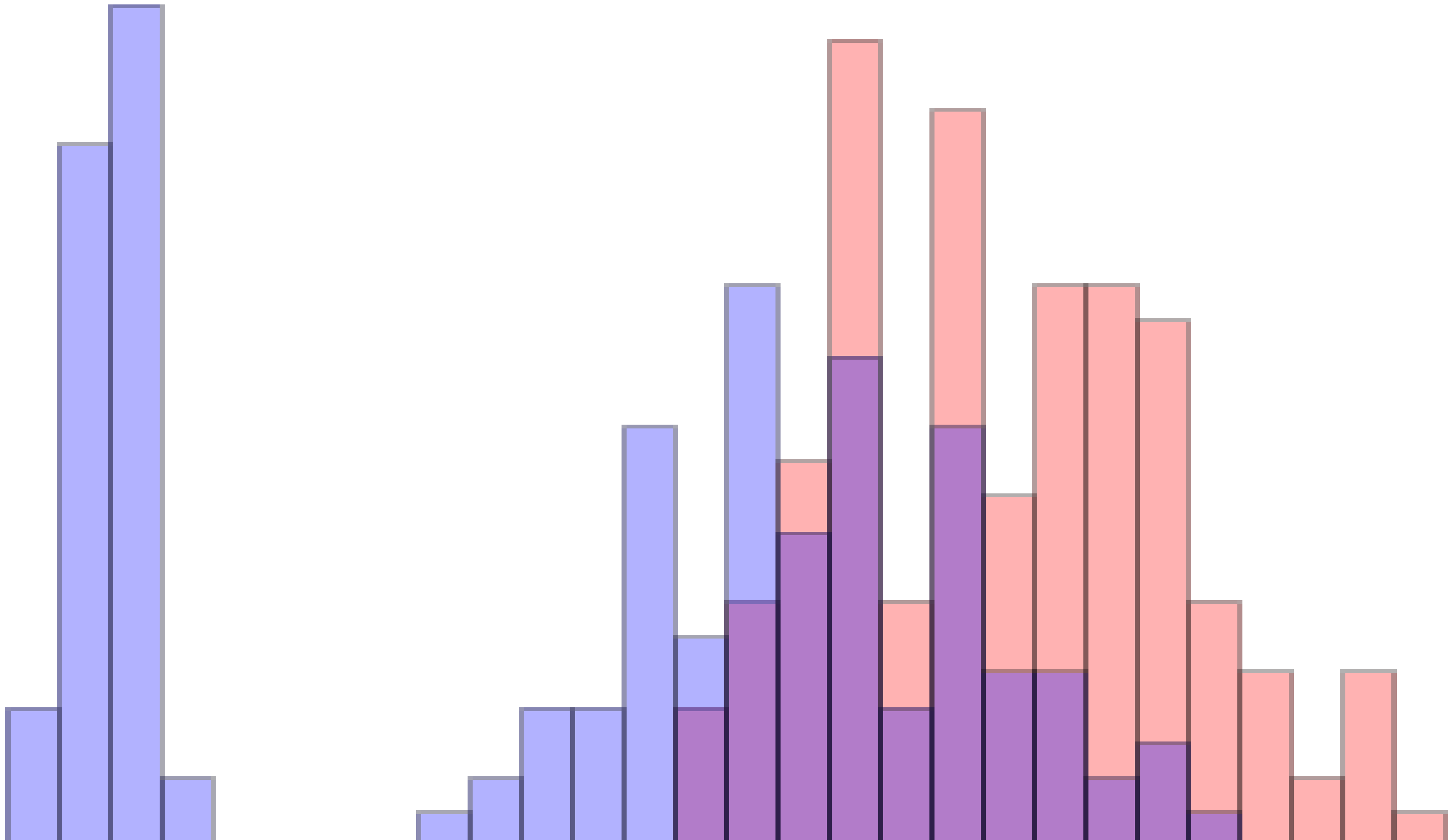


True or False?

- Classification error of the training set is a good measure of the true classification error
- A good estimate of the actual, true error is all we are interested in when building a classification system

Evaluation

› Marco Loog

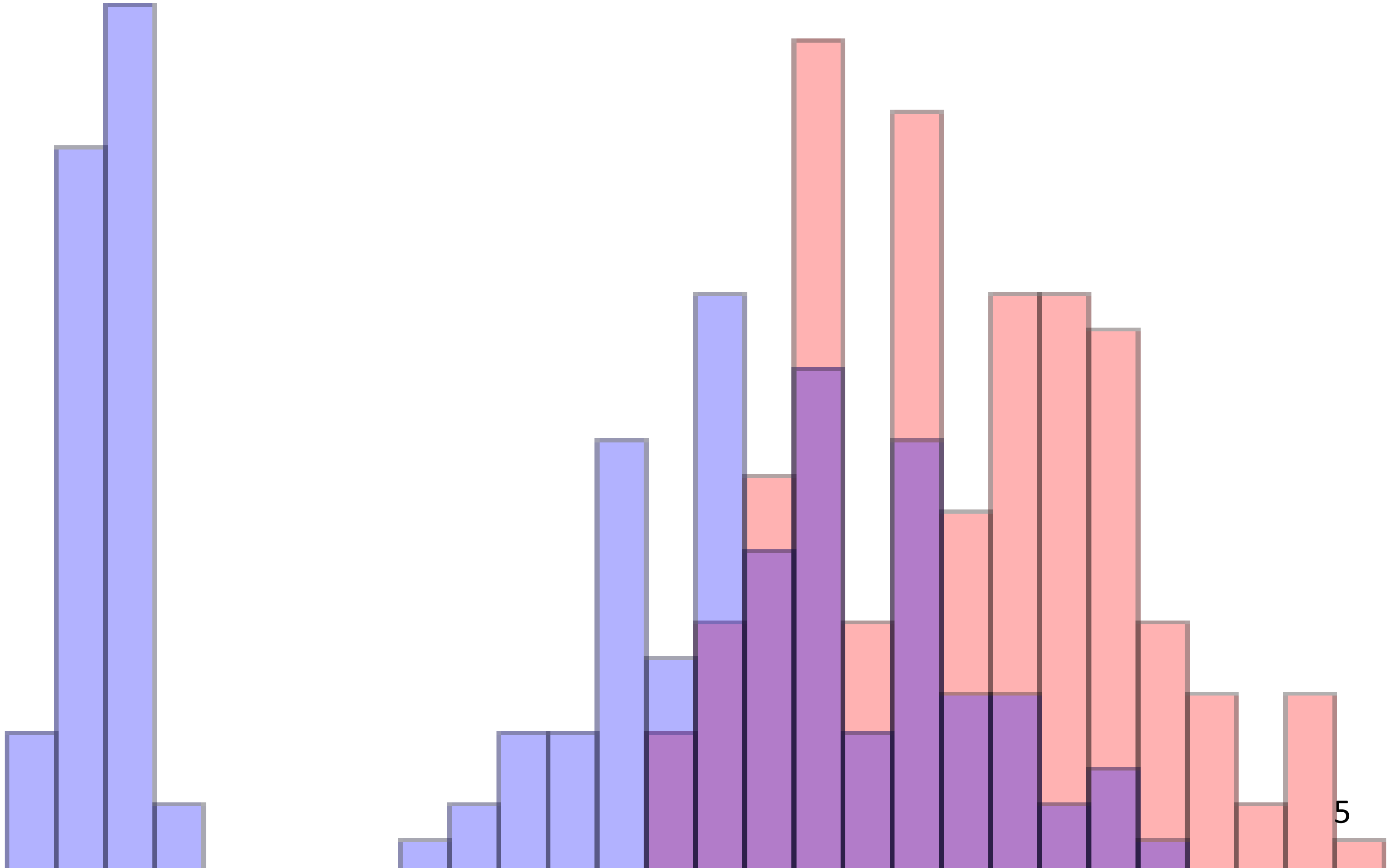
Past

- Regularization
- Bias-variance

- How classifiers and regressers can overtrain…

Let’s Recap a Bit

› Bias-variance for histogram …



Present

- Evaluating learners [focus is on classifiers]
  - Cross validation
  - Learning curves
  - Feature curves
  - Complexity curves
  - Confusion matrix
- Curse of dimensionality
  - Bias / variance

