

Lec19

Thursday, February 27, 2020 4:06 PM

- Focus on downlink. (Uplink can be treated in an analogous manner.)
- Consider a fixed mobile at the origin
- Key assumption: ^{#1} Base-stations (BS) are distributed according to a homogeneous Poisson Point Process (PPP) of intensity λ .

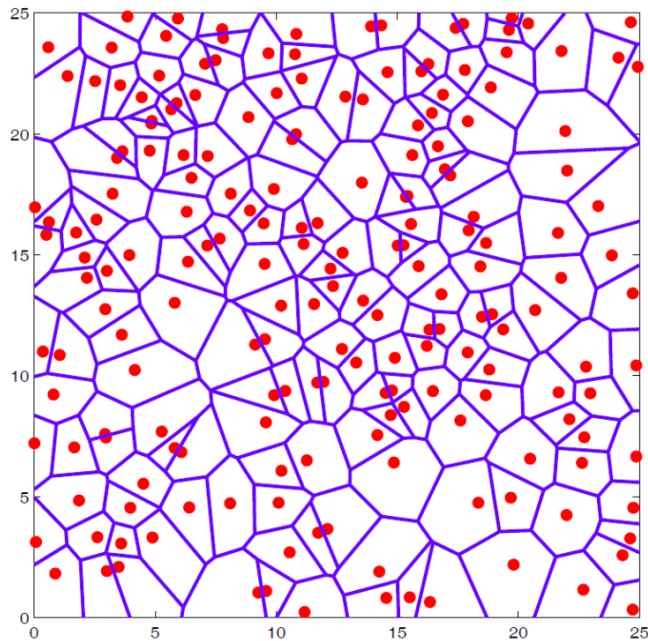
In optimal scheduling we assume that node locations are given.
 \Rightarrow difficult to obtain closed form solutions

- Roughly speaking, in any small area ΔA , the probability of having one BS in the area is $\lambda \Delta A$.

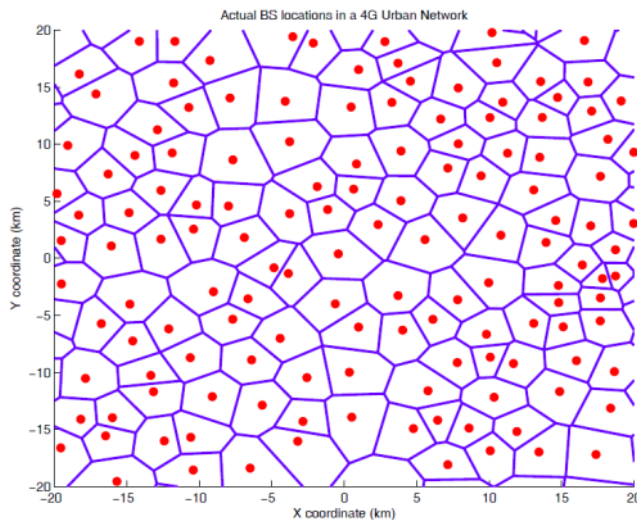
- When ΔA is large, the # of BS is a Poisson random variable with mean $\lambda \Delta A$

$$P\{\# \text{ of BS} = k\} = e^{-\lambda \Delta A} \frac{(\lambda \Delta A)^k}{k!}$$

- Independence:
 - For two disjoint areas, the # of BS in each area is independent of that of others.
 - Given that the # of BS in an area A is n , each BS is uniformly distributed in A , independently of others.
- The independence assumption does not hold when BSs are arranged according to some patterns
 - may be more relevant for small cells in HetNets.
- show Fig. 1 & Fig. 2 in Andrews et al.



