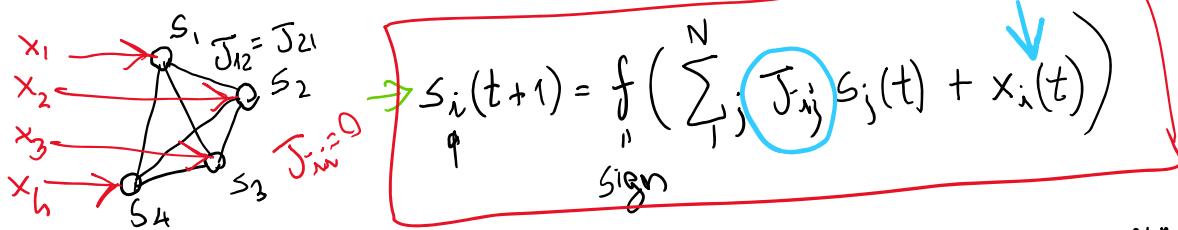


Hopfield and forgetting

Thursday, May 7, 2020 13:49



$$\underline{x} = \underline{\xi}^1, \underline{\xi}^2, \dots, \underline{\xi}^P \quad \underline{s}(t \rightarrow \infty) \quad J_{ij} \quad \underline{s}(t) = \underline{\xi}^m$$

$$J_{ij}(0) \quad J_{ij}(1) \dots \quad J_{ij}(P) \quad \underline{s}(t+1) = \underline{\xi}^m$$

$$\underline{\xi}^2 \rightarrow \underline{s} \rightarrow \underline{\xi}^2$$

Cue $\underline{\xi}^2$

$$\underline{\xi}^1 \dots \underline{\xi}^P$$

$$\underline{\xi}^1 = (+, +, +, \dots, +)$$

$$\underline{\xi}^2 = (-, -, -, \dots, -)$$

$$s_i(t+1) = f\left(\sum_j^N J_{ij} s_j(t)\right)$$

$$\underline{\xi}^m = (+, -, +, \dots, +)$$

$$= f\left(\sum_j^N s_j(t)\right)$$

$$E(\{s_1, \dots, s_N\}) = - \sum_{i,j} s_i J_{ij} s_j = E(t)$$

$$\Rightarrow s_i(t+1) = \text{sign}\left(\sum_j^N J_{ij} s_j(t)\right) \Rightarrow E(t+1) \leq E(t)$$

$$\boxed{J_{ij} = J_{ji}}$$

$$\boxed{J_{ii} = 0}$$

$$\Delta E = E(t+1) - E(t) = - \sum_{i,j} s_i(t+1) J_{ij} s_j(t+1) + \sum_{i,j} s_i(t) J_{ij} s_j(t)$$

$$= - \sum_{i,j}^N s_i(t+1) J_{ij} s_j(t+1) - \sum_{i,j}^N s_i(t+1) J_{ji} s_j(t+1) +$$

$$+ \quad (t) \quad (t) \quad (t) \quad (t)$$

$$J_{ij} = J_{ji}$$

$$\Delta E = -2(s_1(t+1) - s_1(t)) \left(\sum_j^N J_{1j} s_j(t) \right) h_1(t)$$

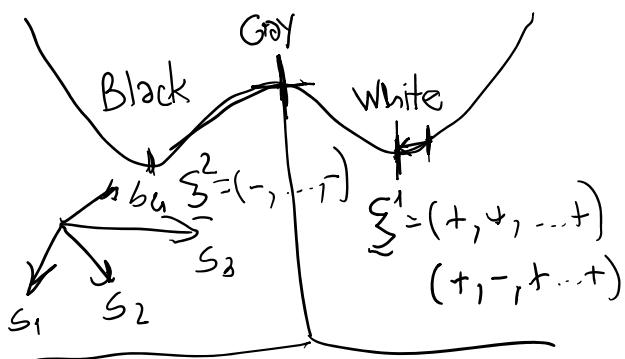
$$\boxed{\Delta E = -2 \Delta s_1 \cdot h_1(t)}$$

