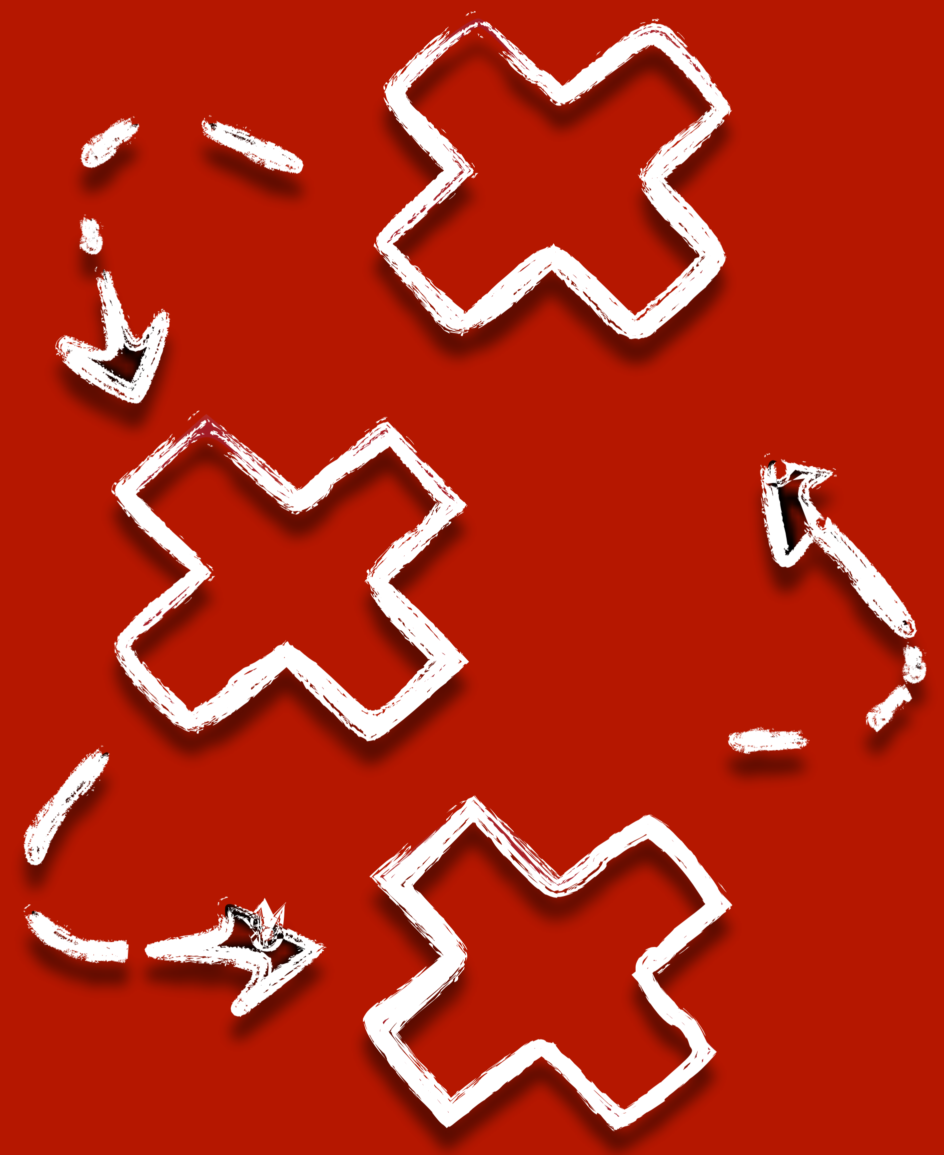

Causality-inspired ML

What can ideas from causality do for ML?

Sara Magliacane (University of Amsterdam, MIT-IBM Watson AI Lab)

(joint work with Thijs van Ommen, Tom Claassen, Stephan Bongers, Philip Versteeg, Joris Mooij, Biwei Huang, Fan Feng, Chaochao Lu and Kun Zhang)

Causality + machine learning (non-exhaustive list)

1. **Machine learning (ML) helps causality**
   - Causal discovery - learning causal graphs from data
   - Causal effect estimation - matching, weighting, double ML
   - (Causal) representation learning

2. **Causality (in the most general definition) helps machine learning**
   - Robustness, Transfer learning
   - Reinforcement Learning
   - Bias mitigation, fairness

https://arxiv.org/pdf/1705.08821.pdf, https://arxiv.org/pdf/1802.05664.pdf, https://arxiv.org/pdf/1605.03661.pdf, https://crl.causalai.net/, https://www.youtube.com/watch?v=Obuu3w809CI&ab_channel=ConnorJerzak and many many others

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Causal Hierarchy [Pearl 2009, 2018]

Most ML

Causality

Level (Symbol)	Typical Activity	Typical Questions	Examples
1. Association $P(y\|x)$	Seeing	What is? How would seeing X change my belief in Y?	What does a symptom tell me about a disease? What does a survey tell us about the election results?
2. Intervention $P(y\|do(x), z)$	Doing Intervening	What if? What if I do X?	What if I take aspirin, will my headache be cured? What if we ban cigarettes?
3. Counterfactuals $P(y_x\|x', y')$	Imagining, Retrospection	Why? Was it X that caused Y? What if I had acted differently?	Was it the aspirin that stopped my headache? Would Kennedy be alive had Oswald not shot him? What if I had not been smoking the past 2 years?

Model-based

Causal Hierarchy [Pearl 2009, 2018]

Most ML

Causality

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3. Counterfactuals $P(y_x\|x', y')$	Imagining, Retrospection	[illegible]	[illegible]

E.g. need many experiments or strong assumptions to identify the causal graph or the causal variables

"Full" causality can be **not necessary** or **too expensive** ->

Causal Hierarchy [Pearl 2009, 2018]

Most ML

Causality

Level (Symbol)	Typical Activity	Typical Questions	Examples
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"Full" causality can be **not necessary** or **too expensive** -> *Causality-Inspired*

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Most ML

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In this talk: examples in domain adaptation, but lots of related work

"Full" causality can be not necessary or too expensive -> Causality-Inspired

Talk outline

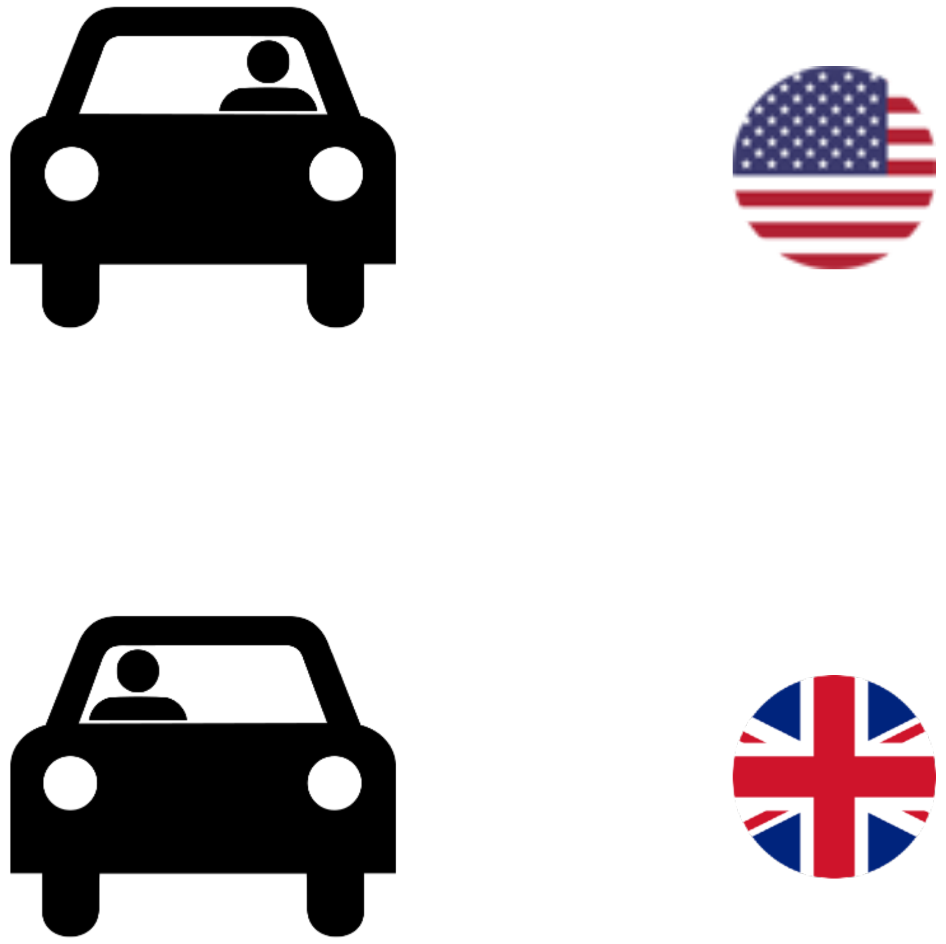
1. Graphical models and d-separation [Pearl 1988] are a principled way to reason about **invariances and distribution shift**

2. **Even when the graph is unknown or missing data:** example in unsupervised domain adaptation

3. **In practice:** an application in fast adaptation in RL

Causality vs Transfer learning

- Transfer learning:
  - How can I predict what happens when the distribution changes?



Causality vs Transfer learning

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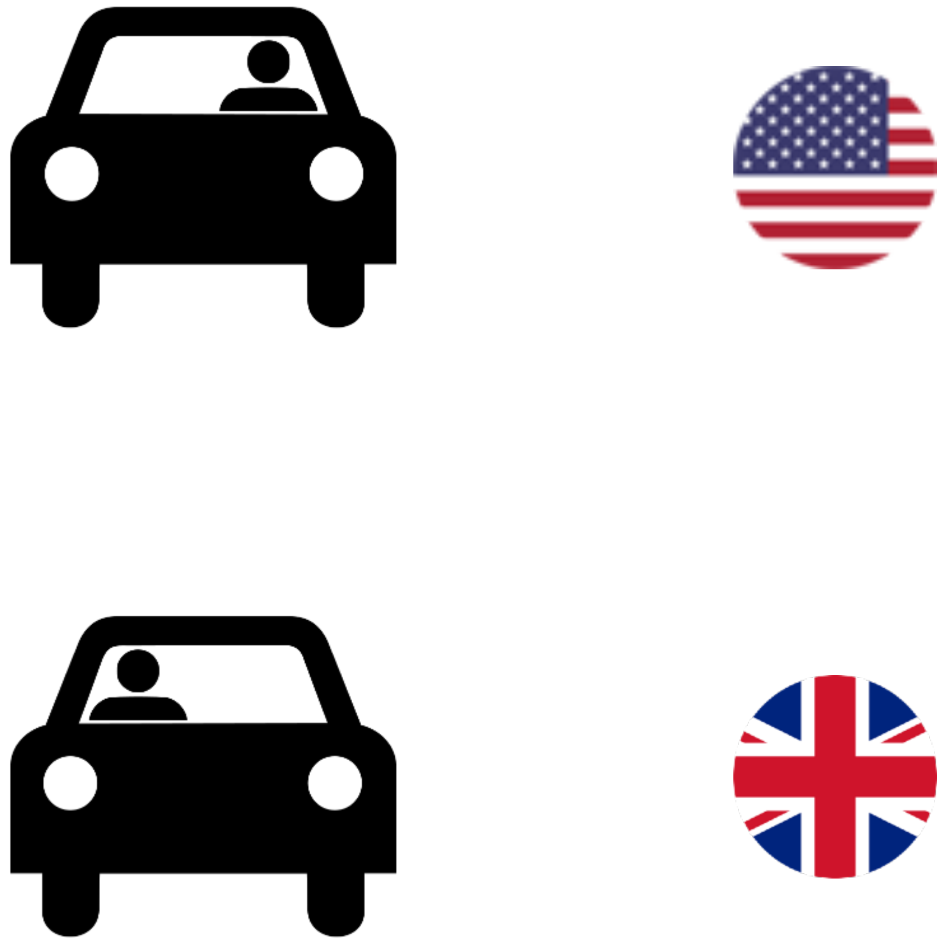
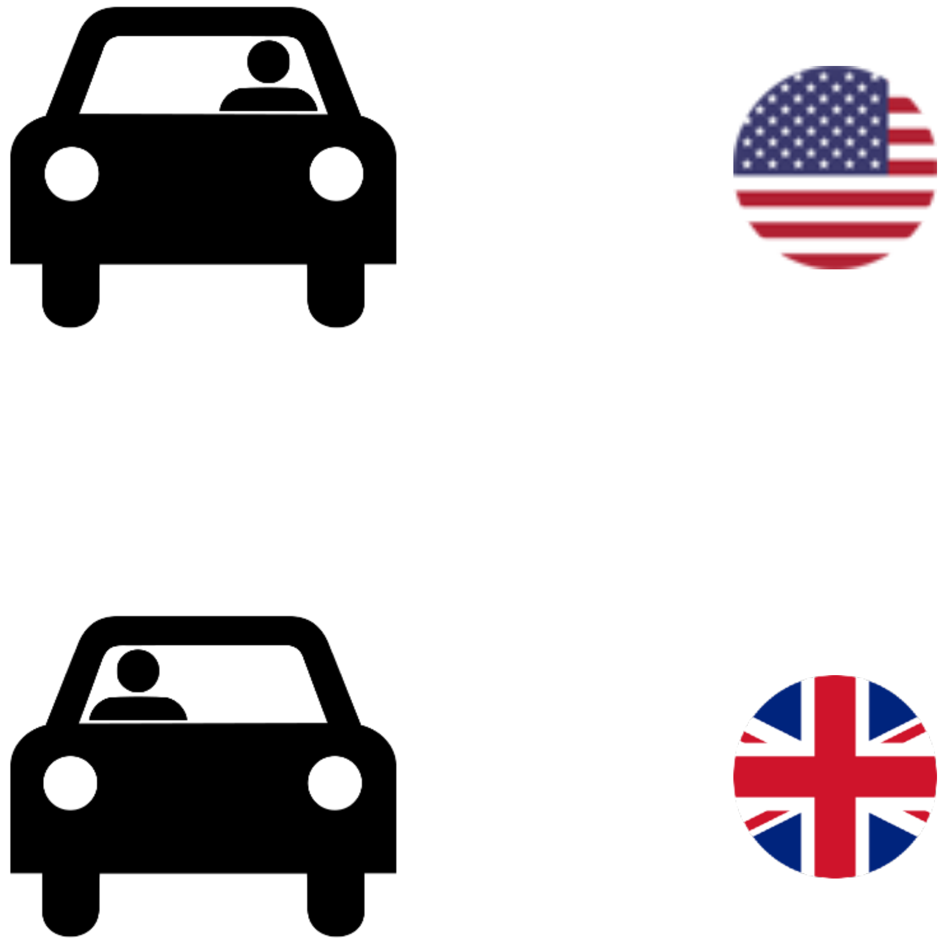


- Causal inference:
  - How can I predict what happens when the distribution changes after an intervention?
    - Perfect intervention do(X):
      - do-calculus [Pearl, 2009]
    - **Soft intervention on X** $\approx$ change of distribution of P(X| parents)

Causality vs Transfer learning

- Transfer learning:
  - How can I predict what ha ... ens when when the distribution chang ... an

Very general - can model also changes in distribution that are not from “real” interventions



- ... t intervention do(X):
  - do-calculus [Pearl, 2009]
- **Soft intervention on X** ≈ change of distribution of P(X| parents)

Causality allows us to reason systematically about distribution shifts, e.g. through graphs

On Causal and Anticausal Learning

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Domain Adaptation as a Problem of Inference on Graphical Models

Kun Zhang[1*], **Mingming Gong**[2*], **Petar Stojanov**[3]
Biwei Huang[1], **Qingsong Liu**[4], **Clark Glymour**[1]
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Anchor regression: heterogeneous data meet causality

Dominik Rothenhäusler, Nicolai Meinshausen, Peter Bühlmann and Jonas Peters

Invariant Risk Minimization

Martin Arjovsky, Léon Bottou, Ishaan Gulrajani, David Lopez-Paz

J. R. Statist. Soc. B (2016)
78, *Part* 5, *pp.* 947–1012

Causal inference by using invariant prediction: identification and confidence intervals

Jonas Peters
Max Planck Institute for Intelligent Systems, Tübingen, Germany, and Eidgenössische Technische Hochschule Zürich, Switzerland
and Peter Bühlmann and Nicolai Meinshausen
Eidgenössische Technische Hochschule Zürich, Switzerland

Invariant Models for Causal Transfer Learning

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Invariance, Causality and Robustness
2018 Neyman Lecture *

Peter Bühlmann †
Seminar for Statistics, ETH Zürich

Counterfactual Invariance to Spurious Correlations: Why and How to Pass Stress Tests

Victor Veitch[1,2], Alexander D'Amour[1], Steve Yadlowsky[1], and Jacob Eisenstein[1]
[1]*Google Research*
[2]*University of Chicago*

Domain Adaptation by Using Causal Inference to Predict Invariant Conditional Distributions

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A Causal View on Robustness of Neural Networks

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Yingzhen Li *
Microsoft Research
Yingzhen.Li@microsoft.com

and many many more....

Causality allows us to reason systematically about distribution shifts, e.g. through graphs

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Even if unknown

Kun Zhang, Mingming Gong, Petar Stojanov[3]
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and many many more....

Causality allows us to reason systematically about distribution shifts, e.g. through graphs

Even if unknown

Without reconstructing the causal graph

Even we have missing data

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Causal in...
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Invariant Models for Causal Transfer Learning

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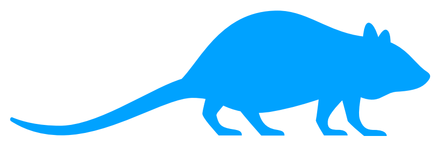
and many many more....

