
Machine Learning Tricks

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- Myth of machine learning
 - given: real world examples
 - automatically build model
 - make predictions■
- Promise of deep learning
 - do not worry about specific properties of problem
 - deep learning automatically discovers the feature■
- Reality: bag of tricks

Today's Agenda



- No new translation model
- Discussion of failures in machine learning
- Various tricks to address them

Fair Warning



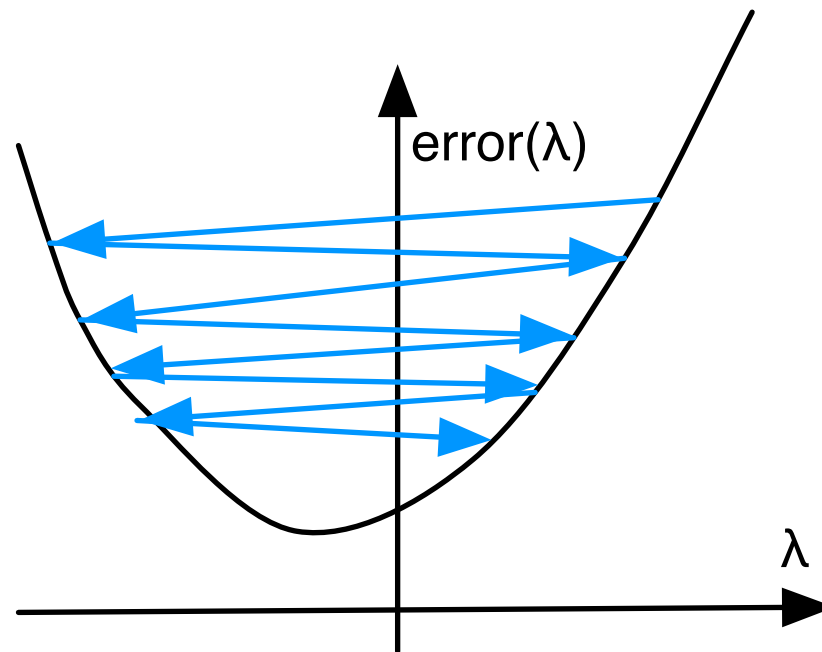
- At some point, you will think:

Why are you telling us all this madness?

