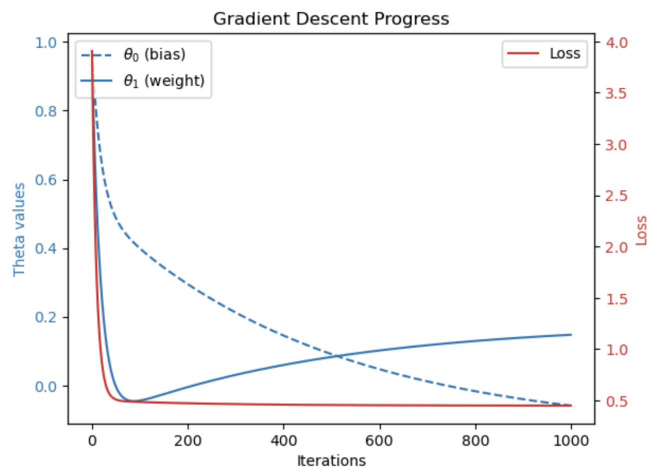
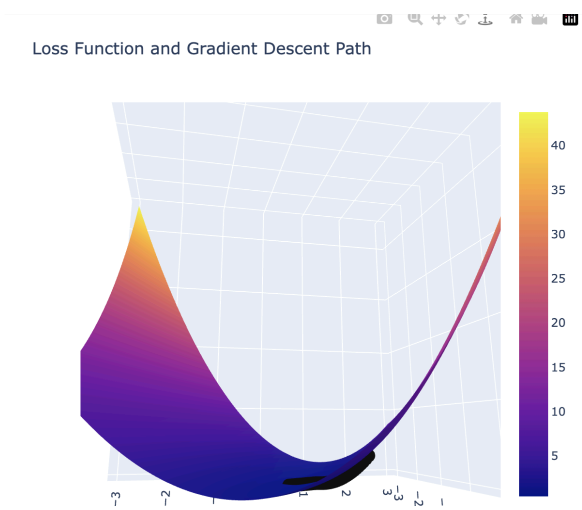
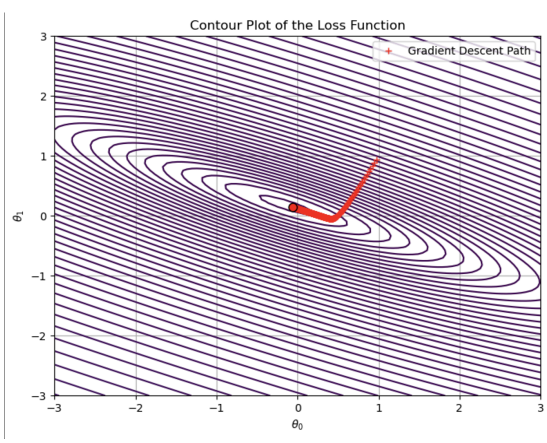
1) MAASTRICHT, 2019

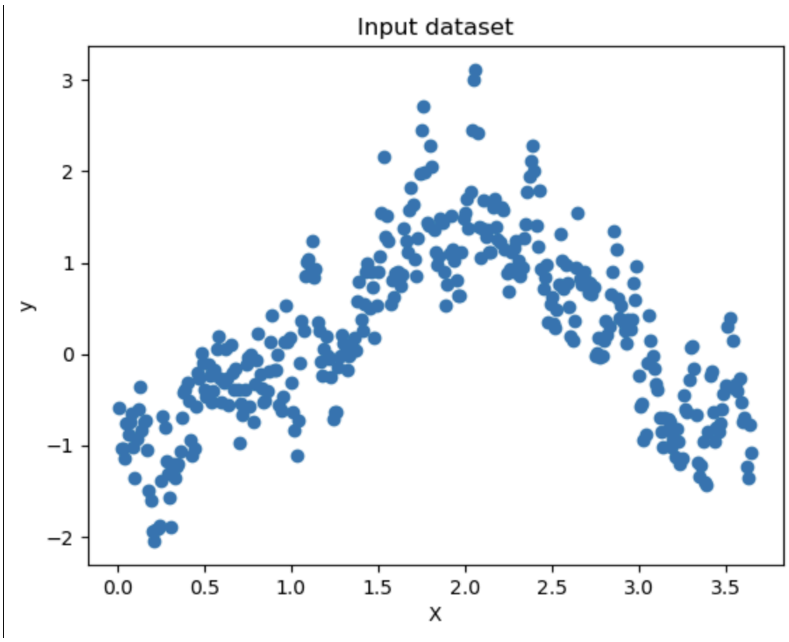






Starting Hyperparameters:
Initial θ_0 = 1.0
Initial θ_1 = 1.0
Alpha (step size) = 0.01
Iterations = 1000

