Multiple Treatment Comparisons

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Methods Seminar
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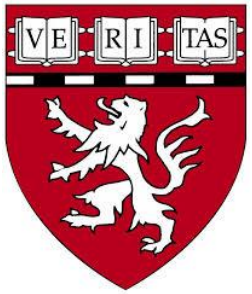
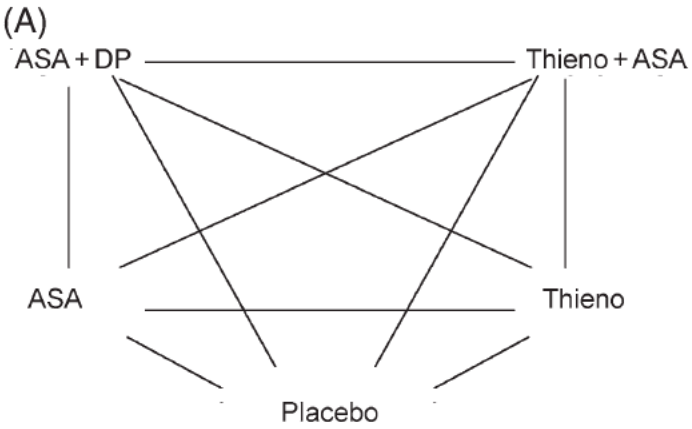
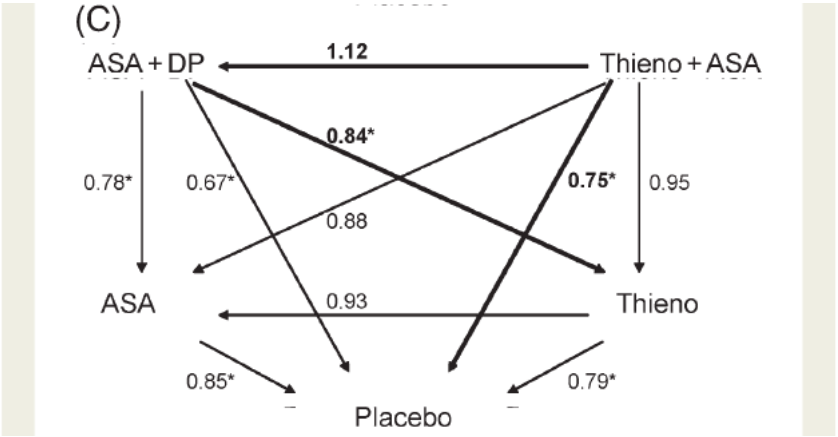


