Computer Vision

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Learning Outcomes

- Implement efficient data handling techniques using PyTorch's Dataset and DataLoader classes
- Apply appropriate data augmentation strategies based on error analysis
- Utilize transfer learning effectively for different scenarios and dataset sizes
- Understand ensemble methods to improve model performance
- Apply regularization techniques like Dropout and Batch Normalization
- Design a complete deep learning training workflow from initial setup to infrence

- Practical Implementation of Deep Learning algorithms is just as much an art as it is a science.
- The main takeaways if not to start from scratch rather to build on top of the previous knowledge.
- Today, we will look at some important tools used in the practical implementation of Deep Learning algorithms.

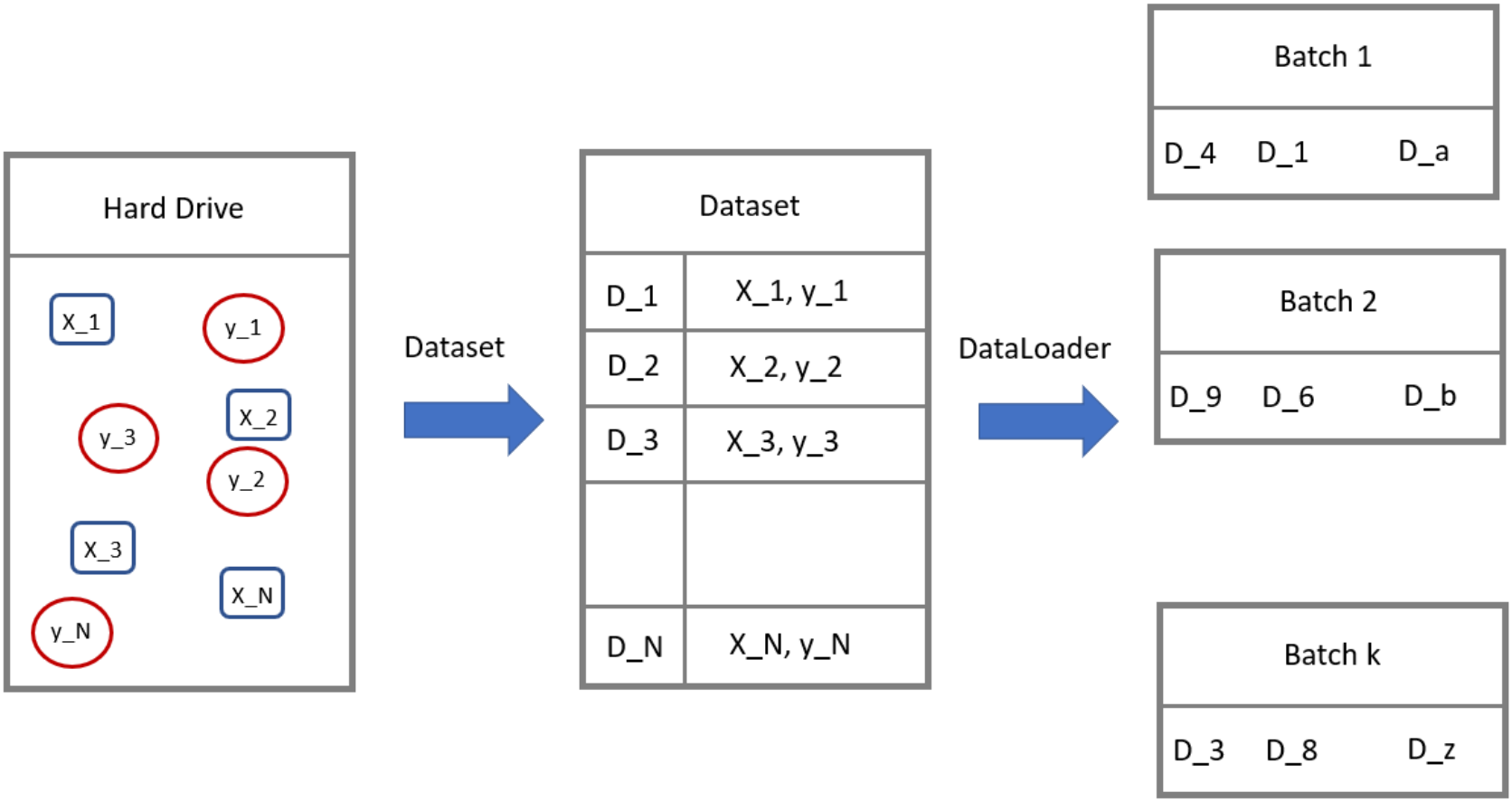
DataLoaders

- As we have previously established that Deep Learning has been made possible by large amount of data and computational resourse
- An important aspect to keep in mind is the data handling:
  - How do we handle large amounts of data?
  - How to we read different components of data (from possible different parts of our hard drive) and provide it to our training algorithms?
  - How do we feed this data to SGD algorthims in a streamlined manner?
- PyTorch provides Dataset and DataLoaders to handle data in an efficient manner.
- We will extend the Dataset and DataLoaders class to construct our own Dataloaders

DataLoaders (cont.)

- Datasets in PyTorch: The `torch.utils.data.Dataset` class is an abstract base class used to define and manage datasets for training and evaluation.
- Custom Dataset Creation: You can create a custom dataset by subclassing `Dataset` and implementing
  - `__len__()` (returns dataset size) and
  - `__getitem__()` (fetches a single data sample).
- DataLoaders for Batching: `torch.utils.data.DataLoader` is used to load data in mini-batches, shuffle data, and utilize multiprocessing for efficiency.
- Built-in Datasets: PyTorch provides datasets in `torchvision.datasets` and `torchtext.datasets`, making it easy to load common datasets like MNIST, CIFAR-10, and IMDB.

DataLoaders (cont.)



