

Estimating Individualized Treatment Effects from Real-world Patient Data with Deep Latent Models

Zheng Feng

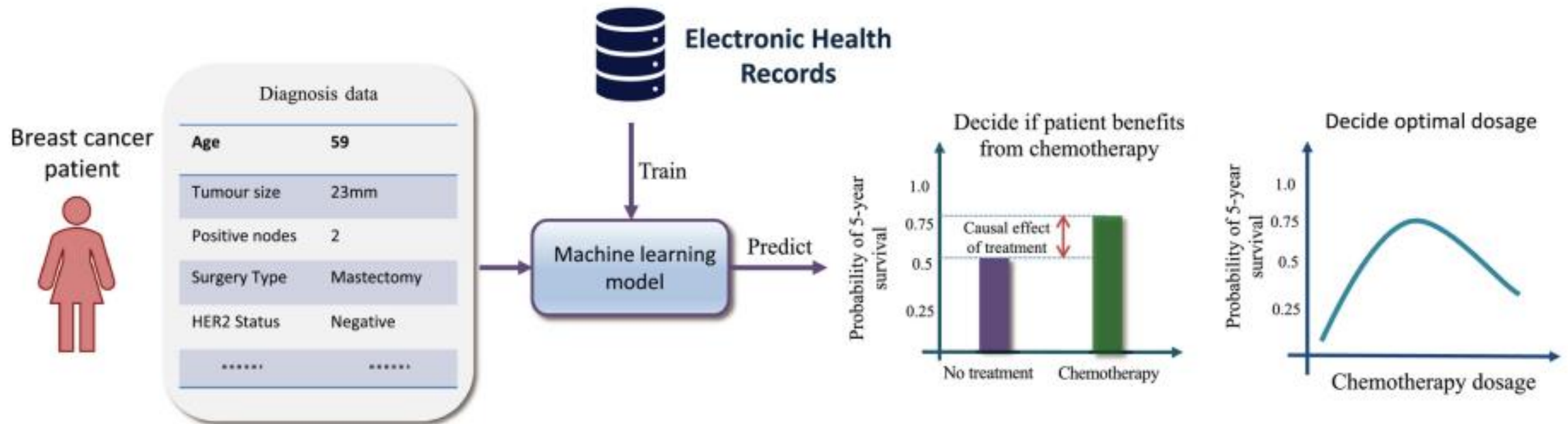


Contents

- Introduction of individualized treatment effects (ITEs)
- Challenges of using observational data for estimating ITEs
- Deep latent models for estimating ITEs
- Recent advances and variational temporal deconfounder

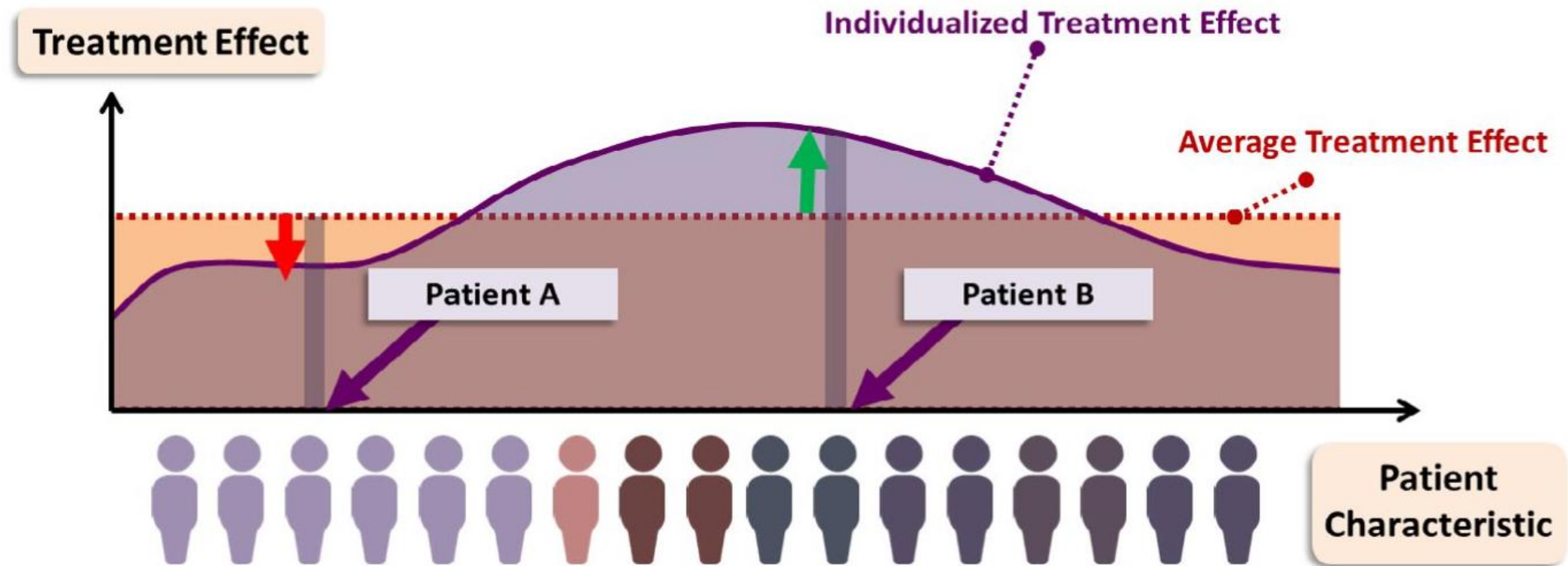
Introduction of Individualized treatment effects (ITEs)

