This class is great, take it.

DS-GA 1015, Text as Data
Arthur Spirling

Feb 2, 2021

Professor and Lectures

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Prof Arthur Spirling

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`arthur.spirling@nyu.edu`

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OH Wednesday, 1030-1130AM.

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Flip Tuesdays 11AM-1240PM, 101, 19W4.

Structure of "Lecture"

$\sim$ 70 mins of pre-recorded lecture material.

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flipped structure is subject to demand: if turnout is low, we will revert to ‘live’ but recorded lectures every week.

TA and Sections

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Ms Lucia Motolinia

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OH Friday, 10–11AM

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Sec Thursday, 2–250PM (remote)

→ (start this week!)

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Text as the new frontier of. . .

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

Overview

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Overview

- Descriptive inference:

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$\rightarrow$ check in with me if unsure.

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- Straightforward to implement via function writing in R.

sample, discrete, uniform, distribution, $\hat{N}$, MLE, biased, consistent, sufficient statistic, Bayesian, estimator, prior, closed form, simulation, function writing, R `sample`, `discrete`, `uniform`, `distribution`, $\hat{N}$, `MLE`, `biased`, `consistent`, `sufficient statistic`, `Bayesian`, `estimator`, `prior`, `closed form`, `simulation`, `function writing`, `R`

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.

Need R version 4.0.3

Writing R: RStudio

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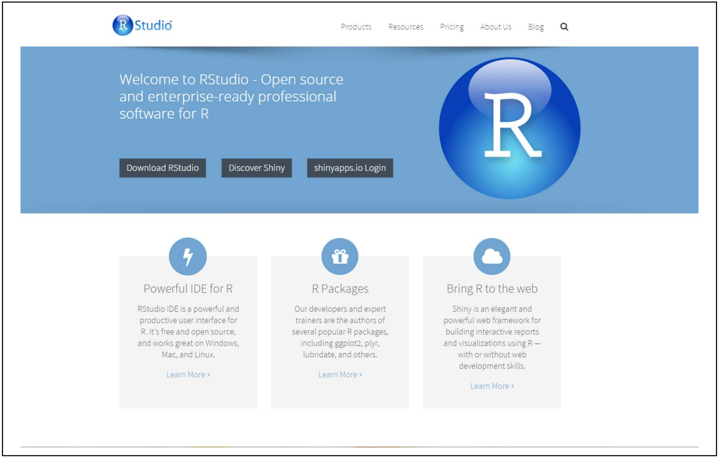

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