ACOUSTIC SCENE CLASSIFICATION IN DCASE 2020 CHALLENGE: GENERALIZATION ACROSS DEVICES AND LOW COMPLEXITY SOLUTIONS

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ABSTRACT
This paper presents the details of Task 1. Acoustic Scene Classification in the DCASE 2020 Challenge. The task consists of two subtasks: classification of data from multiple devices, requiring good generalization properties, and classification using low-complexity solutions. Here we describe the datasets and baseline systems. After the challenge submission deadline, challenge results and analysis of the submissions will be added.

Index Terms—Acoustic scene classification, multiple devices, low-complexity, DCASE Challenge

1. INTRODUCTION
The goal of acoustic scene classification is to classify a test recording into one of the provided predefined classes that characterizes the environment in which it was recorded. Acoustic scene classification is a popular task of the DCASE Challenge, and brings new variations of a supervised classification task each year. In all previous editions, this task has attracted the highest number of participants among the available tasks.

Recent years have seen a boom in deep-learning based solutions for various classification problems, also obvious in the last few editions of the DCASE Challenge. While in 2016 just 22 of the 48 submissions used neural networks [1], in 2019 only five of the 146 systems submitted to the acoustic scene classification subtasks did not include a deep learning component [2]. Generally, deep learning algorithms require large amounts of data for best performance, and the effort to produce more data for the task has resulted in gradual extension of the problem, from a classical textbook example [1][3] to domain adaptation due to mismatched devices [4], and open-set classification [5].

Deep learning solutions are sensitive to mismatch between training and testing data, which is often present in realistic scenarios because of the large variety of devices available for recording audio. While in previous editions of the challenge the device mismatch was treated from the point of view of domain adaptation and targeted for a small number of test devices, it is realistic to assume that any method tested in a real-world scenario would have to face a much higher number of known and unknown devices. On the other hand, because the main application area of acoustic scene classification is context-aware devices, where the algorithms should be running on devices with limited computational capacity, taking into account computational limitations is another important point for real-world applications. The Acoustic Scene Classification task in DCASE 2020 Challenge brings these two topics into the spotlight.

In DCASE 2020 Challenge, the Acoustic Scene classification task comprises two different subtasks, which require system development for two different situations. Subtask A: Acoustic Scene Classification with Multiple Devices requires classification of data from real and simulated devices, and is aimed for developing systems with very good generalization properties across a large number of different devices. For this subtask, the challenge provides new data consisting of real and simulated audio recordings for mobile devices. Subtask B: Low-Complexity Acoustic Scene Classification requires classification of data from a single device, and is aimed for developing low-complexity solutions for the problem. In this subtask, the challenge imposes a maximum model size as a proxy for estimating the model complexity at test time.

This paper introduces the two acoustic scene classification tasks and their results and is organized as follows: Section 2 introduces Subtask A setup, dataset and baseline system. Section 3 introduces Subtask B setup, dataset and baseline system. Section 4 presents the challenge results for both subtasks, and an analysis of selected submissions. Finally, Section 5 presents conclusions and future perspectives on this task for upcoming editions of the challenge.

2. ACOUSTIC SCENE CLASSIFICATION WITH MULTIPLE DEVICES
This subtask is concerned with the basic problem of acoustic scene classification, in which it is required to classify a test audio recording into one of ten known acoustic scene classes. A specific feature for this edition is generalization across a number of different de-
Table 1: Distribution of devices among training and test subsets in the dataset. Some devices are present only in the test set to simulate real situations of encountering an unseen device at the usage end.

| Device | Dataset Type | Total duration | Total segments | Train segments | Test segments | Notes |
|--------|--------------|----------------|----------------|----------------|---------------|-------|
| A      | Real         | 40h            | 14400          | 10215          | 330           |       |
| B      | Real         | 3h each        | 1080           | 750            | 330           |       |
| C      | Real         | 3h each        | 1080           | 750            | 330           |       |
| S1 S2 S3 | Simulated  | 3h each        | 1080           | -              | 330           |       |
| S4 S5 S6 | Simulated  | 3h each        | 1080           | -              | -             | 750 segments not used in train/test split |
| Total  |              | 64h            | 23040          | 13965          | 2970          |       |

2.1. Dataset

A new dataset was created for this task, called TAU Urban Acoustic Scenes 2020 Mobile [5, 6]. The dataset is based on TAU Urban Acoustic Scenes 2019 dataset, containing recording from multiple European cities and ten different acoustic scenes [2]. The new dataset contains the four devices used to record simultaneously (A, B, C, and D), and additional synthetic devices S1-S11 simulated using audio recorded with device A.

Simulated recordings were created using a dataset of impulse responses (IR) measured for multiple angles using mobile devices other than the ones already in the dataset (B, C, D). To simulate the recording from a device S, audio recorded with device A was processed through convolution with the device-specific IR, followed by a dynamic range compression with device-specific parameters. The IR angle was randomly selected among the available ones, and is location-specific, to simulate the case when a long recording has been captured with device S in a certain position.

The development set contains data from ten cities and nine devices: three real devices (A, B, C) and six simulated devices (S1-S6). Data from devices B, C and S1-S6 consists of randomly selected segments from the simultaneous recordings, therefore all overlap with the data from device A, but not necessarily with each other. The total amount of audio in the development set is 64 hours, of which 40 hours are from device A. Audio was provided in single channel 44.1 kHz 24-bit format. The dataset is provided with a training/test split in which 70% of the data for each device is included for training, 30% for testing; some devices appear only in the test subset. Complete details are are presented in Table 1.

