Composition of concrete and its influence on compressive strength

Filipe P. de Farias
Department of Teleinformatics Engineering
Federal University of Ceará
Fortaleza, Brazil
filipepfarias@fisica.ufc.br

Yvo J. M. Sales
Department of Teleinformatics Engineering
Federal University of Ceará
Fortaleza, Brazil
yvo@gtel.ufc.br

***Abstract*—The compressive strength of a concrete is a important property since it impacts directly on its applications. The classical approach to obtain the compressive strength of a specific concrete mixture is to submit a sample to a test on a hydraulic press. However, it takes time to perform this type of test since it is necessary to wait the sample to cure. In this work, we try to find a regression model to accurately estimate the compressive strength of a concrete mixture from the concentration of its components.**

***Index Terms*—Regression models, concrete compressive strength, machine-learning, partial least squares.**

I. Introduction

A material formed by aggregates bonded together by a fluid material that hardens over time has been used by humans for construction since many years ago [3]. Nowadays this material is known as concrete and it's widely used in the construction field. The aggregates used in the mixture of the concrete affect directly its compressive strength which highly impacts its applications. For instance, in general, the concrete for columns or beams needs to have a greater compressive strength than the one for pavement. On the previous work, we have made a statistical analysis on a dataset extracted from the UCI Machine Learning Repository (University of California, Irvine) [4] that collects information about the concentration of some aggregates used to form different mixtures of concretes. In this work, we try to find a regression model to estimate the relation between the concentration of those aggregates and the strength of the concrete mixture. The goal is that such model could be a good replacement to tests of samples on hydraulic press.

This work is divided as follows. A description of the data is given in Section II resulted from the previous work with the addition of the regressor (concrete compressive strength). Section III brings a brief introduction to the regression models that will be used to fit the data. In the sequel, we present and discuss the results in Section V. Finally, the conclusions and considerations are exposed in Section VI.

II. Data description

The composition of each one of the N = 1030 concrete samples is given by the concentrations (kg/m^3) of D components: Cement, Blast Furnace Slag, Fly Ash, Water, Superplasticizer, Coarse Aggregate and Fine Aggregate, as summarized in Table I. The cement is what binds the elements of the concrete together. Indeed his technical name in the literature is *binder* [6]. The other components as blast furnace slag and fly ash, the outcomes of another industrial process reused in the concrete mixture, they have the role of increase the chemical hardness of the concrete, i.e. in a microscopic level. The water is responsible for react with the cement resulting in the cement stone. The superplasticizer gives fluid characteristics to the concrete aiming to better fill the mold and decrease the use of water. The coarse and fine aggregates give some macroscopical mechanical resistance to the concrete but can reduce its compressive strength if bad applied. Their major role is to occupy the spaces in the mold reducing the use of cement. The output is the concrete compressive strength which is measure in the stress test where a force its applied to a sample using a hydraulic press. When the sample reaches the rupture point, the pressure, force per area of the sample, is observed.

TABLE I
Data description

Label	Component	Unit
D_1	Cement	kg/m^3
D_2	Blast Furnace Slag	kg/m^3
D_3	Fly Ash	kg/m^3
D_4	Water	kg/m^3
D_5	Superplasticizer	kg/m^3
D_6	Coarse Aggregate	kg/m^3
D_7	Fine Aggregate	kg/m^3
D_8	Age	days
$\mathbf{D_9}$	**Compressive strength**	**MPa**
Total	N = 1030 samples	

The concrete mixtures were divided into a set $\mathcal{L} = \{L_1, L_2, L_3\}$ of classes [1] based on their compressive strength, following the function $\mathcal{C}\colon \mathcal{R} \mapsto \mathcal{L}$ defined in Eq. **??**. The mixture which is weak and not recommended for structures, the *Non-standard*, was labeled with L_1 and comprises 295 samples. The mixture whose strength is in a range that can be applied to structures is classified as L_2, or *Standard*, and comprises 525 samples. The high performance mixture

L_3, *High-strength* and comprises 210 samples.

$$\mathcal{C}(D_9) = \begin{cases} L_1\,, D_9 < 25 \\ L_2\,, 25 \leq D_9 < 50 \\ L_3\,, D_9 \geq 50 \end{cases} \tag{1}$$

where D_9 is the compressive strength of the concrete mixture.

