# Regularization

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# Regularization

- Regularization - any modification we make to the learning algorithm that is intended to reduce the generalization error, but not its training error.
- Overfitting - training loss<<test loss.
  - very relevant to deep learning , having a lot of parameters.

# Aims of regularization

- make underdetermined model determined[1]
- improve generalization (performance on train may decrease)
  - by encoding prior domain knowledge
  - by solving bias-variance trade-off
    - reduces variance
    - at the expense of small bias increase
  - this can useful when
    - model space is large and complex ($\downarrow$variance)
    - model space can approximate well the true model (bias is low)
    - example: decision trees, neural nets.

[1] examples: linear regression estimated with LS, logistic regression

# Types of regularization

- add restrictions on parameters
- add penalty to objective function (soft restriction)
- ensemble learning

# Soft regularization

- Modified loss:
$$\tilde{J}(\theta) = J(\theta) + \alpha R(\theta)$$
- Specifics of neural networks:
  - On layer h: $i^{h+1} = \beta_0 + \sum \beta_k o_k^h$
  - bias term $\beta_0$ is usually not included in regularization
    - there are comparatively few bias terms
    - model will stay unbiased
  - we may use different $\alpha_h$ for different layers $h = 1, 2, ...H$.

# $L_2$ regularization («weight decay»)

$$\tilde{J}(w, X, Y) = \frac{\alpha}{2} w^T w + J(w, X, Y)$$

$$\nabla_w \tilde{J}(w, X, Y) = \alpha w + \nabla_w J(w, X, Y)$$

Stochastic gradient descent step:

$$w \leftarrow (1 - \varepsilon\alpha) w - \varepsilon \nabla_w J(w, X, Y)$$

Weights are shrunk towards zero.

# Analysis of $L_2$-regularized solution

- Write $\tilde{J}(w)$ for Taylor 2nd order approximation around $w^* = \arg\min_w J(w)$:

$$\widehat{J}(w) = J(w^*) + \frac{1}{2}(w - w^*)^T H(w - w^*) + \frac{\alpha}{2} w^T w$$

where $H = \nabla_w^2 J(w^*) \succeq 0$ and $\nabla_w J(w^*)^T (w - w^*) = 0$, because in minimum $\nabla_w J(w^*) = 0$.

- This expansion is precise for quadratic loss $J(w)$ (e.g. MSE).
- Minimum is achieved when $\nabla \widehat{J}(\tilde{w}) = 0$:

$$\begin{aligned} H(\tilde{w} - w^*) + \alpha \tilde{w} &= 0 \\ (H + \alpha I)\, \tilde{w} &= H w^* \\ \tilde{w} &= (H + \alpha I)^{-1} H w^* \end{aligned} \tag{1}$$

- When $\alpha = 0$ $\tilde{w} = w^*$.

# Analysis of $L_2$-regularized solution

- $H = Q\Lambda Q^T$ (spectral decomposition), where
  - $Q$ is orthonormal basis of eigenvectors
  - $\Lambda$ - diagonal matrix with eigenvalues

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- Substituting spectral decomposition into(1), we obtain:

$$\begin{aligned}\tilde{w} &= (Q\Lambda Q^T + \alpha I)^{-1} Q\Lambda Q^T w^* \\ &= \left[Q(\Lambda + \alpha I)Q^T\right]^{-1} Q\Lambda Q^T w^* \\ &= Q(\Lambda + \alpha I)^{-1}\Lambda Q^T w^*\end{aligned}$$

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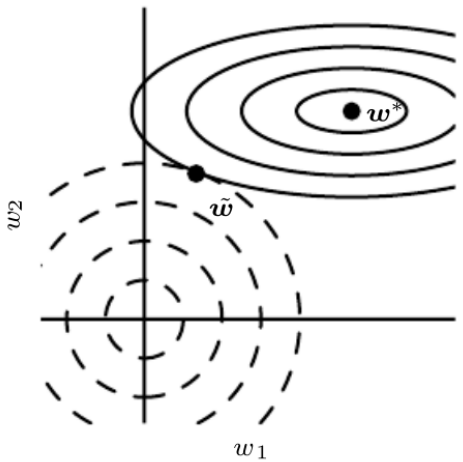
- $\tilde{w}$ is obtained by rescaling $w^*$ along the eigenvectors.
  - along $i$-th eigenvector rescaling factor is $\frac{\lambda_i}{\lambda_i+\alpha}$
  - rescaling effect is
    - high for small $\lambda_i$
    - insignificant for large $\lambda_i$

# Illustration of $L_2$ regularization effect




- Notation
  - Solid: iso-lines of $J(w)$
  - Dashed: iso-lines of $\frac{\alpha}{2} w^T w$
- $\tilde{w}$ - equlibrium point
- Eigenvectors of $H$:
  - $v_1 = [1, 0]$, $\lambda_1$ is small => $|w_1^* - \tilde{w}_1|$ - large
  - $v_2 = [0, 1]$, $\lambda_2$ large => $|w_2^* - \tilde{w}_2|$ - small

# Linear regression with $L_2$ regularization

$$y = x^T w$$

$$\widehat{w} = \arg\min_w \sum_{n=1}^{N} \left( x_n^T w - y_n \right)^2 + \frac{\alpha}{2} w^T w$$

Solution:

$$\widehat{w} = \left( X^T X + \alpha I \right)^{-1} X^T Y$$

For centered features:
$X^T X \propto Ncov[x, x]$, $X^T Y = Ncov[x, y]$
$L_2$ regularization «adds» $\alpha$ variance to each feature.
this forces estimator to reduce weights (based on cov[x,y])

# $L_1$ norm regularization

$$\tilde{J}(w) = J(w) + \alpha \|w\|_1$$
$$\nabla \tilde{J}(w) = \nabla J(w) + \alpha \, \text{sign}(w)$$

When $\alpha > \sup_{w_i} |\nabla J(w)|$ SGD will force $w_i \to 0$.

