CALM: Class-Conditional Sparse Attention Vectors for Large Audio-Language Models

Anonymous ACL submission

Abstract

Large audio-language models (LALMs) show strong zero-shot performance on tasks such as audio question answering, but still lag behind specialized systems on discriminative tasks such as audio classification. Recent work shows that sparse subsets of attention heads can serve as discriminative feature extractors for few-shot classification, but existing methods weight all selected heads equally. We propose **C**lass-Conditional Sparse **A**ttention Vectors for Large Audio-**L**anguage **M**odels (CALM), a few-shot classifier that learns class-conditional importance weights over attention heads. By treating heads as class-specific experts and aggregating them with reliability-weighted soft voting, CALM allows different classes to rely on different subsets of heads. Across diverse few-shot audio, audiovisual, visual, and spoofing benchmarks, CALM consistently outperforms state-of-the-art uniform-voting baselines, with gains of up to 14.52, 1.53, and 8.35 absolute points on audio, audiovisual, and spoofing tasks, respectively. Code repository will be released upon acceptance.

1 Introduction

Large audio-language models (LALMs), such as Qwen2-Audio (Chu et al., 2024) and Qwen2.5-Omni (Xu et al., 2025), have shown strong zero-shot and few-shot performance across a wide range of audio understanding tasks (Chu et al., 2024; Xu et al., 2025). Trained on large-scale paired audio-text data, these models generalize well without task-specific fine-tuning (Radford et al., 2022; Huang et al., 2023; Lyu et al., 2023).

Despite these strengths, repurposing LALMs for discriminative audio classification remains challenging. Specialized audio classifiers often outperform prompt-based approaches, but they require substantial labeled data and task-specific training pipelines (Gao et al., 2022; Xie and Virtanen, 2019; Elizalde et al., 2022; Guzhov et al., 2022). In contrast, directly leveraging frozen LALMs for classification offers reduced training cost (Hanif et al., 2024), lower sample complexity in few-shot settings, and a unified model that supports both generative and discriminative use without retraining (Yang et al., 2024).

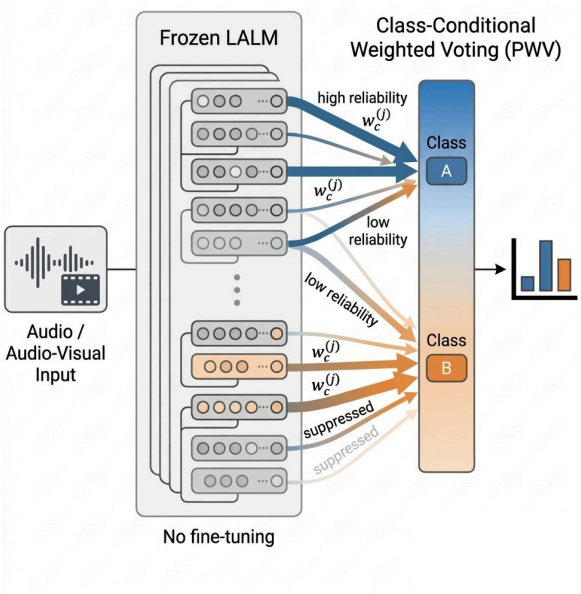


Figure 1: **Fine-tuning-free audio classification with CALM**. Given a frozen audio-language model, we extract per-head last-token hidden-state representations and compute class centroids. Each attention head produces cosine-similarity scores to all class centroids. For every head-class pair, we estimate a reliability score based on the margin to the next most confident class, which is visualized by the arrow width and color in the figure. Highly reliable heads contribute strongly (thick, saturated arrows), while unreliable heads are suppressed by lower weights. At inference time, class predictions are obtained via reliability-weighted soft voting across all heads. This yields accurate classification without task-specific fine-tuning.

Recent work has shown that frozen generative

models can be turned into strong discriminative classifiers by extracting intermediate representations rather than relying on prompt-based predictions (Mitra et al., 2025; Huang et al., 2024; Zhang et al., 2024; Hendel et al., 2023; Hojel et al., 2024; Todd et al., 2024). In particular, Sparse Attention Vectors (SAV) (Mitra et al., 2025) show that a small subset of attention heads in a frozen audio-language model can serve as effective feature extractors for few-shot classification. The method selects the most discriminative heads and aggregates their predictions through majority voting, substantially narrowing the gap between generative models and specialized discriminative systems without requiring fine-tuning on labeled data.

