Deep-n-Cheap

An Automated Search Framework for Low Complexity Deep Learning

Sourya Dey

PhD, University of Southern California

June 20th, 2020

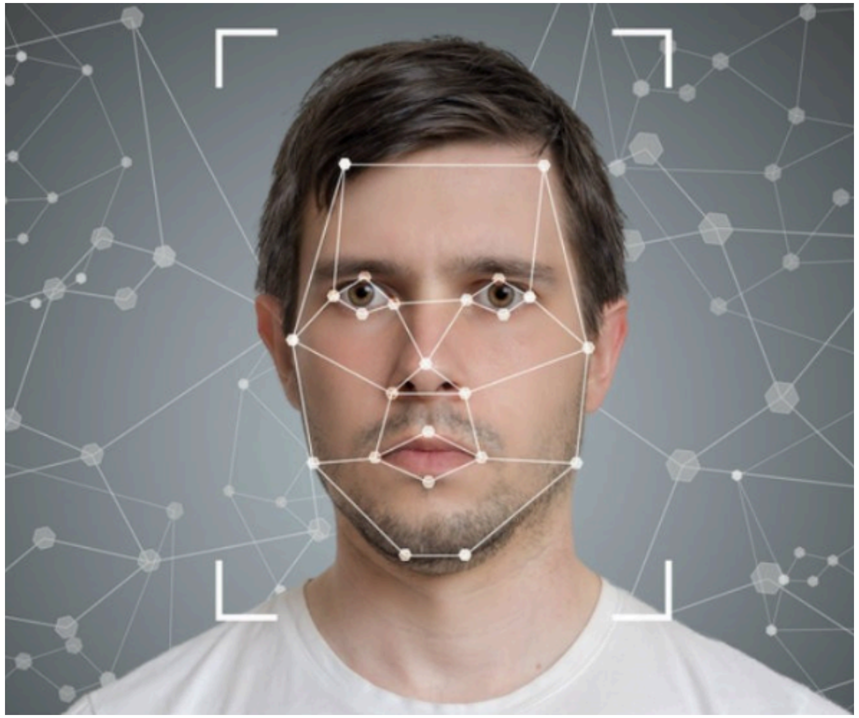
Outline

Overview

Overview

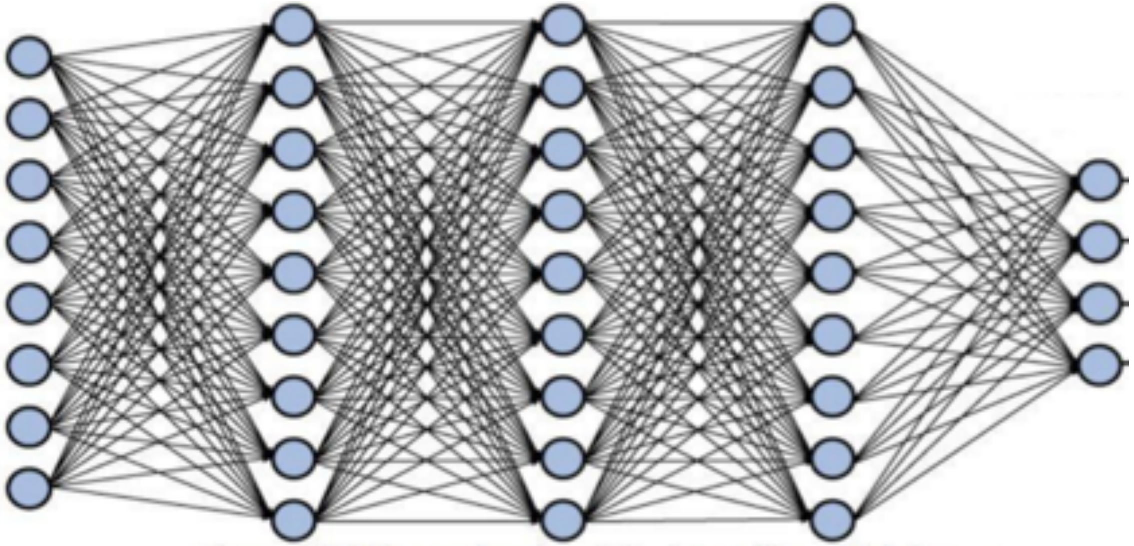
Neural networks (NNs) are key machine learning technologies

- ➢ Artificial intelligence
- ➢ Self-driving cars
- ➢ Speech recognition
- ➢ Face ID
- ➢ and more smart stuff …



The Complexity Conundrum…

Modern neural networks suffer from parameter explosion



Training can take weeks on CPU

Cloud GPU resources are expensive

amazon web services

Google Cloud Platform

Microsoft Azure

He 2016

… and the Design Conundrum

- Deep neural networks have a lot of **hyperparameters**
  - How many layers?
  - How many neurons?
  - Learning rate
  - Batch size
  - and more…

Architecture Hyperparameters

Training Hyperparameters

- Our understanding of NNs is at best vague, at worst, zero!

AutoML (Automated Machine Learning)

- Software frameworks that make design decisions
- Given problem specifications, **search** for NN models

AutoKeras

Jin 2019 – Auto-Keras

GLUON

AWsLabs 2020 – AutoGluon

AutoML.org Freiburg-Hannover

Mendoza 2018 – Auto-PyTorch

Our Work

DnC Deep-n-Cheap

Low Complexity AutoML framework

Reduce training complexity

Target custom datasets and user requirements

Output complete training configs

Framework	Architecture search space	Training hyp search	Adjust model complexity
Auto-Keras	Only pre-existing architectures	No	No
AutoGluon	Only pre-existing architectures	Yes	No
Auto-PyTorch	Customizable by user	Yes	No
Deep-n-Cheap	Customizable by user	Yes	Penalize t_{tr}, N_p

t_{tr} = Training time / epoch

N_p = # Trainable parameters

Relevant Details

- Development started in July 2019
- Supports Pytorch
- Supports classification via CNNs and MLPs

- Latest / ongoing work:
  - Support for Keras
  - Regression
  - Detection / segmentation
  - RNNs

