\[ \gamma = E(Y(1) - Y(0)) \]
\[ = E(Y(1|x, Z=1)) - E(Y(1|x, Z=0)) \]

Average gradient slope

\[ Y(1), Y(0) \text{ line} \perp x \]

ATE.
\[
\frac{\gamma(\mathbf{z}, \mathbf{e}) - E(\gamma(\mathbf{z}) - \gamma(\mathbf{e}))}{\int \left( \gamma(\mathbf{z}, \mathbf{z} + \mathbf{e}) \rho(\mathbf{z}) \right) d\mathbf{z}}
\]

\[\ln(y \sim d + x)\]

random Forests (…)

\[f(y) \sim \mathcal{N}(\mu, \sigma^2)\]

\[f(\mathbf{x}) \sim \mathcal{N}(\mu, \sigma^2)\]

heterogeneity
Statistical Uncertainty in M.L.

- Conformal prediction
  - Prediction intervals
  - Finite sample valid
  - Frequentist coverage (not pointwise)
  - Expensive
  - Not for causal inference

- Inference for tree models
  (Athey & Wager)
asymptotic wage seems to work badly in finite samples
Statistical decision theory

Risk

$$E(L(\theta, \hat{\theta}(x)))$$

Expectation is over $X$ (data) for a fixed $\theta$.

Good performance for any $\theta$

$$E(\text{Risk}(\theta))$$ w.r.t. $\theta$ for prior
Bayesian estimator based on $T(\theta)$ is optimal for Bayes risk.

"True Prior": True range of DGP.s.

I don't want to be restricted to Bayesian Estimators.

- Slow
- Difficult
- Better
But I love Bayes Risk as a target/goal.

Monte Carlo approx of Bayes Risk.

Temporality ... time

Causes came prior to effects.

A \rightarrow B ?

A \leftarrow B ?

"or orienting the edges"
\[ f(x) = \int f(y|x) f(x) \, dx \]

- More complex marginal
- Assume distribution of causes is simple
- Causal mechanisms induce complexity

\[ f(a | b) f(b) \]
\[ f(b | a) f(a) \]
distribution implies something is an effect.

Kolmogorov complexity.