Generalizaiton and Regularizaiton

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Outline

Recap: Optimization in Neural Network

- MLPs are **parameterized** function $f_{\boldsymbol{\theta}}$, where $\boldsymbol{\theta} = \{\boldsymbol{W}^{\ell}, \boldsymbol{b}^{\ell}\}$
- The learning problem involves solving an **optimization** problem to iteratively update the $\boldsymbol{\theta}$

$$\min_{\boldsymbol{\theta}} \quad \mathcal{L}(\boldsymbol{\theta}) = \frac{1}{n} \sum_{i=1}^{n} \ell(f_{\boldsymbol{\theta}}(\boldsymbol{x}_i), \boldsymbol{y}_i)$$

  where ℓ is a **loss** function and $\mathcal{S} := \{\boldsymbol{x}_i, \boldsymbol{y}_i\}_{i=1}^{\ell}$ is a **training set**.
- This optimization problem can be solved using **gradient**-based methods such as *(stochastic) gradient descent (SGD)*, *gradient descent with momentum*, *RMSProp*, *Adam*, etc:

$$\boldsymbol{\theta}^{+} = \boldsymbol{\theta} - \eta \cdot \boldsymbol{v}^{+},$$

  where $\eta > 0$ is a **learning rate** and $\boldsymbol{v}$ is a **search direction**.

Recap: Hyperparameters in Neural Networks

The training process involves several key hyperparameters:

- **Loss Function** $\ell(\cdot, \cdot)$: Square loss, cross-entropy loss, hinge loss
- **Activation Function** $\phi(\cdot)$: Step, sigmoid, ReLU, tanh, GELU
- **Optimizer**: SGD, Momentum, RMSProp, Adam
- **Learning Rate** (η), **Batch Size** (b), **Epochs**
- **Network Type**: MLPs, CNNs, RNNs, Transformers, GNNs
- **Width and Depth**
- **Layers**: Normalization, pooling, dropout, softmax
- **Otherwise**: Initialization (Xavier, He), ℓ_2-regularization, gradient clipping, early stop

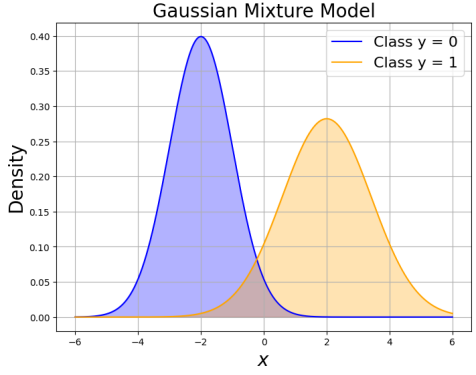
Key Difference: Hyperparameters vs. Trainable Parameters

- Hyperparameters are **not trainable**. Unlike weights and biases, they need to be **tuned manually**.
- Proper tuning is essential for faster convergence during training and achieving good **generalization** performance.

Outline

Gaussian Mixture Model

- Assume the output y follows a *discrete uniform distribution* over $\{0, 1\}$, meaning $y \sim \mathcal{U}\{0, 1\}$.
- For each value of y, the input x follows a *Gaussian distribution*:
  - When $y = 0$, x follows $x|y = 0 \sim \mathcal{N}(\mu_1, \sigma_1^2)$.
  - When $y = 1$, x follows $x|y = 1 \sim \mathcal{N}(\mu_2, \sigma_2^2)$.



- This setup defines a **(binary) Gaussian Mixture Model (GMM)**.
- Both x and y are random variables, with a joint distribution denoted as $\mathcal{D}$, i.e., $(x, y) \sim \mathcal{D}$.

Statistical Learning Theory (SLT)

- Assume the data (x, y) is drawn from an underlying joint distribution $\mathcal{D}$, i.e., $(x, y) \sim \mathcal{D}$.
- The goal of learning is to find a (parameterized) function f such that:

$$f(x) \approx y$$

for "most" (x, y) pairs in a probabilistic sense.

- The **expected risk** of f is defined as:

$$R(f) := \mathbb{E}_{(x,y)\sim\mathcal{D}}[f(x) - y]^2,$$

where we use the squared loss to measure the difference between $f(x)$ and y.