In this paper, we extend this line of work to audio, audiovisual, and visual classification. Compared with vision or text, audio classification presents unique challenges, including multiple overlapping acoustic events (Dogan et al., 2024; Sridhar et al., 2024), higher intra-class and inter-class variability, and temporal ambiguity in semantic cues. These characteristics make it unlikely that a single uniform aggregation strategy over attention heads is optimal across all classes. While effective, SAV relies on a strong simplifying assumption: all selected attention heads are treated as *equally reliable* across all classes. By contrast, prior work on interpretability and representation learning shows that attention heads exhibit *functional specialization*, often responding differently to different semantic patterns or sensory stimuli (Basile et al., 2025; Jo and Myaeng, 2020; Ma et al., 2025; Wang et al., 2025). This exposes a key limitation of uniform voting: weak or noisy heads can still influence predictions for classes where they are not discriminative (Qian et al., 2025). To address this limitation, we propose **C**lass-Conditional Sparse **A**ttention Vectors for Large Audio-**L**anguage **M**odels (CALM), a principled extension of SAV that models attention heads as *class-conditional experts* rather than uniformly reliable voters. CALM estimates a class-specific reliability score for each selected head from few-shot data and uses these scores in a reliability-weighted voting scheme at inference time. Figure 1 shows the overall pipeline. Because CALM operates directly on a frozen LALM, it introduces only minimal computational overhead. Our contributions are threefold:

1. We introduce CALM, a probabilistically weighted framework that models attention heads as class-conditional experts.

2. We present the first application of attention vectors as discriminative classifiers to audio, audiovisual, and visual classification, despite modality-specific challenges.

3. We demonstrate improvements over uniform-voting SAV baselines across audio, audiovisual, visual, and spoofing benchmarks, including ESC-50, VGGSound, AudioSet, EuroSAT, Oxford-IIIT Pets, and LA-Spoof.

2 Related Work

Generative Models for Audio Classification. Recent work adapts large generative audio or multimodal models to classification through prompting, in-context demonstrations, or label-likelihood scoring (Taylor and Mack, 2025; Gong et al., 2024; Brown et al., 2020; Cheng et al., 2019; Kumar et al., 2023; Hendrycks et al., 2021). While appealing because they reuse a single frozen model, these approaches are often sensitive to prompt design and can lag behind specialized discriminative systems or adapted audio-language models (Olvera et al., 2024; Sahoo et al., 2025; Salinas and Morstatter, 2024; Choudhary et al., 2022; Deshmukh et al., 2024). Other methods improve classification through instruction tuning, preference optimization, or test-time adaptation, but they require additional optimization or supervision and therefore move away from the fine-tuning-free setting we target (Choi et al., 2025; Bucher and Martini, 2024; Ouyang et al., 2022; Sun et al., 2020; Zhang et al., 2025a).

Internal Representation of LALMs. A complementary direction uses frozen language or multimodal models as feature extractors rather than relying on decoded outputs (Belinkov, 2021; Hendel et al., 2023; Huang et al., 2024; Taylor and Mack, 2025). In audio, this includes representation-based classifiers formed from audio-text similarity in a shared embedding space, as well as methods that use intermediate hidden states for downstream prediction. Interpretability studies further show that attention heads exhibit functional specialization, suggesting that different heads capture different semantic factors (Clark et al., 2019; Voita et al., 2019; Basile et al., 2025; Jo and Myaeng, 2020). SAV (Mitra et al., 2025) turns this observation into

