Conditional Extreme Value Theory for Open Set Video Domain Adaptation

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1 Introduction

With the emergence of copious streaming media data, dynamically recognising and comprehending human actions and occurrence in online videos have become progressively essential, particularly for tasks like video content recommendation [52, 53], surveillance [34], and video retrieval [24]. Although supervised learning techniques [26, 40, 43, 45, 48, 54] are beneficial for the tasks above, they lead to high expenses of labelling massive amounts of training data. The economical solution could be utilising a learner trained on existing labelled datasets to directly infer the labels of target datasets, yet there is often a domain shift between two datasets. Caused by the varying lighting conditions, camera angles and backgrounds, the domain shift triggers the performance drops of the learner. For example, synthetic video clips cropped from action-adventure games could be plentifully labelled and exploited, but inevitably has a huge domain shift from real-world videos such as action movie clips or sports video recordings. To address the issue of domain shift, unsupervised domain adaptation (UDA) techniques are introduced to align distributions between existing labelled data (source domain) and unlabelled data (target domain). To this end, existing UDA approaches either minimise the distribution distance across the domains [2, 5, 11, 16, 55] or learn the domain-invariant representations [8, 38, 51].

In the same vein, the video-based UDA methods aim to align the features at different levels such as frame, video, or temporal relation [8, 19, 29]. However, existing video-based UDA methodologies fail to address an open-set scenario when target samples come from unknown classes that are not seen during training, and can cause negative transfer across domains. Thus, the ability to recognise the unknown classes and reject them from the domain alignment pipeline is essential to the open-set unsupervised domain adaptation (OUDA) task. Moreover, the existing OUDA frameworks are mainly evaluated on still image recognition datasets which are not effective enough to identify unknown samples when applied on video recognition benchmark datasets [1, 7, 12, 13, 30, 42, 58].

To overcome the above-mentioned limitations, we propose to intensify unknown recognition in open-set video domain adaptation. Our proposed framework consists of three modules. The first module is the Class-conditional Extreme Value Theory (CEVT) module that fits the entropy values of target samples to a set of generalised extreme value (GEV) distributions, where unknown samples can be efficiently identified as they lie on the tail of the distribution [15, 21, 35, 57]. Samples are fitted into the multiple class-conditional GEVs depending on the model’s confidence in predicting those samples. For example, videos predicted as “pull-up” and “golf” are fitted into different GEVs. Then, we adaptively set a collection of thresholds for each GEV to split known and unknown samples. These fitted class-conditional GEVs with thresholds are
employed in the other two modules. The second module is the class-conditional weighted domain adversarial learning pipeline to achieve the distribution alignment among shared classes and separate unknown classes. The weight of each sample is calculated by distance from entropy value to the threshold, which denotes the likelihood of belonging to the shared class or unknown class. At the inference stage, we have the third module of open-set recognition to classify samples with higher entropy than the threshold as the unknown class. This module in conjunction with class-conditional GEVs, is more robust to correctly classify hard classes than the typical approach of setting a global threshold. For example, in most of the existing OUDA approaches, the classifier predicts difficult "push-up" samples with the highest probability as "push-up" and with a lower probability as "pull-up". Subsequently, the entropy values for those samples are high, resulting in all the "push-up" samples getting rejected by the global threshold. However, in our framework, we fit all samples predicted as "push-up" to a GEV first, and then, we can efficiently separate "push-up" samples and unknown samples. This framework is particularly effective for complex video sets that the model encounters more challenging training and inference due to the complex spatio-temporal composition of video features. In general, our contributions are summarised as follows:

- We propose a new Class-conditional Extreme Value Theory (CEVT) based framework for unsupervised video open-set domain adaptation that concentrates on domain-invariant representation learning via weighted domain adversarial learning.
- We investigate a new research direction of open-set video DA and introduce the CEVT model to solve the problem.
- Our proposed framework based on class-conditional extreme value theory is effective on both open-set recognition and adversarial weight generation, and it accurately recognises the unknown samples.
- We conducted extensive experiments to demonstrate the effectiveness of the proposed method on both small and large scale cross-domain video datasets and showed that the CEVT based framework achieves state-of-the-art performance. We released the source code of our proposed approach for reference: https://github.com/zhuoxiao-chen/CEVT.

