Net2Net: Rapidly Transferring Knowledge between Large Networks

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Work was done when all the authors were at Google Brain

Outline

- The Problem
- Proposed Methods
- Experimental Results

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- **The Problem**
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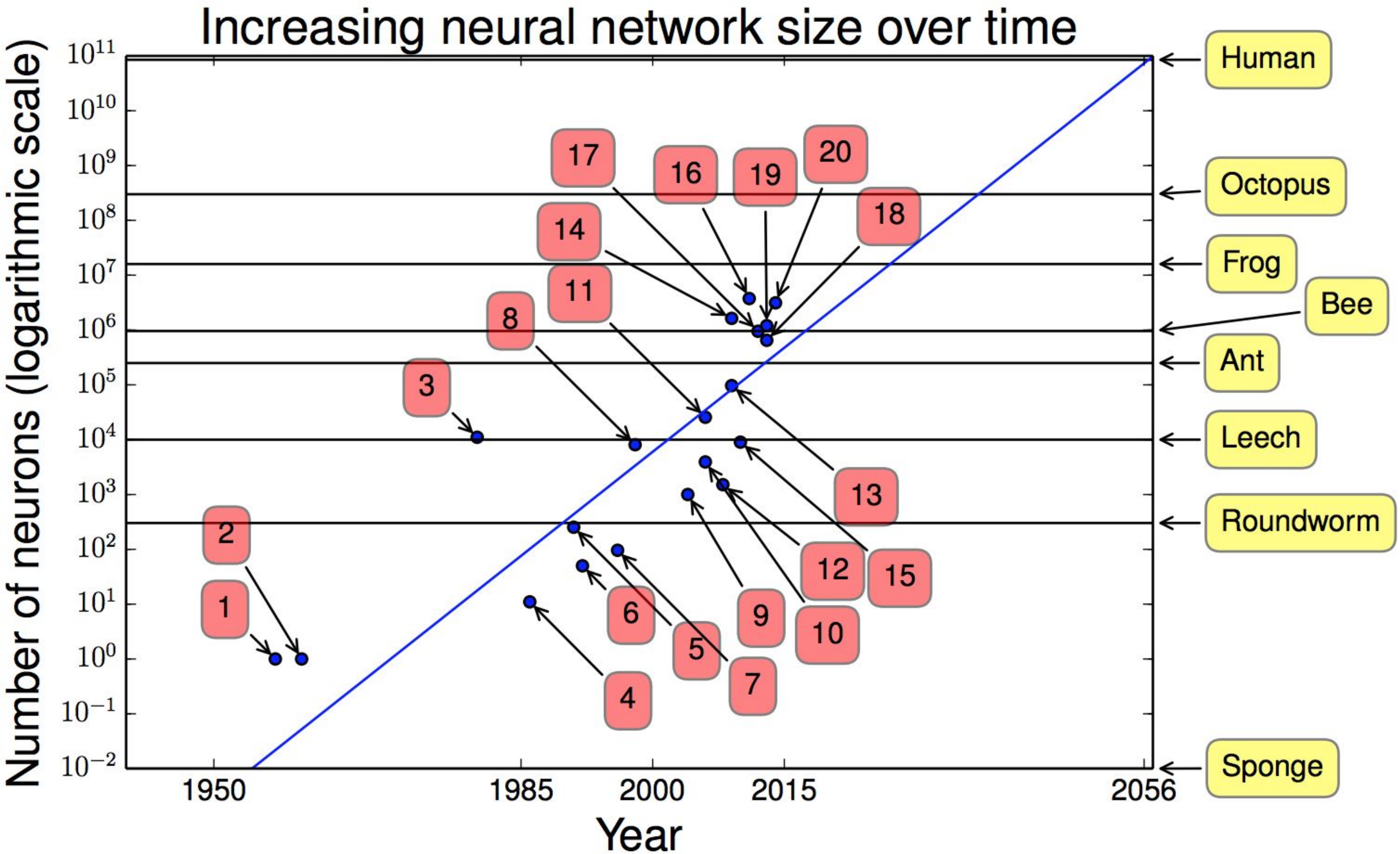
Neural nets are getting larger ...

