Wireless Network Recommendation System in Heterogeneous Networks

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Background

- Extreme densification in 5G
  - Benefit:
    - Reuse of spectrum
    - Higher network capacity
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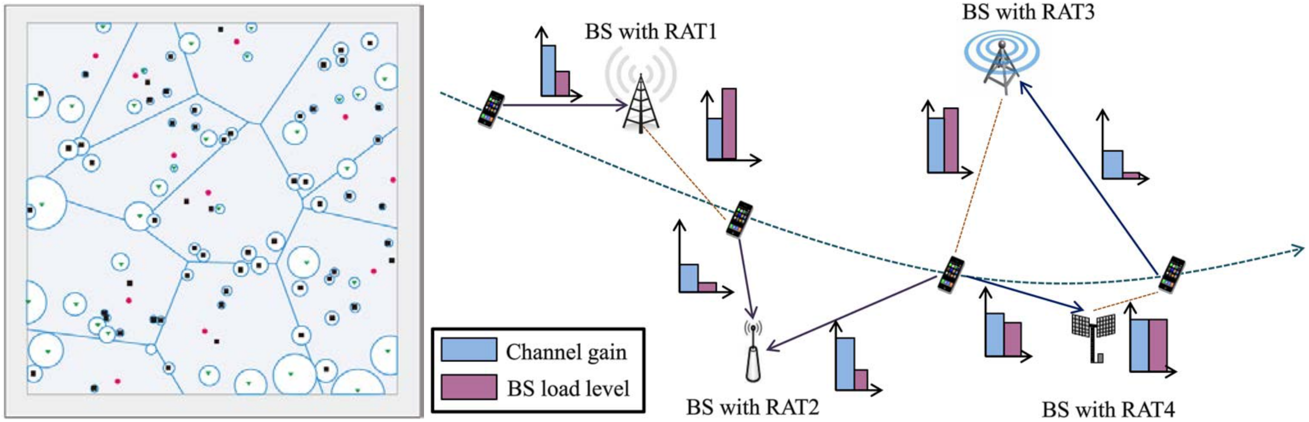
  - User association with small cells with different RATs
    - E.g. mmWave, 4G LTE releases, 3G, WiFi, D2D
    - Frequent handoff
    - Harder to monitor small cell base stations



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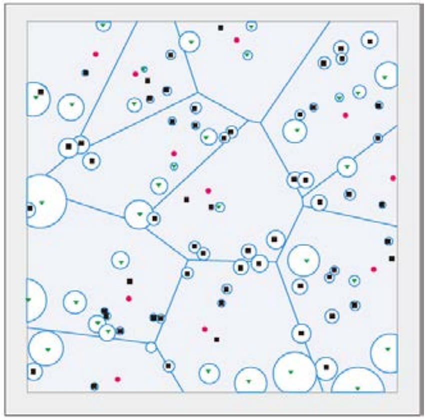
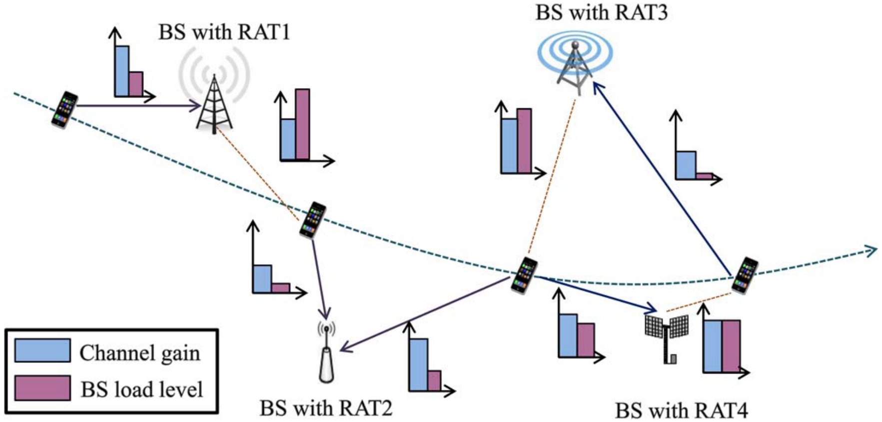
- New user association schemes are needed for better quality of service (QoS).





