# Exploring Joint Embedding Architectures and Data Augmentations for Self-Supervised Representation Learning


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## Introduction

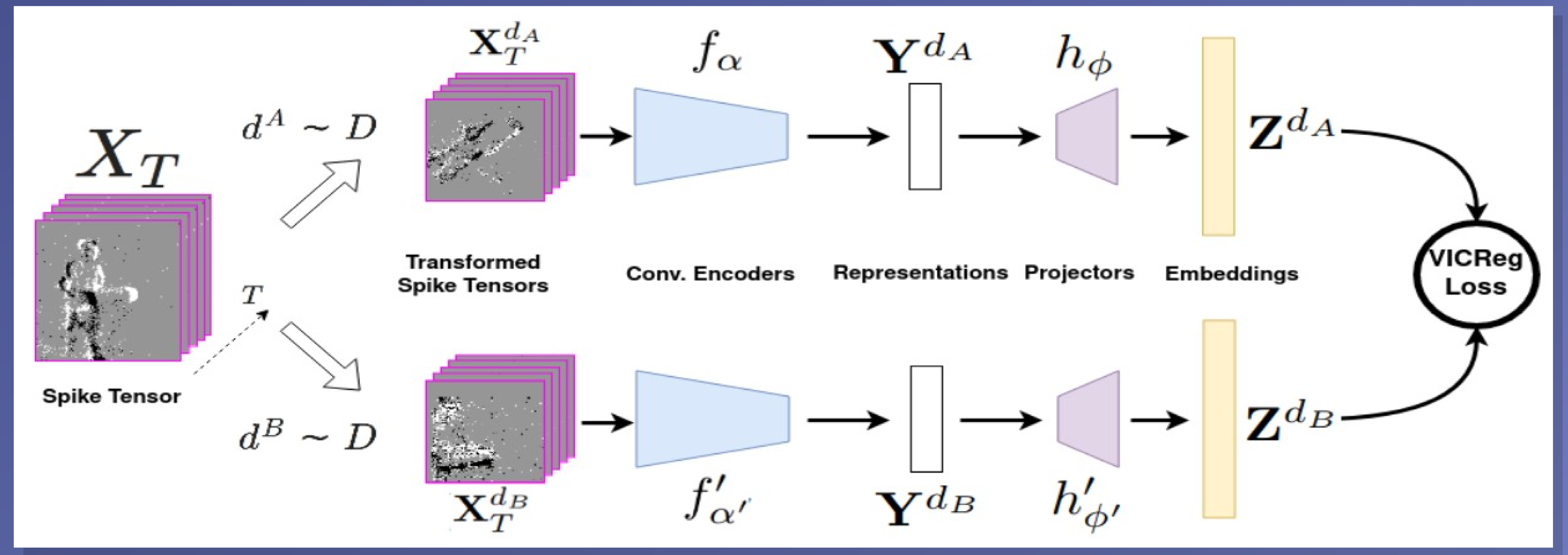
- Many event-based datasets have a limited number of labeled samples
- It presents challenges for the development of event vision algorithms
- Self-Supervised Representation Learning (**SSRL**) is a good solution for reducing the reliance on labeled data

### Contributions

- Event-based SSRL framework
- Evaluation protocols
- Study on EDAs (Event Data Augmentation)
- Analysis of learned features

