

$$|\Psi_k\rangle = |0\rangle^{\otimes(k-1)} |\phi\rangle^{\otimes(n-k+1)} \quad 1 \leq k \leq n$$

[2]

Hence in our case

$$|\Psi_1\rangle = |\phi\rangle_1 |\phi\rangle_2 |\phi\rangle_3 |\phi\rangle_4 |\phi\rangle_5 \quad 1/5$$

$$|\Psi_2\rangle = |0\rangle_1 |\phi\rangle_2 |\phi\rangle_3 |\phi\rangle_4 |\phi\rangle_5 \quad "$$

$$|\Psi_3\rangle = |0\rangle_1 |0\rangle_2 |\phi\rangle_3 |\phi\rangle_4 |\phi\rangle_5 \quad "$$

$$|\Psi_4\rangle = |0\rangle_1 |0\rangle_2 |0\rangle_3 |\phi\rangle_4 |\phi\rangle_5 \quad "$$

$$|\Psi_5\rangle = |0\rangle_1 |0\rangle_2 |0\rangle_3 |0\rangle_4 |\phi\rangle_5 \quad "$$

Greedy strategy:

For particle $s \in \{1, \dots, 5\}$ maximize

$$\mathcal{P}_s = \sum_{k=1}^5 \eta_k^{(s)} \langle \Psi_k | E_k^{(s)} | \Psi_k \rangle$$

$$\mathcal{P}_1 = \frac{1}{5} \sum_{k=1}^5 \langle \Psi_k | E_k^{(1)} | \Psi_k \rangle$$

$$= \frac{1}{5} \langle \Psi_1 | E_1^{(1)} | \Psi_1 \rangle + \frac{4}{5} \sum_{k=2}^5 \langle \Psi_k | E_k^{(1)} | \Psi_k \rangle$$

$$= P_\phi^{(s)} \langle \phi | \Pi_\phi^{(s)} | \phi \rangle + \frac{4}{5} \langle 0 | \Pi_0 | 0 \rangle$$

$$\mathcal{P}_2^{(2)} = \eta_1^{(2)} \langle \psi_1 | E_1^{(2)} | \psi_1 \rangle + \eta_2^{(2)} \langle \psi_2 | E_2^{(2)} | \psi_2 \rangle +$$

$$\eta_3^{(2)} \langle \psi_3 | E_3^{(2)} | \psi_3 \rangle + \eta_4^{(2)} \langle \psi_4 | E_4^{(2)} | \psi_4 \rangle +$$

$$\eta_5^{(2)} \langle \psi_5 | E_5^{(2)} | \psi_5 \rangle.$$

$$= \eta_1^{(2)} \langle \phi | E_1^{(2)} | \phi \rangle + \eta_2^{(2)} \langle \phi | E_2^{(2)} | \phi \rangle +$$

$$\eta_3^{(2)} \langle 0 | E_3^{(2)} | 0 \rangle + \eta_4^{(2)} \langle 0 | E_4^{(2)} | 0 \rangle + \eta_5^{(2)} \langle 0 | E_5^{(2)} | 0 \rangle$$

$$= \langle \phi | \{ \eta_1^{(2)} E_1^{(2)} + \eta_2^{(2)} E_2^{(2)} \} | \phi \rangle +$$

$$\langle 0 | \{ \eta_3^{(2)} E_3^{(2)} + \eta_4^{(2)} E_4^{(2)} + \eta_5^{(2)} E_5^{(2)} \} | 0 \rangle.$$

Now define

$$\mathcal{P}_\phi^{(2)} := \max \{ \eta_1^{(2)}, \eta_2^{(2)} \}$$

$$\mathcal{P}_0^{(2)} := \max \{ \eta_3^{(2)}, \eta_4^{(2)}, \eta_5^{(2)} \}$$

Let $\bar{r}_s \in \{0, 1\}^s$ denote the sequence of result up to and including s . Then the average probability of success is

$$P_s^G = \sum_{k=1}^N \sum_{\bar{r}_s} \eta_k P(R(s) | k) \leq \sum_{\bar{r}_s} \max_{R(s)} P(R(s), k)$$

where $\hat{R}(\bar{r}_s)$ is our decision rule. The inequality is saturated by maximum likelihood. i.e.

$$\hat{R}(\bar{r}_s) = \arg \max_k P(\bar{r}_s, k).$$

where

$$P(\bar{r}_s, k) = \frac{1}{N} P(\bar{r}_{s-1} | k) \langle \psi_k | E_k^{(s)} | \psi_k \rangle$$

$$\begin{aligned} \therefore P_s^G &= \sum_{\bar{r}_{s-1}} P(\bar{r}_{s-1}) \cdot P_s^G(\bar{r}_{s-1}) \\ &= \sum_{\bar{r}_{s-1}} P(\bar{r}_{s-1}) \max_{\{E_k^{(s)}\}} \sum_{k=1}^N \max_k P(k | \bar{r}_{s-1}) \langle \psi_k | E_k^{(s)} | \psi_k \rangle \end{aligned}$$

The optimal measurement & guessing rule depend only on $\eta_k^{(s)}$ and not on the sequence of measurement outcomes.

At step s the average success probability at each step is

$$\sum_{k=1}^n \sum_{\bar{r}_s} p(\bar{r}_s, k) \delta_{k, \hat{k}(\bar{r}_s)} \leq \sum_{\bar{r}_s} \max_k p(\bar{r}_s, k)$$

with equality iff $\hat{k}(\bar{r}_s) = \arg \max_k p(\bar{r}_s, k)$.

$$p(\bar{r}_s, k) = \frac{1}{n} p(\bar{r}_{s-1} | k) \langle \psi_k | E_k^{(s)} | \psi_k \rangle$$

Hence

$$P_s^G = \sum_{\bar{r}_{s-1}} p(\bar{r}_{s-1}) P_s^G(\bar{r}_{s-1})$$

||

$$\max_{\{E_k^{(s)}\}} \sum_{k=1}^n \max_k p(k | \bar{r}_{s-1}) \langle \psi_k | E_k^{(s)} | \psi_k \rangle.$$

$$P^1(H_k | r_1) = \frac{P(r_1 | H_k) n_k}{P(r_1)}$$

$$P^2(H_k | r_1 r_2) = \frac{P(r_2 | H_k) P(H_k | r_1)}{P(r_1 r_2)}$$

$$= \frac{P(r_2 | H_k) P(r_1 | H_k) n_k}{P(r_1) P(r_2)}$$

$$:= \frac{P(r_1 r_2 | H_k) n_k}{P(r_1 r_2)}$$

$$P^{(3)}(H_k | r_3) = \frac{P(r_3 | H_k) P^{(2)}(H_k | r_1 r_2)}{P(r_3)}$$

$$= \frac{P(r_3 | H_k) P(r_2 | H_k) P(r_1 | H_k) n_k}{P(r_1) P(r_2) P(r_3)}$$

This is why
they leave it
normalized.