

KDE for Our Anomaly Detection Case Study

A Few Tweaks

We will work with log probabilities

- This is what sklearn does by default
- ...And simplifies some operations
- I.e. products become sums

Additionally, we will work with negated (log) probabilities

- They can be interpreted as alarm signals
- ...Which is the customary approach in anomaly detection

Overall, our anomaly detection condition becomes:

$$-\log f(x, \omega) \geq \theta$$

...Which is equivalent to the previous formulation

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

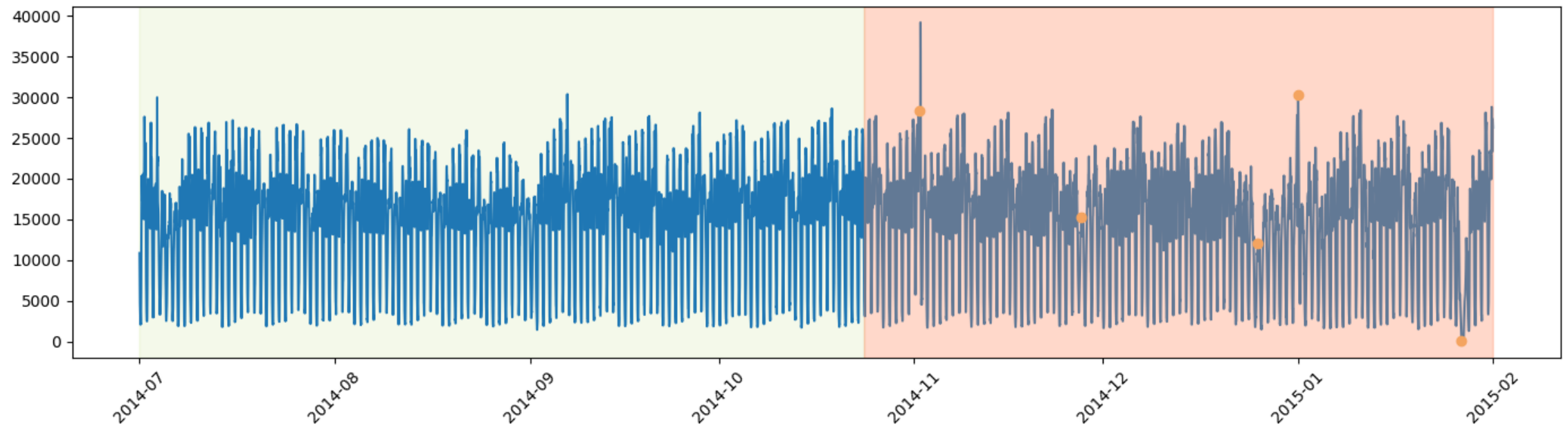
If the training set contains some anomalies

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



■ Green: training set, orange: test set

Fitting the Estimator

Now, we can separate the training set

...And estimate the bandwidth by using the rule of thumb:

```
In [3]: data_tr = data[data.index < train_end]
        q1 = data_tr['value'].quantile(0.25)
        q3 = data_tr['value'].quantile(0.75)
        sigma = data_tr['value'].std()
        m = len(data_tr)
        h = 0.9 * min(sigma, (q3-q1) / 1.34) * m**(-0.2)
        print(f'The estimated bandwidth is {h:.3f}')
```