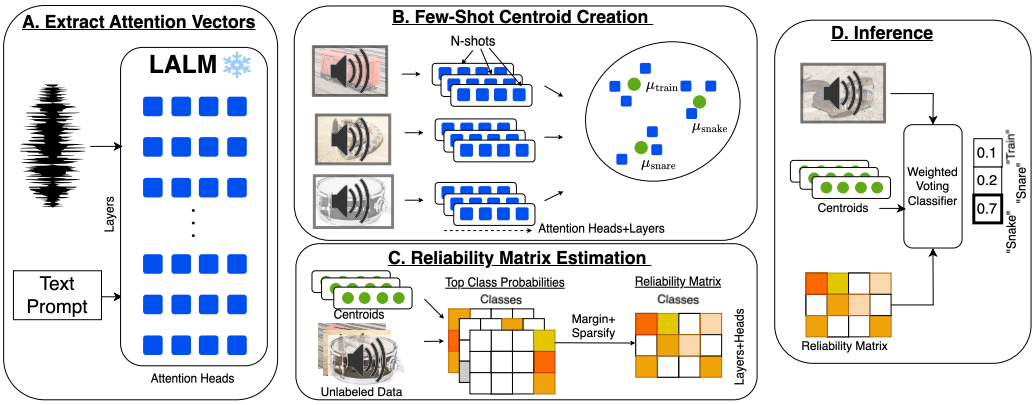


Figure 2: **Overview of CALM**: We extract attention-head vectors from a frozen LALM given an audio input and prompt. Then we build class centroids from few-shot training examples and estimate a class-conditional head reliability matrix using margin-based confidence and sparsifying to k head experts per class. At inference, CALM combines centroid similarities with these reliability weights to perform weighted voting over heads. This allows for fine-tuning-free classification.

a classifier by selecting a sparse set of discriminative heads and aggregating them with uniform voting. Our work builds directly on SAV, but replaces uniform aggregation with class-conditional reliability weighting so that different classes can rely on different expert heads.

3 Methods

We consider a C-way classification problem with a few-shot training set $\mathcal{D}_{\text{train}} = \{(x_i, c_i)\}_{i=1}^{N}$ and a test set $\mathcal{D}_{\text{test}} = \{(x_i, c_i)\}_{i=1}^{N_{\text{test}}}$, where $c_i \in \mathcal{C} = \{1, \ldots, C\}$ and n_c denotes the number of training examples for class c. Given an input x, we prompt a frozen audio-language or multimodal language model and extract the last-token representation from each attention head $j \in \{1, \ldots, K\}$, denoted $h_j(x) \in \mathbb{R}^d$. We then build a fine-tuning-free classifier by computing class centroids in each head space and aggregating head-level evidence. Figure 2 provides an overview.

We first briefly recap SAV (Mitra et al., 2025), then introduce CALM, our class-conditional weighting scheme. We finally describe a simple pseudo-labeling extension for unlabeled data.

3.1 Recap: Sparse Attention Vectors

The SAV classifier (Mitra et al., 2025) forms a nearest-centroid classifier in each attention head and aggregates the top-k heads with uniform voting.

Per-head Centroids. For each class c and head j, SAV computes the class centroid

$$\mu_c^{(j)} = \frac{1}{n_c} \sum_{i:c_i=c} h_j(x_i). \tag{1}$$

It scores a query x against class c in head j using cosine similarity

$$s_j(x, c) = \frac{h_j(x)^\top \mu_c^{(j)}}{\|h_j(x)\|_2 \, \|\mu_c^{(j)}\|_2}. \tag{2}$$

Top-k head selection. Each head is ranked by its nearest-centroid classification accuracy on $\mathcal{D}_{\text{train}}$. Concretely, head j predicts

$$\hat{y}^{(j)}(x) = \arg\max_{c \in \mathcal{C}} \; s_j(x, c), \tag{3}$$

and the top-k heads define $\mathcal{H}_{\text{SAV}}$.

Majority Voting (Uniform Aggregation). At inference time, SAVs aggregates the selected heads by uniform voting:

$$\hat{y}(x_{\text{test}}) = \arg\max_{c \in \mathcal{C}} \sum_{j \in \mathcal{H}_{\text{SAV}}} \mathbf{1}\left[\hat{y}^{(j)}(x_{\text{test}}) = c\right]. \tag{4}$$

This uniform voting scheme assumes that all selected heads are equally reliable across all classes. CALM removes this assumption.

3.2 CALM

CALM keeps the same per-head centroids as SAV, but replaces hard uniform voting with weighted aggregation of per-head posteriors. The key idea is to treat attention heads as *class-specific experts*, so that classes can rely on different subsets of heads with different strengths.

