# Mobile Communications TCS 455 

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Office Hours:
BKD 3601-7
Tuesday 14:00-16:00
Thursday 9:30-11:30

## Announcements

- Read
- Chapter 3: 3.1 - 3.2, 3.5.1, 3.6, 3.7.2
- Posted on the web
- Appendix A. 1 (Erlang B)
- Due date for HW3: Dec 18


## Big Picture

$S=$ total \# available duplex radio channels for the system
Frequency reuse with cluster size $N$


## Assumption

- Blocked calls cleared
- Offers no queuing for call requests.
- For every user who requests service, it is assumed there is no setup time and the user is given immediate access to a channel if one is available.
- If no channels are available, the requesting user is blocked without access and is free to try again later.
- Calls arrive as determined by a Poisson process.
- There are memoryless arrivals of requests, implying that all users, including blocked users, may request a channel at any time.
- There are an infinite number of users (with finite overall request rate).
- The finite user results always predict a smaller likelihood of blocking. So, assuming infinite number of users provides a conservative estimate.
- The duration of the time that a user occupies a channel is exponentially distributed, so that longer calls are less likely to occur.
- There are $m$ channels available in the trunking pool.
- For us, $m=$ the number of channels for a cell (C) or for a sector


## Poisson Process

The number of arrivals $\mathrm{N}_{1}, \mathrm{~N}_{2}$ and $\mathrm{N}_{3}$ during non-overlapping time intervals are independent Poisson random variables with mean $=\lambda \times$ the length of the corresponding interval.


The lengths of time between adjacent arrivals $\mathrm{W}_{1}, \mathrm{~W}_{2}, \mathrm{~W}_{3} \ldots$ are i.i.d. exponential random variables with mean $1 / \lambda$.

## Small Slot Analysis (Poisson Process)

- Aka discrete time approximation


In the limit, there is at most one arrival in any slot. The numbers of arrivals on the slots are i.i.d. Bernoulli random variables with probability $p_{1}$ of exactly one arrivals $=\lambda \delta$ where $\delta$ is the width of individual slot.

##  <br> $\mathrm{D}_{1}$ <br> The number of slots between adjacent arrivals is a geometric random variable. <br> The total number of arrivals on $n$ slots is a binomial random variable with parameter ( $\mathrm{n}, \mathrm{p}_{1}$ )

In the limit, as the slot length gets smaller,

$$
\text { geometric } \longrightarrow \text { exponential }
$$

$$
\text { binomial } \longrightarrow \text { Poisson }
$$

## Assumption (2)

The call request process is Poisson with rate $\lambda$


We want to find out what proportion of time the system has $K=m$.

## Small Slot Analysis (Erlang B)

Suppose each slot duration is $\delta$.


- Consider the $i^{\text {th }}$ small slot.
- Let $K_{\mathrm{i}}=\mathrm{k}$ be the value of $K$ at the beginning of this time slot.
- $\quad k=2$ in the above figure.
- Then, $K_{i+1}$ is the value of $K$ at the end of this slot which is the same as the value of $K$ at the beginning of the next slot.
- $\quad \mathrm{P}[0$ new call request $] \approx 1-\lambda \delta$
- $\quad \mathrm{P}[1$ new call request $] \approx \lambda \delta$
- $\mathrm{P}[0$ old-call end $\left.] \approx(1-\mu \delta)^{k} \approx 1-k \mu \delta \quad\right\rangle$ How do these events affect $K_{\mathrm{i}+1}$ ?
- $\mathrm{P}[1$ old-call end $] \approx k \mu \delta(1-\mu \delta)^{k-1} \approx k \mu \delta$


## Small slot Analysis (2)

$$
\mathrm{K}_{\mathrm{i}+1}=\mathrm{K}_{\mathrm{i}}+(\# \text { new call request })-(\# \text { old-call end })
$$



The labels on the arrows are probabilities.
$\mathrm{P}[0$ new call request $] \approx 1-\lambda \delta$ $\mathrm{P}[1$ new call request $] \approx \lambda \delta$
$\mathrm{P}[0$ old-call end $] \approx 1-k \mu \delta$ $\mathrm{P}[1$ old-call end $] \approx k \mu \delta$

## Small slot Analysis: Markov Chain

- Case: $\mathrm{m}=2$



## Markov Chain

- Markov chains model many phenomena of interest.
- We will see one important property: Memoryless
- It retains no memory of where it has been in the past.
- Only the current state of the process can influence where it goes next.
- Very similar to the state transition diagram in digital circuits.
- In digital circuit, the labels on the arrows indicate the input/control signal.
- Here, the labels on the arrows indicate transition probabilities. (If the system is currently at a particular state, where would it go next on the next time slot?)
- We will focus on discrete time Markov chain.


## Example: The Land of Oz

- Land of Oz is blessed by many things, but not by good weather.
- They never have two nice days in a row.
- If they have a nice day, they are just as likely to have snow as rain the next day.
- If they have snow or rain, they have an even chance of having the same the next day.
- If there is change from snow or rain, only half of the time is this a change to a nice day.
- If you visit the land of Oz next year for one day, what is the chance that it will be a nice day?


