Omni-sourced Webly-supervised Learning for Video Recognition

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Abstract. We introduce OmniSource, a novel framework for leveraging web data to train video recognition models. OmniSource overcomes the barriers between data formats, such as images, short videos, and long untrimmed videos for webly-supervised learning. First, data samples with multiple formats, curated by task-specific data collection and automatically filtered by a teacher model, are transformed into a unified form. Then a joint-training strategy is proposed to deal with the domain gaps between multiple data sources and formats in webly-supervised learning. Several good practices, including data balancing, resampling, and cross-dataset mixup are adopted in joint training. Experiments show that by utilizing data from multiple sources and formats, OmniSource is more data-efficient in training. With only 3.5M images and 800K minutes videos crawled from the internet without human labeling (less than 2% of prior works), our models learned with OmniSource improve Top-1 accuracy of 2D- and 3D-ConvNet baseline models by 3.0% and 3.9%, respectively, on the Kinetics-400 benchmark. With OmniSource, we establish new records with different pretraining strategies for video recognition. Our best models achieve \(80.4\%\), \(80.5\%\), and \(83.6\%\) Top-1 accuracies on the Kinetics-400 benchmark respectively for training-from-scratch, ImageNet pre-training and IG-65M pre-training.

1 Introduction

Following the great success of representation learning in image recognition [21,38,14,16], recent years have witnessed great progresses in video classification thanks to the development of stronger models [37,46,3,42] as well as the collection of larger-scale datasets [3,55,31,30]. However, collecting large-scale human-labeled image datasets [36,58] is well known to be costly and time-consuming. It is even more difficult to do so in the domain of trimmed video recognition. The reason behind is that most online videos are untrimmed, i.e. containing numerous shots with multiple concepts, making it unavoidable to first go through the entire video and then manually cut it into informative video clips based on a specific query. Obviously, such procedure requires far more efforts than image annotation where a simple glance and click is needed. As a result, we note that while the quantity of videos on the web grows exponentially over the past three years, the Kinetics dataset merely grows from 300K videos in 400 classes [18] to 650K in 700 classes [2], partially limiting the scaling-up of video architectures [3].
Fig. 1: OmniSource Framework. We first train a teacher network on the target dataset. Then, we use the teacher network to filter collected web data, including images, short videos, long videos, to reduce noise in web data and improve data quality. Specific transformations are conducted on the filtered out data corresponding to their formats. The target dataset and auxiliary web datasets are used for joint training of the student network.

Instead of confining ourselves to the well-annotated trimmed videos, we move beyond by exploring the abundant visual data that are publicly available on the Internet in a more labor-saving way. These visual data are in various formats, including images, short video clips, and long videos. They capture the same visual world while exhibiting different advantages: e.g. images may be of higher quality and focus on distinctive moments; short videos may be edited by the user, therefore contain denser information; long videos may depict an event in multiple views. We transform the data in different formats into a unified form so that a single model can combine the best of both worlds.

Recent works [28,11] explore the possibility of pre-training from massive unlabeled web images or videos only with hashtags. However, they restrict the scope to the data of a single format. Also, these methods usually require billions of images to obtain a pre-trained 2D CNN model that is resilient to noise, which poses great costs and restricts its practicability. Besides, to take advantage of representation learned from large-scale images for videos, we have to take extra steps to transfer the 2D ConvNets to the 3D counterparts, either by inflating [3] or distillation [12], and then perform fine-tuning on the target dataset, which is tedious and may be suboptimal.

In this work, we propose a simple but unified framework for video classification while utilizing multiple sources of web data including images, trimmed videos and untrimmed videos simultaneously. To enhance data efficiency, we propose a task-driven data collection approach, i.e. obtaining topmost results using the class labels or their simple variants as keywords on search engines, making the supervision most informative. Afterwards, our framework consists of three steps: (1) We train one (or more) teacher network on the labeled dataset; (2) For each source of data collected, we apply the corresponding teacher network to obtain pseudo-labels and filter out those irrelevant samples with low confidence scores; (3) We apply different transforms to convert each type of web data (e.g. images) to the input format needed by the target task (e.g. video clips) and train the student network.

There are two main obstacles during joint training with the labeled dataset and unlabeled web datasets. First, possible domain gaps occur. For example, web images may
focus more on objects and contain less motion blur than videos. Second, the procedure of teacher filtering may lead to unbalanced data distribution across different classes. To mitigate the domain gap, we propose to balance the size of training batches between the labeled dataset and unlabeled web datasets and apply cross-dataset mixup. To cope with data imbalance, we try several simple strategies for resampling. We empirically show that all these techniques contribute to the success of our approach.

Compared to the previous methods, our method excels at the following aspects: (1) Our framework leverages a mixture of web data forms, including images, short videos and untrimmed videos into one student network, aiming at an omni-sourced fashion. (2) Our framework is data-efficient. Empirical results show that only 2M images, a significantly smaller amount compared to the total frame number of Kinetics (240K videos, equivalent to 70M frames), are needed to produce notable improvements (about 1%). For trimmed videos, the required amount is around 0.5M. In stark contrast, 65M videos are collected to obtain a noise-resilient pre-trained model in [11,48]. It is also noteworthy that our framework can also benefit from the massively weakly-supervised pre-training from billions of images or videos.

