# final project

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## Step 1: State scientific question.

(a) The causal question

What is the effect of a large-scale primary care redesign, the Comprehensive Primary Care Plus (CPC+) Initiative, on the monthly Medicare patient expenditures?

(b) The target population

Patients in different primary care practices in 18 regions.

## Step 2: Specify a structural causal model (SCM).

(a) The endogenous variables V are variables that are meaningful for the scientific question and affected by other variables in this model. For this study, we define the following endogenous variables:

- $L_0 = \{V1, V2, V3, V4, V5\}_{t=2}$
- $L_1 = \{V1, V2, V3, V4, V5\}_{t=3}$
- V1: age, continuous variable supported on [0,100]
- V2: income groups, ordinal variable encoded into 0~14 integers.
- V3: sex, 0 for female, 1 for male, appromately equally distributed.
- V4: mean standardized Hierarchical Condition Category (HCC) score, approximately standard normal distribution.
- V5: race categories, white/black/all other, 70:20:10.
- V1-V5 are time variant patient-level covariates
- $X = \{X1, X2, X3, X4, X5, X6, X7, X8, X9\}$
- X1-X9 are time-invariant practice-level covariates.
- $Z$ = Initiative of Comprehensive Primary Care Plus (CPC+) in year 3
- $Y_0$ = Monthly Medicare patient expenditures in year 2
- $Y_1$ = Monthly Medicare patient expenditures in year 3

Here $V = (C_0, C_1, T_0, T_1, Y_0, Y_1)$

(b) The exogenous U include all the unmeasured or unknown factors not included in V that impact the values that the V variables take.

The exogenous nodes are $U = (U_X, U_T, U_{L_0}, U_{L_1}, U_{Y_0}, U_{Y_1})$.

According to the guidance of ACIC competition, the DGPs will be free of unmeasured confounding. In other words, we can place some independence assumptions on the distribution of unmeasured factors $P_U$. To simplify, we assume the all the exogenous variables satisfy pairwise independence.

(c) This would suggest the following structural equations F:

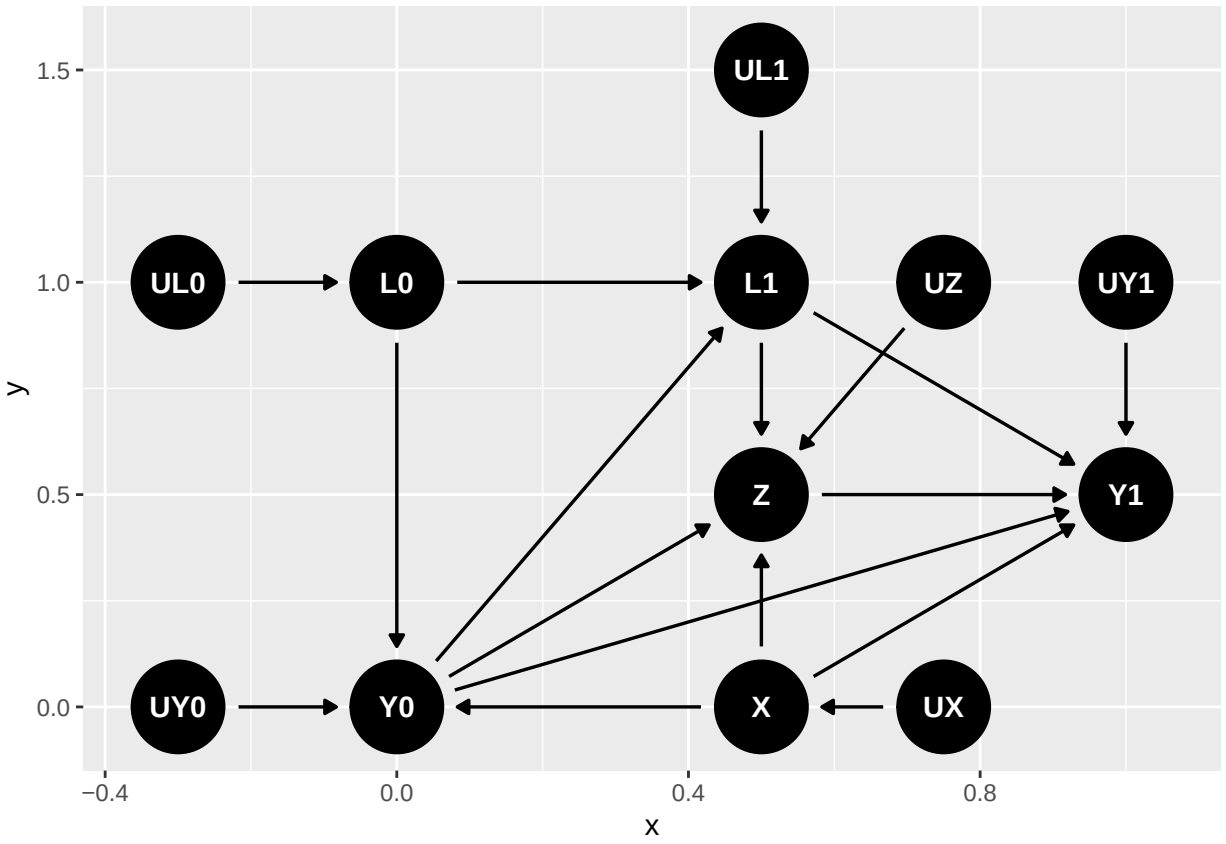
$$X = f_X(U_X)$$
$$L_0 = f_{L_0}(U_{L_0})$$
$$Y_0 = f_{Y_0}(U_{Y_0}, L_0)$$
$$L_1 = f_{L_1}(U_{L_1}, L_0, Y_0)$$
$$Z = f_Z(U_Z, L_1, Y_0, X)$$
$$Y_1 = f_{Y_1}(U_{Y_1}, L_1, T, Y_0, X)$$