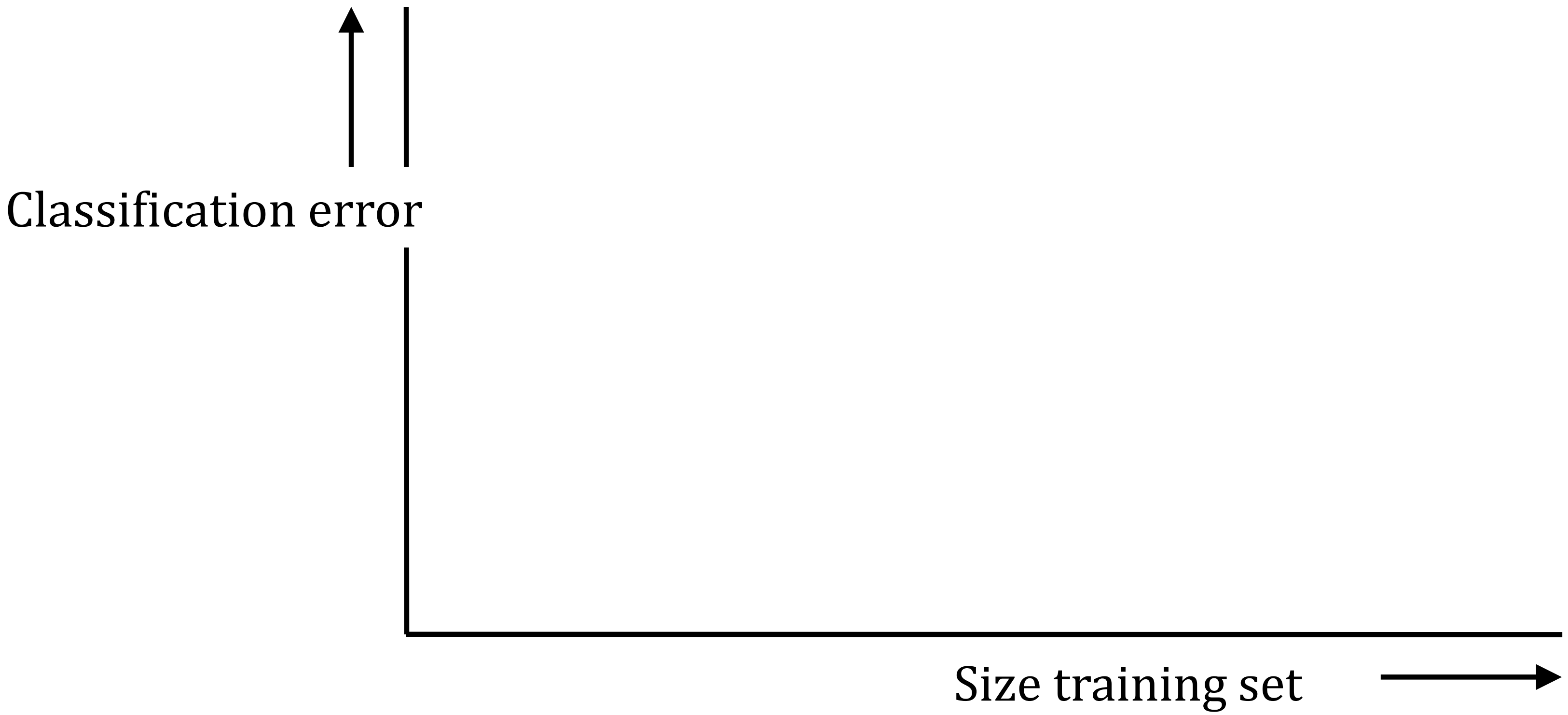
Determining Errors

Determining Errors

› Apparent, resubstitution, or training error
  = error classifier makes on its training data set

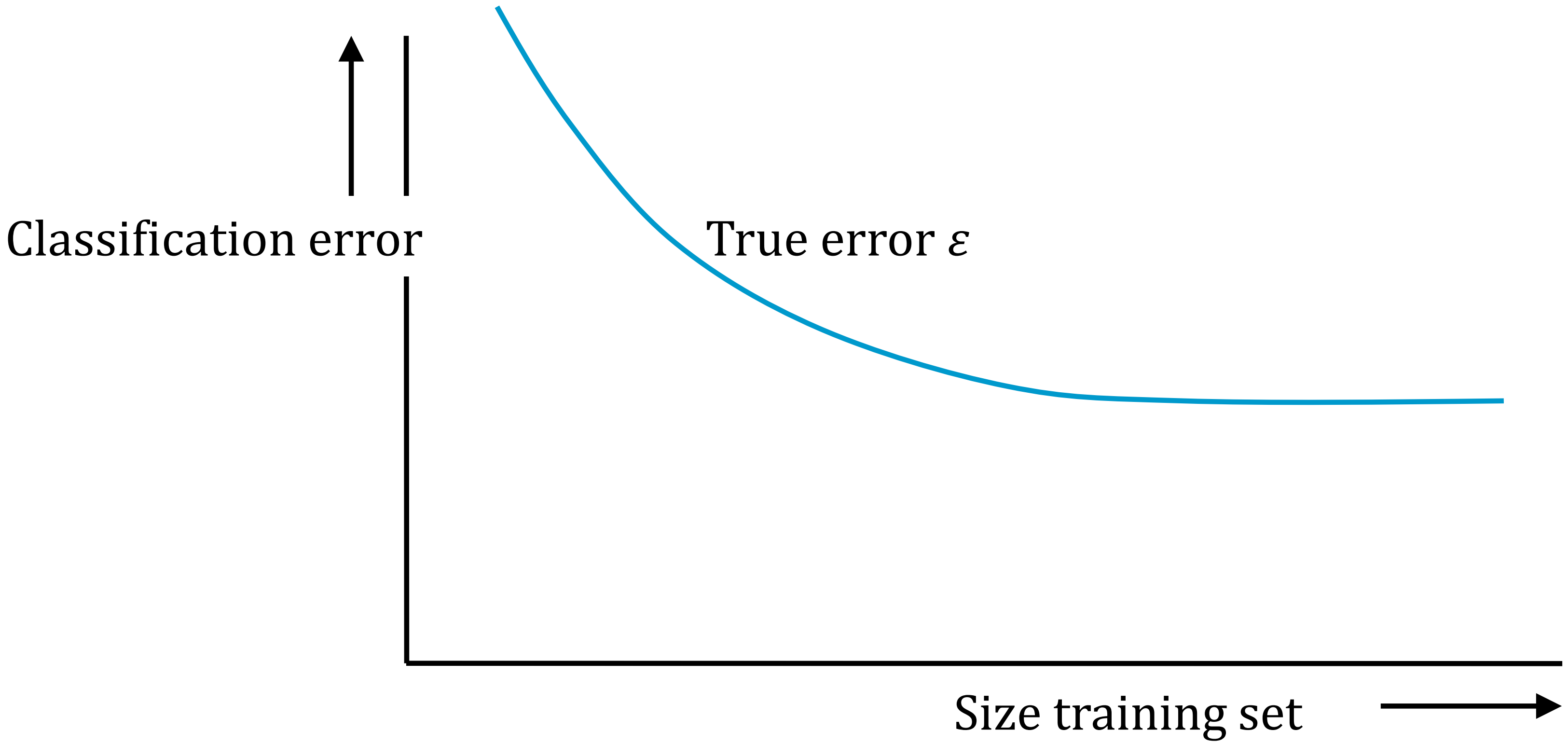
True Classification Error

› How does it behave?



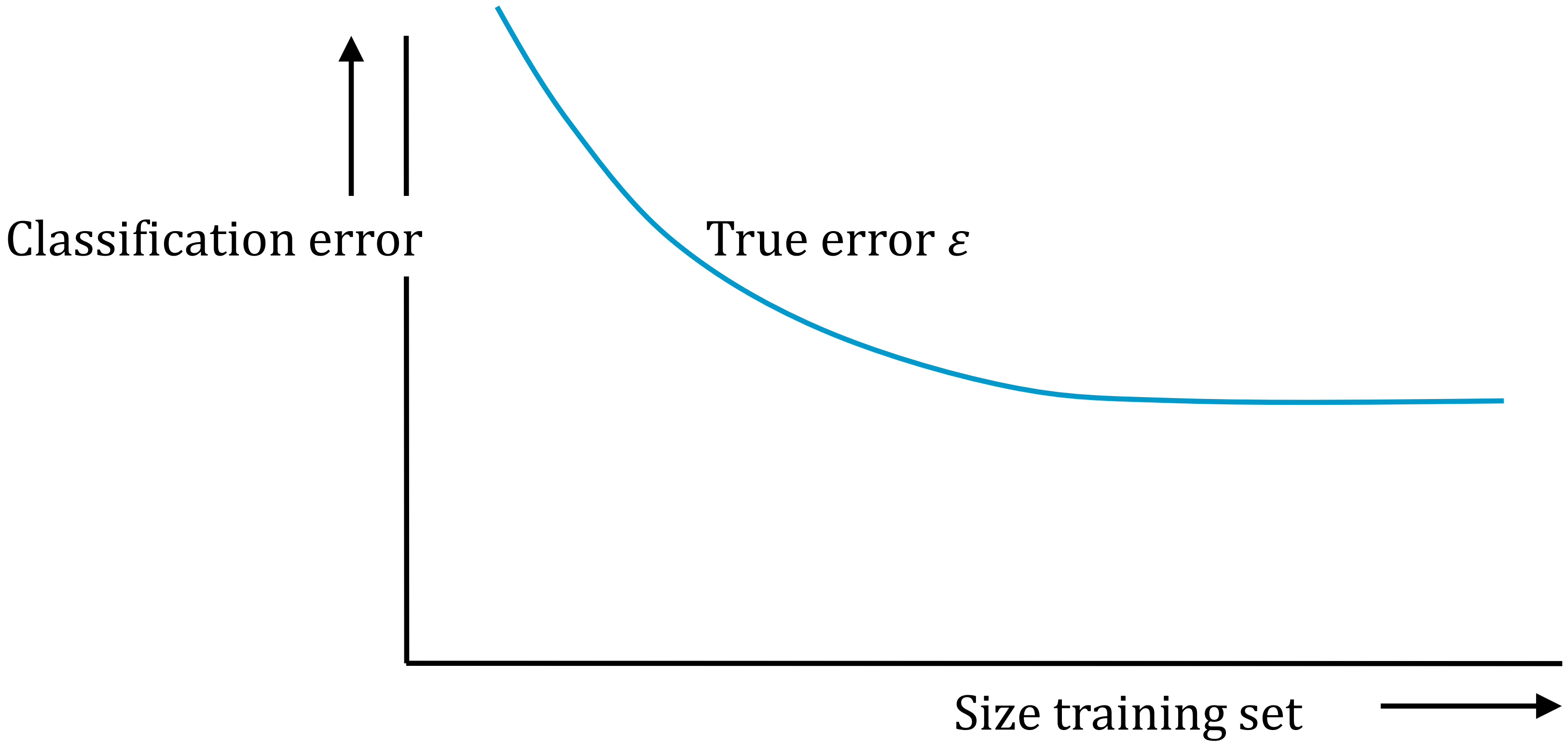
True Classification Error

› How does it behave?