Multiple Treatment Meta-Analysis



Network of direct comparisons

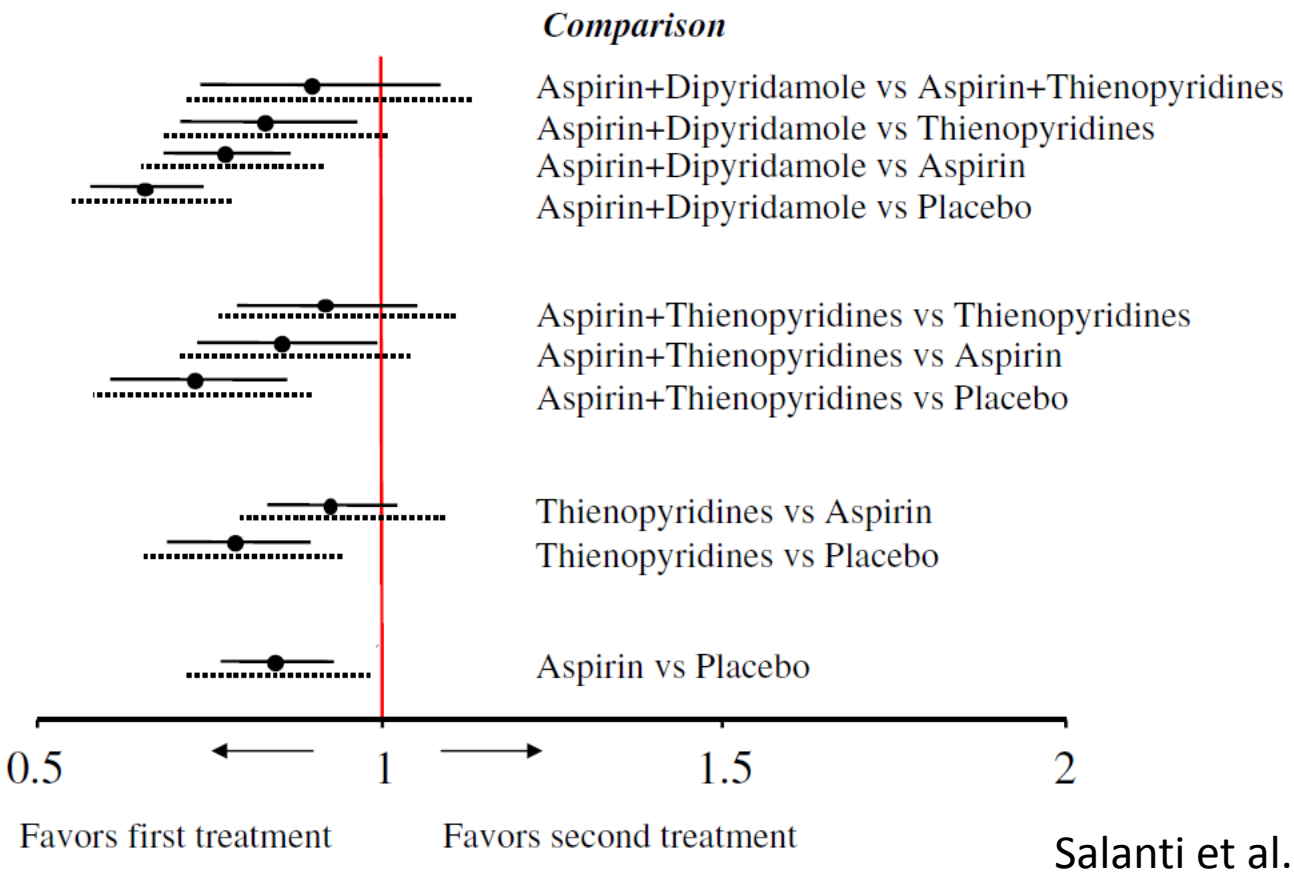


Results of network meta-analysis
(odds ratios for serious vascular events)

Thijs et al. 2008 Eur Heart J

Multiple Treatment Meta-Analysis

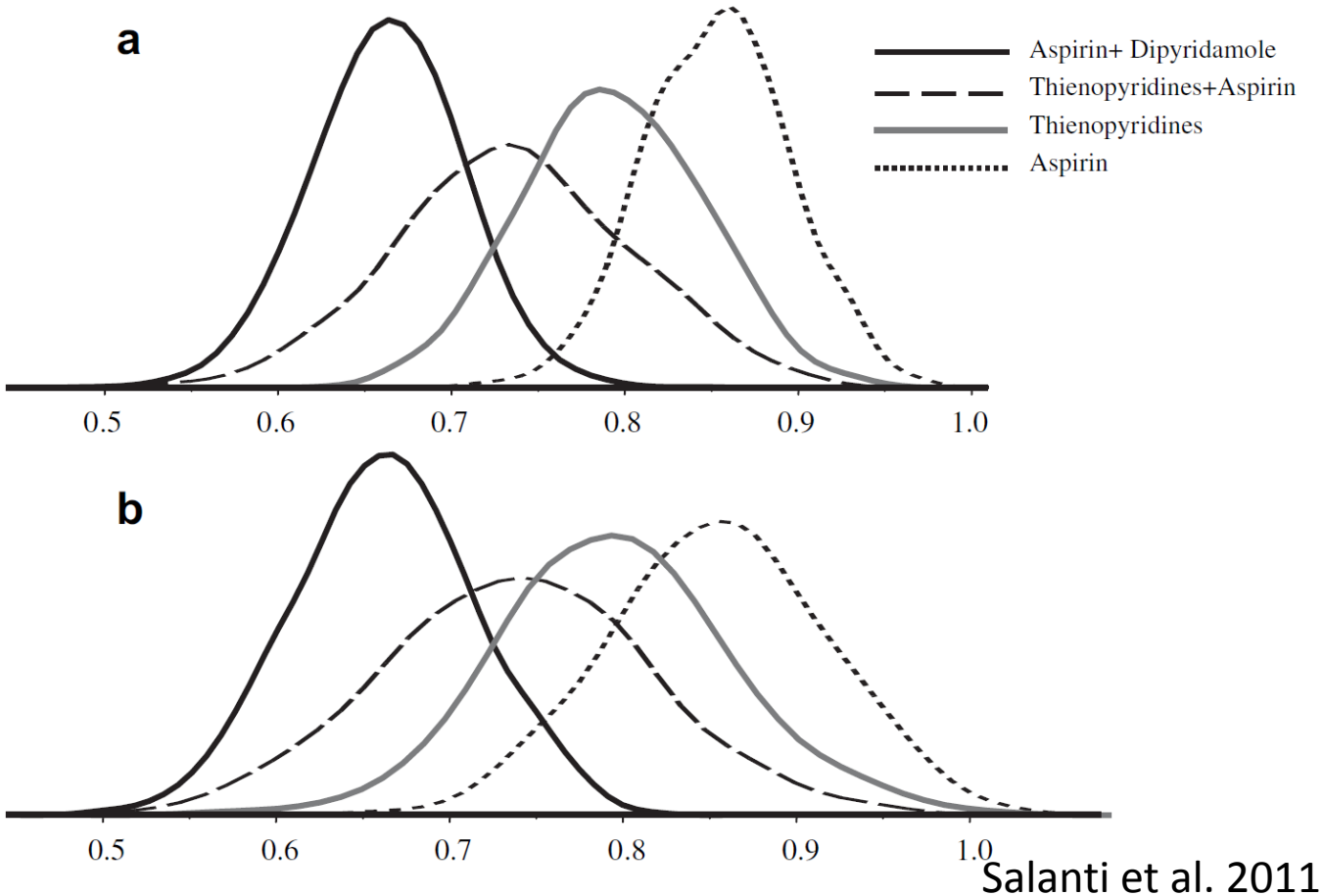
All pairwise comparisons: odds ratios and CIs