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- Existing approaches
  - Biasing
  - Utility function
    - Traffic load, transmission power, spectrum resource, etc…
    - Optimization, game theory, etc…

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Passive approaches

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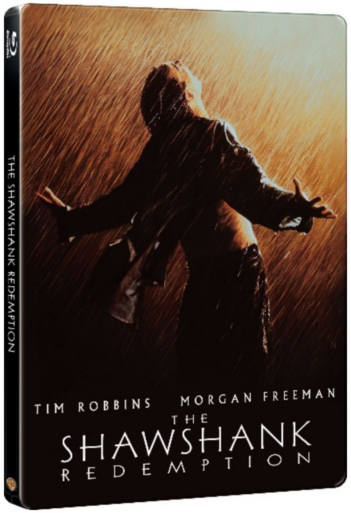
- Choosing movies: a lesson we can learn
  - Past
    - Themes of movies
    - Judgement from others



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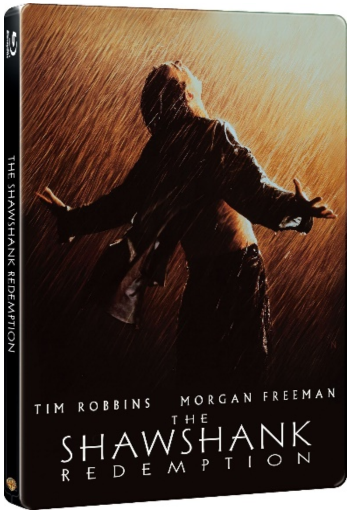
  - Now
    - Recommendation systems!



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- Proactive approaches
  - Historical QoS information
  - Preferences
  - Social interactions

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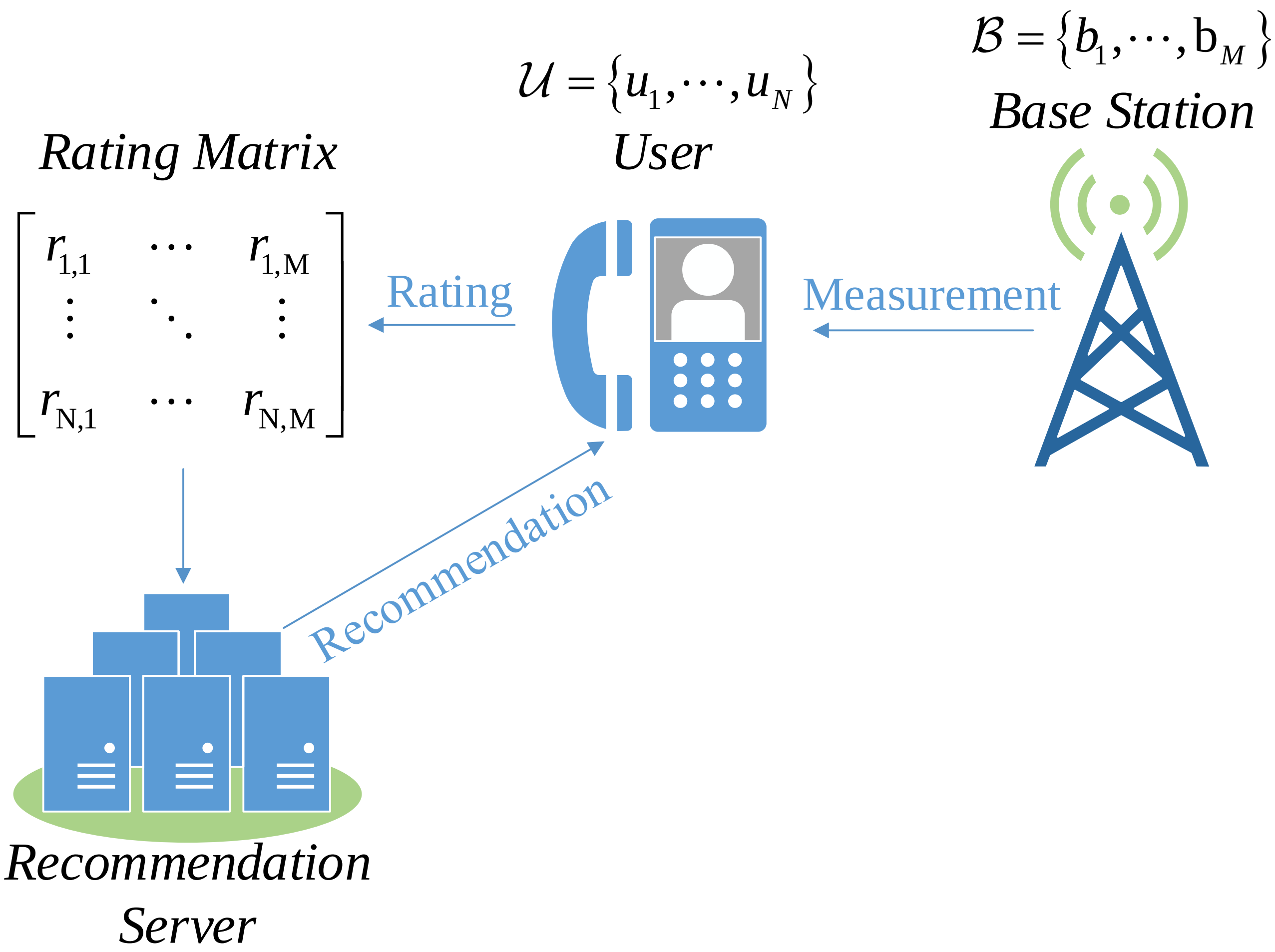
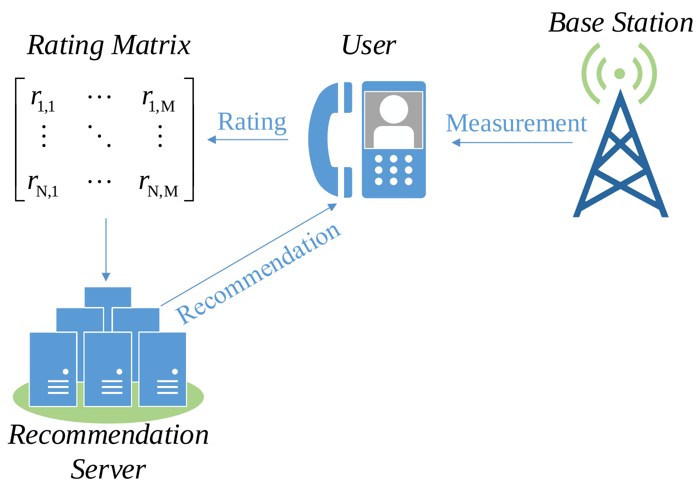
Network Recommendation System!