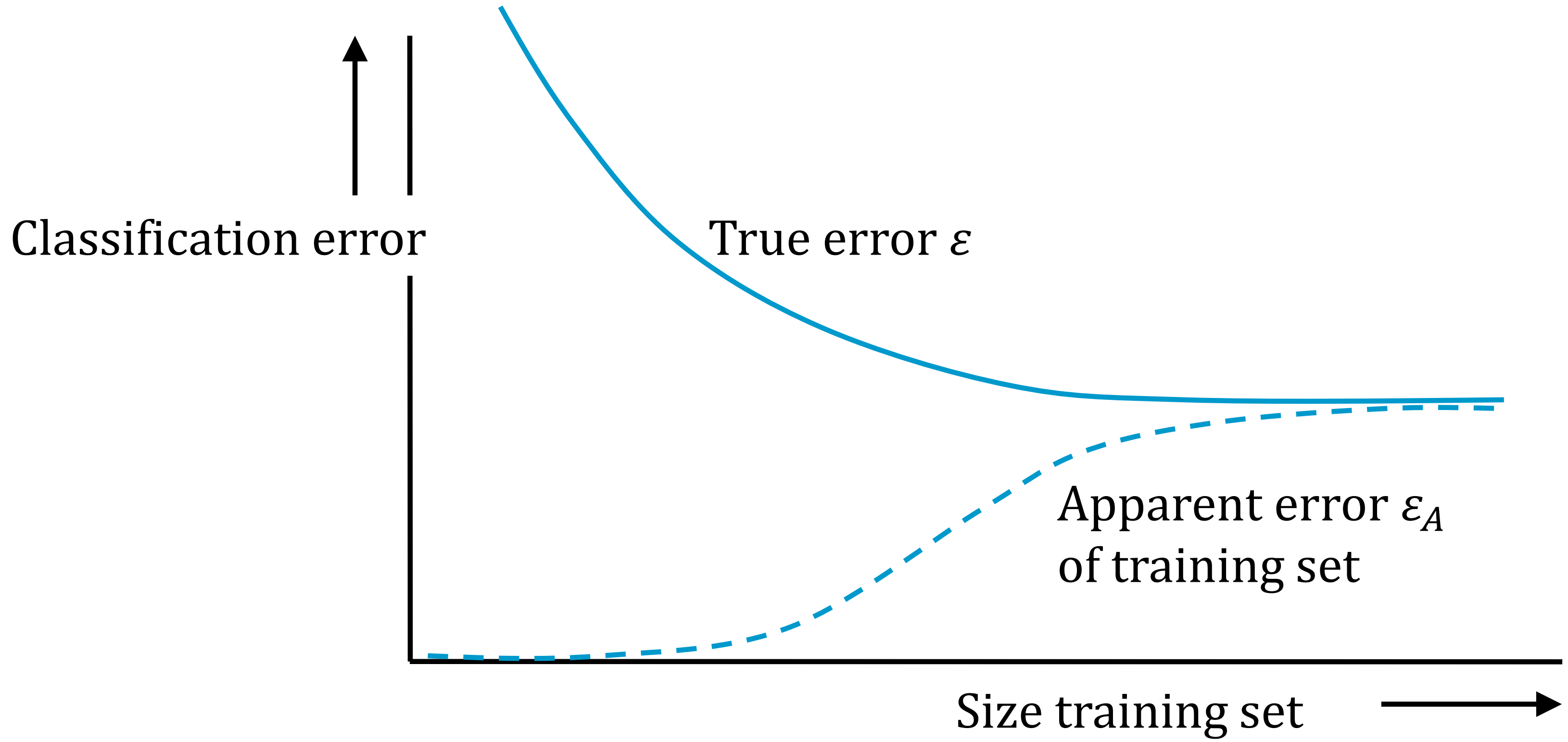


True Classification Error

- How does apparent error behave?



Apparent Classification Error

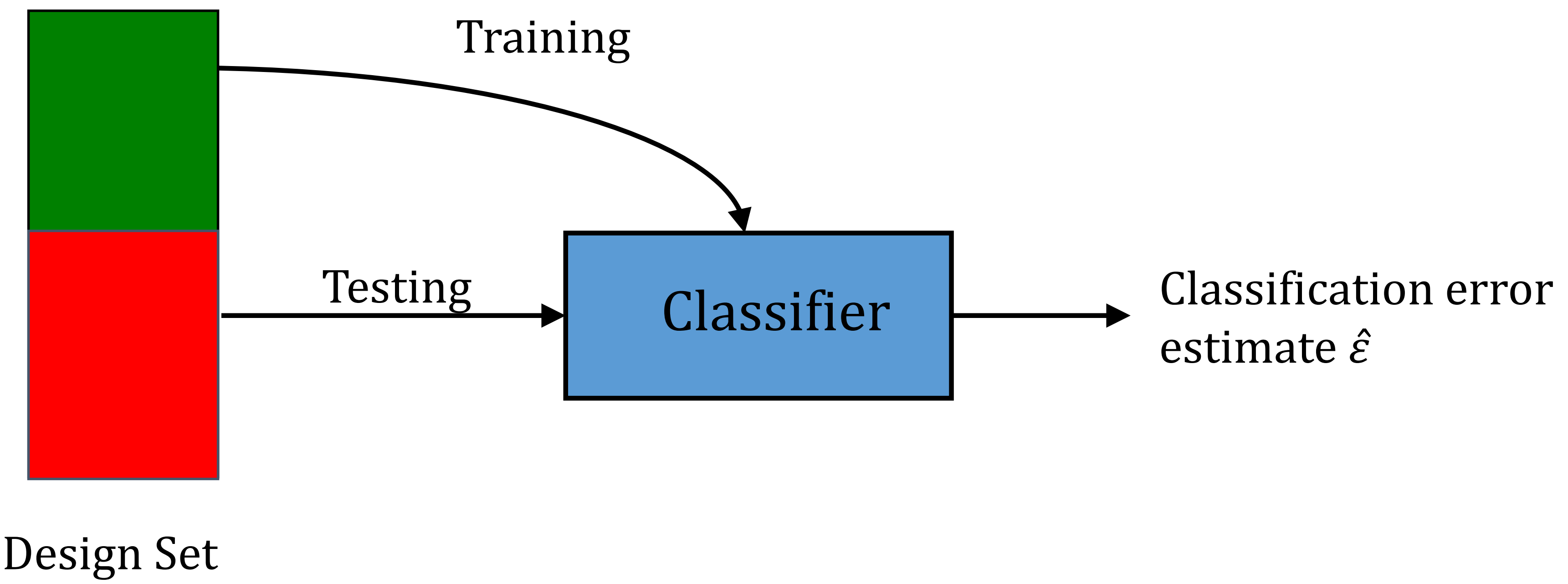


Determining Errors

- Apparent or resubstitution error
  = error classifier makes on its training data set

- How do we determine the true error in practice?

Error Estimation by Test Set



Other training set → other classifier
Other test set → other error estimate

How Variable?

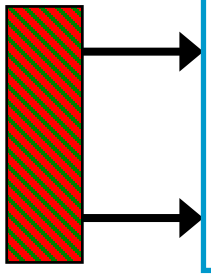
$$\sigma_{\hat{\varepsilon}}^2 = \mathrm{Var}(\hat{\varepsilon} \mid \text{test set size } N) = \frac{\varepsilon(1-\varepsilon)}{N}$$

$$\sigma_{\hat{\varepsilon}} = \sqrt{\frac{\varepsilon(1-\varepsilon)}{N}}$$

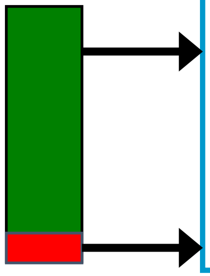
N \ ε	0.01	0.03	0.1
10	0.031	0.054	0.095
100	0.010	0.017	0.030
1000	0.003	0.005	0.009

Training Set Size vs. Test Set Size

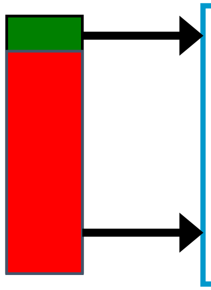
Large training set → good classifiers
Large test set → reliable, unbiased error estimate
In practice often just a single design set is given



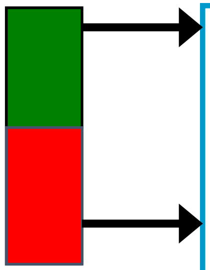
Same set for training and testing may give a good classifier, but will definitely yield an optimistically biased error estimate



A small, independent test set yields an unbiased, but unreliable [large variance] error estimate for a well trained classifier



A large, independent test set yields an unbiased and reliable [small variance] error estimate for a badly trained classifier

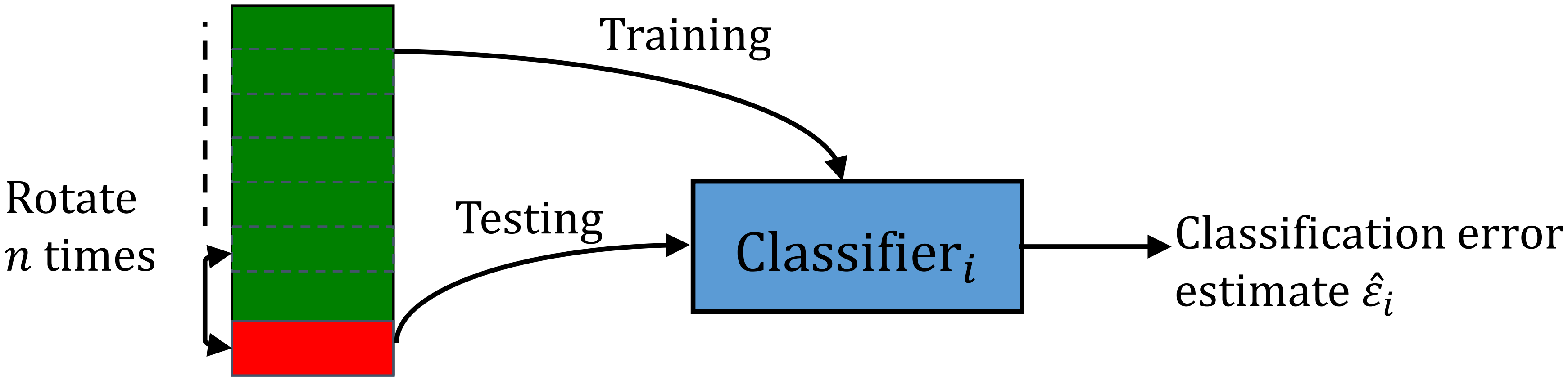


50-50 is an often used standard solution for the sizes for training and testing

But is it really good?

