

# Car Insurance

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# Sumo report - expectations



# Sumo report - reality





# Bc. Jan Tomášek

Deeper look into data set  
Column approach

# Reminder

What the hell is this competition about ???



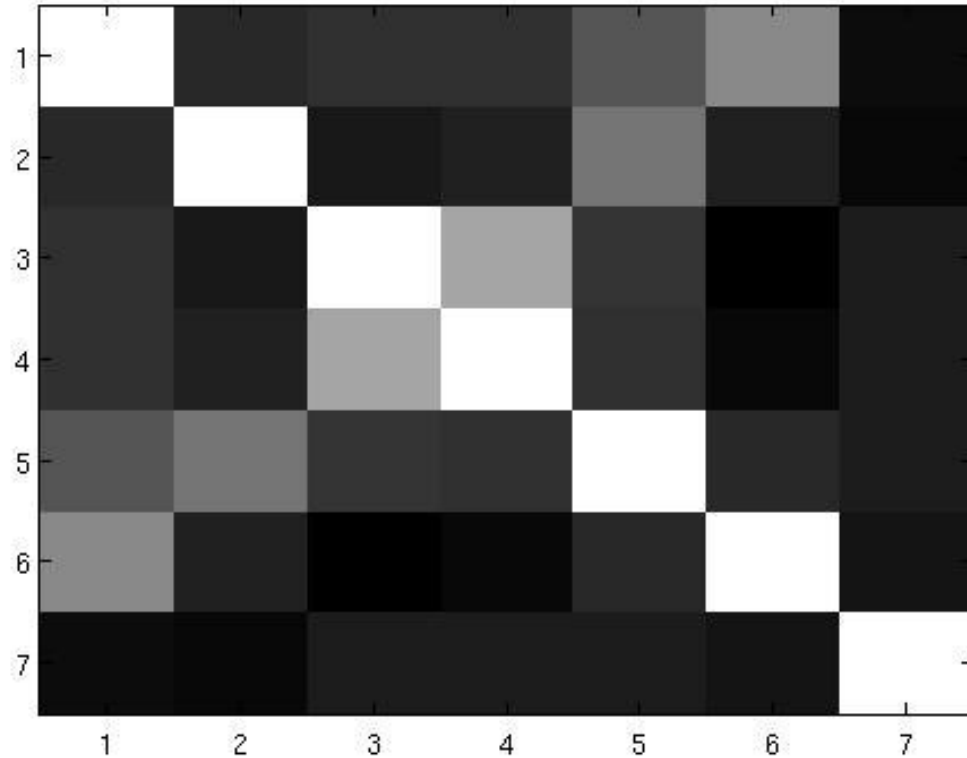
# Attributes overview

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

# Data problems

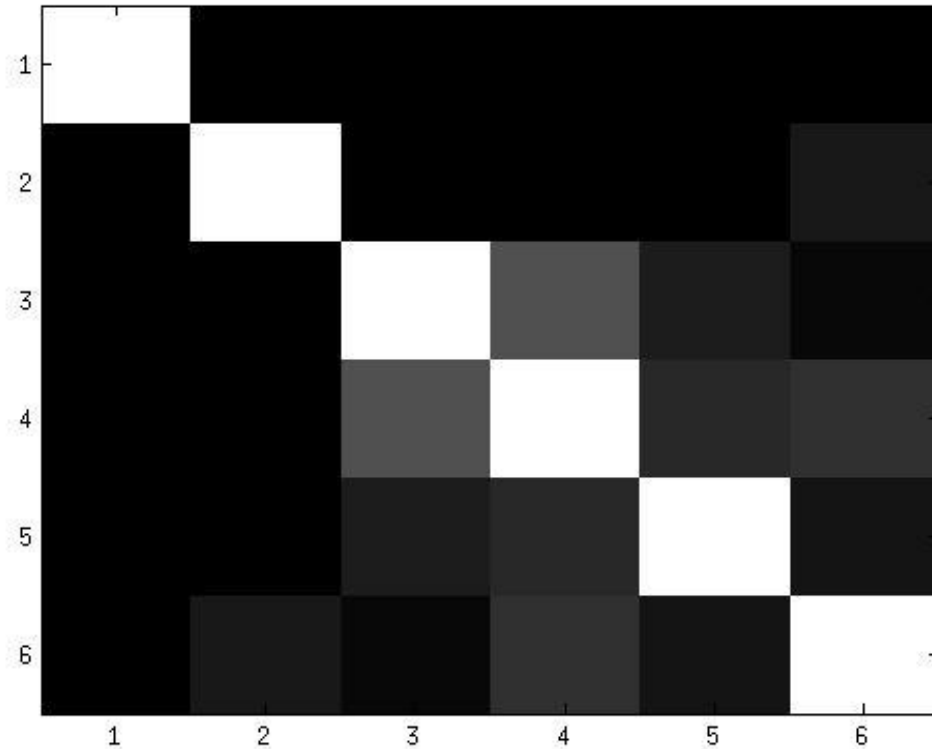
- lot of nan values in
  - risk factor
  - c\_previous
  - nan values replaced with 0
- some attributes have to big granularity
  - date time
    - probably no need to use at all

