



FAU

FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Regularization

A. Maier, V. Christlein, K. Breininger, S. Vesal, F. Meister, C. Liu, S. Gündel, S. Jaganathan, N. Maul,
M. Vornehm, L. Reeb, F. Thamm, M. Hoffmann, C. Bergler, F. Denzinger, W. Fu, B. Geissler, Z. Yang
Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg
May 9, 2020



Outline

Introduction to Regularization

Classical Techniques

Regularization in the Loss Function

Normalization

Dropout

Initialization

Transfer Learning

Multi-Task Learning (MTL)



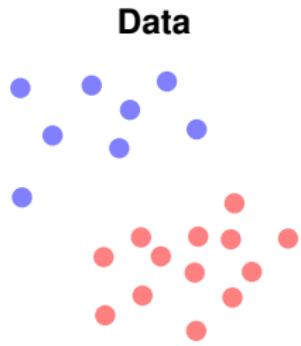
FAU

FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Introduction to Regularization

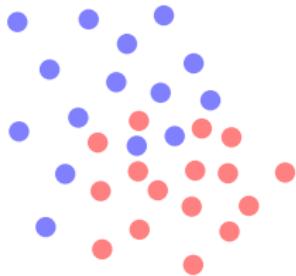


Fitting appropriately



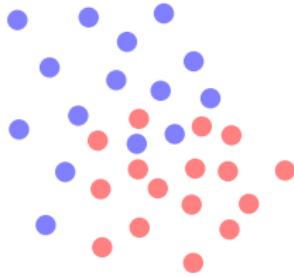
Fitting appropriately

Data

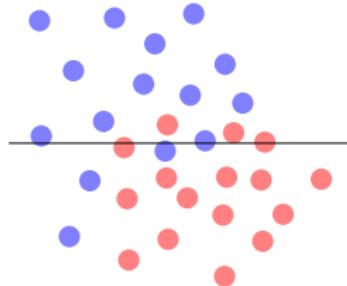


Fitting appropriately

Data

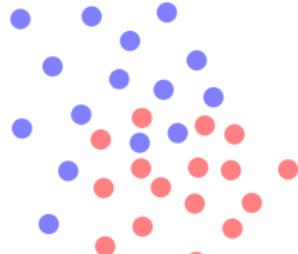


Underfitting

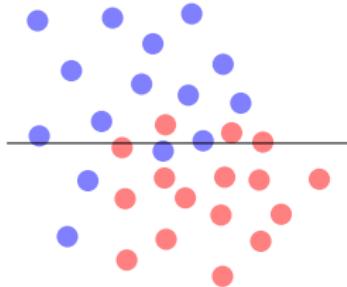


Fitting appropriately

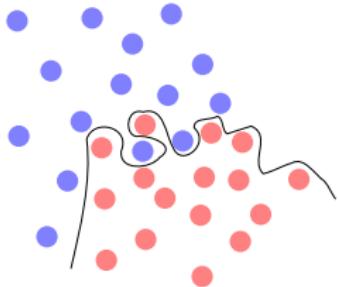
Data



Underfitting

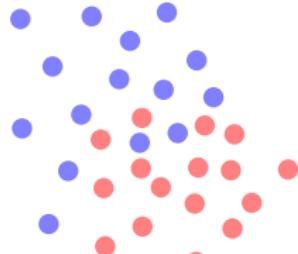


Overfitting

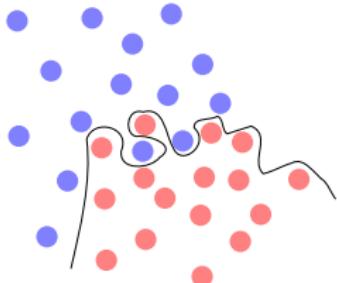


Fitting appropriately

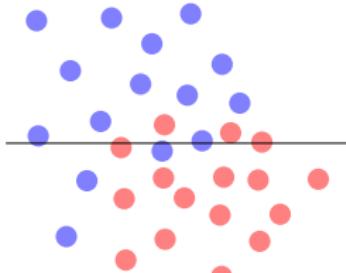
Data



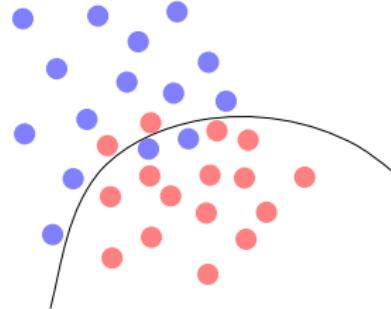
Overfitting



Underfitting



Sensible boundary



Bias Variance Decomposition

- Regression **problem** [3] with **h , ideal** value from the true distribution:

$$\mathbf{h} = h(\mathbf{x}) + \epsilon, \quad \epsilon = \mathcal{N}(0, \sigma_\epsilon).$$

Bias Variance Decomposition

- Regression **problem** [3] with **h**, **ideal** value from the true distribution:

$$\mathbf{h} = h(\mathbf{x}) + \epsilon, \quad \epsilon = \mathcal{N}(0, \sigma_\epsilon).$$

- Using a model: $\hat{\mathbf{y}}_D = \hat{f}(\mathbf{x}|D)$ estimated from a dataset D , the expected **loss** for a single point \mathbf{x} is:

$$\mathbb{E}_D (\ell(\mathbf{x})) = \mathbb{E}_D [(\mathbf{h} - \hat{\mathbf{y}}_D)^2].$$

Bias Variance Decomposition

- Regression **problem** [3] with **h** , **ideal** value from the true distribution:

$$\mathbf{h} = h(\mathbf{x}) + \epsilon, \quad \epsilon = \mathcal{N}(0, \sigma_\epsilon).$$

- Using a model: $\hat{\mathbf{y}}_D = \hat{f}(\mathbf{x}|D)$ estimated from a dataset D , the expected **loss** for a single point \mathbf{x} is:

$$\mathbb{E}_D (\ell(\mathbf{x})) = \mathbb{E}_D [(\mathbf{h} - \hat{\mathbf{y}}_D)^2].$$

- This can be decomposed to:

$$\mathbb{E}_D (\ell(\mathbf{x})) = \underbrace{(\mathbb{E}_D [\hat{\mathbf{y}}_D] - h(\mathbf{x}))^2}_{\text{Bias}^2} + \underbrace{\mathbb{E}_D [(\hat{\mathbf{y}}_D - \mathbb{E}_D [\hat{\mathbf{y}}_D])^2]}_{\text{Variance}} + \underbrace{\sigma_\epsilon^2}_{\text{Irreducible Error}}.$$

Bias Variance Decomposition

- Regression **problem** [3] with **h**, **ideal** value from the true distribution:

$$\mathbf{h} = h(\mathbf{x}) + \epsilon, \quad \epsilon = \mathcal{N}(0, \sigma_\epsilon).$$

- Using a model: $\hat{\mathbf{y}}_D = \hat{f}(\mathbf{x}|D)$ estimated from a dataset D , the expected **loss** for a single point \mathbf{x} is:

$$\mathbb{E}_D (\ell(\mathbf{x})) = \mathbb{E}_D [(\mathbf{h} - \hat{\mathbf{y}}_D)^2].$$

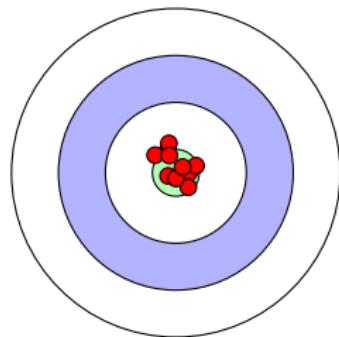
- This can be decomposed to:

$$\mathbb{E}_D (\ell(\mathbf{x})) = \underbrace{(\mathbb{E}_D [\hat{\mathbf{y}}_D] - h(\mathbf{x}))^2}_{\text{Bias}^2} + \underbrace{\mathbb{E}_D [(\hat{\mathbf{y}}_D - \mathbb{E}_D [\hat{\mathbf{y}}_D])^2]}_{\text{Variance}} + \underbrace{\sigma_\epsilon^2}_{\text{Irreducible Error}}.$$

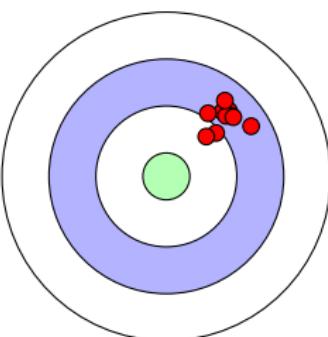
- Integrating this over every datapoint \mathbf{x} we get $L_D(\mathbf{X})$ from the $\ell_D(\mathbf{x})$.
- A similar decomposition exists for classification using the zero-one loss [9, pp. 468-471].

Bias Variance Tradeoff

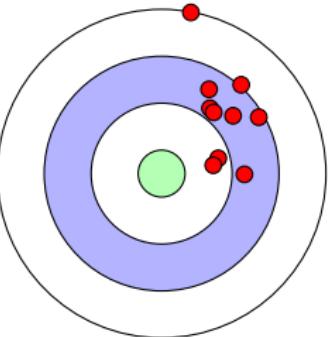
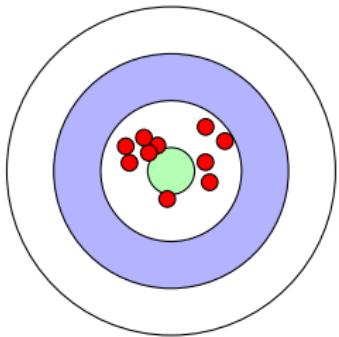
Low variance



High bias



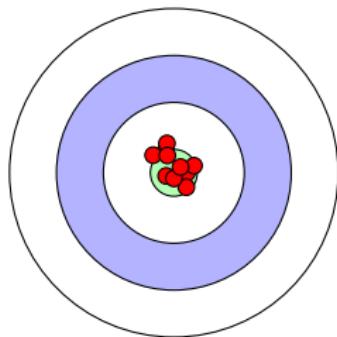
High variance



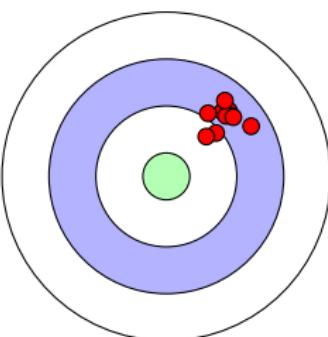
- We'd like to **minimize** bias and variance

Bias Variance Tradeoff

Low variance

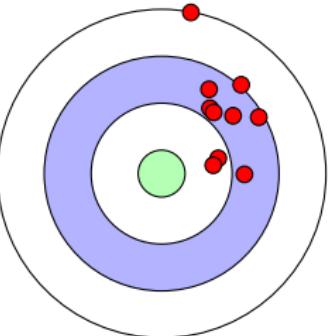
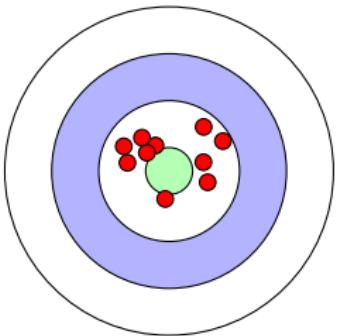


Low bias



High bias

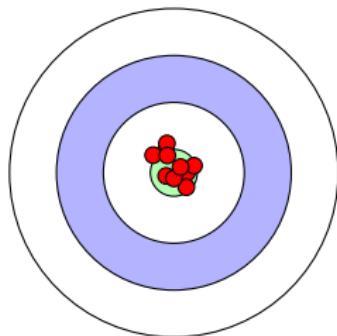
High variance



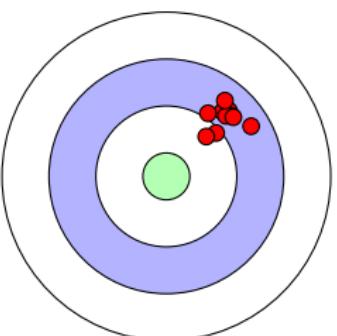
- We'd like to **minimize bias and variance**
- However, if we choose a type of model for a given dataset:
 - Simultaneously optimizing **bias** and **variance** is **impossible** in general

Bias Variance Tradeoff

Low variance

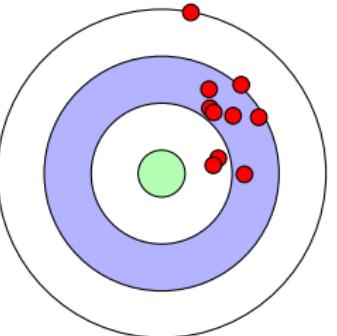
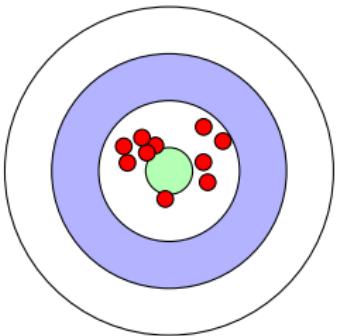


Low bias



High bias

High variance



- We'd like to **minimize bias and variance**
- However, if we choose a type of model for a given dataset:
 - Simultaneously optimizing **bias** and **variance** is **impossible** in general
- Bias and variance can be studied together as **model capacity**

Model Capacity

- **Capacity** of a model \mapsto **variety of functions** it can approximate
- **Related** to number of parameters but **by far not equal**

Model Capacity

- **Capacity** of a model \mapsto **variety of functions** it can approximate
- **Related** to number of parameters but **by far not equal**
- Vapnik-Chervonenkis (VC) dimension provides a **measure** of capacity
 - Based on **counting** how many **points** can be **separated** by a model

