The "something something" video database for learning and evaluating visual common sense

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Abstract

Neural networks trained on datasets such as ImageNet have led to major advances in visual object classification. One obstacle that prevents networks from reasoning more deeply about complex scenes and situations, and from integrating visual knowledge with natural language, like humans do, is their lack of common sense knowledge about the physical world. Videos, unlike still images, contain a wealth of detailed information about the physical world. However, most labelled video datasets represent high-level concepts rather than detailed physical aspects about actions and scenes. In this work, we describe our ongoing collection of the "something-something" database of video prediction tasks whose solutions require a common sense understanding of the depicted situation. The database currently contains more than 100,000 videos across 174 classes, which are defined as caption-templates. We also describe the challenges in crowd-sourcing this data at scale.

Figure 1: An example video, captioned "Picking [something] up", taken from our growing database. Crowd-workers are asked to record videos and to complete caption-templates, by providing appropriate input-text for placeholders. In this example, the text provided for placeholder "something" is *a shoe*. We plan to increase the complexity and sophistication of caption-templates over time, to the degree that models succeed at making predictions.

1. Introduction

Datasets and challenges like ImageNet [3] have been major contributors to the recent dramatic improvements in neural network based object recognition [13, 31, 8], as well as to improvements on a variety of other vision tasks thanks to transfer learning (eg., [4, 28, 20]).

Despite their representational power, neural networks trained on still image datasets fall short of a variety of visual capabilities, some of which are likely to be resolvable using video instead of still image data. Specifically, networks trained to predict object classes from still images never observe any changes of objects, like changes in pose, position or distance from the observer. However, such changes provide important cues about object properties. Multiple different views of a rigid object or scene, for example, provide information about 3-D geometry (and it is common practice in computer vision to extract that information from multiple views [7]).

In addition to the 3-D structure of a rigid object, the very fact that an object is rigid itself can be extracted from multiple views of the object in motion, as well as the fact that an object is, say, articulated as opposed to rigid. Similarly, material properties such as various forms of deformability, elasticity, softness, stiffness, etc. express themselves visually through deformation cues encoded in multiple views.

Closely related to material properties is the notion of *affordance* [36, 9]: An object can, by virtue of its properties, be used to perform certain actions, and often this usability is more important than its "true" inherent object class (which may itself be considered a questionable concept [9]). For example, an object that is soft and deformable, such as a blanket, can be used to cover another object; an object that is sharp and pointy can be used poke a hole into something; etc. It seems unlikely that still image tasks, which encode object properties only indirectly, can provide significant mileage in improving a neural network's understanding of affordances. The same holds true to other physical concepts that we humans intuitively grasp, like understanding that unsupported objects will fall (gravity) or that hidden objects do not cease to exist (object occlusion/permanence).

Motion patterns extracted from a video are not only capable of revealing object properties but also of revealing actions and activities. Not surprisingly, most of the currently popular labeled video datasets are action recognition datasets [27, 17, 24, 11]. It is important to note, however, that in a fine-grained understanding of visual concepts that goes beyond "one-of-K"-labeling, actions and objects are naturally intertwined, and the tasks of predicting one cannot be treated independently of predicting the other. For example, the phrase "opening NOUN" will have drastically different visual counterparts, depending on whether "NOUN" in this phrase is replaced by "door", "zipper", "blinds", "bag", or "mouth". There are also commonalities between these instances of "opening", like the fact that parts are moved to the sides giving way to what is behind. It is, of course, exactly these commonalities which define the concept of "opening". So a true understanding of the underlying meaning of the action word "opening" would require the ability to generalize across these different use cases. A proper understanding of such concepts is closely related to affordances. For example, the fact that a door *can* be opened is much more likely to be taken into consideration, or even learnable by a robot (which is, say, searching for an object), if its feature space is already structured such that it can distinguish between opening and closing doors.

Not only words for objects and actions can be grounded in the visual world, but also many abstract concepts, because these are built by means of analogy on top of the more basic, every-day concepts [14, 9]. The importance of grounding for language understanding is reflected in Winograd schemas [16], which are linguistic puzzles whose solutions require common sense. A Winograd schema is given by two sentences, the second of which refers to the first in a superficially ambiguous way, but where the ambiguity can be resolved by common sense. Consider the following Winograd schema presented in [16]: *"The trophy would not fit in the brown suitcase because it was too big. What was too big?"* To answer this question, it is necessary to understand basic aspects of spatial relations and properties (like sizes), of objects, as well as the activity of putting an object into another. This makes it clear that text understanding from pure text may have its limitations, and that visual (or possibly tactile) grounding may be an inevitable step in seriously advancing language understanding.

In this work, we describe our efforts in generating the "*something something*"-database, whose purpose is to provide visual (and partially acoustic) counterparts of simple, everyday aspects of the world. The goal of this data is to encourage networks to develop the features required for making predictions which, by definition, involve certain aspects of common sense information. The database[1] currently contains $108,499$ *short* video clips (with duration $\in [2, 6]$ seconds), that are labeled with simple textual descriptions. The videos show objects and actions performed on them. Labels are in textual form and represent detailed information about the objects and actions as well as other relevant information. Predicting the textual labels from the videos requires features that are capable of representing physical properties of the objects and the world, such as spatial relations or material properties.

2. Related work

There has been an increasing interest recently in learning representations of physical aspects of the world using neural networks. Such representations are commonly referred to as intuitive or naive physics to contrast them with the symbolic/mathematical descriptions of the world developed in physics. Several recent papers address learning intuitive physics by using physical interactions (robotics) [21, 1]. A shortcoming of this line of work is that it is based on using still images, which show, for example, how objects appear before and after performing a certain action. Physical predictions are made using convolutional networks applied to the images. Any sequential information is thus reduced to predicting a causal relationship between action and observations in a single feedforward computation, and any information encoded in the motion itself is lost.

Some recent work has been devoted to the goal of learning about the world using video instead of robotics. For ex-

[1] We plan to make a version of the dataset available at: https://www.twentybn.com/datasets/something-something

ample, there has been a long-standing endeavor to use future frames of a video as "free" labels for supervised training of neural networks. See, for example, [19, 22] and references therein. The fact that multiple images can reveal qualitatively different information on top of still images has been well-established for many years in both the computer vision and deep learning communities, and it has been exploited in the context of deep learning largely by using bilinear models (see [18] and references therein). Unfortunately, predicting raw pixels is challenging, both for computational and for statistical reasons. There are simply a lot of aspects of the real world that a predictor of raw pixels has to account for. This may be one reason why unsupervised learning through video prediction has hitherto not "taken off".

One way to address the difficulty of predicting raw pixels is to re-define the task to predict high-level features of future frames. In order to obtain features one can, for example, first train a neural network on still image object-recognition tasks [35]. However, a potential problem with that approach is that the purpose of using video in the first place is the creation of features that capture information *beyond* the information already contained in still images. Also, predicting ImageNet-features has not shown yet to yield features that add substantially more information about the physical world.

