

CS 3.307

# Performance Modeling for Computer Systems

**Tejas Bodas**

Assistant Professor, IIIT Hyderabad

# Logistics

- ▶ Feel free to contact me anytime at [tejas.bodas@iiit.ac.in](mailto:tejas.bodas@iiit.ac.in).
- ▶ Office @ A5304.
- ▶ Book– Performance modeling and design of computer systems (Cambridge press) by Mor Harchol-Balter (Professor, CMU)
- ▶ Other books: 1) Stochastic processes by Sheldon Ross 2) Probabilistic modeling by Isi Mitrani.
- ▶ Assignment 1 : 15%. Midsem exam: 25%. Project: 25%  
Endsem 35 %.

# Course Outline

- ▶ Module 1 (2 lectures)
  - ▶ Motivation, Probability refresher, Introduction to Stochastic Processes
- ▶ Module 2 (4 lectures)  
Poisson Process & Markov Chains
- ▶ Module 3 (2 lectures) Elementary Queues
- ▶ Module 4 Renewal theorems and Busy period analysis (3 lectures)
- ▶ Module 5 (3 lectures) Advanced Queues

# Performance modeling for Computer systems

- ▶ How do you measure the performance of your computer?
- ▶ Speed with which it runs programs. RAM, clock speed, GPU, Cores.
- ▶ Storage space ? SSD or not ?
- ▶ What is the key word here ? LATENCY!
- ▶ Performance metrics?
  - ▶ response time (run time, lag, delay, jitter)
  - ▶ blocking probability (screen freeze, no disk space, packet loss, buffer full)

# Modeling ?

- ▶ Design for performance: How many cores or GPU's? which core to use? how to schedule instructions in a core?
- ▶ Routing (which core) and scheduling (which program/instruction to execute)
- ▶ How do you know which is a good design? via experimentation?(costly!)
- ▶ Performance analysis! via stochastic modeling

# Applications Beyond Computers

- ▶ Computer systems
  - ▶ server farms, cloud computing, distributed storage systems
  - ▶ Communication systems, Wifi, Sensor networks.
- ▶ Healthcare
  - ▶ How many OT? How many Specialists or nurses?
  - ▶ Scheduling operations, stocking of medicines, scheduling tests.
- ▶ Hospitality industry
  - ▶ Designing hotel lobbies for faster checkin
  - ▶ Restaurant seating! (How many tables of size 2,4,8?)
- ▶ Transportation systems
  - ▶ Airline or Railway scheduling
  - ▶ Priority scheduling, class differentiation
- ▶ Operation Research!
- ▶ Henceforth use the term Queueing system!

# A single server queue



- ▶ One server, one FIFO queue for jobs to wait.
- ▶  $\mu$  denotes service rate,  $\lambda$  denotes the arrival rate.
- ▶ Service requirements  $S_n$  and inter-arrival times  $A_n$  are typically assumed to be i.i.d.
- ▶ In its simplest form, we will assume  $S_n \sim \text{Exp}(\mu)$  and  $A_n \sim \text{Exp}(\lambda)$ .
- ▶ Jobs face queueing delay due to waiting for other jobs.
- ▶ This is the most basic  $M/M/1$  queue. Modeling this as a Markov chain and solving its stationary distribution gives us mean response time (mean of service time + waiting time).
- ▶  $E[T] = \frac{1}{\mu - \lambda}$

## A single server queue



- ▶  $E[T] = \frac{1}{\mu - \lambda}$ .
- ▶ Let  $N$  is the number of jobs in the system (Queue + server). Then what is  $E[N]$ ?
- ▶ We will see Little's law that says that  $E[N] = \lambda E[T]$ .
- ▶ Mean number of jobs  $E[N] = \frac{\lambda}{\mu - \lambda}$ .
- ▶ This course is about Markov chain analysis to derive such formulas.

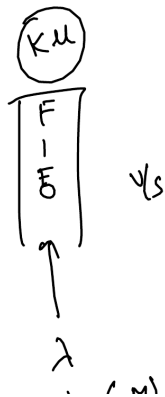


## Example 1: Doubling the arrival rate



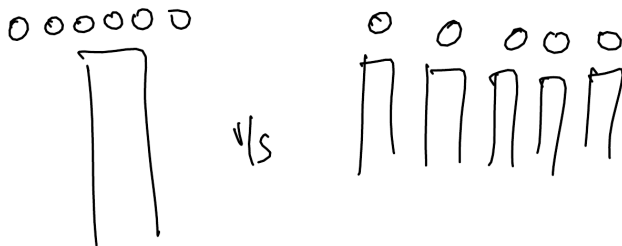
- ▶  $E[T] = \frac{1}{\mu - \lambda}$ .
- ▶ What would happen to  $E[T]$  if  $\lambda \rightarrow 2\lambda$ ?
- ▶ It could blow up if  $\mu < 2\lambda$ .
- ▶ If you want to maintain the same level of response time then do you need to double  $\mu$ ?
- ▶ This course is about making such design choices!

