Interpretable Machine Learning in Healthcare

Team Members

Elaborate on what you want to discuss.

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Agenda

1. Objectives of the project
2. Business: Why causal inference is important in healthcare
3. Technology: Interpretable Machine Learning (IML) / Causal AI
4. Challenges faced by existing IML methods and causal AI

Objectives of the research project

(1) Create classification models with high AUC

(2) Identify the most critical features relevant to the cervical cancer formation

(3) What trade-offs need to be considered while choosing an algorithm to be implemented

Why **Causal Inference** Matters in Healthcare ?

Observational Data $\xrightarrow{?}$ Causal relationships

- Randomized Clinical Trials (RCTs) could be unethical
- Poor generalizability of RCTs
- Differential diagnostic is challenging
- Precision medicine: prediction + intervention

Simpson's Paradox

Task: Choose which treatment to use for your country
Goal: Minimize the death

Treatment A

Treatment B

Scarce

On the treatment level, treatment A looks more effective

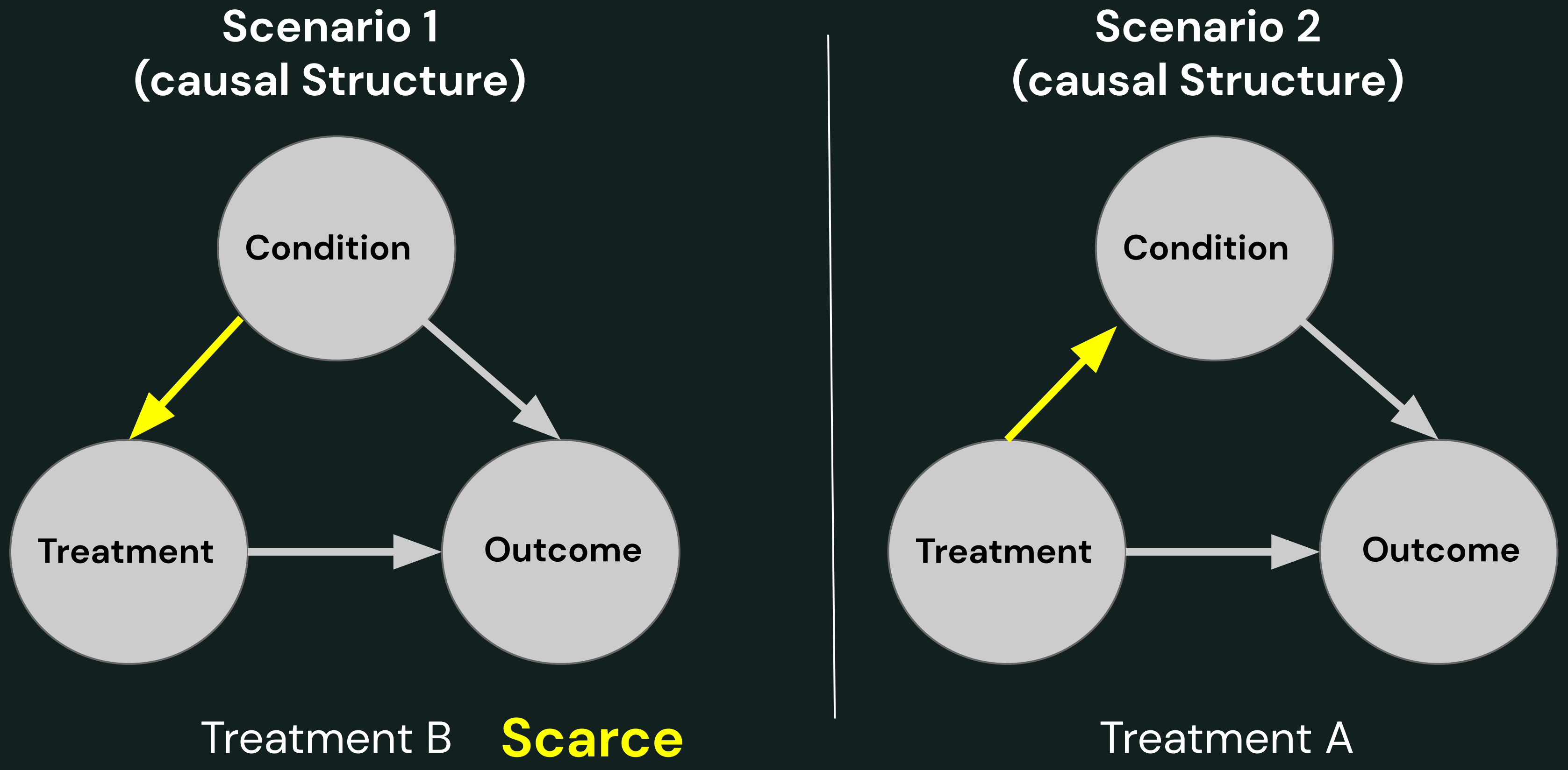
	Treatment A	Treatment B
Mortality rate	16% (240/1500)	19% (105/550)

When we subset the group, the result flips!

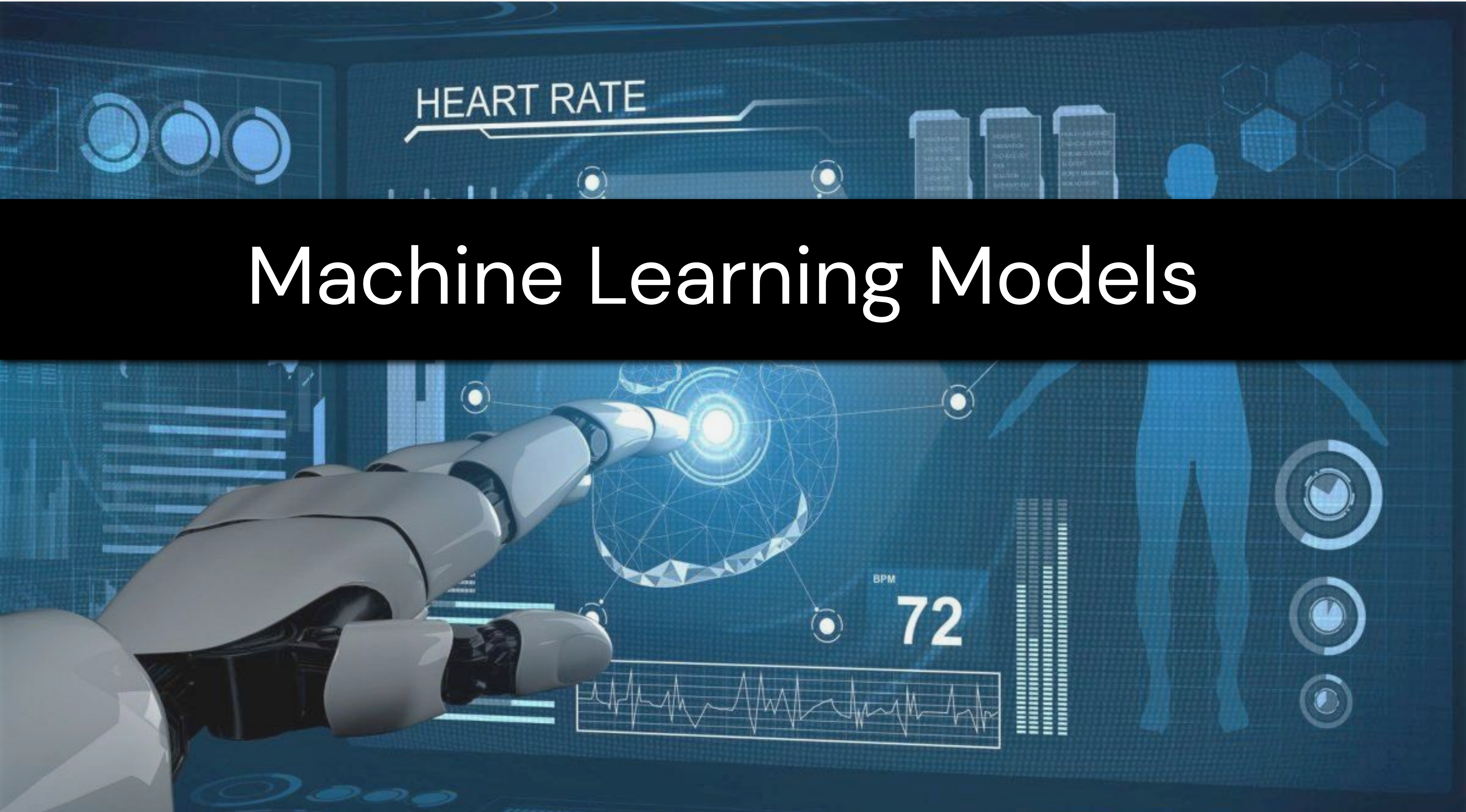
Treatment B performs better in both conditions.

