Generating Counterfactuals for Fairness using VAE

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MAX PLANCK INSTITUTE
FOR SOFTWARE SYSTEMS

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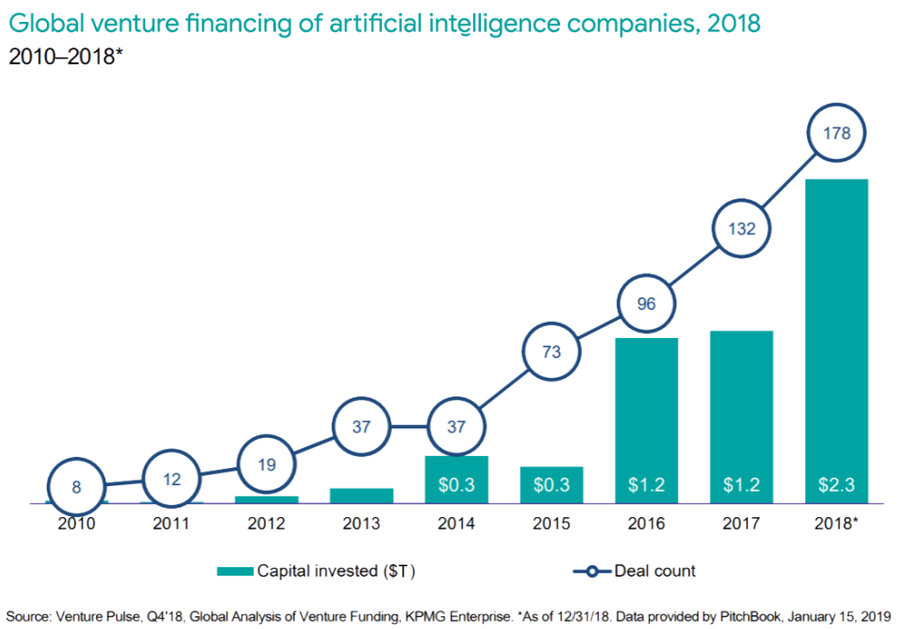
ML and our society

Data-driven ML algorithms **heavily** deployed in today's tech industry.



Increased industry financing for AI and ML

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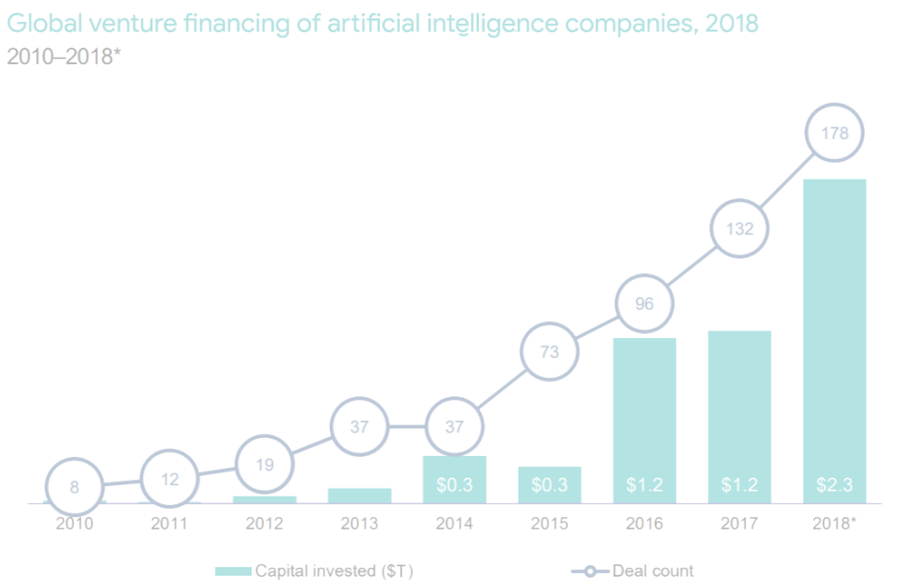
Data-driven ML algorithms more **pervasive** in today's society.



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PredPol
Predict Crime in Real Time.
PredPol provides targeted, real-time crime prediction designed for and successfully tested by officers in the field.

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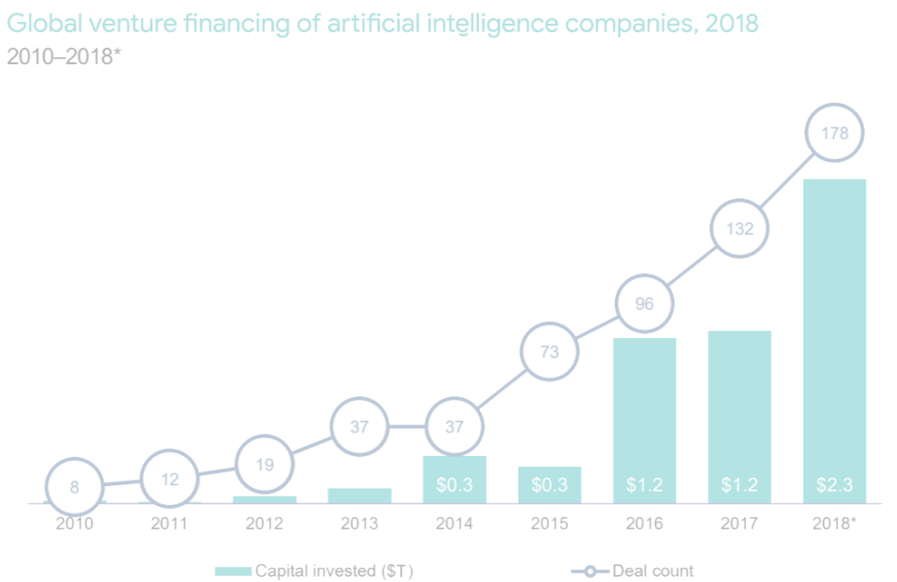

Source: Venture Pulse, Q4'18, Global Analysis of Venture Funding, KPMG Enterprise. *As of 12/31/18. Data provided by PitchBook, January 15, 2019

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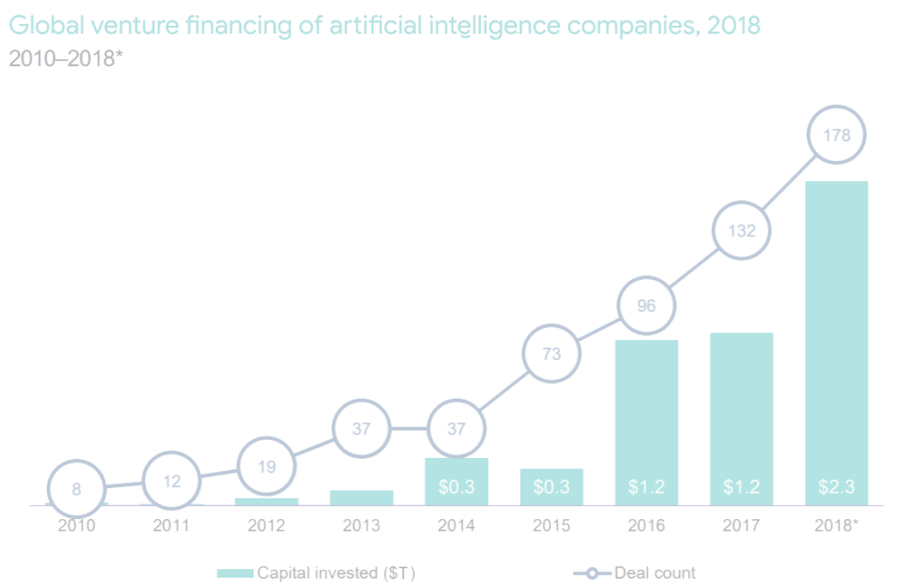

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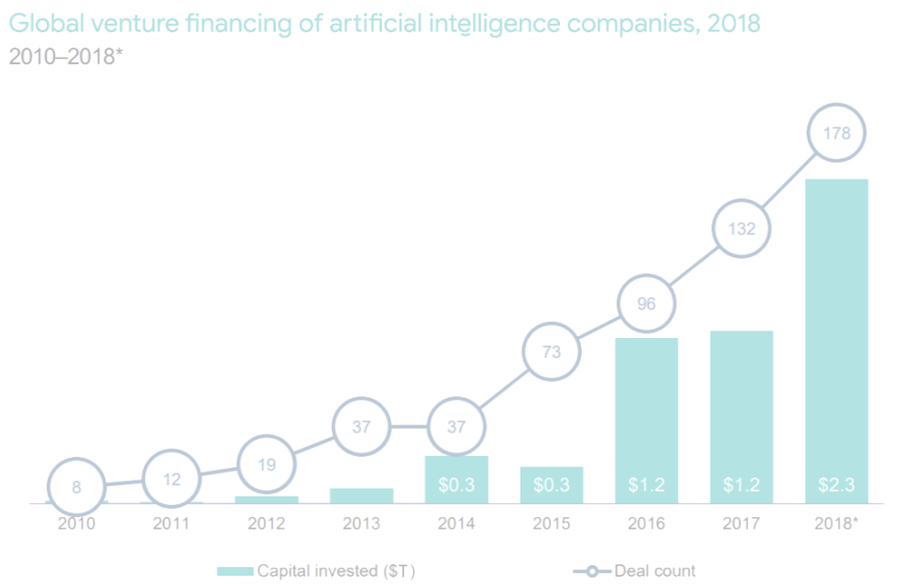


Increased industry financing for AI and ML

Fairness in ML systems

Studies have shown potential **bias** in deployed systems!

