Semester Project

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Abstract
This data analytics project is focused on predicting the size of largest hailstone that comes from any given storm. To do this, reports of more than 20,000 hail events and their associated meteorological data have been collected and tabularized.

Keywords
Meteorology — Numerical Weather Prediction — Machine Learning

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Contents

1. Problem and Data Description

According to the NOAA Annual Severe Weather website, there were 3,762 recorded severe hail events (hail over 0.75”) in the US in 2021 alone. Beyond the noble goal of furthering our understanding of the natural world, the ability to accurately predict which locations will experience hail storms could benefit insurance companies who pay out an average of $12,000 for residential damage claims and $4,000 for automobile claims. Multiplied by thousands of storms per year and hundreds of thousands of possible claims per storm, it is clear that increasing advanced warming times for likely hail conditions could have massive benefits for both the general public and insurance companies alike.

The data for this project consists of approximately 29,000 reports of severe hail events and the meteorological conditions present during the event. The hail event data was collected from the 2012-2016 entries in the NOAA Storm Prediction Center database. After extracting just the hail sizes, coordinates, and dates/times, those parameters were entered into the North American Mesoscale Model to determine vertical profiles of temperature, humidity, and wind within 3 hours and 20 km of the individual hail events. The meteorological profiles were passed to an open-source python program, SHARPpy, to calculate the exclusively continuous, numerical parameters we will be discussing in the following table.

After the data is extracted from the various sources and tabularized, it forms a CSV with 21902 entries and 55 fields, including the target variable of hailstone size.

Index	Parameter Name	Units
1	CAPE	J/kg
2	CIN	J/kg
3	LCL	m
4	LFC	m
5	EL	m
6	LI	°C
7	HGHT0C	m
8	CAP	°C
9	B3KM	J/kg
10	BRN	None
11	SHEAR 0-1 KM	m/s
12	SHEAR 0-6 KM	m/s
13	EFF INFLOW	
14	EBWD	
15	SRH 0-1 KM	m^2/s^2
16	SRH 0-3 KM	m^2/s^2
17	EFF SRH	m^2/s^2
18	SCP	None
19	STP-FIXED	None
20	STP-MIXED	None
21	SHIP	None
22	PWAT	in
23	DCAPE	m/s
24	MLMR	g/kg
25	LRAT	°C/km
26	TEI	°C
27	TLCL	°C
28	T500	°C
29	SWEAT	None
30	K-INDEX	°C
31	CRAV	m^3/s^3
32	HAIL SIZE	in

