A Corpus for Reasoning About Natural Language Grounded in Photographs

Alane Suhr[‡,*], **Stephanie Zhou**[†,*], **Ally Zhang**[‡], **Iris Zhang**[‡], **Huajun Bai**[‡], and **Yoav Artzi**[‡]

[‡]Cornell University Department of Computer Science and Cornell Tech
New York, NY 10044
{suhr, yoav}@cs.cornell.edu {az346, wz337, hb364}@cornell.edu

[†]University of Maryland Department of Computer Science
College Park, MD 20742
stezhou@cs.umd.edu

Abstract

We introduce a new dataset for joint reasoning about natural language and images, with a focus on semantic diversity, compositionality, and visual reasoning challenges. The data contains 107,292 examples of English sentences paired with web photographs. The task is to determine whether a natural language caption is true about a pair of photographs. We crowdsource the data using sets of visually rich images and a compare-and-contrast task to elicit linguistically diverse language. Qualitative analysis shows the data requires compositional joint reasoning, including about quantities, comparisons, and relations. Evaluation using state-of-the-art visual reasoning methods shows the data presents a strong challenge.

1 Introduction

Visual reasoning with natural language is a promising avenue to study compositional semantics by grounding words, phrases, and complete sentences to objects, their properties, and relations in images. This type of linguistic reasoning is critical for interactions grounded in visually complex environments, such as in robotic applications. However, commonly used resources for language and vision (e.g., Antol et al., 2015; Chen et al., 2016) focus mostly on identification of object properties and few spatial relations (Section 4; Ferraro et al., 2015; Alikhani and Stone, 2019). This relatively simple reasoning, together with biases in the data, removes much of the need to consider language compositionality (Goyal et al., 2017). This motivated the design of datasets that require compositional[1] visual reasoning, including NLVR (Suhr et al., 2017) and CLEVR (Johnson et al., 2017a,b). These datasets use synthetic images, synthetic language, or both. The result is a limited representation of linguistic challenges: synthetic languages are inherently of bounded expressivity, and synthetic visual input entails limited lexical and semantic diversity.

The left image contains twice the number of dogs as the right image, and at least two dogs in total are standing.

One image shows exactly two brown acorns in back-to-back caps on green foliage.

Figure 1: Two examples from NLVR2. Each caption is paired with two images.[2] The task is to predict if the caption is True or False. The examples require addressing challenging semantic phenomena, including resolving *twice ... as* to counting and comparison of objects, and composing cardinality constraints, such as *at least two dogs in total* and *exactly two*.[3]

We address these limitations with Natural Language Visual Reasoning *for Real* (NLVR2), a new dataset for reasoning about natural language descriptions of photos. The task is to determine if a caption is true with regard to a pair of images. Figure 1 shows examples from NLVR2. We use im-

[*] Contributed equally.

[†] Work done as an undergraduate at Cornell University.

[1] In parts of this paper, we use the term *compositional* differently than it is commonly used in linguistics to refer to reasoning that requires composition. This type of reasoning often manifests itself in highly compositional language.

[2] Appendix G contains license information for all photographs used in this paper.

[3] The top example is True, while the bottom is False.

ages with rich visual content and a data collection process designed to emphasize semantic diversity, compositionality, and visual reasoning challenges. Our process reduces the chance of unintentional linguistic biases in the dataset, and therefore the ability of expressive models to take advantage of them to solve the task. Analysis of the data shows that the rich visual input supports diverse language, and that the task requires joint reasoning over the two inputs, including about sets, counts, comparisons, and spatial relations.

Scalable curation of semantically-diverse sentences that describe images requires addressing two key challenges. First, we must identify images that are visually diverse enough to support the type of language desired. For example, a photo of a single beetle with a uniform background (Table 2, bottom left) is likely to elicit only relatively simple sentences about the existence of the beetle and its properties. Second, we need a scalable process to collect a large set of captions that demonstrate diverse semantics and visual reasoning.

We use a search engine with queries designed to yield sets of similar, visually complex photographs, including of sets of objects and activities, which display real-world scenes. We annotate the data through a sequence of crowdsourcing tasks, including filtering for interesting images, writing captions, and validating their truth values. To elicit interesting captions, rather than presenting workers with single images, we ask workers for descriptions that compare and contrast four pairs of similar images. The description must be True for two pairs, and False for the other two pairs. Using pairs of images encourages language that composes properties shared between or contrasted among the two images. The four pairs are used to create four examples, each comprising an image pair and the description. This setup ensures that each sentence appears multiple times with both labels, resulting in a balanced dataset robust to linguistic biases, where a sentence's truth value cannot be determined from the sentence alone, and generalization can be measured using multiple image-pair examples.

This paper includes four main contributions: (1) a procedure for collecting visually rich images paired with semantically-diverse language descriptions; (2) NLVR2, which contains 107,292 examples of captions and image pairs, including 29,680 unique sentences and 127,502 images; (3) a qualitative linguistically-driven data analysis showing that our process achieves a broader representation of linguistic phenomena compared to other resources; and (4) an evaluation with several baselines and state-of-the-art visual reasoning methods on NLVR2. The relatively low performance we observe shows that NLVR2 presents a significant challenge, even for methods that perform well on existing visual reasoning tasks. NLVR2 is available at http://lil.nlp.cornell.edu/nlvr/.

2 Related Work and Datasets

Language understanding in the context of images has been studied within various tasks, including visual question answering (e.g., Zitnick and Parikh, 2013; Antol et al., 2015), caption generation (Chen et al., 2016), referring expression resolution (e.g., Mitchell et al., 2010; Kazemzadeh et al., 2014; Mao et al., 2016), visual entailment (Xie et al., 2019), and binary image selection (Hu et al., 2019). Recently, the relatively simple language and reasoning in existing resources motivated datasets that focus on compositional language, mostly using synthetic data for language and vision (Andreas et al., 2016; Johnson et al., 2017a; Kuhnle and Copestake, 2017; Kahou et al., 2018; Yang et al., 2018).[4] Three exceptions are CLEVR-Humans (Johnson et al., 2017b), which includes human-written paraphrases of generated questions for synthetic images; NLVR (Suhr et al., 2017), which uses human-written captions that compare and contrast sets of synthetic images; and GQA (Hudson and Manning, 2019), which uses synthetic language grounded in real-world photographs. In contrast, we focus on both human-written language and web photographs.

Several methods have been proposed for compositional visual reasoning, including modular neural networks (e.g., Andreas et al., 2016; Johnson et al., 2017b; Perez et al., 2018; Hu et al., 2017; Suarez et al., 2018; Hu et al., 2018; Yao et al., 2018; Yi et al., 2018) and attention- or memory-based methods (e.g., Santoro et al., 2017; Hudson and Manning, 2018; Tan and Bansal, 2018). We use FiLM (Perez et al., 2018), N2NMN (Hu et al., 2017), and MAC (Hudson and Manning, 2018) for our empirical analysis.

In our data, we use each sentence in multiple

[4] A tabular summary of the comparison of NLVR2 to existing resources is available in Table 7, Appendix A.

examples, but with different labels. This is related to recent visual question answering datasets that aim to require models to consider both image and question to perform well (Zhang et al., 2016; Goyal et al., 2017; Li et al., 2017; Agrawal et al., 2017, 2018). Our approach is inspired by the collection of NLVR, where workers were shown a set of similar images and asked to write a sentence True for some images, but False for the others (Suhr et al., 2017). We adapt this method to web photos, including introducing a process to identify images that support complex reasoning and designing incentives for the more challenging writing task.