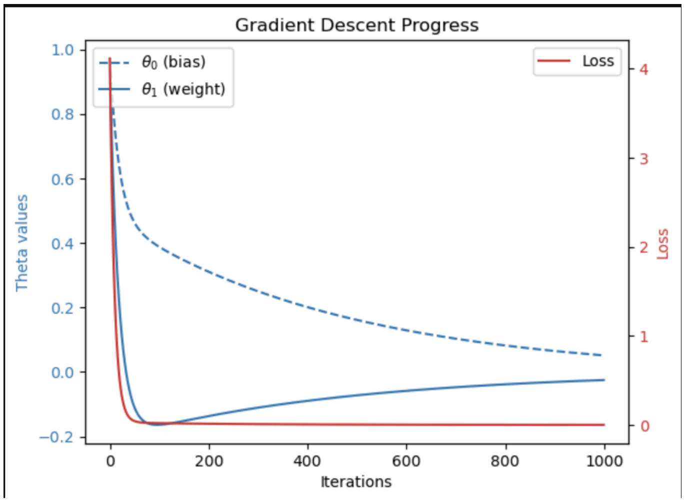
Ending Hyperparameters:
Final θ_0: -0.05866672221581578 (baseline temp slightly below mean)
Final θ_1: 0.14756562393085082 (temps rise gradually across the year)
Final loss: 0.45044111389179353 (okay linear fit, but not perfect (cyclical; seasonal variation))

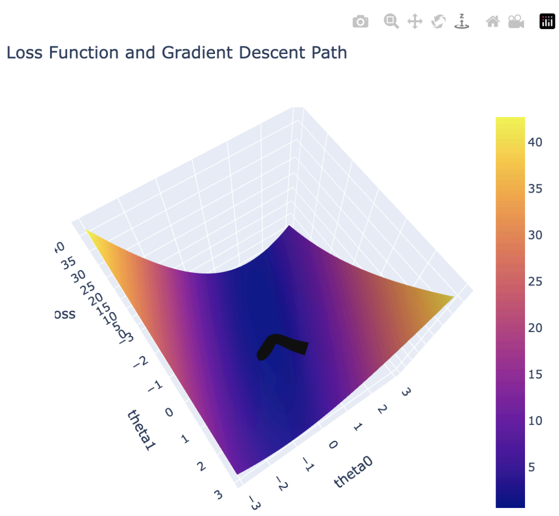


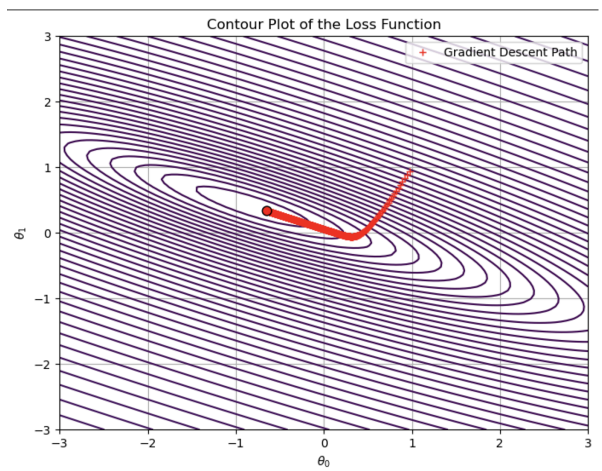
Observations from Scaled Mean Temperature ("Input Dataset")

1. Temperatures in 2019 followed expected seasonal patterns of the Northern Hemisphere, steadily rising, peaking in the summer, and descending into fall and winter.
2.The range of temperature fluctuations stayed consistent: the *vertical spread* of the data points at different "times" (X values) appears relatively consistent, suggesting a consistent level of daily variability or noise throughout the year. In the summer, outliers emerged. Around the peak (X values from ~1.5 to 2.5), there are clearly data points significantly above the general trend, indicating unusually warm days during the summer.
3. It appears that spring, leading into summer, had certain colder outlier days.