2. Data Preprocessing & Exploratory Analysis

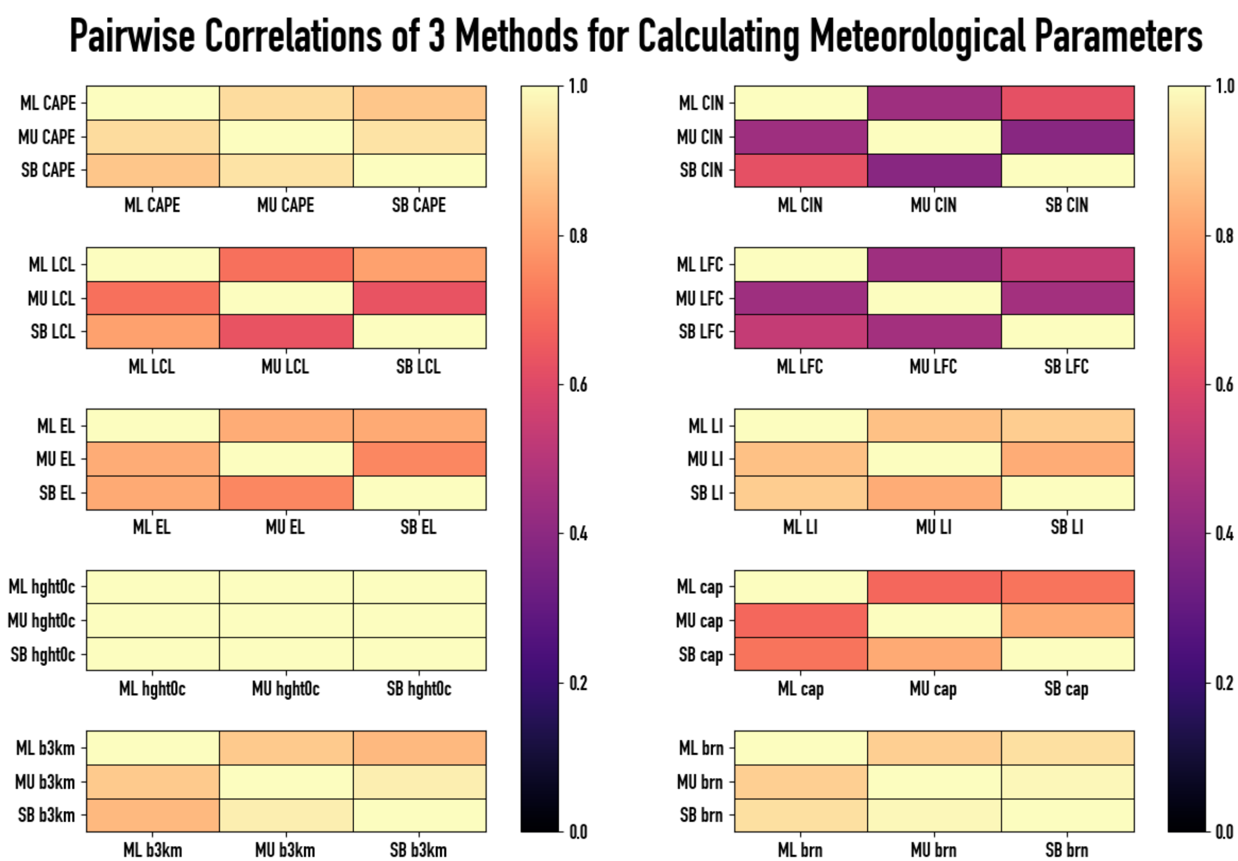
2.1 Parameter Selection

After the pipeline detailed in the Data Description was traversed, there were 53 parameters associated with each severe hail event (not including Hail Size). The 11 of the parameters (index positions 1-10 and 27) were repeated three times throughout the data, with the only difference being slightly different calculation methods for each. The three methods used were SB (Surface Based), ML (Mixed Layer), and MU (Most Unstable), each of which describes a process for calculating thermodynamic and wind related parameters. In short, SB uses the temperature at the surface, ML uses an average of the conditions up to an altitude of 100 mb (millibars), and MU uses the temperature of the most unstable air parcel found in the lowest 300 mb of the atmosphere. For a more in-depth explanation, refer to the NOAA Storm Prediction Center's guide on the subject.

We first attempted to determine how well these these various calculation techniques track each other by generating correlation plots corresponding to each of the first 10 variables. It our hope that they would all perform almost identically and thereby allow only one set to be used for visualization, analysis, and modeling purposes. However, the chart makes it clear that this is not the case.

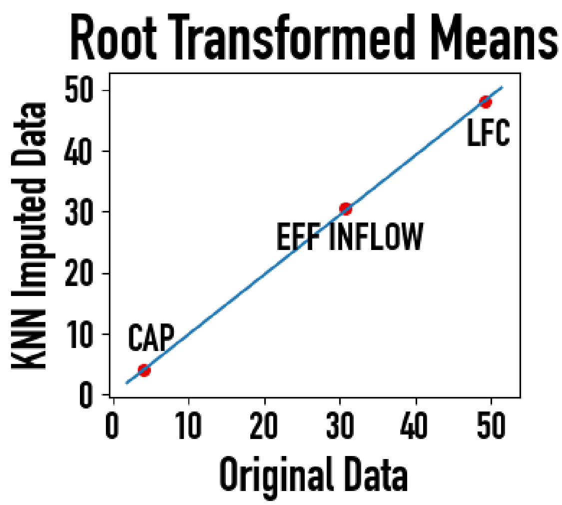
A few of the parameters differ greatly by calculation method; In the most extreme cases (CIN, LFC), MU and ML had a correlation of roughly .4, which is low enough to consider them very different measures. As a result, research was done into which method would yield most accurate results for modeling purposes. While the meteorological field is currently unable to provide conclusive evidence for one method's superiority, it is mentioned in the NOAA Storm Prediction Center source above that ML can produce slightly more accurate predictions of late afternoon cloud base heights. As the severe hail events at the center of our research are exclusively created by thunderstorms (which are most common in the afternoon, when warm and moist air is most often present), it is our opinion that employing the ML parameters in our subsequent visualizations and models will be marginally more effective than the others. Accordingly, any unspecified reference to one of the 11 variables in question will refer to the ML version.

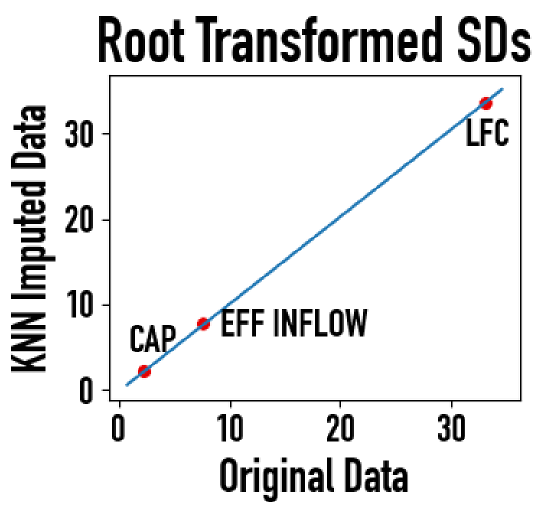
There is, of course, a possibility of revising the data during the modeling phase if results are unsatisfactory, which may include bringing in other parameters that can be found with the same sounding profile described in the Data Description, using the SB or MU methods in addition to ML if they do not excessively increase computational complexity, or even finding a source of higher-resolution sounding profiles (3 hour intervals instead of 6, for example.)



2.2 Handling Missing Values

The data contains 20,920 missing values; 2708 in LFC, 2069 in EFF INFLOW, and 16143 in CAP. Due to the entirely continuous nature of the data, we deemed it acceptable to apply KNN (K-Nearest Neighbors) Imputation over the data. In our case, we do this by calculating the weighted mean (the more similar points are, the more they factor into the mean) of the 5 most similar points for any entry with a missing value. This weighted mean is entered as the new value in place of any missing value. The process has the quality of maintaining both mean and variance between the pre- and post-transformation data, which we visualize below with a scatterplot. Each axis represents either the original or imputed data, and each red point represents the square root of mean or standard deviation for one of the three variables that were modified by KNN Imputation. The blue line has a slope of 1, so any points that fall on the blue line represent variables that maintain their distribution after KNN Imputation.





We can be sure no others variables changed during the application of KNN Imputation over the data, so our only variables of concern are the three we did modify. To be sure that the information they contain was not transformed, we test both their mean and standard deviations before and after transformation; they are nearly identical, so we can confidently conclude that we successfully imputed missing data without modifying the underlying distribution.

2.3 Exploratory Data Analysis

3. Algorithm and Methodology

Briefly explain the algorithms in this section, i.e., linear regressions. You can add more subsections if needed, i.e., regression trees etc.

4. Experiments and Results

5. Summary and Conclusions

Acknowledgments