

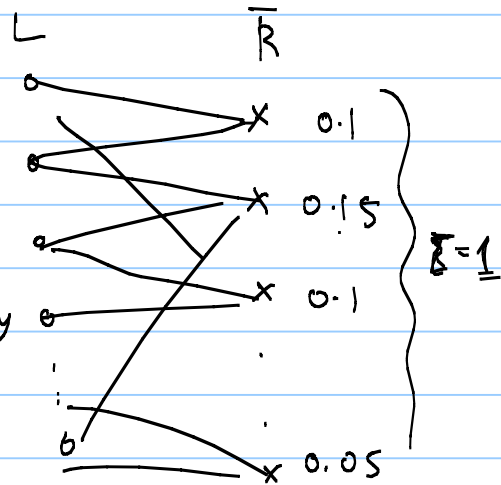
# Online Matching with unknown iid arrivals

Note Title

1/29/2013

- Vertices in  $R$  are sampled (independently & identically) from a distribution.
- Given the offline vertex set  $L$ .
- A probability distribution from which vertices in  $R$  are sampled from. Say the support of this distribution is  $\bar{R}$ . Each element  $j \in \bar{R}$  is identified by its neighbors in  $L$ . The probability of  $j$  is  $p(j)$ .

Distribution graph.



- Each vertex  $j \in R$  is sampled independently from  $p(\cdot)$ .
- Both ALG & OPT are r.v.s.

$\therefore$  we'd like  $E[\text{ALG}] \geq \gamma \cdot E[\text{OPT}]$ .

Def:  $\bar{\text{OPT}}$  = optimum value of the "expected instance" deterministic value, and  $\bar{\text{OPT}} \geq E[\text{OPT}]$ .  
 $\therefore$  Sufficient to prove  $E[\text{ALG}] \geq \gamma \cdot \bar{\text{OPT}}$ .

$m = \#$  vertices in  $R$ .

$$\overline{\text{OPT}} = \max \sum_{i,j} x_{ij} \text{ st. } - \text{ expected LP}$$

$$\forall i \in L \sum_{j \in R} x_{ij} \leq 1.$$

$$\forall j \in R \sum_{i \in L} x_{ij} \leq p(j) \cdot m = \text{times } j \text{ appears in } R$$

$$x_{ij} \geq 0.$$

Lemma:-  $\overline{\text{OPT}} \geq E[\text{OPT}]$ .

Proof:- Let  $x_{ij}^* = \# \text{ of times } j \text{ is matched to } i \text{ in OPT, a r.v.}$

$$\& x_{ij}^* = E[x_{ij}^*]$$

$$\sum_i x_{ij}^* \leq \# \text{ times } j \text{ appears in } R$$

$$\therefore E[\sum_i x_{ij}^*] \leq E[\text{---}] = p(j) \cdot m$$

$$\therefore \sum_i x_{ij}^* \leq p(j) \cdot m$$

$$\text{why } \sum_j x_{ij}^* \leq 1 \quad \forall i$$

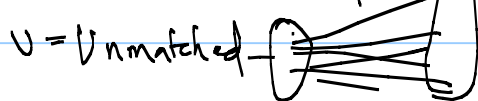
$$\& E[\text{OPT}] = \sum_i x_{ij}^*$$

$x_{ij}^*$  is a feasible soln. to the expected LP.

$$\therefore E[\text{OPT}] \leq \overline{\text{OPT}} \quad \square.$$

Theorem:- The greedy algorithm is  $1-1/e$  competitive in the iid setting.

Proof:- At time  $t$ ,  $L$   $R$   
 - Matched  $\overline{\text{OPT}}$



$p(j)$  [  $j$  has a neighbor in  $U$  ]  
 Use only  $\overline{\text{OPT}}$

$$\overline{\text{OPT}} = \sum_{i,j} X_{ij} = \sum_{i \in U, j} X_{ij} + \underbrace{\sum_{i \in L \setminus U, j} X_{ij}}_{\text{ALG}(t)}$$

$$\therefore \overline{\text{OPT}} - \text{ALG}(t) = \sum_{i \in U, j} X_{ij}$$

$j$  is chosen with probability  $p(j)$ .

