Project 3: Concrete Strength Prediction

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Introduction

The second most consumed substance in the world after water is concrete. Currently, the world produces 4.4 billion of concrete annually. Conventional concrete is a mixture of cement, aggregates (coarse and fine) and water. Many admixtures like mineral and chemical are incorporated in concrete to improve its performance. The main idea is not only to improve its overall performance and durability but also to reduce the emission of carbon dioxide produced by concrete industry itself. Cement production itself is highly energy intensive process. In 2015, it generated around 2.8 billion of CO2 (8% of total). Lots of research have been carried out to decrease the percentage of cement in concrete by using different substitutes. Researchers are opting for more environment friendly and sustainable options. This new idea of unconventional concrete requires backup and standards. The conventional method of testing concrete's strength is to cast concrete cylinders or cubes with different mix ratio of its constituents and test them after 7, 14 or 28 days. This method requires significant amount of labor and time.

2. Method

Exploratory Data Analysis

It is done in order to analyze the data used for the project more comprehensively. In order to do so, the first step is to import the required libraires. And load the training, test and sample data.

Importing required libraries

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
%matplotlib inline

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

EDA-1

Loading Dataset

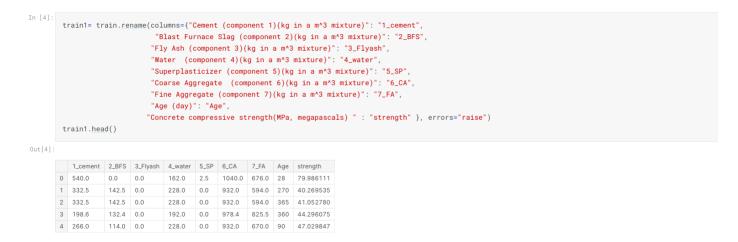
Sample, Two dataset (**test** and **train**) have been created. **Train** dataset will be used to train our model and test dataset will be used to check the model.

```
In [2]:
    sample= pd.read_csv("/kaggle/input/cee-498-project3-forecast-strength-of-concrete/
    sample.csv")
    test= pd.read_csv("/kaggle/input/cee-498-project3-forecast-strength-of-concrete/te
    st.csv")
    train = pd.read_csv("/kaggle/input/cee-498-project3-forecast-strength-of-concrete/
    train.csv")
```

EDA-2

Description of train dataset Exploratory Data Analysis will be carried out on train dataset In [3]: train.describe() Out[3] Blast Furnace Slag (component 2)(kg in a m^3 mixture) Fine Aggregate (component 7)(kg in a Superplasticizer Coarse Aggregate (component 6) (kg in a m^3 3)(kg in a m^3 mixture) onent 5)(kg in a Age (day) (component 7 m^3 mixture) strength(MPa, m^3 mixture) mixture) megapascals) count 707.000000 707.000000 707.000000 707.000000 707.000000 707.000000 707.000000 707.000000 707.000000 mean 280.970325 76.519250 51.837949 182.347709 6.180854 971.419703 772.372588 47.619519 36.156560 105.051424 std 86.971542 63.004123 21.844600 6.029105 77.425959 81.508478 65,464982 16.687748 min 102.000000 0.000000 0.000000 121.750000 0.000000 801.000000 594.000000 1.000000 4.827711 0.000000 0.000000 0.000000 723.400000 194.090000 164.900000 932.000000 14.000000 24.023412 185.700000 193.000000 10.300000 824.000000 56.000000 46.070786 75% 350.000000 144.100000 116.000000 1028.400000 max 540.000000 359.400000 200.000000 247.000000 32.200000 1134.300000 992.600000 365.000000 82.599225

