

# Deep Learning

Ian Goodfellow  
Yoshua Bengio  
Aaron Courville

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# Website

[www.deeplearningbook.org](http://www.deeplearningbook.org)

This book is accompanied by the above website. The website provides a variety of supplementary material, including exercises, lecture slides, corrections of mistakes, and other resources that should be useful to both readers and instructors.