Business

Apple Card algorithm sparks gender bias allegations against Goldman Sachs

Entrepreneur David Heinemeier Hansson says his credit limit was 20 times that of his wife, even though she has the higher credit score

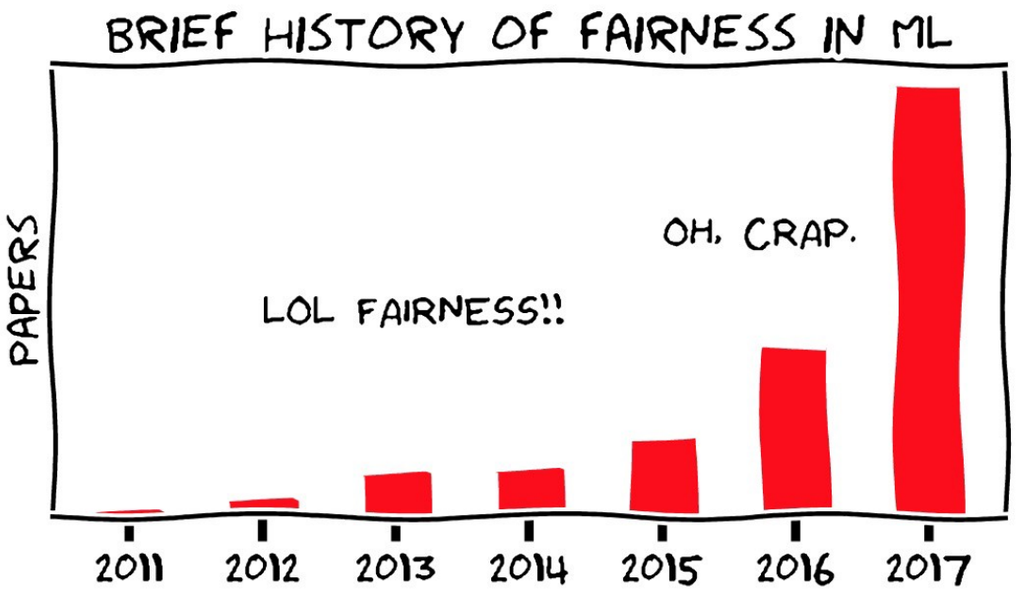
Why Amazon's Automated Hiring Tool Discriminated Against Women

By Rachel Goodman, Staff Attorney, ACLU Racial Justice Program
OCTOBER 12, 2018 | 1:00 PM

TAGS: Women's Rights in the Workplace, Women's Rights, Privacy & Technology

Fairness in ML systems

Led to **extensive** research in the domain…



Credits: Moritz Hardt, CS 294-Fairness in Machine Learning

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Existing notions of fairness

Many definitions

- Group: *Fairness through unawareness, demographic parity, etc.*
- Individual: *individual fairness*

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However…

- How sensitive attributes **cause** bias?
- How to **eliminate** bias?
- How to define **similar** individuals (*individual fairness*)?

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Not clear!

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Such questions of fairness need **counterfactual data**!

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Counterfactuals, simply[1]

- **Change** Jacob's race
- Keep everything else **same**
- **Evaluate** decision outcome

[1] *Greiner et.al., "Causal effects of perceived immutable characteristics", The Review of Economics and Statistics, 2011*

Counterfactuals, ~~simply~~[1]

not so simple!

Simple approach[1]:

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Not enough!

- Very **limited** analysis
- No account for historical **bias** → data bias
  - *E.g. redlining affecting education*[2]

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How do we estimate **bias caused** by **race**?

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Need data **generative** process

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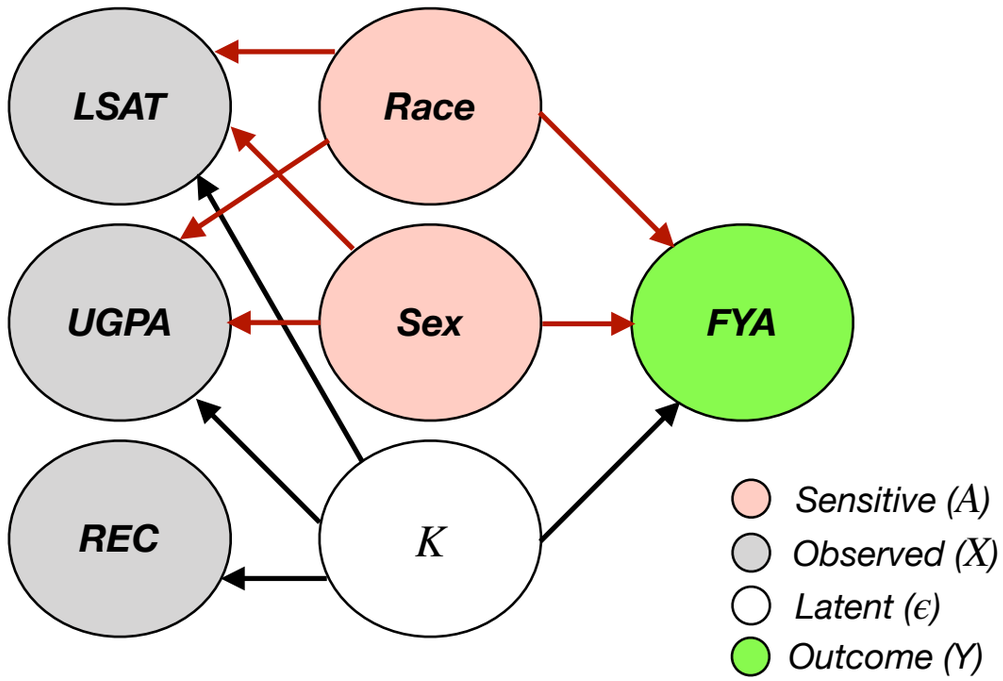
Causal models

Causal models

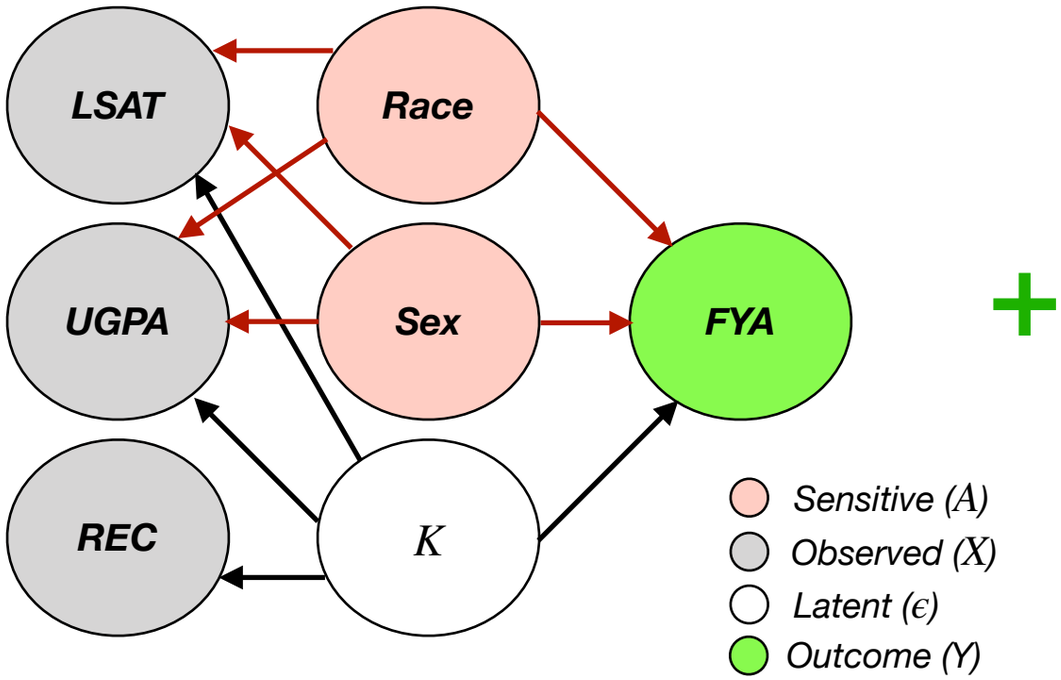
Causal graph



Relations between the features

Causal models

Causal graph



+

Structural equations

$$\textbf{LSAT} := \mathcal{N}(\exp(b_L + w_L^R R + w_L^S S + w_L^K K), \sigma_L)$$

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Relations between the features

Quantification of the relations

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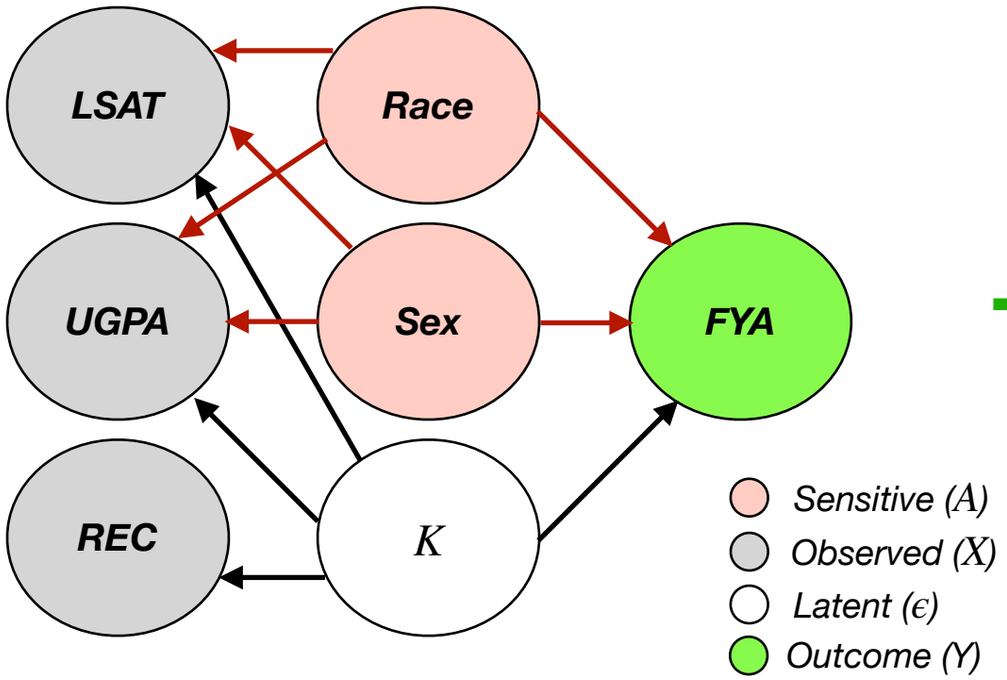

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Relations between the features

Quantification of the relations

Need **complete** access! **Infeasible** in real settings.