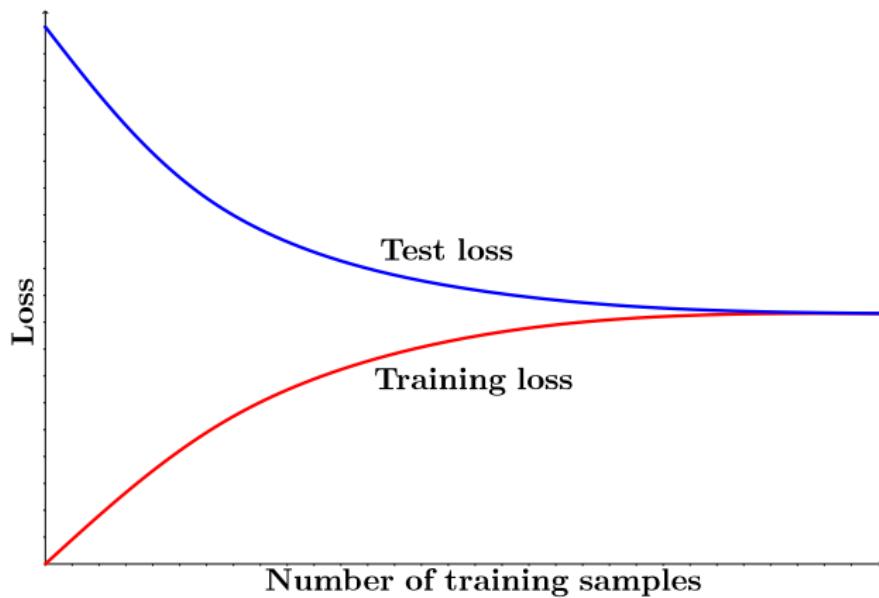
Model Capacity

- **Capacity** of a model \mapsto **variety of functions** it can approximate
- **Related** to number of parameters but **by far not equal**
- Vapnik-Chervonenkis (VC) dimension provides a **measure** of capacity
 - Based on **counting** how many **points** can be **separated** by a model
 - VC dimension of neural networks is usually **extremely high** compared to classical methods
 - Remember the paper learning ImageNet with random labels? [18]

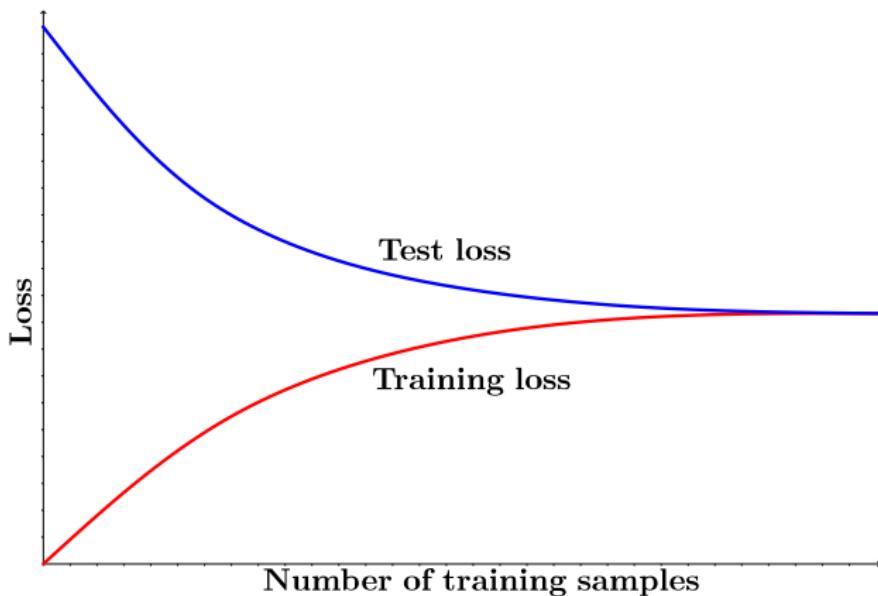
Model Capacity

- **Capacity** of a model \mapsto **variety of functions** it can approximate
- **Related** to number of parameters but **by far not equal**
- Vapnik-Chervonenkis (VC) dimension provides a **measure** of capacity
 - Based on **counting** how many **points** can be **separated** by a model
 - VC dimension of neural networks is usually **extremely high** compared to classical methods
 - Remember the paper learning ImageNet with random labels? [18]
 - VC dimension is **ineffective** in judging the **real capacity** of neural networks
- We can always reduce the **bias** by \uparrow the **model capacity**

The Role of Data

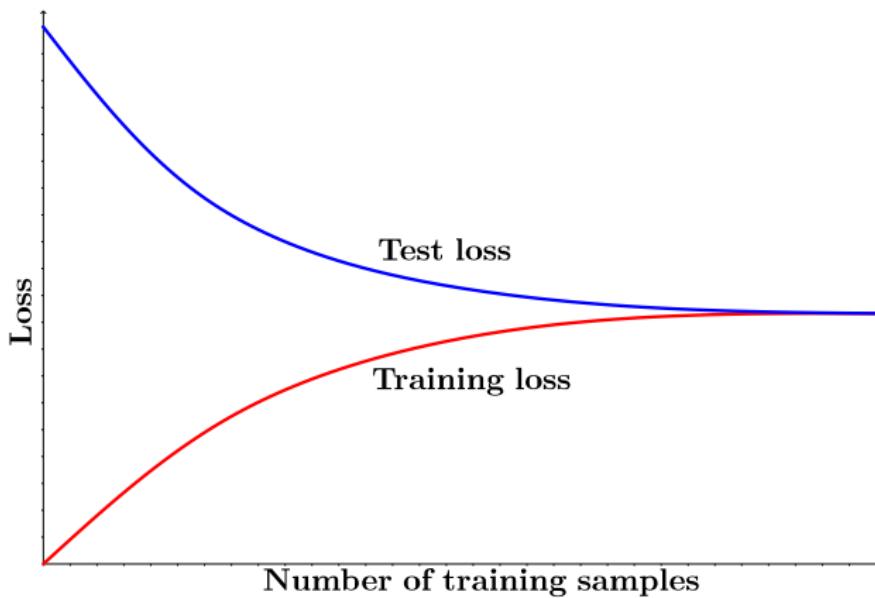


The Role of Data



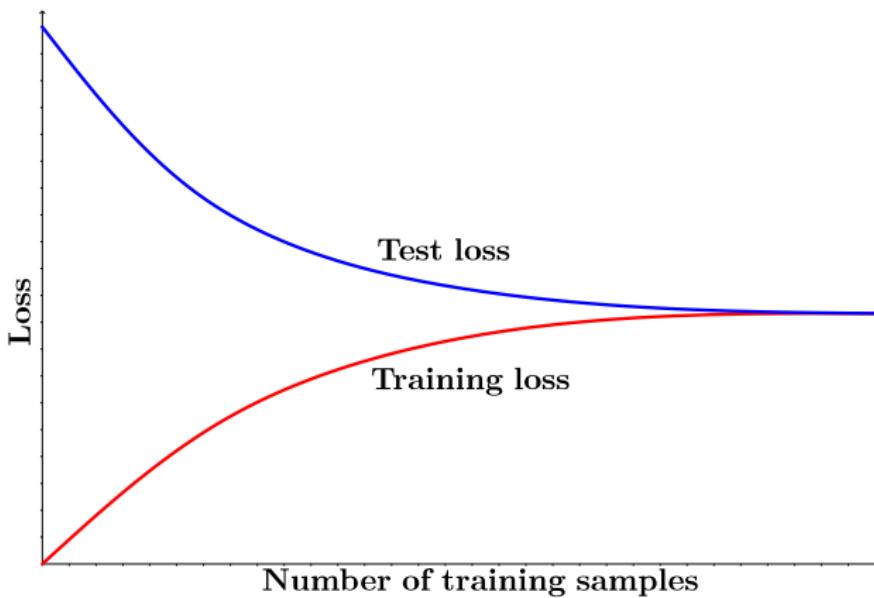
- The **variance** can be optimized by using **more training data**

The Role of Data



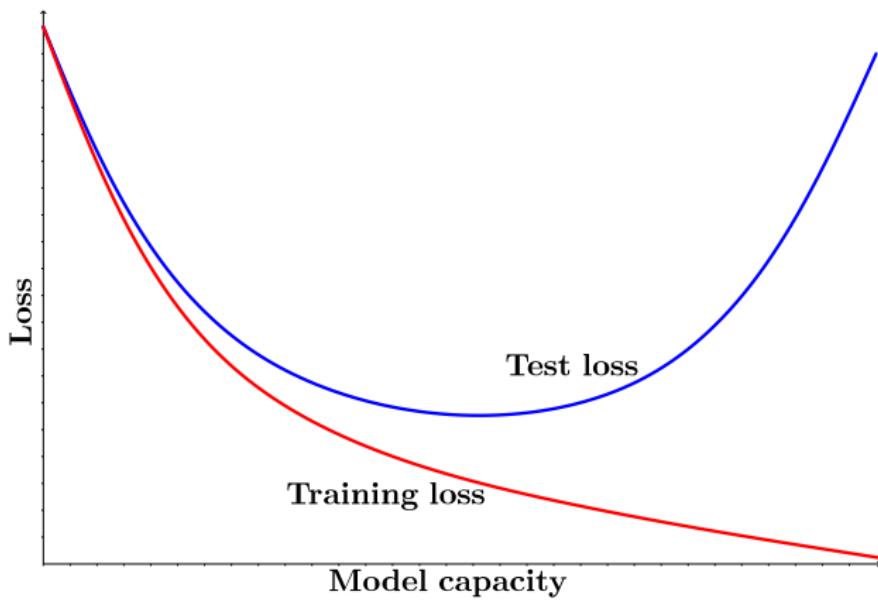
- The **variance** can be optimized by using **more training data**
- The model capacity has to **match** the **size** of the **training set**

The Role of Data

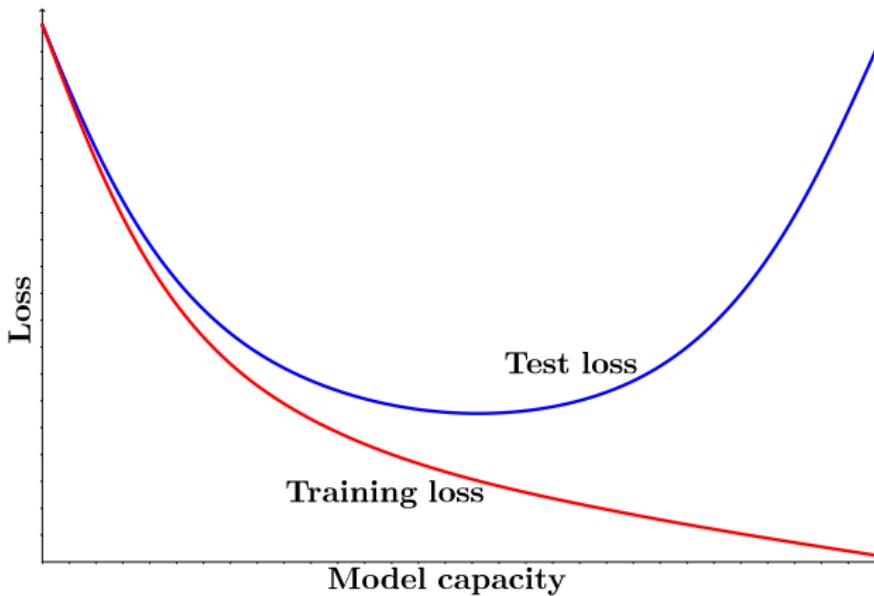


- The **variance** can be optimized by using **more training data**
 - The model capacity has to **match** the **size** of the **training set**
- What if we can't acquire more data?

Finite Dataset

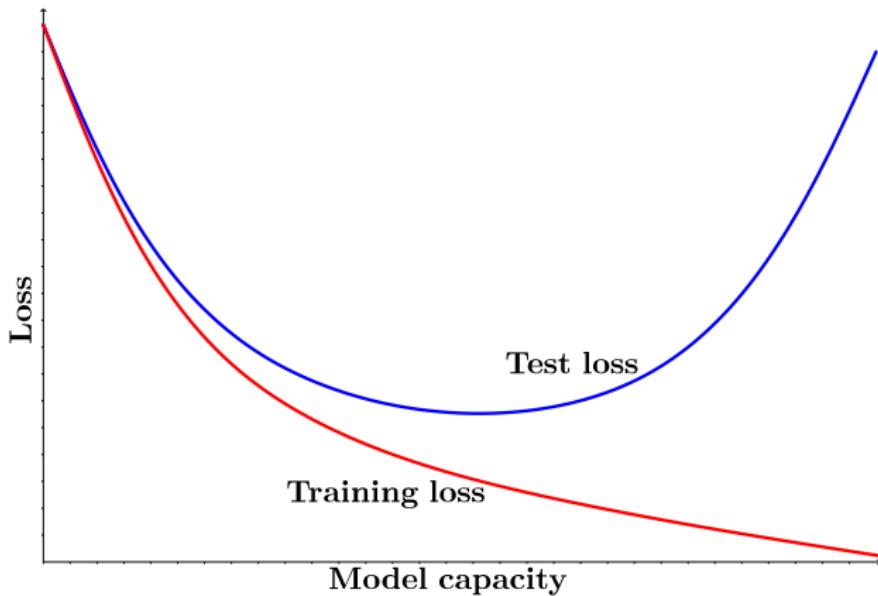


Finite Dataset



- We can trade an \uparrow in **bias** for \downarrow in **variance**

Finite Dataset



- We can trade an \uparrow in **bias** for \downarrow in **variance**
 - For a **specific problem** there might be favorable tradeoffs!

Regularization reduces Overfitting

How can we find such a favorable tradeoff?

- By enforcing prior knowledge

Regularization reduces Overfitting

How can we find such a favorable tradeoff?

→ By enforcing prior knowledge

Model prior knowledge

- Augment data
- Adapt architecture
- Adapt training process
- Preprocessing

Regularization reduces Overfitting

How can we find such a favorable tradeoff?

