INVIGORATE: Interactive Visual Grounding and Grasping in Clutter

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Abstract
This paper presents INVIGORATE, a robot system that uses natural language to communicate with humans and grasps a specified object in cluttered environments. It addresses several challenges: (i) inferring the target object among other occluding objects, from input language instructions and RGB images, (ii) inferring object blocking relationships (OBRs) from the images, and (iii) synthesizing a multi-step plan to ask disambiguation questions about the target object and to grasp the object successfully. INVIGORATE contains several neural network modules trained for object detection, for visual grounding, for question generation, and for OBR detection and grasping. It allows for unrestricted object categories and language expressions, subject to the training datasets. To overcome uncertainties in visual perception and ambiguity in languages, INVIGORATE employs an object-centric partially observable Markov decision process (POMDP) that integrates the learned neural network modules. It tracks the relevant objects by maintaining a history of observations and asks disambiguation questions when necessary. Using the POMDP, it searches for a near-optimal sequence of actions that identify and grasp the target objects. INVIGORATE leverages the advantages of model-based POMDP planning and data-driven deep learning to address the challenge of complex, high-dimensional observations and achieve robust robot performance under uncertainty. Experiments with INVIGORATE on a Fetch robot indicate significant benefits of this integrated approach. A demonstration video is available at https://youtu.be/rQdBrYeVjA.

Keywords
Interaction via Languages, Visual Grounding, Object Grasping, Object Blocking Relationships

1 Introduction
Robots are gradually, but surely entering into our daily life. To become effective human helpers, robots have to understand our physical world through visual perception and interact with humans through natural language. Consider the robot task of following a human verbal instruction to retrieve an object from a cluttered kitchen table (Fig. 1). This seemingly simple task presents multiple challenges:

- Infer the target object among other occluding objects from the input language instruction and images;
- Infer object blocking relationships from images;
- Synthesize a multi-step plan to disambiguate the target object by asking questions and retrieve the target despite other obstructing objects.

Advances in deep learning have yielded powerful neural network (NN) models to process complex visual and language inputs, addressing the first two challenges. However, they alone are not sufficient for two main reasons. Firstly, visual inputs are complex and noisy, leading to errors in perceptual processing. Cluttered scenes are inherently partially observable and exacerbate the difficulty of perceptual processing. For example, the target object may not be detected at all because of visual occlusions (Fig. 1a). Secondly, despite their richness, human languages are sometimes ambiguous. Two distinct objects may both match the language specification (Fig. 1b). A natural question then arises: How can we harness the power of these learned NN models for perceptual and language processing and achieve robust robot performance?

To this end, we have developed and experimented with a robot system, Interactive Visual GROundG and gRAsp in clutTEr (INVIGORATE). See Fig. 1 for examples. INVIGORATE integrates data-driven learning and model-based planning. To address complex visual inputs and language interactions, we train separate NN models to detect objects, to ground verbal references, to generate questions and to grasp objects successfully. A demonstration video is available at https://youtu.be/rQdBrYeVjA.

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that disambiguate object references, and to estimate object spatial relationships for grasping. These NN models are then integrated into an object-centric partially observable Markov decision process (POMDP). In the INVIGORATE POMDP, we model the NN outputs—the detected target object, other objects, and object blocking relationships—as noisy observations and learn a probabilistic observation model of detection failures. Through POMDP planning, INVIGORATE tracks the history of observations on individual objects over time and obtains a robust probabilistic estimate of the objects and their relationships, despite uncertainties in perceptual and language processing.

If a verbal reference to the target object is ambiguous, INVIGORATE gathers information actively by asking disambiguation questions. It reasons systematically about the uncertainty of the target object and balances the potential benefit of additional information against the cost of asking questions. Furthermore, it optimizes the generated questions by predicting possible interpretations by humans.

We deployed INVIGORATE on a Fetch robot. Experimental results show that INVIGORATE achieves an overall success rate of 83% on our test dataset and consistently outperforms a baseline without POMDP integration. Ablation studies further confirm the importance of reasoning about uncertainties in dealing with noisy visual perception and language ambiguity.

One main contribution of this work is to demonstrate a principled approach that integrates data-driven deep learning and model-based planning for complex robot tasks. We build a POMDP model connecting three key elements: robot perception, object manipulation, and human-robot language interaction. The learned NN models enable INVIGORATE to handle complex visual inputs and language interactions. Model-based POMDP planning enables INVIGORATE to achieve robust overall performance under uncertainty in perceptual and language processing.

2 Related Work

2.1 Visual Grounding of Referring Expressions

Visual grounding connects language and vision: it links a language expression with its corresponding visual representation in an image. Given a language instruction and visual observations of the scene, INVIGORATE tries to grasp a target object in clutter. As a first step, it solves a visual grounding problem: recognize and locate in the input image the target object specified by the language instruction. Visual grounding has been studied extensively in computer vision (Qiao et al. 2020), especially, with deep learning techniques (Guadarrama et al. 2014; Nagaraja et al. 2016; Yu et al. 2018). Earlier work typically formulates visual grounding as matching a natural-language referring expression and a set of object proposals from the corresponding image, and uses learning to optimize the matching score. Transformers (Vaswani et al. 2017) have brought significant new progress (Lu et al. 2019; Chen et al. 2020; Deng et al. 2021; Li and Sigal 2021; Kamath et al. 2021; Zeng et al. 2022), by predict directly bounding boxes of referred objects. These methods, however, implicitly assume that objects are clearly visible with little occlusion. To guard against occlusion and other perceptual uncertainties, INVIGORATE integrates observations over time and interacts with human actively via natural language for disambiguation, leading to an effective and robust system.

