# Time series forecasting

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This is an introduction to time series forecasting using TensorFlow. It builds a few different styles of models including Convolutional and Recurrent Neural Networks (CNNs and RNNs).

This is covered in two main parts, with subsections:

- Forecast for a single timestep:
  - A single feature.
  - All features.
- Forecast multiple steps:
  - Single-shot: Make the predictions all at once.
  - Autoregressive: Make one prediction at a time and feed the output back to the model.

# Setup

```
import os
import datetime

import IPython
import IPython.display
import matplotlib as mpl
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import tensorflow as tf

mpl.rcParams['figure.figsize'] = (8, 6)
mpl.rcParams['axes.grid'] = False
```

# The weather dataset

This tutorial uses a weather time series dataset recorded by the Max Planck Institute for Biogeochemistry.

This dataset contains 14 different features such as air temperature, atmospheric pressure, and humidity. These were collected every 10 minutes, beginning in 2003. For efficiency, you will use only the data collected between 2009 and 2016. This section of the dataset was prepared by François Chollet for his book Deep Learning with Python.

```
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)
```

we will just deal with **hourly predictions**, so start by sub-sampling the data from 10 minute intervals to 1h:

```
df = pd.read_csv(csv_path)
# slice [start:stop:step], starting from index 5 take every 6th record.
df = df[5::6]

date_time = pd.to_datetime(df.pop('Date Time'), format='%d.%m.%Y %H:%M:%S')
```

Let's take a glance at the data. Here are the first few rows:

```
df.head()
```

Here is the evolution of a few features over time.

```
plot_cols = ['T (degC)', 'p (mbar)', 'rho (g/m**3)']
plot_features = df[plot_cols]
plot_features.index = date_time
plot_features.plot(subplots=True)

plot_features = df[plot_cols][:480]
plot_features.index = date_time[:480]
plot_features.plot(subplots=True)
```

## Inspect and cleanup

Next look at the statistics of the dataset:

```
df.describe().transpose()
```

## Wind velocity

One thing that should stand out is the `min` value of the wind velocity, `wv (m/s)` and `max. wv (m/s)` columns. This `-9999` is likely erroneous. There's a separate wind direction column, so the velocity should be `>=0`. Replace it with zeros:

```
wv = df['wv (m/s)']
bad_wv = wv == -9999.0
wv[bad_wv] = 0.0

max_wv = df['max. wv (m/s)']
bad_max_wv = max_wv == -9999.0
max_wv[bad_max_wv] = 0.0

# The above inplace edits are reflected in the DataFrame
df['wv (m/s)'].min()
```

## Feature engineering

Before diving in to build a model it's important to understand your data, and be sure that you're passing the model appropriately formatted data.

## Wind

The last column of the data, `wd (deg)`, gives the wind direction in units of degrees. Angles do not make good model inputs, 360° and 0° should be close to each other, and wrap around smoothly. Direction shouldn't matter if the wind is not blowing.

Right now the distribution of wind data looks like this:

```
plt.hist2d(df['wd (deg)'], df['wv (m/s)'], bins=(50, 50), vmax=400)
plt.colorbar()
plt.xlabel('Wind Direction [deg]')
plt.ylabel('Wind Velocity [m/s]')
```

But this will be easier for the model to interpret if you convert the wind direction and velocity columns to a wind **vector**:

```
df.columns
```

```
wv = df.pop('wv (m/s)')
max_wv = df.pop('max. wv (m/s)')

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

# Calculate the wind x and y components.
df['Wx'] = wv*np.cos(wd_rad)
df['Wy'] = wv*np.sin(wd_rad)

# Calculate the max wind x and y components.
df['max Wx'] = max_wv*np.cos(wd_rad)
df['max Wy'] = max_wv*np.sin(wd_rad)
```

The distribution of wind vectors is much simpler for the model to correctly interpret.

```
plt.hist2d(df['Wx'], df['Wy'], bins=(50, 50), vmax=400)
plt.colorbar()
plt.xlabel('Wind X [m/s]')
plt.ylabel('Wind Y [m/s]')
ax = plt.gca()
ax.axis('tight')
```

## Time

Similarly the `Date Time` column is very useful, but not in this string form. Start by converting it to seconds:

```
timestamp_s = date_time.map(datetime.datetime.timestamp)
```

Similar to the wind direction the time in seconds is not a useful model input. Being weather data it has clear daily and yearly periodicity. There are many ways you could deal with periodicity.

