Conditional Generative Models are Sufficient to Sample from Any Causal Effect Estimand

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Causality in Machine Learning

- **Fairness**: Is there any **confounder** in your data which might give you **wrong prediction**?

Causality in Machine Learning

- **Fairness**: Is there any **confounder** in your data which might give you **wrong prediction**?
- **Robustness:** Is there any **bias in your data** that might affect your **model accuracy** in the **test domain**?

Causality in Machine Learning

- Confounder : wrong prediction?
- Bias in your data: worse model accuracy in the test domain?
- **Predictions based on cause effect are free from such harms.**

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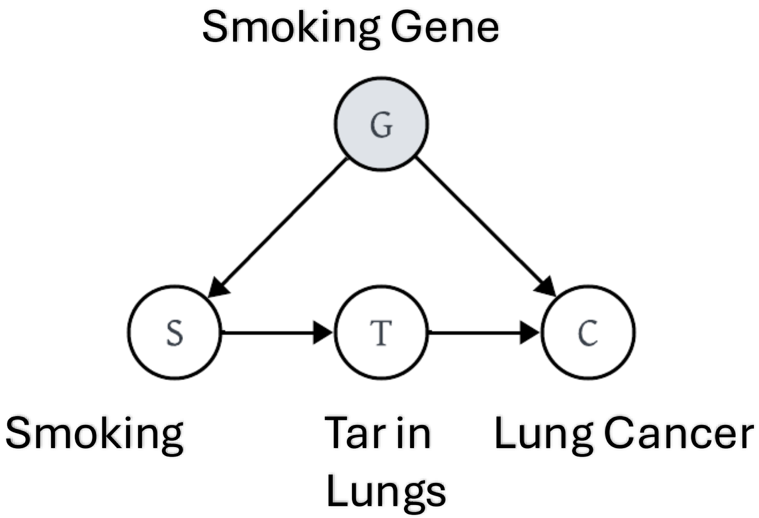

Causal effect of smoking on Lung cancer,

$$P(C|do(S)) = ?$$

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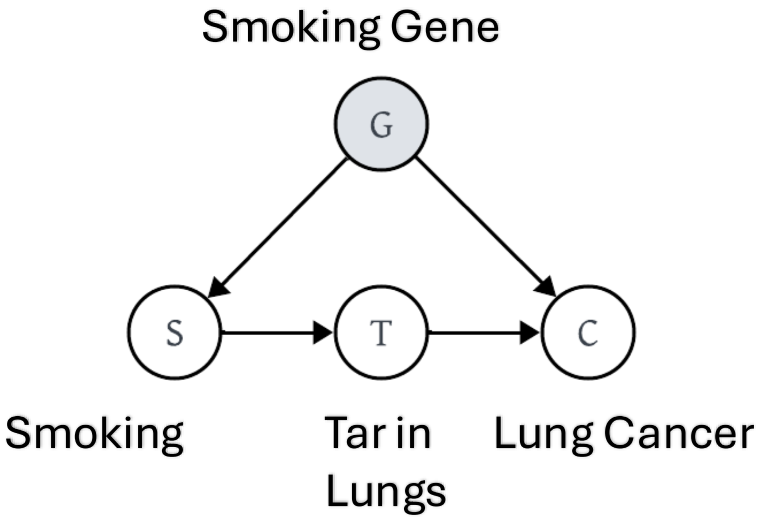

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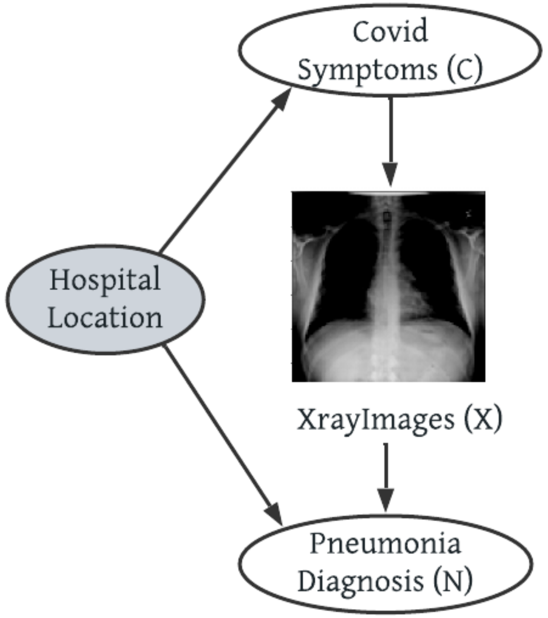
Identification algorithms [1]

