Predictive Model for Concrete Compressive Strength

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Proposal

The team plans to predict the 28^{th} day compressive strength of the concrete given a proportion of water, cement, aggregates, and percentage of additives. The dataset has 8 input parameters and 1 output parameter. The model will predict the interactions between the concrete mix components to the compressive strength. The outputs being considered include a table of proportions for mix design and a formula for the compressive strength.

The model aims to predict the 28^{th} day compressive strength of concrete based on the dataset. Traditionally, to compare the actual compressive strength of concrete (Ca) against designed for strength (Cd), 28 days would need to be passed before a cube sample can be crushed to check the compressive strength. This is usually not a problem, if the 28^{th} day Ca matches the Cd. However, if there is a mismatch in Ca and Cd, there could be massive hacking of concrete or additionally structures put in place to further enhance the strength.

To minimize such errors, this model predicts the 28^{th} day compressive strength instantaneously when a batch of concrete mix is created. Eventually, with enough confidence, it aims to change the default measurement of 28^{th} day compressive strength from cube crushing to using this predictive model.

Dataset

Description

The dataset was retrieved from UCI Machine Learning Repository (Yeh, 2007). It has 1030 observations, 8 quantitative input variables, and 1 quantitative output variable.

Column A/ Component 1: Cement

Cement is an adhesive substance that acts as a binder for all the components in a concrete mix. Ordinary Portland Cement (OPC) is made up of limestone, clay, and iron ore; and it is most commonly used. According to the ASTM standard, there are five types of cement, the difference due to the chemical composition, altering the properties. In this dataset, Type 1 Ordinary Portland Cement will be used. The unit used is kg of cement per 1 m^3 of the concrete mixture (kg/m^3 of mixture).

Column B/ Component 2: Blast Furnace Slag

Blast furnace Ash is a nonmetallic co-product obtained in the production of iron, iron ore, iron scrap and fluxed. It is commonly used in cement production as a substitute for clinker and in concrete production as a substitute for aggregates. The use of slag cement improves performance and durability of concrete. The unit used is kg of per 1 m^3 of the concrete mixture (kg/m^3 of mixture).

Column C/ Component 3: Fly Ash

Fly Ash is byproduct of burning pulverized coal in electric generation. It is a fine powder used to improve the workability, the strength and the durability of Portland Cement Concrete. It also decreases the water demand of the concrete mix and reduces heat of hydration. The unit used is kg of per 1 m^3 of the concrete mixture (kg/m^3 of mixture).

Column D/ Component 4: Water

Water content is the most important factor affecting the consistency of fresh concrete. The higher the water content, the higher the workability but the lower the strenght of the concrete. The unit used is kg per 1 m^3 of the concrete mixture (kg/m^3 of mixture).

Column E/ Component 5: Superplasticizer

Superplasticizers are chemical compounds used to reduce the amount of water content in the concrete mixture to produce high-strength concrete while maintaining enough workability. The used unit is kg of the superplasticizer to 1 m^3 of the concrete mixture (kg/m^3 of mixture).

Column F/ Component 6: Coarse Aggregate

Coarse Aggregates are inert, granular, and inorganic material. Coarse Aggregates are aggregates that are larger or equal to the ASTM sieve size 4.75mm. Typical coarse aggregates are gravel, crushed stone or previously used concrete etc. They occupy a large volume in a concrete mix (~65-75%), as it acts as an economic filler for cement. The unit used is kg of coarse aggregate per 1 m^3 of the concrete mixture (kg/m^3 of mixture).

Column G/ Component 7: Fine Aggregate

Fine Aggregates are inert, granular, and inorganic material. Fine Aggregates are aggregates that are smaller than the ASTM sieve size 4.75mm. Typical fine aggregates are sand, crushed stone or burnt clays etc. The fine aggregates fill in the voids between coarse aggregates. It also provides resistance against shrinking and cracking. The unit used is kg of fine aggregate per 1 m^3 of the concrete mixture (kg/m^3 of mixture).

Column H/ Component 8: Age

This column represents the age of the concrete mixture after pouring. The concrete gains its strength gradually with time, and according to the ASTM, it reaches to 99% of the target compressive strength after 28 days. The strength will continue to increase after years and it can become larger than the target compressive strength (strength percent > 100%). The unit of this column data is in days.

Column I/ Output 1: Concrete compressive strength

It is the capacity of concrete to withstand compression load before failure. Again, based on the ASTM standards, this property reported at 28 days of curing time.