The estimated bandwidth is 1056.061

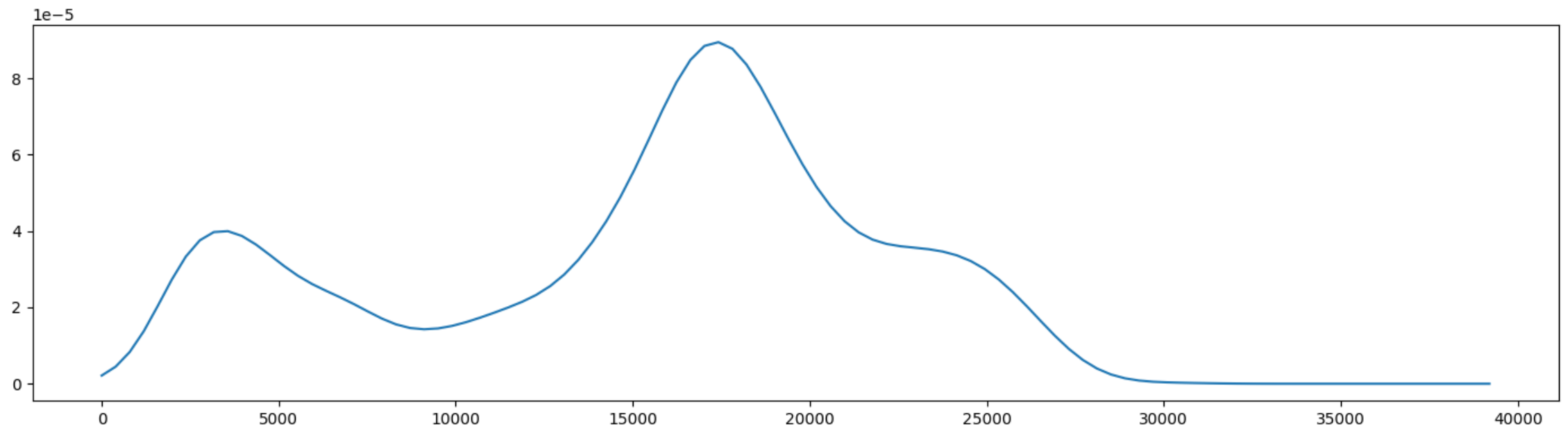
Then we fit a univariate KDE estimator (using scikit-learn)

```
In [4]: kde = KernelDensity(kernel='gaussian', bandwidth=h)
        kde.fit(data_tr.values);
```

Fitting the Estimator

Let's have a look at the estimate distribution:

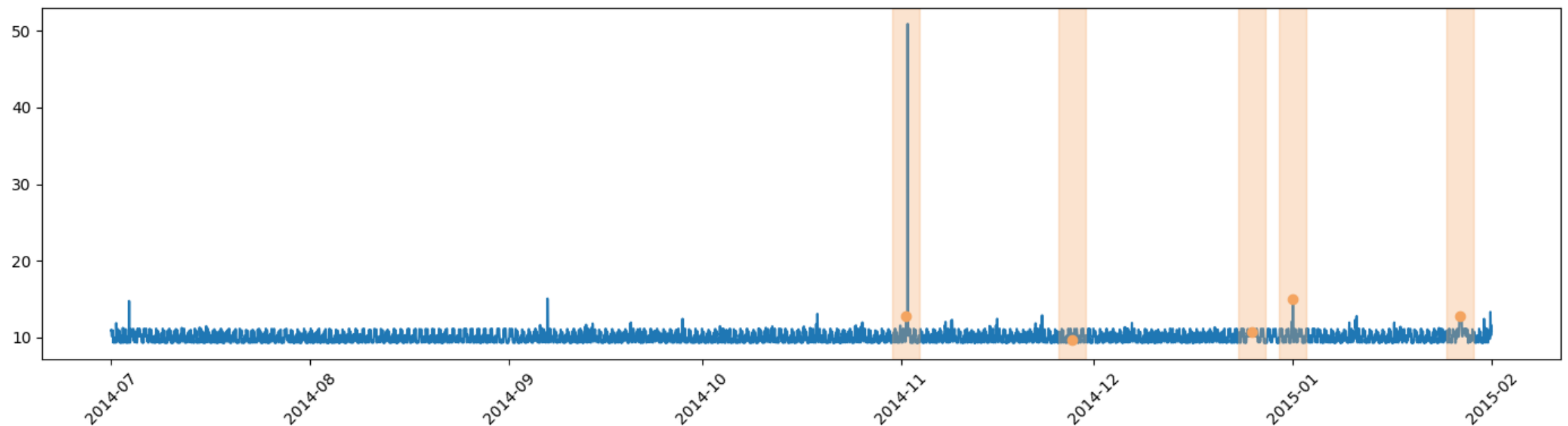
```
In [5]: vmax = data['value'].max()  
xr = np.linspace(0, vmax, 100)  
nab.plot_density_estimator_1D(kde, xr, figsize=figsize)
```



Alarm Signal

We can now obtain (and plot) our **alarm signal**:

```
In [6]: ldens = kde.score_samples(data.values) # Obtain log probabilities  
signal = pd.Series(index=data.index, data=-ldens) # Build series with neg. prob.  
nab.plot_series(signal, labels=labels, windows=windows, figsize=figsize) # Plot
```



- Noticed how the the process (inference) was noticeably slower than training?
- Can you tell why this was the case?

