Neural Network Development for Predicting Instant Fuel Economy

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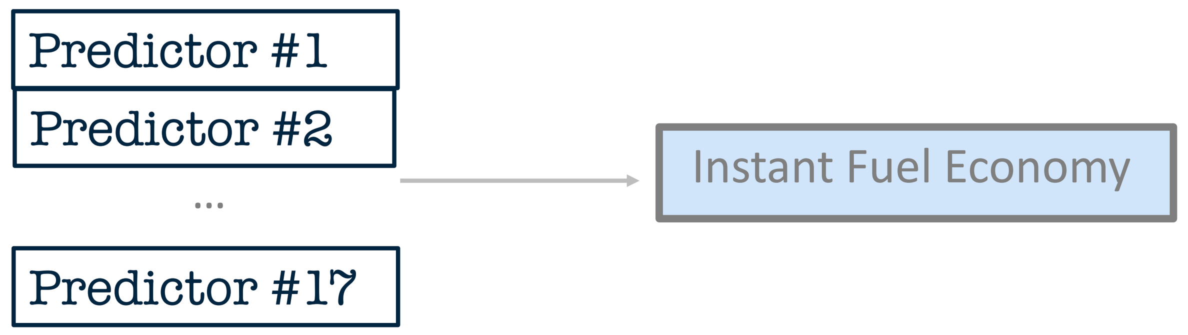
Introduction

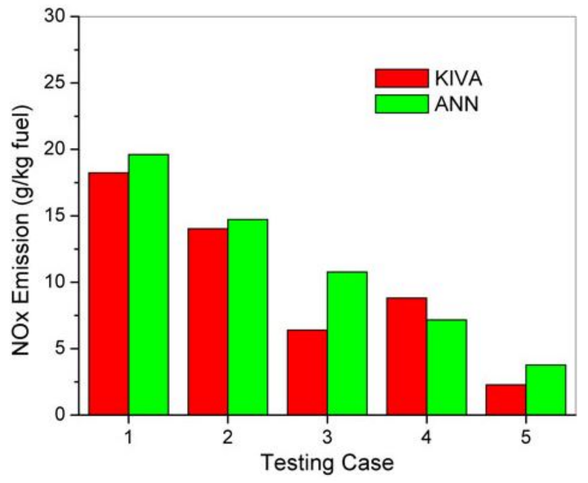
- Engine performance calculation is expensive with traditional techniques, and can take days to simulate with physics equations
- In this project, we aim to predict instant fuel economy within a reasonable range of the true instant fuel economy
- Predicting instant fuel economy with neural nets decreases computation time since it does not rely on physics equations to compute

Motivation

- Traditional physics-based model takes 400 hours to run, which is extremely expensive. [5] Ours takes 2 minutes to run.
- Current models unable to adapt to environment/driver variability.



- Baseline: Linear Regression with 7.51% accuracy



- Similar Performance but slower computational speed

Fig. 1 KIVA vs. ANN

Dataset

Input data:

- Car diagnostic data obtained via OBDLink LX tool from 2017 Mazda 3
- A total of 4,861 examples obtained from 2.05 hours of driving

Dataset

Fig. 2 Experimental Setup

Filtering:

- Redundant features removed such as Long term fuel trim 3, total fuel economy

Regional:

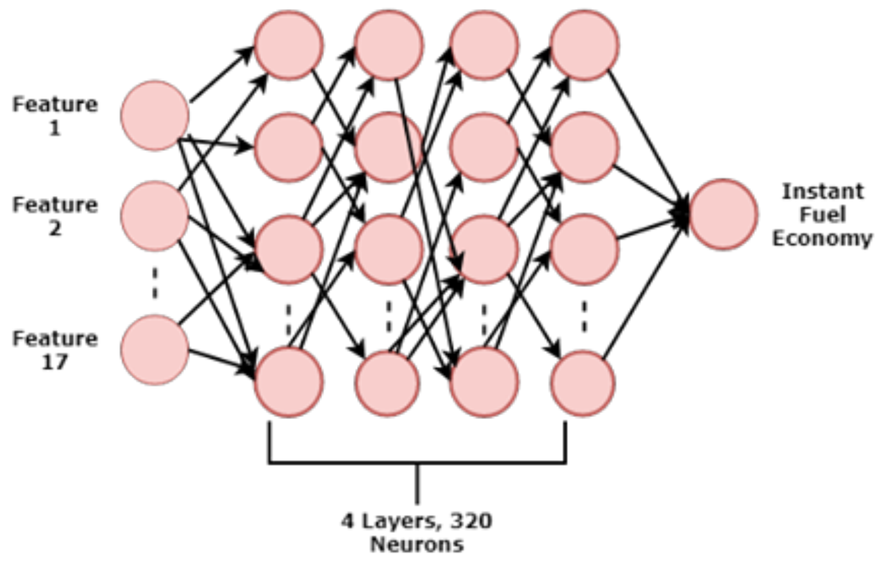
- Data was obtained on the highway and neighborhood streets

	Absolute load value (%)	Absolute throttle position (%)	Ambient air temperature (F)	Barometric pressure (inHg)	Calculated load value (%)	Commanded fuel rail pressure A (inHg)	Engine coolant temperature (F)	Engine RPM (RPM)	Fuel level input (%)
0	21.56863	9.411765	64.4	29.8254	15.29412	885.9030	183.2	1431.00	81.17647
1	19.60784	11.764710	59.0	29.8254	33.72549	933.1512	185.0	575.75	89.41177
2	41.56863	20.392160	59.0	29.8254	44.70588	1866.3020	183.2	1424.75	62.35294
3	25.09804	14.509800	64.4	29.8254	34.11765	1163.4860	186.8	1053.75	70.98039
4	79.21568	32.941180	59.0	29.8254	96.07843	2769.9230	185.0	1400.75	60.39216
5	11.37255	11.764710	71.6	29.5301	13.72549	885.9030	188.6	1221.50	92.94118
6	10.98039	12.156860	62.6	29.5301	12.94118	885.9030	181.4	1477.50	50.19608

Table 1. Raw Data

Models

- Baseline model: linear regression.
- Developed Model: Neural Network



$$error = \sum_i (y_i - \hat{y}_i)^2$$

Fig. 3 Graph of MSE over Epoch for NN Model D

Results

- 2917 samples in training sets, 972 samples in validation sets, and 972 samples in testing data sets
- As we increase our layers and neurons, the loss decreases.

Experiments	Learning Rate	Epochs	Num of Layers	Num of Neurons	Accuracy (%)
Linear Regression	n/a	n/a	n/a	n/a	7.51
NN Model A	0.001	250	1	5	42.19
NN Model B	0.001	250	1	20	57.13
NN Model C	0.001	130	3	15,10,5	74.29
NN Model D	0.001	130	4	330,330,330,330	89.33