(d) Exclusion restrictions.

An exclusion restriction is when a variable is not directly affected by another variable that precedes it in the structural causal model. For our model, we assume $L_0$ didn't directly affect $T$, but has some indirect effect through $L_1$ and $Y_0$. In addition, we assume practice level covariants X only have impact on $Y_0$, $Y_1$, $T$, but do not on those time-variant patient level covariants $L_0$ and $L_1$.

(f) Causal graph.

```
dag_m <- dagitty('dag {
    Y0 [pos="0,0"]
    L0 [pos="0,1"]
    Z [pos="0.5,0.5"]
    X [pos="0.5,0"]
    L1 [pos="0.5, 1"]
    Y1 [pos="1,0.5"]
    UL0[pos="-0.3,1"]
    UL1[pos="0.5,1.5"]
    UY0[pos="-0.3,0"]
    UZ[pos="0.75,1"]
    UX[pos="0.75,0"]
    UY1[pos="1,1"]
    UL0->L0
    UL1->L1
    UY0->Y0
    UZ->Z
    UX->X
    UY1->Y1
    L0->L1
    L0->Y0
    Y0->Z
    Y0->L1
    Y0->Y1
    L1->Y1
    L1->Z
    X->Y0
    X->Z
    X->Y1
    Z->Y1
    }')
ggdag(dag_m, layout = "circle")
```




## Step 3. Specify the target parameter of the observed data distribution

(a) The counterfactuals of interest are Y(1) and Y(0) and they can be defined as

- $Y_1(1)$: Monthly Medicare patient expenditures if all patients had joined CPC+ in year 3.
- $Y_1(0)$: Monthly Medicare patient expenditures if all patients hadn't joined CPC+ in year 3.

(b) Our target parameter is the average causal effect:

$$\Psi_{U,V}(P_0) = \mathbb{E}_{U,V}[Y_1(1) - Y_1(0)]$$

This means the target causal parameter is the difference in the monthly Medicare patient expenditures for patients enrolled in CPC+ for 2 years and not enrolled in CPC+.

## Step 4. Specify the observed data.

Suppose the data is from i.i.d sample from n = 329250 randomly sampled patients.

- $Ti$: whether patient i has enrolled in CPC+ in year 3
- $Xi$: practical level confounders collected for patient i
- $L_{0,i}$: patient level confounders collected for patient i in year 2
- $L_{1,i}$: patient level confounders collected for patient i in year 3
- $Y_{0,i}$: Monthly Medicare patient expenditures for patient i in year 2
- $Y_{1,i}$: Monthly Medicare patient expenditures for patient i in year 3

Further assume that the collected data are independent and identically distributed.

## Step 5. Identify the targeted causal effect with the observed data.

(a) Conditional independent assumption

$$Y_{1,i}(0), Y_{0,i}(0) \perp\!\!\!\perp Z|X, L_1, Y_0$$

(b) By backdoor-path criterion, we can write our causal parameter with the observed data by G-computation:

$$\Psi(P_0) = \mathbb{E}[\mathbb{E}[Y_1|T=1, X, L_1, Y_0]] - \mathbb{E}[\mathbb{E}[Y_1|T=0, X, L_1, Y_0]]$$

Under our causal model and assumptions, average treatment effect equals to the observed difference in mean outcome within confounder strata, standardized to distribution of confounders.

(c) Relevant positivity assumption

## Step 6. Estimation and Statistical Inference.

```
set.seed(252)
ObsData = read.table("filtered_patient_1.csv")
```

result:

```
ltmle.SL = readRDS("result1.rds")
summary(ltmle.SL)
```

```
## Estimator:  tmle
## Call:
## ltmle(data = ObsData, Anodes = "Z", Ynodes = "Y", abar = list(1,
##     0), SL.library = SL.library)
##
## Treatment Estimate:
##    Parameter Estimate:  1211.5
##     Estimated Std Err:  6.2942
##               p-value:  <2e-16
##     95% Conf Interval: (1199.1, 1223.8)
##
## Control Estimate:
##    Parameter Estimate:  1197.3
##     Estimated Std Err:  6.059
##               p-value:  <2e-16
##     95% Conf Interval: (1185.4, 1209.2)
##
## Additive Treatment Effect:
##    Parameter Estimate:  14.189
##     Estimated Std Err:  8.0474
##               p-value:  0.077874
##     95% Conf Interval: (-1.5838, 29.961)
```