Python Data Products

Course 2: Design thinking and predictive pipelines

Lecture: Feature transformations

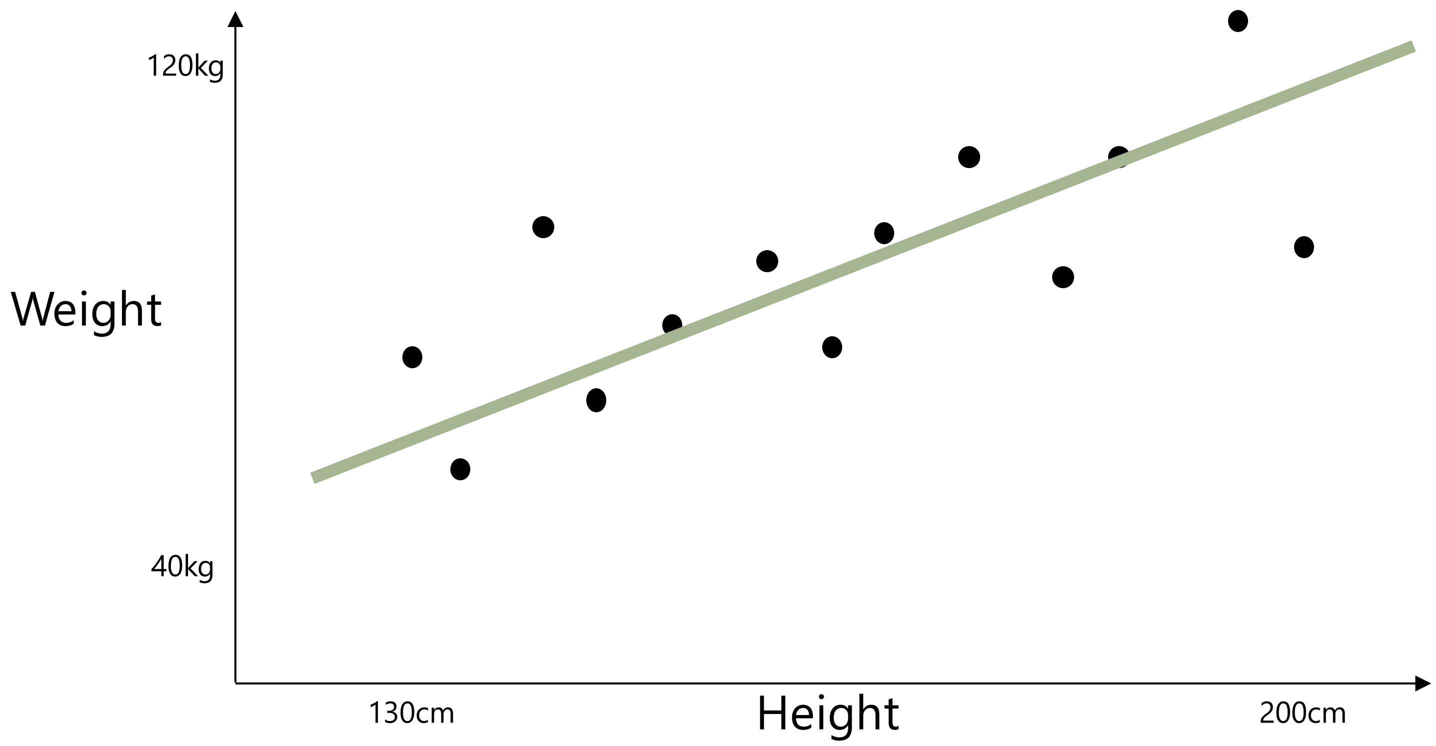
Learning objectives

In this lecture we will…

- Demonstrate the use of **transformations** to incorporate non-linear functions into linear models

Motivating example

We've previously seen simple examples of regression models such as Weight vs. Height:



Motivating example

We've previously seen simple examples of regression models such as Weight vs. Height:

- A linear relationship is probably *okay* for modeling this data, and in practice we'd often get away with using this type of model
- But, it certainly makes some assumptions that aren't totally justified
- How can we fit more suitable, or more general functions

Motivating example

How *should* the right model look for weight vs. height?

- A linear function?
- A quadratic or polynomial function?
- An asymptotic function?
- etc.

Fitting complex functions

Let’s start with a polynomial function (e.g. a cubic function):

$$\text{weight} = \theta_0 + \theta_1 \times \text{height} + \theta_2 \times \text{height}^2 + \theta_3 \times \text{height}^3$$

- Note that this is perfectly straightforward: the model still takes the form

$$\text{weight} = \theta \cdot x$$

- We just need to use the feature vector

```
x = [1, height, height^2, height^3]
```

Fitting complex functions

Note that we can use the same approach to fit arbitrary functions of the features! E.g.:

$$\text{weight} = \theta_0 + \theta_1 \times \text{height} + \theta_2 \times \text{height}^2 + \theta_3 \exp(\text{height}) + \theta_4 \sin(\text{height})$$

- We can perform arbitrary combinations of the **features** and the model will still be linear in the **parameters** (theta):

$$\text{weight} = \theta \cdot x$$

Fitting complex functions

The same approach would **not** work if we wanted to transform the parameters:

$$\text{weight} = \theta_0 + \theta_1 \times \text{height} + \theta_2^2 \times \text{height} + \sigma(\theta_3) \times \text{height}$$

- The **linear** models we've seen so far do not support these types of transformations (i.e., they need to be linear in their parameters)
- There *are* alternative models that support non-linear transformations of parameters, e.g. neural networks

Summary of concepts

- Showed how to apply arbitrary transformations to features in a linear model
- Further explained the restrictions and assumptions of **linear models**

On your own…

- Extend our previous code (on pm2.5 levels vs. air temperature) to handle simple polynomial functions