Head Posteriors. Using the per-head class centroids from Eq. 1 and the similarity scores from Eq. 2, we convert each head's score into a probability distribution over classes.

$$p_c^{(j)}(x) = \frac{\exp\left(s_j(x,c)/\tau_p\right)}{\sum_{c' \in \mathcal{C}} \exp\left(s_j(x,c')/\tau_p\right)}, \quad (5)$$

for some hyperparameter $\tau_p > 0$.

3.2.1 CALM-Global: Head Weighting

We first describe a simpler global-weighting variant, which assigns each head a single reliability shared across all classes. For a labeled example (x_i, c_i), we define the clamped margin

$$m^{(j)}(x,c) = \max\Big(0, p_c^{(j)}(x) - \max_{c' \neq c} \; p_{c'}^{(j)}(x)\Big). \quad (6)$$

The clamp ensures that incorrect or low-confidence cases contribute zero. We then average margins over all training examples to obtain a single global reliability per head:

$$r^{(j)} = \frac{1}{N} \sum_{i=1}^{N} m^{(j)}(x_i, c_i). \quad (7)$$

Retaining the top-k heads with the largest reliabilities gives $\mathcal{H}_G$, and we normalize their weights as

$$w^{(j)} = \begin{cases} \dfrac{\exp(r^{(j)}/\tau_w)}{\sum_{j' \in \mathcal{H}_G} \exp(r^{(j')}/\tau_w)}, & j \in \mathcal{H}_G, \\ 0, & \text{otherwise.} \end{cases} \quad (8)$$

At test time, we aggregate per-head posteriors using these global weights:

$$p_c(x_{\text{test}}) = \sum_{j=1}^{K} w^{(j)} p_c^{(j)}(x_{\text{test}}), \quad (9)$$

$$\hat{y}(x_{\text{test}}) = \arg\max_c \; p_c(x_{\text{test}}). \quad (10)$$

This variant is useful for comparison, but it does not capture class-specific head specialization.

3.2.2 Class-Conditional Head Weighting

Our full CALM model assigns a separate reliability to each head-class pair. After computing the margins in Eq. (6), we average them class-wise:

$$r_c^{(j)} = \frac{1}{n_c} \sum_{i; c_i = c} m^{(j)}(x_i, c). \quad (11)$$

Algorithm 1 CALM (class-conditional weighting)

Require: Frozen LALM, train set $\mathcal{D} = \{(x_i, y_i)\}$, num heads K, and sparsity k

Extract attention-head features $h_j(x_i)$ for all $j \in \{1, \ldots, K\}$
Compute class centroids $\mu_c^{(j)} = \frac{1}{n_c} \sum_{i: y_i = c} h_j(x_i)$
for each class c and head j **do**
  Compute posteriors $p_c^{(j)}(x_i)$ via Eq. 5
  Compute margins via Eq. 6
  $r_c^{(j)} \leftarrow \frac{1}{n_c} \sum_{i: y_i = c} m_i^{(j)}$
end for
Select top-k reliable heads per class and normalize weights $w_c^{(j)}$
Predict $\hat{y} = \arg\max_c \sum_j w_c^{(j)} p_c^{(j)}(x_{\text{test}})$

Let the top-k heads for class c be $\mathcal{H}_c$. We normalize the class-conditional reliabilities with a softmax:

$$w_c^{(j)} = \begin{cases} \dfrac{\exp(r_c^{(j)}/\tau_w)}{\sum_{j' \in \mathcal{H}_c} \exp(r_c^{(j')}/\tau_w)}, & j \in \mathcal{H}_c, \\ 0, & \text{otherwise,} \end{cases} \quad (12)$$

for some hyperparameter $\tau_w > 0$. This generalizes the shared top-k set and uniform voting used by SAV to a class-specific set of head experts.

$$p_c(x_{\text{test}}) = \sum_{j=1}^{K} w_c^{(j)} p_c^{(j)}(x_{\text{test}}), \quad (13)$$

and predict with the same argmax rule as in Eq. (10). Algorithm 1 summarizes the class-conditional CALM procedure.