# Column correlation 1





# Column correlation `corr([location risk_factor cost A B C])`



# Correlation result

- almost no linear dependency
- no chance to categorize with linear regression
- we need to add at least quadratic/cubic coefficients or use svm machines with clever kernel function

# Column approach Motivation

- last quotes benchmark 53%
- 72% buys previously visited product
- Can we bring our result nearer to 72% ?
- average gives 45%
  - need something more clever
  - older are more important than previous views
    - weighted average instead

# Future work

- better data filter and normalization
- clever column approach
- keep compatibility with our interface for result combinations
- don't ever try to win sumo competition again

# .Net & Horizontal data view

Štěpán Havránek



# Machine learning & .Net

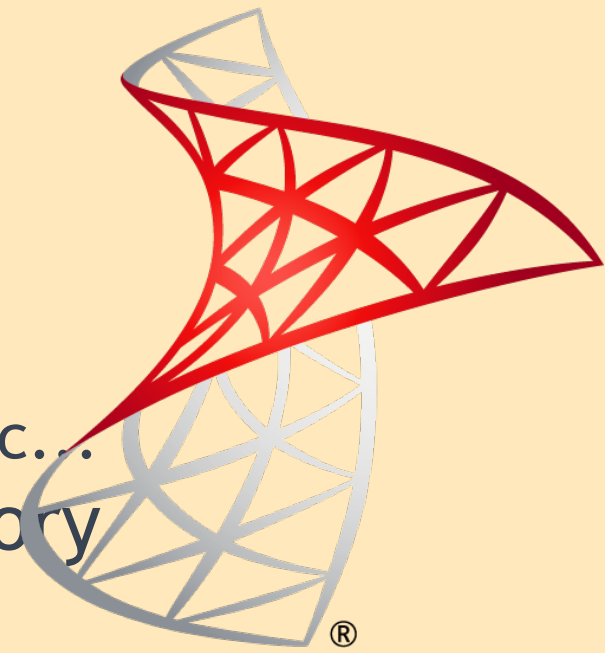
- Accord framework
  - <http://accord-framework.net>
  - Complex Computer science library
    - Math
    - Statistics
    - Machine learning
    - Neural networks
  - Uniform interface
  - Various data manipulation utilities

# Machine learning & .Net

- AForge framework
  - <http://www.aforgenet.com/>
  - Primary for computer vision
  - Libraries for Computer Science
    - Especially Artificial intelligence

