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SYNTHETIC DATA GENERATION

Frie Van Bauwel, Marcin Jedrych, Xueting Li

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INTRODUCTION

- Why synthetic data?

  Data shortage, High acquisition costs,

  Privacy protection

- Benefits :

  More Data, Privacy Protection, Scalability,

  Cost-Effective

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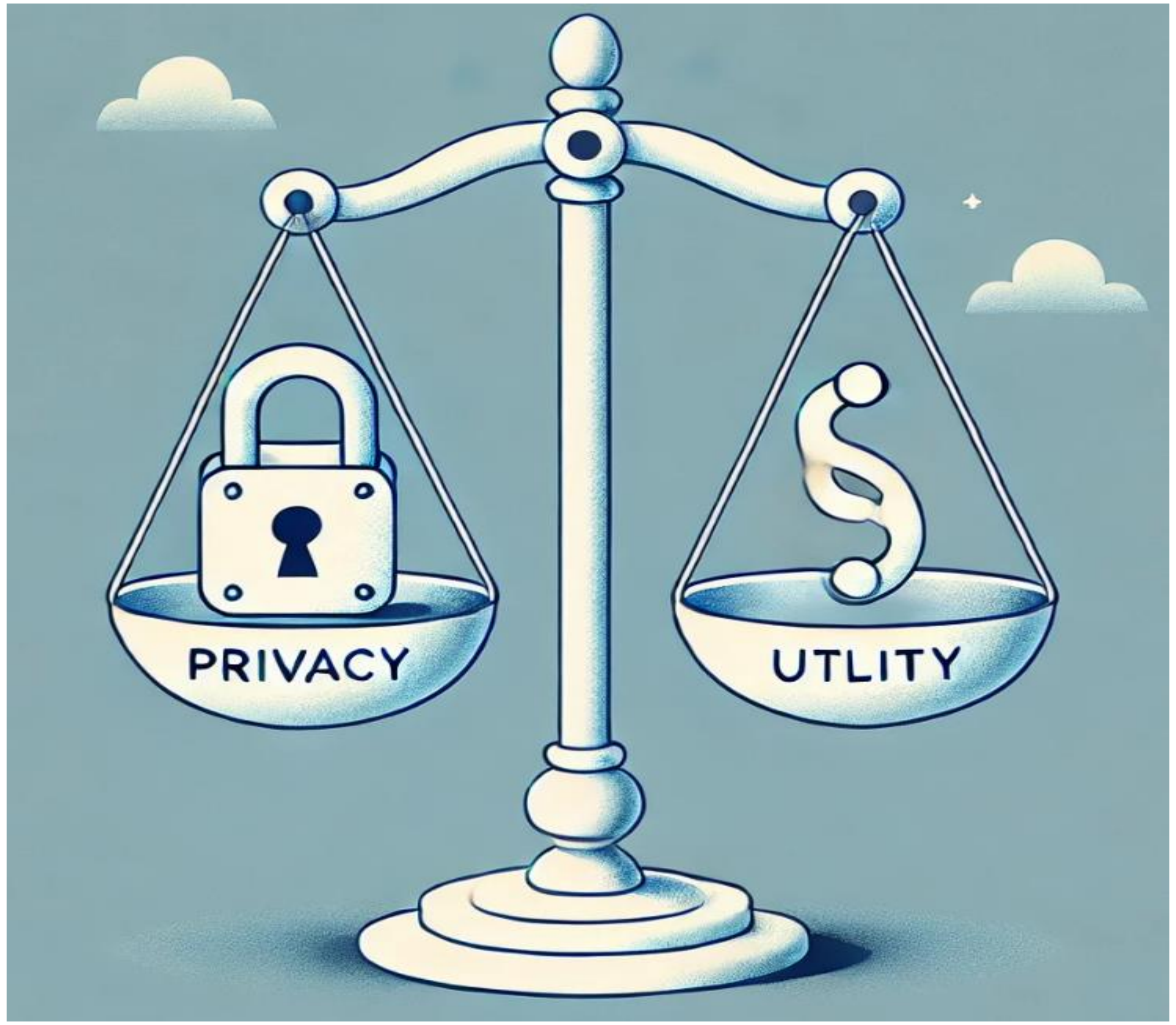
THE TRICK OF USEFUL SYNTHETIC DATA

Privacy-utility trade-off

- Synthetic data with high utility of comes at a cost in privacy

- Stronger privacy often reduces analytical benefits

- Makes it difficult to evaluate synthetic data



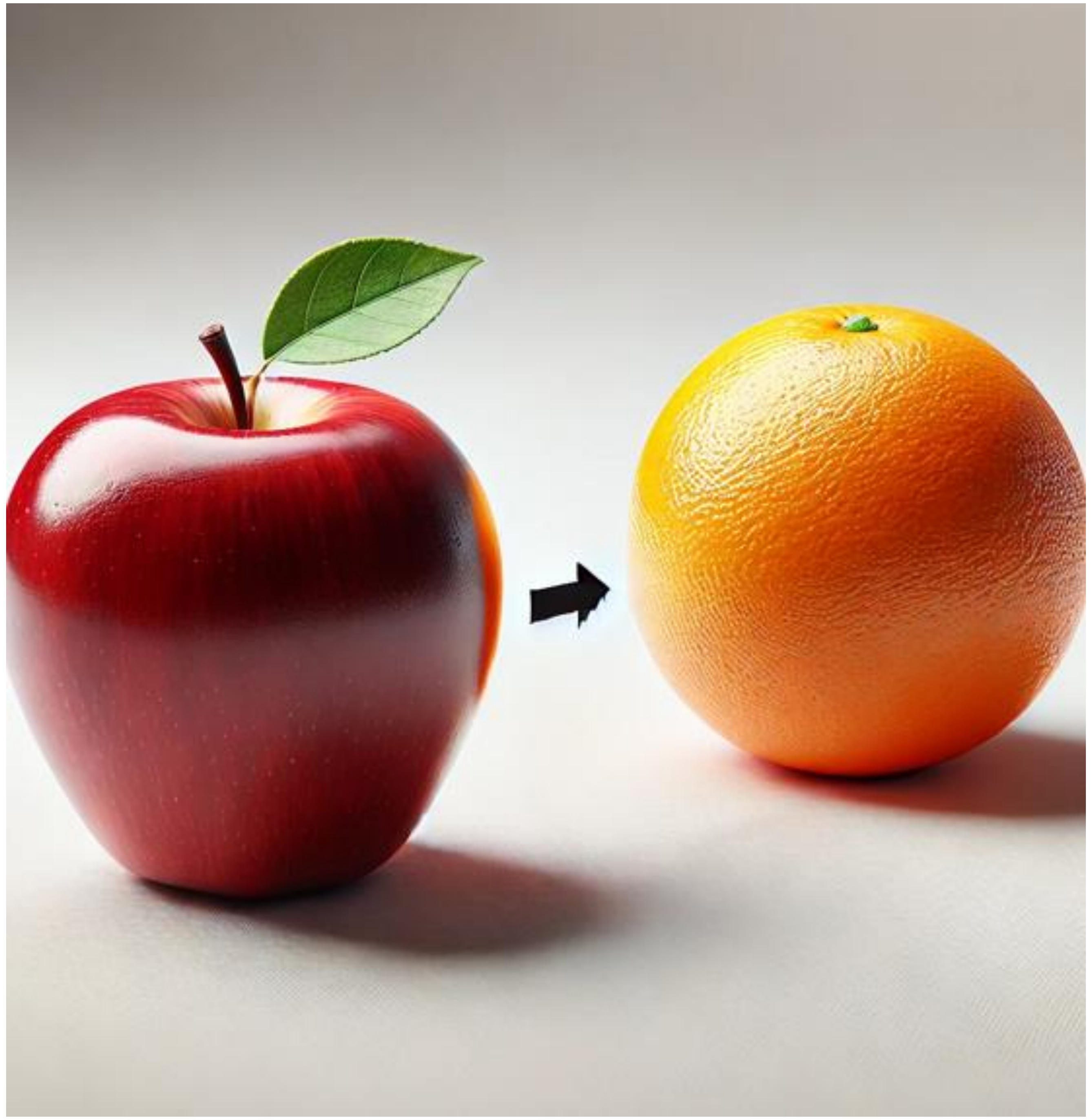
GENERATING SYNTHTETIC DATA

Multiple types of generation techniques

- **Traditional** e.g. Bootstrapping, Monte Carlo, Gaussian Mixture Models

- **Domain-specific** e.g. procedural generation for images, rule-based methods for tabulur data