2.2 Human-Robot Interaction via Natural Language

To resolve ambiguity in language instructions, the robot may ask the human clarification questions. Some earlier robot systems have made important advances: they interact with humans verbally to seek help, when facing ambiguities during navigation (Krujff et al. 2006; Hemachandra and Walter 2015), when collaborating with humans (Rosenthal et al. 2010), or when encountering failures (Deits et al. 2013; Tellex et al. 2014). However, these systems are typically deployed in restrictive settings, as a result of limited model capacity and training data size.

Recent image captioning models based on deep learning (Bernardi et al. 2016; Hossain et al. 2019; Katiyar and Borgohain 2021) show clear advantages over traditional approaches. They take raw image features as input and directly generate captions end-to-end in an auto-regressive manner (Hochreiter and Schmidhuber 1997; Vaswani et al. 2017). Dense captioning models, in particular, generate captions for objects individually (Johnson et al. 2016; Yang et al. 2017). After training on large-scale datasets, they produce much richer and more natural object descriptions. INGRESS (Shridhar et al. 2020) leverages these advances to generate both entity and relational expressions for a target object. The generated expressions are then fitted into a question template to generate disambiguation questions. Again, visual occlusion may degrade the performance of these models, resulting in noisy or even completely wrong expressions.

To address the difficulty, INVIGORATE first generates a set of candidate questions. It predicts how humans interpret these questions and selects the best question through POMDP planning to optimize the overall performance over time.

2.3 Goal-directed Object Grasping in Clutter

Object grasping is widely studied in robotics, with a vast literature (Bohg et al. 2013). In recent years, both data-driven learning and model-based planning have contributed to significant progress in object grasping in general (Lenz et al. 2015; Redmon and Angelova 2015; Mahler et al. 2017, 2019; Garg et al. 2019) and goal-directed object grasping in particular (Jang et al. 2017; Fang et al. 2018; Zeng et al. 2019; Zhang et al. 2019; Murali et al. 2020). It is beyond the scope of this paper to provide a comprehensive survey. We give only a few selected examples closely related to our task.

Several recent methods aim at object retrieval in cluttered scenes (Guo et al. 2016; Zeng et al. 2018; Danieleczuk et al. 2019; Kurenkov et al. 2020; Yang et al. 2020). In particular, Zhang et al. (2019) propose to learn object-blocking relationships for grasping. However, these earlier methods do not address the issue of language interaction between the human and the robot. Hatori et al. (2018) and Chen et al. (2021) propose to fuse visual and text
features in neural networks and grasp the target object based on natural language instructions. Shridhar et al. (2020) formulate a POMDP to ask disambiguation questions about the target object in interactive grasping tasks. Mees and Burgard (2021) propose a robot system capable of grounding language instructions for both object picking and placement. They, however, do not consider visual occlusion and physical obstruction in dense object clutter. INVIGORATE aims to tackle the dual challenges of object grasping in clutter and human-robot natural language interaction together.

2.4 Integration of Learning and Planning

One key strength of INVIGORATE is the integration of learning and planning, an active research direction that has attracted much attention recently.

Learning and planning interact in various ways. One most common approach is to learn models for planning. Models of environment dynamics, observations, and task reward are critical for planning, but are notoriously difficult to design manually, especially for complex systems. One approach is to learn these models from data, through supervised model learning, model-based reinforcement learning (Moerland et al. 2023), or inverse reinforcement learning (Arora and Doshi 2021). We may even do so in the latent space, through representation learning (Hafner et al. 2019; Sekar et al. 2020; Okada and Taniguchi 2021).

One recent, highly successful idea is to insert learned policies or value functions into planning algorithms (Silver et al. 2016; Cai et al. 2019). The learned policies and value functions dramatically speed up forward-search planning algorithms by providing an effective search heuristic and reducing the search horizon.

An opposite, but equally interesting idea is to embed a planning algorithm, or more broadly, any robot algorithm, into a neural network as the structure prior for end-to-end learning (Tamar et al. 2016). These Differentiable Algorithm Networks (DANs) (Karkus et al. 2019) cover a wide variety of essential robot algorithms for state estimation (Jonschkowski et al. 2018; Karkus et al. 2018), planning under full or partial observability (Tamar et al. 2016; Karkus et al. 2017; Guez et al. 2018), and control (Amos et al. 2018). They are structured, interpretable, task-driven, and robust by combining the benefits of model-based planning and data-driven learning.

INVIGORATE does not fall into any of the categories above. It builds on top of a set of NN models learned from data for vision and language processing; it then applies a model-based approach to integrate these NN modules and reasons about their uncertainties systematically in order to achieve robust robot performance.

INVIGORATE uses Q-Net to generate a set of referring expressions of all candidates. It fits the generated expression into a question template and asks the human simple questions for disambiguation and eventually grasps the target object, while avoiding unnecessarily perturbing other objects. See Fig. 2 for an overview.

INVIGORATE integrates data-driven deep learning with model-based POMDP planning. We train four NN modules, O-Net, R-Net, G-Net, and Q-Net, from data for visual and language processing (Fig. 2, bottom). At each time step, O-Net generates from the input image I a set of object proposals. Based on these object proposals, R-Net further processes I and extracts pairwise blocking relationships among the objects, as well as candidate object grasps. G-Net uses the referring expression E in the verbal instruction and the object proposals for visual grounding; it outputs a set of candidates for the target object. If E is ambiguous, there may be multiple candidates. INVIGORATE uses Q-Net to generate a set of referring expressions of all candidates. It fits the generated expression into a question template and asks the human simple questions for disambiguation and eventually grasps the target object, while avoiding unnecessarily perturbing other objects. See Fig. 2 for an overview.

INVIGORATE takes a verbal instruction from the human to grasp an object of interest in clutter. It uses both the natural language instruction and images from its visual sensor to identify the target object. If the referred object in the instruction is ambiguous, INVIGORATE asks the human simple questions for disambiguation and eventually grasps the target object, while avoiding unnecessarily perturbing other objects. See Fig. 2 for an overview.