3 Data Collection

Each example in NLVR2 includes a pair of images and a natural language sentence. The task is to determine whether the sentence is True or False about the pair of images. Our goal is to collect a large corpus of grounded semantically-rich descriptions that require diverse types of reasoning, including about sets, counts, and comparisons. We design a process to identify images that enable such types of reasoning, collect grounded natural language descriptions, and label them as True or False. While we use image pairs, we do not explicitly set the task of describing the differences between the images or identifying which image matches the sentence better (Hu et al., 2019). We use pairs to enable comparisons and set reasoning between the objects that appear in the two images. Figure 2 illustrates our data collection procedure. For further discussion on the design decisions for our task and data collection implementation, please see appendices A and B.

3.1 Image Collection

We require sets of images where the images in each set are detailed but similar enough such that comparison will require use of a diverse set of reasoning skills, more than just object or property identification. Because existing image resources, such as ImageNet (Russakovsky et al., 2015) or COCO (Lin et al., 2014), do not provide such grouping and mostly include relatively simple object-focused scenes, we collect a new set of images. We retrieve sets of images with similar content using search queries generated from synsets from the ILSVRC2014 ImageNet challenge (Russakovsky et al., 2015). This correspondence to ImageNet synsets allows researchers to use pre-trained image featurization models, and focuses the challenges of the task not on object detection, but compositional reasoning challenges.

ImageNet Synsets Correspondence We identify a subset of the 1,000 synsets in ILSVRC2014 that often appear in rich contexts. For example, an `acorn` often appears in images with other `acorns`, while a `seawall` almost always appears alone. For each synset, we issue five queries to the Google Images search engine[5] using query expansion heuristics. The heuristics are designed to retrieve images that support complex reasoning, including images with groups of entities, rich environments, or entities participating in activities. For example, the expansions for the synset `acorn` will include `two acorns` and `acorn fruit`. The heuristics are specified in Table 1. For each query, we use the Google similar images tool for each of the first five images to retrieve the seven non-duplicate most similar images. This results in five sets of eight similar images per query,[6] 25 sets in total. If at least half of the images in a set were labeled as interesting according to the criteria in Table 2, the synset is awarded one point. We choose the 124 synsets with the most points.[7] The 124 synsets are distributed evenly among animals and objects. This annotation was performed by the first two authors and student volunteers, is only used for identifying synsets, and is separate from the image search described below.

Image Search We use the Google Images search engine to find sets of similar images (Figure 2a). We apply the query generation heuristics to the 124 synsets. We use all synonyms in each synset (Deng et al., 2014; Russakovsky et al., 2015). For example, for the synset `timber wolf`, we use the synonym set {`timber wolf`, `grey wolf`, `gray wolf`, `canis lupus`}. For each generated query, we download sets containing at most 16 related images.

Image Pruning We use two crowdsourcing tasks to (1) prune the sets of images, and (2) construct sets of eight images to use in the sentence-writing phase. In the first task, we remove low-

[5] https://images.google.com/

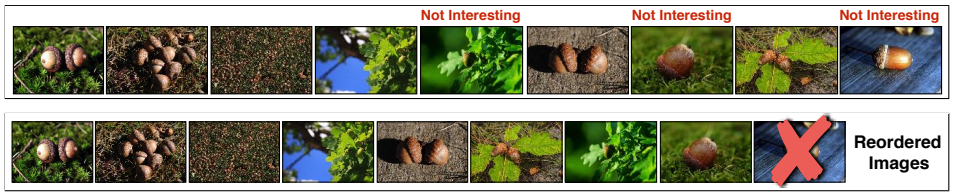
[6] At the time of publication, the similar images tool is available at the "View more" link in the list of related images after expanding the results for each image. Images are ranked by similarity, where more similar images appear higher.

[7] We pick 125 and remove one set due to high image pruning rate in later stages.

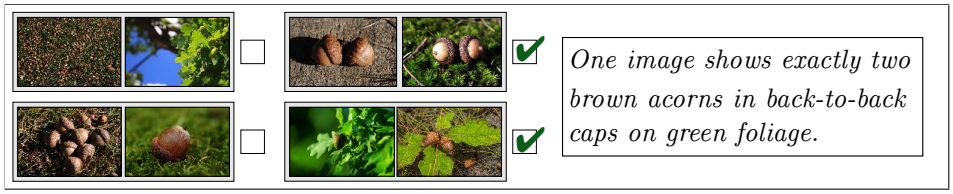
(a) **Find Sets of Images:** The query `two acorns` is issued to the search engine. The leftmost image appears in the list of results. The Similar Images tool is used to find a set of images, shown on the right, similar to this image.

(b) **Image Pruning:** Crowdworkers are given the synset name and identify low-quality images to be removed. In this example, one image is removed because it does not show an instance of the synset `acorn`.

(c) **Set Construction:** Crowdworkers decide whether each of the remaining images is interesting. In this example, three images are marked as non-interesting (top row) because they contain only a single instance of the synset. The images are re-ordered (bottom row) so that interesting images appear before non-interesting images, and the top eight images are used to form the set. In this example, the set is formed using the leftmost eight images.



(d) **Sentence Writing:** The images in the set are randomly paired and shown to the worker. The worker selects two pairs, and writes a sentence that is True for the two selected pairs but False for the other two pairs.



(e) **Validation:** Each pair forms an example with the written sentence. Each example is shown to a worker to re-label.

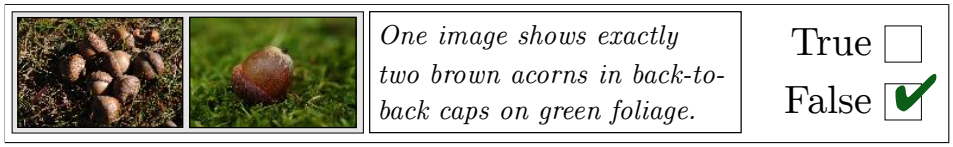


Figure 2: Diagram of the data collection process, showing how a single example from the training set is constructed. Steps (a)–(c) are described in Section 3.1; step (d) in Section 3.2; and step (e) in Section 3.3.

quality images from each downloaded set of similar images (Figure 2b). We display the image set and the synset name, and ask a worker to remove any images that do not load correctly; images that contain inappropriate content, non-realistic artwork, or collages; or images that do not contain an instance of the corresponding synset. This results in sets of sixteen or fewer similar images. We discard all sets with fewer than eight images.

The second task further prunes these sets by removing duplicates and down-ranking non-interesting images (Figure 2c). The goal of this stage is to collect sets that contain enough interesting images. Workers are asked to remove duplicate images, and mark images that are not *interesting*. An image is interesting if it fits any of the criteria in Table 2. We ask workers not to mark an image if they consider it interesting for any other reason. We discard sets with fewer than three interesting images. We sort the images in descending order according to first interestingness, and second similarity, and keep the top eight.

3.2 Sentence Writing

Each set of eight images is used for a sentence-writing task. We randomly split the set into four pairs of images. Using pairs encourages comparison and set reasoning within the pairs. Workers are asked to select two of the four pairs and write a sentence that is True for the selected pairs, but

Heuristic	Examples (`synset synonym` → `query`)	Description
Quantities	`cup` → `group of cups`	Add numerical phrases or manually-identified collective nouns to the synonym. These queries result in images containing multiple examples of the synset.
Hypernyms	`flute` → `flute woodwind`	Add direct or indirect hypernyms from WordNet (Miller, 1993). Applied only to the non-animal synsets. This heuristic increases the diversity of images retrieved for the synset (Deng et al., 2014).
Similar words	`banana` → `banana pear`	Add concrete nouns whose cosine similarity with the synonym is greater than 0.35 in the embedding space of Google News word2vec embeddings (Mikolov et al., 2013). Applied only to non-animal synsets. These queries result in images containing a variety of different but related object types.
Activities	`beagle` → `beagles eating`	Add manually-identified verbs describing common activities of animal synsets. Applied only to animal synsets. This heuristic results in images of animals participating in activities, which encourages captions with a diversity of entity properties.

