Overview

This tutorial will focus on our target problem and dataset

We will include some additional topics, including:

- Building Cartesian plots
- Building histograms
- Building scatter plots

Overview

The lecture relies on the the following proficiencies and tools:

- Python programming
- Data handling using the pandas module
- Plotting using matplotlib

You will need them only if you plan to handle these tasks yourself

An Example Problem

Our Target Problem

Let's assume we want to estimate real-estate prices in Taiwan

Loading the Data

Data for this problem is available (in csv format) from the `data` folder

In [7]:
```
!ls data
```

```
lr_test.txt  lr_train.txt  real_estate.csv  weather.csv
```

We will load the data via a Python library, called pandas

In [8]:
```
data = pd.read_csv('data/real_estate.csv', sep=',')
data.head() # Head returns the first 5 elements
```

Out[8]:

	house age	dist to MRT	#stores	latitude	longitude	price per area
0	14.8	393.2606	6	24.96172	121.53812	7.6
1	17.4	6488.0210	1	24.95719	121.47353	11.2
2	16.0	4066.5870	0	24.94297	121.50342	11.6
3	30.9	6396.2830	1	24.94375	121.47883	12.2
4	16.5	4082.0150	0	24.94155	121.50381	12.8

- The file content is a made accessible in a table-like object (called `DataFrame`)

Loading the Data

Let's have a peek at the data

In [9]:
```
data.head()
```

Out[9]:

	house age	dist to MRT	#stores	latitude	longitude	price per area
0	14.8	393.2606	6	24.96172	121.53812	7.6
1	17.4	6488.0210	1	24.95719	121.47353	11.2
2	16.0	4066.5870	0	24.94297	121.50342	11.6
3	30.9	6396.2830	1	24.94375	121.47883	12.2
4	16.5	4082.0150	0	24.94155	121.50381	12.8

- The first four columns contain quantities that easy to estimate
- ...But that's not true for the last one!

Obtaining price information requires actual houses to be sold and bought

- Our goal is to use the data to learn a model
- ...That can estimate the price based on the easily available information

Inspecting the Dataset

Now that we roughly know our goal, it's a good idea to inspect the dataset

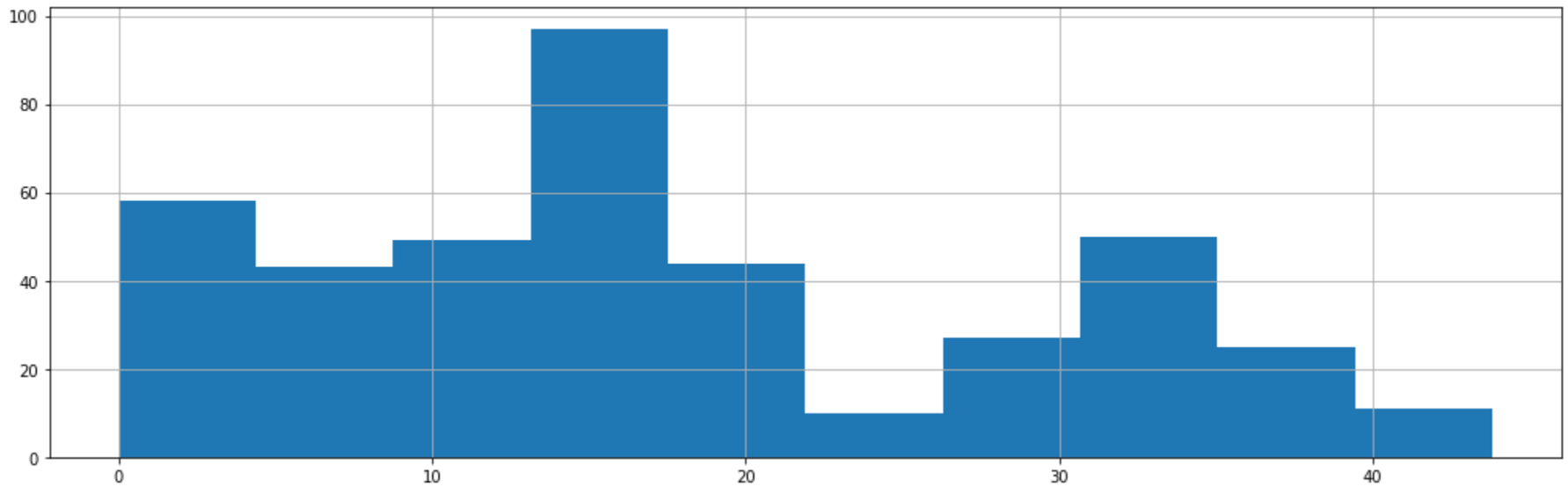
Typically, this is done by building plots, e.g.:

- Histograms
  - x-axis: values for one attribute
  - y-axis: number of occurrences in the dataset
  - Continuous attributes are typically discretized (i.e. binned) first
- Cartesian plots
  - x-axis: table row number
  - y-axis: one attribute
- Scatter plots
  - x-axis: one attribute
  - y-axis: the target

Using Histograms

Let's inspect the "house age" attribute

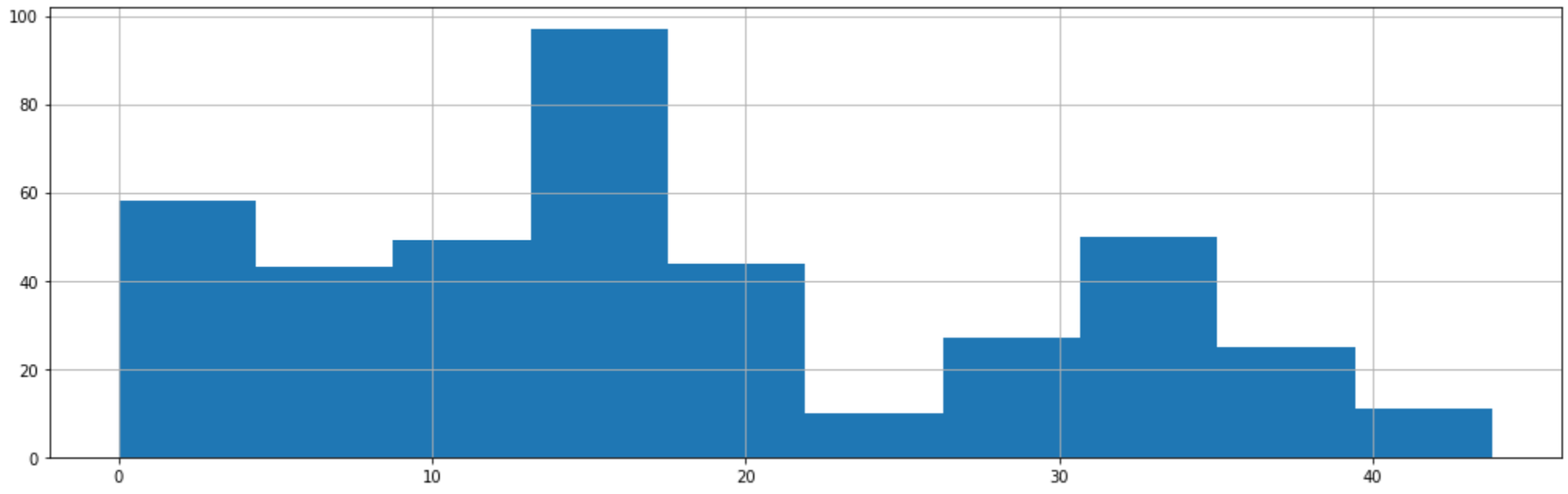
In [11]:
```
plt.figure()
data['house age'].hist(figsize=figsize)
plt.tight_layout()
```



Using Histograms

Let's inspect the "house age" attribute

In [11]:
```
plt.figure()
data['house age'].hist(figsize=figsize)
plt.tight_layout()
```

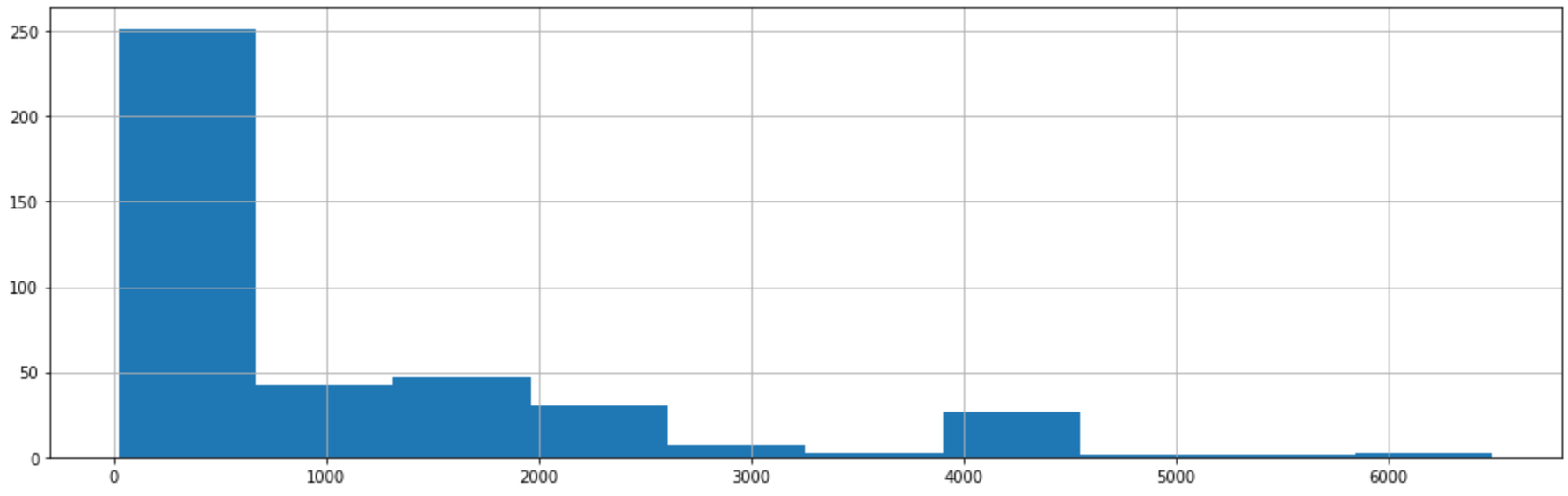


- There seem to be two clusters w.r.t. this attribute

Using Histograms

Let's inspect the "dist to MRT" attribute

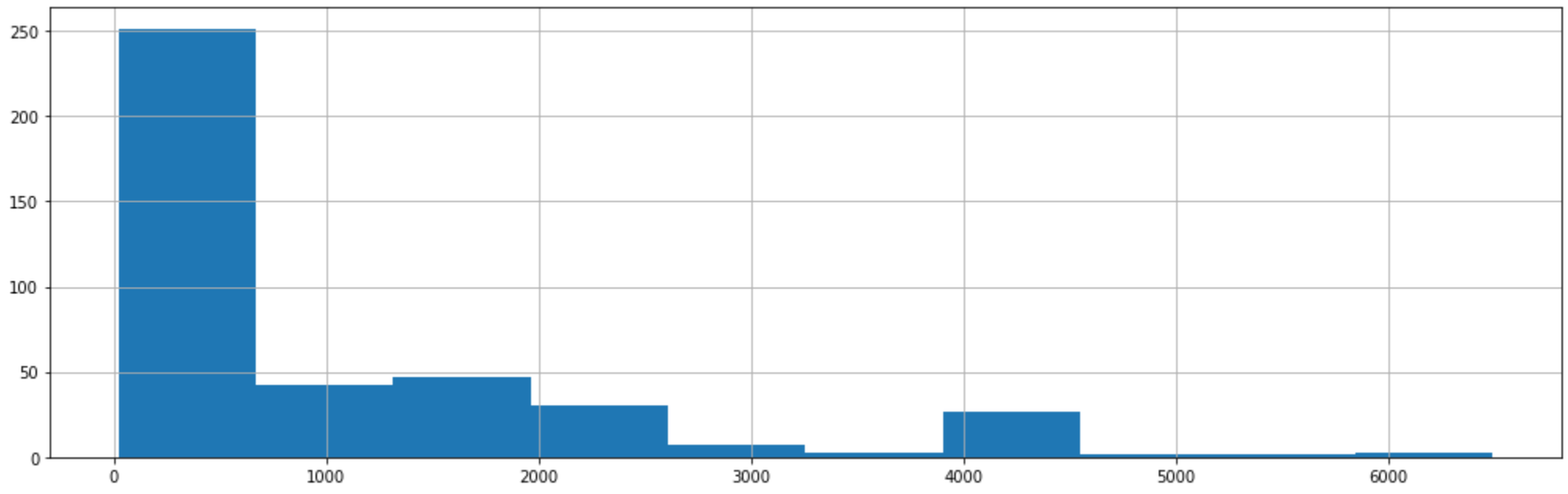
In [12]:
```
plt.figure()
data['dist to MRT'].hist(figsize=figsize)
plt.tight_layout()
```