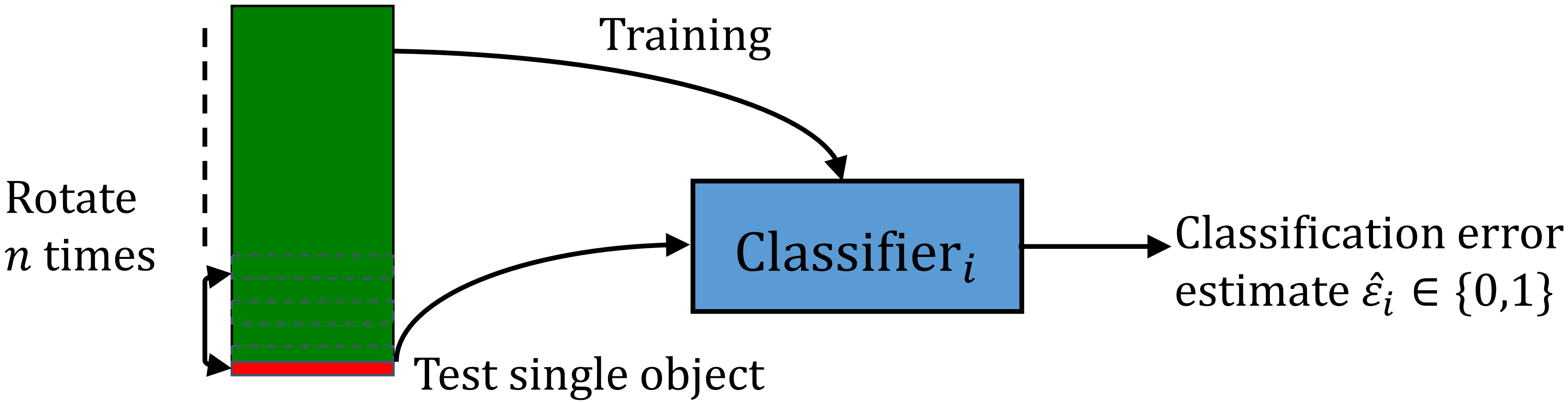
Cross Validation

Cross Validation

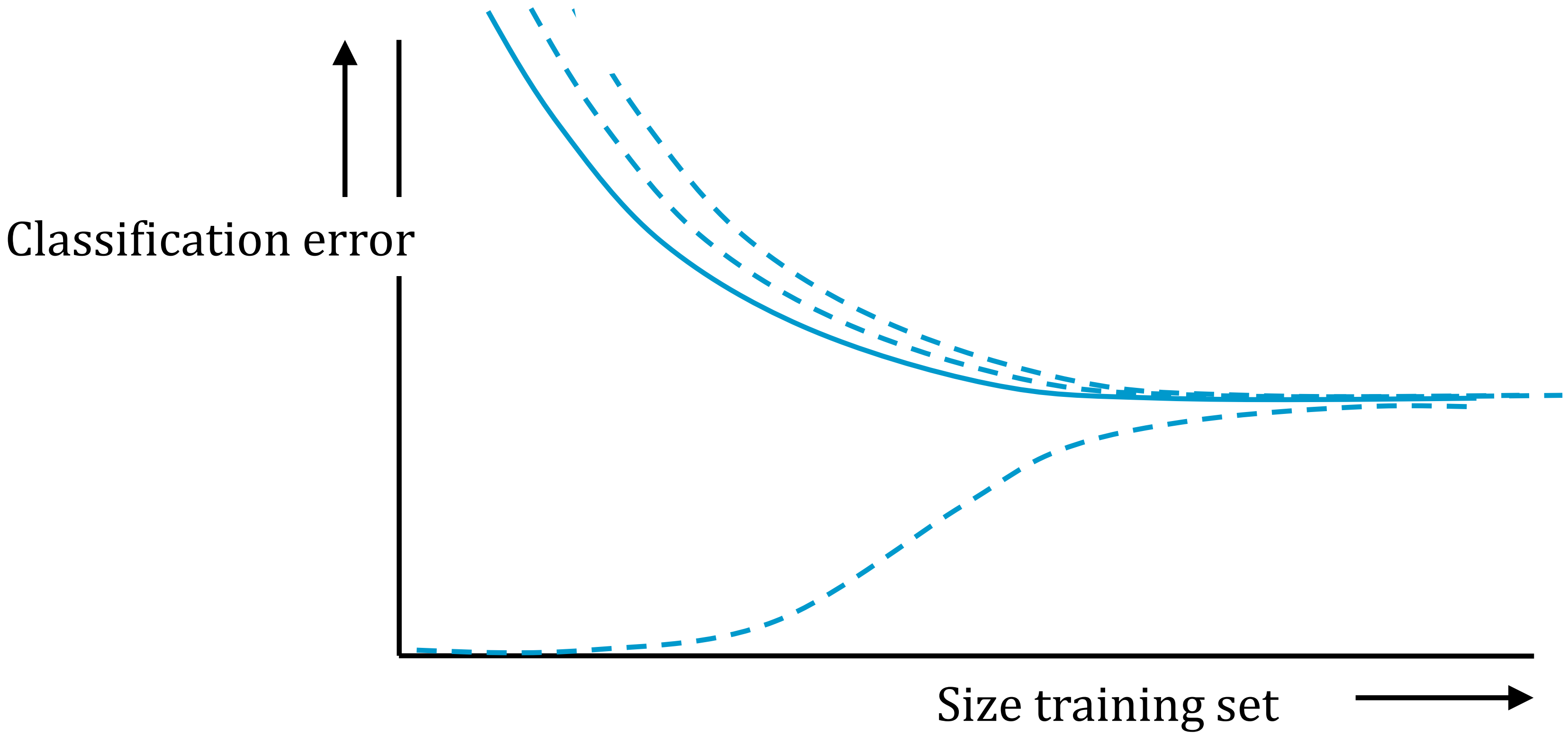


Leave-one-out Procedure

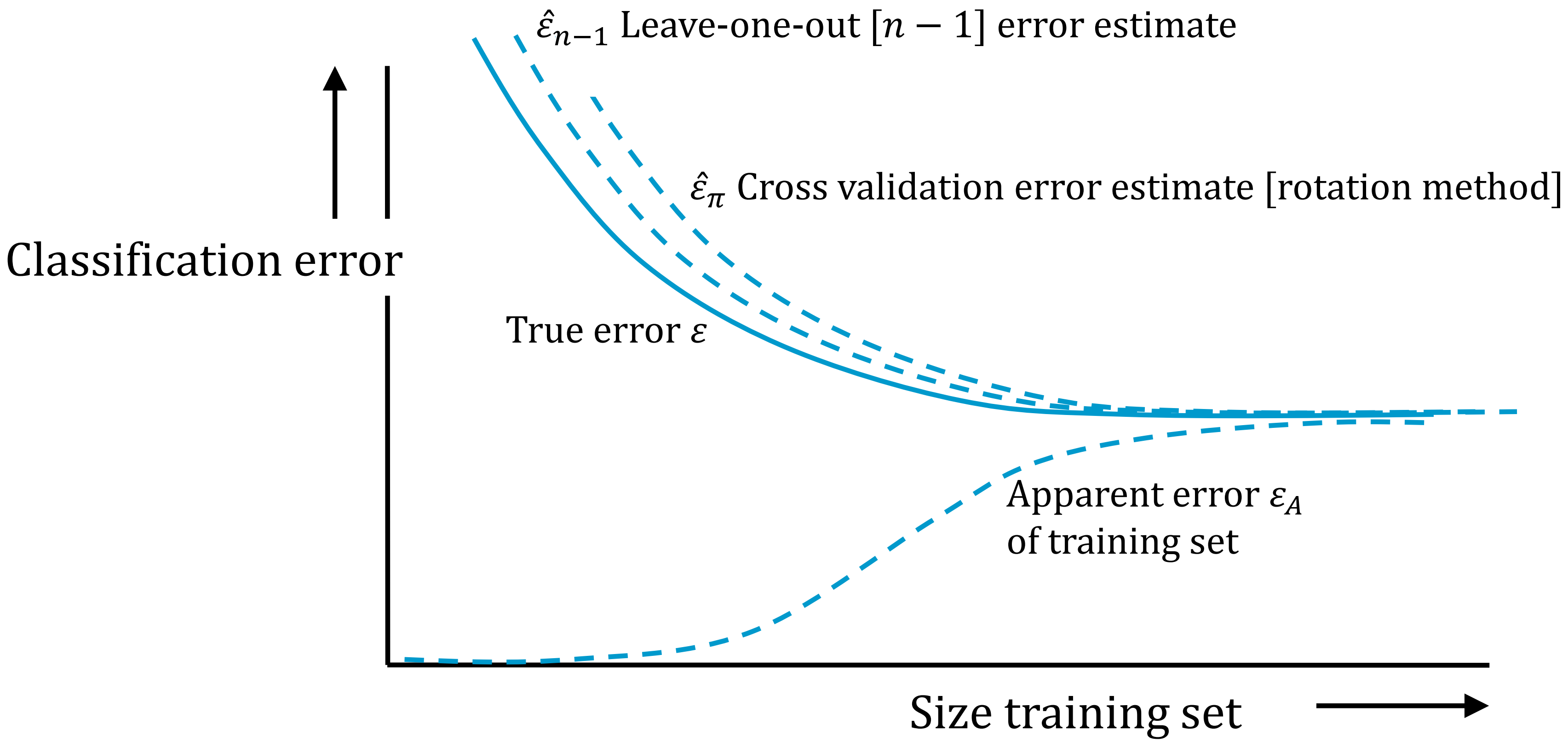
› n equals training set size



Cross Validation Curves and Related



Cross Validation Curves and Related



Learning Curves

Learning Curves

› Curves that plot [estimated] classification errors against the number of samples in training set

Usually plot error both on training and on test set