A hybrid between learning from video and learning from interactions is the work by [15] who use a game engine to render block towers that collapse. A convolutional network is then trained to predict, using an image of the tower as input, whether it will collapse or not, as well as the trajectories of parts while the tower collapses. Similar to [21, 1], predictions are based on still images not videos.

A line of work more similar to ours is Yatskar et al. [41], who introduced a dataset of images associated with fine-grained labels by associating roles with actions and objects. In contrast to our work, the labels in that work describe sophisticated, cultural concepts, such as "clipping a sheep's wool". Our goal in this work is to capture basic physical concepts expressible in simple phrases, which we hope will provide a stepping stone towards more complex relationships and facts. Consequently, we use natural language instead of a fixed data structure to represent labels. More importantly, our starting point towards fine-grained understanding is videos not images.

3. Learning world models from video

Although images still largely dominate research in visual deep learning, a variety of sizeable labeled video datasets have been introduced in recent years. The dominant application domain so far has been action recognition, where the task is to predict a global action label for a given video (for example, [24, 11, 17, 10, 5]). A drawback of action recognition is that it is targeted at fairly high-level aspects of videos and therefore does not encourage a network to learn about motion primitives that can encode object properties and intuitive physics. For example, the task associated with the datasets described in [24, 11] is recognizing sports, and in [17] they include high-level, human-centered activities, such as "getting out of a car" or "fighting".

A related problem is that these tasks amount to taking a long video sequence as input and producing one out of a relatively small number of global class-labels as the output. Rather than requiring a detailed understanding of what happens in a video, these datasets require features that can condense a long sequence (usually including many scene and perspective changes) into a single label. In many cases, labels can be predicted fairly accurately even from a single image cropped from the video. As a result, good classification performance can be achieved on these tasks by frame-wise aggregation of features extracted with a convolutional network that was pre-trained on a *still image* task, such as ImageNet [39]. This is in stark contrast to the goal of using video in order to learn a better world model. One prerequisite for learning more fine-grained information about the world is that labels describe video content that is *restricted to a short time interval*. Only this way can there be a tight synchronization between video content and the corresponding labels, allowing learned features to correspond to physical aspects of the unfolding scene, and to correlate with the low-level aspects that are reflected, for example, also in everyday language.

Detailed labeling has been addressed also in various *video captioning* datasets recently, where the goal is to predict an elaborate description, rather than a single label, for a video [32, 25, 40, 12]. However, similar to many of the action recognition datasets mentioned above, they typically contain descriptions that reflect high-level, cultural aspects of human life and commonly require a good knowledge of rare or unusual facts and language. Furthermore, since descriptions summarize fairly long videos, they do not have a high temporal resolution.

A dataset focussing on lower-level, more physical concepts is described in [37]. The dataset contains $17,408$ videos of a small set of objects involved in a number of physical experiments. These include, for example, letting the object slide down a slope or dropping it onto a surface. The supervision signal is given by (known) physical properties of the experiment, such as the angle of the slope or the material of the object. In contrast to that work, besides scaling to a much larger size, we use language as labels, similar to captioning datasets. This allows us to generate a much larger and more varied set of actions and labels. It also allows us to go beyond a small and highly specialized set of physical properties and actions prescribed by the experimental setup and by what can easily be measured.

Many shortcomings of existing video datasets may be re-

Table 1: Comparison with other video datasets recorded specifically for training machine learning models (information partially taken from [12]).

Dataset	Domain	# Videos	Avg. duration	Remarks
Physics 101 [38]	intuitive physics	17,408	-	101 objects with 4 different scenarios (ramp, spring, fall, liquid)
MPII cooking [26]	action (cooking)	44	600s	-
TACoS [23]	action (cooking)	127	360s	-
Charades [29]	action (human)	10, 000	30s	-
KITTI [6]	action (driving)	21	30s	-
Something-Something (ours)	human-object interaction	108,499	4.03s	174 fine-grained categories of human-object interaction scenarios

lated to the fact that they are generated by annotating (or using closed captionings of) existing video material, including excerpts from Hollywood movies. Recently, [29] proposed a way to overcome this problem by asking crowdworkers to record videos themselves rather than to attach labels to existing videos. In this work, we follow a similar approach using a scalable framework for crowd-sourced video recording. Using our large-scale crowd acting™ framework, we have so far generated several hundred thousand videos, including the dataset discussed in this paper. In contrast to the dataset described in [29] we focus here on basic, physical concepts rather than on higher-level human activities. A comparison with existing similar datasets is shown in Table 1

4. The "something-something" dataset

In this work, we introduce the "something-something"-dataset. It currently contains $108,499$ videos across 174 labels, with duration ranging from 2 to 6 seconds. Labels are textual descriptions based on templates, such as "Dropping [*something*] into [*something*]" containing slots ("[*something*]") that serve as placeholders for objects. Crowdworkers provide videos where they act out the templates. They choose the objects to perform the actions on and enter the noun-phrase describing the objects when uploading the videos.

The dataset is split into train, validation and test-sets in the ratio of 8:1:1. The splits were created so as to ensure that all videos provided by the same worker occur only in one split (train, validation, or test). See Table 2 for some summary information about the dataset.

Including differences in case, stemming, use of determiners, etc., $23,137$ distinct object names have been submitted in the current version of the dataset. We estimate the number of actually distinct objects to be at least a few thousand. Figure 3b shows the frequency of objects for the most common objects.

In its current version, the dataset was generated by 1133 crowd workers with an average of 127.32 workers per class.

Dataset Specifications	
Number of videos	108,499
Number of class labels	174
Average duration of videos (in seconds)	4.03
Average number of videos per class	620

Table 2: Dataset summary

Figure 2 shows a truncated distribution of the number of videos per class, with an average of roughly 620 videos per class, a minimum of 77 for "Poking a hole into [*some substance*]" and a maximum of 986 for "Holding [*something*]". Figure 3a shows a histogram of the duration of videos (in seconds). A few examples of frame samples from the collected videos is shown in Figure 4.

4.1. Crowdsourced video recording

The currently pre-dominant way of creating large, labeled datasets is to start by gathering a large collection of input items, such as images or videos. Usually, these are found using online resources, such as Google image search or Youtube. Subsequently, the gathered input examples are labeled using crowdsourcing services like Amazon Mechanical Turk (AMT) (see, for example, [3]).

As outlined is Section 3 videos available online are largely unsuitable for the goal of learning simple (but fine-grained) visual concepts. We therefore ask crowd-workers to provide videos *given* labels instead of the other way around (a similar approach was recently described in [29]).

