# Generating Structured Pseudo Labels for Noise-resistant Zero-shot Video Sentence Localization


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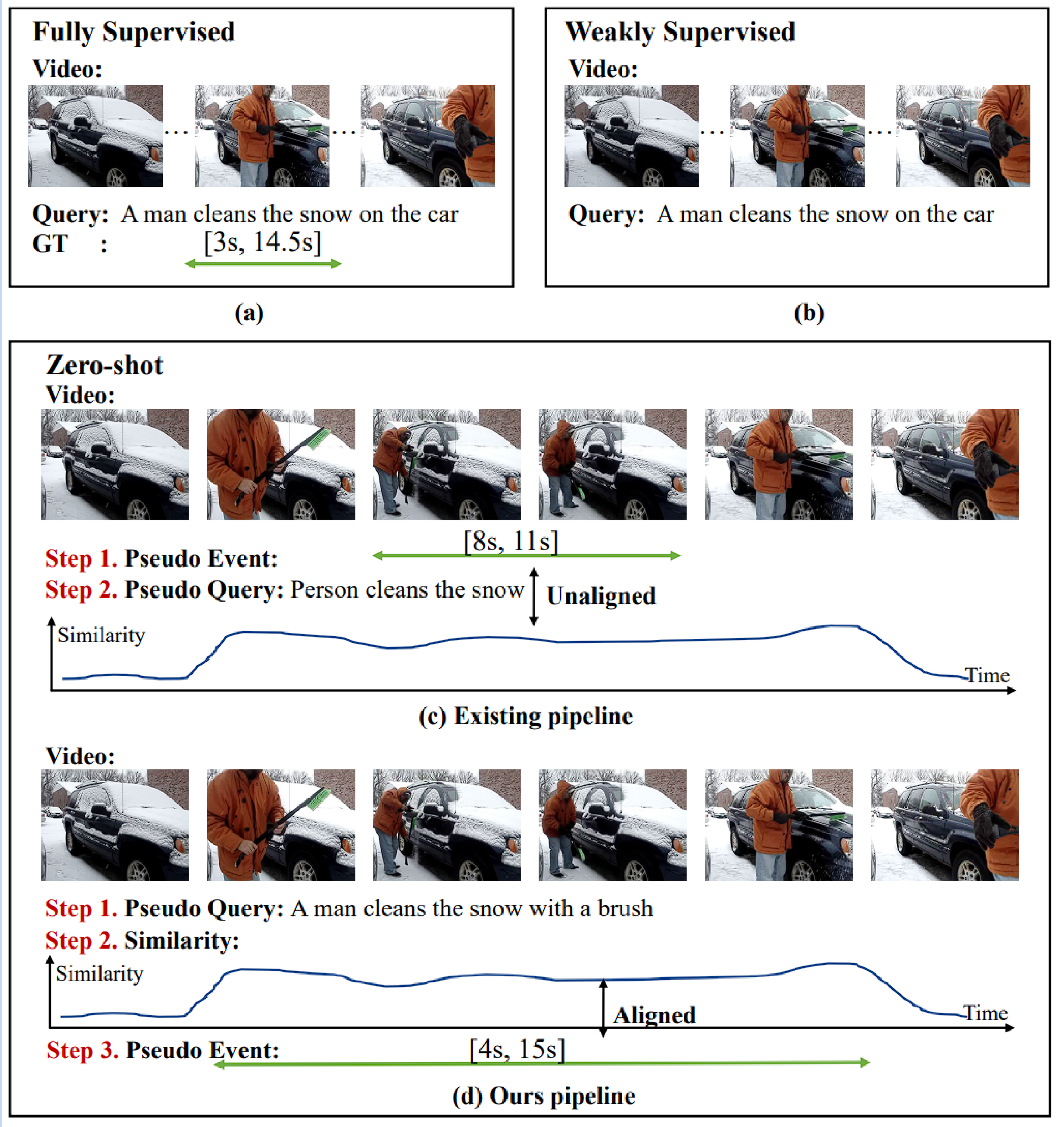
## Introduction




➢ **Task:** Zero-shot Temporal Sentence Localization

- **Inputs:** Video + Sentence query
- **Outputs:** Target video clip (start and end timestamps)
- **Zero-shot Setting:** No manual annotation required

