Classical Planning in Deep Latent Space: From Unlabeled Images to PDDL (and back)

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1. Background

- **Symbols: Labels for distinguishing entities**
- **Symbols in PDDL:**

Propositions	(handempty)
Objects	A, B, C, D
Predicates	(clear ?x)
Actions	(pick-up ?x)

- **Existing Action Model Learning (AML) systems ALL require symbolic (or near-symbolic) inputs**
- **Cannot directly handle complex unstructured high-dimensional data e.g. images, audio**

Action-Relation Modelling System *[Yang et al 07]*
input: symbolic relations (predicates, actions)

Semi-MDP→Classical Planning *[Konidaris et al 14,15]*
Not entirely subsymbolic: converts probabilistic → propositional model
Symbolic action labels: **given** *(SMDP option e.g. move,interact)*
Input sensors: **given,structured,low-dim**
(set of 33 real/int variables with distinct meanings:x/y distance, light level, whether monkey cries)

Learning from Observation: *[Argall et al 09, Mourao et al 12]*
Noisy, incomplete, but symbolic states/actions
Learns the preconditions from state/action sequence
Object/predicate/action labels: **given**

Learning from Video for board game:
Images with strong assumptions (almost symbol)
e.g. 3x3 Ellipse Detector *[Barbu et al 10; Kaiser12; Kirk&Laird16]*
almost immediately provides propositions

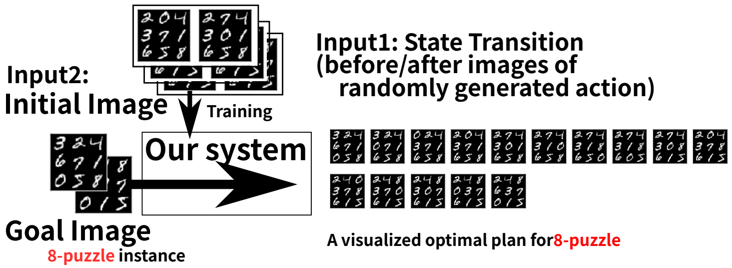
2. Our Objectives

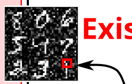
Visually presented classical planning domains

The system should have no idea that this is an 8-puzzle

Initial state image **Goal state image (black/white)**

- with **NO** prior assumptions/symbolic descriptions
("grids","tiles","disks","move","toggle") i.e. domain-independent
- with **NO** expert plan traces





Existing AML systems cannot handle raw images

- High-dimensional input (42x42 pixels = 1764)
- Each pixel does not have a significant meaning
- "Meaning" emerges from nonlin. entanglements
- No simple detector (e.g. stone exisitence)
- Need Robustness & Generalization for noisy inputs

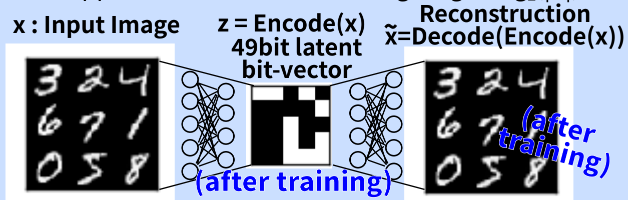
3. OPEN PROBLEM: Convert images/ arbitrary unstructured data to/from symbols

Generate the symbolic inputs for AML Systems !

Raw data → Symbolic data
→ **Exisiting AML methods**
→ Symbolic Planning → **Symbolic plan → Raw output**

4. Solution: State AutoEncoder

- A neural network that learns a **bidirectional mapping** **z=Encode(x)** and **x=Decode(z)** between a subsymbolic input **x** and a discrete boolean vector **z**
- The only specification is the number of bits: An upper bound of state encoding length $\log_2(|S|)$



- For training, optimize the loss via Stoc. Grad. Descent
Minimize reconstruction loss $||x-\tilde{x}||$ (Binary crossentropy etc.)
+ variational loss KL(Z, Categorical(49))
(KL divergence: distance between distributions)

SAE: A Variational AutoEncoder w/ Gumbel-Softmax

- Allows NNs to learn a categorical/discrete distribution

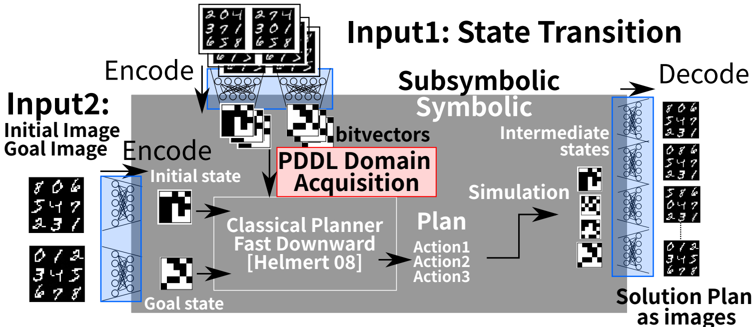
π τ

π τ

Number of categories = 2 : Propositional variables

- the "meaning" of the propositions may or may not correspond to human intuitions about the domain

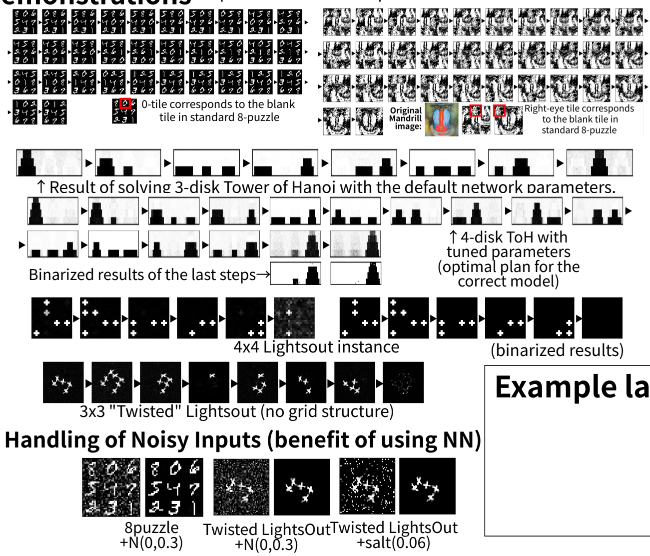
5. Image-based planning architecture: LatPlan



A First Implementation: LatPlan α

- SAE: Trained w/ smaller subset of states (cross validated, SAE learns a generalized/robust state encoding)
- Trivial AML method: action = individual state transition we provide all state transitions (i.e. no action generalization
  - Future work: adapt existing AML method

Demonstrations Optimal solutions to 8-puzzle instances



6. Domain-Independent SearchHeuristics are Effective in Latent-Space Planning

Somewhat surprising result: Heuristics reduce search in domains based on features generated by neural networks

- Exploit common characteristics (e.g. abstraction)
- PDBs can underperform blind search in some standard IPC domains (Edelkamp12)

Example latent-space domain

Example with |z| = 25bits
pre: before-state
eff: state diff