Research Question

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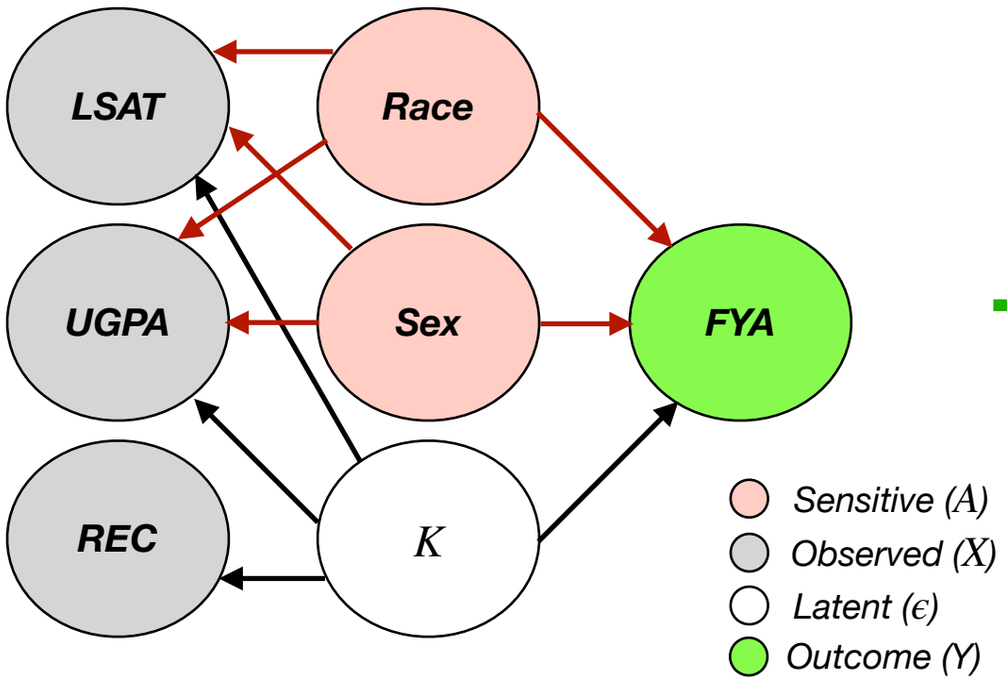
2. Can we use our approach to build a **fair** predictive model?

Background: Causal counterfactuals

Causal graph



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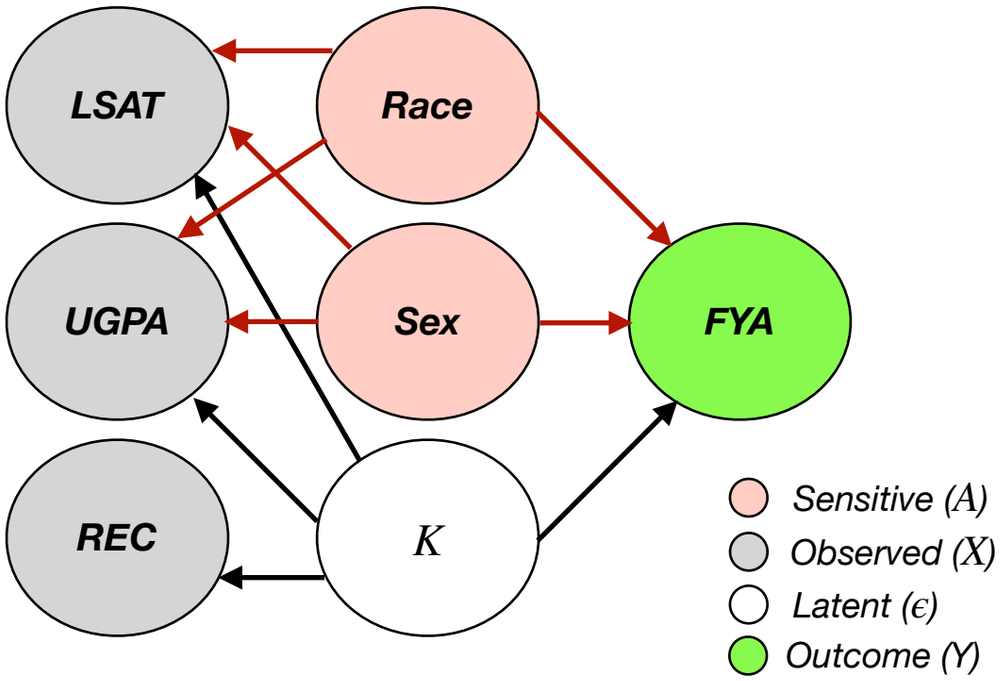
Counterfactuals from causal model[1]



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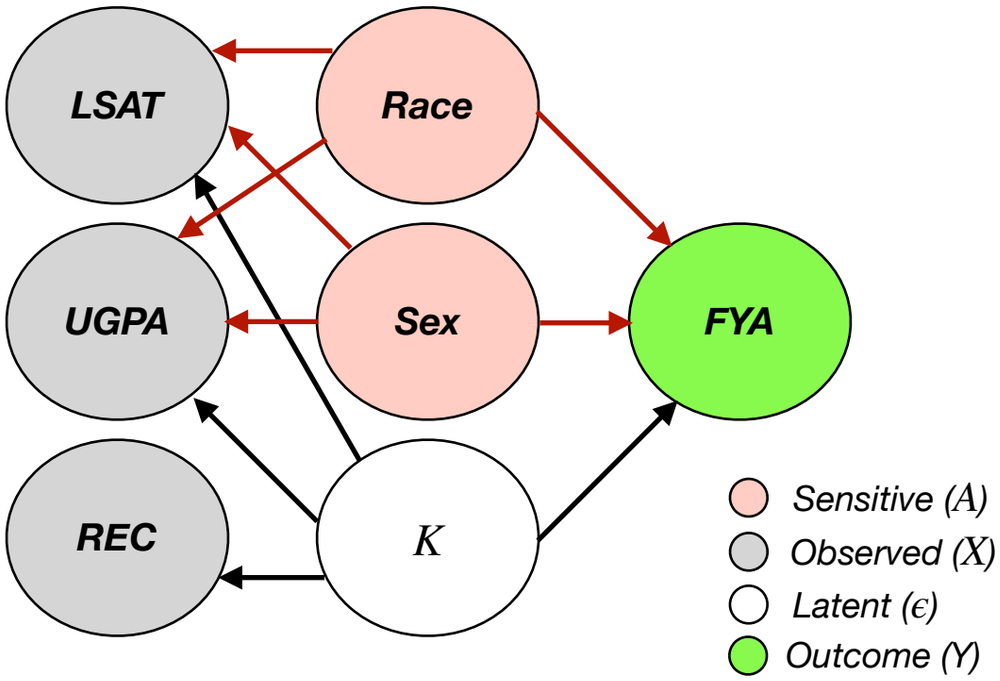

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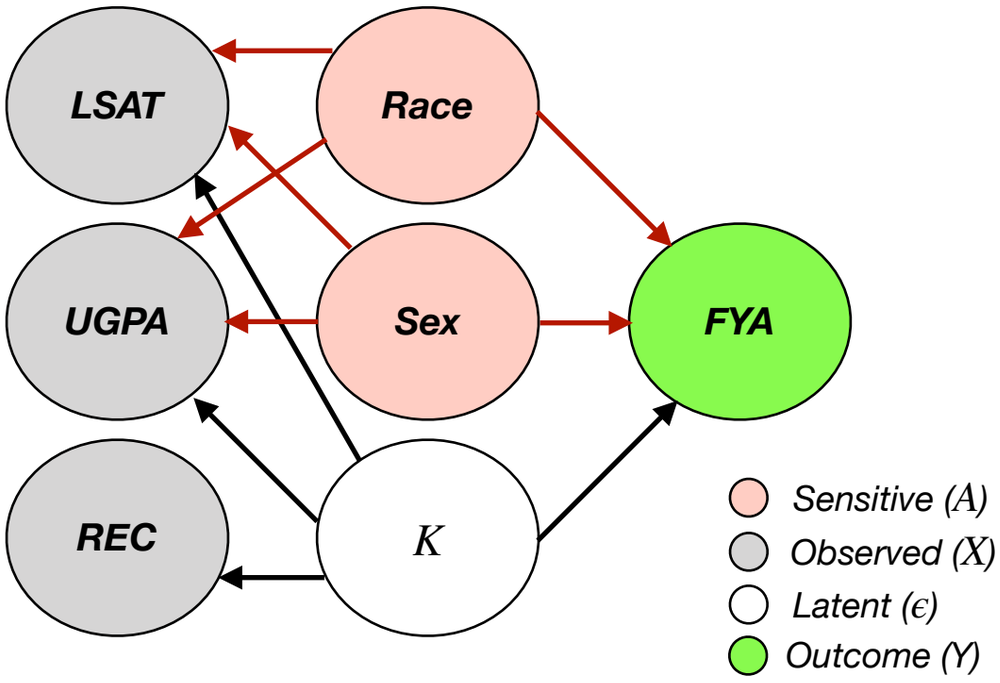