$$1. \Delta s_1 = 0 \Rightarrow \Delta E = 0$$

$$2. \Delta s_1 \neq 0 \Rightarrow s_1(t+1) = \text{Sign}(h_1(t)) = \underline{-s_1(t)}$$

$$\Delta s_1 = \text{Sign}(h_1) - (-\text{Sign}(h_1)) = 2 \text{Sign}(h_1)$$

$$\Delta E = -2 \text{Sign}(h_1) \cdot h_1 = -2 |h_1| < 0$$



$$\underline{\xi}^1 = \{+, -, +, 1, \dots +\}$$

$$\underline{\xi}^2 = \{-, +, -, \dots -\}$$

$$\underline{s_i} = \frac{\pm}{\xi_i^1 \cdot s_i}$$

$$s_n = \xi_n^1$$

$$s_n^1 = \xi_n^1 \xi_n^2 = \\ = (\xi_1^2) = +1$$

$$s_n(t+1) = \text{Sign}\left(\sum_j^N J_{nj} s_j(t)\right)$$

$$\cancel{\xi_n^1 \cdot \xi_n^2} s_n(t+1) = \text{Sign}\left(\sum_j^N \xi_j^1 s_j(t)\right) \cdot \cancel{\xi_n^2}$$

$$- \quad . \quad \sim \quad \text{sign} \cdot 1 \stackrel{N}{\overbrace{(-1)^{s_1(t)} \dots (-1)^{s_N(t)}}}$$

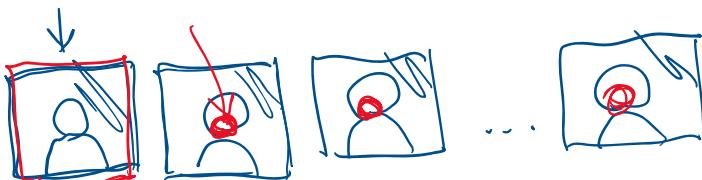
$$S_i(t+1) = \text{sgn} \left(\sum_{j=1}^N \left(\xi_j^1 \xi_j^1 \right) S_j(t) \right)$$

$$J_{ij} = \xi_i^1 \xi_j^1$$

$$\xi_i^2 = -\xi_i^1$$

$$\rightarrow J_{ij} = \sum_{\mu=1}^P \xi_i^\mu \xi_j^\mu$$

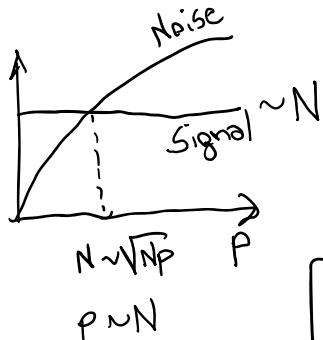
ξ_i^μ Random uncorrelated $\rightarrow \langle \xi_i^\mu \xi_j^\nu \rangle = 0$
 $\forall \mu \neq \nu, i \neq j$



$$h_i = \sum_{j \neq i} J_{ij} \xi_j^1 = \sum_{j \neq i} \sum_{\mu=1}^P \xi_i^\mu \xi_j^\mu \xi_j^1 =$$

$$= \underbrace{\sum_j \xi_i^1 \xi_j^1 \xi_j^1}_{+1} + \underbrace{\sum_{j \neq i} \sum_{\mu=1}^{N-1} \xi_i^\mu \xi_j^\mu \xi_j^1}_{\sim Np} \underbrace{\sum_{\mu=1}^{P-1} \xi_i^\mu \xi_j^\mu \xi_j^1}_{\text{Noise}}$$

$$\frac{N \xi_i^1}{\sqrt{N}} + \eta \rightarrow (0, \sqrt{Np})$$



Amit Gutfreund Sompolinsky

$$P \sim N$$

$$P = 0.15N$$

$P > 0.15N \Rightarrow$ Blackout catastrophe

$$J_{ij} = \sum_{\rho=1}^P \xi_i^{\rho} \xi_j^{\rho} - \begin{cases} +P \\ -P \end{cases} \quad P \sim N$$

