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Efficient Online Recommendation Based on Ensemble Sampling

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GS&P Beta Group

Something about me

- Currently a 2nd year Ph.D. student in Operations Research at Stanford University
  - Research interests: sequential decision making under uncertainty, multi-armed bandits, reinforcement learning
  - My contact outside Adobe – lxy@stanford.edu

- Some interesting projects I've worked on…
  - Ensemble sampling – a computationally efficient variant of Thompson sampling for bandit problems that have intractable posterior distributions

Online Recommendation

- Recommendation systems

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Adobe® Campaign

- Limitations of traditional recommendation systems
  - Slow to adapt to changes in user features
  - No principled way to handle new users and new items

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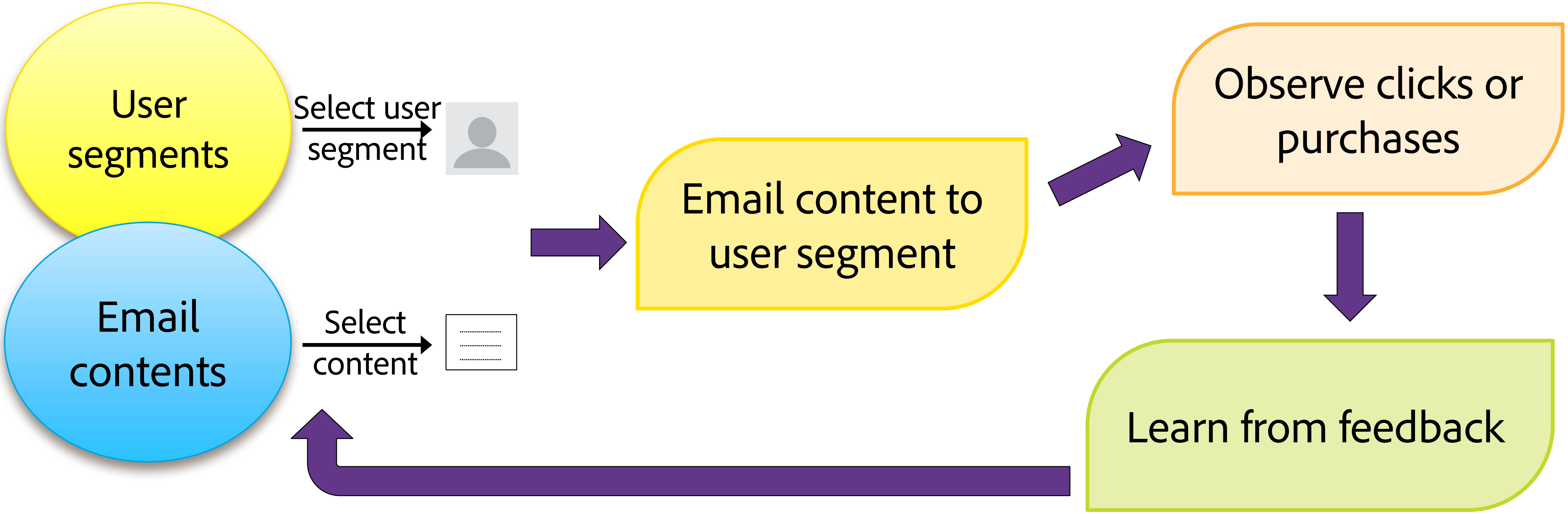
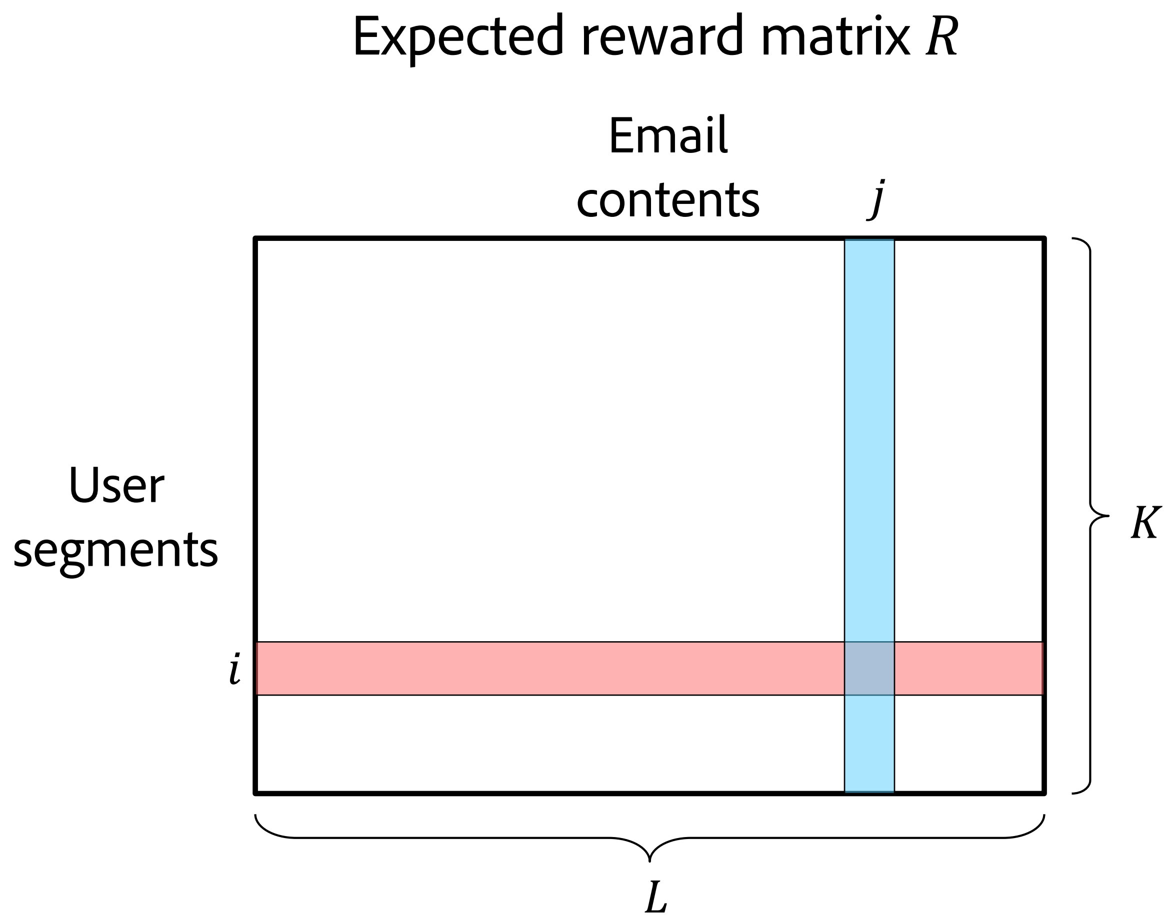
- Online recommendation
  - Easy to adapt to changes
  - Handles the cold start problem naturally
  - Actively learns about users and items, not just limited to training data