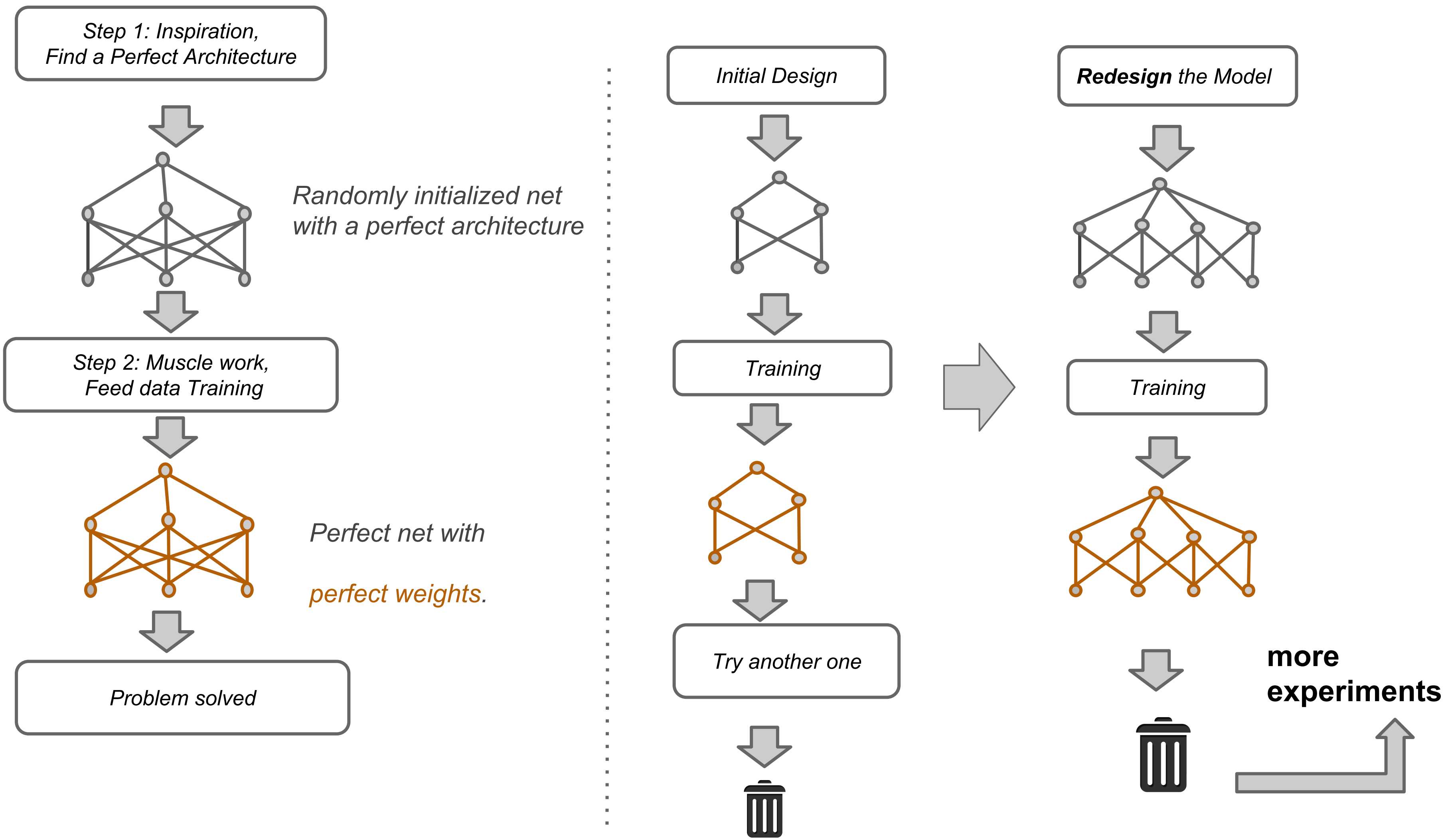


but large model = long training time

Deep Learning: Ideal vs Reality

Ideal World

Reality: the Loop of Experiments



Motivation

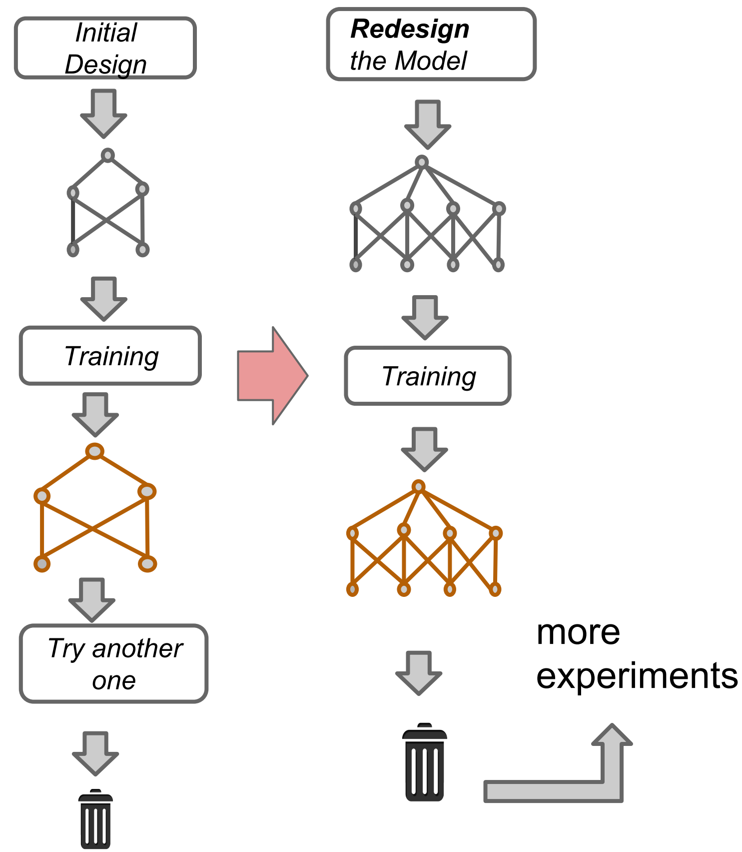
- We usually make a ***wider*** / ***deeper*** net
    - As we get more data.
    - As we explore new models.

- Happens in general machine learning as well
    - Best model complexity need to match the dataset size.
    - Model selection problem.

- Ultimate goal: model evolution and continuous learning.

- Can we **reuse** the old model?

