

1 We thank the reviewers for reading the manuscript and for their feedback and suggestions. We will correct typos pointed  
2 out by the reviewers.

3 **Reviewer 1** We will add an overview of Online Convex Optimization to provide helpful background, as the reviewer  
4 suggested. Regarding the agnostic setting being more realistic; we first note that previous work on realizable agnostic  
5 boosting operates under the assumption that an access to a realizable weak learning oracle is given, meaning that the  
6 number of mistakes made by the weak learner is bounded, and the set of allowable sequences is restricted. In most  
7 real-world problems this assumption does not hold. In the agnostic setting that assumption is removed, and the learner  
8 is only assumed to compete with the best predictor in a given class, where the input sequence is not restricted and can  
9 be chosen adversarially.

10 **Reviewer 3** Online agnostic boosting is the primary contribution of this work, and we provide the first algorithm  
11 in this setting (which therefore cannot be compared to previous works). The application of our methodology to the  
12 other 3 settings is a secondary contribution, which serves as a testament to the generality of the OCO framework. In  
13 particular we did not intend to improve upon the state of the art here. The goal of introducing results in the other 3  
14 settings was to demonstrate the generality and uniformity of our approach. Indeed, our approach does not achieve  
15 quantitative improvement in the 3 settings that were previously studied, but merely demonstrates an abstraction that  
16 applies to all 4 cases.

17 - "interest of the ability to plug-in a generic OCO": First, we believe that an abstract reduction to a generic OCO (rather  
18 than e.g., specifically using OGD) yields a more modular proof which is simpler to comprehend (and a more general  
19 statement). In addition, one can imagine specific constrained settings in which specifically tailored OCOs will exhibit  
20 superior performance compared to general-purpose algorithms such as OGD/Exponential-Weights/etc.

21 - "the adopted boosting setting is not justified": Indeed our definitions are an immediate adaptation of the work [28]  
22 (by Kanade and Kalai) to the online setting. We remark that [28] is the most recent work on agnostic boosting, in a  
23 well-studied learning setting, and thus it is justified in the literature. As an example for such a problem, consider a weak  
24 online learner for a class of experts, and assume that the data comes from a majority vote over  $N/2$  experts. Notice that  
25 learning the class of majority votes over  $N/2$  experts is exponential in  $N$ , whereas our framework enables a mechanism  
26 efficient in  $N$  for learning that class. We will elaborate on such examples in the final version of the paper.

27 - "The assumption that the function  $R_W$  is sublinear is immaterial": The underlying assumption is that there is a  
28 sequence of algorithms, one per each horizon-size  $T$ , with a single sublinear function  $R_W(\cdot)$ . This is in fact an  
29 assumption commonly used in online learning (see e.g., [23]). We need  $R_W(T)/T$  to converge to zero, and hence the  
30 average regret will converge to zero. If we use an algorithm without this property, then the regret bound remains a large  
31 constant, and can be vacuous.

32 - "online-to-batch": Indeed, online-to-batch enables us to convert a weak online learner into a strong statistical learner.  
33 However this is a weaker result than converting a weak statistical learner to a strong statistical learner (which is what  
34 boosting algorithms in the statistical settings achieve). That is, the online weak learning assumption implies the  
35 statistical weak learning assumption, but not vice versa.

36 - "a regret of  $\epsilon$  is obtained": this is a typo, and should be "an average regret of  $\epsilon$  is obtained".

37 - We agree with the reviewer's suggestions on having a better exposition to improve readability for readers less familiar  
38 with the boosting literature, and will incorporate that in our revision.

39 **Reviewer 4** First, we note that the focus of this paper is the theoretical investigation of online boosting reductions  
40 to regret minimization. Let us stress that the main contribution, i.e. the derivation of an **agnostic** online boosting  
41 algorithm, answers a basic question in a well-studied learning setting, and there are no previous results in that setting to  
42 compare against. Nevertheless, it might indeed be interesting to experimentally compare our algorithm to the known  
43 online boosting algorithms in the **realizable** setting.

44 - Regarding notation,  $p$  in line 6 of Algorithm 1 is a parameter of the function (for any  $p \in [-1, 1]$ ), and  $p_t^i \in [-1, 1]$   
45 is a value that is defined by the algorithm (as in line 4), and is essentially the output of the OCO algorithm  $\mathcal{A}$  after  
46 observing all losses up to  $t, i - 1$ . We will try to further clarify this in the paper.