

# Machine Learning in Healthcare

## #C07 Regularization

Technion-IIT, Haifa, Israel

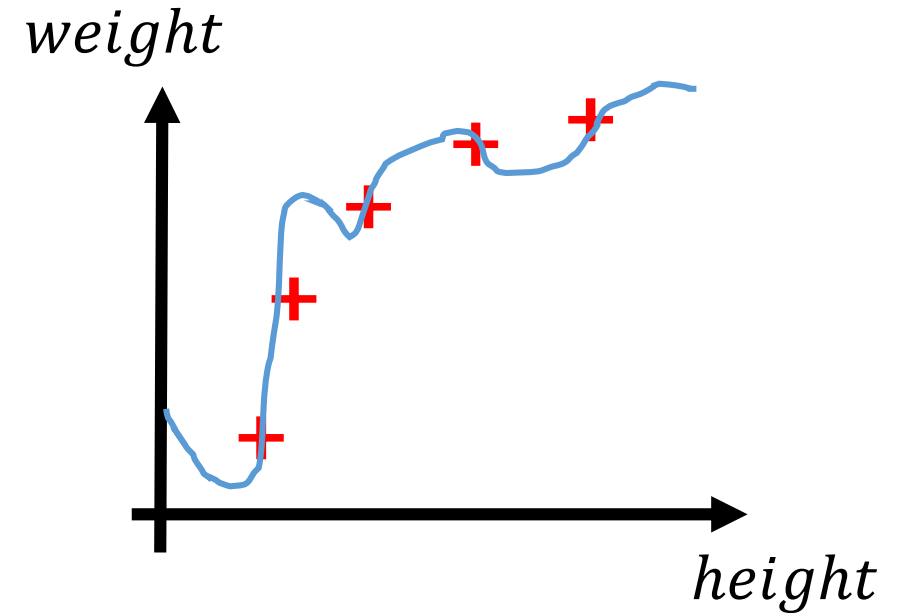
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# Introduction

- You trained a model with its  $J \rightarrow 0$ . You feel very proud!
- Then you go out in the real world and start making predictions. Surprise, results are not good at all! What happened?
- Very likely your model is overfitting the training examples leading to bad generalization.



$$y = w_0 + w_1x + w_2x^2 + w_3x^3$$

# Introduction

**Table 2.** Classification performance measured by  $F_1$ . The table reports the overall and individual rhythm class performance by random forest based and XGBoost based models on the training and unseen test set.

		Recordings	Overall	N	A	O	~
Official challenge entry (Vollmer <i>et al</i> 2017)	Training set	8528	0.94	0.98	0.91	0.94	0.90
	Test set	3658	0.81	0.91	0.81	0.70	0.46
Enhanced post-challenge entry	Training set	8528	0.99	0.99	0.99	0.98	0.99
	Test set	3658	0.82	0.91	0.82	0.74	— <sup>a</sup>

Sodmann, Philipp, et al. "A convolutional neural network for ECG annotation as the basis for classification of cardiac rhythms." Physiological measurement 39.10 (2018): 104005.

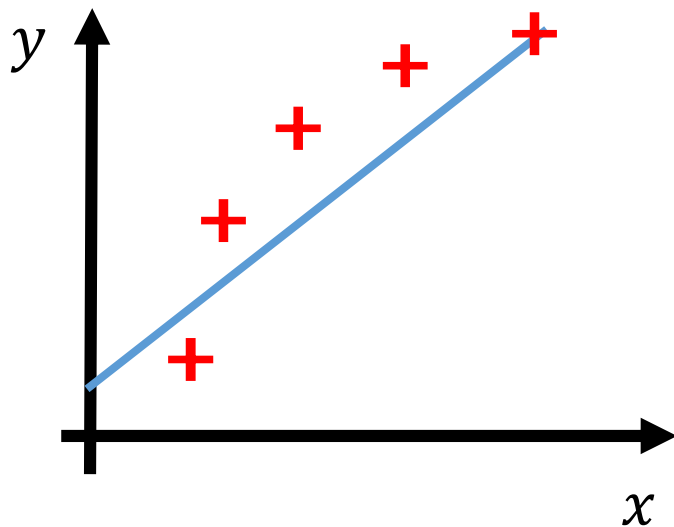
# Overfitting

# Overfitting

- One of the most important consideration when learning a model is how well it will generalize to new observations. This is called **generalization**.
- This is important because we train our model on a population sample dataset which has some noise.
- In other words, generalization refers to how well the concepts learned by a machine learning model will translate to new observations not seen by the model when it was trained.
- This is related to the concept of **overfitting** and **underfitting**.
- In particular, we will focus on overfitting which is a phenomenon that usually happens with complex models.