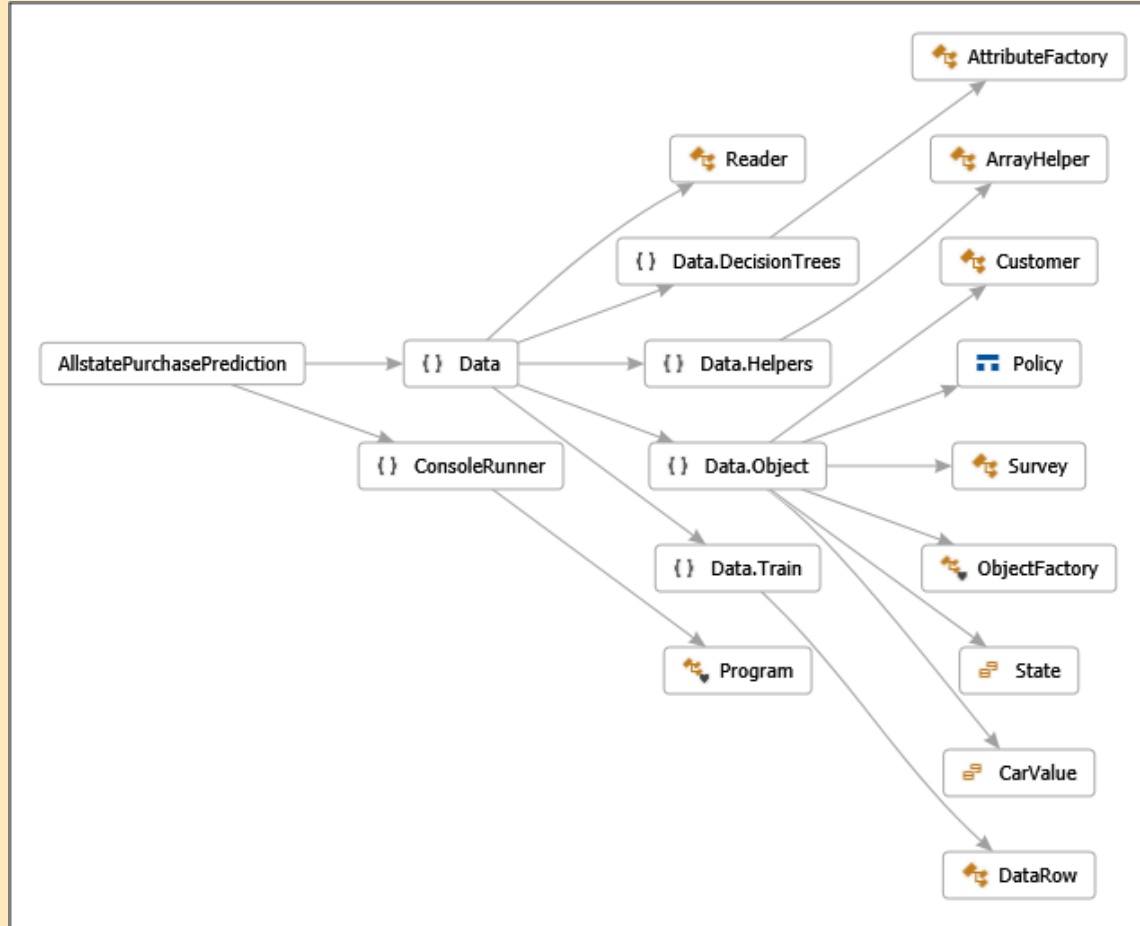
# .Net implementation

- Data in MS SQL Server
  - Easy to fetch, aggregate, view, etc...
- Object model and object factory
  - Easy to transform
  - Made in Object Factory





# .Net implementation



# Data horizontal view

- What the customer info can say about the result purchased product parameters?
  - Seven output parameters
    - mostly 4 options per each
- Let's try to make a model only on customer parameters and verificate it

# Data horizontal view

- Decision trees
  - Input attributes
    - Customer and his car info
      - Ages
      - Car value
      - Group size
      - Is homeowner
      - Is married
      - Risk factor
      - Previous purchase info

# Data horizontal view

- Decision trees
  - Used learning algorithms
    - ID3
    - C4.5
- Model verification
  - 10 times cross validation
    - => 10 different models (trees)
  - Process
    - Split the data
    - Create (learn) model
    - Validate outputs

