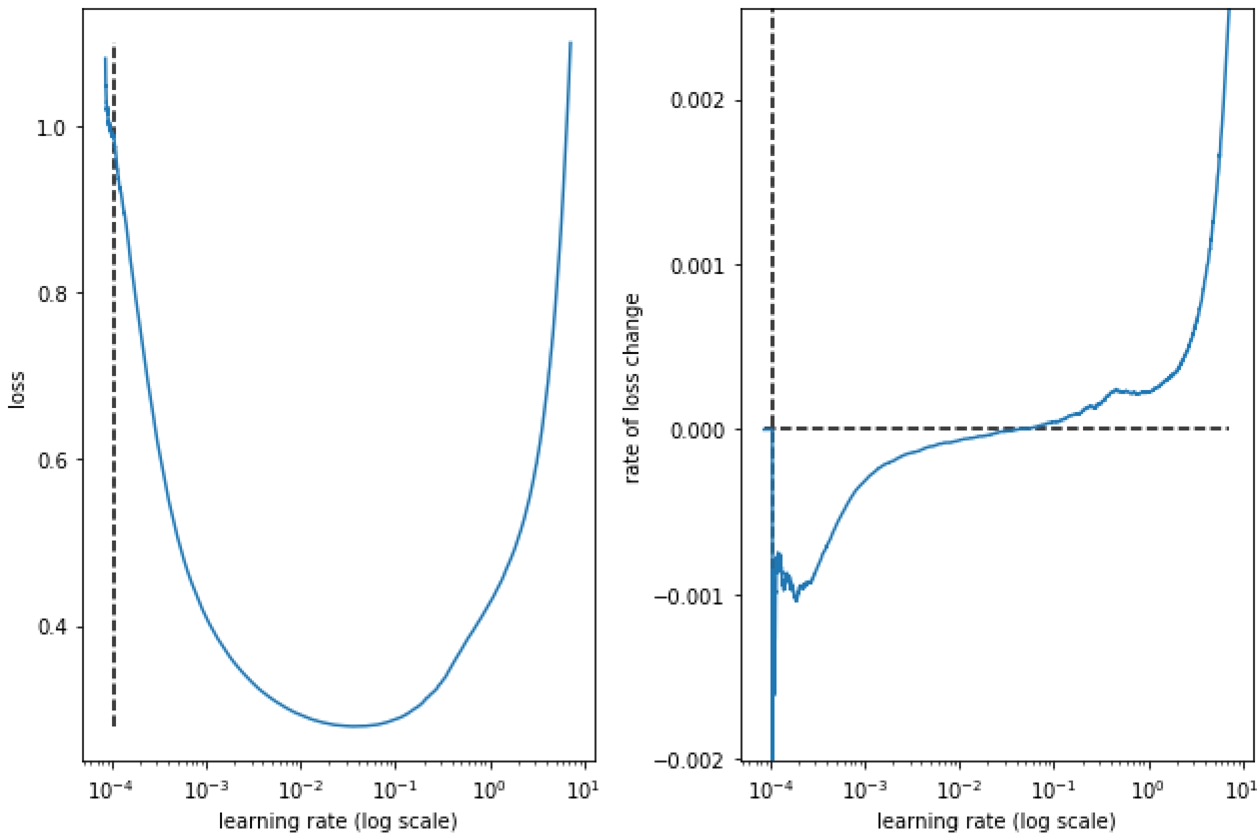


```
best lr: 0.0005364892

Model: "conv1d_lstm_72l_48s_32bs_11fm_62f_4ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_6 (Conv1D)           (None, 69, 62)            2542

 max_pooling1d_6 (MaxPooling  (None, 34, 62)           0
 1D)

 lstm_6 (LSTM)               (None, 11)                3256

 dense_12 (Dense)            (None, 11)                132

 dense_13 (Dense)            (None, 48)                576

 reshape_6 (Reshape)         (None, 48, 1)             0

=================================================================
Total params: 6,506
Trainable params: 6,506
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5878/5878 - 53s - loss: 0.1714 - mae: 0.3099 - val_loss: 0.1449 - val_mae: 0.2
Epoch 2/5
5878/5878 - 51s - loss: 0.1171 - mae: 0.2616 - val_loss: 0.1415 - val_mae: 0.2
Epoch 3/5
5878/5878 - 51s - loss: 0.1121 - mae: 0.2554 - val_loss: 0.1388 - val_mae: 0.2
Epoch 4/5
5878/5878 - 49s - loss: 0.1086 - mae: 0.2511 - val_loss: 0.1355 - val_mae: 0.2
Epoch 5/5
5878/5878 - 51s - loss: 0.1060 - mae: 0.2479 - val_loss: 0.1375 - val_mae: 0.2
```



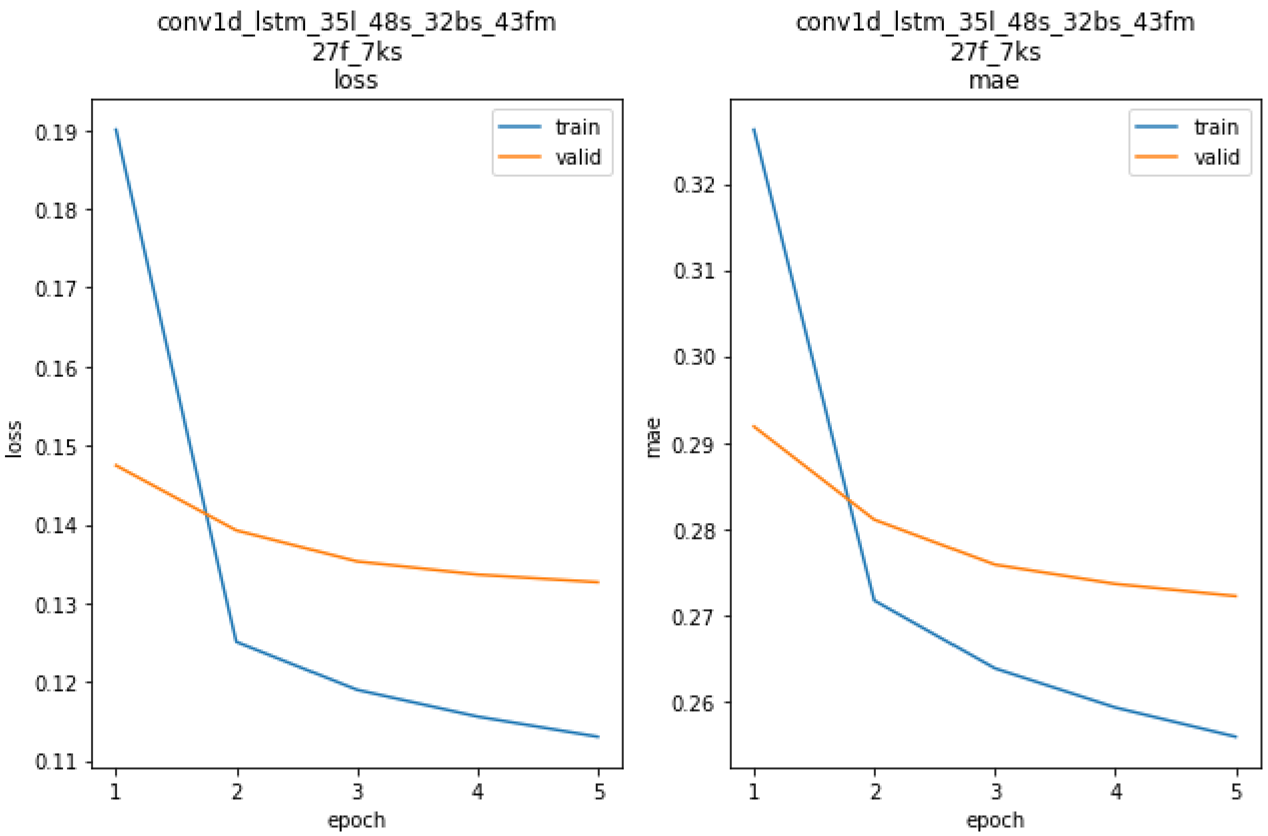



```
conv1d_lstm_72l_48s_32bs_11fm_62f_4ks train min loss: 0.105991  mae: 0.247929
conv1d_lstm_72l_48s_32bs_11fm_62f_4ks valid min loss: 0.135530  mae: 0.276743

conv1d_lstm_72l_48s_32bs_11fm_62f_4ks
Iteration No: 7 ended. Evaluation done at random point.
Time taken: 378.6212
Function value obtained: 0.1355
Current minimum: 0.1304
Iteration No: 8 started. Evaluating function at random point.
lags 35
feat_maps 43
filters 27
kern_size 7
Epoch 1/5
5879/5879 [==============================] - 54s 9ms/step - loss: 1.1164 - mae
```



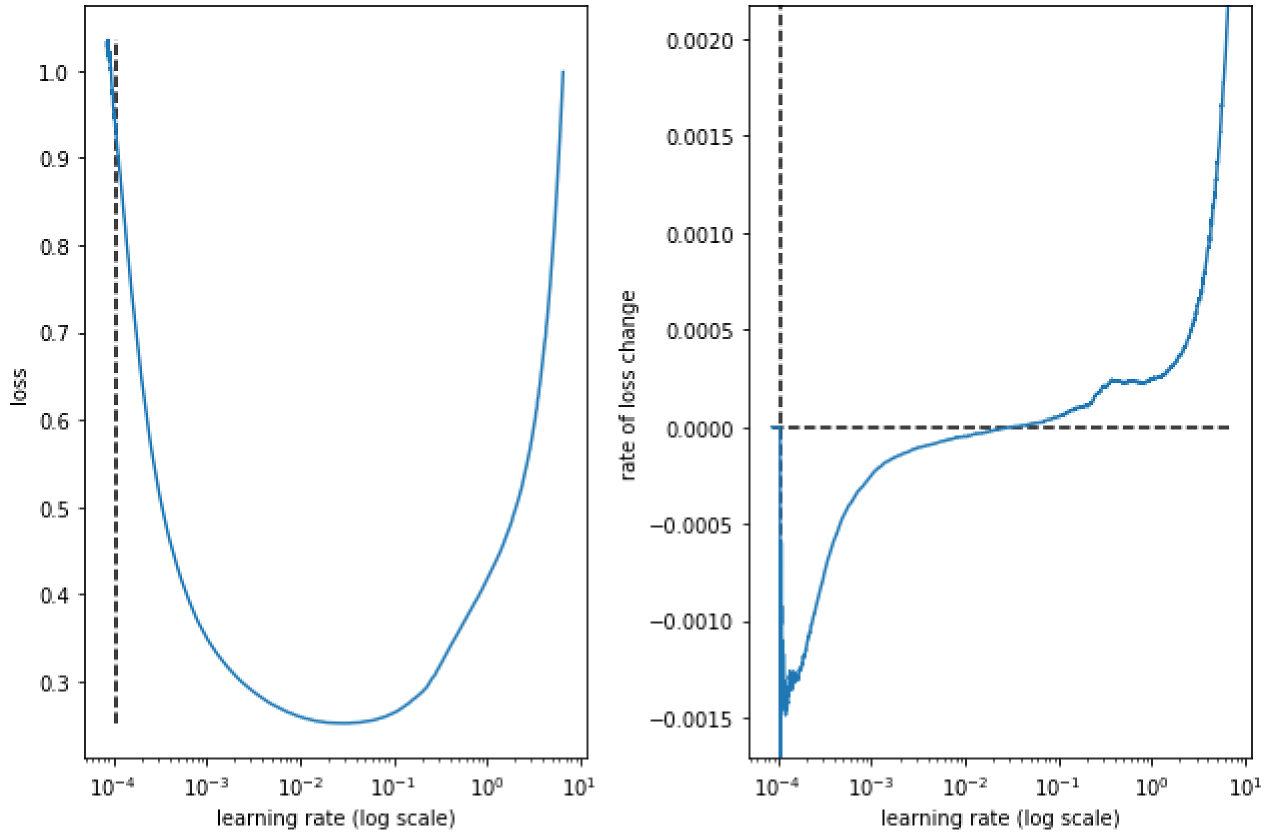

```
best lr: 0.0001058986

Model: "conv1d_lstm_35l_48s_32bs_43fm_27f_7ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_7 (Conv1D)           (None, 29, 27)            1917
```

```
 max_pooling1d_7 (MaxPooling  (None, 14, 27)           0
 1D)

 lstm_7 (LSTM)               (None, 43)                12212

 dense_14 (Dense)            (None, 43)                1892

 dense_15 (Dense)            (None, 48)                2112

 reshape_7 (Reshape)         (None, 48, 1)             0

=================================================================
Total params: 18,133
Trainable params: 18,133
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5879/5879 - 51s - loss: 0.1900 - mae: 0.3263 - val_loss: 0.1475 - val_mae: 0.2
Epoch 2/5
5879/5879 - 50s - loss: 0.1251 - mae: 0.2717 - val_loss: 0.1392 - val_mae: 0.2
Epoch 3/5
5879/5879 - 48s - loss: 0.1190 - mae: 0.2638 - val_loss: 0.1353 - val_mae: 0.2
Epoch 4/5
5879/5879 - 47s - loss: 0.1156 - mae: 0.2593 - val_loss: 0.1336 - val_mae: 0.2
Epoch 5/5
5879/5879 - 47s - loss: 0.1130 - mae: 0.2559 - val_loss: 0.1326 - val_mae: 0.2
```



