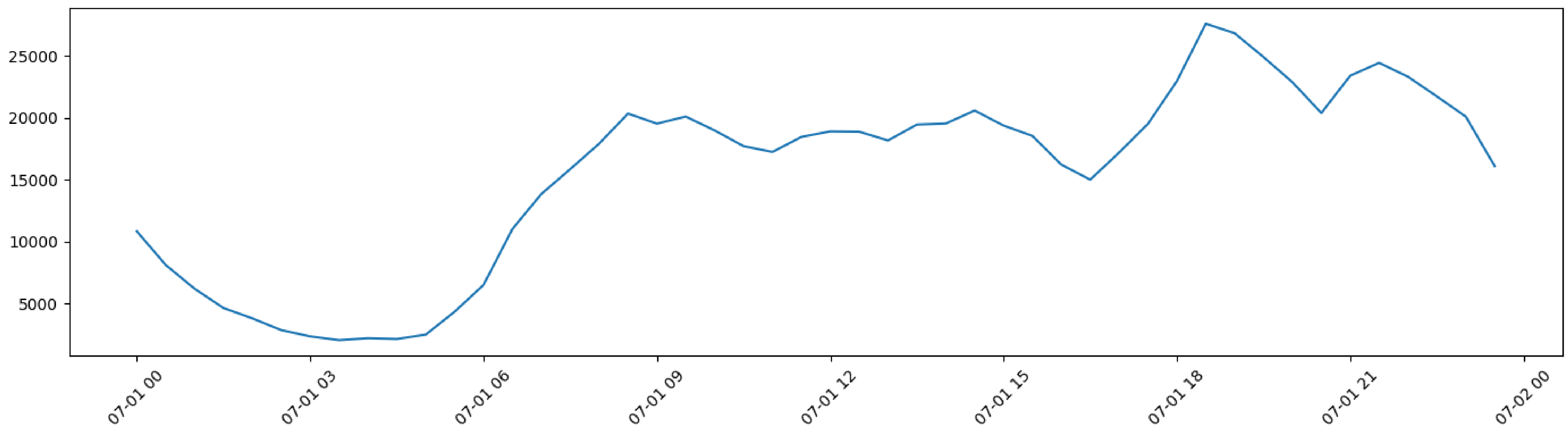
Sliding Windows

Temporal Correlations

Let's have a closer look at our time series

In [2]:
```
nab.plot_series(data.iloc[:48], figsize=figsize)
```



- Nearby points tend to have similar values
- ...Meaning they are correlated

Determine the Period

How can we study such correlation?

A useful tool: autocorrelation plots

- Consider a range of possible lags
- For each lag value l:
  - Make a copy of the series and shift it by l time steps
  - Compute the Pearson Correlation Coefficient with the original series
- Plot the correlation coefficients over the lag values

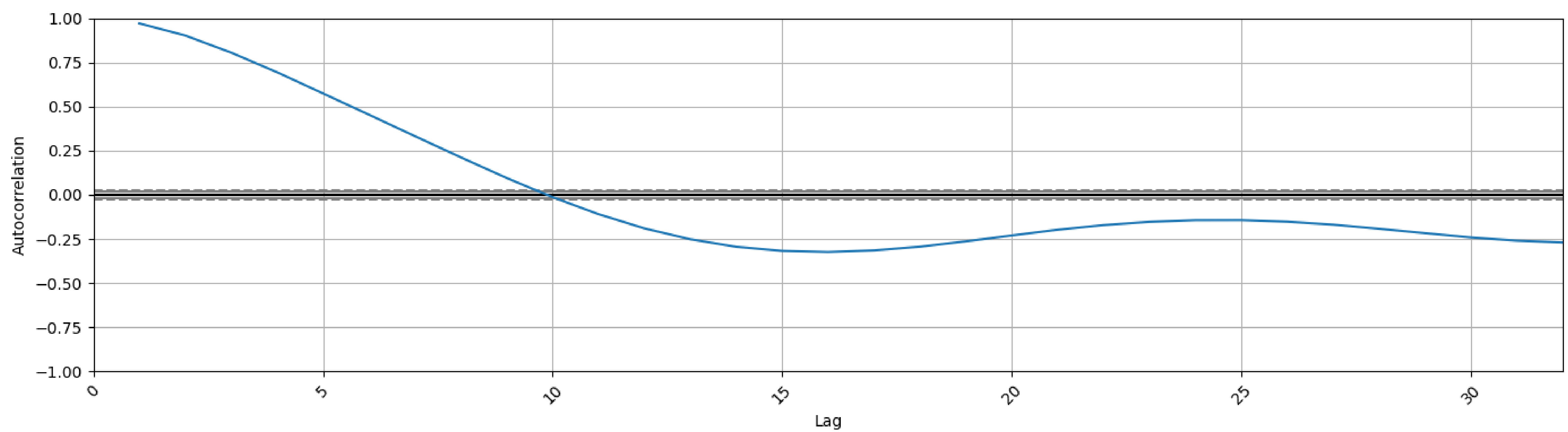
Then we look at the resulting plot:

- Where the curve is far from zero, there is a significant correlation
- Where it gets close to zero, no significant correlation exists

Temporal Correlations

Let's have a look at our plot

In [3]:
```
nab.plot_autocorrelation(data, max_lag=32, figsize=figsize)
```



- The correlation is strong up to 4-5 lags

Temporal Correlations

These correlations are a source of information

- They could be exploited to improve our estimated probabilities
- ...But our models so far make no use of them

How can we take advantage of them?

Temporal Correlations

These correlations are a source of information

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How can we take advantage of them?

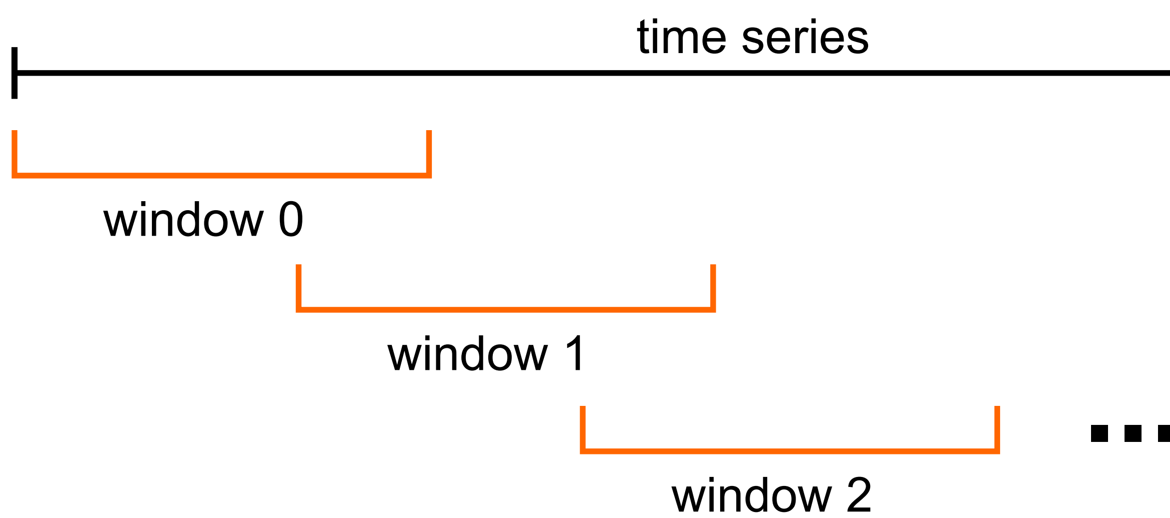
For example, rather then feeding our model with individual observations

We can use sequences of observations as input

- This is a very common approach in time series
- ...And in many cases it's a good idea

Sliding Window

A common approach consist in using a sliding window



- We choose a window length w, i.e. the length of each sub-sequence
- We place the "window" at the beginning of the series
- ...We extract the corresponding observations
- Then, we move the forward by a certain stride and we repeat

Sliding Window

The result is a table

Let m be the number of examples and w be the window length

	$\mathbf{s_0}$	$\mathbf{s_1}$	$\dots$	$\mathbf{s_{w-1}}$
$\mathbf{t_{w-1}}$	x_0	x_1	$\dots$	x_{w-1}
$\mathbf{t_w}$	x_1	x_2	$\dots$	x_w
$\mathbf{t_{w+1}}$	x_2	x_3	$\dots$	x_{w+1}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$\mathbf{t_{m-1}}$	x_{m-w}	x_{m-w+1}	$\vdots$	x_{m-1}