Salanti et al. 2011 J Clin Epi

Multiple Treatment Meta-Analysis

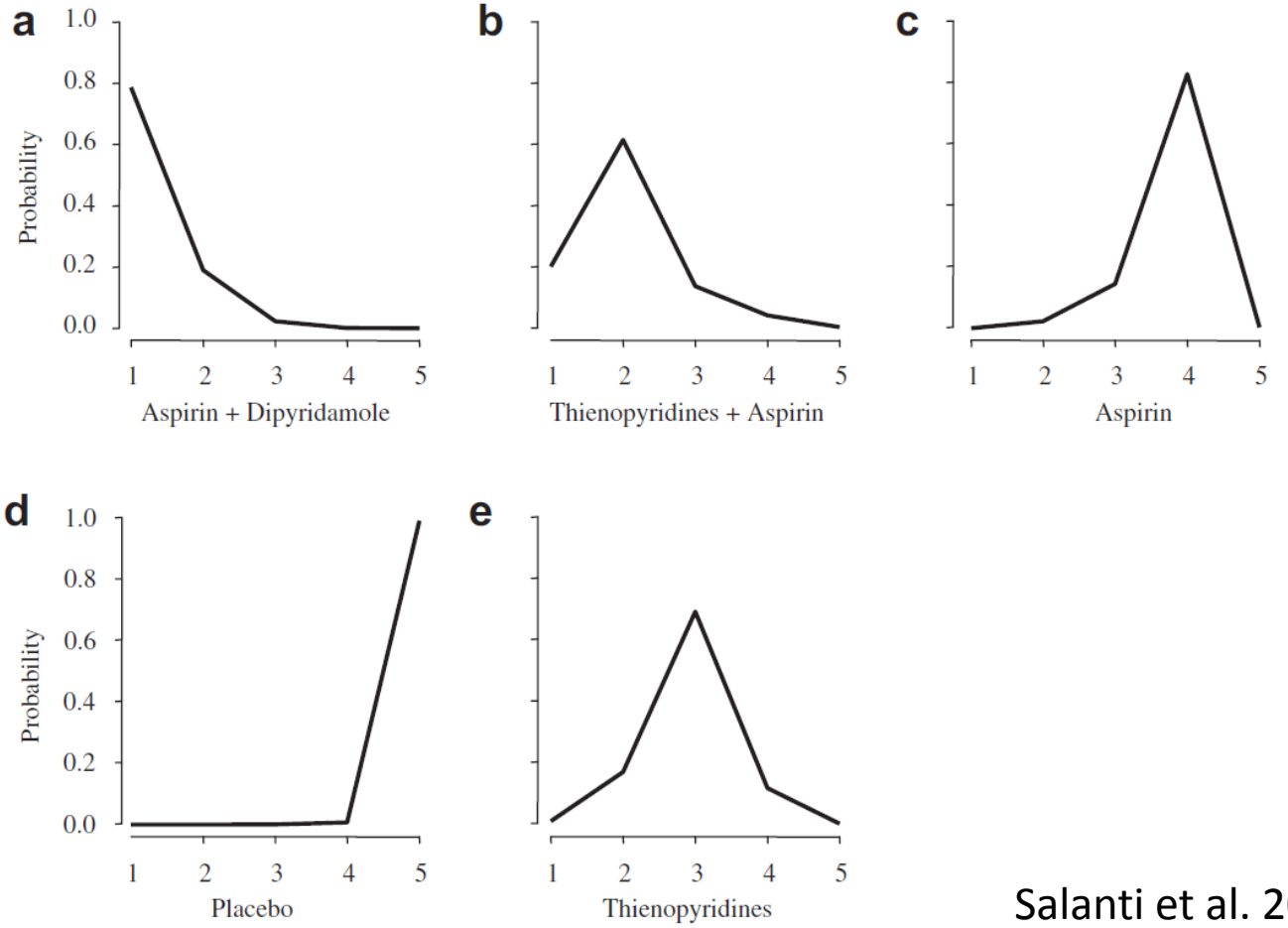
Posterior and posterior predictive distributions