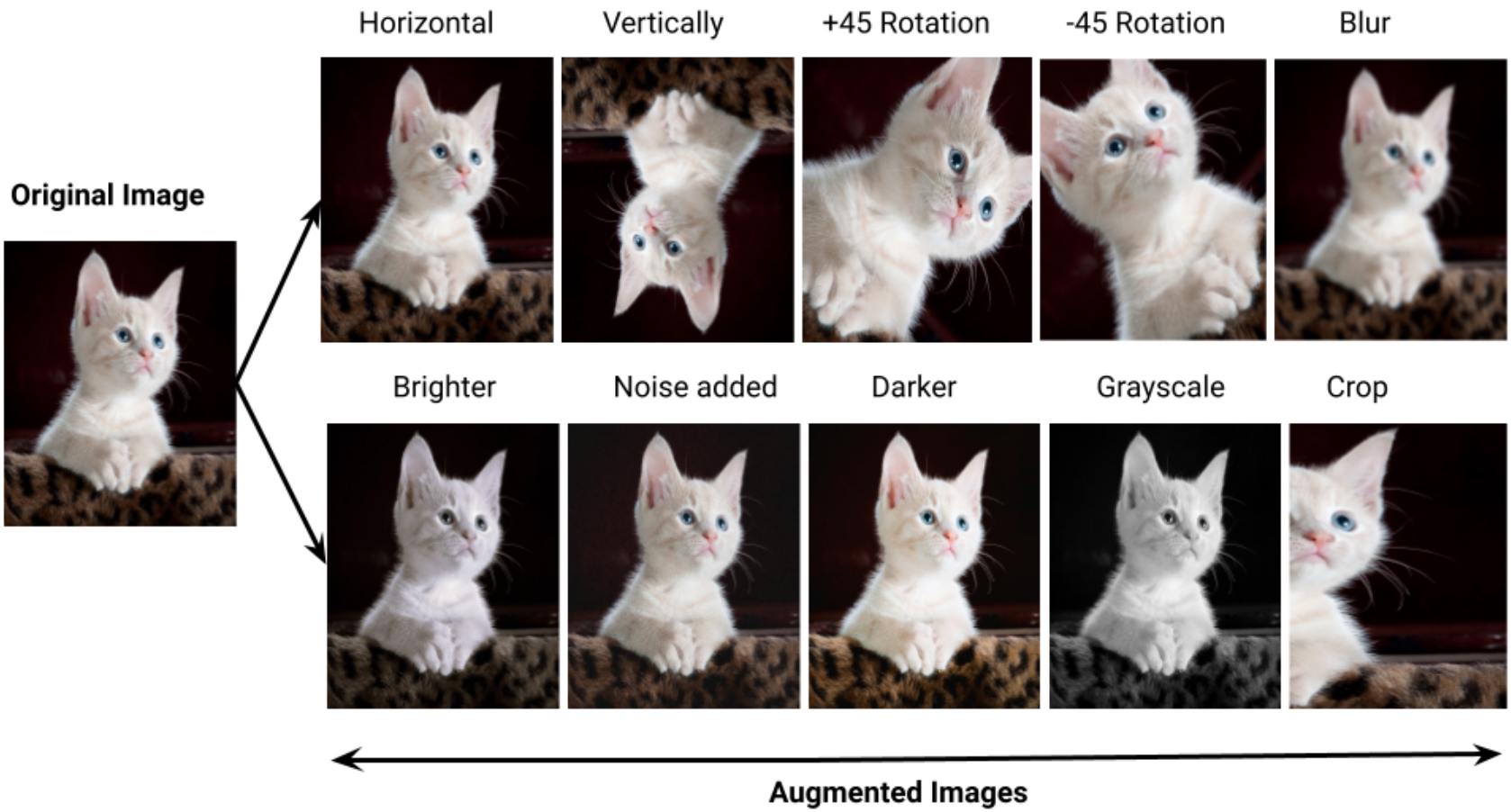
Data Augmentation

- Data is the fundamental building block of any machine learning algorithm
- In several applications we don't have access to unlimited data
- So we use Data Augmentation techniques to improve the preformance of our models
- Note: It is better to spend time on data rather than fine-scale architecture search in deep learning

Data Augmentation (cont.)

- Create virtual training samples
  - Horizontal flip
  - Random crop
  - Color casting
  - Geometric distortion
  - Translation
  - Rotation

Data Augmentation (cont.)



[0] https://pranjal-ostwal.medium.com/data-augmentation-for-computer-vision-b88b818b6010

Data Augmentation (cont.)

[0]To simplify data augmentation, tools like https://github.com/albumentations-team/albumentations

Data Augmentation (cont.)

- But, there are many types of augmentations. How do we choose the right ones for our task?

Data Augmentation (cont.)

- But, there are many types of augmentations. How do we choose the right ones for our task
- **Answer: Error Analysis** – Identify model weaknesses and apply augmentations that address those issues.

Error Analysis for Data Augmentation

- **Steps:**
  1. Train a baseline model.
  2. Make predictions on validation data.
  3. Inspect the worst predictions to identify model weaknesses.
  4. Apply relevant augmentations to address these issues.
- **Examples:**
  - **Failure with small objects** $\rightarrow$ Use *Scale Augmentation*.
  - **Failure with different colors/environments** $\rightarrow$ Use *Color Augmentations*.
  - **Failure with rotated images** $\rightarrow$ Use *Rotation Augmentations*.
  - **Failure with blurry images** $\rightarrow$ Use *Noise Augmentations*.
  - . . . etc.

Data Augmentation

- **Note**: Data augmentation is applied only to the training data.
- Applying it to validation/test data **directly** would lead to **incorrect evaluation and misleading performance metrics**.

Data Augmentation

- However, there is a special inference technique called **Test-Time Augmentation (TTA)** where multiple augmented versions of the same image are passed through the model separately, and the predictions are averaged to improve accuracy.

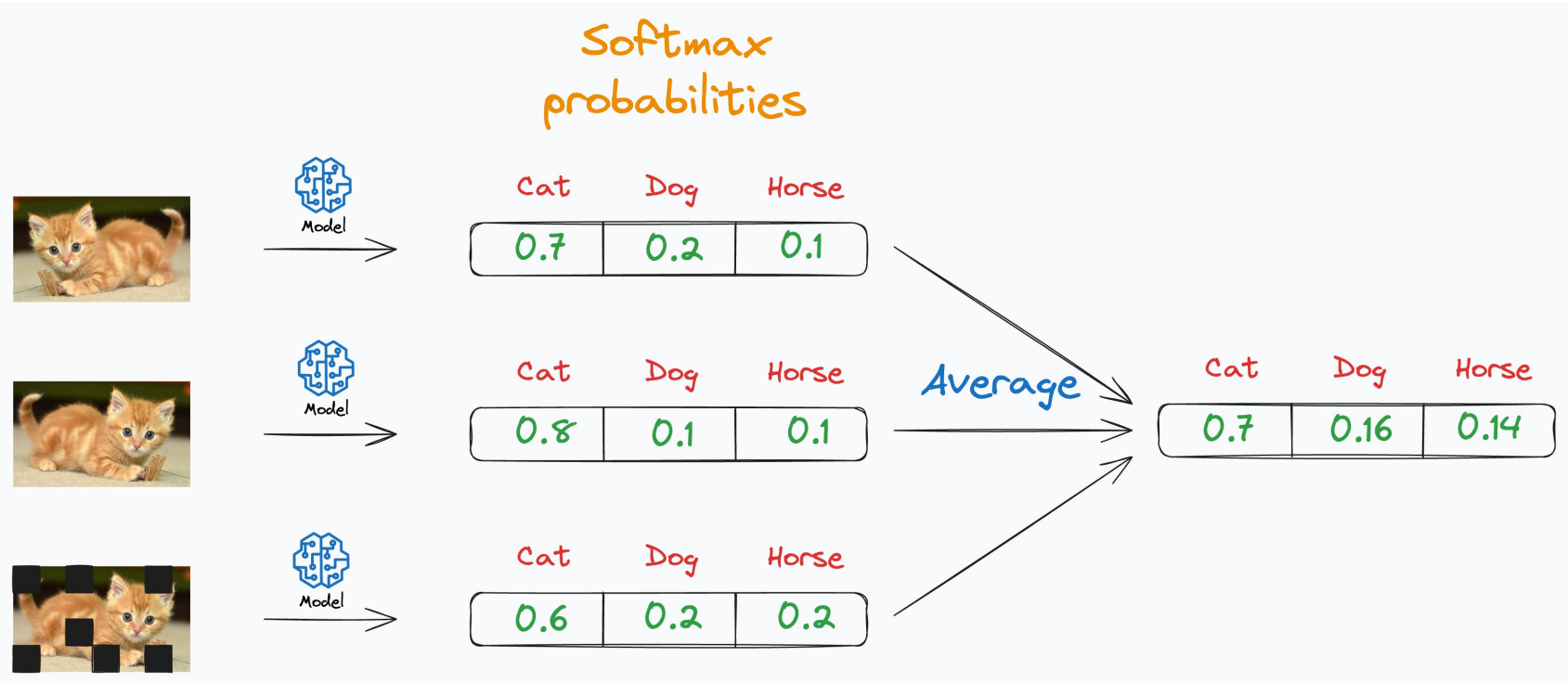


Figure 2: Test-time Augmentation

Data Augmentation

- TTA is an advanced technique.
- Applying it requires **custom scripts** to generate augmented versions of test images, pass them through the model, and aggregate predictions.