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human a disambiguation question, e.g., “Do you mean the cup on top?”.

The trained NN models are powerful and allow for unrestricted object categories and language expressions, subject to the training datasets. However, the outputs of O-Net, R-Net, and G-Net are all noisy, because of sensor noise, visual occlusion, and ambiguity in human languages. To achieve robust robot performance under these uncertainties, we build a POMDP model that integrates the learned NN modules. INVIGORATE maintains a belief, i.e., a probability distribution over the underlying state. INVIGORATE uses a factored, object-centric state representation that consists of the target object, the other objects, and their blocking relationships. It treats the NN outputs as noisy observations on the objects and their relationships, in order to account for the NN prediction errors. At each step, INVIGORATE updates the belief with new observations and actions, through Bayesian filtering (Fig. 2, middle). The belief summarizes the history of observations and actions; it quantifies the uncertainties probabilistically and provides the basis for a principled approach to robust robot decision making.

Given a belief, INVIGORATE performs approximate POMDP planning through look-ahead search to choose the best action (Fig. 2, top). INVIGORATE models two types of actions: ask a disambiguation question or grasp a target object. Intuitively, if the belief over the target object has high uncertainty, INVIGORATE may ask a disambiguation question to gain additional information. Further, it selects the question carefully by predicting possible human interpretations, thus avoiding uninformative questions and enabling natural human interaction. If the belief has low uncertainty, INVIGORATE grasps either the target object directly or an obstructing object according to the estimated object blocking relationships. By reasoning about the belief, POMDP planning enables INVIGORATE to choose a near-optimal sequence of actions.

4 Neural Networks for Visual Perception and Language Interaction

INVIGORATE uses deep learning to build perceptual and interaction modules. We describe each of these modules in the subsections below.

4.1 O-Net for Object Detection and Tracking

INVIGORATE applies the Cascade R-CNN (Cai and Vasconcelos 2018) as the base object detector, which is trained on the union of COCO (Lin et al. 2014) and VMRD (Zhang et al. 2018). Nevertheless, imperfect detection is inevitable due to noisy visual observations, neural network failures, and partial observability in our tasks. Moreover, INVIGORATE is trying to deal with multi-step goal-directed grasping, which means that it needs to track the object states and maintain consistency throughout multi-step results. Hence, we introduce an object detection and cross-step tracking mechanism in this section.

Specifically, to track objects across multiple steps, we maintain an object pool $\mathcal{B}$. In each step, we first feed the raw image $I$ to the base detector and obtain a set of proposals $\mathcal{B}^D$. Then, we feed all historical proposals in $\mathcal{B}$ to the object detector to re-classify them and get a historical set $\mathcal{B}^H$. Subsequently, we merge $\mathcal{B}^H$ into $\mathcal{B}^D$ using Hungarian algorithm with the cost function defined as:

$$H(B_i, B_j) = \alpha_1 \frac{|B_i \cap B_j|}{|B_i \cup B_j|} + \alpha_2 \left\| c_i - c_j \right\|$$  

(1)

where $B_i$ and $B_j$ represent the bounding boxes of object $i$ and $j$. $|B_i \cap B_j|$ is the intersection of union (IoU) between $B_i$ and $B_j$. $c_i$ and $c_j$ mean the normalized confidence scores given by the object detector, and $\alpha_1$ and $\alpha_2$ are the weights to balance the two items and $\alpha_1 + \alpha_2 = 1$. Intuitively, bounding boxes with large IoU and the same category will be merged into one. Finally, the object pool $\mathcal{B}$ will be updated by $\mathcal{B}^D \cup \mathcal{B}^H$ using Hungarian algorithm again with the same cost function defined in (1). Such a detection procedure is more robust against false positives and false negatives. The merging process based on the Hungarian algorithm also enables object tracking across different steps, which is a prerequisite for belief updates.

4.2 G-Net for Visual Grounding

G-Net takes an image $I$, a referring expression $E$, and detected object proposals in $\mathcal{B}$ to estimate the matching scores between each detected object $i$ and the referring expression $E$:

$$g_i = G(B_i, E, I)$$  

(2)

where $G$ denotes G-Net and $g_i$ denotes the output matching score. In INVIGORATE, we train G-Net following Yu et al. (2018) on the RefCOCO dataset. G-Net splits the user expression into three parts: the subject description, the locational description, and the relational description. It extracts the visual feature for each proposal and performs separate visual-text matching. To illustrate, given the expression “the blue cup to the right of the book”, a sentence would be decomposed into a subject description “the blue cup”, a locational description “to the right of” and a relational description “the book”. An embedding is obtained for each description through a language attention network. The image is fed into a CNN-based neural network to generate a visual feature map, which is then pooled into region features using proposals in $\mathcal{B}$. After that, we estimate a similarity score between phrases and pooled visual features together with their location information with a trainable layer. Finally, an attention-based summation of similarity scores for three phrases is used to determine the referred object. All layers are trained in an end-to-end manner. As a result, G-Net is scalable and can handle almost unrestricted referring expressions, e.g., “the red apple”, “the apple on top”, “the blue cup to the right of the book”, etc.

4.3 Q-Net for Question Generation

To ask a disambiguation question, Q-Net first generates a caption about an image region and then fits it into a question template. Specifically, it uses two captioners: a self-referential captioner for object attributes (e.g., object category, color, or shape) and a relational captioner for object relationships. However, visual occlusions can cause noisy and sometimes completely misleading captions, particularly for the self-referential ones. To address this
issue. INVIGORATE takes G-Net as a human response model and selects the best among the generated candidates.

