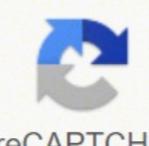
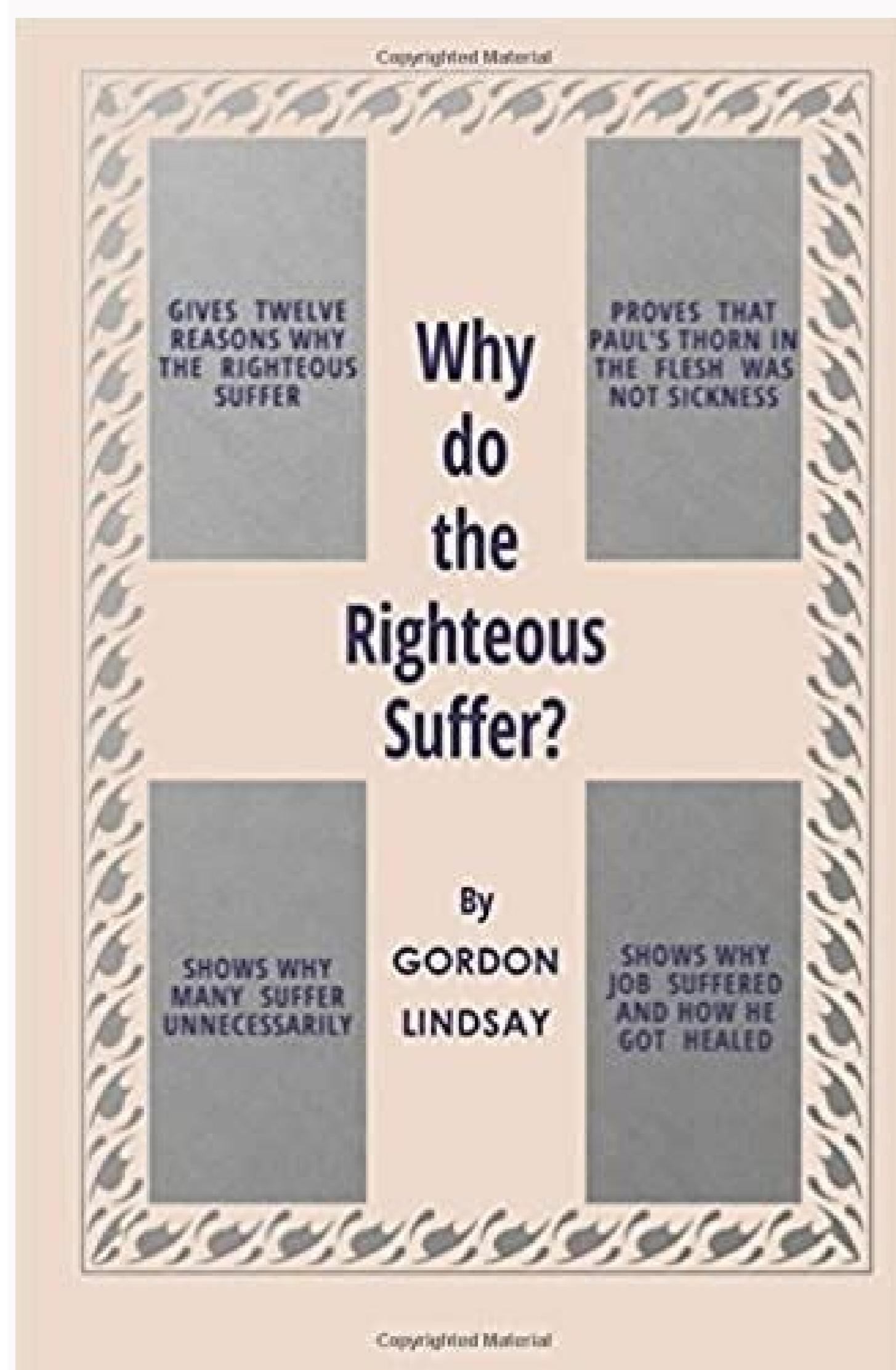
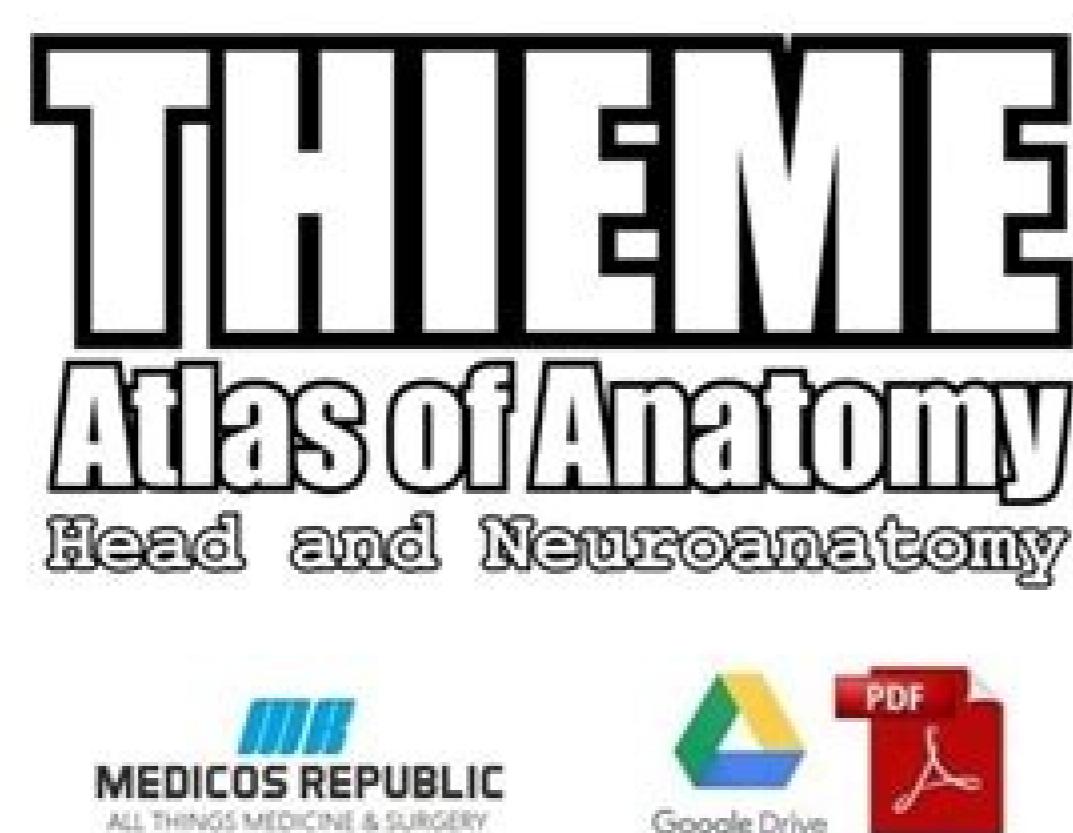
