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Collecting Cross-Modal Presence-Absence Evidence for Weakly-Supervised Audio-Visual Event Perception

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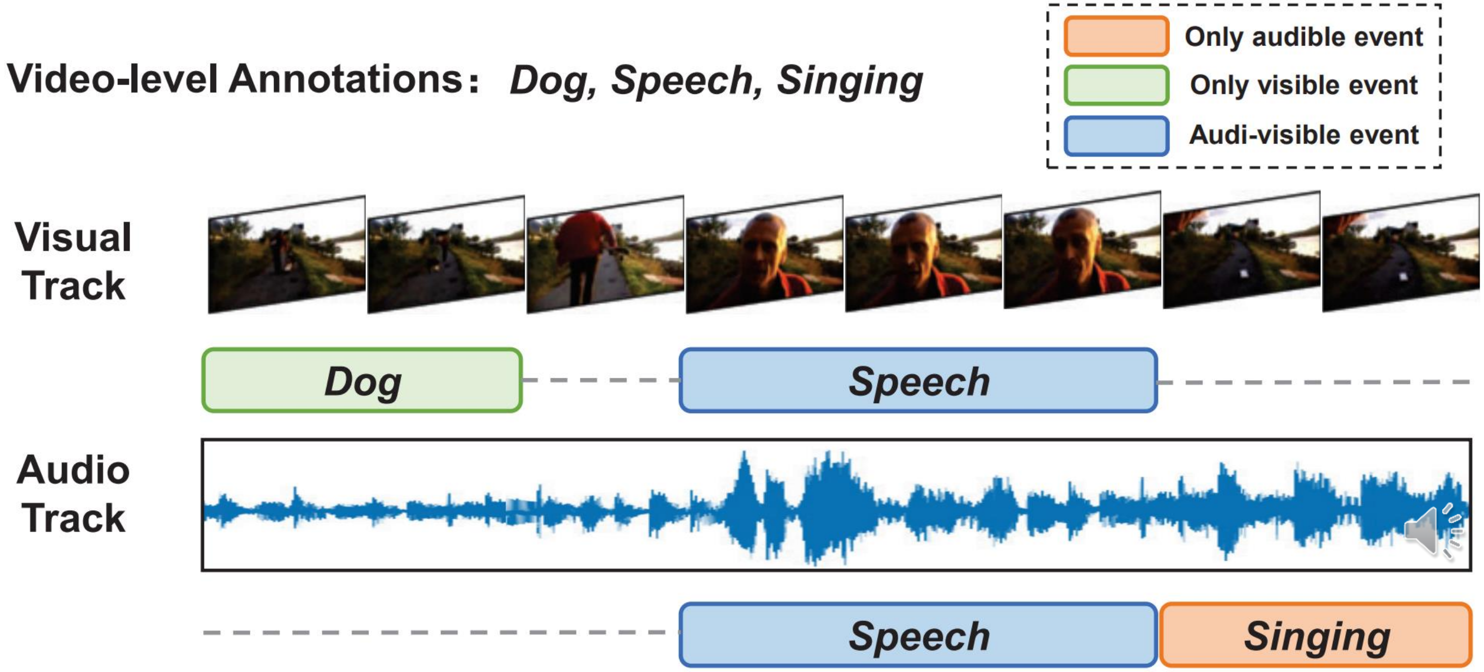
Introduction

■ Weakly-supervised Audio-Visual Event Perception

- With **only video-level annotations**, weakly-supervised audio-visual event perception (WS-AVEP) aims to predict the temporal boundaries of various **only audible** (in orange), **only visible** (in green), or **audi-visible** (in blue) events in a video.



