Pandas and Dataset Inspection

An Example Problem

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

The Data File

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

On Linux/OS X or on the Windows Powershell check it by running this:

```
In [2]: !ls data

real_estate.csv
```

On a classic Windows command prompt you can run instead:

```
In [3]: !dir data

zsh:1: command not found: dir
```

- csv stand for "Comma Separated Values"
- It's a simple text-based data format

Pandas

You can read csv files

- Using notepad or any text editor
- Using excel (which imports them into worksheets)
- ...Or using Python

In particular, we will rely on the pandas package

`pandas` is a python data-analysis library

- It can be used to load, inspect, and manipulate data
- With a focus on tables (called "dataframes" and series)

`pandas` is imported with:

```
In [4]: import pandas as pd
```

Loading the Data

We can then load a csv file with `read_csv`

In [5]:
```
import os
fname = os.path.join('data', 'real_estate.csv')
data = pd.read_csv(fname, sep=',')
data.head()
```

Out[5]:

	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

- We use `os.path.join` to obtain a path that works on both Win and *nix
- `read_csv` returns a `DataFrame` object
- The `head` methods returns a `DataFrame` with the first 5 rows
- Dataframes are displayed as html tables by Jupyter

Indexing a Dataframe

The indexing operator for `DataFrame` objects is heavily overloaded

We can access a whole column by its name:

```
In [6]: data['house age']

Out[6]: 0      14.8
        1      17.4
        2      16.0
        3      30.9
        4      16.5
               ...
        409     0.0
        410     0.0
        411    35.4
        412    37.2
        413    10.8
        Name: house age, Length: 414, dtype: float64
```

- Every column in a `DataFrame` is an object of the `Series` class

Indexing a Dataframe

Every `DataFrame` and `Series` has a special field called an index

In the visualization, it's the first column (in bold font, with no name)

In [7]:
```
data.head()
```

Out[7]:

	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

It is analogous to a primary key in a database

- Every rows has an unique index value
- ...Which is used to identify and quickly access to the row

Indexing a Dataframe

We can access the index with the `index` attribute

```
In [8]: data.index

Out[8]: RangeIndex(start=0, stop=414, step=1)
```

- Our `DataFrame` has a numeric index

We can access a row by its index value using the `loc` property

```
In [9]: data.loc[3]

Out[9]: house age            30.90000
        dist to MRT        6396.28300
        #stores               1.00000
        latitude             24.94375
        longitude           121.47883
        price per area       12.20000
        Name: 3, dtype: float64
```

- The results is once again a `Series` object

Indexing a Dataframe

For a `Series` that corresponds to a row

...The index is the sequence of column names

```
In [10]: data.loc[3].loc['house age']

Out[10]: 30.9
```

- Therefore, we can use `loc` to retrieve a given column value
- We can even do both operations at once, by passing a tuple to `loc`

```
In [11]: data.loc[3, 'house age']

Out[11]: 30.9
```

Indexing a Dataframe

Pandas supports also positional access

To see this, let's consider again the `Series` for row 3

```
In [12]: r3 = data.loc[3]
         r3
```

```
Out[12]: house age             30.90000
         dist to MRT         6396.28300
         #stores                1.00000
         latitude              24.94375
         longitude            121.47883
         price per area        12.20000
         Name: 3, dtype: float64
```

We can access an element by its position using the `iloc` property

```
In [13]: r3.iloc[1] # this is dist to MRT
```

```
Out[13]: 6396.283
```

Indexing a Dataframe

Positional access might be useful

...Since the "normal" index is attached to a row even if it moves around

- For example, if we reorder the rows in a `DataFrame`
- The index values move together with the rows:

In [14]:
```
first_rows = data.loc[[2, 1, 5, 3, 4]]
first_rows
```

Out[14]:

	house age	dist to MRT	#stores	latitude	longitude	price per area
2	16.0	4066.587	0	24.94297	121.50342	11.6
1	17.4	6488.021	1	24.95719	121.47353	11.2
5	32.0	1156.777	0	24.94935	121.53046	12.8
3	30.9	6396.283	1	24.94375	121.47883	12.2
4	16.5	4082.015	0	24.94155	121.50381	12.8

- In most cases, index access is more convenient
- For some algorithms the sequence matters and we need positional access

A Possible Problem Statement

Now that we know better about `pandas`, let's look again at the data

In [16]:
```
data.head()
```

Out[16]:

	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

- Therefore, it might be useful to learn a machine model
- ...That can estimate the price based on the easily available information

Using Histograms

Since our goal is roughly defined, it's a good idea to inspect the dataset

We will start by using histograms, i.e. plots with:

- On the x-axis: values for one attribute
- On the y-axis: occurrency count in the dataset

They are useful to display the distribution of each column

Some comments:

- Continuous attributes are typically discretized (i.e. binned) first
- The counts can be normalized to obtain frequencies

Histograms can be built directly from `pandas`

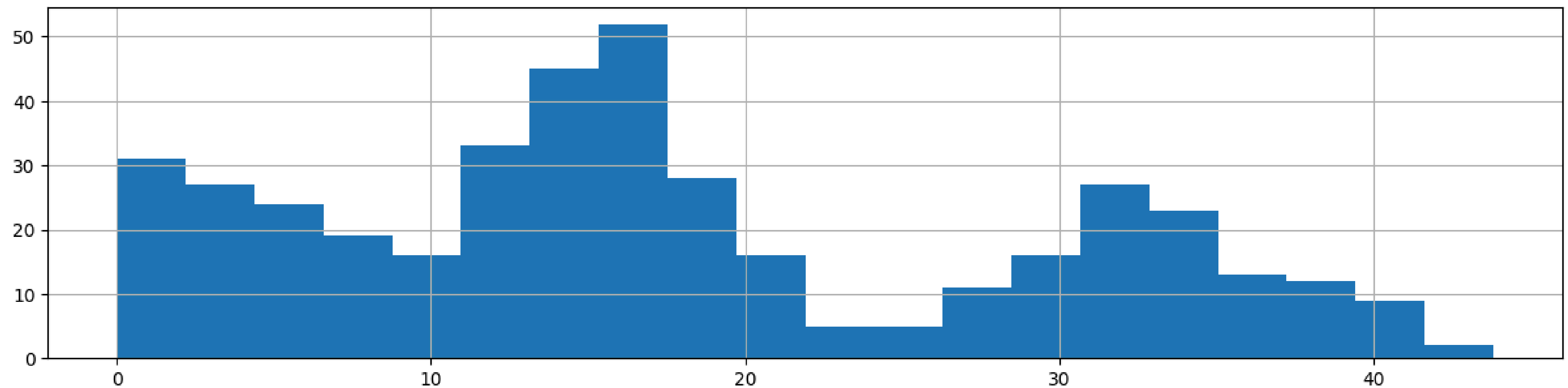
...By using the hist method.

- `matplotlib` is used behind the scens and can be employed to add details
- ...Or as an alernative, if we need a more complex plot

Dataset Inspection via Histograms

Let's inspect the "house age" attribute

In [17]:
```
data['house age'].hist(figsize=figsize, bins=20);
```

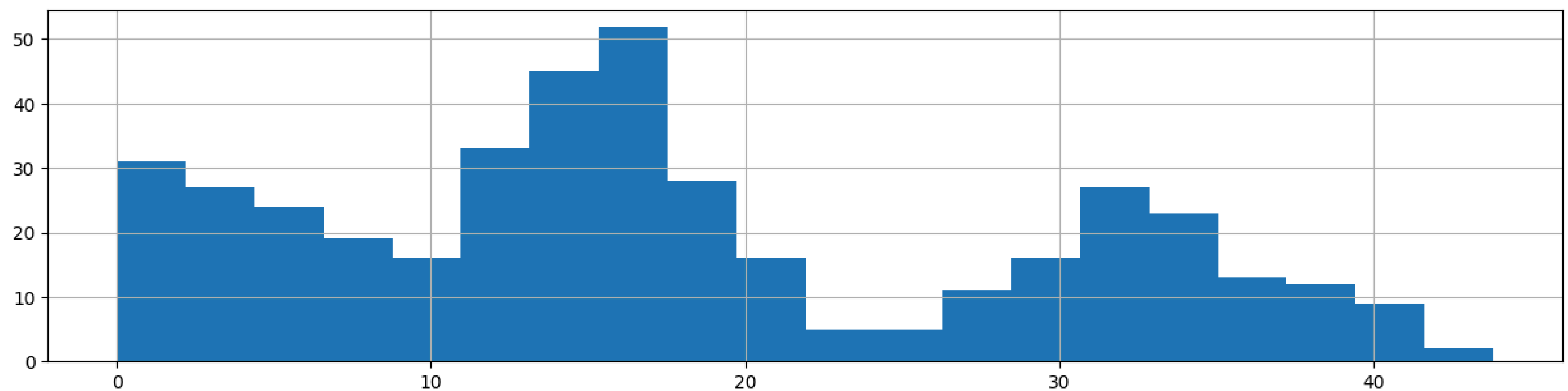


What can you say about that?

