

# **ECGR 4105: Intro to Machine Learning HW 5**

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[Link to GitHub](#)

# Problem 1

## 1. Introduction:

The goal of this task is to predict temperature using a nonlinear regression model based on the equation:

$$t_e = w_2 \cdot t_u^2 + w_1 \cdot t_u + b$$

The dataset includes measured temperature values ( $t_u$ ) and their corresponding actual temperatures ( $t_c$ ). The model parameters ( $w_2$ ,  $w_1$ ,  $b$ ) are optimized to minimize the loss. Training is conducted over 5000 epochs with four different learning rates (0.1, 0.01, 0.001, 0.0001). The final performance of the nonlinear model is compared to a linear baseline model, analyzing whether the nonlinear formulation provides better predictive performance.

## 2. Methodology

### a. Data Preprocessing:

- Input values ( $t_u$ ) were normalized by scaling down by 0.1 to ensure effective training.
- The dataset was split into 80% training and 20% validation sets for evaluating model generalization.

### b. Model Training:

- Two models were trained: a nonlinear regression model based on the equation above and a linear regression model as a baseline.
- For each model:
  - Loss was calculated as the mean squared error (MSE) between predictions and actual values.
  - The training was performed over 5000 epochs using the Stochastic Gradient Descent (SGD) optimizer.

### c. Learning Rate Exploration:

- Four learning rates were tested: 0.1, 0.01, 0.001, and 0.0001.
- Training and validation losses were recorded every 500 epochs for each learning rate to identify the optimal configuration.

### d. Performance Comparison:

- The best nonlinear model was compared to the linear model in terms of final loss.
- Predictions from both models were visualized against the dataset for qualitative comparison.

## 3. Results

Learning Rate	Epoch	Loss
0.1	500	2.0907
	1000	2.0907

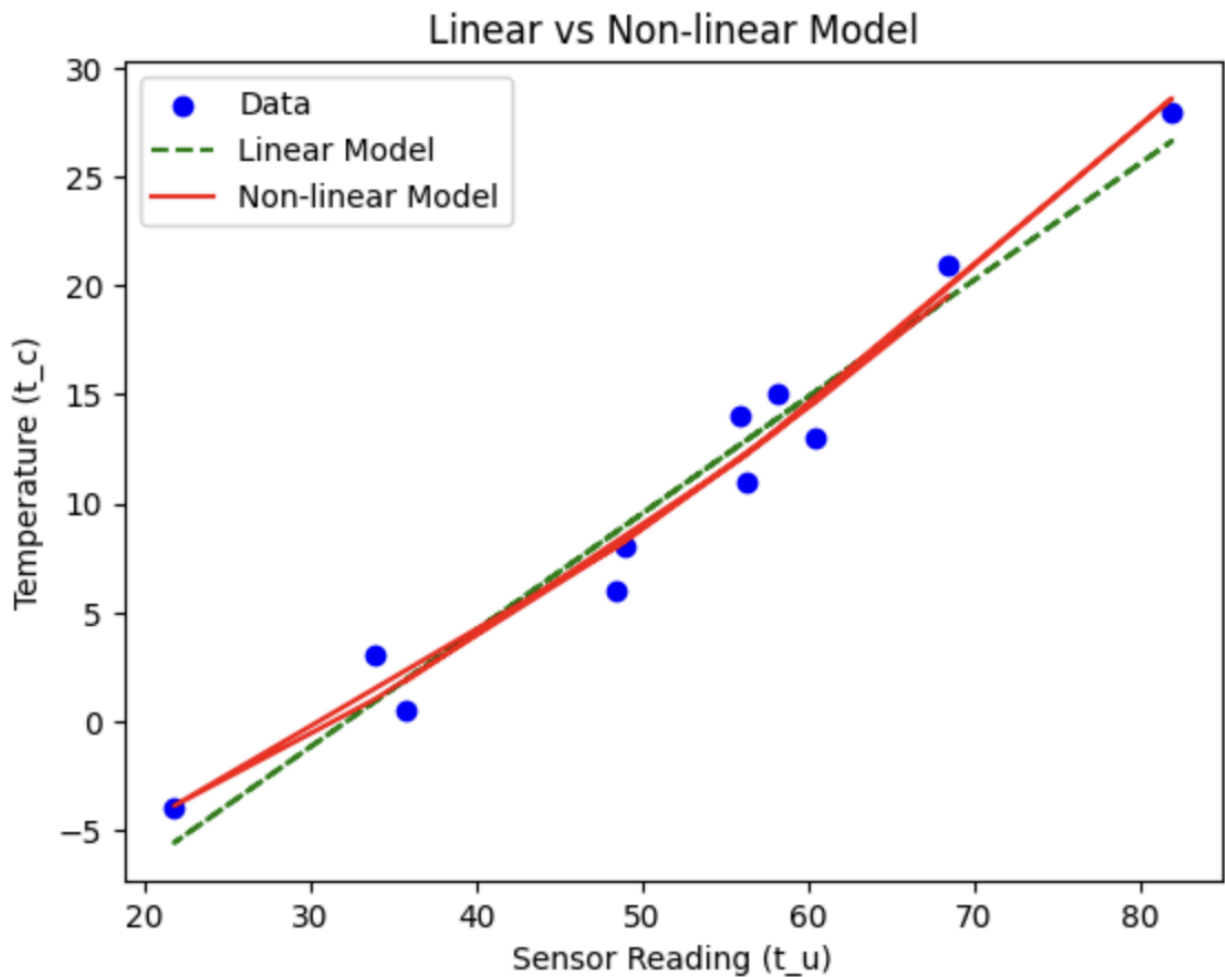
	...	...
	5000	2.0907 (Final)

