Deutsches Forschungszentrum für Künstliche Intelligenz
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Estimating Causal Effects in Partially Directed Parametric Causal Factor Graphs

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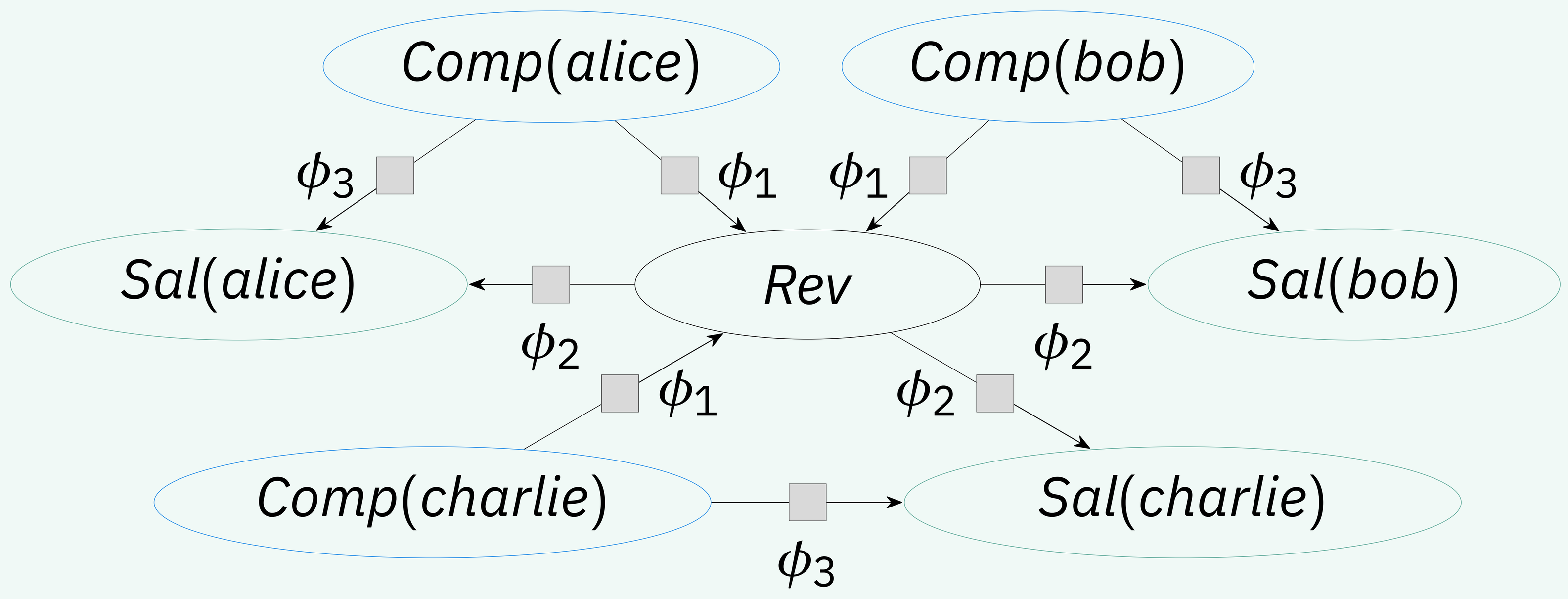
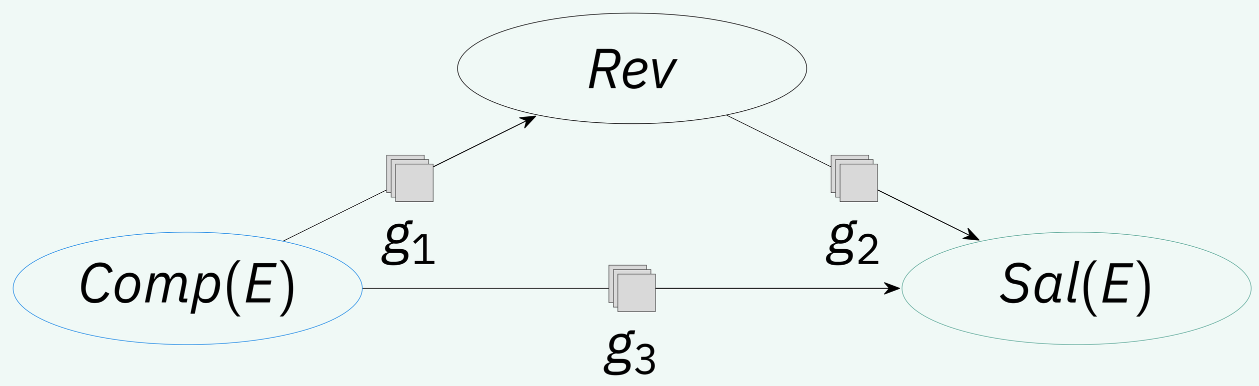
1. Motivation

