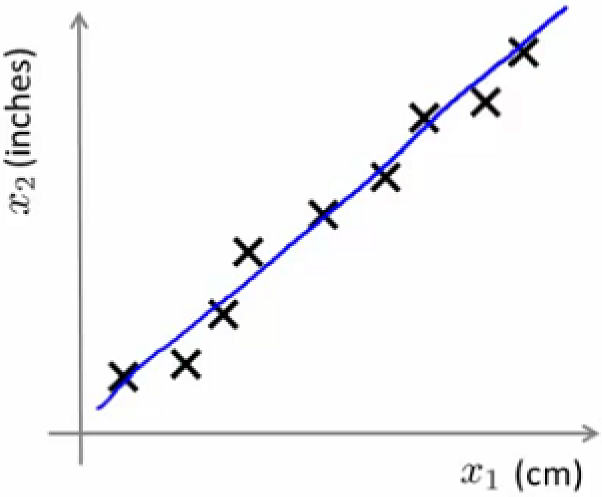
Motivation I: Data Compression

Start talking about a second type of unsupervised learning problem - **dimensionality reduction**, data compression not only allows us to compress the data and have it therefore use up less computer memory or disk space, but it will also allow us to speed up our learning algorithms.

Let's say that we've collected a data set with many features:

- can we "simply" our data set in a rational and useful way?
- redundant data set - different units for same attribute
- reduce data to 1D (2D -> 1D)
- If you have hundreds or thousands of features, it is often this easy to lose track of exactly what features we have.

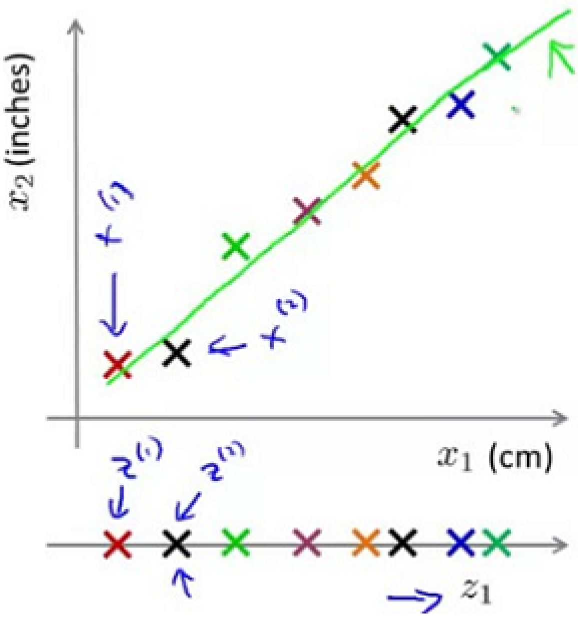


Example above isn't a perfect straight line because of round-off error

- Data redundancy can happen when different teams are working independently
  - Often generates redundant data (especially if we don't control data collection)

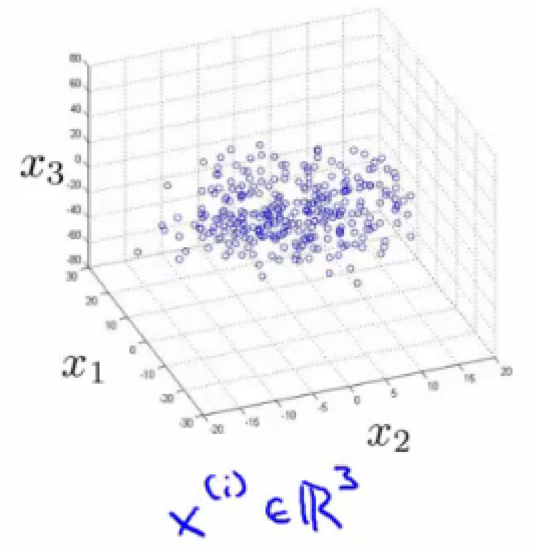
What does dimensionality reduction mean?