- **What is Fine-Tuning?**
  - A strategy in **transfer learning** where a pre-trained model is adapted to a new task.
  - Instead of training from scratch, we start from a model already trained on a related task.
- **Why use Fine-Tuning?**
  - Saves time and computational resources.
  - Improves performance, especially with limited data.

When to fine-tune your model?

- New dataset is small + similar distribution to original dataset:
  - Freeze (or partially freeze) feature extraction layers and fine-tune the classifier.
- New dataset is small + different distribution to original dataset:
  - Use the pretrained network as a generic feature extractor and train a light classifier on top (e.g., SVM).
  - In modern practice, you might also freeze earlier layers and selectively fine-tune later layers.
- New dataset is large, regardless of the original data distribution:
  - Fine-tune the entire network (both features extractor and classifier).

Finetuning

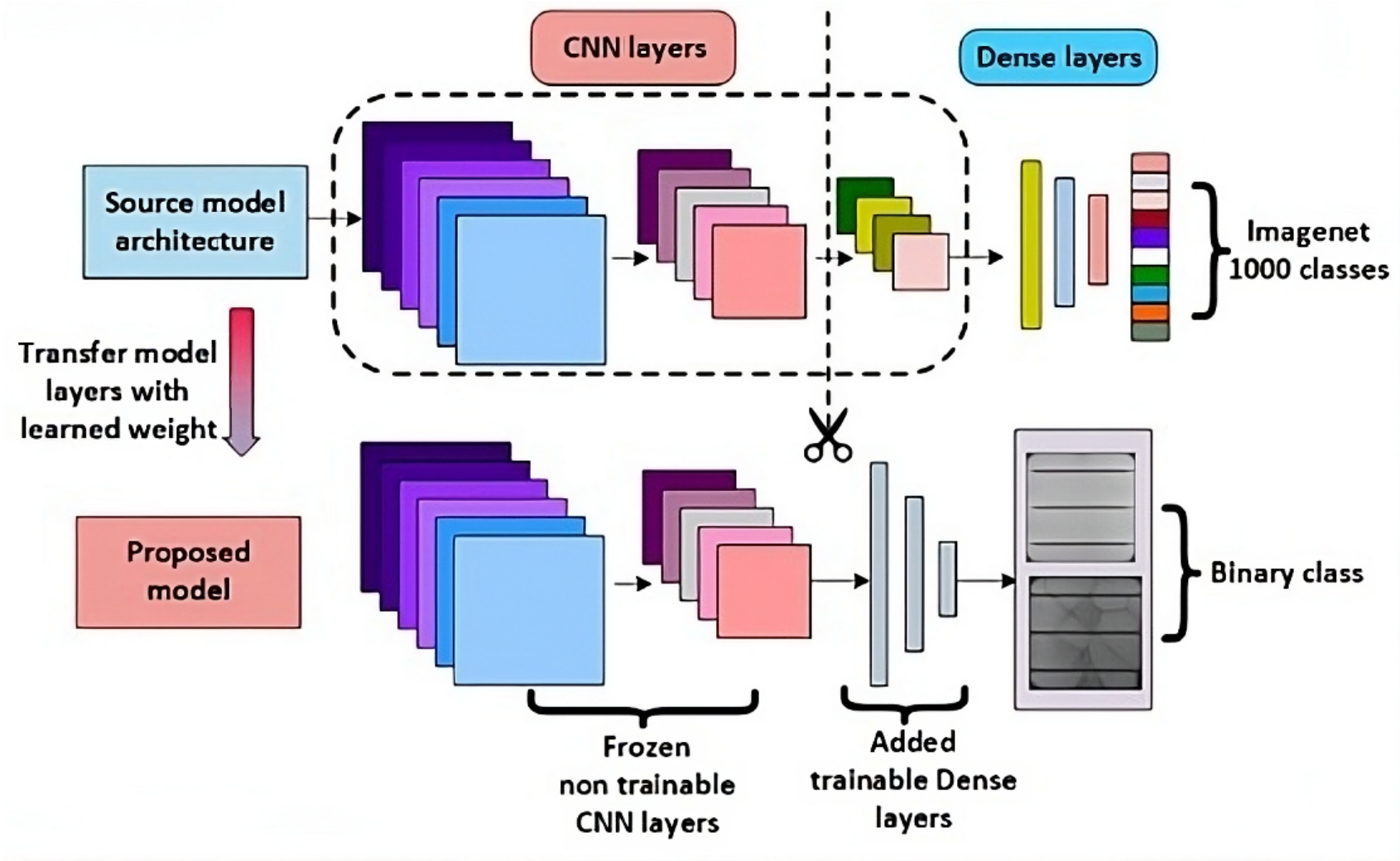


Figure 3: Learning and Transferring Mid-Level Image Representations using Convolutional Neural Networks

Ensembling

- No single model is perfect. Different models make different types of errors.
- Let's visualize the predictions of two different models:

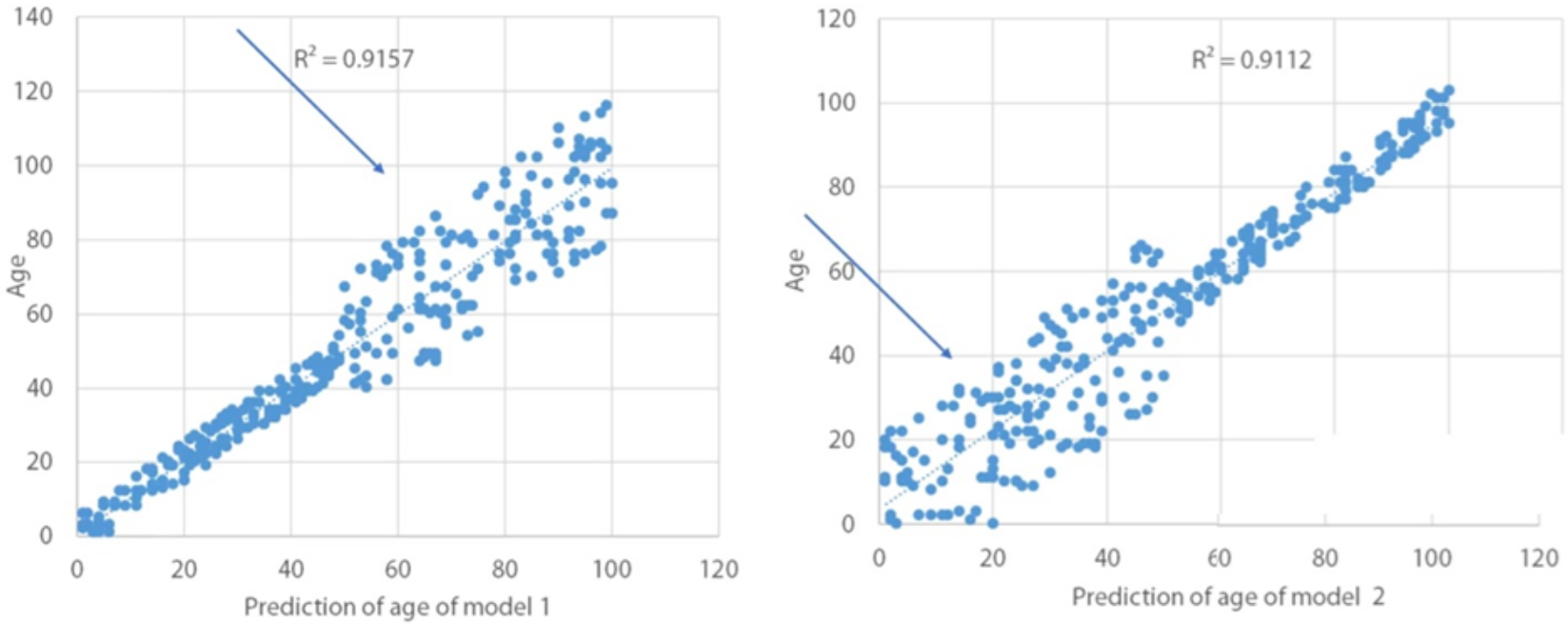


Figure 4: Predictions of Model 1 and Model 2

- Combining predictions of diverse models can reduce errors and improve accuracy. This technique is called **Ensembling**.

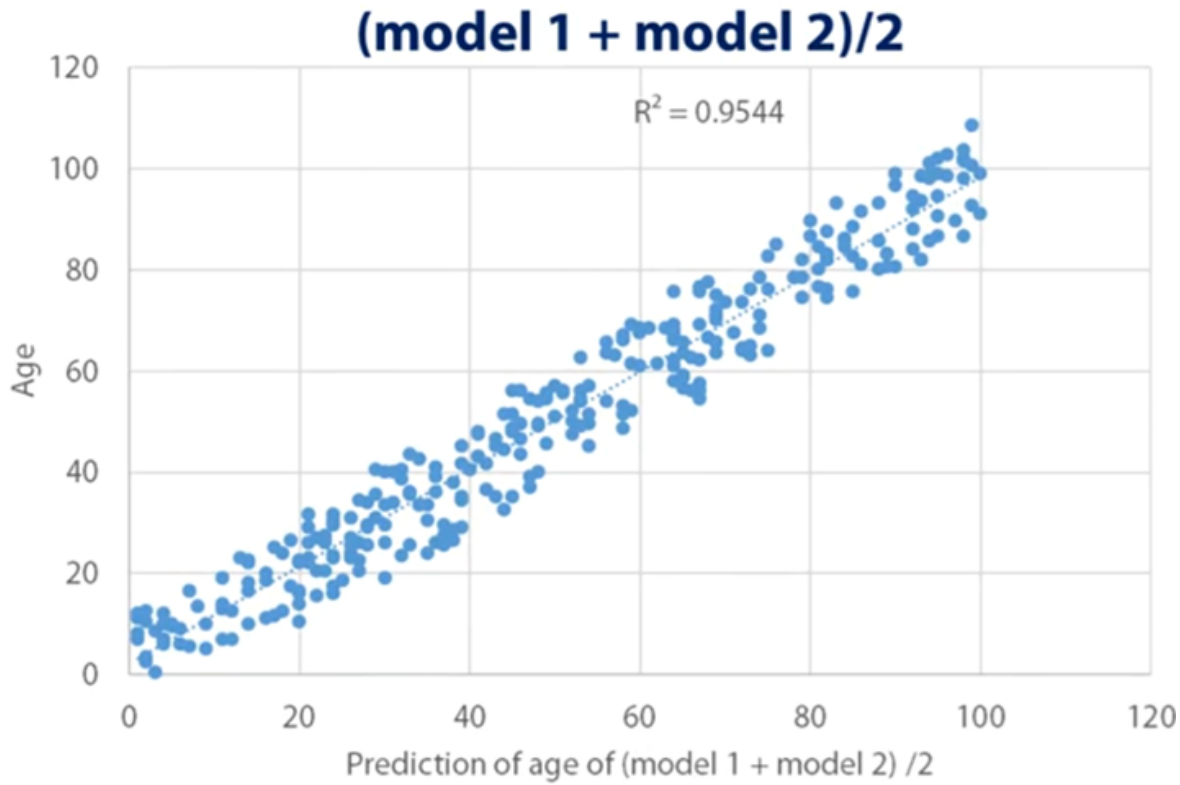


Figure 5: Averaged Predictions: Better Correlation

Ensembling

- Diverse models are key to effective ensembling. Here are two strategies:
  - **Bagging (Bootstrap Aggregating):** Train multiple models on different subsets of data (e.g., Random Forest model).