Introduction

■ Two main pipelines of WS-AVEP

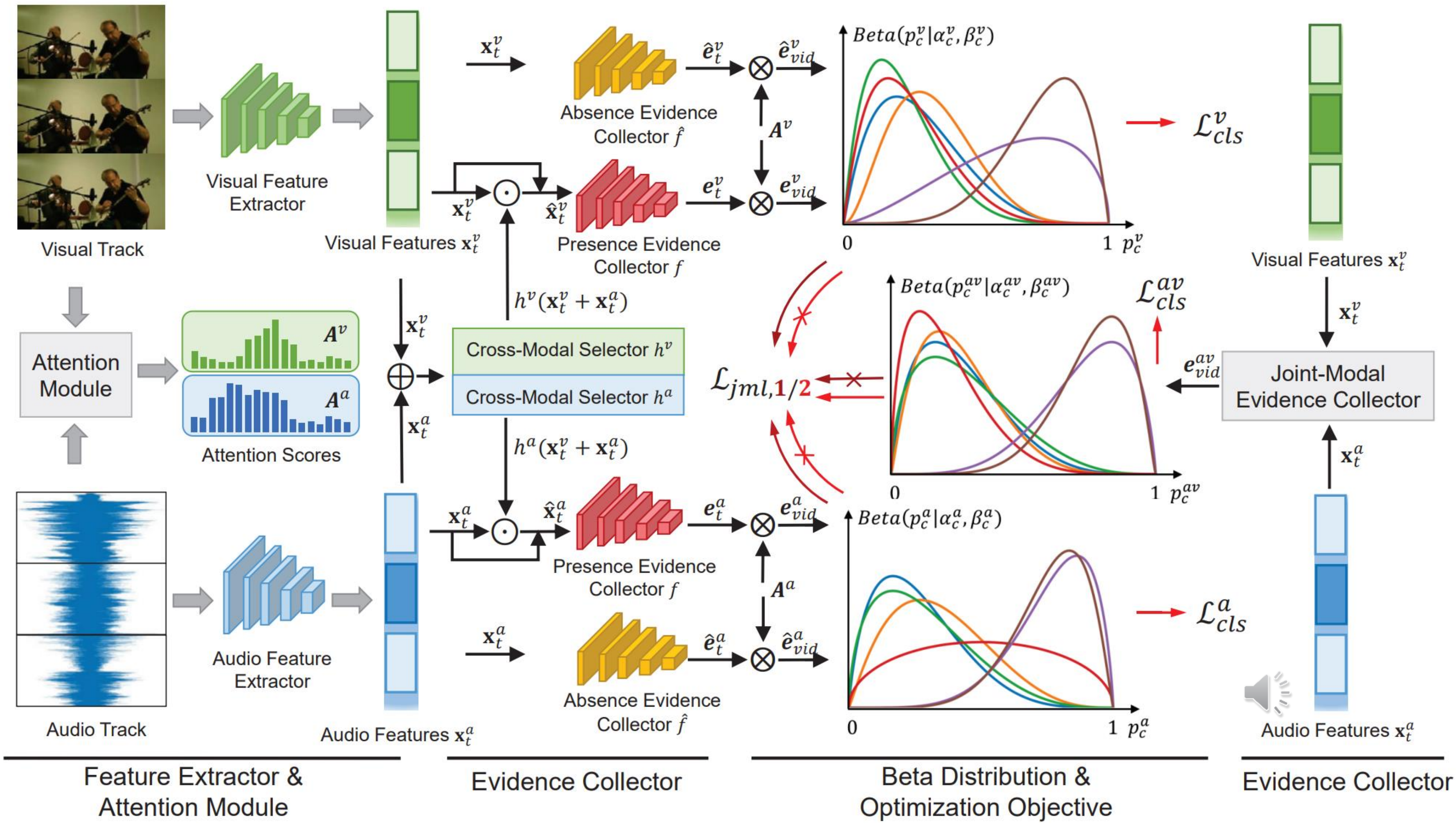
- **AVE**: Events are all **simultaneously audible and visible**.
- **AVVP**: Events are categorized into **only audible, only visible, or audi-visible** ones.
- State-of-the-arts methods can only achieve significant performance in one single WS-AVEP setting, showing that current methods are **in a dilemma of making full use of both uni-modal and cross-modal information.**

Method / Task	CMBS [61]	JoMoLD [6]	**Ours**
AVVP [52]	51.7	**57.3**	**60.1**
AVE [53]	**74.2**	71.8	**74.8**

The modality itself should provide ample presence evidence of this event, while the other complementary modality is encouraged to afford the absence evidence as a reference signal.

