Machine Learning for Depth Thermography: Predicting Volumetric Temperature Distributions from Thermal-Emission Spectral Data

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Abstract

Predicting temperature distributions beneath the surface of objects is of high interest for a variety of science and engineering applications. Here, we develop a machine learning model built from a technique called depth thermography, based on infrared thermal spectrum data that can remotely determine volumetric temperature distributions. Currently, depth thermography uses physical equations to make its predictions—however, these equations are highly noise-sensitive. To solve this problem, we created a feedforward neural network that achieves a Mean Absolute Error (MAE) of 3.53 Kelvin, a significant improvement over the equation's predictions, with noisy input data. In addition, two other network approaches were created and tested. Of the three, the feedforward neural network proved to have both the highest accuracy and efficiency. This model could give depth thermography a novel ability to make volumetric temperature predictions for a wide assortment of objects, ranging from multilayer semiconductor devices to volumes of liquids and gasses.

Motivation

Depth thermography equations are highly sensitive to the noise with experimental radiation spectrum inputs

- A machine learning approach maintains accuracy given noisy input data to use in real-world contexts

Methods

- The spectrum data (3.75-8 microns) was generated from a theoretical silica window model and 1% of noise was added to it
- We developed and tested three different models
  - Feedforward Model: 4 layer feedforward network
  - Individual Layer Model: Feature-selected network that predicts each temperature layer individually
  - Tandem Model: Combines spectrum to temperature network with a temperature to spectrum network

Results

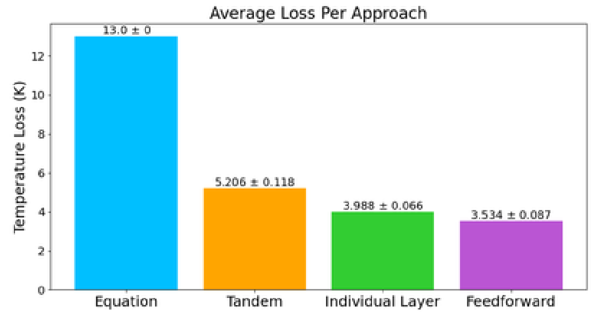


Fig 1: This figure compares the average testing MAE loss (K) achieved by each model. The annotations located above each bar display the average loss of the corresponding model.

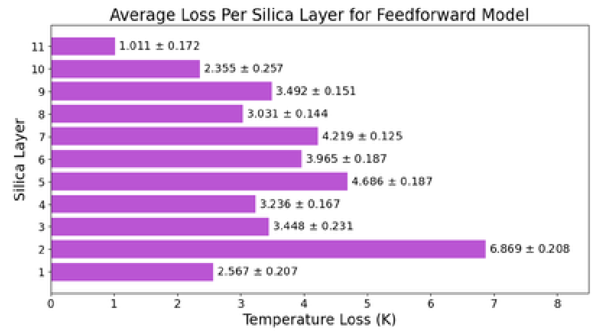


Fig 2: Average loss of Feedforward temperature predictions for each layer of the silica glass.

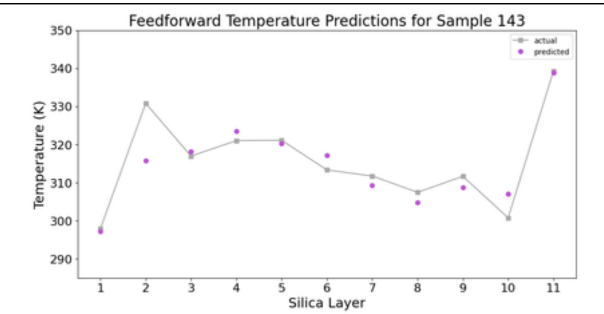
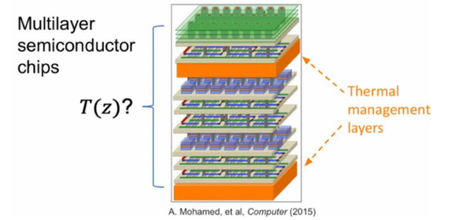


Fig 3: Predicted temperature of a single sample using the feedforward model. Average loss of selected sample 143 (3.534 K) reflects the average loss of a typical sample (3.534 K).

Applications and Future Directions

- Depth thermography may enable volumetric temperature predictions for a variety of objects
  - Microscopic objects like multilayer semiconductor devices (expected research grant of $500,000)
  - Macroscopic objects like volumes of liquids and gasses
- We are currently testing using a theoretical silica window model—in the future, we intend to test on additional models (like multilayer semiconductor chips) using real-world experimental data



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References

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