To sum up, our contributions are as follows:

(1) We propose a simple and efficient framework, called OmniSource, for webly-supervised video classification, which can leverage web data in different formats.

(2) We propose several good practices to deal with problems during joint training on data from multiple sources, including source-target balancing, resampling and cross-dataset mixup.

(3) In experiments, our models trained by OmniSource achieve state-of-the-art performance on the Kinetics-400 benchmark, for all pre-training strategies we tested.

2 Related work

Webly-supervised learning Leveraging information from the Internet, termed webly-supervised learning, has been extensively explored [24,49,13]. Divvala et al in [7] proposes to automatically learn models from online resources for visual concept discovery and image annotation. Chen et al reveals that images crawled from the Internet can yield superior results over the fully-supervised method [5]. When it comes to the domain of video classification, Ma et al proposes to use web images to boost action recognition models in [27] at the cost of manually filtering web action images. To free from additional human labor, efforts have been made to learn video concept detectors [50,25] or to select relevant frames from videos [10,40,51]. These methods are based on frames where an image classifier is applied, failing to consider the rich temporal dynamics of videos. Recent works [28,11] show that webly-supervised learning can produce better pre-training models in the presence of very large scale noisy data (such as billions of images and $\sim 10^7$ videos). Being orthogonal to the pre-training stage, our framework works in a joint-training paradigm and is complementary to large-scale pre-training.

Semi-supervised learning Our framework works under the semi-supervised setting where both labeled data and unlabeled data (from the web) co-exist. Representative classical approaches include label propagation [60], self-training [35], co-training [1], and graph networks [20]. Deep models make it possible to learn directly from unlabeled
data via generative models [19], self-supervised learning [52], or consensus of multiple experts [53]. However, most of the existing methods are validated only on smaller-scale datasets, e.g. partially labeled ImageNet. One concurrent work [48] proposes to first train a student network with unlabeled data with pseudo-labels and then fine-tune it on the labeled dataset. Our framework, however, works on the two data sources simultaneously, free from the complicated two-stage paradigm and is also more data-efficient.

**Distillation** According to the setting of knowledge distillation [15] and data distillation [34], given a set of manually labeled data, we can train one (or even more) base model in the manner of supervised learning. The model(s) is then applied to the unlabeled data or its transforms. Most of the previous efforts [34] are confined to the domain of images. In [12], Rohit et al proposes to distill spatial-temporal features from unlabeled videos with image-based teacher networks. Our framework is capable of distilling knowledge from multiple sources and formats within a single network.

**Domain Adaptation** Since web data from multiple sources are taken as input, domain gaps inevitably exist. Previous efforts [6,44,4] in domain adaptation focus on mitigating the data shift [33] in terms of data distributions. On the contrary, our framework focuses on adapting visual information in different formats (e.g. still images, long videos) into the same format (i.e. trimmed video clips).

**Video classification** Video analysis has long been tackled using hand-crafted feature [23,45]. Following the success of deep learning in the image domain, video classification architectures have been dominated by two families of deep ConvNets, i.e. two-stream approaches [37,46] and 3D ConvNets [3,43]. The former one first uses 2D networks to extract image-level feature and then performs temporal aggregation [46,57,17] on top while the latter learns spatial-temporal features directly from video clips in the form of consecutive frames [43,8,42].

## 3 Method

### 3.1 Overview

We propose a unified framework for omni-sourced webly-supervised video recognition, formulated in Sec. 3.2. Briefly speaking, the framework exploits web data of various forms (images, trimmed videos, untrimmed videos) from various sources (search engine, social media, video sharing platform) in an integrated way. Since web data can be very noisy, we use a teacher network to filter out samples with low confidence scores and obtain pseudo labels for the remaining ones (Sec. 3.4). We devise transformations for each form of data to make them applicable for the target task in Sec. 3.5. In addition, we explore several techniques to improve the robustness of joint training with web data in Sec. 3.6.

### 3.2 Framework formulation

Given a target task (trimmed video recognition in our case) and its corresponding target dataset $D_T = \{(x_i, y_i)\}$, we aim to harness information from unlabeled web resources $U = U_1 \cup U_2 \cup \cdots \cup U_n$, where $U_i$ refers to unlabeled data in a specific source or format. **First**, we construct the pseudo-labeled dataset $\hat{D}_i$ from $U_i$. Samples with low confidence scores are dropped using a teacher model $\mathcal{M}$ trained on $D_T$, and the
remaining data are assigned with pseudo-labels $\hat{y} = \text{PseudoLabel}(M(x))$. **Second,** we devise appropriate transforms $T_i(x) : \mathcal{D}_i \to \mathcal{D}_{A,i}$ to process data in a specific format (*e.g.* still images or long videos) into the data format (trimmed videos in our case) in the target task. We denote the union of $\mathcal{D}_{A,i}$ to be the auxiliary dataset $\mathcal{D}_A$. **Finally,** a model $M'$ (not necessarily the original $M$), can be jointly trained on $\mathcal{D}_T$ and $\mathcal{D}_A$. In each iteration, we sample two mini-batches of data $B_T, B_A$ from $\mathcal{D}_T, \mathcal{D}_A$ respectively. The loss is a sum of cross entropy loss on both $B_T$ and $B_A$, indicated by Eq 1.

$$L = \sum_{x,y \in B_T} L(F(x; M'), y) + \sum_{x,\hat{y} \in B_A} L(F(x; M'), \hat{y})$$

For clarification, we compare our framework with some recent works on billion-scale webly-supervised learning in Table 1. OmniSource is capable of dealing with web data in multiple sources and is also significantly more data-efficient. It is also noteworthy that our framework can also benefit from webly-supervised pre-training [11].