Using Histograms

Let's inspect the "house age" attribute

In [18]:
```
data['house age'].hist(figsize=figsize, bins=20);
```



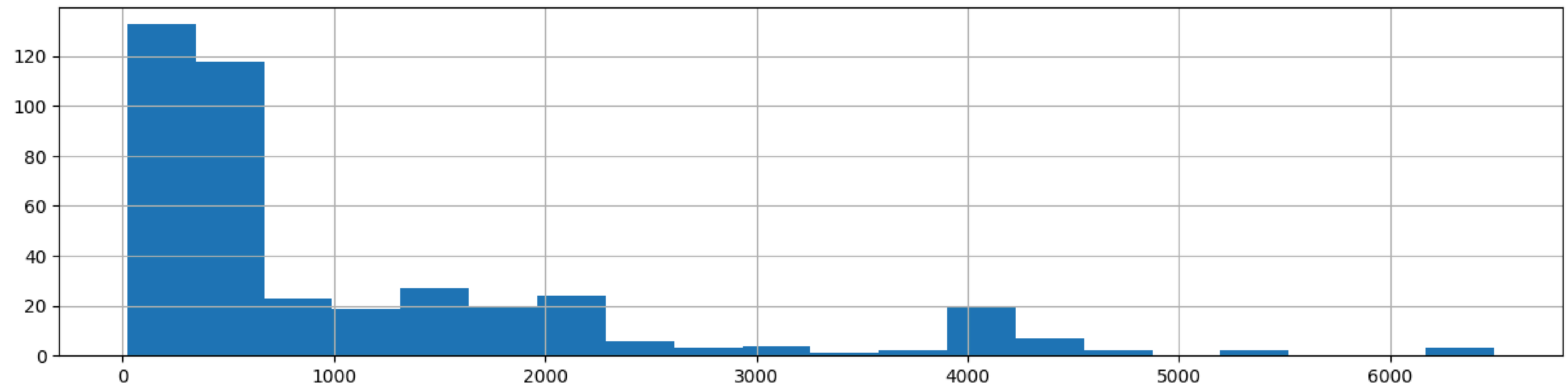
- There seems to be two main clusters, roughly normally distributed
- Lower age values are roughly uniformly likely

Now, try building histograms for the other columns

Exercise: Using Histograms

Let's inspect the "dist to MRT" attribute

In [19]:
```
data['dist to MRT'].hist(figsize=figsize, bins=20);
```

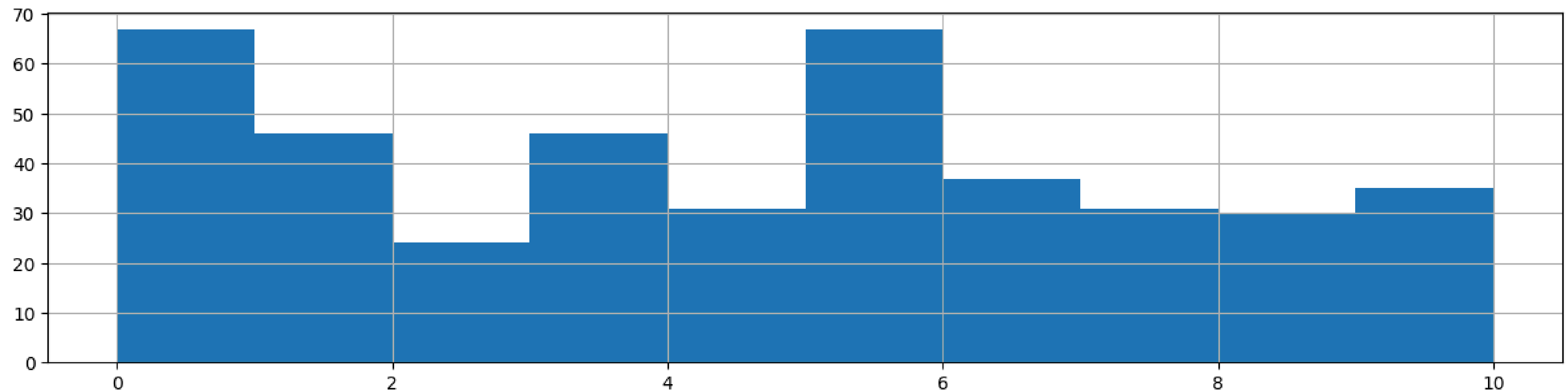


- This attribute has a large range and low values are much more prevalent

Exercise: Using Histograms

Let's inspect the "#stores" attribute

In [20]:
```
data['#stores'].hist(figsize=figsize, bins=10);
```

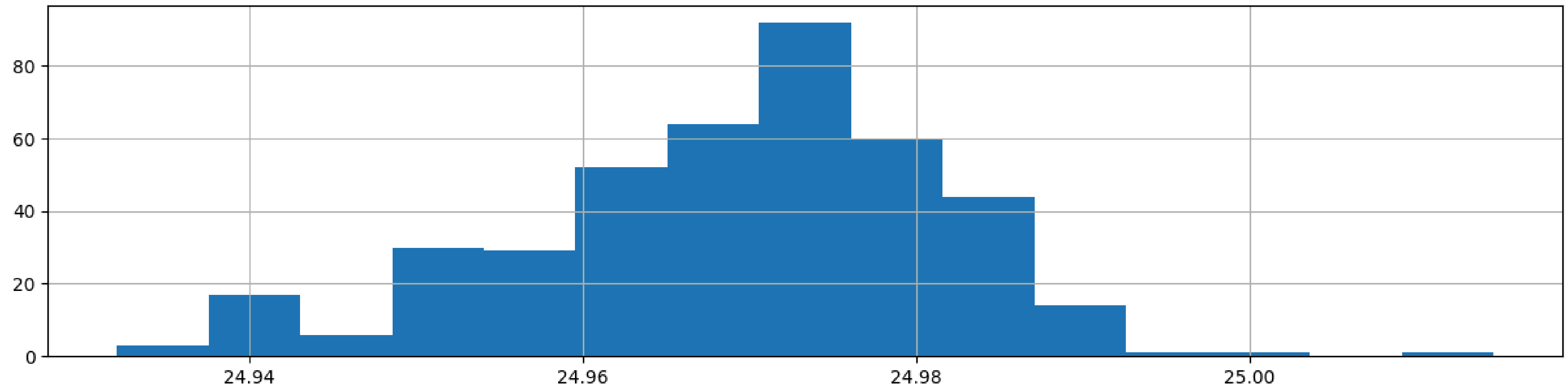


- The dataset covers rather uniformly the range for this attribute

Exercise: Using Histograms

Let's inspect the "latitude" attribute

```
In [21]: data['latitude'].hist(figsize=figsize, bins=15);
```

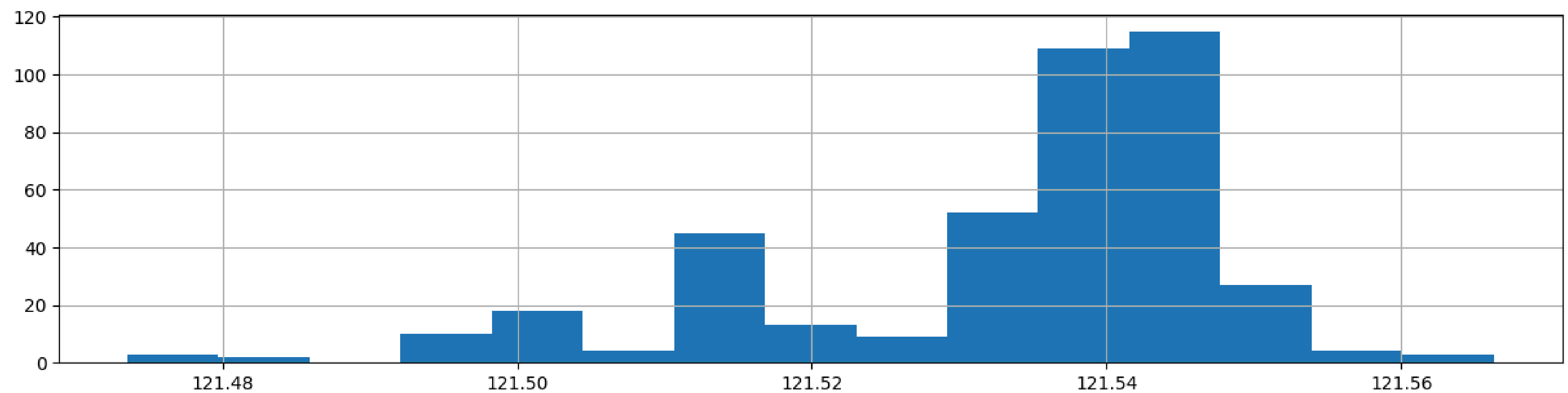


- There is a central cluster w.r.t. this attribute

Exercise: Using Histograms

Let's inspect the "longitude" attribute

```
In [22]: data['longitude'].hist(figsize=figsize, bins=15);
```

