

# From *Lifestyle Vlogs* to Everyday Interactions

David F. Fouhey, Wei-cheng Kuo, Alexei A. Efros, Jitendra Malik  
University of California, Berkeley

## Abstract

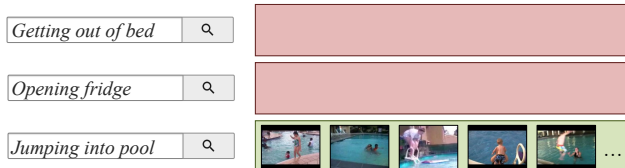
A major stumbling block to progress in understanding basic human interactions, such as getting out of bed or opening a refrigerator, is lack of good training data. Most past efforts have gathered this data explicitly: starting with a laundry list of action labels, and then querying search engines for videos tagged with each label. In this work, we do the reverse and search implicitly: we start with a large collection of interaction-rich video data and then annotate and analyze it. We use Internet Lifestyle Vlogs as the source of surprisingly large and diverse interaction data. We show that by collecting the data first, we are able to achieve greater scale and far greater diversity in terms of actions and actors. Additionally, our data exposes biases built into common explicitly gathered data. We make sense of our data by analyzing the central component of interaction – hands. We benchmark two tasks: identifying semantic object contact at the video level and non-semantic contact state at the frame level. We additionally demonstrate future prediction of hands.

## 1. Introduction

The lack of large amounts of good training data has long been a bottleneck for understanding everyday interactions. Past attempts to find this data have been largely unsuccessful: there are large action recognition datasets but not for everyday interaction [38, 21], and laboriously obtained datasets [35, 23, 43, 11] which depict everyday interaction, but in which people are hired to act out each datapoint.

The problem is that past methods have taken the approach of **explicit** data gathering – starting with a predetermined taxonomy, they attempt to directly find examples of each category. Along the way, they have fallen victim to dataset bias [40] in the form of a discrepancy between the world of reality and the *world of tagged things*. This discrepancy dooms attempts to explicitly search for examples of everyday interactions (“opening a microwave”, for instance, yields few good results **Try it!**) because there are few reasons to tag these videos. Accordingly, most video efforts have focused on actions that can be found directly

## Explicit Data Gathering



## Implicit Data Gathering

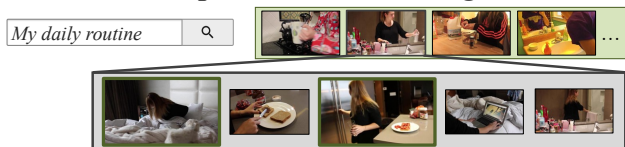


Figure 1. Past work aimed at gathering everyday interaction data has been *explicit*, directly searching for a predetermined list of categories. Unfortunately, direct search does not work for everyday interactions like getting out of bed or opening a refrigerator since they are rarely tagged. Effort has thus focused on things which are tagged, often unusual events. We present *implicit* gathering as an alternative: everyday interactions exist buried in other data; we can search for data that contains them and mine them. We demonstrate this by finding a new 14-day/114K video/10.7K uploader dataset of everyday interaction occurring naturally.

in the world of tagged things (e.g., high jump) as opposed to everyday ones that are impossible to find directly (e.g., opening a fridge). Some researchers have identified this problem, and have proposed the solution of *collection-by-acting* [35, 23, 43, 11] in which people are hired to act out a script. This moves us considerably closer towards understanding everyday interactions, but collection-by-acting is difficult to scale and make diverse. But even if we ignore the struggle to find data, this explicit approach is still left with two serious bias issues, both of which we document empirically. First, the examples we recover from the world of tagged things tend to be atypical: Internet search results for a concept as basic as “bedroom” (**Try it!**) are hopelessly staged, taken at a particular distance, and almost always depict made beds. Second, there are glaring gaps in terms of both missing categories and missing negatives.

This paper proposes the alternative of *implicit* data gathering. The intuition is that while we cannot find *tagged*



Figure 2. An overview of our dataset **VLOG**, which we obtain by mining the vast amounts of everyday interaction that exists implicitly in other data. We compare sample frames from our dataset in comparison with video-collection-by-acting efforts such as [35, 23, 8, 28].

everyday interaction data, it exists implicitly inside other content that has different tags. We can find this superset of data, mine it for the data we want, and then annotate and analyze it. For us, this superset is *Lifestyle Vlogs*, videos that people purportedly record to show their lives. As described in Section 3, we mine this data semi-automatically for interaction examples to produce **VLOG**, a new large-scale dataset documenting everyday interactions. **VLOG**, illustrated in Figure 2, is far larger and orders of magnitude more diverse than past efforts, as shown in Section 4. This shows the paradoxical result that while implicit searching is less direct, it is more effective at obtaining interaction data.

While implicit gathering is more effective than explicit gathering for interaction data, it also poses challenges. Explicitly gathered data has a list of categories predefining the data, but implicitly gathered data depicts a natural long-tail of interaction types and must be annotated post-hoc. We focus on the central figure of interaction, human hands, and propose two concrete tasks in Section 5: (1) identifying hand contact state in a frame irrespective of category, which naturally covers the entire dataset; (2) identifying if one of a number of objects was interacted with in the video. This quantifies interaction richness, provides an index for other researchers, and permits benchmarking of standard methods. We additionally provide labels like scene categories and hand bounding-boxes that we use to explore our data.

Our data and labels let us explore a large world of humans interacting with their environment naturally. We first show that **VLOG** reveals biases built into popular explicitly-gathered datasets in Section 6. Having demonstrated this, we analyze how well current algorithms work on our **VLOG** data and tasks in Section 7. Finally, looking towards the grand goal of understanding human interaction, we show applications of our data and labels for tasks like hand future prediction in Section 8.