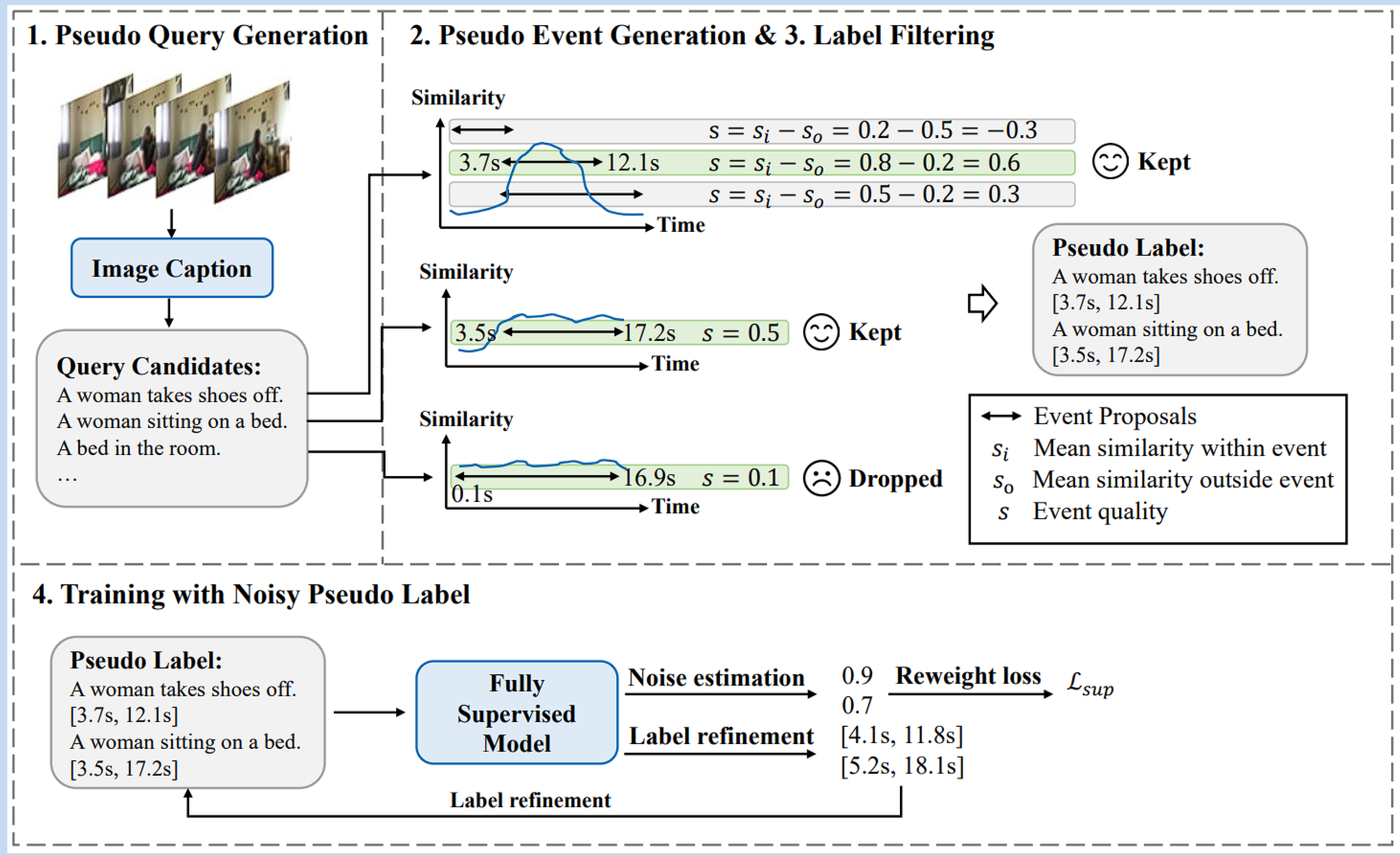
➢ **Existing methods:**

- Generating **pseudo-events** and **pseudo-queries**
  - Pseudo queries are too **simple**
  - **Unalignment** between pseudo-events and pseudo-queries
- Training with pseudo-event and pseudo-query
  - Ignoring the **noise** in the pseudo labels

➢ **Ours method:**

- Generating **free-form** pseudo-queries
- Generate pseudo-events based on the **event temporal structure**
- **Reduce noise** during training

## Method




➢ **Pseudo Query Generation**

- Generate **free-form** pseudo-queries using pretrained image caption model

➢ **Pseudo Event Generation**

- Generate pseudo-event by **event temporal structure**
  - Videos **within** events have **high** relevance to queries
  - Videos **outside** events have **low** relevance to queries
- Calculate similarity $S$ between pseudo-query and video frames
- Event quality: $Q_{ik} = \frac{1}{N_{p_k}} \sum_{j \in p_k} S_{ij} - \frac{1}{N - N_{p_k}} \sum_{j \notin p_k} S_{ij}$
- Choose the event proposal with highest quality

➢ **Label Filtering**

- **Filter out low-quality** pseudo-query event pairs.
- Use non-maximum suppression to **eliminate** pseudo-query-event pairs with **high event overlap**.

