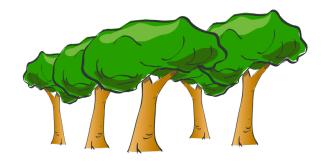
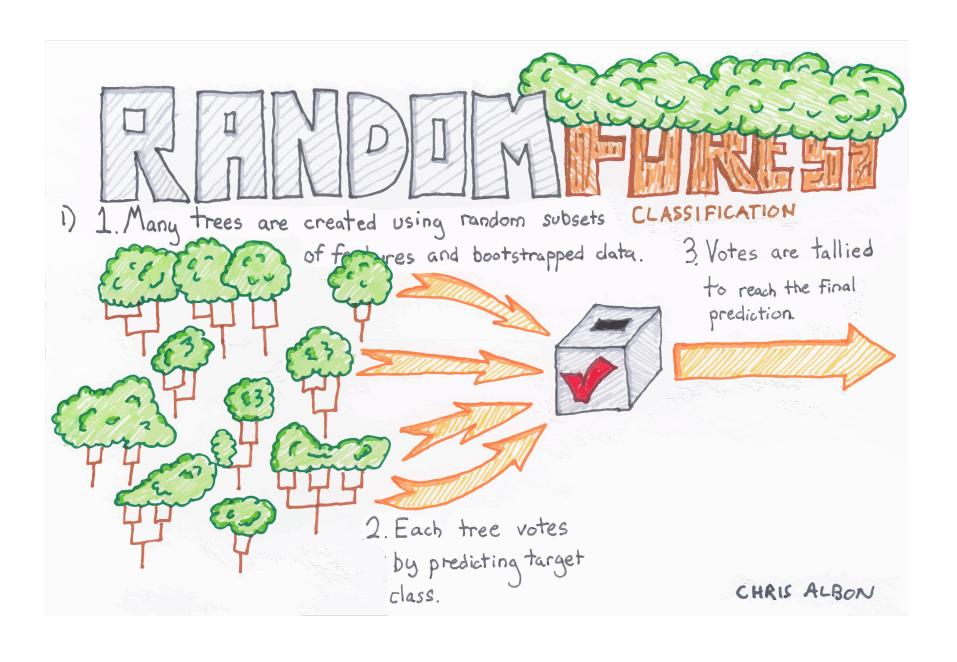
# What's better than a tree?

# **Random Forest**



- Can often improve performance of decision tree classifiers using a set of decision trees (a forest)
- Each tree trained on a random subset of training data
- Classify a data instance using all trees
- Combine answers to make classification
  - -E.g., vote for most common class



## cf. Wisdom of the Crowd



- Statistician Francis Galton observed a 1906 contest to guess an ox's weight at a country fair. 800 people entered. He noted that their average guess (1,197lb) was very close to the actual weight (1,198lb)
- When getting human annotations training data for machine learning, standard practice is get ≥ 3 annotations and take majority vote

#### **Random Forests Benefits**

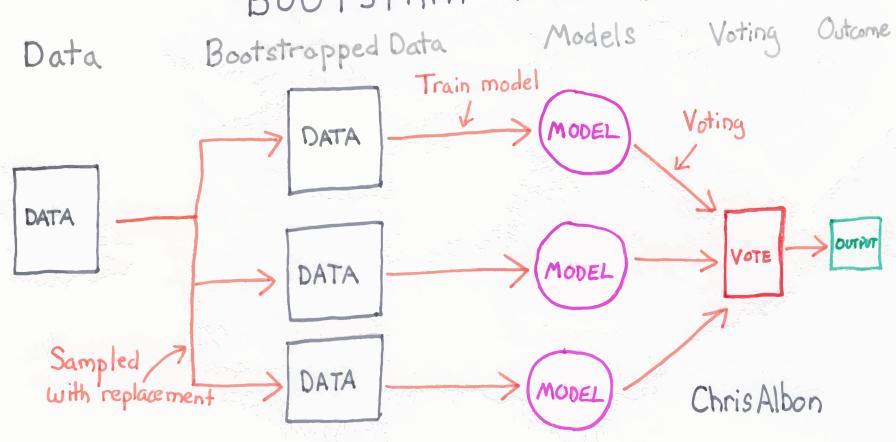
- Decision trees not the strongest modeling approach
- Random forests make them much stronger
- •=> more **robust** than a single decision tree
  - Limit overfitting to given dataset
  - Reduce errors due to training data bias
  - Stable performance if some noise added to training data