Condition	Treatment A (mortality rate)	Treatment B (mortality rate)
Mild	15% (210/1400)	10% (5/50)
Severe	30% (30/100)	20% (100/500)
Total	16% (240/1500)	19% (105/550)

Which treatment should you choose?



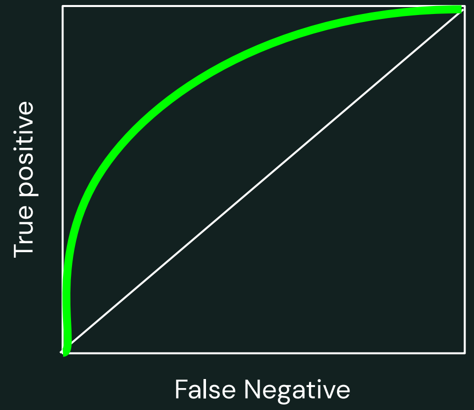
Machine Learning Models



Evaluation Methods

- What to consider for implementation?

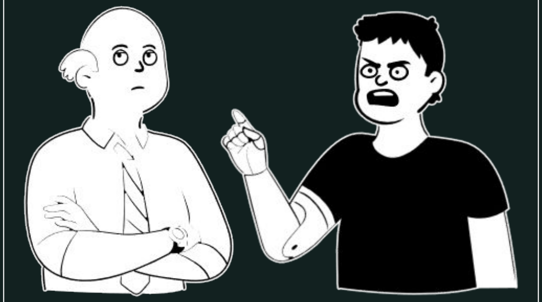
AUC Recall / True-Positive Rate



True Negative	False Negative
False Positive	True Positive

HIgh TP & Low FN/FP would be better

Stakeholders' Opinion



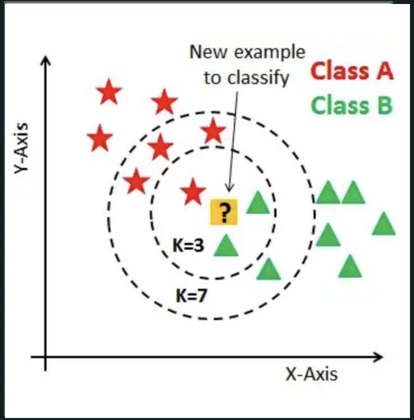
Hospital, Person, etc.
Model Quality vs Total Cost

Source: V. Dey, "Understanding the AUC-ROC Curve in Machine Learning Classification," Analytics India Magazine, Sep. 05, 2021. https://analyticsindiamag.com/understanding-the-auc-roc-curve-in-machine-learning-classification/

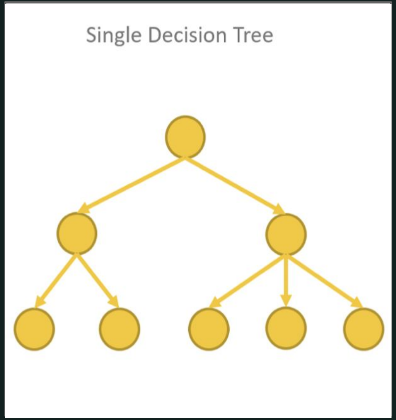
General classification models

- Interpretable - Can observe how to perform the model
- Observe the associations: Input features → Output

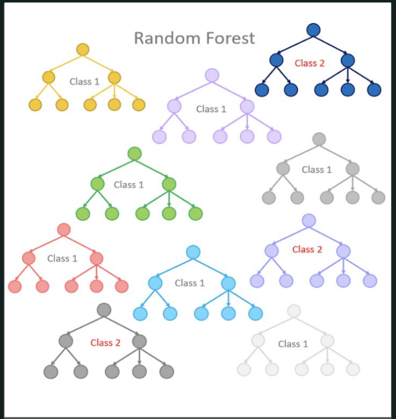
K-Nearest Neighbors



Decision Tree



Random Forest



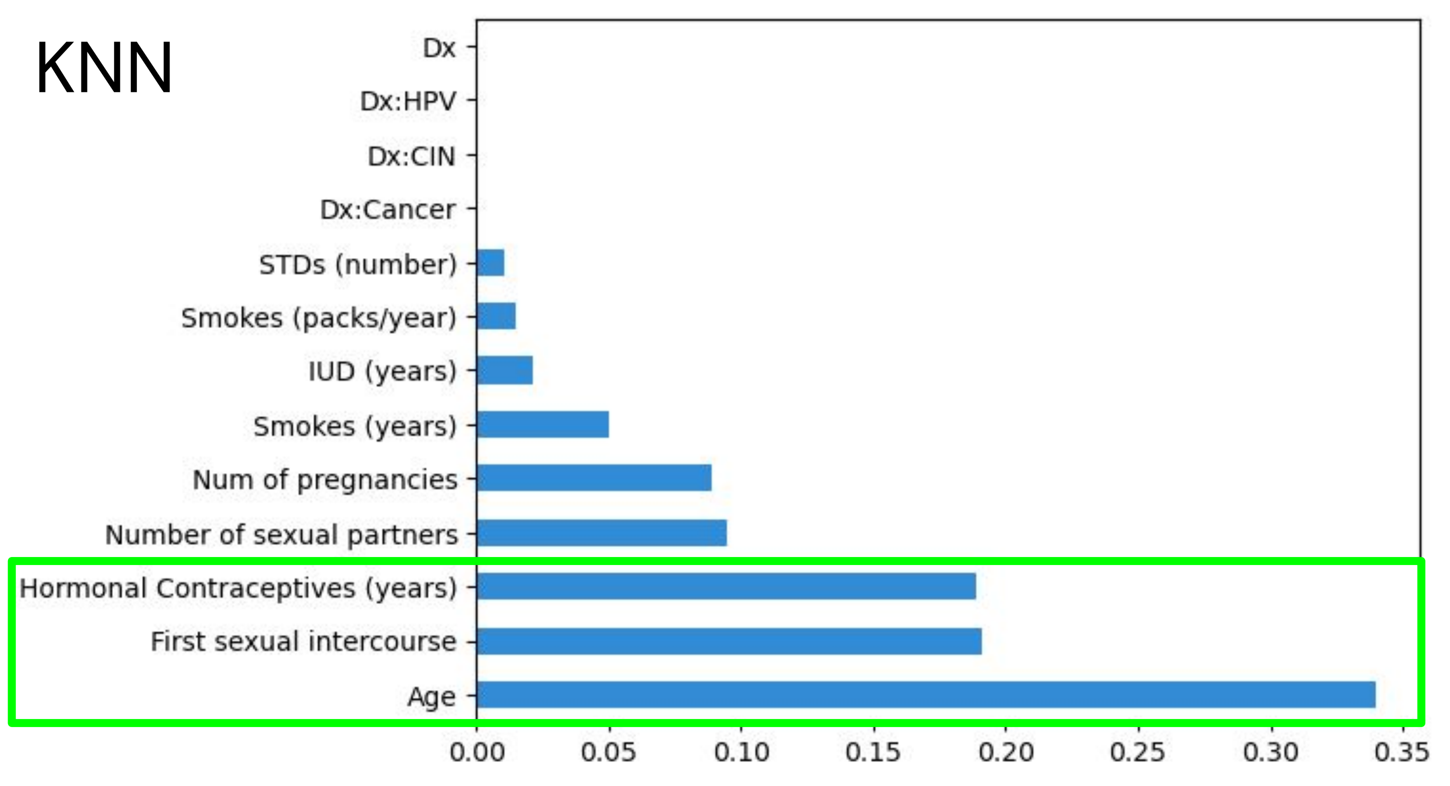
Ensemble Model (Mixing Three models)