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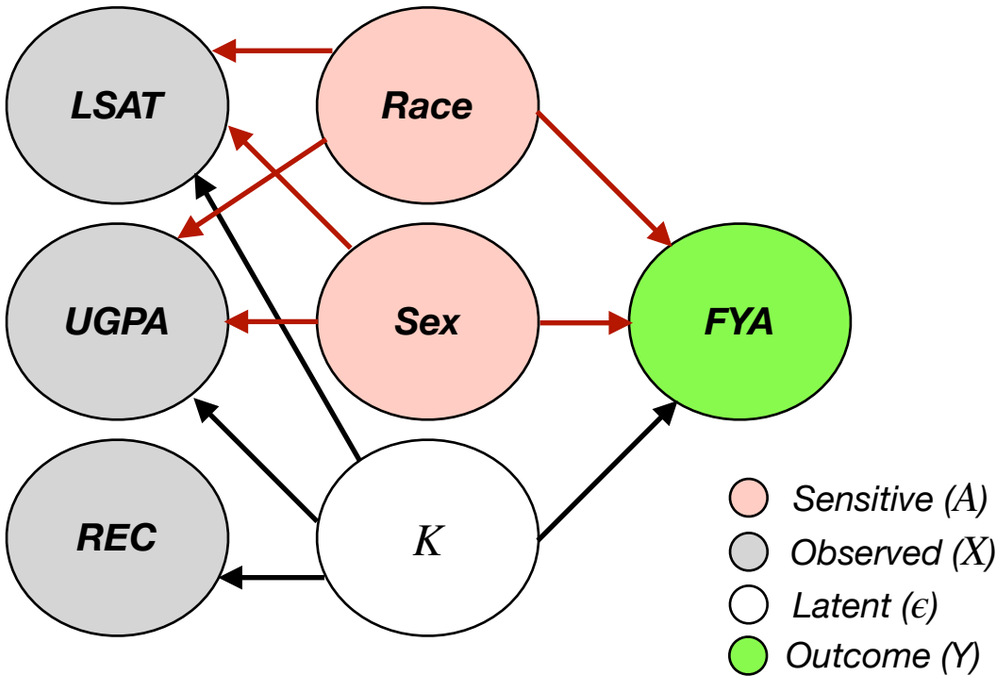

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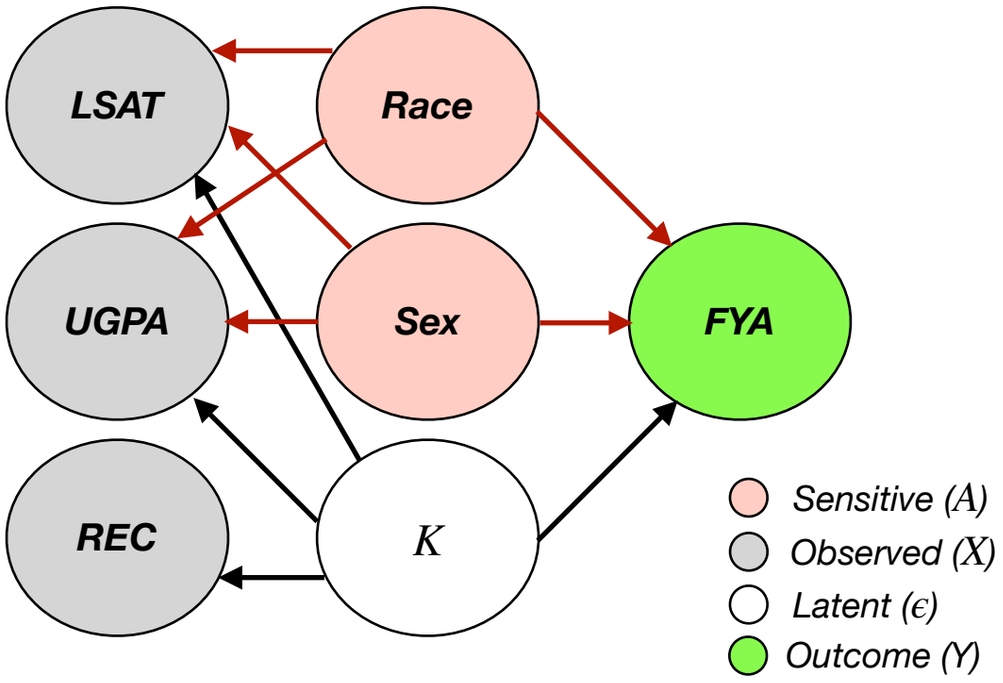

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How to approximate in the absence of whole causal model?

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Assumptions

✗ **Problem:** No access to complete causal model

- Exact *causal graph* over all features **not known**

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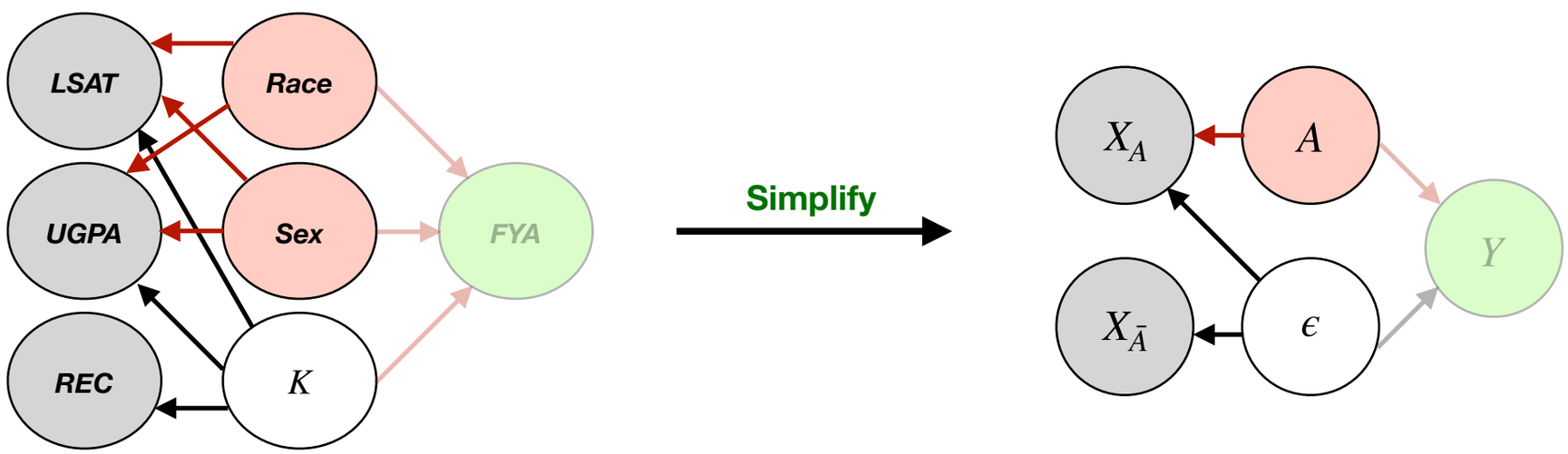
✓ **Simplify** assumptions on data generative process

- A are *root* nodes
- A can *affect* some features (X_A) or not ($X_{\bar{A}}$)
- Latent ϵ *affect* features X independent of A



Modeling

✗ **Problem:** No access to complete causal model

- Exact *structural equations* of all features **not known**

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✓ **Model** by approximating data generative process

- Use variational generative model *(Conditional VAE)*
- Learn generative process conditional on A
- Estimate latent factors of data via z

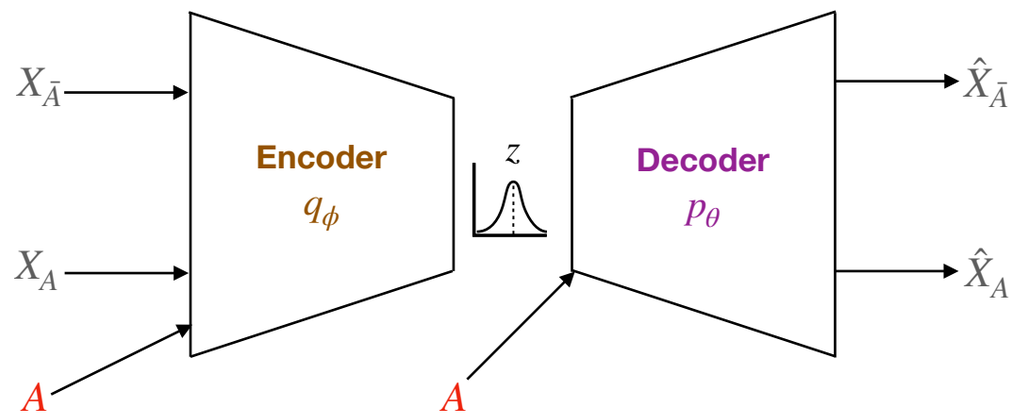
LSAT $\sim \ldots$ **UGPA** $\sim \ldots$

REC $\sim \ldots$ $\epsilon \sim \ldots$

Structural equations

Learn

from data



CVAE architecture

CVAE Model: Encoder

★ **Goal:** Learn latent distribution conditional on A given data

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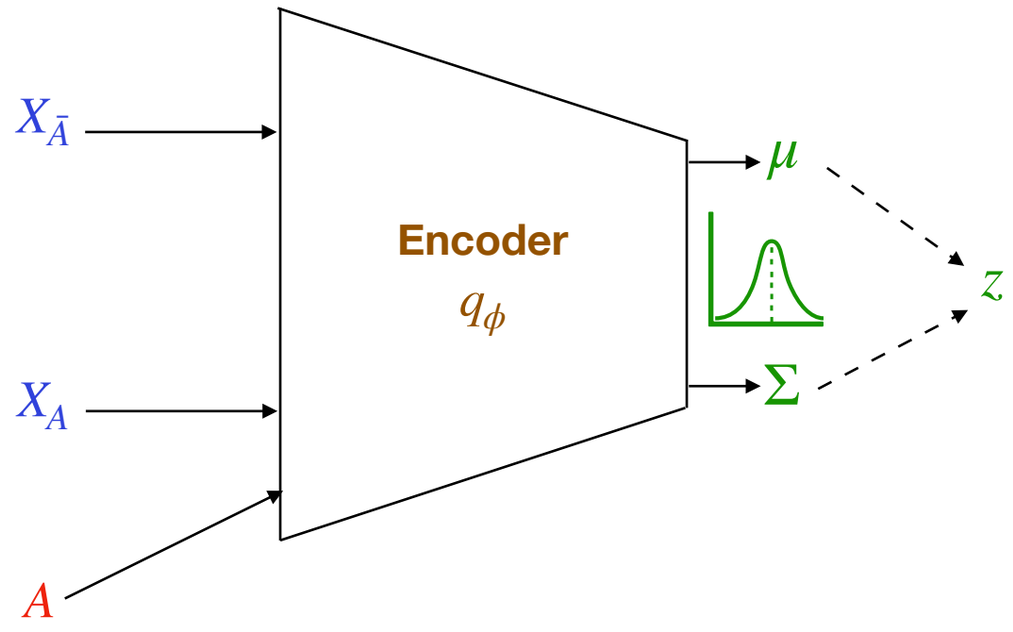
- Use **Encoder** of CVAE:
  - Deep neural net q with parameters ϕ
  - **Input**: *Data* $X_{\bar{A}}, X_A$; *Sensitive* A
  - **Output**: Latent z



