SELF-SUPERVISED LEARNING FOR VIDEOS: A SURVEY

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ABSTRACT

The remarkable success of deep learning in various domains relies on the availability of large-scale annotated datasets. However, obtaining annotations is expensive and requires great effort, which is especially challenging for videos. Moreover, the use of human-generated annotations leads to models with biased learning and poor domain generalization and robustness. As an alternative, self-supervised learning provides a way for representation learning which does not require annotations and has shown promise in both image and video domains. Different from the image domain, learning video representations are more challenging due to the temporal dimension, bringing in motion and other environmental dynamics. This also provides opportunities for video-exclusive ideas that advance self-supervised learning in the video and multimodal domain. In this survey, we provide a review of existing approaches on self-supervised learning focusing on the video domain. We summarize these methods into four different categories based on their learning objectives: 1) *pretext tasks*, 2) *generative learning*, 3) *contrastive learning*, and 4) *cross-modal agreement*. We further introduce the commonly used datasets, downstream evaluation tasks, insights into the limitations of existing works, and the potential future directions in this area. ¹

1 Introduction

The requirement of labelled samples at scale limits the use of deep networks for problems where data is limited and obtaining annotations is not trivial, such as medical imaging Dargan et al. [2020] and biometrics Sundararajan and Woodard [2018]. While pre-training on a large-scale labelled dataset such as ImageNet Krizhevsky et al. [2012a] and Kinetics Kay et al. [2017] does improve performance, there are several limitations and drawbacks in this approach. These drawbacks include annotation cost Yang et al. [2017], Cai et al. [2021], presence of annotation bias Chen and Joo [2021], Rodrigues and Pereira [2018], lack of domain generalization Wang et al. [2022a], Hu et al. [2020], Kim et al. [2021], and lack of robustness Hendrycks and Dietterich [2019], Hendrycks et al. [2021].

Self-Supervised learning (SSL) has emerged as a successful way for pre-training deep models to overcome some of these issues. It is a promising alternative where a model can be trained on large-scale datasets without the need of labels Jing and Tian [2020] and with improved generalizability. SSL trains the model using a learning objective derived from the training samples itself. Typically, the pre-trained model is then finetuned on the target dataset as shown in Figure 1.

SSL has been found effective for different domains such as images Radford et al. [2021], Komodakis and Gidaris [2018], Doersch et al. [2015], Noroozi and Favaro [2016], Wei et al. [2019], Kim et al. [2018], natural language Radford et al. [2021], Kenton and Toutanova [2019], Vaswani et al. [2017], graphs Liu et al. [2022], point-clouds Sharma and Kaul

¹GitHub Project Link: https://github.com/Maddy12/SSL4VideoSurvey

Figure 1: An illustration of using a pre-trained model trained using self-supervised learning for a downstream task. The process starts by pre-training a model on an unlabeled dataset using a self-supervised learning objective. Once trained, the learned weights are used as model initialization for a smaller, labelled dataset on a downstream task

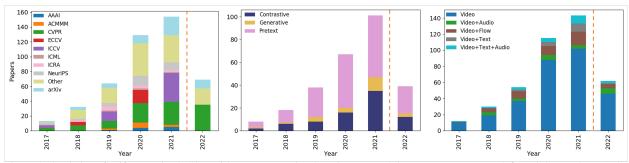


Figure 2: Statistics of self-supervised (SSL) video representation learning research in recent years. From left to right we show a) the total number of SSL related papers published in top conference venues, b) categorical breakdown of the main research topics studied in SSL, and (c) modality breakdown of the main modalities used in SSL. The year 2022 remains incomplete because a majority of the conferences occur later in the year.

[2020], Huang et al. [2021], Guo et al. [2020], etc. Motivated by the success in the image domain, there has been great interest in adopting SSL for the video domain. However, it is not trivial to extend the image-based approaches directly to video due to time. Some early works in this area have focused on extending works in the image-domain for videos without consideration for time Jing et al. [2019], Tao et al. [2020a], Wang et al. [2019], Noroozi and Favaro [2016], Ahsan et al. [2019], Huo et al. [2021], Kim et al. [2019]. Some recent approaches focused on temporal signal where the learned representations also capture the temporal dimension of videos Yao et al. [2020], Wang et al. [2020], Jenni et al. [2020], Benaim et al. [2020], Knights et al. [2021], Misra et al. [2016], Lee et al. [2017], Fernando et al. [2017], Xu et al. [2019]. While not trivial, work in this area has more attention of researchers as shown in Figure 2. This figure shows a breakdown of the number of papers published on "self-supervised video learning" in top conference venues, research category, and modalities. There has been a significant increase in the number of papers and it is expected to continue to do so in future years. This survey aims to summarize the representative recent works in this area.

This increase in interest from multiple domains results in a wide variety of approaches all trying to solve this important issue of training without large-scale, expensively annotated datasets. There are some recent surveys on SSL for images Jaiswal et al. [2021], Jing and Tian [2020]. In Jaiswal et al. [2021], the authors discussed contrastive self-supervised learning focusing on the image domain. Multiple categories were covered in Jing and Tian [2020] including generation-based, context-based, free-semantic labeled base, and cross-modal based (i.e. optical flow), also focused on image domain. While both these works briefly cover video, they focus more on the image domain and do not comprehensively discuss the multimodal aspect. Similarly in Liu et al. [2021a], the authors focus on a wider scope which covers computer vision, natural language processing, and graph learning. In contrast to these existing surveys, our focus is very specific to the video domain with the inclusion of multimodal approaches that have not been covered in previous surveys.

Multimodal learning is an important research area to cover because it is increasingly demonstrating improved performances for zero-shot learning Miech et al. [2020], Xu et al. [2021a]. When we refer to multimodal or cross-modal learning, we are referring to learning using video, audio and/or text. These approaches generalize to a greater variety of visual tasks including action step localization, action segmentation, text-to-video retrieval, video captioning, etc Miech et al. [2019, 2020], Xu et al. [2021a], Luo et al. [2020], Xu et al. [2021b]. These multimodal approaches can expand to other single-modality tasks such as classification of audio events Piczak [2015]. As shown in Figure 3, the increase in performance of multimodal SSL has led to more approaches and more combinations of approaches that need to be organized in a comprehensive way. With the increase in utilizing text as a modality, contrastive learning has also appeared more and more in the SSL research landscape (see Figure 3). While Jaiswal et al. [2021] does touch on video-based contrastive learning, our survey expands on the recent approaches that includes the use of multiple

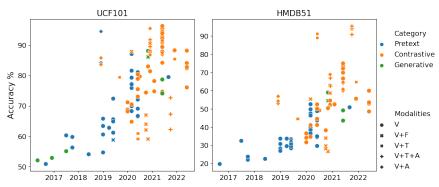


Figure 3: Action recognition performance of models over time for different self-supervised strategies including different modalities: video-only (V), video-text (V+T), video-audio (V+A), video-text-audio (V+T+A). More recently, contrastive learning has become the most popular strategy.

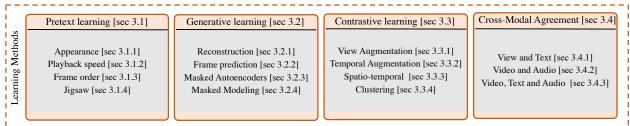


Figure 4: Works in this survey can be categorized by their self-supervised learning (SSL) method: Pretext, Generative, Contrastive and Cross-Modal agreement.

modalities for contrastive learning. With this in mind, we cover works in multimodal areas and present a summary of results for additional tasks that these models can be evaluated on.

In summary, this survey categorizes work into four general learning categories: pre-text, generative, contrastive and cross-modal agreement. Within these categories, some works make use of additional modalities, such as text, to develop better learning objectives. We make the following contributions in this survey,

- We provide a comprehensive review of recent works on self-supervised learning in the video domain, including multimodal approaches.
- We present a categorization of existing works into four groups; 1) pretext learning, 2) generative approaches, 3) contrastive learning, and 4) cross-modal agreement. We believe this will guide future research in this area.
- We summarize the tasks used for evaluation in this domain, corresponding datasets, and evaluation metrics along with performance comparison. This will be useful for benchmarking future works.
- Finally, we discuss the limitations, open problems and future directions in this research area.

This survey is organized as follows: Section 2 will go over the preliminary knowledge of self-supervised learning for videos including terminology, backbone architectures used in pre-training, datasets, and downstream tasks. Section 3.1 will go over works that use a pretext task. Section 3.2 will go over works that use generative approaches. Section 3.3 will go over works that use different methods to generate positive and negative pairs for contrastive learning. Section 3.4 will go over learning based on agreement between signals from video, text and/or audio. The breakdown of approaches for these categories are shown in Figure 4. Finally, we will conclude with a discussion on the limitations, some open problems, and future directions in Section 4 and Section 5.

2 Preliminaries

We first introduce the building blocks of self-supervised learning in videos. This includes various downstream tasks in section 2.1, the backbone network architectures used for training in section 2.2, and the datasets widely used in this research in section 2.3.

2.1 Downstream Evaluation

In order to evaluate learned video representations from pre-training, a target downstream task is solved by either fine-tuning, linear probing, or zero-shot learning. In zero-shot learning, the learned representations are used without any training on the target dataset; whereas fine-tuning and linear-probing involves additional training. We focus on the following downstream tasks for evaluation:

Action Recognition is the most common evaluation task for video only self-supervised learning. It is a classification problem where the goal is to classify each input video into one of the target action categories. Typically, linear layers are added to the pre-trained model to predict the action class of the input video. The model's performance for this task is measured using classification metrics: *accuracy*, *precision*, and *recall*.

Temporal Action Segmentation is a task that detects the start and end time of actions in a video. This task may also be referred to as *action segmentation*. Performance is typically measured using *frame accuracy* (FA), a metric that calculates the model's accuracy when predicting actions frame-by-frame.

Temporal Action Step Localization aims to detect which segments in a video belong to which steps in a complex activity. For each frame, a recall metric is used to define the number of step assignments that fall into the ground truth time interval, divided by the total number of steps in the video Zhukov et al. [2019a], Miech et al. [2019]. This task is used with instructional videos where a complex task, such as "how to change a tire", is broken down into action steps, such as "loosen the lug nuts" and "replace lug nuts".

Video Retrieval aims to find videos that are similar or near-duplicates of a given video. The evaluation protocol includes a gallery of videos and a set of videos with which to query. The performance is measured using standard retrieval metrics including *retrieval*, *recall* and *similarity measures*. Recall is the fraction of retrieved videos that are relevant to the queried video. This is done at different top-k levels; typically top 1 (R@1), top 5 (R@5) and top 50 (R@50) are reported.

Text-to-Video Retrieval takes a text query as input and returns corresponding matching video(s). This is commonly used when there are joint embeddings of text and video in the pre-trained representations. The metrics used are the same as that for Video-Retrieval. The key difference is the query is a textual description rather than a video. This task is often used in zero-shot learning to evaluate the quality of learned representations between text and video.

Video Captioning is a generative task where the input is a video clip and the output is a caption. The goal being to generate a textual caption that accurately describes the contents of the video. Accuracy is measured using a combination of *BLEU* Papineni et al. [2002], *METEOR* Banerjee and Lavie [2005], *Rouge-L* Lin [2004] and *CIDEr* Vedantam et al. [2015] metrics. BLEU is a precision based metric that calculates the fraction of tokens from the prediction that appear in the ground-truth. It also uses a brevity penalty that penalizes words that appear in the prediction more times than it appears in any of the ground-truth captions. Rouge-L is similar, but is a recall based metric that measures the longest common subsequence (LCS) between predicted and ground-truth. METEOR calculates a one-to-one mapping of words in predicted and ground-truth captions. Finally, Consensus-based Image Description Evaluation (CIDEr) calculates how well a predicted caption matches the consensus of a set of ground-truth captions.

2.2 Building Blocks

Next, we will cover the backbone network architectures used to encode videos, text, and audio.