3.3 Self-supervised CALM

To use CALM without ground-truth labels, we generate M stochastic predictions for each unlabeled example using decoding temperatures $\tau \sim \mathcal{U}(1, 2.5)$. We assign a pseudo-label by majority vote, retain only examples where at least 50% of rollouts agree, and then run SAV or CALM on the retained pseudo-labeled set $\tilde{\mathcal{D}}_{\text{train}} = \{(x_i, \tilde{c}_i)\}$.

4 Experiments and Results

We evaluate our method on a range of audio and audiovisual classification benchmarks. We first describe the implementation details, models, datasets, and evaluation protocols, and then analyze the impact of head sparsity and class-specific weighting through ablations.

Dataset	ZS	SAV	SAV+PL	CALM	CALM+PL
Qwen2-Audio					
ESC-50	73.75	99.00	96.50	**99.00**	98.75
VGGSound	72.94	85.64	85.65	**88.15**	87.67
AudioSet	46.59	44.88	49.06	**59.40**	51.80
LA-Spoof	16.19	**72.00**	70.03	61.10	22.73
Qwen2.5-Omni					
ESC-50	86.00	99.00	91.00	**99.25**	98.50
VGGSound	61.57	87.11	81.78	**87.85**	86.28
AudioSet	61.52	69.52	63.54	**70.50**	66.70
VGGVideo	70.71	89.49	–	**91.02**	–
LA-Spoof	15.82	73.64	67.01	**81.99**	70.13
EuroSAT	59.67	68.72	58.10	**72.80**	62.70
Pets	96.05	98.27	97.92	**99.23**	97.16

Table 1: **Main classification results.** Accuracy (%) for zero-shot (ZS), SAV, and CALM with and without pseudo-labeling (PL). Best results within each model block are shown in **bold**.

4.1 Implementation Details

All experiments are implemented in PyTorch and run on NVIDIA A6000 GPUs. We use frozen pretrained models from the Qwen family (Chu et al., 2024; Xu et al., 2025). *Qwen2-Audio* (Chu et al., 2024) is an audio-language model in which an audio encoder feeds into the language model. The language model consists of 32 Transformer layers with 32 attention heads per layer (1024 heads total), each with a hidden dimension of 128. We extract attention head activations from the language model layers rather than the audio encoder to capture cross-modal audio-text interactions. *Qwen2.5-Omni* (Xu et al., 2025) is a multimodal model supporting audio, image, video, and speech inputs. As with Qwen2-Audio, we extract attention activations exclusively from the language tower. To select τ_p and τ_w, we perform a hyperparameter sweep either on a small labeled validation split or purely from pseudo-labeled data (see Hyperparameter Selection without Labels). We sweep $\tau_p, \tau_w \in \{0.001, 0.03, 0.1, 0.5, 1, 2\}$. We use $\tau_p = 0.03$ and $\tau_w = 0.5$ for almost all datasets; for AudioSet, we use $\tau_p = 0.001$ and $\tau_w = 0.5$. For ESC-50, VGGSound, and AudioSet, an example prompt is: `What caption does the given audio belong to? A. washing_machine B. toilet_flush C. car_horn D. wind`. For spoofing detection, an example prompt is: `Is this audio bona fide or spoofed? A. bona_fide B. spoofed`. We use the same input-formatting logic for image inputs.

4.2 Datasets

We primarily evaluate our approach on audio classification benchmarks, and further extend it to audiovisual recognition and audio spoofing detection. Across all datasets, we follow the input formatting protocol of SAV (Mitra et al., 2025), casting each task into a multiple-choice question-answering formulation suitable for LALMs.

ESC-50 (Piczak, 2015) is a standard environmental sound classification benchmark consisting of 2,000 five-second audio clips across 50 classes. We sample class-balanced subsets according to the desired shot setting and frame the task as multiple-choice audio classification.

VGGSound (Chen et al., 2020) is a large-scale audiovisual dataset containing over 200k videos spanning 309 sound event classes. Compared to ESC-50, it exhibits substantially greater semantic and acoustic diversity. We adopt the same multiple-choice formulation and use both audio and video modalities for audiovisual experiments.

AudioSet (Gemmeke et al., 2017) is a large-scale ontology-based audiovisual dataset with 527 non-mutually exclusive sound event classes. Due to its multi-label nature, we decompose each audio clip into independent classification queries, one per ground-truth label, and report strict *exact-match* accuracy at the clip level.