0.1G N

$$J_{ij} = \text{sign}\left(\sum_{\rho=1}^P \xi_i^{\rho} \xi_j^{\rho}\right) = \pm 1 \Rightarrow P \sim N \quad P = 0.08N$$

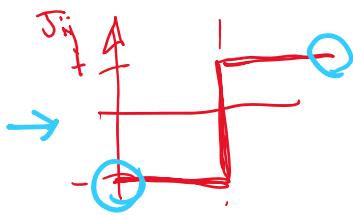
↑

$J_{ij} = \pm 1$

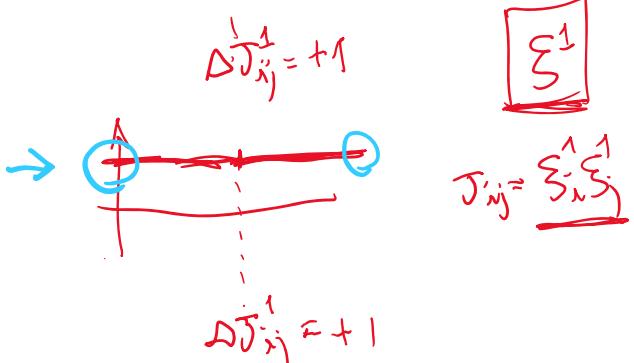
M

$$\text{Signal}^1 = \sum_{i,j}^M \xi_i^1 h_i^1 = \sum_{i,j} \xi_i^1 J_{ij} \xi_j^1 =$$

$$= \sum_{i,j} \left(\xi_i^1 \xi_j^1 \right) \cdot \frac{J_{ij}}{\Delta J_{ij}^1 = \pm 1}$$



$$qM \cdot (1-q) (1-q) = qM (1-q)^{p-1}$$



$$\xi^1 \quad \xi^2 \quad \xi^3$$

$$J_{ij} = \xi_i^1 \xi_j^1$$

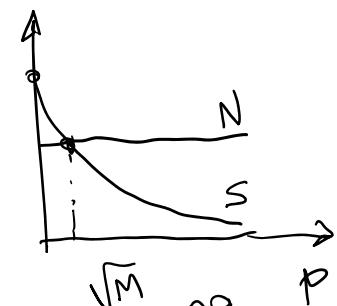
$$qM (1-q)^p = qM e^{\log(1-q)^p} = qM e^{p \log(1-q)} =$$