2.2.1 Visual Backbone Architectures

There are a wide range of network architectures which are used to learn video representations. These are often deep convolutional neural networks (CNNs) that use either 2D convolutions, 3D convolutions, or a combination of both. 2D CNNs encode videos at the "frame-level" where each frame is treated as an image. 3D CNNs encode videos with the dimension of time, running convolutions over both time and space. ResNet Hara et al. [2018] is the most popular architecture for both 2D and 3D CNNs. Other popular 3D CNN networks for video include I3D Carreira and Zisserman [2017], C3D Tran et al. [2015] and S3D Xie et al. [2018], all of which use a 3D inception module. Another popular architecture is the R(2+1)D Tran et al. [2018a]; separating traditional 3D convolutions into a spatial 2D convolutions and a temporal 1D convolution. To improve R(2+1)D, the architecture R(2+3)D Feichtenhofer et al. [2018], Han et al. [2019, 2020a] modify the last two blocks so they have 3D kernels. We have seen an increase in the use of video encoding architectures based on transformers, such as TimeSformer Bertasius et al. [2021], MViT Fan et al. [2021], ViViT Arnab et al. [2021], Swin Liu et al. [2021b].

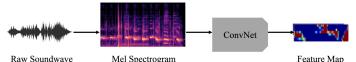


Figure 5: Audio backbone encoders convert audio waveforms to Mel Spectrograms and are typically 2D CNN-based architectures.

2.2.2 Audio Backbone Architectures

Audio is encoded by first converting it into spectograms (Figure 5). This representation of audio signal is generated by splitting the signal into bins. Fourier Transform is then applied to each bin to determine their respective frequencies. The most popular type of spectrogram in deep learning is the Mel Spectrogram, replacing frequency with the mel scale. CNN Models with a 2D or 3D architecture, such as ResNet He et al. [2016], are then used to extract audio features from these Mel Spectograms. More details on the audio-visual deep learning can be found in Zhu et al. [2021]. There are several backbone approaches discussed in this survey Zhu et al. [2021], and most of them rely on 2D or 3D ResNets to extract audio features.

2.2.3 Text Backbone Architectures

The two most common approaches for text encoding are either a Word2Vec approach Mikolov et al. [2013] or a Bidirectional Encoder Representations from Transformers (BERT) approach Kenton and Toutanova [2019]. Word2Vec is a skip-gram model that uses a central word to predict n-words before and after its occurrence. BERT uses a self-attention mechanism Vaswani et al. [2017] trained using either a Masked Language Model (MLM) Taylor [1953] or Next Sentence Prediction (NSP) task to train. In the MLM task, shown in Figure 6, a percentage of the word tokens are masked and the model predicts the masked tokens. NSP pair sentences with either their predecessors or ones chosen at random, and the model must predict whether they are a "good" pair or not.

2.3 Datasets

In self-supervised learning for videos, we have a large-scale dataset which is used in pre-training to learn representations. We have several smaller "down-stream" datasets that have annotations for specific tasks. Table 1 summarizes the videobased datasets used in self-supervised learning. The most commonly used datasets for pre-training are the Kinetics Chen et al. [2020a] and HowTo100M Miech et al. [2019] datasets. The most common datasets used for downstream evaluation are UCF101 Soomro et al. [2012] and HMDB51 Kuehne et al. [2011]. Because there have been recent studies demonstrating that these two datasets do not necessarily require temporal learning Huang et al. [2018], the Something-Something (SS) Goyal et al. [2017] dataset has been proposed, but is not widely adopted for evaluation.

2.3.1 Video-Based Datasets

ActivityNet This dataset contains 19,995 untrimmed usergenerated videos from YouTube covering 200 different types of activities Caba Heilbron et al. [2015]. Each video is annotated with temporal boundaries and has on average 1.41 activities.

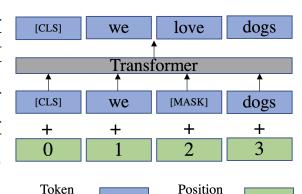


Figure 6: The Masked Language Modeling Taylor [1953] approach using transformers Vaswani et al. [2017] where each word is encoded and the transformer uses self-attention to decode each encoding to a predicted word, filling in the blanks of masked words.

Embeddings

Embeddings

AVA This dataset Gu et al. [2018], Li et al. [2020a], Roth et al. [2020] focuses on atomic visual actions and contains 430 videos. This dataset has three variations in total. AVA-Actions are densely annotated videos with 80 atomic visual actions localized in space in time totaling 430 15-minute movie clips. AVA-Kinetics, which is a crossover between AVA and Kinetics with localized action labels. AVA-ActiveSpeaker is an audio-visual grounding dataset that temporally labels face tracks in video. Each face instance is labeled as speaking or not and the corresponding audio. There are a total of 3.65 million human labeled frames.

Table 1: Video datasets for self-supervised training and/or evaluation and the respective tasks associated with the annotations

provided.					
Dataset	Labels	Modalities	Classes	Videos	Tasks
	Activity	Video			Action-Recognition
ActivityNet (ActN) Caba Heilbron et al. [2015]	Captions	Video+Text	200	19,995	Video Captioning Krishna et al. [2017a]
	Bounding Box				Video Grounding Zhou et al. [2019]
AVA Gu et al. [2018], Li et al. [2020a]	Activity	Video	80	430	Action-Recognition
AVA Gu et al. [2018], Li et al. [2020a]	Face Tracks	Video+Audio	80	430	Audio-Visual Grounding Roth et al. [2020]
Breakfast Kuehne et al. [2014]	Activity	Video	10	1,989	Action Recognition
Dicariast Rueline et al. [2014]	rictivity	Video	10	1,707	Action Segmentation
	Activity				Action-Recognition
Charades Sigurdsson et al. [2016]	Objects	Video	157	9,848	Object Recognition
Characes Sigurdsson et al. [2010]	Indoor Scenes	Video	137	2,040	Scene Recognition
	Verbs				Temporal Action Step Localization
	Activity	Video			Action-Recognition
COIN Tang et al. [2019]	Temporal Actions		180	11,827	Action Segmentation
	ASR	Video+Text			Video-Retrieval
CrossTask Zhukov et al. [2019b]	Temporal Steps	Video	83	4,700	Temporal Action Step Localization
Cross task Zhukov et al. [20170]	Activity	Video	0.5	4,700	Recognition
HMDB51 Kuehne et al. [2011]	Activity	Video	51	6,849	Action-Recognition
Thyldda Rueinic et al. [2011]	rictivity	Video	31	0,047	Video-Retrieval
HowTo100M (How2) Miech et al. [2019]	ASR	Video+Text	_	136M	Text-to-Video Retrieval
. , ,					VideoQA Li et al. [2021]
Kinetics Kay et al. [2017]	Activity	Video	400/600/700	½M	Action-Recognition
					Action-Recognition
MSRVTT Xu et al. [2016]	Activity	Video+Text	20	10,000	Video-Captioning
More 11 Au et al. [2010]	Captions	VIGCOTICAL	20	10,000	Video-Retrieval
					Visual-Question Answering
MultiThumos Yeung et al. [2018]	Activity	Video	65	400	Action Recognition
Walti Thamos Teang et al. [2016]	Temporal Steps	Video	03	400	Temporal Action Step Localization
UCF101 Soomro et al. [2012]	Activity	Video	101	13,320	Recognition
OCI 101 300milo et al. [2012]	Activity	Video	101	13,320	Video-Retrieval
YouCook2 Zhou et al. [2018]	Captions	Video+Text	89	2,000	Video Captioning
	•			· ·	Video-Retrieval
YouTube-8M Abu-El-Haija et al. [2016]	Activity	Video	4,716	8M	Action Recognition

Breakfast This dataset consists of 1,989 filmed videos made of 10 actions related to breakfast preparation, performed by 52 different individuals in 18 different kitchens. All videos were down-sampled to a resolution of 320×240 pixels with a frame rate of 15 fps.

Charades This dataset is a collection of 9,848 videos of daily indoor activities with an average length of 30 seconds with a total of 157 action classes Sigurdsson et al. [2016]. Videos were generated by users recording themselves acting out sentences which were presented to them. These sentences contained objects and actions from a fixed vocabulary. These videos involve interactions with 46 different object classes, in 15 types of different indoor scenes and a vocabulary of 30 verbs. This dataset contains 66,500 temporal annotations for 157 action classes, 41,104 labels for 46 object classes, and 27,847 textual descriptions of the videos.

COIN This dataset is a small-scale dataset of instructional videos Tang et al. [2019]. This dataset is a collection of 11,827 videos of 180 different tasks in 12 domains such as vehicles and gadgets. These videos are annotated with a task and temporal boundaries, allowing for models to be evaluated on action-localization. The average length of these videos is 2.36 minutes where each annotated segment lasts an average of 14.91 seconds with a total of 46,354 annotated segments.

CrossTask A dataset that consists of 4,700 YouTube videos of 83 tasks Zhukov et al. [2019b]. Each task has a set of steps with manual description, allowing models to be evaluated on action localization of steps that make up a task. The dataset has 18 primary tasks and 65 related tasks. Videos associated with the primary tasks are collected manually and are annotated for temporal step boundaries while the videos associated with related tasks are not annotated.

HMDB51 This dataset contains videos collected from a variety of sources, including commercial movies and public video hosting services Kuehne et al. [2011]. There are 6,849 video clips in total averaging 10 seconds each with 51 action categories. Each action category contains at least 101 clips. The action categories are split into five types: facial actions (e.g. smiling), face-to-object interaction (e.g. eating), general body movement, body-to-object interactions (e.g. brush hair) and human-to-human interaction (e.g. hugging).

HowTo100m One of the largest collections of user-generated instructional videos, HowTo100M (How2) Miech et al. [2019] is a collection of 136 million video clips with captions sourced from 1.2 million YouTube videos. These

Dataset Labels Modalities Classes **Audio Clips** Tasks AudioSet (AS) Gemmeke et al. [2017] Event Video+Audio Classification 632 2MDCASE Mesaros et al. [2016] 20 Event Audio Classification ESC-50 Piczak [2015] 2,000 Activity Audio 50 Classification LRS2 Son Chung et al. [2017] Video+Audio 96,318 Action-Recognition VGG-Sound Chen et al. [2020a] 310 210,00 Event Video+Audio

Video+Audio

Classification

Speaker Verification

6,000

Table 2: Audio based datasets that are used for multimodal self-supervised representation learning with video.

videos are categorized into 23,000 activities from domains such as cooking, hand crafting, personal care, gardening or fitness. The associated text is collected from subtitles downloaded from YouTube which are either user-uploaded or automatically generated. These videos are untrimmed and are often minutes-long. Some of the other dataset videos, such as those in COIN Tang et al. [2019], are part of this collection but lack the more detailed annotation.

Kinetics The most popular pre-training dataset for video-only self-supervised learning approaches Kay et al. [2017]. It is a large-scale, human-action dataset containing 650,000 video clips covering either 400, 600, or 700 human action classes. Each video clip lasts around 10 seconds and is labeled with a single action class.

MSRVTT A dataset that consists of 10,000 video clips from 20 action categories Xu et al. [2016]. Each video clip is annotated with 20 English sentences with a total of 200,000 clip-sentence pairs. The duration of each clip is between 10 and 30 seconds. This dataset is often used for video-captioning and retrieval tasks.

MultiTHUMOS This dataset consists of 400 untrimmed videos collected from YouTube with 65 action classes. Each video has dense, multi-label, frame-level action annotations with a total of 38,690 annotations with an average of 1.5 labels per frame and 10.5 action classes per video.

Something-Something This dataset focuses on evaluating temporal elements in videos using everyday human activities. It is a large-scale dataset with 220,847 videos with a total of 174 activities. Some examples are "putting something into something", "turning something upside down" and "covering something with something".

UCF-101 One of the most popular benchmarks to evaluate models on action-recognition because of its smaller size Soomro et al. [2012]. It has only 13,320 video clips which are classified into 101 categories. The categories fall within five types of activity: body motion, human-to-human interaction, human-to-object interaction, playing musical instruments and sports. The videos are user-generated, collected from YouTube, and have a fixed frame rate of 25 FPS and fixed resolution of 320×240 .