Q-Net uses DenseCap (Johnson et al. 2016) as the self-referential captioner. It takes as inputs object features derived from its bounding box and then generates descriptions using LSTM (Hochreiter and Schmidhuber 1997) in an autoregressive manner, i.e., words are generated one by one based on the input features and all previous words. For each object \( i \), it generates a noisy object-specific caption \( q^i_s \), and thus it constructs a self-referential caption set \( \mathcal{Q} = \{ q^i_s \}_{i=1}^N \) for the workspace, where \( N \) is the number of detected objects.

Q-Net uses UMD RefExp (Nagaraja et al. 2016; Shridhar et al. 2020) as the relational captioner. It takes as input the visual and spatial features of the object of interest \( i \) and a context object \( i_c \), which may be the whole image. The generation of relational captions is similar to self-referential captions, also based on auto-regression and LSTM. To ensure that the relational description of the object \( i \) is informative, we feed all possible pairs \((i, i_c)\) consisting of object \( i \) and every possible context object \( i_c \) to the relational captioner, and choose the one with maximum confidence score:

\[
q^i_R = \underset{q^i_R}{\arg \max} \, P(q^i_R | i, i_c, I) \tag{3}
\]

Relational captioner finally outputs a set of relational captions \( \mathcal{Q}_R = \{ q^i_R \}_{i=1}^N \) for every object \( i \).

In addition, Q-Net generates a set of mixed captions \( \mathcal{Q}_M = \{ q^i_M \}_{i=1}^N \), containing both self-referential captions and relational captions to provide richer, more specific object descriptions. To generate a mixed caption for object \( i \), we first extract attributes from \( q^i_s \) and the relational description from \( q^i_R \). We then concatenate the self-referential attributes, the class name, and the relational description into a single expression.

Finally, to choose the best disambiguation question, we use G-Net again as a human response model to predict how humans interpret each caption. We call this critiqued question generation. Specifically, among all candidate captions \( \mathcal{Q} = \mathcal{Q}_S \cup \mathcal{Q}_R \cup \mathcal{Q}_M \) the one that best matches the interested object according to G-Net:

\[
q^i = \underset{q^i \in \mathcal{Q}}{\arg \max} \, G(B, q, I) \tag{4}
\]

Q-Net and G-Net play the role of an actor and a critic, respectively. Experiments show that critiqued question generation provides much more robust performance, especially, under visual occlusion in clutter.

We follow Johnson et al. (2016) to train our self-referential captioner on Visual Genome dataset (Krishna et al. 2017) and Shridhar et al. (2020) to train our relational captioner on RefCOCO dataset (Kazemzadeh et al. 2014) using Multi-Instance Learning (Foulds and Frank 2010). Subject to the dataset, our captioners typically generates descriptions such as “the red apple” (self-referential), “the apple on the right of the cup” (relational) and “the apple in the back of the image” (relational).

### 4.4 R-Net for OBR and Grasp Detection

In INVIGORATE, a single network R-Net outputs both grasps and OBRs of detected objects in \( \mathcal{B} \).

For OBR detection, we formulate it as a classification problem, which takes object pairs as inputs and classifies pair-wise OBRs. Following Zhang et al. (2018), there are three kinds of OBRs: “parent”, “child”, and “none”. “Parent” relation between A and B means A should be grasped after B, and vice versa for the “child” relation. To classify OBR, we first represent each object by a pooled feature with a fixed size \((7 \times 7)\), which is extracted using ROI pooling based on bounding boxes and image features. Then we form all possible pair-wise permutations of object features. The feature of an object pair \((i, j)\) includes the features of \( i, j \) and the union bounding box. Finally, the pair-wise OBR for object \((i, j)\) is directly classified based on the corresponding pair-wise feature and results in an OBR score \( r_{ij} \):

\[
r_{ij} = R(B_i, B_j, I) \tag{5}
\]

where \( R \) represents the R-Net. For grasp detection, since our task is goal-directed, the grasp should be object-specific. To do so, we detect grasps on each object instead of the input scene. Concretely, the grasp detector regresses grasps using the \( 7 \times 7 \) pooled feature of each object with a few convolutional layers.

We follow Zhang et al. (2019) to train our R-Net on VMRD (Zhang et al. 2018), which contains around 4300 images and 100k grasps. In practice, we found that the grasp detector sometimes returns unstable grasps. Therefore, based on the detection result, we finetune the grasp pose through local search. In detail, we do a grid search by discretizing the area along five dimensions \((x, y, z, \theta)\) near the detected grasp, where \((x, y, z)\) is the center of the grasp, \( w \) is the width of the gripper, and \( \theta \) represents the rotation angle w.r.t. the approaching vector. We traverse all possible grasp poses to find the best one, whose closing area contains more points of the object.

### 5 INVIGORATE POMDP

To tackle uncertainties in visual perception and ambiguity in language interaction, INVIGORATE forms a POMDP to integrate the NN modules.

#### 5.1 State Space

To grasp the specified target in clutter, the state of INVIGORATE can be decomposed into two parts, the visual grounding state \( s^v \) and OBR state \( s^r \), i.e., \( s = s^v \cup s^r \). \( s^v = \cup_{i=1}^N s^i \) is an object-centric state (Diuk et al. 2008; Wandzel et al. 2019), with each \( s^i \) indicating whether object \( i \) is a
Figure 4. An example of grasping macro for the blue box in the scene. Left: the scene image with a red box of the target blue box. Right: the object blocking graph of the left image, with a grasping macro marked by red dashed line to grasp the blue box.

5.2 Action Space and Transition Model

To handle possible ambiguity, INVIGORATE allows active interaction with human to gather more information. Therefore, INVIGORATE has two types of actions: 1) grasping; 2) asking a question.

