Inferring and Executing Programs for Visual Reasoning

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Problem definition

• Inferring and Executing Programs

• Visual Reasoning:
  • the process of thinking about something in order to make a decision [Cambridge dictionary]

• Given: Image and question

• Come up with decision

Is there a pedestrian in my lane?
Agenda

• Problem definition
  • CLEVER Dataset

• Method
  • Programs
  • Functions
  • Program generator
  • Execution engine
  • Training

• Experiments
  • Comparison training procedures
  • What do the modules learn?
  • Generalizing to new attribute combinations
  • Generalizing to new question types
  • CLEVER-Humans

• Conclusion
Clever Dataset

• Attribute identification, counting, comparison, spatial relationships, logical operations
• Are there an equal number of large things and metal spheres?
• What size is the cylinder that is left of the brown metal thing that is left of the big sphere?
• There is a sphere with the same size as the metal cube; is it made of the same material as the small red sphere?
Method Overview

• Separate program generator and execution engine
• Program generator and execution engine are neural networks
• Trained by backpropagation and REINFORCE
Programs

• The programs are composed of functions
• -> like in a normal programming language
• Fixed set of functions
• Functions have a predefined arity -> 1 or 2 inputs
Functions

- **Output CxHxW**
- **SCENE**
  - Visual features (output of conv4 from ResNet-101) as input
  - 4 convolutional layers
- **Unary functions**
  - Residual block
  - e.g. count

- **Binary functions**
  - Concatenate inputs along channel dim
  - Reduce channels using 1x1 convolution
  - Residual block
  - e.g. greater_than

- **Classifier**
  - Final output flattened
  - multilayer perceptron classifier
Program generator

• Predicts program from natural language question
• Programs are traversed to receive sequence of functions
• Use standard LSTM sequence-to-sequence model for program prediction
Execution engine

- Predicts answer given program and input image
- Implemented using neural networks
- Every syntactically correct program is executable
Training

• Supervised
  • Program generator: with question and program
    • Standard LSTM training
  • Execution engine (functions): with image, program and answer
    • Standard classification training

• Benefits
  • Best performance achievable

• Limitations
  • Ground truth program for all questions needed
  • Not possible if no ground-truth program is available (CLEVER Humans)
Training

• REINFORCE
  • Training program generator and execution engine jointly end to end

• Benefits
  • Needs only images, questions and answers for training, no programs

• Limitations
  • Training without ground truth programs is hard:
    • Generator needs to produce programs without understanding what functions mean
    • Execution engine has to produce the right answer from programs, which may not implement the question correctly
  • Only for fine tuning applicable
REINFORCE

• Reward: Negative zero-one loss of the execution engine
  • 0 if correct, -1 if wrong

• Moving-average baseline
  • Subtracts moving average of rewards
  • Reduces variance of gradient directions

• Correct answering is reinforced
Training

Combined semi-supervised:
1. Train program generator on small subset of ground truth programs
2. Fix program generator and train execution engine using predicted programs on large dataset
3. Use REINFORCE to finetune program generator and execution engine

• Ground truth programs are only used to train program generator in the beginning

• Benefits
  • Possible to finetune on datasets without ground truth programs
Strongly and semi-supervised learning

**Strongly supervised**
1. Trained program generator and execution engine separately using all ground-truth programs

**Semi-supervised**
1. Train program generator on small set of ground-truth programs
2. Train execution engine with predicted programs
3. Finetune together without ground-truth programs
## Results

<table>
<thead>
<tr>
<th>Method</th>
<th>Exist</th>
<th>Count</th>
<th>Compare Integer</th>
<th>Query</th>
<th>Compare</th>
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<td></td>
<td></td>
<td></td>
<td>Equal</td>
<td>Less</td>
<td>More</td>
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<td>Q-type mode</td>
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<td>51.4</td>
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<td>LSTM</td>
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<td>Ours-strong (700K prog.)</td>
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</tr>
</tbody>
</table>

- Overall accuracy even better than humans on Mechanical Turk
- <4% of Questions sufficient to generalize to 450k unique questions
Results

- 20k ground-truth programs sufficient to have almost exact programs
- 3% better answer accuracy if trained on ground-truth programs
- Finetuning can eliminate some of the error
What do the modules learn?

- Attention is on correct objects
- Changing single module changes answer and module attention drastically
- Learned meaningful functions
Generalizing to new attribute combinations

- Split dataset A:
  - Cubes: gray, blue, brown, or yellow
  - Cylinders: red, green, purple, or cyan

- Split B:
  - Colors exchanged

- No complete generalization possible if features not in training set
- Accuracy on A lost after finetuned on B

<table>
<thead>
<tr>
<th>Method</th>
<th>Train A</th>
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<th>Finetune B</th>
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<tr>
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<td>A</td>
<td>B</td>
<td>A</td>
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<td>LSTM</td>
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<tr>
<td>Ours (18K prog.)</td>
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Generalizing to new question types

- Split long/short questions
- No good performance on long questions if not trained on them
- Generalization possible with finetuning program generator
CLEVER-Humans

- Training on CLEVER
- Random initialization of new word embeddings
- Finetune program generator on CLEVER-Humans
- Answer linguistically more diverse questions
- Reuses reasoning
- Fails if functions are not appropriate to answer question
- Outperforms Baselines
Conclusion

• Increased explainability by step through explainable functions
• Capability to adapt to new question types
• Model exceeds human performance
References

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