EVALUATING VISUAL "COMMON SENSE" USING FINE-GRAINED CLASSIFICATION AND CAPTIONING TASKS

Raghav Goyal, Farzaneh Mahdisoltani, Guillaume Berger, Waseem Gharbieh, Ingo Bax, Roland Memisevic
Twenty Billion Neurons Inc.
{firstname.lastname}@twentybn.com

1 INTRODUCTION

Understanding concepts in the world remains one of the well-sought endeavours of ML. Whereas ImageNet enabled success in object recognition and various related tasks via transfer learning, the ability to understand physical concepts prevalent in the world still remains an unattained, yet desirable, goal. Video as a vision modality encodes how objects change across time with respect to pose, position, distance of observer, etc.; and has therefore been researched extensively as a data domain and for studying "common sense" physical concepts of objects.

The current standard approach to video data collection uses videos from existing resources on the web such as YouTube, Vimeo or Flickr that are passed through a pipeline of annotators to gather labels. Instances of this approach include the Kinetics (Kay et al., 2017) or Moments in Time (Monfort et al.)) datasets. Since this approach provides for limited control of variations in pose, motion and other aspects of the objects relevant to learning, recently novel datasets based on "*crowd-acting*" have emerged, where crowd workers are asked to generate videos according to pre-defined labels. Examples include the first version of the something-something (Goyal et al., 2017) dataset and the Charades dataset (Sigurdsson et al., 2017).

In this work, we describe an updated version of the something-something dataset and a variety of novel experiments on this data. The first version of this dataset, that was introduced by (Goyal et al., 2017), is generated by asking crowd workers to act out template-based labels, such as "Dropping *something* into *something*" and to fill in the "something" placeholders with the object used to generate the video. The work is aimed specifically at learning physical aspects of the world rather than focusing on action detection or recognition. In this paper, we build on and extend that work through the following contributions: First, we release version 2 of the dataset - *something-something-v2*[1], containing $220,847$ videos across 174 action classes and in contrast to the first version of the dataset containing *object categories*. Second, we propose an approach to quantify progress on the dataset constructed using contrastive examples. Third, we present baseline results, which show surprisingly strong performance on the arguably hard discrimination tasks represented by this metric. Fourth, we show how temporally-sensitive saliency maps can be used to visualize regions of interest within a video and reveal the dependency of subtle classification decisions on spatio-temporal patterns in the video. Fifth, we show captioning results on the data, as predicting the expanded labels containing object categories can be viewed as a (very hard) captioning task.

2 PROPOSED COMMON SENSE METRIC

We argue that for datasets which focus on fine-grained visual aspects, a metric is needed that can evaluate discriminating properties of the model apart from top-k accuracy. As a first step, for something-something-v2, we looked at the topmost confusions from a baseline model (described later in Section 3), and found that the confusions are ambiguous enough even for humans to differentiate, and these are inevitably accounted in the accuracy. For e.g. 55.42% of the samples from "*Moving something across a surface until it falls down*" label are confused with "*Pushing something so that it falls off the table*" (Please refer to Table 3 in Appendix for a list of top 10 confusions).

[1]We plan to make the dataset available after acceptance of the paper

Contrastive groups In order to avoid models picking up indirect cues from object type, hand position, camera shake, etc., we propose to measure performance by forming groups of classes, which are superficially similar (but distinct) and easily confused by networks. Many of the classes within a group contain multiple similar actions with minute visual differences such that fine-grained understanding and attention to detail is necessary to yield correct classification. For example, the actions "Throwing something in the air and catching it" and "Throwing something in the air and letting it fall" belong to one contrastive group. The following aspects went into the definition of the action groups:

Pretending classes: Action classes are grouped with their corresponding "pretending" classes if it exists ***Aggregating similar classes***: To reduce ambiguity, we combine semantically similar classes into a single class, e.g. "Moving something across a surface until it falls down" and "Pushing something so that it falls off the table" ***Antonyms***: e.g. Digging/Burying, Folding/Unfolding, Dropping/Putting, Collide/Pass, Opening/Closing. ***Different object properties***: e.g. "Falling like a rock/paper", "Wringing something wet/twisting something". ***Different prepositions***: Classes differentiating between relative position of an object, e.g. behind/in front of/next to, into/onto, etc. ***Different final state***: Classes differentiating between final state of an object, e.g. tearing a bit/into two pieces, poking so that a stack collapses/doesn't collapse, continues spinning/stops spinning, catching/letting it fall, falls/doesn't fall down, etc.