**Table 1: Difference with previous works.** The notions follow Sec. 3.2, where $U$ is the unlabeled web data, and $\mathcal{D}_T$ is the target dataset. $|U|$ and $|\mathcal{D}_A|$ denotes the scale of web data or filtered auxiliary dataset

| Procedure | Webly-supervised pretrain [28,11] | Web-scale semi-supervised [48] | OmniSource (Ours) |
|-----------|----------------------------------|-------------------------------|-------------------|
| 1.        | Train a model $M$ on $U$.        | 1. Train a model $M$ on $\mathcal{D}_T$. | 1. Train one (or more) model $M$ on $\mathcal{D}_T$. |
| 2.        | Fine-tune $M$ on $\mathcal{D}_T$. | Run $M$ on $U$ to pseudo-labeled $\hat{\mathcal{D}}$. | Run $M$ on $\bigcup_i U_i$ to pseudo-labeled $\bigcup_i \hat{\mathcal{D}}_i$. (Samples under certain threshold are dropped.) |
|           |                                 | 3. Train a student model $M'$ on $\hat{\mathcal{D}}$. | 3. Apply transforms $T_i : \hat{\mathcal{D}}_i \to \mathcal{D}_{A,i}$. |
|           |                                 | 4. Fine-tune $M'$ on $\mathcal{D}_T$. | 4. Train model $M'$ (or $M$) on $\mathcal{D}_T \cup \mathcal{D}_A$. |
| $|U|\,$   | 3.5B images or 65M videos         | 3.5B images or 65M videos      | $|U|$: 13M images and 1.4M videos (0.4%~2%) |
|           |                                 |                               | $|\mathcal{D}_A|$: 3.5M images and 0.8M videos (0.1%~1%) |

### 3.3 Task-specific data collection

When a target recognition task comes in, we obtain a bunch of keywords for each class name in the taxonomy, with permutation and stemming optionally. Then we crawl web data from various sources, including search engine, social media and video sharing platform. Comparing with previous works such as [28,11] which rely on large-scale web data with hashtags, our task-specific collection uses keywords which are highly correlated with labels, making the supervision stronger. Moreover, it hugely reduces the required amount of web data by 2 orders of magnitude (*e.g.* from 65M to 0.5M videos on Instagram).

Since web data may contain samples very similar to data in the validation set, data de-duplication is essential for a fair comparison. We perform content-based data de-duplication based on feature similarity. First, we extract frame-level features using an ImageNet-pretrained ResNet50. Then, we calculate the cosine similarity of features between the web data and target dataset after whitening. For each class, the average similarity among different crops of the same frame is used as the threshold for near-duplicate detection. Similarity above it indicates suspicious duplicates. For **Kinetics-400**, in particular, we filter out 4,000 Instagram/Google images (out of 3.5M, 0.1%) and 400 Instagram videos (out of 0.5M, 0.1%), not using them for joint training. We manually inspect a subset of them and find that less than 10% are real duplicates.

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4 For example, “beekeeping” can be transformed to “beekeep”, and “keeping bee”.
3.4 Teacher filtering

Data crawled from the web are inevitably noisy. In our preliminary study, directly using web data without preprocessing for joint training leads to a significant performance drop (over 3%). To prevent irrelevant data from polluting the training dataset, we first train a teacher network $M$ on the target dataset and discard those web data with low confidence scores. For web images, we observe performance deterioration when deflating 3D teachers to 2D and therefore only use 2D teachers. For web videos, we find both applicable and 3D teachers outperform 2D counterparts consistently.

3.5 Transforming to the target domain

Web Images. To prepare web images for video recognition training, we devise several ways to transform a single image into a pseudo video. The first naïve way is to replicate the image $n$ times to form an $n$-frame clip. However, such static video clips may not be optimal since there is a visible gap between static video clips and natural video clips which visually change over time. Therefore, we propose to generate video clips from static images by viewing them with a moving camera. Given an image $I$, under the standard perspective projection model [9], an image with another perspective $\tilde{I}$ can be generated by a homographic transform $\mathcal{H}$ which is induced by a homographic matrix $H \in \mathbb{R}^{3 \times 3}$, i.e., $\tilde{I} = \mathcal{H}(I) = \mathcal{F}(I; H)$. To generate an $N$-frame video clip $J = \{J_1, \cdots, J_N\}$ from $I$, starting from $J_0 = I$, we have

$$J_i = \mathcal{H}_i(J_{i-1}) = (\mathcal{H}_i \circ \mathcal{H}_{i-1} \circ \cdots \circ \mathcal{H}_1)(I)$$

(2)

Each matrix $H_i$ is randomly sampled from a multivariate Gaussian distribution $\mathcal{N}(\mu, \Sigma)$, while the parameters $\mu$ and $\Sigma$ are estimated using maximum likelihood estimation on the original video source. Once we get pseudo videos, we can leverage web images for joint training with trimmed video datasets.