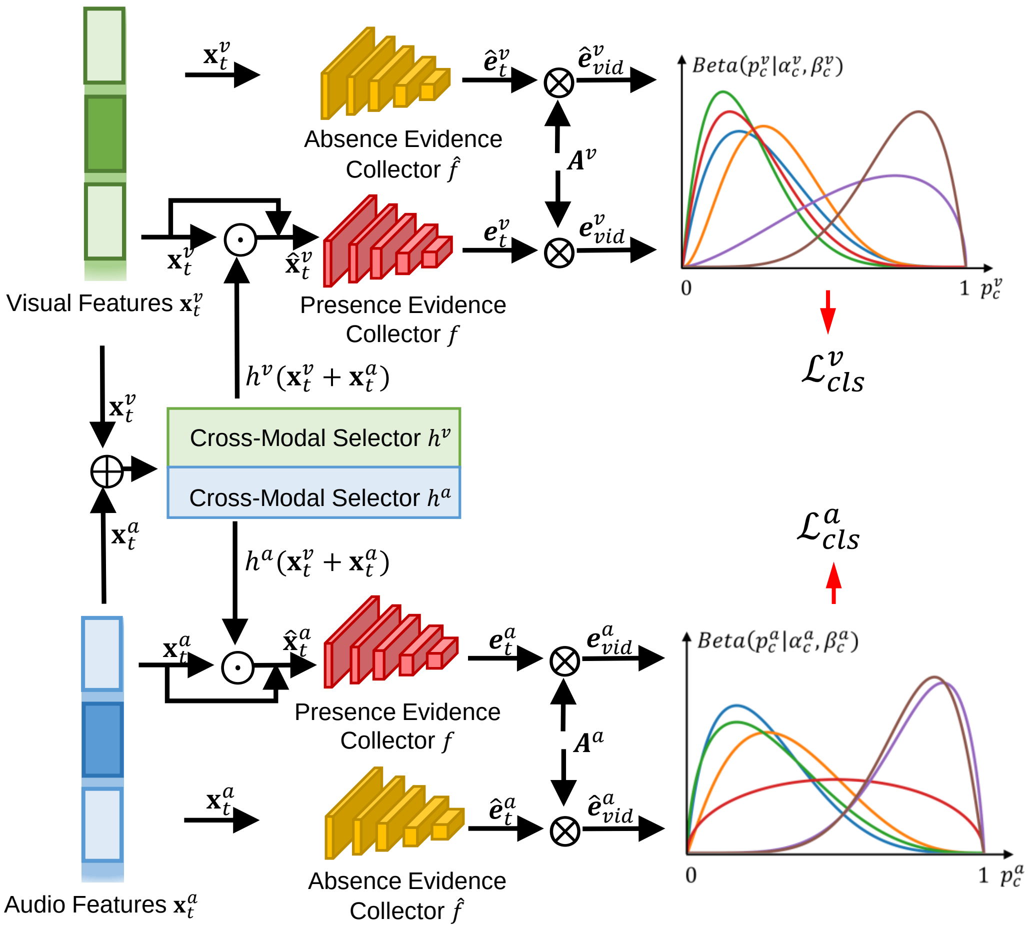
Method

■ Cross-modal Presence-absence Evidence Learning



Method

■ Presence-absence Evidence Collector



➢ **Presence evidence**

$$e_{t,c}^m = g\left(f_c(\mathbf{x}_t^m; \boldsymbol{\theta}_1)\right)$$

➢ **Absence evidence**

$$\hat{e}_{t,c}^m = g\left(\hat{f}_c(\hat{\mathbf{x}}_t^m; \boldsymbol{\theta}_2)\right),$$

$$\hat{\mathbf{x}}_t^m = \mathbf{x}_t^m \odot \left(h^m(\mathbf{x}_t^m + \mathbf{x}_t^{\hat{m}}; \boldsymbol{\theta}_3^m) + \mathbf{1}\right)$$

