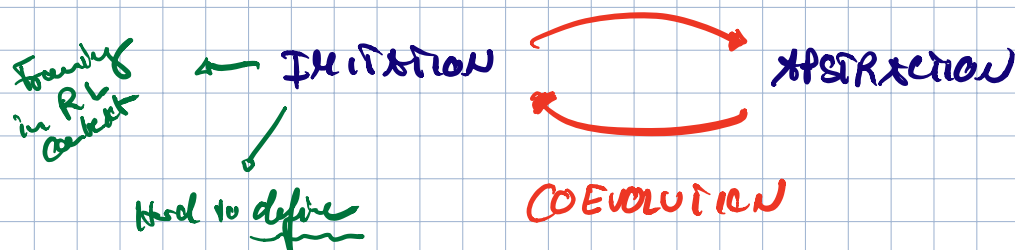


- 'Machine Learning Advances on Imitation' -

• Abstraction / Symbolic Reasoning \Rightarrow Efficient exploration!

\hookrightarrow Identification of successful behaviors \Rightarrow Imitation $\rightarrow \oplus$ Abstraction



Desirable in ML

1. One-shot rapid imitation.
2. Third-person imitation.
3. High-fidelity imitation.
4. Goal-driven/intentional imitation.
5. Long-term imitation.
6. Selective imitation.

\hookrightarrow Abstraction / who counter different way to achieve goal

• One-shot Imitation \rightarrow Model-Agnostic Meta-L. (MAML)

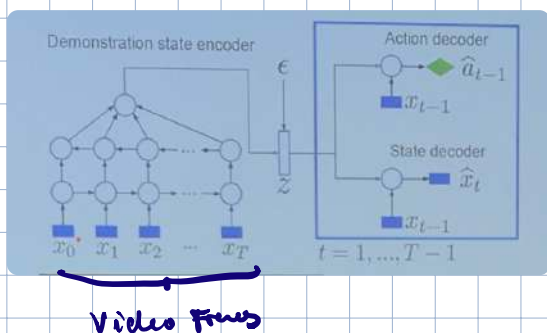
\rightarrow Domain Adaptive Meta-L. \Rightarrow MAML \rightarrow Two neural losses

\hookrightarrow Relationship to Hierarchical Bayes \rightarrow Empirical Bayes \rightarrow Infer / Fix Hypothesis

\hookrightarrow Application: Carline Mover demos w. Robot demos

\hookrightarrow Problem MAML: Only works with short video sequences

\rightarrow Generative Models Approach



\hookrightarrow learn encoding vector \Rightarrow behavioral (continuous) description! via Embedding

\hookrightarrow Continuous \Rightarrow allows as behaviors!

\hookrightarrow allows to generalize at test time given sequence of frames!

\hookrightarrow Reed and de Freitas 16' \rightarrow Neural Programmer-Interpreters (NPIs)

\Rightarrow here: Backup through behavior \rightarrow before: Only reconstructive loss!

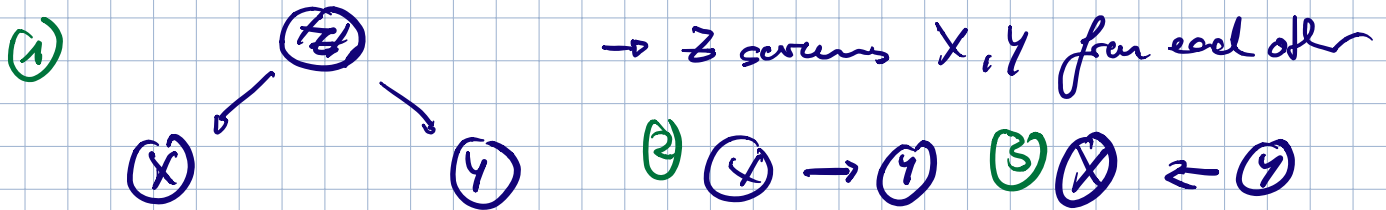
\hookrightarrow Towers of Hanoi \rightarrow Train NPI with AlphaZero

\rightarrow General approach: Fixed Core \oplus Flexible Embedding

Bernhard Schölkopf - 'Causal Learning'