Untrimmed Videos. Untrimmed videos form an important part of web data. To exploit web untrimmed videos for video recognition, we adopt different transformations respectively for 2D and 3D architectures.

For 2D TSN, snippets sparsely sampled from the entire video are used as input. Thus we first extract frames from the entire video at a low frame rate (1 FPS). A 2D teacher is used to get the confidence score of each frame, which also divides frames into positive ones and negative ones. In practice, we find that only using positive frames to
construct snippets might be a sub-optimal choice. Instead, combining negative frames and positive frames can form harder examples, resulting in better recognition performance. In our experiments, we use 1 positive frame and 2 negative frames to construct a 3-snippet input.

For 3D ConvNets, video clips, which are continuous frames densely sampled, are used as input. We first cut an untrimmed video into 10-second clips. Then we use a 3D teacher to obtain the confidence scores. Only positive clips are used for joint training.

![Web data distribution](image)

**Fig. 3: Web Data Distribution.** The inter-class data distribution of three web datasets is visualized in (a) - (c), both before and after filtering. (d) gives out samples of filtered out images (cyan box) and remained images (blue box) for GG-k400. Although teacher filtering successfully filters out a lot of negative examples, it makes inter-class data distribution more uneven.

### 3.6 Joint training

Once web data are filtered and transformed into the same format of that in the target dataset $D_T$, we construct an auxiliary dataset $D_A$. A network can then be trained with both $D_T$ and $D_A$ using sum of cross-entropy loss in Eq. 1. As shown in Fig. 3, web data across classes are extremely unbalanced, especially after teacher filtering. Also there exists potential domain gap between $D_T$ and $D_A$. To mitigate these issues, we enumerate several good practices as follows.

**Balance between target and auxiliary mini-batches.** Since the auxiliary dataset may be much larger than the target dataset and the domain gap may occur, the data ratio between target and auxiliary mini-batches is crucial for the final performance. We empirically find that $|B_T| : |B_A| = 2 : 1 \sim 1 : 1$ works reasonably well.

**Resampling strategy.** Web data are extremely unbalanced, especially after teacher filtering (see Fig 3). To alleviate this problem, we explore several sampling policies: (1) sampling from a clipped distribution, in which those classes whose samples exceeds threshold $N_c$ are clipped; (2) sampling from distribution modified by a power law, where the probability of choosing class with $N$ samples is proportional to $N^p$, where $p \in (0, 1)$. In experiments, we find that (2) parameterized by $p = 0.2$ is generally a better practice than sampling from the original distribution.
Cross-dataset mixup. Mixup [54] is a widely used strategy in image recognition. It uses convex combinations of pairs of examples and their labels for training, thus improving the generalization of deep neural networks. We find that technique also works for video recognition. When training teacher networks on $D_T$ only, we use the linear combination of two clip-label pairs as training data, termed as intra-dataset mixup. When both target and auxiliary datasets are used, the two pairs are samples randomly chosen from both datasets, termed as cross-dataset mixup. Mixup works fairly well when networks are trained from scratch. For fine-tuning, the performance gain is less noticeable.

4 Datasets

In this section, we briefly introduce the datasets on which experiments will be conducted. Then we go through different sources from which web data are collected.

4.1 Target datasets

Kinetics-400 The Kinetics dataset [3] is one of the largest video datasets. We use the version released in 2017 which contains 400 classes and each category has more than 400 videos. In total, it has around 240K, 19K, and 38K videos for training, validation and testing subset respectively. In each video, a 10-second clip is annotated and assigned a label. These 10-second clips constitute the data source for the default supervised learning setting, which we refer to K400-tr. The rest part of training videos is used to mimic untrimmed videos sourced from the Internet which we refer to K400-untr.

Youtube-car Youtube-car dataset [59] is a fine-grained video recognition task, which contains 196 types of different cars. It has around 10K videos for training and 5K videos for testing. The videos are untrimmed, lasting around several minutes. Following [59], the frames are extracted from videos at 4 FPS.

UCF101 UCF101 [39] is a small scale video recognition dataset, which has 101 classes and each class has around 100 videos. We use the official split-1 in our experiments, which has about 10K and 3.6K videos for training and testing respectively.

4.2 Web sources

We collect web images and videos from various sources including search engine (e.g. Google Image), social media (e.g. Instagram) and video sharing platform (YouTube).

GoogleImage GoogleImage is a search engine based web data source for Kinetics-400, Youtube-car and UCF101. We query each class name in the target dataset on Google to get related web images. We crawl 6M, 70K, 200K URLs for Kinetics-400, Youtube-car and UCF101 respectively. After data cleaning and teacher filtering, about 2M, 50K, 100K images are used for training on these three datasets. We denote the three datasets as GG-k400, GG-car, and GG-UCF respectively.