- **Deep Learning** e.g. GANs, VAEs



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GENERATIVE ADVERSARIAL NETWORKS (GAN)

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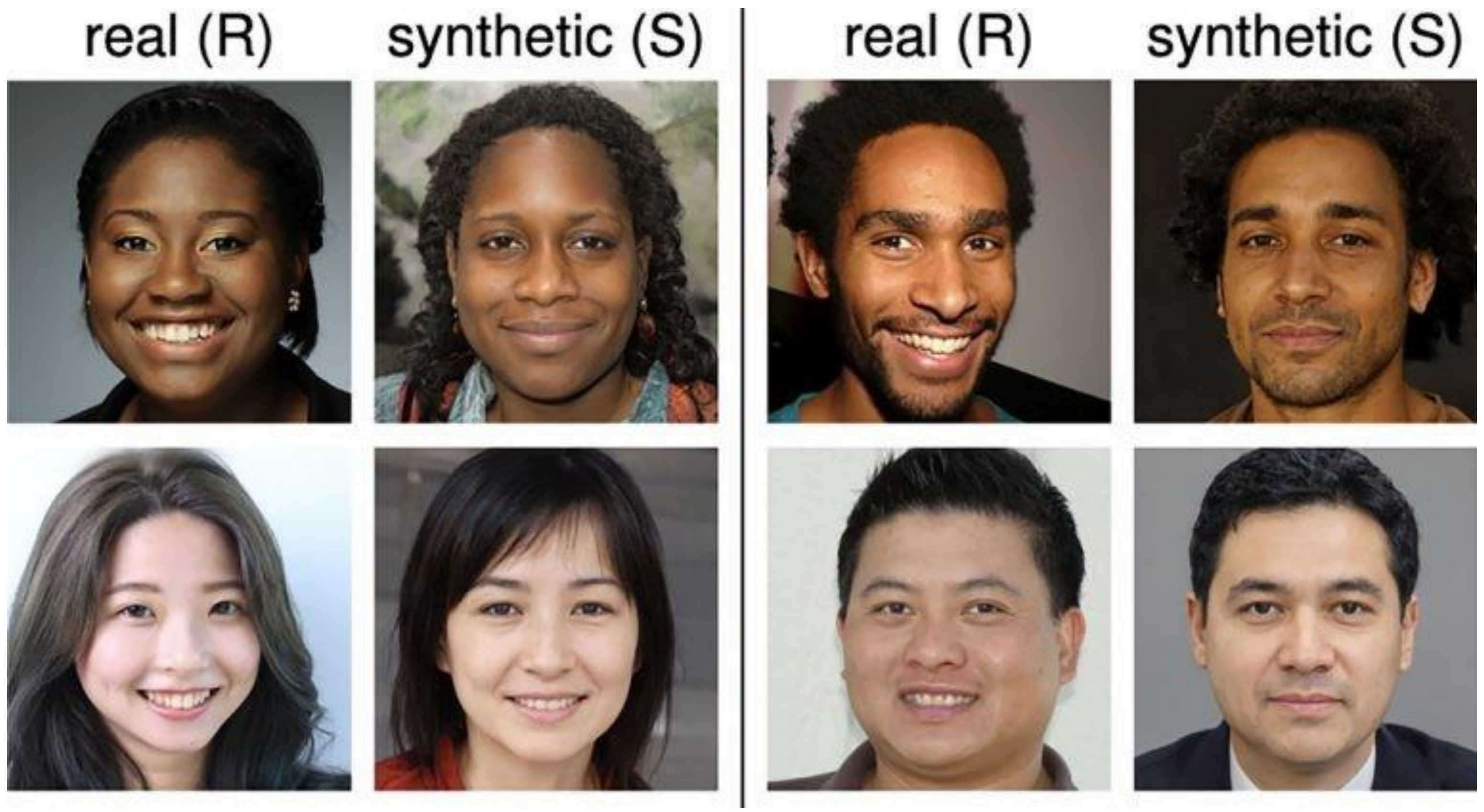
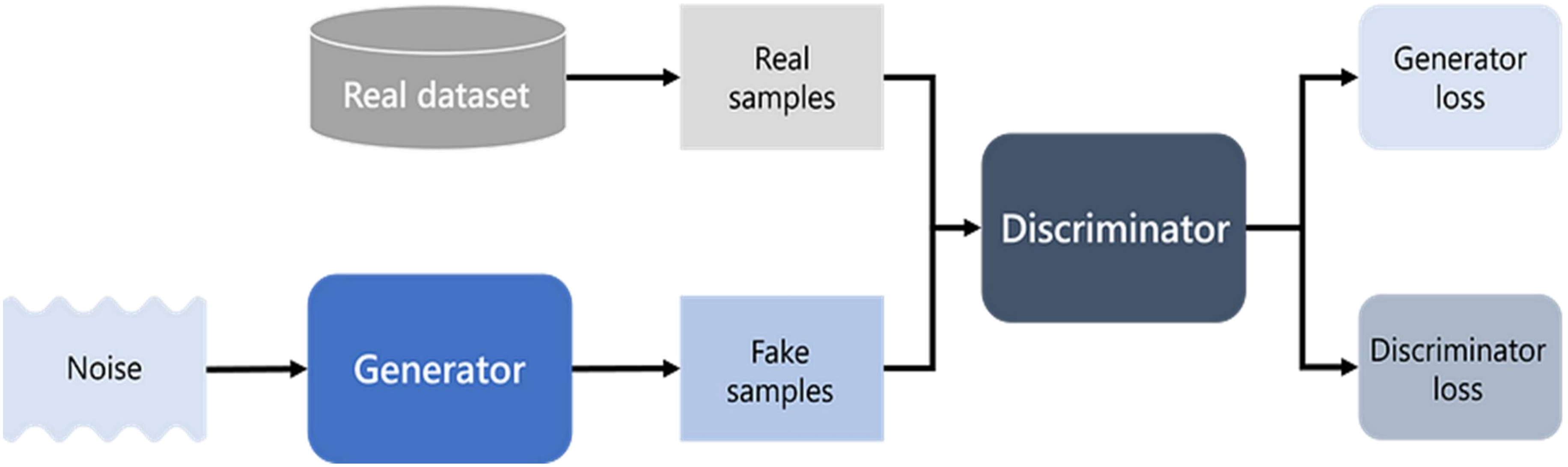
GENERATIVE ADVERSARIAL NETWORKS (GAN)

- Deep learning technique by Ian Goodfellow (2014)

- Used for realistic data generation

- Applications: deepfakes, data augmentation, etc.