The Loop



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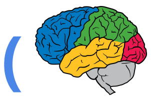
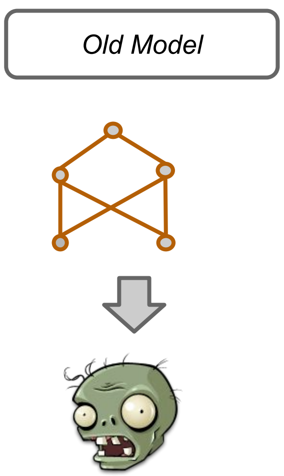
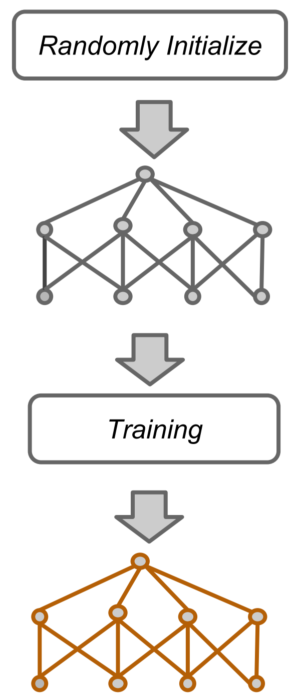
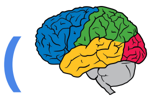
Possible ways to Deal with an Old Net ()

Possible ways to Deal with an Old Net ()

- To Eat (dump the model)
  - Break into proteins.., and rebuild from scratch





Possible ways to Deal with an Old Net ()

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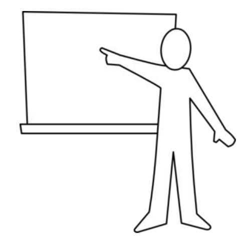
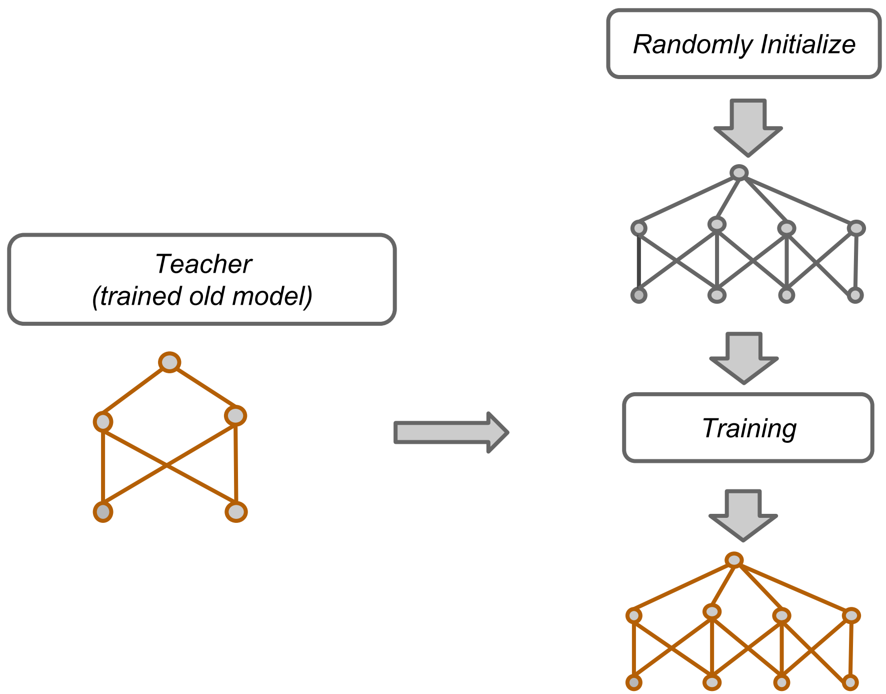
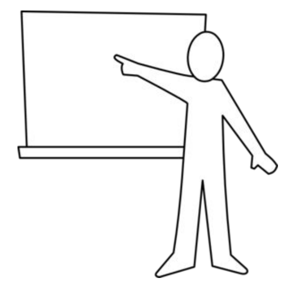
- To Learn from
  - Ask old net to “teach” the new one





Initial Attempt: Learning from Old Model

Ask new model to predict the activations of each layers of teacher model

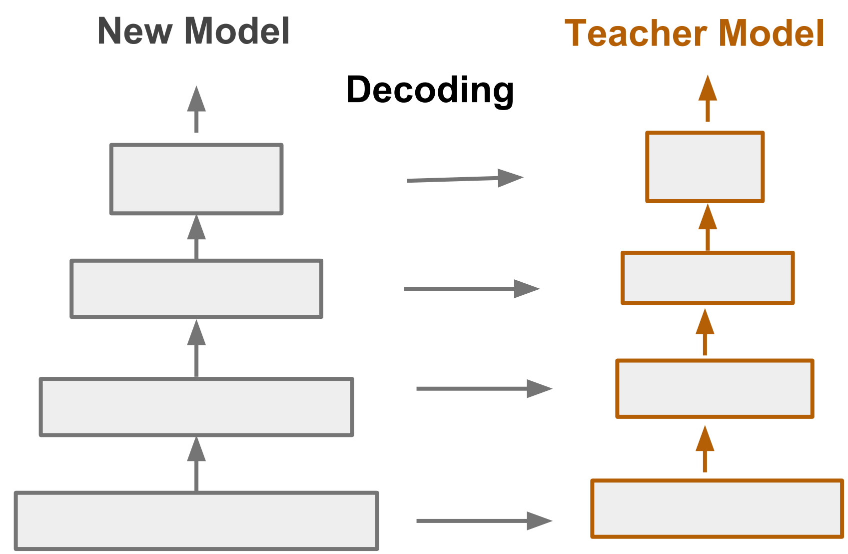


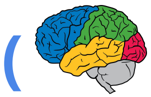
-> Intuition: The new model should be as smart as old ones in each layer

-> This should let us learn lower layers quicker

-> It did not work,
possibly due to too many random initialized components (next slide)

-> It takes time to train a new kid, even with a great teacher...



