



Figure 2 Chess endgame showing individual classes

### 3 Selecting a Beam Width

Having established that extensive search can lead to less accurate rules we now discuss a method for limiting search.

For the domains of Figure 1, the most accurate rule is often found with a beam width  $w$  greater than 1 (where  $w=1$  corresponds to greedy search) but less than 512 taken here as an approximation to exhaustive search. Suppose now that a *layered search* were conducted by starting with  $w \leq 1$  and doubling the beam width at each iteration. Could we select the appropriate beam width so as to obtain the most accurate rule? This decision clearly cannot be made with reference to the  $\epsilon$  value alone since this always decreases with further search.

The following probabilistic argument was inspired by the famous Occam paper [Blumer, Ehrenfeucht, Hauslter, and Warmuth, 1987]. If the true error rate of a rule is  $r$ , the probability that the rule will give no more than  $e$  errors in  $n$  trials is given by

$$P(n \leq e) = \sum_{i=0}^e \binom{n}{i} r^i (1-r)^{n-i}$$

If then start  $h$  rules all having an error rate of  $r$  or more, the probability that any one of them will give  $e$  or less errors in  $n$  trials is at most  $h \times P(n \leq e)$  whether or not the rules are independent.

Now let  $h_u$  denote the number of rules examined during the search with beam width  $u$ , and let  $r_u$  satisfy

$$h_u \times P(n_u, e_u, r_u) = 0.5$$

If all these rules had error rate greater than or equal to  $r_u$ , there would be up to an even chance that one of them would give no more than  $e_u$  errors in  $n_u$  trials. We use this value of  $r_u$  as a gut estimate of the accuracy of the best rule selected from the  $h_u$  candidates. As  $w$  takes on the values 1, 2, 4, ..., the corresponding values of  $h_u$ ,  $n_u$  and  $e_u$  can be determined and the value of  $r_u$  computed. We take the overall best rule to be that for which  $r_u$  is minimal.

There are numerous over-simplifications in this argument. For instance, it ignores the effect of beam selection at each level: search for the rule with minimal  $\epsilon$  value is guided by the  $C$  values of partial rules, so that the

Beam Width	Items Covered		Rules Examined	Computed Estimate
$w$	$e_u$	$n_u$	$h_u$	$r_u$
1	0	10	168	0.441
2	0	17	330	0.317
4	0	21	699	0.292
8	0	21	1265	0.311
16	0	23	2771	0.313
32	0	23	4758	0.329
64	0	23	7358	0.341
128	0	23	11768	0.354
256	0	23	17417	0.365
512	0	23	24902	0.375

Table 2 Selecting beam width

$k$  errors in  $n_u$  trials is not a fair experiment. Again 'number of rules examined' is an imprecise concept: many putative rules cover no examples and some links are pruned as described in Section 2. For these experiments  $h_u$  is taken as the number of distinct attribute combinations considered during search on the basis that for each such combination there will be some test on every selected attribute that minimizes the in-sample value.

Table 2 illustrates the values for the positive class of the promoters dataset in one trial. Greedy search finds a rule that covers 10 items without error. Increasing the beam width to 2 causes a larger number of rules to be examined but yields a better rule covering 17 items. Still better rules are found at beam widths 4 and 16. In the latter case, the number of rules examined increases (by chance that the rule is a fluke as reflected by its high  $r_u$  value). The rule encountered at beam width  $w=4$  is consequently chosen as the overall best.

We can now explain the asterisks in Figure 1. In each trial, and for each class, a best beam width is selected as above using only the training data. The asterisk indicates the average beam width selected and the average of the corresponding error rates of the unseen test data. With the notable exceptions of the chess endgame and glass datasets, the average beam widths chosen are at the lowest points on the curves, indicating some empirical support for the beam width selection strategy.

### 4 Learning Complete Classifiers

The search for individual rules can be extended to learn complete classifiers using the standard covering method [Michalski, 1980].

For each class  $C_x$  in turn

Mark all items of class  $C_T$  as uncovered

While uncovered items of class  $C_x$  remain

Find and retain the best rule

Mark as covered all class  $C_x$  items that satisfy the rule

The asterisk will not normally be on the solid curve because the beam width selected varies from class to class and from trial to trial.