#### Overview

Daniel Hsu

COMS 4772

"Advanced machine learning"

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- ► Courseworks, Piazza: links on website

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  - Suggest new algorithmic techniques

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- applications: Gaussian mixtures, ICA, latent Dirichlet allocation