Applied Machine Learning

Feature Selection: Wrapper Methods

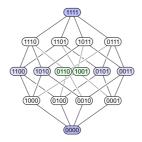


Learning goals

- Objective Functions
- Greedy Forward Search
- Greedy Backward Search

INTRODUCTION

- Wrapper methods emerge from the idea that different sets of features can be optimal for different learners
- Wrapper is a discrete search strategy for S, where objective criterion is test error of learner as function of S. Criterion can also be calculated on train set, approximating test error (AIC, BIC)
- ⇒ Use the learner to assess the quality of the feature sets



Hasse diagram illustrating search space. Knots are connected if Hamming distance = 1 (Source: Wikipedia)



OBJECTIVE FUNCTION

Given p features, **best-subset selection problem** is to find subset $S \subseteq \{1, \dots p\}$ optimizing objective $\Psi : \Omega \to \mathbb{R}$:

$$\mathcal{S}^* \in \operatorname*{arg\,min}_{\mathcal{S} \in \Omega} \{ \Psi(\mathcal{S}) \}$$

- Ω = search space of all feature subsets $S \subseteq \{1, \dots, p\}$. Usually we encode this by bit vectors, i.e., $\Omega = \{0, 1\}^p$ (1 = feat. selected)
- ullet Objective Ψ can be different functions, e.g., AIC/BIC for LM or cross-validated performance of a learner
- Poses a discrete combinatorial optimization problem over search space of size = 2^p , i.e., grows exponentially in p (power set)
- Unfortunately can not be solved efficiently in general (NP hard; see, e.g.,
 Natarajan 1995)
- Can avoid searching entire space by employing efficient search strategies, traversing search space in a "smart" way

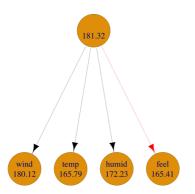


GREEDY FORWARD SEARCH

Let $S \subset \{1, \dots, p\}$ be subset of feature indices.

- Start with the empty feature set $S = \emptyset$
- **2** For a given set S, generate all $S_j = S \cup \{j\}$ with $j \notin S$.
- **3** Evaluate the classifier on all S_j and use the best S_j

Example GFS on a subset of bike sharing data with features windspeed, temp., humidity and feeling temp. Node value is RMSE.

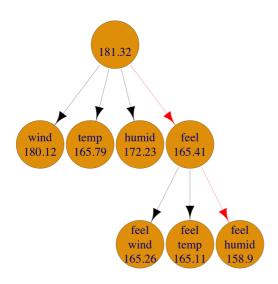




VISUALIZATION OF GFS

Iterate over this procedure

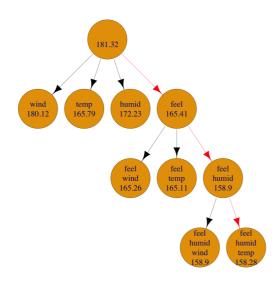




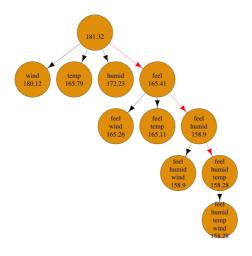
VISUALIZATION OF GFS

Iterate over this procedure





VISUALIZATION OF GFS





Terminate if performance does not improve further or max. number of features is used

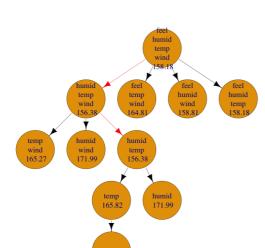
GREEDY BACKWARD SEARCH

- Start with the full index set of features $S = \{1, \dots, p\}$.
- For a given set S generate all $S_j = S \setminus \{j\}$ with $j \in S$.
- Evaluate the classifier on all S_j and use the best S_j .
- Iterate over this procedure.
- Terminate if:
 - the performance drops drastically, or
 - falls below given threshold.
- GFS is much faster and generates sparser feature selections
- GBS much more costly and slower, but sometimes slightly better.



VISUALIZATION OF GBS

Example Greedy Backward Search on bike sharing data



181.32



ADVANTAGES AND DISADVANTAGES

Advantages

- Inducer-agnostic
- Any performance measure can be used
- Optimizes the desired performance measure directly

Disadvantages

- Expensive
- Does not scale well with the number of features
- Does (in general) not use additional info about model structure
- Nested resampling becomes necessary