## 2. Related Work

This paper takes a step towards understanding everyday interactions and thus touches on a number of areas of computer vision.

At the motivational level, the work is about affordances, or opportunities for interaction with the world [10]. This area has been extensively studied in vision, typically aiming to infer affordances in still images [12, 14, 32, 47, 46], understand scenes by observing them over time [9, 6], or use them as a building block for scene understanding [20]. A fundamental stumbling block for these efforts has been the difficulty of gathering interaction-rich video data at scale. While egocentric/life-logging efforts like [37, 30, 8, 28] do offer ways to obtain large amounts of data in terms of volume, achieving diversity and coverage is an open challenge. One contribution of this paper towards these efforts is demonstrating how to obtain large scale interaction-rich data at scale while achieving diversity as well as a concrete dataset that can be used to study humans “in-the-wild” from a variety of angles, including benchmarks.

In this paper, we gather a large collection of videos and annotate it post-hoc with a variety of interaction labels. From this angle, our paper could be viewed as similar to other action recognition efforts such as [35, 7, 8, 31, 42]. The primary distinction is that we focus on everyday actions and gather our data implicitly, rather than explicitly searching for it. Most work focuses on non-everyday actions like “high jump”; the work that does focus on everyday actions [35, 23, 11] gathers it explicitly by acting. As we show, we can gather this data without searching for it directly, achieving greater scale and diversity and, as we will show, avoiding some sources of data bias. The contemporary effort of [13] also gathers data implicitly, but from films; its data is complementary and has more human-human interaction and



Figure 3. An illustration of the automatic gathering process. Starting with a set of templated queries, we (a) search youtube (b) identify promising videos using their thumbnails (c) break these videos into clips (d) identify promising clips. Throughout the process, the amount of data steadily decreases but the purity steadily increases. Finally, the remaining clips are cleaned by humans.

less human-object interaction.

### 3. Collecting Interaction-Rich Episodes

We aim to get find data that is rich in everyday interactions. As argued in the introduction, direct search does not work, leading to efforts aimed at “acting out” daily activities [39, 23, 35, 11]. By virtue of their gathering approach, these datasets often have many desirable properties for studying interaction compared to random Youtube videos. For instance, many depict a single scene and feature a static camera, which make many learning tasks easier. We now show how to achieve a large scale while retaining features of manual gathering efforts.

Our insight is that one can find interaction-rich genres and mine these videos for data. As a concrete example, we show how to do this with a genre of YouTube video referred to as *Lifestyle Vlogs* (Video-log<sup>1</sup>). These are an immensely popular and multicultural phenomenon of videos that purport to document the ordinary daily lives of their recorders and feature titles like “Daily Cleaning Routine!” or “A day in the life of a stay at home mom”. As [22] notes, the routines are, at some level, aspirational as opposed to accurate. Nonetheless, even if the series of actions (waking at 7AM with a cup of black coffee) represents an ideal, at an interaction level (e.g., pouring a cup of coffee), the data is realistic. Unfortunately, examples of interaction are interspersed between camera pans of a well-kept house and monologues.

We thus distill our dataset semi-automatically, illustrated in Fig. 3. Each step hones in on an increasingly pure subset. We (i) we generate a large candidate video pool; (ii) filter with relevance feedback; (iii) segment videos into clips; (iv) filter clips by motion and content; (v) filter the clips with annotators. Additional details are in the supplemental.

**Finding Videos.** We first find a Lifestyle VLOG corpus. We define a positive video as one that depicts people interacting with the indoor environment from a 3rd person. We additionally exclude videos only about makeup and “unboxing” videos about purchases.

<sup>1</sup>An archetypal example that appears in our dataset is [https://youtu.be/DMZ\\_pRBd0dg](https://youtu.be/DMZ_pRBd0dg)

We use templated queries based on themes (“daily routine 2013”) or activities involved (“tidying bedroom”), including 6 main English query templates and 3 templates translated into 13 European languages. These give 823 unique queries. We retrieve the top 1K hits on YouTube, yielding 216K unique candidate videos. The results are 23% pure at a video level: failures include polysemy (e.g., “gymnastic routine”), people talking about routines, and product videos.

This candidate corpus is too large (~14TB) and noisy to contemplate downloading and we thus filter with the four thumbnails that can be fetched from YouTube independently of the video. We labeled 1.5K videos as relevant/irrelevant. We then represent each video by summary statistics of the `pool5` activations of an ILSVRC-pretrained [33] Alexnet [24] on its thumbnails, and train a linear SVM. We threshold and retrieve 20K videos.

**Finding Episodes Within Videos.** This gives an initial dataset of lifestyle VLOGs with high purity at the *video level*; however, the interaction events are buried among a mix of irrelevant sequences and camera motion.

We first segment the videos into clips based on camera motion. Since we want to tag the start of a slow pan while also not cutting at a dramatic appearance change due to a fridge opening, we use an approach based on homography fitting on SIFT [26] matches. The homography and SIFT match count are used to do shot as well as static-vs-moving detection. After discarding clips shorter than 2s, this yields a set of 572K static clips.

Many remaining clips are irrelevant, such as subscription pleas or people talking to the camera. Since the irrelevant clips resemble the irrelevant videos, we reuse the SVM on CNN activations approach for filtering. This yields 139K clips that mostly depict human interactions.

**Manual Labeling.** Finally, workers flag adult content and videos without humans touching something with their hands. This yields our final set of 114K video clips, showing the automatic stages work at 82% precision.