Using Histograms

Let's inspect the "dist to MRT" attribute

In [12]:
```
plt.figure()
data['dist to MRT'].hist(figsize=figsize)
plt.tight_layout()
```

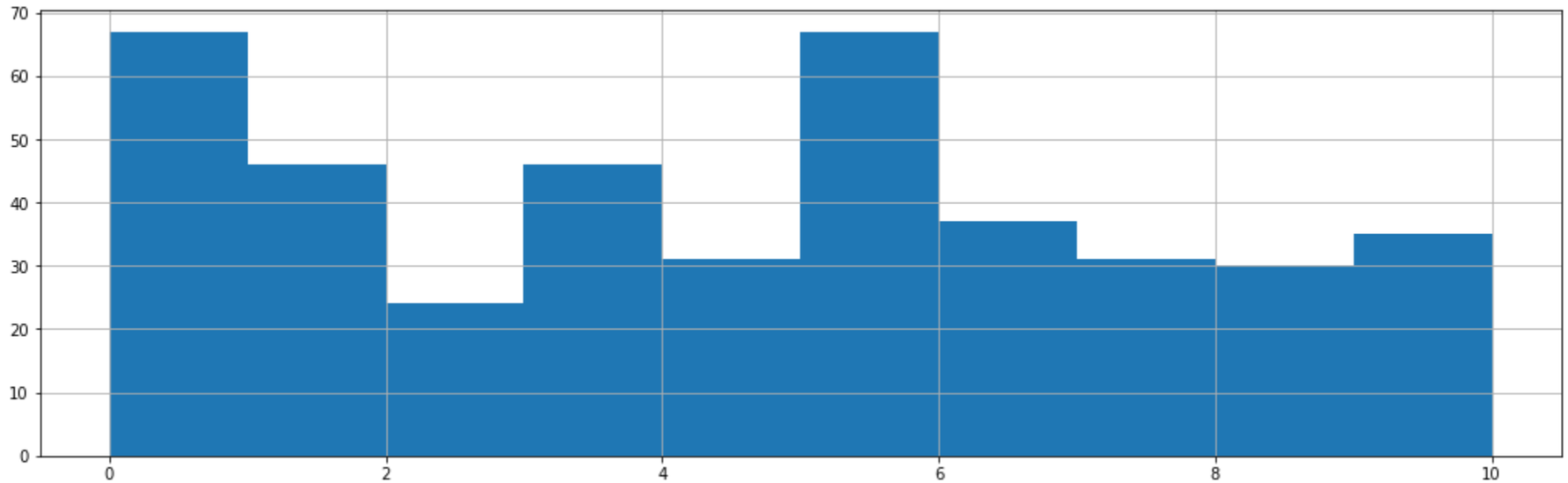


- This attribute has a large range and low values are much more prevalent

Using Histograms

Let's inspect the "#stores" attribute

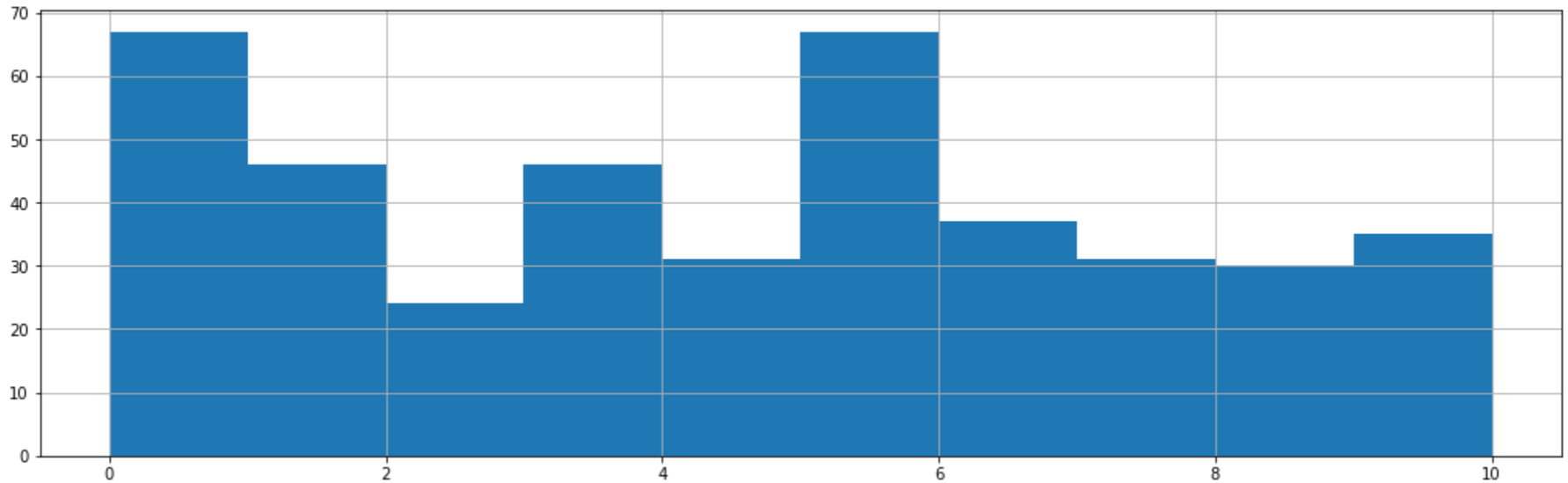
In [13]:
```
plt.figure()
data['#stores'].hist(figsize=figsize)
plt.tight_layout()
```



Using Histograms

Let's inspect the "#stores" attribute

In [13]:
```
plt.figure()
data['#stores'].hist(figsize=figsize)
plt.tight_layout()
```

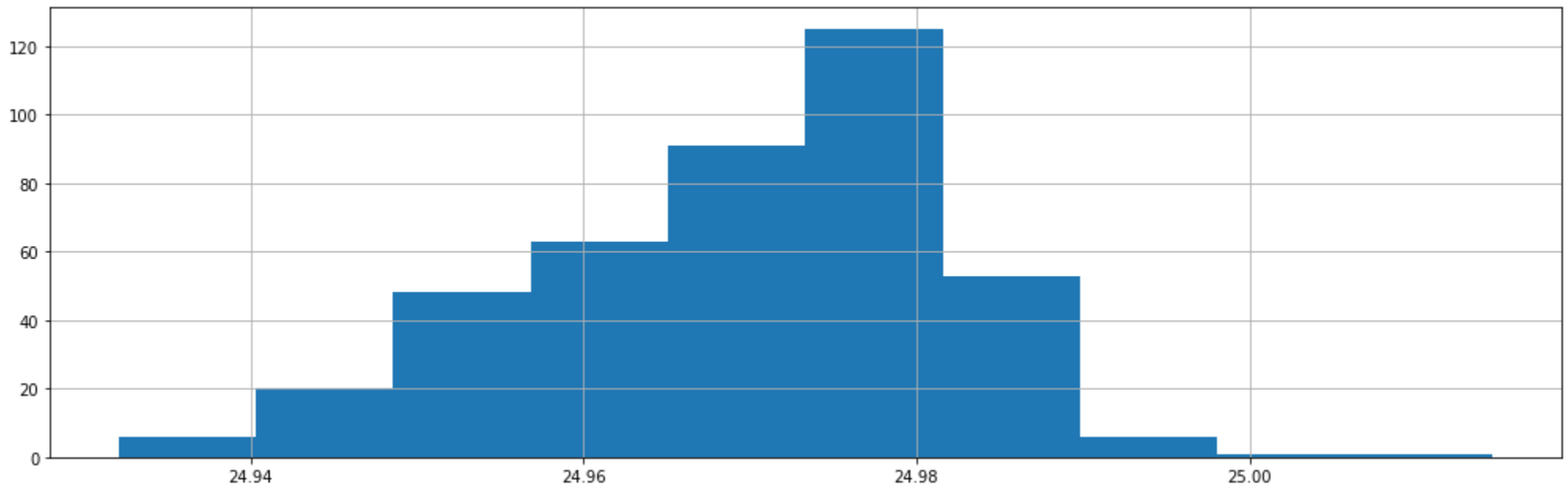


- The dataset covers rather uniformly the range for this attribute

Using Histograms

Let's inspect the "latitude" attribute

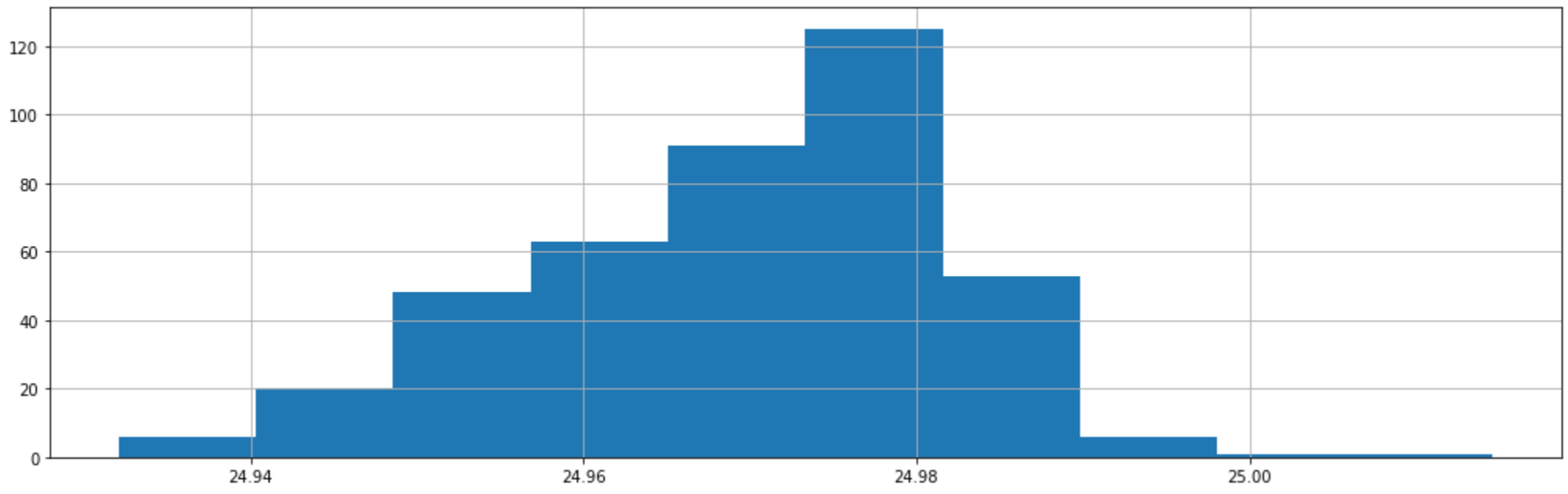
In [14]:
```
plt.figure()
data['latitude'].hist(figsize=figsize)
plt.tight_layout()
```



