Fundamental Methods of Data Science

Class 6

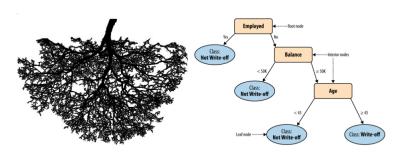
Tomer Libal

Tree-Structured Models

- ► In the previous class, you learned how to choose the most informative attributes
- ▶ Is it enough for creating a good model?

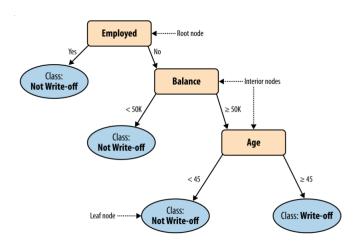
Tree-Structured Models

- ► In the previous class, you learned how to choose the most informative attributes
- ▶ Is it enough for creating a good model?



Tree-Structured Models

- Classify 'John Doe'
 - ▶ Balance=115K, Employed=No, and Age=40



Tree-Structured Models: "Rules"

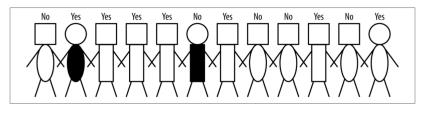
- No two parents share descendants
- There are no cycles
- The branches always "point downwards"
- Every example always ends up at a leaf node with some specific class determination
 - Probability estimation trees, regression trees (to be continued ...)

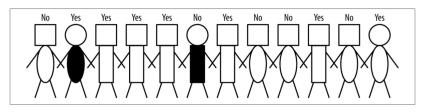
▶ How do we create a classification tree from data?

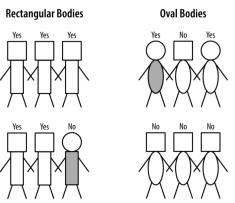
- ▶ How do we create a classification tree from data?
 - divide-and-conquer approach
 - take each data subset and recursively apply attribute selection to find the best attribute to partition it

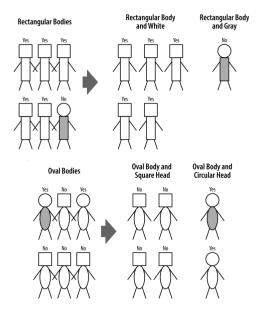
- ▶ How do we create a classification tree from data?
 - divide-and-conquer approach
 - take each data subset and recursively apply attribute selection to find the best attribute to partition it
- ▶ When do we stop?

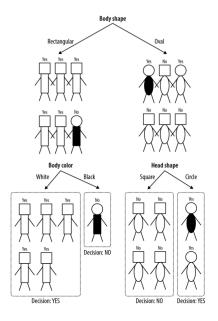
- ▶ How do we create a classification tree from data?
 - divide-and-conquer approach
 - take each data subset and recursively apply attribute selection to find the best attribute to partition it
- ▶ When do we stop?
 - ▶ The nodes are pure, or
 - there are no more variables, or
 - even earlier (over-fitting, to be continued . . .)











Why Trees?

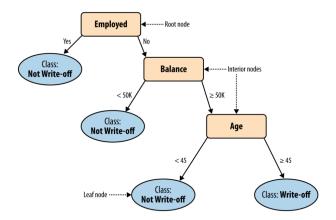
- ▶ Decision trees (DTs), or classification trees, are one of the most popular data mining tools
- ► They are:
 - Easy to understand
 - ► Easy to implement
 - Easy to use
 - Computationally cheap
- Almost all data mining packages include DTs
- They have advantages for model comprehensibility, which is important for:
 - model evaluation
 - communication to non-DM-savvy stakeholders

Trees as Sets of Rules

- ▶ The classification tree is equivalent to this rule set
 - Each rule consists of the attribute tests along the path connected with AND

Trees as Sets of Rules

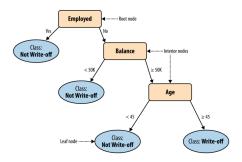
- ▶ The classification tree is equivalent to this rule set
 - Each rule consists of the attribute tests along the path connected with AND



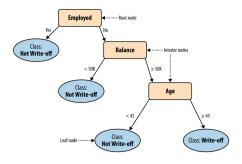
► Would a yes/no answer be enough? How can you improve over that?

