Emergency Deparment Management Problems

Emergency Room @ Maggiore Hospital

We will now consider a problem from the healthcare sector

We will use a dataset for the "Maggiore" hospital in Bologna

- In particular, we will focus on predicting arrivals
- ...To the Emergency Department (Pronto Soccorso)

A Look at the Dataset

We will start as usual by having a look at the dataset

In [2]:
```
data = util.load_ed_data(data_file)
data
```

Out[2]:

	year	ID	Triage	TkCharge	Code	Outcome
0	2018	1	2018-01-01 00:17:33	2018-01-01 04:15:36	green	admitted
1	2018	2	2018-01-01 00:20:33	2018-01-01 03:14:19	green	admitted
2	2018	3	2018-01-01 00:47:59	2018-01-01 04:32:30	white	admitted
51238	2018	51239	2018-01-01 00:49:51	NaT	white	abandoned
51240	2018	51241	2018-01-01 01:00:40	NaT	green	abandoned
...	...	...	...	...	...	...
95665	2019	95666	2019-10-31 23:26:54	2019-10-31 23:41:13	yellow	admitted
95666	2019	95667	2019-10-31 23:46:43	2019-11-01 09:30:25	green	admitted
108622	2019	108623	2019-10-31 23:54:05	NaT	green	abandoned
95667	2019	95668	2019-10-31 23:55:32	2019-11-01 00:18:46	yellow	admitted
108623	2019	108624	2019-10-31 23:59:21	NaT	green	abandoned

108625 rows × 6 columns

A Look at the Dataset

In [3]:
```
data.iloc[:3]
```

Out[3]:

	year	ID	Triage	TkCharge	Code	Outcome
0	2018	1	2018-01-01 00:17:33	2018-01-01 04:15:36	green	admitted
1	2018	2	2018-01-01 00:20:33	2018-01-01 03:14:19	green	admitted
2	2018	3	2018-01-01 00:47:59	2018-01-01 04:32:30	white	admitted

- Each row refers to a single patient
- `Triage` is the arrival time of each patient
- `TKCharge` is the time when a patient starts the first visit
- `Code` refers to the estimated priority (white < green < yellow < red)
- `Outcome` discriminates some special conditions (people quitting, fast tracks)

A Look at the Dataset

Let's also have a look at the data types

In [4]:
```
data.dtypes
```

Out[4]:
```
year                   int64
ID                     int64
Triage        datetime64[ns]
TkCharge      datetime64[ns]
Code                category
Outcome             category
dtype: object
```

As we said, we will focus for on predicting arrivals

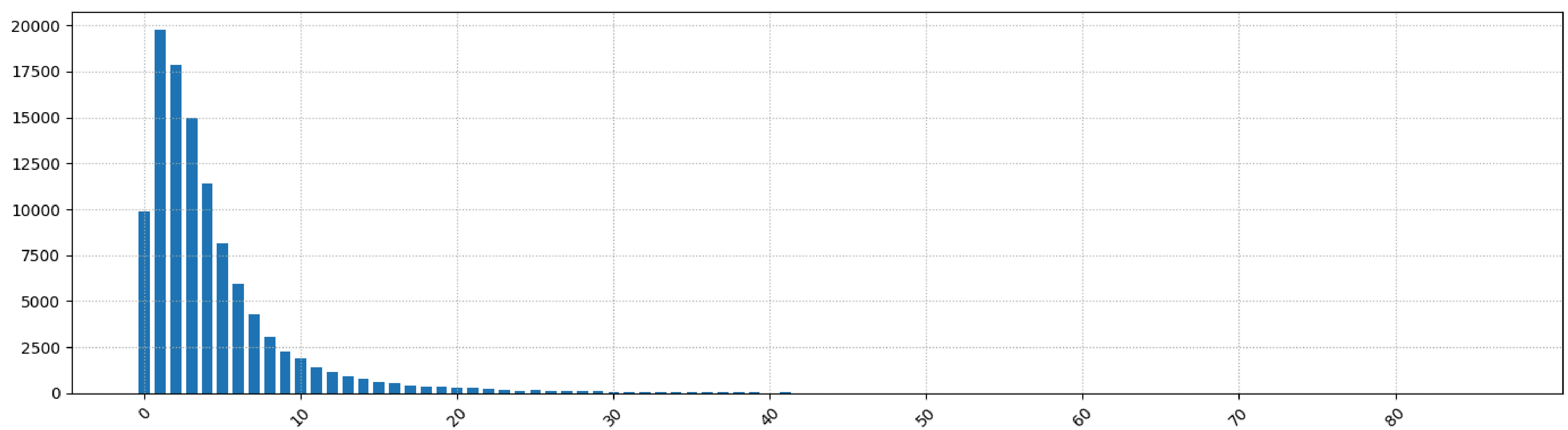
...Hence, it makes sense to sort rows by increasing triage time:

In [5]:
```
data.sort_values(by='Triage', inplace=True)
```

Inter-Arrival Times

Let's check empirically the distribution of the inter-arrival times

In [6]:
```python
delta = data['Triage'].iloc[1:].dt.round('2min') - data['Triage'].iloc[:-1].dt.round('2min'
tmp = delta.value_counts().sort_index().values
tmp = pd.Series(index=np.arange(len(tmp)), data=tmp)
util.plot_bars(tmp, tick_gap=10, figsize=figsize)
```

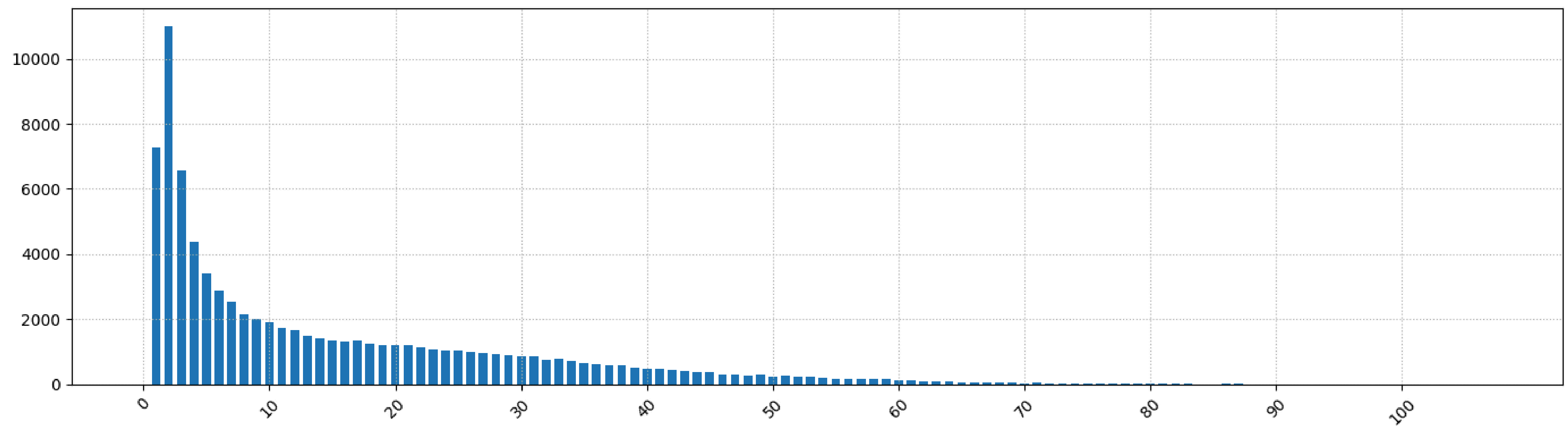


- There is a number of very low inter-arrival times
- This is due to how triage is performed (bursts, rather than a steady flow)

Waiting Time

Here is the distribution of the waiting times

In [7]:
```
tmp = data[~data['TkCharge'].isnull()]
wait_time = tmp['TkCharge'].dt.round('10min') - tmp['Triage'].dt.round('10min')
tmp = wait_time.value_counts().sort_index().values
tmp = pd.Series(index=np.arange(len(tmp)), data=tmp)
util.plot_bars(tmp, tick_gap=10, figsize=figsize)
```