4.2. Natural language labels and curriculum learning

The number of "everyday concepts" that we want to capture with this dataset is gigantic, and it cannot be captured within a fixed set of one-hot labels. Natural language descriptions are a natural and obvious solution to this problem: natural language is capable of representing an extremely large number of "classes" and it is compositional and thereby able to express this number highly economi-

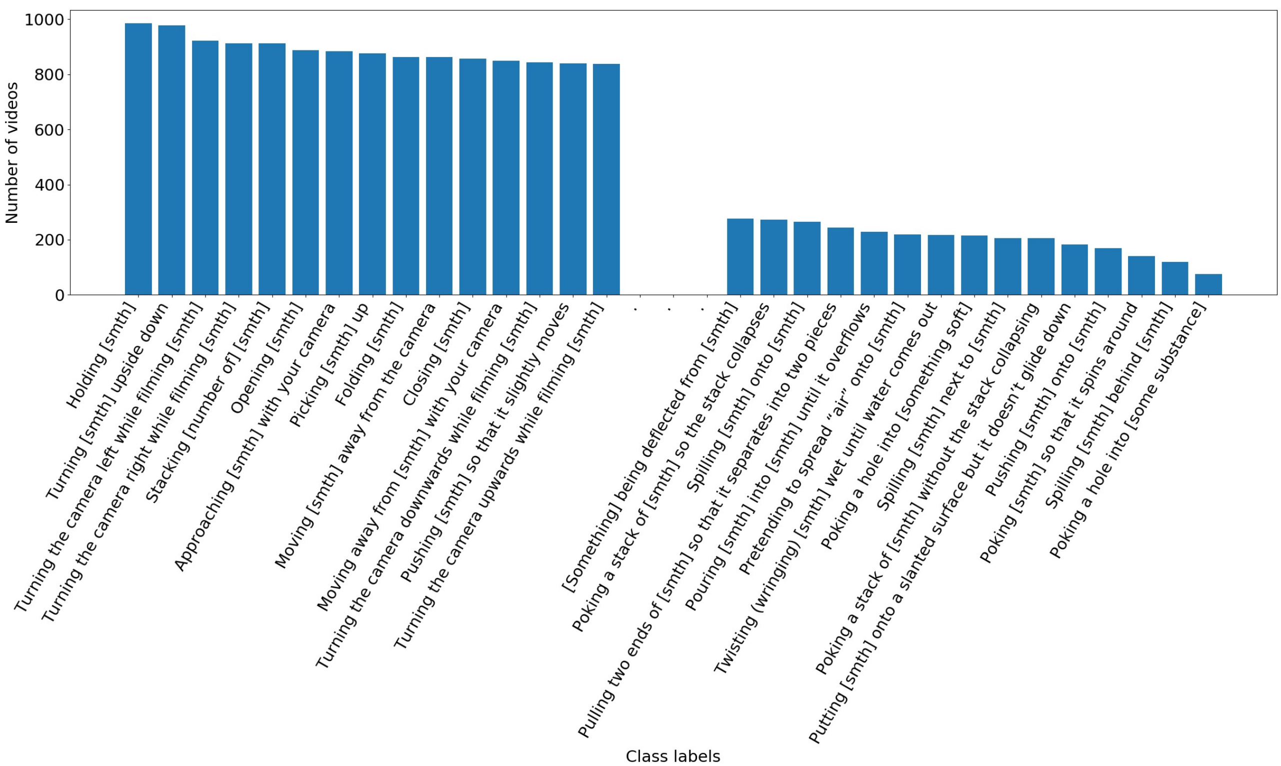
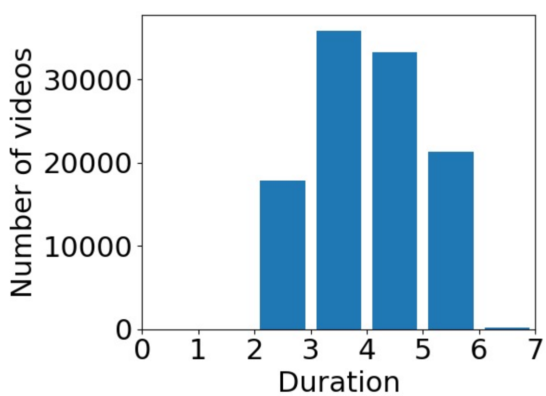
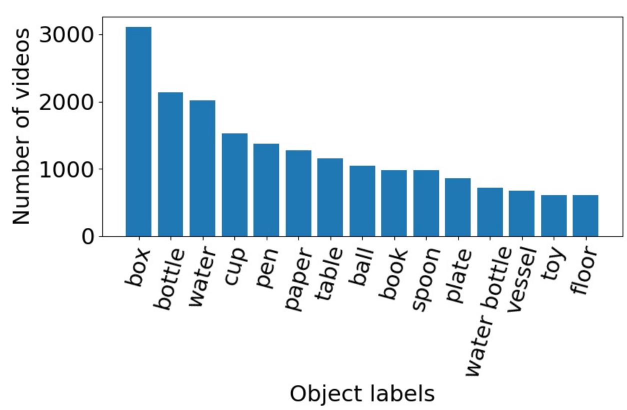


Figure 2: Numbers of videos per class (truncated for better visualisation).



(a) Video lengths (in seconds), ranging between 2 and 6 seconds (inclusive)



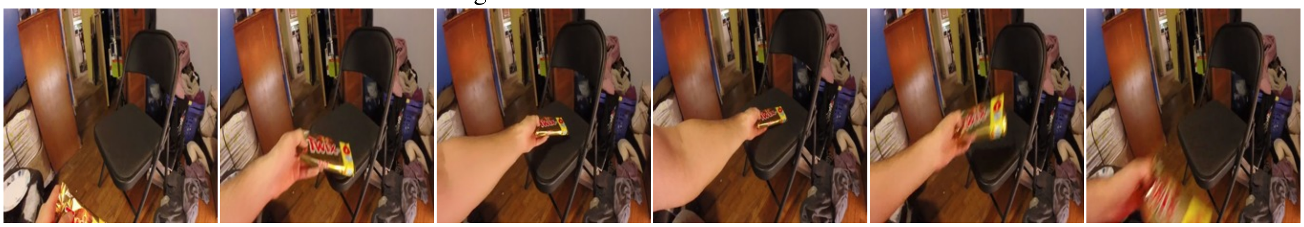
(b) Frequencies of occurrence of 15 most common objects

cally.

Unfortunately, natural language provides a much weaker learning signal than a one-hot label. This is one reason why image and video captioning systems are currently trained using an ImageNet pre-trained network as the vision component.

To obtain useful natural-language labels, but also be able to train, and potentially bootstrap, networks to learn from the data, we generate natural language descriptions automatically by appropriately combining partly pre-defined, and partly human-generated, parts of speech. Natural language descriptions take the form of *templates* that AMT workers provide along with videos, as we shall describe in the next section. Analogous to how probabilistic graphical

Putting *a white remote* into *a cardboard box*



Pretending to put *candy* onto *chair*

Pushing *a green chilli* so that it falls off the table

Moving *puncher* closer to *scissor*

Figure 4: Example videos and corresponding descriptions. Object entries shown in italics.

models impose independence assumptions on a multivariate distribution, these "structured captions", can be viewed as approximations to full natural language descriptions, that allow us to control the complexity of learning by imposing a rich (but restricted) structure on the labels.

