Problem and Data

Anomaly Detection on Taxi Calls

We are contacted by a Taxi company:

Anomaly Detection on Taxi Calls

We are contacted by a Taxi company:

- They have historical data about taxi calls in NYC
- They are interested in detecting "abnormal situations" (so called anomalies)

Goals:

- Analyze anomalies (e.g. better size the fleet)
- Anticipate anomalies (so we can prepare)

Typically referred to as anomaly detection:

- An important industrial problem
- Many context and possible applications

Loading the Data

In [44]:
```
data_folder = os.path.join('data', 'nab')
file_name = os.path.join('realKnownCause', 'nyc_taxi.csv')
data, labels, windows = util.load_taxi_series(file_name, data_folder)
data.head()
```

Out[44]:

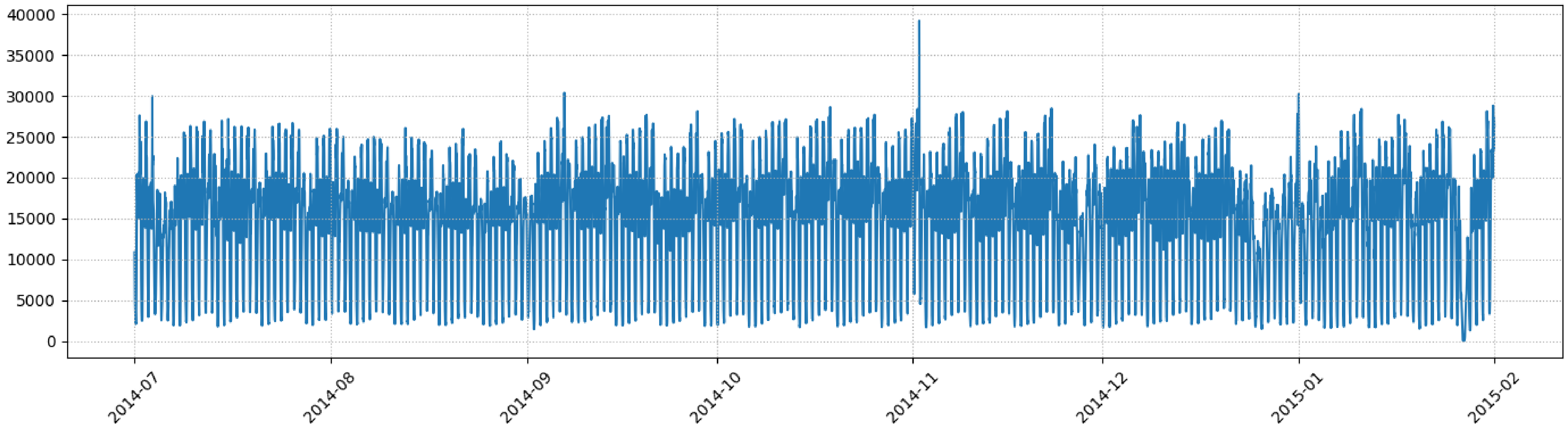
	value
timestamp	
2014-07-01 00:00:00	10844
2014-07-01 00:30:00	8127
2014-07-01 01:00:00	6210
2014-07-01 01:30:00	4656
2014-07-01 02:00:00	3820