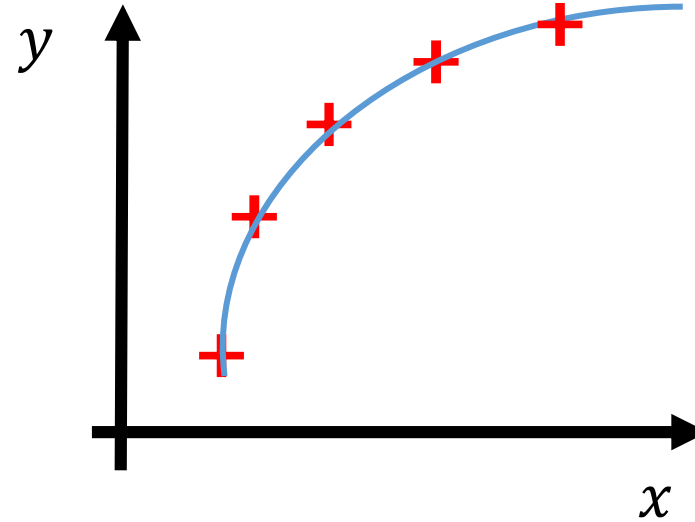
# Overfitting - Regression

**Overfitting:** refers to a model where the learned hypothesis fits the training set very well ( $J(w) \rightarrow 0$ ) but fails to generalize to new observations.

