

1 Dear reviewers,

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4 Thank you for your feedback. Here are our responses to your questions and comments:

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6 **Reviewer 1:** Regarding Web and data mining conferences, we agree that this work is relevant to them as well. However,
7 we believe that due to stronger emphasis on optimization and ML rather than, say, on the empirical details of web page
8 change modelling, it will be more appreciated by the NeurIPS audience. Indeed, of the three recent works most related
9 to ours topic-wise (citations [2], [30], and [32]), two were published in ICML and NeurIPS.

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11 **Reviewer 2:** To answer your question about domain-level modeling of change rates: absolutely! This can
12 be and is done in practice. In the same vein, it is common to do it at the site level. The easiest way to incorporate
13 these change rate correlations into our approach is to use, e.g., a historical change rate average computed over pages
14 from a given domain as the initial change rate "guess" for new pages from this domain, with appropriately chosen
15 pseudocounts. (In Algorithm 4 the pseudocounts are 0.5, but for informed change rate estimates they should be higher.)
16 This won't affect our RL algorithm's theoretical guarantees, but will certainly improve its empirical convergence rate.

17 Concerning the scarce description of the dataset, experiments, and their analysis, we indeed had to make some hard
18 decisions in this area to conform to the initial submission's 8-page limit. However, if the paper is accepted, we will
19 use the extra 9th page to accommodate a shortened version of the evaluation metrics' and benchmark algorithms'
20 description from the Supplement (Sections 8.2 and 8.3). We will also move some of analysis from the Supplement's
21 Sections 8.4, 8.5, and 8.6's to that 9th page — a condensed version of most of their content is in Figure 1, 2, and 3's
22 captions in the main paper already. Last but not least, we will move a few details from the Supplement's Section
23 8.1 (*Dataset, Implementation, Hardware*) into the paper too. Much of Section 8.1's content will be in the writeup
24 accompanying the dataset itself though, which we will make public prior to NeurIPS. These changes will make the
25 paper's final version more self-contained than it currently is, and even leave space for a short conclusion.

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27 **Reviewer 3:** To clarify the claim about the optimality of our complete-observation algorithm: currently, we
28 can only claim that the policy it computes is optimal within its policy class, defined in Equation 6. We *believe* that
29 de-randomizing this class's best policy in some way should yield a globally optimal policy, but so far don't have a proof.

30 Mentioning interior-point methods is an excellent suggestion, we'll do that. Their complexity varies depending
31 on their assumptions about the objective and optimization region. Table 1.1 in <http://sbubeck.com/Bubeck15.pdf>
32 summarizes relevant results for interior-point as well as other convex optimization algorithms. For those whose single
33 iteration is equivalent to an iteration of Newton's method, the per-iteration complexity would indeed be around $O(|W|^3)$.

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35 Best regards,

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—The authors of submission #315.