# 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 [33]:
```
!ls data
```

```
real_estate.csv
```

On a classic Windows command prompt you can run instead:

In [34]:
```
!dir data
```

```
real_estate.csv
```

- 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 [35]: import pandas as pd
```

# Loading the Data

## We can then load a csv file with `read_csv`

In [36]:
```python
import os
fname = os.path.join('data', 'real_estate.csv')
data = pd.read_csv(fname, sep=',')
data.head()
```

Out[36]:

| | 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 [37]: data['house age']

Out[37]: 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 [38]:
```
data.head()
```

Out[38]:

| | 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 [39]: data.index

Out[39]: 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 [40]: data.loc[3]

Out[40]: 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 [41]: data.loc[3].loc['house age']

Out[41]: 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 [42]: data.loc[3, 'house age']

Out[42]: 30.9
```

# Indexing a Dataframe

## Pandas supports also positional access

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

```
In [43]: r3 = data.loc[3]
         r3

Out[43]: 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 [44]: r3.iloc[1] # this is dist to MRT

Out[44]: 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 [45]: first_rows = data.loc[[2, 1, 5, 3, 4]]
         first_rows
```

Out[45]:

| | 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

# Indexing a Dataframe

## We can use just the `[]` operator (without `loc` or `iloc`)

...Pandas tries to understand which of the two we need:

```
In [46]: print(r3[3])
         print(r3['latitude'])

24.94375
24.94375
```

If there is an abiguity, we get an error:

```
In [47]: data[3]

---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
File /opt/conda/lib/python3.10/site-packages/pandas/core/indexes/base.py:3802, in Index.get_lo
c(self, key, method, tolerance)
   3801 try:
-> 3802     return self._engine.get_loc(casted_key)
   3803 except KeyError as err:

File /opt/conda/lib/python3.10/site-packages/pandas/_libs/index.pyx:138, in pandas._libs.inde
x.IndexEngine.get_loc()
```

# A Possible Problem Statement

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

```
In [48]: data.head()
```

Out[48]:

| | 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`**

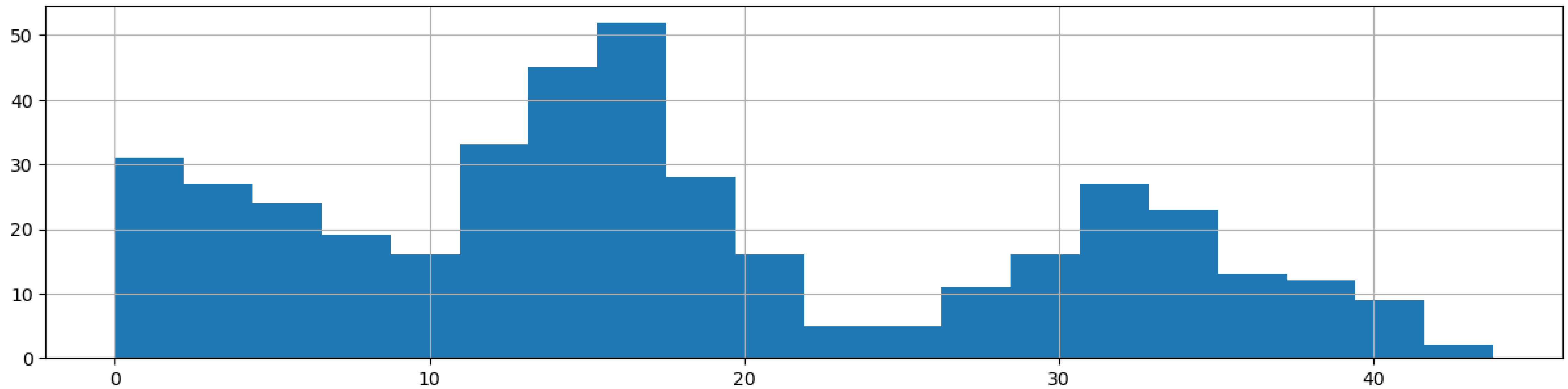
...By using the hist method.

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

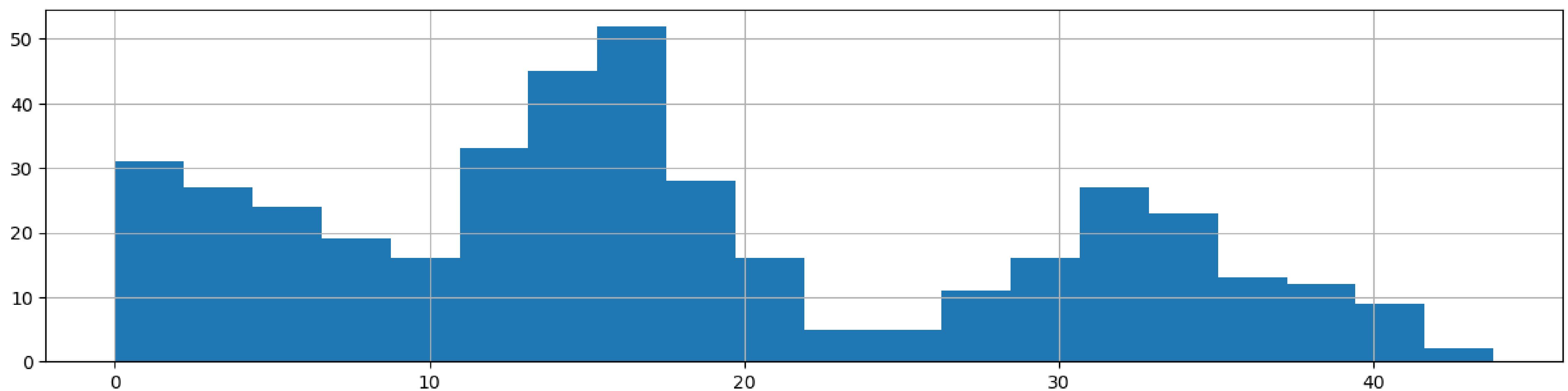



## What can you say about that?

# Using Histograms

## Let's inspect the "house age" attribute

```
In [51]: data['house age'].hist(figsize=figsize, bins=20);
```



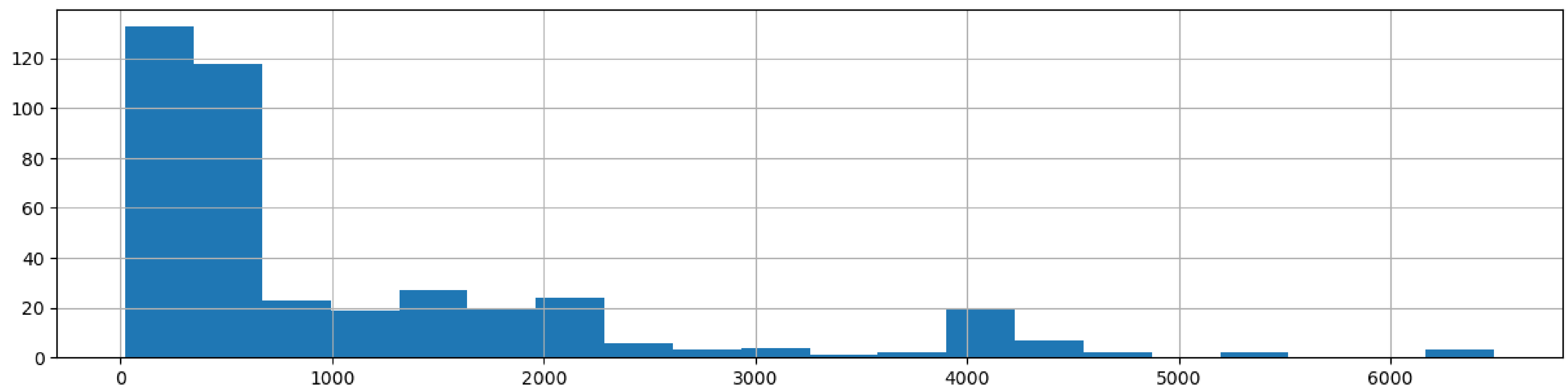

- There seems to be two main clusters, roughly normally distributed
- Lower age values are roughly uniformly likely