→ By enforcing prior knowledge

Model prior knowledge

- Augment data
- Adapt architecture
- Adapt training process
- Preprocessing

Actual regularizers

- Equality constraints
- Inequality constraints

**NEXT TIME
ON DEEP LEARNING**



FAU

FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Regularization - Part 2

A. Maier, V. Christlein, K. Breininger, S. Vesal, F. Meister, C. Liu, S. Gündel, S. Jaganathan, N. Maul,
M. Vornehm, L. Reeb, F. Thamm, M. Hoffmann, C. Bergler, F. Denzinger, W. Fu, B. Geissler, Z. Yang
Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg

May 9, 2020





FAU

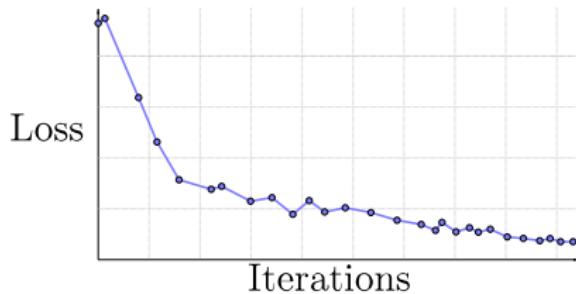
FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Classical Techniques



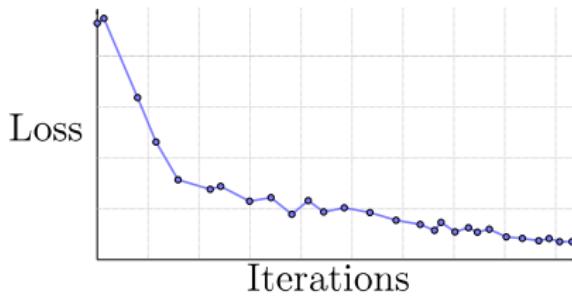
Overfitting on Learning Curve

Training set

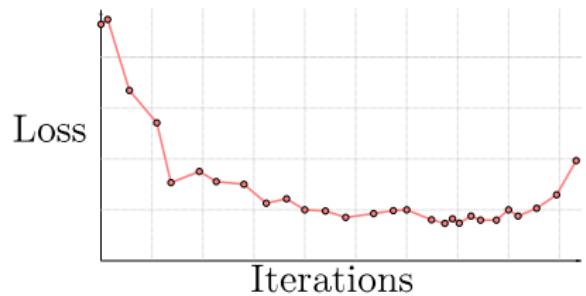


Overfitting on Learning Curve

Training set

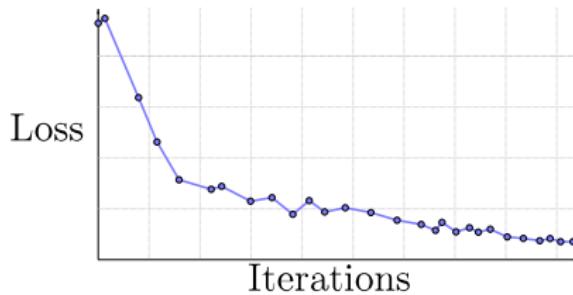


Test set

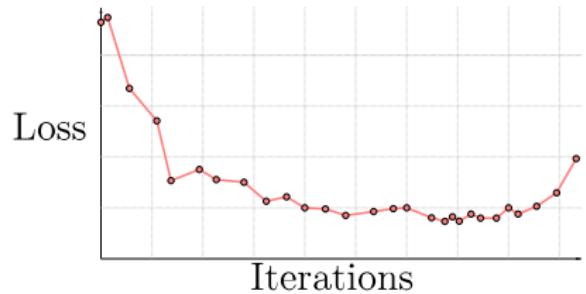


Overfitting on Learning Curve

Training set



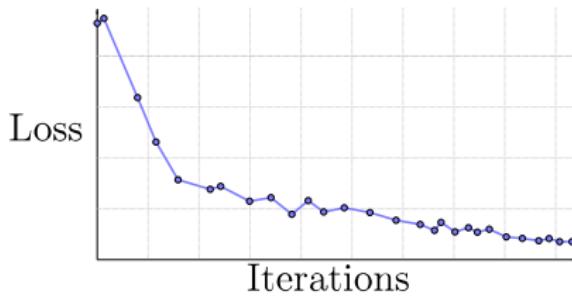
Test set



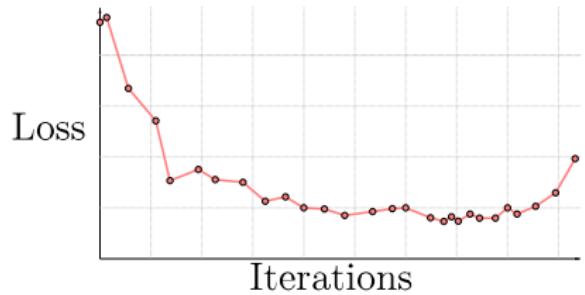
- Test set **must not** be used for training!

Overfitting on Learning Curve

Training set



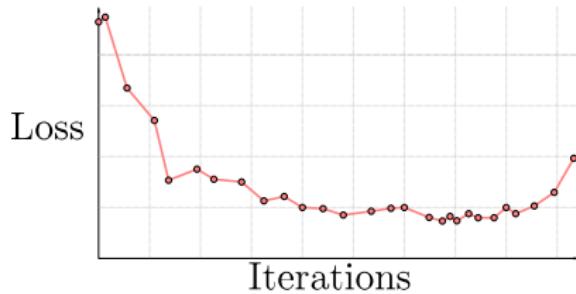
Test set



- Test set **must not** be used for training!
- ➔ Split of **validation set** from training data

Early Stopping

Validation set

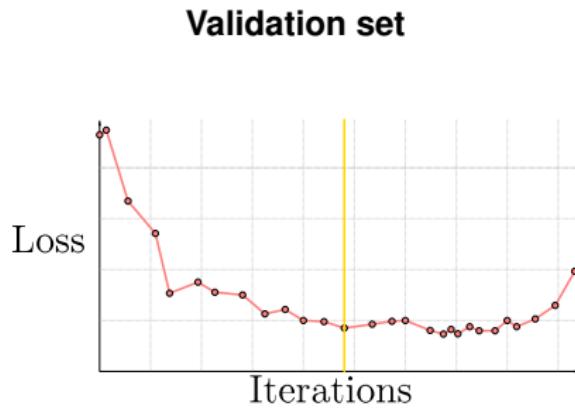


Early Stopping



- Define stopping criterion

Early Stopping



- Define stopping criterion
- Use parameters with
minimum validation loss

Data Augmentation

→ Artificially enlarge dataset

Data Augmentation

- Artificially enlarge dataset
 - But how?

Data Augmentation

→ Artificially enlarge dataset

- But how?
- Every **transformation** which the **label** should be **invariant** to:

Probably the same class:



Data Augmentation

→ Artificially enlarge dataset

- But how?
- Every transformation which the **label** should be **invariant** to:

Probably the same class:



Still you have to be careful!



Data Augmentation

Common transformations:

Data Augmentation

Common transformations:

1. random spatial transformations:
 - affine transformations
 - elastic transformations
 - ...

Data Augmentation

Common transformations:

1. random spatial transformations:

- affine transformations
- elastic transformations
- ...

2. pixel transformations

- changing resolution
- random noise
- changing pixel distribution
- ...

Regularization in the Loss Function

Maximum A Posteriori Estimation

- **Bayesian** approach considering the weights uncertain: $\mathbf{w} \mapsto p(\mathbf{w})$
- and we have a dataset \mathbf{X} with associated labels \mathbf{Y}

Maximum A Posteriori Estimation

- **Bayesian** approach considering the weights uncertain: $\mathbf{w} \mapsto p(\mathbf{w})$
- and we have a dataset \mathbf{X} with associated labels \mathbf{Y}
 - Now we can state:

$$p(\mathbf{w}, \mathbf{Y}, \mathbf{X}) = p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) p(\mathbf{Y}, \mathbf{X})$$

Maximum A Posteriori Estimation

- **Bayesian** approach considering the weights uncertain: $\mathbf{w} \mapsto p(\mathbf{w})$
- and we have a dataset \mathbf{X} with associated labels \mathbf{Y}
 - Now we can state:

$$\begin{aligned} p(\mathbf{w}, \mathbf{Y}, \mathbf{X}) &= p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) p(\mathbf{Y}, \mathbf{X}) \\ &= p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{X}, \mathbf{w}) \end{aligned}$$

Maximum A Posteriori Estimation

- **Bayesian** approach considering the weights uncertain: $\mathbf{w} \mapsto p(\mathbf{w})$
- and we have a dataset \mathbf{X} with associated labels \mathbf{Y}
 - Now we can state:

$$\begin{aligned} p(\mathbf{w}, \mathbf{Y}, \mathbf{X}) &= p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) p(\mathbf{Y}, \mathbf{X}) \\ &= p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{X}, \mathbf{w}) \\ p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) &= \frac{p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{X}, \mathbf{w})}{p(\mathbf{Y}, \mathbf{X})} \end{aligned}$$

Maximum A Posteriori Estimation

- **Bayesian** approach considering the weights uncertain: $\mathbf{w} \mapsto p(\mathbf{w})$
- and we have a dataset \mathbf{X} with associated labels \mathbf{Y}
 - Now we can state:

$$\begin{aligned}
 p(\mathbf{w}, \mathbf{Y}, \mathbf{X}) &= p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) p(\mathbf{Y}, \mathbf{X}) \\
 &= p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{X}, \mathbf{w}) \\
 p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) &= \frac{p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{X}, \mathbf{w})}{p(\mathbf{Y}, \mathbf{X})} \\
 p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) &= \frac{p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{X}) p(\mathbf{w})}{p(\mathbf{Y}|\mathbf{X}) p(\mathbf{X})}
 \end{aligned}$$

Maximum A Posteriori Estimation

- Bayesian approach considering the weights uncertain: $\mathbf{w} \mapsto p(\mathbf{w})$
- and we have a dataset \mathbf{X} with associated labels \mathbf{Y}
 - Now we can state:

$$\begin{aligned} p(\mathbf{w}, \mathbf{Y}, \mathbf{X}) &= p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) p(\mathbf{Y}, \mathbf{X}) \\ &= p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{X}, \mathbf{w}) \\ p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) &= \frac{p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{X}, \mathbf{w})}{p(\mathbf{Y}, \mathbf{X})} \\ p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) &= \frac{p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{X}) p(\mathbf{w})}{p(\mathbf{Y}|\mathbf{X}) p(\mathbf{X})} \end{aligned}$$

- Because $p(\mathbf{Y}|\mathbf{X})$ does not depend on \mathbf{w} , and \mathbf{X} and \mathbf{w} are independent, we can obtain an estimate as:

$$\text{MAP}(\mathbf{w}) := \underset{\mathbf{w}}{\text{maximize}} \quad \left\{ p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{w}) \right\}$$

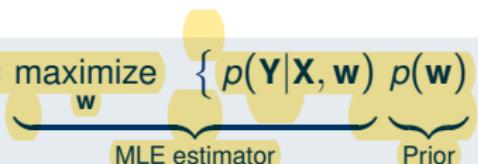
Maximum A Posteriori Estimation

- Bayesian approach considering the weights uncertain: $\mathbf{w} \mapsto p(\mathbf{w})$
- and we have a dataset \mathbf{X} with associated labels \mathbf{Y}
 - Now we can state:

$$\begin{aligned} p(\mathbf{w}, \mathbf{Y}, \mathbf{X}) &= p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) p(\mathbf{Y}, \mathbf{X}) \\ &= p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{X}, \mathbf{w}) \\ p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) &= \frac{p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{X}, \mathbf{w})}{p(\mathbf{Y}, \mathbf{X})} \\ p(\mathbf{w}|\mathbf{Y}, \mathbf{X}) &= \frac{p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{X}) p(\mathbf{w})}{p(\mathbf{Y}|\mathbf{X}) p(\mathbf{X})} \end{aligned}$$

- Because $p(\mathbf{Y}|\mathbf{X})$ does not depend on \mathbf{w} , and \mathbf{X} and \mathbf{w} are independent, we can obtain an estimate as:

$$\text{MAP}(\mathbf{w}) := \underset{\mathbf{w}}{\text{maximize}} \quad \left\{ p(\mathbf{Y}|\mathbf{X}, \mathbf{w}) p(\mathbf{w}) \right\}$$



Augmenting the Loss Function

Enforce

Augmenting the Loss Function

Enforce ...small norm:

$$\tilde{L}(\mathbf{w}, \mathbf{X}, \mathbf{Y}) = L(\mathbf{w}, \mathbf{X}, \mathbf{Y}) + \lambda \|\mathbf{w}\|_2^2$$

Augmenting the Loss Function

Enforce ...small norm:

$$\tilde{L}(\mathbf{w}, \mathbf{X}, \mathbf{Y}) = L(\mathbf{w}, \mathbf{X}, \mathbf{Y}) + \lambda \|\mathbf{w}\|_2^2$$

When λ is positive, we can identify this as the Lagrangian function of:

$$\underset{\mathbf{w}}{\text{minimize}} \quad \{L(\mathbf{w}, \mathbf{X}, \mathbf{Y})\} \quad \text{s.t. : } \|\mathbf{w}\|_2^2 \leq \alpha$$

with an unknown data-dependent α .

Augmenting the Loss Function

Enforce ...small norm:

$$\tilde{L}(\mathbf{w}, \mathbf{X}, \mathbf{Y}) = L(\mathbf{w}, \mathbf{X}, \mathbf{Y}) + \lambda \|\mathbf{w}\|_2^2$$

When λ is positive, we can identify this as the Lagrangian function of:

$$\underset{\mathbf{w}}{\text{minimize}} \quad \left\{ L(\mathbf{w}, \mathbf{X}, \mathbf{Y}) \right\} \quad \text{s.t. : } \|\mathbf{w}\|_2^2 \leq \alpha$$

with an unknown data-dependent α .

