

# Scaling

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# Decision Making

Is about controlling linked variables:

- ▶ Learning correlation
- ▶ Optimize trajectories

Mathematically:

- ▶ Manipulate Cartesian Product (Set Theory)
- ▶ Estimate functions
- ▶ Exploring large graph

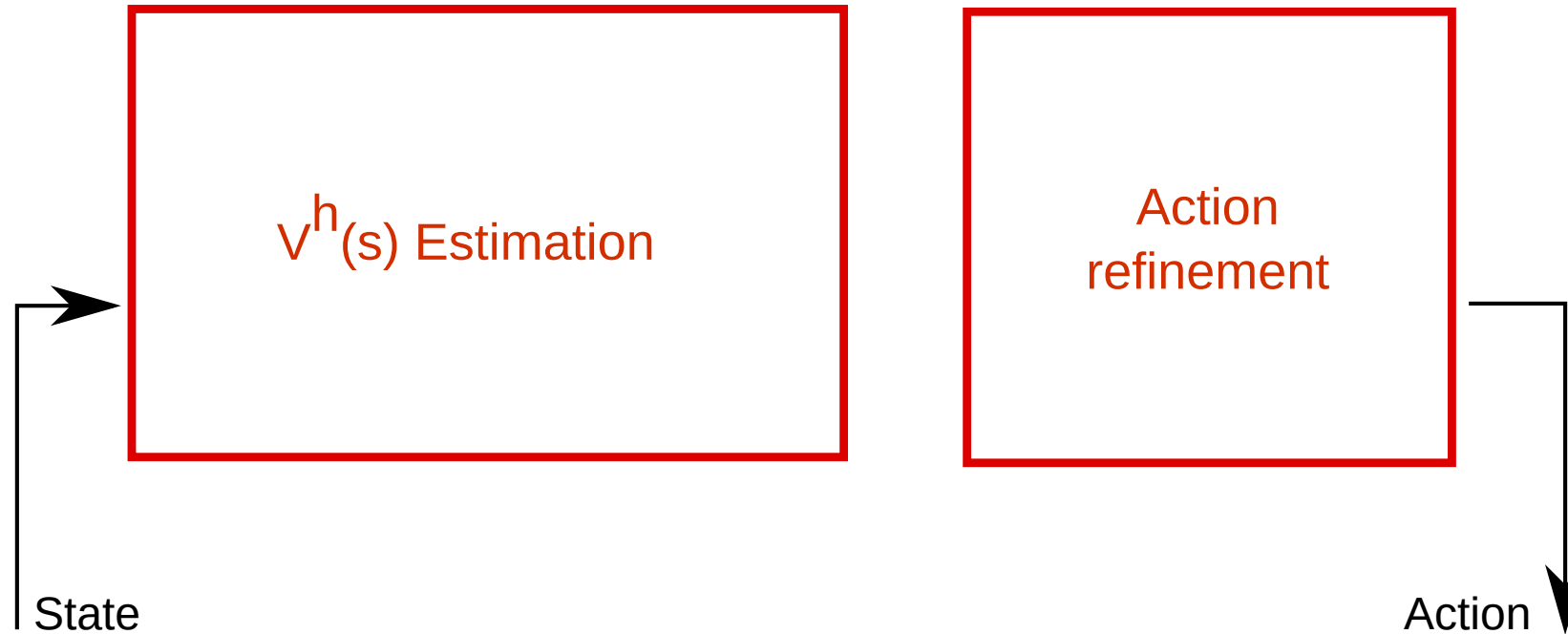
# Dealing with large State Space

Reduce the state space

