ML HW4

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Author: Alvin B. Lin
Student ID: 112652040

Problem 1: Programming assignment

Please first download the dataset: O-A0038-003.xml. This dataset comes from the Central Weather Bureau's observation platform: "Temperature Distribution – Hourly Temperature Observation Analysis Gridded Data".

Dataset Description:

- Each grid point represents a temperature observation value (°C).
- Invalid value: -999.
- Resolution of latitude/longitude: 0.03 degrees in both directions.
- The lower-left corner grid point coordinate:
  - Longitude: 120.00°E
  - Latitude: 21.88°N
- Data layout:
  - Longitude increases first (67 values in each row), then latitude increases (total 120 rows).
  - Therefore, the data forms a 67×120 numerical grid.

Questions

(1) Data Transformation

Convert the original dataset into two supervised learning datasets:

(a) Classification Dataset

Format: (`Longitude, Latitude, Label`)

- If the temperature value = -999 (invalid), then Label = 0.
- If the temperature value is valid, then Label = 1.

(b) Regression Dataset

Format: (`Longitude, Latitude, Value`)

- Only keep valid temperature values (remove all -999).
- Value = corresponding temperature (°C).

(2) Model Training

Using the two datasets from (1), train one simple machine learning model each:

- Classification Model:

  Use (Longitude, Latitude) to predict whether a grid point is valid (0 or 1).
- Regression Model:

  Use (Longitude, Latitude) to predict the corresponding temperature value.

Project:

(1) The data frames is made at **section 2B** in the code, here are the head aspect of them:

```
--- 2B. Generating Pandas DataFrames (Label 0/1) ---

Classification Dataset (Head):
   Longitude  Latitude  Label
0     120.00     21.88      0
1     120.03     21.88      0
2     120.06     21.88      0
3     120.09     21.88      0
4     120.12     21.88      0
Classification Dataset Shape: (8040, 3)

Regression Dataset (Head):
   Longitude  Latitude  Value
0     120.84     21.94   28.1
1     120.72     21.97   28.6
2     120.75     21.97   28.6
3     120.78     21.97   27.8
4     120.81     21.97   26.5
Regression Dataset Shape: (3495, 3)
```

(2) (a) For the categorical part, we need some **Basic setups:**

- The training set and the testing set compose 80% and 20% of the dataset.
- Two hypothesis functions are assumed:

$$h_1(x, y) = ax^2 + by^2 + cxy + dx + ey + f$$

and one with logistic regression,

$$h_2(x, y) = \sigma(h_1(x, y)) = \sigma(ax^2 + by^2 + cxy + dx + ey + f).$$

We aim to compare which do better.

- For the hypothesis without logistic regression, we use **SVM (LinearSVC)** method to find the coefficients; while we use **liblinear** solver to solve the one with logistic regression. Both have `max_iter = 5000`.
- To train a single function is regarded difficult, so I separate the whole dataset into four regions, with boundaries `LON_SPLIT_1` = 121.50, `LON_SPLIT_2` = 120.77 and `LAT_SPLIT` = 24.0. For which:

$$(\text{lat, lon}) \in \text{Region} \begin{cases} 1, & \text{lat} \in [120.00,\ 121.50), \text{lon} \in (24.00,\ 25.45] \\ 2, & \text{lat} \in [121.50,\ 121.98], \text{lon} \in (24.00,\ 25.45] \\ 3 & \text{lat} \in [120.00,\ 120.77), \text{lon} \in [21.88,\ 24.00] \\ 4 & \text{lat} \in [120.77,\ 121.98], \text{lon} \in [21.88,\ 24.00] \end{cases}$$

And in each region, we train an independent quadratic curve.