- In practice, the distribution $\mathcal{D}$ is **unknown**.
- Instead, we collect a **random training sample** $\mathcal{S} := \{(x_i, y_i)\}_{i=1}^n$ and compute the **empirical risk** or **training error**:

$$R_S(f) := \frac{1}{n}\sum_{i=1}^{n}[f(x_i) - y_i]^2.$$

- By the **law of large numbers**, we have:

$$R_S(f) \longrightarrow R(f) \quad \text{as} \quad n \to \infty.$$

Example of Expected and Empirical Risk using GMM

Suppose (x, y) follows GMM, and the function $f(x) = \theta x$.

- The expected risk $R(f)$ is given by

$$\begin{aligned} R(f) =& \mathbb{E}_{(x,y)\sim\mathcal{D}}\ell(f(x), y) \\ =& \int [f(x) - y]^2 \, p(x, y)dxdy = \int [f(x) - y]^2 \, p(x|y)p(y)dxdy \\ =& \frac{1}{2}\int [f(x)]^2 \, p(x|y = 0)dx + \frac{1}{2}\int [f(x) - 1]^2 \, p(x|y = 1)dx \\ =& \frac{1}{2}\int [\theta x]^2 \cdot \mathcal{N}(x; \mu_1, \sigma_1^2)dx + \frac{1}{2}\int [\theta x - 1]^2 \cdot \mathcal{N}(x; \mu_2, \sigma_1^2)dx \\ \triangleq& R(\theta), \end{aligned}$$

  where $p(x, y)$ is the joint density, and $\mathcal{N}(x; \mu, \sigma^2)$ is the Gaussian density defined by

$$\mathcal{N}(x; \mu, \sigma^2) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2}.$$

- The empirical risk $R_S(f)$ over a training sample is given by

$$R_S(f) = \frac{1}{n}\sum_{i=1}^{n} [\theta x_i - y_i]^2 \triangleq R_S(\theta).$$

Hypothesis Class

In practice, we cannot evaluate all possible functions f. Instead, we restrict our search to a family of functions called a **hypothesis class** $\mathcal{H}$. Each function $h \in \mathcal{H}$ is called a **hypothesis**.

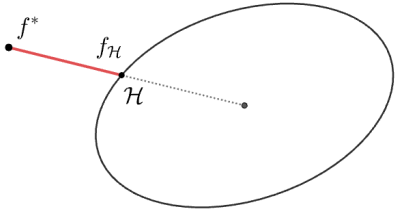
- The collection of all linear models or the collection of all two-layer neural networks:

$$\mathcal{H}_1 = \{h : h(\mathbf{x}) = \mathbf{w}^\top \mathbf{x}\}$$
$$\mathcal{H}_2 = \{h : h(\mathbf{x}) = \mathbf{v}^\top \phi(\mathbf{W}\mathbf{x})\}.$$

- A learning algorithm aims to find the best hypothesis $h \in \mathcal{H}$ that minimizes the expected risk:

$$f_{\mathcal{H}} := \operatorname*{argmin}_{f \in \mathcal{H}} R(f).$$

- The difference $\|f^* - f_{\mathcal{H}}\|$ is called the **approximation error**, where f^* is the ground true function.
- The **Universal Approximation Theorem (UAT)** implies $\|f^* - f_{\mathcal{H}}\| \approx 0$ if $f_{\mathcal{H}} \in \mathcal{H}_2$.

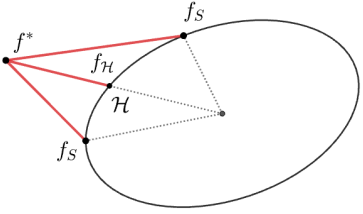


Decomposition of Expected Risk

- Given a learned hypothesis f_S from a sample S, the expected risk of f_S can be decomposed as:

$$R(f_S) = \underbrace{R_S(f_S)}_{\textbf{Training Error}} + \underbrace{[R(f_S) - R_S(f_S)]}_{\textbf{Generalization Error}}.$$

- The **generalization error** is the difference between the expected risk and the empirical risk.



- In practice, the generalization error is estimated using the **test error** on an independent test set.