$$P(C|do(S)) = \sum_{T} P(T|S) \sum_{S'} P(C|S', T) P(S')$$

High dimensional interventional sampling

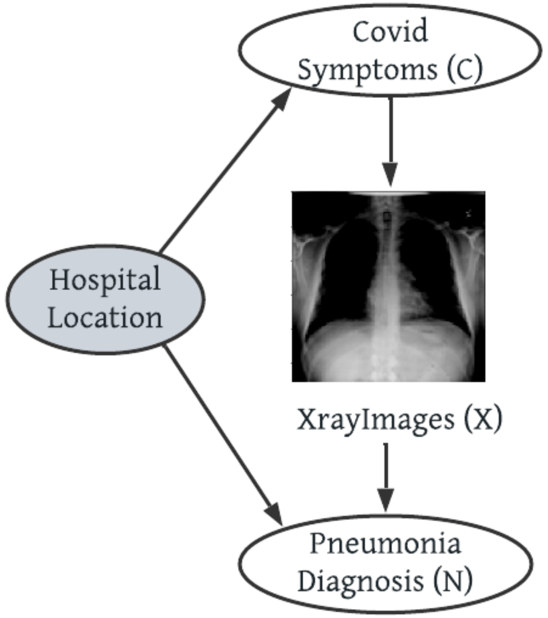


COVIDx CXR-3 dataset

$$P(N|do(C)) = \sum_X P(X|C) \sum_{C'} P(N|X, C')P(C')$$

High dimensional interventional sampling

- P(X|C)= ? 🙁
- Train a conditional model G_X ? $X \sim G_X(C)$. 😎



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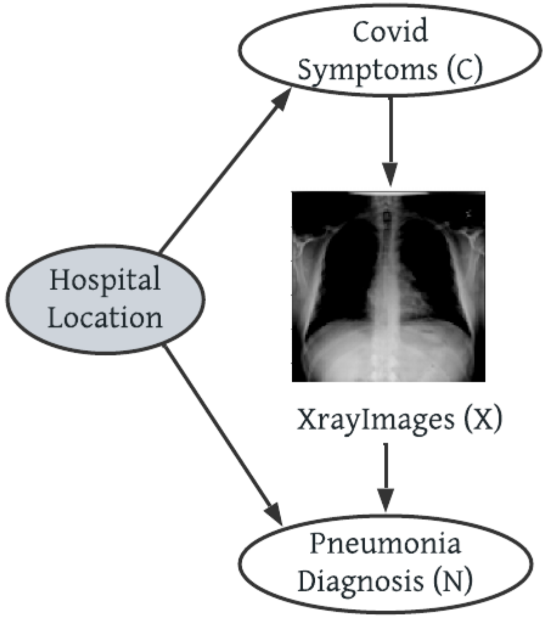


COVIDx CXR-3 dataset

- Conditional distributions:
- Interventional distributions: P(N|do(C)) or P(M|do(V))?

$$P(N|do(C)) = \sum_{X} P(X|C) \sum_{C'} P(N|X,C')P(C')$$

An approach to sample from high-dimensional interventional distribution!

Problem Definition

- Input:
  - Observational training data
  - A causal graph
- Goal:
  - Perform an intervention do(X=x)
  - Estimate numeric values of the causal effect.
  - Or Sample from the high-dimensional interventional distribution
  - .

$$do(X = x) \qquad P(y|do(x)) \qquad Y \sim P(y|do(x))$$

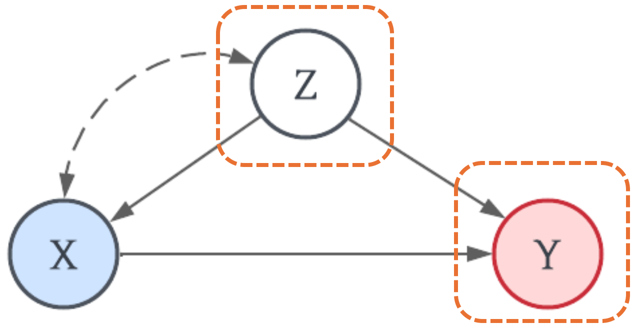
We propose ID-GEN
a sampling version of the Identification algorithm
for semi-Markovian causal models
using conditional generative models.