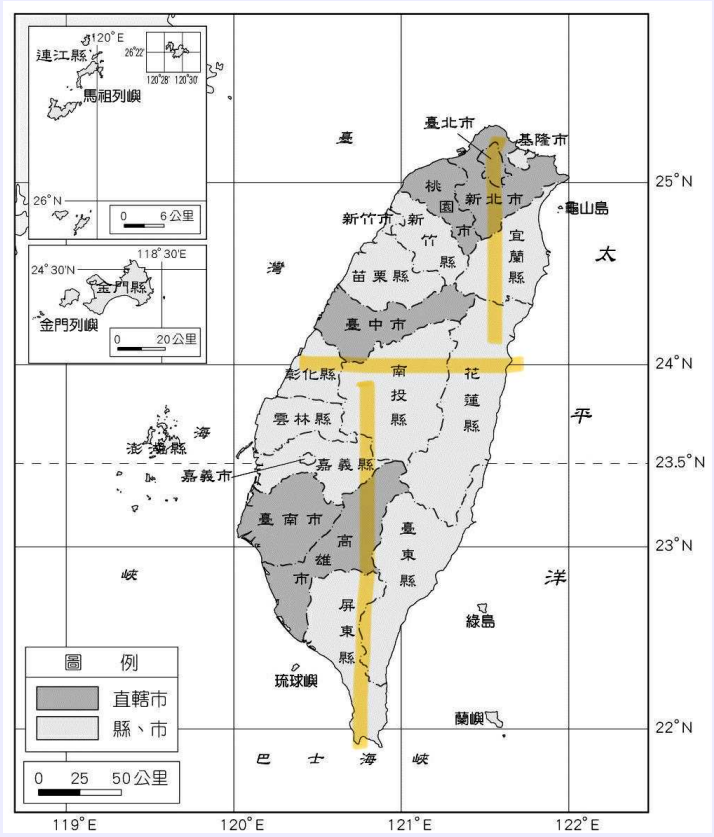


Figure 1: Illustration of region grouping

Results

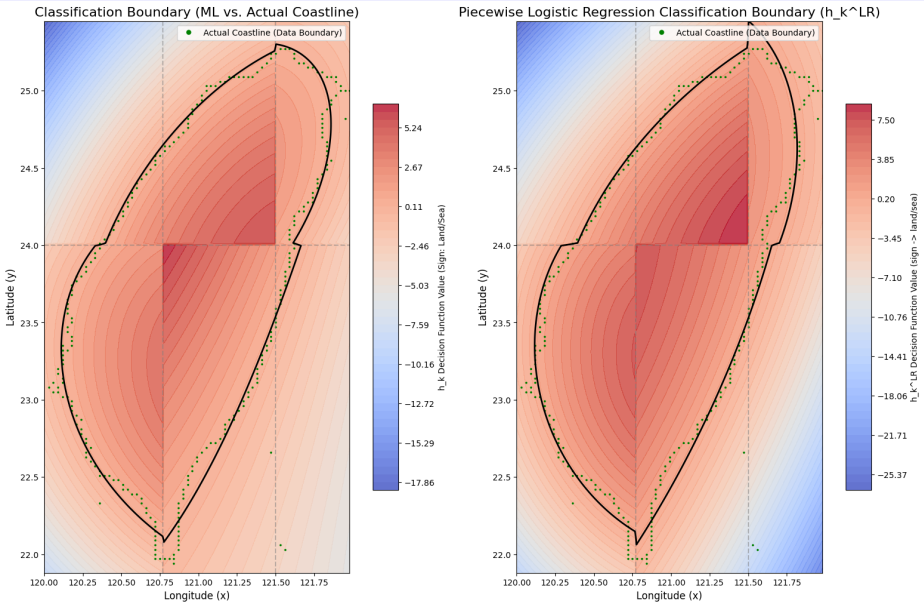
Both methods seem to have a very good categorical result, the frading is as follows:

```
--- Classification Test Results (h^LR vs. h^SVC) ---
1. Piecewise Logistic Regression (h^LR) Accuracy: 0.9596
2. Piecewise LinearSVC (h^SVC) Accuracy: 0.9714
```

The `accuracy_score` is given in `sklearn` for which compares how many data is in right position. The score shows that the hypothesis function **without logistic regression** performs slightly better.

