Learning Conditional Invariances through Non-Commutativity

ICLR
International Conference on Learning Representations

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Outline

- Foundations
- Formalization
- Implementation
- Experiments
- Conclusion and Open Problems

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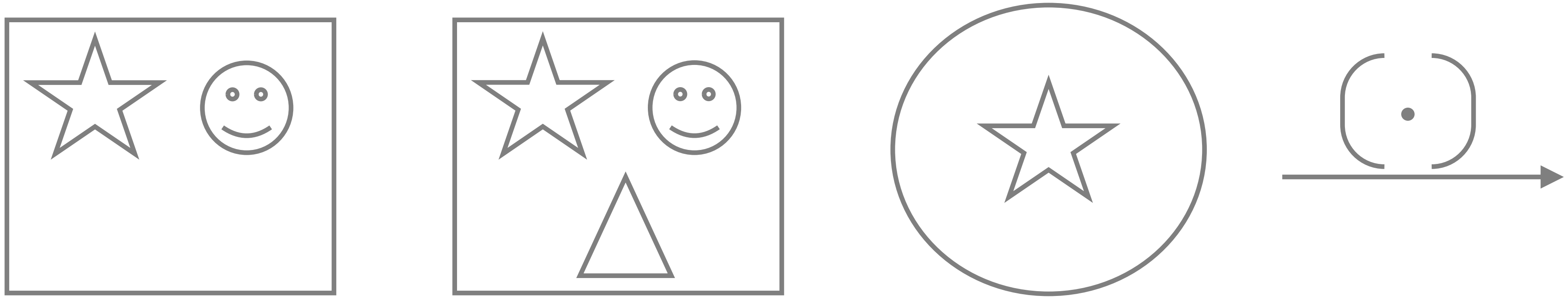
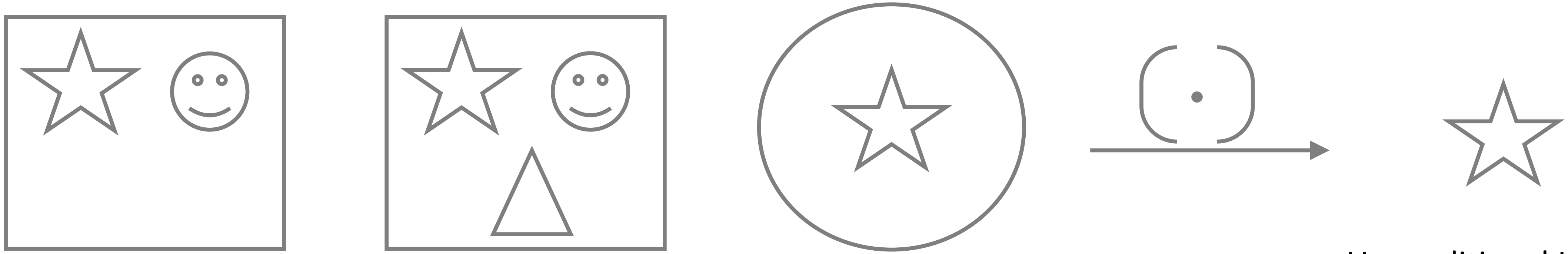
Invariants