➢ **Training with Noisy Pseudo Labels**

- Train model using pseudo-labels and **reduce noise** in the pseudo-labels.
- **Sample re-weight: Estimate noise** and **re-weight** sample loss

$$w = \alpha \frac{1}{1 - s^{iou}} + (1 - \alpha) \frac{1}{1 - s^{conf}}$$

- **Label refinement:** If the model's prediction confidence is high, **update the pseudo-label** with the prediction.

## Experiments

➢ **Comparing with SOTA**

- Best zero-shot performance on most metrics

| Method | Sup. | Charades-STA R@0.3 | Charades-STA R@0.5 | Charades-STA R@0.7 | Charades-STA mIoU | ActivityNet Captions R@0.3 | ActivityNet Captions R@0.5 | ActivityNet Captions R@0.7 | ActivityNet Captions mIoU |
|---|---|---|---|---|---|---|---|---|---|
| 2D-TAN (Zhang et al., 2020) | fully | - | 39.81 | 23.25 | - | 58.75 | 44.05 | 27.38 | - |
| EMB (Huang et al., 2022) | fully | **72.50** | 58.33 | 39.25 | **53.09** | **64.13** | 44.81 | 26.07 | **45.59** |
| MGSL-Net (Liu et al., 2022) | fully | - | **63.98** | **41.03** | - | - | **51.87** | **31.42** | - |
| CRM (Huang et al., 2021) | weakly | 53.66 | 34.76 | 16.37 | - | 55.26 | 32.19 | - | - |
| CNM* (Zheng et al., 2022a) | weakly | 60.39 | 35.43 | 15.45 | - | 55.68 | **33.33** | - | - |
| CPL (Zheng et al., 2022b) | weakly | **66.40** | **49.24** | **22.39** | - | **55.73** | 31.37 | - | - |
| Gao et al.* (Gao and Xu, 2021) | no | 46.69 | 20.14 | 8.27 | - | 46.15 | 26.38 | 11.64 | - |
| PSVL* (Nam et al., 2021) | no | 46.47 | 31.29 | 14.17 | 31.24 | 44.74 | 30.08 | 14.74 | 29.62 |
| PZVMR* (Wang et al., 2022) | no | 46.83 | 33.21 | 18.51 | 32.62 | 45.73 | 31.26 | **17.84** | 30.35 |
| Kim et al.* (Kim et al., 2023) | no | 52.95 | 37.24 | 19.33 | 36.05 | 47.61 | **32.59** | 15.42 | 31.85 |
| SPL* (ours) | no | **60.73** | **40.70** | **19.62** | **40.47** | **50.24** | 27.24 | 15.03 | **35.44** |

➢ **Ablation Studies**

- Better pseudo-queries and pseudo-events
- Reducing label noise improves the performance

| Event | Query | Model | R@0.5 | mIoU |
|---|---|---|---|---|
| PSVL | PSVL | PSVL | 31.29 | 31.24 |
| PSVL | PSVL | Ours | 29.62 | 33.45 |
| PSVL | Ours | Ours | 36.94 | 38.31 |
| Ours | Ours | Ours | **40.70** | **40.47** |

| Reweight | Refine | R@0.5 | mIoU |
|---|---|---|---|
| ✗ | ✗ | 38.74 | 39.38 |
| ✗ | ✓ | 39.68 | 40.07 |
| ✓ | ✗ | 39.76 | 39.91 |
| ✓ | ✓ | **40.70** | **40.47** |

## Conclusion

➢ Propose a **zero-shot** video sentence localization method based on structured pseudo-label generation that is **robust to noise**

➢ Generate **free-form** pseudo-queries and generate pseudo-events based on **event temporal structure**

➢ Reduce the influence of noise in pseudo-labels by **sample reweight** and **label refinement**

➢ Best zero-shot performance on two datasets

## Acknowledgments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## Code