

# Optimization on Deep Learning

## Course: Deep Learning for Image Analysis

### 19 - 24 November, Paris

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- 1 Optimizers for Deep Learning
- 2 Difficulties in Deep Network Optimisation
- 3 How to fight against overfitting
- 4 References

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# Gradient Descent [Cauchy, 1847]

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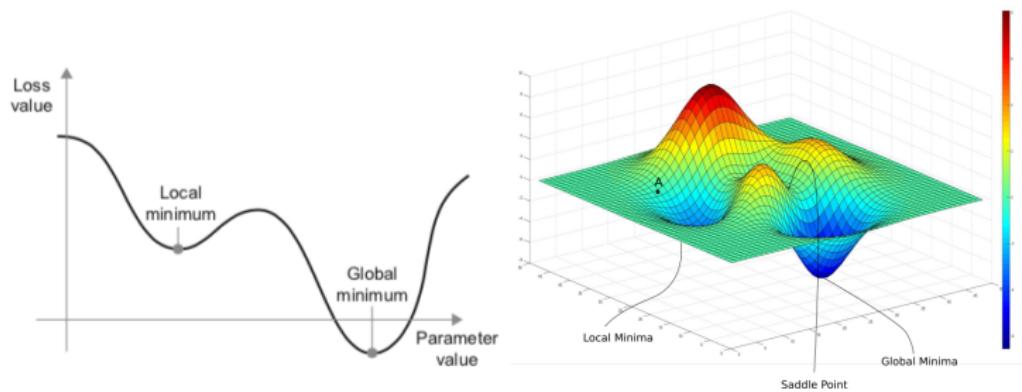
## Algorithm 1 pseudocode gradient descent

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- 1: **given** initial learning rate  $\eta \in \mathbb{R}$  and dataset  $\mathbf{X}$
  - 2: **initialize** time step  $t = 0$ , parameter vector  $\boldsymbol{\theta}_{t=0} \in \mathbb{R}^P$ ,
  - 3: **repeat**
  - 4:    $t=t+1$
  - 5:    $\mathbf{g}_t = \nabla f_i(\mathbf{X}, \boldsymbol{\theta}_{t-1})$  Return parameter gradient
  - 6:    $\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} - \eta \mathbf{g}_t$
  - 7: **until** stopping criterion is met
  - 8: **return** optimized parameters  $\boldsymbol{\theta}_i$
-

# Difficulties in Deep Network Optimisation

- A Local minima / Global minima
- B Saddle Point (Plateaus or Flat Regions)



## SGD [Robbins and Monro, 1985]

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**Algorithm 2** pseudocode for stochastic gradient descent

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- 1: **given** initial learning rate  $\eta \in \mathbb{R}$  and dataset  $\mathbf{X}$
  - 2: **initialize** time step  $t = 0$ , parameter vector  $\boldsymbol{\theta}_{t=0} \in \mathbb{R}^P$ ,
  - 3: **repeat**
  - 4:    $t=t+1$
  - 5:    $\mathbf{X}_t = \text{SelectBatch}(\mathbf{X})$  Select a batch from data, whole data, only one, ...
  - 6:    $\mathbf{g}_t = \nabla f_i(\mathbf{X}_t, \boldsymbol{\theta}_{t-1})$  Return parameter gradient
  - 7:    $\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} - \eta \mathbf{g}_t$
  - 8: **until** stopping criterion is met
  - 9: **return** optimized parameters  $\boldsymbol{\theta}_i$
-

## SelectBatch( $\mathbf{X}$ )

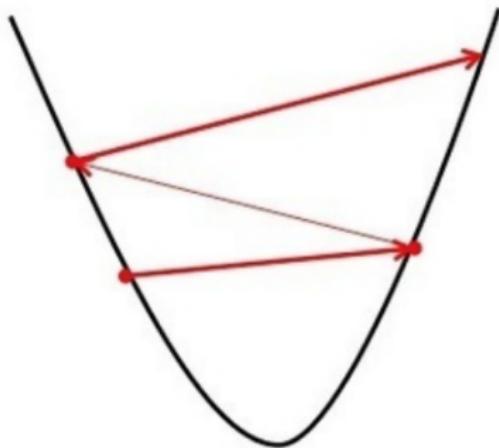
- ① Vanilla gradient descent, a.k.a. *batch gradient descent*, computes the gradient of the cost function w.r.t. to the parameters  $\theta$  for the entire training dataset.
- ② *Stochastic gradient descent (SGD)* in contrast performs a parameter update for each training example.
- ③ *Mini-batch gradient descent* performs an update for every mini-batch of  $N$  training examples.

Some difficulties:

- ① Choosing a proper learning rate can be difficult.
- ② Same learning rate applies to all parameter updates
- ③ Highly non-convex error functions common for neural networks is avoiding getting trapped in their numerous suboptimal local minima.

## Learning Rate

Big learning rate



Small learning rate



# Learning Rate in Training Process

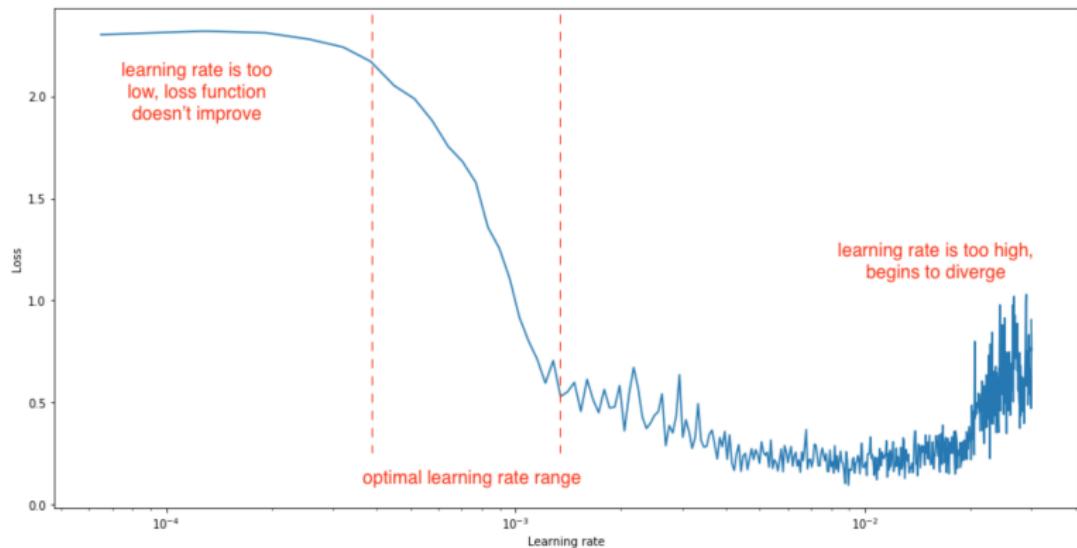


Image by Jeremy Jordan via  
<https://www.jeremyjordan.me/nn-learning-rate/>

# SGD with Learning Rate Schedule

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**Algorithm 3** pseudocode for SGD with Learning Rate Schedule