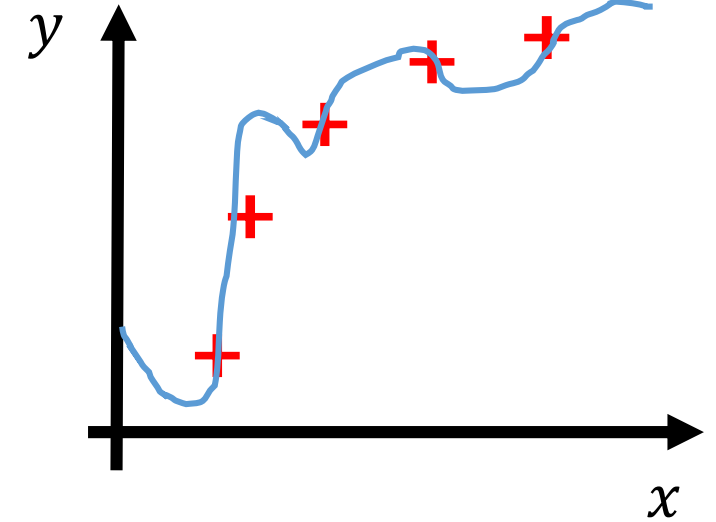


$$y = w_0 + w_1x$$

- Underfitting
- High bias



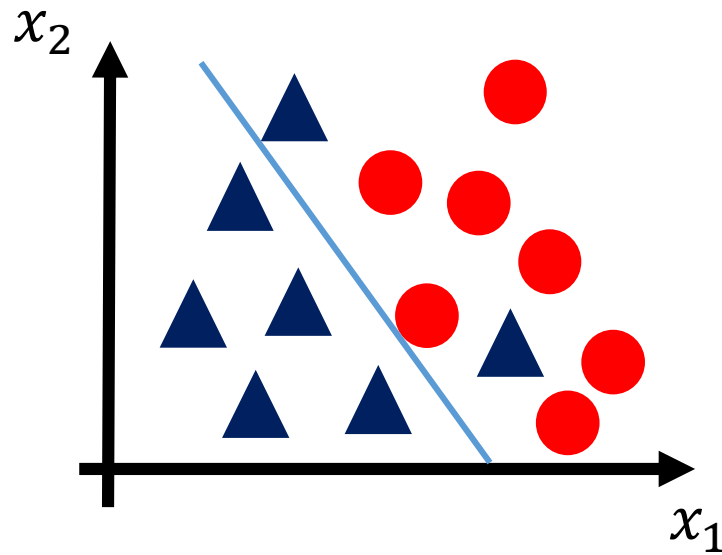
$$y = w_0 + w_1x + w_2x^2$$



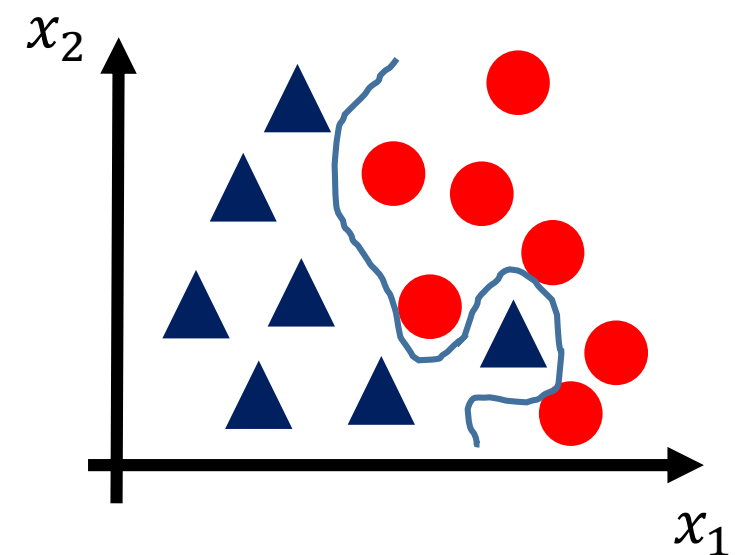
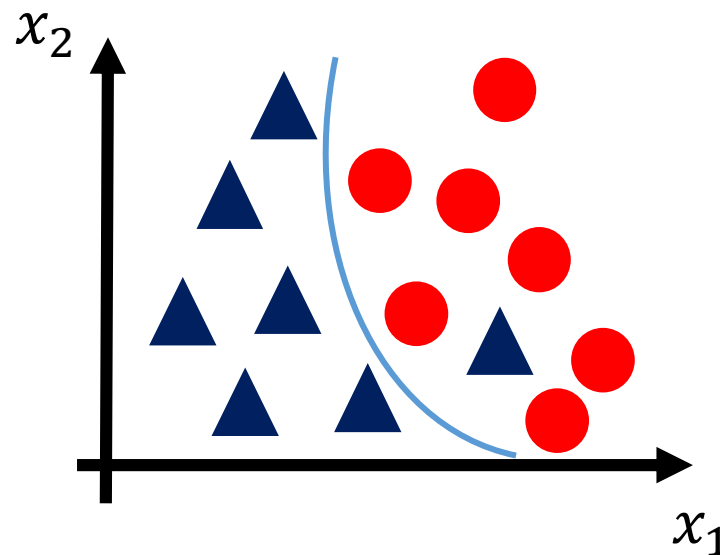
$$y = w_0 + w_1x + w_2x^2 + w_3x^3$$