2 RELATED WORK

2.1 Video Action Recognition

Video action recognition is becoming increasingly important in the field of computer vision with many real-world applications, such as video surveillance [34], video captioning and environment monitoring [10, 22, 47, 56]. To classify actions according to individual video frames or local motion vectors, a typical process employs a two-stream convolutional neural network [20, 43]. Some works utilise attention [28, 31], 3D convolutions [45], recurrent neural networks [9], and temporal relation modules [60] to better extract long-term temporal features. Another branch of work, including 3D human skeleton recognition [26, 40], complex object interactions [31] and pose representations [54], supplements the extracted RGB and optical flow features to alleviate the view dependency and noise caused by various lighting conditions. However, the above work necessitates costly annotations and could hardly be extended to an unseen situation, which significantly impedes the practical feasibility.

2.2 Domain Adaptation

To overcome such a limitation, Unsupervised Video Domain Adaptation (UDA) attempts to transfer knowledge from a labelled source domain to an unlabelled target domain. To tackle the domain shift referred to as the discrepancy of two domains, there are mainly two types of approaches. One is the discrepancy-based method that aims to minimise the distribution distance between two domains [3, 4, 16, 37, 39, 55]. The other is the adversary-based method that learns the domain-invariant representation [14, 32, 50]. In addition, adversarial generative and self-supervision-based methods are also investigated by researchers [59]. Recently, existing work has extended the UDA for harder video-based datasets. AMLS [19] applies pre-extracted C3D [45] features to a Grassmann manifold derived from PCA and utilises adaptive kernels and adversarial learning to perform UDA. TA$^2$N [8] attempts to simultaneously align and learn temporal dynamics with entropy-based attention. Using the topology property of the bipartite graph network, ABG [29] explicitly models source-target interactions to learn a domain-agnostic video classifier. Nevertheless, all methods mentioned above assume that the source domain and target domain share the same label set, which is not realistic in real-world scenarios. To address such issue, OUDA that assumes the target domain contains unknown classes, has made efforts at both theoretical and experimental level [1, 6, 7, 30, 42, 58]. DMD [49] attempts to perform OUDA for videos, but fails to evaluate open recognition with the appropriate metric. Despite significant progress in a broader set of video classification and OUDA, domain adaptation has received little attention for knowledge transfer across videos under the open-set setting.

3 METHODOLOGY

In this section, we first give a formal definition of the Open-set Unsupervised Video Domain Adaptation (OUVDA), and then go through the details of our proposed CEVT framework, illustrated in Figure 1.

3.1 Problem Formulation

We are given a labelled source video set $\mathcal{S} = \{(X^s_i, y_i)\}_{i=1}^{N_s} \sim \mathbb{P}^s$ and an unlabelled target video collection $\mathcal{T} = \{(X^t_j)\}_{j=1}^{N_t} \sim \mathbb{Q}^t$, where $N_s$ and $N_t$ are the number of videos in each domain, respectively. Video samples in the source domain $\mathcal{S}$ and the target domain $\mathcal{T}$ are drawn from different probability distributions, i.e., $\mathbb{P}^s \neq \mathbb{Q}^t$. The two domains share $C$ common classes as the known classes. There is the additional class in the target domain $\mathcal{T}$ not shared with the source domain $\mathcal{S}$, which is regarded as the $C + 1$, i.e., the unknown class. Each source video $X^s_i$ or target video $X^t_j$ is composed of $K$ frames, i.e., $X^s_i = (x^s_{ik})_{k=1}^{K}$ and $X^t_j = (x^t_{jk})_{k=1}^{K}$, where $x^s_{ik}, x^t_{jk} \in \mathbb{R}^D$ represent the $D$ dimensional feature vector of $k$-th frame in $i$-th source video and $j$-th target video, respectively. The primary goal of our method is to learn a classifier: $F_{\theta}(\cdot; \theta_r)$ for predicting the $C$ labels of unlabelled videos in target domain and a collection of
We first feed both source videos and target videos into ResNet [17] to align the distributions of the video-level source and target features, we propose a novel class-conditional EVT to generate class-conditional entropy groups.