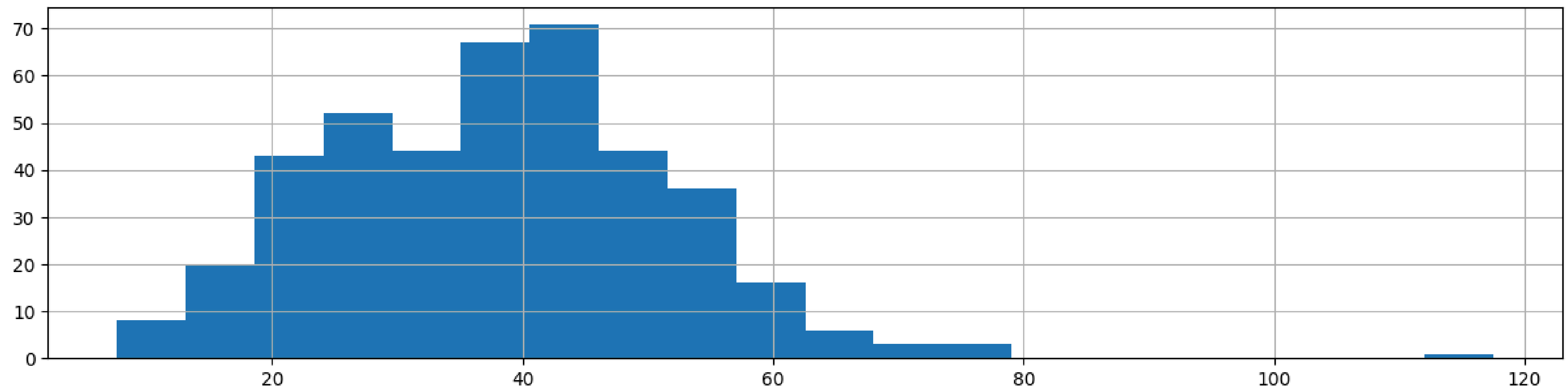


- The dataset is a bit less uniformly distributed w.r.t. longitude

Exercise: Using Histograms

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

In [23]:
```
data['price per area'].hist(figsize=figsize, bins=20);
```



- There are a few significant outliers here

Dataset Inspection via Cartesian Plots

We can obtain information about the distribution of each column

...By using statistics. For example we can call:

In [24]:
```
data.describe()
```

Out[24]:

	house age	dist to MRT	#stores	latitude	longitude	price per area
count	414.000000	414.000000	414.000000	414.000000	414.000000	414.000000
mean	17.712560	1083.885689	4.094203	24.969030	121.533361	37.980193
std	11.392485	1262.109595	2.945562	0.012410	0.015347	13.606488
min	0.000000	23.382840	0.000000	24.932070	121.473530	7.600000
25%	9.025000	289.324800	1.000000	24.963000	121.528085	27.700000
50%	16.100000	492.231300	4.000000	24.971100	121.538630	38.450000
75%	28.150000	1454.279000	6.000000	24.977455	121.543305	46.600000
max	43.800000	6488.021000	10.000000	25.014590	121.566270	117.500000

- Statistics are a very compact way to convey information
- ...But they are also less rich than using a histogram

Dataset Inspection via Cartesian Plots

The third tool we'll use for dataset inspection

...Is given by Cartesian plots, which have:

- On the x-axis: the index value
- On the y-axis: the value of one attribute
- Consecutive points are connected by a line

A few comments

- Cartesian plot are extremely useful with time series
- ...Where the index represents time, or a sequence number

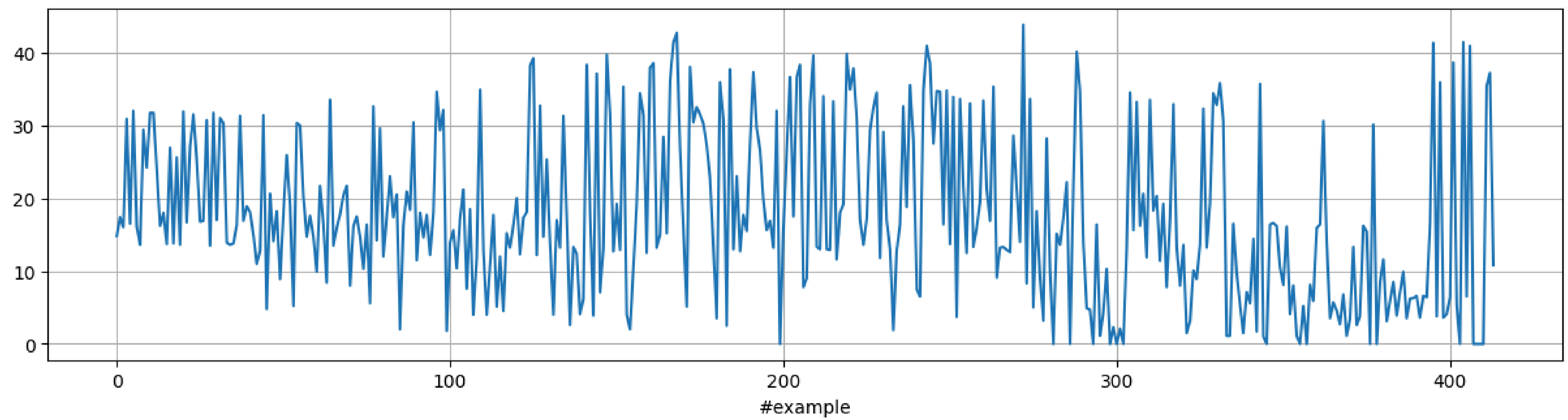
They are far less useful with non-sequential data

That said, we are going to use them all the same

Using Cartesian Plots

Let's inspect the "house age" attribute

```
In [25]: data['house age'].plot(xlabel='#example', grid=':', figsize=figsize);
```



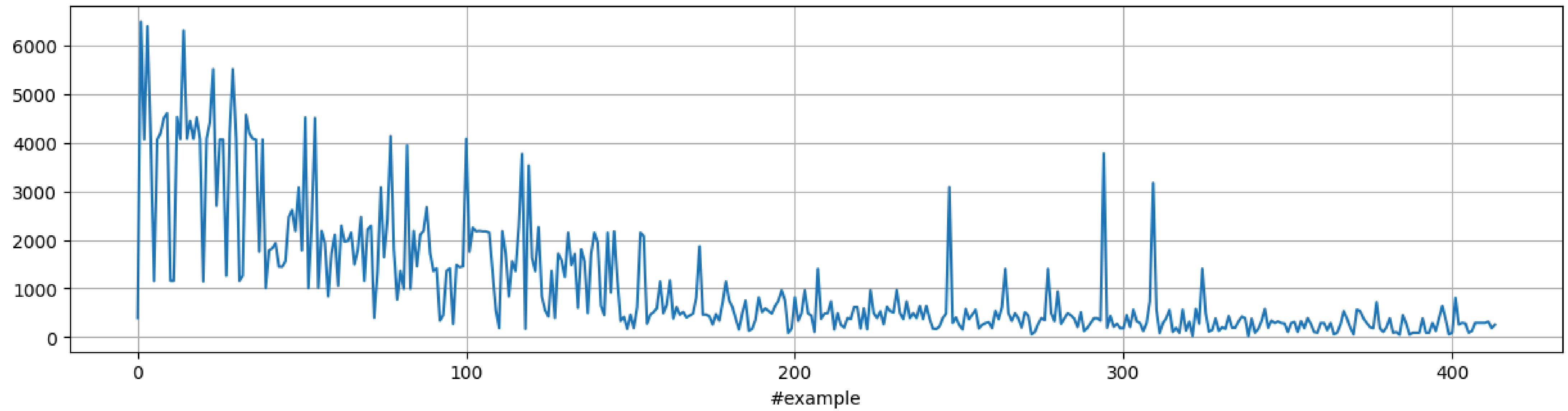
- As expected, there is no significant patter

Try making Cartesian plots for all attributes

Exercise: Using Cartesian Plots

Let's inspect the "dist to MRT" attribute

In [26]:
```
data['dist to MRT'].plot(xlabel='#example', grid=':', figsize=figsize);
```

