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 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. Also, small human error in designing or preparing can lead to drastic change in strength and increase the waiting time. Recently, researchers are developing models using machine learning and artificial neural network to predict the compressive strength of concrete. This is very useful in predicting the performance using complex non-linear relations.

Problem Statement

Since conventional methods for checking the performance of concrete are time consuming and prone to human error. This project aims to predict the compressive strength of concrete using different emerging soft computer techniques like Linear Regression, Lasso Regression, Artificial Neural Network, Random Forest, and Decision Tree Regression. A comparison is made using the root mean square error and model with better performance was chosen. The dataset was collected from UCI Machine Learning Repository. It has total 1030 instances with 9 attributes (8 quantitative input variable and 1 quantitative output variables). The eight independent variables are: cement (kg/m3), blast furnace slag (kg/m3), fly ash (kg/m3), water (kg/m3), superplasticizer (kg/m3), coarse aggregates (kg/m3), fine aggregates (kg/m3), and age of curing (days). The dependent/output variable is compressive strength in MPa.

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

In [1]:

```
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/test.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]:

	Cement (component 1)(kg in a m^3 mixture)	Blast Furnace Slag (component 2)(kg in a m^3 mixture)	Fly Ash (component 3)(kg in a m^3 mixture)	Water (component 4)(kg in a m^3 mixture)	Superplasticizer (component 5)(kg in a m^3 mixture)	Coarse Aggregate (component 6)(kg in a m^3 mixture)	Fine Aggregate (component 7)(kg in a m^3 mixture)	Age (day)	Concrete compressive strength(MPa, 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
std	105.051424	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
25%	194.090000	0.000000	0.000000	164.900000	0.000000	932.000000	723.400000	14.000000	24.023412
50%	275.000000	26.000000	0.000000	185.700000	6.350000	967.080000	779.320000	28.000000	34.770275
75%	350.000000	144.100000	116.000000	193.000000	10.300000	1028.400000	824.000000	56.000000	46.070786
max	540.000000	359.400000	200.000000	247.000000	32.200000	1134.300000	992.600000	365.000000	82.599225

EDA-3

Rename Columns Name

In [4]:
```
train1= train.rename(columns={"Cement (component 1)(kg in a m^3 mixture)": "1_cement",
                     "Blast Furnace Slag (component 2)(kg in a m^3 mixture)": "2_BFS",
                    "Fly Ash (component 3)(kg in a m^3 mixture)": "3_Flyash",
                    "Water  (component 4)(kg in a m^3 mixture)": "4_water",
