機械学習を用いた因果推論

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因果推論 at glance

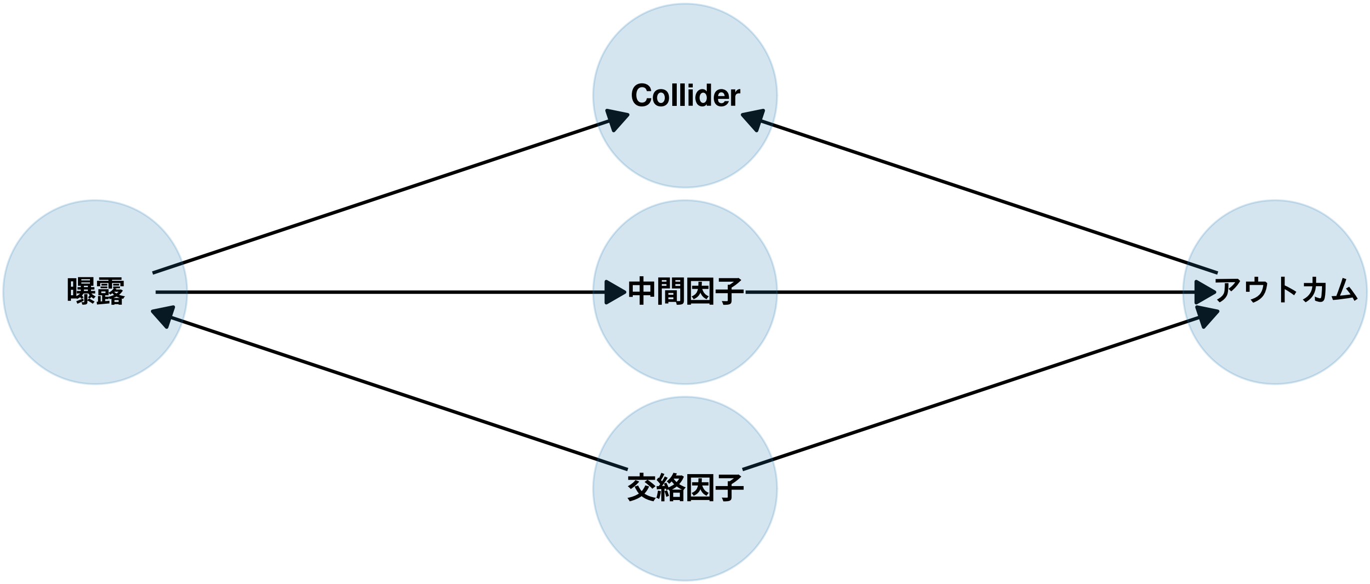
因果関係

- 医学研究の第一の目標と言っても過言ではない
- A の薬を使うと患者の予後は良くなるか？
- 実際は口で言うほど簡単ではない

因果関係の考え方

- 大きく分けて 2 つの考え方がある
  $\rightarrow$ 潜在的アウトカムを考える Rubin 流
  $\rightarrow$ DAG を作り、do operator を使う Pearl 流
- 詳細は省くが、今回は Pearl 流の DAG を中心に考える

DAG の基本



通常の統計学的手法

- 通常は交絡因子の調整により因果関係を推測する

交絡因子の調整の方法

- 回帰
- Matching
- 層別化

例えば単純な回帰だと

term	Coef	Std.Err	t	P
Intercept	−1174.13	2456.31	−0.48	0.63
treat	1548.24	781.28	1.98	0.05
age	12.98	32.49	0.4	0.69
educ	403.94	158.91	2.54	0.01
race_hispan	1739.54	1018.52	1.71	0.09
race_white	1240.64	768.76	1.61	0.11
married	406.62	695.47	0.58	0.56
nodegree	259.82	847.44	0.31	0.76
re74	0.3	0.06	5.09	0
re75	0.23	0.1	2.21	0.03

Matching だと

- 一番有名なのは Propensity score matching

```
     treat  age  educ  ...  race_hispan  race_white  propensity_score
19       1   26    12  ...            0           0          0.619048
42       1   17     8  ...            0           0          0.619048
156      1   18     9  ...            0           0          0.217391
111      1   17     9  ...            1           0          0.217391
148      1   26    11  ...            0           0          0.217391

[5 rows x 11 columns]
```

```
matched size: (296, 11)
```

```
ATT (diff in means on matched sample): 1008.6141578378374
```

DAG つき

```
Model to find the causal effect of treatment ['treat'] on outcome ['re78']
```

```
Estimand type: EstimandType.NONPARAMETRIC_ATE

### Estimand : 1
Estimand name: backdoor
Estimand expression:
  d
────────────────(E[re78|married,age,re75,nodegree,educ])
d[treat]
Estimand assumption 1, Unconfoundedness: If U→{treat} and U→re78 then P(re78|
treat,married,age,re75,nodegree,educ,U) = P(re78|treat,married,age,re75,nodegree,educ)

### Estimand : 2
Estimand name: iv
Estimand expression:
```

