We thank all reviewers for their valuable comments. This paper presents a novel weakly-supervised learning approach in which the model keeps predicting the class of each unlabeled sample and learns from the feedback that whether the prediction is correct. The reviewers are generally satisfied with our writing and experiments. The most important concern (**R1**, **R2**, **R4**) lies in whether the annotation cost is indeed related to the number of supervision bits – we answer it in the common part. Other concerns are minor – we carefully respond below and will revise the paper accordingly.

Q0: *Can one-bit supervision reduce annotation costs? Any study on the actual comparison between full supervision and one-bit supervision?* **A0:** Thanks for this question! We asked three labelers to annotate 100 images from ImageNet using the one-bit setting, and the average annotation time is 2.72 seconds per image (with a precision of 92.3%). According to the authors of ILSVRC2012 [Russakovsky et al., IJCV'15], the average time for a full-bit annotation is around 1 minute, much higher than $10\times$ of the one-bit cost. This validates our motivation in a many-class dataset.

Response to Reviewer #1

Q1: *# of information bits not necessarily proportional to labeling time?* **A1:** Please refer to the common question.

Q2: *How the model would perform with only one-bit labels?* **A2:** Very good question! Using pure one-bit supervision will lead to lower accuracy than the mixed schedule (first using fully-supervised samples and then using one-bit-supervised samples) used in the paper. This aligns with our diagnosis in Section 3.3 showing that the best performance is achieved under a balanced configuration (a moderate number of fully-supervised samples). We agree that pure one-bit supervision is interesting in research (Section 4.2), we point out that in practice, it is reasonable to label a small number of fully-supervised or make use of existing annotation, so that the scenario is closer to that studied in the paper.

Q3: *Some minor grammatical mistakes?* **A3:** Thanks for the kind reminder! We will fix them in the final paper.

Response to Reviewer #2

Q1: *Omitted related work?* **A1:** Thanks for the kind reminder. We will cite and discuss this paper in Section 4.1.

Q2: *How to handle the samples selected twice in the second training stage?* **A2:** Thanks for the question! For each sample in Stage 2, if it is a wrongly predicted sampled in Stage 1, we first guarantee that the previously guessed label is not guessed again. Then, if the guess in Stage 2 is correct, this sample gets the true label, it is removed from $\mathcal{D}^{\mathrm{O}-}$ and added to $\mathcal{D}^{\mathrm{O}+}$. If the guess wrong again, it has two negative labels and still stay in $\mathcal{D}^{\mathrm{O}-}$.

Q3: *Results on ImageNet have not achieved SOTA?* **A3:** We agree. We have used Mean-Teacher as the baseline model and demonstrated improvement over it. We believe our pipeline can benefit other semi-supervised models and even self-supervised-then-semi-supervised models. We will try to report more results in the final paper.

Q4: *Whether the proposed method can reduce the annotation cost?* **A4:** Please refer to the common question.

Response to Reviewer #3

Q1: *This work is incrementally novel, however, it brings up a broader, mode interesting question...* **A1:** Thanks for the comments! Our work can be considered as reducing the basic unit of supervision, that is, from an entire sample that can contain multiple bits to a single bit. As mentioned by the reviewer, our method is easy to implement and works well, which inspires the community to study a new mechanism of improving the efficacy of learning and annotation. We believe this idea as well as our simple baseline is worth announcing to the community to facilitate future research.

Q2: *A few typos and grammatical errors?* **A2:** Thanks for the kind reminder! We will fix them in the final paper.

Q3: *Table 4 appears to be incomplete?* **A3:** Sorry for misleading. The 'missing' contents of Table 4 are the baseline results which we have provided in Table 2. We will add them back to Table 4 to avoid misleading. Thanks!

Response to Reviewer #4

Q1: *A realistic study of annotation with this technique would be interesting.* **A1:** Please refer to the common question.

Q2: *The paper is a well executed proof of concept with limited scope.* **A2:** We agree with your summary. The current status of this work is a proof-of-concept in image classification, and we believe that the idea as well as our simple baseline can inspire the community for future work (see Section 4.2). While the reviewer accepted that 'our experiments can be deemed enough for showing potential of the idea', we will try to generalize our algorithm to more models/tasks.

Q3: *Confusion of the statements in Section 3.3.* **A3:** Sorry for misleading. (i) We hope to highlight the impact brought by the 1st-stage quota, which is shown as a 0.7%–0.8% gap in accuracy, and we consider it significant. (ii) We will rewrite the statement as follows. Though 3-stage training brings a considerable accuracy gain (around 1%) over 2-stage training, we point out that the gain is much smaller than 2.63% (2-stage training over 1-stage training). Considering the tradeoff between accuracy and computational costs, we use two-stage training with balanced quota over two stages.

Q4: *Issues in Figure 1 and Table 4?* **A4:** Thanks for the reminder! For Figure 1, we will use a better representation to avoid misunderstanding. For Table 4, they are indeed the number of training samples per class – please refer to Table 1.