main

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1 Machine Learning Project – Feed-Forward vs LSTM vs Transformers

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2 Weather forecasting

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import tensorflow as tf
from keras import models, layers, datasets
from keras.callbacks import LearningRateScheduler, EarlyStopping,␣
↪ReduceLROnPlateau, ModelCheckpoint

import os

import random
import pprint
```

[ ]:
```
zip_path = tf.keras.utils.get_file(
    origin='https://storage.googleapis.com/tensorflow/tf-keras-datasets/
↪jena_climate_2009_2016.csv.zip',
    fname='jena_climate_2009_2016.csv.zip',
    extract=True)
csv_path, _ = os.path.splitext(zip_path)
```

3 Load data

Hourly predictions

[ ]:
```
data = pd.read_csv(csv_path)
```

[ ]:
```
data.shape
```

[ ]: (420551, 15)

3.1 Preprocessing

[ ]:
```
data.head(5)
```

[ ]:
```
             Date Time  p (mbar)  T (degC)  Tpot (K)  Tdew (degC)  rh (%)  \
0  01.01.2009 00:10:00    996.52     -8.02    265.40        -8.90    93.3
1  01.01.2009 00:20:00    996.57     -8.41    265.01        -9.28    93.4
2  01.01.2009 00:30:00    996.53     -8.51    264.91        -9.31    93.9
3  01.01.2009 00:40:00    996.51     -8.31    265.12        -9.07    94.2
4  01.01.2009 00:50:00    996.51     -8.27    265.15        -9.04    94.1

   VPmax (mbar)  VPact (mbar)  VPdef (mbar)  sh (g/kg)  H2OC (mmol/mol)  \
0          3.33          3.11          0.22       1.94             3.12
1          3.23          3.02          0.21       1.89             3.03
2          3.21          3.01          0.20       1.88             3.02
3          3.26          3.07          0.19       1.92             3.08
4          3.27          3.08          0.19       1.92             3.09

   rho (g/m**3)  wv (m/s)  max. wv (m/s)  wd (deg)
0       1307.75      1.03           1.75     152.3
1       1309.80      0.72           1.50     136.1
2       1310.24      0.19           0.63     171.6
3       1309.19      0.34           0.50     198.0
4       1309.00      0.32           0.63     214.3
```

[ ]:
```
data.tail(5)
```

[ ]:
```
                  Date Time  p (mbar)  T (degC)  Tpot (K)  Tdew (degC)  \
420546  31.12.2016 23:20:00   1000.07     -4.05    269.10        -8.13
420547  31.12.2016 23:30:00    999.93     -3.35    269.81        -8.06
420548  31.12.2016 23:40:00    999.82     -3.16    270.01        -8.21
420549  31.12.2016 23:50:00    999.81     -4.23    268.94        -8.53
420550  01.01.2017 00:00:00    999.82     -4.82    268.36        -8.42

        rh (%)  VPmax (mbar)  VPact (mbar)  VPdef (mbar)  sh (g/kg)  \
420546   73.10          4.52          3.30          1.22       2.06
420547   69.71          4.77          3.32          1.44       2.07
420548   67.91          4.84          3.28          1.55       2.05
420549   71.80          4.46          3.20          1.26       1.99
420550   75.70          4.27          3.23          1.04       2.01

        H2OC (mmol/mol)  rho (g/m**3)  wv (m/s)  max. wv (m/s)  wd (deg)
420546             3.30       1292.98      0.67           1.52     240.0
420547             3.32       1289.44      1.14           1.92     234.3
420548             3.28       1288.39      1.08           2.00     215.2
```

```
420549              3.20       1293.56      1.49          2.16      225.8
420550              3.23       1296.38      1.23          1.96      184.9
```

[ ]:
```
data.describe().transpose().drop(["count"], axis=1)
```

[ ]:
```
                      mean        std      min      25%      50%      75%  \
p (mbar)           989.212776   8.358481   913.60   984.20   989.58   994.72
T (degC)             9.450147   8.423365   -23.01     3.36     9.42    15.47
Tpot (K)           283.492743   8.504471   250.60   277.43   283.47   289.53
Tdew (degC)          4.955854   6.730674   -25.01     0.24     5.22    10.07
rh (%)              76.008259  16.476175    12.95    65.21    79.30    89.40
VPmax (mbar)        13.576251   7.739020     0.95     7.78    11.82    17.60
VPact (mbar)         9.533756   4.184164     0.79     6.21     8.86    12.35
VPdef (mbar)         4.042412   4.896851     0.00     0.87     2.19     5.30
sh (g/kg)            6.022408   2.656139     0.50     3.92     5.59     7.80
H2OC (mmol/mol)      9.640223   4.235395     0.80     6.29     8.96    12.49
rho (g/m**3)      1216.062748  39.975208  1059.45  1187.49  1213.79  1242.77
wv (m/s)             1.702224  65.446714 -9999.00     0.99     1.76     2.86
max. wv (m/s)        3.056555  69.016932 -9999.00     1.76     2.96     4.74
wd (deg)           174.743738  86.681693     0.00   124.90   198.10   234.10

                       max
p (mbar)           1015.35
T (degC)             37.28
Tpot (K)            311.34
Tdew (degC)          23.11
rh (%)              100.00
VPmax (mbar)         63.77
VPact (mbar)         28.32
VPdef (mbar)         46.01
sh (g/kg)            18.13
H2OC (mmol/mol)      28.82
rho (g/m**3)       1393.54
wv (m/s)             28.49
max. wv (m/s)        23.50
wd (deg)            360.00
```

3.1.1 Manage errors

Obviously, wind speed and max wind speed should be >=0

[ ]:
```
wv = data["wv (m/s)"]
bad_wv = wv == -9999.0
wv[bad_wv] = 0.0

max_wv = data["max. wv (m/s)"]
bad_max_wv = max_wv == -9999.0
max_wv[bad_max_wv] = 0.0
```

```
data["wv (m/s)"].min()
```

```
/var/folders/h_/r3j4_s3d5973t55ttlf7h3vh0000gn/T/ipykernel_6882/3224106521.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  wv[bad_wv] = 0.0
/var/folders/h_/r3j4_s3d5973t55ttlf7h3vh0000gn/T/ipykernel_6882/3224106521.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  max_wv[bad_max_wv] = 0.0
```

[ ]:
```
0.0
```

3.1.2 Convert Wind direction (radian) to a vector (cos (θ), sin(θ))

Indeed, the wind direction is given in degrees and angles do not make a good model inputs. 360° and 0° should be close to each others, however the model will not get that. Moreover, wind speed and wind direction are decoupled, but the wind direction should not matter if the wind is not blowing. Thus, we will convert the wind direction / velocity into a vector wind / max wind with respect to x, and with respect to y

[ ]:
```
wv = data.pop("wv (m/s)")
max_wv = data.pop("max. wv (m/s)")

# Convert to radians
wd_rad = data.pop("wd (deg)") * np.pi / 180

# Calculate the wind x and y components
data["wx"] = wv * np.cos(wd_rad)
data["wy"] = wv * np.sin(wd_rad)

# Same for max wind speed
data["max wx"] = max_wv * np.cos(wd_rad)
data["max wy"] = max_wv * np.sin(wd_rad)
```

3.1.3 Manage date time

Convert to seconds

[ ]:
```
date_time = pd.to_datetime(data.pop('Date Time'), format='%d.%m.%Y %H:%M:%S')
timestamp = date_time.map(pd.Timestamp.timestamp)
```

Display periodicity

[ ]:
```
day = 24 * 60 * 60
year = (365.2425) * day

data["Day sin"] = np.sin(timestamp / (2 * np.pi / day))
data["Day cos"] = np.cos(timestamp / (2 * np.pi / day))

data["Year sin"] = np.sin(timestamp / (2 * np.pi / year))
data["Year cos"] = np.cos(timestamp / (2 * np.pi / year))
```

[ ]:
```
data.head(5)
```

[ ]:
```
   p (mbar)  T (degC)  Tpot (K)  Tdew (degC)  rh (%)  VPmax (mbar)  \
0    996.52     -8.02    265.40        -8.90    93.3          3.33
1    996.57     -8.41    265.01        -9.28    93.4          3.23
2    996.53     -8.51    264.91        -9.31    93.9          3.21
3    996.51     -8.31    265.12        -9.07    94.2          3.26
4    996.51     -8.27    265.15        -9.04    94.1          3.27

   VPact (mbar)  VPdef (mbar)  sh (g/kg)  H2OC (mmol/mol)  rho (g/m**3)  \
0          3.11          0.22       1.94             3.12       1307.75
1          3.02          0.21       1.89             3.03       1309.80
2          3.01          0.20       1.88             3.02       1310.24
3          3.07          0.19       1.92             3.08       1309.19
4          3.08          0.19       1.92             3.09       1309.00

         wx        wy    max wx    max wy   Day sin   Day cos  Year sin  \
0 -0.911955  0.478787 -1.549439  0.813474  0.701851 -0.712323 -0.716728
1 -0.518797  0.499249 -1.080827  1.040103 -0.502528  0.864561 -0.173856
2 -0.187962  0.027756 -0.623242  0.092032  0.271592 -0.962412  0.912186
3 -0.323359 -0.105066 -0.475528 -0.154508 -0.025525  0.999674 -0.851669
4 -0.264351 -0.180328 -0.520442 -0.355021 -0.224028 -0.974583  0.045302

   Year cos
0 -0.697352
1  0.984771
2 -0.409776
3 -0.524080
4  0.998973
```

3.1.4 Split data

70% training, 20% validation and 10% testing

[ ]:
```
# No shuffle!
n = len(data)

train_data = data[: int(n * 0.7)]
validation_data = data[int(n * 0.7): int(n * 0.9)]
```

```
test_data = data[int(n * 0.9):]

num_features = data.shape[1]
```

3.1.5 Normalization

[ ]:
```
train_mean = train_data.mean()
train_std = train_data.std()

train_data = (train_data - train_mean) / train_std
validation_data = (validation_data - train_mean) / train_std
test_data = (test_data - train_mean) / train_std
```

3.1.6 Data windowing

Take n previous days et predict the next m days

[ ]:
```
class WindowGenerator():
        def __init__(self, input_width, label_width, shift, train_df, val_df,␣
 ↪test_df, label_columns=None):
                # Store the raw data
                self.train_df = train_df
                self.val_df = val_df
                self.test_df = test_df

                # Work out the label column indices
                self.label_columns = label_columns
                if label_columns is not None:
                        self.label_columns_indices = {
                                name: i
                                for i, name in enumerate(label_columns)
                                }

                self.column_indices = {
                        name: i
                        for i, name in enumerate(train_df.columns)
                }

                # Work out the window parameters
                self.input_width = input_width
                self.label_width = label_width
                self.shift = shift

                self.total_window_size = input_width + shift

                self.input_slice = slice(0, input_width)
```

```
                self.input_indices = np.arange(self.total_window_size)[self.
↪input_slice]

                self.label_start = self.total_window_size - self.label_width
                self.label_slice = slice(self.label_start, None)
                self.label_indices = np.arange(self.total_window_size)[self.
↪label_slice]



        def __repr__(self):
                return '\n'.join([
        f'Total window size: {self.total_window_size}',
        f'Input indices: {self.input_indices}',
        f'Label indices: {self.label_indices}',
        f'Label column name(s): {self.label_columns}'])

        def split_window(self, features):
                inputs = features[:, self.input_slice, :]
                labels = features[:, self.label_slice, :]

                if self.label_columns is not None:
                        labels = tf.stack(
                                [labels[:, :, self.column_indices[name]] for␣
↪name in self.label_columns],
                                axis=-1
                        )

                # Slicing doesn't preserve static shape information, so set the␣
↪shapes manually. This way, the "tf.data.Datasets" are easier to inspect
                inputs.set_shape([None, self.input_width, None])
                labels.set_shape([None, self.label_width, None])

                return inputs, labels


        def plot(self, model=None, y_label="T (degC)", x_label="Time (h)",␣
↪max_subplots=3):
                inputs, labels = self.example
                plt.figure(figsize=(12, 8 * max_subplots / 3))
                plot_col_index = self.column_indices[y_label]
                max_n = min(max_subplots, len(inputs))

                for n in range(max_n):
                        plt.subplot(max_n, 1, n+1)
                        plt.ylabel(f'{y_label} [normed]')
```

```
                        plt.plot(self.input_indices, inputs[n, :,␣
↪plot_col_index],
                                                 label='Inputs', marker='.',␣
↪zorder=-10)

                        if self.label_columns:
                                label_col_index = self.label_columns_indices.
↪get(y_label, None)
                        else:
                                label_col_index = plot_col_index

                        if label_col_index is None:
                                continue

                        plt.scatter(self.label_indices, labels[n, :,␣
↪label_col_index],
                                                 edgecolors='k', label='Labels',␣
↪c='#2ca02c', s=64)
                        if model is not None:
                                predictions = model(inputs)

                                plt.scatter(self.label_indices, predictions[n, :
↪, 0],
                                                         marker='X',␣
↪edgecolors='k', label='Predictions',
                                                         c='#ff7f0e', s=64)