ASVspoof (Wang et al., 2020) is used for spoofing detection. We study the LA (Logical Access) subset of ASVspoof 2019, which requires distinguishing bona fide speech from synthetic audio generated via speech synthesis and voice conversion methods. Given the class imbalance, we report Macro-F1 as the primary evaluation metric (Zhang

et al., 2025b).

EuroSAT (Helber et al., 2019) is a vision classification dataset for land-cover recognition. It contains 10 classes with approximately 2,000–3,000 images per class. We randomly sample a 20-shot support set and use the remaining images for evaluation.

Oxford-IIIT Pets (Parkhi et al., 2012) is another vision classification dataset, containing 37 cat and dog breeds. The main challenge is the subtle visual differences between breeds. We follow the same multiple-choice protocol as above, pairing the ground-truth breed with three randomly sampled distractor breeds.

4.3 Results

4.3.1 Main Results

Table 1 summarizes the main comparison against zero-shot inference, SAV, and the pseudo-labeling variant from Section 3.3. Across both LALMs and most datasets, CALM improves over uniform SAV aggregation, with the largest gains appearing on the most challenging tasks. On ESC-50, both methods are near saturation, so the margin is small. On VGGSound, CALM improves over SAV by +2.51 points on Qwen2-Audio and +0.74 points on Qwen2.5-Omni. The strongest gain appears on AudioSet, where CALM improves over SAV by +14.52 points on Qwen2-Audio, suggesting that class-conditional weighting is especially useful when the label space is large and heterogeneous.

The same trend extends beyond audio-only classification. On Qwen2.5-Omni, CALM improves over SAV on VGGVideo, EuroSAT, and Oxford-IIIT Pets, showing that class-conditional head weighting transfers not only to audiovisual recognition but also to pure image classification. LA-Spoof is the main exception: CALM improves over SAV for Qwen2.5-Omni but underperforms for Qwen2-Audio. This is consistent with the binary nature of spoofing detection, where estimating separate class-specific weights from few examples can overfit more easily than in large multi-class problems.

Pseudo-labeling is best viewed as a complementary self-training setting rather than the main source of CALM's gains. As shown in Table 1, CALM+PL is usually below fully supervised CALM, although it remains competitive on most settings where additional unlabeled data helps stabilize the centroids.

Comparison to Fine-tuning. Table 2 compares CALM against standard fine-tuning techniques such as linear probing and LoRA, and additional few-shot baselines such as nearest neighbors using CLAP embeddings (Elizalde et al., 2022). CALM matches the best result on ESC-50, improves over both LoRA and SAV on VGGSound, and remains substantially stronger than CLAP. The main failure case is again LA-Spoof, where discriminative fine-tuning is more effective.

Method	ESC-50	VGGSound	LA-Spoof F1
CLAP	95.50	35.12	59.79
Linear Probe	97.50	81.48	**85.13**
LoRA	98.00	87.23	69.68
SAV	99.00	85.64	72.00
CALM	**99.00**	**88.15**	61.10

Table 2: **Comparison to stronger baselines.** CALM remains competitive with linear probing and LoRA while outperforming SAV on VGGSound.

4.3.2 Class-Specific Head Specialization

To better understand head specialization, Figure 3 visualizes per-class weight survival functions for representative VGGSound classes, while Figure 4 shows the most influential head for each class across the 309 VGGSound classes. Under SAV, all selected heads receive the same weight $\frac{1}{k}$, shown by the dashed baselines in Figure 3. In contrast, CALM learns class-conditional, non-uniform weightings: the survival curves differ substantially across classes, and several have heavy tails, indicating that a small subset of heads carries most of the evidence. Figure 4 further shows that the strongest heads concentrate in later layers, suggesting that LALMs contain both class-specific experts and a smaller set of broadly useful heads and that CALM exploits structured specialization rather than diffuse contributions from all heads.

4.3.3 Ablations

We next validate the two main design choices in CALM: class-conditional weighting and sparse reliability-based aggregation.