### 3.2 Source Classification

We first feed both source videos and target videos into ResNet [17] to obtain the frame-level features, i.e., \( \{x_{ik}^s\}_{k=1}^{K} \) for source domain and \( \{x_{jk}^t\}_{k=1}^{K} \) for target domain, respectively. Then the frame-level features are transformed into video-level features, i.e., \( \{V_i^s\}_{i=1}^{N_s} \) and \( \{V_i^t\}_{i=1}^{N_t} \) by frame aggregation techniques, with \( V_i^s, V_i^t \in \mathbb{R}^D \). Without loss of generality, we utilise the mean Average Pooling (Avg-Pool), which is to produce a unified video representation by temporal averaging of the frame features. Thus, each source video-level feature \( V_i^s \) and target video-level feature \( V_i^t \) are defined as below:

\[
V_i^s = \frac{1}{K} \sum_{k=1}^{K} x_{ik}^s, \quad V_i^t = \frac{1}{K} \sum_{k=1}^{K} x_{jk}^t.
\]

(1)

Next, the aggregated features with labels \( \{\{V_i^s, y_i\}\}_{i=1}^{N_s} \) from the source domain are fed into the source classifier \( F_S(\cdot; \theta_c) \), which is trained to minimise the cross entropy loss,

\[
L_c = -\mathbb{E}_{(V,y) \sim p}\left[ \log F_S(V) \right].
\]

(2)

The parameters of the source classifier \( F_S(\cdot; \theta_c) \) are shared with the target classifier \( F_T(\cdot; \theta_c) \), which is used to predict \( C \) classes for target samples. Figure 1 shows the entire source classification process by a green arrow that starts from the videos on the left to the classification loss \( L_c \).

### 3.3 Entropy-based Weights for Domain Adversarial Learning

To align the distributions of the video-level source and target features, we propose a novel class-conditional EVT to generate conditional weights for domain adversarial learning by fitting the entropy values of target samples. The weighted domain adversarial learning can effectively align the known samples from both domains and separate the unknown samples from the target domain simultaneously by assigning instance-level weight to each sample. The samples which come by high probability from known classes are assigned a large weight. Conversely, samples that are likely to be unknown are given a small weight. Finally, all the features are multiplied by their weights and fed into the standard domain adversarial learning module \( F_d(\cdot; \theta_d) \) with the Gradient Reversal Layer (GRL), as shown in Figure 1.

**Class-conditional Extreme Value Theory.** To obtain the weight for each sample, we feed target samples \( \{V_i^t\}_{i=1}^{N_t} \) into target classifier \( F_T(\cdot; \theta_c) \) to get the predictions for shared \( C \) classes. Then, the entropy value of each target sample can be computed from its prediction,

\[
H(V^t) = -\sum_{c=1}^{C} F_T(V^t)_{c} \log F_T(V^t)_{c},
\]

(3)

where \( F_T(\cdot; \theta_c) \) denotes the prediction of class \( c \) by the classifier. Then, the entropy values of target samples are partitioned into \( C \) entropy groups, i.e., \( G = \{G_i\}_{i=1}^{C} \). Target samples predicted to be from \( i \)-th class are allocated to the group \( G_i \). The set of class-conditional entropy group is formulated as:

\[
G = \{H(V^t) : \arg\max_{i} F_T(V^t)_{i} \} \in \{G_i\}_{i=1}^{C}.
\]

