MEASURING TREATMENT EFFECT WITH NEURAL NETWORKS

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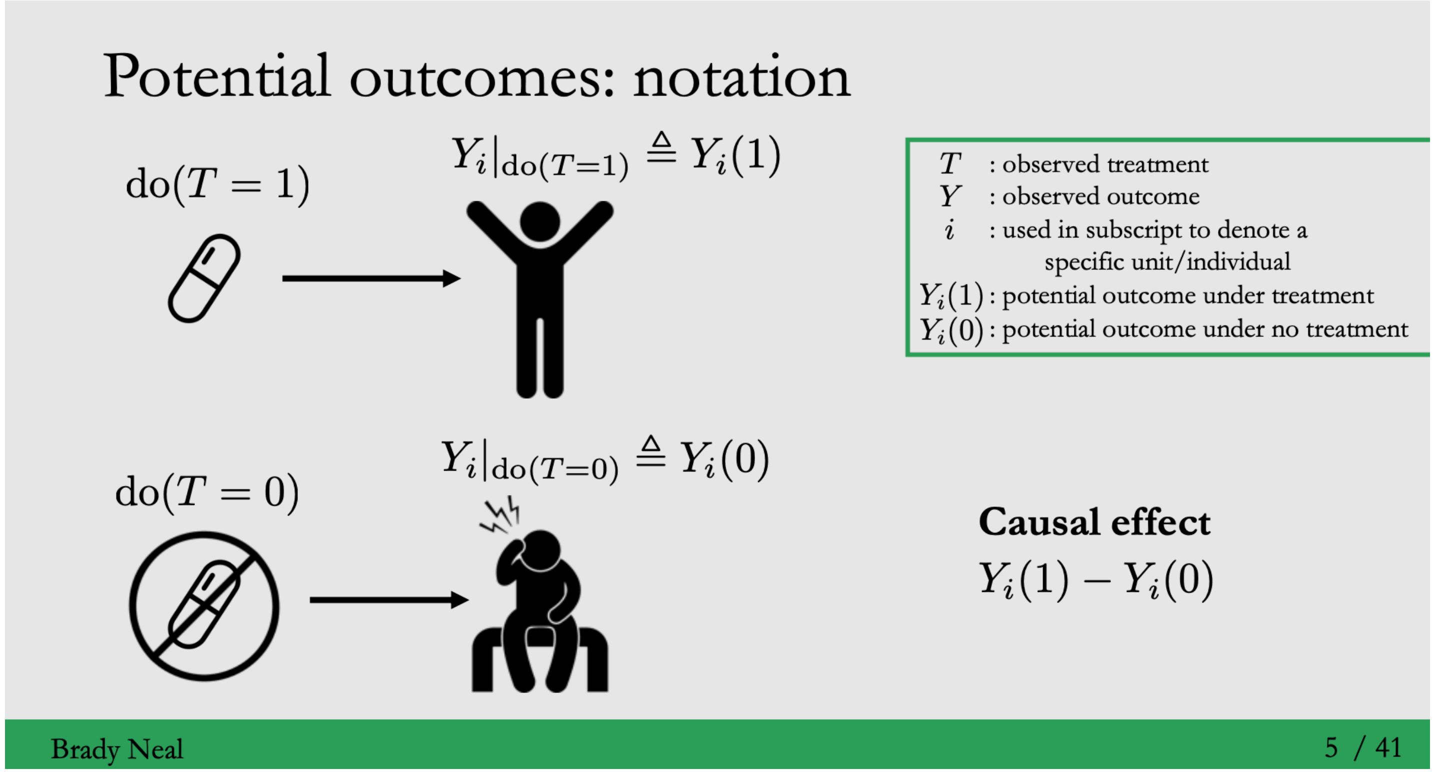
SETTING

1. Data: {(x, y, t)}
2. t is treatment, can discrete or continuous value;
   there could be even multiple treatments
3. Regress y on x
4. Want to measure the causal effect / treatment effect