In the current version of the dataset, we emphasize short and simple descriptions, most of which contain only the most important parts of speech, such as verbs, nouns and prepositions. This choice was made, because common neural networks are not yet able to represent elaborate captions and high-level concepts.

However, it is possible to increase the degree of complexity as well as the sophistication of language over time as the dataset grows. This approach can be viewed as "curriculum learning" [2], where simple concepts are taught first, and more complicated concepts are added progressively over time. From this perspective, the level of complexity of the current version of the dataset may be viewed approximately as "teaching a one-year-old child". Unlike labels that are encoded using a fixed datatype, as described, for example, in [41], natural language labels allow us to represent a spectrum of complexity, from simple objects and actions encoded as one-hot labels, to full-fledged captions. The use of natural language encodings for classes furthermore allows us to dynamically adjust the label structure in response to how learning progresses. In other words, the complexity of videos and natural language descriptions can be increased as a function of the validation-accuracy achievable by networks trained on the data so far.

4.3. Non-uniform sampling of the Cartesian product of actions and objects

Although it is more restricted than captions, the cross product of actions and objects constitutes a space that is so large that there is no hope to sample it sufficiently densely as needed for practical applications. But the empirical probability density of real-world cases in the space of permissible actions and objects is far from uniform. Many actions, such as "Moving an elephant on the table" or "Pouring paper from a cup", for example, have almost zero density. And more reasonable combinations can still have highly variable probabilities. Consider, for example, "drinking from a plastic bag" (highly rare) vs. "dropping a piece of paper" (highly common).

It is possible to exploit the low entropy of this distribution, by using the following sampling scheme: Each crowdworker is presented with an action in the form of a template that contains one or several placeholders for objects. Workers then get to decide which objects to perform the action on and generate a video clip. When uploading the video, workers are required to enter their object choice(s) into a provided mask.

4.4. Grouping and contrastive examples

The goal of the "something-something" collection effort is to provide fine-grained discrimination tasks, whose solution will require a fairly deep understanding of the physical world. However, especially in the early stage, where simple descriptions focussed on verbs and nouns dominate, networks can learn to "cheat", for example, by extracting the object type from one or several individual frames, and by extracting the action using indirect cues, such as hand position, overall velocity, camera shake, etc. This is an example of *dataset bias* [33].

As a way to reduce bias, by forcing networks to classify the actual actions and the underlying physics, we provide *action groups* for most action types. An action group contains multiple similar actions with minor visual differences, so that fine-grained understanding of the activity is required to distinguish the actions within a group. Providing action groups to the AMT workers also encourages these to perform the multiple different actions with the same object, such that a close attention to detail is required to correctly identify the action within the group. We found that action groups also serve the communication with crowdworkers in clarifying to them the kinds of fine-grained distinctions in the uploaded videos we expect.

Some groups contain *pretending* actions in addition to the actual action to be performed. This will require any system training on this data to closely observe the object instead of secondary cues such as hand positions. It will also require the networks to learn and represent indirect visual cues, such as the fact that an object is present or not present in a particular region in the image. Preventing a network from "cheating" by distinguishing between actual and pretended actions is reminiscent of teaching a child by asking it to tell the difference between genuine and false actions. Examples of action groups we use include:

- Putting *something* on top of *something* / Putting *something* next to *something* / Putting *something* behind *something*
- Putting *something* behind *something* / Pretending to put *something* behind *something* (but not actually leaving it there)
- Poking *something* so lightly that it does not or almost does not move / Poking *something* so it slightly moves / Poking *something* so that it falls over.
- Poking *something* / Pretending to poke *something*

A more comprehensive list of action groups and descriptions examples are provided in the supplementary materials.

4.5. Data collection platform

Besides the requirements outlined above, crowdsourcing the recording of video data according to a pre-defined label structure poses a variety of technical challenges:

- *Batch submission:* Crowd workers need to be able to initiate a job, and come back to it later potentially multiple times until it is completed, so that they can record videos outside or at other places or times of the day, or after having gathered the objects needed for the task.
- *Worker-conditional choice of labels:* To generate data with sufficient variability, it is important that each label is represented by videos from as many different crowdworkers as possible. To this end, it is necessary to keep track of the set of labels recorded by each individual crowdworker. 'The list of labels or action groups (as defined below) to choose from can be generated dynamically once the crowdworker logs on to the platform.
- *Feedback on completed or partially completed submissions:* In the case of submissions that are fully or partially rejected it is important that the crowd sourcing operators can quickly provide feedback to the crowd workers regarding what was wrong with the submission.
- *Convenience:* To reduce cost, crowd workers need to face a convenient, easy-to-use and highly responsive interface.

To address these challenges, we created a data collection platform, with which both crowd workers and our operators overseeing the crowdsourcing efforts interact during the ongoing crowdsourcing operation.

When an AMT crowdworker accepts a task on the AMT interface he/she gets re-directed to our platform, where the task is then completed and reviewed. After completion of a task, our platform communicates with AMT to communicate the result (accept/reject) and allow for payments for the accepted tasks.

On the platform, workers get presented with a list of action-templates to choose from (with action-templates grouped as described in the previous section). By selecting action-templates, the platform creates video upload-boxes where workers can upload the videos as required, along with label-templates with variable-roles to be filled by workers. After uploading a video, all variable-roles in the label template (represented by the word "something" in most of our label templates) turn into input masks, and the worker is asked to fill in the correct word (such as the noun describing the object used). Each uploaded video is displayed (as screenshot) in a video playback-box and it can be played back for easy inspection by the workers (as well as by the operators as we describe below). After the worker reaches the number of requested videos, a button "Submit Hit" gets released, that allows the worker to submit the assignment and get paid.

A submission is accepted automatically, if it passes a number of quality control checks, which verify aspects such as length and uniqueness of the videos. Every submission is subsequently verified for correctness by a human operator. For more details on the crowd acting platform and screenshots we refer to the supplementary materials.

5. Baseline experiments

We performed a few baseline experiments to assess the difficulty of the task of predicting label templates from the videos. In this work, we discuss classification tasks on the label templates. Full captioning and performance on the expanded labels will be discussed elsewhere. On the classification tasks, we found 3d-convolutional networks to generally outperform 2d-convolutional networks and their combination to work best. But we also found that many of the subtle classes that were chosen explicitly to make the task harder (Section 4.4), are hardly distinguishable using these fairly standard architectures. More sophisticated architectures are necessary to obtain better performance on this data. A difficulty for both training and interpreting results is the presence of ambiguities in the labels. For reporting, these can be dealt with to some degree by resorting to top-K error rate. Both ambiguities and the overall difficulty of the prediction tasks can be alleviated by choosing label subsets and by combining labels into groups, which can allow fairly simple architectures to achieve reasonable performance. We shall discuss several such simplified subsets of classes below. We also found that this grouping can help as an initialization for networks that are subsequently fine-tuned on more complex class-choices.