**Now, try building histograms for the other columns**

# Exercise: Using Histograms

## Let's inspect the "dist to MRT" attribute

In [53]:
```
data['dist to MRT'].hist(figsize=figsize, bins=20);
```

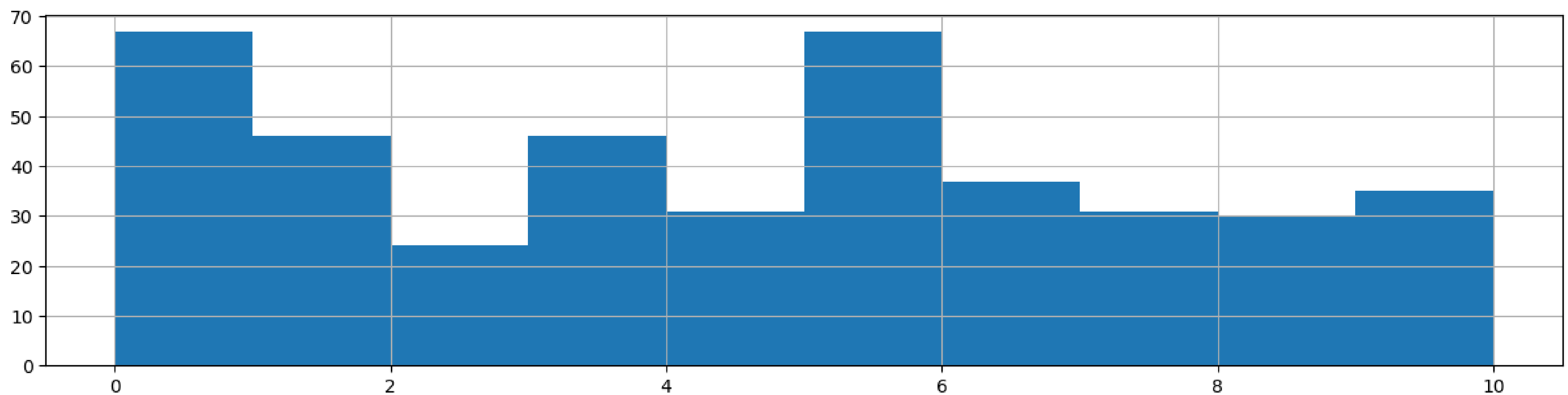



- This attribute has a large range and low values are much more prevalent

# Exercise: Using Histograms

## Let's inspect the "#stores" attribute

```
In [54]: data['#stores'].hist(figsize=figsize, bins=10);
```

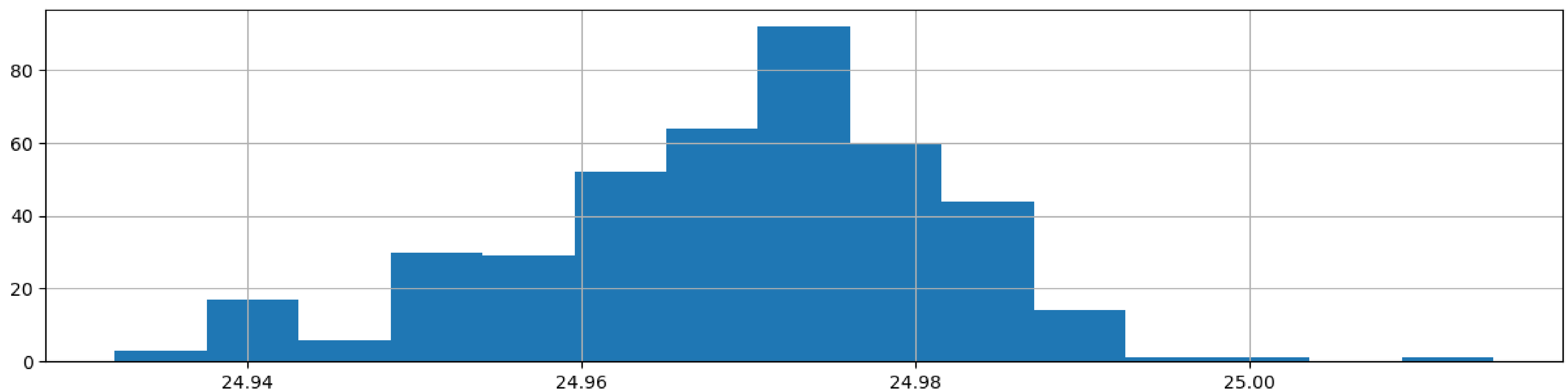



- The dataset covers rather uniformly the range for this attribute

# Exercise: Using Histograms

## Let's inspect the "latitude" attribute

In [55]:
```
data['latitude'].hist(figsize=figsize, bins=15);
```

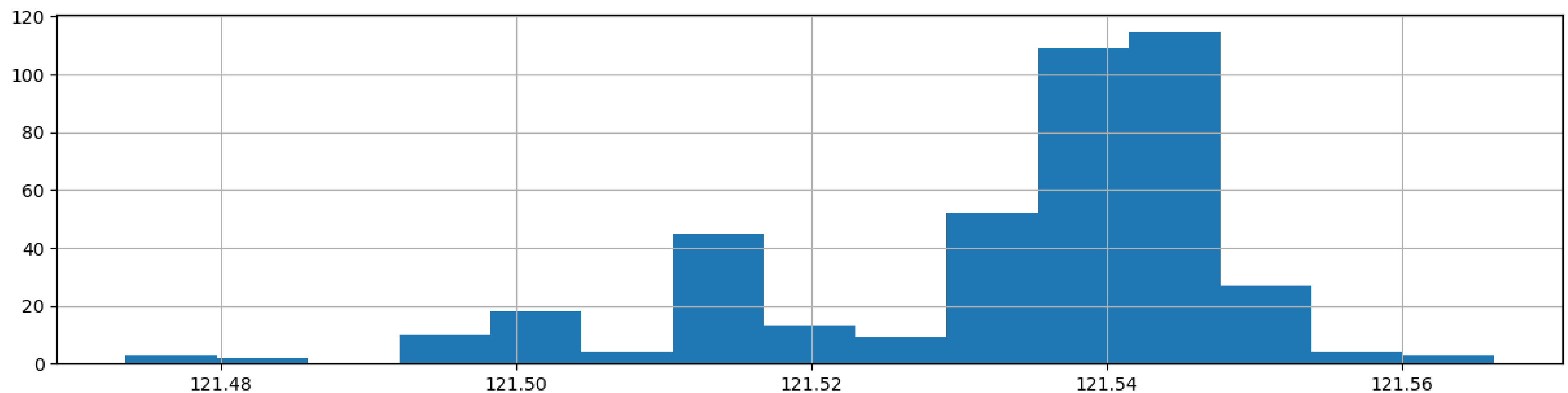



- There is a central cluster w.r.t. this attribute

# Exercise: Using Histograms

## Let's inspect the "longitude" attribute

In [56]:
```
data['longitude'].hist(figsize=figsize, bins=15);
```

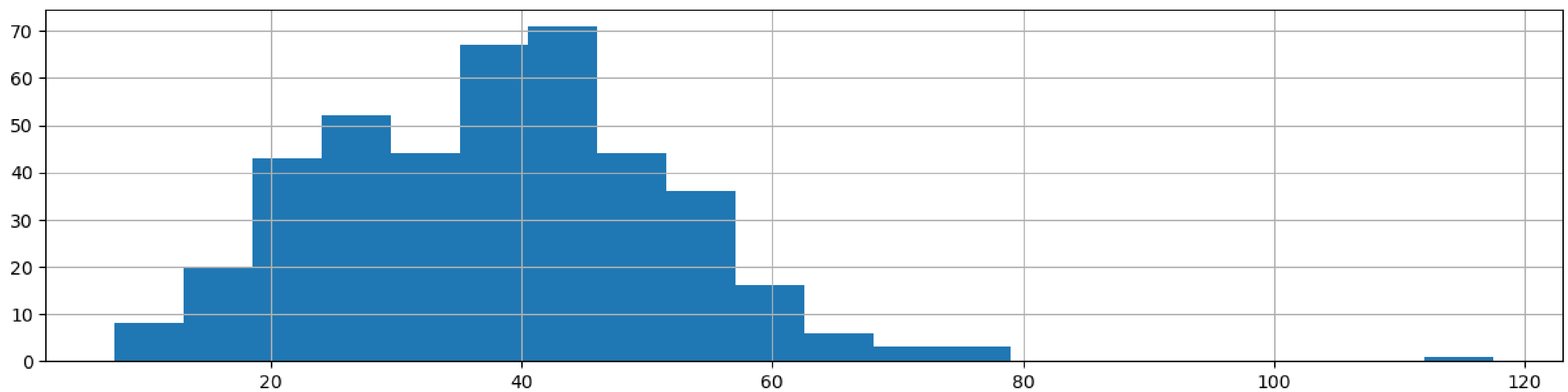



- The dataset is a bit less uniformly distributed w.r.t. longitude