- Goal: Make decisions under uncertainty
- Need to compute the effect of actions
- Need to apply the semantics of an intervention instead of conditioning

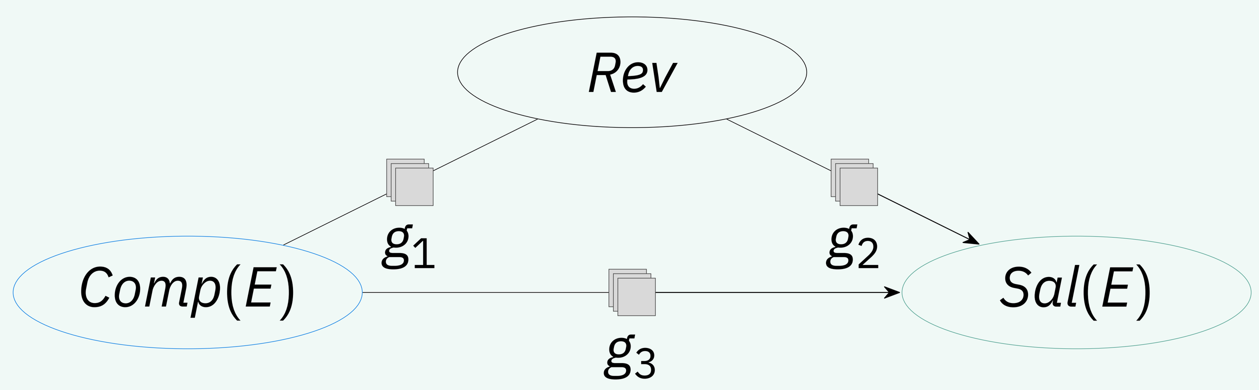


- We would like to have a first-order (lifted) representation
- Lifting uses a representative of indistinguishable individuals for computations and thereby speeds up inference



2. Problem Setup

- In general, we do not know all causal relationships
- Goal: Incorporate partial causal knowledge in a lifted representation
- Estimate causal effects in a partially directed lifted representation

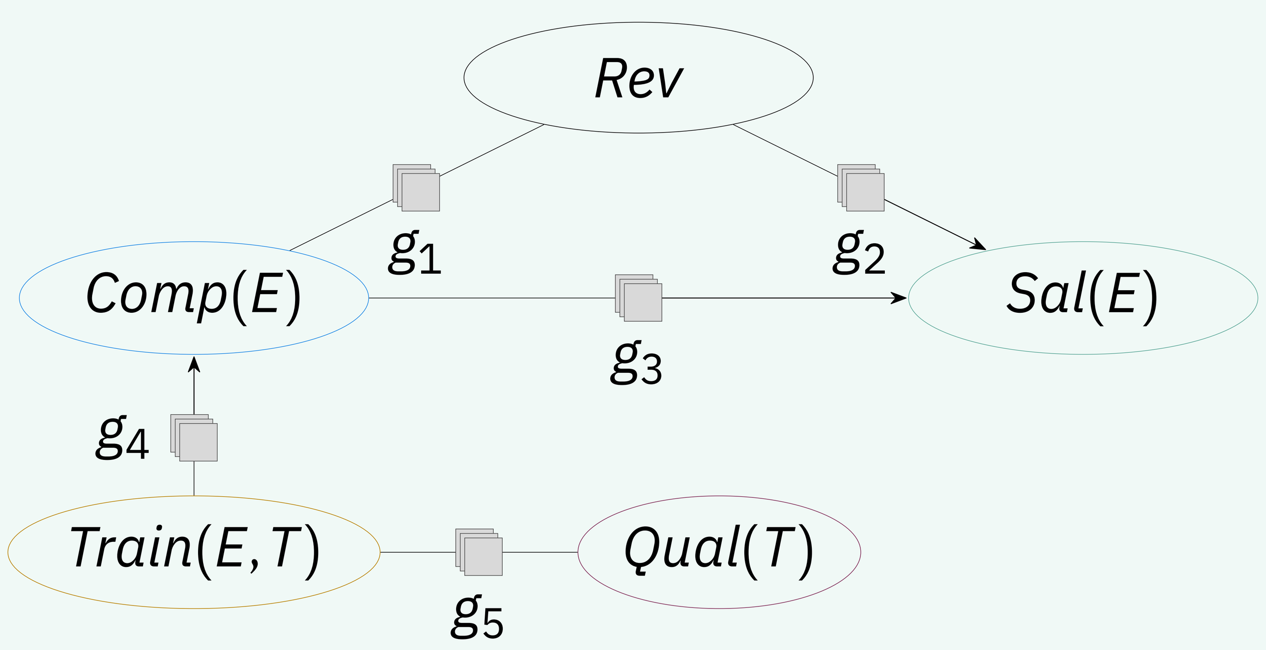


Main Contribution

A formalism to enable first-order decision making with partial causal knowledge.