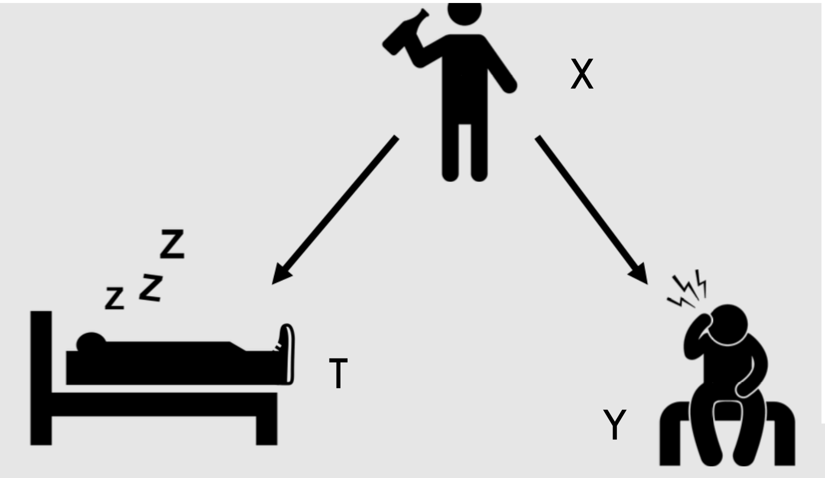
PROBLEM OF CAUSAL INFERENCE

Average treatment effect (ATE)

$$\mathbb{E}[Y(1) - Y(0)] = \mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] \neq \underbrace{\mathbb{E}[Y \mid T = 1] - \mathbb{E}[Y \mid T = 0]}_{\text{associational difference}}$$

i	T	Y	$Y(1)$	$Y(0)$	$Y(1) - Y(0)$
1	0	0		0	?
2	1	1	1		?
3	1	0	0		?
4	0	0		0	?
5	0	1		1	?
6	1	1	1		?
			$^2/_3$	$-\ ^1/_3$	$=\ ^1/_3$

T : observed treatment
Y : observed outcome
i : used in subscript to denote a specific unit/individual
$Y_i(1)$: potential outcome under treatment
$Y_i(0)$: potential outcome under no treatment

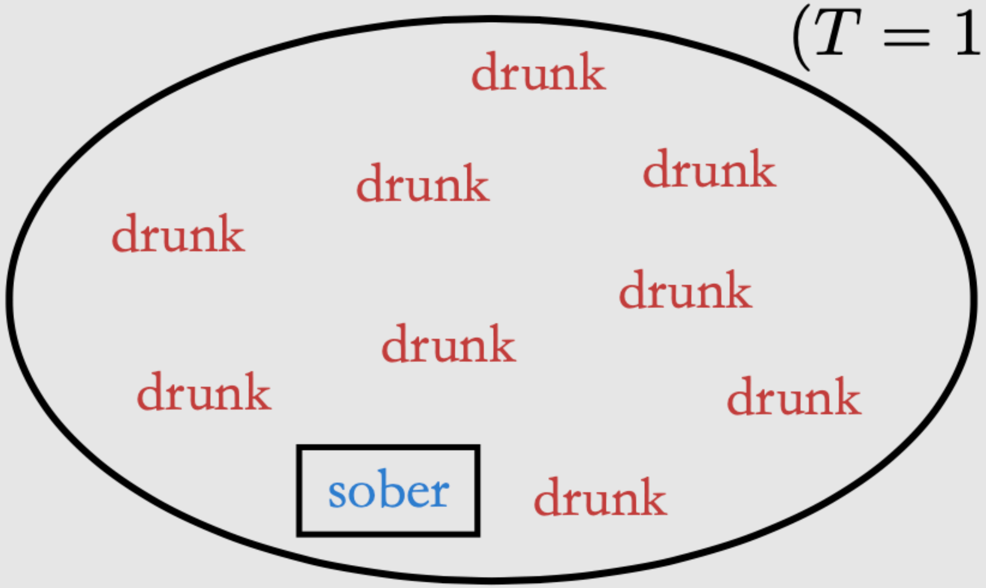


Y(1) and T=0 or 1 is not independent!

