Come Again? Re-Query in Referring Expression Comprehension

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Abstract
To build a shared perception of the world, humans rely on the ability to resolve misunderstandings by requesting and accepting clarifications. However, when evaluating visiolinguistic models, metrics such as accuracy enforce the assumption that a decision must be made based on a single piece of evidence. In this work, we relax this assumption for the task of referring expression comprehension by allowing the model to request help when its confidence is low. We consider two ways in which this help can be provided: multimodal re-query, where the user is allowed to point or click to provide additional information to the model, and rephrase re-query, where the user is only allowed to provide another referring expression. We demonstrate the importance of re-query by showing that providing the best referring expression for all objects can increase accuracy by up to 21.9% and that this accuracy can be matched by re-querying only 12% of initial referring expressions. We further evaluate re-query functions for both multimodal and rephrase re-query across three modern approaches and demonstrate combined replacement for rephrase re-query, which improves average single-query performance by up to 6.5% and converges to as close as 1.6% of the upper bound of single-query performance.

Introduction
Referring expression comprehension embodies a simple yet meaningful goal at the intersection of computer vision and natural language processing: given a natural language expression and an image, identify the object in the image that the expression refers to. This may be used, for example, to tell a robot which object to pick up (Mees and Burgard 2020), to specify an object to remove from a video (Kim et al. 2019), or to perform a number of other tasks that require or benefit from the specification of a visual object (Kristan et al. 2016; Perazzi et al. 2016; Antol et al. 2015). Like many tasks in computer vision (Deng et al. 2009) and visiolinguistic understanding (Zhou et al. 2019), it has been formalized into a few datasets and a common performance metric.

Although these formalizations encourage rapid improvement by allowing algorithms to be directly compared, they may not provide a complete picture: high accuracy can be achieved on long-tailed data without modeling underrepresented classes (Horn et al. 2018), comparing inpainted videos to the original penalizes plausible solutions (Szeto and Corso 2021), and captioning models may produce good captions for incorrect reasons (Hendricks et al. 2018).

In referring expression comprehension, the shortcoming of the common formalization is that evaluating accuracy across the set of all referring expressions (Hu, Rohrbach, and Darrell 2016) encodes the assumption that the model must make its decision based on only one referring expression. From the perspective of our motivating applications—e.g., selecting objects for inpainting—it is more appropriate to consider referring expression comprehension as a real-time task where the model does not need to respond to a single referring expression, but can re-query the user when it does not understand.

We consider two re-query methods, shown in Figure 1: multimodal re-query and rephrase re-query that improve performance by re-querying the user.

Figure 1: While current evaluation methods assume the referring expression model must understand the referring expression immediately, we introduce two methods, multimodal re-query and rephrase re-query that improve performance by re-querying the user.
the task of referring expression comprehension. We demonstrate the importance of a re-query function by showing that, for multimodal re-query, our method can achieve the upper bound single-query accuracy while only re-querying 12% of referring expressions and, for rephrase re-query, accuracy can differ by up to 21.9% based on which referring expressions are used.

Second, we introduce combined re-query and show it outperforms the previous state-of-the-art re-query method (Lemmer, Song, and Corso 2021) in all but one scenario. We further discuss the convergence of this method and its implications, and empirically show that it outperforms randomly selected referring expressions by up to 6.5% and converges to as close as 1.6% of the single-query upper bound.

Our key contributions are as follows:

- We introduce the problem of re-query for referring expression comprehension under two realistic sets of assumptions: multimodal re-query, where a secondary input mode is available, and rephrase re-query, where the re-query response is another referring expression.
- We evaluate the established methods across three referring expression comprehension models including, to our knowledge, the first analysis of Monte Carlo dropout (Gal and Ghahramani 2016) on the task of referring expression comprehension. This evaluation shows we can match the upper bound single-query accuracy by re-querying only 12% of initial referring expressions.
- We evaluate the same referring expression comprehension models under accuracy criteria that operate across objects instead of expressions. Through this, we show that using the best referring expression can improve over using a random referring expression by up to 9.7%, and over using the worst referring expression by up to 21.9%.
- We propose a novel method for rephrase re-query, combined replacement, in which the inference is performed using information from multiple referring expressions. We show this method has both empirical and theoretical advantages over the previous state of the art and converges to a high-quality answer—up to 6.5% above random accuracy and only 1.6% worse than the upper bound single-query accuracy in our experiments.