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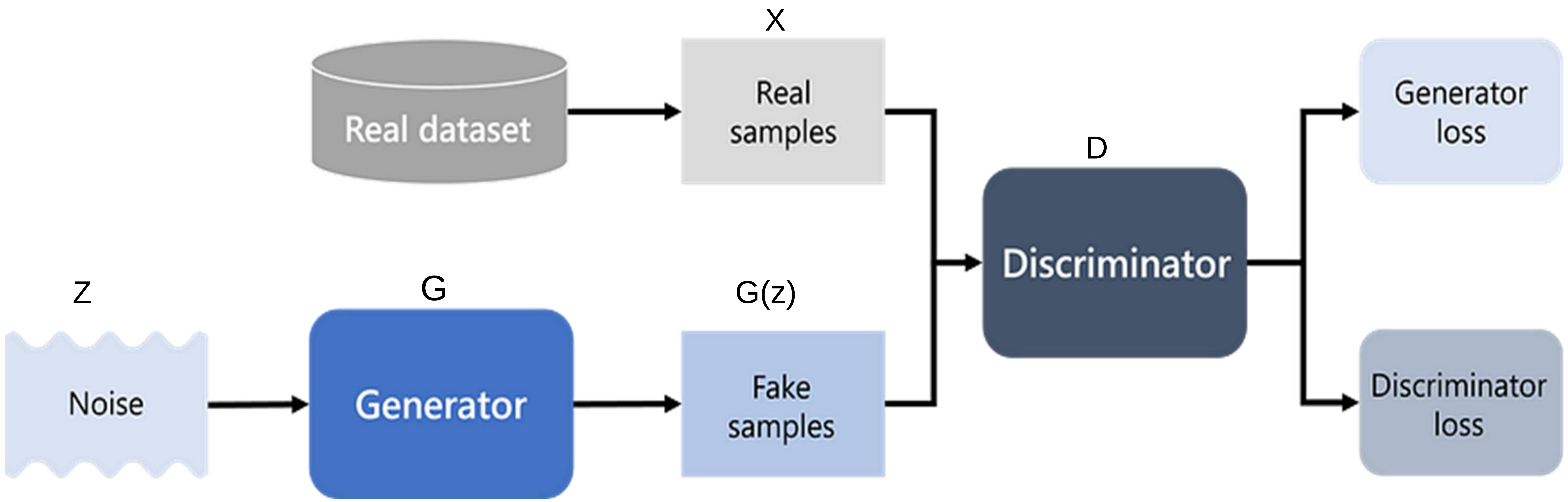
GENERATIVE ADVERSARIAL NETWORKS (GAN)



$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim p_{\text{data}}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]$$

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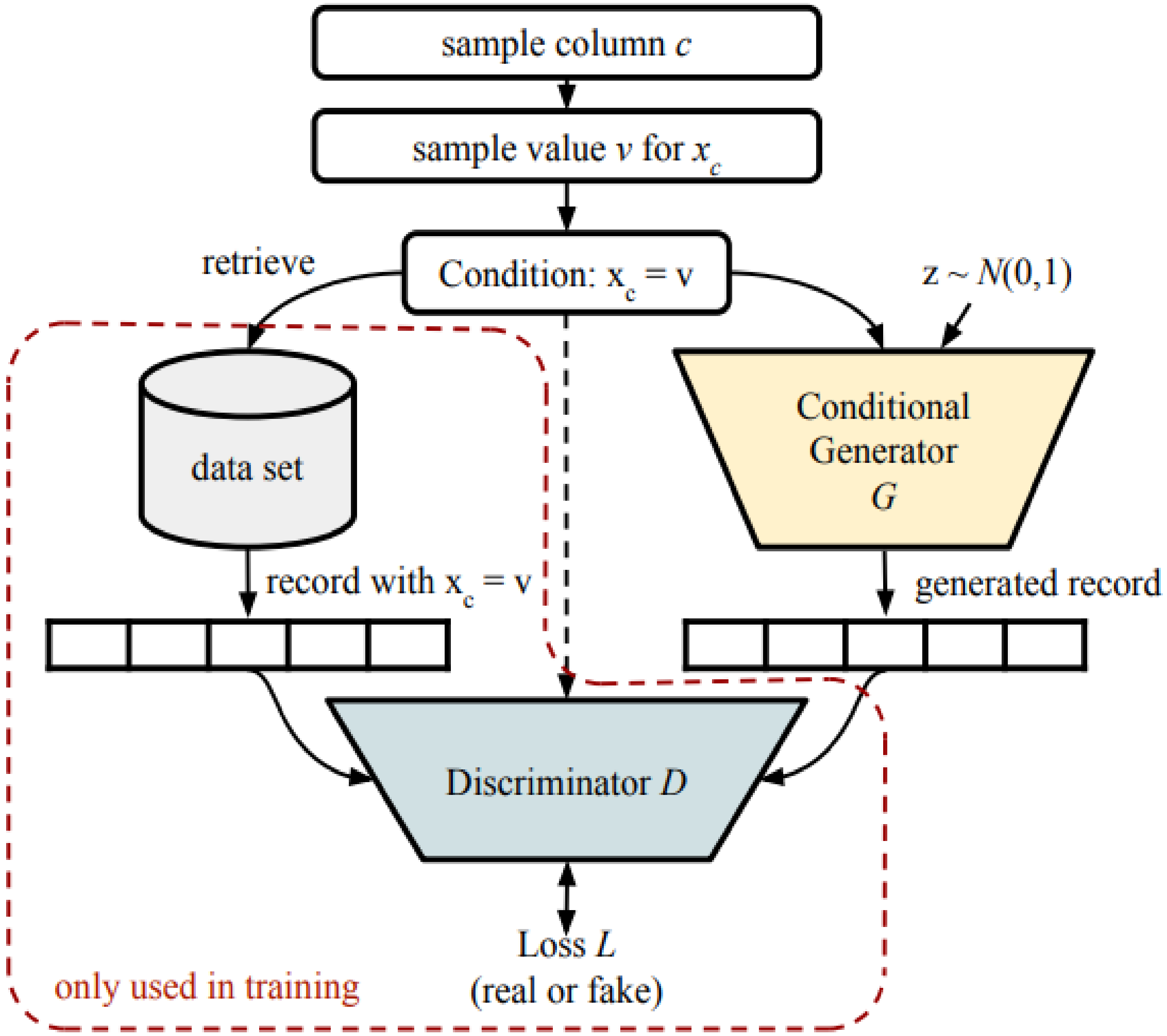
CTGAN

- CTGAN is optimized for **tabular data** (often a mix of categorical and continuous variables)

- CTGAN uses a **conditional generator** which makes it better in capturing dependencies between features.

- In Python: CTGANSythesizer from **SDV package**



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VARIATIONAL AUTOENCODERS (VAE)

