Regularization Techniques for Deep Learning

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Regularizing Neural Networks

We have several means by which to help "regularize" neural networks – that is, to prevent overfitting

- Regularization penalty in cost function
- Dropout
- Early stopping
- Stochastic / Mini-batch Gradient descent (to some degree)

Penalized Cost function

- One option is to explicitly add a penalty to the loss function for having high weights.
- This is a similar approach to Ridge Regression

$$J = \frac{1}{2n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 + \lambda\sum_{j=1}^{m}W_i^2$$

- Can have an analogous expression for Categorical Cross Entropy

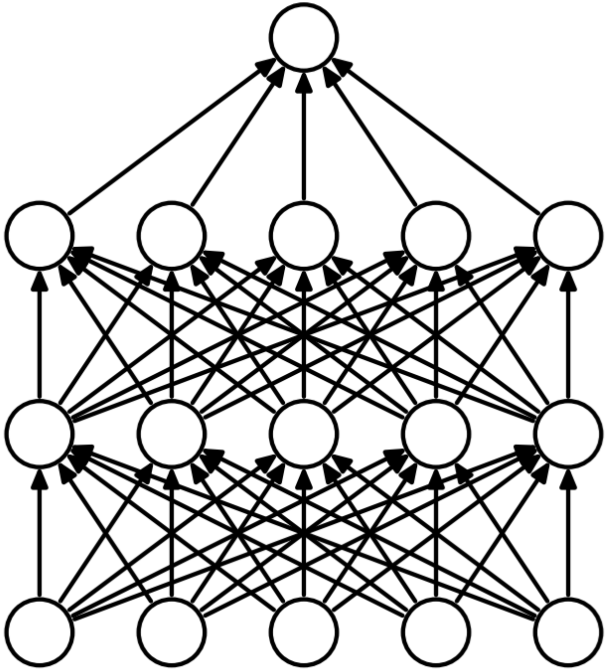
Dropout

- Dropout is a mechanism where at each training iteration (batch) we randomly remove a subset of neurons

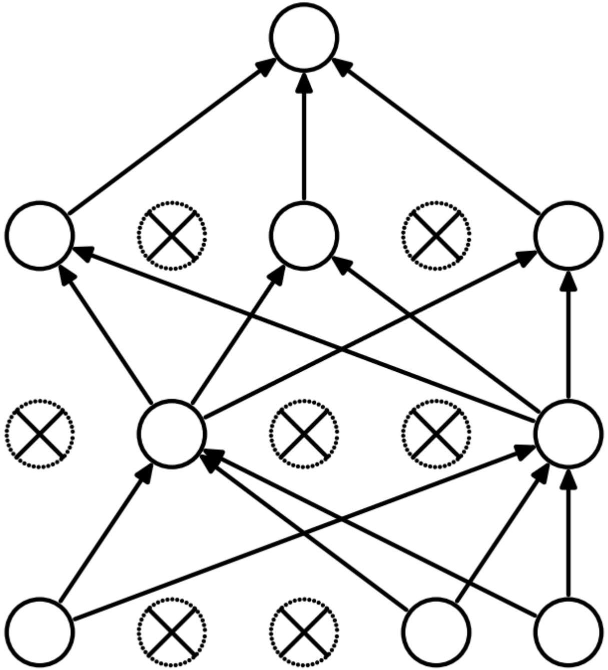
- This prevents the neural network from relying too much on individual pathways, making it more “robust”

- At test time we “rescale” the weight of the neuron to reflect the percentage of the time it was active

Dropout - Visualization



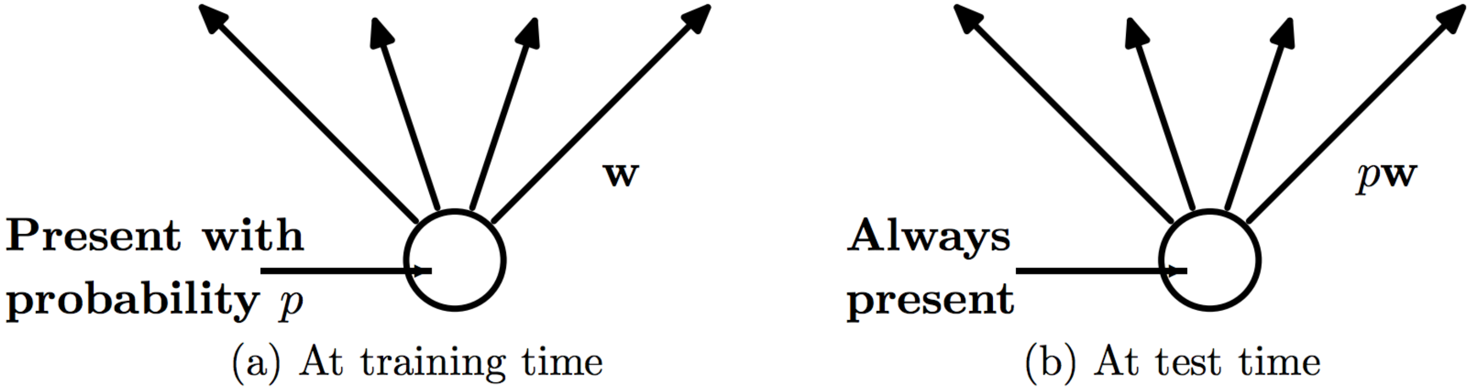
(a) Standard Neural Net



(b) After applying dropout.