Table 1: The four heuristics used to generate search queries from synsets.

Positive Examples and Criteria	
	Contains more than one instance of the synset.
	Shows an instance of the synset interacting with other objects.
	Shows an instance of the synset performing an activity.
	Displays a set of diverse objects or features.
Negative Examples	
	

Table 2: Positive and negative examples of interesting images.

False for the unselected pairs. Allowing workers to select pairs themselves makes the sentence-writing task easier than with random selection, which may create tasks that are impossible to complete. Writing requires finding similarities and differences between the pairs, which encourages compositional language (Suhr et al., 2017).

In contrast to the collection process of NLVR, using real images does not allow for as much control over their content, in some cases permitting workers to write simple sentences. For example, a worker could write a sentence stating the existence of a single object if it was only present in both selected pairs, which is avoided in NLVR by controlling for the objects in the images. Instead, we define more specific guidelines for the workers for writing sentences, including asking to avoid subjective opinions, discussion of properties of photograph, mentions of text, and simple object identification. We include more details and examples of these guidelines in Appendix B.

3.3 Validation

We split each sentence-writing task into four examples, where the sentence is paired with each pair of images. Validation ensures that the selection of each image pair reflects its truth value. We show each example independently to a worker, and ask them to label it as True or False. The worker may also report the sentence as nonsensical. We keep all non-reported examples where the validation label is the same as the initial label indicated by the sentence-writer's selection. For example, if the image pair is initially selected during sentence-writing, the sentence-writer intends the sentence to be True for the pair, so if the validation label is False, this example is removed.

3.4 Splitting the Dataset

We assign a random 20% of the examples passing validation to development and testing, ensuring that examples from the same initial set of eight images do not appear across the split. For these examples, we collect four additional validation judgments to estimate agreement and human performance. We remove from this set examples where two or more of the extra judgments disagreed with the existing label (Section 3.3). Finally, we create

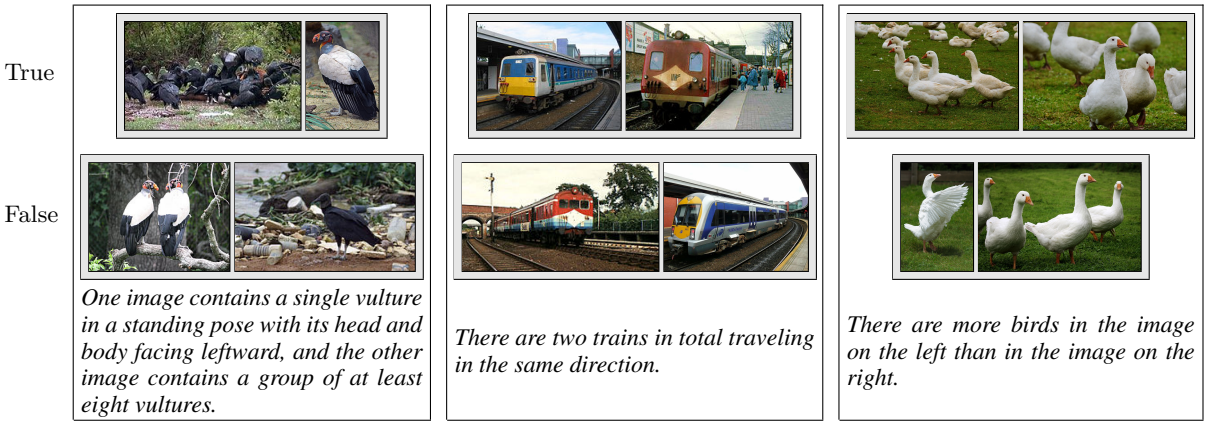


Table 3: Six examples with three different sentences from NLVR2. For each sentence, we show two examples using different image-pairs, each with a different label.

equal-sized splits for a development set and two test sets, ensuring that original image sets do not appear in multiple splits of the data (Table 4).

3.5 Data Collection Management

We use a tiered system with bonuses to encourage workers to write linguistically diverse sentences. After every round of annotation, we sample examples for each worker and give bonuses to workers that follow our writing guidelines well. Once workers perform at a sufficient level, we allow them access to a larger pool of tasks. We also use qualification tasks to train workers. The mean cost per unique sentence in our dataset is \$0.65; the mean cost per example is \$0.18. Appendix B provides additional details about our bonus system, qualification tasks, and costs.

3.6 Collection Statistics

We collect 27,678 sets of related images and a total of 387,426 images (Section 3.1). Pruning low-quality images leaves 19,500 sets and 250,862 images. Most images are removed for not containing an instance of the corresponding synset or for being non-realistic artwork or a collage of images. We construct 17,685 sets of eight images each.

We crowdsource 31,418 sentences (Section 3.2). We create two writing tasks for each set of eight images. Workers may flag sets of images if they should have been removed in earlier stages; for example, if they contain duplicate images. Sentence-writing tasks that remain without annotation after three days are removed.

During validation, 1,875 sentences are reported as nonsensical. 108,516 examples pass validation; i.e., the validation label matches the initial selection for the pair of images (Section 3.3). Removing low-agreement examples in the development and test sets yields a dataset of 107,292 examples, 127,502 unique images, and 29,680 unique sentences. Each unique sentence is paired with an average of 3.6 pairs of images. Table 3 shows examples of three unique sentences from NLVR2. Table 4 shows the sizes of the data splits, including train, development, a public test set (Test-P), and an unreleased test set (Test-U).

	Unique sentences	Examples
Train	23,671	86,373
Development	2,018	6,982
Test-P	1,995	6,967
Test-U	1,996	6,970
Total	29,680	107,292

Table 4: NLVR2 data splits.

4 Data Analysis

We perform quantitative and qualitative analysis using the training and development sets.

Agreement Following validation, 8.5% of the examples not reported during validation are removed due to disagreement between the validator's label and the initial selection of the image pair (Section 3.3).[8] We use the five validation labels we collect for the development and test sets to compute Krippendorff's α and Fleiss' κ to measure agreement (Cocos et al., 2015; Suhr et al., 2017). Before removing low-agreement examples

[8]The validator is the same worker as the sentence-writer for 11.5% of examples. In these cases, the validator agrees with themselves 96.7% of the time. For examples where the sentence-writer and validator were not the same person, they agree in 90.8% of examples.

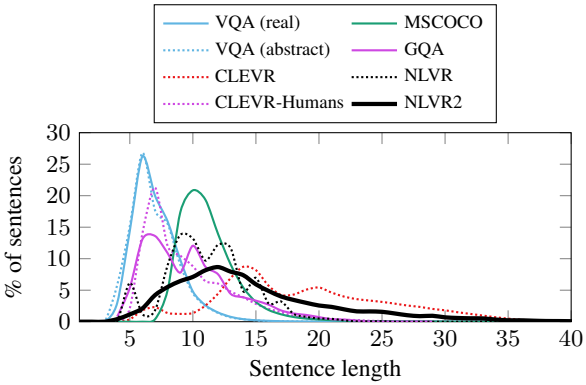


Figure 3: Distribution of sentence lengths. Dotted curves represent datasets with synthetic images.

(Section 3.4), $\alpha = 0.906$ and $\kappa = 0.814$. After removal, $\alpha = 0.912$ and $\kappa = 0.889$, indicating almost perfect agreement (Landis and Koch, 1977).

Synsets Each synset is associated with $\mu = 752.9 \pm 205.7$ examples. The five most common synsets are `gorilla`, `bookcase`, `bookshop`, `pug`, and `water buffalo`. The five least common synsets are `orange`, `acorn`, `ox`, `dining table`, and `skunk`. Synsets appear in equal proportions across the four splits.

