Missing Data in Time Series

Traffic Data, Again

Say we are contacted from a local transportation authority

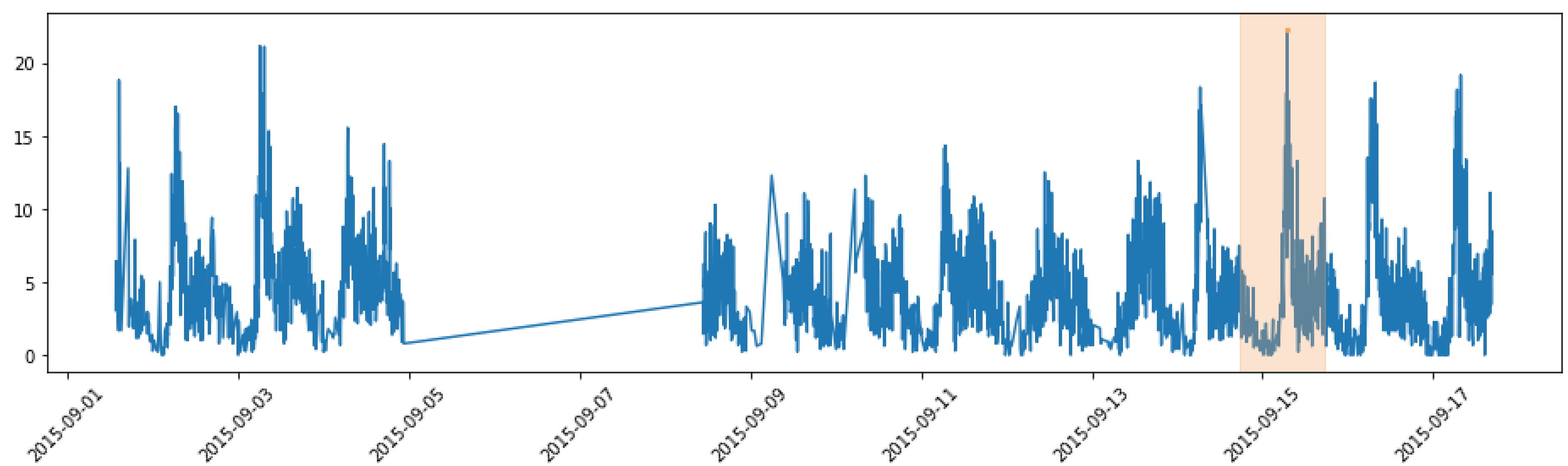
They want to improve their traffic monitoring system

Traffic Data, Again

They give us data from an occupancy sensor

Our data refers to real traffic in the Minnesota Twin Cities Area

```
In [4]: nab.plot_series(data, labels, windows, figsize=figsize)
```

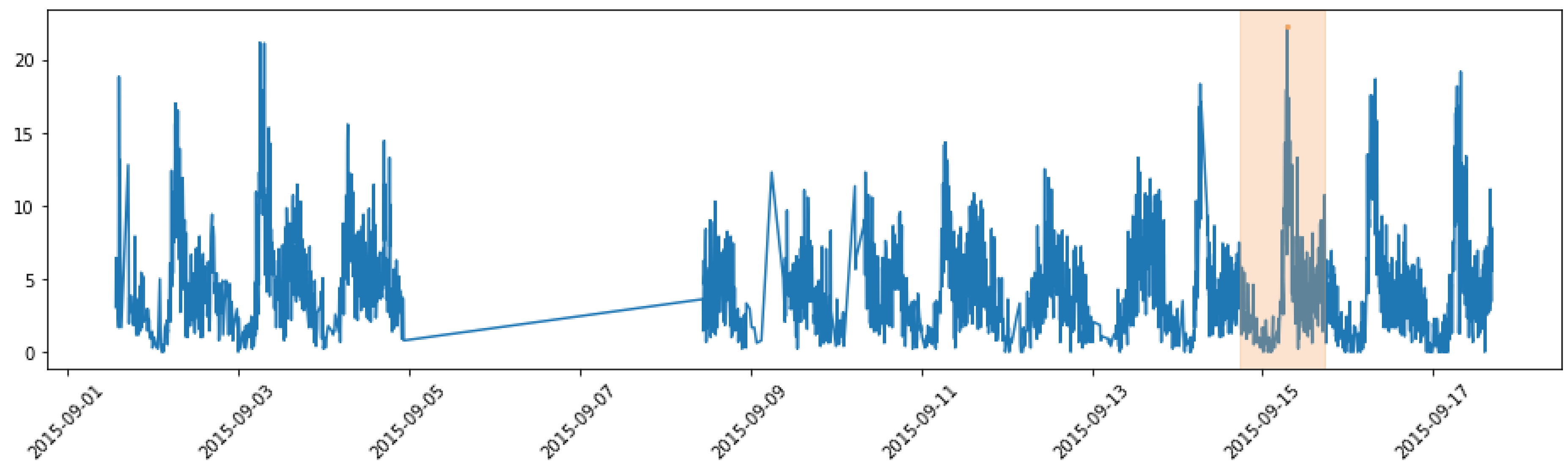


- They have pre-labeled an (easy) anomaly that they wish to detect
- ...But that is not the most striking aspect of this series