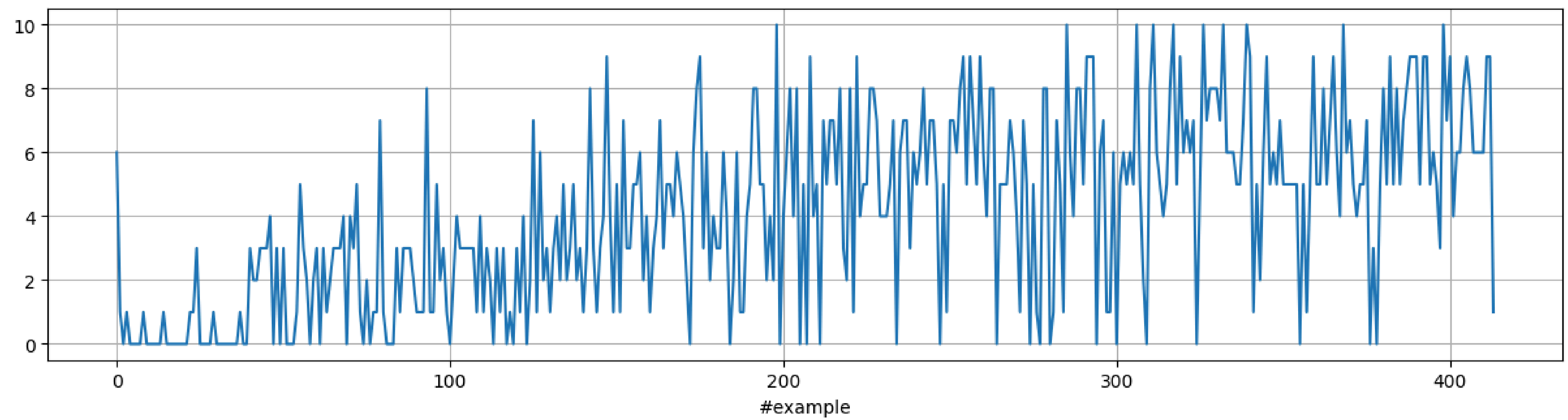


- This attribute roughly decreases along the table

Exercise: Using Cartesian Plots

Let's inspect the "#stores" attribute

In [27]:
```
data['#stores'].plot(xlabel='#example', grid=':', figsize=figsize);
```

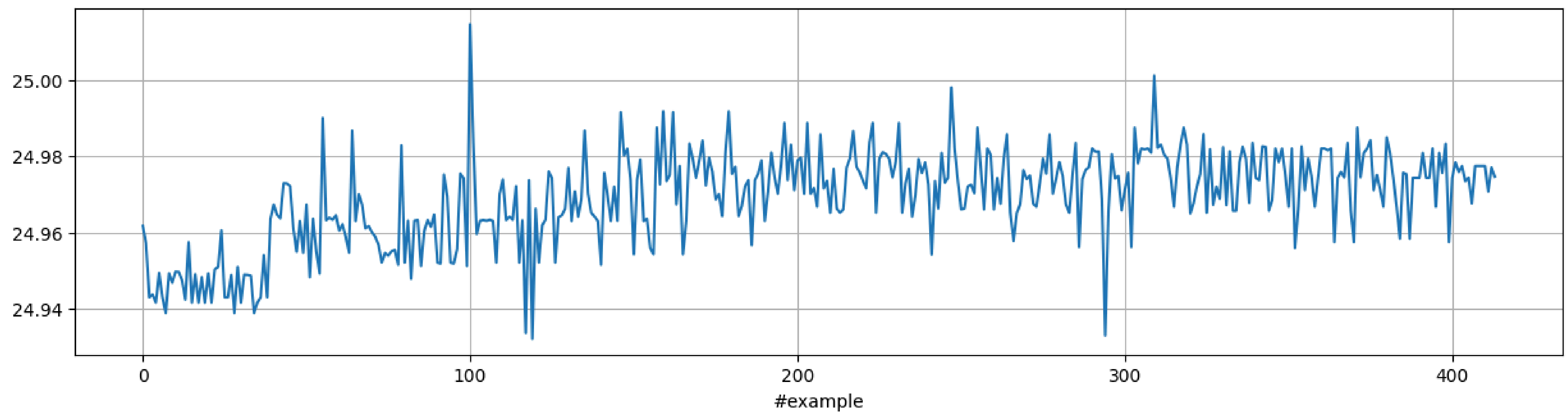


- This attribute roughly increases along the table

Exercise: Using Cartesian Plots

Let's inspect the "latitude" attribute

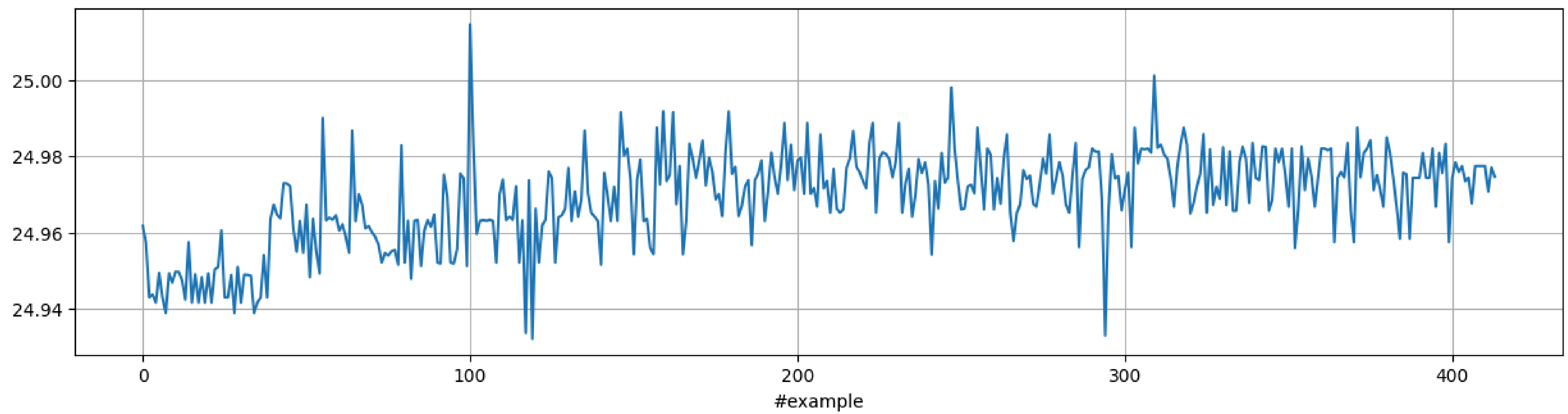
In [28]:
```
data['latitude'].plot(xlabel='#example', grid=':', figsize=figsize);
```



Exercise: Using Cartesian Plots

Let's inspect the "latitude" attribute

```
In [28]: data['latitude'].plot(xlabel='#example', grid=':', figsize=figsize);
```

