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Dynamic prompting class distribution optimization for semi-supervised sound event detection

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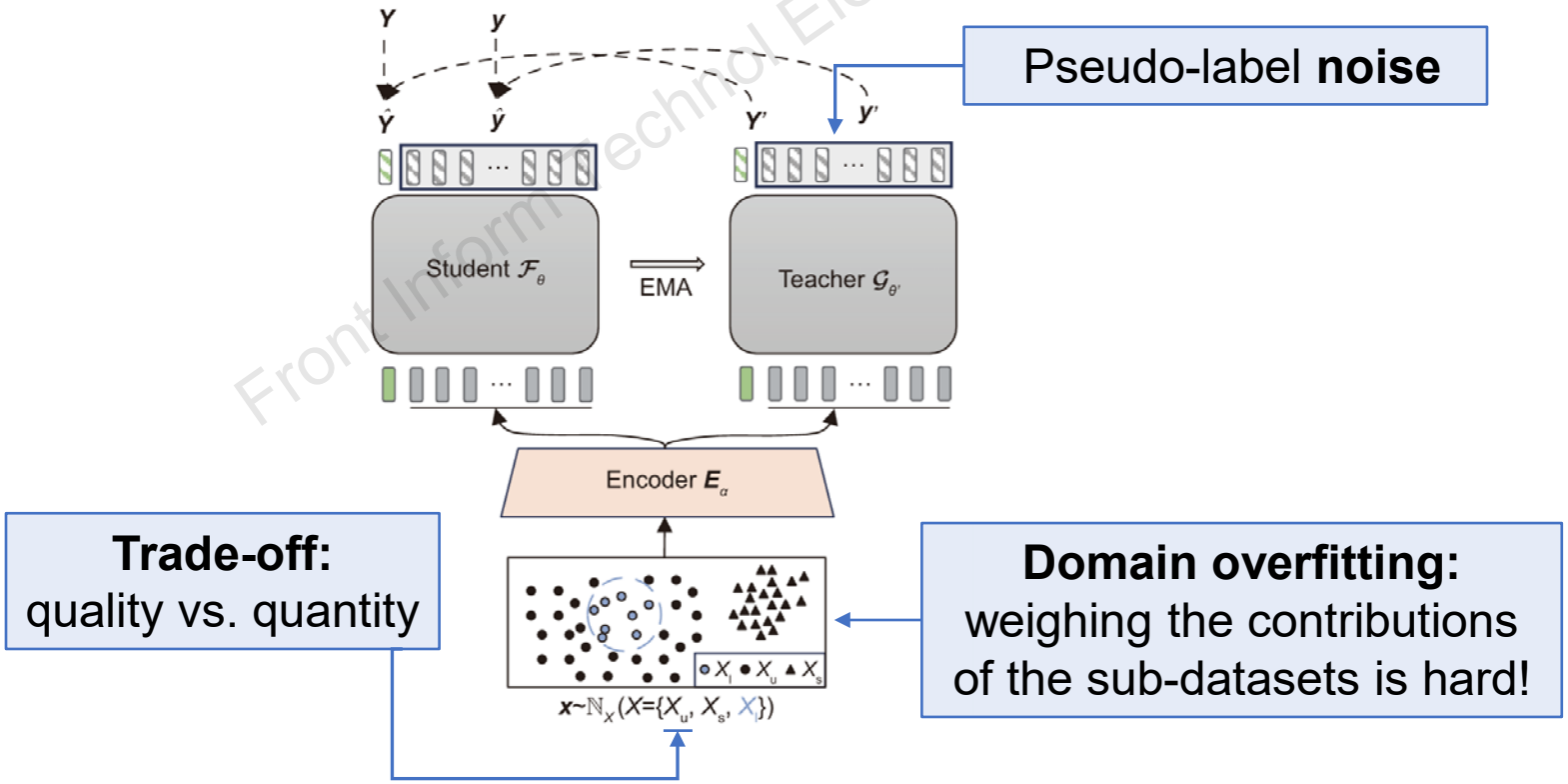
Key words: Prompt tuning; Class distribution learning; Semi-supervised learning; Sound event detection

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Challenges

- **Noisy interference in class distribution learning**: pseudo-label noise and domain knowledge bias;
- **Trade-off between quality and quantity**: low efficiency in the utilization of unlabeled data;
- **Domain overfitting with increased algorithm complexity**: domain adaptation algorithms require careful design.