# **Bagging**



- Idea can be used on any classifier!
- Improve classification by combining classifycations of randomly selected training subsets
- Bagging = <u>Bootstrap aggregating</u>
  <u>ensemble</u> meta-algorithm that can improve stability & accuracy of algorithms for statistical classification and regression
- Helps avoid overfitting
- AKA ensembling





# **Choosing training data subsets**

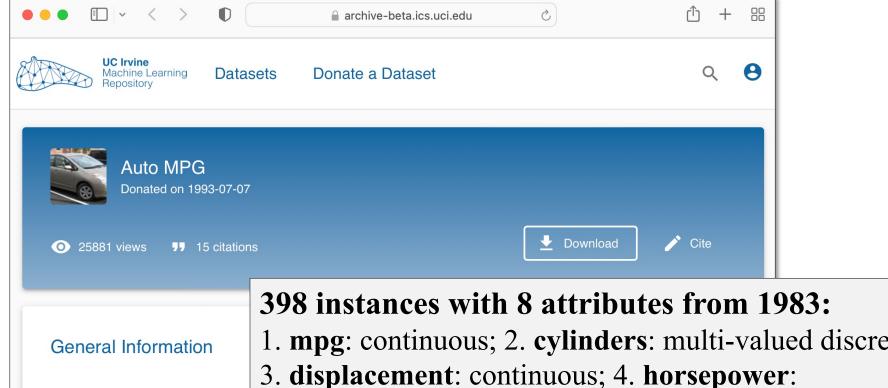
- Classic bagging: select random subset of training instances with replacement
- Pasting: select random subset of training instances (i.e., without replacement)
- Random Subspaces: use all training instances, but with a random subset of features
- Random Patches: random subset of instances and random subset of features
- Best? depends on problem, training data, algorithm

## **Examples**

- Two examples using Weka
  - -UCI Auto mpg prediction dataset
  - -UCI Adult income prediction dataset
- RandomForest improves over J48 for the smaller dataset, but not for the larger
- Takeaway: more data is always best

### **UCI Auto MGP Dataset**





Predict MPG from other 7 attributes

Revised from CMU StatLib librar

**Abstract** 

- 1. **mpg**: continuous; 2. **cylinders**: multi-valued discrete;

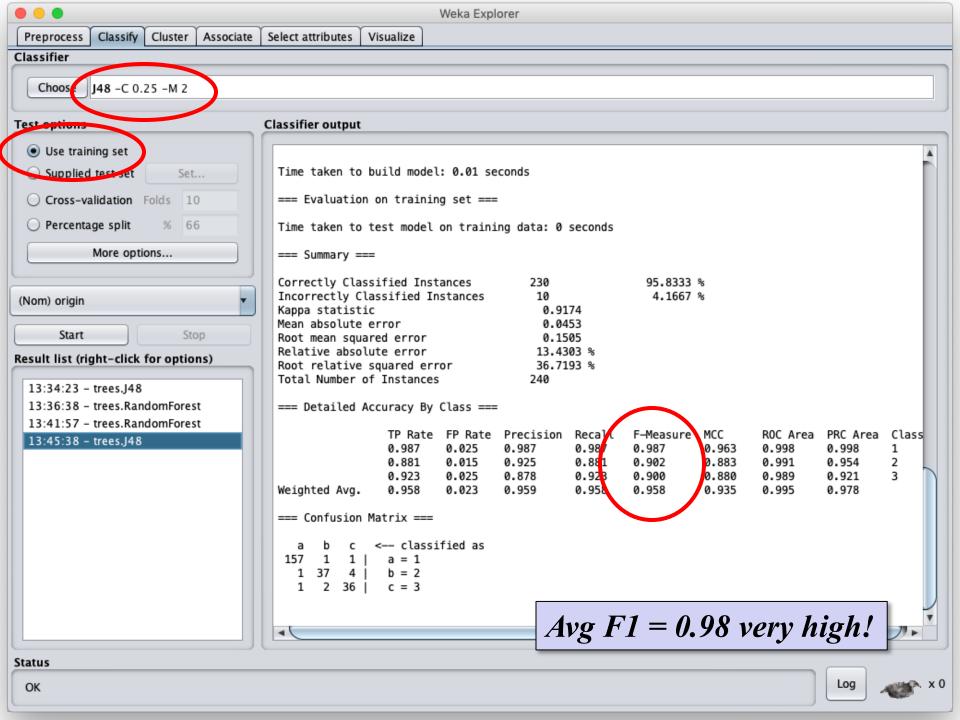
continuous; 5. weight: continuous; 6. acceleration:

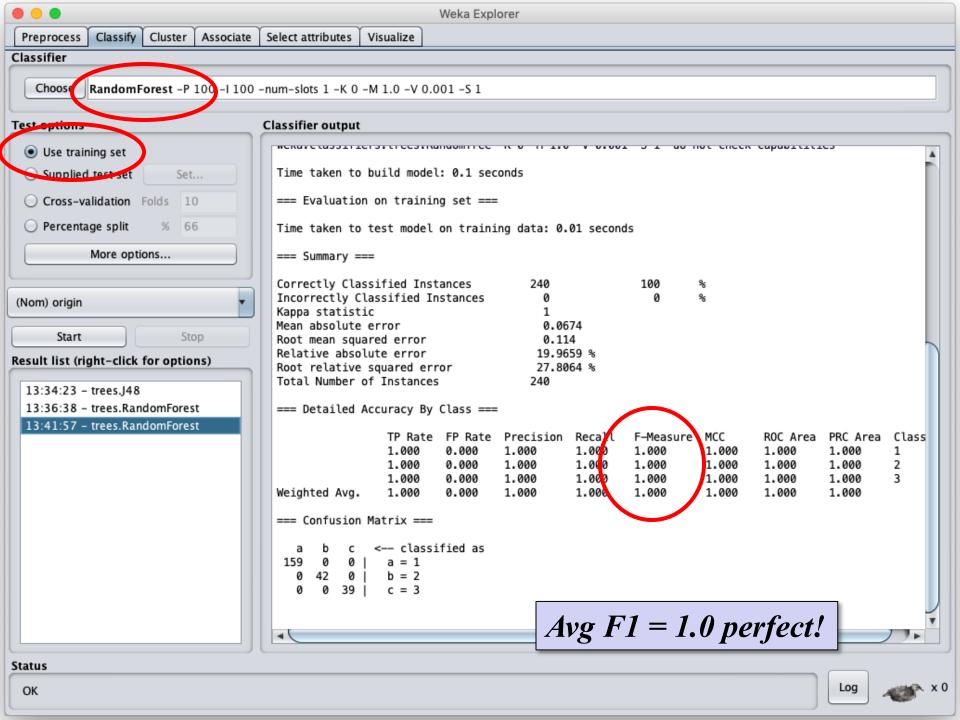
continuous; 7. model year: multi-valued discrete; 8.

origin: multi-valued discrete; 9. car name: string

(unique for each instance)

Arff training data (240); test data (132)