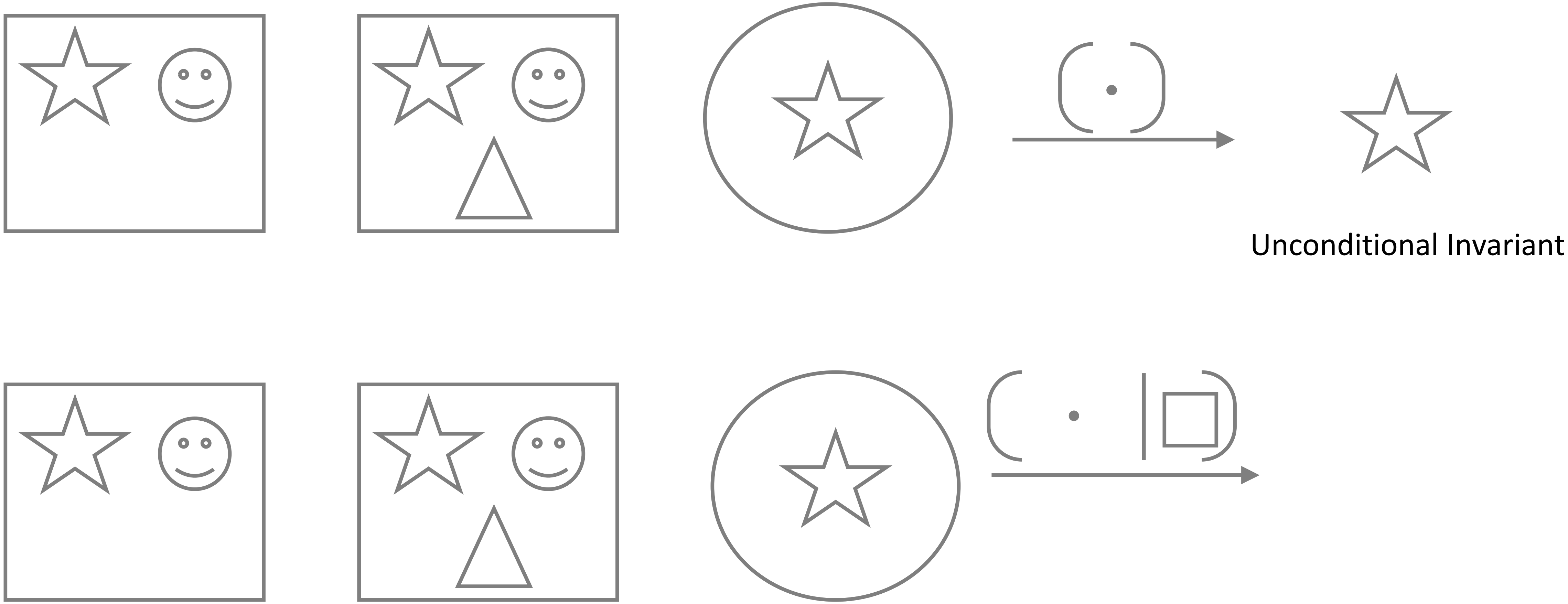


Invariants

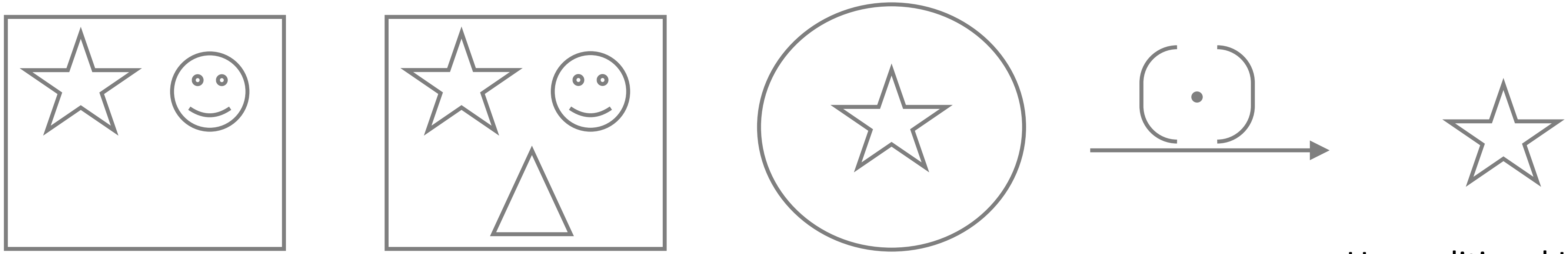


Unconditional Invariant

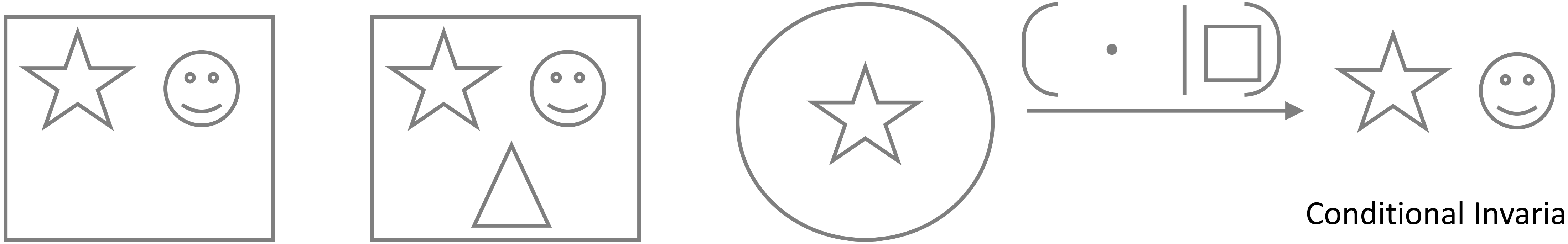
Invariants



Invariants

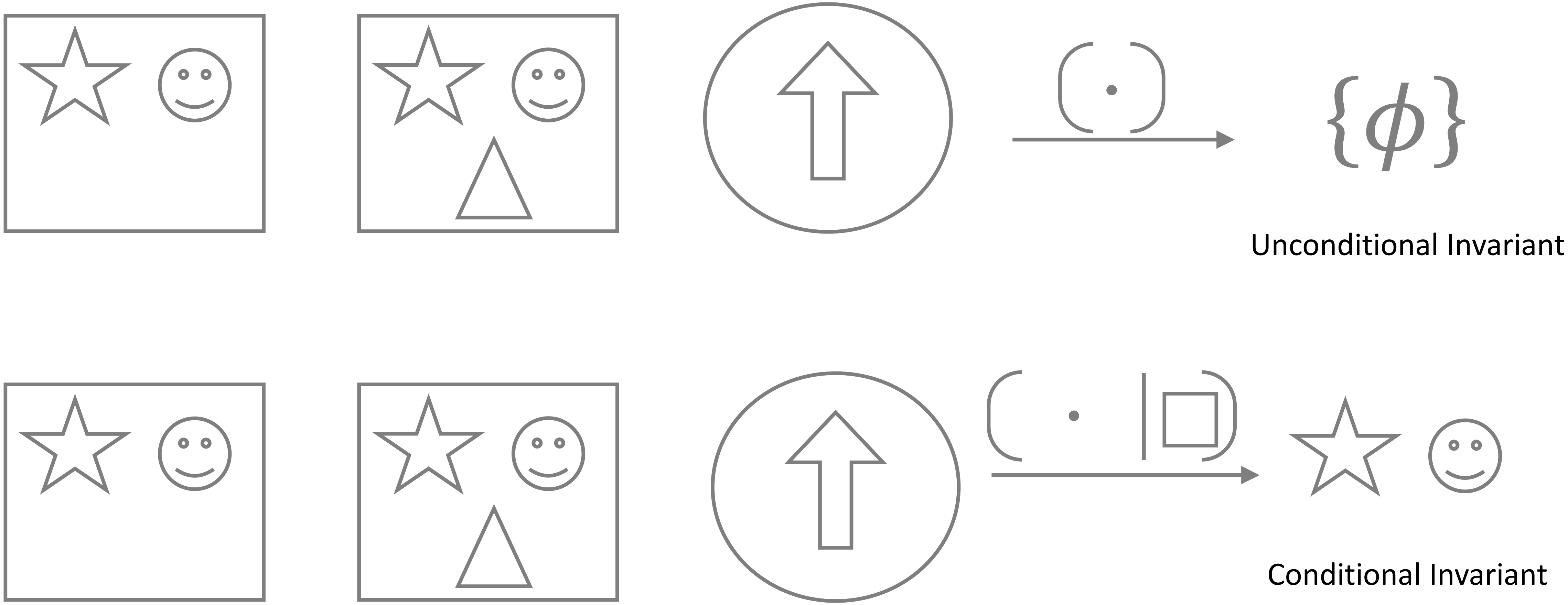


Unconditional Invariant



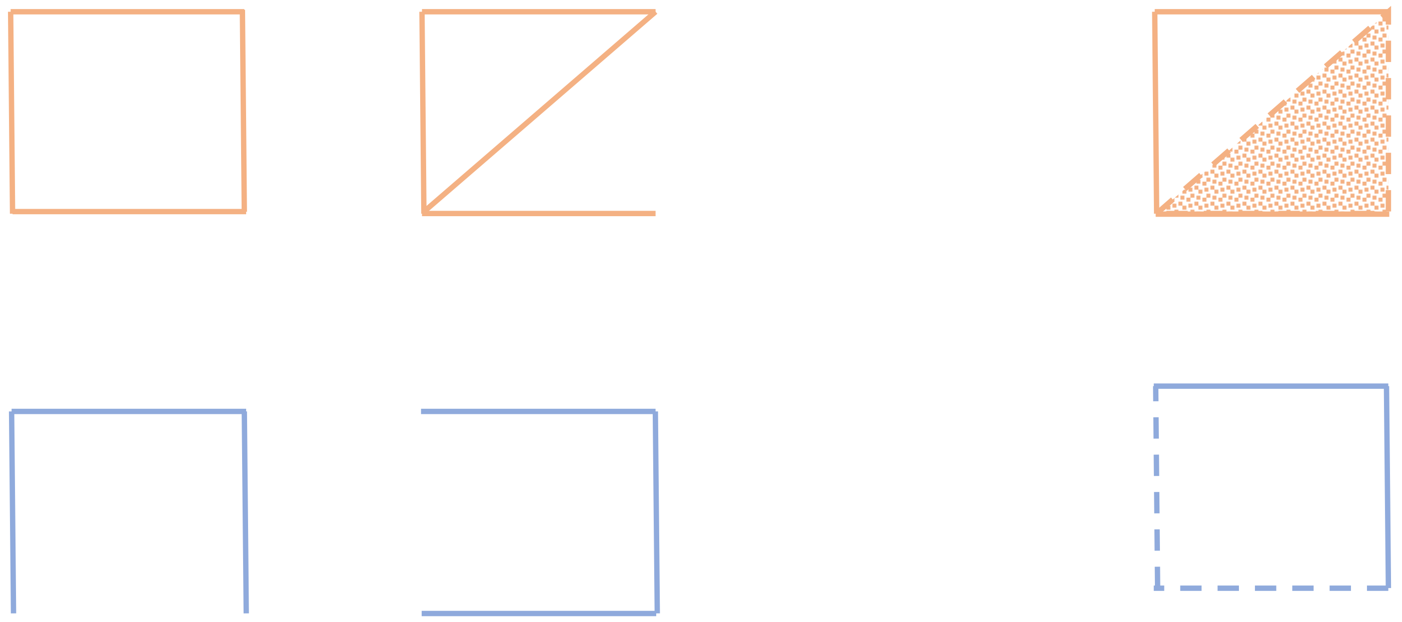
Conditional Invariants

Invariants



Problem: Geometry Estimation

Samplers: $\mathrm{edges1}()$, $\mathrm{edges2}()$ Error rates (η): 0.25, 0.3 Sample Complexity: 2 Samples per sampler: 2