# Exercise: Using Histograms

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

In [57]:
```
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 [58]:
```
data.describe()
```

Out[58]:

| | 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

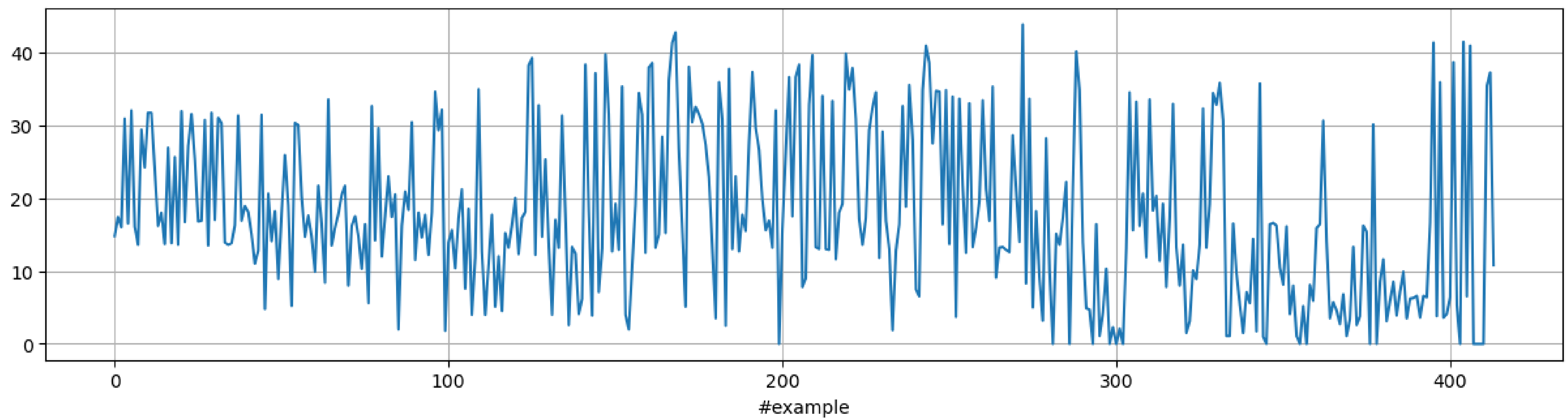
They are far less useful with non-sequential data

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

# Using Cartesian Plots

## Let's inspect the "house age" attribute

In [59]:
```
data['house age'].plot(xlabel='#example', grid=':', figsize=figsize);
```



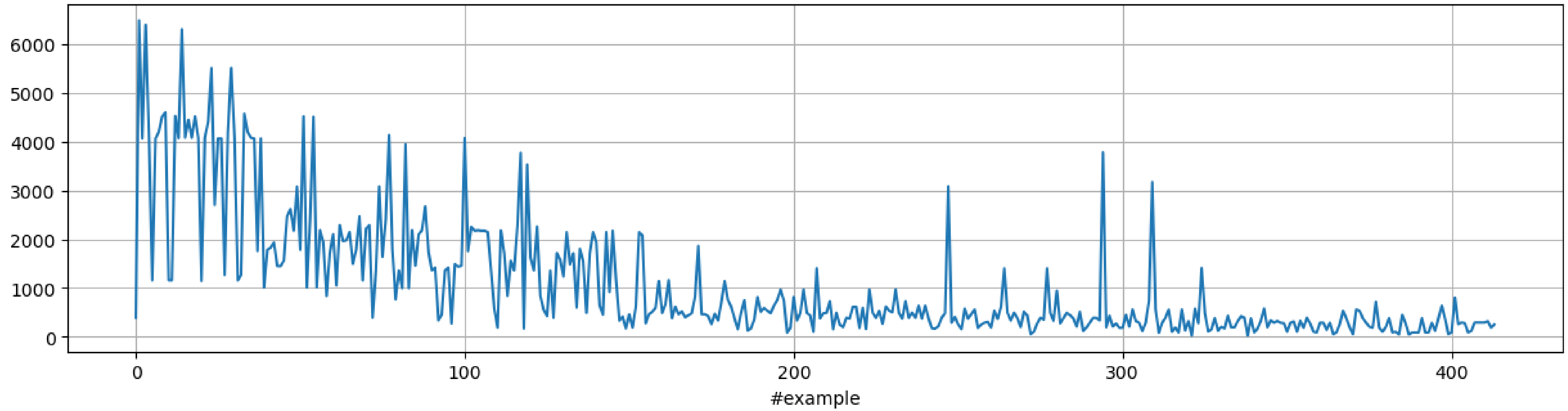

- As expected, there is no significant patter

## Try making Cartesian plots for all attributes

# Exercise: Using Cartesian Plots

## Let's inspect the "dist to MRT" attribute

In [60]:
```
data['dist to MRT'].plot(xlabel='#example', grid=':', figsize=figsize);
```

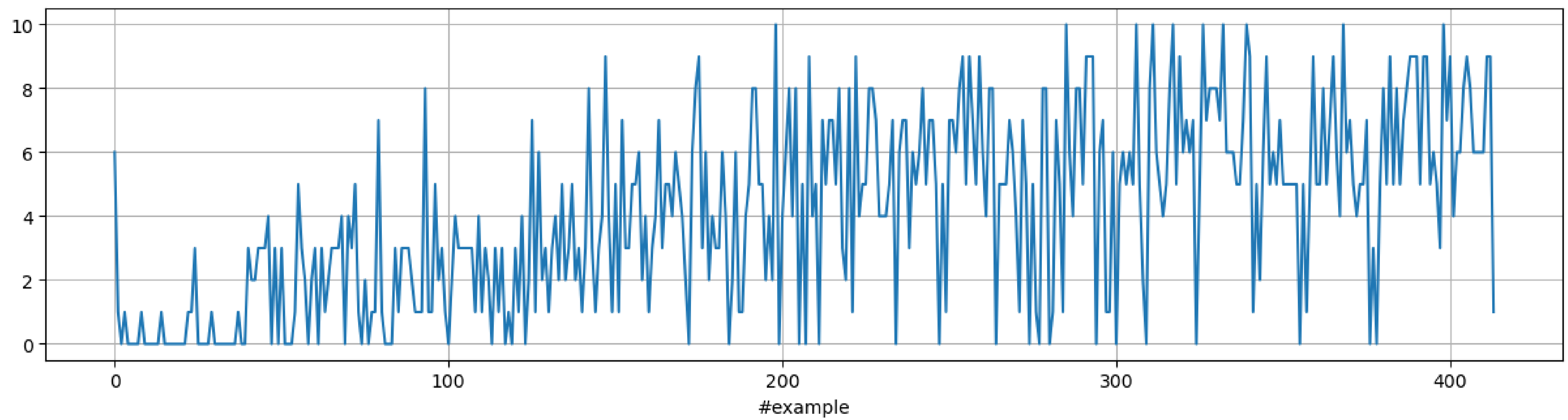



- This attribute roughly decreases along the table

# Exercise: Using Cartesian Plots

## Let's inspect the "#stores" attribute