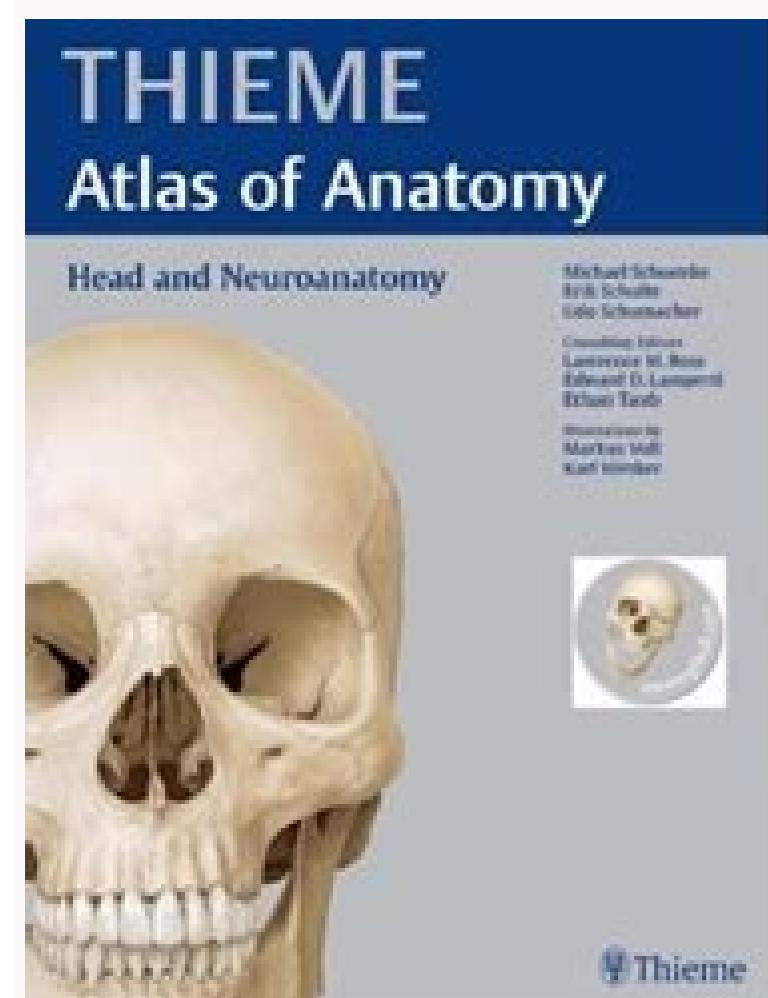
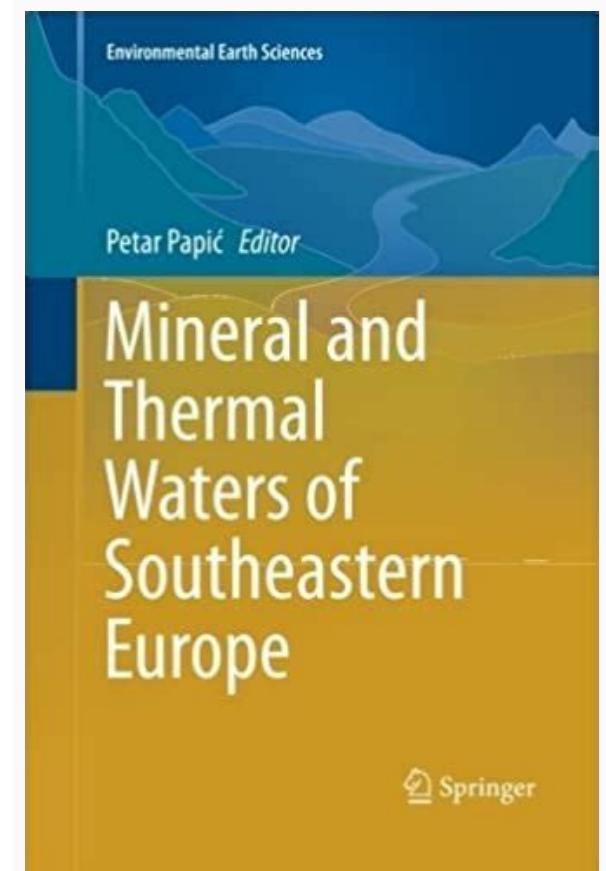


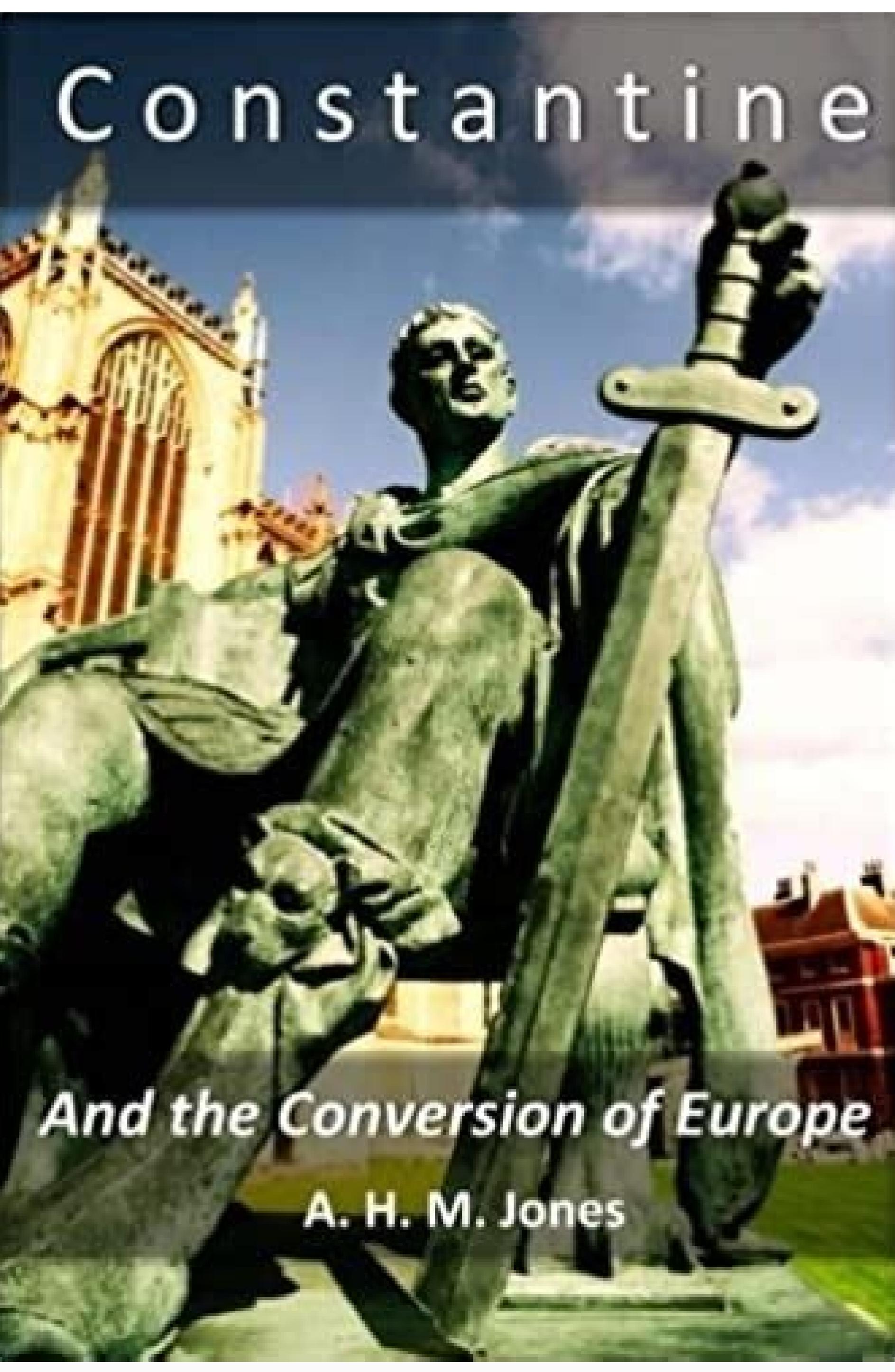