Salanti et al. 2011 J Clin Epi

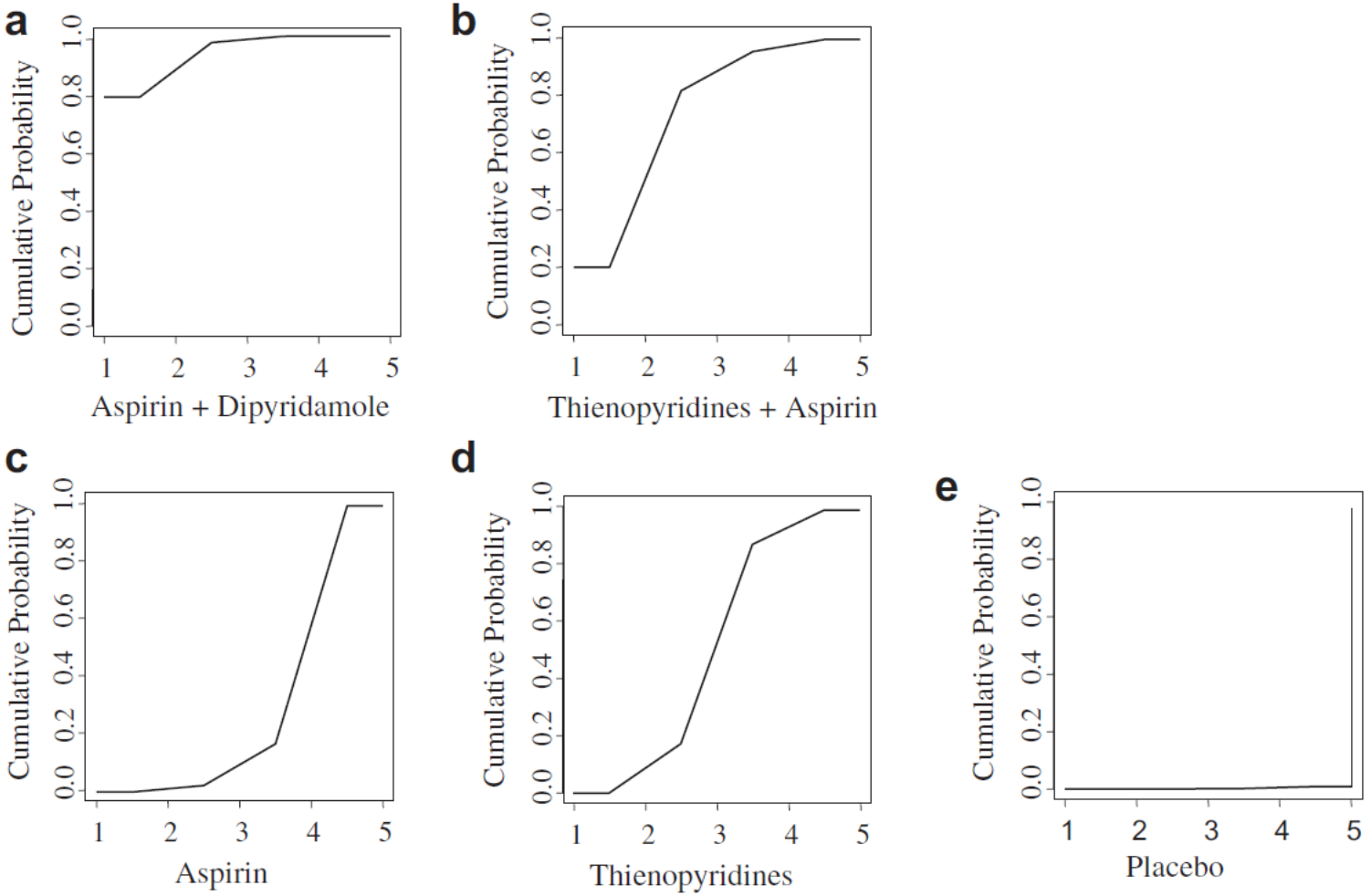
Multiple Treatment Meta-Analysis

Rankograms



Salanti et al. 2011 J Clin Epi

Multiple Treatment Meta-Analysis



Salanti et al. 2011 J Clin Epi

Multiple Treatment Meta-Analysis

Surface under the cumulative ranking (SUCRA):

$$SUCRA = \frac{\sum_{b=1}^{a-1} cum_b}{a-1}$$

Where cum_b is the cumulative probability that the treatment is among the *b* best treatment

Treatment	SUCRA (%)	Median rank (95% credible interval)	Probability to be no worse than 1.1-fold
Aspirin + dipyridamole	94	1 (1, 2)	Reference
Thienopyridines + aspirin	74	2 (1, 3)	51
Thienopyridines	52	3 (2, 4)	18
Aspirin	30	4 (3, 4)	2
Placebo	0	5 (5, 5)	0

Salanti et al. 2011 J Clin Epi

Causal Inference