Gives insight, e.g. into

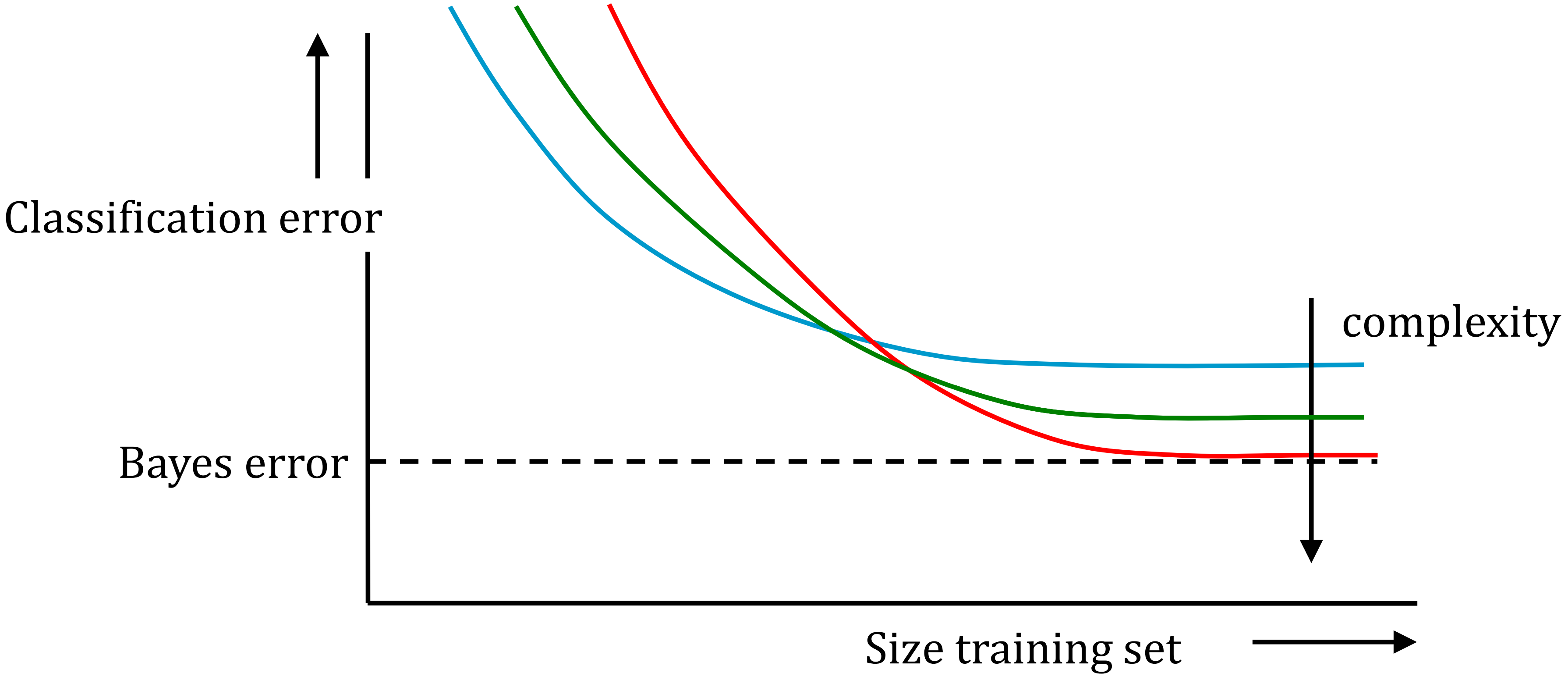
Amount of overtraining

Usefulness of additional data

How different classifiers compare

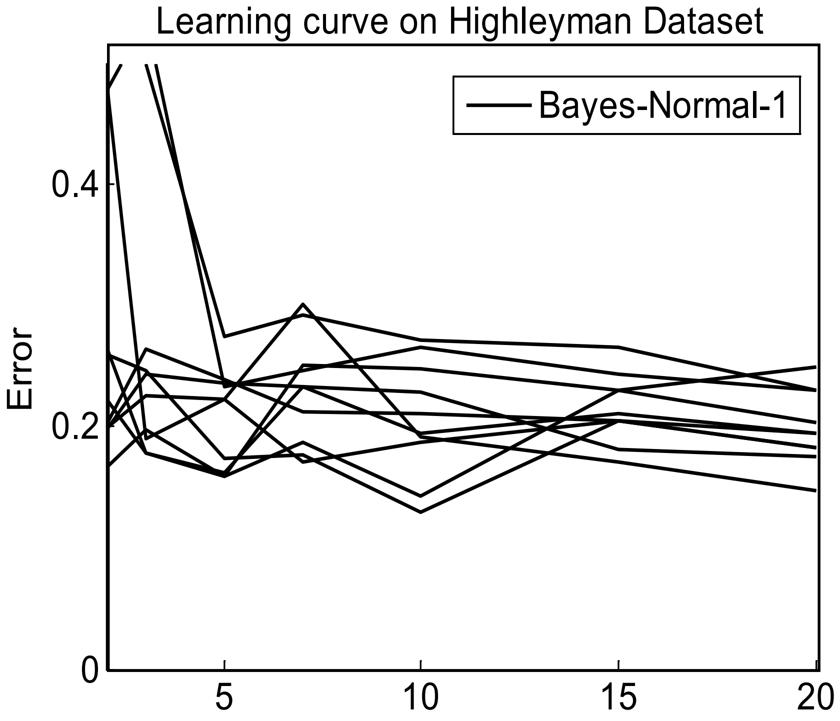
...

Different Classifier Complexities



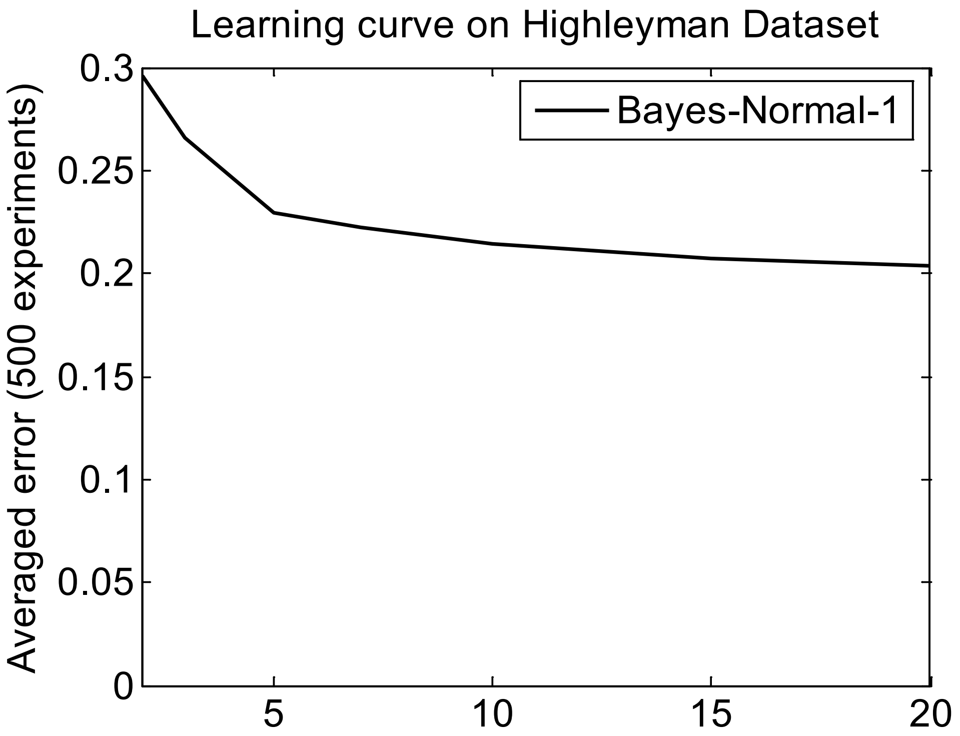
Real-world Learning Curves

› Small sample sizes have a large variability




```
a = gendath([200 200]);
for j=1:10
  e = cleval(a,ldc,[2,3,5,7,10,15,20],1);
  hold on; plote(e);
end
```