Class-Conditional vs Global Weighting. Table 3 and the left panel of Figure 5 compare the full class-conditional method with the simpler global variant from Section 3.2.1. Local weighting is consistently better on VGGSound, where class-specific head specialization matters most, while global weighting is better on LA-Spoof. This reinforces the interpretation from Table 1: in a binary setting with limited support data, sharing one re-

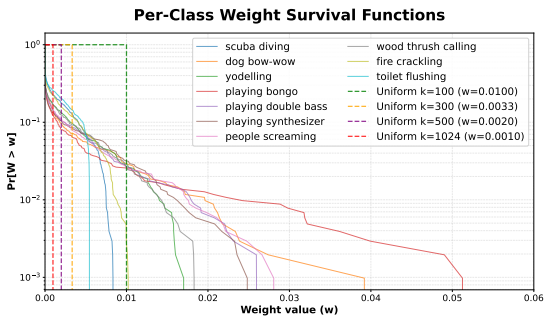


Figure 3: **Per-class weight survival functions for VGGSound.** Different classes concentrate weight on different subsets of attention heads. Dashed lines show the corresponding uniform-voting baselines for $k = 100, 300, 500$, and 1024 heads.

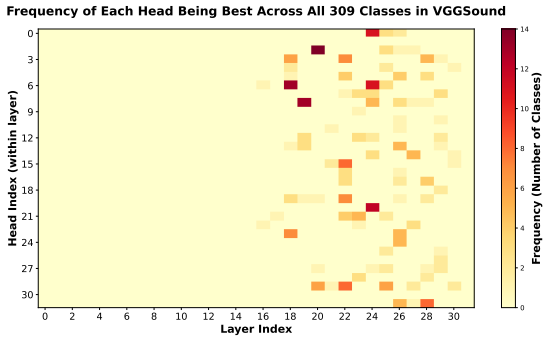
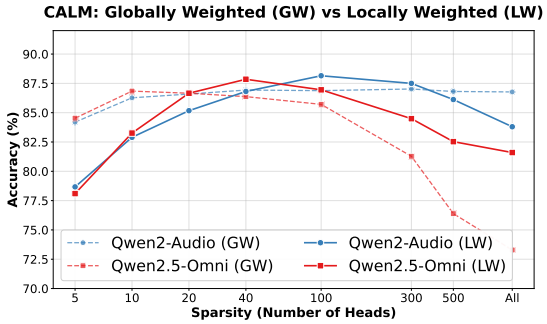


Figure 4: **Most influential attention heads across classes.** Heatmap of the most influential head (highest $w^{(j)}$) for each VGGSound class.



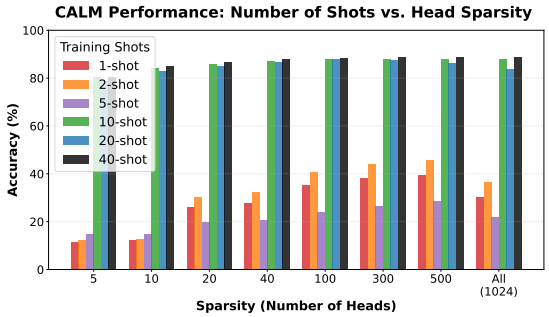


Figure 5: **CALM ablations. Left:** class-conditional local weighting consistently outperforms global weighting, especially when more heads are retained, supporting the hypothesis that attention heads specialize by class. **Right:** performance improves with more training shots and typically peaks at intermediate sparsity levels, showing that CALM benefits from both better centroid estimates and selective head pruning.

liability score per head can regularize better than fitting separate class-wise weights. The pattern is also consistent with the head specialization analysis in Section 4.3.2: if different classes repeatedly route through different late-layer heads, then class-conditional weighting should outperform any scheme that forces all classes to share a single reliability profile.

Component Ablations. Table 4 isolates the effect of the two main ingredients in CALM. Removing L2 normalization consistently hurts performance, which suggests that raw head activations have scale variation that degrades centroid quality. Removing margin-based reliability also lowers accuracy, especially for Qwen2.5-Omni, showing that selecting heads by discriminability is important in addition to sparse aggregation. Together, these results show that both normalization and reliability weighting are necessary parts of the final method.