# Effect of $L_1$ regularization on solution

- To get analytical solution need to assume that Hessian is diagonal.
- Consider 2nd order Taylor approximation to $\widehat{J}(w)$:

$$\widehat{J}(w) = J(w^*) + \sum_i \left[ \frac{1}{2} H_{i,i} (w_i - w_i^*)^2 + \alpha |w_i| \right]$$

- Solution[2]:

$$w_i = \text{sign}(w_i^*) \max \left\{ \left| w_i^* - \frac{\alpha}{H_{i,i}} \right|, 0 \right\}$$

- Analysis:
  - solution is sparse (many $w_i$ may be 0)
  - shift in weights is smaller along directions with high $H_{i,i}$
  - $\frac{\alpha}{H_{i,i}} > w_i^*$ : regularizer dominates $J(w)$ improvements.

[2] $L_2$ regularized solution would be here $w_i = \frac{H_{i,i}}{H_{i,i}+\alpha} w_i^*$

# $L_1$ regularizer: feature selection

- $||w||_1$ regularizer will do feature selection.
- Consider

$$\tilde{J}(w) = J(w) + \alpha \sum_{d=1}^{D} |w_d|$$

- if $\alpha > \sup_w \left| \frac{\partial J(w)}{\partial w_i} \right|$, then it becomes optimal to set $w_i = 0$
- For higher $\alpha$ more weights will become zeroes.

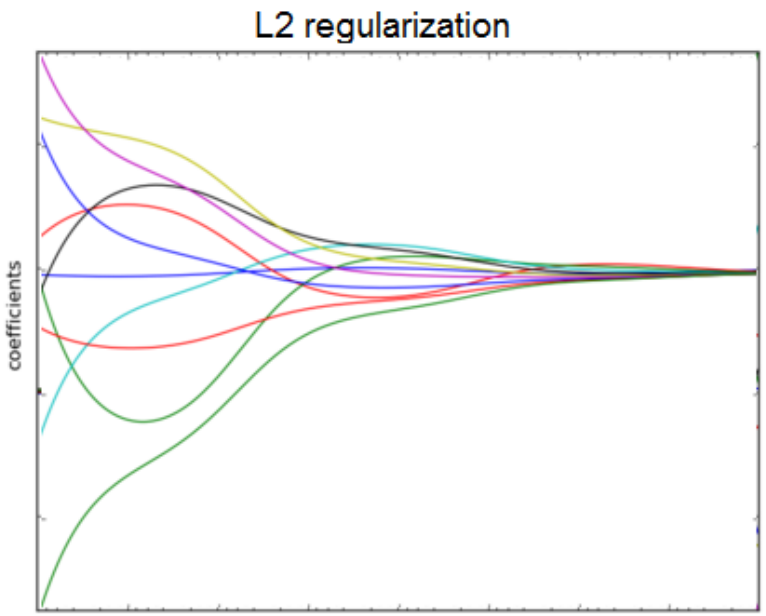
# $L_2$ regularizer: no feature selection

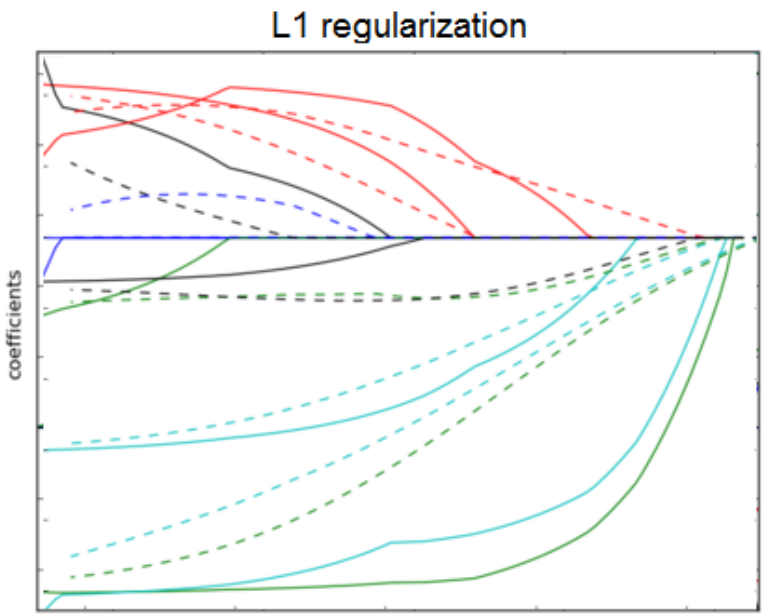
- Consider $R(w) = \frac{\alpha}{2} \|w\|_2^2 = \frac{\alpha}{2} \sum_d w_d^2$

$$\tilde{J}(w) = J(w) + \frac{\alpha}{2} \sum_{d=1}^{D} w_d^2$$

- $\frac{\partial R(w)}{\partial w_i} = \alpha w_i \to 0$ when $w_i \to 0$.

# Illustration



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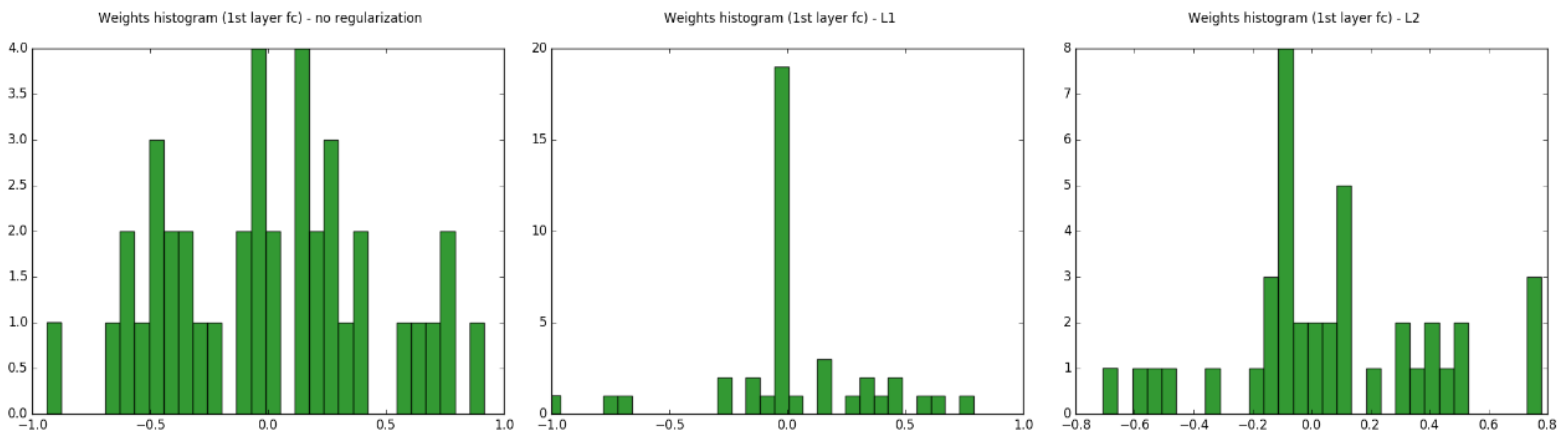
# Example of unregularized, $L_1$ and $L_2$ regularized weights



