In [1]:

```
# ============================================================
# Notebook setup
# ============================================================

%load_ext autoreload
%autoreload 2

# Control figure size
figsize=(14, 4)

from util import util
import os
import pandas as pd
import numpy as np

# Load data
data_file = os.path.join('..', 'data', 'er.csv')
#data = util.load_ed_data(data_file)
```

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*

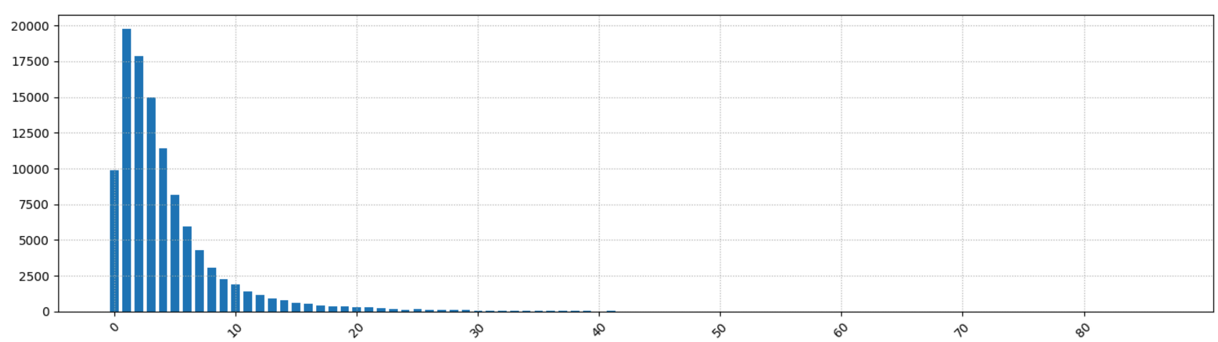
...Hence, it makes sense to sort rows by increasing triage time:

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]:
```
delta = data['Triage'].iloc[1:].dt.round('2min') - data['Triage'].iloc[:-1].
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)
```

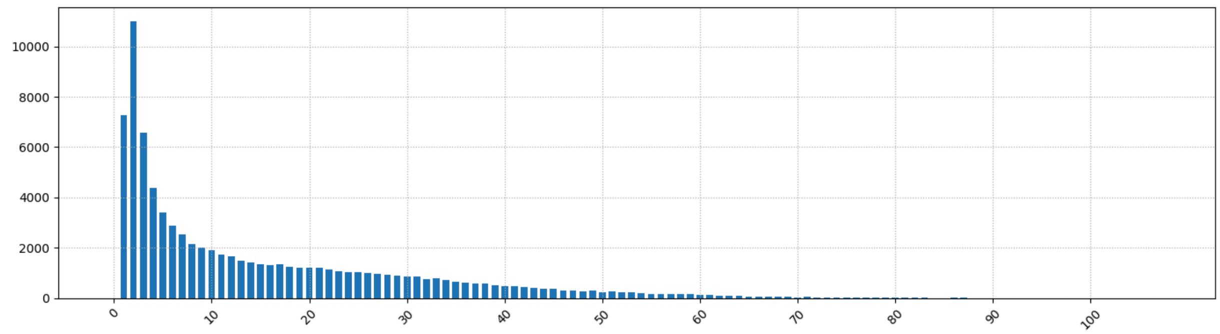


- There is a number of very low inter-arrival times
- This is due to how triage is performed (bursts, rather than a steady flow)

