NEW ALGORITHM TO IDENTIFY COLDEST AND HOTTEST TIME PERIODS.
CASE STUDY: COLDEST WINTERS RECORDED AT ARMAGH OBSERVATORY OVER 161 YEARS BETWEEN 1844 AND 2004

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ABSTRACT

A novel algorithm has been developed that ranks cold and/or hot annual time periods using daily maximum and/or minimum air temperature for a given archived dataset. The author used a version of the algorithm that he developed and extensively used to find similar structural patterns in databases containing millions of different molecules. However, in this paper, the method is applied to assess the similarity of ‘winter’ daily tmax patterns to the cold boundary pattern, wMIN, of an ultimately cold winter.

The fundamental problem with the current practices of weather forecasting is the use of the mean as a predictive variable which has no usable predictive power. The paper clearly shows that very small variations in the mean values are totally lost in very large natural variations of daily temperatures measured by a calibrated thermometer.

The key feature of this algorithm is to identify two extreme boundaries, the coldest one and the hottest, from a given archive dataset of daily tmax and/or tmin observed temperatures, and then calculate the distance between each annual time period chosen against those two reference patterns. In our case, the ranking of the coldest winters recorded at Armagh Observatory (UK) identified the two most unusually cold winters of 1963 and 1895. Definition of winter is a variable that is chosen by the user, in this case it was first 60 days of the year, and therefore each winter was treated as a pattern or if you wish a fingerprint, consisting of 60 daily tmax readings. Since the objective was to rank the winters from the coldest to the hottest, the cold reference pattern or a cold boundary was obtained by identifying the coldest daytime, tmax, reading for each day of the winter. The ranking algorithm then calculates the Euclidean Distance between each winter and the cold reference boundary and then sorts the winters by that distance, from the smallest to the largest, i.e., in ascending order. The results of the ranking algorithm were then compared

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with the observations and found that not only did the findings reflect the real observations for Armagh, but that the findings for Armagh can be applied to the whole of the UK.

**INTRODUCTION**

*If we do not understand the past or the present, what hope have we to project into the future?*

This opening statement represents a generic approach in building a knowledge database which can then be used to predict some future events. The key to understand any future events is to fully understand the past and present events, i.e., the ability to quantify relationships within a given dataset.

To demonstrate the predictive power of a given knowledge database we will look at a well described and understood dataset from the experimental sciences, drug discovery, and in this particular case the model for predicting a very important physicochemical property of molecules called logP:

![Figure 1](image)

Figure 1. Plot of predicted logP (X-axis) vs experimentally measured or observed logP (Y-axis).

The first number to look at is in the bottom-right corner which states that $R^2 = 0.973$. The simplest way to explain $R^2$ (pronounced R squared) is to multiply it by 100 which gives us a measure of the model’s accuracy. In this case, $R^2$ of 97.3% tells us that the model can explain 97.3% (out of 100%) of variations in the measured data while it can’t explain 2.7% of those variations, a difference between 100 and 97.3. The statement in the bottom right corner $N =$
11061 tells us that the model was built using measured logP of 11061 different molecules, while the statements in the top left corner tells us that the model was tested on 1759 molecules \((N = 1759)\) which have not been part of the training set and that the model was correct in 97.1\% \((R^2 = 0.971)\) of time.

One of the most important points to emphasise here, is that the ultimate test of the accuracy of any computational model in experimental sciences, is the ability to physically make and measure another set of new molecules and therefore further test the accuracy of the model by actually measuring those molecules.

_In other words, the model is assessed by more observations rather than by more calculations!_

So, what is the accuracy of current models that are used to forecast air temperatures at a given location, say 7 days ahead?

To find this out all we need to do is to go to the BBC Weather website and check for air temperatures predicted 7 days ahead at a given location - the small town of Armagh. The main reason for choosing Armagh, a seaside town in Northern Ireland, as a case study for this paper is that the Armagh Observatory has one of the oldest, well documented and freely available for download archive data of daily maximum \((t_{\text{max}})\) temperatures during daytime and minimum \((t_{\text{min}})\) temperatures during night-time, between 1844 and 2004, in total 161 years of data. In this way, we can then compare the accuracy of prediction of the daily temperatures that the UK Met Office is currently providing for the UK government and general public, against the historical observations.