Instagram Instagram is a social media based web data source for Kinetics-400. It consists of InstagramImage and InstagramVideo. We generate several tags for each class in Kinetics-400, resulting in 1,479 tags and 8.7M URLs. After removing corrupted data and teacher filtering, about 1.5M images and 500K videos are used for joint training, which we denote as IG-img and IG-vid, respectively. As shown in Fig 3, IG-img
is significantly unbalanced after teacher filtering. Therefore, in the coming experiments, IG-img is used in combination with GG-k400.

**YoutubeVideo** YoutubeVideo is a video sharing platform based web data source for Youtube-car. We crawl 28K videos from youtube by querying class names of Youtube-car. After de-duplicating (remove video IDs appearing in the original Youtube-car dataset) and teacher filtering, 17K videos remain for training, which we denote as YT-car-17k.

## 5 Experiments

### 5.1 Video architectures

We mainly study two families of video classification architectures, namely Temporal Segment Networks [46] and 3D ConvNets [3], to verify the effectiveness of our design under the setting of both snippet-based sampling and clip-based sampling. Unless otherwise specified, we use ImageNet-pretrained models for initialization. We conduct all the experiments using MMAction [56].

**2D TSN** Different from the original setting in [46], we choose ResNet-50 [14] to be the backbone, unless otherwise specified. The number of segments is set to be 3 for Kinetics/UCF-101 and 4 for Youtube-car, respectively.

**3D ConvNets** For 3D ConvNet, we use the SlowOnly architecture proposed in [8] in most of our experiments. It takes 64 consecutive frames as a video clip and sparsely samples 4/8 frames to form the network input. Different initialization strategies are explored, including training from scratch and fine-tuning from a pre-trained model. Besides, more advanced architecture like Channel Separable Network [42] and more powerful pre-training (IG-65M [11]) is also explored.

### 5.2 Verifying the efficacy of OmniSource

In this section, we verify our framework’s efficacy by examining several questions. **Why do we need teacher filtering and are search results good enough?** Some may question the necessity of a teacher network for filtering under the impression that a modern search engine might have internally utilized a visual recognition model, possibly trained on massively annotated data, to help generate the search results. However, we argue that web data are inherently noisy and we observe nearly half of the returned results are irrelevant. More quantitatively, 70% - 80% of the web data are rejected by the teacher. On the other hand, we conduct an experiment without teacher filtering. Directly using collected web data for joint training leads to a significant (over 3%) performance drop on TSN. This reveals that teacher filtering is necessary to help retain the useful information from the crawled web data while eliminating the useless. **Does every data source contribute?** We mainly explore the contribution of different source types, namely, images, trimmed videos and untrimmed videos. For each data source, we construct auxiliary dataset and use it for joint training with K400-tr. Results in Table 2 reveal that every source can contribute to improving accuracy on the target task. When these sources are combined, the performance is further improved.
Table 2: Every source contributes. We find that each source contributes to the target task. When all sources are combined, the improvement can be more considerable. The conclusion holds for both 2D TSN and 3D ConvNets (Format: Top-1 Acc/ Top-5 Acc)

| Arch/Dataset | K400-tr | +GG-k400 | +GG&IG-img | +IG-vid | K400-untr | + All |
|--------------|---------|----------|------------|---------|----------|-------|
| TSN-3seg R50 | 70.6/89.4 | 71.5/89.5 | 72.0/90.0  | 72.0/90.3 | 71.7/89.6 | 73.6/91.0 |
| SlowOnly 4x16,R50 | 73.8/90.9 | 74.5/91.4 | 75.2/91.6  | 75.2/91.7 | 74.5/91.1 | 76.6/92.5 |

For images, when the combination of GG-k400 and IG-img is used, the Top-1 accuracy increases around 1.4%. For trimmed videos, we focus on IG-vid. Although being extremely unbalanced, IG-vid still improves Top-1 accuracy by over 1.0% in all settings. For untrimmed videos, we use the untrimmed version of Kinetics-400 (K400-untr) as the video source and find it also works well.

Do multiple sources outperform a single source? Seeing that web data from multiple sources can jointly contribute to the target dataset, we wonder if multiple sources are still better than a single source with the same budget. To verify this, we consider the case of training TSN on both K400-tr and \( D_A = GG-k400 + IG-img \). We fix the scale of auxiliary dataset to be that of GG-k400 and vary the ratio between GG-k400 and IG-img by replacing images from GG-k400 with those in IG-img. From Fig. 4, we observe an improvement of 0.3% without increasing \( |D_A| \), indicating that multiple sources provide complementary information by introducing diversity.