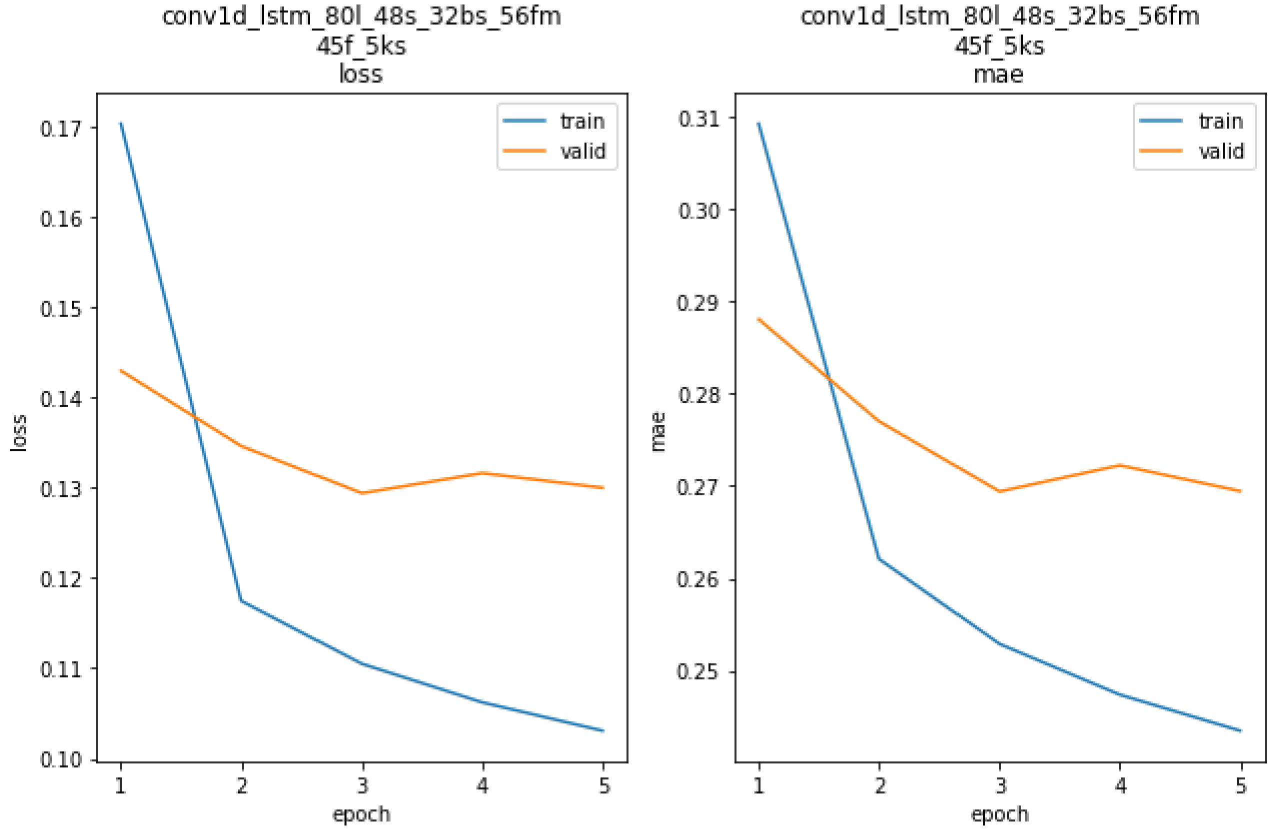

```
conv1d_lstm_35l_48s_32bs_43fm_27f_7ks train min loss: 0.113030  mae: 0.255896
conv1d_lstm_35l_48s_32bs_43fm_27f_7ks valid min loss: 0.132648  mae: 0.272207

conv1d_lstm_35l_48s_32bs_43fm_27f_7ks
Iteration No: 8 ended. Evaluation done at random point.
Time taken: 397.8110
Function value obtained: 0.1326
Current minimum: 0.1304
Iteration No: 9 started. Evaluating function at random point.
```

```
lags 80
feat_maps 56
filters 45
kern_size 5
Epoch 1/5
5878/5878 [==============================] - 58s 9ms/step - loss: 1.0112 - mae
```

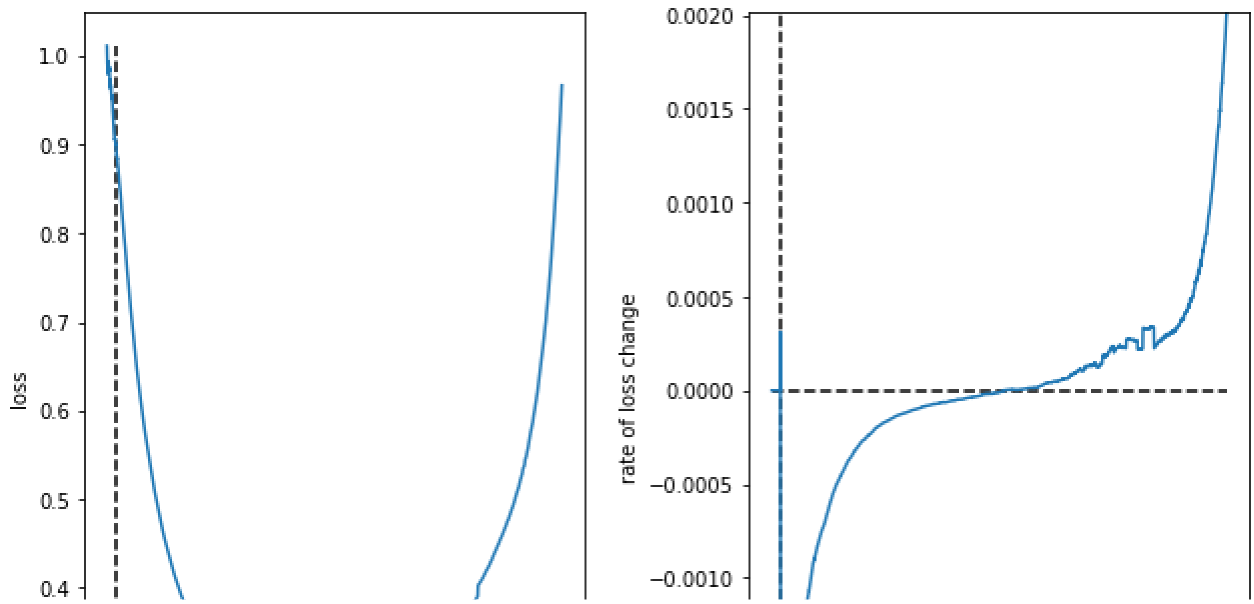


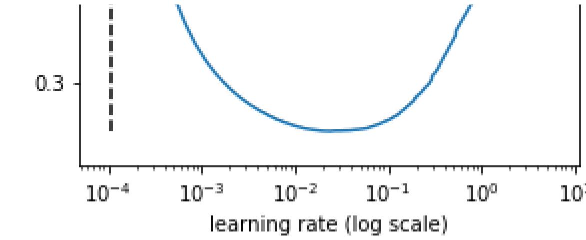

```
best lr: 0.00010561274

Model: "conv1d_lstm_80l_48s_32bs_56fm_45f_5ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_8 (Conv1D)           (None, 76, 45)            2295

 max_pooling1d_8 (MaxPooling  (None, 38, 45)           0
 1D)

 lstm_8 (LSTM)               (None, 56)                22848

 dense_16 (Dense)            (None, 56)                3192

 dense_17 (Dense)            (None, 48)                2736

 reshape_8 (Reshape)         (None, 48, 1)             0

=================================================================
Total params: 31,071
Trainable params: 31,071
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5878/5878 - 54s - loss: 0.1703 - mae: 0.3093 - val_loss: 0.1429 - val_mae: 0.2
Epoch 2/5
5878/5878 - 52s - loss: 0.1175 - mae: 0.2621 - val_loss: 0.1346 - val_mae: 0.2
Epoch 3/5
5878/5878 - 50s - loss: 0.1105 - mae: 0.2529 - val_loss: 0.1294 - val_mae: 0.2
```

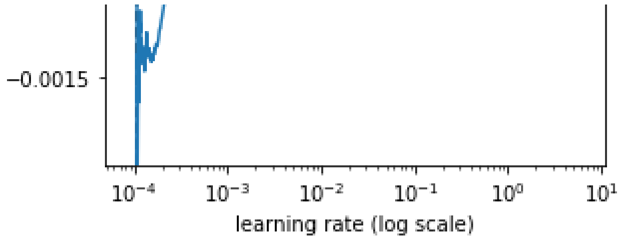
```
Epoch 4/5
5878/5878 - 50s - loss: 0.1062 - mae: 0.2474 - val_loss: 0.1316 - val_mae: 0.2
Epoch 5/5
5878/5878 - 51s - loss: 0.1031 - mae: 0.2435 - val_loss: 0.1300 - val_mae: 0.2
```



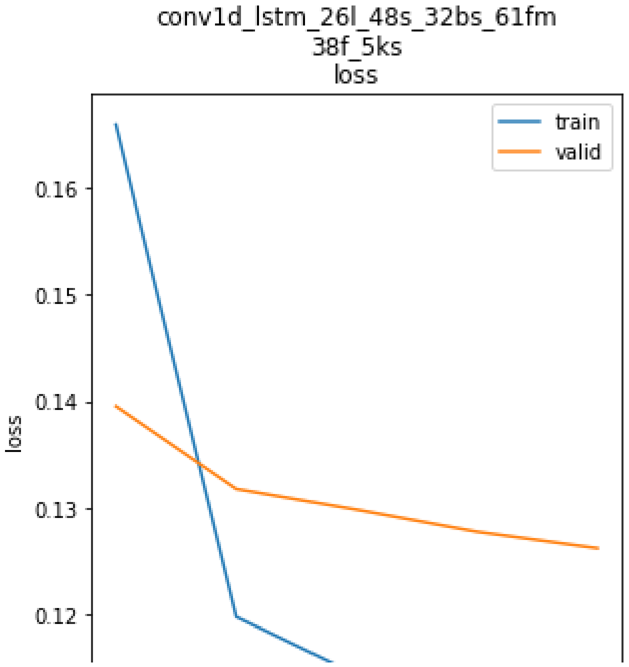

```
conv1d_lstm_80l_48s_32bs_56fm_45f_5ks train min loss: 0.103084  mae: 0.243499
conv1d_lstm_80l_48s_32bs_56fm_45f_5ks valid min loss: 0.129383  mae: 0.269415

conv1d_lstm_80l_48s_32bs_56fm_45f_5ks
Iteration No: 9 ended. Evaluation done at random point.
Time taken: 438.5019
Function value obtained: 0.1294
Current minimum: 0.1294
Iteration No: 10 started. Evaluating function at random point.
lags 26
feat_maps 61
filters 38
kern_size 5
Epoch 1/5
5880/5880 [==============================] - 54s 9ms/step - loss: 0.9802 - mae
```