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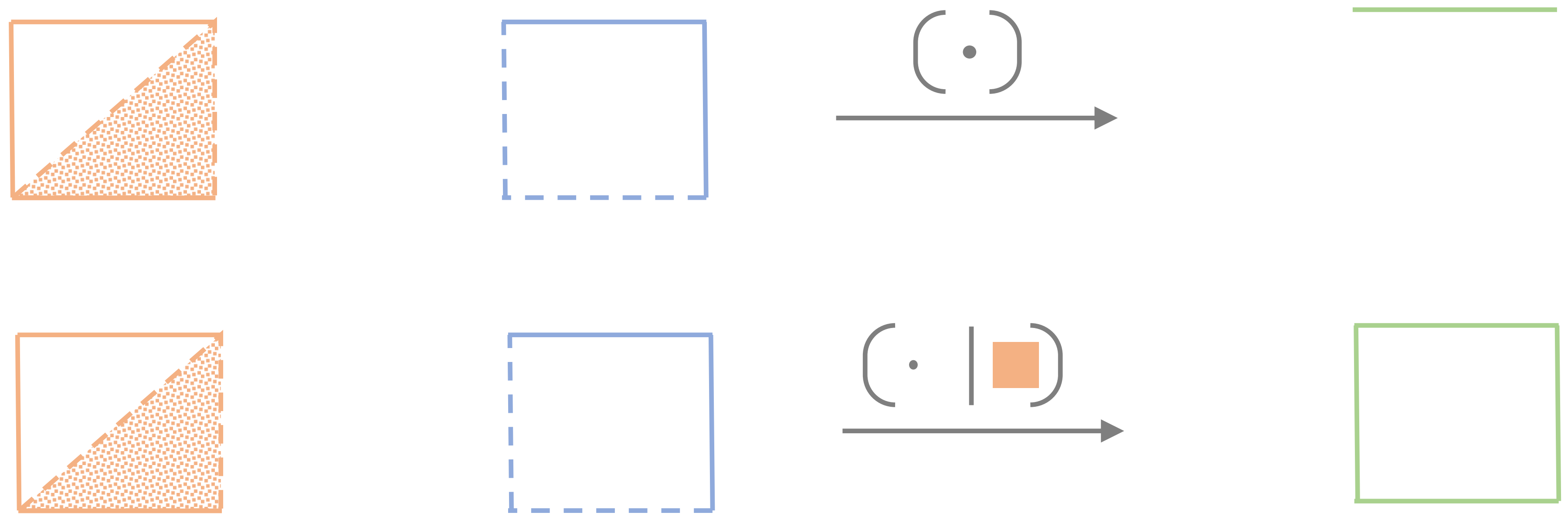

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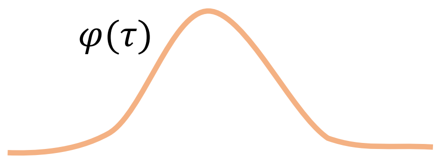
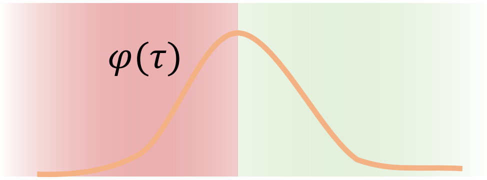
Commutative Invariance



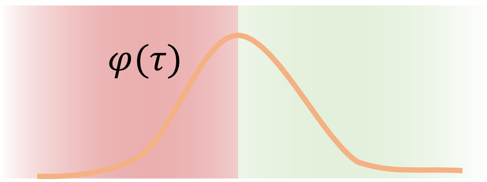
Target

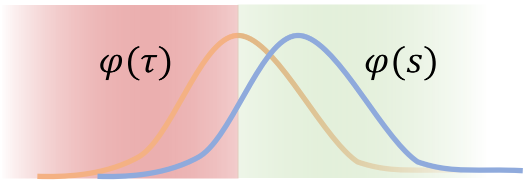
Commutative Invariance



Target Spurious Causal

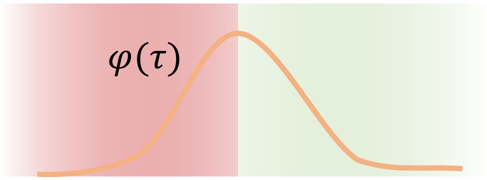
Commutative Invariance

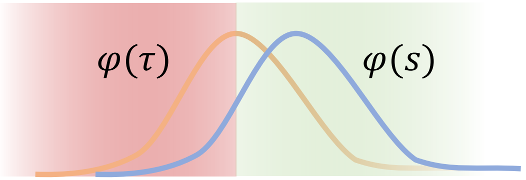


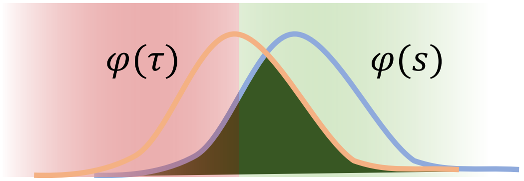


Target Source Spurious Causal

Commutative Invariance







Target Source Spurious Causal

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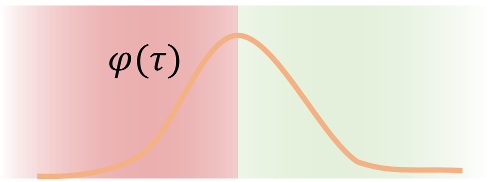
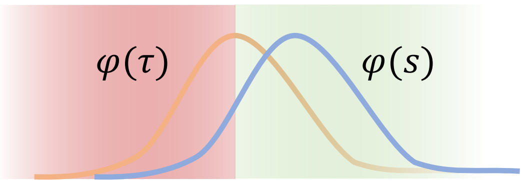
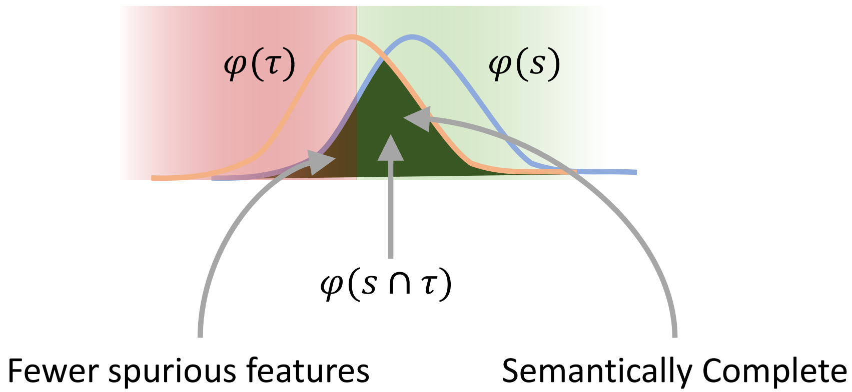
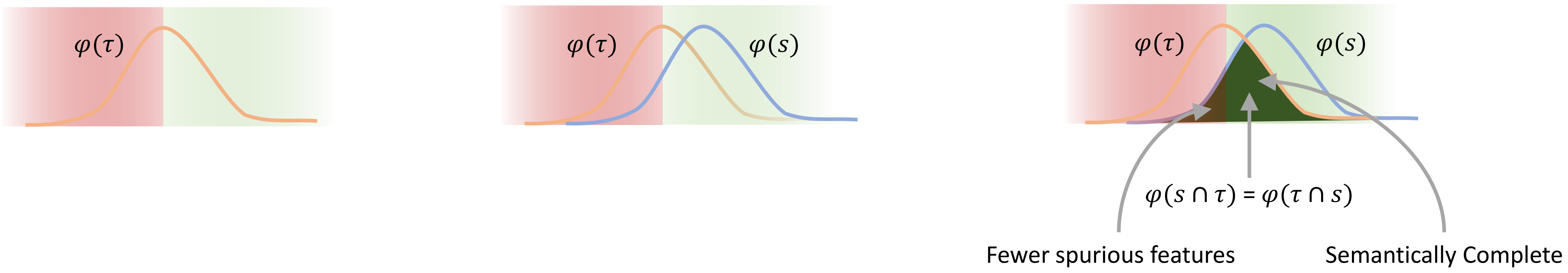