Table 1. **How VLOG compares to the most similar recent existing video datasets that could be used to study everyday interactions. For comparison, we list representative action recognition datasets with any overlap.** VLOG achieves the scale of many contemporary action recognition efforts while also having features desirable for studying interaction: high demonstrator diversity, high resolution, static cameras, and open-world-like data. *Legend:* Diversity: # of unique uploaders or actors; %VGA+: what % is at least VGA resolution; 1st/3rd: person perspective; Implicit: whether the data was gathered without explicitly finding the actions of interest.

Dataset	Video Scale			Diversity	Resolution		Attributes			
	Frames	Length	Count	Participants	Mean	% VGA+	1st/3rd	Static	Implicit	
VLOG	37.2M	14d, 8h	114K	10.7K	660 × 1183	86%	3rd	✓	✓	
Something-Something [11]	13.1M	5d, 1h	108K	1.1K	100 × 157	0%	3rd	×	×	
Charades [35]	8.6M	3d, 8h	9.8K	267	671 × 857	56%	3rd	×	×	
AVA [13]	5.2M	2d	192	192	451 × 808	26%	3rd	×	✓	
Instructions [1]	795.6K	7h, 22m	150	< 150	521 × 877	51%	3rd	×	×	
Watch-n-Patch [43]	78K	3h, 50m	458	7	1920 × 1080	100%	3rd	✓	×	
CAD-120 [23]	61.5K	41m	120	4	480 × 640	100%	3rd	✓	×	
GTEA [8]	544.1K	5h, 2m	30	5	960 × 1280	100%	1st	×	✓	
ADL [28]	978.6K	9h, 4m	20	20	960 × 1280	100%	1st	×	✓	
MPI Cooking [31]	881.8K	9h, 48m	5.6K	12	1224 × 1624	100%	3rd	✓	✓	
	↑ Everyday Interaction ↑				↓ Activity Recognition ↓					
Kinetics [21]	91M	35d, 7h	305K	-	658 × 1022	69%	3rd	×	×	
ActivityNet [7]	69M	27d, 0h	20K	-	640 × 1040	76%	3rd	×	×	
UCF 101 [38]	2.2M	1d, 1h	23K	-	240 × 320	0%	3rd	×	×	

## 4. The VLOG Dataset

We now analyze the resulting underlying data in context of past efforts. **We have freely released this data along with all annotations and split information to the community.** Here, we focus on the data itself: as a starting point, we provide a number of annotations; however, since our data was gathered before our labels were defined, the data can be easily relabeled, and the videos themselves can serve as labels for unsupervised learning.

As shown in Table 1, VLOG is closer in sheer volume to traditional activity datasets like ActivityNet and two days longer than all of the every other dataset listed. However, VLOG is distinguished not just in size but also in diversity: it has  $\approx 9.4\times$  more source than Something-Something and  $\approx 40\times$  more sources than Charades (and is more balanced in terms of uploaders, Gini coefficient 0.57 vs 0.74). We can put this diversity in perspective by calculating how many frames you could sample before expecting to see the same person (for datasets where this information is available). In CAD-120, it is just 2; Watch-n-Patch is 3; Charades is 10; and VLOG 58. We report additional dataset statistics about VLOG (e.g., scene types, distribution of video length) in the supplemental.

Compared to direct gathering efforts (e.g., CAD-120) in which there are direct incentives for quality, crawling efforts come at the cost of a lack of control. Nonetheless, our average resolution approaches that of in-lab efforts. This is because our content creators are motivated: some intrinsically and some because they make money via advertising. Indeed, many videos are shot from tripods and, as the figures show, most are lit and exposed well.

Our paper is best put in context with video datasets, but of course there are image-based interaction datasets such as HICO [5] and V-COCO [15]. As image-based data, though, both depend on someone taking, uploading, and tagging a photo of the interaction. Accordingly, *despite directly searching* for refrigerator and microwave interactions, HICO contains only 59 and 22 instances of each. VLOG, as we will next see, has far more despite directly searching for neither.

## 5. Labels

While implicit gathering scales better, it presents challenges for annotation. Explicitly gathered data naturally maps to categories and tasks since it was obtained by finding data for these categories; implicitly gathered data, on the other hand, naturally depicts a long tail distribution. We can quantify this in VLOG by analyzing the entry-level categories (examples appear in supplemental) being interacted with in a 500 image sample: standard species richness estimation techniques [3] give an estimate of 346 categories in the dataset. This is before even distinguishing objects more finely (e.g., wine-vs-shampoo bottles) or before distinguishing interactions in terms of verbs (e.g., open/pick up/pour from bottle).

Faced with this vast tail, we focus on the crucial part of the interaction, the hands, and pose two tasks. The first is whether the hands interact with one of a set of semantic objects in the clip. As a side benefit, this helps quantify our data in comparison to explicit efforts and gives an index into the dataset, which is useful for things like imitation learning. The second task is the contact state of the hands



Figure 4. Examples of each of our 30 objects being interacted with.

at a frame level. This describes human behavior in a way that is agnostic to categories and therefore works across all object categories in the dataset.

In addition to labels, we use the YouTube uploader id to define standard 50/25/25 train/val/test splits where each uploader appears only in one split.

### 5.1. Hand/Semantic Object Annotations

We frame this as whether a human interacts with any instance of each of a set of 30 objects (i.e., 30 *binary, clip-level tasks*). We focus on clip-level annotation because our many of our clips are short, meaning that clip-level supervision is quite direct in these cases. Note independent tasks are necessary since people may do multiple things.

**Vocabulary.** Since our data was collected implicitly, we must determine a vocabulary. An entirely new one would preclude studying transfer, but an entirely existing one would spend effort on objects that are not present. We resolve these competing aims by taking an empirical approach but favoring COCO objects. We exhaustively described which objects were interacted with in a subset of our data; we select 30 categories by identifying frequent objects specific to our dataset (e.g., bedding, doors) and COCO objects that are sufficiently frequent (e.g., fridges, microwaves).

