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Our group is pursuing the Concrete Strength project. Within this project we will be examining data sets and tables with the intent of fabricating data simulations. The purpose of said data frame is to simulate a test, or use pre-existing data, to digitally generate an accurate strength test result without the need of excessive man hours or labor.

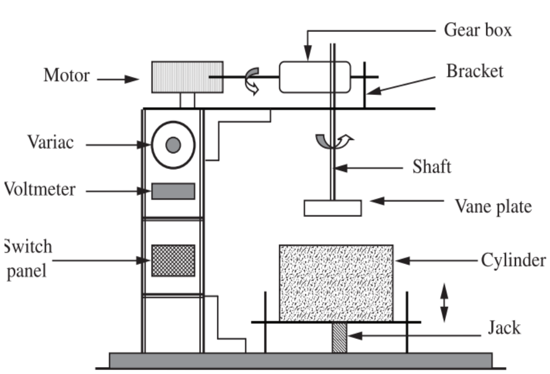
There are multiple types of tests used to test the quality of concrete. One test is called the slump test. The slump test is used to test some of the rheological features of concrete and to see if the concrete is workable. One of the issues with this test, however, is that it can sometimes give the same results for two different mixtures. The other test is a form of a compression test. The compression test uses a machine to test the compressive strength of concrete. This test better presents which mixtures and tells what mixture proportions work best for a desired outcome. But why is the compressive strength an important factor?

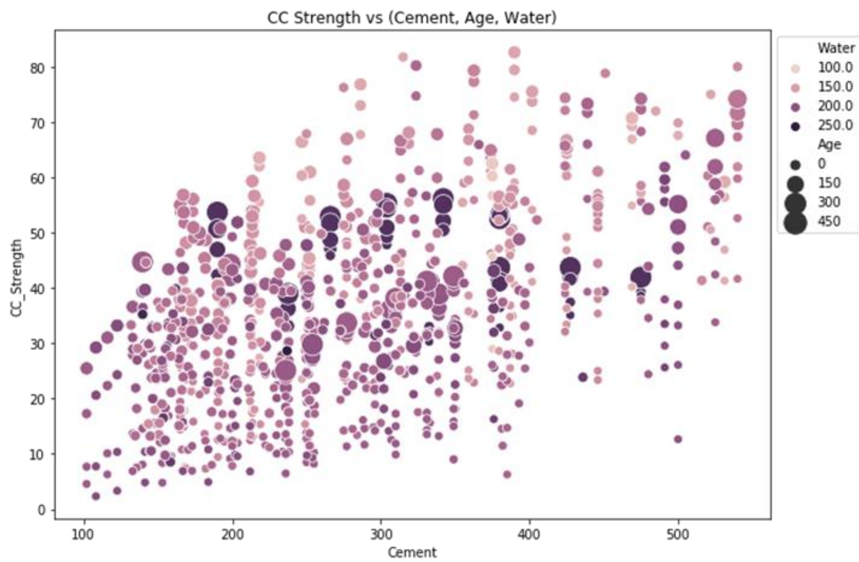
“Traditionally, the behavior of fresh concrete is associated with its workability, a term that refers to properties of the material before it has set and hardened.” (Castro et al. 08, p. 2) There are obvious advantages to knowing the workability of concrete. Concrete may need to be put in compromising situations which require a certain level of workability. For instance, some concrete has to be able to run between supporting bars for assured strength. This test, however, has its issues. This test does not account well for high flowability which is more common in high performance concrete. “Moreover, in practice, it is known that concretes with the same slump value or flow value are able to present different workabilities.” (Castro et al. 08, p. 2) The test for compressive strength however is much more reliable in its own right.

There is a test that shows compressive strength more reliably displays the strength in correlation to mixtures. The test uses a cylinder of concrete to test the compressive strength. A cylinder of concrete is placed into a machine designed to press down on it. Based of the readings from this machine the observer can pair the strength to the cement mixture. Overall this is the best test for concrete's strength.

As good at determining the strength of concrete as this test is, it still has its problems. First of all, there is the issue of time. It takes 28 days before a sample is ready for testing. Testing before this will result in inconclusive or incorrect results. There is also the issue of human error. The process required to test the compressive strength is very laborious. "…one small mistake can cause the wait time to drastically increase." (Modukuru, 2020) So how do we reduce both time and human error?

With the amount of data we have gathered, would it be possible to create a program to accurately guess the strength of concrete. According to some the answer is yes. "A first product, entitled Bétonlab [1, 2] and proposed in 1992, was created for tutorial purposes." (Larrad et al, 2002, p. 2) This 'tutorial' was used as a way for scientists to test concrete at their desk. It was also used to test concrete faster than the 28 days that is normally required. Others have also used machine learning algorithms to accurately assume the concrete's strength. Using a large dataset of different mixture combinations and already measure strengths they can guess the strength of a new mixture without physically testing it.





The “Concrete Data” database consists of 1030 rows and 9 columns. According to the database Comprehensive strength seems to increase as the cement component value increases. The value for comprehensive strength increases as the age of the cement itself increases. Younger cement seems to also requires a higher cement component (higher quantity of cement). The values for the water component seem to inversely correlate with the comprehensive concrete strength. According to the scatter plot in the *Towards Data Science* article the comprehensive strength of the concrete increases the amount of Superplasticizer used.

