Coincidence, Categorization, and Consolidation: Learning to Recognize Sounds with Minimal Supervision

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Google Research

Getting Started On A New ML Application

- **Goal:** Collect N examples for each of K classes

<u>Case #1: Have Unlabeled Data</u>

- **Common Strategy:** Randomly sample examples for rating
- **Problem:** biased class distribution and abundance of out-of-set classes

<u>Case #2: No Unlabeled Data</u>

- **Common Strategy:** Collect artificially prompted examples
- **Problem:** not fully representative of data in deployment setting

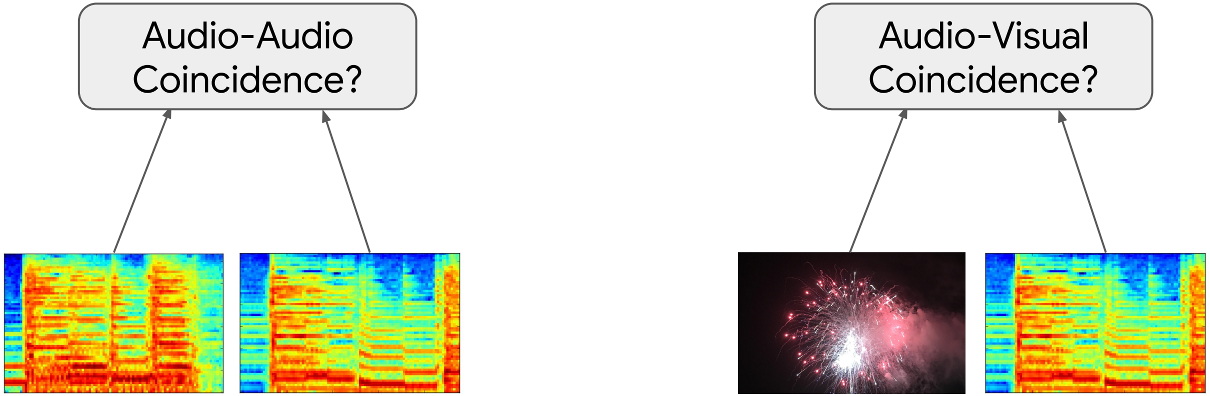
Inspiration from Infant/Child Cognitive Learning

- Humans enter the world with no ability to:
    - Track and recognize objects
    - Recognize speech and environmental sounds
- Abilities only emerge throughout first year after several months of largely unsupervised exposure to natural stimuli
- Once two-way communication is established:
    - Children know what they don't know and ask for labels for novel classes
    - **However:** they don't need a label for every instance

Coincidence, Categorization, and Consolidation

Goal: Go from unlabeled dataset to semantic classifier similar to how children acquire cognitive skills:

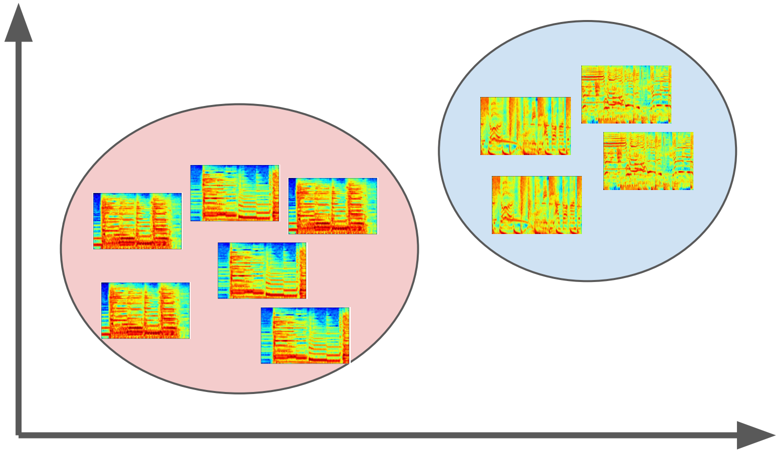
1. **Coincidence:** observe which stimuli do and don't coincide to learn a semantic representation



Coincidence, Categorization, and Consolidation

Goal: Go from unlabeled dataset to semantic classifier similar to how children acquire cognitive skills:

2. **Categorization:** Apply cluster-based category discovery methods to representation and reinforce with clustering loss