- Overfitting
- High variance <sub>6</sub>

# Overfitting – Classification

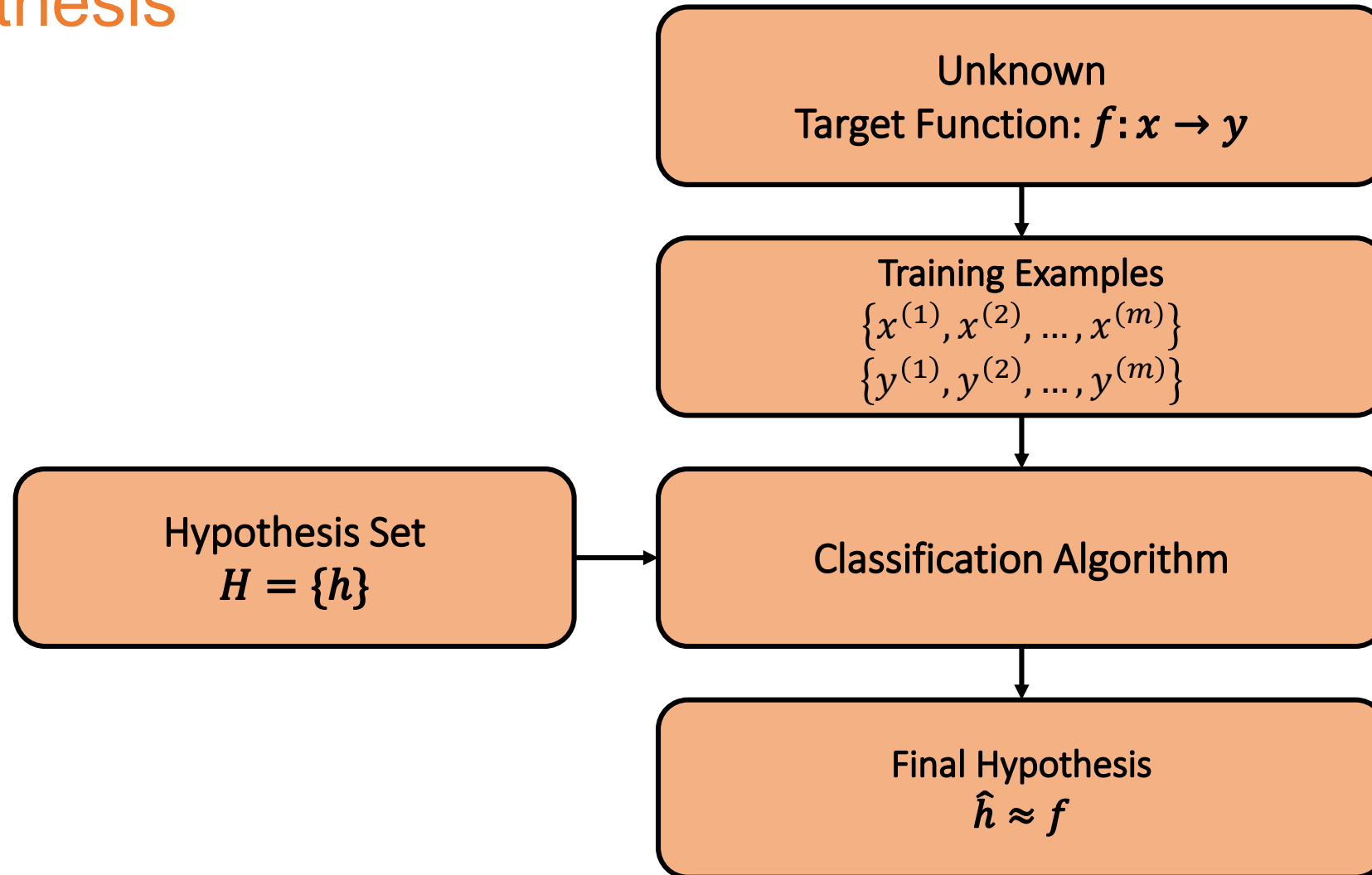


- Underfitting
- High bias



- Overfitting
- High variance

# Hypothesis





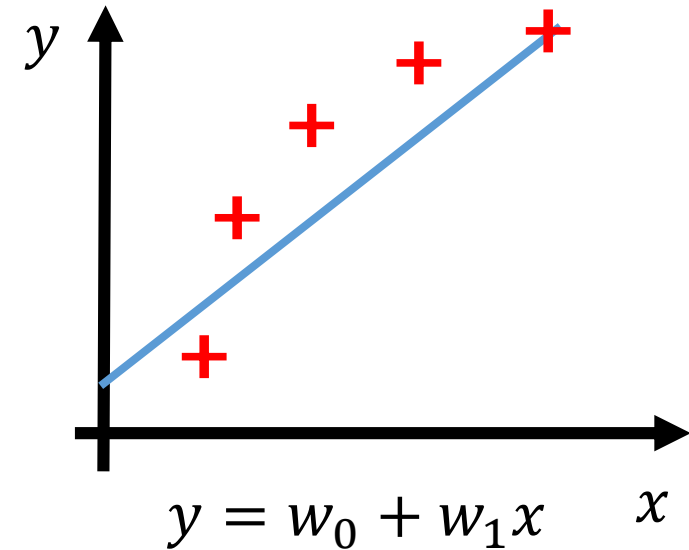
# Bias-Variance

# Bias-Variance

- The prediction error ( $\mathcal{E}$ ) of a model can be divided into:
  - $\mathcal{E} = \mathcal{E}_b + \mathcal{E}_v + \mathcal{E}_i$
  - $\mathcal{E}_b$ : Bias error
  - $\mathcal{E}_v$ : Variance error
  - $\mathcal{E}_i$ : Irreducible error.
- The irreducible error is the one that we cannot fix whatever model we use because of the way the problem is framed.

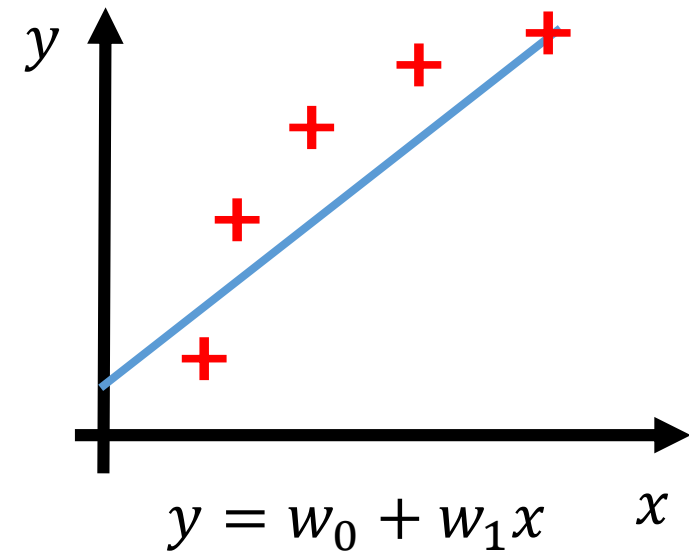
# Bias

- The bias error comes from erroneous assumptions in the learning algorithm. Often these assumptions are made to use a simple model.
  - Low bias: suggests good or too complex hypothesis representation.
  - High bias: suggests the need for a more flexible hypothesis representation.
- A high bias may cause the algorithm to miss the relationship between features and the target output and lead to **underfitting**.