- Adobe Campaign
  - Sends marketing emails to users
  - Decisions are multi-dimensional



Problem Formulation



- Formulate as a multi-armed bandit
- At each time step t:
  - Select segment i and content j
  - Receive stochastic reward with mean R_{ij}
- **Goal** is to maximize expected cumulative reward over time, i.e., we want to learn the best combination of user segments and email contents over time

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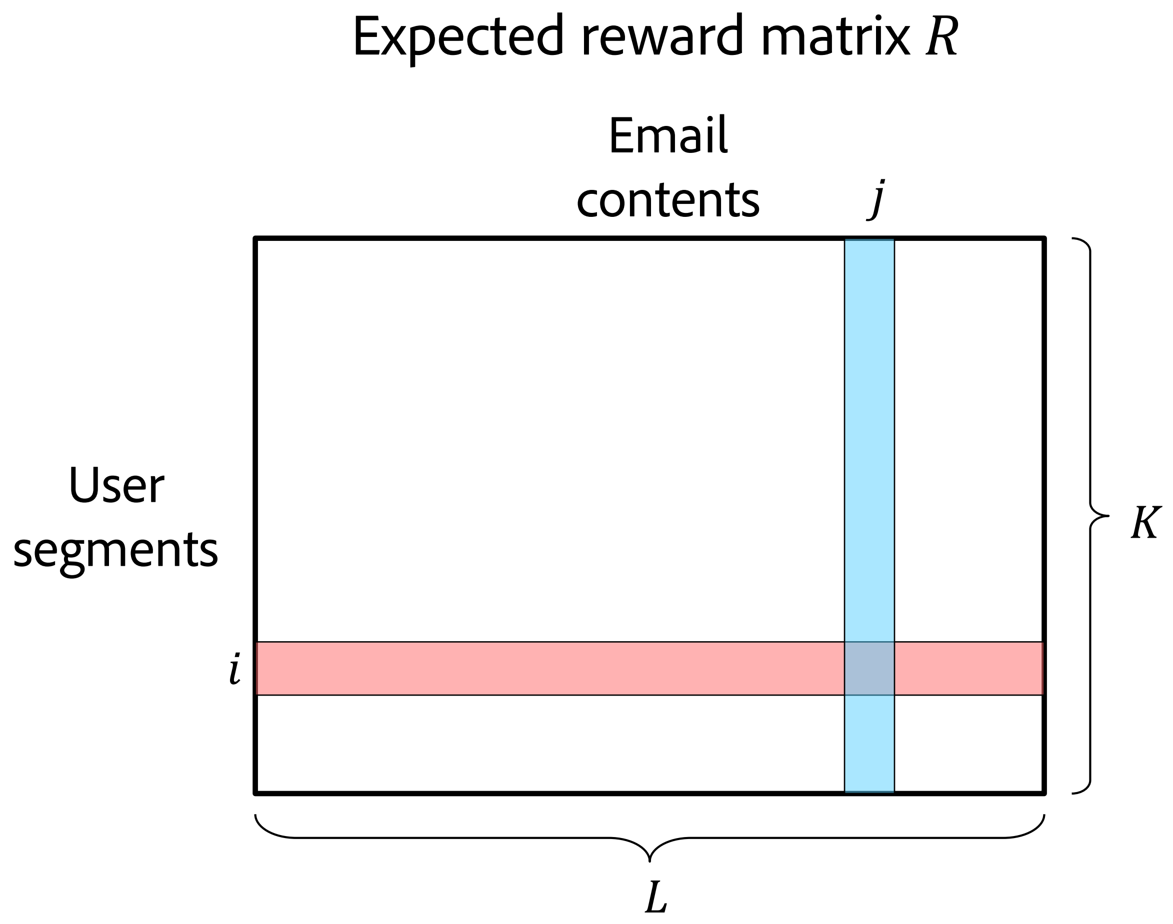

