Abstract. We humans regularly ask for clarification if we are confused when discussing the visual world, yet the commonplace requirement in visiolinguistic problems like Visual Dialog, VQA, and Referring Expression Comprehension is to force a decision based on a single, static language input. Since this assumption does not match human practice, we relax it and allow our model to request new language inputs to refine the prediction for a task. Through the exemplar task of referring expression comprehension, we formalize and motivate the problem, introduce an evaluation method, and propose Iterative Multiplication of Probabilities for Re-query Of Verbal Expressions (IMPROVE)—a re-query method that updates the model’s prediction across multiple queries. We demonstrate IMPROVE on two different referring expression comprehension models and show it can improve accuracy by up to 6.23% without additional training or modification to the model’s architecture.

Keywords: Re-Query, Uncertainty Estimation, Seed Rejection, Visiolinguistic Tasks, Referring Expression Comprehension

1 Introduction

The goals of visiolinguistic tasks are both intuitive and practical in a visual world shared between humans and machines: visual question answering [1] and visual dialog [12] have meaningful accessibility applications [4], and referring expression comprehension may be used, for example, to tell an elder-care robot [81] which object to pick up [57], to specify an object to remove from a video [38], or to perform a number of other tasks that require the specification of a visual object [2,40,41,60,75].

Current work on these tasks generally evaluates a model’s ability to produce the correct answer given a vision-language pair. In other words, every query needs an immediate response. Though this evaluation is reasonable for the purpose of comparing models, the goal in a real-world setting is not to parse individual queries, but to provide the correct answer. Further, in a real-world application, the user—a visually-impaired individual asking a visual question, an artist selecting objects for inpainting, or an older individual commanding a home service robot—will be present to rephrase any provided language inputs if needed. If we consider this, along with the fact that the specific language can result in a better
Fig. 1. Since different language inputs for the same target often result in different answers, performance can be improved through a low-cost re-query of the language component. Objects boxed in green are correctly identified, objects boxed in purple are incorrectly identified. Best viewed in color.

or worse inference (see Figure 1), it makes sense to allow a model to re-query. A quantitative analysis (Section 3) shows the potential benefit: the percentage of objects correctly identified by a referring expression comprehension model can vary by up to 21.9% depending on which referring expression from the RefCOCO dataset [35] is used.

In our formalization of visiolinguistic re-query, we assume the re-query response is of the same form as the initial query (e.g., a visual question will be replaced by another visual question), which allows us to improve the effective performance of state-of-the-art models without retraining or modifying the architecture. We evaluate re-query as a trade-off between accuracy and the number of queries: at one extreme, the model never re-queries—resulting in unnecessary error—while at the other the model re-queries hundreds of times for every initial query. In the latter case, the inference will be accurate, yet completely unusable: a human will typically give a virtual assistant between two and six attempts to perform a task before giving up and reverting to simpler tasks [52]. Motivated by this, we evaluate using three different measurements: performance for a target re-query rate, performance in aggregate, and performance at convergence.

We then consider methods for implementing re-query, and break the problem into two components: a rejection function that determines when to re-query, and a selection function that determines how to process the re-query response(s). For the former, we evaluate a number of confidence measures and sampling-based distributions. For the latter, we introduce Iterative Multiplication of Probabilities for Re-query Of Verbal Expressions (IMPROVE), a method that chooses language inputs to re-query and updates its output distribution across re-queries. Not only does this method have theoretical benefits over baselines, but we show on our exemplar task of referring expression comprehension that it outperforms them empirically. Specifically, IMPROVE performs best in all cases where at least 1.5 queries are allowed for every target on average, has a better aggregate performance in all cases, and improves converged performance by up to 6.23% over the current paradigm of always using the first referring expression. Notably,
Explicitly stated, our contributions are:

- We introduce re-query for visiolinguistic tasks: problem statement, motivation, and evaluation method.
- We propose Iterative Multiplication of Probabilities for Re-query Of Verbal Expressions (IMPROVE), which chooses language inputs to re-query and updates its output distribution across multiple re-queries.
- We evaluate our implementation on the task of referring expression comprehension, demonstrating the effectiveness of IMPROVE.

