RULE-BASED PREDICTION OF SHORT TERM ELECTRIC LOAD

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Abstract

In this study we discuss the possibility to apply symbolic data mining methods to the problem of prediction. We employ our original algorithm KEX that is used for extraction of classification or prediction rules from data. When new data is coming, the active rules (rules with a fulfilled left-hand side) from the rule base are applied to the data and their weights are composed by the inference mechanism to the resulting weight of a given prediction. The presented approach is applied to the problem of short-term electric load forecasting.

Keywords: Data mining, rule learning, electric load prediction

Introduction

One central insight of artificial intelligence (AI) is that expert performance requires domain-specific knowledge. Machine learning is the subfield of AI that studies the automated acquisition of such knowledge. The aim is to create intelligent systems that learn-that is, that improve their performance as the result of experience. The mainstream of machine learning techniques is inductive learning (also called similarity-based learning). Let us assume, that there is a set of examples which should be classified into some (small amount of) classes. In case of supervised learning, the examples are pre-classified by the expert (or the class membership can be directly observed from the data). In case of unsupervised learning, the machine learning algorithm does the grouping into classes itself. Based on this limited number of examples we then try to induce some kind of general description of each class. The underlying idea of this methodology is that there are some characteristics (usually values of attributes) of these examples such, that examples belonging to the same class have similar values of these attributes. Thus examples belonging to the same class create clusters in the attribute space. The various inductive machine learning algorithms differ in the way how the induced knowledge is represented (decision trees, decision rules, neural networks, Bayesian networks, support vectors, prototypical instances) and how it is used for decision support. Among the tasks solved by machine learning methods, classification and prediction play a key role. While classification can be understood as the task of assigning new (unseen) examples into one of the predefined class, prediction can be understood as the task of "computing" a next value of a variable that evolves in time. So for classification, methods that produce symbolic output are used while for prediction, methods that produce subsymbolic (numeric) output are preferred.

An interesting alternative to subsymbolic approach to prediction (and forecasting) represent methods based on application of the (symbolic) prediction rules. The rules can be specified by experts or can be extracted automatically from data. Following the steps in the data mining process, the original data (e.g. time series) are selected, preprocessed and transformed. The main aim is to build a specific set of categorial indicators which can influence the attribute to be predicted. This is the most crucial and difficult step, especially when there is no apriori knowledge. The left-hand side (antecedent) of a prediction rule is the conjunction of the indicators and the right-hand side (succedent) is the categorial prediction goal, which can be easily specified in many practical situations.

In the paper we present our algorithm KEX, that learns weighted decision rules from data. This algorithm is used for the short-term electric load forecasting problem by using the daily data of average load and average temperature.

Short Term Electric Load Prediction

The Problem

Knowledge about the future behavior of the electric load is very important for power generation, control, transmission, etc. The prediction horizon varies from several minutes up to months and years. In our study we try to predict the daily averaged value of the electric load for the next day. The crucial question here is, whether the electric load of the next day will exceed the given limit and whether additional power units (generators) should be started.

The Data

The data that were available for the analysis consists of the values of the 963 daily average loads and daily average temperatures. Beside this, we also knew the weekday and whether this day was holiday or not. We turned this original data (as shown in Table 1) into following attributes:

LT	"long trend", coded to up/down by the comparing the load values from the two following weeks
ST	"short trend", coded to up/down by comparing the load values from the two following days
TT	"temperature trend", coded up/down by comparing the temperatures from the two following days
T1	"previous temperature trend", it is the shifted "temperature trend"
TYPEDAY	type of the day to be predicted, (Mo: Monday, Tu: Tuesday,...,Su: Sunday)
HOLIDAY	holiday (yes/no)

The prediction goal was set to "next load up" to predict the increase or decrease of the today's load.