Bounding the Generalization Error

- The generalization error can be upper bounded by the **complexity** of the hypothesis class:

$$\sup_{h \in \mathcal{H}} |R(h) - R_S(h)| \leq \text{Complexity Term},$$

where the "Complexity Term" quantifies how flexible or complex the hypothesis class $\mathcal{H}$ is.

- One commonly used complexity measure is the **(empirical) Rademacher complexity**:

$$\mathfrak{R}_S(\mathcal{H}) := \mathbb{E}_\sigma \left[\min_{h \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^{n} \ell(h(x_i), \sigma_i) \right],$$

where $\ell(h(x), \sigma) = \sigma h(x)$ and $\sigma_i \in \{-1, 1\}$ are i.i.d. Rademacher random variables (uniformly distributed), *i.e.*, $\sigma \sim \mathcal{U}\{-1, 1\}$, and the expectation is taken over these random labels.

- Rademacher complexity measures the ability of the hypothesis class to fit **random noise** (i.e., how well the hypothesis class can fit random labels).
- Using model complexity, we can derive the following generalization bound:

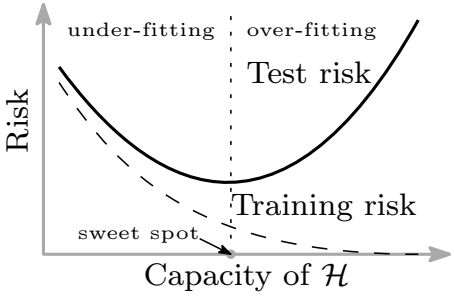
$$R(f_S) \leq R_S(f_S) + \mathfrak{R}_S(\mathcal{H}) + \tilde{\mathcal{O}}(n^{-1}),$$

where the expected risk is upper bounded by the training error and the complexity of the model.

Model Complexity Trade-Off

The expected risk $R(f_S)$ is upper bounded by the training error and the model complexity:

$$R(f_S) \leq R_S(f_S) + \mathfrak{R}_S(\mathcal{H}) + \tilde{\mathcal{O}}(n^{-1}).$$



Key Insights on Generalization Bound

- If the model is too simple, it may fail to fit the training data well. This is known as **underfitting**.
- Conversely, if the model is highly flexible, it may achieve low training error, but perform poorly on unseen data. This is known as **overfitting**.
- The goal is to find a "**sweet spot**" balancing underfitting and overfitting to minimize the overall expected risk.

Optimal Hypothesis f^*

Claim: $f^*(x) = \mathbb{E}[y|x]$ is the **optimal hypothesis** that minimizes the expected risk.

Proof.

For any function f, we can decompose the expected risk as follows:

$$\begin{aligned} R(f) =& \mathbb{E}(f-y)^2 = \mathbb{E}(f-f^*+f^*-y)^2 \\ =& \mathbb{E}(f-f^*)^2 + 2\mathbb{E}(f-f^*)(f^*-y) + \mathbb{E}(f^*-y)^2 \\ =& \mathbb{E}(f-f^*)^2 + \mathbb{E}(f^*-y)^2 \\ \geq& \mathbb{E}(f^*-y)^2 \\ =& R(f^*) \end{aligned}$$

where the cross term $\mathbb{E}(f-f^*)(f^*-y) = 0$, because $f^*(x) = \mathbb{E}[y|x]$. □

- This is another **existence** result.
- The optimal hypothesis f^* is not directly accessible unless we know the joint distribution $\mathcal{D}$.
- Generally, we may have $R(f^*) \neq 0$. For example, consider $y = \theta x + \varepsilon$, where $\varepsilon \sim \mathcal{N}(0, \sigma^2)$

$$\begin{aligned} f^*(x) =& \mathbb{E}[y|x] = \mathbb{E}[\theta x + \varepsilon | x] = \theta x \\ R(f^*) =& \mathbb{E}_x[f^*(x) - y]^2 = \mathbb{E}_x[\theta x - (\theta x + \varepsilon)]^2 = \sigma^2 \quad \Longrightarrow \quad \textbf{irreducible error.} \end{aligned}$$