As shown in Fig. 4, grasp actions are defined by grasp macros. Each grasp macro is a sequence of grasps resulting in a terminal state. Assuming that $N$ objects are detected, there will be $N + 1$ grasp macros, including $N$ goal-directed choices and 1 clearing choice. Each goal-directed grasp macro $a^g_i$ targets at object $i$. According to $b^c$, it sequentially removes exposed objects that most likely blocks object $i$, until it retrieves $i$. The clearing grasp macro $a^c_{i,j}$ is used to remove all detected objects when none of them is the target. According to $b^c$, it sequentially removes the most exposed objects. It is non-trivial to analytically find the most exposed object blocking one specified target since all relations are probabilistic. Therefore, we apply Monte Carlo method to estimate the probability of each object to be exposed and block the target, and then select the most probable one. Note that in practice, for each step, we only execute the first grasp and then do re-planning, which helps to improve robustness.

For each object $i$, action $a^g_i$ means asking the human whether $i$ is the target. The questions are generated from Q-Net. Each question follows a template “Do you mean $X$?”, where $X$ is a caption from Q-Net. Noticeably, each asking action is associated with a specific object. To achieve so, we utilize multi-modal interaction (Goodrich et al. 2008) by introducing pointing actions when asking questions, i.e., when the robot is asking a question about object $i$, it will also point to it using its end effector. Therefore, the number of available asking actions is equal to $|N|$.

As a result, the size of action space $|A| = 2N + 1$. Since we assume that human does not change their mind about the target object, for any $a^g$, the transition model is:

$$T(s'|s,a^g) = \begin{cases} 1, & s' = s \\ 0, & s' \neq s \end{cases}$$

On the other hand, any grasp macro results in a terminal state. Therefore, we simply ignore the associated transition model.

5.3 Visual Observations

INVIGORATE takes the output of the G-Net and R-Net as the visual observations after each grasping action. At time step $t$, we denote the visual grounding observation from G-Net as $o^g_t$ and OBR observation from R-Net as $o^r_t$. For brevity, we denote observation $o_t$ as $o$. Both $o^g$ and $o^r$ are object-centric and accord with the state, i.e., $o^g = \cup_{i=1}^N g_i$ and $o^r = \cup_{i,j=1}^N r_{ij}$. Accordingly, our visual observation model captures the distribution over $o^g$ and $o^r$ using visual grounding observation model $Z^g$ and OBR observation model $Z^r$ in a factorized way. Formally:

$$Z^g = Z(g_i | s^g_i) \quad Z^r = Z(r_{ij} | s^r_{ij})$$

where $g_i$ is the output of G-Net and $r_{ij}$ is the output of R-Net.

Unfortunately, $Z^g$ and $Z^r$ cannot be specified manually. Thus, we resort to data-driven methods. Specifically, we collect a dataset in clutter using G-Net, in which each data is represented by $\{g_i, s^g_i\}$, where $s^g_i$ is a binary label that indicates whether the object $i$ is the referred target. Similarly, we collect a dataset in clutter using R-Net containing tuples $\{r_{ij}, s^r_{ij}\}$, where $s^r_{ij}$ is the ground truth OBR between object $i$ and $j$. We then apply Gaussian kernel density estimation to learn an approximate model for $Z^g$ and $Z^r$.

5.4 Textual Observations

After the robot asks a question $o^q_i$, it receives an answer from the human, which is the textual observation $o^t_i = ans$. Each textual observation is an unrestricted natural language expression including a response phrase $ans_i$ (e.g., “Yes” or “No”) that may be followed by an additional description $ans_d$ (e.g., “No, the left one”). We assume that the textual observation model is orthogonal to the OBR state $s'$. To reduce the computation cost of POMDP planning, during the forward search, we use a simplified observation model over $ans_i$ that effectively ignores the additional description:

$$Z^t = Z(ans | s^g, s^d) \approx Z(ans | s^g, s^d)^\epsilon$$

where $\epsilon$ belongs to either positive phrases $Res^d = \{\text{“Yes”, “Yeah”, “Yep”, “Sure”}\}$ or negative phrases $Res^n = \{\text{“No”, “Nope”}\}$. During the belief update, we handle $ans_i$ according to (8), but merge $ans_d$ into $E$ which will be used for visual grounding in subsequent steps.

We assume that the human is truthful. Once the human confirms a target, the robot needs not consider other objects anymore. Under this assumption, the factorized observation model for asking questions is shown in Table 1. $\epsilon$ is a small positive constant, and in practice, it is set to 0.01. Intuitively, a positive answer for object $i$ makes object $i$ the only target while a negative answer eliminates object $i$ as a target but does not affect the belief of other objects.
5.5 Reward

We want the robot to grasp the correct target while asking a minimal number of questions. Thus, we impose a small penalty, i.e., a reward of -2, when it asks a question, and a large penalty when it fails the task (e.g., grasping the wrong object). When multiple objects seemingly satisfy the user expression, the robot cannot accurately differentiate between ambiguity and multi-target. Thus, to encourage disambiguation and avoid grasping wrong targets in such cases, we empirically engineer the reward for goal-directed grasp macros \( R(s, a^g) \):

\[
R(s, a^g) = \begin{cases} 
-10 + \frac{10}{\sum s^g_i}, & s^g_i = 1 \\
-10, & s^g_i = 0 
\end{cases} 
\] (9)

If there is only one object satisfying the human’s instruction, grasping it will result in no penalty. Otherwise, to encourage disambiguation, the reward of grasping decreases as the number of targets increases. The robot receives a reward of -10 if it fails to grasp the target.

For the clearing grasp macro \( a^g_{-1} \), the reward is:

\[
R(s, a^g_{-1}) = \begin{cases} 
0, & \forall s^g_i = 0 \\
-10, & \text{otherwise} 
\end{cases} 
\] (10)

That is, the robot will not be penalized only if all detected objects are not the target. Otherwise, it receives a reward of -10 since it removes the target without passing it to the human.