# Constrained optimization

$$\tilde{J}(\theta) = J(\theta) + \alpha R(\theta) \to \min_{\theta}$$

is equivalent to constrained maximization task for some $\gamma = \gamma(\alpha)$:

$$\begin{cases} J(\theta) \to \min_{\theta} \\ R(\theta) \leq \gamma \end{cases} \tag{2}$$

$\alpha \downarrow \Longleftrightarrow \gamma \uparrow$
To solve (2) repeat:
$\theta \leftarrow \theta - \varepsilon \nabla J(\theta)$ (or any other optimization update)
project $\theta$ onto region $\{\theta : R(\theta) \leq \gamma\}$

# When to use constrained optimization

- Penalty addition may force algorithm get stuck in local optima around zero:
  - causing «dead units» with very small weights
  - inefficient local solution
- Constrained maximization has no such problem
- Constrained maximization: more stable
  - weights cannot take arbitrary values
  - may use higher learning rate!

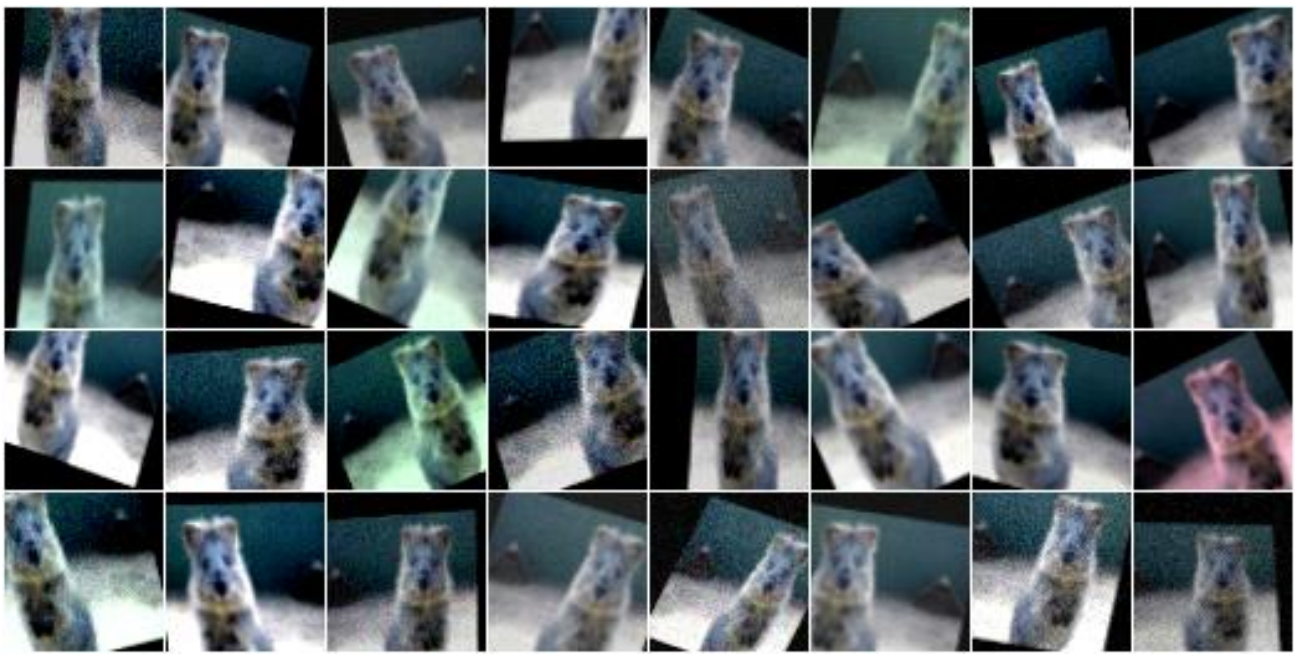
# Constrained optimization

- We can impose constraints on:
  - all weights
  - all weights within each layer
  - all incoming weights to each neuron
- Bias weights are usually not constrained.