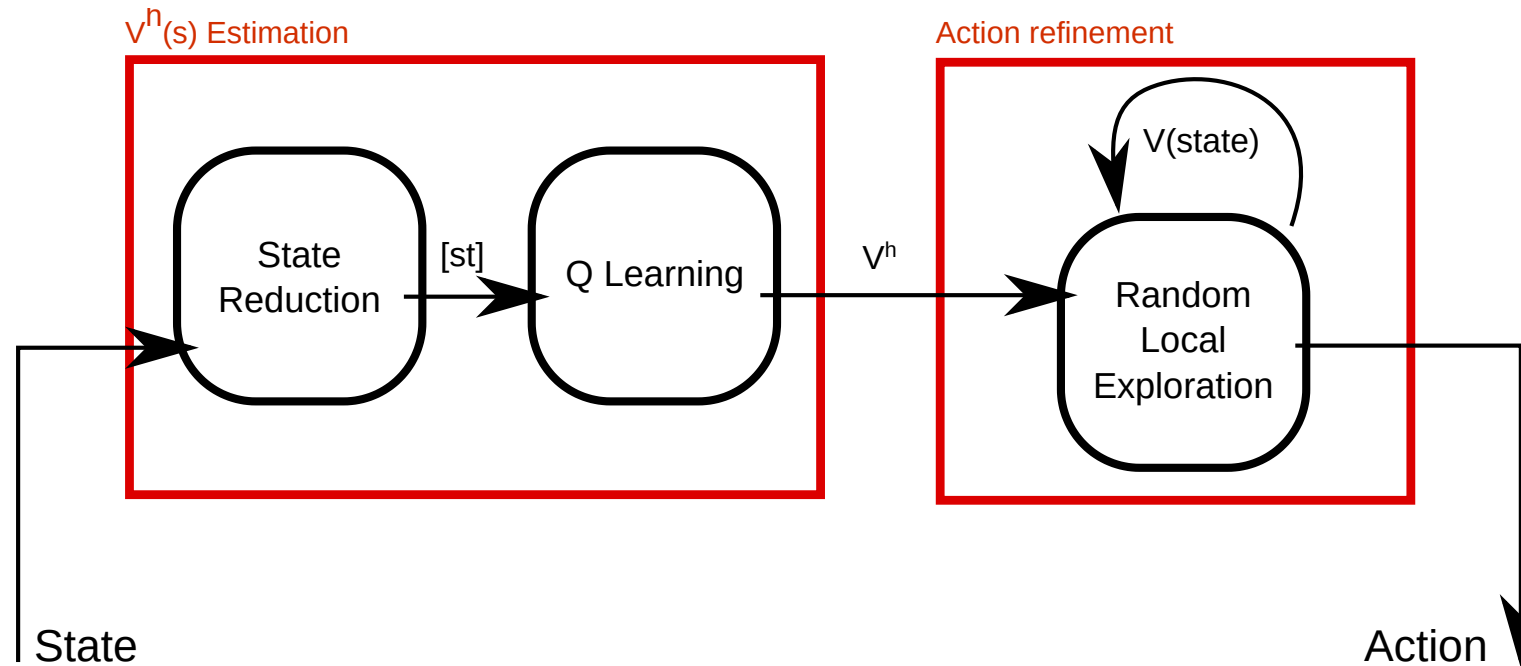
Work locally

A combination of these 2 solutions

# A Complete Decision Architecture



# A Complete Decision Architecture



# State reduction (or identification)

## Approach:

Distance based approach:

- ▶ Principal Component Analysis (**PCA**) (+ Discretization)
- ▶ Clustering: **k-means**, Simple Vector Machine (**SVM**)