➢ **Loss function**

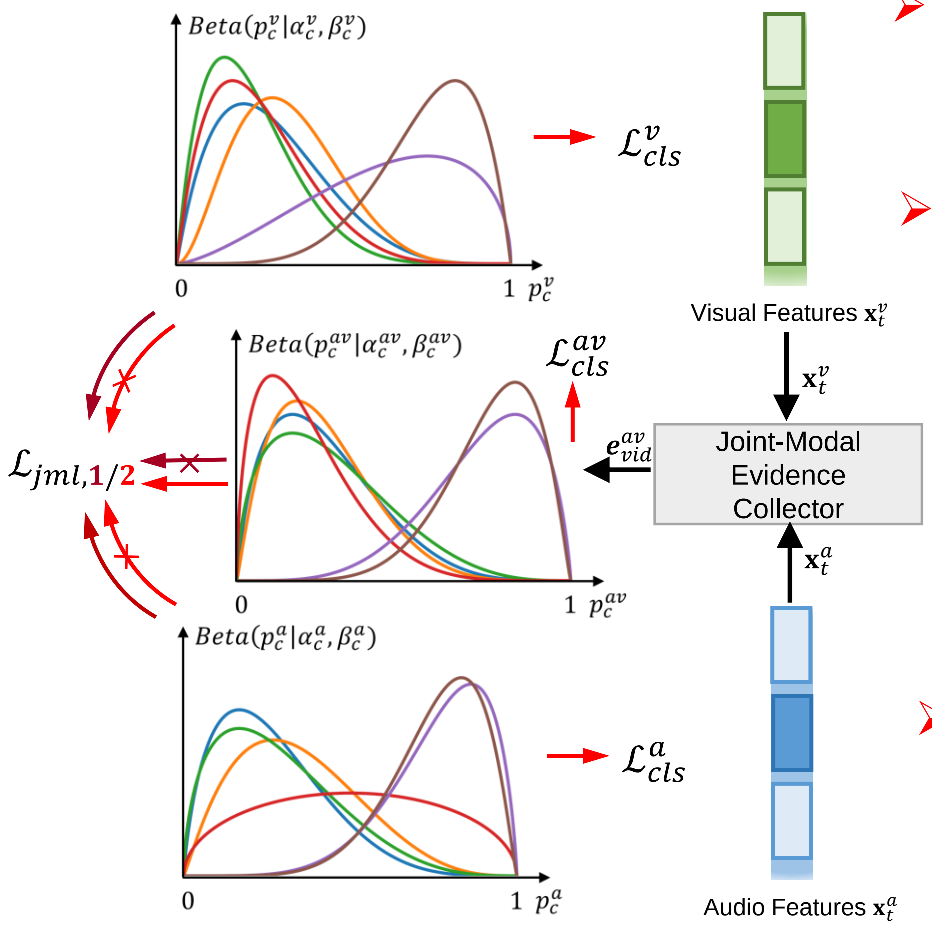
$$\mathrm{Beta}(p_c|\alpha_c, \beta_c) = \frac{1}{B(\alpha_c, \beta_c)} p_c^{\alpha_c - 1}(1 - p_c)^{\beta_c - 1}$$

$$\mathcal{L}_{cls}^m = \int \left[\sum_{c=1}^{C} -y_c^m \log(p_c)\right] \mathrm{Beta}(p_c|\alpha_c, \beta_c) dp$$

$$= \sum_{c=1}^{C} \left[\psi(\alpha_c + \beta_c) - \psi\left(y_c^m \alpha_c + (1 - y_c^m)\beta_c\right)\right]$$

Method

■ Joint-modal Mutual Learning



- **Video-level presence/absence evidence**

$$e_{vid,c}^{av}, \hat{e}_{vid,c}^{av} = \sum_t A_{t,c}^{av} \cdot g(f_c^{av}(\mathbf{x}_t^a + \mathbf{x}_t^v; \boldsymbol{\theta}_4))$$

- **Cross-modal fusion**

$$p_c^m = \frac{e_c^m + 1}{e_c^m + \hat{e}_c^m + 2}, \quad u_c^m = \frac{2}{e_c^m + \hat{e}_c^m + 2}$$

$$\{u_c^{uni}, p_c^{uni}\} = \delta(c)\{u_c^a, p_c^a\} + (1 - \delta(c))\{u_c^v, p_c^v\}$$

$$\delta(c) = \begin{cases} 1, & p_c^a > p_c^v, y_c = 1, \\ 0, & p_c^a \le p_c^v, y_c = 1, \\ 1/2, & y_c = 0. \end{cases}$$

- **Loss function for mutial learning**

$$\mathcal{L}_{jml,1} = \sum_c (1 - u^{av})\left(1 - u_c^{uni}\right) * l\left(s(p_c^{av}), p_c^{uni}\right)$$

$$\mathcal{L}_{jml,2} = \sum_c u^{av}\left(1 - u_c^{uni}\right) * l\left(p_c^{av}, s(p_c^{uni})\right),$$

Experiments

■ Evaluation on AVVP / AVE / AVEP

Table 2. AVVP performance comparison with existing methods on the LLP dataset.