$$\mathbb{E}[Y(1)] - \mathbb{E}[Y(0)] \neq \mathbb{E}[Y \mid T = 1] - \mathbb{E}[Y \mid T = 0]$$

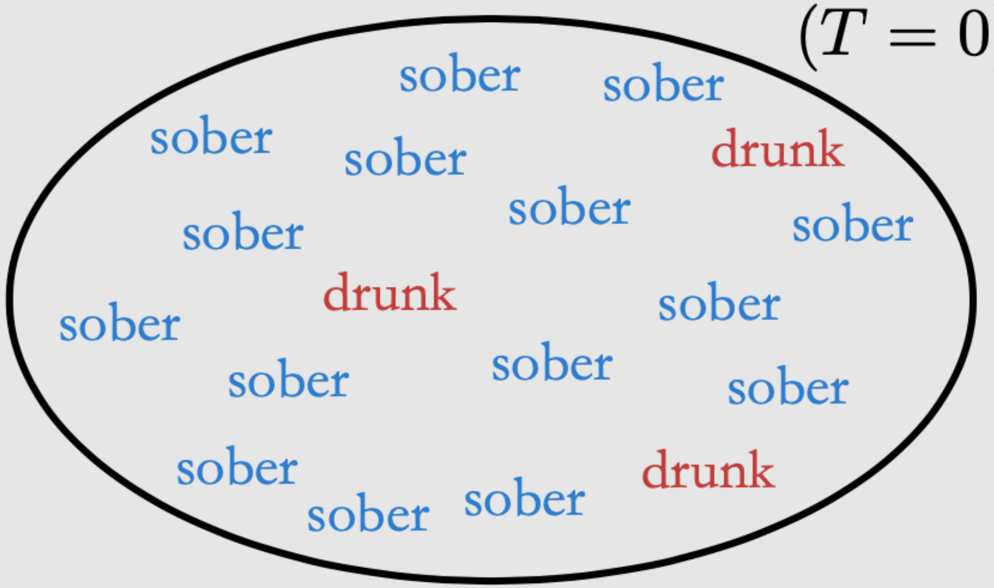
Went to sleep **with shoes** on

$(T = 1)$



Went to sleep **without shoes** on

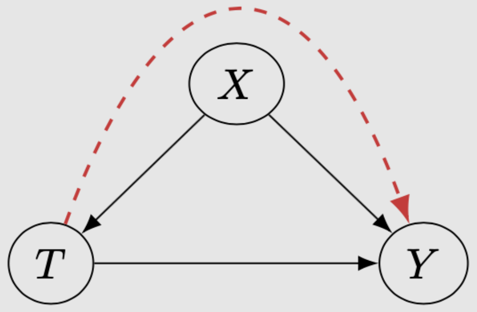
$(T = 0)$



WITH SOME ASSUMPTIONS...

The Adjustment Formula (identification of ATE)

$$
\begin{aligned}
\mathbb{E}[Y(1) - Y(0)] &= \mathbb{E}_X \mathbb{E}[Y(1) - Y(0) \mid X] \\
&= \mathbb{E}_X \left[\mathbb{E}[Y \mid T = 1, X] - \mathbb{E}[Y \mid T = 0, X] \right]
\end{aligned}
$$



Conditional average treatment effects (CATEs):

$$\tau(x) \triangleq \mathbb{E}[Y(1) - Y(0) \mid X = x]$$

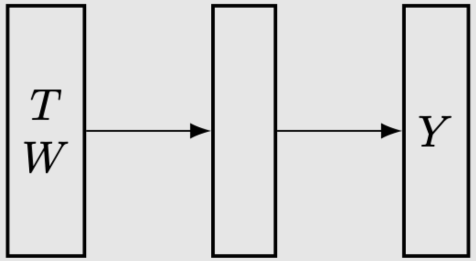
ESTIMATE THE TREATMENT EFFECTS

$$\hat{\tau} = \frac{1}{n}\sum_i (\hat{\mu}(1, w_i) - \hat{\mu}(0, w_i))$$

The feature is high dimensional, while T is scalar!