- In our example we plot a line
- Take exact example and record position on that line



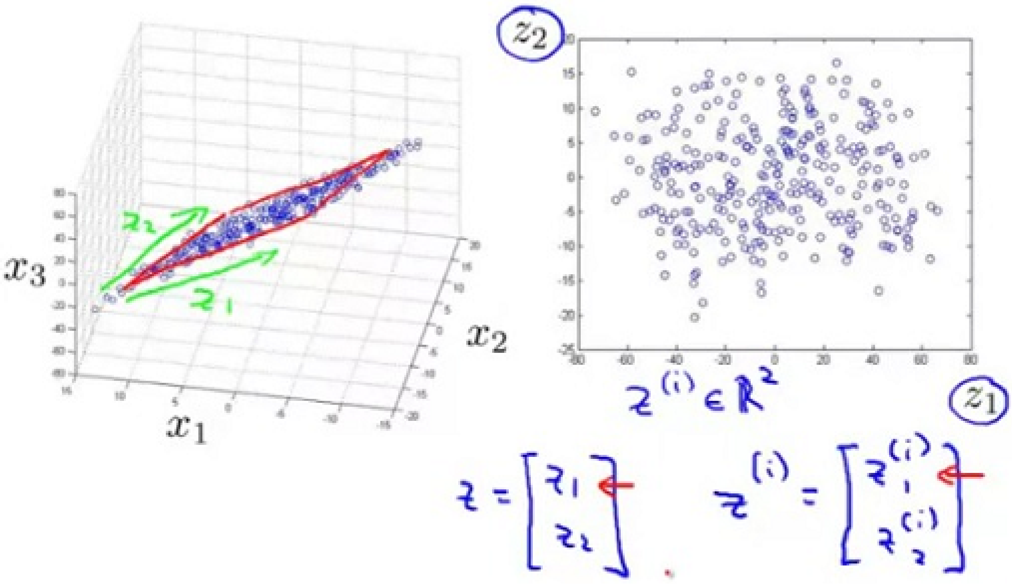
- So before $x^{(1)}$ was a 2D feature vector ($x^{(1)} \in \mathbb{R}^2$)
- Now we can represent $x^{(1)}$ as a 1D number ($z^{(1)} \in \mathbb{R}$ dimension)
  - **Reduce data from 2D to 1D**
    - $x^{(1)} \in \mathbb{R}^2 \rightarrow z^{(1)} \in \mathbb{R}$
    - $x^{(2)} \in \mathbb{R}^2 \rightarrow z^{(2)} \in \mathbb{R}$
    - $\dots$
    - $x^{(m)} \in \mathbb{R}^2 \rightarrow z^{(m)} \in \mathbb{R}$
    - So we approximate original examples
- Allows us to half the amount of storage
- Gives lossy compression, but an acceptable loss

Previously we saw an example of reducing data from 2D to 1D, and now we're going to see another example of reducing data from three dimensional 3D to two dimensional 2D. So here's our data:



In the more typical example of dimensionality reduction we might have a thousand dimensional data or 1000D data that we might want to reduce to let's say a hundred dimensional or 100D.

In this example we're going to use examples of 3D to 2D, or 2D to 1D, and so what we can do with dimensionality reduction, is take all of this data and project the data down onto a **two dimensional plane**, what that means, is that we can now represent each example, each training example, using two numbers $z^{(i)} \in \mathbb{R}^2$.



So we've now reduced our 3D vector to a 2D vector (in reality we'd normally try and do 1000D -> 100D)

Video Question: Suppose we apply dimensionality reduction to a dataset of m examples $\{x^{(1)}, x^{(2)}, \dots, x^{(m)}\}$, where $x^{(i)} \in \mathbb{R}^n$. As a result of this, we will get out:

- A lower dimensional dataset $\{z^{(1)}, z^{(2)}, \dots, z^{(k)}\}$ of k examples where $k \leq n$.
- A lower dimensional dataset $\{z^{(1)}, z^{(2)}, \dots, z^{(k)}\}$ of k examples where $k > n$.

> A lower dimensional dataset $\{z^{(1)}, z^{(2)}, \dots, z^{(m)}\}$ of m examples where $z^{(i)} \in \mathbb{R}^k$ for some value of k and $k \leq n$.

- A lower dimensional dataset $\{z^{(1)}, z^{(2)}, \dots, z^{(m)}\}$ of m examples where $z^{(i)} \in \mathbb{R}^k$ for some value of k and $k > n$.