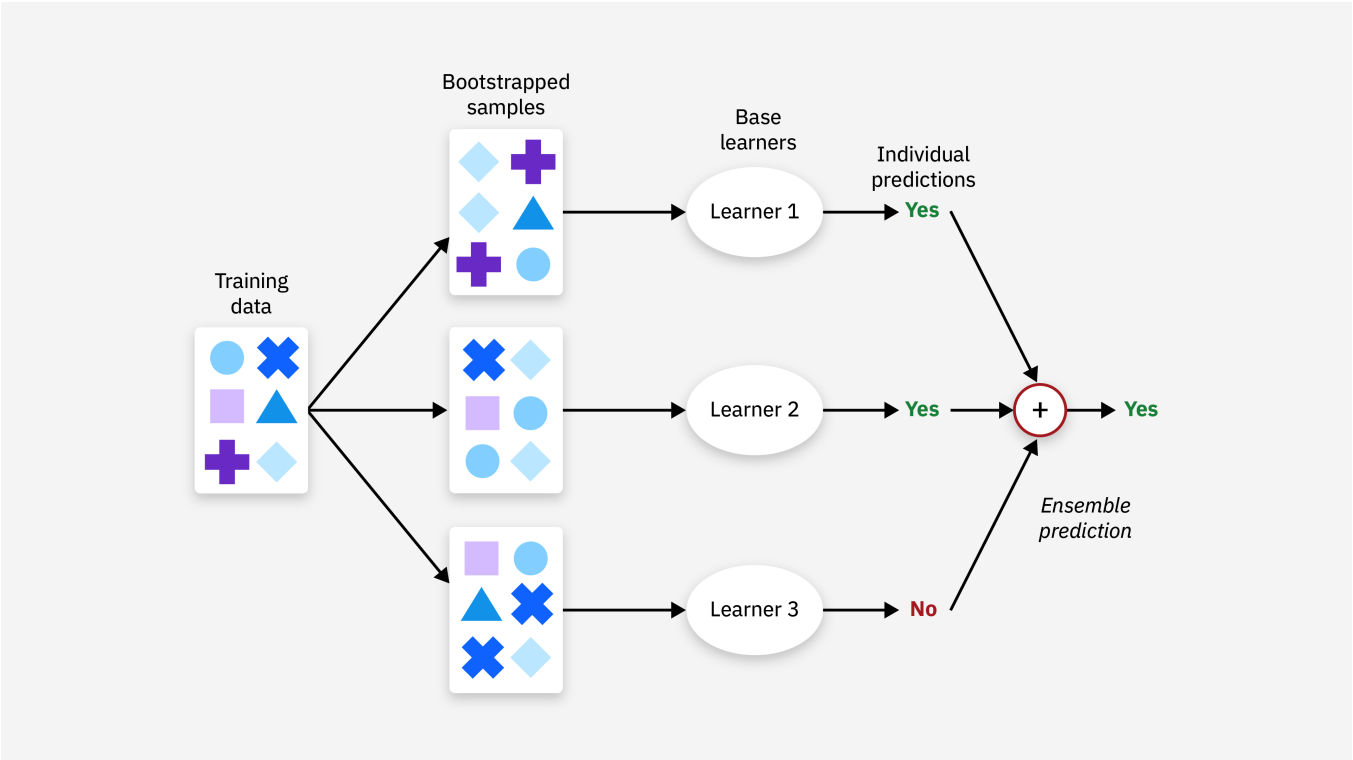


Figure 6: Bagging example

- **Boosting:** Train models sequentially, where each model focuses on the errors of the previous one (e.g., AdaBoost, Gradient Boosting).

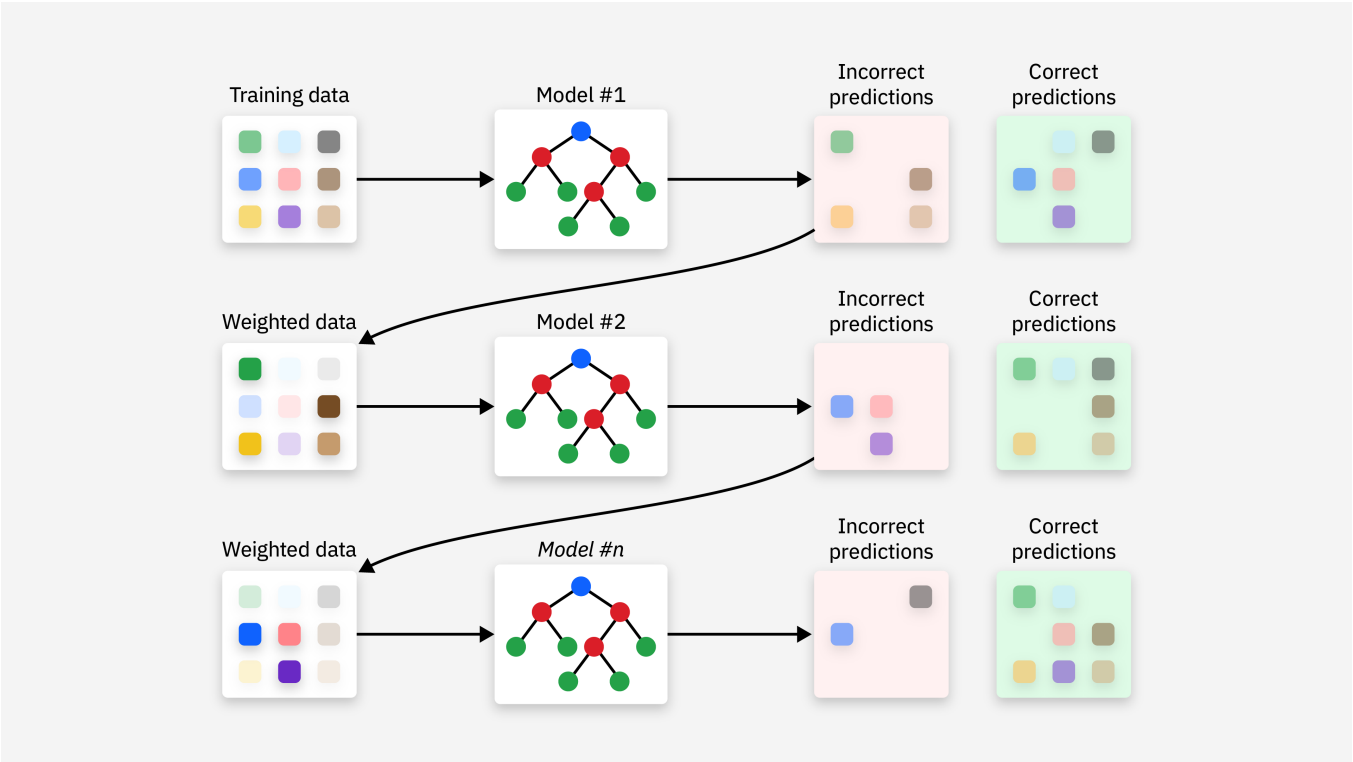


Figure 7: Boosting Example

Ensembling

- These stratigies introduce diversity in models, but how can we combine their predictions?

- We can combine classifiers predictions using two ways:
  - **Hard Voting:**
    - Each model votes for a class.
    - The class with the majority of votes is selected.
  - **Soft Voting:**
    - Average the predicted probabilities from each model.
    - The class with the highest average probability is selected.

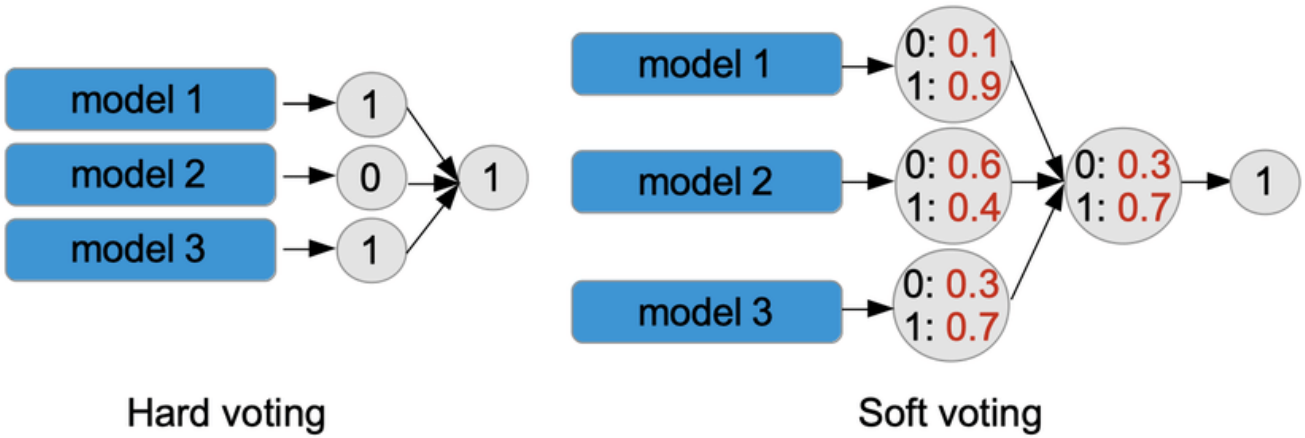


Figure 8: Illustration of Hard and Soft Voting for Classifiers

Ensembling

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  - **Hard Voting:**
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  - **Soft Voting:**
    - Average the predicted probabilities from each model.
    - The class with the highest average probability is selected.
- For regressors:
  - Take the average of predictions from all models.

