Improved Models and Queries for Grounded Human-Robot Dialog

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Doctoral Dissertation Proposal
Natural Language Interaction with Robots
Understanding Commands

Bring the blue mug from Alice’s office
Sources of Imperfect Understanding

- Language is inherently ambiguous
  - Mug: 🕵️‍♂️ vs 🕵️‍♀️ vs 🕵️‍♂️

- Imperfect models
  - Fail to detect the mug

- Missing domain specific knowledge
  - Alice’s office is missing in the directory
Bring the blue mug from Alice’s office

Where should I bring a blue mug from?

Alice Ashcraft’s office

I should bring a blue mug from 3502?

Yes
Dialog - Improve Models

Bring the blue mug from Alice’s office

Where should I bring a blue mug from?

Alice Ashcraft’s office

I should bring a blue mug from 3502?

Yes

Alice’s office ≃

Alice Ashcraft’s office ≃

3502
Dialog - Acquiring Labels

Bring the blue mug from Alice’s office

Would you use the word “blue” to refer to this object?

Yes
This Proposal

Improving grounded human-robot dialog by

• Learning dialog policies from interactions
• Improved queries to be used in dialogs
• Improved models for perceptual grounding
Outline

• Background
• Completed Work
  – Integrating Learning of Dialog Strategies and Semantic Parsing (Padmakumar et.al., 2017)
  – Opportunistic Active Learning for Grounding Natural Language Descriptions (Thomason et. al., 2017)
  – Learning a Policy for Opportunistic Active Learning (Padmakumar et. al., 2018)
• Proposed Work
• Conclusion
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Background: Parts of a Dialog System

Bring the blue mug from Alice’s office

Where should I bring a blue mug from?

Semantic Understanding → Grounding

Natural Language Generation

Dialog Policy
Background: Semantic Understanding

Bring the blue mug from Alice’s office

Semantic Understanding → Grounding

Where should I bring a blue mug from?

Natural Language Generation

Dialog Policy
Background: Semantic Understanding

Convert natural language into a machine understandable representation
Background: Semantic Understanding

Convert natural language into a machine understandable representation

Bring the blue mug from Alice’s office

\[
\text{bring}(\lambda x. (\text{blue}(x) \land \text{mug}(x)), \\
\text{the}(\lambda y. (\text{office}(y) \land \text{owns}(\text{alice}, y))))
\]

Semantic parsing -
- Converts language to a structured meaning representation
- Compositionality - meaning of “blue mug” from meaning of “blue” and meaning of “mug”
Background: Semantic Understanding

Convert natural language into a machine understandable representation

Vector Space Representations -
- Converts words/sentences to vectors that represent meaning.
- Typically non compositional.
- Less initial handcrafting
- More training data

Bring the blue mug from Alice’s office
Bring the blue mug from Alice’s office

Background: Grounding

Where should I bring a blue mug from?

Semantic Understanding

Grounding

Dialog Policy

Natural Language Generation
Background: Grounding

Map meaning representations to real world entities
Background: Grounding

Map meaning representations to real world entities

\[\text{the}(\lambda y. (\text{office}(y) \land \text{owns}(\text{alice}, y)))\]

<table>
<thead>
<tr>
<th>Person</th>
<th>Office</th>
</tr>
</thead>
<tbody>
<tr>
<td>alice</td>
<td>3502</td>
</tr>
<tr>
<td>bob</td>
<td>3324</td>
</tr>
</tbody>
</table>

3502
Background: Grounding

Map meaning representations to real world entities

Perceptual Grounding

\[ \lambda x. (\text{blue}(x) \land \text{mug}(x)) \]

Classifier
blue/not blue

blue

Classifier
mug/not mug

mug
Background: Dialog Policy

Bring the blue mug from Alice’s office

Where should I bring a blue mug from?