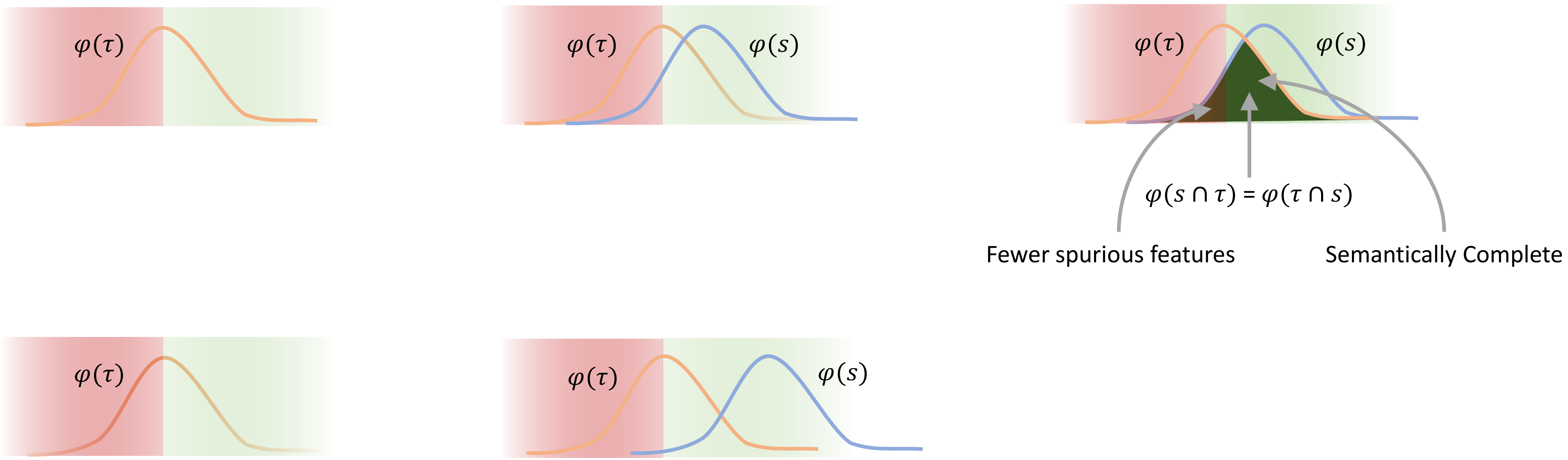
Target Source Spurious Causal

The Commutativity in Commutative Invariance



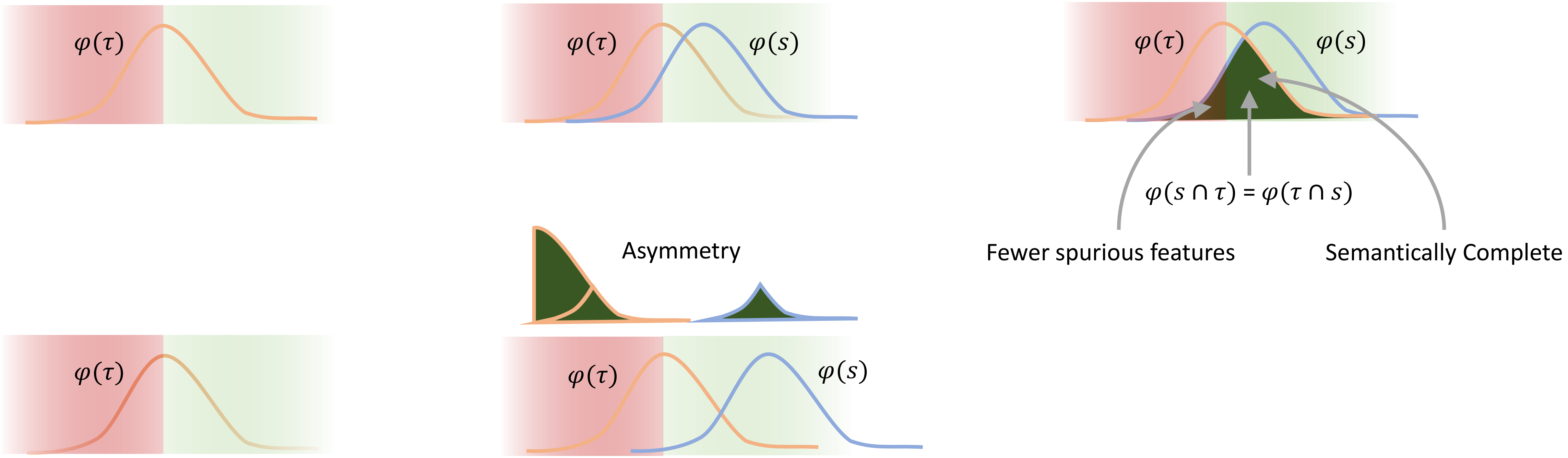
Target Source Spurious Causal

Divergent Source and Target



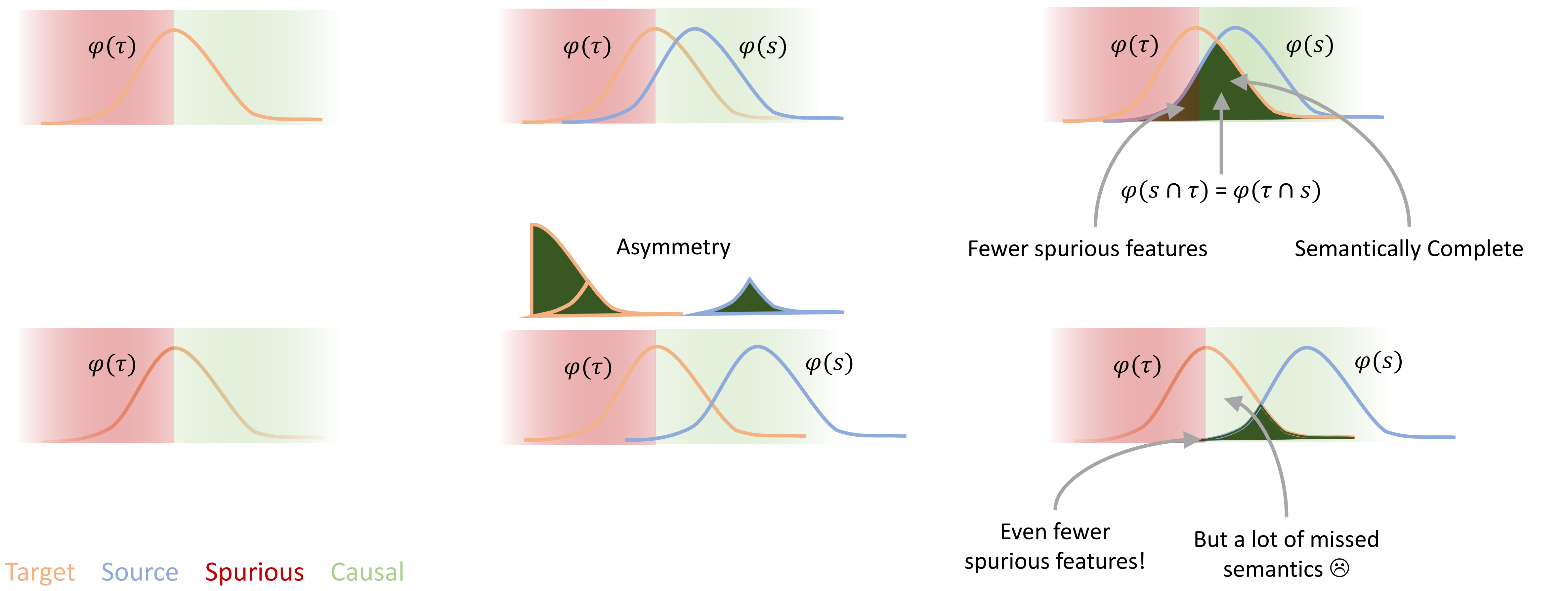
Target Source Spurious Causal

Asymmetry

