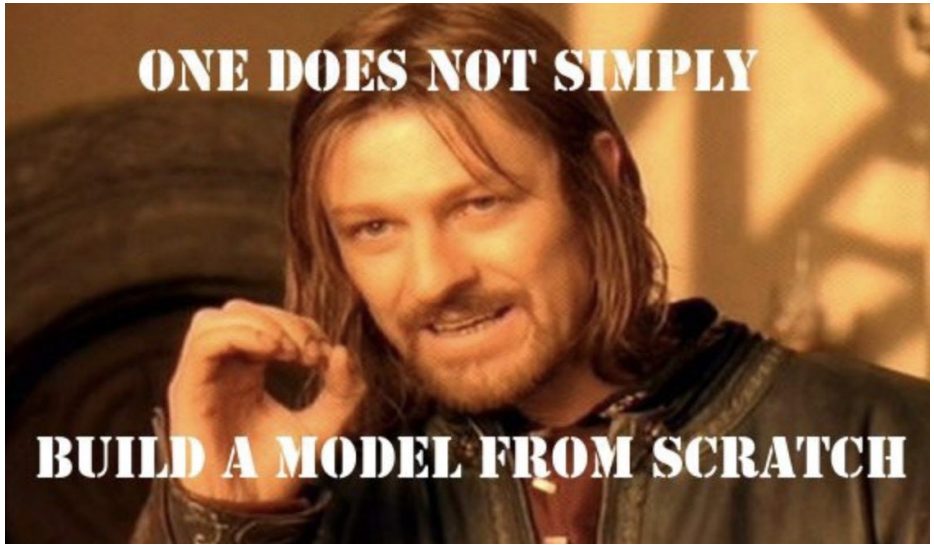
Tutorial: Best Practices of CNNs

Neural Networks and Deep Learning February 20, 2025

What we'll cover

- Transfer Learning
- Label Imbalance
- Normalization

Transfer Learning

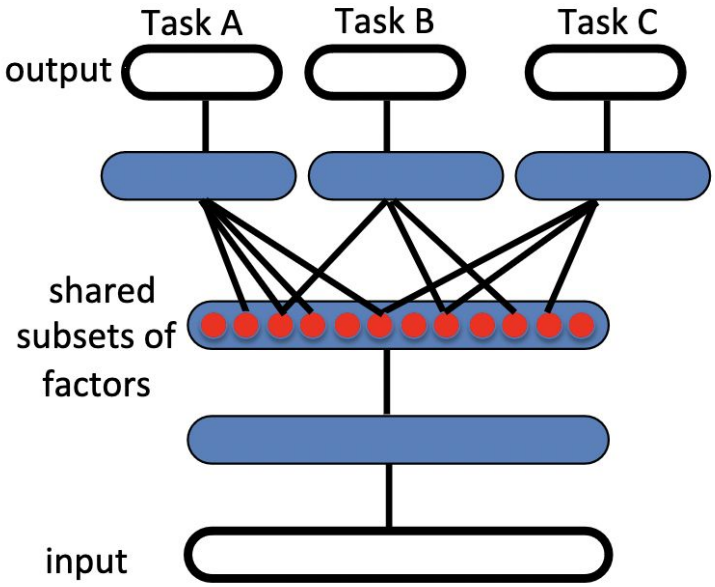

ONE DOES NOT SIMPLY
BUILD A MODEL FROM SCRATCH

Neural Network Feature Embeddings

NNs learn transformations of the data that make it easier to extract useful information for performing a wide range of downstream tasks