                    "Superplasticizer (component 5)(kg in a m^3 mixture)": "5_SP",
                    "Coarse Aggregate  (component 6)(kg in a m^3 mixture)": "6_CA",
                    "Fine Aggregate (component 7)(kg in a m^3 mixture)": "7_FA",
                    "Age (day)": "Age",
                   "Concrete compressive strength(MPa, megapascals) " : "strength" }, errors="raise")
train1.head()
```

Out[4]:

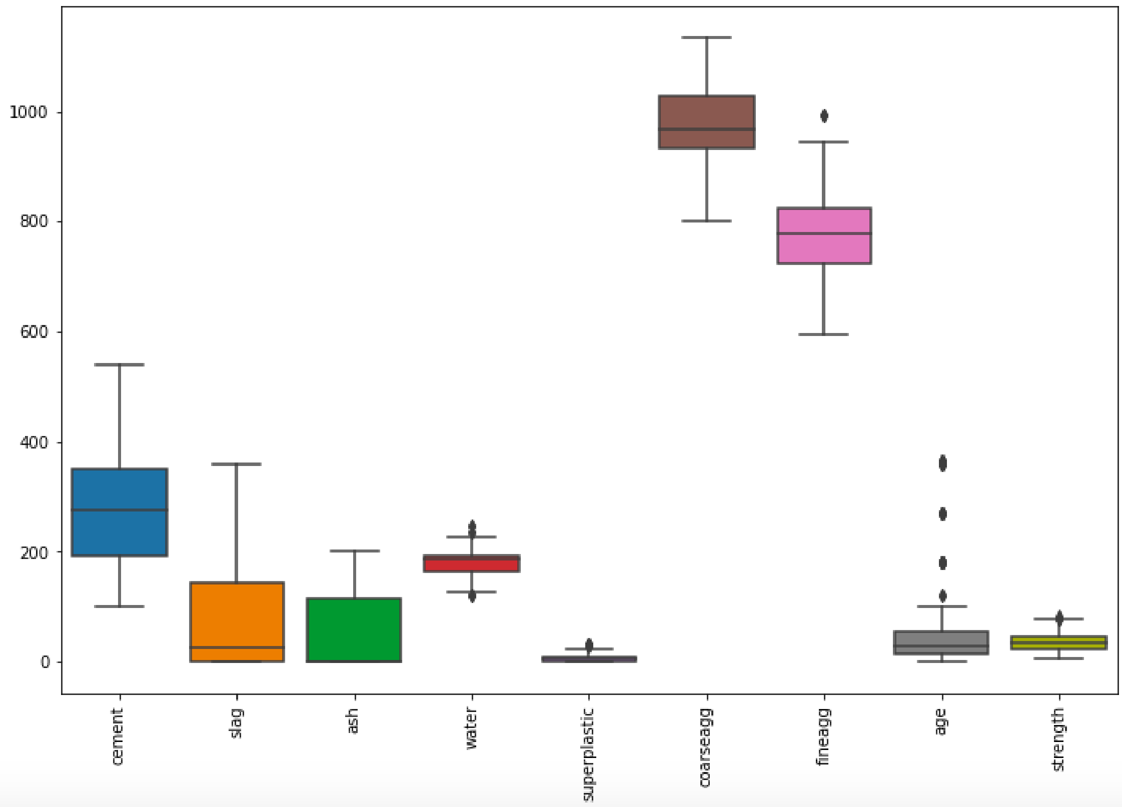
	1_cement	2_BFS	3_Flyash	4_water	5_SP	6_CA	7_FA	Age	strength
0	540.0	0.0	0.0	162.0	2.5	1040.0	676.0	28	79.986111
1	332.5	142.5	0.0	228.0	0.0	932.0	594.0	270	40.269535
2	332.5	142.5	0.0	228.0	0.0	932.0	594.0	365	41.052780
3	198.6	132.4	0.0	192.0	0.0	978.4	825.5	360	44.296075
4	266.0	114.0	0.0	228.0	0.0	932.0	670.0	90	47.029847

EDA-4

Box plot analysis was performed:

Box plots

In [8]:
```
plt.subplots(figsize=(12, 8))
ax = sns.boxplot(data=data)
ax.set_xticklabels(ax.get_xticklabels(), rotation=90);
```



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.

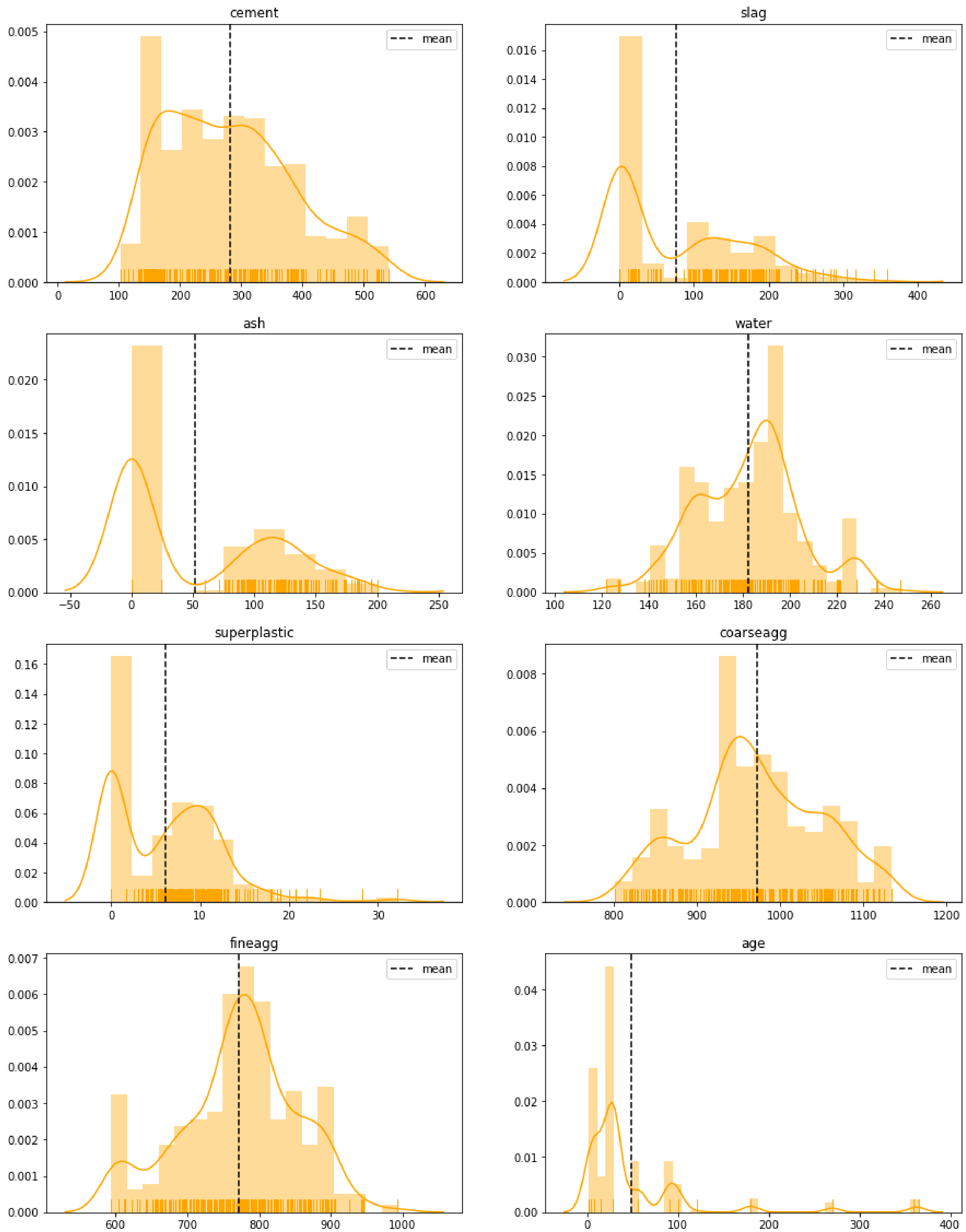
2: The data from water, superplastic, age, and strength appears to have some outliers, amidst them the age data has a long extension of the plot suggesting the highest amount of outliers amongst all of data columns mentioned.

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

Distribution of independent variables

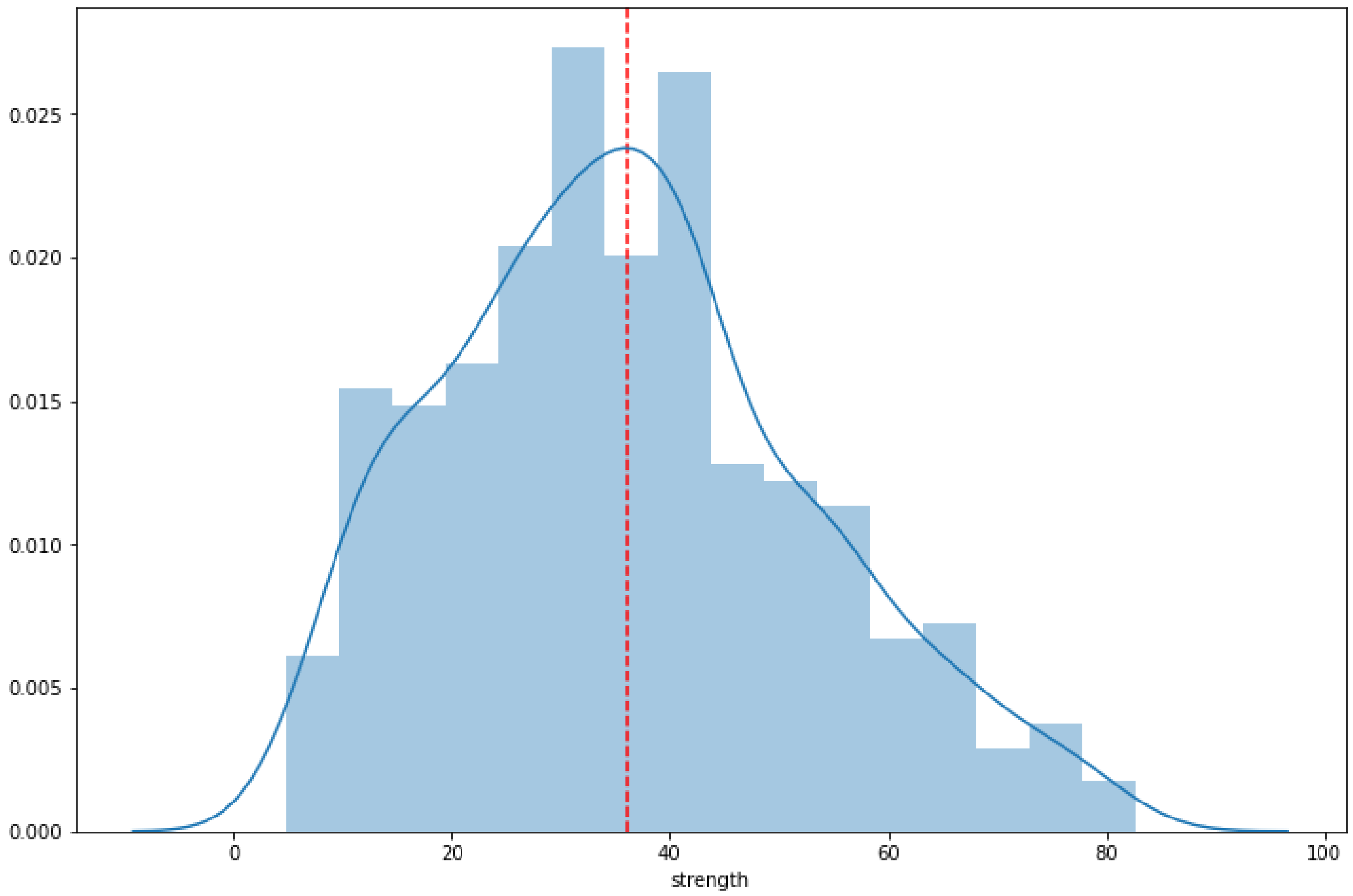
In [9]:
```
import itertools