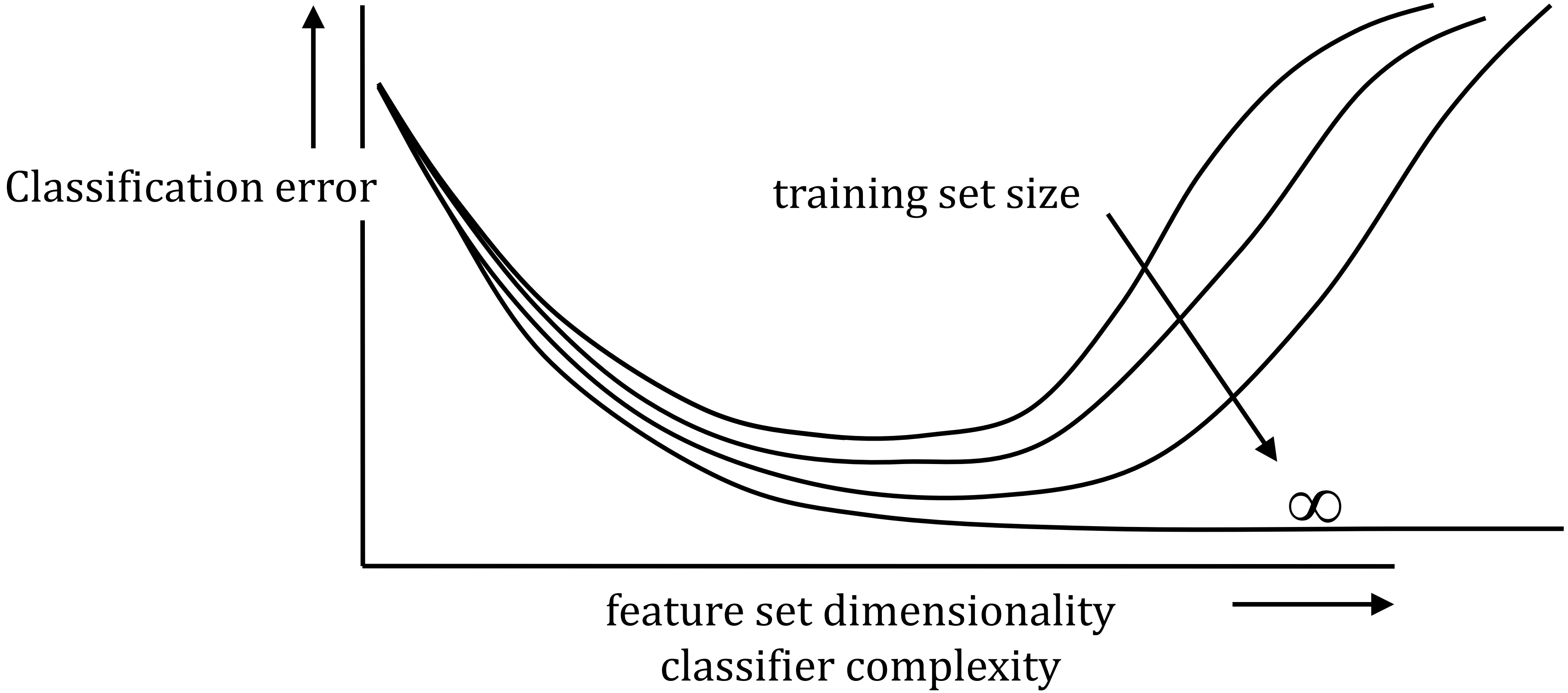
Averaged Learning Curve



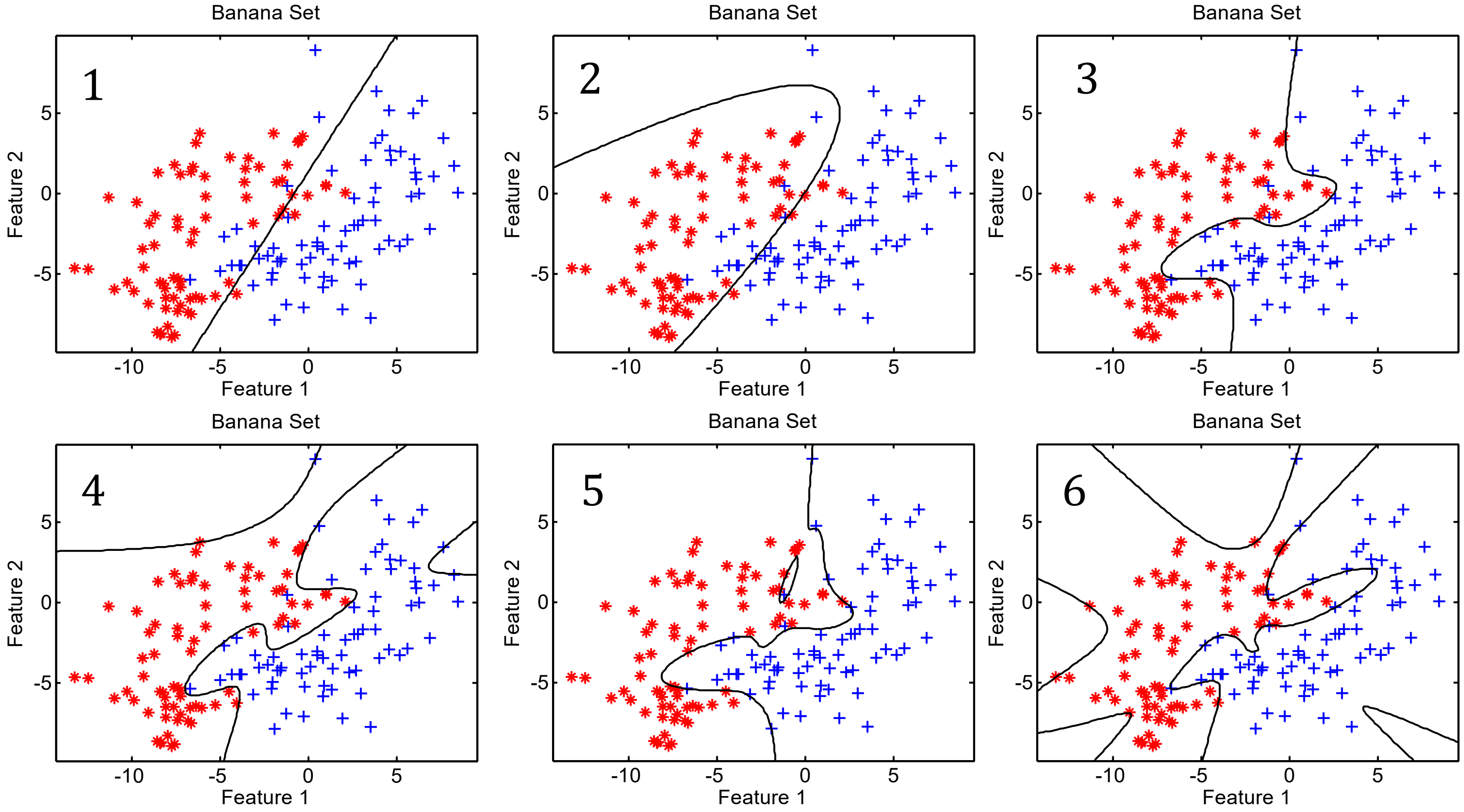

```
a = gendath([200 200]);
e = cleval(a,ldc,[2,3,5,7,10,15,20],500);
plote(e);
```