```
In [62]: data['#stores'].plot(xlabel='#example', grid=':', figsize=figsize);
```

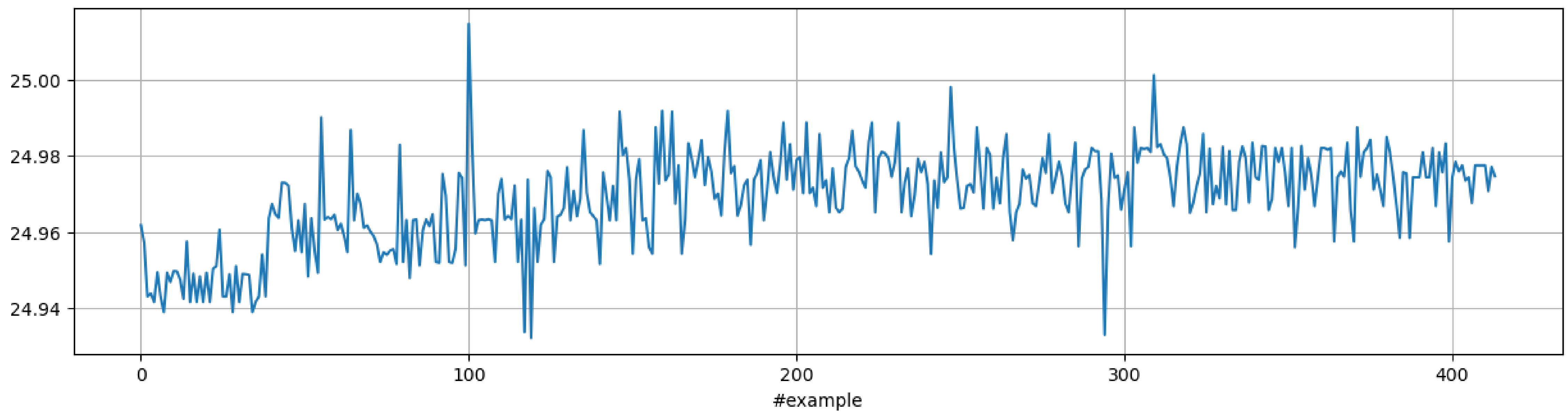



- This attribute roughly increases along the table

# Exercise: Using Cartesian Plots

## Let's inspect the "latitude" attribute

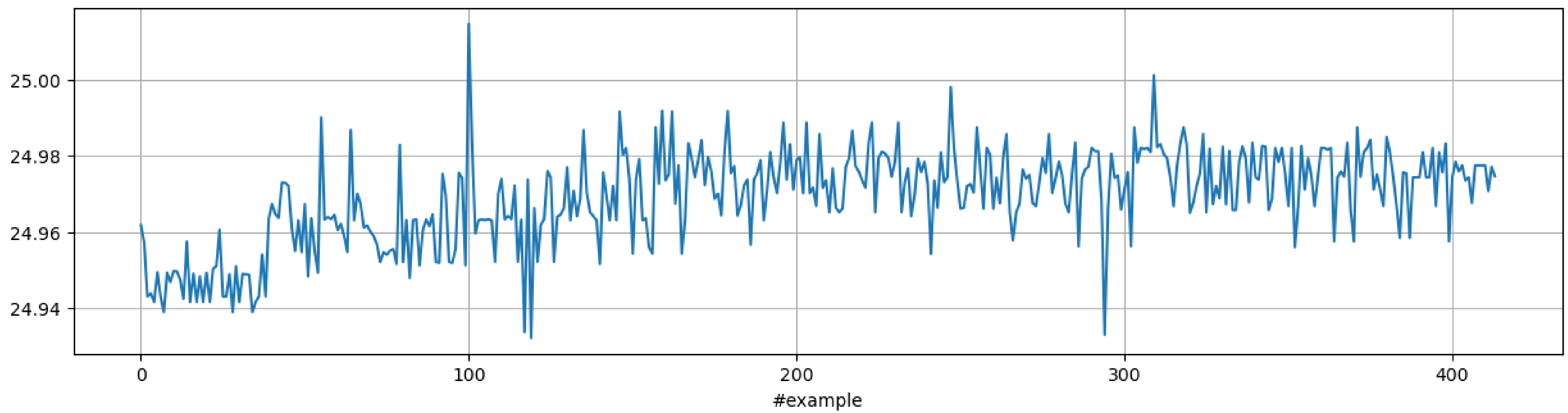
In [63]:
```
data['latitude'].plot(xlabel='#example', grid=':', figsize=figsize);
```



# Exercise: Using Cartesian Plots

## Let's inspect the "latitude" attribute

```
In [63]: data['latitude'].plot(xlabel='#example', grid=':', figsize=figsize);
```

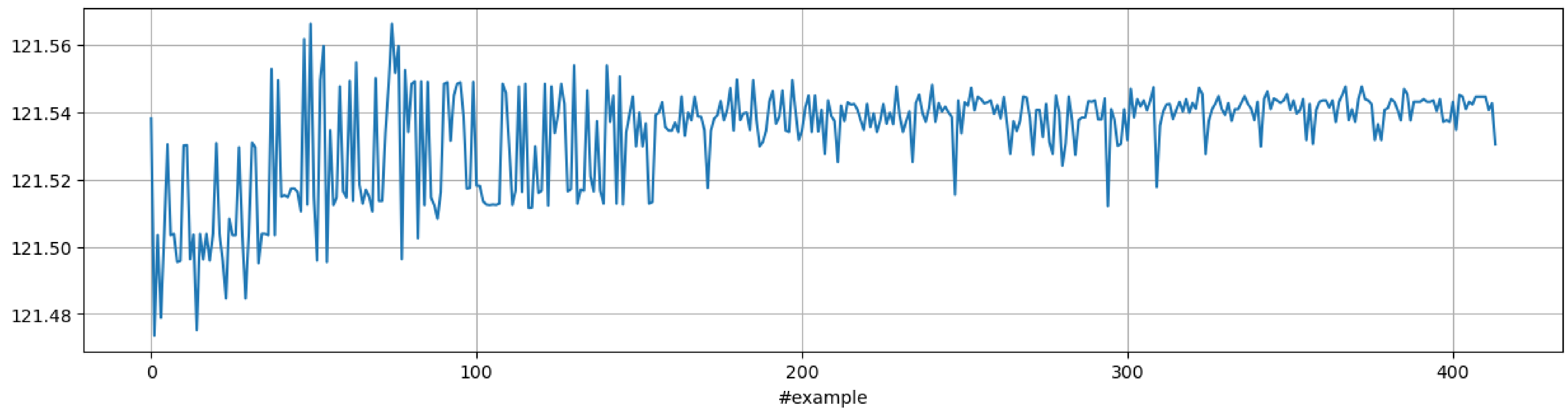



- This attribute roughly increases along the table

# Exercise: Using Cartesian Plots

## Let's inspect the "longitude" attribute

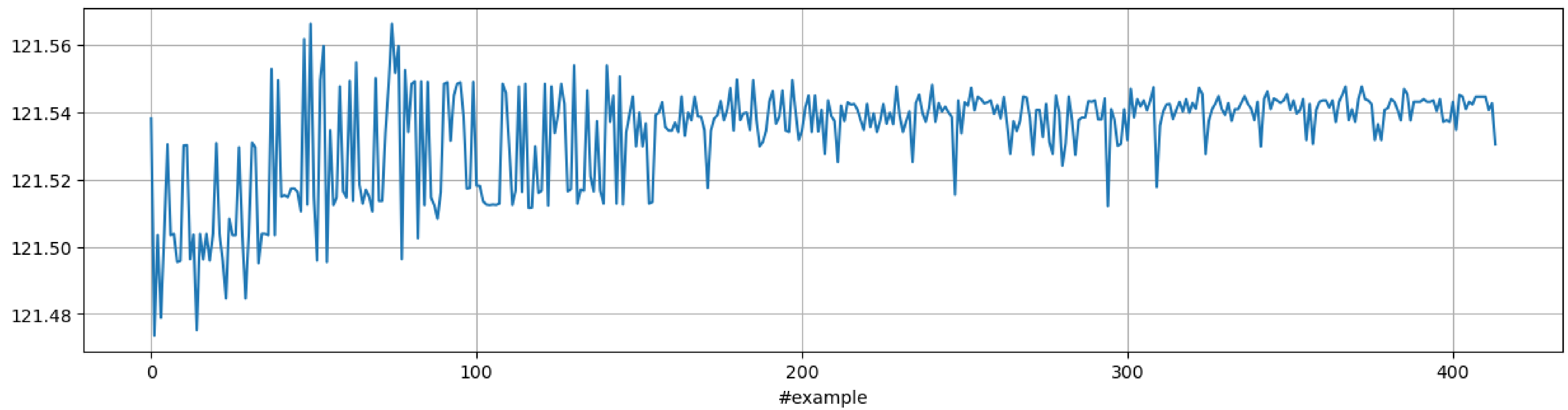
In [64]:
```
data['longitude'].plot(xlabel='#example', grid=':', figsize=figsize);
```



# Exercise: Using Cartesian Plots

## Let's inspect the "longitude" attribute