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- 1: **given** initial learning rate  $\eta \in \mathbb{R}$  and a dataset  $\mathbf{X}$
  - 2: **initialize** time step  $t = 0$ , parameter vector  $\theta_{t=0} \in \mathbb{R}^P$ , schedule multiplier  $\eta_{t=0} \in \mathbb{R}$
  - 3: **repeat**
  - 4:    $t=t+1$
  - 5:    $\mathbf{X}_t = \text{SelectBatch}(\mathbf{X})$  Select a batch from data, whole data, only one, ...
  - 6:    $\mathbf{g}_t = \nabla f_i(\mathbf{X}_t, \theta_{t-1})$  Return parameter gradient
  - 7:    $\eta_t = \text{SetScheduleMultiplier}(t)$  Can be fixed, decay, warm restarts, ...
  - 8:    $\theta_t = \theta_{t-1} - \eta_t \eta \mathbf{g}_t$
  - 9: **until** stopping criterion is met
  - 10: **return** optimized parameters  $\theta_i$
-

# Visualizing the Loss Landscape of Neural Net

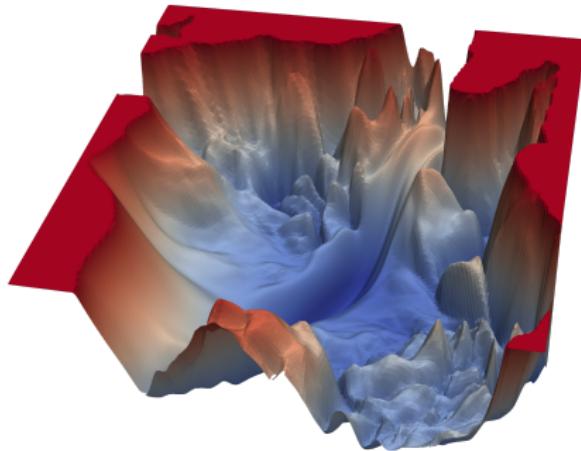
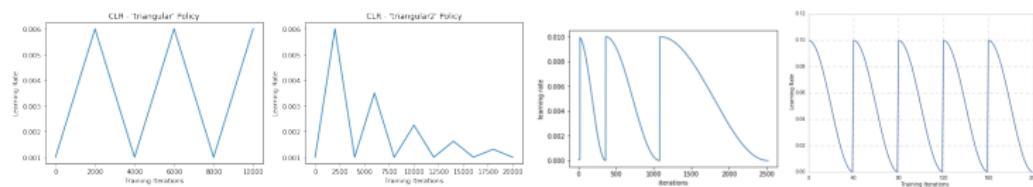


Figure: Loss Function for VGG56 [Li et al., 2017]

# SGD with Learning Rate Schedule: New problems.... new ideas!

- Exponential Moving Decay [Dozat and Manning, 2017]
- Cyclical Learning Rates [Smith, 2017]
- Decay with restarts [Loshchilov and Hutter, 2016]



**Figure:** Schedules: Triangular / Triangular with exponential decay / Exponential Decay with Restarts / Snapshot

- Snapshot Ensembles: Train 1, Get M for free [Huang et al., 2017]
- Don't Decay the Learning Rate, Increase the batch size [Smith et al., 2018]

# Optimizer in Keras

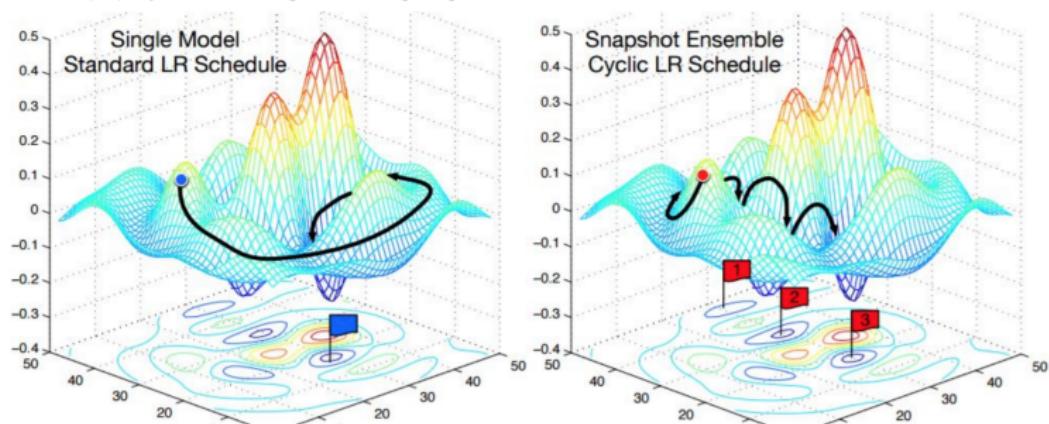


Figure: [Huang et al., 2017]

```
sgd = optimizers.SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=True)
model.compile(loss='mean_squared_error', optimizer=sgd)
```

## Practical Work 1: Cyclic LR

## SGD with momentum [Qian, 1999]

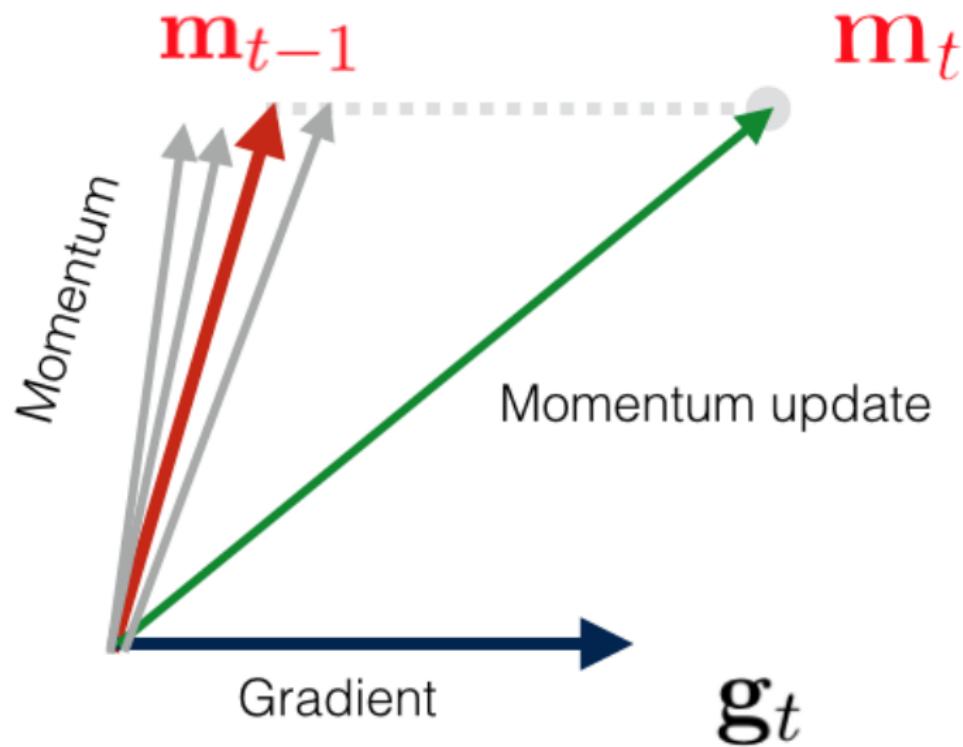
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**Algorithm 4** pseudocode for stochastic gradient descent **with Momentum**