5.6 Belief Tracking

Based on the imperfect observation \( o^g \) in each step, we update the belief \( b_i \) to obtain a more accurate estimate of the underlying true state. Since our state is object-centric, it can naturally be factorized. We factor target belief \( b^g_i \) into belief over each object \( b_i(s^g_i) \), and relationship belief \( b^r_i \) into belief over each pair of object \( b_i(s^g_{ij}) \). This factorization allows us to perform belief tracking on each object and object pair separately.

The robot receives visual observations \( o^g \) and \( o^r \) after it performs a grasping and a textual observation \( o^f \) after it asks a question. As mentioned, we factor each \( o^g \) into target observation over each objects, \( o^g = \cup_{i=1}^{N} g_i \), and \( o^r \) into relationship observation over each pair of objects, \( o^r = \cup_{i,j=1}^{N} r_{ij} \). We then track each factorized belief using Bayesian filter:

\[
b_{t+1}(s^g_i) \propto Z^g \cdot b_t(s^g_i) \\
b_{t+1}(s^g_{ij}) \propto Z^r \cdot b_t(s^g_{ij}) \] (11)

where \( Z^g \) and \( Z^r \) are learned observation model for target and relation respectively. Since the human’s answer does not affect OBR, \( ans \) is only used to update \( b^g \)

\[
b_{t+1}(s^g_i) \propto Z^g \cdot b_t(s^g_i) \] (12)

5.7 POMDP Planning

Intuitively, our POMDP planner evaluates the trade-off between gathering more information and directly retrieving the target. This setting is similar to the Tiger problem (Kaelbling et al. 1998). Therefore, we utilize the policy tree search introduced by Kaelbling et al. (1998) as the POMDP planner.

As shown in Fig. 5, our POMDP planner takes the current belief \( b_t \) as the input, and performs look-ahead search for the optimal action sequence \( a^* \) that maximizes the cumulative reward:

\[
a^* = \arg \max \sum_a E_{s,t} R(s_t, a_t) \] (13)

In our policy tree, each node \( b \) represents a belief. The parent node \( b_t \) and child node \( b_{t+1} \) are connected with an observation-action pair. Since \( a^g \) results in a terminal state, observation-action pairs are all based on \( a^g \) during planning. The maximum search depth is set to 3 to limit the number of questions the robot can ask. By traversing all possible trajectories, the planner returns an optimal trajectory that maximizes the expected cumulative reward (denoted as the red path in Fig. 5). The robot then executes the first action in the optimal trajectory (denoted as the pink square). If the action is a grasp macro, the robot grasps the first object in the grasp sequence. If the action is to ask a question, the robot simply says the caption generated by Q-Net. After the action is performed, the robot transits into the next step where it receives a new observation, updates its belief, and performs the search again.

6 Experimental Setup

6.1 Implementation Details

We deploy INVIGORATE on a Fetch robot under the framework of the Robot Operating System (ROS). All deep neural networks run on a single external NVIDIA Titan X GPU. We use Intel Realsense D435 camera to capture RGB images for visual inputs and point cloud for grasping and Google Cloud APIs to translate human verbal...
instructions into texts as well as synthesize speech for generated questions.

6.2 Benchmark

To ensure fair comparisons between different variants of the system, we run all experiments on a test dataset consisting of 10 cluttered scenes shown in Fig. 6. We generate 100 test cases by recruiting 10 participants and asking them to select a target object and give a corresponding description for each scenario. For a comprehensive evaluation, we split test cases into two parts:

1. **Test A**: Targets are selected before the participants see the clutter but are described after the clutter is shown. Participants therefore do not know where the target object will be located at the time of target selection.
2. **Test B**: Targets are selected by participants after they see the clutter. Participants exactly know which object is challenging for the robot to grasp.

As we encourage participants to choose challenging targets, **Test B** is generally harder than **Test A**.

6.3 Baseline

**INVIGORATE** combines data-driven learning and model-based planning. Given the success of deep learning, the natural tendency is to use it directly. We build up the baseline method based purely on learned NN modules. The baseline, called **MAttNet+VMRN**, utilizes MAttNet (Yu et al. 2018) for visual grounding and VMRN (Zhang et al. 2019) for OBR and grasp detection. It greedily follows the output of MAttNet to locate the most probable target while following OBR and grasp detection. It greedily follows the output of MAttNet to locate the most probable target while following OBR and grasp detection.

6.4 Ablations

**INVIGORATE** POMDP consists mainly of three components: interaction, belief tracking, and policy tree search. In ablation studies, we aim to determine their respective contribution. Our ablation studies include:

- **w/o interaction**: the robot never asks questions but maintains the visual history to track the belief.
- **w/o pointing**: the robot asks questions without pointing to the corresponding object. The question will be generated using the critiqued captioner.
- **w/o history**: the robot remembers neither visual nor QA history. The POMDP planner works on the belief estimated only by the current observation.
- **w/o visual history**: the robot remembers QA history but not historical visual observations. The POMDP planner works on the belief estimated by the current visual observation and QA history.
- **w/o tree search**: it utilizes a heuristic method instead of tree search. Concretely, we apply two-class K-Means to the expected rewards of all grasp macros to check if multiple grasp macros have similar expected rewards. If that is the case, the robot will ask a question. Otherwise, it will execute the grasp macro with the max reward.

6.5 Procedures

We conduct three experiments on the real robot using the collected dataset.