**Related Work**

**Referring Expression Comprehension** In referring expression comprehension a model is asked to identify—via bounding box or segmentation—an object specified by a natural language expression in an image. While it is often considered a task that should be solved for its own sake (Zhang, Niu, and Chang 2018; Huang et al. 2020; Hu et al. 2020; Bojanowski et al. 2013), it has recently become a platform for demonstrating the versatility of generalized visiolinguistic representations and pretraining (Li et al. 2020; Lu et al. 2019).

This work evaluates three referring expression comprehension methods that approach the problem in fundamentally different ways. Two of these methods, MAttNet (Yu et al. 2018) and UNITER (Chen et al. 2020) follow the standard approach of treating the task as classification across a set of externally provided objects, though MAttNet uses explicit language modeling while UNITER uses a generalized visiolinguistic representation. In contrast, the third method we evaluate, MDETR (Kamath et al. 2021), performs detection and selection in one step. While this method achieves higher performance on the referring expression comprehension task, it is not compatible with some of our proposed re-query methods. We address the implications of this throughout the work.

**Difficulties of Natural Language** Human language allows for many ways to say the same thing that are not equally interpretable. Current work addresses this in a few ways: some works attempt to eliminate the worst of these inconsistencies through careful construction of the dataset (Mao et al. 2016), while others embrace the difficulty of natural language as an explicit inference-time challenge. In the latter category, works driven by the realities of building question answering systems for the visually impaired (Gurari et al. 2018; Bhattacharya, Li, and Gurari 2019; Mahendru et al. 2017) designate questions as unanswerable for various reasons and propose methods for detecting them, (Shah et al. 2019) proposes a method to improve the robustness of visual question answering models to wording variations, and some works (Banerjee, Thomason, and Corso 2020; Gupta et al. 2021) enumerate or intentionally introduce linguistic imperfections that must be overcome, but do not explicitly seek to detect them.

Notably, none of these works perform re-query or consider referring expression comprehension. The closest work to ours in this respect is that of (Mees and Burgard 2020), which allows users to select between generated captions for candidate regions in a pick-and-place task, but does not formally evaluate re-query, instead reporting results for comprehension, generation, and pick-and-place separately.

**Re-Query Approaches** A number of works have focused on recognizing difficult inputs in deep neural networks, either through the selective classification framework (Geifman and El-Yaniv 2019) or by estimating uncertainty using methods such as ensembling (Lakshminarayanan, Pritzel, and Blundell 2017), explicitly learning distributions on weights (Blundell et al. 2015; Maddox et al. 2018), or treating weights as a Bernoulli distribution by enabling dropout at inference time (Gal and Ghahramani 2016). The task of seed rejection (Lemmer and Corso 2021) extends these approaches to scenarios where the input can be separated into an immutable primary input (e.g., the image) and a seed that can be re-queryed (e.g., the referring expression). Seed rejection has been approached from the perspective of replacing the rejected candidate seed with a gold-standard seed (Lemmer and Corso 2021) and choosing which potentially noisy seed from the crowd to use (Lemmer, Song, and Corso 2021), but has never examined the effects of combining seeds or the task of referring expression comprehension.
Re-Query Problem Setup

Problem Statement

In this work, we consider a referring expression comprehension model, \( f(x, s) \), that accepts an image, \( x \), and a candidate, \( s_c \), or gold-standard, \( s_{gs} \), referring expression (a seed), \( s \in \{s_c, s_{gs}\} \). This model produces an estimate, \( \hat{y} \), of the true location of the target object, \( y \), with the goal of minimizing the error, \( \ell(\hat{y}, y) \). We define the error, \( \ell \), to be the standard referring expression comprehension error metric: the estimate is correct if the target and predicted bounding boxes have an Intersection-over-Union (IoU) greater than 0.5, and incorrect otherwise. We use the values 0 and 100 for correct and incorrect respectively, such that the mean of a set of \( \ell \) corresponds to the set’s error rate in percent.

\[ AE(\hat{y}_c, y_{gs}, y|\ell) = \max(\ell(\hat{y}_c, y) - \ell(y_{gs}, y), 0) \]  
(1)