Semantic Understanding

Grounding

Natural Language Generation

Dialog Policy
Background: Dialog Policy

- Decides each response type - clarification, label queries, task completion
- Dialog state - Information from the dialog so far
- Dialog policy - Mapping from dialog states to dialog actions (response types/ responses)
- Learned using Reinforcement Learning
Background: Reinforcement Learning

Markov Decision Process (MDP)

- Agent
- Environment
- State
- Action
- Reward
Background: Reinforcement Learning

Partially Observable Markov Decision Process (POMDP)

Agent (Belief)

Environment (State)

Action

Reward

Observation
Background: Natural Language Generation

Bring the blue mug from Alice’s office

Semantic Understanding ➔ Grounding ➔ Dialog Policy

Where should I bring a blue mug from?

Natural Language Generation
Background: Natural Language Generation

Converting an action to a natural language response

```latex
ask_param(
    action=bring,
    patient=\lambda x. (\text{blue}(x) \land \text{mug}(x))
    src=?
)
```

Where should I bring a blue mug from?
Background: Active Learning

Bring the blue mug from Alice’s office

Semantic Understanding → Grounding

Where should I bring a blue mug from?

Natural Language Generation

Dialog Policy
Background: Active Learning

Query for labels most likely to improve the model.
Bring the blue mug from Alice's office

Would you use the word “blue” to refer to this object?

Yes
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Integrating Learning of Dialog Strategies and Semantic Parsing

Bring the blue mug from Alice’s office

Semantic Understanding → Grounding

Where should I bring a blue mug from?

[Padmakumar et. al., 2017]
Prior work: Improving Semantic Parsers from Clarification Dialogs

Bring the blue mug from Alice’s office

Where should I bring a blue mug from?

Alice Ashcraft’s office

I should bring a blue mug from 3502?

Alice’s office

Alice Ashcraft’s office

3502

[Thomason et. al., 2015]
Prior Work: Dialog Policy Learning

Modelling dialog system as a Partially Observable Markov Decision Process (POMDP)

[Young et. al., 2013]
Why is joint learning challenging?

**Assumption:**
Constant probability distribution

**Our system:**
Variable probability distribution
Why is joint learning challenging?

- Assumption:
  - Constant probability distribution
  - Non-stationary Environment

Diagram:
- Agent (Belief)
- Environment (State)
- Action
- Observation
Choosing a Policy Learning Algorithm

- Robust to non-stationary environment - to allow simultaneous learning of a semantic parser
- Learns how the mapping from states and actions to observations varies with time
- Low Sample Complexity - Learn a good policy from a small number of dialogs
- Kalman Temporal Differences (KTD) Q Learning (Geist and Pietquin, 2010)
Experiments - Mechanical Turk

**TASK TO COMPLETE**

Dave Daniel wants the item in slot 5.

<table>
<thead>
<tr>
<th>Robotic Response</th>
<th>Human Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>How can I help?</td>
<td>Please bring the item in slot 5 to Dave Daniel</td>
</tr>
<tr>
<td>To whom should I bring something?</td>
<td>Dave Daniel</td>
</tr>
<tr>
<td>What action did you want me to take involving Dave Daniel?</td>
<td>5</td>
</tr>
<tr>
<td>What should I bring to Dave Daniel?</td>
<td>A calendar</td>
</tr>
<tr>
<td>I'm sorry, but I couldn't pinpoint what you meant by that.</td>
<td>A day planner</td>
</tr>
<tr>
<td>What should I bring to Dave Daniel?</td>
<td>Calendar</td>
</tr>
<tr>
<td>You want me to bring calendar to Dave Daniel?</td>
<td>Yes</td>
</tr>
<tr>
<td>I thought so</td>
<td>Happy to help</td>
</tr>
</tbody>
</table>

**DIRECTORY**

**People:**
- Alice Ashcraft; Secretary
- Francis ("Frannie") Foster
- Robert ("Bob") Brown
- Carol Clark, PhD
- Dave Daniel, PhD
- George Green; Intern
- Evelyn ("Eve") Eckhart
- Mallory Morgan; Director
- Peggy Parker, PhD
- Walter Ward; Supervisor

