Reinforcement learning

s, s'	State	s_t, s_{t+1}
a	Action	a_t
p	State transition probability	$s' \sim p\left(s'\|s, a\right)$
r	Reward	$r_t = r(s_t, a_t)$
π	Policy	$a \sim \pi(a\|s)$, $a = \pi(s)$
γ	Discount factor	$\gamma \in [0, 1]$
G_t	Discounted return	$G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$
V^π	Value function	$V^\pi(s) = \mathbb{E}\left[G_0\|s_0 = s\right]$
$V^\star$	Optimal value function	The above, but better
Q^π	State-action value function	
$Q^\star$	Optimal value function	

Control

x	State	x_t
u	(Control) input	u_t
f	State transition function	$x_{t+1} = f(x_t, u_t)$
ℓ	(Stage) cost	$\ell(x, u) = x^T M x + u^T R u$
K	Gain matrix	$u = -Kx$

Acronyms

RL	Reinforcement learning
MPC	Model predictive control
LQR	Linear quadratic regulator
PID	Proportional-integral-derivative