# NeSSA: Near-Storage Data Selection for Accelerated ML Training

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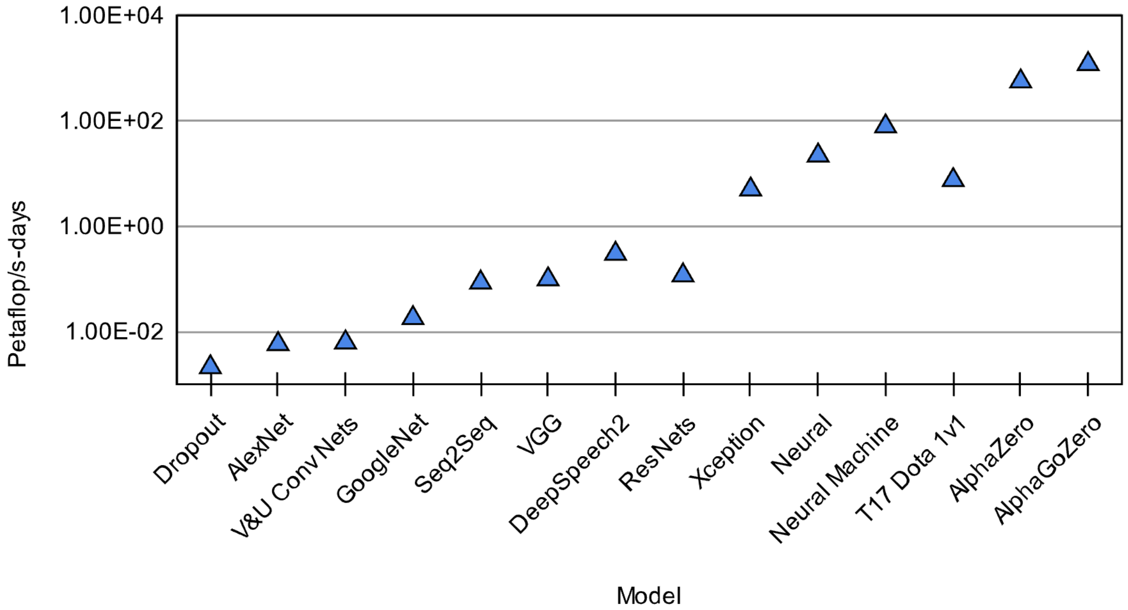
# Motivation

- **Training a GPT-3 on 45 TB of data:**
  - 💰 12 M
  - ⏰ 34 days on 1024 A100 GPUs
  - 🏠 17.5x the average yearly energy consumption of one American house.
  - 🚭 $CO_2$ release of a car driving 2x the distance between the Earth and the Moon.