Dropout - Visualization

- If the neuron was present with probability *p*, at test time we scale the outbound weights by a factor of *p*.



Early Stopping

- Another, more heuristical approach to regularization is early stopping.
- This refers to choosing some rules after which to stop training.
- Example:
  - Check the validation log-loss every 10 epochs.
  - If it is higher than it was last time, stop and use the previous model (i.e. from 10 epochs previous)

Optimizers

- We have considered approaches to gradient descent which vary the number of data points involved in a step.
- However, they have all used the standard update formula:

$$\mathrm{W} \coloneqq W - \alpha \cdot \nabla J$$

- There are several variants to updating the weights which give better performance in practice.
- These successive “tweaks” each attempt to improve on the previous idea.
- The resulting (often complicated) methods are referred to as “optimizers”.

Momentum

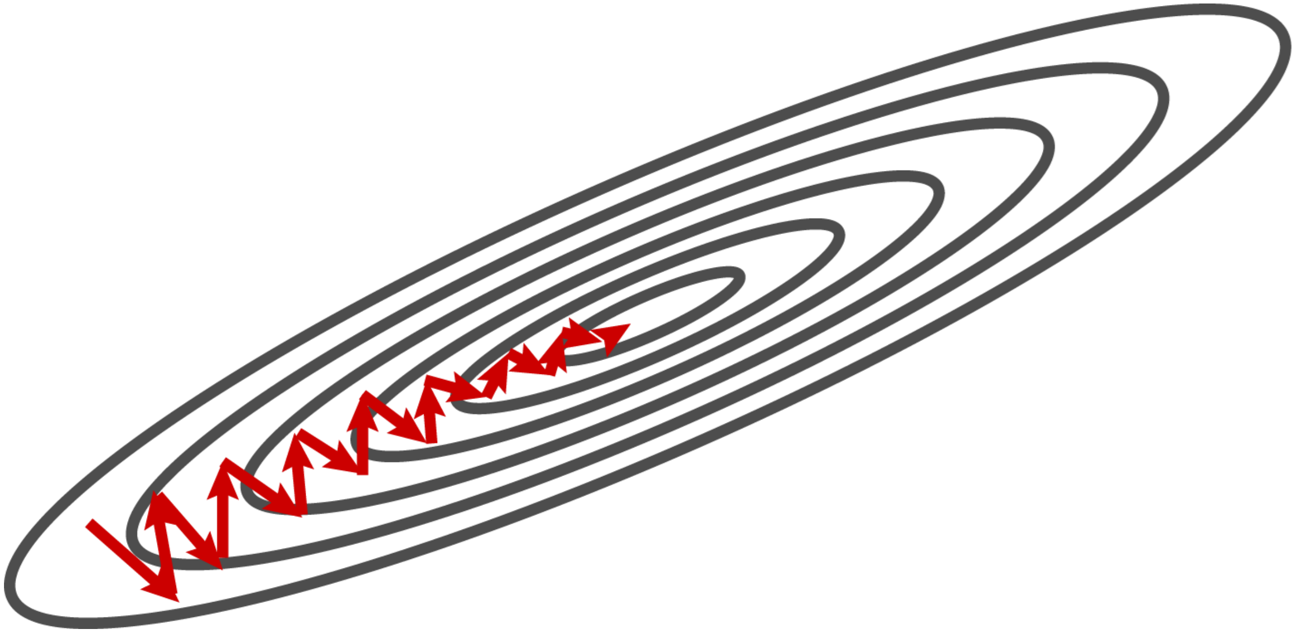
- Idea, only change direction by a little bit each time.
- Keeps a "running average" of the step directions, smoothing out the variation of the individual points.

