### ACAV100M:

# Automatic Curation of Large-Scale Datasets for Audio-Visual Video Representation Learning



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## Are existing audio-visual datasets large enough?

#### **Visual-Audio** datasets

- Kinetics-Sounds
- VGG-Sound
- AudioSet

#### Visual-Text datasets

HowTo100M

2 days

23 days

8 months

15 years

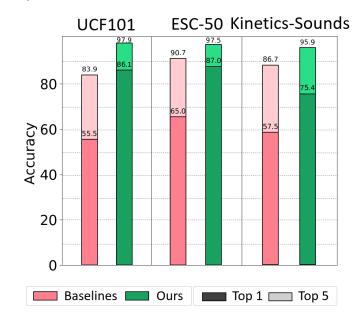
## ACAV100M: A new video dataset for audio-visual learning

AudioSet HowTo100M

#### ACAV100M (31 years)

- Two orders of magnitude larger than the current largest video dataset used in the audio-visual learning literature: AudioSet (8 months)
- Twice as large as the largest video dataset: HowTo100M (15 years)

Best performance in downstream tasks



## The curation process should be **automatic** for **scalability**

There is no large-scale (100M) audio-visual dataset

Visual-Text



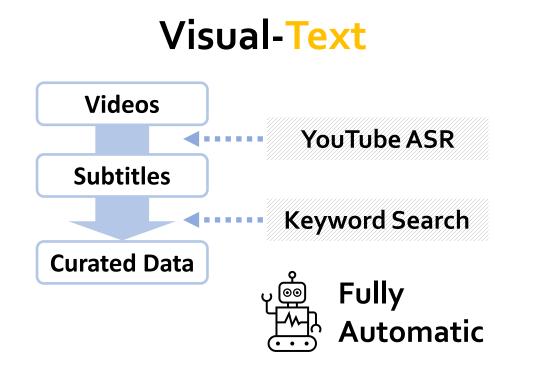
HowTo100M (136M clips)

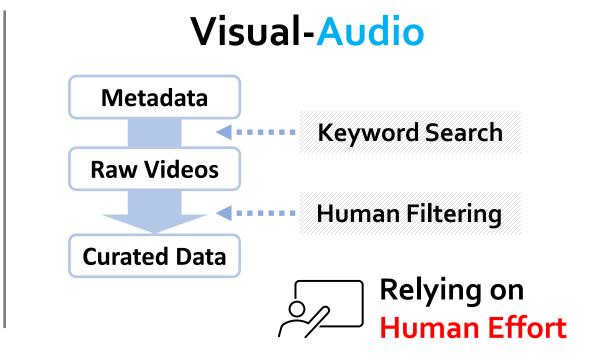
Visual-Audio



## The curation process should be **automatic** for **scalability**

There is no **large-scale** (100M) audio-visual dataset since it is hard to scale up the curation process



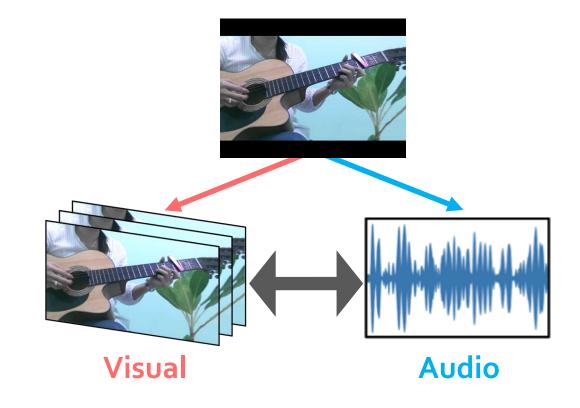


## What criterion should we use for data construction?

Recent self-supervised learning tasks leverage audio-visual correspondence

#### Goal:

Find a **subset** of videos with maximum **AV Correspondence** 



**High AV Correspondence** 

### Subset maximization idea:

Find a subset that maximizes the MI between audio and visual channels

Population U

Subset *S* w/ budget *s* 

$$\max_{S \subset U} \sum_{i \in S} MI(A_i, V_i) \ s.t. |S| = s$$

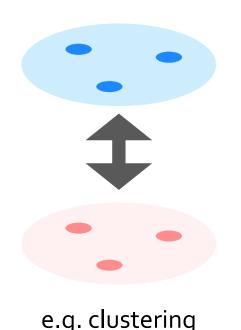
Challenge:
How to estimate MI
over high dimensional signals

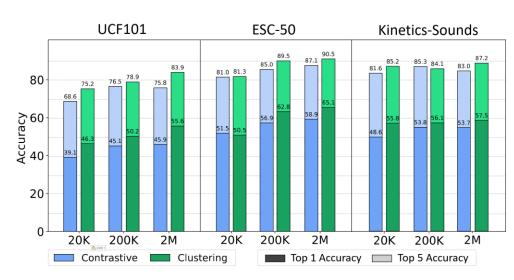
### MI estimation: instance-level vs. set-level

MI estimators can utilize instance-level or set-level information We opt for **set-level** method due to its superior empirical performance