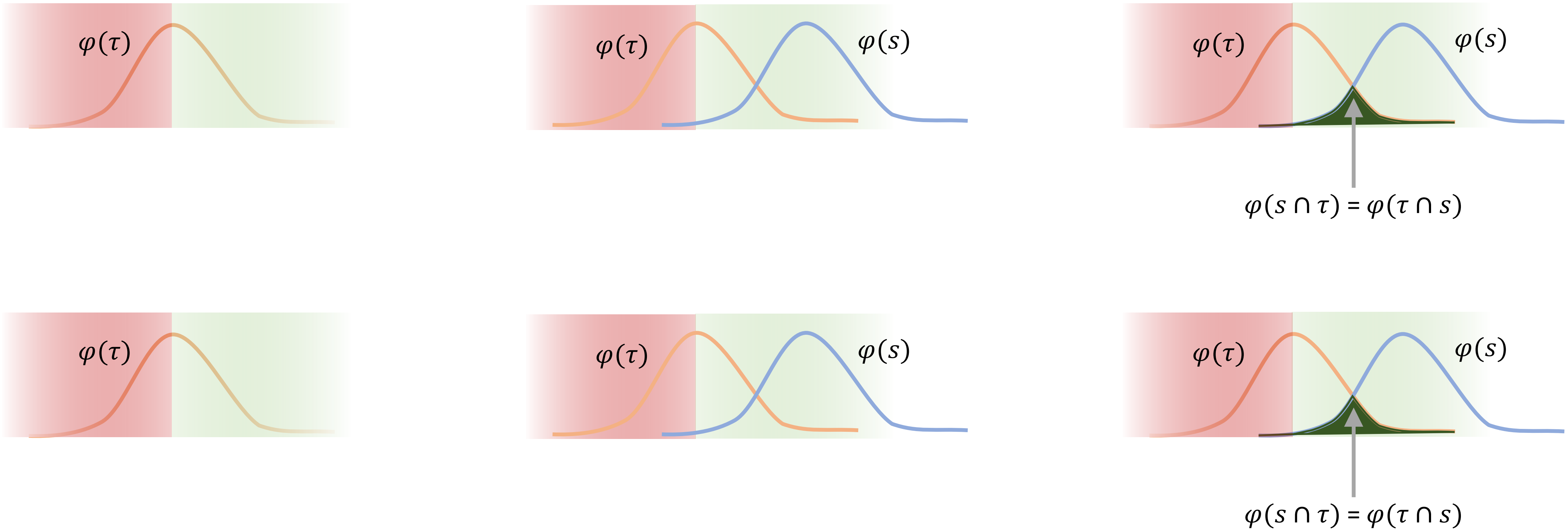


Target Source Spurious Causal

Commutative Invariance under Asymmetry

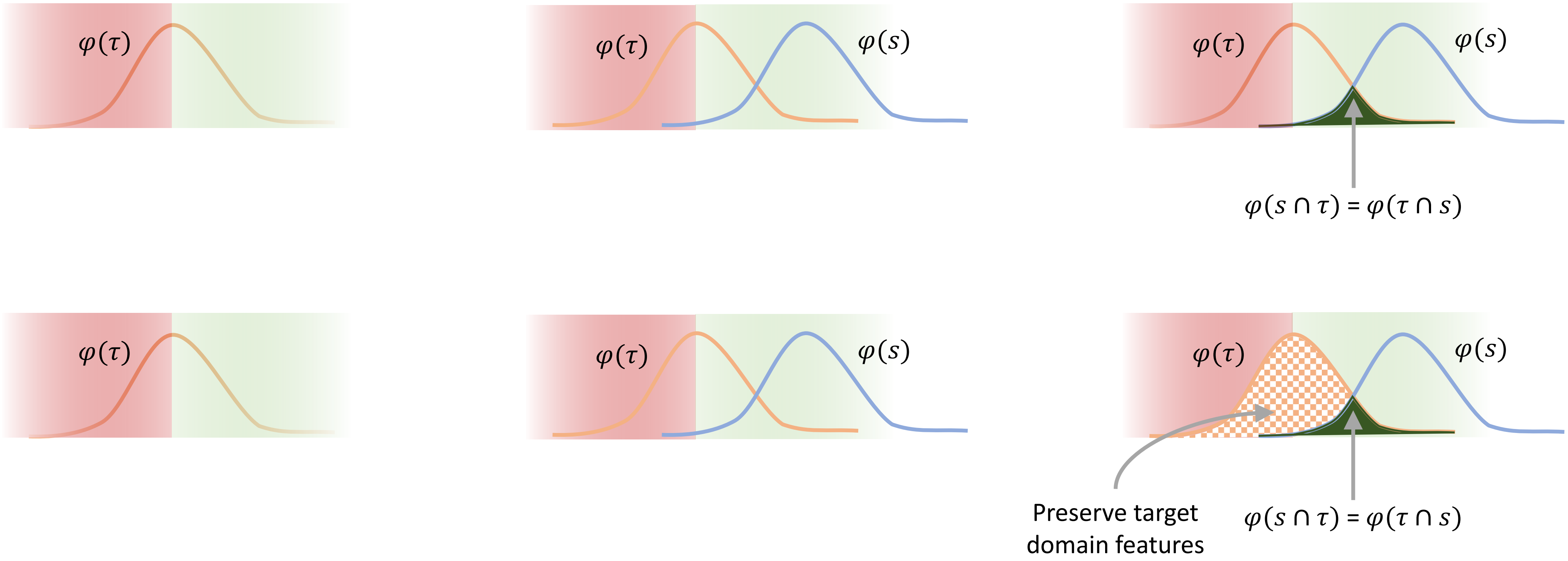


Commutative Invariance under Asymmetry



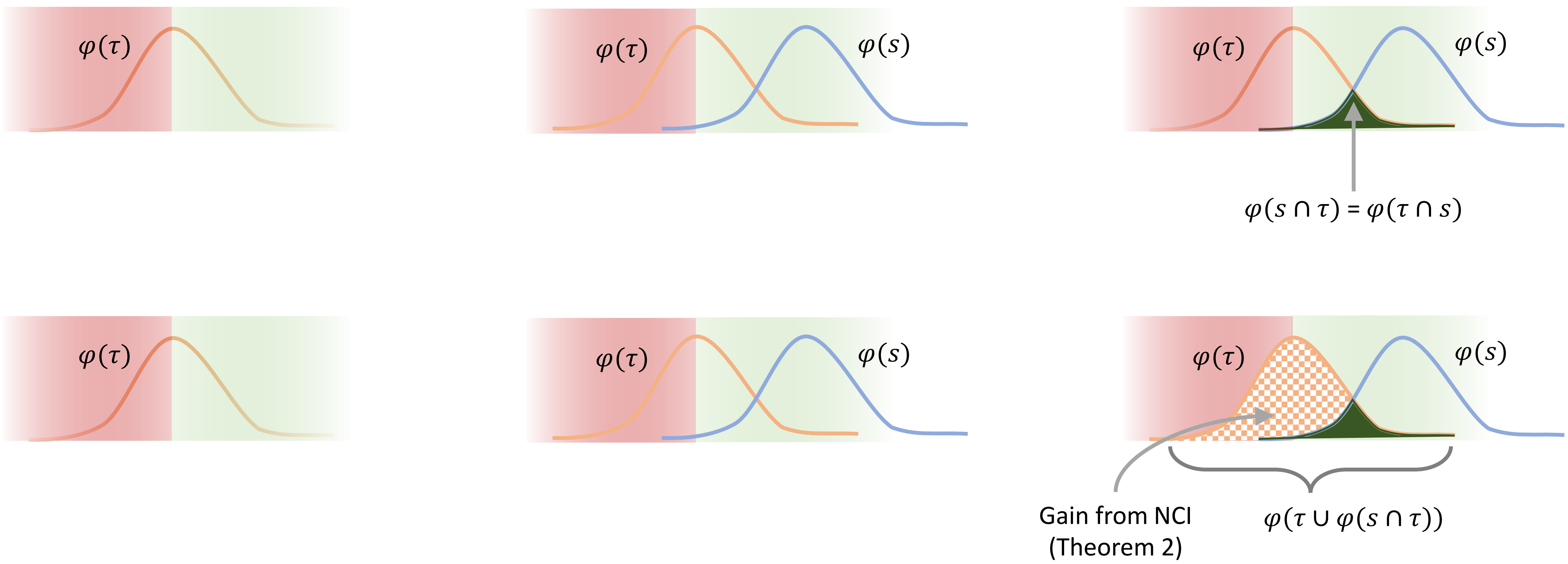
Target Source Spurious Causal

Commutative *vs.* Non-Commutative Invariance (NCI)



