# 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:**

*Talking to the customer* to understand:

- Their priorities
- How their business works
- Any expectation on the data
- ...

...And also *inspecting the data*

- ...So that we get a "feel" of how it works
- 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
```

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

Out[5]:

| | value |
|---|---|
| **timestamp** | |
| **2014-07-01 00:00:00** | 10844.0 |
| **2014-07-01 00:30:00** | 8127.0 |
| **2014-07-01 01:00:00** | 6210.0 |
| **2014-07-01 01:30:00** | 4656.0 |
| **2014-07-01 02:00:00** | 3820.0 |

- `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

**Our data is a *time series***

I.e. a sequence whose index represents time

- Specifically, we have a *univariate* time series...
- ...Since we are tracking only quantity (i.e. one variable)

**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
  - ...

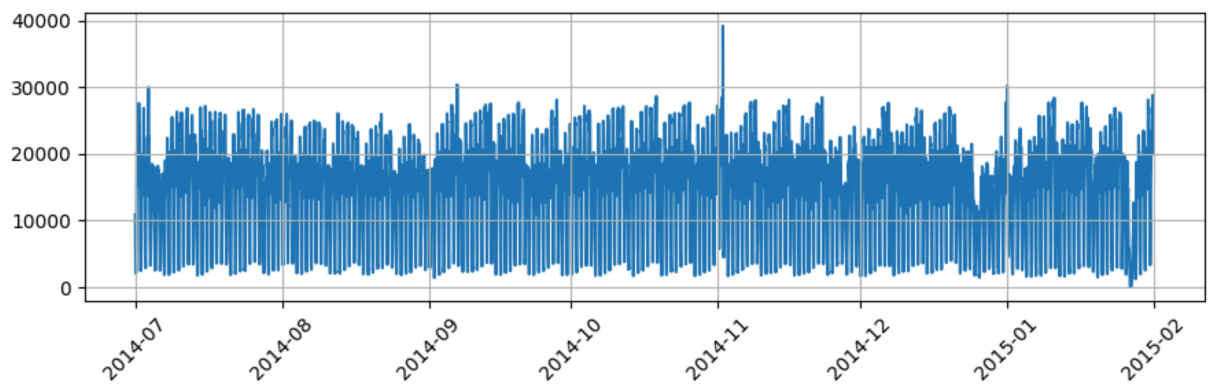
That said, we still deal with normal `DataFrame` or `Series` objects

# A Look at the Data

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

Our module contains a function to plot NAB series:

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




# 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 [7]:
```
labels.head()
```

Out[7]:
```
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***

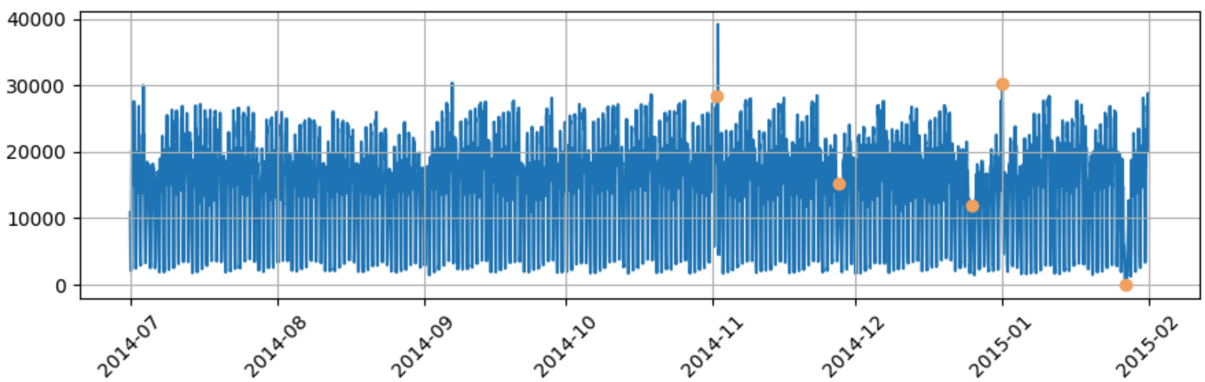
- They are all hand-labeled

# 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 [8]:
```
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 [9]:
```
windows.head()
```

Out[9]:

| | 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

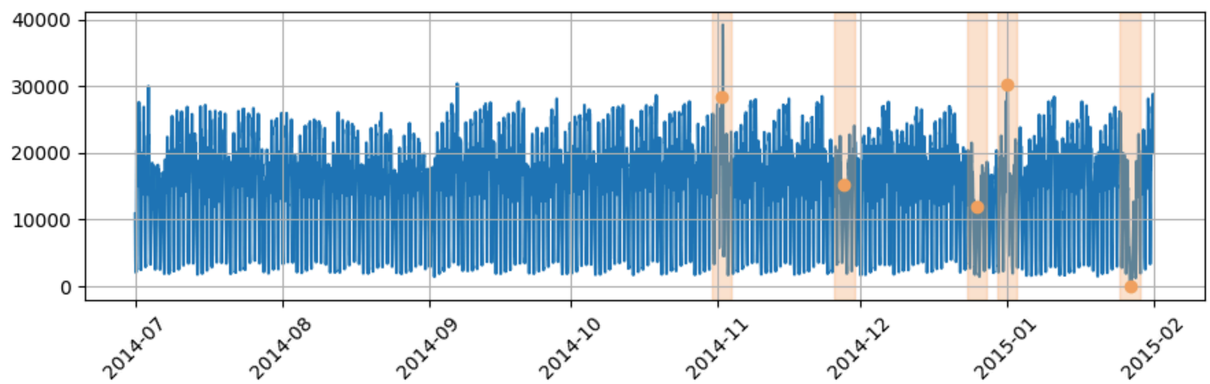
- They represent a suitable "resolution" for detecting anomalies
- Reporting the presence of anomalies at any point of the window...
- ...Has some value for the company

# 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 [10]:
```
util.plot_series(data, labels, windows)
```




- Detections that occur too early/late count as misses