Causal Imputation via Synthetic Interventions

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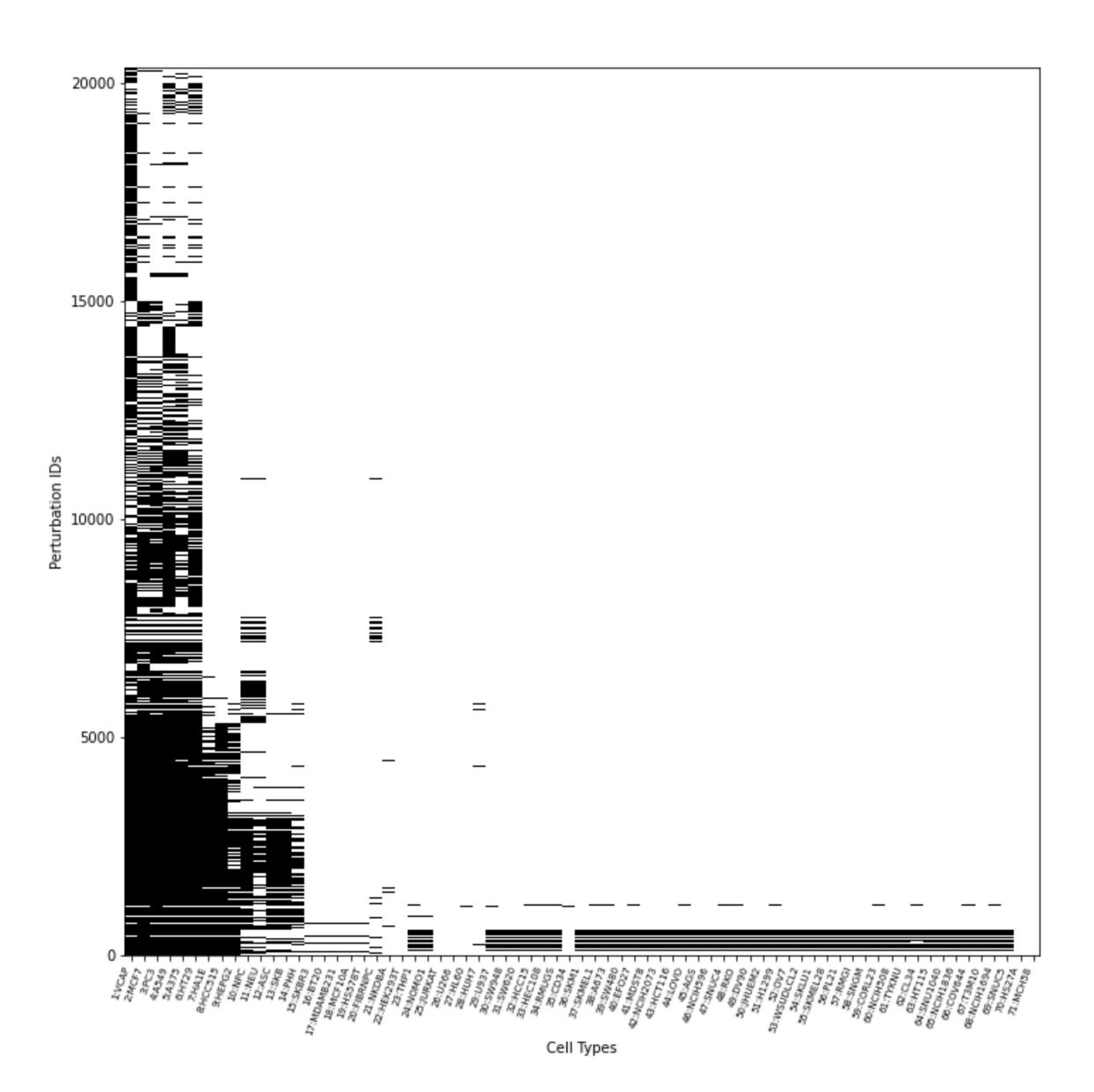
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GOAL: TRANSPORT THE EFFECT OF A DRUG FROM ONE CELL TYPE TO OTHER CELL TYPES



Availability of (cell type, perturbation) outcomes in the Connectivity Map (CMap) dataset [1]. Each outcome x^{ca} in cell type c under drug a is a p=978-dimensional vector of gene expression levels.