                        if n == 0:
                                plt.legend()

                plt.xlabel(x_label)



        def plot_test(self, model, y_label="T (degC)", x_label="Time (h)",␣
↪batch_size=32):
                plt.figure(figsize=(12, 4))
                size = 20
                iter_data = iter(self.make_dataset(self.test_df, shuffle=False))

                i_max = len(self.test_df) // batch_size
                iter_random = random.randint(0, i_max - 1)

                for _ in range(iter_random):
                        next(iter_data)
```

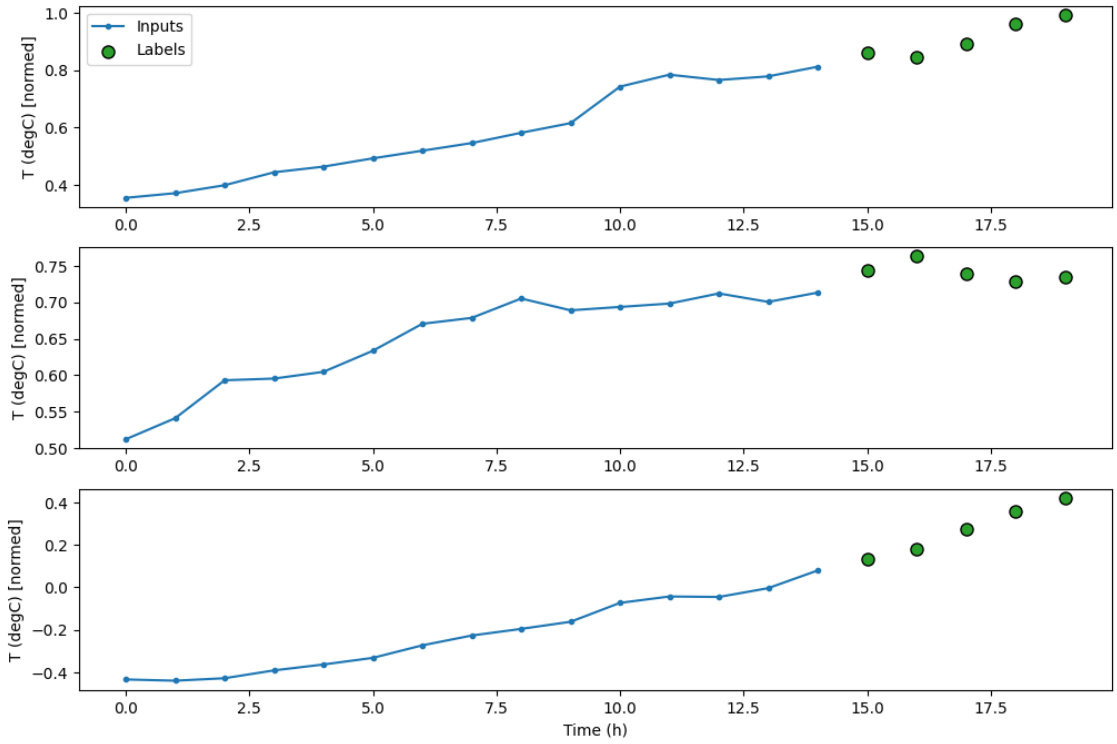
```
            inputs, labels = next(iter_data)

            plot_col_index = self.column_indices[y_label]
            label_col_index = 0
            if self.label_columns:
                        label_col_index = self.label_columns_indices.
↪get(y_label, None)
            else:
                    label_col_index = plot_col_index


            x = [i for i in range(size + 4)]

            predictions = model(inputs)

            plt.plot(x, [labels[i, :, label_col_index] for i in␣
↪range(len(x))], marker='.', zorder=-10, label='Inputs')

            plt.scatter(x[4:], [labels[i + 4, :, label_col_index] for i in␣
↪range(size)], edgecolors='k', label='Labels', c='#2ca02c', s=64)
            plt.scatter(x[4:], [predictions[i + 4, :, label_col_index] for␣
↪i in range(size)], marker='X', edgecolors='k', label='Predictions',
                                                    c='#ff7f0e', s=64)


            plt.xlabel(x_label)
            plt.ylabel(y_label)
            plt.legend()


    def make_dataset(self, data, shuffle=True):
            data = np.array(data, dtype=np.float32)
            ds = tf.keras.utils.timeseries_dataset_from_array(
                    data=data,
                    targets=None,
                    sequence_length=self.total_window_size,
                    sequence_stride=1,
                    shuffle=shuffle,
                    batch_size=32
            )
            ds = ds.map(self.split_window)
            return ds


    def display_shapes(self, num=1):
            for example_inputs, example_labels in self.train.take(num):
```

```
                        print(f"Inputs shape (batch, time, features):␣
↪{example_inputs.shape}")
                        print(f"Labels shape (batch, time, features):␣
↪{example_labels.shape}")

        def shapes(self):
                for example_inputs, example_labels in self.train.take(1):
                        return example_inputs.shape, example_labels.shape


        @property
        def train(self):
                return self.make_dataset(self.train_df)

        @property
        def val(self):
                return self.make_dataset(self.val_df)

        @property
        def test(self):
                return self.make_dataset(self.test_df)

        @property
        def example(self):
                """Get and cache an example batch of inputs, labels for␣
↪plotting"""
                result = getattr(self, '_example', None)
                if (result is None):
                        # No example batch was found, so get one from the .
↪train dataset
                        result = next(iter(self.train))
                        # And cache it for the next time
                        self._example = result
                return result
```

3.1.7 Test windowing

[ ]:
```
# Takes 15 previous hours
IN_STEP = 15

# To predict the 5 next
OUT_STEP = 5

window = WindowGenerator(input_width=IN_STEP, label_width=OUT_STEP,␣
↪shift=OUT_STEP, train_df=train_data, val_df=validation_data,␣
↪test_df=test_data, label_columns=["T (degC)"])
```

```
window.plot()
```



[ ]:
```
window.display_shapes()
```

```
Inputs shape (batch, time, features): (32, 15, 19)
Labels shape (batch, time, features): (32, 5, 1)
```

[ ]:
```
print(window.shapes())
```

```
(TensorShape([32, 15, 19]), TensorShape([32, 5, 1]))
```

4 General functions

[ ]:
```
def compile_and_fit(model: models.Sequential, window: WindowGenerator,␣
↪max_epochs=1000, batch_size=None, patience=5, learning_rate=0.001):
        early_stopping = tf.keras.callbacks.EarlyStopping(monitor="val_loss",␣
↪patience=patience, mode="min")

        model.compile(
                loss=tf.keras.losses.MeanSquaredError(),
                optimizer=tf.keras.optimizers.Adam(learning_rate),
                metrics=[tf.keras.metrics.MeanAbsoluteError()]
        )
```

```
        return model.fit(
                window.train,
                epochs=max_epochs,
                validation_data=window.val,
                batch_size=batch_size,
                callbacks=early_stopping
        )
```

[ ]:
```
def evaluate_model(model: models.Sequential, window: WindowGenerator):
        total_loss = model.evaluate(window.test)
        print(f"Total loss = {total_loss}")

        return total_loss
```

[ ]:
```
def plot_res(history, start: int, validation_loss=True):
        plt.plot(history.history["loss"][start:], label="Training loss")
        if validation_loss:
                plt.plot(history.history["val_loss"][start:], label="Validation␣
 ↪loss")
        plt.title("Loss over epochs")
        plt.ylabel("Loss value")
        plt.xlabel("Epochs")
        plt.legend()
```

[ ]:
```
def save_model(model: models.Sequential, name: str):
        model.save(f"../../resources/weather_forecasting/{name}.h5")
```

[ ]:
```
def load_model(name: str):
        return models.load_model(f"../../resources/weather_forecasting/{name}.
 ↪h5")
```

[ ]:
```
performance = {}
validation_perf = {}

performance_multi = {}
validation_perf_multi = {}
```

5 Single Output

[ ]:
```
in_dim = 5
out_dim = 1

# Given a 5 hours input, predict the next hour (Temperature in °C)
window = WindowGenerator(in_dim, out_dim, out_dim, train_data, validation_data,␣
 ↪test_data, label_columns=["T (degC)"])
```

```
input_shapes = window.shapes()[0]
label_shapes = window.shapes()[1]
```

5.1 Feed-forward network

[ ]:
```
def create_feed_forward(output_dim=1):
        model = models.Sequential()
        # Shapes (time, features) => (time*features)
        model.add(layers.Flatten())

        model.add(layers.Dense(32, activation="relu"))
        model.add(layers.Dense(32, activation="relu"))

        model.add(layers.Dense(output_dim))

        # Add back the time dimension: Shape (outputs) => (1, outputs)
        model.add(layers.Reshape([output_dim, -1]))

        return model
```

[ ]:
```
ff_model = create_feed_forward()
```

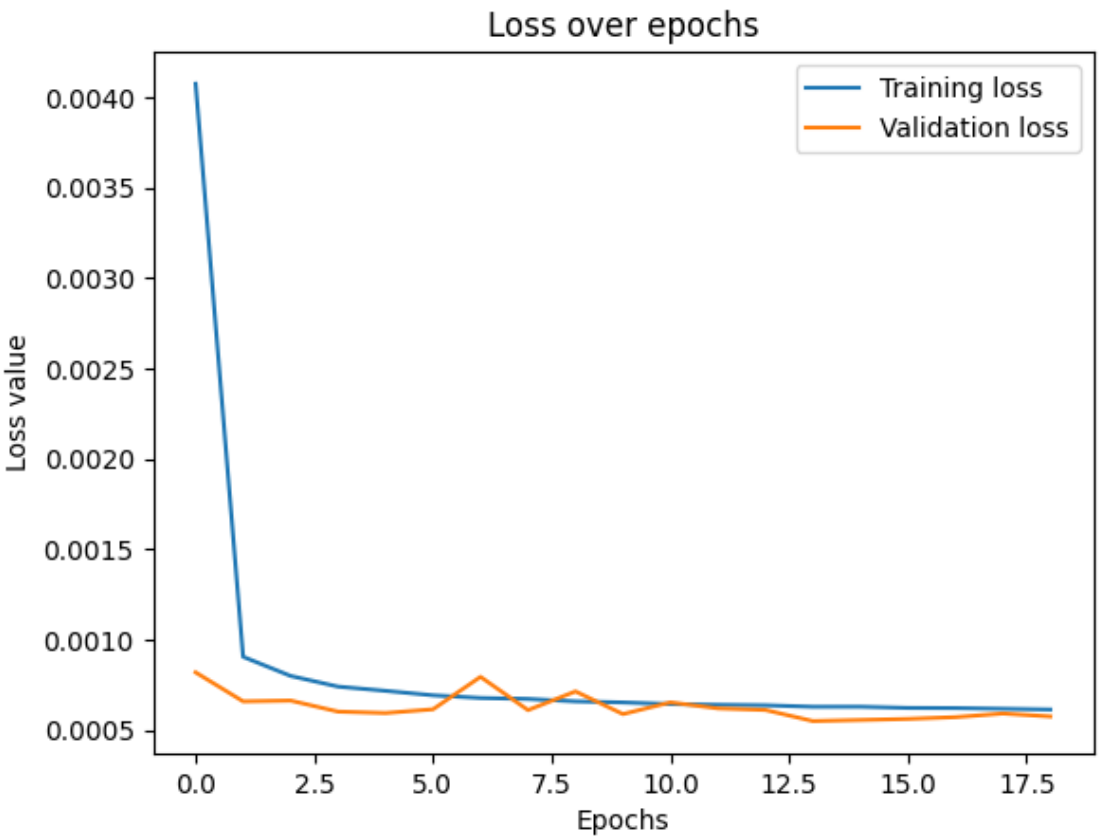
[ ]:
```
ff_model.summary()
```

```
Model: "sequential_17"
_________________________________________________________________
 Layer (type)                 Output Shape              Param #
=================================================================
 flatten_5 (Flatten)          (None, 95)                0

 dense_32 (Dense)             (None, 32)                3072

 dense_33 (Dense)             (None, 32)                1056

 dense_34 (Dense)             (None, 1)                 33

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

=================================================================
Total params: 4,161
Trainable params: 4,161
Non-trainable params: 0
_________________________________________________________________
```

[ ]:
```
ff_history = compile_and_fit(ff_model, window, patience=5)
save_model(ff_model, "ff_model")
```