Bias-Variance Decomposition of Expected Risk

- The learned function f_S depends on the random sample S, making f_S a **random variable**.
- Hence, the expected risk $R(f_S)$ is also **random**, and it varies across different random samples S.
- To capture this variability, we consider the expectation of the $R(f_S)$ over all possible samples S, i.e., $\mathbb{E}_S[R(f_S)]$.
- Let $\bar{f} := \mathbb{E}_S[f_S]$, the average hypothesis over all random samples S.
- Using $\bar{f}$, we can decompose $\mathbb{E}_S[R(f_S)]$ as follows:

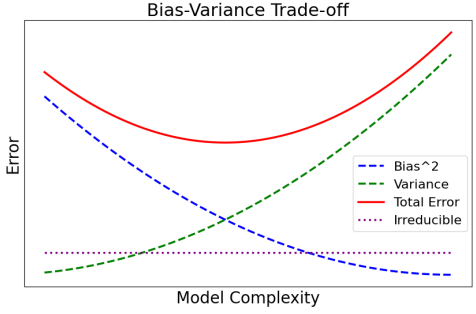
$$
\begin{aligned}
\mathbb{E}_S[R(f_S)] =& \mathbb{E}_S \mathbb{E}_{(x,y)\sim\mathcal{D}}[f_S(x) - y]^2 \\
=& \mathbb{E}_S \mathbb{E}_{\mathcal{D}}[f_S - f^*)]^2 + R(f^*) \\
=& \mathbb{E}_S \mathbb{E}_{\mathcal{D}}\left[f_S - \bar{f} + \bar{f} - f^*\right]^2 + R(f^*) \\
=& \mathbb{E}_S \mathbb{E}_{\mathcal{D}}\left[(f_S - \bar{f})^2 + (\bar{f} - f^*)^2\right] + R(f^*) \\
=& \underbrace{\mathbb{E}_S(f_S - \bar{f})^2}_{\textbf{Variance term}} + \underbrace{\mathbb{E}_{\mathcal{D}}(\bar{f} - f^*)^2}_{\textbf{Bias term}} + \underbrace{R(f^*)}_{\textbf{irreducible}}
\end{aligned}
$$

where the cross term $\mathbb{E}_{S,\mathcal{D}}(f_S - \mathbb{E}_S[f_S])(\mathbb{E}_S(f_S) - f^*) = 0$ cancels out.

Bias-Variance Trade-Off

The expected risk $\mathbb{E}_S[R(f_S)]$ can be broken down into three parts:

- **Squared Bias**: $\mathbb{E}_{\mathcal{D}}[(f^* - \mathbb{E}_S(f_S))^2]$ measures the error from approximating the optimal function f^* with the learned model f_S. It reflects the error caused by using a simple model that cannot capture all the data patterns.
- **Variance**: $\mathrm{Var}(f_S) = \mathbb{E}_S[(f_S - \mathbb{E}_S(f_S))^2]$ measures how much the learned function f_S varies with different training samples. It represents the error due to the model's sensitivity to fluctuations in the random training sample S.
- **Irreducible Error**: $R(f^*)$ represents the inherent noise in the data, which no model can eliminate. It is the error we cannot reduce.



- **High bias, low variance**: Simple models (e.g., linear models) have *low variance* since they are less sensitive to training data, but have *high bias* because they are too simple to capture all patterns in the data.
- **Low bias, high variance**: Complex models (e.g., polynomial model) have *low bias* as they can model complex relations, but *high variance* due to overfitting to the training data.

Summary of Statistical Learning Theory

- The goal is to find a hypothesis f within a hypothesis class $\mathcal{H}$ that minimizes the **expected risk**:

$$R(f) = \mathbb{E}_{(x,y)\sim\mathcal{D}}\left[(f(x) - y)^2\right].$$

- Since the underlying distribution $\mathcal{D}$ is **unknown**, we approximate f by minimizing the **empirical risk** based on a **random** training sample S:

$$R_S(f) = \frac{1}{n}\sum_{i=1}^{n}(f(x_i) - y_i)^2.$$

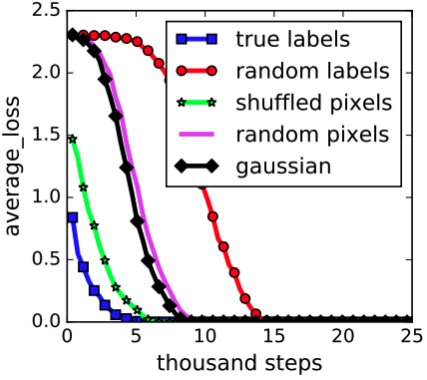
- Using model complexity $\mathfrak{R}_S(\mathcal{H})$, the expected risk is upper bound as:

$$R(f_S) \leq R_S(f_S) + \mathfrak{R}_S(\mathcal{H}) + \tilde{\mathcal{O}}(n^{-1}),$$