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- 1: **given** initial learning rate  $\epsilon \in \mathbb{R}$ , dataset  $\mathbf{X}$ , **momentum factor**  $\beta_1 \in \mathbb{R}$
  - 2: **initialize** time step  $t = 0$ , parameter vector  $\theta_{t=0} \in \mathbb{R}^P$ , first momentum factor  $\mathbf{m}_{t=0} = 0 \in \mathbb{R}^P$ , schedule multiplier  $\eta_{t=0} \in \mathbb{R}$
  - 3: **repeat**
  - 4:    $t=t+1$
  - 5:    $\mathbf{X}_t = \text{SelectBatch}(\mathbf{X})$  Select a batch from data
  - 6:    $\mathbf{g}_t = \nabla f_t(\mathbf{X}_t, \theta_{t-1})$  Return parameter gradient
  - 7:    $\eta_t = \text{SetScheduleMultiplier}(t)$  Can be fixed, decay, warm restarts, ...
  - 8:    $\mathbf{m}_t = \beta_1 \mathbf{m}_{t-1} + \eta_t \mathbf{g}_t$
  - 9:    $\theta_i = \theta_{t-1} - \mathbf{m}_t$
  - 10: **until** stopping criterion is met
  - 11: **return** optimized parameters  $\theta_i$
-

## Momentum



# SGD with Nesterov's momentum [Nesterov, 1983]

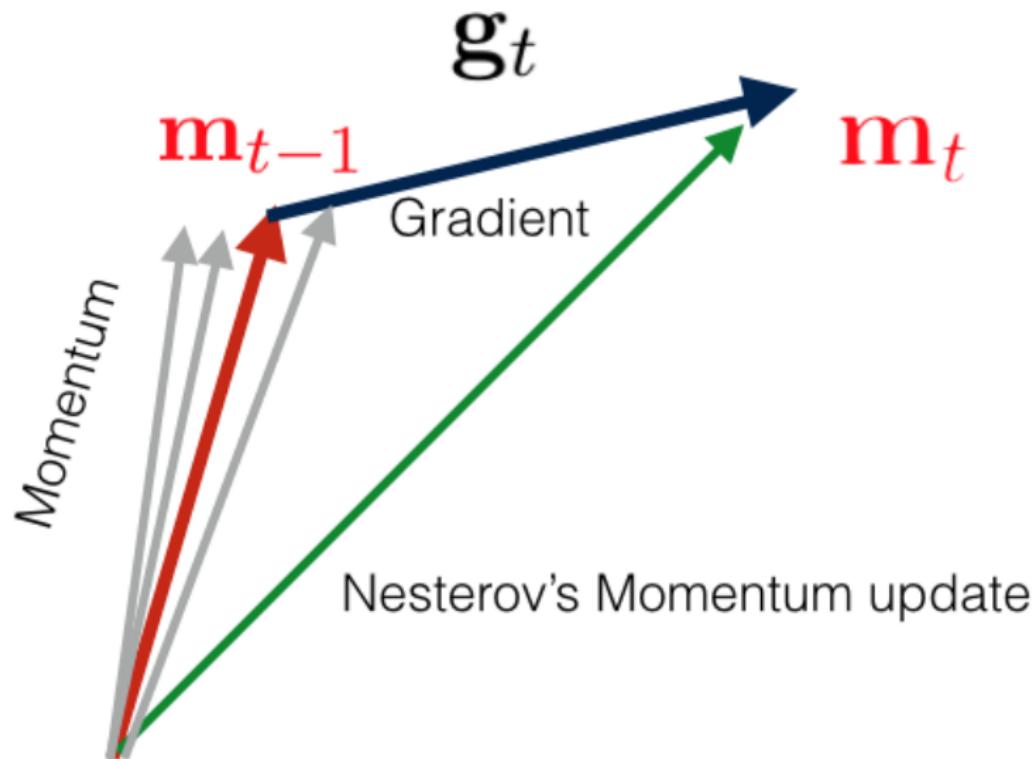
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**Algorithm 5** pseudocode for stochastic gradient descent **with Momentum**

---

- 1: **given** initial learning rate  $\epsilon \in \mathbb{R}$ , dataset  $\mathbf{X}$ , momentum factor  $\beta_1 \in \mathbb{R}$
  - 2: **initialize** time step  $t = 0$ , parameter vector  $\theta_{t=0} \in \mathbb{R}^P$ , first momentum factor  $\mathbf{m}_{t=0} = 0 \in \mathbb{R}^P$ , schedule multiplier  $\eta_{t=0} \in \mathbb{R}$
  - 3: **repeat**
  - 4:    $t=t+1$
  - 5:    $\mathbf{X}_t = \text{SelectBatch}(\mathbf{X})$  Select a batch from data
  - 6:    $\mathbf{g}_t = \nabla f_t(\mathbf{X}_t, \theta_{t-1} + \mathbf{m}_{t-1})$  Return parameter gradient
  - 7:    $\eta_t = \text{SetScheduleMultiplier}(t)$  Can be fixed, decay, warm restarts, ...
  - 8:    $\mathbf{m}_t = \beta_1 \mathbf{m}_{t-1} + \eta_t \mathbf{g}_t$
  - 9:    $\theta_i = \theta_{t-1} - \mathbf{m}_t$
  - 10: **until** stopping criterion is met
  - 11: **return** optimized parameters  $\theta_i$
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## Nesterov's Momentum



**Table:** Summary: Some Optimizers I

Method	Update
SGD	$\theta_{t+1} = \theta_t - \eta g(\theta_t)$
Momentum	$\theta_{t+1} = \theta_t + m_t, m_t = \beta_1 m_{t-1} - \eta g(\theta_t)$
Nesterov Mom.	$\theta_{t+1} = \theta_t + m_t, m_t = \beta_1 m_{t-1} - \eta g(\theta_t + \beta_1 m_{t-1})$

## Motivation

- ➊ SGD bounces around in high curvature directions and makes slow progress in low curvature directions.



**Figure:** Gradient Descent has poor performance on loss functions having contours that are very long "ellipsoids"

## Motivation: Invariance

Suppose we would like to fit a linear regression on  $y$  by using  $\mathbf{x} = [x_1, x_2]$ , i.e.  $\hat{y} = \theta_1 x_1 + \theta_2 x_2$ :

Table: default

$x_1$	$x_2$	$y$
134.2	0.01234	1.2
124.4	0.0294	2.2
92.2	0.0194	1.56
:	:	:
98.2	0.0214	1.76

- ① This can happen since the inputs have arbitrary units.
- ② Which weight,  $\theta_1$  or  $\theta_2$ , should receive a larger gradient descent update?

# Motivation

- ① SGD bounces around in high curvature directions and makes slow progress in low curvature directions.
- ② This can happen with highly correlated parameters.