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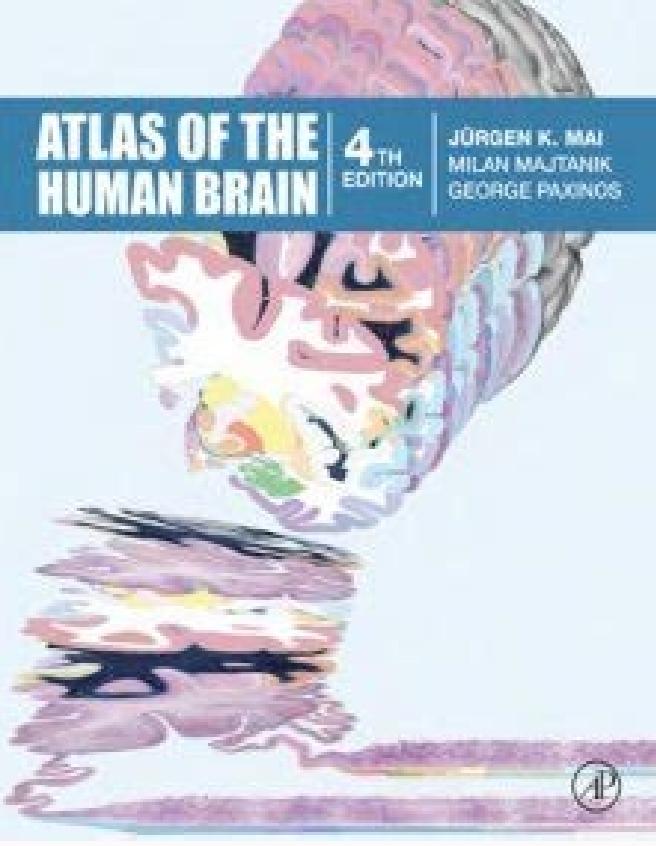


# Constantine



# *And the Conversion of Europe*

A. H. M. Jones



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