Backpropagation of the augmented loss:

$$\mathbf{w}^{(k+1)} = \underbrace{(1 - \eta \lambda) \mathbf{w}^{(k)}}_{\text{Shrinkage}} - \eta \frac{\partial L}{\partial \mathbf{w}^{(k)}}$$

- Often called “weight decay”

Augmenting the Loss Function

Enforce ...small norm:

$$\tilde{L}(\mathbf{w}, \mathbf{X}, \mathbf{Y}) = L(\mathbf{w}, \mathbf{X}, \mathbf{Y}) + \lambda \|\mathbf{w}\|_2^2$$

When λ is positive, we can identify this as the Lagrangian function of:

$$\underset{\mathbf{w}}{\text{minimize}} \quad \left\{ L(\mathbf{w}, \mathbf{X}, \mathbf{Y}) \right\} \quad \text{s.t. : } \|\mathbf{w}\|_2^2 \leq \alpha$$

with an unknown data-dependent α .

Backpropagation of the augmented loss:

$$\mathbf{w}^{(k+1)} = \underbrace{(1 - \eta \lambda) \mathbf{w}^{(k)}}_{\text{Shrinkage}} - \eta \frac{\partial L}{\partial \mathbf{w}^{(k)}}$$

- Often called “weight decay”
- If we optimize the **training-loss** for λ we will usually receive $\lambda = 0$.

Augmenting the Loss Function

Enforce ...small norm:

$$\tilde{L}(\mathbf{w}, \mathbf{X}, \mathbf{Y}) = L(\mathbf{w}, \mathbf{X}, \mathbf{Y}) + \lambda \|\mathbf{w}\|_2^2$$

When λ is positive, we can identify this as the Lagrangian function of:

$$\underset{\mathbf{w}}{\text{minimize}} \quad \left\{ L(\mathbf{w}, \mathbf{X}, \mathbf{Y}) \right\} \quad \text{s.t. : } \|\mathbf{w}\|_2^2 \leq \alpha$$

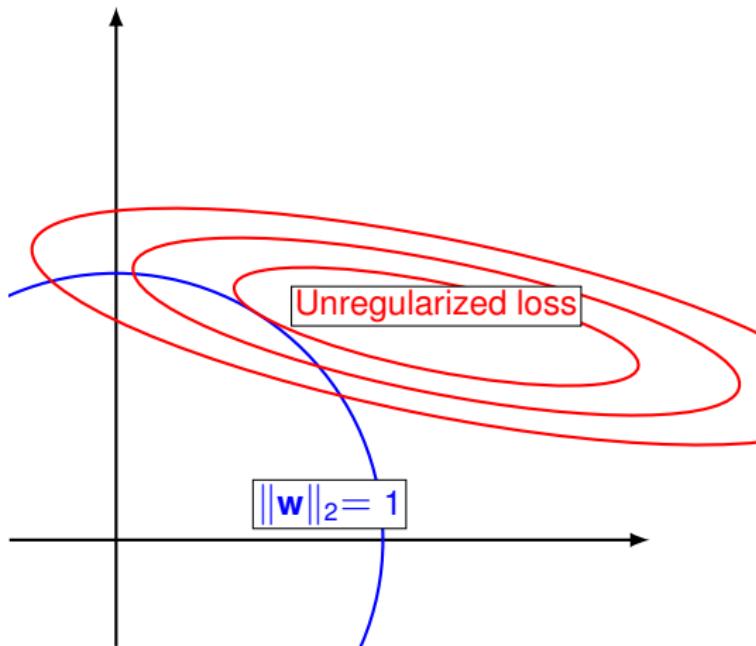
with an unknown data-dependent α .

Backpropagation of the augmented loss:

$$\mathbf{w}^{(k+1)} = \underbrace{(1 - \eta \lambda) \mathbf{w}^{(k)}}_{\text{Shrinkage}} - \eta \frac{\partial L}{\partial \mathbf{w}^{(k)}}$$

- Often called “weight decay”
- If we optimize the **training-loss** for λ we will usually receive $\lambda = 0$.
- We trade increased **bias** for reduced **variance**

Graphical Effect of L₂ Regularization



Augmenting the Loss Function (cont.)

Enforce

Augmenting the Loss Function (cont.)

Enforce ...sparsity:

$$\tilde{L}(\mathbf{w}, \mathbf{X}, \mathbf{Y}) = L(\mathbf{w}, \mathbf{X}, \mathbf{Y}) + \lambda \|\mathbf{w}\|_1$$

Augmenting the Loss Function (cont.)

Enforce ...sparsity:

$$\tilde{L}(\mathbf{w}, \mathbf{X}, \mathbf{Y}) = L(\mathbf{w}, \mathbf{X}, \mathbf{Y}) + \lambda \|\mathbf{w}\|_1$$

When λ is positive, we can identify this as the Lagrangian function of:

$$\underset{\mathbf{w}}{\text{minimize}} \quad \{L(\mathbf{w}, \mathbf{X}, \mathbf{Y})\} \quad s.t. : \|\mathbf{w}\|_1 \leq \alpha,$$

with an unknown data-dependent α .

Augmenting the Loss Function (cont.)

Enforce ...sparsity:

$$\tilde{L}(\mathbf{w}, \mathbf{X}, \mathbf{Y}) = L(\mathbf{w}, \mathbf{X}, \mathbf{Y}) + \lambda \|\mathbf{w}\|_1$$

When λ is positive, we can identify this as the Lagrangian function of:

$$\underset{\mathbf{w}}{\text{minimize}} \quad \{L(\mathbf{w}, \mathbf{X}, \mathbf{Y})\} \quad \text{s.t. : } \|\mathbf{w}\|_1 \leq \alpha,$$

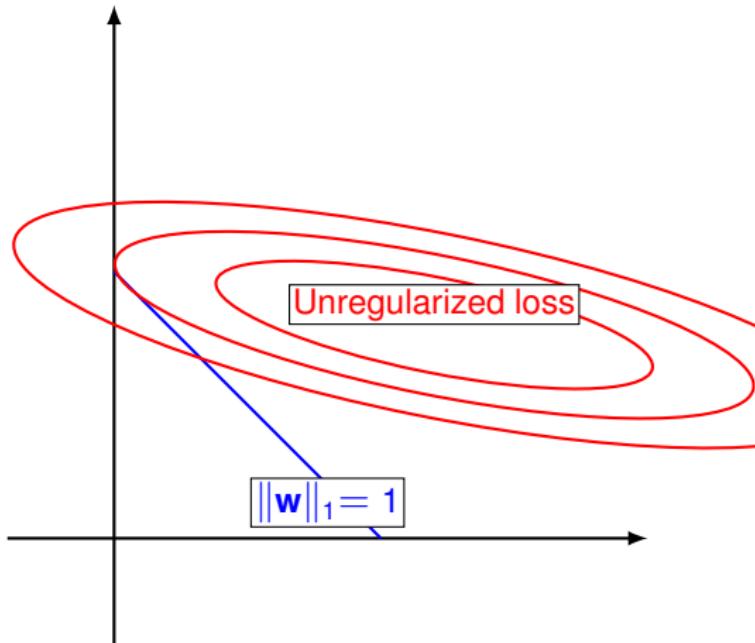
with an unknown data-dependent α .

Backpropagation of the augmented loss with the corresponding **subgradient**:

$$\mathbf{w}^{(k+1)} = \underbrace{\mathbf{w}^{(k)} - \eta \lambda \text{sign} \left(\mathbf{w}^{(k)} \right)}_{\text{Other shrinkage}} - \eta \frac{\partial L}{\partial \mathbf{w}^{(k)}}$$

→ Same as before

Graphical Effect (cont.)



Norm constraints

Can't we just set a limit on a norm of the weights?

Norm constraints

Can't we just set a limit on a norm of the weights?

Enforce ... norm below a maximum:

$$\underset{\mathbf{w}}{\text{minimize}} \quad \{L(\mathbf{w}, \mathbf{X}, \mathbf{Y})\} \quad \text{s.t. : } \|\mathbf{w}\| \leq \alpha, \quad \alpha > 0$$

Norm constraints

Can't we just set a limit on a norm of the weights?

Enforce ... norm below a maximum:

$$\underset{\mathbf{w}}{\text{minimize}} \quad \{L(\mathbf{w}, \mathbf{X}, \mathbf{Y})\} \quad \text{s.t. : } \|\mathbf{w}\| \leq \alpha, \quad \alpha > 0$$

- Perform parameter update, then project to unit-“ball”
- Still a kind of shrinkage
- Prohibits **exploding gradients** but also hides it

Other Variants of Changing the Loss

- We can have a **constraint** and a λ **individual** for every layer
 - Possible but **no gains** are reported

Other Variants of Changing the Loss

- We can have a **constraint** and a λ **individual** for every layer
 - Possible but **no gains** are reported
- Instead of the weights, **activations** can be **constrained**

Other Variants of Changing the Loss

- We can have a **constraint** and a λ **individual** for every layer
 - Possible but **no gains** are reported
- Instead of the weights, **activations** can be **constrained**
- Different variants have been used for **sparse autoencoders**
- We will cover this when we talk about unsupervised learning

NEXT TIME
ON DEEP LEARNING



FAU

FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Regularization - Part 3

A. Maier, V. Christlein, K. Breininger, S. Vesal, F. Meister, C. Liu, S. Gündel, S. Jaganathan, N. Maul,
M. Vornehm, L. Reeb, F. Thamm, M. Hoffmann, C. Bergler, F. Denzinger, W. Fu, B. Geissler, Z. Yang
Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg

May 9, 2020





FAU

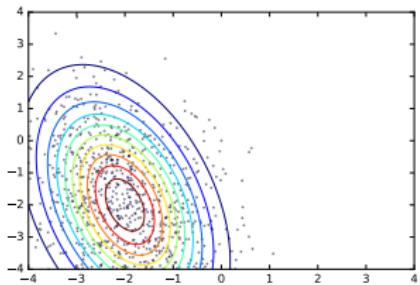
FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Normalization



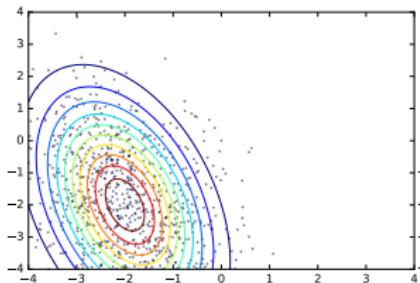
Data Normalization

Original data

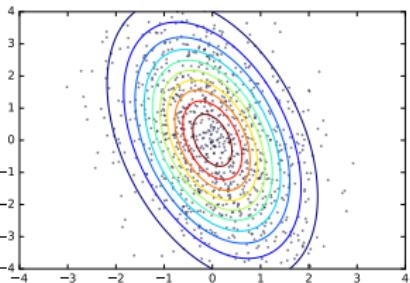


Data Normalization

Original data

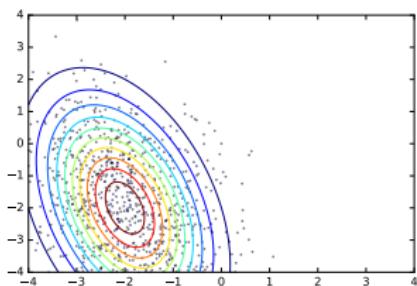


Mean subtracted

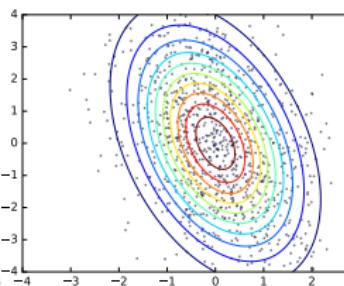


Data Normalization

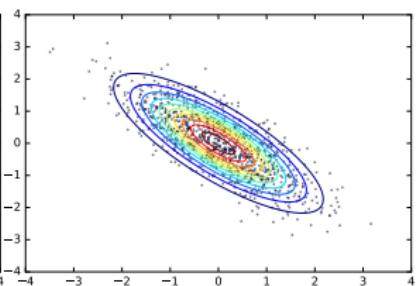
Original data



Mean subtracted

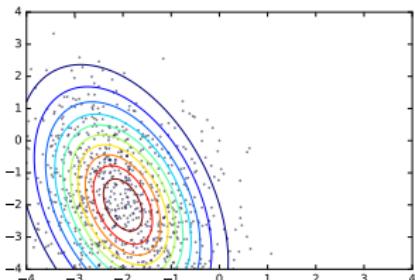


Normalized variance

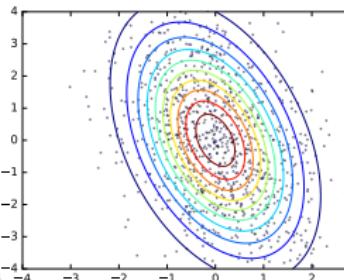


Data Normalization

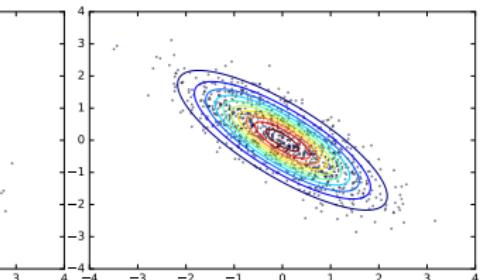
Original data



Mean subtracted



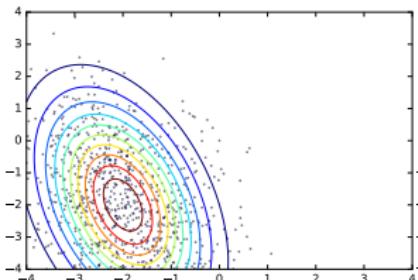
Normalized variance



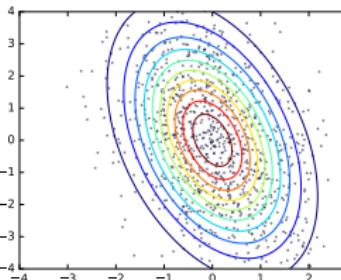
- Normalization: min/max or **variance**
- Only use **training data** to calculate normalization!