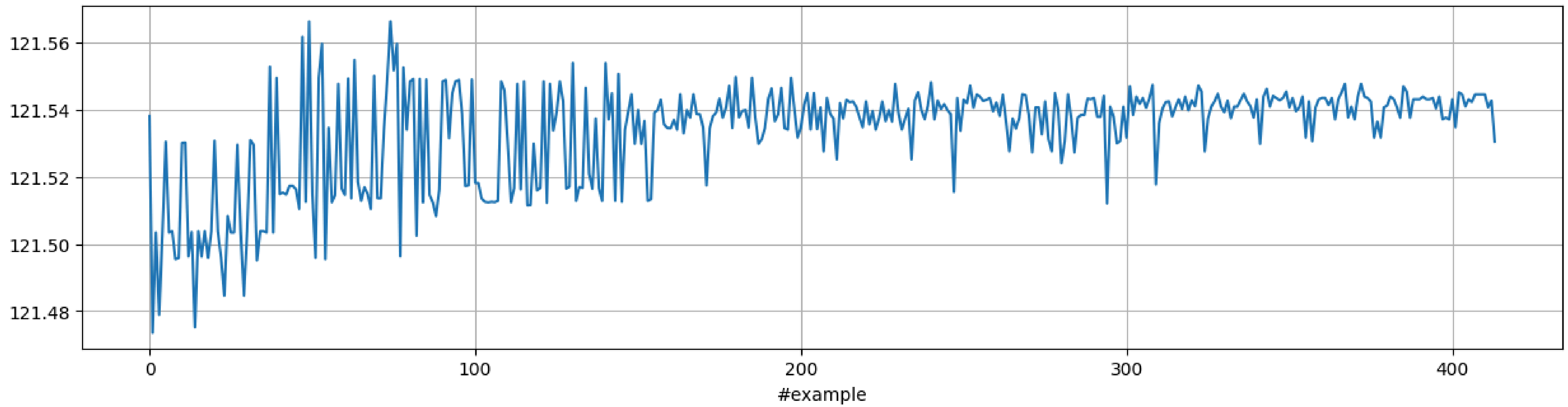


- This attribute roughly increases along the table

Exercise: Using Cartesian Plots

Let's inspect the "longitude" attribute

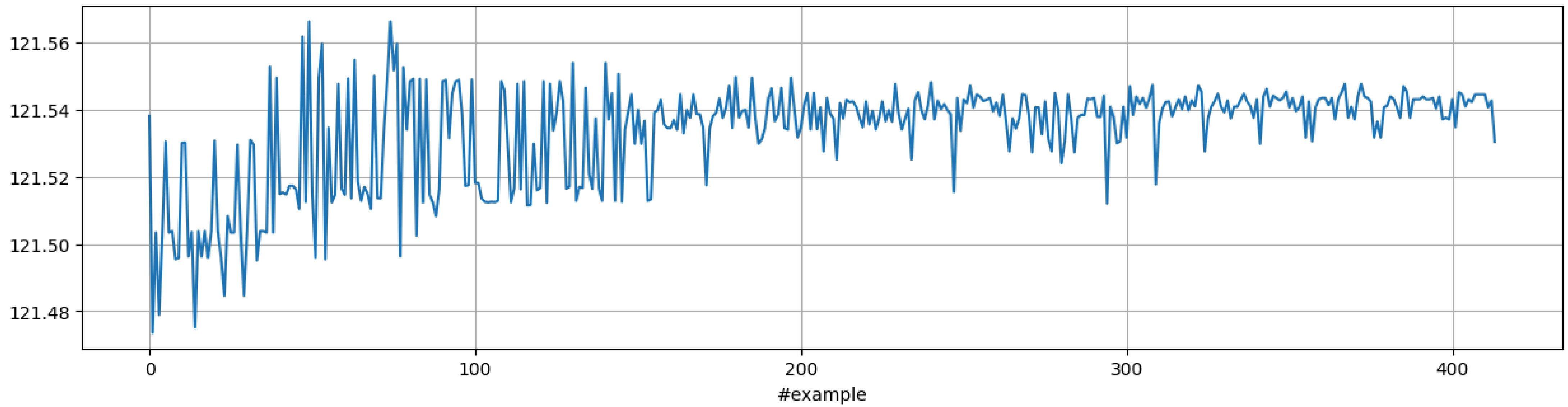
In [29]:
```
data['longitude'].plot(xlabel='#example', grid=':', figsize=figsize);
```



Exercise: Using Cartesian Plots

Let's inspect the "longitude" attribute

```
In [29]: data['longitude'].plot(xlabel='#example', grid=':', figsize=figsize);
```

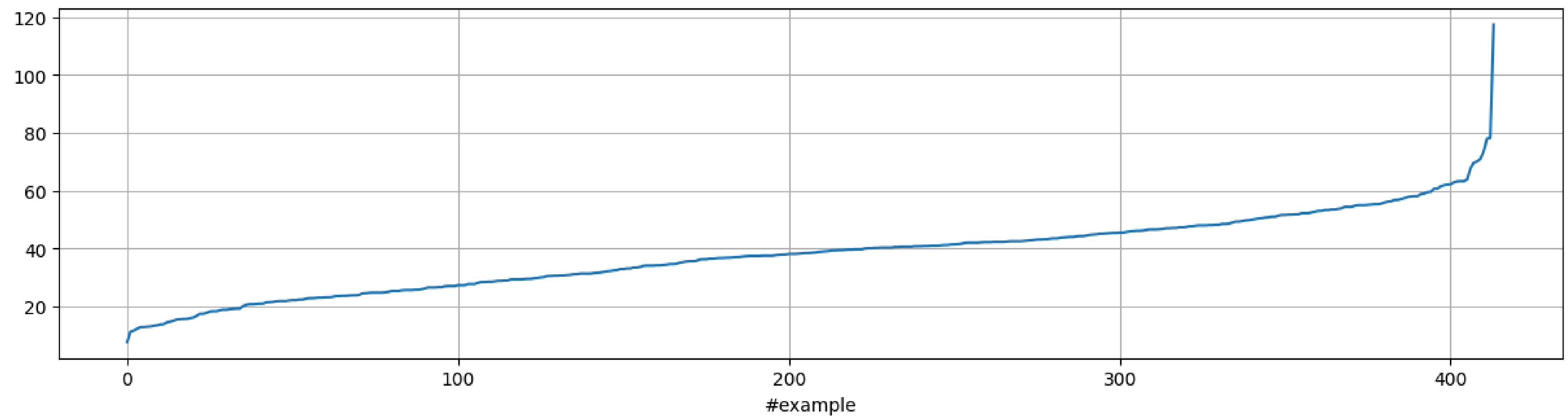


- This attribute roughly increases along the table

Exercise: Using Cartesian Plots

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

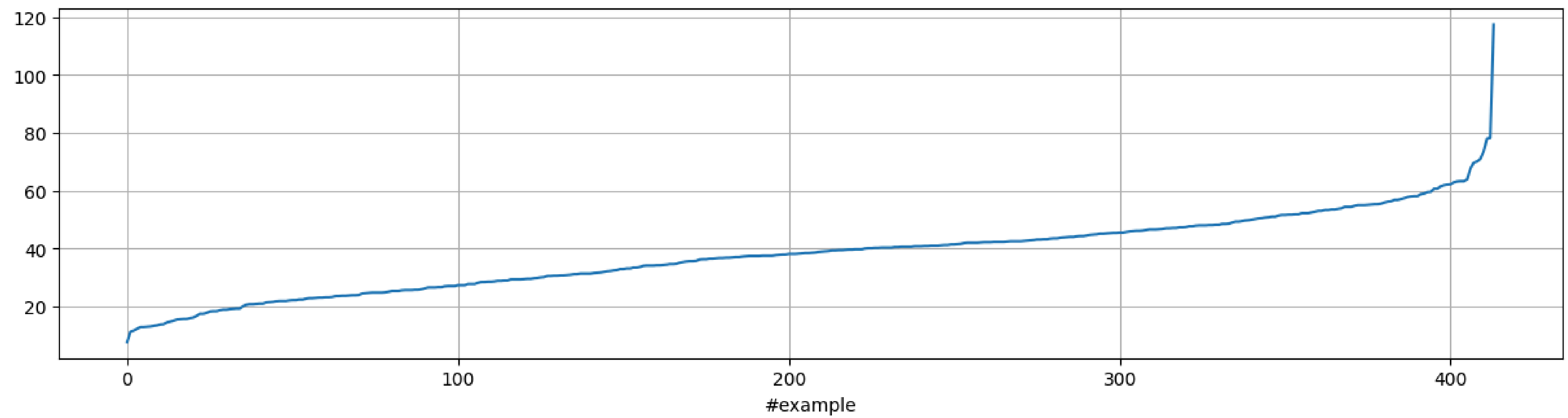
In [30]:
```python
data['price per area'].plot(xlabel='#example', grid=':', figsize=figsize);
```



Exercise: Using Cartesian Plots

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

```
In [30]: data['price per area'].plot(xlabel='#example', grid=':', figsize=figsize);
```



- The dataset is sorted according to this attribute!
- ...Which explains also the other observed patterns

Dataset Inspection via Scatter Plots

The fourth tool we'll use for dataset inspection

...Is given by scatter plots, which have:

- On the x-axis: the values for one attribute
- On the y-axis: the values for anotehr attribute (usually the target)
- Points in scatter plot are not connected by a line

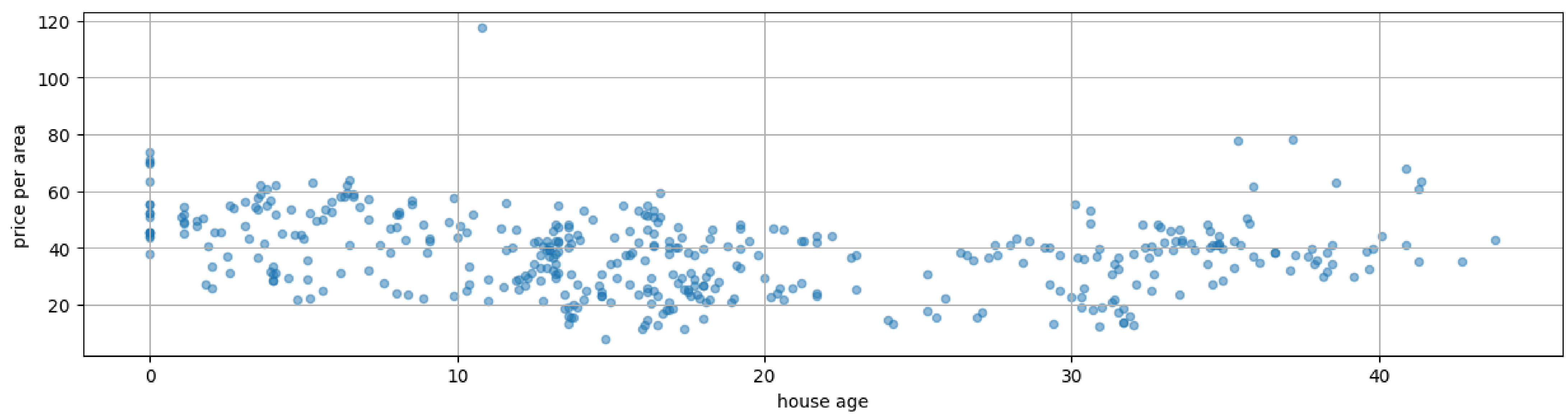
Some comments:

- These are great for the visual identification of correlations
- By looking at the shape of the "cloud of points"
- ...It is possible to get insight on how the attributes are connected

Using Scatter Plots

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

In [31]:
```
data.plot.scatter(x='house age', y='price per area', figsize=figsize, grid=':', alpha=0.5);
```



