# Basic Approaches for Missing Values

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**We will now discuss a few simple approaches to deal with missing values**

- We cannot easily assess them on our traffic data
- ...Since we do not know the ground truth of each missing value

**Therefore, we will initially use partially synthetic data**

- We will start from a time series without any missing value, then remove values artificially
- ...And measure the accuracy of our filling approaches via the Root MSE

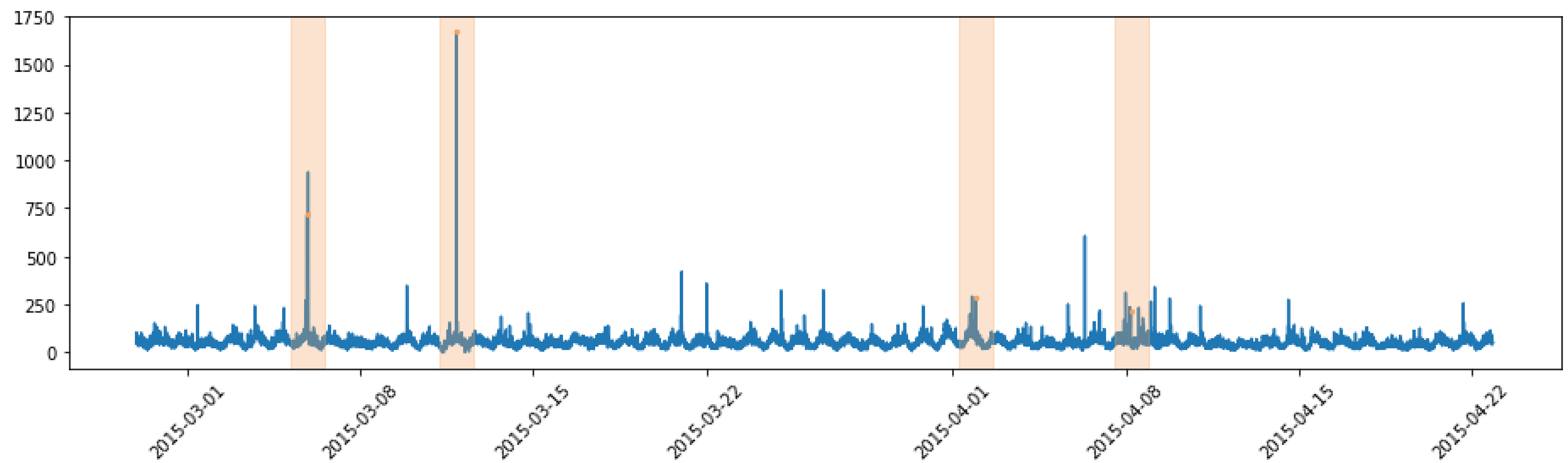
$$RMSE = \sqrt{\frac{1}{n} \sum_{i=0}^{n} (\tilde{x}_i - \hat{x}_i)^2}$$

Where $\tilde{x}_i$ is a value from the filled series and $\hat{x}_i$ the ground truth

# The Benchmark Dataset

## Our benchmark dataset consists of twitter volume related to amazon.com

In [2]:
```
nab.plot_series(data1, labels1, windows1, figsize=figsize)
```




- There are a few anomalies, but we are not concerned with them
- Then series has a seasonal/periodic component

# The Benchmark Dataset

## We now introduce some missing values

First, we draw some starting points at random

```
In [3]: np.random.seed(42) # seed (to get reproducible results)
        mv_num = 30 # number of intervals with missing values
        mv_starts = np.random.choice(range(len(data1.index)), mv_num, replace=False)
        mv_starts.sort()
        mv_starts[:4]

Out[3]: array([ 88, 123, 169, 304])
```

Then, we clear values over increasingly long intervals:

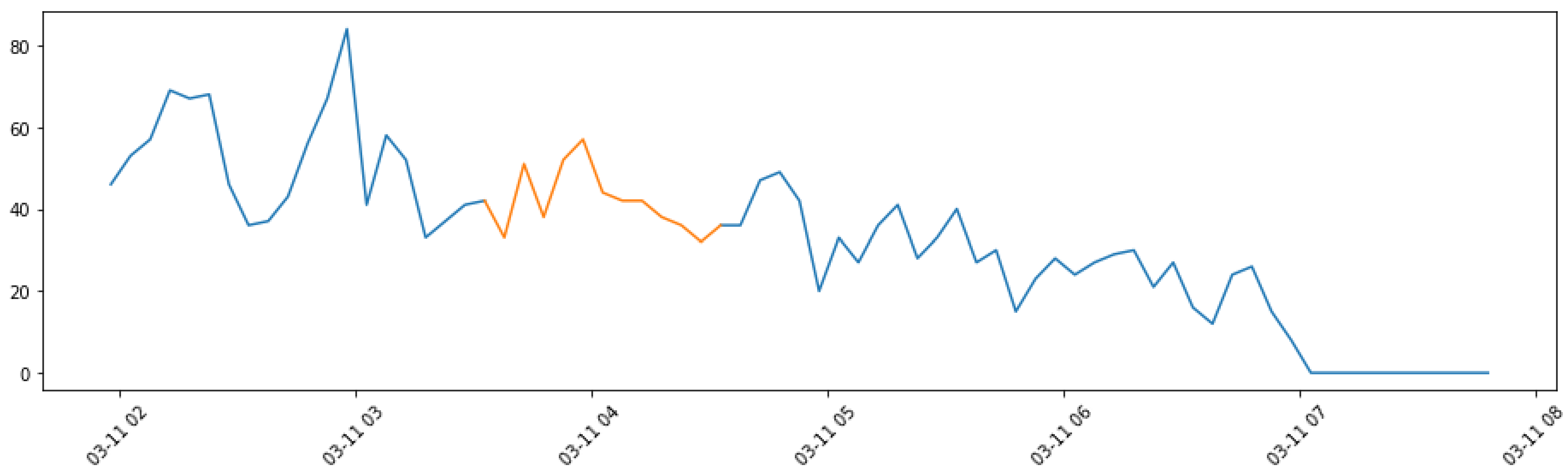
```
In [4]: data1_mv = data1.copy()
        for i in range(mv_num):
            data1_mv.iloc[mv_starts[i]:mv_starts[i]+i+1] = np.NaN
```

- The first interval contains 1 missing value, the second 2, the third 3...

# The Benchmark Dataset

## Let's have a look at the results around one of the "holes"

```
In [7]: idx, pad = 10, 20
        nab.plot_series(data1_mv.iloc[mv_starts[idx]-pad:mv_starts[idx]+mv_num+pad+1], figsize=figsize)
        plt.plot(data1.iloc[mv_starts[idx]-1:mv_starts[idx]+idx+2]);
```




- The orange part corresponds to the removed values

# Forward/Backward Filling

**The easiest approach for missing values consists in replicating nearby observations**

- Forward filling: propagate forward the last valid observation
- Backward filling: propagate backward the next valid observation

**An important observation:**

- When filling missing values, we have access to the whole series
- ...So we can reason both forward and backwards

**Forward/backward filling are simple methods, but they can work well**

- Rationale: most time series have a certain "inertia"
- ...I.e.: a strong level of local correlation
- For this reason, the last observation is a good predictor for the next one
- ...Remember the persistence predictor?

# Forward/Backward Filling

## Forward and backward filling are pre-implemented in pandas

They are available through the `fillna` method:

```
DataFrame.fillna(..., method=None, ...)
```

- `fillna` replaces `NaN` values in a `DataFrame` or `Series`
- The `method` parameter can take the values:
  - "pad" or "ffill": these correspond to forward filling
  - "backfill" or "bfill": these correspond to backward filling

They are generally applied to datasets with a dense index

- Remember that our benchmark dataset already has a dense index

# Forward/Backward Filling on the Benchmark

## We can finally test forward/backward filling

```
In [8]: ffseries = data1_mv.fillna(method='ffill')
        bfseries = data1_mv.fillna(method='bfill')
```

We can check the corresponding MSE:

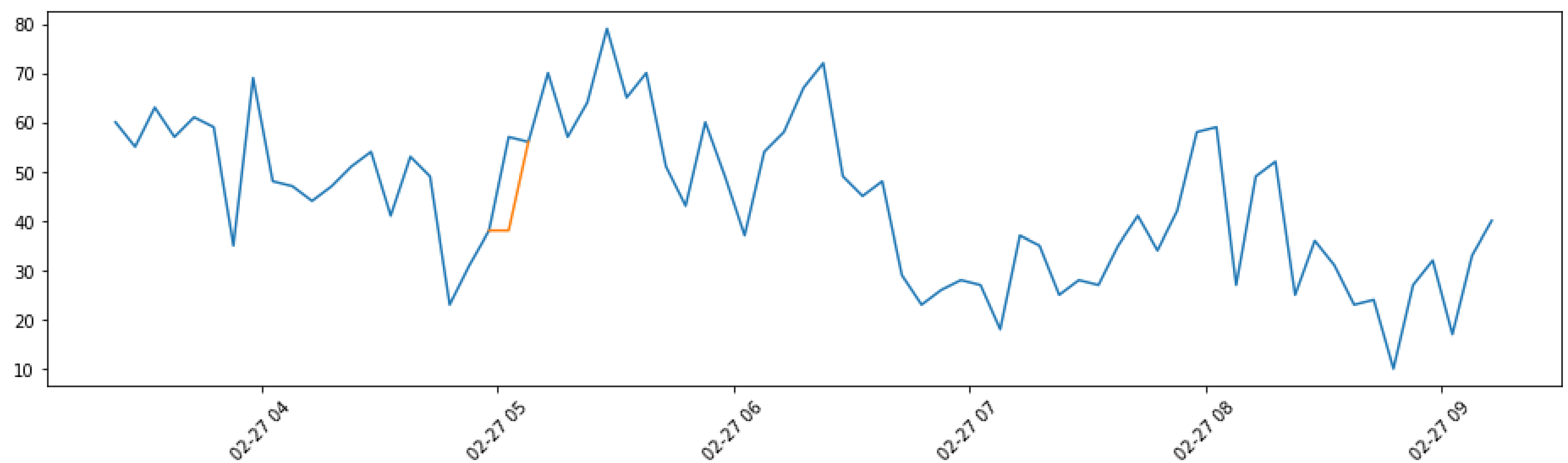
```
In [9]: from sklearn.metrics import mean_squared_error
        rmse_ff = np.sqrt(mean_squared_error(data1, ffseries))
        rmse_bf = np.sqrt(mean_squared_error(data1, bfseries))
        print(f'RMSE for forwad filling: {rmse_ff:.2f}, for backward filling {rmse_bf:.2f}')

RMSE for forwad filling: 3.18, for backward filling 6.45
```

- In this case forward filling seems to work better
- The results are of course application-dependent

# Forward/Backward Filling on the Benchmark

## Let's have a close look at forward filling around some of the missing values

In [10]:
```
idx, pad = 0, 20
nab.plot_series(data1.iloc[mv_starts[idx]-pad:mv_starts[idx]+mv_num+pad+1], figsize=figsize)
plt.plot(ffseries.iloc[mv_starts[idx]-1:mv_starts[idx]+idx+2]);
```