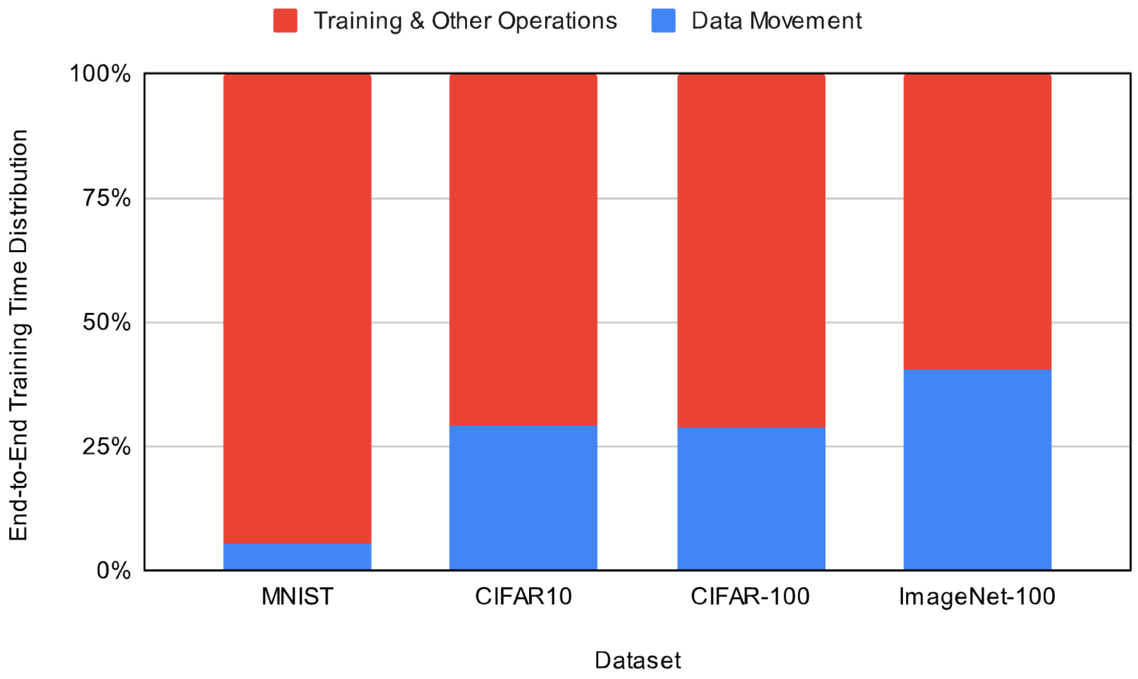

Training time of image classification models has been doubling every 3.4 months (OpenAi, 2018)

- **Grand challenges in ML (Asi & Duchi, 2019)**

# Contributors to Training Cost

- **Two main bottlenecks:**
  - Number of gradient computations
  - Data movement and I/O cost

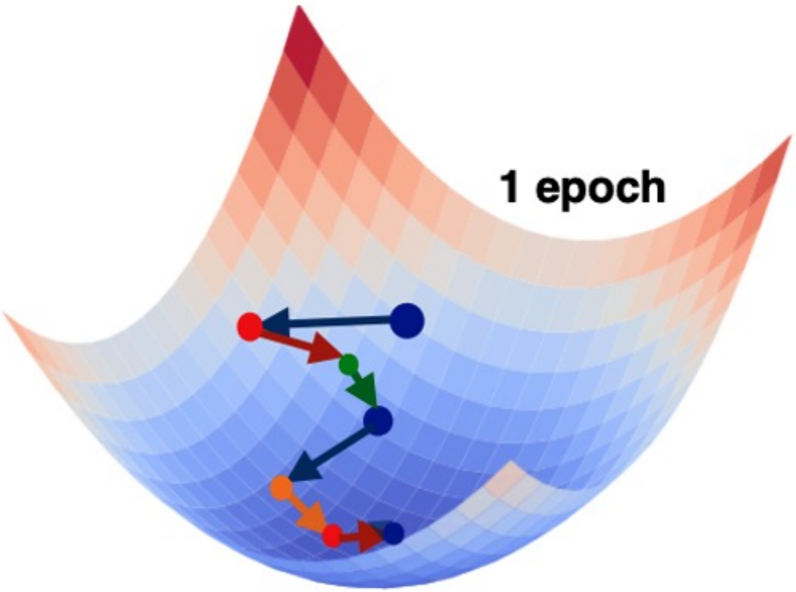
**Is it equally important to train on every data point?**


Distribution of training time for training a ResNet50 model using an NVIDIA V100 GPU.

# Subset Selection

- Training dataset $D = \{(x_i, y_i)\}_{i=1}^{N}$
- The goal of training is to find optimal parameters $\theta$ of a model $\Psi(.\,;\theta)$ such that:
- $\theta * = min \frac{1}{N} \sum_{i=1}^{N} L(\Psi(x_i;\theta), y_i)$
- Goal: Find subset $S \subseteq D$ such that:
  - $S = \min|S|\ st.$
  - $max_\theta \parallel \sum_{i \in D} \nabla L_i(\theta) - \sum_{j \in S} \nabla L_j(\theta) \parallel \ \leq \epsilon$, where $\epsilon \geq 0$.