System Architecture



System Architecture

- Measurement
  - Signal strength, delay, packet loss rate…



System Architecture

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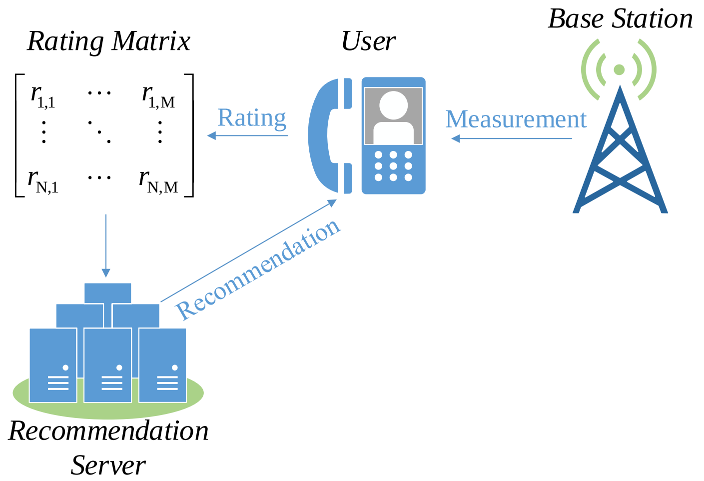
- Rating
  - Mean opinion score (MOS)
  - E.g. E-model (VoIP, ITU-T G.107)



E-model

- Transmission rating factor

$$R = Ro - Is - Id - Ie_{eff} + A$$

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Ro → SNR

Id → delay

Ie_{eff} → packet loss

E-model

- Transmission rating factor

$$R = Ro - Is - Id - Ie_{eff} + A$$

- Mean Opinion Score

$$MOS = \begin{cases} 1 & T < 0, \\ 1 + 0.035R + R(R-60)(100-R) \cdot 7 \cdot 10^{-6} & 0 < T < 100, \\ 4.5 & T > 100, \end{cases}$$