- Our data contains the number of taxi calls per time interval

A Look at the Data

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

In [45]:
```
util.plot_series(data, figsize=figsize)
```

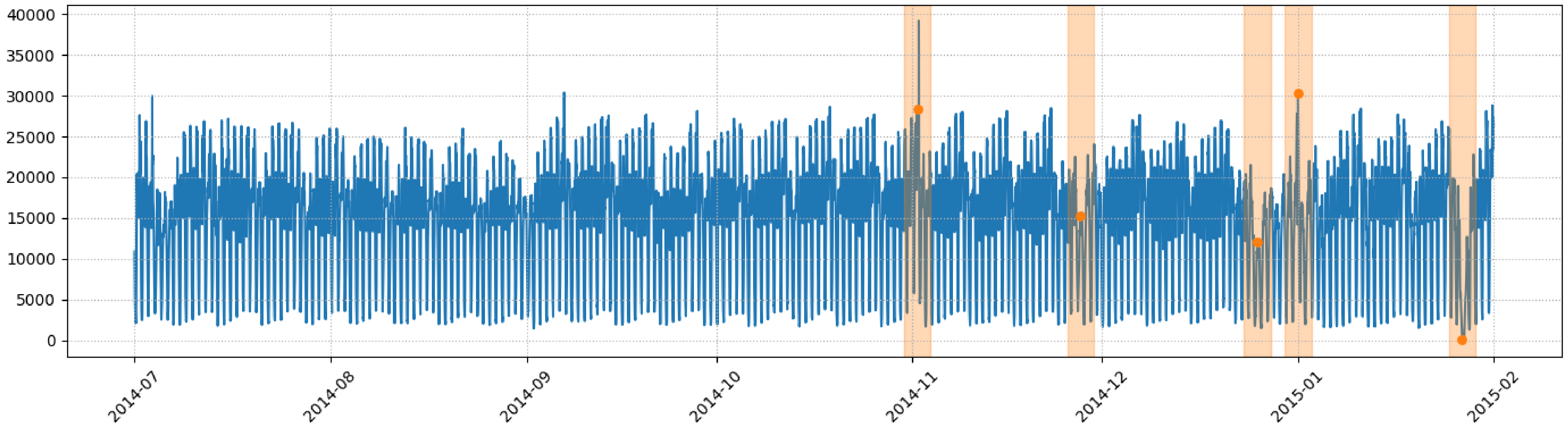


- Some outliers are visible, but there might be more anomalies

A Look at the Data

Anomalies for this time series are labeled

In [46]:
```
util.plot_series(data, labels, windows, figsize=figsize)
```



- We also have access to windows the define where a detection is meaningful
- Detections outside the windows count as a miss

Problem Formalization

A possible approach: we know that anomalies are (often) unlikely

- If we can estimate the probability of every occurring observation x
- ...Then we can spot anomalies based on their low probability

We turn a liability into a strenght!

Formally, our detection condition can be stated as:

$$f(x) \leq \theta$$

- Where $f(x)$ is a Probability Density Function (PDF)
- ...And θ is a (scalar) threshold

However, we lack ground truth information for the probabilities!

Density Estimation

Luckily, we can still obain an estimator

Say we have a parameterized approximator $\tilde{f}(x, \omega)$ for the true density $f(x)$

- We can try to choose the parameters ω
- ...So as to maximize the estimate probability of the training sample:

$$\text{argmax}_\theta \prod_{i=1}^{m} \tilde{f}(x_i, \omega)$$

This is an example of an unsupervised learning problem

- Even if we lack supervision (we know nothing about the anomalies)
- ...We can still make some use of our data

Training and Testing

We will split our data in two segments

A training set:

- This will include only data about the normal behavior
- Ideally, there should be no anomalies here (we do not want to learn them!)
- We will use it to fit a KDE model

A test set:

- To assess how well the approach can generalize

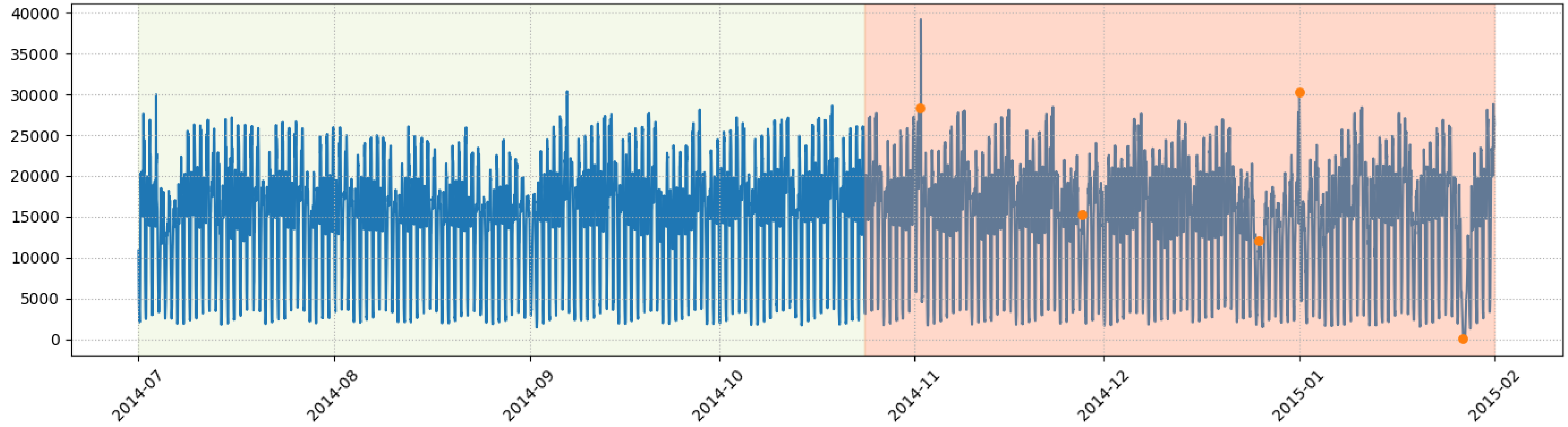
If the training set contains some anomalies

- Things may still be fine, as long as they are very infrequent
- ...Since we will still learn that they have low probability

Training and Testing

In time series data sets are often split chronologically:

```
In [47]: train_end = pd.to_datetime('2014-10-24 00:00:00')
         util.plot_series(data, labels, test_start=train_end, figsize=figsize)
```



- Green: training set, orange: test set

Input Choice

We have some flexibility in choosing our input

We know that we are going to train an estimator:

$$\tilde{f}(x, \omega)$$

...But what does $\boldsymbol{x}$ represent?

- For sure, the number of taxi calls
- ...But we can add more pieces of information if that is useful

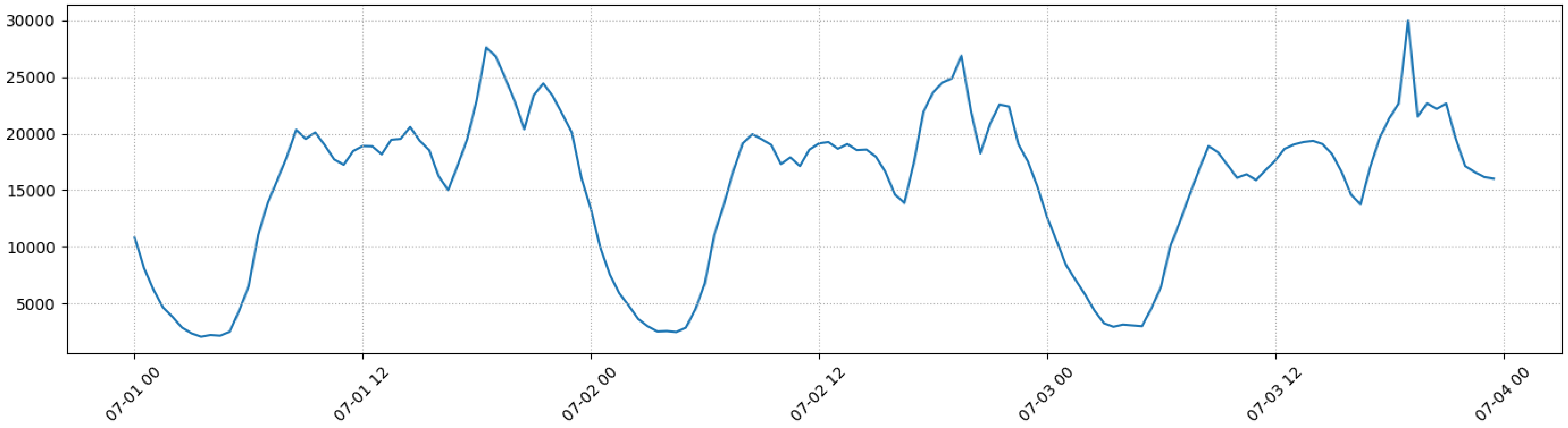
With times series a useful piece of information is given by time