Exploratory Data Analysis

Summary Statistics

This section illustrates the general statistics of the dataset. The purpose is to show simple trends in the dataset.

Table 1: Summary Statistics in Table Form.

variable	mean	std	min	q25	median	q75	max
Cement (kg/m3)	281.168	104.506	102.000	192.375	272.900	350.000	540.000
Water (kg/m3)	181.567	21.354	121.800	164.900	185.000	192.000	247.000
Coarse Aggregate (kg/m3)	972.919	77.754	801.000	932.000	968.000	1029.400	1145.000
Fine Aggregate (kg/m3)	773.580	80.176	594.000	730.950	779.500	824.000	992.600
Blast Furnace Slag (kg/m3)	73.896	86.279	0.000	0.000	22.000	142.950	359.400
Fly Ash (kg/m3)	54.188	63.997	0.000	0.000	0.000	118.300	200.100
Superplasticizer (kg/m3)	6.205	5.974	0.000	0.000	6.400	10.200	32.200
Age (day)	45.662	63.170	1.000	7.000	28.000	56.000	365.000
Compressive strength (MPa)	35.818	16.706	2.330	23.710	34.445	46.135	82.600

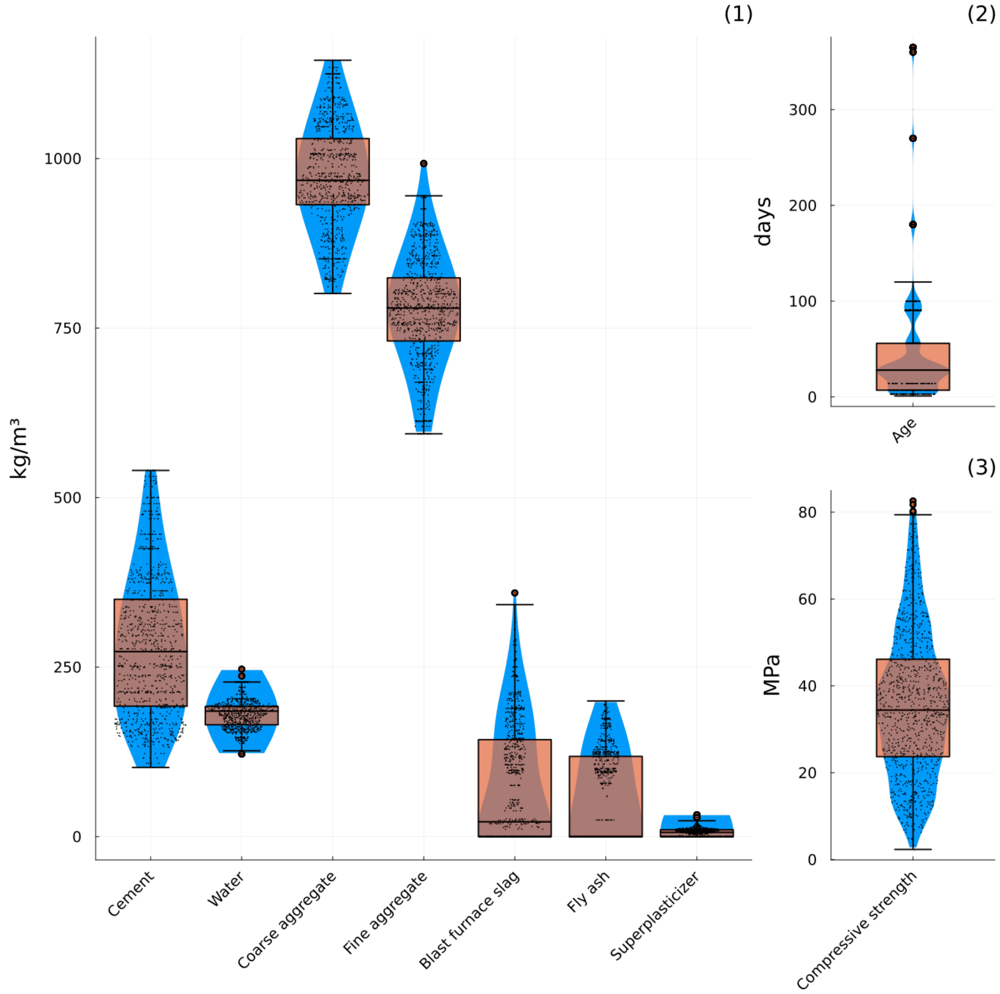

Figure 1: Violin, Box, and Dot Plots of Dataset. (1) Mass Axis (2) Days Axis (3) Strength Axis

Table 1 shows the mean, standard deviation, minimum & maximum, first quartile, median, and third quartile. Figure 1 shows a visual form of Table 1.