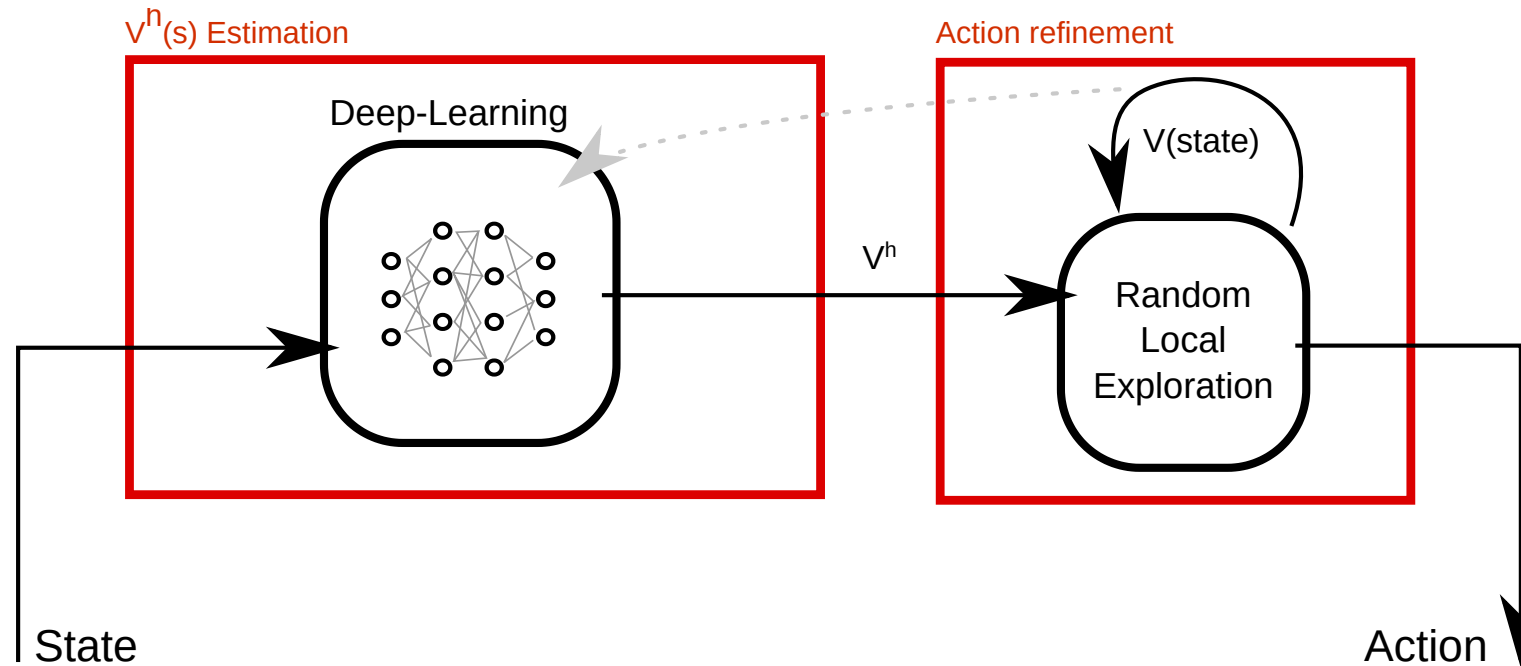
Discrete approach:

- ▶ Decision-Tree (ID3 algorithm family)

## Goals:

**Macro-States** merge states with supposed similar values.

# Deep-Learning-based Decision Architecture



## Requirement:

Labeled data with valid *values*...

# Action refinement at run time

**Local computation of the Values and the policy from current state.**

- ▶ Constrained Value Iteration (from the current state, with a limited horizon)
- ▶ Monte Carlo Approach (based on deep, but random trajectories)

