# High-Efficiency Online Data Generation to Improve Pretraining Scaling Laws of Deep Networks

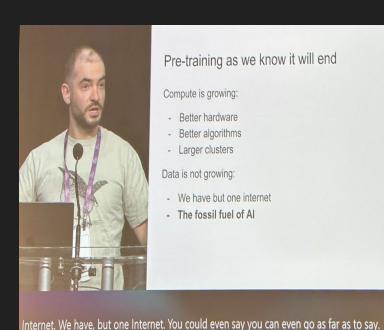
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## **Research Question**

How can we integrate on-the-fly data generation with reinforcement learning to optimize neural network training in data-constrained environments?

- **Goal:** Build a system that generates data in real-time, tailored to the model's current weaknesses, optimizing training.
- Novelty: Merges efficient on-the-fly data generation with reinforcement learning's adaptive decision-making—unexplored territory.

# Motivation: The Data Dilemma in Machine Learning



That data is the fossil fuel of Al. It was like, created somehow. And now we use it.

#### **Challenges:**

- Data scarcity and high costs in acquiring real data.
- Privacy and regulatory restrictions limit data access.
- Vast storage requirements hinder training with large datasets.

#### **Impact:**

- Example: Facebook trained face recognition on ~4.4 million images.
- Many industries (healthcare, finance, autonomous vehicles) face similar hurdles.

# **Motivation: Automatic Data Augmentation**

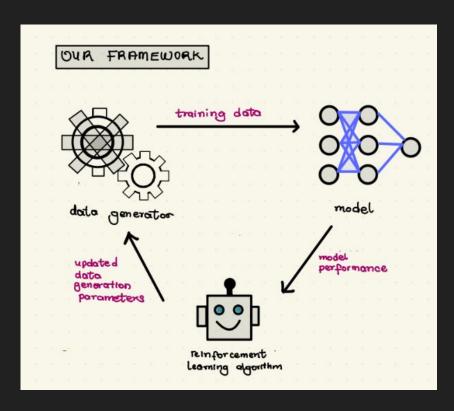
Dataset	GPU hours	Best published results	Our results
CIFAR-10	5000	2.1	1.5
CIFAR-100	0	12.2	10.7
SVHN	1000	1.3	1.0
Stanford Cars	0	5.9	5.2
ImageNet	15000	3.9	3.5

Table 1. Error rates (%) from this paper compared to the best results so far on five datasets (Top-5 for ImageNet, Top-1 for the others). Previous best result on Stanford Cars fine-tuned weights originally trained on a larger dataset [66], whereas we use a randomly initialized network. Previous best results on other datasets only include models that were not trained on additional data, for a single evaluation (without ensembling). See Tables 2,3, and 4 for more detailed comparison. GPU hours are estimated for an NVIDIA Tesla P100.

Selecting data augmentation instances that conform with a learning model's apparent weaknesses is a powerful way to improve model performance.

Cubuk et al, AutoAugment: Learning
Augmentation Policies from Data, 2019

# **Proposed Methodology**



#### **Dynamic Data Generation:**

Generate data in batches on demand using the OTF framework.

#### **Minimal Storage:**

• Store only essential parameters (e.g., 21,600 parameters per day vs. 86,400 raw values).

#### **RL-Driven Optimization:**

- An RL agent observes current model performance (state) and selects the next data generation action to maximize improvements (reward).
- This forms a Markov Decision Process (MDP) guiding the cycle.

## **Literature Review**

- 1. "On the Fly" Framework (Vejdan et al., 2019)
- 2. Infigen: Pure Procedural Photorealistic Image Generation (Raistrick et al, 2023)
- 3. Cheaper, Faster Automatic Data Augmentation (Li et al, 2020; Lim et al, 2020)
- On-the-fly Dataset Augmentation with Synthetic Data (Li et al, 2025)
- 5. Procedural Image Generation Resources <a href="https://procgen.space/resources">https://procgen.space/resources</a>
- 6. ...

## **Next Up**

### First prototype of framework

- Data Generator
  - a. Write procedural MNIST and Fashion-MNIST generators
  - b. Use procedural libraries (like firesim and infigen) on relevant classification problems
- 2. Image Classifier
  - a. Small convolutional model
- 3. Reinforcement Learning Algorithm
  - a. AutoAugment, Fast AutoAugment and Differentiable AutoAugment

Then evaluation and reiteration with bigger generators and a bigger neural net...

# **Applications**

#### 1. Healthcare

Generate synthetic patient records for training diagnostic models while preserving privacy.

#### 2. Finance

Create synthetic transaction data for fraud detection and risk modeling.

Fraud detection, in particular, has a data imbalance problem

#### 3. Autonomous Vehicles

Produce real-time simulated driving scenarios for training under rare conditions.

#### And More...