Suppose we Match  $j$  to  $i$  with prob.  $\frac{X_{ij}}{m \cdot p(j)}$

$$\begin{aligned} \text{Then } \Pr[i \text{ gets matched}] &= \sum_j p(j) \cdot \frac{X_{ij}}{m \cdot p(j)} \\ &= \sum_j X_{ij} / m. \end{aligned}$$

$$\therefore \Pr[\text{Some } i \in U \text{ gets matched}] = \frac{\sum_{i \in U} X_{ij}}{m}$$

$$\therefore \Pr[\text{ALG finds a match in step } t] \geq \frac{\overline{\text{OPT}} - \text{ALG}(t)}{m}$$

$$\therefore E[\text{ALG}(t+1) | \text{ALG}(t)] \geq \text{ALG}(t) + \frac{\overline{\text{OPT}} - \text{ALG}(t)}{m}$$

$$\therefore E[\overline{\text{OPT}} - \text{ALG}(t+1)] \leq (\overline{\text{OPT}} - \text{ALG}(t)) \left(1 - \frac{1}{m}\right)$$

$$\therefore E[\overline{\text{OPT}} - \text{ALG}(m)] \leq \overline{\text{OPT}} \left(1 - \frac{1}{m}\right)^m \leq \frac{\overline{\text{OPT}}}{e}$$

$$\therefore E[\text{ALG}] \geq \overline{\text{OPT}} \left(1 - \frac{1}{e}\right)$$

## Suggested Exercise:

- Generalize to (Integral) Budgeted Allocation without the assumption  $b_{ij} \ll B_i$ .

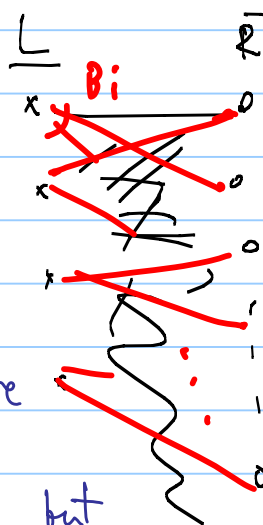
B-matching: Each  $i \in L$  can be matched  $B_i$  times. All  $B_i \geq k$ .

Assume:-  $|\bar{R}| = m$ , &  $p(j) = \frac{1}{m} \forall j \in \bar{R}$ .

$\therefore p(j) \cdot m = 1$ . The expected instance is simply an integral matching problem.

Further, suppose  $\exists$  a perfect matching in the expected instance. i.e. each  $j$  is matched to  $M(j)$  & each  $i \in L$  is matched  $B_i$  times.

$$\therefore \text{OPT} = m = \sum_i B_i.$$



## Pure-Random Algorithm:

- Knows expected instance,  $G$ , & the matching.
- Is non-adaptive, makes all the decisions ahead of time.
- Always matches  $j$  to  $M(j)$ , but gets credit only if  $\leq B_i$  matches

\*steps,

$$\Pr[i \text{ is matched in 1 step}] = \frac{B_i}{m} = \frac{\# \text{ j's matched to } i}{\text{total } \# \text{ j's}}$$

$\therefore$  uniform distribution

≡ Balls and bins procedure.

Independent of the Graph!

- Each  $i$  ≡ bin with capacity  $B_i$ .  $\sum_i B_i = m$ .
- In each round, throw a ball in bin  $i$  with prob.  $B_i/m$ .
- Repeat  $m$  times.