PPP



Actual BS
in 4G
networks

Such a PPP assumption allows us to derive key quantities in closed form

- The mobile is connected to the nearest BS \hat{b}_0 at a distance r .
- How far is r ? For any value a

$$P[r > a] = P[\# \text{ of BS} = 0 \text{ in area } \pi a^2]$$

$$= e^{-\lambda \pi a^2}$$

\Rightarrow The pdf of r is

$$f(r) = \frac{d}{dr} [1 - e^{-\lambda \pi r^2}] = 2\lambda \pi r e^{-\lambda \pi r^2}$$

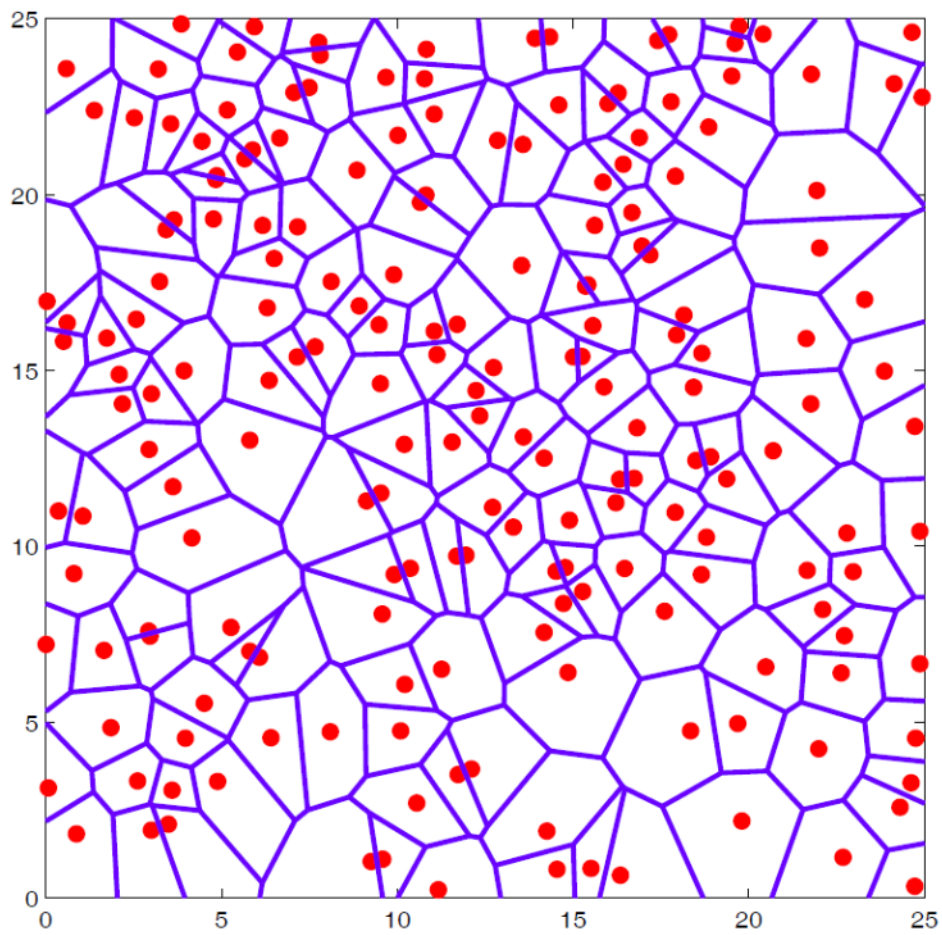
⇒ The pdf of r is

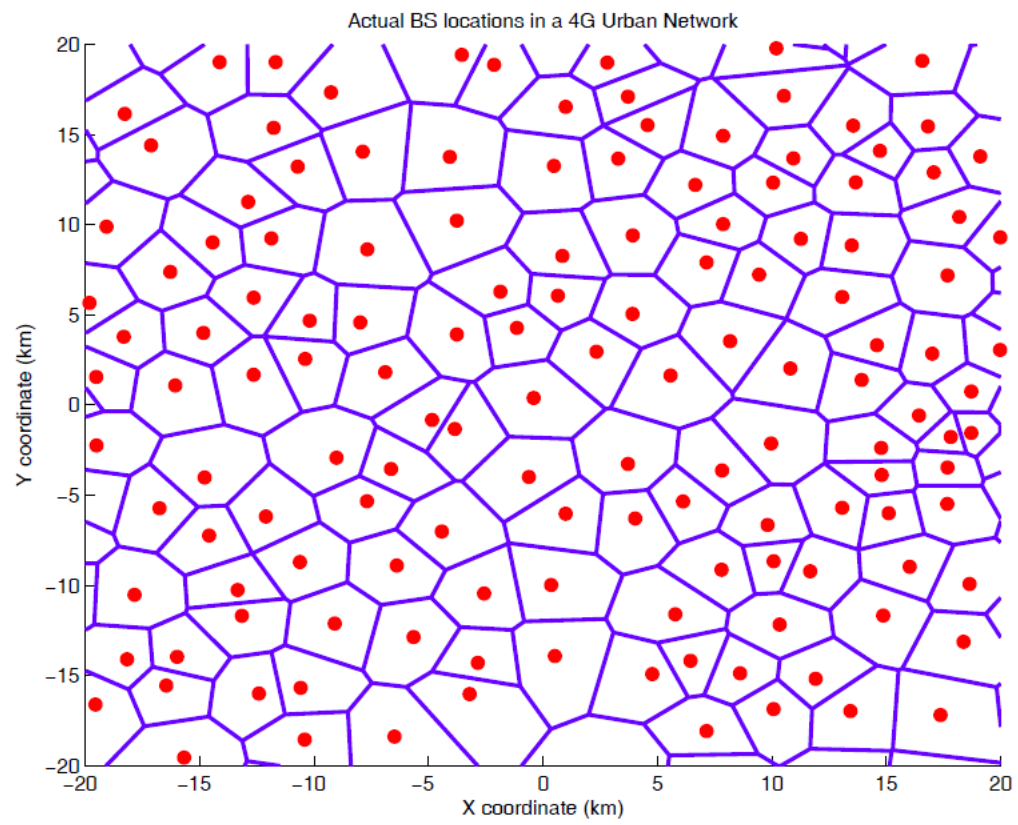
$$f(r) = \frac{d}{dr} [1 - e^{-\lambda r^2}] = 2\lambda r \cdot e^{-\lambda r^2}$$

— we then then derive the distribution of received power

Tessellation

Tuesday, February 13, 2018 4:42 PM





- On the other hand, interference power is contributed as a sum over all over BSs. We need the following key property.

Key property of PPP:

-
- For a given area ΔA , conditioned on the # of points of the PPP inside ΔA is k , the k points are uniformly distributed in ΔA , independently of each other.
 - Suppose that is a "mark" function $f(x)$ for each location x .
 - Let x_1, x_2, \dots be the PPP realization.
 - Consider $\mathbb{E} \left[\prod_{i=1}^{+\infty} e^{-f(x_i)} \right] = \mathbb{E} \left[e^{-\sum_{i=1}^{+\infty} f(x_i)} \right]$