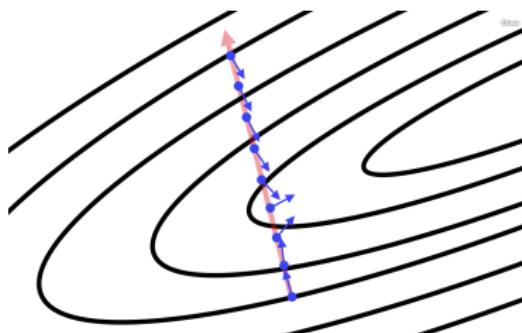
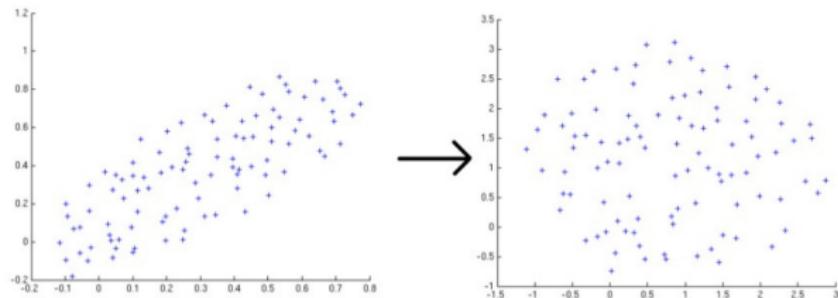


Figure: SGD

# Motivation



**Figure:** Which transformation can "decorrelate data? (Statistical Whitening Transform).

# Motivation

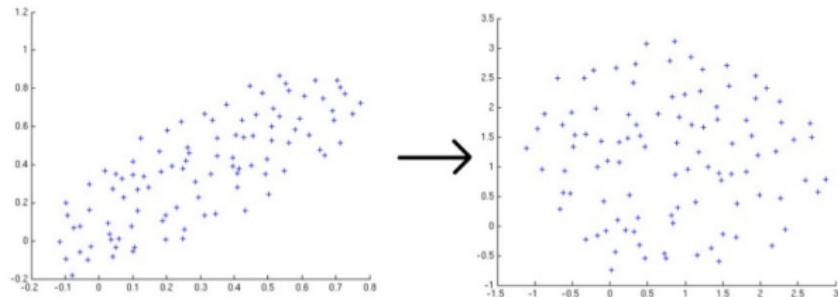


Figure: Which transformation can "decorrelate data? (Statistical Whitening Transform).

Inverse Covariance matrix do the work!

# Motivation

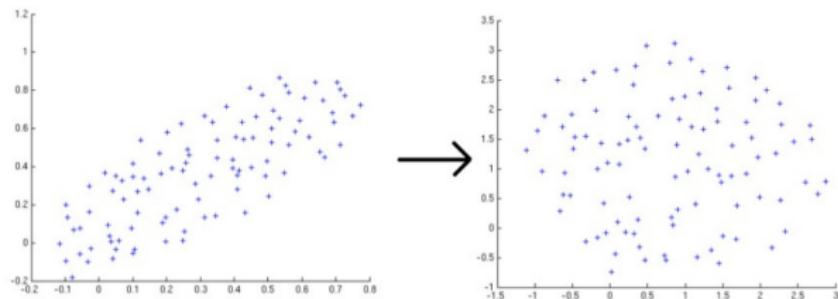


Figure: Which transformation can "decorrelate data? (Statistical Whitening Transform).

Inverse Covariance matrix do the work! Note that one can decompose  $\Sigma^{-1}$  into  $\mathbf{V}\Lambda^T\mathbf{V}^{-1}$  (Singular value decomposition), then with  $\Omega = \{1/\sqrt{\lambda_i}\}_{i=1}^P$

$$\begin{aligned}\mathbf{x}^T \Sigma^{-1} \mathbf{x} &= \mathbf{x}^T \mathbf{V} \Omega \Omega^T \mathbf{V}^T \mathbf{x} \\ &= (\Omega \mathbf{V}^T \mathbf{x})^T \Omega \mathbf{V}^T \mathbf{x} \\ &= \|\Omega \mathbf{V}^T \mathbf{x}\|_2^2\end{aligned}\tag{1}$$

Euclidean distance in the projected space

# From SGD to Natural Gradient Descend

Table: Natural Gradient Descend [Amari et al., 2000]

Method	Update
SGD	$\theta_{t+1} = \theta_t - \eta g(\theta_t)$
Natural Gradient Descend	$\theta_{t+1} = \theta_t - \eta \Sigma_{\theta_t}^{-1} g(\theta_t)$

Two interpretations for the same method:

- ① Second order optimization: Newton Algorithm  
[LeCun et al., 2012]
- ② Gradient Descend in the Riemannian Manifold [Amari, 1998]  
= Fisher Information Matrix (empirical version)

There are many other methods ... What is the problem with  $\Sigma_{\theta}^{-1}$ ?

## Adagrad

In the Adagrad formulation [Duchi et al., 2011],

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{G_{ii,t} + \epsilon}} g(\theta_t) \quad (2)$$

where  $G_{ii,t}$  is the sum of the squares of the gradients of  $\theta_i$  up to time step  $t$  while  $\epsilon$  is a smoothing term that avoids division by zero.  
 $G_{ii,t} = \sum_{j=1}^t g_i^2(\theta_j)$ , where  $g_i$  denote the i-th component of  $g$ .

Note that only elements in the diagonal of  $\Sigma_\theta^{-1}$  are estimated.

## RMSprop [Hinton et al., 2012]

In RMSprop [Hinton et al., 2012] proposes a rule update model's parameter by

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\text{RMS}(G_{ii})_t + \epsilon}} \mathbf{g}(\theta_t) \quad (3)$$

where  $\text{RMS}(G_{ii,t})$  is a momentum estimation of  $\sqrt{G_{ii,t} + \epsilon}$ , i.e., defining the sequence

$$E(\mathbf{g}^2)_t = \rho E(\mathbf{g}^2)_{t-1} + (1 - \rho) \mathbf{g}_t^2,$$

and we define  $\text{RMS}(G_{ii,t}) = E(\mathbf{g}^2)_t + \epsilon$ .

## Adadelta [Zeiler, 2012]

However, the unit in the learning rate don't correspondent with unit in the denominator. Thus, Adadelta optimiser [Zeiler, 2012] update by:

$$\theta_{t+1} = \theta_t - \frac{\text{RMS}(\partial\theta)_{t-1}}{\sqrt{\text{RMS}(G_{ii,t} + \epsilon)}} g(\theta_t) \quad (4)$$

here is a diagonal matrix where each diagonal element  $i, i$  is the sum of the squares of the gradients w.r.t.  $\theta_i$  up to time step  $t$

**Table:** Summary: Some Optimizers II

Method	Update
SGD	$\theta_{t+1} = \theta_t - \eta g(\theta_t)$
Momentum	$\theta_{t+1} = \theta_t + m_t, m_t = \beta_1 m_{t-1} - \eta g(\theta_t)$
Nesterov Mom.	$\theta_{t+1} = \theta_t + m_t, m_t = \beta_1 m_{t-1} - \eta g(\theta_t + \beta_1 m_{t-1})$
Adagrad	$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{G_{ii,t} + \epsilon}} g(\theta_t)$
RMSprop	$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\text{RMS}(G_{ii,t}) + \epsilon}} g(\theta_t)$
Adadelta	$\theta_{t+1} = \theta_t - \frac{\text{RMS}(\partial\theta)_{t-1}}{\sqrt{\text{RMS}(G_{ii})_t + \epsilon}} g(\theta_t)$

# ADAM

Adam can be looked at as a combination of RMSprop and Stochastic Gradient Descent with momentum  
[Kingma and Ba, 2014]