YouCook2 This dataset is a task-oriented, instructional video dataset of 2,000 YouTube videos showing a third-person perspective of individuals cooking 89 separate recipes Zhou et al. [2018]. On average, each recipe has 22 videos. The recipe steps for each video are annotated with temporal boundaries and described by imperative English sentences. This dataset is often evaluated in conjunction with MSRVTT as it requires more temporal information in comparison Bain et al. [2021], Buch et al. [2022], Schiappa et al. [2022].

YouTube-8M This dataset Abu-El-Haija et al. [2016] is a collection of 8 million YouTube videos with 4,716 classes. These are categorized into 24 topics: including sports, games, arts, and entertainment.

2.3.2 Audio-Based Datasets

VoxCeleb Chung et al. [2018]

While the video datasets used in multimodal problems have associated text, they do not always have associated audio. Additional audio datasets are typically used when the approach includes audio but the video-based dataset does not have audio as a signal. Table 2 lists audio based datasets which are commonly used for multimodal self-supervised representation learning with video. These datasets are used for tasks such as event classification, text-to-video retrieval, text-to-audio retrieval, video-captioning, video description, and text summarization.

AudioSet This dataset Gemmeke et al. [2017] is a collection of over 2 million human-annotated user-generated clips from YouTube. These clips are 10-seconds each and have an ontology of 632 event classes. This dataset is a multi-label dataset, meaning one clip can have more than one activity class.

DCASE This dataset Mesaros et al. [2016] is a small collection of 20 short mono sound files for 11 sound classes with annotations of event temporal boundaries. This dataset is most commonly used for event classification.

ESC-50 This dataset Piczak [2015] is a collection of 2000 audio clips that are 5 seconds along. There are a total of 50 classes used for event classification.

LRS2 This dataset Son Chung et al. [2017] is a collection of lip reading from news and talk shows. Each lip reading sentence is 100 characters long with 96,318 utterances in total.

VGG-Sound This dataset Chen et al. [2020a] is a collection of 200,000 short videos from YouTube where the audio source is visually present and consists of 310 audio events. This dataset is used as a multimodal dataset for joint audio and visual tasks.

VoxCeleb This dataset Chung et al. [2018] is a collection of over 1 million utterances from 6,112 celebrities extracted from user-generated videos on YouTube. This dataset is also multilingual covering 145 different nationalities. This dataset is most commonly used for visual speech synthesis, speech separation, cross-modal transfer and face recognition.

3 Self-Supervised Learning Approaches

We split the works in video self-supervised learning into four high level categories: pretext, generative, contrastive, and cross-modal agreement. We will discuss each in the following subsections.

3.1 Pretext Learning

A pretext task is a self-supervised training objective that uses **pre-defined tasks for the network to solve** in order to learn representations that can be used later for downstream tasks. The idea is, if a model is able to solve a complicated task that requires a high-level understanding of its input, then it will learn more generalizable features. Emerging from the image domain, these tasks often relate to appearance statistics including context prediction Doersch et al. [2015], colorization Deshpande et al. [2015], Iizuka et al. [2016], Larsson et al. [2016, 2017], ordering shuffled image patches Carlucci et al. [2019], Goyal et al. [2019], Mundhenk et al. [2018], Noroozi and Favaro [2016], Noroozi et al. [2018], Wei et al. [2019], Kim et al. [2018], and geometric transformation recognition Komodakis and Gidaris [2018]. These appearance-based tasks have also been extended to the video domain Jing et al. [2019], Tao et al. [2020a], Wang et al. [2019], Noroozi and Favaro [2016], Ahsan et al. [2019], Huo et al. [2021], Kim et al. [2019], often coupled with additional tasks that are specific to motion dynamics in videos. Video-specific tasks are related to the time domain, such as playback speed Yao et al. [2020], Wang et al. [2020], Jenni et al. [2020], Benaim et al. [2020], Knights et al. [2021] and temporal order Fernando et al. [2017], Xu et al. [2019], Misra et al. [2016], Lee et al. [2017]. Because these tasks require a greater understanding of activities and their relation to time, the learned representations generalize well to other video tasks. In summary, this survey covers the following pretext tasks: 1) appearance statistics Jing et al. [2019], Wang et al. [2019], 2) temporal order Fernando et al. [2017], Xu et al. [2019], Misra et al. [2016], Lee et al. [2017], Wei et al. [2018], Pathak et al. [2017], 3) jigsaw Noroozi and Favaro [2016], Ahsan et al. [2019], Huo et al. [2021], Kim et al. [2019], 4) and playback speed Yao et al. [2020], Wang et al. [2020], Jenni et al. [2020], Benaim et al. [2020], Knights et al. [2021].

3.1.1 Appearance Statistics Prediction

In this task, a model is asked to predict, or classify, an appearance modifying augmentation applied to a video clip. Example augmentations could be color, rotation, and random noise. Rotation based augmentation is inspired from the image domain in Jing et al. [2019]. This image based approach was extended to video Jing et al. [2019], where each frame in a video is rotated by four different degrees, separately. The four, different variations are then all passed separately to a 3D CNN. A cross-entropy loss is then used between the predicted rotation and the actual rotation during training. A toy example of this task is shown in Figure 7. While this approach performed well, it only extended the image-based approach to each frame in a video, and did not take into account the temporal dimension. In order to directly address time, Wang et al. [2019] uses optical flow as a pretext task. Using vertical and horizontal grid lines, the model predicts motion and spatial statistics according to the locations in the frame's grid. For example, the model is asked to predict in a frame where the largest motion statistic is, and where the dominant orientation statistic is.



Figure 7: Toy examples of pretext learning tasks. The appearance statistics prediction example (left) shows a series of frames augmented by rotation and the model is asked to predict the degree of rotation used. Similarly, in the playback speed prediction example (right) augmentation is applied on the temporal dimension by changing the speed in which a clip is played and the model is asked to predict the magnitude of that change.

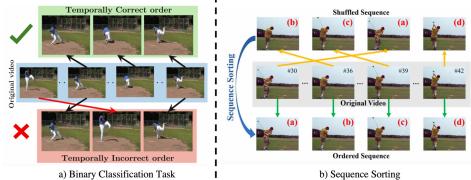


Figure 8: Examples of frame ordering tasks. Images in (a) show order classification from Misra et al. [2016]. This task encodes both the original sequence of frames and a shuffled version and the model must classify a clip on whether it is the correct or shuffled version. Images in (b) show sequence sorting from Lee et al. [2017]. This task takes a shuffled version of a clip and must predict the correct order of the frames.

3.1.2 Playback Speed

This task classifies the playback speed of an augmented clip Yao et al. [2020], Wang et al. [2020], Jenni et al. [2020], Benaim et al. [2020], Knights et al. [2021]. This task often starts by taking clips of t frames from each video $V \in \mathbb{R}^{T \times C \times H \times W}$ and selecting frames in a way that the playback speed is altered. This is done by collecting every p frames, where p is the playback rate, either speeding up the video or slowing it down. As illustrated in Figure 7, the task is to classify p or to reconstruct a clip at the original speed p. A simple approach was proposed in Jenni et al. [2020] that adds a motion-type permutation that results in either the modified speed, random, periodic or warped transformations. The task has two multi-class classifications, one detecting which transformation was used and the other detecting speed p. To improve the performance, later approaches utilize additional tasks to the classification of p. For example, in Yao et al. [2020] the authors introduced a reconstruction loss as an additional signal. The model would encode a modified version of a clip and use the encodings to reconstruct the clip at its original playback rate. However, in Wang et al. [2020] a contrastive loss performed better as an additional signal. This method defined the anchor as the original clip, positive samples are a modified speed of the same clip, and negative samples are clips from other videos.

3.1.3 Temporal Order

In temporal order classification, each video V is split into clips of t frames. Each set of clips contains a single clip in the correct order, and the remaining clips are modified by shuffling the order. For example, (t_2, t_1, t_3) is incorrect while (t_1, t_2, t_3) is correct Fernando et al. [2017], Xu et al. [2019]. The task is called *odd-one-out learning*, defined in Fernando et al. [2017], where a model is trained to classify whether the input clip is in the correct order, most often using a binary-classifier (see Figure 8a). When using frame ordering, the difference between two frames is not enough to recognize a change in motion for some activities. To address this issue, Xu et al. [2019] extracts short sub-clips and shuffles their order. This clip-based order prediction allows for better comparison because the dynamics of an action are maintained in a sub-clip. To further improve retention of motion dynamics, time windows are extracted where the motion was at its highest, to ensure the model would be able to differentiate between two frames and their motion Misra et al. [2016], Lee et al. [2017]. More specifically, Misra et al. [2016] extracts tuples of three frames for each video sampled from varying temporal windows. The frames selected are those that contain the largest amount of motion, computed by optical flow. Negative samples are tuples that are out of order, and positive samples are those in order,

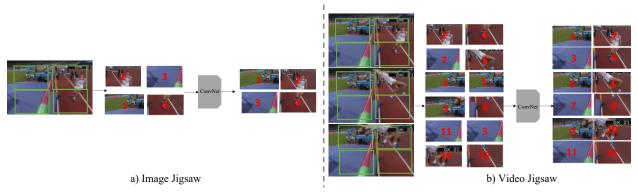


Figure 9: An example of the jigsaw pretext task for images Noroozi and Favaro [2016] compared to an example of the jigsaw pretext task for video from Ahsan et al. [2019]. a) An example of image jigsaw using a frame from the UCF101 dataset Soomro et al. [2012], where the process starts with splitting image(s) into a grid and extracting the pixels from those grids into isolated patches. These patches are then shuffled and the model must predict the correct ordering of the patches. b) An example of video jigsaw using multiple frames, where the process starts by splitting each frame into a 2D grid or splits multiple frames into 3D grids. The patches are then shuffled and the model is asked to predict the correct order or the permutation used to shuffle the patches.

including a reverse order e.g. (t_3, t_2, t_1) . The model is trained using the *odd-one-out* strategy. The authors in Lee et al. [2017] improved learning further by sorting the frames using pairwise feature extraction on each pair of frames, rather than *odd-one-out*. This approach predicts the actual clip order using shuffled high-motion clips as input (shown in Figure 8b).

3.1.4 Video Jigsaw

Jigsaw task was first introduced in the image domain Noroozi and Favaro [2016] where an image is split into multiple patches and then shuffled. Each patch is assigned a number and the permutation P that is used to change the order of those numbers (e.g. 9, 4, 6, 8, 3, 2, 5, 1, 7). The seminal work Noroozi and Favaro [2016] generated the set of possible permutations to choose from by maximizing the Hamming distance between the original patch order and the permuted order. The final list of possible permutations are the top-k most distant permutations, resulting in a final set of permutations S. The objective is a multi-class classification problem, where the classifier predicts which permutation $S_k \in S$ was applied to the image. This approach has been extended to video domain in several works Ahsan et al. [2019], Zhao and Dong [2020], Huo et al. [2021], Kim et al. [2018, 2019], Santa Cruz et al. [2017] where three dimensional patches are used as illustrated in Figure 9. One of the challenges in extending Jigsaw to videos, is the increased number of patches. The larger the number of patches, the larger the number of permutations to select from when using the image-based approach. In Ahsan et al. [2019], a video is split into clips of three frames that are treated as one large image, where all the patches in all the frames are shuffled. The permutation sampling strategy was modified by constraining spatial coherence over time. The patches in a given frame were shuffled before shuffling the frames themselves. Combining the jigsaw task with frame ordering, Zhao and Dong [2020] handles the increase in permutations by adopting a multi-stream CNN that receives a shuffled sequence of visual samples as input, where a sample in the sequence goes through a different branch. To address time, Huo et al. [2021], Kim et al. [2019] proposed approaches that use a cubic representation of video clips over time and space. In Kim et al. [2019], a video clip is considered as a cuboid which consists of 3D grid cells. The model learns to classify which permutation was used to modify the clip. In order to improve the permutation sampling strategy, Huo et al. [2021] invoked a constraint where three spatio-temporal dimensions $(T \times W \times H)$ are shuffled sequentially, rather than simultaneously, to improve continuity of the cuboid. Each jigsaw group of pieces is shuffled rather than each jigsaw piece individually.