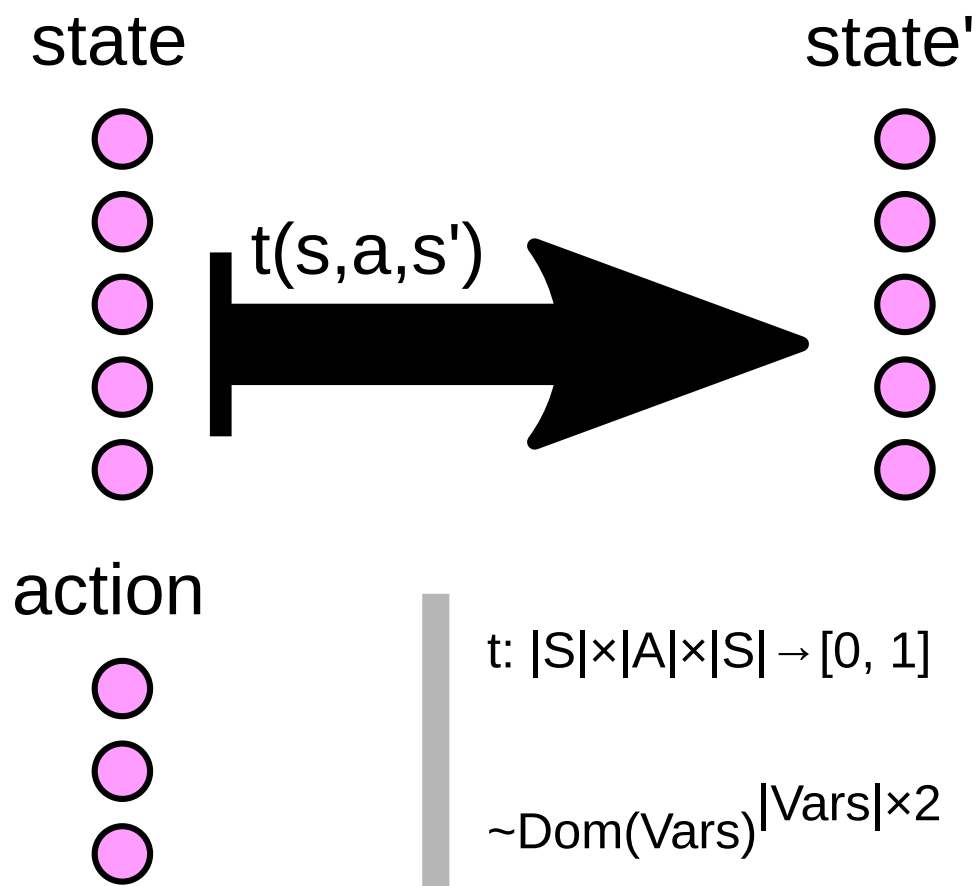
## **Requirement:**

Simulation: a model of the controlled system



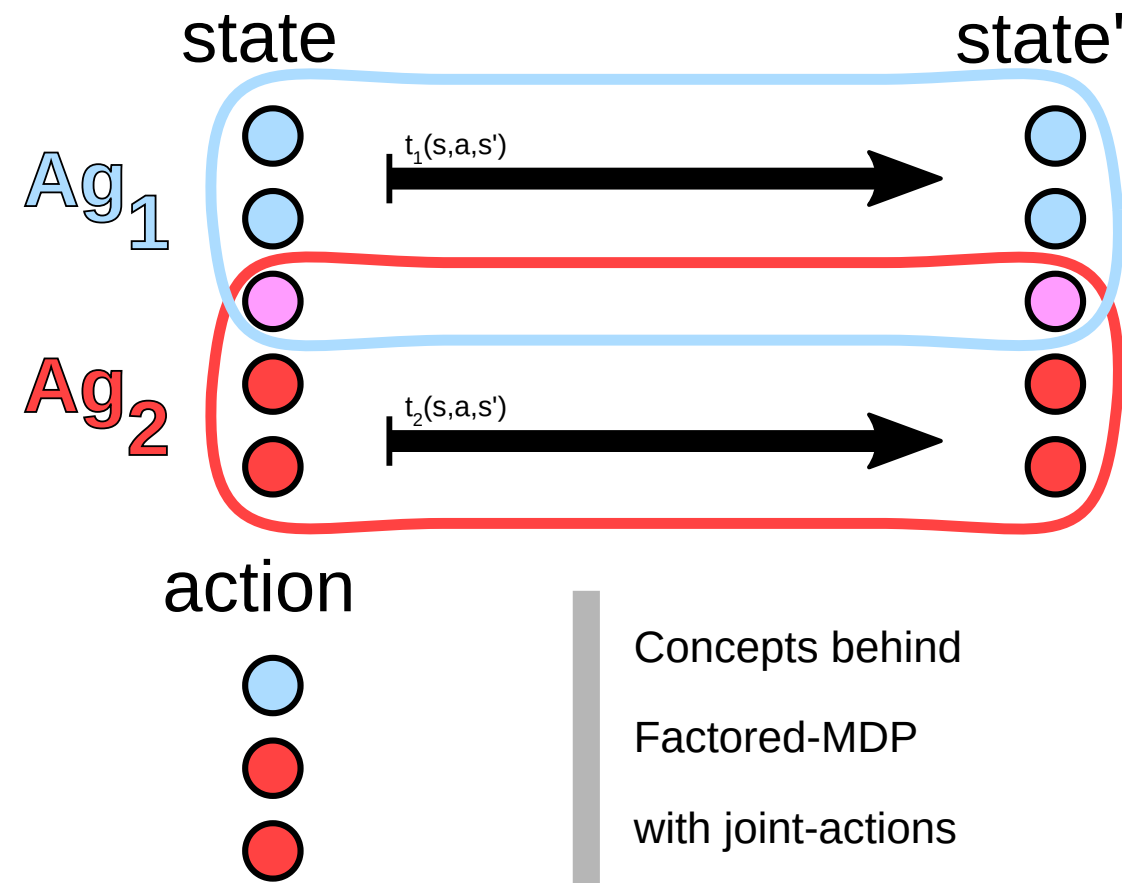
# The Curse of Dimensionality in MDP

## Fonction