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# Supplementary Material

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## Appendix: Parameter Sensitivity

Each of our non-linear extensions adds one additional hyper parameter to the LMNN problem. In section 6, we set these parameters by evaluation on a hold-out set. Here we explicitly examine their effect on the learned metric. For GB-LMNN, the new hyper-parameter is the regression tree depth. Figure 3(left) compares depths 4–7 for several of the datasets evaluated in section 6. The figure depicts the ratio of  $k$ NN classification error for each depth setting to the  $k$ NN error of linear LMNN. GB-LMNN appears to be largely insensitive to tree depth within range.

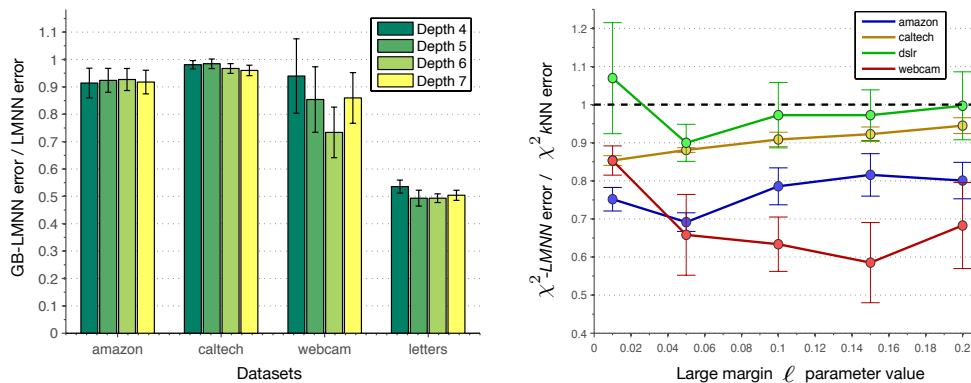


Figure 3: Parameter sensitivity measurements. *Left*: Varying tree depth for GB-LMNN. The measurement is the ratio between GB-LMNN error and LMNN error (lower is better). *Right*: Varying the large margin  $\ell$  for  $\chi^2$ -LMNN. The measurement is the ratio between  $\chi^2$ -LMNN error and the  $\chi^2$  baseline error (lower is better).

For  $\chi^2$ -LMNN, the additional hyper-parameter is the size of the large margin. Figure 3(right) examines several margin values: 0.01, 0.05, 0.10, 0.15 and 0.20. The figure depicts the ratio of  $k$ NN classification error for each margin setting to the  $k$ NN error of the  $\chi^2$  distance baseline. For all but two settings, the transformation learned by  $\chi^2$ -LMNN improves over the  $\chi^2$  baseline, generally by a large extent. However, the margin size parameter is clearly important to achieving the best performance. Fortunately, the parameter seems to be well-behaved and easily set by evaluation on a hold-out set.