3.1.5 Discussion

In pretext self-supervised pre-training, we discussed several techniques: 1) data augmentation on spatial and temporal elements of a video in which the model was asked to make predictions about the related statistics; 2) altering the playback speed of a video in which the model is asked to predict the speed or reconstruct the original speed; 3) shuffled frames where tasks included predicting the odd-one-out and/or sorting the frames to the original order; 4) shuffled frame patches using a permutation selected from a set of derived, possible permutations in which the model is asked to predict the permutation that was selected.

Figure 10 shows the mean accuracy on downstream action recognition for models using pretext learning on both UCF101 Soomro et al. [2012] and HMDB51 Kuehne et al. [2011] datasets. This figure shows that the *pretext tasks*

Table 3: Downstream evaluation of action recognition on pretext self-supervised learning measured by prediction accuracy. Top scores are in **bold** and second best are <u>underlined</u>. Playback speed related tasks typically perform the best.

Model	Subcategory	Visual Backbone	Pre-Train	UCF101	HMDB51
Geometry Gan et al. [2018]	Appearance	AlexNet	UCF101/HMDB51	54.10	22.60
Wang et al. Wang et al. [2019]	Appearance	C3D	UCF101	61.20	33.40
3D RotNet Jing et al. [2019]	Appearance	3D R-18	MT Monfort et al. [2019]	62.90	33.70
VideoJigsaw Ahsan et al. [2019]	Jigsaw	CaffeNet	Kinetics	54.70	27.00
3D ST-puzzle Kim et al. [2019]	Jigsaw	C3D	Kinetics	65.80	33.70
CSJ Huo et al. [2021]	Jigsaw	R(2+3)D	Kinetics+UCF101+HMDB51	79.50	<u>52.60</u>
PRP Yao et al. [2020]	Speed	R3D	Kinetics	72.10	35.00
SpeedNet Benaim et al. [2020]	Speed	S3D-G	Kinetics	81.10	48.80
Jenni et al. Jenni et al. [2020]	Speed	R(2+1)D	UCF101	87.10	49.80
PacePred Wang et al. [2020]	Speed	S3D-G	UCF101	87.10	52.60
Shuffle&Learn Misra et al. [2016]	Temporal Order	AlexNet	UCF101	50.90	19.80
OPN Lee et al. [2017]	Temporal Order	VGG-M	UCF101	59.80	23.80
O3N Fernando et al. [2017]	Temporal Order	AlexNet	UCF101	60.30	32.50
ClipOrder Xu et al. [2019]	Temporal Order	R3D	UCF101	72.40	30.90

Table 4: Performance for the downstream video retrieval task with top scores for each category in **bold** and second best scores <u>underlined</u>. K/U/H indicates using all three datasets for pre-training, i.e. Kinetics, UCF101, and HMDB51.

Model	Category	Subcategory	Visual Backbone	Pre-train		UCF101	l		HMDB5	1
Woder	Category	Subcategory	ategory visual backbone Fr		R@1	R@5	R@10	R@1	R@5	R@10
SpeedNet Benaim et al. [2020]	Pretext	Speed	S3D-G	Kinetics	13.00	28.10	37.50	-	_	_
ClipOrder Xu et al. [2019]	Pretext	Temporal Order	R3D	UCF101	14.10	30.30	40.00	7.60	22.90	34.40
OPN Lee et al. [2017]	Pretext	Temporal Order	CaffeNet	UCF101	19.90	28.70	34.00	_	_	_
CSJ Huo et al. [2021]	Pretext	Jigsaw	R(2+3)D	K/U/H	21.50	40.50	53.20	_	_	_
PRP Yao et al. [2020]	Pretext	Speed	R3D	Kinetics	23.20	38.50	46.00	10.50	27.20	<u>40.40</u>
Jenni et al. Jenni et al. [2020]	Pretext	Speed	3D R-18	Kinetics	26.10	<u>48.50</u>	<u>59.10</u>	-	_	_
PacePred Wang et al. [2020]	Pretext	Speed	R(2+1)D	UCF101	31.90	49.70	59.20	12.90	32.20	45.40
MemDPC-RGP Han et al. [2020a]	Generative	Frame Prediction	R(2+3)D	Kinetics	20.20	40.40	52.40	7.70	25.70	65.30
MemDPC-Flow Han et al. [2020a]	Generative	Frame Prediction	R(2+3)D	Kinetics	40.20	63.20	71.90	15.60	37.60	52.00
DSM Wang et al. [2021]	Contrastive	Spatio-Temporal	I3D	Kinetics	17.40	35.20	45.30	8.20	25.90	38.10
IIC Tao et al. [2020b]	Contrastive	Spatio-Temporal	R-18	UCF101	42.40	60.90	69.20	19.70	42.90	57.10
SeLaVi Asano et al. [2020]	Cross-Modal	Video+Audio	R(2+1)D	Kinetics	52.00	68.60	84.50	24.80	<u>47.60</u>	75.50
CoCLR Han et al. [2020b]	Contrastive	View Augmentation	S3D-G	UCF101	55.90	70.80	<u>76.90</u>	26.10	45.80	<u>57.90</u>
GDT Patrick et al. [2020a]	Cross-Modal	Video+Audio	R(2+1)D	Kinetics	62.80	79.00	-	26.10	51.70	_

relating to playback speed, or temporal consistency, typically perform better. This is further supported in Table 4 which shows results for video-retrieval where we observe that playback speed is again outperforming other pretext tasks. Limitations to these findings is the use of a variety of backbone architectures and pre-training datasets making direct comparison of the proposed approaches difficult.

3.2 Generative Approaches

Generative learning utilizes the **generative power of neural networks to synthesize video or other signals** Vondrick et al. [2016]. These tasks originated in the image domain, where the most common techniques are Generative Adversarial Networks (GANs) Goodfellow et al. [2014], Zhu et al. [2017a] and Masked Autoencoders (MAE) He et al. [2022].

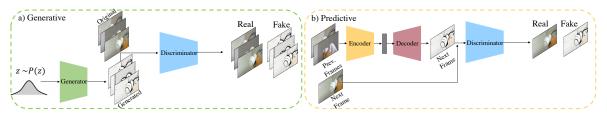


Figure 11: A toy example of generative approaches and their respective loss functions. (a) Shows a generator taking random noise from a normal distribution to generate images. The generated images, and original images, are then passed to a discriminator, which classifies which is real (original) or fake (generated). (b) Shows frame predicting where the previous frames are fed to an encoder-decoder to generate the next frame in the sequence. The original frames, and the next frame predictions, are then passed to a discriminator, which classifies which are real (original) or fake (generated).

These generative approaches for images have been extended to video in Srivastava et al. [2015], Tulyakov et al. [2018], Vondrick et al. [2016], Wei et al. [2022], Yang et al. [2022], Feichtenhofer et al. [2022], Wang et al. [2022b]. GANs involve data synthesis where the synthesized data point is approximated with the actual data point. These are used with an **encoder-decoder architecture** Goodfellow et al. [2014], where an encoder first takes input and projects it to a latent space. A decoder then takes the latent features and projects them to the original space, attempting to reconstruct an original data point. A discriminator is then used to distinguish the generated output from the original data point (see Figure 11). There can be many variations in the learning objective depending upon the target data point. For example, the target data point could be the input itself Vondrick et al. [2016] or maybe some unseen point such as future frames in videos Han et al. [2020a], Tulyakov et al. [2018], Tian et al. [2020a]. Masked Modeling (MM) is another generative learning framework and is typically used with transformer architectures. Similar to masked language modeling (MLM) from the natural language processing (NLP) domain Kenton and Toutanova [2019], Vaswani et al. [2017], masked modeling takes a sequence as input, where some input tokens are randomly masked, and the model generates these masked tokens using the context of the other tokens in the sequence (see Figure 6). For just video, these approaches are MAEs Wei et al. [2022], Yang et al. [2022], Feichtenhofer et al. [2022], Wang et al. [2022b]. With the success of MAEs using only RGB frames and motion, additional signals like audio and text have been shown to further improve generalizability of learned features Sun et al. [2019a], Lei et al. [2021], Owens and Efros [2018], Zhu and Yang [2020], Xu et al. [2021b], Li et al. [2020b], Luo et al. [2020]. These approaches are called Multimodal Masked Modeling.

3.2.1 Adversarial and Reconstruction

Typically, GANs are used for video-to-video synthesis tasks and are not often used for self-supervised pretraining. However, Vondrick et al. [2016] proposed VideoGAN, a generator that uses a two-stream network of 2D and 3D visual features and a discriminator that classifies realistic scenes from synthetically generated scenes and recognizes realistic motion between frames. The methods in Chen et al. [2019], Bansal et al. [2018] added time and motion to successful works in image domain Zhu et al. [2017b] to extend them to video, although more focused on video-to-video translation. In Bansal et al. [2018], the cycle-consistency loss, a type of reconstruction loss, from Zhu et al. [2017b] was extended to a recycle loss. The original cycle-consistency loss learned two mappings, $G: X \to Y$ and $F: Y \to X$ to reduce the space of possible mapping functions by enforcing forward and backward consistency. The recycle loss utilizes a recurrent loss which predicts future samples, in a temporal stream, given its past, making use of cycleconsistency. This was further extended in Chen et al.

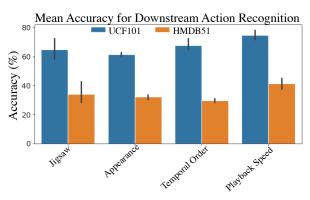


Figure 10: Mean performance on action recognition for video-only pretext learning approaches from Table 3. Using temporal-based approaches, like Temporal Order and Speed, typically outperforms appearance-based approaches.

[2019] by focusing on motion. This method explicitly employs motion across frames by enforcing motion consistency through optical flow. The most recent work Hadji et al. [2021] utilized dynamic time warping (DTW) to admit a global cycle consistency loss that verifies correspondences over time.

3.2.2 Frame Prediction

Rather than focusing on reconstructing motion, Liang et al. [2017] and Tian et al. [2020a] focused on generating motion from RGB frames and vice versa for future unseen frames. A discriminator and variational autoencoder (VAE) is used to measure the quality of these generated predictions when compared to the ground truth RGB frames and optical flow. Instead of using optical flow as the motion signal, Tian et al. [2020a] proposed the use of encoded features between two frames to decode and extract low-resolution motion maps. High-resolution motion maps are generated using contextual features extracted from spatial regions. Both of these motion maps are then used to make a prediction of the next frame at various resolutions where a *reconstruction loss* is used to measure the quality of the reconstructions.

To address time directly, Tulyakov et al. [2018] formulates a sequence of frame representations as paths, therefore modeling videos of varying lengths. A recurrent neural network (RNN) constrains the learning of a path in the motion subspace to physically plausible motion. Recurrent structures have also been utilized in Han et al. [2020a] which propose Memory-augmented Dense Predictive Coding (MemDPC). MemDPC splits a video into blocks, containing an equal number of frames, and passes them to an encoder to generate embeddings. These embeddings are then aggregated over time using RNNs. During training, a *predictive addressing mechanism* is used to access a memory bank shared

Table 5: Downstream evaluation of action recognition on self-supervised learning measured by prediction accuracy for Something-Something (SS) and Kinetics400 (Kinetics). SS is a more temporally relevant dataset and therefore is more challenging. Top scores for each category are in **bold** and second best scores <u>underlined</u>.

Model	Category	Subcategory	Visual Backbone	Pre-Train	SS	Kinetics
pSwaV Feichtenhofer et al. [2021]	Contrastive	View Aug.	R-50	Kinetics	51.7	62.7
pSimCLR Feichtenhofer et al. [2021]	Contrastive	View Aug.	R-50	Kinetics	52.0	62.0
pMoCo Feichtenhofer et al. [2021]	Contrastive	View Aug.	R-50	Kinetics	54.4	69.0
pBYOL Feichtenhofer et al. [2021]	Contrastive	View Aug.	R-50	Kinetics	55.8	71.5
BEVT Wang et al. [2022b]	Generative	MAE	SWIN-B Liu et al. [2021b]	Kinetics+ImageNet Krizhevsky et al. [2012a]	71.4	81.1
MAE Feichtenhofer et al. [2022]	Generative	MAE	ViT-H Dosovitskiy et al. [2020]	Kinetics	74.1	81.1
MaskFeat Wei et al. [2022]	Generative	MAE	MViT Fan et al. [2021]	Kinetics	74.4	86.7
VideoMAE Tong et al. [2022]	Generative	MAE	ViT-L Dosovitskiy et al. [2020]	ImageNet	<u>75.3</u>	<u>85.1</u>
MotionMAE Yang et al. [2022]	Generative	MAE	ViT-B Dosovitskiy et al. [2020]	Kinetics	75.5	81.7

between the entire dataset to draw a hypothesis and predict future blocks. Another approach Pan et al. [2021] uses a **temporal mask** to indicate the importance of each frame rather than generating frames. Both the masked set of frames and the original set of frames are sent to a discriminator where the latent representations became similar over training. A *contrastive loss* is used to train the discriminator, measuring the similarity between the query and a set of other samples, called keys, stored in a dictionary He et al. [2020].