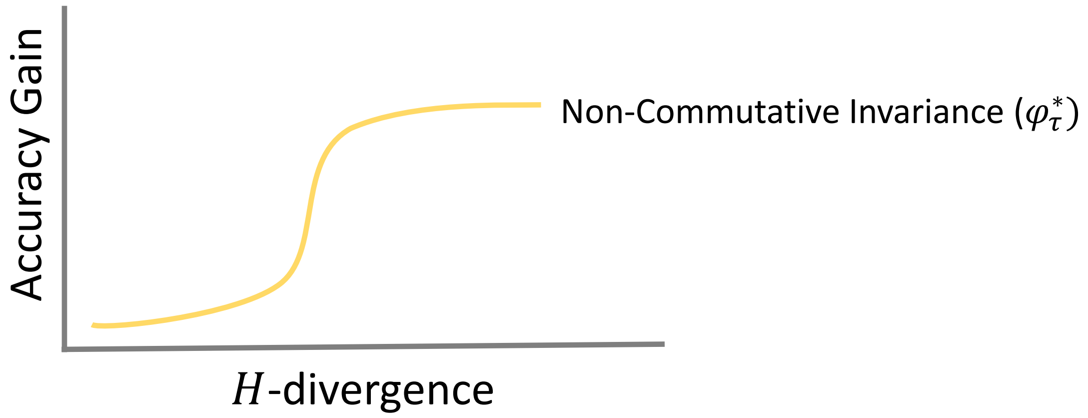
Target Source Spurious Causal

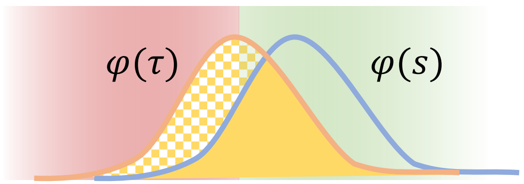
Gains from NCI

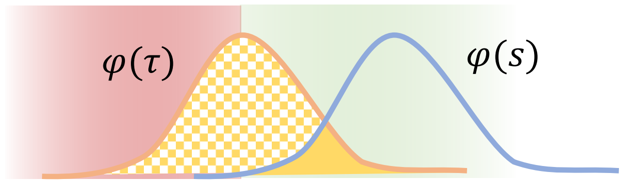


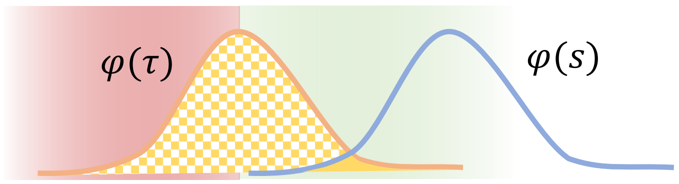
Target Source Spurious Causal

NCI with Increasing Separation between Domains



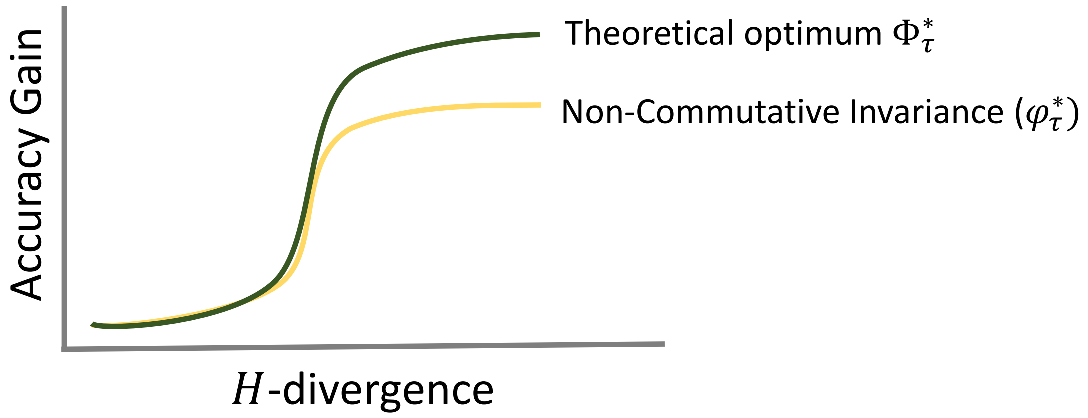


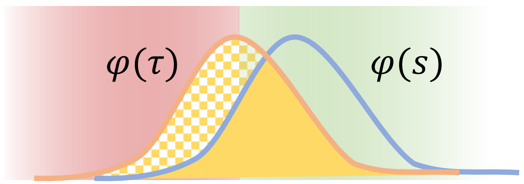


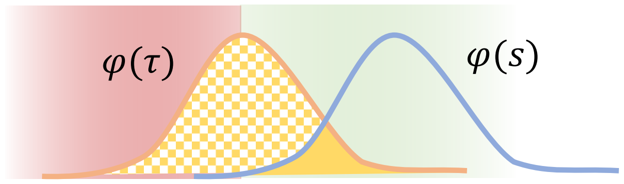


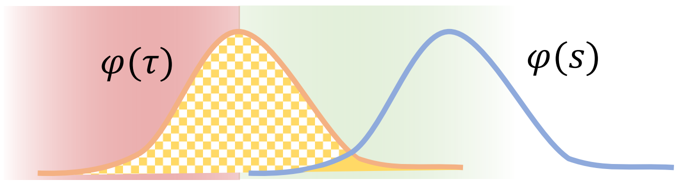
Target Source Spurious Causal

NCI with Increasing Separation between Domains



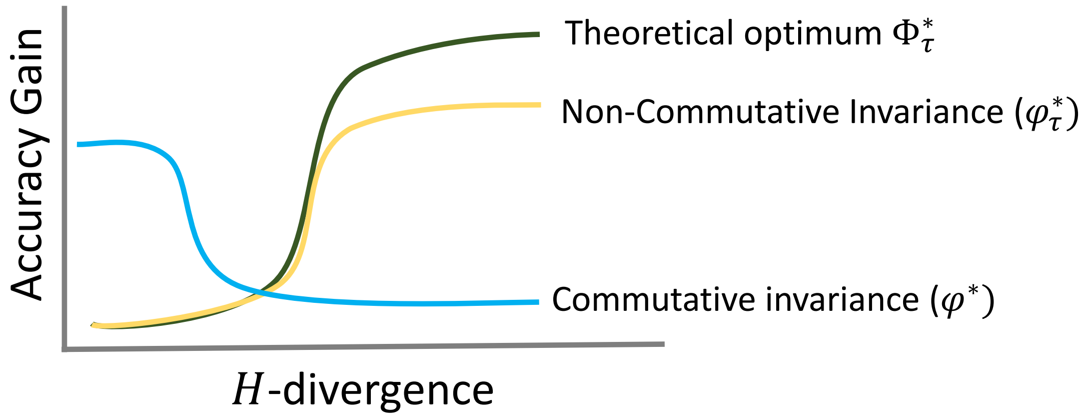


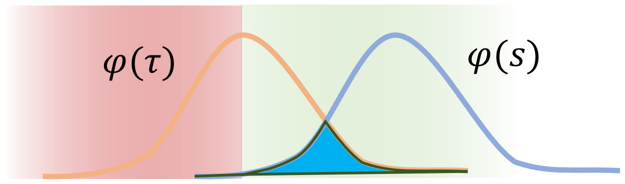




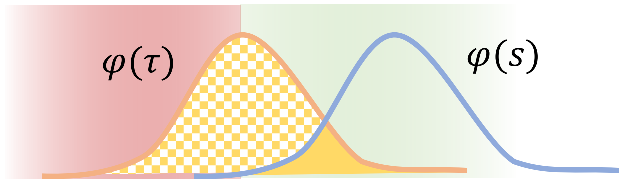
Target Source Spurious Causal

Spectrum of Invariance Learners

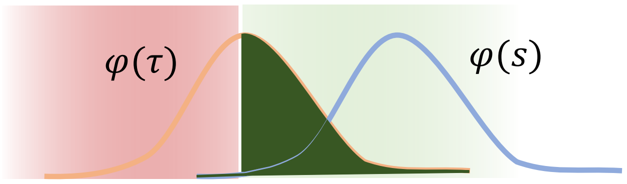