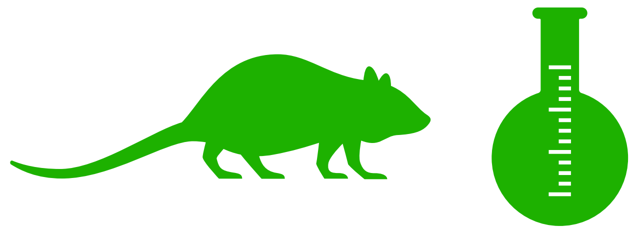
Unsupervised domain adaptation - toy example



	X1	X2	Y
Wildtype	0,1	2	0
Wildtype	0,2	3	0
Wildtype	1,1	2	1
Wildtype	0,1	3	0

Source domain

No labels in target

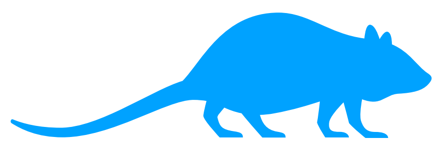


	X1	X2	Y
Gene A	3,1	2	?
Gene A	3,2	3	?
Gene A	4	2	?
Gene A	3,2	3	?

Target domain

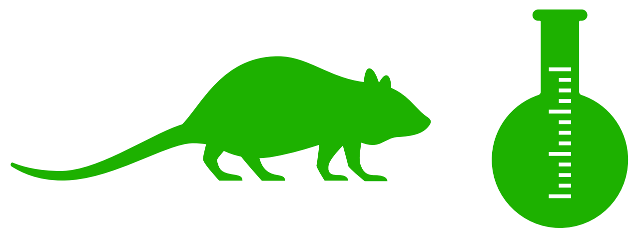
- **Task:** Learn a model Y = $\hat{f}$(X1, X2) on the source domain so that it can reliably estimate Y in target domain

Domain adaptation from the graphical perspective



C	X1	X2	Y
0	0,1	2	0
0	0,2	3	0
0	1,1	2	1
0	0,1	3	0

Source domain

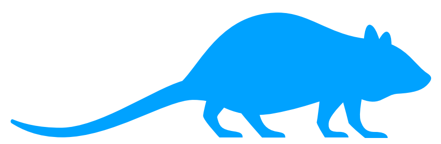


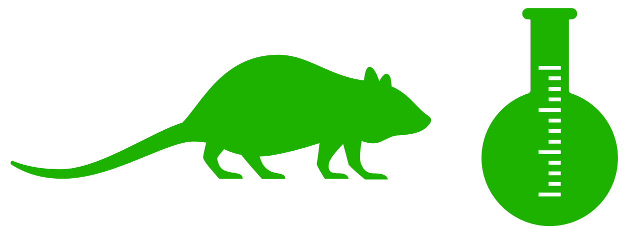
C	X1	X2	Y
1	3,1	2	?
1	3,2	3	?
1	4	2	?
1	3,2	3	?

Target domain

1. We add a context variable C to distinguish the domains

Domain adaptation from the graphical perspective

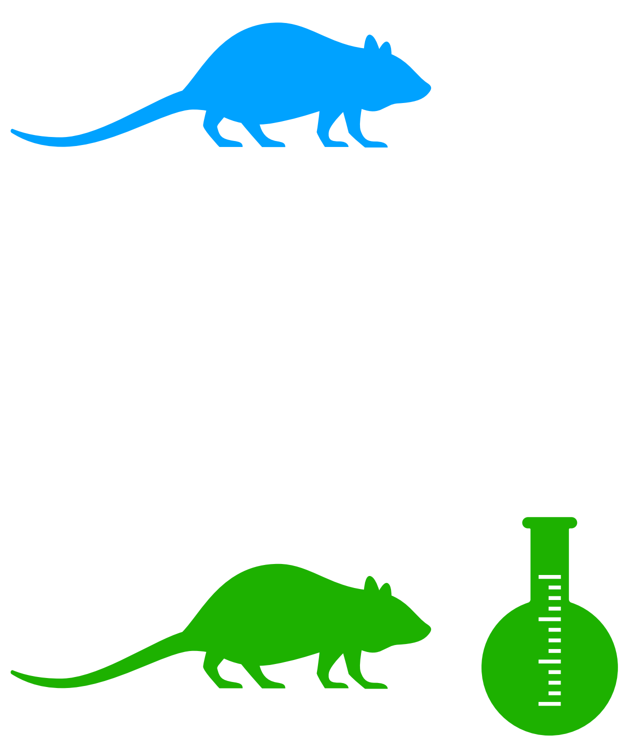




C	X1	X2	Y	
0	0,1	2	0	Source domain
0	0,2	3	0	
0	1,1	2	1	
0	0,1	3	0	
1	3,1	2	?	Target domain
1	3,2	3	?	
1	4	2	?	
1	3,2	3	?	

1. We add a context variable C to distinguish the domains
2. We consider the data as coming from a single distribution P(X1, X2,Y, C)

Domain adaptation from the graphical perspective



C	X1	X2	Y
0	0,1	2	0
0	0,2	3	0
0	1,1	2	1
0	0,1	3	0
1	3,1	2	?
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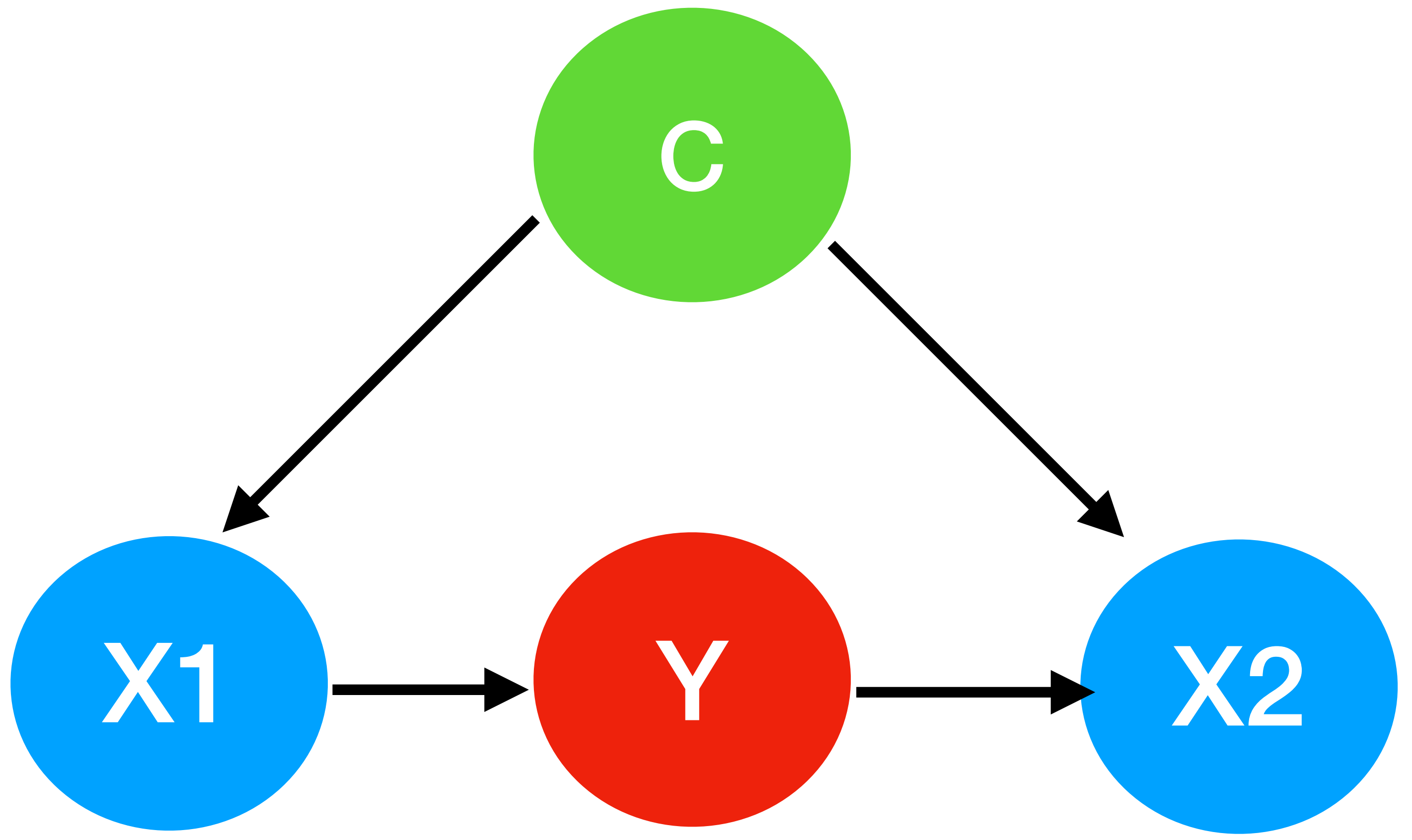
1	3,2	3	?

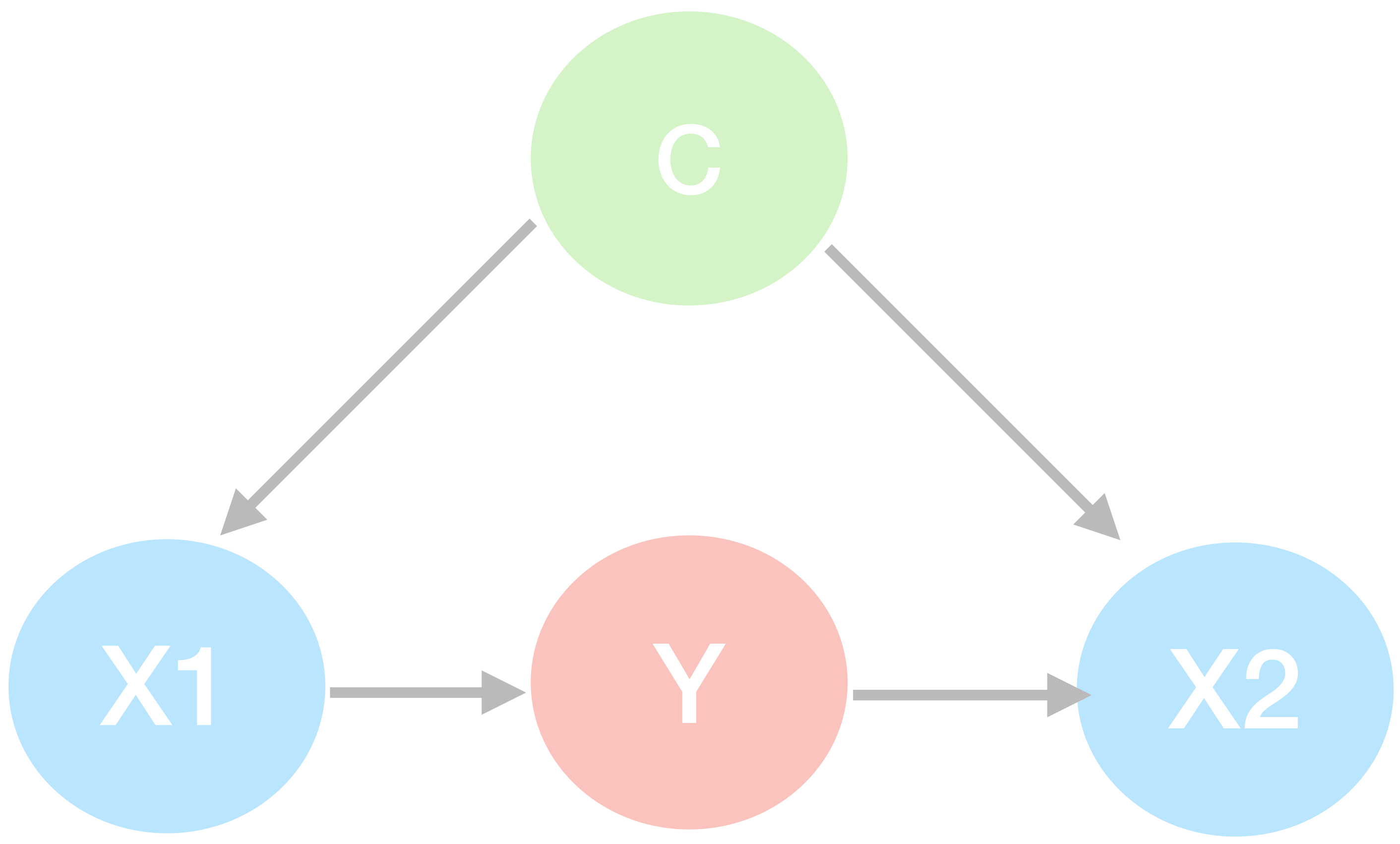


We can represent P(X1, X2,Y, C) with an **(unknown)** causal graph

1. We add a context variable C to distinguish the domains
2. We consider the data as coming from a single distribution P(X1, X2,Y, C)

Separating features = safe for (adversarial) domain adaptation

- **Separating features:** sets of features that d-separate Y from the context



Step 1: Known causal graph

Separating features = safe for (adversarial) domain adaptation

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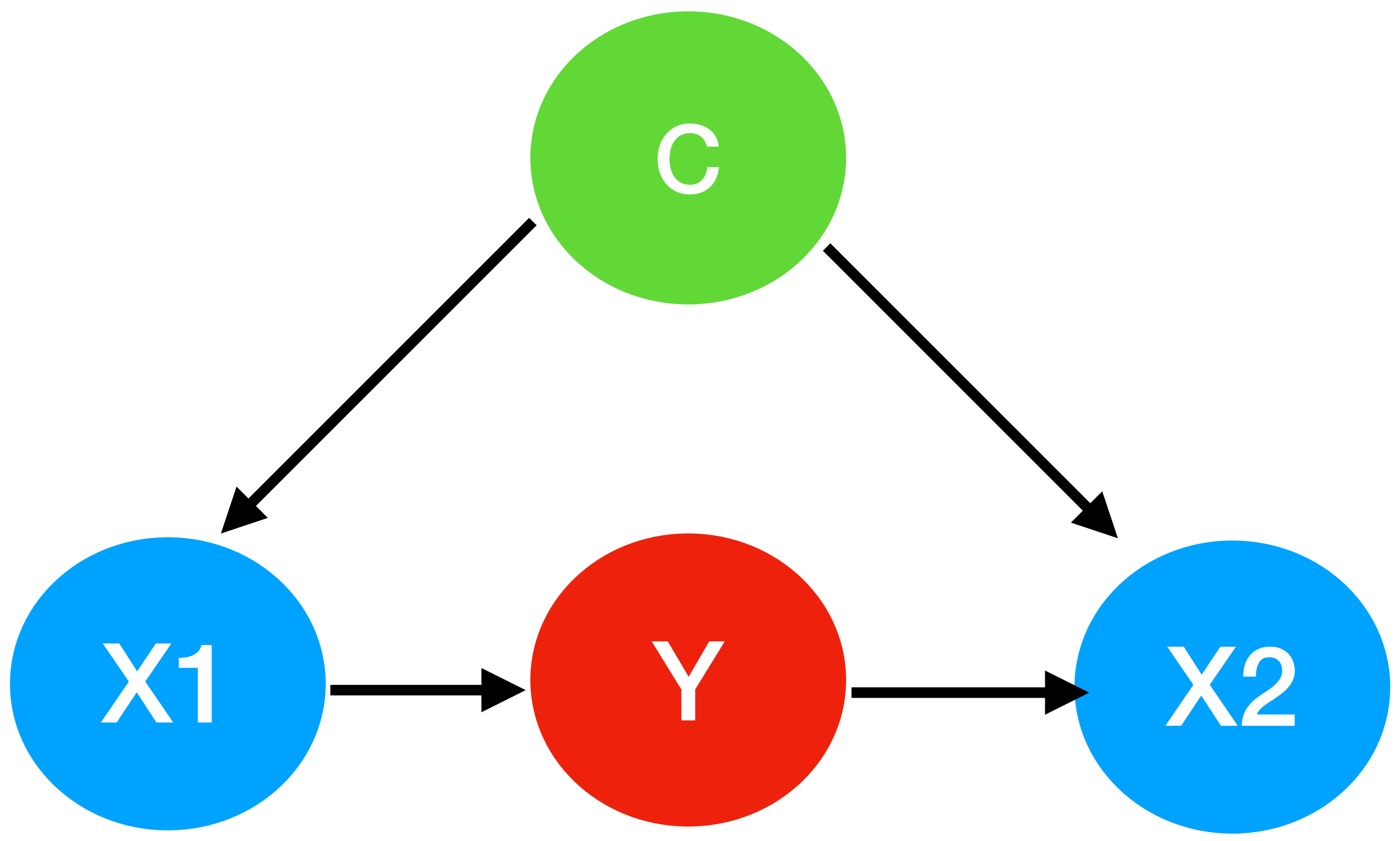