Language NLVR2's vocabulary contains 7,457 word types, significantly larger than NLVR, which has 262 word types. Sentences in NLVR2 are on average 14.8 tokens long, whereas NLVR has a mean sentence length of 11.2. Figure 3 shows the distribution of sentence lengths compared to related corpora. NLVR2 shows a similar distribution to NLVR, but with a longer tail. NLVR2 contains longer sentences than the questions of VQA (Antol et al., 2015), GQA (Hudson and Manning, 2019), and CLEVR-Humans (Johnson et al., 2017b). Its distribution is similar to MSCOCO (Chen et al., 2015), which also contains captions, and CLEVR (Johnson et al., 2017a), where the language is synthetically generated.

We analyze 800 sentences from the development set for occurrences of semantic and syntactic phenomena (Table 5). We compare with the 200-example analysis of VQA and NLVR from Suhr et al. (2017), and 200 examples from the balanced split of GQA. Generally, NLVR2 has similar linguistic diversity to NLVR, showing broader representation of linguistic phenomena than VQA and GQA. One noticeable difference from NLVR is less use of hard cardinality. This is possibly due to how NLVR is designed to use a very limited set of object attributes, which encourages writers to rely on accurate counting for discrimination more often. We include further analysis in Appendix C.

5 Estimating Human Performance

We use the additional labels of the development and test examples to estimate human performance. We group these labels according to workers. We do not consider cases where the worker labels a sentence written by themselves. For each worker, we measure their performance as the proportion of their judgements that matches the gold-standard label, which is the original validation label. We compute the average and standard deviation performance over workers with at least 100 such additional validation judgments, a total of 68 unique workers. Before pruning low-agreement examples (Section 3.4), the average performance over workers in the development and both test sets is 93.1 ± 3.1. After pruning, it increases to 96.1 ± 2.6. Table 6 shows human performance for each data split that has extra validations. Because this process does not include the full dataset for each worker, it is not fully comparable to our evaluation results. However, it provides an estimate by balancing between averaging over many workers and having enough samples for each worker.

6 Evaluation Systems

We evaluate several baselines and existing visual reasoning approaches using NLVR2. For all systems, we optimize for example-level accuracy.[9]

We measure the biases in the data using three baselines: (a) MAJORITY: assign the most common label (True) to each example; (b) TEXT: encode the caption using a recurrent neural network (RNN; Elman, 1990), and use a multilayer perceptron to predict the truth value; and (c) IMAGE: encode the pair of images using a convolutional neural network (CNN), and use a multilayer perceptron to predict the truth value. The latter two estimate the potential of solving the task using only one of the two modalities.

We use two baselines that consider both language and vision inputs. The CNN+RNN baseline concatenates the encoding of the text and images, computed similar to the TEXT and IMAGE baselines, and applies a multilayer perceptron to predict a truth value. The MAXENT baseline computes features from the sentence and objects de-

[9] System and learning details are available in Appendix E.

	VQA (real) %	GQA %	NLVR %	NLVR2 %	Example from NLVR2
Semantics					
Cardinality (hard)	11.5	0	66	41.1	***Six*** *rolls of paper towels are enclosed in a plastic package with the brand name on it.*
Cardinality (soft)	1	0	23.6	22.5	***No more than two*** *cheetahs are present.*
Existential	11.5	16.5	88	23.6	***There are*** *at most 3 water buffalos in the image pair.*
Universal	1	4.5	7.5	16.8	*In one image there is a line of fence posts with one large darkly colored bird on top of* ***each*** *post.*
Coordination	5	21.5	17	33.3	*Each image contains only one wolf,* ***and*** *all images include snowy backdrops.*
Coreference	6.5	0.5	3	14.6	*there are four or more animals very close to* ***each other*** *on the grass in the image to the left.*
Spatial Relations	42.5	43	66	49	*A stylus is* ***near*** *a laptop in one of the images.*
Comparative	1	2	3	8	*There are* ***more*** *birds in the image on the right* ***than*** *in the image on the left.*
Presupposition	80	79	19.5	20.6	*A cookie sits in* ***the dessert*** *in the image on the left.*
Negation	1	2.5	9.5	9.6	*The front paws of the dog in the image on the left are* ***not touching*** *the ground.*
Syntactic Ambiguity					
CC Attachment	0	2.5	4.5	3.8	*The left image shows a cream-layered dessert in a footed clear glass which includes sliced peanut butter cups* ***and*** *brownie chunks.*
PP Attachment	3	6.5	23	11.5	*At least one panda is sitting near a fallen branch* ***on the ground****.*
SBAR Attachment	0	5	2	1.9	*Balloons float in a blue sky with dappled clouds on strings* ***that*** *angle rightward, in the right image.*

Table 5: Linguistic analysis of sentences from NLVR2, GQA, VQA, and NLVR. We analyze 800 development sentences from NLVR2 and 200 from each of the other datasets for the presence of semantic and syntactic phenomena described in Suhr et al. (2017). We report the proportion of examples containing each phenomenon.

tected in the paired images. We detect the objects in the images using a Mask R-CNN model (He et al., 2017; Girshick et al., 2018) pre-trained on the COCO detection task (Lin et al., 2014). We use a detection threshold of 0.5. For each n-gram with a numerical phrase in the caption and object class detected in the images, we compute features based on the number present in the n-gram and the detected object count. We create features for each image and for both together, and use these features in a maximum entropy classifier.

Several recent approaches to visual reasoning make use of modular networks (Section 2). Broadly speaking, these approaches predict a neural network layout from the input sentence by using a set of modules. The network is used to reason about the image and text. The layout predictor may be trained: (a) using the formal programs used to generate synthetic sentences (e.g., in CLEVR), (b) using heuristically generated layouts from syntactic structures, or (c) jointly with the neural modules with latent layouts. Because sentences in NLVR2 are human-written, no supervised formal programs are available at training time. We use two methods that do not require such formal programs: end-to-end neural module networks (N2NMN; Hu et al., 2017) and feature-wise linear modulation (FiLM; Perez et al., 2018). For N2NMN, we evaluate three learning methods: (a) N2NMN-CLONING: using supervised learning with gold layouts; (b) N2NMN-TUNE: using policy search after cloning; and (c) N2NMN-RL: using policy search from scratch. For N2NMN-CLONING, we construct layouts from constituency trees (Cirik et al., 2018). Finally, we evaluate the Memory, Attention, and Composition approach (MAC; Hudson and Manning, 2018), which uses a sequence of attention-based steps. We modify N2NMN, FiLM, and MAC to process a pair of images by extracting image features from the concatenation of the pair.