Result

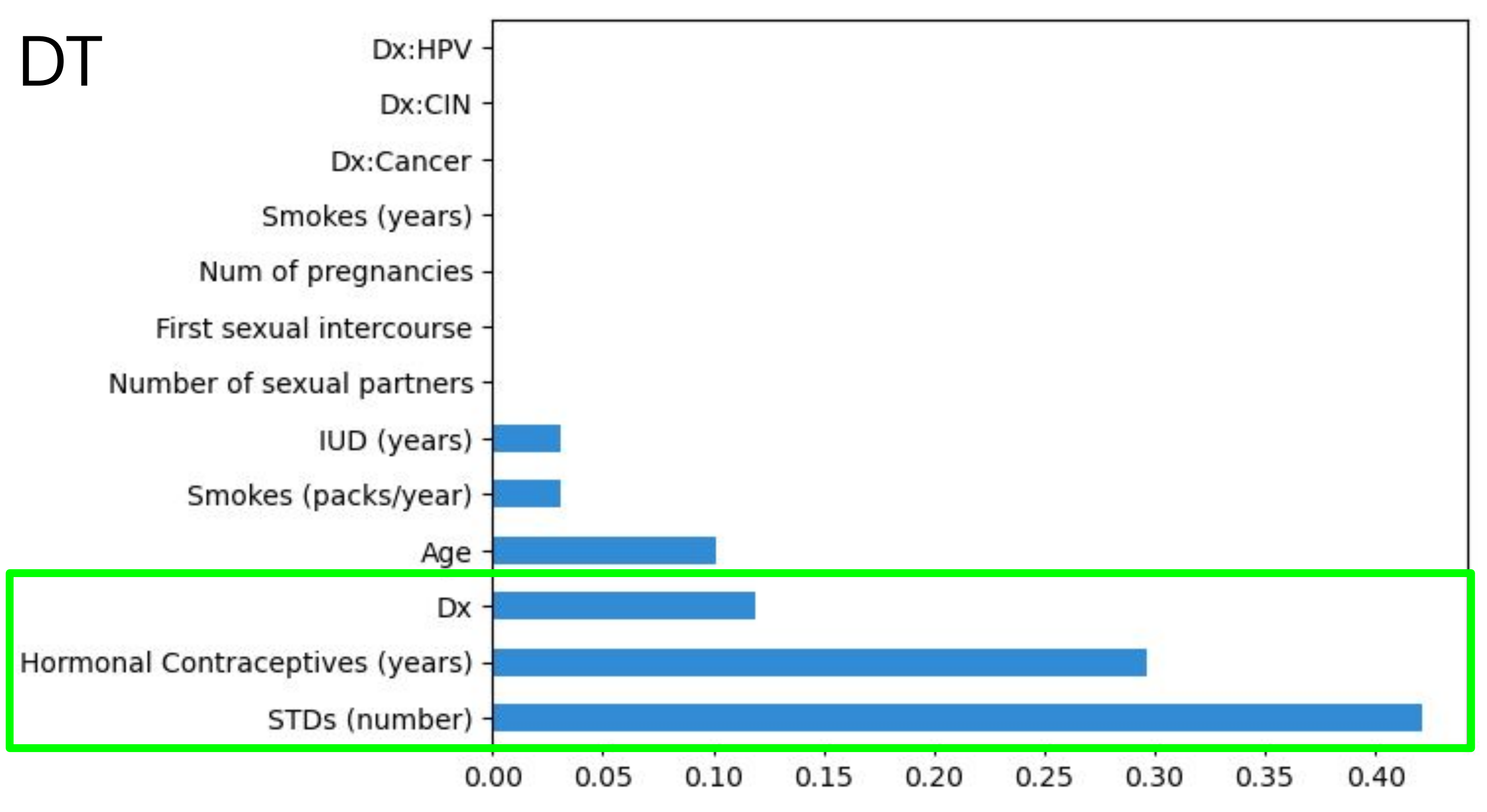
Random Forest is accurately detect positive patients

Algorithm	AUC	True Positive	False Negative
KNN	0.6381	7	4
Decision Tree	0.7199	6	5
Random Forest	**0.7569**	9	2
Ensemble	0.6846	7	4

