Interim Report
Weather Conditions and Climate Change with ClimateWins

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Objective

Use machine learning to help predict the consequences of climate change while working as a data analyst at a European nonprofit organization.

Hypothesis

- If we use temperature data from European weather stations, then a machine learning model can predict whether a day is “pleasant” or “unpleasant.”
- Models that need scaling (ANN/MLP) perform better on scaled features than unscaled features.
- Machine learning models can spot early signs of long-term climate change such as average rising in temperatures or more frequent extreme weather.

Data Sets

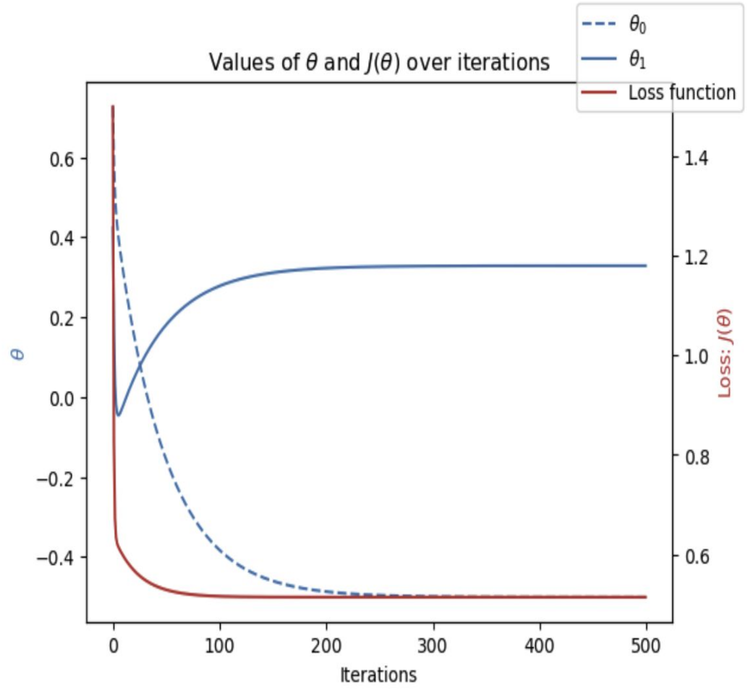
- Data was collected by the European Climate Assessment & Data Set project.
- Dataset based on weather observations from 18 different weather stations across Europe ranging from the late 1800s to 2022.
- It includes values such as temperature, wind speed, snow, global radiation for everyday.

Data Bias and Data Accuracy

- Geographic bias: The data comes from European weather stations, so the model may not work as well for other regions.
- Station coverage bias: Some stations may have more complete records than others, which can make the model better for certain locations and worse for others.
- Time period: The dataset spans a very long time (late 1800s-2022). Older measurements may be less accurate or collected differently that modern data.
- Human error: I humans define what counts as “pleasant” that choice can bake opinions into the model and affect predictions.
- Model accuracy (KNN) average 88% across stations (range 83%-100%).

Data Optimization

- For optimization, i used gradient descent to find the best model parameters.
- Features used: mean temperature columns by station, Date/Month removed, scaling improved convergence.
- The goal is to reduce the loss function step by step.
- I tested step size and number of iterations until the loss converged.
- Scaling the data helped gradient descent converge more smoothly and consistently.



Supervised Learning Approach

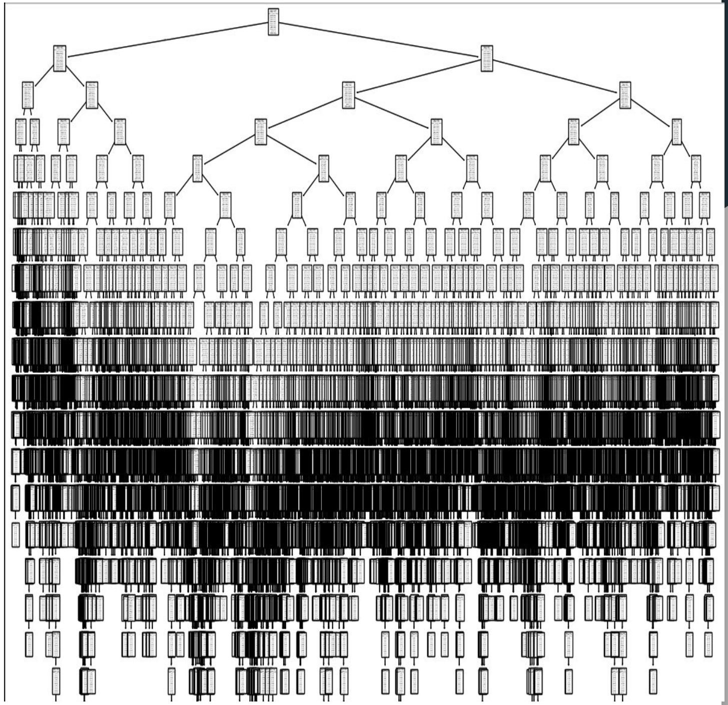
1. K-nearest neighbour (KNN)

- Average accuracy across stations is 88%.
- Most stations fall between 83% and 90% accuracy.
- Strongest results are Sonnblick (100%). Valentia (95%), and Kassel (90%).
- Lowest result is Munchenb (83%), but it's still reasonably good.
- The model makes both false positive and false negative, so its not perfect.
- Sonnblick’s 100% may be influenced by imbalance data.