## State Transition Diagram


$\mathrm{R}=$ Rain
$\mathrm{N}=$ Nice
S = Snow

## Markov Chain (2)

- Let $K_{i}$ be the weather status for the $i^{\text {th }}$ day (from today).
- Suppose we know that it is snowing in the land of Oz today. Then

$$
K_{0}=\mathrm{S}
$$

where S means snow.

- Goal: We want to know whether $K_{365}=\mathrm{N}$ where N means nice.
- Of course, the weather are controlled probabilistically; so we can only find $\mathbf{P}\left[K_{365}=\mathbf{N}\right]$.
- From the specification (or from the state transition diagram), we know that

$$
P\left[K_{1}=\mathrm{R}\right]=\frac{1}{4}, \quad P\left[K_{1}=\mathrm{N}\right]=\frac{1}{4}, \quad P\left[K_{1}=\mathrm{S}\right]=\frac{1}{2}
$$

- Define vector

$$
\vec{p}(i)=\left[P\left[K_{i}=\mathrm{R}\right] \quad P\left[K_{i}=\mathrm{N}\right] \quad P\left[K_{i}=\mathrm{S}\right]\right]
$$

- Then,

$$
\vec{p}(0)=\left[\begin{array}{lll}
0 & 0 & 1
\end{array}\right] \text { and } \vec{p}(1)=\left[\begin{array}{lll}
\frac{1}{4} & \frac{1}{4} & \frac{1}{2}
\end{array}\right]
$$

## The Land of Oz: Transition Matrix

$$
\begin{aligned}
& \bar{p}(i+1)=\bar{p}(i) \times P \\
& \vec{p}(n)=\vec{p}(0) \times P^{n} \\
& \text { S }\left[\begin{array}{lll}
\frac{1}{4} & \frac{1}{4} & \frac{1}{2}
\end{array}\right] \\
& \bar{p}(2)=\left[\begin{array}{lll}
0.3750 & 0.1875 & 0.4375
\end{array}\right] \\
& \bar{p}(3)=\left[\begin{array}{lll}
0.3906 & 0.2031 & 0.4063
\end{array}\right] \\
& \bar{p}(5)=\left[\begin{array}{lll}
0.3994 & 0.2002 & 0.4004
\end{array}\right] \\
& \bar{p}(7)=\left[\begin{array}{lll}
0.4000 & 0.2000 & 0.4000
\end{array}\right]=\vec{p}(8)=\vec{p}(9)=\bar{p}(10)=\cdots=\vec{p}(365)
\end{aligned}
$$

## Finding Pn for "large" $n$

$$
\begin{aligned}
P=\left[\begin{array}{lll}
\frac{1}{2} & \frac{1}{4} & \frac{1}{4} \\
\frac{1}{2} & 0 & \frac{1}{2} \\
\frac{1}{4} & \frac{1}{4} & \frac{1}{2}
\end{array}\right] \Longrightarrow P^{2}=\left[\begin{array}{lll}
0.4375 & 0.1875 & 0.3750 \\
0.3750 & 0.2500 & 0.3750 \\
0.3750 & 0.1875 & 0.4375
\end{array}\right] \\
P^{3}=\left[\begin{array}{lll}
0.4063 & 0.2031 & 0.3906 \\
0.4063 & 0.1875 & 0.4063 \\
0.3906 & 0.2031 & 0.4063
\end{array}\right] \\
P^{5}=\left[\begin{array}{lll}
0.4004 & 0.2002 & 0.3994 \\
0.4004 & 0.1992 & 0.4004 \\
0.3994 & 0.2002 & 0.4004
\end{array}\right] \\
P^{7}=\left[\begin{array}{lll}
0.4000 & 0.2000 & 0.4000 \\
0.4000 & 0.2000 & 0.4000 \\
0.4000 & 0.2000 & 0.4000
\end{array}\right]=P^{8}=P^{9}=P^{10}=\cdots
\end{aligned}
$$

## Land of Oz: Answer

- Recall that

$$
\vec{p}(n)=\vec{p}(0) \times P^{n}
$$

- So,

$$
\vec{p}(7)=\vec{p}(0) P^{7}=\left[\begin{array}{lll}
0.4 & 0.2 & 0.4
\end{array}\right]
$$

- Note that the above result is true regardless of the initial $\vec{p}(0)$
- $\vec{p}(365)=\vec{p}(0) P^{365}=\left[\begin{array}{lll}0.4 & 0.2 & 0.4\end{array}\right]$

$$
\mathrm{P}\left[K_{365}=\mathrm{N}\right]
$$

## Tip: Alternative look

$$
P=\left[\begin{array}{ll}
2 / 5 & 3 / 5 \\
1 / 2 & 1 / 2
\end{array}\right]
$$