## Example 2: A fast server versus many slow servers



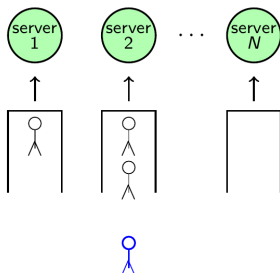
- ▶ Which system will have lower  $E[T]$ ?
- ▶ Is a fast server ( $K\mu$ ) better than  $K$  normal servers ( $\mu$ )?
- ▶ Does job variability impact this decision? Suppose job sizes were  $XS, S, M, L, XL$ .
- ▶ In the first model, an  $S$ , or  $M$  job has to possibly wait behind  $XL$ . This is avoided in the second scenario.

## Example 3: Central queue or individual



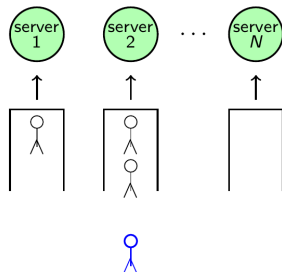
- ▶ At Airport immigration, Hotel check-ins you often see central queues.
- ▶ But at movie theatres, metro/train ticket counters, you see the second model.
- ▶ Which setting has a lower  $E[T]$ ?
- ▶ This course will help you answer such performance modeling questions.

## Example 4: Supermarket queue and load balancing



- ▶ Load balancing concerns the questions which queue to join/assign?
- ▶ Popular policy is Join shortest Queue (JSQ).
- ▶ What should be ideally done is Join smallest work (JSW).
- ▶  $N$  is typically large and the overhead in obtaining queue length information is huge ( $2N$ ).

## Example 4: Supermarket queue and load balancing



- ▶ In that case, sample  $d$  servers randomly and join appropriate queue using  $JSQ(d)$  or  $JSW(d)$ .
- ▶ Problem with  $JSW$  or  $JSW(d)$  is that the workload information is typically unknown. How to implement it then?
- ▶ How about replicating jobs on  $d$  servers and cancelling copies when one copy starts service ?
- ▶ This is redundancy- $d$  with cancel on start.
- ▶ We do this at super-markets all the time!

# Probability Refresher

# Random experiments and Sample space

- ▶ Random experiment : Experiment involving randomness
  - ▶ Coin toss
  - ▶ Roll a dice
  - ▶ Pick a number at random from  $[0, 1]$ .
- ▶ Sample space  $\Omega$ : set of all possible outcomes of the random experiment. It could be a finite or infinite set.
  - ▶  $\Omega_c = \{H, T\}$
  - ▶  $\Omega_d = \{1, 2, \dots, 6\}$
  - ▶  $\Omega_u = [0, 1]$

# Events

- ▶ A subset  $A \subseteq \Omega$  is called an **event**.
- ▶ Examples of events
  - ▶ Events in the coin experiment:  $C_1 = \{T\}$ .
  - ▶ Events in the dice experiment:  $D_1 = 6, D_2 = \{1, 3, 5\}$
  - ▶ Events in  $U[0, 1]$  experiment:  $U_1 = \{0.5\}, U_2 = [.25, .75]$ .
- ▶ Probability of event  $A$  is denoted by  $\mathbb{P}(A)$ .



# Probability theory

{Random experiment, Sample space, Events} are the key ingredients in probability theory.

In probability theory, we are interested in **measuring** the probability of subsets of  $\Omega$  (events).

Probability measure  $\mathbb{P}$  is a **set function**, i.e. it acts on sets and measures the probability of such sets.

## *sigma-algebra* as domain for $\mathbb{P}$

- ▶ Event space or *sigma-algebra*  $\mathcal{F}$  is a collection of measurable sets that satisfy
  - $\emptyset \in \mathcal{F}$    •  $A \in \mathcal{F} \implies A^c \in \mathcal{F}$   
•  $A_1, A_2, \dots, A_n, \dots \in \mathcal{F} \implies \bigcup_{n=1}^{\infty} A_n \in \mathcal{F}$
- ▶ The  $\sigma$ -algebra is said to be closed under formation of compliments and countable unions.
- ▶ Is it also closed under the formation of countable intersections?