**Items available to robot:**

<table>
<thead>
<tr>
<th>Item 1</th>
<th>Item 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coffee cup</td>
<td>Hamburger</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Item 3</th>
<th>Item 4</th>
<th>Item 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phone</td>
<td>Trash can</td>
<td>Calendar</td>
</tr>
</tbody>
</table>
Experimental Conditions

Parser Learning
- **Initial parser**
- **Initial policy**
- **Collect Dialogs**
- **Update parser**
- **Collect Dialogs**
- **Final parser**
- **Initial policy**

Dialog Learning
- **Initial parser**
- **Initial policy**
- **Collect Dialogs**
- **Update policy**
- **Collect Dialogs**
- **Final parser**
- **Initial policy**
Experimental Conditions

Parser and Dialog Learning - Full (Naive)

Parser and Dialog Learning - Batchwise (Ours)
Hypotheses

1. Combined parser and dialog learning is more useful than either alone.
Hypotheses

2. Changes in the parser need to be seen by the dialog management module.
Results - Dialog Success

- Higher is better
- Parser learning is mostly responsible for improvement in dialog success rate
- Best system: parser and dialog learning - batchwise
Results - Dialog Length

- Lower is better
- Dialog learning is mostly responsible for lowering dialog length
- Best system: parser and dialog learning - batchwise
Conclusion

• Jointly learning a parser and dialog policy is more effective than learning either alone - qualitative and quantitative.
• Changes in other components need to be propagated to the policy.
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Opportunistic Active Learning for Grounding Natural Language Descriptions

Bring the blue mug from Alice’s office

Semantic Understanding

Grounding

Where should I bring a blue mug from?

Natural Language Generation

[Thomason et. al., 2017]
Opportunistic Active Learning

• Asking locally convenient questions during an interactive task.
• Questions may not be useful for the current interaction but expected to help future tasks.
Opportunistic Active Learning

Bring the blue mug from Alice’s office

Would you use the word “blue” to refer to this object?

Yes
Opportunistic Active Learning

Bring the **blue mug** from Alice’s office

Would you use the word “**tall**” to refer to this object?

Yes
Opportunistic Active Learning

Still query for labels most likely to improve the model.
Opportunistic Active Learning

Why?

- Robot may have good models for on-topic concepts.
- No useful on-topic queries.
- Some off-topic concepts may be more important because they are used in more interactions.
Opportunistic Active Learning - Challenges

Some other object might be a better candidate for the question

Purple?
Opportunistic Active Learning - Challenges

The question interrupts another task and may be seen as unnatural

Bring the **blue mug** from Alice’s office

Would you use the word “**tall**” to refer to this object?
Opportunistic Active Learning - Challenges

The information needs to be useful for a future task.

Red?
Object Retrieval Task

Human: This is a yellow bottle with water filled in it.
Object Retrieval Task

• User describes an object in the active test set
• Robot needs to identify which object is being described
Object Retrieval Task

• Robot can ask questions about objects on the sides to learn object attributes
Two Types of Questions

Would you use the word “bottle” to describe this object?

Robot
Two Types of Questions

Can you show me an object you would describe as “yellow”?

Robot
Experimental Conditions

- Baseline (on-topic) - the robot can only ask about “yellow”, “bottle”, “water”, “filled”
- Inquisitive (opportunistic) - the robot can ask about any concept it knows, possibly “red” or “heavy”
Results

- Inquisitive robot performs better at understanding object descriptions.
- Users find the robot more comprehending, fun and usable in a real-world setting, when it is opportunistic.
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Bring the blue mug from Alice’s office

Learning a Policy for Opportunistic Active Learning

Semantic Understanding

Grounding

Dialog Policy

Where should I bring a blue mug from?