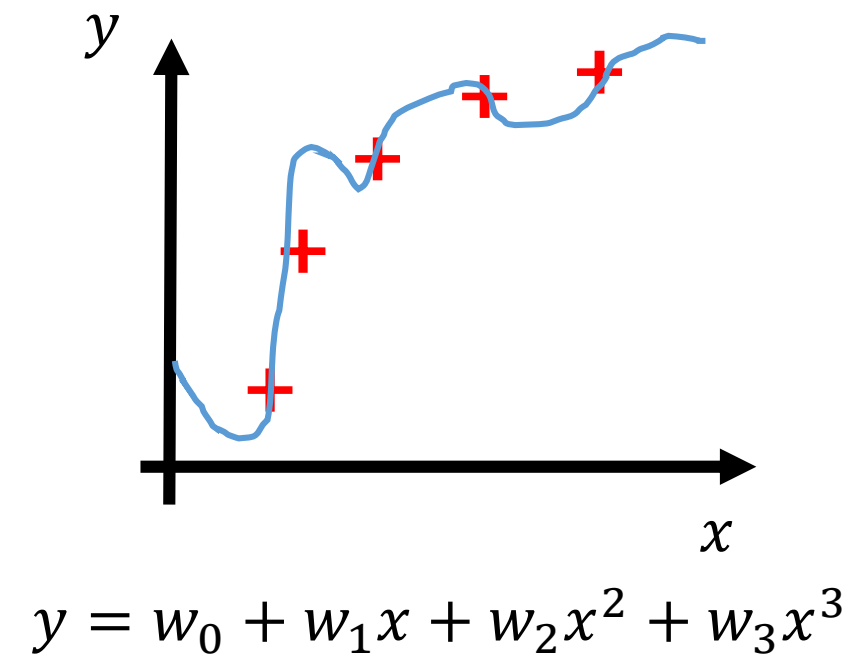
# Bias

- Low-bias ML algorithms:
  - Decision Trees,
  - k-Nearest Neighbors,
  - Support Vector Machines.
- High-bias ML algorithms:
  - Linear Regression,
  - Linear Discriminant Analysis,
  - Logistic Regression.



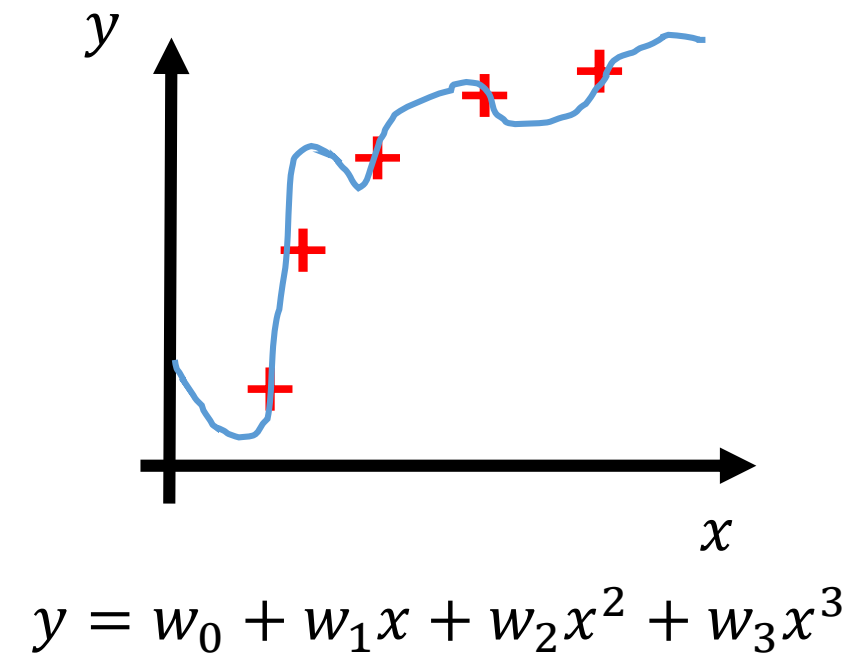
# Variance

- The variance reflects how much the target function will change if different training data was used.
  - Low variance: suggests that changing the training dataset will lead to small changes to the estimate of the target function.
  - High variance: suggests that changing the training dataset will lead to large changes to the estimate of the target function.
- High variance can cause to model the noise in the training set which will lead to **overfitting**.
- Nonparametric machine learning algorithms have more flexibility and generally a higher variance.