5.1. Pre-processing

For the baseline runs, we sample frames from the videos using a frame rate of 24 fps and resize them to a resolution of 84×84 pixels, except for those runs where we use a pre-trained model (in which case we use the resolution is determined by that model). We lowpass-filter the resulting videos in time using a Gaussian kernel with zero mean and variance of 48 pixels, which was chosen to largely eliminate frequencies above the Nyquist-frequency, taking into consideration the target frame-rate of 6 frames per second (as discussed below).

10 selected classes
Dropping [something]
Moving [something] from right to left
Moving [something] from left to right
Picking [something] up
Putting [something]
Poking [something]
Tearing [something]
Pouring [something]
Holding [something]
Showing [something] (almost no hand)

Table 3: Subset of 10 hand-chosen "easy" classes.

We also perform temporal augmentation by choosing a random offset between 0 and the downsampling factor (4) during training. We use a fixed offset of 0 for validation and testing. We have also experimented with other types of data augmentation including flipping frames for invariant classes and random rotation by a small angle, but we did not find any significant performance gains for these.

5.2. Model specifications

Here we report results on the task of predicting action templates using multiple different encoding methods. We found dropout on the first fully-connected layer and batch-normalization on the last layer to significantly improve training. The encoding methods we used are:

2D-CNN + Avg: Using the VGG-16 net architecture [30] to represent individual frames and averaging the obtained features for each frame in the video to form the final encoding. The weights of the network were trained from scratch.

Pre-2D-CNN + Avg: Using an Imagenet-trained VGG-16 architecture to represent individual frames and averaging the obtained features for each frame in the video to form the final encoding.

Pre-2D-CNN + LSTM: Using the above pre-trained VGG network to represent individual frames and passing the extracted features to an LSTM layer with a hidden state size of 256. The last hidden state of the LSTM is then taken as the video encoding.

3D-CNN + Stack: Using a 3D-CNN model trained from scratch with specifications following [34], but with a size of 1024 units for the fully-connected layers and a clip size of 9 frames. We extract these features from non-overlapping clips of size 9 frames (after padding all videos to a maximal length of 36 frames), and stack the obtained features

Method	Error rate (%)						
	10 classes		40 classes		174 classes		
	top-1	top-2	top-1	top-2	top-1	top-2	top-5
2D CNN + Avg	76.5	58.9	88.0	78.5	-	-	-
Pre-2D CNN + Avg	54.7	39.0	79.2	70.0	-	-	-
Pre-2D CNN + LSTM	52.3	34.1	77.8	68.0	-	-	-
3D CNN + Stack	58.1	38.7	70.3	57.3	-	-	-
Pre-3D CNN + Avg	47.5	29.2	66.2	52.7	88.5	81.5	70.0
2D+3D-CNN	**44.9**	**27.1**	**63.8**	**50.7**	-	-	-

Table 4: Error rates on different subsets of the data.

to obtain a 4096 dimensional representation (4 columns), masking the column features, such that invalid frames (due to padding) do not affect training.

Pre-3D-CNN + Avg: Using a 3D-CNN model initialized on the sports-1m dataset [34] and finetuned on our dataset. In this case, we use the framerate 8 fps for training and extract columns of size 16 frames with 8 frames overlap between columns, such that the total number of columns is 5. We average the features across the clips.

2D+3D-CNN: A combination of the best performing 2D-CNN and 3D-CNN trained models, obtained by concatenating the two resulting video-encodings.

5.3. Results

We compared these networks mainly on two subsets of the dataset with classes hand-picked to simplify the task and benchmark the complexity of the dataset (we refer to the supplementary materials for more details on selection of classes): **10 selected classes:** We first pre-select 41 "easy" classes. We then generate 10 classes to train the networks (shown in Table 3), where each class is formed by grouping together one or more of the original 41 classes with similar semantics. The mapping from 41 to 10 classes is shown in Table 7 in the appendix. The total number of videos in this case is 28198. **40 selected classes:** Keeping the above 10 groups, we select 30 additional common classes. The total number of samples in this case is 53267. Some example predictions from the 10-class model are shown in Figure 5.

We show the error rates for these subsets using the baselines described above in Table 4. It shows that the difficulty of the task grows significantly as the number of classes are increased (despite the corresponding growth of the training-set). Similar to datasets like Imagenet, ambiguities in the labels make the naive classification performance look deceptively weak. However, even the top-2 performance shows that there the dataset poses a significant challenge for these architectures.

We also experimented on **all 174 classes** using a 3D CNN model pre-trained on the 40 selected classes, and obtained error rates of top-1: 88.5%, top-5: 70.3%.

Overall, our results demonstrate that the presence of subtle distinctions (using grouping, contrastive examples and other design choices) makes this an extraordinarily difficult problem for standard architectures.

6. Discussion

Advances in common sense reasoning can come mainly from two sources: through learning from interactions with the world, and through learning from observing the world. The first, interactions, rely crucially on advances in robotics. Unlike human interactions, however, robotic interactions lack the sophisticated tactile sensing that allows, for example, blind humans to learn about the world without any vision. It seems likely that even a robotics-based approach to learning common sense will rely on highly capable visual perception and on visuomotor policies that can deal with video input.

The dataset and learning methods that we describe in this work fall into the second category: learning about the world through vision. In contrast to unsupervised approaches, based on video-prediction, we propose approaching the problem through supervised learning on fine-grained labeling tasks.

The database introduced in this paper is an ongoing collection effort. We will continue to grow and extend the dataset over time in response to, and as a function of, the ability of networks to learn from this data.

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1. Pouring [something]: 77.47%
2. Putting [something]: 8.48%

Original: Pouring [something]

1. Dropping [something]: 65.6%
2. Poking [something]: 14.38%

Original: Dropping [something]

1. Putting [something]: 97.41%
2. Picking [something] up: 0.72%

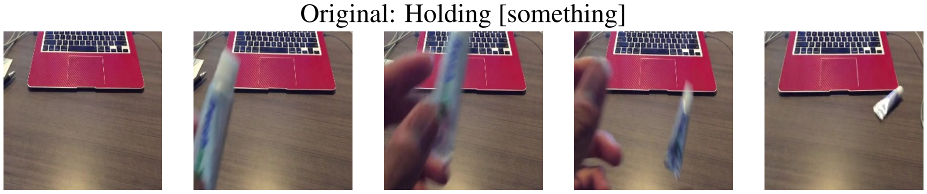
Original: Putting [something]

1. Picking [something] up: 62.07%
2. Putting [something]: 29.52%

Original: Picking [something] up

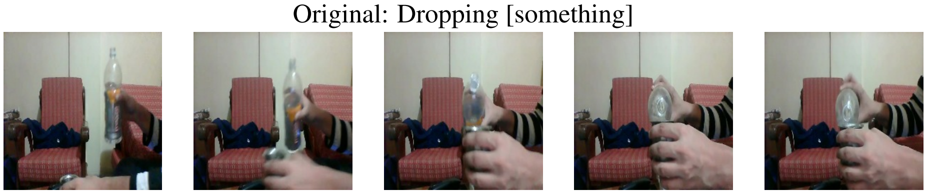
1. Showing [something] (almost no hand): 69.64%
2. Holding [something]: 15.19%