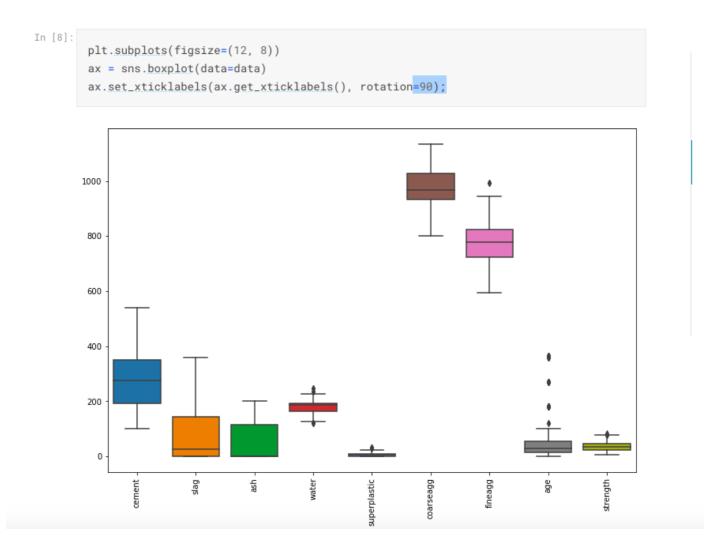
Rename Columns Name



EDA-4

Box plot analysis was performed:

Box plots



EDA-6

The observations and comments that can be made from the above box plot is as follows:

- 1:The data in cement, slag, ash doesn't appear to have any significant outliers.
- 2: The data from water, superplastic, age, and strength appears to have some outliers, amidst them the age data has a long extension of the plot suggesting the highest amount of outliers amongst all of data columns mentioned.

Dsitribution of the variables in the dataset have been plotted to gain better understanding.

Distribution of independent variables

```
import itertools

cols = [i for i in data.columns if i != 'strength']

fig = plt.figure(figsize=(15, 20))

for i,j in itertools.zip_longest(cols, range(len(cols))):
    plt.subplot(4,2,j+1)
    ax = sns.distplot(data[i],color='orange',rug=True)
    plt.axvline(data[i].mean(),linestyle="dashed",label="mean", color='black')
    plt.legend()
    plt.title(i)
    plt.xlabel("")
```

EDA-8



Distribution plot for strength variable



EDA-10

Degree of skewness

Out[11]:

	Features	Skewness degree
7	age	3.153869
4	superplastic	0.951027
1	slag	0.754229
2	ash	0.592097
0	cement	0.500008
8	strength	0.410593
3	water	0.089452
5	coarseagg	0.015180
6	fineagg	-0.269003

The observations and comments that can be made from the distribution plots and skewness degreee data is as follows:

- 1: The strength data is normally distributed.
- 2: Water and cement data seems to be very near to being normally distributed.
- 3: The data from age column as seen from box plot had a lot of outliers which is re-affirmed here with the distribution plot having very lengthy un-symmetrical extension beyond its mean value.

Pair plot

```
In [12]:
    g = sns.PairGrid(data)
    g.map_upper(plt.scatter)
    g.map_lower(sns.lineplot)
    g.map_diag(sns.kdeplot, lw=3, legend=True);
```

EDA-12



EDA-13

The observations and comments that can be made from the pair plots is as follows:

- 1: There is strong positive correlation between cement and strength which seems theoretically consistent.
- 2: In addition age also has a strong positive correlation to strength.
- 3: Water and strength have a negative correlation which aagain seems theoretically consistent.
- 4: Water and superplastic have a negeative correlation.
- 5: Slag, ash, coarseagg and fineagg are having poor correlation to strength so they aren't the best predctors of strength.

Heat map



EDA-14

The observations and comments that can be made from the heat map is as follows:

- 1: Cement and age have strong correlation with strength
- 2: Water and superplastic have strong correlation
- 3: Superplastic has somewhat smaller but a postive correlation with strength

3. Discussion

3.1 Model Training and Evaluation

3.1.1 Linear Regression

Linear Regression is the simplest but powerful model. In the previous studies, it was widely used in the prediction of concrete strength. This model assumes a linear relationship between independent and dependent variables.

Code for Linear Regression Model

```
from sklearn.linear_model import LinearRegression
lin_reg = LinearRegression()
lin_reg.fit(train_x, train_y)
y_pred_lin= lin_reg.predict(test_x)
```

Accuracy of Model is: 0.5177053629131334

Root Mean Squared Error of Model is: 11.420285520195613

3.1.2 Lasso Method

The Lasso is a shrinkage and selection method for linear regression. It minimizes the usual sum of squared errors, with a bound on the sum of the absolute values of the coefficients.