de Transition:



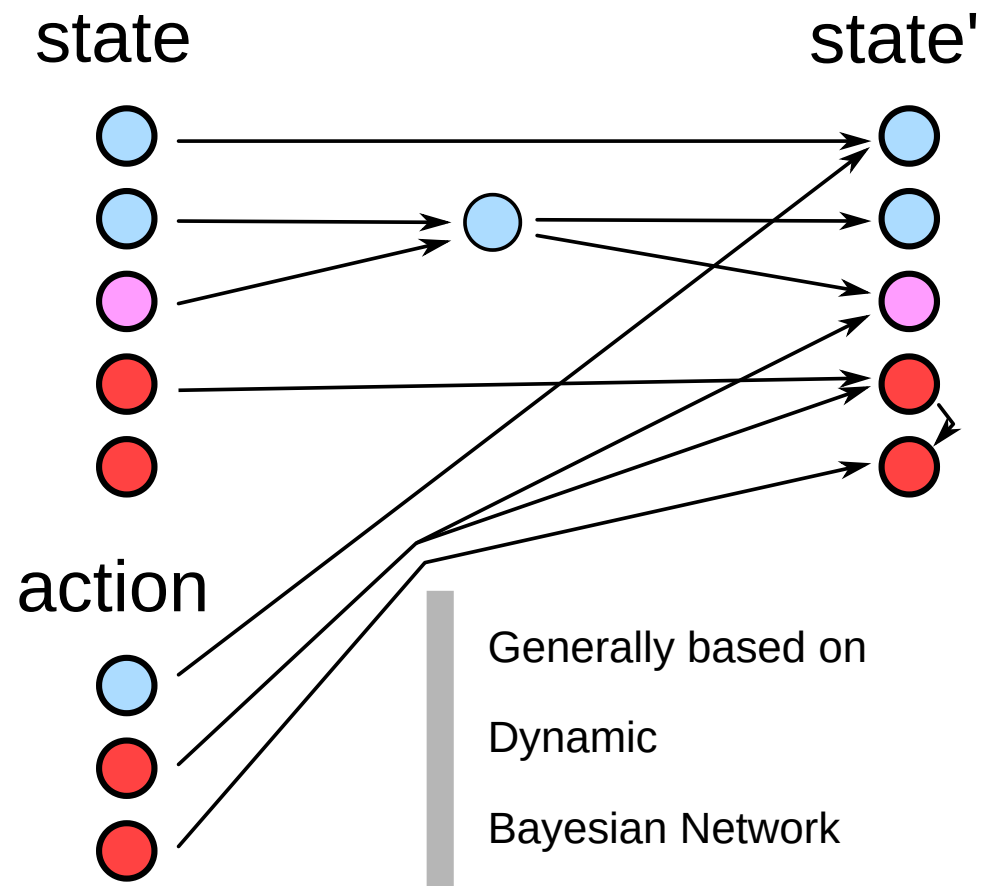
# Factored Model:

## Factored Transition function:



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## Factored Transition function:

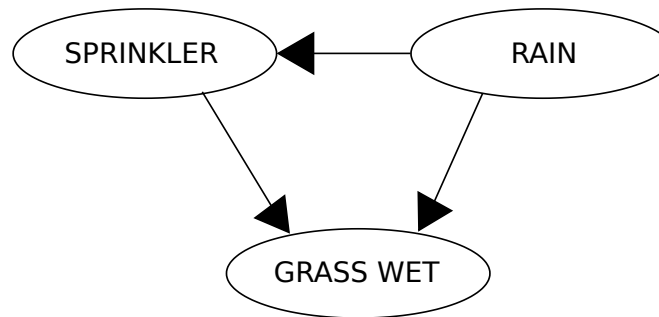


# Bayesian Network:

Model complex system from local dependencies

## Example: Rain, Sprinkler and Grass Wet:

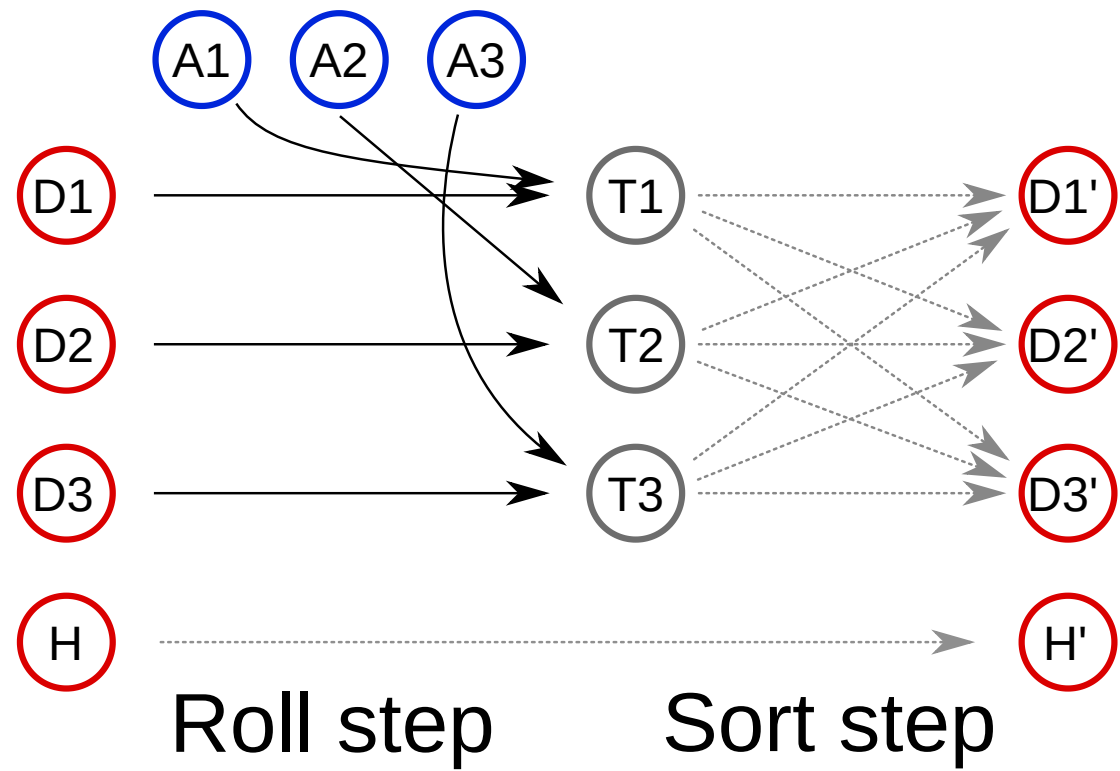
| RAIN | SPRINKLER |      |
|------|-----------|------|
|      | T         | F    |
| F    | 0.4       | 0.6  |
| T    | 0.01      | 0.99 |



|  | RAIN |     |
|--|------|-----|
|  | T    | F   |
|  | 0.2  | 0.8 |

| SPRINKLER | RAIN | GRASS WET |      |
|-----------|------|-----------|------|
|           |      | T         | F    |
| F         | F    | 0.0       | 1.0  |
| F         | T    | 0.8       | 0.2  |
| T         | F    | 0.9       | 0.1  |
| T         | T    | 0.99      | 0.01 |