3.2.3 Masked Autoencoders

This approach was originally proposed in the image-domain He et al. [2022] where patches of an image are masked. The model encodes the visible patches and decodes both the visible and masked patches. This has been extended to video in several works Wei et al. [2022], Yang et al. [2022], Feichtenhofer et al. [2022], Wang et al. [2022b] with an emphasis on temporal elements. These approaches typically use a visual-transformer backbone in order to allow for the masking task. MAE Feichtenhofer et al. [2022] extends image-based Masked Autoencoders to video using spatio-temporal learning. They randomly mask out space-time patches in videos and learn an autoencoder to reconstruct them in pixels. BEVT Wang et al. [2022b] both extends image based MAE and uses images by utilizing both an image and video stream during pre-training. MotionMAE Yang et al. [2022] masks patches and adds emphasis to temporal elements by feeding the encoder output to a Time head and a Space head. These heads process visible and masked tokens for reconstruction of frame patches and motion. Similarly, in MaskFeat Wei et al. [2022] a few space-time cubes of video and the model is asked to predict those using what is remaining. The idea is the model must recognize objects using context as well as how they move. Because these approaches emphasize temporal elements, they have been evaluated on the Something-Something dataset Goyal et al. [2017] as shown in Table 5.

3.2.4 Multimodal Masked Modeling

Masked modeling was first introduced in the natural language processing (NLP) community as Masked Language Modeling (MLM) with the popular Bidirectional Encoder Representations from Transformers (BERT) Kenton and Toutanova [2019] model. Several works have adapted this approach into multimodal approaches for self-supervised learning with video, typically including additional modalities. A number of these works have used combinations of visual, text and/or audio tokens for masked modeling to learn a joint space of the different modalities. This was first introduced in Sun et al. [2019a] where BERT was extended to video domain by transforming the raw visual data into a discrete sequence of tokens using hierarchical k-means. This allows a combination of textual and visual tokens in a sequence used in a BERT architecture. ASR is used as the text signal in order to add tokens that specify the joining of two sentences [SEP] and the beginning of each sequence [CLS]. For both video and text tokens, the model predicts whether the linguistic sentence is temporally aligned to the visual sentence using the hidden state of the [CLS] token. The temporal alignment task has also been used between video and audio in Owens and Efros [2018]. Here the authors proposed a binary classification task between video and audio that is synchronized from the same video, or video with audio that was shifted several seconds.

To improve the cross-modal feature embedding, some recent works proposed a **masked modeling (MM)** approach between modalities where tokens from one modality are used to recover tokens from another modality Sun et al. [2019a], Zhu and Yang [2020], Xu et al. [2021b], Li et al. [2020b], Luo et al. [2020]. These approaches utilized multiple pre-training tasks that alter the masked modeling approach and/or combine it with other tasks for learning. Some works even extend modalities into further subcategories such as object and action features: object features are spatial regions in a frame, text object descriptions and action features are verbs in text, and 3D CNN features over a set of frames Zhu and Yang [2020]. MM would then be used to predict the tokens from one of the subcategories in one modality using the tokens from the same subcategory in a different modality.

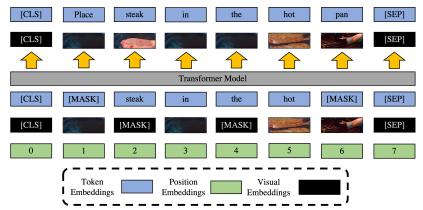


Figure 12: Inspired by the Masked Language Modelling (MLM) task in NLP, approaches that use masked modeling with multiple modalities convert visual data into discrete tokens that allow a combination of textual and visual tokens in a sequence. In this example, random text and visual tokens are masked and the model is asked to "fill in the blanks".

Table 6: Downstream action recognition evaluation for models that use a generative self-supervised pre-training approach. Top scores are in **bold** and second best are underlined.

	Subcategory	Visual Backbone	Pre-train	UCF101	HMDB51
Model					
Mathieu et al. Mathieu et al. [2016]	Frame Prediction	C3D	Sports1M	52.10	_
VideoGan Vondrick et al. [2016]	Reconstruction	VAE	Flickr	52.90	_
Liang et al. Liang et al. [2017]	Frame Prediction	LSTM	UCF101	55.10	_
VideoMoCo Pan et al. [2021]	Frame Prediction	R(2+1)D	Kinetics	78.70	49.20
MemDPC-Dual Han et al. [2020a]	Frame Prediction	R(2+3)D	Kinetics	86.10	54.50
Tian et al. Tian et al. [2020a]	Reconstruction	3D R-101	Kinetics	88.10	59.00
VideoMAE Tong et al. [2022]	MAE	ViT-L Dosovitskiy et al. [2020]	ImageNet	91.3	62.6
MotionMAE Yang et al. [2022]	MAE	ViT-B Dosovitskiy et al. [2020]	Kinetics	96.3	-

While these approaches used **cross-modal learning**, it did not use any **joint-modal learning**. In order to additionally use joint-learning, the authors in Luo et al. [2020] used both known tokens and other modality tokens to predict masked features in several MM pre-training tasks. To better address the dimension of time in learning, Li et al. [2020b] focused on both *local* and *global* levels of video representation where *global* is specific to time. Inspired by Lu et al. [2019], Chen et al. [2020b], Vaswani et al. [2017], *local* contextual cues were captured using a Cross-Modal Transformer between the subtitles and associated frames. The encodings from this transformer for the entire video clip, rather than frame-wise, were then fed into a Temporal Transformer to learn *global* contextual cues and the final representation. Two of the pre-training tasks were a masked modeling approach, one masking word tokens and the other masking frames.

3.2.5 Discussion

In self-supervised generative learning, we discussed several techniques: 1) the reconstruction of altered input/and or noise; 2) using previous frames to generate future frames in a sequence; 3) generating masked input that can be patches in frames or entire frames; 4) generating masked input of video, text and/or audio.

Generative approaches evaluated on action-recognition for the UCF101 and HMDB51 dataset are shown in Table 6. We observe that the approaches that use transformers to generate masked input as their pre-training task are the highest performers. Of the approaches that use the frame prediction and/or reconstruction tasks, methods that use temporal elements like motion and frame sequence are higher performers Tian et al. [2020a], Han et al. [2020a].

Generative approaches evaluated on action-recognition with the more temporal specific Something-Something (SS) Goyal et al. [2017] and Kinetics400 (Kinetics) dataset are shown in Table 5. The focus on using visual-transformers and temporal-specific learning mechanisms shows a large performance increase for both SS and Kinetics.

Because Multimodal masked modeling (MM) uses text, these generative approaches can additionally be evaluated on caption generation. Generative approaches evaluated on caption generation are shown in Table 7 on the YouCook2 dataset Zhou et al. [2018]. We observe better performance when the models are pre-trained on the HowTo100M dataset. Additionally, MM shows high performance without pre-training/fine-tuning on the target dataset.

Table 7: Downstream evaluation for video captioning on the YouCook2 dataset for video-language models. Top scores are in **bold** and second best scores are <u>underlined</u>. MM: Masked modeling with video and text, and K/H: Kinetics+HowTo100M.

			Backb	one						
Model	Category	Subcategory	Visual	Text	Pre-train	BLEU3	BLEU4	METEOR	ROUGE	CIDEr
CBT Sun et al. [2019b]	Cross-Modal	Video+Text	S3D-G	BERT	Kinetics	=	5.12	12.97	30.44	0.64
COOT Ging et al. [2020]	Cross-Modal	Video+Text	S3D-g	BERT	YouCook2	17.97	11.30	19.85	37.94	_
VideoBert Sun et al. [2019a]	Generative	MM	S3D-g	BERT	Kinetics	7.59	4.33	11.94	28.80	0.55
ActBERT Zhu and Yang [2020]	Generative	MM	3D R-32	BERT	K/H	8.66	5.41	13.30	30.56	0.65
VLM Xu et al. [2021b]	Generative	MM	S3D-g	BERT	How2	<u>17.78</u>	12.27	18.22	41.51	1.39
UniVL Luo et al. [2020]	Generative	MM	S3D-g	BERT	How2	23.87	17.35	22.35	46.52	1.81

3.3 Contrastive Learning

Contrastive learning provides a self-supervised way to push positive input pairs closer together while pushing negative input pairs farther apart. Figure 13 shows how a positive pair is generated from an anchor frame, in a video, and a frame at a different time in the same video (e.g. an adjacent frame in the same clip). To generate a set of negative samples, pairs are created between the anchor frame and frames from other videos. There are numerous ways of generating positive and negative samples which is the main differentiating factor between contrastive approaches.

There are three main objectives to contrastive learning: binary cross-entropy Knights et al. [2020], Yao et al. [2021], discriminator Tian et al. [2020a], Wang et al. [2021], Tao et al. [2020b], Xue et al. [2020], and Noise-Contrastive Estimation (NCE) Mnih and Kavukcuoglu [2013a], Qian et al. [2021], Tian et al. [2020a], Yao et al. [2021], Han et al. [2020b], Tian et al. [2020a], Knights et al. [2020], Hjelm and Bachman [2020], Lorre et al. [2020]. **Cross-entropy** is used with a binary classifier to determine whether a pair is "good" or not. **Discriminators** are used to return scores that are higher for positive pairs and smaller for negative pairs. The most commonly used contrastive training objectives are variations of the NCE and originated from the NLP domain. The **NCE loss** takes as input a positive pair of samples and a set of negative samples, minimizing the distance between the positive pair and maximizing the distance between the negative pairs Gutmann and Hyvärinen [2010], Smith and Eisner [2005], Mnih and Kavukcuoglu [2013b], Collobert and Weston [2008], Oord et al. [2018].

The majority of these works vary how positive and negative pairs are generated to minimize and maximize the distance between them respectively. In the image domain, this is *traditionally done by augmenting an image in different ways to generate positive samples* Wu et al. [2018], Ye et al. [2019], He et al. [2020], Chen et al. [2020c], Misra and Maaten [2020]. Such augmentations include rotation, cropping, random grey scale and color jittering Ye et al. [2019], Chen et al. [2020c]. To extend these works in video can be difficult because each videos comparison adds to the memory required, especially if using multiple augmentations for multiple positive samples. Another challenge is including time in the augmentations. Some approaches simply apply the same augmentations as in images to each frame Hjelm and Bachman [2020], Han et al. [2020b], Tian et al. [2020b], Feichtenhofer et al. [2021]. Some approaches include additional permutations that may be temporal based, such as shuffling frames Knights et al. [2020], Lorre et al. [2020]. Finally, some rely on motion and flow maps as the positive samples Rai et al. [2021].

Approaches also vary in how they maintain collections of negative pairs in order to keep computation and space low, typically using a *memory bank* or *momentum encoder* Jaiswal et al. [2021]. To further improve the memory use and performance, contrastive learning expanded into using other modalities from video that includes audio and/or text Patrick et al. [2020b], Amrani et al. [2021], Xu et al. [2021a], Miech et al. [2019, 2020]. Approaches that are referred to as multimodal or cross-modal learning are referring to learning between video, audio and/or text. Text is a common secondary modality because the NCE loss originated in the NLP domain Mnih and Kavukcuoglu [2013a] with great success. Text also adds semantic knowledge something that would otherwise require in-depth annotations for video. To train using these signals, the existing approaches often use pair-wise comparisons between separate embeddings of each signal.