For example, on January 6, 2016 the UK Met Office (via BBC Weather) made the following air temperature forecast for air temperatures on January 13, 2016 in Armagh (UK) (7 days ahead):

![Temperature Forecast](Image)

_Figure 2. Forecast seven days ahead for Jan 13 made on Jan 6, 2016._

The terminology used is as follow:

**Likely High** refers to the expected \(t_{\text{max}}\) temperature during daytime of 4C but it can be as high as 9C or as low as 2C with a possible error of +5C or -2C

**Likely Low** refers to the expected temperature during night time of 2C, \(t_{\text{min}}\), which can be as high as 6C or as low as -1C with a possible error of +4C or -3C
The table above shows quite a large discrepancy between the observations, row 2, and the model, row 3, for January 13 2016. The model predicts an average Tmax value of 4C which could be 5C above the mean, max2mean, or 2C below, mean2min, with total variation of 7C, TotRange.

However, if we look at the actual temperature records for January 13 between 1844 and 2004 at Armagh Observatory (www.arm.ac.uk/), we find out that the mean value for Tmax is 7C (3C higher than the model), the range between maximum and minimum Tmax of 15C (almost twice as large as the model). In other words, the model is very badly representing the observations that it had to be based upon:

![Figure 3. Daytime temperature variations, Tmax, for Jan 13 around the mean at Armagh Observatory between 1844 and 2004.](image)

Variations around the mean had a total range of 15C, on two occasions at 6C above the mean, and on three occasions at 9C below the mean. Figure 3 also tells us that the largest switch-over within two consecutive years occurred on two separate occasions. In 1866 Jan 13 was 6C above the mean while the following year, 1867, was 7C below the mean (points in black). One hundred and twenty years later, in 1986, Jan 13 was 4C above the mean while the following year, 1987, it was 9C below the mean, again points in black. On both occasions the size of switch-over was 13C. As can be seen from the figure above, use of the mean as a reference point is nonsensical since it is lost in the noise of natural daily variations in daytime temperatures.

The fundamental question that we have not asked, so far, is whether it is possible to find any correlation between time and the air temperatures at the ground level, which is what the meteorologists are trying to do? If we plot historical Tmax readings against time and apply a
simple trend line, i.e., a linear model that is generated by excel, we see that the accuracy is 0% ($R^2 = 0.0$):

![Figure 4. Historical observations for January 13 between 1844 and 2004.](image)

As it can be seen from the figure above, the linear model’s line is basically a slightly tilted mean of the data, i.e., a flat line, and highlighting the main points that we have discussed so far – the use of the mean in analysis of daily temperatures is not an appropriate computational tool since it has 0% accuracy in predicting future temperatures!

Furthermore, each day of the year has its own and a very complex historical pattern, Butina 2012, 2013 and 2015 papers [1, 2, 3], which means that any model has to treat a given time period, say a month, not as a single number obtained by some averaging, but as a pattern or a unique fingerprint of say 30 daily temperature readings.

Apart from the problem with modelling datasets with large variations around their mean, or in statistical terms, the large standard deviation, there is an even worse problem to deal with, a very complex and non-linear relationship between two temperature patterns:

![Figure 5. Differences in daily temperatures between winters (first 60 days of the year) of 1903 and 2003.](image)
Let us ask a very specific question, for example, which of the two winters, 1903 or 2003, is colder? It becomes immediately obvious by looking at Figure 5 that a simple answer to the question is not possible since there is this notorious problem with daily temperatures data across the globe – the switch-over problem. What is the above figure telling us that 1903 can switch-over from being a few days hotter to a few days colder than 2003 in some chaotic way that we don’t understand and therefore we simply cannot treat that problem by some simple mathematical formula or model!

Now we come to the key part of this paper and propose the new algorithm which will help us to rank user specified annual time periods by their daily air temperatures in a quantitative and reproducible manner.

The first and the most important step is to identify two extreme time period patterns which define the boundaries of any chosen time period so that not a single datapoint can be outside those two boundaries. Those two patterns will be then used as a reference pattern that each annual time period will be compared to.

The second step is than to calculate a distance between two patterns using one of many so called similarity distance indices, in this case, Euclidean Distance or ED in short.

Let us now start with a relatively simple example to introduce the algorithm, using real data but applied only to 6 daily temperature readings.