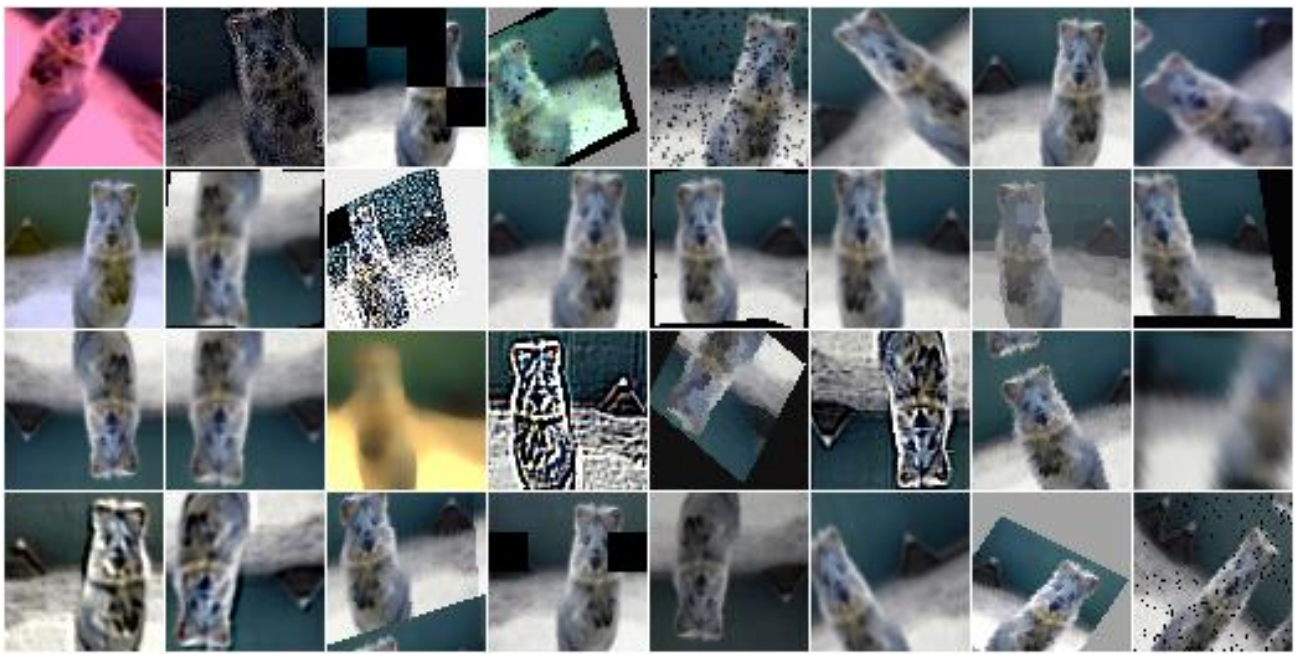
# Dataset augmentation

- Dataset augmentation - applying a wide array of domain-specific invariant transformations to synthetically expand a training set.
- More data - more accurate model.
- Examples for image classification:
  - translation, scaling, cropping
  - reflection
    - counterexample: b->d
  - rotation
    - not big, otherwise 6->9, p->d
  - adding small random noise
- See more invariant transformations here.

# Examples of augmented images



# Examples of augmented images



2 Regularization for deep learning
- Constrained optimization
- Dataset augmentation
- Adding noise
- Semi-supervised, multitask approaches
- Dense-sparse-dense training
- Early stopping
- Sparse representation
- Dropout
- Batch normalization
- Weights initialization

# Adding noise

- Add noise to inputs
  - solution becomes robust to input noise
- Add noise to hidden unit inputs
  - this is dataset augmentation with different levels of abstraction
- Add noise to weights (=adding it to gradient)
  - pushes weights to «plateu» regions where small weight changes do not affect output

# Add noise to gradient[3]

$$\nabla J(\theta) \leftarrow \nabla J(\theta) + N(0, \sigma_t)$$

Recommended schedule:

$$\sigma_t = \frac{\eta}{(1+t)^\gamma}$$

where $\eta \in \{0.01, 0.3, 1.0\}$, $\gamma = 0.55$.

Improvements obtained:

- for networks with poor initialization (all zeroes)
- for very deep networks
- for memory networks

[3] Neelakantan, Arvind et al. Adding Gradient Noise Improves Learning for Very Deep Networks. 2015.

# Add noise to outputs

- When incorrect labels $y$ are present - the model may overfit to them.
- Idea: to force model not to take $y$ too seriously - slightly spread $y$ over all classes.
- For $(x_n, y_n)$ replace hard targets with soft targets:

| | hard target | soft target |
|---|---|---|
| $y = 1$ | 0 | $\frac{\varepsilon}{C}$ |
| $\dots$ | | |
| $y = y_n - 1$ | 0 | $\frac{\varepsilon}{C}$ |
| $y = y_n$ | 1 | $1 - \frac{C-1}{C}\varepsilon$ |
| $y = y_n + 1$ | 0 | $\frac{\varepsilon}{C}$ |
| $\dots$ | | |
| $y = C$ | 0 | $\frac{\varepsilon}{C}$ |

- Smoothed likelihood:

$$\prod_{n=1}^{N} \prod_{} \left(\right)^{1-\frac{C-1}{C}\varepsilon}$$

# Semi-supervised learning

- In semi-supervised learning we use:
  - labelled data $(x_1, y_1), ...(x_N, y_N)$
  - unlabelled data $x_{N+1}, ...x_{N+M}$.
- Motivation:
  - labelling is expensive
  - $N$ is small and $M \gg N$.
  - $p(x)$ and $p(y|x)$ have shared parametrization.

# Semi-supervised learning - neural nets[4]

$$\mathcal{L}_{hybrid}(X,Y) = \mathcal{L}_{disc}(X,Y) + \gamma \mathcal{L}_{unsup}(X)$$

where

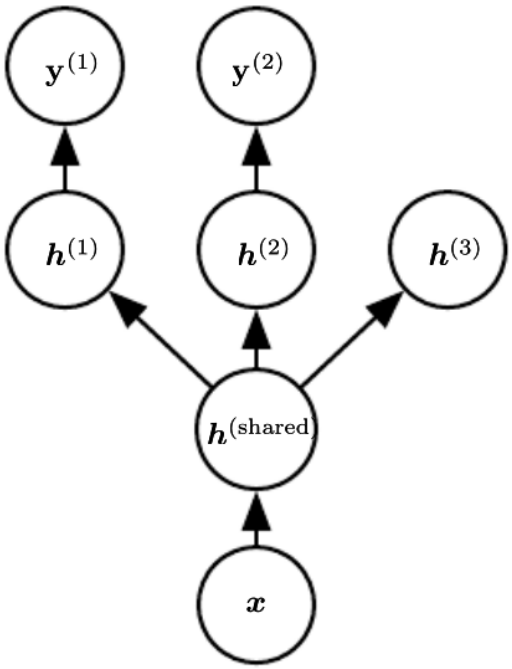
- $\mathcal{L}_{disc}(X,Y) = \sum_{n=1}^{N} \ln p(y_n|x_n)$ - discriminative log-likelihood
- $\mathcal{L}_{unsup}(X,Y) = \sum_{n=1}^{N+M} \ln p(x_n)$ - unsupervised log-likelihood
- $\gamma$ - trade-off hyperparameter (tuned on validation set)

Results:

- In article Bolzmann machines were used
- Significant reduction of error-rate on MNIST, 20 newsgroups.