**Annotation.** We asked workers to annotate the videos at a clip level based on whether the human made hand contact with an instance of that object category. Following [34], multiple annotators were asked to annotate a few objects (8) after watching a video. Video/object set pairs where annotators could not come to a consensus were marked as inconclusive. This and all labeling was done through a crowdsourcing service, which used standard quality-control such as consensus labeling, qualifications, and sentinels. Sample labels are shown in Fig. 4

**Labels.** Fig. 5 shows that the human/object interactions are unevenly distributed. Microwaves, for instance, are interacted with far less frequently ( $< 0.3\%$ ) than cell phones or beds. Nonetheless, there are 296 instances, making it the largest collection available. Moreover, since this was ob-

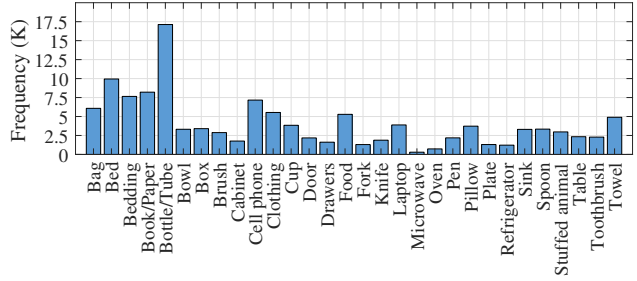


Figure 5. Hand/Semantic Object Label frequency

tained *without searching for* microwave, we expect similar quantities of many other objects can be obtained easily.

**Comparison.** We now compare the scope of VLOG in terms of object interaction with any existing dataset. We examined 15 VLOG categories that overlap cleanly with any of [35, 23, 43, 5, 15]. First, most datasets have catastrophic gaps: [35] has 2 microwaves, for instance, and [23] has no laptops among many other things. Averaging across the categories, VLOG has  $5\times$  the number of examples compared to the largest of past work. This measure, moreover, does not account for diversity: all 36 microwave videos of [23] depict the same exact instance, for example. Bed is the largest relative difference since many source videos start in the morning. The only category in which VLOG lags is doors with only 2179 compared to Charades’ 2663.

### 5.2. Hand Contact State Annotations

We then annotate the hand contact state of a large set of frames. This automatically entirely covers the space of videos: irrespective of which object is being interacted with, we can identify that there is interaction.

**Vocabulary.** Our vocabulary first identifies whether 0, 1, or 2+ people are present; images with 1 person are labeled with how many hands are *visible* and how many (but not which) visible hands are in contact, defined as touching something other than the human’s body or worn clothing. This gives 6 hand states and 8 total categories.

**Annotation.** We annotate a random 219K subset of frames; images without worker agreement are marked as inconclusive. We can trivially convert these labels into “future” labels for problems like contact anticipation.

### 5.3. Additional Data Annotations

Finally, to better understand the nature of the data, we annotated it with additional labels. Since our videos are single scenes taken from a static camera, we mark frames from the middle of the video.

**Scene Classification.** We annotate scenes as being shot in one of 5 categories (bathroom, bedroom, dining room, kitchen, living room) or none-of-the-above. The five categories cover 76% of our data.

**Proxemics.** We annotate distance to the nearest object via



Figure 6. We show examples of frequent confusions as well as their top prediction and confidence. Often the model is confident and wrong; sometimes it is baffled by easy images.

Hall’s proxemic categories [16]: intimate ( $< .45\text{m}$ ), personal ( $< 1.2\text{m}$ ), social ( $< 3.7\text{m}$ ), public ( $3.7\text{m}+$ ).

**Human Configurations.** To characterize the distribution of people, we annotate 20K images with the visibility of the head, torso, hands, and feet by categorizing the image into the six common visibility configurations (capturing 92% of the data), as well as none of the above or no human visible.

**Hand Location.** We further annotate 5K images with bounding box locations of hands from our contact images.

## 6. Exploring Biases of Explicit Data

We first examine to what extent current recognition systems can make sense of VLOG by applying standard models for scene classification and object detection that were trained on standard datasets (both gathered explicitly). Before describing the experiments, we note that VLOG has no blatant domain shift issues: it shows objects and scenes in normal configurations shot from real sensors with little blur. Nonetheless, our experiments show failures that we trace back to biases caused by explicit gathering. We note that our claim is that VLOG captures a chunk of the visual world that is poorly documented by existing datasets, not that VLOG is an unbiased look at the world – all datasets have biases, especially in prior probabilities.

**Scene Classification.** We take a Densenet-161 [19] model trained on the 1.8M image Places365-Standard dataset [50] and apply it to VLOG. Specifically we classify each frame labeled with scene class into 365 scene categories from Places365. We quantify performance with top-5 accuracy.

The off-the-shelf network struggles: in contrast to 85% top-5 accuracy on the original dataset, it gets just 45% on VLOG. The degradation is not graceful: kitchens are often seen as laboratories or an ice cream parlor (sample mistakes are in Fig 6), and reaching 80% accuracy requires using the top-27 error. One hypothesis might be that VLOG is just intrinsically harder: however, humans were all able to come to a consensus on these frames and a simple model with no fine-tuning (linear SVM on pretrained Resnet-50 [17] activations) is able to achieve 72% top-1 accuracy.

