

EXTRA ARTICLES

DM-09: DETERMINISTIC POLICY GRADIENTS ALGORITHMS

- THEY EXIST, NOT FOUR BEFORE. FOLLOW GRADIENT OF ACTION-VALUE FCN + INTEGRATES OVER STATE SPACE ONLY
- ON-POLICY/OFF-POLICY DETERMINISTIC ACTOR-CRITIC. • ANALOGOUS TO Q-LEARNING IN POLICY GRADIENT CONTEXTS
- $a = \mu_\theta(s)$

DM-15: BAYES-ADAPTIVE SIMULATION-BASED SEARCH WITH VALUE FUNCTION APPROXIMATION.

- FCN APPROX TO ESTIMATE VALUE OF INTERACTION HISTORIES. BOUNDED SEARCH \rightarrow GENERALIZATION. FCN APPROX FOR VALUES OF POSSIBLE SIMULATED HISTORIES.
- IMPORTANCE SAMPLING OF POSTERIOR SAMPLES TO COMPRESS HISTORIES INTO FINITE-DIM VECTOR
- UNCERTAINTY ON MODEL DYNAMICS \rightarrow CERTAINTY ABOUT CURRENT STATE IN AUGMENTED SPACE (POSSIBLE HISTORIES)
- SIMULATIONS ARE RUN FROM CUR BELIEF STATE \rightarrow ONLINE PARAM UPDATES ON SIM EXPERIENCE
- HISTORIES WITH SAME/SIMILAR BELIEF \rightarrow SAME/SIMILAR REPRESENTATIONS

DM-23 COMPRESS AND CONTROL

POLICY EVALUATION BY LEARNING TIME-INDEPENDENT STATE-ACTION CONDITIONAL DISTRIBUTIONS. THESE ARE COMPRESSED, $P(z|s, a)$

DM-26 TOWARDS MINIMAX OFF-POLICY VALUE ESTIMATION

MATH. HARD. IMPORTANCE/WEIGHTED IMPORTANCE SAMPLING ALREADY SO GOOD

DM-41 VARIATIONAL INFORMATION MAXIMIZATION FOR INTRINSICALLY MOTIVATED RL

MUTUAL INFORMATION \rightarrow EMPOWERMENT. INTRINSIC MOTIVATION: CHANNEL CAPACITY OF INFO IN ACTION SEQUENCE ABOUT FUTURE STATE. FOR INTERNAL PLANNING, EXPLORATION POLICY

EXTERNAL + INTERNAL (CRITIC) ENVIRONMENT. EVERYTHING IS A DEEP NETWORK. WE SIMULATE ALSO FOR BEHAVIOR POLICIES. VISION, MAZE TASKS

DM-44 USING LOCALIZATION AND FACTORIZATION TO REDUCE THE COMPLEXITY OF REINFORCEMENT LEARNING

AIXI STUFF. HUTTER & SUMERAG. AC IDEG

DM-51 RATIONALITY, OPTIMISM AND GUARANTEES IN GENERAL RL

AIXI HUTTER & SUMERAG. JOURNAL VERSION. 50 PP MONSTER.

FRAMEWORK FOR GENERAL RL WITH RATIONALITY AXIOMS FOR OPTIMISM \rightarrow CRUCIAL FOR SYSTEMATIC EXPLORATIVE BEHAVIOR.

DM-53 LEARNING CONTINUOUS CONTROL POLICIES BY STOCHASTIC VALUE GRADIENTS.

ESTIMATES (VIA A DIFFERENTIABLE ENVIRONMENT MODEL) POLICY, MODEL, REWARD FCN VIA BACKPROP.

ANALYTIC POLICY GRADIENT BY BACKPROP OF REWARD ALONG TRAJECTORY \rightarrow VALUE GRADIENT

STOCHASTIC VALUE GRADIENT OFPOLY THROUGH STOCHASTIC BELLMAN EQUATION \rightarrow REDDAM TRICK

MODELS AS MODEL + JOINT MODEL + POLICY TRAINING. SVG TO, SVG 1, SVG 0, ALGOS.

LOW RISKY FINITE HORIZON \rightarrow OFF POLICY W REWARD MODEL FREE. ANALOGUE OF DETERMINISTIC POLICY GRADIENT

MOAR-11 CHANGING THE ENVIRONMENT BASED ON EMPOWERMENT AS INTRINSIC MOTIVATION.

RL + EMPOWERMENT + MINECRAFT-ISH WORLD. FUN QUALITY

MOAR-15 GRADIENT DESCENT FOR GENERAL REINFORCEMENT LEARNING

IS POLICY GRADIENT. POLICY AND VALUE FCN TOGETHER. GENERAL FORMULATION. VAPS ALSO

MOAR-16 DETERMINISTIC POLICY GRADIENT ALGORITHMS

IS EXPECTED GRADIENT OF ACTION-VALUE FUNCTION, DETERMINISTIC POLICIES. MORE EFFICIENT THAN STOCHASTIC PG. OFF POLICY ACTOR CRITIC. TARGET: DETERMINISTIC BEHAVIOR; EXPLORATORY

MOAR-20 HOW CAN WE DEFINE INTRINSIC MOTIVATION?

SURVEY. INFORMATION THEORY PERSPECTIVE, KNOWLEDGE BASED MODELS, COMPETENCE, MORPHOLOGICAL

MOAR-24 POLICY GRADIENT METHODS FOR RL WITH FUNCTION APPROXIMATION
POLICY IS A FUNCTION \rightarrow IE A ANN

MOAR-27 REINFORCE
PROTO POLICY GRADIENTS. 1992