Traffic Data, Again

There is a period, and straight lines in the plot

```
In [6]: nab.plot_series(data, labels, windows, figsize=figsize)
```

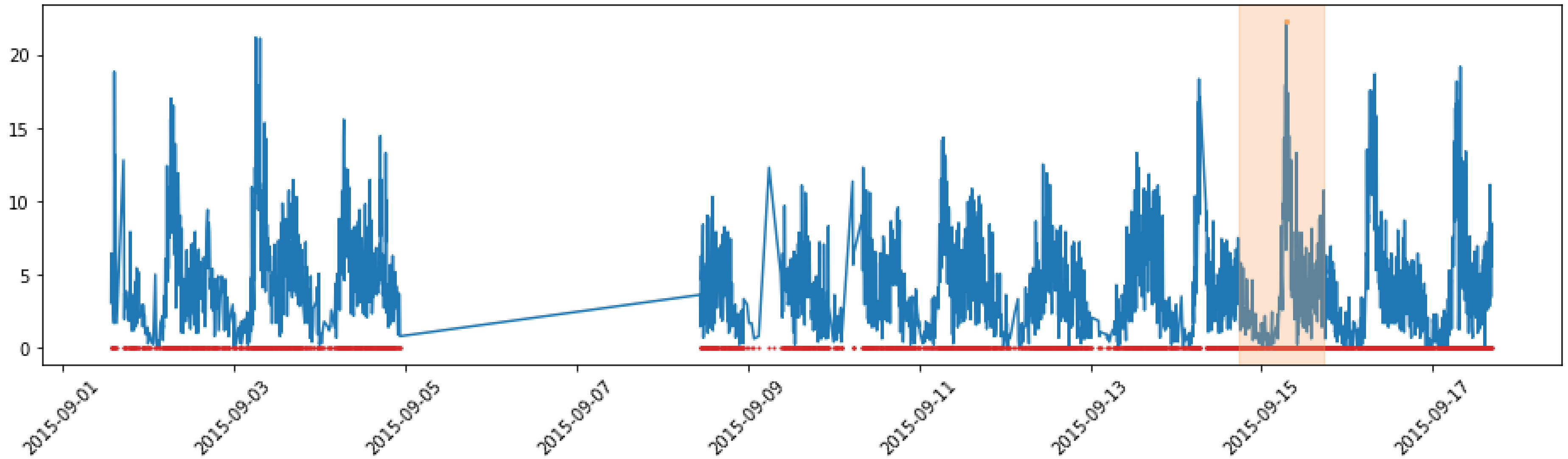


They are artefacts, due to missing values in the time series

Missing Values

We can make it clearer by explicitly plotting the sampling points

In [8]:
```
nab.plot_series(data, labels, windows, show_sampling_points=True, figsize=figsize)
```



There is a large gap, plus scattered missing values here and there

Missing Values in Time Series

Missing values in real-world time series are very common

They arise for a variety of reasons:

- Malfunctioning sensors
- Network problems
- Lost data
- Sensor maintenance/installation/removal
- ...

...And can be very annoying to deal with

- They prevent the application of sliding windows
- They complicate the detection of periods
- ...

Preparing the Ground

Preparing the Ground

Before we can deal with missing values we need to tackle an issue

I.e. our main series has a sparse index

- ...Meaning that index values are non-contiguous
- ...And missing values are represented as gaps

If we want to fill the missing values...

- ...We need to decide where the missing values are

In other words, we need a dense (temporal) index

With a dense index:

- Missing values can be represented as NaN (Not a Number)
- ...And can be filled by replacing NaN with a meaningful value

Choosing a Sampling Frequency

First, we need to pick a frequency for the new index

We start by having a look at the typical sampling step in our series:

In [9]:
```
data.head()
```

Out[9]:

	value
timestamp	
2015-09-01 13:45:00	3.06
2015-09-01 13:50:00	6.44
2015-09-01 13:55:00	5.17
2015-09-01 14:00:00	3.83
2015-09-01 14:05:00	4.50

- The interval between consecutive measurements seems to be 5 minute long
- ...But looking at just a few data points is not enough

Choosing a Sampling Frequency

It is much better to compute the distance between consecutive index values

```
In [10]: delta = data.index[1:] - data.index[:-1]
         delta[:3]

Out[10]: TimedeltaIndex(['0 days 00:05:00', '0 days 00:05:00', '0 days 00:05:00'], dtype='timedelta64[n
         s]', name='timestamp', freq=None)
```