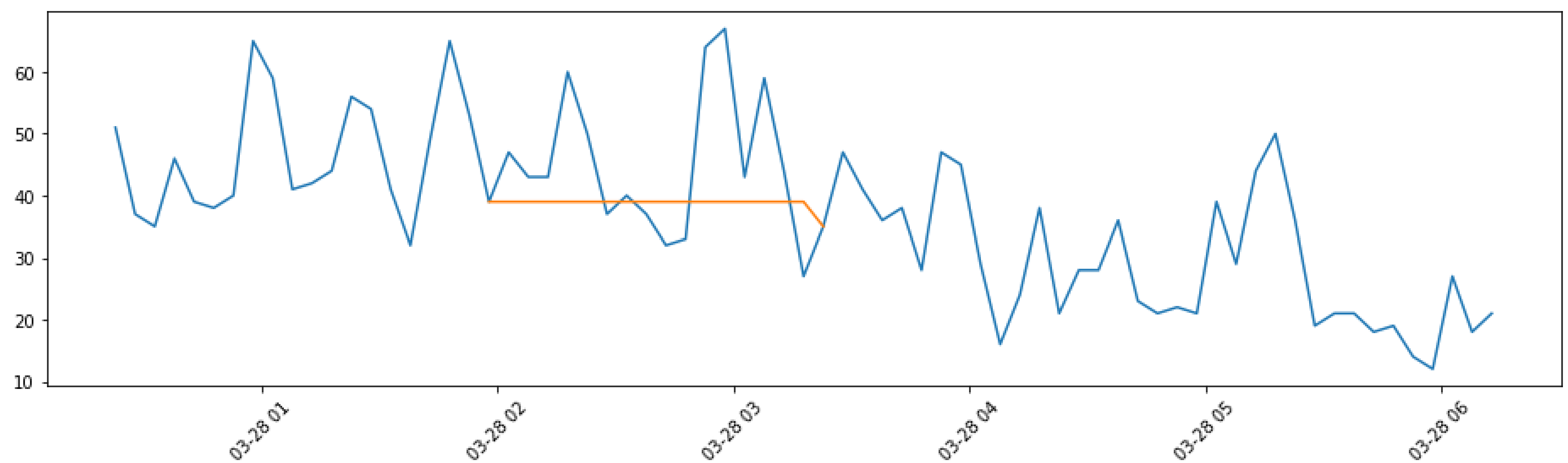



- This is the first (and shortest) gap

# Forward/Backward Filling on the Benchmark

## Let's have a close look at forward filling around some of the missing values

In [11]:
```
idx, pad = mv_num//2, 20
nab.plot_series(data1.iloc[mv_starts[idx]-pad:mv_starts[idx]+mv_num+pad+1], figsize=figsize)
plt.plot(ffseries.iloc[mv_starts[idx]-1:mv_starts[idx]+idx+2]);
```

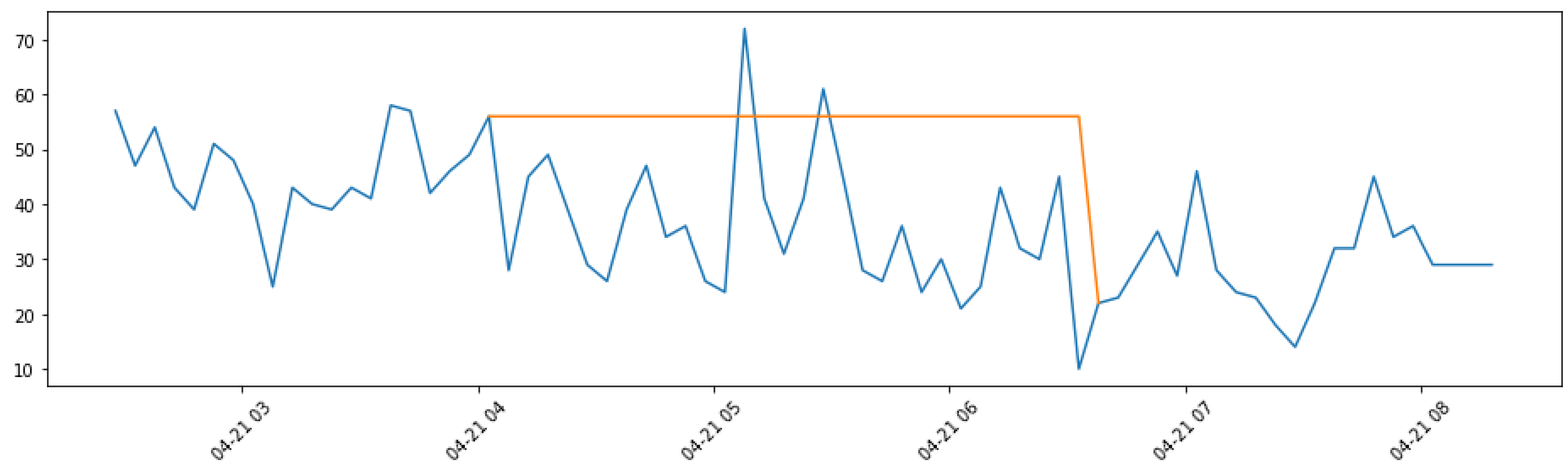



- This is an intermediate-length gap

# Forward/Backward Filling on the Benchmark

## Let's have a close look at forward filling around some of the missing values

In [12]:
```
idx, pad = mv_num-1, 20
nab.plot_series(data1.iloc[mv_starts[idx]-pad:mv_starts[idx]+mv_num+pad+1], figsize=figsize)
plt.plot(ffseries.iloc[mv_starts[idx]-1:mv_starts[idx]+idx+2]);
```




- This is the longest gap

# Forward/Backward Filling on the Traffic Data

## Let's now consider the traffic data

We will limit ourselves to forward filling:

```
In [13]: ddata2 = data2.resample('5min').mean()
         ddata2_ff = ddata2.fillna(method='ffill')
```

