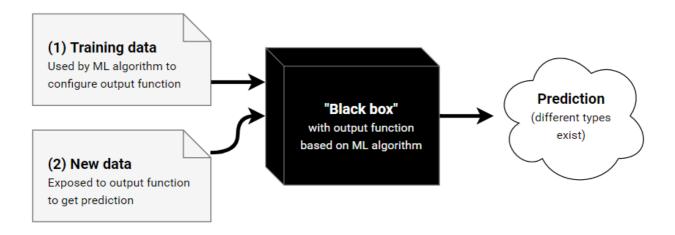
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# Lecture 2

# **Linear Regression Models**



# Cat Hearts example:

#### **Experience \$E\$**

- The dataset consists of \$n\$ data points
  - $((x_1,y_1),...,(x_n,y_n)\in \mathbb{R}^d\times \mathbb{R})$
  - \$x\_i \in \R^d\$ is the "input" for the \$i^{th}\$ data point as a feature vector with \$d\$ elements, \$d\$ being the # of dimensions in the feature space, in this case 1.
  - \$y\_i \in \R\$ is the "output" for the \$i^{th}\$ data point, in this case the weight of the corresponding cat heart.

## Learning Task, \$T\$

- In this example, our task is: Linear Regression
- Find a "model", i.e. a function:
  - \$f:\R^d\rightarrow\R\$
- s.t. our future observations produce output "close to" the true output.

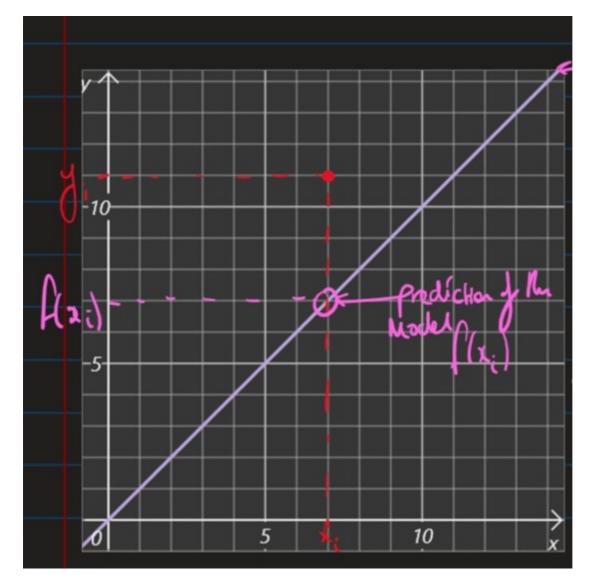
#### **Linear Regression Model**

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- A linear regression model has the form:
  - $f(x) = (\sum_{i=1}^{d} w_i \cdot x_i) + b$
  - where:
    - \$x \in \R^d\$ is the input vector (feature)
    - \$w \in \R^d\$ is the weight vector (parameters)
    - \$b \in \R\$ is a bias (parameter)
    - \$f(x) \in \R\$ is the predicted output
- In our cat example we have:
  - \$d=1\$ as "body weight" is our only feature
  - \$b=0\$ as from intuition we expect a cat of 0 weight to have a heart of 0 weight.
  - Our model has one parameter: \$w\$

### Performance Measure, \$P\$

• Want a function, \$J(w)\$ which quantifies the error in the predictions for a given parameter \$w\$



- The following empirical loss function, \$J\$ takes into account the errors \$\forall n\$ data points.
  - $J(w) = (1/2N)\sum_{i=1}^N(y_i-wx_i)^2$
  - where the summation term is squared so that:

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- we ignore the sign
- we penalise large errors more
- To find the optimum weight, solve:
  - \$\frac{\delta J}{\delta w}\$ = 0