Table 3: Improvement under various experiment configurations. We test OmniSource framework extensively on various architectures, with various pretraining strategies. The improvement is significant in ALL choices we tested. Even for the SOTA setting, which uses 65M web videos for pretraining, OmniSource still improves the Top-1 accuracy by over 1.0% (Format: Top-1 Acc/ Top-5 Acc)

| Arch      | Backbone | Pretrain | w/o. Omni | w. Omni | \( \Delta \) |
|-----------|----------|----------|-----------|---------|------------|
| TSN-3seg  | ResNet50 | ImageNet | 70.6 / 89.4 | 73.6 / 91.0 | +3.0 / +1.6 |
| TSN-3seg  | Efficient-b4 | ImageNet | 73.3 / 91.0 | 75.2 / 92.0 | +1.9 / +1.0 |
| SlowOnly-4x16 | ResNet50 | -        | 72.9 / 90.9 | 76.8 / 92.5 | +3.9 / +1.6 |
| SlowOnly-4x16 | ResNet50 | ImageNet | 73.8 / 90.9 | 76.6 / 92.5 | +2.8 / +1.6 |
| SlowOnly-8x8 | ResNet101 | -        | 76.3 / 92.6 | 80.4 / 94.4 | +4.1 / +1.8 |
| SlowOnly-8x8 | ResNet101 | ImageNet | 76.8 / 92.8 | 80.5 / 94.4 | +3.7 / +1.6 |
| irCSN-32x2 | irCSN-152 | IG-65M   | 82.6 / 95.3 | 83.6 / 96.0 | +1.0 / +0.7 |

Table 4: Multi-source is better. Mixing multiple sources leads to better performance when the number of web images used is constrained.

Does OmniSource work with different architectures? We further conduct experiments on a wide range of architectures and obtain the results in Table 3. For TSN, we use EfficientNet-B4 [41] instead as the backbone, on which OmniSource improves Top-1 accuracy by 1.9%. For 3D-ConvNets, we conduct experiments on the SlowOnly-8x8-ResNet101 baseline, which takes longer input and has a larger backbone. Our framework also works well in this case, improving the Top-1 accuracy from 76.3% to 80.4% when training from scratch, from 76.8% to 80.5% with ImageNet pretraining. The improvement on larger networks is higher, suggesting that deeper networks are more prone to suffering from the scarcity of video data and OmniSource can alleviate this.
Is OmniSource compatible with different pre-training strategies? As discussed, OmniSource alleviates the data-hungry issue by utilizing auxiliary data. One natural question arises: how does it perform when training 3D networks from scratch? In other words, can we simply drop ImageNet pretraining in pursuit of a more straightforward training policy? Indeed, we find that OmniSource works fairly well under this setting and interestingly the performance gain is more significant than fine-tuning. For example, SlowOnly-(4x16, R50) increases the Top-1 accuracy by 3.9% when training from scratch while fine-tuning only increases by 2.8%. The model trained from scratch beats the fine-tuned counterpart by 0.2% with OmniSource though being 0.9% lower with only K400-untr. Similar results can be observed for SlowOnly-(8x8, R101).

| Arch            | UCF101-split1 w/o. Omni | UCF101-split1 w/ Omn | HMDB51-split1 w/o. Omni | HMDB51-split1 w. Omn |
|-----------------|-------------------------|----------------------|------------------------|---------------------|
| TSN-3seg R50[FT]| 91.5                    | 93.3                 | 63.5                   | 65.9                |
| SlowOnly 4x16, R50[FT] | 94.7                    | 96.0                 | 69.4                   | 70.7                |
| SlowOnly 4x16, R50[SC] | 94.1                    | 96.0                 | 65.8                   | 71.0                |

Table 4: Features learned by OmniSource transfer well. We finetune on UCF101 and HMDB51 with k400-trim pretrained weight. The reported accuracy is on the split-1 of each dataset. Pretraining with OmniSource improves the performance of downstream tasks significantly.

Do features learned by OmniSource transfer to other tasks? Although OmniSource is designed for a specific video recognition task, it turns out that the learned features also transfer well to other video recognition tasks. To evaluate the capability of transferring, we fine-tune the learned model on two relatively smaller video recognition benchmark: UCF101 [39] and HMDB51 [22]. Table 4 indicates that on both benchmarks, pretraining with OmniSource framework leads to significant performance improvements. Following standard evaluation protocol, our best model (SlowOnly-8x8-R101) achieves 97.3% Top-1 accuracy on UCF101, 79.0% Top-1 accuracy on HMDB51 with RGB input only. When combined with optical flow, it achieves 98.6% and 83.8% Top-1 accuracy on UCF101 and HMDB51 respectively, which is the new state-of-the-art. More results on transfer learning will be provided in the supplementary material.

Does OmniSource work in different target domains? Our framework is also effective and efficient in various domains. On a fine-grained recognition benchmark called Youtube-car with 10K training videos, only 50K web images (GG-car) and 17K web videos (YT-car-17k) are used for training. As shown in Table 5, the performance gain is significant: 5% in both Top-1 accuracy and mAP. Note that the baseline we use is finely tuned comparing to the original paper [59], i.e. better performance with a lighter backbone. On UCF-101, we train a two-stream TSN network with BNInception as the backbone. The RGB stream is trained either with or without GG–UCF. The results

Fig. 5: Improved Confusing pairs. The discriminative power on confusing pairs improves when trained with OmniSource. Black numbers denote original accuracy, color numbers denote the change.
are listed in Table 6. The Top-1 accuracy of the RGB stream improves by 2.7%. When fused with the flow stream, there is still an improvement of 1.1%.