Separating features = safe for (adversarial) domain adaptation

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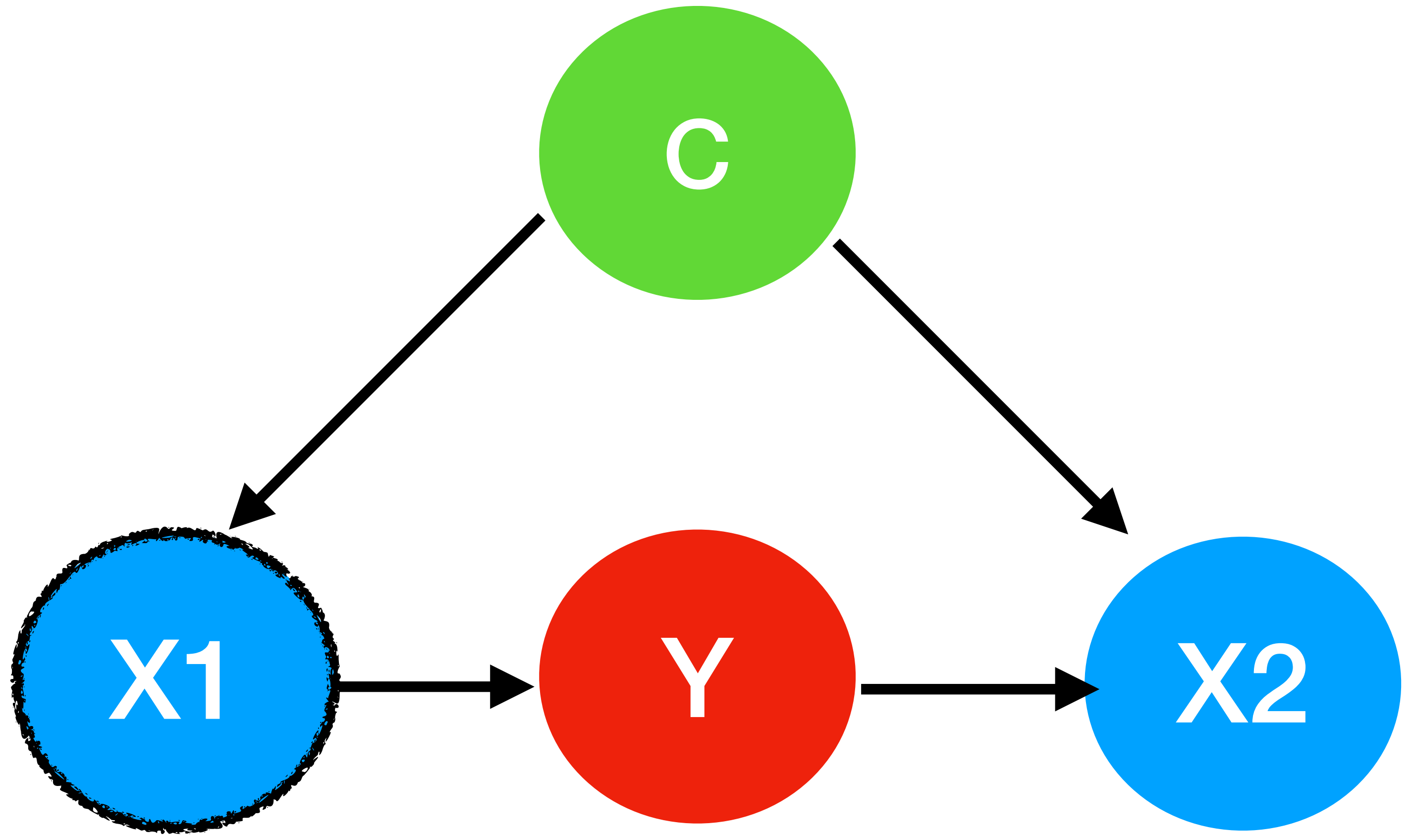

$$Y \perp\!\!\!\perp_d C \mid X_1 \iff Y \perp\!\!\!\perp C \mid X_1$$

(under Markov and faithfulness assumptions)

Separating features = safe for (adversarial) domain adaptation

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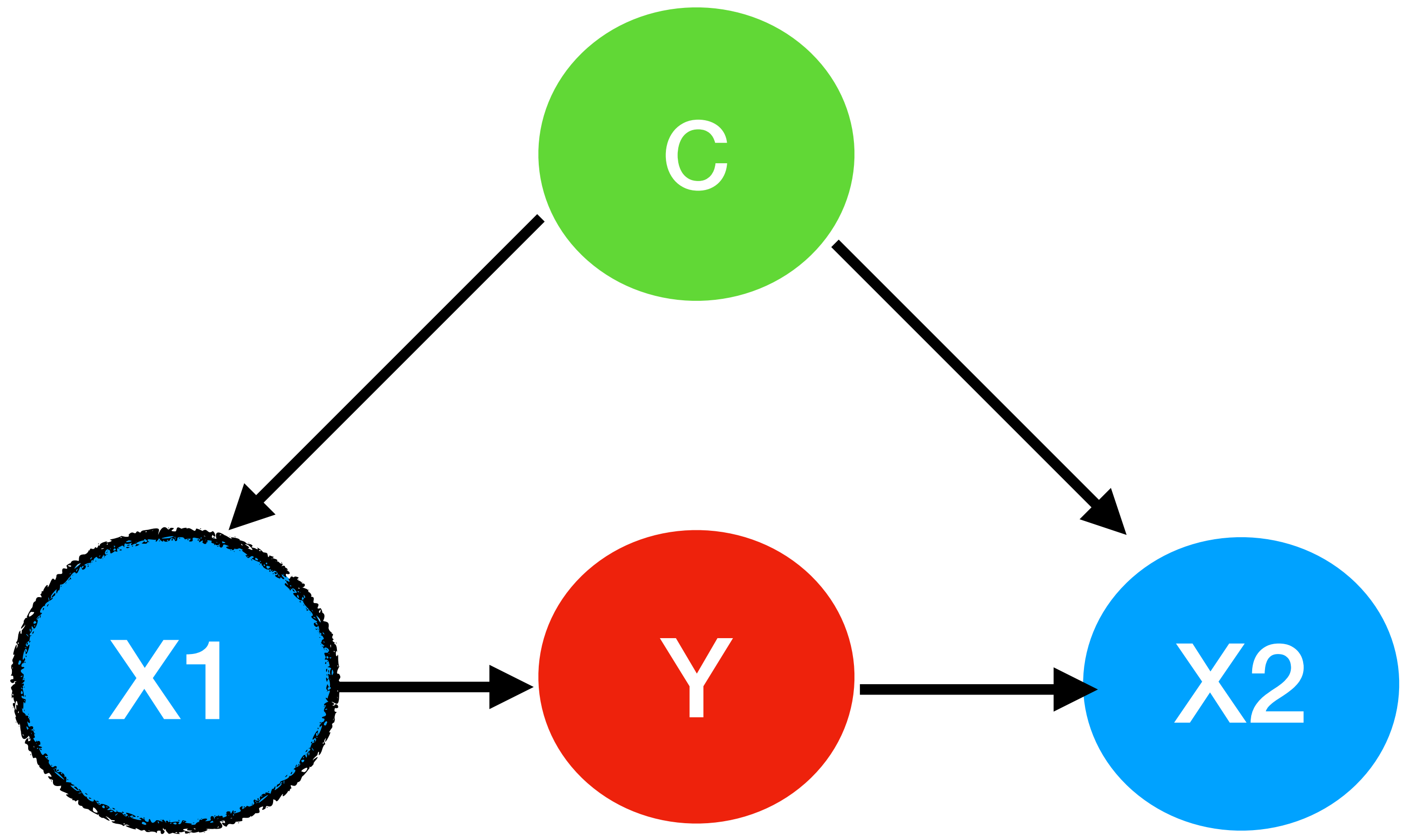
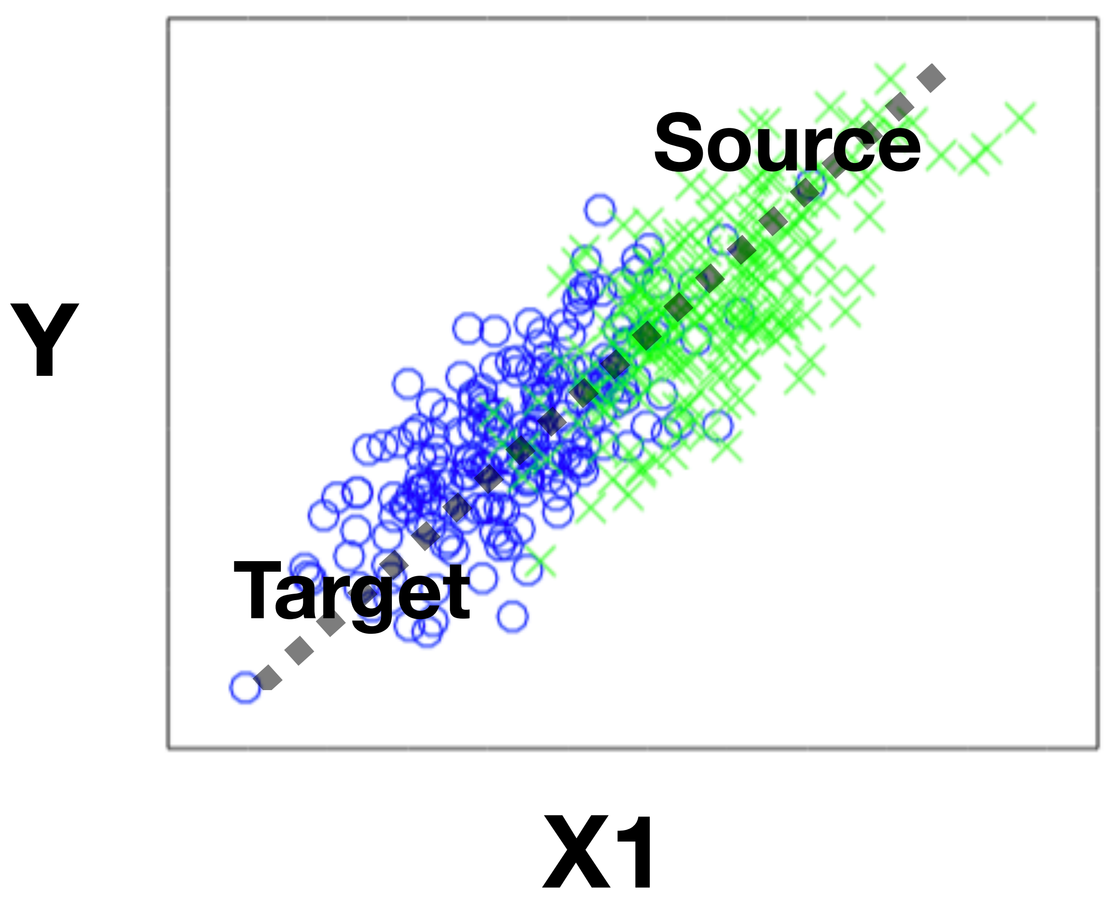




$$Y \perp\!\!\!\perp_d C \mid X_1 \iff Y \perp\!\!\!\perp C \mid X_1$$

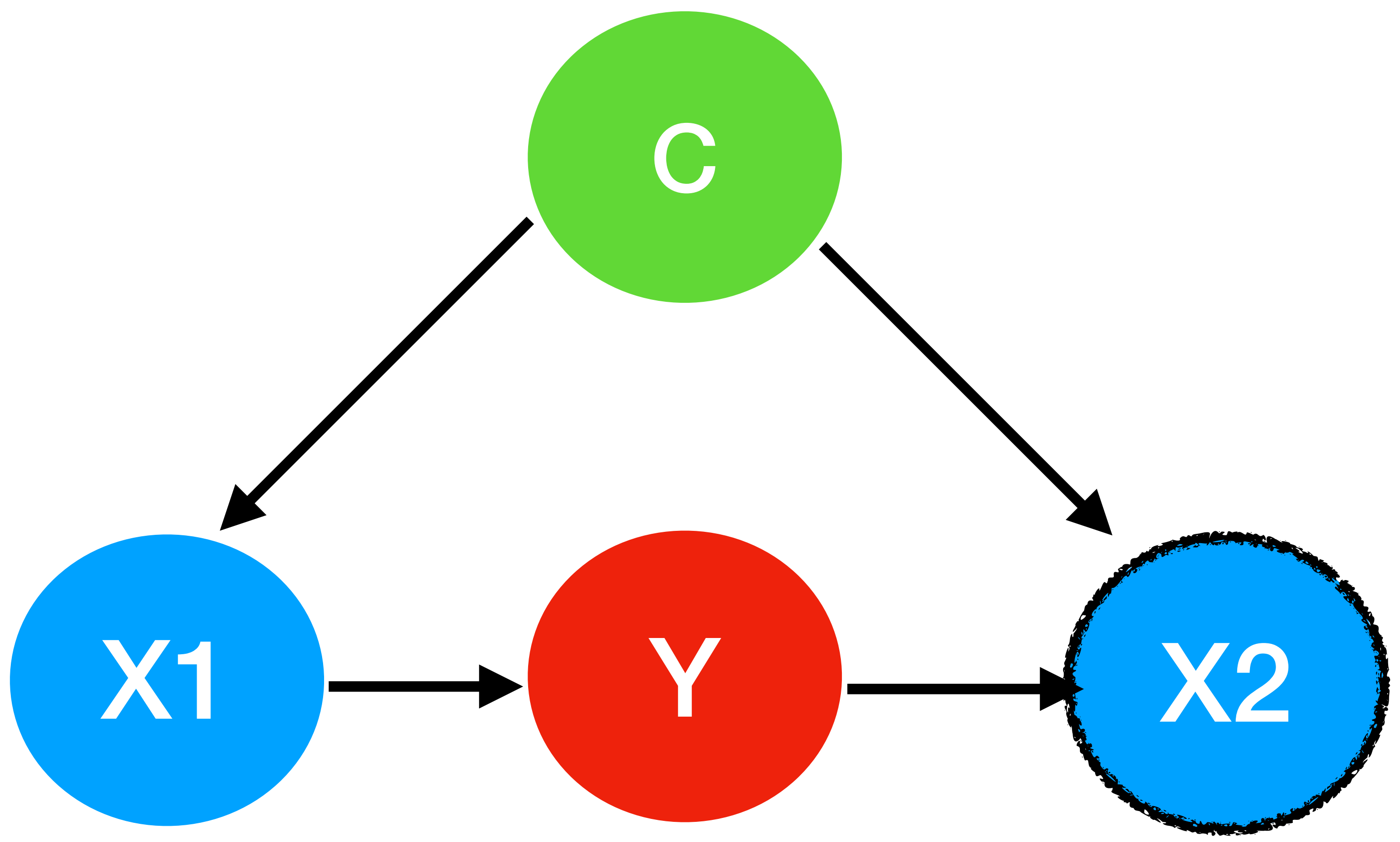
(under Markov and faithfulness assumptions)

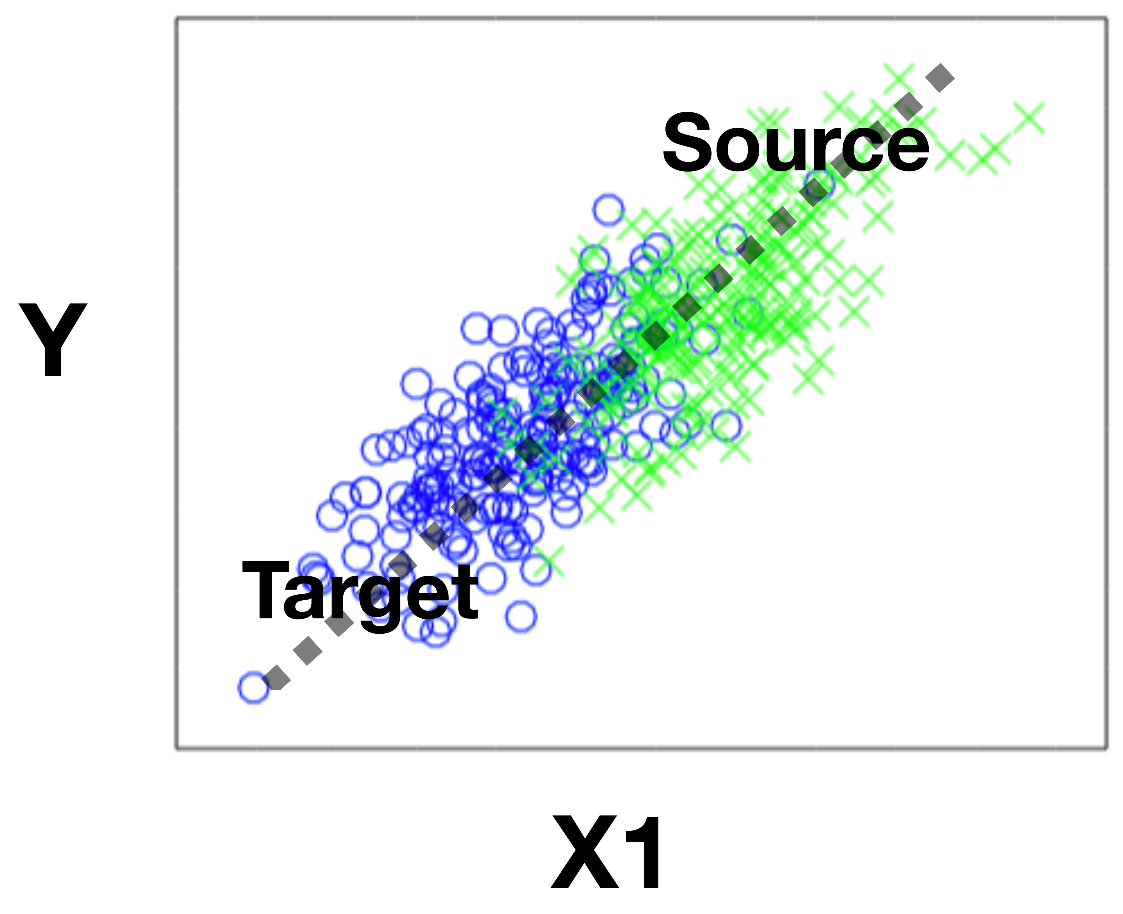
$$Y \perp\!\!\!\perp C \mid X_1 \equiv$$