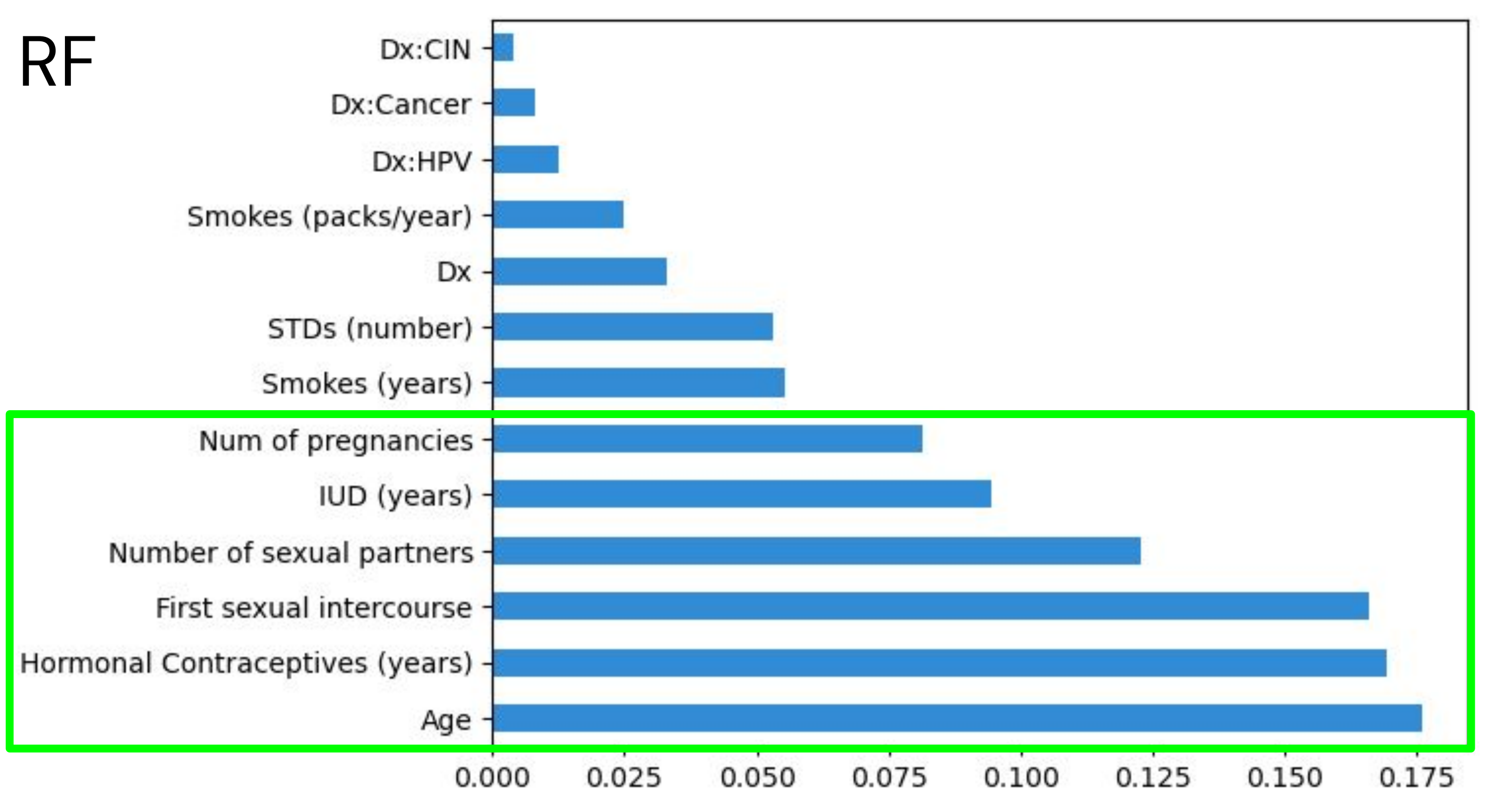
Feature Importance – KNN



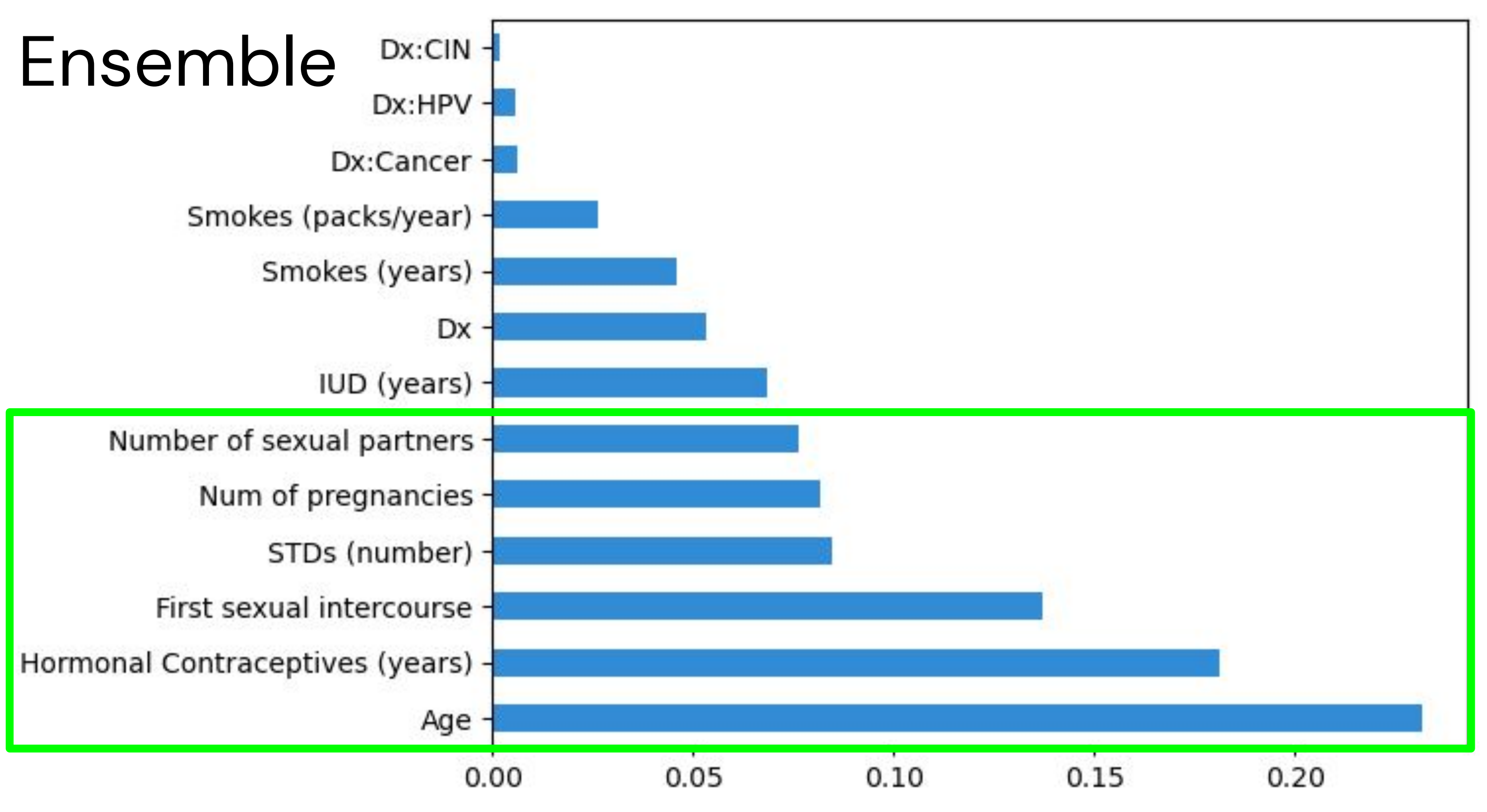
Feature Importance – Decision Tree



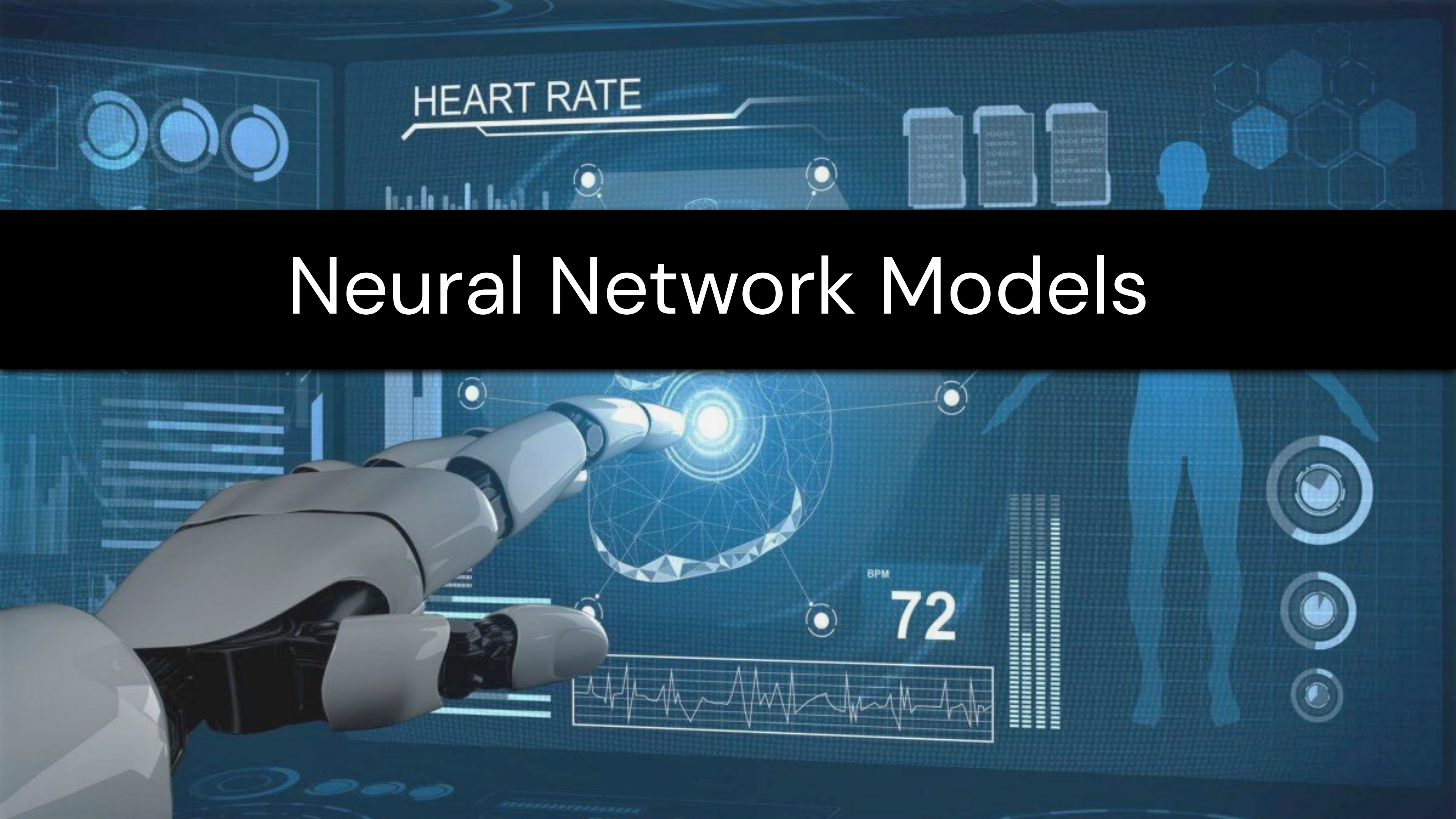
Feature Importance – Random forest



Feature Importance – Ensemble Model