Next, each group is fitted into a GEV distribution to obtain a set of CDFs of GEV, i.e., \( \{F_{GEV}(\cdot | \text{class } = i)\}_{i=1}^{C} \), where \( F_{GEV}(\cdot | \text{class } = i) \) indicates the CDF function fitted by entropy values in \( i \)-th group \( G_i \). The CDF of GEV is calculated as

\[
F_{GEV}(x; \mu, \sigma, \xi) = \exp\left(-\left(1 + \frac{1}{\xi} \left(\frac{x - \mu}{\sigma}\right)\right)^{-\frac{1}{\xi}}\right),
\]

(5)

where \( \mu, \sigma, \) and \( \xi \) are three parameters of GEV, determined by fitting data. Utilising the class-conditional EVT can complement the lack of class information for entropy.

**Class-conditional EVT.** After fitting GEVs using entropy values of each entropy group, we set a global threshold \( \delta \) for all the
CDFs in \( \{F_{GEV}(\cdot \mid \text{class } = i)\}_{i=1}^C \). Then, a set of class-conditional entropy threshold is computed for each group, denoted as,
\[
\{e_i : F_{GEV}(e_i \mid \text{class } = i) = \delta_i\}_{i=1}^C.
\]

Given the target sample, \( V^t \) is classified in \( i \)-th class, if \( H(V^t) \) is much greater or smaller than \( e_i \), meaning this sample is very likely to be known or unknown. Then, we assign the weight as 1 or 0 to \( V^t \). If the \( H(V^t) \) is close to \( e_i \), meaning the classifier is unsure about \( H(V^t) \), we assign it a weight which linearly depends on the distance from its entropy value to the corresponding class conditional entropy threshold \( e_i \). The interval for linear variation of weight is named as mixture entropy interval, where most known or unknowns are mixed within this interval. The class-conditional weight can be formulated as,
\[
W(V^t \mid \text{class } = i) = 0.5 + \frac{e_i - H(V^t)}{\min(e_i, (H_{\text{max}}(C) - e_i))},
\]

where \( H_{\text{max}}(C) \) is the entropy value of the evenly spaced vector with norm \( |C| \), with each element of the vector being \( 1/C \). Two black line segments shown in the left bottom of Figure 1 shows the total entropy interval \([0, H_{\text{max}}] \), on which all the entropy values lie. The mixture entropy interval is \([e_i - \min(e_i, (H_{\text{max}}(C) - e_i)), e_i + \min(e_i, (H_{\text{max}}(C) - e_i))\] demonstrated by the dashed rectangles. The length of the entropy mixture interval varies depending on the distance from \( e_i \) to either 0 or \( H_{\text{max}} \), shown by red and yellow dashed rectangles of different length. The entropy threshold \( e_i \) that is close to either 0 or \( H_{\text{max}} \) indicates if the \( i \)-th class is easy or hard, and the distribution of class group \( G_i \) has small variance. Thus, we need a small mixture for those dense group of entropy values to smoothly assign the weights.

**Weighted Domain Adversarial Learning.** After obtaining weights for all the target samples by the class-conditional EVT technique, we train the domain classifier on the target video features multiplied with instance-level weights. The weighted domain classification loss is calculated by,
\[
\mathcal{L}_d = \mathbb{E}_{V \sim \mathcal{D}} [\log F_d(V)] + \mathbb{E}_{V \sim \mathcal{Q}_T} [W(V \mid \text{class } = \text{argmax}(F_T(V)) \times \log(1 - F_d(V))].
\]

Gradually, with the proposed conditional EVT and weighted domain adversarial learning modules, known samples of both domains are aligned, and unknown samples of the target domain get separated from known samples.

### 3.4 Entropy Maximisation

To further separate the unknown samples, we utilise entropy maximum loss to progressively increase the entropy values of the overall target samples, defined as,
\[
\mathcal{L}_e = -\mathbb{E}_{V \sim \mathcal{Q}_T} [\sum_{i=1}^C F_T(V) \log F_T(V)|C].
\]

With the weighted domain adversarial learning, known target samples become similar to source samples. The entropy values of source samples gradually decreases because the source classifier is fully trained to optimise the cross-entropy loss \( \mathcal{L}_e \). Thus, in the target domain, the entropy values of known samples decrease as well when optimising the two losses of \( \mathcal{L}_e \) and \( \mathcal{L}_d \), while the entropy values of unknown samples increase when optimising \( \mathcal{L}_e \) loss. Eventually, the unknown samples are optimally separated from known samples.