```
In [64]: data['longitude'].plot(xlabel='#example', grid=':', figsize=figsize);
```

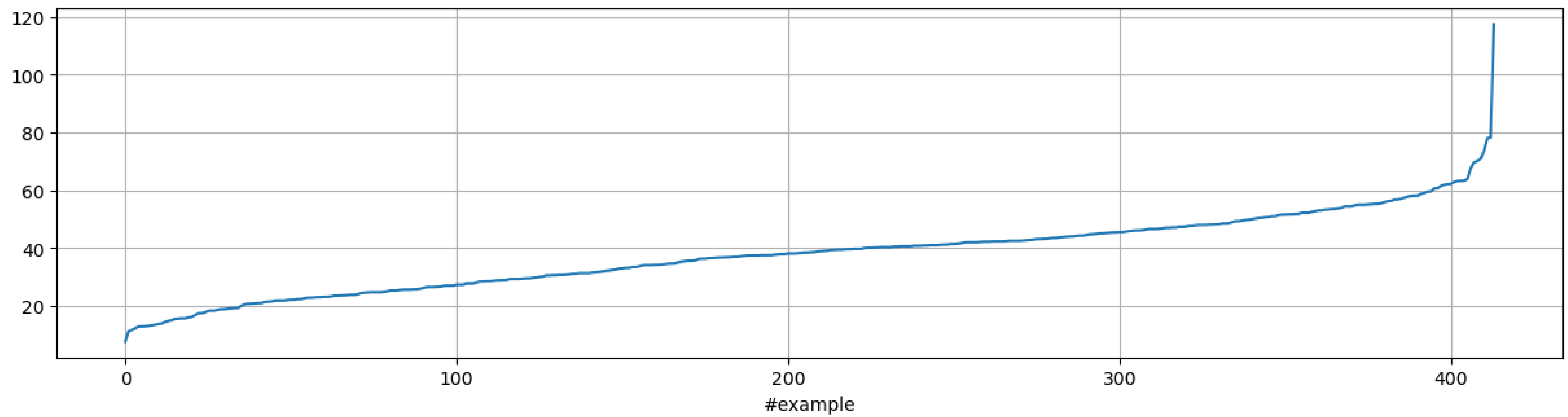



- This attribute roughly increases along the table

# Exercise: Using Cartesian Plots

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

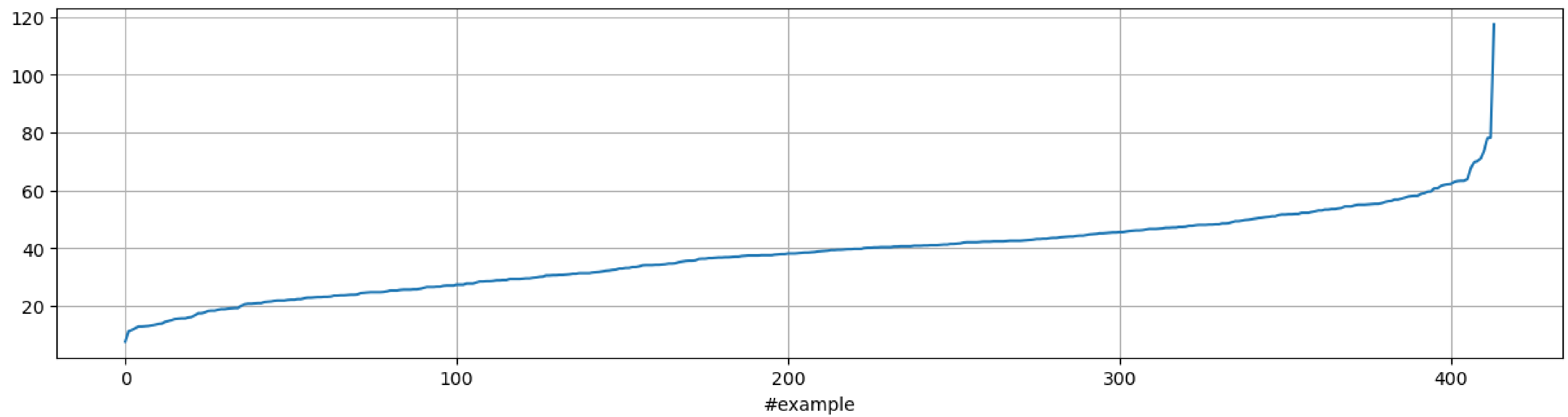
In [65]:
```
data['price per area'].plot(xlabel='#example', grid=':', figsize=figsize);
```



# Exercise: Using Cartesian Plots

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

In [65]:
```
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

