CSE 559A: Computer Vision

Fall 2018: T-R: 11:30-1pm @ Lopata 101

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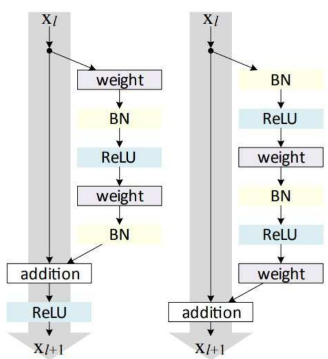
http://www.cse.wustl.edu/~ayan/courses/cse559a/

November 20, 2018

GENERAL

- Problem Set 5: Deadline Extended to Dec 4th.
- Recitation on Nov 30th (Friday after Thanksgiving)

BATCH NORMALIZATION



(a) original (b) proposed

He et al., "Identity Mappings in Deep Residual Networks". 2016.

REGULARIZATION

- Given a limited amount of training data, deep architectures will begin to overfit.
- **Important**: Keep track of training and dev-set errors
  Training errors will keep going down, but dev will saturate. Make sure you don't train to a point when dev errors start going up.
- So how do we prevent, or delay, overfitting so that our dev performance increases ?

Solution 1: Get more data.

REGULARIZATION

Data Augmentation

- Think of transforms to the images that you have that would still keep them in the distribution of real images.
- Typical Transforms
  - Scaling the image
  - Taking random crops
  - Applying Color-transformations (change brightness, hue, saturation randomly)
  - Horizontal Flips (but not vertical)
  - Rotations upto +- 5 degrees.
- Are a good way of getting more training data for 'free'.
- Teaches your network to be invariant to these transformations ....
- Unless your output isn't. If your output is a bounding box, segmentation map, or other quantities that would change with these augmentation operations, you need to apply them to the outputs too.

REGULARIZATION

Weight Decay

- Add a squared or absolute value penalty on all weight values (for example, on each element of every convolutional kernel, matmul matrix) except biases. $\sum_i w_i^2$ or $\sum_i |w_i|$
- So now your effective loss is $L' = L + \lambda \sum_i w_i^2$
- How would you train for this ?
  - Let's say you use backprop to compute $\nabla_{w_i} L$.
  - What gradient would you apply to your weights ? What is $\nabla_{w_i} L'$?

$$\nabla L' = \nabla L + 2\lambda w_i$$

- So in addition to the standard update, you will also be subtracting a scaled version of the weight itself.
- What about for $L' = L + \lambda \sum_i |w_i|$?

$$\nabla L' = \nabla L + \lambda Sign(w_i)$$

REGULARIZATION

Regularization: Dropout

- Key Idea: Prevent a network from "depending" too much on the presence of a specific activation.
- So, randomly drop these values during training.

g =Dropout(f,p): f and g will have the same shape.

Different behavior during training and testing.

- Training
- For each element f_i of f,
  - Set $g_i = 0$ with probability p, and $\frac{f_i}{(1-p)}$ with probability $(1-p)$
- Testing: $g_i = f_i$
- Why does this make sense ? Because in *expectation*, our value during training and test will be the same.
- Dropout is a layer. You will backpropagate through it ! How ?

REGULARIZATION

Regularization: Dropout

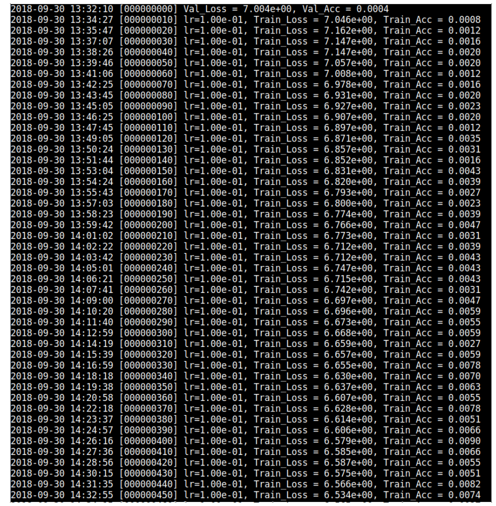
- Write the function as $g = f \cdot \epsilon$
  - Here ϵ is a random array same size as f, with values 0 and $1/(1-p)$ with probability p and $(1-p)$.
  - $\cdot$ denotes element-wise multiplication.
- $\nabla_f = \nabla_g \cdot \epsilon$
  - Even though ϵ is random, you must use the same ϵ in the backward pass that you generated for the forward pass.
  - Don't backpropagate to ϵ because it is not a function of the input.
- Like RELU, but kills gradients based on an external random source---whether you dropped that activation or not in the forward pass. If you didn't, remember to multiply by the $1/(1-p)$.

