A MULTI-OBJECTIVE APPROACH FOR SUSTAINABLE DEEP LEARNING

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Abstract

In recent years, the deep learning community has largely focused on the accuracy of deep generative models resulting in impressive improvements in several research fields. However, this scientific race for accuracy comes at a tremendous computational cost, which incurs vast energy consumption and greenhouse gas emissions. At the heart of this problem are the measures that we use as a scientific community to evaluate our work. We introduce here the idea of relying on a multi-objective measure based on Pareto optimality, which simultaneously integrates the models accuracy, as well as the environmental impact of their training and inference.

Generative models for audio

Generative models are a flourishing class of deep learning approaches

- Deal to generate novel data based on existing examples.
- Common models are auto-regressive, VAEs, GANs, normalizing flows

When applied to audio generation, models are generally heavy:

- Waveform is a high dimensionality vector
- Strong temporal dependencies at different scales

Deep accuracy madness

Deep learning holds most state-of-the-arts in various tasks. However some problems of deep learning:

- Networks can have up to billions of parameters
- Gains in accuracy now appear always linked to increased size
- Extremely demanding in computation, energy and memory

Example of GPT-3 model (NLP)

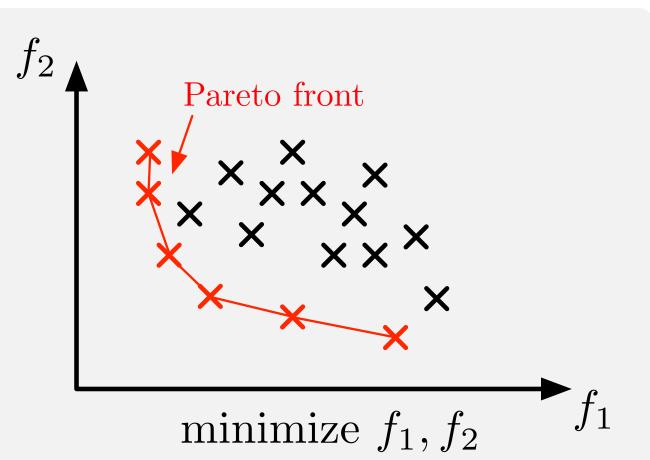
- 175 billon parameters where training takes 355 years on a V100 GPU
- Carbon footprint for training equivalent to driving to the moon and back

Pareto optimality

Optimization problems involving conflicting objectives to be optimized simultaneously:

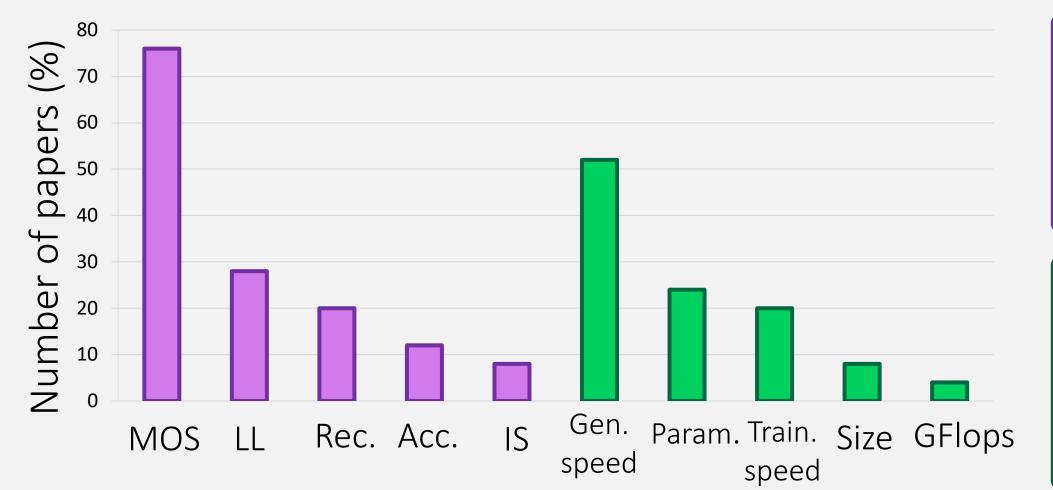
$$\min_{x \in X} (f_1(x), f_2(x), \dots, f_k(x))$$

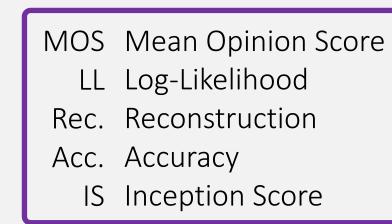
The set of all these pareto optimal solution is called the *Pareto front*.



Experiments

- We reviewed all state-of-the-art audio generative models (2016 2020)
- We study the metrics for the evaluation and comparison:





Gen. speed Generation speed Param. Number of parameters Train. speed Training speed Size Memory size Gflops Gigaflops

Difficulties to find a common metric to evaluate models

- Most of used metrics are on accuracy either than performance
- No energy-based criterion
- Best trade-off: accuracy or energy efficiency?