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Motivation & novelties

- By optimizing only a small portion of the parameters (i.e., prompt tokens), **prompt tuning** (PT) effectively tailors class distribution information for specific downstream tasks while retaining the generalization capacity of pre-trained models.
- In **semi-supervised learning** tasks that typically exclude the involvement of pre-trained models, the application of PT to **alleviate noisy-class distribution information** emerges as a critical challenge demanding immediate attention.

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- ✓ Propose an advanced **semi-supervised class distribution learning** framework (i.e., PADO)
  - PADO leverages real labeled data to explore prior knowledge of class distribution, dynamically interacts with noisy-class distribution information learned from the unlabeled and synthetic data, and effectively alleviates noisy interference for semi-supervised learning.
- ✓ Avoid the decline in generalization capability
  - PADO models prior knowledge as prompt information during only supervised training to dynamically guide the learning of class distribution.

Methodology: PADO framework

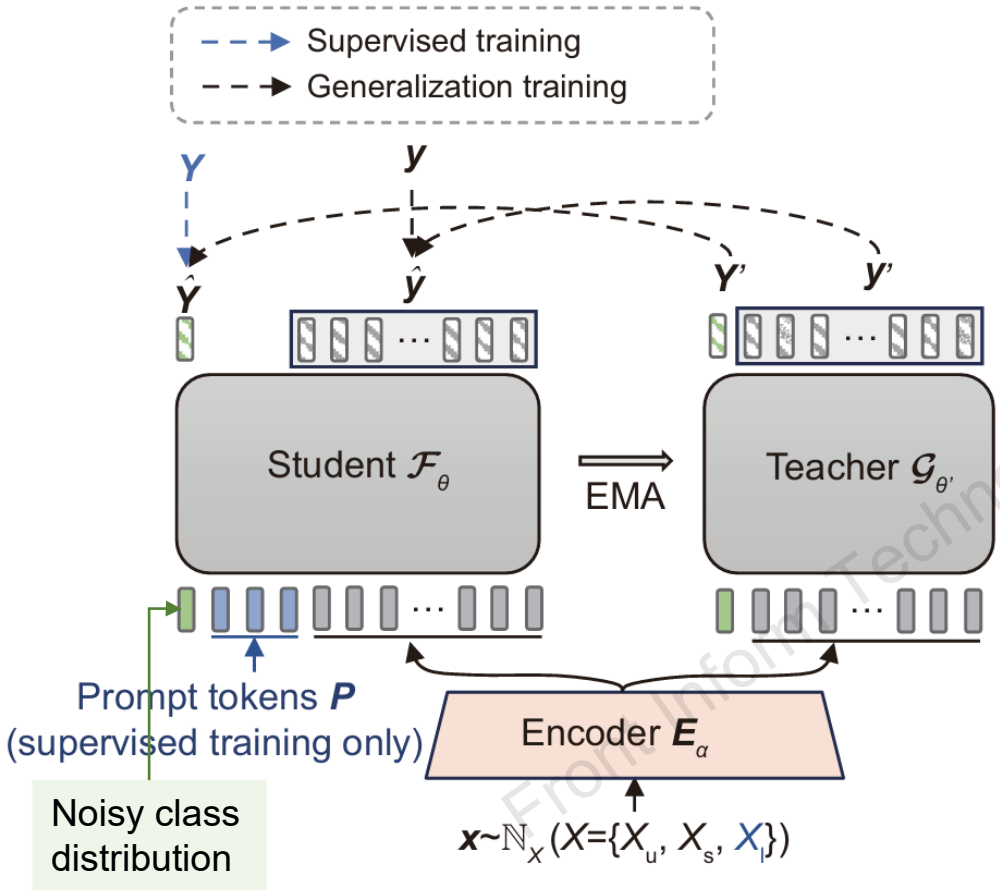


Fig. 2 Framework of the PADO-based SSED, containing supervised training and generalization training

➢ **Generalization training**

→ Learning from pseudo-labels:

1. Get $\boldsymbol{x}$ from $\{X_u, X_s\}: \boldsymbol{x} \sim \mathbb{N}_X(X_u, X_s)$
2. Generate pseudo-labels:

$$(\boldsymbol{Y}', \boldsymbol{y}') = \mathcal{G}'_\theta(\mathcal{C}[\boldsymbol{h}_{\text{cls}}, \boldsymbol{E}_\alpha(\boldsymbol{x})]),$$

3. Minimize the consistency error.

Generalization performance is improved, but the **class distribution is noisy**!