- The first window includes observations from x_0 to x_{w-1}
- The second from x_1 to x_w and so on
- t_i is the time window index (where it was applied)
- s_j is the position of an observation within a window

Sliding Window in pandas

pandas provides a sliding window iterator

```
DataFrame.rolling(window, ...)
```

```
In [4]: wlen = 10
        for i, w in enumerate(data['value'].rolling(wlen)):
            print(w)
            if i == 2: break # We print the first three windows
```

```
timestamp
2014-07-01    10844
Name: value, dtype: int64
timestamp
2014-07-01 00:00:00    10844
2014-07-01 00:30:00     8127
Name: value, dtype: int64
timestamp
2014-07-01 00:00:00    10844
2014-07-01 00:30:00     8127
2014-07-01 01:00:00     6210
Name: value, dtype: int64
```

Notice how the first windows are not full (shorter than `wlen`)

Sliding Window in pandas

We can build our dataset using the `rolling` iterator

- We discard the first `wlen-1` (incomplete) applications
- Then we store each window in a list, and we wrap everything in a `DataFrame`

```
In [5]: %%time
        rows = []
        for i, w in enumerate(data['value'].rolling(wlen)):
            if i >= wlen-1: rows.append(w.values)

        wdata_index = data.index[wlen-1:]
        wdata = pd.DataFrame(index=wdata_index, columns=range(wlen), data=rows)
```

```
CPU times: user 449 ms, sys: 5.18 ms, total: 455 ms
Wall time: 454 ms
```

- The `values` field allows access to the `Series` content as a numpy array
- We use it to discard the index
- ...Since the series for multiple iterations have inconsistent indexes

Sliding Window in pandas

This method works, but it's a bit slow

- We are building our table by rows...
- ...But it is usually faster to do it by columns!
- After all, there are usually fewer columns than rows

Let us look again at our table:

	$\mathbf{s_0}$	$\mathbf{s_1}$	$\dots$	$\mathbf{s_{w-1}}$
$\mathbf{t_{w-1}}$	x_0	x_1	$\dots$	x_{w-1}
$\mathbf{t_w}$	x_1	x_2	$\dots$	x_w
$\mathbf{t_{w+1}}$	x_2	x_3	$\dots$	x_{w+1}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$\mathbf{t_{m-1}}$	x_{m-w}	x_{m-w+1}	$\vdots$	x_{m-1}

Sliding Window in pandas

We can build the columns by slicing the original `DataFrame`

```
In [6]: m = len(data)
        c0 = data.iloc[0:m-wlen+1]   # first column
        c1 = data.iloc[1:m-wlen+1+1] # second column
        print(c0.iloc[0:3])
        print(c1.iloc[0:3])
```

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

- `iloc` in pandas allows to address a `DataFrame` by position

Sliding Window in pandas

Now we collect all columns in a list and we stack them

In [7]:

```
lc = [data.iloc[i:m-wlen+i+1].values for i in range(0, wlen)]
lc = np.hstack(lc)
wdata = pd.DataFrame(index=wdata_index, columns=range(wlen), data=lc)
wdata.head()
```

Out[7]:

timestamp	0	1	2	3	4	5	6	7	8	9
2014-07-01 04:30:00	10844	8127	6210	4656	3820	2873	2369	2064	2221	2158
2014-07-01 05:00:00	8127	6210	4656	3820	2873	2369	2064	2221	2158	2515
2014-07-01 05:30:00	6210	4656	3820	2873	2369	2064	2221	2158	2515	4364
2014-07-01 06:00:00	4656	3820	2873	2369	2064	2221	2158	2515	4364	6526
2014-07-01 06:30:00	3820	2873	2369	2064	2221	2158	2515	4364	6526	11039

Sliding Window in pandas

We can wrap this approach in a function:

```
def sliding_window_1D(data, wlen):
    m = len(data)
    lc = [data.iloc[i:m-wlen+i+1] for i in range(0, wlen)]
    wdata = np.hstack(lc)
    wdata = pd.DataFrame(index=data.index[wlen-1:], data=wdata, columns=range(wlen))
    return wdata
```

```
In [8]: %%time
        wdata = nab.sliding_window_1D(data, wlen=wlen)

CPU times: user 1.71 ms, sys: 0 ns, total: 1.71 ms
Wall time: 1.25 ms
```

- This is available in the (updated)) `nab` module
- The function works for univariate data (but the approach is general)