Learning Video Representations from Textual Web Supervision

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Abstract

Videos on the Internet are paired with pieces of text, such as titles and descriptions. This text typically describes the most important content in the video, such as the objects in the scene and the actions being performed. Based on this observation, we propose to use text as a method for learning video representations. To accomplish this, we propose a data collection process and use it to collect 70M video clips shared publicly on the Internet, and we then train a model to pair each video with its associated text. We evaluate the model on several downstream action recognition tasks, including Kinetics, HMDB-51, and UCF-101. We find that this approach is an effective method of pre-training video representations. Specifically, it outperforms all existing methods for self-supervised and cross-modal video representation learning.

1. Introduction

Video representations are typically learned in a fully-supervised fashion. For this approach to be successful, we require large amounts of labeled data, typically on the order of hundreds of thousands of labels. Acquiring these labels can cost tens of thousands of hours of human time to annotate [23], and furthermore, when datasets become large, the benefit of gathering more labels appears to diminish [27]. At a certain point, it becomes too costly to simply label more data to improve performance. In this regime, we look to alternative sources of supervision to learn video representations without costly manual labels.

In our work, we draw this supervision from textual metadata available publicly on the Internet. Specifically, we use videos from YouTube, where videos are associated with freeform text in the form of titles, descriptions, tags, and channel/creator names. These four pieces of textual metadata provide rich information about each video’s content. Frequently, they describe the exact types of information which labelers are asked to annotate in labeled datasets, such as objects, scenes, and human actions. For example, consider the title, “Learning how to swim!” or the channel name “PotteryMaker”. Both of these indicate what actions will take place in their respective videos, and we can leverage this information to learn representations, in much of the same way we use labels in supervised learning.

One advantage of using text from internet videos is that the text is open-ended and therefore more descriptive than class labels. Consider the title “Outdoor free-climbing in Yosemite”. In supervised learning, this video would be labeled “rock climbing”, but this label ignores important information about the scene and the specific type of action, potentially missing out on valuable supervisory signal. In our experiments, we demonstrate that using text, and using multiple sources of text, translates into impressive downstream performance, without the need for class labels during pre-training. We compare our method with other self-supervised and cross-modal approaches, showing that our method produces video representations which improve downstream performance by 8.9% on HMDB-51 [36] and 2.1% on UCF 101 [57] (Section 5).

Another advantage of this approach is that the amount of available data is immense; e.g. over 500 hours of content is uploaded every minute to YouTube alone [24], and each video is labeled with text. To leverage this data, we propose a data collection process called Weak Textual Supervision (WTS). We use a text-based video search engine to query for common words and collect a large-scale video dataset with matched pieces of text metadata. Using this process, we collect a dataset of 70 million videos, which is comparable in scale to the recent HowTo100M dataset [46], but includes paired metadata, is drawn from a higher number of unique videos (70M vs 1M), and is not limited to only instructional videos (Section 3). Few truly large-scale video datasets like ours are currently available (Table 1), and even fewer are available publicly. We intend to release the list of videos used in our experiments to facilitate future research.

Our goal with this data is to learn video representations, that is, feature vectors which encode a video clip, which are
then useful for downstream tasks. To learn these representations, we propose a training scheme in which the video representation are used to pair each video with its associated metadata. We use powerful 3D Convolutional Neural Network (3D CNN) architectures to produce these representations, and we train the video representations end-to-end on WTS-70M (Section 3). We evaluate the representations’ effectiveness on a suite of downstream tasks. We find that, for both fine-tuned and frozen embeddings, pre-training with our approach significantly improves downstream performance, achieving state of the art results. This is particularly true in low-data regimes, but we also show that our pre-training is useful in settings where is complementary to strongly-supervised pre-training (Section 5).

Our key finding is that textual metadata is a rich source of supervision which can be acquired freely from public sources. Specifically, we make the following contributions:

- We propose a data collection process (WTS), which uses text-based search to gather a large-scale dataset of video clips and their associated metadata, including titles, descriptions, tags, and channel names.

