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**Guiding questions:**

The questions below are intended to guide you in putting together the different pieces of your projects. Please fill in these questions and submit them (see link on course website). This will account for 10% of your project’s grade, so invest time and effort appropriately. (Note: these questions may not be a perfect fit for all topics and projects; if you feel yours does not fit well within these guidelines - talk to us about it)

1. Chosen topic:
   1. Primary: Model-Induced Distribution Shift.
   2. Secondary: Discrete Choice and Strategic Dynamics.
2. Relevant course unit(s):
   1. Unit 4; Dynamics (user distribution shift).
   2. Unit 5; Strategy - Strategic Recommende
3. What is your project about? State concrete and testable research question(s).
   1. Primary:

Assumption: the model predicting users’ distribution shift is time and user invariant.

Research Question: will a recommender benefit from this underlying model assumption, in a sense of maximizing users-items set ARRI?

* 1. Secondary:

Introduction: given a population of users affected by the similarity context effect, suppliers can use this information to improve their benefits by including outlier items in their items set and price it highly.

Research Question: what would be the consequences when multiple suppliers try to be strategic and utilize the same context effect by using the same methodologies?

1. State your hypotheses and/or conjectures. For each, explain how you plan to test it.
   1. Primary: we hypothesis that the recommender can perform a “one step lookahead approximation” and improve its long-term ARRI given a learned model of users’ distribution shift.

*Notes for future selves:*

(i) a sufficient number of active users is needed for the recommender to be sample-efficient given each user contributes one sample on each time step.

(ii) The distribution shift function can be learned in a supervised fashion from one time step to in subsequent, by minimizing some distribution-to-distribution distance measure such as KL divergence or EM.

* 1. Secondary: The similarity context effect will be “canceled-out” if all suppliers apply the same methodologies for utilizing it at the same time.

1. Describe the setting or environment you plan to experiment in. Give concrete details, and state which parts are based on real data (if at all), and which are simulative (remember that fully simulative is also fine if it justifies its purpose).
2. Describe your approach. Which learning algorithms will you use? How do you intend to construct the simulation? What experiments do you plan to run? What parameters do you intend to vary? Connect these to your research goal and hypotheses and/or conjectures.

We will tackle the problem by supervising the learning of . The training of the recommender’s predictive model will be kept with no change. When moving from time step to , we would know how the distribution has shifted, thus we can engage the model learning to learn this shift. By providing it the distribution at time , we supervise its prediction to be close to the new distribution at time (w.r.t to some distance measure).

TBD …

1. What code do you plan to use, and from what sources? E.g., public packages/repos, code from homework/workshops, new code (if so, describe it in brief).
2. List three potential pitfalls that you anticipate may occur. Try to plan your response.

1. Simultaneous training on two dependent models tends to be highly unstable and hard to converge properly. We plan to try and fit the following models alternately: The recommender predictive model of users’ preferences’ distribution, defined by its weights , and the distribution shift model . Response: TBD.

2.

3.