Loss function

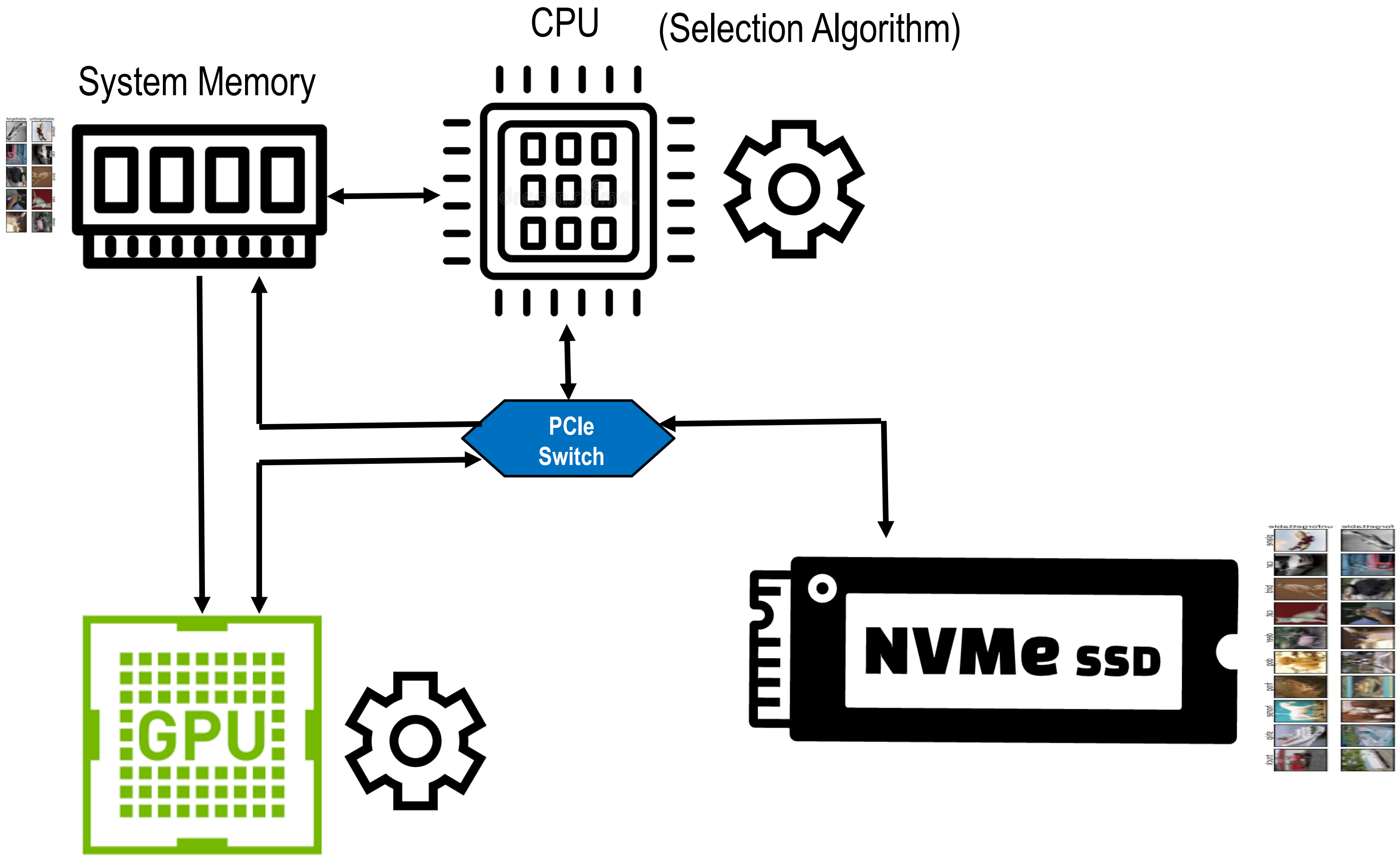
# Subset Selection – Assigning Importance

| Selection Method | Key Idea | Pros | Cons | Examples |
|---|---|---|---|---|
| Trained models | Infer importance post-training | High accuracy | Incurs more gradient computations than model trained on all data samples. | Toneva, ICLR'19<br>Zhang, NeurIPS'19<br>Coleman, ICLR'20<br>Zhao, ICLR'21<br>…. |
| Training dynamics | Infer importance during training – loss values, clustering | Low cost solution | Accuracy degradation | Sener, ICLR'18<br>Katharopoulos, ICLR'18<br>Mirzasoleiman, ICML'20<br>…. |

Different methods of assigning importance.