The first experiment aims to compare the overall performance of INVIGORATE against the baseline and conduct ablation studies. Each variant of the system receives the same initial image and expression from the dataset as input. It then computes an action for the robot to execute. In each experimental scene, the experimenter is only required to describe one of the objects freely using its name, without any further detailed instructions to avoid possible interaction biases. During the process, if a question is asked, the experimenter will provide an answer (e.g., “yes/no”) according to whether the object being asked is the true target. Though the experimenter is allowed to give additional descriptions when being asked, we found that in our experiments they did not tend to do so. Therefore, if there exist multiple ambiguous objects, the robot might ask several rounds of questions to disambiguate. Since grasp failures are not handled by any variant of the system and do not offer a meaningful comparison, if the robot fails to grasp an object, the experimenter would manually remove it. We record the success rate of each variant. A test case is regarded as a success only if the robot retrieves the true target. For ablation studies, we in addition record the **Normalized Cumulative Reward and Number of Questions** to give a comprehensive comparison.

The second experiment aims to compare INVIGORATE’s visual grounding performance against the SOTA method. We run INVIGORATE and ViLBERT side-by-side. No action is planned or executed by INVIGORATE. The experimenter instead manually removes blocking objects sequentially to retrieve the final target. In each step, we record the target probabilities estimated by both systems. Since ViLBERT is trained with cross-entropy loss, we directly apply exponential on its output to get the target probabilities.

The third experiment aims to compare INVIGORATE’s captioning performance against baseline methods. Concretely, we run the captioner in INVIGORATE to generate captions for each object in our collected dataset. To compare the captioning performance, we first label the real-robot dataset manually with a detailed and distinct caption for each object bounding box. Based on the labeled captions, we evaluate the quality of the generated captions from different captioners using several well-known metrics, including BLEU (Papineni et al. 2002), METEOR (Banerjee and Lavie 2005), ROUGH (Lin 2004), CIDEr (Vedantam et al. 2015), and SPICE (Anderson et al. 2016). Since our question generator is based on DenseCap (Johnson et al. 2016) and...
INVIGORATE shows a higher success rate than the baseline. While the baseline MAttNet+VMRN achieves a higher success rate of 76% on Test A, its performance drops severely to 60% when applied on the harder Test B. In contrast, the performance of INVIGORATE only drops by 6%. A closer look at the experiment result shows that the baseline’s performance drop in Test B is mainly due to the increase in target detection failures. In fact, the baseline nearly fails in all cases where the target object is not visible or not detected at the beginning. In such cases, without a probabilistic estimate of the true underlying state, the baseline simply chooses the most likely target among visible objects and retrieves it for the user. On the other hand, INVIGORATE is able to reason that the target is not directly visible and would choose the clearing action to look for the target at the bottom.

### 7 Ablation Studies

We now answer the second question, which aims to identify the main contributors the performance of INVIGORATE. Table 2 also shows the results of ablation studies. We found that interaction significantly improves the overall success rate ($p < 0.01$ in t-test). w/o Interaction suffers about 17% success rate loss, mainly from grasping the wrong target. The information gathered from interaction greatly helps to obtain an accurate belief and prevents the robot from target failures. From the comparison between w/o pointing and INVIGORATE, it is also noticeable that the pointing action is important for disambiguation. The pointing action can bridge the gap between the robot and the user to understand the same description, which is sometimes ambiguous. On the other hand, from the comparison between w/o pointing and w/o interaction, we can conclude that interaction is helpful even without pointing actions.

In addition, we conclude that history reduces the number of questions. Compared to INVIGORATE, w/o History and w/o Visual History ask more questions (both with $p < 0.01$ in t-test). In w/o Visual History, the robot uses only the current observation to estimate the belief over the state which is less accurate. Therefore, it has to ask more questions to refine its belief. Besides, w/o History asks the most number of questions as the robot does not remember previous answers from the human. Though it achieves a high success rate, the system’s behavior is annoying, resulting in a low cumulative reward.

For comparison between INVIGORATE and w/o tree search, we found that only 100 experiments do not show a statistically significant difference due to high variance. Therefore, we conducted 100 more experiments with the
shows a higher cumulative reward than w/o tree search does. In this section, we want to answer the following question: how to show some significant difference. We will conduct more experiments in the future to explore the effects of the planner.

The intrinsic reason should lie in the two-class K-Means policy, which is quite close to the one-step planning and seems to be confident about its judgment without asking questions. The intrinsic reason should lie in the two-class K-Means policy, which is quite close to the one-step planning and might be myopic. Unfortunately, 200 experiments still fail to show some significant difference. We will conduct more experiments in the future to explore the effects of the planner.

7.3 Visual Grounding

In this section, we want to answer the following question: how does INVIGORATE perform well in visual grounding in clutter, a key component of the system?

We compare target probability L1 loss and mean average accuracy between INVIGORATE and ViLBERT. Results are shown in Table 3. In order to calculate the accuracy of both systems, we treat visual grounding as a binary classification problem. The object is regarded as the target once its target probability is higher than a certain threshold. The mean accuracy reported is computed by averaging accuracies computed on 9 different thresholds (0.1 to 0.9 with interval 0.1).

Our results show that the visual grounding performance of INVIGORATE consistently outperforms ViLBERT in clutter. Despite its SOTA performance on visual grounding in uncluttered scenes, ViLBERT suffers from visual occlusions and language ambiguities in our test dataset and becomes inaccurate and unstable. On the other hand, INVIGORATE treats neural network’s outputs as noisy observations. It learns an observation model and uses the Bayesian filter to constantly update its belief of the state across multiple steps. Our results confirm that such a principled approach for visual grounding exhibits more robust performance in clutter.

7.4 Question Generation

In this section, we compare the quality of question generation by various methods and provide examples to illustrate the advantage of our critiqued question generation method.