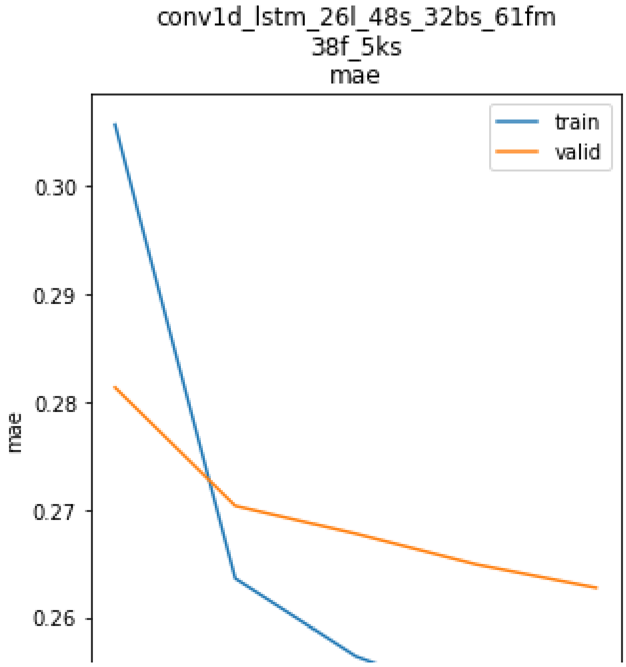


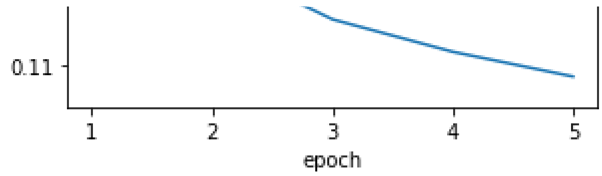


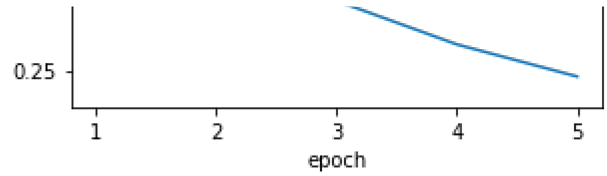



```
best lr: 0.00010735912

Model: "conv1d_lstm_26l_48s_32bs_61fm_38f_5ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_9 (Conv1D)           (None, 22, 38)            1938

 max_pooling1d_9 (MaxPooling  (None, 11, 38)           0
 1D)

 lstm_9 (LSTM)               (None, 61)                24400

 dense_18 (Dense)            (None, 61)                3782

 dense_19 (Dense)            (None, 48)                2976

 reshape_9 (Reshape)         (None, 48, 1)             0

=================================================================
Total params: 33,096
Trainable params: 33,096
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5880/5880 - 51s - loss: 0.1659 - mae: 0.3057 - val_loss: 0.1395 - val_mae: 0.2
Epoch 2/5
5880/5880 - 49s - loss: 0.1198 - mae: 0.2636 - val_loss: 0.1318 - val_mae: 0.2
Epoch 3/5
5880/5880 - 47s - loss: 0.1144 - mae: 0.2564 - val_loss: 0.1298 - val_mae: 0.2
Epoch 4/5
5880/5880 - 47s - loss: 0.1113 - mae: 0.2524 - val_loss: 0.1277 - val_mae: 0.2
Epoch 5/5
5880/5880 - 48s - loss: 0.1090 - mae: 0.2494 - val_loss: 0.1262 - val_mae: 0.2
```

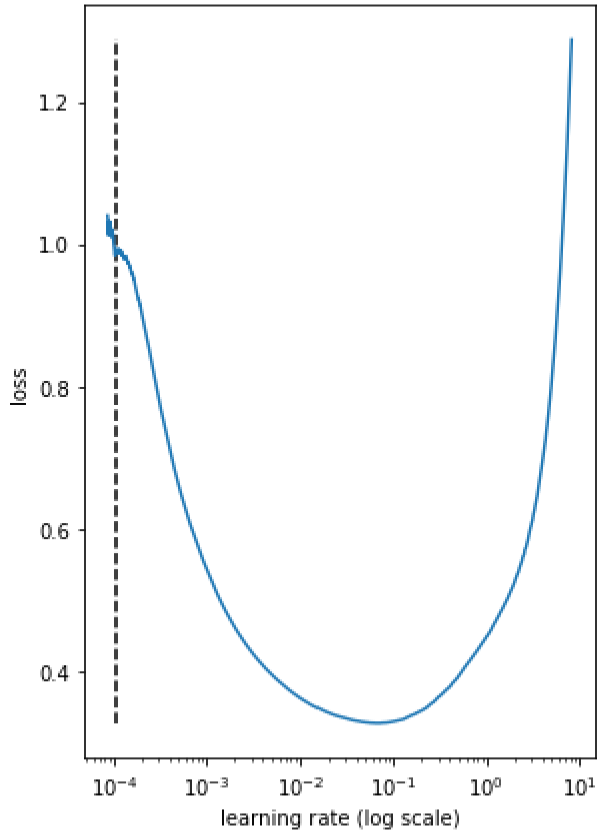


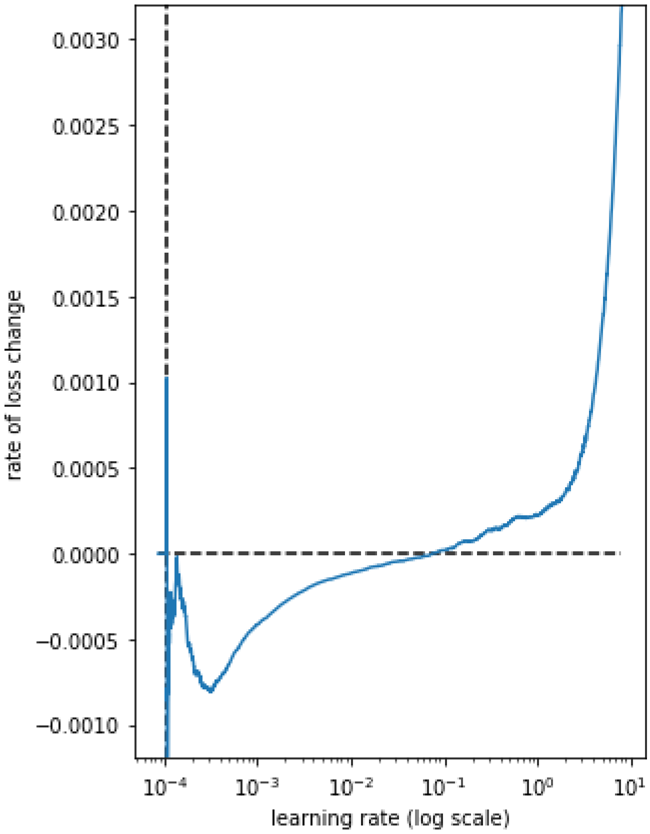







```
conv1d_lstm_26l_48s_32bs_61fm_38f_5ks train min loss: 0.109002  mae: 0.249419
conv1d_lstm_26l_48s_32bs_61fm_38f_5ks valid min loss: 0.126199  mae: 0.262742

conv1d_lstm_26l_48s_32bs_61fm_38f_5ks
Iteration No: 10 ended. Evaluation done at random point.
Time taken: 400.1731
Function value obtained: 0.1262
Current minimum: 0.1262
Iteration No: 11 started. Evaluating function at random point.
lags 26
feat_maps 21
filters 18
kern_size 6
Epoch 1/5
5880/5880 [==============================] - 57s 9ms/step - loss: 1.3115 - mae
```

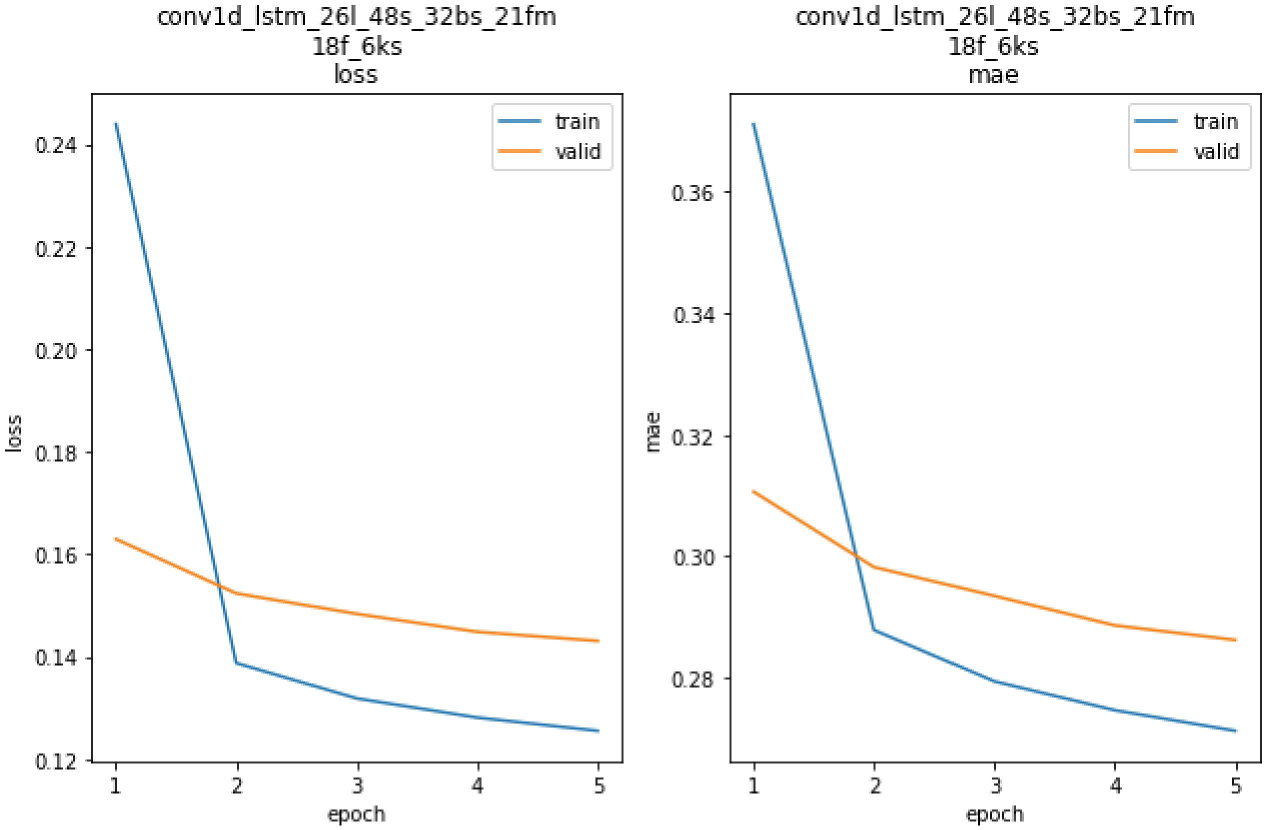




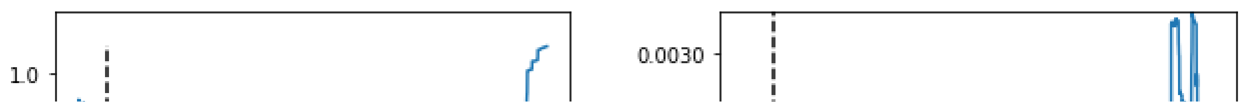

```
best lr: 0.00010735912

Model: "conv1d_lstm_26l_48s_32bs_21fm_18f_6ks"
```