Code for Lasso Model

```
from sklearn.linear_model import Lasso

las = Lasso(alpha=0.1)
model2 = las.fit(train_x, train_y)
predictions2 = las.predict(test_x)
```

Accuracy of Model is: 0.38967572787640603

Root Mean Squared Error of Model is: 11.988560504390488

3.1.3 K-nearest Neighbor

The k-nearest neighbor is a simple, supervised machine learning algorithm that can be used to solve both classification and regression problems.

Code for K-nearest Neighbor Model

```
from sklearn.neighbors import KNeighborsRegressor
knn = KNeighborsRegressor()
model3=knn.fit(train_x, train_y)
predictions3 = knn.predict(test_x)
```

Accuracy of Model is: 0.34345271643724284

Root Mean Squared Error of Model is: 12.434253663809674

3.1.4 Support Vector Machine

Support vector machine is a supervised machine learning algorithm used for classification, regression and outlier detection. We use a linear Support Vector Machine model.

Code for Support Vector Machine Model

```
from sklearn.svm import SVR

svm= SVR(kernel='linear')
model4=svm.fit(train_x, train_y)
predictions4 = svm.predict(test_x)
```

Accuracy of Model is: 0.34808748601553163

Root Mean Squared Error of Model is: 12.390287319386937

3.1.5 Neural Network

Neural Nework is also used in previous studies to predict concrete strength. A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data. A neural network consists of input layer, hidden layers and output layer. It's able to learn and model non-linear and complex relationships between independent and dependent variables.

Code for Neural Network Model

```
import tensorflow as tf
layer_width = 128
l1 = 0.0
12 = 0.05
model1_split = tf.keras.Sequential()
model1_split.add(tf.keras.layers.Dense(512, activation="relu",
        kernel_regularizer = tf.keras.regularizers.l1_l2(l1=l1, l2=l2)))
model1_split.add(tf.keras.layers.BatchNormalization())
model1_split.add(tf.keras.layers.Dense(256, activation="relu"))
model1_split.add(tf.keras.layers.BatchNormalization())
model1_split.add(tf.keras.layers.Dense(128, activation="relu"))
model1_split.add(tf.keras.layers.BatchNormalization())
model1_split.add(tf.keras.layers.Dense(128, activation="relu"))
model1_split.add(tf.keras.layers.Dense(32, activation="relu"))
model1_split.add(tf.keras.layers.Dense(1))
model1_split.compile(optimizer=tf.keras.optimizers.Adam(lr=0.0015),
                 loss='mean_squared_error',
                 metrics=[tf.keras.metrics.RootMeanSquaredError()]
                 )
history_split = model1_split.fit(train_x, train_y, batch_size=1000,
                  epochs=500, shuffle=True)
epochs_split = history_split.epoch
hist_split = pd.DataFrame(history_split.history)
rmse_split = hist_split["root_mean_squared_error"]
model1_split.summary()
model1_split_prediction = model1_split.predict(test_x)
```

Accuracy of Model is: 0.8565038038524211

Root Mean Squared Error of Model is: 6.229324285295386

3.1.6 Decision Tree Regressor

Decision-tree algorithm is a kind of supervised learning algorithms. It can be used in classification and regression problems.

Code for Decision Tree Regressor

```
from sklearn.tree import DecisionTreeRegressor

dtregressor = DecisionTreeRegressor(random_state = 0, min_samples_split=5)
dtregressor.fit(train_x, train_y)
y_pred_dt= dtregressor.predict(test_x)
```

Accuracy of Model is: 0.8204795438030693

Root Mean Squared Error of Model is: 6.9675118677407

3.1.7 Random Forest Regression

Random Forest Regression is a type of supervised learning algorithms. It constructs multiple decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the prediction accuracy and it controls over-fitting as well.