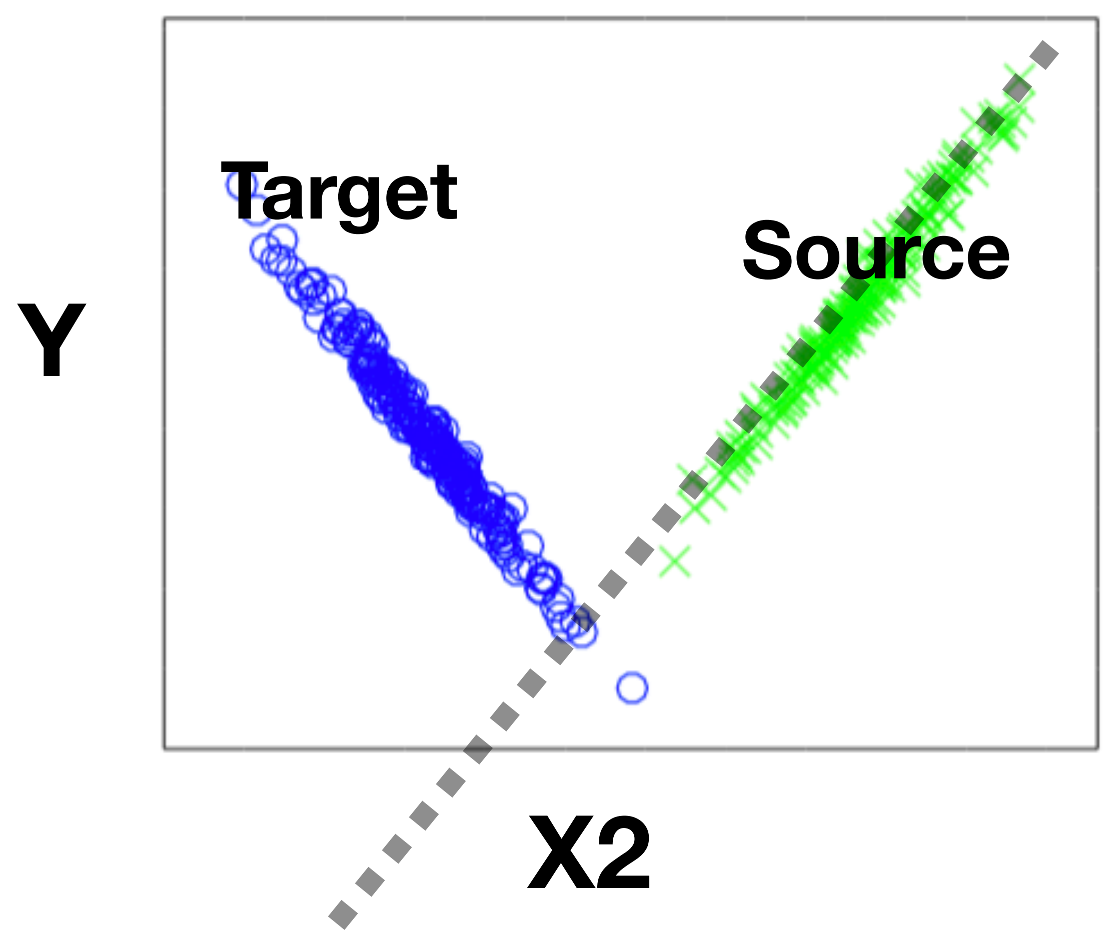
$$P(Y \mid X_1, C = 0) = P(Y \mid X_1, C = 1)$$

Separating features = safe for (adversarial) domain adaptation

- **Separating features:** sets of features that d-separate Y from the context







$Y \not\perp\!\!\!\perp_d C \,|\, X_2 \iff Y \not\perp\!\!\!\perp C \,|\, X_2$

(under Markov and faithfulness assumptions)

$Y \perp\!\!\!\perp C \,|\, X_1 \equiv$

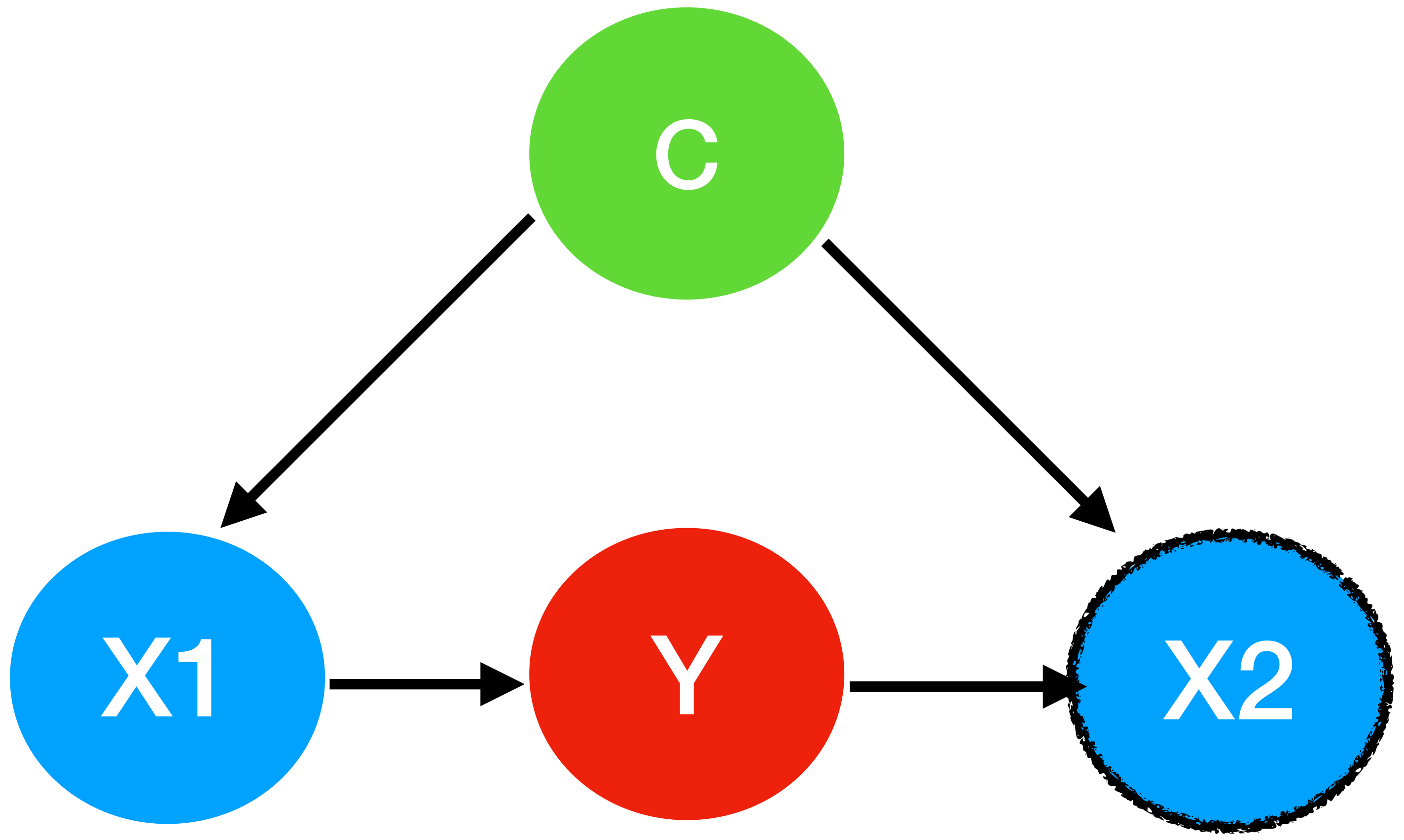
$P(Y|X_1, C=0) = P(Y|X_1, C=1)$

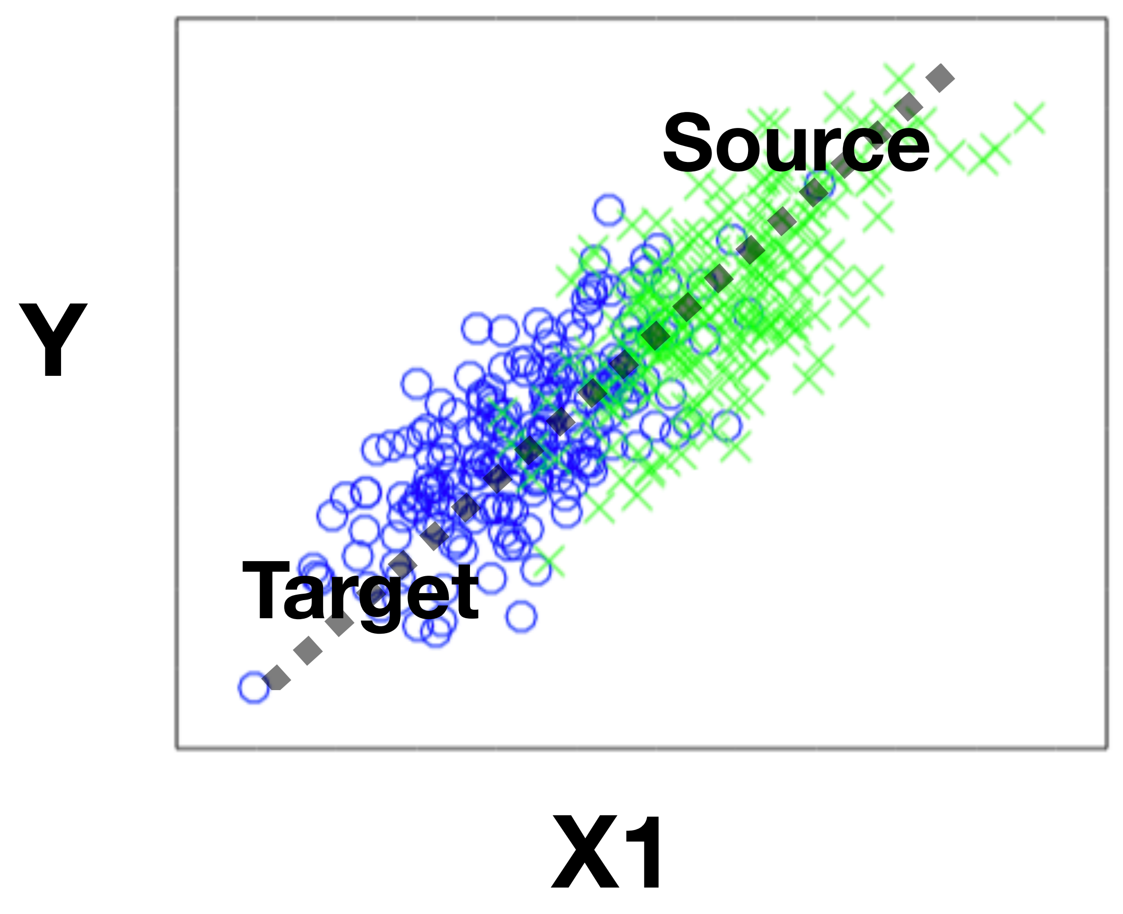
$Y \not\perp\!\!\!\perp C \,|\, X_2 \equiv$

$P(Y|X_2, C=0) \neq P(Y|X_2, C=1)$

Separating features = safe for (adversarial) domain adaptation

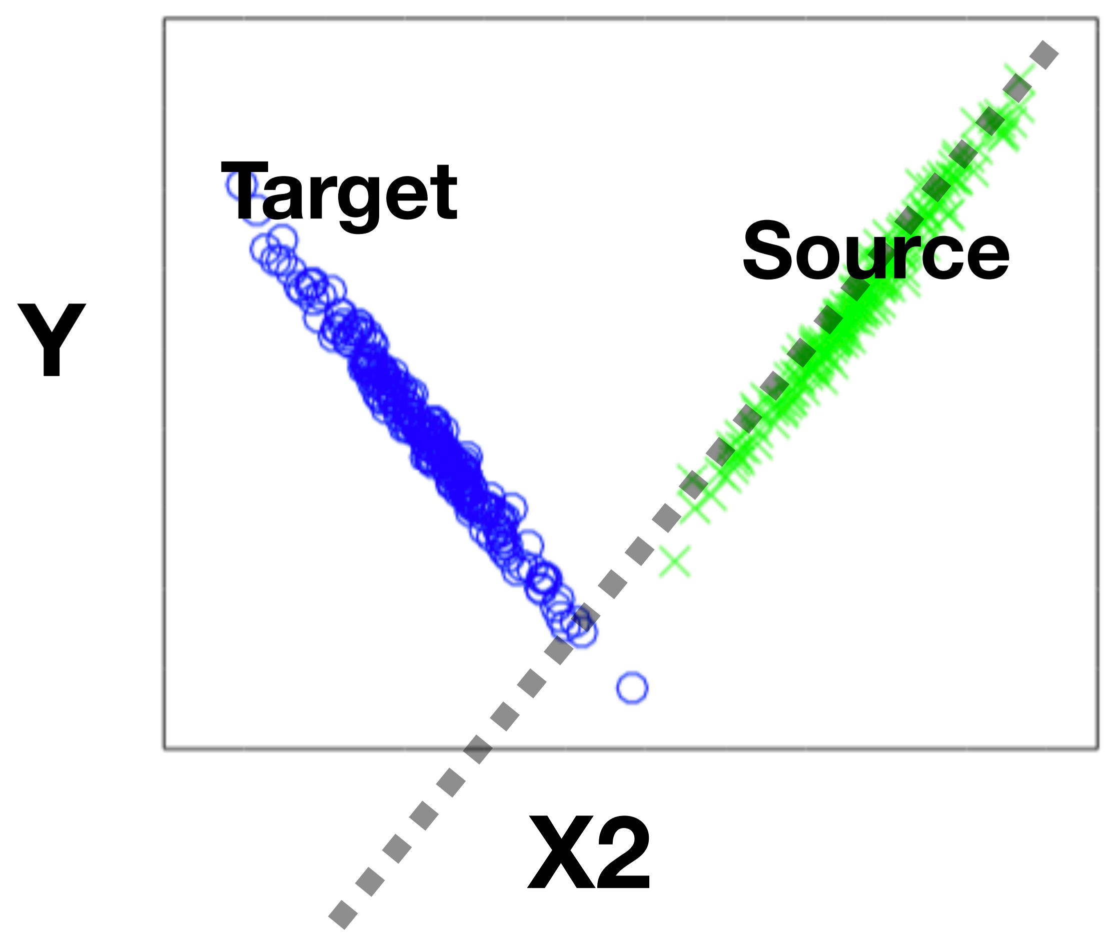
- **Separating features:** sets of features that d-separate Y from the context





$Y \perp\!\!\!\perp C \mid X_1 \equiv$

$P(Y \mid X_1, C = 0) = P(Y \mid X_1, C = 1)$



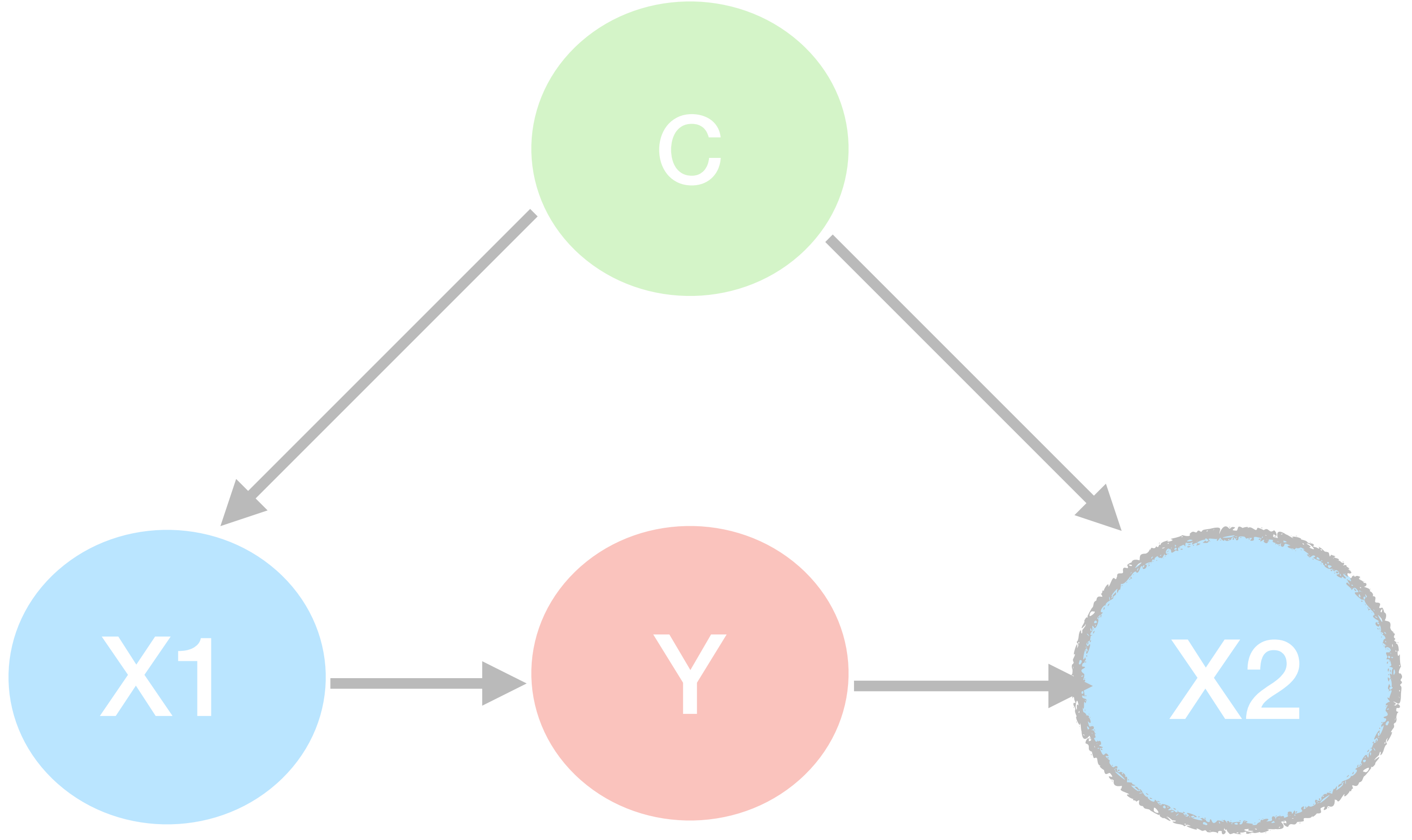
$Y \not\!\perp\!\!\!\perp C \mid X_2 \equiv$