### 3.5 Optimisation

The ultimate objective is to learn the optimal parameters for the CEVT model,
\[
(\theta_e^*, \theta_d^*) = \arg\min \mathcal{L}_c + \beta \mathcal{L}_e - \gamma \mathcal{L}_d,
\]

\[
(\theta_e^*) = \arg\min \mathcal{L}_c + \beta \mathcal{L}_e + \gamma \mathcal{L}_d,
\]

with \( \beta \) and \( \gamma \) the coefficients of the entropy maximisation loss and weighted adversarial loss, respectively.

### 3.6 Inference

In this section, we explain the inference stage of the proposed CEVT after the model parameters are optimised. The inference process is denoted by grey arrays shown in Figure 1. The target videos are fed into the convolution network, frame aggregator, and the target classifier \( F_T(\cdot ; \theta_e^*) \). Then, the predictions are passed into the class-conditional EVT module for open-set recognition. The predicted class \( y \in [C + 1] \) of each input target video is represented as,
\[
y = F_T(V^t)
y = C + 1 \text{ if } F_{GEV}(V^t \mid \text{class } = \text{argmax}(F_T(V^t))) > \delta.
\]

### 4 EXPERIMENTS

In this section, we empirically evaluate the performance of the proposed CEVT model on two datasets, UCF-HMDB and UCF-Olympic for unsupervised open-set domain adaptation.
4.1 Datasets
The UCF-HMDB is the intersected subset covering 12 highly relevant categories of two large-scale video action datasets, the UCF101 [44] and HMDB51 [23], including Climb, Fencing, Golf, Kick Ball, pull-up, Punch, push-up, Ride Bike, Ride Horse, Shoot Ball, Shoot Bow and Walk. The UCF-Olympic have six common categories from the UCF101 and Olympic Sports Dataset [33], which involves Basketball, Cleary and Jerk, Diving, Pole Vault, Tennis and Discus Throw. These dataset partitioning strategies follow [8] to make a fair comparison. Likewise, we utilise the pre-extracted frame-level features by ResNet101 model pre-trained on ImageNet. In terms of known/unknown category splitting, we select the first half categories as known classes, and all the remaining categories are labelled as unknown, for both UCF-HMDB and UCF-Olympic.

4.2 Evaluation Metrics
To compare the performance of the proposed CEVT and the baseline methods, we adopt four widely used metrics [6] [42] for evaluating OUDA tasks. The accuracy (ALL) is the correctly predicted target samples over all target samples. OS is the average class accuracy over the classes. OS* is the average class accuracy over the known classes. UNK is the unknown class accuracy. HOS is the harmonic mean of OS* and UNK formulated as: $2 \times \frac{OS \times UNK}{OS + UNK}$. HOS is the most meaningful metric for evaluating OUDA tasks because it can best reflect the balance between OS* and UNK.

4.3 Baselines
We compare our proposed CEVT with three types of state-of-the-art domain adaptation methods: the close-set method for images, the open-set method for videos and the open-set method for images. The close-set domain adaptation methods for images are extended to align the distributions of aggregated frames from source and target domains, which include Domain-Adversarial Neural Network (DANN) [14], Joint Adaptation Network (JAN) [27], Adaptive Batch Normalisation (AdaBN) [25] and Maximum Classier Discrepancy (MCD) [41]. In terms of the close-set approach for videos, Temporal Adverisarial Adaptation Network (TA*N) [8] and Temporal Adversarial Adaptation Network (TA*N) [8] are adopted for comparison. We equip the above open-set methods with the OSVM [18] for open recognition. As for the open-set method for images, OUDA by Backpropagation (OSBP) [42] extended by frame aggregator is made into comparison.

