This class is great, take it.

DS-GA 3001, Text as Data
Arthur Spirling

Jan 29, 2019

Professor and Lectures

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`arthur.spirling@nyu.edu`

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OH Tues, 2-3PM.

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Lect Tuesdays 11AM-1240PM, Lecture 60 Fifth Avenue, 110

TA and Sections

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Pedro Rodriguez

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plr250@nyu.edu

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422, 19 West 4th St.

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OH Fri, 4–6PM

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Sec Thursday, 2:00–250pm, 60 Fifth Avenue, 110 (start this week!)

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Introduction to quantitative 'text-as-data' approaches as strategies to learn more about social scientific phenomena of interest.

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$\rightarrow$ check in with me if unsure.

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- Straightforward to implement via function writing in `R`.

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If the terms in blue were familiar to you (even if you can't recall their exact meaning), `sample`, `discrete`, `uniform`, `distribution`, $\hat{N}$, `MLE`, `biased`, `consistent`, `sufficient statistic`, `Bayesian`, `estimator`, `prior`, `closed form`, `simulation`, `function writing`, `R`

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We will use quanteda and other packages.

Writing R: RStudio

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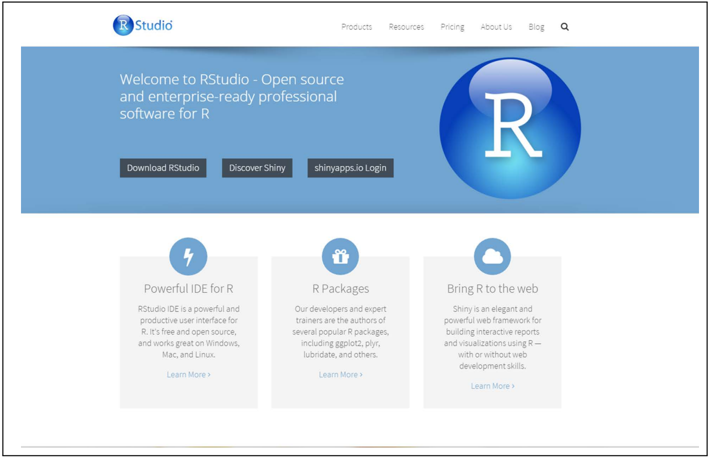

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