Methods	Segment-level					Event-level				
	A	V	AV	Type	Event	A	V	AV	Type	Event
AVE [53], ECCV2018	49.9	37.3	37.0	41.4	43.6	43.6	32.4	32.6	36.2	37.4
AVSDN [29], ICASSP2019	47.8	52.0	37.1	45.7	50.8	34.1	46.3	26.5	35.6	37.7
HAN [52], ECCV2020	60.1	52.9	48.9	54.0	55.4	51.3	48.9	43.0	47.7	48.0
CVCMS [30], NeurIPS2021	60.8	63.5	57.0	60.5	59.5	53.8	58.9	49.5	54.0	52.1
MA [58], CVPR2021	59.8	57.5	52.6	56.6	56.6	52.1	54.4	45.8	50.8	49.4
DHHN [22], MM2022	61.4	63.4	56.8	60.5	59.5	54.6	60.8	51.1	55.5	53.3
MM-Pyramid [65], MM2022	61.1	60.3	55.8	59.7	59.1	53.8	56.7	49.4	54.1	51.2
CMBS* [61], CVPR2022	60.2	54.3	50.0	54.8	55.7	51.1	50.8	43.7	48.5	48.3
JoMoLD [6], ECCV2022	61.3	63.8	57.2	60.8	59.9	53.9	59.9	49.6	54.5	52.5
CMPAE(Ours)	**64.2 (+2.9)**	**66.4 (+2.6)**	**59.2 (+2.0)**	**63.3 (+2.5)**	**62.8 (+2.9)**	**56.6 (+2.7)**	**63.7 (+3.8)**	**51.8 (+2.2)**	**57.4 (+2.9)**	**55.7 (+3.2)**

Table 3. AVE performance comparison.

Methods	Accuracy(%)
AVEL [53], ECCV2018	66.7
AVRB [47], WACV2020	68.9
CMRAN [62], MM2020	72.9
PSP [70], CVPR2021	73.5
CMAN [63], AAAI2022	70.4
MM-Pyramid [65], MM2022	73.2
CMBS [61], CVPR2022	74.2
DPNet [48], ECCV2022	74.5
CMBS [61], fully-supervised	79.3
JoMoLD* [6], ECCV2022	71.8
CMPAE(Ours)	**74.8**

* denotes the reproduced results.

Table 4. AVEP performance comparison with existing methods.

Methods	Segment-level					Event-level				
	A	V	AV	Type	Event	A	V	AV	Type	Event
CMBS [61], CVPR2022	58.0	56.2	52.3	55.5	54.8	51.5	53.6	46.4	50.5	49.4
JoMoLD [6], ECCV2022	60.6	58.9	54.5	58.0	57.7	53.6	55.8	48.6	52.7	51.0
CMPAE(Ours)	**64.1 (+3.5)**	**64.4 (+5.5)**	**58.8 (+4.3)**	**62.4 (+4.4)**	**62.2 (+4.5)**	**57.2 (+3.6)**	**61.9 (+6.1)**	**52.3 (+3.7)**	**57.1 (+4.4)**	**55.6 (+4.6)**

Experiments

- **Ablation study**

Table 5. Ablation studies of our method.

