COMPSCI 589
Lecture 7: Ensembles and Classification

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Outline

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- An ensemble of different models that all achieve similar generalization performance often outperforms any of the individual models.
- **Question:** How is this possible?

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- A simple majority vote can significantly improve classification performance by *decreasing variance* in this setting.
- **Question:** How can we come up with such an ensemble?

Independent Training Sets

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- **Question:** What is the weakness of this approach?

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Bagging

- Bootstrap aggregation or *Bagging* is an approximation to the previous method that takes a single training set Tr and randomly sub-samples from it K times (with replacement) to form K training sets $Tr_1, ..., Tr_K$.

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- Each of these training sets is used to train a different instance of the same classifier obtaining K classification functions $f_1(\mathbf{x}), ..., f_K(\mathbf{x})$.
- The errors won't by totally independent because the data sets aren't independent, but the random re-sampling usually introduces enough diversity to decrease the variance and give improved performance.

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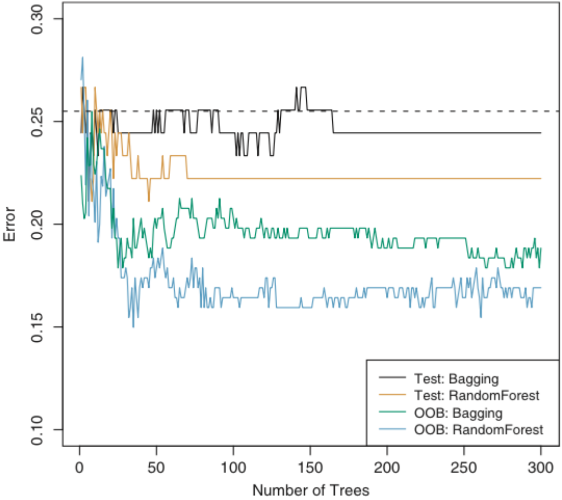
- Historically, it is most closely associated with decision tree models.
- A very successful extension of bagged trees is the random forest classifier.
- The random forests algorithm further decorrelates the learned trees by only considering a random sub-set of the available features when deciding which variable to split on at each node in the tree.

Example: Bagging vs Random Forests



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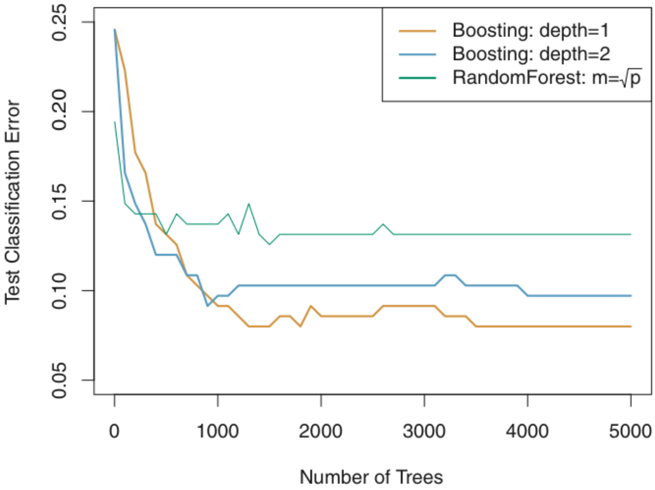
- Assuming that the base classifier can always achieve an error of less than 0.5 on any data sample, the boosting ensemble can be shown to decrease error.

AdaBoost Algorithm

1. **Input:** $S = \{(\boldsymbol{x}_1, y_1), \ldots, (\boldsymbol{x}_N, y_N)\}$, Number of Iterations T
2. **Initialize:** $d_n^{(1)} = 1/N$ for all $n = 1, \ldots, N$
3. **Do for** $t = 1, \ldots, T$,
   (a) Train classifier with respect to the weighted sample set $\{S, \mathbf{d}^{(t)}\}$ and obtain hypothesis $h_t : \boldsymbol{x} \mapsto \{-1, +1\}$, i.e. $h_t = \mathfrak{L}(S, \mathbf{d}^{(t)})$
   (b) Calculate the weighted training error ε_t of h_t:
   $$\varepsilon_t = \sum_{n=1}^{N} d_n^{(t)} \mathbf{I}(y_n \neq h_t(\boldsymbol{x}_n)) \ ,$$
   (c) Set:
   $$\alpha_t = \frac{1}{2} \log \frac{1 - \varepsilon_t}{\varepsilon_t}$$
   (d) Update weights:
   $$d_n^{(t+1)} = d_n^{(t)} \exp\{-\alpha_t y_n h_t(\boldsymbol{x}_n)\} / Z_t \ ,$$
   where Z_t is a normalization constant, such that $\sum_{n=1}^{N} d_n^{(t+1)} = 1$.
4. **Break if** $\varepsilon_t = 0$ or $\varepsilon_t \geq \frac{1}{2}$ and set $T = t - 1$.
5. **Output:** $f_T(\boldsymbol{x}) = \sum_{t=1}^{T} \frac{\alpha_t}{\sum_{r=1}^{T} \alpha_r} h_t(\boldsymbol{x})$