For baseline comparison, we use DenseCap (Johnson et al. 2016) and UMD RefExp (Nagaraja et al. 2016; Shridhar et al. 2020) to generate referring expressions, as they form the basis of our question generator. We fit the generated object referring expressions into a common template for question generation. Our experiments indicate, however, that these two state-of-the-art methods alone are not reliable in cluttered scenes and often generate wrong subject nouns for objects partially occluded. We thus introduce two stronger baselines: DenseCap + Class Name and UMD RefExp + Class Name. Since DenseCap usually generates reliable attributes, e.g., color, for an interested object, we first parse the generated captions and extract the adjectives. We then form the referring expression by concatenating the extracted attributes and the class name from O-Net (DenseCap + Class Name). Similarly, UMD RefExp is good at predicting relationships among interested objects. We concatenate the generated relational phrase and the class name from O-Net (UMD RefExp + Class Name).

The results are reported in Table 4. Following the common evaluation protocol of natural language processing, we compare our critiqued question generation with the baselines on several widely-used metrics for image captioning, including BLEU (word-level precision) (Papineni et al. 2002), ROUGE (word-level recall) (Lin 2004), METEOR (word-level F1 score) (Banerjee and Lavie 2005), CIDEr (Vedantam et al. 2015), and SPICE (Anderson et al. 2016). The two most recent metrics, CIDEr and SPICE, focus on the semantics of expressions rather than merely match individual words one by one. Also, BLEU-4 captures semantics better than BLEU-1, as BLEU-4 uses multiple words to gain contextual information. Overall, our critiqued question generation performs well at the semantic level, according to CIDEr and SPICE. At the word level, our performance is comparable to UMD RefExp + Class Name and much better than DenseCap + Class Name.

We also provide some examples to help understand the improved performance of critiqued question generation (Fig. 7). Our method tends to favor the color as the primary attribute for object reference (Fig. 7a–b). This preference is consistent with that of humans, according to the study of Li et al. (2016), as our models are trained on human-labeled data and encode human preferences in the neural networks.

Table 3. Comparison of visual grounding performance.

|                      | Test A | Test B | Overall |
|----------------------|--------|--------|---------|
| ViLBERT              | 0.855  | 0.817  | 0.831   |
| INVIGORATE           | 0.879  | 0.873  | 0.875   |

Table 4. Comparison of question generation performance.

|                      | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | METEOR | ROUGE | CIDEr | SPICE |
|----------------------|--------|--------|--------|--------|--------|-------|-------|-------|
| DenseCap + Class Name| 0.150  | 0.112  | 0.095  | 0.000  | 0.158  | 0.433 | 1.480 | 0.329 |
| UMD RefExp + Class Name| 0.429  | 0.273  | 0.210  | 0.162  | 0.185  | 0.569 | 2.056 | 0.377 |
| INVIGORATE           | 0.363  | 0.285  | 0.240  | 0.193  | 0.213  | 0.561 | 2.456 | 0.420 |
Further, the critic filters out the incorrect “hallucinated” words (Fig. 7b). However, the critic sometimes chooses a correct, but verbose expression (Fig. 7c), because it has not been trained to prefer concise expressions.

7.5 Additional Examples

Fig. 8 shows examples of INVIGORATE. In Fig. 8(a), the user gives an ambiguous expression. As there are two mice in the scene, INVIGORATE asks a question to disambiguate. Fig. 8(b-d) show some complex scenarios where the target cannot be easily identified. In Fig. 8(b), the relational clue object “book”, which is the blue book lying under the right apple, is not detected. In Fig. 8(c), the black mouse is covered by a white toothbrush while the target white mouse is not detected. In Fig. 8(d), the red box is detected, but its visual features are not strong since it is occluded by the bottle and mouse on top. To tackle these difficulties, INVIGORATE asks questions to query for more information. Fig. 8(e) shows a case where the target is not detected. INVIGORATE therefore removes the cup on top to look for the target at the bottom. Fig. 8(f) shows a simple case where the target is not occluded or obstructed, INVIGORATE therefore directly grasps the target without asking any question.

Fig. 8(g) shows that the object detector fails to detect the scissors that are blocking the true target without asking any question. In Fig. 8(h), the user gives an ambiguous expression “remote” while the true target is the black remote in the back. Due to occlusion, the visual grounding module places a very low score on the true target, INVIGORATE therefore grasps the white remote controller directly, believing that it is the only target in the scene. Fig. 8(i) shows a case of relationship detection failure. INVIGORATE directly grasps the banana although it is blocked by the scissors, violating the true OBR.

8 Conclusion

INVIGORATE enables the robot to interact with human through the natural language and perform goal-directed object grasping in clutter. It takes advantage of a POMDP model that integrates the learned neural network models for visual perception and language interaction. By integrating data-driven deep learning and model-based POMDP planning, INVIGORATE successfully tackles complex visual inputs and language interactions and achieves strong overall performance, despite the inevitable errors of the learned neural network models in perceptual and language processing.

Many exciting challenges lie ahead. First, the neural network models for visual perception and language interaction are trained independently. It would be interesting to embed the INVIGORATE POMDP into the network and apply end-to-end training. Previous work demonstrates that such an end-to-end architecture may bring considerable performance improvement (Karkus et al. 2017; Tamar et al. 2016). Second, INVIGORATE cannot fully address the systematic errors from the deep neural network models for visual perception. Calibration of the learned models (Vaicenavicius et al. 2019) can potentially improve the uncertainty estimate for INVIGORATE in the future. Finally, INVIGORATE assumes that the human would get annoyed if the robot asks more than 3 questions. It is reasonable simplification, but neglects the nuance of human-robot interaction. For humans, seamless interaction depends on conventions shaped by shared experiences and culture. For robots to achieve the same, it may be necessary to model the human cognitive state and adapt information exchange accordingly (Goodrich et al. 2008), an interesting yet challenging direction for future work.

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Figure 8. Qualitative results. (a-f): some selected successful cases of INVIGORATE with different kinds of uncertainty and ambiguity. (g-i): some selected failures. The sentence on top is the action of the robot and the sentence at the bottom is the human’s instruction. Best viewed in color.

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