- Personalized therapeutics



Introduction of Individualized treatment effects (ITEs)

- Randomized controlled trials (RCTs)



Introduction of Individualized treatment effects (ITEs)

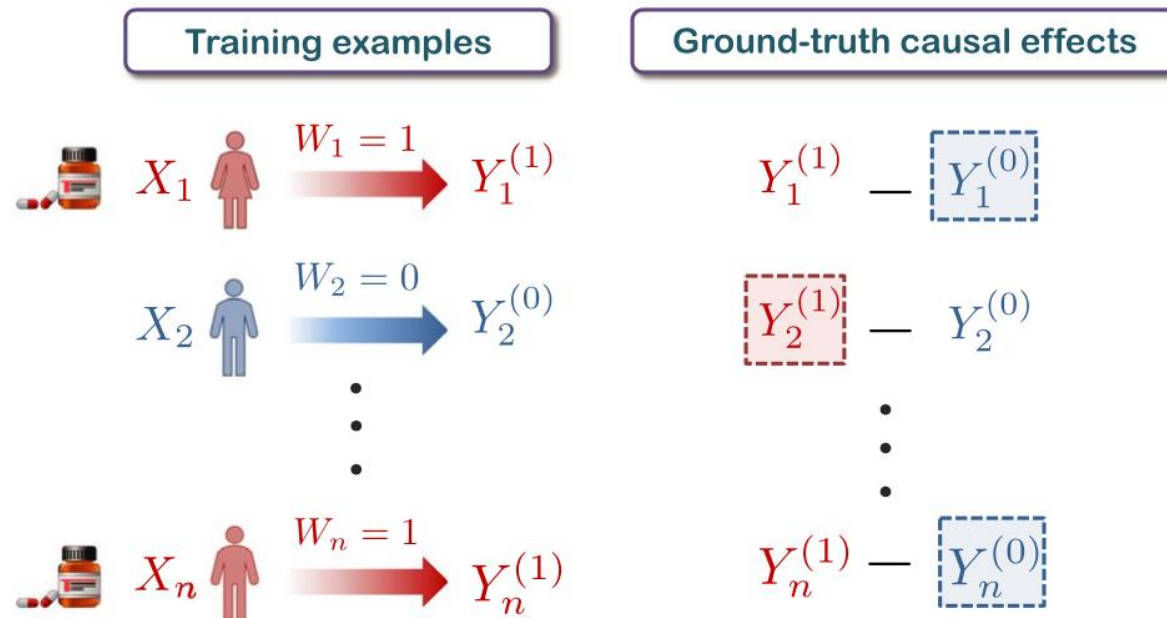
- Average treatment effects – population level
 - Small sample size
 - Not representative for heterogeneous patients
 - Costly and time consuming

Introduction of Individualized treatment effects (ITEs)

- Individual treatment effects (ITEs) – patient-centric
- Estimate ITEs from observational data, e.g. electronic health records
 - Large volume
 - Representative for heterogeneous patients
 - Fast and inexpensive
 - Scalable and adaptive

Challenges of using observational data for estimating ITEs

- Difficulty of applying supervised machine learning models
 - Counterfactuals – answering “What if?” questions



We never observe counterfactual outcomes

Not a simple supervised
ML problem – no explicit label

Challenges of using observational data for estimating ITEs

- Limitation of using observational data
 - Unmeasured variables – hidden factors
 - Socio-economic status
 - Personal preferences
 - Most genetic & environmental factors
 - Proxy variables
 - E.g. socio-economic status → zip code & job type