- Because pretty much all of it is commonly used

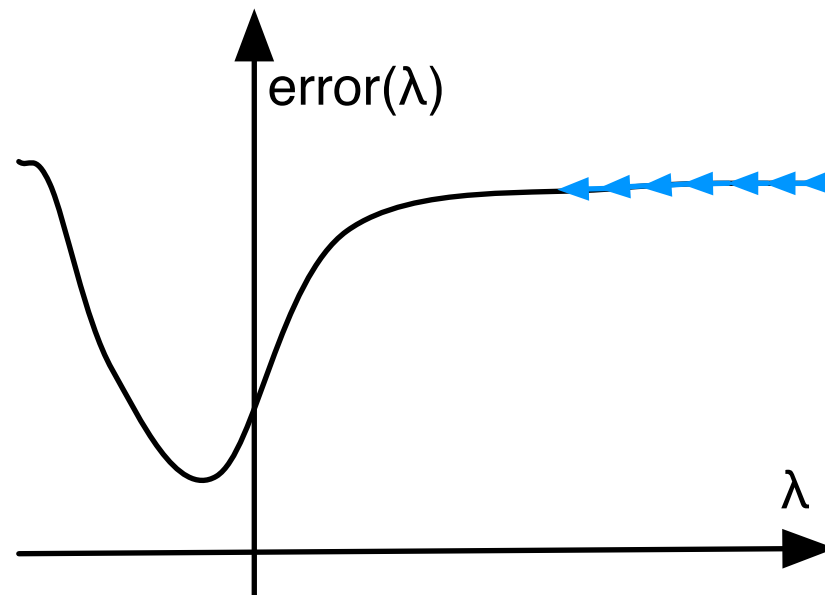
failures in machine learning

Failures in Machine Learning



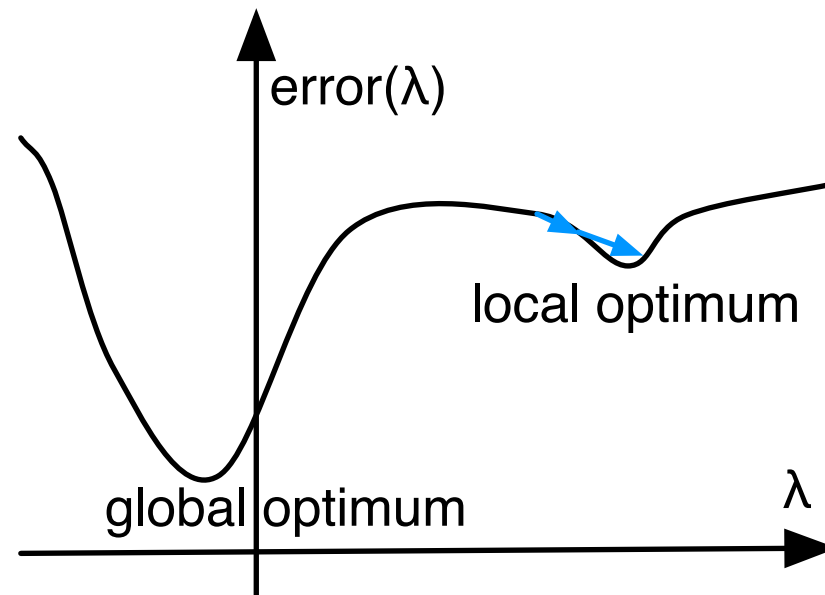
Too high learning rate may lead to too drastic parameter updates
→ overshooting the optimum

Failures in Machine Learning



Bad initialization may require many updates to escape a plateau

Failures in Machine Learning



Local optima trap training

Learning Rate

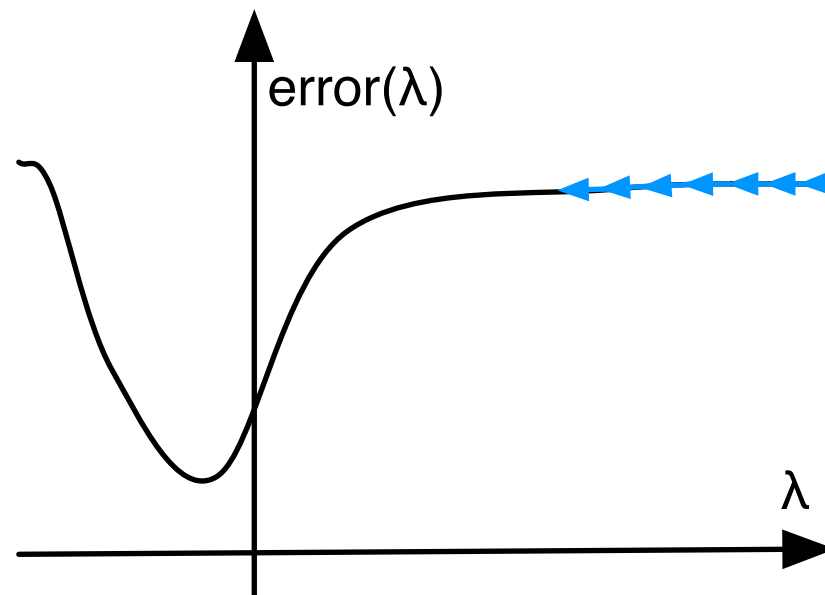


- Gradient computation gives direction of change
- Scaled by learning rate
- Weight updates■
- Simplest form: fixed value■
- Annealing
 - start with larger value (big changes at beginning)
 - reduce over time (minor adjustments to refine model)