When  $\Omega$  is countable and finite, we will consider power-set  $\mathcal{P}(\Omega)$  as the domain.

# Formal definition of Probability measure $\mathbb{P}$

## Definition

A probability measure  $\mathbb{P}$  on the *measurable space*  $(\Omega, \mathcal{F})$  is a function  $\mathbb{P} : \mathcal{F} \rightarrow [0, 1]$  s.t.

1.  $\mathbb{P}(\emptyset) = 0, \quad \mathbb{P}(\Omega) = 1$
2. For a disjoint collection of event sets  $A_1, A_2, \dots$  from  $\mathcal{F}$  we have

$$\mathbb{P}\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} \mathbb{P}(A_i)$$

(countable additivity)

- The trio  $(\Omega, \mathcal{F}, \mathbb{P})$  is called as a probability space.

# Conditional probability

- ▶ Given/If dice rolls odd, what is the probability that the outcome is 1?
- ▶ Given/If  $\bar{\omega} \in [0, 0.5]$  what is the probability that  $\bar{\omega} \in [0, 0.25]$ ?
- ▶ The conditional probability of event  $B$  given event  $A$  is defined as  $\mathbb{P}(B/A) := \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(A)}$  when  $\mathbb{P}(A) > 0$ .
- ▶ Bayes rule:  $P(B/A) = \frac{P(A/B)P(B)}{P(A)}$ .

# Independence and Mutually exclusive

- ▶ Two events  $A, B$  are independent iff  $P(A/B) = P(A)$  and  $P(B/A) = P(B)$ .
- ▶ Two events  $A, B$  are independent iff  $P(A \cap B) = P(A)P(B)$ .

- ▶ If  $A$  and  $B$  are independent, then so are  $A^c$  and  $B^c$ .
- ▶ What about  $A$  and  $B^c$ ? Are they independent?
- ▶ Two events  $A$  and  $B$  are mutually exclusive if occurrence of one implies that the other event cannot occur. Are they independent?
- ▶ If  $A$  and  $B$  are mutually exclusive, then they are not independent (and vice versa).

## Random variable

- ▶ Given a random experiment with associated  $(\Omega, \mathcal{F}, \mathbb{P})$ , it is sometimes difficult to deal directly with  $\omega \in \Omega$ . eg. rolling a dice ten times.
- ▶ Notice that each sample point  $\omega \in \Omega$  is not a number but a sequence of numbers.
- ▶ Also, we may be interested in functions of these sample points rather than samples themselves. eg: Number of times 6 appears in the 10 rolls.
- ▶ In either case, it is often convenient to work in a new *simpler* probability space rather than the original space.
- ▶ Random variable is a device which precisely helps us make this mapping from  $(\Omega, \mathcal{F}, \mathbb{P})$  to a 'simpler'  $(\Omega', \mathcal{F}', P_X)$ .
- ▶  $P_X$  is called as an induced probability measure on  $\Omega'$ .

# Random variable

- ▶ If  $\Omega'$  is countable, then the random variable is called a discrete random variable.
- ▶ In this case it is convenient to use  $\mathcal{F}'$  as power-set.
- ▶ If  $\Omega' \subseteq \mathbb{R}$  or uncountable, then the random variable is a continuous random variable.
- ▶ In this case,  $\mathcal{F}' = \mathcal{B}(\mathbb{R})$ .
- ▶ Notation: Random variables denoted by capital letters like  $X, Y, Z$  etc. and their realizations by small letters  $x, y, z$ ..

## PMF and CDF of a Discrete r.v.

- ▶ Let  $X : \Omega \rightarrow \Omega'$  be a discrete r.v.
- ▶ Let  $p_X(x)$  for  $x \in \Omega'$  denote the probability that  $X$  takes the value  $x$ .
- ▶  $p_X(x)$  is called as a probability mass function.
- ▶ The cumulative distribution function (CDF)  $F_X(\cdot)$  is defined as  $F_X(x_1) := \sum_{x \leq x_1} p_X(x) = \mathbb{P}\{\omega \in \Omega : X(\omega) \leq x_1\}$ .