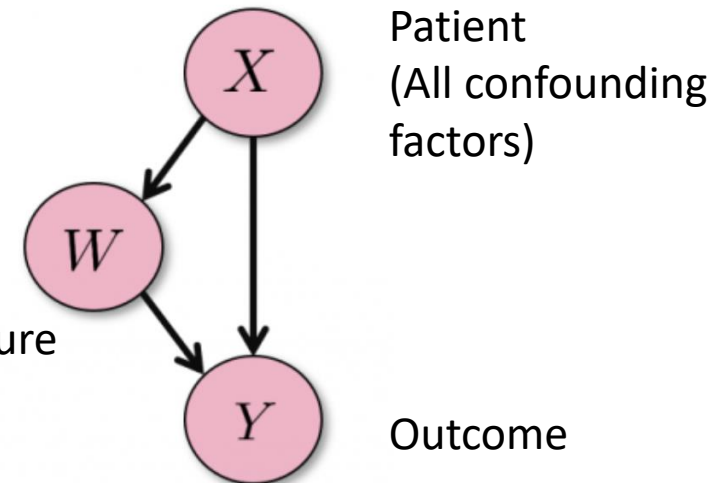
Challenges of using observational data for estimating ITEs

- Answering the question “will a treatment benefit for an individual patient?” from observational data is difficult because of
 - Confounding
 - bias

Formalize as causal questions

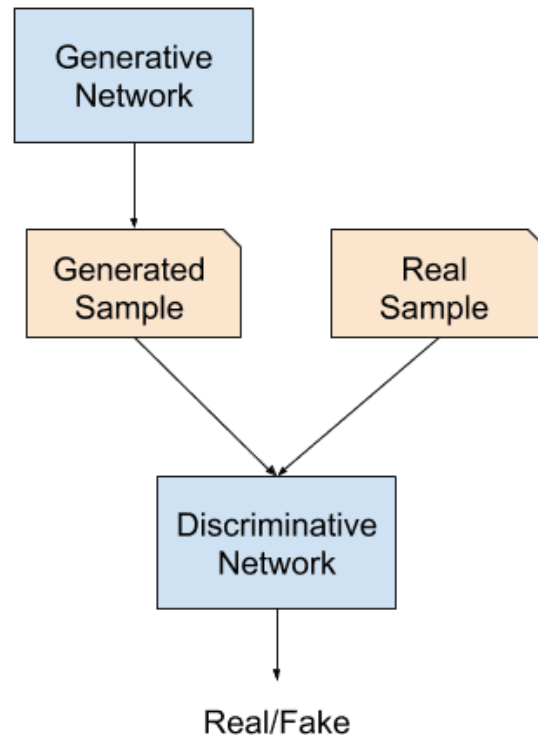


Intervention
(medication, procedure
etc.)



Deep latent models for estimating ITEs

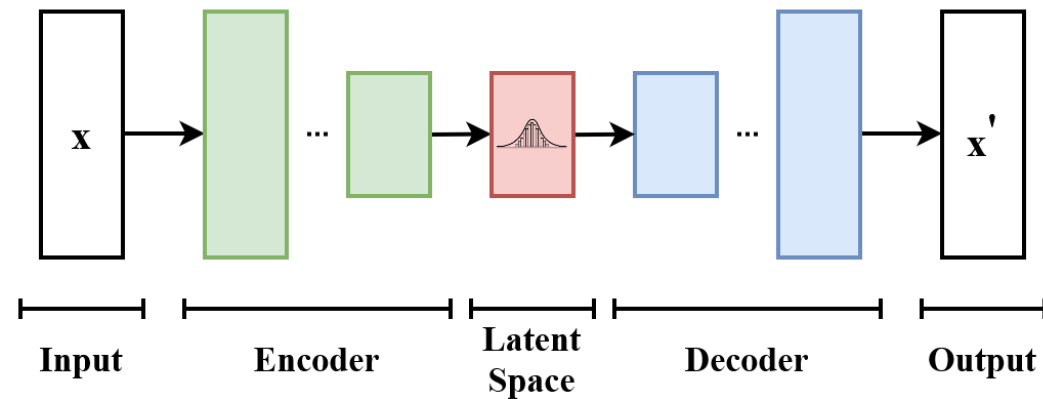
- Generative adversarial nets (GANs)



GANs can be used to create new plausible samples on demand

Deep latent models for estimating ITEs

- Variational autoencoders (VAEs)