We used the data recorded for two consecutive years (first 730 days) for training and the data for next January till September (next 233 days) for testing.

day	weekday	holiday	avg load	avg temp.
1	6	0	5789	2
2	7	0	6193	0,5
3	1	0	7607	2,7
4	2	0	7856	4,6
5	3	0	7805	4,3
6	4	0	7784	4,4
7	5	0	7681	6,6
8	6	0	6609	4,3
9	7	0	6368	3,5
10	1	0	7695	3,6
. . .				

Tab. 1: Example of original data

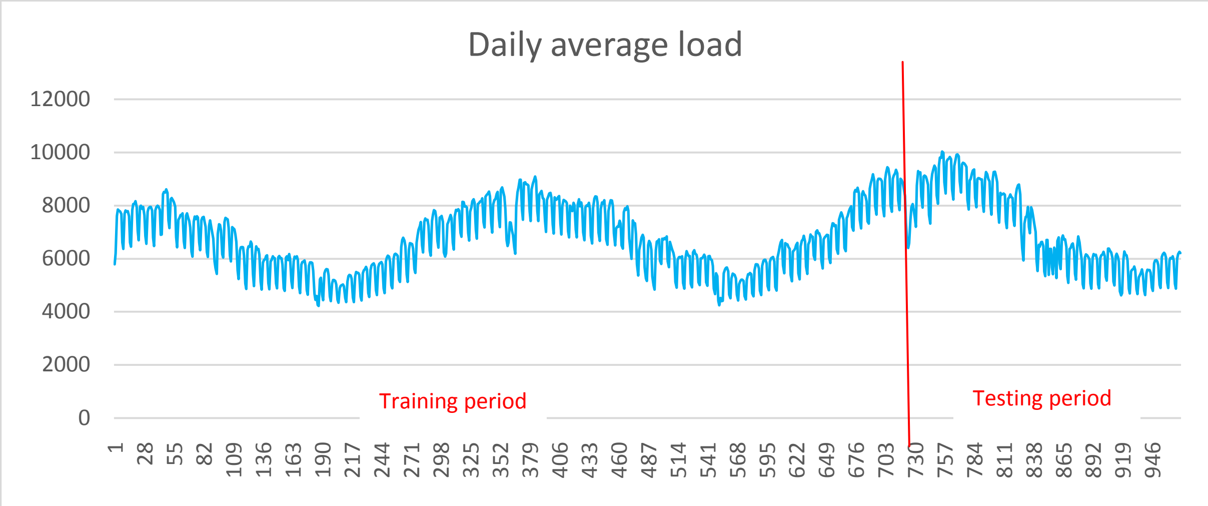

Fig. 1: Daily average load data

The Method

To find reasonable rules that will allow to predict the daily load for the next day, we used the KEX (Knowledge EXplorer) algorithm (Berka, Ivánek, 1994; Berka, 2012). KEX performs symbolic empirical multiple concept learning from examples, where the induced concept description is represented as weighted decision rules in the form

Ant ==> C(w)

where: Ant is a combination (conjunction) of selectors,

C is a single category (class), and

weight w from the interval [0,1] expresses the uncertainty of the rule.

During knowledge acquisition, KEX works in an iterative way, in each iteration testing and expanding an implication Ant ==> C. This process starts with an „empty rule“ weighted with the relative frequency of the class C and stops after testing all implications created according to the user defined criteria. During testing, the validity (conditional probability P(C|Ant)) of an implication is computed. If this validity significantly differs from the composed weight (value obtained when composing weights of all subrules of the implication Ant ==> C, then this implication is added to the knowledge base. To test the difference between validity and composed weight, we use the chi-square goodness-of-fit test. The weight of this new rule is computed from the validity and from the composed weight using inverse composing function (Hájek, 1985). For composing weights we use a pseudobayesian (Prospector-like) combination function (Duda and Gashing, 1979):

$$x \oplus y = \frac{xy}{xy \oplus (1-x)(1-y)} \,. \qquad (1)$$

The Results

Table 3 presents the found prediction rules. Each row in the table shows the number of the rule, the number of examples covered by the left-hand side of the rule (frequency left), the number of examples covered by the right-hand side of the rule (frequency right), the number of examples covered by both left-hand and right-hand side of the rule (frequency both), the weight used when combining rules (weight) and the rule itself. Notice, that weights smaller than 0.5 denote rules that will predict the decrease of the load.