4.4 Implementation Details
All the baselines and our approach are implemented by PyTorch [36] on one server with two GeForce GTX 2080 Ti GPUs. We follow [8] to sample a specified number of frames with uniform spacing from each video for training and extract a 2048-D feature vector from each frame by the Resnet-101 pre-trained on ImageNet. To ensure a fair comparison, we fix K to 16 for all methods using average pooling, and follow the optimisation strategy in [8] to utilise the stochastic gradient descent (SGD) as the optimiser, and learning-rate-decreasing techniques from DANN [14], with learning rate, momentum, and weight decay of 0.03, 0.9 and $1 \times 10^{-4}$, respectively. The scale of datasets determines the size of the source batch, 32 for UCF-Olympic and 128 for UCF-HMDB. The size of the target batch is computed by multiplying the source batch with the ratio between the source and target datasets. The loss coefficient $\beta$ is set as 1, 0.1, 0.19, 0.22, and $\gamma$ is set as 0.9, 0.7, 1.83, 5, for UCF→HMDB, HMDB→UCF, UCF→Olympic and Olympic→UCF, respectively. The EVT threshold is set as 0.4, 0.45, 0.6 and 0.29 for the above tasks, respectively.

4.5 Comparisons with State-of-The-Art
We clearly report the performance of the proposed CEVT and baseline methods on UCF→HMDB and UCF→Olympic as shown in Table 1, Table 2, Table 3 and Table 4. The proposed CEVT model outperforms all the compared state-of-the-art domain adaptation approaches, improving the HOS by 4.92%, 5.44%, 1.32% and 0.67% on the adaptation task UCF→HMDB, HMDB→UCF, UCF→Olympic and Olympic→UCF, respectively. It is worth noting that the proposed model achieves significant performance boosts for the larger-scale datasets of UCF-Olympic. Also, note that the outstanding performance gain of the proposed framework for the most challenging transfer task, i.e., UCF→HMDB, illustrates the better adaptation ability of our approach. Some methods achieve 100% on OS* or UNK for the UCF→Olympic task because this task is relatively easier than other tasks, and the validation set has limited samples. Also, there is usually a trade-off between these two metrics. For example, JAN achieves 100% on OS* but gets the lowest score (86.95%) on UNK. Conversely, AdaBN achieves 100% on UNK but has the worst performance (78.48%) on OS*. The proposed CEVT is superior to all baselines, as it achieves remarkably high OS* and UNK simultaneously.

4.6 Ablation Study
We use the UCF-HMDB dataset to investigate the performance of the proposed modules of the model CEVT. Table 5 summarises
Figure 2: The t-SNE visualisation of the learned source and target video representations on the UCF→HMDB task.

Figure 3: Performance (HOS) comparisons of the proposed CEVT with respect to the varying loss coefficients on the UCF→HMDB (shown in the upper row) and HMDB→UCF (shown in the bottom row) adaptation tasks.

4.8 Visualisation
To intuitively show how our model closes the domain shift between source and target domains as well as effectively recognises the unknown samples, we apply the t-SNE [46] to visualise the extracted features from baseline models, DANN, OSPB, TA³N and our proposed CEVT on the UCF→HMDB task as shown in Figure 2. Different colours denote different classes, and unknown samples are grey. The source videos are represented by circles, while triangles represent the target videos. Compared to the baseline methods, it is noticeable that the features extracted by CEVT produce tighter clusters, and unknown samples are better clustered to the centre.

5 CONCLUSION
In this work, we propose a CEVT framework to tackle the problem of open-set unsupervised video domain adaptation. Unlike previous works, we intensify the open recognition to jointly improve the accuracy of the both known and unknown classes. Experiments demonstrate that the proposed algorithm outperforms state-of-the-art methods on both large and small video datasets. Future work includes testing CEVT for still images, and equipping the proposed CEVT with other frame aggregators for videos.
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