## Event-Based SSRL Framework

Joint embedding architecture

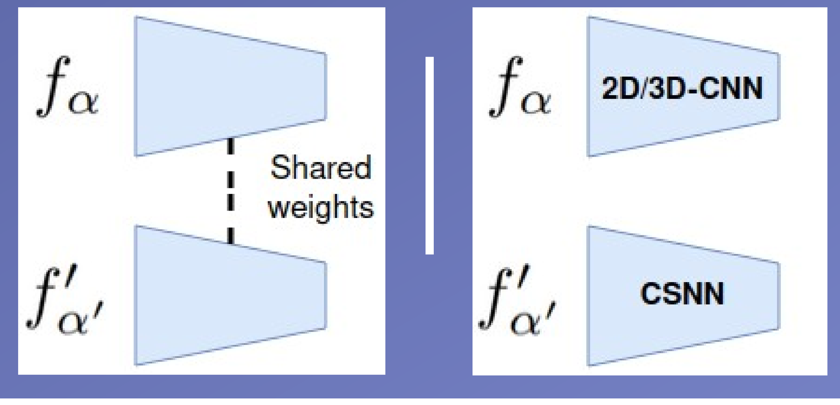



**Three** types of ConvEncs : **2D-CNN, 3D-CNN, CSNN**

Variants

Twins

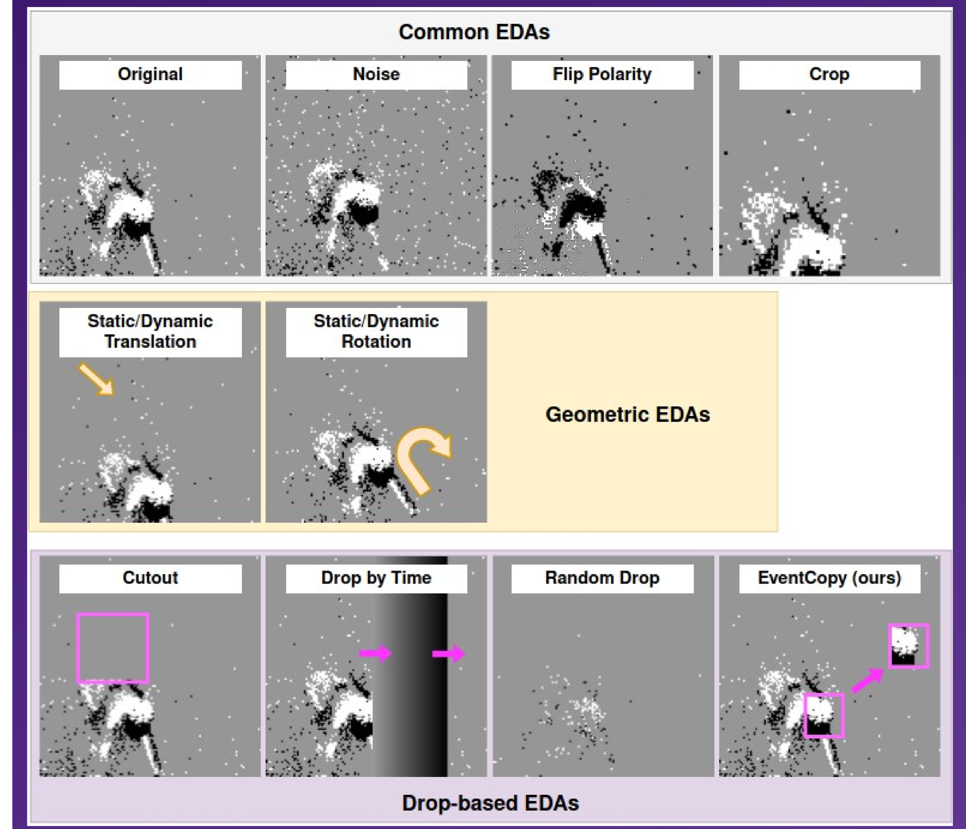
Student-Teacher




## Study on Event Data Augmentations

### How to design an effective EDA Distribution for pretraining?

**Incremental experiments:** we keep the best-performing EDA configuration from the previous stage




| Stage 1: Common EDAs | | | Twins CSNN | Twins 2D | Twins 3D | Student-Teacher CSNN | Student-Teacher 2D | Student-Teacher CSNN | Student-Teacher 3D |
|---|---|---|---|---|---|---|---|---|---|
| Noise | Crop | PolFlip | | | | | | | |
| | | | 12.12 | 11.36 | 57.95 | 59.47 | 61.36 | 58.33 | 55.68 |
| ✓ | | | **60.23** | 74.24 | 69.70 | 62.12 | 64.02 | 68.26 | 60.23 |
| ✓ | ✓ | | 56.44 | 81.82 | 74.62 | **73.86** | **76.89** | 69.32 | 64.02 |
| ✓ | ✓ | ✓ | 56.44 | **83.33** | **76.52** | 73.11 | 74.62 | **70.63** | **67.80** |