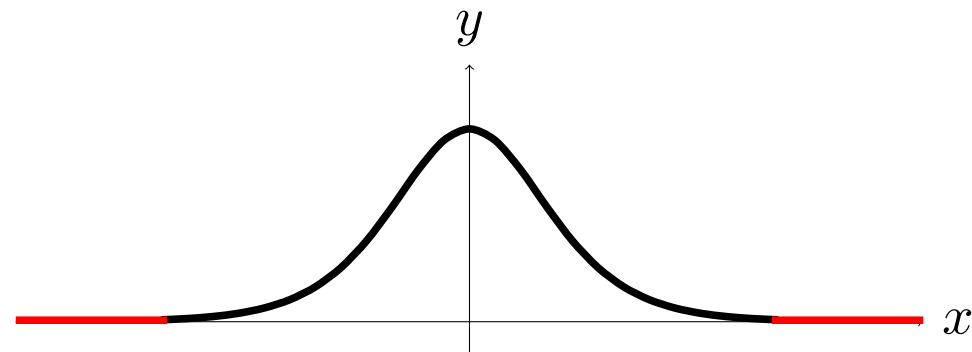
Initialization of Weights



- Initialize weights to random values
- But: range of possible values matters

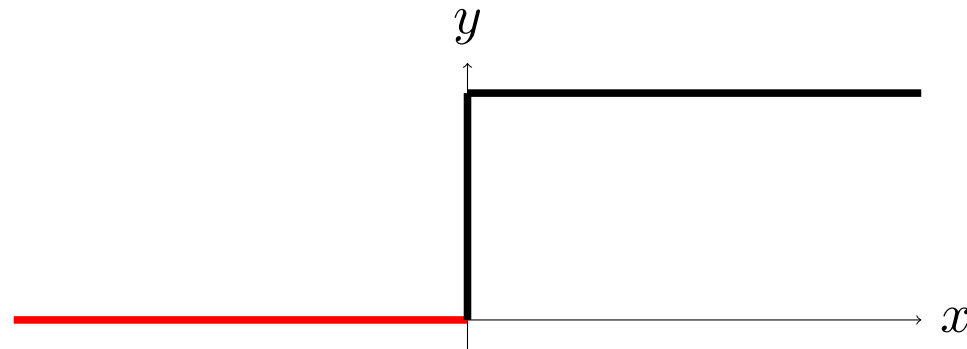


Sigmoid Activation Function



Near zero for large positive and negative values

Rectified Linear Unit

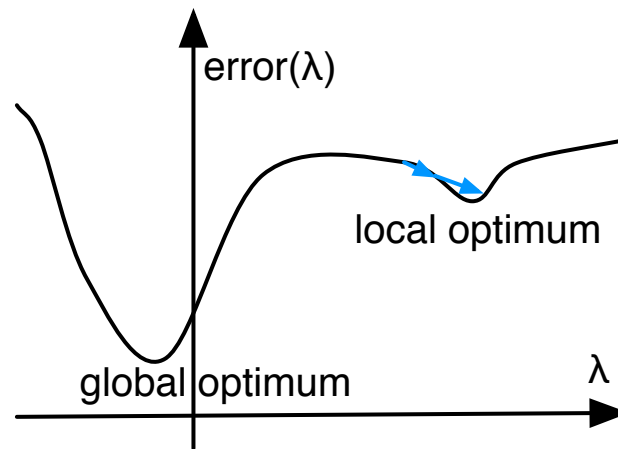


Flat and for large interval: Gradient is 0

“Dead cells” elements in output that are always 0, no matter the input

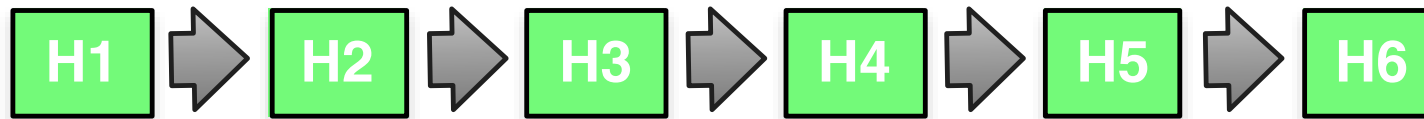
Local Optima

- Cartoon depiction



- Reality
 - highly dimensional space
 - complex interaction between individual parameter changes
 - "bumpy"