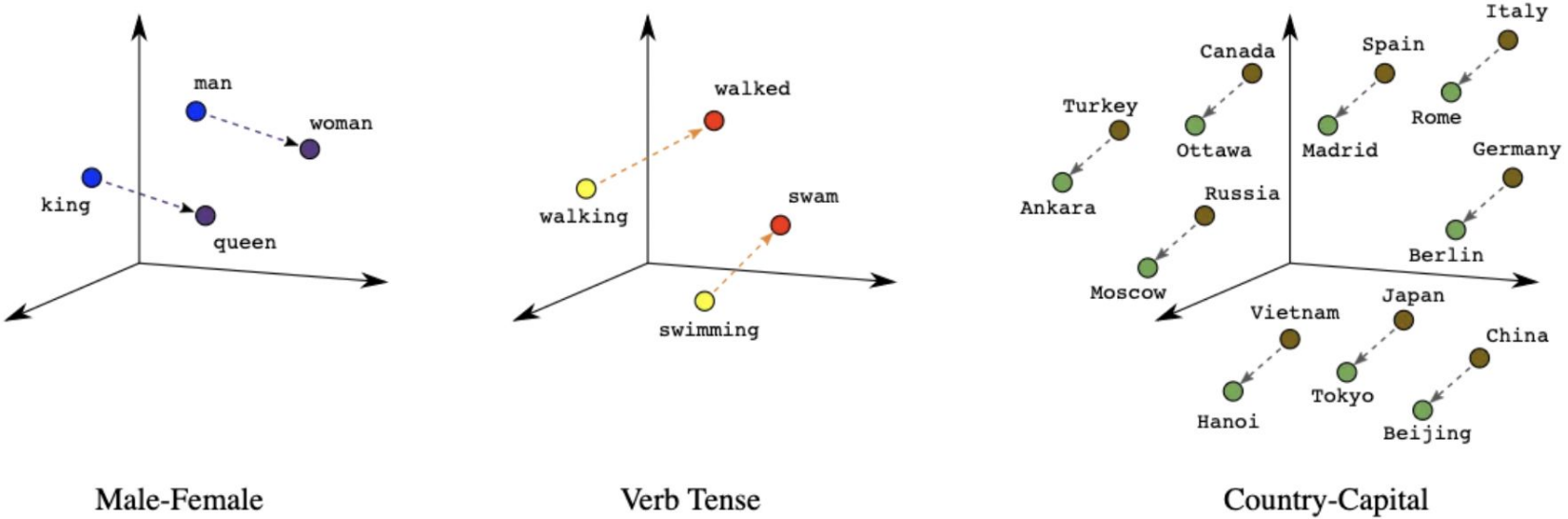
In deep learning, usually:
→representation = last layer before classifier

Desirable traits:
Compression
Distributed
Clustered
Invariant



Bengio et al. (2013)

Visualizing the Representation Space



Male-Female Verb Tense Country-Capital

Image Source: (Embeddings: Translating to a Lower-Dimensional Space) by Google.

- What is it?