Ensembling

- Team-work is the best policy.
- We can train multiple networks for the same task then ensemble to get better results.

Ensembling - A simple Analysis

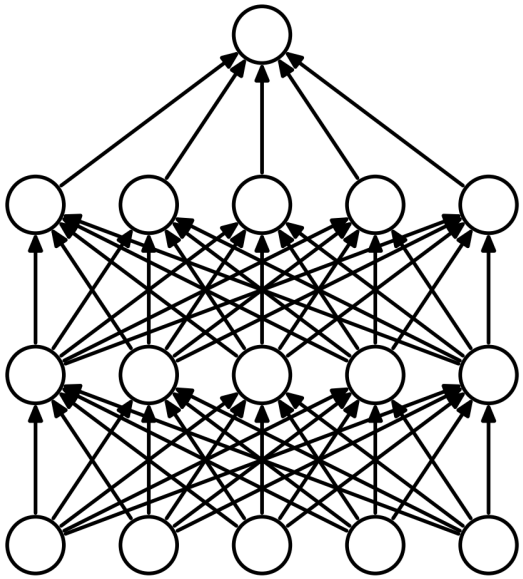
- Let's assume that we have a test dataset with N elements and an ensemble of M models.
- Also assume that the probability of error of the label for an image on a model in the ensemble is denoted by $p(e)$ and is Independent and Identically Distributed (i.i.d)
- For an example assume $M = 3$ and $e = 0.01$
- Then probability of error of label for the max voting ensemble will be

$$p(e) = 1 - (1 - e)^3 - \binom{3}{2}(1 - e)^2 e$$

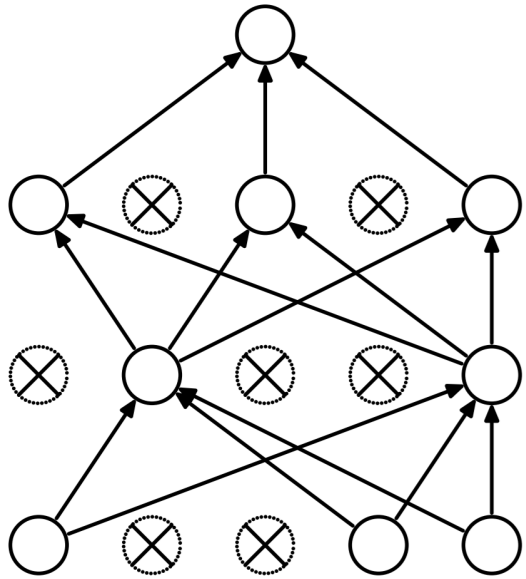
- For the above example $p(e) = 0.0003$, which is significantly lower than a single model

Dropout

- **Dropout** is a regularization technique used to prevent overfitting in neural networks.
- During training, it randomly drops (set to 0) a fraction of neurons in each layer based on a specified probability for every forward pass.



(a) Standard Neural Net



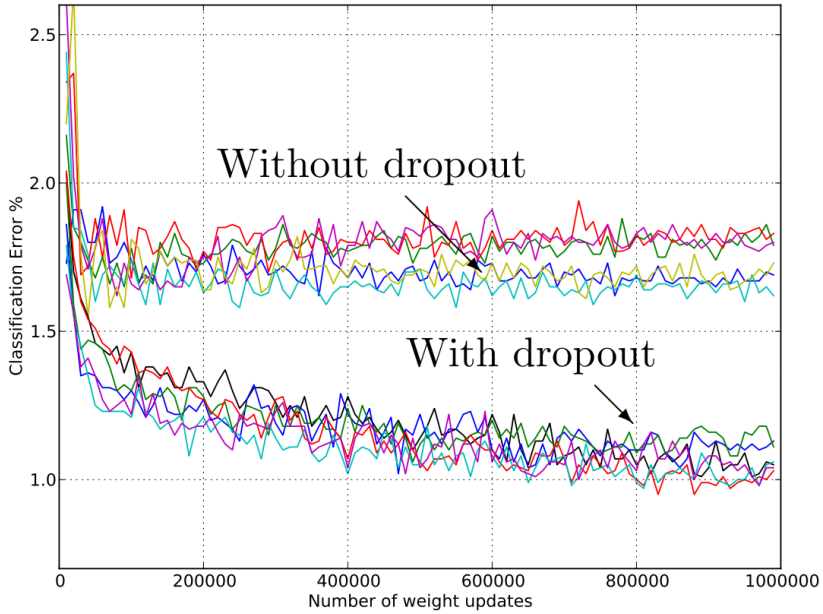
(b) After applying dropout.

[0] Srivastava JMLR 2014

Dropout

- Why is dropping neurons randomly useful?
  1. By dropping a subset of neurons during each forward pass, the network learns **not to rely too heavily on specific connections**, encouraging the network to use more connections.
  2. Dropout acts as an **efficient ensemble** of multiple smaller networks, each trained on a random subset of neurons.
  3. More Connections + Diverse Ensemble = **less overfitting**.

Dropout



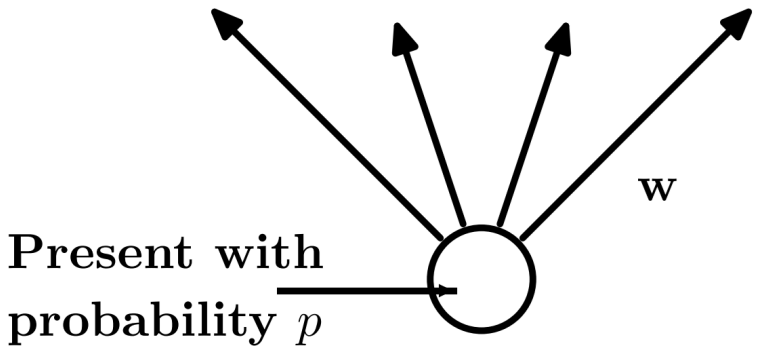
Model	Top-1 (val)	Top-5 (val)	Top-5 (test)
SVM on Fisher Vectors of Dense SIFT and Color Statistics	-	-	27.3
Avg of classifiers over FVs of SIFT, LBP, GIST and CSIFT	-	-	26.2
Conv Net + dropout (Krizhevsky et al., 2012)	40.7	18.2	-
Avg of 5 Conv Nets + dropout (Krizhevsky et al., 2012)	38.1	16.4	16.4

Table 6: Results on the ILSVRC-2012 validation/test set.

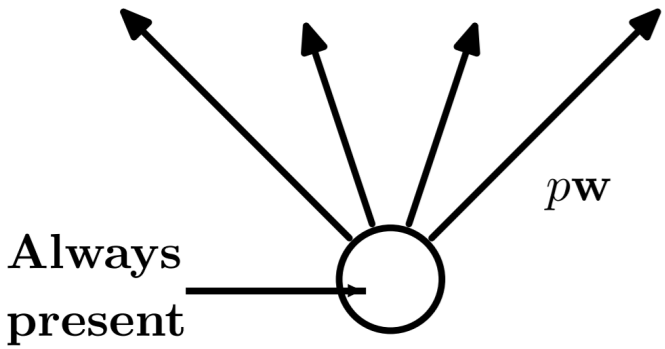
[0] Srivastava JMLR 2014

Dropout

- We drop neurons during training, but what should we do during inference?
- **During inference:** We use all neurons.