Table: Summary: Some Optimizers

Method	Update
SGD	$\theta_{t+1} = \theta_t - \eta g(\theta_t)$
Momentum	$\theta_{t+1} = \theta_t + m_t, m_t = \beta_1 m_{t-1} - \eta g(\theta_t)$
Nesterov Mom.	$\theta_{t+1} = \theta_t + m_t, m_t = \beta_1 m_{t-1} - \eta g(\theta_t + \beta_1 m_{t-1})$
Adagrad	$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{G_{ii,t} + \epsilon}} g(\theta_t)$
RMSprop	$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\text{RMS}(G_{ii})_t + \epsilon}} g(\theta_t)$
Adadelta	$\theta_{t+1} = \theta_t - \frac{\text{RMS}(\partial \theta)_{t-1}}{\sqrt{\text{RMS}(G_{ii})_t + \epsilon}} g(\theta_t)$
ADAM	Momentum and RMSprop
NADAM	Nesterov Momentum and RMSprop

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# Difficulties in Deep Network Optimisation

- A Local minima / Global minima
- B Saddle Point (Plateaus or Flat Regions)
- C Initialization issues
- D Vanishing Gradient
- E Overfitting

## Initialization Issues

- ① **Gaussian:** From Imagenet 2012, [Krizhevsky et al., 2012] recommends initialization with  $\mathcal{N}(0, .01)$  and adding bias equal to one for some layers become very popular. It is not possible to train very deep network from scratch with it [Simonyan and Zisserman, 2014]. The problem is caused by the activation (and/or) gradient magnitude in final layers [He et al., 2016].
- ② **Glorot:** [Glorot and Bengio, 2010] proposed a formula for estimating the standard deviation on the basis of the number of input and output channels of the layers under assumption of no non-linearity between layers. Despite invalidity of the assumption, Glorot initialization works well.
- ③ **Orthogonal:** Saxe et al. [Saxe et al., 2014] showed that orthonormal matrix initialization works much better for linear networks than Gaussian noise, which is only approximate orthogonal. It also work for networks with non-linearities.
- ④ Recommended lecture: All you need is a good init [Mishkin and Matas, 2016]

## Difficulties in Deep Network Optimisation

- D Vanishing Gradient: If feedback signal has to be propagated through a deep stack of layers, the signal may become tenuous or even be lost entirely, rendering the network untrainable. During training, it causes the model's parameter to grow so large so that even a very tiny amount change in the input can cause a great update in later layers' output. The value of layer weights sometimes overflow and the value becomes **NaN**.

# Fighting against Vanishing Gradient [Pascanu et al., 2013]

- 1 Initialization of Weights: Don't initialize to values that are too large.
- 2 Gradient clipping: clips parameters gradients during backpropagation by a maximum value or maximum norm

```
from keras import optimizers

# All parameter gradients will be clipped to
# a maximum value of 0.5 and
# a minimum value of -0.5.
sgd = optimizers.SGD(lr=0.01, clipvalue=0.5)

# All parameter gradients will be clipped to
# a maximum norm of 1.
sgd = optimizers.SGD(lr=0.01, clipnorm=1.)
```

# Fighting against Vanishing Gradient

3 Skip connections or Shortcuts (Residual Networks):

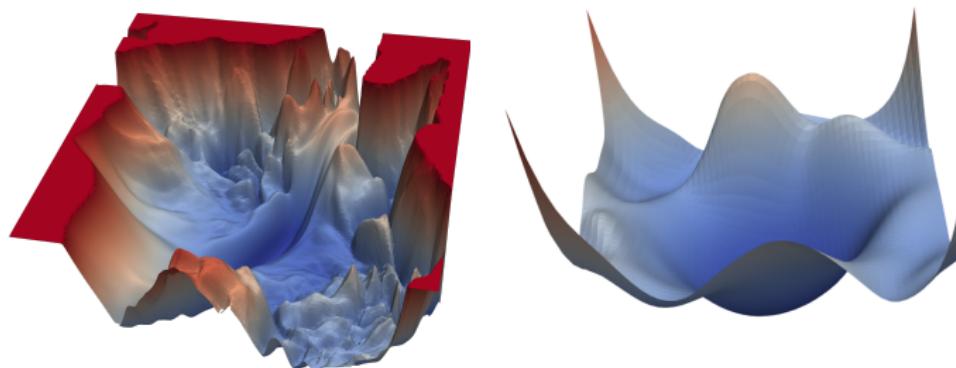
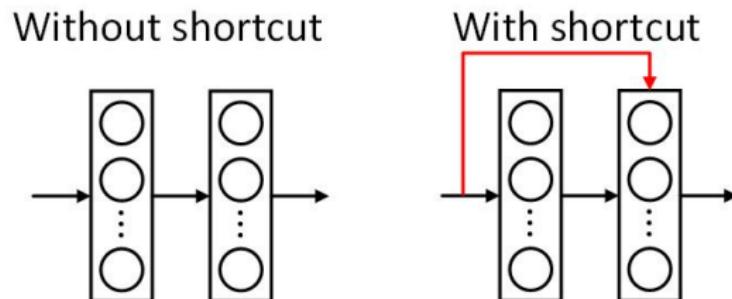
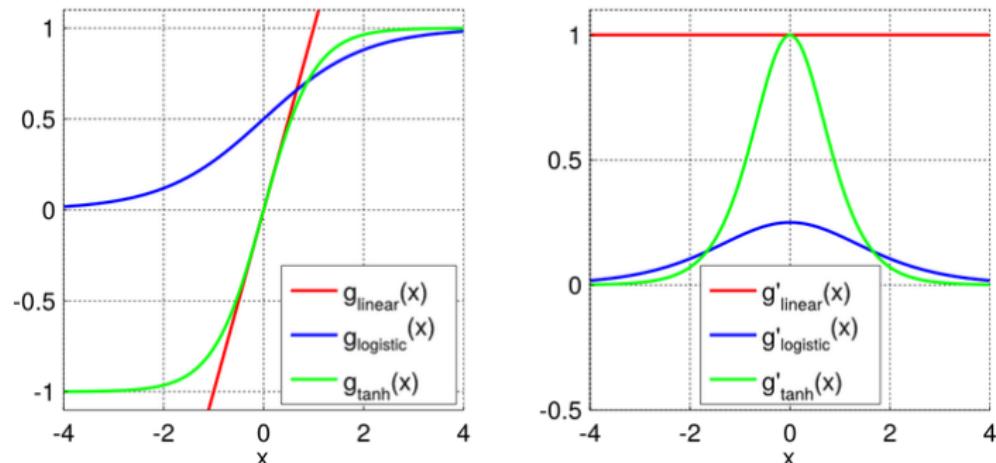


Figure: From [Li et al., 2017]

# Fighting against Vanishing Gradient

4 Avoid ‘stuck states’ induced by activation function:



**Figure:** Left: Three activation function Right: Derivative of activation function.

# Fighting against Vanishing Gradient

- 5 Regularization:  $L_2$  or  $L_1$  norm applies "weight decay" in the cost function of the network. Note that for many activation function, when the activation value is small, that will be almost linear.

```
from keras import regularizers
model.add(Dense(64, input_dim=64,
                kernel_regularizer=regularizers.l2(0.01),
                activity_regularizer=regularizers.l2(0.01)))
```

## 6. Batch Normalization [Ioffe and Szegedy, 2015] [Mishkin and Matas, 2016]

BatchNorm (BN) is a transformation applied before the applying activation in a given layer, i.e. if  $x_i$  are the output of a layer for a mini-batch, the BN is defined by

$$\hat{x}_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2}}, \quad BN_{\gamma, \beta}(x_i) := \gamma \hat{x}_i + \beta$$

where  $\mu_B$  and  $\sigma_B^2$  are respectively the mini-batch mean and variance.  $\gamma$  scale and  $\beta$  shift learned parameters.

