

# Prophet Secretary

December 12, 2019

Given that  $F_1, F_2, \dots, F_n$  are the initial distribution and  $V_1, V_2, \dots, V_n$  are the corresponding sampled values. For any  $t \in [0, 1]$ , define:

$\theta(t)$  = The probability that nothing is selected till time  $t$ .

$q_{-i}(t)$  = The probability that nothing is selected till time  $t$  conditioned that  $V_i$  arrives at time  $t$ .

$\alpha : [0, 1] \rightarrow [0, 1]$  and  $\beta : [0, 1] \rightarrow \mathbb{R}$ , both non-increasing such that,

$$Pr(\max_i \{V_1, V_2, \dots, V_n\} \leq \alpha(t)) = \beta(t)$$

**LEMMA 1:**  $\forall i \in [n], t \in [0, 1]$

$$q_{-i}(t) \geq \frac{\theta(t)}{1 - t + \int_0^t Pr(V_i \leq \beta(x))dx}$$

*Proof.*

$$\begin{aligned} \theta(t) &= \int_0^1 Pr(T > t \mid t_i = x)dx \\ &= \int_0^t Pr(T > t \mid t_i = x)dx + \int_t^1 Pr(T > t \mid t_i = x)dx \end{aligned}$$

For any  $x$  greater than  $t$ ,

$$Pr(T > t \mid t_i = x) = Pr(T > t \mid t_i > t) \leq q_{-i}(t)$$

For any  $x$  less than  $t$  and arbitrary small  $\epsilon$ ,

$$Pr(T > t \mid t_i = x) = Pr(V_i \leq \beta(x))(Pr(\text{Nothing is chosen before } x) + Pr(\text{Nothing is chosen in } [x+\epsilon, t]))$$

Since thresholds are non-increasing, for any  $V_k$  appearing at  $t_k \in [x+\epsilon, t]$ ,  $Pr(V_k < \beta(t_k)) \leq Pr(V_k < \beta(t_k - \epsilon))$ . Therefore,

$$\begin{aligned} Pr(T > t \mid t_i = x) &\leq Pr(V_i \leq \beta(x))(Pr(\text{Nothing is chosen before } x) + Pr(\text{Nothing is chosen in } [x, t-\epsilon])) \\ &\leq Pr(V_i \leq \beta(x))(q_{-i}(t)) \end{aligned}$$

Putting the inequalities and rearranging gives the result. □

**LEMMA 2:**  $\forall t \in [0, 1/2]$

$$\sum_{i=1}^n \frac{Pr(V_i > \beta(t))}{1 - \int_0^t Pr(V_i > \beta(x))dx} \geq \frac{Pr(\max_i \{V_i\} > \beta(t))}{1 - tPr(\max_i \{V_i\} > \beta(0))}$$

*Proof.*

$$\begin{aligned}
\sum_{i=1}^n \frac{Pr(V_i > \beta(t))}{1 - \int_0^t Pr(V_i > \beta(x))dx} &= \sum_{i=1}^n \frac{Pr(V_i > \beta(t))}{1 - t + \int_0^t Pr(V_i \leq \beta(x))dx} \\
&\geq \sum_{i=1}^n \frac{Pr(V_i > \beta(t))}{1 - t + tPr(V_i \leq \beta(0))} \\
&= \sum_{i=1}^n \frac{1 - F_i(\beta(t))}{1 - t + tF_i(\beta(0))}
\end{aligned}$$

Using the following inequality (Proof in the paper)

$$\frac{1 - F_1(\beta(t))}{1 - t + tF_1(\beta(0))} + \frac{1 - F_2(\beta(t))}{1 - t + tF_2(\beta(0))} \geq \frac{1 - F_1(\beta(t))F_2(\beta(t))}{1 - t + tF_1(\beta(0))F_2(\beta(0))}$$

and repeating it  $n$  times, we get the required result.  $\square$

For the competitive ratio of 0.669, we define  $\alpha_1, \alpha_2, \dots, \alpha_m$  and set  $\alpha(t) = \alpha_{ceil(tm)}$ . We also define a non-decreasing function  $g$ , for  $t \in [0, 1]$ ,

$$g_p(t) = \begin{cases} \frac{1}{1-t(1-p)} & ; t \leq 1/2 \\ \frac{2}{1+p} & ; t > 1/2 \end{cases}$$