The example dataset consists of daytime, tmax, temperature readings for the first 6 days of the year, tmax1 to tmax6 (Jan1 to Jan6) from the archive data at the Armagh Observatory and covers 161 years of data between 1844 and 2004. Let us define ‘winter’ as a time period consisting of the first 6 days of a year (for simplicity and a visual display) and therefore we have a table consisting of 6 columns of data where each column represents one day of tmax readings, and 161 rows where each row contains winter data for each year.

In order to generate the max and min reference patterns, we find the minimum and maximum values for each column and create the boundaries for that dataset, labelling the maximum values as wMAX (winter MAX) and minimum values as wMIN (Table 2 and Figure 5):

Table 2. Starting table for the algorithm consisting of 6 columns and 161 rows of tmax data

<table>
<thead>
<tr>
<th>Year</th>
<th>tmax1</th>
<th>tmax2</th>
<th>tmax3</th>
<th>tmax4</th>
<th>tmax5</th>
<th>tmax6</th>
</tr>
</thead>
<tbody>
<tr>
<td>w1844</td>
<td>2</td>
<td>0</td>
<td>7</td>
<td>11</td>
<td>12</td>
<td>9</td>
</tr>
<tr>
<td>w1845</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>10</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>w1846</td>
<td>6</td>
<td>9</td>
<td>10</td>
<td>5</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>w1847</td>
<td>7</td>
<td>6</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
</tr>
<tr>
<td>.....</td>
<td>.....</td>
<td>.....</td>
<td>.....</td>
<td>.....</td>
<td>.....</td>
<td>.....</td>
</tr>
<tr>
<td>w2001</td>
<td>10</td>
<td>7</td>
<td>7</td>
<td>3</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>w2002</td>
<td>4</td>
<td>8</td>
<td>8</td>
<td>9</td>
<td>7</td>
<td>9</td>
</tr>
<tr>
<td>w2003</td>
<td>8</td>
<td>8</td>
<td>6</td>
<td>5</td>
<td>-1</td>
<td>3</td>
</tr>
<tr>
<td>w2004</td>
<td>8</td>
<td>6</td>
<td>9</td>
<td>10</td>
<td>12</td>
<td>11</td>
</tr>
<tr>
<td>Winter</td>
<td>tmax1</td>
<td>tmax2</td>
<td>tmax3</td>
<td>tmax4</td>
<td>tmax5</td>
<td>tmax6</td>
</tr>
<tr>
<td>wMAX</td>
<td>13</td>
<td>13</td>
<td>13</td>
<td>14</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>wMIN</td>
<td>-1</td>
<td>-1</td>
<td>-3</td>
<td>-6</td>
<td>-3</td>
<td>-4</td>
</tr>
</tbody>
</table>
New Algorithm to Identify Coldest and Hottest Time Periods

Figure 6. Boundaries for 6-datapoints winters, wMAX (red) and wMIN (blue) with a random winter, w2001 (green), inside the two boundaries.

When we want to identify the coldest winters, each winter will be compared to the wMIN (a cold reference pattern), while the process is reversed when the hottest winters are being identified where wMAX is used as a hot reference pattern. If we simply use the visual inspection of the Figure above, we can see that winter of 2001 is closer to wMAX than wMIN, but we can be much more specific and calculate a distance between two patterns using one of the golden standards, the Euclidean Distance, to be referenced as ED throughout the rest of the paper:

\[
D = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2}
\]

To calculate ED one has to square the difference between each datapoint pair, get the sum of those squared differences and then take the square root of the sum.

We have now highlighted the main problems with the current practices of forecasting air temperatures and introduced the key steps of the new algorithm.

The main part of this paper will be to identify the most extreme winters in Armagh, which by the way has a very mild climate and not too many sub-zero temperatures, and see whether those findings can be extended to the rest of the UK.

Ranking the Cold and the Hot Time Periods at Armagh between 1844 and 2004

Several definitions are needed at this stage for the clarity and scientific integrity of this paper.

The definition of winter is the first 60 days of the year where daytime temperature readings are labelled from tmax1 to tmax60 which corresponds to a time period between January 1 and March 1. All the readings for Feb 29 in leap years have been omitted to ensure that each winter
has the same number of daily readings. It is important to emphasise here that this algorithm can be applied to any time period that the user wants to analyse, as short as 2 days and as long as the whole calendar year, 365 days.

