Machine Learning & Causal Inference
A Practical Approach using Python

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Requirements:

- Undergraduate Statistics & Econometrics.
- Python-capable machine.
- Ideally, agent-based IDE for coding (e.g., Cursor, Claude Code).

Recommended Readings:

- Intro to Causal Inference w/ examples in Python: *Causal Inference for The Brave and True.* Matheus Facure
- Causal Inference Theory: *Causal Inference: A Statistical Learning Approach.* Stefan Wager
- Machine Learning Theory: *The Elements of Statistical Learning.* Hastie, Tibshirani, Friedman
- Some resources on Prompt Engineering:
  - Prompt Engineering Guide by Google
  - Context Engineering for AI Agents by Anthropic

Content:

Lecture 1: 18-Feb. Basic Elements of Coding

1. Python. Virtual environments. Basic libraries. Data loading.
2. Basic programming logic: “for”, “while” loops. “if” conditions.
3. User-defined functions. Classes.
4. Scripts vs notebooks.

5. Version control: Github.
6. AI Agents. Prompts. Good practices.

Lecture 2: 20-Feb. Treatment Effects & Randomized Controlled Trials (RCT)

1. Fundamental Problem of Causal Inference.
2. Data simulations. Seeds for reproducibility. Visualizations.
3. RCTs. Difference in means estimator.
4. Variance reduction. Lin (2013) adjustment.

Lecture 3: 23-Feb. Treatment Effect Estimation under Unconfoundedness

1. Unconfoundedness assumption.
2. Stratified estimator.
3. Propensity score.
4. Inverse-Propensity Weighting (IPW) estimator.
5. Bootstrap.
6. Balance checks.

Lecture 4: 24-Feb. Machine Learning & Treatment Effects I

1. Introduction to Supervised Learning.
2. Regression vs Classification.
3. Linear models. Logistic Regression.
4. Tree-based models.