ID-GEN: Proposed Approach

- First, we decompose the interventional sampling problem into multiple sub-problems based on c-components.

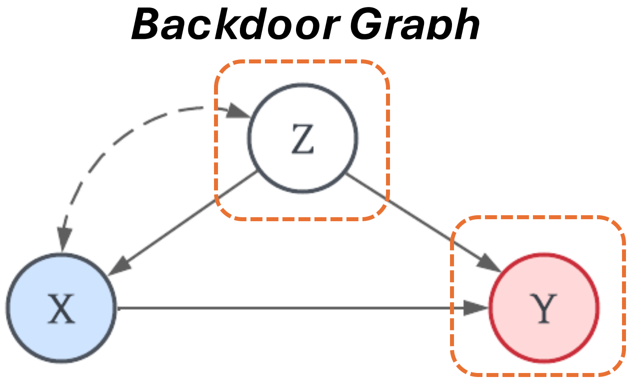
$$\textbf{if } C(G \setminus \mathbf{X}) = \{S_1, \ldots, S_k\} \textbf{ then } \{\text{Step 4}\}$$
$$\quad \textbf{for } \boxed{\text{each } S_i} \in C(G \setminus \mathbf{X}) = \{S_1, \ldots, S_k\} \textbf{ do}$$
$$\qquad \mathcal{H}_i \textbf{=ID-GEN}(S_i, \mathbf{X} = \mathbf{V} \setminus S_i, G, \hat{\mathbf{X}}, \hat{G}, \mathcal{D})$$

Backdoor Graph



$$P(y|do(x)) = \sum_z \boxed{P(z|do(x))}\,\boxed{P(y|do(x,z))}$$

ID-GEN: Proposed Approach



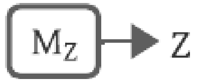
- Next, we train a set of conditional models for each factor.

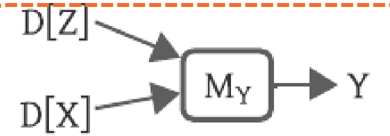
Algorithm 2 `ConditionalGMs`$(\mathbf{Y}, \mathbf{X}, G, \mathcal{D}, \hat{\mathbf{X}}, \hat{G})$

for each $V_i \in \{\mathbf{X} \cup \hat{\mathbf{X}}\}$ **do**
  Add node $(V_i, \emptyset)$ to $\mathcal{H}$ {Initialized $\mathcal{H} = \emptyset$}
for each $V_i \in \mathbf{Y}$ in the topological order $\pi_{\hat{G}}$ **do**
  Let M_{V_i} be a model trained on $\mathcal{D}[V_i, V_\pi^{(i-1)}]$ such that $M_{V_i}(V_\pi^{(i-1)}) \sim P(v_i | v_\pi^{(i-1)})$
  Add node (V_i, M_{V_i}) to $\mathcal{H}$
  Add edge $V_j \to V_i$ to $\mathcal{H}$ for all $V_j \in V_\pi^{(i-1)}$
Return $\mathcal{H}$.