The main components, cement, water, and aggregates are present in all concrete mixes. The aggregates make a major portion of the concrete mix. The portion of water in the observations do not vary as much as the other main components.

Table 2: Secondary Component Observation Count.

With Blast Furnace Slag	With Fly Ash	With Superplasticizer	Observations
false	false	false	209
false	false	true	23
false	true	false	6
false	true	true	233
true	false	false	164
true	false	true	170
true	true	true	225

Blast furnace slag, fly ash, and super plasticizer are not present in all observations. Table 2 shows that there are 209 observations without secondary components. Out of the secondary components, superplasticizer is the most prevalent with 651 total observations. However, superplasticizer has the least average mass in the concrete mix. There are no observations with both blast furnace slag and fly ash.

The median age of concrete strength measurement is at 28 days. Typical concrete testing in the industry is made on the 28th day. Some observations were measured after a year from casting.

The mean age of concrete strength for the dataset is 35.8 MPa. The minimum and maximum concrete strength observed is 2.3 MPa and 82.6 MPa respectively.

Correlation

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Specific Correlation

In this section, the specific interactions between variables will be further discussed.

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Predictive Modelling

Plan

The predictive model for this project will be a supervised regression predictive model. The goal is to predict the 28th day concrete compressive strength, given cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate.

The dataset is a labelled dataset as such supervised learning method will be used train the model. The dataset will be split into training, testing and validation set using cross validation method. The training set will be used to train the model, the testing set will be used to optimize the model, and the validation set will be used to evaluate the performance of the model based on unseen data. The dataset will also be standardized to ensure there is no mismatch of the different scales for the variables.

The preliminary model will be a linear or polynomial model, using gradient descent and an error function such as MSE to train model. To ensure that the model does not overfit the training model, a regularization term either L1 or L2 will be used to optimize the model. L1 in the case of feature selection by reducing non-essential variables to zero, and L2 for the case of lowering the influence of non- essential variables.

Another preliminary predictive model is to use PCA for regression. By transforming the standardized training data into PCA coordinate systems, key variables can be selected while retraining confounding variables.

The output of the model will be able to predict the 28th day concrete compressive strength. The purpose is to use the model to achieve the instantaneous 28th day strength the moment a batch of concrete is mixed, as traditionally to achieve the 28th day strength, a cube sample will be crushed on the 28th day to find out the strength. By having instantaneous 28th day strength, faulty batches that do not meet the 28th day design strength requirements can be rectified immediately. Preventing additional cost from hacking or additional supporting structures.