# Prior Work – Limitations

- **Limitation 1: High data movement.**
- **Traditional subset selection:**
  - Load data from disk to CPU memory
  - Run selection algorithm to assign importance.
  - Pass selected data samples to the GPU.
  - Train on the selected data samples.
  - Repeat every epoch



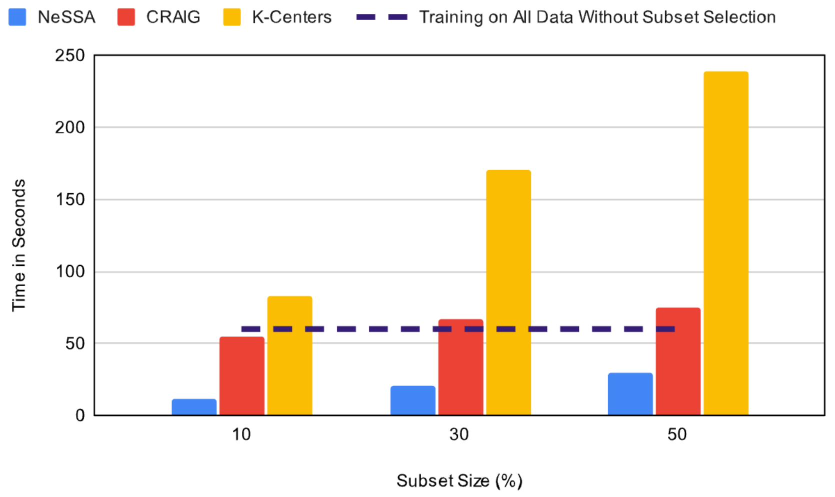

Steps involved in traditional subset selection

# Prior Work – Limitations

- **Traditional subset selection using training dynamics:**
  - Limitation 2: CPU-based selection – High selection time
  - Limitation 3: Limited information - Accuracy degradation

| Subset (%) | CRAIG | K-Center | NeSSA | Goal |
|---|---|---|---|---|
| 10 | 87.07 | 65.72 | **87.75** | 92.44 |
| 30 | 89.12 | 88.49 | **90.68** | 92.44 |
| 50 | 90.32 | 90.14 | **91.92** | 92.44 |

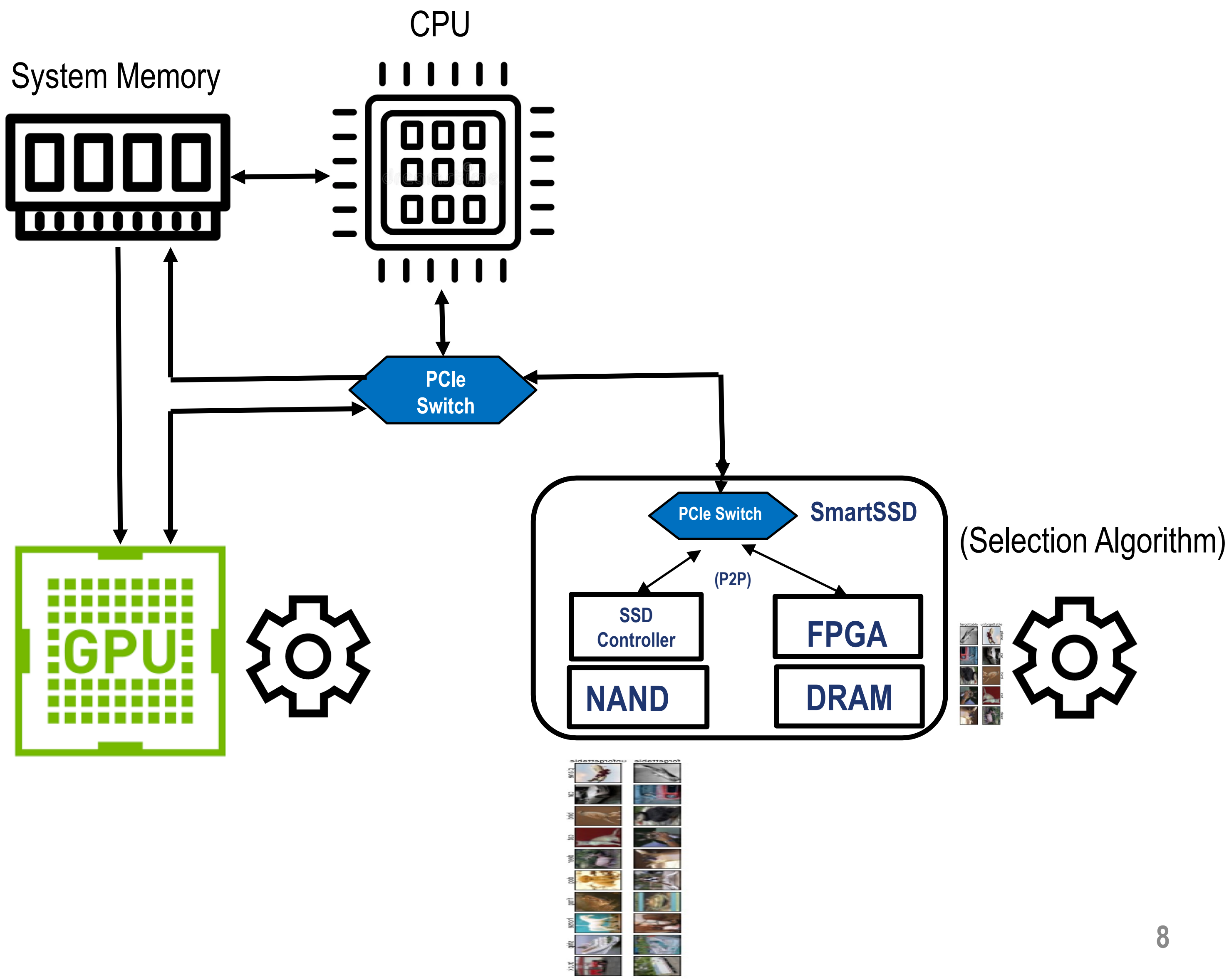
Accuracy when trained on different subset sizes on the CIFAR10 dataset using a ResNet20 model.




