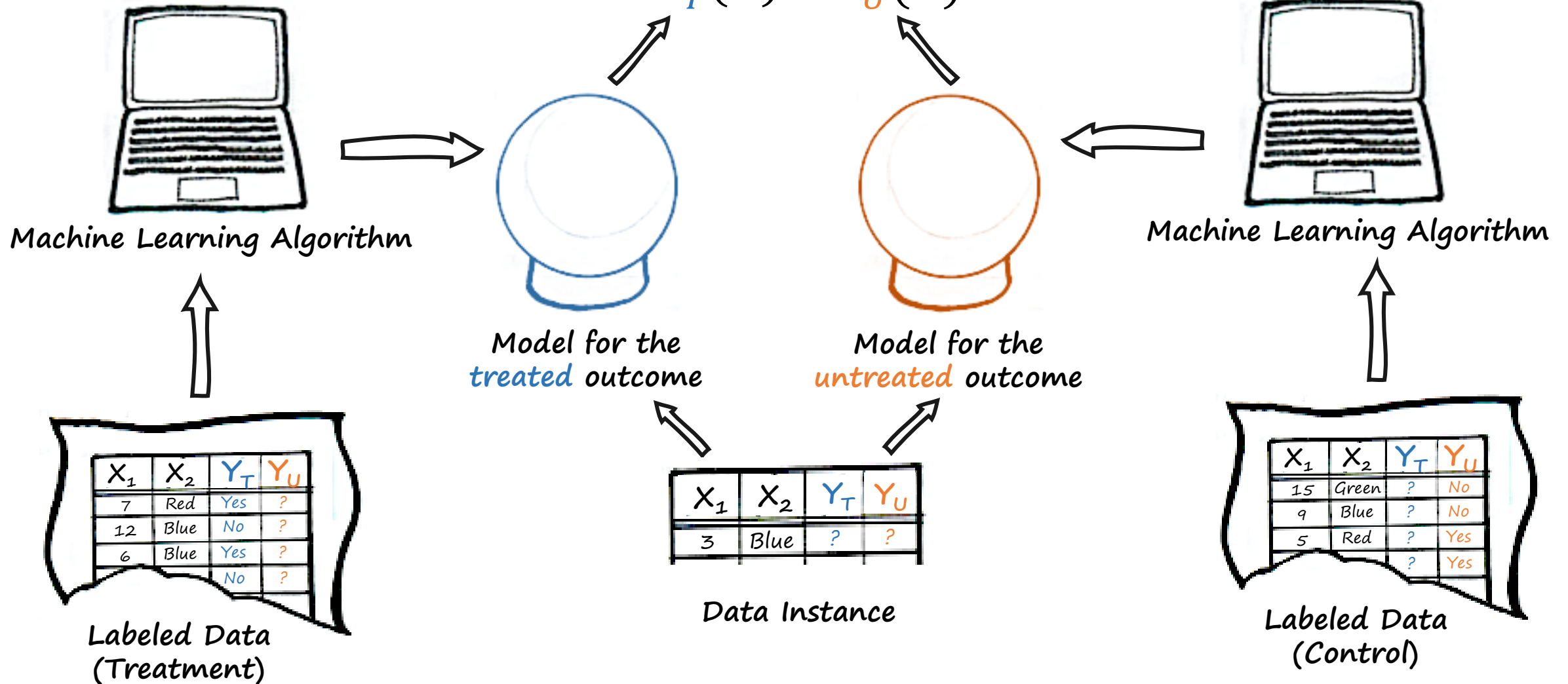


We can use Machine Learning + A/B Test to predict how effects vary.

$$\widehat{\text{Effect}} = \hat{Y}_T(X) - \hat{Y}_U(X)$$



Key Takeaway

We can also use A/B test data to evaluate causal decisions.

$$N \times \mathbb{P}[D = 1] \times (\mathbb{E}[Value|D = 1, T = 1] - \mathbb{E}[Value|D = 1, T = 0])$$



Fraction treated by
the decision rule.



Average effect for those treated
by the decision rule.

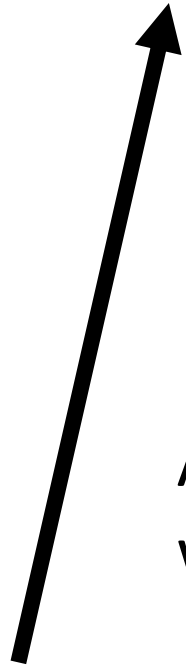
Effect of Decision Rule

$$N \times \mathbb{P}[D = 1] \times (\mathbb{E}[Value|D = 1, T = 1] - \mathbb{E}[Value|D = 1, T = 0])$$

- T : Treatment condition in the A/B Test Data; 1 = Treat, 0 = Control
- D : Decision made with predictive models; 1 = Treat, 0 = Control
- N : Number of decisions to be made.
- $Value$: Based on benefit matrix.

Effect of Decision Rule

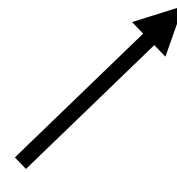
$$N \times \mathbb{P}[D = 1] \times (\mathbb{E}[Value|D = 1, T = 1] - \mathbb{E}[Value|D = 1, T = 0])$$



Fraction of treat decisions (average of D).



Average value when treated (estimate from cases where treatment is decided and applied).



Average value when not treated (estimate from cases where treatment is decided but not applied).