We selected models with sufficient training: hardware and training time

We create a Pareto front with:

 f_1 : environmental cost (either for training or for inference)

 f_2 : accuracy of the model

Training cost

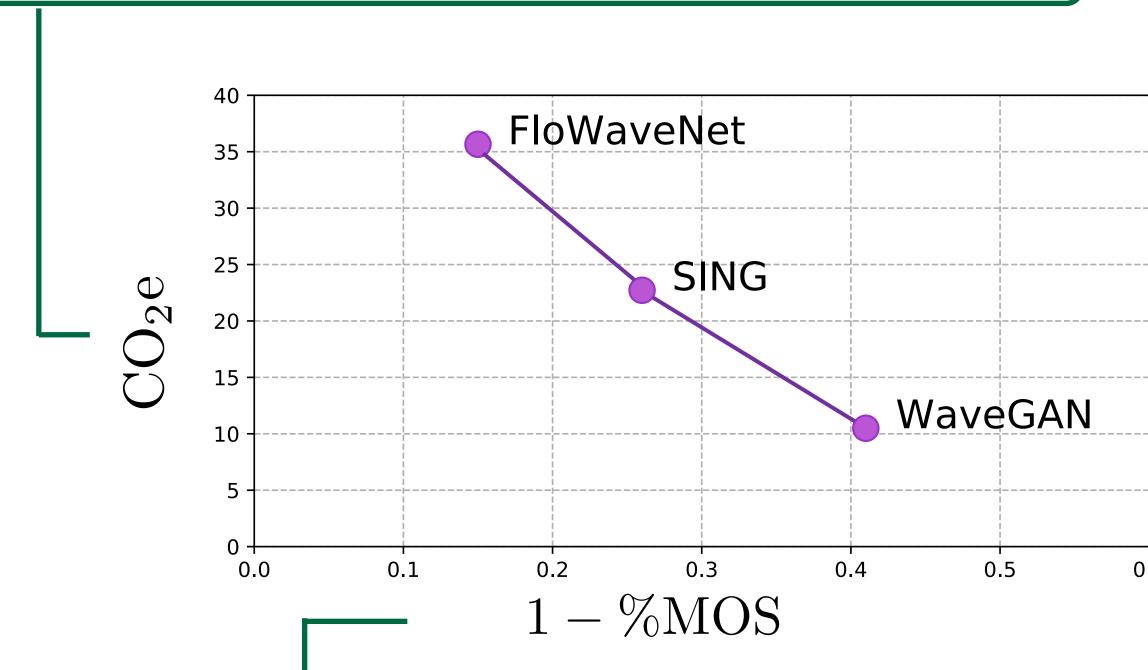
Carbon emissions estimation (in kgC0₂eq) per training can be expressed as: $CO_2e = \alpha \times n \times p_{max} \times t$

> α Average electricity emission factor p_{max} Maximum Power of the GPU

n Number of GPUs

t Training time

We took $\alpha = 0.437 \, \mathrm{kgCO_2eq/kWh}$ (2018 global average)



Accuracy score

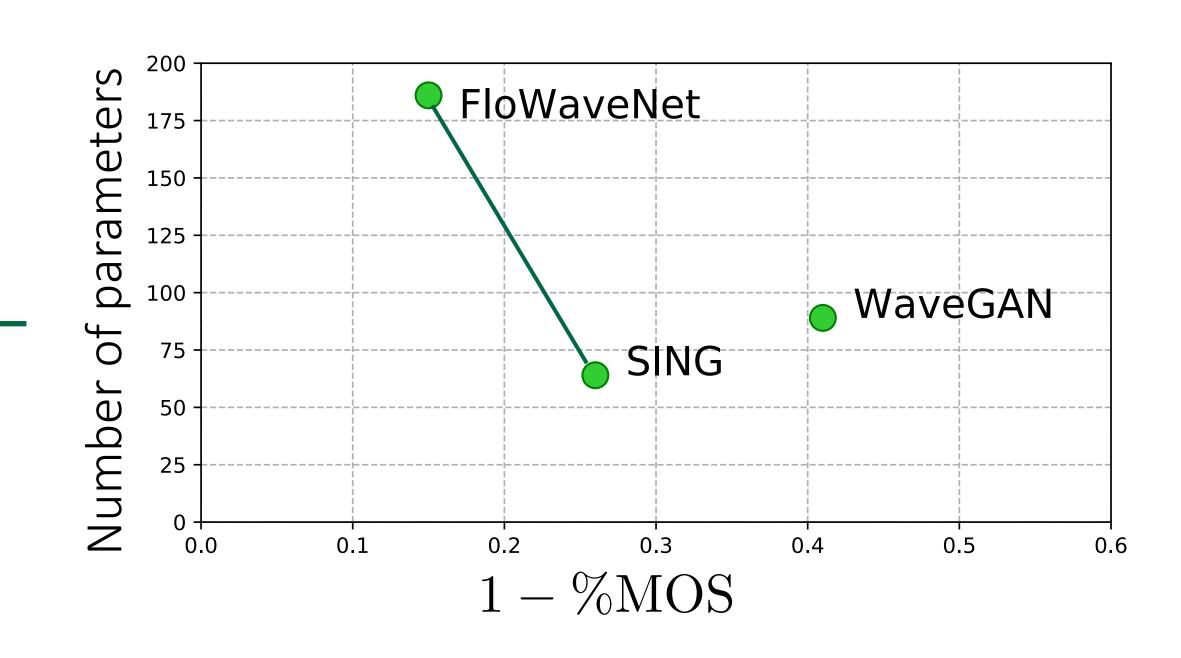
We rely on the MOS as it is the most popular measure among our surveyed papers. This score is highly dependent on each experimental setup, we compute:

 $\%MOS = \frac{MOS(model)}{5.5}$

The goal is to maximize this ratio, and thus to minimize $1-\% \mathrm{MOS}$

Inference cost

The number of parameters of a model is straightforward and correlates with the number of operation of a model, and thus the power consumption of any device used to run the model.



The three models are Pareto optimal in training, whereas WaveGan is sub-optimal in inference.

Conclusions

- The lack of training details affected our work: authors must report the training time & hardware or use online tool¹ to report actual CO₂
- Models that are sub-optimal should be discredited
- Our approach is generic, and could be applied to any type of model or input data

¹ https://mlco2.github.io/impact/