Training time averaged across epochs for NeSSA, prior work, and a model trained on the full dataset.

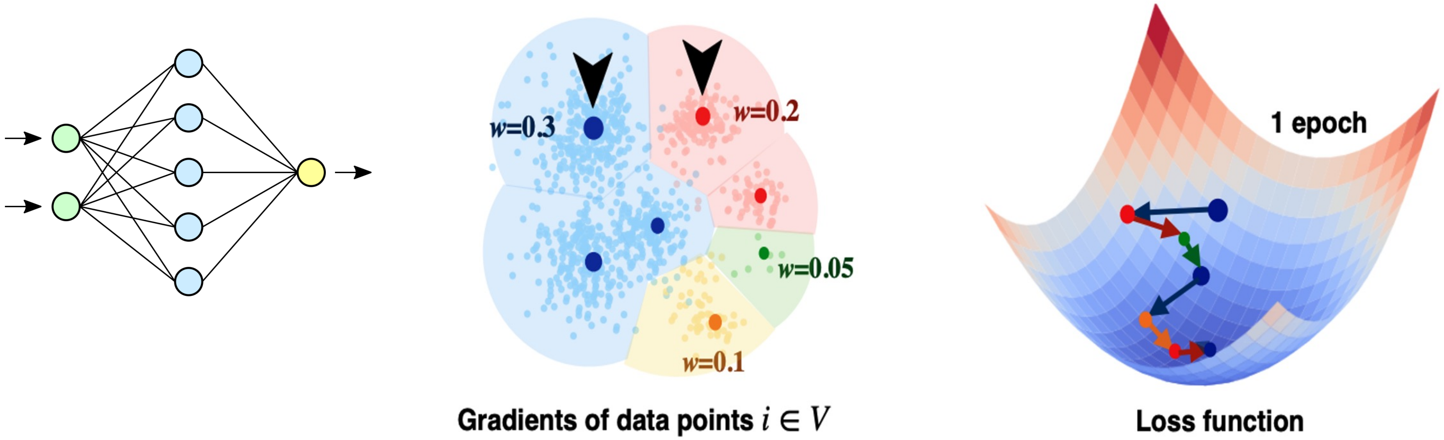
# NeSSA System Design

- **Subset selection using FPGA-based near-storage acceleration:**
  - Reduces data movement by |D|/|S|
  - High-speed selection compared to CPU-based selection
  - Energy efficient compared to GPU-based selection
  - Reconfigurable and scalable for different models and datasets compared to ASIC-based selection