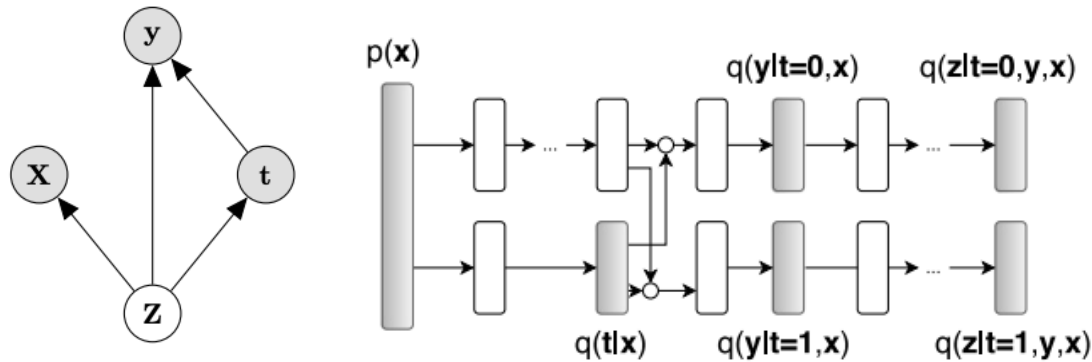


The encoder of VAE transforms input x into the latent space

Recent progress

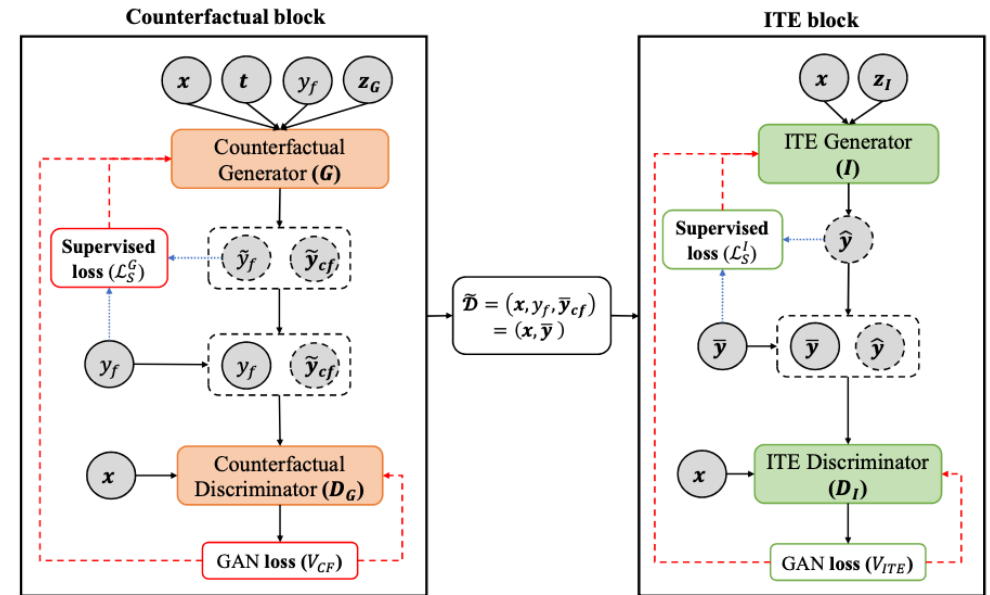
CEVAE: Causal effect inference with deep latent-variable models

[Louizos, Shalit, Mooij, Sontag, Zemel, & Welling. (2017)]



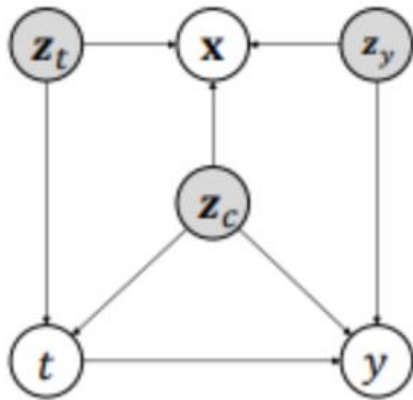
Ganite: Estimation of individualized treatment effects using generative adversarial nets

[Yoon, Jordon, Van Der Schaar. (2018)]