Since there are an effectively infinite number of referring expressions for an object we assume that there always exists a referring expression that results in the correct object being selected. While one can argue that this is false if the target object is not detected, not all methods allow us to distinguish between an undetected object and a misunderstood referring expression. Thus, we maintain this assumption to allow uniform analysis across methods and maintain the nomenclature of seed rejection to allow this assumption to be relaxed in the future. In summary, our assumption is \( f(x, s_{gs}) = y \forall x \), and therefore \( \ell(y_{gs}, y) = 0 \forall y \) and \( AE = \ell(\hat{y}_c, y) \).

We seek a re-query score, \( q(x, s_c|f) \), to which a threshold can be applied such that referring expressions that cause a high additional error (i.e., are incorrect) are re-queried, and referring expressions that cause low additional error (i.e., are correct) are accepted without re-query. By applying this re-query function to an evaluation dataset, we produce two sets of referring expressions: \( \mathcal{P} \) is the first received set of referring expressions and its cardinality is the size of the evaluation dataset, and \( \mathcal{R} \) contains a set of re-query responses for the examples for which our re-query score is greater than the threshold. Both sets contain four-tuples of \( (x, y, s_c, s_{gs}) \). Consistent with previous work, \( \mathcal{R} \) can be any size less than or equal to \( \mathcal{P} \).

In order to evaluate the effectiveness of re-query scores, these sets are used in two sequential evaluations. The first evaluation finds the performance of a re-query score at a fixed coverage—the proportion of referring expressions that are not re-queried—calculated:

\[ \text{coverage} = \frac{|\mathcal{P}| - |\mathcal{R}|}{|\mathcal{P}|} \]  
(2)

Definitions and intuition for the coverage-dependent performance metrics (MAE and RMAE) are given in the appropriate section.

Once the coverage-dependent evaluation is performed for every potential coverage, resulting in \( |\mathcal{P}| \) evaluations, we can summarize the overall quality of a re-query score by numerically integrating (via rectangular integration in this work) these values across all coverages.

Models and Dataset

We evaluate re-query across three architectures: MAttNet (Yu et al. 2018), UNITER (Chen et al. 2020), and MDETR (Kamath et al. 2021). For MAttNet and UNITER, we train 5 instances of each network using the procedure described in the original works, allowing us to perform trials across multiple models. For MDETR, we were unable to perform the recommended finetuning due to hardware limitations, and instead use the finetuned weights provided by the original authors. For this reason, standard error for MDETR experiments are reported across the same number of trials but only one training run.

Our evaluations are performed on the RefCOCO dataset (Kazemzadeh et al. 2014), as it has multiple referring expressions for almost all target objects. In contrast, the other two commonly used referring expression datasets, RefCOCO+ and RefCOCOg (Mao et al. 2016), have only one referring expression for 3% and 10% of objects respectively. Full counts are available in the supplemental material.

Re-Query Scores

To determine whether to re-query a referring expression we calculate a re-query score, \( q(x, s_c|f) \), that is used in our analysis to select the \( |\mathcal{R}| \) referring expressions that we think would benefit most from re-query, where \( |\mathcal{R}| \) is chosen to target a specific coverage. We refer the reader to works in selective prediction (Geifman and El-Yaniv 2017) for finding thresholds for re-query on streaming data.

Two independent factors go into the calculation of a re-query score: the confidence measure and the distribution to which it is applied. Throughout this section, we define \( O_x \) as the set of all detected objects in image \( x \) and represent the estimated probability of a specific object as \( p(o|x, s_c) \), where \( o \in O_x \).