S. Dey, S. C. Kanala, K. M. Chugg and P. A. Beerel, “Deep-n-Cheap: An Automated Search Framework for Low Complexity Deep Learning”, submitted to ACML 2020.

https://arxiv.org/abs/2004.00974

Approach

Search Objective

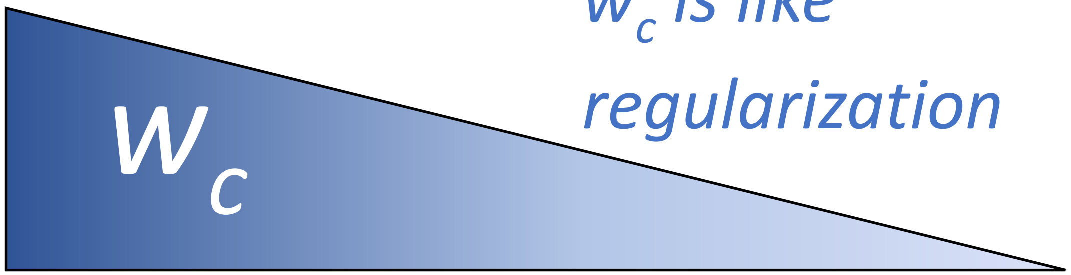
Optimize performance and complexity

Modified loss function: $f(\text{ NN Config } \mathbf{x}\ ) = \log(\ f_p + w_c * f_c\ )$

Example config ***x***:
[#layers, #channels] = [3, (29,40,77)]

f_p = 1 - (Best Validation Accuracy)
f_c = Normalized t_{tr} or N_p
= t_{tr}(config) / t_{tr}(baseline)