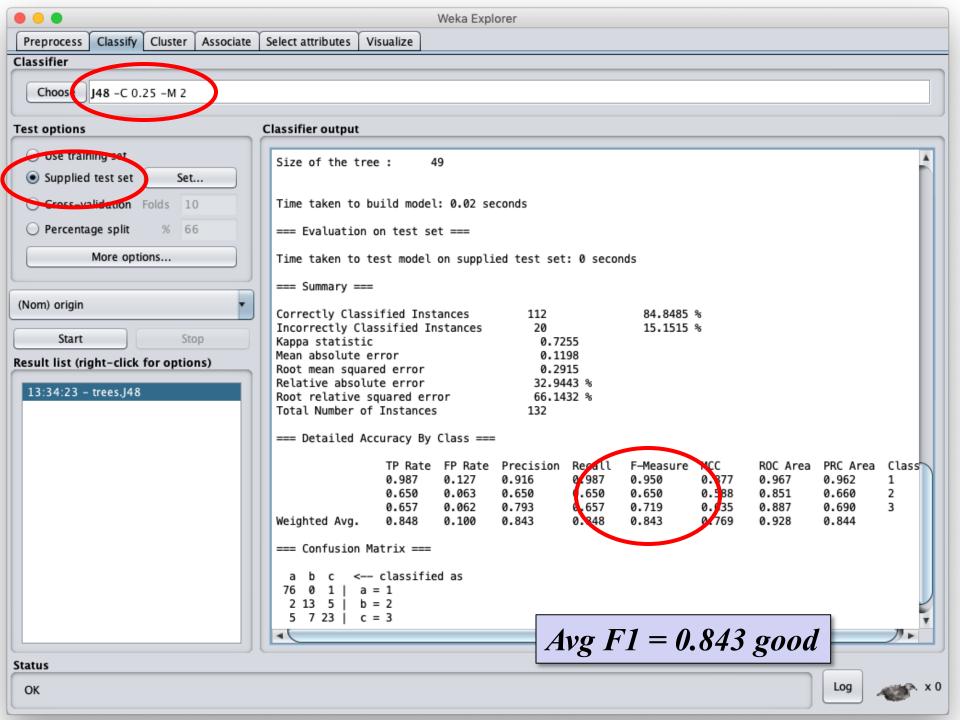
## 100% ... Wait, What?

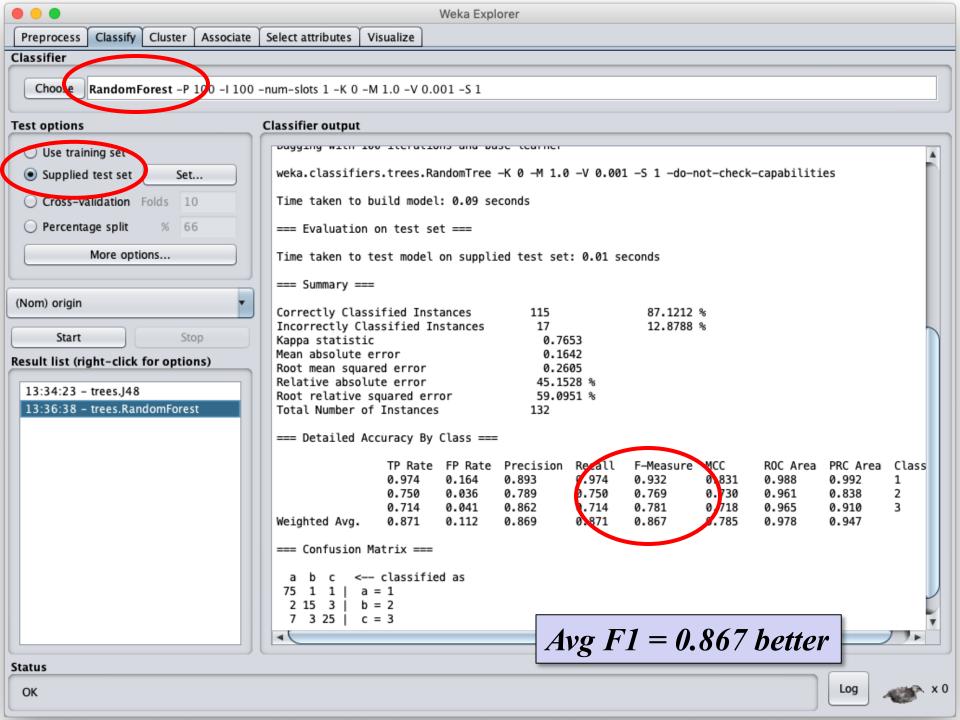


- Results are too good to be true!
  - -Something must be wrong
- ML results tend to be asymptotic
  - Asymptotic lines approach a curve but never touch
- Closer you get to F1=1.0, the harder it is to improve
- What did we do wrong?