Example: AdaBoost



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- The trained classifiers are used to make predictions on the validation data set and a new feature representation is then created where each data case consists of the vector of predictions of each classifier in the ensemble $\tilde{\mathbf{x}} = [f_1(\mathbf{x}), \ldots, f_K(\mathbf{x})]$.

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- The extra layer of combiner learning can deal with correlated classifiers as well as classifiers that perform poorly.

Example: Netflix Prize (2009)

Netflix Prize COMPLETED

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Leaderboard

Showing Test Score. Click here to show quiz score

Display top 20 **leaders.**

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22
3	Grand Prize Team	0.8582	9.90	2009-07-10 21:24:40
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31
5	Vandelay Industries !	0.8591	9.81	2009-07-10 00:32:20
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Winning team used stacked predictor of 450+ different models.

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- We've covered a good mix of classical and state-of-the-art classifiers including KNN, decision trees, naive Bayes, LDA, logistic regression, SVMs, neural networks and ensembles.

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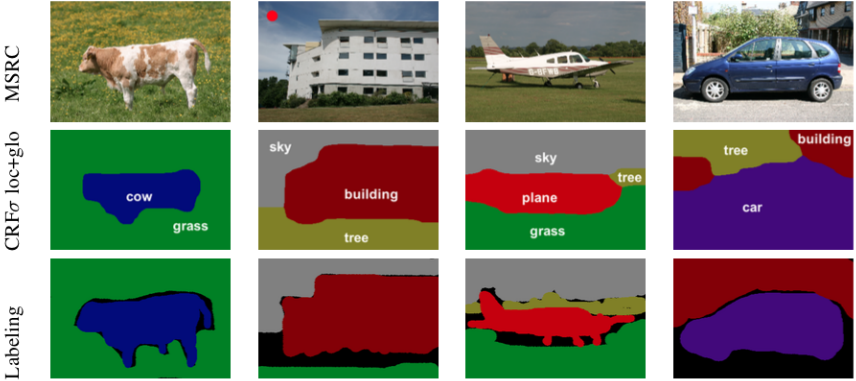
- Things we didn't cover: feature selection, feature engineering, dealing with class imbalance, covariate shift, cost of errors, classifier evaluation beyond accuracy, structured prediction, sequential decisions...

Classifier Evaluation

		actual value		
		p	*n*	total
prediction outcome	*p'*	True Positive	False Positive	P'
	n'	False Negative	True Negative	N'
	total	P	N	

Image Segmentation



Mesh Segmentation

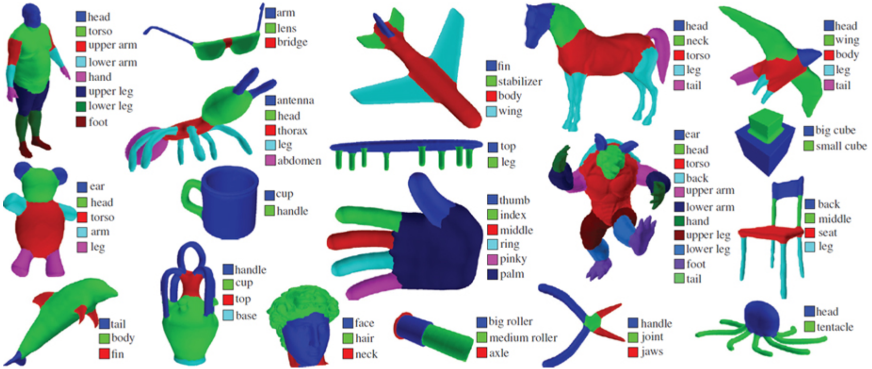


Image to Text

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A very cute looking cat in a hat

Playing Atari Breakout

https://www.youtube.com/watch?v=EfGD2qveGdQ