- `data2` contains the traffic series

## We now isolate the filled values

This is needed so that we can highlight them in the forthcoming plots

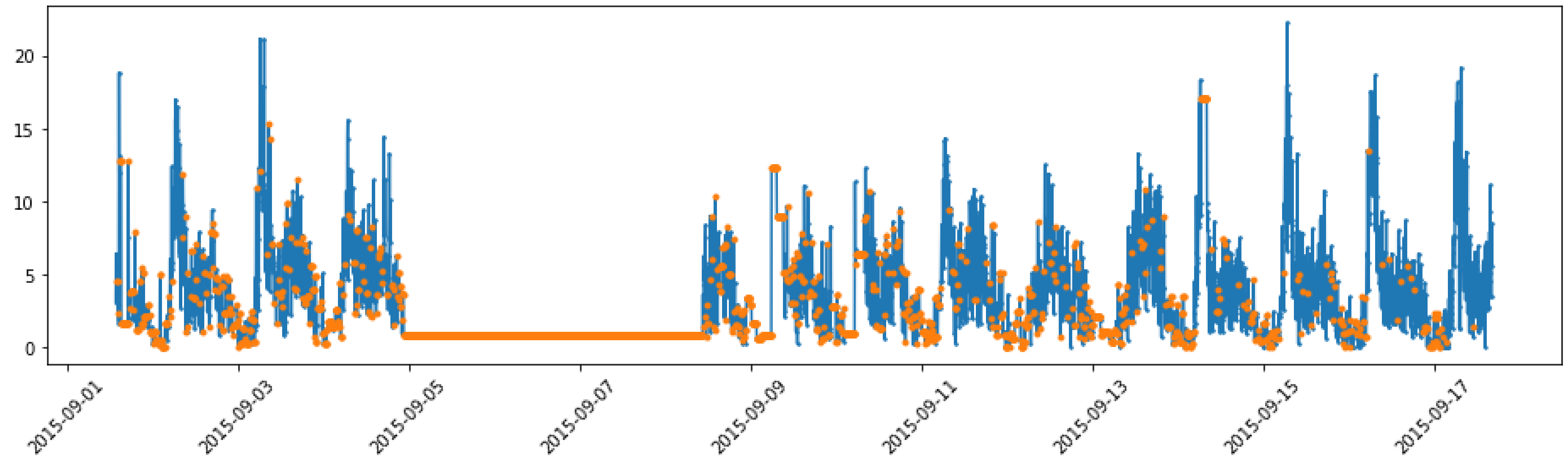
```
In [14]: ddata2_ffonly = ddata2_ff.copy()
         ddata2_ffonly[~ddata2['value'].isnull()] = np.nan
```

- `ffseries` and `bfseries` now contain only the filled values

# Forward/Backward Filling on the Traffic Data

## Let us have a look at the results of forward filling:

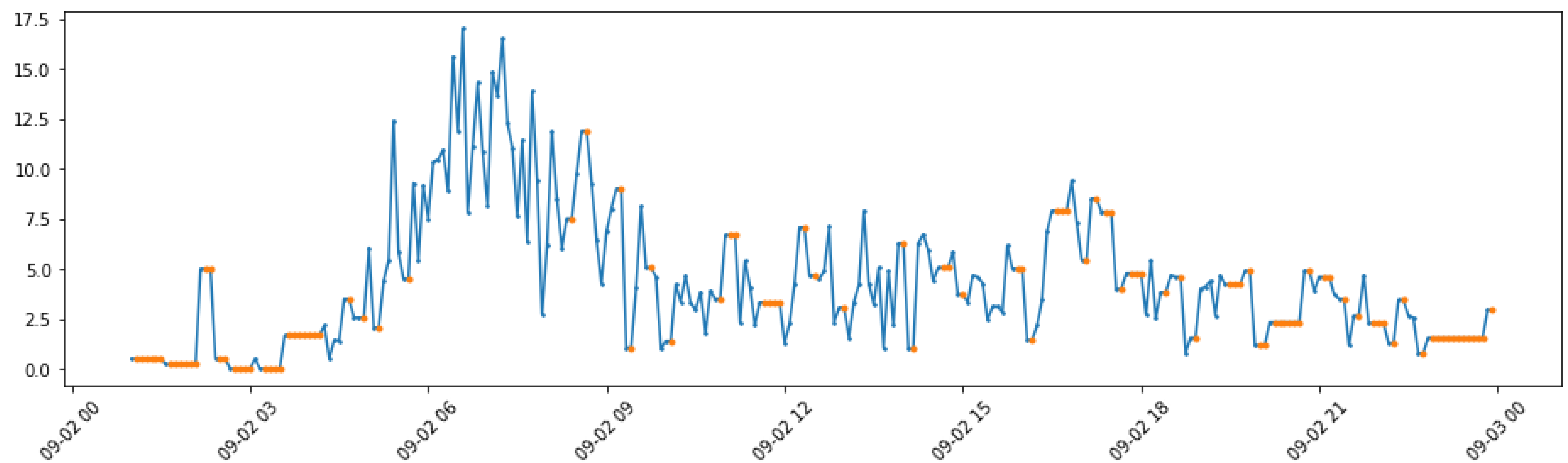
In [16]:
```
nab.plot_series(ddata2_ff, show_markers=True, figsize=figsize)
plt.scatter(ddata2_ffonly.index, ddata2_ffonly, marker='.', c='tab:orange');
```