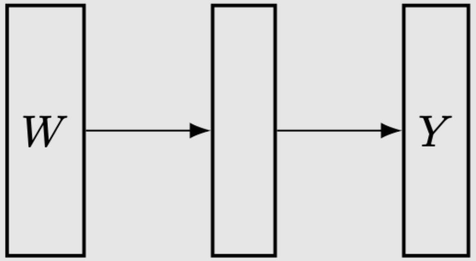
Grouped COM (GCOM) estimation

COM: $\hat{\tau} = \frac{1}{n}\sum_i (\hat{\mu}(1, w_i) - \hat{\mu}(0, w_i))$

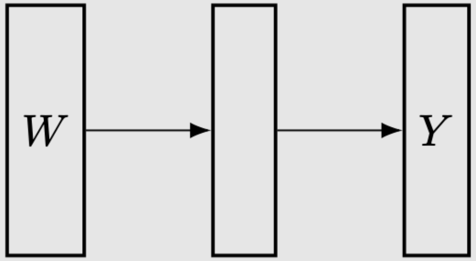


GCOM: $\hat{\tau} = \frac{1}{n}\sum_i (\hat{\mu}_1(w_i) - \hat{\mu}_0(w_i))$

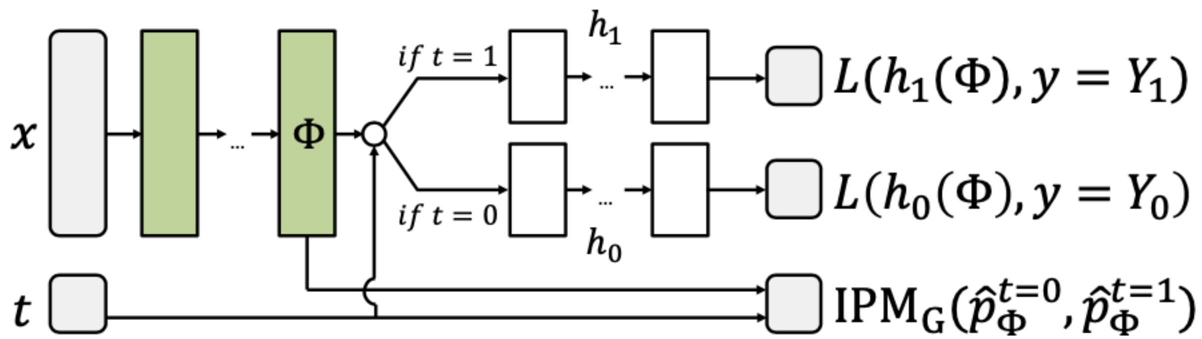
T = 1 network

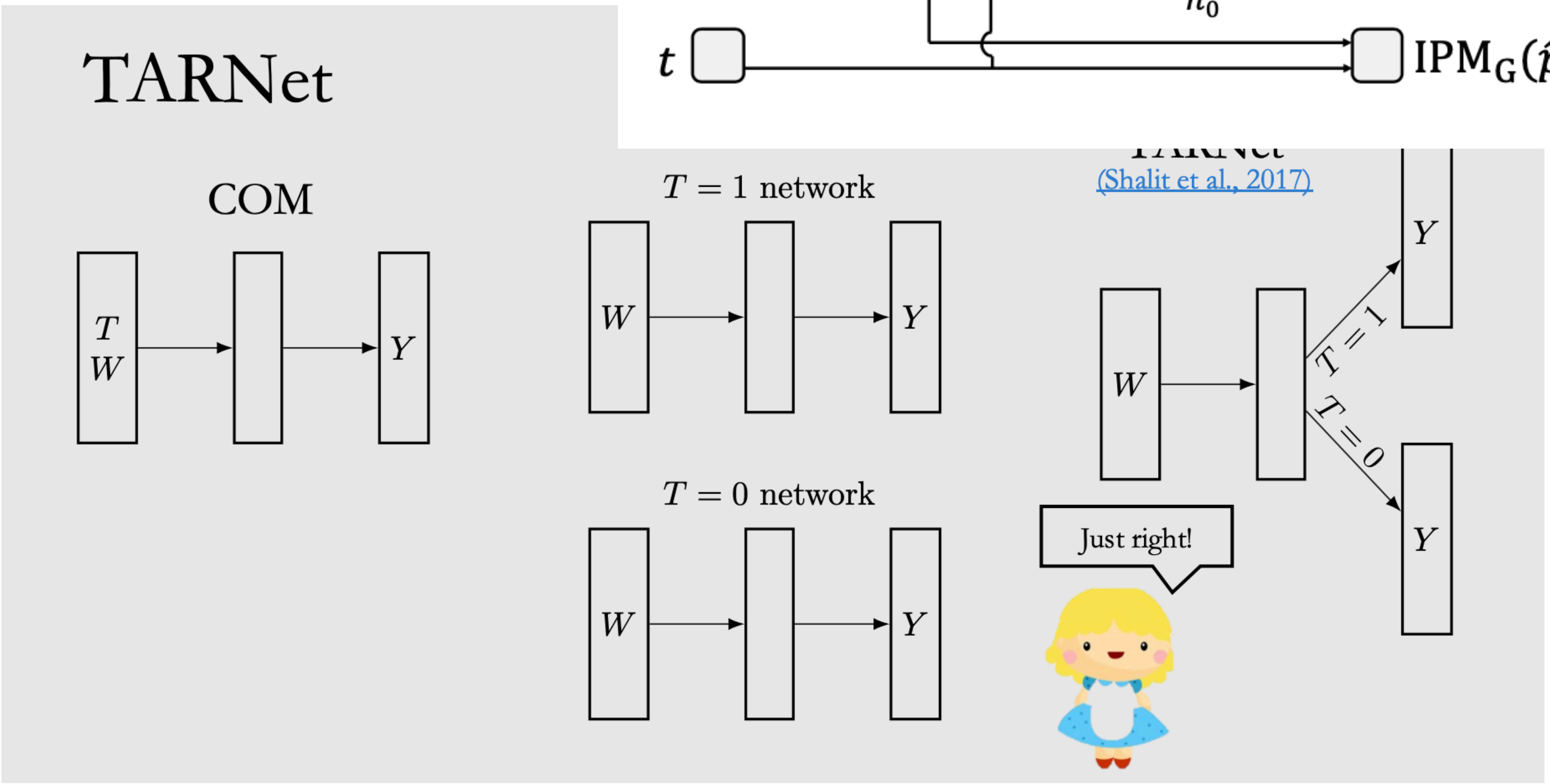


T = 0 network