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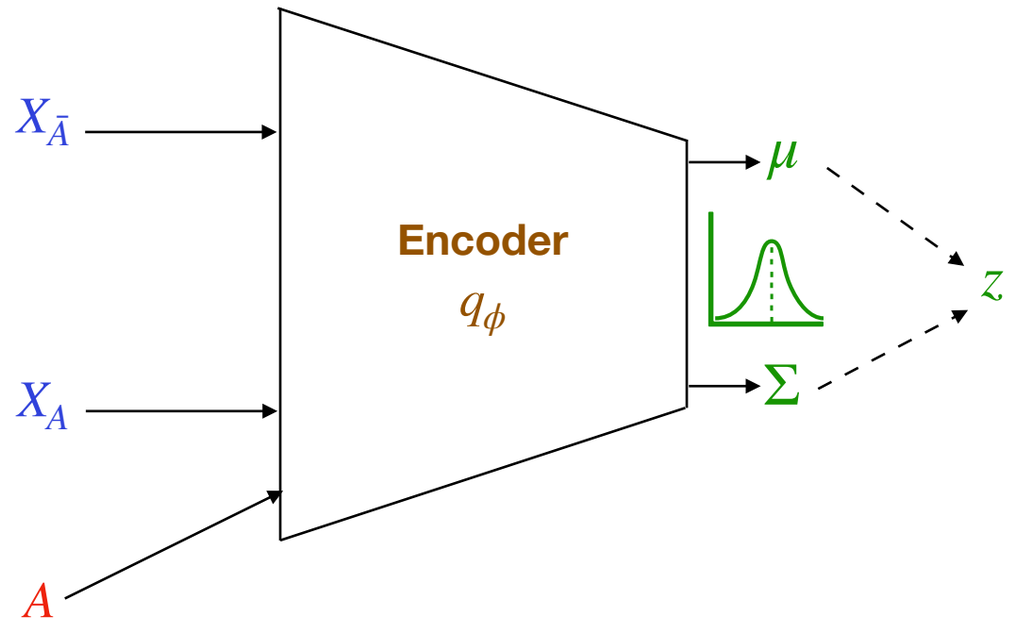
- z must match prior distribution
  - E.g. $p(z) \sim \mathcal{N}(0,1)$



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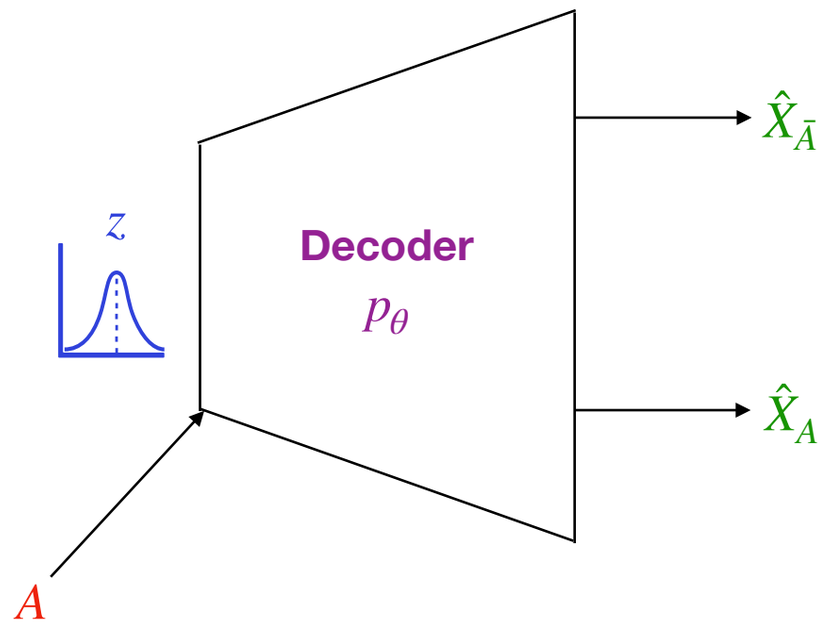
  - Output: Reconstructed data $\hat{X}_{\bar{A}}, \hat{X}_A$



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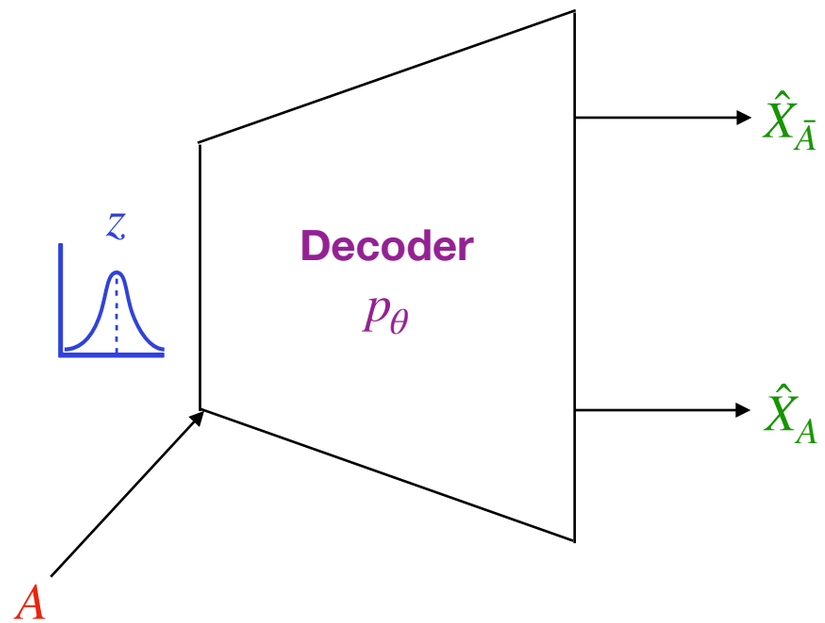

What do we optimize for?

Train models end-to-end

Evidence **L**ower **BO**und (**ELBO**) Loss

$$\log p_\theta(X \mid A) \geq \mathbb{E}_{q_\phi(z|X,A)}[\log p_\theta(X \mid z, A)] - \mathbb{D}_{KL}[q_\phi(z \mid X, A) \mid\mid p(z)]$$

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Encoder

- **Encoder**: z should match prior → *minimize KL* ***divergence***

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- **Encoder**: z should match prior → *minimize KL* ***divergence***
- **Decoder**: Estimated z should maximize data-likelihood → *minimize reconstruction* ***loss***

CVAE Counterfactuals

Causal **CVAE**

CVAE Counterfactuals

Causal

CVAE

Infer ϵ from $X, A = a$

1. Abduction

Infer z from $X, A = a$

CVAE Counterfactuals

Causal		CVAE
Infer ϵ from $X, A = a$	**1. Abduction**	Infer z from $X, A = a$
Set $A = a'$ in the graph	**2. Action**	Set $A = a'$ at decoder

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Get X from ϵ and $A = a'$	**3. Prediction**	Get X from z and $A = a'$

Counterfactual fairness

How to achieve fairness with counterfactuals?

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$$P\left(\hat{Y}_{A\leftarrow a}(\epsilon) = y \mid X = x, A = a\right) = P\left(\hat{Y}_{A\leftarrow a'}(\epsilon) = y \mid X = x, A = a\right)$$

A should not **cause** $\hat{Y}$ in any **individual** instance![1]

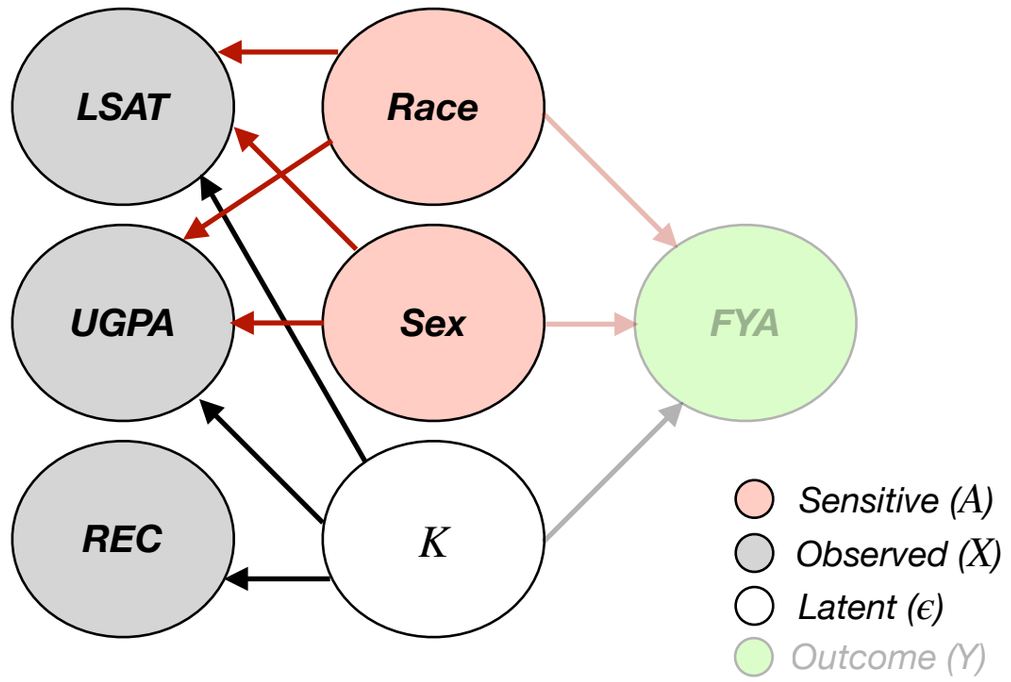
[1] *Matt J Kusner et al. "Counterfactual Fairness". In Advances in Neural Information Processing Systems 30.*

Results

How well can we approximate?

