View Reviews

Paper ID
6037

Paper Title
Bayesian experimental design using regularized determinantal point processes

Reviewer #1

Questions

1. Contributions: Please list three things this paper contributes (e.g., theoretical, methodological, algorithmic, empirical contributions; bridging fields; or providing an important critical analysis). For each contribution, briefly state the level of significance (i.e., how much impact will this work have on researchers and practitioners in the future?). If you cannot think of three things, please explain why. Not all good papers will have three contributions.
This paper proposes novel approximate algorithms for experimental design problems under different optimality criteria. The theoretical analysis is strong and might be relevant to other researchers.

2. Detailed comments: Please provide a thorough review of the submission, including its originality, quality, clarity, and significance. Hover over the "?" next to this prompt to see a brief description of these metrics.
Originality. With the caveat that I am not an expert in this subfield, my understanding is that this paper gives solutions to several experimental design criteria (A,C,D,V), therefore is pretty general, and also gives a new bound for the number of elements k that we can perform experiments.

Quality. As far as I can tell, this paper explores reasonable research questions and presents technically correct statements.

Clarity. The material is dense but the presentation is very clear. I am not an expert in this particular area and I really appreciate the exposition.

Significance. Experimental design is an important topic of research and this paper provides contributes to the understanding of the problem with respect to its limitations and algorithmic solutions.

3. Please provide an "overall score" for this submission.
6: Marginally above the acceptance threshold. I tend to vote for accepting this submission, but rejecting it would not be that bad.

4. Please provide a "confidence score" for your assessment of this submission.
3: You are fairly confident in your assessment. It is possible that you did not understand some parts of the submission or that you are unfamiliar with some pieces of related work. Math/other details were not carefully checked.

5. Improvements: What would the authors have to do for you to increase your score?
I think it is important to add, at least, a paragraph for conclusion. Changing the references to numbers might give you tow or three lines, for example.

Reviewer #3

Questions

1. Contributions: Please list three things this paper contributes (e.g., theoretical, methodological, algorithmic, empirical contributions; bridging fields; or providing an important critical analysis). For each contribution, briefly state the level of significance (i.e., how much impact will this work have on researchers and practitioners in the future?). If you cannot think of three things, please explain why. Not all good papers will have three contributions.

1. Connection between Determinantal Point Processes and Bayesian experimental design.
2. new algorithm
3. some theoretical results

2. Detailed comments: Please provide a thorough review of the submission, including its originality, quality, clarity, and significance. Hover over the "?" next to this prompt to see a brief description of these metrics.

Review of "Bayesian experimental design using regularized determinantal point processes."

Summary: the paper proposes a new algorithm for Bayesian experimental design (selecting k<n rows to sample / gather labels from a n x p matrix). Section 1 gives an extended introduction to the problem setting and related work in Bayesian experimental design and Determinantal Point Processes (DPPs). A linear model with a prior precision matrix A is assumed. Section 2 discusses additional related work. Section 3 provides an introduction to DPPs, and some theoretical results. Section 4 provides some proofs about DPPs for Bayesian experimental design. Section 5 provides empirical evidence that the proposed algo achieves lower A-optimality criteria values than several baselines, in the mg_scale data set.

Strengths:

The problem/topic of the paper, algorithms for optimal sample selection, is clearly interesting to the field of machine learning.

Empirical results in Figure 1 suggest that the upper bound of Theorem 1 holds in real data.

Weaknesses:

There are many Theorems/Lemmas and it is not always clear which are new results, and which are previous work. Can you please clarify/simplify?

There are no cross-validation (CV) experiments, so it is not clear whether or not the proposed algorithm provides predictions which are

significant better than previously proposed baselines. It would be
much more convincing to add another figure that shows mean/sd of test
error in k-fold CV.

Comments/Suggestions:

Table 1 is a useful summary of previous work.

Figure 1 (left) is difficult/impossible to read (difficult to match
legend entries to corresponding lines). Can you use direct labels
instead please? i.e. put the method names next to the corresponding
lines.

3. Please provide an "overall score" for this submission.

3: A clear reject. I vote and argue for rejecting this submission.

4. Please provide a "confidence score" for your assessment of this submission.

4: You are confident in your assessment, but not absolutely certain. It is unlikely, but not impossible, that you did not understand some parts of the submission or that you are unfamiliar with some pieces of related work.

5. Improvements: What would the authors have to do for you to increase your score?

1. experiments
2. clarifications

(see detailed comments)

Reviewer #4

Questions

1. Contributions: Please list three things this paper contributes (e.g., theoretical, methodological, algorithmic, empirical contributions; bridging fields; or providing an important critical analysis). For each contribution, briefly state the level of significance (i.e., how much impact will this work have on researchers and practitioners in the future?). If you cannot think of three things, please explain why. Not all good papers will have three contributions.

1. Propose an algorithm of experimental design for finding the subset of the designs to experiment, and prove the conditions for the algorithm to achieve epsilon optimality. This may be a highly significant result, but the significance is not well presented in the paper.

2. The numerical experiments show that the proposed approach outperforms baselines. The level of significance is low. The performance of the proposed approach is not much different from the greedy bottom-up approach, and the practical merit of the proposed approach appears to be limited.

3. These two contributions are the main contributions.

2. Detailed comments: Please provide a thorough review of the submission, including its originality, quality, clarity, and significance. Hover over the "?" next to this prompt to see a brief description of these metrics.

This paper proposes a Bayesian approach to experimental design for linear regression. Given a prior precision matrix, the proposed approach finds the subset of input feature vectors to experiment (and obtain output values) in a way that some optimality is guaranteed with epsilon-approximation. The proposed approach relies on sampling from a determinantal point process (DPP). Numerical experiments show that the proposed approach outperforms baselines with respect to A-optimality, which is a way to measure the size of the posterior covariance.

Overall, this paper appears to make mathematical contributions, but their implications to machine learning tasks are not well demonstrated either through experiments or through qualitative explanation. Introduction should clarify the contributions in the context of machine learning. Also, it would be helpful if the algorithms are summarized as pseudo-code and pointed from Introduction.

The main theorems (Theorem 1-2) rely on sampling from DPPs, but the statement does not involve probabilistic modifications (in expectation, with high probability, etc.). If these theorems indeed hold as they are stated, what mechanisms of the proposed approach enables such deterministic guarantee?

3. Please provide an "overall score" for this submission.
4: An okay submission, but not good enough; a reject. I vote for rejecting this submission, although I would not be upset if it were accepted.

4. Please provide a "confidence score" for your assessment of this submission.
3: You are fairly confident in your assessment. It is possible that you did not understand some parts of the submission or that you are unfamiliar with some pieces of related work. Math/other details were not carefully checked.

5. Improvements: What would the authors have to do for you to increase your score?
Demonstrate the advantages of the proposed approach in machine learning tasks.