# Selection Algorithm – High Accuracy, Low-Cost

- **Goal: Find subset $S \subseteq D$ such that:**
- $S = \min|S|\ st.$
  - $max_\theta \parallel \sum_{i \in D} \nabla L_i(\theta) - \sum_{j \in S} \nabla L_j(\theta) \parallel \ \leq \epsilon$, where $\epsilon \geq 0$.
- **Upper bound:**
  - $min_{S \subseteq V} \parallel \sum_{i \in C} \nabla L_i(\theta) - \sum_{j \in S} \nabla L_j(\theta) \parallel \leq \sum_{i \in D} min_{j \in S} \parallel \nabla L_i(\theta) - \nabla L_j(\theta) \parallel$
  - RHS: k-medoids problem
  - S is the set of medoids!

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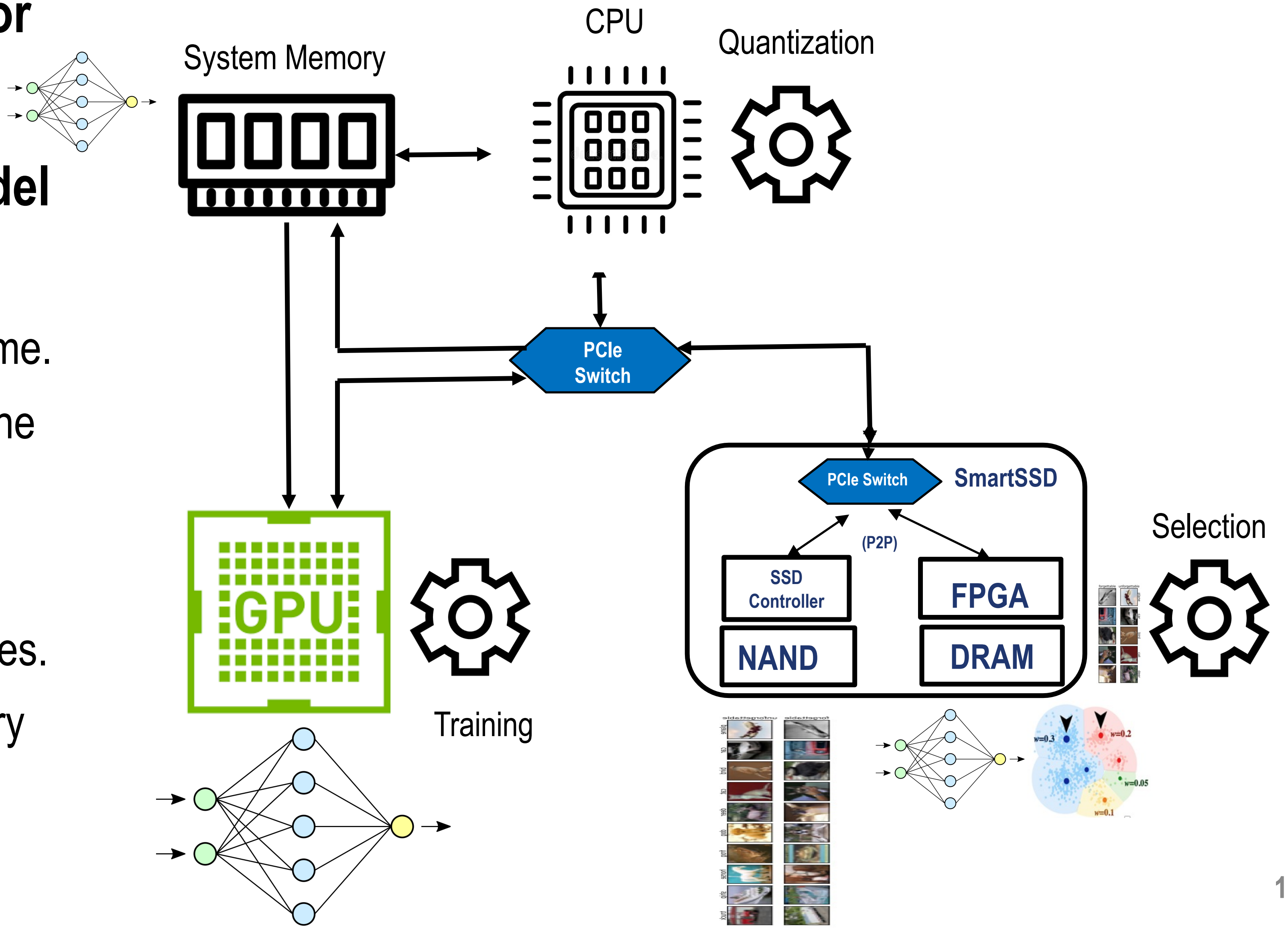
Overview of the selection algorithm