[4] Larochelle, H. and Bengio, Y. (2008). Classification using discriminative restricted Boltzmann machines. In ICML'2008.

# Multi-task learning




- Applicable when several tasks have shared factors.
- Statistical benefit - more accurate estimation

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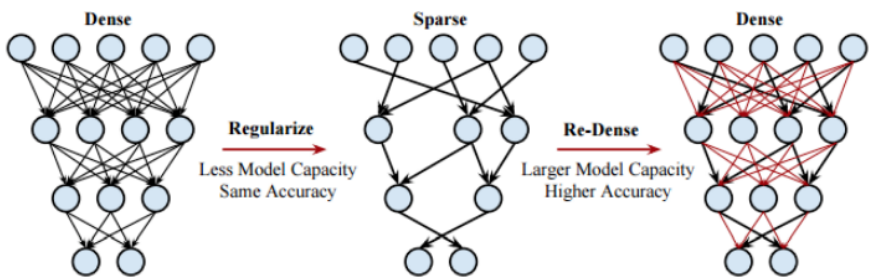
# Dense-sparse-dense training[5]

1. initial regular training, but with the main purpose of seeing which weights are important, not learning the final weight values.
2. Drop the connections where the weights are under a particular threshold. Retrain the sparse network to learn the weights of the important connections.
3. Make the network dense again and retrain it using small learning rate, a step which adds back capacity.




- Improves AlexNet, GoogleNet, ResNet performance.

[5] https://arxiv.org/pdf/1607.04381v1.pdf

# Algorithm

**Initialization:** $W^{(0)}$ *with* $W^{(0)} \sim N(0, \Sigma)$
**Output**: $W^{(t)}$.

*Initial Dense Phase*

**while** *not converged* **do**
  $\tilde{W}^{(t)} = W^{(t-1)} - \eta^{(t)} \nabla f(W^{(t-1)}; x^{(t-1)})$;
  $t = t + 1$;
**end**

*Sparse Phase*

$S = sort(|W^{(t-1)}|)$; $\lambda = S_{k_i}$; $Mask = \mathbb{1}(|W^{(t-1)}| > \lambda)$;
**while** *not converged* **do**
  $\tilde{W}^{(t)} = W^{(t-1)} - \eta^{(t)} \nabla f(W^{(t-1)}; x^{(t-1)})$;
  $\tilde{W}^{(t)} = W^{(t)} \cdot Mask$;
  $t = t + 1$;
**end**

*Final Dense Phase*

**while** *not converged* **do**
  $\tilde{W}^{(t)} = W^{(t-1)} - \eta^{(t)} \nabla f(W^{(t-1)}; x^{(t-1)})$;
  $t = t + 1$;
**end**
**goto** *Sparse Phase* for iterative DSD;

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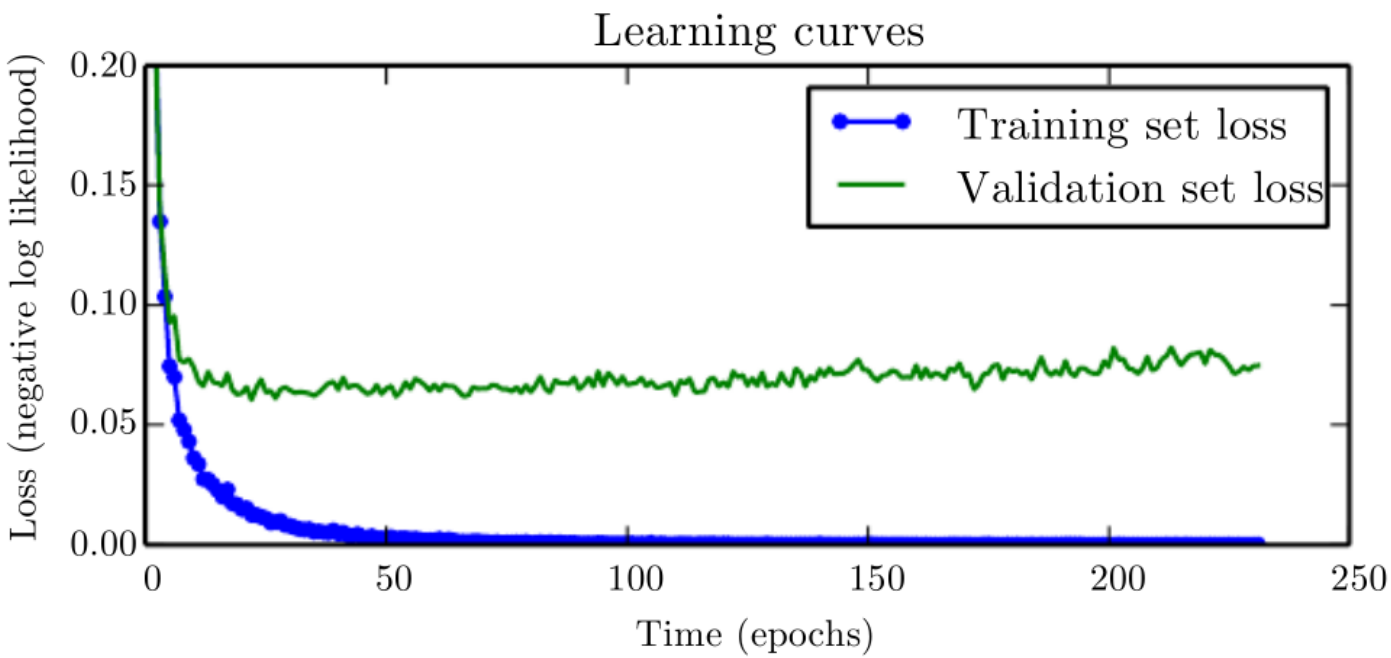
# Early stopping



# Early stopping

- Needs separate validation set.
- Is similar to weight decay (from close to zero initialization).
- Parameters:
  - **period of steps (P)** when validation performance is reevaluated
    - smaller period - more accurate, but more computationally intensive
  - after how many **«bad» evaluations** (quality didn't improve) set to stop
    - if small - may stop too early due to noisy performance estimation.
- In practice model is evaluated fixed amount of epochs, but serialized every P epochs.