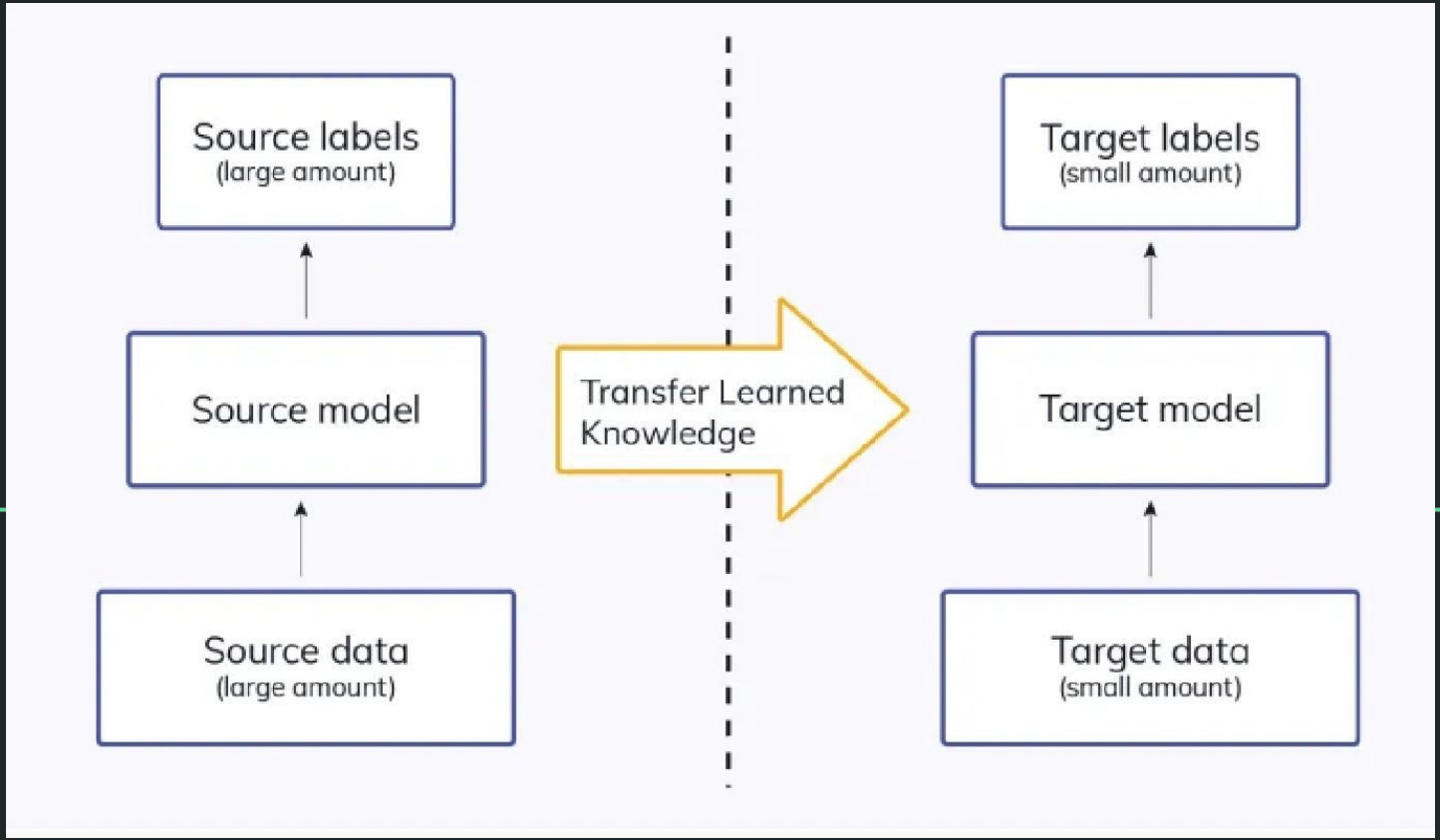
Pre-trained models are used as the starting point for a model on a second task.

- Why do we need it?

Small datasets may cause overfitting or bias.

- When is it useful?

This turns out to be very useful when the **training dataset** and the **computing power** both are limited. It helps improve **generalization** too.


Source labels
(large amount)
Source model
Source data
(large amount)
Transfer Learned
Knowledge
Target labels
(small amount)
Target model
Target data
(small amount)

Transfer Learning Scenarios

- $\mathbf{X_S \neq X_T}$: The feature spaces of the source and target domain are different.
- $\mathbf{P(X_S) \neq P(X_T)}$: The marginal probability distributions of source and target domain are different.
- $y_S \neq y_T$: The label spaces between the two tasks are different.
- $\mathbf{P(}y_S\mathbf{|X_S) \neq P(}y_T\mathbf{|X_T)}$: The conditional probability distributions of the source and target tasks are different.

What's transferred?

- **Instance**: Utilize training instances from the source domain for improvements in the target task.
- **Feature Representation**: Identifying good feature representations that can be utilized from the source to target domains.
- **Parameters**: Assumption that the models for related tasks share some parameters or prior distribution of hyperparameters.
- **Relational-Knowledge**: Deals with data, where each data point has a relationship with other data points.

Supervised Pretraining Examples

Training data

Test domains

MNIST

USPS

SVHN

Training data (GTA)

Test data (real world)

Self-supervised Pretraining Examples

Input: a diverse range of input examples (possibly from many environments)

Test distributions: a range of related, but not identical tasks

What do you do with the layers of the Source Model?

