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3.1-3.4

April 24

Lecture 2,
3.4 - 3.5.9

May 8
(May 1
is labor day)

Lecture 3,
3.6.1 to 3.6.4

May 15

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June 12th
(June 1-7 is
Whitsun
break)

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