$$v_{\mathrm{t}} \coloneqq \eta \cdot v_{t-1} - \alpha \cdot \nabla J$$

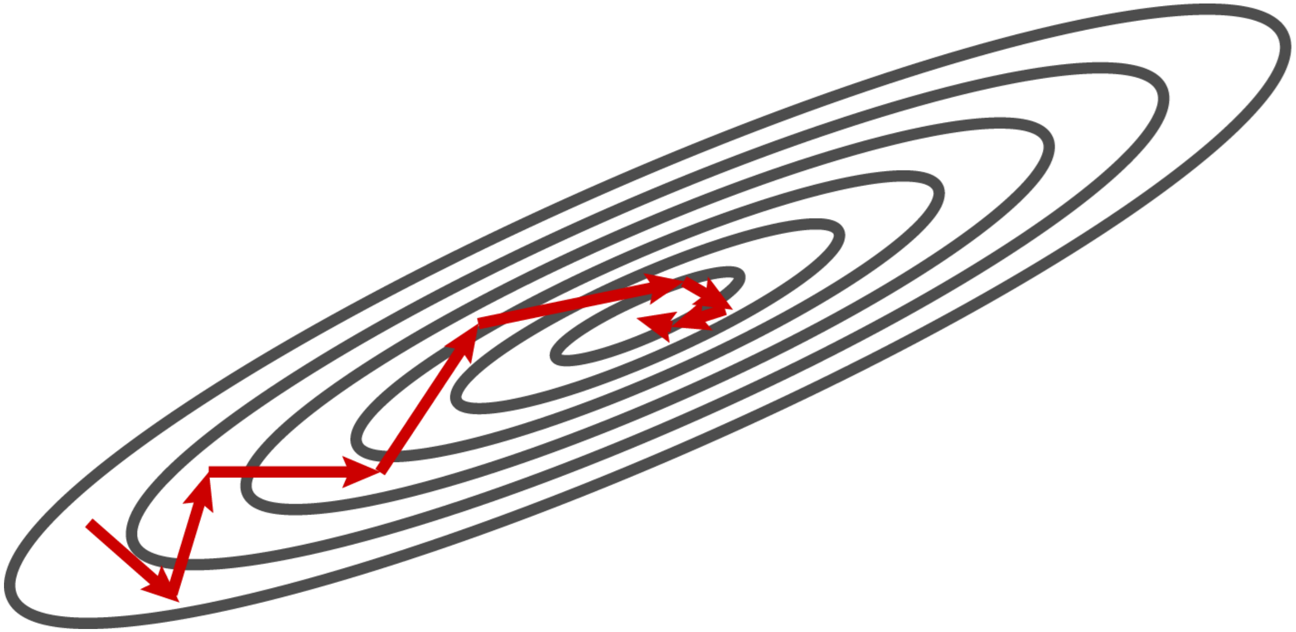
$$\mathrm{W} \coloneqq W - v_t$$

- Here, η is referred to as the "momentum". It is generally given a value <1

Gradient Descent vs Momentum



Gradient Descent vs Momentum



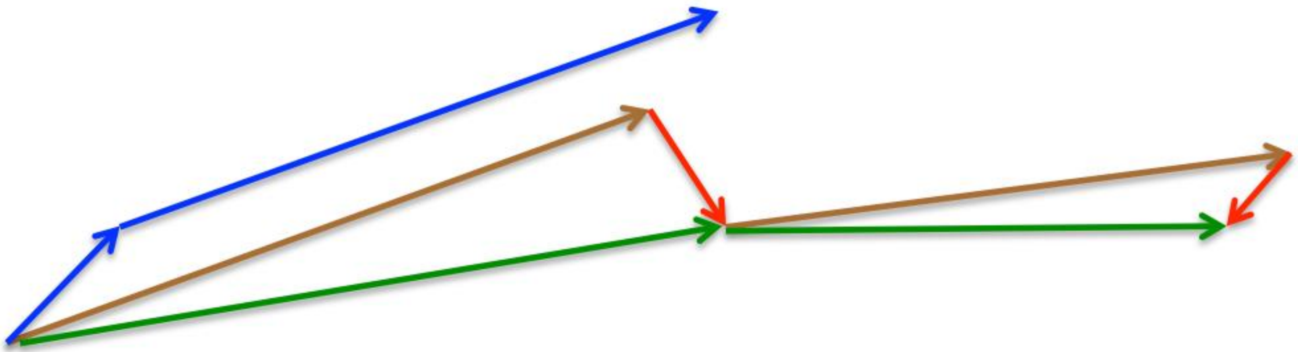
Nesterov Momentum

- Idea: Control "overshooting" by looking ahead.
- Apply gradient only to the "non-momentum" component.

$$v_t = \eta \cdot v_{t-1} - \alpha \cdot \nabla(J - \eta \cdot v_{t-1})$$

$$\mathrm{W} := W - v_t$$

Nesterov Momentum



Momentum Vector

Nesterov steps

Gradient/correction

Standard momentum steps

AdaGrad

- Idea: scale the update for each weight separately.
- Update frequently-updated weights less
- Keep running sum of previous updates
- Divide new updates by factor of previous sum

$$W := W - \frac{\eta}{\sqrt{G_t + \epsilon}} \odot \nabla J$$

RMSProp

- Quite similar to AdaGrad.
- Rather than using the sum of previous gradients, decay older gradients more than more recent ones.
- More adaptive to recent updates

Adam

- Idea: use both first-order and second-order change information and decay both over time.

$$\mathrm{m_t} = \beta_1 \mathrm{m_{t-1}} + (1 - \beta_1)\nabla \mathrm{J}$$

$$\mathrm{v_t} = \beta_2 \mathrm{v_{t-1}} + (1 - \beta_2)\nabla \mathrm{J}$$

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_1^t}$$

$$W := W - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \odot \widehat{m}_t$$

Which one should I use?!

- RMSProp and Adam seem to be quite popular now.
- Difficult to predict in advance which will be best for a particular problem.
- Still an active area of inquiry.

Software