Problem and Data

Anomaly Detection on Taxi Calls

We are contacted by a Taxi company:

Anomaly Detection on Taxi Calls

They have historical data about taxi calls in NYC

- In particular, they recorded the number of calls
- ...Over regular time intervals

A major decision for the company is choosing the size of the car pool

- This depends on how many calls are expected
- ...So, we'd like to figure that out

Moreover, sometimes the number of calls deviates from the usual patterns

- The company is interested in detecting such "anomalies"
- ...And anticipating them, if possible

We will focus on the task of detecting anomalies

How would you start to tackle this problem?

Getting Started

A couple of good ideas:

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- Formally: until we understand better its statistical distribution

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- Formally: until we understand better its statistical distribution

Doing both these things early is always a good idea

Basic Setup

Let us start by setting up the notebook:

In [1]:
```
%load_ext autoreload
%autoreload 2
#%matplotlib widget
```

Our module contains a pre-built function to load the data:

```
def load_series(file_name, data_folder):
    ...
```

- We will use data from the Numenta Anomaly Benchmark (NAB)
- NYC taxi data `nyc_taxi.csv` is in the `data/realKnownCause` folder

In [2]:
```
from util import util # Import our submodule
data_folder = '../data/nab'
file_name = 'realKnownCause/nyc_taxi.csv'
data, labels, windows = util.load_series(file_name, data_folder)
```

A Look at the Data

Let's have a look at all the data we loaded

```
In [3]: data.head()
```

Out[3]:

	value
timestamp	
2014-07-01 00:00:00	10844
2014-07-01 00:30:00	8127
2014-07-01 01:00:00	6210
2014-07-01 01:30:00	4656
2014-07-01 02:00:00	3820

- `data` is a pandas `DataFrame` object
- It is essentially a table, in this case representing a time series
- There are well defined column names (here "value")
- There is a well defined row index (here "timestamp")
- Jupyter displays DataFrame objects as HTML tables

Time Series and Pandas

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I.e. a sequence whose index represents time

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Times series have one difference w.r.t. classical table datasets

- ...I.e. their row index is meaningful
- Since it represents the position of the example in the sequence

That said, we do not care about how time is represented

- Hence, time series are stored just as usual!
- Their peculiarities arise when we start to manipulate them

Time Series and Pandas

In pandas:

- Time series are stored as usual, via `DataFrame` or `Series` objects
- ...You just need to pay more attention to the index

It *may* be convenient using a `datetime` index

- A `datetime` object in python allows to manipulate dates/hours directly
  - E.g. get year/month/day/hour/minute...
- In pandas they can be used as indices, so that for example:
  - Time stamps are easier to read
  - We can sort rows by time
  - We can represent arbitrarily long gaps between measurements
  - ...