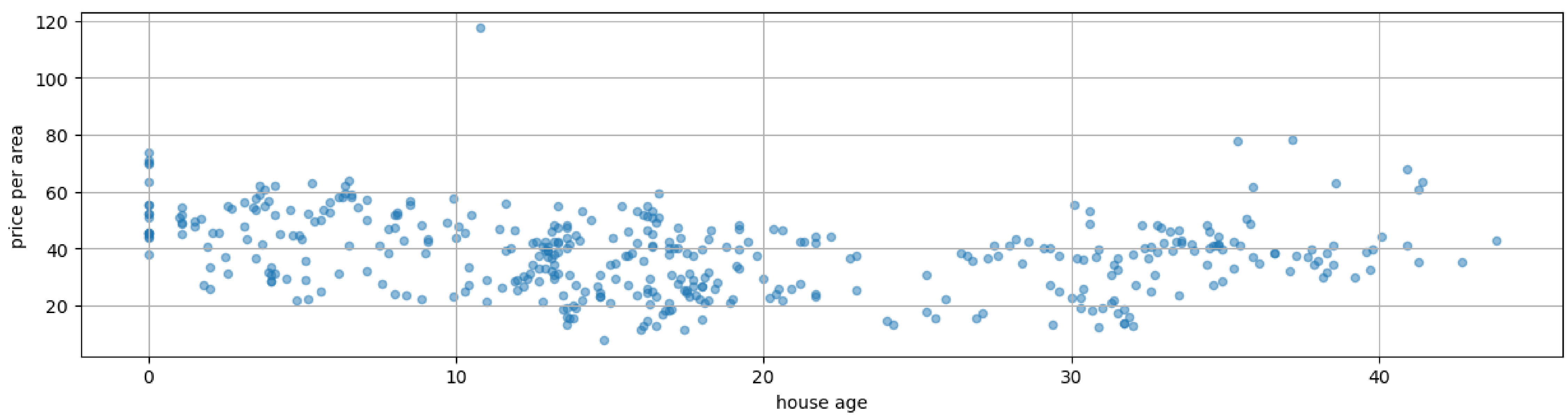
**Some comments:**

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



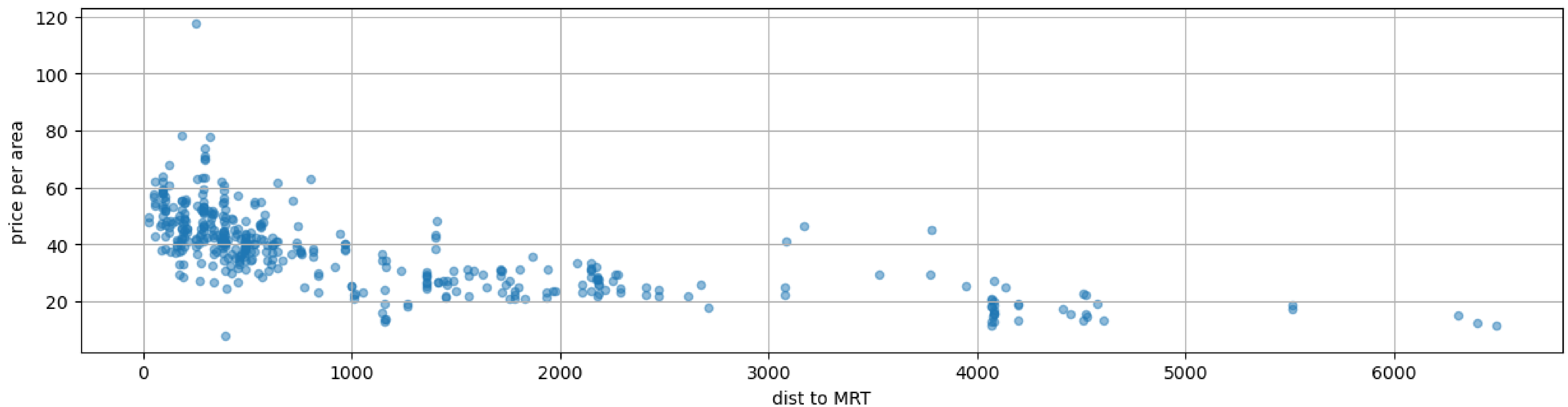

- There does not seem to be a strong correlation here

## 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

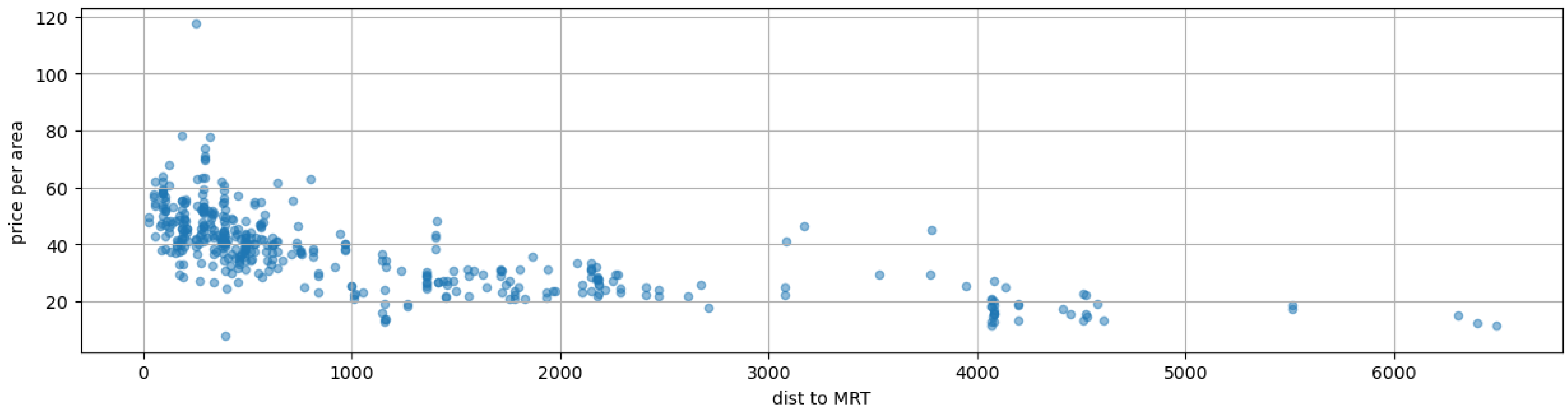
In [80]:
```
data.plot.scatter(x='dist to MRT', y='price per area', figsize=figsize, grid=':', alpha=0.5);
```



# Exercise: Using Cartesian Plots

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

In [80]:
```
data.plot.scatter(x='dist to MRT', y='price per area', figsize=figsize, grid=':', alpha=0.5);
```

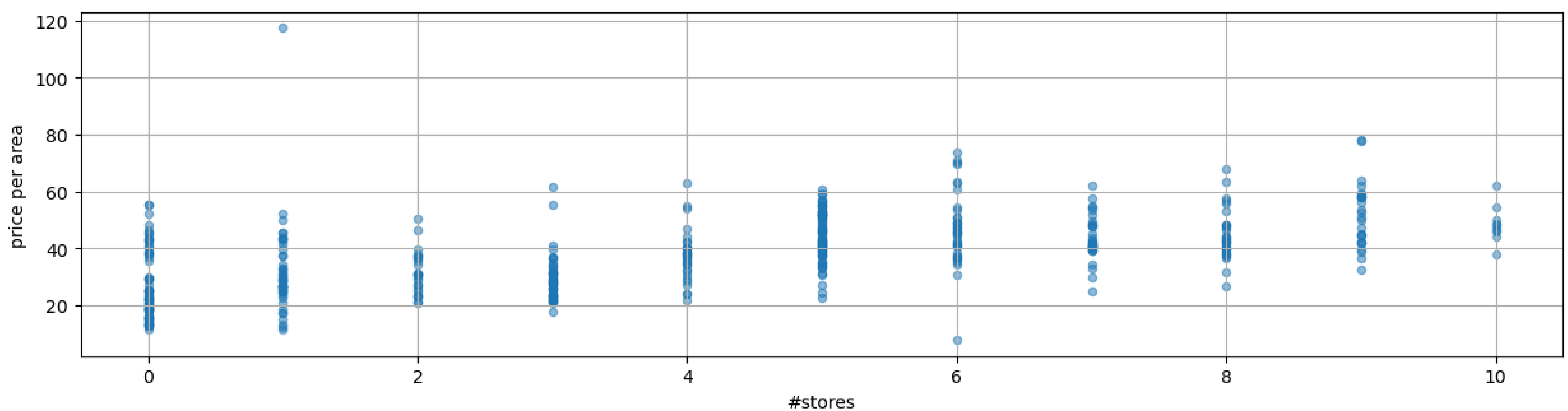



- The correlation is a bit stronger here

# Exercise: Using Cartesian Plots

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

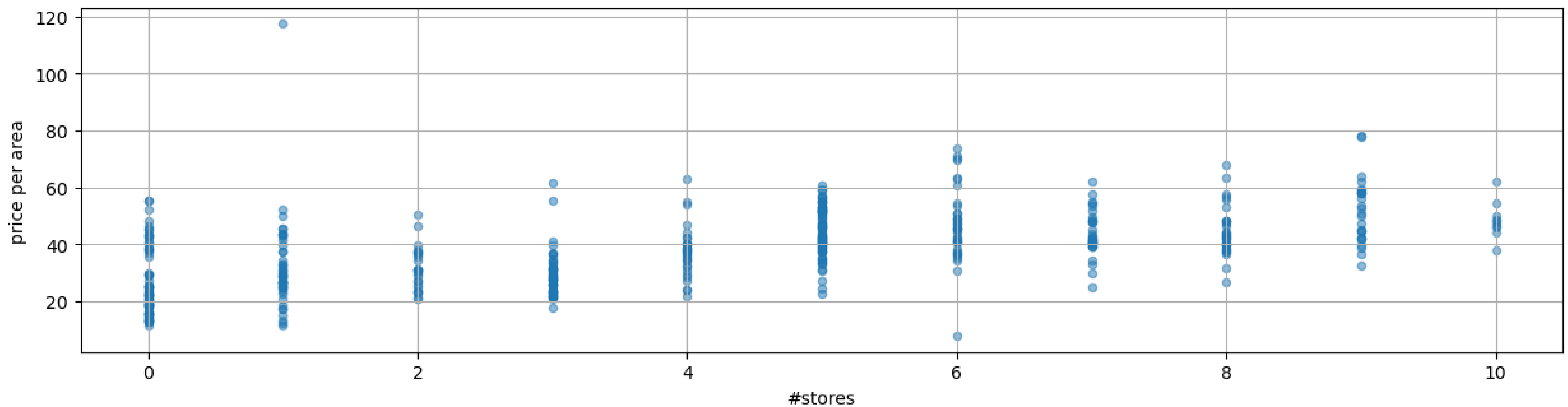
In [81]:
```
data.plot.scatter(x='#stores', y='price per area', figsize=figsize, grid=':', alpha=0.5);
```



# Exercise: Using Cartesian Plots

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

```
In [81]: data.plot.scatter(x='#stores', y='price per area', figsize=figsize, grid=':', alpha=0.5);
```