$$\boxed{\approx qM e^{-pq}}$$

$$\boxed{\approx qM e^{-pq}}$$

$$\text{Signal} \sim qM e^{-pq}$$

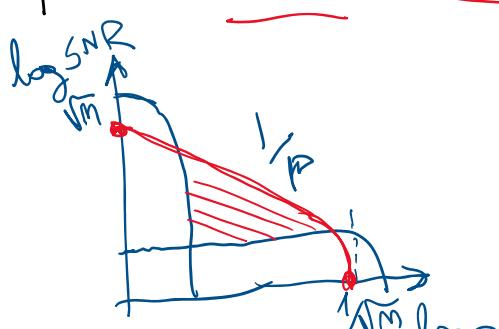
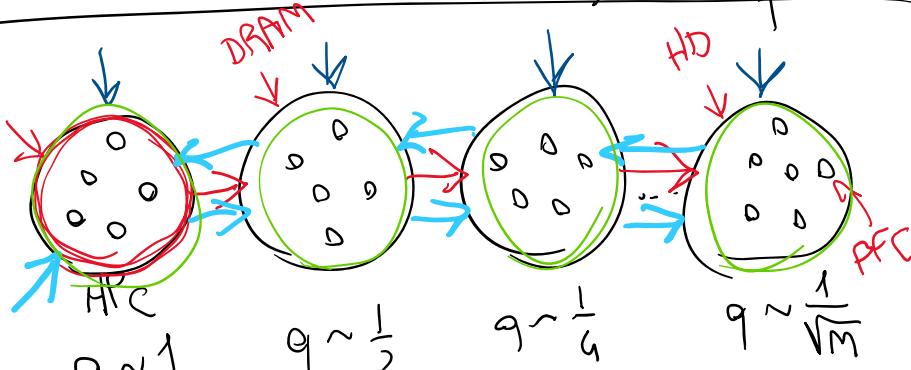
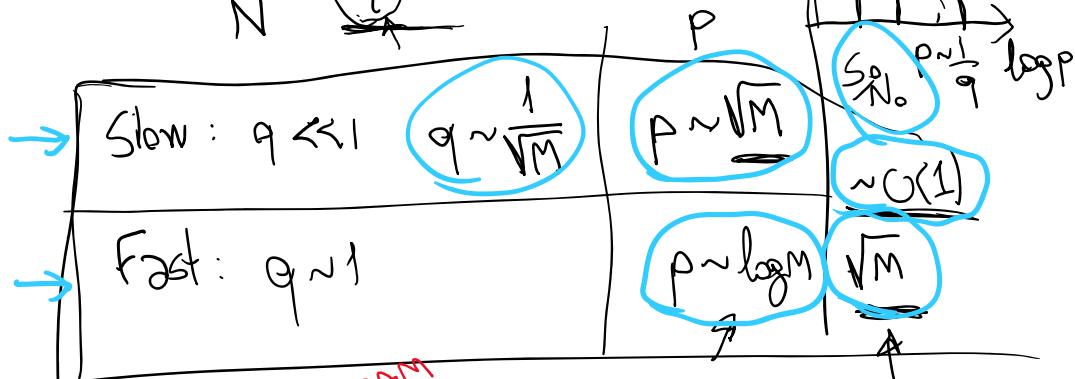
$$\text{Noise} \sim \sqrt{M}$$