Possible ways to Deal with an Old Net ()

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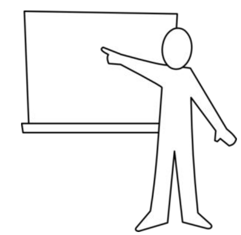
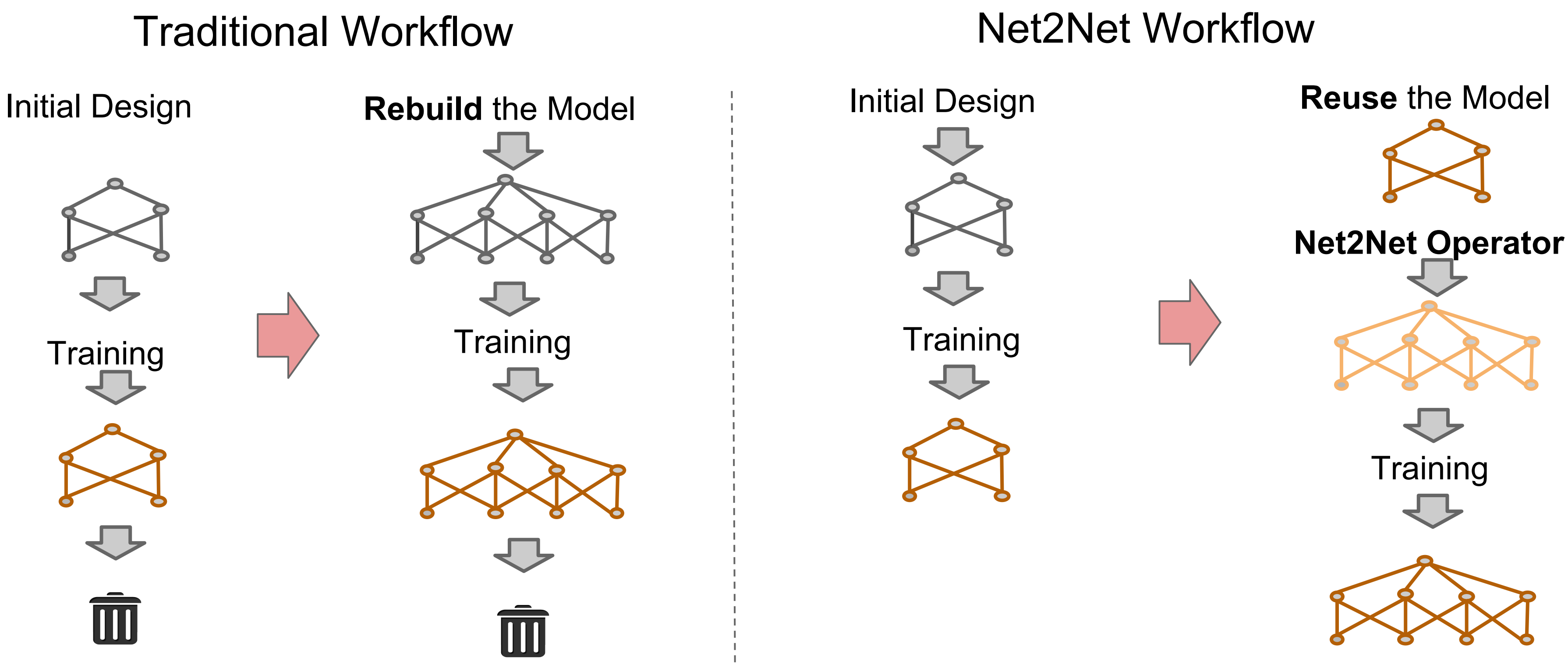


- To Learn from
  - Ask old net to “teach” the new one

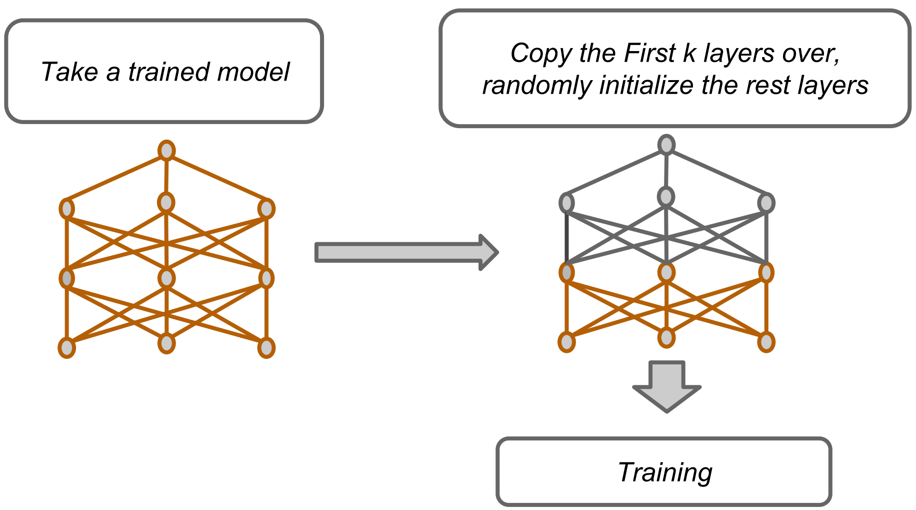
- **Net2Net**
  - Use old model to initialize new model.
  - In another word, transform old net to new one.