- We release a dataset of 70M videos collected with this process, including their associated metadata, and pre-trained models used in this work.

- We propose a method for learning video representations by learning to match these representations with their associated metadata, and demonstrate that our approach outperforms all other pre-training approaches.

2. Related Work

Unsupervised and Self-Supervised Learning. Many prior works have learned video representations without manual labels. In unsupervised and self-supervised learning, the supervision instead comes purely from the video itself. For example, prior approaches have successfully leveraged supervision from clip and frame ordering [47, 16, 38, 66, 68, 33], geometry [17, 29], motion [53, 37], colorization [62], cycle consistency [14, 64], video prediction [44, 42, 61, 60, 63], tempo [62], and in-video consistency [22, 34]. Generally, these approaches are outperformed by those leveraging supervision from other modalities or from web-based metadata. In addition, they have the disadvantage that they typically use curated datasets for pre-training, and ignore the existing labels from the dataset. In our approach, we do not use pre-labeled videos as our source of videos. These videos provide a more realistic reflection of the videos available in the wild.

Webly-Supervised Learning. Many prior works have leveraged webly-labeled data for visual representation learning, both for images as well as videos. In general, these approaches use metadata found on the Internet to infer weak labels for a set of images or videos, and they differ in how these weak labels are created. The most commonly-used approach is to use image search results, and to label each image with the query that was used to find it [65, 15, 56, 6, 11, 13, 21, 10, 18, 35]. Another approach is to use text captions, and label each image with key words present in the caption [50, 30, 59, 48]. Other approaches use user-defined keywords or tags [20, 28, 43, 19] or algorithmically-generated topics [11, 31] to the same end. These approaches have consistently demonstrated that webly-supervised learning is scalable and that it improves performance on downstream tasks, suggesting that webly-acquired class labels provide valuable supervision.

Cross-Modal Learning. Several prior works have used other modalities, such as text or audio, as a source of supervision for video. This approach is convenient because videos are almost always paired other modalities such as audio, and often works well because these other modalities are tightly correlated with what is happening in the video. Prior works have leveraged ambient sound [52, 5, 4, 71, 34, 51, 55], dialogue [49], and narration [20, 2, 72, 73, 46, 45, 3], all of which of which serve as useful signals. Those approaches using narration typically do so with instructional videos, such as in the recent HowTo100M dataset [46], since instructional videos typically contain narration which describes the actions being performed. Another recent approach, like ours, uses text data which is paired with videos, such as titles [40]. This approach reaps the benefits offered by rich, descriptive supervision, and can be used with any genre of videos. Our work differs in that we also use other forms of metadata, such as descriptions. In addition, this prior work uses curated data from Kinetics-400, while we introduce WTS as our source of videos, which is more representative of videos in the wild.

3. Data Collection

We propose a data collection process in which we search for common action categories using a text-based video search engine. We begin by manually selecting the set of action categories; in our experiments we use the 700 action categories in Kinetics-700 [8]. We choose these categories primarily because they are designed to cover a broad range of human actions. In addition, this choice helps make a fair comparison with fully-supervised pre-training on Kinetics when evaluating on downstream tasks such as HMDB-51 and UCF101, since we know that the change in performance is not just due to a different choice of action categories. Using the Kinetics classes may also help improve performance on Kinetics itself. In practice, this is a useful feature of using videos from the internet: researchers who reproduce this pipeline may opt to use a different set of action categories to better match the downstream tasks that they are targeting.
Once we have these action categories, we search YouTube for these terms and collect the resulting videos. We then apply two selection criteria to filter videos. First, we discard videos which are less than 10 seconds long, since we use 10-second clips during training. Second, we discard videos which were uploaded in the past 90 days, because newer videos are more likely to be deleted, improving reproducibility of our experiments. In total, we collect 100K videos from each of the 700 queries, resulting in a dataset of 70M videos. From each video, we randomly select a 10-second clip to download.