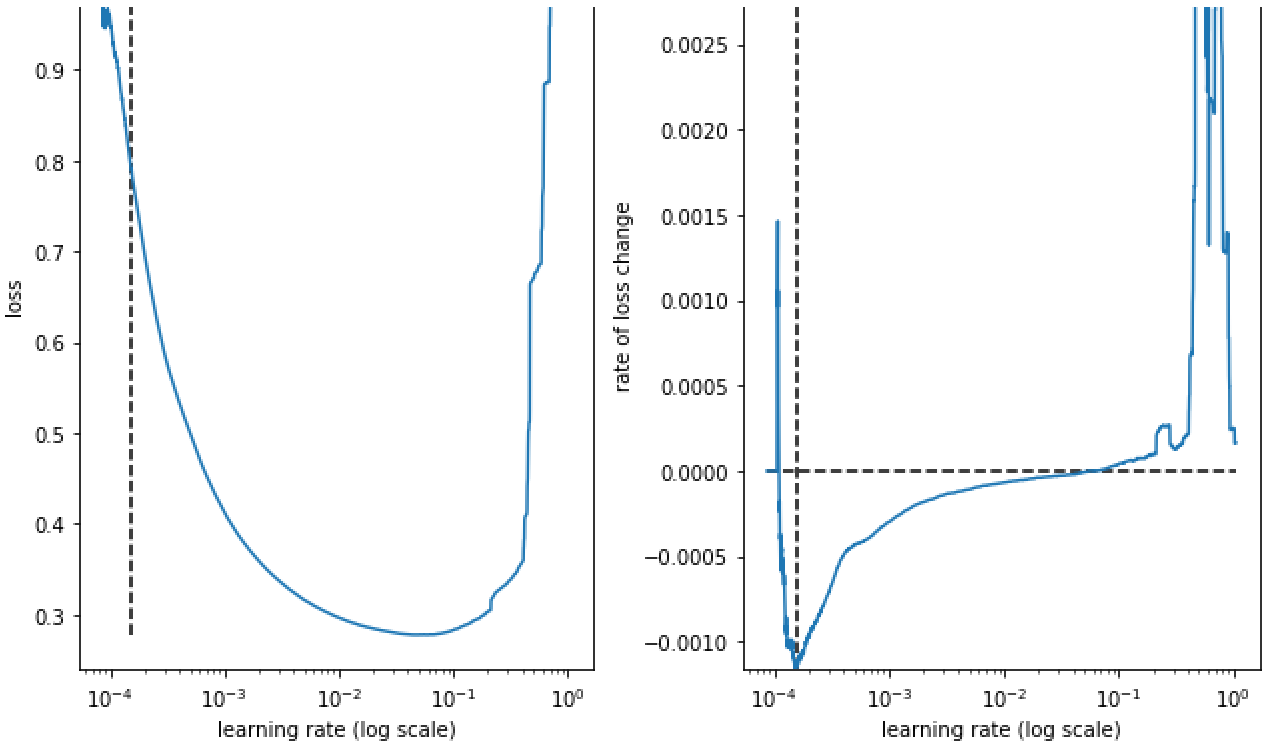
Layer (type)	Output Shape	Param #
conv1d_10 (Conv1D)	(None, 21, 18)	1098
max_pooling1d_10 (MaxPooling1D)	(None, 10, 18)	0
lstm_10 (LSTM)	(None, 21)	3360
dense_20 (Dense)	(None, 21)	462
dense_21 (Dense)	(None, 48)	1056

```
 reshape_10 (Reshape)        (None, 48, 1)            0

=================================================================
Total params: 5,976
Trainable params: 5,976
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5880/5880 - 49s - loss: 0.2439 - mae: 0.3712 - val_loss: 0.1630 - val_mae: 0.3
Epoch 2/5
5880/5880 - 48s - loss: 0.1388 - mae: 0.2879 - val_loss: 0.1524 - val_mae: 0.2
Epoch 3/5
5880/5880 - 49s - loss: 0.1319 - mae: 0.2794 - val_loss: 0.1484 - val_mae: 0.2
Epoch 4/5
5880/5880 - 47s - loss: 0.1281 - mae: 0.2746 - val_loss: 0.1449 - val_mae: 0.2
Epoch 5/5
5880/5880 - 46s - loss: 0.1255 - mae: 0.2712 - val_loss: 0.1431 - val_mae: 0.2
```

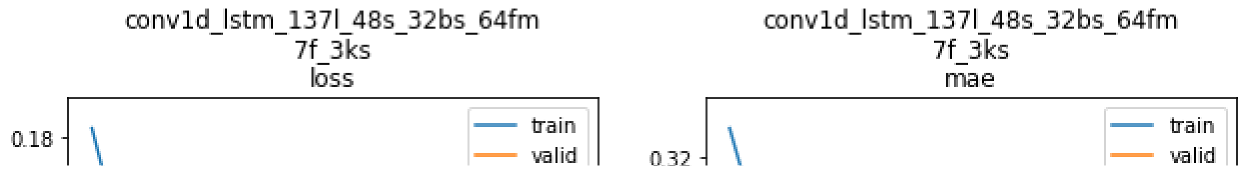


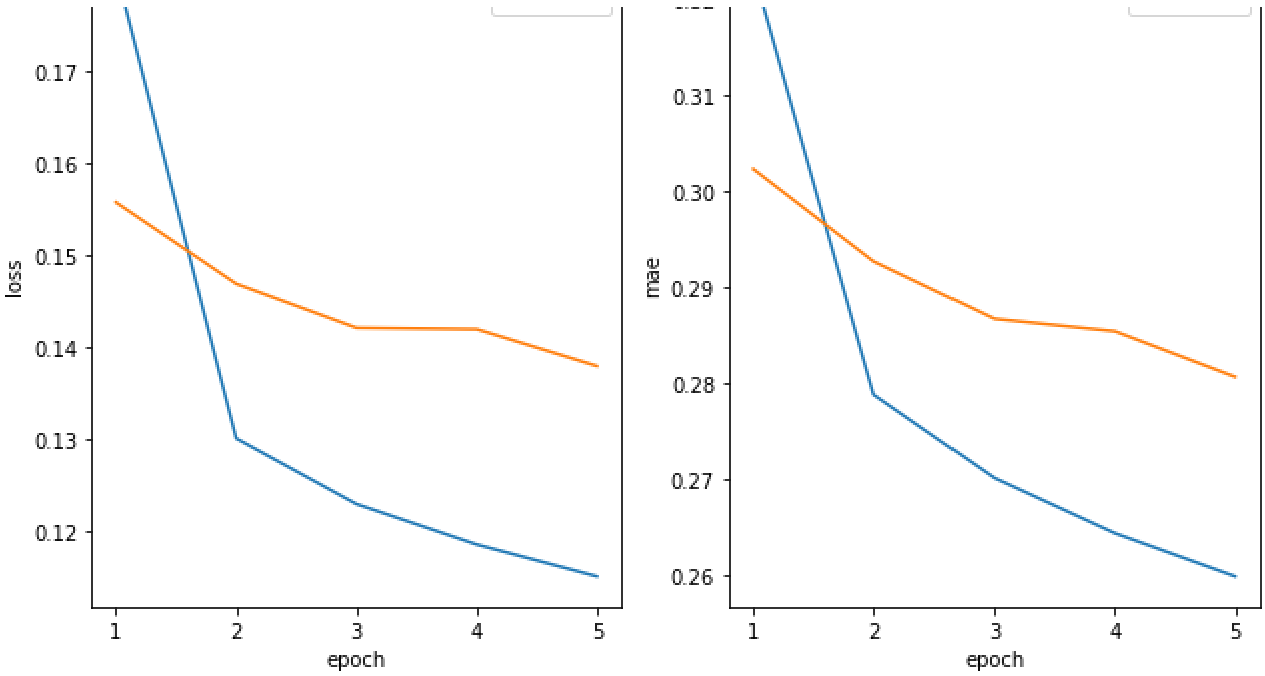

```
conv1d_lstm_26l_48s_32bs_21fm_18f_6ks train min loss: 0.125546  mae: 0.271239
conv1d_lstm_26l_48s_32bs_21fm_18f_6ks valid min loss: 0.143099  mae: 0.286212

conv1d_lstm_26l_48s_32bs_21fm_18f_6ks
Iteration No: 11 ended. Evaluation done at random point.
Time taken: 428.1412
Function value obtained: 0.1431
Current minimum: 0.1262
Iteration No: 12 started. Evaluating function at random point.
lags 137
feat_maps 64
filters 7
kern_size 3
Epoch 1/5
5876/5876 [==============================] - 54s 9ms/step - loss: 1.1634 - mae
```



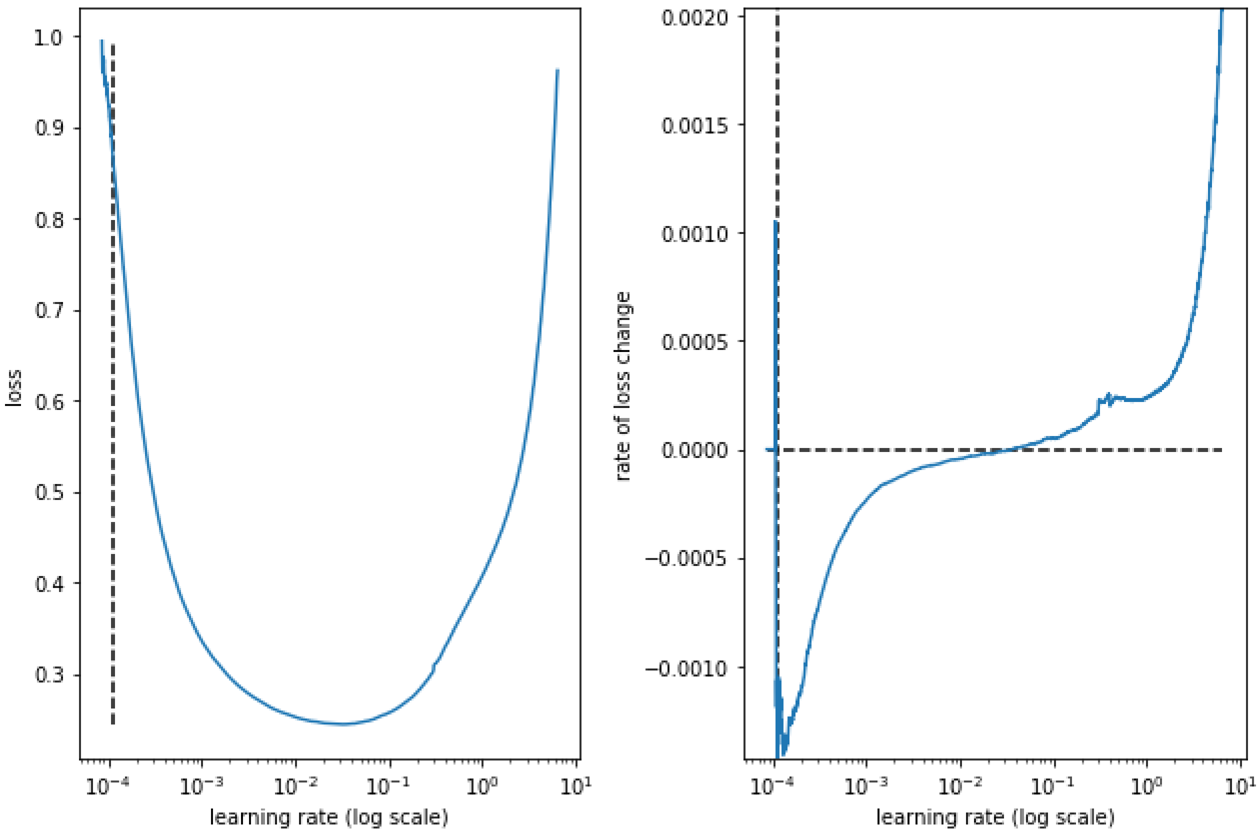



```
best lr: 0.0001543938

Model: "conv1d_lstm_137l_48s_32bs_64fm_7f_3ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_11 (Conv1D)          (None, 135, 7)            217

 max_pooling1d_11 (MaxPoolin  (None, 67, 7)            0
 g1D)

 lstm_11 (LSTM)              (None, 64)                18432

 dense_22 (Dense)            (None, 64)                4160

 dense_23 (Dense)            (None, 48)                3120

 reshape_11 (Reshape)        (None, 48, 1)             0

=================================================================
Total params: 25,929
Trainable params: 25,929
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5876/5876 - 56s - loss: 0.1810 - mae: 0.3230 - val_loss: 0.1558 - val_mae: 0.3
Epoch 2/5
5876/5876 - 54s - loss: 0.1301 - mae: 0.2788 - val_loss: 0.1469 - val_mae: 0.2
Epoch 3/5
5876/5876 - 54s - loss: 0.1230 - mae: 0.2701 - val_loss: 0.1422 - val_mae: 0.2
Epoch 4/5
5876/5876 - 55s - loss: 0.1186 - mae: 0.2643 - val_loss: 0.1420 - val_mae: 0.2
Epoch 5/5
5876/5876 - 54s - loss: 0.1152 - mae: 0.2598 - val_loss: 0.1380 - val_mae: 0.2
```