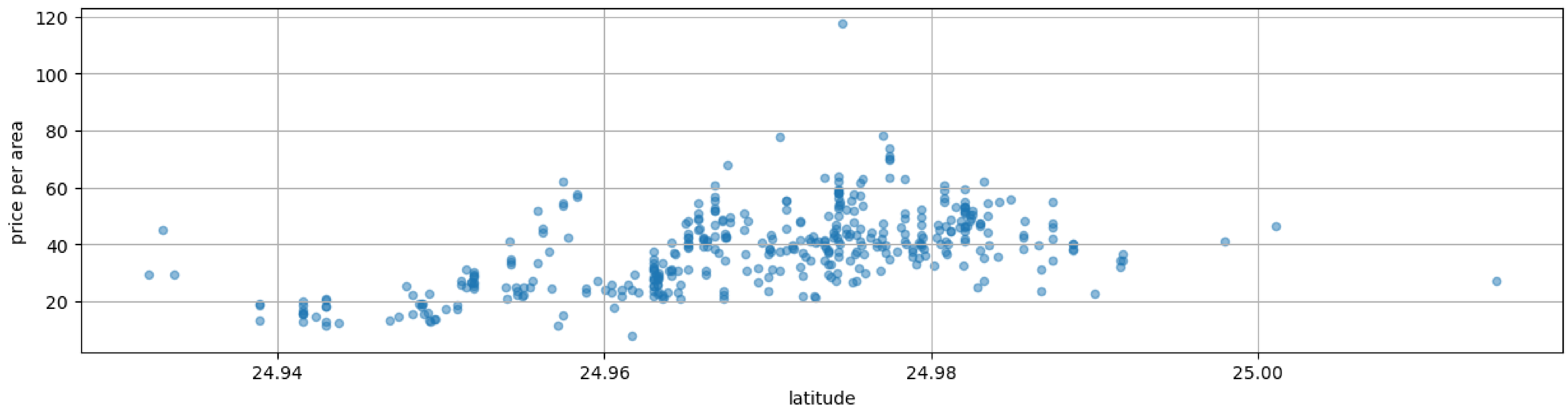



- A slightly positive correlation here

# Exercise: Using Cartesian Plots

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

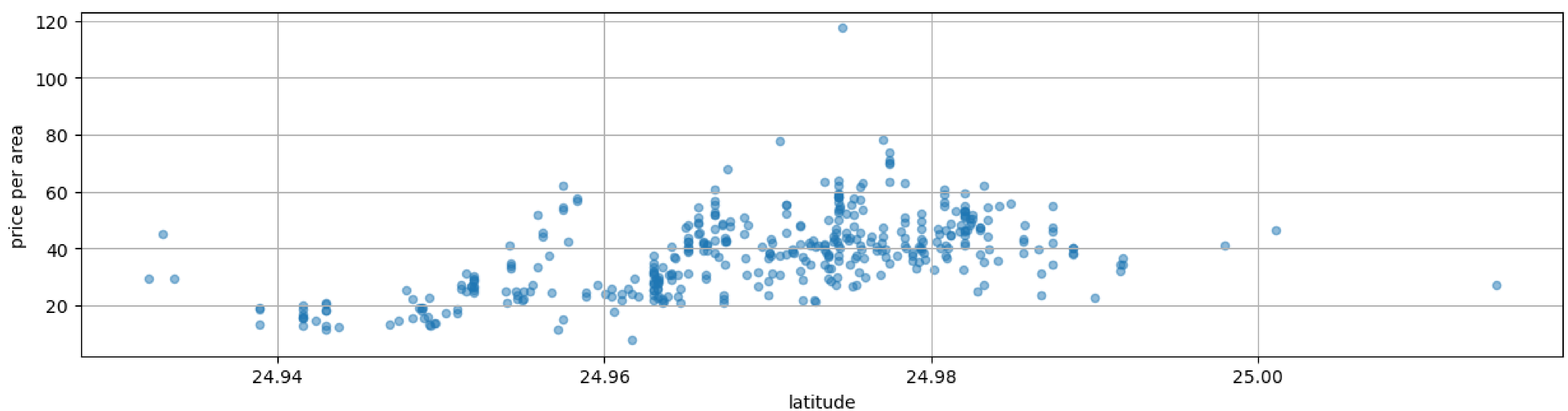
In [82]:
```
data.plot.scatter(x='latitude', y='price per area', figsize=figsize, grid=':', alpha=0.5);
```



# 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);
```

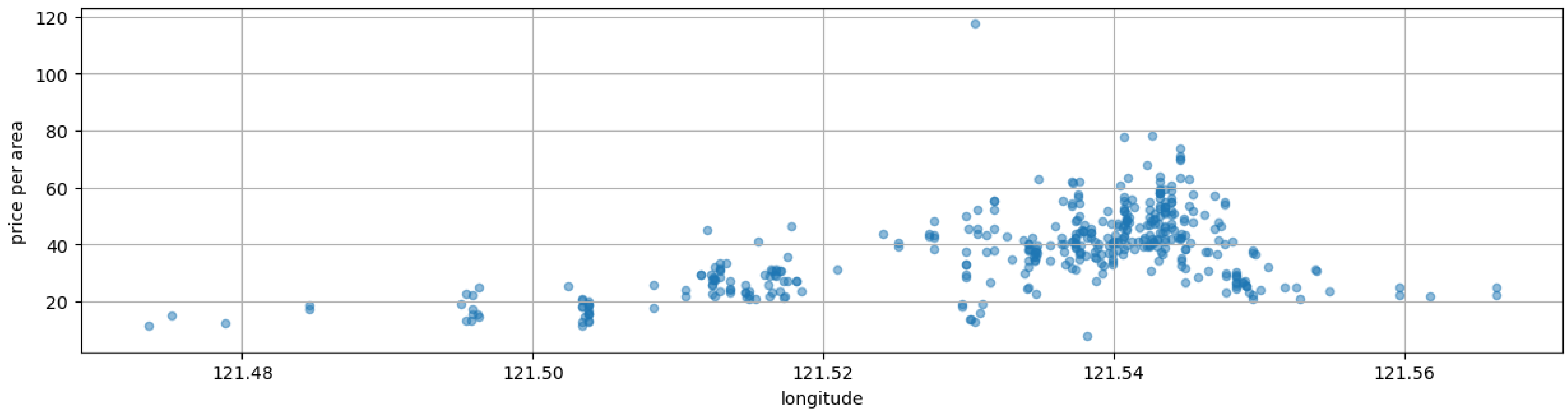



- A somewhat complicated relation

# Exercise: Using Cartesian Plots

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

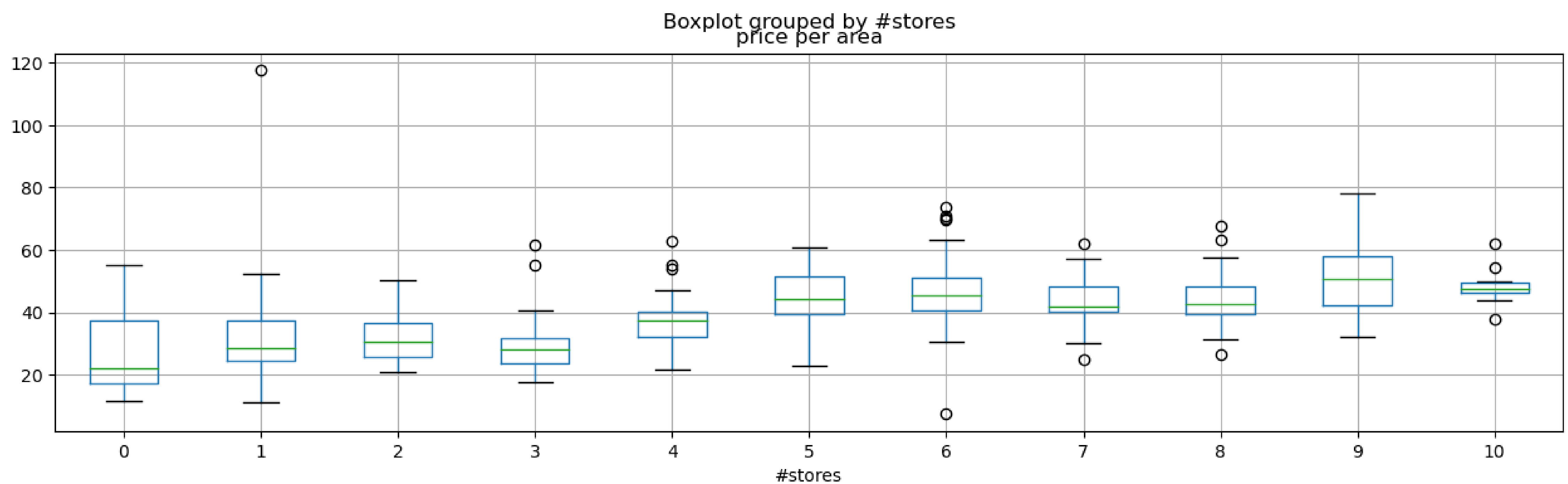
```
In [83]: data.plot.scatter(x='longitude', y='price per area', figsize=figsize, grid=':', alpha=0.5);
```



# 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));
```