2 Related Work

**Visual Tasks with Linguistic Prompts** Many tasks [5,12,23,56,72,74,87] begin with visual data and use a linguistic query—such as a question in VQA [1] or an object description in Referring Expression Comprehension [56]—to define the problem. While we focus on improving performance on difficult or incorrect language via re-query, current works treat every language input as correct and equally difficult, and require an answer regardless of how well the model understands the query. Additionally, when works do consider linguistic challenges in these tasks [2,3,21,54,65], their focus is exclusively on evaluating semantic correctness, which is related—but not identical—to our goal of improving performance.

A number of methods have been proposed for visiolinguistic tasks, from early work [1,68,80,82,84] that propose architectures based on linguistic intuition to recent work [8,29,30,33,51] that leverage pretraining for high-capacity transformer [77] architectures. Despite the shift in architecture and approach, the output format for many problems remains largely unchanged: a softmax or sequence of softmaxes is placed across a discrete set of choices. This common output space allows us to develop a method that can be implemented across a variety of tasks with minimal modification.

**Hybrid Artificial Intelligence** While dataset-focused evaluations downplay the role of the human, some works consider how to utilize the complementary skills of humans and machines. This is often implemented as a simple loop: human information is provided, the model presents a new hypothesis, and the human provides new information or accepts the hypothesis [11,14,19,32]. While effective for tasks where the fundamental challenge is increasing speed of an annotation that could be performed manually (e.g., producing panoptic segmentations [76]), these methods extend poorly to the use cases we consider in this work—why would one ask a visual question if the answer is already known?

Some works don’t require the user to always know the answer a-priori, for example, by asking questions until the model decides to terminate [7,63,64], only requiring user annotation when the inference is judged as low quality [22], or asking the user to choose between options when the model is uncertain [57]. While
an improvement over requiring the human to provide the stopping condition, these works generally propose architectures that do not extend to different tasks or apply to state-of-the-art architectures in the intuitive manner of IMPROVE.

**Identifying Low-Confidence Inferences** The challenge of understanding and adjusting behavior when a model is likely to be incorrect is a broad field of study for which many methods—both for evaluation and execution—have been proposed. For evaluation, metrics include calibration [20], rejection order [18,83], probabilistic measures [42], and performance on downstream tasks [6,16,43,44]. Strategies for performing this task in deep neural networks are similarly diverse, ranging from measuring model’s output response [17,20], to explicit training [24,25,58], to placing distributions across a network’s weights [15,36,53], and others [10,48,62,88]. While some work has been done regarding uncertainty on linguistic transformers [13,67,89], such methods for visiolinguistic tasks generally focus on active learning [34] or explainability [59], with limited analysis on explicit detection of incorrect inferences.

These evaluation and implementation methods are most often investigated on single-input tasks such as image classification [45] or object detection [24], and thus do not consider re-querying the human-provided portion of an input—a critical component of our work. A work on the task of single-target visual object tracking [47] considers re-query of a bounding box initialization, but methods used in this work are task-specific, and do not consider the effect of combining re-query responses or performance at convergence.

### 3 Motivation

Here, we use the experimental setup described in Section 5.1 to quantitatively motivate the intuitive argument of the introduction by showing the effect of specific language inputs on accuracy on the task of referring expression. To do so, we evaluate the accuracy of two referring expression comprehension models under five conditions:

1. **Per-Expression**: The current evaluation method, where every referring expression in the dataset is counted as either correct or incorrect.
2. **Per-Object Random**: For every target object, a referring expression is randomly chosen from the set of expressions for that object.
3. **Per-Object Best**: If at least one referring expression in the dataset for the target object results in a correct answer, that object is counted as correct.
4. **Per-Object Worst**: If at least one referring expression in the dataset for the target results in an incorrect answer, that object is counted as incorrect.
5. **Detection Rate**: The percentage of target objects that have been detected. This serves as an absolute upper limit on accuracy.

In addition to demonstrating the effect of current evaluations using an imbalanced number of referring expressions per object (per-expression vs. per-object
Table 1. Accuracy under five different conditions. Mean and standard error are calculated across five models for all conditions except per-object random, which uses the setup described in Section 5.1, and detection rate, where we report one run.