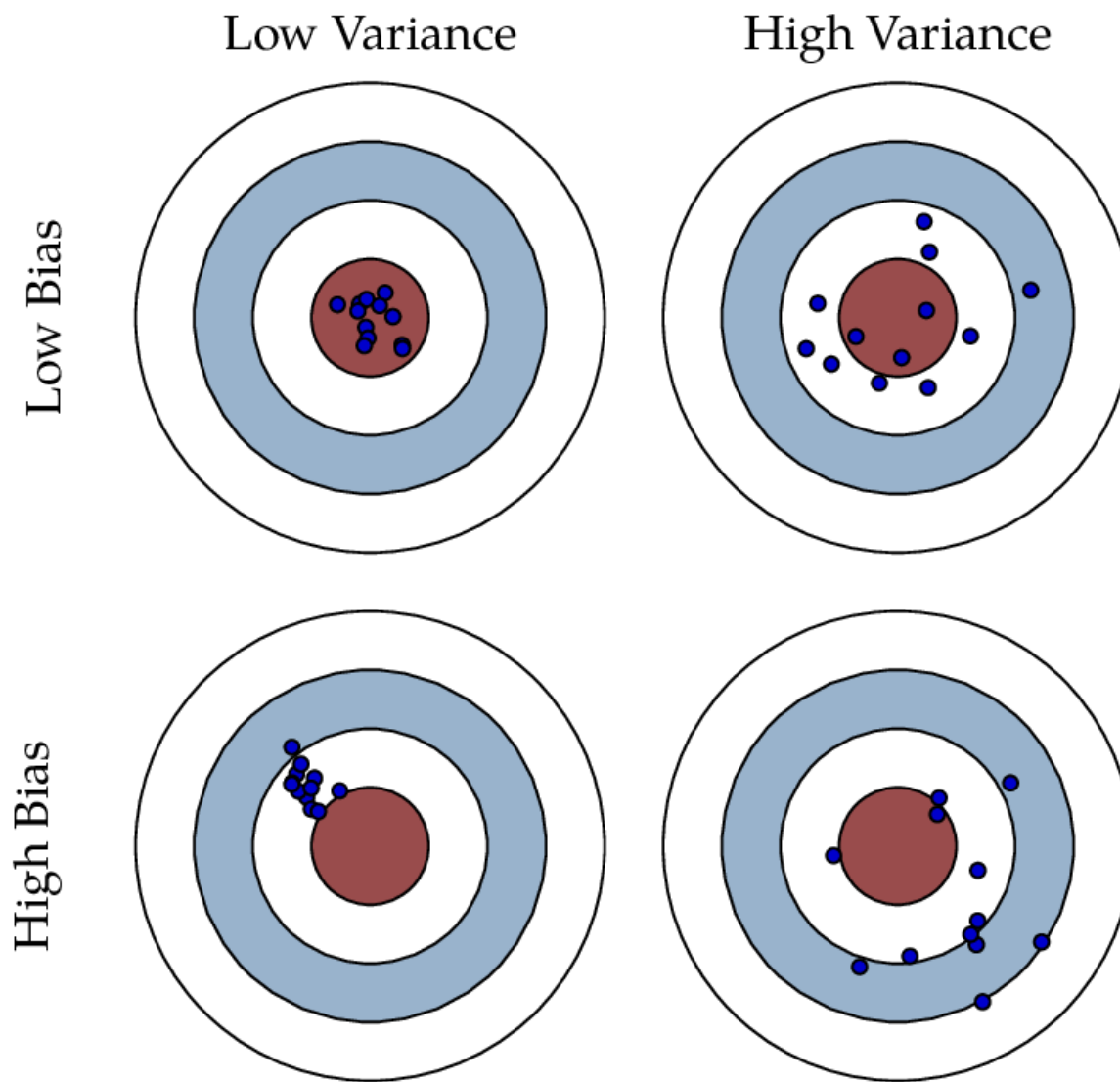


# Variance

- Low variance ML algorithms:
  - Linear Regression,
  - Linear Discriminant Analysis,
  - Logistic Regression.
- High variance ML algorithms:
  - Decision Trees,
  - k-Nearest Neighbors,
  - Support Vector Machines.



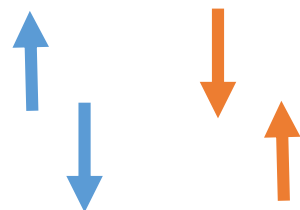
# Bias-Variance



# Bias-Variance Tradeoff

- In training a classifier we want a **low bias** and a **low variance**.
- Parametric or linear machine learning algorithms will often have a high bias but a low variance.
- Non-parametric or non-linear machine learning algorithms will often have a low bias but a high variance.
- In training any classifier we will need to find a **tradeoff between bias and variance**. This is not an easy task because:
  - Increasing the bias will lead to a lower variance.
  - Increasing the variance will lead to a lower bias.

Bias-variance tradeoff.





# Addressing overfitting

- How can we address overfitting?
  - Visualize and adjust your model
  - But does not very help when we have many features
  - What else can we do?
    - Reduce the number of features (manually or using some algorithm).
    - Increase training data set.
    - Ensemble prediction from final models.
    - **Regularization**: keep all the features but reduce  $||w_j||$ .