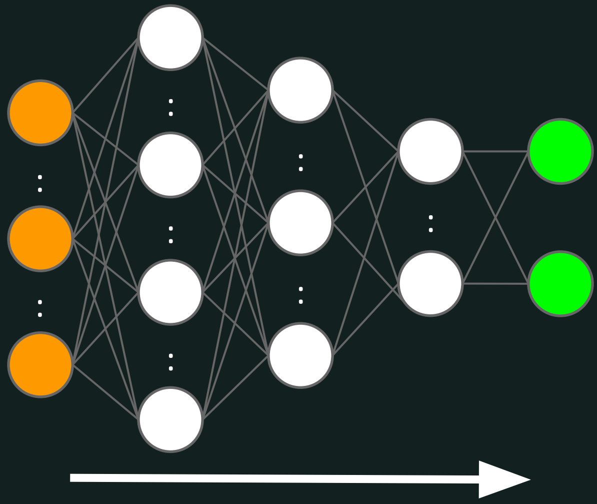


Neural Network Models

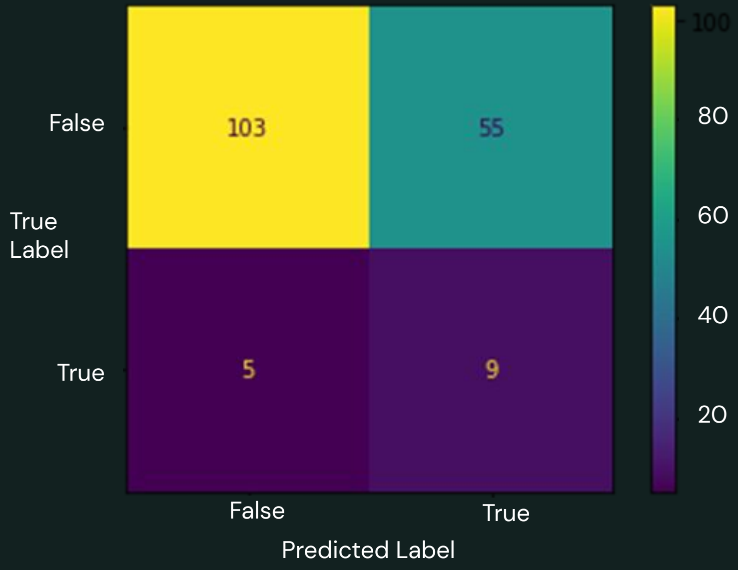


Neural Network Interpretation

- Inputs: Same the other models (13 variables)
- Architecture: Inverse Pyramid[13, 256, 128, 64, 2]