|                      | Val       | TestA     | TestB     | Val       | TestA     | TestB     |
|----------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| Per-Expression       | 77.39 ± 0.07 | 81.51 ± 0.05 | 70.78 ± 0.18 | 80.85 ± 0.06 | 86.53 ± 0.08 | 73.77 ± 0.07 |
| Per-Object Random    | 77.03 ± 0.04 | 81.13 ± 0.05 | 70.17 ± 0.06 | 80.49 ± 0.03 | 86.06 ± 0.05 | 73.16 ± 0.05 |
| Per-Object Best      | 85.63 ± 0.03 | 90.43 ± 0.07 | 77.24 ± 0.10 | 86.14 ± 0.06 | 91.92 ± 0.05 | 78.28 ± 0.05 |
| Per-Object Worst     | 65.80 ± 0.17 | 68.53 ± 0.11 | 61.01 ± 0.33 | 72.64 ± 0.08 | 77.72 ± 0.10 | 66.13 ± 0.23 |
| Detection Rate       | 90.08     | 94.18     | 83.09     | 88.56     | 93.77     | 80.39     |

random), the results shown in Table 1 demonstrate the potential benefit of re-query: if we limit our referring expressions to those that are available in the dataset, using the best referring expression in all cases (per-object best) improves over accepting the first referring expression (per-object random) by at least 5.15% and up to 9.82%, and over using the worst possible referring expression by up to 21.9%. If every detected object can be selected, which is reasonable due to the immense size of the linguistic space, an increase in accuracy of up to 13.05% is possible. In other words, an ideal re-query method could increase the effective accuracy over the current paradigm by up to 13.05% (absolute).

4 Re-Query in Visiolinguistic Tasks

Re-query increases the effective accuracy of a trained and frozen task model by intelligently requesting and integrating additional language inputs from the user. The overall process for a re-query method, shown in Figure 2, breaks into two functions: the rejection function, which determines when to re-query, and the selection function, which uses the initial query and all re-query responses to produce an updated output. We discuss metrics and methods in general terms here, and provide task-specific implementation details in Section 5.1.

4.1 Evaluation

Since human patience is finite, analysis of a re-query method must consider not only accuracy, but also user burden. While prior work [17,46] has measured this using the proportion of inputs that are not rejected (coverage), we find this metric to be a poor match for the intuitions of re-query. When considering re-query, it is more natural to ask how many re-queries are performed for each target, which incorporates an intuitive notion of the burden placed upon the user, and removes the implicit upper limit imposed by the metric of coverage. To measure this, we introduce the re-query rate:

\[
    r = \frac{n_{\text{queries}}}{n_{\text{targets}}}. \tag{1}
\]
Using re-query rate, we can characterize our methods by asking three questions: what is the performance at a given re-query rate? measured by Replacement Error (RE), what is the performance in aggregate? measured by Area under the Replacement Error curve (ARE), and what is the performance given infinite re-queries (at convergence)? measured in terms of the task’s error function.

Performance at Re-query Rate In practice, re-query will target an accuracy or re-query rate, and the best selection and rejection functions for an implementation are dependent on this target. For this reason, we propose a metric, Replacement Error (RE), that can compare performance of methods at different re-query rates. Replacement Error is defined as the error across a set of targets when some number of re-queries have occurred (the error metric itself is task-dependent). To provide an implementation-agnostic understanding of performance, we present RE visually as a line (Figure 3) or bar (Figure 5) plot, which allows a practitioner to easily select the rejection and selection function based on their requirements. In our evaluation, we consider re-query rates between 0 and 1 for reasons that are both technical—some methods are constrained to one re-query—and practical—a method that never accepts the first language input is unlikely to be widely accepted.

Aggregate Performance When comparing methods, it is often useful to provide a value that summarizes the method’s quality. Like previous methods in selective prediction [18] and seed rejection [47], we provide this measure by calculating the area under the curve described above and shown in Figure 3. This results in our Area under the Replacement Error curve (ARE) metric.

Convergence While it is necessary to limit the re-query rate in the previous two analyses, evaluating re-query methods outside of these bounds can provide meaningful insight related to how well a method integrates information from multiple re-query responses. For this reason, we additionally report the converged
accuracy of our re-query methods. As we discuss in Section 4.3, convergence is a requirement of the selection function.

4.2 Rejection Functions: Determining when to re-query

A rejection function is given a vision-language pair, and determines whether to accept or re-query that language based on the predicted benefit of a new linguistic input: is the current answer correct and, if not, is a new linguistic input likely to correct it (e.g., for VQA, is the answer in the answer set?).

The binary accept/re-query decision is implemented as a threshold applied to a numerical rejection score in practice, but since we focus on implementation-agnostic evaluation, we do not consider setting this threshold. Instead, we note methods from selective prediction, such as selective guaranteed risk [17].