First proposed by Kingma & Welling, 2013

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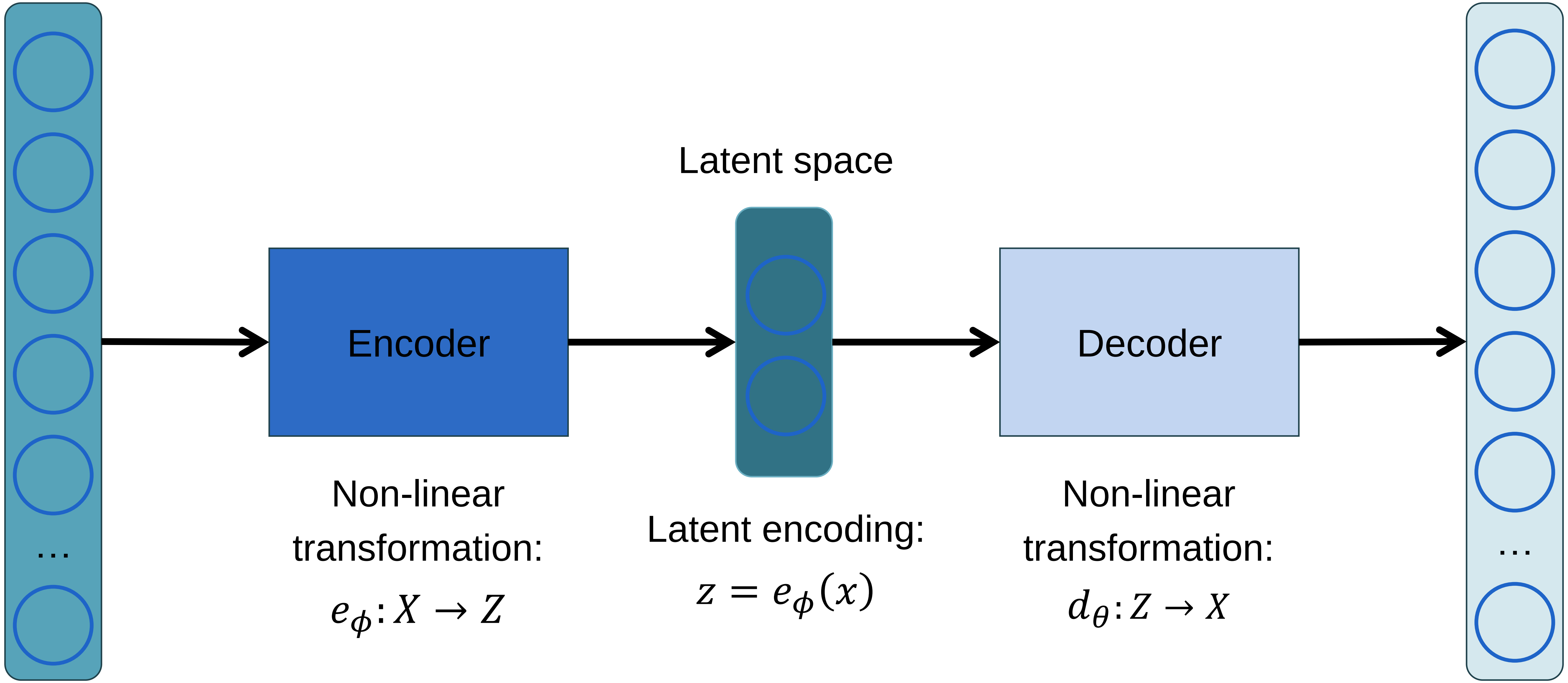
AUTO- ENCODER

$$f(x) = d_\theta(e_\phi(x))$$



Input data: X

Synthetic data: $\hat{X}$

$\hat{x} = d_\theta(z)$

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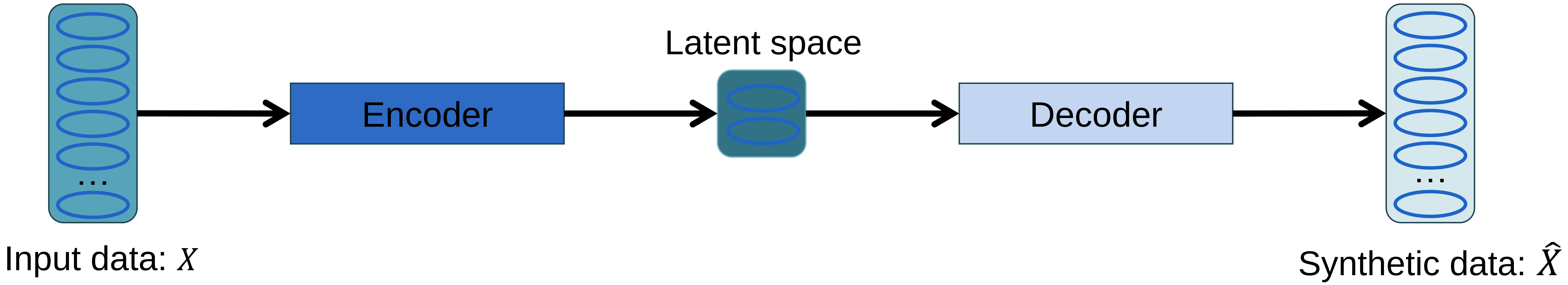
AUTO-ENCODER



Challenges auto-encoder:

- Similar samples not necessarily close to each other in the latent space
- Realistic outcomes not guaranteed

--> Variational auto-encoder

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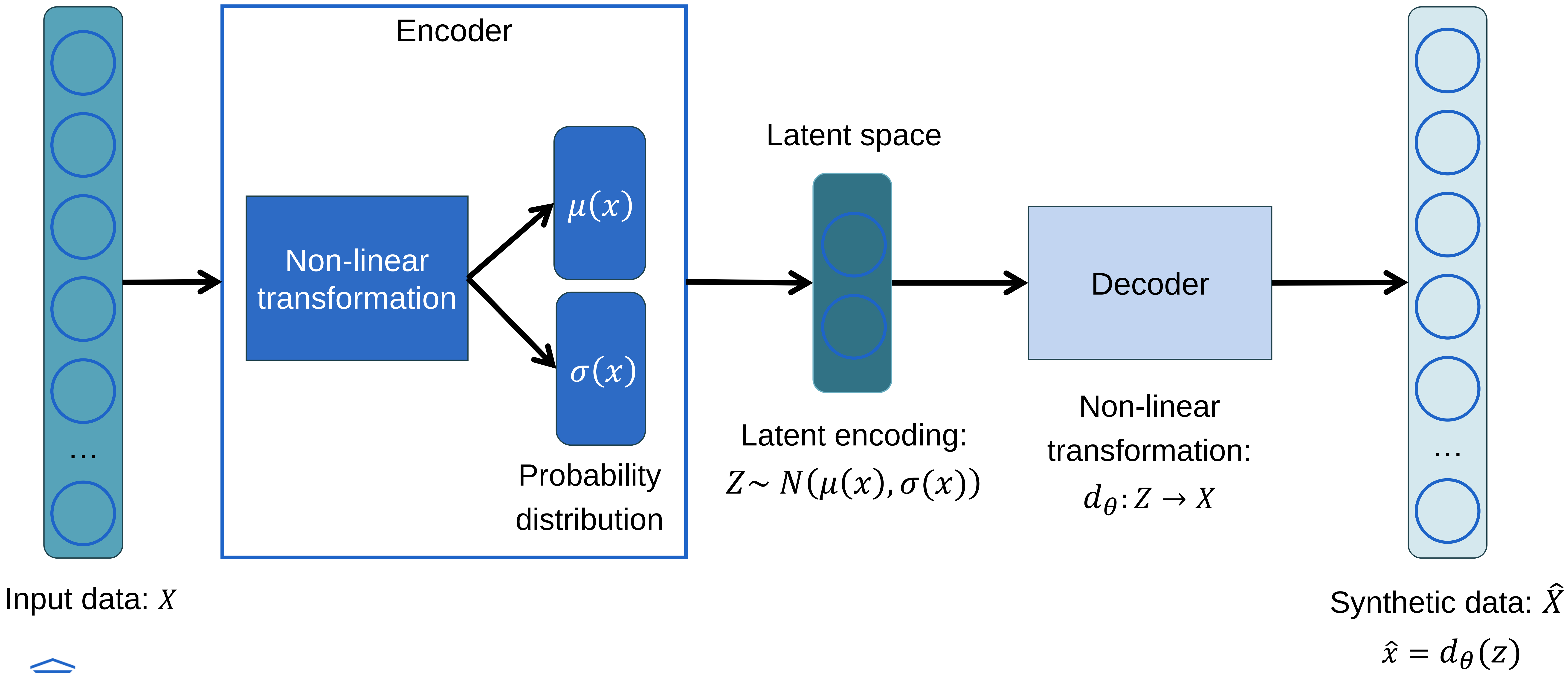
VARIATIONAL AUTO-ENCODER