Each video is paired with four pieces of textual metadata: its title, description, tags, and channel name. These were chosen for two reasons. First, they are all manually written by the user, as opposed to being automatically generated. Second, from manual inspection, we see that these pieces of text consistently contain informative references to content in the video. These references are written deliberately by the user, who generally will choose a title, description, and tags which help other users find their video. The user will also select a channel name (an identifier used to represent the user) which is informative, typically one which is indicative of the types of videos that the channel contains. The channel name provides context which the other signals may not, for example, a channel for guitar lessons, “Jeff’s Guitar Lessons”, may not say “guitar lesson” in each video title, but the channel name makes this obvious. For some examples of videos and their metadata, see Figure 1.

We note that WTS is a data collection process, and the datasets used in this work (denoted WTS-X) are not intended to serve as static datasets. This is made possible by the fact that our data collection process is entirely automatic, and does not rely on any manual annotation. Therefore, it is possible for WTS to be repeated or expanded flexibly with any desired action vocabulary, depending on the needs of the downstream tasks. Our experiments show that, even with 70M videos, WTS has not plateaued in terms of performance gains, suggesting that a static dataset would be limiting. Our non-static dataset provides an additional advantage over large-scale labeled datasets (such as Kinetics [32]), in which videos can be deleted by their owners at any time. When a labeled video is deleted, it leads to a decay in the number of labeled videos, but in our case, no videos are labeled, so we can simply repeat WTS to account for the lost videos.

One additional advantage of using unlabeled videos is that it results in a dataset that is less curated than those which were originally labeled but had the labels stripped from them. While it is quite common to use labeled datasets in this way for unsupervised learning, these datasets are guaranteed to not have examples outside of the class label vocabulary, and it is not clear whether the results will generalize to uncurated datasets where this assumption does not hold. Our dataset does not require any labels to construct at any step of the process, and therefore it does not have this issue. Our dataset is not purely uncurated, since we intentionally use a targeted set of action classes to search for videos (as do other uncurated datasets, including HowTo100M [46]). However, it is not curated in a way that requires any manual human effort.

In Table 1, we compare WTS-70M to other unlabeled datasets for video representation learning. In terms of the number of videos, WTS-70M is on par with the largest datasets in prior work, with 5M more unique source videos than [19]. We acknowledge that, conceptually, any of these prior datasets could be scaled to much larger sizes simply by collecting more data, making dataset size a dubious method of comparison. However, it is still important to study how these methods behave when scaled to extreme dataset sizes, and therefore our experiments on 70M videos are a valuable contribution in this space. These experiments are particularly important because there are non-trivial issues associated with scaling unsupervised learning to extreme dataset sizes. The key issue is that we use search results to collect...
data, and the quality of these results declines as we move deeper into the search rankings to collect more videos. Despite this, we demonstrate that performance does not saturate by the time we hit 70M videos (Section 5.2).

To analyze the scaling properties of WTS, we collect increasingly-large subsets of the dataset and measure indicators of their quality, shown in Figure 4. The dataset size is scaled up as one would do in practice, by selecting more and more of the top search results from each query, rather than by performing a random sample from the full WTS-70M dataset. The indicators measure, for each piece of metadata, the mean length (in words), the rate of missing-ness (for descriptions and tags, which can be omitted by the user), and the mean number of tags. We find that search results are imbalanced in terms of how these indicators are distributed. Specifically, descriptions and tags tend to get shorter with larger dataset sizes, but titles and channel names in fact get longer. We also find that the percentage of videos which have any tags or a description stays relatively constant, but the average number of unique tags drops. These analyses indicate that the quality of descriptions and tags tend to decrease, that is, they get shorter and therefore less descriptive, for larger dataset sizes. Notably, we do not see the same for titles or channel names, indicating that these may be a more reliable source of supervision at the largest dataset sizes. This is reflected in our experiments in Section 5.2, where we find that using all sources of metadata is helpful for smaller dataset sizes, but that these additional sources of metadata reduce performance when scaled to the largest dataset sizes.

Implementation Details and Deduplication. Since Kinetics videos are also collected from the Internet, we discard videos from WTS which appear in the Kinetics validation or test sets. Since many videos do not contain a description or tags, we code the missing information as an empty string, rather than discarding these videos. We perform all searches in English, so WTS contains primarily (though not exclusively) English-language videos and metadata. However, our approach is extensible to any language.