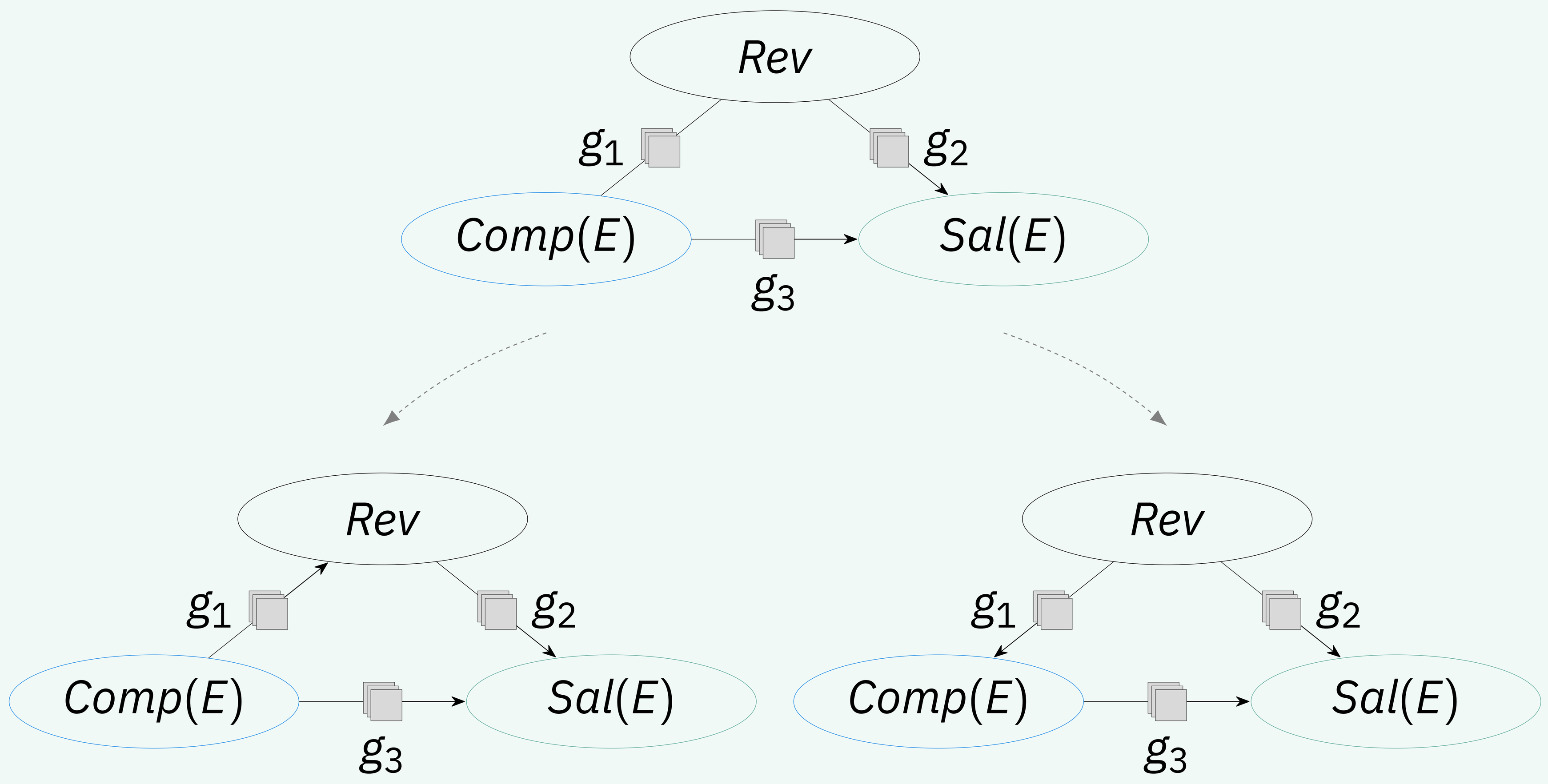
3. Partially Directed Parametric Causal Factor Graphs

- Directed edges to represent known causal relationships
- Undirected edges for relationships with unknown causal directions
- Logical variables to represent groups of random variables