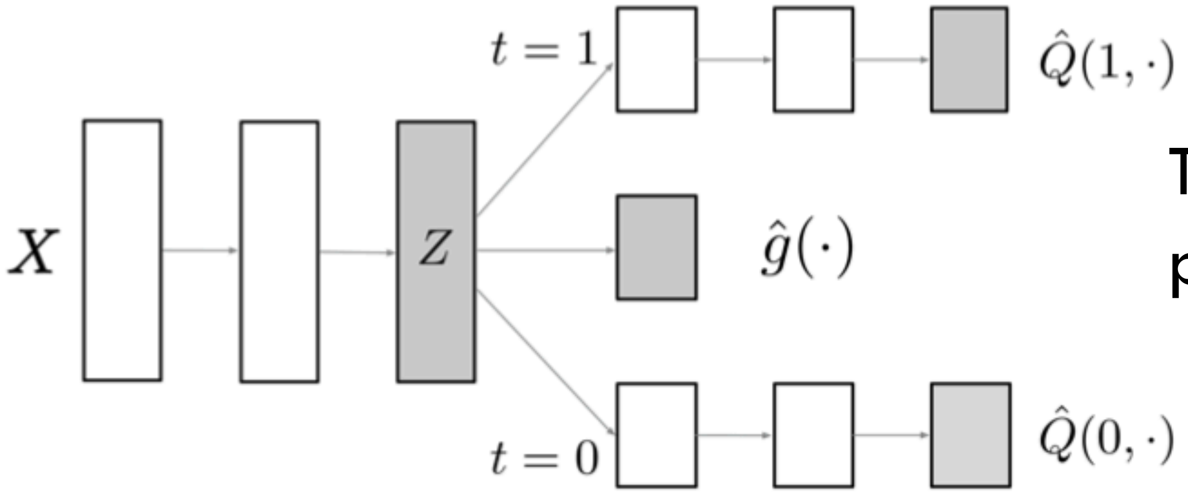
TARNET





Estimating individual treatment effect: generalization bounds and algorithms

DRAGONNET



This middle branch is to estimate propensity score P(t=1|x)

$$\hat{R}(\theta; \boldsymbol{X}) = \frac{1}{n} \sum_i \left[(Q^{\mathrm{nn}}(t_i, x_i; \theta) - y_i)^2 + \alpha \mathrm{CrossEntropy}(g^{\mathrm{nn}}(x_i; \theta), t_i) \right],$$