2) VALENTIA, 1968





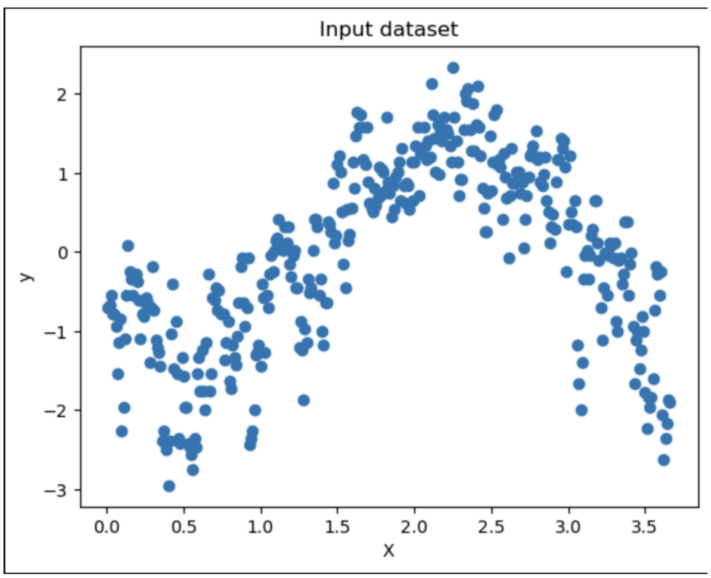


Starting Hyperparameters:
Initial θ_0 = 1.0
Initial θ_1 = 1.0
Alpha (step size) = 0.01
Iterations = 1000

Ending Hyperparameters:
Final θ_0: -0.6468891300538064 (at the very beginning of the year (X close to 0), the model predicts a scaled mean temperature of about -0.65; plausible for early winter/spring temperatures, with data is centered around zero)
Final θ_1: 0.33637527183627053 (temperatures gradually rise across the year)

Final loss: 0.6076946763625244 (same issue as Maastricht, 2019; the *model itself* (a simple straight line) is **too simplistic** to capture the actual seasonal patterns of temperature change over a year. To improve the fit and reduce the loss further, we would need to choose a more complex model (e.g., polynomial regression, or a model incorporating sinusoidal terms) that can represent the curvilinear nature of temperature trends over time.)

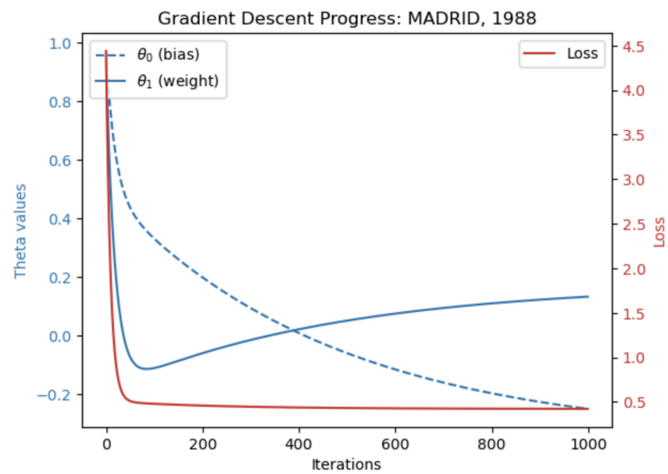
Residual Loss: The fact that you have a final loss of **0.608** (which is not zero) confirms this inadequacy. This non-zero loss represents the average squared error that the simple linear model *could not explain*. It's the irreducible error for this specific model architecture because a straight line cannot accurately follow a curved, cyclical path. (GeminiAI)