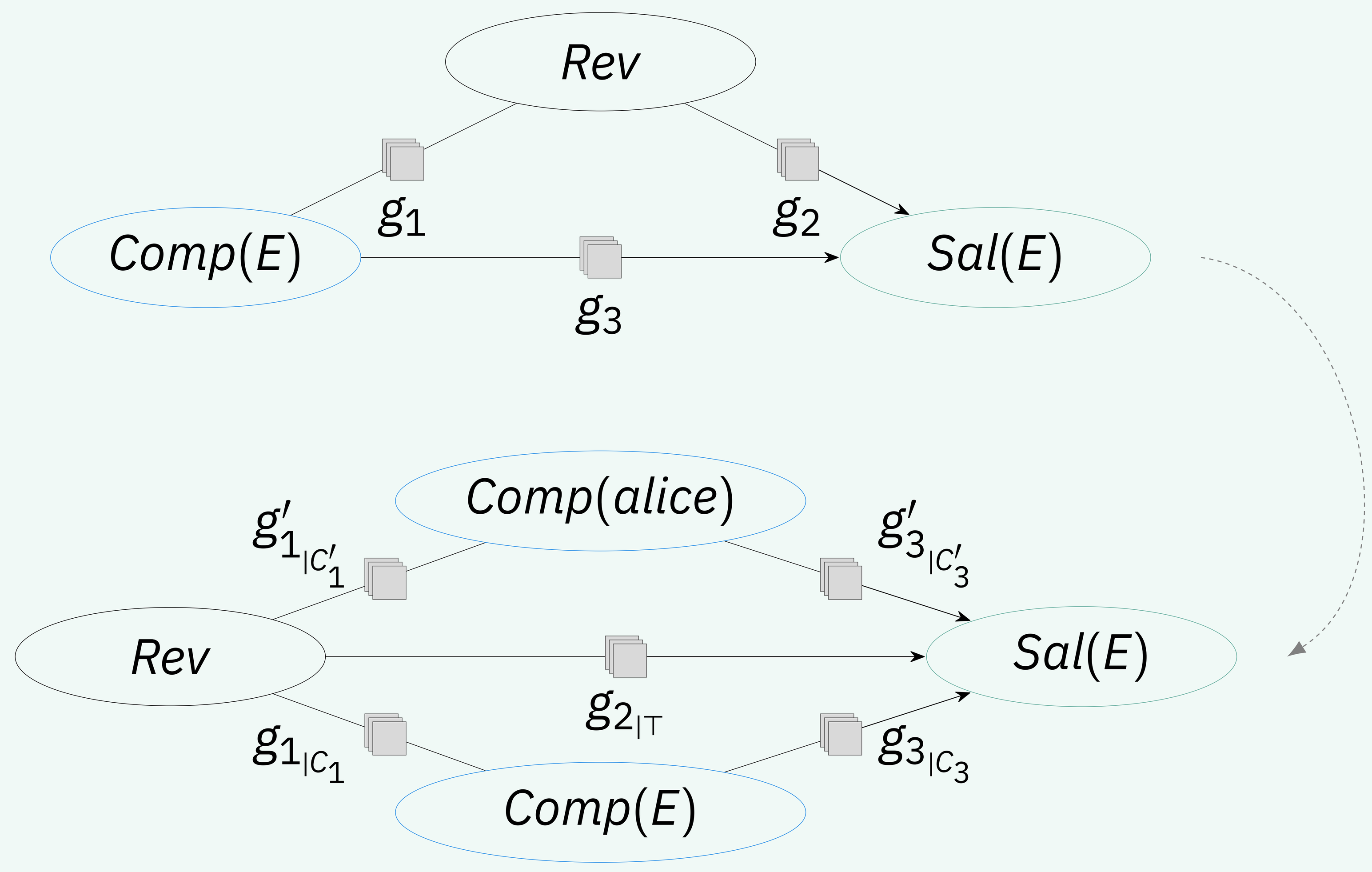
4. Interventions

- We want to compute the effect of actions
  - Is it worth the costs to send an employee to a training course?
  - What effect has sending all employees to a training course on the revenue?
- An intervention is defined on a fully directed graph
- E.g., $P(Rev \mid do(Comp(E) = \mathrm{high}))$
  - Sets fixed value $Comp(E) = \mathrm{high}$
  - Removes incoming influences from $Comp(E)$



5. Splitting

- An intervention on a propositional random variable requires splitting of nodes
- E.g., $P(Rev \mid do(Comp(alice) = high))$
  - Removes $alice$ from $Comp(E)$
  - Adds an additional node $Comp(alice)$



6. The Extended Lifted Causal Inference Algorithm

Main idea:

(1) Split nodes of interventional variables (avoid full grounding as much as possible)

(2) Enumerate relevant edge directions to compute the effect of an action

Properties:

- Only grounds necessary parts of the model
- Theorem: To compute the effect of an intervention, it is sufficient to consider the directions of the undirected edges that are connected to the random variables on which we intervene