Original: Holding [something]



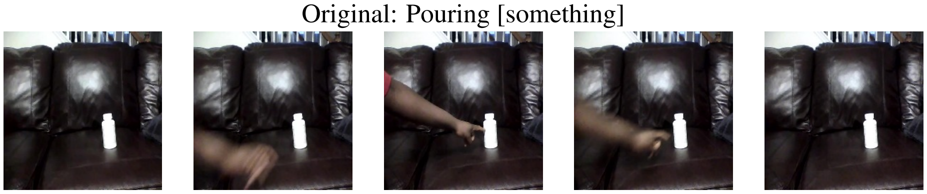
1. Putting [something]: 53.69%
2. Dropping [something]: 40.28%

Original: Dropping [something]



1. Picking [something] up: 65.58%
2. Putting [something]: 11.41%

Original: Pouring [something]



1. Picking [something] up: 72.49%
2. Putting [something]: 25.07%

Original: Poking [something]

Figure 5: Some example predictions from the best performing baseline model on 10 selected classes experiment

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A. Dataset

A.1. 10-selected classes

The mapping used for generating the classes used in the 10-class experiments is shown in Table 7. The 10 classes were defined by first selecting 41 classes by hand (based on class-definitions and on visual inspection of the videos) and subsequently remapping these into 10 groups.

Class names	Index
Dropping [something]	0
Holding [something]	1
Moving [something] from left to right	2
Moving [something] from right to left	3
Picking [something] up	4
Poking [something]	5
Pouring [something]	6
Putting [something]	7
Showing [something] (almost no hand):	8
Tearing [something]	9

Table 5: Subset of 10 selected classes used in some of the experiments.

A.2. 40-selected classes

We took the above 10 selected classes and select 30 additional common classes to form this subset of data. The list of classes used is shown in the Table 6.

The confusion matrix for predictions on 40 selected classes using the best performing model is shown in Figure 6 and the corresponding dictionary to read classes off from the matrix is shown in the Table 6.

A.3. All data - 175 classes

The complete list of 175 classes and their corresponding action-groups is shown in Table 8.

Class names	Index
Approaching [something] with your camera	0
Closing [something]	1
Dropping [something]	2
Folding [something]	3
Holding [something]	4
Holding [something] next to [something]	5
Moving [something] away from [something]	6
Moving [something] away from the camera	7
Moving [something] closer to [something]	8
Moving [something] down	9
Moving [something] from left to right	10
Moving [something] from right to left	11
Moving [something] towards the camera	12
Moving away from [something] with your camera	13
Opening [something]	14
Picking [something] up	15
Plugging [something] into [something]	16
Poking [something]	17
Pouring [something]	18
Pretending to pick [something] up	19
Pretending to put [something] next to [something]	20
Pretending to put [something] on a surface	21
Pretending to take [something] from [somewhere]	22
Pushing [something] so that it slightly moves	23
Pushing [something] with [something]	24
Putting [something]	25
Putting [something] into [something]	26
Showing [something] (almost no hand)	27
Showing a photo of [something] to the camera	28
Showing that [something] is empty	29
Stacking [number of] [something]	30
Tearing [something]	31
Throwing [something] against [something]	32
Turning [something] upside down	33
Turning the camera downwards while filming [something]	34
Turning the camera left while filming [something]	35
Turning the camera right while filming [something]	36
Turning the camera upwards while filming [something]	37
Uncovering [something]	38
Unfolding [something]	39

Table 6: Subset of 40 selected classes used in some of the experiments.

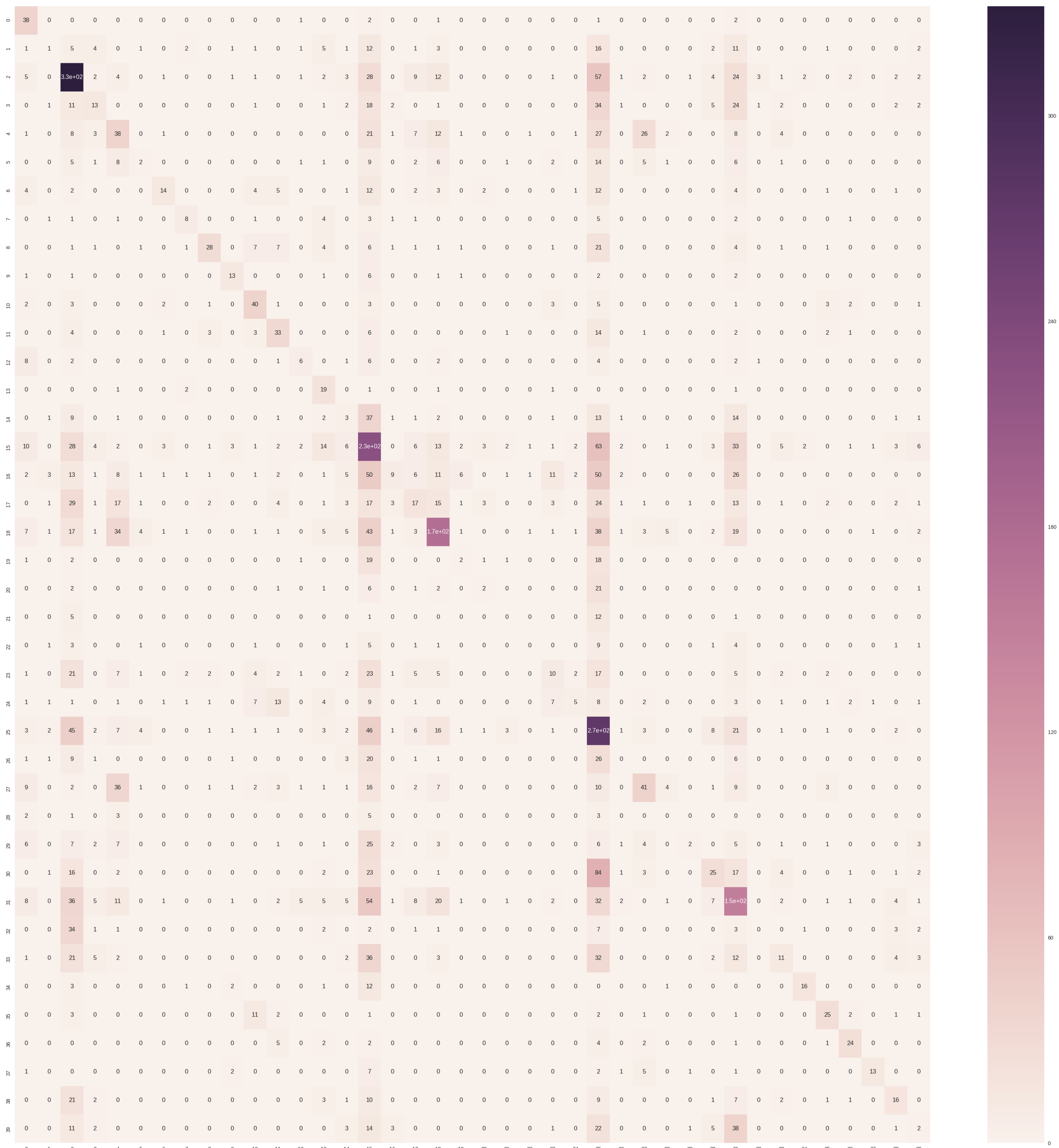

Figure 6: Confusion matrix for the best model trained on the 40 selected classes. Corresponding class-names are listed in Table 6.