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('10mi
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)
```

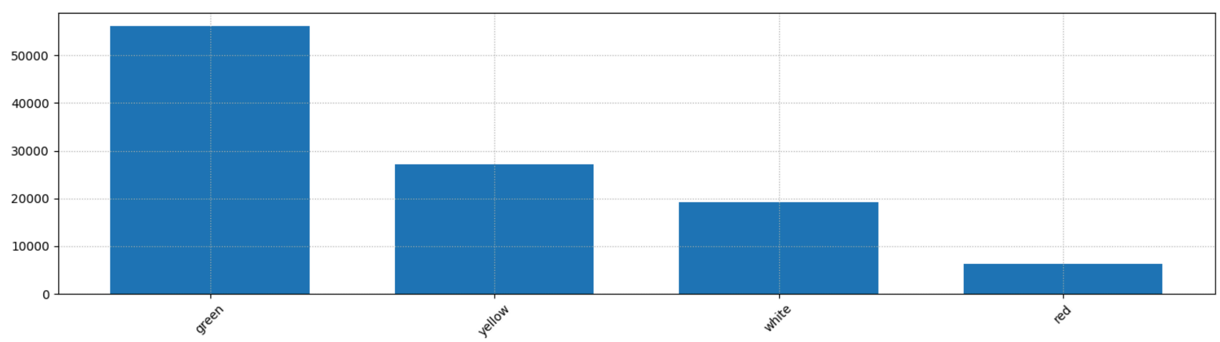


- The distritbution is *heavy-tailed*
- I.e. the probability of very long waiting times is non-negligible

Code Distribution

The distribution of the priority codes

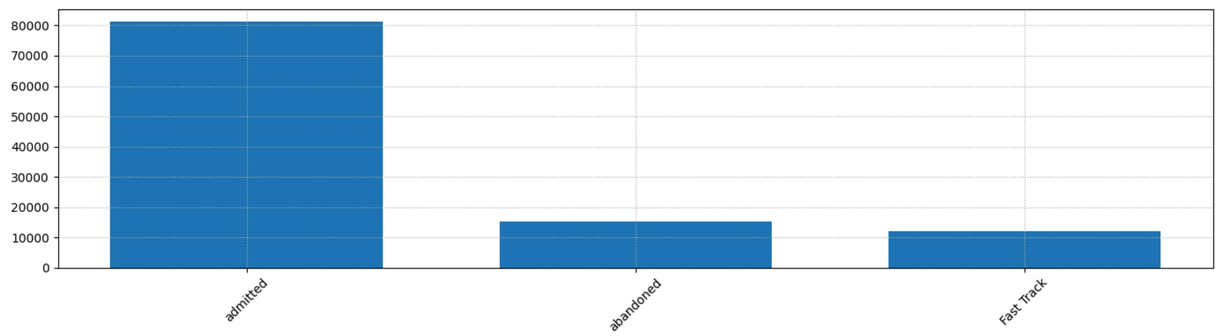
In [8]:
```
util.plot_bars(data['Code'].value_counts(), figsize=figsize)
```



- 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)
```