The similarity index – Euclidean Distance (ED) has the following formulae:

\[ \sqrt{\sum_{t=1}^{n} (p_t - q_t)^2} \]

**Summary for Winters at the Armagh Observatory**

Number of years: 161; temperature ranges observed: -6C to +16C (total range 22C); total number of temperature readings: 9660:

![Figure 7. Each differently coloured line represents one winter at Armagh Observatory between 1844 and 2004.](image)

The first step in this new ranking algorithm is to identify the coldest and the hottest boundaries of the winter days at Armagh Observatory by identifying minimum and maximum temperature values for each day. We will then use those two extreme winter temperature patterns as our reference points for the ranking algorithm:

![Diagram showing temperature readings with 'wMAX' and 'wMIN' labels](image)
Figure 8. Coldest (blue, min) and hottest (red, max) daily records for tmax1 to tmax60 at Armagh (1844-2004).

The main step of the ranking algorithm is to calculate distance, ED, between each winter and the cold reference point, wMIN, using formula for ED and then sort the distances in ascending order.

The full matrix for the analysis therefore consists of 60 columns (tmax1 through to tmax60) and 161 rows (year 1844 to year 2004), in total 9660 datapoints of information:

**Table 3. Winter matrix consisting of 60 daily readings (columns) and 161 years of data (rows)**

<table>
<thead>
<tr>
<th></th>
<th>tmax1</th>
<th>tmax2</th>
<th>......</th>
<th>tmax59</th>
<th>tmax60</th>
</tr>
</thead>
<tbody>
<tr>
<td>w1844</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>w1845</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>......</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>w2003</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>w2004</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

After calculating ED between each winter and wMIN, sorting distances in ascending order and assigning their ranking order and display top 10 and bottom 10 winters:

**Table 4. Ten coldest (left) and ten hottest winters (right) between 1844 and 2004**

<table>
<thead>
<tr>
<th>Winters</th>
<th>ED to wMIN</th>
<th>Rank</th>
<th>Winters</th>
<th>ED to wMIN</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>w1963</td>
<td>35.65</td>
<td>1</td>
<td>w1859</td>
<td>77.62</td>
<td>152</td>
</tr>
<tr>
<td>w1895</td>
<td>37.11</td>
<td>2</td>
<td>w1849</td>
<td>78.09</td>
<td>153</td>
</tr>
<tr>
<td>w1979</td>
<td>45.14</td>
<td>3</td>
<td>w1990</td>
<td>78.52</td>
<td>154</td>
</tr>
<tr>
<td>w1881</td>
<td>47.28</td>
<td>4</td>
<td>w1851</td>
<td>78.99</td>
<td>155</td>
</tr>
<tr>
<td>w1879</td>
<td>47.77</td>
<td>5</td>
<td>w1949</td>
<td>79.37</td>
<td>156</td>
</tr>
<tr>
<td>w1947</td>
<td>49.93</td>
<td>6</td>
<td>w1998</td>
<td>80.85</td>
<td>157</td>
</tr>
<tr>
<td>w1941</td>
<td>50.52</td>
<td>7</td>
<td>w1989</td>
<td>81.02</td>
<td>158</td>
</tr>
<tr>
<td>w1985</td>
<td>50.86</td>
<td>8</td>
<td>w2002</td>
<td>82.49</td>
<td>159</td>
</tr>
<tr>
<td>w1855</td>
<td>51.59</td>
<td>9</td>
<td>w1921</td>
<td>83.64</td>
<td>160</td>
</tr>
<tr>
<td>w1986</td>
<td>53.49</td>
<td>10</td>
<td>w1846</td>
<td>83.95</td>
<td>161</td>
</tr>
</tbody>
</table>

So far, our ranking algorithm has sorted 161 winters from the coldest, 1963, to the hottest, 1846, by their Euclidean Distance to the ‘cold’ reference point, wMIN.