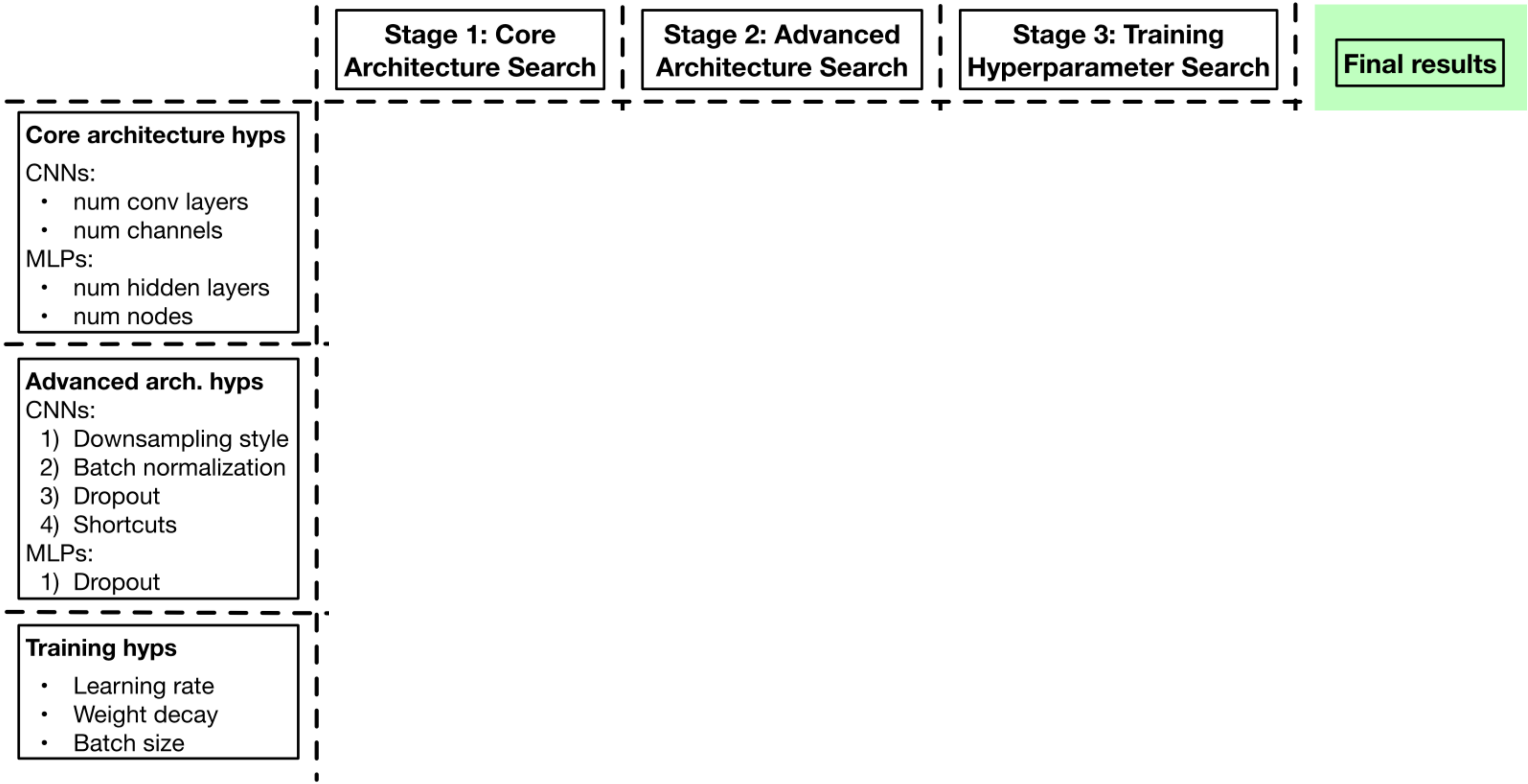
w_c is like regularization



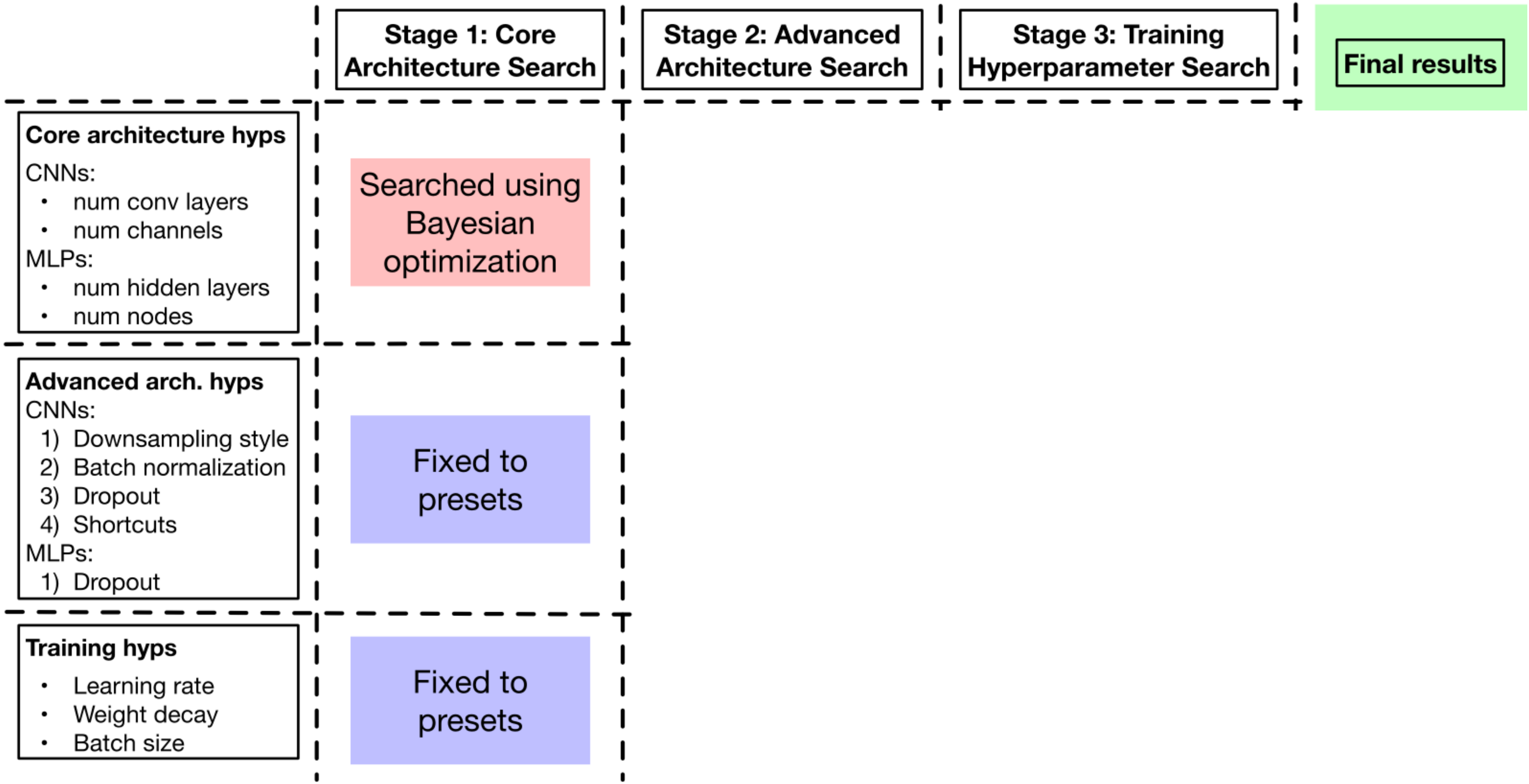
Quick to train
Sacrifice performance

Good performance
Slow to train
Slow search process

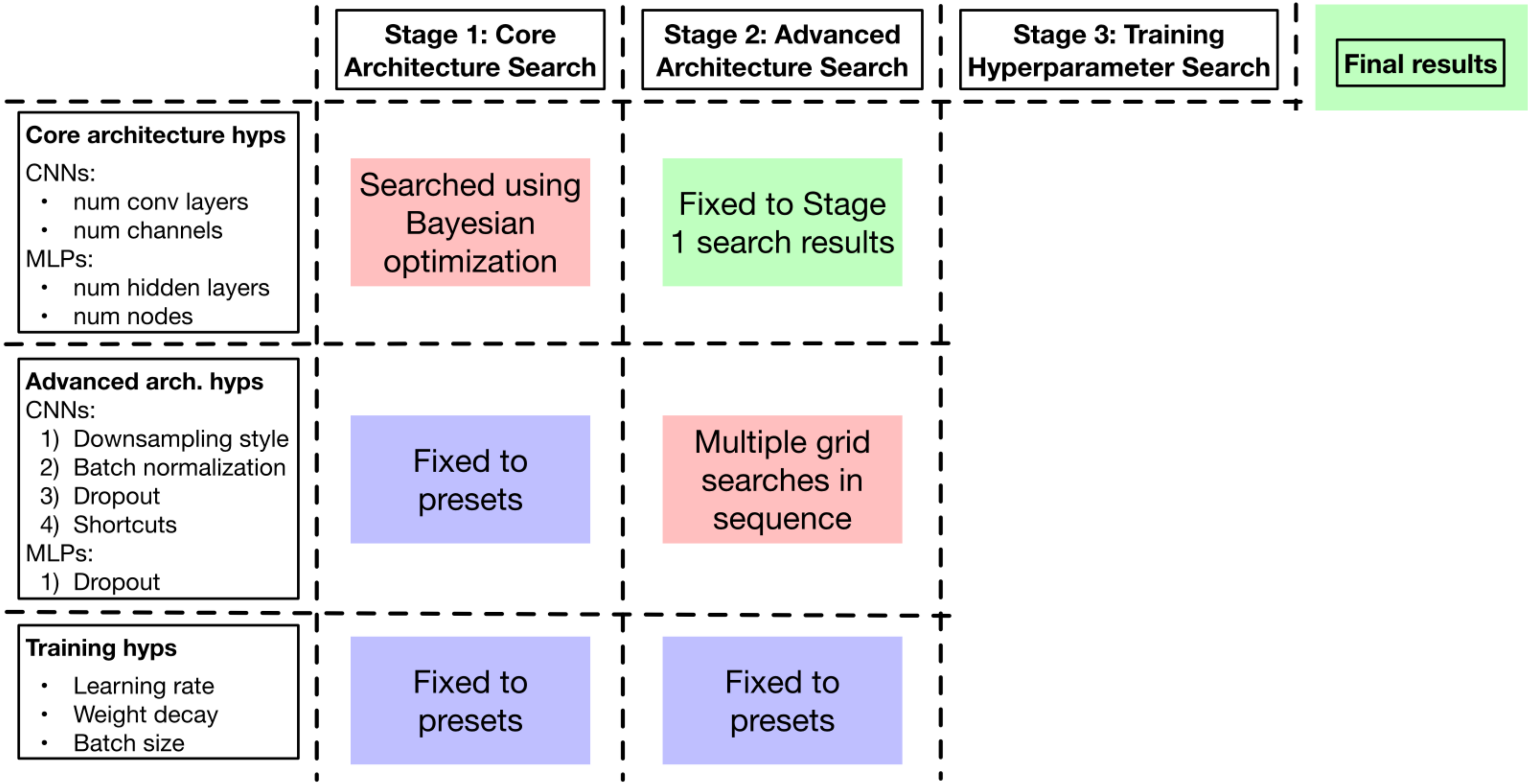
Three-stage search process



Three-stage search process



Three-stage search process



Three-stage search process

	Stage 1: Core Architecture Search	Stage 2: Advanced Architecture Search	Stage 3: Training Hyperparameter Search	Final results
Core architecture hyps CNNs: • num conv layers • num channels MLPs: • num hidden layers • num nodes	Searched using Bayesian optimization	Fixed to Stage 1 search results	Fixed to Stage 1 search results	Stage 1 search results
Advanced arch. hyps CNNs: 1) Downsampling style 2) Batch normalization 3) Dropout 4) Shortcuts MLPs: 1) Dropout	Fixed to presets	Multiple grid searches in sequence	Fixed to Stage 2 search results	Stage 2 search results