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



EDA-9

Distribution plot for strength variable



EDA-10

Degree of skewness

In [11]:
```
from scipy.stats import skew
numerical_features = data.select_dtypes(include=[np.number]).columns
categorical_features = data.select_dtypes(include=[np.object]).columns
skew_values = skew(data[numerical_features], nan_policy = 'omit')
dummy = pd.concat([pd.DataFrame(list(numerical_features), columns=['Features']),
          pd.DataFrame(list(skew_values), columns=['Skewness degree'])], axis = 1
)
dummy.sort_values(by = 'Skewness degree' , ascending = False)
```

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

EDA-11

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.

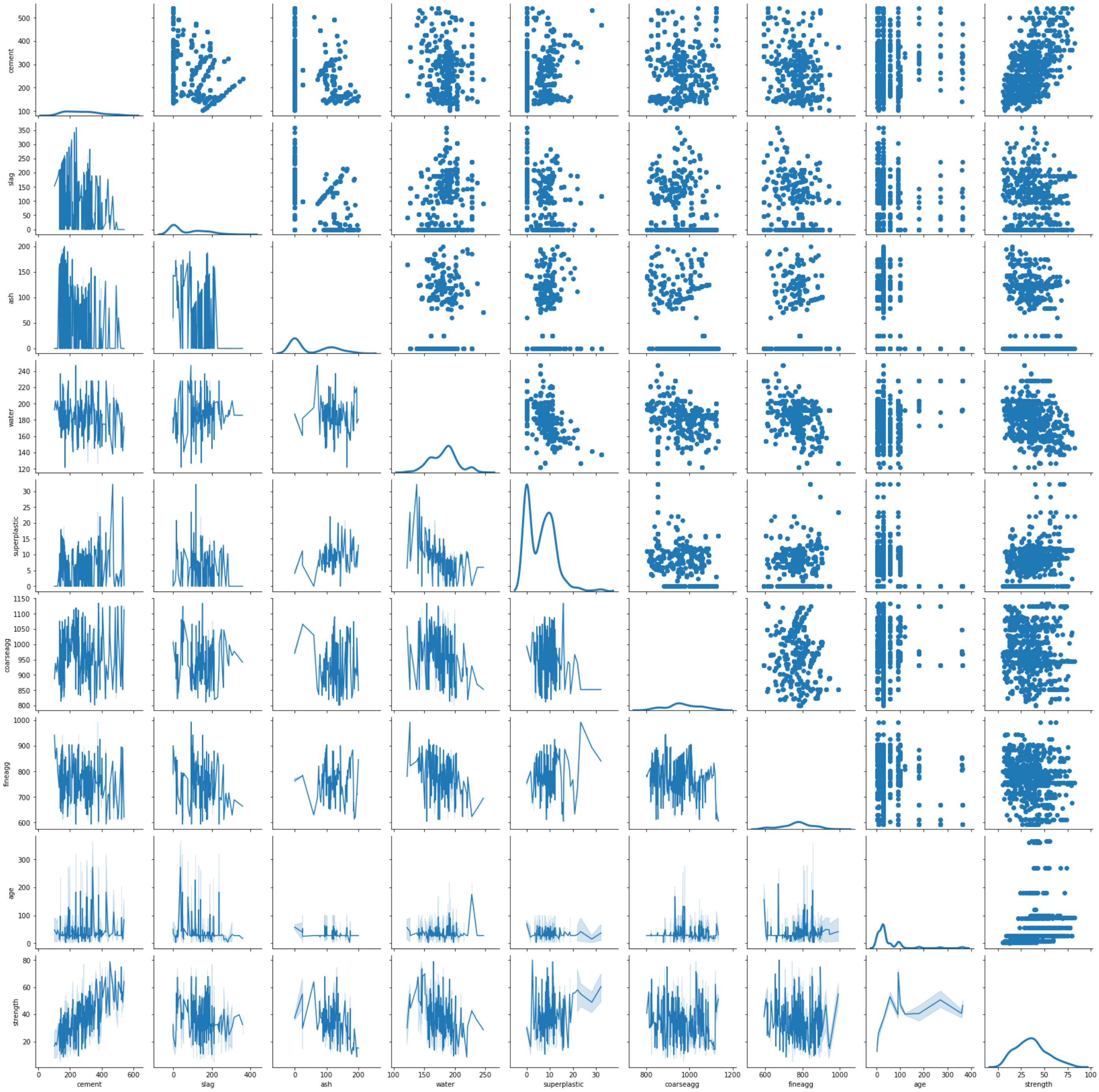
3: The data from age column as seen from box plot had a lot of outliers which is re-affirmed here with the distribution plot having very lengthy un-symmetrical extension beyond its mean value.

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.

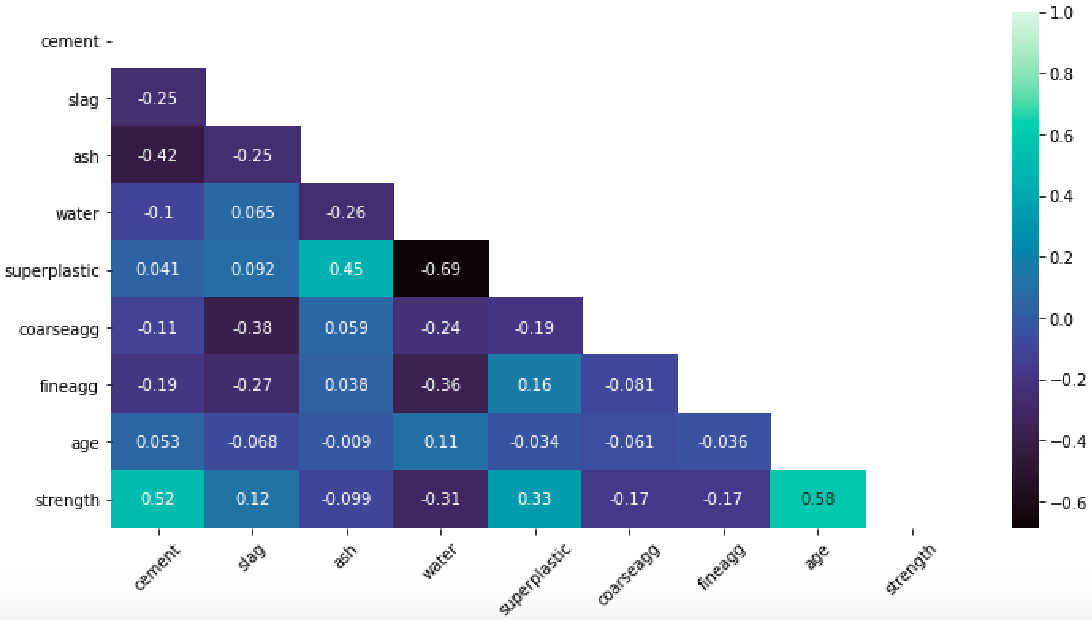
4: Water and superplastic have a negeative correlation.

