RF + RLSC

Kari Torkkola

Motorola Intelligent Systems Lab Tempe, AZ, USA

Kari.Torkkola@motorola.com

Eugene Tuv

Intel Analysis and Control Technology Chandler, AZ, USA

eugene.tuv@intel.com



NIPS 2003 Feature Selection Workshop

RF + RLSC

- Random Forests (RF) for feature selection
- Regularized Least Squares Classifiers (RLSC)
- Stochastic ensembles of RLSCs



Why Random Forests for Feature Selection?

- Basic idea: Train a classifier, then extract features that are important to the classifier
- Features are not chosen in isolation!
- RF is extremely fast to train
- Allows for mixed data types, missing values



- RF
 - Trains a large forest of decision trees
 - Samples the training data for each tree
 - Samples the features to make each split
 - Error estimation from out-of-bag cases
 - Proximity measures, importance measures, ...
- An Importance Measure
 - A split in a tree by using a particular variable results in a decrease of the gini index
 - Sum of these decreases over the forest ranks features by importance



Challenge Examples

<u>Madelon</u>

- 500 variables, training set has 2000 cases
- Constructed 500 trees
- Variable importance has a clear cut-off point at 19 variables
- Validation set: 600 cases
- The top 19 variables are the same, but the cut-off point is not that clear



Dexter

- 20000 variables, 300 cases in both the training and the validation sets
- Top 50 variables from both sets are 70% shared (stability)

Why Ensembles of RLSCs as Classifiers?

- Why not just use RF? The base learner is not good enough!
- RLSC solves a simple linear problem

Given data $(x_i, y_i)_{i=1}^m$, find $f: X \to Y$ that generalizes:

1. Choose a kernel, such as $K(x, x') = e^{-\frac{||x-x'||^2}{2\sigma^2}}$,

2.
$$f(x) = \sum_{i=1}^{m} c_i K_{x_i}(x)$$
, where c_i is a solution to $(m\gamma \mathbf{I} + \mathbf{K})\mathbf{c} = \mathbf{y}$

- Square loss function works well in binary classification (Poggio, Smale, et al.)
- Use minimum regularization (just to guarantee solution) to reduce bias, sample cases to produce diversity in base learners

Things to worry about with RLSC Ensembles

- Kernel and its parameters?
- How many classifiers in the ensemble?
- What fraction of data to use to train each?
- How much to regularize (if at all)?
- Determine all of the above by cross-validation

Future Directions

- RF as one type of supervised kernel generator using the pairwise similarities
- Similarity between 2 cases could be defined (for a single tree) as total number of common parent nodes, normalized by level of the deepest case, and summed up for the ensemble
- Minimum number of common parents to define nonzero similarity is another parameter acting like width in Gaussian kernels.
- Works for any type of data (numeric, categorical, mixed, missing values)!
- Feature selection bypassed altogether!





Conclusion

- RF: Fast and robust feature selection
- RLSC: linear problem-solving
- Supervised kernels
- What we don't know...