- Often framed in a binary treatment setting:

$$\begin{aligned} \psi_{RD} &= E_W[E(Y \mid A=1, W) - E(Y \mid A=0, W)] \\ &= E(Y_1) - E(Y_0) \\ &= P(Y_1 = 1) - P(Y_0 = 1) \end{aligned}$$

Y is the outcome, A the exposure, and W baseline covariates.

Causal Inference: Multiple Treatments

- If we wish to study many treatments, we can smooth across treatments to obtain a **summary measure** using working **marginal structural models (MSMs)**.

- MSMs are **NOT estimators**.

- MSMs are a way to define your parameter of interest. Can choose from several estimators.

Marginal Structural Models

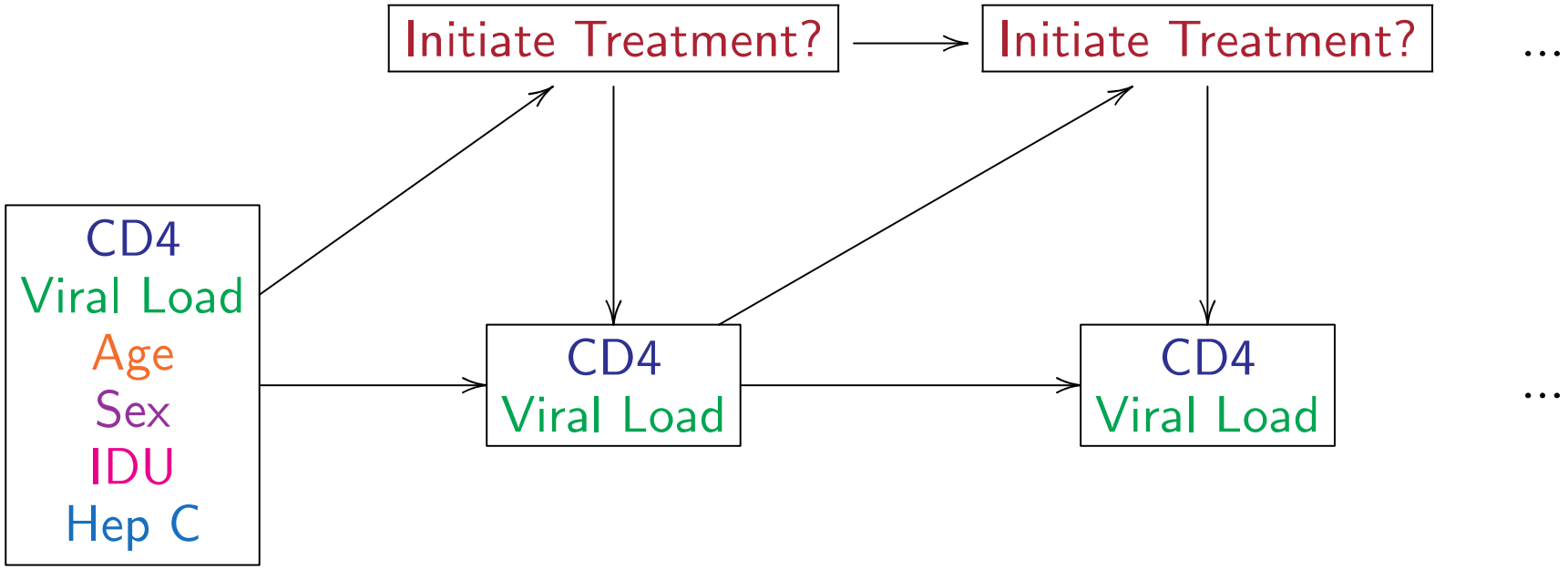
- **Formally:** A working MSM m_β allows us to define $\Psi(P)$ as a projection of the true counterfactual outcomes under various treatments onto m_β.