Natural Language Generation

[Padmakumar et. al., 2018]
Learning a Policy for Opportunistic Active Learning

- Goal of this work - Learn a dialog policy that decides how many and which questions to ask to improve grounding models.
- To learn an effective policy, the agent needs to learn
  - To identify good queries in the opportunistic setting.
  - When a guess is likely to be successful.
  - To trade off between model improvement and task completion.
Task Setup

Active Training Set

- Train_1
- Train_2
- Train_3
- Train_4
- Train_5
- Train_6
- Train_7
- Train_8

Dialog

<table>
<thead>
<tr>
<th>Robot</th>
<th>Human</th>
<th>Target Description</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Describe the object I should find.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>A white umbrella</td>
<td></td>
</tr>
</tbody>
</table>

Active Test Set

- Test_1
- Test_2
- Test_3
- Test_4
## Task Setup

### Active Training Set

<table>
<thead>
<tr>
<th>Train_1</th>
<th>Train_4</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image4.png" alt="Image" /></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Train_2</th>
<th>Train_5</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image5.png" alt="Image" /></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Train_3</th>
<th>Train_6</th>
<th>Train_7</th>
<th>Train_8</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image3.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
</tr>
</tbody>
</table>

### Dialog

<table>
<thead>
<tr>
<th>Robot</th>
<th>Human</th>
<th>Robot</th>
<th>Human</th>
</tr>
</thead>
<tbody>
<tr>
<td>Describe the object I should find.</td>
<td>A white umbrella</td>
<td>Is there something in Train_6 that can be described as yellow?</td>
<td>No</td>
</tr>
</tbody>
</table>

### Active Test Set

<table>
<thead>
<tr>
<th>Test_1</th>
<th>Test_2</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image10.png" alt="Image" /></td>
<td><img src="image11.png" alt="Image" /></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Test_3</th>
<th>Test_4</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image12.png" alt="Image" /></td>
<td><img src="image13.png" alt="Image" /></td>
</tr>
</tbody>
</table>
Task Setup

### Active Training Set
- Train_1
- Train_2
- Train_3
- Train_4
- Train_5
- Train_6
- Train_7
- Train_8

### Dialog

**Robot:** Describe the object I should find.

**Human:** A white umbrella

**Robot:** Is there something in Train_6 that can be described as yellow?

**Human:** No

**Robot:** Can you show me an image with something that can be described as white?

**Human:** Train_1

**Robot:** My guess is Test_4

**Human:** Correct

### Active Test Set
- Test_1
- Test_2
- Test_3
- Test_4
Grounding Model

A white umbrella $\rightarrow$ \{white, umbrella\} $\downarrow$

Pretrained CNN

\begin{align*}
\text{SVM} & \quad \text{white/ not white} \\
\text{SVM} & \quad \text{umbrella/ not umbrella}
\end{align*}
Active Learning

• Agent starts with no classifiers.
• Labeled examples are acquired through questions and used to train the classifiers.
• Agent needs to learn a policy to balance active learning with task completion.
MDP Model

Action:
- Label query
- Example Query
- Guess

State:
- Target description
- Train and test objects
- Agent’s perceptual classifiers

Reward: Max correct guesses with short dialogs

User

Dialog Agent
Challenges

- What information about classifiers should be represented?
- Variable number of actions
- Size of action space increases over time
- Number of classifiers increases over time
- Very large action space after initial interactions.
Tackling challenges

- Features based on active learning methods
  - Representing classifiers
- Featurize state-action pairs
  - Variable number of actions and classifiers
- Sampling a beam of promising queries
  - Large action space
Feature Groups

• Query features - Active learning metrics used to determine whether a query is useful
• Guess features - Features that use the predictions and confidences of classifiers to determine whether a guess will be correct
Experiment Setup

• Policy learning using REINFORCE.
• Baseline - A hand-coded dialog policy that asks a fixed number of questions selected using the same sampling distribution.
Experiment Phases