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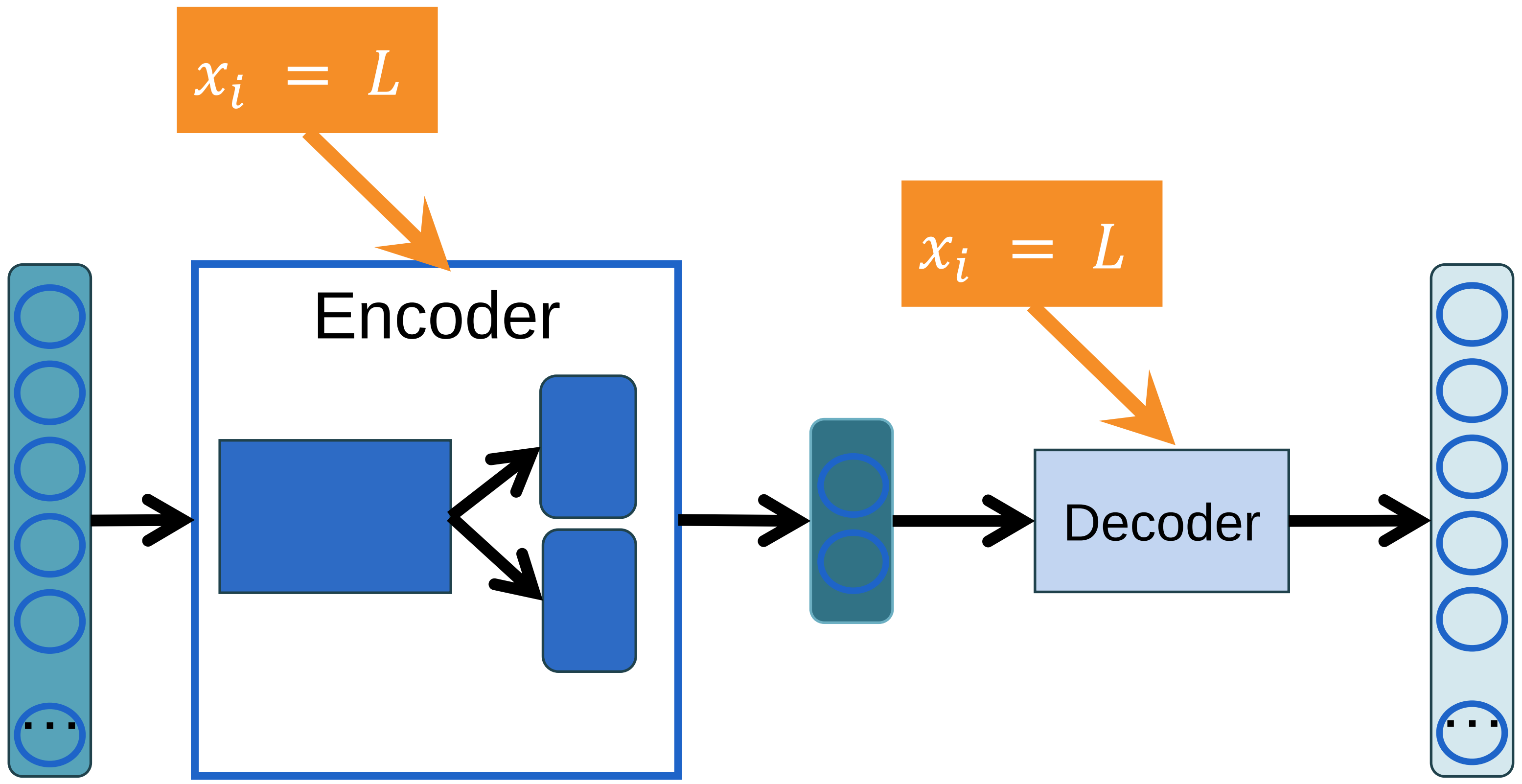
POSSIBLE EXTENSIONS

– CVAE *(Doersch, 2021)*
  - Fill gaps in existing entries
  - Condition the model on input

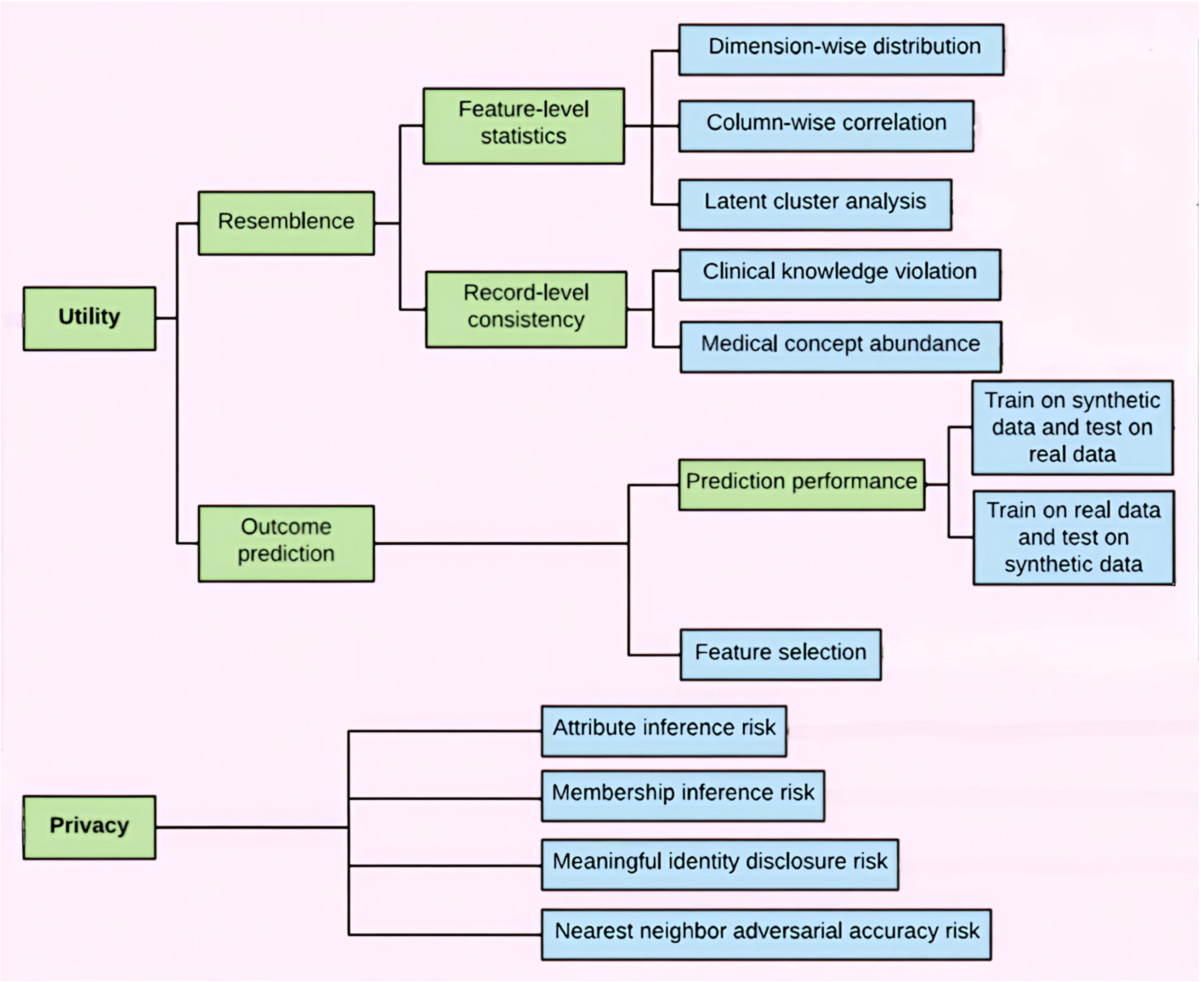


– TVAE *(Xu et al. 2019)*
  - Tabular data
  - SDV python package

EVALUATION OF SYNTHETIC DATA

EVALUATION OF SYNTHETIC DATA

- Univariate / Bivariate
- Utility (e.g. prediction performance)
- Privacy (e.g. MIA)