$P(Y \mid X_2, C = 0) \neq P(Y \mid X_2, C = 1)$

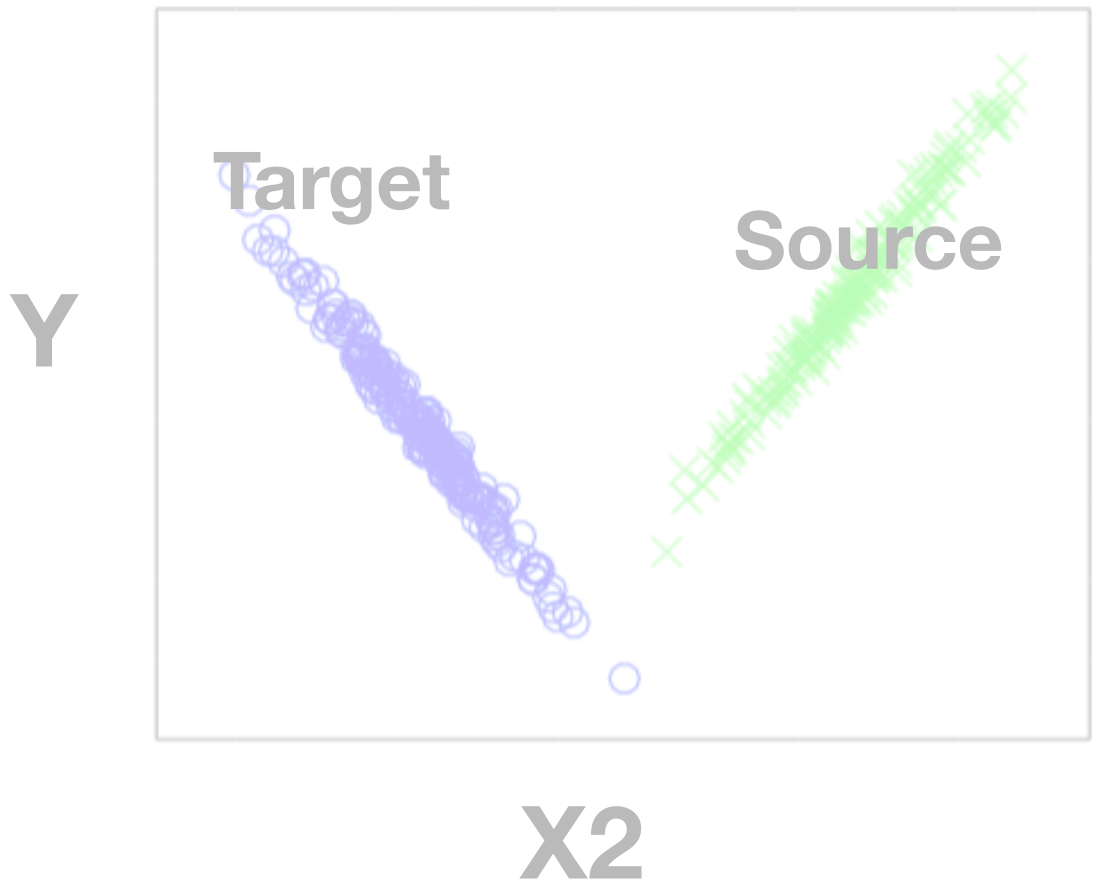
{X1} is a separating feature, {X2} and {X1, X2} are not -> **arbitrarily large error**

Separating features = safe for (adversarial) domain adaptation

- **Separating features:** sets of features that d-separate Y from the context



Step 2: Unknown graph and no labels in target!



$Y \not\perp\!\!\!\perp_d C \mid X_2$

$Y \perp\!\!\!\perp C \mid X_1 \equiv$

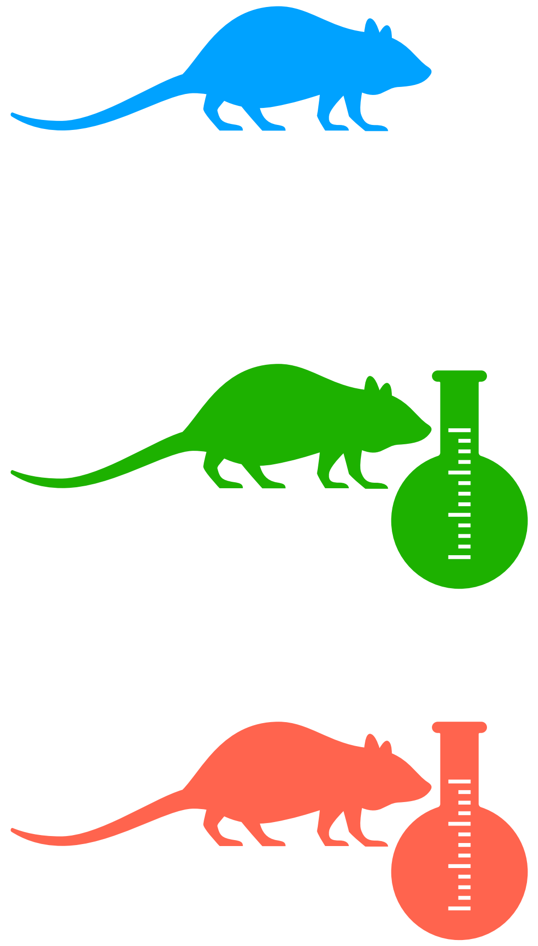
$P(Y \mid X_1, C=0) = P(Y \mid X_1, C=1)$

$Y \not\perp\!\!\!\perp C \mid X_2 \equiv$

$P(Y \mid X_2, C=0) \neq P(Y \mid X_2, C=1)$

{X1} is a separating feature, {X2} and {X1, X2} are not -> **arbitrarily large error**

Unsupervised multi-source domain adaptation - toy example



X1	X2	Y
0,1	1	0
0,2	1	0
1,1	2	1
3,1	2	1
3,2	3	1
4	3	1
0,2	0	?
0,3	0	?
0,3	1	?

Source domains

Target domain

https://arxiv.org/abs/1707.06422

Domain Adaptation by Using Causal Inference to Predict Invariant Conditional Distributions NeurIPS 2018

Sara Magliacane, Thijs van Ommen, Tom Claassen, Stephan Bongers, Philip Versteeg, Joris M. Mooij

C1	C2	X1	X2	Y
0	0	0,1	1	0
0	0	0,2	1	0
0	0	1,1	2	1
0	1	3,1	2	1
0	1	3,2	3	1
0	1	4	3	1
1	0	0,2	0	?
1	0	0,3	0	?
1	0	0,3	1	?

Source domains

Target domain

- We assume we can model all the domains in with a **single unknown acyclic causal graph** with **multiple context variables** [Mooij et al. 2020]

https://arxiv.org/abs/1707.06422

Domain Adaptation by Using Causal Inference to Predict Invariant Conditional Distributions NeurIPS 2018

Sara Magliacane, Thijs van Ommen, Tom Claassen, Stephan Bongers, Philip Versteeg, Joris M. Mooij

- We search for **separating features** that d-separate Y from C_1 (target)
- We assume **no extra dependences involving Y** in target domain C1=1

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C1	C2	X1	X2	Y
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0	0	0,2	1	0
0	0	1,1	2	1
0	1	3,1	2	1
0	1	3,2	3	1
0	1	4	3	1
1	0	0,2	0	?
1	0	0,3	0	?
1	0	0,3	1	?

$$Y \not\perp\!\!\!\perp C_2 \mid C_1 = 0$$

$$Y \perp\!\!\!\perp C_2 \mid X_1, C_1 = 0$$

$$X_2 \perp\!\!\!\perp C_2 \mid Y, C_1 = 0$$

Perform allowed CI tests

https://arxiv.org/abs/1707.06422

Domain Adaptation by Using Causal Inference to Predict Invariant Conditional Distributions NeurIPS 2018

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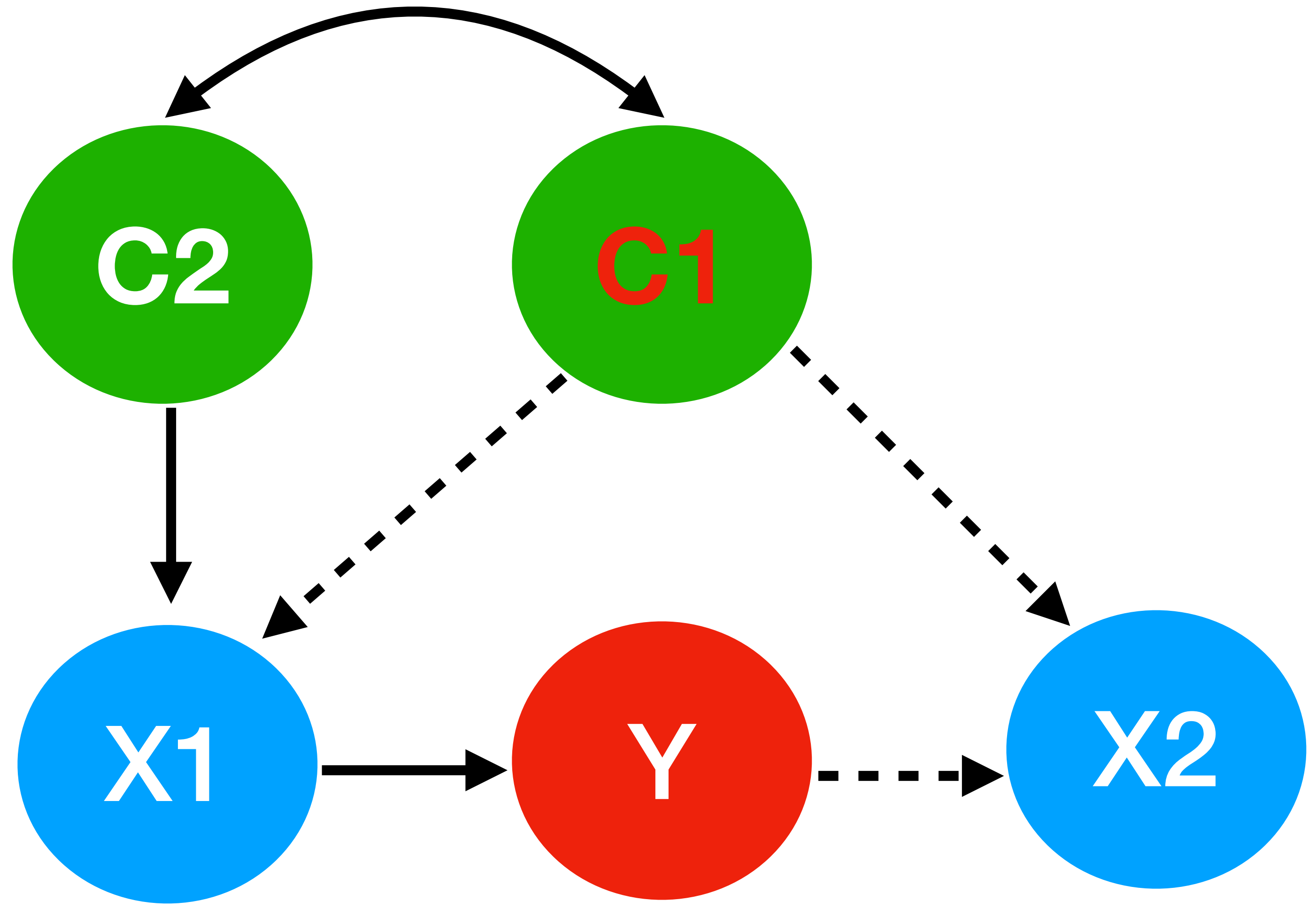
C1	C2	X1	X2	Y
0	0	0,1	1	0
0	0	0,2	1	0
0	0	1,1	2	1
0	1	3,1	2	1
0	1	3,2	3	1
0	1	4	3	1
1	0	0,2	0	?
1	0	0,3	0	?
1	0	0,3	1	?

$$Y \not\perp\!\!\!\perp C_2 \mid C_1 = 0$$

$$Y \perp\!\!\!\perp C_2 \mid X_1, C_1 = 0$$

$$X_2 \perp\!\!\!\perp C_2 \mid Y, C_1 = 0$$

Perform allowed CI tests



All possible compatible graphs

$$Y \perp\!\!\!\perp C_1 \mid X_1 ?$$

https://arxiv.org/abs/1707.06422

Inferring separating sets of features

Query $Y \perp\!\!\!\perp C_1 \mid X_1 ?$

Assumptions

All testable conditional independences from data

$$X_1 \perp\!\!\!\perp X_3 \mid X_4$$

$$Y \perp\!\!\!\perp C_2 \mid X_1, C_1 = 0$$

$$X_2 \perp\!\!\!\perp C_2 \mid Y, C_1 = 0$$

$$\dots$$

Logic encoding of d-separation [Hyttinen et al. 2014]

Theorem prover

Bounded generalization error

Provably separating

$$Y \perp\!\!\!\perp C_1 \mid X_1$$

Provably not separating

$$Y \not\perp\!\!\!\perp C_1 \mid X_1$$

?

Not identifiable

https://arxiv.org/abs/1707.06422

Inferring separating sets of features

Query $Y \perp\!\!\!\perp C_1 \mid X_1 ?$

Assumptions

All testable conditional independences from data

$$X_1 \perp\!\!\!\perp X_3 \mid X_4$$

$$Y \perp\!\!\!\perp C_2 \mid X_1, C_1 = 0$$

$$X_2 \perp\!\!\!\perp C_2 \mid Y, C_1 = 0$$

$$\dots$$

Logic encoding of d-separation [Hyttinen et al. 2014]

Theorem prover

Provably separating $Y \perp\!\!\!\perp C_1 \mid X_1$

Provably not separating $Y \not\perp\!\!\!\perp C_1 \mid X_1$

? Not identifiable

We can test incrementally each set of features selected by standard feature selection (e.g. random forests)

https://arxiv.org/abs/1707.06422

Inferring separating sets of features

Query $Y \perp\!\!\!\perp C_1 \mid X_1$?

Assumptions

All testable conditional independences from data

$X_1 \perp\!\!\!\perp X_3 \mid X_4$

$Y \perp\!\!\!\perp C_2 \mid X_1, C_1 = 0$

$X_2 \perp\!\!\!\perp C_2 \mid Y, C_1 = 0$

Log

A big (current) limitation: Scalability

Provably separating $Y \perp\!\!\!\perp C_1 \mid X_1$

Provably not separating $Y \not\perp\!\!\!\perp C_1 \mid X_1$

? Not identifiable

Other limitations: current only feature selection

We

fea

sele

Other limitations: the concept of separating sets might be too conservative

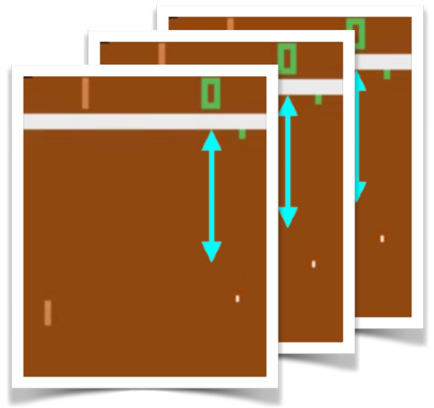
https://arxiv.org/abs/1707.06422

AdaRL: What, Where, and How to Adapt in Transfer RL

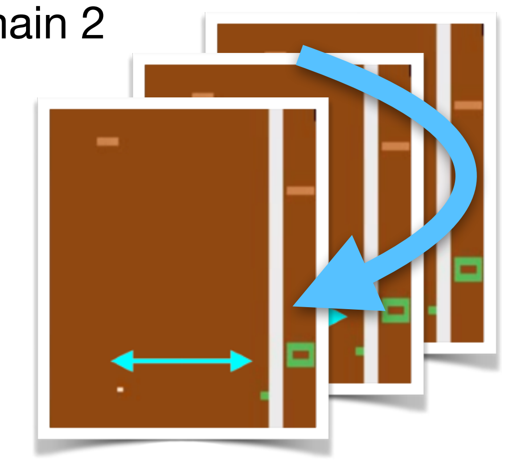
Biwei Huang, Fan Feng, Chaochao Lu, Sara Magliacane, Kun Zhang ICLR 2022

Source domains

Domain 1

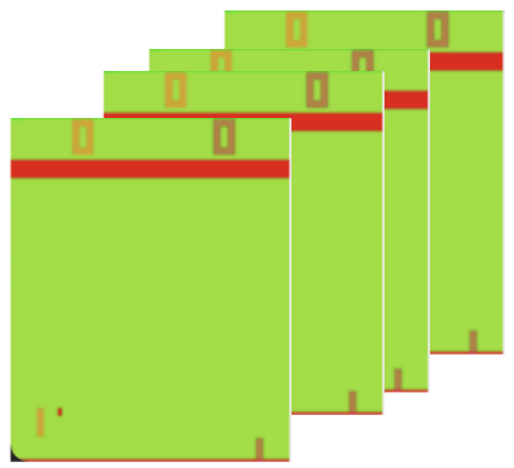


Domain 2



. . .