$$P(z|do(x))$$

$$[Z] \sim P(Z)$$



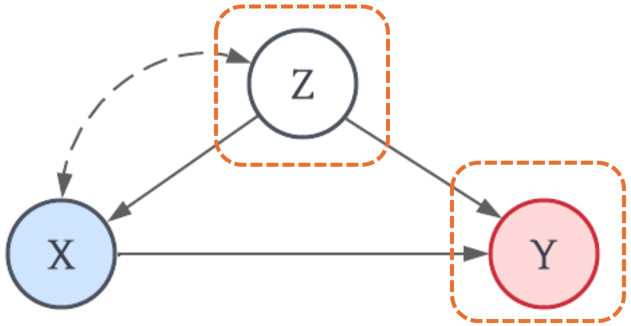


$$[Y] \sim P(Y|X, Z)$$

$$P(y|do(x, z))$$

ID-GEN: Proposed Approach

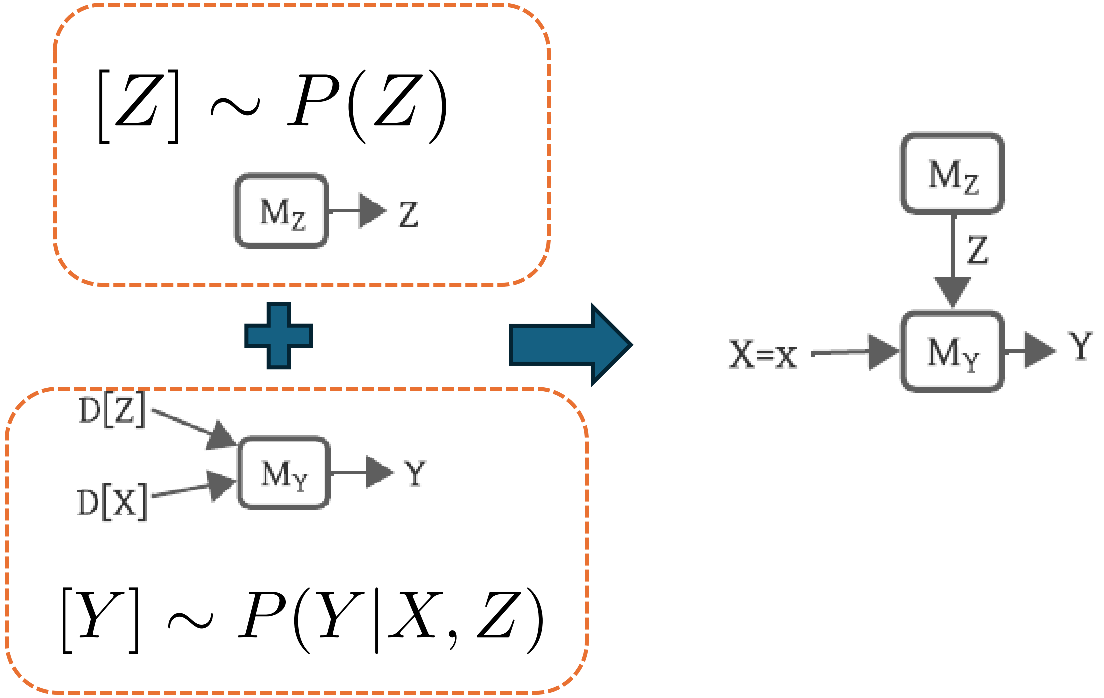
Backdoor Graph



- Finally, we connect them to build a neural network called sampling network.

Algorithm 3 $\texttt{MergeNetwork}(\{\mathcal{H}_i\}_{\forall i})$

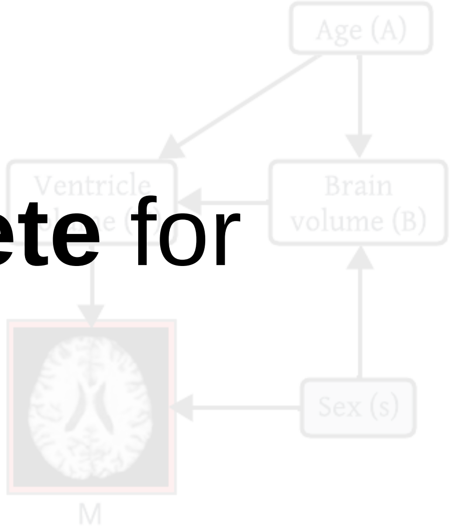
Input: Set of sampling networks $\{\mathcal{H}_i\}_{\forall i}$.
Output: A connected DAG sampling network $\mathcal{H}$.
for $H_i \in \{\mathcal{H}_i\}_{\forall i}$ **do**
  for $M_{V_j} \in \mathcal{H}_i$ **do**
    if $M_{V_j} = \emptyset$ and $\exists M_{V_k} \in \mathcal{H}_r, \forall r$ such that $V_j = V_k$ and $M_{V_k} \neq \emptyset$ **then**
      $M_{V_j} = M_{V_k}$
Return $\mathcal{H} = \{\mathcal{H}_i\}_{\forall i}$ {All $\mathcal{H}_i$ are connected.}



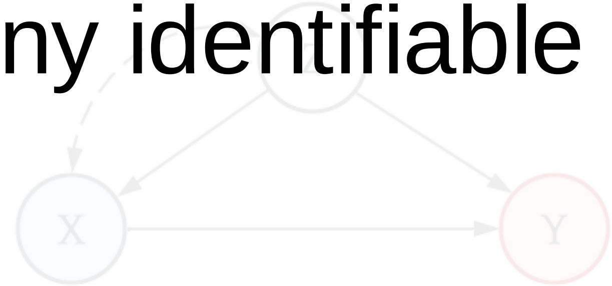
We can generate interventional samples!