Generate counterfactuals

- **Train** CVAE on synthetic **generated data.**



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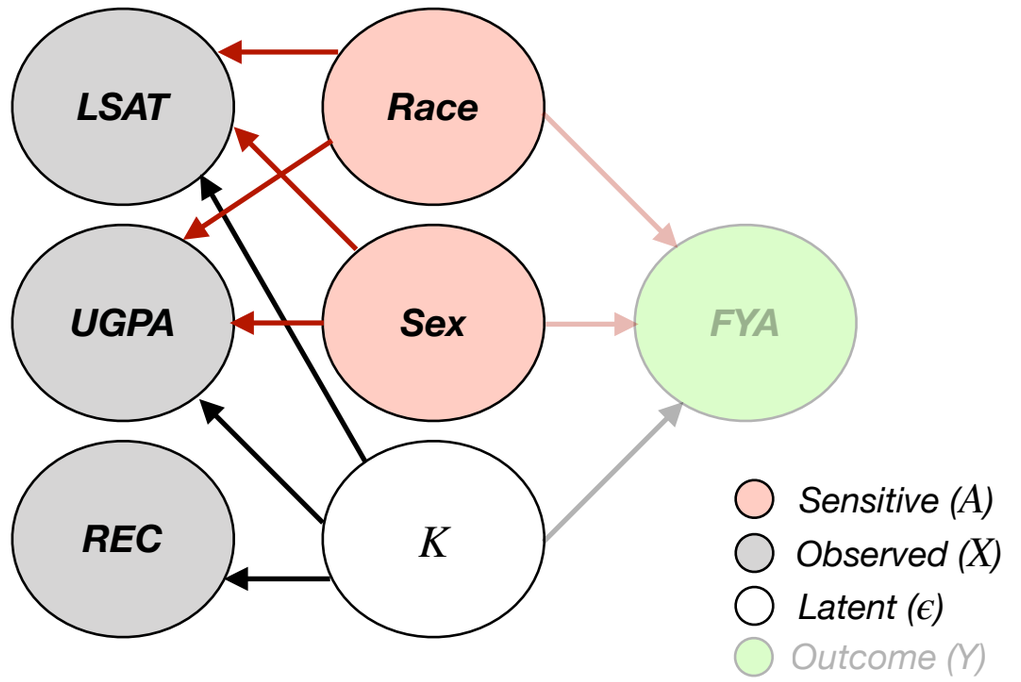

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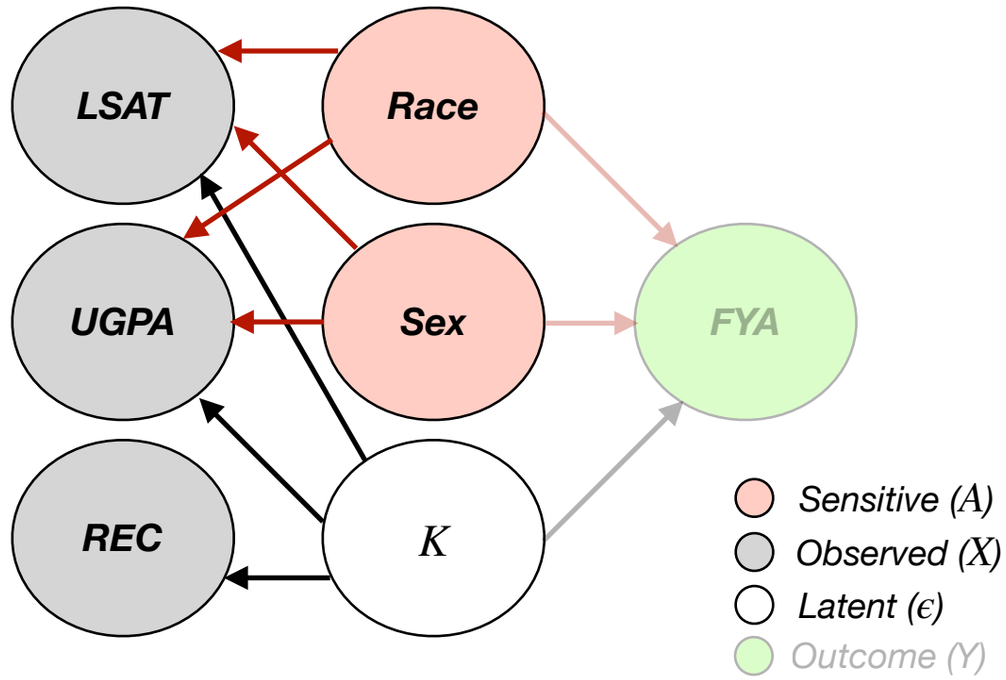

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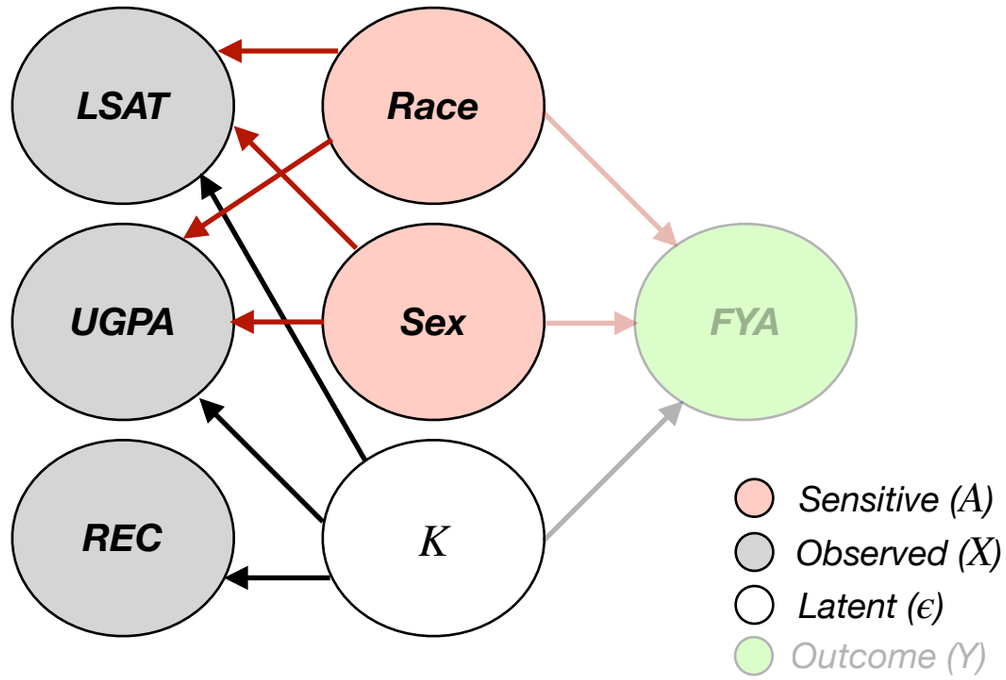

LSAT Err	UGPA Err	REC Err	Cos. Sim.
0.016	0.008	0.02	0.9998

Counterfactual generation quality (Race: White to Black).

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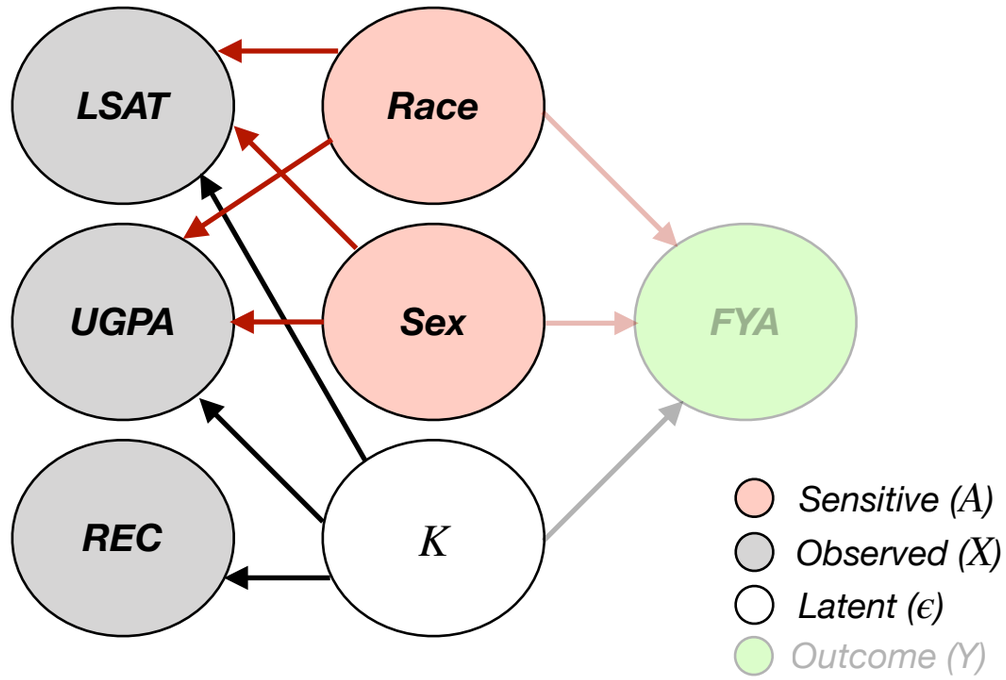

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CVAE can generate faithful counterfactuals!

Can we use generated **counterfactuals** for auditing?