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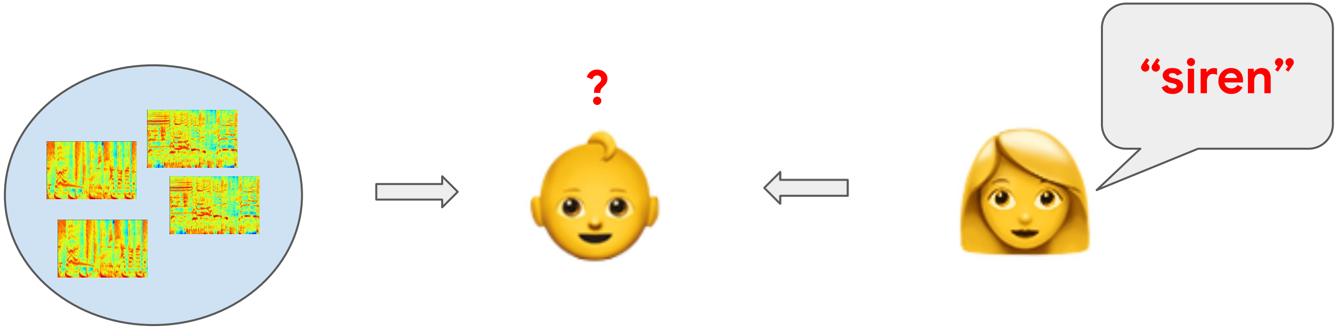
Coincidence, Categorization, and Consolidation

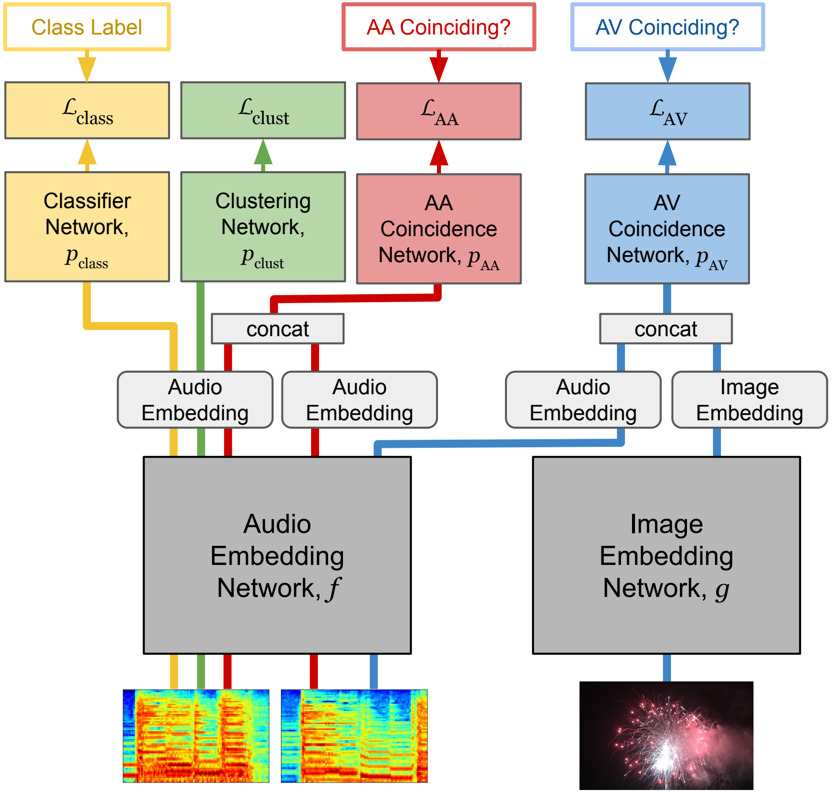
Goal: Go from unlabeled dataset to semantic classifier similar to how children acquire cognitive skills:

3. **Consolidation:** Solicit semantic label for each cluster and train an additional classifier layer.



Plus: Do It With a Single Network

- **Training data:**
  - (audio, audio) pairs
  - (audio, image) pairs
  - either nearby in time or not
- **Result:**
  - Audio and image embeddings
  - Clustering network
  - Semantic classifier