Domain n

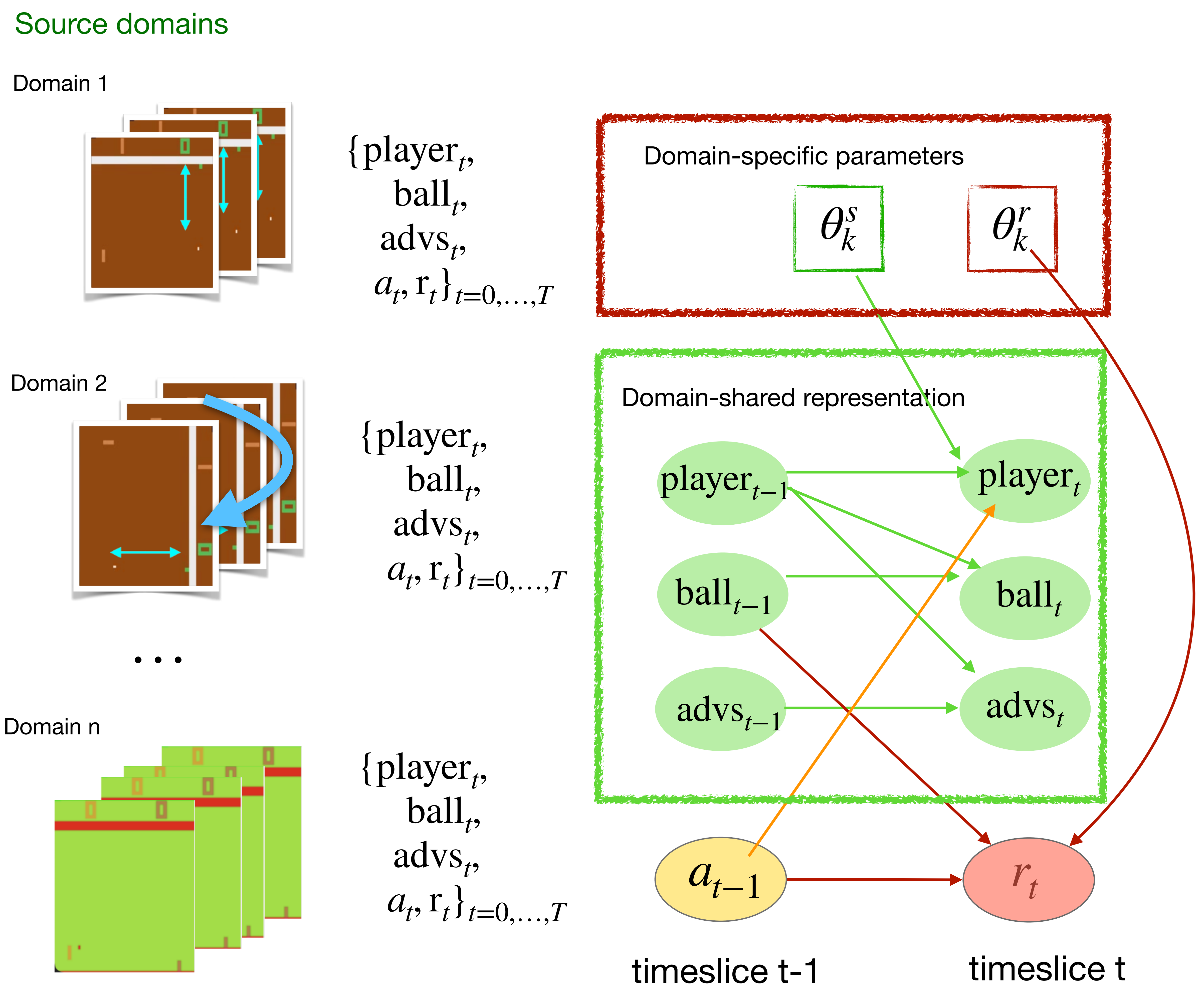


Simplifying assumption: no new edges in target domain

https://arxiv.org/abs/2107.02729

AdaRL: What, Where, and How to Adapt in Transfer RL

Biwei Huang, Fan Feng, Chaochao Lu, Sara Magliacane, Kun Zhang **ICLR 2022**

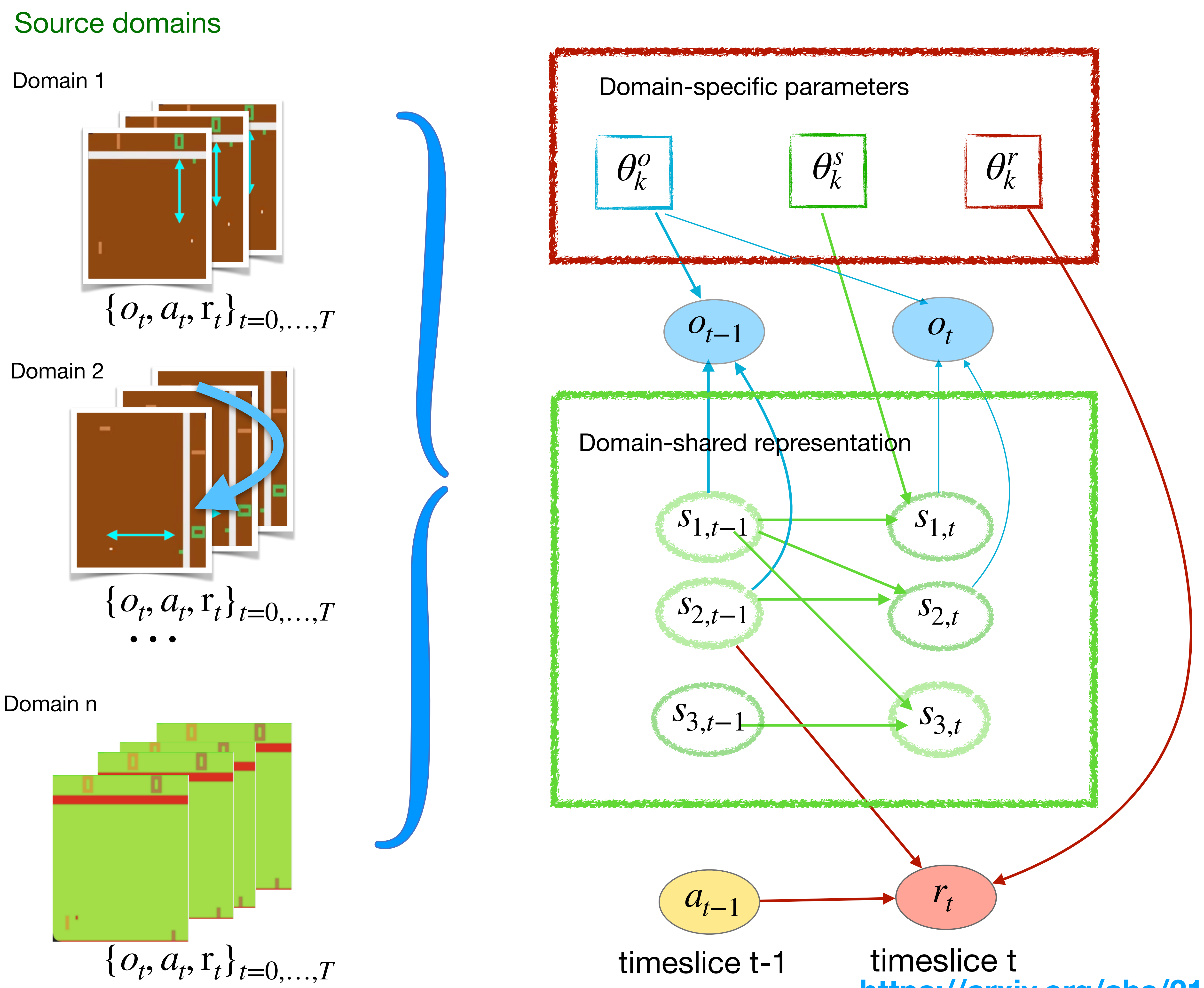


When we learn from symbolic inputs, the causal graph can be identified, but we don't have guarantees on what the latent change factors are

https://arxiv.org/abs/2107.02729

AdaRL: What, Where, and How to Adapt in Transfer RL

Biwei Huang, Fan Feng, Chaochao Lu, Sara Magliacane, Kun Zhang ICLR 2022



https://arxiv.org/abs/2107.02729

When we learn from images, we cannot identify the causal variables, so what we learn is not necessarily causal… but it is still useful

AdaRL: What, Where, and How to Adapt in Transfer RL

Biwei Huang, Fan Feng, Chaochao Lu, Sara Magliacane, Kun Zhang

ICLR 2022

Source domains

Estimate graph over estimated s_k, θ_k

Identify $s_t^{min}, \theta_t^{min}$ from the estimated graph

Learn optimal policy $\pi^*(s_k^{min}, \theta_k^{min})$ on source domains

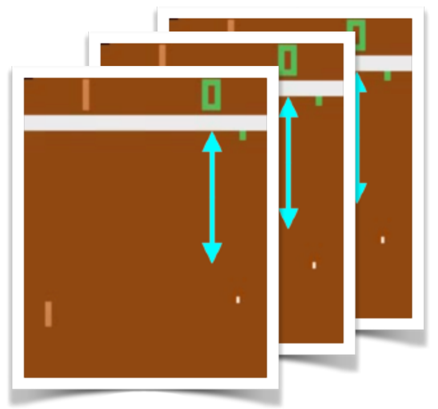
https://arxiv.org/abs/2107.02729

AdaRL: What, Where, and How to Adapt in Transfer RL

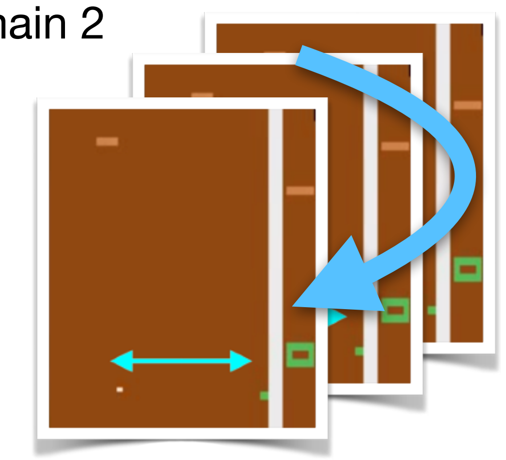
Biwei Huang, Fan Feng, Chaochao Lu, Sara Magliacane, Kun Zhang ICLR 2022

Source domains

Domain 1



Domain 2



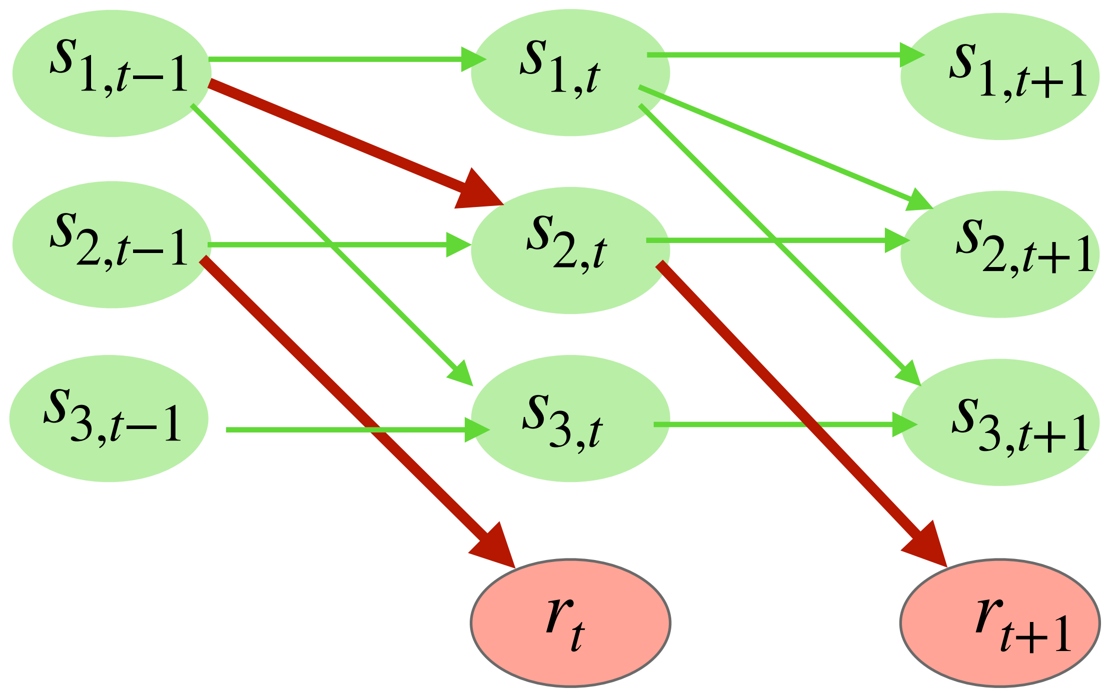
...

Estimate graph over estimated s_k, θ_k

Identify $s_t^{min}, \theta_t^{min}$ from the estimated graph

Learn optimal policy $\pi^*(s_k^{min}, \theta_k^{min})$ on source domains

- Identify the dimensions of the state and change factors that are **necessary and sufficient** for policy optimisation



https://arxiv.org/abs/2107.02729

AdaRL: What, Where, and How to Adapt in Transfer RL

Biwei Huang, Fan Feng, Chaochao Lu, Sara Magliacane, Kun Zhang ICLR 2022

Source domains

Domain 1

Domain 2

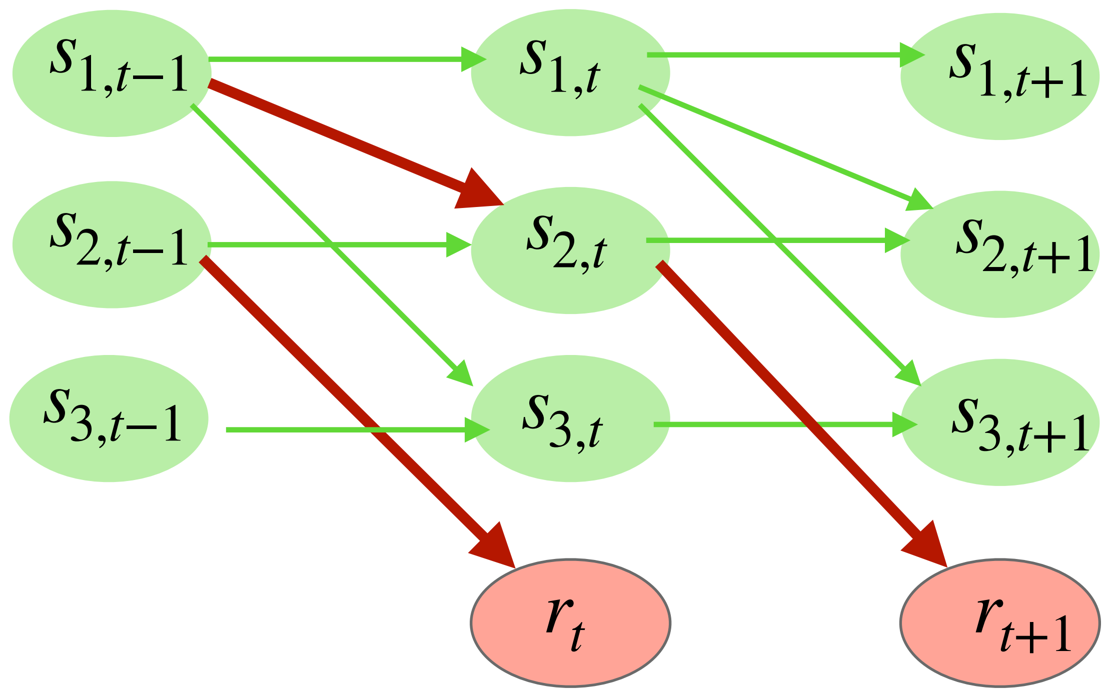
. . .

Estimate graph over estimated s_k, θ_k

Identify s_t^{min}, θ_t^{min} from the estimated graph

Learn optimal policy $\pi^*(s_k^{min}, \theta_k^{min})$ on source domains

- Identify the dimensions of the state and change factors that are **necessary and sufficient** for policy optimisation



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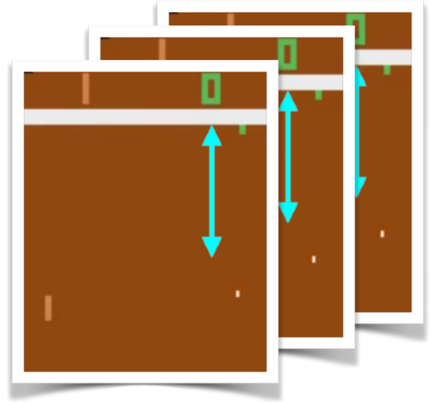
AdaRL: What, Where, and How to Adapt in Transfer RL

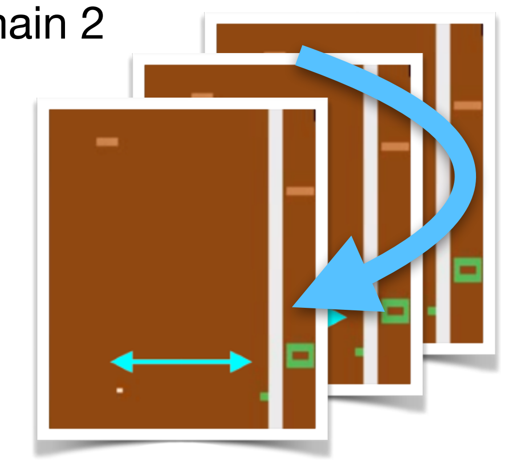
Biwei Huang, Fan Feng, Chaochao Lu, Sara Magliacane, Kun Zhang ICLR 2022

Source domains

Domain 1



Domain 2



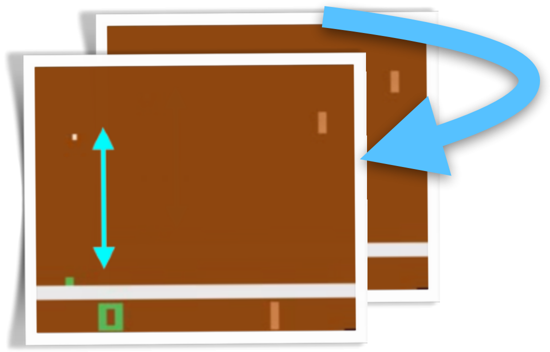
...