Data Normalization

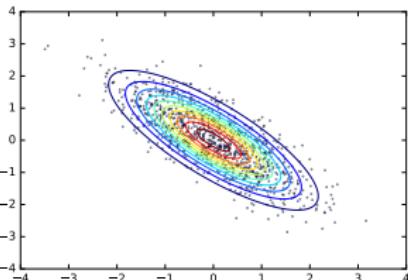
Original data



Mean subtracted



Normalized variance



- Normalization: min/max or **variance**
- Only use **training data** to calculate normalization!
- Normalization of input data
- Normalization **within** the network

Batch normalization (BN)

- Normalization as a new layer with 2 parameters, γ and β

Batch normalization (BN)

- Normalization as a new layer with 2 parameters, γ and β

$$\tilde{x}_i = \frac{x_i - \mu_{B,i}}{\sqrt{\sigma_{B,i}^2 + \epsilon}}$$

μ_B and σ_B from **mini-batch**

Batch normalization (BN)

- Normalization as a new layer with 2 parameters, γ and β

$$\tilde{x}_i = \frac{x_i - \mu_{B,i}}{\sqrt{\sigma_{B,i}^2 + \epsilon}}$$

μ_B and σ_B from **mini-batch**

$$\hat{y}_i = \gamma_i \tilde{x}_i + \beta_i$$

Batch normalization (BN)

- Normalization as a new layer with 2 parameters, γ and β

$$\tilde{x}_i = \frac{x_i - \mu_{B,i}}{\sqrt{\sigma_{B,i}^2 + \epsilon}}$$

μ_B and σ_B from **mini-batch**

$$\hat{y}_i = \gamma_i \tilde{x}_i + \beta_i$$

Test-time: replace μ_B and σ_B with μ and σ of the **training set**

Batch normalization (BN)

- Normalization as a new layer with 2 parameters, γ and β

$$\tilde{x}_i = \frac{x_i - \mu_{B,i}}{\sqrt{\sigma_{B,i}^2 + \epsilon}}$$

μ_B and σ_B from **mini-batch**

$$\hat{y}_i = \gamma_i \tilde{x}_i + \beta_i$$

Test-time: replace μ_B and σ_B with μ and σ of the **training set**

- So the μ and σ are **vectors, of the same dimension** as the **activation vector**.

Batch normalization (BN)

- Normalization as a new layer with 2 parameters, γ and β

$$\tilde{x}_i = \frac{x_i - \mu_{B,i}}{\sqrt{\sigma_{B,i}^2 + \epsilon}}$$

μ_B and σ_B from mini-batch

$$\hat{y}_i = \gamma_i \tilde{x}_i + \beta_i$$

Test-time: replace μ_B and σ_B with μ and σ of the training set

- So the μ and σ are vectors, of the same dimension as the activation vector.
- Paired with convolutional layers batch normalization is different by computing a scalar μ and σ for every channel.

Why does batch normalization help?

- Overwhelming **practical evidence** that batch normalization helps
- Original motivation by Ioffe and Szegedy [1]:
BN reduces **Internal Covariate Shift**

Why does batch normalization help?

- Overwhelming **practical evidence** that batch normalization helps
- Original motivation by Ioffe and Szegedy [1]:
BN reduces **Internal Covariate Shift**

Internal Covariate Shift

- ReLU is not **zero-centered**
- Initialization and input distribution might not be normalized
 - Input distribution **shifts** over time
- **Deeper nets** \mapsto amplified effect

Why does batch normalization help?

- Overwhelming **practical evidence** that batch normalization helps
- Original motivation by Ioffe and Szegedy [1]:
BN reduces **Internal Covariate Shift**

Internal Covariate Shift

- ReLU is not **zero-centered**
- Initialization and input distribution might not be normalized
- Input distribution **shifts** over time
- **Deeper nets** \mapsto amplified effect
- Layers constantly adapt

Why does batch normalization help?

- Overwhelming **practical evidence** that batch normalization helps
- Original motivation by Ioffe and Szegedy [1]:
BN reduces **Internal Covariate Shift**

Internal Covariate Shift

- ReLU is not **zero-centered**
- Initialization and input distribution might not be normalized
 - Input distribution **shifts** over time
- **Deeper nets** \mapsto amplified effect
- Layers constantly adapt
 - **Slow learning**

Why does batch normalization help?

- Overwhelming **practical evidence** that batch normalization helps
- Original motivation by Ioffe and Szegedy [1]:
BN reduces **Internal Covariate Shift**

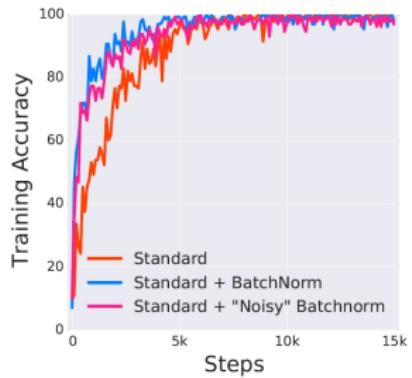
Internal Covariate Shift

- ReLU is not **zero-centered**
- Initialization and input distribution might not be normalized
- Input distribution **shifts** over time
- Deeper nets → amplified effect
- Layers constantly adapt
- **Slow learning**
- **But:** Little concrete evidence to support this theory

Why does batch normalization help? (cont.)

NeurIPS 2018: How Does Batch Normalization Help Optimization? [19]:

- BN helps **even** if internal covariate shift is introduced again afterwards

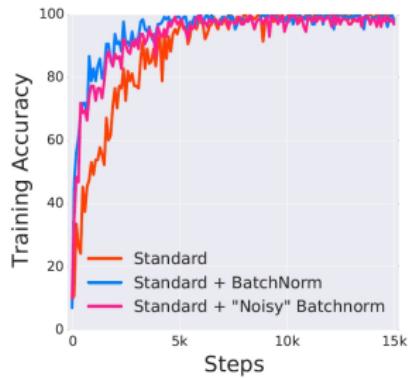


Source: [19]

Why does batch normalization help? (cont.)

NeurIPS 2018: How Does Batch Normalization Help Optimization? [19]:

- BN helps **even** if internal covariate shift is introduced again afterwards
- Experimental evidence that BN **smooths the loss landscape**

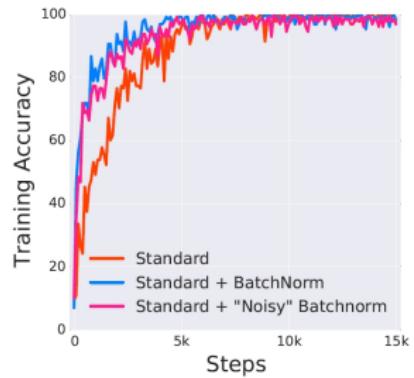


Source: [19]

Why does batch normalization help? (cont.)

NeurIPS 2018: How Does Batch Normalization Help Optimization? [19]:

- BN helps **even** if internal covariate shift is introduced again afterwards
- Experimental evidence that BN **smooths the loss landscape**
- Reminder: function f is L -Lipschitz if $|f(x_1) - f(x_2)| \leq L||x_1 - x_2|| \quad \forall x_1, x_2$

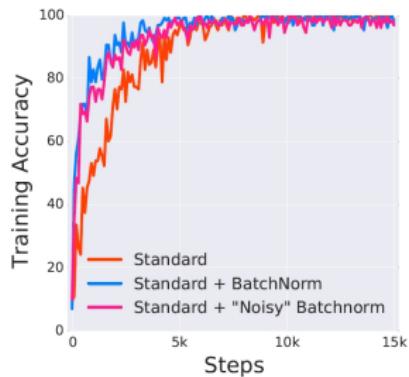


Source: [19]

Why does batch normalization help? (cont.)

NeurIPS 2018: How Does Batch Normalization Help Optimization? [19]:

- BN helps **even** if internal covariate shift is introduced again afterwards
- Experimental evidence that BN **smooths the loss landscape**
- Reminder: function f is L -Lipschitz if $|f(x_1) - f(x_2)| \leq L||x_1 - x_2|| \quad \forall x_1, x_2$
- Proof that BN improves Lipschitzness
 - of the loss function
 - of the gradient → gradient is more predictive

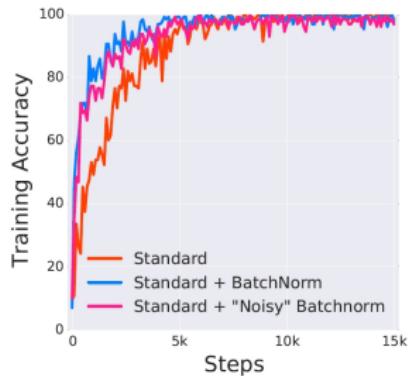


Source: [19]

Why does batch normalization help? (cont.)

NeurIPS 2018: How Does Batch Normalization Help Optimization? [19]:

- BN helps even if internal covariate shift is introduced again afterwards
- Experimental evidence that BN smooths the loss landscape
- Reminder: function f is L -Lipschitz if $|f(x_1) - f(x_2)| \leq L||x_1 - x_2|| \quad \forall x_1, x_2$
- Proof that BN improves Lipschitzness
 - of the loss function
 - of the gradient → gradient is more predictive
- BN improves stability e.g. with respect to hyperparameters, initialization, convergence
- Similar properties also observed for ℓ_p -normalization



Source: [19]

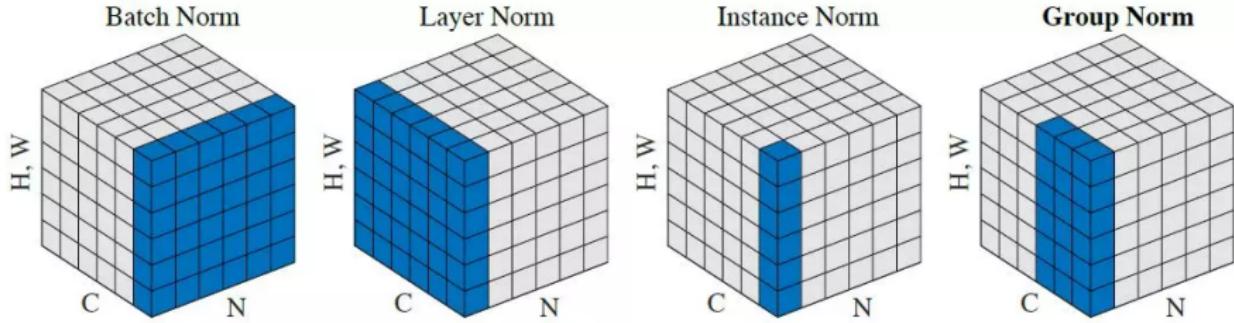
Generalizations

$$\hat{y} = f\left(g \frac{x - \mu}{\sigma} + b\right)$$

y : output
 f : activation function
 x : input
 g, b : adaptive gain and bias
 μ, σ : mean and std dev.

Calculating μ, σ over

- ... activations of a batch [1], a layer [15], spatial dims [13], a group [11]
- ... weights of a layer [20]



Source: Wu et al. [11]

Self Normalizing Neural Networks

- Method that **addresses** the **stability problem** of SGD [14]

Self Normalizing Neural Networks

- Method that **addresses** the **stability problem** of SGD [14]
- Key element: **SeLU** + specific weight initialization

$$f(x) = \lambda \begin{cases} x & \text{if } x > 0 \\ \alpha(\exp(x) - 1) & \text{else} \end{cases}$$

With $\lambda_{01} = 1.0507$ and $\alpha_{01} = 1.6733$ for $\mu = 0$ and $\sigma = 1$

- Guarantee that μ and the σ of the activations stays near 0 and 1 through the network
 - Stable activations, stable training

Self Normalizing Neural Networks

- Method that **addresses** the **stability problem** of SGD [14]
- Key element: **SeLU** + specific weight initialization

$$f(x) = \lambda \begin{cases} x & \text{if } x > 0 \\ \alpha(\exp(x) - 1) & \text{else} \end{cases}$$

With $\lambda_{01} = 1.0507$ and $\alpha_{01} = 1.6733$ for $\mu = 0$ and $\sigma = 1$

- Guarantee that μ and the σ of the activations stays near 0 and 1 through the network
 - Stable activations, stable training
- Require special form of drop-out: Instead of dropping to zero, drop to

$$-\lambda \cdot \alpha$$

- Additionally they use an **affine transform** to restore variance and mean

Self Normalizing Neural Networks

- Method that **addresses** the **stability problem** of SGD [14]
- Key element: **SeLU** + specific weight initialization

$$f(x) = \lambda \begin{cases} x & \text{if } x > 0 \\ \alpha(\exp(x) - 1) & \text{else} \end{cases}$$

With $\lambda_{01} = 1.0507$ and $\alpha_{01} = 1.6733$ for $\mu = 0$ and $\sigma = 1$

- Guarantee that μ and the σ of the activations stays near 0 and 1 through the network
 - Stable activations, stable training
- Require special form of drop-out: Instead of dropping to zero, drop to

$$-\lambda \cdot \alpha$$

- Additionally they use an **affine transform** to restore variance and mean
- The **SNN** concept resembles **batch normalization**