- We have it "for free" (this is a time series, after all)
- ...And it naturally plays a role in many phenomena

Time and Taxi Calls

Let's zoom a bit on our series

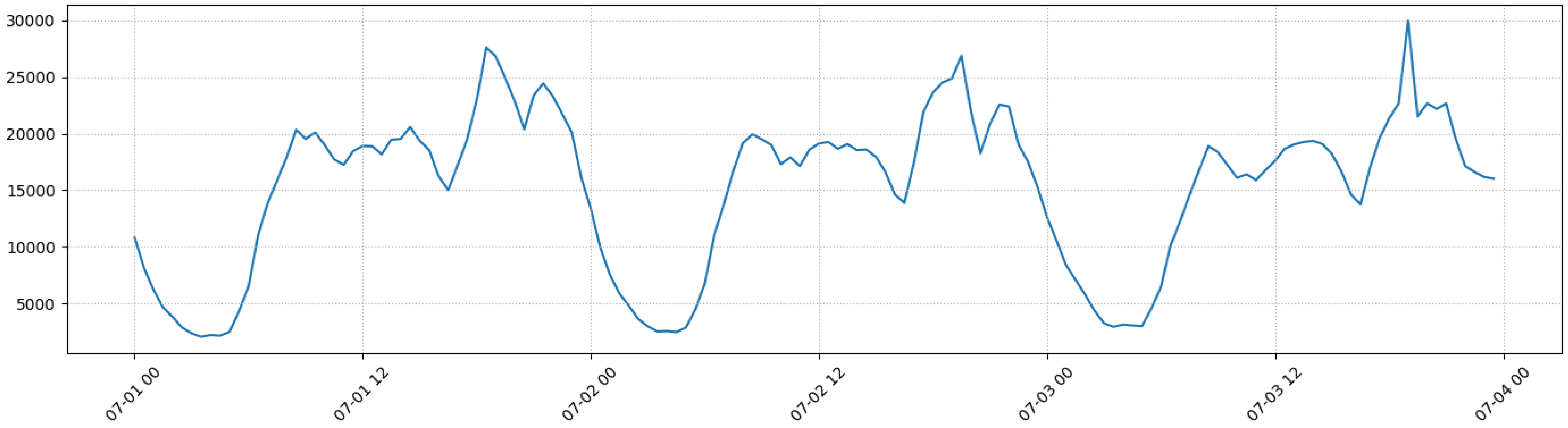
In [48]:
```
util.plot_series(data.iloc[:3*48], figsize=figsize)
```



Time and Taxi Calls

Let's zoom a bit on our series

In [48]:
```
util.plot_series(data.iloc[:3*48], figsize=figsize)
```



- There is recurring pattern! This is natural for many human activities
- In other words: at least some aspects of time have a strong impact

Time as an Additional Input

One way to look at that:

- The distribution depends on the time of the day
- Equivalently: our observed variable has two components, i.e. $y = (t, x)$
  - The first component t is the time of the day
  - The second component x is the number of called taxis

Let us extract (from the index) this new information:

```
In [49]: dayhour = (data.index.hour + data.index.minute / 60)
```

We can then add it as a separate column to the data:

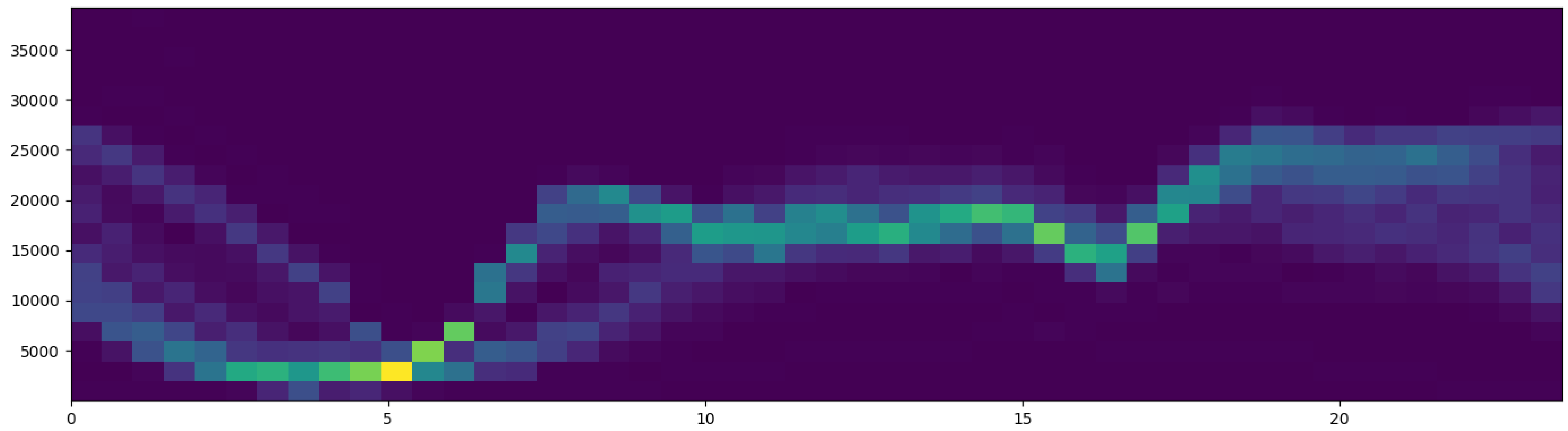
```
In [50]: data2 = data.copy()
         data2['dayhour'] = dayhour
```

Multivariate Distribution

Let us examine the resulting multivariate distribution

We can use a 2D histogram:

```
In [51]: util.plot_histogram2d(data2['dayhour'], data2['value'], bins=(48, 20), figsize=figsize)
```



- x = time, y = value, color = frequency of occurrence

Anomaly Detection with Controlled Variables

We need ot be a bit careful with our new estimator

If we just check this condition:

$$\tilde{f}((t, x), \omega) \leq \theta$$

...We might get some strange results:

- If a value of time is under-represented in our data
- ...The model will think it is unlikely

Once we are aware of the issue, it can be solved by tweaking the formula

$$\frac{\tilde{f}((t, x), \omega)}{\tilde{f}''(t, \omega'')} \leq \theta$$

Basically, we use a conditional probability rather than a joint probability

Data Preparation and Training

We start by separating the training set and applying normalization

```
In [52]: scaler = MinMaxScaler()
         data2_n_tr = data2[data2.index < train_end].copy()
         data2_n_tr[:] = scaler.fit_transform(data2_n_tr)
         data2_n = data2.copy()
         data2_n[:] = scaler.transform(data2)
```

Then we can then train a density estimator

```
In [54]: from sklearn.model_selection import GridSearchCV
         params = {'bandwidth': np.linspace(0.001, 0.01, 10)}
         opt = GridSearchCV(KernelDensity(kernel='gaussian'), params, cv=5)
         opt.fit(data2_n_tr);
```