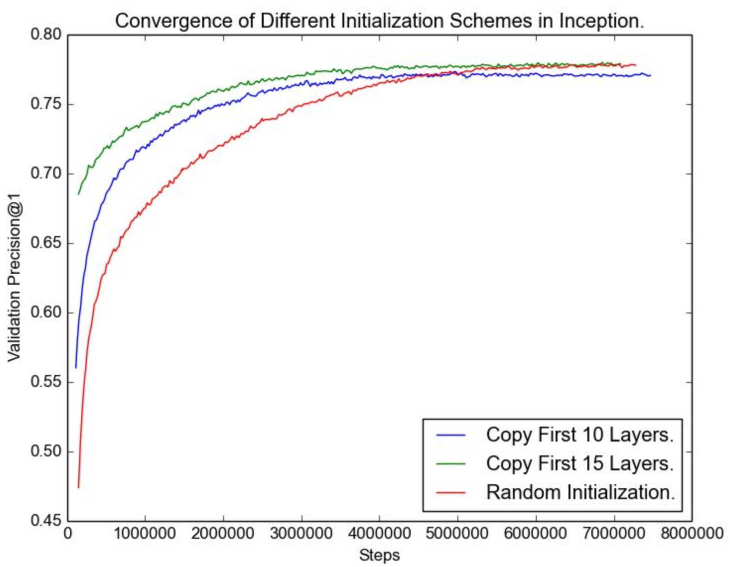
Net2Net Workflow



The Obstacle: (Partial) Random Initialized Components in the Net

Idealized Experiment on ImageNet (Inception-BN) Setup





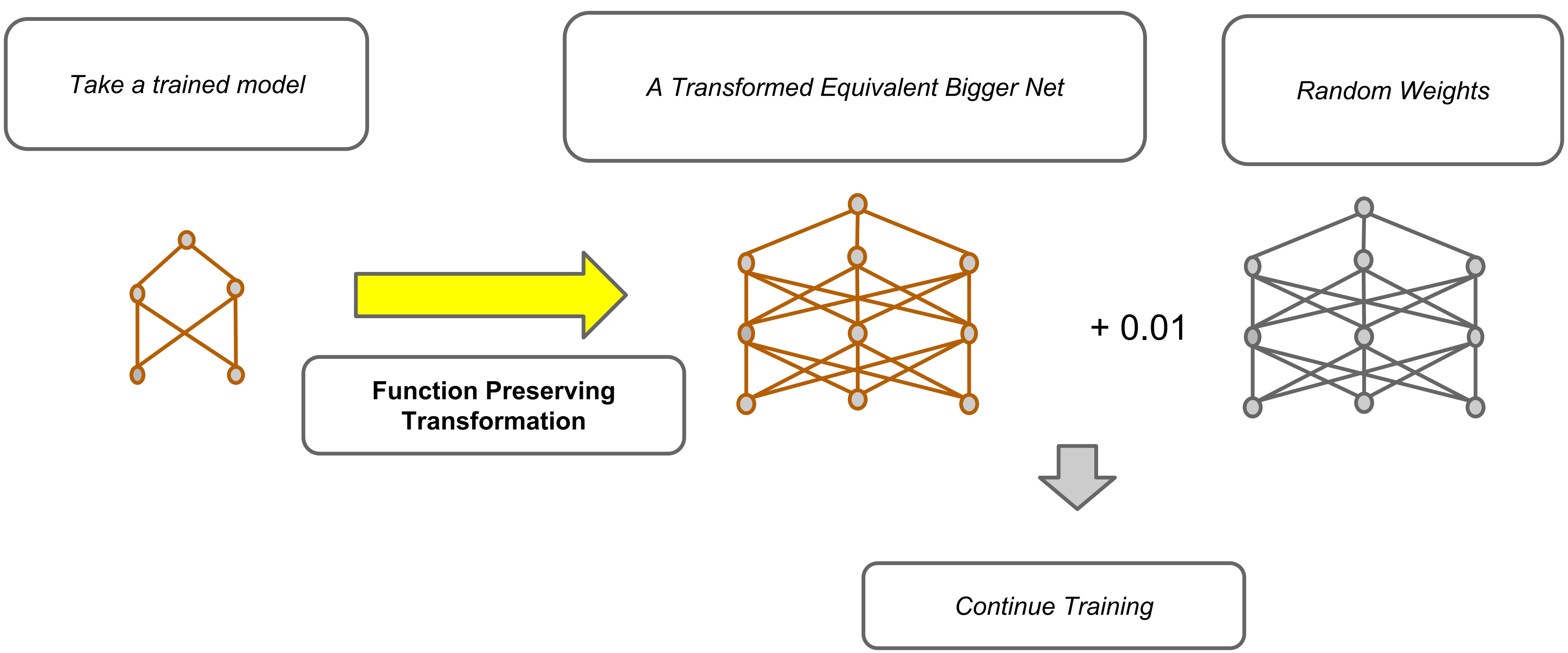
More uninitialized components in the model, -> Less gain we get in initial bootstrap phase

Motivated Solution to the Problem

We want to be *at least as good as* the old model to start with.