The Contrastive approaches used for self-supervised learning in the video domain are split into four main categories: *view augmentation*, *temporal augmentation*, *spatio-temporal augmentation*, *multimodal alignment clustering*, *multimodal clustering* and *multimodal cross-modal agreement*.

3.3.1 View Augmentation

Originally proposed in the image-domain, view augmentation, or data augmentation, *focuses on changes in appearance through various transformations*. These include random resized crop, channel drop, random color jitter, random grey, and/or random rotation Wu et al. [2018], Ye et al. [2019], He et al. [2020], Chen et al. [2020c], Misra and Maaten [2020]. In video, these augmentations are applied to each frame in a clip Hjelm and Bachman [2020], Tian et al. [2020b], Han

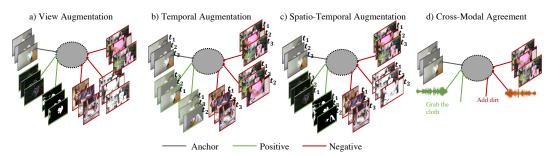


Figure 13: Toy examples of how positive samples are generated for a contrastive loss aiming to bring an anchor sample (grey) closer to the positive samples (green) in latent space while pushing negative samples (red) further away. In a) view augmentation, positive examples are perturbed versions of the anchor clip using color changes and/or geometric changes for each frame. In b) temporal augmentation positive examples are generated by shuffling the order of frames c) and spatio-temporal is a combination of view and temporal changes. The last example d) shows cross-modal agreement where positive samples are audio or text samples from the anchor clip and negative samples are audio, video and/or text from other clips.

et al. [2020b]. Positive pairs are augmented versions of the original clip while negative pairs are clips from other videos. Each type of augmentation results in a different "view" of the original clip.

To extend to videos, Feichtenhofer et al. [2021] applied the popular image-based approaches MoCo He et al. [2020], SimCLR Chen et al. [2020c], BYOL Grill et al. [2020] and SwAV Caron et al. [2020] by using the same perturbations across a series of frames. They showed that the approaches performed well when a temporal persistency objective was added. More specific to video, and utilizing an encoder-decoder network, Hjelm and Bachman [2020] combined augmentations with a view generator that split clips into two down-sampled sequences. These sequences are then passed to a decoder that processes global features at later layers and local patches at earlier layers. An NCE loss is applied to the individual layers across all locations of the encoder, maximizing the mutual information across all locations over all layers. Instead of relying only on an NCE loss, Tian et al. [2020b] additionally uses a discriminator to predict high values for positive pairs and low values for negative pairs.

3.3.2 Temporal Augmentation

A more video-specific augmentation is temporal. It is used to generate pairs from modifying the temporal order or the start and end point of a clip interval Knights et al. [2020], Lorre et al. [2020]. In Knights et al. [2020], temporal coherency is used by maximizing a similarity function between two temporally adjacent frames in the same video, while minimizing similarity between frames from other videos. The NCE loss uses multiple negative samples that are selected by their embedding distance outside a hypersphere. As training progresses, the number of selected negative samples is increased, which results in a random sampling. Rather than using the next single frame as a positive, Lorre et al. [2020] uses an autoregressive model to generate a sequence of future frames as positive samples. The model is then trained using an NCE objective which uses the actual latent representations as an anchor, the generated representations as positive samples, and the generated latent representations from other videos as negative.

3.3.3 Spatio-Temporal Augmentation

While temporal augmentations perform well, some recent works which incorporate both time and space have been found to be more effective. In Han et al. [2020b] an encoder for augmented RGB frames and an encoder for augmented optical flow are used. The encoders are trained using a modified InfoNCE loss that compares a given sample to multiple positive samples by finding the top-k most similar samples. It first mines for samples of the same type, e.g. RGB to RGB, and then switches them, e.g. RGB samples are paired with the top-k most similar flow samples and vice versa. The authors in Yao et al. [2021] propose a two pairing strategy: inter-frame instance discrimination using NCE, which highlights temporal elements, and intra-frame instance discrimination using cross-entropy which highlights spatial. Similarly in Wang et al. [2021], compares multiple signals using InfoNCE, where temporal and spatial are considered separately and jointly. Three versions of each clip are generated from 1) basic augmentation 2) Thin-Plate-Spline (TPS) Jaderberg et al. [2015], Shi et al. [2016] generated spatial local disturbance and 3) pace changing with optical-flow scaling combined with temporal shift for temporal local disturbance (TLD). In order to focus more on the spatio-temporal relationship rather than the two separately, Qian et al. [2021] uses both temporal and spatial augmentation to generate positive pairs for an InfoNCE loss Chen et al. [2020c]. Inspired by this, Tao et al. [2020b] used multi-view augmentation to generate positive samples while negative samples were generated from frame repeating or frame shuffling to distort the

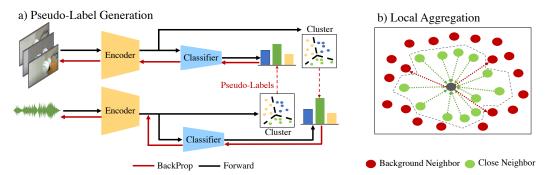


Figure 14: Toy examples of how clustering is used in self-supervised learning for video. a) Pseudo-Label generation uses cluster assignments as pseudo labels with multiple modalities as in Alwassel et al. [2020]. The cluster assignments from one signal are used as pseudo-labels for the other. b) Local Aggregation focuses on the latent space where for each sample "close" neighbors are pulled closer and "background" neighbors are pushed further away like in Zhuang et al. [2019], He et al. [2017], Wang and Schmid [2013], Tokmakov et al. [2020].

original temporal order. To focus on both local and global representations, Dave et al. [2022] uses a local loss that treats non-overlapping clips as negatives and spatially augmented versions of the same clip as positives.

3.3.4 Clustering

Clustering is an approach to self-supervised learning that focuses on the optimal grouping of videos in a cluster. In the image-based approach Zhuang et al. [2019] two sets of neighbors are defined for each sample: background neighbors \mathbf{B}_i , and close neighbors \mathbf{C}_i . The model learns to make \mathbf{C}_i closer to a video's representation, while \mathbf{B}_i is used to set the distance scale that defines "closeness". In Zhuang et al. [2020], this approach was extended to videos using a two-branch architecture: one that embeds static, single frames and another that embeds dynamically, multiple frames. At each step, all videos are compared and processed via loss functions adapted from Zhuang et al. [2019], Wu et al. [2018]: Instance Recognition (IR) and Local Aggregation (LA). The LA loss function use dynamic online k-means clustering to find "close" neighbors. This two branch approach is also utilized in Tokmakov et al. [2020] where the first branch use a 3D ConvNet to embed video features, while the second branch embed the trajectory of videos using dimensionality reduction on IDT descriptors Wang and Schmid [2013] of Mask-RCNN human detections He et al. [2017]. Both branches use k-means clustering to identify close neighbors and background neighbors as described in Zhuang et al. [2019]. After several epochs of training, joint IDT and 3DConvNet embeddings are generated by concatenating their respective features for the k-means clustering objective. To improve clustering further, the authors in Peng et al. [2021] introduced generative learning to their approach. This approach uses a 3D U-Net to encode spatio-temporal features. The output of the U-Net is both a reconstruction module and a classification module that predicts a pseudo-label for each sample using the reconstruction (similar to Figure 14).

3.3.5 Discussion

In self-supervised contrastive learning, we discussed approaches that generate positive and negative samples via 1) temporal augmentation or 2) spatio-temporal augmentation. We also discussed approaches that 3) directly utilize the embedding space via clustering.

When these approaches are evaluated on action recognition (shown in Table 11 and Figure 15), spatio-temporal augmentation for generating samples had the highest success. The most successful approaches were those that were directly extended from image-based research to video by adding a temporal consistency Feichtenhofer et al. [2021]. This indicates that *image-based methods may work just as well for video as long as temporal elements are added*. The clustering approach that performed the best was Alwassel et al. [2020] which used audio and video signal to generate pseudo-labels for the other. These results indicate that using additional signals may provide equally well performance without the need of data augmentation.

3.4 Cross-Modal Agreement

We have already discussed several works which utilize cross-modal signals in a hybrid setting, but this section will provide an comprehensive overview of approaches that solely use cross-modal agreement as their self-supervised learning objective. These works primarily use a contrastive NCE loss comparing positive and negative pairs.

3.4.1 Video and Text

The foundational work in this area pairs text and video Miech et al. [2019, 2020]. A new loss formulation was proposed in Miech et al. [2020] that is tailored to the challenges of using large-scale user-generated videos as found in the dataset HowTo100M Miech et al. [2019], where 50% of clip-narration pairs were misaligned. This loss, termed as *Multiple Instance Learning Noise Contrastive Estimation* (MIL-NCE) loss, is a variation of the NCE loss and is shown in equation 1,

$$\max_{f,g} \sum_{i=1}^{n} \log \left(\frac{\sum_{(x,y) \in \mathcal{P}_i} e^{f(x)^{\top} g(y)}}{\sum_{(x,y) \in \mathcal{P}_i} e^{f(x)^{\top} g(y)} + \sum_{(x',y') \sim \mathcal{N}_i} e^{f(x')^{\top} g(y')}} \right)$$
(1)

where (x,y) is a clip-narration pair and f,g are visual and text encoders. The proposed method constructs a bag of positive candidate pairs \mathcal{P}_i from the nearest captions in an initial time-range, then nearest captions when the initial-time range is tripled in duration. Negative samples are selected from the set of negative video/narration pairs \mathcal{N}_i . Miech et al. [2019] proposed a baseline for such an approach using instructional videos. More recently, VideoCLIP Xu et al. [2021a] uses a contrastive loss of overlapping positive and negative text pairs by performing the reverse of Miech et al. [2019]'s strategy. The proposed method first samples a text snippet and then samples a video timestamp, within the boundaries of the clip, as a center. It then extended the video clip with a random duration from this center timestamp. In Amrani et al. [2021], the authors propose to use a pairwise comparison where, in latent space, if two video clips are similar, then their captions should also be similar. A pairs' local k-NN density estimation was used to measure the probability of a pair being correctly matched. The objective is formulated as a *Soft Max Margin Ranking loss* Wang et al. [2014], Schroff et al. [2015] where positive and negative pairs are from the same video/caption and different caption/video respectively, which are then weighted by the similarity weights.

Some recent works, such as Patrick et al. [2020b], Amrani et al. [2021], extend the contrastive loss for HowTo100M pre-training by enforcing both global and local representations across samples. The authors in Patrick et al. [2020b] proposed to replace the visual encoder with a transformer, as in Gabeur et al. [2020], and used both a contrastive loss between video and text features as well as a generative loss using the entire batch. A reconstruction is generated as a weighted combination of video embeddings from a "support-set" of video clips selected via attention to enforce

Table 8: Downstream action segmentation evaluation on COIN for models that use a cross-modal agreement self-supervised pre-training approach. The top score is in **bold** and the second best is <u>underlined</u>.

Backbone							
Model	Visual	Text	Pre-train	Frame-Acc			
CBT Sun et al. [2019b]	S3D-G	BERT	Kinetics+How2	53.90			
ActBERT Zhu and Yang [2020]	3D R-32	BERT	Kinetics+How2	56.95			
VideoClip (zs) Xu et al. [2021a]	S3D-g	BERT	How2	58.90			
MIL-NCE Miech et al. [2020]	S3D	Word2Vec	How2	61.00			
VLM Xu et al. [2021b]	S3D-g	BERT	How2	68.39			
VideoClip (ft) Xu et al. [2021a]	S3D-g	BERT	How2	68.70			
UniVL Luo et al. [2020]	S3D-g	BERT	How2	70.20			

representation sharing between different samples.

The methods discussed so far learned independent encodings for each modality. In contrast, some of the approaches have attempted to learn joint-embedding for multiple signals Sun et al. [2019a,b], Liu et al., Gabeur et al. [2020], Miech et al. [2018], Wray et al. [2019]. In Wray et al. [2019], the authors propose a cross-modal margin triplet loss where a video is paired with text and the text is also paired with a video. This method uniquely process text by separating nouns and verbs in two separate branches and pairs them separately with video using four different encoders. Then noun, verb and video representations are aggregated together via two encoders using the output from the other branches. The two final representations are then paired together for the final loss while negative pairs are generated from a mismatch between video and text.