A simple approach to convert it to a usable signal is to use `sin` and `cos` to convert the time to clear "Time of day" and "Time of year" signals:

```
day = 24*60*60
year = (365.2425)*day

df['Day sin'] = np.sin(timestamp_s * (2 * np.pi / day))
df['Day cos'] = np.cos(timestamp_s * (2 * np.pi / day))
df['Year sin'] = np.sin(timestamp_s * (2 * np.pi / year))
df['Year cos'] = np.cos(timestamp_s * (2 * np.pi / year))
```

```
plt.plot(np.array(df['Day sin'])[:25])
plt.plot(np.array(df['Day cos'])[:25])
plt.xlabel('Time [h]')
plt.title('Time of day signal')
```

This gives the model access to the most important frequency features. In this case we knew ahead of time which frequencies were important.

If you didn't know, you can determine which frequencies are important using an `fft`. To check our assumptions, here is the `tf.signal.rfft` of the temperature over time. Note the obvious peaks at frequencies near `1/year` and `1/day`:

```
fft = tf.signal.rfft(df['T (degC)'])
f_per_dataset = np.arange(0, len(fft))

n_samples_h = len(df['T (degC)'])
hours_per_year = 24*365.2524
years_per_dataset = n_samples_h/(hours_per_year)

f_per_year = f_per_dataset/years_per_dataset
plt.step(f_per_year, np.abs(fft))
plt.xscale('log')
plt.ylim(0, 400000)
plt.xlim([0.1, max(plt.xlim())])
plt.xticks([1, 365.2524], labels=['1/Year', '1/day'])
_ = plt.xlabel('Frequency (log scale)')
```

## Split the data

We'll use a `(70%, 20%, 10%)` split for the training, validation, and test sets. Note the data is **not** being randomly shuffled before splitting. This is for two reasons.

1. It ensures that chopping the data into windows of consecutive samples is still possible.
2. It ensures that the validation/test results are more realistic, being evaluated on data collected after the model was trained.

```
column_indices = {name: i for i, name in enumerate(df.columns)}

n = len(df)
train_df = df[0:int(n*0.7)]
val_df = df[int(n*0.7):int(n*0.9)]
```

```
test_df = df[int(n*0.9):]

num_features = df.shape[1]
```

## Normalize the data

It is important to scale features before training a neural network. Normalization is a common way of doing this scaling. Subtract the mean and divide by the standard deviation of each feature.

The mean and standard deviation should only be computed using the training data so that the models have no access to the values in the validation and test sets.

It's also arguable that the model shouldn't have access to future values in the training set when training, and that this normalization should be done using moving averages. That's not the focus of this tutorial, and the validation and test sets ensure that we get (somewhat) honest metrics. So in the interest of simplicity this tutorial uses a simple average.

```
train_mean = train_df.mean()
train_std = train_df.std()

train_df = (train_df - train_mean) / train_std
val_df = (val_df - train_mean) / train_std
test_df = (test_df - train_mean) / train_std
```

Now peek at the distribution of the features. Some features do have long tails, but there are no obvious errors like the `-9999` wind velocity value.

```
df_std = (df - train_mean) / train_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=90)
```

## Data windowing

The models in this tutorial will make a set of predictions based on a window of consecutive samples from the data.

The main features of the input windows are:

- The width (number of time steps) of the input and label windows
- The time offset between them.
- Which features are used as inputs, labels, or both.

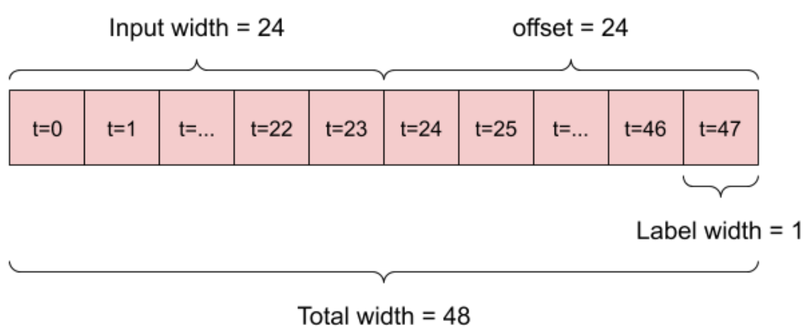
This tutorial builds a variety of models (including Linear, DNN, CNN and RNN models), and uses them for both:

- *Single-output*, and *multi-output* predictions.
- *Single-time-step* and *multi-time-step* predictions.

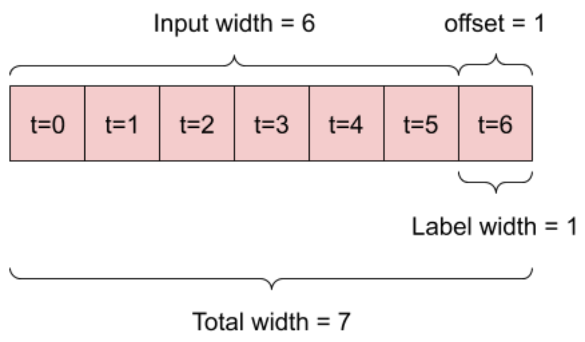
This section focuses on implementing the data windowing so that it can be reused for all of those models.