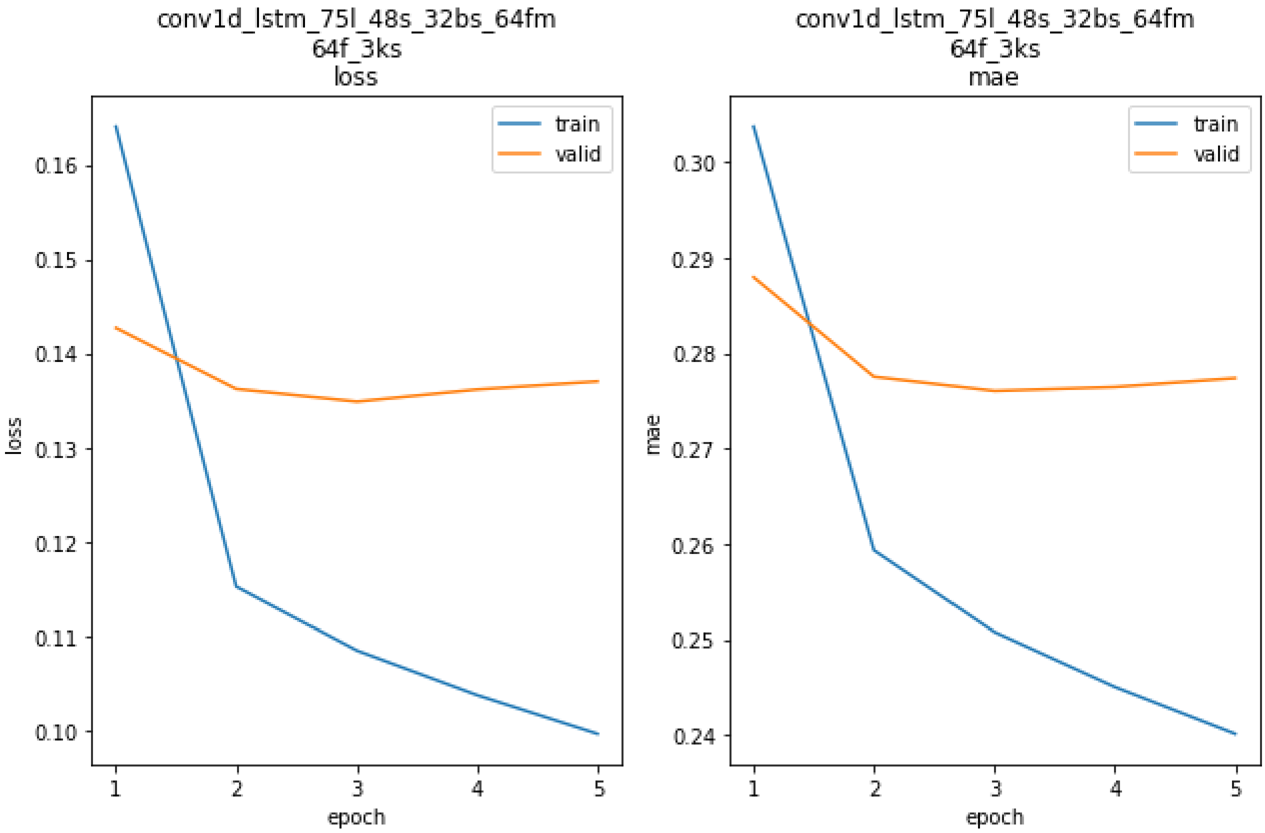



```
conv1d_lstm_137l_48s_32bs_64fm_7f_3ks train min loss: 0.115175  mae: 0.259849
conv1d_lstm_137l_48s_32bs_64fm_7f_3ks valid min loss: 0.138006  mae: 0.280619

conv1d_lstm_137l_48s_32bs_64fm_7f_3ks
Iteration No: 12 ended. Evaluation done at random point.
Time taken: 413.2274
Function value obtained: 0.1380
Current minimum: 0.1262
Iteration No: 13 started. Searching for the next optimal point.
lags 75
feat_maps 64
filters 64
kern_size 3
Epoch 1/5
5878/5878 [==============================] - 59s 10ms/step - loss: 0.9825 - ma
```



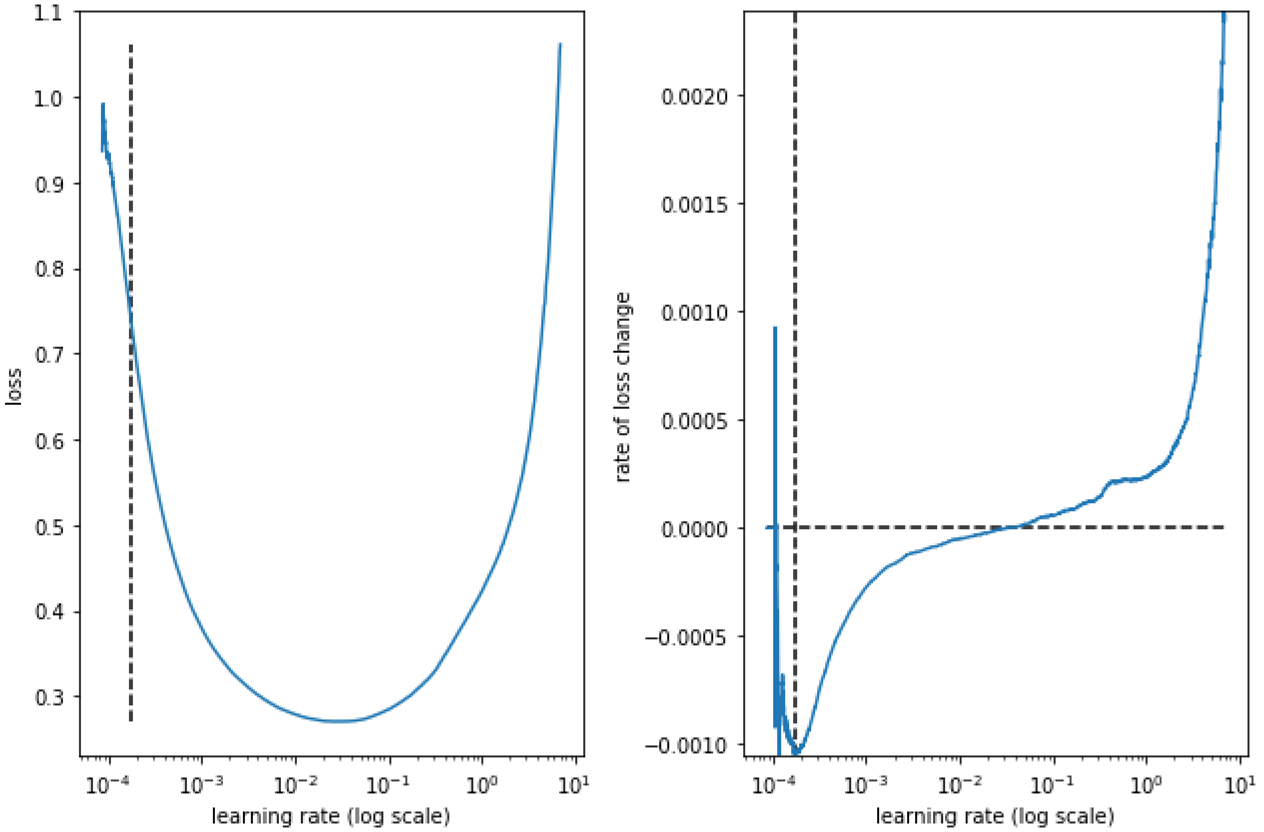

```
best lr: 0.000111584224
```

```
Model: "conv1d_lstm_75l_48s_32bs_64fm_64f_3ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_12 (Conv1D)          (None, 73, 64)            1984

 max_pooling1d_12 (MaxPoolin  (None, 36, 64)           0
 g1D)

 lstm_12 (LSTM)              (None, 64)                33024

 dense_24 (Dense)            (None, 64)                4160

 dense_25 (Dense)            (None, 48)                3120

 reshape_12 (Reshape)        (None, 48, 1)             0

=================================================================
Total params: 42,288
Trainable params: 42,288
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5878/5878 - 52s - loss: 0.1640 - mae: 0.3037 - val_loss: 0.1427 - val_mae: 0.2
Epoch 2/5
5878/5878 - 49s - loss: 0.1152 - mae: 0.2594 - val_loss: 0.1362 - val_mae: 0.2
Epoch 3/5
5878/5878 - 49s - loss: 0.1085 - mae: 0.2508 - val_loss: 0.1349 - val_mae: 0.2
Epoch 4/5
5878/5878 - 48s - loss: 0.1037 - mae: 0.2451 - val_loss: 0.1362 - val_mae: 0.2
Epoch 5/5
5878/5878 - 48s - loss: 0.0996 - mae: 0.2402 - val_loss: 0.1370 - val_mae: 0.2
```