Adapting Neural Networks for the Estimation of Treatment Effects

X-LEARNER

1. Estimate the response functions

$$\mu_0(x) = \mathbb{E}[Y(0)|X = x],$$
$$\mu_1(x) = \mathbb{E}[Y(1)|X = x],$$

2a. Impute ITEs

Treatment group:
$$\hat{\tau}_{1,i} = Y_i(1) - \hat{\mu}_0(x_i)$$

Control group:
$$\hat{\tau}_{0,i} = \hat{\mu}_1(x_i) - Y_i(0)$$

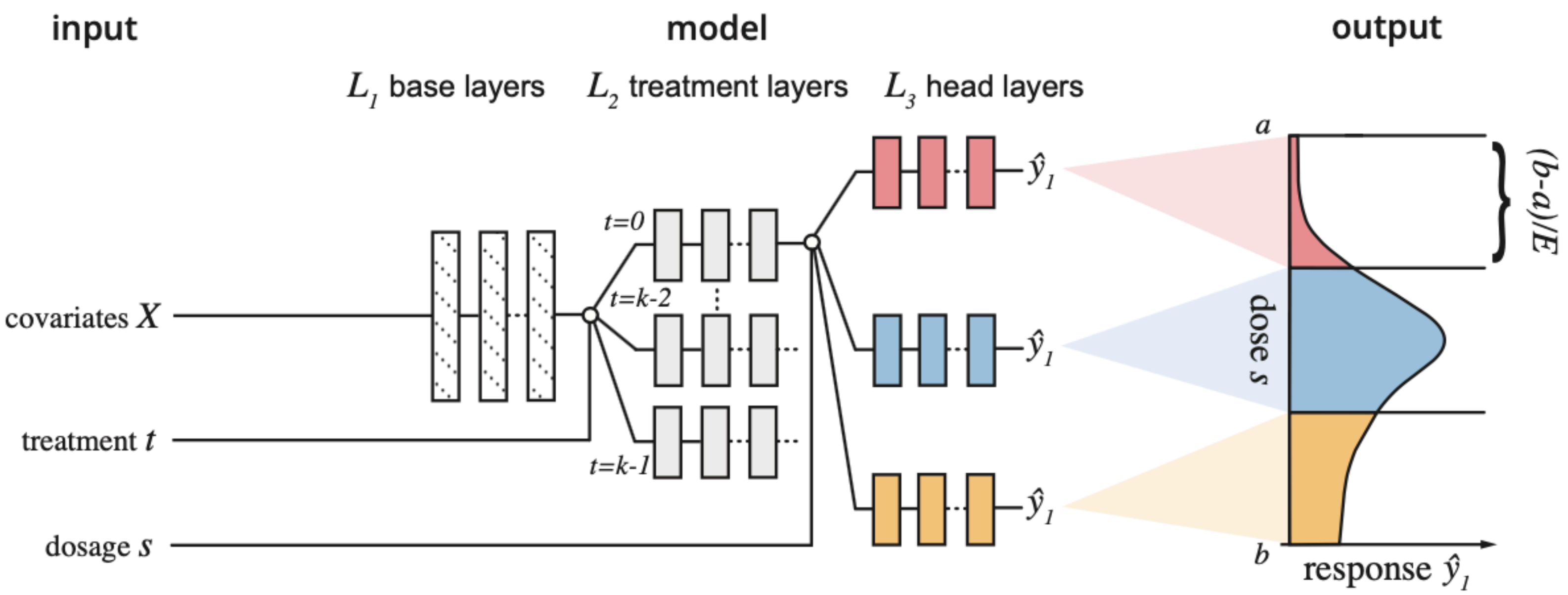
2b. Fit a model $\hat{\tau}_1(x)$ to predict $\hat{\tau}_{1,i}$ from x_i in treatment group

Fit a model $\hat{\tau}_0(x)$ to predict $\hat{\tau}_{0,i}$ from x_i in control group

3. $$\hat{\tau}(x) = g(x)\,\hat{\tau}_0(x) + (1 - g(x))\,\hat{\tau}_1(x)$$

Meta-learners for Estimating Heterogeneous Treatment Effects using Machine Learning