## Example: 421



*Transition in two steps, but only the first is stochastic.*

# Example: Zombie Dice



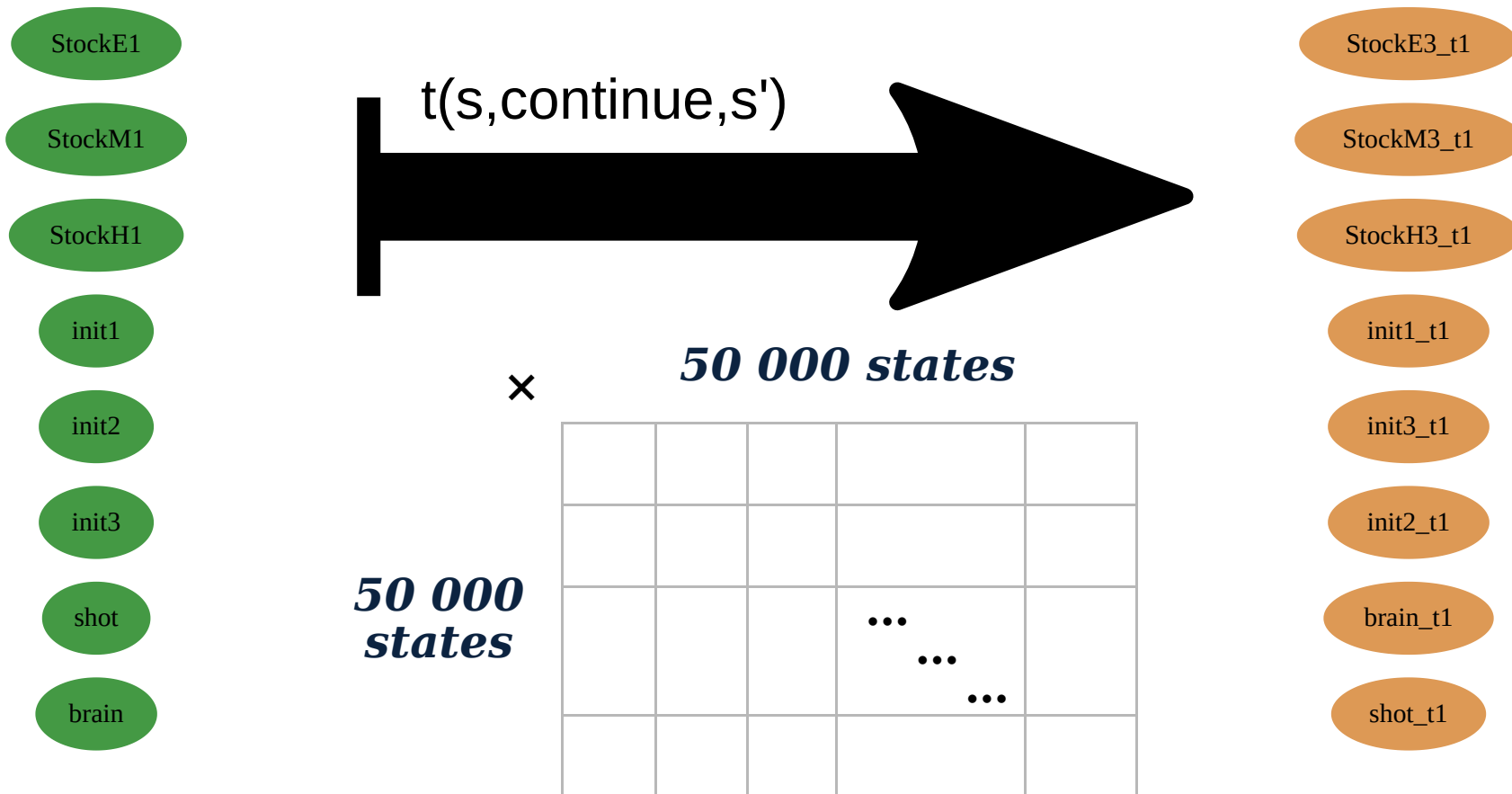
**Eat maximum brains**

**without dying (3 damages)**

- ▶ Players are zombies.
- ▶ They try to catch humans three at a time.
- ▶ Humans are dice with probability to fight back.