Detecting Anomalies

Let us pick a threshold (at random, for now) and try to detect some anomalies:

```
In [7]: thr = 12
pred = pd.Series(signal.index[signal >= thr])
print(pred.head(), f'#anomalies: {len(pred)}')
```

```
0    2014-07-03 19:00:00
1    2014-09-06 22:30:00
2    2014-09-06 23:00:00
3    2014-09-06 23:30:00
4    2014-09-27 23:00:00
Name: timestamp, dtype: datetime64[ns] #anomalies: 49
```

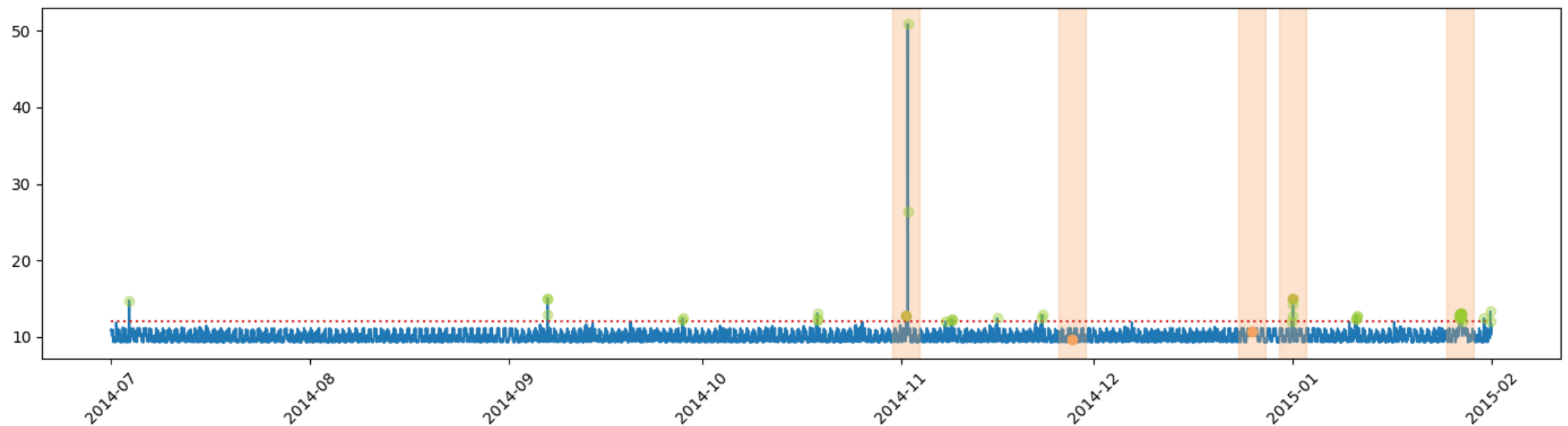
- We just apply the filter `signal >= thr` to the signal index
- This yields a number of (predicted) anomalous timestamps
- Our module contains a function to perform this step:

```
def get_pred(signal, thr)
```


Detecting Anomalies

Let us plot our predictions on the series:

```
In [8]: nab.plot_series(signal, labels=labels, windows=windows, predictions=pred, threshold=thr, figsize=(12, 6))
```



- Not very good, but the threshold **is** random
- There are a many false positives, which are **very common** in anomaly detection

Metrics for Anomaly Detection

How do we evaluate the quality of our system?

Metrics for Anomaly Detection

Evaluating the quality of an Anomaly Detection system can be tricky

- Usually, we do not need to match the anomalies exactly
- Sometimes we wish to anticipate anomalies
- ...But sometimes we just want to detect them in past data

There is no "catch-all" metric, like accuracy in classification

It is much better to devise a cost model

- We evaluate the cost and benefits of our predictions:
- By doing this, we focus on the value for our customer

This is important for all industrial problems!