When using this set of rules for prediction, all applicable rules are found and their weights are combined using the formula (1). Thus the result of prediction is the weight assigned to the class "load up". We can use these weights in following decision strategy:

if the weight of the prediction > α, then the next load will be UP,

if the weight of the prediction < (1 - α), then the next load will be DOWN, if the weight is in the interval [1 - α, α], then we do not predict.

Here α is a threshold that can be set by the user. Table 2 shows the impact of this parameter on the accuracy of our prediction model (in terms of percentage of correctly predicted testing days) and on the number of days for which no prediction is done. It can be seen, that when increasing the value of α, the percentage of correct prediction increases but the number of days, for which the model makes a decision decreases.

α	Correct predictions	Wrong predictions	no. of predictions	prediction accuracy
0.5	206	27	233	88.0%
0.55	200	17	217	92.2%
0.6	197	15	212	92.9%
0.7	189	12	201	94.0%
0.8	159	8	167	95.2%
0.9	136	4	140	97.1%

Tab. 2: Prediction performance of KEX on testing data for various values of α

RULE BASE

	Frequency				
No.	left	right	both	weight	rule
1.	730	325	325	0.4452	0 ==> load up
2.	405	325	132	0.3760	ST=down ==> load up
3.	333	325	167	0.5563	TT=down ==> load up
4.	325	325	193	0.6456	ST=up ==> load up
5.	324	325	162	0.5548	TT1=down & holiday=no ==> load up
6.	241	325	89	0.4219	TT1=up & TT=up ==> load up
7.	171	325	85	0.4033	ST=up & TT=up ==> load up
8.	105	325	1	0.0118	typeday=Sa ==> load up
9.	105	325	4	0.0470	typeday=Su ==> load up
10.	104	325	99	0.9610	typeday=Mo ==> load up
11.	104	325	94	0.9213	typeday=Tu ==> load up
12.	104	325	57	0.6018	typeday=We ==> load up
13.	104	325	18	0.2069	typeday=Fr ==> load up
14.	99	325	89	0.3420	typeday=Tu & ST=up ==> load up
15.	98	325	98	0.9082	typeday=Mo & holiday=no ==> load up
16.	95	325	47	0.4011	ST=up & LT=up & TT1=up ==> load up
17.	94	325	55	0.3896	typeday=We & ST=up ==> load up
18.	75	325	57	0.6334	ST=up & TT=down & LT=down ==> load up
19.	52	325	32	0.6660	typeday=Th & TT1=down ==> load up
20.	49	325	49	0.8915	typeday=Mo & LT=up & ST=down ==> load up
21.	48	325	34	0.7071	typeday=Th & TT=down ==> load up
22.	39	325	35	0.2606	typeday=Mo & TT=down ==> load up
23.	29	325	4	0.2146	typeday=Th & TT1=up & TT=up ==> load up
24.	18	325	1	0.1336	typeday=Fr & ST=up & TT1=up ==> load up
25.	17	325	2	0.1425	holiday=yes ==> load up
26.	6	325	1	0.0573	holiday=yes & typeday=Mo ==> load up

Tab. 3: A rule base generated by KEX using 730 daily averaged electric load and temperature data.

Conclusion

The problem of short-term electric load prediction (forecasting) can be treated by different machine learning approaches. Ceperic et al. (Ceperic et al., 2012) or Matijac et al.

(Matijac et al., 2011) use support vector machines, Ling et. al. (Ling et al., 2003) use fuzzy-neural network, Gupta and Sarangi (Gupta and Saranagi, 2012) combine genetic algorithms and neural networks. In this paper we present an alternative method based on symbolic prediction rules. We see the advantage of our approach in the fact, that the learned rules can be better understood by the domain experts.

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