# Expectation, Moments, Variance

- ▶ The mean or expectation of a random variable  $X$  is denoted by  $E[X]$  and is given by  $E[X] = \sum_{x \in \Omega'} xp_X(x)$ .
- ▶ The  $n^{th}$  moment of a random variable  $X$  is denoted by  $E[X^n]$  and is given by  $E[X^n] = \sum_{x \in \Omega'} x^n p_X(x)$ .
- ▶ Functions of random variables are random variables.
- ▶ For a function  $g(\cdot)$  of a random variable  $X$ , its expectation is given by  $E[g(X)] := \sum_{x \in \Omega'} g(x)p_X(x)$
- ▶  $Var(X) := E[(X - E[X])^2]$
- ▶ HW: Prove that  $E[(X - E[X])^2] = E[X^2] - E[X]^2$
- ▶ For  $Y = aX + b$ , what is  $E[Y]$ ?  $E[Y] = aE[X] + b$ .  
(Linearity of expectation)

# Bernoulli random variable

- ▶ Bernoulli random variable  $X = \begin{cases} 1, & \text{with probability } p \\ 0, & \text{otherwise.} \end{cases}$
- ▶ Basic models of Multi-arm bandit problem assume Bernoulli Bandits.
- ▶  $E[X] = p, E[X^n] = p.$

## Binomial $B(n, p)$ random variable.

- ▶ Consider a biased coin (head with probability  $p$ ) and toss it  $n$  times.
- ▶ Denote head by 1 and tail by 0.
- ▶ Let random variable  $N$  denote the number of heads in  $n$  tosses.
- ▶ PMF of  $N$ ?.  $P_N(k) = \binom{n}{k} p^k (1 - p)^{n-k}$ .
- ▶ HW: What is  $E[N]$ ,  $E[N^2]$ ,  $\text{Var}(X)$ ?

# Geometric random variable

- ▶ Consider a biased coin (head with probability  $p$ ) and suppose you keep tossing it till head appears the first time.
- ▶ Let random variable  $N$  denote the number of tosses needed for head to appear first time.
- ▶ What is the PMF of  $N$ ?  $p_N(k) = (1 - p)^{k-1}p$ .
- ▶ HW: What is  $E[N]$ ,  $E[N^2]$ ,  $Var(N)$ ?

# Poisson random variable

- ▶ A Poisson random variable  $X$  comes with a parameter  $\lambda$  and has  $\Omega' = \mathbb{Z}_{\geq 0}$
- ▶ PMF:  $p_X(k) = e^{-\lambda} \frac{\lambda^k}{k!}$
- ▶ Intuitively its a limiting case of the Binomial distribution with  $n$  increasing and  $p$  decreasing such that  $np$  converges to  $\lambda$ .
- ▶ Mean of binomial is  $np$  so  $p$  should decrease while  $n$  increases.

# Continuous random variables

- ▶ A random variable  $X$  is continuous if there exists a non-negative real valued probability density function (PDF)  $f_X(\cdot)$  such that  $F_X(x) = \int_{u=-\infty}^x f_X(u)du$ .
- ▶  $P_X(a \leq X \leq b) = \int_a^b f_X(u)du$ . (Area under the curve)

$$\frac{dF_X(x)}{dx} = f_X(x) \text{ or } P_X(x < X \leq x + h) \simeq f_X(x)h.$$

# Mean, Variance, Moments

- ▶  $E[X] = \int_{-\infty}^{\infty} uf_X(u)du$
- ▶  $E[X^n] = \int_{-\infty}^{\infty} u^n f_X(u)du$
- ▶  $E[g(X)] = \int_{-\infty}^{\infty} g(u)f_X(u)du$
- ▶  $\text{Var}[X] = E[g(X)]$  where  $g(x) = (x - E[X])^2$ .
- ▶ For  $Y = aX + b$ ,  $E[Y] = aE[X] + b$ .

# Exponential random variable ( $Exp(\lambda)$ )

- ▶ This is a non-negative r.v. with parameter  $\lambda$ .
- ▶ Its pdf  $f_X(x) = \lambda e^{-\lambda x}$  for  $x \geq 0$ .
- ▶ Its CDF is given by  $F_X(x) = 1 - e^{-\lambda x}$  for  $x \geq 0$ .
- ▶  $E[X] = \frac{1}{\lambda}$  and  $Var(X) = \frac{1}{\lambda^2}$
- ▶  $E[X^n] = \frac{n!}{\lambda^n}$



## Summary: Multiple random variables

$$p_{XY}(x, y) := \mathbb{P}\{\omega \in \Omega : X(\omega) = x \text{ and } Y(\omega) = y\}.$$

$$F_{XY}(x, y) := \mathbb{P}\{\omega \in \Omega : X(\omega) \leq x \text{ and } Y(\omega) \leq y\}.$$

The marginal PMF's  $p_X$  and  $p_Y$  can be obtained from the joint PMF as follows:

$$p_X(x) = \sum_y p_{XY}(x, y) \text{ and } p_Y(y) = \sum_x p_{XY}(x, y).$$

Two random variables,  $X$  and  $Y$  are independent if the following is true:

$$p_{XY}(x, y) = p_X(x)p_Y(y), F_{XY}(x, y) = F_X(x)F_Y(y) \text{ and } E[XY] = E[X]E[Y].$$

$$E[g(X, Y)] = \sum_{xy} g(xy)p_{XY}(xy)$$

The rules for continuous random variables are similar.  
Also revise conditioning of variables.

