Car Insurance

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Competition details Jan Tomášek

Official text

- As a customer shops an insurance policy, he/she will receive a number of quotes with different coverage options before purchasing a plan.
- Using a customer's shopping history, can you predict what policy they will end up choosing?

Evaluation

Submissions are evaluated on an all-or-none accuracy basis. You must predict every coverage option correctly to receive credit for a given customer. Your score is the percent of customers for whom you predict the exact purchased policy.

Prizes

- First place: \$25,000
- Second place: \$15,000
- Third place: \$10,000

Data structure

customer_ID, **record_type**, dateTime, location, group_size, homeowner, **car_age**, **car_value**, **risk_factor**, **age_oldest**, **age_youngest**, married_couple, **C_previous**, duration_previous, **A,B,C,D,E,F,G**, cost

Product options

Option name	Possible values
Α	0, 1, 2
В	0, 1
С	1, 2, 3, 4
D	1, 2, 3
E	0, 1
F	0, 1, 2, 3
G	1, 2, 3, 4

Solution 0

- Last quoted plan benchmark
 53%
- don't use exactly last quoted but average
 - weighted sum
 - deduce weights on train set
 - using genetic
 - based on user info
 - regresion
 - based on column only

Our common interface

- Meta level script combining various solutions
 BASH
- Aggregates solution's outputs using their confidence flag

Weka

- Weka is a collection of machine learning algorithms for data mining tasks
- University of Waikato
- Very complex software

Weka live example

weather

Better features and problem reductions

Michal Pokorný

Better features, problem reductions

- Exponential distribution of plans
 283 plans w/ >100 purchases, 1700 plans total
- Most customers (~73%) choose some offered plan
- Some features seem less relevant
 Time

Ideas to try

- Basic classifier trained on crude features was no better than naive solution
 - Naive: always pick the last plan
- Benchmark other naive solutions
 - Weight plan features by how many times were they picked, etc.
- Gain insights to meaning of individual plan properties

Ideas to try

- Train classifiers on mutilated original training data
- How many customers change their properties during the quoting process?
- Train a classifier just to decide when to use naive heuristic (performance ~53%)

Implementation: scikit-learn (Python)

Unsupervised learning approach

Štěpán Havránek

Unsupervised learning

• Mix of

- Clustering
- Evolution (genetic programming)

Clustering

- Somehow split the data items into categories
- Each category stands for one output
- New item is categorized and sets its output according to its category

Clustering



Clustering - our case

- Large input dimension
- Big value range of some input dimensions
- Not always ordered set
 - Enums
 - Date/Time
 - Geographic data
- Quite large output dimension
 - 7 output variables (ranges between 2 4)

Clustering - customization

- Choose only some features
- Overridden metric
 - Weighted distance for each dimension
 - Own ordering
 - Binary metric
 - Proprietary total order

Clustering - customization

Output

- Clustered categories for group of outputs instead of one particular output
 - Particular output will be decided by aggregation of category outputs
- \circ = Classification -> characteristic vector
- Output can carry information about its certainty

Clustering - categorization

• K nearest neighbours

- Parameter K
- Static/dynamic version
- M means (gravity centers)
 - M is given by number of categories we want to differentiate
 - Static/dynamic version
- Hierarchical clustering

Clustering - model complexity

• Our model is quite complex

- A lot of parameters
 - Categorization technique
 - Its parameters
 - Feature weights
 - Own metrics
 - Output policy
- How to guess this parameters?
 - Tryout
 - Let the evolution do the work

Clustering and genetics

- Population member
 - Vector of numeric values
 - Weights
 - Parameters for categorization technique
 - Enum values
 - Categorization technique
 - Output aggregation type