- By considering variations across different random training samples S, the expected risk $\mathbb{E}_S[R(f_S)]$ can be decomposed into three components: **bias**, **variance**, and **irreducible error**:
  - **High bias, low variance**: Simple models **underfit** and miss important patterns in the data.
  - **Low bias, high variance**: Complex models **overfit** and perform poorly on unseen data.
- Find the "sweet spot" between underfitting and overfitting to minimize the overall expected risk.

Outline

DNNs Can Fit Random Labels and Random Data



- **Label corruption**: Replace true label with *random label*
- **Shuffled pixels**: The pixels of each image are rearranged using a *fixed* random permutation
- **Random pixels**: Each image has a *unique* random arrangement of pixels).
- **Gaussian**: The pixels in images are replaced with random Gaussian *noise*.
- **Average loss**: *Training error* using the cross-entropy loss

Key Observation

DNNs can perfectly fit random labels or data, achieving **zero training error** even on completely unstructured inputs.

Zhang et al. "Understanding deep learning requires rethinking generalization" ICLR 2017.

Weight Decay

- Regularization typically involves adding an extra term, called the **regularizer**, to the training loss:

$$\mathcal{L}_\lambda(\boldsymbol{\theta}) := \mathcal{L}(\boldsymbol{\theta}) + \frac{\lambda}{2}\|\boldsymbol{\theta}\|^2,$$

  where $\lambda > 0$ is the **regularization hyperparameter**, and $\|\cdot\|$ is the Euclidean norm.
- In deep learning, this regularization is known as **weight decay** because gradient descent on the regularized loss automatically shrinks (or decays) parameter $\boldsymbol{\theta}$ by the factor $(1 - \eta\lambda)$:

$$\begin{aligned}\boldsymbol{\theta}^+ =& \boldsymbol{\theta} - \eta\nabla_{\boldsymbol{\theta}}\mathcal{L}_\lambda(\boldsymbol{\theta}) = \boldsymbol{\theta} - \eta\left[\nabla_{\boldsymbol{\theta}}\mathcal{L}(\boldsymbol{\theta}) + \lambda\boldsymbol{\theta}\right] \\ =& \underbrace{(1-\eta\lambda)}_{\textbf{decaying weights}}\ \boldsymbol{\theta} - \eta\nabla_{\boldsymbol{\theta}}\mathcal{L}(\boldsymbol{\theta}).\end{aligned}$$

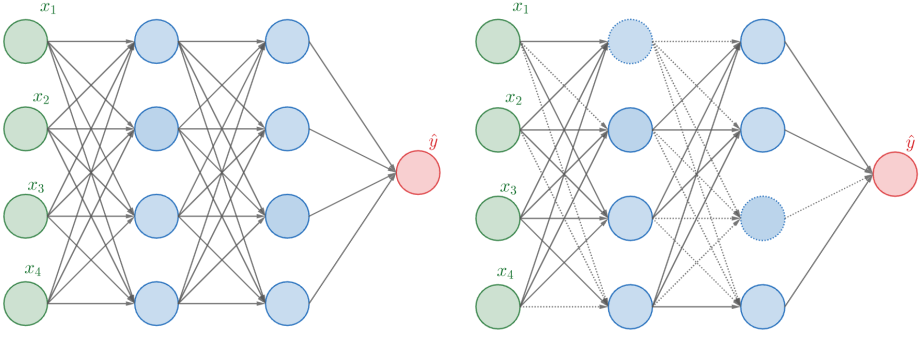
- However, $\boldsymbol{\theta}$ does **not** shrink to zero, as it must maintain a certain value to minimize the cost $\mathcal{L}(\boldsymbol{\theta})$.