7 Experiments and Results

We use two metrics: accuracy and consistency. Accuracy measures the per-example prediction accuracy. Consistency measures the proportion of unique sentences for which predictions are correct for all paired images (Goldman et al., 2018). For training and development results, we report mean and standard deviation of accuracy and con-

	Train	Dev	Test-P	Test-U
MAJORITY (assign True)	50.8/2.1	50.9/3.9	51.1/4.2	51.4/4.6
TEXT	50.8±0.0/2.1±0.0	50.9±0.0/3.9±0.0	51.1/4.2	51.4/4.6
IMAGE	60.1±2.9/14.2±4.2	51.6±0.2/8.4±0.8	51.9/7.4	51.9/7.1
CNN+RNN	94.3±3.3/84.5±10.2	53.4±0.4/12.2±0.7	52.4/11.0	53.2/11.2
MAXENT	89.4/73.4	54.1/11.4	**54.8/11.5**	**53.5/12.0**
N2NMN (Hu et al., 2017):				
N2NMN-CLONING	65.7±25.8/30.8±49.7	50.2±1.0/5.7±3.1	–	–
N2NMN-TUNE	96.5±1.6/94.9±0.4	50.0±0.7/9.8±0.5	–	–
N2NMN-RL	50.8±0.3/2.3±0.3	51.0±0.1/4.1±0.3	51.1/5.0	51.5/5.0
FiLM (Perez et al., 2018)	69.0±16.9/32.4±29.6	51.0±0.4/10.3±1.0	52.1/9.8	53.0/10.6
MAC (Hudson and Manning, 2018)	87.4±0.8/64.0±1.7	50.8±0.6/11.0±0.2	51.4/11.4	51.2/11.2
HUMAN	–	96.2±2.1/–	96.3±2.9/–	96.1±3.1/–

Table 6: Performance (accuracy/consistency) on NLVR2.

sistency over three trials as $\mu_{\text{acc}} \pm \sigma_{\text{acc}} / \mu_{\text{cons}} \pm \sigma_{\text{cons}}$. The results on the test sets are generated by evaluating the model that achieved the highest accuracy on the development set. For the N2NMN methods, we report test results only for the best of the three variants on the development set.[10]

Table 6 shows results for NLVR2. MAJORITY results demonstrate the data is fairly balanced. The results are slightly higher than perfect balance due to pruning (Sections 3.3 and 3.4). The TEXT and IMAGE baselines perform similar to MAJORITY, showing that both modalities are required to solve the task. TEXT shows identical performance to MAJORITY because of how the data is balanced. The best performing system is the feature-based MAXENT with the highest accuracy and consistency. FiLM performs best of the visual reasoning methods. Both FiLM and MAC show relatively high consistency. While almost all visual reasoning methods are able to fit the data, an indication of their high learning capacity, all generalize poorly. An exception is N2NMN-RL, which fails to fit the data, most likely due to the difficult task of policy learning from scratch. We also experimented with recent contextualized word embeddings to study the potential of stronger language models. We used a 12-layer uncased pre-trained BERT model (Devlin et al., 2019) with FiLM. We observed BERT provides no benefit, and therefore use the default embedding method for each model.

8 Conclusion

We introduce the NLVR2 corpus for studying semantically-rich joint reasoning about photographs and natural language captions. Our focus on visually complex, natural photographs and human-written captions aims to reflect the challenges of compositional visual reasoning better than existing corpora. Our analysis shows that the language contains a wide range of linguistic phenomena including numerical expressions, quantifiers, coreference, and negation. This demonstrates how our focus on complex visual stimuli and data collection procedure result in compositional and diverse language. We experiment with baseline approaches and several methods for visual reasoning, which result in relatively low performance on NLVR2. These results and our analysis exemplify the challenge that NLVR2 introduces to methods for visual reasoning. We release training, development, and public test sets, and provide scripts to break down performance on the 800 examples we manually analyzed (Section 4) according to the analysis categories. Procedures for evaluating on the unreleased test set and a leaderboard are available at http://lic.nlp.cornell.edu/nlvr/.

[10] For reference, we also provide NLVR results in Table 11, Appendix D.

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A Frequently Asked Questions

In what applications do you expect to see the kind of language NLVR2 allows to study? Composition of reasoning skills including counting, comparing, and reasoning about sets is critical for robotic agents following natural language instructions. Consider a robot on a factory floor or in a cluttered workshop following the instruction *get the two largest hammers from the toolbox at the end of the shelf*. Correctly following this instruction requires reasoning compositionally about object properties, comparisons between these properties, counts of objects, and spatial relations between observed objects. The language in NLVR2 reflects this type of linguistic reasoning. While the task we define does not use this kind of application directly, our data enables studying models that can understand this type of language.

How can I use NLVR2 to build an end application? The task and data are not intended to directly develop an end application. Our focus is on developing a task that drives research in vision and language understanding towards handling diverse set of reasoning skills. It is critical to keep in mind that this dataset was not analyzed for social biases. Researchers who wish to apply this work to an end product should take great care in considering what biases may exist.

Doesn't using a binary prediction task limit the ability to gain insight into model performance? Because our dataset contains both positive and negative image pairs for each sentence, we can measure consistency (Goldman et al., 2018), which requires a model to predict each label correctly for each use of the sentence. This metric requires generalization across at most four image pair contexts.

Why collect a new set of images rather than use existing ones like COCO (Lin et al., 2014)? Our goal was to achieve similar semantic diversity to NLVR, but using real images. Like NLVR, we use a sentence-writing task where sets of similar images are compared and contrasted. However, unlike NLVR, we do not have control over the image content, so cannot guarantee image sets where the content is similar enough (e.g., where the only difference is the direction in which the same animal is facing) such that the written sentence does not describe trivial image differences (e.g., the types of objects present). In addition to image similarity within sets, we also prioritize image interestingness, for example images with many instances of an object. Existing corpora, including like COCO and ImageNet (Russakovsky et al., 2015), were not constructed to prioritize interestingness as we define it, and are not comprised of sets of eight very similar images as required for our task.

1. We select a set of 124 ImageNet synsets which often appear in visually rich images.

2. We generate search queries which result in visually rich images, e.g., containing multiple instances of a synset.

3. We use a similar images tool to acquire sets of images with similar image content, for example containing the same objects in different relative orientations.

4. We prune images which do not contain an example of the synset it was derived from.

5. We apply a re-ranking and pruning procedure that prioritizes visually rich and interesting images, and prunes set which do not have enough interesting images.

These steps result in a total of 17,685 sets of eight similar, visually rich images.

Why use pairs of images instead of single images? We use pairs of images to elicit descriptions that reason over the pair of images in addition to the content within each image. This setup supports, for example, comparing the two images, requiring that a condition holds in both images or in one but not the other, and performing set reasoning about the objects present in each image. This is analogous to the three-box setup in NLVR.

Why allow workers to select the pairs themselves during sentence writing? We found that for some image pair selections, it was too difficult for workers to write a sentence which distinguishes the pairs. Allowing the workers to choose the pairs avoids this feasiblity issue.

Why get multiple validations for development and test splits? This ensures the test splits are of the highest quality and have minimal noise, as required for reliable measure of task performance. The additional annotatiosn also allow us to measure agreement and estimate human performance.

How does the NLVR2 data compares to the NLVR data? NLVR and NLVR2 share the task of determining whether a sentence is true in a given visual context. In NLVR, the visual input is synthetic and includes a handful of shapes and properties. In NLVR2, each visual context is a pair of real photographs obtained from the web. Grounding sentences in image pairs rather than single images is related to NLVR's use of three boxes per image.

How does the NLVR2 data collection process compare to NLVR? We adapt the NLVR sentence-writing and validation tasks. However, rather than using four related synthetic images for writing, we use four pairs of real images. The pairing of images encourages set comparison. This was accomplished in NLVR through careful control of the generated image content, something that is not possible with real images. The NLVR image generation process is also controlled for the type of differences possible between images and the visual complexity, by ensuring the objects present in the selected and unselected images were the same. This guarantees that the only differences are in the object configurations and distribution among the three boxes in each image. Neither form of control is possible with real images. Instead, we rewrite the guidelines and develop a process to educate workers to follow them. In our process, we use the similar images tool to identify images that require linguistically-rich descriptions to distinguish. While using the similar images tool does not guarantee that the objects in the selected images are also present in the unselected images, our process successfully avoids this issue; in practice, only around 13% of examples take advantage of this by mentioning objects only present in the selected images.