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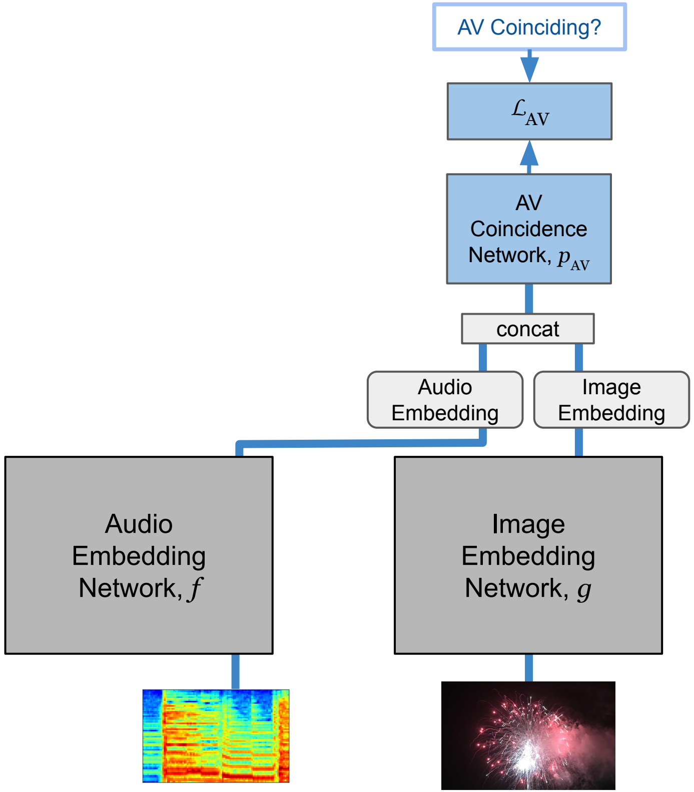
Curriculum Stage #1: AV Coincidence Prediction

- **Baseline: AV Correspondence**
  - Predict whether AV frames overlap
  - “Look, Listen, and Learn” (2017)
- **We generalize to AV Coincidence**
  - Predict whether AV frames temporally proximal (< ΔT)
- **Why?**
  - Do not need to see source making sound
  - Allows unification with audio-only coincidence prediction
- **Other changes:**
  - VGG → ResNet-50
  - Random negatives → all-pairs batch construction



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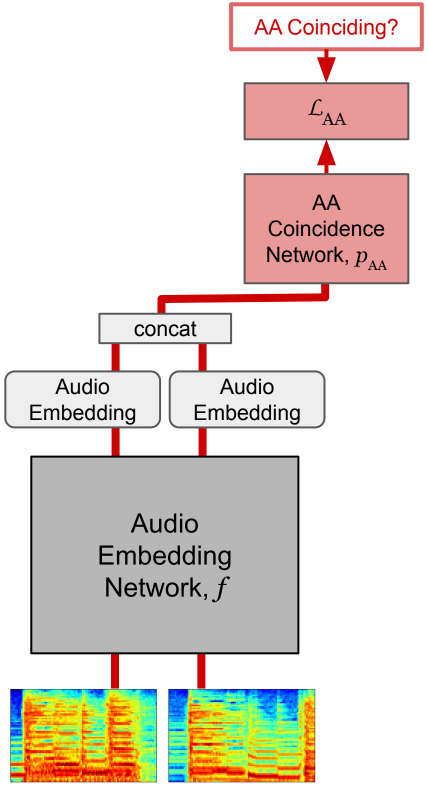
Curriculum Stage #2: AA + AV Coincidence Prediction

- Like AV Coincidence prediction, but with two audio inputs and dedicated prediction network
- Conceptually equivalent to our temporal proximity triplet embedding technique from [Jansen et al., ICASSP 2018]



Curriculum Stage #3: AV + AA + Entropy-Based Clustering

- Entropy-based loss function and optimization with SGD:

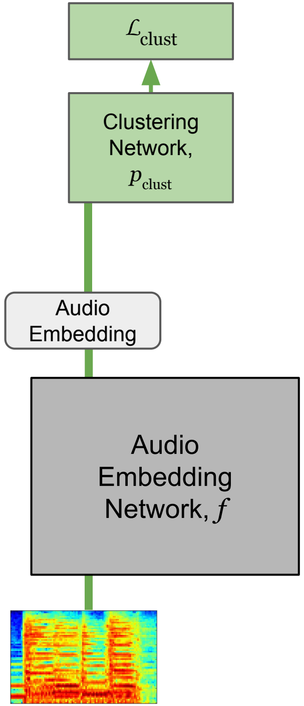
Confident Assignments

$$\mathcal{L}_{\text{clust}}(X) = \frac{1}{B}\sum_{i=1}^{B} H[p_{\text{clust}}(f(x_i))]$$

$$-\gamma H\left[\frac{1}{B}\sum_{i=1}^{B} p_{\text{clust}}(f(x_i))\right]$$

Diverse Assignments

- Easily scales to 1M clusters and all in TensorFlow
- Out-of-sample extension is just regular forward pass