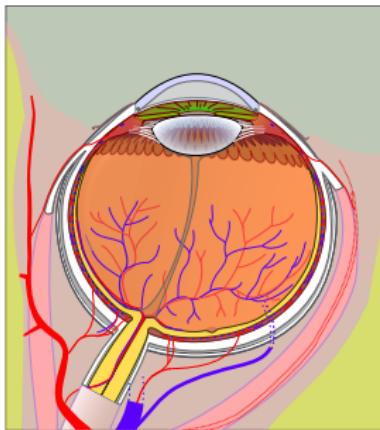
FAU

FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Dropout



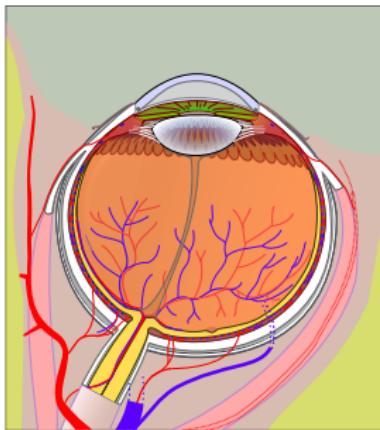
Co-adaptation



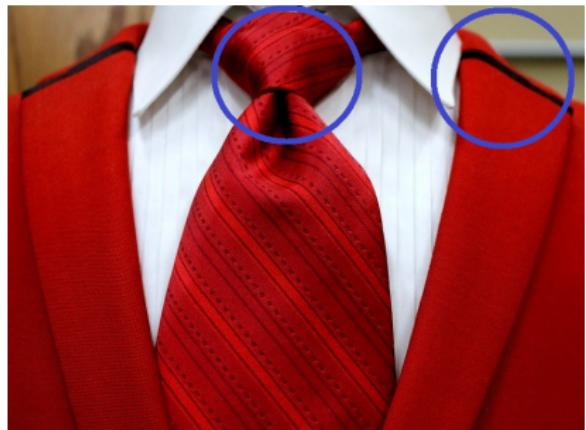
All elements **depend** on each other

Source: Jordi March / CC-BY-SA-3.0

Co-adaptation



All elements **depend** on each other

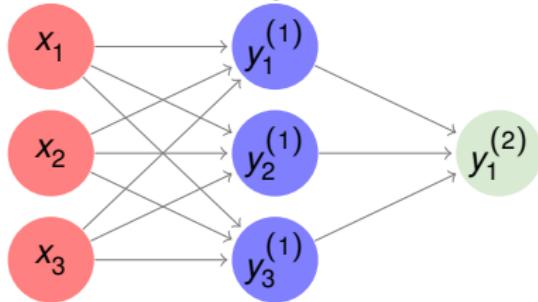


→Contrary to **independent** features

Source: Jordi March / CC-BY-SA-3.0

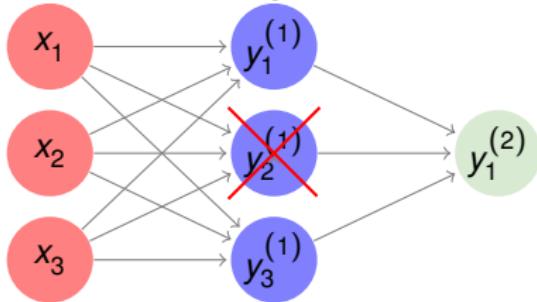
Dropout and Dropconnect

Dropout



Dropout and Dropconnect

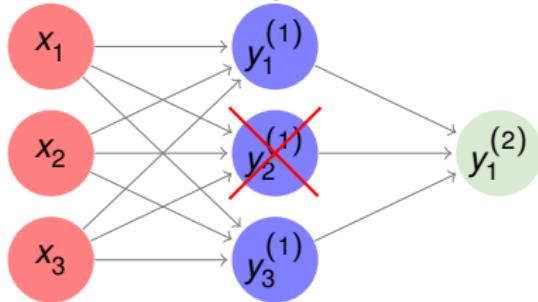
Dropout



- Randomly set activations to zero with probability $1 - p$

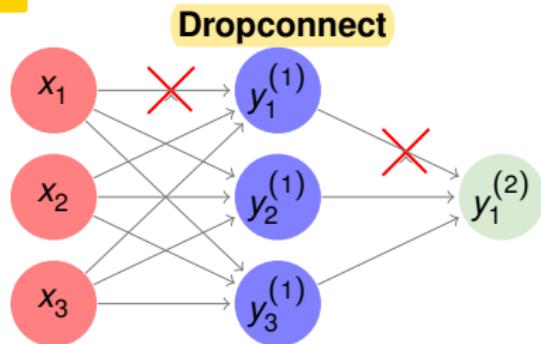
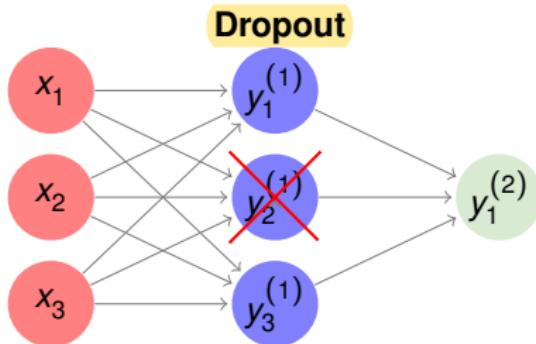
Dropout and Dropconnect

Dropout



- Randomly set activations to zero with probability $1 - p$
- Test-time: multiply activation with p

Dropout and Dropconnect



- Randomly set activations to zero with probability $1 - p$
- Test-time: multiply activation with p

- Generalizes Dropout
- Less efficient implementation (masking)

**NEXT TIME
ON DEEP LEARNING**



FAU

FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Regularization - Part 4

A. Maier, V. Christlein, K. Breininger, S. Vesal, F. Meister, C. Liu, S. Gündel, S. Jaganathan, N. Maul,
M. Vornehm, L. Reeb, F. Thamm, M. Hoffmann, C. Bergler, F. Denzinger, W. Fu, B. Geissler, Z. Yang
Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg

May 9, 2020





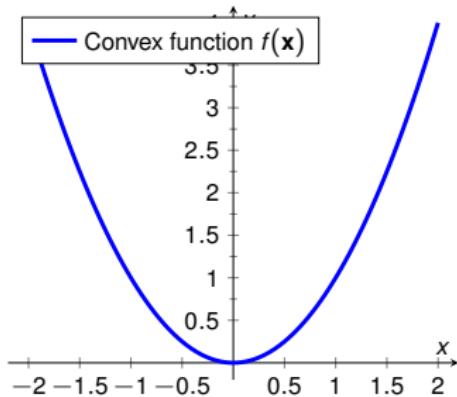
FAU

FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

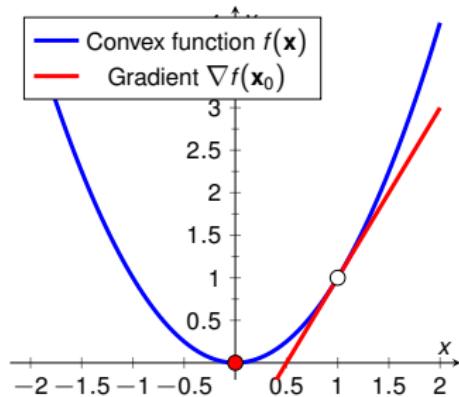
Initialization



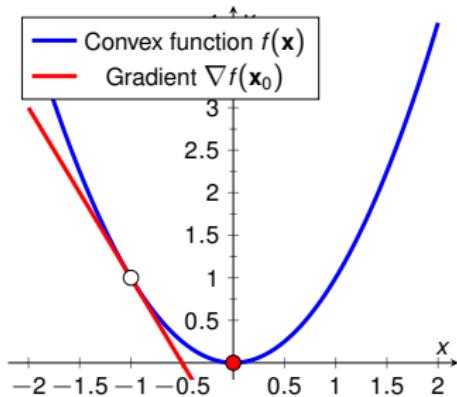
Does initialization matter?



Does initialization matter?

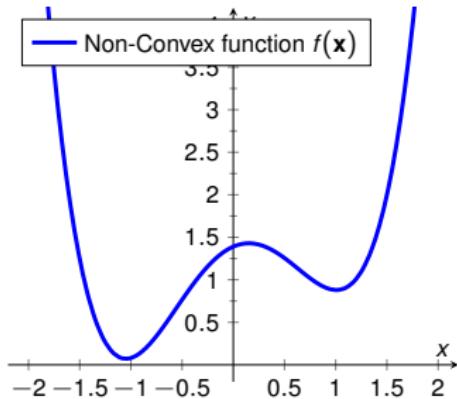


Does initialization matter?



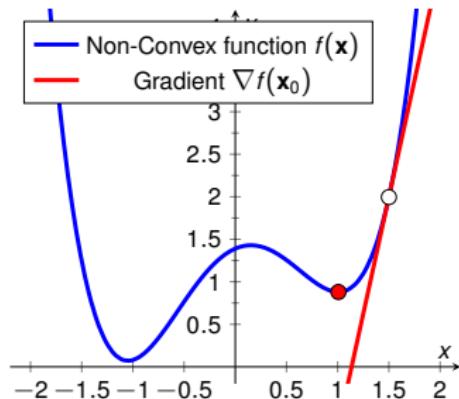
- No it doesn't for **convex** optimization problems

Does initialization matter?



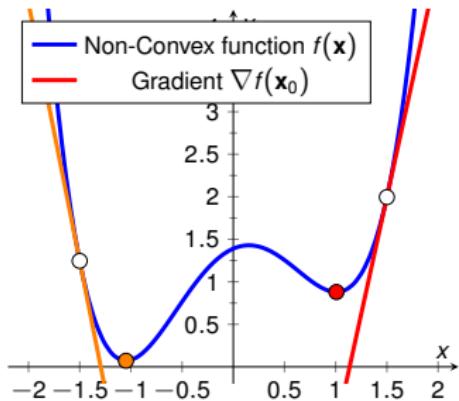
- No it doesn't for **convex** optimization problems

Does initialization matter?



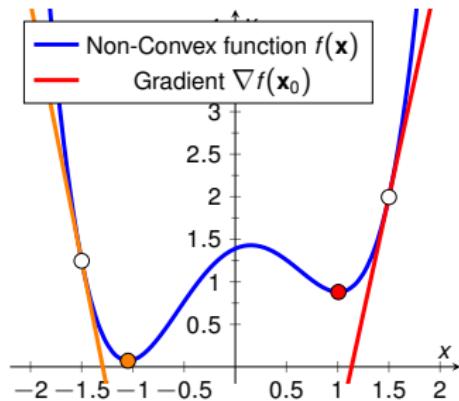
- No it doesn't for **convex** optimization problems

Does initialization matter?



- No it doesn't for **convex** optimization problems
- But it **does** for every **non-convex** problem

Does initialization matter?



- No it doesn't for **convex** optimization problems
- But it **does** for every **non-convex** problem
- Neural Networks with a non-linearity are in general **non-convex**

Simple Initialization

Bias

- **Bias** units can simply be **initialized to zero**

Weights

Simple Initialization

Bias

- **Bias** units can simply be **initialized to zero**
- Using **ReLUs** a **small positive** constant (0.1) is better because of the **dying ReLU issue**

Weights

Simple Initialization

Bias

- **Bias** units can simply be **initialized to zero**
- Using **ReLUs** a **small positive** constant (0.1) is better because of the **dying ReLU issue**

Weights

- **Weights** need to be **random** to **break symmetry**
- It's **especially bad** to **initialize** them **with zeros** because the gradient is **zero!**

Simple Initialization

Bias

- Bias units can simply be initialized to zero
- Using ReLUs a small positive constant (0.1) is better because of the dying ReLU issue

Weights

- Weights need to be random to break symmetry
- It's especially bad to initialize them with zeros because the gradient is zero!
- Similar to the learning rate their variance influences the stability of learning
- Small uniform/Gaussian values work

Calibrating the variances

- Suppose we have a single **linear** neuron with weights **W** and an input **X**
- Capital letters here mark them as **random variables!**

Calibrating the variances

- Suppose we have a single **linear** neuron with weights **W** and an input **X**
- Capital letters here mark them as **random variables!**
- Output is:

$$\hat{Y} = \mathbf{WX} = \left(\sum_{n=1}^N W_n X_n \right) + b$$

Calibrating the variances

- Suppose we have a single **linear** neuron with weights \mathbf{W} and an input \mathbf{X}
- Capital letters here mark them as **random variables!**
- Output is:

$$\hat{Y} = \mathbf{WX} = \left(\sum_{n=1}^N W_n X_n \right) + b$$

- We are interested in $\text{Var}(\hat{Y})$

Calibrating the variances

- Suppose we have a single **linear** neuron with weights \mathbf{W} and an input \mathbf{X}
- Capital letters here mark them as **random variables!**
- Output is:

$$\hat{Y} = \mathbf{WX} = \left(\sum_{n=1}^N W_n X_n \right) + b$$

- We are interested in $\text{Var}(\hat{Y})$
- If we assume the W_n and X_n independent, the variance of every product is:

$$\text{Var}(W_n X_n) = \mathbb{E}[X_n]^2 \text{Var}(W_n) + \mathbb{E}[W_n]^2 \text{Var}(X_n) + \text{Var}(W_n) \text{Var}(X_n)$$

Calibrating the variances

- Suppose we have a single **linear** neuron with weights \mathbf{W} and an input \mathbf{X}
- Capital letters here mark them as **random variables!**
- Output is:

$$\hat{Y} = \mathbf{WX} = \left(\sum_{n=1}^N W_n X_n \right) + b$$

- We are interested in $\text{Var}(\hat{Y})$
- If we assume the W_n and X_n independent, the variance of every product is:

$$\text{Var}(W_n X_n) = \mathbb{E}[X_n]^2 \text{Var}(W_n) + \mathbb{E}[W_n]^2 \text{Var}(X_n) + \text{Var}(W_n) \text{Var}(X_n)$$

- If W_n and X_n have zero-mean: $\text{Var}(W_n X_n) = \text{Var}(W_n) \text{Var}(X_n)$

Calibrating the variances

- Suppose we have a single **linear** neuron with weights \mathbf{W} and an input \mathbf{X}
- Capital letters here mark them as **random variables!**
- Output is:

$$\hat{Y} = \mathbf{WX} = \left(\sum_{n=1}^N W_n X_n \right) + b$$

- We are interested in $\text{Var}(\hat{Y})$
- If we assume the W_n and X_n independent, the variance of every product is:

$$\text{Var}(W_n X_n) = \mathbb{E}[X_n]^2 \text{Var}(W_n) + \mathbb{E}[W_n]^2 \text{Var}(X_n) + \text{Var}(W_n) \text{Var}(X_n)$$

- If W_n and X_n have zero-mean: $\text{Var}(W_n X_n) = \text{Var}(W_n) \text{Var}(X_n)$
- Now we assume the X_n and W_n to be **Independent and Identically Distributed**:

$$\text{Var}(\hat{Y}) = \underbrace{N \text{Var}(W_n)}_{\text{scales Var}} \text{Var}(X_n)$$

Xavier initialization

- We can “calibrate” the variances for the forward-pass by initializing with a zero-mean Gaussian: $\mathcal{N}(0, \sigma)$ with $\sigma^2 = \frac{1}{\text{fan_in}}$ where “fan_in” is the **input** dimension of the weights