The observations are the measured compressive strengths of each sample and, as the predictors $D_1 - D_7$, are real valued. The Age (D_8) of the concrete is extremely discrete. All the data was normalised, by centering at the mean and scaling by the standard deviation to avoid any of the methods to be sensitive to different scales. At Fig. 1 we note the strongest positive correlation is between the strength and the cement component ($D_9 \times D_1$). Another important factors are the presence of the superplasticizer ($D_9 \times D_5$) and the age that represents the time of cure ($D_9 \times D_8$). In all these components is noted a subtle correlation. And the most important fact that can be observed is the decrease of the necessity of water when the superplasticizer is used ($D_5 \times D_4$), which was its proposal in the first place.

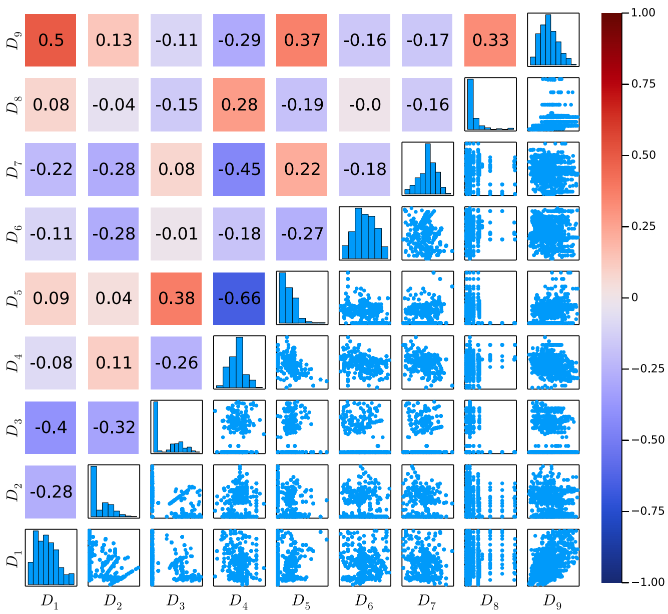

Fig. 1. Pairwise scatter, correlation and histogram plots of each concrete component.

III. Regression models

Regression models try to find relations between the *independent variables* and the *dependent variables*, which are named, respectively, predictors and outcomes in this work. These relations can occur in different forms. The simplest one is the linear relationship, which is when the curve predictors *vs* outcomes, in the case that both are one-dimensional, forms a simple line and, in the general case, a hyperplane. Continuing the discussion of the last work, we now change the strategy to use a non-linear method for regression, in this case using neural networks.

A. Neural networks regression

In this method, expressed in Eq.1, each predictor x_k is weighted by a real-valued constant w_k. The outcome is inputed in an activation function ϕ which will "activate" when that sum be enough to reach a given output Y. This output will be the data, specifically the value of the compressive strength.

$$Y = \phi\left(\sum_k w_k \cdot x_k\right) \tag{2}$$

The shape of ϕ is a choose of the one who is modelling. Some of them are the sigmoid and the step functions. In this work, the ReLU function was used, which is defined as

$$\phi_{\text{ReLU}}(x) = \max(0, x). \tag{3}$$

The next step, which is to optimise a cost function is quite similar to the ordinary linear squares, but now observing that the function is different, but yet the cost will be defined as the distance between the data and the values of the model.

IV. Classification models

A. Linear discriminant analysis

B. Neural networks

C. Nearest neighbors

D. Support vector classifier

V. Results

VI. Conclusions

The database of concrete is not easy to analyse if there is no previous knowledge about the problem of the components mixture, as was noticed in the previous work and a more deep literature research was needed. Although the models worked, the authors were not capable to determine if the errors found imply in safe conditions for the concrete, neither is the objective of this work. What we can conclude is that the model is not linear given the R^2 statistics and the original work of the data [4].

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