Selected Topics in Applied Machine Learning: An integrating view on data analysis and learning algorithms

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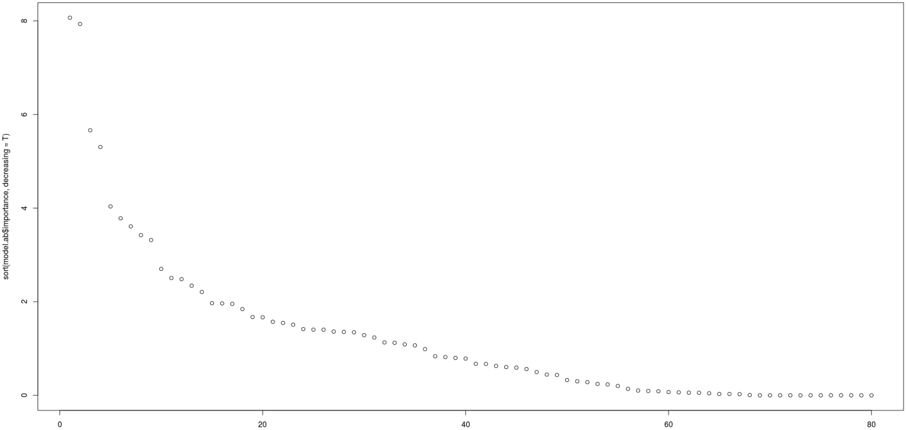
Block 5.1
Practical methods for feature selection

- **Filters and wrappers**
- **Variable importance produced by ensembles**
- **Feature selection by Lasso**
- **SVM-RFE – Recursive Feature Elimination**

Variable importance (AdaBoost) – *cry*



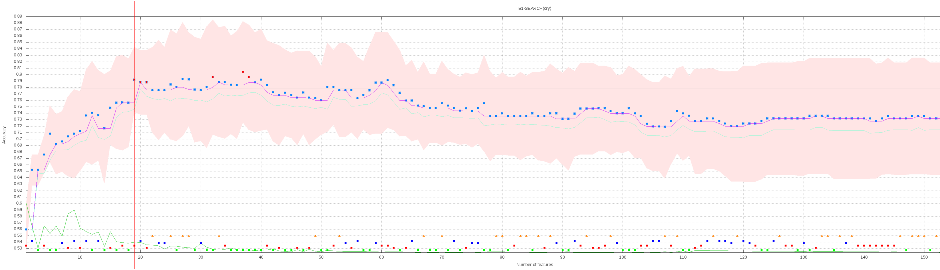
SVM-RFE feature selection algorithm

Algorithm 2 Recursive feature elimination using the SVM learner with cross-validated optimization of the SVM parameter *cost* in each iteration step.

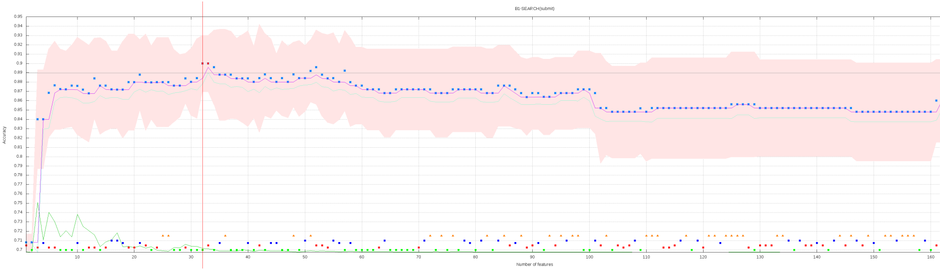
Input: Training data set and the initial feature set
Output: The best SVM classifier $\mathrm{M}_{\max}$ and the corresponding feature subset $\mathrm{S}_{\max}$

$K \leftarrow$ *the initial feature set size*
$S_K \leftarrow$ *the initial feature set*
for $k \leftarrow K$ **downto** 1 **do**
  learn a linear SVM model using the feature set S_k *and tune its parameter* cost
  $\mathrm{M}_k \leftarrow$ *the best tuned linear SVM model using the feature set* S_k
  $f_{\text{worst}} \leftarrow$ *the least useful feature in the model* M_k
  $S_{k-1} \leftarrow S_k \setminus \{f_{\text{worst}}\}$
end for
$\mathrm{M}_{\max} \leftarrow$ *choose the best model from* $\{\mathrm{M}_i\}_{i=1}^{K}$
$\mathrm{S}_{\max} \leftarrow$ *the best feature subset corresponding to the best model* $\mathrm{M}_{\max}$

SVM-RFE – *cry*



SVM-RFE – *submit*



Block 5.2
Summarizing remarks on VPR task
– model assesment and selection

Goal

A complex comparison of competing models trained for the VPR task

- **Model** = method + set of features + learning parameters
  – feature set may be considered as a parameter of the model (!)