Depending on the task and type of model you may want to generate a variety of data windows. Here are some examples:

1. For example, to make a single prediction 24h into the future, given 24h of history you might define a window like this:




2. A model that makes a prediction 1h into the future, given 6h of history would need a window like this:




The rest of this section defines a `WindowGenerator` class. This class can:

1. Handle the indexes and offsets as shown in the diagrams above.
2. Split windows of features into a `(features, labels)` pairs.
3. Plot the content of the resulting windows.
4. Efficiently generate batches of these windows from the training, evaluation, and test data, using `tf.data.Dataset` s.

## 1. Indexes and offsets

Start by creating the `WindowGenerator` class. The `__init__` method includes all the necessary logic for the input and label indices.

It also takes the train, eval, and test dataframes as input. These will be converted to `tf.data.Dataset` s of windows later.

```
class WindowGenerator():
  def __init__(self, input_width, label_width, shift,
               train_df=train_df, val_df=val_df, test_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.labels_slice = slice(self.label_start, None)
    self.label_indices = np.arange(self.total_window_size)[self.labels_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}'])
```

Here is code to create the 2 windows shown in the diagrams at the start of this section:

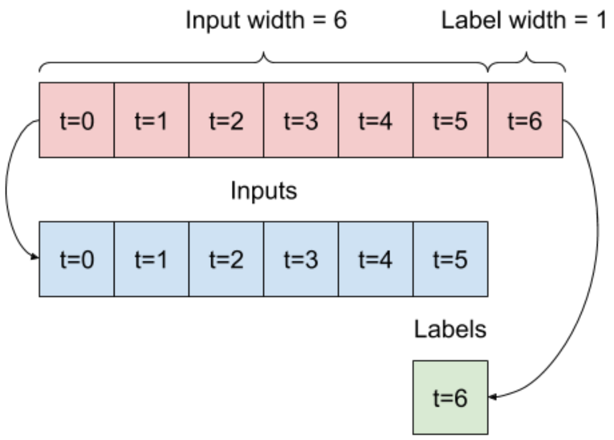
```
w1 = WindowGenerator(input_width=24, label_width=1, shift=24,
                     label_columns=['T (degC)'])
w1
```

```
w2 = WindowGenerator(input_width=6, label_width=1, shift=1,
                     label_columns=['T (degC)'])
w2
```

## 2. Split

Given a list consecutive inputs, the `split_window` method will convert them to a window of inputs and a window of labels.

The example `w2`, above, will be split like this:




This diagram doesn't show the `features` axis of the data, but this `split_window` function also handles the `label_columns` so it can be used for both the single output and multi-output examples.

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

WindowGenerator.split_window = split_window
```

## 4. Create `tf.data.Dataset`s

Finally this `make_dataset` method will take a time series `DataFrame` and convert it to a `tf.data.Dataset` of `(input_window, label_window)` pairs using the `preprocessing.timeseries_dataset_from_array` function.

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

  ds = ds.map(self.split_window)

  return ds

WindowGenerator.make_dataset = make_dataset
```

The `WindowGenerator` object holds training, validation and test data. Add properties for accessing them as `tf.data.Datasets` using the above `make_dataset` method. Also add a standard example batch for easy access and plotting:

```
@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 next time
    self._example = result
  return result

WindowGenerator.train = train
WindowGenerator.val = val
WindowGenerator.test = test
WindowGenerator.example = example
```

Now the `WindowGenerator` object gives you access to the `tf.data.Dataset` objects, so you can easily iterate over the data.

The `Dataset.element_spec` property tells you the structure, `dtypes` and shapes of the dataset elements.

```
# Each element is an (inputs, label) pair
w2.train.element_spec
```

Iterating over a `Dataset` yields concrete batches:

```
for example_inputs, example_labels in w2.train.take(1):
  print(f'Inputs shape (batch, time, features): {example_inputs.shape}')
  print(f'Labels shape (batch, time, features): {example_labels.shape}')
```

## Single step models

The simplest model you can build on this sort of data is one that predicts a single feature's value, 1 timestep (1h) in the future based only on the current conditions.

So start by building models to predict the `T (degC)` value 1h into the future.