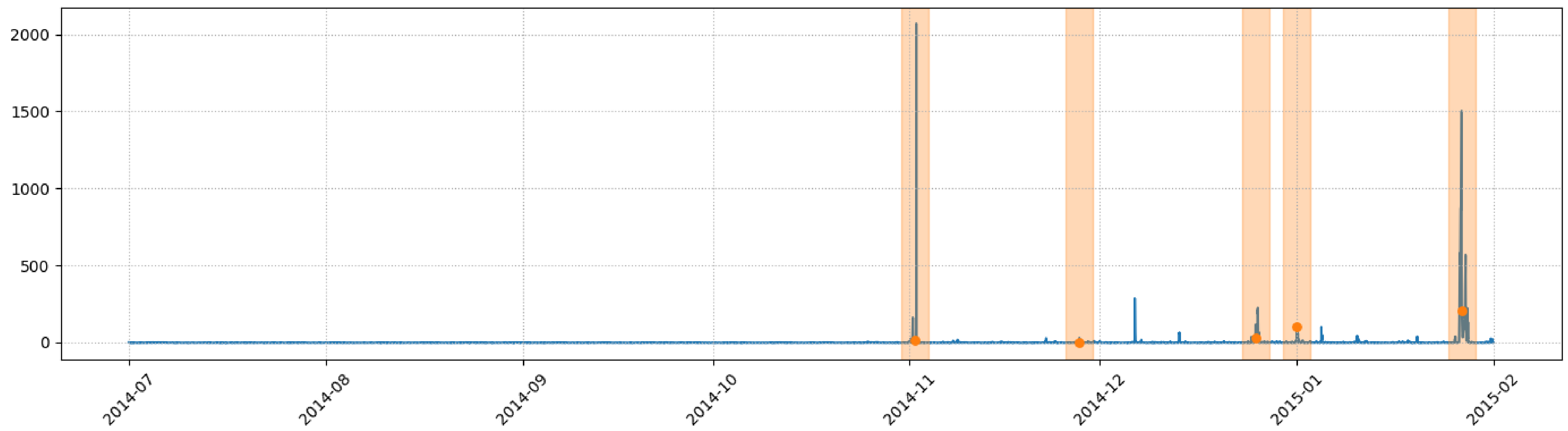
- We are using Kernel Density Estimation to obtain $\tilde{f}$
- ...Which is a relatively simple technique

Alarm Signal

It is customary to show alarm signals rather than probabilities

We can obtain one by computing $-\log \tilde{f}(x, \omega)$

```
In [59]: ldens = opt.score_samples(data2_n)
         signal = pd.Series(index=data2.index, data=-ldens2)
         util.plot_series(signal2, labels=labels, windows=windows, figsize=figsize)
```