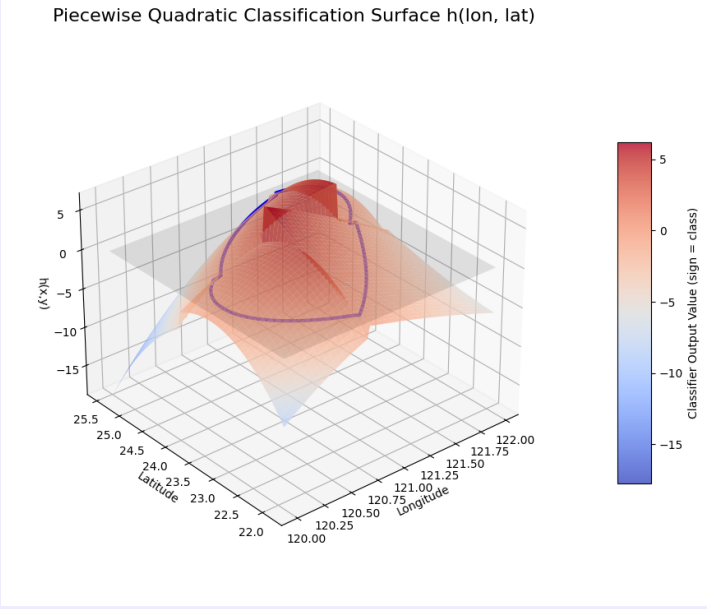
Visualisation

I've plot the boundary of the intersection with $z = 0$, or $h(\text{lon}, \text{lat}) = 0$ and compare to the actual coastline of the mainland Taiwan (dotted line), we get the figure like this:



Inside the contour, we will flag the label 1 because it is on the land; in contrast, 0 when outside the contour, because it is determined in the ocean area, for which the temperature is not measurable.

For the left one is the **non-logistic-regression** one while the right one is **logistic-regressioned**. Both have done a good job predicting the **label**, the contours almost fit the coastline. A 3D version result can also be seen below.



(b) In this part, we also need some setups:

- The training set and the testing set compose 80% and 20% of the dataset.
- This time hypothesis function has **only one**, in order to ensure the **smoothness** of the temperature.
- The hypothesis function is assumed cubic and

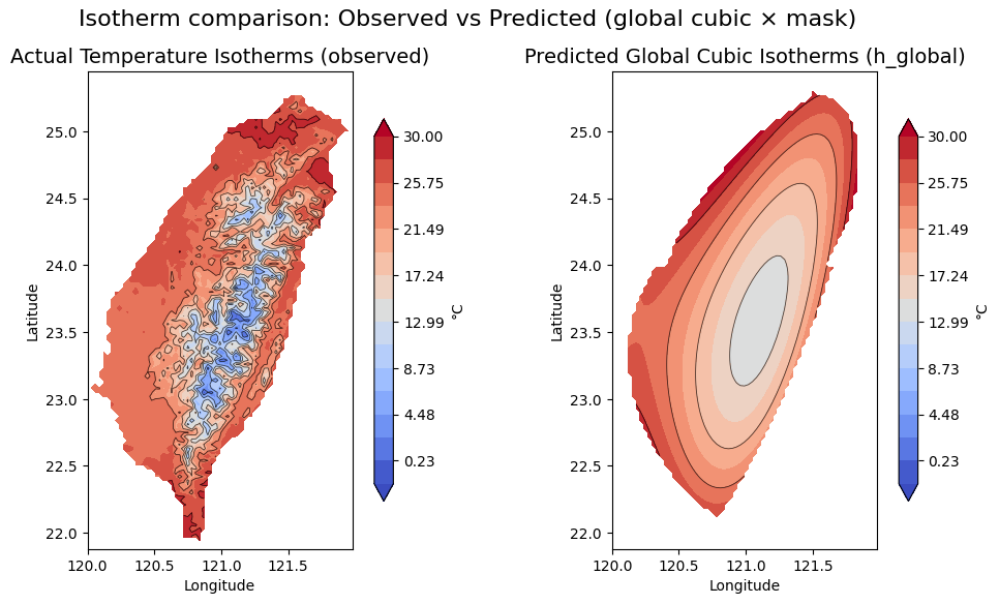
$$g_{\text{global}}(x, y) = ax^3 + by^3 + cx^2y + dxy^2 + ex^2 + fy^2 + hxy + jx + ky + l$$