Learning Rate	Epoch	Loss
0.01	500	2.0921
	1000	2.0907
	...	...
	5000	2.0907 (Final)

Learning Rate	Epoch	Loss
0.001	500	27.0089
	1000	8.1365
	1500	3.8408
	2000	2.6622
	2500	2.2908
	3000	2.1633
	3500	2.1175
	4000	2.1007
	4500	2.0944
	5000	2.0921 (Final)

Learning Rate	Epoch	Loss
0.0001	500	141.9213
	1000	110.5746
	1500	88.3050
	2000	71.9661

	2500	59.6113
	3000	50.0164
	3500	42.3951
	4000	36.2298
	4500	31.1699
	5000	26.9705 (Final)



- Best Performing Model:**

The nonlinear model with a learning rate of 0.001 achieved the best final loss of 2.0921, demonstrating strong convergence and predictive capability. Learning rates of 0.1 and 0.01 achieved slightly lower losses of 2.0907, but all three performed significantly better than the slower-converging learning rate of 0.0001.
- Comparison with Linear Model:**

- **Nonlinear Model Final Loss (Best):** 2.0921
- **Linear Model Final Loss:** 7.632

The nonlinear model significantly outperformed the linear baseline, reducing the loss by more than 70%. This highlights the advantage of incorporating nonlinearity into the predictive model.

## Problem 2

### 1. Introduction:

This problem aims to predict housing prices using a linear regression model based on five input features: area, bedrooms, bathrooms, stories, and parking. The dataset is split into 80% for training and 20% for validation. Four learning rates (0.1, 0.01, 0.001, and 0.0001) are explored, with models trained for 5000 epochs. Training and validation losses are reported every 500 epochs to identify the best-performing model. The results are also compared to the linear regression results from Homework 1.

### 2. Methodology:

#### a. Data Preprocessing:

- The housing dataset was cleaned and features were scaled using StandardScaler to normalize the data.
- The target (price) and input features (area, bedrooms, bathrooms, stories, parking) were separated, and the data was split into training (80%) and validation (20%) subsets.

#### b. Model and Training Setup:

- A linear regression model was implemented using PyTorch
- MSE was used as the loss function.
- A stochastic Gradient Descent (SGD) optimizer with varying learning rates was used.
- Loss values for training and validation were recorded every 500 epochs.

### 3. Results

Loss Progression for Different Learning Rates:

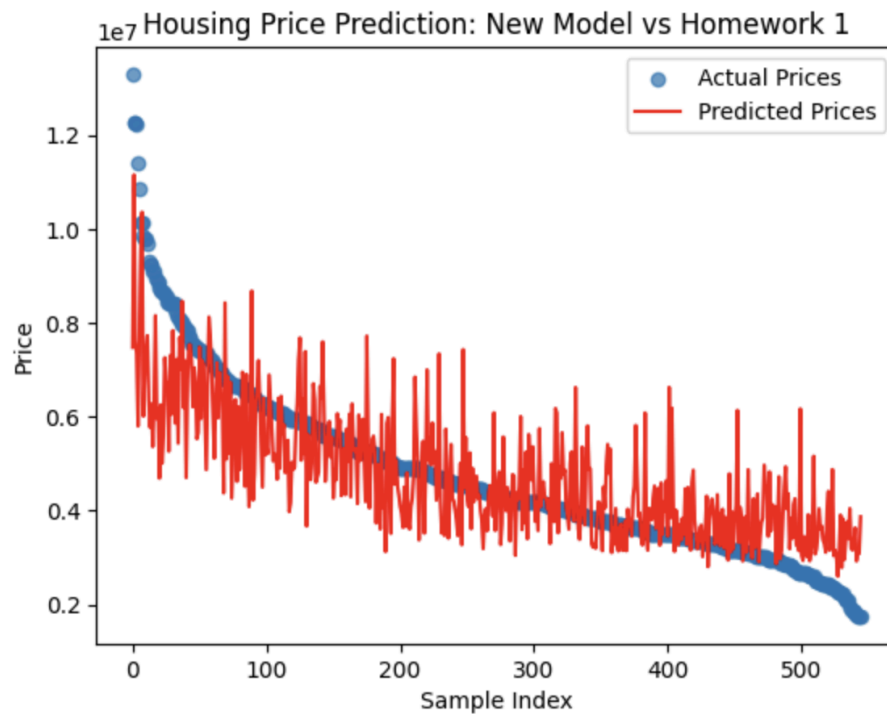
Learning Rate	Epoch	Training Loss	Validation Loss
0.1	500	1350008045568.0000	2292721647616.0000
	1000	1350008045568.0000	2292721647616.0000
	...	...	...
	5000	1350008045568.0000 (Final)	2292721647616.0000 (Final)