In total we formed 69 contrastive groups, a full list can be found in Appendix in Table 2. We excluded classes containing concepts that we deem are fairly easy to distinguish, such as ***Relative motions***: e.g. left/right, camera movements (up/down, approaching/moving away), etc. ***Static***: Classes that have no motion, e.g. Showing, Holding, Squeezing, etc.

Metric construction For each group, we filter examples from the validation set corresponding to only the classes contained in the group and compute the accuracy. We average the accuracy across all the groups to obtain the mean accuracy (mA1). To account for class imbalance we also compute the accuracy that follows from always predicting the most common class in the group (mA2).

To arrive at the final metric, we normalize the above scores, computed as a percentage difference between mA1 and mA2: $(\text{mA1} - \text{mA2})/(100 - \text{mA2})$. The metric measures how well the model performs compared to predicting the most common class within each group. Table 1 shows the scores on the validation set. We refer to the normalized score on the contrastive groups as *Common sense score*. The Table also shows performance on the action groups (which are not designed to measure performance on detailed prediction tasks) proposed in (Goyal et al., 2017).

3 Experiments and Results

3.1 Performance of models

We compare a baseline model on something-something-v2 with the features from models pre-trained on well-established datasets - ImageNet and Kinetics. We use a length of 72 frames per video, covering a max duration of 6 secs at 12 fps, and padding short videos with their last frame.

Baseline Model We use a VGG-style 3D-CNN with 11 layers of 3D convs, operating on 84×84 frames. It is trained from scratch on something-something-v2 and is referred to as *smth_3D_scratch*.

Pre-trained models We took a Kinetics pre-trained I3D model[2] trained on RGB stream (Carreira & Zisserman, 2017) and extracted "Mixed_5c" layer features from the something-something-v2 dataset; and trained a 3D convolution and a fully-connected layer on top for classification. The model is referred to as *kinetics_feat_smth*.

We took an ImageNet-trained ResNet-152 model and extracted features for each frame in something-something-v2 dataset, and trained a 1D convolution and a fully-connected layer on top for classification, referred to as *imagenet_feat_smth*. Surprisingly, we find that despite the extraordinarily hard tasks inherent in this grouping, even the comparably simple baseline model yields performance that is significantly beyond chance. In the next section, we investigate the dependence of the classification decisions on local aspects of the input video.

[2]https://github.com/deepmind/kinetics-i3d

Method	Accuracy(%)		Action groups score(%)		Common sense score(%)	
	top-1	top-5	Actual mA1 (mA2)	Normalized	Actual mA1 (mA2)	Normalized
imagenet_feat_smth	22.67	48.32	64.10 (51.93)	25.31	74.81 (64.93)	28.17
kinetics_feat_smth	27.93	55.75	66.70 (51.93)	30.72	77.13 (64.93)	34.78
smth_3D_scratch	50.28	79.51	79.41 (51.93)	57.16	88.90 (64.93)	68.34

Table 1: Comparison among models trained from scratch and pre-trained features (from Kinetics and ImageNet) fine-tuned on something-something-v2 dataset.

3.2 Saliency Maps

To visualize the regularities that models learned from the data, we extracted *temporally-sensitive* saliency maps using Grad-CAM (Selvaraju et al., 2017). We extended the implementation[3] in time dimension and projected back the weighted activation maps to the input space. Figure 1 shows saliency maps of examples predicted as "*Opening something*". Some additional visualizations of the feature space learned by the model using T-SNE are shown in the appendix.