# Regularization

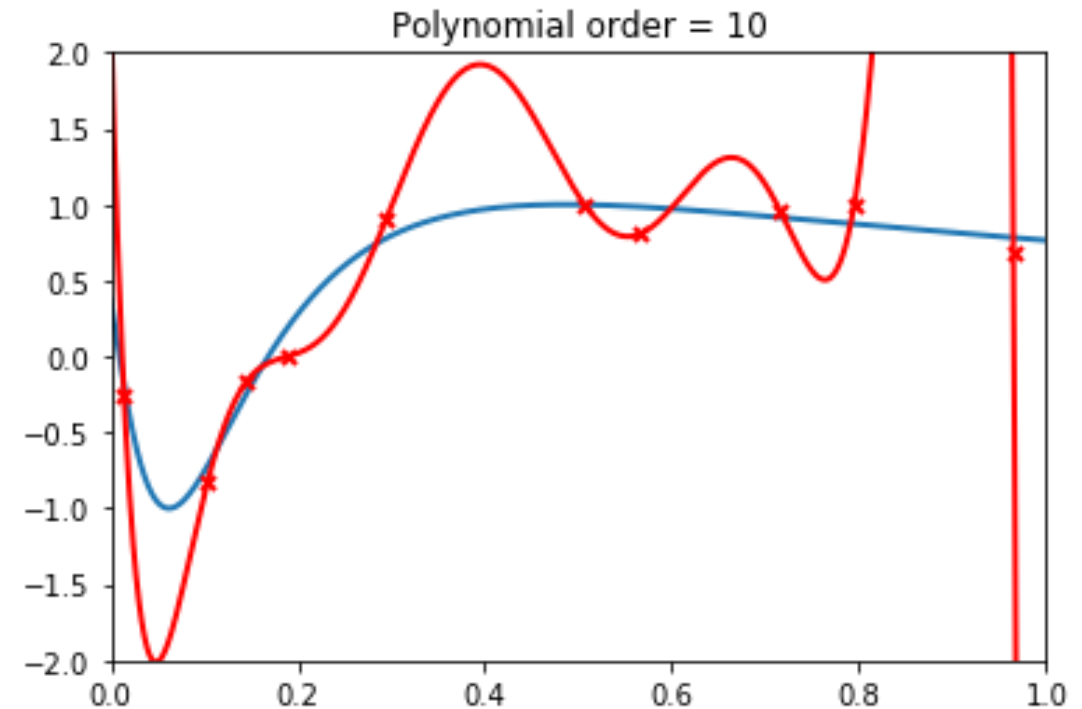
## Regularization- General

- We seek to control the magnitude of the  $w_j$
- Small values are preferable because it will lead to a simpler hypothesis representation.
- A simpler hypothesis representation is less prone to overfitting.
- $J(w) = \frac{1}{2m} \left[ \sum_{i=1}^m (h_w(x^{(i)}) - y^{(i)})^2 + \lambda \sum_{j=1}^m w_j^2 \right]$ 
  - Blue: the regularization term
  - $\lambda$ : Regularization parameter. It controls the tradeoff between good fitting and keeping the  $w_j$  small i.e. a more simple hypothesis representation.
  - $\lambda \rightarrow 0$ : no regularization.
  - $\lambda \rightarrow \infty$ : underfitting ( $h_w(x) = w_0$ ).
  - Thus the  $\lambda$  parameter should be chosen carefully.


# Regularized Linear Regression

# Regularized Linear Regression

- Why regularization? We want to avoid overfitting.
- We saw two ways to find the solution to the linear regression problem:
  - Using gradient descent.
  - Using the normal equation.
- How do we regularize?
- Intuition:
  - We introduce a penalization term  $E(w)$
  - $J(w) = \frac{1}{2} \sum_{i=1}^m (y^{(i)} - w^T \cdot x^{(i)})^2 + E(w)$
  - We want this term to “push away” the Value of  $w$  from the original overfitted optimal value.



# Regularized Linear Regression

- Sum-of-square error for regularization (Ridge Regression):
  - $J(w) = \frac{1}{2} \sum_{i=1}^m (y^{(i)} - w^T \cdot x^{(i)})^2 + \frac{\lambda}{2} w^T \cdot w$
- Closed form solution (prove it!):
  - $w = (\lambda \cdot I + X^T X)^{-1} X^T y$
- Gradient descent:
  - $w_j := w_j - \alpha \left[ \frac{1}{m} \sum_{i=1}^m (h_w(x^{(i)}) - y^{(i)}) x_j^{(i)} + \frac{\lambda}{m} w_j \right]$  
- Assuming a sum-of-square regularization term we obtained a closed form solution.
- In statistics this provides an example of parameters shrinkage method because the weights are dragged to be small.
- What about the more general case where the regularization term is not sum-of-square?