REGULARIZATION

Regularization: Early Stopping

- Keep track of dev set error. Stop optimization when it starts going up.
- This is a legitimate regularization technique !
- Essentially, you are restricting your hypothesis space to functions that are reachable within N iterations of a random initialization.

TRAINING IN PRACTICE



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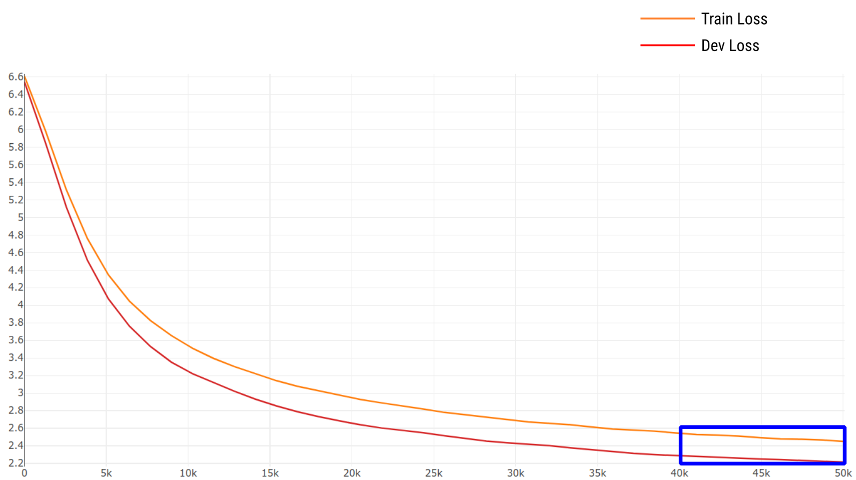
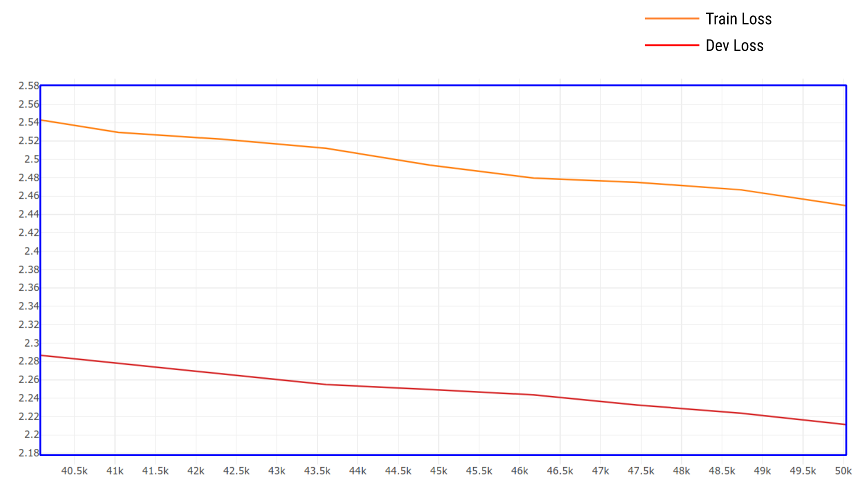
```

Don't look at this !

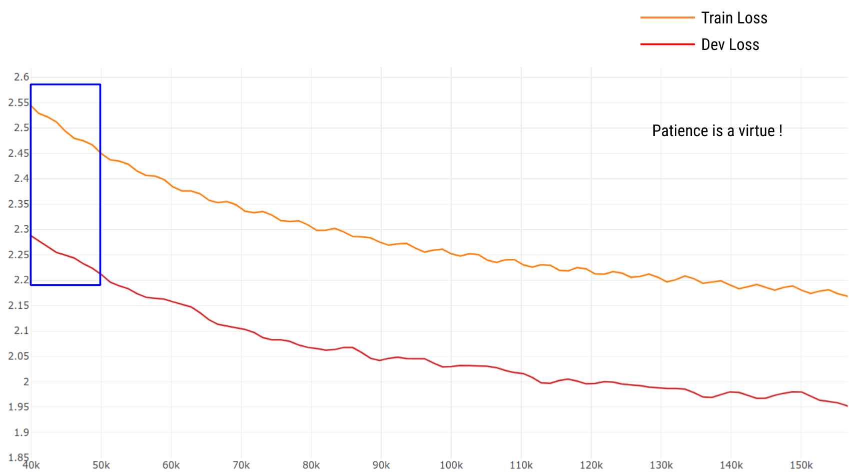
TRAINING IN PRACTICE



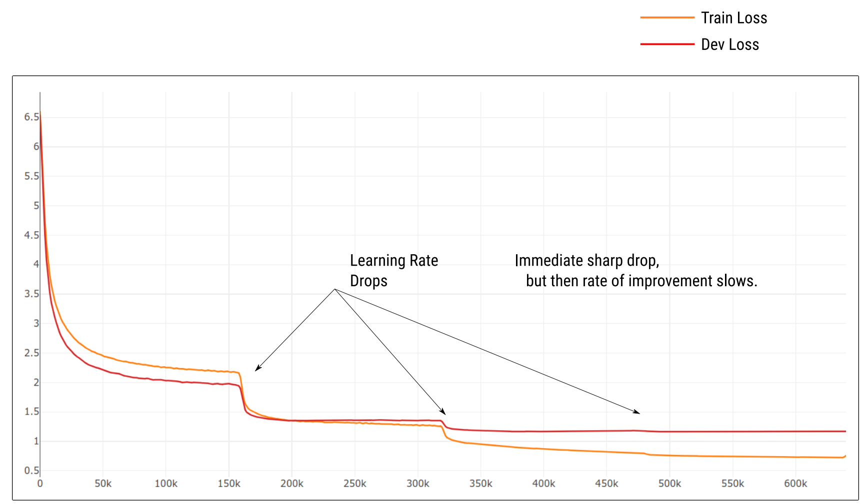
TRAINING IN PRACTICE



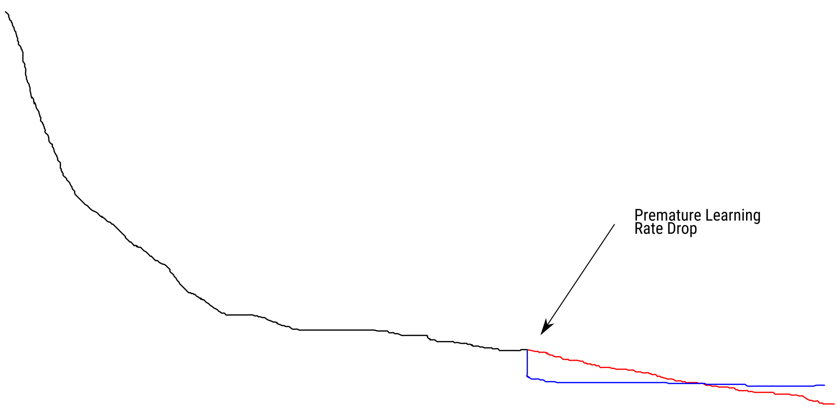
TRAINING IN PRACTICE



TRAINING IN PRACTICE



TRAINING IN PRACTICE



DIFFERENT OPTIMIZATION METHODS

- Standard SGD

$$w_i \leftarrow w_i - \lambda \nabla_{w_i}$$

- Momentum

$$g_i \leftarrow \nabla_{w_i} + \gamma g_i$$
$$w_i \leftarrow w_i - \lambda g_i$$

- But we are still applying the same learning rate for all parameters / weights.

DIFFERENT OPTIMIZATION METHODS

Adaptive Learning Rate Methods

Key idea: Set the learning rate for each parameter based on the magnitude of its gradients.

- Adagrad

$$g_i^2 \leftarrow g_i^2 + (\nabla_{w_i})^2$$
$$w_i \leftarrow w_i - \lambda \frac{\nabla_{w_i}}{\sqrt{g_i^2 + \epsilon}}$$

Global learning rate divided by sum of magnitudes of past gradients.

Problem: Will always keep dropping the effective learning rate.