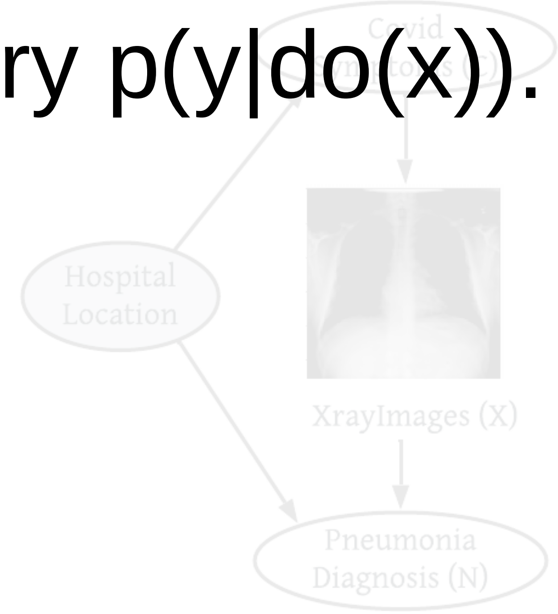
$$[Z, Y] \sim P(Z) * P(Y|X, Z)$$

Can we always do this?



Theorem: ID-GEN is **sound and complete** for any identifiable query p(y|do(x)).





Fairness: CelebA Image to Image Translation.

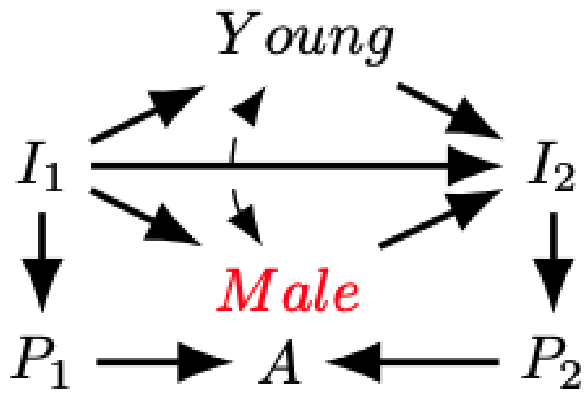
- Assess large generative models for the Male to the Female domain translation task.
- Translation: Causal or spurious?
- Correlation among different attributes learned by models.

CelebA Image to Image Translation:

- Original image I_1
- Edited image I_2 based on sex and age.
- All attributes of I_1 and I_2.
- A: new additional attributes (ex: Makeup)

- What is the causal effect of changing the Male domain to the Female domain on the appearance of a new attribute?

  $P(A|do(Male = 0))$.



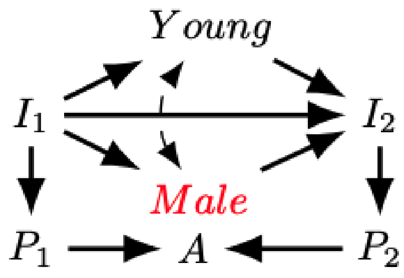
Conditional Generative Models are Sufficient to Sample from Any Causal Effect Estimand