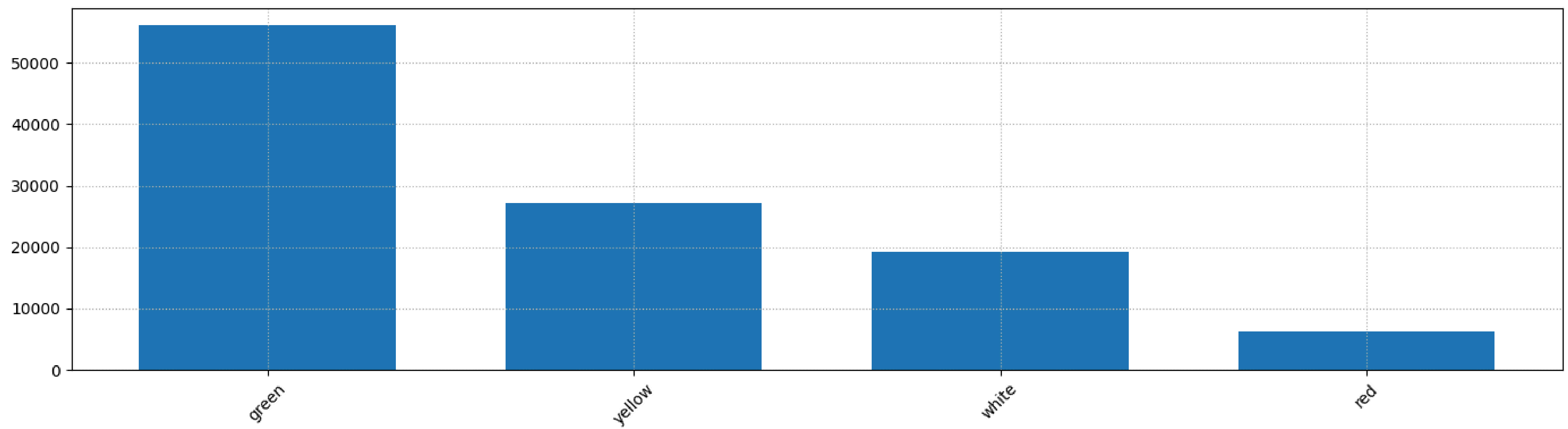


- The distritbution is heavy-tailed
- I.e. the probability of very long waiting times is non-negligible

Code Distribution

The distribution of the priority codes

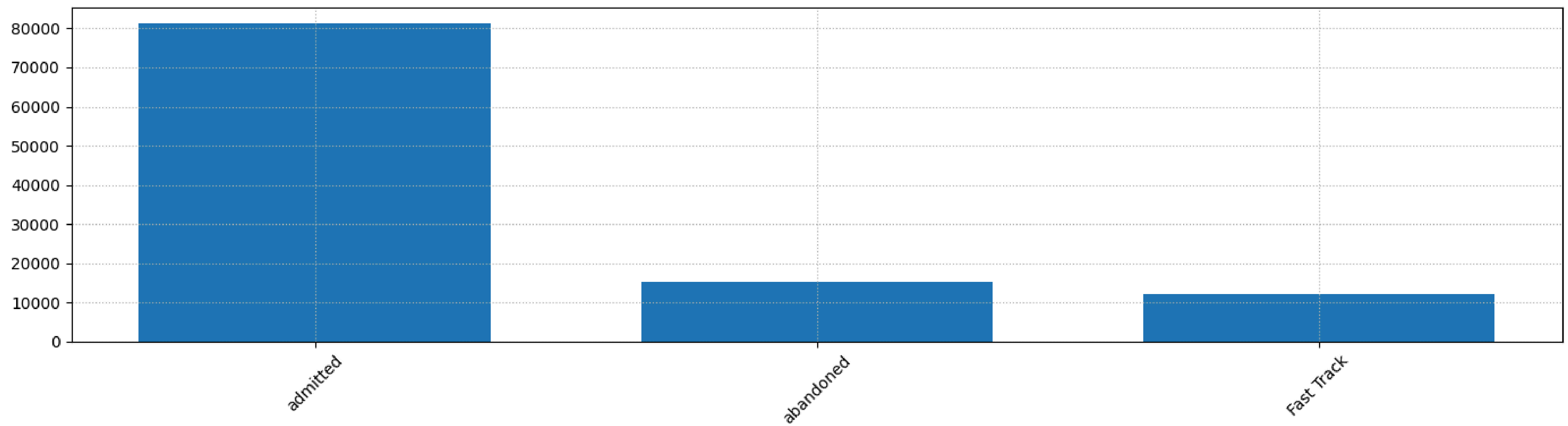
```
In [8]: util.plot_bars(data['Code'].value_counts(), figsize=figsize)
```



- Green code (low severity) form the majority of arrivals
- Yellow and red codes (mid and high severity) are in smaller numbers
- White codes (lowest priority) are also not very frequent

Outcome Distribution

```
In [9]: util.plot_bars(data['Outcome'].value_counts(), figsize=figsize)
```