5: Slag, ash, coarseagg and fineagg are having poor correlation to strength so they aren't the best predctors of strength.

Heat map

In [13]:

```
plt.subplots(figsize=(12, 6))
corr = data.corr('spearman')

mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True

ax = sns.heatmap(data=corr, cmap='mako', annot=True, mask=mask)
ax.set_xticklabels(ax.get_xticklabels(), rotation=45);
```



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
l2 = 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 =
        10)]
# 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

```
# create a model
model2_split = RandomForestRegressor(n_estimators =
        rf_random_split.best_params_['n_estimators'],
                              min_samples_split =
        rf_random_split.best_params_['min_samples_split'],
                              min_samples_leaf =
        rf_random_split.best_params_['min_samples_leaf'],
                              max_features =
        rf_random_split.best_params_['max_features'],
                              max_depth =
        rf_random_split.best_params_['max_depth'],
                              bootstrap =
        rf_random_split.best_params_['bootstrap'])

model2_split.fit(train_x, train_y)

model2_split_prediction = model2_split.predict(test_x)
```

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

```
# First create the base model to tune
rf = RandomForestRegressor()
# Random search of parameters, using 3 fold cross validation,
# search across 100 different combinations, and use all available cores
rf_random = RandomizedSearchCV(estimator = rf, param_distributions =
        random_grid, n_iter = 100, cv = 3, verbose=2, random_state=None,
        n_jobs = -1)
# Fit the random search model
rf_random.fit(x, y)
```

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

```
model2 = RandomForestRegressor(n_estimators =
        rf_random.best_params_['n_estimators'],
                              min_samples_split =
        rf_random.best_params_['min_samples_split'],
                              min_samples_leaf =
        rf_random.best_params_['min_samples_leaf'],
                              max_features =
        rf_random.best_params_['max_features'],
                              max_depth =
        rf_random.best_params_['max_depth'],
                              bootstrap =
        rf_random.best_params_['bootstrap'])

model2.fit(x, y)
```

prediction Code for recreate a model

```
prediction2 = model2.predict(test_df)
prediction2 = pd.DataFrame(prediction2, columns=['Concrete compressive
        strength(MPa, megapascals)'])
prediction2.index.name='index'
prediction2.to_csv('prediction2.csv')
```

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	Entries	Last
1	▲1	Qinyu Zhang			5.50396	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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> 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:

```python
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
Exporting DOCX manuscript
Exporting PDF manuscript
```

Figures

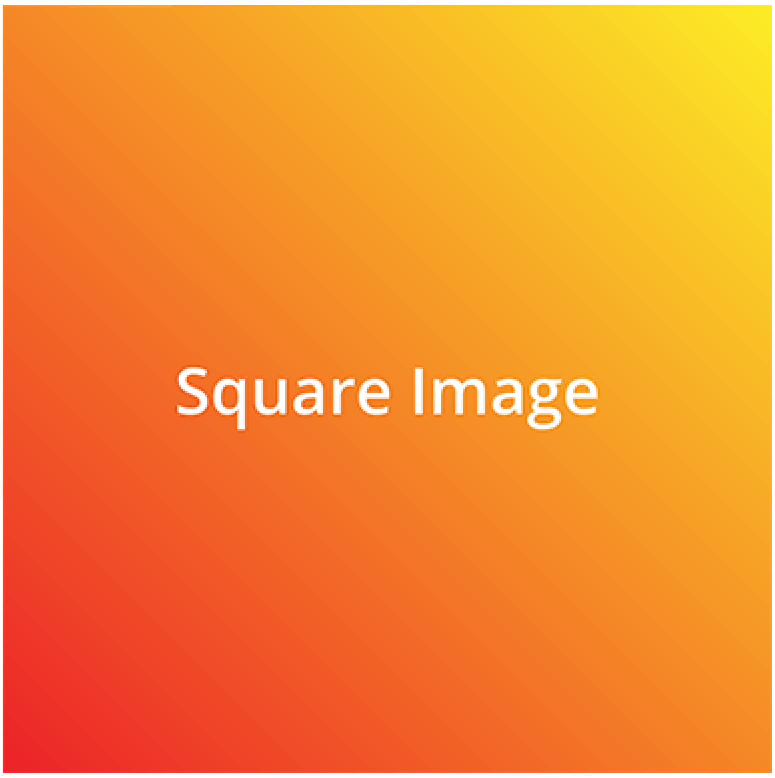

Figure 1: A square image at actual size and with a bottom caption. Loaded from the latest version of image on GitHub.