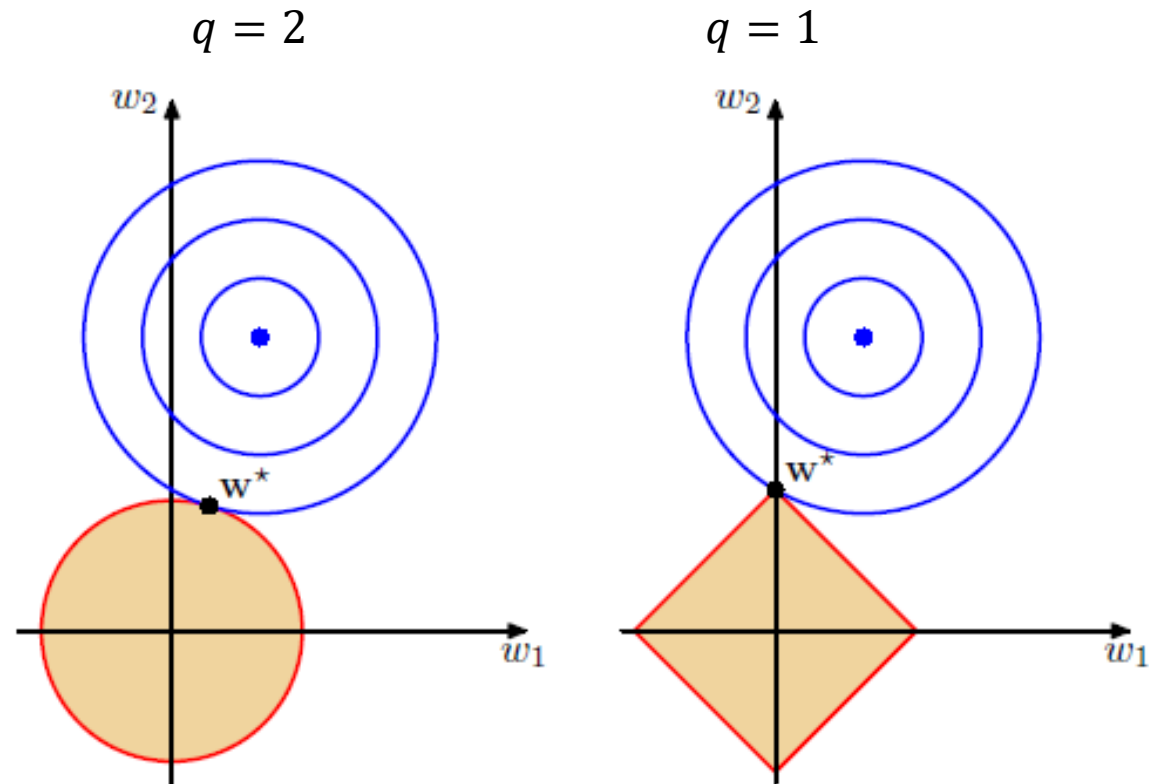
# Regularized Linear Regression

- More general expression:
  - $J(w) = \frac{1}{2} \sum_{i=1}^m (y^{(i)} - w^T x^{(i)})^2 + \frac{\lambda}{2} \sum_{j=1}^m |w_j|^q, q \in \mathbb{N}$
  - If  $q = 2$  this is known as **Ridge Regression**. It makes use of the  $L2$  norm.
  - If  $q = 1$  this is known as **Lasso Regression**. It makes use of the  $L1$  norm.
  - In the case of Lasso, if  $\lambda$  is sufficiently large then some coefficients  $w$  are driven to zero.
    - $w_j := w_j - \alpha \left[ \frac{1}{m} \sum_{i=1}^m (h_w(x^{(i)}) - y^{(i)}) x_j^{(i)} + \frac{\lambda}{m} \text{sign}(w_j) \right]$
    - $w_j := w_j - \lambda \text{sign}(w_j) - \dots$
    - So if  $w_j > 0$  then the correction term will drag  $w_j \rightarrow 0$
    - So if  $w_j < 0$  then the correction term will drag  $w_j \rightarrow 0$ .
- So in practice **Lasso Regression** tends to zeros some coefficients. It does some form of feature selection.

# Regularized Logistic Regression

- Graphical interpretation:

**Figure 3.4** Plot of the contours of the unregularized error function (blue) along with the constraint region (3.30) for the quadratic regularizer  $q = 2$  on the left and the lasso regularizer  $q = 1$  on the right, in which the optimum value for the parameter vector  $\mathbf{w}$  is denoted by  $\mathbf{w}^*$ . The lasso gives a sparse solution in which  $w_1^* = 0$ .





# Regularized Logistic Regression

# Regularized Logistic Regression

- Cost function for LR:
  - $J(w) = \frac{1}{m} \sum_{i=1}^m \left[ -y^{(i)} \log(h_w(x^{(i)})) - (1 - y^{(i)}) \log(1 - h_w(x^{(i)})) \right]$
- If we add the regularization term:
  - $J(w) = \frac{1}{m} \sum_{i=1}^m \left[ -y^{(i)} \log(h_w(x^{(i)})) - (1 - y^{(i)}) \log(1 - h_w(x^{(i)})) \right]$

## Take Home

- Underfitting and overfitting are not desirable effects and reflect some limitations on our choice made of the hypothesis function. This is related to the **tradeoff** between **bias and variance**.
- **Bias** is the reflection of the hypothesis function complexity.
- **Variance** reflects how the model generalizes to new observations.
- We want a model with low bias and low variance.
- However, when increasing the bias we decrease the variance and when increasing the variance we decrease the bias. So we need to find a **tradeoff**.
- **Regularization**. In particular, **Ridge regression** ( $q = 2$ ), **Lasso regression** ( $q = 1$ ).
- **Lasso** has a nice property of cancelling some weights thus enabling some **sparsity** which is a form of feature selection while keeping the cost function **convex**.

# References

- [1] Machine Learning Mastery:  
<https://machinelearningmastery.com/gentle-introduction-to-the-bias-variance-trade-off-in-machine-learning/>
- [2] Pattern recognition and Machine Learning. Christopher M. Bishop. 2006 Springer Science.
- [3] Coursera, Andrew Ng. Regularization.