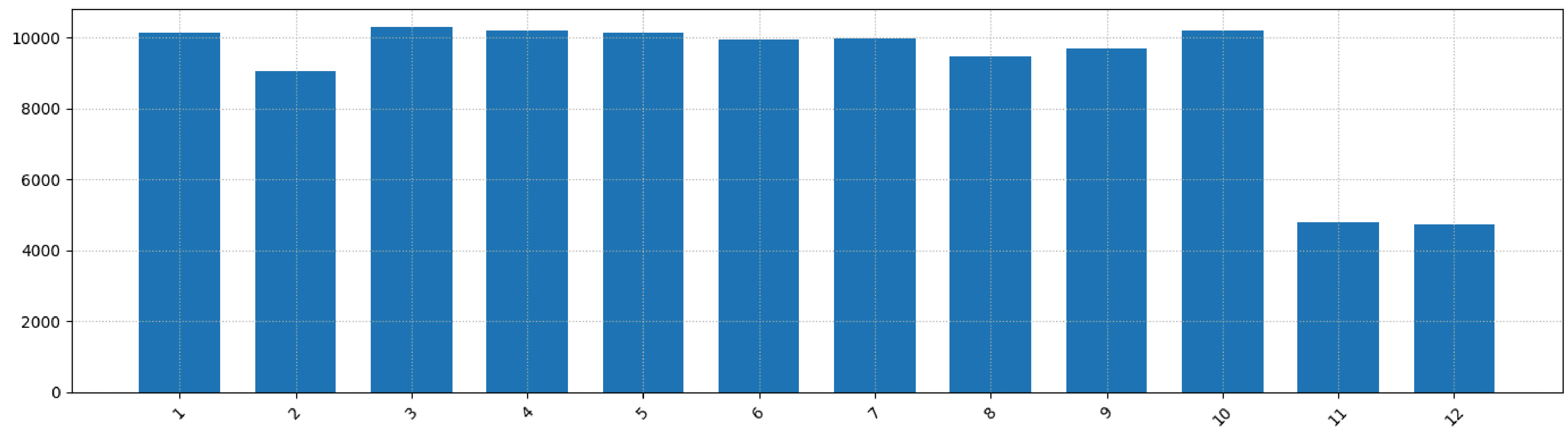


- Abandons are infrequent, as are "fast track" patients

Arrival Distribution over Months

Let's look at the arrival distribution over months

In [10]:
```
months = data['Triage'].dt.month
util.plot_bars(months.value_counts().sort_index(), figsize=figsize)
```

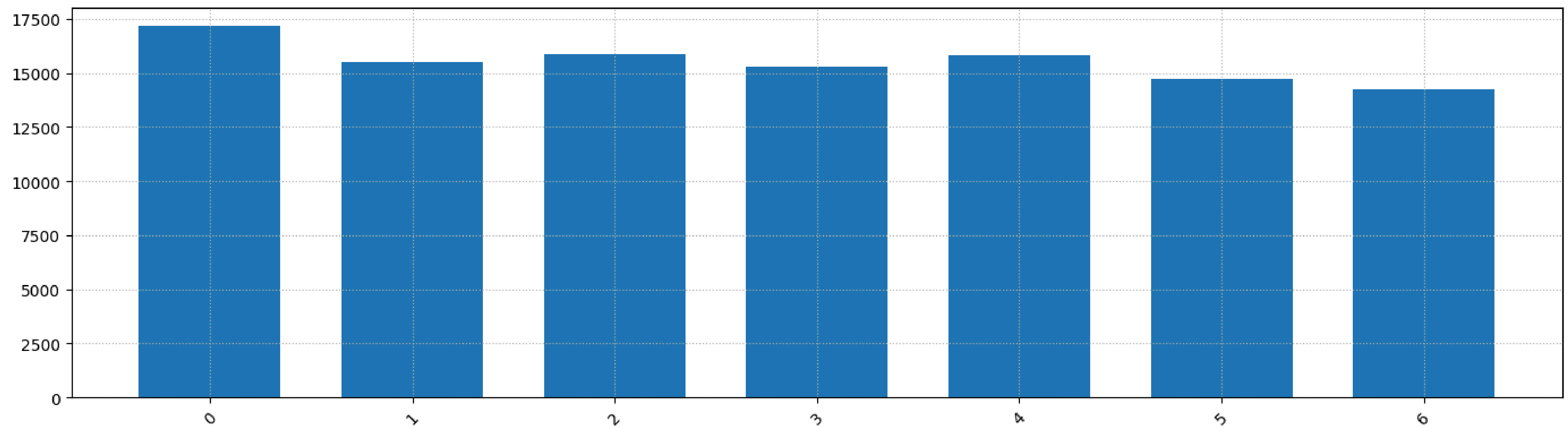


- The low values for Nov. and Dec. are due to the 2019 series ending in October
- The distribution seems stable (but we are not plotting standard deviations!)

Arrival Distribution over Weekdays

Let's look at the distribution over weekdays

In [11]:
```
weekdays = data['Triage'].dt.weekday
util.plot_bars(weekdays.value_counts().sort_index(), figsize=figsize)
```