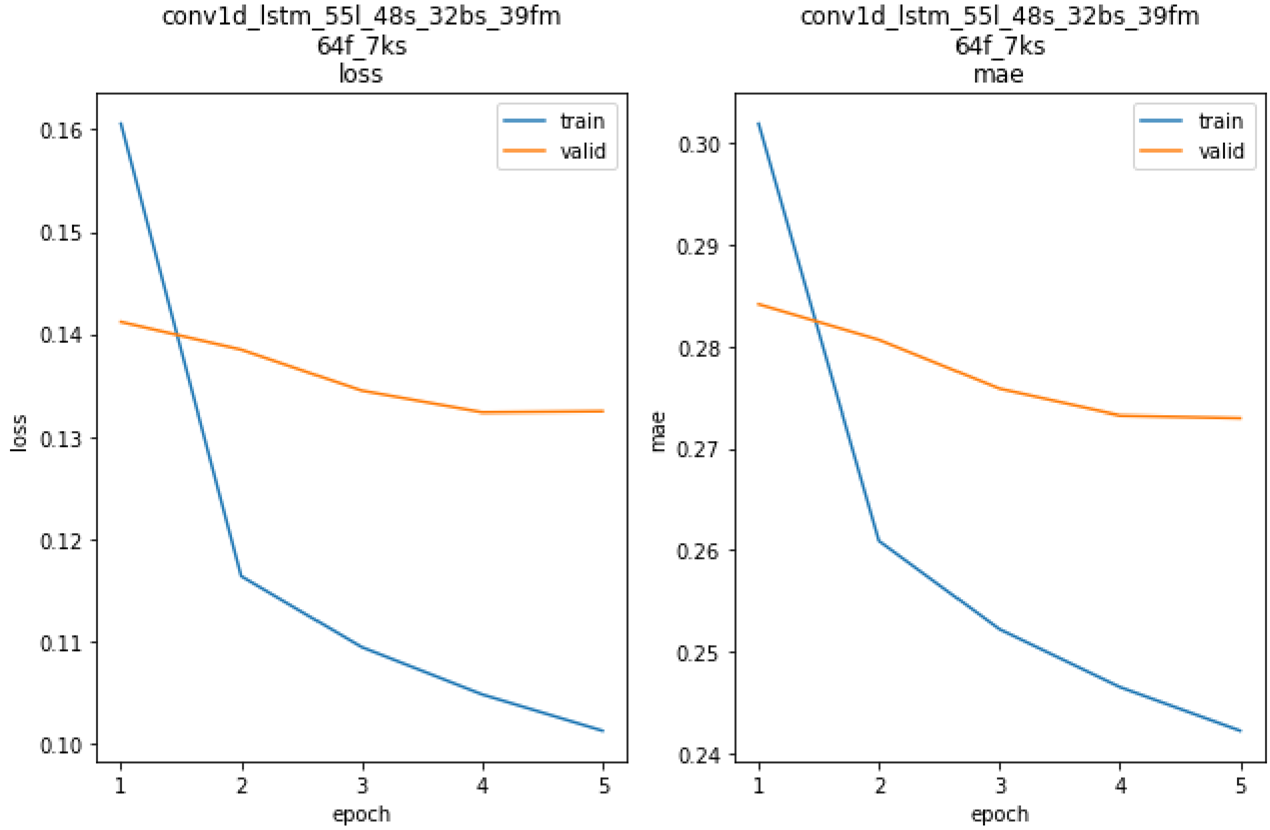

```
conv1d_lstm_75l_48s_32bs_64fm_64f_3ks train min loss: 0.099634  mae: 0.240154
conv1d_lstm_75l_48s_32bs_64fm_64f_3ks valid min loss: 0.134875  mae: 0.276042

conv1d_lstm_75l_48s_32bs_64fm_64f_3ks
```

```
conv1d_lstm_75l_48s_32bs_64fm_64f_5ks
Iteration No: 13 ended. Search finished for the next optimal point.
Time taken: 407.6773
Function value obtained: 0.1349
Current minimum: 0.1262
Iteration No: 14 started. Searching for the next optimal point.
lags 55
feat_maps 39
filters 64
kern_size 7
Epoch 1/5
5879/5879 [==============================] - 57s 9ms/step - loss: 1.0820 - mae
```

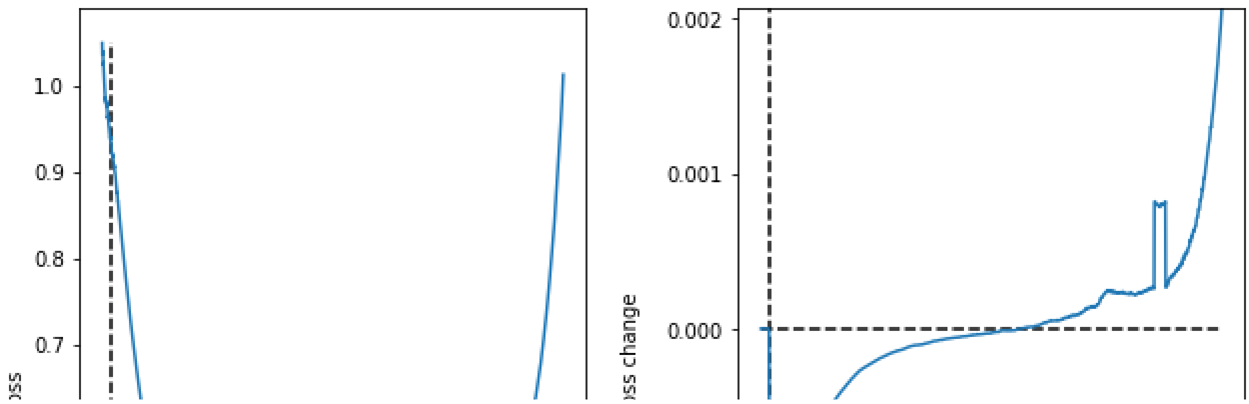


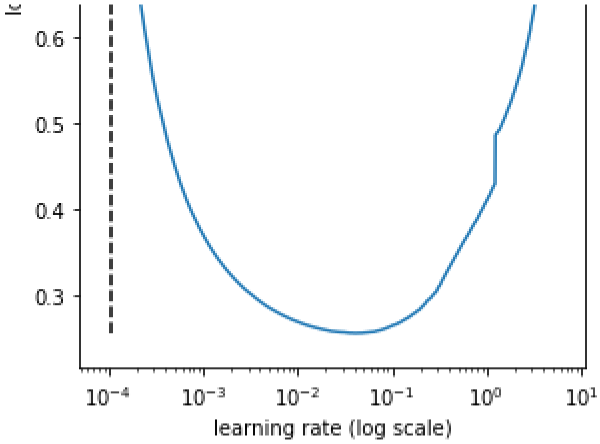

```
best lr: 0.00017611736

Model: "conv1d_lstm_55l_48s_32bs_39fm_64f_7ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_13 (Conv1D)          (None, 49, 64)            4544

 max_pooling1d_13 (MaxPoolin  (None, 24, 64)           0
 g1D)

 lstm_13 (LSTM)              (None, 39)                16224

 dense_26 (Dense)            (None, 39)                1560

 dense_27 (Dense)            (None, 48)                1920

 reshape_13 (Reshape)        (None, 48, 1)             0

=================================================================
Total params: 24,248
Trainable params: 24,248
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
```

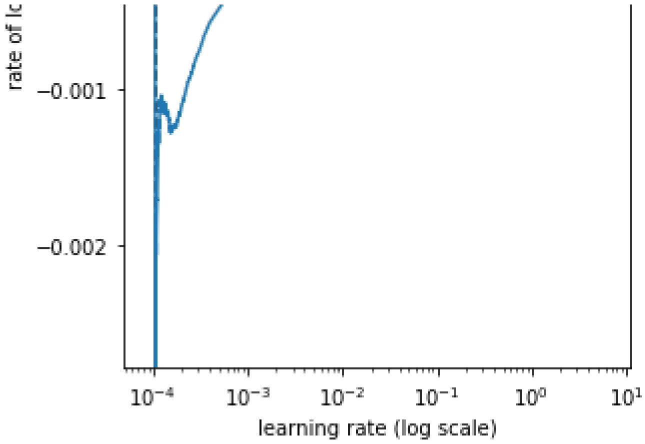
```
Epoch 1/5
5879/5879 - 53s - loss: 0.1606 - mae: 0.3019 - val_loss: 0.1412 - val_mae: 0.2
Epoch 2/5
5879/5879 - 47s - loss: 0.1164 - mae: 0.2609 - val_loss: 0.1385 - val_mae: 0.2
Epoch 3/5
5879/5879 - 49s - loss: 0.1094 - mae: 0.2522 - val_loss: 0.1345 - val_mae: 0.2
Epoch 4/5
5879/5879 - 47s - loss: 0.1048 - mae: 0.2465 - val_loss: 0.1323 - val_mae: 0.2
Epoch 5/5
5879/5879 - 50s - loss: 0.1013 - mae: 0.2422 - val_loss: 0.1325 - val_mae: 0.2
```



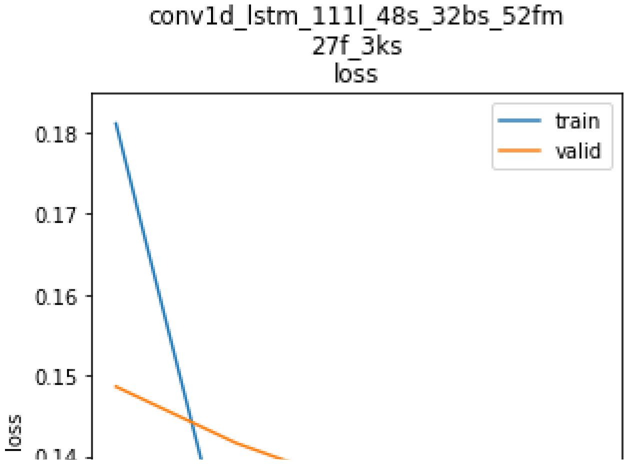

```
conv1d_lstm_55l_48s_32bs_39fm_64f_7ks train min loss: 0.101267  mae: 0.242201
conv1d_lstm_55l_48s_32bs_39fm_64f_7ks valid min loss: 0.132346  mae: 0.273222

conv1d_lstm_55l_48s_32bs_39fm_64f_7ks
Iteration No: 14 ended. Search finished for the next optimal point.
Time taken: 405.7796
Function value obtained: 0.1323
Current minimum: 0.1262
Iteration No: 15 started. Searching for the next optimal point.
lags 111
feat_maps 52
filters 27
kern_size 3
Epoch 1/5
5877/5877 [==============================] - 61s 10ms/step - loss: 1.0243 - ma
```