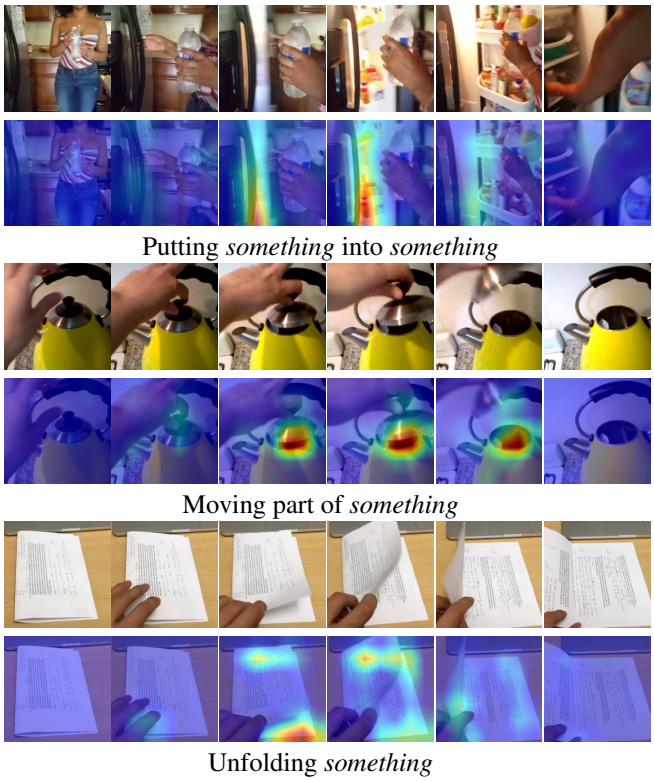


Figure 1: Video examples predicted as "*Opening something*" having different ground-truth labels.

3.3 Video Captioning

Along with each video in something-something-v2, a string caption is provided which describes the video in a natural language sentence. As baseline, we use a basic encoder-decoder model for captioning something-something videos, which models the conditional probability distribution over word sequence c given the video v $p(c|v) = \sum_{i=1}^{m} \log p(c_{i+1}|c_{\leq i}, h)$. The encoder is a 3D-convnet similar to the one described above. Please refer to the appendix for some captioning examples.

[3]https://github.com/jacobgil/pytorch-grad-cam

REFERENCES

Joao Carreira and Andrew Zisserman. Quo vadis, action recognition? a new model and the kinetics dataset. In *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 4724–4733. IEEE, 2017.

Raghav Goyal, Samira Ebrahimi Kahou, Vincent Michalski, Joanna Materzynska, Susanne Westphal, Heuna Kim, Valentin Haenel, Ingo Fruend, Peter Yianilos, Moritz Mueller-Freitag, Florian Hoppe, Christian Thurau, Ingo Bax, and Roland Memisevic. The "something something" video database for learning and evaluating visual common sense. In *The IEEE International Conference on Computer Vision (ICCV)*, Oct 2017.

Will Kay, Joao Carreira, Karen Simonyan, Brian Zhang, Chloe Hillier, Sudheendra Vijayanarasimhan, Fabio Viola, Tim Green, Trevor Back, Paul Natsev, et al. The kinetics human action video dataset. *arXiv preprint arXiv:1705.06950*, 2017.

Mathew Monfort, Bolei Zhou, Sarah Adel Bargal, Tom Yan, Alex Andonian, Kandan Ramakrishnan, Lisa Brown, Quanfu Fan, Dan Gutfruend, Carl Vondrick, et al. Moments in time dataset: one million videos for event understanding.

Ramprasaath R. Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. In *The IEEE International Conference on Computer Vision (ICCV)*, Oct 2017.

Gunnar A. Sigurdsson, Olga Russakovsky, and Abhinav Gupta. What actions are needed for understanding human actions in videos? In *The IEEE International Conference on Computer Vision (ICCV)*, Oct 2017.

A CONTRASTIVE GROUPS LIST

Table 2: List of 69 contrastive groups. Please note that some of the classes are aggregated together using "+" to represent one class, since they convey semantically similar concepts (e.g. group 25).