Interpretation: Sparsity

- The regularized optimization can be reformulated as:

$$\min_{\boldsymbol{\theta}} \mathcal{L}(\boldsymbol{\theta}), \quad \textbf{s.t.} \quad \|\boldsymbol{\theta}\| \leq C_\lambda,$$

  where $C_\lambda > 0$ is a constant that depends on λ.
- In deep learning, $\boldsymbol{\theta}$ is called **sparse** if most parameters are zero or close to zero (i.e., $\boldsymbol{\theta}_i \approx 0$).
- Sparse $\boldsymbol{\theta}$ reduces the flexibility and complexity of the DNN, leading to a **simpler** model.

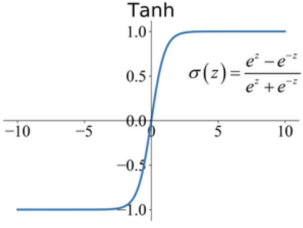


Interpretation: Linearity

Consider a simple two-layer neural network:

$$f_{\boldsymbol{\theta}}(x) = \sum_{i=1}^{n} v_i \phi(w_i x),$$

where $x \in \mathbb{R}$ is a scalar and $\phi(\cdot)$ is $\tanh$.



- When $w_i \approx 0$, then $w_i x \approx 0$, and the network operates near the **linear** region of $\tanh$:

$$v_i \phi(w_i x) \approx v_i (w_i x) \approx (v_i w_i) x = u_i x \quad \Longrightarrow \quad \textbf{a linear model},$$

where $u_i := v_i w_i$.

- If $v_i \approx 0$, then

$$v_i \phi(w_i x) \approx 0,$$

indicating **fewer** neurons are used.

Interpretation: Stability

A learning algorithm is **stable** if small changes to its input do not result in large changes to its output.

- Consider the same two-layer neural network:

$$f_{\boldsymbol{\theta}}(x) = \sum_{i=1}^{n} v_i \phi(w_i x).$$

- The derivative of $f_{\boldsymbol{\theta}}$ with respect to the **input** x is:

$$\nabla_x f_{\boldsymbol{\theta}}(x) = \sum_{i=1}^{n} v_i \phi'(w_i x) w_i.$$

- If either v_i or w_i is small, then $\nabla_x f_{\boldsymbol{\theta}}(x)$ is small.
- Hence, DNNs with *sparse* parameters are generally more **stable** than those with dense parameters.

Dropout Regularization

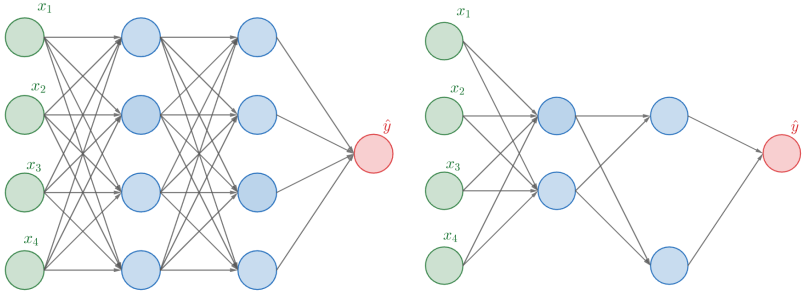
Recall the forward propagation:

$$\boldsymbol{z}^{\ell} = \boldsymbol{W}^{\ell}\boldsymbol{x}^{\ell-1}, \quad \boldsymbol{x}^{\ell} = \phi(\boldsymbol{z}^{\ell}).$$

- During **training**, each neuron is randomly **dropped** with probability p (a **hyperparameter**):

$$\hat{\boldsymbol{x}}^{\ell-1} = \boldsymbol{r}^{\ell} \odot \boldsymbol{x}^{\ell-1}, \quad \boldsymbol{z}^{\ell} = \boldsymbol{W}^{\ell}\hat{\boldsymbol{x}}^{\ell-1}$$

  where $\boldsymbol{r}_i^{\ell} \sim \text{Bernoulli}(p)$.