Commutative invariance (φ^*)



Non-Commutative Invariance (φ_τ^*)



Theoretical optimum $\Phi^*(\tau)$

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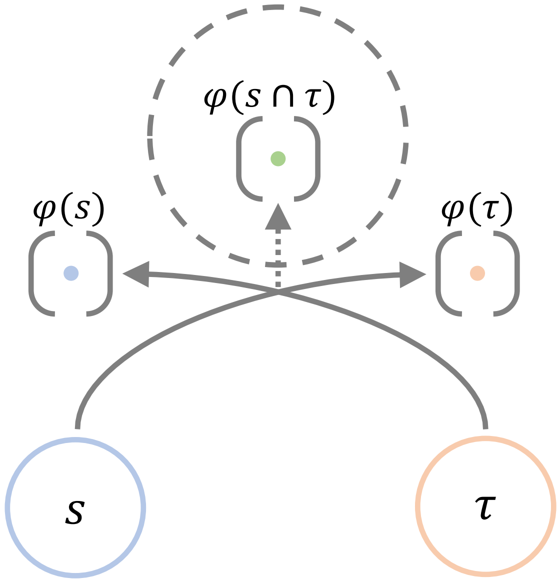
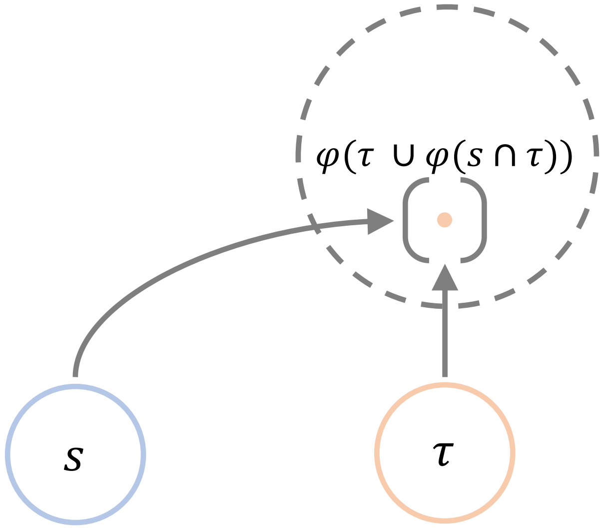
Learning Non-Commutative Invariances

Domain Classifier Adversary



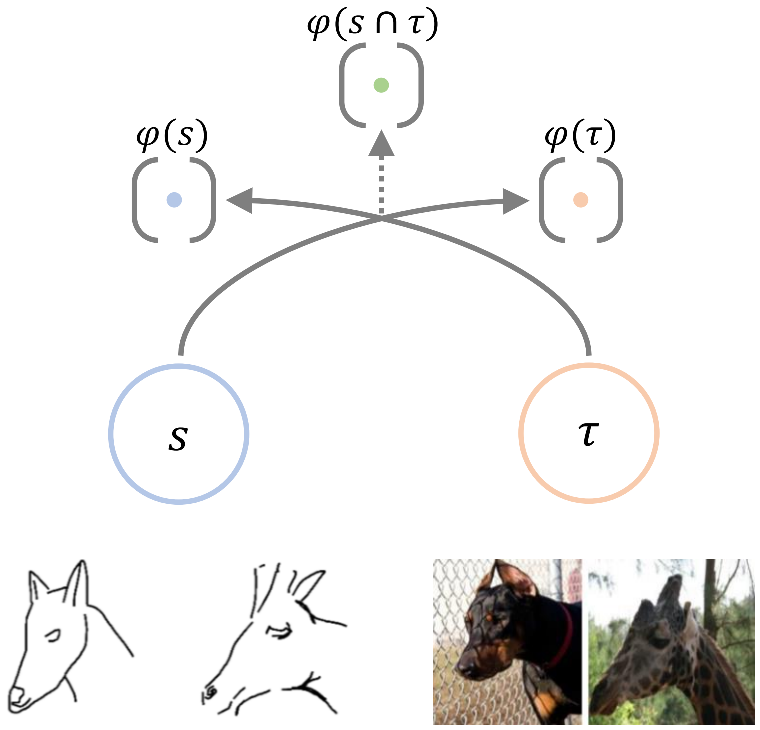
Commutative Invariance
(E.g.: Domain Adversarial Neural Networks)

Domain Classifier Adversary
grounded in the target domain

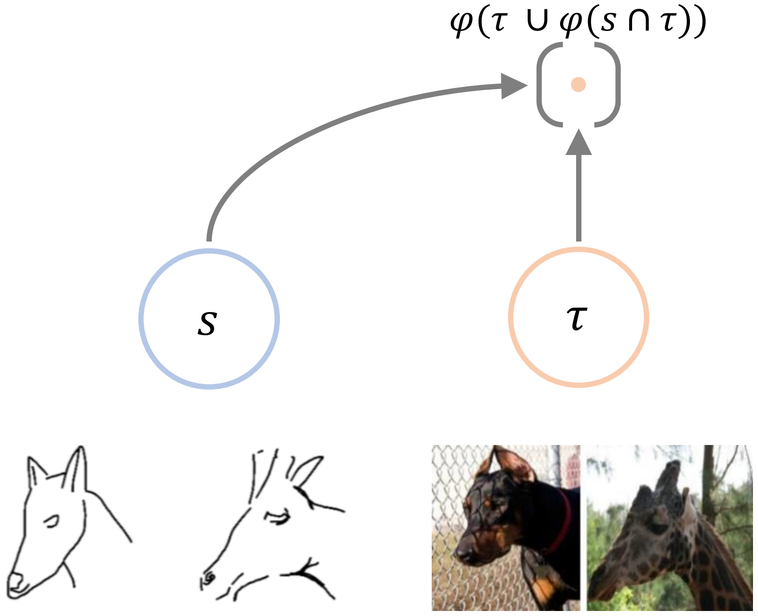


Non-Commutative Invariance

Learning Non-Commutative Invariances (Example)



Commutative Invariance



Non-Commutative Invariance

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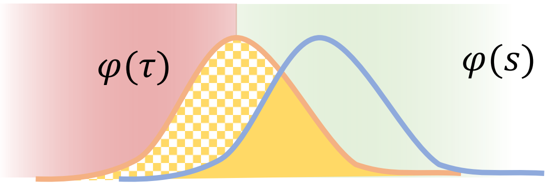
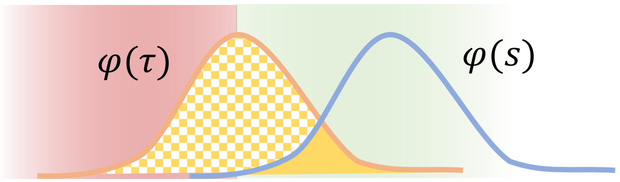
Comparison with SOTA