Rather than relying on separate embeddings, the authors in Sun et al. [2019b] concatenated text and video embeddings together before passing them to a cross-modal transformer. The joint-embeddings are formulated to generate positive and negative pairs of aligned and unaligned ASR and video to measure the NCE loss. A more complex approach in Gabeur et al. [2020] extended prior work Liu et al., Miech et al. [2018]. This model learns to maximize the similarity between the associated text of a video and a cross-modal

Table 9: Downstream temporal action step localization evaluation on CrossTask for models that use a contrastive multimodal self-supervised pre-training approach. Top scores are in **bold** and second best underlined.

	Bac	kbone		
Model	Visual	Text	Pre-train	Recall
VideoClip (zs) Xu et al. [2021a]	S3D-g	BERT	How2	33.90
MIL-NCE Miech et al. [2020]	S3D	Word2Vec	How2	40.50
ActBERT Zhu and Yang [2020]	3D R-32	BERT	Kinetics+How2	41.40
UniVL Luo et al. [2020]	S3D-g	BERT	How2	42.00
VLM Xu et al. [2021b]	S3D-g	BERT	How2	46.50
VideoClip (ft) Xu et al. [2021a]	S3D-g	BERT	How2	47.30

Table 10: Performance for the downstream video retrieval task. Top scores for each category are in **bold** and second best <u>underlined</u>. Masked Modeling (MM) is a generative approach that uses both video with text. Cross-modal agreement include a variety of contrastive approaches that can use video with audio and/or text. Cross-modal agreement pre-training approaches typically perform best. Some models have dedicated variations in what they report with fine-tuning (*) on the target dataset, YouCook2 or MSRVTT. The pre-training datasets titled COMBO are CC3M Sharma et al. [2018], WV-2MBain et al. [2021] and COCO Lin et al. [2014].

	F	Backbone			YouCool	:2		MSRVT	Г
Model	Visual	Text	Pre-Train	R@1	R@5	R@10	R@1	R@5	R@10
		Masked Modeling							
ActBERT Zhu and Yang [2020]	3D R-32	BERT	Kinetics+How2	9.60	26.70	38.00	8.60	23.40	33.10
HERO Li et al. [2020b]	SlowFast	WordPieces	How2+TVGeest et al. [2016]	-	-	-	16.80	43.40	57.70
ClipBERT Lei et al. [2021]	R-50	WordPieces	VisualGenome Krishna et al. [2017b]	-	-	-	22.00	46.80	59.90
VLM Xu et al. [2021b]	S3D-g	BERT	How2	27.05	56.88	69.38	28.10	55.50	67.40
UniVL Luo et al. [2020]	S3D-g	BERT	How2	28.90	57.60	70.00	21.20	49.60	63.10
		Cross-Modal Agreen	nent						
Amrani et al. Amrani et al. [2021]	R-152	Word2Vec	How2	-	-	-	8.00	21.30	29.30
MIL-NCE Miech et al. [2020]	S3D	Word2Vec	How2	15.10	38.00	51.20	9.90	24.00	32.40
COOT Ging et al. [2020]	S3D-g	BERT	How2+YouCook2	16.70	40.20	52.30	-	-	-
CE* Liu et al.	Experts	NetVLAD Arandjelovic et al. [2016]	MSRVTT	-	-	-	10.00	29.00	41.20
VideoClip Xu et al. [2021a]	S3D-g	BERT	How2	22.70	50.40	63.10	10.40	22.20	30.00
VATT Akbari et al. [2021]	Linear Proj.	Linear Proj.	AS+How2	-	-	40.60	-	-	23.60
MEE Miech et al. [2018]	Experts	NetVLAD Arandjelovic et al. [2016]	COCOLin et al. [2014]	-	-	-	14.20	39.20	53.80
JPoSE Wray et al. [2019]	TSN Wang et al. [2016]	Word2Vec	Kinetics	-	-	-	14.30	38.10	53.00
Amrani et al.* Amrani et al. [2021]	R-152	Word2Vec	How2	-	-	-	17.40	41.60	53.60
AVLnet* Rouditchenko et al. [2020]	3D R-101	Word2Vec	How2	30.20	55.50	66.50	22.50	50.50	64.10
MMT Gabeur et al. [2020]	Experts	BERT	How2	-	-	-	-	14.40	-
MMT* Gabeur et al. [2020]	Experts	BERT	How2	-	-	-	-	55.70	_
Patrick et al.* Patrick et al. [2020b]	Experts	T-5 Raffel et al. [2020]	How2	-	-	-	30.10	58.50	69.30
VideoClip* Xu et al. [2021a]	S3D-g	BERT	How2	33.20	62.60	75.50	30.90	55.40	66.80
FIT Bain et al. [2021]	ViT Dosovitskiy et al. [2020]	BERT	COMBO	-	-	-	32.50	61.50	71.20

embedding for video using "experts" Liu et al.

and a complex aggregation procedure. Each expert encodes either motion, audio, scene, OCR, face, speech and appearance of video clips which are concatenated together. To know which of these features came from which encoder, it generates a mapping vector. The temporal representations indicates the time in the video where each feature is extracted. These three vectors are then aggregated together and passed to a transformer to output the final representation. Text is embedded using BERT and gated embedding modules Miech et al. [2018], one for each expert on the video embedding side.

3.4.2 Video and Audio

Visual representation learning using both audio and video has been proposed in several works Cramer et al. [2019], Morgado et al. [2021], Korbar and Torresani [2018]. Using basic data augmentation, multiple types of transformations that were hierarchically sampled and applied to each batch were used in Patrick et al. [2020a]. This generated distinct and/or invariant positive pairs. These transformations are temporal, cross-modal, and spatial/aural augmentations. The cross-modal transformation projected the video to either its visual or audio component.

Temporal augmentation has been used for contrastive synchronization tasks between audio and video modalities Morgado et al. [2021], Rouditchenko et al. [2020], Owens and Efros [2018], Afouras et al. [2020], Korbar and Torresani [2018]. Traditional approaches used a two branch network, one for audio and another for video, followed by a fusing procedure Korbar and Torresani [2018], Owens and Efros [2018]. The authors in Owens and Efros [2018] used a binary classification task between video and audio that is synchronized from the same video, or video with audio that was shifted several seconds. Meanwhile in Korbar and Torresani [2018], a contrastive loss used traditionally for Siamese networks Koch et al. [2015] was used with easy negatives and hard negatives. Easy negatives were frames and audio from two different videos whilst hard negatives were frames and audio from the same video with short time-gaps positioned between them. In recent works, Morgado et al. [2021] uses an audio-visual correspondence task, first proposed in Arandjelovic and Zisserman [2018], by taking an exponential moving average of representations, called memory representations, for video and audio features that are maintained to make contrastive and cross-modal comparisons. The probability that a memory representation for a sample, \overline{v}_i or \overline{a}_i , belongs to a given sample v_i or a_i , is modeled as a softmax function. Negative samples are a number of instances, drawn from the distribution at random, from different videos. Whereas positive samples were the memory representations and their corresponding samples. The authors use a cross-modal NCE contrastive loss and an cross-modal agreement loss. The cross-modal agreement use positive samples that are the top-k most similar to the anchor sample in both spaces while negative are the top-k most distant.

Clustering pseudo-labels has also been used with audio and video. Inspired by DeepCluster for images Caron et al. [2018], Alwassel et al. [2020] uses audio signals to generate pseudo-labels for video and vice versa. This is achieved using a classification task as opposed to contrastive learning as shown in Figure 14. This approach uses a video encoder and an audio encoder to embed RGB frames and audio spectrograms respectively. In each iteration, the features are clustered separately. Video uses cluster assignments from audio while audio uses cluster assignments from video

Table 11: Downstream action recognition on UCF101 and HMDB51 for models that use contrastive learning and/or cross-modal agreement. Top scores for each category are in **bold** and second best are <u>underlined</u>. Modalities include video (V), optical flow (F), human keypoints (K), text (T) and audio (A). Spatio-temporal augmentations with contrastive learning typically are the highest performing approaches.

		Back	bone					uracy
Model	Subcategory	Visual	Text	Audio	Modalities	Pre-Train	UCF101	HMDB51
VIE Zhuang et al. [2020]	Clustering	Slowfast	_	_	V	Kinetics	78.90	50.1
VIE-2pathway Zhuang et al. [2020]	Clustering	R-18	_	-	V	Kinetics	80.40	52.5
Tokmakov et al. Tokmakov et al. [2020]	Clustering	3D R-18	-	_	V	Kinetics	83.00	50.4
TCE Knights et al. [2020]	Temporal Aug.	R-50	-	-	V	UCF101	71.20	36.6
Lorre et al. Lorre et al. [2020]	Temporal Aug.	R-18	-	_	V+F	UCF101	87.90	55.4
CMC-Dual Tian et al. [2020b]	Spatial Aug.	CaffeNet	-	-	V+F	UCF101	59.10	26.7
SwAV Feichtenhofer et al. [2021]	Spatial Aug.	R-50	_	_	V	Kinetics	74.70	_
VDIM Hjelm and Bachman [2020]	Spatial Aug.	R(2+1)D	-	_	V	Kinetics	79.70	49.2
CoCon Rai et al. [2021]	Spatial Aug.	R-34	_	_	V+F+K	UCF101	82.40	53.1
SimCLR Feichtenhofer et al. [2021]	Spatial Aug.	R-50	_	_	V	Kinetics	84.20	_
CoCLR Han et al. [2020b]	Spatial Aug.	S3D-G	_	_	V+F	UCF101	90.60	62.9
MoCo Feichtenhofer et al. [2021]	Spatial Aug.	R-50	_	_	V	Kinetics	90.80	_
BYOL Feichtenhofer et al. [2021]	Spatial Aug.	R-50	_	_	V	Kinetics	91.20	_
MIL-NCE Miech et al. [2020]	Cross-Modal	S3D-G	Word2Vec	-	V+T	How2	61.00	91.3
GDT Patrick et al. [2020a]	Cross-Modal	R(2+1)D	Word2Vec	2D CNN	V+T+A	Kinetics	72.80	95.5
CBT Sun et al. [2019b]	Cross-Modal	S3D-G	BERT	_	V+T	Kinetics	79.50	44.6
VATT Akbari et al. [2021]	Cross-Modal	Transformer	Transformer	_	V+T	AS+How2	85.50	64.8
AVTS Korbar and Torresani [2018]	Cross-Modal	MC3 Tran et al. [2018b]	_	VGG	V+A	Kinetics	85.80	56.9
AVID+Cross Morgado et al. [2021]	Cross-Modal	R(2+1)D	_	2D CNN	V+A	Kinetics	91.00	64.1
AVID+CMA Morgado et al. [2021]	Cross-Modal	R(2+1)D	_	2D CNN	V+A	Kinetics	91.50	64.7
MMV-FAC Alayrac et al. [2020]	Cross-Modal	TSM Lin et al. [2019]	Word2Vec	R-50	V+T+A	AS+How2	91.80	67.1
XDC Alwassel et al. [2020]	Cross-Modal	R(2+1)D	_	ResNet	V+A	Kinetics	95.50	68.9
DVIM Xue et al. [2020]	Spatio-Temporal Aug.	R-18	-	-	V+F	UCF101	64.00	29.7
IIC Tao et al. [2020b]	Spatio-Temporal Aug.	R3D	_	_	V+F	Kinetics	74.40	38.3
DSM Wang et al. [2021]	Spatio-Temporal Aug.	I3D	_	_	V	Kinetics	78.20	52.8
pSimCLR Chen et al. [2020c]	Spatio-Temporal Aug.	R-50	_	_	V	Kinetics	87.90	_
TCLR Dave et al. [2022]	Spatio-Temporal Aug.	R(2+1)D	_	_	V	UCF101	88.20	60.0
SeCo Yao et al. [2021]	Spatio-Temporal Aug.	R-50	_	_	V	ImageNetKrizhevsky et al. [2012b]	88.30	55.6
pSwaV Caron et al. [2020]	Spatio-Temporal Aug.	R-50	-	_	V	Kinetics	89.40	_
pBYOL Grill et al. [2020]	Spatio-Temporal Aug.	R-50	_	-	V	Kinetics	93.80	-
CVRL Qian et al. [2021]	Spatio-Temporal Aug.	3D R-50	_	_	V	Kinetics	93.90	69.9
pMoCo He et al. [2020]	Spatio-Temporal Aug.	R-50	_	_	V	Kinetics	94.40	_
pBYOL Feichtenhofer et al. [2021]	Spatio-Temporal Aug.	S3D-G	_	-	V	Kinetics	96.30	75.0

representations. The authors in Asano et al. [2020] also utilize clustering but use information from both audio and video during each iteration. The clustering optimization is formulated as an optimal transport problem with a tail-end prior distribution for clustering assignments. This method extracts a sample's average latent representations from encoders using modality splicing and data augmentations. The activations that are used for clustering are averaged over these augmentations. This results in clusters that are invariant to augmentations and choice of modality.

