Welcome! MS in Data Science

Ryan T. Moore

American University

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➤ Political methodologist (Dept of Government, SPA)

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- Assoc Director, Center for Data Science (AU, SPA)

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- ➤ Methods Fellow (Office of Evaluation Sciences, US GSA)

Connections

▶ Winter Institute in Data Science

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- RAs with The Lab @ DC

Data Science

Particular intersection of

- ► Statistical practice
- Computational tools
- Substantive knowledge

➤ Stats: prediction (vs. explanation), algorithms (vs. models)

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- Computing: addressing problems with data *per se* (size, tidy-ness, un/structure, replicability)

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- ➤ Substance: social science

Description

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- ▶ Prediction

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Models/algorithms central to all three.

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Hernán, Hsu, and Healy (2019)

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- \triangleright E.g., k-means clustering to discover groups

Prediction

▶ Components

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- E.g., regression, random forests, neural networks, ...

Causal Inference

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- ▶ E.g., experiments, observational causal designs, ...

Goals

- Computational tools (R, Python, etc.)
- ➤ Varied data experience, original work
- ➤ Apply knowledge in academia, government, industry
- Communicate understanding

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- Catalog ('25-'26): https://t.ly/Ib43y https://catalog.american.edu/preview_program.php?catoid=21&poid=10388

Courses

- **DATA-612:** R
- ▶ DATA-613: Data Science (modeling, Shiny, etc.)
- ► STAT-615: Regression
- ► STAT-627: Stat Machine Learning
- One of
 - ▶ GOVT/STAT-618: Bayes
 - ► GOVT-650: Political Analysis
- One of
 - ▶ GOVT-653: Intro Quant Methods in Pol Sci
 - ➤ STAT-614: Stat Methods
- ▶ DATA-793: Capstone
 - ► (The Lab @ DC DHS connections ...)
- ► Three more courses
 - ► (Electives, depend on track)
 - Substance or methods (computer vision, AI, ML, deep learning, NLP, survey sampling, ...)

Directors

- ▶ Jeff Gill: jeffgill.org
- ▶ Betty Malloy: malloy@american.edu

Questions?

Thanks!

rtm@american.edu
www.ryantmoore.org

References

Hernán, Miguel A., John Hsu, and Brian Healy. 2019. "A Second Chance to Get Causal Inference Right: A Classification of Data Science Tasks." *CHANCE* 32 (1): 42–49. https://doi.org/10.1080/09332480.2019.1579578.