#	Contrastive groups
1	Wiping something off of something Pretending or failing to wipe something off of something
2	Closing something Pretending to close something without actually closing it
3	Opening something Pretending to open something without actually opening it
4	Picking something up Pretending to pick something up
5	Turning something upside down Pretending to turn something upside down
6	Putting something into something Pretending to put something into something
7	Putting something behind something Pretending to put something behind something
8	Putting something next to something Pretending to put something next to something
9	Putting something on a surface Pretending to put something on a surface
10	Putting something onto something Pretending to put something onto something
11	Putting something underneath something Pretending to put something underneath something
12	Scooping something up with something Pretending to scoop something up with something
13	Throwing something Pretending to throw something
14	Taking something out of something Pretending to take something out of something
15	Spreading something onto something Pretending to spread air onto something
16	Sprinkling something onto something Pretending to sprinkle air onto something
17	Pouring something out of something Pretending to pour something out of something, but something is empty
18	Taking something from somewhere Pretending to take something from somewhere
19	Twisting (wringing) something wet until water comes out Twisting something
20	Tearing something into two pieces Tearing something just a little bit
21	Opening something Closing something
22	Poking a stack of something so the stack collapses Poking a stack of something without the stack collapsing
23	Attaching something to something Trying but failing to attach something to something because it doesn't stick
24	Folding something Unfolding something

25	(Moving something across a surface until it falls down + Pushing something so that it falls off the table) (Moving something across a surface without it falling down + Pushing something so that it almost falls off but doesn't)
26	Covering something with something Uncovering something
27	Throwing something in the air and catching it Throwing something in the air and letting it fall
28	Lifting up one end of something without letting it drop down Lifting up one end of something, then letting it drop down
29	Lifting something up completely without letting it drop down Lifting something up completely, then letting it drop down
30	Lifting a surface with something on it but not enough for it to slide down Lifting a surface with something on it until it starts sliding down
31	Pulling two ends of something so that it gets stretched Pulling two ends of something so that it separates into two pieces
32	Moving something and something so they collide with each other Moving something and something so they pass each other
33	Something falling like a feather or paper Something falling like a rock
34	Spinning something so it continues spinning Spinning something that quickly stops spinning
35	Putting something that can't roll onto a slanted surface, so it slides down Putting something that can't roll onto a slanted surface, so it stays where it is
36	Something colliding with something and both are being deflected Something colliding with something and both come to a halt
37	Plugging something into something Plugging something into something but pulling it right out as you remove your hand
38	Tilting something with something on it slightly so it doesn't fall down Tilting something with something on it until it falls off
39	Burying something in something Digging something out of something
40	Poking a hole into some substance Poking a hole into something soft
41	(Poking something so it slightly moves + Poking something so lightly that it doesn't or almost doesn't move) Poking something so that it falls over Poking something so that it spins around
42	Pouring something into something Trying to pour something into something, but missing so it spills next to it
43	Pouring something into something Pouring something into something until it overflows Pouring something onto something
44	Burying something in something Covering something with something
45	Covering something with something Digging something out of something
46	Bending something so that it deforms Bending something until it breaks
47	Dropping something behind something Dropping something in front of something
48	Dropping something into something Dropping something onto something
49	Dropping something behind something Putting something behind something
50	Dropping something in front of something Putting something in front of something

51	Dropping something into something Putting something into something
52	Dropping something next to something Putting something next to something
53	Dropping something onto something Putting something onto something
54	Picking something up Putting something on a surface
55	Failing to put something into something because something does not fit Putting something into something
56	Scooping something up with something Picking something up
57	Tipping something over Touching (without moving) part of something
58	Tipping something over Tipping something with something in it over, so something in it falls out
59	Tipping something with something in it over, so something in it falls out Touching (without moving) part of something
60	Putting something behind something Putting something in front of something Putting something underneath something Putting something next to something Putting something onto something Putting something into something
61	Putting something similar to other things that are already on the table Taking one of many similar things on the table
62	Putting something into something Taking something out of something
63	Putting something on a surface Putting something on the edge of something so it is not supported and falls down
64	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
65	Pretending to put something behind something Pretending to put something next to something Pretending to put something underneath something Pretending to put something into something Pretending to put something onto something
66	Putting something on a flat surface without letting it roll Rolling something on a flat surface
67	Spilling something behind something Spilling something next to something Spilling something onto something
68	(Letting something roll along a flat surface + Rolling something on a flat surface) Putting something on a flat surface without letting it roll
69	Putting something onto a slanted surface but it doesn't glide down Letting something roll down a slanted surface