```
Epoch 10/1000
9200/9200 [==============================] - 65s 7ms/step - loss: 6.5260e-04 -
mean_absolute_error: 0.0176 - val_loss: 5.8814e-04 - val_mean_absolute_error:
0.0166
Epoch 11/1000
9200/9200 [==============================] - 64s 7ms/step - loss: 6.4369e-04 -
mean_absolute_error: 0.0174 - val_loss: 6.5290e-04 - val_mean_absolute_error:
0.0183
Epoch 12/1000
9200/9200 [==============================] - 66s 7ms/step - loss: 6.3950e-04 -
mean_absolute_error: 0.0174 - val_loss: 6.1980e-04 - val_mean_absolute_error:
0.0171
Epoch 13/1000
9200/9200 [==============================] - 73s 8ms/step - loss: 6.3686e-04 -
mean_absolute_error: 0.0173 - val_loss: 6.1095e-04 - val_mean_absolute_error:
0.0167
Epoch 14/1000
9200/9200 [==============================] - 67s 7ms/step - loss: 6.2866e-04 -
mean_absolute_error: 0.0172 - val_loss: 5.4956e-04 - val_mean_absolute_error:
0.0154
Epoch 15/1000
9200/9200 [==============================] - 66s 7ms/step - loss: 6.2883e-04 -
mean_absolute_error: 0.0172 - val_loss: 5.5553e-04 - val_mean_absolute_error:
0.0158
Epoch 16/1000
9200/9200 [==============================] - 84s 9ms/step - loss: 6.2237e-04 -
mean_absolute_error: 0.0171 - val_loss: 5.6148e-04 - val_mean_absolute_error:
0.0157
Epoch 17/1000
9200/9200 [==============================] - 81s 9ms/step - loss: 6.2140e-04 -
mean_absolute_error: 0.0170 - val_loss: 5.7127e-04 - val_mean_absolute_error:
0.0161
Epoch 18/1000
9200/9200 [==============================] - 83s 9ms/step - loss: 6.1762e-04 -
mean_absolute_error: 0.0170 - val_loss: 5.9119e-04 - val_mean_absolute_error:
0.0165
Epoch 19/1000
9200/9200 [==============================] - 64s 7ms/step - loss: 6.1337e-04 -
mean_absolute_error: 0.0169 - val_loss: 5.7518e-04 - val_mean_absolute_error:
0.0162
```

[ ]:
```
plot_res(ff_history, 0)
```



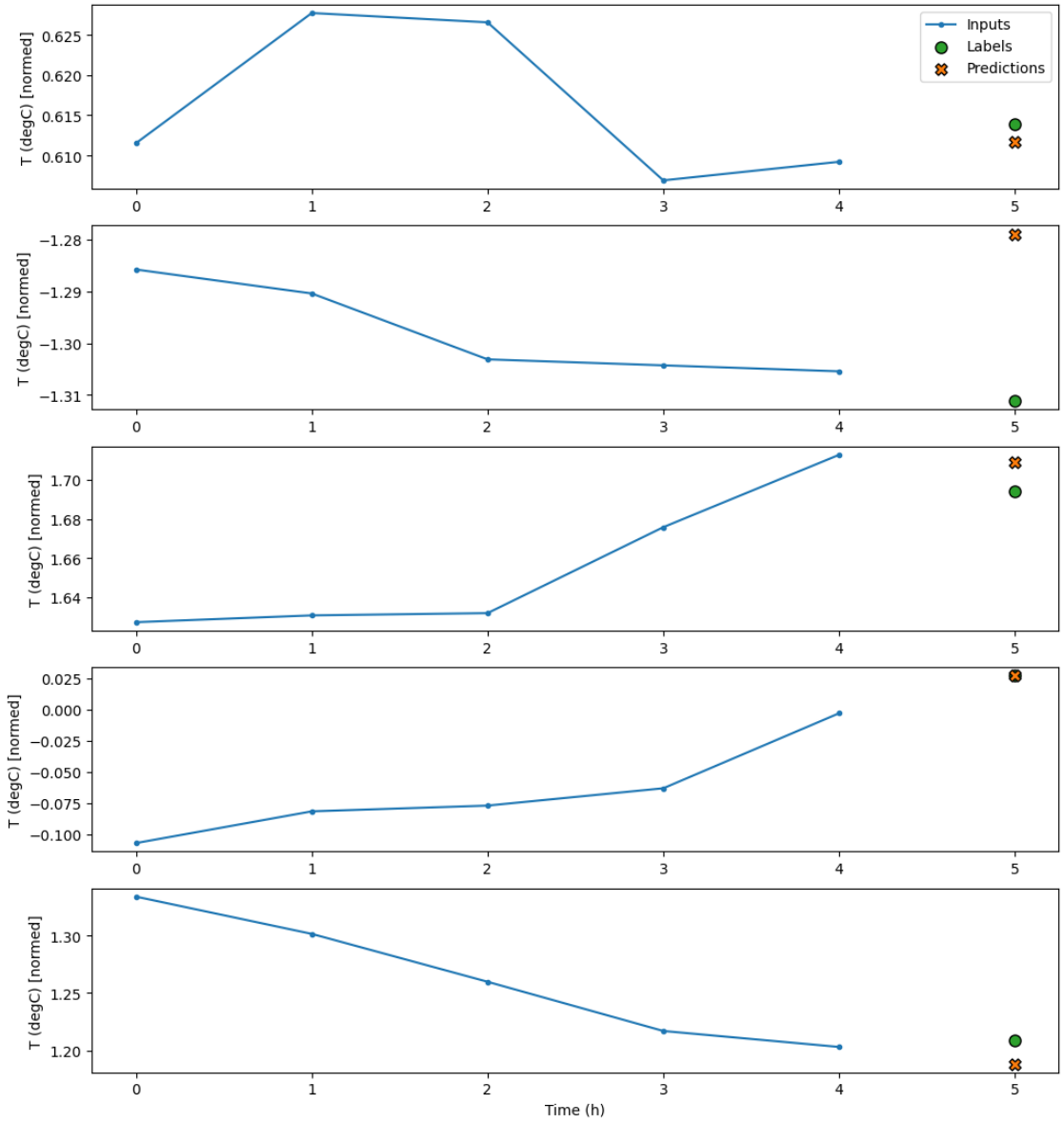
[ ]:
```
validation_perf["ff"] = ff_model.evaluate(window.val)
```

```
2629/2629 [==============================] - 14s 5ms/step - loss: 5.7519e-04 -
mean_absolute_error: 0.0162
```

[ ]:
```
performance["ff"] = evaluate_model(ff_model, window)
```

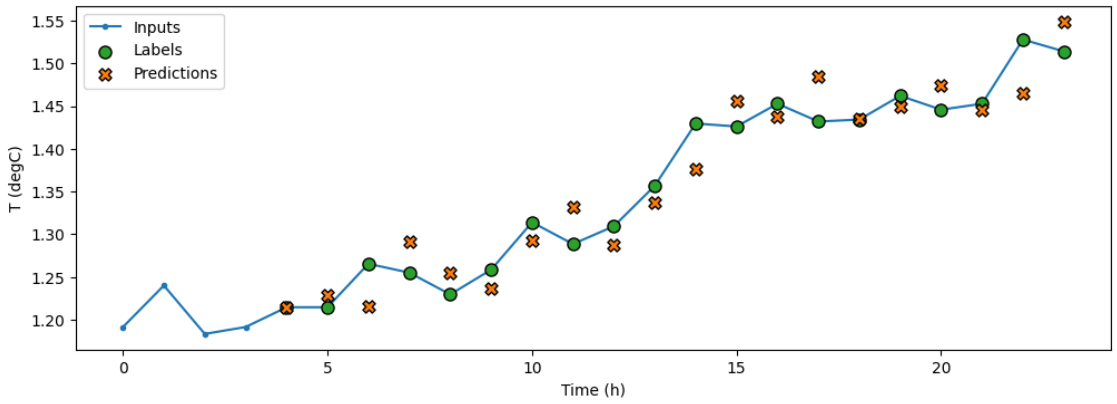
```
1315/1315 [==============================] - 7s 5ms/step - loss: 6.1459e-04 -
mean_absolute_error: 0.0169
Total loss = [0.000614590710029006, 0.01689978502690792]
```

[ ]:
```
window.plot(ff_model, max_subplots=5)
```



5.1.1 Plot on test data

[ ]:
```
window.plot_test(ff_model)
```



5.2 LSTM

[ ]:
```
def create_lstm(output_dim=1):
        model = models.Sequential()

        # Shape [samples, time steps, features]
        model.add(layers.LSTM(32, return_sequences=True))
        model.add(layers.LSTM(2))

        model.add(layers.Dense(output_dim))

        model.add(layers.Reshape([output_dim, -1]))

        return model
```

[ ]:
```
lstm_model = create_lstm()
```

[ ]:
```
lstm_model.build((None, input_shapes[1], input_shapes[2]))
```

[ ]:
```
lstm_model.summary()
```

```
Model: "sequential_44"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_73 (LSTM)              (None, 5, 32)             6656

 lstm_74 (LSTM)              (None, 2)                 280

 dense_459 (Dense)           (None, 1)                 3

 reshape_115 (Reshape)       (None, 1, 1)              0
```

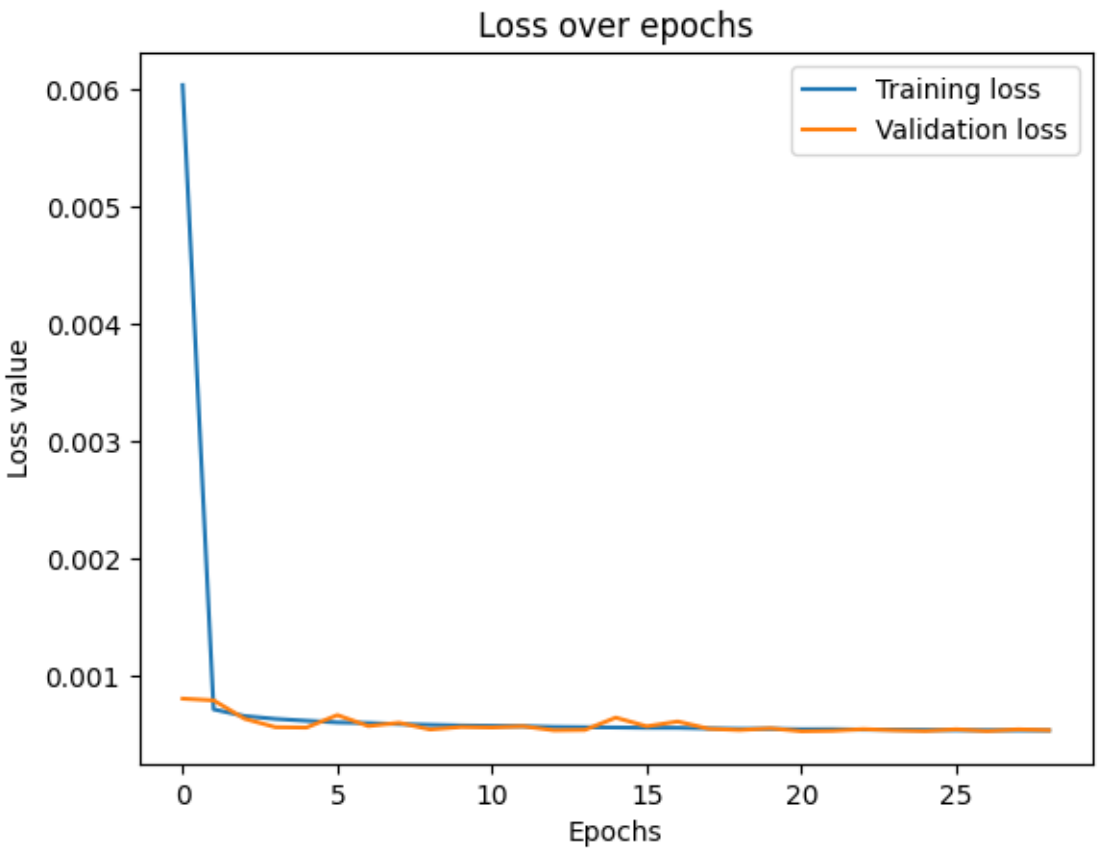
```
=================================================================
Total params: 6,939
Trainable params: 6,939
Non-trainable params: 0
_________________________________________________________________
```

[ ]:
```
# Run on CPU, faster here
with tf.device('/CPU:0'):
        lstm_history = compile_and_fit(lstm_model, window, patience=5)

save_model(lstm_model, "lstm_model")
```

```
Epoch 1/1000

2022-11-20 18:46:33.651106: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.

9191/9200 [============================>.] - ETA: 0s - loss: 0.0060 -
mean_absolute_error: 0.0341

2022-11-20 18:47:22.107558: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.