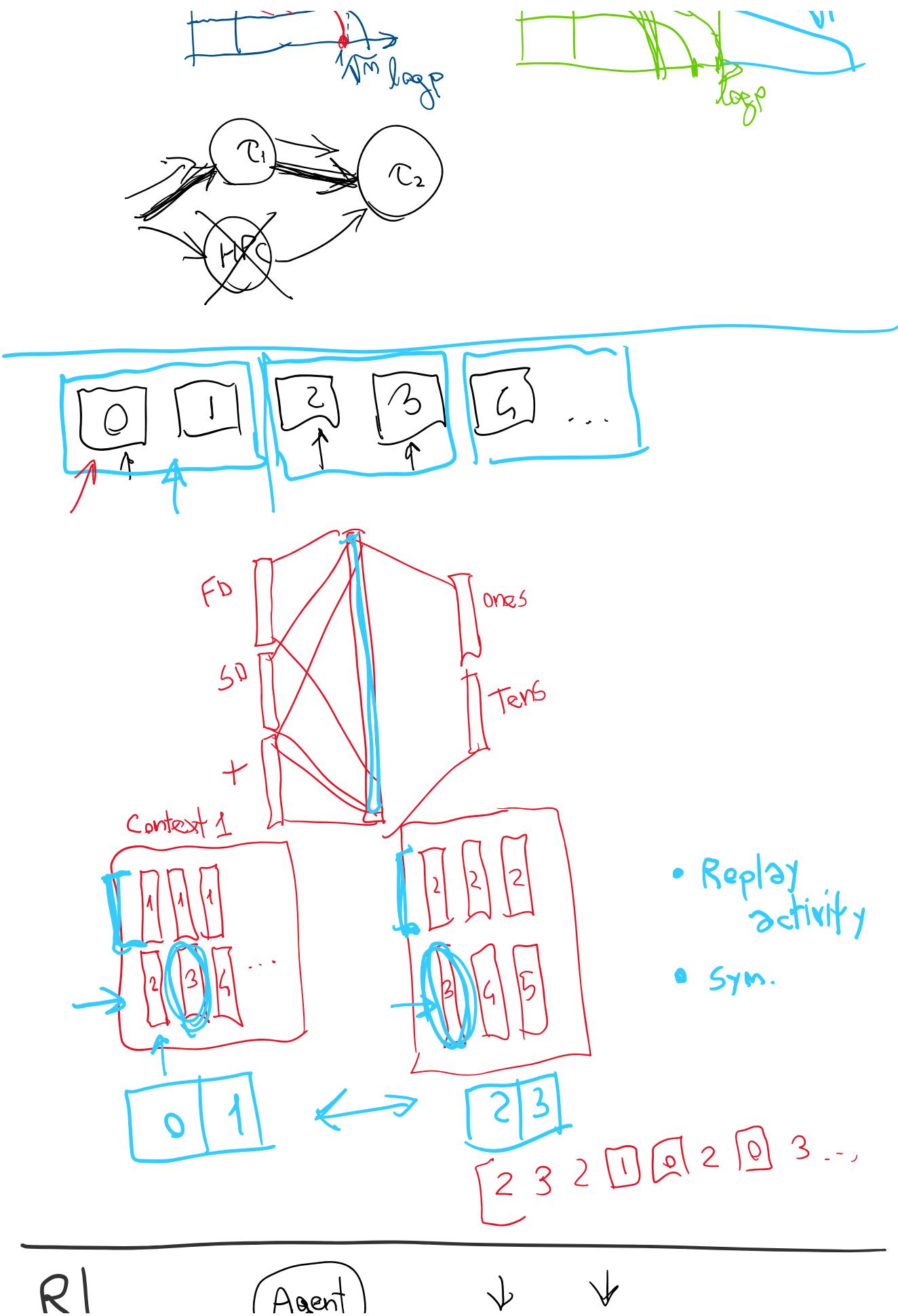


$$\boxed{P \sim N}$$

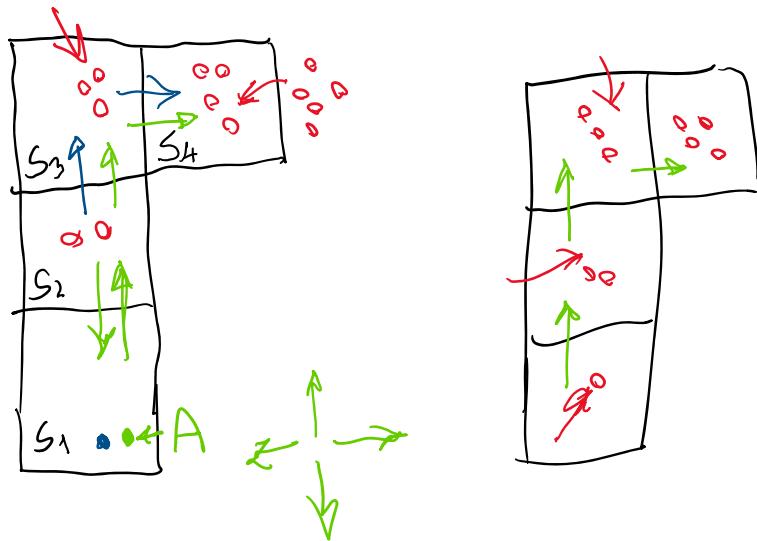
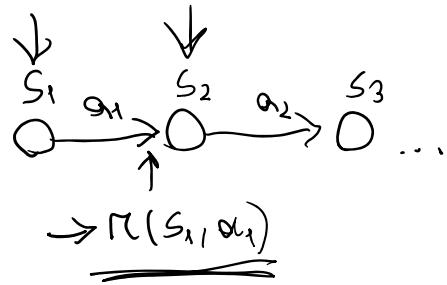
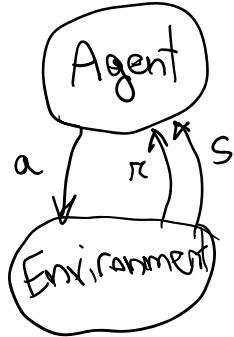
$$\boxed{P \sim \frac{1}{q} \log q \sqrt{M}}$$