Previous work on similar problems [46], which refers to the re-queryable component of an input as a seed, has proposed learning the rejection function by separating the inference into two parts: whether the seed is correct and whether the answer is correct given an incorrect seed. While effective for some tasks, such methods do not generalize well to visiolinguistic tasks for a few reasons: first, determining whether a language input is correct is a meaningful research problem on its own [3,54] for which current approaches are unlikely to generalize to novel tasks and has, to our knowledge, never considered whether combinations of (potentially ambiguous) language inputs are correct. Next, asking if the answer is correct despite the seed being incorrect implies that the inference can be performed—though not as well—without the seed.

Since learned rejection methods do not intuitively extend to our setting, we base our rejection score on the task model output. This is done by considering the task model output in two parts: the confidence measure and the distribution to which the confidence measure is applied. Throughout this work, we define our image as $x$, the set of all labels as $L$, and the language input as $s$. The estimated probability of a specific label is $\hat{p}(\ell|x,s)$, where $\ell \in L$ and $\sum_{\ell \in L} \hat{p}(\ell|x,s) = 1$.

### Confidence Measures

We evaluate two confidence measures for producing our rejection score. The first is softmax response, the largest value in the model’s output distribution, which can effectively detect incorrect answers without additional uncertainty methods in some cases [17]. The second measure is the basic information-theoretic metric of entropy, calculated:

$$q(x,s) = -\sum_{\ell \in L} \hat{p}(\ell|x,s) \log \left( \hat{p}(\ell|x,s) \right).$$

### Distributions

In addition to the standard softmax output, we consider four distributions based on the method of Monte Carlo Dropout [15], which aggregates the output of many dropout-enabled forward passes. Motivated by isolating linguistic error—which can be re-queried—from visual error—which can not—we apply dropout to both the full architecture and the text embeddings only.
additionally consider two potential methods to aggregate the stochastic forward passes: dropout mean and variation ratio. For $T$ forward passes, dropout mean for an object is:

$$\hat{p}(\ell|x, s) = \frac{1}{T} \sum_{n=1}^{T} \hat{p}_n(\ell|x, s) ,$$

and variation ratio is the proportion of dropout passes for which an object is selected, or:

$$\hat{p}(\ell|x, s) = \frac{1}{T} \sum_{n=1}^{T} 1(\ell = \arg\max_{u \in L} \hat{p}_n(u|x, s)) .$$

To summarize, we evaluate two confidence measures: softmax response and entropy, and five distributions: the standard network output, dropout mean, dropout variation ratio, dropout mean on text embeddings only, and dropout variation ratio on text embeddings only.

### 4.3 Selection Functions: Handling the Re-Query Response

A selection function must satisfy two criteria: it must be able to perform an inference when given multiple verbal inputs and it must have a meaningful stopping criteria. Previous work in re-query [47] considers tasks such as single-target Visual Object Tracking [41] where the human input will always provide a full definition and it is not straightforward to combine the resulting outputs. Because of this, this work selects between human-provided choices. In contrast, visiolinguistic tasks must be able to consider ambiguous language inputs and, for this reason, would benefit greatly from being able to combine the language inputs.

As a stopping criteria, previous work uses a fixed number of re-queries. This is necessary for many rejection scores, as the inability to isolate error caused by the seed from error caused by the visual component means there is no guarantee that the rejection score will ever cross a given threshold. While successful at preventing infinite re-query, this strategy does not consider when more—or fewer—re-queries are needed than the pre-set amount.

### 5 IMPROVE

With the requirements of selection functions established, we propose iteratively refining probabilities as new linguistic inputs are introduced. We call this Iterative Multiplication Of Probabilities for Re-query Of Verbal Expressions, or IMPROVE. For $n$ language inputs and image $x$, we can calculate the probability of label $\ell \in \mathcal{L}$ as:

$$\hat{p}(\ell|x, s_1, ..., s_n) = \frac{\prod_{k=1}^{n} \hat{p}(\ell|x, s_k)}{\sum_{u \in \mathcal{L}} \prod_{k=1}^{n} \hat{p}(u|x, s_k)} .$$

(5)
Fig. 3. Replacement Error (lower is better) plotted against re-query rate for different rejection functions on IMPROVE. Confidence measures are represented by line style, and distributions by color. Best viewed in color.

This formulation allows us to meet both the requirements of a selection function in an ideal way: instead of simply choosing between multiple language inputs, we can combine the available information and turn multiple ambiguous expressions into correct inferences (see Figure 6).

