YOHO model for Audio Segmentation and Sound Event Detection

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Contents

Audio Segmentation and Sound Event Detection

The goal of automatic sound event detection (SED) methods is to recognize what is happening in an audio signal and when it is happening[1]. In practice, the goal is to recognize at what temporal instances different sounds are active within an audio signal. An example of sound event detection is presented below.

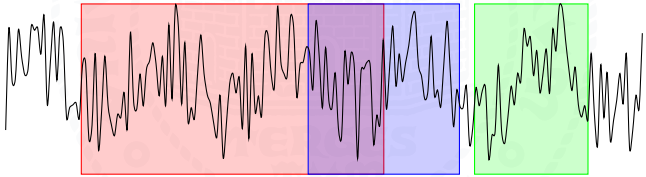

Figure 1: Event Detection in an audio track.

[1] Annamaria Mesaros et al. "Sound Event Detection: A tutorial". In: *IEEE Signal Processing Magazine* 38 (2021), pp. 67–83. URL: https://api.semanticscholar.org/CorpusID:235795366.

Datasets

Common datasets for Audio Segmentation and Sound Event Detection problems are:

- **TUT Sound Event Detection**: primarily consists of street recordings with traffic and other activity, with audio examples of 2.56 s and a total size of approximately 1.5 h. It has six unique audio classes – Brakes Squeaking, Car, Children, Large Vehicle, People Speaking, and People Walking;
- **Urban-SED**: purely synthetic dataset, with audio example of 10 s and a total size of about 30 h. It has ten unique audio classes – Air Conditioner, Car Horn, Children Playing, Dog Bark, Drilling, Engine Idling, Gun Shot, Jackhammer, Siren, and Street Music.

The first dataset is too small to train a Neural Network model and requires use of augmentation techniques (we used **SpecAugment**[2]).

[2] Daniel S. Park et al. "SpecAugment: A Simple Data Augmentation Method for Automatic Speech Recognition". In: *Interspeech 2019*. 2019, pp. 2613–2617. DOI: 10.21437/Interspeech.2019-2680.

Metrics

A popular toolbox for Polyphonic Sound Event Detection models evaluation is **SED Eval**[3].

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \qquad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F}_1\text{-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

[3] Annamaria Mesaros, Toni Heittola, and Tuomas Virtanen. "Metrics for Polyphonic Sound Event Detection". In: *Applied Sciences* 6.6 (2016). ISSN: 2076-3417. DOI: 10.3390/app6060162. URL: https://www.mdpi.com/2076-3417/6/6/162.

YOHO model

Presented in 2021[4]...

[4] Satvik Venkatesh, David Moffat, and Eduardo Reck Miranda. "You Only Hear Once: A YOLO-like Algorithm for Audio Segmentation and Sound Event Detection". In: *Applied Sciences* 12.7 (Mar. 2022), p. 3293. ISSN: 2076-3417. DOI: 10.3390/app12073293. URL: http://dx.doi.org/10.3390/app12073293.

Input shape

...

Network Architecture

...

Output shape

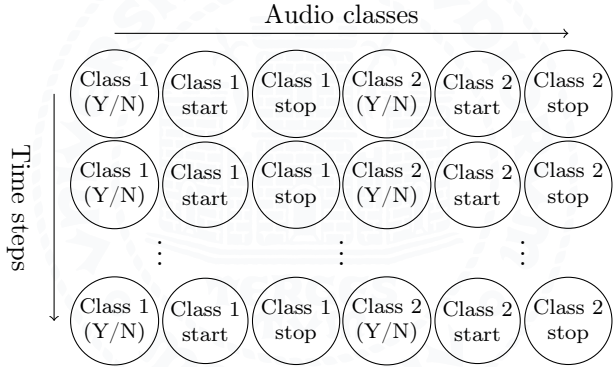

Figure 2: The YOHO output shape.

Loss Function

$$\mathcal{L}_c(\hat{y}, y) = \begin{cases} (\hat{y}_1 - y_1)^2 + \\ (\hat{y}_2 - y_2)^2 + (\hat{y}_3 - y_3)^2 & \text{if } y_1 = 1 \\ (\hat{y}_1 - y_1)^2, & \text{if } y_1 = 0 \end{cases}$$

where y and $\hat{y}$ are the ground-truth and predictions respectively. $y_1 = 1$ if the acoustic class is present and $y_1 = 0$ if the class is absent. y_2 and y_3, which are the start and endpoints for each acoustic class are considered only if $y = 1$. In other words, $(\hat{y}_1 - y_1)^2$ corresponds to **the classification loss** and $(\hat{y}_2 - y_2)^2 + (\hat{y}_3 - y_3)^2$ corresponds to **the regression loss**.

Other Details

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Implementation details

...

Problems

...

Conclusions

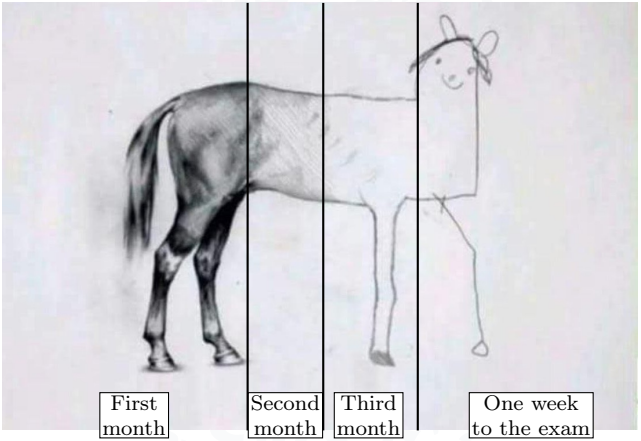

Figure 3: The roadmap of our journey.

Conclusions

But, after all...

It's all about the journey, not the destination.

Thank you for your attention.