The cause is a domain shift from the world of images tagged with scene classes to the world of images from those

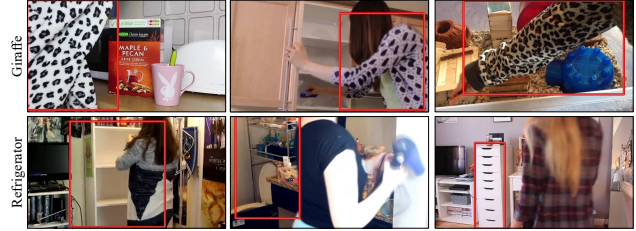


Figure 7. **Detection False Positives.** We show sample high-confidence ( $>0.9$ ) detections from Faster RCNN on VLOG. These suggest COCO contains shortcut solutions to some classes, namely blobby textures for giraffes and shelves for refrigerators.

scenes classes. Examining the source dataset, Places365, reveals sterile kitchens with uncluttered counters and bedrooms with made beds (7% were unmade in a 200 image sample). The photos are also taken from a distance to show off the scene (34% at social and 18% at intimate distance compared to 8% and 40% in VLOG). Thus it is not surprising that the network fails on views of a dresser in a bedroom or an in-use stovetop, and accuracy at social/personal/intimate distance is 66.8%/48.7%/27.9%.

**Object detection.** We take the publicly available VGG-16 [36]-based faster RCNN [29] network. This was trained on COCO [25] to detect 80 categories of objects. We run this detector at 3Hz and max-aggregate over the video.

We find a number of failure modes that we trace back to a lack of the right negatives. Fig. 7 shows sample confident detections for giraffe and refrigerator; these are thresholded at  $>0.9$ , corresponding to  $>99\%$  and  $>96\%$  precision on COCO and come from a larger set of false positives on blobby textures and shelf-like patterns. Since VLOG has many refrigerators, we can quantify performance at this operating point for refrigerators. We count a detection as correct if it contains the object of interest: the 96% precision on COCO (computed the same way) translates to a far worse 44% precision on VLOG, with similar recall.

We hypothesize these failures occur because of missing negatives due to explicit gathering. COCO was gathered explicitly looking for giraffes rather than documenting the savannah and so there are no leopards to force the network to go beyond texture classification. We find similar false positive issues for zebras, whose texture is unique, but not for bears (whose texture must be distinguished from dogs). Similarly, most refrigerator false positives are photos that are unlikely – e.g., cleaning an empty bookshelf. Finally, we note that finding this out via COCO is difficult – giraffe has the highest overall AP for the method, and refrigerator is the second highest of the appliances.

## 7. Benchmarking Interactions

Now that we have analyzed some difficulties current off-the-shelf models have in interpreting VLOG, we analyze how well we can learn to understand hands interacting with

Table 2. Results on Hand/Semantic Object Interaction Classification (Average precision).

	mAP	bag	bed	bedding	book/papers	bottle/tube	bowl	box	brush	cabinet	cell-phone	clothing	cup	door	drawers	food	fork	knife	laptop	microwave	oven	pen/pencil	pillow	plate	refrigerator	sink	spoon	stuffed animal	table	toothbrush	towel
Key R50	31.3	21.7	62.5	57.6	50.7	51.0	25.6	17.3	11.2	16.4	39.9	34.0	19.6	34.8	19.9	40.1	12.5	26.1	47.4	39.3	20.5	23.8	33.2	7.2	46.4	48.7	24.3	44.6	19.9	24.5	17.9
$\mu$ R50	36.1	27.0	67.4	63.0	57.4	56.0	29.3	20.3	17.4	20.0	45.8	39.4	21.9	45.0	25.4	45.3	14.8	30.2	53.9	42.5	22.1	29.8	36.4	8.7	52.8	54.0	28.0	52.0	21.2	33.3	23.6
I3D K	28.1	20.2	56.9	54.3	47.1	45.3	21.8	14.8	22.8	16.3	36.5	32.4	16.6	32.7	12.5	36.1	12.6	29.4	35.6	17.7	13.3	25.3	30.5	6.6	27.3	45.1	23.9	30.0	15.1	39.1	24.2
FT R50	40.5	<b>29.8</b>	68.9	65.8	<b>64.5</b>	<b>58.3</b>	<b>32.9</b>	<b>22.1</b>	19.0	<b>24.3</b>	<b>53.9</b>	45.6	<b>28.8</b>	49.1	<b>28.8</b>	49.6	<b>19.5</b>	37.7	<b>62.9</b>	<b>48.2</b>	<b>23.8</b>	36.6	39.2	12.3	<b>56.3</b>	58.7	31.1	<b>57.2</b>	<b>26.8</b>	39.9	22.8
FT I3D-K	39.6	24.9	<b>71.7</b>	<b>71.4</b>	61.9	57.1	27.1	19.2	<b>33.9</b>	20.7	50.2	<b>45.7</b>	24.6	<b>54.7</b>	19.2	<b>50.5</b>	19.3	<b>41.9</b>	53.2	27.5	21.3	<b>36.9</b>	<b>42.9</b>	<b>12.6</b>	42.2	<b>59.9</b>	<b>33.9</b>	46.0	23.5	<b>59.6</b>	<b>34.7</b>

the world in VLOG. Our goal in this section is to understand how well *existing techniques* work on VLOG; introducing new architectures for video and image understanding is beyond the scope of this work, although our error modes suggest likely future directions.

### 7.1. Hand/Semantic Object Interaction

We first analyze our human-object contact benchmark, a set of 30 video-level binary decisions. We quantify performance with average precision.