DAG つき

```
⎡                                                -1⎤
⎢         d              ⎛         d             ⎞ ⎥
E⎢──────────────────────────────────────────────────(re78)⋅⎢──────────────────
⎢
⎣d[race_black  race_hispan]   ⎝d[race_black  race_hispan]        ⎠ ⎦
Estimand assumption 1, As-if-random: If U→→re78 then ¬(U →→{race_black,race_hispan})
Estimand assumption 2, Exclusion: If we remove {race_black,race_hispan}→{treat}, then
¬({race_black,race_hispan}→re78)

### Estimand : 3
Estimand name: frontdoor
No such variable(s) found!

### Estimand : 4
Estimand name: general_adjustment
Estimand expression:
  d
```

DAG つき

```
────────────(E[re78|married,age,re75,nodegree,educ])
d[treat]
Estimand assumption 1, Unconfoundedness: If U→{treat} and U→re78 then P(re78|
treat,married,age,re75,nodegree,educ,U) = P(re78|treat,married,age,re75,nodegree,educ)
```

```
*** Causal Estimate ***

## Identified estimand
Estimand type: EstimandType.NONPARAMETRIC_ATE

### Estimand : 1
Estimand name: backdoor
Estimand expression:
   d
────────────(E[re78|married,age,re75,nodegree,educ])
d[treat]
```

DAG つき

```
Estimand assumption 1, Unconfoundedness: If U→{treat} and U→re78 then P(re78|
treat,married,age,re75,nodegree,educ,U) = P(re78|treat,married,age,re75,nodegree,educ)

## Realized estimand
b: re78~treat+married+age+re75+nodegree+educ
Target units: ate

## Estimate
Mean value: 959.0309546416938
```

```


Refuting Estimates:   0%|⊠[32m          ⊠[0m| 0/100 [00:00<?, ?it/s]
Refuting Estimates:  11%|⊠[32m#1        ⊠[0m| 11/100 [00:00<00:01, 74.20it/s]
Refuting Estimates:  31%|⊠[32m###1      ⊠[0m| 31/100 [00:00<00:00, 134.03it/s]
Refuting Estimates:  51%|⊠[32m#####1    ⊠[0m| 51/100 [00:00<00:00, 158.77it/s]
Refuting Estimates:  71%|⊠[32m#######1  ⊠[0m| 71/100 [00:00<00:00, 172.03it/s]
```

DAG つき

```
Refuting Estimates:  89%|⌧[32m########9 ⌧[0m| 89/100 [00:00<00:00, 165.96it/s]
Refuting Estimates: 100%|⌧[32m##########⌧[0m| 100/100 [00:00<00:00, 154.33it/s]
```

```
Refute: Add a random common cause
Estimated effect:959.0309546416938
New effect:959.0309546416939
p value:1.0
```

Doubly robust estimation

```
DR ATE: 1394.87
```

```
SE: 926.77
```

```
95% CI: (-421.60, 3211.33)
```

ここらへんの問題

- Misspecification の問題
- Estimand の問題 = 治療効果の異質性

機械学習 at glance

代表的な機械学習

- Logistic 回帰
- tree-based model
  - $\rightarrow$ Random forest
  - $\rightarrow$ XGBoost
- Neural network

疑問

- 機械学習を用いて因果関係を推測出来るんじゃないか？

機械学習を用いた因果推論の Pros and Cons

- Pros
  - → モデルの Misspecification を避けられる
  - → 因果関係の異質性を柔軟に捉えられる
- Cons
  - → Overfitting の問題
  - → 解釈が難しい時がある
  - → 信頼区間が出しにくい

```
<econml.metalearners._metalearners.TLearner object at 0x70104e8c57f0>
```

```
<econml.metalearners._metalearners.SLearner object at 0x70104e88aea0>
```

```
[-1530.55967406   369.38136095 -1198.06865549   -86.11625054
  -833.38280696   171.70918773     0.           171.70918773
```

機械学習を用いた因果推論の Pros and Cons

```
  319.60055729  3232.14589762 -1326.64678003    62.06342827
  973.47414377   503.67373985  -498.5500903   -128.93867654
  485.25799913   489.9931725   1943.89516126  -269.05807531
 2651.3162438    251.02443635 -3528.65968649  -591.89366066
  436.53410022    32.09860508  -149.43314728   214.47455118
  -86.11625054    32.09860508  3232.14589762    32.09860508
  664.43858698   215.4353309   3451.76242614 -3558.48624607
-1148.88963224  2872.53054803   524.46483345  -544.94289508
  632.3399819   -545.38598944  2651.3162438    144.60637046
  -20.61071748    95.79529433   -86.11625054  -544.94289508
  179.0257057  -2760.46335128  -957.9515668   1897.03733375
  650.11851089   189.4222147     29.11044322   848.41449744
 -352.45433824  2642.76190818 -1788.65634271  -988.00134014
-1198.06865549  3232.14589762  -522.42034513  -325.05097239
   32.09860508  -167.70521158  2297.82108649    18.95269302
-1323.72233293   -35.38360418    74.66266901  -263.26905945
 -289.37725534  3185.71468272  -122.99846869   -86.11625054
```