| Stage 2: Geometric EDAs | | | | | Twins CSNN | Twins 2D | Twins 3D | Student-Teacher CSNN | Student-Teacher 2D | Student-Teacher CSNN | Student-Teacher 3D |
|---|---|---|---|---|---|---|---|---|---|---|---|
| StatTran | StatRot | DynTran (ours) | DynRot (ours) | StatDynGeo (ours) | | | | | | | |
| ✓ | ✓ | | | | 49.24 | 77.65 | 65.15 | 60.98 | 68.18 | 65.53 | 62.5 |
| | | ✓ | ✓ | | 68.56 | 75.38 | 76.14 | **74.24** | **73.11** | **72.73** | 67.05 |
| | | | | ✓ | **68.94** | **79.55** | **77.27** | 67.05 | 70.45 | 71.97 | **68.18** |

| Stage 3: Drop-based EDAs | | | | Twins CSNN | Twins 2D | Twins 3D | Student-Teacher CSNN | Student-Teacher 2D | Student-Teacher CSNN | Student-Teacher 3D |
|---|---|---|---|---|---|---|---|---|---|---|
| Cutout | EventDrop | Event-Copy (ours) | EventCopyDrop (ours) | | | | | | | |
| ✓ | | | | **71.59** | 85.11 | 88.64 | 71.59 | 72.35 | 68.56 | 65.91 |
| | ✓ | | | 68.18 | **87.12** | 75 | 75 | 76.52 | **76.52** | **76.14** |
| | | ✓ | | 65.16 | 81.82 | 83.33 | 76.52 | **77.52** | 73.86 | 68.94 |
| | | | ✓ | 70.83 | **87.12** | **89.39** | **76.89** | 75.76 | 75 | 73.48 |

*Accuracy on DVSGesture (Linear Eval. Protocol)*

**A good EDA distribution consists of :**

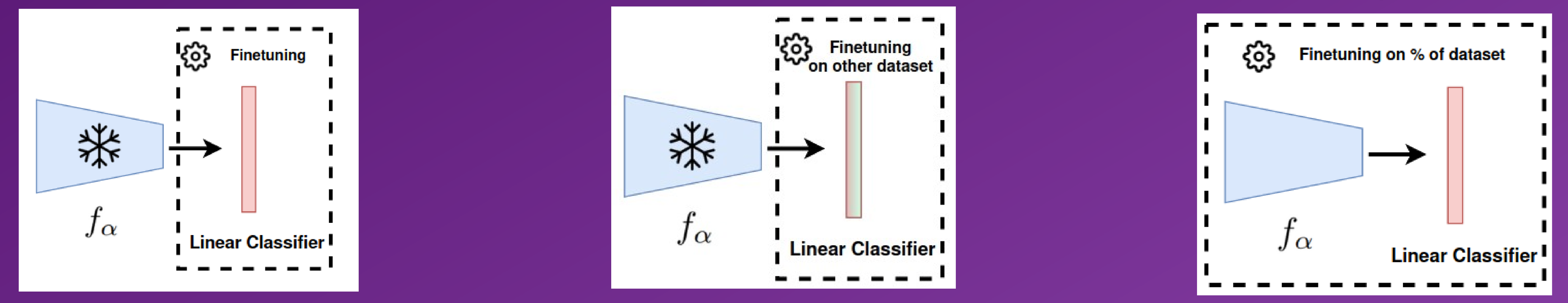
- More common EDAs
- Strictly one Geometric and one Drop-based EDA
- OneOf functions (*e.g., EventCopyDrop, StatDynGeo,...)*

## Evaluation Protocols

Linear Evaluation

Transfer Learning

Semi-Supervised




| Dataset | Protocol | CSNN | 2D | 3D | $CSNN_{2D}$ | $CSNN_{3D}$ |
|---|---|---|---|---|---|---|
| DVSGesture | Linear | 70.83 | 87.12 | **89.39** | 76.89 | 76.52 |
| | SemiSup-10% | 60.98 | 75.52 | **81.44** | 66.67 | 69.31 |
| | SemiSup-25% | 75.00 | 87.12 | **90.15** | 76.14 | 80.30 |
| N-Caltech101 | Linear | 64.29 | 64.39 | **69.46** | 62.34 | 65.67 |
| | SemiSup-10% | 56.72 | **64.64** | 62.80 | 53.96 | 53.50 |
| | SemiSup-25% | 66.02 | **72.79** | 71.64 | 62.22 | 59.93 |
| ASL-DVS | Linear | 95.32 | **99.38** | 98.68 | 97.87 | 97.30 |
| | SemiSup-05% | 95.66 | **97.06** | 96.62 | 93.54 | 95.66 |
| | SemiSup-10% | 99.51 | 99.64 | **99.70** | 99.48 | 99.48 |