# Forward/Backward Filling on the Traffic Data

## Forward filling works reasonably for small gaps

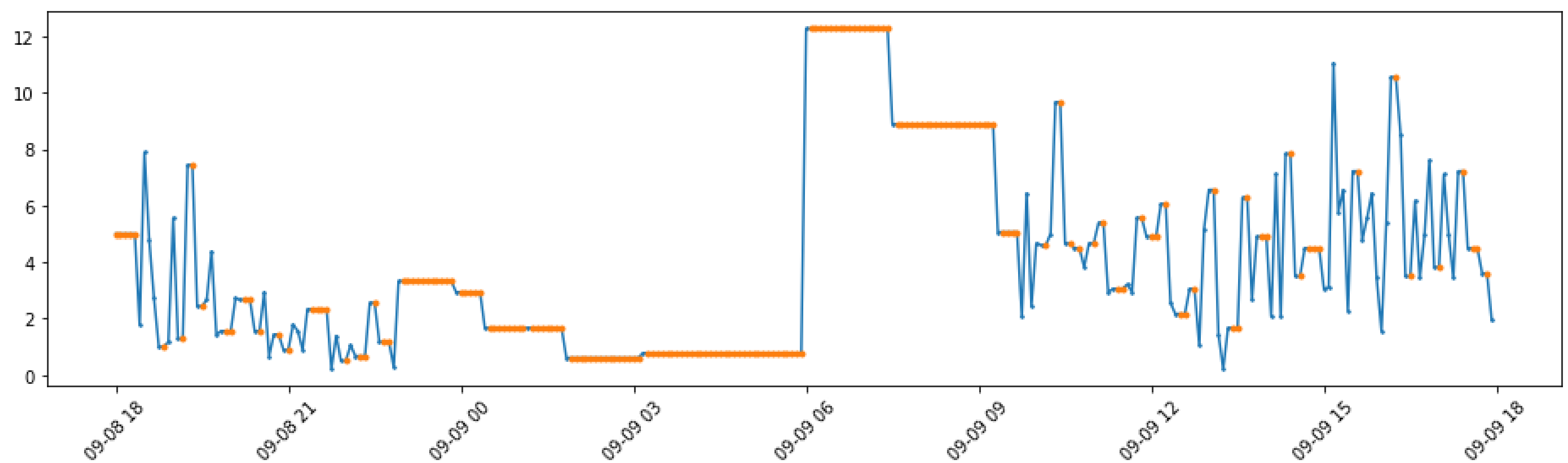
In [17]:
```
mask = (ddata2_ff.index >= '2015-09-02 01:00') & (ddata2_ff.index < '2015-09-03 00:00')
nab.plot_series(ddata2_ff[mask], show_markers=True, figsize=figsize)
plt.scatter(ddata2_ffonly.index[mask], ddata2_ffonly[mask], marker='.', c='tab:orange');
```



# Forward/Backward Filling with our Series

## ...But it is not particularly effective for larger gaps

In [18]:
```
mask = (ddata2_ff.index >= '2015-09-08 18:00') & (ddata2_ff.index < '2015-09-09 18:00')
nab.plot_series(ddata2_ff[mask], show_markers=True, figsize=figsize)
plt.scatter(ddata2_ffonly.index[mask], ddata2_ffonly[mask], marker='.', c='tab:orange');
```



# (Geometric) Interpolation

**A few more options are available via [the `interpolate` method]**

```
DataFrame/Series.interpolate(method='linear', ...)
```

The `method` parameter determines how NaNs are filled:

- "linear" uses a linear interpolation, assuming uniformly spaced samples
- "time" uses a linear interpolation, but supports non-uniformly spaced samples
- "nearest" uses the closest value
- "polynomial" uses a polynomial interpolation
- Even "ffill" and "bfill" are available

Both "polynomial" and "spline" require to specify the additional parameter `order`

- E.g. `df.interpolate(method='polynomial', order='3')`

# (Geometric) Interpolation

## Let us check the performance of some approaches

In [19]:
```
args = [{'method':'linear'}, {'method':'time'}, {'method':'nearest'},
        {'method':'polynomial', 'order': 2}]

for a in args:
    tmp = data1_mv.interpolate(**a)
    rmse = np.sqrt(mean_squared_error(data1, tmp))
    print(f'RMSE for {a["method"]}: {rmse:.2f}')
```

```
RMSE for linear: 4.42
RMSE for time: 4.42
RMSE for nearest: 4.95
RMSE for polynomial: 17.89
```

- "linear" and "time" are equivalent in this case (we have uniformly-spaced samples)
- "polynomial" is the most complex, and in this case also the worst

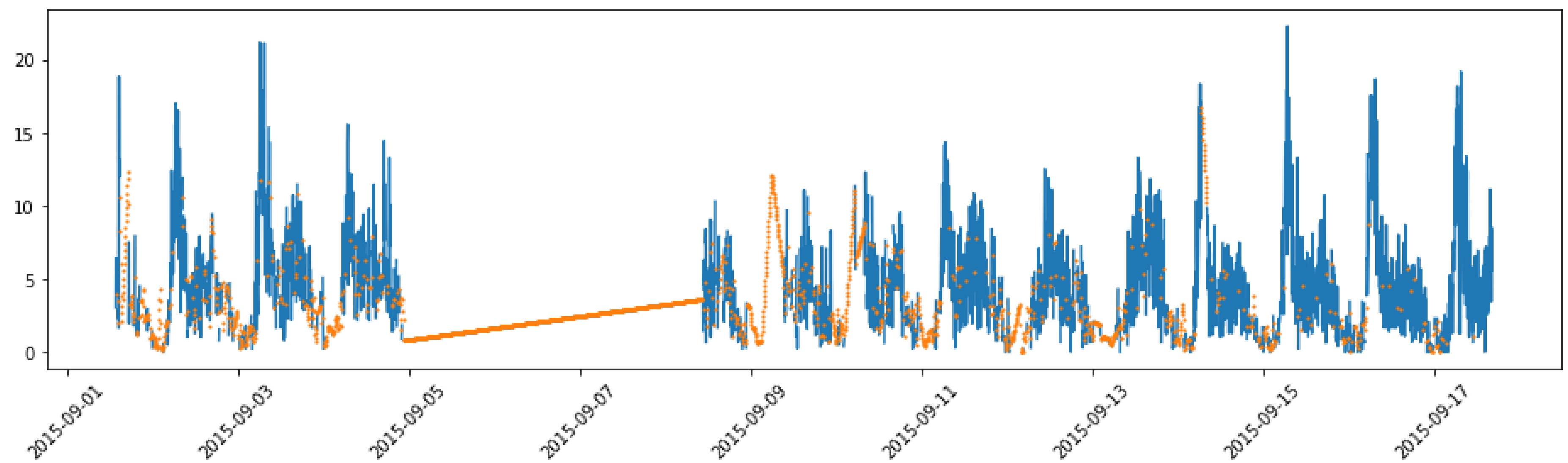
All perform worse than forward filling (at least in this case)!

# Curve Interpolation on Traffic Data

## On real data, we cannot (easily) compare interpolation methods

- This is because typically we have no ground truth
- For now, we will settle for a visual inspection

In [20]:
```
ddata2_ln = ddata2.interpolate(method='linear')
nab.plot_series(ddata2, filled_version=ddata2_ln, figsize=figsize)
```



## Considerations

**All these methods for dealing with missing values:**

- Work ok for small gaps, but loose effectiveness as the gap size grows
- This is true even for the more advanced filling methods!
- Better methods just degrade a bit more slowly

**MSE comparisons can be very effective:**

- But requires access to ground truth!
- An idea: make your ground truth by artificially removing values
- ...Then comparing filling methods based on their performance on the artificial gaps

**MSE is not everything**

- Every filling method makes mistakes: it's important not to make the wrong ones
- Think about how you plan to use your (filled) time series
- Can you expect the series to have uniform variance?