Confidence Measures

We use two measures for selecting referring expressions to re-query. The first is softmax response, which has been demonstrated as an effective measure of the model’s confidence for selective prediction (Geifman and El-Yaniv 2017). Softmax response is

\[ q(x, s_c|f) = \max_{o \in O_x} p(o|x, s_c) \]  
(3)

The second is entropy, calculated:

\[ q(x, s_c|f) = \sum_{o \in O_x} -p(o|x, s_c) \log(p(o|x, s_c)) \]  
(4)

Distributions

We apply our confidence measures to three different distributions. The first distribution is the single-pass distribution given by the network: for MAttNet and UNITER this is a softmax output, while for MDETR this is the normalized inverse of the “no object” label. Next, we consider two distributions using the method of Monte Carlo Dropout (Gal 2016), which estimates uncertainty across the model’s weights by enabling dropout at inference time—asserting that dropout layers represent a Bernoulli distribution that can be sampled from. While a limited amount of work has used this method on transformer architectures for tasks such as sentiment classification (Shelmanov et al.
Table 1: Mean and Standard Error AMAE (lower is better) across 100 samples for a selection of evaluations. We additionally include detection rates as applicable (for consistency with original works, we use the provided instantiations of the object detectors). Outright best performance is shown in bold, while methods within one standard error are bolded and italicized.

| Object Source | Model    | Confidence Measure | Distribution | Val AMAE ↓ | TestA AMAE ↓ | TestB AMAE ↓ |
|---------------|----------|--------------------|--------------|------------|--------------|--------------|
| Ground Truth  | MAttNet  | Entropy            | Variation Ratio | 4.62 ± 0.04 | 4.86 ± 0.04 | 5.13 ± 0.05 |
|               |          | Softmax Response   | Variation Ratio | 4.74 ± 0.03 | 4.98 ± 0.05 | 5.20 ± 0.05 |
| Detector      | MAttNet  | Detection Rate     |              | 90.08%     | 94.18%      | 83.09%      |
|               |          | Entropy            | Variation Ratio | 12.65 ± 0.04 | 7.68 ± 0.05 | 18.30 ± 0.08 |
|               |          | Softmax Response   | Variation Ratio | 12.67 ± 0.05 | 7.76 ± 0.05 | 18.13 ± 0.08 |
| Detector      | UNITER   | Detection Rate     |              | 88.56%     | 93.77%      | 80.39%      |
|               |          | Entropy            |              | 10.60 ± 0.03 | 4.26 ± 0.03 | 17.77 ± 0.06 |
|               |          | Softmax Response   |              | 8.30 ± 0.04 | 5.16 ± 0.05 | 14.41 ± 0.06 |
| Detector      | MDETR    | Softmax Response   | Standard     | 3.86 ± 0.02 | 2.76 ± 0.02 | 5.71 ± 0.03 |

Table 2: The percentage of referring expressions that can be accepted while still achieving upper bound accuracy.
classifications. However, aggregating samples via variation ratio works best for the MAttNet architecture, while using the mean works best for the UNITER architecture.

To more concretely show the benefit of multimodal re-query, we consider the number of re-queries required to match the upper bound single-query accuracy (per-object best in Table 3). The results of this are in Table 2, where we see that we can exceed this upper bound by re-querying as few as 12% of referring expressions.

Rephrase Re-Query
In rephrase re-query, the user is only allowed to communicate using referring expressions. This introduces two questions that must be answered in addition to choosing which referring expressions to re-query: what is the effect of individual referring expressions and how do we determine what to do with a second referring expression?

Effect of Selected Expression
To answer the first question, we evaluate the effect of individual referring expressions on the final inference. For example, we see in Figure 2 that slight changes in the phrasing of referring expressions can have a negative impact on the model’s output. For a thorough analysis, we evaluate all models and splits across four definitions of a correct answer:

1. Per-Expression: Every referring expression in the dataset counts once, corresponding to how evaluation is typically performed.
2. Per-Object Random: Accuracy is calculated across 100 random sets of one referring expression per object.
3. Per-Object Best: Accuracy is calculated across objects, where an object is correct if at least one given referring expression for that object results in a correct answer.
4. Per-Object Worst: Accuracy is calculated across objects, where an object is correct if all given referring expressions for that object result in a correct answer.

The results of this evaluation are shown in Table 3. We first note the per-expression accuracy is more than one standard error higher than random per-object accuracy in all cases. Since many objects are correctly localized with all referring expressions (i.e., per-object worst is high), this suggests that easily described objects bias the per-expression evaluation. In other words, easily localized objects artificially increase the accuracy under standard evaluation.

We also see that always providing the best answer results in a substantial improvement over both sampled (up to 9.7%) and worst (up to 21.9%) accuracies. That is, while there are many “easy” instances for which the network identifies the correct object for all expressions, selecting the correct referring expression in other instances can provide the correct answer for the majority of cases where the object is detected.