For stopping criteria, we note that while baselines and previous methods rely on a manually-defined limit on the number of queries, IMPROVE allows us to use a fixed threshold on our rejection score as a rejection function. To show this, we assume that every possible text input for image \( x \) and target \( y \) (\( S_{xy} \)) has some probability, \( p(s|x,y) \) of being used. The probability of a label \( \ell \) given \( n \) re-queries can then be written:

\[
\hat{p}(\ell|x,s_1,\ldots,s_n) \propto \left( \prod_{s \in S_y} \hat{p}(\ell|x,s)p(s|x,y) \right)^n.
\]  

As \( n \) increases, the output that is most likely in the probability-weighted product will shrink more slowly than all the others. This means that once the normalizing factor is added, the distribution will become a one-hot—below any potential threshold—at this guess. While there is an edge case where multiple labels have the same weighted probability, we expect this to be only a theoretical concern. Having proposed IMPROVE, we validate it experimentally, beginning with selecting the best rejection function.
Table 2. ARE for various rejection functions with IMPROVE (lower is better). All values within one standard error of best are bolded.

| Rejection Function | MAttNet Val | TestA | TestB | UNITER Val | TestA | TestB |
|--------------------|-------------|-------|-------|------------|-------|-------|
| Softmax            | 21.63 ± 0.07 | 17.13 ± 0.09 | 28.79 ± 0.05 | 19.05 ± 0.03 | 12.20 ± 0.07 | 26.70 ± 5.6e\(^{-3}\) |
| Dropout Mean       | 21.52 ± 0.07 | 17.11 ± 0.09 | 28.67 ± 0.05 | 17.60 ± 0.07 | 11.37 ± 0.09 | 25.57 ± 0.06 |
| Text Dropout Mean  | 21.60 ± 0.07 | 17.27 ± 0.09 | 28.77 ± 0.06 | 18.73 ± 0.04 | 11.86 ± 0.08 | 26.60 ± 0.01 |
| Variation Ratio    | 20.88 ± 0.08 | 15.89 ± 0.12 | 27.84 ± 0.07 | 17.55 ± 0.07 | 11.30 ± 0.09 | 25.31 ± 0.06 |
| Softmax            | 22.09 ± 0.05 | 17.87 ± 0.06 | 29.21 ± 0.03 | 19.08 ± 0.03 | 12.04 ± 0.08 | 26.79 ± 5.1e\(^{-3}\) |
| Dropout Mean       | 22.10 ± 0.05 | 17.91 ± 0.06 | 29.18 ± 0.03 | 17.58 ± 0.07 | 11.35 ± 0.09 | 25.60 ± 0.06 |
| Text Dropout Mean  | 22.06 ± 0.05 | 17.89 ± 0.06 | 29.17 ± 0.03 | 18.65 ± 0.04 | 11.81 ± 0.08 | 26.69 ± 0.01 |
| Variation Ratio    | 20.81 ± 0.08 | 15.90 ± 0.11 | 27.84 ± 0.07 | 17.53 ± 0.07 | 11.31 ± 0.08 | 25.38 ± 0.06 |

5.1 Comparing Rejection Functions for IMPROVE

Experimental Setup We embody our method on the task of referring expression comprehension, where the task model uses a language input to localize a target object in an image. Though some works on this task return a segmentation output [26,27,28,31,49], we evaluate two methods—MAttNet [84] and UNITER [8]—that follow a common [9,50,51,56,85,86] convention of selecting between externally provided bounding boxes via a softmax. In this framework, an output is correct if it has an IoU of greater than 0.5 with the target.

For both models, we train 5 instances of each network using the procedure and source code from the original works and, unless otherwise stated, report mean and standard error over 100 runs. For our Monte Carlo dropout distributions, we use 100 stochastic forward passes \((T = 100)\) to match the original work [15], and add a value of \(1e^{-6}\) to all variation ratio probabilities to soften the model’s prediction and allow calculation of entropy.

We perform our experiments on the RefCOCO dataset [35], which provides multiple referring expressions for all target objects except one (per-target counts are included in the supplemental material). This dataset is divided into three splits [85]: the val split contains unsorted images, testA contains images with multiple people, and testB contains images with multiple instances of non-person classes. Since TestA has the lowest number of semantic classes, it generally has higher accuracy and lower predictive entropy, while the opposite is true for TestB.