Table 1. Datasets for video representation learning. WTS-70M contains 70 million clips, each from a unique source video, and each video is paired with textual metadata.

| Dataset          | Videos | Duration (hrs) | Supervision |
|------------------|--------|---------------|-------------|
| Sports-1M [31]   | 1.1M   | 15K           | Topics      |
| Youtube-8M [11]  | 8M     | 500K          | Topics      |
| HowTo100M [46]   | 1.2M   | 136K          | Speech      |
| IG-Kinetics [19] | 65M    | 72K           | Hashtags    |
| WTS-70M (ours)   | 70M    | 194K          | Metadata    |

4. Model

At a high level, our approach (Figure 3) learns video representations by creating representations of the video’s metadata, and encouraging the video representations to match these metadata representations. The video representation is a vector \( f_v \in \mathbb{R}^{D_v} \), and the metadata representation is a vector \( f_t \in \mathbb{R}^{D_t} \), where the vector dimensions \( D_v \) and \( D_t \) are dependent on the models used to extract each representation and do not need to be the same.

Intuitively, the video and its metadata contain similar information, and therefore their representations \( f_v \) and \( f_t \) should contain similar information. However, the information contained in the video and its metadata are not exactly the same. The video will always contain information which is not present in the metadata. For example, the description of a rock climbing video will not list every hold the climber uses on their route. Likewise, the text will provide context which is not present in the video, such as listing the time and location where the video was shot. With our approach, we leverage this observation by encouraging the video representations to be similar, but not the same as, the corresponding metadata representation.

Specifically, the video representations (a 1-D vector for each video) are trained by predicting the metadata representations (a 1-D vector for each piece of text). We predict the metadata representations from the video representations by applying a simple linear transformation, that is \( \hat{f}_t = W f_v + b \), where \( W \in \mathbb{R}^{D_t \times D_v} \) and \( b \in \mathbb{R}^{D_t} \). We then apply a ranking loss which penalizes \( f_v \) if \( \hat{f}_t \) is similar to the metadata representation for another video \( f_v' \). That is,

\[
L_{\text{rank}}(f_v, f_t, f_v') = \max(0, m + d(\hat{f}_t, f_v) - d(\hat{f}_t, f_v')) \tag{1}
\]

where \( d \) is a distance metric, and \( m \) is the minimum allowable margin between \( d(\hat{f}_t, f_v) \) and \( d(\hat{f}_t, f_v') \). In our experiments, we set \( d \) as the cosine distance, \( d(u, v) = 1 - \frac{u^T v}{\|u\|_2 \|v\|_2} \), and choose the margin to be \( m = 0.1 \).

For the loss, we require a “negative” metadata representation \( f_v' \), that is, one drawn from a different video than \( f_v \). We draw the negative example \( f_v' \) from another video in the dataset uniformly at random. In addition, we use multiple negative examples \( \{f_v' | i = 1 \ldots K\} \) for each positive example, and take the mean of their respective losses to get the final loss, \( L = \frac{1}{K} \sum_{i=1}^{K} L_{\text{rank}} \). In practice, we use \( K = 15 \), giving a ratio of 1 positive example for every 15 negative examples. We do not perform any hard-negative mining; we find that uniformly sampled negatives are sufficient. These negative examples are taken from the same batch of SGD training for convenience of implementation.

Multiple Sources of Metadata. When using more than one source of metadata for pre-training, we compute separate metadata representations \( f_v \) for each source. Then, for each
Figure 2. Scaling properties of WTS. **Left:** Rate of missing descriptions and tags, and number of tags. Both descriptions and tags are empty for a large number of videos, at all dataset sizes. **Right:** Mean length (in words) of each metadata type. Descriptions and tags tend to get shorter with larger dataset sizes, but titles and channel names tend to get slightly longer.

![Diagram](image)

Figure 3. Model architecture for cross-modal unsupervised learning from textual metadata. We encode the video using R3D-50 [26], and the metadata using BERT [12]. We then train the video representation by matching it with the correct metadata representation.