- What might this look like?

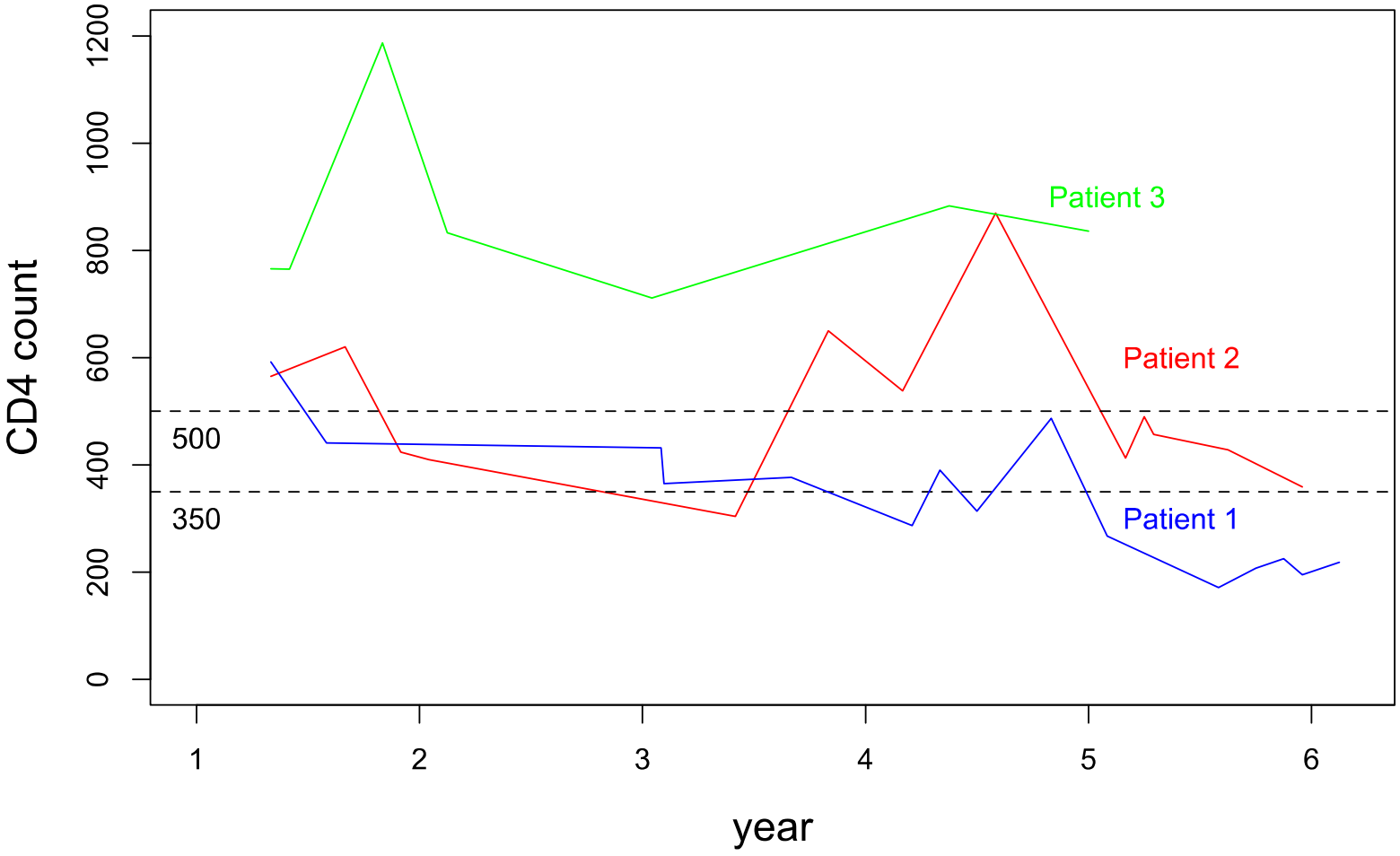
$$\text{MSM}: E(Y_a) = \beta_0 + \beta_1 \times a.$$