# Data horizontal view

- Results

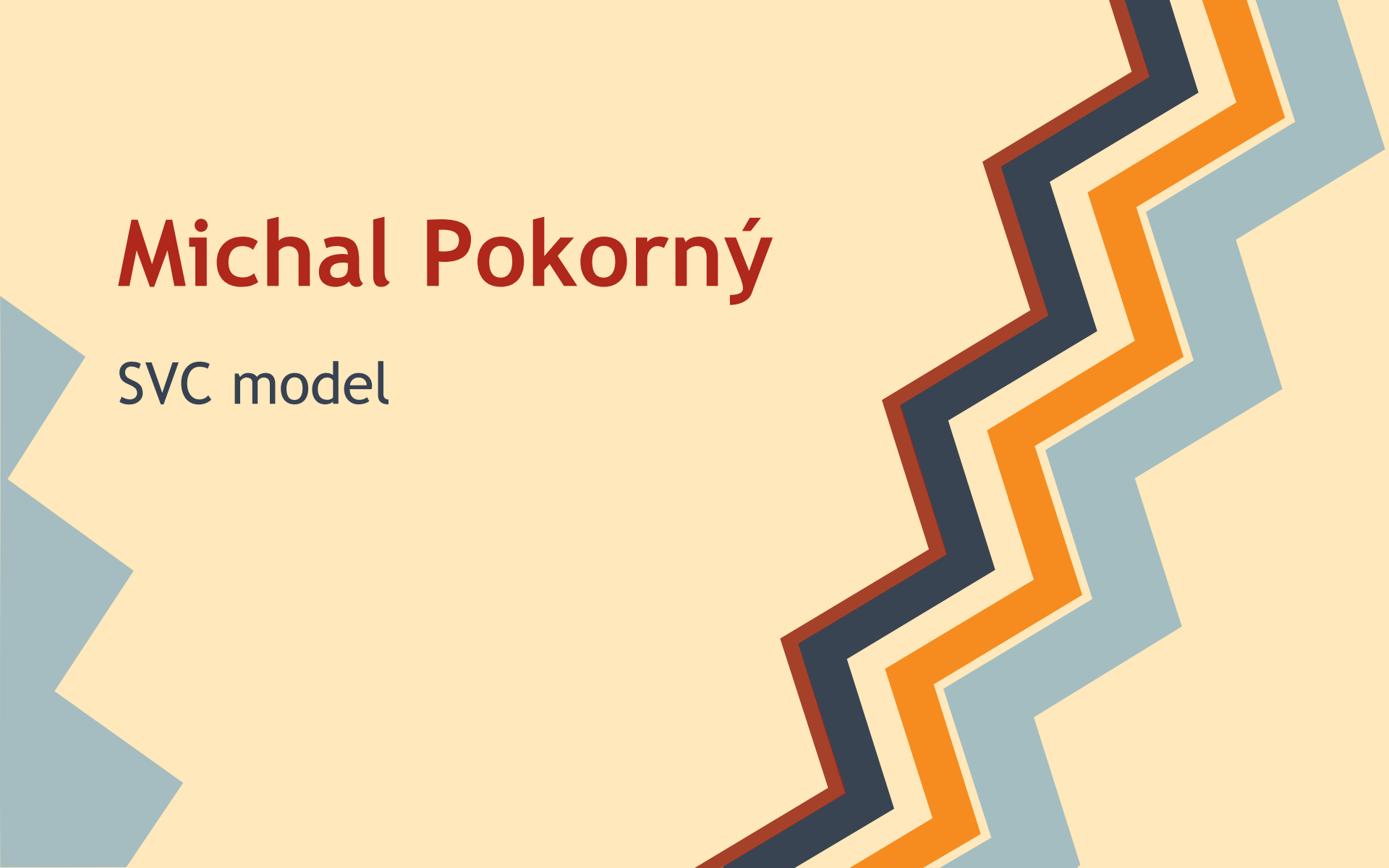
- 50 - 79% mean validation error
  - Actual competition leader has score 54%
- At least two output parameters (A, E) are very dependent on customer
- C, D are less dependent
- B, F, G can't be resolved from the customer info

# Future work

- Environment for experiments is ready...
- Spread out the horizontal data object
  - Add product browsing history
- Divide the output parameters between different models and input parameter sets
- Pruning overfits
- Use as much as possible from the Accord Framework
  - Unify interfaces, lots of data and ML utilities

# Michal Pokorný

SVC model



# scikit-learn

- Python (3)
- NumPy, SciPy, matplotlib
- BSD licence
  
- Classification, regression, clusterization, dimensionality reduction, cross-validation, ...