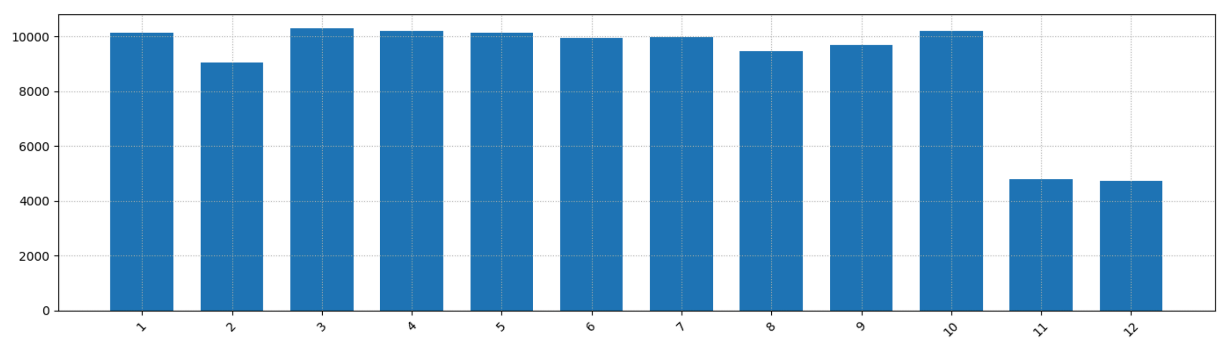


- Abandons are infrequent, as are "fast track" patients

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)
```

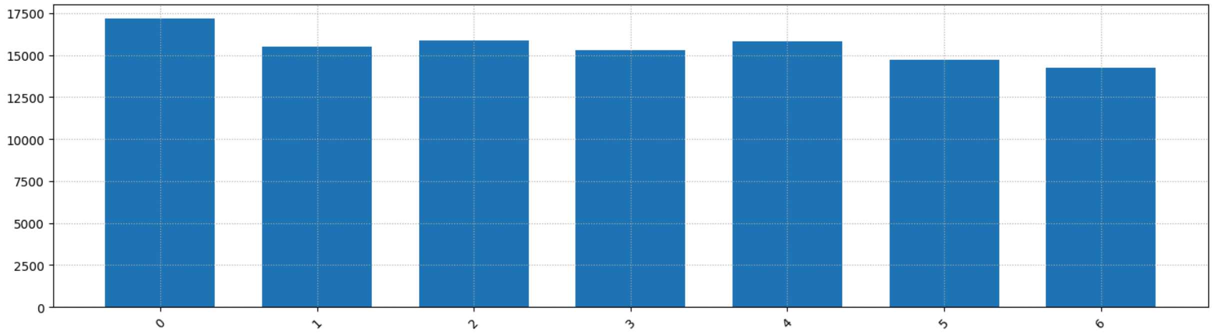


- The low values for Nov. and Dec. are due to the 2019 series ending in October
- The distribution seems stable (but we are not plotting standard deviations!)

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)
```

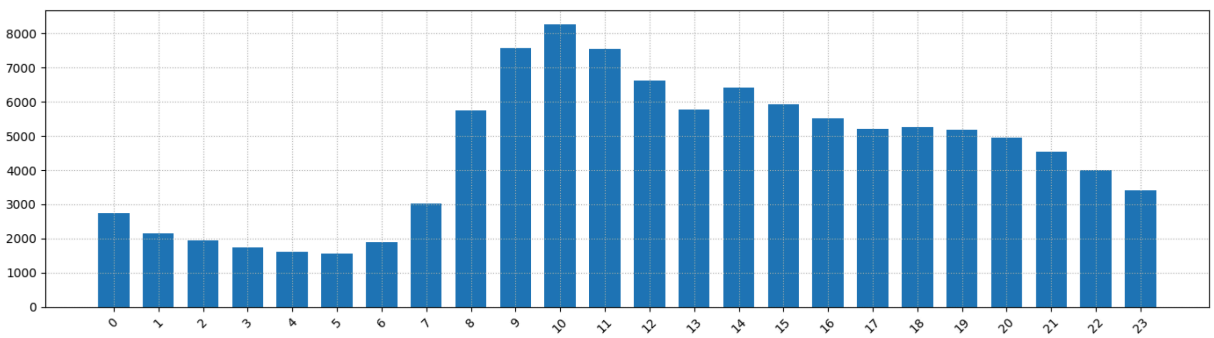


- Similarly to months, weekdays are likelly to have little predictive power
- ...But it's better not to rush conclusions (we still are not plotting the stddev!)

