

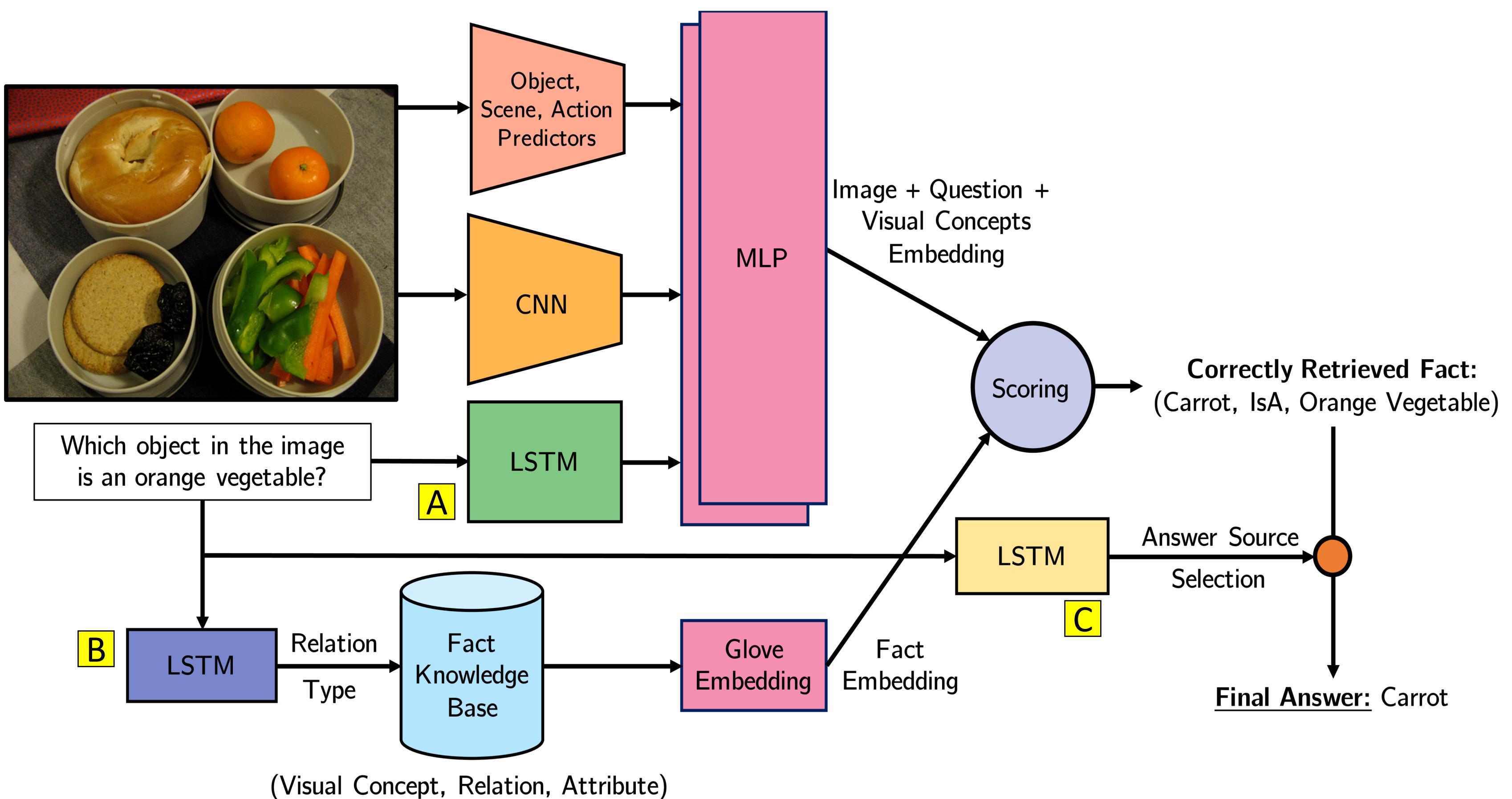
# Straight to the Facts: Learning Knowledge Base Retrieval for Factual Visual Question Answering

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## Introduction

- Motivation.** To answer open ended questions about an image using facts from an external knowledge base while handling **synonyms** and **homographs**. Answering a question correctly involves retrieving the right supporting fact and extracting the answer from it.
- FVQA Dataset.** 2,190 images, 5,286 questions, and 4,126 unique facts corresponding to the questions.
- FVQA Knowledge Base.** 193,449 facts, constructed by extracting the top visual concepts for all the images in the dataset and querying for those concepts in the three knowledge bases - WebChild, ConceptNet, and DBpedia.