**Metric:** classification accuracy (%)

*Transfer learning protocol*

| Datasets Pretrain | Linear | CSNN | 2D | 3D | $CSNN_{2D}$ | $CSNN_{3D}$ |
|---|---|---|---|---|---|---|
| **DVSGesture** | **DailyAction-DVS** | 77.93 | 88.28 | 84.83 | **91.03** | 87.59 |
| **ASL-DVS** | **N-CARS** | 92.81 | 94.61 | **95.64** | 93.30 | 93.35 |

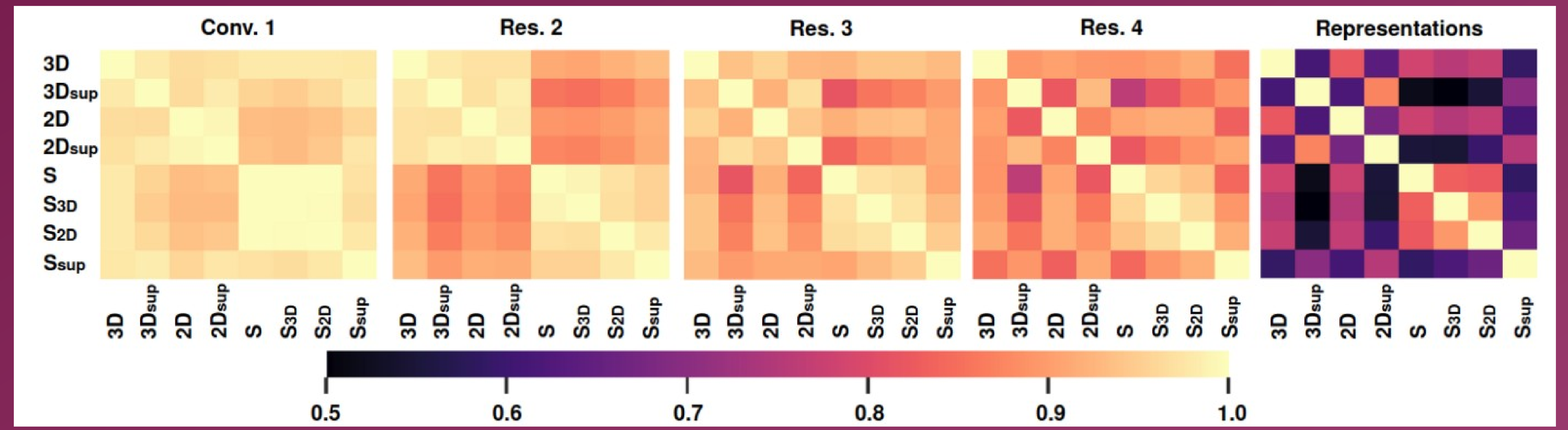
## Analysis of Learned Features

### 1 Uniformity - Tolerance Trade-Off

**Assumption from frame-based vision:** balanced values of Uniformity and Tolerance result in optimal representation quality


- The original assumption does not prevail
- Student-Teacher variant increases the tolerance of the CSNNs

### 2 Linear CKA for Similarity Assessment




- The divergence increases with deeper layers
- The impact of Student-Teacher variants on the learned features of CSNNs

## Conclusion

- We propose a method for **event-based SSRL** that utilizes a joint embedding architecture and event data augmentations
- The **evaluation protocols** established in this study emphasize the efficiency and transferability of the learned features, as well as the reduced dependence on labeled data facilitated by our framework
- We thoroughly **investigate the impacts of popular EDAs** and introduce **additional methods** to achieve an optimal distribution for event-based SSRL
- Our method creates exciting possibilities for designing future event-based vision applications that do not require large-scale training sets