Causal Inference

→ So far, purely predictive questions!

→ If there are signs that there is correlation between features and target of interest, that's good enough

→ Causal Directionality is irrelevant. (Not completely true)

→ When there is dataset shift, or non-stationary data, causality matters. Understanding the data deeply is very helpful!

→ In healthcare especially, causal questions are important to answer.

→ For example, it is more important to prevent Type 2 diabetes (causal) vs early diagnosis of Type 2 diabetes (predictive).

→ Naive way of inferring causality:

- Let's say we trained a DL model to predict onset of Type 2 diabetes
- Look at most negative feature (lowest weight), let's say it is Gastrogenic Bypass Surgery (yes or no)
- Then does that mean that if a patient underwent this surgery, he/she won't get diabetes?

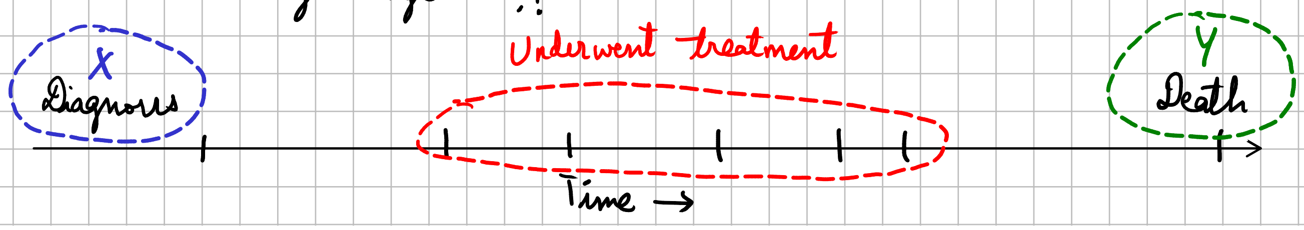
→ Look at predictive weights is not enough.

→ We need to come up with a mathematical model for causality

→ Another example:

- Let's say we train a DL model for predicting survival of breast cancer patient based on radiological mammogram and histopathological slides.
- Let's say one patient diagnosed with breast cancer survived for longer than 5 years.
- When a new patient, with similar diagnosis as the model's examples is given to the model, a higher survival is predicted.
- Does this mean we shouldn't treat the patient?

→ This is very dangerous!!



→ A longer survival time maybe because of treatment! Not solely because of diagnosis

→ But the model only learns the X (diagnosis) → Y (survival) mapping

Guiding Treatment Decisions

→ Another question that needs to be answered is: How do we guide treatment decisions?

→ How do we tell who is likely to be benefitted by a given treatment?

→ But people respond differently to treatments?

→ Also, data used to guide treatments is biased on existing treatment guidelines.

→ Naive way to guide treatment decisions:

Train a predictive model that learns to predict treatment decisions.

David → Treatment A

John → Treatment B

Juana → Treatment A

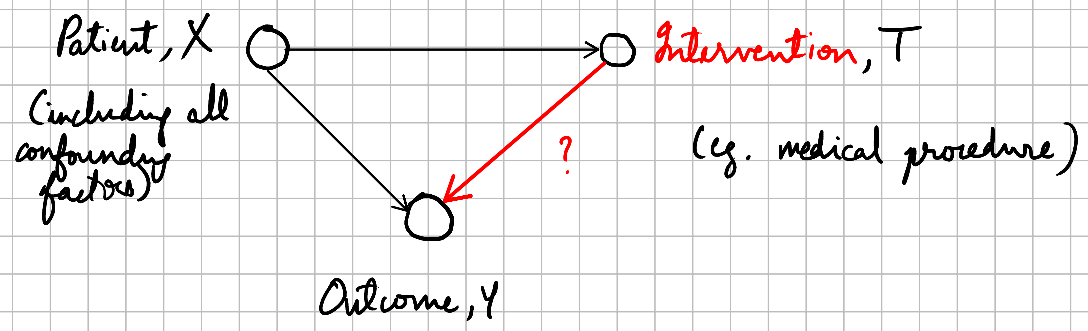
→ Best this can do is match current medical guidelines!

→ How do go we beyond this? We need to capture heterogeneity in treatment response. We need to change how we ask our question.

→ One last example:

- Traditional, does X cause Y?
- Does smoking cause cancer?
- Doing a randomized controlled trial is unethical.
- Could we just compare P(lung cancer | smoker) vs P(lung cancer | non smoker)?
- No because of confounding factors (see below)

→ To properly answer, we need to formulate as causal questions.



High dimensional

Observational data

Causal Graphs

→ Instead of just $D \in \{x^{(i)}, y^{(i)}\}$, we need to think in terms of triplets : $D \in \{x^{(i)}, T^{(i)}, y^{(i)}\}$ Interventions

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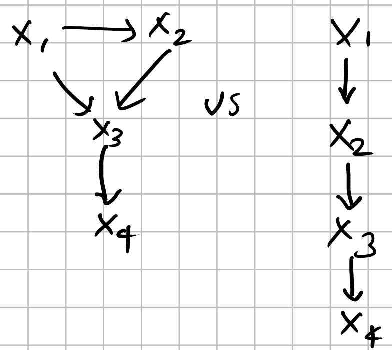
→ Earlier Causal Inference might take a form like so: (Can Skip! Won't be discussed further)

Data

x_1	x_2	x_3	x_4
0	1	0	0
0	0	1	0
⋮			
1	1	1	0

we try to find right graph →



What is the underlying causal graph?

For Two random variables and x_1 and x_2

$x_1 \to x_2$ i.e., $P(x_1)\, P(x_2 | x_1)$

$x_2 \to x_1$ i.e, $P(x_2)\, P(x_1 | x_2)$

Are indistinguishable (because of conditional probability and bayes theorem)

Then we might wanna add interventions to $x_1 \to x_2$ and $x_2 \to x_1$ to disentangle the causalities.

→ This is the simplest possible case!

→ X is highdimensional, T and Y and single random variable.

→ The causal graph is assumed here.

→ We just don't know the connection weights' strength!