9200/9200 [==============================] - 55s 6ms/step - loss: 0.0060 -
mean_absolute_error: 0.0341 - val_loss: 8.1070e-04 - val_mean_absolute_error:
0.0196
Epoch 2/1000
9200/9200 [==============================] - 51s 5ms/step - loss: 7.1977e-04 -
mean_absolute_error: 0.0188 - val_loss: 7.9625e-04 - val_mean_absolute_error:
0.0209
Epoch 3/1000
9200/9200 [==============================] - 52s 6ms/step - loss: 6.6239e-04 -
mean_absolute_error: 0.0178 - val_loss: 6.3982e-04 - val_mean_absolute_error:
0.0176
Epoch 4/1000
9200/9200 [==============================] - 51s 6ms/step - loss: 6.3814e-04 -
mean_absolute_error: 0.0174 - val_loss: 5.6766e-04 - val_mean_absolute_error:
0.0161
Epoch 5/1000
9200/9200 [==============================] - 52s 6ms/step - loss: 6.2241e-04 -
mean_absolute_error: 0.0171 - val_loss: 5.6449e-04 - val_mean_absolute_error:
0.0159
Epoch 6/1000
9200/9200 [==============================] - 49s 5ms/step - loss: 6.0810e-04 -
mean_absolute_error: 0.0168 - val_loss: 6.7061e-04 - val_mean_absolute_error:
0.0187
Epoch 7/1000
9200/9200 [==============================] - 50s 5ms/step - loss: 6.0288e-04 -
```

```
mean_absolute_error: 0.0158 - val_loss: 5.4345e-04 - val_mean_absolute_error:
0.0155
Epoch 20/1000
9200/9200 [==============================] - 59s 6ms/step - loss: 5.5352e-04 -
mean_absolute_error: 0.0159 - val_loss: 5.5784e-04 - val_mean_absolute_error:
0.0160
Epoch 21/1000
9200/9200 [==============================] - 60s 7ms/step - loss: 5.5006e-04 -
mean_absolute_error: 0.0158 - val_loss: 5.3326e-04 - val_mean_absolute_error:
0.0154
Epoch 22/1000
9200/9200 [==============================] - 53s 6ms/step - loss: 5.5083e-04 -
mean_absolute_error: 0.0158 - val_loss: 5.3690e-04 - val_mean_absolute_error:
0.0152
Epoch 23/1000
9200/9200 [==============================] - 49s 5ms/step - loss: 5.4740e-04 -
mean_absolute_error: 0.0157 - val_loss: 5.5100e-04 - val_mean_absolute_error:
0.0156
Epoch 24/1000
9200/9200 [==============================] - 52s 6ms/step - loss: 5.4672e-04 -
mean_absolute_error: 0.0158 - val_loss: 5.4133e-04 - val_mean_absolute_error:
0.0153
Epoch 25/1000
9200/9200 [==============================] - 50s 5ms/step - loss: 5.4468e-04 -
mean_absolute_error: 0.0157 - val_loss: 5.3506e-04 - val_mean_absolute_error:
0.0154
Epoch 26/1000
9200/9200 [==============================] - 57s 6ms/step - loss: 5.4258e-04 -
mean_absolute_error: 0.0157 - val_loss: 5.4974e-04 - val_mean_absolute_error:
0.0159
Epoch 27/1000
9200/9200 [==============================] - 58s 6ms/step - loss: 5.4220e-04 -
mean_absolute_error: 0.0157 - val_loss: 5.3431e-04 - val_mean_absolute_error:
0.0155
Epoch 28/1000
9200/9200 [==============================] - 55s 6ms/step - loss: 5.4100e-04 -
mean_absolute_error: 0.0157 - val_loss: 5.4906e-04 - val_mean_absolute_error:
0.0157
Epoch 29/1000
9200/9200 [==============================] - 52s 6ms/step - loss: 5.4017e-04 -
mean_absolute_error: 0.0156 - val_loss: 5.4212e-04 - val_mean_absolute_error:
0.0153
```

[ ]:
```
plot_res(lstm_history, 0)
```



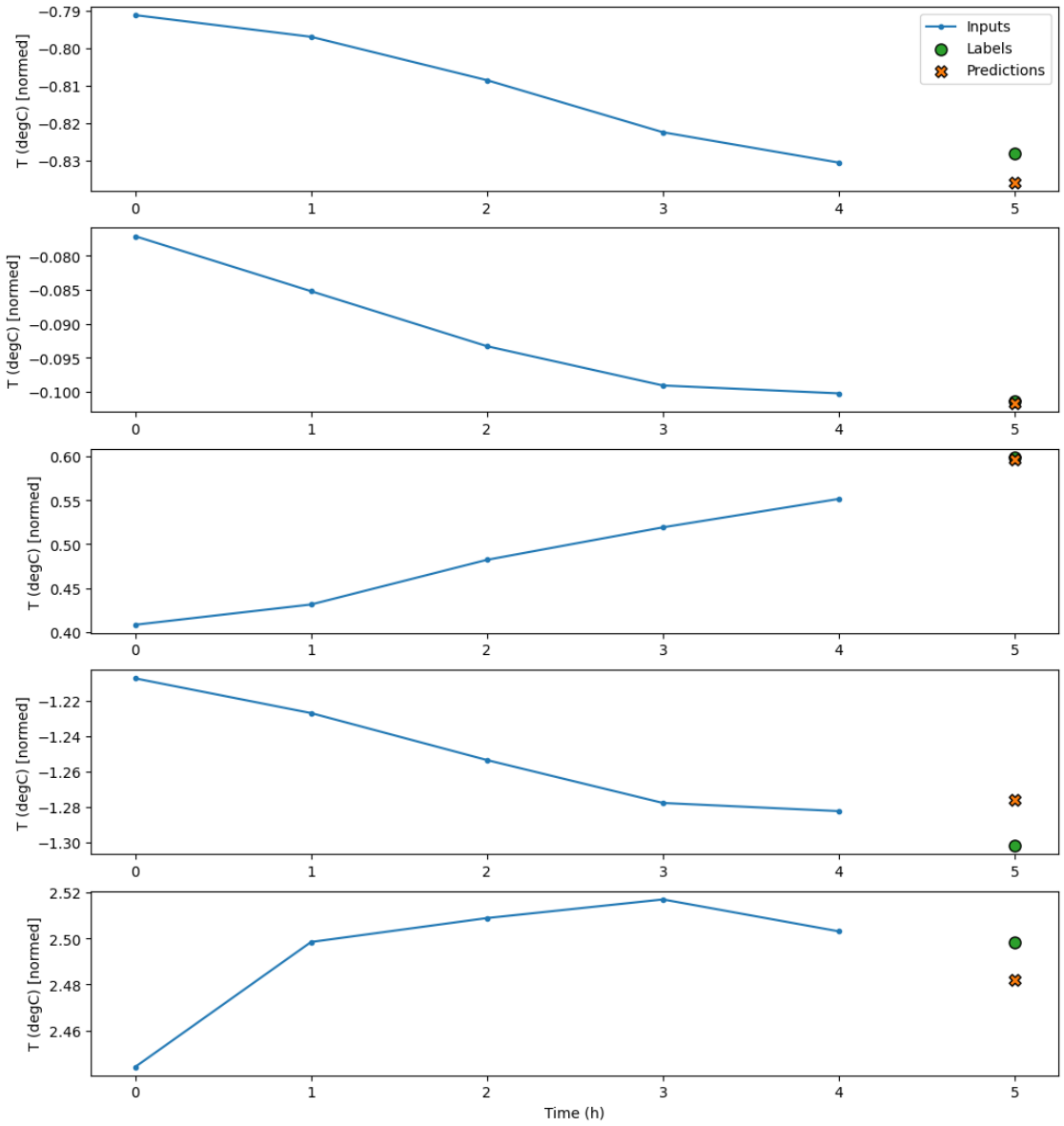
[ ]:
```
validation_perf["lstm"] = lstm_model.evaluate(window.val)
```

```
2629/2629 [==============================] - 27s 10ms/step - loss: 5.4212e-04 -
mean_absolute_error: 0.0153
```

[ ]:
```
performance["lstm"] = evaluate_model(lstm_model, window)
```

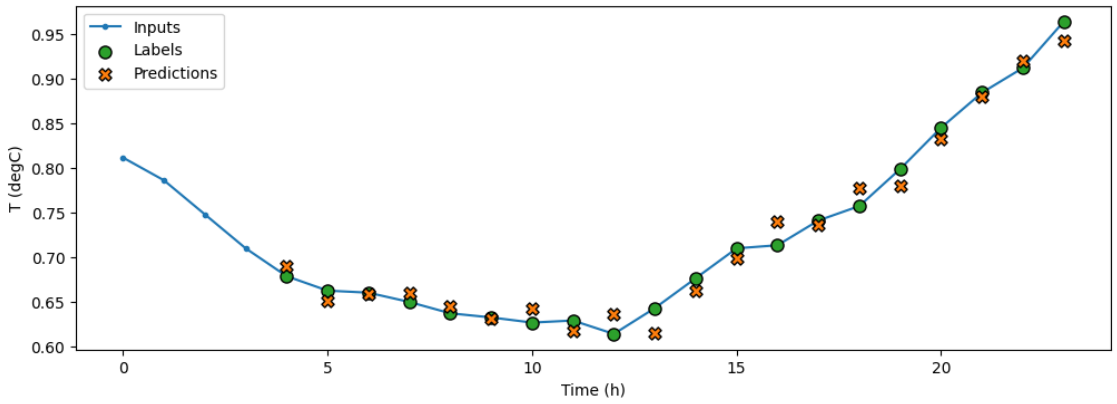
```
1315/1315 [==============================] - 12s 9ms/step - loss: 6.1048e-04 -
mean_absolute_error: 0.0168
Total loss = [0.0006104842177592218, 0.016763756051659584]
```

[ ]:
```
window.plot(lstm_model, max_subplots=5)
```



5.2.1 Plot on test data

[ ]:
```
window.plot_test(lstm_model)
```



5.3 Transformer

[ ]:
```
class FeedForward(layers.Layer):
        def __init__(self, units, activation="relu", **kwargs):
                self.units = units
                self.activation = activation

                self.dense = layers.Dense(units, activation=activation)
                self.norm= layers.LayerNormalization()
                self.add = layers.Add()

                super(FeedForward, self).__init__(**kwargs)

        def get_config(self):
                config = super(FeedForward, self).get_config()
                config.update({"activation": self.activation})
                config.update({"units": self.units})

                return config


        @tf.function
        def call(self, x):
                y = self.dense(x)
                y = self.add([x, y])
                return self.norm(y)
```

[ ]:
```
class BaseAttention(layers.Layer):
        def __init__(self, **kwargs):
                super().__init__()
                self.multi_head_attention = layers.MultiHeadAttention(**kwargs)
                self.add = layers.Add()
```

```
                self.norm = layers.LayerNormalization()
```

[ ]:
```
class MultiHeadAttention(BaseAttention):
        @tf.function
        def call(self, x, context=None, masked=False):
                y = self.multi_head_attention(
                        query = x,
                        key = context if context != None else x,
                        value = context if context != None else x,
                        use_causal_mask = masked
                )
                y = self.add([y, x])
                y = self.norm(y)
                return y
```

[ ]:
```
class TransformerEncoderBlock(layers.Layer):
        def __init__(self, num_heads, key_dim, inp_shape,␣
 ↪dense_activation="relu", **kwargs):
                self.inp_shape = inp_shape
                self.num_heads = num_heads
                self.key_dim = key_dim
                self.dense_activation = dense_activation

                self.feed_fw = FeedForward(inp_shape[2],␣
 ↪activation=dense_activation)
                self.attention = MultiHeadAttention(num_heads=num_heads,␣
 ↪key_dim=key_dim)

                super(TransformerEncoderBlock, self).__init__(**kwargs)

        def get_config(self):
                config = super(TransformerEncoderBlock, self).
 ↪get_config()
                config.update({"inp_shape": self.inp_shape})
                config.update({"num_heads": self.num_heads})
                config.update({"key_dim": self.key_dim})
                config.update({"dense_activation": self.
 ↪dense_activation})
                return config


        @tf.function
        def call(self, x):
                res = self.attention(x)
                return self.feed_fw(res)
```

[ ]:
```
class TransformerDecoderBlock(layers.Layer):
        def __init__(self, num_heads, key_dim, inp_shape,␣
↪dense_activation="relu", **kwargs):
                self.inp_shape = inp_shape
                self.context = None

                self.num_heads = num_heads
                self.key_dim = key_dim
                self.dense_activation = dense_activation

                self.feed_fw = FeedForward(inp_shape[2],␣
↪activation=dense_activation)
                self.masked_attention = MultiHeadAttention(num_heads=num_heads,␣
↪key_dim=key_dim)

                self.cross_attention = MultiHeadAttention(num_heads=num_heads,␣
↪key_dim=key_dim)

                super(TransformerDecoderBlock, self).__init__(**kwargs)

        def get_config(self):
                config = super(TransformerDecoderBlock, self).
↪get_config()
                config.update({"inp_shape": self.inp_shape})
                config.update({"context": self.context})
                config.update({"num_heads": self.num_heads})
                config.update({"key_dim": self.key_dim})
                config.update({"dense_activation": self.
↪dense_activation})
                return config


        @tf.function
        def call(self, x, context):
                y = self.masked_attention(x, masked=True)
                y = self.cross_attention(y, context=context)

                return self.feed_fw(y)
```

[ ]:
```
class TransformerEncoder(layers.Layer):
        def __init__(self, num_layers, num_heads, key_dim, inp_shape,␣
↪dense_activation="relu", **kwargs):

                self.num_layers = num_layers
                self.num_heads = num_heads
                self.key_dim = key_dim
                self.inp_shape = inp_shape
```