Selection Functions
In rephrase re-query, we make the assumption that the only input mode is natural language, but the user can provide multiple referring expressions to target an object. This makes it essential for us to evaluate not only re-query scores, such as in multimodal replacement, but also methods for integrating multiple referring expressions.

In line with previous work (Lemmer, Song, and Corso 2021), we refer to these methods as selection functions. We generalize the definition from previous work by defining a selection function as \( \hat{y} = h(x, s_{c1}, ..., s_{cn}|f) \) and consider two different selection functions: smart replacement (Lemmer, Song, and Corso 2021) and our novel method of combined replacement.

Smart Replacement
In smart replacement, we select between multiple referring expressions:

\[
h(x, s_{c1}, ..., s_{cn}|f) \in \{f(x, s_{c1}), ..., f(x, s_{cn})\}.
\]

Where the selection is made by choosing the referring expression that results in the best the re-query score. While this
straightforward method was shown to outperform naively accepting a re-query, it has the meaningful shortcoming that a manual re-query limit must be imposed: there is no convergence across re-queries, and no consistent threshold across target objects. Consistent with previous work, we use a maximum of one re-query for every object.

**Combined Replacement** The goal of combining outputs is to provide a solution based on information that the model can infer from different referring expressions—that is, which object best satisfies all statements? This is significant not only because of potential semantic ambiguities in the referring expression, but also because of ambiguities caused by shortcomings in the model’s comprehension. For our two-stage methods (MAAttNet and UNITER), detections are constant for a given input image, so we can simply combine and normalize the output distribution:

\[
p(o|x, s_{c1}, ..., s_{cn}) = \frac{\prod_{k=0}^{n} p(o|x, s_{ck})}{\sum_{o \in O_x} \prod_{k=0}^{n} p(o|x, s_{ck})} \tag{9}
\]

**Results** We evaluate our re-query and selection functions using the Replacement Mean Additional Error (RMAE) (Lemmer, Song, and Corso 2021),

\[
RMAE = \frac{1}{|\mathcal{P}|} \sum_{(x_T, y_T, s_T, s_R) \in \mathcal{P}} \sum_{s_c} \text{AE}(h(\{(x, y, s_c) \in \mathcal{R}, \mathcal{P} | s_c = x_T, y_c = y_T\} | f(\ell), f(x_T, s_R), y_T) \tag{10}
\]

which corresponds to the error rate over all objects using the given set of referring expressions under the assumptions of this work. To calculate the RMAE at a specific coverage, we repeatedly select a new referring expression for the object with the highest re-query score, until the target coverage has been reached. For smart replacement, there is the additional constraint that each target object can only be queried once. As in the multimodal re-query scenario, we calculate the RMAE at all potential coverages, then use the area under this curve (ARMAE) to provide a summary comparison between re-query and selection functions.

We provide a subset of results in Table 4, where only the best method(s) for every model/split are shown to save space. We note that in addition to the best re-query scores being generally consistent with our AMAE results (unlike previous work (Lemmer, Song, and Corso 2021)), our combined distribution method is best or within one standard error in all cases except UNITER-Ground Truth-TestB. For further insight on this case we examine the RMAE-coverage curve (Figure 3), where we see that while combined replacement reaches a lower RMAE, it does so slowly. This is likely due to the difference in data present in the two splits: TestA
Table 5: The coverage below which combined replacement has a lower RMAE than smart replacement. Calculated as the intersection of the means.

| Object Source | Model       | Val Acc  | TestA Acc | TestB Acc |
|---------------|-------------|----------|-----------|-----------|
| Ground Truth  | MAttNet     | 0.634    | 0.623     | 0.468     |
| Detector      | MAttNet     | 0.487    | 0.671     | 1.000     |

Correlation

Table 6: The accuracy that can be obtained from various methods given unlimited re-queries.

| Object Source | Model       | Selection Fn | Val Acc  | TestA Acc | TestB Acc |
|---------------|-------------|--------------|----------|-----------|-----------|
| Ground Truth  | MAttNet     | P.O. Best    | 95.31 ± 0.06 | 96.16 ± 0.07 | 94.8      |
| Detector      | MAttNet     | P.O. Best    | 97.83 ± 0.06 | 98.19 ± 0.11 | 94.8      |
|               | Detector    | P.O. Random  | 86.14 ± 0.06 | 91.92 ± 0.05 | 88.05     |