- The difference between two `datetime` objects is a `timedelta` object
- They are all parts of [the `datetime` module]

Then we can check the value counts

- This can be done with the `value_counts` method

The methods returns a series:

- The index contains values
- The series data are the corresponding counts

Choosing a Sampling Frequency

Let's have a look at our value counts

In [11]:
```
vc = pd.Series(delta).value_counts()
vc.iloc[:10]
```

Out[11]:
```
0 days 00:05:00    1754
0 days 00:10:00     340
0 days 00:15:00     106
0 days 00:20:00      37
0 days 00:04:00      26
0 days 00:25:00      22
0 days 00:06:00      18
0 days 00:30:00       9
0 days 00:35:00       8
0 days 00:11:00       7
Name: timestamp, dtype: int64
```

By far the most common value is 5 minutes

- Some values are not multiples of 5 minutes (e.g. 4, 6, 11 minutes)
- I.e. they are out of alignment

Resampling the Original Dataset

Therefore, first we need to realign the original index

This is also called resampling (or binning), and can be done in pandas with:

```
DatetimeIndex.resample(rule=None, ...)
```

- `rule` specifies the length of each individual interval (or "bin")
- The method has many additional options to control its behavior

*Resample is an iterator: we need to choose what to do with each bin *

E.g. compute the mean, stdev, take the first value

```
In [12]: ddata = data.resample('5min').mean()
         ddata.head()
```

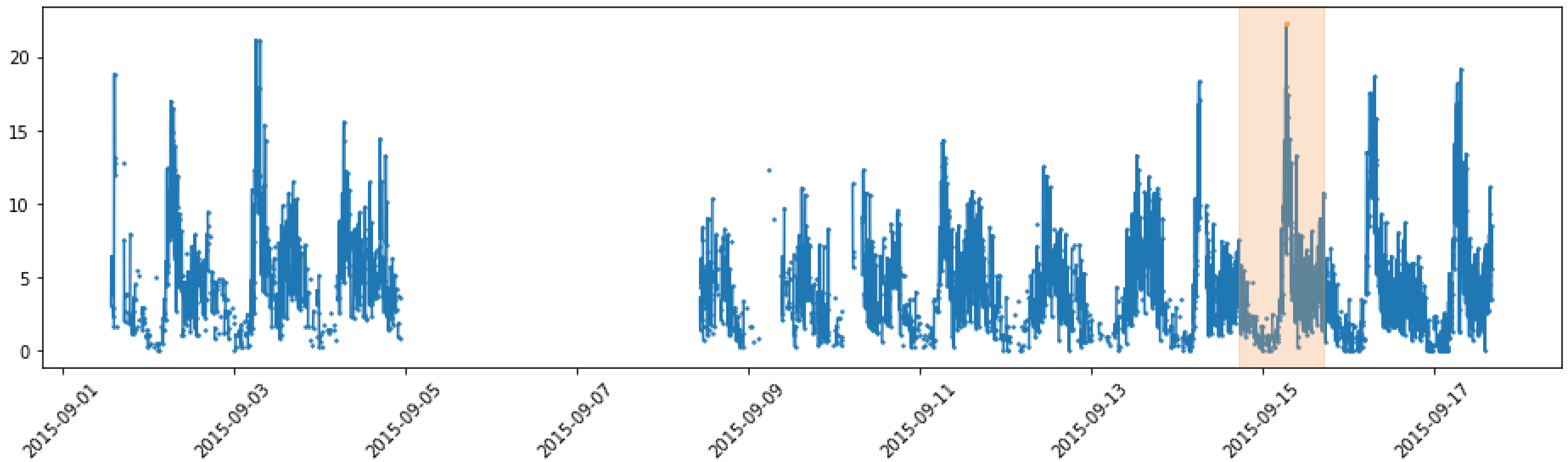
Out[12]:

timestamp	value
2015-09-01 13:45:00	3.06
2015-09-01 13:50:00	6.44
2015-09-01 13:55:00	5.17
2015-09-01 14:00:00	3.83

Inspecting the Resampled Dataset

Now we can inspect this new "dense" series

In [13]:
```
nab.plot_series(ddata, labels, windows, show_markers=True, figsize=figsize)
```



- The artifacts have disappeared!
- ...And the true extent of our problem becomes apparent :-)

Considerations

Some considerations and take-home messages

Missing values are extremely common in real world data

- Time series are no exception

Missing values are particularly problematic with time series

- Mostly, they prevent the application of a (classical) sliding window
- ...Though some forms of sliding windows are still fine

Realigning a time series can be useful in many context

- E.g. data from sensors with misaligned clocks
- E.g. data from sensors with different sampling frequencies
    - This case is however a bit more complicated