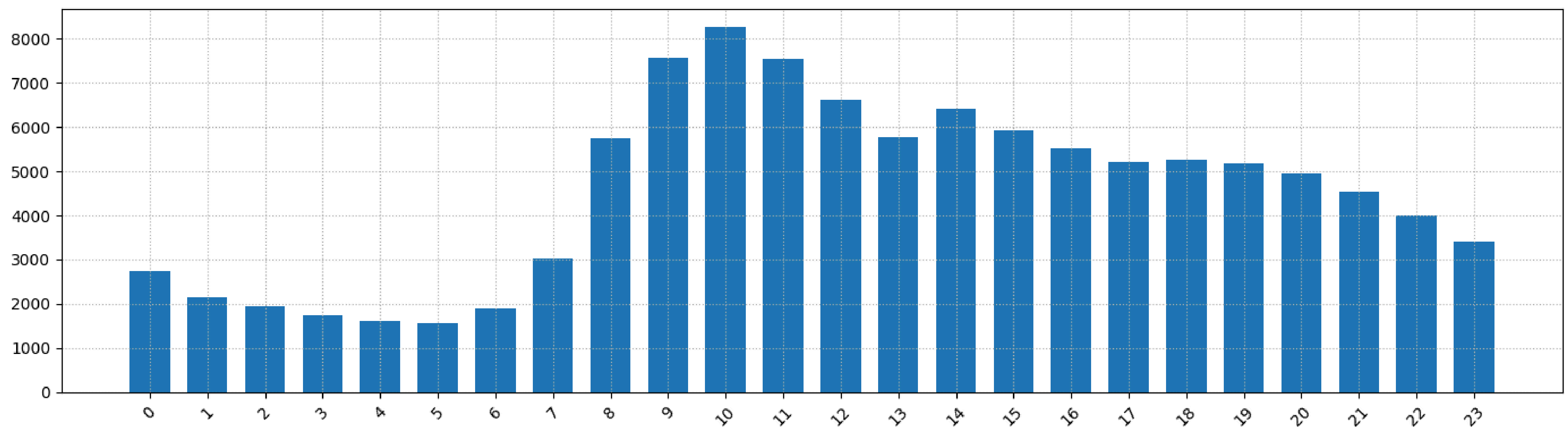


- Similarly to months, weekdays are likelly to have little predictive power
- ...But it's better not to rush conclusions (we still are not plotting the stddev!)

Arrival Distribution over Hours

Let's see now the arrival distribution over the hours of the day

```
In [12]: hours = data['Triage'].dt.hour
         util.plot_bars(hours.value_counts().sort_index(), figsize=figsize)
```



- There is a clear pattern: the hour of the day will have strong predictive power
- Again, analyzing the standard deviation may provide better insights

Data Preparation

Binning

In our considered problem:

- We are not going to revise our decisions continuosly
- We are not interested in predicting the next arrival

Rather:

- We will take decisions at fixed intervals
- We care about the expected arrivals in a given horizon

Overall, we need to choose a meaningful time unit

In other words, we need to perform some kind of binning

- We used binning to downsample high-frequency data
- Here we will use binning to aggregate events with a variable frequency

Code-Based Counts

We will prepare the data to track counts for all priority codes

In [13]:
```
codes = pd.get_dummies(data['Code'])
codes.set_index(data['Triage'], inplace=True)
codes.columns = codes.columns.to_list()
print(f'Number of examples: {len(codes)}')
codes.head()
```

```
Number of examples: 108625
```

Out[13]:

	green	red	white	yellow
Triage				
2018-01-01 00:17:33	True	False	False	False
2018-01-01 00:20:33	True	False	False	False
2018-01-01 00:47:59	False	False	True	False
2018-01-01 00:49:51	False	False	True	False
2018-01-01 01:00:40	True	False	False	False

- The `get_dummies` function applies a one-hot encoding to categorical value
- The method generates a categorial column index (then converted to list)

Resampling

Then, we need to aggregate data with a specified frequency

In [14]:
```
codes_b = codes.resample('h').sum()
print(f'Number of examples: {len(codes_b)}')
codes_b.head()
```

```
Number of examples: 16056
```

Out[14]:

	green	red	white	yellow
Triage				
2018-01-01 00:00:00	2	0	2	0
2018-01-01 01:00:00	7	1	1	1
2018-01-01 02:00:00	4	1	4	3
2018-01-01 03:00:00	7	0	1	1
2018-01-01 04:00:00	3	0	2	0

- We used the `resample` iterator
- `resample` generater a dataframe with a dense index
- We chose 1 hours are our time unit

Computing Totals

We also compute the total number of arrivals for each interval

In [15]:
```
cols = ['white', 'green', 'yellow', 'red']
codes_b['total'] = codes_b[cols].sum(axis=1)
codes_b
```

Out[15]:

	green	red	white	yellow	total
Triage					
2018-01-01 00:00:00	2	0	2	0	4
2018-01-01 01:00:00	7	1	1	1	10
2018-01-01 02:00:00	4	1	4	3	12
2018-01-01 03:00:00	7	0	1	1	9
2018-01-01 04:00:00	3	0	2	0	5
...	...	...	...	...	...
2019-10-31 19:00:00	3	1	0	4	8
2019-10-31 20:00:00	9	0	2	0	11
2019-10-31 21:00:00	3	0	0	2	5
2019-10-31 22:00:00	1	2	3	1	7
2019-10-31 23:00:00	5	0	0	2	7

16056 rows × 5 columns

- The total count will be less noisy, if the individual terms are independent

Adding Time Information

Finally, we add time information (for later convenience)

In [16]:

```
codes_bt = codes_b.copy()
codes_bt['month'] = codes_bt.index.month
codes_bt['weekday'] = codes_bt.index.weekday
codes_bt['hour'] = codes_bt.index.hour
codes_bt
```