Xavier initialization

- We can “calibrate” the variances for the forward-pass
 - by initializing with a zero-mean Gaussian: $\mathcal{N}(0, \sigma)$
 - with $\sigma^2 = \frac{1}{\text{fan_in}}$
 - where “fan_in” is the **input** dimension of the weights
- However the backward-pass
 - needs $\sigma^2 = \frac{1}{\text{fan_out}}$
 - where “fan_out” is the **output** dimension of the weights

Xavier initialization

- We can “calibrate” the variances for the forward-pass
 - by initializing with a zero-mean Gaussian: $\mathcal{N}(0, \sigma)$
 - with $\sigma^2 = \frac{1}{\text{fan_in}}$
 - where “fan_in” is the **input** dimension of the weights
 - However the backward-pass
 - needs $\sigma^2 = \frac{1}{\text{fan_out}}$
 - where “fan_out” is the **output** dimension of the weights
 - So we average those two:
 - Named “**Xavier**” initialization after the first author [21]
- $$\sigma = \sqrt{\frac{2}{\text{fan_out} + \text{fan_in}}}$$

He initialization

- the assumption of **linear** neurons is a problem
- He et al. [12] showed, for ReLUs it's better to use:

$$\sigma = \sqrt{\frac{2}{\text{fan_in}}}$$

Conventional Initial Choices

- L₂ regularization
- Dropout using $p = 0.5$ for FCN, use selectively in CNNs
- Mean subtraction
- Batch normalization
- He initialization



FAU

FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Transfer Learning



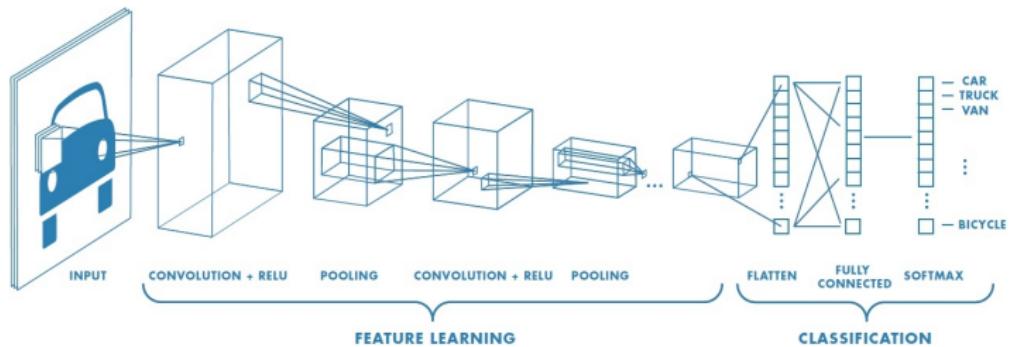
Transfer Learning

- Most **medical datasets** are prohibitively **small**

Transfer Learning

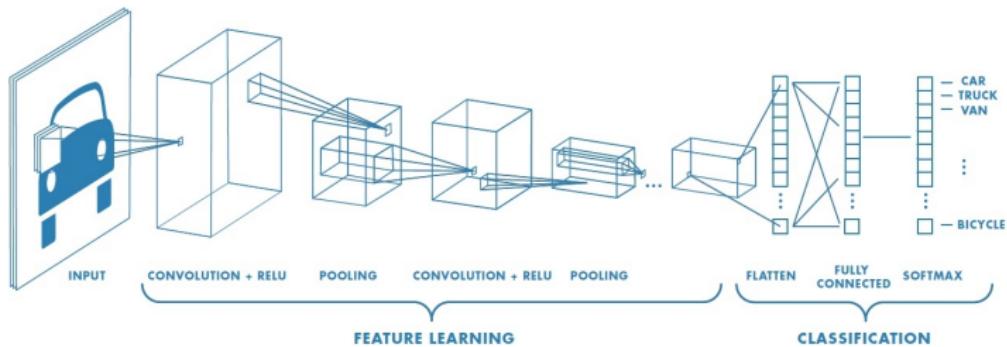
- Most **medical datasets** are prohibitively **small**
- **Reuse models** trained on e.g. ImageNet
 - for a **different task** on the **same data**
 - on **different data** for the **same task**
 - on **different data** for a **different task**

Weight Transfer



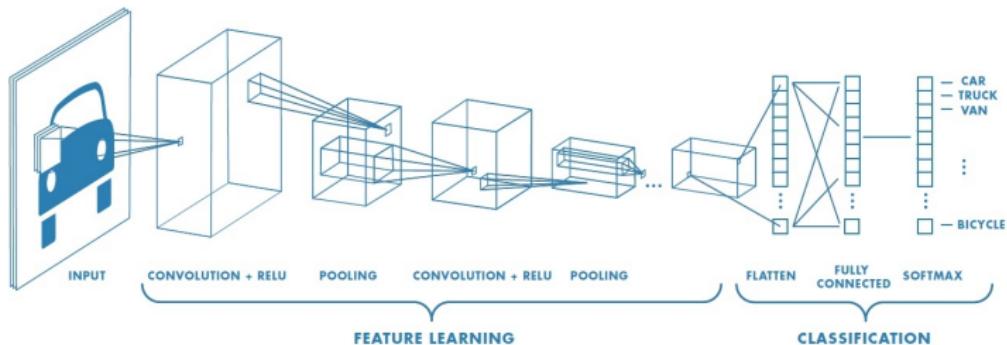
- What should we transfer?

Weight Transfer



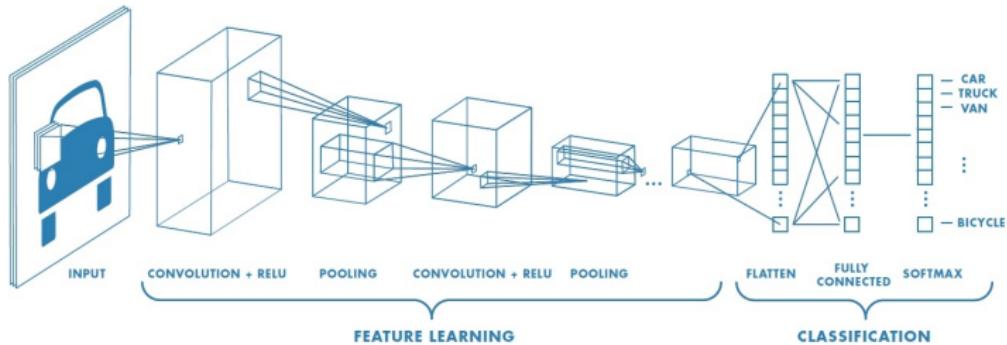
- What should we transfer?
 - Convolutional layers extract features

Weight Transfer



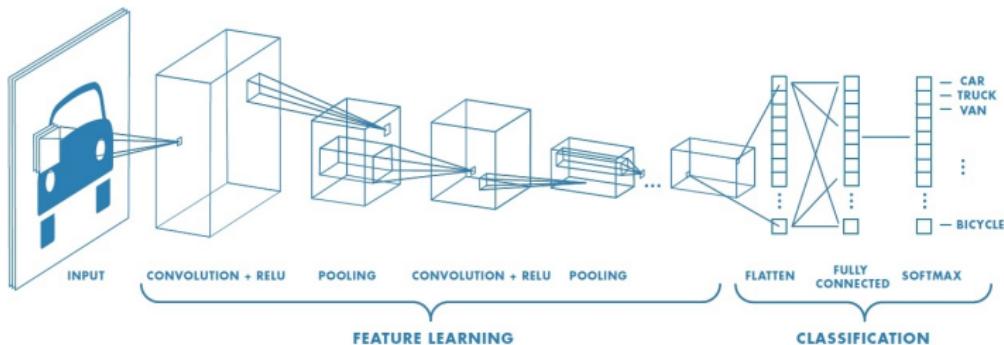
- What should we transfer?
 - Convolutional layers extract features
 - Expectation: Less task-specific in earlier layers

Weight Transfer



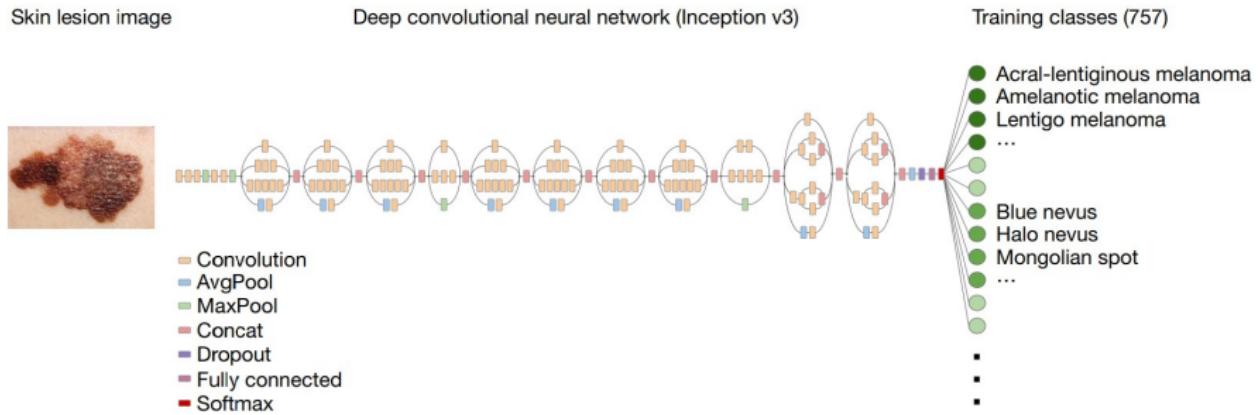
- What should we transfer?
 - Convolutional layers extract features
 - Expectation: Less task-specific in earlier layers
- We cut the network at some depth in the feature extraction part

Weight Transfer



- What should we transfer?
 - Convolutional layers extract features
 - Expectation: Less task-specific in earlier layers
- We cut the network at some depth in the feature extraction part
- The extracted parts can be
 1. fixed by setting $\eta = 0$
 2. **fine-tuned**

Example: Skin Cancer classification



- State-of-the-art architecture, pre-trained on ImageNet
 - Fine-tuned on skin cancer data [5]

Source: <https://www.nature.com/articles/nature21056>

Transfer between modalities

- Also found to be **beneficial** if we transfer from RGB images to X-ray

Transfer between modalities

- Also found to be **beneficial** if we transfer from RGB images to X-ray
 - It's sufficient to simply copy the input three times
- Finetuning usually necessary

Transfer between modalities

- Also found to be **beneficial** if we transfer from RGB images to X-ray
 - It's sufficient to simply copy the input three times
- Finetuning usually necessary
- Alternative: Use feature representations of other network as a loss function
 - Perceptual loss

Transfer between modalities

- Also found to be **beneficial** if we transfer from RGB images to X-ray
 - It's sufficient to simply copy the input three times
- Finetuning usually necessary
- Alternative: Use feature representations of other network as a loss function
 - Perceptual loss
- Always use transfer learning!

NEXT TIME
ON DEEP LEARNING



FAU

FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Regularization - Part 5

A. Maier, V. Christlein, K. Breininger, S. Vesal, F. Meister, C. Liu, S. Gündel, S. Jaganathan, N. Maul,
M. Vornehm, L. Reeb, F. Thamm, M. Hoffmann, C. Bergler, F. Denzinger, W. Fu, B. Geissler, Z. Yang
Pattern Recognition Lab, Friedrich-Alexander-Universität Erlangen-Nürnberg

May 9, 2020





FAU

FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

Multi-Task Learning (MTL)



Concept

- So far: One network for one task
- Transfer learning: **Reuse** a network
- Can we do more?

Concept

- So far: One network for one task
- Transfer learning: **Reuse** a network
- Can we do more?
- Real world examples:
 - Learning to play the piano and the violin
 - Both require good hearing, sense of rhythm, music notation, ...



Source: <https://commons.wikimedia.org/wiki/File:Klavierquintett.JPG>

Concept

- So far: One network for one task
- Transfer learning: **Reuse** a network
- Can we do more?
- Real world examples:
 - Learning to play the piano and the violin
 - Both require good hearing, sense of rhythm, music notation, ...
 - Soccer and basketball training
 - Both require stamina, speed, body awareness, body-eye coordination, ...



Source: <https://commons.wikimedia.org/wiki/File:Klavierquintett.JPG>

Concept

- So far: One network for one task
- Transfer learning: **Reuse** a network
- Can we do more?
- Real world examples:
 - Learning to play the piano and the violin
 - Both require good hearing, sense of rhythm, music notation, ...
 - Soccer and basketball training
 - Both require stamina, speed, body awareness, body-eye coordination, ...



Even better than reusing: Learning them **simultaneously** can provide a better understanding of the **shared underlying concepts**.

Source: <https://commons.wikimedia.org/wiki/File:Klavierquintett.JPG>

Concept (cont.)

- Idea: Train a network **simultaneously** on **multiple related** tasks

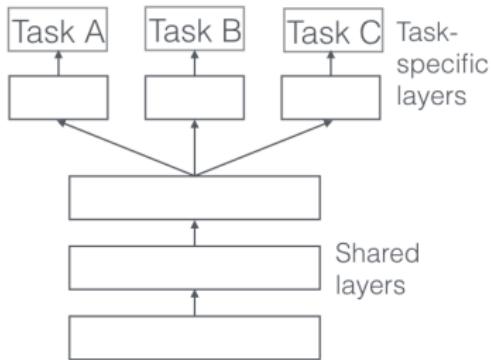
Concept (cont.)

- Idea: Train a network **simultaneously** on **multiple related** tasks
- Adapt loss function to assess performance for multiple tasks

Concept (cont.)