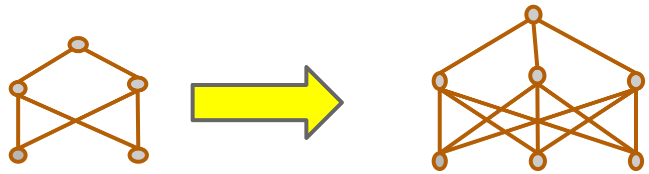
Avoid Adding Randomly Initialized Components

- Transform to bigger net using **Function-preserving Transformations**
- Definition of Function-Preserving Transformation:
    - -> For any inputs, the two nets produces identical outputs

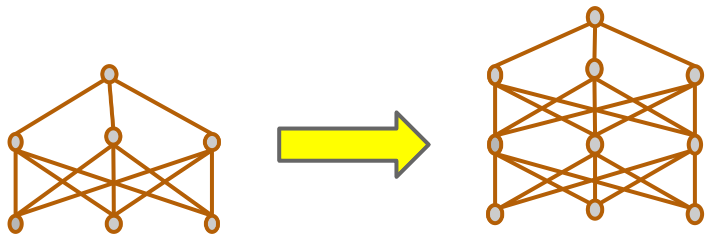


Two Ways to Expand Model Capacity

Net2WiderNet



Net2DeeperNet



Problem

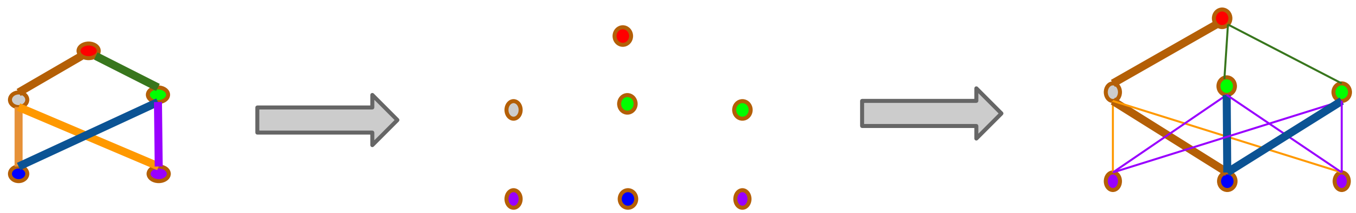
Find Function Preserving Transformations in both cases

Function-Preserving Transformation for Wider Nets

Original Model

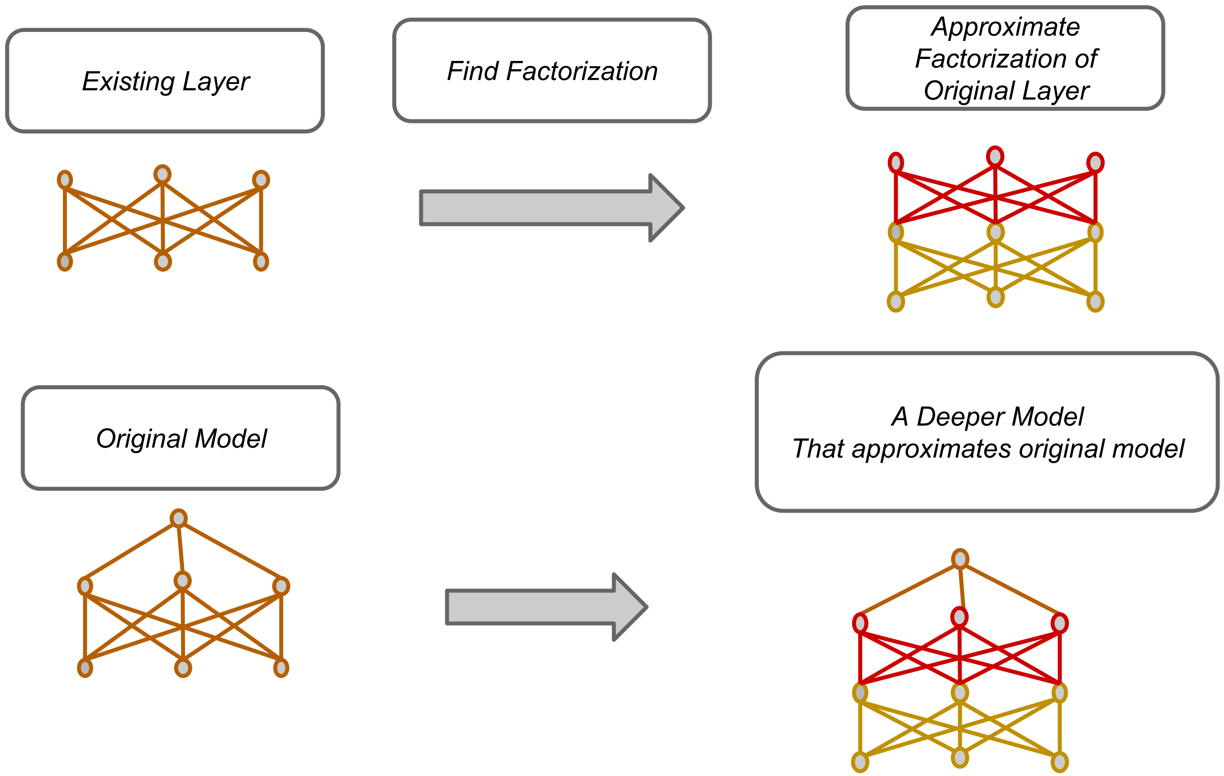
Randomly Remap the Nodes to Wider Model

Connects the weights, divide by duplication factor of input node.