- **Initialization** - Collect experience using the baseline to initialize the policy.
- **Training** - Improve the policy from on-policy experience.
- **Testing** - Policy weights are fixed, and we run a new set of interactions, starting with no classifiers, over an independent test set with different predicates.
Results

Ablations of major feature groups

Fraction of successful dialogs

- Static: 0.29
- -Guess: 0.35
- -Query: 0.37
- Learned: 0.44
Results

Average Dialog Length - Number of System Turns

- Static: 16
- Guess: 6.16
- Query: 6.12
- Learned: 12.95

Ablations of major feature groups
Summary

• We can learn a dialog policy that learns to acquire knowledge of predicates through opportunistic active learning.
• The learned policy is more successful at object retrieval than a static baseline, using fewer dialog turns on average.
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• Proposed Work
  – Learning to Ground Natural Language Object Descriptions Using Joint Embeddings
  – Identifying Useful Clarification Questions for Grounding Object Descriptions
  – Learning a Policy for Clarification Questions using Uncertain Models
  – Bonus Contributions
Perceptual Grounding Using Classifiers

Perceptual Grounding

blue mug $\rightarrow \lambda x. (\text{blue}(x) \land \text{mug}(x))$

Classifier
blue/not blue

Classifier
mug/not mug

 Classifier
blue/not blue

Classifier
mug/not mug

blue

mug

not blue

mug

mug
Grounding Using a Joint Vector Space
Grounding Using a Joint Vector Space

- Represent words and images as vectors in the same space.
- Words are near images they apply to and vice versa.
Grounding Using a Joint Vector Space

To ground a description, such as “blue mug”, find the image which minimizes the sum of distances to the words.
Grounding Using a Joint Vector Space

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Grounding Using a Joint Vector Space

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Grounding Using a Joint Vector Space

To ground a description, such as “blue mug”, find the image which minimizes the sum of distances to the words.
Grounding Using a Joint Vector Space

Related prior work

- Word vectors in learned joint spaces are more useful for many tasks, e.g., semantic relatedness [Lazaridou et. al., 2015]
- Neural networks that score an image-description pair perform well at grounding but use sentence embeddings [Hu et. al. 2016, Xiao et. al. 2017].
- We expect that words would generalize better than phrases/sentences.
Learning the Joint Space

- **f(i)**
  - FC Layer
  - CNN

- **g(w)**
  - FC Layer
  - word2vec/GloVe

- **i:** blue
- **w:** blue
Learning the Joint Space

\[ d(f(\text{blue}), g(\text{blue})) \leq d(f(\text{pink}), g(\text{blue})) \]
\[ d(f(\text{blue}), g(\text{blue})) \leq d(f(\text{blue}), g(\text{pink})) \]

Constraints captured using a ranking loss
Outline

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Identifying Useful Clarification Questions for Grounding Object Descriptions

Bring the blue mug from Alice’s office

The blue coffee mug

What should I bring?

What should I bring?
Identifying Useful Clarification Questions for Grounding Object Descriptions

Bring the blue mug from Alice’s office

Is this the object I should bring?

No
Recent Related Work

[Das, et. al., 2017]  [De Vries et. al., 2017]
Identifying Useful Clarification Questions for Grounding Object Descriptions

- Clarification questions that help narrow down the object being referred to.
- More specific than a new description.
- More general than showing each possible object.
- Provide ground truth answers to questions at training time to learn human semantics.
Attribute Based Queries

Bring the blue mug from Alice’s office

Is the object I should bring a cup?
Yes
Choosing a Good Query

- Query that is most likely to reduce the search space.
- Choose the attribute with respect to which the dataset has highest entropy.
In a joint embedding space how do you determine whether an attribute is applicable?
Possible solutions

- Distance threshold, clustering to get classifier-like predictions.
- Might be possible to formulate an optimization problem using distances.
Outline

