#### Crowdsourcing Multi-label Audio Annotation Tasks with Citizen Scientists

Mark Cartwright, Graham Dove, Ana Elisa Méndez Méndez, Juan P. Bello, Oded Nov

New York University Music and Audio Research Lab Department of Computer Science and Engineering









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### 60130,000,00041

Sensors

Recordings

Years of Audio

#### SONYC Urban Sound Tagging Classes



#### Citizen Science Audio Annotation Campaign



# How does the type of multi-label annotation task affect throughput and quality?

- Do we adopt norms of paid crowdsourcing audio tasks<sup>\*</sup> and break annotation into *multiple binary annotation* tasks?
- Or do we adopt norms of image annotation with citizen scientists and use multi-label annotation tasks?

\*Lawrence, R Channing Moore, Manoj Plakal, and Marvin Ritter. 2017. Audio Set: An ontology and human-labeled dataset for audio events. In Proceedigns of the IEEE International Conference on Acoustics, Speech, and Signal Processing

\*Eric Humphrey, Simon Durand, and Brian McFee. 2018. OpenMIC-2018: an open dataset for multiple instrument recognition. In Proceedings of the International Society for Music Information Retrieval Conference.

#### **Binary-labeling Annotation Task**





#### Multi-label Annotation Task

Sounds of New York City (SONYC)	ABOUT	CLASSIFY	TALK COLL	ECT RECENTS	
		TASK		TUTORIAL	
and the second		Category			
		Small-sounding engine	Large rotating saw	Other/unknown music	
		Medium- sounding engine	Other/unknown saw	Person or small group talking	
		Large-sounding engine	Car horn	Person shouting	
		Other/unknown engine	Car alarm	Crowd	
		Rock drill	Siren	Amplified speech	
► 0:00 / 0:10 ■		Jackhammer	Reverse beeper	Dog barking/whining	
	• ♡ ≣	Hoe ram	Other/unknown alert signal	Other/unknown human or animal vocalization sound	
		Pile driver	Stationary music	Artificial/Interference Noise	
		Other/unknown impact sound	Mobile music	Other/unknown construction sound	
		Chainsaw	Ice cream truck	Other/unknown sound	
		Small/medium rotating saw			
		Sho	wing 31 of 31 Ø Clear	filters	
		Done & Tell		10 <b>0</b> 0	

#### Hierarchical Multi-label Annotation Task



#### Hierarchical Multi-label Annotation Task



#### Hierarchical Multi-label Annotation Task



#### Annotation Throughput

• Binary labeling task generated more overall positive labels per recording



#### Annotation Throughput

 Binary labeling task took half as long as multi-label for an individual annotation



#### Annotation Throughput

 However, for a full 23 class multi-label annotation binary labeling took 9x as long as multi-labeling



#### Annotation Quality



#### Feedback from Participants (Binary Labeling)

- "There might be a better way than is that X sound yes or no to classify quicker. People will get tired of listening to sound clips faster than other quick options, like the animal diaries. You want to squeeze as much data out of each audio clip."
- "I hear drums, observer/audience yelling applause, at least one large size dog that is very unhappy about the noise. This takes place outside. I have no way to label more than two features, so it will probably be more frustrating than I can deal with to participate."
- "In my opinion, this project should use the same model as the animal camera trap projects, that is, have a list of sound categories that one can click on for each clip, and give the opinion to choose more than one category."

#### Conclusions of Study

- Overall quality of multi-label annotations from binary and multi-label tasks are comparable. They have differences but they can be balanced.
- Multi-label is much more efficient, but only if you need full multi-label annotation
- Hierarchical multi-label tends to propagates error, leading to lower recall
- Informal feedback indicates that volunteers much preferred multi-label, opposite of paid crowdworkers
- Results side with the common practice of citizen science image annotation rather than that of paid audio crowdsourcing.

#### Ongoing Citizen Science Annotation Campaign

## 1,051

Registered Annotators

### 30,376

Full Multi-label Annotations **9,765** Completed

Recordings

#### Ongoing Citizen Science Annotation Campaign



#### SONYC Urban Sound Tagging Dataset

- Released in March
- 2351 training recordings and 443 validation
- Multi-label annotation on 23 classes
- 3 Zooniverse annotators per recording
- Validation set annotated by SONYC team
- <u>https://doi.org/10.5281/zenodo.2590742</u>



#### DCASE 2019 Challenges Tasks:

- Acoustic scene classification
  - Audio tagging with noisy labels and minimal supervision
  - Sound event localization and detection
  - Sound event detection in domestic environments

Urban Sound Tagging

#### SONYC Urban Sound Tagging Dataset

 How do annotations from Zooniverse volunteers compare to those of the SONYC team?



#### Conclusions of Study

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