B TOP-10 CONFUSIONS

Table 3: Top 10 confusions from the baseline model

True class	**Predicted class**	**% of true instances predicted**
Moving something across a surface until it falls down	Pushing something so that it falls off the table	55.42
Letting something roll along a flat surface	Rolling something on a flat surface	44.77
Pushing something off of something	Pushing something so that it falls off the table	41.67
Throwing something onto a surface	Throwing something	39.02
Poking a stack of something without the stack collapsing	Poking something so lightly that it doesn't or almost doesn't move	37.50
Lifting a surface with something on it but not enough for it to slide down	Tilting something with something on it slightly so it doesn't fall down	36.84
Spilling something next to something	Pouring something into something	36.67
Pouring something into something until it overflows	Pouring something into something	36.00
Trying to pour something into something, but missing so it spills next to it	Pouring something into something	32.50
Pretending to take something from somewhere	Pretending to pick something up	31.20

C T-SNE PLOTS

Using Tensorboard's[4] implementation of t-SNE, we ran the optimization on validation set features (24777 examples, each with 512 dimensions) for 4k iteration with perplexity of 50 and learning rate of 10. A 2D representation is shown in the Figure 2.

[4]https://github.com/tensorflow/tensorboard

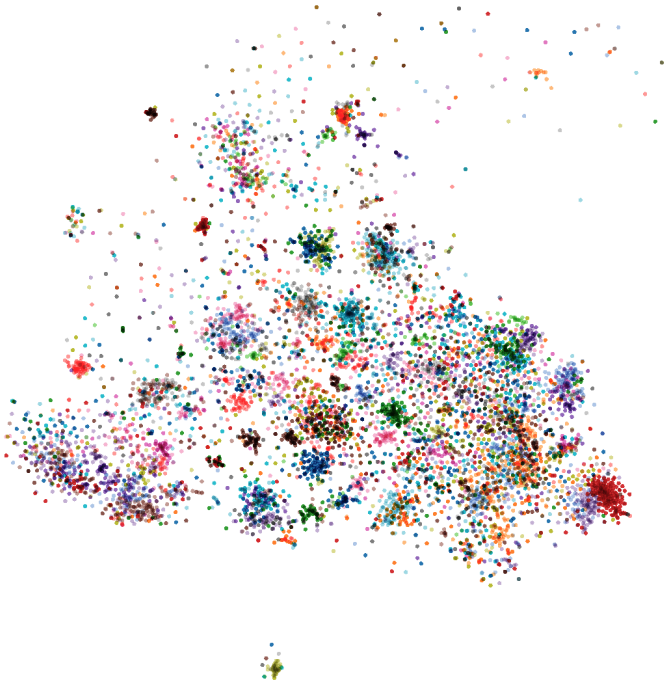
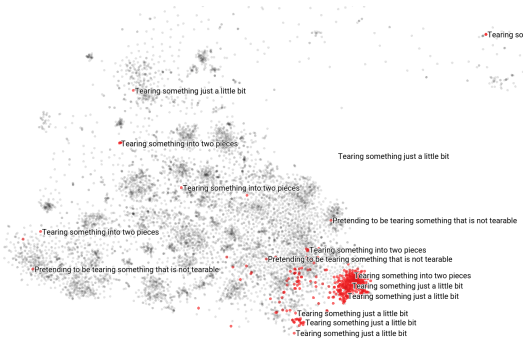
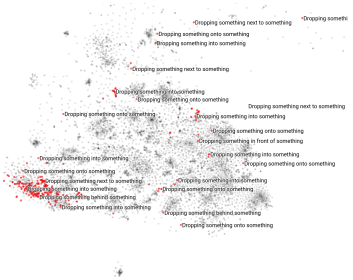


Figure 2: t-SNE of learned representations

Turning *something* upside down

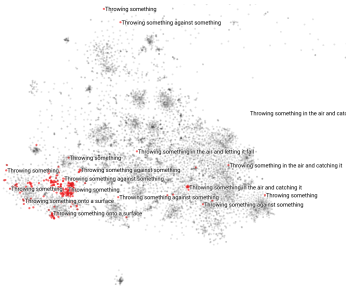


Tearing *Something*



Dropping *something*

Something falling like a rock/paper



Throwing *something*

Figure 3: The above three classes are mapped to regions "near" to each other and also convey semantically similar meaning