# Machine Learning Basics

Lecture slides for Chapter 5 of Deep Learning

www.deeplearningbook.org

## Challenges Motivating Deep Learning

- Curse of Dimensionality: the challenge of generalizing to new examples becomes exponentially more difficult when working with high-dimensional data
- The core idea in deep learning: we assume that the data was generated by the composition of factors or features, potentially at multiple levels in a hierarchy
- Many other similarly generic assumptions can further improve deep learning algorithms.
- The exponential advantages conferred by the use of deep, distributed representations counter the exponential challenges posed by the curse of dimensionality

# Manifold Learning

- A manifold is a connected region.
  - Mathematically, it is a set of points, associated with a neighbourhood around each point.
  - The definition of a neighbourhood implies the existence of transformations that can be applied to move on the manifold from one position to a neighbouring one.
- In ML it tends to be used more loosely to designate a connected set of points that can be approximated well by considering only a small number of degrees of freedom, or dimensions, embedded in a higher-dimensional space.
- Each dimension corresponds to a local direction of variation

# Manifold Learning

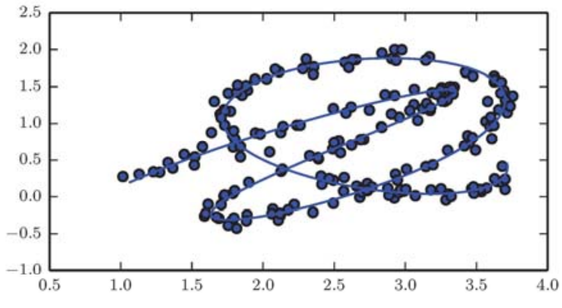


Figure 5.11

(Goodfellow 2016)

# Manifold Learning Assumptions

- Manifold learning algorithms assume that
  - most of $\mathcal{R}^n$ consists of invalid inputs
  - interesting inputs occur only along a collection of manifolds containing a small subset of points
  - with interesting variations in the output of the learned function occurring only along directions that lie on the manifold
  - or with interesting variations happening only when we move from one manifold to another.

# Manifold hypothesis

- We argue that in the context of AI tasks, such as those that involve processing images, sounds, or text, the manifold assumption is at least approximately correct.
- Obs1: the probability distribution over images, text strings, and sounds that occur in real life is highly concentrated
- Obs 2. we can also imagine such neighbourhoods and transformations informally.
  - Images: we can think of transformations that allow us to trace out a manifold in image space
    - we can gradually dim or brighten the lights,
    - gradually move or rotate objects in the image,
    - gradually alter the colours on the surfaces of objects, etc.
  - It remains likely that there are multiple manifolds involved in most applications. For example, the manifold of images of human faces may not be connected to the manifold of images of cat faces.

# Manifold

- When the data lies on a low-dimensional manifold, it can be most natural for machine learning algorithms to represent the data in terms of coordinates on the manifold, rather than in terms of coordinates in $\mathcal{R}^n$.