```
                self.dense_activation = dense_activation

                self.layers = [
                        TransformerEncoderBlock(num_heads, key_dim, inp_shape,␣
↪dense_activation)
                        for _ in range(num_layers)
                ]
                super(TransformerEncoder, self).__init__(**kwargs)

        def get_config(self):
                config = super(TransformerEncoder, self).
↪get_config()
                config.update({"num_layers": self.num_layers})

                config.update({"inp_shape": self.inp_shape})
                config.update({"num_heads": self.num_heads})
                config.update({"key_dim": self.key_dim})
                config.update({"dense_activation": self.dense_activation})
                return config

        @tf.function
        def call(self, x):
                y = x
                for layer in self.layers:
                        y = layer(y)

                return y
```

[ ]:
```
class TransformerDecoder(layers.Layer):
        def __init__(self, num_layers, num_heads, key_dim, inp_shape,␣
↪dense_activation="relu", **kwargs):

                self.num_layers = num_layers
                self.num_heads = num_heads
                self.key_dim = key_dim
                self.inp_shape = inp_shape
                self.dense_activation = dense_activation

                self.layers = [
                        TransformerDecoderBlock(num_heads, key_dim, inp_shape,␣
↪dense_activation)
                        for _ in range(num_layers)
                ]
                self.context = None

                super(TransformerDecoder, self).__init__(**kwargs)
```

```
        def get_config(self):
                config = super(TransformerDecoder, self).
↪get_config()
                config.update({"num_layers": self.num_layers})

                config.update({"inp_shape": self.inp_shape})
                config.update({"num_heads": self.num_heads})
                config.update({"key_dim": self.key_dim})
                config.update({"dense_activation": self.dense_activation})
                return config

        @tf.function
        def call(self, x, context=None):
                y = x
                for layer in self.layers:
                        y = layer(y, context)

                return y
```

[ ]:
```
class Transformer(layers.Layer):
        def __init__(self, encoder: TransformerEncoder, decoder:␣
↪TransformerDecoder, **kwargs):
                self.encoder = encoder
                self.decoder = decoder

                super(Transformer, self).__init__(**kwargs)

        def get_config(self):
                config = super(Transformer, self).get_config()
                config.update({"encoder": self.encoder})
                config.update({"decoder": self.decoder})
                return config

        @tf.function
        def call(self, x):
                y = self.encoder(x)
                y = self.decoder(y, x)
                return y
```

[ ]:
```
def create_transformer(input_shape, output_dim=1):
        input_tensor = layers.Input(shape=input_shape)

        encoder = TransformerEncoder(1, 3, 4, input_tensor.shape)
        decoder = TransformerDecoder(1, 3, 4, input_tensor.shape)

        x = Transformer(encoder, decoder)(input_tensor)
```

```
        y = layers.Flatten()(x)
        y = layers.Dense(32, activation="relu")(y)

        y = layers.Dense(output_dim)(y)

        output_tensor = layers.Reshape([output_dim, -1])(y)

        return models.Model(input_tensor, output_tensor)
```

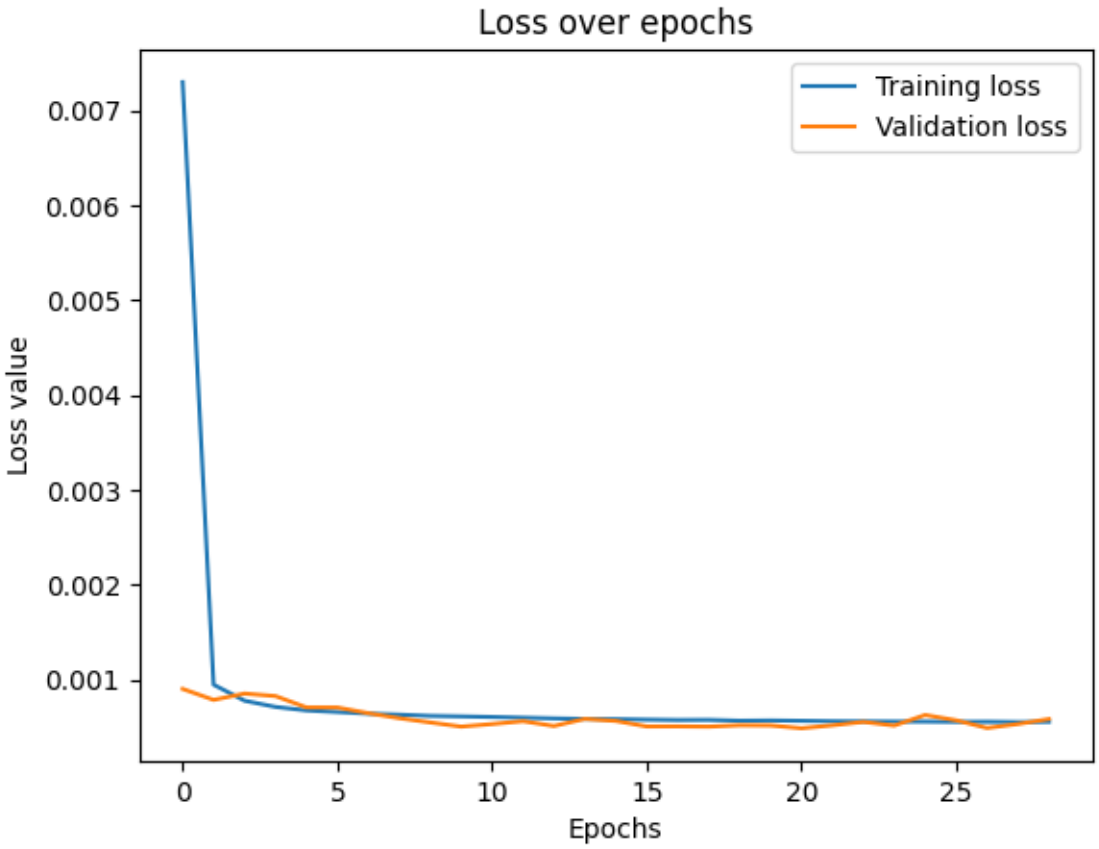
[ ]:
```
def save_transformer_model(model: models.Model, name: str):
        model.save(f"../../resources/weather_forecasting/{name}.h5")

def load_transformer_model(name: str):
        models.load_model(f"../../resources/weather_forecasting/{name}.h5",␣
 ↪custom_objects={
                "Transformer": Transformer,
                'TransformerEncoderBlock': TransformerEncoderBlock,
                "TransformerDecoderBlock": TransformerDecoderBlock,
                "TransformerEncoder": TransformerEncoder,
                "TransformerDecoder": TransformerDecoder
                })
```

[ ]:
```
transformer_model = create_transformer((input_shapes[1], input_shapes[2]),␣
 ↪output_dim=label_shapes[1])
transformer_model.summary()
```

```
Model: "model_96"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_219 (InputLayer)      [(None, 5, 19)]           0

 transformer_9 (Transformer)  (None, 5, 19)            3851

 flatten_102 (Flatten)       (None, 95)                0

 dense_505 (Dense)           (None, 32)                3072

 dense_506 (Dense)           (None, 1)                 33

 reshape_125 (Reshape)       (None, 1, 1)              0

=================================================================
Total params: 6,956
Trainable params: 6,956
Non-trainable params: 0
_________________________________________________________________
```

[ ]:
```
with tf.device('CPU'):
        transformer_history = compile_and_fit(transformer_model, window,␣
 ↪patience=5)

save_transformer_model(transformer_model, "transformer_model")
```

[ ]:
```
plot_res(transformer_history, 0)
```



[ ]:
```
validation_perf["transformer"] = transformer_model.evaluate(window.val)
```

```
2022-11-20 22:24:44.583708: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.

2629/2629 [==============================] - 53s 20ms/step - loss: 4.9730e-04 -
mean_absolute_error: 0.0145
```

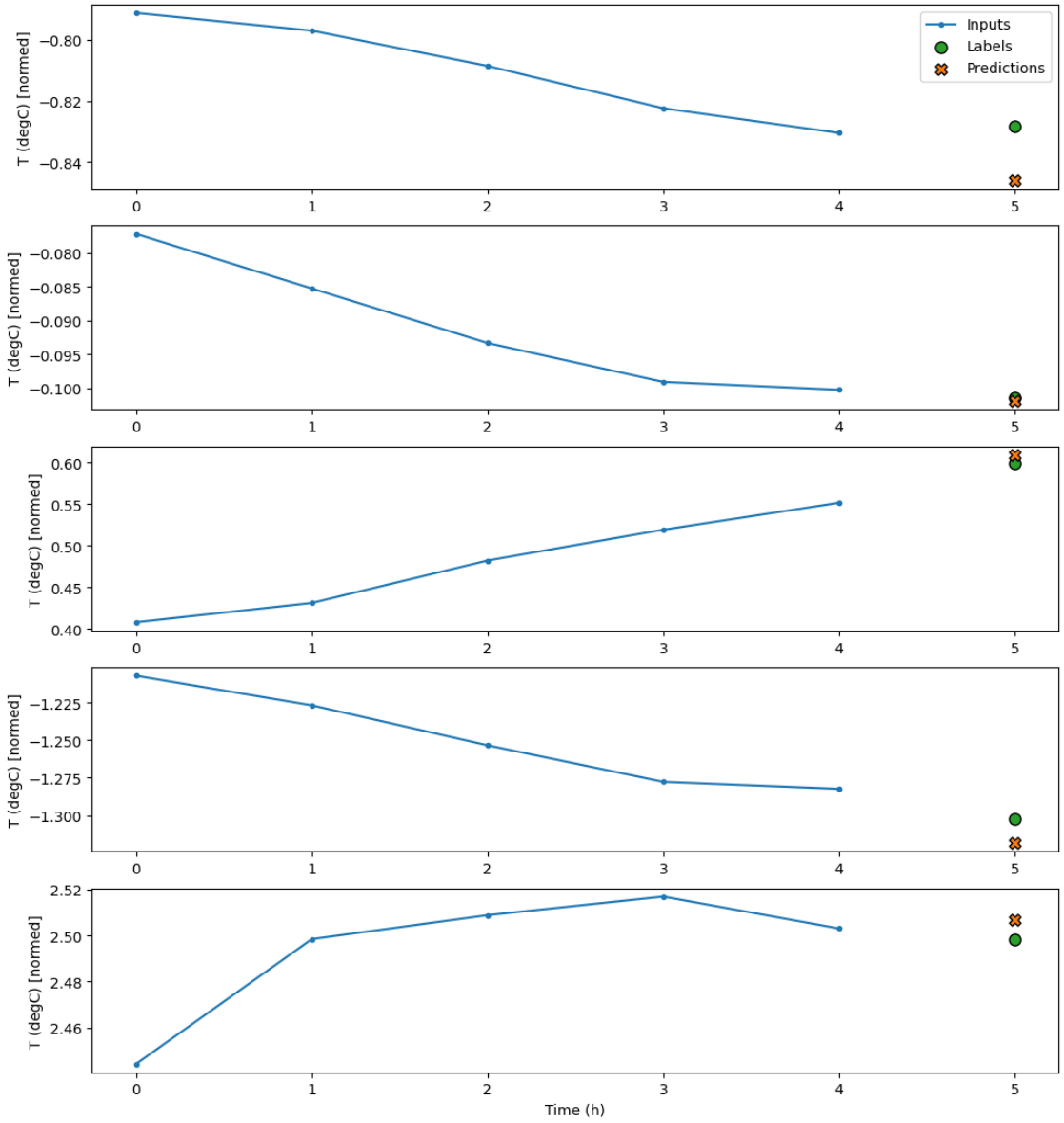
[ ]:
```
performance["transformer"] = evaluate_model(transformer_model, window)
```

```
1315/1315 [==============================] - 26s 20ms/step - loss: 5.4007e-04 -
mean_absolute_error: 0.0155
```

```
Total loss = [0.0005400656373240054, 0.015513748861849308]
```

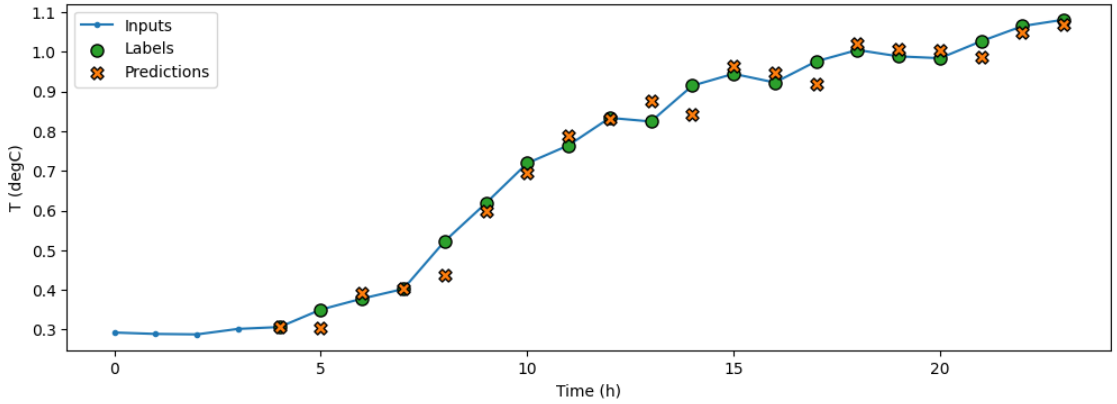
[ ]:
```
window.plot(transformer_model, max_subplots=5)
```

