# Stochastic Control Sequential Learning Algorithms

**Course Information** 

D Manjunath & Jayakrishnan Nair

EE, IIT Bombay

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- A strong background in probability theory will be assumed.



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Homework and Quizzes	20%
Midsem Exam	25%
Endsem/Project	50%



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■ There may be minor changes to these weights as the course progresses; they will be advertised sufficiently in advance.





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#### Sources

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- It is critical that you read from textbook and not just depend on the notes from the lectures.



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- It would be good to put in the extra effort and not tag on some work you are doing elsewehere or its minor variant.