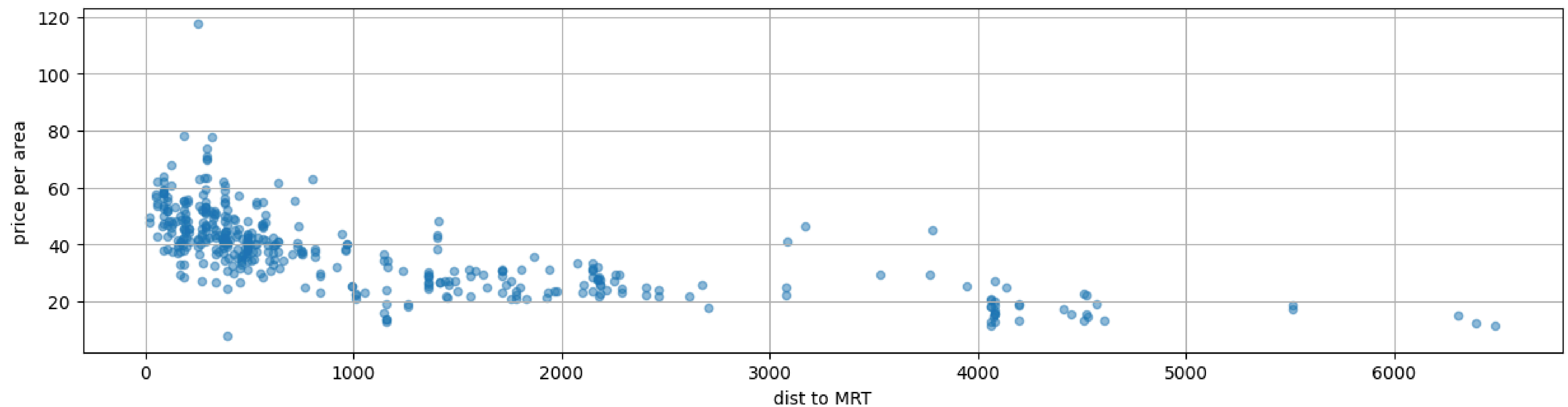
- There does not seem to be a strong correlation here

Try building some scatter plots w.r.t. the target

Exercise: Using Cartesian Plots

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

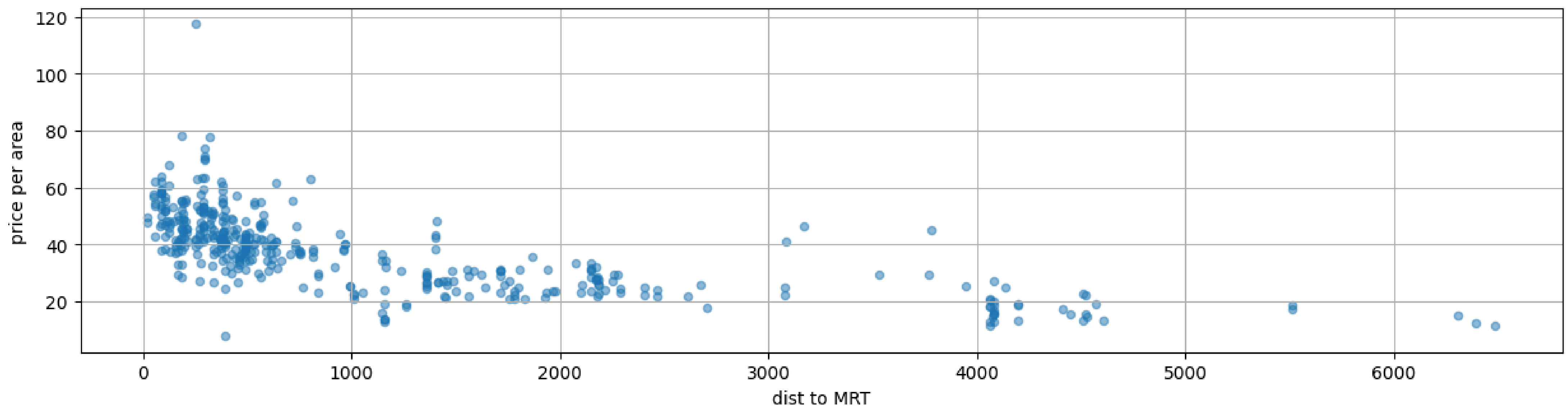
In [32]:
```
data.plot.scatter(x='dist to MRT', y='price per area', figsize=figsize, grid=':', alpha=0.5)
```



Exercise: Using Cartesian Plots

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

```
In [32]: data.plot.scatter(x='dist to MRT', y='price per area', figsize=figsize, grid=':', alpha=0.5
```

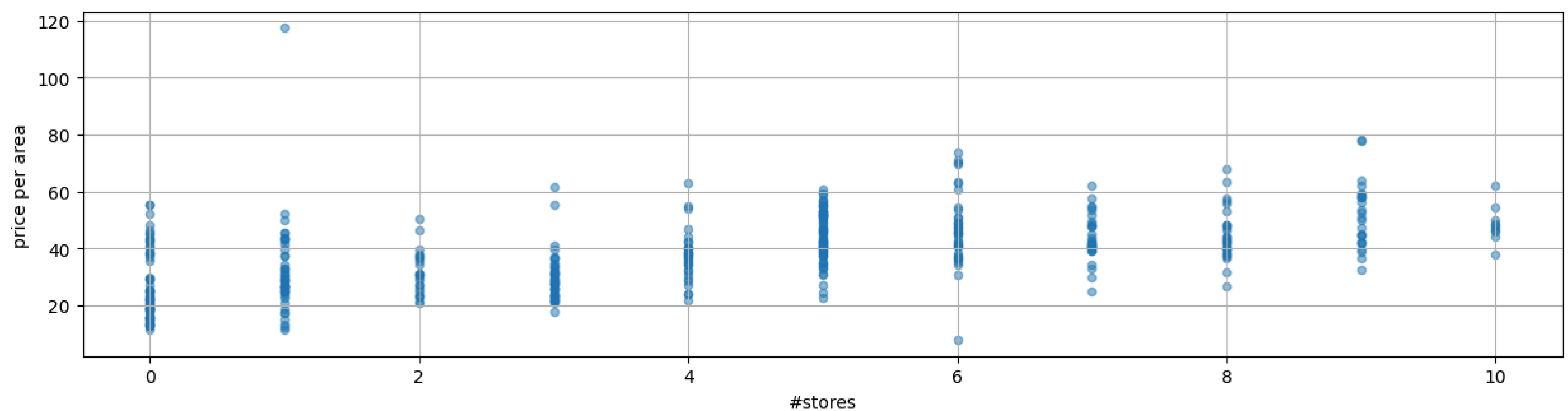


- The correlation is a bit stronger here

Exercise: Using Cartesian Plots

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

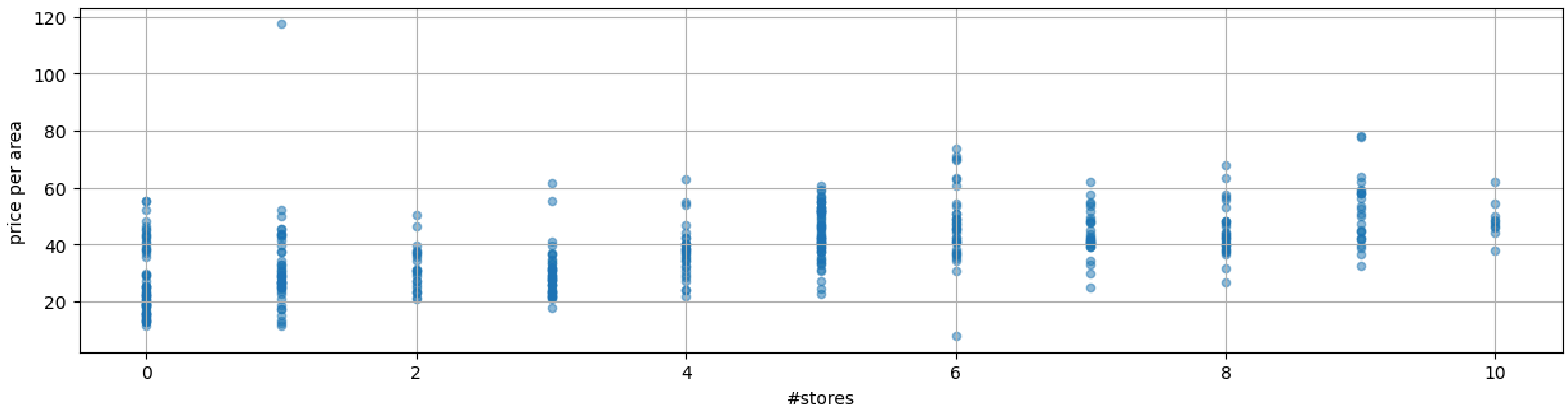
In [33]:
```python
data.plot.scatter(x='#stores', y='price per area', figsize=figsize, grid=':', alpha=0.5);
```



Exercise: Using Cartesian Plots

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

In [33]:
```
data.plot.scatter(x='#stores', y='price per area', figsize=figsize, grid=':', alpha=0.5);
```