The next step is to identify winters which are either unusually/extremely cold or hot using a statistical parameter called z or z-score which tells us how many standard deviations each datapoint (ED) is from the mean of the data’s distribution. To calculate the z-score we need to transform the ED using the following formulae:
\[
z = \frac{(x - \mu)}{\sigma}
\]

X is a ED from the wMIN, \(\mu\) is the mean of all EDs and \(\sigma\) is the standard deviation of EDs. In short, we have transformed the distance matrix of Euclidian Distances to the wMIN, to the ED’s distances in standard deviations to the mean of all EDs.

Since detailed discussion about z-scores and normal distribution is outside of the remit of this paper, let me just summarise the topic:

![Normal distribution curve and z-scores.](image)

Assuming normal distribution, all the EDs that are more than 2 standard deviations from the mean in either direction are considered unusual or extreme. In case of normal distribution, one would expect about 2.5% of datapoints at either end of the curve. For more details on that topic read any basic book on statistics.

**Applying z-score Analysis to the Ranking Algorithm**

**Table 5.** z-scores for 10 coldest (left) and 10 hottest winters (right). z-scores at -2 or lower highlighted in blue, while those at +2 or more in red

<table>
<thead>
<tr>
<th>wMIN</th>
<th>ED</th>
<th>Rank</th>
<th>z-score</th>
<th>wMIN</th>
<th>ED</th>
<th>Rank</th>
<th>z-score</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>w1963</strong></td>
<td>35.65</td>
<td>1</td>
<td>-3.72</td>
<td><strong>w1859</strong></td>
<td>77.62</td>
<td>152</td>
<td>1.26</td>
</tr>
<tr>
<td><strong>w1895</strong></td>
<td>37.11</td>
<td>2</td>
<td>-3.55</td>
<td><strong>w1849</strong></td>
<td>78.09</td>
<td>153</td>
<td>1.31</td>
</tr>
<tr>
<td><strong>w1979</strong></td>
<td>45.14</td>
<td>3</td>
<td>-2.59</td>
<td><strong>w1990</strong></td>
<td>78.52</td>
<td>154</td>
<td>1.37</td>
</tr>
<tr>
<td><strong>w1881</strong></td>
<td>47.28</td>
<td>4</td>
<td>-2.34</td>
<td><strong>w1851</strong></td>
<td>78.99</td>
<td>155</td>
<td>1.42</td>
</tr>
<tr>
<td><strong>w1879</strong></td>
<td>47.77</td>
<td>5</td>
<td>-2.28</td>
<td><strong>w1949</strong></td>
<td>79.37</td>
<td>156</td>
<td>1.47</td>
</tr>
<tr>
<td><strong>w1947</strong></td>
<td>49.93</td>
<td>6</td>
<td>-2.03</td>
<td><strong>w1998</strong></td>
<td>80.85</td>
<td>157</td>
<td>1.64</td>
</tr>
<tr>
<td>w1941</td>
<td>50.52</td>
<td>7</td>
<td>-1.96</td>
<td>w1989</td>
<td>81.02</td>
<td>158</td>
<td>1.66</td>
</tr>
<tr>
<td>w1985</td>
<td>50.86</td>
<td>8</td>
<td>-1.92</td>
<td>w2002</td>
<td>82.49</td>
<td>159</td>
<td>1.84</td>
</tr>
<tr>
<td>w1855</td>
<td>51.59</td>
<td>9</td>
<td>-1.83</td>
<td>w1921</td>
<td>83.64</td>
<td>160</td>
<td>1.97</td>
</tr>
<tr>
<td>w1986</td>
<td>53.49</td>
<td>10</td>
<td>-1.60</td>
<td><strong>w1846</strong></td>
<td><strong>83.95</strong></td>
<td><strong>161</strong></td>
<td><strong>2.01</strong></td>
</tr>
</tbody>
</table>
We can have summarised table 6 in the following way: Out of 161 winters, six winters can be described as unusually or extremely cold (1963, 1895, 1979, 1881, 1879 and 1947), while only one can be described as unusually or extremely hot, 1846. Two of those winters, 1963 and 1895 were over 3 standard deviations from the mean making them extra unusual.

**Table 6. Distribution of z-scores from the mean for the Armagh tmax winters data**

<table>
<thead>
<tr>
<th>Distribution</th>
<th>Counts</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>-2 &lt; z-score &lt; +2</td>
<td>154</td>
<td>95.7</td>
</tr>
<tr>
<td>z-score &lt; -2</td>
<td>6</td>
<td>3.7</td>
</tr>
<tr>
<td>z-score &gt; +2</td>
<td>1</td>
<td>0.6</td>
</tr>
</tbody>
</table>

In terms of overall distribution, 95.7% (154/161) of winters are considered to be normal, 3.7% (6/161) extremely cold and 0.6% (1/161) extremely hot.