# Early stopping - utilizing validation set

Early stopping returned:

- optimal number of steps $i^*$
- optimal parameters $\theta^*$
- performance on validation $P_{val}$ and train $P_{train}$

Two approaches how to utilize validation set:

1. reinitialize NN and run $i^*$ steps using training+validation set.
   - use the same number of passes through objects or dataset (epochs)?
2. continue training NN with initialization $\theta^*$ on the validation set until quality on validation reaches $P_{train}$.
   - may not reach

# Sparse representation

- Suppose
  - $\theta$ is a vector of estimated model parameters
  - $h$ is inner representation:
- Optimized criterion in sparse representation becomes:

$$\tilde{J}(\theta) = J(\theta) + \alpha R(h(\theta)) \rightarrow \min_{\theta}$$

where $R(h)$ is sparsity provoking prior such as $R(h) = \sum_i |h_i|$.

# Example of sparse representation: sparse coding

- Definitions:
  - $X \in \mathbb{R}^{NxD}$ - design matrix
  - $D \in \mathbb{R}$ - dictionary matrix (rows-code words)
  - $W \in \mathbb{R}$ - representation matrix (rows-object representations)
- Sparse coding is found with optimization task:

$$\|X - WD\|_2^2 + \|W\|_1 \to \min_{D,W}$$

where $\|A\|_2^2 := \sum_{i,j} a_{i,j}^2$ and $\|A\|_1 := \sum_{i,j} |a_{i,j}|$.

# Sparse coding: estimation

- Sparse coding is found with optimization task:

$$\|X - WD\|_2^2 + \|W\|_1 \to \min_{D,W} \tag{3}$$

- Task (3) is not convex with respect to $D, W$ but is convex with respect to $D$ or $W$ only (holding another matrix fixed).

**INPUT**: design matrix $X$

initialize $D$ randomly
while stop condition not met:
    $W = \arg\min_W \|X - WD\|_2^2 + \|W\|_1$
    $D = \arg\min_D \|X - WD\|_2^2 + \|W\|_1$

**OUTPUT**: dictionary $D$ and sparse representation $W$

- For $W$ solve $N$ LASSO regressions (for each row of $W$)
- For $D$ solve $K$ OLS regressions (for each column of $D$)

# Sparse coding: encoder & decoder

- Sparse coding is MSE-based sparse autoencoder.
- Suppose we get some observation $x$
- Encoder $x \to w$
  - dictionary $D$ is fixed
  - solve 1 LASSO regression:

$$\left\|x^T - w^T D\right\|^2 + \|w\|_1 \to \min_w$$

- Decoder $w \to \widehat{x}$:
  - $\widehat{x}^T = w^T D$

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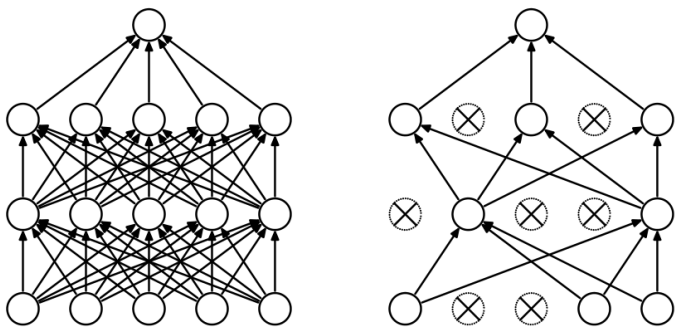
# Dropout idea

Each node in the neural network is removed with probability $1 - p$ independently from decisions about other nodes:

Comparison neural net without/with dropout



(a) Standard Neural Net (b) After applying dropout.

- Output layer nodes are never removed.
- Recommended parameters:
  - $p = 0.5$ for inner layer nodes
  - $p = 0.8$ for input layer nodes (feature subsampling)
- Removal probabilities can be finetuned on cross-validation.

# Dropout motivation

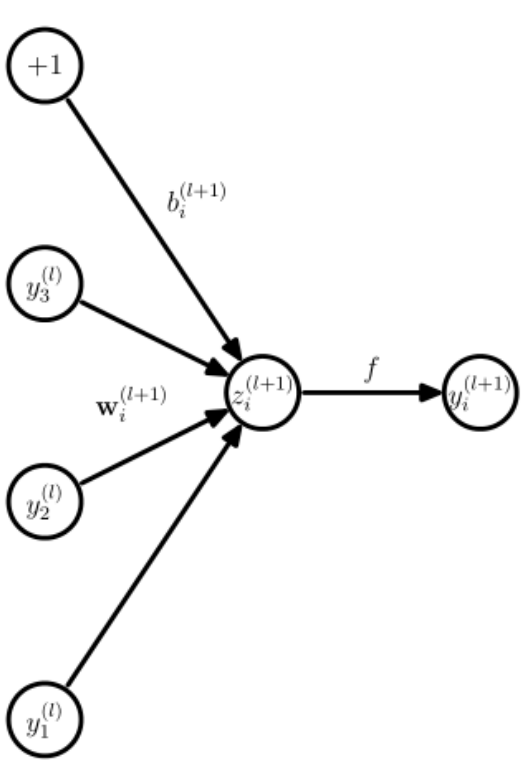
- Motivation from genetic theory of evolution:
  - sexual reproduction involves taking half the genes of one parent and half of the other.
  - best fit genes get mixed with 0.5 probabilities
  - best genes should learn "by themselves", not relying on complex outer gene structure
    - less ovefitting
- Construction works
  - team of workers and the overall goal is to learn how to erect a building
  - if each of the workers is overly specialized, if one gets sick or makes a mistake, the whole building will be severely affected
  - pick randomly every week some of the workers and send them to business trip during training.
  - team becomes more resilient to noise or workers being on vacation.