Table 2. Hyperparameters for Each Model

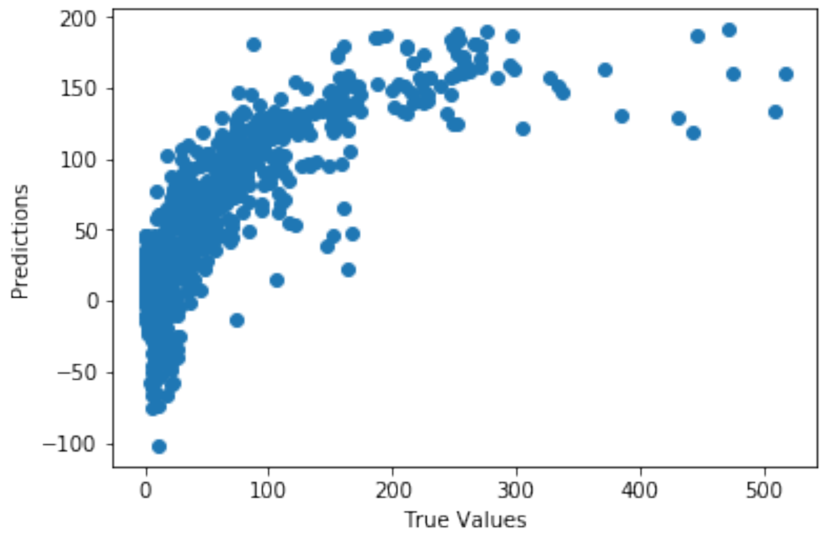


Fig. 4 Prediction for Linear Regression

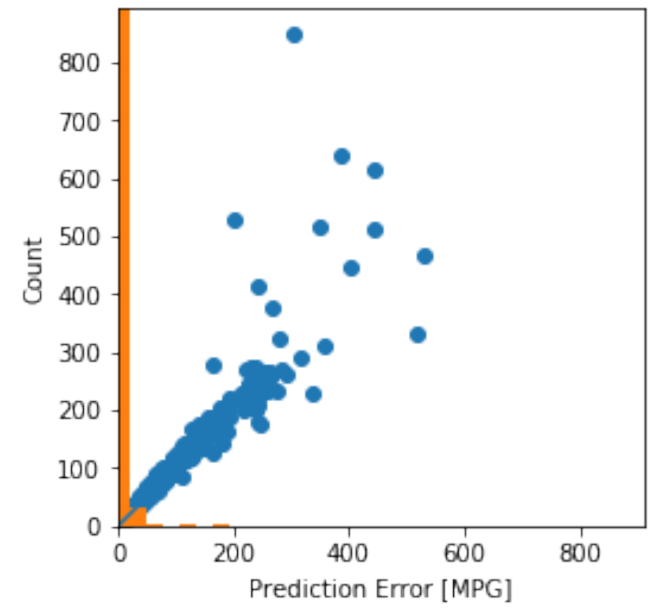


Fig. 5 Prediction for NN Model D

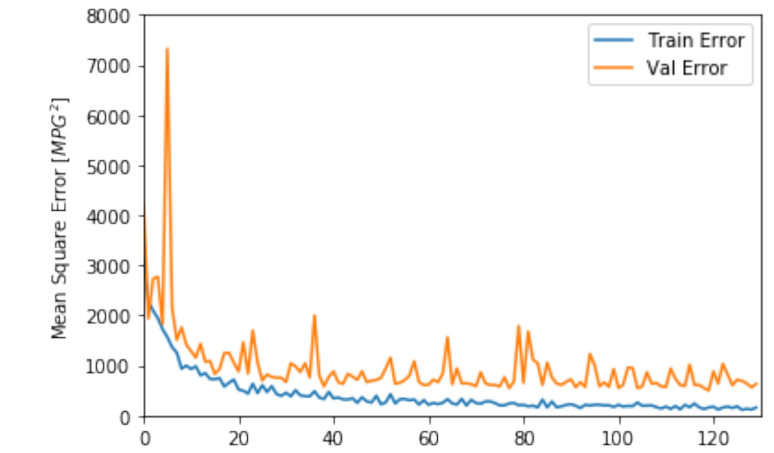


Fig. 6 Graph of MSE over Epoch for NN Model D

Results

Model	Training Error	Test Error
Linear Regression	132	402.02
NN Model A	2122.2996	1690.693
NN Model B	817.5392	2006.672
NN Model C	293.29	512.43
NN Model D	233.2	839

Table 3. Training and Test Errors for Each Models

Discussion and Future Work

Insights

- Model D with 4 hidden layers and 330 neurons in each layer has the best accuracy rate.
- Expected, because it is the most complex model to predict a non-linear relationship.
- Acceptable, because it has an accuracy rate close to 90%.
- Nonetheless, the loss graph indicates modest to high variance.

Future work:

- More data in a variety of regions because we want to increase our variability
- More data from other cars

References

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5. Van Blagarian, A. et al "Spark-ignited engine NOx emissions in a low-nitrogen oxycombustion environment"