Freeze or Fine-Tune?

The bottom *n* layers can be frozen or fine-tuned.

Learning rates can be played around with to find a trade-off between freezing a layer or fine tuning it.

Why not use the same learning rate?

Same can’t be used because it caters to different kind of data and model.

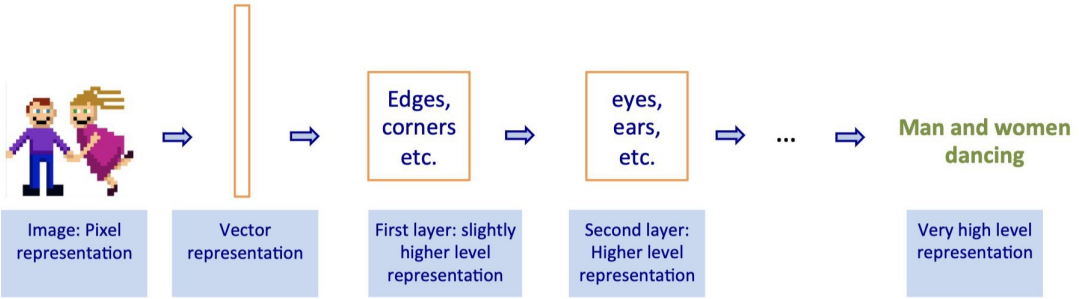
Smaller learning rates fine-tunes better but might take longer.

Larger learning rates can deviate the model from its learnt weights, thus making it forget what it previously learnt.

Why does Fine-tuning work?

The initial layers learn generic information - not target specific. These can be frozen since this generic information is still needed and in the same capacity.
Deeper layers are more problem/target specific. They can be fine-tuned to fit the particular needs of the problem at hand.

How the Network Works



Transfer Learning: Rule of Thumb

	Target Dataset is small	Target Dataset is large
Similar to Source dataset	**Freeze**	**Fine-tune many**
Dissimilar to Source dataset	**Train SVM from low-level features first**	**Train from scratch**

Transfer Learning from ImageNet

When dealing with a classification model, a good choice of a random source dataset to begin with is **ImageNet**.

ImageNet properties:

- 130M images
- Hierarchical labels (eg: Vehicle: Planes, etc)
- Can be used for object detection
- More than 20k categories (labels)

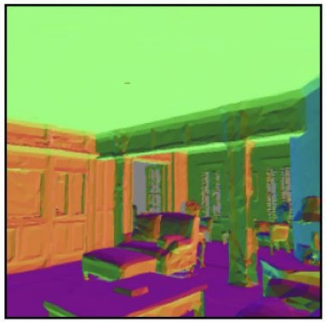
(for more details and to participate - ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

Task Transfer Learning

- Same domain, different tasks
- Task relationships exist
- Can be computationally measured
- Tasks belonging to a structured space

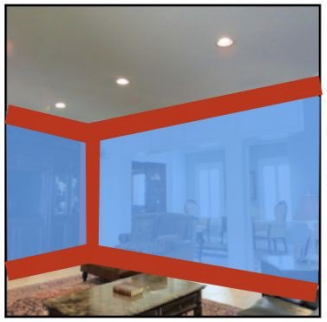
http://taskonomy.stanford.edu/taskonomy_CVPR2018.pdf