- ► Would a yes/no answer be enough? How can you improve over that?
 - MegaTelCo might want to rank customers according to their probability of leaving

- ▶ Would a yes/no answer be enough? How can you improve over that?
 - MegaTelCo might want to rank customers according to their probability of leaving



- Would a yes/no answer be enough? How can you improve over that?
 - MegaTelCo might want to rank customers according to their probability of leaving



How can you improve your answer?

From Classification Trees to Probability Estimation Trees

- Frequency-based estimate
 - Basic assumption: Each member of a segment corresponding to a tree leaf has the same probability to belong in the corresponding class
 - ▶ If a leaf contains n positive instances and m negative instances (binary classification), the probability of any new instance being positive may be estimated as $\frac{n}{n+m}$

From Classification Trees to Probability Estimation Trees

- Frequency-based estimate
 - Basic assumption: Each member of a segment corresponding to a tree leaf has the same probability to belong in the corresponding class
 - ▶ If a leaf contains n positive instances and m negative instances (binary classification), the probability of any new instance being positive may be estimated as $\frac{n}{n+m}$
- Prone to over-fitting, why?

Laplace Correction

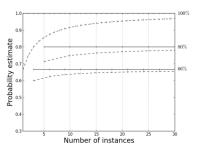
$$p(c) = \frac{n+1}{n+m+2}$$

where n is the number of occurrences of c in the set and m is the number of all other occurrences

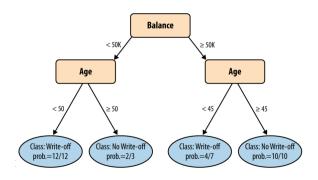
Laplace Correction

$$p(c) = \frac{n+1}{n+m+2}$$

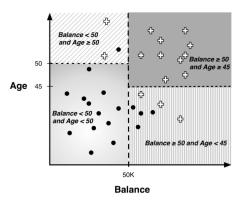
▶ where n is the number of occurrences of c in the set and m is the number of all other occurrences



Visualizing Segmentations



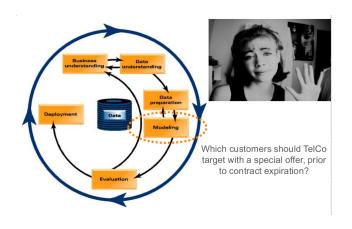
Visualizing Segmentations



The many faces of classification: Classification / Probability Estimation / Ranking

- Classification Problem
 - Most general case: The target takes on discrete values that are NOT ordered
 - Most common: binary classification where the target is either 0 or 1
- 2 Different Solutions to Classification
 - Classifier model: Model predicts the same set of discrete value as the data had
 - ▶ Probability estimation: Model predicts a score between 0 and 1 that is meant to be the probability of being in that class

Let's focus back in on actually mining the data..

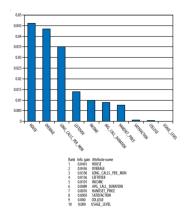


MegaTelCo: Predicting Churn with Tree Induction

| Variable | Explanation |
|-------------------------|--|
| COLLEGE | Is the customer college educated? |
| INCOME | Annual income |
| OVERAGE | Average overcharges per month |
| LEFTOVER | Average number of leftover minutes per month |
| HOUSE | Estimated value of dwelling (from census tract) |
| HANDSET_PRICE | Cost of phone |
| LONG_CALLS_PER_MONTH | Average number of long calls (15 mins or over) per month |
| AVERAGE_CALL_DURATION | Average duration of a call |
| REPORTED_SATISFACTION | Reported level of satisfaction |
| REPORTED_USAGE_LEVEL | Self-reported usage level |
| LEAVE (Target variable) | Did the customer stay or leave (churn)? |

What is the first step?

MegaTelCo: Predicting Churn with Tree Induction



▶ How will you build the tree?

MegaTelCo: Predicting Churn with Tree Induction