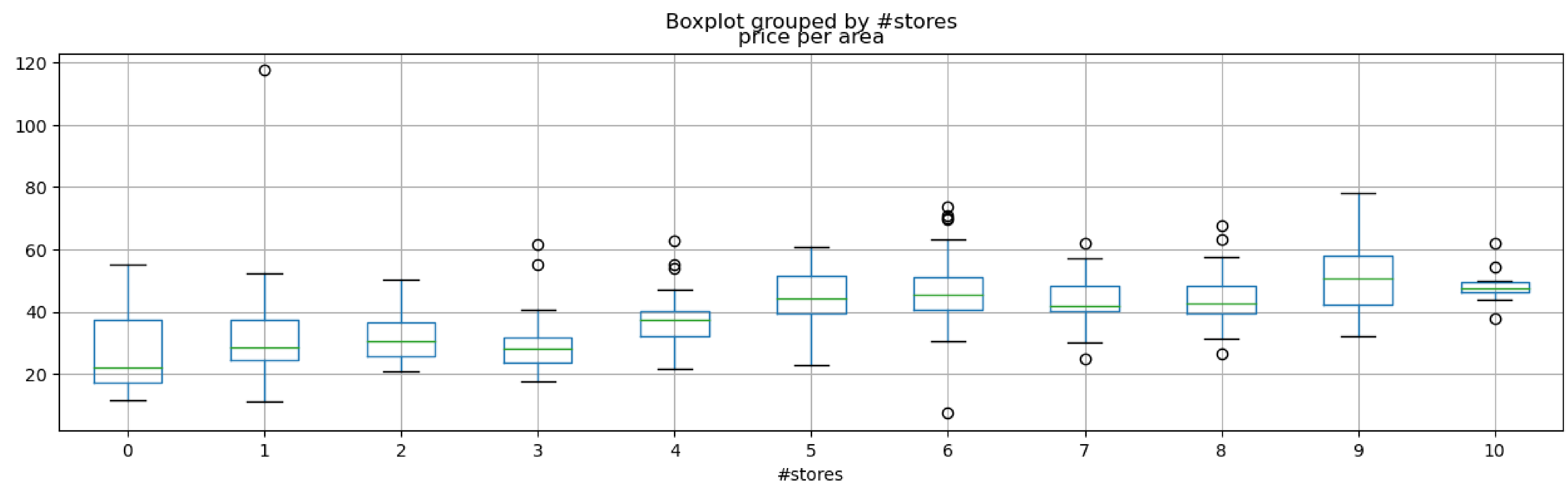



- We have one box per value of an attribute
- On the $y$ axis, we have a second attribute (usually the target)

# 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));
```

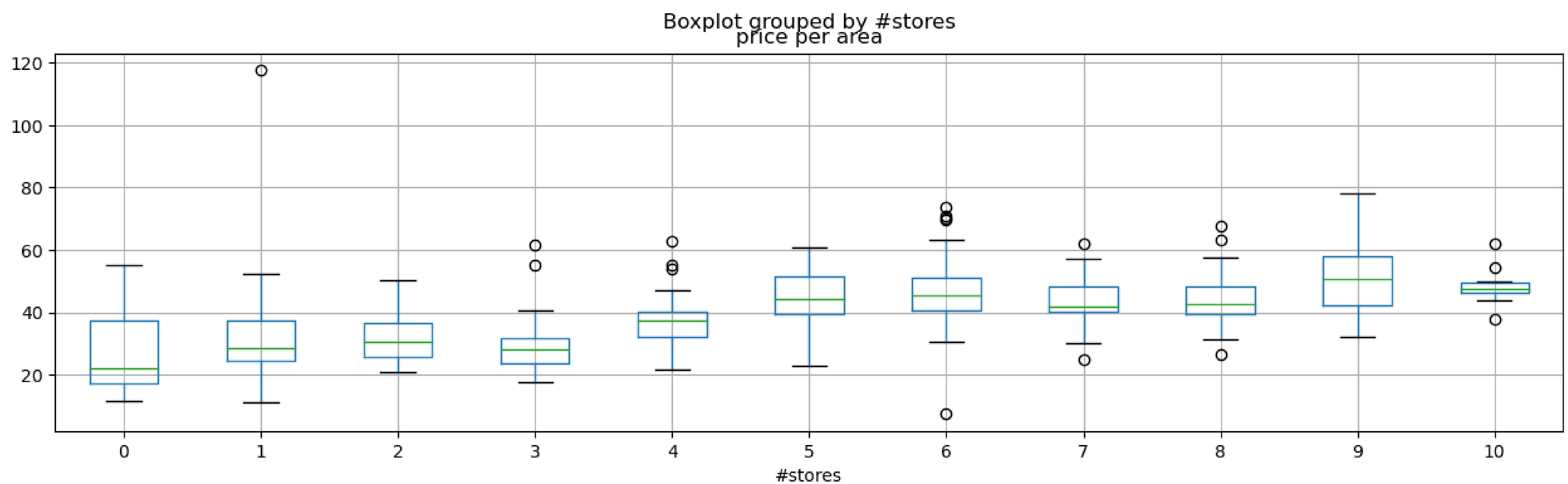



- The box boundaries are the 1st and 3rd quartile
- The green line represents the mean

# 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));
```

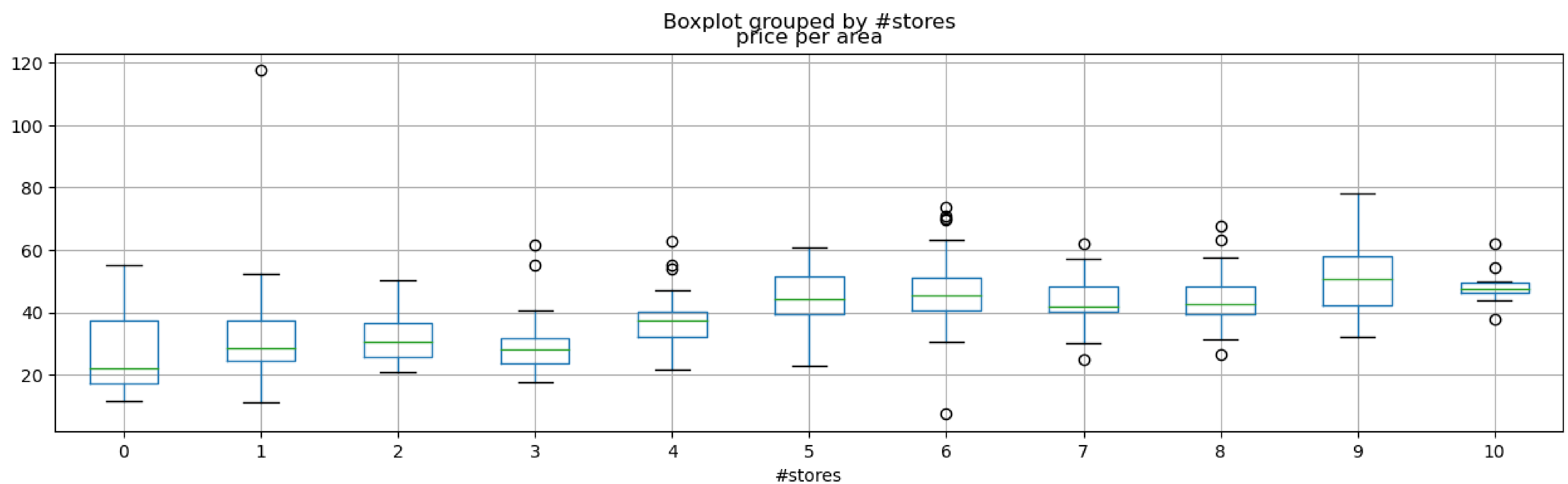



- The "whiskers" extend for 1.5 the inter-quartile range
- Values outside the whiskers are plotted directly

# 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