 - Laplace functional of PPP
 - Think of $f(x_i)$ as the interference power of BS at x_i .

Then

$$\mathbb{E} \left[\prod_{i=1}^{+\infty} e^{-f(x_i)} \right] = \exp \left\{ -\lambda \iint_{\mathbb{R}^2} (1 - e^{-f(x)}) dx \right\}$$

Alternatively, if $f(x) > 0$,

$$\mathbb{E} \left[\prod_{i=1}^{+\infty} f(x_i) \right] = \exp \left\{ -\lambda \iint_{\mathbb{R}^2} (1 - f(x)) dx \right\}$$

- We will show a stronger version over an area A

$$E \left[\prod_{i=1}^n e^{-f(x_i)} \right] \\ = \exp \left\{ -\lambda \iint_A (1 - e^{-f(x)}) dx \right\}$$

— To see this, for an area A , suppose the # of points in A is n .

$$— \text{let } g(x) = f(x) \cdot 1_{\{x \in A\}}$$

$$\Rightarrow E \left[\prod_{i=1}^n e^{-g(x_i)} \right]$$

$$= E \left[\prod_{i=1}^n e^{-g(x_i)} \right]$$

$$= \frac{n!}{n!} \iint_A e^{-g(x)} \frac{1}{A} dx = \left(\iint_A e^{-g(x)} \frac{1}{A} dx \right)^n$$

$$\Rightarrow E \left[\prod_{i=1}^n e^{-g(x_i)} \right] \\ = e^{-\lambda A} \sum_{n=0}^{\infty} \frac{(\lambda A)^n}{n!} \cdot \left(\iint_A e^{-g(x)} \frac{1}{A} dx \right)^n$$

$$= e^{-\lambda A} \cdot e^{\lambda A \cdot \iint_A e^{-g(x)} \frac{1}{A} dx}$$

$$= e^{-\lambda \iint_A (1 - e^{-g(x)}) dx}$$

— Taking $A \rightarrow \mathbb{R}^d$ gives the result.