derivative



Depth

Normals



spatial prior

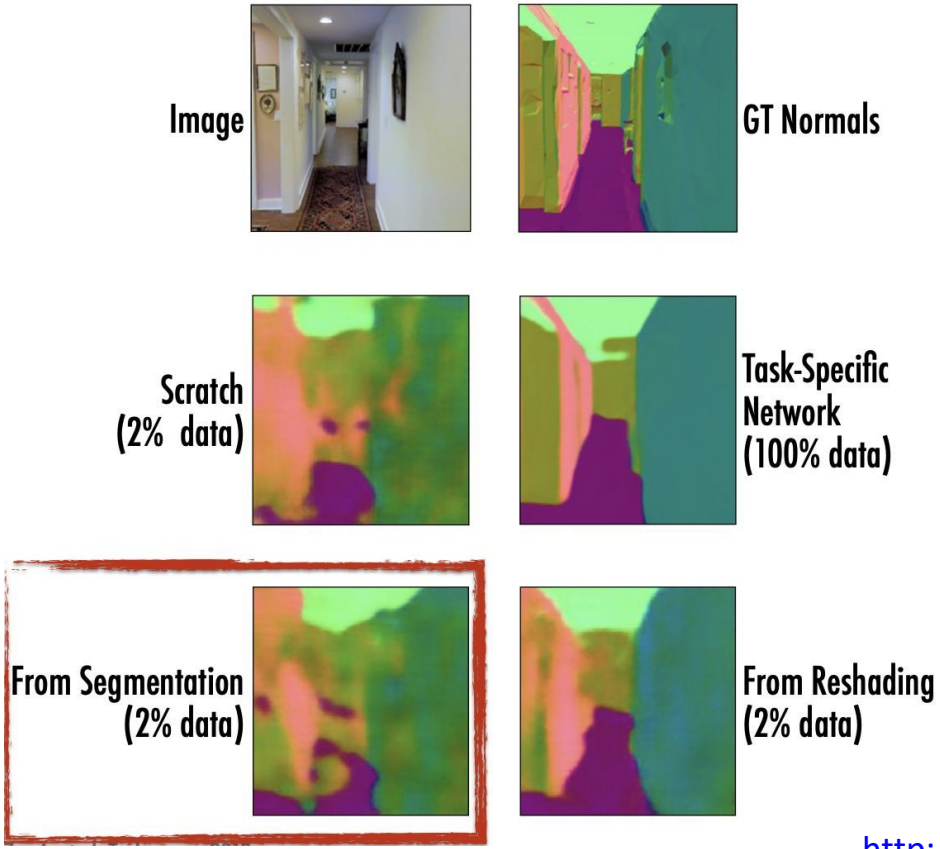
Layout

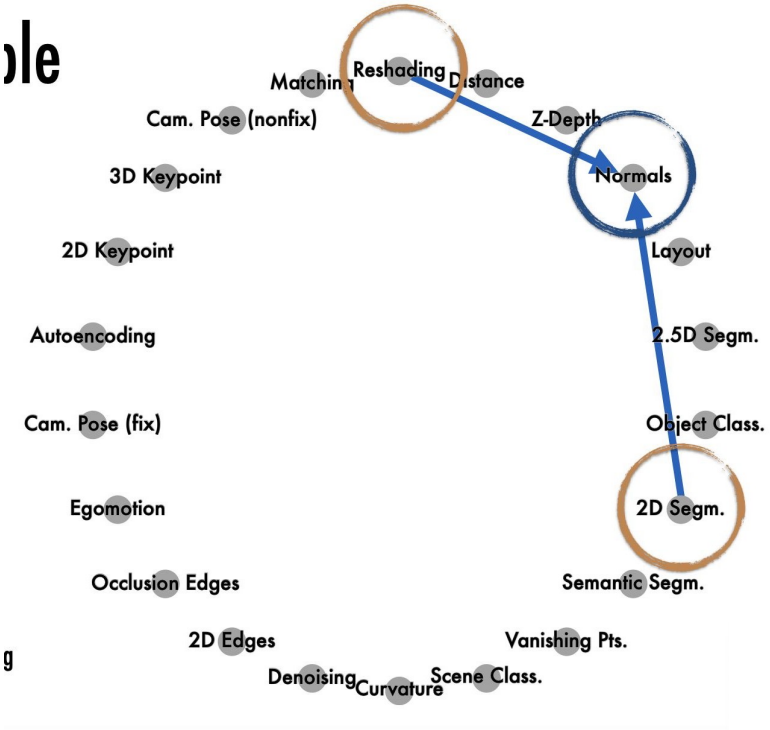
Objects

Image

http://taskonomy.stanford.edu/taskonomy_CVPR2018.pdf

Task Transfer Learning Examples





http://taskonomy.stanford.edu/taskonomy_CVPR2018.pdf

Disadvantages of Transfer Learning

- Negative transfer
- It’s very hard to get it right but very easy to mess up!

