CAUSAL Lab@SUFE Onboarding Guide (V1.0)

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Welcome to our lab!

This is the on-boarding guide for interdisciplinary research on causality. **It is mandatory reading for all interns, master's students, and PhD students** in CAUSAL lab@SUFE. We first provide instructions on preparing for causality research, and then directly present frontier topics in causality research to promote further comprehension and collaboration.

Disclaimer: This document reflects the primary research directions of our lab. It does **not** represent the only or the optimal pathway to learning causal inference.

1 Getting Started with Causal Inference: A Guide for Students in CS, Statistics, and Economics

We follow a fundamental causal learning progression: from introductory to proficient, and ultimately to advanced mastery. I will outline tailored learning paths for two groups: CS(ML) and Stats(Econ).

Requirement: Each Student with either a CS(ML) or Stats(Econ) background are required to select and thoroughly read at least one resource from Section 1.1 and Section 1.2, respectively.

1.1 Introductory part

- [PM18] The Book of Why: The New Science of Cause and Effect (CS & Stats).
- [HR22] What If: The Counterfactuals of Modern Epidemiology (CS & Stats).

1.2 Formal part

- [Din24] The First Course in Causal Inference (Stats).
- [WB24] Causal Inference: A Statistical Learning Approach (Stats).
- https://web.stanford.edu/~swager/stats361.pdf (CS & Stats).
- Online courses of ML and Causality:
  - Susan Athey: https://www.gsb.stanford.edu/faculty-research/labs-initiatives/sil/research/methods/ai-machine-learning/short-course?utm_source=chatgpt.com(CS & Stats).
  - Brady neal: https://www.bilibili.com/video/BV1nZ4y1K78i/?vd_source=ace5e5a325c2dff9ac92e50fa21 & Stats).

1.3 Advanced part

- Online causality inference seminar(YouTube): https://www.youtube.com/channel/UCiiOj5GSES6uw21kfXnxj3A (CS & Stats).
- Literature: Students could read from the following literature to follow up on frontiers:
  Journal: JASA, AOS, JRSSB, Biometrika, PNAS;
  Conference: ICML, NeurIPS, ICLR, UAI, AISTATS, COLT

Additional comment:

- If you come from a mathematical major, you should also take the class on (high-dimensional) statistics and probability; otherwise, you are required to run the code demo in one of the above course links.
- You should develop an intuitive understanding of the statistical ideas behind causality and be able to critically compare the strengths and limitations of Judea Pearl's causal graphical framework and Donald Rubin's potential outcomes framework (refer to [RR13]).

2 Frontier Research Topics under Active Development

In the study of causality, on the one hand, aiming at the real-world setting, there are two kinds of methods: **observational studies** and **experimental design**. On the other hand, aiming at the objectives, there are three central pillars: Identification, Estimation, and Learning. Each corresponds to a classical type of causal inference task[1].

However, we do not wish to define our causal research merely through the conventional paradigm of scenario-based or goal-specific classifications. The long-term vision of our lab is to build a unified and simple causal framework, combined with disciplinary researchers, that widely empowers both theory and real-world applications:

- On the theoretical side: to write killer papers under the simplest and most elegant assumptions;
- On the applied side: to write healer papers upon real-world pain points by tackling the most pressing and complex challenges in industry/society.

Inspired by it, we separate the taste of research into the progressive parts: **rethink, innovate, embrace, and apply**, focusing on the procedure **input, structure, and output**. I have listed the key papers that are recommended to be read.

2.1 Rethink Assumptions

Challenge conventional wisdom and commonly held assumptions (investigate the definitions and implications of these assumptions on your own). See the video [2].

• **Violate the OVERLAP assumption** [KSU24], [CKM+25] (https://www.youtube.com/watch?v=LJIoFKBxCKE), [JRYW22].

• **Violate the SUTVA assumption** [Leu22], [LWZ24], [MT21], [Viv25] (also other series of papers of Davide Viviano).

• **Violate the UNCONFOUNDEDNESS assumption** [CKM+25], [Zha], [KMU21].

2.2 Innovate with Statistical/ML Methods

Modern causal frameworks are driven by new statistical and ML innovations.

• **Conformal prediction** [LC21].
• **Prediction-powered inference** [WSF+24].
• **(Prediction and then) Optimization** [BM25], [WHBG24], [EG22].
• **Optimal transport** [JLS23], [LGBG25].
• **Representation learning (including negative part)** [MFF23], [MFSF25].
• **Mini-max optimality** [JS24].
• **Online learning and trade-off** [SLW23], [ZW24], [NFBR25].

[1] Identification This addresses the fundamental question: "Can the causal quantity of interest be expressed as a function of the observed data distribution under certain assumptions?" It focuses on deriving conditions under which causal effects are identifiable, often using tools like causal graphs, do-calculus, and potential outcomes. Estimation Once a causal estimand is identified, estimation concerns "How can we construct statistical estimators to recover it from data?" This step bridges theory and practice, involving methods such as inverse probability weighting, g-computation, doubly robust estimators, and semiparametric theory. Learning Learning moves beyond point estimation to ask "How can we make optimal or robust decisions based on causal knowledge?" This includes topics like policy learning, individualized treatment rules, off-policy evaluation, and online/active experimentation, often leveraging machine learning and reinforcement learning frameworks.

[2] (https://www.youtube.com/watch?v=LJIoFKBxCKE)

2.3 Embrace Constraints

Focus on real-world constraints and make reasonable solutions.

- **Noisy scenario** [GYWJ22], [ZDC+23].
- **Active sampling (Limited samples)** [KOKI24], [ZWLL], [WCG+25], [HSSZ24].
- **Privacy** [OA25], [SHF25].
- **Functional data** [THZY25].
- **Time delay** [ZBMC+25].
- **Heterogeneity and fusion** [DY25], [LD24], [XKP+23], [LRVP25].

2.4 Apply to Impact

Apply to the real world.

- **Foundation model(LLM)** [JYG+25], [GJR24], [PLOZ24].
- **Multi agent and game** [LWL+24], [LWW+], [SNH24], [MWX21], [ATM21].
- **Recommendation system** [ZHHJ24], [BPT18], [YLN+23].
- **Ride-sharing** [DWZ+24].

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