Results We choose the rejection function for IMPROVE by evaluating across all three measurements: the RE at specific re-query rates, shown in Figure 3, the ARE, shown in Table 2, and the converged accuracy in Table 3. Overall, we see that the distribution plays the larger role across all three metrics and that it is better to perform dropout on both modes than only the text embeddings. Notably, this experiment does not determine whether the latter is due to the addition of more stochastic layers or the intuition of isolating the language component being broadly untrue.
Table 3. Converged accuracies for rejection functions with IMPROVE. Error is considered converged after 5,000 re-queries where accuracy only changes by one answer. Values within one standard error of best in bold.

| Softmax Response | MAttNet Val | TestA | TestB | UNITER Val | TestA | TestB |
|------------------|-------------|-------|-------|------------|-------|-------|
| Softmax          | 82.03 ± 0.01 | 87.42 ± 0.02 | 74.21 ± 0.03 | 82.55 ± 0.03 | 88.34 ± 0.04 | 74.40 ± 0.08 |
| Dropout Mean     | 82.10 ± 0.02 | 87.34 ± 0.02 | 74.31 ± 0.03 | 83.97 ± 0.02 | 90.05 ± 0.02 | 76.52 ± 0.03 |
| Text Dropout Mean| 81.08 ± 0.02 | 87.30 ± 0.02 | 74.38 ± 0.03 | 82.90 ± 0.05 | 89.97 ± 0.03 | 74.99 ± 0.08 |
| Variation Ratio  | 81.03 ± 0.03 | 86.01 ± 0.03 | 73.66 ± 0.04 | 83.62 ± 0.02 | 89.57 ± 0.03 | 76.10 ± 0.03 |

Due to its faster convergence, variation ratio performs best for most re-query rates and under the ARE metric. Dropout mean and entropy—with one exception—performs best at convergence, suggesting it provides the most correct distribution but needs to re-query many times to become confident. For this reason, we use the entropy confidence measure with the variation ratio distribution for subsequent analyses, and additionally report dropout mean and entropy for convergence.

6 Quantifying Benefit of IMPROVE

We now compare IMPROVE to baseline selection functions using the same setup described in Section 5.1. Our baselines, illustrated in Figure 4, are:

- Naive Replacement: Always use the second referring expression—equivalent to a model that chooses not to classify and restarts with no memory.
- Smart Replacement [47]: Given two referring expressions, use the one with a lower rejection score.

![Fig. 4. How IMPROVE and candidate selection functions respond to two expressions](image-url)
Coverage-Specific Performance In Figure 5, we show the best selection function for every re-query rate. Overall, the method that is best at lower re-query rates varies, but IMPROVE is always best when more re-queries are available. This suggests that IMPROVE will converge to a higher accuracy, but may require more re-queries to do so. This exact crossover re-query rate varies by method and split—from 0.20 for UNITER-TestA to 0.50 for UNITER-TestB.

Aggregate Performance As shown in Table 4, IMPROVE’s ability to combine information to reach higher accuracy—even if it takes more time—means it has the lowest ARE for all splits and models. In all cases except UNITER-TestB, where the lack of a manual re-query limit leads to slower convergence for the larger class diversity, the difference is significant.

Table 4. ARE across selection functions (lower is better). We report best performance across rejection functions for baselines, and use variation ratio/entropy for IMPROVE. Values within one standard error of best in bold.
**Table 5.** Converged accuracy. For baselines the best performance across rejection functions is reported. Re-query is converged when no change of greater than one guess in either direction has occurred for more than 5,000 steps.

| Method                  | MAttNet Val | TestA | TestB | UNITER Val | TestA | TestB |
|-------------------------|-------------|-------|-------|------------|-------|-------|
| Ensemble Consensus      | 78.61 ± 0.03| 82.96 ± 0.04| 71.52 ± 0.06| 81.80 ± 0.03| 87.51 ± 0.04| 74.15 ± 0.04|
| Ensemble Mean           | 81.60 ± 0.02| 86.69 ± 0.03| 73.97 ± 0.03| 82.87 ± 0.02| 88.85 ± 0.03| 75.42 ± 0.04|
| Naive Replacement       | 77.07 ± 0.04| 81.13 ± 0.05| 70.29 ± 0.06| 80.52 ± 0.03| 86.11 ± 0.04| 73.22 ± 0.04|
| Smart Replacement       | 79.19 ± 0.03| 83.87 ± 0.04| 72.04 ± 0.05| 82.24 ± 0.02| 88.32 ± 0.04| 74.82 ± 0.03|
| IMPROVE (VR)            | 80.98 ± 0.04| 85.96 ± 0.03| 73.67 ± 0.03| 83.66 ± 0.02| 89.53 ± 0.03| 76.07 ± 0.03|
| IMPROVE (Mean)          | 82.16 ± 0.02| 87.36 ± 0.02| 74.33 ± 0.03| 84.06 ± 0.02| 90.21 ± 0.02| 76.51 ± 0.03|