Can you summarize the key linguistic differences between NLVR2 and NLVR? NLVR contains significantly[11] more examples of hard cardinality, existential quantifiers, spatial relations, and prepositional attachment ambiguity. NLVR2 contains significantly[11] more examples of universal quantifiers, coordination, coreference, and comparatives. NLVR2's descriptions are longer on average than NLVR (14.8 vs. 11.2 tokens), and the vocabulary is much larger ($7{,}457$ vs. 262 word types). This demonstrates both the lexical diversity and challenges of understanding a wide range of image content in NLVR2 that are not present in NLVR. However, NLVR allows studying compositionality in isolation from lexical diversity, an intended feature of the dataset's design. NLVR has also been used as a semantic parsing task, where images are represented as structured representations (Goldman et al., 2018), a use case that is not possible with NLVR2. NLVR remains a challenging dataset for visual reasoning; recent approaches have shown moderate improvements over the initial baseline performance, yet remain far from human accuracy, which we compute in Table 11.

How does NLVR2 compare to existing visual reasoning datasets? Table 7 compares NLVR2 with several existing, related corpora. In the last several years there has been an increase in the number of datasets released for vision and language research. One trend includes building datasets for compositional visual reasoning (SHAPES, CLEVR, CLEVR-Humans, ShapeWorld, NLVR, FigureQA, COG, and GQA), all of which use synthetic data either for at least one of the inputs. While NLVR2 requires related visual reasoning skills, it uses both real natural language and real visual inputs.

How does NLVR2 compare to recent attempts to avoid biases in vision and language datasets? Recently, several approaches were proposed to identify unintended biases present in vision-and-language tasks, such as the ability to answer a question without using the paired image (Zhang et al., 2016; Goyal et al., 2017; Li et al., 2017; Agrawal et al., 2017, 2018). The data collection process of NLVR2 is designed to automatically pair each sentence with both labels in different visual contexts. This makes NLVR2 robust to implicit linguistic biases. This is illustrated by our initial experiments with BERT, which have been shown to be extremely effective at capturing language patterns for various tasks (Devlin et al., 2019). With our balanced data, using BERT does not help identifying and using language biases.

Are the differences in the linguistic analysis between the datasets significant? We measure significance using a χ^2 test with $p < 0.05$. Our qualitative linguistic analysis shows several differences from VQA (Antol et al., 2015) and GQA (Hudson and Manning, 2019). NLVR2 contains significantly more examples of hard cardinality, soft cardinality, existential quantifiers, uni-

[11] Using a χ^2 test with $p < 0.05$.

versal quantifiers, coordination, coreference, spatial relations, comparatives, negation, and preposition attachment ambiguity than both GQA and VQA. However, VQA and GQA both contain significantly more examples of presupposition than NLVR2.

Given your linguistic analysis, how does GQA compare to VQA? We found that the distribution of phenomena in VQA and GQA are roughly similar, with notable differences being significantly[11] more examples of hard cardinality and coreference in VQA, and significantly[11] more examples of universal quantifiers, coordination, and coordination and subordinating conjunction attachment ambiguity in GQA.

B Data Collection Details

Image Collection We consider the images of each search query in the order of the search results. For each result associated with a set of similar images, we save the URL of the result image and the URLs of the fifteen most similar images, giving us a set of sixteen images. We skip and ignore URLs from a hand-crafted list of stock photo domains; images from these domains include large, distracting watermarks. We stop after observing 60 result images, saving 30 sets of image URLs, or observing five consecutive results that do not have similar images.[12]

After downloading a set of 16 URLs of related images (Section 3.1), we automatically prune the images. We remove any broken URLs or any URLS that appeared in other previously-downloaded sets from the same search query. We remove downloaded images smaller than 200×200 pixels. We apply basic duplicate removal by removing any images which are exact duplicates of a previously-downloaded image in the set. This automatic pruning may result in image sets consisting of fewer than 16 images. We discard any sets after this stage with fewer than 8 images.

Sentence Writing Table 8 shows the types of sentences we ask workers to avoid in their writing. Analysis of 100 sentences from the development set shows that almost all sentences follow our guidelines, only 13% violate our guidelines. The most common violation was mentioning an object not present in the unselected images. Such sentences can trivially be labeled as False in the context of the unselected pairs, as the mentioned object will not be present. In the context of the selected pairs, however, a model must still perform compositional joint reasoning about the sentence and the image pair to determine whether the label should be True at test time. This is because the sentence often includes additional constraints. The bottom example in Table 12 illustrates this violation. A system may easily determine that because neither a hole nor a golf flagpole are present in either image, the sentence is False. However, if these objects were present, the system must reason about counts and spatial relations of the mentioned objects to verify that the sentence is True.

Data Collection Management We use two qualification tasks. For the set construction and sentence writing tasks, we qualify workers by first showing six tutorial questions about the guidelines and task. We then ask them to validate guidelines for nineteen sentences across two sets of four pre-selected image pairs, and to complete a single sentence-writing task for pre-selected image pairs. We validate the written sentence by hand. We qualify workers for validation with eight pre-selected validation tasks.

We use a bonus system to encourage workers to write linguistically diverse sentences. We conduct sentence writing in rounds. After each round, we sample twenty sentences for each worker from that round. If at least 75% of these sentences follow the guidelines, they receive a bonus for each sentence written during the last round. If between 50% and 75% follow our guidelines, they receive a slightly lower bonus. This encourages workers to follow the guidelines more closely. In addition, each worker initially only has access to a limited pool of sentence-writing tasks. Once they successfully complete an evaluation round where at least 75% of their sentences followed the guidelines, they get access to the entire pool of tasks.

Table 9 shows the costs and number of workers per task. The final cost per unique sentence in our dataset is $0.65; the cost per example is $0.18.

C Additional Data Analysis

Synsets Figure 4 shows the counts of examples per synset in the training and development sets.

Image Pair Reasoning We use a 200-sentence subset of the sentences analyzed in Table 5 to analyze what types of reasoning are required over the

[12] For collective nouns and the numerical phrase `two <synset>`, we instead observe at most 100 top images or save at most 60 sets.

Dataset	Task	Prevalent Linguistic Phenomena	Natural Language?	Natural Images?
NLVR2	Binary Sentence Classification	(1) Hard and (2) soft cardinality; (3) existential and (4) universal quantifiers; (5) coordination; (6) coreference; (7) spatial relations; (8) presupposition; (9) preposition attachment ambiguity	✔	✔
VQA1.0 (Antol et al., 2015), VQA-CP (Agrawal et al., 2017), VQA2.0 (Goyal et al., 2017)	Visual Question Answering	(1) Hard cardinality; (2) existential quantifiers; (3) spatial relations; (4) presupposition	✔	✔
NLVR (Suhr et al., 2017)	Binary Sentence Classification	(1) Hard and (2) soft cardinality; (3) existential quantifiers; (4) coordination; (5) spatial relations; (6) presupposition; (7) preposition attachment ambiguity	✔	
GQA (Hudson and Manning, 2019)	Visual Question Answering	(1) Existential quantifiers; (2) coordination; (3) spatial relations; (4) presupposition		✔