A Simple Cost Model

We will use a simple cost model

Remember that our goals are:

- Analyzing anomalies
- Anticipating anomalies

First, we define:

- **True Positives** as windows for which we detect at least one anomaly
- **False Positives** as detected anomalies that do not fall in any window
- **False negatives** as anomalies that go undetected
- **Advance** as the time between an anomaly and when first we detect it

A Simple Cost Model

They can be computed using a function in our module:

```
def get_metrics(pred, labels, windows)
```

```
In [9]: tp, fp, fn, adv = nab.get_metrics(pred, labels, windows)
print('True Positives', tp.head(), f'#true positives: {len(tp)}')
```

```
True Positives 0    2014-11-01 19:00:00
1    2015-01-01 01:00:00
2    2015-01-27 00:00:00
dtype: datetime64[ns] #true positives: 3
```

```
In [10]: print('Advance', adv.head(), 'For each true positive')
```

```
Advance 0    0 days 00:00:00
1    0 days 04:00:00
2    0 days 01:00:00
dtype: timedelta64[ns] For each true positive
```

A Simple Cost Model

They can be computed using a function in our module:

```
def get_metrics(pred, labels, windows)
```

```
In [11]: print('False Positives', fp.head(), f'#false positives: {len(fp)}')
```

```
False Positives 0    2014-07-03 19:00:00
1    2014-09-06 22:30:00
2    2014-09-06 23:00:00
3    2014-09-06 23:30:00
4    2014-09-27 23:00:00
dtype: datetime64[ns] #false positives: 23
```

```
In [12]: print('False Negatives', fn.head(), f'#false negatives: {len(fn)}')
```

```
False Negatives 0    2014-11-27 15:30:00
1    2014-12-25 15:00:00
dtype: datetime64[ns] #false negatives: 2
```

A Simple Cost Model

Then we introduce:

- 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)

Our cost model (simple, but serviceable) is then given by:

```
In [13]: c_alarm = 1 # Cost of investigating a false alarm
c_missed = 10 # Cost of missing an anomaly
c_late = 5 # Cost for late detection

# A simple cost model
cost = c_alarm * len(fp) + \
      c_missed * len(fn) + \
      c_late * (len([a for a in adv if a.total_seconds() <= 0]))
print(f'The cost with the current predictions is: {cost}')
```

The cost with the current predictions is: 48

Threshold Choice

Refactoring the Cost Model

We will use this cost model for **choosing our threshold**

With this aim, we encapsulate the formula in a Python class in our module:

```
class ADSimpleCostModel:
    def __init__(self, c_alarm, c_missed, c_late):
        # Store cost parameters
        ...

    def cost(self, signal, labels, windows, thr):
        # Compute the cost
        ...
```

Refactoring the Cost Model

We can now evaluate our cost by:

- Instantiating the class with our values for c_{alarm} , c_{missed} , c_{late}
- Calling the `cost` function with different threshold values

```
In [14]: cmodel = nab.ADSimpleCostModel(c_alarm, c_missed, c_late)
cost = cmodel.cost(signal, labels, windows, thr)
print(f'The cost with the current predictions is: {cost}')
```

```
The cost with the current predictions is: 48
```

The process is rather efficient:

- When we change the threshold
- ...We **do not need to rebuild** the alarm signal

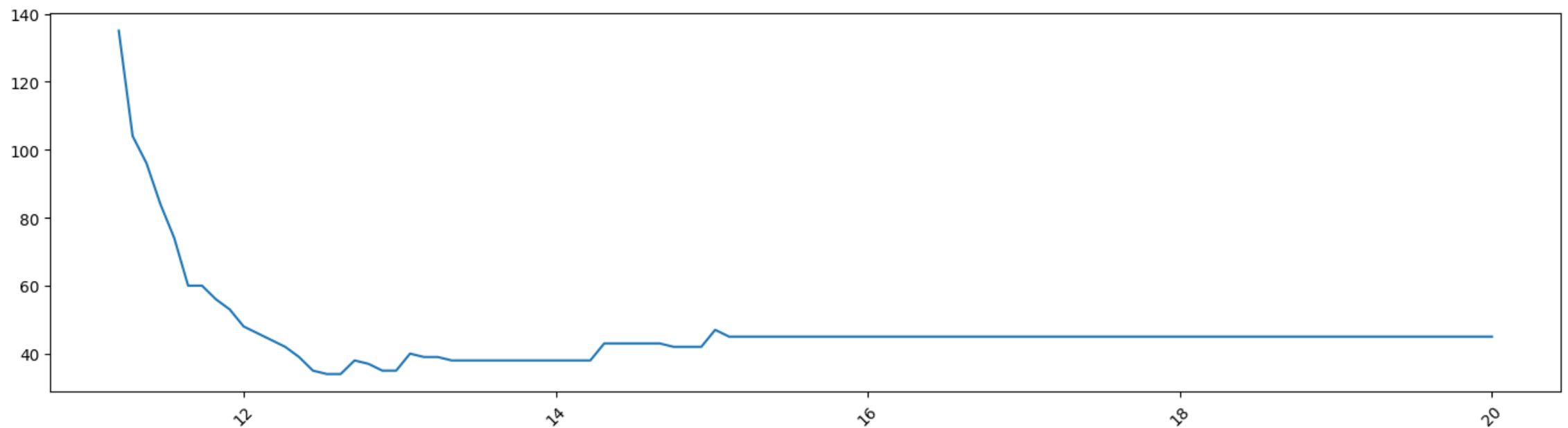
So, no need to repeat either training or inference