Estimate graph over estimated s_k, θ_k

Identify s_t^{min} , θ_t^{min} from the estimated graph

Learn optimal policy $\pi^*(s_k^{min}, \theta_k^{min})$ on source domains

Target domain



$\{o_t, a_t, r_t\}_{t=0,\ldots,T}$

Use model to estimate $s_{target}^{min}, \theta_{target}^{min}$ with few samples

Apply policy $\pi^*(s_{target}^{min}, \theta_{target}^{min})$

Simplifying assumption: no new edges in target domain

https://arxiv.org/abs/2107.02729

AdaRL: What, Where, and How to Adapt in Transfer RL

Biwei Huang, Fan Feng, Chaochao Lu, Sara Magliacane, Kun Zhang **ICLR 2022**

- **Results:** we consistently outperform the state-of-the-art **thanks to the graph**

	Oracle Upper bound	Non-t lower bound	CAVIA (Zintgraf et al., 2019)	PEARL (Rakelly et al., 2019)	AdaRL* Ours w/o masks	AdaRL Ours
G_in	2486.1 (±369.7)	1098.5 • (±472.1)	1603.0 (±877.4)	1647.4 (±617.2)	1940.5 (±841.7)	2217.6 (±981.5)
G_out	693.9 (±100.6)	204.6 • (±39.8)	392.0 • (±125.8)	434.5 • (±102.4)	439.5 • (±157.8)	**508.3** (±138.2)
M_in	2678.2 (±630.5)	748.5 • (±342.8)	2139.7 (±859.6)	1784.0 (±845.3)	1946.2 • (±496.5)	2260.2 (±682.8)
M_out	1405.6 (±368.0)	371.0 • (±92.5)	972.6 • (±401.4)	793.9 • (±394.2)	874.5 • (±290.8)	**1001.7** (±273.3)
G_in & M_in	1984.2 (±871.3)	365.0 • (±144.5)	1012.5 • (±664.9)	1260.8 • (±792.0)	1157.4 • (±578.5)	**1428.4** (±495.6)
G_out & M_out	939.4 (±270.5)	336.9 • (±139.6)	648.2 • (±481.5)	544.32 • (±175.2)	596.0 • (±184.3)	**689.4** (±272.5)

Average final scores on Cartpole (MDP) with N_target=50

	Oracle Upper bound	Non-t lower bound	PNN (Rusu et al., 2016)	PSM (Agarwal et al., 2021a)	MTQ (Fakoor et al., 2020)	AdaRL* Ours w/o masks	AdaRL Ours
O_in	18.65 (±2.43)	6.18 • (±2.43)	9.70 • (±2.09)	11.61 • (±3.85)	15.79 • (±3.26)	14.27 • (±1.93)	**18.97** (±2.00)
O_out	19.86 (±1.09)	6.40 • (±3.17)	9.54 • (±2.78)	10.82 • (±3.29)	10.82 • (±4.13)	12.67 • (±2.49)	**15.75** (±3.80)
C_in	19.35 (±0.45)	8.53 • (±2.08)	14.44 • (±2.37)	19.02 (±1.17)	16.97 • (±2.02)	18.52 • (±1.41)	19.14 (±1.05)
C_out	19.78 (±0.25)	8.26 • (±3.45)	14.84 • (±1.98)	17.66 • (±2.46)	15.45 • (±3.30)	17.92 (±1.83)	19.03 (±0.97)
S_in	18.32 (±1.18)	6.91 • (±2.02)	11.80 • (±3.25)	12.65 • (±3.72)	13.68 • (±3.49)	14.23 • (±3.19)	**16.65** (±1.72)
S_out	19.01 (±1.04)	6.60 • (±3.11)	9.07 • (±4.58)	8.45 • (±4.51)	11.45 • (±2.46)	12.80 • (±2.62)	**17.82** (±2.35)
N_in	18.48 (±1.25)	5.51 • (±3.88)	12.73 • (±3.67)	11.30 • (±2.58)	12.67 • (±3.84)	13.78 • (±2.15)	**16.84** (±3.13)
N_out	18.26 (±1.11)	6.02 • (±3.19)	13.24 • (±2.55)	11.26 • (±3.15)	15.77 • (±2.12)	14.65 • (±3.01)	**18.30** (±2.24)

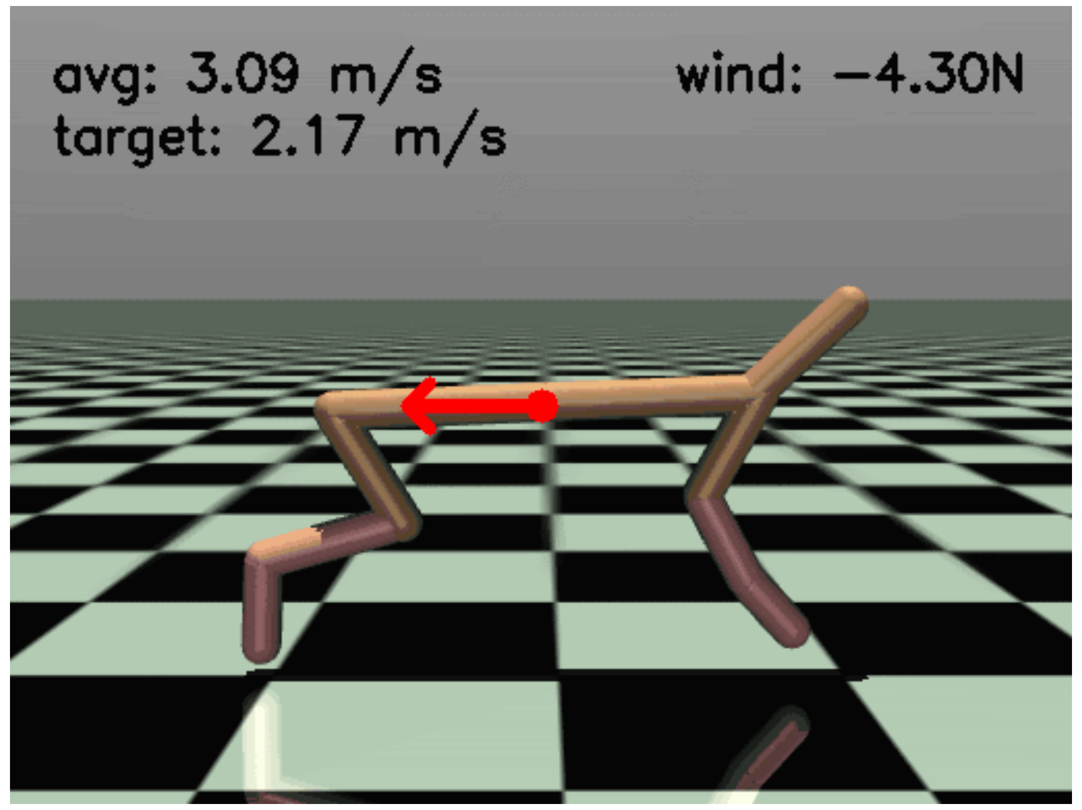
Average final scores on Pong (POMDP) with N_target=50

https://arxiv.org/abs/2107.02729

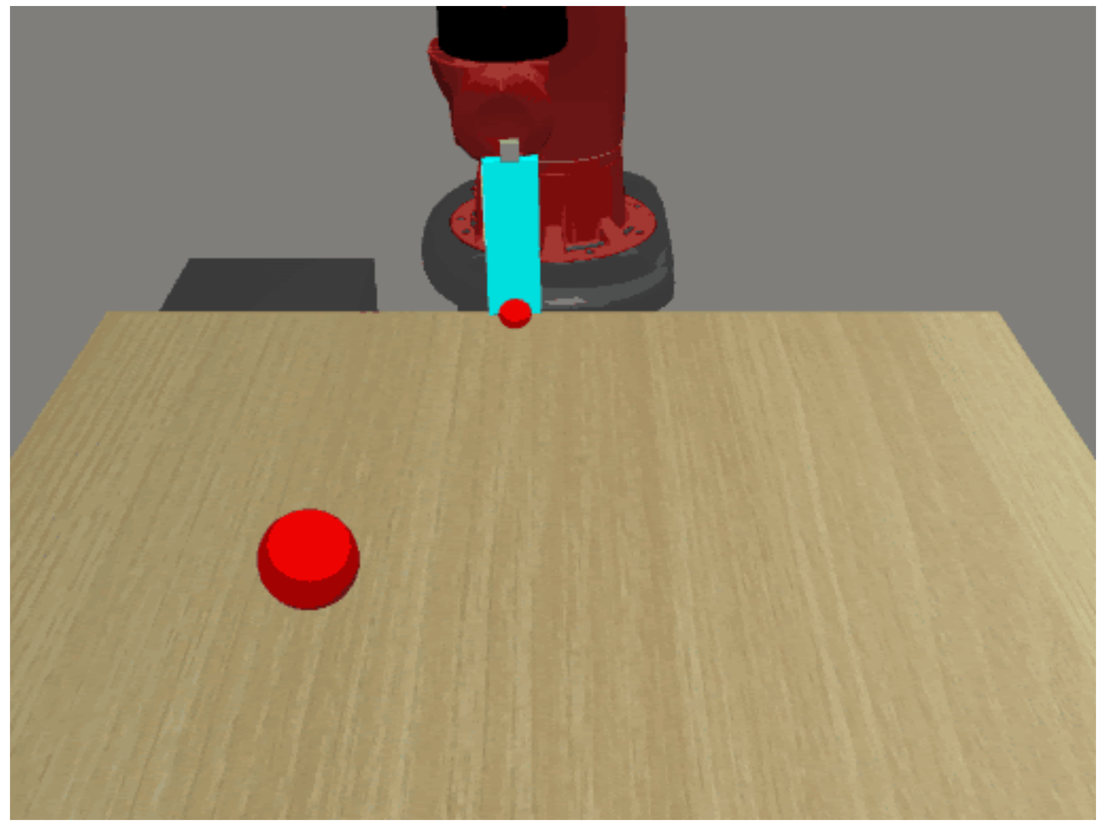
FansRL: Factored Adaptation for Non-Stationary Reinforcement Learning

Fan Feng, Biwei Huang, Kun Zhang, Sara Magliacane **NeurIPS 2022**

- **Task:** RL agent has to learn a policy that is robust to different types of non-stationarity, including **multiple simultaneous changes of different types**

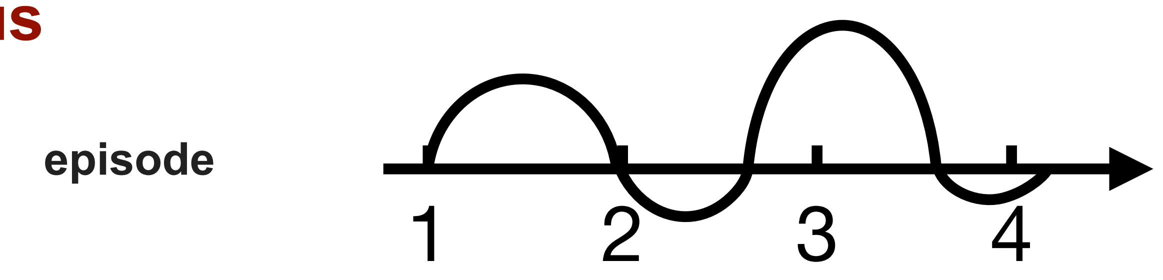


Non-stationary environments (wind changes)



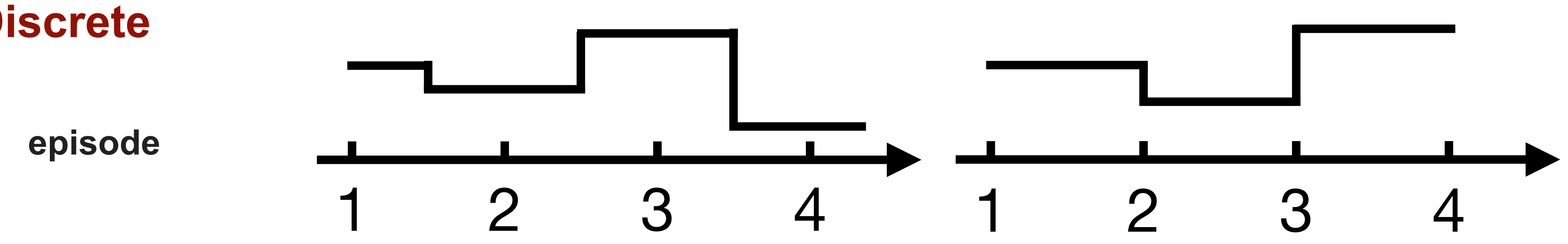
Non-stationary rewards (target changes)

Continuous



Different functions, e.g. sine, linear, damping

Discrete



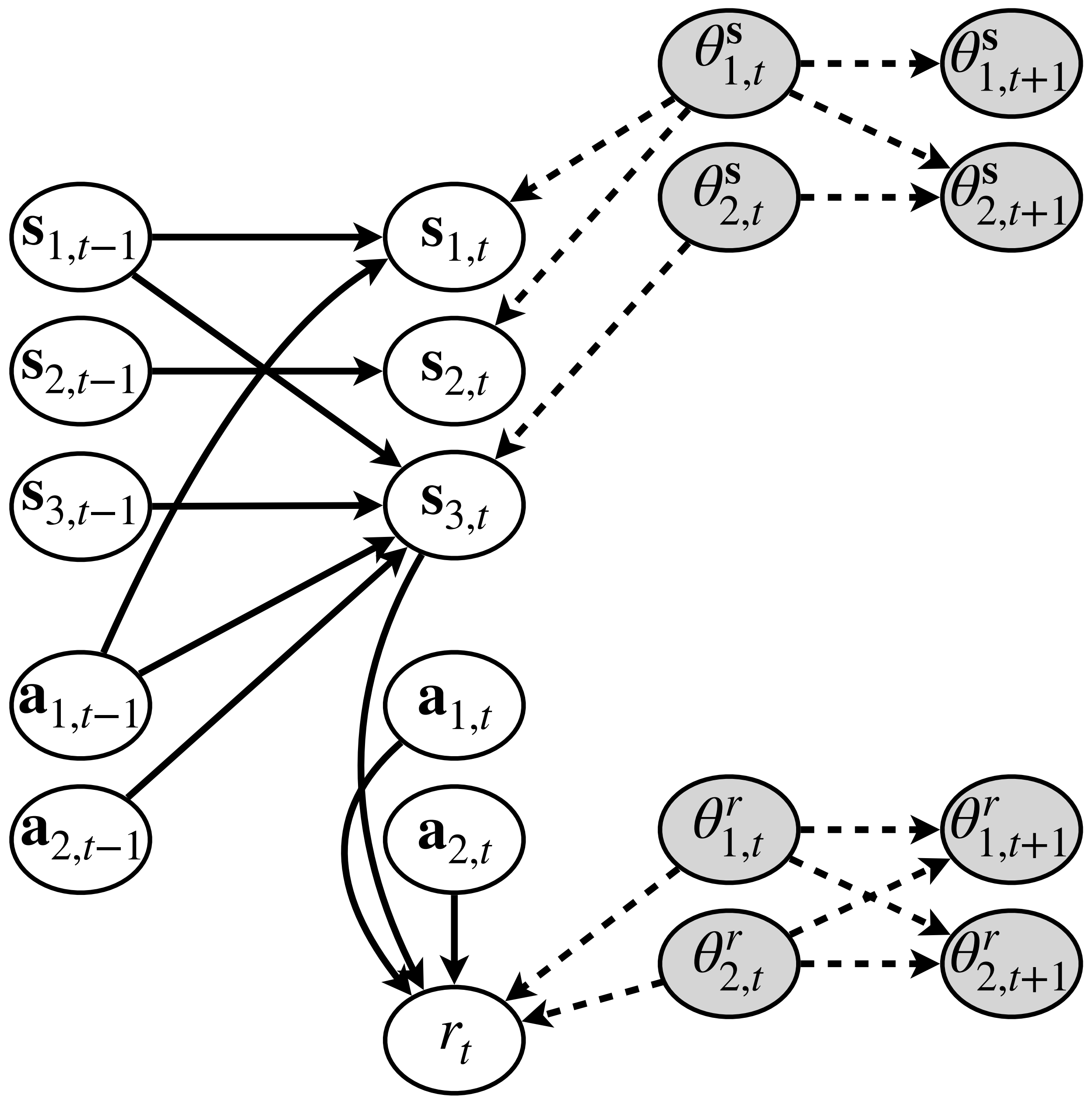
Within-episode **Across-episode**

https://arxiv.org/abs/2203.16582

FansRL: Factored Adaptation for Non-Stationary Reinforcement Learning

Fan Feng, Biwei Huang, Kun Zhang, Sara Magliacane NeurIPS 2022

- The **latent change factors** are not constant anymore and they model **non-stationarity**