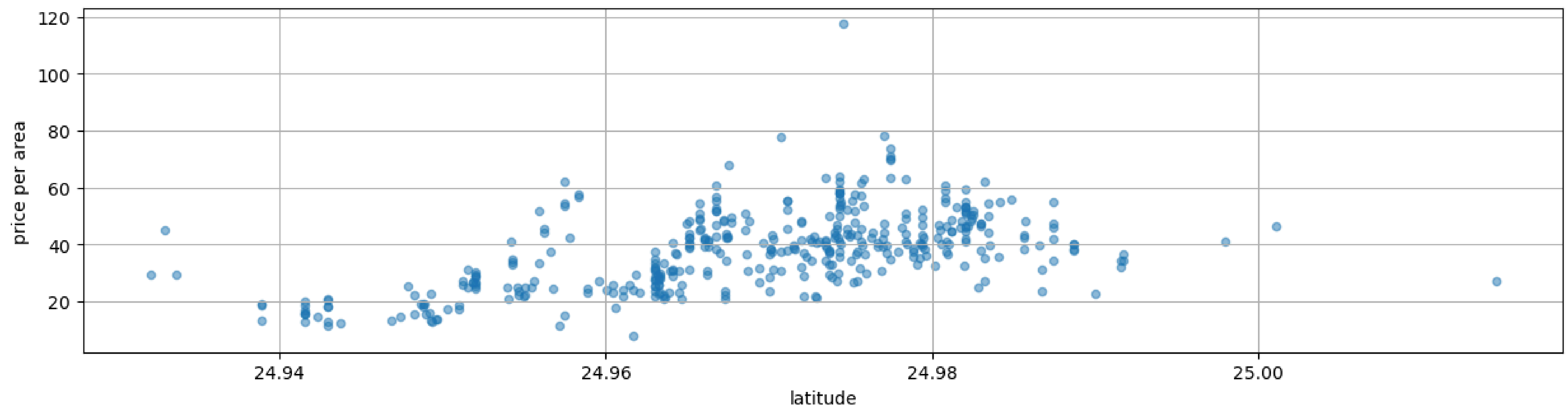


- A slightly positive correlation here

Exercise: Using Cartesian Plots

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

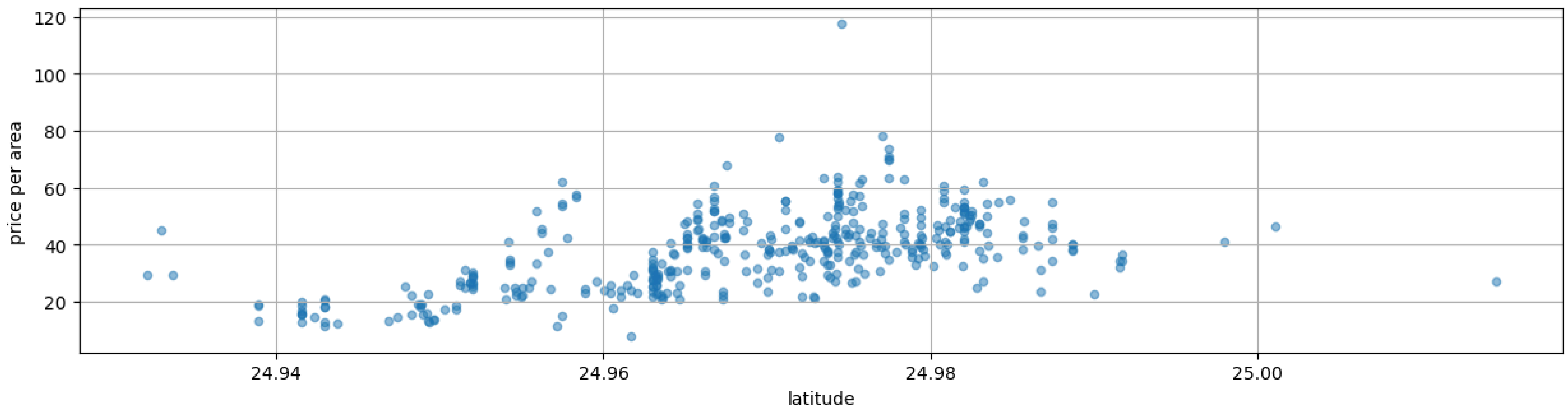
In [82]:
```
data.plot.scatter(x='latitude', y='price per area', figsize=figsize, grid=':', alpha=0.5);
```



Exercise: Using Cartesian Plots

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

In [82]:
```
data.plot.scatter(x='latitude', y='price per area', figsize=figsize, grid=':', alpha=0.5);
```

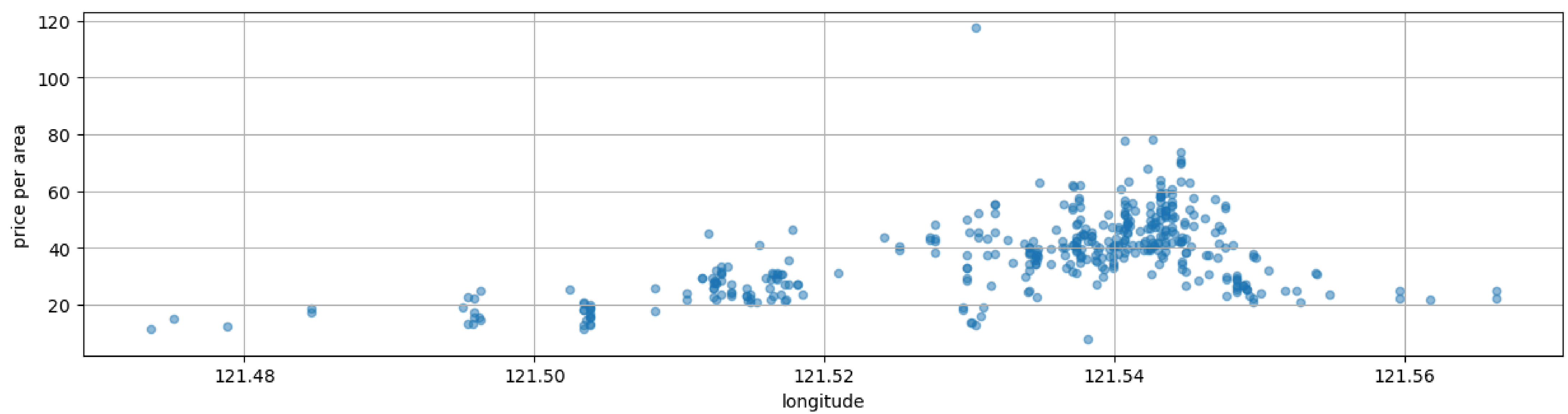


- A somewhat complicated relation

Exercise: Using Cartesian Plots

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

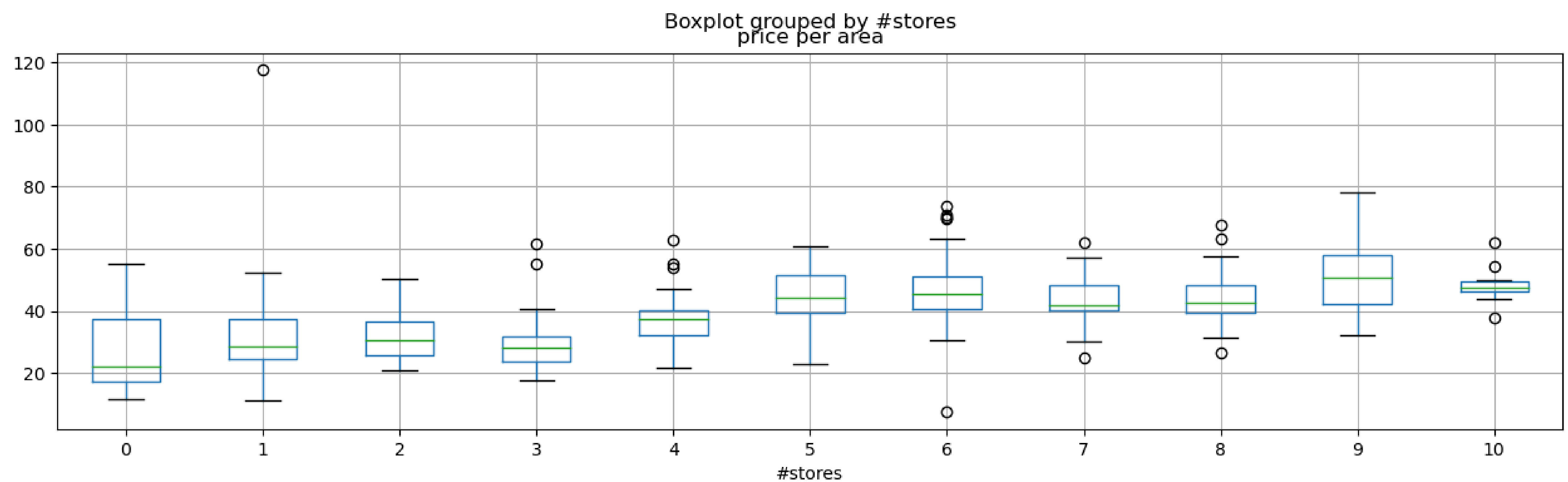
In [83]:
```
data.plot.scatter(x='longitude', y='price per area', figsize=figsize, grid=':', alpha=0.5);
```