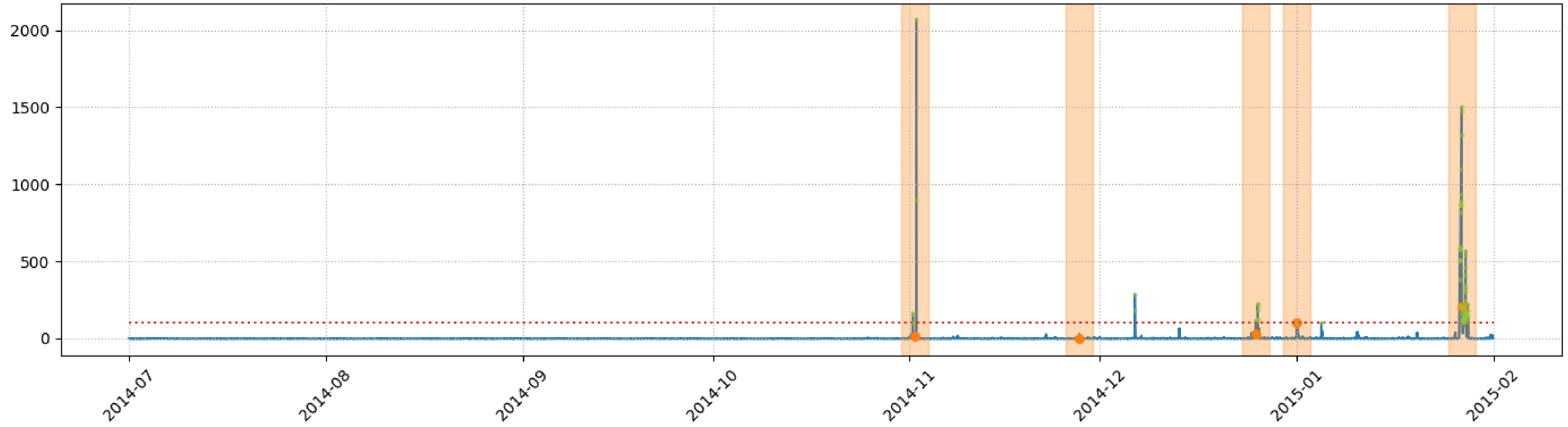


Even at a glance, we are doing a decent job

Detecting Anomalies

Let's see what happens when we fix a threshold

```
In [63]: thr = 100
         util.plot_series(signal, labels=labels, windows=windows, predictions=pd.Series(signal.index[sign
```



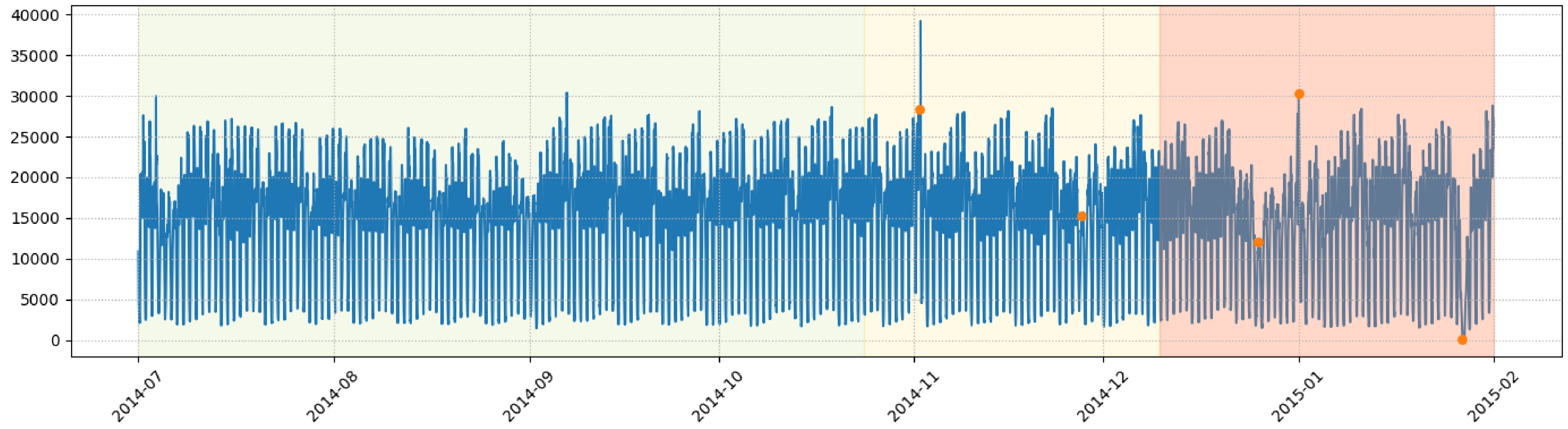
- Points above the threshold will be detected as anomalies

Choosing a Threshold

For choosing a threshold, we need two ingredients

The first is a validation set, containing some anomalies

```
In [65]: val_end = pd.to_datetime('2014-12-10 00:00:00')
         util.plot_series(data, labels, val_start=train_end, test_start=val_end, figsize=figsize)
```



- Some data still needs to be left out for the final evaluation

Choosing a Threshold

The second is a cost model

In other words, we need to asses how using the system costs to us

- In an industrial setting, we care about the value generated by a system
- Standard accuracy metrics fail to capture this

