Decision forests

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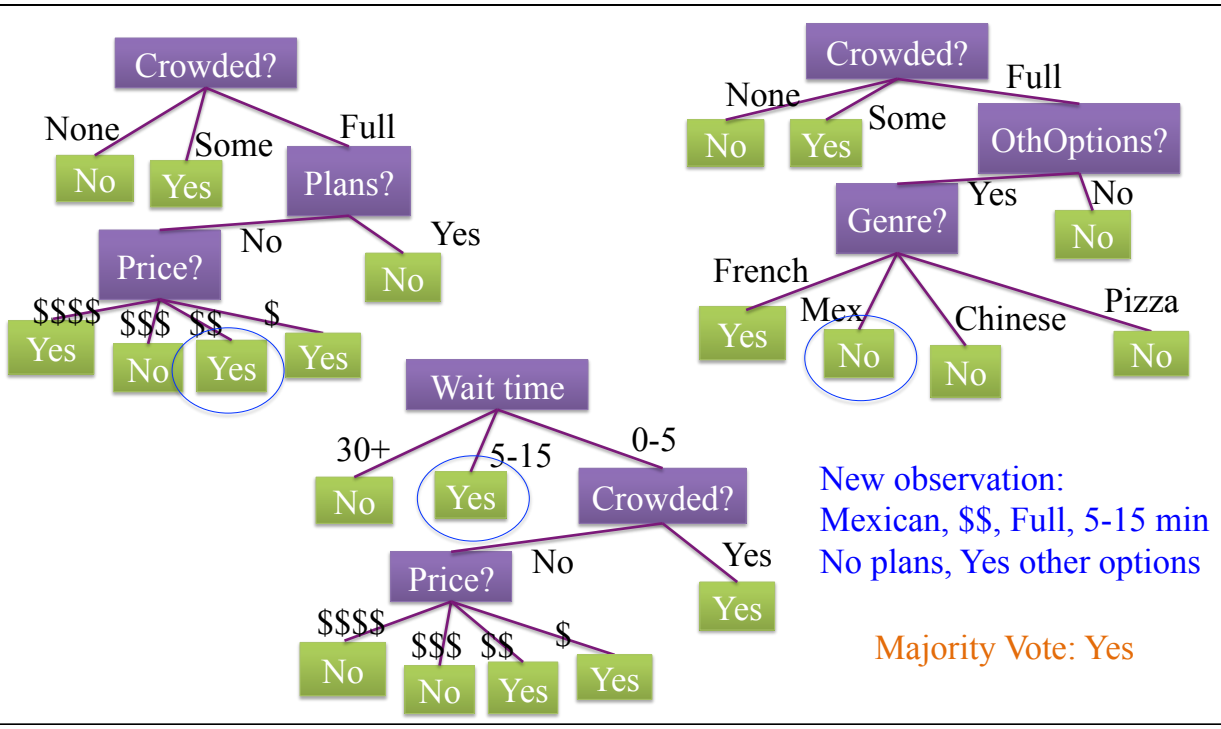
Decision Forests

- Complex and powerful prediction tool
- Black-box
- Uses similar idea to boosted decision trees: if you average many uncorrelated yet accurate models, it reduces variance.

Decision Forests

- Example: Will the customer wait for a table at a restaurant?
  - OthOptions: Other options, True if there are restaurants nearby.
  - Weekend: This is true if it is Friday, Saturday or Sunday.
  - Area: Does it have a bar or other nice waiting area to wait in?
  - Plans: Does the customer have plans just after dinner?
  - Price: This is either $, $$, $$$, or $$$$
  - Precip: Is it raining or snowing?
  - Genre: French, Mexican, Thai, or Pizza
  - Wait: Wait time estimate: 0-5 min, 5-15 min, 15+
  - Crowded: Whether there are other customers (no, some, or full)

Credit: Adapted from Russell and Norvig



Decision Forests

A bootstrap sample of size n: Draw n points *with replacement* at random from the training data.

(So you have some repeated points, and that's ok.)

Decision Forests

For t=1 to T:

- Draw a bootstrap sample of size n from the training data.
- Grow a tree ($tree_t$) using this splitting and stopping procedure:
  - Choose m features at random (out of p)
  - Evaluate the splitting criteria on all of them
  - Split on the best feature
  - If the node has less than n_{min} then stop splitting.

Output all the trees.

To predict on a new observation x, use the majority vote of the trees on x.

Decision Forests

Make trees diverse, which reduces variance

Comparison with decision trees:

- Bootstrap resamples
- Splitting considers only m possible (randomly chosen) features
- No pruning

Make trees fit more tightly, reduces bias

- Majority vote of several trees is used to make predictions

Decision Forests: Measuring Variable Importance

- Let us measure the "importance" of variable j.
- Take the data not used to construct $tree_t$. Call it "out-of-bag", OOB_t.
- Compute $error_t$, using model $tree_t$ on data OOB_t.
- Now randomly permute only the j^{th} feature values.

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Reorder me!

OOB →

$$\begin{pmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ x_{31} & x_{32} & x_{33} \end{pmatrix}$$

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Decision Forests: Measuring Variable Importance

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- Take the data not used to construct $tree_t$. Call it "out-of-bag", OOB_t.
- Compute $error_t$, using model $tree_t$ on data OOB_t.
- Now randomly permute only the j^{th} feature values. Call this $OOB_{t,permuted}$.
- Compute $error_{t,permuted}$, using model $tree_t$ on data $OOB_{t,permuted}$.
- The "raw importance" of variable j is then the average over trees of the difference: $\frac{1}{T}\sum_{\text{trees } t}\left(\text{error}_t - \text{error}_{t,\text{ permuted}}\right)$

Decision Forests for Regression

For t=1 to T:

- Draw a bootstrap sample of size n from the training data.
- Grow a tree ($tree_t$) using this splitting and stopping procedure:
  - Choose m features at random (out of p)
  - Evaluate the splitting criteria on all of them
  - Split on the best feature
  - If the node has less than n_{min} then stop splitting.

Output all the trees.

To predict on a new observation x, use the average vote of the trees on x.

Decision Forests

Advantages

- Complex and powerful prediction tool, highly nonlinear

Disadvantages

- Black-box
- Tends to overfit unless tuned carefully (not always intuitive with the R package)
- Slow