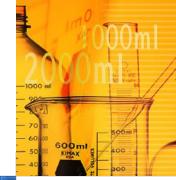
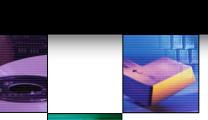
#### **Machine learning**



Chapter 7

# **Model evaluation**

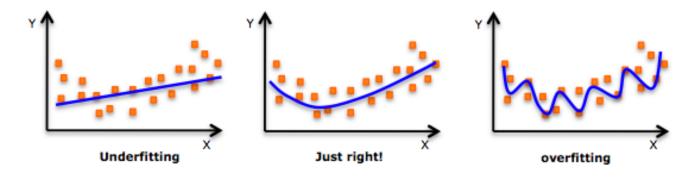


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#### Content

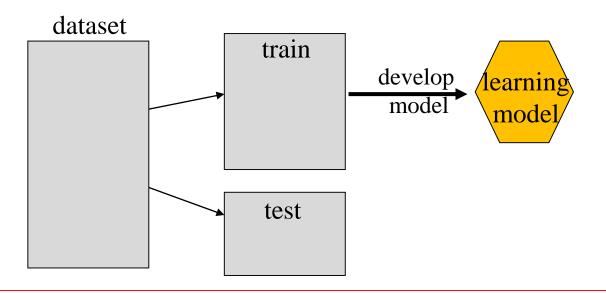
- Overfitting/underfitting
- error
- K-fold validation
- 모델 개발 절차 정리

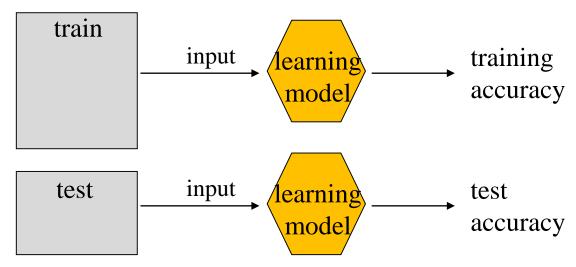
- Overfitting이란 문자 그대로 너무 과도하게 데이터에 대해 모델을 learning을 한 경우를 의미
- 주어진 훈련데이터에 꼭 맞는 모델 생성

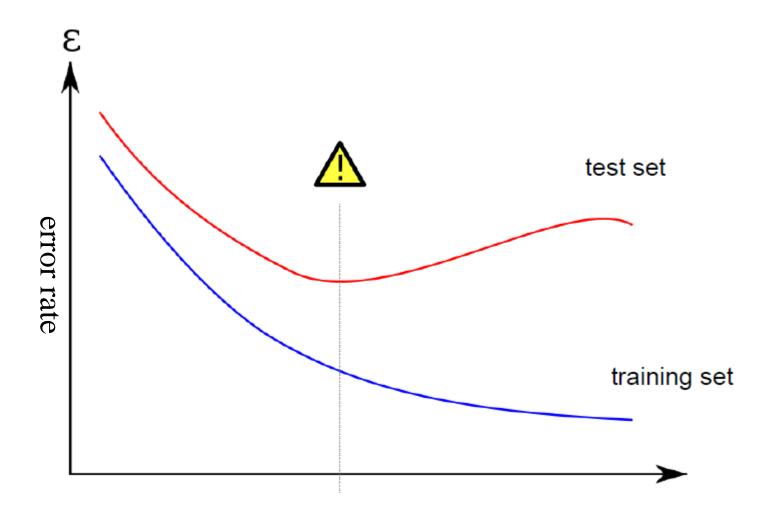


(http://sanghyukchun.github.io/59/)

Low error on training data and high error on test data!







- Variance & Bias : Model 의 error 를 일으키는 요소
- Variance of model: 훈련자료가 바뀌었을 때 모형이 바뀌는 정도 (훈련자료 에 대한 모형 변동성)
- Bias of model : 개발된 모형과 실제 모형간의 차이
- Bias-Variance tradeoff
  - 모형에 대한 가정이 약할수록 편향은 작아지고 분산이 커지는 반면, 모형에 대한 가정이 강할수록 편향은 커지고 분산은 줄어든다
- 분산과 편향을 조절하여 최적의 성능을 가지는 모델을 만드는 것이 machine learning 의 과제

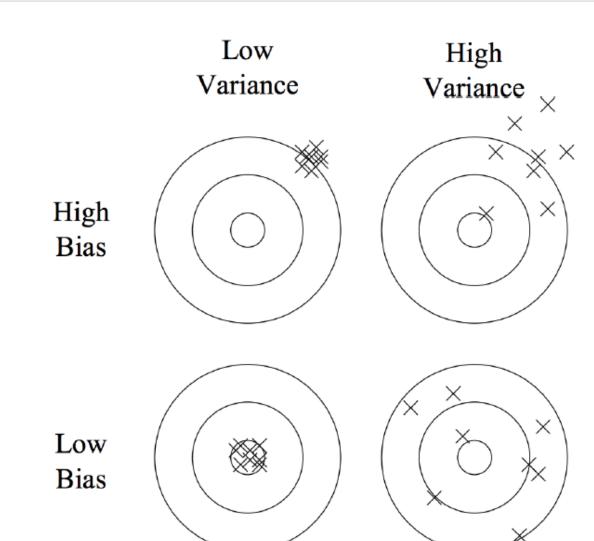
Underfitting:

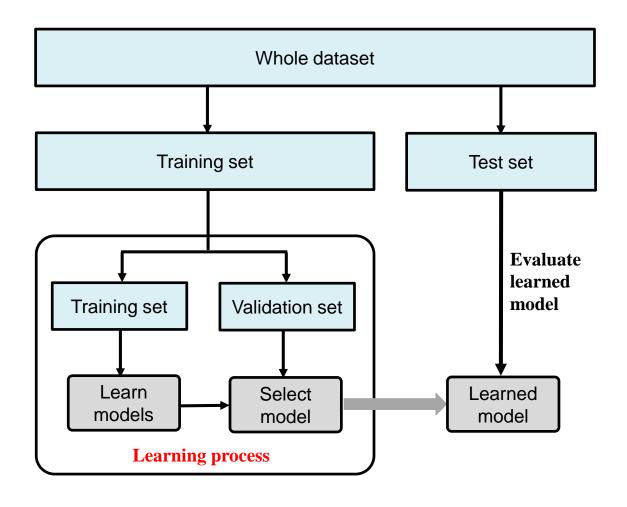
High Bias Low Variance

Overfitting:

Low Bias

High Variance

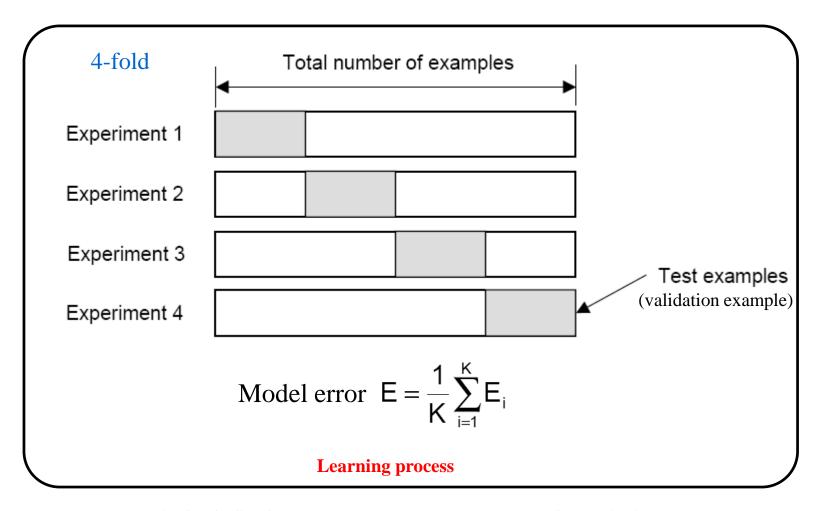






- Learning process
  - Choose learning algorithm (svm, NN, RF, C5.0, ...)
  - Parameter tuning

K-fold cross validation



E 를 가장 작게 만드는 model parameter 를 찾는 것이 learning

- LOOCV (Leave-one-out cross-validation)
  - For each training example (xi, yi)
    - Train a classifier with all training data except (xi, yi)
    - Test the classifier's accuracy on (xi, yi)
  - LOOCV accuracy = average of all n accuracies
  - LOOCV = N-fold cross-validation where N is # of examples

## Example

- liver.csv 데이터셋에 대해 SVM learning model 을 만들고 평가
  - SVM 모델의 parameter 중 최적 kernel 과 gamma 값을 결정
  - Use 5-fold cross validation

```
## 1. define kfold test function
kfold.svm <- function (ds,cl, ker, gam=NULL, fold=5) {</pre>
                        # for createFolds
  library(caret)
  library("e1071")
                           # for SVM
  set.seed(100)
  k.fold <-createFolds(as.vector(cl),k=fold)</pre>
  cl = factor(cl)
                            # classification result
  acc = c()
  for (i in 1:fold) {
    this.fold = k.fold[[i]]
    train.ds = ds[-c(this.fold),]
    train.cl = cl[-c(this.fold)]
    test.ds = ds[c(this.fold),]
    test.cl = cl[c(this.fold)]
   model = NULL
    if (is.null(gam)) {
       model = svm(train.ds,train.cl, kernel=ker)
    } else {
      model = svm(train.ds,train.cl, kernel=ker, gamma=gam)
    result = predict(model, test.ds)
    acc[i] = mean(result==test.cl)
  print(mean(acc))
  return (mean (acc)) # average accuracy of k-fold test
```

```
## 2. Read dataset
setwd("D:/work")
whole.ds = read.csv("liver.csv")
str(whole.ds)
## 3. divide train/test dataset
tsidx = sample(1:nrow(whole.ds), 100, replace=F)
train.ds = whole.ds[-tsidx,]
test.ds = whole.ds[tsidx,]
## 4. setup candidate kernel and gamma
ker = c("linear", "polynomial", "radial", "sigmoid")
gam = c(1/6, 1/4, 1/8)
```

```
## 5. find best kernel, gamma
max.acc = 0
max.ker = 0
max.gam = 0
for (k in 1:4) { # kernel
  if (k==1) {  # linear kernel
    acc = kfold.svm(train.ds[,-1],factor(train.ds[,1]),
                    ker=ker[k])
    if (acc > max.acc) {
      max.acc = acc; max.ker=k; max.gam=0;
    next
  for (g in 1:3) { # gamma
      acc = kfold.svm(train.ds[,-1],factor(train.ds[,1]),
                      ker=ker[k], gam=gam[g])
      if (acc > max.acc) {
        max.acc = acc; max.ker=k; max.gam=q;
      }
```

```
print(max.acc)
print(max.ker) # 3
print(max.gam) # 3
## 6. build final model using all train data
model2 = svm(train.ds[,-1],factor(train.ds[,1]),
             kernel=ker[max.ker], gamma=gam[max.gam])
## 7. Evaluate final model
result = predict(model2, test.ds[,-1])
acc= mean(result==test.ds[,1]) # accuracy
acc
# Analysis of prediction result
library(qmodels)
CrossTable(test.ds[,1], result,
           prop.chisq = FALSE, prop.c = FALSE, prop.r = FALSE,
           dnn = c('actual default', 'predicted default'))
```