Training hyps • Learning rate • Weight decay • Batch size	Fixed to presets	Fixed to presets	Searched using Bayesian optimization	Stage 3 search results

ARCHITECTURE + TRAINING

Bayesian Optimization – Gaussian process

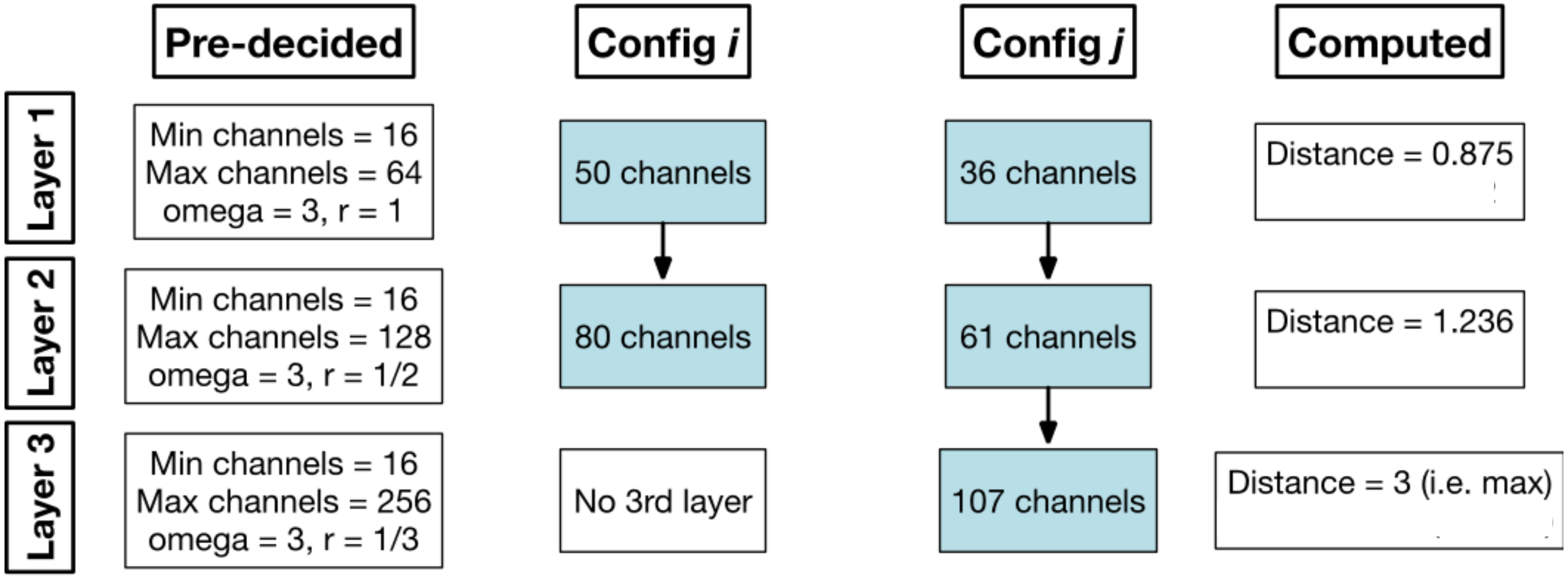
$$f\left(\boldsymbol{X}_{1:n}\right) \sim \mathcal{N}\left(\underset{n\times 1}{\boldsymbol{\mu}}, \underset{n\times n}{\boldsymbol{\Sigma}}\right)$$

$$\boldsymbol{\mu} = \begin{bmatrix} \mu\left(\boldsymbol{x}_1\right) \\ \vdots \\ \mu\left(\boldsymbol{x}_n\right) \end{bmatrix} \qquad \boldsymbol{\Sigma} = \begin{bmatrix} \sigma\left(\boldsymbol{x}_1, \boldsymbol{x}_1\right) & \cdots & \sigma\left(\boldsymbol{x}_1, \boldsymbol{x}_n\right) \\ \vdots & \ddots & \vdots \\ \sigma\left(\boldsymbol{x}_n, \boldsymbol{x}_1\right) & \cdots & \sigma\left(\boldsymbol{x}_n, \boldsymbol{x}_n\right) \end{bmatrix}$$