Out[16]:

	green	red	white	yellow	total	month	weekday	hour
Triage								
2018-01-01 00:00:00	2	0	2	0	4	1	0	0
2018-01-01 01:00:00	7	1	1	1	10	1	0	1
2018-01-01 02:00:00	4	1	4	3	12	1	0	2
2018-01-01 03:00:00	7	0	1	1	9	1	0	3
2018-01-01 04:00:00	3	0	2	0	5	1	0	4
...	...	...	...	...	...	...	...	...
2019-10-31 19:00:00	3	1	0	4	8	10	3	19
2019-10-31 20:00:00	9	0	2	0	11	10	3	20
2019-10-31 21:00:00	3	0	0	2	5	10	3	21
2019-10-31 22:00:00	1	2	3	1	7	10	3	22
2019-10-31 23:00:00	5	0	0	2	7	10	3	23

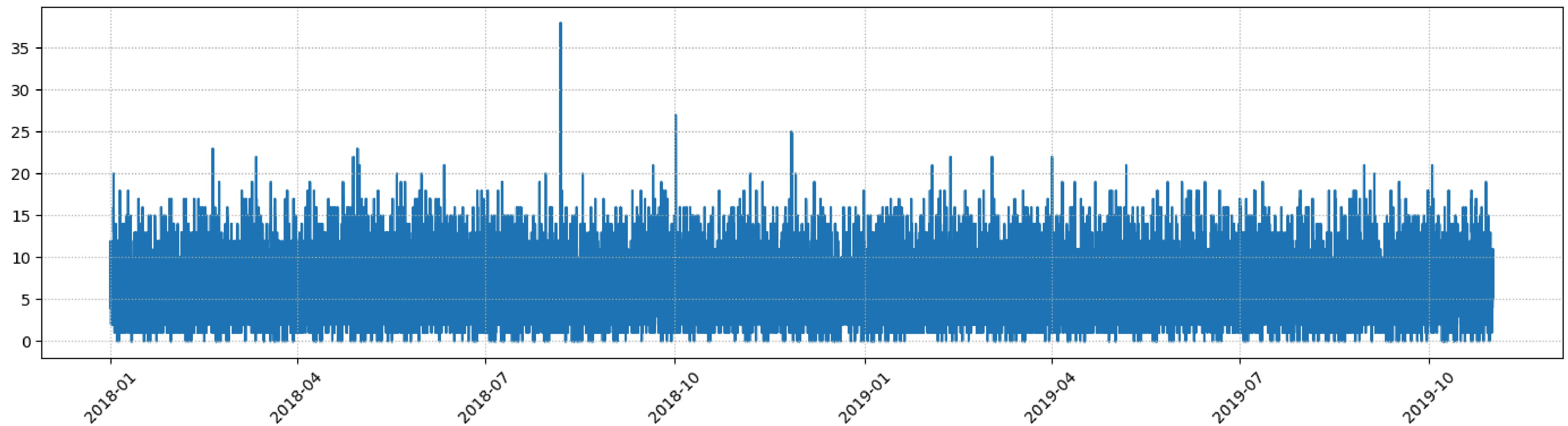
16056 rows × 8 columns

Counts over Time

Our resampled series can be plotted easily over time

Let's see the total counts as an example:

In [23]:
```
util.plot_series(codes_b['total'], figsize=figsize)
```

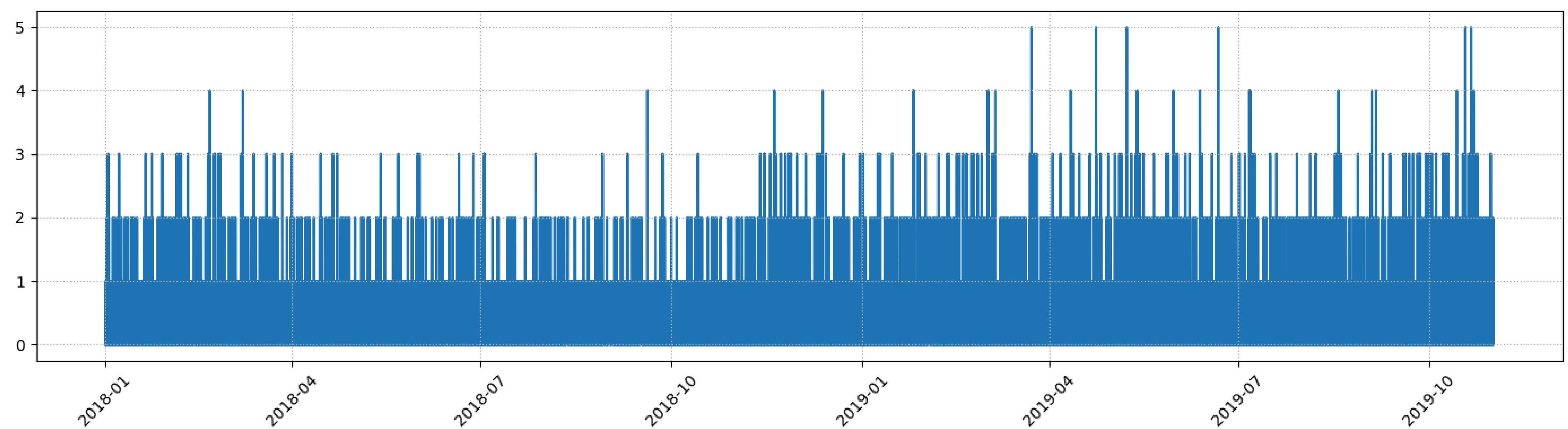


Counts over Time

Our resampled series can be plotted easily over time

The same plot, for the red codes (the counts are significanly lower):

```
In [24]: util.plot_series(codes_b['red'], figsize=figsize)
```

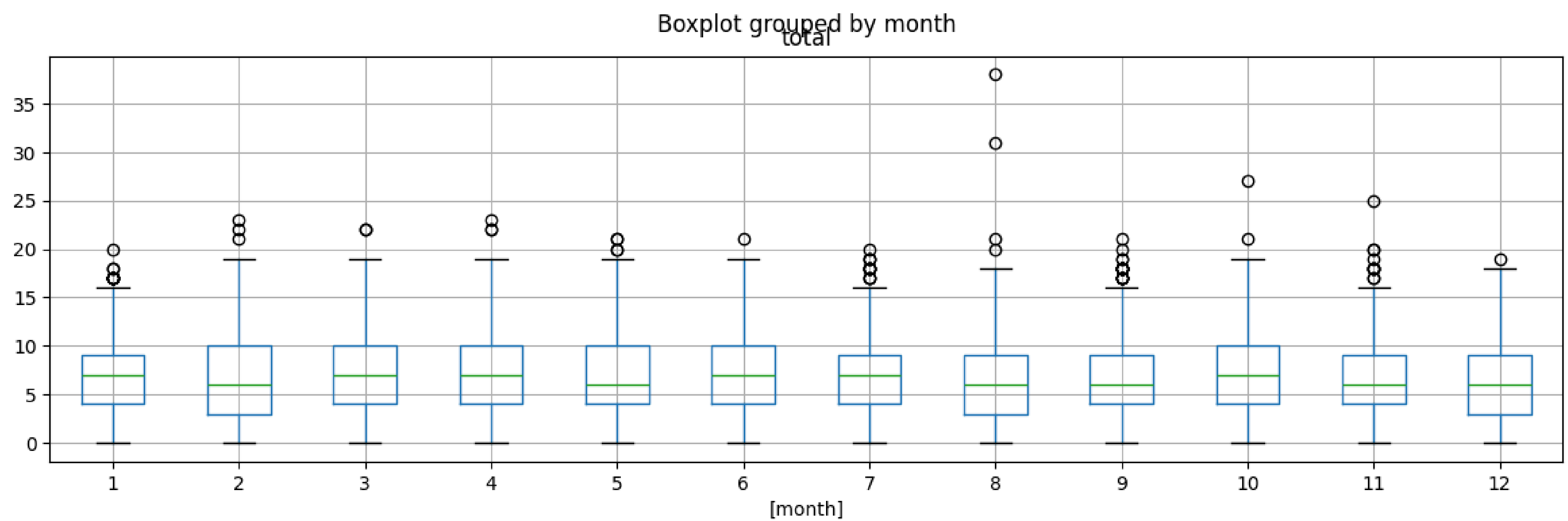


Variability

With our binned series, we can assess the count variability

Let's check it over different months:

In [25]:
```
codes_bt[['month', 'total']].boxplot(by='month', figsize=figsize);
```