**Convergence** We compare the converged accuracy of IMPROVE to our baseline selection functions in Table 5. Overall, IMPROVE with the dropout mean distribution performs best by a significant margin, while ensemble mean—the other method capable of integrating information from multiple text inputs—is significantly better than non-IMPROVE baselines. While IMPROVE with variation ratio is outperformed by ensemble mean for the MAttNet architecture, it is better by a significant margin when the distributions match: Ensemble mean using the variation ratio distribution has converged accuracies of 80.63 ± 0.02, 84.67 ± 0.04, and 72.72 ± 0.05 for val, testA, and testB, respectively. Notably, IMPROVE increases accuracy over a random referring expression by up to 6.23% and, in all cases except testA with variation ratio, enables the weaker MAttNet model to successfully identify more objects than the more recent UNITER model with no re-query.

7 Discussion

**IMPROVE-ing Other Architectures and Tasks** As discussed in Section 2, application of IMPROVE to tasks where the output is a discrete distribution is straightforward, even when the re-queryable input is not language [39,70]. In these cases, the most pressing challenge is data: while quantity and diversity of referring expressions for a given target may be considered a limitation of our experiments, referring expression comprehension is, to our knowledge, the only common application that intentionally collects multiple language inputs for the same target. In some cases (e.g., visual question answering) collecting appropriate data is straightforward, but for tasks that operate across multiple dependent steps of human input (e.g., vision-language navigation), some reformulation of the problem may be necessary to evaluate re-query.

For other forms of output, the challenge is greater, and varies in difficulty. For example, a model for referring expression comprehension that outputs segmentation may only require a new confidence measure, since the output is an image-sized set of classifications, while tasks such as single-target VOT will require changing the form of the output to enable combination.
Semantic Ambiguity  The data collection method for RefCOCO [35] sought to minimize semantic ambiguity by having different annotators provide and understand the linguistic descriptions. Since semantic ambiguity is likely to increase in less structured interaction, it is worthwhile to consider the possible effects of increasing semantic ambiguity: first, the increase in absolute number of cases—that can be improved by combining information would increase the importance of IMPROVE's ability to handle these cases. Second, an increase in semantic ambiguity would mean more error due to incomplete information—aerial uncertainty—and less due to gaps in the model’s knowledge—epistemic uncertainty. Since the effectiveness of different methods varies with the type of uncertainty—softmax response cannot effectively differentiate between SVHN and CIFAR-10 [43] but outperforms Monte Carlo dropout within the same dataset [17]—this can have an effect on which rejection function is best. The need for embracing semantic ambiguity will also increase over time: models can and will reduce epistemic uncertainty via more or better training [37], but the quality of human input will remain relatively constant.

Updated Uncertainty Methods  While we focus on the commonly used and easy to implement Monte Carlo dropout method, many other methods have been proposed for modeling uncertainty in DNNs [55,61,66,71,73]. As we discussed in Section 2, these methods generally seek to maximize accuracy of the distribution, which is likely to lead to findings similar to our comparison of IMPROVE using dropout mean and variation ratio: like dropout mean, updated methods will produce a higher accuracy at convergence due to their more accurate probability estimates, but variation ratio may still perform better for lower re-query rates due to the faster convergence caused by the sharpness of its distributions.
8 Conclusion

Visiolinguistic models are motivated by interaction with humans, yet evaluation often assumes the human ceases to exist after the initial query. In this work, we remove this assumption and propose Iterative Multiplication of Probabilities for Re-query Of Verbal Expressions (IMPROVE), which more closely follows the human paradigm of asking for clarification and maintaining previous understanding. Using the exemplar task of referring expression comprehension, we show that IMPROVE outperforms strong baselines on three metrics and two models and improves accuracy by up to 6.23% without any change to the model.