機械学習を用いた因果推論の Pros and Cons

```
 -128.93867654  1179.17631607 -2787.07045179  1789.97076026
   32.09860508  -263.26905945  -843.00231034 -1539.13799559
  125.67766335   425.69190007  2199.59715977 -2259.89874238
 2651.3162438  -1539.13799559   261.5062125   -495.49910709
-1218.45302373 -1539.13799559  2297.82108649   278.45737341
 1861.49985719   664.43858698    95.79529433  2420.81146399
  903.14992197  -329.34261136   894.79147023   194.23270811
-1179.12813405   171.70918773   171.70918773 -1089.00156337
  341.10564214   369.38136095  -591.89366066   -86.11625054
-1131.29106563  -410.70666473   -20.61071748  -591.89366066
  207.64243233   -86.11625054   319.60055729  2063.90546808
-2635.07325719  -662.79260714   715.06165279]
```

```
<econml.metalearners._metalearners.XLearner object at 0x70104e6781d0>
```

```
<econml.metalearners._metalearners.DomainAdaptationLearner object at 0x70104e6 >
```

機械学習を用いた因果推論の Pros and Cons

```
> af500>
```

```
<econml.dr._drlearner.DRLearner object at 0x70104e70d8e0>
```

機械学習の因果推論における使い方

- 交絡因子の調整で機械学習を用いる
  $\rightarrow$ AIPW, tlme など
- 因果をダイレクトに推論する学習機を作る
  $\rightarrow$ Meta-learner
- CATE を測定する
  $\rightarrow$ Causal forest など

因果 forest

- HTE を計測するのに有名
- Ashey et al 2019

Survival model

```
  id study      rx sex age obstruct perfor adhere nodes status differ extent
1  1     1 Lev+5FU   1  43        0      0      0     5      1      2      3
2  1     1 Lev+5FU   1  43        0      0      0     5      1      2      3
3  2     1 Lev+5FU   1  63        0      0      0     1      0      2      3
4  2     1 Lev+5FU   1  63        0      0      0     1      0      2      3
5  3     1     Obs   0  71        0      0      1     7      1      2      2
6  3     1     Obs   0  71        0      0      1     7      1      2      2
  surg node4 time etype
1    0     1 1521     2
2    0     1  968     1
3    0     0 3087     2
4    0     0 3087     1
5    0     1  963     2
6    0     1  542     1
```

Survival model

```
        control   treated
[1,]  -656.5976  656.5976
[2,]   116.6024 -116.6024
[3,]  -583.4266  583.4266
[4,]  -572.1474  572.1474
[5,]  -221.8854  221.8854
[6,] -1511.0419 1511.0419
```

Survival model

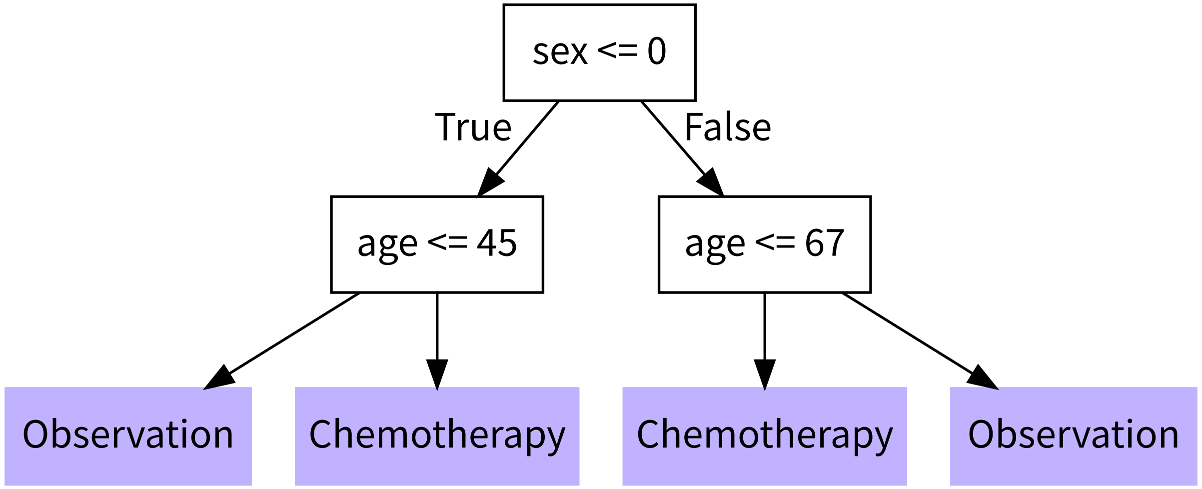


Figure 1: Treeplot