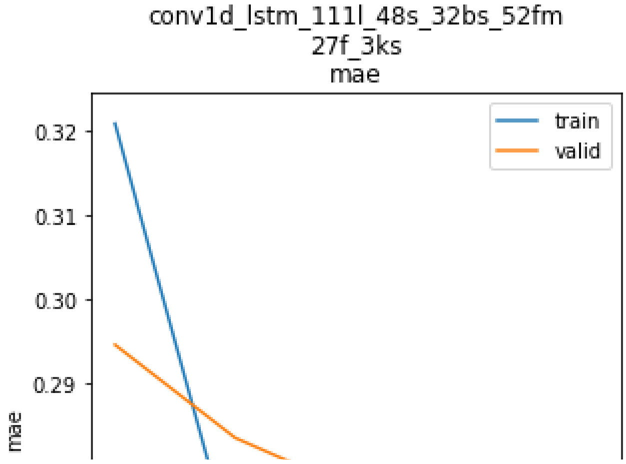


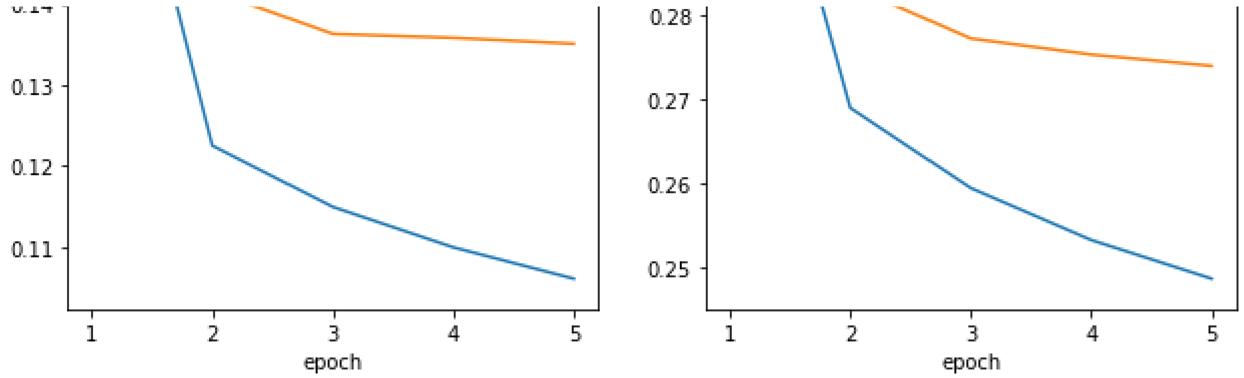




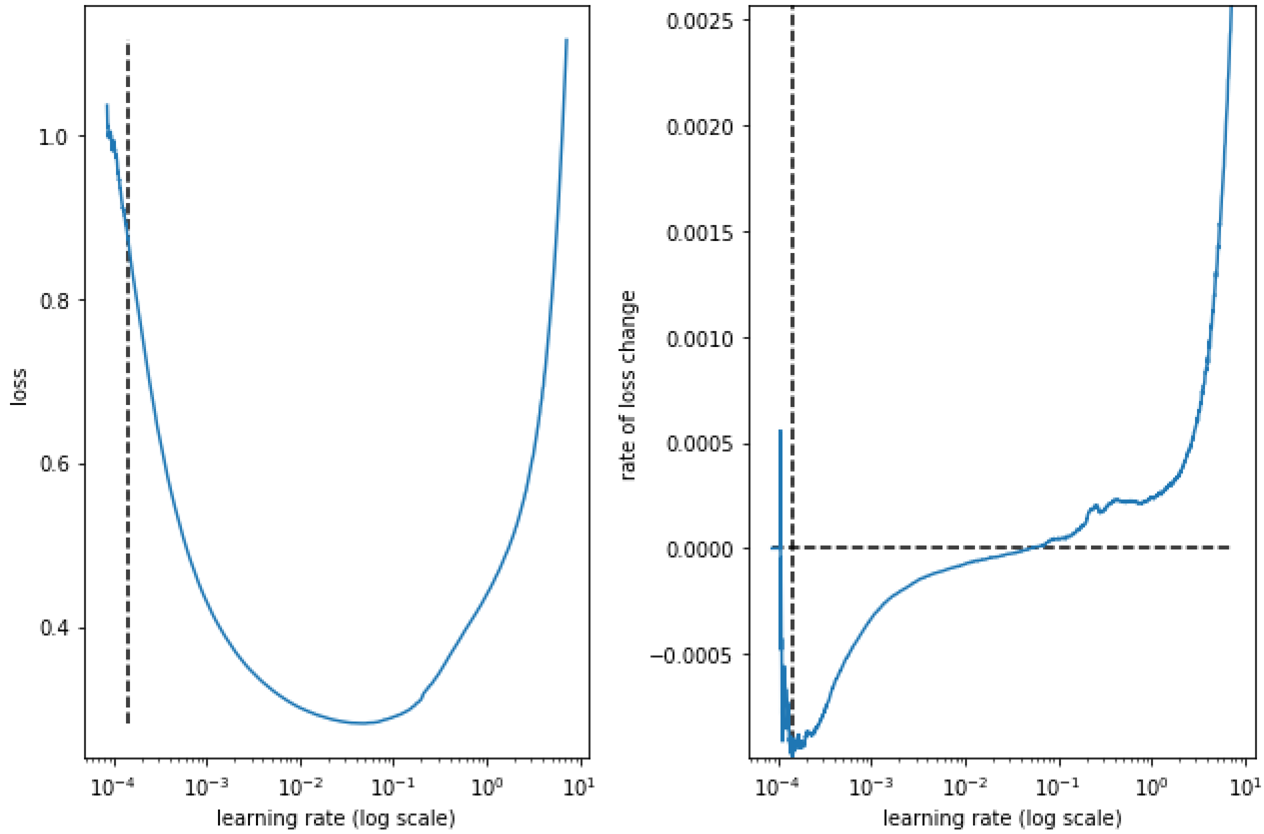

```
best lr: 0.0001059087

Model: "conv1d_lstm_111l_48s_32bs_52fm_27f_3ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_14 (Conv1D)          (None, 109, 27)           837

 max_pooling1d_14 (MaxPoolin  (None, 54, 27)           0
 g1D)

 lstm_14 (LSTM)              (None, 52)                16640

 dense_28 (Dense)            (None, 52)                2756

 dense_29 (Dense)            (None, 48)                2544

 reshape_14 (Reshape)        (None, 48, 1)             0

=================================================================
Total params: 22,777
Trainable params: 22,777
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5877/5877 - 55s - loss: 0.1811 - mae: 0.3208 - val_loss: 0.1486 - val_mae: 0.2
Epoch 2/5
5877/5877 - 50s - loss: 0.1225 - mae: 0.2689 - val_loss: 0.1416 - val_mae: 0.2
Epoch 3/5
5877/5877 - 53s - loss: 0.1149 - mae: 0.2594 - val_loss: 0.1363 - val_mae: 0.2
Epoch 4/5
5877/5877 - 52s - loss: 0.1099 - mae: 0.2532 - val_loss: 0.1358 - val_mae: 0.2
Epoch 5/5
5877/5877 - 54s - loss: 0.1061 - mae: 0.2487 - val_loss: 0.1351 - val_mae: 0.2
```





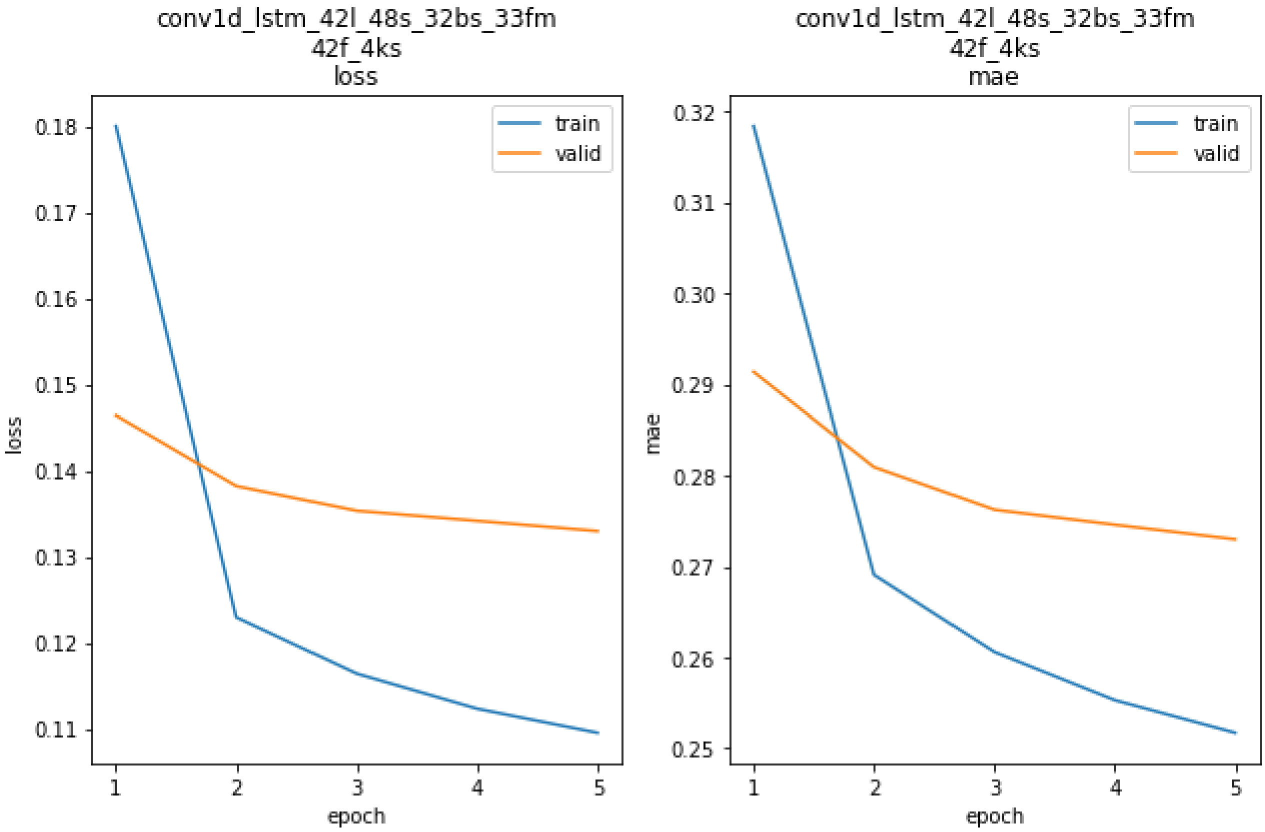



```
conv1d_lstm_111l_48s_32bs_52fm_27f_3ks train min loss: 0.106059 mae: 0.248661
conv1d_lstm_111l_48s_32bs_52fm_27f_3ks valid min loss: 0.135100 mae: 0.273929

conv1d_lstm_111l_48s_32bs_52fm_27f_3ks
Iteration No: 15 ended. Search finished for the next optimal point.
Time taken: 387.4706
Function value obtained: 0.1351
Current minimum: 0.1262
Iteration No: 16 started. Searching for the next optimal point.
lags 42
feat_maps 33
filters 42
kern_size 4
Epoch 1/5
5879/5879 [==============================] - 57s 9ms/step - loss: 1.1298 - mae
```



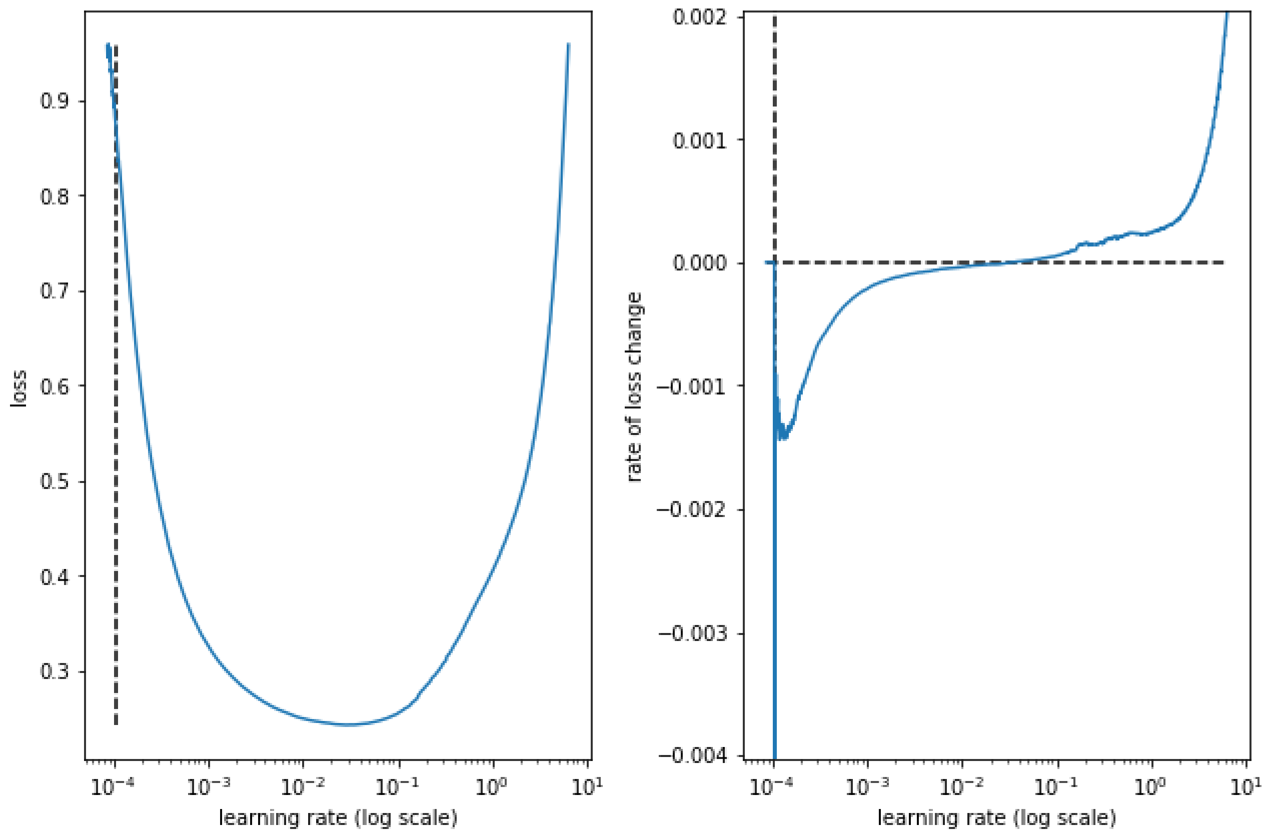

```
best lr: 0.00014290558

Model: "conv1d_lstm_42l_48s_32bs_33fm_42f_4ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_15 (Conv1D)          (None, 39, 42)            1722

 max_pooling1d_15 (MaxPoolin  (None, 19, 42)           0
 g1D)
```

```
 lstm_15 (LSTM)              (None, 33)                10032

 dense_30 (Dense)            (None, 33)                1122

 dense_31 (Dense)            (None, 48)                1632

 reshape_15 (Reshape)        (None, 48, 1)             0

=================================================================
Total params: 14,508
Trainable params: 14,508
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5879/5879 - 51s - loss: 0.1800 - mae: 0.3184 - val_loss: 0.1464 - val_mae: 0.2
Epoch 2/5
5879/5879 - 48s - loss: 0.1229 - mae: 0.2691 - val_loss: 0.1382 - val_mae: 0.2
Epoch 3/5
5879/5879 - 45s - loss: 0.1164 - mae: 0.2606 - val_loss: 0.1353 - val_mae: 0.2
Epoch 4/5
5879/5879 - 46s - loss: 0.1123 - mae: 0.2553 - val_loss: 0.1342 - val_mae: 0.2
Epoch 5/5
5879/5879 - 46s - loss: 0.1095 - mae: 0.2517 - val_loss: 0.1330 - val_mae: 0.2
```