$$\frac{S}{N} \sim q \sqrt{M} e^{-pq}$$





RL



$$\pi : S \rightarrow A$$

$$\pi(s_t) = a_t \quad \gamma < 1$$

$$V^\pi(s_t) = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \dots =$$

$$= \sum_{k=0}^{\infty} r_k \gamma^{k-1}$$

$$\pi^* = \arg\max_{\pi} V^\pi(s) \quad \forall s$$

$$V^{\pi^*}(s) = \boxed{V^*(s)}$$

$$\hat{V}(s) \rightarrow V^*(s)$$

$$s_{t+1} = f(s_t, a_t)$$

$$\hat{V}(s) \rightarrow V^*(s) \quad s_{t+1} = f(\hat{s}_t, a_t)$$

s_t , act randomly

$$s_t \xrightarrow{r_t} s_{t+1}$$

$$\hat{V}(s_t) \leftarrow r_t + \gamma \hat{V}(s_{t+1})$$

$$V^*(s_t) = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \dots$$

$$= r_t + \gamma(r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \dots)$$

$$= r_t + \gamma V^*(s_{t+1})$$

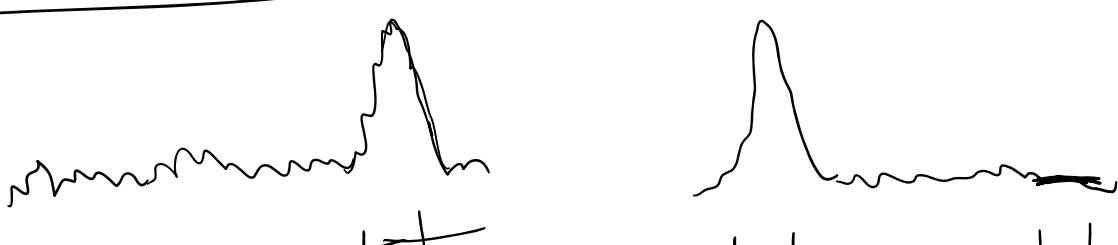
$$\hat{V}(s_t) = (1-\alpha)\hat{V}(s_t) + \alpha(r_t + \gamma \hat{V}(s_{t+1}))$$