```
2022-11-20 20:35:23.982172: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
```



5.3.1 Plot on test data

[ ]:
```
window.plot_test(transformer_model)
```



6 Multi outputs (same models)

[ ]:
```
in_dim = 15
out_dim = 5

# Given a 15 hours input, predict the next 5 hours (Temperature in °C)
window_multi = WindowGenerator(in_dim, out_dim, out_dim, train_data,␣
 ↪validation_data, test_data, label_columns=["T (degC)"])

input_shapes = window_multi.shapes()[0]
label_shapes = window_multi.shapes()[1]
```

[ ]:
```
input_shapes
```

[ ]:
```
TensorShape([32, 15, 19])
```

[ ]:
```
label_shapes
```

[ ]:
```
TensorShape([32, 5, 1])
```

6.1 Feed Forward

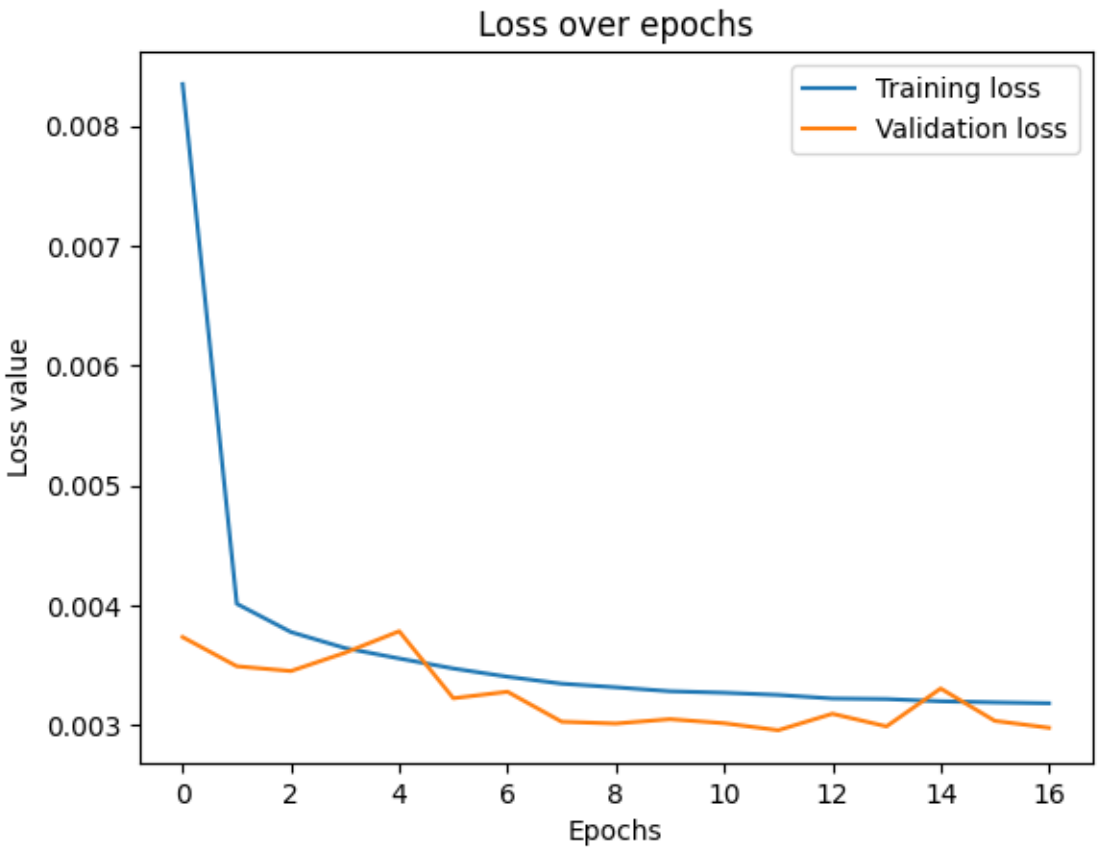
[ ]:
```
ff_model_multi = create_feed_forward(label_shapes[1])
```

[ ]:
```
ff_history_multi = compile_and_fit(ff_model_multi, window_multi, patience=5)
save_model(ff_model_multi, "ff_model_multi")
```

```
Epoch 1/1000
```

```
Epoch 14/1000
9199/9199 [==============================] - 68s 7ms/step - loss: 0.0032 -
mean_absolute_error: 0.0374 - val_loss: 0.0030 - val_mean_absolute_error: 0.0358
Epoch 15/1000
9199/9199 [==============================] - 68s 7ms/step - loss: 0.0032 -
mean_absolute_error: 0.0373 - val_loss: 0.0033 - val_mean_absolute_error: 0.0388
Epoch 16/1000
9199/9199 [==============================] - 67s 7ms/step - loss: 0.0032 -
mean_absolute_error: 0.0372 - val_loss: 0.0030 - val_mean_absolute_error: 0.0360
Epoch 17/1000
9199/9199 [==============================] - 66s 7ms/step - loss: 0.0032 -
mean_absolute_error: 0.0371 - val_loss: 0.0030 - val_mean_absolute_error: 0.0351
```

[ ]:
```
plot_res(ff_history_multi, 0)
```



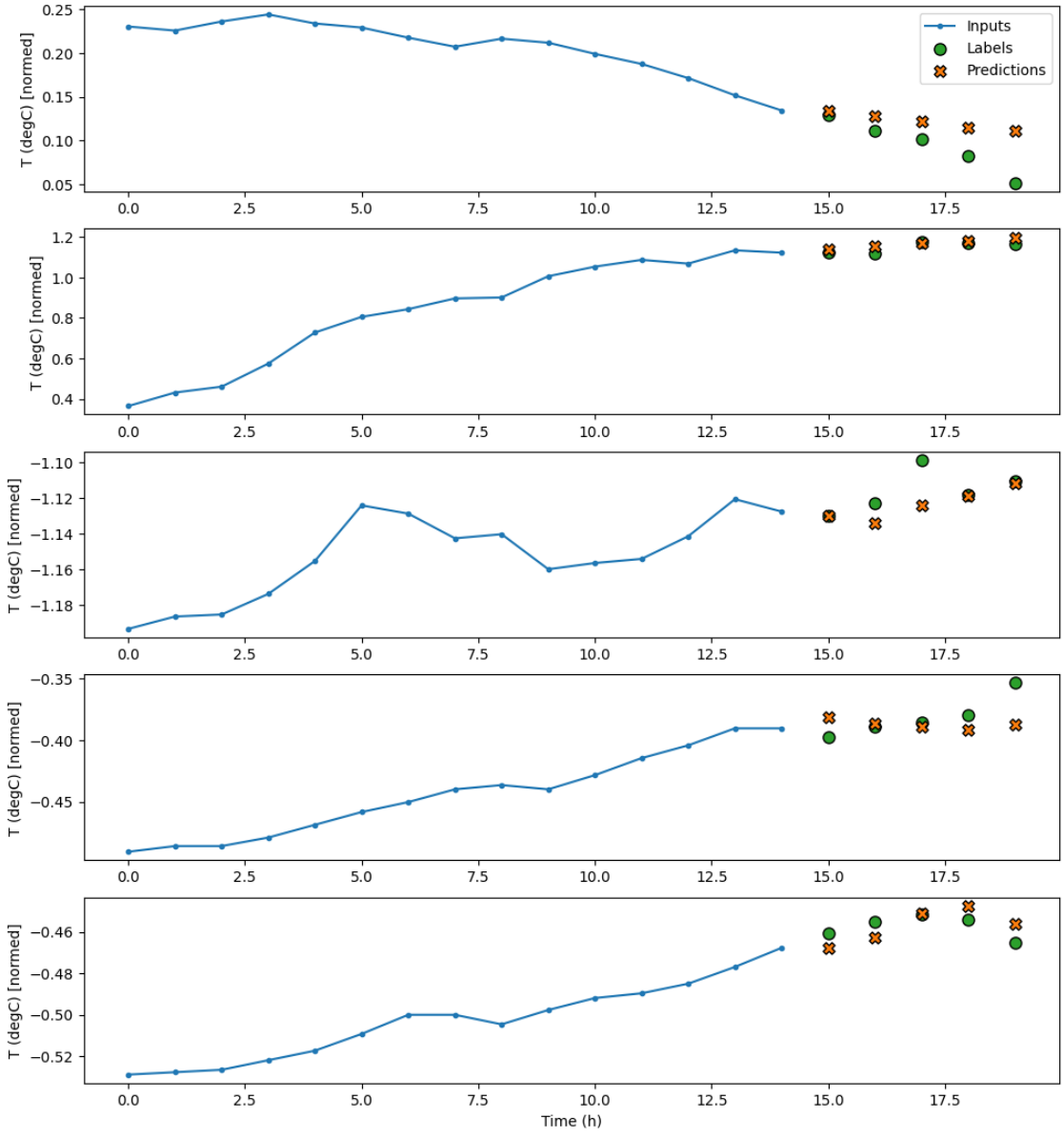
[ ]:
```
validation_perf_multi["ff"] = ff_model_multi.evaluate(window_multi.val)
```

```
2628/2628 [==============================] - 13s 5ms/step - loss: 0.0030 -
mean_absolute_error: 0.0351
```

[ ]:
```
performance_multi["ff"] = evaluate_model(ff_model_multi, window_multi)
```

```
1314/1314 [==============================] - 6s 5ms/step - loss: 0.0030 -
mean_absolute_error: 0.0361
Total loss = [0.003044005949050188, 0.03610309213399887]
```

[ ]:
```
window_multi.plot(ff_model_multi, max_subplots=5)
```



6.2 LSTM

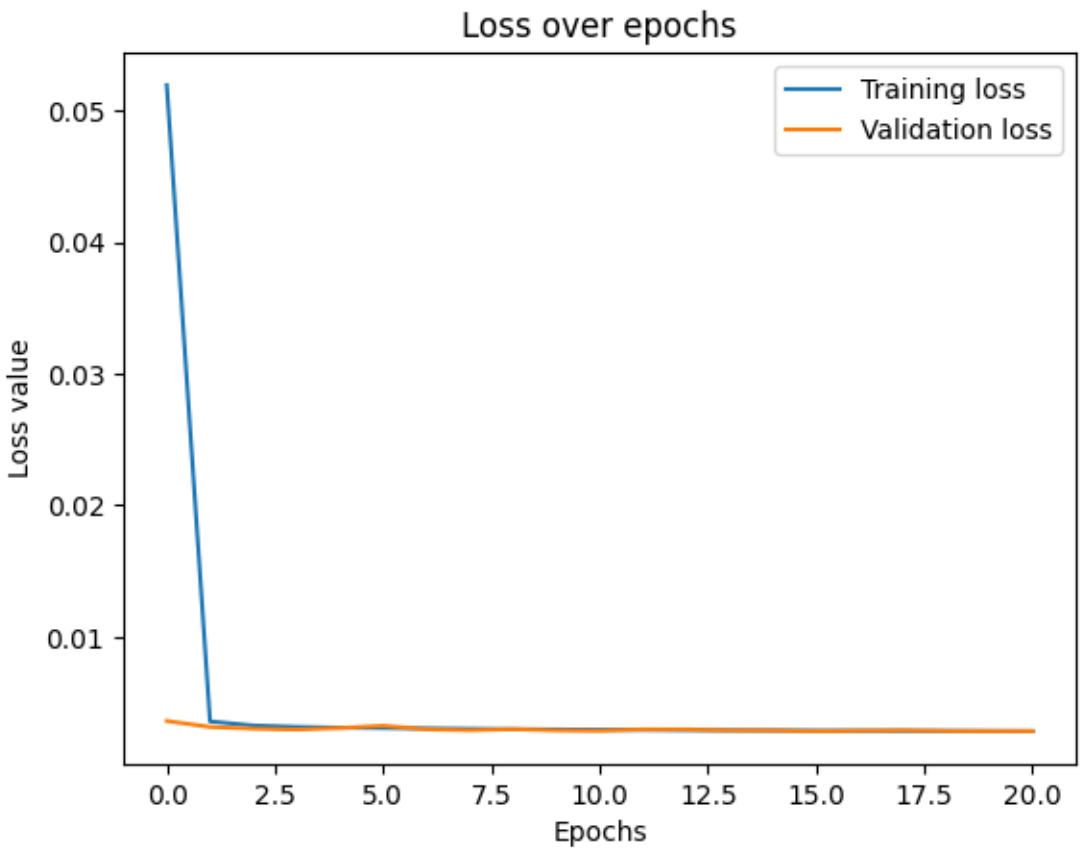
[ ]:
```
lstm_model_multi = create_lstm(label_shapes[1])
```

[ ]:
```
# Run on CPU, faster here
with tf.device('/CPU:0'):
        lstm_history_multi = compile_and_fit(lstm_model_multi, window_multi,␣
 ↪patience=5)

save_model(lstm_model_multi, "lstm_model_multi")
```

```
Epoch 1/1000

2022-11-20 20:56:03.386829: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.

