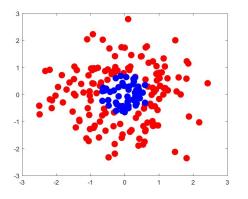
09 - Introduction to Nonlinear Models Numerical Methods for Deep Learning

February 7, 2018

Impossible to find a linear separator between points



Goal/Trick

Embed the point in higher dimension or move the points to make them linearly separable

Consider regression try to find \boldsymbol{W} such that

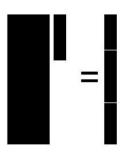
$$\mathbf{C} = \mathbf{Y}\mathbf{W}$$

Assume $\mathbf{C} \in R^m$, $\mathbf{Y} \in R^{m \times n}$ and $m \gg n$. If \mathbf{Y} is full rank impossible to fit the data.

Consider regression try to find W such that

$$C = YW$$

Assume $C \in \mathbb{R}^m$, $Y \in \mathbb{R}^{m \times n}$ and $m \gg n$. If Y is full rank over-determined impossible to fit the data.



Use a linear transformation of the points

$$\mathbf{C} = (\mathbf{Y}\mathbf{K})\hat{\mathbf{W}}$$

Assume $\mathbf{C} \in \mathbb{R}^m$, $\mathbf{K} \in n \times s$ is an arbitrary matrix.

 $(\mathbf{YK}) \in R^{m \times s}$ and s arbitrary.

If \mathbf{Y} is full rank over-determined (still) impossible to fit the data.





The size of **YK** is $m \times s$ but the problem is still over-determined

$$\operatorname{rank}(\mathbf{YK}) = n \ll m$$



$$\operatorname{rank}(\mathbf{YK}) = n \ll m$$

But if we use a "smart" nonlinear function f then

$$\operatorname{rank}(f(\mathbf{YK}+b))=\min(m,s)$$

The fundamental theorem

Given the data $\mathbf{Y} \in R^{m \times n}$ and $\mathbf{C} \in R^m$ with m > n There is a transformation f and a matrix $\mathbf{K} \in R^{n \times s}$ such that $f(\mathbf{Y}\mathbf{K})$ is of full rank m and therefore we can find a vector \mathbf{W} such that

$$f(YK + b)W = C$$

The fundamental theorem

$$f(YK + b)W = C$$

- ▶ How to find *f*?
- ▶ How to find **K** and *b*?

The fundamental theorem

$$f(\mathbf{YK} + b)\mathbf{W} = \mathbf{C}$$

- ▶ How to find *f*?
- ▶ How to find **K** and *b*?

Early days - motivated by neurons

- f is a smooth step function tanh(t)
- ▶ Better choices for f is the relu $f = \max(x, 0)$
- ▶ **K**, *b* can be
 - Random (random kernels recently branded as extreme learning machines)
 - Optimized (learned) to fit the data

Random kernels

Choose ${\bf K}$ randomly and solve the least-squares/classification problem

- Can interpolate any function
- May require very large K (size of the data)
- May not generalize well
- Large dense linear algebra
- Very easy to program.
- Can serve as a benchmark to more sophisticated methods

Random kernels - programming

Homework assignment I

▶ Regression: Given the data {Y, C} write a code that computes the weights such that

$$f(YK)W \approx C$$

- ▶ Classification: Given the data $\{Y, C\}$ write a code that computes the weights such that f(YK)W classifies C
- ▶ Try different activation functions and different size of **K**.

Test your code on a validation set and report.

Prize to the best winning team