Learning Rate	Epoch	Training Loss	Validation Loss
0.01	500	1350011191296.0000	2292620984320.0000
	1000	1350008176640.0000	2292724269056.0000
	1500	1350008176640.0000	2292724531200.0000
	...	...	...
	5000	1350008176640.0000	2292724531200.0000

Learning Rate	Epoch	Training Loss	Validation Loss
0.001	500	4518918488064.0000	6247418953728.0000
	1000	1789859594240.0000	2950104088576.0000
	1500	1414199508992.0000	2423372906496.0000
	2000	1360248438784.0000	2323572064256.0000
	2500	1351896662016.0000	2300741419008.0000
	3000	1350425509888.0000	2294730981376.0000
	3500	1350116704256.0000	2293078687744.0000
	4000	1350039633920.0000	2292664762368.0000
	4500	1350017875968.0000	2292601323520.0000
	5000	1350011322368.0000 (Final)	2292626489344.0000 (Final)

Learning Rate	Epoch	Training Loss	Validation Loss
0.0001	500	20798509154304.0000	25025291747328.0000
	1000	17197346848768.0000	20892188934144.0000
	1500	14275511844864.0000	17537841496064.0000
	2000	11901298802688.0000	14809655410688.0000

		0	00
	2500	9969596366848.0000	12586381737984.0000
	3000	8396162465792.0000	10771268370432.0000
	3500	7113319907328.0000	9286883213312.0000
	4000	6066528583680.0000	8071045185536.0000
	4500	5211738865664.0000	7073687928832.0000
	5000	4513281867776.0000	6254368391168.0000



#### 4. Summary of Findings:

##### a. Best Learning Rate:

- The learning rate of 0.001 achieved the lowest final validation loss (2292626489344.0), making it the most effective among the tested rates.

##### b. Training Observations:

- 0.1 and 0.01 exhibited stable but stagnant loss values, indicating potential overshooting or inability to refine parameter updates.

- 0.001 demonstrated steady convergence with reduced loss over time, balancing step size and stability.
  - 0.0001 was too slow, with high training and validation losses even after 5000 epochs.
- c. Comparison with Homework 1
- Validation losses for all learning rates were significantly higher than the baseline linear regression model in Homework 1.
  - This indicates the need to reassess feature selection, model design, or preprocessing to improve performance.

## Problem 3

### 1. Introduction:

This task aimed to predict housing prices using a linear regression model trained on all input features in the housing price dataset. The dataset includes features such as area, bedrooms, bathrooms, stories, parking, main road, guestroom, basement, hot water heating, air conditioning, and furnishing status. Following the approach in Problem 2, the data was split into 80% training and 20% validation, and four learning rates (0.1, 0.01, 0.001, 0.0001) were evaluated over 5000 epochs. The training and validation losses were recorded at regular intervals to determine the optimal learning rate and model performance.

### 2. Methodology:

Model and Training Setup:

- A linear regression model was implemented using PyTorch.
- MSE was used as the loss function.
- The optimizer was SGD with varying learning rates.
- Loss values for training and validation were recorded every 500 epochs.
- Visualization of actual vs predicted prices is plotted to visualize the model's performance

### 3. Results:

Learning Rate	Epoch	Training Loss	Validation Loss
0.1	500	992480985088.0000	1800794013696.0000
	1000	992480985088.0000	1800794013696.0000
	...	...	...
	5000	992480985088.0000 (Final)	1800794013696.0000 (Final)