Feature Curves

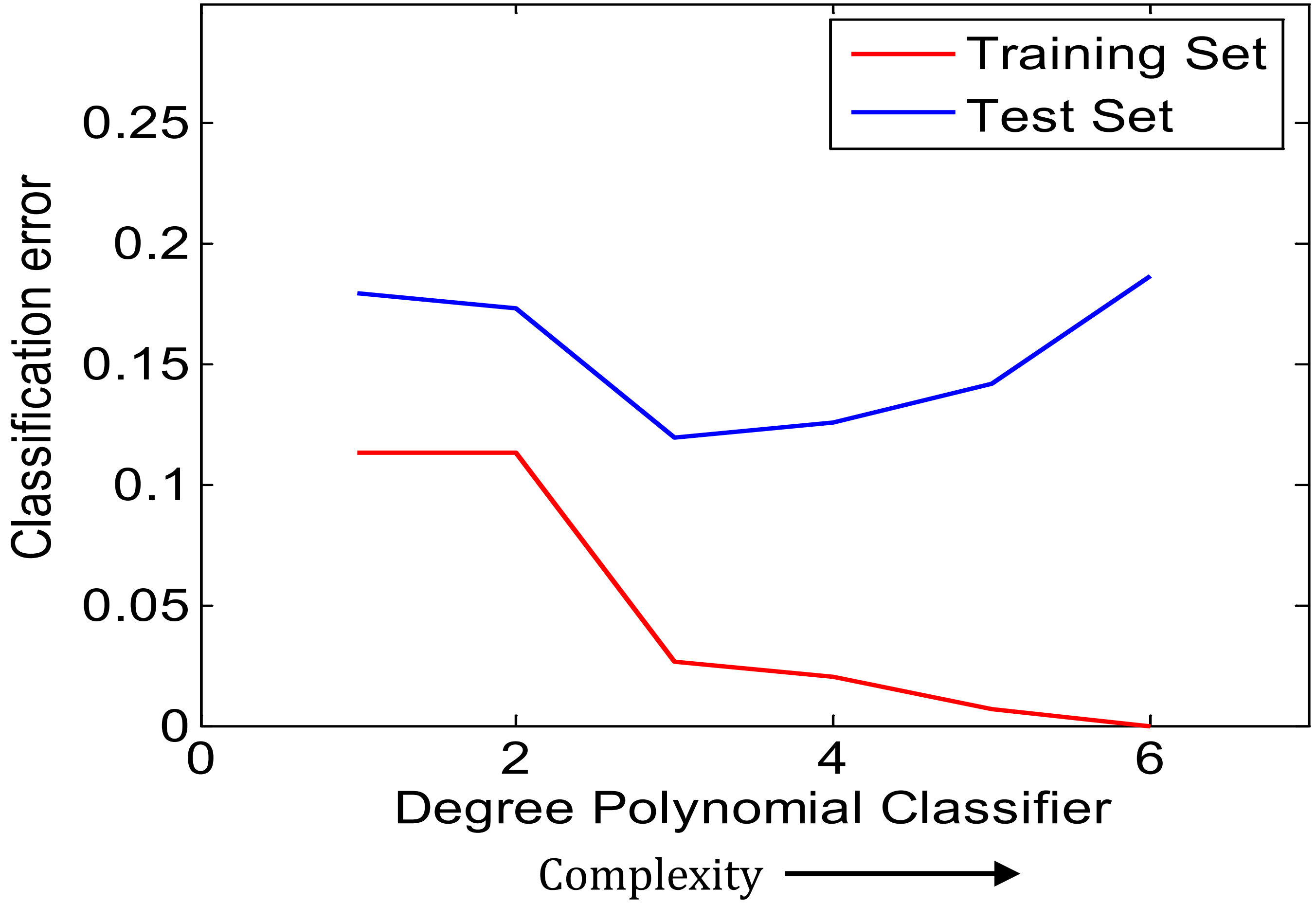
Feature Curves



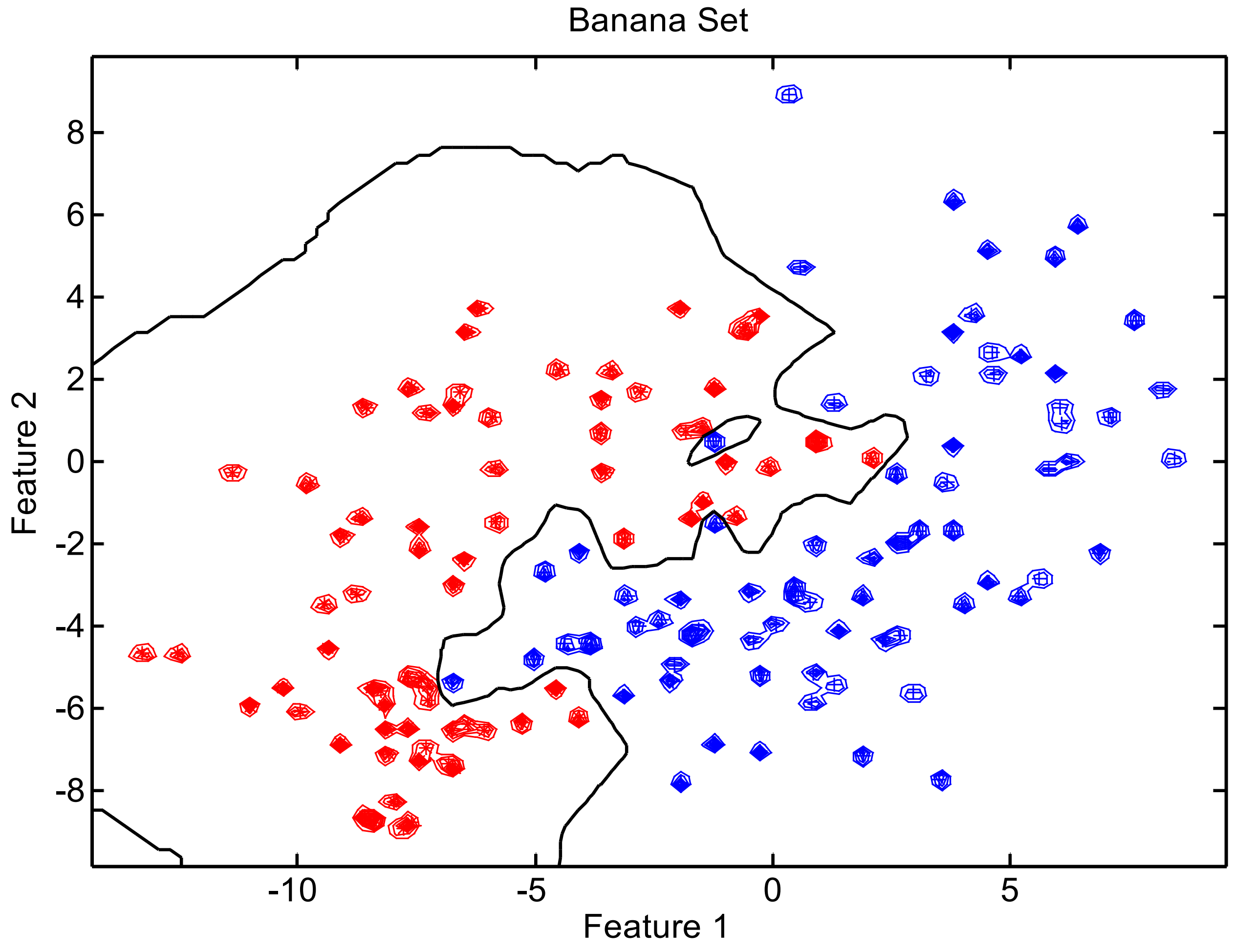
Polynomial Complexity Example

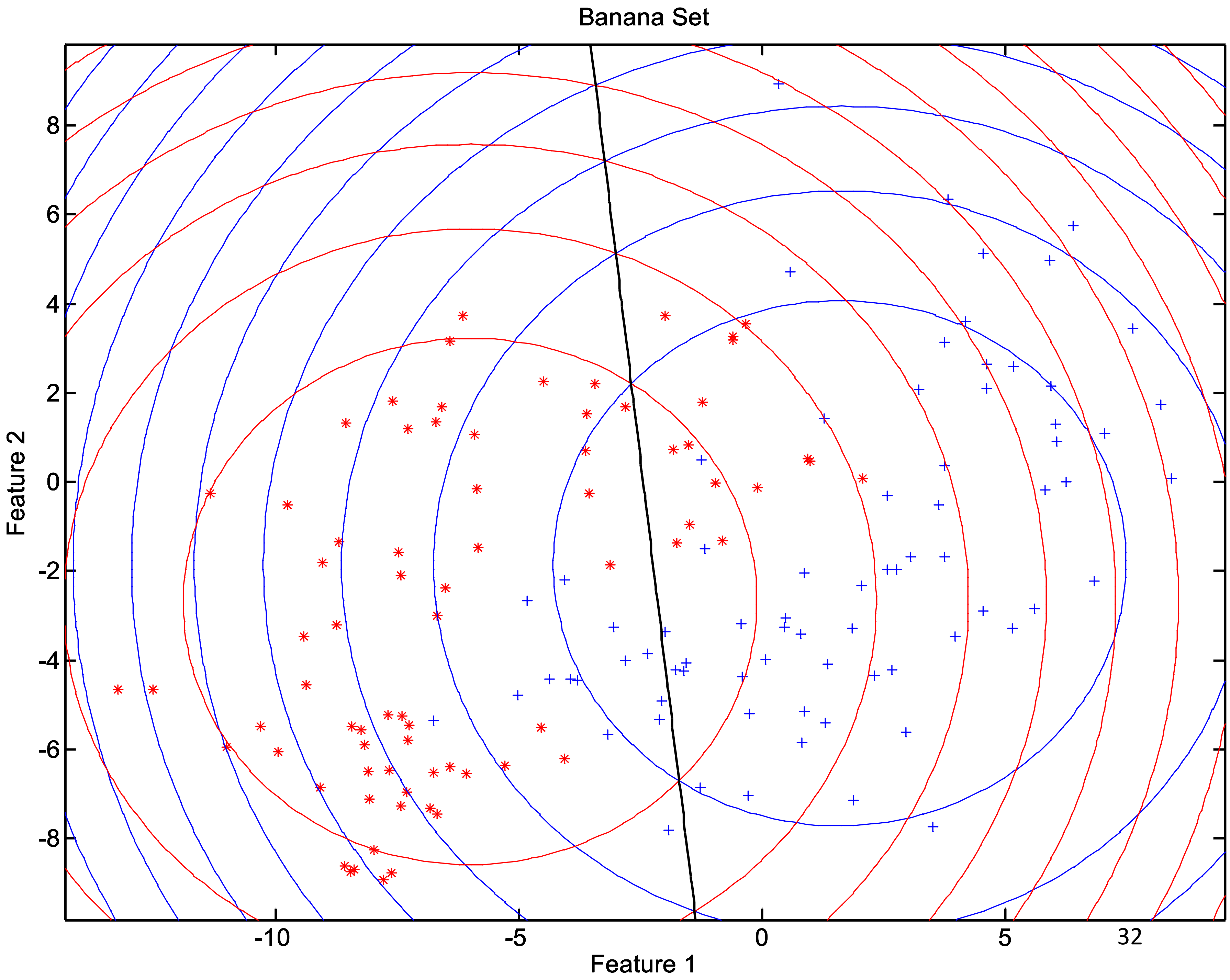


Polynomial Complexity Example

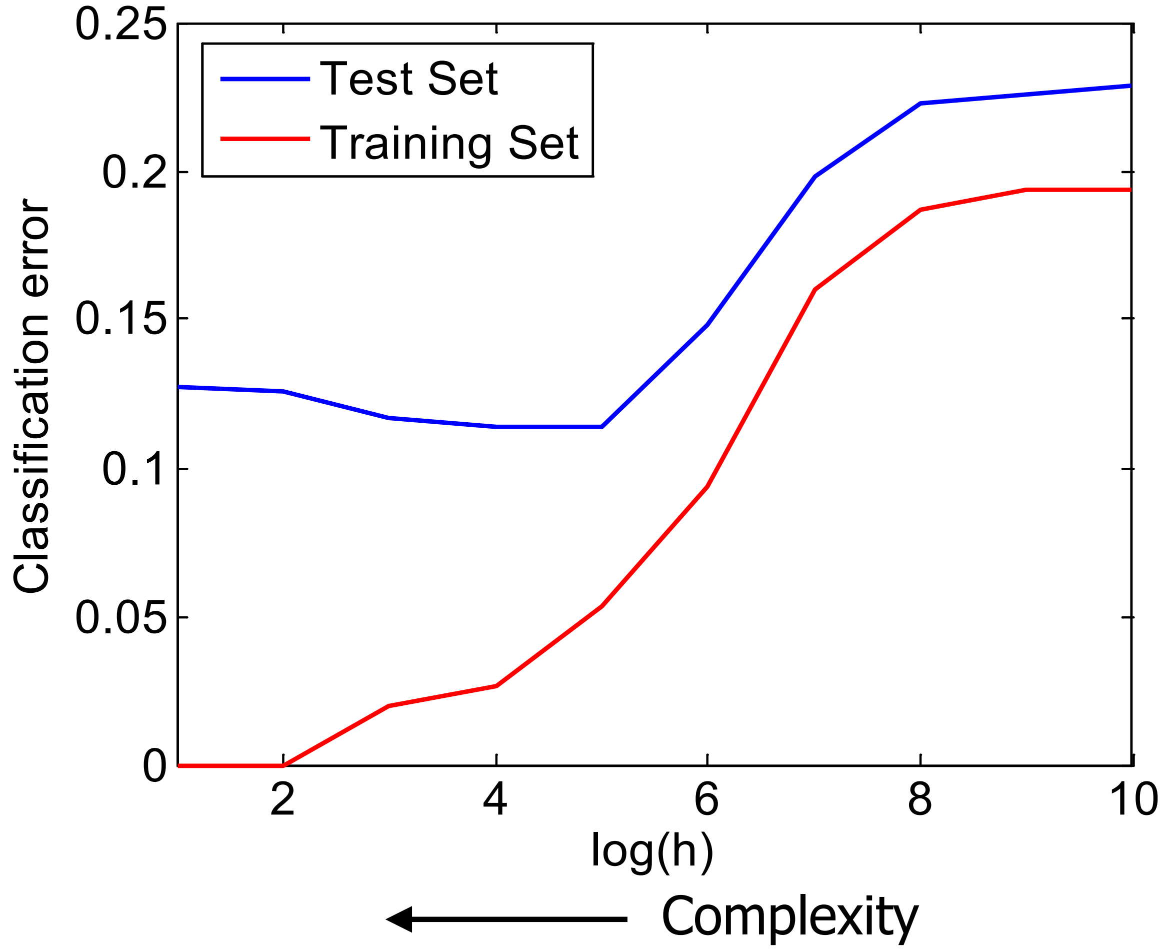


Parzenc Complexity Example



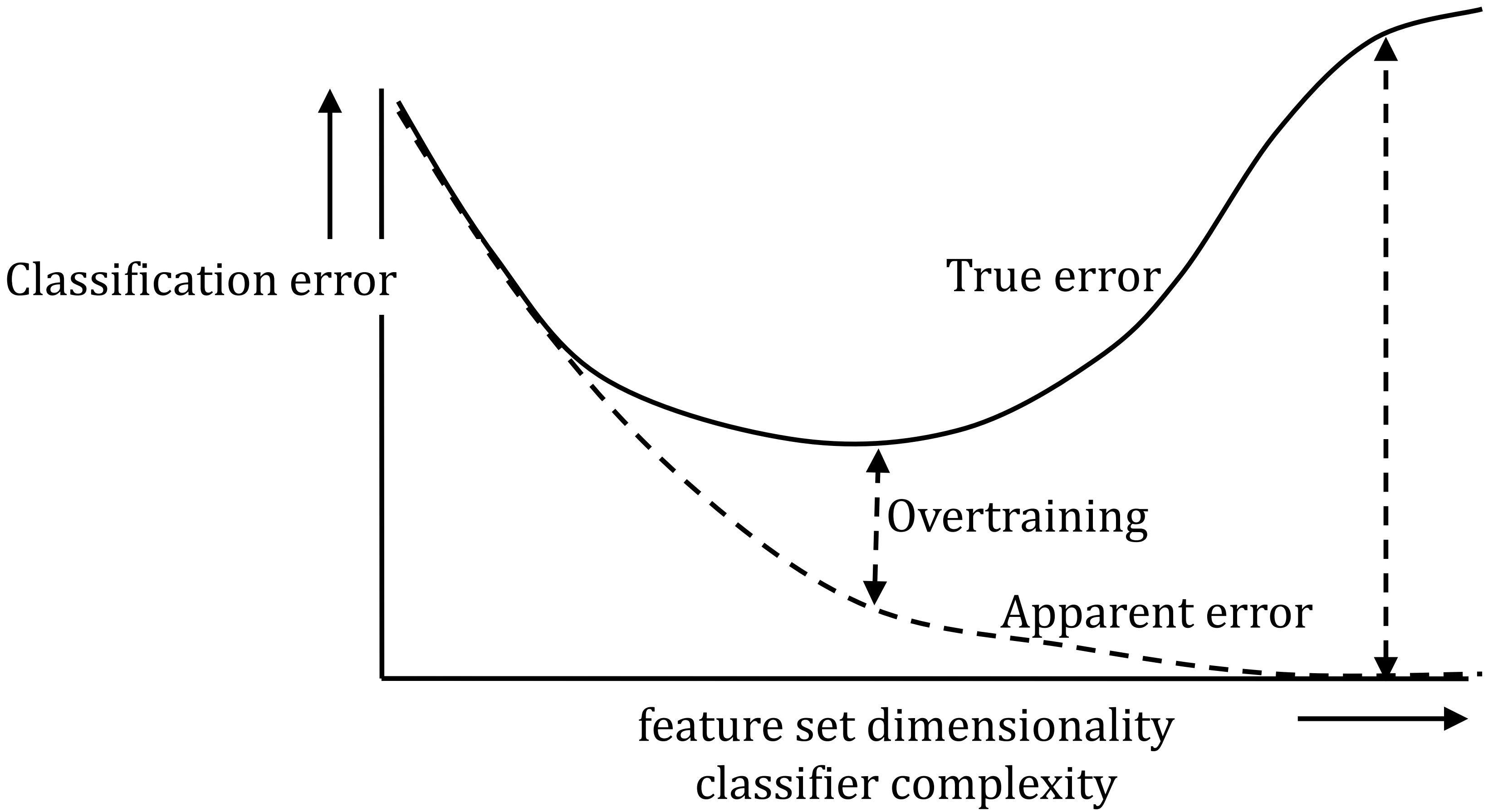

Banana Set
Feature 2
Feature 1
8
6
4
2
0
-2
-4
-6
-8
-10
-5
0
5
32

Parzenc Complexity Example



Curse of Dimensionality

Curse of Dimensionality



Some Concluding Claims…

- Larger training sets yield better classifiers
- Independent test sets needed for unbiased error estimates
- Larger test sets yield more accurate error estimates
- LOO cross validation “optimal”, but might be infeasible
- More complex classifiers need larger training sets
  - Same holds for larger feature set sizes