3.4.3 Video, Text and Audio

Some approaches utilize signals from audio, visual and text associated with a video. Using the three signals was first proposed in the image domain Kaiser et al. [2017], Aytar et al. [2017] for tasks such as cross-modal retrieval and the transferring of classifiers between modalities. In Rouditchenko et al. [2020], features are extracted using encoders designed specifically for each signal. A non-linear feature gating is then used to generate a joint-embedding between the three. Using a Masked Margin Softmax Loss Ilharco et al. [2019], Oord et al. [2018], comparisons were made between audio-visual pairs, visual-text pairs, and audio-text pairs. Clustering for pseudo-labels has also been used similar to Alwassel et al. [2020] and Figure 14. The authors in Chen et al. [2021] added text as one of the signals with this approach. More specifically, the authors aggregated text, audio, and visual features into a joint space and then performed clustering. The overall objective used three tasks: a contrastive loss, a clustering loss, and a reconstruction loss simultaneously.

To account for the differences in video, audio, and text modalities, Alayrac et al. [2020] proposes to first joint-embed video and audio because they are at a fine-grained granularity. Then the joint-embedding is embedded with text, which is coarse-grained. This architecture uses a two-branch embedding of audio and visual features separately. Training uses a traditional NCE loss between the joint audio-visual embeddings and an MIL-NCE loss Miech et al. [2019] between the joint visual-audio-text embeddings. This common space projection method is later used in Akbari et al. [2021] as a Multimodal Projection Head. This approach discretized video, audio and text signal before passing to a traditional transformer. To reduce computational complexity, the authors propose DropToken, randomly dropping these tokens before passing to a transformer. The Multimodal Projection Head uses the output of the transformer for final shared space projection and contrastive learning.

3.4.4 Discussion

In cross-modal learning, we discussed generating positive and negative samples via 1) video and audio signals 2) video and text signals 3) and video, audio and text signals. These multimodal approaches typically pre-train on the

HowTo100M dataset Miech et al. [2019]. Many of these models, such as UniVL Luo et al. [2020], VideoClip Xu et al. [2021a] and COOT Ging et al. [2020], rely on pre-extracting features from the S3D-g visual encoder from Miech et al. [2020]. Future work should attempt to understand more what these models are capable of learning by using raw video as input, especially with transformer based architectures like VATT Akbari et al. [2021].

When these approaches are evaluated on action recognition (shown in Table 11 and Figure 15), the multimodal approach that performed the best was Alwassel et al. [2020], which used audio and video signal to generate psuedo-labels for the other, using a classification task as opposed to contrastive learning. The other multimodal approach that performed well was Alayrac et al. [2020], which used a contrastive loss between embeddings of text, audio and video, using joint-modal embeddings. Multimodal approaches also generalize to more downstream tasks as shown in Table 8, 10, and 9. In Table 10, multimodal contrastive losses outperform masked modelling (MM). Models that are fine-tuned on the target dataset, as expected, perform the best as seen with VideoClip Xu et al. [2021a]. This may indicate that *cross-modal learning shows better performance than joint-modal learning for some tasks* like text-to-video retrieval and temporal action step localization.

4 Summary and Future Directions

This survey discussed pretext, generative, contrastive and multimodal approaches to self-supervised video representation learning. *Pretext tasks* that are most commonly used includes frame order, appearance statistics, jigsaw, and playback speed related tasks. Of the pretext learning tasks, classifying playback speed performs the best on downstream action recognition and is one of the more recent video only based approaches. This approach performs better than frame ordering because it has multiple ways to use temporal signal by modifying the speed while frame order has limited permutations. Generative approaches commonly used include generative adversarial networks, masked auto-encoders and multimodal masked modeling. Some of these approaches used a sequence of previous frames to generate the next sequence of frames. Other approaches used a model to generate masked input using the unmasked input of one or multiple modalities.

The approaches that performed the best used masked modeling. *Contrastive approaches* are the most common approach to self-supervised learning of video. There are

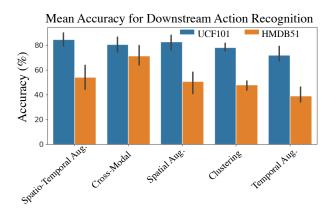


Figure 15: Mean performance on action recognition for approaches mentioned in Table 11. Using spatio-temporal augmentations with contrastive learning typically perform best.

many ways positive and negative samples are generated for an anchor clip including view augmentation, temporal augmentation, spatio-temporal augmentation, clustering and multimodal. Contrastive learning is the best performing learning objective in all action based downstream tasks. These approaches have also entered a multimodal domain with *cross-modal agreement*. These approaches both improve performance in action-recognition tasks and expand into other tasks like text-to-video retrieval and action segmentation using text and audio modalities.

4.1 Limitations and Future Work

While the existing approaches improved the generalizability of learned representations, there are still some limitations which need to be addressed. For example, when evaluating on downstream action recognition, the majority of approaches use the UCF101 Soomro et al. [2012] and HMDB51 Kuehne et al. [2011] datasets that lack temporal specificity. More approaches should additionally evaluate on temporal specific datasets like the Something-Something dataset Goyal et al. [2017]. Specific to the different categories, future work should attempt to understand the performance and robustness between cross-modal approaches. Moreover, detection tasks such as video object detection, action detection, video semantic segmentation, etc. are not well explored from self-supervision point of view and are promising future directions. Additionally, combining learning objectives from multiple categories, such as masked modeling and contrastive learning, can be be further explored as preliminary works already show increased performance Chung et al. [2021], Luo et al. [2020], Ging et al. [2020].

Long-term video representation. Current approaches mostly focus on small video clips and do not learn representations for a long video. In most approaches, a video is split into clips as part of their pre-processing. While these approaches improve the learning using temporal elements of the video, they lack long-term temporal learning. Furthermore, it

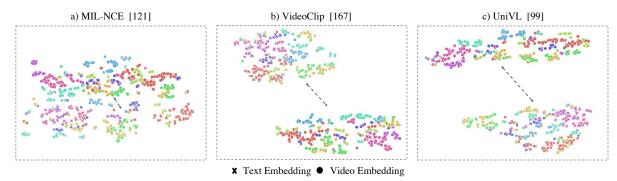


Figure 16: T-sne visualizations of multimodal features where video and text are in a joint space. The colors indicate the recipe of clips from the YouCook2 dataset. The shapes of each point indicate either text or video embeddings. When visualized, even though the VideoClip Xu et al. [2021a] and UniVL Luo et al. [2020] models significantly outperform the MIL-NCE model Miech et al. [2020] on downstream tasks, the text and visual embeddings show a large gap in the latent space compared to to MIL-NCE. Future work should look at why these higher performing models produce multimodal embeddings that look distant from each other.

has been demonstrated that datasets like MSRVTT and UCF101 do not necessarily need temporal learning Huang et al. [2018], Buch et al. [2022]. Future research should evaluate on more temporally relevant datasets like Something-Something Goyal et al. [2017] and NExT-QA Xiao et al. [2021]. Future research should also attempt to learn a representation from a long video as a whole, focusing on temporal learning rather than only using the temporal signal as a guidance for training.

Simple end-to-end approaches. Most of the approaches use a pre-trained backbone as a dependency for feature extraction. For example, many of the multimodal approaches use the S3Dg from MIL-NCE Miech et al. [2019]. This model is already pre-trained using a contrastive loss function on text and video and is a large, computational approach out-of-the-box. These new approaches extract features from the S3Dg, then add-on large, computational approaches. There has been little focus on reducing the size of these models or to create an approach that does not rely on previous works directly. Additionally, this prevents probing models for better understanding of what these models are learning, especially when there is semantic information available via text. This is also the same for video-only approaches using networks like I3D Carreira and Zisserman [2017], when the downstream task is also action recognition. There are recent approaches that utilize a transformer visual encoder, such as Akbari et al. [2021] and Ranasinghe et al. [2022], that takes raw video as input, but there is limited research in this area but great potential for future works. Future work should focus more on simple end-to-end approaches that do not rely on previous work so directly and therefore can reduce the computational costs and dependencies.

Interpretability and Explainability. Downstream tasks have focused on specific areas to each modality, such as action recognition, event recognition for audio, and caption generation for text. While these help understand the generalizability of the learned representations, they do not provide insight to what these models are actually learning. While this has been done in the image-domain by probing models Thrush et al. [2022], there is no approach that demonstrates the understanding a model uses to generate the representations in the video domain. This lack of interpretability enforces the 'black-box model" approach. Future research should focus on understanding what these models are learning and why their representations are more generalizable. With this understanding, models can be further improved and provide more understanding about videos. While multimodal approaches typically are the best performers for downstream tasks, the lack of insight on what the models are learning prevents an understanding of how these modalities are interacting. For example, when using two modalities, what does the resulting joint-embedding space look like? In Figure 16, an example of this joint space is visualized using t-sne. The samples are clips from different recipes in the YouCook2 dataset, where visual features are depicted as \cdot and text features are x. While the cross-modal VideoClip Xu et al. [2021a] and joint-modal UniVL Luo et al. [2020] models significantly outperform the MIL-NCE model Miech et al. [2020] on the text-to-video retrieval task, the feature embeddings for each modality are distant from each other. Future work should investigate questions like this. More interpretable models would allow better representation of how text, video and audio are interacting and could lead to improved semantic graphs, temporal understanding of event interactions, and more.

Standard Benchmarking. The variation in backbone encoders and pre-training protocols makes direct comparisons difficult. While this survey attempts to organize such differences and discusses several existing benchmarks Feichtenhofer et al. [2021], Huang et al. [2018], Buch et al. [2022], it would be beneficial to the community to have a benchmark evaluation for self-supervised learning that allows better comparisons between the many different approaches. While in the image domain, robustness has been investigated for self-supervised learning Hendrycks and Dietterich [2018],

Bhojanapalli et al. [2021], Hendrycks et al. [2021], there is a shortage of similar work in the video domain Schiappa et al. [2022], Liang et al. [2021]. These models are often evaluated on zero-shot learning, so understanding the robustness to different types of distribution shifts will provide further improvements. Future work should generate benchmarks for evaluation on the performance of self-supervised learning as well as the robustness of different approaches.

5 Conclusion

This survey discussed self-supervised learning for video and analyzed the current landscape. From our analysis, we observed the following interesting points; 1) playback speed or temporal consistency, typically performed better for pretext tasks, 2) image-based augmentation methods for contrastive learning work just as well for video, as long as temporal elements are included 3), and multimodal approaches can provide equally as well performance to unimodal approaches without the need of data augmentations. This survey also discussed several limitations in existing works. These limitations include: 1) lack of standardized benchmarks for performance, 2) heavy reliance on existing visual encoders which operates on trimmed video clips, 3) and a lack of understanding on what these models are actually learning and what makes them more generalizable. From the limitations discussed, we put forward areas for future work. These include: 1) long-term video representation, 2) simple end-to-end approaches, 3) interpratibility and explainability, 4) and standard benchmarking. We believe this survey will serve as an important resource for the research community and guide future research in self-supervised video representation learning.

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