Algorithmic Ablations		
Model	**VGGSound**	**LA-Spoof**
Global		
Qwen2-Audio	87.02	**69.07**
Qwen2.5-Omni	86.84	**83.60**
Class-cond.		
Qwen2-Audio	**88.15**	61.10
Qwen2.5-Omni	**87.85**	81.99

Table 3: **Algorithmic ablations.** Comparison between global and class-conditional weighting on VGGSound and LA-Spoof.

Shot and Sparsity Sensitivity. The right panel of Figure 5 shows that CALM improves as the number of support examples increases, with the largest gains appearing between 5 and 10 shots. The same plot also shows that the best performance is usually obtained with intermediate sparsity rather than either extreme, which supports the central design

L2 Norm and Margin Weighting		
Method	**Qwen2-Audio**	**Qwen2.5-Omni**
SAV Baseline	85.64	87.11
CALM	**88.15**	**87.85**
– L2 Norm	87.03	87.00
– Margin	87.33	85.52

Table 4: **CALM component ablations.** Effect of removing L2 normalization or margin-based reliability weighting.

top-k	Random	CALM
5	27.35	**78.10**
10	38.04	**83.26**
20	53.08	**86.66**
40	68.52	**87.85**
100	79.79	**86.95**

Table 5: **Random-head counterfactual.** Results with Qwen2.5-Omni on VGGSound.

intuition: too few heads discard useful evidence, while too many heads dilute the contribution of the most discriminative experts.

Random-head Counterfactual. Table 5 tests whether CALM's gains come from many heads or from structured selection and weighting. Random head selection with random weights degrades performance sharply in sparse regimes (27.35% vs. 78.10% at top-$k = 5$ on VGGSound), and CALM remains significantly better across all k.

Seed Stability. Table 6 measures robustness across 10 random 20-shot VGGSound splits on Qwen2-Audio. CALM consistently outperforms SAV across all tested top-k values with low variance, showing stable gains across support-set sampling and sparsity choices.

Hyperparameter Selection without Labels. Hyperparameters can be selected using either a small labeled validation split or selecting hyperparameters on zero-shot pseudo-labeled test-data. On VGGSound, pseudo-label-selected hyperparameters match labeled-validation selection and yield 88.15% test accuracy, improving over the 72.94% zero-shot baseline by +15.21 points without labeled tuning.

Cross-architecture Transfer. To test transfer beyond our main LALMs, we apply CALM to

top-k	SAV	CALM
20	85.22 ± 0.18	$\mathbf{86.38 \pm 0.16}$
40	85.20 ± 0.24	$\mathbf{87.46 \pm 0.13}$
100	85.37 ± 0.19	$\mathbf{88.22 \pm 0.10}$
300	85.65 ± 0.12	$\mathbf{88.45 \pm 0.11}$

Table 6: **Seed stability.** Results with Qwen2-Audio on VGGSound across 10 random 20-shot splits.

Backbone	SAV	CALM
Qwen2-VL-7B	71.03	**73.93**
Phi-4-Multimodal	47.99	**49.72**

Table 7: **Cross-architecture transfer**. Results with Qwen2-VL-7B and Phi-4-Multimodal on VGGSound.

Qwen2-VL-7B and Phi-4-Multimodal (Abouelenin et al., 2025) (Table 7). CALM improves over SAV on both settings (71.03%→73.93% and 47.99%→49.72%), suggesting benefits across architectures and modality combinations.

5 Conclusion

We presented **CALM**, a fine-tuning-free classifier that treats attention heads in frozen LALMs as class-conditional experts. Across audio, audiovisual, and visual benchmarks, CALM improves over uniform SAV voting. Ablations show that class-specific margin-based reliability and normalization are key to these gains, indicating that reliability-aware sparse aggregation exposes discriminative structure already present in frozen multimodal models.

Limitations

CALM remains sensitive to label scarcity and label noise because class-specific reliabilities are estimated from small support sets, reflected in weaker binary spoofing results and the gap between supervised and pseudo-labeled settings. The method also introduces dataset-dependent temperature hyperparameters (τ_p, τ_w) and validation-dependent sparsity selection, though these can be chosen *from unlabeled* data as in CALM+PL. Finally, we evaluate only a limited set of frozen backbones and benchmarks; broader architecture, modality, and task coverage is needed to fully assess generality.

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