Auditing setup

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  - Predict FYA score (standardized)
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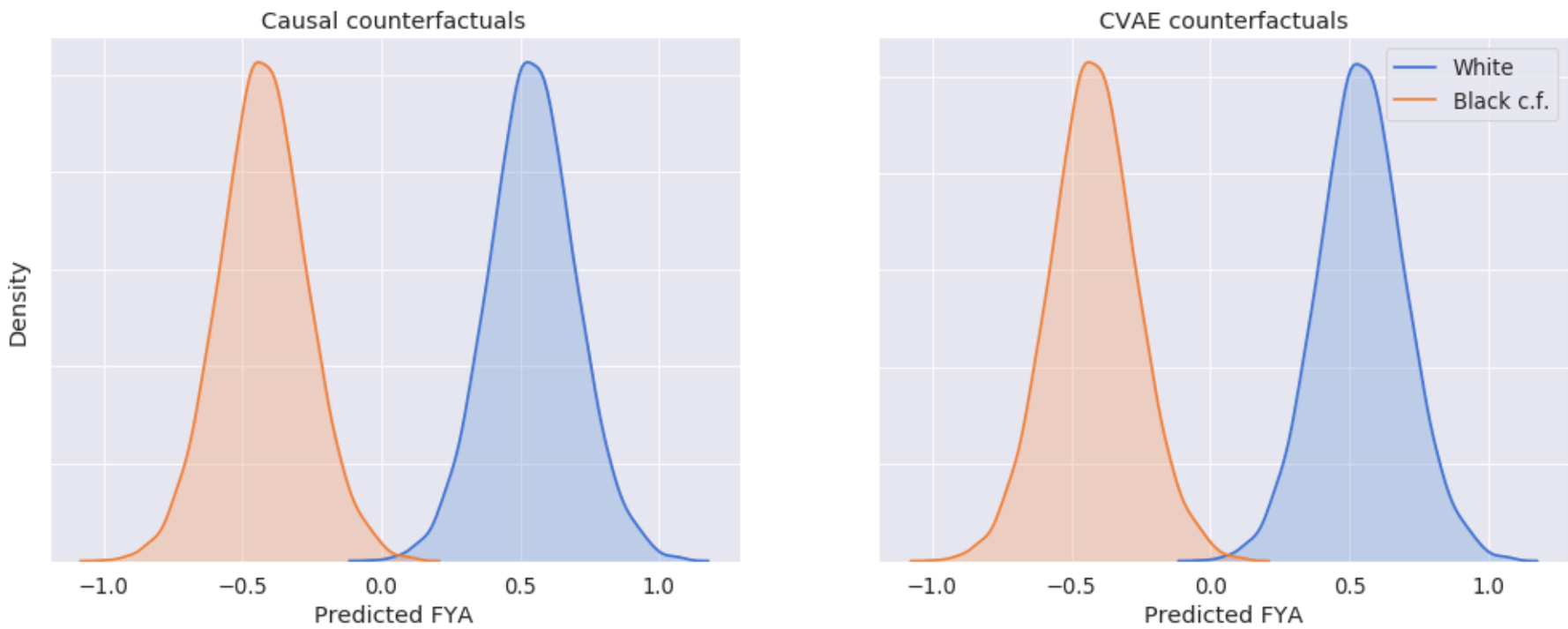
- CVAE generated counterfactuals to audit model
  - Compare with true causal auditing

Audit counterfactual fairness



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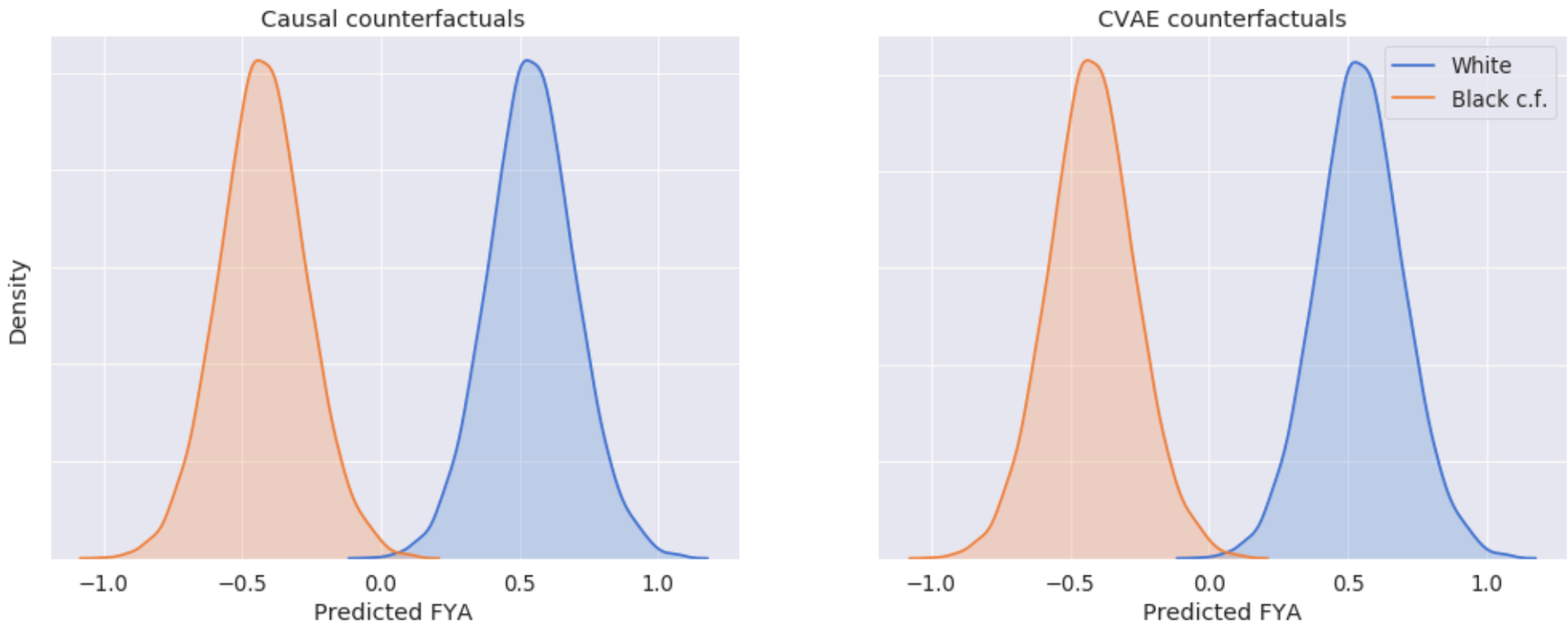

White → Black

Change in predicted scores:

Causal: ***0.97*** ↓ *; CVAE:* ***0.96*** ↓

White → Black : : Predicted score reduces!

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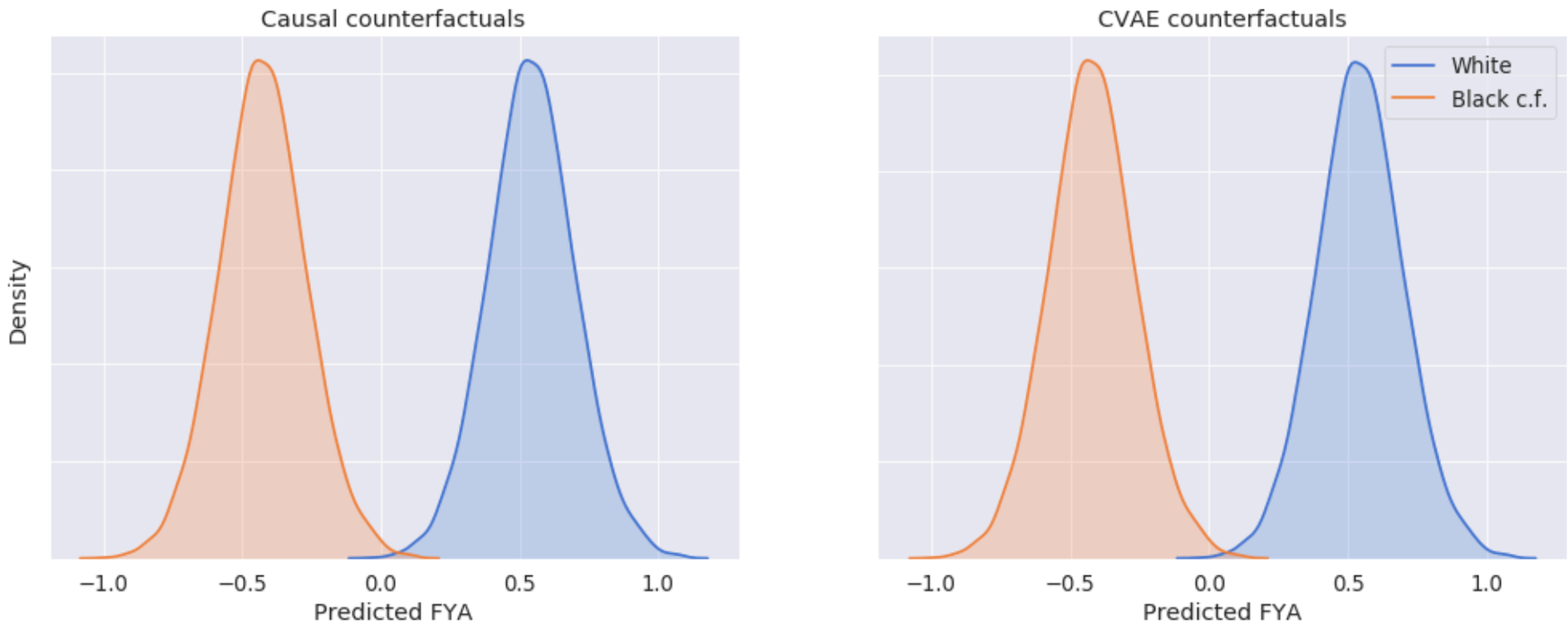

