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

**Case #1: Have Unlabeled Data**
- **Common Strategy:** Randomly sample examples for rating
- **Problem:** biased class distribution and abundance of out-of-set classes

**Case #2: No Unlabeled Data**
- **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
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
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
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:
  \[
  L_{\text{clust}}(X) = \frac{1}{B} \sum_{i=1}^{B} H[p_{\text{clust}}(f(x_i))]
  \]
  \[
  -\gamma H \left[ \frac{1}{B} \sum_{i=1}^{B} p_{\text{clust}}(f(x_i)) \right]
  \]

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