## Results are too good

- Relatively small dataset allows construction of a DT model that does very well
- Using Random Forest still got perfect results!
- We trained and tested on the same data!
- Very poor methodology since it overfits to this particular training set
- This training dataset has a separate test data set
  - We can also try 10-fold cross validation



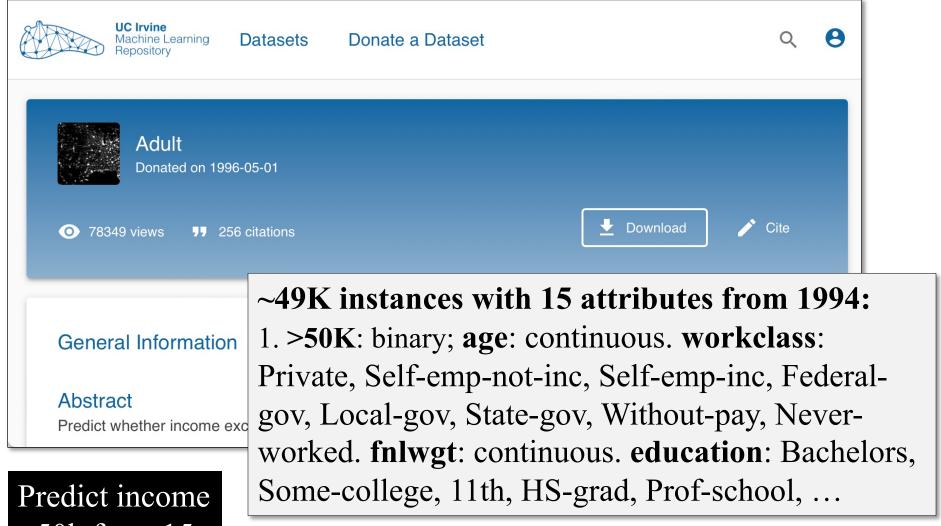


#### **New AUTO MPG Results**

- Using an independent test set shows more realistic balanced F1 score of .843
- Using Random Forest raises this to .867
- While the increase is not large, it is probably statistically significant
- F1 scores this high are difficult to increase dramatically
  - -Human scores for many tasks are often in this range (i.e., 0.8 0.9)

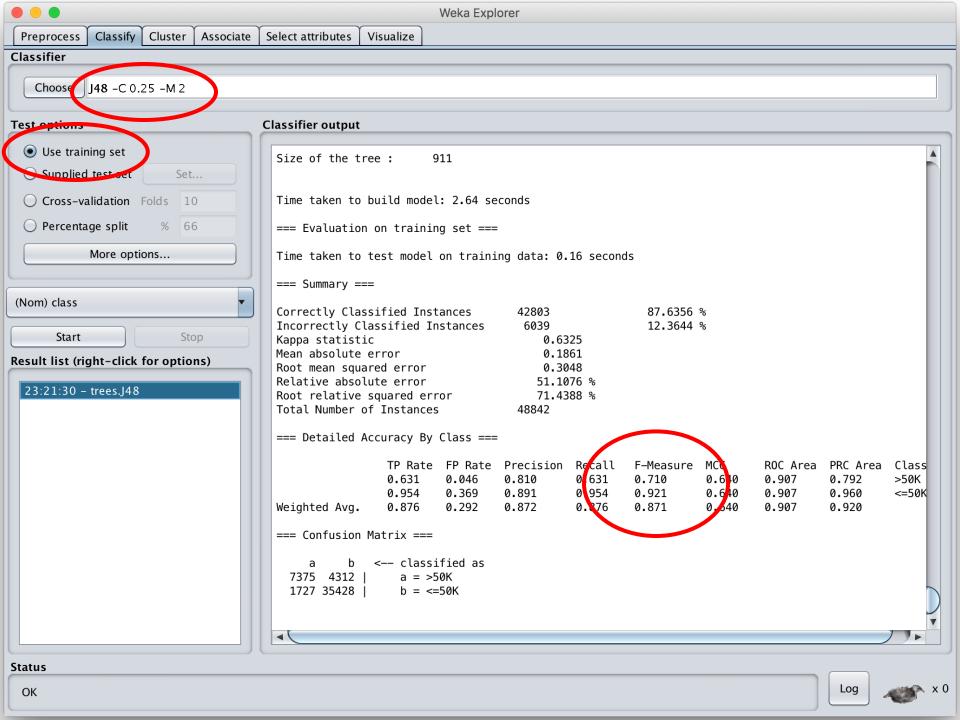
#### **UCI Adult Census Income Dataset**