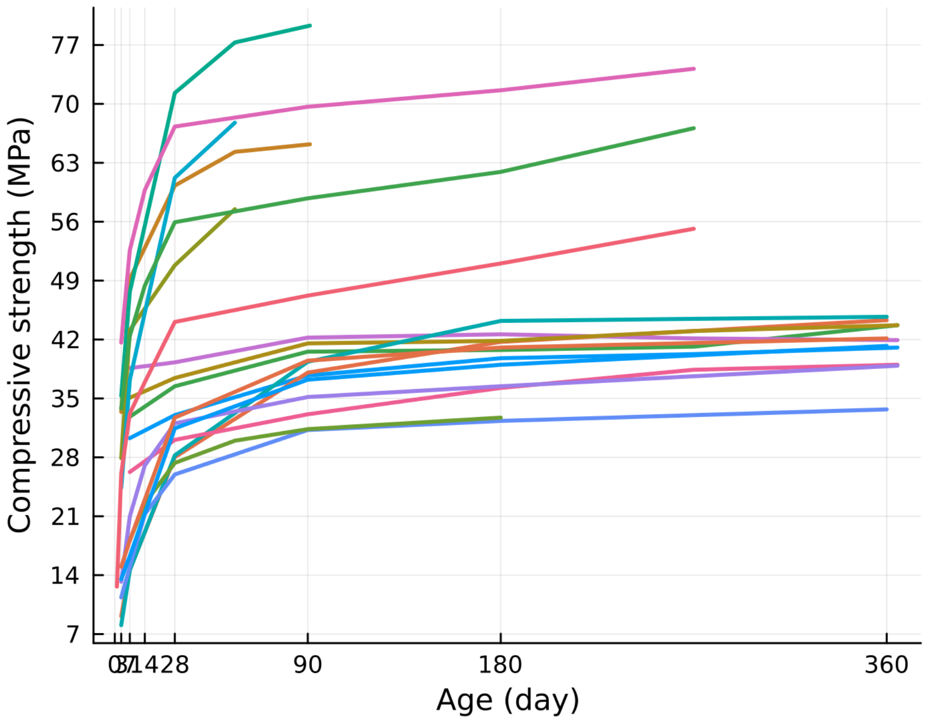


Figure 2: Original