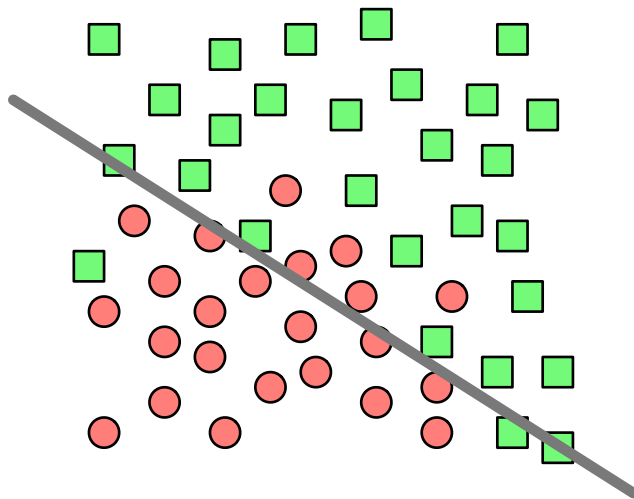
Vanishing and Exploding Gradients



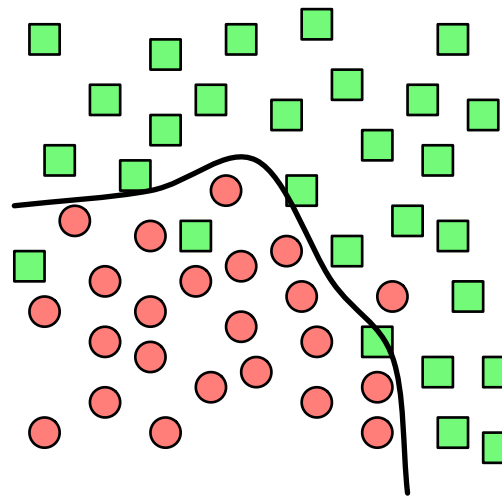
- Repeated multiplication with same values
- If gradients are too low $\rightarrow 0$
- If gradients are too big $\rightarrow \infty$

Overfitting and Underfitting

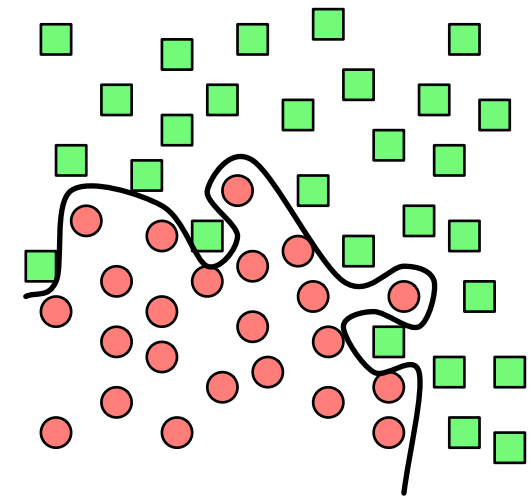
Under-Fitting



Good Fit



Over-Fitting



- Complexity of the problem has too match the capacity of the model
- Capacity \simeq number of trainable parameters

ensuring randomness

Ensuring Randomness

- Typical theoretical assumption

independent and identically distributed

training examples■

- Approximate this ideal
 - avoid undue structure in the training data
 - avoid undue structure in initial weight setting■
- ML approach: Maximum entropy training
 - Fit properties of training data
 - Otherwise, model should be as random as possible (i.e., has maximum entropy)