Code for Hyperparameter Tuning

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestRegressor
#Use the random grid to search for best hyperparameter
# Number of trees in random forest
n_{estimators} = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 2000, stop = 2000, stop = 2000, num = 2000, stop = 2000, st
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 110, num = 11)]
max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 4]
# Method of selecting samples for training each tree
bootstrap = [True, False]
# Create the random grid
random_grid = {'n_estimators': n_estimators,
                                     'max_features': max_features,
                                     'max_depth': max_depth,
                                     'min_samples_split': min_samples_split,
                                     'min_samples_leaf': min_samples_leaf,
                                     'bootstrap': bootstrap}
# First create the base model to tune
rf_split = RandomForestRegressor()
# Random search of parameters, using 3 fold cross validation,
# search across 100 different combinations, and use all available cores
rf_random_split = RandomizedSearchCV(estimator = rf_split,
                    param_distributions = random_grid, n_iter = 100, cv = 3, verbose=2,
                     random_state=None, n_{jobs} = -1)
# Fit the random search model
rf_random_split.fit(train_x, train_y)
```

The best parameters for the model is:

{'n_estimators': 1200, 'min_samples_split': 2, 'min_samples_leaf': 1, 'max_features': 'auto', 'max_depth': 100, 'bootstrap': True}

Code for Random Forest Model

Accuracy of Model is: 0.9053846430868259

Root Mean Squared Error of Model is: 5.058264806966998

3.2 Comparison and Result

The accuracy and root mean squared error are two parameters to evaluate the model performance. The two parameters of all the seven models we used are shown in the following table.

Table: Summary of Model Performance

Method	Accuracy	Root Mean Squared Error
Linear Regression	0.5177053629131334	11.420285520195613
Lasso Method	0.38967572787640603	11.988560504390488
K-nearest Neighbor	0.34345271643724284	12.434253663809674
Support Vector Machine	0.34808748601553163	12.390287319386937
Neural Network	0.8565038038524211	6.229324285295386
Decision Tree Regressor	0.8204795438030693	6.9675118677407
Random Forest Regression	0.9053846430868259	5.058264806966998

As shown in the table, Linear Regression, Lasso Method, K-nearest Neighbor and Support Vector Machine do not perform well in predicting concrete strength. The other three methods: Neural Network, Decision Tree Regressor and Random Forest Regression are relatively better.

The accuracy of Random Forest Regression and Neural Network are in the first and second place, respectively. The comparison of these two methods is as follows.

- When creating a model, Neural Network is more complicated. Setting appropriate values for its parameter such as layer numbers, learning rate, batch size, etc. is extremely improtant to the performace of the model, so that it requires more efforts to find better parameters. Random Forest is much easier to find the best parameters.
- Random Forest is less computationally expensive. It can be trained faster than Neural Network.
- When using Neural Network, we should pay attention to avoiding overfitting. However, Random Forest is less prone to overfitting.

Compared with previous studies, the linear regression and neural network models we used do not show the same level of accuracy. One reason could be that the dataset we used to train the model is not big enough. Since we split 20% of the train dataset into test dataset for evaluating model performance, the total number of data we used for training is 565 rows. In the future study, we are expected to use larger dataset to train models, hoping to get a similar accuracy.

What's more, a key insight of our project is that random forest regression shows a great potential to predict concrete strength, however, it has not been used widely in previous studies. We will further confirm wether random forest regression only shows a great performance in the dataset we used or can be applied to other dataset.

For this project, Random Forest Model works best. We recreate a random forest model using the whole given train dataset and use it to predict the given test dataset.

Code for Hyperparameter Tuning

The best parameters for the model is:

{'n_estimators': 600, 'min_samples_split': 2, 'min_samples_leaf': 2, 'max_features': 'auto', 'max_depth': 70, 'bootstrap': True}

Code for recreate a model

prediction Code for recreate a model

After submitting the *prediction2.csv* to Kaggle Competition, it provides a score of 5.50396 which indicates Root Mean Squared Error. We can expect a model accuracy of 85%-90% for such a score.

# ∆pub Team Name Notebook Team Members Score ② 1 ▲1 Qinyu Zhang 5.50396	Entries	Last
1 •1 Oinyu 7hang 5 50396		
3.30390	8	11d
2 ▼1 Sonali Srivastava 5.71618	5	6d
3 — Pratyush Kumar62 13.22915	1	6d
♀ sample.csv 40.97523		

Figure: Kaggle Competition Page

4. Conclusion

From the Exploratory Data analysis, it was found that Concrete strength has a very strong positive correlation with age and cement content. The correlation states that with the increase in the amount of curing time and cement content the strength of concrete would increase sharply. There was a significant negative correlation between concrete strength and water suggesting that increase in water content within the mix leads to degradation of strength. Prior to training of the model scaling of the dataset was needed and the high amount of outliers in the age variable data was taken into account.

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- 2. Ordered list item
 - a. Sub-item
 - b. Sub-item
 - i. Sub-sub-item
- 3. Ordered list item
 - a. Sub-item
- List item
- List item
- List item

subscript: H₂O is a liquid

superscript: 2¹⁰ is 1024.

unicode superscripts 0123456789

unicode subscripts 0123456789

A long paragraph of text. Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

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Line break without starting a new paragraph by putting two spaces at end of line.

Document organization

Document section headings:

Heading 1

Heading 2

Heading 3

Heading 4

Heading 5

Heading 6



Horizontal rule:

Heading 1's are recommended to be reserved for the title of the manuscript.

Heading 2's are recommended for broad sections such as Abstract, Methods, Conclusion, etc.

Heading 3's and Heading 4's are recommended for sub-sections.

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Link with text

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Figure 1

Figure 2

