Supporting Slab Formwork Selection with Different Types of Classifier Ensembles

Anna Krawczynska-Piechna 1

1 Warsaw University of Technology, Faculty of Civil Engineering, Mechanics and Petrochemistry, Łukasiewicza 17 St., 09-400 Płock, Poland

Anna.Krawczynska@pw.edu.pl

Abstract. Formwork is the largest single cost item in cast-in-place reinforced concrete structure. A properly selected formwork system, in particular slab formwork, affects pace of concrete works and therefore has an influence on the efficiency of the building performance as a whole. When the formwork items are leased to perform building works, choosing the right system gains in importance. This is why the problem of formwork selection has been discussed widely since early 90’s until now by various researchers all over the world. The present paper introduces different classifier ensembles as a tool that can be applied to solve formwork selection problem and presents the mathematical model of the decision problem. In literature, boosted classifiers were already used to solve formwork selection problem by Korean researchers. However, boosting (AdaBoost) algorithm is not the only one that can be applied in the subject matter. In this paper different classifier ensembles are investigated. The comparison includes both different aggregation methods and different types of classifiers that are being combined. In order to compare ensembles’ accuracy, the data collected on the national construction sites are used. The paper also includes remark and indications that improve classification precision.

1. Introduction

Formwork is the largest single cost item in cast-in-place reinforced concrete structure and it can be estimated as 40-50% of the cost of the concrete skeleton. A properly selected formwork system, in particular slab formwork, affects pace of concrete works and therefore has an influence on the efficiency of the building performance as a whole. In Poland, almost 90% contractors lease formwork items to perform building works. This is why, the choice of a right formwork system is of great importance.

The problem of formwork selection has been discussed widely since early 90’s until now by various researchers all over the world. Numerous methods were applied to solve the problem, in particular: linear programming [1], binary and integer programming [2], multiple-criteria decision analysis methods like Electre and Topsis [3,4], expert systems [5], neural networks [6], probabilistic networks [7], fuzzy logic [8] and others.

Among the commonly used methods of prediction, a close attention should be paid to classifier ensembles, which, in contrast to other prediction methods, consist in building different models of the same phenomenon and then combining their judgments [9,10]. The multi-model supervised learning in statistical data analysis has been used successfully in picture recognition, medical and biological sciences, in customer segmentation, business modeling, credit analysis etc. It is still less popular in project planning, which is a pity, as the aggregation algorithms, especially those based on decision tress or random forests, are thought to be the most effective classifiers, which do not require any initial data treatment, pre-processing and analysis [11].
2. Supporting formwork selection problem with classifier ensembles

Boosting algorithms were investigated by Korean researchers in order to support slab formwork selection [12,13] and retaining wall formwork [14]. The proposed by the Koreans models cannot be applied straightforward in any country, i.e. in Poland, because:

- the high-rise construction is not the dominant one in monolithic concrete construction in Poland,
- girder formwork is the most often used type of formwork, panel and table formwork slowly gain in popularity, while in Asiatic countries the share of particular types of formwork in concrete construction is quite the opposite,
- formwork items are usually leased by the Polish contractors to perform concrete works, while Asiatic companies use owned formwork or owned and personalized (individually produced, prefabricated) formwork items,
- Polish contractors select formwork primarily at the leasing costs, secondly at formwork ergonomics and safety, which was the subject matter of [15].

Concerning all above, Author’s research attempts to adapt the computational methods used in literature to the conditions and specifics of the monolithic concrete construction in Poland. The first such attempt was done in [16], where the structure of the decision problem was defined.

2.1. Model of the decision problem

Let’s consider set $U$ containing $N$ observations, which are different monolithic concrete constructions. Each observation can be described by a vector of attributes $[x_{i1}, x_{i2}, \ldots, x_{iL}, y_i]$. There are two kinds of attributes: predictors $X_1, \ldots, X_L$ (input data) and one target attribute $Y$ (output data). In the discussed formwork selection problem, predictors should be understood as the observed circumstances of the building performance, while the target attribute is the type of formwork used to complete construction works. Variables $x_{i1}, x_{i2}, \ldots, x_{iL}, y_i$ describe attributes’ values for the observation $i$. The value of the target attribute is a class label. Therefore, set $U$ can be defined as (1):

$$
[x_i, y_i]_{N \times (L+1)} = 
\begin{bmatrix}
X_1 & X_L & Y \\
x_{i1} & \ldots & x_{i1L} & y_1 \\
x_{i2} & \ldots & x_{i2L} & y_2 \\
\vdots & \vdots & \vdots & \vdots \\
x_{iN} & \ldots & x_{iNL} & y_N
\end{bmatrix}
$$