**DISCUSSION**

Let us briefly summarise the key features of the new ranking algorithm before we start with this section of the paper. The first step was to identify the coldest and the hottest boundaries of the dataset consisting of 60 daily tmax temperatures and use those patterns as the reference points. Next, we calculated ED (Euclidean Distance) for each of the 161 winters to the coldest reference pattern, wMIN, and ranked winters in ascending order, the winter closest to the wMIN ranked as number 1, while the furthest away one as number 161.

So how do we now quantify the success of this algorithm?

The starting point of this analysis, Figure 7, clearly shows that there are huge overlaps between winters’ 60 days’ patterns and it is impossible to visually separate coldest from the hottest winters. However, by using ED, a single number as an indicator of how cold a winter is, we can not only rank the winters by their coldness but also quantify that abstract term cold or hot.

The figure below summarises the power of the ranking algorithm at several levels:
Figure 10. Second coldest winter, 1895 (light blue) and the hottest, 1846 (dark red) are plotted against wMAX (top in red), wMIN (bottom in dark blue) and the mean of all winters (green).

The first thing to notice is that the winters of 1895 (cold, light blue) and 1846 (hot, dark red) are clearly separated as two lines that do not touch or cross over at any point. In other words, the winter of 1846 is unequivocally hotter at every single point than the winter of 1895:

![Figure 10](image)

Figure 10. Daily differences in temperatures between the hottest winter (1846) and second coldest (1895).

What is interesting to note is that it took a period of 49 years to go from the hottest to one of the coldest recorded winters observed at Armagh Observatory. We can also see that all but three tmax readings for 1895 are below the mean, while the opposite is true for 1846, Figure 9.

In contrast, if we pick two winters with the z-score = 0, i.e. distance to the mean of 0, we would expect to see a lot of overlap and cross-overs between the two winters:

![Figure 12](image)

Figure 12. Differences in daily tmax readings between w1857 and w1909, both with z-score = 0.
As expected, we can see from the histogram above that we cannot differentiate the winters of 1857 and 1909 due to the frequent cross-overs of the two 60-days patterns, i.e., one year is a few days warmer than colder than another winter, the standard pattern for majority of winter pairs, see reference [1].

**z-score Analysis Based on Temperatures**

One of the most important feature of working with the original temperature readings is that we kept the link between the EDs and observed temperatures and therefore allowed us to identify the unusually cold or hot days during the analysis step. For example, a detailed analysis of two coldest winters, 1895 and 1963, clearly identified 3 clusters of unusually cold days in January and February:

![Figure 13](image-url)  

**Table 7. Unusually cold winter days (z-score at or below -2) for winter 1895 (left) and 1963 (right)**

<table>
<thead>
<tr>
<th>dd</th>
<th>Temperature-w1895</th>
<th>z-w1895</th>
<th>z-w1895 &lt; -2</th>
<th>dd</th>
<th>Temperature-w1963</th>
<th>z-w1963</th>
<th>z-w1963 &lt; -2</th>
</tr>
</thead>
<tbody>
<tr>
<td>tmax37</td>
<td>-1.7</td>
<td>-2.90</td>
<td>-2.90</td>
<td>tmax12</td>
<td>-0.5</td>
<td>-2.51</td>
<td>-2.51</td>
</tr>
<tr>
<td>tmax38</td>
<td>-1.0</td>
<td>-2.67</td>
<td>-2.67</td>
<td>tmax13</td>
<td>0.4</td>
<td>-2.22</td>
<td>-2.22</td>
</tr>
<tr>
<td>tmax9</td>
<td>-0.8</td>
<td>-2.61</td>
<td>-2.61</td>
<td>tmax27</td>
<td>0.6</td>
<td>-2.16</td>
<td>-2.16</td>
</tr>
<tr>
<td>tmax28</td>
<td>-0.6</td>
<td>-2.55</td>
<td>-2.55</td>
<td>tmax1</td>
<td>1.0</td>
<td>-2.03</td>
<td>-2.03</td>
</tr>
<tr>
<td>tmax41</td>
<td>0.0</td>
<td>-2.35</td>
<td>-2.35</td>
<td>tmax33</td>
<td>1.1</td>
<td>-2.00</td>
<td>-2.00</td>
</tr>
<tr>
<td>tmax39</td>
<td>0.3</td>
<td>-2.25</td>
<td>-2.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>tmax26</td>
<td>0.4</td>
<td>-2.22</td>
<td>-2.22</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>tmax46</td>
<td>0.4</td>
<td>-2.22</td>
<td>-2.22</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>tmax42</td>
<td>0.7</td>
<td>-2.13</td>
<td>-2.13</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>tmax40</td>
<td>0.8</td>
<td>-2.09</td>
<td>-2.09</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>tmax8</td>
<td>1.0</td>
<td>-2.03</td>
<td>-2.03</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Please note that Figure 13 and Table 7 are based on transformation of the observed temperatures for the two coldest winters using the following protocol:

- Calculate the mean and the standard deviation for ALL winters
- Calculate z-scores for two winters of interest, 1895 and 1963.
- Identify daily temperature readings with z-scores at or below -2.

What Table 7 is telling us is that the winter of 1895 had recorded unusually cold temperatures on 11 separate days with temperatures between 1C and -1.7C, while the winter of 1963 had only 5 days with temperatures between 1.1C and -0.5C.

In other words, any recorded temperature at Armagh Observatory below 1C is considered as unusually cold and could be labelled as extremely cold since it is 2 or more standard deviations away from the average, the mean, winter temperature.

*Please note that the two numbers that pre-define calculation of z-scores are the mean and the standard deviation of the given time period and therefore one would expect different results if one defines winter as say first 30 days of the year rather than first 60 days, as it is case in this paper!*

What Figure 12 is telling us is that those unusually cold days are clustered in three different time periods, **tmax1 to tmax12, tmax26 to tmax32** and **tmax37 to tmax46**.

One more point warrants a brief discussion. The two coldest winters ranked 1 and 2 are 1963 and 1895 respectively, but the detailed analysis steps have shown that 1895 has twice as many unusually cold daily temperatures. So how do we explain that? The answer to the question is that the ED is calculated by taking the difference across 60 datapoints, each equally contributing to the final number. Since both years have a very similar ED to wMIN, 35.65 (1963) and 37.11 (1895), all that is needed is that one or two temperature differences, out of 60, are much higher for one year (1895), for that year to be ranked 2!

*For that reason, one has to always follow the ranking step with a detailed analysis of the top coldest or hottest winters and adjust the final ranking accordingly.*

We can now summarise the historical temperature patterns for winters at Armagh between 1844 and 2004 in the following way:

- In terms of unusually cold and hot winters, the cold winters outnumber the hot winters in a 6:1 ratio
- In terms of actual temperature readings, daily readings of 1C and below are considered as statistically significantly cold since they are 2 or more standard deviations **below** the mean of all winters

**Can daily temperatures recorded at Armagh Observatory (Northern Ireland) be applied to the rest of British Isles and specifically to UK?**

To answer that question one can use the Google search using key words like ‘coldest winters in UK’ and two winters that come to the top of the list are the winters of 1894/95 and 1962/63.

**Winter of 1894/1895**

Below is a summary of the quotes from different sources (archived newspaper reports or church records) but with similar conclusions:
The winter of 1894-95 was severe for the British Isles and one of the coldest since the Little Ice Ages of 1650. The river Thames was frozen for the last time with numerous skating festivals organised on The Serpentine Lake in London's Hyde Park and the Thames itself!

The coldest temperatures on record were reported at -13°C at Loughborough, -22°C at Rutland, -24°C at Buxton and -27°C at Braemer.

**Winter of 1962/1963**

The winter of 1962–1963 (also known as the Big Freeze of 1963) was one of the coldest winters on record in the United Kingdom. Temperatures plummeted and lakes and rivers began to freeze over. On 29–30 December 1962 a blizzard swept across the South West of England and Wales. Snow drifted to over 20 feet (6.1 m) deep in places, driven on by gale force easterly winds, blocking roads and railways. January 1963 was the coldest month of the twentieth century, indeed the coldest since January 1814, with an average temperature of -2.1°C. Much of England and Wales was snow-covered throughout the month. The country started to freeze solid, with temperatures as low as -19.4°C at Achany in Sutherland on the 11th. Freezing fog was a hazard for most of the country.