**Where does the performance gain come from?** To find out why web data help, we delve deeper into the collected web dataset and analyze the performance improvement of individual classes. The models compared are both TSN with ResNet-50 as its backbone, trained either with or without **GG-k400**. Training with GG-k400 leads to 0.9% Top-1 accuracy improvement on average. We mainly focus on the confusion pairs that web images can improve. Here, we define the *confusion score* of a label pair as:

\[
s_{ij} = \frac{n_{ij} + n_{ji}}{n_{ij} + n_{ji} + n_{ii} + n_{jj}}. \tag{3}
\]

\(n_{ij}\) denotes the number of images whose ground-truth are class \(i\) while being recognized as class \(j\). Lower confusion score denotes better discriminating power between the two classes. We visualize some confusing pairs in Fig 5. We find the improvement can be mainly attributed to the following two reasons: (1) Web data usually focus on key objects of action. For example, we find that in those pairs with the largest confusion score reduction, there exist pairs like “drinking beer” vs.“drinking shots”, and “eating hotdog” vs.“eating chips”. Training with web data leads to better object recognition ability in some confusing cases. (2) Web data usually include discriminative poses, especially for those actions which last for a short time. For example, the pair “rock scissors paper” vs.“shaking hands” has the second-largest confusion score reduction. Other examples including “sniffing”-“headbutting”, “break dancing”-“robot dancing”, etc.

**Table 5:** Youtube-car

| Setting         | Top-1 mAP  |
|-----------------|------------|
| Baseline        | 77.05 71.95|
| +GG-car         | 80.96 77.05|
| +YT-car-17k     | 81.68 78.61|
| +[GG-]+[YT-]    | 81.95 78.67|

**Table 6:** UCF-101

| Setting         | + Flow Top-1 |
|-----------------|--------------|
| Baseline        | 86.04        |
| + GG-UCF        | 88.74        |
| Baseline        | 93.47        |
| + GG-UCF        | 94.58        |

**Table 7:** Comparisons with the state-of-the-art on Kinetics-400

| Method          | backbone | pretrain | Top-1 | Top-5 |
|-----------------|----------|----------|-------|-------|
| TSN-7seg [46]   | Inception-v3 | ImageNet | 73.9  | 91.1  |
| TSM-8seg [26]   | ResNet50  | ImageNet | 72.8  | N/A   |
| TSN-3seg (Ours) | ResNet50  | ImageNet | 73.6  | 91.0  |
| TSN-3seg (Ours) | Efficient-b4 | ImageNet | 75.2  | 92.0  |
| SlowOnly-8x8    | ResNet101 | -        | 75.9  | N/A   |
| SlowFast-8x8    | ResNet101 | -        | 77.9  | 93.2  |
| SlowOnly-8x8 (Ours) | ResNet101 | -        | 80.4  | 94.4  |
| I3D-64x1 [3]    | Inception-V1 | ImageNet | 72.1  | 90.3  |
| NL-128x1 [47]   | ResNet101 | ImageNet | 77.7  | 93.3  |
| SlowOnly-8x8    | ResNet101 | ImageNet | 77.9  | 93.2  |
| LGD-3D (RGB) [32] | ResNet101 | ImageNet | 79.4  | 94.4  |
| STDFB [29]      | ResNet152 | ImageNet | 78.8  | 93.6  |
| SlowOnly-8x8 (Ours) | ResNet101 | ImageNet | 80.5  | 94.4  |
| irCSN-32x2      | irCSN-152 | IG-65M   | 82.6  | 95.3  |
| irCSN-32x2 (Ours) | irCSN-152 | IG-65M   | **83.6** | **96.0** |

**5.3 Comparisons with state-of-the-art**

In Table 7, we compare our framework with current state-of-the-art methods on Kinetics-400. Our framework can achieve comparable or better performance with a much simpler (also lighter) backbone design and smaller input size. For 2D TSN, we use fewer segments and lighter backbones but still obtain competitive performance. For 3D ConvNets, there is a considerable improvement for all settings of pre-training when
OmniSource is applied. In particular, when using irCSN-152 [42] pre-trained on IGG-65M [11], OmniSource achieves a Top-1 accuracy of 83.6%, an absolute improvement of 1.0% with only 1.2% relatively more data, establishing a new record on Kinetics-400.

Table 8: Comparison of different ways to transform images into video clips. Still inflation is a strong baseline, while agnostic perspective warping performs best

| Transformation Method               | Top-1 | Top-5 |
|-------------------------------------|-------|-------|
| N/A                                 | 73.8  | 90.9  |
| replication (still)                 | 74.1  | 91.2  |
| translation (random)                | 73.7  | 90.9  |
| translation (constant)              | 73.8  | 90.8  |
| perspective warp [spec]             | 74.4  | 91.3  |
| perspective warp [agno]             | 74.5  | 91.4  |

Table 9: Mixup technique can be beneficial to the discriminative power of recognizer, both for intra- and cross-dataset cases. However, it works only when the model is trained from scratch

| Pretraining Method | Top-1  | Top-5  |
|--------------------|--------|--------|
| ImageNet           | 73.8   | 90.9   |
| ImageNet w. mixup  | 73.6   | 91.1   |
| None               | 72.9   | 90.9   |
| None w. mixup      | 73.3   | 90.9   |
| None w. mixup      | 74.1   | 91.0   |
| None w. mixup      | 74.4   | 91.4   |

5.4 Validating the good practices in OmniSource

We conduct several ablation experiments on the techniques we introduced. The target dataset is K400-tr and the auxiliary dataset is GG-k400 unless specified.