- RMSProp

$$g_i^2 \leftarrow \gamma g_i^2 + (1-\gamma)(\nabla_{w_i})^2$$
$$w_i \leftarrow w_i - \lambda \frac{\nabla_{w_i}}{\sqrt{g_i^2 + \epsilon}}$$

DIFFERENT OPTIMIZATION METHODS

Adaptive Learning Rate Methods

- Adam: RMSProp + Momentum

$$m_i \leftarrow \beta_1 m_i + (1-\beta_1)\nabla_{w_i}$$
$$v_i \leftarrow \beta_2 v_i + (1-\beta_2)(\nabla_{w_i})^2$$
$$w_i \leftarrow w_i - \frac{\lambda}{\sqrt{v_i} + \epsilon} m_i$$

- How do you initialize m_i and v_i ? Typically as 0 and 1.
- This won't matter once the values of m_i, v_i stabilize. But in initial iterations, they will be biased towards their initial values.

DIFFERENT OPTIMIZATION METHODS

Adaptive Learning Rate Methods

- Adam: RMSProp + Momentum + Bias Correction

$$m_i \leftarrow \beta_1 m_i + (1-\beta_1)\nabla_{w_i}$$
$$v_i \leftarrow \beta_2 v_i + (1-\beta_2)(\nabla_{w_i})^2$$
$$\hat{m}_i = \frac{m_i}{1-\beta_1^t}$$
$$\hat{v}_i = \frac{v_i}{1-\beta_2^t}$$
$$w_i \leftarrow w_i - \frac{\lambda}{\sqrt{\hat{v}_i} + \epsilon} \hat{m}_i$$

Here, t is the iteration number.

As $t \rightarrow \infty$, $1 - \beta^t = 1$.

DISTRIBUTED TRAINING

- Neural Network Training is Slow.
- But many operations are parallelizable. In particular, operations for different batches are independent.
- That's why GPUs are great for deep learning! But even so, you will begin to saturate the computation (or worse, memory) on a GPU.
- Solution: Break up computation across multiple GPUs.