Effect of the Threshold

We can now look at the effect of changing the threshold:

First, we'll do this for an idealized problem (i.e. over all the data)

```
In [15]: cmodel = nab.ADSimpleCostModel(c_alm, c_missed, c_late)
thr_range = np.linspace(11.2, 20, 100)
cost_range = pd.Series(index=thr_range, data=[cmodel.cost(signal, labels, windows, thr) for thr
nab.plot_series(cost_range, figsize=figsize)
```



Choosing the Threshold

Ideally, we wish to choose the best threshold

However, we have two problems:

- We cannot really use all the data
- ...we need to keep some away to test generalization
- The threshold-to-cost function is non-smooth and non-differentiable

Choosing the Threshold

Ideally, we wish to choose the best threshold

However, we have two problems:

- We cannot really use all the data
- ...we need to keep some away to test generalization
- The threshold-to-cost function is non-smooth and non-differentiable

Luckily, both are easy to address

We can:

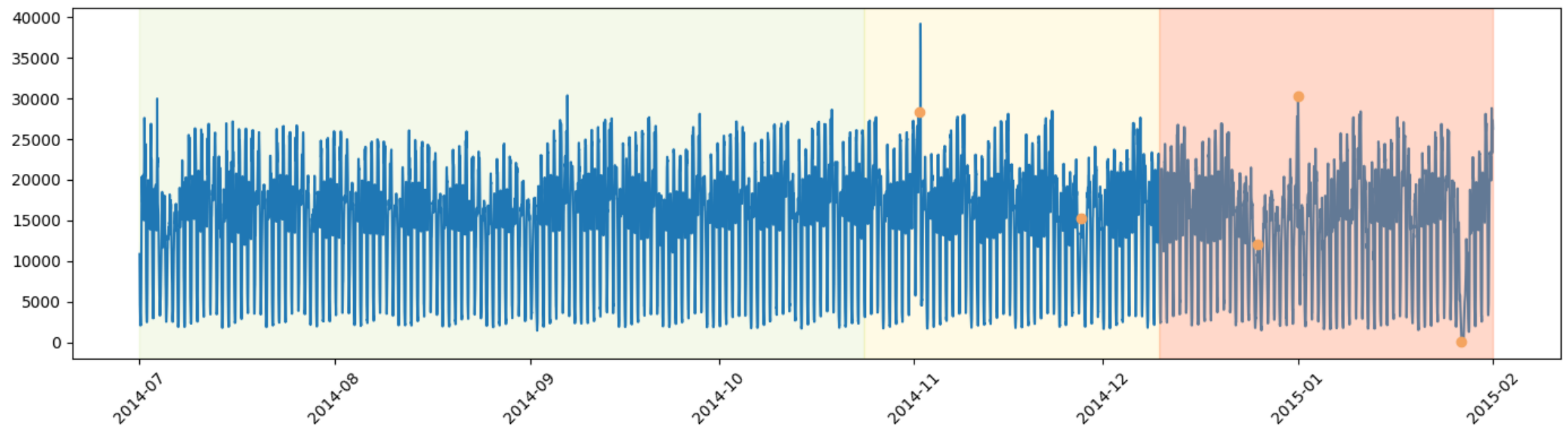
- Define a validation set to use when optimizing the threshold
- Use a simple line search approach, since θ is a scalar

Define a Validation Set

First, we define our validation set:

- It should contain some anomalies
- ...But some should be left out (for testing)

```
In [16]: val_end = pd.to_datetime('2014-12-10 00:00:00')  
nab.plot_series(data, labels, val_start=train_end, test_start=val_end, figsize=figsize)
```



Optimize the Threshold

We will use a line sampling approach:

We build the validation set and define a range of "sampled" thresholds:

```
In [17]: signal_opt = signal[signal.index < val_end]
labels_opt = labels[labels < val_end]
windows_opt = windows[windows['end'] < val_end]
```

Then, we use a function from our module to pick the best one:

```
def opt_thr(signal, labels, windows, cmodel, thr_range):
    costs = # compute costs as before
    best_idx = np.argmin(costs)
    return thr_range[best_idx], costs[best_idx]
```


Validation Set?