Q:- How many balls are in bin  $i$ ? ( $X_i$ )

A:- There are  $l$  balls with prob.

$$\binom{m}{l} \left(\frac{B_i}{m}\right)^l \left(1 - \frac{B_i}{m}\right)^{m-l}$$

$$\text{Want: } E[\min\{X_i, B_i\}] = \sum_{l=1}^{B_i} \binom{m}{l} \left(\frac{B_i}{m}\right)^l \left(1 - \frac{B_i}{m}\right)^{m-l} \cdot l \\ + B_i \sum_{l=B_i+1}^m \binom{m}{l} \left(\frac{B_i}{m}\right)^l \left(1 - \frac{B_i}{m}\right)^{m-l}$$

- monotonically decreasing in  $m$

- as  $m \rightarrow \infty$ ,  $E[\min\{X_i, B_i\}] \rightarrow B_i - \sqrt{\frac{B_i}{2\pi}}$

$$\therefore E[PR] = \sum_i B_i \left(1 - \sqrt{\frac{1}{2\pi B_i}}\right)$$

$$\geq \sum_i B_i \left(1 - \frac{1}{\sqrt{2\pi k}}\right) \quad \text{Since } B_i \geq k \quad \forall i$$

$$= \text{OPT} \left(1 - \frac{1}{\sqrt{2\pi k}}\right) \geq \text{OPT} (1 - \varepsilon)$$

$$\text{if } k \geq \frac{1}{2\pi \varepsilon^2} \Leftrightarrow \varepsilon \geq \frac{1}{\sqrt{2\pi k}}$$

(compare to  $\frac{B_i}{\sqrt{m}}$   $\geq \frac{c n \log(mn)}{\varepsilon^2}$ )

But we started out with unknown distribution!

Algorithm for unknown distribution: Define inductively

Say we've already matched  $t-1$  vertices, denote by

$$\mathcal{H}^t := A_1 A_2, \dots, A_{t-1} \quad ? \quad P_{t+1} P_{t+2}, \dots, P_m.$$

Suppose after this step, we could magically run the pure-Random algorithm. Let  $\mathcal{H}^t$  be the "Hybrid Algorithm".

Given  $j$  in the  $t^{\text{th}}$  step,  $\forall$  choices of  $i \in j$ ,  $i$  unmatched, evaluate the expected # of matches in the remaining time for  $\mathcal{H}^t$ .

Match  $j$  to  $i$  that maximizes this. i.e.  
Match  $j$  to  $\arg\max_{i: i \in j} \{ E[\mathcal{H}^t | A_t = i] \}$

This defines  $A_t$ , & hence the algorithm.

Compare:

$$\begin{array}{l} \mathcal{H}^t \\ \mathcal{H}^t \end{array} \quad \begin{array}{l} A_1 A_2, \dots, A_{t-1} \boxed{P_t} P_{t+1}, \dots, P_m \\ A_1 A_2, \dots, A_{t-1} \boxed{A_t} P_{t+1}, \dots, P_m \end{array}$$

→ only difference.

claim:  $E[\mathcal{H}^t] \geq E[\mathcal{H}^{t+1}]$ , almost by definition.

$$\therefore E[H^m] \geq E[H^{m+1}] \geq \dots \geq E[H^0]$$

$$\quad \quad \quad \parallel \quad \quad \quad \quad \quad \quad \quad \parallel$$

$$E[ALG] \quad \quad \quad \quad \quad \quad \quad \quad \quad \quad E[PR]$$

$\therefore$  ALG is atleast as good as PR!  $\square$

How can we perform the "magical step"?

We can estimate the expected # of matches  
 $\therefore$  it is  $\equiv$  some balls & bins procedure.

Given remaining capacity, prob. of match in 1 step & # of steps, can calculate exp. # of matches.

Suggested Exercise:

- Generalize to Budgeted Allocation. (Integral).

Sketch: -  $X_i = \text{sum of } b_{ij}'\text{'s. } E[X_i] = B_i. E[X_i^2] = \frac{B_i^2}{m}$   
 $E[\min\{X_i, B_i\}]$  is smallest when

$$b_{ij} \in \{0, b_i^{\max}\}$$

Algo: evaluate profit in this step + remaining profit.

estimate assuming

$$ALG \geq OPT \left(1 - \frac{1}{\sqrt{2\pi k}}\right) \text{ where } \frac{B_i}{b_i^{\max}} \geq k.$$

- observe everything works for non-uniform dist'n.