- Moving values to zero (activation works better!)
- Large learning rates can scale the parameters which could amplify the gradients, thus leading to an explosion. In Batch normalization small changes in parameter to one layer do not get propagated to other layers.
- This makes it possible to use higher learning rates for the optimizers, which otherwise would not have been possible.
- It also makes gradient propagation in the network more stable.

## 6. Batch Normalization

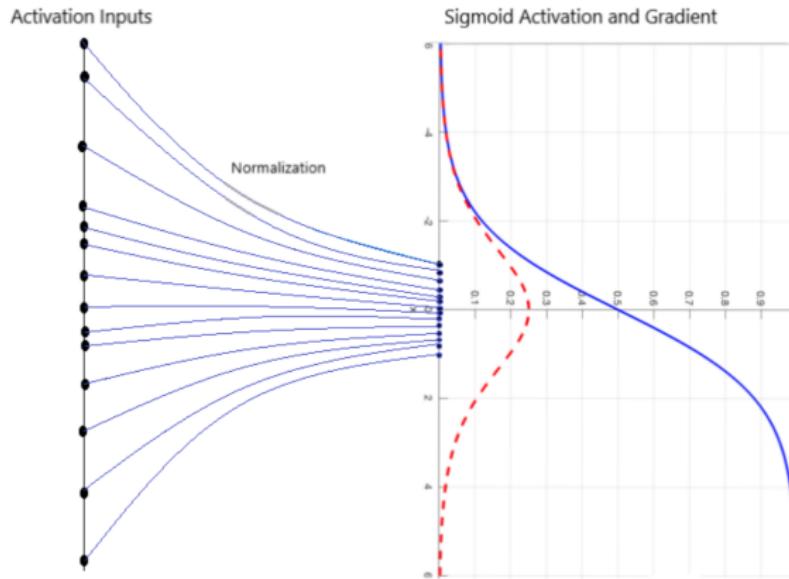


Figure: Image from "Intuit and Implement: Batch Normalization"

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# Supervised Learning (Machine Learning)

- **Data:**  $N$  observations  $(\mathbf{x}_i, y_i) \in \mathcal{X} \times \mathcal{Y}, i = 1, \dots, N$ , **i.i.d.**
- **Model:**  $\text{Model}(\mathbf{x}) := \boldsymbol{\theta}^T \phi(\mathbf{x})$  of features  $\phi(\mathbf{x}) \in \mathbb{R}^P$   
**Prediction as linear mapping of features**
- **Minimization of Regularized Empirical Risk:** We would like to find  $\boldsymbol{\theta}^*$  the solution of:

$$\boldsymbol{\theta}^* := \min_{\boldsymbol{\theta} \in \mathbb{R}^P} \frac{1}{N} \sum_{i=1}^N L(y_i, \boldsymbol{\theta}^T \phi(\mathbf{x}_i)) + \alpha \mathcal{R}(\boldsymbol{\theta})$$

Data fitting + regularizer

where  $L(\cdot, \cdot)$  is called the *loss function*.

## Other loss functions, other models

- ① Support Vector Machine (SVM): "Hinge" Loss

$$L(y, \boldsymbol{\theta}^T \phi(\mathbf{x})) = \max\{1 - y\boldsymbol{\theta}^T \phi(\mathbf{x}), 0\} \quad (5)$$

- ② Logistic Regression:

$$L(y, \boldsymbol{\theta}^T \phi(\mathbf{x})) = \log(1 + \exp(-y\boldsymbol{\theta}^T \phi(\mathbf{x}))) \quad (6)$$

- ③ Mean Squared Regression:

$$L(y, \boldsymbol{\theta}^T \phi(\mathbf{x})) = \frac{1}{2}(y - \boldsymbol{\theta}^T \phi(\mathbf{x}))^2 \quad (7)$$

- ④ Adaboost

$$L(y, \boldsymbol{\theta}^T \phi(\mathbf{x})) = \exp^{-(y - \boldsymbol{\theta}^T \phi(\mathbf{x}))} \quad (8)$$

- ⑤ Others ...

## Minimizing Empirical Risk = Problems!

- Empirical Risk:  $\hat{f}(\boldsymbol{\theta}) := \frac{1}{N} \sum_{i=1}^N L(y_i, \boldsymbol{\theta}^T \phi(\mathbf{x}_i))$

# Minimizing Empirical Risk = Problems!

- Empirical Risk:  $\hat{f}(\boldsymbol{\theta}) := \frac{1}{N} \sum_{i=1}^N L(y_i, \boldsymbol{\theta}^T \boldsymbol{\phi}(\mathbf{x}_i))$   
Loss in a training set

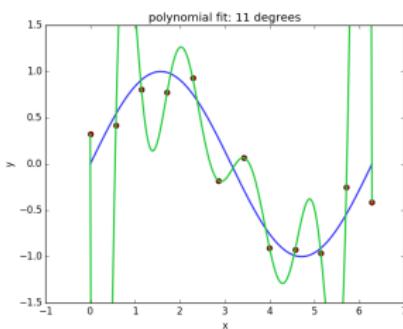


Figure: There are infinity minimizer of the empirical risk!

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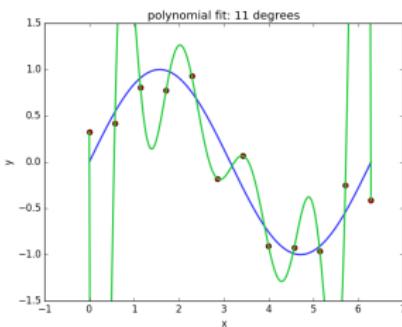


Figure: There are infinity minimizer of the empirical risk!

- Expected Risk :  $f(\boldsymbol{\theta}) := \mathbb{E}_{(\mathbf{x},y)} L(y, \boldsymbol{\theta}^T \phi(\mathbf{x}))$

# Minimizing Empirical Risk = Problems!

- Empirical Risk:  $\hat{f}(\boldsymbol{\theta}) := \frac{1}{N} \sum_{i=1}^N L(y_i, \boldsymbol{\theta}^T \phi(\mathbf{x}_i))$   
Loss in a training set

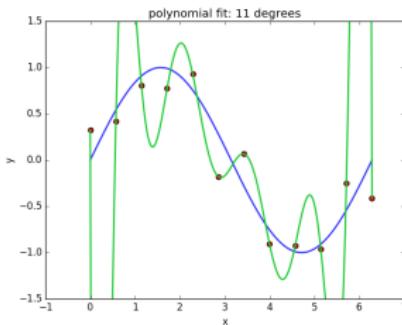


Figure: There are infinity minimizer of the empirical risk!

- Expected Risk :  $f(\boldsymbol{\theta}) := \mathbb{E}_{(\mathbf{x},y)} L(y, \boldsymbol{\theta}^T \phi(\mathbf{x}))$   
Loss in a testing set

There are infinity minimizers of the empirical risk, but most of them have a large expected risk (**overfitting**).