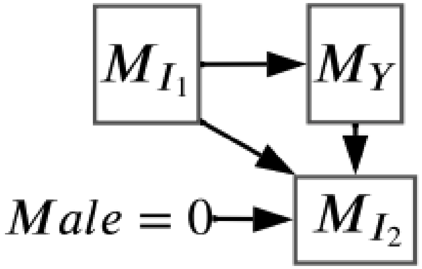
$$P(I_2|Do(Male = 0)) =$$

$$\int_{Young, I_1} P(I_2|Male = 0, Young, I_1)P(Young, I_1)$$

$$\boxed{I_1 \sim M_{I_1}}, \boxed{Young \sim M_Y(I_1)}$$

$$I_2 \sim M_{I_2}(Male = 0, Young, I_2)$$

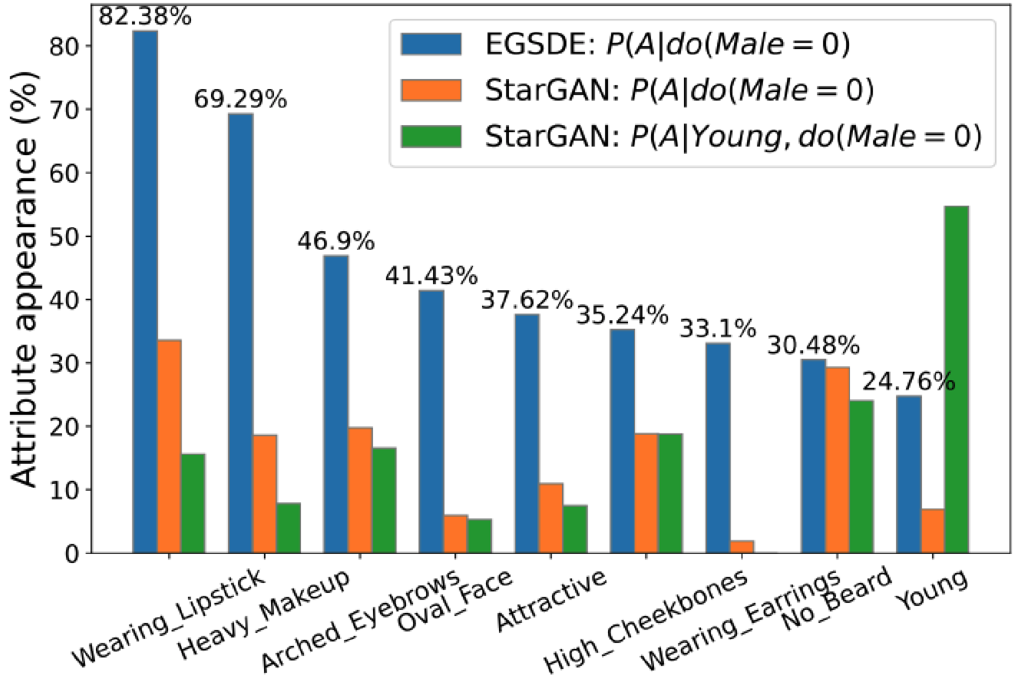




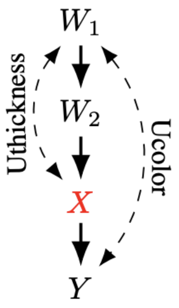
- For M_{I_2} use the following generative models:
  - EGSDE [4]
  - StarGAN [5]

Observations

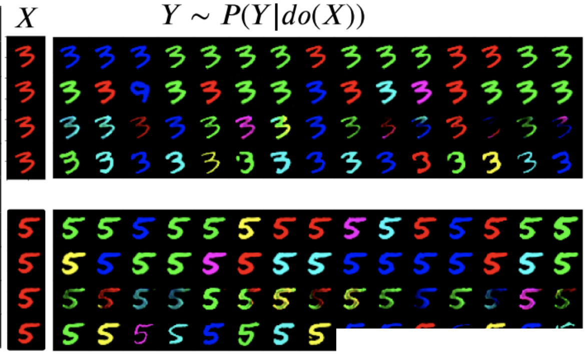
- EGSDE adds
  - Causal
    - WearingLipstick attribute to 82%.
    - HeavyMakeup: 69.28%
  - Non-causal
    - Attractive(37.61%) ?
    - Young(24.76%) ?



ID-GEN for Spurious Correlation & Explainability

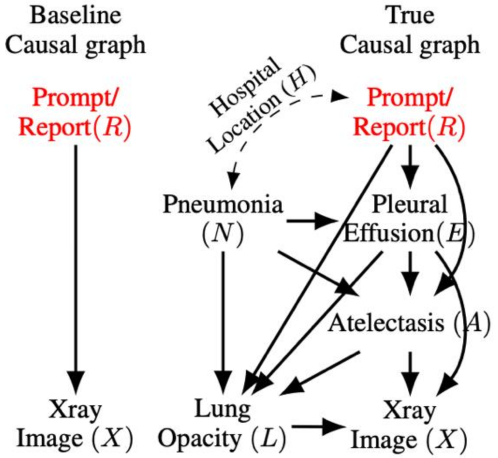


		FID ↓
$X=3$	Cond	50.83
	DCM	66.57
	NCM	61.11
	Ours	**25.66**
$X=5$	Cond	41.35
	DCM	60.61
	NCM	71.50
	Ours	**22.67**