Longitudinal Data

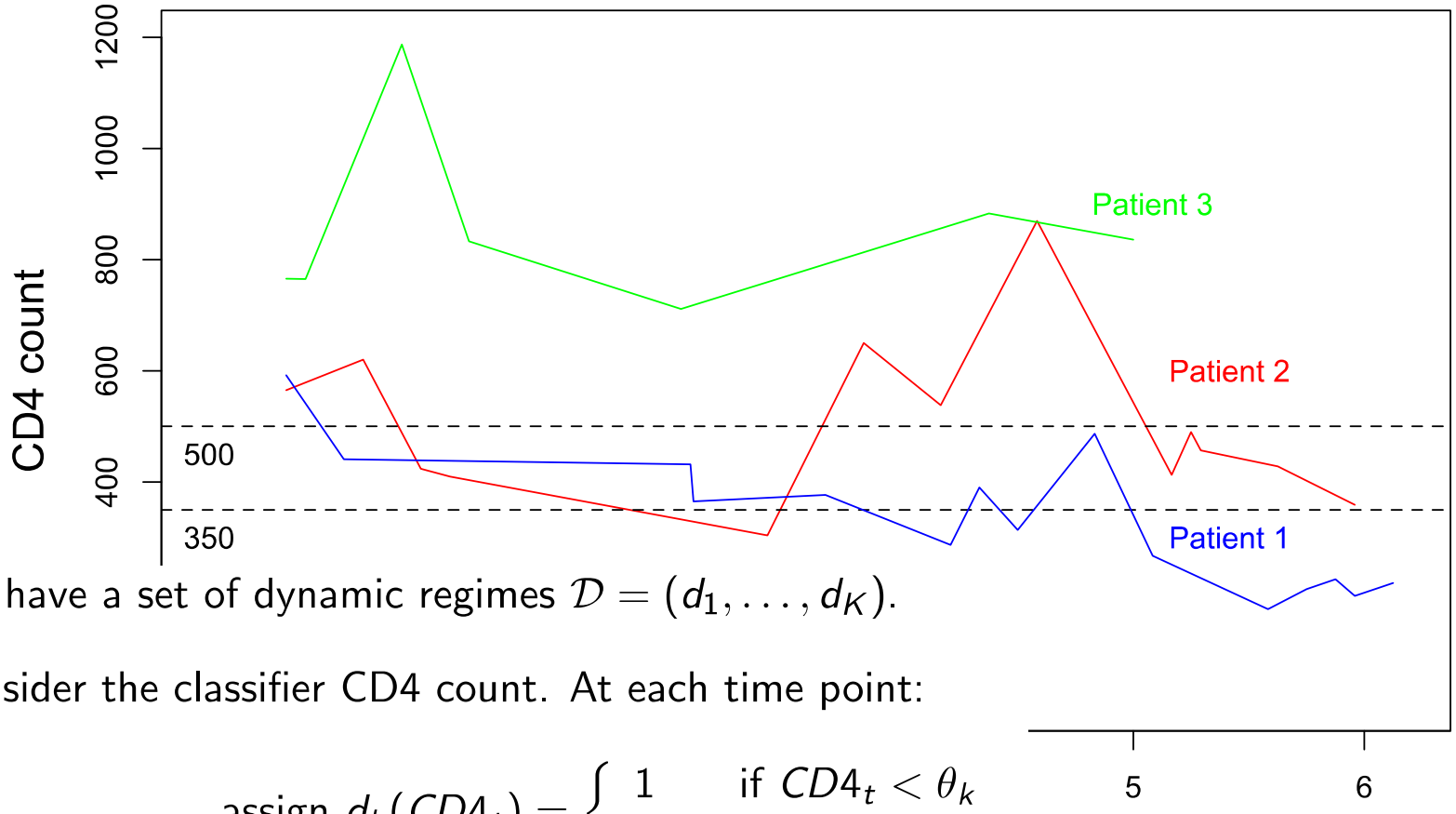
- MSMs are especially useful in longitudinal data.
- May have multiple *dynamic* treatments.



Dynamic Regimes



Dynamic Regimes



We have a set of dynamic regimes $\mathcal{D} = (d_1, \ldots, d_K)$.