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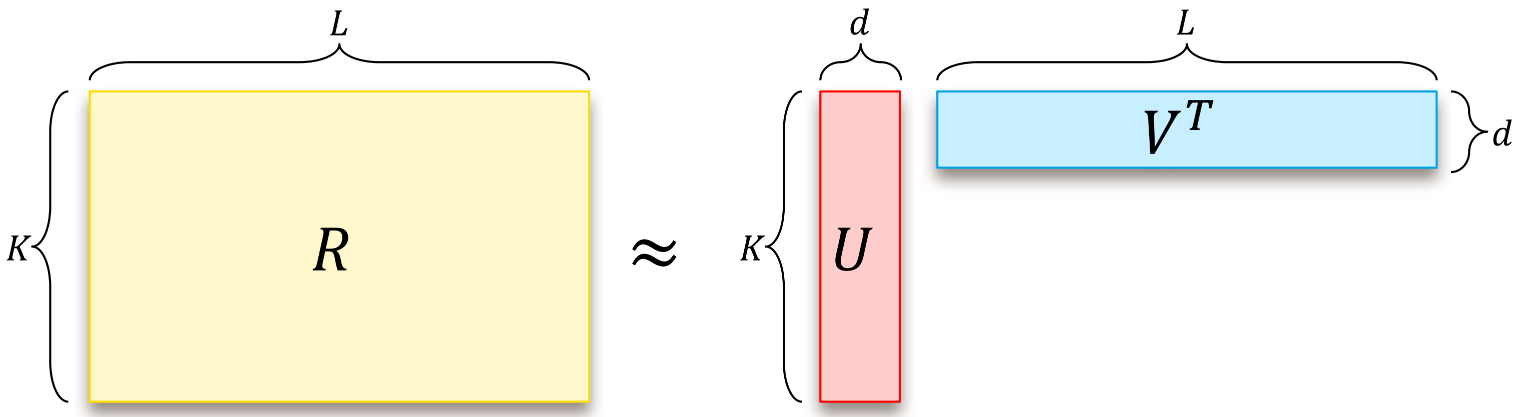
- If we don't know anything about R, we would need to sample every entry at least once, but KL could be extremely large!

Problem Formulation

- Key assumption: R can be approximated by a low-rank matrix
  - Typical in recommendation problems