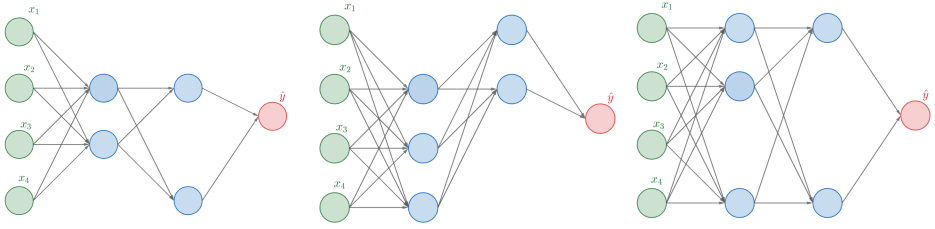


- The gradient update applies only to a **thinned subbnet** of the network.
- At **test time**, dropout is turned off, and weights are scaled by p to respect the dropout probability:

$$\boldsymbol{z}^{\ell} = p\boldsymbol{W}^{\ell}\boldsymbol{x}^{\ell-1}.$$

Interpretation: Implicit Ensemble Learning

- By randomly dropping units, a different **thinned subnet** is trained at each gradient descent step.
- With n neurons in the full network, we are effectively training 2^n **different subnets** simultaneously that all **share** the same weights.
- At test time, the output is an **ensemble** prediction, aggregating the contributions of all subnets.



Key Insight

Dropout ensures that **no** single neuron or small group of neurons can dominate the prediction. By **spreading** the responsibility across all units, it improves model robustness to the input change and prevents overfitting.

Summary

- DNNs can fit random labels and data, achieving **zero training error**.
- Weight decay controls large weights, promoting **sparsity**, **linearity**, and **stability**.
- During training, dropout randomly drops units, effectively training an **exponential number** of **thinned subnets** simultaneously.
- At test time, the output is an **ensemble** prediction, aggregating contributions from all subnets.

Outline

Validation Set

- Split the dataset into three parts: **training set**, **validation set**, and **test set**.
- Build the model using the *training set*.
- Optimize or tune hyperparameters on the *validation set*.
- After tuning, **evaluate** the final model on the test set.
- Suggested split ratios:
  - For datasets between 100 and 1,000,000 samples: 60/20/20.
  - For datasets larger than 1,000,000 samples: 98/1/1.
- Ensure the validation and test sets come from the **same** distribution.
  - Example: Training and validation images from the web, but test images from user cell phones can cause a mismatch.

Tuning Process

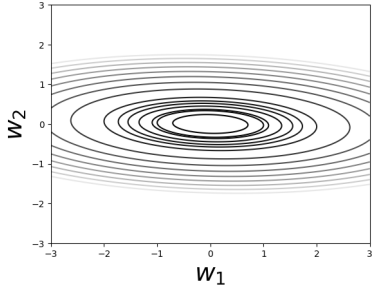
- **Random Search**: Randomly sample hyperparameters; more efficient than grid search when some hyperparameters are less important.
- **Hyperband/Successive Halving**: Dynamically allocate resources and discard poor configurations early, ideal for deep networks with long training times.
- Start with **coarse** tuning, then **refine** gradually.
- Use **log scale** for hyperparameter search when appropriate.
- Leverage **parallelization** to run multiple experiments simultaneously to accelerate the search.

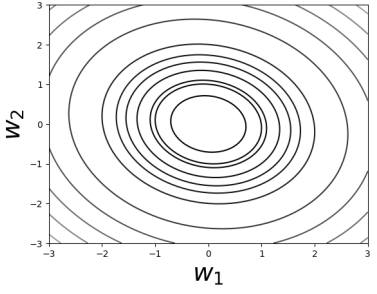
Input Normalization

- Normalize the inputs using **training set**:

$$\boldsymbol{\mu} = \frac{1}{n}\sum_{i=1}^{n} \boldsymbol{x}_i, \quad \bar{\boldsymbol{x}}_i = \boldsymbol{x}_i - \boldsymbol{\mu}, \quad \boldsymbol{\sigma}^2 = \frac{1}{n}\sum_{i=1}^{n} \bar{\boldsymbol{x}}_i^2, \quad \hat{\boldsymbol{x}}_i = \bar{\boldsymbol{x}}_i / \boldsymbol{\sigma},$$