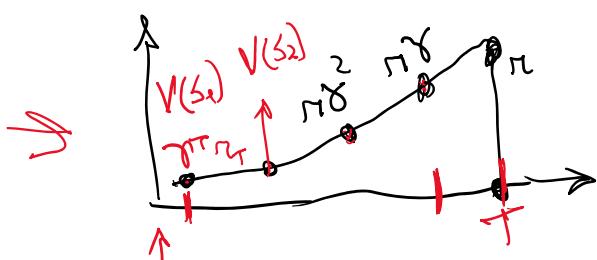
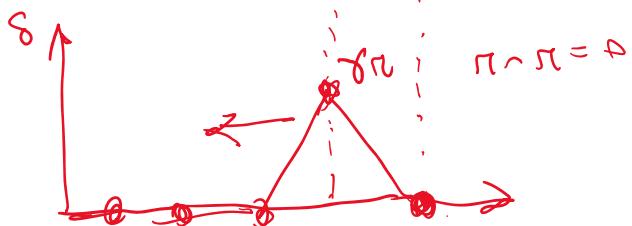
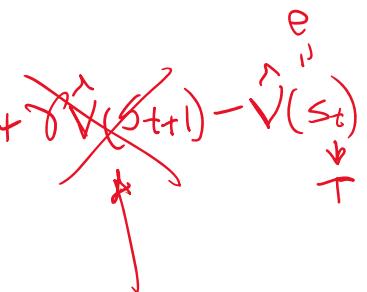
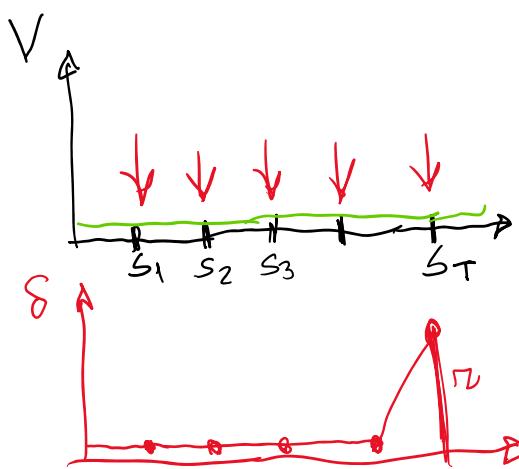
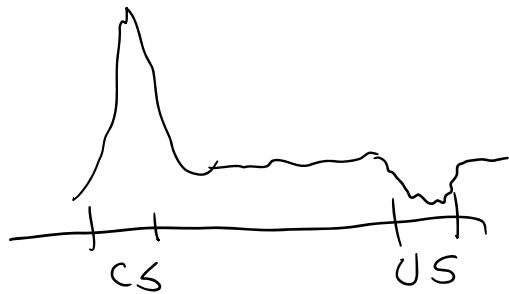
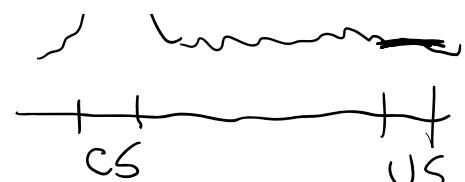
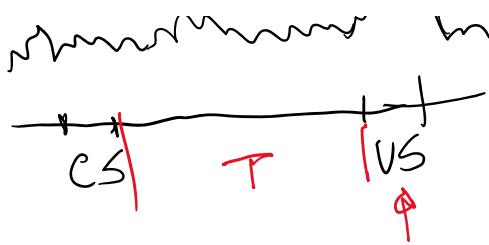
$$\rightarrow \Delta \hat{V}(s_t) = \underbrace{\alpha(r_t + \gamma \hat{V}(s_{t+1}) - \hat{V}(s_t))}_{\text{RPE } \delta}$$

s_t = terminal

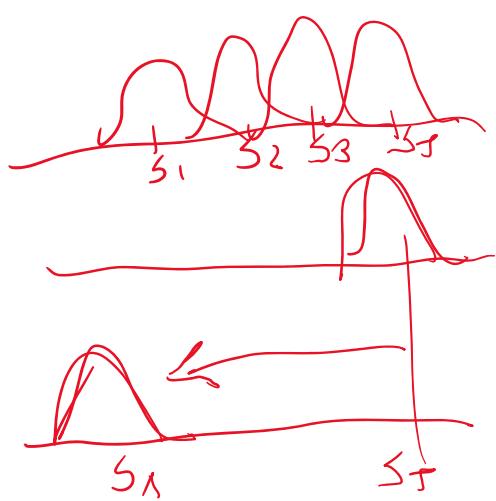
$$\Delta \hat{V}(s_t) = \alpha(r_t - \hat{V}(s_t))$$

$$\Delta \hat{V}(s_t) = \alpha(\underbrace{\gamma \hat{V}(s_{t+1})}_{\text{target}} - \underbrace{\hat{V}(s_t)}_{\text{current}})$$





$$\sum V^*(S_1) = \underline{r_1} + \gamma r_2 + \gamma^2 r_3 + \dots + \gamma^{T-1} r_T$$



$$\left. \begin{aligned} V^*(s_1) &= r_1 + \gamma r_2 + \gamma r_3 + \dots \quad \uparrow r_T \\ &\quad \uparrow \quad \uparrow \\ V^*(s_2) &= r_2 + \gamma r_3 + \dots \quad \circlearrowleft \quad \gamma^{T-1} \quad r_T \\ V^*(s_T) &= r_T \end{aligned} \right\}$$

$V^*(s), \quad s_{t+1} = f(s_t, a_t)$

$$\rightarrow Q(s, a) = r(s, a) + \gamma V^*(f(s, a))$$

$$+ \max_{a'} Q(f(s, a'), a')$$