- Motivieren: Caus at beach misclassified \Rightarrow ML \Rightarrow Correlations!
 - \rightarrow IID assumption \Rightarrow Violated in adversarial examples!
 - \rightarrow causal relationship (asymmetry) vs. Merit info (symmetry)

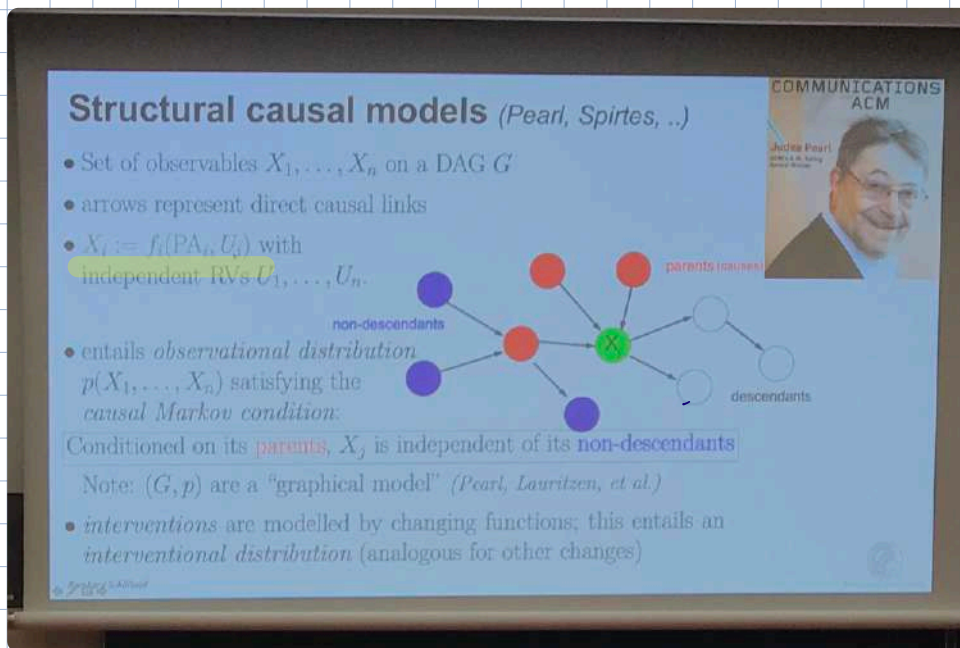
REICHENBACH'S COMMON CAUSE PRINCIPLE



\rightarrow all lead to same observation $P(X, Y)$!

\rightarrow Berkson's paradox \Rightarrow Introducing variable Z leads to correlation

- Structural Causal Models \rightarrow Pearl \Rightarrow Do-Calculus



\rightarrow Predictive to V

\rightarrow Traditionally fM perspective does not focus on intervention!

\rightarrow Global \Rightarrow Local Markov condition

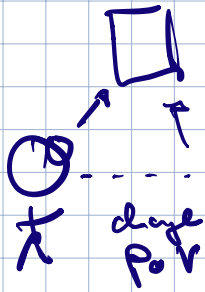
\rightarrow Not implied by existence of graph!

\rightarrow Factorization of joint distributions $\prod p(X_i | p_{\pi(i)})$

- How to learn about graphs without interventions?
 - \rightarrow Message passing \rightarrow learn about graph structure

- INVARIANCE \leftrightarrow Causality \rightarrow invariance allows for clear causal experiments!

\hookrightarrow Get sense of 3d structure since object does not change / is invariant!



\rightarrow Spine interventions! \Rightarrow LINK CAUSAL & STATISTICAL STRUCTURE

- Interesting ideas to infer direction of time from video frames
- Kolmogorov vs. Shannon entropy \rightarrow Fuel-arrow of time

Covariate Shift and Semi-Supervised Learning

Goal: learn $X \mapsto Y$, i.e., estimate (properties of) $p(Y|X)$

Semi-supervised learning: improve estimate by more data from $p(X)$

Covariate shift: $p(X)$ changes between training and test

Causal assumption: $p(C)$ and mechanism $p(E|C)$ "independent"

Causal learning

$p(X)$ and $p(Y|X)$ independent

1. semi-supervised learning impossible
2. $p(Y|X)$ invariant under change in $p(X)$