Discussion

Effect of Architecture

While we have avoided comparing results across architectures due to differences in baseline performance, the fact that MDETR performs best across most scenarios while being incompatible with combined replacement and Monte Carlo dropout merits further discussion. Critically, the DETR detector (Carion et al. 2020) on which MDETR is based has been shown to substantially outperform the FasterRCNN (Ren et al. 2017) detector used for both UNITER and MAttNet, particularly at the IoU threshold used for referring expression comprehension. Since UNITER with ground-truth bounding boxes outperforms MDETR, it is conceivable—or even likely—that using UNITER with Monte Carlo dropout, combined replacement, and a more accurate detector would be preferable to MDETR. Alternately, future research could explore extending our methods to MDETR by running a matching algorithm across bounding boxes, similar to the work done for Monte Carlo dropout in object detection (Miller et al. 2019).

Dataset Shortcomings

While RefCOCO is the most suitable existing dataset for re-query, we note that it was not designed with re-query in mind. An ideal dataset for this task would improve upon RefCOCO in two areas: first, the number of referring expressions per object would be increased such that they could be considered representative of the full distribution. Second, it would introduce some of the semantic ambiguities present in human speech. Since combined replacement has the potential to resolve such ambiguities while smart replacement relies on one of the set of referring expressions having all the information, resolving this shortcoming represents an interesting avenue for future research.

Conclusion

In this work, we have introduced, motivated, and proposed solutions for the problem of re-query in referring expression comprehension. Through experiments on three unique models, we have shown that not only does accuracy vary significantly depending on the referring expression given, but also that intelligent re-query methods can meaningfully increase performance. While we are confident in the significance of our results, we have also noted a number of challenges and assumptions, such as the importance of the object detector and the assumption of perfect detection, that we believe provide a pathway to further innovations on this topic.

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Supplemental Material
Come Again? Re-Query in Referring Expression Comprehension

Introduction
In the main body of this work, our results focus on the best performing combinations of confidence measures, distributions, and selection functions for each model. In this supplemental material, we provide results for all combinations, as well as additional information about the distributions of referring expression comprehension datasets. Where possible, we refer to the corresponding table in the main text for easy reference.

Distribution of Referring Expression Counts

| # Referring Expressions | RefCOCO Val | RefCOCO TestA | RefCOCO TestB | RefCOCO+ Val | RefCOCO+ TestA | RefCOCO+ TestB | RefCOCOg 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            |

Table S1: Evaluating re-query methods requires multiple referring expressions per object. We motivate our use of the RefCOCO dataset by reporting the number of objects with \( x \) referring expressions for each dataset and split. Critically, RefCOCO has multiple referring expressions for all objects except one.
Table S2: The Area under the Mean Additional Error curve (AMAE) for all combinations of models, confidence measures, distributions, and object sources. Standard error was calculated across 100 samples on all models. This table expands upon Table 1 in the main document.
## Coverages Matching Single Query Upper Bound