  where all operations are taken element-wise.
- Consider a binary classification problem using linear model: $f_{\boldsymbol{\theta}}(x) = w_1 x_1 + w_2 x_2$
  - if $x_1 = \mathcal{O}(100)$ and $x_2 = \mathcal{O}(1)$, to have output $f_{\boldsymbol{\theta}} = \mathcal{O}(1)$, we must have $w_1 = \mathcal{O}\left(\frac{1}{100}\right)$ and $w_2 = \mathcal{O}(1)$.
  - After normalization, $\bar{x_1} = \mathcal{O}(1)$ and $\bar{x_2} = \mathcal{O}(1)$, so we have $w_1 = \mathcal{O}(1)\,1$ and $w_2 = \mathcal{O}(1)$.





- At test time, apply $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ from **training** to test set.

Learning Rate Decay

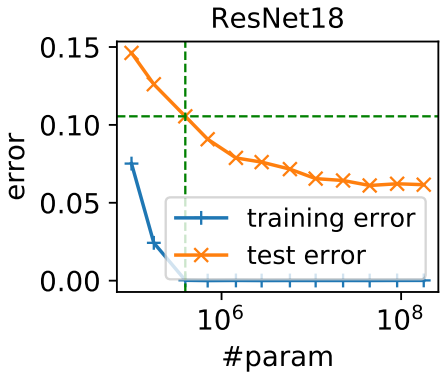
- Recall that an **epoch** k is one pass through all **mini-batches** in SGD
- Instead of using a fixed learning rate, one can consider using **learning rate decay**

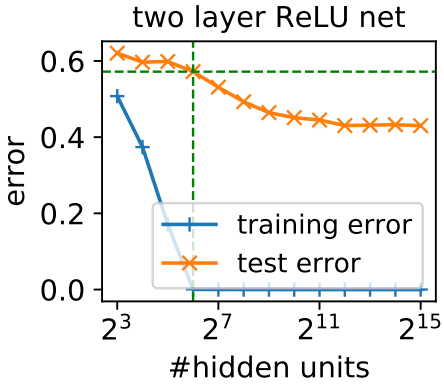
$$\eta_k = \frac{\eta}{k}, \qquad \eta_k = \frac{\eta}{\sqrt{k}}, \qquad \eta_k = (0.95)^k \eta$$

Outline

Overparameterization

- A deep neural network (DNN) is said to be **overparameterized** when the number of neurons or parameters is much larger than the number of training samples.
- This might seem counterintuitive, but it has been found to be surprisingly beneficial in practice.





Behnam, et al. "Towards Understanding the Role of Over-Parametrization in Generalization of Neural Networks," ICLR 2019.

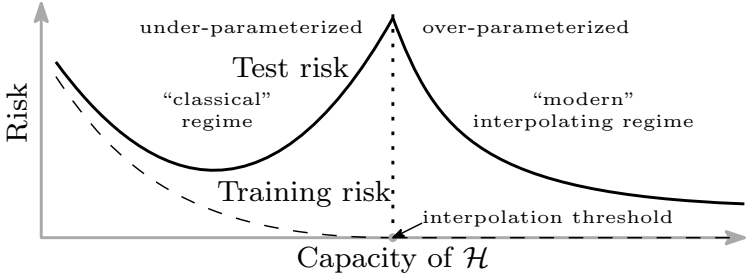
Double Descent

Overparameterized neural networks can **perfectly fit** or **interpolate** the training data.

- Mathematically, there exists a set of parameters $\boldsymbol{\theta}$ such that

$$f_{\boldsymbol{\theta}}(x_i) = y_i, \quad \forall i \in [n]. \tag{1}$$

- Overparameterization implies there are **infinitely** many interpolation solutions.
- Some interpolation solutions generalize much better than those in the *underparameterized* regime. This phenomenon is called **double descent**.



Implicit Regularization

- It is important to understand that different global minima lead to varying **test** performances.
- A **flat** minimum typically results in better generalization than a **sharp** minimum.
- Different optimizers may converge to different minima, each with different generalization outcomes. This is known as **implicit regularization**.
- Thus, even if your current optimizer achieves low training error, tuning or adjusting it may still be necessary to achieve better test performance.