Lecture 3: 12 April, 2021

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Data Mining and Machine Learning
April–July 2021

Market-Basket Analysis

- Items $I = \{i_1, i_2, \ldots, i_N\}$, transactions $T = \{t_1, t_2, \ldots, t_M\}$
- Identify all association rules $X \to Y$ meeting two thresholds
  - Confidence: $\dfrac{(X \cup Y).count}{X.count} \geq \chi$
  - Support: $\dfrac{(X \cup Y).count}{M} \geq \sigma$
- First identify frequent itemsets Z, such that $Z.count \geq \sigma M$
- Apriori algorithm
  - If X is not frequent, no $Y \supseteq X$ can be frequent
  - Find frequent sets levelwise: $F_1, F_2, \ldots$ are frequent itemsets of size $1, 2, \ldots$
- How do we generate association rules from frequent itemsets?

Naïve strategy

- For every frequent itemset Z
  - Enumerate all pairs $X, Y \subseteq Z$, $X \cap Y = \emptyset$
  - Check $\dfrac{(X \cup Y).count}{X.count} \geq \chi$
- Can we do better?
- Sufficient to check all partitions of Z
  - If $X, Y \subseteq Z$, $X \cup Y$ is also a frequent itemset

Association rules

- Sufficient to check all partitions of Z
- Suppose $Z = X \uplus Y$, $X \rightarrow Y$ is a valid rule and $y \in Y$
- What about $(X \cup \{y\}) \rightarrow Y \setminus \{y\}$?
  - Know $\dfrac{(X \cup Y).count}{X.count} \geq \chi$
  - Check $\dfrac{(X \cup Y).count}{(X \cup \{y\}).count} \geq \chi$
  - X.count $\geq (X \cup \{y\})$.count, always
  - Second fraction has smaller denominator, so $(X \cup \{y\}) \rightarrow Y \setminus \{y\}$ is also a valid rule

Observation: Can use apriori principle again!

Apriori for association rules

- If $X \to Y$ is a valid rule, and $y \in Y$, $(X \cup \{y\}) \to Y \setminus \{y\}$ must also be a valid rule
- If $X \to Y$ is not a valid rule, and $x \in X$, $(X \setminus \{x\}) \to Y \cup \{x\}$ cannot be a valid rule
- Start by checking rules with single element on the right
  - $Z \setminus z \to \{z\}$
- For $X \to \{x, y\}$ to be a valid rule, both $(X \cup \{x\}) \to \{y\}$ and $(X \cup \{y\}) \to \{x\}$ must be valid
- Explore partitions of each frequent itemset “level by level”

Association rules for classification

- Classify documents by topic
- Consider the table on the right
- Items are regular words and topics
- Documents are transactions — set of words and one topic
- Look for association rules of a special form
  - $\{$student, school$\} \rightarrow \{$Education$\}$
  - $\{$game, team$\} \rightarrow \{$Sports$\}$
- Right hand side always a single topic
- Class Association Rules

Words in document	**Topic**
student, teach, school	Education
student, school	Education
teach, school, city, game	Education
cricket, football	Sports
football, player, spectator	Sports
cricket, coach, game, team	Sports
football, team, city, game	Sports

Supervised learning

- A set of items
  - Each item is characterized by attributes $(a_1, a_2, \ldots, a_k)$
  - Each item is assigned a class or category c
- Given a set of examples, predict c for a new item with attributes $(a'_1, a'_2, \ldots, a'_k)$
- Examples provided are called training data
- Aim is to learn a mathematical model that generalizes the training data
  - Model built from training data should extend to previously unseen inputs
- Classification problem
  - Usually assumed to binary — two classes

Example: Loan application data set

ID	Age	Has_job	Own_house	Credit_rating	Class
1	young	false	false	fair	**No**
2	young	false	false	good	**No**
3	young	true	false	good	**Yes**
4	young	true	true	fair	**Yes**
5	young	false	false	fair	**No**
6	middle	false	false	fair	**No**
7	middle	false	false	good	**No**
8	middle	true	true	good	**Yes**
9	middle	false	true	excellent	**Yes**
10	middle	false	true	excellent	**Yes**
11	old	false	true	excellent	**Yes**
12	old	false	true	good	**Yes**
13	old	true	false	good	**Yes**
14	old	true	false	excellent	**Yes**
15	old	false	false	fair	**No**

Basic assumptions

Fundamental assumption of machine learning

- Distribution of training examples is identical to distribution of unseen data

What does it mean to learn from the data?

- Build a model that does better than random guessing
  - In the loan data set, always saying Yes would be correct about $9/15$ of the time
- Performance should ideally improve with more training data

How do we evaluate the performance of a model?

- Model is optimized for the training data. How well does it work for unseen data?
- Don't know the correct answers in advance to compare — different from normal software verification

The road ahead

Many different models

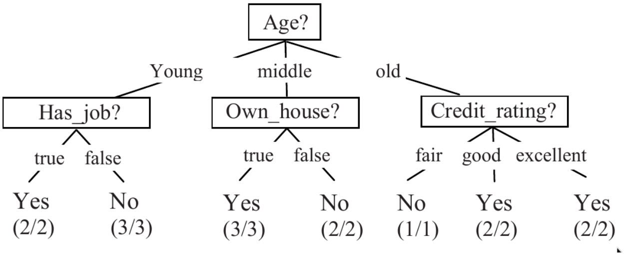
- Decision trees
- Probabilistic models — naïve Bayes classifiers
- Models based on geometric separators
  - Support vector machines (SVM)
  - Neural networks

Important issues related to supervised learning

- Evaluating models
- Ensuring that models generalize well to unseen data
  - A theoretical framework to provide some guarantees
- Strategies to deal with the training data bottleneck

Decision trees

- Play "20 Questions" with the training data
- Query an attribute
  - Partition the training data based on the answer
- Repeat until you reach a partition with a uniform category
- Queries are adaptive
  - Different along each path, depends on history



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Decision tree algorithm

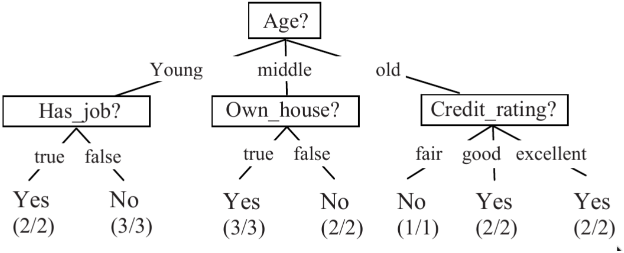
A : current set of attributes

Pick $a \in A$, create children corresponding to resulting partition with attributes $A \setminus \{a\}$

Stopping criterion:

- Current node has uniform class label
- A is empty — no more attributes to query

If a leaf node is not uniform, use majority class as prediction



- Non-uniform leaf node — identical combination of attributes, but different classes
- Attributes do not capture all criteria used for classification

Decision trees

- Tree is not unique
- Which tree is better?
- Prefer small trees
  - Explainability
  - Generalize better (see later)

Unfortunately

- Finding smallest tree is NP-complete — for any definition of "smallest"
- Instead, greedy heuristic