(a) At training time

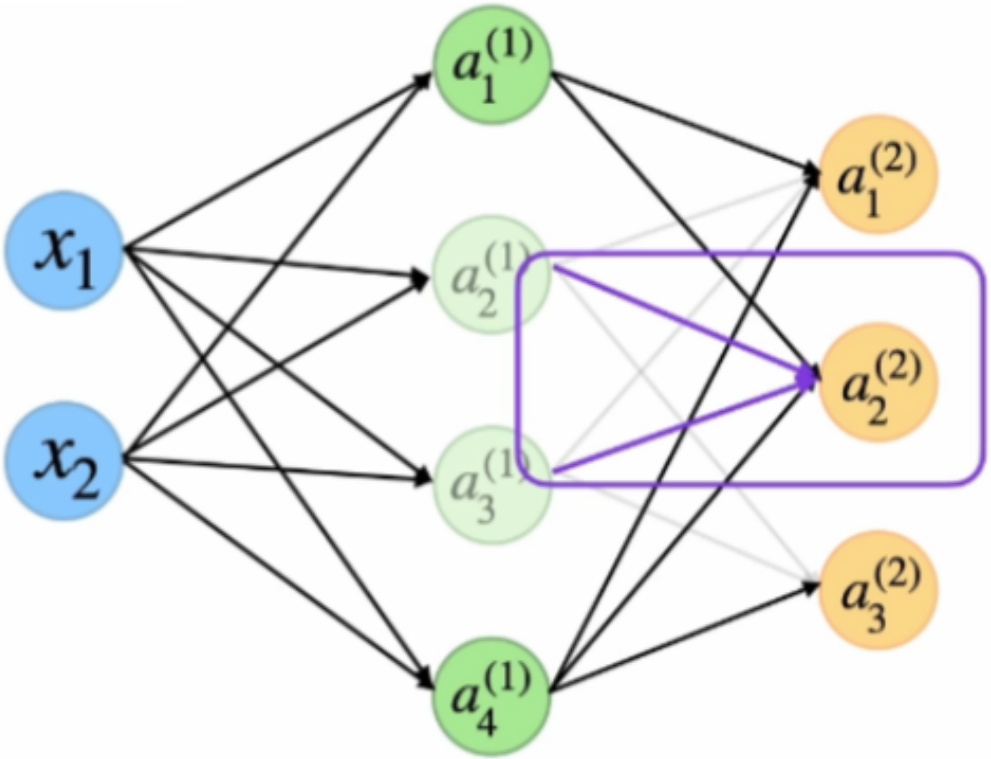


(b) At test time

- but...

[0] Srivastava JMLR 2014

Dropout



Assume we have present probability $p = 0.5$

During testing, when nodes are present again, activations are $2\times$ as large!

[0] Deep Learning Fundamentals - Lightning AI

Dropout

- **Problem:** Having inconsistent values during inference compared to training can cause the network to produce worse results.
- **Solution:** Scale the output during inference by p to keep the same expected activation as in training.
- **Example:**
  - **During training (p=0.1)**:
    - Activation value $= 2$
    - Active only 10% of the time
    - $\Rightarrow$ Effective contribution $= 2 \times 0.1 = 0.2$
  - **During inference**:
    - Always active ($\Rightarrow$ Activation value $= 2$)
    - Scale by $(p) = 0.1$

      $$2 \times 0.1 = 0.2$$

  - Result: Consistent activation scale between training and inference.

Dropout

- In PyTorch, dropout behavior is controlled by the model's mode:

```
# Training Mode:  Enables dropout
model.train()
output = model(input)
# Evaluation Mode:  Disables dropout, scales activations
model.eval()
output = model(input)
```

Batch Normalization

- **Key Insight**: Networks train better when inputs are normalized
- So why not normalize intermediate layers too?
- **Problem**: forcing every layer to output zero-mean, unit-variance values might be too restrictive (not always optimal).
- **Solution**: Let the network learn if it wants normalization!

Batch Normalization

For each feature in a layer:

1. First normalize: $\hat{x} = \frac{x-\mu}{\sqrt{\sigma^2+\epsilon}}$
   - μ: mean across batch dimension
   - σ^2: variance across batch dimension
   - Computed separately for each feature/channel
2. Then give the network control: $y = \gamma\hat{x} + \beta$
   - γ (scale): Can amplify or reduce the normalized values
   - β (shift): Can move the values away from zero
   - These are learned during training like normal weights!

Why γ and β Matter

- After normalization, outputs are always zero-mean, unit-variance
- But this might not be optimal for every layer!
- γ and β let each layer learn:
  - γ: "How much variance do I want?"
  - β: "What should my mean activation be?"
- Two extremes the network can learn:
  - "Keep normalization": $\gamma \approx 1$, $\beta \approx 0$
  - "Undo normalization": γ and β restore original scale and shift
- Network learns what's best for each layer!

Batch Normalization

Mathematically, for batch size N, at each feature/channel j:

$$\mu_j = \frac{1}{N}\sum_{i=1}^{N} x_{i,j} \quad \text{(batch mean)}$$

$$\sigma_j^2 = \frac{1}{N}\sum_{i=1}^{N}(x_{i,j} - \mu_j)^2 \quad \text{(batch variance)}$$

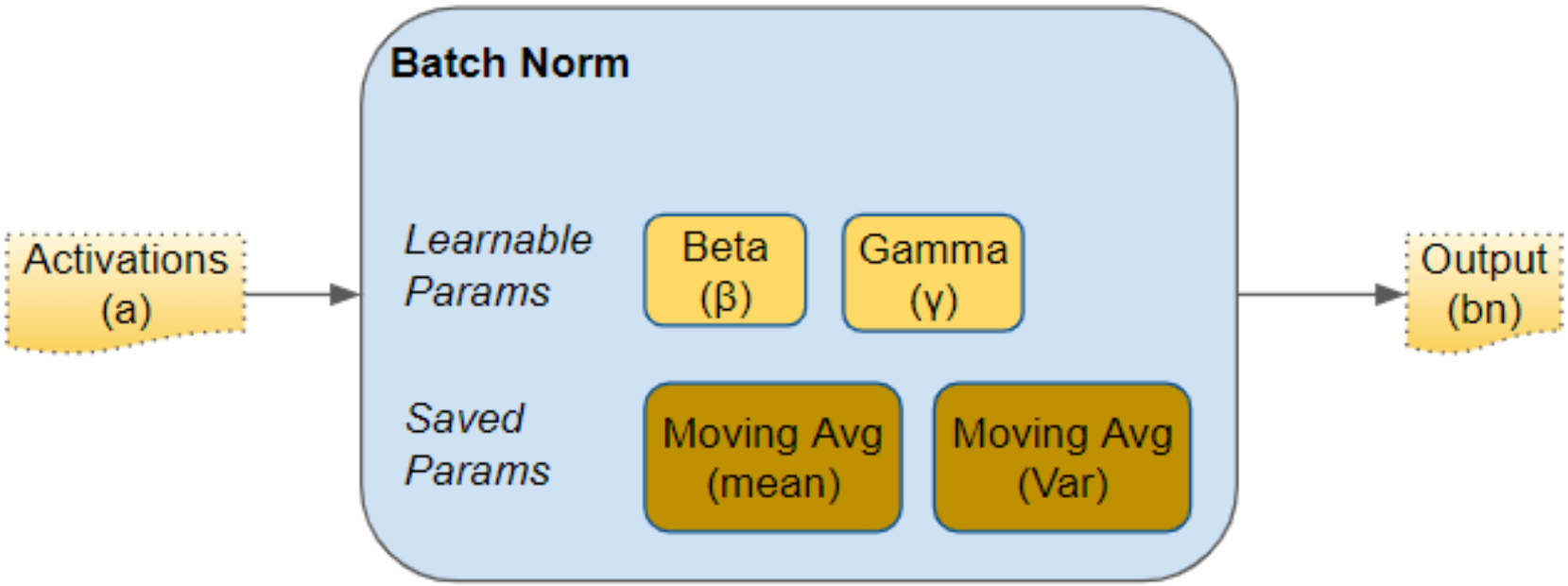
$$\hat{x}_{i,j} = \frac{x_{i,j} - \mu_j}{\sqrt{\sigma_j^2 + \epsilon}} \quad \text{(normalize)}$$