Shuffling the Training Data

- Typical training data in machine translation
 - different types of corpora
 - * European Parliament Proceedings
 - * collection of movie subtitles
 - temporal structure in each corpus
 - similar sentences next too each other (e.g., same story / debate)■
 - Online updating: last examples matter more■
 - Convergence criterion: no improvement recently
 - stretch of hard examples following easy examples: prematurely stopped■
- ⇒ randomly shuffle the training data
(maybe each epoch)

Weight Initialization

- Initialize weights to random values
- Values are chosen from a uniform distribution
- Ideal weights lead to node values in transition area for activation function

For Example: Sigmoid

- Input values in range $[-1; 1]$

⇒ Output values in range $[0.269; 0.731]$ ■

- Magic formula (n size of the previous layer)

$$\left[-\frac{1}{\sqrt{n}}, \frac{1}{\sqrt{n}} \right] \blacksquare$$

- Magic formula for hidden layers

$$\left[-\frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}}, \frac{\sqrt{6}}{\sqrt{n_j + n_{j+1}}} \right]$$

- n_j is the size of the previous layer
- n_{j+1} size of next layer

Problem: Overconfident Models

- Predictions of the neural machine translation models are surprisingly confident
- Often almost all the probability mass is assigned to a single word (word prediction probabilities of over 99%)■
- Problem for decoding and training
 - decoding: sensible alternatives get low scores, bad for beam search
 - training: overfitting is more likely■
- Solution: label smoothing■
- Jargon notice
 - in classification tasks, we predict a *label*
 - jargon term for any output
 - here, we smooth the word predictions

Label Smoothing during Decoding

- Common strategy to combat peaked distributions: smooth them
- Recall
 - prediction layer produces numbers for each word
 - converted into probabilities using the softmax

$$p(y_i) = \frac{\exp s_i}{\sum_j \exp s_j}$$

- Softmax calculation can be smoothed with so-called **temperature** T

$$p(y_i) = \frac{\exp s_i/T}{\sum_j \exp s_j/T}$$

- Higher temperature \rightarrow distribution smoother
(i.e., less probability is given to most likely choice)

Label Smoothing during Training

- Root of problem: training
- Training object: assign all probability mass to single correct word
- Label smoothing
 - truth gives some probability mass to other words (say, 10% of it)
 - uniformly distributed over all words
 - relative to unigram word probabilities
(relative counts of each word in the target side of the training data)

adjusting the learning rate

Adjusting the Learning Rate

- Gradient descent training: weight update follows the gradient downhill
- Actual gradients have fairly large values, scale with a learning rate (low number, e.g., $\mu = 0.001$)
- Change the learning rate over time
 - starting with larger updates
 - refining weights with smaller updates
 - adjust for other reasons
- Learning rate schedule

Momentum Term

- Consider case where weight value far from optimum
- Most training examples push the weight value in the same direction
- Small updates take long to accumulate
- Solution: momentum term m_t
 - accumulate weight updates at each time step t
 - some decay rate for sum (e.g., 0.9)
 - combine momentum term m_{t-1} with weight update value Δw_t

$$m_t = 0.9m_{t-1} + \Delta w_t$$

$$w_t = w_{t-1} - \mu m_t$$

Adapting Learning Rate per Parameter

- Common strategy: reduce the learning rate μ over time
- Initially parameters are far away from optimum \rightarrow change a lot
- Later nuanced refinements needed \rightarrow change little
- Now: different learning rate for each parameter

Adagrad

- Different parameters at different stages of training
→ different learning rate for each parameter
- Adagrad
 - record gradients for each parameter
 - accumulate their square values over time
 - use this sum to reduce learning rate■
- Update formula
 - gradient $g_t = \frac{dE_t}{dw}$ of error E with respect to weight w
 - divide the learning rate μ by accumulated sum

$$\Delta w_t = \frac{\mu}{\sqrt{\sum_{\tau=1}^t g_{\tau}^2}} g_t$$

- Big changes in the parameter value (corresponding to big gradients g_t)
→ reduction of the learning rate of the weight parameter