Using Histograms

Let's inspect the "latitude" attribute

In [14]:
```
plt.figure()
data['latitude'].hist(figsize=figsize)
plt.tight_layout()
```

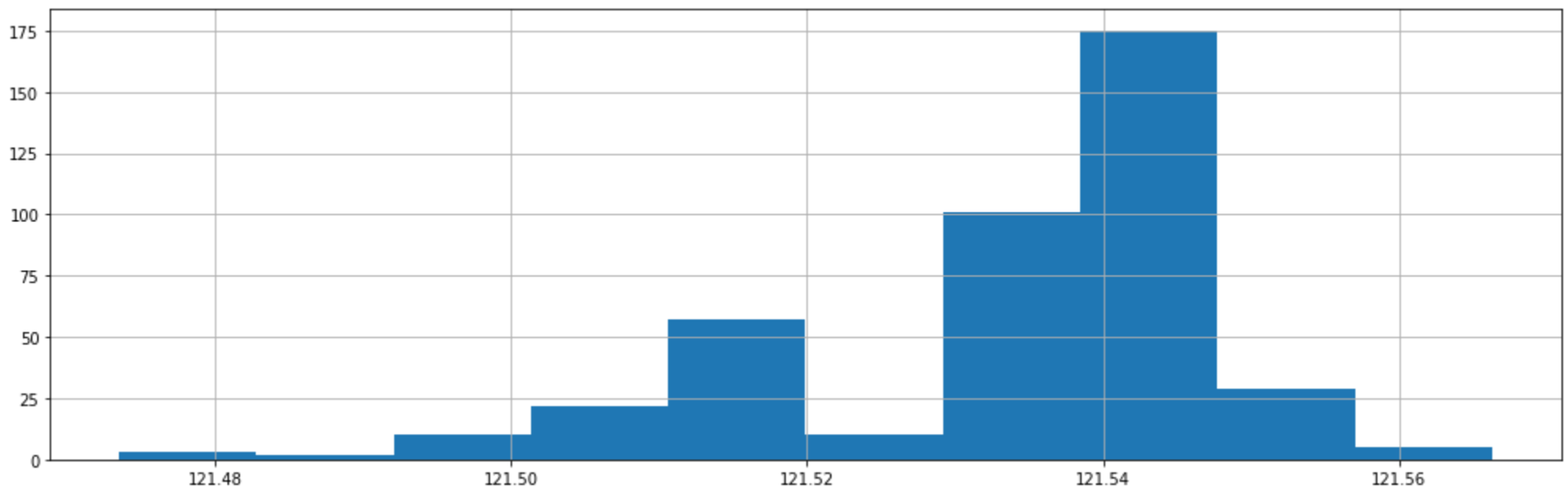


- There is a central cluster w.r.t. this attribute

Using Histograms

Let's inspect the "longitude" attribute

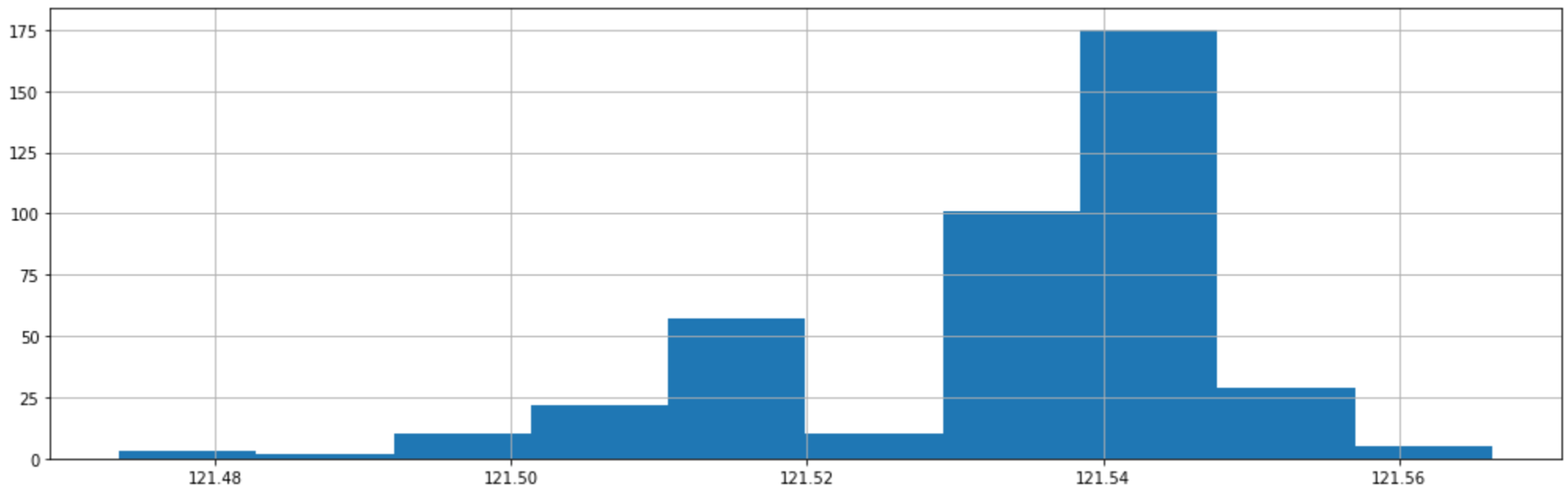
In [15]:
```
plt.figure()
data['longitude'].hist(figsize=figsize)
plt.tight_layout()
```



Using Histograms

Let's inspect the "longitude" attribute

In [15]:
```
plt.figure()
data['longitude'].hist(figsize=figsize)
plt.tight_layout()
```

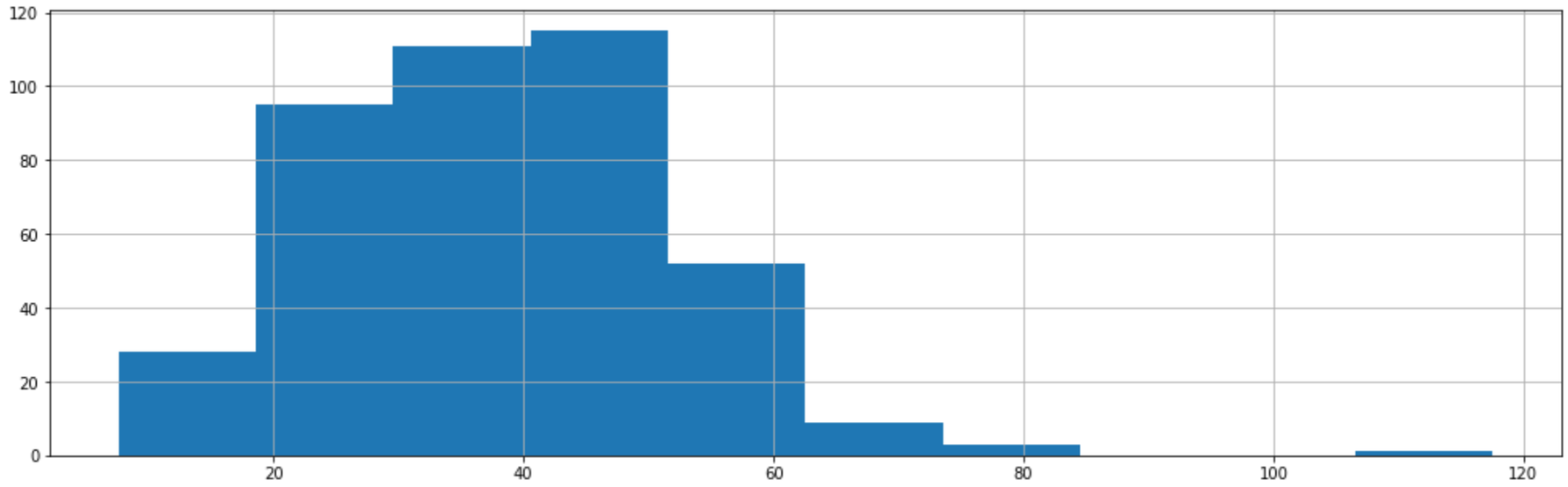


- The dataset is a bit less uniformly distributed w.r.t. longitude

Using Histograms

Let's inspect the target (i.e. "price per area")

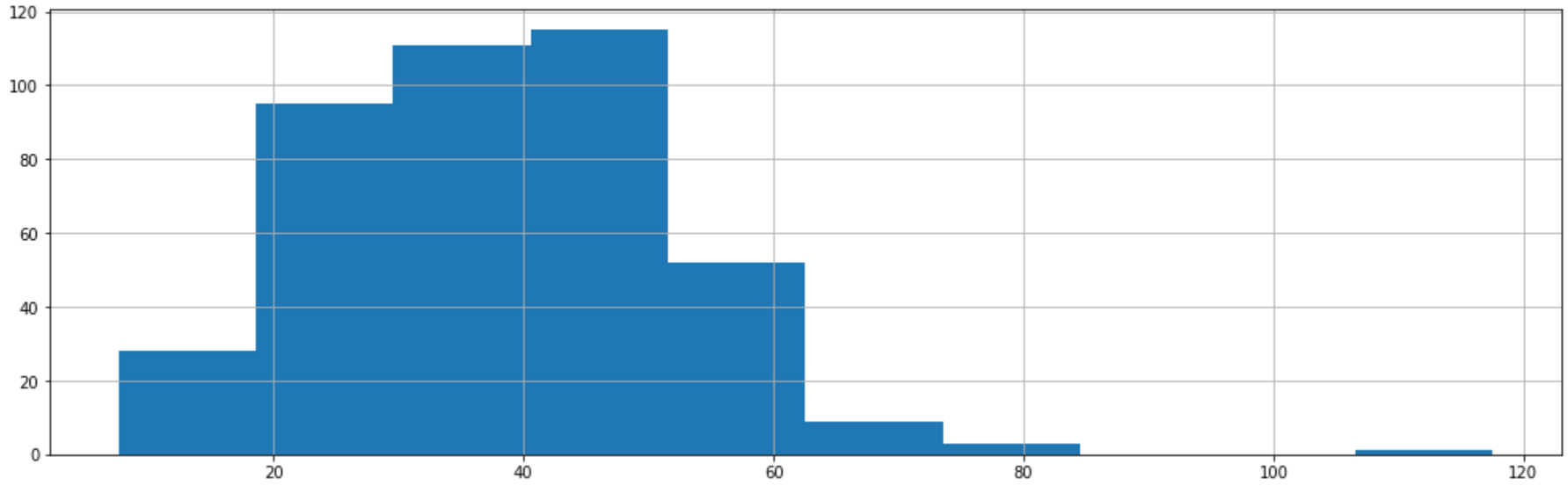
In [16]:
```
plt.figure()
data['price per area'].hist(figsize=figsize)
plt.tight_layout()
```



Using Histograms

Let's inspect the target (i.e. "price per area")

In [16]:
```
plt.figure()
data['price per area'].hist(figsize=figsize)
plt.tight_layout()
```