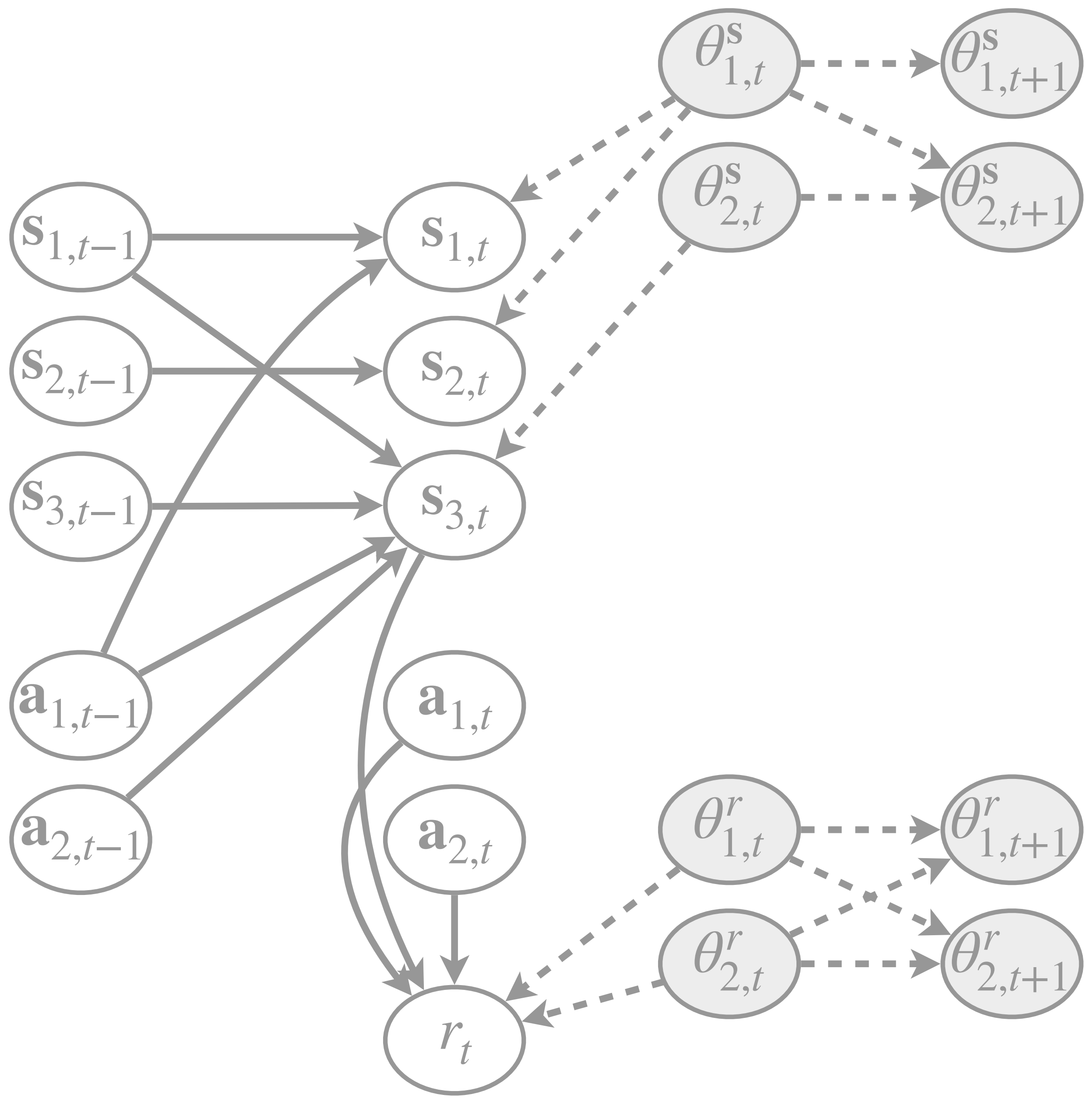
Factored Non-Stationary MDP

https://arxiv.org/abs/2203.16582

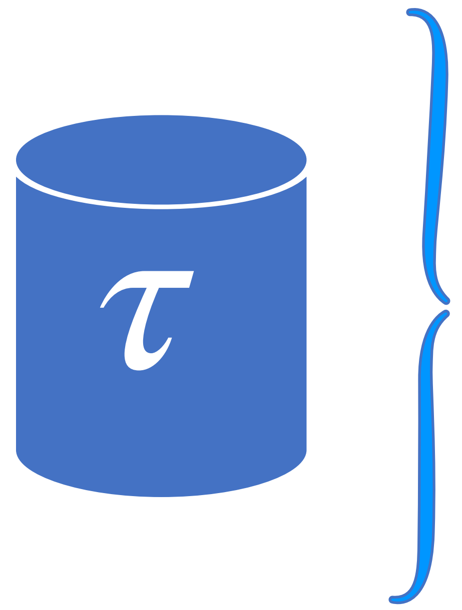
FansRL: Factored Adaptation for Non-Stationary Reinforcement Learning

Fan Feng, Biwei Huang, Kun Zhang, Sara Magliacane **NeurIPS 2022**

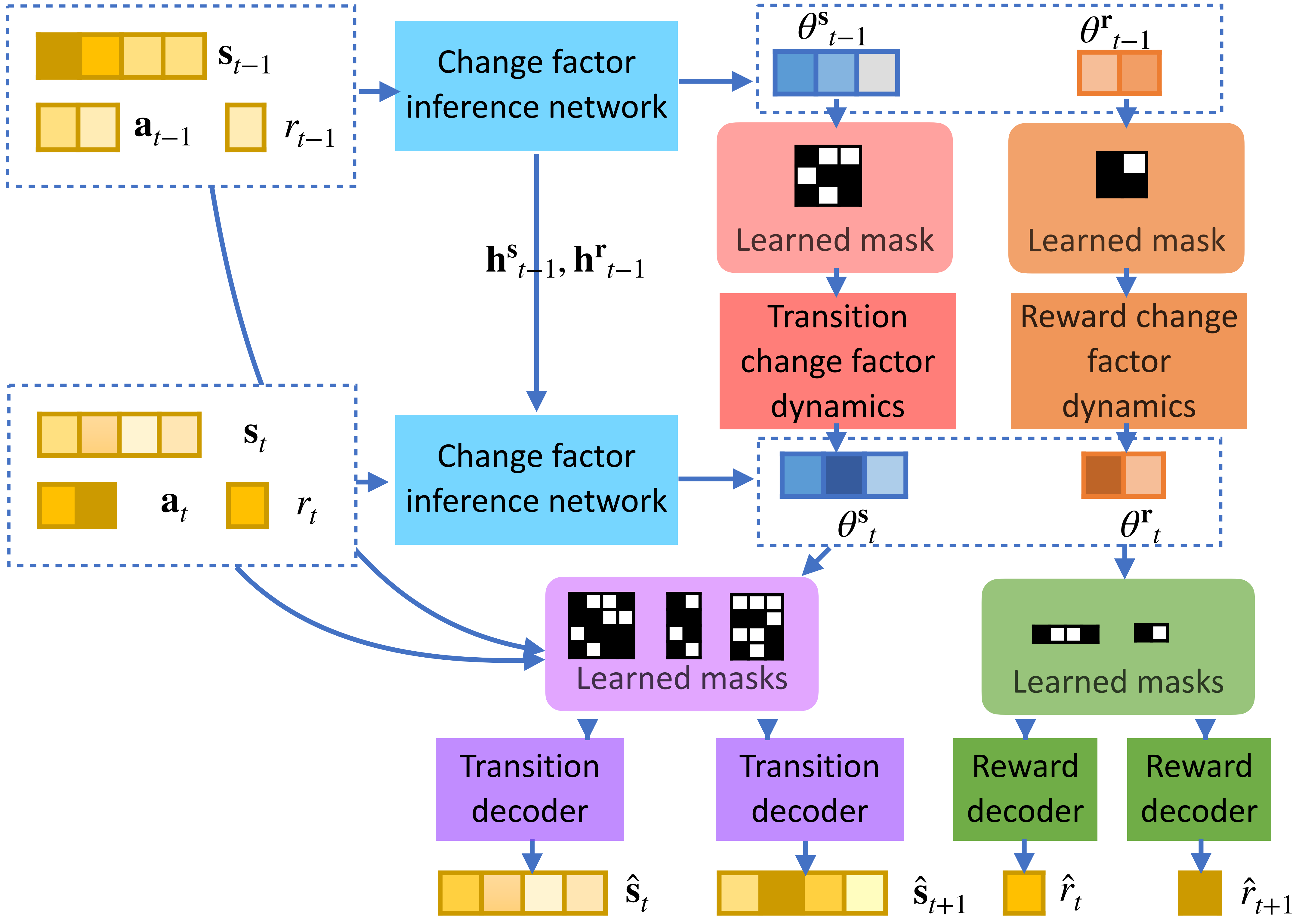
- The **latent change factors** are not constant anymore and they model **non-stationarity**



Factored Non-Stationary MDP



Trajectories collected with an initial policy (e.g. random)



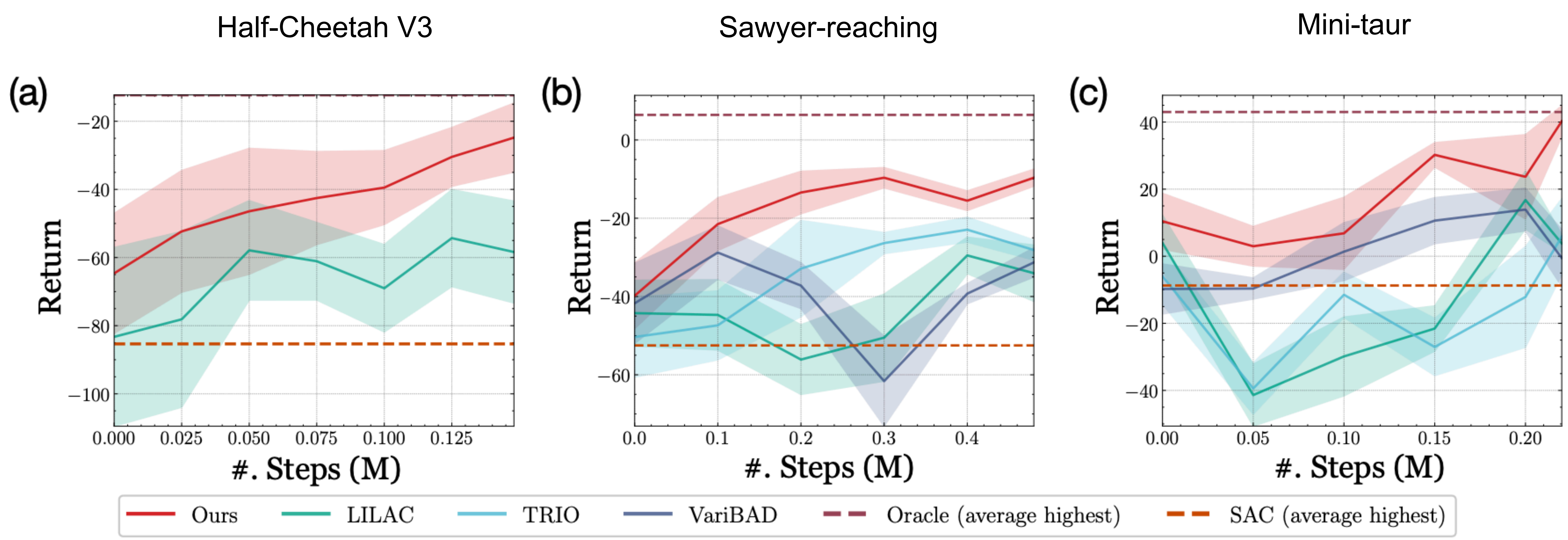
Factored Non-Stationary Variational Autoencoder

https://arxiv.org/abs/2203.16582

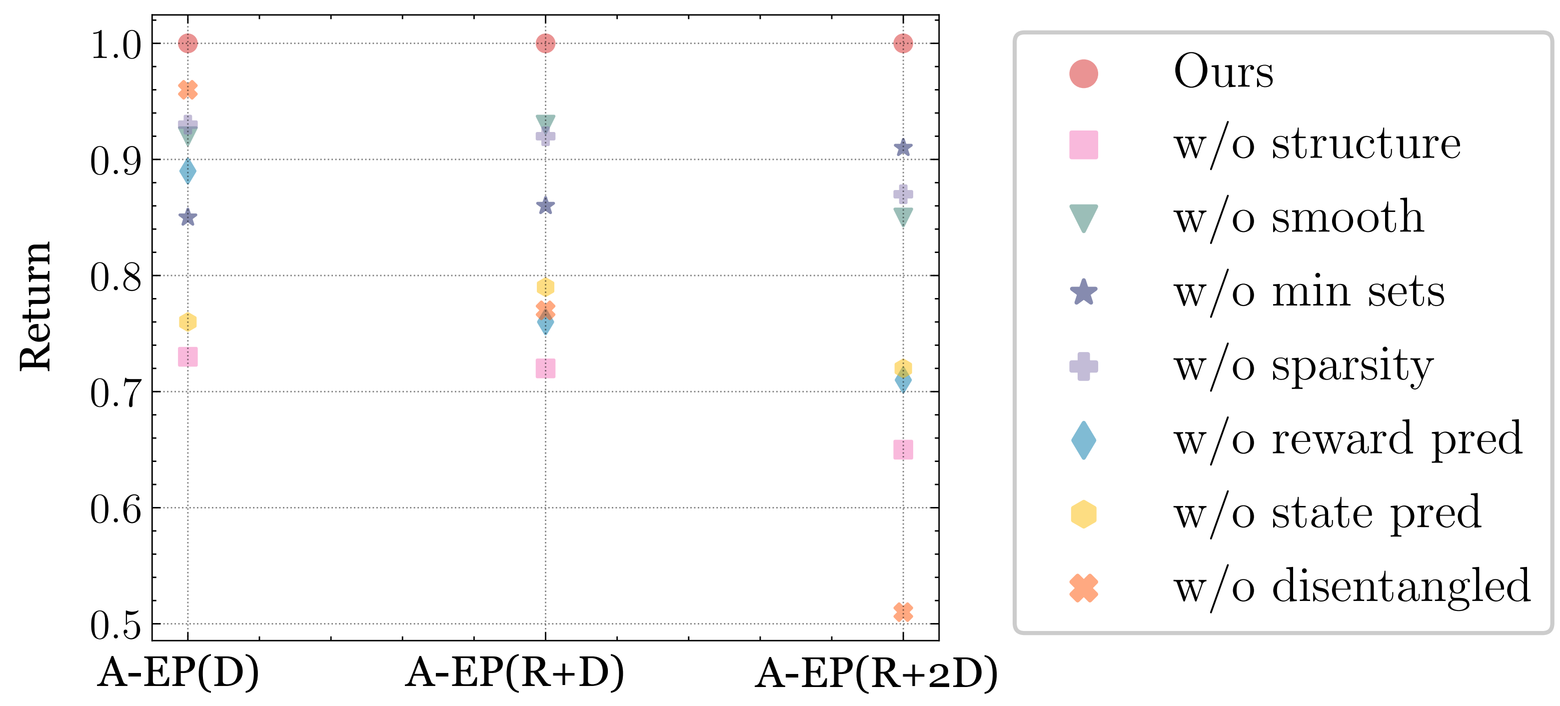
FansRL: Factored Adaptation for Non-Stationary Reinforcement Learning

Fan Feng, Biwei Huang, Kun Zhang, Sara Magliacane NeurIPS 2022

- **Policy learning:** estimate latent change factors, learn policy as if they were observed
- **Results:** we consistently outperform the state-of-the-art **thanks to the graph**



Ablation studies



Continuous changes on dynamics (sine wind)

Across-episode changes on rewards (changing target)

Across-episode changes on both dynamics (mass) and reward (target velocity)

The biggest difference in performance is switching off learning the graph

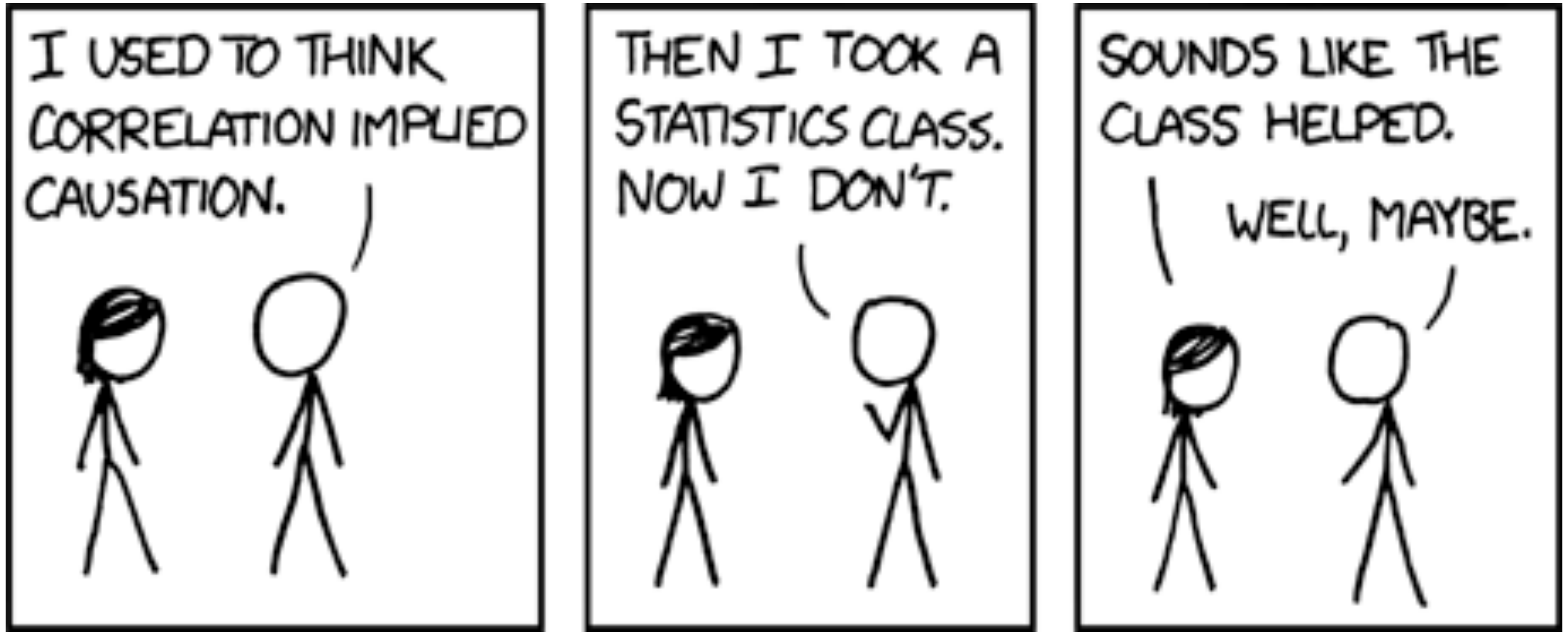
https://arxiv.org/abs/2203.16582

Conclusions

- Graphical models and d-separation [Pearl 1988] are a principled way to reason about **invariances and distribution shift**
  - Not a new observation, known since [Schoelkopf et al 2012]
  - Even with **unknown causal graphs, Missing data/zero-shot settings**
- Often we **do not need to reconstruct the causal graph**, we only need to infer missing conditional independences
- These ideas seem empirically useful even if we **cannot guarantee** that we are **learning the true causal variables or the true causal graph**

Thanks! Questions?

(joint work with Thijs van Ommen, Tom Claassen, Stephan Bongers, Philip Versteeg, Joris Mooij, Biwei Huang, Fan Feng, Chaochao Lu and Kun Zhang)



https://xkcd.com/552/