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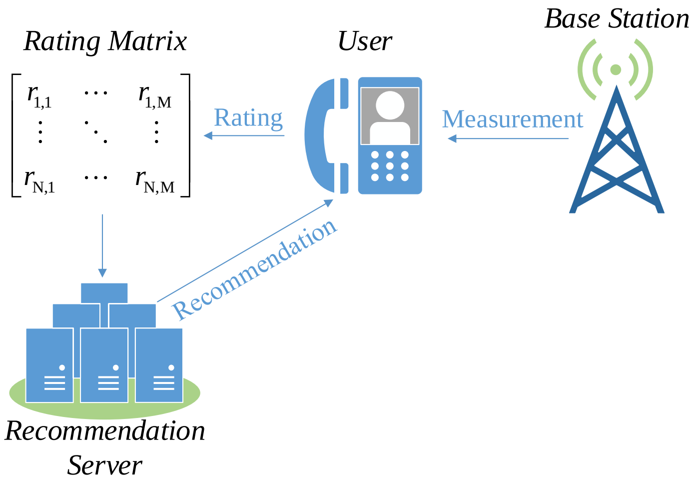
- Recommendation
  - Collaborative filtering



Collaborative Filtering

- Recommendation value

$$f_{ij}^{CF}(\mathbf{R}) = \frac{\sum_{k \in Neighbor(i)} r_{kj} F_{sim}(i,k)}{\sum_{k \in Neighbor(i)} F_{sim}(i,k)}$$

- Similarity $F_{sim}(i,k)$
  - Rating vector
  - Location

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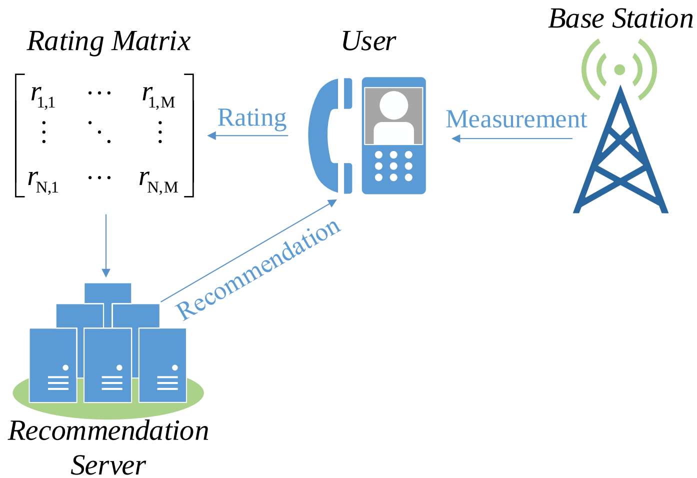
- Selection
  - Selection probability proportional to recommendation value



To Rate or Not?

- Rating improves recommendation quality
  - More historical information
- Rating takes costs
  - Computational resource
  - Privacy
- Tradeoff
  - Satisfaction game

Game Formulation

- Player: $\mathcal{U} = \{u_1, \cdots, u_N\}$
- Action: $\{\mathcal{A}_i\}_{i \in \{1,\cdots,N\}}$
  - $\mathbf{a}_i = (a_{i,1}, a_{i,2}) \in \mathcal{A}_i$
  - $a_{i,1}$: Choice of base station
  - $a_{i,2}$: Decision on whether to rate
- Correspondence: $f_i(\mathbf{a}_i) = \{\mathbf{a}_i \in \mathcal{A}_i : h_i(\mathbf{a}_i, \mathbf{a}_{-i}) \geq \Gamma_i\}$
  - Utility: $h_i(\mathbf{a}_i, \mathbf{a}_{-i}) = C\left(w\sigma_i + (1-w)\sigma_{-i}\right)\log(1 + SNR_i / K_i)$

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Rating completeness

Number of users connecting to the same base station

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    Rating completeness

    Number of users connecting to the same base station
  - Utility expectation: Γ_i

Game Formulation

- Satisfaction equilibrium (SE)
  - An action profile $\mathbf{a}^{+}$ is a satisfaction equilibrium for the satisfaction game, if $\forall u_i \in \mathcal{U}$, we have $\mathbf{a}_i^{+} \in f_i\left(\mathbf{a}_{-i}^{+}\right)$.