| Object Source | Model  | Confidence Measure | Distribution | Val | TestA | TestB |
|---------------|--------|--------------------|--------------|-----|-------|-------|
| Ground Truth  | MAttNet| Entropy            | Standard     | 5.14| 3.54  | 25.41 |
|               |        |                    | Dropout Mean | 5.20| 3.65  | 25.97 |
|               |        |                    | Variation Ratio | 74.34| 70.84 | 76.69 |
| Softmax Response |      | Standard           | 13.72        | 12.00| 33.76 |
|               |        | Dropout Mean       | 12.70        | 12.66| 33.09 |
|               |        | Variation Ratio    | 74.44        | 70.38| 76.41 |
| UNITER        | Entropy|                    | Standard     | 74.91| 74.63 | 74.92 |
|               |        | Dropout Mean       | 76.96        | 77.11| 78.56 |
|               |        | Variation Ratio    | 76.99        | 76.91| 78.29 |
| Softmax Response |      | Standard           | 74.86        | 28.00| 75.08 |
|               |        | Dropout Mean       | 77.25        | 77.37| 78.34 |
|               |        | Variation Ratio    | 77.09        | 76.86| 77.96 |
| Detector      | MAttNet| Entropy            | Standard     | 0.00 | 2.13  | 20.50 |
|               |        | Dropout Mean       | 0.00         | 2.43 | 20.66 |
|               |        | Variation Ratio    | 79.37        | 78.13| 82.65 |
| Softmax Response |      | Standard           | 0.00         | 12.10| 34.86 |
|               |        | Dropout Mean       | 0.00         | 12.20| 33.15 |
|               |        | Variation Ratio    | 79.24        | 78.13| 82.32 |
| UNITER        | Entropy|                    | Standard     | 78.72| 85.47 | 87.90 |
|               |        | Dropout Mean       | 87.48        | 86.18| 88.12 |
|               |        | Variation Ratio    | 87.43        | 85.82| 87.90 |
| Softmax Response |      | Standard           | 87.64        | 85.47| 88.01 |
|               |        | Dropout Mean       | 87.30        | 86.23| 87.84 |
|               |        | Variation Ratio    | 87.17        | 85.82| 87.51 |
| MDETR         | Entropy|                    | Standard     | 62.26| 66.08 | 68.34 |
|               |        | Dropout Mean       | 69.66        | 71.54| 71.49 |

Table S3: The percentage of examples that can be accepted while matching the single-query upper bound accuracy given in Tables S4 and S5. We report the intersection of the mean MAE across 100 samples. This table expands upon Table 2 in the main document.
Table S4: The accuracy under four different conditions when the ground-truth bounding box is used. For per-object random, 100 sets of referring expressions (one per object) are drawn to calculate standard error. For all other accuracies, standard error is calculated across five trained models. While the differences between methods reach significance in some instances, no distribution reliably performs best. This table is similar to Table 3 in the main document, but uses ground-truth bounding boxes instead of detected bounding boxes.
### Table S5: The accuracy under four different conditions when the bounding boxes are provided by an object detector. For per-object random, 100 sets of referring expressions (one per object) are drawn to calculate standard error. For all other accuracies, standard error is calculated across trained models—five for MAttNet and UNITER, one for MDETR. While the differences between methods reach significance in some instances, no distribution reliably performs best. This table expands upon Table 3 in the main document.