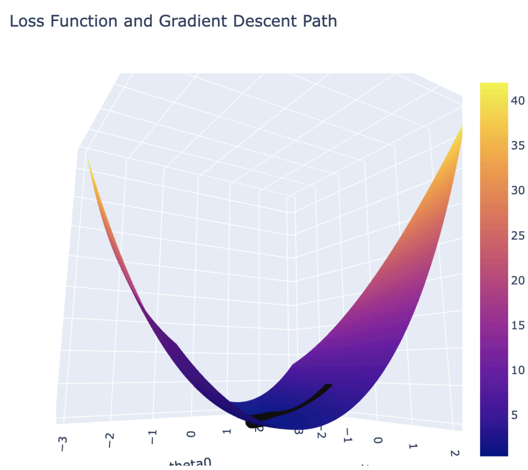


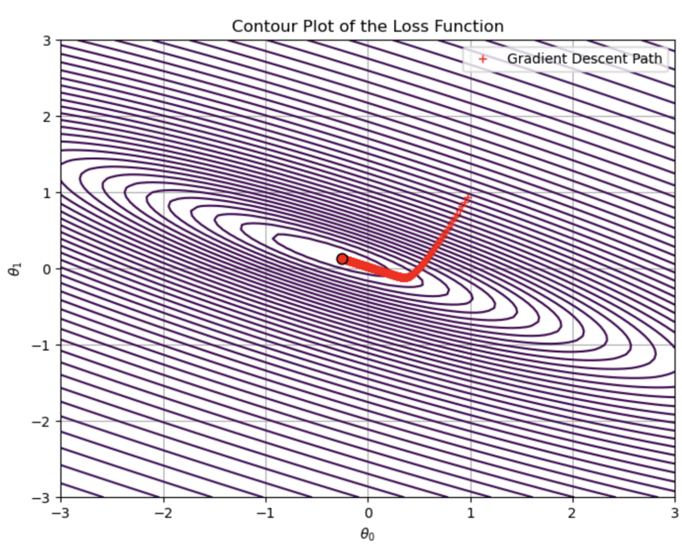
Observations for VALENTIA, 1968:

1) The **vertical spread** (indicating daily temperature variability or noise) is notably wide during the cooler months.
2) The absolute coldest scaled temperature occurs notably in the early part of the year. This is rather late in the winter or very early spring.
3) Fall has some outlier below average temperatures, with a noticeable downward divergence or "gap" from the main cluster of temperatures around 300 day mark).