➢ **Supervised training**

→ Optimizing distribution by real labeled data X_l :

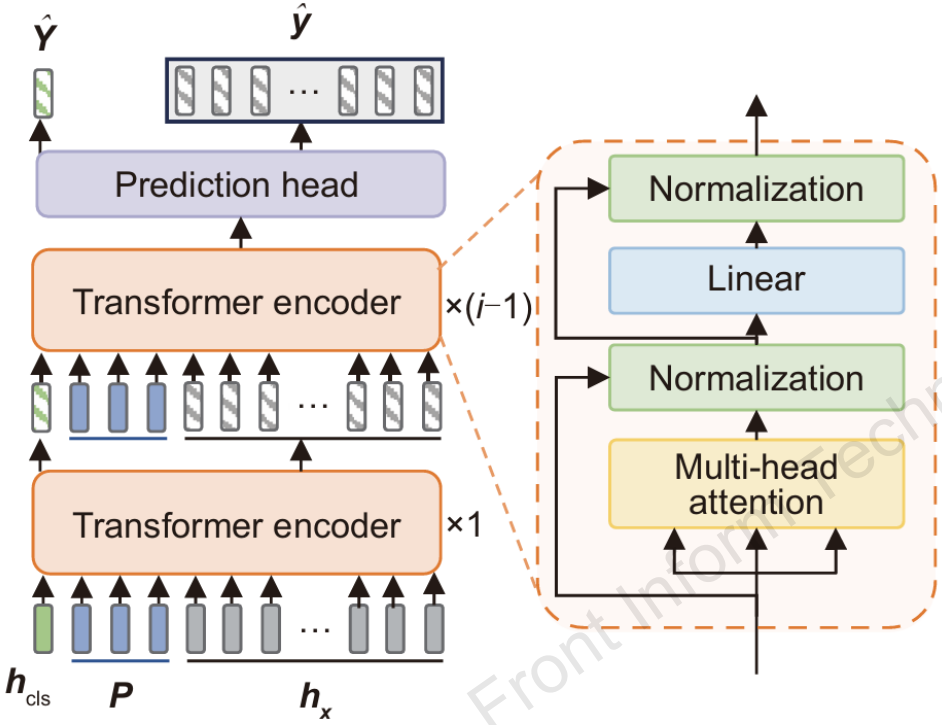
1. Build a real distribution by prompts ***P***;
2. Interact with the noisy distribution dynamically to optimize joint loss.

$$(\hat{\boldsymbol{Y}}, \hat{\boldsymbol{y}}) = \begin{cases} \mathcal{F}_\theta(\mathcal{C}[\boldsymbol{h}_{\text{cls}}, \boldsymbol{h}_{\boldsymbol{x}}]), & \text{if } \boldsymbol{x} \in \{X_u, X_s\}, \\ \mathcal{F}_\theta(\mathcal{C}[\boldsymbol{h}_{\text{cls}}, \boldsymbol{P}, \boldsymbol{h}_{\boldsymbol{x}}]), & \text{if } \boldsymbol{x} \in \{X_l\}. \end{cases}$$

Maintaining the generalization ability while optimizing the noise distribution!