## Learning Knowledge Base Retrieval



## Inference

### 1. Image, Question, and Visual Concept Embedding

- Image: Low-level fc7 features extracted from a ResNet-152 model pre-trained on ImageNet
- Question: Embedding of dimension 100 learned using LSTM [A]
- Visual Concepts: Objects, scenes, and actions detected using pre-trained models
- Fusion: Image, question, and visual concept features are combined using an MLP to form a 200d vector

### 2. Fact Embedding

- Fact consists of (visual concept, relation, attribute), e.g., (Orange, IsA, Fruit)
- One relation out of 13 possible is obtained from the question by using an LSTM [B]
- Fact space reduced by filtering according to the predicted relation, e.g., IsA
- Fact is encoded using 100d GloVe embeddings

### 3. Scoring the facts

- Facts are scored by computing the cosine distance between the output of the MLP and the fact embeddings
- Fact with highest score is chosen

### 4. Answer from fact

- The answer is either the visual concept or the attribute within the chosen fact
- Answer source is predicted from the question using an LSTM [C]

## Learning

### 1. Predicting the Relation and Answer Source

- The LSTM [B] is trained using ground truth question-relation pairs and standard cross-entropy loss
- The LSTM [C] is trained using ground truth question-answer source pairs and binary cross-entropy loss

### 2. Scoring the facts

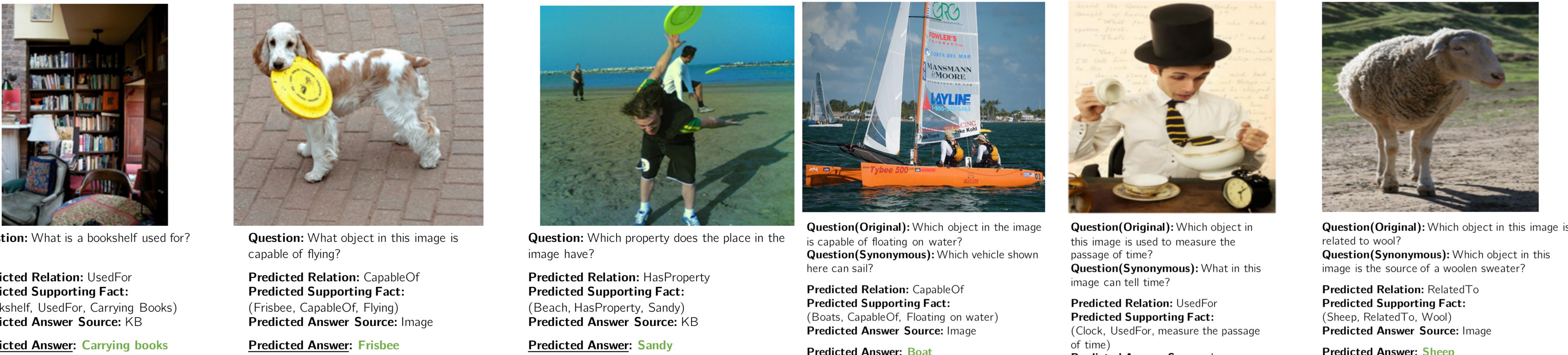
- The score function is trained in multiple time steps by mining hard negatives in each step. Every iteration consists of the ground truth fact and 99 negatives
- The parameters are learned using a classical margin loss that assigns the highest score to the image-question-ground truth fact embedding
- The LSTM [A], the MLP, and the score function are trained end-to-end