In [14]:
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1 df.describe()
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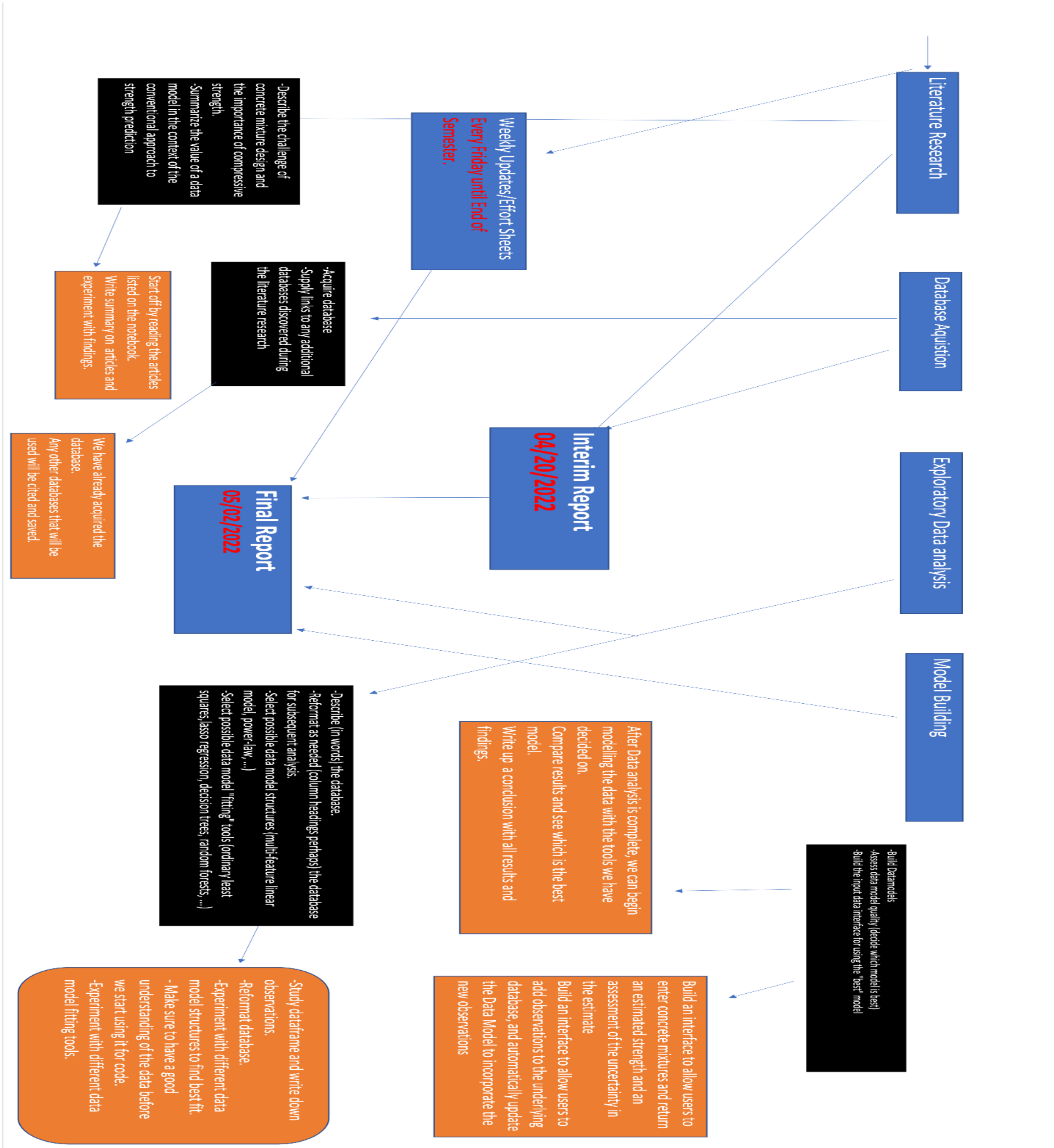
Out[14]:

	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	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000	1030.000000
mean	281.165631	73.895485	54.187136	181.566359	6.203112	972.918592	773.578883	45.662136	35.817836
std	104.507142	86.279104	63.996469	21.355567	5.973492	77.753818	80.175427	63.169912	16.705679
min	102.000000	0.000000	0.000000	121.750000	0.000000	801.000000	594.000000	1.000000	2.331808
25%	192.375000	0.000000	0.000000	164.900000	0.000000	932.000000	730.950000	7.000000	23.707115
50%	272.900000	22.000000	0.000000	185.000000	6.350000	968.000000	779.510000	28.000000	34.442774
75%	350.000000	142.950000	118.270000	192.000000	10.160000	1029.400000	824.000000	56.000000	46.136287
max	540.000000	359.400000	200.100000	247.000000	32.200000	1145.000000	992.600000	365.000000	82.599225

By using the describe() function associated with the pandas library I was able to find out that the mean value for the comprehensive concrete strength is 35.817836 and the standard deviation 16.705679.

(ZOOM IN IF UNCLEAR)



Building Models: Quinton and Miles will start by building data models to use for the data frame analysis. They will research all possible options and choose which ones are the best to choose from.

Assessing the Models: Khalid will assess all of the models which Quinton and Miles provide and decide which one to use.

Input: Samuel will then form an input interface that works best for the data model Khalid chose. We will not only be able to put in our own mixture values, but also be able to add more results to the original data frame.

Final Output. Lastly, we will give provided inputs to the data models we chose to use to get a prediction. From this we should be able to accurately predict which mixes will best suit our strength needs.

References

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