**End-to-End Video Representation Training.** We train the video representation $f_v$ end-to-end with the linear transformation parameters $W, b$ to compute a source-specific $f_v$. We then separately compute a loss for each source as in Equation 1. The final loss is the sum.

We train the model using stochastic gradient descent, with Nesterov momentum of 0.9 [59] and a weight decay of 1e-5. We apply dropout with a rate of 0.5 to the video features. We use a batch size of 2048 split into chunks of 16 videos across each of 128 accelerators, trained synchronously. The learning rate schedule begins with 1500 warmup steps for S3D-G or 2000 for R3D-50 (exponentially increasing from 0.001 to 1.0 for S3D-G and 1.6 for R3D-50), followed by a cosine-decaying [41] schedule for the remaining steps (140K for S3D-G, 120K for R3D-50). Due to the large batch size, training takes less than 3 days.

**4.1. Video Representation**

We create the video representation $f_v \in \mathbb{R}^{D_v}$ using a 3D Convolutional Neural Network (3D CNN) which operates directly on the RGB video frames. The input to the 3D CNN is therefore a $H \times W \times T \times 3$ video clip. To get the video representation, we take the final hidden layer of the network and mean-pool across the spatial and temporal dimensions, resulting in a vector of length $D_v$.

In our work, we use S3D-G [67] and 3D ResNet-50 (R3D-50) [26] as the backbone 3D CNN architectures. We choose these two architectures because R3D-50 provides high capacity and performance, while S3D-G offers lower computational cost while still outperforming well-known architectures such as I3D [9]. During training, we apply the 3D CNN on 64-frame clips drawn uniformly at random from the video at 25fps. For R3D-50 we sample 32 frames with stride 2 to match with [54]. We resize the frames to 256px on the shortest edge, and then take a random $224 \times 224$ crop. We additionally perform brightness, contrast, and flipping augmentation. During inference, we use 250-frame clips (with circular padding where necessary), and take a center $224 \times 224$ crop. Similarly, we use 124 frames with stride 2 for R3D-50.

**4.2. Metadata Representation**

For each piece of textual metadata, we create a metadata representation $f_t \in \mathbb{R}^{D_t}$ using BERT [12], a state of the art text encoder. BERT returns a 768-dimensional embedding for each token in the text, and we take the mean of these token-level embeddings to get a single 768-dimensional representation of the metadata, that is, $D_t = 768$.

Specifically, we use the multilingual, cased version of
BERT which was pre-trained on 104 languages, and has 12 layers and 110M parameters. We use the multilingual version because non-English text appears in WTS-70M. Since our goal is to learn video representations, we do not fine-tune the BERT model. This also significantly alleviates the computational cost of training; otherwise fine-tuning the text model would dominate the computational cost.

When computing features for tags (where each video can have zero to many tags), we compute a BERT embedding for each individual tag and take the mean of the results. For videos with no tags, we replace it with an empty string. Each of the three other pieces of metadata (titles, descriptions, and channel names) are treated the same.

5. Experiments

For some of our experiments, we use a subset of the full 70M-video dataset. These subsets are denoted by the approximate number of videos they include: 500K, 1M, 6M, 12M, 40M, and 70M. These subsets are not selected at random, instead each subset is chosen by selecting a smaller number of the top search results from each query, such that the 500K subset contains approximately the top 700 results per query and 70M contains 100K results per query. This reflects the way that such a method could be used in practice; one would search for queries relevant to their particular downstream task and collect as many of the top search results as they can, subject to space or bandwidth constraints.

We do not segment WTS-70M into a validation or test split, and instead evaluate our learned model purely by its performance on downstream tasks. We evaluate on three downstream video classification tasks: HMDB-51, HMDB-51 [36] is an action recognition dataset consisting of short video clips associated with one of 51 classes. It contains 7000 videos, and is commonly used as a benchmark for video representation learning. We report results on the first test split, except where otherwise noted. When fine-tuning on HMDB-51, we use a learning rate of 1e-3 with an exponential decay schedule, a weight decay of 1e-7, and we train for 30 epochs.