```
Figure 3

Figure 4

Table 1

Equation 1

Equation 2
```

Quotes and code

Quoted text

Quoted block of text

Two roads diverged in a wood, and I—I took the one less traveled by, And that has made all the difference.

Code in the middle of normal text, aka inline code.

Code block with Python syntax highlighting:

```
from manubot.cite.doi import expand_short_doi

def test_expand_short_doi():
    doi = expand_short_doi("10/c3bp")
    # a string too long to fit within page:
    assert doi == "10.25313/2524-2695-2018-3-vliyanie-enhansera-copia-i-
        insulyatora-gypsy-na-sintez-ernk-modifikatsii-hromatina-i-
        svyazyvanie-insulyatornyh-belkov-vtransfetsirovannyh-geneticheskih-
        konstruktsiyah"
```

Code block with no syntax highlighting:

```
Exporting HTML manuscript
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Exporting PDF manuscript
```

Figures



Figure 1: A square image at actual size and with a bottom caption. Loaded from the latest version of image on GitHub.



Figure 2: An image too wide to fit within page at full size. Loaded from a specific (hashed) version of the image on GitHub.



Figure 3: A tall image with a specified height. Loaded from a specific (hashed) version of the image on GitHub.



Figure 4: A vector .svg image loaded from GitHub. The parameter sanitize=true is necessary to properly load SVGs hosted via GitHub URLs. White background specified to serve as a backdrop for transparent sections of the image.

Tables

Table 1: A table with a top caption and specified relative column widths.

Bowling Scores	Jane	John	Alice	Bob
Game 1	150	187	210	105
Game 2	98	202	197	102
Game 3	123	180	238	134

Table 2: A table too wide to fit within page.

	Digits 1-33	Digits 34-66	Digits 67-99	Ref.
pi	3.14159265358979323 846264338327950	28841971693993751 0582097494459230	78164062862089986 2803482534211706	piday.org
е	2.71828182845904523 536028747135266	24977572470936999 5957496696762772	40766303535475945 7138217852516642	nasa.gov

 Table 3: A table with merged cells using the attributes plugin.

	Colors	
Size	Text Color	Background Color
big	blue	orange
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Equations

A LaTeX equation:

$$\int_0^\infty e^{-x^2} dx = \frac{\sqrt{\pi}}{2} \tag{1}$$

An equation too long to fit within page:

$$x = a + b + c + d + e + f + g + h + i + j + k + l + m + n + o + p + q + r + s + t + u + v + w + x + y + z + 1 + 2 + 3 + 4 + 5 + 6 + 7 + 8 + 9$$
(2)

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useful for general information - manubot.org

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♦ Light Red Banner useful for *warnings* - <u>manubot.org</u>

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Douglas Heaven

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cOAlition S

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DOI: <u>10.1371/journal.pcbi.1007128</u> · PMID: <u>31233491</u> · PMCID: <u>PMC6611653</u>