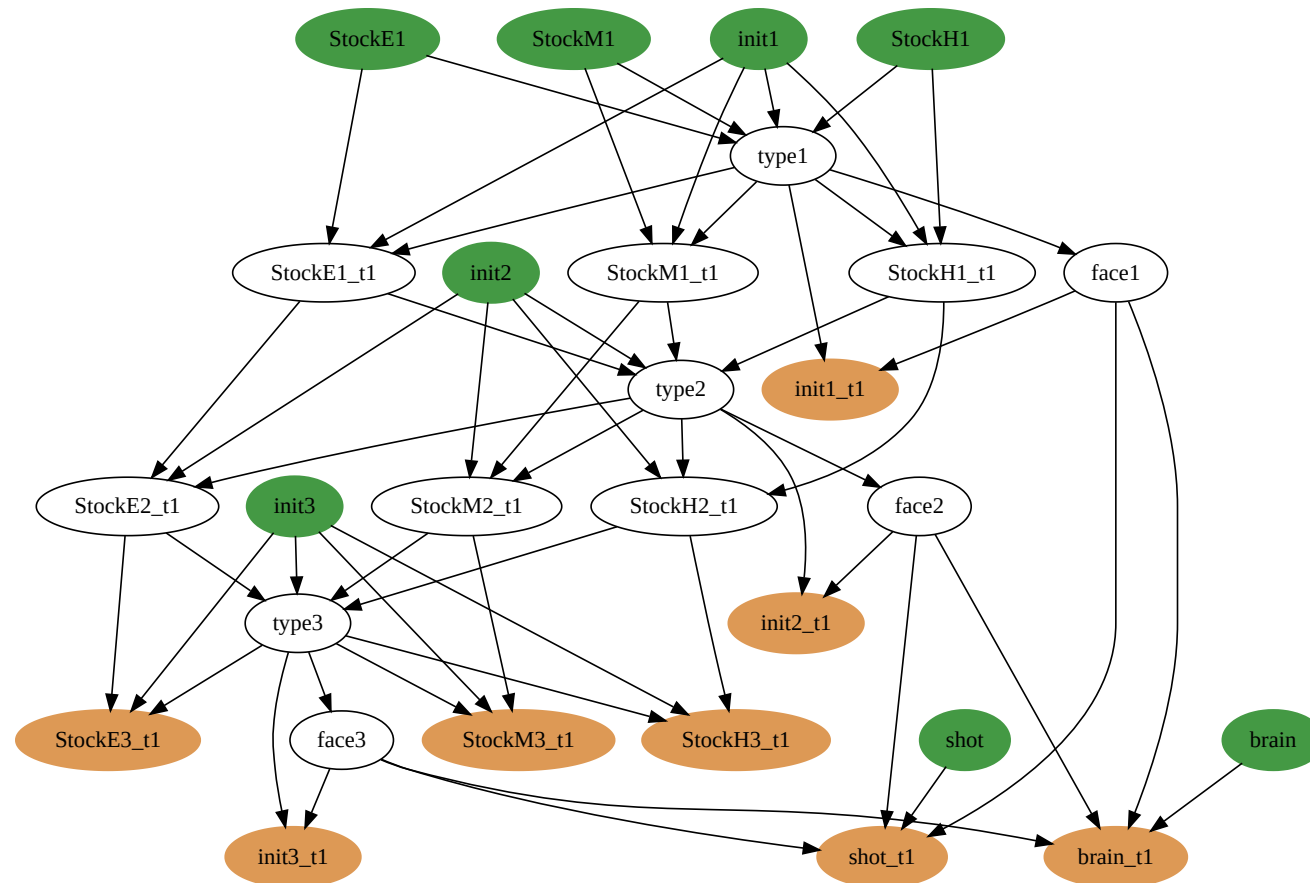
# Example: Zombie Dice

## Matrice complète



# Example: Zombie Dice

## Dynamic Bayesian Network:





# Model-Based Learning:

**It's more about estimate variable correlations than transition probabilities.**

- ▶ Determines variable dependencies (ie. Bayesian Network)
- ▶ Learn conditional probabilities (Gaussian Noise, Poisson's law)
- ▶ Validate the model regarding its entropy

**Then decide from exploring limited search spaces**

- ▶ Limited horizon Value or Policy Iteration
- ▶ random trajectories: Algorithm Monte-Carlo



**To conclude**

# Conclusion

- ▶ Problem: Control Dynamic System
- ▶ Hypothesis: Markov Decision Process (but unknown)
- ▶ Reinforcement Learning:
  - Model-free: QLearning
  - Model-based: Bellman Values function
- ▶ The root difficulty: the curse of dimensionality
  - Use factored model
- ▶ The solution requires to:
  - identify the model structure
  - have a lot of data
- ▶ Optimisation from an iterative/incremental process