In January 1963 the sea froze for 1 mile (1.6 km) out from shore at Herne Bay, Kent, 4 miles out to sea from Dunkirk, and BBC television news expressed a fear that the Strait of Dover would freeze across.

![Figure 14. British Isles and Armagh Observatory in Northern Ireland (red).](image)

The above figure shows the relationship between Armagh where the Observatory is situated and the rest of the UK. The thing to notice is that the British Isles are a relatively small geographical unit surrounded by huge masses of water that serve as a natural thermostat and explain the rather mild climate that is observed over the British Isles.
CONCLUSION

There are several key findings in this work that need emphasising.

The fundamental problem with the current practices of weather forecasting is the use of the mean as a predictive variable which has the 0% accuracy of prediction (Figure 4)

The only way to learn from the historically observed tmmax or/and tmin data is to treat any chosen time period, like weeks, month, season or the whole year as a complex pattern consisting of unique daily patterns

Due to the great natural variations around the mean of the data (Figure 7) the key to this algorithm is identification of the cold, wMIN, and hot, wMAX, boundaries by simply extracting the min or max for each daily reading (Figure 8)

Calculating the Euclidean Distance between each winter and the cold (wMIN) or the hot (wMAX) reference point we can quantify in terms of temperatures how close each winter is to the lower or upper boundary which by definition was not exceeded in the past

Since each individual weather station will have its own and unique historical air temperature patterns, this ranking algorithm will simply reflect the local historical patterns

This paper has established the winters’ patterns at Armagh using one of the largest dataset of daily temperature dataset in existence and identified six coldest winters that are statistically significant, 1963, 1895, 1979, 1881, 1879 and 1947, using z-scores generated from their Euclidean Distance to the ultimate winter, the wMIN

Top two coldest winters, 1963 and 1895 are rather special since they were over 3 standard deviations away from the mean

The ranking for Armagh can be, in this case, applied to the rest of the British Isles due to specific geography of the Isles, surrounded by the masses of water and being a relatively small geographical unit (Figure 14)

The use of ED to the cold reference point reflect the physical reality since it can be translated back to the actual temperature ranges that helps us to declare any given winter as a normal or unusual/extreme

In case of Armagh, all daily readings of 1C and below are considered as unusually cold since they are 2 or more standard deviations below the mean of all winters (Figure 13).

ACKNOWLEDGMENT

I acknowledge Armagh Observatory for the free use of their daily tmmax/tmin data for Armagh between 1844 and 2004. I also like to thank my wife Judy Glasman for proof reading and Dr Simon Lister for numerous scientific discussions

REFERENCES

[1] Butina D., Should we worry about the Earth calculated warming at 0.7C over last 100 years?, Int. J. of Chemical Modeling., 2012, 4, Number 2-3, 233-253.
[2] Butina D., Quantifying the effect that N2, O2 and H2O have on night-to-day warming trends at ground level, Int. J. of Chemical Modeling., 2013, 5, Number 4, 457-478.
NOTE ABOUT THE AUTHOR

Dr Darko Butina is a retired scientist with 20 years of experience in experimental organic and medicinal chemistry plus a further 20 years work in field of pattern recognition and datamining of experimental data. He was part of the team that designed and synthesise the first effective drug, Sumatriptan, for treatment of migraine – an achievement for which Glaxo received The Queens Award. For more than twenty years Sumatriptan has improved quality of life for millions of migraine sufferers worldwide. While working in computational drug discovery, the author developed a novel clustering algorithm, dbclus, that became de facto standard for quantifying diversity in world of molecular structures. He recently successfully applied his clustering algorithm to the analysis of archived thermometer-based temperature data for weather stations in UK, Canada and Australia, see [1]. The author developed another numerical tools which was extensively used to find similar structural patterns in databases containing millions of different molecules. However, in this paper, the method is applied to assess the similarity of ‘winter’ daily tmax patterns to the cold boundary pattern, wMIN, of an ultimately cold winter. His work on looking for patterns in thermometer-based temperature data recorded at numerous weather stations across the globe can be found at his website www.l4patterns.com