

Ensemble

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Which Classifier/Model to Choose?

- Possible strategies:
- Go from simplest model to more complex model until you obtain desired accuracy
- Discover a new model if the existing ones do not work for you
- Combine all (simple) models

Common Strategy: Bagging

(Bootstrap Aggregating)

Originally designed for combining multiple models, to improve classification “stability” [Leo Breiman, 94]

Uses random training datasets
(sampled from one dataset)

<http://statistics.about.com/od/Applications/a/What-Is-Bootstrapping.htm>

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Consider the data set $S = \{(X_i, Y_i)\}_{i=1, \dots, n}$

- Pick a sample S^* with **replacement** of size n
(S^* called a “bootstrap sample”)

$$S \rightarrow x = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 9 & 10 & 11 & 12 \\ 20 & 21 & 22 & 23 \\ 5 & 6 & 7 & 8 \end{bmatrix} y = \begin{bmatrix} 1 \\ 1 \\ -1 \\ -1 \end{bmatrix}$$

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Consider the data set $S = \{(X_i, Y_i)\}_{i=1, \dots, n}$

- Pick a sample S^* with **replacement** of size n
(S^* called a “bootstrap sample”)
- Train on S^* to get a classifier f^*
- Repeat above steps B times to get f_1, f_2, \dots, f_B
- Final classifier $f(x) = \text{majority}\{f_b(x)\}_{j=1, \dots, B}$

Common Strategy: Bagging

Why would bagging work?

- Combining multiple classifiers reduces the variance of the final classifier

When would this be useful?

- We have a classifier with high variance

Bagging decision trees

Consider the data set S

- Pick a sample S^* with replacement of size n
- Grow a decision tree T_b
- Repeat B times to get T_1, \dots, T_B
- The final classifier will be

$$f(x) = \text{majority}\{f_{T_b}(x)\}_{b=1, \dots, B}$$

Random Forests

Almost identical to bagging decision trees,
except we introduce some randomness:

- Randomly pick m of the d available attributes, at every split when growing the tree
(i.e., $d - m$ attributes ignored)

Bagged **random** decision trees =
Random forests

What are our Hyper-Parameters in Random Forest

m = *Number of randomly chosen attributes*

Usual values for $m = \sqrt{d}, 1, 10$

d is number of dimensions or features or attributes

How to optimize m ? Cross-Validation

B = *Number of models or decision trees in Random Forest*

Keep adding trees until training error stabilizes (reaches to a plateau)

Important points about random forests

Algorithm (hyper) parameters

- Size/#nodes of each tree
 - as in when building a decision tree
- May randomly pick an attribute, and may even randomly pick the split point!
 - Significantly simplifies implementation and increases training speed
 - PERT - Perfect Random Tree Ensembles
<http://www.interfacesymposia.org/I01/I2001Proceedings/ACutler/ACutler.pdf>
 - Extremely randomized trees
<http://orbi.ulg.be/bitstream/2268/9357/1/geurts-mlj-advance.pdf>