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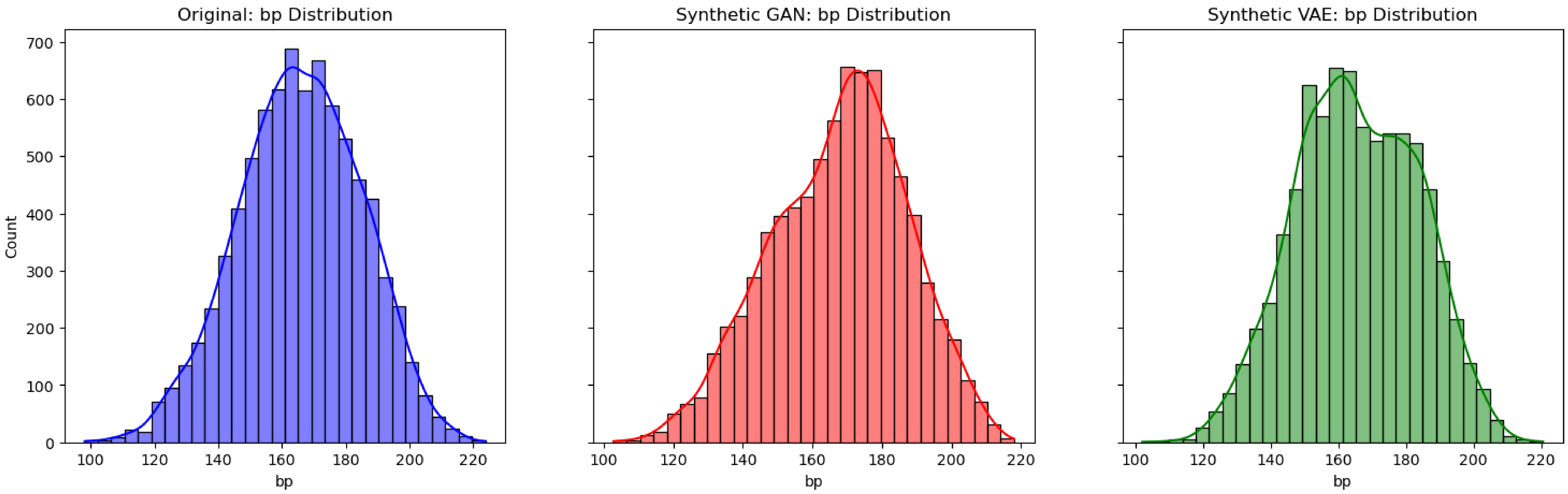
UNIVARIATE

How similar are distributions?



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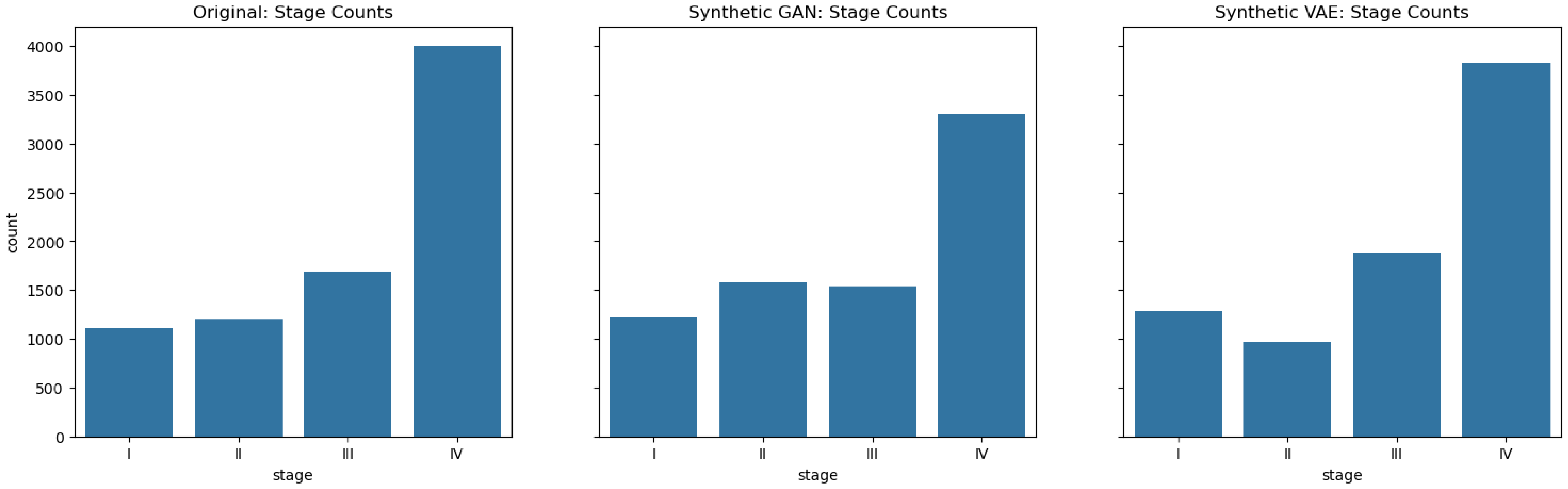
How similar are distributions?