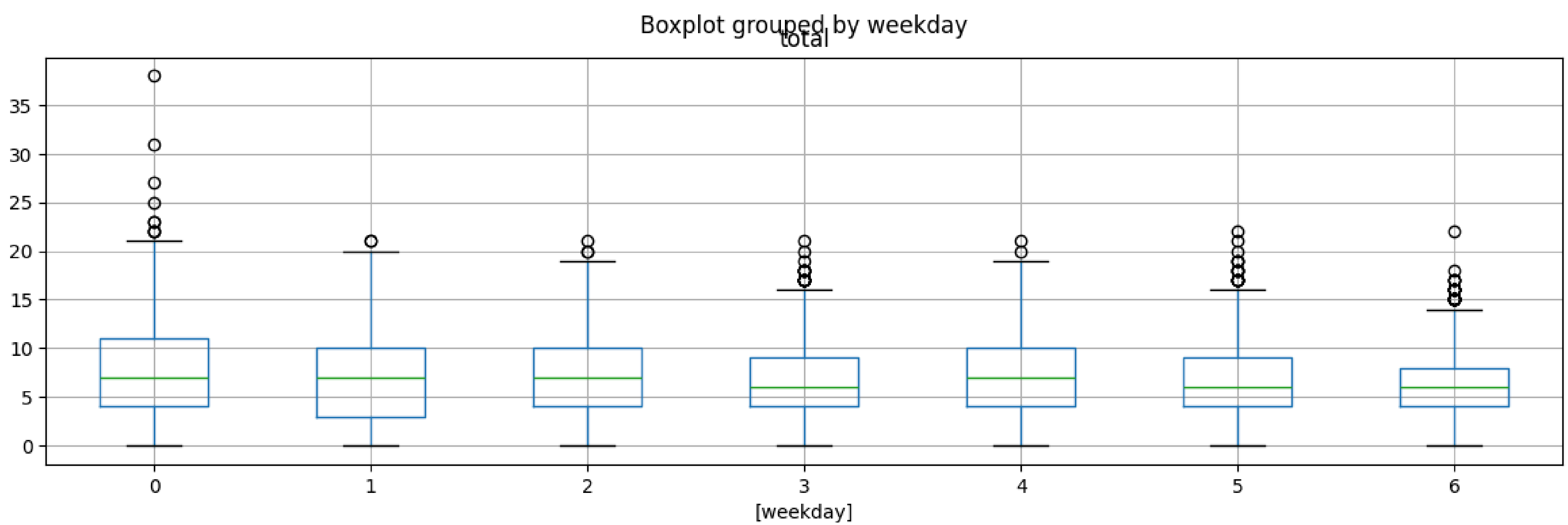


- The variability does not change much over different months

Variability

Here is the standard deviation over weekdays

In [26]:
```
codes_bt[['weekday', 'total']].boxplot(by='weekday', figsize=figsize);
```

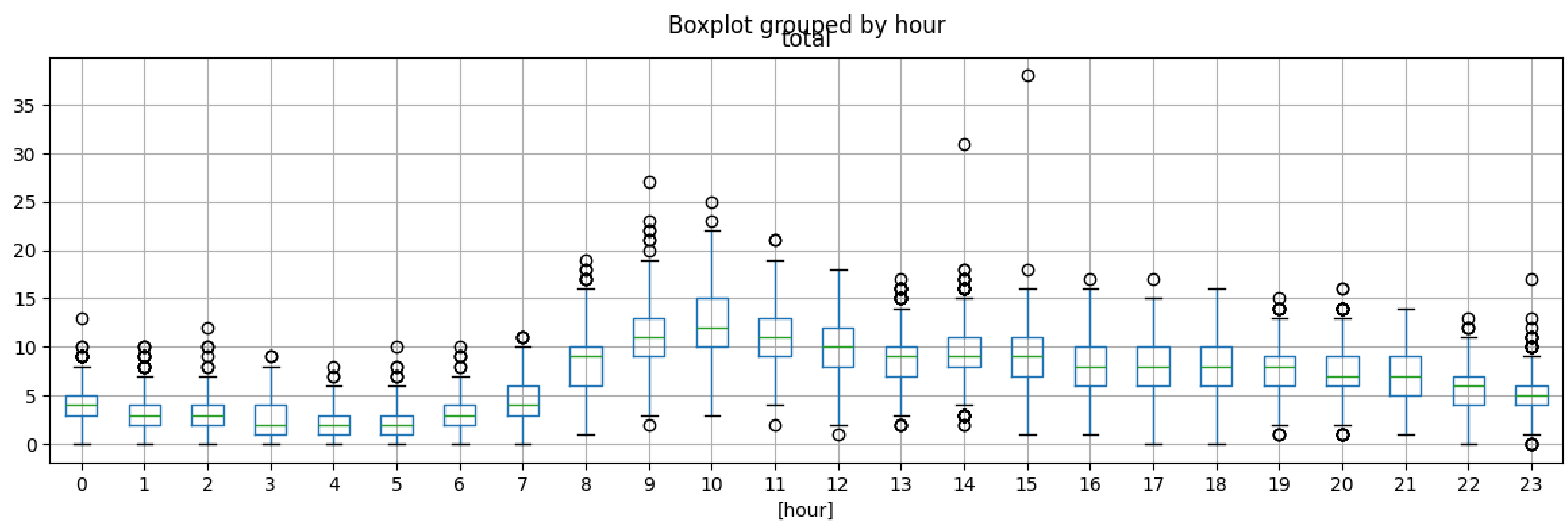


- There is a trend, but rather weak

Variability

...And finally over hours

In [27]:
```
codes_bt[['hour', 'total']].boxplot(by='hour', figsize=figsize);
```



- Variance and mean seem to be quite correlated