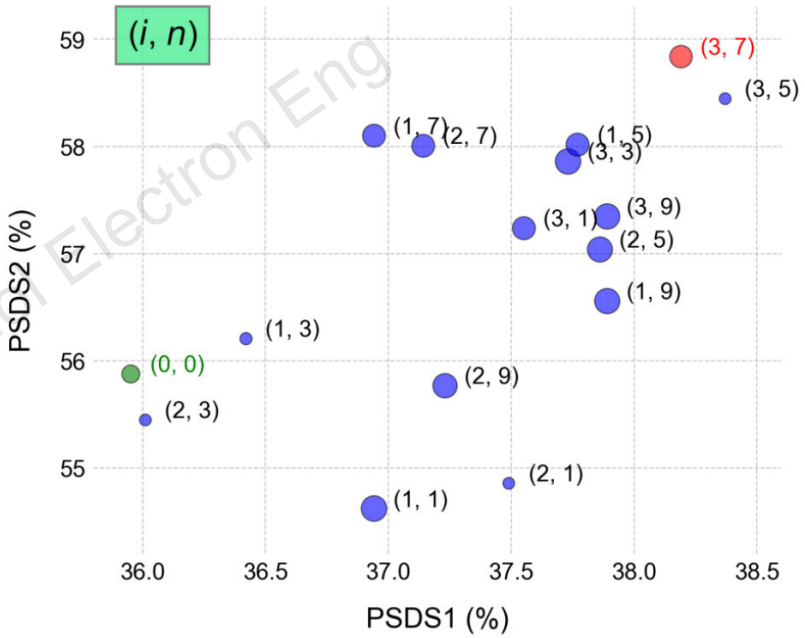
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Methodology: model ablations



Details of the backbone models in PADO

- Grid search for the optimal setting in PADO



The best setting for the number of encoder layers (*i*) and the number of prompt tokens (*n*) is *i*=3 and *n*=7 (red point), indicating that deep prompt tuning performs better.

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Results

Table 3 Performance of PADO-based SSED methods and MT-based baselines on DCASE 2019, 2020, and 2021 validation sets (%)

Model	DCASE 2019 Val. set			DCASE 2020 Val. set			DCASE 2021 Val. set		
	EB-F1	PSDS1	PSDS2	EB-F1	PSDS1	PSDS2	EB-F1	PSDS1	PSDS2
Transformer	41.0	25.5	40.0	42.1	27.7	43.5	38.7	24.4	42.1
PADO-Transformer	**41.3**	**26.6**	**41.2**	**42.3**	**27.8**	**44.3**	**40.8**	**25.0**	**42.2**
ConformerSED (Miyazaki et al., 2020a)	41.4	25.9	44.3	41.7	27.5	46.6	40.3	24.7	43.4
PADO-Conformer	**41.8**	**27.5**	**45.2**	**43.6**	**29.1**	**47.8**	**40.7**	**26.0**	**45.3**
Joint-Former (Gao LJ et al., 2023)	**42.9**	27.2	43.6	43.2	27.8	44.6	**42.1**	26.9	45.8
PADO-Joint-Former	42.3	**27.9**	**44.2**	**44.4**	**29.7**	**48.0**	41.9	**27.7**	**46.6**

EB-F1: event-based F1; Val.: validation; MT: mean teacher; PADO: prompting class distribution optimization; PSDS: polyphonic sound detection score; SSED: semi-supervised sound event detection. The methods underlined indicate reproduced results. The better performing results between our methods and the reproduced related SOTA methods are in bold, respectively

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- **Comparisons with MT-based baseline models**
- ✓ The proposed PADO-based semi-supervised learning framework achieves significant performance improvements for the aforementioned advanced MT-based SSED models.

Results

Table 4 Performance of PADO-based SSED methods and SOTA methods on DCASE 2019, 2020, and 2021 evaluation sets (%)

Model	DCASE 2019 Eval. set			DCASE 2020 Eval. set			DCASE 2021 Eval. set		
	EB-F1	PSDS1	PSDS2	EB-F1	PSDS1	PSDS2	EB-F1	PSDS1	PSDS2
GL (Lin et al., 2020)	42.7	–	–	–	–	–	–	–	–
ConformerSED (Miyazaki et al., 2020a)	–	–	–	46.0	–	–	–	–	–
SparseTrans (Guan et al., 2022)	–	–	–	47.6	–	–	–	–	–
Joint-Former (Gao LJ et al., 2023)	51.3	–	–	49.5	–	–	–	33.9	55.1
SAN (Wakayama and Saito, 2022)	–	–	–	–	–	–	–	29.2	55.0
SCT (Koh et al., 2021)	–	–	–	45.1	–	–	–	–	–
CNMF (Chan and Chin, 2021)	–	–	–	46.3	–	–	–	–	–
MMT (Zheng et al., 2021a)	–	–	–	49.4	–	–	–	–	–
Transformer	46.6	35.3	53.1	46.4	38.1	55.6	42.4	32.9	52.1
PADO-Transformer	**47.9**	**36.9**	**54.0**	**50.9**	**39.6**	**57.8**	**44.9**	**33.2**	**54.0**
ConformerSED (Miyazaki et al., 2020a)	47.9	36.0	55.9	46.7	36.8	58.2	42.9	32.9	56.2
PADO-Conformer	**49.9**	**38.2**	**58.8**	**49.9**	**40.1**	**61.6**	**44.2**	**33.8**	**56.4**
Joint-Former (Gao LJ et al., 2023)	50.9	40.0	60.1	50.7	39.3	59.3	44.5	34.4	56.9
PADO-Joint-Former	**51.4**	**42.1**	**61.2**	**50.9**	**41.8**	**61.9**	**46.7**	**36.9**	**57.0**