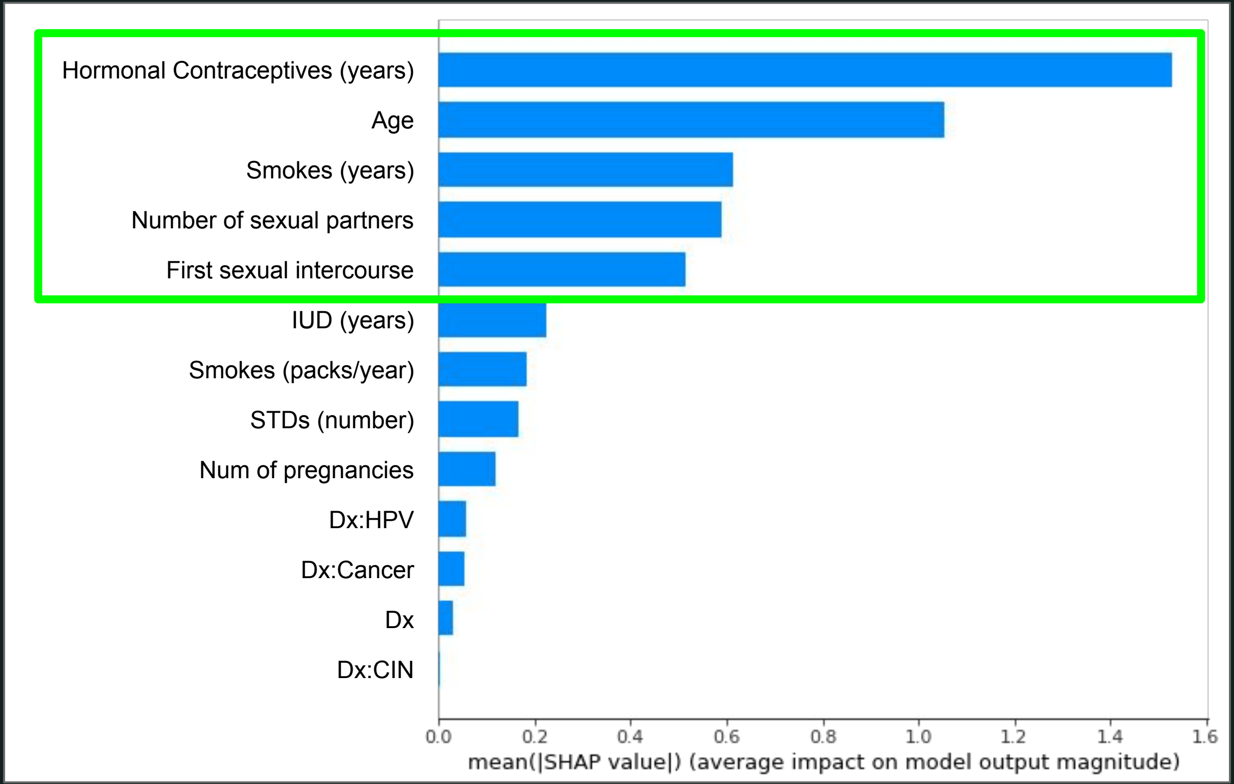


- Test data result: Detect positive patients with TPR 64.3%

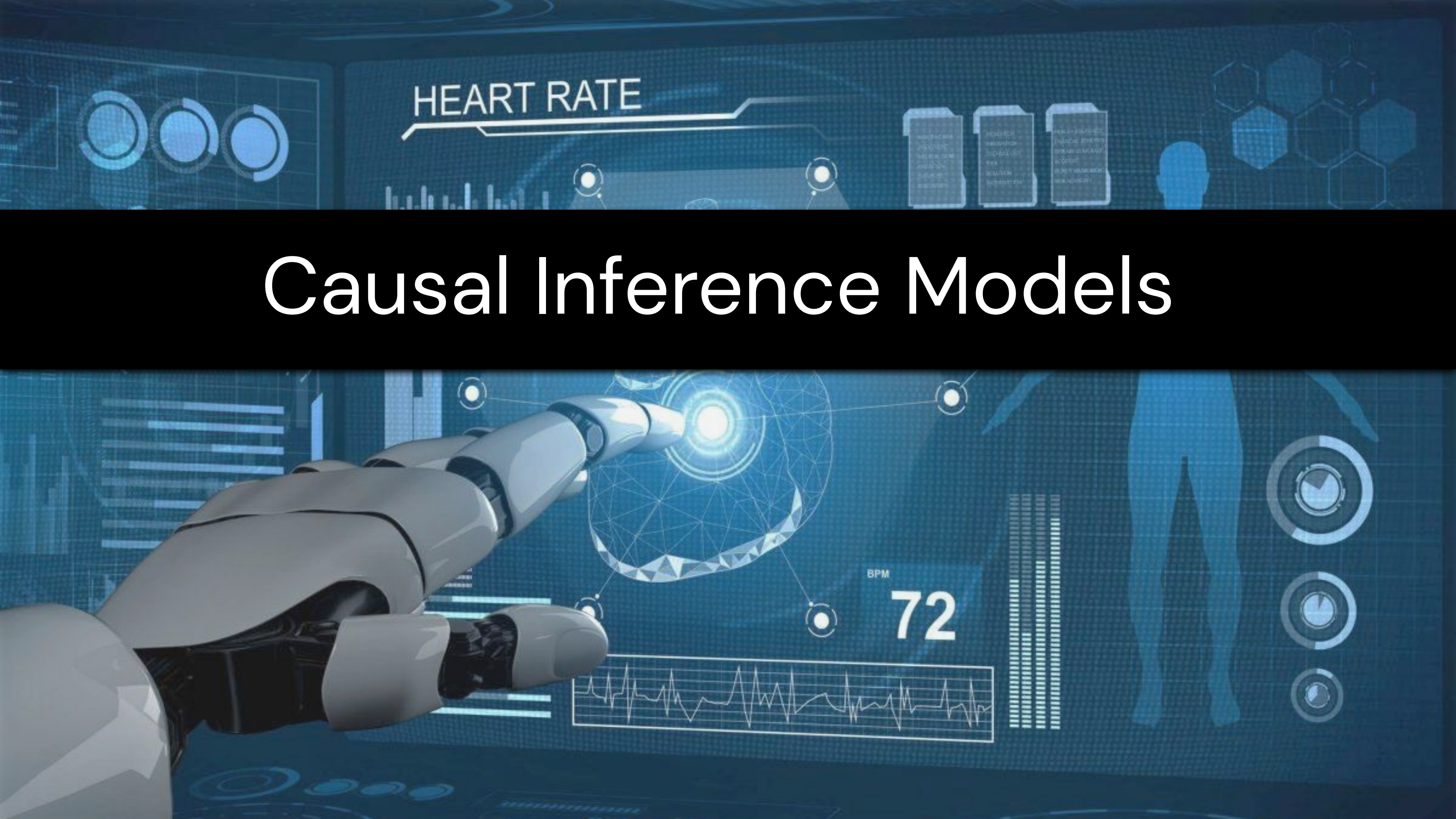


Neural Network Interpretation

- Extract feature importance with SHAPLEY; similar to the ML models' results



Causal Inference Models

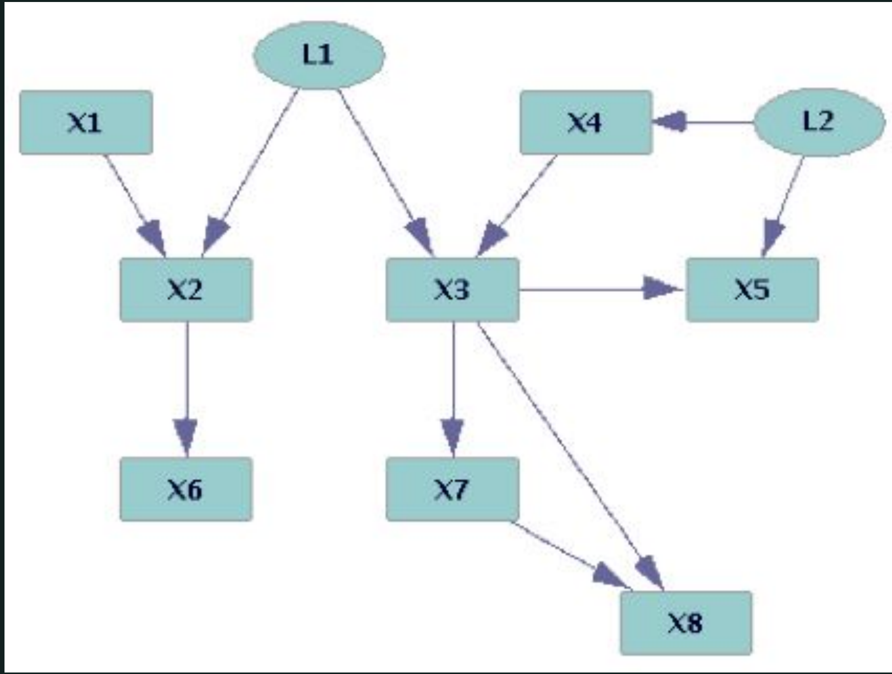


Causal Inference Experiment

Apply **Fast Causal Inference**

- constraint-based algorithm
- Non-parametric model
- Detect causation with latent unmeasured variables
- Expert knowledge will clarify causal direction