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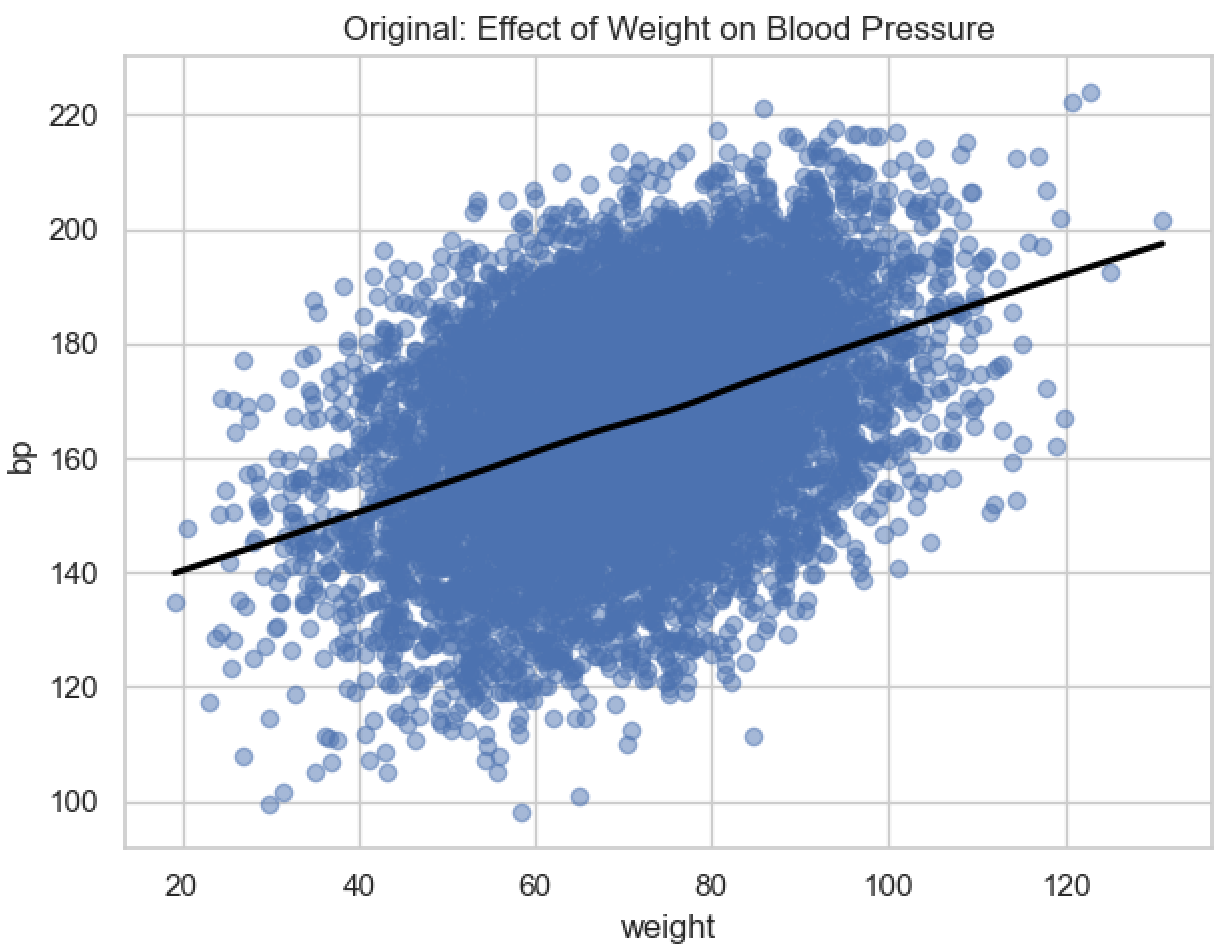
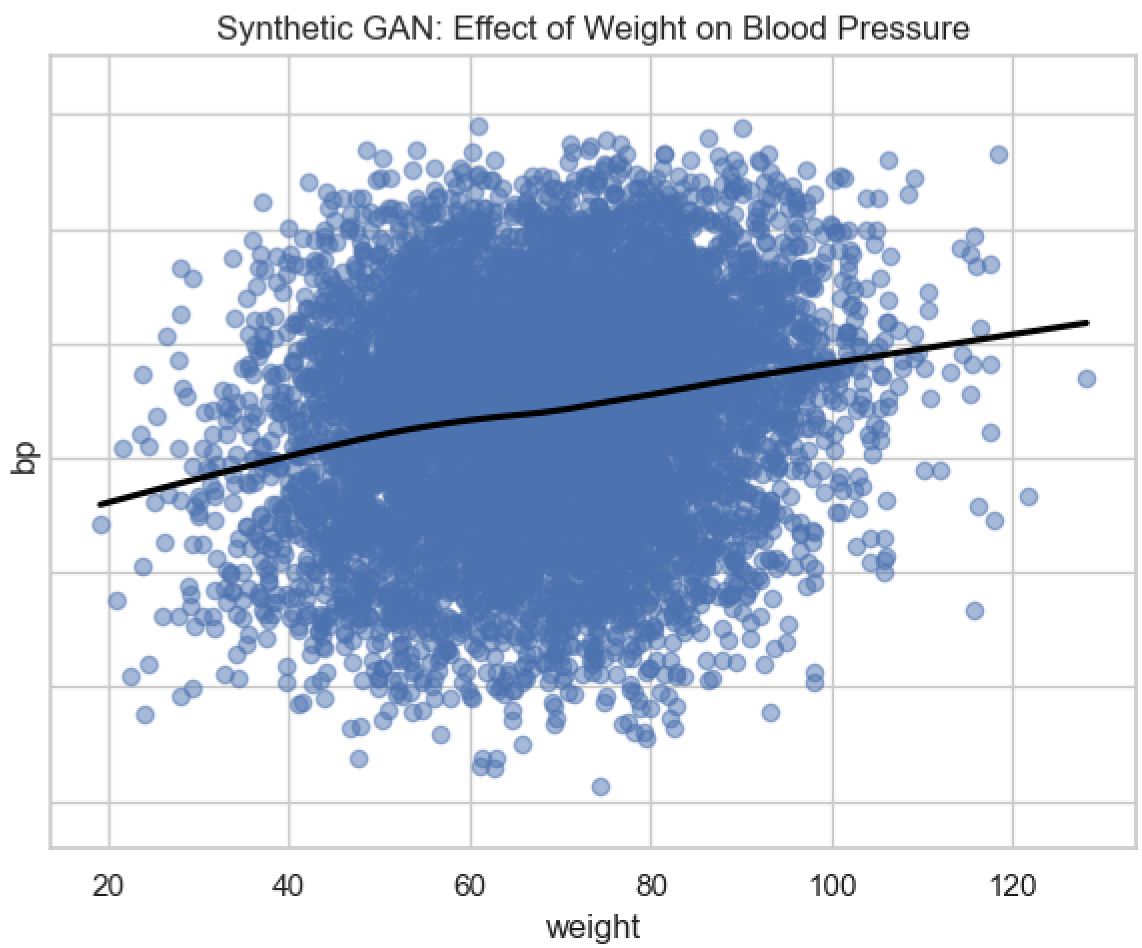
BIVARIATE

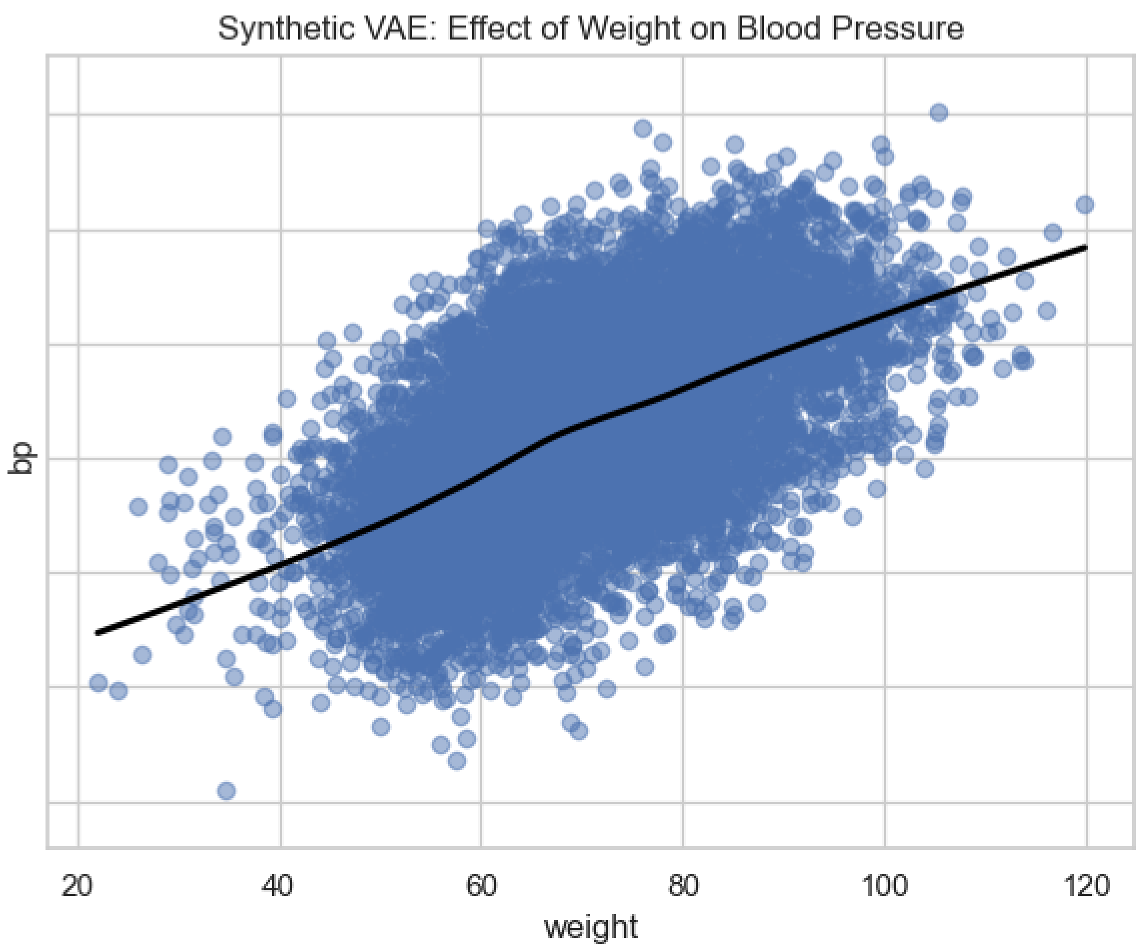
How similar are dependencies?