Table 7: Mapping used for 10 selected classes

Actual class	**Mapped class**
[Something] falling like a rock [Something] falling like a feather or paper Throwing [something] Throwing [something] onto a surface Throwing [something] in the air and letting it fall	Dropping [something]
Pushing [something] from right to left Pulling [something] from right to left	Moving [something] from right to left
Pulling [something] from left to right Pushing [something] from left to right	Moving [something] from left to right
Picking [something] up Lifting [something] up completely without letting it drop down Moving [something] up Lifting [something] with [something] on it Taking [something] from [somewhere] Taking [one of many similar things on the table] Taking [something] out of [something]	Picking [something] up
Putting [something] next to [something] Putting [something] onto [something] Putting [something] on a surface Putting [something similar to other things that are already on the table] Putting [something] behind [something] Putting [something], [something] and [something] on the table Putting [something] and [something] on the table Putting [something] on a flat surface without letting it roll Putting [something] that can't roll onto a slanted surface, so it stays where it is	Putting [something]
Poking [something] so that it falls over Poking [something] so lightly that it doesn't or almost doesn't move Poking a stack of [something] so the stack collapses Poking a stack of [something] without the stack collapsing	Poking [something]
Tearing [something] into two pieces Tearing [something] just a little bit	Tearing [something]
Pouring [something] into [something] Pouring [something] onto [something] Pouring [something] out of [something] Pouring [something] into [something] until it overflows Trying to pour [something] into [something], but missing so it spills next to it	Pouring [something]
Holding [something] Holding [something] in front of [something]	Holding [something]
Showing [something] on top of [something] Showing [something] behind [something] Showing [something] next to [something]	Showing [something] (almost no hand)

Table 8: Class labels and their corresponding action-groups for all 175 classes

Class Labels	**Action Groups**
Trying but failing to attach [something] to [something] because it doesn't stick Attaching [something] to [something]	Attaching/Trying to attach
Bending [something] until it breaks Trying to bend [something unbendable] so nothing happens Bending [something] so that it deforms	Bending something
Digging [something] out of [something] Burying [something] in [something]	Burying or digging something
Moving away from [something] with your camera Turning the camera right while filming [something] Approaching [something] with your camera Turning the camera left while filming [something] Turning the camera upwards while filming [something] Moving [something] away from the camera Moving [something] towards the camera Turning the camera downwards while filming [something]	Camera motions
[Something] colliding with [something] and both are being deflected [Something] being deflected from [something] [Something] colliding with [something] and both come to a halt	Collisions of objects
Uncovering [something] Covering [something] with [something]	Covering
Putting [something similar to other things that are already on the table] Taking [one of many similar things on the table]	Crowd of things
Dropping [something] into [something] Dropping [something] onto [something] Dropping [something] next to [something] Dropping [something] in front of [something] Dropping [something] behind [something]	Dropping something
Showing [something] next to [something] Showing [something] on top of [something] Showing [something] behind [something]	Filming objects, without any actions
Folding [something] Unfolding [something]	Folding something
Hitting [something] with [something]	Hitting something with something
Holding [something] in front of [something] Holding [something] behind [something] Holding [something] next to [something] Holding [something] Holding [something] over [something]	Holding something
Lifting up one end of [something], then letting it drop down Lifting up one end of [something] without letting it drop down Lifting [something] up completely, then letting it drop down Lifting [something] up completely without letting it drop down	Lifting and (not) dropping something
Tilting [something] with [something] on it until it falls off Lifting [something] with [something] on it Tilting [something] with [something] on it slightly so it doesn't fall down	Lifting/Tilting objects with other objects on them
Moving [something] up Moving [something] down	Moving something

Moving [something] and [something] away from each other Moving [something] and [something] closer to each other Moving [something] closer to [something] Moving [something] away from [something]	Moving two objects relative to each other
Moving [part] of [something] Touching (without moving) [part] of [something]	Moving/Touching a part of something
Opening [something] Pretending to close [something] without actually closing it Pretending to open [something] without actually opening it Closing [something]	Opening or closing something
Picking [something] up Pretending to pick [something] up	Picking something up
Piling [something] up	Piles of stuff
Plugging [something] into [something] but pulling it right out as you remove your hand Plugging [something] into [something]	Plugging something into something
Poking [something] so it slightly moves Poking [something] so lightly that it doesn't or almost doesn't move Poking a stack of [something] without the stack collapsing Poking a hole into [something soft] Pretending to poke [something] Poking [something] so that it falls over Poking a stack of [something] so the stack collapses Poking a hole into [some substance] Poking [something] so that it spins around	Poking something
Trying to pour [something] into [something], but missing so it spills next to it Pretending to pour [something] out of [something], but [something] is empty Pouring [something] out of [something] Pouring [something] onto [something] Pouring [something] into [something] Pouring [something] into [something] until it overflows	Pouring something
Pulling [something] from behind of [something] Pulling [something] from right to left Pulling [something] out of [something] Pulling [something] onto [something] Pulling [something] from left to right	Pulling something
Pulling two ends of [something] but nothing happens Pulling two ends of [something] so that it separates into two pieces Pulling two ends of [something] so that it gets stretched	Pulling two ends of something
Pushing [something] onto [something] Pushing [something] from right to left Pushing [something] with [something] Pushing [something] so that it falls off the table Pushing [something] so that it almost falls off Pushing [something] off of [something] Pushing [something] so that it slightly moves Pushing [something] from left to right	Pushing something
Pretending to put [something] on a surface Putting [something] on a surface	Putting something somewhere
Laying [something] on the table on its side, not upright Putting [something that cannot actually stand upright] upright on the table, so it falls on its side Putting [something] upright on the table	Putting something upright/on its side