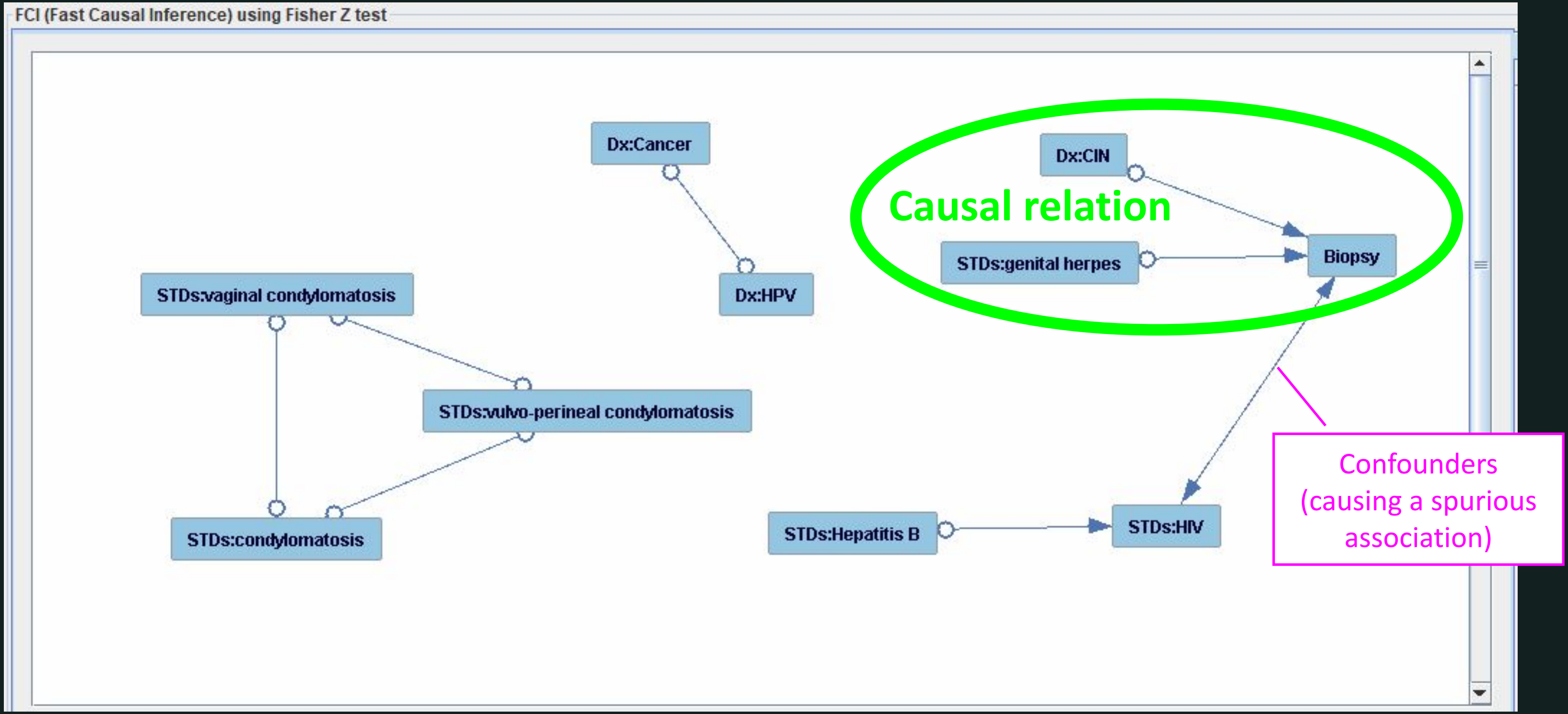
Use Tetrad:
Java-based desktop application



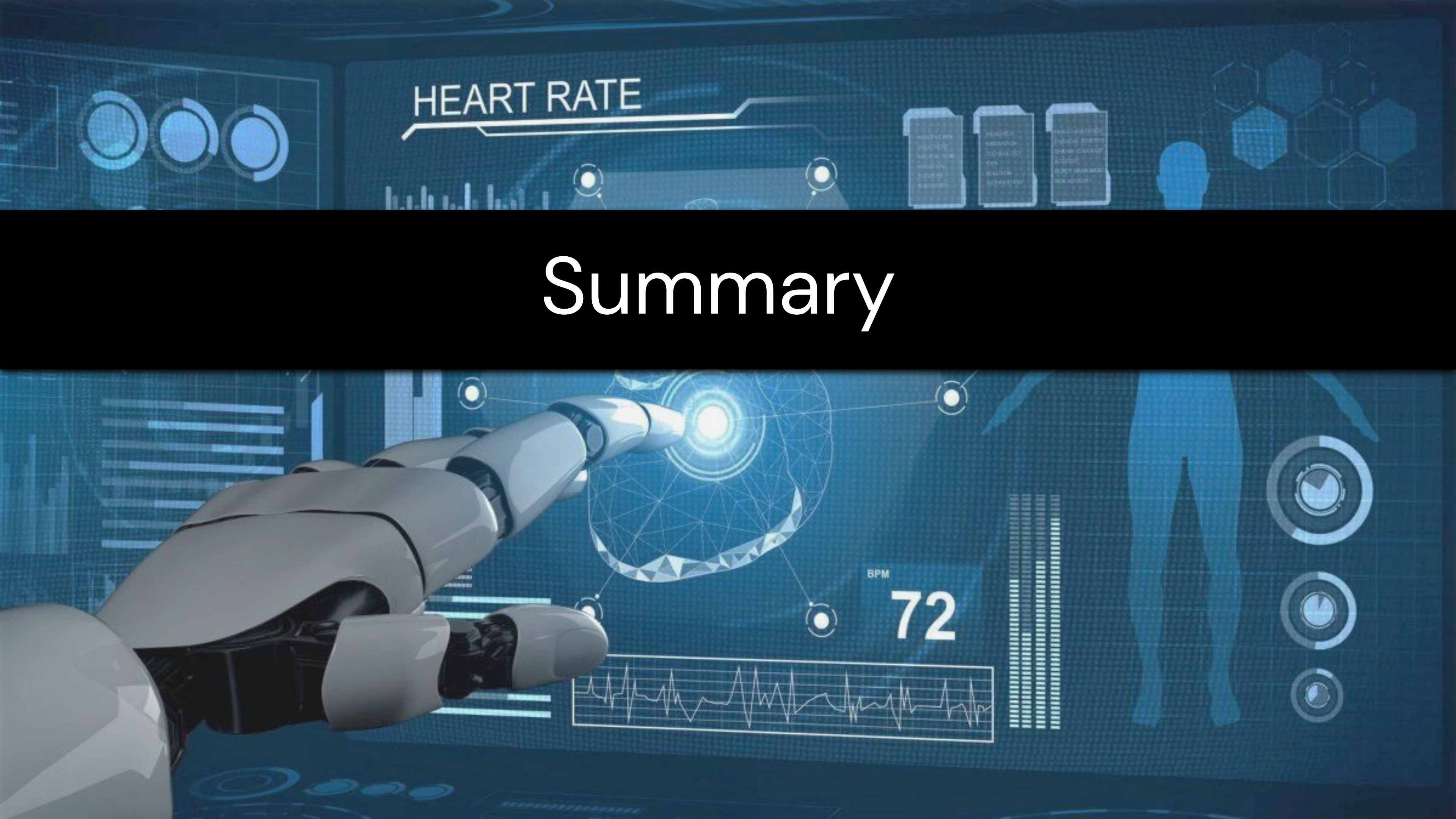
Source: "cmu-phil/tetrad." https://github.com/cmu-phil/tetrad
"Tetrad Single HTML Manual." https://cmu-phil.github.io/tetrad/manual/#completeRuleSetUsed