The evaluation dataset contains 33 hours of audio from all 12 cities, ten acoustic scenes, 11 devices. Five of the 11 devices from the evaluation set are unseen in training (not available in the development set): real device D and simulated devices S7-S11. Device and city information is not provided in the evaluation set, as the systems are expected to be robust to different devices.

2.2. Evaluation

Evaluation of submissions will be performed using two metrics: accuracy and multi-class cross-entropy. Accuracy will be calculated as macro-average (average of the class-wise accuracy for the acoustic scene classes). Multi-class cross-entropy (log loss) is used in order to have a metric which is independent of the operating point. Ranking of the systems will be done by accuracy.

2.3. Baseline system results

The baseline system provided for the task uses Open L3 embeddings [7] as feature representation, followed by two fully-connected feed-forward layers, in an architecture that mimics the original publication introducing the embeddings. The system uses a window size of one second for analysis, with a hop size of 100 ms, input representation through 256 mel filters, content type music, and an embedding size of 512. This is followed by two fully connected layers of 512 and 128 hidden units, respectively. The learning is performed for 200 epochs with a batch size of 64, and data shuffling between epochs, using Adam optimizer [8] with a learning rate 0.001. Model selection is performed using validation data consisting of approximately 30% of the original training data. Model performance after each epoch is evaluated on the validation set, and the best performing model is selected.

Results of the baseline system are presented in Table 2. The results were calculated using TensorFlow in GPU mode; the system was trained and tested 10 times, and the mean and standard deviation of the performance from these 10 independent trials are shown in the table.

The baseline system does not have any mechanism for explicitly dealing with the device mismatch, which is evident from the results: device-wise system performance decreases according to the amount of data available in training. Highest accuracy is obtained on device A, while the other devices for which a small amount of data is available in training provide about 50-60% accuracy, and the lowest accuracy is observed for the completely unknown devices.

3. LOW-COMPLEXITY ACOUSTIC SCENE CLASSIFICATION

3.1. Description

This subtask is concerned with classification of audio into three major acoustic scene classes, with focus on low complexity solutions for the classification problem in term of model size, and uses audio recorded with a single device (device A).

3.2. Dataset and performance evaluation

A new dataset was created for this task, called TAU Urban Acoustic Scenes 2020 3Class [9, 10], based on the same TAU Urban Acoustic Scenes 2018. The ten acoustic scenes from the original data were grouped into three higher level acoustic scene classes as follows: indoor (airport, indoor shopping mall, and metro station), outdoor (pedestrian street, public square, street with medium level of traffic, and urban park), and transportation (travelling by bus,
travelling by tram, travelling by underground metro). This dataset contains audio recorded with a single device (device A), provided in binaural, 48kHz 24-bit format. The development dataset contains audio data from ten cities, provided with a training/test split. The amount of audio in the development dataset is 40 hours. The evaluation set contains a total of 30 hours of audio data, recorded in 12 cities (two cities not encountered in training). Evaluation will be performed similarly to Subtask A, using average accuracy across the three acoustic scene classes, and multi-class cross-entropy. The systems will be ranked by the average accuracy.

### 3.3. System complexity requirements

This task imposed a classifier complexity expressed in terms of model size on disk. The chosen limit was 500 KB for the non-zero parameters, which means 128K parameters in the 32-bit float data type (128000 parameters * 32 bits per parameter / 8 bits per byte = 512000 bytes = 500 KB). This approach for limiting the model size allows participants some flexibility in design, for example minimizing the number of non-zero parameters of the network in order to comply with this size limit (sparsity), or quantization of model parameters in order to use lower number of bits.

The computational complexity of the feature extraction stage is not included in the system complexity estimation. Even though feature extraction is an integral part of the system complexity, there is no established method for estimating and comparing complexity of different feature extraction implementations, therefore we do not take it into consideration, in order to keep the complexity estimation straightforward across different approaches. Some special situations for feature representations apply. Some implementations may use a feature extraction layer as the first layer in the neural network - in this case the limit is applied only to the following layers, in order to exclude the feature calculation as if it were a separate processing block. However, in case of embeddings (e.g. VGGish[11], OpenL3[7] or EdgeL3[12]), the network used to generate the embeddings counts in the number of parameters. Additionally, layers not used in the classification process (at test stage), such as batch normalization layers, are also skipped from the model size calculation.

### 3.4. Baseline system results

The baseline system for the task implements a convolutional neural network (CNN) based approach, similar to the DCASE 2019 Task 1 baseline [2]. It uses 40 log mel-band energies, calculated with an analysis frame of 40 ms and 50% hop size, to create an input shape of 40 × 500 for each 10 second audio file. The neural network consists of two CNN layers and one fully connected layer, followed by the softmax output layer. Learning is performed for 200 epochs with a batch size of 16, using Adam optimizer and a learning rate of 0.001. Model selection and performance calculation are done similar to the Subtask A system.

The model size of the system is 450 KB. For comparison, Table 3 presents the model size of the baseline system from Subtask A, together with the performance of both systems on Subtask B.

According to the class-wise results presented in Table 3, the transportation class has the highest accuracy as a high-level class, while indoor is the most difficult to classify. However, as can be seen in Table 4, the average accuracy of this low-complexity system is not much lower than the accuracy of the baseline from Subtask A on the same problem.

### 4. CHALLENGE RESULTS

Challenge results and analysis of the submitted systems will be added for the official submission of the paper to the DCASE 2020 Workshop.

### 5. CONCLUSIONS AND FUTURE WORK

This paper presented an analysis of the solutions submitted to DCASE 2020 Challenge Task 1 Acoustic Scene Classification. The two different subtasks tackle the research problem from the point of view of real-world applications, in one case robustness and generalization to multiple devices, and in the other case requiring a low-complexity solution.
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