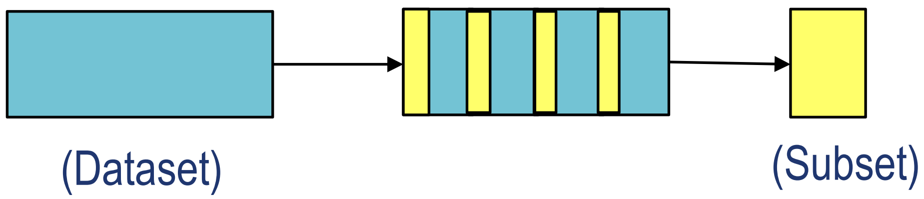
# Software Optimizations – High Accuracy, Speed, Minimum Subset Size

- **Quantize model on FPGA for inference.**
- **Feedback of quantized model weights:**
  - Improve selection model over time.
  - Select only those points which the model needs in that epoch.
- **Subset biasing:**
  - Selecting from unlearned samples.
  - Drop samples with low loss every 20 epochs.



# Hardware Optimizations – High-Speed Selection, Low-Cost

- **Quantization of model weights:**
  - 1-bit weights
  - 2-bit activations
  - 4-bit residuals
  - 8-bit first / last layer weights
- **Dataset partitioning:**
  - Randomly partition dataset into several chunks and select a smaller subset from each chunk.
  - No need to fit gradients of an entire class onto on-chip memory.
  - Example:
    - ❖Mini-batch size m, subset size k, dataset size N
    - ❖Partition dataset into k/m random chunks
    - ❖Select m examples from each chunk

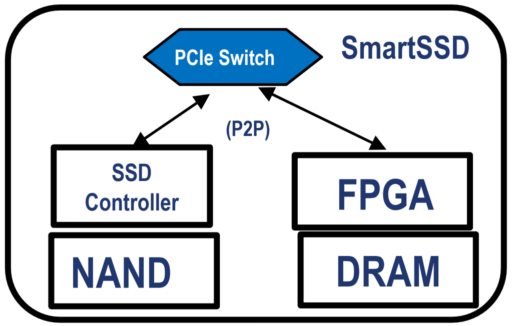


# Evaluation Setup

- **Datasets and models evaluated:**

| Dataset | Classes | Number of training samples | Network |
|---|---|---|---|
| CIFAR-10 | 10 | 50K | ResNet-20 |
| SVHN | 10 | 73K | ResNet-18 |
| CINIC-10 | 10 | 90K | ResNet-18 |
| CIFAR-100 | 100 | 50K | ResNet-18 |
| TinyImageNet | 200 | 100K | ResNet-18 |
| ImageNet-100 | 100 | 130K | ResNet-50 |

- **GPU used: NVIDIA A100**
- **SmartSSD v1.0:**
  - 3.84TB NAND
  - Xilinx Kintex UltraScale+ KU15P FPGA
  - 4GB DDR4 SDRAM



# Performance – Accuracy, Convergence Speed-Up

| Dataset | All data (%) | NeSSA (%) | Subset (%) |
|---|---|---|---|
| CIFAR-10 | 92.02 | 90.17 | 28 |
| SVHN | 95.81 | 95.18 | 15 |
| CINIC-10 | 81.49 | 80.26 | 30 |
| CIFAR-100 | 70.98 | 69.23 | 38 |
| TinyImageNet | 63.40 | 63.66 | 34 |
| ImageNet-100 | 84.60 | 83.76 | 28 |

Accuracy comparison between NeSSA and training on the full data.

