First Principles of ML

A Peek Inside the 'Black Box' of Machine Learning

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As we progress you will slowly build up your own ML toolkit, built entirely from scratch!

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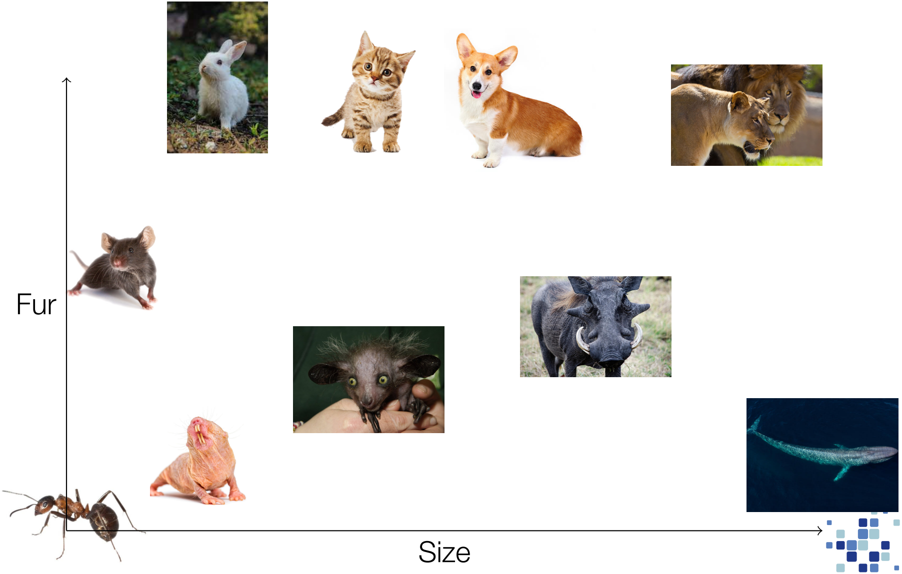
Please, please, please, ask if you want clarification on the underlying mathematics and theory! That's why you're here today!

Part 1
The Perceptron

Basic Decision Making: Defining Cuteness



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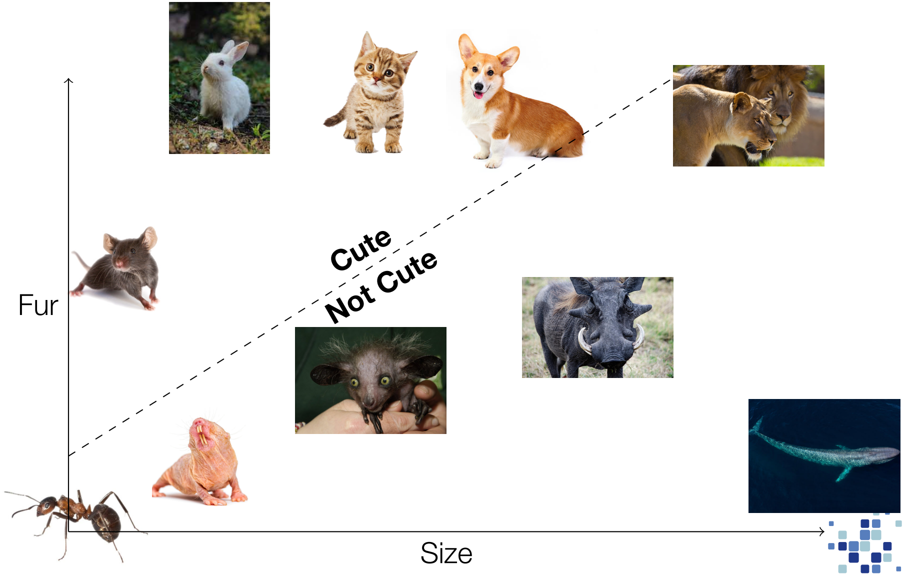

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Question: Why then do we need $N + 1$ dimensions?

The Perceptron

We need 3 parameters to define out bi-directional line. The Perceptron classifier algorithm is:

$$P(\mathbf{x}) = \begin{cases} 1 & \text{if } \tilde{\mathbf{x}} \cdot \mathbf{w}^{1} > 0 \\ 0 & \text{else} \end{cases} \tag{1}$$

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$\mathbf{w}$ our the **weights**.

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Exercise 1: Perceptron Classifier