

## Introduction: Zero-Shot Action Recognition

- Task: classifying actions without any training data (**unseen target classes**)
- How? By linking visual and semantic features through **seen source classes**



## Contributions & Summary

### Motivation

- Recent work shows extraordinary results when using external data sources for zero-shot action recognition
- Problem:** in a cross-dataset setup source and target categories are often not disjoint

### Contributions

- We show that external sources often **have actions excessively similar to the target classes**, strongly influencing the performance and **violating the ZSL premise**
- We propose an **evaluation procedure** that enables fair use of external data for zero-shot action recognition
- Side-contribution: we propose the **hybrid evaluation regime**, which uses the available training data of the source domain **and** the large-scale external datasets

## Fair transfer of foreign categories

### Evaluation regimes for ZSL

**Intra-dataset: same origin of training- and test data**

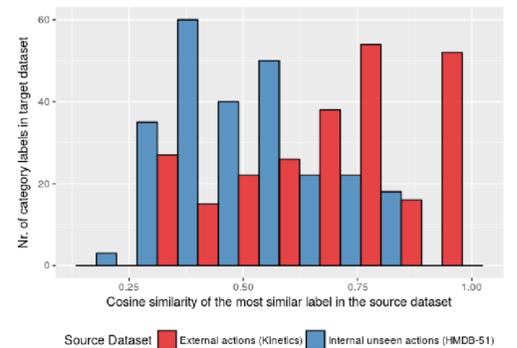
| Approach                           | Description   | Standard Approaches |
|------------------------------------|---|---------------------|
| Supervised Action Recognition (AR) | Classifying the already known categories<br>$T \subset S$   | standard approaches |
| Zero-Shot AR Intra-dataset         | Source from the <b>same domain</b> : $S = S_{native}$<br>$T \cap S_{native} = \emptyset \rightarrow$ <b>ZSL premise satisfied</b> 😊 |                     |

**Cross-dataset: utilize large-scale external data sources**

| Approach                                      | Description  | Novel Approaches |
|---|--|------------------|
| Zero-Shot AR Cross-dataset (Zhu et. al, 2018) | Source from a different domain: $S = S_{ext}$<br>Boost in accuracy<br>$T \cap S_{ext} \neq \emptyset$ . <b>ZSL premise not given by default</b> 😞<br><b>Our corrective protocol eliminates too unfamiliar concepts <math>\rightarrow</math> ZSL premise given</b>  | novel approaches |
| Zero-Shot AR Hybrid (ours)                    | Source from native and external domains:<br>$S = S_{ext} \cup S_{native}$<br>Boost in accuracy, <b>lower-bounded by the intra- and cross-dataset regimes</b><br>Same evaluation issues as in cross-dataset<br><b>Our corrective protocol eliminates too unfamiliar concepts <math>\rightarrow</math> ZSL premise given</b> |                  |

### Problem with the source-target synonyms

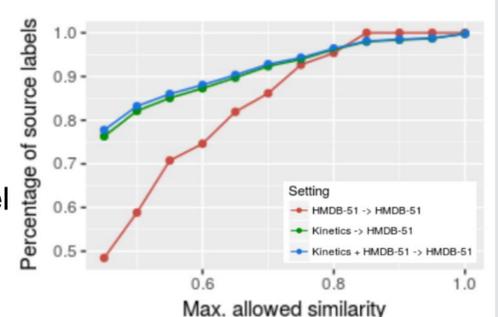
- A dataset does not contain the same action class twice
- External datasets intersect with datasets for zero-shot AR!
- Example: *brushing hair* in ActivityNet, Kinetics and HMDB51 (*brush hair*)



- Specializations: *drinking beer* vs. *drinking*  
 $\rightarrow$  **Getting rid of the direct matches is not enough!**

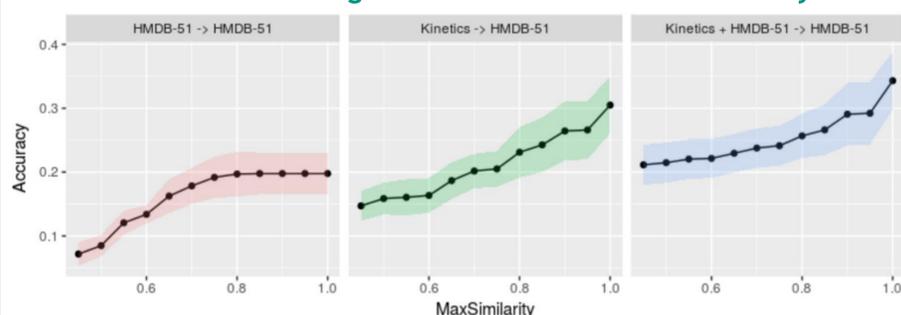
### Proposed corrective protocol for fair cross-dataset transfer

- Calculate the maximum intra-dataset similarity as our threshold  $s_{th}$ :  
$$s_{th} = \max_{a_k \in S_{intra}, t_m \in T} s(\omega(a_k), \omega(t_m))$$
- Purge the source category, if the label is too similar:  
$$\forall t_m \in T, s(\omega(a_k), \omega(t_m)) \leq s_{th}$$



## Experiments

### Similar source and target classes influence the accuracy

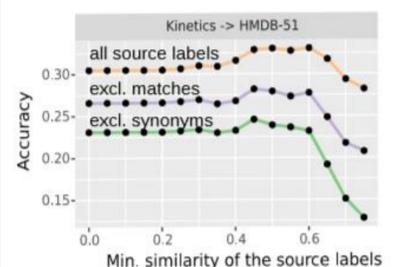


### Setup Details

- ZSL Method: Convex Combination of Semantic Embeddings (ConSE)
- Language Model: word2vec, visual model: I3D
- Ten random splits into seen/unseen categories (26/25) for HMDB-51.
- Kinetics as external source (400 activity classes)

| Exclusion protocol            | Source           | # source labels | Accuracy                   | ZSL premise |
|-------------------------------|------------------|-----------------|----------------------------|-------------|
| n. a.                         | HMDB-51          | 26              | 19.92 ( $\pm 3.3$ )        | ✓           |
| Use all source labels         | Kinetics         | 400             | 30.72 ( $\pm 4.4$ )        | —           |
|                               | Kinetics+HMDB-51 | 426             | <b>34.77</b> ( $\pm 4.5$ ) | —           |
| Exclude exact labels          | Kinetics         | $\approx 394.8$ | 26.6 ( $\pm 4.6$ )         | —           |
|                               | Kinetics+HMDB-51 | $\approx 420.8$ | <b>29.22</b> ( $\pm 4.9$ ) | —           |
| Exclude similar labels (ours) | Kinetics         | $\approx 384.7$ | 23.1 ( $\pm 3.9$ )         | ✓           |
|                               | Kinetics+HMDB-51 | $\approx 410.7$ | <b>25.67</b> ( $\pm 3.5$ ) | ✓           |

### Eliminating too unfamiliar concepts



An additional **lower bound** on the source similarity improves the performance