- Combine idea of momentum term and reduce parameter update by accumulated change
- Momentum term idea (e.g., $\beta_1 = 0.9$)

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

- Accumulated gradients (decay with $\beta_2 = 0.999$)

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

Adam: Technical Correction

- Initially, values for m_t and v_t are close to initial value of 0
- Adjustment

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

- With $t \rightarrow \infty$ this correction goes away

$$\lim_{t \rightarrow \infty} \frac{1}{1 - \beta^t} \rightarrow 1$$

- Given
 - learning rate μ
 - momentum \hat{m}_t
 - accumulated change \hat{v}_t
- Weight update per Adam (e.g., $\epsilon = 10^{-8}$)

$$\Delta w_t = \frac{\mu}{\sqrt{\hat{v}_t} + \epsilon} \hat{m}_t$$

Batched Gradient Updates

- Accumulate all weight updates for all the training example → update (converges slowly)■
- Process each training example → update (stochastic gradient descent) (quicker convergence, but last training disproportionately higher impact)■
- Process data in batches
 - compute all their gradients for individual word predictions errors
 - use sum over each batch to update parameters→ better parallelization on GPUs■
- Process data on multiple compute cores
 - batch processing may take different amount of time
 - asynchronous training: apply updates when they arrive
 - mismatch between original weights and updates may not matter much

avoiding local optima

Avoiding Local Optima

- One of the hardest problem for designing neural network architectures and optimization methods
- Ensure that model converges to at least to a set of parameter values that give results close to this optimum on unseen test data.
- There is no real solution to this problem.
- It requires experimentation and analysis that is more craft than science.
- Still, this section presents a number of methods that generally help avoiding getting stuck in local optima.

Overfitting and Underfitting

- Neural machine translation models
 - 100s of millions of parameters
 - 100s of millions of training examples (individual word predictions)
- No hard rules for relationship between these two numbers
- Too many parameters and too few training examples → overfitting
- Too few parameters and many training examples → underfitting

