

## Abstract

We introduce *ARCA23K*, an Automatically Retrieved and Curated Audio dataset comprised of 23 727 labelled Freesound clips. *ARCA23K* was created to study real-world label noise, a phenomenon that is prevalent in datasets that lack manual verification. The *ARCA23K* dataset was constructed in such a way so as to facilitate the study of label noise in a controlled manner. To characterise the noise present in the dataset, we conducted listening tests. Experiments were also carried out to examine the impact of label noise on training a deep neural network. This includes comparisons to synthetic label noise.

## 2. Retrieval and Curation

- Two datasets were curated: **ARCA23K** and **ARCA23K-FSD**.
- Both datasets contain **23727 audio clips** (training/validation/test split) that each belong to one of **70 classes**.
- *ARCA23K-FSD* is the ‘clean’ (manually verified) counterpart of *ARCA23K*. It is a single-label subset of *FSD50K*.
- To create *ARCA23K*, audio clips were retrieved from Freesound.org using a **keyword-based retrieval algorithm**.
- The keywords used to retrieve the clips were derived from the (AudioSet) labels that would eventually be assigned to the clips.
- A subset of the audio clips deemed relevant were used to create *ARCA23K*.
- **Download Page:** <http://zenodo.org/record/5117901>
- **Source code:** <https://github.com/tqbl/arca23k-dataset>

## 1. Motivation

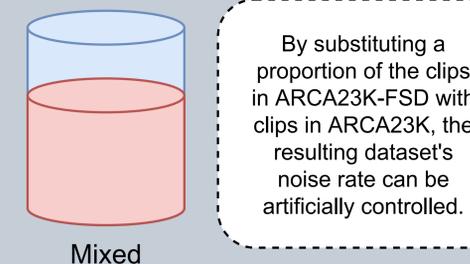
- Many annotated audio clips are available on the web (e.g. Freesound).
- These clips can be assigned labels using an automated procedure.
- Manual verification of labels is costly. We can skip manual verification, but this means labelling errors (label noise) may be present.
- Understanding the impact of label noise on learning is important.
- Existing ‘webly-labelled’ datasets such as *FSDKaggle2018* and *FSDnoisy18k* have not been designed for studying label noise in a controlled manner.

## 3. Listening Tests

- Listening tests were carried out to characterise the label noise.
- Three individuals listened to 100 randomly sampled clips each.
- They were asked to classify them as either present and predominant (PP), present but not predominant (PNP), not present (NP), or Unsure (U).
- If PNP or NP, they further had to classify the sound as in-vocabulary (IV) or out-of-vocabulary (OOV). PP clips are necessarily IV.
- The noise rate was estimated to be  $(46.4 \pm 4.8)\%$ .
- 79.5% of the clips were found to be OOV  $\implies$  Open-set label noise.

	PP	PNP	NP
IV	$(52.7 \pm 5.8)\%$	$(2.3 \pm 1.3)\%$	$(8.7 \pm 3.5)\%$
OOV	N/A	$(1.3 \pm 0.7)\%$	$(33.3 \pm 5.6)\%$

For every audio clip in *ARCA23K-FSD*, there is a corresponding clip in *ARCA23K* with the same label.



By substituting a proportion of the clips in *ARCA23K-FSD* with clips in *ARCA23K*, the resulting dataset's noise rate can be artificially controlled.

## 4. Experiments

- An 11-layer convolutional network was trained with mel-spectrogram inputs.
- To examine the effects of label noise, we compared the model's performance when trained on *ARCA23K* (noisy) and *ARCA23K-FSD* (clean).
- Two types of synthetic noise were also compared: uniform and class-conditional label noise. The noise rate was set to match *ARCA23K*'s noise rate.
- The results show that the label noise present in *ARCA23K* has a significant effect on learning. The mAP score dropped by 14%.
- The synthetic instances of noise were far more detrimental, however.
- The graph on the right measures performance as the noise rate is varied from 0 to 0.45. It can be seen that the label noise in *ARCA23K* has a very different profile compared to synthetic label noise.