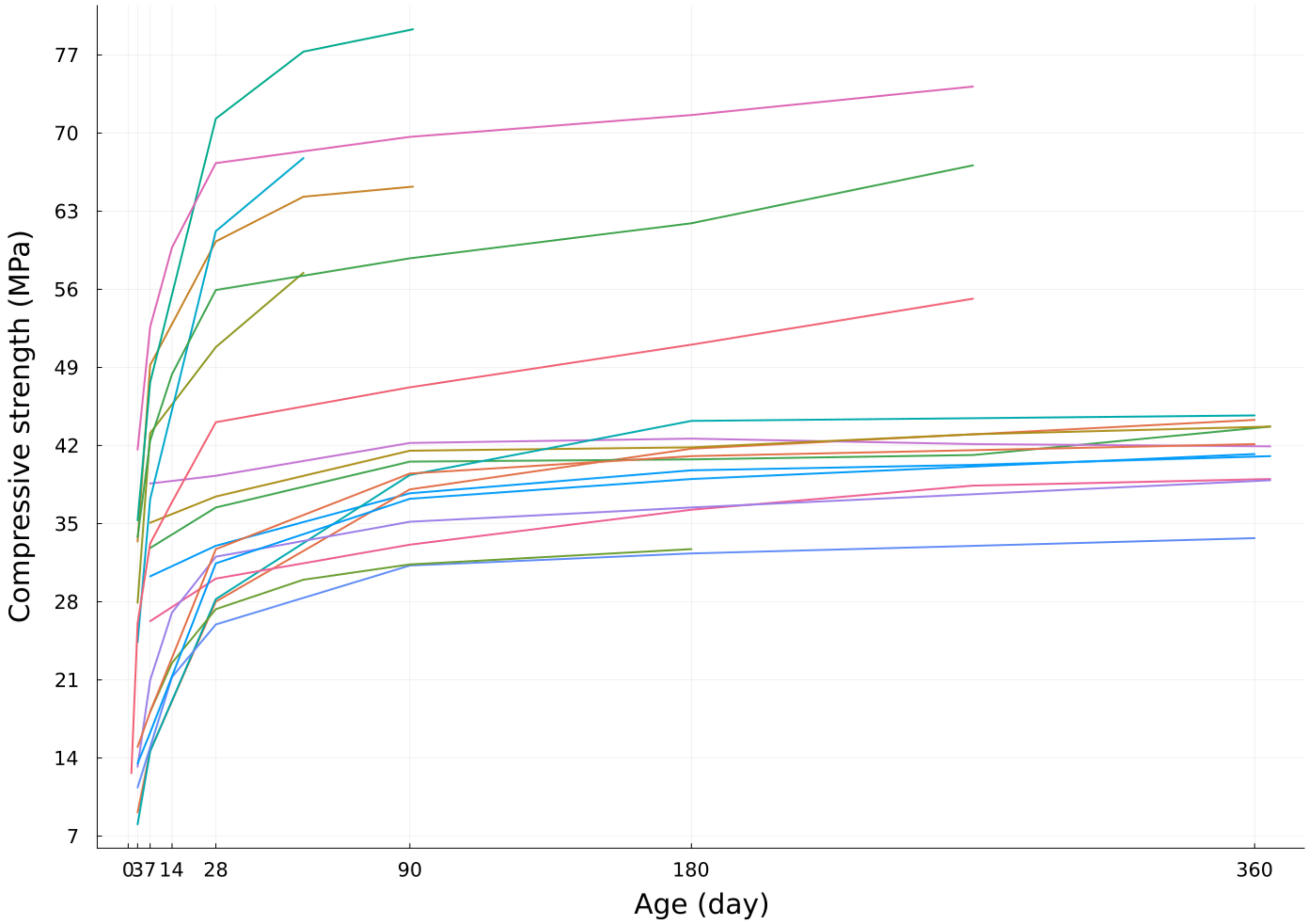
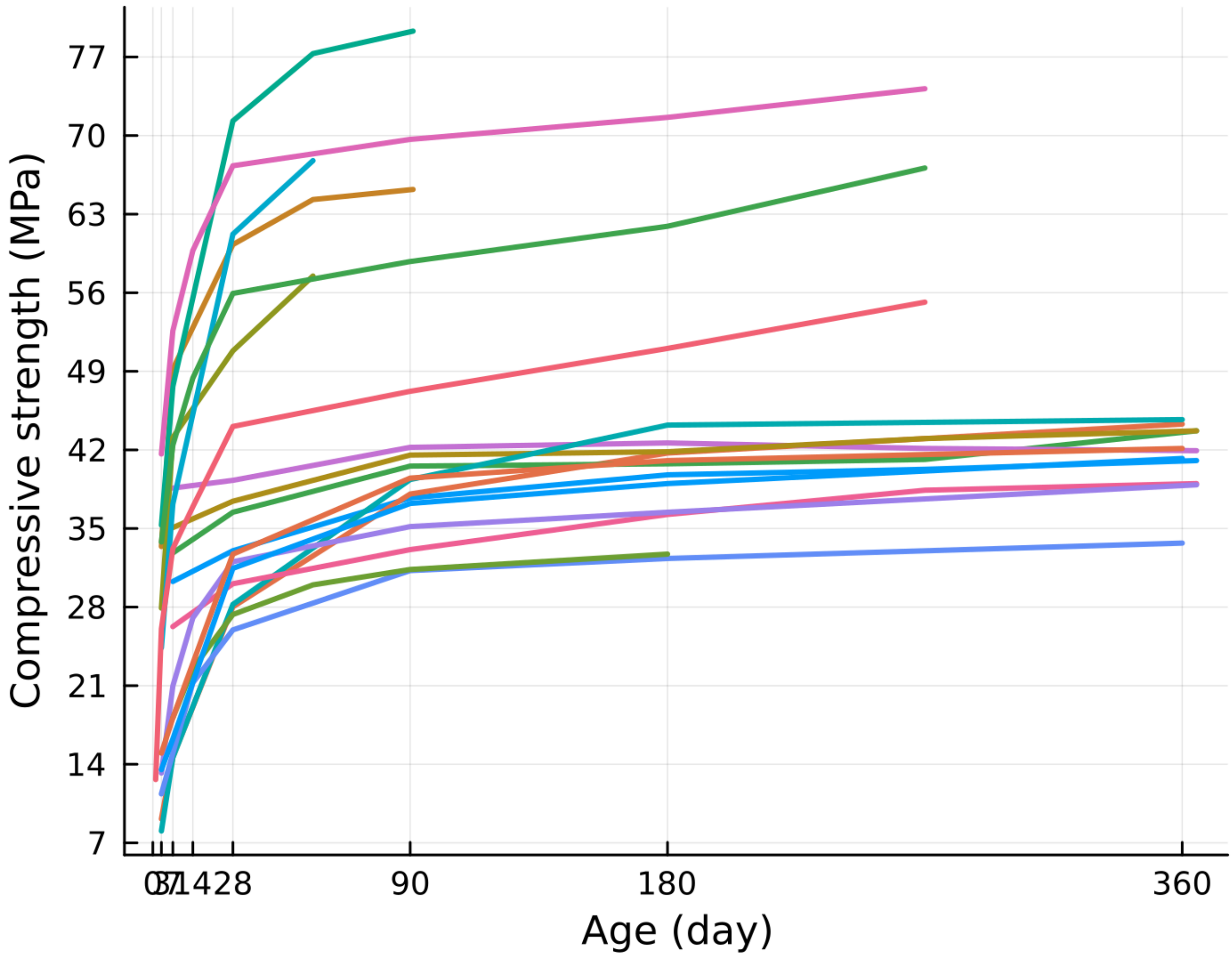