Label Imbalance

What is it?

Data where the classes are not represented equally. **Why is this bad?**

Model doesn’t have enough data to learn relationship between features and each class properly.

Example: Detection of cancer or anomaly detection in general, spam filtering

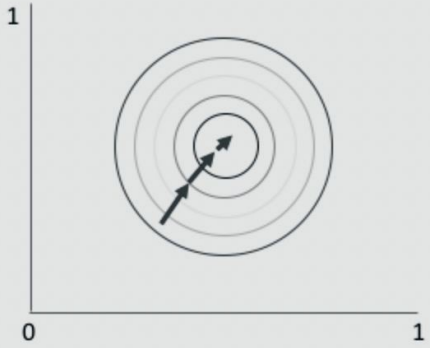
How do we fix this?

- Resampling the dataset
  - Adding copies of instances from the under-represented class called over-sampling
  - Deleting instances from the over-represented class, called under-sampling.
- Reweight the loss by class ratio
- Batch Sampling

Normalization

Why normalize?

Gradient of larger parameter dominates the update



Both parameters can be updated in equal proportions

Types of Normalization

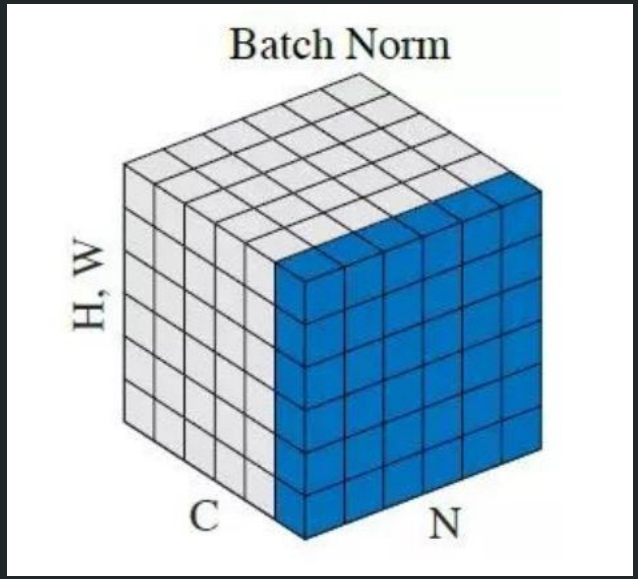
- Batch normalization
- Layer normalization
- Instance normalization
- Group normalization

Batch Normalization

Scales the inputs to a layer to a common value for every mini-batch during the training of deep neural networks.

The network trains faster!

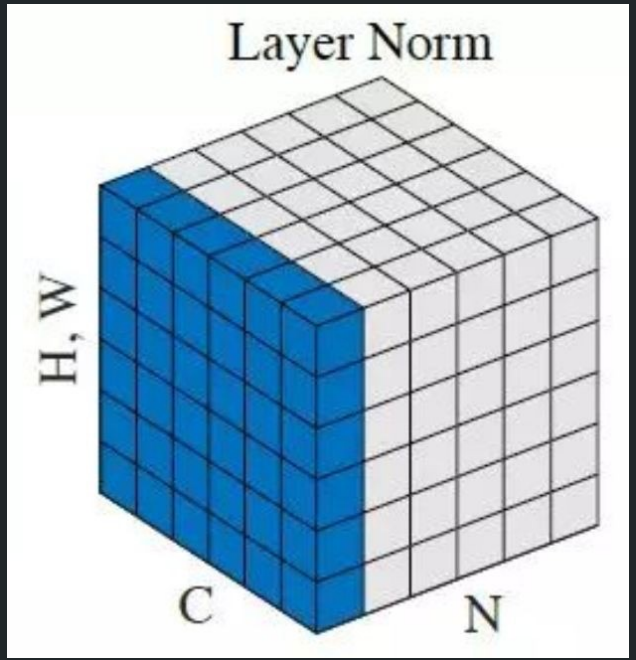
N books
C pages / book
H*W words / page



Layer Normalization

Normalizes the summed input across the features.