Anticausal learning

$p(Y)$ and $p(X|Y)$ independent

hence $p(X)$ and $p(Y|X)$ dependent

1. semi-supervised learning possible
2. $p(Y|X)$ changes with $p(X)$

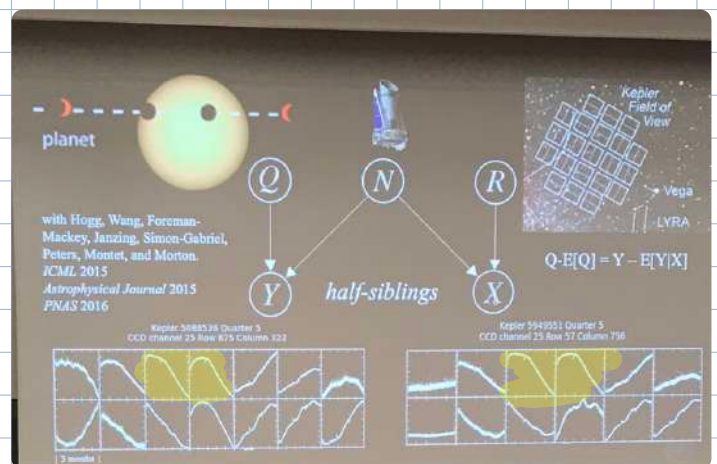
Schölkopf, Janzing, Peters, Spirtes, Zhang, Mooij, 2012, cf. Starkey, 2009, Bareinboim & Pearl, 2012

- ICM paper 18!
- \hookrightarrow specialisation of expert for transference!
- \hookrightarrow Robustness

- Learn + Independent Methods
- \hookrightarrow Beygel + Robinson!

A Modeling Taxonomy

	statistical model	causal model	differential equation model
i.i.d. prediction, pattern recognition, "generalization"	y	y	y
Predict under shift & intervention, "horizontal generalization"	n	y	y
Provide physical insight, understand predictions	n	(y)	y
Think/Reason, "act in an imagined space" (K. Lorenz)	n	?	?
Learn from data	y	(y)	n

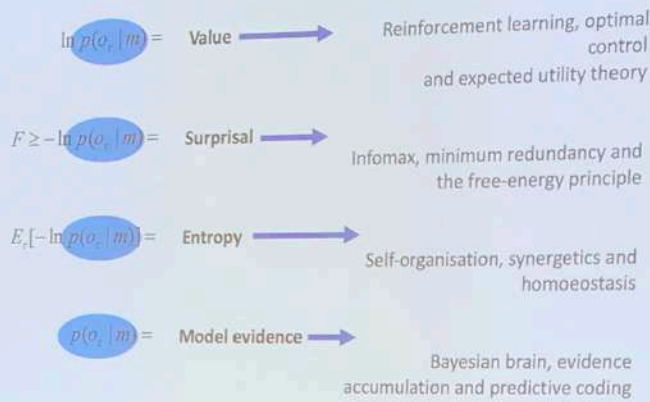


\hookrightarrow predict y from working of X !

Debate: The Free Energy Principle - Karl Friston // Jeff Beck

A neat explanation for everything: self-evidencing or minimizing free energy

$$F = \underbrace{D[Q(s_t) \| P(s_t)]}_{\text{complexity}} - \underbrace{E_{Q(s_t)}[\ln P(o_t | s_t)]}_{\text{accuracy}} \geq -\underbrace{\ln P(o_t | m)}_{\text{evidence}}$$



PXL20 V

SARLOW

WELM HOLTZ

- Active inference to exploration
- Bayesian Surprise
- Mutual Info
- KL / Risk-sensitive control
- Exp. Utility Theory
- ↳ IMPERATIVE: Min. Free Energy

→ Jarzynski equality & Landauer's principle

• FEP as concept vs. theory of cognitive capabilities

• Surprise \rightarrow sensory \rightarrow Difference RL vs Active Inference FEP

\rightarrow motor

Equivalence of Reward and Default Policy

- In the absence of control you move randomly according to some prior distribution $p(s_{t+1} | s_t)$
- Exerting a control signal, u_t , changes this to $p(s_{t+1} | s_t, u_t)$
- If movement cost is a KL divergence then

$$C_{t+1}^{\text{total}} = \log \frac{p(s_{t+1} | s_t, u_t)}{p(s_{t+1} | s_t)} + C(s_{t+1}) = \log \frac{p(s_{t+1} | s_t, u_t)}{p(s_{t+1} | s_t) \exp(-C(s_{t+1}))}$$