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- **Comparisons with SOTA methods**
- ✓ Our PADO-based methods achieve remarkable performance on all metrics in SSED tasks, outperforming the SOTA models.
- ✓ The PADO-Joint-Former achieves a new SOTA performance in SSED tasks on all three benchmark datasets.

Results

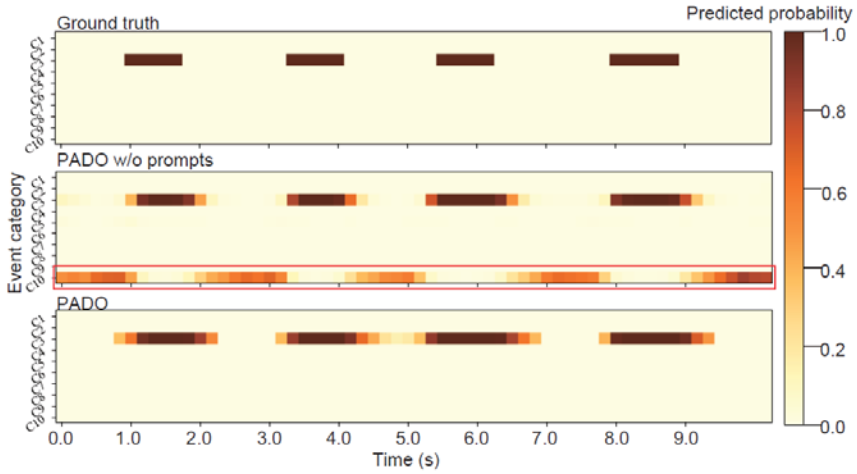


Fig. 4 Visualization of event localization for a test sample (1LKP1ZyHgVg_0_10.wav) from DCASE 2020 evaluation set, where the sound event "Cat" is active

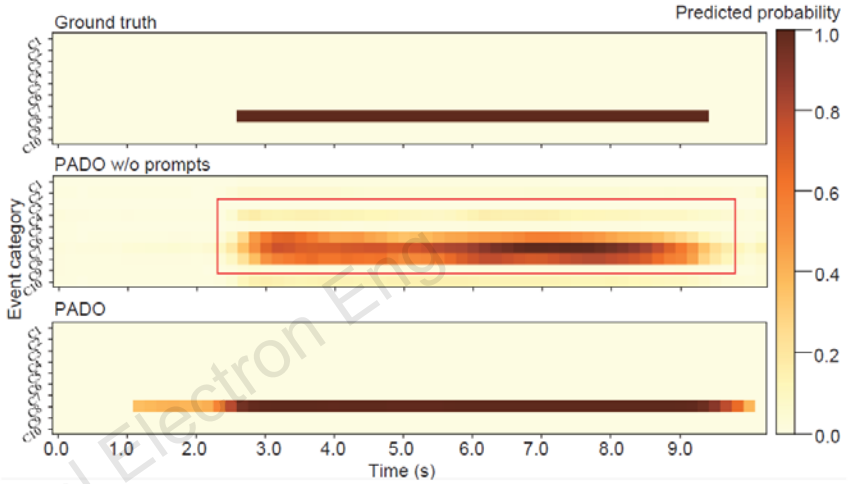


Fig. 5 Visualization of event localization for a test sample (dfRtayqQAls_14_24.wav) from DCASE 2020 evaluation set, where the sound event "Running water" is active

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- ➢ **Qualitative visualization of localization**
- ✓ After embedding the prompt token, the **false detection rate** is significantly reduced.
- ✓ After embedding the prompt token, the **confusion between classes** is significantly reduced.

PADO effectively improves the efficiency of class distribution learning!



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