9189/9199 [============================>.] - ETA: 0s - loss: 0.0520 -
mean_absolute_error: 0.0922

2022-11-20 20:56:45.500757: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.

9199/9199 [==============================] - 49s 5ms/step - loss: 0.0520 -
mean_absolute_error: 0.0922 - val_loss: 0.0036 - val_mean_absolute_error: 0.0393
Epoch 2/1000
9199/9199 [==============================] - 45s 5ms/step - loss: 0.0036 -
mean_absolute_error: 0.0400 - val_loss: 0.0032 - val_mean_absolute_error: 0.0363
Epoch 3/1000
9199/9199 [==============================] - 43s 5ms/step - loss: 0.0033 -
mean_absolute_error: 0.0374 - val_loss: 0.0030 - val_mean_absolute_error: 0.0353
Epoch 4/1000
9199/9199 [==============================] - 43s 5ms/step - loss: 0.0032 -
mean_absolute_error: 0.0365 - val_loss: 0.0030 - val_mean_absolute_error: 0.0349
Epoch 5/1000
9199/9199 [==============================] - 46s 5ms/step - loss: 0.0031 -
mean_absolute_error: 0.0362 - val_loss: 0.0031 - val_mean_absolute_error: 0.0369
Epoch 6/1000
9199/9199 [==============================] - 45s 5ms/step - loss: 0.0031 -
mean_absolute_error: 0.0359 - val_loss: 0.0032 - val_mean_absolute_error: 0.0380
Epoch 7/1000
9199/9199 [==============================] - 45s 5ms/step - loss: 0.0030 -
mean_absolute_error: 0.0357 - val_loss: 0.0030 - val_mean_absolute_error: 0.0350
Epoch 8/1000
9199/9199 [==============================] - 45s 5ms/step - loss: 0.0030 -
mean_absolute_error: 0.0355 - val_loss: 0.0029 - val_mean_absolute_error: 0.0345
Epoch 9/1000
9199/9199 [==============================] - 45s 5ms/step - loss: 0.0030 -
mean_absolute_error: 0.0353 - val_loss: 0.0030 - val_mean_absolute_error: 0.0351
```

```
Epoch 10/1000
9199/9199 [==============================] - 46s 5ms/step - loss: 0.0030 -
mean_absolute_error: 0.0352 - val_loss: 0.0029 - val_mean_absolute_error: 0.0341
Epoch 11/1000
9199/9199 [==============================] - 47s 5ms/step - loss: 0.0029 -
mean_absolute_error: 0.0350 - val_loss: 0.0029 - val_mean_absolute_error: 0.0339
Epoch 12/1000
9199/9199 [==============================] - 45s 5ms/step - loss: 0.0029 -
mean_absolute_error: 0.0350 - val_loss: 0.0030 - val_mean_absolute_error: 0.0351
Epoch 13/1000
9199/9199 [==============================] - 45s 5ms/step - loss: 0.0029 -
mean_absolute_error: 0.0348 - val_loss: 0.0030 - val_mean_absolute_error: 0.0353
Epoch 14/1000
9199/9199 [==============================] - 44s 5ms/step - loss: 0.0029 -
mean_absolute_error: 0.0347 - val_loss: 0.0029 - val_mean_absolute_error: 0.0349
Epoch 15/1000
9199/9199 [==============================] - 44s 5ms/step - loss: 0.0029 -
mean_absolute_error: 0.0347 - val_loss: 0.0029 - val_mean_absolute_error: 0.0343
Epoch 16/1000
9199/9199 [==============================] - 45s 5ms/step - loss: 0.0029 -
mean_absolute_error: 0.0346 - val_loss: 0.0028 - val_mean_absolute_error: 0.0337
Epoch 17/1000
9199/9199 [==============================] - 53s 6ms/step - loss: 0.0029 -
mean_absolute_error: 0.0345 - val_loss: 0.0029 - val_mean_absolute_error: 0.0340
Epoch 18/1000
9199/9199 [==============================] - 45s 5ms/step - loss: 0.0029 -
mean_absolute_error: 0.0345 - val_loss: 0.0029 - val_mean_absolute_error: 0.0347
Epoch 19/1000
9199/9199 [==============================] - 44s 5ms/step - loss: 0.0028 -
mean_absolute_error: 0.0344 - val_loss: 0.0029 - val_mean_absolute_error: 0.0339
Epoch 20/1000
9199/9199 [==============================] - 44s 5ms/step - loss: 0.0028 -
mean_absolute_error: 0.0343 - val_loss: 0.0028 - val_mean_absolute_error: 0.0339
Epoch 21/1000
9199/9199 [==============================] - 45s 5ms/step - loss: 0.0028 -
mean_absolute_error: 0.0343 - val_loss: 0.0028 - val_mean_absolute_error: 0.0336
```

[ ]:
```
plot_res(lstm_history_multi, 0)
```



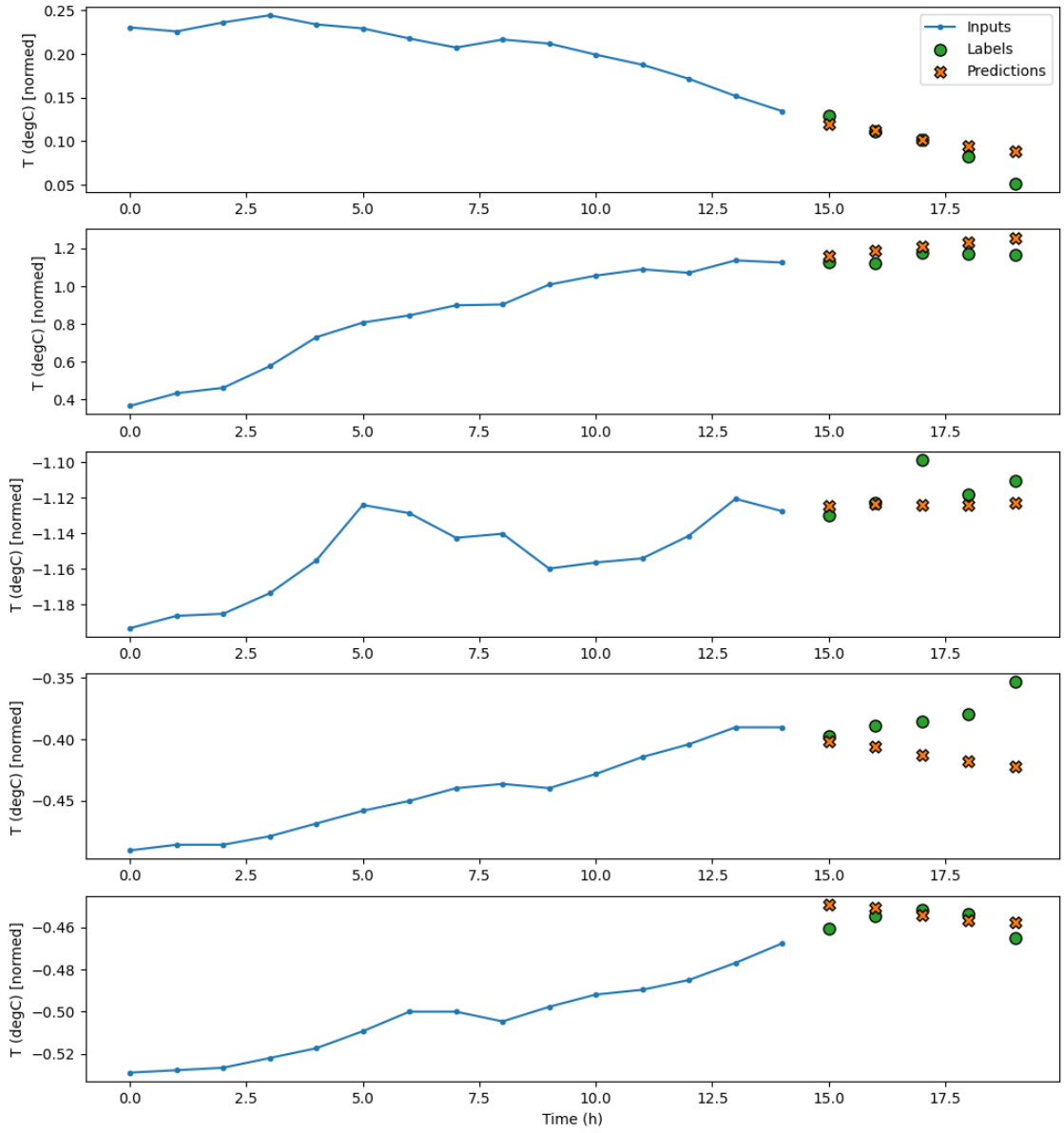
[ ]:
```
validation_perf_multi["lstm"] = lstm_model_multi.evaluate(window_multi.val)
```

```
2628/2628 [==============================] - 33s 13ms/step - loss: 0.0028 -
mean_absolute_error: 0.0336
```

[ ]:
```
performance_multi["lstm"] = evaluate_model(lstm_model_multi, window_multi)
```

```
1314/1314 [==============================] - 17s 13ms/step - loss: 0.0029 -
mean_absolute_error: 0.0348
Total loss = [0.0028848147485405207, 0.0347813256084919]
```

[ ]:
```
window_multi.plot(lstm_model_multi, max_subplots=5)
```

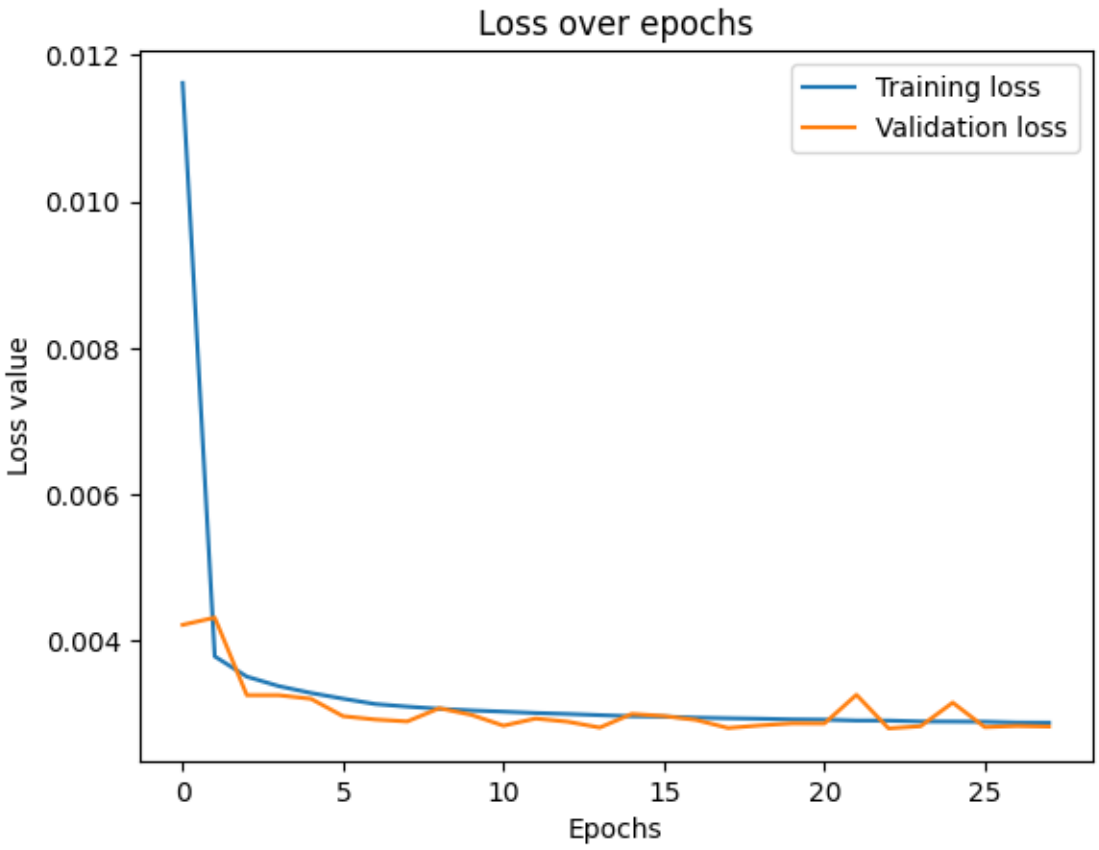


6.3 Transformer

[ ]:
```
transformer_model_multi = create_transformer((input_shapes[1],␣
↪input_shapes[2]), output_dim=label_shapes[1])
```

[ ]:
```
with tf.device('CPU'):
        transformer_history_multi = compile_and_fit(transformer_model_multi,␣
↪window_multi, patience=5)