Addendum: Using Boxplots

For categorical attributes, a box plot may be more appropriate

In [91]:
```
data.boxplot(by='#stores', column='price per area', figsize=(15, 4));
```

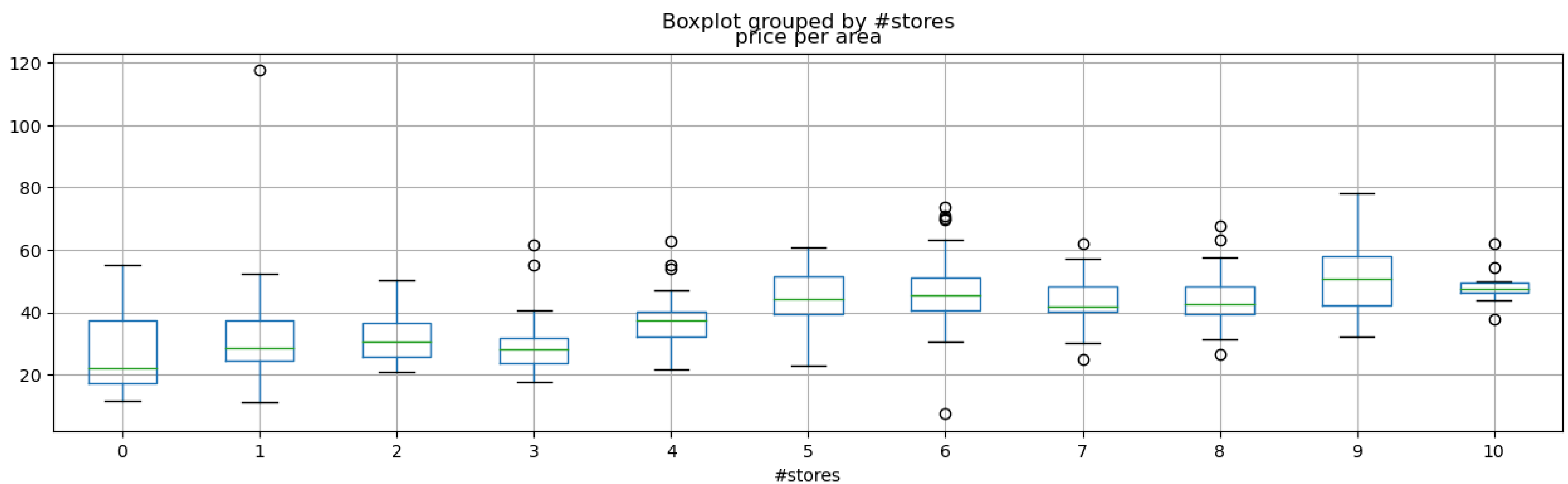


- We have one box per value of an attribute
- On the y axis, we have a second attribute (usually the target)

Addendum: Using Boxplots

For categorical attributes, a box plot may be more appropriate

```
In [91]: data.boxplot(by='#stores', column='price per area', figsize=(15, 4));
```

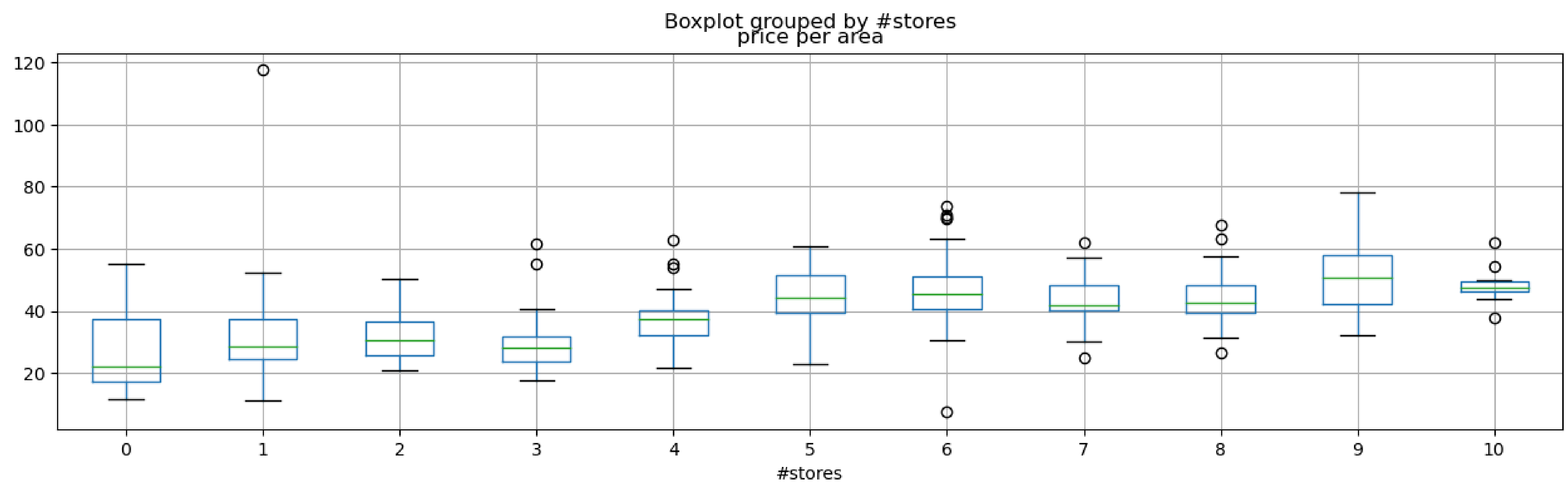


- The box boundaries are the 1st and 3rd quartile
- The green line represents the mean

Addendum: Using Boxplots

For categorical attributes, a box plot may be more appropriate

In [91]:
```
data.boxplot(by='#stores', column='price per area', figsize=(15, 4));
```

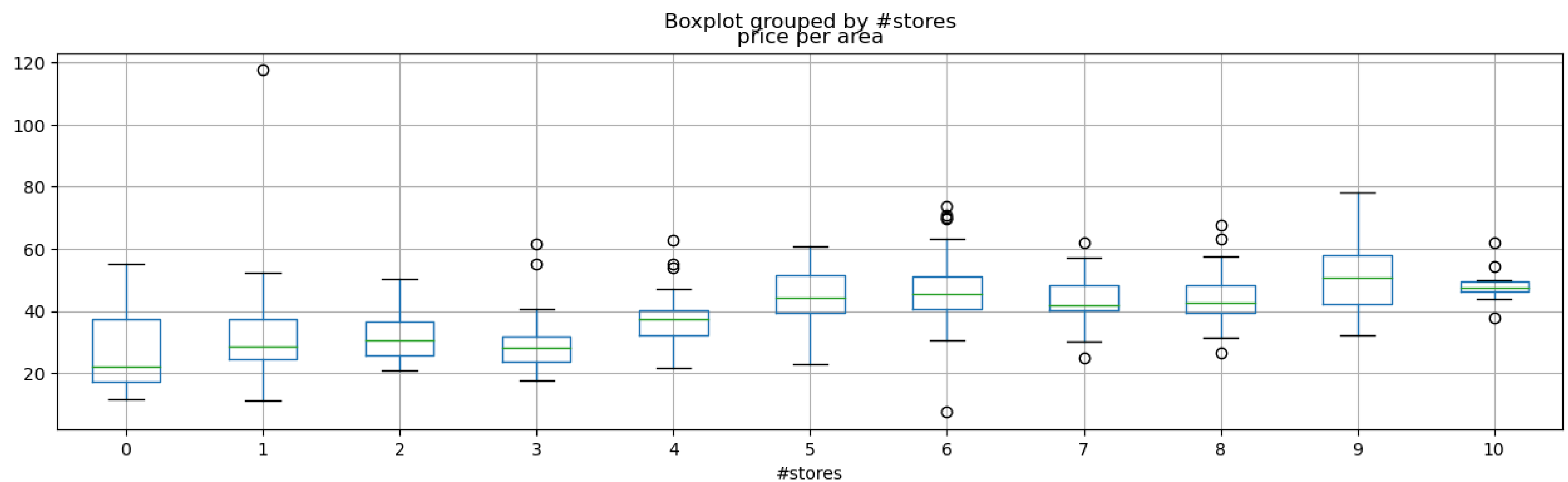


- The "whiskers" extend for 1.5 the inter-quartile range
- Values outside the whiskers are plotted directly

Addendum: Using Boxplots

For categorical attributes, a box plot may be more appropriate

```
In [91]: data.boxplot(by='#stores', column='price per area', figsize=(15, 4));
```



- Box plots are great to see how the distribution of a y depends on x
- They can be used with continuous attributes, if we first discretize them

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 thing is just to keep them in mind