Figure 3: 96



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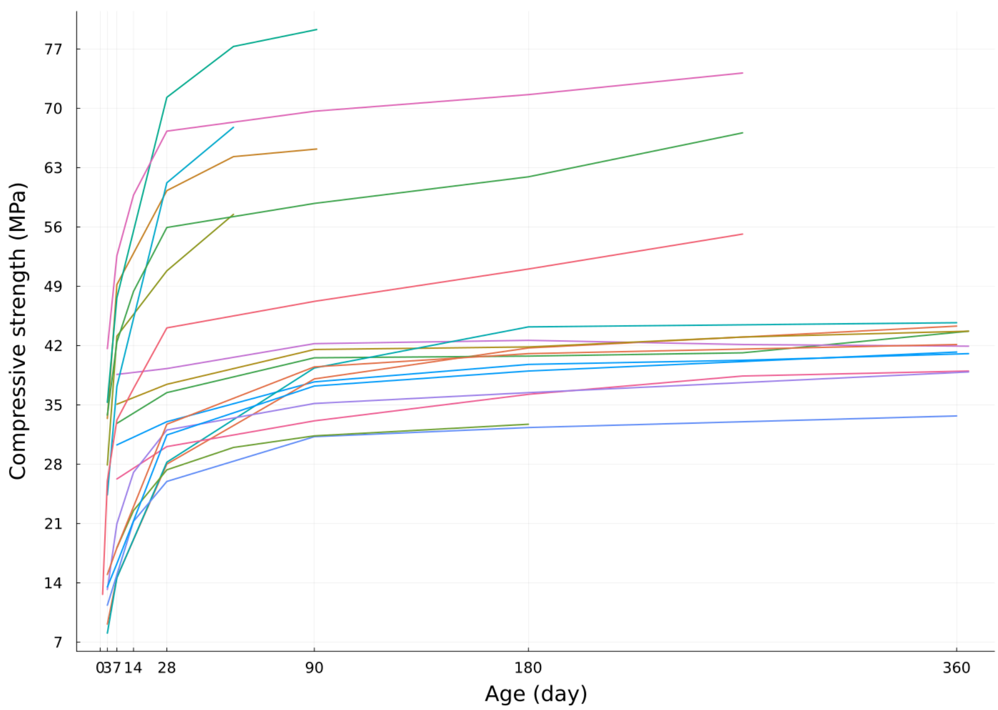

Figure 5: 96 500

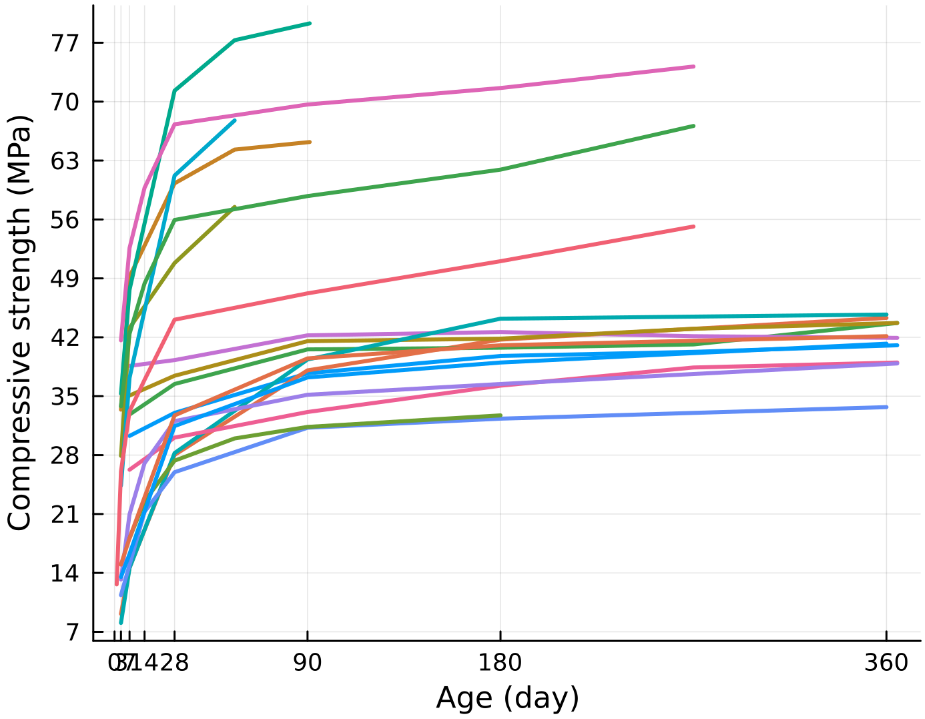

Figure 6: 300 500

References

Yeh, I., 2007. UCI Machine Learning Repository: Concrete Compressive Strength Data Set. [online] Archive.ics.uci.edu. Available at: https://archive.ics.uci.edu/ml/datasets/concrete+compressive+strength [Accessed 19 September 2022].