Dataset	Task	Natural Language?	Natural Images?
SAIL (MacMahon et al., 2006)	Instruction Following	✔	
Mitchell et al. (2010)	Referring Expression Resolution	✔	
Matuszek et al. (2012)	Referring Expression Resolution	✔	
FitzGerald et al. (2013)	Referring Expression Generation	✔	
VQA (Abstract) (Zitnick and Parikh, 2013)	Visual Question Answering	✔	
ReferItGame (Kazemzadeh et al., 2014)	Referring Expression Resolution	✔	✔
SHAPES (Andreas et al., 2016)	Visual Question Answering		
Bisk et al. (2016)	Instruction Following	✔	
MSCOCO (Chen et al., 2016)	Caption Generation	✔	✔
Google RefExp (Mao et al., 2016)	Referring Expression Resolution	✔	✔
ROOM-TO-ROOM (Anderson et al., 2018)	Instruction Following	✔	✔
Visual Dialog (Das et al., 2017)	Dialogue Visual Question Answering	✔	✔
CLEVR (Johnson et al., 2017a)	Visual Question Answering		
CLEVR-Humans (Johnson et al., 2017b)	Visual Question Answering	✔	
TDIUC (Kafle and Kanan, 2017)	Visual Question Answering	✔	✔
ShapeWorld (Kuhnle and Copestake, 2017)	Binary Sentence Classification		
FigureQA (Kahou et al., 2018)	Visual Question Answering		
TVQA (Lei et al., 2018)	Video Question Answering	✔	✔
LANI & CHAI (Misra et al., 2018)	Instruction Following	✔	✔
Talk the Walk (de Vries et al., 2018)	Dialogue Instruction Following	✔	✔
COG (Yang et al., 2018)	Visual Question Answering; Instruction Following		
VCR (Zellers et al., 2019)	Visual Question Answering	✔	✔
TallyQA (Acharya et al., 2019)	Visual Question Answering	✔	✔
TOUCHDOWN (Chen et al., 2019)	Instruction Following; Spatial Description Resolution	✔	✔
COCO-BISON (Hu et al., 2019)	Binary Image Selection	✔	✔
SNLI-VE (Xie et al., 2019)	Visual Entailment	✔	✔

Table 7: Comparison between NLVR2 and existing datasets for language and vision research. The top table details prevalent linguistic phenomena in some of the most related datasets according to our analysis, listing each linguistic phenomenon with at least 10% representation as prevalent. For each dataset, we count the number of prevalent phenomena. NLVR2 has the broadest representation. The bottom table lists other tasks in language and vision.

What to avoid	Example of erroneous sentence
Subjective opinions	*The dog's fur has a nice color pattern.*
Discussing properties of the photograph	*In both images, the cat's paw is cropped out of the photo.*
Mentioning text in the photograph	*Both trains are numbered 72.*
Mentioned object not present in unselected pairs	*There is a cup on top of a chair.* – for a set of images where the selected pairs contain a chair, but the unselected pairs do not.
Mentioning the presence of a single object	*There is a hammer.*
Disjunction on images in the pair	*The left image contains a penguin, and the right image contains a rock.*

Table 8: Types of sentences workers are discouraged from writing. The bottom two are permissible as long as the sentence includes other kinds of reasoning.

	Cost	Unique Workers
Image Pruning	$1,310.76	53
Set Construction	$1,798.84	46
Sentence Writing	$9,570.46	99
Validation	$6,452.93	125
Total	$19,132.99	167

Table 9: Cost and worker statistics.

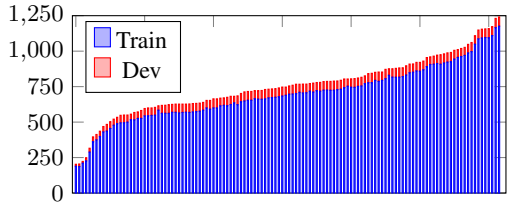


Figure 4: Number of examples per synset, sorted by number of examples in each synset.

two images (Table 10). We observe that sentences commonly use the pair structure used to display the images: 11% of sentences require that a property to hold in both images, 19% simply require that a property holds in at least one image, and 26.5% of sentences require a property to be true in the left or right images specifically. The pair is also used for comparison, with 6% of sentences requiring comparing properties of the two images. Finally, 39.5% of sentences simply state a property that must be true across the image pair, e.g., *One sliding door is closed.*

D Results on NLVR

Table 11 shows previously published results using raw images in NLVR from Suhr et al. (2017) and more recent approaches.[13] We also report results for visual reasoning systems originally developed for CLEVR. We compute human performance for each split of the data using the procedure described in Section 5; a threshold of 100 covers 100% of annotators. NMN (Andreas et al., 2016), N2NMN, and FiLM achieve the best results for methods that were not developed using NLVR. However, both perform worse than CNN-BIATT (Tan and Bansal, 2018) and CMM (Yao et al., 2018), which were developed originally using NLVR.[14]

[13] Not all previously evaluated methods report consistency.

E Implementation Details

For the TEXT, IMAGE, and CNN+RNN baselines, we first compute a representation of the input(s). We then process this representation using a multilayer perceptron (MLP). The MLP's output is used to predict a distribution over the two labels using a softmax. The MLP includes learned bias terms and ReLu nonlinearities on the output of each layer, except the last one. In all cases, the layer sizes of the MLP follow the series $[8192, 4096, 2048, 1024, 512, 256, 128, 64, 32, 16, 2]$.

E.1 Single Modality

TEXT The caption's representation is computed using an RNN encoder. We use 300-dimensional GloVe vectors trained on Common Crawl as word embeddings (Pennington et al., 2014). We encode the caption using a single-layer long short-term memory (LSTM, Hochreiter and Schmidhuber, 1997) RNN of size 4096. The hidden states of the caption are averaged and processed with the MLP described above to predict the truth value.

IMAGE The image pair's representation is computed by extracting features from a pre-trained model. We resize and pad each image with whitespace to a size of 530×416 pixels, which is the size of the image displayed to the workers during sentence-writing. Each padded image is resized to 224×224 and passed through a ResNet-152 pre-trained model (He et al., 2016). The features from the final layer before classification are extracted

[14] Consistency for CNN-BIATT was taken from the NLVR leaderboard.

Required Reasoning	%	Example from NLVR2
Exactly one image	3	***Only one image*** *shows warthogs butting heads.*
Existential quantification	19	***In one image****, hyenas fight with a big cat.*
Universal quantification	11	*There are people walking* ***in both images****.*
Explicit reference to left and/or right image	26.5	***The left image*** *contains exactly two dogs.*
Comparison between images	6	*There are* ***more*** *mammals in* ***the image on the right****.*

Table 10: Types of reasoning over the pair of images required in NLVR2, including the proportion of examples requiring each type and an example.

	Train	Dev	Test-P	Test-U
MAJORITY (assign True)	56.4/–	55.3/–	56.2/–	55.4/–
TEXT	58.4±0.6/–	56.6±0.5/–	57.2±0.6/–	56.2±0.4/–
IMAGE	56.8±1.3/–	55.4±0.1/–	56.1±0.3/–	55.3±0.3/–
CNN+RNN	58.9±0.2/–	56.6±0.3/–	58.0±0.3/–	56.3±0.6 /–
NMN	98.4±0.6/–	63.1±0.1/–	66.1±0.4/–	62.0±0.8/–
CNN-BIATT (Tan and Bansal, 2018)	–	66.9/–	69.7/–	**66.1/28.9**
W-MEMNN (Pavez et al., 2018)	–	65.6/–	65.8/–	–
CMM (Yao et al., 2018)	–	68.0/–	**69.9**/–	–
N2NMN (Hu et al., 2017):				
N2NMN-CLONING	95.6±1.3/79.9±4.7	57.9±1.1/9.7±0.8	–	–
N2NMN-TUNING	97.5±0.4/92.7±2.6	58.7±1.4/11.6±0.8	–	–
N2NMN-RL	95.4±2.4/81.2±10.6	65.3±0.4/16.2±1.5	69.1/20.7	66.0/17.7
FiLM (Perez et al., 2018)	95.5±0.4/84.6±2.7	60.1±1.2/14.6±1.3	62.2/18.4	61.2/18.1
MAC (Hudson and Manning, 2018)	64.2±4.7/12.6±0.2	55.4±0.5/7.4±0.6	57.6/11.7	54.3/8.6
HUMAN (approximation)	–	94.6±3.5/–	95.4±3.4/–	94.9±3.6/–

Table 11: Performance (accuracy/consistency) on NLVR.

for each image and concatenated. This representation is processed with the MLP described above to predict a truth value.