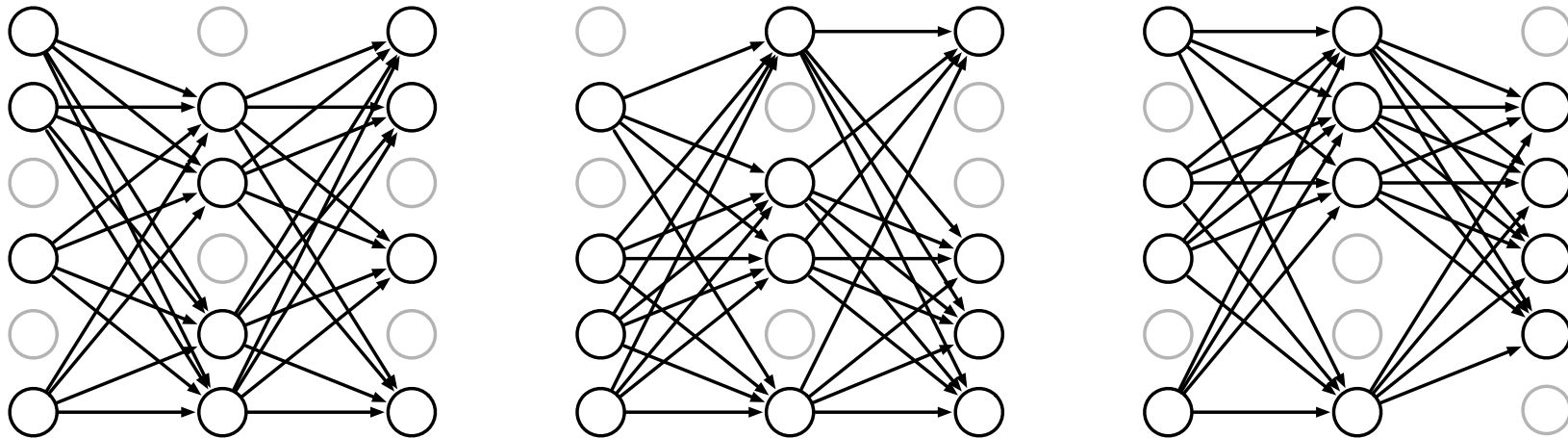
Regularization

- Motivation: prefer as few parameters as possible
- Strategy: set un-needed parameters a value of 0
- Method
 - adjust training objective
 - add cost for any non-zero parameter
 - typically done with L2 norm
- Practical impact
 - derivative of L2 norm is value of parameter
 - if not signal from training: reduce value of parameter
 - also called weight decay
- Not common in deep learning, but other methods understood as regularization

- Human learning
 - learn simple concepts first
 - learn more complex material later
- Early epochs: only easy training examples
 - only short sentences
 - create artificial data by extracting smaller segments
(similar to phrase pair extraction in statistical machine translation)
 - Later epochs: all training data
- Not easy to calibrate

- Training may get stuck in local optima
 - some properties of task have been learned
 - discovery of other properties would take it too far out of its comfort zone.
- Machine translation example
 - model learned the language model aspects
 - but cannot figure out role of input sentence
- Drop out: for each batch, eliminate some nodes

Dropout



- Dropout
 - For each batch, different random set of nodes is removed
 - Their values are set to 0 and their weights are not updated
 - 10%, 20% or even 50% of all the nodes
- Why does this work?
 - robustness: redundant nodes play similar nodes
 - ensemble learning: different subnetworks are different models

Gradient Clipping

- Exploding gradients: gradients become too large during backward pass

⇒ Limit total value of gradients for a layer to threshold (τ)

- Use of L2 norm of gradient values g

$$L2(g) = \sqrt{\sum_j g_j^2}$$

- Adjust each gradient value g_i for each element i in the vector

$$g'_i = g_i \times \frac{\tau}{\max(\tau, L2(g))}$$

Layer Normalization

- During inference, average node values may become too large or too small
- Has also impact on training (gradients are multiplied with node values)

⇒ Normalize node values

- During training, learn bias layer

Layer Normalization: Math

- Feed-forward layer h^l , weights W , computed sum s^l , activation function

$$s^l = W h^{l-1}$$

$$h^l = \text{sigmoid}(s^l)$$

- Compute mean μ^l and variance σ^l of sum vector s^l

$$\mu^l = \frac{1}{H} \sum_{i=1}^H s_i^l$$

$$\sigma^l = \sqrt{\frac{1}{H} \sum_{i=1}^H (s_i^l - \mu^l)^2}$$

Layer Normalization: Math

- Normalize s^l

$$\hat{s}^l = \frac{1}{\sigma^l}(s^l - \mu^l)$$

- Learnable bias vectors g and b

$$\hat{s}^l = \frac{g}{\sigma^l}(s^l - \mu^l) + b$$

Shortcuts and Highways

- Deep learning: many layers of processing

⇒ Error propagation has to travel farther

- All parameters in processing change have to be adjusted
- Instead of always passing through all layers, add connections from first to last
- Jargon alert
 - shortcuts
 - residual connections
 - skip connections