# Impact of Each Optimization

- **Vanilla: Medoid-based selection without any optimizations.**
- **SB: medoid-based selection with subset biasing.**
- **PA: medoid-based selection with dataset partitioning.**
- **SB+PA: Medoid-based selection with both optimizations.**
- **Goal: Accuracy when trained on the full dataset.**

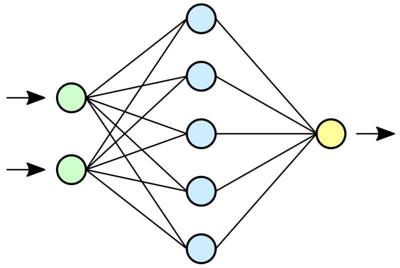
| Subset (%) | Vanilla (%) | SB (%) | PA (%) | SB+PA(%) | Goal (%) |
|---|---|---|---|---|---|
| 10 | 82.76 | 87.61 | 83.75 | 87.75 | 92.44 |
| 30 | 89.51 | 90.42 | 90.68 | 90.42 | 92.44 |
| 50 | 90.59 | 91.81 | 91.91 | 91.92 | 92.44 |

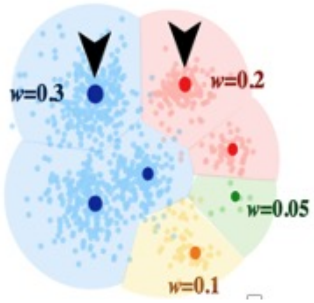
Impact of each optimization when training a ResNet20 model on the CIFAR-10 dataset.

# Accelerator Design for Selection

- **Inference accelerator generated using FINN compiler:**
  - Deep neural network inference for FPGAs
  - Dataflow-style quantized neural networks
  - Takes as input ONNX model trained in Brevitas:
    - ❖Pytorch library for quantization-aware training.

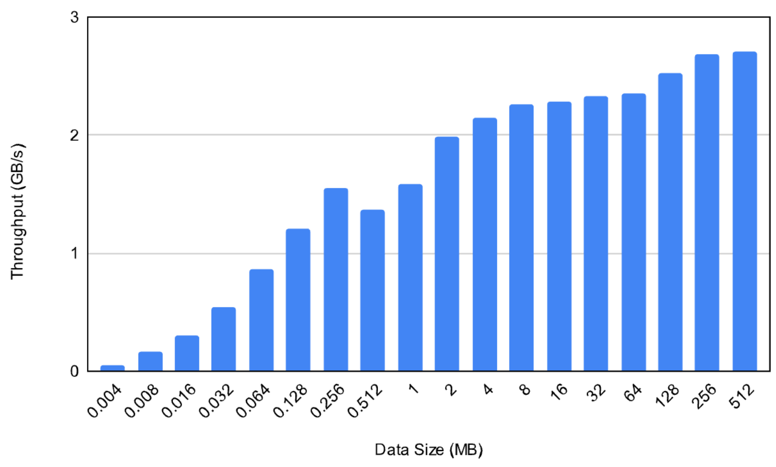
| Resource | Available | Utilization (%) |
|---|---|---|
| LUT | 432K | 67.53 |
| FF | 919K | 23.14 |
| BRAM | 738 | 50.30 |
| DSP | 1962 | 42.67 |





# Benefits of Using FPGA-Based Near-Storage Acceleration

- **4.3x faster than CPU-based selection.**
- **Without P2P between SSD and FPGA:**
  - Achievable bandwidth reduces from 3GBps to 1.4GBps.
- **Overall reduction of data movement over host-drive interconnect by an average of 3.5x.**
- **Effects of increasing dataset size:**
  - ❖CIFAR-10: 0.003MB/image, throughput: 1.46GBps
  - ❖ImageNet-100: 0.126MB/image, throughput: 2.28GBps.
- **As dataset size increases, storage-assisted training becomes more effective and essential.**
- **Overall end-to-end training speed-up of 5.4x.**




Data transfer throughput between FPGA and on-board SSD on SmartSSD

# Conclusion

- **Motivation:**
  - Significantly reduce model training costs without affecting final model accuracy.
- **Key Ideas:**
  - Use FPGA-based near-storage data selection to reduce training & data movement costs.
  - Use feedback from target model to improve selection.
  - Automatically reduce subset size over time.
  - Quantize selection model to improve speed.
- **Key Results:**
  - Data movement reduction of 3.5x.
  - Training speed-up of 5.4x.

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Repository:

Link: https://github.com/nehaprakriya/Near-SSD-Data-Selection

# Thank you!
# Questions?