Covariance kernel – Similarity between NN configs

Individual Distance

$$d\left(x_{ik}, x_{jk}\right) = \omega_k \left(\frac{|x_{ik} - x_{jk}|}{u_k - l_k}\right)^{r_k}$$



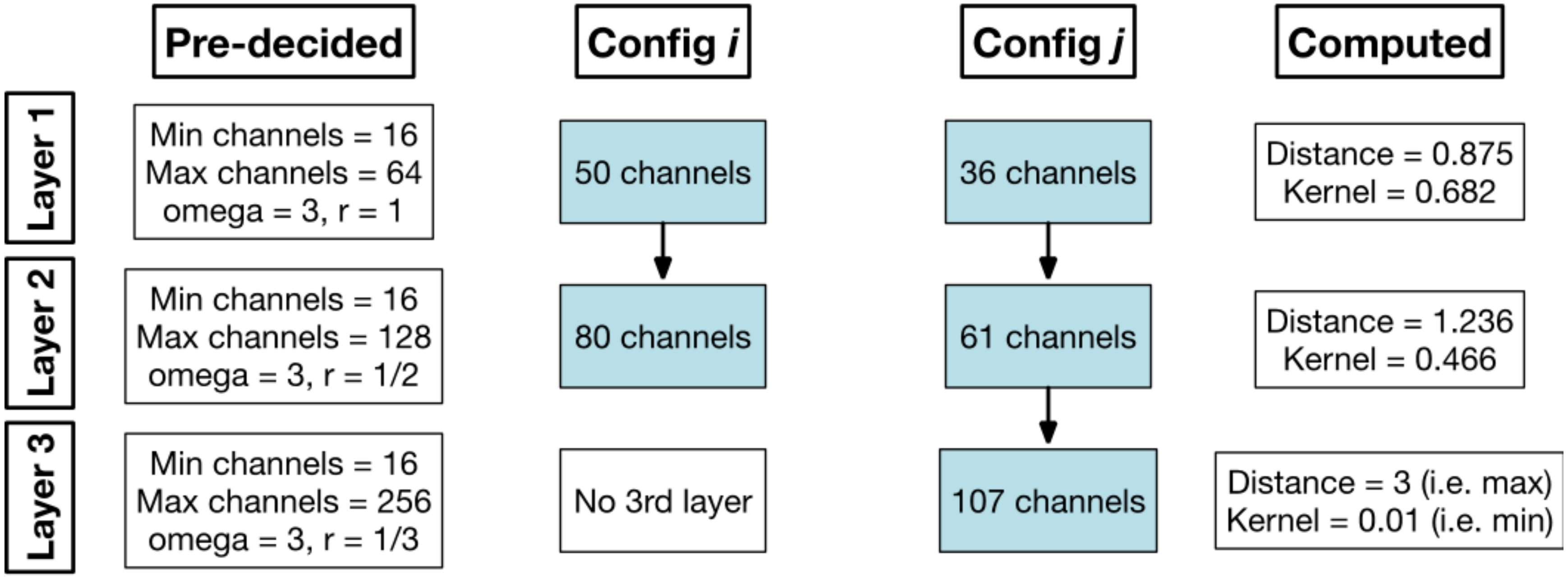
Covariance kernel – Similarity between NN configs

Individual Distance

$$d\left(x_{ik}, x_{jk}\right) = \omega_k \left(\frac{\left|x_{ik} - x_{jk}\right|}{u_k - l_k}\right)^{r_k}$$

Individual Kernel

$$\sigma\left(x_{ik}, x_{jk}\right) = \exp\left(-\frac{d^2\left(x_{ik}, x_{jk}\right)}{2}\right)$$



Covariance kernel – Similarity between NN configs

Individual Distance

$$d\left(x_{ik}, x_{jk}\right) = \omega_k \left(\frac{\left|x_{ik} - x_{jk}\right|}{u_k - l_k}\right)^{r_k}$$

Individual Kernel

$$\sigma\left(x_{ik}, x_{jk}\right) = \exp\left(-\frac{d^2\left(x_{ik}, x_{jk}\right)}{2}\right)$$

Complete Kernel

$$\sigma\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right) = \sum_{k=1}^{K} s_k \sigma\left(x_{ik}, x_{jk}\right)$$

Convex combination

	Pre-decided	**Config *i***	**Config *j***	**Computed**
Layer 1	Min channels = 16 Max channels = 64 omega = 3, r = 1	50 channels	36 channels	Distance = 0.875 Kernel = 0.682
Layer 2	Min channels = 16 Max channels = 128 omega = 3, r = 1/2	80 channels	61 channels	Distance = 1.236 Kernel = 0.466
Layer 3	Min channels = 16 Max channels = 256 omega = 3, r = 1/3	No 3rd layer	107 channels	Distance = 3 (i.e. max) Kernel = 0.01 (i.e. min)