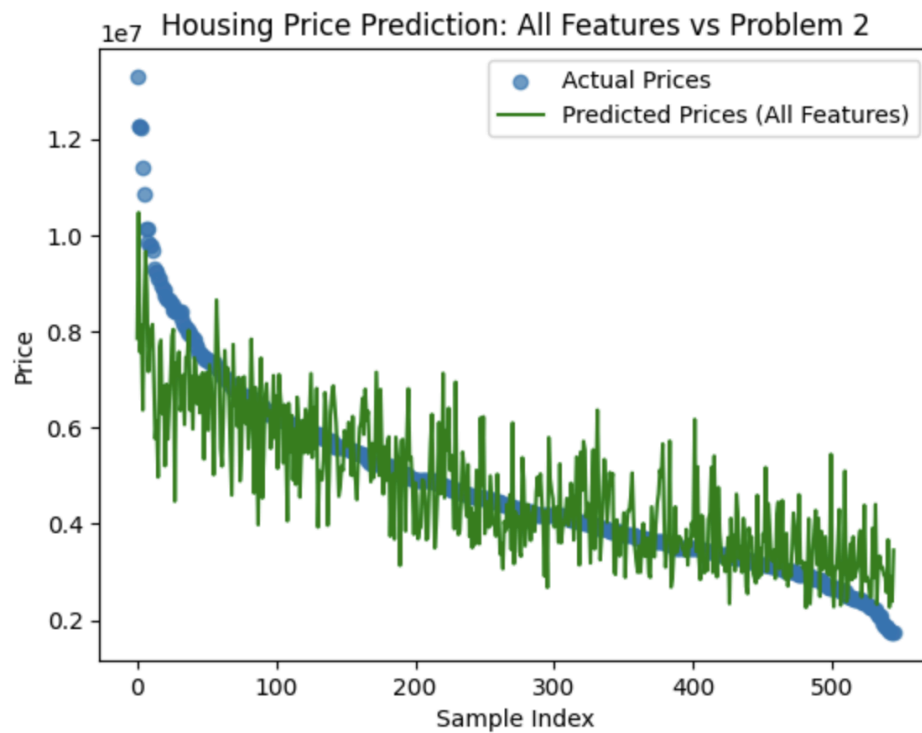


Learning Rate	Epoch	Training Loss	Validation Loss
0.01	500	992489635840.0000	1799817527296.0000
	1000	992480985088.0000	1800789295104.0000
	1500	992480919552.0000	1800797421568.0000
	...	...	...
	5000	992480919552.0000 (Final)	1800797421568.0000 (Final)

Learning Rate	Epoch	Training Loss	Validation Loss
0.001	500	4130178334720.0000	5655571726336.0000
	1000	1431569956864.0000	2410643718144.0000
	1500	1057671282688.0000	1901780402176.0000
	2000	1003309629440.0000	1812829306880.0000
	2500	994653503488.0000	1797181800448.0000
	3000	993030701056.0000	1795751149568.0000
	3500	992650461184.0000	1796922540032.0000
	4000	992540426240.0000	1798213861376.0000
	4500	992503463936.0000	1799169900544.0000
	5000	992489897984.0000 (Final)	1799800619008.0000 (Final)

Learning Rate	Epoch	Training Loss	Validation Loss
0.0001	500	20567379935232.0000	24715454316544.0000
	1000	16847102541824.0000	20412058566656.0000
	1500	13869536772096.0000	16969179856896.0000

	2000	11474180243456.0000	14199481696256.0000
	2500	9539315302400.0000	11960991088640.0000
	3000	7971384328192.0000	10144820756480.0000
	3500	6697527017472.0000	8666430308352.0000
	4000	5660508946432.0000	7459651977216.0000
	4500	4814929395712.0000	6472202715136.0000
	5000	4124585230336.0000 (Final)	5662539513856.0000 (Final)



#### 4. Summary of Findings

##### a. Best Learning Rate:

- The learning rate of 0.001 achieved the lowest final validation loss (1799800619008.0) among all tested rates, confirming it as the optimal choice.

##### b. Training Observations:

- 0.1 and 0.01 quickly converged but plateaued at higher validation loss values, suggesting a lack of further refinement.
- 0.001 exhibited a steady decline in loss values, demonstrating its suitability for balancing step size and convergence stability.
- 0.0001 was too slow, with high losses even after 5000 epochs.

c. Comparison with Problem 2:

- Including additional features slightly reduced the final validation loss (e.g., 1799800619008.0 vs. 2292626489344.0 for the best learning rate). This indicates that the additional input features improved the model's ability to predict housing prices.

d. Conclusion

- The linear regression model trained with all input features and a learning rate of 0.001 was the best-performing model, achieving a final validation loss of 1799800619008.0. Including more features improved performance over Problem 2 but highlighted potential limitations of the dataset and the chosen model.

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