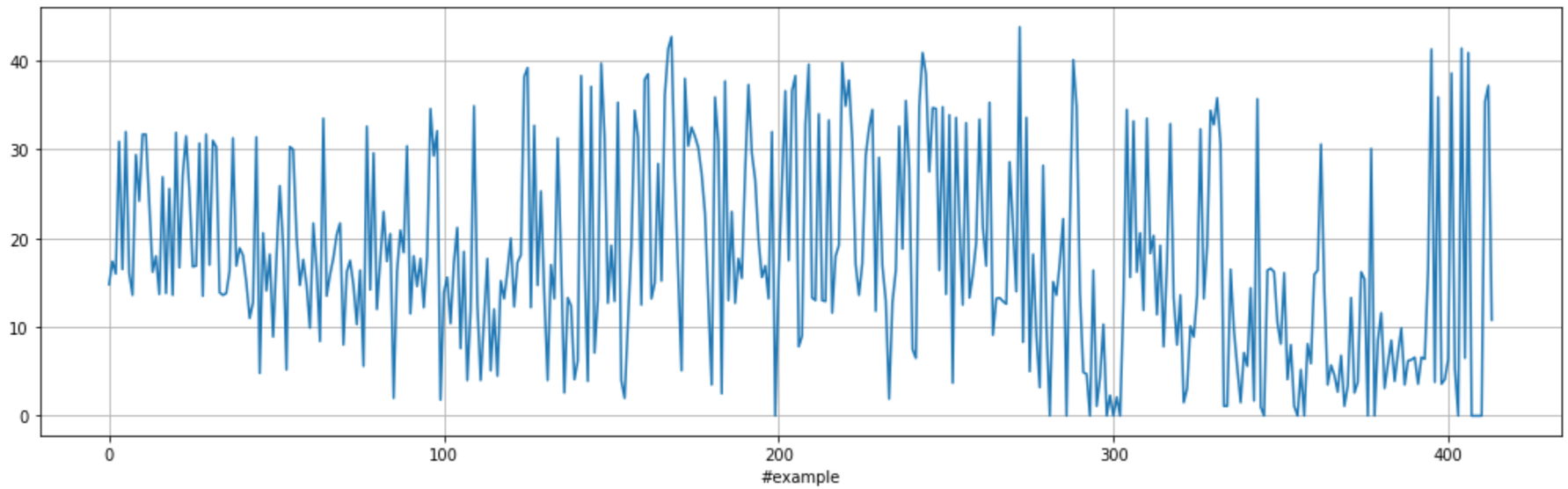


- There are a few significant outliers here

Using Cartesian Plots

Let's inspect the "house age" attribute

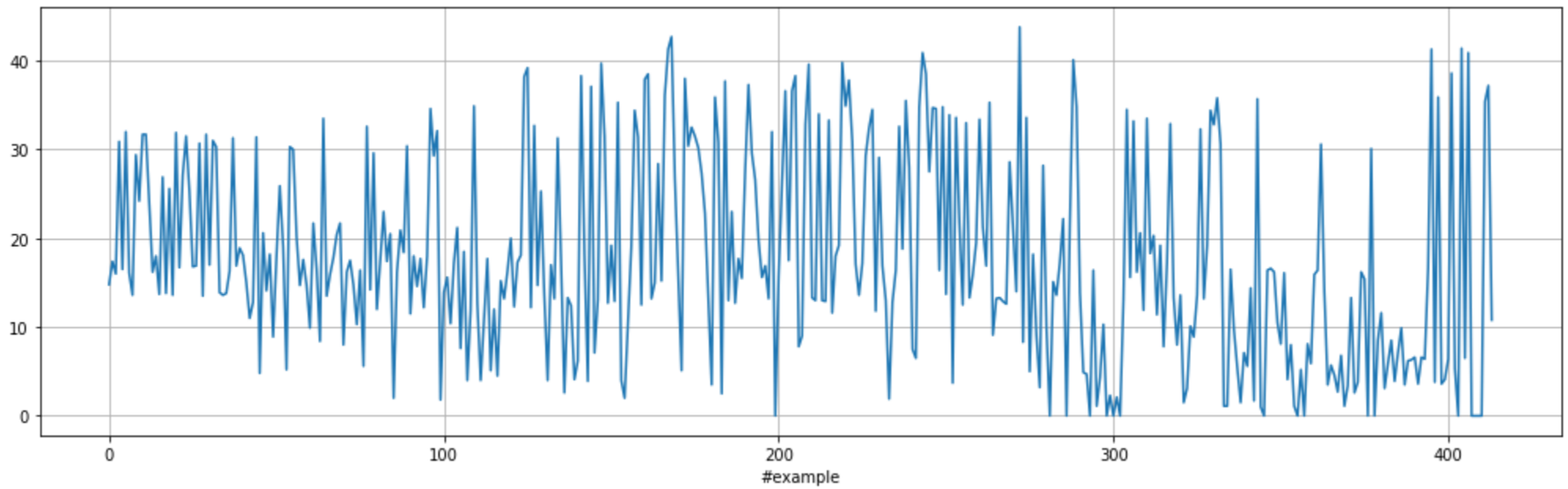
In [17]:
```
plt.figure()
data['house age'].plot(xlabel='#example', grid=':', figsize=figsize)
plt.tight_layout()
```



Using Cartesian Plots

Let's inspect the "house age" attribute

In [17]:
```
plt.figure()
data['house age'].plot(xlabel='#example', grid=':', figsize=figsize)
plt.tight_layout()
```

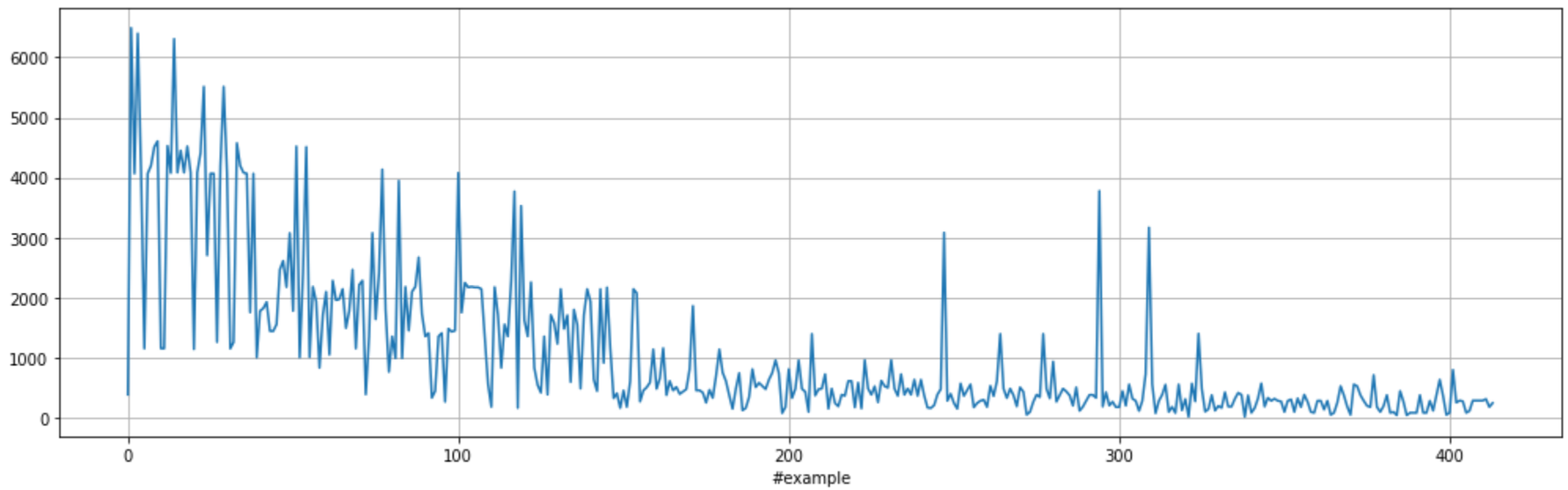


- No significant pattern here

Using Cartesian Plots

Let's inspect the "dist to MRT" attribute

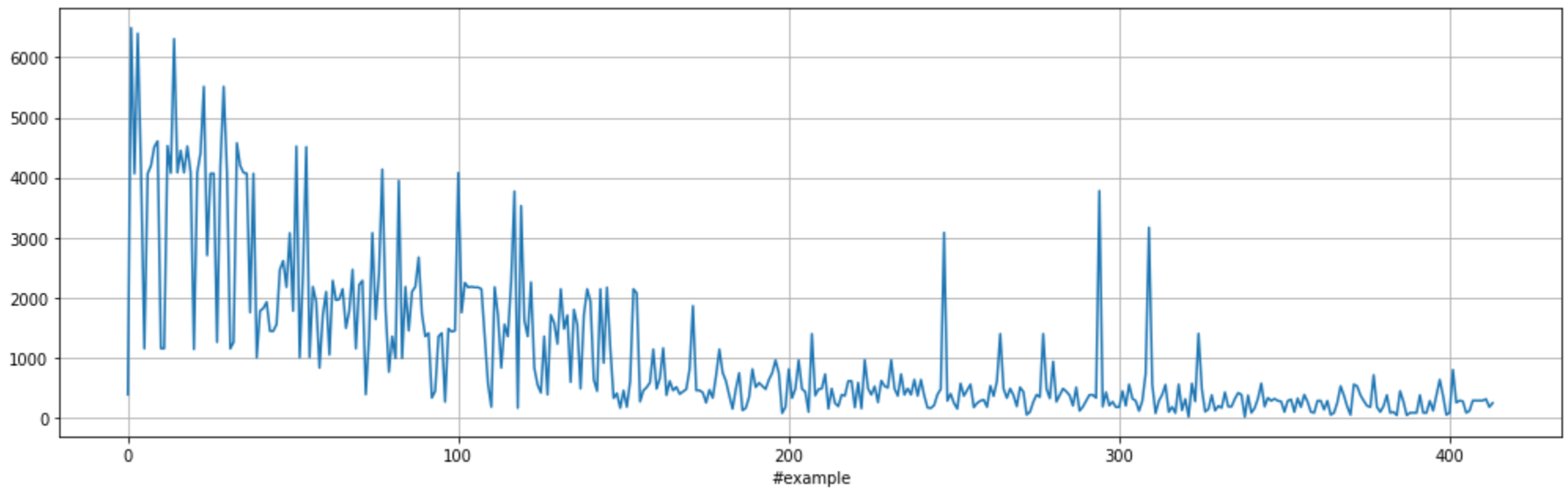
In [18]:
```
plt.figure()
data['dist to MRT'].plot(xlabel='#example', grid=':', figsize=figsize)
plt.tight_layout()
```



Using Cartesian Plots

Let's inspect the "dist to MRT" attribute

In [18]:
```
plt.figure()
data['dist to MRT'].plot(xlabel='#example', grid=':', figsize=figsize)
plt.tight_layout()
```