Learning the SE

- Choosing base station

$$\pi_{i,1}^{(j)}(n) = \hat{r}_{ij}(n) / \sum_{k=1}^{M} \hat{r}_{ik}(n)$$

$$a_{i,1}(n) \sim \boldsymbol{\pi}_{i,1}(n)$$

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- Judging satisfaction

$$v_i(n) = \begin{cases} 0, & h_i(\mathbf{a}_i, \mathbf{a}_{-i}) < \Gamma_i, \\ 1, & h_i(\mathbf{a}_i, \mathbf{a}_{-i}) \geq \Gamma_i. \end{cases}$$

Learning the SE

- Deciding whether to rate
  - $v_i(n) = 0$：

$$\begin{cases} \pi_{i,2}^{(0)}(n) \sim \sigma_i(n)\alpha^{-c_i(0)} \\ \pi_{i,2}^{(1)}(n) \sim \left(1-\sigma_i(n)\right)\alpha^{-c_i(1)} \end{cases}$$

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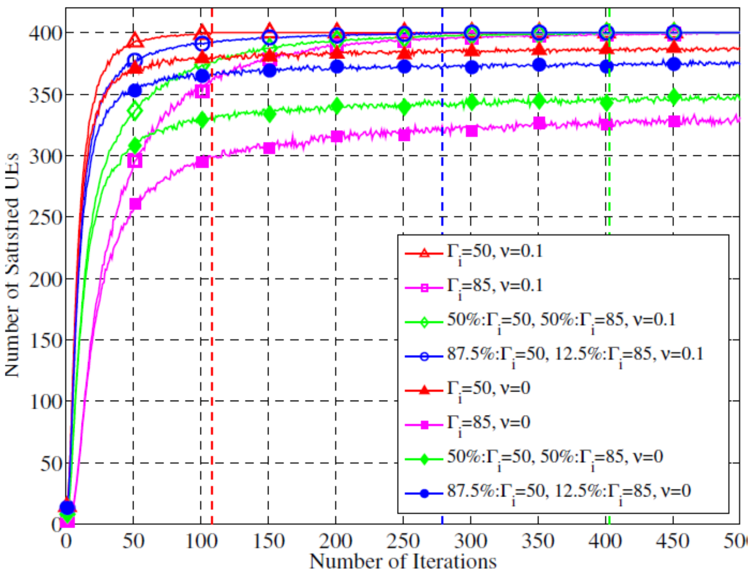
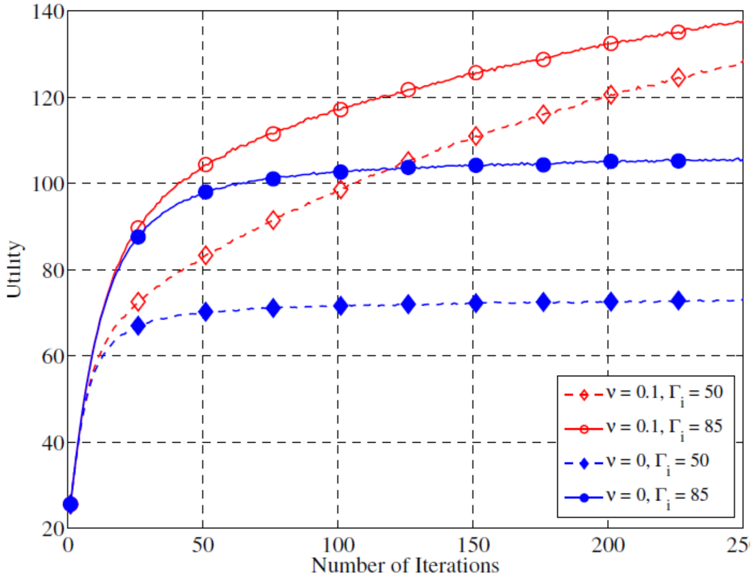
Simulation Results



(a) The number of satisfied UEs vs. the number of iteration.



(b) The utility vs. the number of iteration.

Conclusion

- We propose a novel wireless network recommendation system.
- We formulate a satisfaction game to address the tradeoff between rating or not.
- We propose an algorithm to learn the satisfaction equilibrium and perform simulations to verify it.

Thank you!

If you have any questions or suggestions, please contact:
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for further discussion.