Key property of PPP - handout

Friday, February 9, 2018 10:49 AM

$$\begin{aligned} & \mathbb{E} \left[\prod_{i=1}^{+\infty} e^{-f(x_i)} \right] \\ &= \exp \left\{ -\lambda \int_{\mathbb{R}^d} (1 - e^{-f(x)}) dx \right\} \end{aligned}$$

— To see this, for an area A , suppose the # of points in A is n .

— Then, one can show that, conditioned on n , each point x_i is uniform in A , independently of other points.

— let $g(x) = f(x) \cdot \mathbb{1}_{\{x \in A\}}$

$$\Rightarrow \mathbb{E} \left[\prod_{i=1}^{+\infty} e^{-g(x_i)} \right]$$

$$\Rightarrow \mathbb{E} \left[\prod_{i=1}^{+\infty} e^{-g(x_i)} \right]$$

=

$$= e^{-\lambda A} \cdot e^{\lambda A \cdot \int_A e^{-g(x)} \frac{1}{A} dx}$$

$$= e^{-\lambda \int_A (1 - e^{-g(x)}) dx}$$

— Taking $A \rightarrow \mathbb{R}^d$ gives the result.

Alternatively, if $f(x) > 0$,

$$\mathbb{E} \left[\frac{1}{n} \sum_{i=1}^n f(x_i) \right] = \exp \left\{ -\lambda \iint_{\mathbb{R}^2} (1 - f(x)) dx \right\}$$

Total Interference Power - 15min

Friday, February 9, 2018 10:49 AM

- Assume unit transmission power at all BS
- The channel between the mobile and the nearest BS has two components
- The path-loss component is r^{-n}
- Key assumption #2: The multi-path fading component is Rayleigh, i.e.; α is distributed as

$$f(\alpha) = \frac{\alpha}{A^2} e^{-\frac{\alpha^2}{2A^2}}$$
- This implies that α^2 is exponential with mean $\frac{1}{2A^2}$
- Hence, the overall received power at the mobile is

$$h \cdot r^{-n}$$
 - where h is exponential with mean $\frac{1}{\mu}$.

$$P[h \geq a] = e^{-\mu a}$$
- The SNR is

$$SNR = \frac{h r^{-n}}{I_r + \sigma^2}$$
 - where I_r is the total interference

$$I_r = \sum_{i \neq b_0} \underbrace{\delta_i}_{\text{fading}} \cdot \underbrace{R_i^{-n}}_{\text{path loss}}$$

unit power

- Given that h , S_i , r & R_i are all random, it seems very difficult to obtain a single form for the SINR in the average sense.
- Below, we will see the Rakeleigh & PPP assumption simplifies the calculation.
- Our first goal is to derive a simple expression for the coverage probability, i.e., the probability that the SINR is above a threshold τ .
- In particular, we will show that when $\sigma^2 = 0$

$$P(\text{SINR} > \tau)$$

$$= \frac{1}{1 + p(\tau, \alpha)}$$



a number independent of λ & μ .

- Let us first study the coverage probability, i.e. the SNR at the mobile is greater than a threshold T .
- First, condition on r (the distance to the serving BS).

$$\begin{aligned}
 & P[SNR > T | r] \\
 &= P\left[\frac{hr^{-n}}{I_r + \sigma^2} > T \mid r\right] \\
 &= E\left[P\left[\frac{hr^{-n}}{I_r + \sigma^2} > T \mid I_r, r\right]\right] \\
 &= E\left[P[h > Tr^n(I_r + \sigma^2) \mid I_r, r]\right] \\
 &= E\left[e^{-\mu Tr^n(I_r + \sigma^2)} \mid r\right] \\
 &= e^{-\mu Tr^n \cdot \sigma^2} \cdot \underbrace{E\left[e^{-\mu Tr^n \cdot I_r} \mid r\right]}_{\text{the m.g.f. of } I_r}
 \end{aligned}$$

- Define $L_X(s) = E[e^{-sX}]$
- This term is $L_{I_r}(\mu Tr^n)$

- In other words, if we know the Laplace transform of I_r , we can express the coverage probability in closed-form.