DRNET

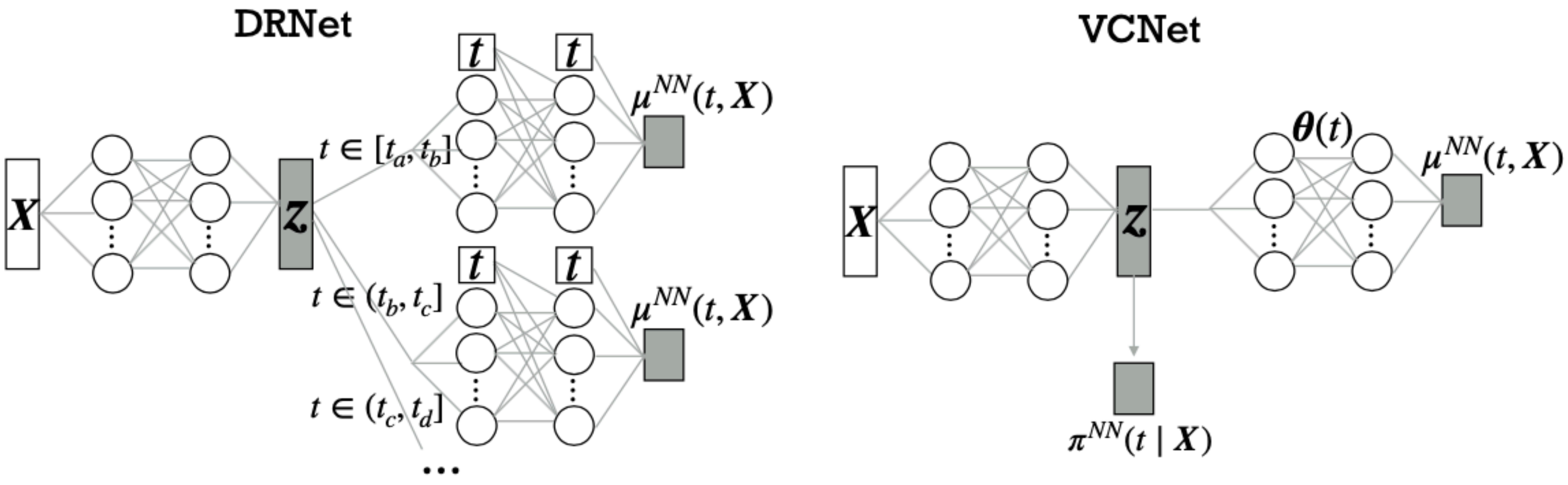


Multiple treatment

continuous value of dose

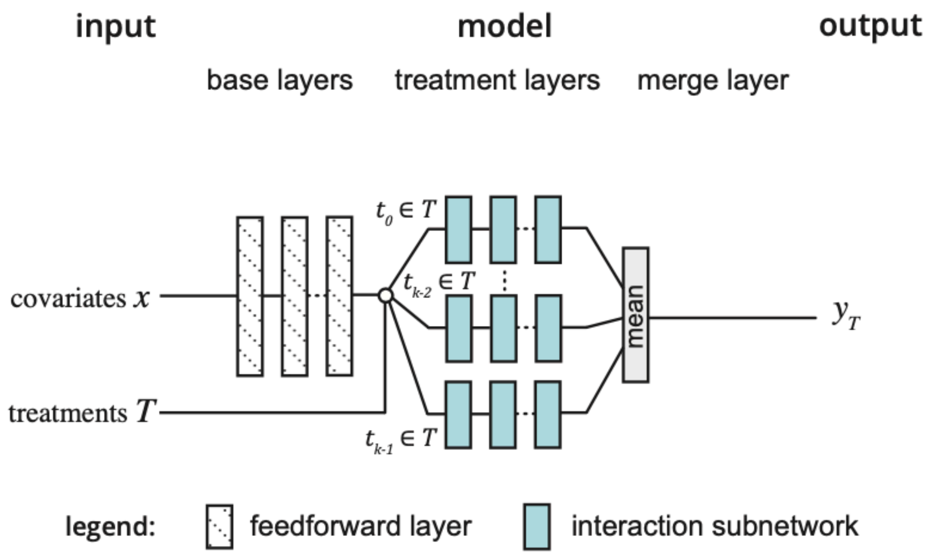
Learning Counterfactual Representations for Estimating Individual Dose-Response Curves