- Feed-forward layer

$$y = f(x)$$

- Pass through input x

$$y = f(x) + x$$

- Note: gradient is

$$y' = f'(x) + 1$$

- Constant 1 \rightarrow gradient is passed through unchanged

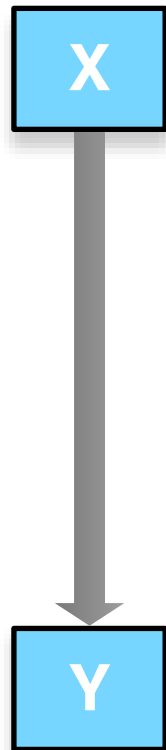
Highways

- Regulate how much information from $f(x)$ and x should impact the output y
- Gate $t(x)$ (typically computed by a feed-forward layer)

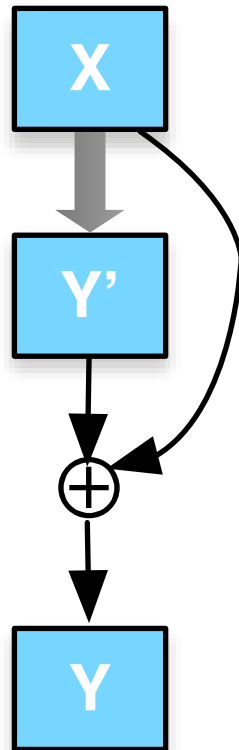
$$y = t(x) f(x) + (1 - t(x)) x$$

Shortcuts and Highways

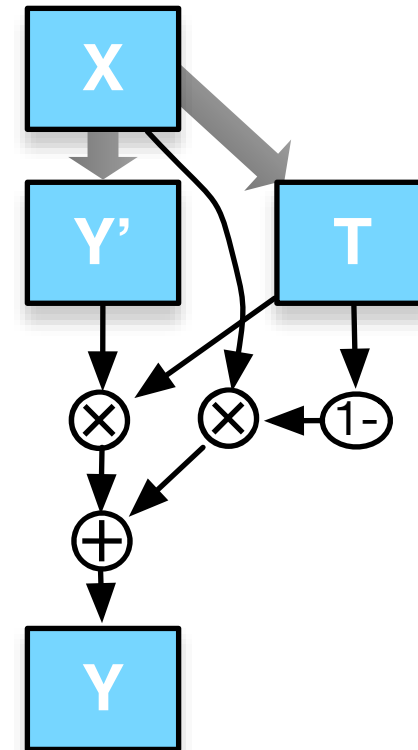
Basic Layer



Skip Connection



Highway Network



LSTM and Vanishing Gradients

- Recall: Long short term memory (LSTM) cells
- Pass through of memory

$$\text{memory}^t = \text{gate}_{\text{input}} \times \text{input}^t + \text{gate}_{\text{forget}} \times \text{memory}^{t-1}$$

- Forget gate has values close to 1 \rightarrow gradient passed through nearly unchanged

generative adversarial training

Sequence-Level Training

- Traditional training
 - predict one word at a time
 - compare against correct word
 - proceed training with correct word
- Sequence-level training
 - predict entire sequence
 - measure translation with sentence-level metric (e.g., BLEU)
- May use n-best translations, beam search, etc.

- Game between two players
 - generator proposes a translation
 - discriminator distinguishes between generator's translation and human translation
 - generator tries to fool discriminator
- Training example: input sentence x and output sentence y
- Generator
 - traditional neural machine translation model
 - generates full sentence translations t for each input sentence
- Discriminator
 - is trained to classify (x, y) as correct example
 - is trained to classify (x, t) as generated example



1. First train generator to some maturity
 2. Train discriminator on generator predictions and human reference translations
 3. Train jointly
 - generator with additional objective to fool discriminator
 - discriminator to do well on detecting generator's output as such
- In practice, this is hard to calibrate correctly

Relationship to Reinforcement Learning

- No immediate feedback
 - chess playing: quality of move only revealed at end of game
 - walk through maze to avoid monsters and find gold
- Policy: decision process to which steps to take
(here: generator, traditional neural machine translation model)
- Reward: end result
(here: ability to fool discriminator)
- Popular technique: Monte Carlo search
(here: Monte Carlo decoding)
- Training is called policy search