Assuming all {s} are equal, **final kernel value = 0.386**

Results

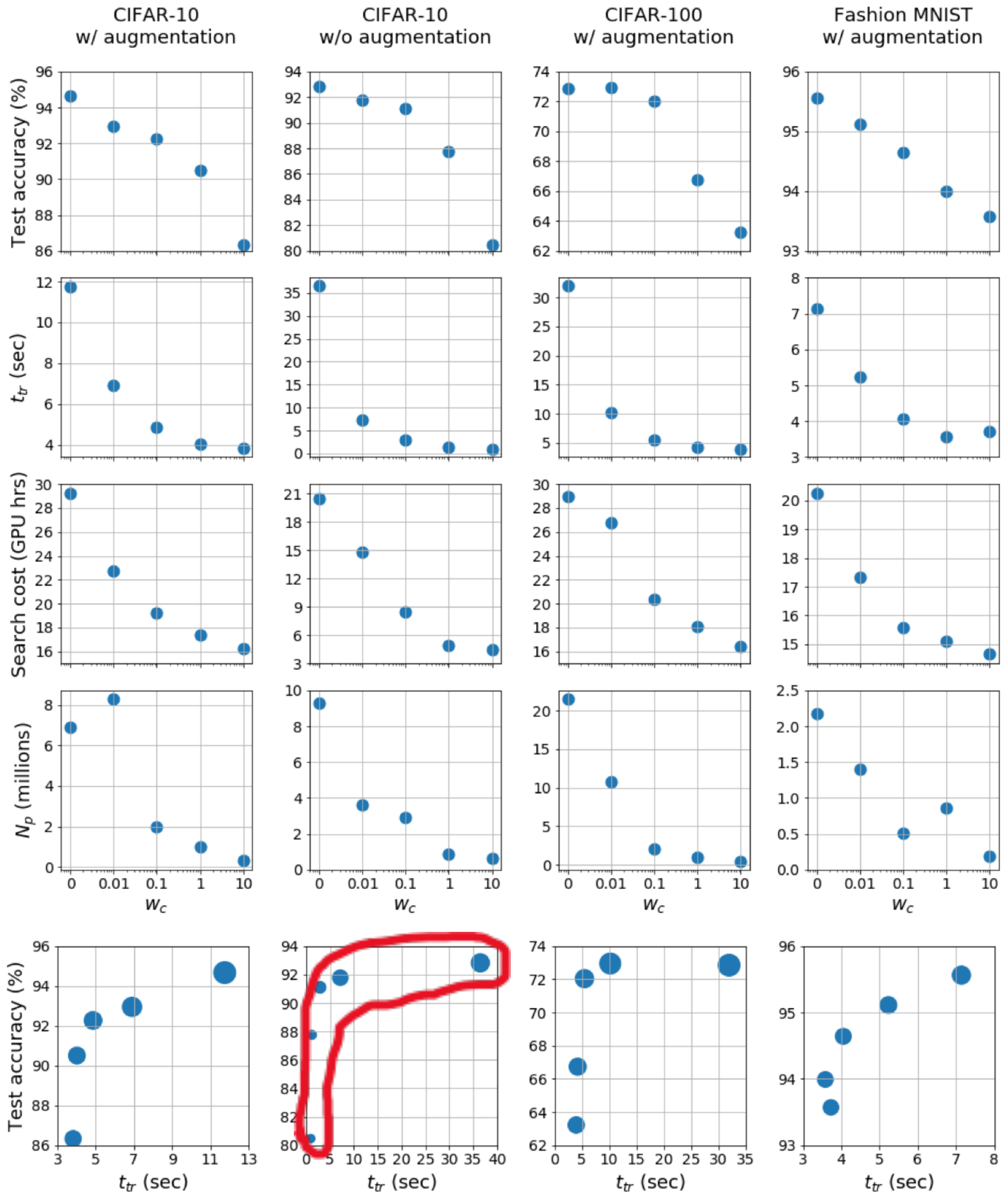
CNN Results

Complexity Penalty =
Training time / epoch

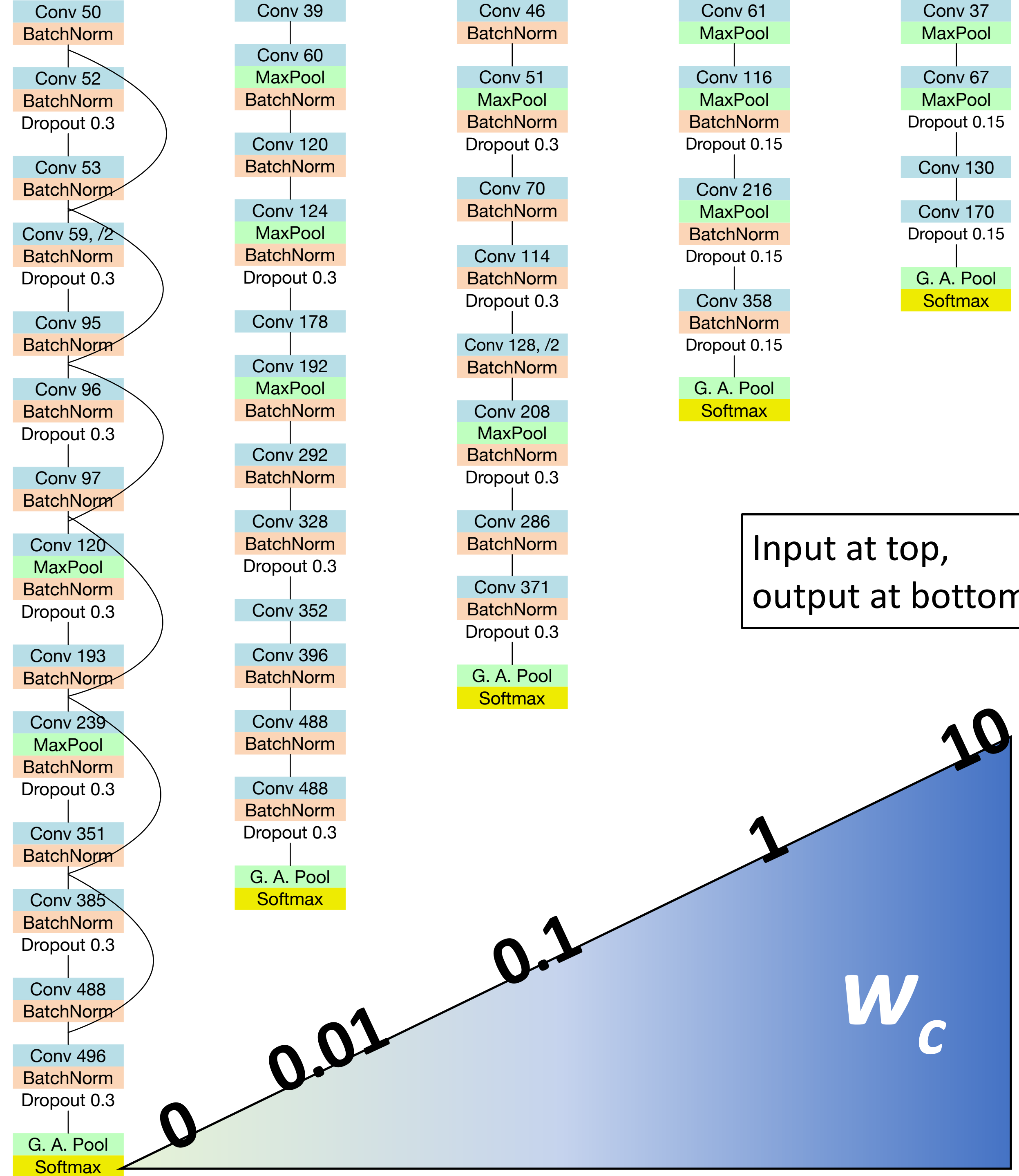
AWS p3.2xlarge
with 1 V100 GPU

We are not penalizing this, but it's correlated

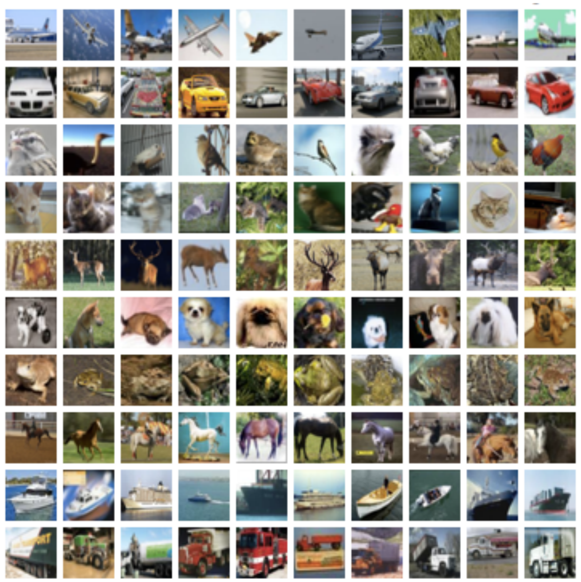
Performance-complexity tradeoff



CIFAR-10 w/ aug



Input at top,
output at bottom



w_c	0	0.01	0.1	1	10