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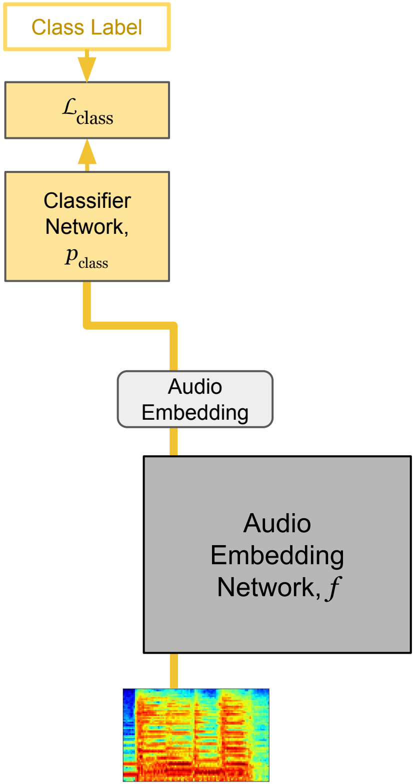
Curriculum Stage #4: Weakly-Supervised Classification

- Solicit label for one random example per cluster
- Propagate label to unlabeled examples in each cluster
- Add classifier network to audio embedding
- Apply standard cross-entropy classification loss using weak labels

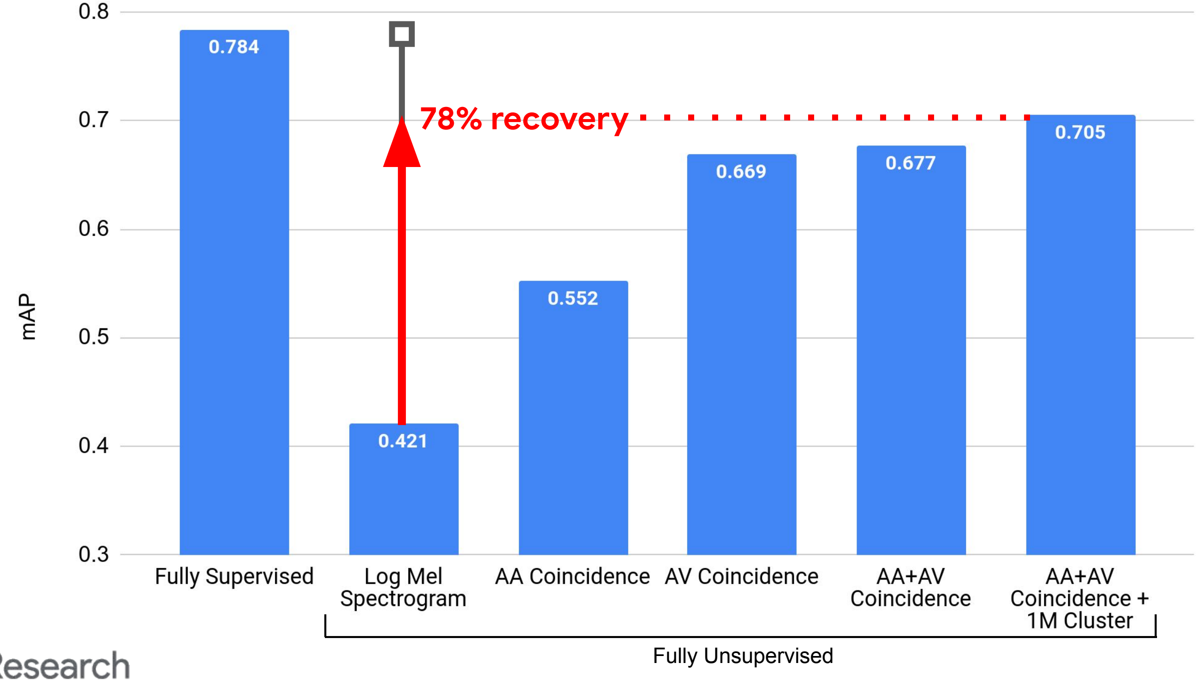


AudioSet Benchmark (g.co/audioset)

- **AudioSet:** 2M YouTube training segments, 527 classes, prior imbalance up to 10,000:1
- **Embedding Models:** ResNet-50 ⟶ 128-dimensional embedding
- **Topline Representation:** fully-supervised semantic embedding (trained with triplet loss)
- **Baseline Representation:** input log mel spectrogram features