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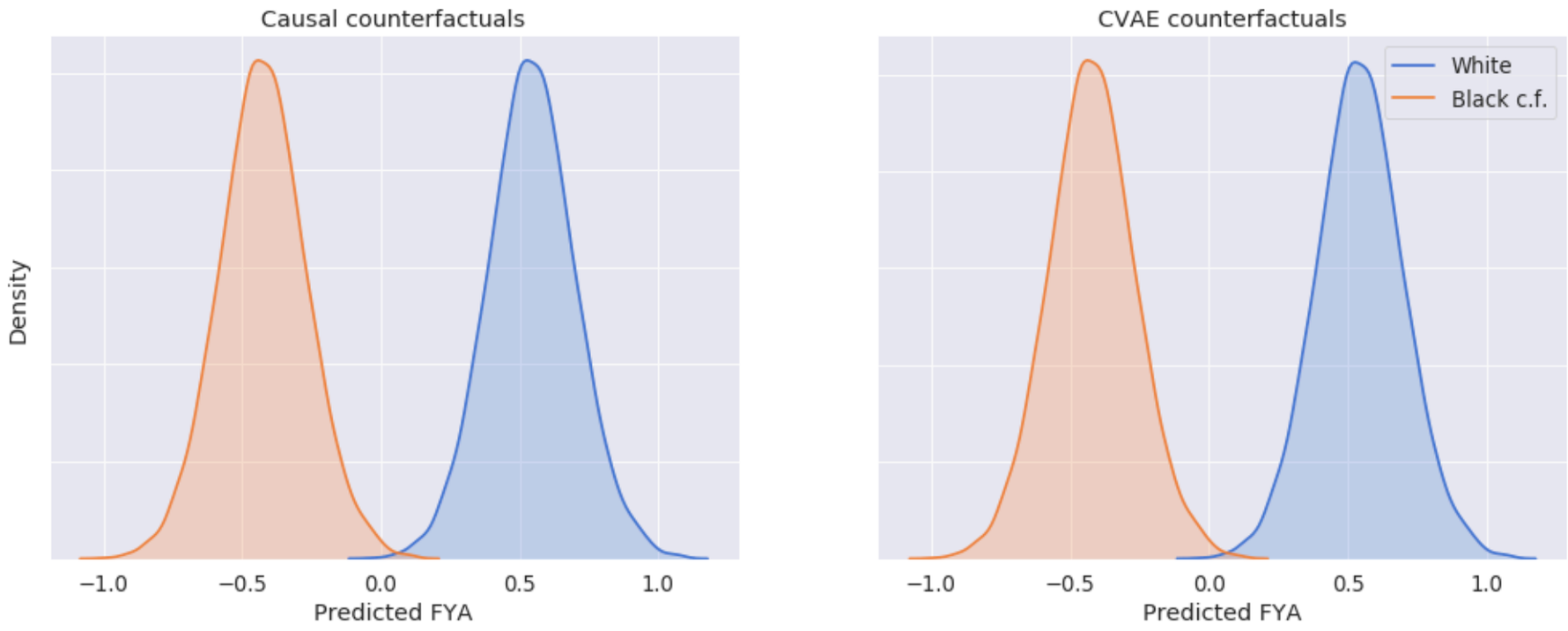

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CVAE auditing ≃ True causal auditing

Can we train a **fair** predictive system using our model?

Fair predictor setup

★ **Goal:** Train fair regression model to predict FYA

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Compare following models:

- **Aware**: Use all data features (incl. A)

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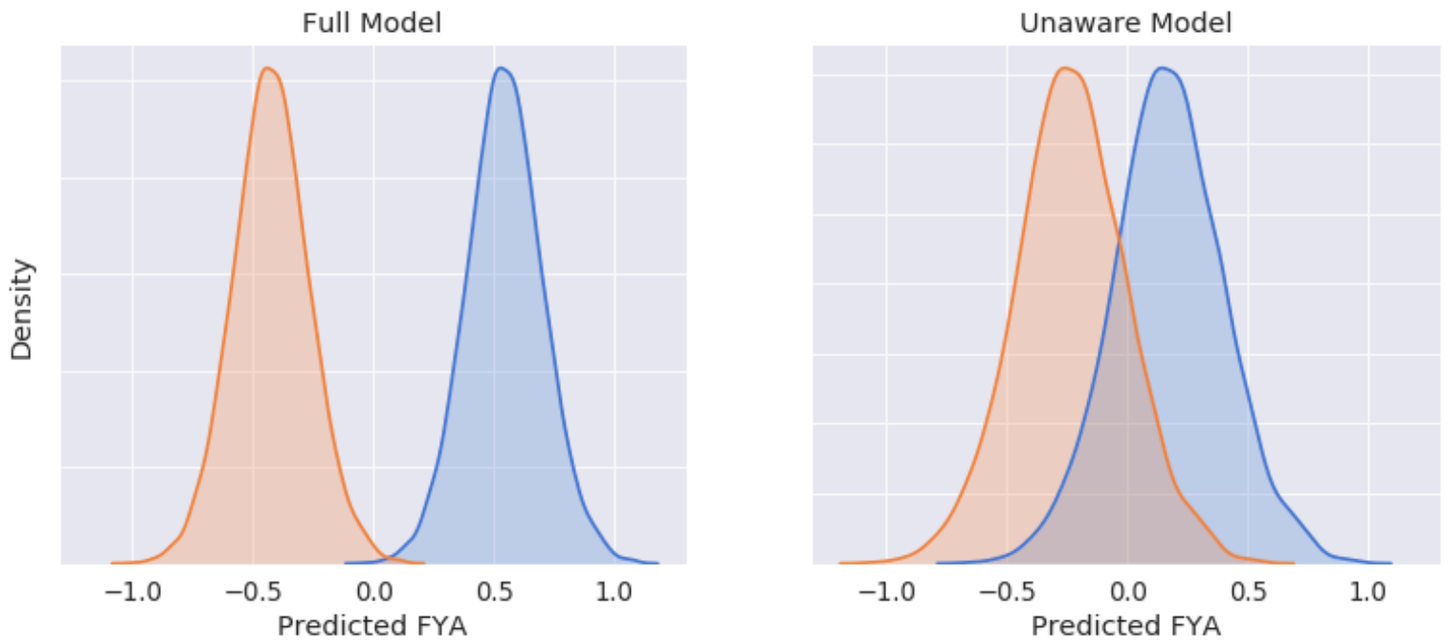
Use data and its **causal counterfactual** for testing

Training fair predictor

Training fair predictor



Distribution of predicted FYA output (White and counterfactual Black)

Model	Pred. Error (*RMSE*)	Unfairness (*Abs. Diff.*)
Full	**0.94 (very accurate)**	**0.97 (highly biased)**
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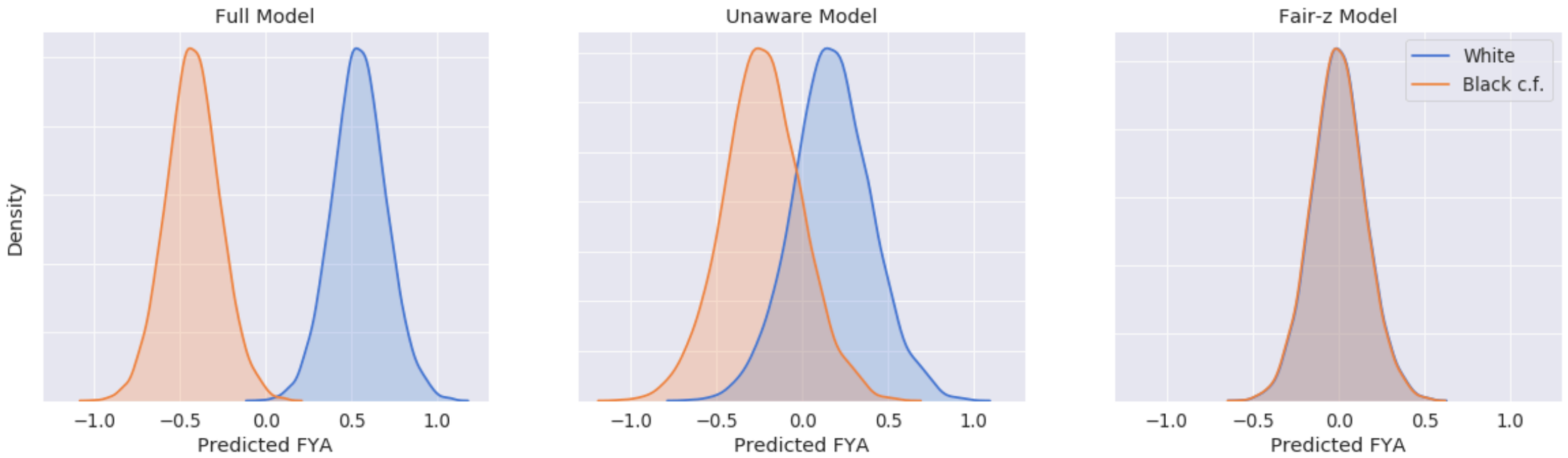
Training fair predictor



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Fair-z	**1.07 (less accurate)**	**0.003 (fair)**

Related Work

FlipTest[1]

- Use GANs to approximate optimal transport
- No causal assumptions

Variational Fair Autoencoders[2]

- Representation learning to achieve demographic parity
- Use outcome label to encode representation

Fairness through Causal Awareness[3]

- VAE in causal setup
- Learns fair treatments w.r.t. outcome

[1] *Emily Black et al. “FlipTest: fairness testing via optimal transport”: 2020 Conference on Fairness, Accountability and Transparency*
[2] *Christos Louizos et al. "The Variational Fair Autoencoder": 2016 International Conference on Learning Representations*
[3] *David Madras et al. "Fairness through Causal Awareness: Learning Causal Latent-Variable Models for Biased Data": 2019 Conference on Fairness, Accountability and Transparency*

Conclusions

- Causal analysis **vital** tool for fairness: use counterfactuals
- Used CVAE to generate counterfactuals under **minimal** causal assumptions
- Applied system to **audit** existing models for counterfactual fairness
- Used **latent** features extracted by system to train fair prediction model

Next steps

- In-depth comparison of our system with related methods
- Relate counterfactual and other notions of fairness w.r.t. our system
- Analyze limitations of our system w.r.t. counterfactual generation
- Explore applications in the real-world setting

Thank you!