# Bias/Variance Tradeoff

Let  $\hat{y} := \text{Model}(\mathbf{x})$  the prediction of a deterministic model evaluated at  $\mathbf{x}$

$$\mathbb{E}_{(\mathbf{x},y)} [(y - \text{Model}(\mathbf{x}))^2] = \\ \text{Var}[y] + \text{Var}[\text{Model}(\mathbf{x})] + (\text{Bias}[\text{Model}(\mathbf{x})])^2$$

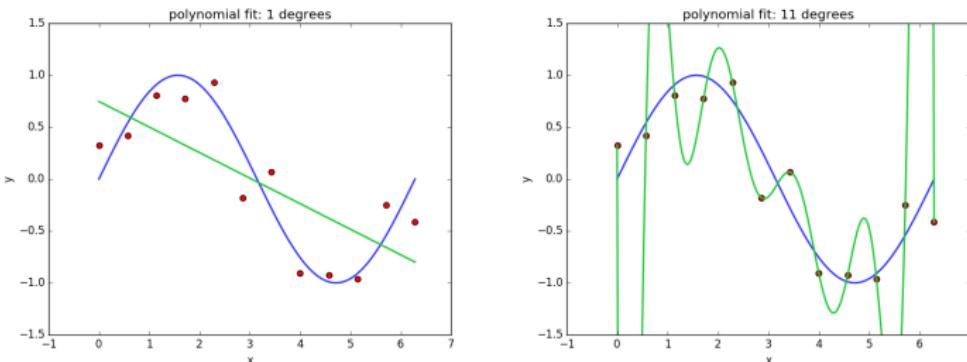
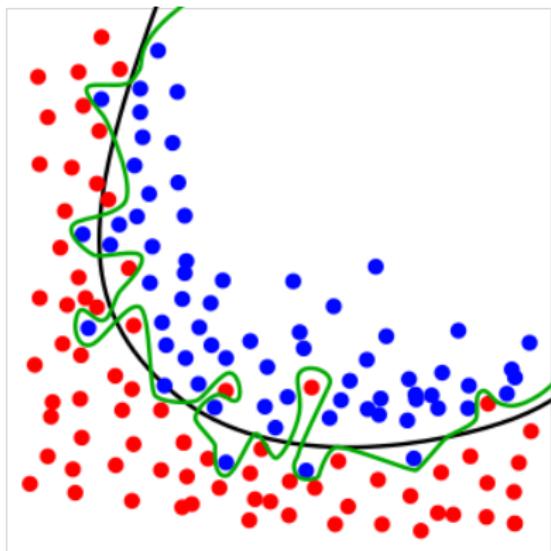


Figure: Underfitting / Overfitting

Underfitting : Prediction with less variance but more bias

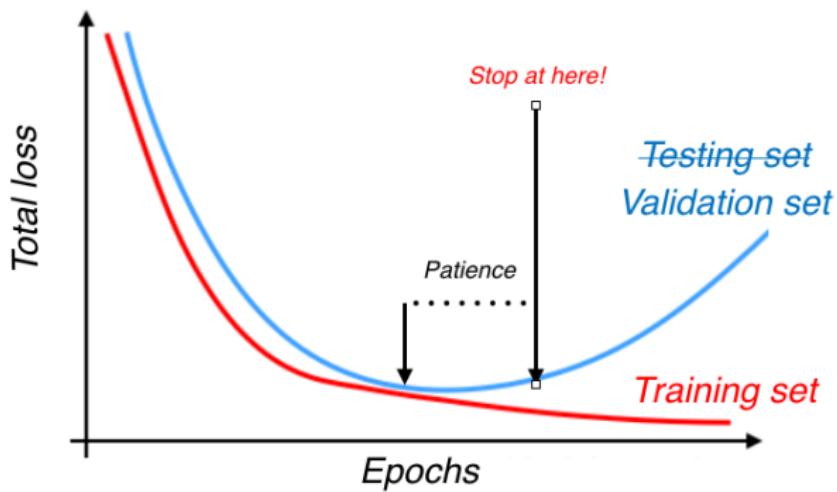
Overfitting : Prediction with more variance but less bias

# How to judge if a deep machine learning model is overfitting or not?



- Training Set / Testing Set
- Cross-Validation
- $\|\theta\|_p$  is large

# 1. Early Stopping / ReduceLROnPlateau / Learning Rate Scheduler



# 1. Early Stopping / ReduceLROnPlateau / Learning Rate Scheduler

```
ES=EarlyStopping(monitor='loss', patience=3)

#Reduce learning rate when a metric has stopped improving.
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2,patience=5, min_lr=0.001)

#Only Using Early Stopping
model.fit(x_train, y_train,epochs=100,batch_size=64,shuffle=True,callbacks=[ES])

#Using Early Stopping and ReduceLRonPLateau
model.fit(x_train, y_train,epochs=100,batch_size=64,shuffle=True,callbacks=[ES, reduce_lr])
```

Figure: Callbacks in Keras

## 2. We need more data!

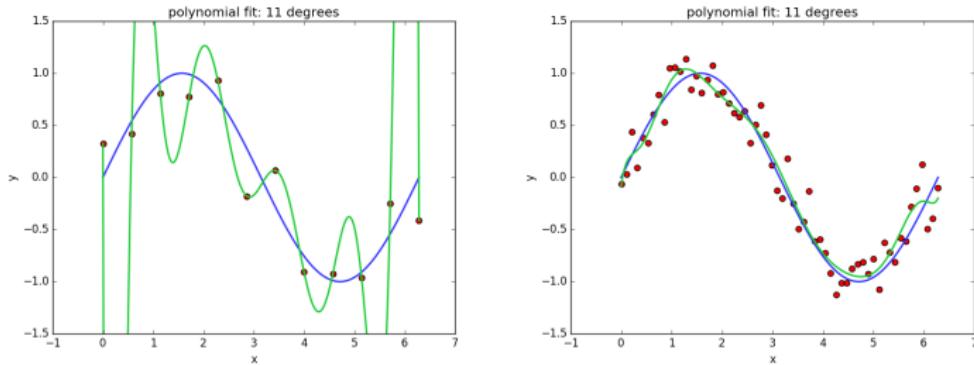


Figure: Same model complexity but more data

- ➊ Additive Gaussian noise.
- ➋ Data augmentation.
- ➌ Adversarial Training (Not in this talk)

## Expected Risk (again)

The expected risk

$$\mathbb{E}_{(\mathbf{x},y)} L(y, \text{Model}) = \int L(y, \text{Model}(\mathbf{x})) dP(\mathbf{x}, y) := R(\text{Model})$$

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The expected risk

$$\mathbb{E}_{(\mathbf{x},y)} L(y, \text{Model}) = \int L(y, \text{Model}(\mathbf{x})) dP(\mathbf{x}, y) := R(\text{Model})$$

But the distribution  $P$  is **unknown** in most practical situations. We usually have access to a set of training data  $T = \{(\mathbf{x}_i, y_i)\}_{i=1}^N$ , where  $(\mathbf{x}_i, y_i) \sim P$ , for all  $i = 1, \dots, N$ . Thus, we may approximate  $P$  by the *empirical distribution*:

$$P_\delta(\mathbf{x}, y) = \frac{1}{N} \sum_{i=1}^N \delta(\mathbf{x} = \mathbf{x}_i, y = y_i)$$

## Empirical Risk (again)

Using the empirical distribution  $P_\delta$ , we can now approximate the expected risk, by the called *empirical risk*

$$R_\delta(\text{Model}) = \int L(y, \text{Model}(\mathbf{x})) dP_\delta(\mathbf{x}, y) = \frac{1}{N} \sum_{i=1}^N L(\text{Model}(\mathbf{x}_i), y_i) \quad (9)$$

Learning the function  $f$  by minimizing (9) is known as the Empirical Risk Minimization (ERM) principle [Vapnik, 1999]. If the number of parameters are comparable to  $N$ , one trivial way to minimize (9) is to **memorize** the whole set of training data (overfitting).

