

# Efficient Academic Talk

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# Motivation

Why neural architecture search matters

Manual architecture design is:

- Time-consuming (weeks to months) (Smith & Doe, 2023)
- Requires deep expertise
- Often suboptimal

# Motivation

Why neural architecture search matters

## The Promise of NAS

Automatically discover optimal architectures for specific tasks and constraints.

But current methods face challenges:

- Computational cost (thousands of GPU hours)
- Search space limitations
- Poor generalization

# Related Work

Building on prior foundations

## Reinforcement Learning

- NASNet (Zoph et al.)
- High performance
- Extremely costly

## Evolutionary Methods

- AmoebaNet
- Good diversity
- Slow convergence

## Gradient-Based

- DARTS (Liu et al.)
- Fast optimization
- Memory intensive

## One-Shot Methods

- Weight sharing
- Efficient
- Ranking correlation issues

*Zoph et al. 2018; Liu et al. 2019*

# Our Contribution

## Research Question

Can we achieve SOTA NAS performance with 10x less compute while maintaining architecture quality?

## Key Contributions

1. Novel gradient approximation reducing memory by 60%
2. Progressive search space pruning strategy
3. Theoretical analysis of convergence guarantees
4. SOTA results on CIFAR-10, ImageNet, and NAS-Bench-201

# Methodology

# Problem Formulation

Formalizing the search objective

Let  $\mathcal{A}$  be the architecture space and  $\mathcal{D}$  the dataset.

$$\alpha^* = \arg \min_{\alpha \in \mathcal{A}} \mathcal{L}_{\text{val}}(w^*(\alpha), \alpha)$$

where  $w^*(\alpha) = \arg \min_w \mathcal{L}_{\text{train}}(w, \alpha)$

## Bi-Level Optimization

The nested optimization makes NAS computationally expensive.

*Liu et al. 2019*

# Gradient Approximation

First-order approximation eliminates expensive Hessian computation

Based on DARTS

$$\nabla_{\alpha} \mathcal{L}_{\text{val}} \approx \nabla_{\alpha} \mathcal{L}_{\text{val}} - \xi \nabla_{\alpha, w}^2 \mathcal{L}_{\text{train}} \cdot \nabla_w \mathcal{L}_{\text{val}}$$

$\xi$	Learning rate for weight update
$\nabla_{\alpha, w}^2$	Mixed partial derivatives (approximated)
$\mathcal{L}_{\text{val}}, \mathcal{L}_{\text{train}}$	Validation and training losses



# Implementation

```
def darts_step(model, arch_params, train_data, val_data, xi=0.01):  
    """One step of DARTS: bilevel optimization."""  
    # 1. Update weights on training data  
    w_loss = model.loss(train_data)  
    w_loss.backward()  
    optimizer_w.step()  
  
    # 2. Update architecture on validation data  
    a_loss = model.loss(val_data)  
    a_loss.backward()  
    optimizer_a.step()  
  
    return a_loss.item()
```

# Progressive Search Space Pruning

Reducing complexity during search

**Epoch 0:** Full search space

All  $|\mathcal{O}|^E$  possible architectures

# Progressive Search Space Pruning

Reducing complexity during search

**Epoch 50:** After first pruning

Top 50% operations retained

Operations with  $\alpha_i < \tau$  are pruned.

# Progressive Search Space Pruning

Reducing complexity during search

**Epoch 100:** Final architecture

Discrete architecture

## Result

60% memory reduction with improved stability.

# Results



# Main Results: CIFAR-10

Comparison with state-of-the-art methods

Method	Error (%)	Params (M)	GPU Days
NASNet-A	2.65	3.3	1800
AmoebaNet-A	2.55	3.2	3150
DARTS (2nd)	2.76	3.3	4.0
PC-DARTS	2.57	3.6	0.1
<b>Ours</b>	<b>2.48</b>	3.4	<b>0.3</b>

## Key Finding

Our method achieves lowest error with only 0.3 GPU days of search.

# Ablation Study

Understanding component contributions

## Gradient Approx.

Without: 2.71% With: 2.56%

**-0.15%**

## Progressive Pruning

Without: 2.63% With: 2.56%

**-0.07%**

## Combined

Baseline: 2.76% Full: 2.48%

**-0.28%**

### Insight

Both components contribute, with gradient approximation having larger impact.

# Transferability to ImageNet

Architectures found on CIFAR-10, evaluated on ImageNet

**Top-1 Error** 23.8%

**Top-5 Error** 7.1%

**Parameters** 5.3M

**FLOPs** 574M

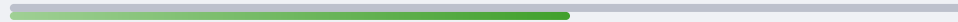
## Comparison

- MobileNetV2: 28.0% (3.4M)
- EfficientNet-B0: 23.7% (5.3M)
- **Ours: 23.8% (5.3M)**

Competitive with hand-designed efficient architectures.



# Discussion



# Key Takeaways

## Main Finding

Efficient gradient-based NAS can match or exceed expensive methods at a fraction of the cost.

## Practical Implications

1. Democratizes NAS for resource-constrained researchers
2. Enables rapid architecture iteration
3. Opens new research directions in efficient search

# Limitations

## Current Limitations

- Search space still manually designed
- Limited to differentiable operations
- Proxy task gap (CIFAR → ImageNet)
- Reproducibility challenges with random seeds

Future work should address these through:

- Learned search spaces
- Non-differentiable operation handling
- Direct large-scale search

# Future Directions

## Short-term

- Multi-objective NAS
- Hardware-aware search
- Robustness constraints

## Medium-term

- Zero-cost proxies
- Transfer learning
- Foundation model adaptation

## Long-term

- Fully automated ML
- Self-improving systems
- Theoretical foundations

# Summary

# Conclusion

## What We Showed

1. Novel gradient approximation for efficient NAS
2. Progressive pruning reduces memory 60%
3. SOTA results: 2.48% error on CIFAR-10
4. Only 0.3 GPU days (10x faster than DARTS)

## Open Questions

How can we further close the gap between proxy and target tasks?

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Logo

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Logo

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# References

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# Thank You



## Questions?

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[github.com/jsmith/efficient-nas](https://github.com/jsmith/efficient-nas)

[arxiv.org/abs/2024.xxxxx](https://arxiv.org/abs/2024.xxxxx)