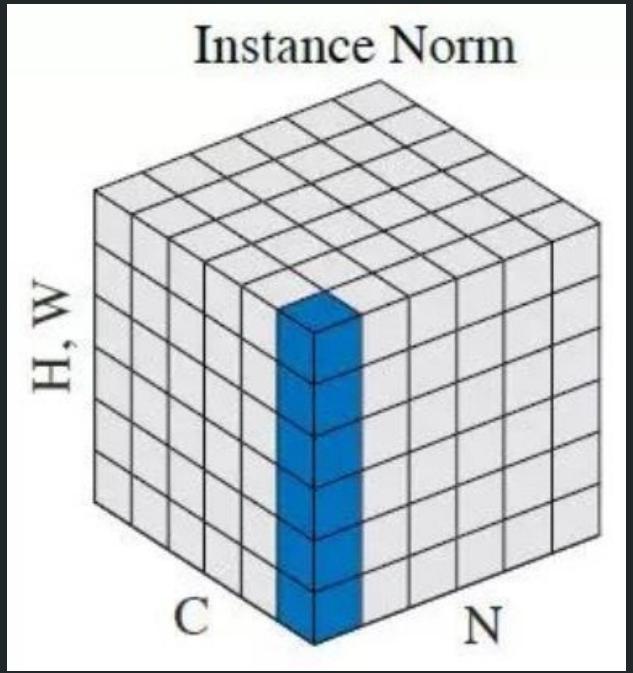
N books
C pages / book
H*W words / page



Instance Normalization

Normalizes across each channel of the training data

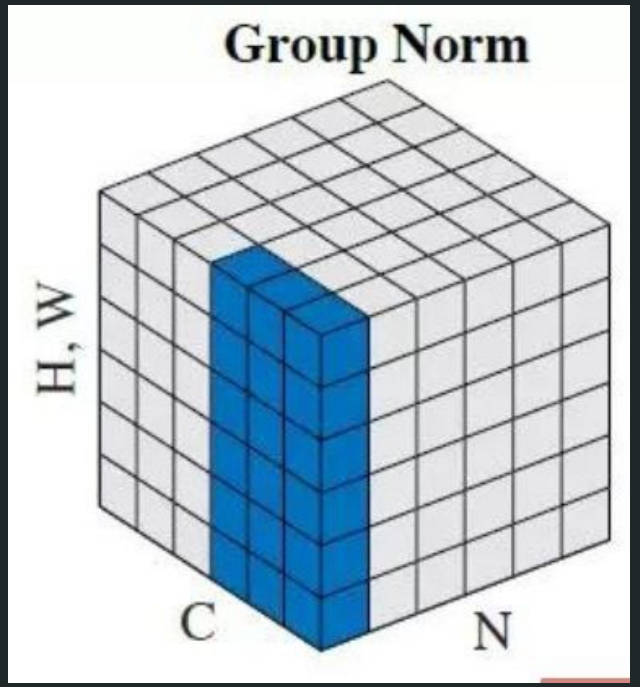
N books
C pages / book
H*W words / page



Group Normalization

Divides the channels into groups and normalizes them for each training example

N books
C pages / book
H*W words / page



Batch Normalization Disadvantages

- With a batch size of 1, the variance would be 0 (x_{norm}=x), which defeats the purpose, and batch normalization wouldn't work.

$$x_{normalized} = \frac{x - m}{s}$$

- Increased training time, extra computation
- Different results for training and test

Thank you!