Did you notice how we included the training data in the validation set?

Is that good or bad?

Validation Set?

Did you notice how we included the training data in the validation set?

Is that good or bad?

It's totally fine!

The reason is that our "validation set"

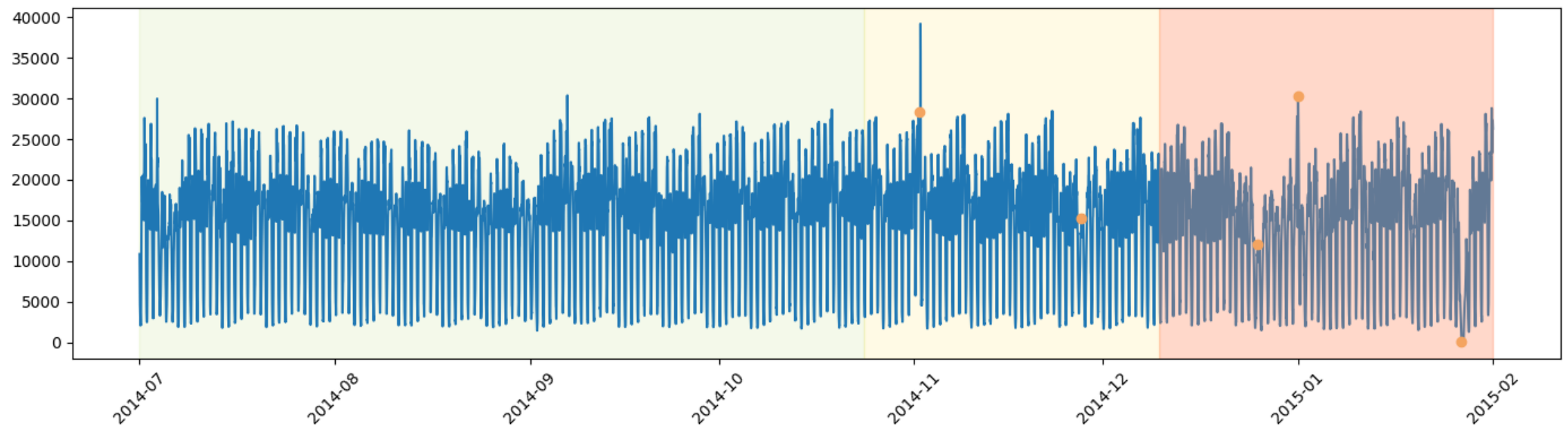
- ...Is **not needed to ward off against overfitting**
- ...But just to optimize one more parameter (i.e. θ)

It is actually **part of the training data**

Get Accustomed to Drift

One more thing: see how the anomaly frequency changes over time?

```
In [18]: nab.plot_series(data, labels, val_start=train_end, test_start=val_end, figsize=figsize)
```



- In time series, the data distribution often drifts over time
- When this happens, it is usually good to split the series in contiguous chunks
- I.e. the training, validation, and test set should be sequences

Optimize the Threshold

Let's see the results of threshold optimization

```
In [19]: best_thr, best_cost = nab.opt_thr(signal_opt, labels_opt, windows_opt, cmodel, thr_range)
         print(f'Best threshold: {best_thr}, corresponding cost: {best_cost}')
```

```
Best threshold: 15.11111111111111, corresponding cost: 15
```

- The reported cost is on the training and validation set

For all the data (yes, we are cheating a bit) we have:

```
In [20]: ctst = cmodel.cost(signal, labels, windows, best_thr)
         print(f'Cost on the whole dataset {ctst}')
```

```
Cost on the whole dataset 45
```

- This is, as expected, **suboptimal**
- ...But it works! We have our **first complete anomaly detection approach**