Effective viral load testing and synthetic counterfactual trials via causal data generation

A pitch for the Workshop on AI for HIV prevention

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(Alphabetical)

Background (simplified)

- There was a trial…
  - A person has covariates X, and has preference for treatment arm T
  - Test viral load after 18 months
  - If viral load load detected, prescribe more costly (but much more effective) treatment
  - Note: viral load should not be detectable if there is adherence and no resistance
- Trial outcome: Across **all** treatment arms, ~90% of people have no viral load

Effective viral load testing

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- Implication
  - Some people are advocating to remove testing going forward, to save costs
  - Push back: No testing → ~10% with viral load not getting proper treatment!
- Question: Can we spend ~10% of original cost to identify these 10%?
- Simple solution: Train and run a classifier should_test(X)
  - If it works, great!
  - If not, … ideas?

Synthetic counterfactual trials via causal data generation

- There was a trial…
  - A person has covariates X, and has preference for treatment arm T
  - Test viral load after 18 months
  - If viral load load detected, prescribe more costly (but much more effective) treatment
  - Note: viral load should not be detectable if there is adherence and no resistance
- Trial outcome: Across **all** treatment arms, ~90% of people have no viral load
- Observation
  - Trials take time and resources
  - Hypothesis: Certain demographics would "perform the same" in treatment arm T and T'
- Question: Can we explore such questions without running more trials?
  - Require causal thinking and appropriate assumptions for valid causal inference