Putting [something] underneath [something] Putting [something] onto [something else that cannot support it] so it falls down Failing to put [something] into [something] because [something] does not fit Putting [something], [something] and [something] on the table Pretending to put [something] behind [something] Putting [something] in front of [something] Taking [something] out of [something] Pretending to put [something] onto [something] Putting [something] and [something] on the table Pretending to take [something] out of [something] Putting [something] onto [something] Pretending to put [something] into [something] Pretending to put [something] underneath [something] Putting [something] next to [something] Putting [something] behind [something] Putting [something] on the edge of [something] so it is not supported and falls down Removing [something], revealing [something] behind Pretending to put [something] next to [something] Putting [something] into [something]	Putting/Taking objects into/out of/next to/ other objects
Letting [something] roll along a flat surface Rolling [something] on a flat surface Putting [something] that can't roll onto a slanted surface, so it slides down Lifting a surface with [something] on it until it starts sliding down Letting [something] roll down a slanted surface Lifting a surface with [something] on it but not enough for it to slide down Letting [something] roll up a slanted surface, so it rolls back down Putting [something] onto a slanted surface but it doesn't glide down Putting [something] that can't roll onto a slanted surface, so it stays where it is Putting [something] on a flat surface without letting it roll	Rolling and sliding something
Pretending to scoop [something] up with [something] Scooping [something] up with [something]	Scooping something up
Showing [something] to the camera Showing a photo of [something] to the camera	Showing objects and photos of objects
Showing that [something] is empty Showing that [something] is inside [something]	Showing that something is full/empty
Moving [something] across a surface without it falling down Moving [something] across a surface until it falls down	Something (not) falling over an edge
[Something] falling like a feather or paper [Something] falling like a rock	Something falling
Moving [something] and [something] so they collide with each other Moving [something] and [something] so they pass each other	Something passing/hitting another thing
Spilling [something] next to [something] Spilling [something] onto [something] Spilling [something] behind [something]	Spilling something
Spinning [something] so it continues spinning Spinning [something] that quickly stops spinning Pushing [something] so it spins	Spinning something
Spreading [something] onto [something] Pretending to spread 'air' onto [something]	Spreading something onto something
Pretending to sprinkle 'air' onto [something] Sprinkling [something] onto [something]	Sprinkling something onto something
Squeezing [something] Pretending to squeeze [something]	Squeezing something

Stacking [number of] [something] Putting [number of] [something] onto [something]	Stacking or placing N things
Stuffing [something] into [something]	Stuffing/Taking out
Taking [something] from [somewhere] Pretending to take [something] from [somewhere]	Taking something
Tearing [something] just a little bit Pretending to be tearing [something that is not tearable] Tearing [something] into two pieces	Tearing something
Throwing [something] against [something] Throwing [something] Throwing [something] in the air and catching it Pretending to throw [something] Throwing [something] in the air and letting it fall Throwing [something] onto a surface	Throwing something
Tipping [something] with [something in it] over, so [something in it] falls out Tipping [something] over	Tipping something over
Pretending to turn [something] upside down Turning [something] upside down	Turning something upside down
Twisting (wringing) [something] wet until water comes out Pretending or trying and failing to twist [something] Twisting [something]	Twisting something
Pretending or failing to wipe [something] off of [something] Wiping [something] off of [something]	Wiping something off of something

A.4. Data Collection Platform

We show some snapshots of our data collection platform in Figures 7 and 8. They demonstrate the platform used by the crowd-workers to select classes and to upload corresponding videos.

Figure 7: Left Column: Crowd-workers can choose the classes they want to generate videos for (often the available classes are controlled so as to maintain class balance as much as possible). Right Column: An interface to upload videos and enter input-text.

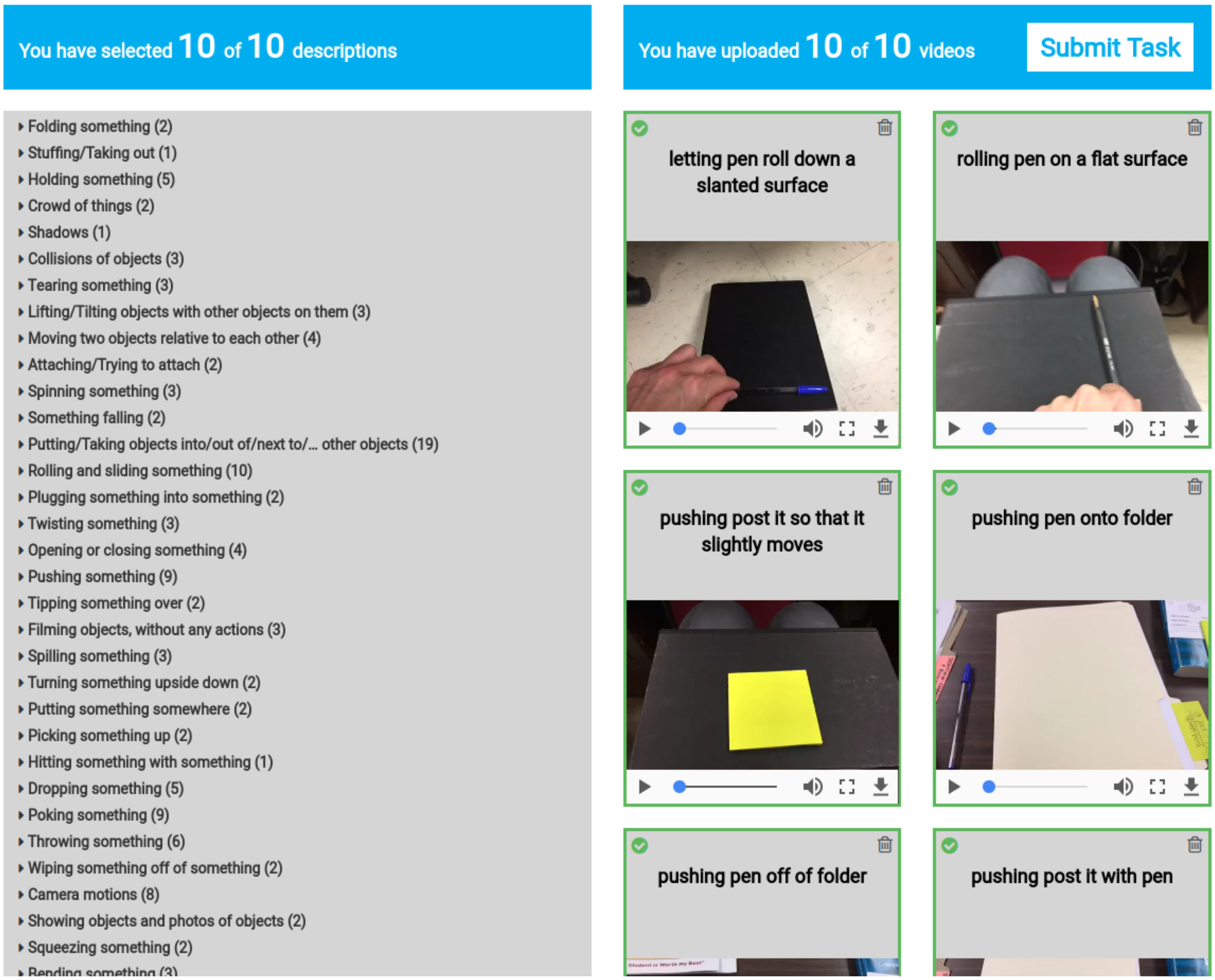

Figure 8: An example of the upload interface after uploading videos and entering input-text.