Initial learning rate η	0.001	0.001	0.001	0.003	0.001
Weight decay λ	3.3×10^{-5}	8.3×10^{-5}	1.2×10^{-5}	0	0
Batch size	120	256	459	452	256

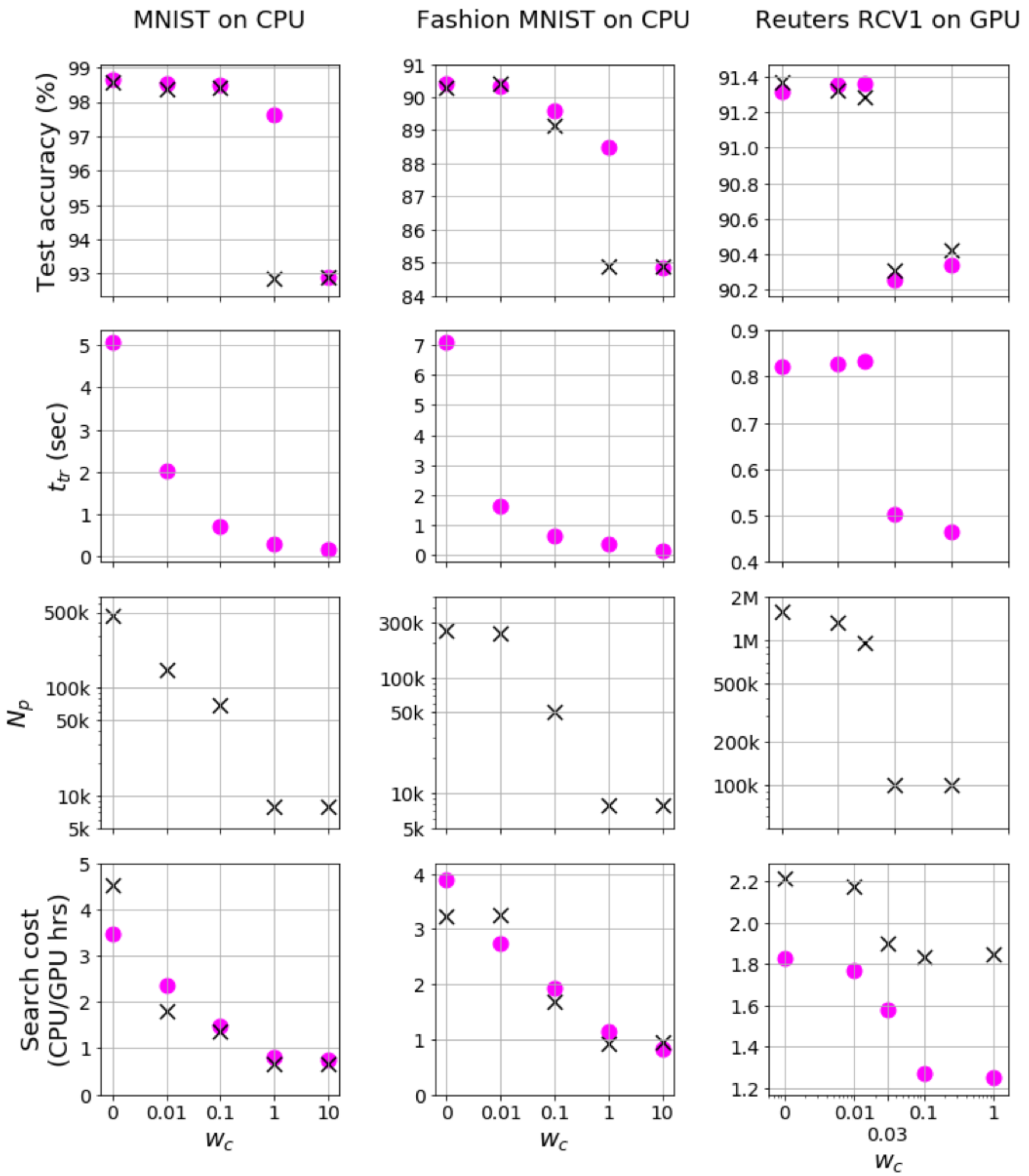
λ strictly correlated with N_p

MLP Results

Pink dots:
Complexity Penalty =
Training time / epoch

Black crosses:
Complexity Penalty =
 # Trainable Params

CPU = Macbook Pro with 8GB RAM, no CuDA
GPU = (Same) AWS p3.2xlarge with V100



Comparison (CNNs on CIFAR-10)