## Quantitative Results

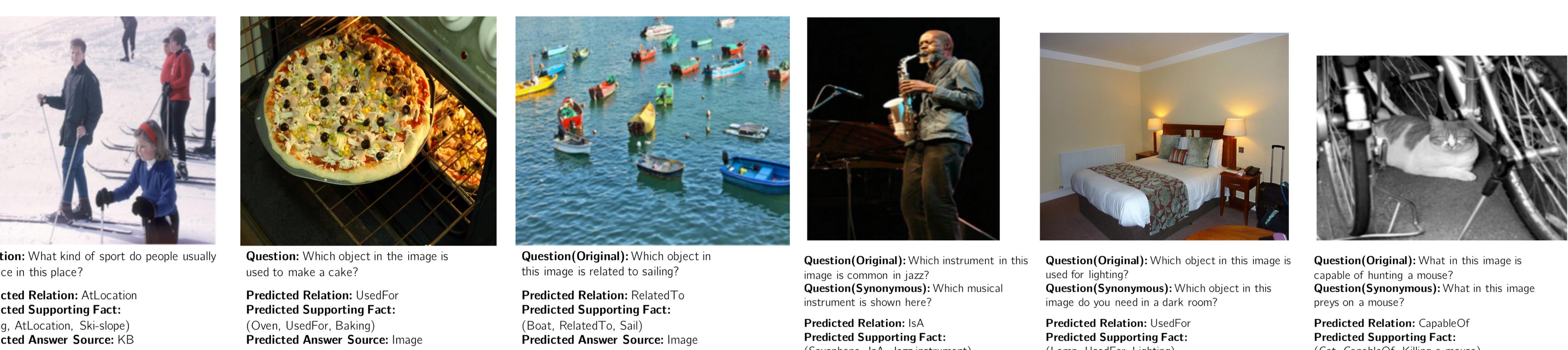
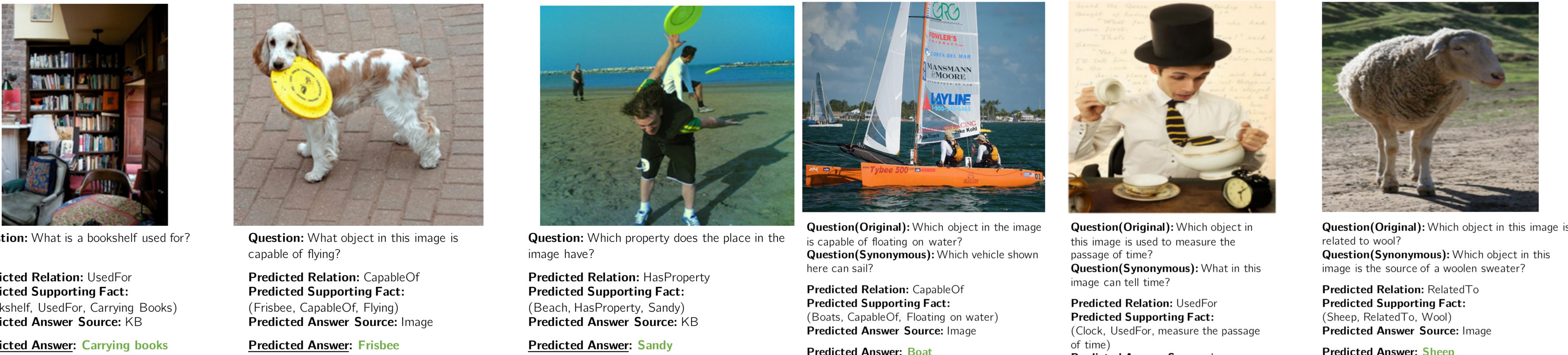
Method	Relation Prediction		Answer Source Prediction		Method	Fact Prediction		Answer Prediction		
	Accuracy @1	Accuracy @3	Accuracy @1	Accuracy @3		Accuracy @1	Accuracy @3	Accuracy @1	Accuracy @3	
FVQA	64.94	82.42	—	—	FVQA	38.76	42.96	56.91	64.65	
Ours	<b>75.40</b>	<b>91.97</b>	<b>97.30</b>	<b>100.00</b>	FVQA Ensemble	—	—	58.76	—	
Method	Synonyms (FVQA)		Synonyms (Ours)		Homographs (FVQA)		Fact Prediction		Answer Prediction	
	78	61	61	66.3	Ours – Q + I	28.98	32.34	26.68	30.27	
Ours	<b>91.6</b>	<b>89</b>	<b>79.4</b>	<b>75.60</b>	Ours – Q + I + VC	62.30	74.90	60.30	73.10	
					Ours – Q + VC	<b>64.50</b>	<b>75.20</b>	<b>62.20</b>	<b>75.60</b>	

## Qualitative Results

### Correctly Answered Questions



### Correctly Answered Synonymous Questions



### Visual Concepts Prediction and Retrieved Facts



### Incorrectly Answered Questions

## Follow Up: Upcoming NIPS Paper

### Out of the Box: Reasoning with Graph Convolution Networks for Factual Visual Question Answering