**Models.** Our models are inspired by what was done in Charades [35]. We begin with single frame models. The first two use a linear SVM on aggregated final-layer activations of a single-frame ILSVRC-pretrained [33] Resnet-50. We try the following, all L2-normalized: (*Key R50*) one middle frame, which shows how much is explained by a scene glimpse; ( $\mu$  *R50*) the mean of the feature vector over time. Finally, we fine-tune the model on VLOG (*FT R50*); at test time, we average over evenly spaced locations. We next use standard action recognition, using the Kinetics-pretrained [21] RGB version of I3D [4], the class of models that is state of the art on [35]. We train a linear SVM on average activations (*I3D-K*); as well as fine-tune it on VLOG (*FT I3D-K*). Note the base architecture, Inception-v1, has lower spatial resolution and depth than Resnet50.

**Results.** We show quantitative results in Table 2. Fine-tuning improves results, and the I3D exhibits far larger gains compared to Resnet50, suggesting a large domain gap between Kinetics and VLOG. Some objects, mainly textureless or small ones interacted with in distinctive motions – bedding, brushes, toothbrushes, and towels – benefit tremendously from the temporal signal in I3D. Others, usually appliances like microwaves and refrigerators, benefit from Resnet50’s higher spatial resolution and depth.

We see a number of areas for improvement. A single frame does poorly but also gets 78% of the performance relative to the best method, suggesting that current techniques are missing lots of information. Further analysis shows that mAP drops at social distance: FT I3D-K 39.6%  $\rightarrow$  28.2%, with large drops for manipulated objects like cups or knives.

Table 3. Accuracy for hand-state prediction in the present as well as 6, 12, 30, and 60 frames in the future.

	Now	+6f	+12f	+30f	+60f
R50	43.6	41.9	40.4	37.5	35.7
FT R50	56.4	49.6	45.9	41.0	37.8
FT R50+Pseudo Labels	<b>58.2</b>	<b>53.1</b>	<b>49.6</b>	<b>43.8</b>	<b>39.4</b>

This suggests we may need architectures that can transfer from up-close examples to far-away ones or focus more closely on hands.

### 7.2. Hand Contact State

While semantic labels provide one view of our data, VLOG’s long-tail ensures that many interactions will go uncategorized since they do not fall into one of the 30 categories we have labeled. We therefore also investigate hand contact state, in particular in both the current frame and in the future (by simply training on frames before the labeled one). This is an 8-way image classification task and we quantify it with accuracy.

**Models.** We use the same Resnet50 models (pretrained and fine-tuned). Our labels are sparse temporally; we generate *Pseudo-labels* by adding the predictions of an initial model on 1M training video frames into the training set.

**Results.** We show results in Table 3; for reference, simply reporting the training mode gets 20%. The models consistently outperform this, even 2s into the future. The most common confusions are issues in terms of counting the number of hands visible. The pseudo-labels consistently give a boost (and training longer on the same data did not).

One concern we had was that the system may be exploiting a bias to solve the task. We examined CAM activations [49] and found the network focused on hands and faces; to quantify it further, we tried to decode the features to hand pixel labels. We freeze the convolutional layers and learn a linear model on top in a fully convolutional fashion. As a proxy to the segmentation, we use the hand bounding boxes. Using 10/100/3000 labeled images for training, this model gets 31.3/40.5/47.8 IoU, substantially outperforming the Imagenet pretrained model (17.3/33.5/41.5). This sug-

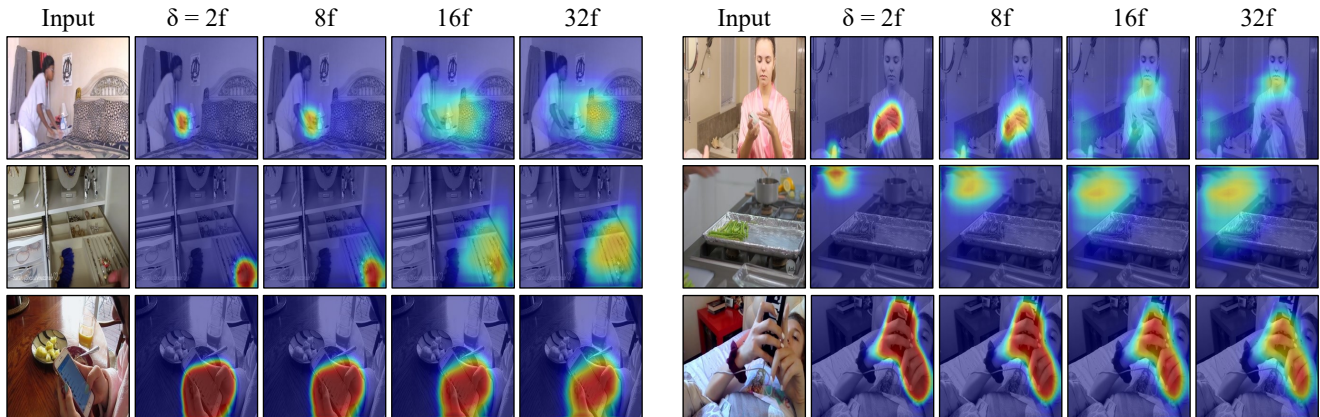


Figure 8. **Where will the hands go?** By having an enormous dataset of hands interacting with the world, we can begin learning models of how everyday interactions play out. Here, we show outputs from a model that predicts where hands will be in the future 2, 8, 16, and 32 frames in the future. It has learned plausible dynamics, including identifying that people using cellphones are unlikely to put them down.

gests that the network has indeed learned about hands.

### 7.3. Hand Detection

We then analyze hand detection, testing on other datasets. This shows that our data is sufficiently varied to work on other datasets un-finetuned. Additionally, this serves the practical purpose of having a detector that works on the wide variety of poses in VLOG, such as: upper-half views with a torso and head (37%), egocentric-like hands-only views (31%), and full body (7%).