Framework	Additional settings	Search cost (GPU hrs)	Best model found from search			
			Architecture	t_{tr} (sec)	Batch size	Best val acc (%)
Proxyless NAS	Proxyless-G	96	537 conv layers	429	64	93.22
Auto-Keras	Default run	14.33	Resnet-20 v2	33	32	74.89
AutoGluon	Default run	**3**	Resnet-20 v1	37	64	88.6
	Extended run	101	Resnet-56 v1	46	64	91.22
Auto-Pytorch	'tiny cs'	6.17	30 conv layers	39	64	87.81
	'full cs'	6.13	41 conv layers	31	106	86.37
Deep-n-Cheap	$w_c = 0$	29.17	14 conv layers	10	120	**93.74**
	$w_c = 0.1$	19.23	8 conv layers	4	459	91.89
	$w_c = 10$	16.23	4 conv layers	**3**	256	83.82

Penalizes inference complexity, <u>not</u> training

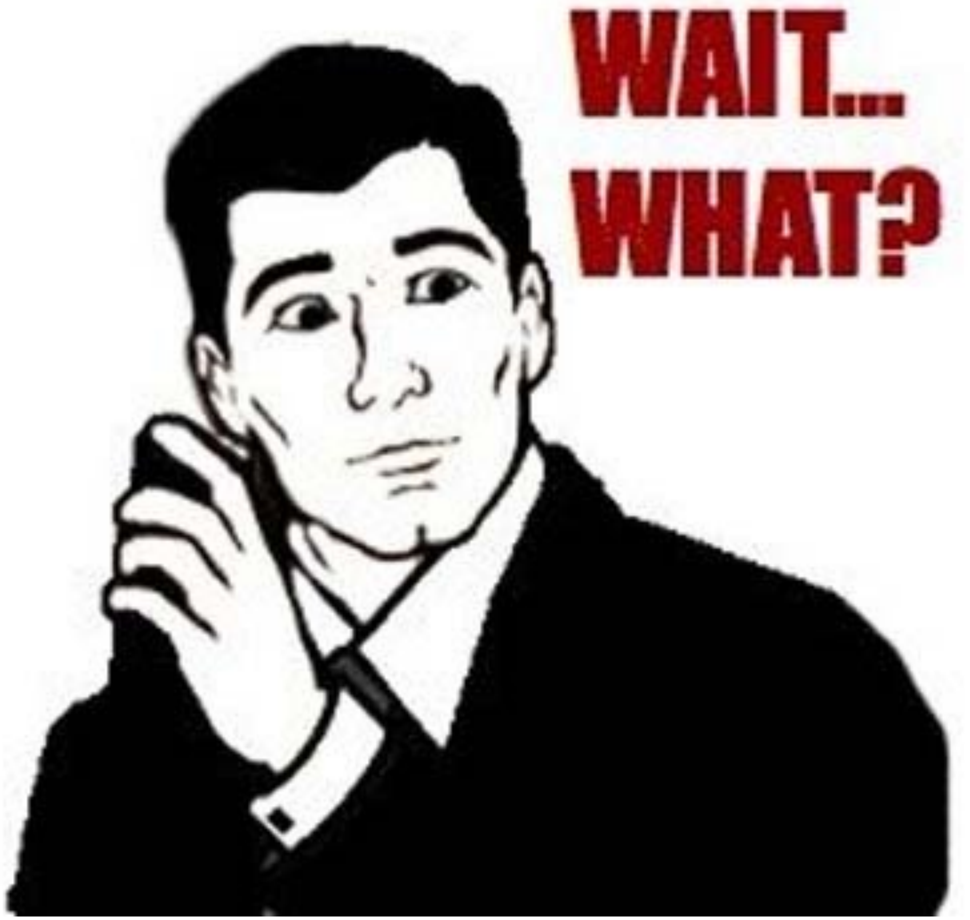
Auto Keras and Gluon don't support getting final model out, so we compared on best val acc found during search instead of final test acc

Comparison (MLPs)

Framework	Additional settings	Search cost (GPU hrs)	Best model found from search				
			MLP layers	N_p	t_{tr} (sec)	Batch size	Best val acc (%)
Fashion MNIST							
Auto-Pytorch	'tiny cs'	6.76	50	27.8M	19.2	125	**91**
	'medium cs'	5.53	20	3.5M	8.3	184	90.52
	'full cs'	6.63	12	122k	5.4	173	90.61
Deep-n-Cheap (penalize t_{tr})	$w_c = 0$	0.52	3	263k	0.4	272	90.24
	$w_c = 10$	**0.3**	1	**7.9k**	**0.1**	511	84.39
Deep-n-Cheap (penalize N_p)	$w_c = 0$	0.44	2	317k	0.5	153	90.53
	$w_c = 10$	0.4	1	**7.9k**	0.2	256	86.06
Reuters RCV1							
Auto-Pytorch	'tiny cs'	7.22	38	19.7M	39.6	125	88.91
	'medium cs'	6.47	11	11.2M	22.3	337	90.77
Deep-n-Cheap (penalize t_{tr})	$w_c = 0$	1.83	2	1.32M	0.7	503	**91.36**
	$w_c = 1$	**1.25**	1	**100k**	**0.4**	512	90.34
Deep-n-Cheap (penalize N_p)	$w_c = 0$	2.22	2	1.6M	0.6	512	**91.36**
	$w_c = 1$	1.85	1	**100k**	5.54	33	90.4

Takeaway

We may not need very deep networks!



Also see Zagoruyko 2016 – WRN

Thank you!

Q&A ??

https://souryadey.github.io/