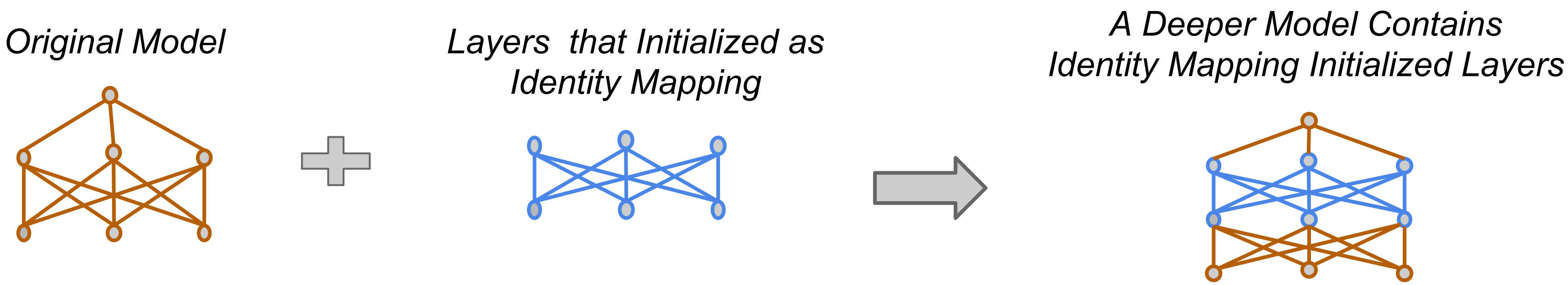


Ready to Apply for ConvNets (Inception)
-> Each node represent a depth channel in feature map

Function-Preserving Transformations for Deeper Nets (General Idea)



Function-Preserving Transformations for Deeper Nets: Add Identity Layer



Function-Preserving Initializations for Common modules in ConvNets

- Convolution: Identity Filter
- Batch Norm: gamma = stdvar, beta = mean
- Batch Norm without rescale
    - beta = mean/stdvar
    - rescale connection in later layer with stdvar

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Experimental Setup

- All the experiments are conducted on Inception model on ImageNet dataset.

- Use smaller learning rate to match end of schedule of source model.

- Terminology:
  - ***Source model*** the trained smaller model
  - ***Target model*** the new model we want to train

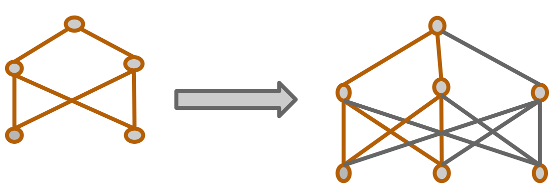
Experiment Results for Net2WiderNet

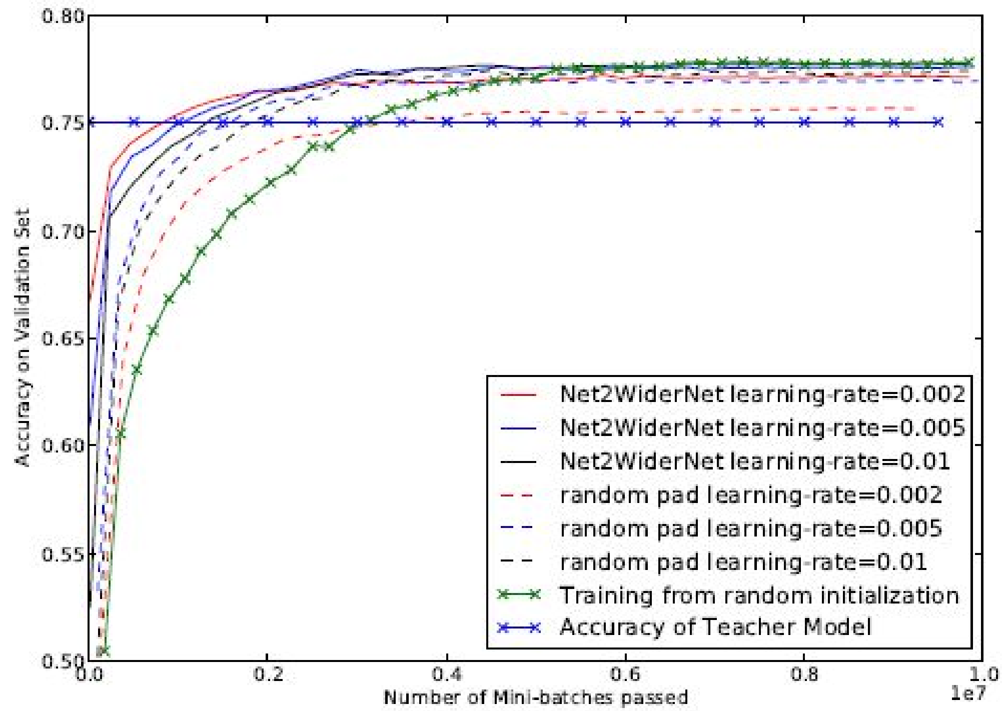
Source An inception with 0.54 number of channels in inception towers as original inception.

Target Standard Inception.

