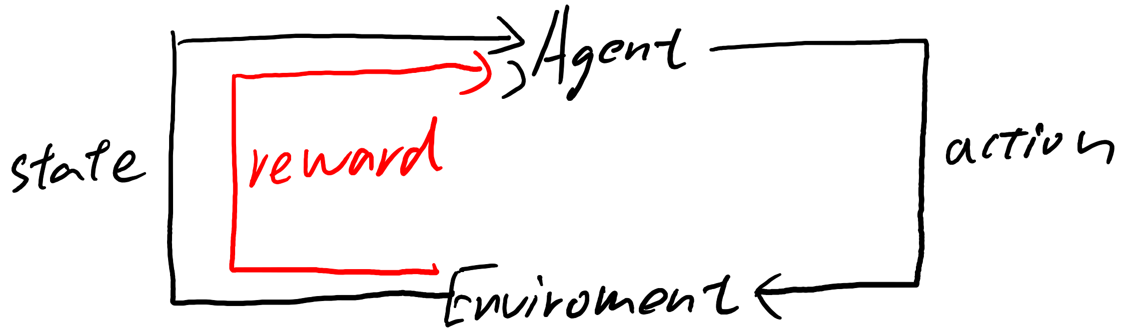
- Supervised learning : fit + predict
  Unsupervised 〃 : fit + transform

- RL has no specific obj, but to max reward



- RL is a balance of collecting data and keep an accurat measurement of significances
  explore & exploit

- Three strategies for explore & exploit

- Epsilon-greedy
  - Pseudo code :
    Initial high value θ >> true mean
    p = random( )

if p < eps :

do random actions

else :

do the current best action j which has highest mean among all possible action

update action

— UCB1

- Chernoff-bound:

$$P(|\bar{x}-\mu| \geq \epsilon) \leq 2\exp(-2\epsilon^2 N)$$

$$\Rightarrow X_{UCB-j} = \bar{x}_j + \sqrt{2\frac{\ln N}{N_j}}$$

N is total # of actions used so far

N_j is # of time action j is used

This encourage taking actions that haven't been taken many times.

- Pseudo code:

for n in range(N):

$j = \text{argmax}\left[\text{actions.mean} + \sqrt{2\frac{\ln n}{n_{action}}}\right]$

do action j
update action j

- Baysian / Thopson sampling
  - $\bar{X}_j \sim N(\mu, \sigma^2/N_j)$, Assume each action is Gaussian

    max $p(\theta|X)$, use data X to guide us to find best θ in parameter space

    $p(\theta|X) = p(X|\theta) \cdot p(\theta)$

    posterior = likelihood × prior
  - different to posterior & prior in ML, which is

    $P(y|X) = P(X|y) \cdot P(X)$

    max $P(y|X)$: MAP

    max $p(X|y)$: ML
  - Special pair of $p(X|\theta)$, $P(\theta)$ are needed
  - $X \sim N(\mu, \lambda)$, $\mu \sim N(\mu_0, \lambda_0^{-1})$

    $\lambda = \lambda_0 + eN$

    $$\mu = \frac{\mu_0 \lambda_0 + e \Sigma x_n}{\lambda_0 + eN}$$

Randomness controls sampling
More times an action is taken, the more it will converge to true stat

- Pseudo code

Initialize $\mu_1 = 0$, $\lambda_0 = 1$, $\tau = 1$

for n in range(N):

take a sample from each action

$$\text{sample} = \frac{N(0,1)}{\lambda} + \mu$$

find the max of those sample

update: $\lambda = \lambda + \tau n$

$$\mu = \frac{\mu\lambda + \tau \Sigma x_n}{\lambda + \tau N}$$

- Non stationary Bayesian

— Components of RL

- Agent : thing that plays the game
- Enviroment : things agent interact with
- State : specific env agent senses
- Action : things agent can do to effect the state
- Reward : conseequenses of changing state
  how good the action is
  just a number
  instantanuous
- $S(t), A(t) \rightarrow R(t+1), S(t+1)$
- Terminal state : when to finish, bad & good
- Unstable system $\Rightarrow$ infinit states $\Rightarrow$ hard to deal

— Rewards:

- Needs to define how to give rewards
- Tell agent what you want to achieve, not how to achieve.
- Value function : assign value to current state to reflect future.

- Assign correct credit to past action
  we care about which "path" to get reward too
- Value: possible future reward
  Value func: $E\left[\text{all future rewards} \mid S_{(t)}\right]$

  $$V_{(S_t)} \leftarrow V_{(S_t)} + \alpha\left(V_{(S_{t+1})} - V_{(S_t)}\right)$$
- We explore to update Value functions !!!
- Playing the game more, more likely we get to true probability
- Order is important !
- If $V_{(S_{t+1})} < V_{(S_t)}$, update doesn't help