| Model     | Distribution | Val     | TestA    | TestB    |
|-----------|--------------|---------|----------|----------|
| Per-Expression | MAttNet      | Normal  | 77.39 ± 0.08 | 81.51 ± 0.06 | 70.78 ± 0.20 |
|           |              | Dropout | 77.34 ± 0.09 | 81.50 ± 0.04  | 70.87 ± 0.16  |
|           |              | Variation Ratio | 77.34 ± 0.09 | 81.41 ± 0.06  | 70.82 ± 0.17  |
| UNITER    | Normal       | 80.85 ± 0.07 | 86.53 ± 0.08 | 73.77 ± 0.08 |
|           | Dropout Mean | 80.89 ± 0.05 | 86.57 ± 0.04 | 73.80 ± 0.08 |
|           | Variation Ratio | 80.89 ± 0.03 | 86.57 ± 0.04 | 73.81 ± 0.07  |
| MDETR     | Normal       | 87.12    | 89.78     | 82.00     |
| Per-Object Random | MAttNet | Normal  | 77.01 ± 0.03 | 81.01 ± 0.05 | 70.12 ± 0.07 |
|           | Dropout Mean | 76.94 ± 0.04 | 81.09 ± 0.05 | 70.17 ± 0.06 |
|           | Variation Ratio | 76.99 ± 0.04 | 80.98 ± 0.05 | 70.16 ± 0.06 |
| UNITER    | Normal       | 80.59 ± 0.03 | 86.03 ± 0.05 | 73.23 ± 0.04 |
|           | Dropout Mean | 80.46 ± 0.03 | 86.01 ± 0.03 | 73.20 ± 0.04 |
|           | Variation Ratio | 80.54 ± 0.03 | 86.10 ± 0.04 | 73.19 ± 0.04 |
| MDETR     | Normal       | 86.87 ± 0.03 | 89.46 ± 0.04 | 81.59 ± 0.05 |
| Per-Object Best | MAttNet | Normal  | 85.62 ± 0.03 | 90.43 ± 0.07 | 77.23 ± 0.11 |
|           | Dropout Mean | 85.64 ± 0.06 | 90.33 ± 0.06 | 77.58 ± 0.12 |
|           | Variation Ratio | 85.65 ± 0.06 | 90.33 ± 0.05 | 77.56 ± 0.15 |
| UNITER    | Normal       | 86.14 ± 0.06 | 91.92 ± 0.05 | 78.28 ± 0.06 |
|           | Dropout Mean | 86.13 ± 0.04 | 91.89 ± 0.06 | 78.24 ± 0.06 |
|           | Variation Ratio | 86.15 ± 0.04 | 91.90 ± 0.05 | 78.27 ± 0.05 |
| MDETR     | Normal       | 94.80    | 96.46     | 91.33     |
| Per-Object Worst | MAttNet | Normal  | 65.80 ± 0.19 | 68.53 ± 0.12 | 61.01 ± 0.36 |
|           | Dropout Mean | 65.49 ± 0.24 | 68.55 ± 0.11 | 60.90 ± 0.17 |
|           | Variation Ratio | 65.52 ± 0.23 | 68.51 ± 0.11 | 60.80 ± 0.20 |
| UNITER    | Normal       | 72.64 ± 0.09 | 77.72 ± 0.12 | 66.13 ± 0.25 |
|           | Dropout Mean | 72.69 ± 0.10 | 77.83 ± 0.10 | 66.17 ± 0.21 |
|           | Variation Ratio | 72.70 ± 0.09 | 77.82 ± 0.06 | 66.17 ± 0.21 |
| MDETR     | Normal       | 76.38    | 80.25     | 69.45     |
## Table S6: The Area under the Replacement Mean Additional Error curve (AR-MAE) for all combinations of models, confidence measures, distributions, and object sources. 100 trials were performed, where the re-queried referring expression was replaced with a referring expression randomly drawn from the set of referring expressions for that object. This table expands upon Table 4 in the main document.
Final Accuracies for Smart Replacement

Table S7: The final accuracy of smart replacement across distributions and scoring functions. Over 100 trials, the scoring function was used to select between two referring expressions for every object in the dataset. This corresponds to Table 6 in the main document.
## Final Accuracies for Combined Replacement

| Object Source | Architecture | Distribution | Val    | TestA   | TestB   |
|---------------|--------------|--------------|--------|---------|---------|
| Ground Truth  | MAttNet      | Normal       | 91.33 ± 0.04 | 92.38 ± 0.10 | 89.16 ± 0.15 |
|               |              | Dropout Mean | 91.65 ± 0.19 | 92.64 ± 0.16 | 89.78 ± 0.21 |
|               |              | Variation Ratio | 88.59 ± 0.23 | 88.65 ± 0.15 | 87.51 ± 0.21 |
| UNITER        | Normal       | 95.33 ± 0.12 | 95.98 ± 0.15 | 94.91 ± 0.16 |
|               | Dropout Mean | 95.74 ± 0.14 | 96.47 ± 0.13 | 95.17 ± 0.21 |
|               | Variation Ratio | 93.50 ± 0.22 | 94.19 ± 0.16 | 92.88 ± 0.20 |
| Detector      | MAttNet      | Normal       | 82.10 ± 0.05 | 87.57 ± 0.09 | 74.49 ± 0.19 |
|               |              | Dropout Mean | 82.30 ± 0.03 | 87.47 ± 0.12 | 74.39 ± 0.07 |
|               |              | Variation Ratio | 79.60 ± 0.07 | 83.61 ± 0.16 | 72.84 ± 0.19 |
| UNITER        | Normal       | 84.05 ± 0.06 | 90.07 ± 0.04 | 76.38 ± 0.10 |
|               | Dropout Mean | 84.41 ± 0.07 | 90.37 ± 0.11 | 76.74 ± 0.14 |
|               | Variation Ratio | 82.62 ± 0.08 | 88.35 ± 0.16 | 75.30 ± 0.12 |

Table S8: The converged accuracy of combined replacement with various selection functions. Standard error is calculated across five models for both evaluations. This corresponds to Table 6 in the main document.