DESIDERATA

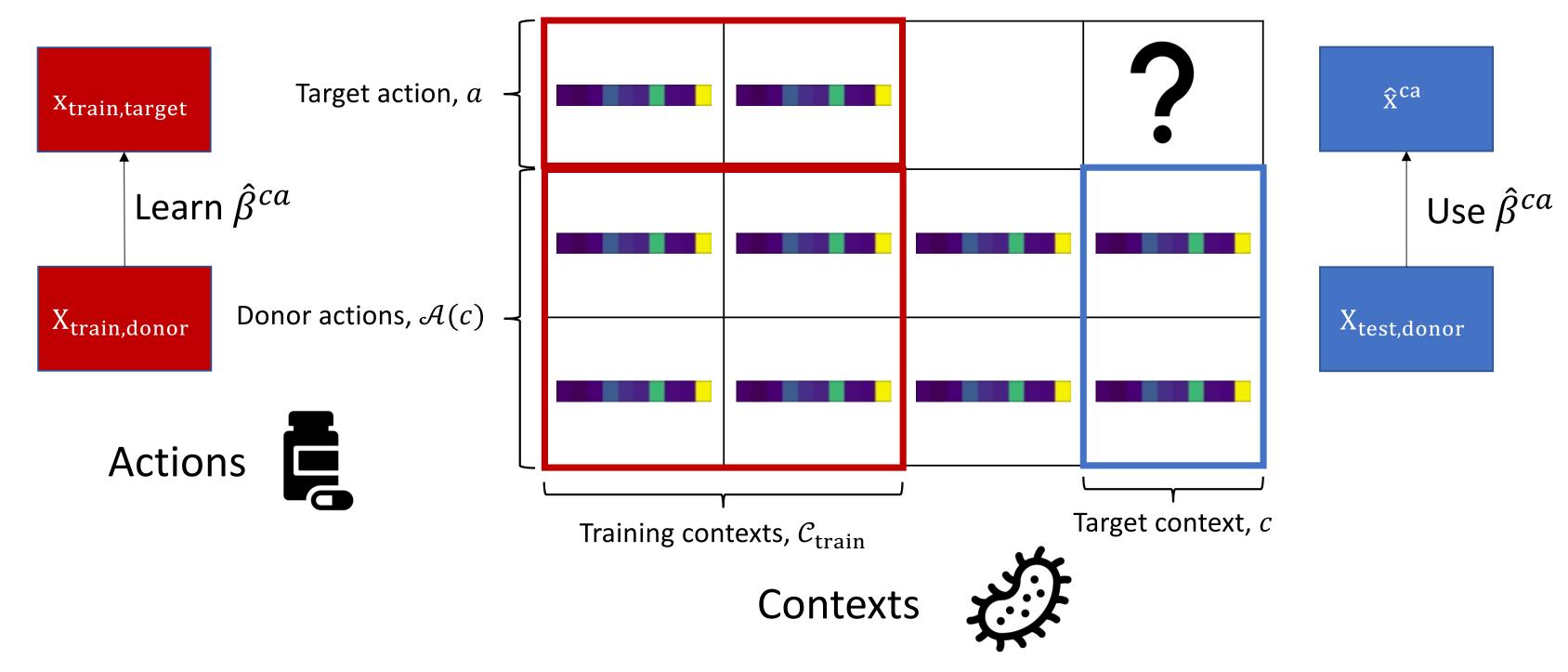
- Fast
- Flexible/effective model of heterogenous effects
- Theoretical consistency guarantees
- Detailed causal model (i.e., selection diagram) not necessary

	Fast	Heterogeneous Effects	Guarantees	Needs selection diagram
Fixed Effects (FE)	√	X	√	×
Autoencoding + FE	\checkmark	\checkmark	X	×
Causal Transportability	\checkmark	\checkmark	\checkmark	\checkmark
MICE/MissForest	X	\checkmark	×	×
Synthetic Interventions	\checkmark	\checkmark	\checkmark	×

Existing methods do not satisfy our desiderata:

- Fixed effects [2] isn't expressive enough.
- Fixed effects + autoencoding [3] and traditional imputation methods [4,5] don't have guarantees.
- Transportability methods [6] need selection diagrams.

METHOD: SYNTHETIC INTERVENTIONS ON ACTIONS (SI-A)



Target context: the context (cell type) for which we want a prediction.

Target action: the action (drug) for which we want a prediction.

Donor actions: actions whose outcomes have been measured in the target context.

Training contexts: contexts for which the outcomes of both donor actions and the target action are measured.

ASSUMPTIONS

Linear Factor Model

The outcome $x^{ca} \in \mathbb{R}^p$ can be written as $x^{ca} = U^c v^a$ for $U^c \in \mathbb{R}^{p \times r}$ and $v^a \in \mathbb{R}^r$.

Sufficient Donor Actions

There exists $\boldsymbol{\beta}_{a,c} \in \mathbb{R}^{|\mathcal{A}(c)|}$ such that $\boldsymbol{v}^a = \boldsymbol{\beta}_{a,c}^{\top} \, \boldsymbol{v}^{\mathcal{A}(c)}$.

Sufficient Training Contexts

 $rowspan(X_{test,donor})$ is a subset of $rowspan(X_{train,donor})$.