## Instance-Level **Audio** Visual e.g. contrastive learning

#### **Set-Level**





### MI estimation: implementation

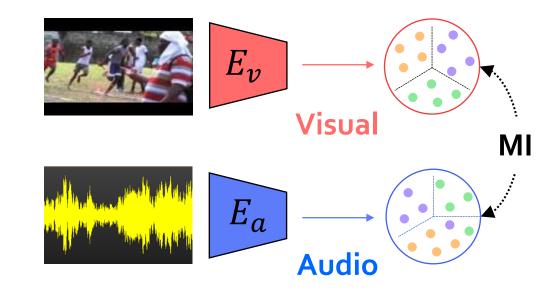
Estimate MI in a discrete space by clustering audio and visual signals, respectively

#### **MI Estimator**

$$MI(\mathcal{A}, \mathcal{V}) = \sum_{i=1}^{|\mathcal{A}|} \sum_{j=1}^{|\mathcal{V}|} \frac{|A_i \cap V_j|}{|X|} \log \frac{|X||A_i \cap V_j|}{|A_i||V_j|}$$

X: Raw dataset

$$\mathcal{A} = \{A_i, ..., A_{|\mathcal{A}|}\}$$
: Partitions of  $X$  w.r.t. audio clustering  $\mathcal{V} = \{V_i, ..., V_{|\mathcal{V}|}\}$ : Partitions of  $X$  w.r.t. visual clustering



### Scalability of the selection algorithm

Estimate MI in a discrete space induced by clustering

-> Combinatorial subset selection problem (NP-Hard)

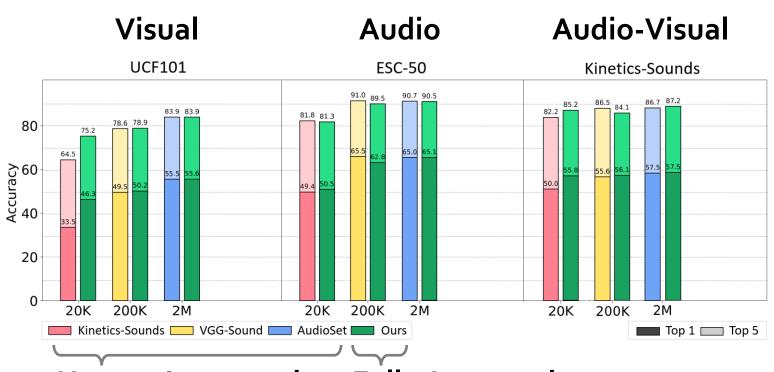
We exploit the most scalable approximation (batch-greedy)

Approximation Scalability  $\uparrow$   $O(2^N)$ : Brute-Force  $O(N^2)$ : Greedy  $O(N \times B)$ : Batch Greedy

**B**: Mini-batch size

#### Results on Real-World Problems

Linear evaluation on visual, audio and audio-visual classification tasks

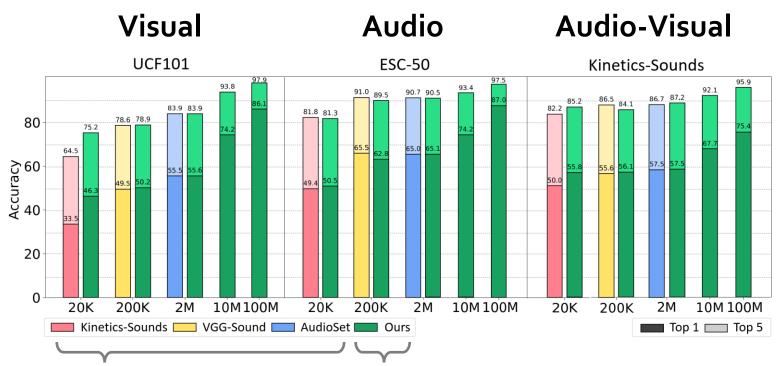


Our **automatic** pipeline achieves slightly better or comparable to the baselines **without human effort** 

**Human Intervention Fully Automatic** 

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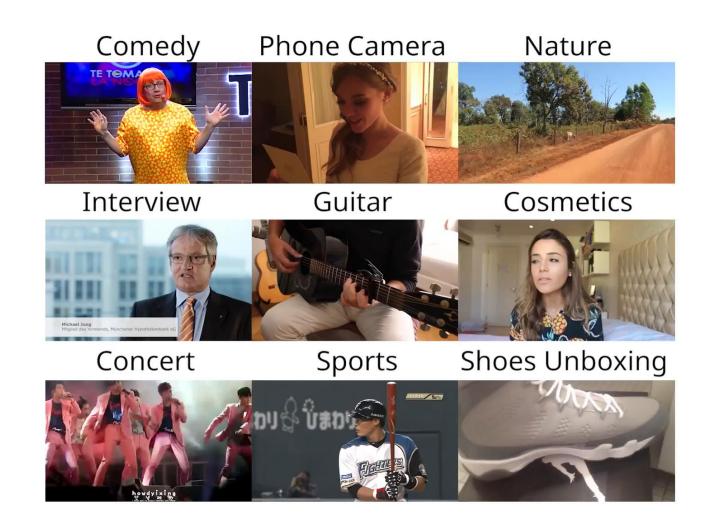


Our **automatic** pipeline achieves slightly better or comparable to the baselines **without human effort** 

Scalable to **10M/100M** videos with **best performances** 

**Human Intervention Fully Automatic** 

### Video Diversity



Our curation process is not confined to a human-defined taxonomy of concepts

Thus, our datasets contain diverse concepts such as shoes unboxing

### Project Webpage

We provide the dataset, paper, code and sample explorers from the webpage <a href="https://acav1oom.github.io/">https://acav1oom.github.io/</a>