# Current plan

- Most customers choose some browsed plan
- Make some predictors of plan choice probabilities
- From browsed plans, pick the one with highest probability prediction

# Plan probability predictor

- RBF support vector machine classifier
  - (Plus feature scaling)
- Possible features:
  - Vector of “customer constants” (no location & time for now)
  - Most commonly browsed plan, last browsed plan, ...
  - Histogram of browsing for every plan feature

# Closer look on features

- One-hot
  - Day, previous C, home owner?, married couple?
  - A: 3, B: 2, C: 4, D: 4, E: 2, F: 4, G: 4
- Scalar
  - Group size, car age, car value, risk factor, age of oldest & youngest, cost of offer

# Results so far

- Relatively slow training on all 77607 customers :(
- Current best result: 53.793% (same as trivial benchmark [doesn't give the same outputs, through])
  - But this was on scalar representations of categories, so there might be some progress after training on better representation finishes :)

# Scalar vs. one-hot (small dataset)

		precision	recall	f1-score	support
135					
136					
137	0	0.81	0.45	0.57	56
138	1	0.67	0.97	0.80	181
139	2	0.00	0.00	0.00	55
140					
141	avg / total	0.57	0.69	0.60	292
142					
143		precision	recall	f1-score	support
144					
145	0	0.81	0.45	0.57	56
146	1	0.67	0.97	0.80	181
147	2	0.00	0.00	0.00	55
148					
149	avg / total	0.57	0.69	0.60	292
150					
151		precision	recall	f1-score	support
152					
153	0	0.53	0.38	0.44	146
154	1	0.52	0.66	0.58	146
155					
156	avg / total	0.52	0.52	0.51	292
157					
158		precision	recall	f1-score	support
159					
160	0	0.53	0.38	0.44	146
161	1	0.52	0.66	0.58	146
162					
163	avg / total	0.52	0.52	0.51	292
164					
165		precision	recall	f1-score	support
166					
167	0	0.52	0.43	0.47	79
168	1	0.00	0.00	0.00	64
169	2	0.50	0.90	0.64	125
170	3	0.00	0.00	0.00	24
171					
172	avg / total	0.35	0.50	0.40	292
173					

		precision	recall	f1-score	support
209					
210					
211	0	0.96	0.95	0.95	56
212	1	0.93	0.99	0.96	181
213	2	0.98	0.78	0.87	55
214					
215	avg / total	0.94	0.94	0.94	292
216					
217		precision	recall	f1-score	support
218					
219	0	0.94	0.93	0.93	146
220	1	0.93	0.94	0.94	146
221					
222	avg / total	0.93	0.93	0.93	292
223					
224		precision	recall	f1-score	support
225					
226	0	0.94	0.96	0.95	79
227	1	0.95	0.86	0.90	64
228	2	0.92	0.98	0.95	125
229	3	0.95	0.79	0.86	24
230					
231	avg / total	0.94	0.93	0.93	292
232					
233		precision	recall	f1-score	support
234					
235	0	0.77	0.97	0.86	31
236	1	0.97	0.88	0.92	69
237	2	0.98	0.97	0.97	192
238					
239	avg / total	0.95	0.95	0.95	292
240					

# What's next?

- “Naive Bayes assumption”: category membership classifier scores are multiplied...
  - Higher-order classifiers?
- Do something about missing values
  - scikit Imputer
- Throw in more features if nothing works...
- Ensemble if something works...