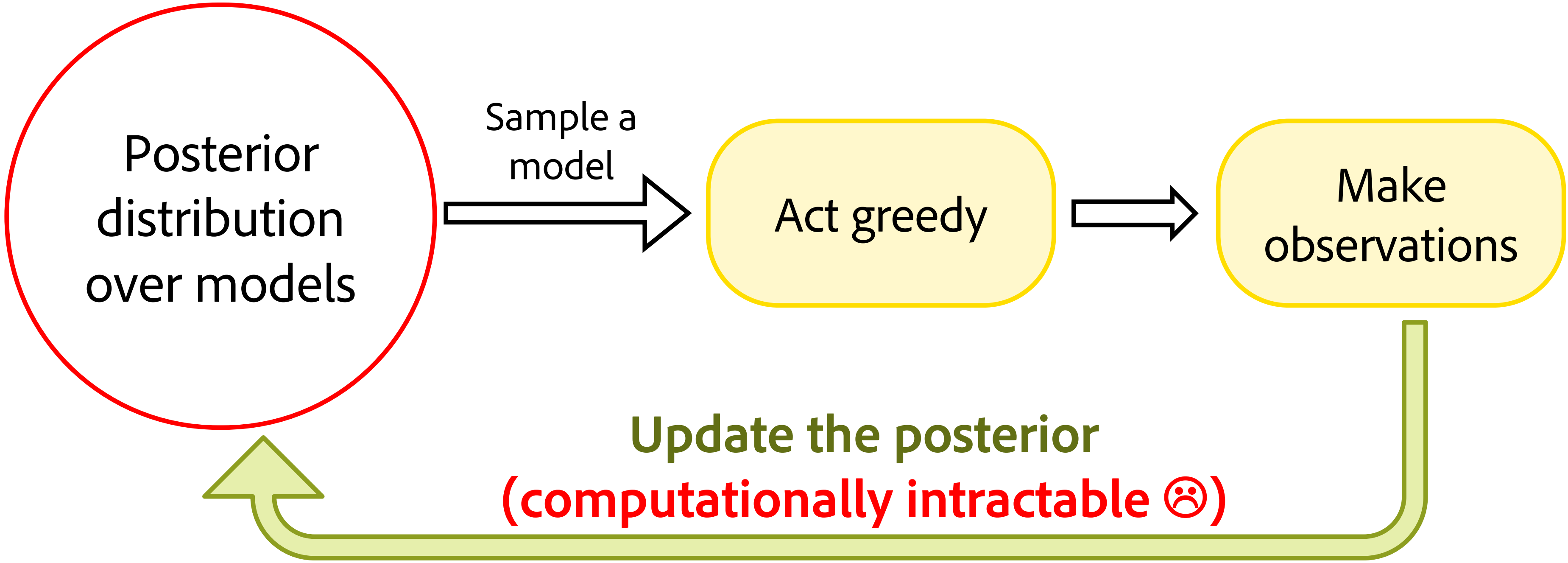


  - Number of parameters reduces from KL to $(K + L)d$

- We can exploit the low-rank structure to design better bandit algorithms!

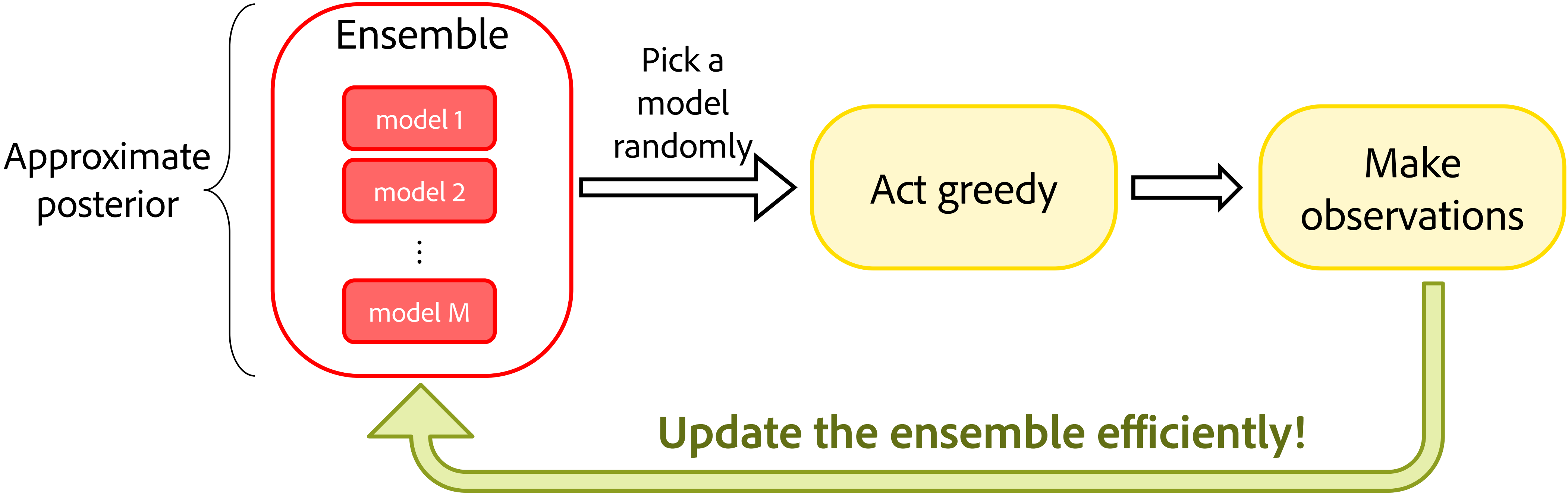
Thompson Sampling

- Thompson sampling is a popular algorithm for bandit problems.
- It selects actions according to their probabilities of being the optimal action.



Ensemble Sampling

- One potential solution is to use ensemble sampling, which is an approximation to Thompson sampling.
- The idea is to use an ensemble of models to approximate the posterior.



This Summer's Internship Goal

- Design efficient ensemble sampling algorithms for low-rank matrices
- Perform theoretical analysis on the algorithms
- Conduct computational experiments with both synthetic and real-world data

Timeline

- Week 1-3
  - Define project
  - Review literature
- Week 4-10
  - Design algorithms
  - Run experiments
  - Analyze algorithms
- Week 10-11
  - Prepare deliverables

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