- Small training sets need simpler classifiers or smaller feature sets
- There is no single best classifier!

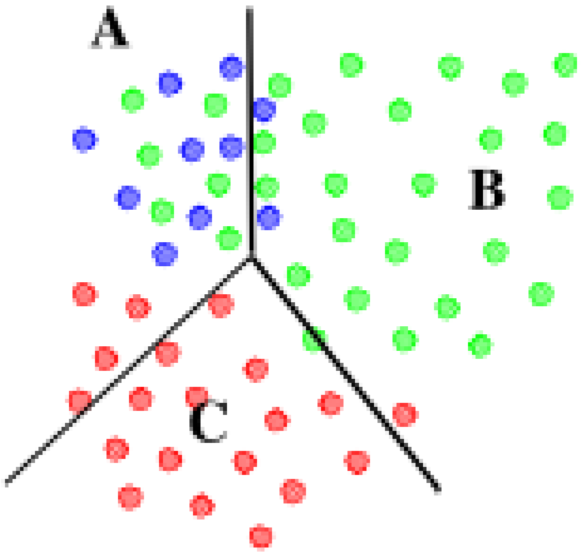
Confusion Matrices

› Provides counts of class-dependent errors : How many object have been classified as A that should have been classified as B?

Give a more detailed view than overall error rate

Can be used to estimate overall cost for particular classifier

Confusion Matrices



$$N_A = 10,\ N_B = 30,\ N_C = 20$$

$$E = \frac{c_{12} + c_{13} + c_{21} + c_{23} + c_{31} + c_{32}}{N_A + N_B + N_C}$$

$$E = 14/60 = 0.2333$$

$C = \mathrm{confmat}(\Lambda, L)$

Λ real labels

L obtained labels

classified to

objects from	A	B	C
class A	8	2	0
class B	6	23	1
class C	4	1	15

0.20 error in class A
0.23 error in class B
0.25 error in class C

0.228 averaged error

› Q?

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