Cor(x,y) = 0.40



Cor(x,y) = 0.18



Cor(x,y) = 0.54

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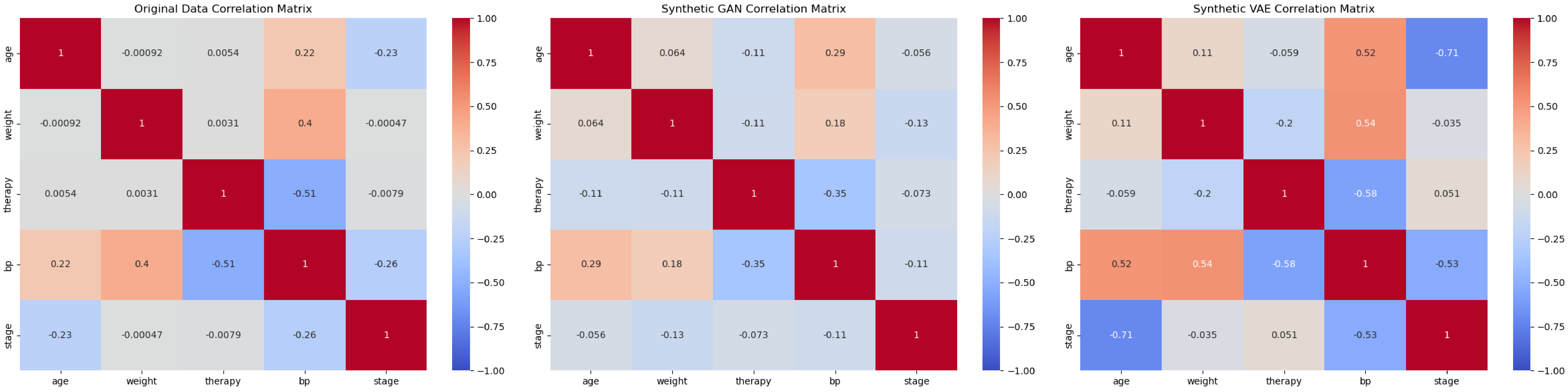
BIVARIATE

How similar are dependencies?



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UTILITY

Predictive performance

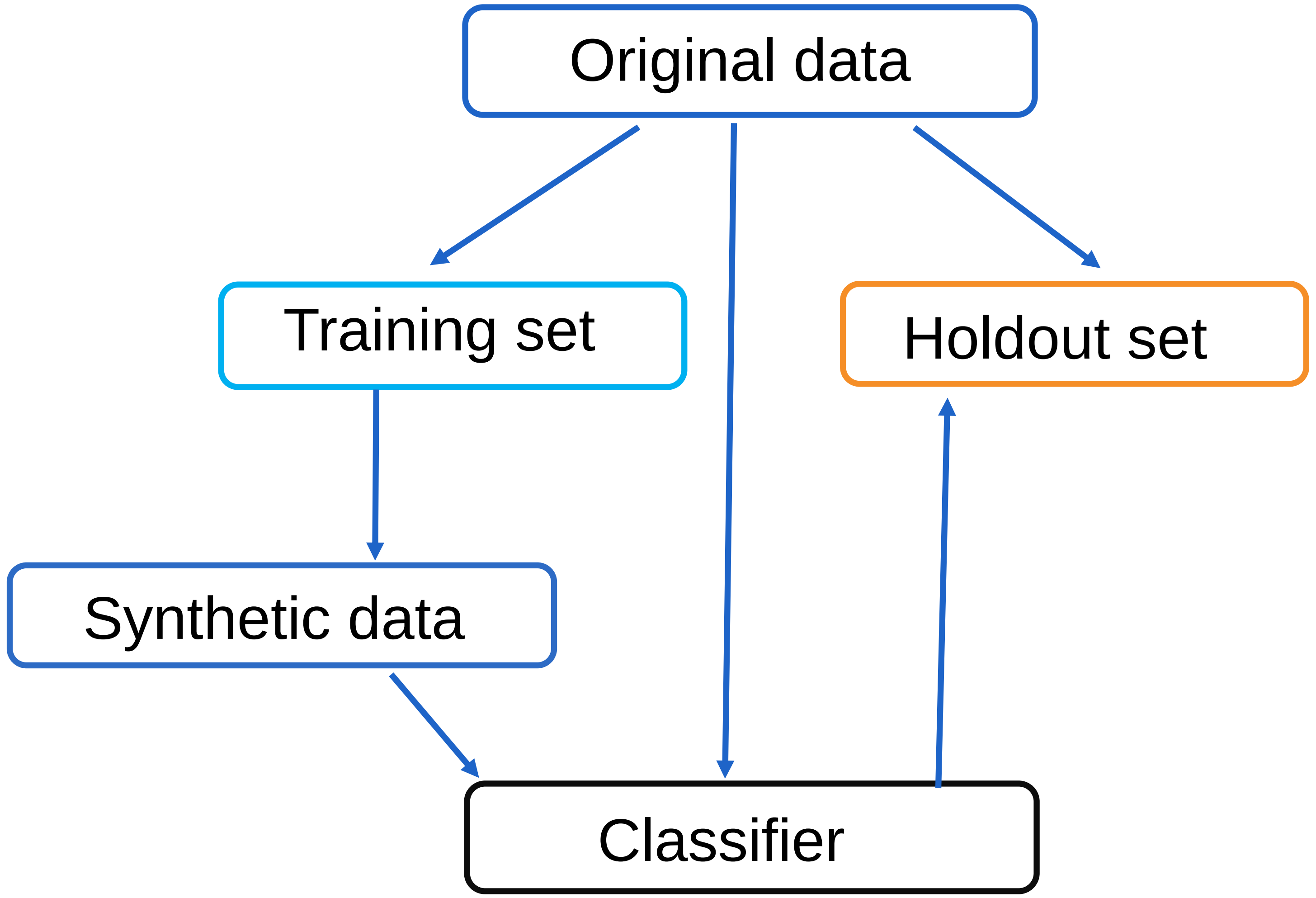
	Original	Synthetic CTGAN	Synthetic TVAE
MSE	95.66	203.19	119.03
Adjusted R^2	0.74	0.45	0.68

Multiple linear regression to predict bloodpressure

PRIVACY

Membership Inference Attack

How well an attacker can determine if a specific individual's data was used to train the synthetic data generator.



	Original	Synthetic CTGAN	Synthetic TVAE
Accuracy	0.50	0.72	0.62

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CONCLUSION

- Synthetic data is promising for applications with sensitive data
- Multiple techniques exist (e.g. GAN, VAE)
- Difficult to evaluate
  - Trade-off
  - No standardized method

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Github: https://github.com/marcinjedrych/Project-BDA.git

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