# Deep learning motivation

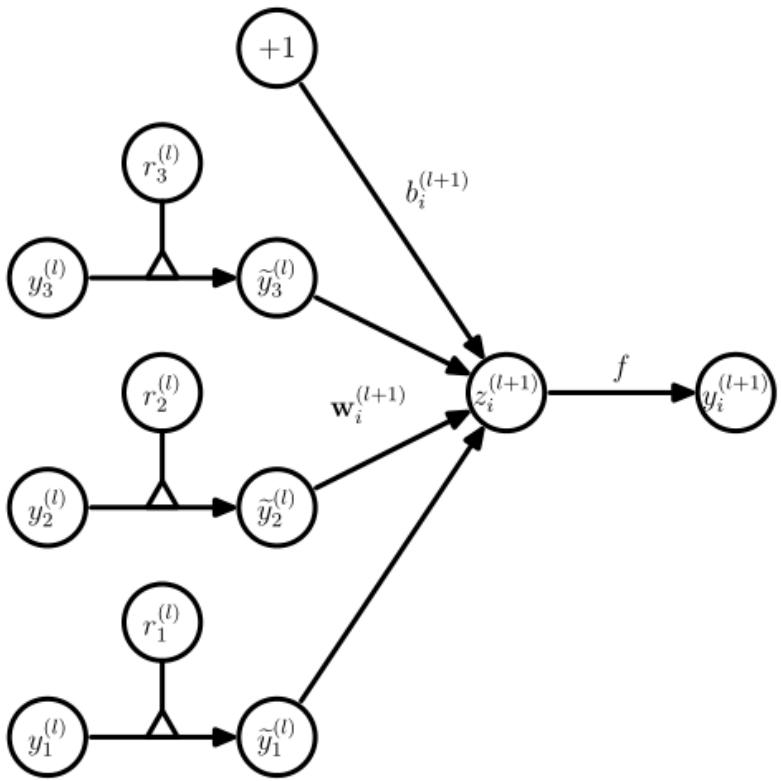
- nodes rely less on outputs of other nodes
- try more to learn something by themselves
- behave in a more robust way
- resulting network becomes less overfitted.

# Dropout algorithm

Comparison of usual and dropout network for one node




(a) Standard network




(b) Dropout network

# Definitions

Define:

- $f(x)$ - an activation function.
- $y^l$ - vector of outputs at layer $l$
- $z^l$ - vector of inputs to layer $l$
- $a * b$ defines element-wise product of elements.
- $L$ - number of layers in neural network
- $y^{(0)} = x$ - input feature vector
- $Bernoulli(p)$ returns a vector of independent Bernoulli random variables with parameter $p$.

# Forward propagation algorithm

We need to repeat forward propagation recurrently for $l = 0, 1, ...L-1$.

1. Usual feed-forward neural network:

$$z_i^{(l+1)} = w_i^{(l+1)} y^l + b_i^{(l+1)}$$
$$y_i^{(l+1)} = f(z_i^{(l+1)})$$

2. Feed-forward network with dropout:

$$r_j^{(l)} \sim Bernoulli(p)$$
$$\tilde{y}^l = r^{(l)} * y^{(l)}$$
$$z_i^{(l+1)} = w_i^{(l+1)} \tilde{y}^l + b_i^{(l+1)}$$
$$y_i^{(l+1)} = f(z_i^{(l+1)})$$

# Application of dropout

- **Learning**
  - while weights not converge:
    1. sample random subnetwork ("thinned network") with dropout
    2. apply one step of stochastic gradient descent to thinned network

  Comment: due to weights sharing across all thinned networks the number of parameters is the same as in original network.

# Application of dropout

- **Prediction**
  - use full networks with all nodes, but multiply each weight by $p$[6].
  - such scaling will yield the same output as average thinned network.
- Comments:
  - $p \geq 0.5$
  - $p$ higher if applied to input layer.

[6] precise for networks without non-linearities. With non-linearities Monte-Carlo sampling may work better.

# Complexity

- $O(W)$ operations during each step to generate binary mask.
- $O(W)$ memory to store the mask
- Complexity of forward and backward pass - the same
- BUT: total number of steps until convergence may increase
  - dropout shrinks model capacity
  - to offset this, need to increase the network, make more optimization steps

# Modifications

- Additive Gaussian noise:
  - $h_i \leftarrow h_i * N(1,1)$
  - at test time: no scaling needed
- Dropconnect

# Conclusion

- Dropout behaves similar to generating $2^W$ networks and taking weighted average of their predictions ($W$ is the number of weights in the original neural network).
- Dropout performes intelligent high-level information destruction
  - model becomes more robust (at high levels of abstraction as well)
- Properties:
  - number of parameters is the same
  - training complexity is reduced
  - complexity of prediction is the same
- Dropout provides accuracy improvement in many domains.
- More details in: *"Dropout: A Simple Way to Prevent Neural Networks from Overfitting". Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, Ruslan Salakhutdinov. Journal of Machine Learning Research 15 (2014) 1929-1958.*

# Problems solved by batch normalization[7]

- Weights in the network are updated jointly. Let some weight $w_i$ be improved by step of SGD. This improvement may get lost, because simultaneously other weight were updated.
- In the context of other updated weights performed update of $w_i$ may lose sense.
- In short: distribution of neuron outputs change making it hard to keep weight up-to-date.
- Consequences:
  - Slows down convergence
  - Need to use smaller error rate
  - If using saturating activations this may lead to neuron saturation.
  - Hard to choose proper initialization to omit these saturations.

[7] Sergey Ioffe, Christian Szegedy. Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift. 2015.