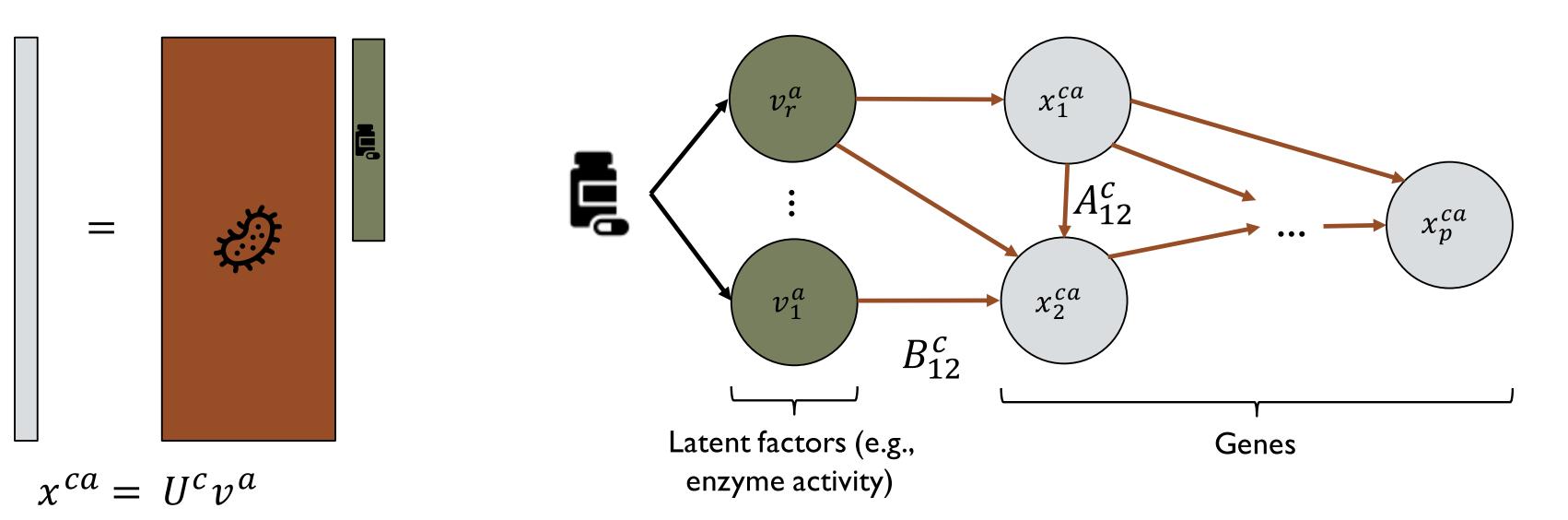
THEORETICAL RESULTS

IDENTIFIABILITY (THEOREM 1):

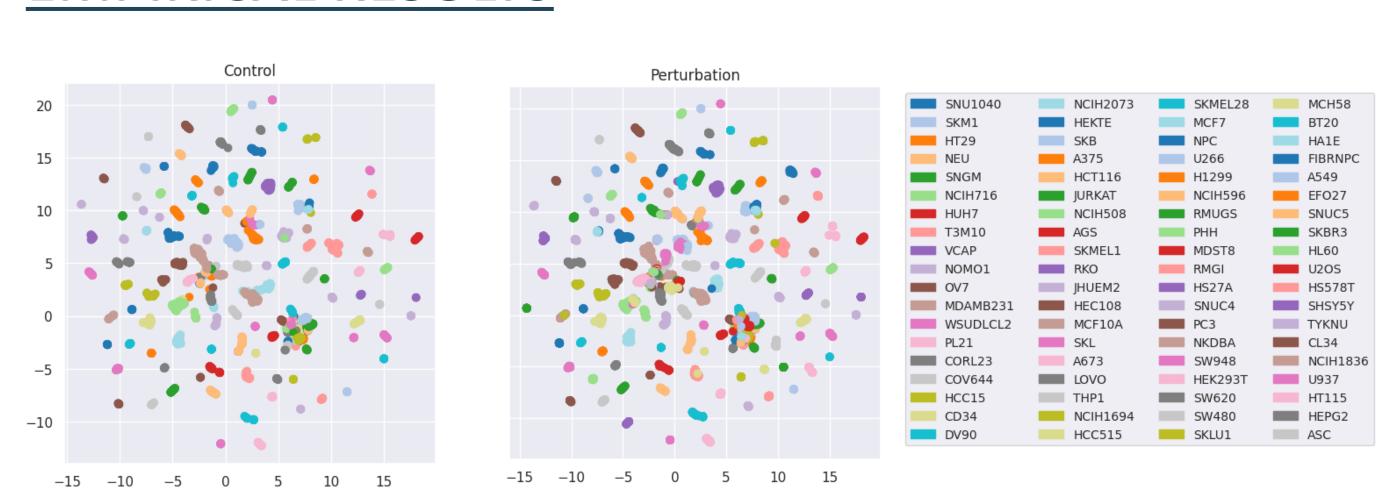
Under the above assumptions, the SI-A method identifies the outcome x^{ca} .