E.2 Image and Text Baselines

CNN+RNN The caption and image pair are encoded as described in Appendix E.1, then concatenated and passed through the MLP described above to predict a truth value.

MAXENT We use n-grams where $2 \leq n \leq 6$. We train a maximum entropy classifier with Megam.[15]

E.3 Module Networks

End-to-End Neural Module Networks We use the publicly available implementation.[16] The model parameters used for NLVR2 are the same as those used for the original experiments on VQA. We use GloVe vectors of size 300 to embed words (Pennington et al., 2014). The model parameters used for NLVR are the same as those used for the original N2NMN experiments on CLEVR. This includes learning word embeddings from scratch and embedding images using the *pool5* layer of VGG-16 trained on ImageNet (Simonyan and Zisserman, 2014; Hu et al., 2017). The two paired images are resized and padded with white space to size 530×416, then concatenated horizontally and resized to a single image of 448×448 pixels. The resulting image is embedded using the *res5c* layer of ResNet-152 trained on ImageNet (He et al., 2016; Hu et al., 2017).

FiLM We use the publicly available implementation.[17] For NLVR2, we first resize and pad both images with whitespace to images of size 530×416. The two images are concatenated horizontally and resized to a single image of 224×224 pixels. This image is passed through a ResNet-101 pretrained model and the features from the *conv4* layer are extracted (He et al., 2016; Perez et al., 2018). For NLVR, we resize images to 224×224 and use the raw pixels directly. The parameters of the models are the same as described in Perez et al. (2018)'s experiments on featurized images, except for the following: RNN hidden size of 1096, classifier projection dimension of size 256, final MLP hidden size of 512, and 28 feature maps. Us-

[15] https://www.umiacs.umd.edu/~hal/megam

[16] https://github.com/ronghanghu/n2nmn

[17] https://github.com/ethanjperez/film

ing the original parameters did not result in significant differences in accuracy, while updates using our parameters were computed faster and the computation graph used less memory.

E.4 MAC

We use the implementation provided online.[18] For experiments on NLVR2, we adapt the image processing procedure. Both images are resized and padded with white space to images of size 530×416, then concatenated horizontally and resized to 224×224 pixels. We use the same image featurization approach used in Hudson and Manning (2018). For experiments on NLVR, we use the NLVR configuration provided in the repository.

E.5 Training

For the TEXT, IMAGE, and CNN+RNN methods on NLVR2, we perform updates using ADAM (Kingma and Ba, 2014) with a global learning rate of 0.0001. The weights and biases are initialized by sampling uniformly from $[-0.1, 0.1]$. All fully-connected and output layers use a learned bias term. For MAC, we use the same training setup as described in Hudson and Manning (2018), stopping early based on performance over the development set. For all other experiments, we use early stopping with patience, where patience is initially set to a constant and multiplied 1.01 at each epoch the validation accuracy improves over a global maximum. We use 5% of the training data as a validation set, which is not used to update model parameters. We choose a validation set such that unique sentences do not appear in both the validation and training sets. For FiLM and N2NMN, we set the initial patience to 30. For TEXT, IMAGE and CNN+RNN baselines, initial patience was set to 10. For MAXENT, we use at most 100 epochs.

F Additional Examples

Table 12 includes additional examples sampled from the training and development sets of NLVR2, as well as license information for each image. All images in this paper were sampled from websites known for hosting non-copyrighted images, for example Wikimedia.

[18] https://github.com/stanfordnlp/mac-network

G Lisence Information

Tables 13, 14, 15, and 15 detail license and attribution information for the images included in the main paper.

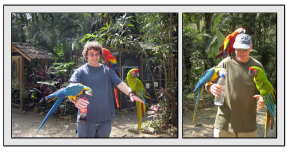
Image Pair	Sentence	Label
 *Kropsoq (CC BY-SA 3.0); subhv150 (Pixabay)*	*Two hot air balloons are predominantly red and have baskets for passengers.*	True
 *babasteve (CC BY 2.0); Yathin S Krishnappa (CC BY-SA 3.0)*	*All elephants have ivory tusks.*	False
 *NatashaG (Pixabay); Photoman (Pixabay)*	*There are entirely green apples among the fruit in the right image.*	True
 *Pedi68 (Pixabay); Andrea Schafthuizen (PDP)*	*The animal in the image on the right is standing on its hind legs.*	False
 *Ben & Katherine Sinclair (CC BY 2.0); Zhangzhugang (CC BY-SA 3.0)*	*One of the images contains one baby water buffalo.*	True
 *Pelikana (CC BY-SA 3.0); violetta (Pixabay)*	*The sled in the image on the left is unoccupied.*	False
 *Frans de Waal (CC BY 2.5); Adam Jones (CC BY-SA 3.0)*	*Each image shows two animals interacting, and one image shows a monkey grooming the animal next to it.*	True
 *Burtonpe (CC BY-SA 3.0); Ville de Montréal (CC BY-SA 3.0)*	*In 1 of the images, the oars are kicking up spray.*	False
 *Sarah and Jason (CC BY-SA 2.0); Sarah and Jason (CC BY-SA 2.0)*	*In one image, a person is standing in front of a roofed and screened cage area with three different colored parrots perched them.*	True
 *Petey21 (CC0); Santeri Viinamäki (CC BY-SA 4.0)*	*In one of the images there are at least two golf balls positioned near a hole with a golf flagpole inserted in it.*	False

Table 12: Additional examples from the training and development sets of NLVR2, including license information for each photograph beneath the pair and the label of the example.

Image	Attribution and License
	MemoryCatcher (CC0)
	Calabash13 (CC BY-SA 3.0)
	Charles Rondeau (CC0)
	Andale (CC0)

Table 13: License information for the images in Figure 1.

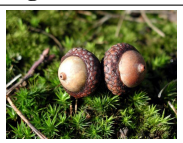
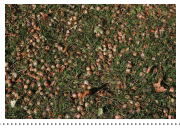
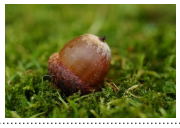
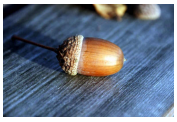
Image	Attribution and License
	Hagerty Ryan, USFWS (CC0)
	Charles Rondeau (CC0)
	Peter Griffin (CC0)
	Petr Kratochvil (CC0)
	George Hodan (CC0)
	Charles Rondeau (CC0)
	Andale (CC0)
	Maksym Pyrizhok (PDP)
	Sheila Brown (CC0)
	ulleo (CC0)

Table 14: License information for the images in Figure 2.

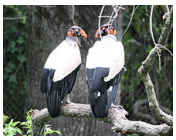
Image	Attribution and License
	JerryFriedman (CC0)
	Eric Kilby (CC BY-SA 2.0)
	Angie Garrett (CC BY 2.0)
	Ben HaTeva (CC BY-SA 2.5)
	Manfred Kopka (CC BY-SA 4.0)
	Aubrey Dale (CC BY-SA 2.0)
	Albert Bridge (CC BY-SA 2.0)
	Randwick (CC BY-SA 3.0)
	Alexas_Fotos (Pixabay)
	Alexas_Fotos (Pixabay)
	Ralph Daily (CC BY 2.0)
	hobbyknipse (Pixabay)

Table 15: License information for the images in Table 3.

Image	Attribution and License
	Nedih Limani (CC BY-SA 3.0)
	Jean-Pol GRANDMONT (CC BY-SA 3.0)
	Scott Robinson (CC BY 2.0)
	Tokumeigakarinoaoshima (CC0 1.0)
	CSIRO (CC BY 3.0)
	Dan90266 (CC BY-SA 2.0)
	Raimond Spekking (CC BY-SA 4.0)
	SamHolt6 (CC BY-SA 4.0)

Table 16: License information for the images in Table 2.