That said, we still deal with normal `DataFrame` or `Series` objects

A Look at the Data

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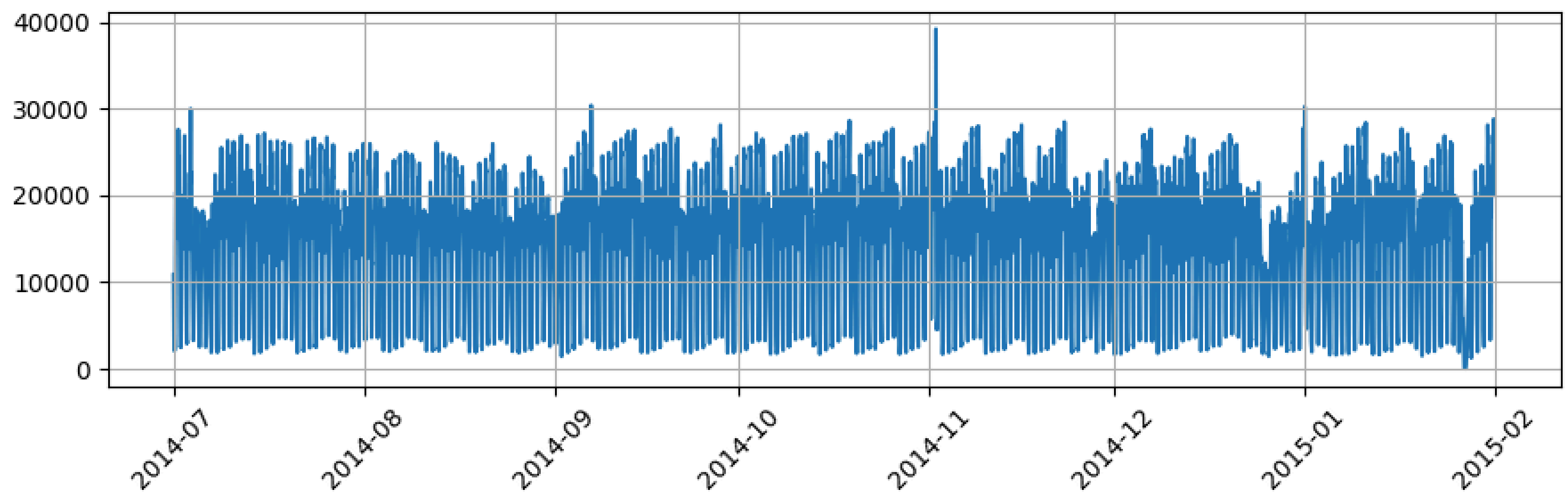
Our module contains a function to plot NAB series:

In [4]:
```
util.plot_series(data)
```



- If are curious, you can look up the function code in the module

A Look at the Data

Let's have a look at all the data we loaded

We can now move to other data structures

```
In [5]: labels.head()

Out[5]: 0   2014-11-01 19:00:00
        1   2014-11-27 15:30:00
        2   2014-12-25 15:00:00
        3   2015-01-01 01:00:00
        4   2015-01-27 00:00:00
        dtype: datetime64[ns]
```

`labels` is a pandas `Series` object

- Similar to a 1D array
- ...But with a well defined row index

This series contains the timestamp of all known anomalies

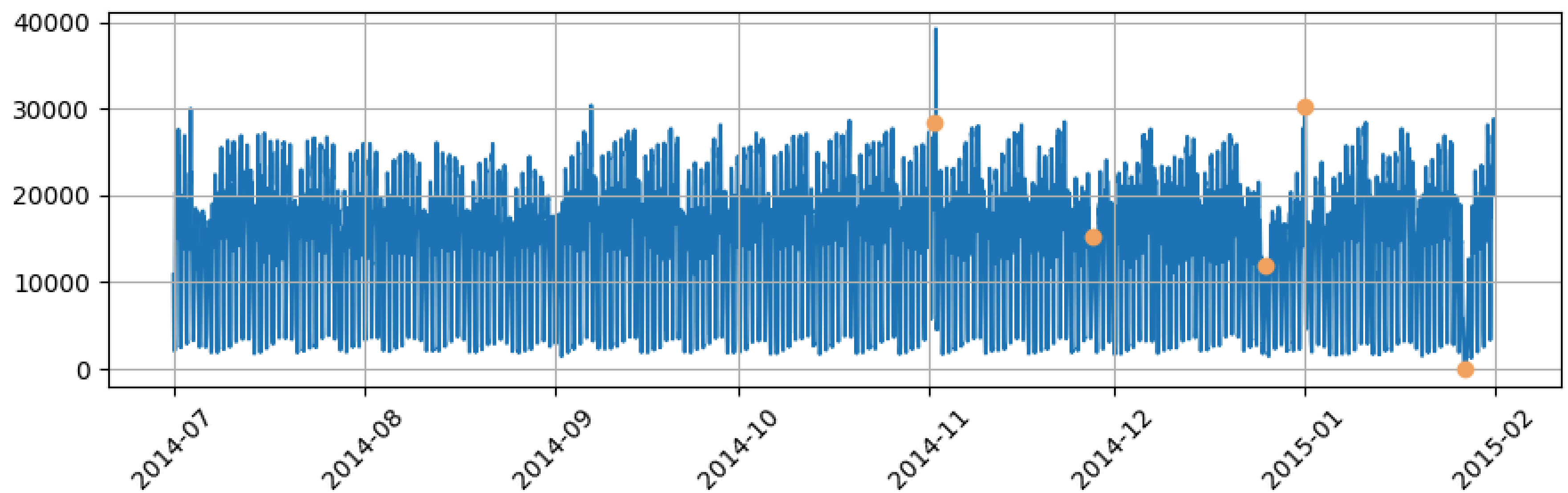
- They are all hand-labeled

A Look at the Data

Let's have a look at all the data we loaded

Let's plot both the series and the labels:

In [6]:
```
util.plot_series(data, labels)
```



- Anomalies occur rarely (which is typical for this kind of problem)

A Look at the Data

Let's have a look at all the data we loaded

Now the "windows" data structure:

In [7]:
```
windows.head()
```

Out[7]:

	begin	end
0	2014-10-30 15:30:00	2014-11-03 22:30:00
1	2014-11-25 12:00:00	2014-11-29 19:00:00
2	2014-12-23 11:30:00	2014-12-27 18:30:00
3	2014-12-29 21:30:00	2015-01-03 04:30:00
4	2015-01-24 20:30:00	2015-01-29 03:30:00

`windows` is a pandas `DataFrame` object

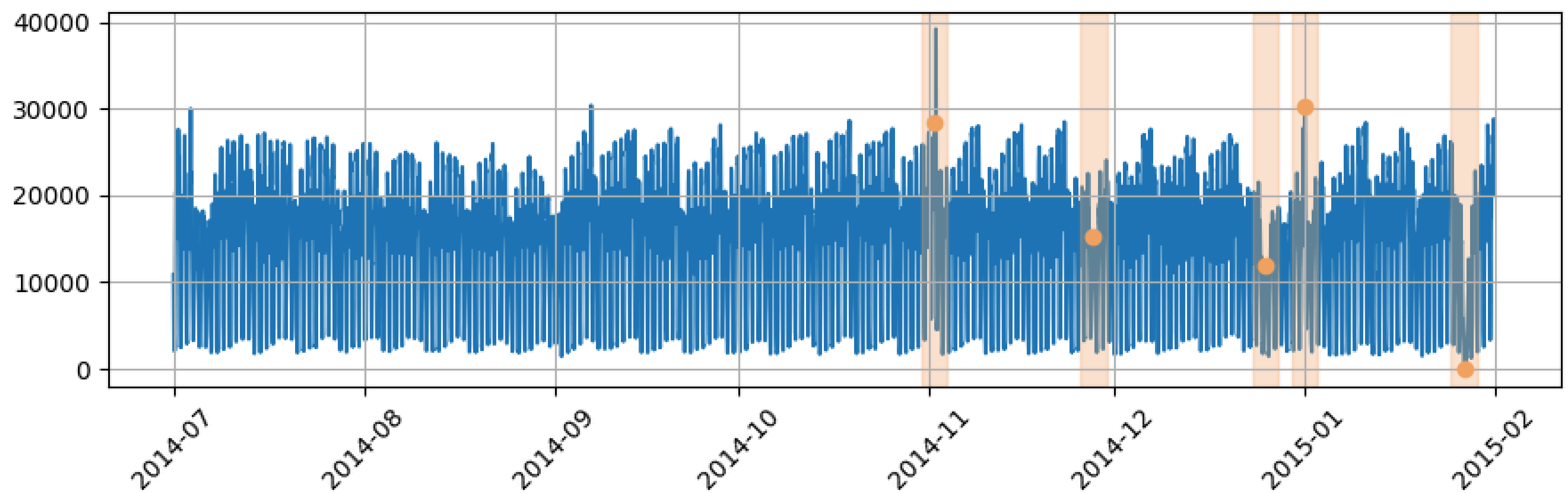
- Contains the start/end of windows containing anomalies
- They represent a suitable "resolution" for detecting anomalies
- Reporting the presence of anomalies at any point of the window...
- ...Has some value for the company

A Look at the Data

Let's have a look at all the data we loaded

Let's plot the series, the labels, and the windows all together:

```
In [8]: util.plot_series(data, labels, windows)
```



- Detections that occur too early/late count as misses