Using the result from the last section, if  $z$  is the reward, for any  $t \in [0, 1]$ , we can write,

$$Pr(z > \beta(t)) = \frac{1 - \theta(t)}{1 - \alpha(t)}(1 - \alpha(t)) + \sum_{i \in [n]} Pr(V_i > \beta(t)) \int_t^1 q_{-1}(x)dx$$

Using the bound for  $\theta(t)$  derived in the last part, the first term can be written as,

$$\frac{1 - \theta(t)}{1 - \alpha(t)}(1 - \alpha(t)) \geq \frac{\int_0^t 1 - \alpha(x)dx}{1 - \alpha(t)} (Pr(\max_i \{V_i\} > \beta_t))$$

For the second term, first we use Lemma 1 to write,

$$q_{-i}(x) \geq \frac{\theta(x)}{1 - \int_0^x Pr(V_i > \beta(y))dy}$$

Then interchanging the order of sums,

$$\sum_{i \in [n]} Pr(V_i > \beta(t)) \int_t^1 q_{-1}(x)dx \geq \int_t^1 \theta(x) \sum_{i \in [n]} \frac{Pr(V_i > \beta(t))}{1 - \int_0^x Pr(V_i > \beta(y))dy} dx$$

Now, using Lemma 2, for  $x \leq 1/2$

$$\begin{aligned}
\sum_{i \in [n]} \frac{Pr(V_i > \beta(t))}{1 - \int_0^x Pr(V_i > \beta(y))dy} &\geq \frac{Pr(\max_i \{V_i\} > \beta(x))}{1 - xPr(\max_i \{V_i\} > \beta(0))} \\
&= g_{\alpha(0)}(x) Pr(\max_i \{V_i\} > \beta(x))
\end{aligned}$$

Now, for  $x > 1/2$ , it can be observed that

$$\begin{aligned} \sum_{i \in [n]} \frac{Pr(V_i > \beta(t))}{1 - \int_0^x Pr(V_i > \beta(y)) dy} &\geq \frac{Pr(\max_i \{V_i\} > \beta(x))}{1 - \frac{1}{2} Pr(\max_i \{V_i\} > \beta(0))} \\ &= g_{\alpha(0)}(x) Pr(\max_i \{V_i\} > \beta(x)) \end{aligned}$$

Finally, we divide  $x$  according to the  $m$  thresholds, and use the bound for  $\theta(t)$  derived in the last section to get the final result.

$$\begin{aligned} \int_t^1 \theta(x) g_{\alpha(0)}(x) dx &= \sum_{i=tm}^m \int_{i/m}^{(i+1)/m} \theta(x) g_{\alpha(0)}(x) dx \\ &\geq \sum_{i=tm}^m \int_{i/m}^{(i+1)/m} \theta(i/m) Pr(V_{time=x} < \beta_i)^{x-i/m} g_{\alpha(0)}(i/m) dx \\ &\geq \sum_{i=tm}^m g_{\alpha(0)}(i/m) e^{\int_0^{i/m} \ln(\alpha(y)) dy} \int_{i/m}^{(i+1)/m} \alpha_i^{x-i/m} dx \\ &= \sum_{i=tm}^m g_{\alpha(0)}(i/m) \left( \prod_{k=1}^i \alpha_k \right)^{1/m} \int_{i/m}^{(i+1)/m} \alpha_i^{x-i/m} dx \\ &= \sum_{i=tm}^m g_{\alpha(0)}(i/m) \left( \prod_{k=1}^i \alpha_k \right)^{1/m} \frac{1 - \alpha_i^{1/m}}{-\ln(\alpha_i)} \end{aligned}$$

Hence, we proved that:

$$Pr(z > \beta(t)) \geq \left( \frac{\int_0^t 1 - \alpha(x) dx}{1 - \alpha(t)} + \sum_{i=tm}^m g_{\alpha(0)}(i/m) \left( \prod_{k=1}^i \alpha_k \right)^{1/m} \frac{1 - \alpha_i^{1/m}}{-\ln(\alpha_i)} \right) Pr(\max_i \{V_i\} > \beta_t)$$

Where optimization of values for  $\alpha$  lead to a competitive ratio of 0.669