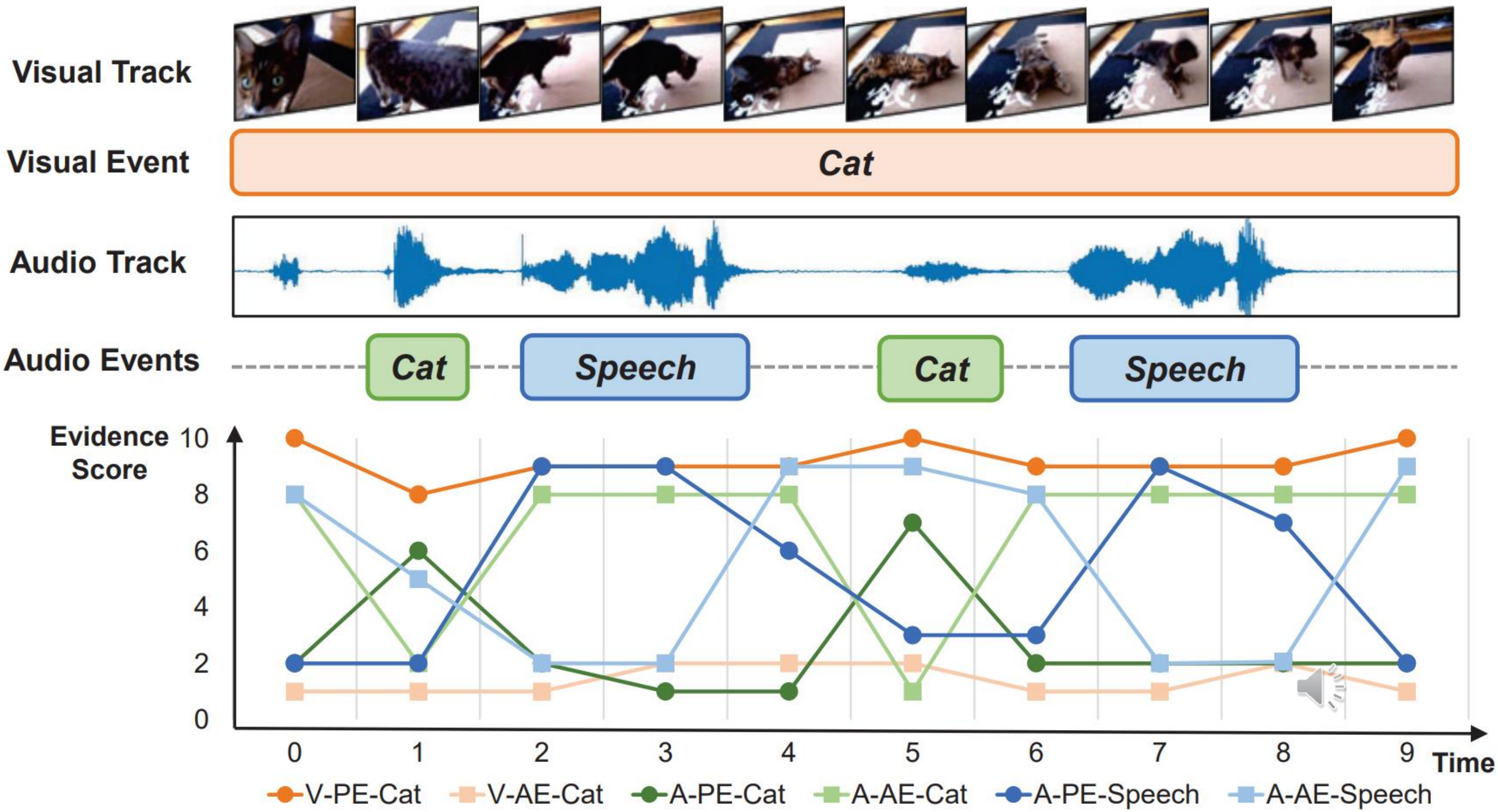
EDL	PAEC	JML	Seg-level Type AVVP	Seg-level Type AVEP	Eve-level Type AVVP	Eve-level Type AVEP
✗	✗	✗	60.8	58.0	54.5	52.7
✓	✗	✗	61.0	58.9	54.9	53.8
✓	✓	✗	61.9	61.5	56.1	55.9
✓	✗	✓	61.4	60.8	55.3	54.6
✓	✓	✓	**63.3**	**62.4**	**57.4**	**57.1**

Table 6. In-depth analysis of our proposed PAEC and JML.

Models	Seg-level Type AVVP	Seg-level Type AVEP	Eve-level Type AVVP	Eve-level Type AVEP
both uni-modal	61.2	60.9	55.2	54.4
both cross-modal	61.7	61.3	55.7	55.9
exchange uni/cross	62.1	61.6	56.4	56.0
w/o u^{av}	62.2	61.8	56.5	56.3
w/o u^{uni}	62.0	61.7	56.4	56.0
w/o $\delta(c)$	62.5	61.8	56.3	56.5
CMPAE	**63.3**	**62.4**	**57.4**	**57.1**

Experiments

- **Visualization Analysis**



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Code & Model

Any problem, please feel free contact the primary author:

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