# Sums of independent random variable

- ▶ Consider  $Z = X + Y$ . What is the pdf of  $Z$  when  $X$  and  $Y$ ?
- ▶ What is  $p_Z(z)$  or  $f_Z(z)$ ?
- ▶  $p_Z(z) = \sum_{(x,y):x+y=z} p_{X,Y}(x,y)$
- ▶  $f_Z(z) = \int_{(x,y):x+y=z} f_{X,Y}(x,y) dx dy$ .
- ▶ Since  $X$  and  $Y$  are independent  $p_{X,Y}(x,y) = p_X(x)p_Y(y)$  and  $f_{X,Y}(x,y) = f_X(x)f_Y(y)$ . This gives us

Convolution formula

$$p_Z(z) = \sum_x p_X(x)p_Y(z-x)$$

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(x)f_Y(z-x)dx$$

HW: What if  $X$  and  $Y$  are not independent?

## MGF of Sums of independent random variable

- ▶ Consider  $Z = X + Y$ . What is the pdf of  $Z$  when  $X$  and  $Y$ ?
- ▶ Let  $M_X(t)$  and  $M_Y(t)$  be their MGF's. What is  $M_Z(t)$  ?
- ▶  $M_Z(t) = E[e^{Zt}] = E[e^{(X+Y)t}]$ .
- ▶  $M_Z(t) = E[e^{Xt}.e^{Yt}]$ .
- ▶ If  $X$  and  $Y$  are independent,  $E[XY] = E[X]E[Y]$  and  $E[g(X)h(Y)] = E[g(X)]E[h(Y)]$ .
- ▶  $M_Z(t) = E[e^{Xt}].E[e^{Yt}]$ .

$$M_Z(t) = M_X(t)M_Y(t).$$

## MGF of Sums of independent random variable

- ▶ Consider  $Z = X + Y$ . What is the MGF of  $Z$  when  $X$  and  $Y$ ?

$$M_Z(t) = M_X(t)M_Y(t).$$

- ▶ What about  $M_Z(t)$  when  $Z = X_1 + X_2 + \dots X_n$  and  $X_i$  are iid.?
- ▶  $M_Z(t) = (M_X(t))^n$ .
- ▶ What about  $M_Z(t)$  when  $Z = X_1 + X_2 + \dots X_N$  where  $N$  is a positive discrete random variable? section 4.5

# Convergence of Random Variables

# Summary

Pointwise  
convergence

$$\lim_{n \rightarrow \infty} X_n(\omega) = X(\omega) \text{ for every } \omega$$

Almost sure  
convergence

$$\lim_{n \rightarrow \infty} X_n(\omega) = X(\omega) \text{ almost surely}$$

Convergence  
in probability

$$\lim_{n \rightarrow \infty} P(|X_n - X| > \epsilon) = 0 \text{ for any } \epsilon > 0$$

Mean-square  
convergence

$$\lim_{n \rightarrow \infty} E[(X_n - X)^2] = 0$$

Convergence  
in distribution

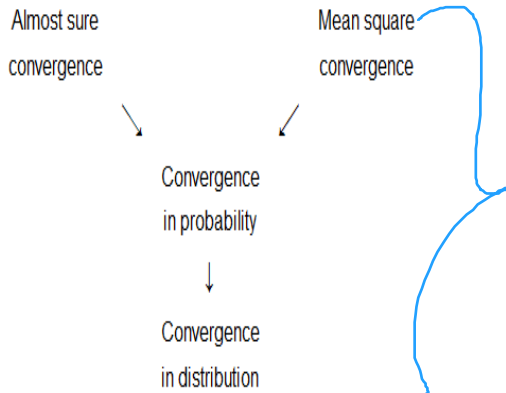
$$\lim_{n \rightarrow \infty} F_n(x) = F(x) \text{ for any continuity point } x$$

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<sup>1</sup>Image from probabilitycourse.com

# Relation between modes of convergence (no proofs)



[https://en.wikipedia.org/wiki/Proofs\\_of\\_convergence\\_of\\_random\\_variables](https://en.wikipedia.org/wiki/Proofs_of_convergence_of_random_variables)