The goal of the classification is to construct a model using the historical data that accurately predicts the label (class) of the unlabeled examples, which means we want to find the relationship $Y = f(X)$ between the type of formwork $Y$ and the specifics of building performance $X=[X_1, \ldots, X_L]$.

Classification can be done using a single classifier (i.e. random tree) or a classifier ensemble, where a variety of classifiers (either different types of classifiers or different instantiations of the same classifier) are pooled before a final decision is made. Intuitively and mathematically, classifier ensembles provide an extra degree of freedom in the classical bias/variance trade-off, allowing solutions that would be difficult or impossible to reach with only a single classifier [17]. There are several methods of classifier combining:

- **bagging** (bootstrap aggregation) [18] method based on a $k$-fold drawing with replacement of $n$ training sets from the $n$-element reference set; each individual classifier in the ensemble is generated with a different random sampling of the training set.
- **boosting** [19,20], which encompasses a family of methods that focus on producing series of classifiers. The training set used for each member of the series is chosen basing on the performance of the earlier classifier in the series. Observations wrongly classified by a single
classifier receive a higher weight to be chosen to the next training set, so the algorithm is "forced" to learn using them; the final classifier arises as a result of weighted component voting;

- random forest [21] - in which every node of the classification tree introduces the best (in the sense of the division quality criterion) variable from a small subset, which is randomly selected and counts from 1 to 10% of all variables.

All of the methods mentioned above will be considered in the present paper.

2.2. Solving the decision problem with different classifier ensembles

Basing on the data collected on 30 different construction sites, the prediction accuracy of four aggregating algorithms is being analyzed. The observed predictors and the range of their historical values are collected in table 1.

Table 1. Predictors and their values

| Predictor’s name                  | Type of predictor’s value | Observed predictor’s value |
|-----------------------------------|---------------------------|---------------------------|
| number of floors                  | numeric [pcs.]            | from 2 to 40              |
| average height of the floor       | numeric [m]               | from 2.75 m to 9.0 m      |
| average floor area                | numeric [sqm]             | from 310 m² to 2800 m²    |
| dominant type of supporting       | nominal                   |                           |
| structure                          |                           |                           |
| - flat slab                       |                           |                           |
| - slab on beams                   |                           |                           |
| - slab on walls                   |                           |                           |
| - other                           |                           |                           |

In order to evaluate the possibility of using classifier ensembles to support the selection of formwork type for the particular data collection, the following aggregation algorithms were investigated: boosting (AdaBoost.M1 and Logit Boost algorithm), bagging and random forest. Two weak classifiers were aggregated: the Naive Bayes classifier, Decision Stump tree as well as Random Tree classifier. In order to obtain training sets and avoid classifier’s overfitting [22, 23], a 10-fold and 15-fold cross-validation was made, as well as leave-one-out cross-validation (30-fold), due to the small size of the historical data. All the calculations were performed in Weka 3.8. environment.

Classification results for all ensembles investigated are presented and explained in [16]. The best predicting algorithms are gathered in table 2 and they will be improved in further research. Prediction accuracy, mentioned in table 2, is a percentage of correctly classified instances, MAE stands for a mean absolute error, while Kappa coefficient is used to quantify the level of agreement.

Table 2. Classification accuracy obtained with different classifier ensembles

| Method of aggregation | Aggregated algorithm | Prediction accuracy | MAE   | Kappa |
|-----------------------|----------------------|---------------------|-------|-------|
| Boosting (AdaBoost.M1)| Random Tree          | 70.0 %              | 0.20  | 0.48  |
| Bagging               | Random Tree          | 73.3 %              | 0.39  | 0.53  |
| Random Forest         | -                    | 80.0 %              | 0.28  | 0.65  |
| Boosting (LogitBoost) | Decision Stump       | 80.0 %              | 0.18  | 0.65  |

The calculations proved that aggregated classifier algorithms classify better (more precisely) than non-combined ones. Aggregating decision trees, both one-level ones or complex, provided the best quality of prediction, however not amazing.