Simplifying the Laplace transform

$$I_r = \sum_{i \neq b_0} g_i R_i^{-n}$$

r is the location of the other BSs: Φ

— Condition on the location of the other BSs : $\underline{\Phi}$

$$\begin{aligned} & \mathbb{E}[e^{-sI_r} | \underline{\Phi}] \\ &= \mathbb{E}\left[e^{-s \sum_{i \neq b_0} \delta_i R_i^{-n}} \middle| \underline{\Phi}\right] \\ &= \prod_{i \neq b_0} \mathbb{E}\left[e^{-s R_i^{-n} \cdot \delta_i} \middle| \underline{\Phi}\right] \end{aligned}$$

- And then we need to take the integral over R_i
- When δ_i is also exponential with mean $\frac{1}{\mu}$, the above expression can be greatly simplified.

$$\begin{aligned} \mathbb{E}[e^{-s\delta}] &= \int_0^{+\infty} e^{-s} \cdot e^{-\mu a} \mu da \\ &= \frac{\mu}{s + \mu} \end{aligned}$$

$$\Rightarrow \mathbb{E}[e^{-sI_r} | \underline{\Phi}] = \prod_{i \neq b_0} \frac{\mu}{\mu + s R_i^{-n}}$$

Integrating over R_i 's

— Each R_i is independent and is only outside r .

$$L_{I_r}(s) = \mathbb{E}\left[\prod_{i \neq b_0} \frac{\mu}{\mu + s R_i^{-n}}\right]$$

$$= \exp\left\{-\lambda \int_r^{+\infty} \left(1 - \frac{\mu}{\mu + s R^{-n}}\right) 2\pi R dR\right\}$$

$$\Rightarrow L_{I_r}(\mu T r^n) = \exp\left\{-\lambda \int_r^{+\infty} \left(1 - \frac{\mu}{\mu + \mu T \left(\frac{r}{R}\right)^n}\right) 2\pi R dR\right\}$$

$$\rightarrow L_{Ir}(\mu T) = \exp \left\{ -\lambda \int_0^{\infty} \frac{1}{\frac{1}{T} \left(\frac{R}{r}\right)^n + 1} 2\pi r^2 dr \right\}$$

The integral can be written as

$$\begin{aligned} & \int_0^{\infty} \frac{1}{\frac{1}{T} \left(\frac{R}{r}\right)^n + 1} d\left(\frac{R}{r}\right)^2 \cdot r^2 \\ &= \int_1^{\infty} \underbrace{\frac{1}{\frac{1}{T} u^n + 1}}_{p(\tau, n) \text{ a number}} \cdot du^2 \cdot r^2 \end{aligned}$$

$$\text{Then } L_{Ir}(\mu T r^n) = e^{-2\lambda r^2 p(\tau, n)}$$

$$- P[SINR > T]$$

$$= \int_0^{\infty} 2\lambda r e^{-\lambda \pi r^2} dr.$$

$$e^{-\mu T r^n \cdot \sigma^2} \cdot e^{-2\lambda r^2 p(\tau, n)}$$

$\sigma^2 = 0$: noise is negligible compared to signals.

$$P(SINR > T)$$

$$= \int_0^{\infty} 2\lambda e^{-2\lambda r^2 (1 + p(\tau, n))} dr^2$$

$$= \frac{1}{1 + p(\tau, n)}$$

- Let us first study the coverage probability, i.e. the SNR at the mobile is greater than a threshold T .
- First, condition on r (the distance to the serving BS).

$$\begin{aligned}
 & P[SNR > T | r] \\
 &= P\left[\frac{hr^{-n}}{I_r + \sigma^2} > T \mid r\right] \\
 &= E\left[P\left[\frac{hr^{-n}}{I_r + \sigma^2} > T \mid I_r, r\right]\right] \\
 &= E\left[\quad \mid I_r, r\right] \\
 &= E\left[\quad \mid r\right] \\
 &= e^{-\mu T r^n \cdot \sigma^2} \cdot \underbrace{E\left[e^{-\mu T r^n \cdot I_r} \mid r\right]}_{\text{the m.g.f. of } I_r}
 \end{aligned}$$

- Define $L_X(s) = E[e^{-sX}]$
- This term is $L_{I_r}(\mu T r^n)$

- In other words, if we know the Laplace transform of I_r , we can express the coverage probability in closed-form.