save_transformer_model(transformer_model_multi, "transformer_model_multi")
```

[ ]:
```
plot_res(transformer_history_multi, 0)
```



[ ]:
```
validation_perf_multi["transformer"] = transformer_model_multi.
↪evaluate(window_multi.val)
```

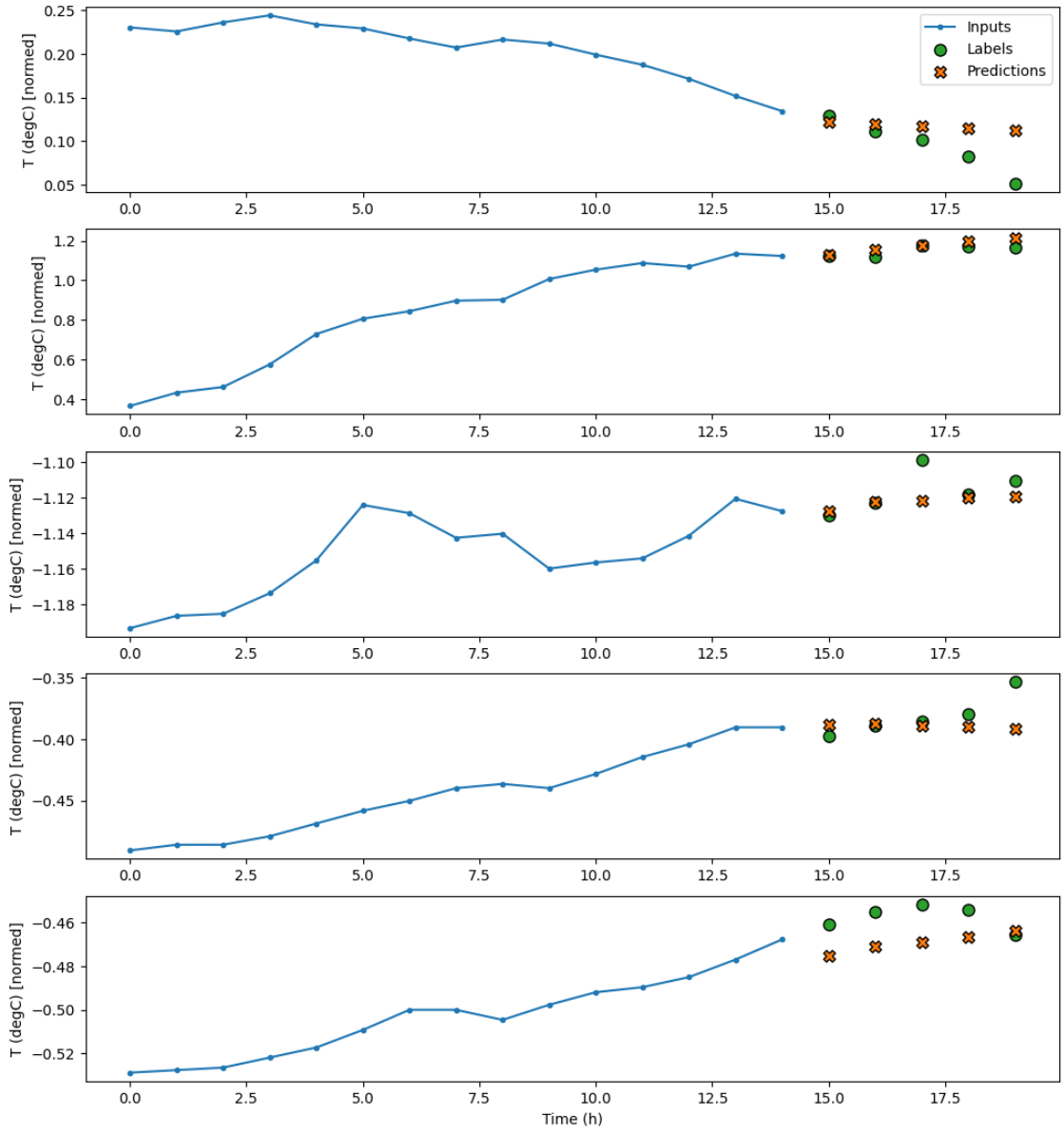
```
2628/2628 [==============================] - 52s 20ms/step - loss: 0.0028 -
mean_absolute_error: 0.0331
```

[ ]:
```
performance_multi["transformer"] = evaluate_model(transformer_model_multi,␣
↪window_multi)
```

```
1314/1314 [==============================] - 26s 19ms/step - loss: 0.0029 -
mean_absolute_error: 0.0346
Total loss = [0.002888784511014819, 0.0345788411796093]
```

[ ]:
```
window_multi.plot(transformer_model_multi, max_subplots=5)
```

```
2022-11-20 22:20:14.516731: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:114]
Plugin optimizer for device_type GPU is enabled.
```

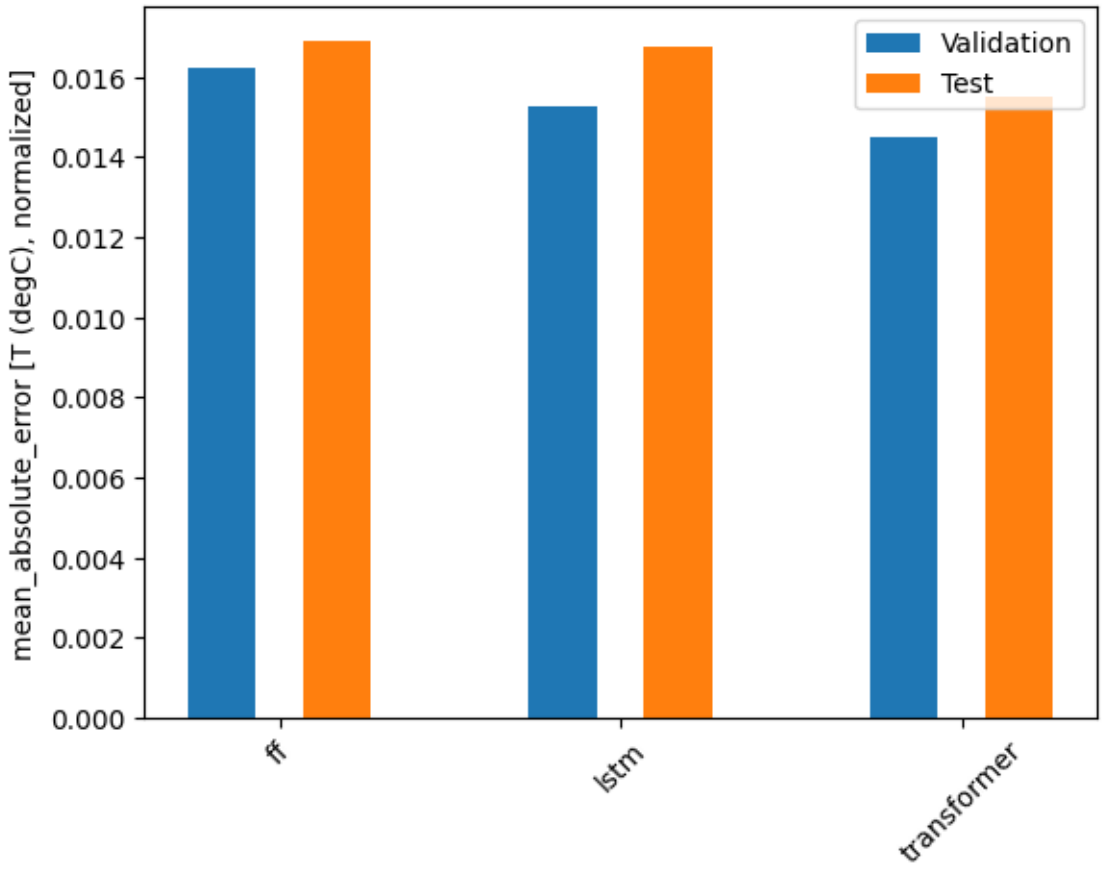


7 Performances

7.0.1 Single Output

[ ]:
```
performances = np.arange(len(performance))
width = 0.2
metric_name = "mean_absolute_error"
metric_index = lstm_model.metrics_names.index("mean_absolute_error")
val_mae = [v[metric_index] for v in validation_perf.values()]
test_mae = [v[metric_index] for v in performance.values()]
```

```
plt.ylabel("mean_absolute_error [T (degC), normalized]")
plt.bar(performances - 0.17, val_mae, width, label="Validation")
plt.bar(performances + 0.17, test_mae, width, label="Test")
plt.xticks(ticks=performances, labels=performance.keys(), rotation=45)
_ = plt.legend()
```



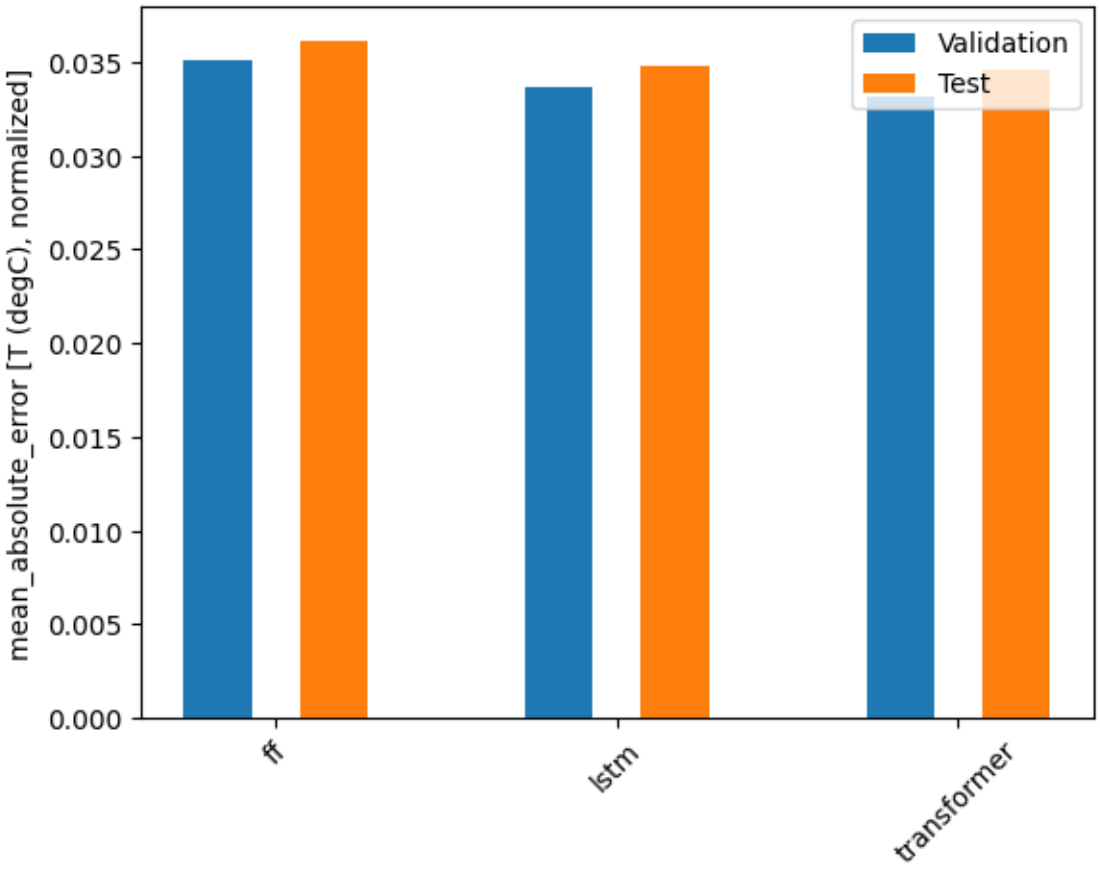
[ ]:
```
for key in performance.keys():
        print(f"\n---------------------- {key.upper()} ----------------------\n")
        print(f"Validation: {round(validation_perf[key][1], 5)}")
        print(f"Test: {round(performance[key][1], 5)}")
```

```
---------------------- FF ----------------------

Validation: 0.01621
Test: 0.0169

---------------------- LSTM ----------------------
```

```
Validation: 0.01527
Test: 0.01676

---------------------- TRANSFORMER ----------------------

Validation: 0.01449
Test: 0.01551
```

7.0.2 Multiple Outputs

[ ]:
```python
performances = np.arange(len(performance_multi))
width = 0.2
metric_name = "mean_absolute_error"
metric_index = lstm_model.metrics_names.index("mean_absolute_error")
val_mae = [v[metric_index] for v in validation_perf_multi.values()]
test_mae = [v[metric_index] for v in performance_multi.values()]

plt.ylabel("mean_absolute_error [T (degC), normalized]")
plt.bar(performances - 0.17, val_mae, width, label="Validation")
plt.bar(performances + 0.17, test_mae, width, label="Test")
plt.xticks(ticks=performances, labels=performance.keys(), rotation=45)
_ = plt.legend()
```




```
[ ]: for key in performance_multi.keys():
         print(f"\n---------------------- {key.upper()} ----------------------\n")
         print(f"Validation: {round(validation_perf_multi[key][1], 5)}")
         print(f"Test: {round(performance_multi[key][1], 5)}")
```

```
---------------------- FF ----------------------

Validation: 0.03508
Test: 0.0361

---------------------- LSTM ----------------------

Validation: 0.03364
Test: 0.03478

---------------------- TRANSFORMER ----------------------

Validation: 0.03313
Test: 0.03458
```