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Supplemental Material
IMPROVE Visiolinguistic Performance with Re-Query

1 Distribution of Referring Expressions per-Object

In Table 1, we show the number of target objects with \( n \) referring expressions for the RefCOCO, RefCOCO+ [1], and RefCOCOg [2] datasets available at https://github.com/lichengunc/refer. UNC splits [3] are used to designate TestA, TestB, and Val.

| Expression Count | RefCOCO | | RefCOCO+ | | RefCOCOg |
|------------------|---------|-----------|---------|-----------|---------|
| \( n \)          | Val     | TestA     | TestB   | Val       | TestA   | TestB   | Val     |
| 1                | 1       | 0         | 0       | 110       | 29      | 90      | 257     |
| 2                | 605     | 288       | 354     | 482       | 162     | 336     | 2309    |
| 3                | 3197    | 1667      | 1498    | 3169      | 1763    | 1361    | 7       |
| 4                | 8       | 20        | 17      | 43        | 21      | 11      | 0       |
| 5                | 0       | 0         | 1       | 1         | 0       | 0       | 0       |
| Total Objects    | 3811    | 1975      | 1870    | 3805      | 1975    | 1798    | 2753    |
| Total Expressions| 10834   | 5657      | 5275    | 10758     | 5726    | 4889    | 4896    |

2 Convergence of IMPROVE

An advantage of IMPROVE is that it will converge to a one-hot vector, meaning a simple threshold can be applied to the rejection score to create the rejection function. Here, we show this theoretically.

Assumptions We use the following assumptions:

- The set of labels is finite, and does not change between language inputs for a target.
- There exists a discrete set of language inputs of unspecified size, each of which has some probability of occurring for a given image-target pair.
- Language inputs are independent.
Variables We use the following variables:

- $x$ represents the image.
- $y$ represents the target.
- $n$ represents the number of language inputs given.
- $S_{xy}$ is the set of all language inputs for an image and target.
- $s_k$ represents the $k^{th}$ language input.
- $\hat{p}(\ell|x, s_k)$ is the estimated probability of label $\ell \in \mathcal{L}$ when language input $s_k$ is given.
- $p(s|x, y)$ is the probability of a language input, $s$, occurring for a target-image pair.
- $\mathcal{L}$ represents the set of output labels.

Proof For a set of $n$ language inputs, IMPROVE defines the probability of a label as:

$$\hat{p}(\ell|x, s_1, ..., s_n) = \frac{\prod_{k=1}^{n} \hat{p}(\ell|x, s_k)}{\sum_{u \in \mathcal{L}} \prod_{k=1}^{n} \hat{p}(u|x, s_k)} .$$

(1)

The discrete nature of language inputs under this formulation makes it impossible to make any statements about behavior as $n \to \infty$. For this reason, we instead assume each language input has some probability of occurring, and approximate the probability over $n$ language inputs as:

$$\hat{p}(\ell|x, s_1, ..., s_n) \propto \prod_{s \in S_{xy}} \hat{p}(\ell|x, s)^{np(s|x, y)} .$$

(2)

This trivially simplifies to:

$$\hat{p}(\ell|x, s_1, ..., s_n) \propto \left( \prod_{s \in S_{xy}} \hat{p}(\ell|x, s)^{p(s|x, y)} \right)^n .$$

(3)

We define $\ell_{\text{max}}$ as $\arg\max_{\ell \in \mathcal{L}} \prod_{k=1}^{n} \hat{p}(\ell|x, s_k)^{p(s|x, y)}$ and assume $\ell_{\text{max}}$ is unique, then:

$$\text{as } n \to \infty : \quad \hat{p}(\ell_{\text{max}}|x, s_1, ..., s_n) \gg \hat{p}(\ell|x, s_1, ..., s_n) \quad \forall \ell \in \mathcal{L} \text{ where } \ell \neq \ell_{\text{max}} .$$

(4)

It follows that:
\[ \lim_{n \to \infty} p(\ell|x, s_1, \ldots, s_n) = \lim_{n \to \infty} \left( \prod_{s \in S_{xy}} \hat{p}(\ell|x, s)p(s|x,y) \right)^n \]

\[ \sum_{\ell \in L} \left( \prod_{s \in S_{xy}} \hat{p}(\ell|x, s)p(s|x,y) \right)^n = \begin{cases} 1 & \text{if } \ell = \ell_{\text{max}} \\ 0 & \text{otherwise} \end{cases} \quad (5) \]

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