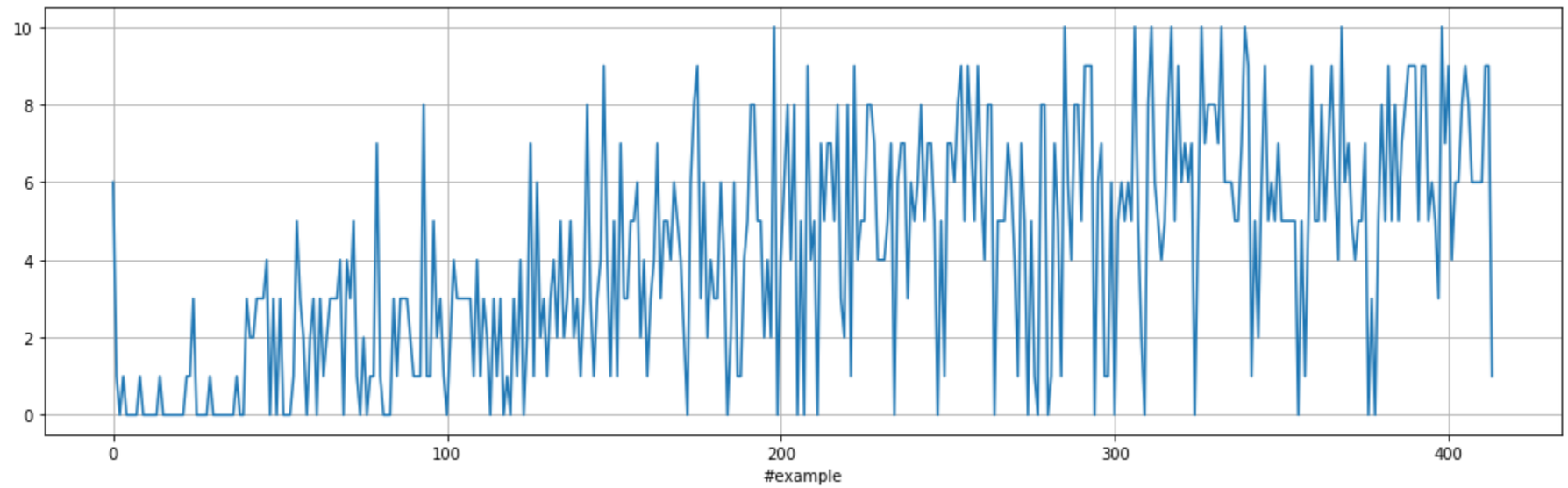


- This attribute roughly decreases along the table

Using Cartesian Plots

Let's inspect the "#stores" attribute

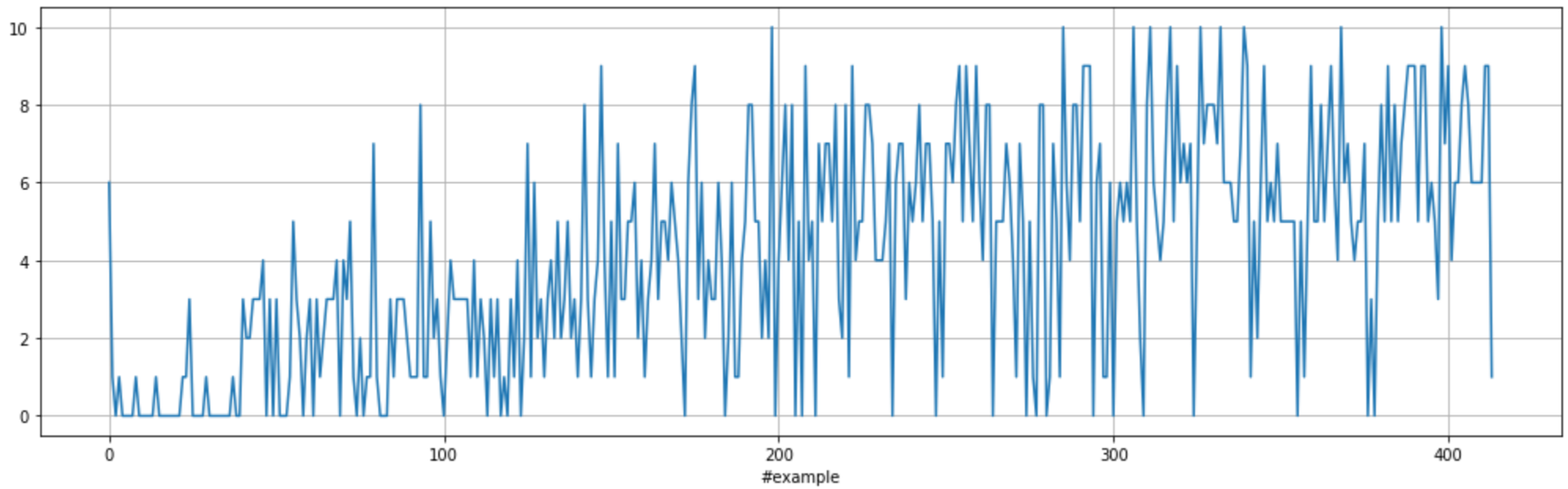
In [19]:
```
plt.figure()
data['#stores'].plot(xlabel='#example', grid=':', figsize=figsize)
plt.tight_layout()
```



Using Cartesian Plots

Let's inspect the "#stores" attribute

In [19]:
```
plt.figure()
data['#stores'].plot(xlabel='#example', grid=':', figsize=figsize)
plt.tight_layout()
```

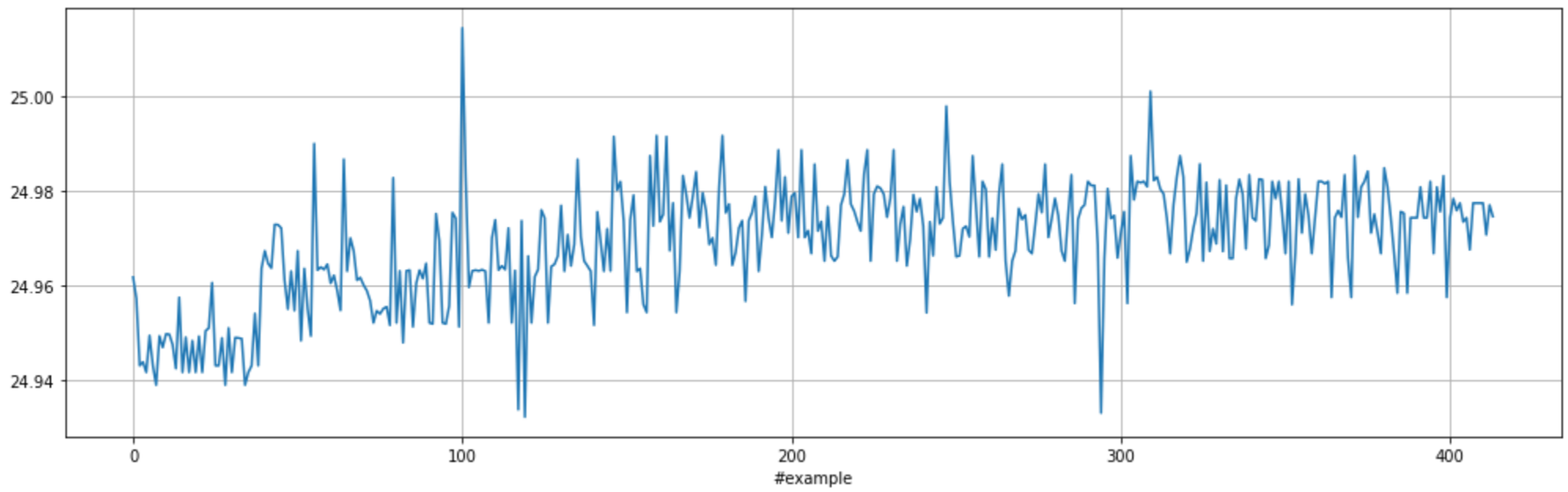


- This attribute roughly increases along the table

Using Cartesian Plots

Let's inspect the "latitude" attribute

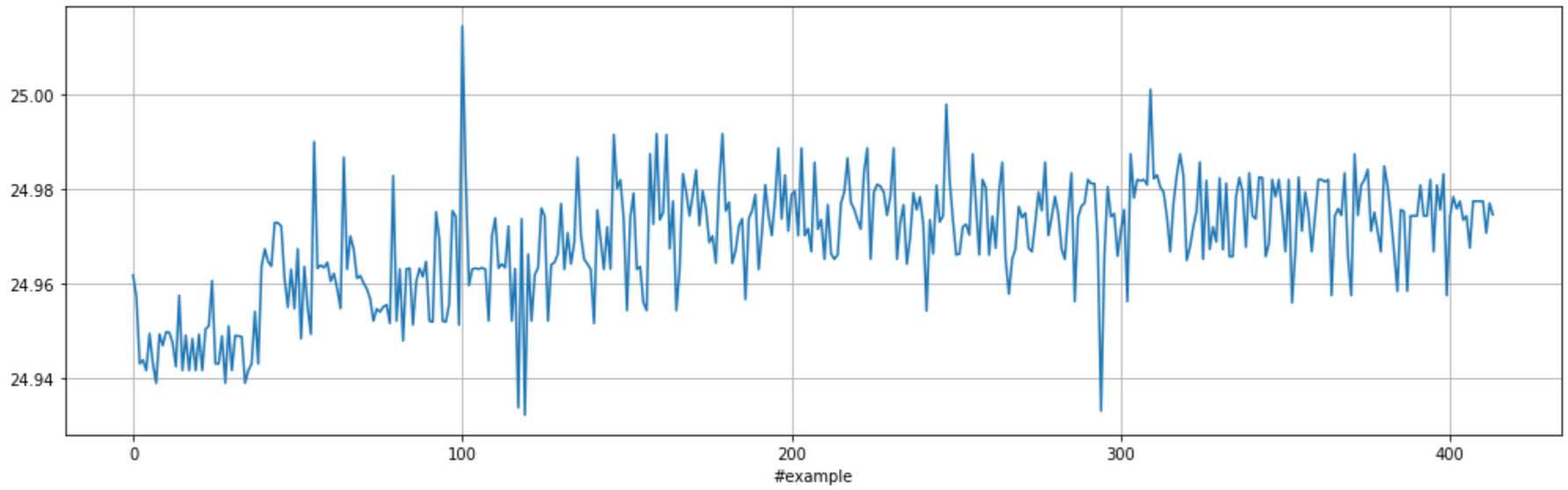
In [20]:
```
plt.figure()
data['latitude'].plot(xlabel='#example', grid=':', figsize=figsize)
plt.tight_layout()
```



Using Cartesian Plots

Let's inspect the "latitude" attribute

In [20]:
```
plt.figure()
data['latitude'].plot(xlabel='#example', grid=':', figsize=figsize)
plt.tight_layout()
```