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  - Learning a Policy for Clarification Questions using Uncertain Models
  - Bonus Contributions
Learning a Policy for Clarification Questions using Uncertain Models
Learning a Policy for Clarification Questions using Uncertain Models
Learning a Policy for Clarification Questions using Uncertain Models

• Proposed method for identifying good queries assumes that the learned space is “good”.
• If predictions for some attribute are especially unreliable, it might be preferable to choose another attribute that is less informative but more reliable.
Learning a Policy for Clarification Questions using Uncertain Models

Bring the blue mug from Alice's office
Learning a Policy for Clarification Questions using Uncertain Models

Bring the blue mug from Alice’s office

Dialog Policy
Challenge

• The policy needs features that measure “how good” the space is.
  – Number of training examples
  – How often are the space constraints satisfied?

$$d(f(\text{blue}), g(\text{blue})) \leq d(f(\text{pink}), g(\text{blue}))$$

$$d(f(\text{blue}), g(\text{blue})) \leq d(f(\text{blue}), g(\text{pink}))$$
Outline

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Incorporating Linguistic and Visual Context

- water *glass*
- wine *glass*
- looking *glass*
- *glass* swan
- the big bottle
- the small bottle
Using Multimodal Object Representations

Grasp

Lift

Lower

Drop

Press

Push
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Improving Natural Language Understanding Through Dialog

Bring the blue mug from Alice’s office

Where should I bring a blue mug from?

Alice Ashcraft’s office

I should bring a blue mug from 3502?

Yes
Bring the blue mug from Alice’s office

Would you use the word “blue” to refer to this object?

Yes
Joint Parser and Policy Learning

Bring the blue mug from Alice’s office

Semantic Understanding

Grounding

Dialog Policy

Where should I bring a blue mug from?

Natural Language Generation
## Policy Learning for Opportunistic Active Learning

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<tr>
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<th>Dialog</th>
<th>Active Test Set</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Train_1</strong></td>
<td>Robot: Describe the object I should find.</td>
<td><strong>Test_1</strong></td>
</tr>
<tr>
<td></td>
<td>Human: A white umbrella</td>
<td></td>
</tr>
<tr>
<td><strong>Train_2</strong></td>
<td>Robot: Is there something in Train_6 that can be described as yellow?</td>
<td><strong>Test_2</strong></td>
</tr>
<tr>
<td></td>
<td>Human: No</td>
<td></td>
</tr>
<tr>
<td><strong>Train_3</strong></td>
<td>Robot: Can you show me an image with something that can be described as white?</td>
<td><strong>Test_3</strong></td>
</tr>
<tr>
<td><strong>Train_4</strong></td>
<td>Human: Train_1</td>
<td><strong>Test_4</strong></td>
</tr>
<tr>
<td><strong>Train_5</strong></td>
<td>Robot: My guess is Test_4</td>
<td></td>
</tr>
<tr>
<td><strong>Train_6</strong></td>
<td>Human: Correct</td>
<td></td>
</tr>
<tr>
<td><strong>Train_7</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Train_8</strong></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Improved Perceptual Grounding Model
Clarification Questions for Object Descriptions

Bring the blue mug from Alice’s office

Is the object I should bring a cup?

Yes
Improved Models and Queries for Grounded Human-Robot Dialog

Aishwarya Padmakumar

Doctoral Dissertation Proposal
Incorporating Context

• Visual Context
  – Representations of other objects
  – Representation of the entire scene and the object’s bounding box

• Linguistic Context - ELMo embeddings
Learning Joint Embeddings with Multimodal Object Representations

- Not all modalities are equally informative for each object-word pair.
- Not all modalities may be available for each object.
- Project features of each modality to the same space and combine during grounding.
Computing Distance

- Average distance of the word to object representation in all modalities.
- Distance of the word to nearest object representation - allows only one modality to be relevant.