**Model.** We train a VGG16-based [36] faster RCNN [29] using standard settings and joint training.

**Results.** The most similar dataset with human hands in videos with both egocentric and third person hands is EgoHands [2], which has a similar number of labeled images (and slightly more annotated boxes). EgoHands fails on VLOG, getting 29.5 AP compared to 67.6 training on VLOG. In the other direction, training on VLOG does well, getting 70.9 compared to 90.4 from training on EgoHands (note EgoHands tests on people seen at training). As further evidence, on a third dataset [27], training on VLOG far surpasses using EgoHands (56.3 vs 31.4).

## 8. Exploring A Large Set of Hands in Contact

Independent of particular tasks and benchmarks, VLOG represents a world of humans interacting with objects that has been indexed in many ways. This has obvious applications in tasks like future prediction [41], intuitive physics [44], imitation learning from videos [45], and grasp analysis [18]. We look forward to seeing what can be done with the dataset, but conclude with a concrete demonstration of the sorts of things that can be done with a large collection of hands in action: we predict future locations of hands.

We build a model that takes an image and predicts the hand locations  $\delta$  frames in the future. This problem has been tackled in lab settings such as in [23]; here, we do

it on large-scale web data. We modify a standard dilated Resnet-54 [48] (details in supplemental) as follows: we introduce a 2-layer network that maps  $\delta$  to feature maps; the base feature map and  $\delta$  feature map are then concatenated and fused by 3 convolutional layers to predict hand segmentation. As training data, we run the segmentation model from Section 7.3 on training frames; we trim these to 156K frames where there is significant change. We then learn a model for  $\delta = 2, \dots, 32$ . Note training this way requires video data from a stationary camera.

We show some predictions in Fig. 8 on held-out data while varying the timescale  $\delta$ . Our model has learned reasonable dynamics of where hands go: in many cases, the hand will continue moving in the direction of likely motion; in others, such as when humans are holding cell phones, our model has learned that people will keep their hands still.

## 9. Discussion

We conclude with a few lessons learnt. The most important to us is that explicitly asking for what you want is counterproductive: it is easier, not harder, to be implicit. In the process, we find a slice of the visual world that is not documented well by existing explicitly gathered data, including popular datasets. There is good news though: there are ways to get this data easily and computer vision has reached a maturity where it can automate much of the process. Additionally, it can make headway on the difficult problem of understanding hands in action. There is still a long way to go until we understand everyday interactions, but we believe this data puts us on the right path.

**Acknowledgements.** This work was supported in part by Intel/NSF VEC award IIS-1539099. We gratefully acknowledge NVIDIA corporation for the donation of GPUs used for this research. DF thanks David Forsyth, Saurabh Gupta, Phillip Isola, Andrew Owens, Abhinav Shrivastava, and Shubham Tulsiani for advice throughout the process.