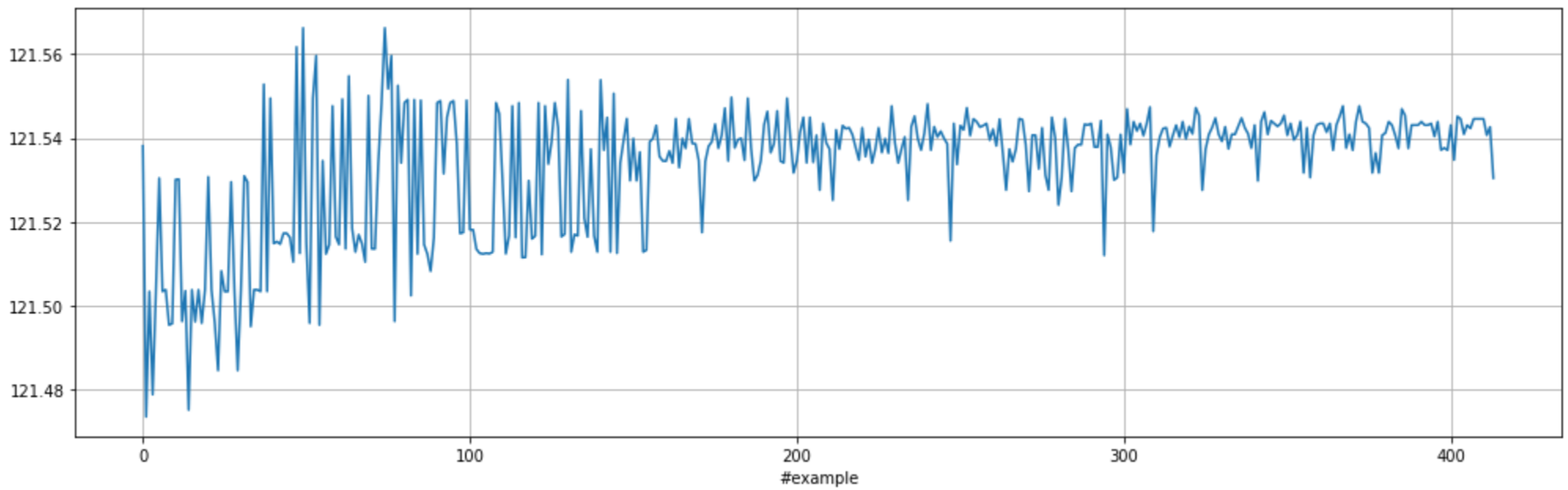


- This attribute roughly increases along the table

Using Cartesian Plots

Let's inspect the "longitude" attribute

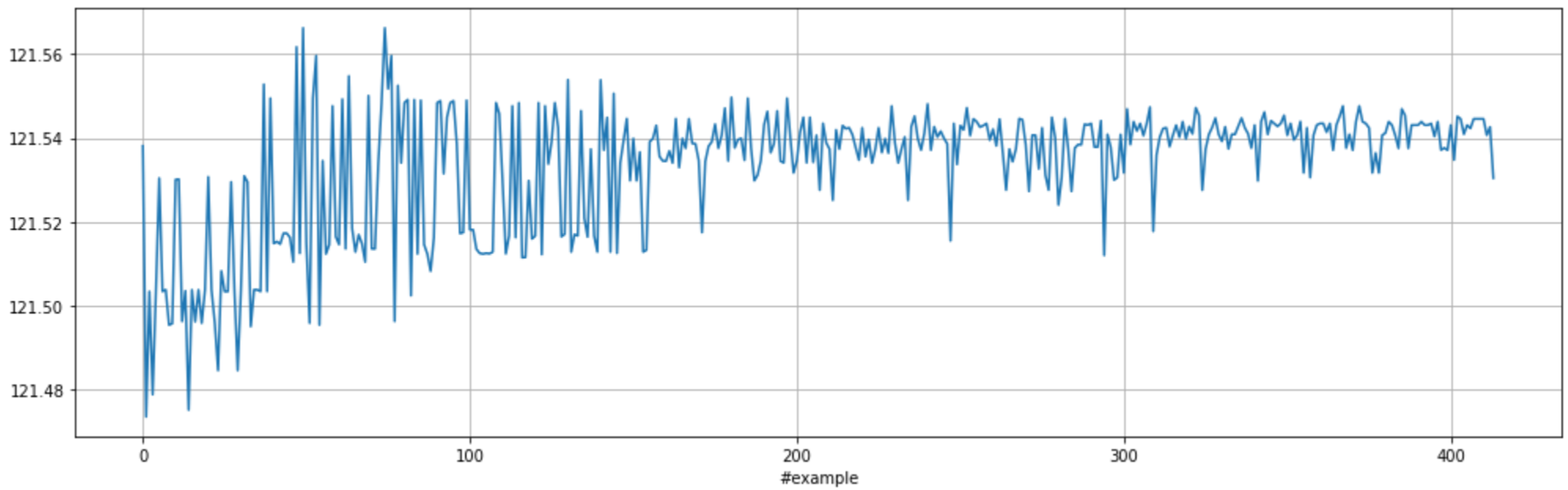
In [21]:
```
plt.figure()
data['longitude'].plot(xlabel='#example', grid=':', figsize=figsize)
plt.tight_layout()
```



Using Cartesian Plots

Let's inspect the "longitude" attribute

In [21]:
```
plt.figure()
data['longitude'].plot(xlabel='#example', grid=':', figsize=figsize)
plt.tight_layout()
```

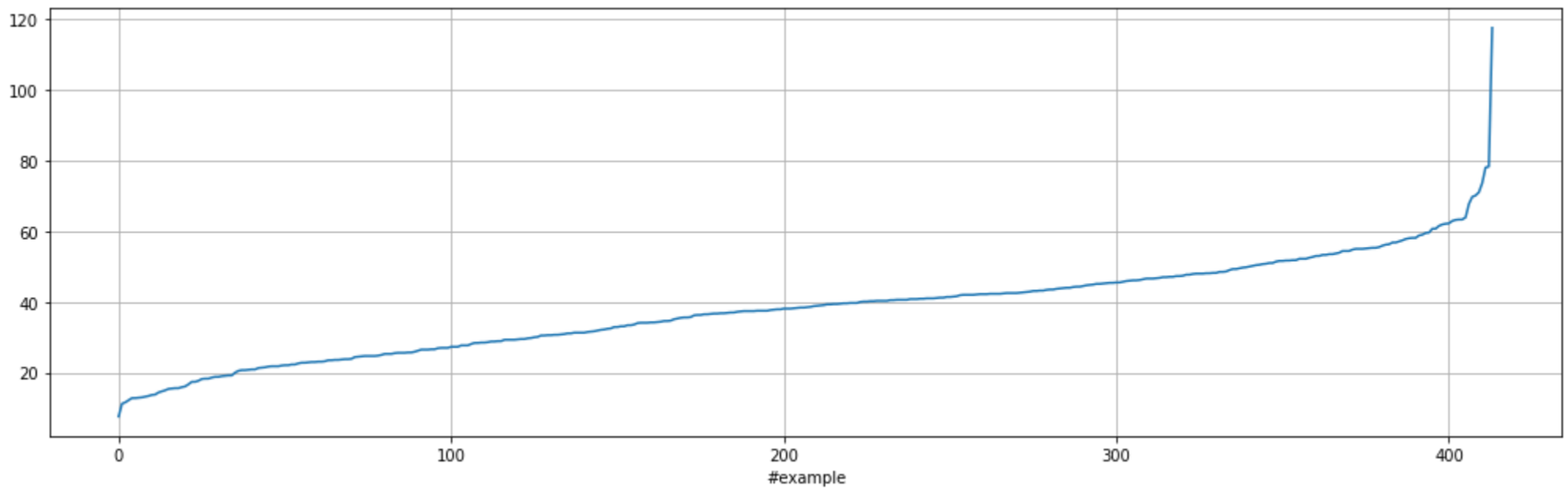


- This attribute roughly increases along the table

Using Cartesian Plots

Let's inspect the target (i.e. "price per area")

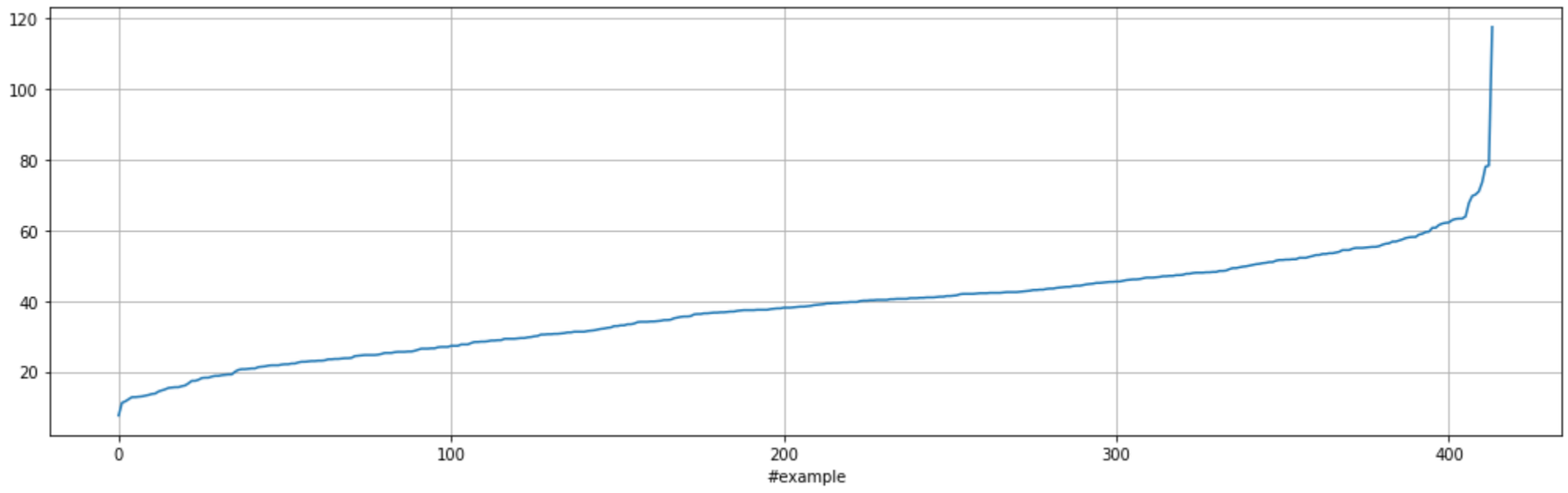
In [22]:
```
plt.figure()
data['price per area'].plot(xlabel='#example', grid=':', figsize=figsize)
plt.tight_layout()
```



Using Cartesian Plots

Let's inspect the target (i.e. "price per area")

In [22]:
```
plt.figure()
data['price per area'].plot(xlabel='#example', grid=':', figsize=figsize)
plt.tight_layout()
```

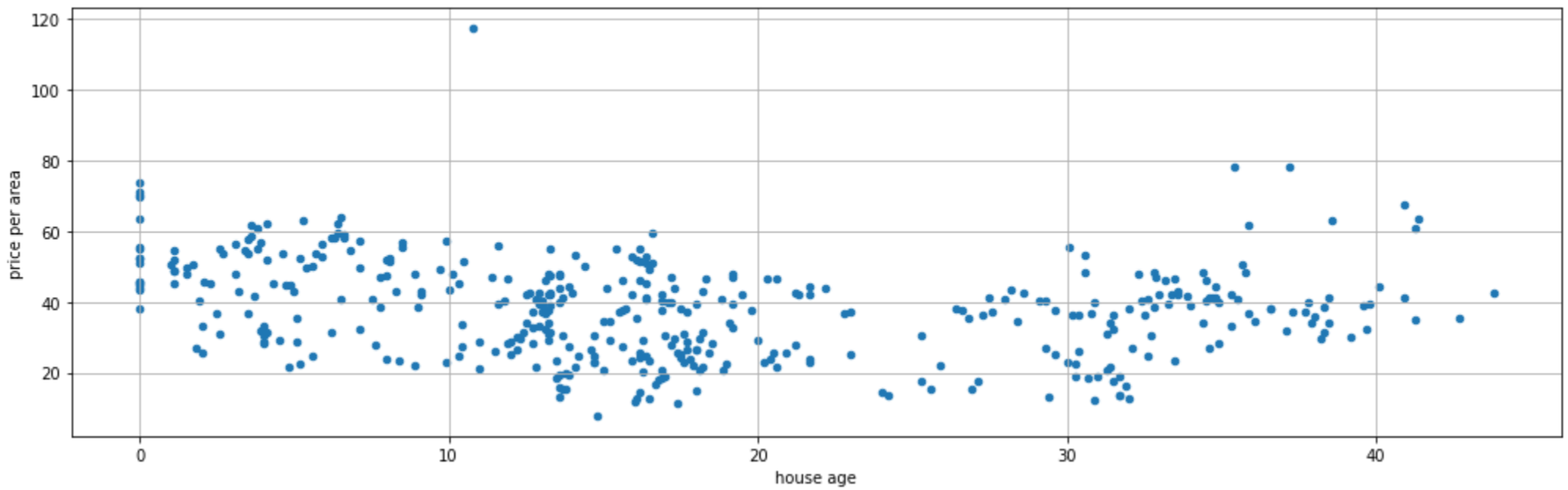


- The dataset is sorted according to this attribute!