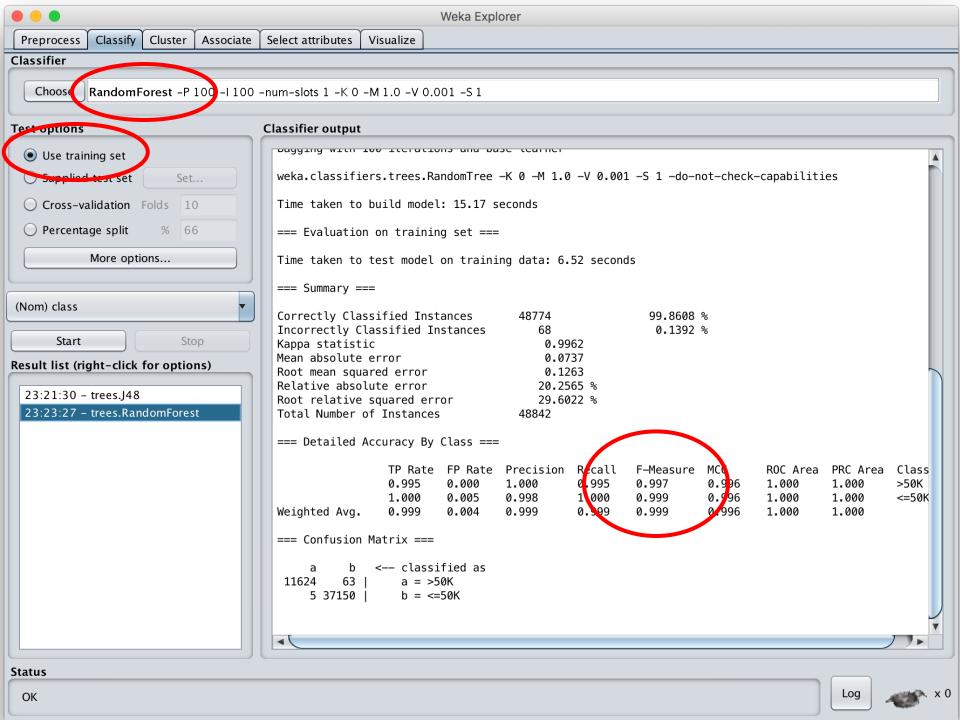




>50k from 15 attributes

Arff data



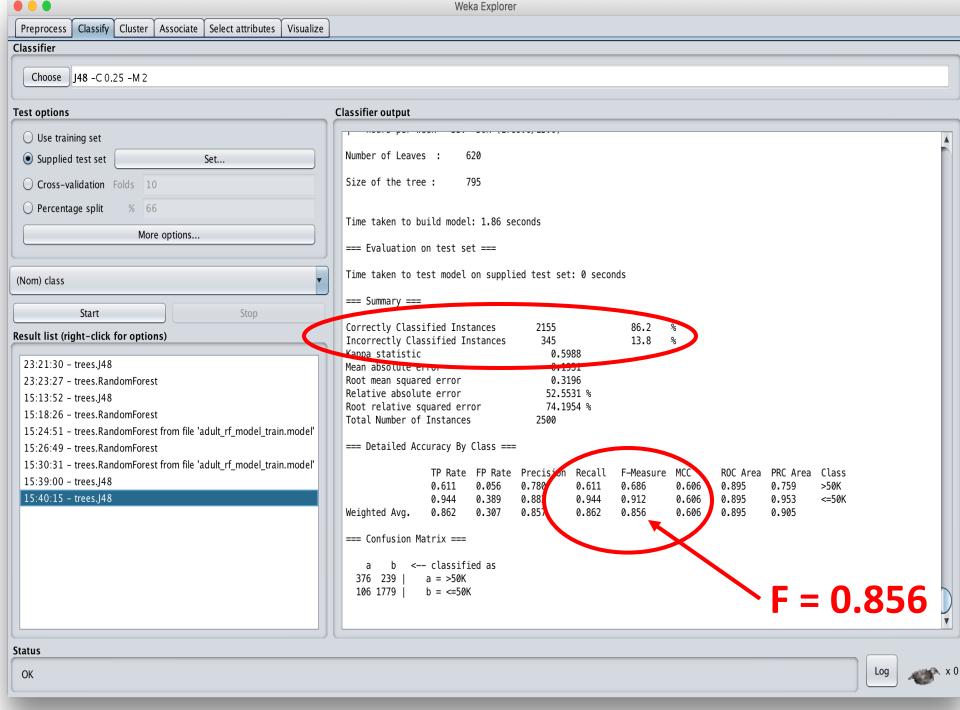


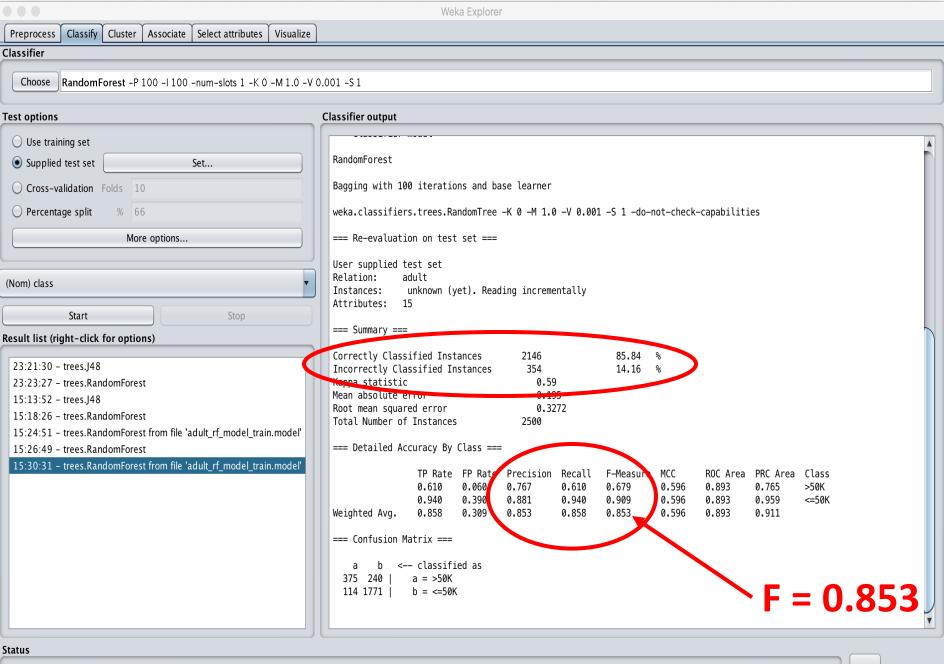
#### Result

- Significant increase on F1 scores when both trained and evaluated on training set
- This is considered to be poor methodology since it overfits to the particular training set

#### Create train and test collection

- Train has ~95% of data, test 5%
- Trained models for J48 and random forest using train dataset
- Tested on test data set
- Results were that random forest was (at best) about the same as J48
- Large dataset reduced problem of overfitting, so random forest did not help





OK

Log

## Conclusions

- Bagging helps, especially if training data adequate, but not as large as it should be
  - With lots of data, <u>overfitting</u> less of a problem, so bagging may not help
- While we explore it using decision trees, it can be applied to any classifier
  - Scikit-learn has a general module for bagging
- In general, using any of several **ensemble** approaches to classification often helpful
- Training neural networks uses a different approach (<u>dropout</u>) to control overfittting

## Conclusions

- Wait, there's more...
- A classification problem can change over time
  - E.g.: recognizing a spam message from its content and metadata
- We showed that an ensemble approach can detect a change in the nature of spam
  - Which tells us its time to retrain with new data
  - D. Chinavle, P. Kolari, T. Oates, and T. Finin, Ensembles in Adversarial Classification for Spam, ACM CIKM, 2009. <a href="https://link.pubm.nih.gov/link.org/">link</a>

## **Recognizing Concept Drift**

- Build ensemble of five models to classify spam comments left on a blog at time T1
- Note the relative level of agreement
- Detect when one of the models starts to diverge from the others with at time T2
  - -Time to get new data and retrain
  - Examining disagreements can be enlightening
- Used temporal data spanning several years to prove effectiveness
  - -E.g., spam focus shift from *viagra* to *weight loss*