Transforming images to video clips. We compare different ways of transforming web images into video clips in Table 8. Naively replicating still image into several frames to form a pseudo clip brings limited improvement (0.3%). Furthermore, we try to apply translation with randomized or constant speed while forming the pseudo clip. However, the performance deteriorates slightly, suggesting translation cannot mimic the camera motion well. Finally, we resort to perspective warping to hallucinate camera motion, with the distribution parameter of the homographic transform estimated from the data. We find that estimating class-agnostic distribution parameters is slightly better, suggesting that videos from different classes might share similar camera motion statistics.

Cross-Dataset mixup In Table 9, we find that mixup is effective for video recognition in both intra- and cross-dataset cases when the model is trained from scratch. The effect is unclear when fine-tuning from ImageNet. In particular, mixup can lead to 0.4% and 0.3% Top-1 accuracy improvement for both intra- and inter-dataset cases, respectively.

Impact of teacher choice. Since both teacher and student networks can be 2D or 3D ConvNets, there are 4 possible combinations for teacher network choosing. For images, we find that deflating 3D ConvNets down to 2D versions yields a dramatic drop of performance (less than 30% Top-1 accuracy on K400-tr). Therefore, using 3D ConvNet teachers for web images is not a good idea. For videos, however, 3D ConvNets lead to better filtering results comparing to its 2D counterpart.

To examine the effect of different teachers, we fix the student model to be a ResNet-50 and vary the choices of teacher models based on different architectures (ResNet-50, EfficientNet-b4, and an ensemble of ResNet-152 plus EfficientNet-b4). Consistent improvement is observed against the baseline TSN (70.6%). Also, the accuracy of the student network is increased when a better teacher network is used. The conclusion also holds for 3D ConvNets on video sources.

Effectiveness when labels are limited. OmniSource can be more effective when the amount of labeled data is limited. To validate this, we construct 3 subsets of kinetics-
400, which contain 3%, 10% and 30% training data of K400-tr respectively. We rerun the entire framework including data filtering with a weaker teacher. The final classification result on the validation set of K400-tr is shown in Fig 7. Our framework turns out to consistently improve the performance as the percentage of labeled videos varies. Particularly, the gain is more significant when data are scarce, e.g. a relative increase of over 30% when only 3% labeled data are available.

**Fig. 6:** Auxiliary dataset filtered by better teachers leads to students with better performance

**Fig. 7:** Video classification accuracy with different proportions of labeled videos along with auxiliary data

**Fig. 8:** Video classification accuracy on Kinetics with different ratios between \(|B_T|\) and \(|B_A|\)

**Table 10:** Resampling strategies. Simple resampling strategies lead to nontrivial improvement

| Strategy          | Top-1 | Top-5 |
|-------------------|-------|-------|
| None (original)   | 71.5  | 89.5  |
| Clipped \(N_c = 5000\) | 71.9  | 90.0  |
| Power \(\sim N^p, p = 0.5\) | 71.8  | 89.7  |
| Power \(\sim N^p, p = 0.2\) | 72.0  | 90.0  |

**Balancing between the target and auxiliary dataset.** We tune the ratio between the batch size of the target dataset \(|B_T|\) and that of the auxiliary dataset \(|B_A|\) and obtain the accuracy on Fig 8. We consider three scenarios: (1) the original GG–k400, clarified in Sec 4.2; (2) [GG+IG]–k400, the union of GG–k400 and IG–img; (3) [GG+IG]–k400–half which is the half of (2). We observe that the performance gain is robust to the choice of \(|B_T|/|B_A|\) in most of the cases. However, when the auxiliary data are less, the ratio has to be treated more carefully. For example, smaller \(|D_A|\) but larger \(|B_A|\) may cause the model to overfit on the auxiliary samples and hurt the overall performance.

**Resampling strategies.** The target dataset with clean labels is usually tailored to be balanced across classes. This nice property, however, does not necessarily hold for the auxiliary dataset. To alleviate this issue, we examine several strategies of resampling. From Table 10, We see that some simple techniques to tailor the original distribution into a more balanced one yield nontrivial improvements.

**6 Conclusion**

In this work, we propose OmniSource, a simple yet effective framework for webly-supervised video recognition. Our method can utilize web data from multiple sources and formats by transforming them into the type that is suitable for the model of interests. In addition, our approach leverages task-specific data collection and is more data-efficient, which greatly reduces the amount of data required, often 100×, over previous methods. The framework is generalizable to various video tasks such as video recognition and fine-grained categorization. Under all settings of pretraining strategies, we obtain state-of-the-art performance on multiple benchmarks.
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