UCF-101. UCF-101 [57] is a similar action recognition dataset consisting of video clips associated with one of 101 classes. It is larger than HMDB-51, consisting of over 13,000 videos. We report results on the first test split, except where otherwise noted. When fine-tuning on UCF-101, we use a learning rate of 1e-3 with an exponential decay schedule, a weight decay of 1e-7, and we train for 30 epochs.

Kinetics-400, 600, 700. Kinetics is a widely-used action recognition dataset consisting of 10-second clips drawn from videos annotated with action categories [52]. Kinetics-400, 600, and 700 are increasingly large versions of the dataset, containing 400, 600, and 700 action categories, respectively [7, 8]. Kinetics contains over 545K videos, and due to its scale, it is commonly used to pre-train video representations. We compare against Kinetics as a pre-training scheme, in addition to as a downstream task.

Kinetics videos can be deleted by their uploaders at any time, and then can no longer be recovered by researchers. Therefore, Kinetics gradually deteriorates over time, which generates discrepancies between both training and evaluation performed at different times. Our experiments were conducted using a snapshot of the Kinetics dataset collected in February 2020, when Kinetics-400 contained 225K of the original 247K training examples (-8.9%), Kinetics-600 contained 378K of the original 393K training examples (-3.8%), and Kinetics-700 contained 541K of the original 545K training examples (-0.7%).

5.1. Different Forms of Metadata

We collect four types of metadata for each video: the title, description, tags, and channel name (Section 3). We observe that each type of metadata contains a different level of detail and is affected by different sources of noise (Figure 1). Therefore, we expect the different types of metadata to have different impacts on downstream performance. We investigate which of these are the most useful for pre-training in Table 2. For these experiments, we pre-train the model on WTS-500K and fine-tune on HMDB-51.

We find that all types of metadata are useful sources of supervisory signal for pre-training. Titles are the most effective, achieving an increase in downstream accuracy of 15.3% over a from-scratch baseline. Channel names are the least effective, resulting in only a 1.2% improvement over the baseline. However, we find that these sources of supervision provide complementary signals, and that we achieve the best performance by including all of them during pre-training. This achieves a down-stream accuracy of 50.0% on HMDB-51, a 22.1% improvement over from-scratch.

In addition, these experiments can be used to show

| Supervision      | HMDB-51 |
|------------------|---------|
| Scratch          | 27.9    |
| Titles           | 43.2    |
| Descriptions     | 37.7    |
| Tags             | 36.2    |
| Channel Name     | 29.1    |
| Titles + Desc.   | 43.9    |
| Titles + Desc. + Tags | 46.5 |
| All              | 50.0    |

Table 2. Sources of metadata used and their effect on downstream performance, as measured on HMDB-51 with an S3D-G backbone. Each source of metadata contributes individually to the final accuracy. For these experiments, we pre-train on WTS-500K. All reported accuracies are on HMDB-51 split 1.
Figure 4. Performance of our approach on HMDB-51 (split 1) with an S3D-G backbone for increasingly larger pre-training dataset sizes, compared to a baseline S3D-G model trained from scratch and one trained on HowTo100M with MIL-NCE [45]. Our approach can learn effectively from 70M videos and exceeds the performance of MIL-NCE with 12M videos.

Table 3. Comparison with self-supervised pre-training prior work on HMDB-51 and UCF-101. “Data” refers to the source of pre-training videos, however, these approaches do not use the available labels. “Mod.” refers to the modalities used to train each model. All numbers are quoted directly from the original authors. Our results are averaged across all three splits of HMDB-51 and UCF-101. *Reimplemented by [58].
Table 4. Experiments on Kinetics. Our method and baselines are trained without labels and we report classification performance for both frozen feature and fine-tuning experiments.