Having confusion matrices analysed, it was possible to state, that all the considered aggregation algorithms failed in table formwork classification. It was systemically incorrectly classified, while girder formwork was classified the most accurately. This was due to the small number of observations in which
table formwork was a target value. Moreover, predictors’ values in observations, in which table formwork was the target value, did not differ significantly from the predictors’ values observed in instances, in which the target value was panel formwork. Therefore, in further calculations, the table formwork class is suggested to be merged together with panel class into one class label.

2.3. Improving classification accuracy by merging classes
The second run of calculations was done for two class labels: girder formwork and panelized formwork, which contains panel and preassembled table formwork. Predictors were the same as in table 1. Only weak classifiers were aggregated (the Naive Bayes classifier and Decision Stump). All parameters, so the number of iterations (50) and a 15-fold cross-validation were used, as in preliminary analysis. The classification precision obtained in the second run of calculations is gathered in table 3.

Table 3. Classification accuracy in case of merged classes

| Method of aggregation | Aggregated algorithm | Prediction accuracy | MAE | Kappa |
|-----------------------|----------------------|---------------------|-----|-------|
| Boosting (AdaBoost.M1)| Decision Stump       | 86.7 %              | 0.13| 0.73  |
| Bagging               | Decision Stump       | 76.7 %              | 0.22| 0.52  |
| Random Tree           | Decision Stump       | 82.8 %              | 0.21| 0.65  |
| Boosting (LogitBoost) | Decision Stump       | 86.7 %              | 0.08| 0.73  |

As we can see, the most promising ensemble method is boosting; in case of bagging and random forest no significant improvement in the quality of the prediction is noticed (from 73% to 77% and from 80 up to 83%). Prediction accuracy of AdaBoost algorithm (algorithm based on exponential loss function) increased the most (c.a.17%) and together with AdaBoost’s modification, LogitBoost algorithm (which is based on logistic loss function), boosting algorithms provide the best prediction models. Detailed accuracy measures of both classifier ensembles are collected in table 4, where:

- K&B Info score is Kononenko and Bratko Information score, which measures predictive accuracy but eliminates the influence of prior probabilities [24]; the higher it is, the better;
- ROC area is an area below ROC (receiver operating characteristic) curve, which is created by plotting the true positive rate (TPR, instances correctly classified as a given class) against the false positive rate (FPR, instances falsely classified as a given class) at various threshold settings; an optimal classifier will have ROC area values approaching 1;
- PRC area is an area below Precision and Recall Curve, which is created by plotting the ratio of true positive (TP) instances to the sum of true positive and false positive (TP+FP) instances against the recall (TPR).

Table 4. Detailed accuracy measures by class

| Aggregation algorithm / algorithm combined | K&B Info Score | Formwork class | ROC Area | PRC Area |
|------------------------------------------|----------------|---------------|----------|----------|
| AdaBoost.M1 / Decision Stump             | 2011,9 %       | girder        | 0.905    | 0.781    |
|                                          |                | panelized     | 0.905    | 0.953    |
| LogitBoost / Decision Stump              | 2043,7%        | girder        | 0.910    | 0.798    |
|                                          |                | panelized     | 0.910    | 0.953    |

Detailed accuracy measures indicate, that whatever the loss function is, logit or exponential, boosting method provides the best prediction accuracy for the investigated data. There is a slight advantage for LogitBoost method, which is less sensitive to outliers and label noise.
3. Conclusions
The research shows that classifier ensembles are a valuable tool to aid slab formwork selection problem, especially when the set of historical data used to learn the classifier is relatively small. The paper described, if and how the precision of classification changes in case of merging classes.

Boosting one-level decision trees with AdaBoost.M1 or LogitBoost algorithm gives comparable and satisfactory results even on small training datasets. Classification accuracy raises up from 80% to 87%, when two label classes, panel formwork and table formwork are merged together into one class, while girder formwork class remains unchanged. Such approach, on the beginning seems to be a simplification, but finally may be useful, especially in countries, where girder formwork is dominant in the construction performance, as it may encourage contractors to rent and apply different alternatives of girder formwork.

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