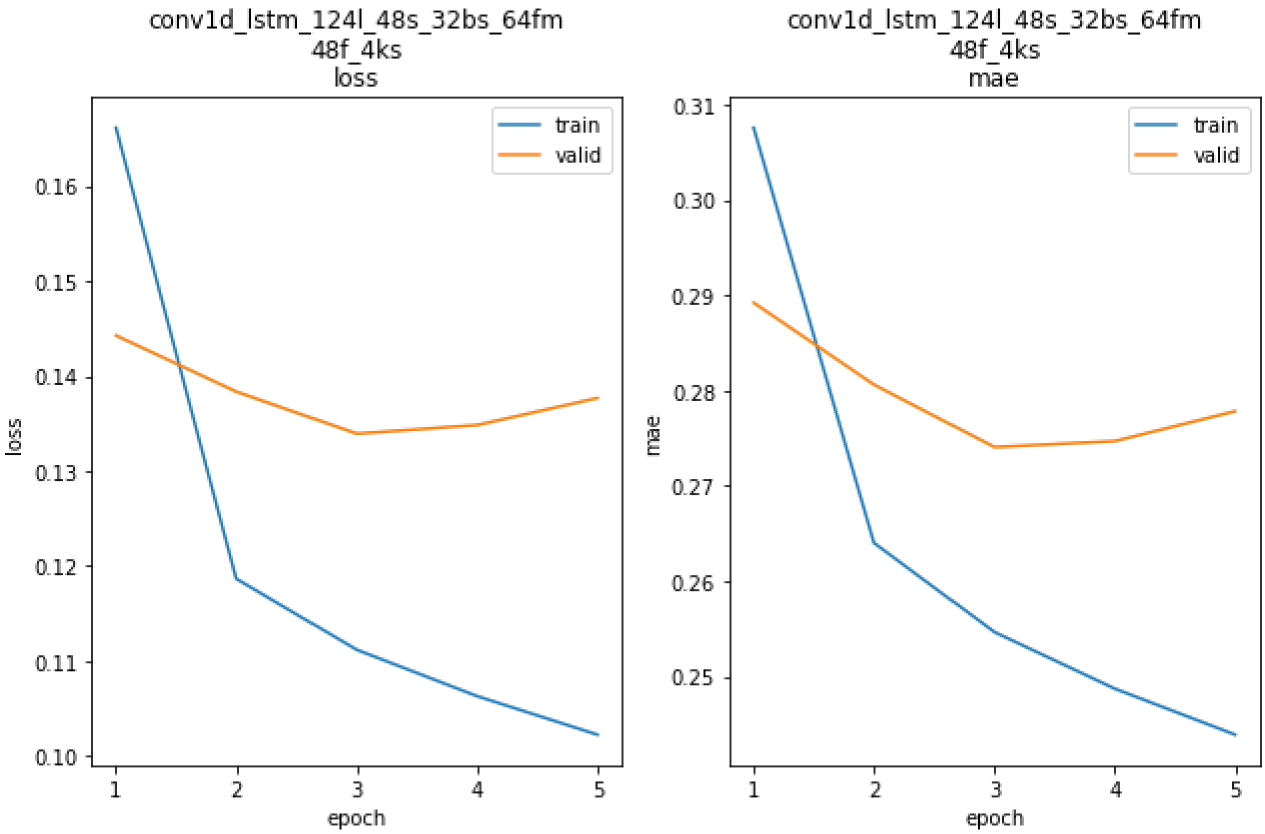

```
conv1d_lstm_42l_48s_32bs_33fm_42f_4ks train min loss: 0.109507  mae: 0.251726
conv1d_lstm_42l_48s_32bs_33fm_42f_4ks valid min loss: 0.132977  mae: 0.273003

conv1d_lstm_42l_48s_32bs_33fm_42f_4ks
Iteration No: 16 ended. Search finished for the next optimal point.
Time taken: 391.9264
Function value obtained: 0.1330
Current minimum: 0.1262
Iteration No: 17 started. Searching for the next optimal point.
lags 124
feat_maps 64
filters 48
```

```
kern_size 4
Epoch 1/5
5877/5877 [==============================] - 62s 10ms/step - loss: 0.9710 - ma
```

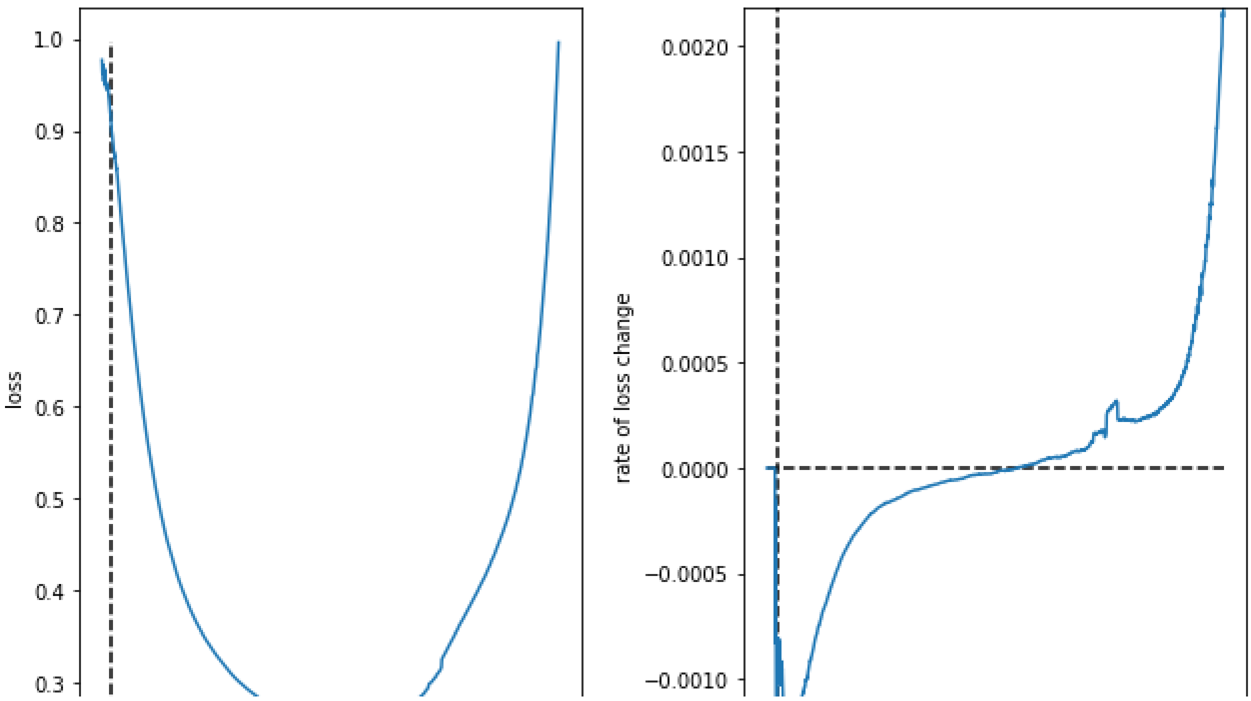


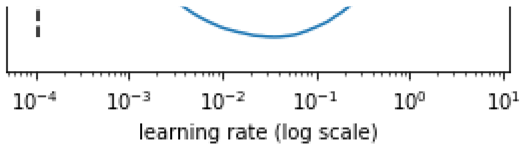

```
best lr: 0.0001053277

Model: "conv1d_lstm_124l_48s_32bs_64fm_48f_4ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_16 (Conv1D)          (None, 121, 48)           1968

 max_pooling1d_16 (MaxPoolin  (None, 60, 48)           0
 g1D)

 lstm_16 (LSTM)              (None, 64)                28928

 dense_32 (Dense)            (None, 64)                4160

 dense_33 (Dense)            (None, 48)                3120

 reshape_16 (Reshape)        (None, 48, 1)             0

=================================================================
Total params: 38,176
Trainable params: 38,176
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5877/5877 - 54s - loss: 0.1661 - mae: 0.3076 - val_loss: 0.1443 - val_mae: 0.2
Epoch 2/5
5877/5877 - 51s - loss: 0.1187 - mae: 0.2640 - val_loss: 0.1384 - val_mae: 0.2
Epoch 3/5
5877/5877 - 52s - loss: 0.1112 - mae: 0.2546 - val_loss: 0.1339 - val_mae: 0.2
Epoch 4/5
5877/5877 - 56s - loss: 0.1063 - mae: 0.2487 - val_loss: 0.1348 - val_mae: 0.2
Epoch 5/5
```

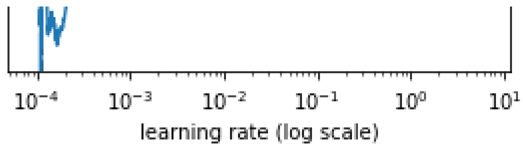
```
5877/5877 - 55s - loss: 0.1023 - mae: 0.2439 - val_loss: 0.1377 - val_mae: 0.2
```




```
conv1d_lstm_124l_48s_32bs_64fm_48f_4ks train min loss: 0.102255 mae: 0.243878
conv1d_lstm_124l_48s_32bs_64fm_48f_4ks valid min loss: 0.133939 mae: 0.274065

conv1d_lstm_124l_48s_32bs_64fm_48f_4ks
Iteration No: 17 ended. Search finished for the next optimal point.
Time taken: 472.0520
Function value obtained: 0.1339
Current minimum: 0.1262
Iteration No: 18 started. Searching for the next optimal point.
lags 29
feat_maps 64
filters 18
kern_size 6
Epoch 1/5
5880/5880 [==============================] - 60s 10ms/step - loss: 1.0121 - ma
```








```
best lr: 0.000109445115

Model: "conv1d_lstm_29l_48s_32bs_64fm_18f_6ks"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_17 (Conv1D)          (None, 24, 18)            1098

 max_pooling1d_17 (MaxPoolin  (None, 12, 18)           0
 g1D)

 lstm_17 (LSTM)              (None, 64)                21248

 dense_34 (Dense)            (None, 64)                4160

 dense_35 (Dense)            (None, 48)                3120

 reshape_17 (Reshape)        (None, 48, 1)             0

=================================================================
Total params: 29,626
Trainable params: 29,626
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
5880/5880 - 50s - loss: 0.1735 - mae: 0.3134 - val_loss: 0.1451 - val_mae: 0.2
Epoch 2/5
5880/5880 - 48s - loss: 0.1252 - mae: 0.2712 - val_loss: 0.1364 - val_mae: 0.2
Epoch 3/5
5880/5880 - 48s - loss: 0.1194 - mae: 0.2636 - val_loss: 0.1330 - val_mae: 0.2
Epoch 4/5
5880/5880 - 47s - loss: 0.1157 - mae: 0.2587 - val_loss: 0.1307 - val_mae: 0.2
Epoch 5/5
5880/5880 - 49s - loss: 0.1131 - mae: 0.2552 - val_loss: 0.1294 - val_mae: 0.2
```