- We use **SVM (LinearSVC)** method to find the coefficients, and the `max_iter` is set 5000.

Result

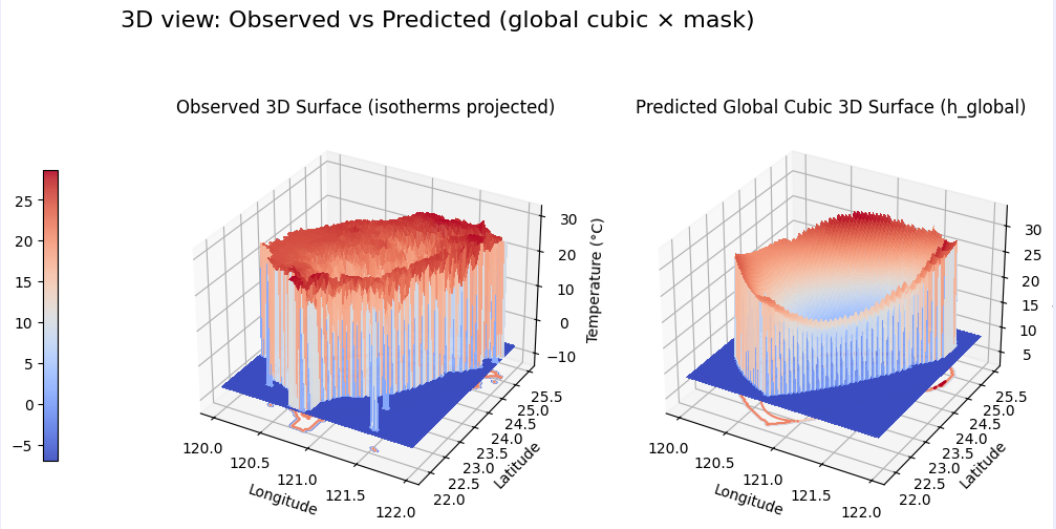
```
--- 8. Training Global Cubic Regression Model (g_global) ---
Global Cubic Regression trained with 2796 points.
Global Test RMSE for g_global: 4.4450 °C
```

The measured **root mean square error (RMSE)** is 4.4450°C, which is a little bit high; the result shows that maybe degree 3 polynomial is still not enough to fit the temperature distribution. **Visualisation** For this part, we show the **isotherm** in 2D and 3D to compare with the real data:



The 2D isotherms shows that the real-world temperature distribution is fairly **complex**, especially the mountain part. Our hypothesis function is too smooth so that we cannot do a good prediction on temperature.

I'm thinking of whether using $\sin\cdot$, $\cos\cdot$ is a better option, even though the trig functions have more **drastic volatility**, but they often occurs at the **"cliff"** of the function, seems still not fitting the distribution pattern.



The 3D version shows that not only we perform bad at the mountain part, the boundary/edge of the island has bad performance too.

My Question 1: Function Selection

In the report part, we see that temperature near the mountain area seems to have drastic volatilities, but at the boundary, the distribution is smooth. Is there a good candidate for hypothesis function? Is $x \sin \frac{1}{x}$; $x \to 0$ an option?