Method	PACS				Office-Home			
	Photo	Art	Cartoon	Sketch	Photo	Clipart	Product	Real
ERM (Wiley 1998)	81.33	77.60	88.76	78.30	49.15	45.66	54.32	60.60
DANN (ICML'15)	78.86	75.32	90.37	80.66	47.31	46.15	54.79	58.17
CDANN (ECCV'18)	78.95	76.72	90.02	80.00	47.64	46.02	54.50	59.45
MDAN (NeurIPS'18)	79.37	77.05	88.90	79.15	48.00	45.77	54.45	60.90
MDD (ICML'19)	79.55	77.62	87.61	79.48	47.99	45.31	54.37	59.16
CICyc (GCPR'21)	80.02	76.67	89.35	78.86	48.96	45.50	55.11	60.02
IB-IRM (NeurIPS'21)	77.01	75.11	90.78	80.95	45.40	46.91	55.25	57.96
EQRM (NeurIPS'22)	80.35	78.00	90.11	78.10	49.55	45.10	55.21	60.90
CIRCE (ICLR'23)	80.78	79.48	89.72	80.55	48.20	44.97	54.21	60.75
SDAT+ELS (ICLR'23)	81.25	80.21	89.32	80.27	48.50	45.43	55.39	60.97
NCI (Ours)	**83.40**	**81.55**	**91.05**	**81.37**	**50.02**	**47.90**	**56.00**	**63.50**

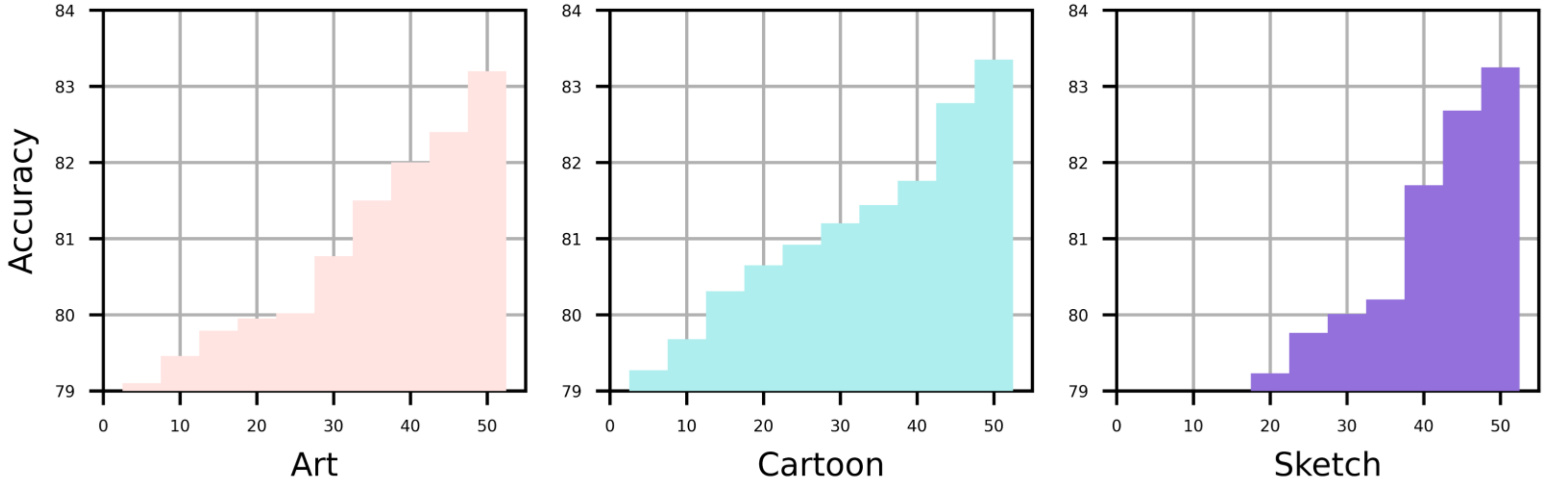
Leveraging Complementary Semantics



Low Complementarity



High Complementarity



Asymmetries & Comparison with Oracle

Backbone	Standalone				NCI				Oracle
	Image	AOLP	DOLP	NIR	Image	AOLP	DOLP	NIR	
TopFormer (CVPR'22)	45.10	33.60	29.80	28.77	**48.10**	39.30	35.82	29.60	48.44
DPT (ICCV'21)	37.86	30.55	23.86	23.40	**42.72**	32.33	27.52	25.23	43.50
SegFormer (NeurIPS'21)	41.81	24.90	29.00	22.99	**46.37**	34.33	36.24	35.81	47.25
FPN (CVPR'19)	30.20	28.68	33.21	26.79	39.86	32.79	**41.35**	29.22	41.68
DeepLabV3+ (ECCV'18)	35.86	27.76	22.56	25.87	**41.96**	30.76	29.82	30.50	42.90
PSPNet (CVPR'17)	27.99	25.71	32.50	23.60	37.68	30.50	**39.20**	27.45	40.06
UNet (MICCAI'15)	29.00	26.02	23.51	21.27	**36.93**	31.58	27.29	25.63	37.70

RGB | Near Infra-Red | Angle of Polarization | Degree of Polarization | Material Segmentation Annotation

Yupeng Liang, Ryosuke Wakaki, Shohei Nobuhara, and Ko Nishino. "Multimodal material segmentation". In CVPR, 2022.

Improvements over Flatness-based OoD Generalizers

Method	PACS				Office-Home			
	Photo	**Art**	**Cartoon**	**Sketch**	**Photo**	**Clipart**	**Product**	**Real**
Fishr (ICML'22)	81.19	80.06	89.05	79.68	48.25	45.15	54.39	59.92
+ **NCI**	**84.90**	**82.22**	**92.00**	**82.55**	**51.37**	**48.07**	**56.86**	**64.02**
SDAT (ICML'22)	81.00	79.95	88.11	79.32	48.07	45.20	54.55	60.37
+ **NCI**	**83.80**	**82.06**	**91.92**	**82.07**	**51.44**	**48.05**	**56.95**	**64.22**
Model Soups (ICML'22)	81.26	79.37	89.76	79.05	48.55	45.71	54.48	60.91
+ **NCI**	**85.09**	**82.56**	**92.77**	**82.62**	**51.95**	**48.49**	**57.20**	**64.50**

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- **Open Problems:**
    - Uniqueness

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  - Does φ_τ^* approach Φ_τ^* in a measure-theoretic sense?

Conclusion & Open Problems

- Non-Commutativity is a sample-efficient way to preserve target domain information that would have otherwise been lost under invariance.
- NCI drives the optimization towards the true minimizer of the target risk Φ_τ^*.
- **Open Problems:**
  - Uniqueness
  - Does φ_τ^* approach Φ_τ^* in a measure-theoretic sense?
  - Relationship with class-conditional invariance learning.

Conclusion & Open Problems

- Non-Commutativity is a sample-efficient way to preserve target domain information that would have otherwise been lost under invariance.
- NCI drives the optimization towards the true minimizer of the target risk Φ_τ^*.
- **Open Problems:**
  - Uniqueness
  - Does φ_τ^* approach Φ_τ^* in a measure-theoretic sense?
  - Relationship with class-conditional invariance learning.
  - Provable orthogonality to flatness-based OoD generalizers?

Learning Conditional Invariances through Non-Commutativity

Get in touch:

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https://arxiv.org/abs/2402.11682

https://github.com/abhrac/nci