Multi-Arm Bandit for Recommendation Systems

Algorithm:

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A simple bandit algorithm  \begin{aligned} &\text{Initialize, for } a = 1 \text{ to } k \text{:} \\ &Q(a) \leftarrow 0 \\ &N(a) \leftarrow 0 \end{aligned}   \begin{aligned} &\text{Loop forever:} \\ &A \leftarrow \left\{ \begin{array}{ll} \arg \max_a Q(a) & \text{with probability } 1 - \varepsilon \\ &\text{a random action } & \text{with probability } \varepsilon \end{array} \right. \end{aligned}   \begin{aligned} &R \leftarrow bandit(A) \\ &N(A) \leftarrow N(A) + 1 \\ &Q(A) \leftarrow Q(A) + \frac{1}{N(A)} \left[ R - Q(A) \right] \end{aligned}
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- Based on the MAB algorithm defined above, we need to first define the actions and rewards for our problem setting.
- Let's assume we have a movie recommendation system, where we need to recommend movies to the
 user based on their preferences.
- Actions being in our case is to select a optimal action of preferred movie for the user. Each set of
 actions can represent a collection of movies and each movie can have a corresponding reward
 distribution.
- The reward can be defined based on user interactions such as clicks, ratings, or watch time after a
 movie is recommended.
- Our Goal is to maximize the overall reward that is for the system to recommend movies that can engage the user.
- We could model the system/bandit to have an exploit explore factor based on a probability epsilon.