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

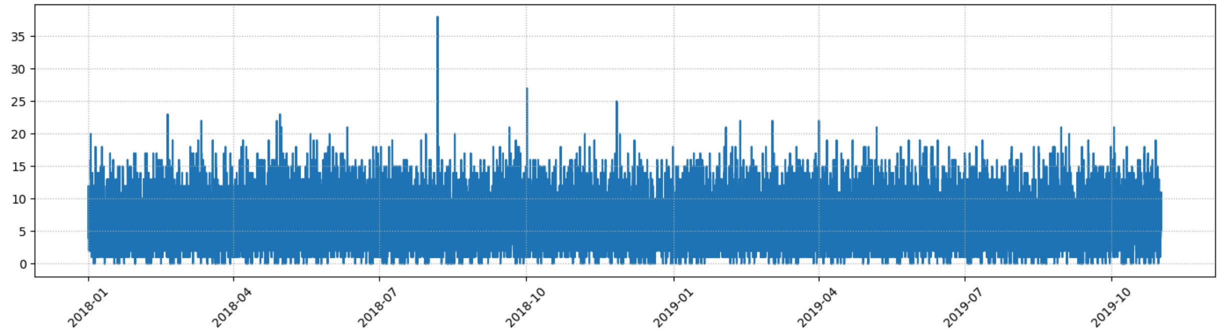
16056 rows × 8 columns

Counts over Time

Our resampled series can be plotted easily over time

Let's see the total counts as an example:

In [17]:
```
util.plot_series(codes_b['total'], figsize=figsize)
```

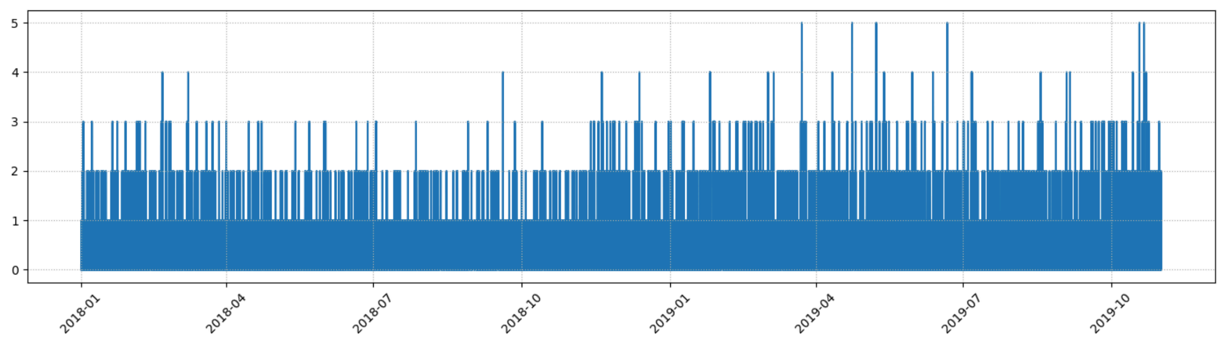


Counts over Time

Our resampled series can be plotted easily over time

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

In [18]:
```
util.plot_series(codes_b['red'], figsize=figsize)
```

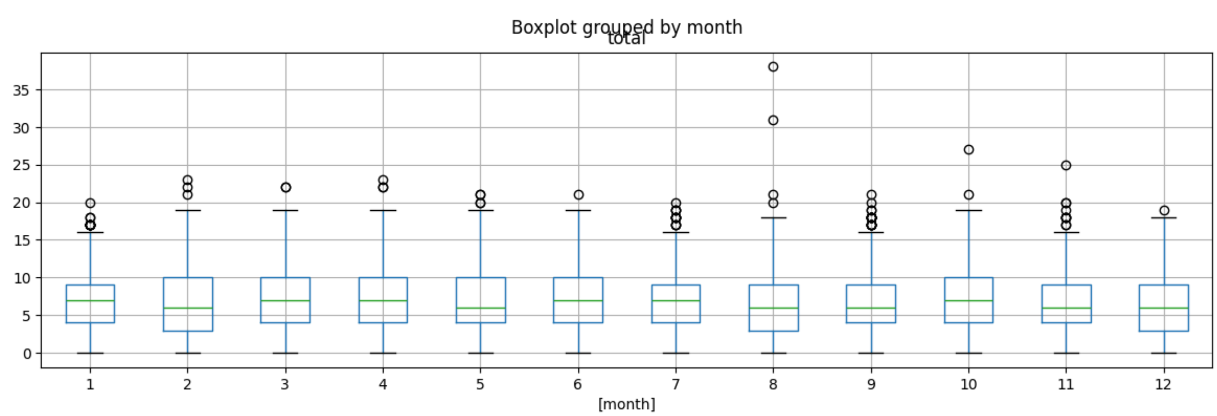


Variability

With our binned series, we can assess the count variability

Let's check it over different months:

In [19]:
```
codes_bt[['month', 'total']].boxplot(by='month', figsize=figsize);
```

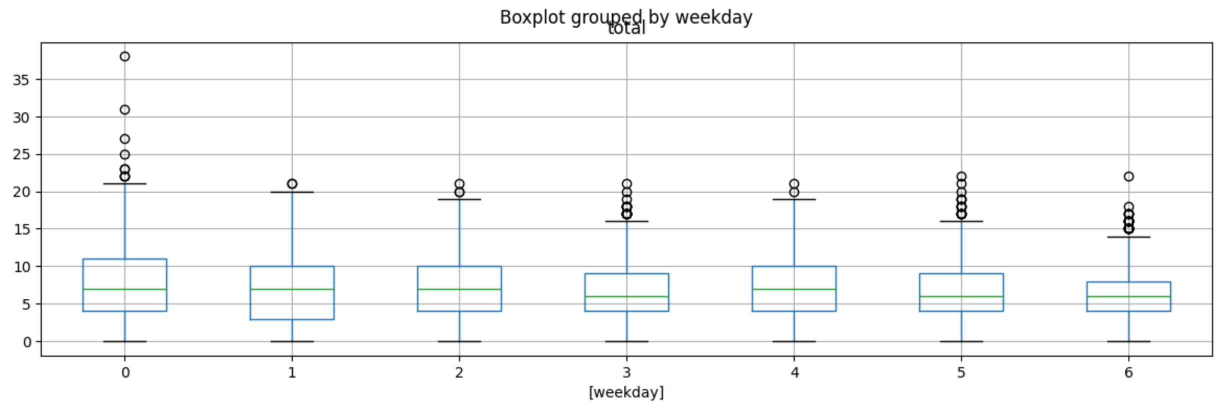


- The variability does not change much over different months

Variability

Here is the standard deviation over weekdays

In [20]:
```
codes_bt[['weekday', 'total']].boxplot(by='weekday', figsize=figsize);
```

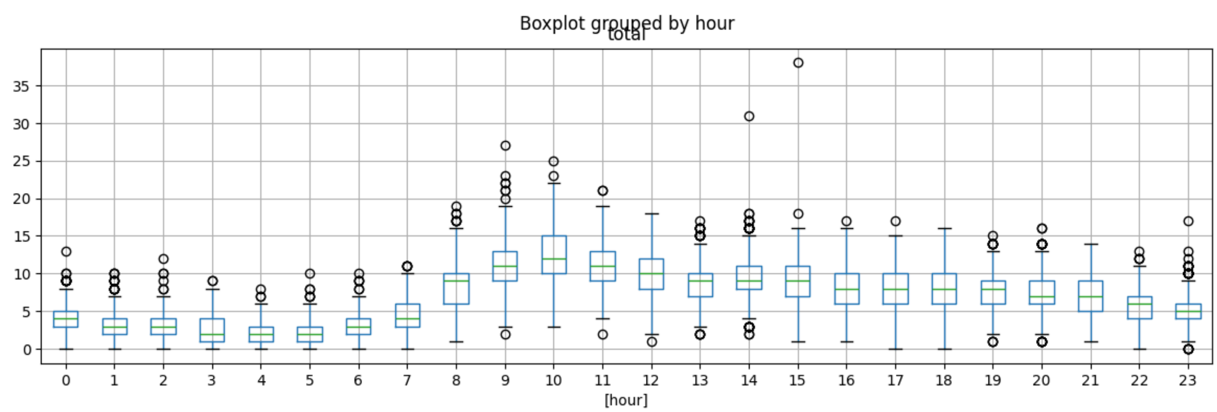


- There is a trend, but rather weak

Variability

...And finally over hours

In [21]:
```
codes_bt[['hour', 'total']].boxplot(by='hour', figsize=figsize);
```



- Variance and mean seem to be quite correlated