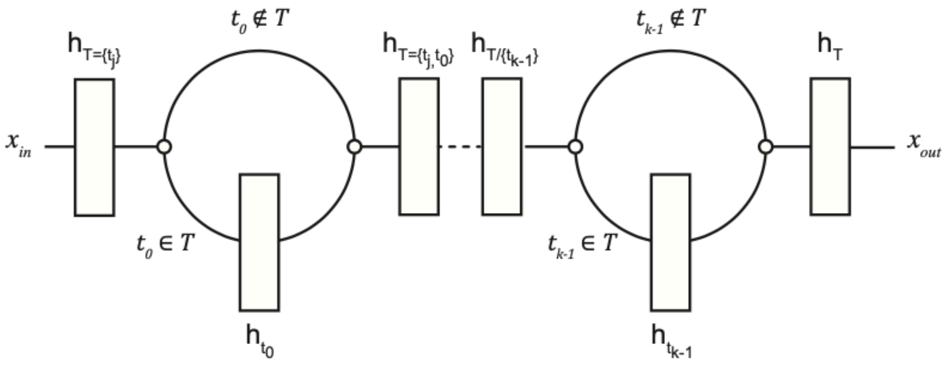
VCNET



(single treatment)

NCORE





Neural Counterfactual Representation Learning for Combinations of Treatments

THANK YOU FOR LISTENING!