Causal Inference Experiment

- FCI algorithm can detect existence of confounder



Summary



Conclusion

- Interpretability $\neq$ Explainability
- Interpretable AI $\longrightarrow$ Explainable AI
  (One approach: Causal ML/AI)

Challenges

Limitation of Interpretable ML

Interpretation extracted by tool is not statistically rigorous

Domain Expert Knowledge

Engaging domain experts is necessary = Human + AI

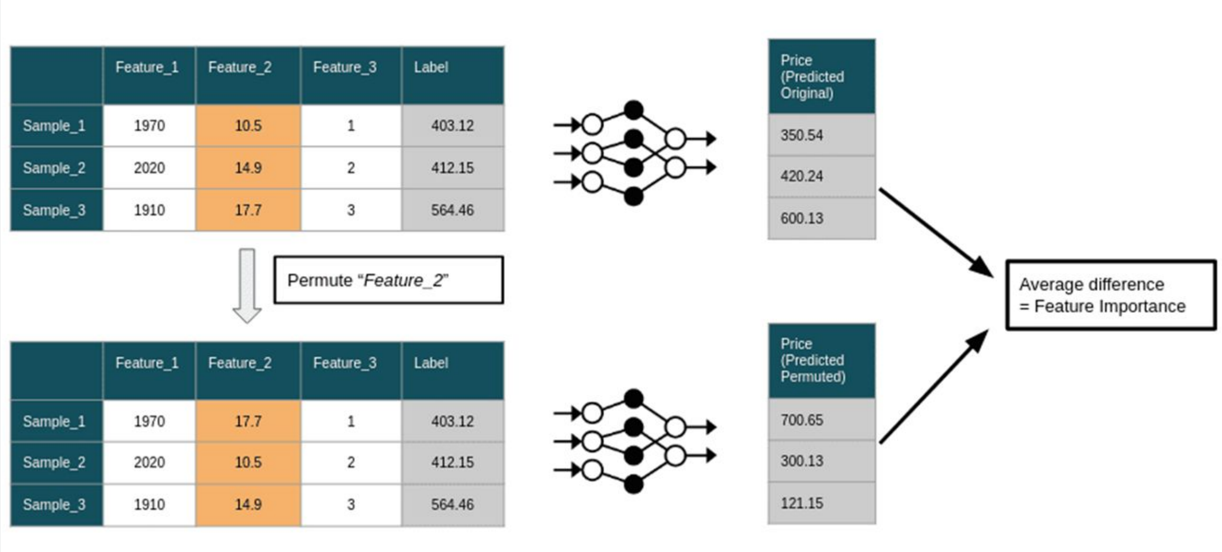
Thank you !!

Appendix

Interpretation Mechanism:
Permutation Feature Importance

Permutation by **shuffling variable values**

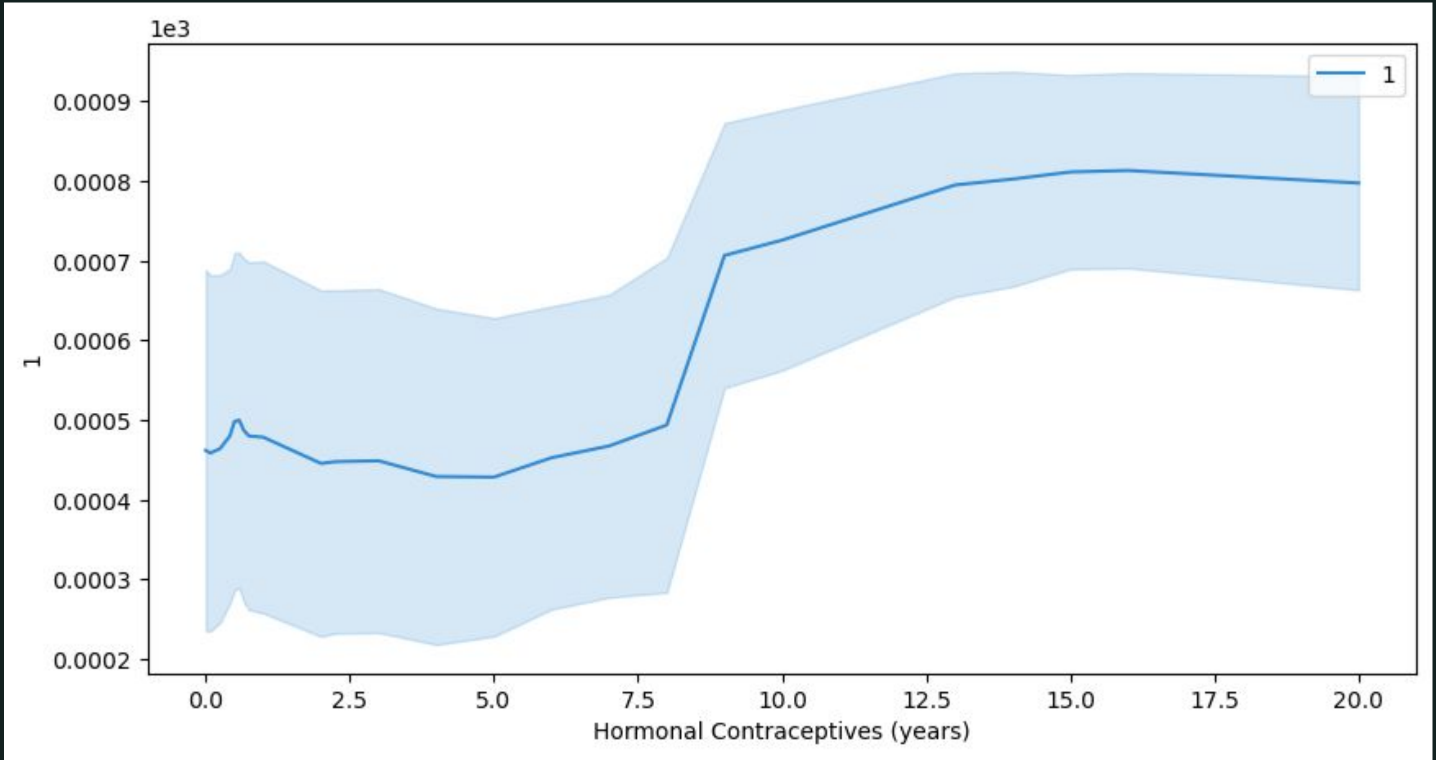
- Pros: Nice interpretation, Comparable different problems
- Cons: Generating unrealistic data, and correlation vulnerable



Source: https://www.modulos.ai/blog/permutation-feature-importance-deep-dive/

Partial Dependence Plot

- Non-Linear dependency



Causal Inference Experiment

- FCI algorithm can detect causal relationship and reject association