- Two possibilities:
  - Model Parallelism
  - Data Parallelism

DISTRIBUTED TRAINING

Model Parallelism

- Less popular, doesn't help for many networks.
- Essentially, if you have two independent "paths" in your network, you can place them on different devices. And sync, when they join.

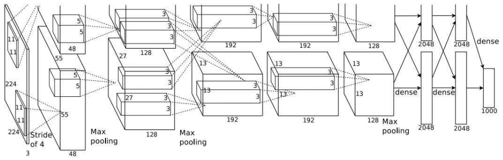


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

Was used in the Sutskever et al., 2012 ImageNet paper.

DISTRIBUTED TRAINING

Data Parallelism

- Begin with all devices having the same model weights.
- One each device, load a separate batch of data.
- Do forward-backward to compute weight gradients on each GPU with its own batch.
- Have a single device (one of the GPUs, or a CPU) recover gradients from all devices.
- Average these gradients and apply the update to the weights.
- Distribute new weights to all devices.
- Works well in practice, especially for multiple GPUs in the same machine.
- Communication overhead of transferring gradients and weights back and forth. Can be large if distributing across multiple machines.
- Approximate Distributed Training
    - Let each worker keep updating its own weights independently for multiple iterations. Then, transmit back weights to single device, average weights, and sync to all devices.
    - Other options, quantize gradients when sending back and forth (while making sure all workers have the same models).