$$y_{i,j} = \gamma_j \hat{x}_{i,j} + \beta_j \quad \text{(learnable transform)}$$

Batch Normalization

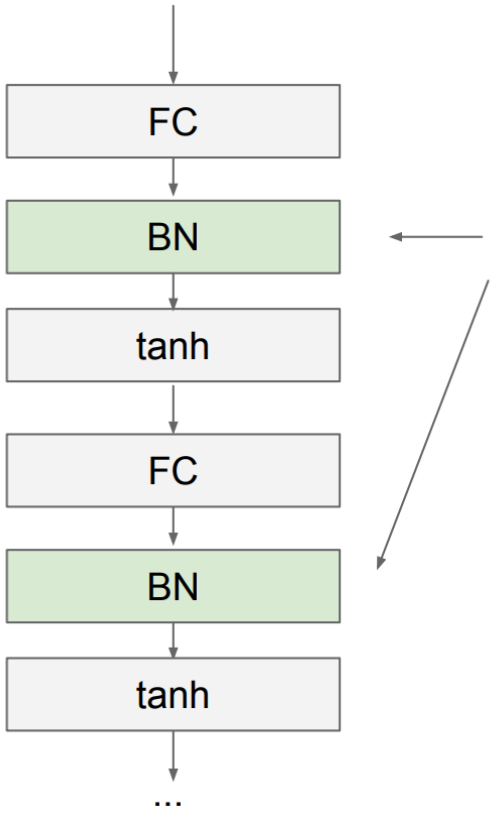
- During Training:
  - Use statistics from current batch
  - Keep running average of mean and variance (to use later in inference):
    $\mu_{running} = 0.9 \times \mu_{running} + 0.1 \times \mu_{batch}$
- During Inference (We can't depend on mini-batches):
  - Use stored running averages ($\mu_{running}$, $\sigma^2_{running}$)
  - These are fixed values from training
  - No batch statistics needed!

Batch Normalization



[0] Ketan Doshi

Batch Normalization



Usually inserted after Fully Connected or Convolutional layers, and before nonlinearity.

[0] Ioffe and Szegedy 2015

Batch Normalization

- In Pytorch, batch normalization behavior is controlled by model's mode:

```
# Training Mode:  Use batch statistics
model.train()
output = model(input)
# Evaluation Mode:  Use running statistics
model.eval()
output = model(input)
```

Batch Normalization

- Advantages:
  - Makes deep networks much easier to train!
  - Improves gradient flow
  - Allows higher learning rates, faster convergence
  - Networks become more robust to initialization
  - Acts as regularization during training
  - Zero overhead at test-time: can be fused with conv!

[0]Slide based on CS231n by Fei-Fei Li, Yunzhu Li & Ruohan Gao

Batch Normalization

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  - Networks become more robust to initialization
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  - Zero overhead at test-time: can be fused with conv!
- Disadvantages:
  - Behaves differently during training and testing: this is a very common source of bugs!

[0]Slide based on CS231n by Fei-Fei Li, Yunzhu Li & Ruohan Gao

Batch Normalization

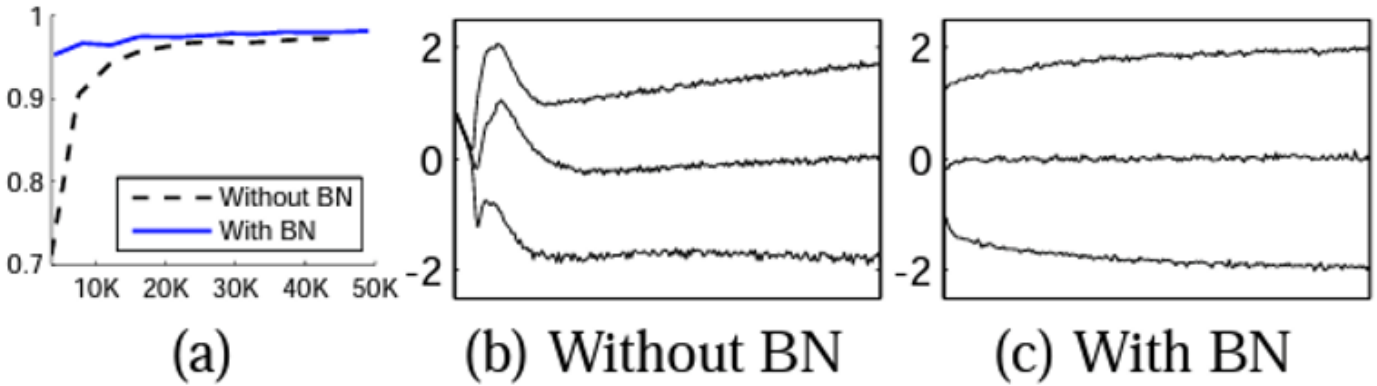

Figure 1: (a) *The test accuracy of the MNIST network trained with and without Batch Normalization, vs. the number of training steps. Batch Normalization helps the network train faster and achieve higher accuracy.* (b, c) *The evolution of input distributions to a typical sigmoid, over the course of training, shown as* $\{15, 50, 85\}$ *th percentiles. Batch Normalization makes the distribution more stable and reduces the internal covariate shift.*

[0] Ioffe and Szegedy 2015

Full Training Workflow

- **Step 1: Initial Setup**
  - Start with a pretrained model and just finetune when possible; it saves time and improves results.
  - Define an initial architecture without regularization (e.g., dropout) or augmentations.
  - Set up validation strategy and choose an appropriate evaluation loss and metric.
  - Train the model to get a **baseline score**.

Full Training Workflow

- **Step 2: Improvement Process**
  - Overfitting is common at the start; use regularization techniques like:
    - Dropout, batch normalization,...
  - Perform error analysis to identify weaknesses and choose appropriate augmentations or preprocessing.
  - Tune hyperparameters: layers, epochs, learning rate, batch size, etc.
  - Optionally, use ensembling to boost scores (requires more resources).
- **Key Tip:** Track scores and improvements at every step to measure progress effectively.

Full Training Workflow

- **Step 3: Finalization**
  - Save the optimized model for deployment.
  - Use the model for inference in real-world applications.