- Total Expected Cost of a given policy: u

$$\langle C \rangle = \sum_t \sum_{s_{t+1}} p(s_{t+1} | s_t, u_t) \log \frac{p(s_{t+1} | s_t, u_t)}{p(s_{t+1} | s_t) \exp(-C(s_{t+1}))}$$

$$= \sum_t KL(p(s_{t+1} | s_t, u_t), \chi(s_{t+1} | s_t))$$

- To maximize reward you adopt a default policy

$$\chi(s_{t+1} | s_t) \propto p(s_{t+1} | s_t) \exp(-C(s_{t+1}))$$

Policy Prior / Default

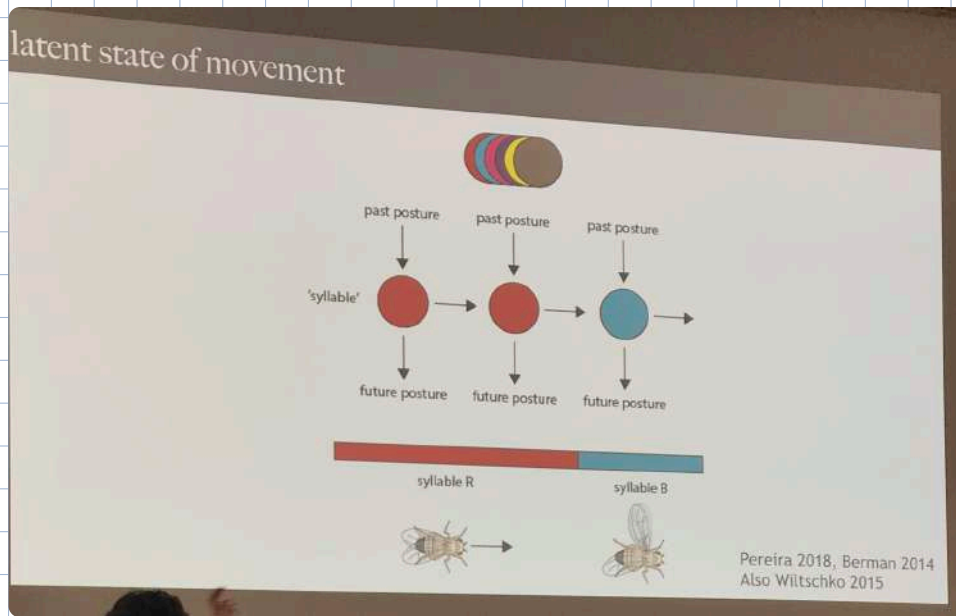
Re-defining an organism



- Standard Decision making formulation
 - An organism is defined by its
 - Inference engine: $q(s|D)$
 - Reward function: $R(a, s)$
 - Actions maximize expected Reward by identifying a policy
- Free Energy formulation
 - An organism is defined by
 - Inference engine: $q(s, a|D)$ applied to generative model $p_m(D|s, a)p_m(s)$
 - Policy $p_m(a|s)$
 - Beliefs and actions are both selected by minimizing Free Energy

Interacting Minds \Rightarrow Cross-Collaboration \rightarrow Rethink lots

- Cozin (2009) \rightarrow Models Review!
- Tinbergen \rightarrow Funder ethology discipline
- No trial averaging! \Rightarrow One continuous process of behavior!
 \hookrightarrow Hard to define episodes
- Fruit flies modify behavior \rightarrow Song male to signal threat!



Adrian
Calhoun
- Spencer -

* Pay attention to style-trial dynamics

* Unpack abstract of actions // of relationships \rightarrow ways of thinking!

Social Psychology
John Thornton
- Spencer -

- Perception of other minds \rightarrow Risk-assessment \rightarrow FP
 \rightarrow Thus want to be fooled \Rightarrow Trust test too easy
- How to represent actions \Rightarrow Thornton & Tenen, 19'