## References

- [1] J.-B. Alayrac, P. Bojanowski, N. Agrawal, I. Laptev, J. Sivic, and S. Lacoste-Julien. Unsupervised learning from narrated instruction videos. In *CVPR*, 2016. 4
- [2] S. Bambach, S. Lee, D. Crandall, and C. Yu. Lending a hand: Detecting hands and recognizing activities in complex egocentric interactions. In *ICCV*, 2015. 8
- [3] K. P. Burnham and W. S. Overton. Estimation of the size of a closed population when capture probabilities vary among animals. *Biometrika*, 65(3):625–633, 1978. 4
- [4] J. Carreira and A. Zisserman. Quo vadis, action recognition? a new model and the kinetics dataset. In *CVPR*, 2017. 7
- [5] Y.-W. Chao, Z. Wang, Y. He, J. Wang, and J. Deng. HICO: A benchmark for recognizing human-object interactions in images. In *ICCV*, 2015. 4, 5
- [6] V. Delaitre, D. Fouhey, I. Laptev, J. Sivic, A. Efros, and A. Gupta. Scene semantics from long-term observation of people. In *ECCV*, 2012. 2
- [7] B. G. Fabian Caba Heilbron, Victor Escorcia and J. C. Niebles. Activitynet: A large-scale video benchmark for human activity understanding. In *CVPR*, 2015. 2, 4
- [8] A. Fathi, Y. Li, and J. M. Rehg. Learning to recognize daily actions using gaze. In *ECCV*, 2012. 2, 4
- [9] D. F. Fouhey, V. Delaitre, A. Gupta, A. A. Efros, I. Laptev, and J. Sivic. People watching: Human actions as a cue for single-view geometry. In *ECCV*, 2012. 2
- [10] J. Gibson. *The ecological approach to visual perception*. Boston: Houghton Mifflin, 1979. 2
- [11] R. Goyal, S. E. Kahou, V. Michalski, J. Materzynska, S. Westphal, H. Kim, V. Haenel, I. Fruend, P. Yianilos, M. Mueller-Freitag, F. Hoppe, C. Thureau, I. Bax, and R. Memisevic. The “something something” video database for learning and evaluating visual common sense. In *ICCV*, 2017. 1, 2, 3, 4
- [12] H. Grabner, J. Gall, and L. van Gool. What makes a chair a chair? In *CVPR*, 2011. 2
- [13] C. Gu, C. Sun, D. A. Ross, C. Vondrick, C. Pantofaru, Y. Li, S. Vijayanarasimhan, G. Toderici, S. Ricco, R. Sukthankar, C. Schmid, and J. Malik. AVA: A video dataset of spatio-temporally localized atomic visual actions. In *CVPR*, 2018. 2, 4
- [14] A. Gupta, S. Satkin, A. Efros, and M. Hebert. From 3D scene geometry to human workspace. In *CVPR*, 2011. 2
- [15] S. Gupta and J. Malik. Visual semantic role labeling. *CoRR*, abs/1505.04474, 2015. 4, 5
- [16] E. T. Hall. *The Hidden Dimension*. 1966. 6
- [17] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In *CVPR*, 2016. 6
- [18] D.-A. Huang, W.-C. Ma, M. Ma, and K. M. Kitani. How do we use our hands? discovering a diverse set of common grasps. In *CVPR*, 2015. 8
- [19] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger. Densely connected convolutional networks. In *CVPR*, 2017. 6
- [20] Y. Jiang and A. Saxena. Hallucinated humans as the hidden context for labeling 3D scenes. In *CVPR*, 2013. 2
- [21] W. Kay, J. Carreira, K. Simonyan, B. Zhang, C. Hillier, S. Vijayanarasimhan, F. Viola, T. Green, T. Back, P. Natsev, M. Suleyman, and A. Zisserman. The kinetics human action video dataset. *CoRR*, abs/1705.06950, 2017. 1, 4, 7
- [22] R. Kiberd. Youtube’s ‘my daily routine’ is a beautiful lie. <http://kernelmag.dailydot.com/issue-sections/staff-editorials/14643/youtube-daily-routine-stepford-wives/>. 3
- [23] H. S. Koppula, R. Gupta, and A. Saxena. Learning human activities and object affordances from RGB-D videos. *The International Journal of Robotics Research*, 32(8):951–970, 2013. 1, 2, 3, 4, 5, 8
- [24] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *NIPS*, 2012. 3
- [25] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollr, and C. L. Zitnick. Microsoft COCO: Common objects in context. In *ECCV*, 2014. 6
- [26] D. Lowe. Distinctive Image Features from Scale-Invariant Keypoints. *IJCV*, 60(2):91–110, 2004. 3
- [27] A. Mittal, A. Zisserman, and P. H. S. Torr. Hand detection using multiple proposals. In *BMVC*, 2011. 8
- [28] H. Pirsiavash and D. Ramanan. Detecting activities of daily living in first-person camera views. In *CVPR*, 2012. 2, 4
- [29] S. Ren, K. He, R. Girshick, and J. Sun. Faster R-CNN: Towards real-time object detection with region proposal networks. In *NIPS*, 2015. 6, 8
- [30] N. Rhinehart and K. M. Kitani. Learning action maps of large environments via first-person vision. In *CVPR*, 2016. 2
- [31] M. Rohrbach, S. Amin, M. Andriluka, and B. Schiele. A database for fine grained activity detection of cooking activities. In *CVPR*, 2012. 2, 4
- [32] A. Roy and S. Todorovic. A multi-scale CNN for affordance segmentation in RGB images. In *ECCV*, 2016. 2
- [33] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein, A. C. Berg, and L. Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *IJCV*, April 2015. 3, 7
- [34] G. A. Sigurdsson, O. Russakovsky, A. Farhadi, I. Laptev, and A. Gupta. Much ado about time: Exhaustive annotation of temporal data. In *HCOMP*, 2016. 5
- [35] G. A. Sigurdsson, G. Varol, X. Wang, A. Farhadi, I. Laptev, and A. Gupta. Hollywood in homes: Crowdsourcing data collection for activity understanding. In *ECCV*, 2016. 1, 2, 3, 4, 5, 7
- [36] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *CoRR*, abs/1409.1556, 2014. 6, 8
- [37] K. K. Singh, K. Fatahalian, and A. A. Efros. Krishnacam: Using a longitudinal, single-person, egocentric dataset for scene understanding tasks. In *WACV*, 2016. 2
- [38] K. Soomro, A. R. Zamir, and M. Shah. UCF101: A dataset of 101 human actions classes from videos in the wild. *CoRR*, abs/1212.0402, 2012. 1, 4
- [39] J. Sung, C. Ponce, B. Selman, and A. Saxena. Unstructured human activity detection from rgb-d images. In *ICRA*, 2012. 3

- [40] A. Torralba and A. A. Efros. Unbiased look at dataset bias. In *CVPR*, 2011. 1
- [41] J. Walker, C. Doersch, A. Gupta, and M. Hebert. An uncertain future: Forecasting from static images using variational autoencoders. In *ECCV*, 2016. 8
- [42] X. Wang, A. Farhadi, and A. Gupta. Actions ~ transformations. In *CVPR*, 2016. 2
- [43] C. Wu, J. Zhang, S. Savarese, and A. Saxena. Watch-n-patch: Unsupervised understanding of actions and relations. In *CVPR*, 2015. 1, 4, 5
- [44] J. Wu, J. J. Lim, H. Zhang, J. B. Tenenbaum, and W. T. Freeman. Physics 101: Learning physical object properties from unlabeled videos. In *BMVC*, 2016. 8
- [45] Y. Yang, Y. Li, C. Fermüller, and Y. Aloimonos. Robot learning manipulation action plans by watching unconstrained videos from the world wide web. In *AAAI*, 2014. 8
- [46] B. Yao and L. Fei-Fei. Grouplet: A structured image representation for recognizing human and object interactions. In *CVPR*, 2010. 2
- [47] B. Yao and L. Fei-Fei. Modeling mutual context of object and human pose in human-object interaction activities. In *CVPR*, 2010. 2
- [48] F. Yu, V. Koltun, and T. Funkhouser. Dilated residual networks. In *CVPR*, 2017. 8
- [49] B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba. Learning deep features for discriminative localization. In *CVPR*, 2016. 7
- [50] B. Zhou, A. Lapedriza, A. Khosla, A. Oliva, and A. Torralba. Places: A 10 million image database for scene recognition. *TPAMI*, 2017. 6