Color	True $P_x(y)$	Cond	DCM	**Ours**
R	0.17	0.17	0.24	**0.13**
G	0.17	0.45	0.27	**0.24**
B	0.17	0.15	0.28	**0.21**
Yw	0.17	0.19	0.05	**0.14**
Mg	0.17	0.02	0.07	**0.11**
Cy	0.17	0.10	0.09	**0.18**
TVD	0	0.54	0.58	**0.25**

Figure 4: (Left:) Causal graph with color and thicl
the better) of each algorithm and images generatec
the $P_x(y)$ images generated by each algorithm. W



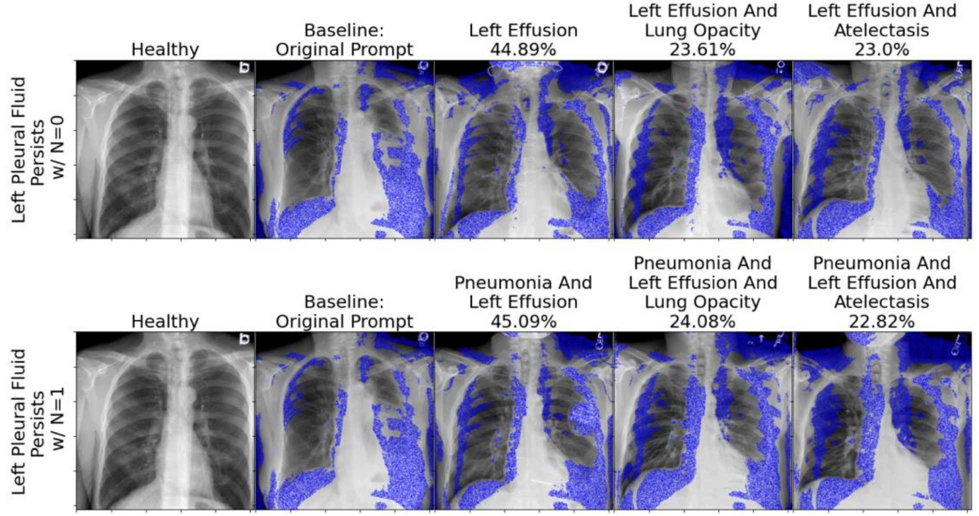


Figure 6: Left: Baseline vs our causal graph. Right: images for specific prompt w/ and w/o pneumonia. Inferred attributes are shown with their likelihood. Blue indicates changes compared to healthy.

Takeaway!

- Given observational data and a causal graph,
- Conditional generative models are **indeed** sufficient to sample from any causal effect estimand.

- Codes are available at: github.com/musfiqshohan/IDGEN

Thank you!

References

- [1] Shpitser, Ilya, and Judea Pearl. "Complete identification methods for the causal hierarchy." *Journal of Machine Learning Research* 9 (2008): 1941-1979
- [2] Ho, Jonathan, and Tim Salimans. "Classifier-free diffusion guidance." *arXiv preprint arXiv:2207.12598* (2022).
- [3] Jung, Yonghan, Jin Tian, and Elias Bareinboim. "Learning causal effects via weighted empirical risk minimization." *Advances in neural information processing systems* 33 (2020): 12697-12709.
- [4] Ribeiro, Fabio De Sousa, et al. "High Fidelity Image Counterfactuals with Probabilistic Causal Models." (2023).
- [5] Pearl, Judea. "The do-calculus revisited." arXiv preprint arXiv:1210.4852 (2012).
- [6] Report to Xray generation: Chambon, Pierre, et al. "Roentgen: Vision-language foundation model for chest x-ray generation." arXiv preprint arXiv:2211.12737 (2022).
- [7] Report to symptoms extraction: Gu, Jawook, et al. "CheX-GPT: Harnessing Large Language Models for Enhanced Chest X-ray Report Labeling." arXiv preprint arXiv:2401.11505 (2024).
- [8] Invariant Prediction: Subbaswamy, Adarsh, Peter Schulam, and Suchi Saria. "Preventing failures due to dataset shift: Learning predictive models that transport." The 22nd International Conference on Artificial Intelligence and Statistics. PMLR, 2019.
- [9] Lee, Kenneth, Md Musfiqur Rahman, and Murat Kocaoglu. "Finding invariant predictors efficiently via causal structure." Uncertainty in Artificial Intelligence. PMLR, 2023.