Consider the classifier CD4 count. At each time point:

$$\text{assign } d_k(CD4_t) = \begin{cases} 1 & \text{if } CD4_t < \theta_k \\ 0 & \text{otherwise,} \end{cases}$$

where $\theta = (500, 350)$. Therefore we have that $\mathcal{D} = (d_1, d_2)$

MSMs & Dynamic Regimes

Data structure:

$$O = (L_0, A_0, L_1, A_1, \ldots, L_T, A_T, L_{T+1} = Y) \sim P,$$

with $\bar{L} = (L_0, L_1, \ldots, L_{T+1})$ covariates and $\bar{A} = (A_0, A_1, \ldots, A_T)$ intervention nodes.

We introduce the working model

$$m_\beta(d) = \text{logit}^{-1}(\beta_0 + \beta_1 \mathbf{1}_{d=d_1} + \cdots + \beta_{K-1} \mathbf{1}_{d=d_{K-1}}),$$

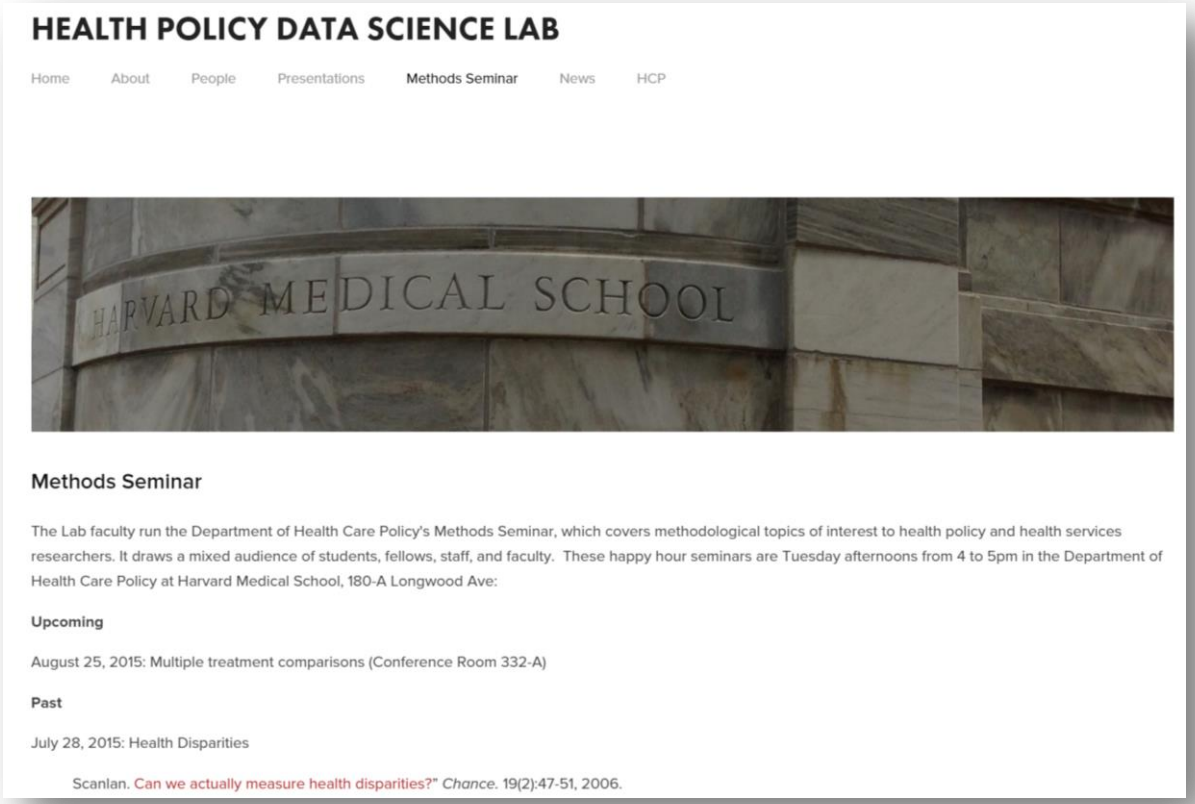
where the $\mathbf{1}_{d=d_k}$ are indicator variables for the dynamic rules.

We now define our target parameter as

$$\Psi(P) = \arg\min_\beta - E \sum_{d \in \mathcal{D}} \{ Y^d \log m_\beta(d) + (1 - Y^d) \log(1 - m_\beta(d)) \},$$

and can be written as: $\Psi(P) = f(E(Y^d) : d \in \mathcal{D})$.

Find materials from Methods Happy Hours healthpolicydatascience.org



Salanti, Ades, and Ioannidis. 2011. *Journal of Clinical Epidemiology*. 64:163-171.

Moore, Neugebauer, van der Laan, and Tager. 2012. *Statistics in Medicine*. 31: 1380-1404.