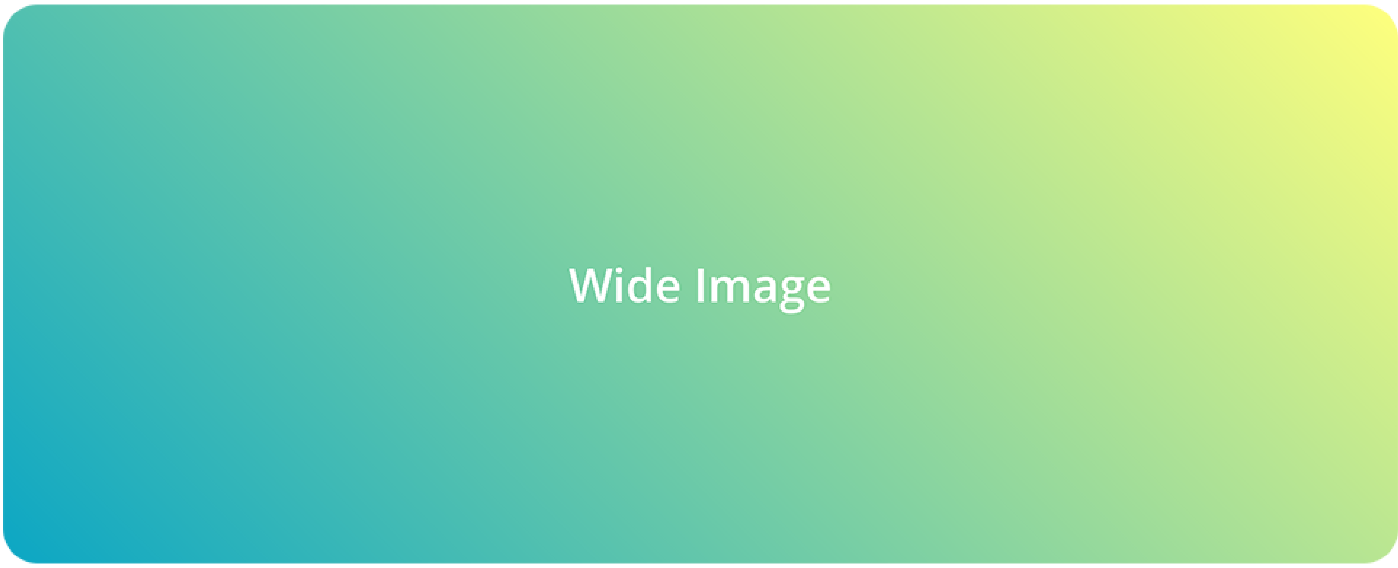

Figure 2: An image too wide to fit within page at full size. Loaded from a specific (hashed) version of the image on GitHub.

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`
e	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
small	black	white

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:

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

Special

⚠ WARNING *The following features are only supported and intended for `.html` and `.pdf` exports. Journals are not likely to support them, and they may not display correctly when converted to other formats such as `.docx`.*

LINK STYLED AS A BUTTON

Adding arbitrary HTML attributes to an element using Pandoc's attribute syntax:

> Manubot Manubot Manubot Manubot Manubot. Manubot Manubot Manubot Manubot. Manubot Manubot Manubot. Manubot Manubot. Manubot.

Adding arbitrary HTML attributes to an element with the Manubot `attributes` plugin (more flexible than Pandoc's method in terms of which elements you can add attributes to):

> Manubot Manubot Manubot Manubot Manubot. Manubot Manubot Manubot Manubot. Manubot Manubot Manubot. Manubot Manubot. Manubot.

Available background colors for text, images, code, banners, etc:

`white` `lightgrey` `grey` `darkgrey` `black` `lightred` `lightyellow` `lightgreen` `lightblue` `lightpurple` `red` `orange` `yellow` `green` `blue` `purple`

Using the [Font Awesome](https://fontawesome.com/) icon set:

✔ ? ★ 🔔 ⊗ ⋯

Light Grey Banner
useful for *general information* - manubot.org

Blue Banner
useful for *important information* - manubot.org

Light Red Banner
useful for *warnings* - manubot.org

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