We will use a very simple cost model:

$$c_{alarm} \times \#\text{false\_alarms} + c_{missed} \times \#\text{missed\_anomalies} + c_{late} \times \#\text{late\_de}$$

- A cost c_{alarm} for loosing time in analyzing false positives
- A cost c_{missed} for missing an anomaly
- A cost c_{late} for a late detection (partial loss of value)

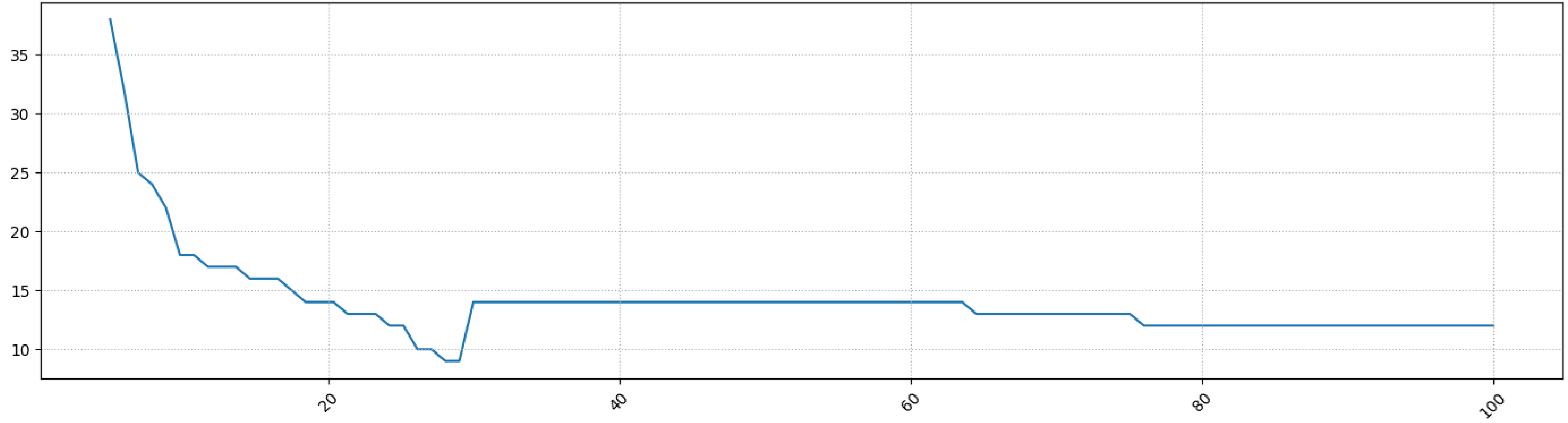
In [76]:

```
c_alrm, c_missed, c_late = 1, 10, 5
```

Threshold Optimization

Now, let us optimize our threshold:

In [86]:
```
cmodel = util.ADSimpleCostModel(c_alrm, c_missed, c_late)
thr_range = np.linspace(5, 100, 100)
cost_range = pd.Series(index=thr_range, data=[cmodel.cost(signal[signal.index <= val_end], label
util.plot_series(cost_range, figsize=figsize)
```



- On the x-axis we have θ, on the y-axis the cost

Threshold Optimization

Now, let us optimize our threshold:

```
In [91]: signal_opt = signal[signal.index < val_end]
         labels_opt = labels[labels < val_end]
         windows_opt = windows[windows['end'] < val_end]
         thr_range = np.linspace(5, 100, 100)
         best_thr, best_cost = util.opt_thr(signal_opt, labels_opt, windows_opt, cmodel, thr_range)
         print(f'Best threshold: {best_thr}, corresponding cost: {best_cost}')

         Best threshold: 28.03030303030303, corresponding cost: 9
```

And finally we can check the performance on the whole dataset:

```
In [90]: ctst = cmodel.cost(signal2, labels, windows, best_thr)
         print(f'Cost on the whole dataset {ctst}')

         Cost on the whole dataset 18
```