| Method   | Model  | Frozen | K400 | K600 |
|----------|--------|--------|------|------|
| VINCE [22] | R3D-50 | ✓      | 36.2 | -    |
| VTHCL [69] | R3D-50 | ✓      | 37.8 | -    |
| CVRL [54] | R3D-50 | ✓      | 66.1 | 70.4 |
| WTS-70M (Ours) | R3D-50 | ✓      | 72.7 | 75.5 |
| Scratch   | R3D-50 |        | 73.4 | 78.8 |
| WTS-70M (Ours) | R3D-50 |        | 75.1 | 79.3 |

Table 5. Comparison with semi-supervised learning on Kinetics-600. We finetune WTS using a fraction of the labeled videos in Kinetics-600. CVRL [54] uses unlabeled Kinetics-600 videos for pre-training, which makes their approach semi-supervised.

| Method   | Model  | Label fraction 1% | Label fraction 10% |
|----------|--------|------------------|-------------------|
| Scratch   | R3D-50 | 4.3              | 45.3              |
| CVRL [54] | R3D-50 | 36.7             | 56.1              |
| WTS-70M (Ours) | R3D-50 | 40.9             | 61.5              |

Table 6. Complementary nature of our approach and fully-supervised learning (using S3D-G backbone). We pre-train the model on WTS-70M, then fine-tune it on Kinetics, then apply it to HMDB-51 (split 1). KX = Kinetics-X.

| Pre-training | Model  | HMDB-51 |
|--------------|--------|---------|
| 70M          | S3D-G  | 67.4    |
| K700         | S3D-G  | 71.1    |
| 70M+K400     | S3D-G  | 72.2    |
| 70M+K600     | S3D-G  | 74.5    |
| 70M+K700     | S3D-G  | 75.9    |

5.4. Semi-Supervised Learning

We additionally perform an experiment in the extreme low-data regime. Specifically, we use random subsets of Kinetics-600 to fine-tune a WTS pre-trained R3D-50 model. These subsets have as few as 6.5 examples per class on average, making them much more challenging than the full Kinetics-600 dataset. In Table 5, we show that WTS-70M pre-training strongly outperforms from-scratch training, and also outperforms CVRL [54].

5.5. Complementary Strong and Weak Supervision

Our approach learning has the capacity to exceed the performance of strongly-supervised learning, without any labels (Section 5.2). However, in practice, one would use all sources of supervision available, including labeled datasets. Therefore, we ask whether our approach and strongly-supervised learning can be applied in combination, to further improve the performance on downstream tasks. We test this in Table 6 by training in a three-step process: first, we pre-train our model on WTS-70M. Then, we fine-tune this model on Kinetics. Finally, we apply the resulting model to HMDB-51.

We find that our approach and strongly-supervised learning are indeed complementary. When using both WTS-70M and Kinetics-700 in combination, the downstream accuracy on HMDB-51 increases by a further 8.5% over Kinetics-700 alone. This demonstrates that our method is effective even in situations where labeled data is already plentiful.

6. Conclusions

We demonstrate that textual metadata serves as a useful signal for pre-training video representations, without the need for any manually annotated labels. Specifically, we find that each textual signal is complementary (Section 5.1), and that this approach exceeds the performance of supervised pre-training when scaled to tens of millions of videos (Section 5.2). We also show that it outperforms competitive approaches for both self-supervised and webly-supervised...
learning (Section 5.3). Finally, we demonstrate that it works in extreme low-data regimes (Section 5.4) and is complementary with full supervision (Section 5.5). These findings suggest that textual metadata can be used as an effective pre-training strategy for a wide variety of downstream tasks.

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Appendix A. Scaling to 70M Details

In Table 7, we show the number of pre-training iterations used for the scaling experiments (Fig. 4 in the main paper). Other than changing the number of pre-training iterations, we do not modify any hyper-parameters when training on the smaller subsets of WTS-70M.

| Dataset | Iters | HMDB-51 |
|---------|-------|---------|
| Scratch | N/A   | 27.9    |
| 500K    | 20K   | 43.2    |
| 1M      | 25K   | 50.5    |
| 6M      | 30K   | 58.9    |
| 12M     | 50K   | 63.2    |
| 40M     | 100K  | 65.2    |
| 70M     | 120K  | 71.1    |
| K700    | 30K   | 67.4    |

Table 7. Number of pre-training iterations and resulting accuracy for scaling experiments with S3D-G backbone. K700 = fully supervised pretraining on Kinetics-700 (not comparable).