Baseline

Copy part of nets, randomly initialize rest



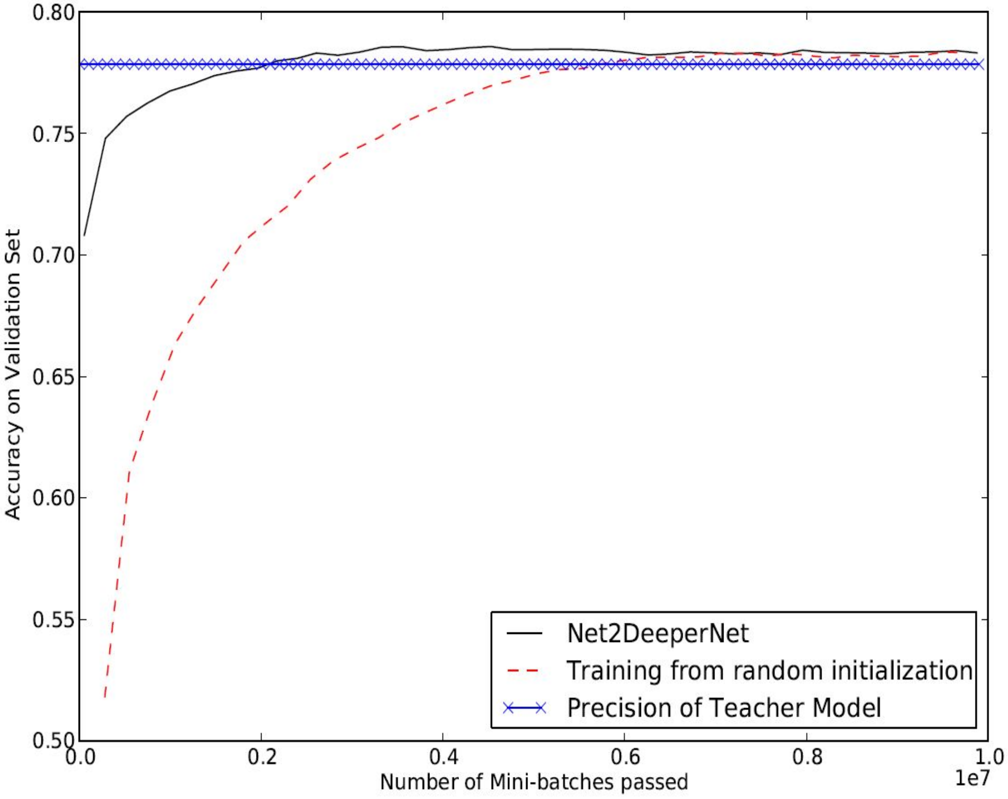


Experiment Results for Net2DeeperNet

Source Standard Inception

Target
Add four layers of conv to each inception tower

Baseline
Training from random initialization



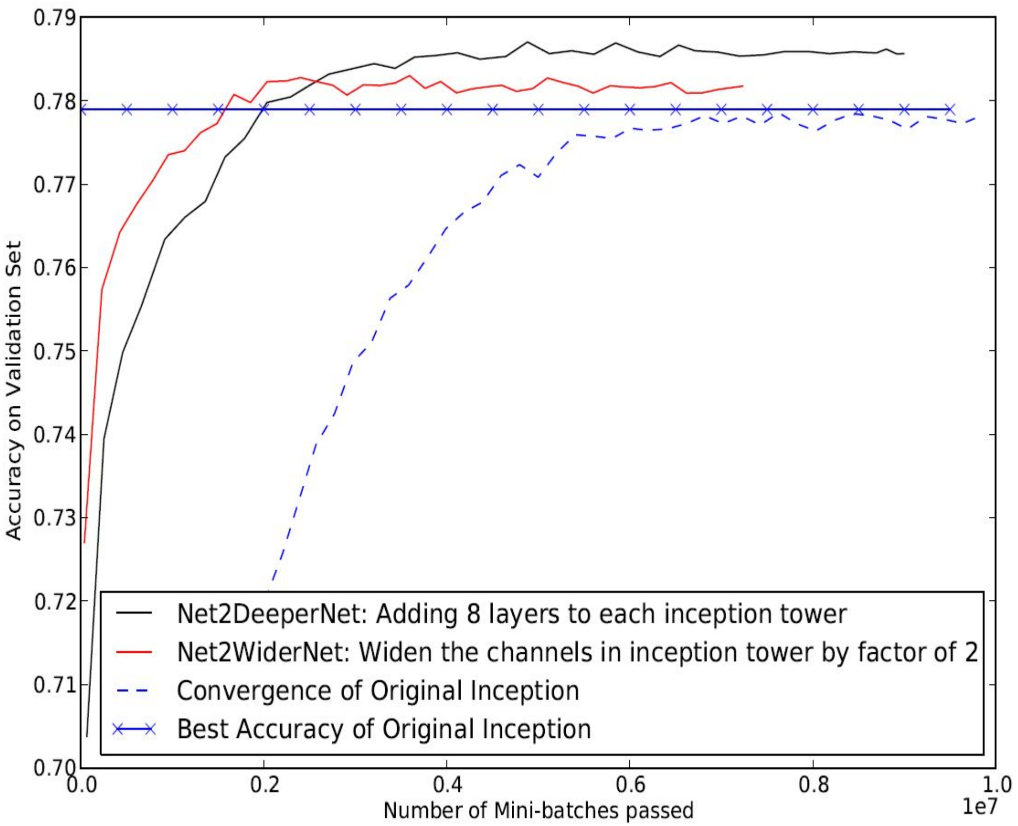
Exploring New Design Space

Source Standard Inception Model

Targets

- Wider Inception: increase channels by 2 times

- Deeper Inception: add 8 identity conv to each inception tower



Take-aways

- It is possible to reuse the existing model help training bigger models.

- Avoid adding random components.

- Use Function-preserving transformation

- Use smaller learning rate when continue training.

- LearningModel Evolution

Thank You