- Idea: Train a network **simultaneously** on **multiple related** tasks
- Adapt loss function to assess performance for multiple tasks
- Multi task learning introduces an **inductive bias**: We prefer a model that can explain more than one task
- Reduces risk of **overfitting** on one particular task [2]
→ model generalizes better

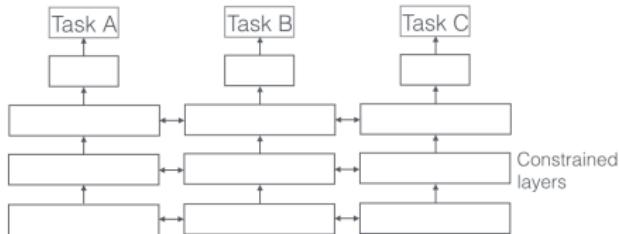
Hard parameter sharing



- Several hidden layers shared between all tasks
- Additional task-specific output layers
- Baxter '97 [2]: Multi-task learning of N tasks reduces chance of overfitting by an order of N

Source: <http://ruder.io/multi-task/>

Soft parameter sharing



- Each model has its own parameters
- Instead of forcing equality, distance between parameters is regularized as part of the loss function
- Options e.g. l_2 -norm, trace-norm, ...

Source: <http://ruder.io/multi-task/>

Auxiliary tasks

- Additional tasks have own purpose or are just **auxiliary** to the original task

Auxiliary tasks

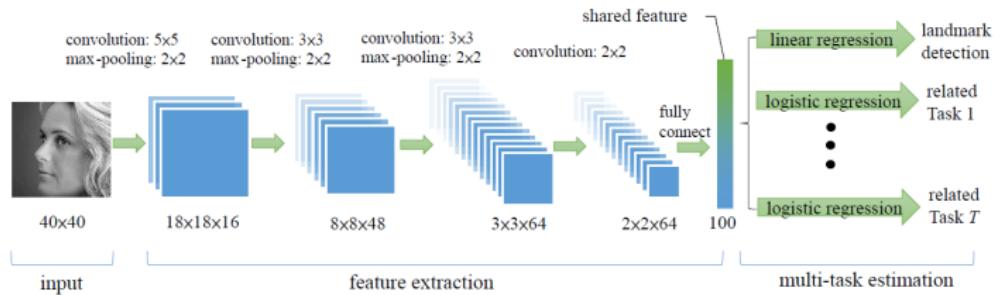
- Additional tasks have own purpose or are just **auxiliary** to the original task
- Example: **Facial Landmark Detection** by Zhang et al. 2014 [22]

Auxiliary tasks

- Additional tasks have own purpose or are just **auxiliary** to the original task
- Example: **Facial Landmark Detection** by Zhang et al. 2014 [22]
- Facial landmark detection impeded by occlusion and pose variances

Auxiliary tasks

- Additional tasks have own purpose or are just **auxiliary** to the original task
- Example: **Facial Landmark Detection** by Zhang et al. 2014 [22]
- Facial landmark detection impeded by occlusion and pose variances
- Simultaneously learn to estimate landmarks **and** “subtly” related task:
 - Face pose
 - Smiling/not smiling
 - Glasses/no glasses (occlusion)
 - Gender



Network architecture

Source: [22]

Auxiliary tasks (cont.)

Auxiliary Tasks

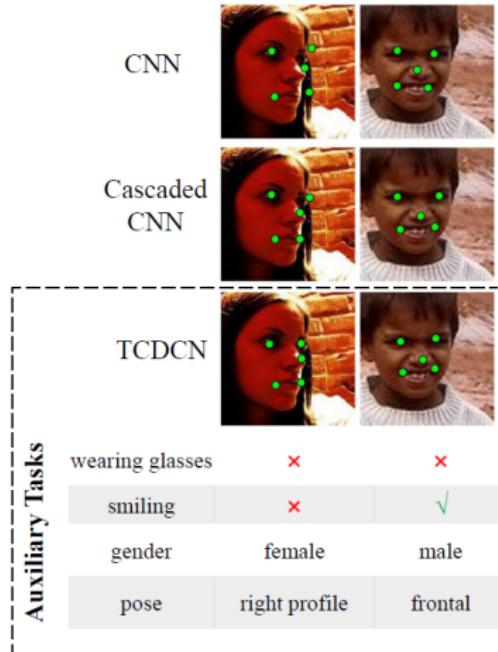
CNN							
Cascaded CNN							
TCDCN							
wearing glasses	✗	✗	✓	✗	✓	✗	✗
smiling	✗	✓	✗	✗	✗	✗	✗
gender	female	male	female	female	male	male	female
pose	right profile	frontal	frontal	left	frontal	frontal	right profile

Landmark detection

Source: [22]

Auxiliary tasks (cont.)

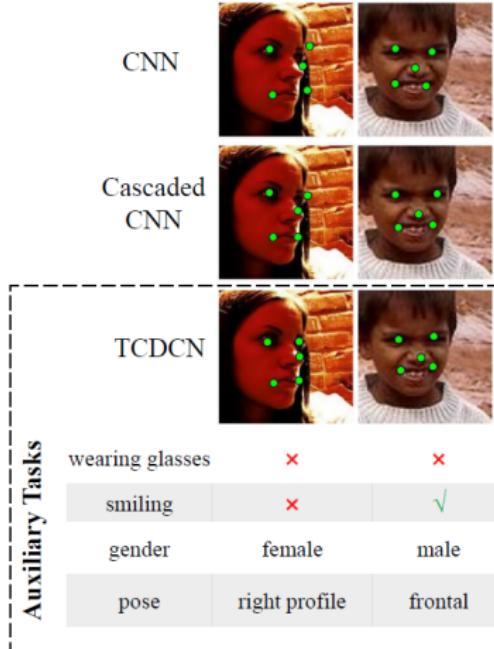
- Certain features difficult to learn for one task but easy for a related one [4]



Source: [22]

Auxiliary tasks (cont.)

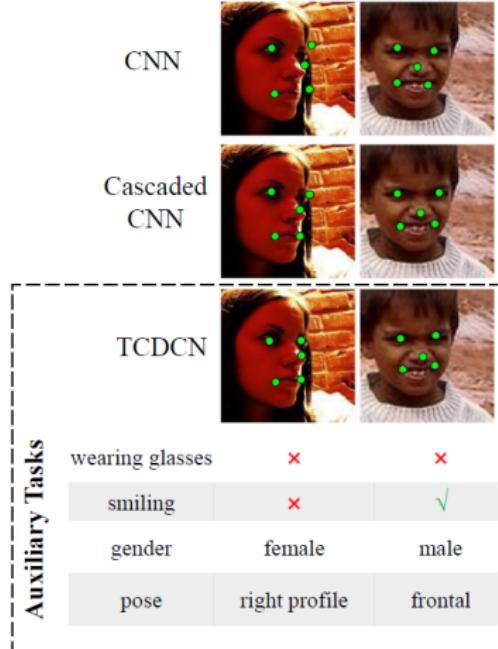
- Certain features difficult to learn for one task but easy for a related one [4]
- Auxiliary tasks can help to “steer” training in a specific direction
- Include prior knowledge by choosing appropriate auxiliary tasks



Source: [22]

Auxiliary tasks (cont.)

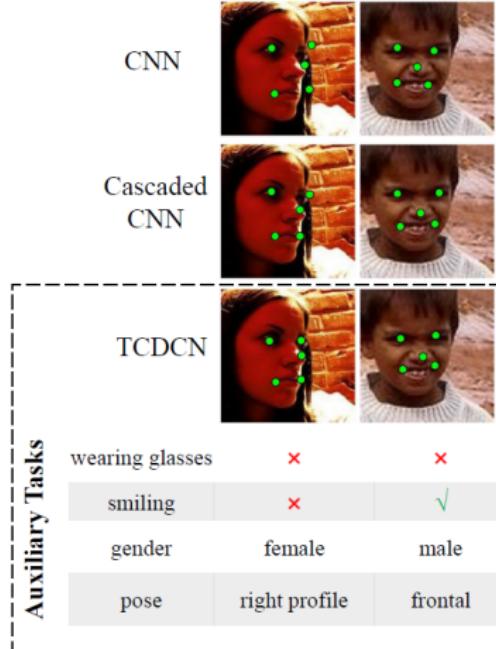
- Certain features difficult to learn for one task but easy for a related one [4]
- Auxiliary tasks can help to “steer” training in a specific direction
- Include prior knowledge by choosing appropriate auxiliary tasks
- Tasks can have different convergence rates
→ Task-based early-stopping



Source: [22]

Auxiliary tasks (cont.)

- Certain features difficult to learn for one task but easy for a related one [4]
- Auxiliary tasks can help to “steer” training in a specific direction
- Include prior knowledge by choosing appropriate auxiliary tasks
- Tasks can have different convergence rates
→ Task-based early-stopping
- Open research question: **What are appropriate auxiliary tasks?**



Source: [22]

NEXT TIME
ON DEEP LEARNING

Coming Up

- Practical recommendations to make training work
- Evaluation of performance
- Methods to deal with common problems
- Concrete case studies using all the pieces you now learned

Comprehensive Questions

- What is the bias-variance tradeoff?
- What is model capacity?
- Describe three techniques to address overfitting in a neural network.
- Why do we often need a validation set?
- Can we optimize the hyperparameter λ by gradient descend on the training set?
- What connects the covariate shift problem and the ReLU?
- How can we address the covariate shift problem?
- Which problem do current initialization schemes try to address?
- What is transfer learning?

Further Reading

- [Link](#) - for details on Maximum A Posteriori estimation and the bias-variance decomposition
- [Link](#) - for a comprehensive text about practical recommendations for regularization
- [Link](#) - the paper about calibrating the variances



FAU

FRIEDRICH-ALEXANDER-
UNIVERSITÄT
ERLANGEN-NÜRNBERG
SCHOOL OF ENGINEERING

References



References I

- [1] Sergey Ioffe and Christian Szegedy. "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift". In: Proceedings of The 32nd International Conference on Machine Learning. 2015, pp. 448–456.
- [2] Jonathan Baxter. "A Bayesian/Information Theoretic Model of Learning to Learn via Multiple Task Sampling". In: Machine Learning 28.1 (July 1997), pp. 7–39.
- [3] Christopher M. Bishop.
Pattern Recognition and Machine Learning (Information Science and Statistics)
Secaucus, NJ, USA: Springer-Verlag New York, Inc., 2006.

References II

- [4] Richard Caruana. "Multitask Learning: A Knowledge-Based Source of Inductive Bias". In: Proceedings of the Tenth International Conference on Machine Learning. Morgan Kaufmann, 1993, pp. 41–48.
- [5] Andre Esteva, Brett Kuprel, Roberto A Novoa, et al. "Dermatologist-level classification of skin cancer with deep neural networks". In: Nature 542.7639 (2017), pp. 115–118.
- [6] C. Ding, C. Xu, and D. Tao. "Multi-Task Pose-Invariant Face Recognition". In: IEEE Transactions on Image Processing 24.3 (Mar. 2015), pp. 980–993.
- [7] Li Wan, Matthew Zeiler, Sixin Zhang, et al. "Regularization of neural networks using dropconnect". In: Proceedings of the 30th International Conference on Machine Learning (ICML-2013), pp. 1058–1066.

References III

- [8] Nitish Srivastava, Geoffrey E Hinton, Alex Krizhevsky, et al. "Dropout: a simple way to prevent neural networks from overfitting.". In: Journal of Machine Learning Research 15.1 (2014), pp. 1929–1958.
- [9] R. O. Duda, P. E. Hart, and D. G. Stork. Pattern Classification. John Wiley and Sons, inc., 2000.
- [10] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. Deep Learning. <http://www.deeplearningbook.org>. MIT Press, 2016.
- [11] Yuxin Wu and Kaiming He. "Group normalization". In: arXiv preprint arXiv:1803.08494 (2018).
- [12] Kaiming He, Xiangyu Zhang, Shaoqing Ren, et al. "Delving deep into rectifiers: Surpassing human-level performance on imagenet classification". In: Proceedings of the IEEE international conference on computer vision. 2015, pp. 1026–1034.

References IV

- [13] D Ulyanov, A Vedaldi, and VS Lempitsky.
Instance normalization: the missing ingredient for fast stylization. CoRR abs/1608.07375
- [14] Günter Klambauer, Thomas Unterthiner, Andreas Mayr, et al.
“Self-Normalizing Neural Networks”. In:
Advances in Neural Information Processing Systems (NIPS).
Vol. abs/1706.02515. 2017. arXiv: 1706.02515.
- [15] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. “Layer normalization”. In: arXiv preprint arXiv:1607.06450 (2016).
- [16] Nima Tajbakhsh, Jae Y Shin, Suryakanth R Gurudu, et al. “Convolutional neural networks for medical image analysis: Full training or fine tuning?” In: IEEE transactions on medical imaging 35.5 (2016), pp. 1299–1312.

References V

- [17] Yoshua Bengio. "Practical recommendations for gradient-based training of deep architectures". In: [Neural networks: Tricks of the trade](#). Springer, 2012, pp. 437–478.
- [18] Chiyuan Zhang, Samy Bengio, Moritz Hardt, et al. "Understanding deep learning requires rethinking generalization". In: [arXiv preprint arXiv:1611.03530](#) (2016).
- [19] Shibani Santurkar, Dimitris Tsipras, Andrew Ilyas, et al. "How Does Batch Normalization Help Optimization?" In: [arXiv e-prints](#), arXiv:1805.11604 (May 2018), arXiv:1805.11604. arXiv: 1805.11604 [stat.ML].
- [20] Tim Salimans and Diederik P Kingma. "Weight Normalization: A Simple Reparameterization to Accelerate Training of Deep Neural Networks". In: [Advances in Neural Information Processing Systems 29](#). Curran Associates, Inc., 2016, pp. 901–909.

References VI

- [21] Xavier Glorot and Yoshua Bengio. "Understanding the difficulty of training deep feedforward neural networks". In: Proceedings of the Thirteenth International Conference on Artificial Intelligence 2010, pp. 249–256.
- [22] Zhanpeng Zhang, Ping Luo, Chen Change Loy, et al. "Facial Landmark Detection by Deep Multi-task Learning". In: Computer Vision – ECCV 2014: 13th European Conference, Zurich, Switzerland Cham: Springer International Publishing, 2014, pp. 94–108.