Eval #1: Query-By-Example

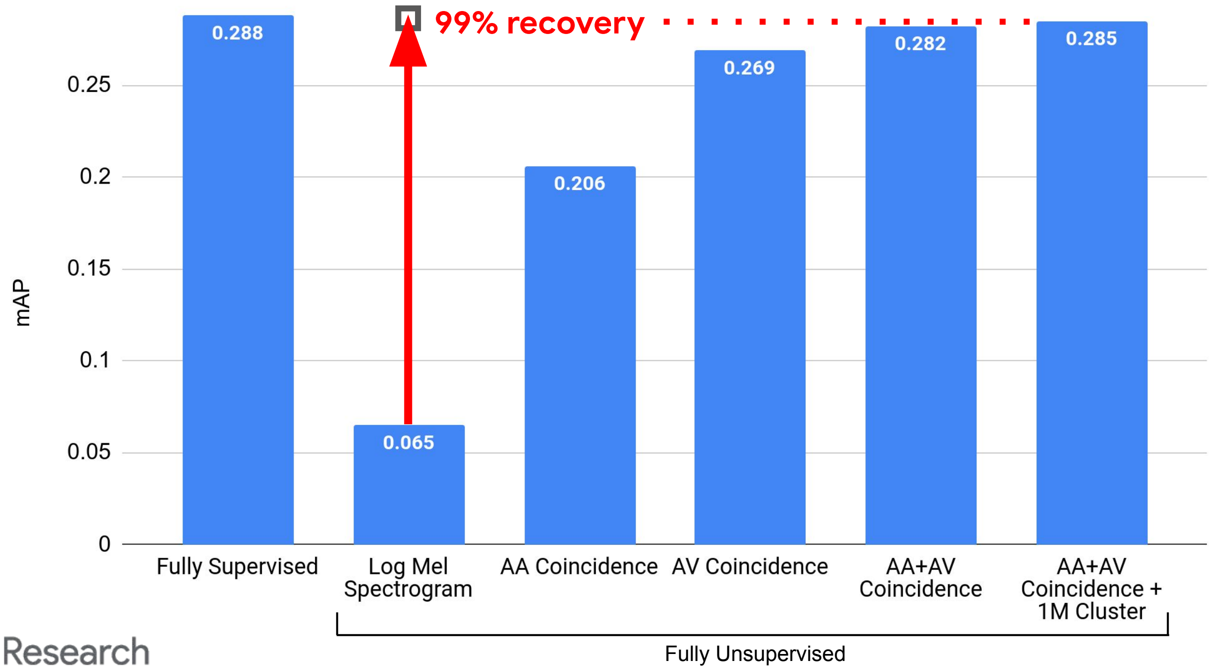
- **Eval:** Rank same/different class example pairs by cosine distance
- **Measures:** Intrinsic semantic quality of representation



Unsupervised representation recovers 78% of the fully supervised gap!

Eval #2: Shallow Classifier

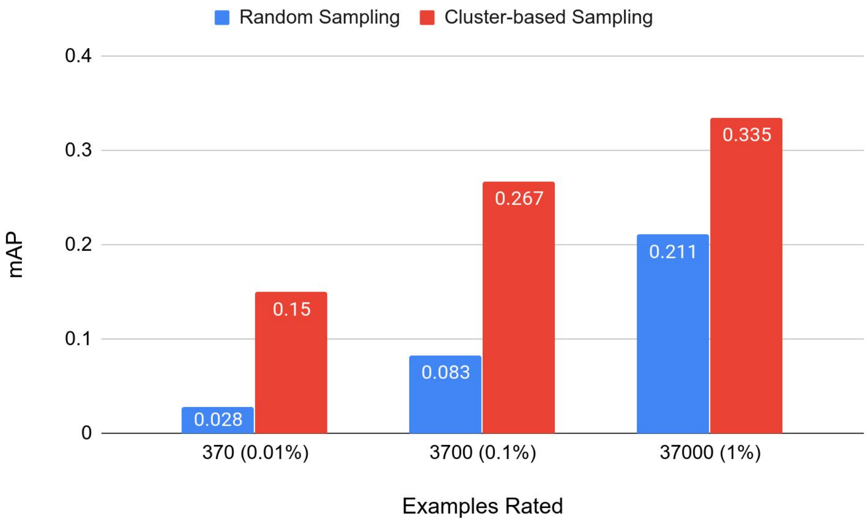
- **Eval:** Shallow fully-connected (FC1x512) classifier holding representation fixed
- **Measures:** Representation support of downstream classification tasks



Unsupervised representation recovers 99% of the fully-supervised gap!

Eval #3: Unsupervised Active Learning

1. Cluster dataset using unsupervised semantic representation
2. Label N biggest clusters by rating a random example from each
3. Train classifier with noisy cluster-based labels



Unsupervised active learning reduces label requirement by more than 10X

Conclusions

- In-domain unsupervised audio embedding reaches supervised performance
- Unsupervised active learning gives 10X reduction in label requirements
- Lessons for audio ML and beyond:
  - Collect unlabeled data when it is free/cheap
  - Collect second modality when you can
  - Cluster-based sampling > random sampling (given good representation)