Using Scatter Plots

Let's inspect how "house age" and the target are linked

In [23]:
```
data.plot.scatter(x='house age', y='price per area', figsize=figsize, grid=':')
plt.tight_layout()
```



Using Scatter Plots

Let's inspect how "house age" and the target are linked

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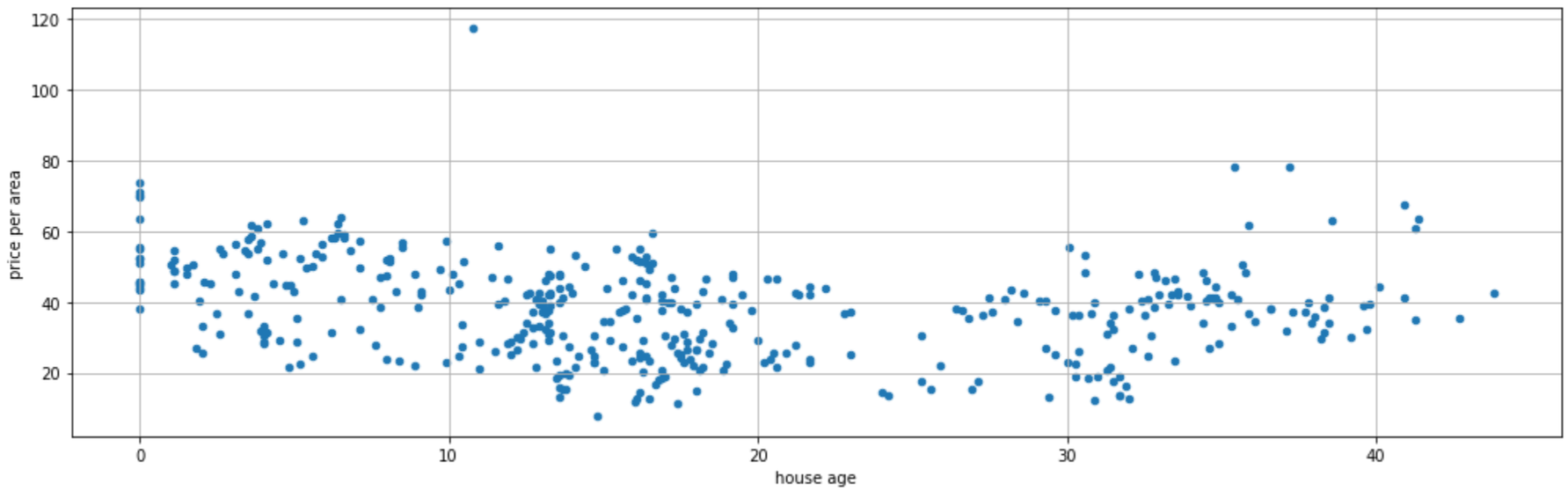
data.plot.scatter(x='house age', y='price per area', figsize=figsize, grid=':')
plt.tight_layout()
```

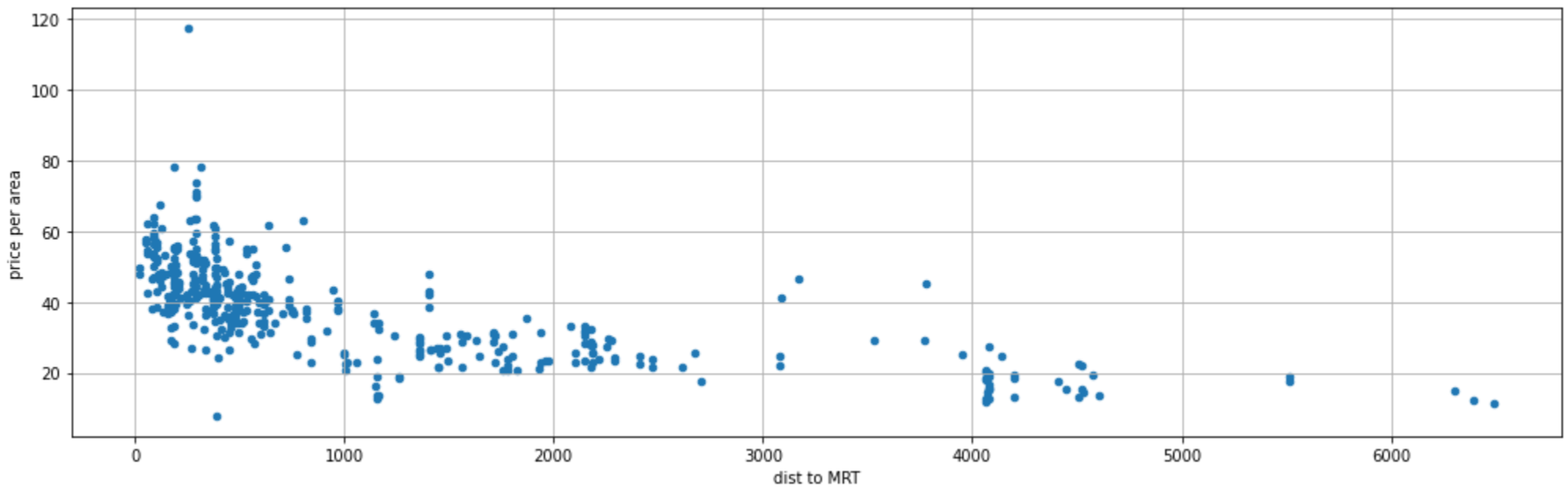


- There does not seem to be a strong correlation here

Using Cartesian Plots

Let's inspect how "dist to MRT" and the target are linked

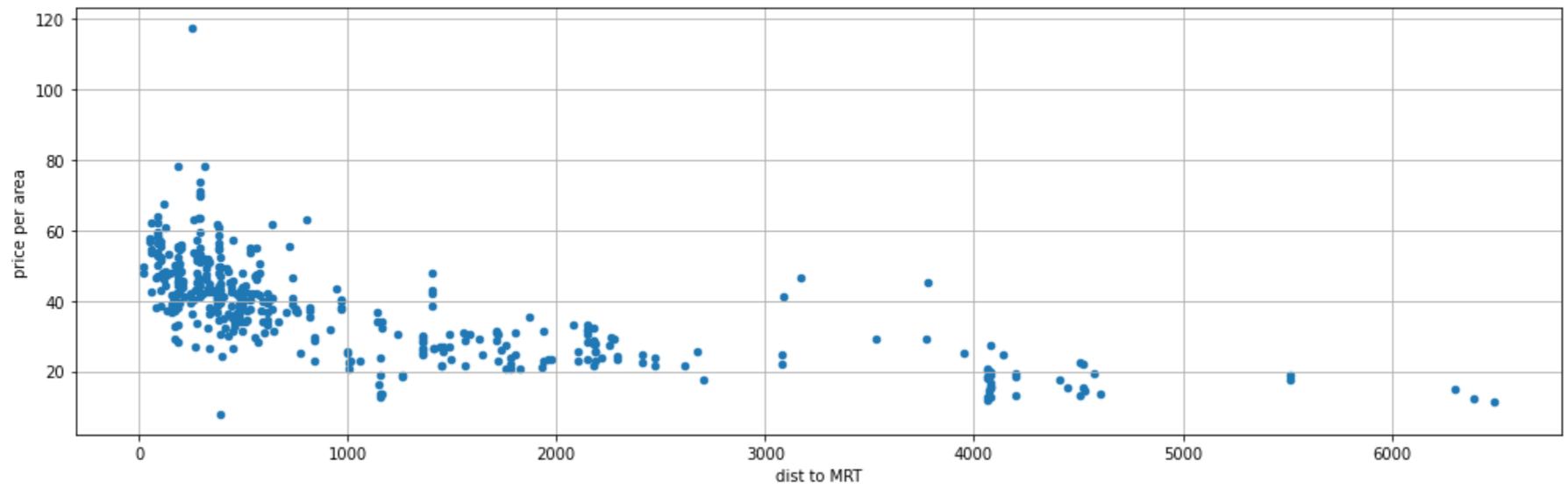
In [24]:
```
data.plot.scatter(x='dist to MRT', y='price per area', figsize=figsize, grid=':')
plt.tight_layout()
```



Using Cartesian Plots

Let's inspect how "dist to MRT" and the target are linked

In [24]:
```
data.plot.scatter(x='dist to MRT', y='price per area', figsize=figsize, grid=':')
plt.tight_layout()
```



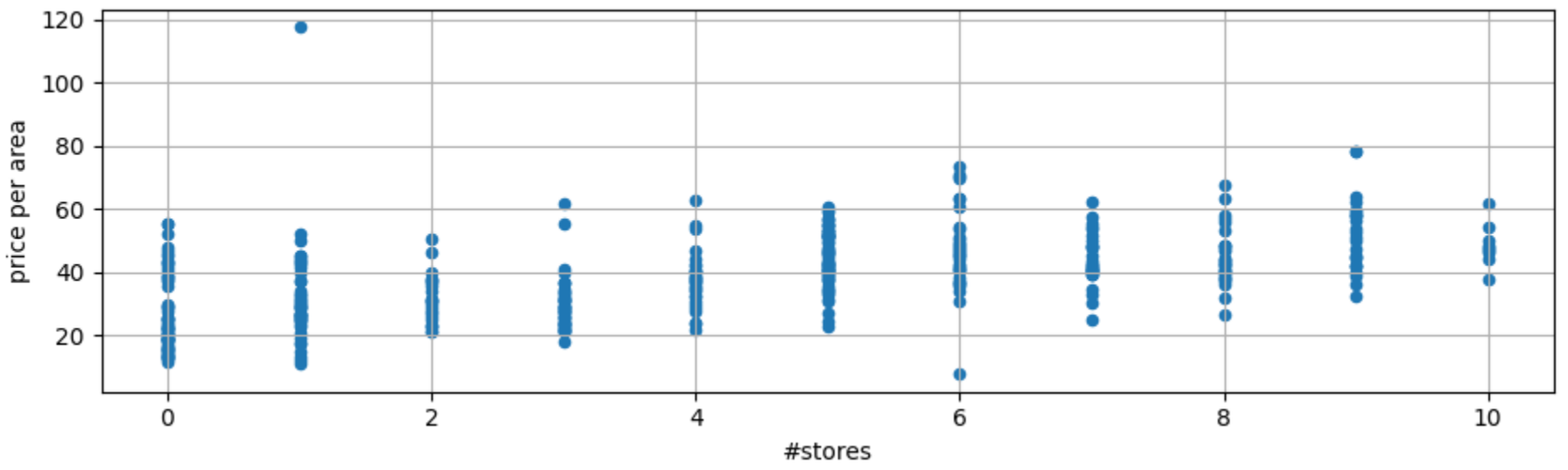
- The correlation is a bit stronger here

Using Cartesian Plots

Let's inspect how "#stores" and the target are linked

In [116]:
```
data.plot.scatter(x='#stores', y='price per area', figsize=figsize, grid=':')
plt.tight_layout()
```

Figure

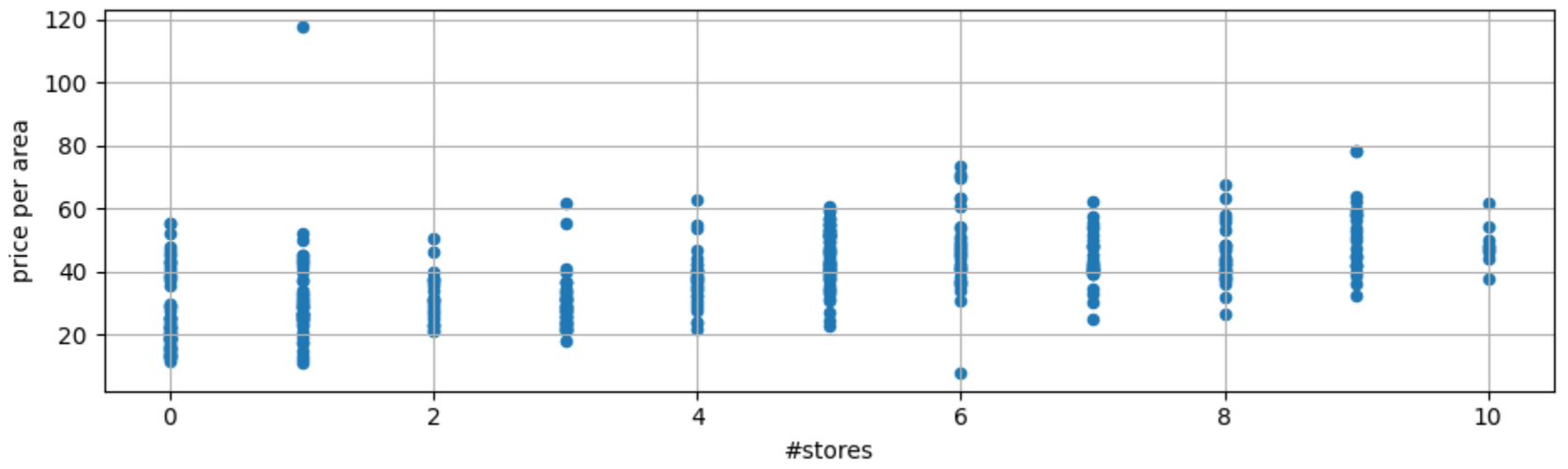


Using Cartesian Plots

Let's inspect how "#stores" and the target are linked

In [116]:
```
data.plot.scatter(x='#stores', y='price per area', figsize=figsize, grid=':')
plt.tight_layout()
```

Figure



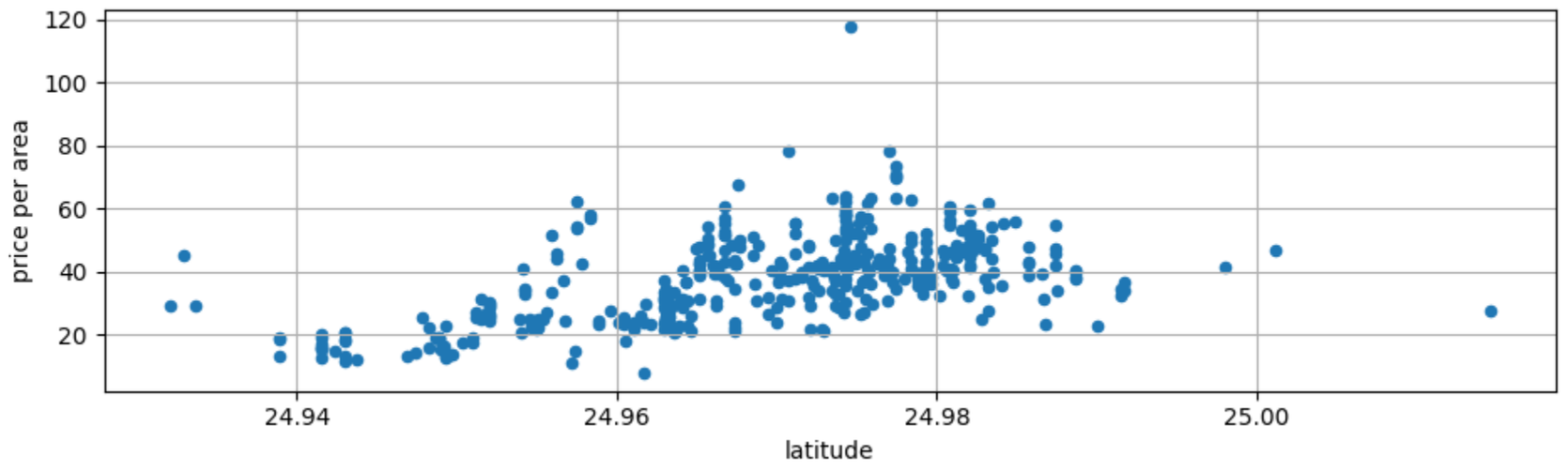