Simplifying the Laplace transform

$$I_r = \sum_{i \neq b_0} g_i R_i^{-n}$$

r is the location of the other BSs: \vec{r}

— Condition on the location of the other BSs : $\underline{\Phi}$

$$\begin{aligned} & \mathbb{E}[e^{-sI_r} | \underline{\Phi}] \\ &= \mathbb{E}[e^{-s \sum_{i \neq b_0} g_i R_i^{-n}} | \underline{\Phi}] \\ &= \end{aligned}$$

- And then we need to take the integral over R_i
- When g_i is also exponential with mean $\frac{1}{\mu}$, the above expression can be greatly simplified.

$$\mathbb{E}[e^{-st}] =$$

$$\Rightarrow \mathbb{E}[e^{-sI_r} | \underline{\Phi}] =$$

Integrating over R_i 's

— Each R_i is independent and is only outside r .

$$L_{I_r}(s) = \mathbb{E}\left[\prod_{i \neq b_0} \frac{\mu}{\mu + s R_i^{-n}}\right]$$

$$\Rightarrow L_{I_r}(\mu_T r^n) = \exp\left\{-\lambda \int_r^{+\infty} \left(1 - \frac{\mu}{\mu + \mu_T (\frac{r}{\kappa})^n}\right) \kappa d\kappa\right\}$$

" $r < \infty$ " 1

$$\begin{aligned}
 \rightarrow L_{Ir}(\mu T r^n) &= \exp \left\{ -\lambda \int_r^{+\infty} \frac{\mu T (\frac{r}{R})^n}{\mu + \mu T (\frac{r}{R})^n} 2 dr^2 \right\} \\
 &= \exp \left\{ -\lambda \int_r^{+\infty} \frac{1}{\frac{1}{T} (\frac{R}{r})^n + 1} 2 dr^2 \right\}
 \end{aligned}$$

The integral can be written as

$$\begin{aligned}
 &\int_r^{+\infty} \frac{1}{\frac{1}{T} (\frac{R}{r})^n + 1} d(\frac{R}{r})^2 \cdot r^2 \\
 &= \underbrace{\hspace{10em}}_{p(\tau, n) \text{ a number}}
 \end{aligned}$$

$$\text{Then } L_{Ir}(\mu T r^n) = e^{-2\lambda r^2 p(\tau, n)}$$

$$\begin{aligned}
 - P[SINR > T] &= \\
 &= \int_0^{+\infty} 2\lambda r e^{-\lambda 2r^2} dr \cdot \\
 &\quad e^{-\mu T r^n \cdot \sigma^2} \cdot e^{-2\lambda r^2 p(\tau, n)}
 \end{aligned}$$

$\sigma^2 = 0$: noise is negligible compared to signals.

$$\begin{aligned}
 P(SINR > T) &= \\
 &= \int_0^{+\infty} 2\lambda e^{-2\lambda r^2 (1 + p(\tau, n))} dr^2 \\
 &= \frac{1}{1 + p(\tau, n)}
 \end{aligned}$$

$$= \frac{1}{1 + \rho(\tau, \alpha)}$$

— When fading is Rayleigh and $\sigma^2 = 0$, the coverage probability is independent of λ

Implication

Sunday, February 11, 2018 11:39 AM

- When fading is Rayleigh and $\sigma^2 = 0$, the coverage probability is independent of λ
- In other words, the network can be arbitrarily dense ^{or sparse}, but the coverage probability remains the same.
- Even if $\sigma^2 \neq 0$, likely hold when $\lambda \rightarrow +\infty$.