- Model flexibility is model's ability to fit the data well

- Higher flexibility implies higher complexity **but not vice versa**

Outline

- **Concluding remarks on methods for reducing the variance**
  – ensembles vs. feature selection vs. regularization
- **The "Bayes classifier" – the limit of the test error**
- **A bootstrap method for estimating the generalization error**
- **More complex comparison of the developed VPR classifiers**
  – confidence intervals, an indicator of the model variance
- **Concluding remarks & concluding questions**

Model assessment and model selection

Assessment – a dictionary definition

- *Assessment means the evaluation or estimation of the nature, quality, or ability of someone or something.*

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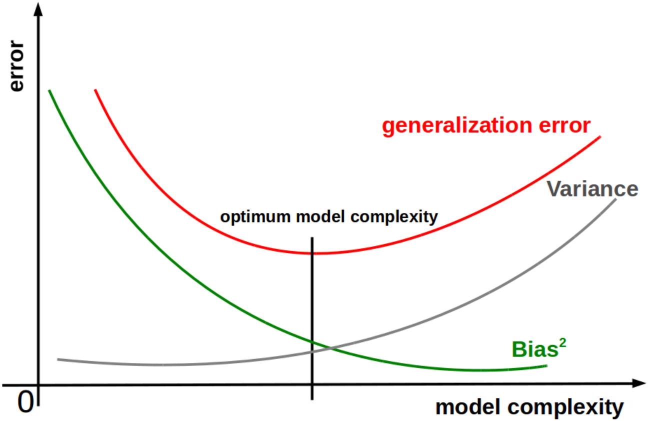
- **Model assessment**
  – the process of evaluating a model's performance
- **Model selection**
  – the process of selecting the proper level of flexibility

Model assessment and model selection

Finding a model that minimizes generalization error



Model assessment and model selection

In a linguistic research, we are also interested in the interpretability of the model, namely in

- recognizing/discovering important features
- error analysis

Unstable classifiers and ensembles

Leo Breiman:
"Instability (of base learners) is an essential ingredient for bagging or arcing to improve accuracy."

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- Unstable classifiers are characterized by high variance
- Decision trees are especially suitable for building ensembles because
  - they are extremely flexible to fit "any data",
    i.e they can have very low bias
  - they are unstable, i.e. they have high variance

Ensembles and feature selection and regularization

How and why do the techniques for decreasing variance work?

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- bagging-based ensembles average a large set of low correlated results

Ensembles and feature selection and regularization

How and why do the techniques for decreasing variance work?

- feature selection and regularization decrease model complexity
- bagging-based ensembles average a large set of low correlated results
- AdaBoost decreases bias in the early iterations
  – it decreases variance as well, namely in later iterations

What is the lowest possible error rate

Bayes classifier assigns each example to the most likely class, given its feature values

$$\hat{y} = max_y \Pr(y \,|\, \mathbf{x})$$

The Bayes classifier produces the lowest possible test error rate, so called **Bayes error rate**

$$1 - \mathrm{E}\left(max_y \Pr(y \,|\, \mathbf{x})\right)$$

What is the lowest possible error rate

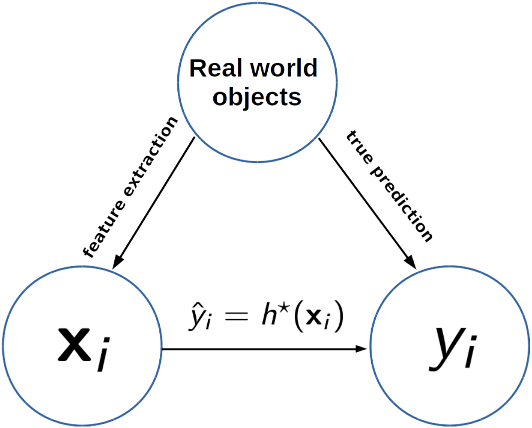
Identical feature vectors?

What is the lowest possible error rate

Identical feature vectors?

- Get the same feature vectors
- How many of them have the same target value?

What is the lowest possible error rate



Competing models for VPR

- **Confidence intervals**

Generalization error estimation by bootstrapping

- Suppose a development data of n examples
- Train a model on the data
- Test the model on the data
- Get training error = optimistic error e_l
- Repeat 200 times
  - Randomly select n examples with replacement and train a model
    on average, 63.2% of the original sample
  - Test the model on the examples not used in the training
    on average, 36.8% of the orginal sample
  - Get test error
- Get mean test error = pesimistic error e_o
- **generalization error estimation =** $0.368 * e_l + 0.632 * e_o$

Final look at our competing models

Overview of all models developed

Farewell

It's Friday afternoon! No more slides, no more lectures!

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It's Friday afternoon! No more slides, no more lectures!

- **It was a pleasure for us to be here with you.**
- **We are glad that we could teach you something.**
- **You were the bright audience.**

Thank you!