- A slightly positive correlation here

Using Cartesian Plots

Let's inspect how "latitude" and the target are linked

In [117]:
```
data.plot.scatter(x='latitude', y='price per area', figsize=figsize, grid=':')
plt.tight_layout()
```

Figure

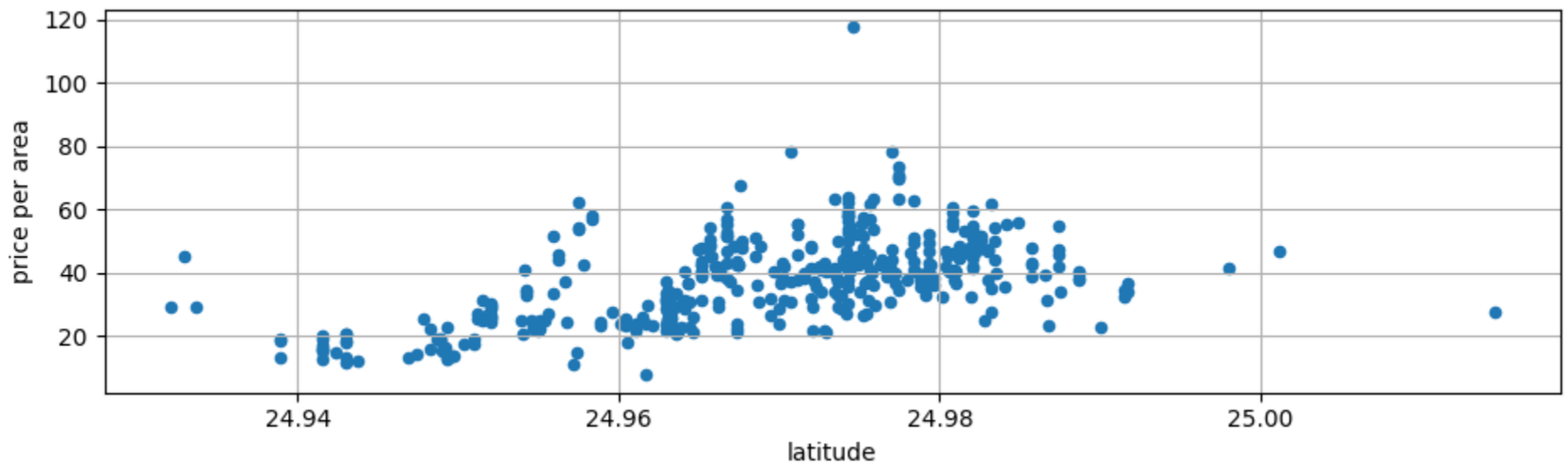


Using Cartesian Plots

Let's inspect how "latitude" and the target are linked

In [117]:
```
data.plot.scatter(x='latitude', y='price per area', figsize=figsize, grid=':')
plt.tight_layout()
```

Figure

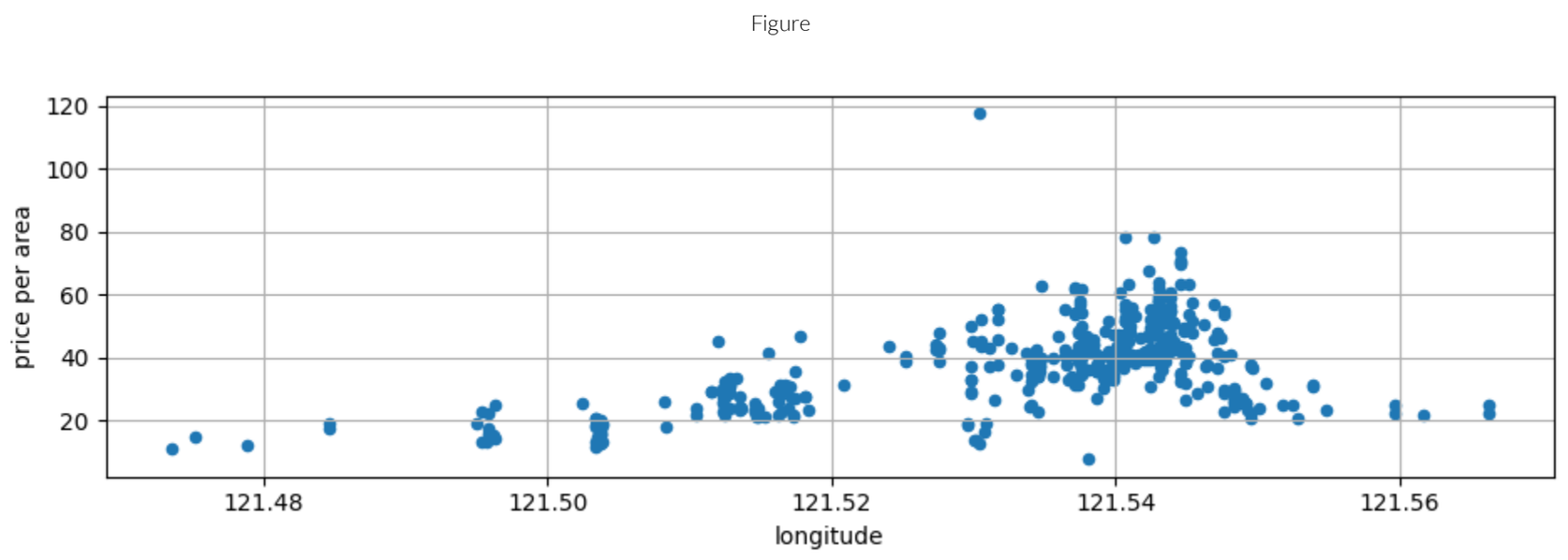


- A somewhat complicated relation

Using Cartesian Plots

Let's inspect how "longitude" and the target are linked

In [118]:
```
data.plot.scatter(x='longitude', y='price per area', figsize=figsize, grid=':')
plt.tight_layout()
plt.tight_layout()
```

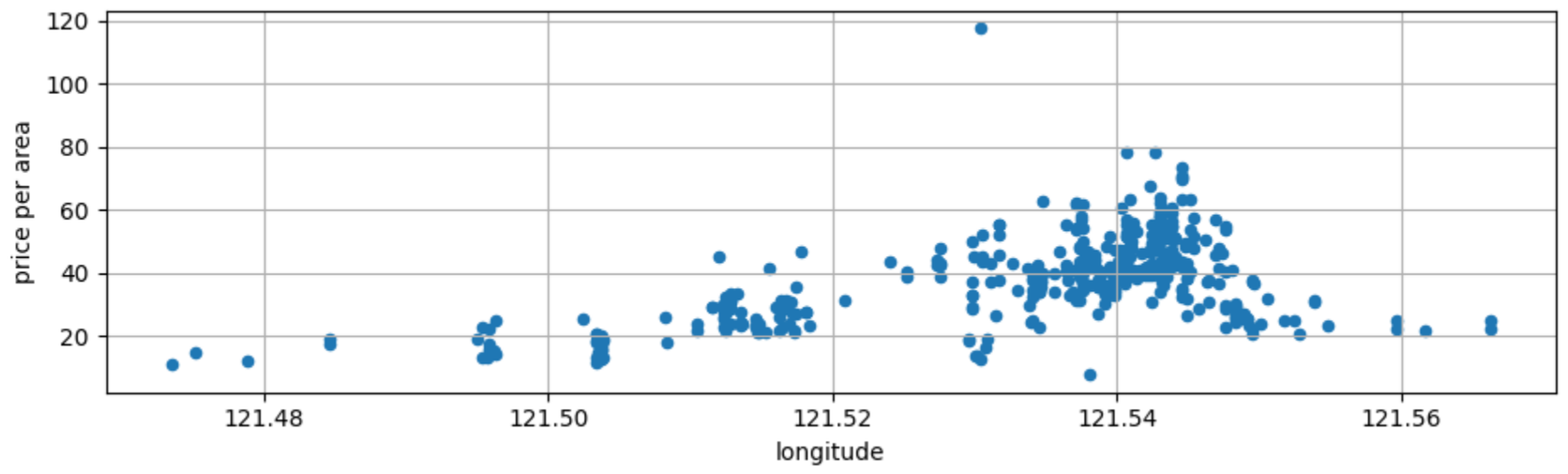


Using Cartesian Plots

Let's inspect how "longitude" and the target are linked

In [118]:
```
data.plot.scatter(x='longitude', y='price per area', figsize=figsize, grid=':')
plt.tight_layout()
plt.tight_layout()
```

Figure



- Another complicated one

Conclusions and Take-Home Messages

Inspecting a new dataset is very important

- We can get a sense of the dataset
- We can spot the main challenges we will have to face
- ...Including potentially some critical issues (inadequate data)
- It may prevent us from making some mistakes later
- ...And it will allow us some sanity check over the results

Of course, these benefits depend a lot on your experience

- Perhaps some of you already got idea by looking at the plots
- ...But for now the important things is just to keep them in mind