3) MADRID, 1988

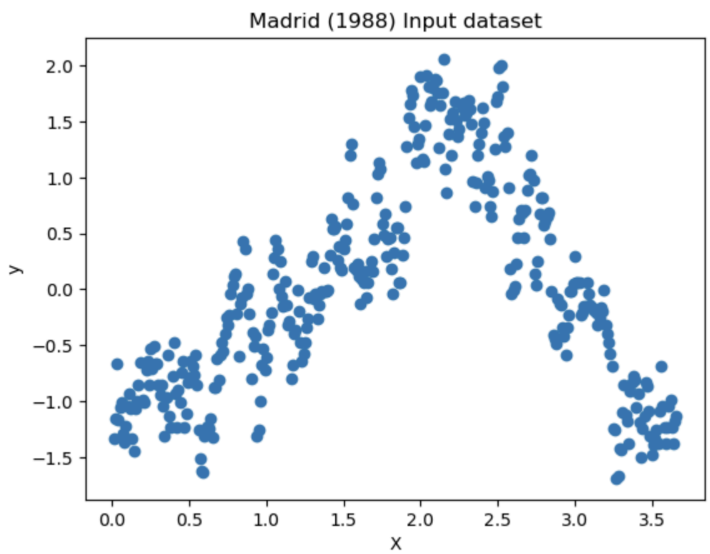






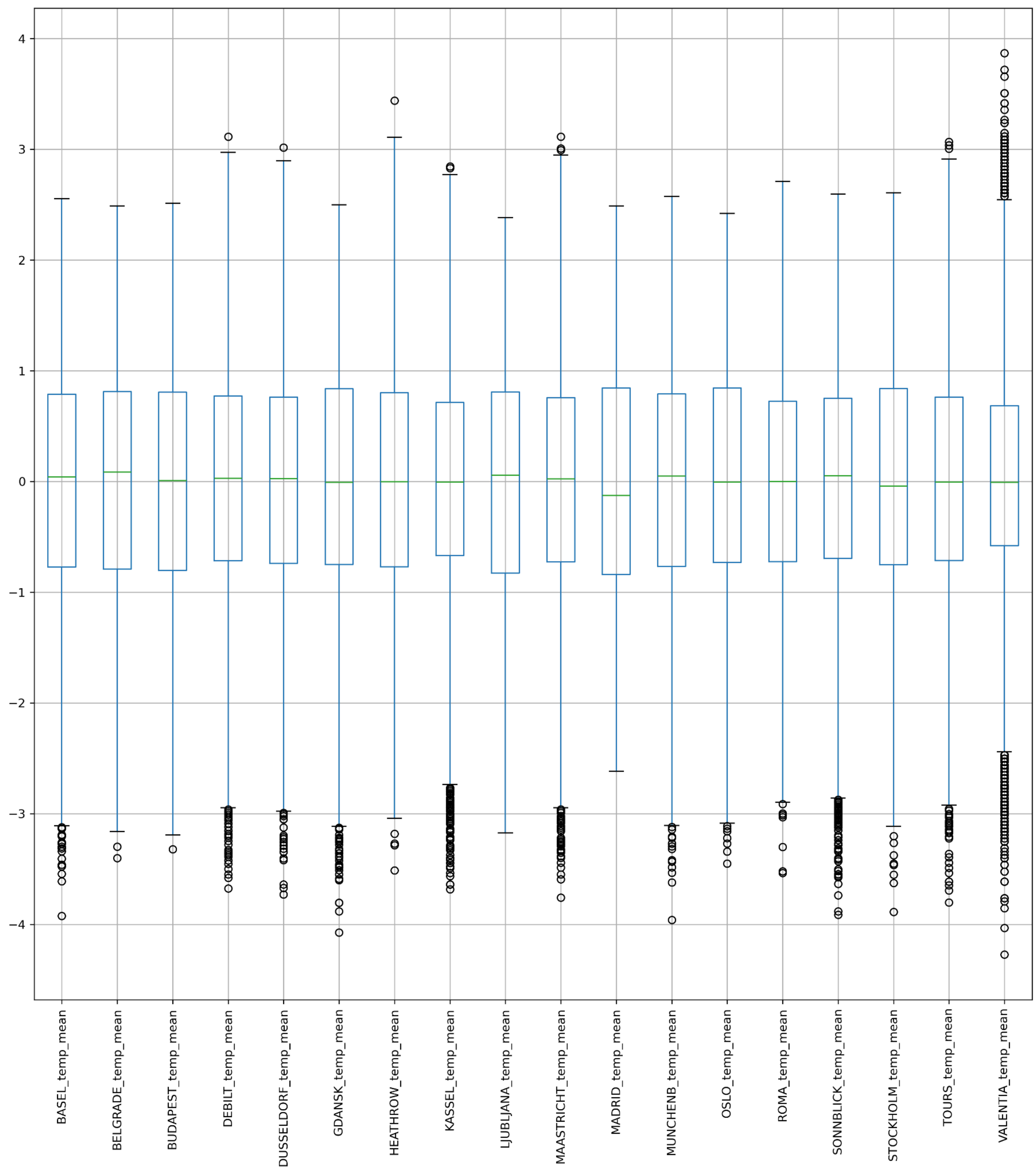
Starting Hyperparameters:
Initial θ_0 = 1.0
Initial θ_1 = 1.0
Alpha (step size) = 0.01
Iterations = 1000

Ending Hyperparameters:
Final θ_0: -0.24877471367752954
Final θ_1: 0.13365832974448524
Final loss: 0.4228413035128448



Observations for Madrid 1988:
1) Almost a right angle, linear climb up until 200/250 day
2) Vertical spread larger for the first "arm" of the graph (winter/spring)
3) Temperatures drop in a more compressed amount of time than they climb.

Three Observations re: Weather Station Temperatures for 60 Years



1) Valencia has the largest variance in scaled mean temperatures; the weather station displays the **most extreme and numerous outliers at both the upper and lower ends** of the temperature spectrum. Valentia seems to have experienced the most volatile and extreme temperature fluctuations over the 60-year period.

2) Ljublana and Madrid have the most stable temperatures in the past 60 years; no outliers; compact boxes; shorter whiskers.

3) On the whole, there's a general tendency towards extreme cold outliers (left skew). Outliers are more prevalent on the whole towards the lower (colder) extreme. There's a higher occurrence or greater severity of exceptionally cold days, leading to a **left-skewed (or negatively skewed) distribution** for these stations.