# Batch normalization

- Idea of method: standardize outputs of neurons
  - i.e. input features and outputs of hidden neurons
- Benefits:
  - Gradient becomes invariant to scale of neuron outputs.
  - Distribution of inputs is preserved.
  - Can ensure staying away from neuron saturation regions
  - May use higher learning rates
- Approach has beaten state-of-the-art ImageNet model (2015).

# Training algorithm

For minibatch $x_1, ...x_m$ of $m$ random objects:

- find minibatch mean
- find minibatch std. deviation
- normalize all samples of the minibatch.
- form output as $y_i = \gamma \widehat{x}_i + \beta$ ($\gamma$ and $\beta$ are additional parameters that are learned).

**Input:** Values of $x$ over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: $\gamma, \beta$
**Output:** $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

**Algorithm 1:** Batch Normalizing Transform, applied to activation $x$ over a mini-batch.

# Derivatives for back-propagation

$$\frac{\partial \ell}{\partial \widehat{x}_i} = \frac{\partial \ell}{\partial y_i} \cdot \gamma$$

$$\frac{\partial \ell}{\partial \sigma_{\mathcal{B}}^2} = \sum_{i=1}^m \frac{\partial \ell}{\partial \widehat{x}_i} \cdot (x_i - \mu_{\mathcal{B}}) \cdot \frac{-1}{2}(\sigma_{\mathcal{B}}^2 + \epsilon)^{-3/2}$$

$$\frac{\partial \ell}{\partial \mu_{\mathcal{B}}} = \left( \sum_{i=1}^m \frac{\partial \ell}{\partial \widehat{x}_i} \cdot \frac{-1}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \right) + \frac{\partial \ell}{\partial \sigma_{\mathcal{B}}^2} \cdot \frac{\sum_{i=1}^m -2(x_i - \mu_{\mathcal{B}})}{m}$$

$$\frac{\partial \ell}{\partial x_i} = \frac{\partial \ell}{\partial \widehat{x}_i} \cdot \frac{1}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} + \frac{\partial \ell}{\partial \sigma_{\mathcal{B}}^2} \cdot \frac{2(x_i - \mu_{\mathcal{B}})}{m} + \frac{\partial \ell}{\partial \mu_{\mathcal{B}}} \cdot \frac{1}{m}$$

$$\frac{\partial \ell}{\partial \gamma} = \sum_{i=1}^m \frac{\partial \ell}{\partial y_i} \cdot \widehat{x}_i$$

$$\frac{\partial \ell}{\partial \beta} = \sum_{i=1}^m \frac{\partial \ell}{\partial y_i}$$

# Batch normalization: algorithm

**Input:** Network $N$ with trainable parameters $\Theta$;
subset of activations $\{x^{(k)}\}_{k=1}^{K}$

**Output:** Batch-normalized network for inference, $N_{\text{BN}}^{\text{inf}}$

1: $N_{\text{BN}}^{\text{tr}} \leftarrow N$ // Training BN network
2: **for** $k = 1 \ldots K$ **do**
3: Add transformation $y^{(k)} = \text{BN}_{\gamma^{(k)},\beta^{(k)}}(x^{(k)})$ to $N_{\text{BN}}^{\text{tr}}$ (Alg. 1)
4: Modify each layer in $N_{\text{BN}}^{\text{tr}}$ with input $x^{(k)}$ to take $y^{(k)}$ instead
5: **end for**
6: Train $N_{\text{BN}}^{\text{tr}}$ to optimize the parameters $\Theta \cup \{\gamma^{(k)}, \beta^{(k)}\}_{k=1}^{K}$
7: $N_{\text{BN}}^{\text{inf}} \leftarrow N_{\text{BN}}^{\text{tr}}$ // Inference BN network with frozen // parameters

# Prediction

At prediction $x_i$ is shifted by $\mathbb{E}x_i$ and scaled by $\sqrt{Var[x_i]}$ obtained by averaging their estimates for all minibatches.

8: **for** $k = 1 \dots K$ **do**
9: // For clarity, $x \equiv x^{(k)}, \gamma \equiv \gamma^{(k)}, \mu_{\mathcal{B}} \equiv \mu_{\mathcal{B}}^{(k)}$, etc.
10: Process multiple training mini-batches $\mathcal{B}$, each of size $m$, and average over them:

$$\mathrm{E}[x] \leftarrow \mathrm{E}_{\mathcal{B}}[\mu_{\mathcal{B}}]$$
$$\mathrm{Var}[x] \leftarrow \frac{m}{m-1}\mathrm{E}_{\mathcal{B}}[\sigma^2_{\mathcal{B}}]$$

11: In $N^{\mathrm{inf}}_{\mathrm{BN}}$, replace the transform $y = \mathrm{BN}_{\gamma,\beta}(x)$ with $y = \frac{\gamma}{\sqrt{\mathrm{Var}[x]+\epsilon}} \cdot x + \left(\beta - \frac{\gamma\,\mathrm{E}[x]}{\sqrt{\mathrm{Var}[x]+\epsilon}}\right)$
12: **end for**

**Algorithm 2:** Training a Batch-Normalized Network

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2 Regularization for deep learning
- Constrained optimization
- Dataset augmentation
- Adding noise
- Semi-supervised, multitask approaches
- Dense-sparse-dense training
- Early stopping
- Sparse representation
- Dropout
- Batch normalization
- Weights initialization

# Random weights initialization

- random with distribution $w_i \sim F(0, \sigma^2)$, having
  - zero mean
  - varaince equal to $\frac{1}{n_{in}}$ or $\frac{2}{n_{in}+n_{out}}$ where
    - $n_{in}$ is the number of incoming connections for neuron $i$.
    - $n_{out}$ is the number of outgoing connections for neuron $i$.

# Weights initialization with unsupervised pretraining

Unsupervised pretraining:

1. Train an autoencoder.
2. Initialize first layers of supervised network with autoencoder weights.

Comments:

- was used in the first works on deep learning
- now not very popular, random schemes are used or initialization from supervised nets for similar tasks.

# Conclusion

Most popular regularization strategies:

- early stopping
- batch normalization
- dropout
- $L_1/L_2$ regularization.