## Vicinal Risk Minimization (VRM)

$P_\delta$  is only one of the possibility to approximate the true distribution  $P$ . [Chapelle et al., 2001] proposed to approximate  $P$  by:

$$P_v(\mathbf{x}, y) = \frac{1}{N} \sum_{i=1}^N v(\tilde{\mathbf{x}}, \tilde{y}, |\mathbf{x}_i, y_i)$$

where  $v$  is *vicinity distribution* that measure the probability for a "virtual" pair  $(\tilde{\mathbf{x}}, \tilde{y})$  to be in the *vicinity* of the training pair  $(\mathbf{x}, y)$ .

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- 1 Gaussian vicinities:  $v(\tilde{\mathbf{x}}, \tilde{y}, |\mathbf{x}_i, y_i) = \mathcal{N}(\tilde{\mathbf{x}} - \mathbf{x}, \sigma^2 \mathbf{I}) \delta(\tilde{y} = y)$

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which is equivalent to augmenting the training data with additive Gaussian noise

## Keras Gaussian Noise Layer

```
import keras
from keras import Input
from keras.layers import GaussianNoise
dim_input=(256,256)
input_img = Input(shape=dim_input)
x =GaussianNoise(.01)(input_img)
...
```

Figure: Gaussian vicinities in Keras

# Why do we use data-augmentation?

2 Data-augmentation based vicinities:

$P_{agg}(\mathbf{x}, y) = \frac{1}{N} \sum_{i=1}^N \delta(\tilde{\mathbf{x}}, y_i)$ , where  $\tilde{\mathbf{x}}$  is a random transformation applied  $\mathbf{x}$



Figure: Example of a set of images produced by random transformations (translations, rotations, zooming, ...)

```
training_generator = ImageDataGenerator(  
    rotation_range=40,  
    width_shift_range=0.2,  
    height_shift_range=0.2,  
    rescale=1./255,  
    shear_range=0.2,  
    zoom_range=0.2,  
    horizontal_flip=True,  
    fill_mode='nearest')
```

```
training_generator = train_datagen.flow_from_directory(  
    'data/train', # this is the target directory  
    target_size=(224, 224), # all images will be resized to 150x150  
    batch_size=batch_size)
```

```
model.fit_generator(generator=train_gen.flow(x_train, y_train),  
                    steps_per_epoch=steps_per_epoch,  
                    epochs=epochs,  
                    validation_data=valid_gen.flow(x_validation, y_validation),  
                    workers=32)
```

Figure: Data Generator in Keras

# Regularization vs Overfitting

- ① "Weight Decay": Again?
- ② Early Stopping
- ③ More data! : Data Augmentation
- ④ More data! Bad data! : Adversarial Examples
- ⑤ Summing-up: Dropout

## How can we reduce the variance of a model?

- Remember: given  $N$  i.i.d. obsevations  $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$  each of them with variance equal to  $\sigma^2$ .
- What is the variance of  $\bar{\mathbf{x}} = \frac{1}{N} \sum_{i=1}^N \mathbf{x}_i$ ?

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- Remember: given  $N$  i.i.d. observations  $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N$  each of them with variance equal to  $\sigma^2$ .
- What is the variance of  $\bar{\mathbf{x}} = \frac{1}{N} \sum_{i=1}^N \mathbf{x}_i$ ?  $\frac{\sigma^2}{N}$
- **Hint:** Train model on different training sets, and use the mean of predictions as final model of prediction.

## Dropout: [Srivastava et al., 2014]

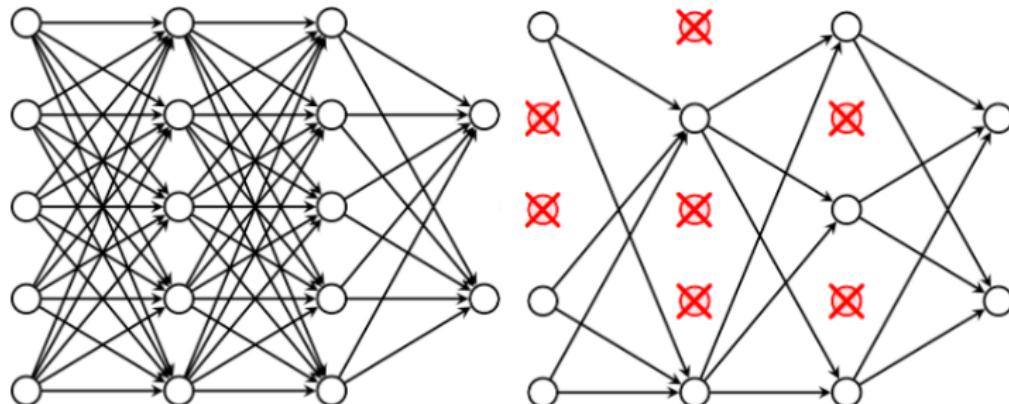
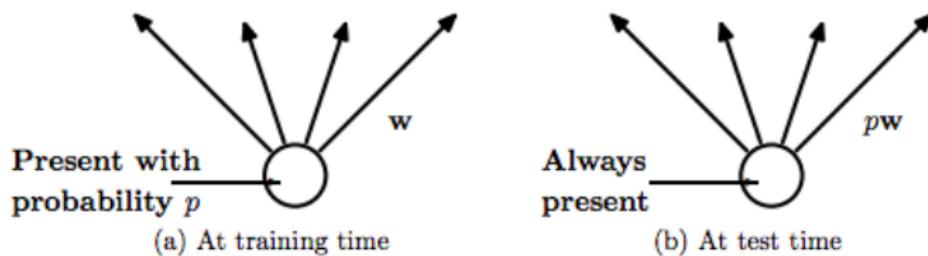


Figure: Left: No Dropout Right: Dropout

- Avoid memorization!
- Dropout forces to learn more robust features that are useful in conjunction with many different random subsets.
- With  $H$  hidden units, each of which can be dropped, we have  $2^H$  possible models!

# Dropout



**Figure:** Left: A unit at training time that is present with probability  $p$  and is connected to units in the next layer with weights  $\mathbf{W}$ . Right: At test time, the unit is always present and the weights are multiplied by  $p$ . The output at test time is same as the expected output at training time.

## Dropout

```
from keras.layers import Dropout  
...  
x=Dense(50, activation='relu')(x)  
x=Dropout(0.5)(x)  
...
```

Figure: Dropout in Keras. Layer with a dropout of  $p = .5$

Practical Work 2: Dropout on Fashion MNIST

# Contents

- 1 Optimizers for Deep Learning
- 2 Difficulties in Deep Network Optimisation
- 3 How to fight against overfitting
- 4 References

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