Predict the next time step

Configure a `WindowGenerator` object to produce these single-step `(input, label)` pairs:

```
single_step_window = WindowGenerator(
    input_width=1, label_width=1, shift=1,
    label_columns=['T (degC)'])
single_step_window
```

The `window` object creates `tf.data.Datasets` from the training, validation, and test sets, allowing you to easily iterate over batches of data.

```
for example_inputs, example_labels in single_step_window.train.take(1):
  print(f'Inputs shape (batch, time, features): {example_inputs.shape}')
  print(f'Labels shape (batch, time, features): {example_labels.shape}')
```

## Linear model

The simplest **trainable** model you can apply to this task is to insert linear transformation between the input and output. In this case the output from a time step only depends on that step:

A single step prediction

A `layers.Dense` with no `activation` set is a linear model. The layer only transforms the last axis of the data from `(batch, time, inputs)` to `(batch, time, units)`, it is applied independently to every item across the `batch` and `time` axes.

```
linear = tf.keras.Sequential([
    tf.keras.layers.Dense(units=1)
])
```

```
print('Input shape:', single_step_window.example[0].shape)
print('Output shape:', linear(single_step_window.example[0]).shape)
```

This tutorial trains many models, so package the training procedure into a function:

```
MAX_EPOCHS = 20

def compile_and_fit(model, window, patience=2):
  early_stopping = tf.keras.callbacks.EarlyStopping(monitor='val_loss',
                                                    patience=patience,
                                                    mode='min')

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

  history = model.fit(window.train, epochs=MAX_EPOCHS,
                      validation_data=window.val,
                      callbacks=[early_stopping])
  return history
```

Train the model and evaluate its performance:

```
history = compile_and_fit(linear, single_step_window)

linear.evaluate(single_step_window.val)
linear.evaluate(single_step_window.test, verbose=0)
```

One advantage to linear models is that they're relatively simple to interpret. You can pull out the layer's weights, and see the weight assigned to each input:

```
plt.bar(x = range(len(train_df.columns)),
        height=linear.layers[0].kernel[:,0].numpy())
axis = plt.gca()
axis.set_xticks(range(len(train_df.columns)))
_ = axis.set_xticklabels(train_df.columns, rotation=90)
```

Sometimes the model doesn't even place the most weight on the input `T (degC)`. This is one of the risks of random initialization.

## Dense

Before applying models that actually operate on multiple time-steps, it's worth checking the performance of deeper, more powerful, single input step models.

Here's a model similar to the `linear` model, except it stacks several a few `Dense` layers between the input and the output:

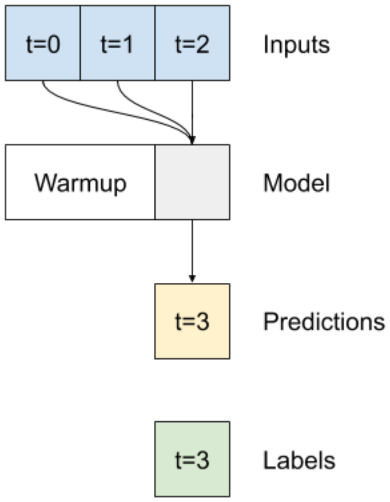
```
dense = tf.keras.Sequential([
    tf.keras.layers.Dense(units=64, activation='relu'),
    tf.keras.layers.Dense(units=64, activation='relu'),
    tf.keras.layers.Dense(units=1)
])

history = compile_and_fit(dense, single_step_window)

val_performance['Dense'] = dense.evaluate(single_step_window.val)
performance['Dense'] = dense.evaluate(single_step_window.test, verbose=0)
```

## Multi-step dense

A single-time-step model has no context for the current values of its inputs. It can't see how the input features are changing over time. To address this issue the model needs access to multiple time steps when making predictions:




The `baseline`, `linear` and `dense` models handled each time step independently. Here the model will take multiple time steps as input to produce a single output.

Create a `WindowGenerator` that will produce batches of the 3h of inputs and, 1h of labels:

Note that the `Window`'s `shift` parameter is relative to the end of the two windows.

```
CONV_WIDTH = 3
conv_window = WindowGenerator(
    input_width=CONV_WIDTH,
    label_width=1,
    shift=1,
    label_columns=['T (degC)'])

conv_window
```

You could train a `dense` model on a multiple-input-step window by adding a `layers.Flatten` as the first layer of the model:

```
multi_step_dense = tf.keras.Sequential([
    # Shape: (time, features) => (time*features)
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(units=32, activation='relu'),
    tf.keras.layers.Dense(units=32, activation='relu'),
    tf.keras.layers.Dense(units=1),
    # Add back the time dimension.
    # Shape: (outputs) => (1, outputs)
    tf.keras.layers.Reshape([1, -1]),
])

history = compile_and_fit(multi_step_dense, conv_window)

IPython.display.clear_output()
multi_step_dense.evaluate(conv_window.val)
multi_step_dense.evaluate(conv_window.test, verbose=0)
```