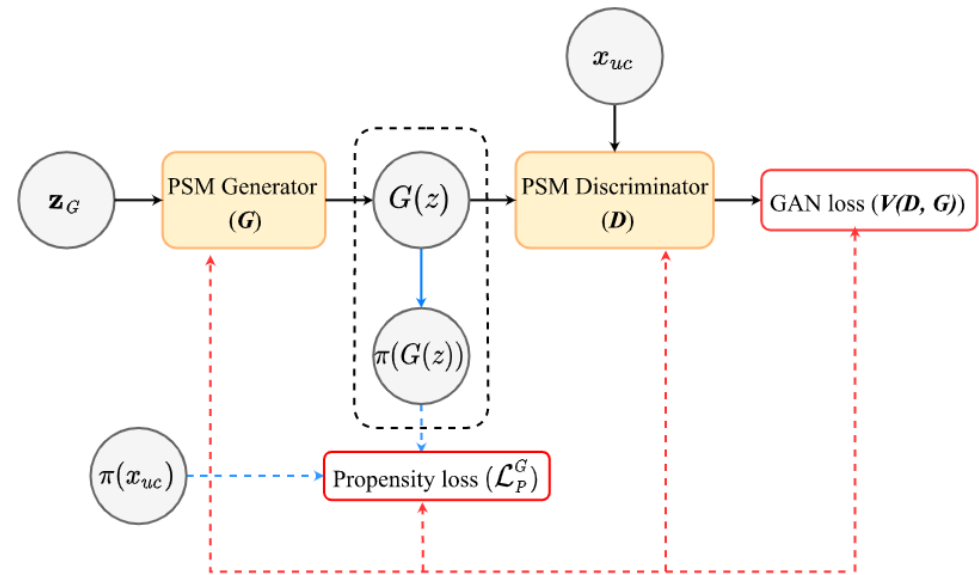


Recent progress

TEDVAE: Treatment effect estimation with disentangled latent factors
[Zhang, Liu, & Li. (2020)]

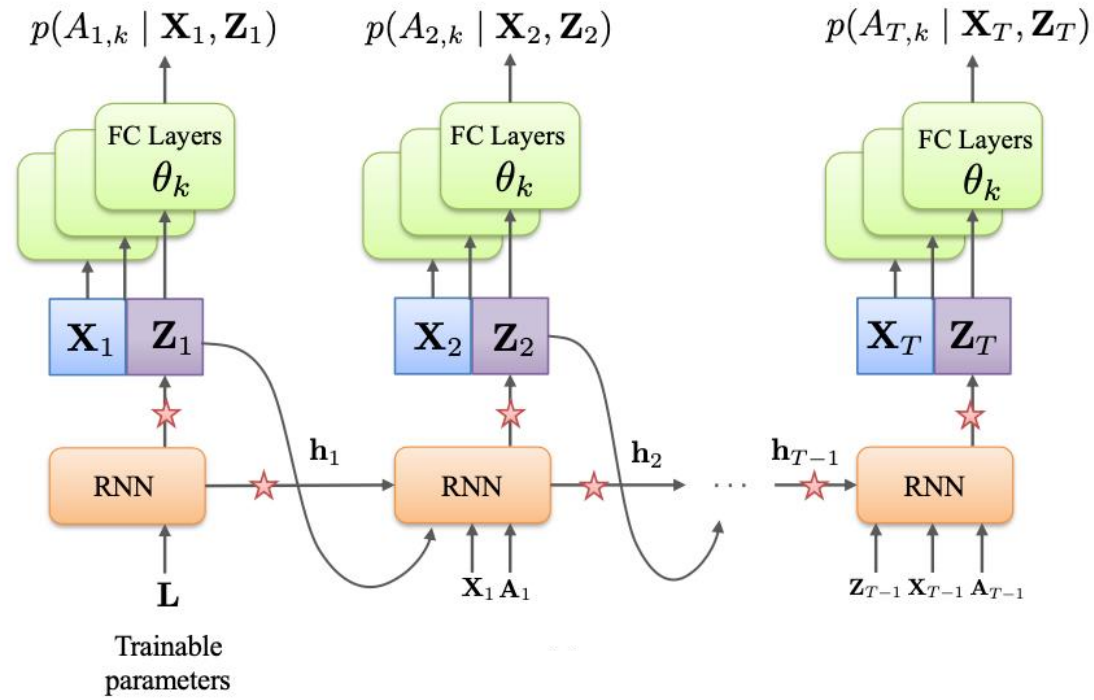


PSSAM-GAN: Propensity score synthetic augmentation matching using generative adversarial networks
[Ghosh, Boucher, Bian, & Prospero. (2021)]



Variational temporal deconfounder

- Estimating ITEs with variational RNN on temporal clinical data



Proposed variational temporal deconfounder implementation

Thank you