

# Seminar: Bayesian Causal Inference

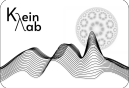
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<https://rc-trust.ai/klein/>

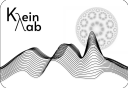
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# Structure of the seminar

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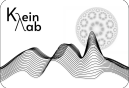
- Groups  $\approx 2/3$  people
- Each group will develop a specific topic related to BCI
- Regular meetings (every 2 weeks) with their supervisor to discuss their progress
- Grading: Presentation of the project at the end of the term (30 min=20+10Q&A)



# Organizational stuff

## Organization

- Seminar meetings: Friday, 10–12, Room M/E 21
- Website: <https://moodle.tu-dortmund.de/course/view.php?id=41860>  
**Enrollment key: BCI23/24**
- The course grants 4 ECTS
- Target audience: Master students in Statistics, Econometrics and Data Science
- Course limit: 20 students



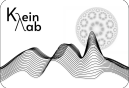
# Goals of the seminar

## Overall goals

- Develop advanced methodological proficiency in Bayesian causal inference
- Gain practical experience in data science project settings (incl. literature review, implementation, and effective communication)
- Improve research skills (critical thinking, independence, time management and collaboration)

## Topic-specific goals

- Acquire a comprehensive knowledge of the chosen topic
- Apply state-of-the-art BCI approaches
- Develop familiarity with relevant software libraries

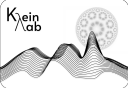


# Potential topics\*







Potential topics will be related to the study of the following:

- Model specification
  - Pro/cons Bayesian Additive Regression Tree (BART) [Chipman et al., 2010]
  - Large number of parameters (non-parametric/ semi-parametric models) [Linero and Yang, 2018]
  - Large number of covariates (sparsity-inducing priors, e.g. spike-and-slab, Lasso) [Oganisian and Roy, 2021]
- Role of propensity score
  - Dependent priors [Wang et al., 2012]
- Quantifying unmeasured confounding (sensitivity analyses) [Franks et al., 2020]
- Time-varying interventions and confounding [Saarela et al., 2015]

**\*The final list of topics will be announced in the first session**



# References I

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-  Franks, A., D'Amour, A., & Feller, A. (2020). Flexible sensitivity analysis for observational studies without observable implications. *Journal of the American Statistical Association*, *115*(532), 1730–1746.
-  Linero, A. R., & Yang, Y. (2018). Bayesian regression tree ensembles that adapt to smoothness and sparsity. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *80*(5), 1087–1110.
-  Oganisian, A., & Roy, J. A. (2021). A practical introduction to bayesian estimation of causal effects: Parametric and nonparametric approaches. *Statistics in medicine*, *40*(2), 518–551.
-  Saarela, O., Stephens, D. A., Moodie, E. E., & Klein, M. B. (2015). On bayesian estimation of marginal structural models. *Biometrics*, *71*(2), 279–288.
-  Wang, C., Parmigiani, G., & Dominici, F. (2012). Bayesian effect estimation accounting for adjustment uncertainty. *Biometrics*, *68*(3), 661–671.