Weather station	Accurate Predictions		False positive	False negative	Accuacy rate
Basel	3917	961	421	439	85%
Belgrade	3252	1544	524	418	84%
Budapest	3424	1462	476	376	85%
Debilt	4320	723	317	378	88%
Dusseldorf	4164	810	343	421	87%
Heathrow	4138	744	432	424	85%
Kassel	4563	614	252	309	90%
Ljubljana	3740	1180	455	363	86%
Maastricht	4253	824	309	352	88%
Madrid	2750	2261	418	309	87%
Munchenb	4237	792	309	400	83%
Oslo	4637	512	242	347	89%
Sonnblick	5738	0	0	0	100%
Stockholm	4483	607	283	365	89%
Valentia	5404	74	58	202	95%
Average					88%

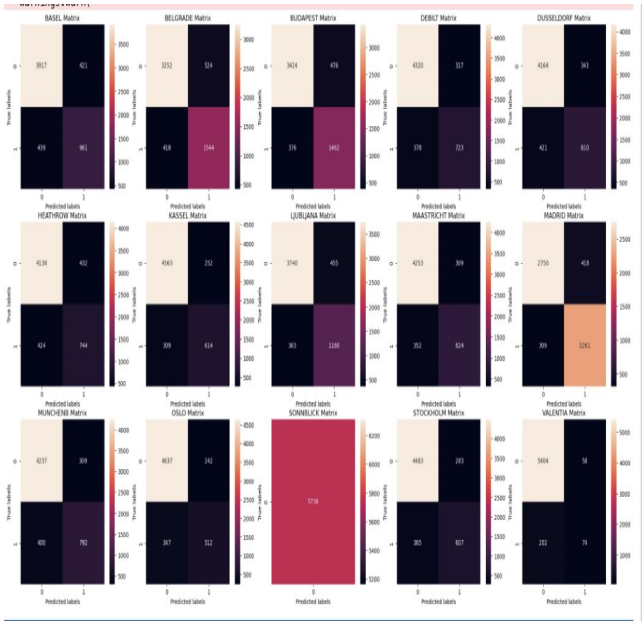
2. Decision Tree

- Uses a tree of yes/no rules to classify days as “pleasant” or “unpleasant”.
- The tree shown is very large/deep, which can mean the model is trying to fit many small patterns.
- A very large tree can lead to overfitting.
- Can be sensitive to the data, small changes in training data can change the tree structure.
- Works well when features have clear cut offs (egg. Temperature above/below certain values).



3. Artificial Neural Network

- An Artificial Neural Network learns patterns by adjusting internal “weights” across layers of connected nodes.
- Scaling the data usually helps ANN perform better because all features are on a similar range.
- I tested different setting by changing the number of layers, nodes per layer, max iterations and tolerance to improve accuracy.
- If the ANN gets very high training accuracy but lower test accuracy that suggests overfitting.
- ANN can give strong overall results, but it is harder to interpret than KNN or Decision Trees.



Summary

Hypothesis tested:

- We can predict whether a day is “pleasant” or “unpleasant” using temperature data form multiple European weather stations.
- Scaling the data will improve model performances, especially for ANN.
- Some models with handle imbalanced classes better than others.

Methods used:

- Optimization (Gradient Descent): optimization used to understand how loss decreases and how parameters converge over iterations.
- Supervised Learning: compared KNN, Decision Tree, And ANN to classify pleasant vs unpleasant days.
- Evaluation: used train/test accuracy and multi station confusions matrix to compare performance across stations.

Key Takeaway and Next Steps

Key takeaway:

- KNN performed strongly overall (average around 88%), Decision Tree are interpretable but can overfit, and scaled ANN is a strong option when accuracy is the priority.
- Recommended mode for ClimateWins: Scaled ANN (best when accuracy matters most) with KNN as a strong baseline

Next steps:

- Try more settings to improve the models (choose a different K for KNN, limit the tree depth, and change the ANN layers/nodes) and use cross validation for more reliable scoring.

Future analysis:

- Test the model on new year's/stations to confirm generalization.
- Add more climate features and track long-term trends in extreme events and changing temperature patterns.

Questions

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