STRUCTURAL EQUATION MODELS INDUCE LINEAR FACTOR MODELS (PROPOSITION 1):

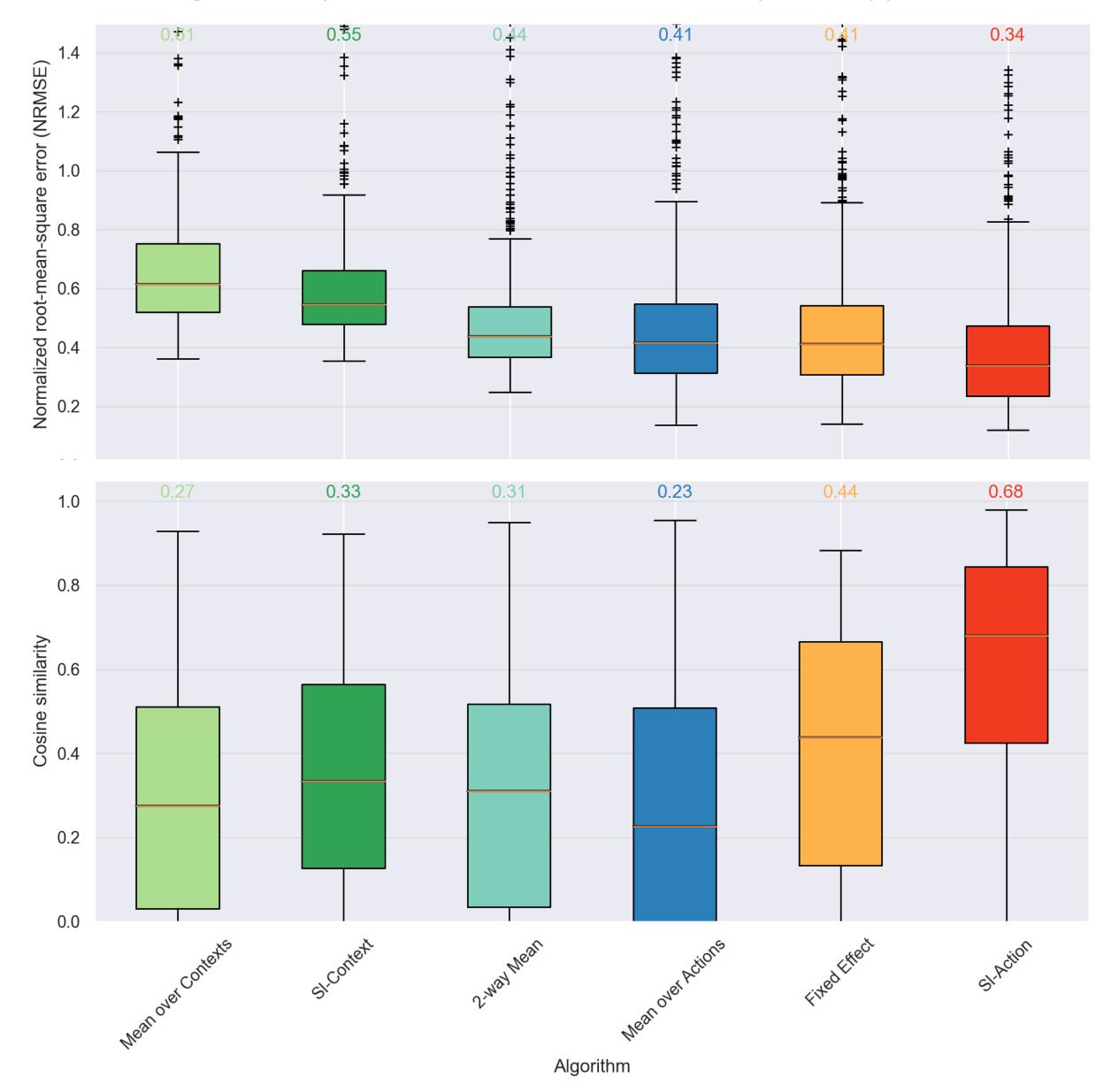
If $x^{ca} = A^c x^{ca} + B^c v^a$ with A^c acyclic, then it satisfies a linear factor model.



EMPIRICAL RESULTS



Most of the variation in the CMAP dataset is attributed to cell type, not drug. The plots show a UMAP embedding of gene expression levels, colored by cell type.



SI-A outperforms baselines on a randomly selected subset of the CMAP dataset.

REFERENCES:

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