Appendix B. Semi-Supervised Learning

In Table 8, we show extended results from our semi-supervised learning experiments (Table 5).

| Videos Used | Scratch | WTS-70M |
|-------------|---------|---------|
| 1%          | 6.0     | 40.9    |
| 2%          | 14.1    | 47.7    |
| 5%          | 22.5    | 56.7    |
| 10%         | 47.4    | 61.5    |
| 25%         | 58.0    | 65.4    |
| 50%         | 72.8    | 74.0    |
| 100%        | 78.8    | 79.3    |

Table 8. Number of K600 videos used and resulting accuracy for few-shot experiments with R3D-50 backbone.

Appendix C. Metadata Analysis

We present additional analyses and examples of the metadata in the WTS-70M dataset in Tables 9, 10, and 11, each of which shed some light on why titles are generally the most useful piece of metadata for supervision. Table 9 shows the portion of unique instances for each metadata type. Titles have the highest proportion of unique instances, and are also the most useful signal for pre-training, implying that having many unique titles may be helpful. Table 10 shows the distribution of lengths of each metadata type. Here, titles again show different characteristics from other forms of metadata; the median title contains 4 words, while the median description contains only 3 (despite descriptions being much longer on average). This indicates one other reason my titles might be the most useful, because longer metadata contains more information about the video. Table 11 shows some examples of the most common titles and tags found in the dataset. We find that titles, even when repeated many times in the dataset, are generally informative about the content of the video. Other forms of metadata are less informative.

| Metadata    | Num. Unique | % Unique |
|-------------|-------------|----------|
| Titles      | 43.0M       | 61.5     |
| Descriptions| 29.3M       | 41.9     |
| Tags        | 34.0M       | 48.6     |
| Channel Name| 21.0M       | 29.9     |

Table 9. Number of unique instances for each metadata type in WTS-70M. All metadata types contain repeats though some are repeated more often than others. Many channels are repeated, and we on average collect 3.3 videos per channel.

| Metadata    | Min  | 25  | 50  | 75  | Max  |
|-------------|------|-----|-----|-----|------|
| Titles      | 0    | 2   | 4   | 6   | 158  |
| Descriptions| 0    | 0   | 3   | 12  | 4249 |
| Tags        | 0    | 0   | 0   | 5   | 161  |
| Channel Name| 0    | 1   | 2   | 2   | 306  |

Table 10. Quartiles of length (in words) of each metadata type. All have a long-tailed distribution, meaning that in extreme cases, the metadata may be hundreds or thousands of words long. However, all metadata types also contain examples which are empty or contain zero words. Titles are shortest in the most extreme cases, but longest in the median case.
Table 11. Top ten most often-repeated titles and tags. For titles, these are descriptive and reflect the content of the video. For tags, these often contain automatically-generated metadata which reflect the method by which the video was uploaded.

| Metadata | Text                  | Instances |
|----------|-----------------------|-----------|
| **Titles** | “Free fire”          | 92K       |
|          | “Dance”               | 50K       |
|          | “Dancing”             | 47K       |
|          | “Baby”                | 34K       |
|          | “Bottle flip”         | 31K       |
|          | “Free Fire”           | 29K       |
|          | “Cute baby”           | 29K       |
|          | “Playing games”       | 27K       |
|          | “Games”               | 21K       |
|          | “Snow”                | 20K       |
| **Tags** | “PlayStation 4”       | 752K      |
|          | “Sony Interactive Entertainment” | 695K       |
|          | “funny”               | 672K      |
|          | “video”               | 547K      |
|          | “mobile”              | 539K      |
|          | “YouTube Capture”     | 523K      |
|          | “#PS4Live”            | 490K      |
|          | “how to”              | 467K      |
|          | “tutorial”            | 442K      |
|          | “fun”                 | 371K      |