We wish to thank you all for your constructive comments with valuable insights to refine the paper.

Reviewer 1

You are right, the categories are assumed to be known in advance. Yet this is actually natural in e-commerce (think of the main "categories" in Amazon, as "high-tech", "smartphone", "wine", "clothes", etc.). The major difficulty is that the "optimal" category, with the best arm, is unknown and eliminating the other categories is not that trivial. In particular, just comparing the μ_1^j incurs a sub-optimal regret. It is necessary to build statistics using information gathered on all arms of a given category to eliminate it efficiently. For instance, it might be the case that μ_1^j are arbitrarily close to each other (even indistinguishable) but the information gathered on other, sub-optimal, arms can be used to eliminate sub-optimal categories.

This is where the different dominance relations kick in: the stronger the relation, the "easier" it is to distinguish them. Again, the main point is that, using this assumption, it is possible to aggregate information gathered on **all** arms to eliminate categories, way quicker than without it (roughly speaking, if the category has K arms, then the time needed is more or less divided by K with the stronger concept of dominance).

As you noticed - and mentioned in the paper -, there are other papers focusing on similar (and sometimes more general) settings; yet algorithms previously developed cannot leverage the dominance assumption at their full extent. They incur a much larger regret (say, multiplied by K in some cases, which prevents practical implementation). Our contributions are to derive specific algorithms with well-designed statistics (again, using all arms of a category) to increase drastically the learning speed of algorithms.

Reviewer 2

1. The learning agent knows the categories and the type of dominance between the best category and the other ones (as you noticed, sub-optimal categories might not be comparable with each other, only the optimal one needs to dominate the others).
2. The dominance assumptions are strongly related to stochastic dominances between random variables. It is easier to consider the definition in terms of cumulative distribution function between 2 categories. Denote them by F and G. Strong dominance of G states that $G(x) > 0$ only if $F(x) = 1$. On the other hand, first-order states that $F(x) \leq G(x)$. Thus strong dominance is actually the "limit case" of first-order dominance.
3. Indeed, in real applications, most categories are not immediately comparable for these notions of dominance if data are aggregated over all users (since some users prefer high-tech to wine and vice versa). However, if users are clustered using other data (past behavior say) with "similar" appetence for categories, dominances arise. The main difficulty is actually that categories contains too many items with almost zero value (almost nobody buys them). This long tail property "kills" the dominances. However, dominance does exist between the "top-K" items of categories (with K of the order of 10 or 20 depending on the granularity). The practical implementation of our algorithms focuses on those items.
4. The regret curves are straight lines in Figure 3(a) (in log-scale) because the logarithmic regime is already attained at the time step in which the curves begin (we truncated the initialization regime as it blurs the plot). We will add the error bars.

Reviewer 3

Thank you for the reference. We will add it and discuss their results.

You are correct, the CATSE algorithm can be improved for the group-sparse case. We will mention it in the revised version of the paper even if it only improves a term independent of the horizon T. Concerning this specific setting: you are right, it is not really natural for e-commerce applications (it would be weird to know the threshold in advance). Yet we believe it is still interesting for the completeness of the theoretical understanding. Moreover, group-sparsity is a standard assumption in learning and our analysis could be useful to other practitioners. This said, if reviewers all agree with you on that point, we are willing to postpone that section to the Appendix to gain some space and then detail more the other sections.

The code will be available on a git-hub (unfortunately, it does not seem to be possible to do it right now for anonymity reason).