ID2223 Project

Salman Niazi, Shadi Issa

Jan 10, 2017

Project Description

▶ Predict the solar radiation near Earth surface

Data Samples

- ► 0.4 million samples
- ► A typical sample looks like

lev	p	Т	q	lwhr
0	19.231	-80.0	0.0	0.122
1	57.692	-80.0	0.0	0.451
2	96.154	-70.874	0.029	-1.229
3	134.615	-51.083	0.262	-2.732
4	173.077	-36.489	0.977	-3.429
5	211.538	-25.816	2.211	-3.574
6	250.0	-17.87	3.756	-3.536
7	288.462	-10.404	5.431	-3.802
8	326.923	-6.608	4.226	-2.198
9	365.385	-2.388	8.776	-4.203
10	403.846	1.264	10.375	-3.567
11	442.308	4.462	11.895	-3.146
12	480.769	7.318	13.347	-2.829
13	519 231	9 903	14 733	-2 598

Data Samples

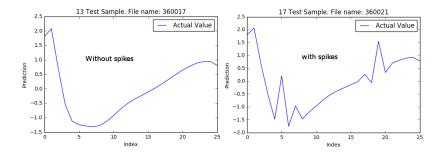


Figure 1: Data Samples

Solution

- Regresstion Problem
 - with 26 outputs
- Could be implemented using
 - ► Multivariate Regression
 - Feed Forward Neural Networks
 - Convolution Neural Networks

Feedforward Neural Network

- ► Feedforward neural networks with a single hidden layer can approximate continuous functions
- ▶ This can be efficient to replace an analytical model

Feedforward Neural Network Model

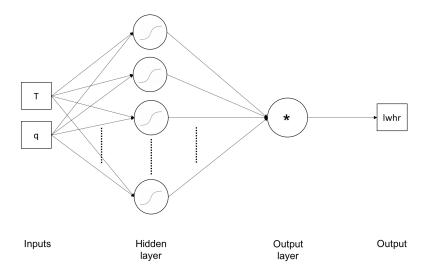


Figure 2: Architecture of feedforward neural network

Feedforward Neural Network Setup

Evaluation

Discussion

- ▶ low MSE
- does not capture the spikes

Convolution Neural Network

- Spikes are more affected by adjacent values
- ► To try to capture the spikes we opt to CNNs
- Kernels within CNN can detect local patterns

Input

- ▶ The input can be morphed into 26 x 2 matrix
 - did not produce very promissing results, as pooling can not shink the width of the input matrix.
 - ▶ Min MSE observed was 0.3

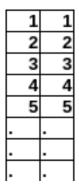


Figure 3: 26x2 Input Matrix

Input (Cont'd)

- ▶ The input can be morphed into 8 x 8 matrix
 - padding is needed as there are only 52 input features

1	2	3	4	5	6	7	8
9	10	11	12	13	14	15	16
17	18	19	20	21	22	23	24
25	26	27	28	29	30	31	32
33	34	35	36	37	38	39	40
41	42	43	44	45	46	47	48
49	50	51	52	0	0	0	0
0	0	0	0	0	0	0	0

Figure 4: 8 x 8 Input Matrix

Convolution Neural Network Model

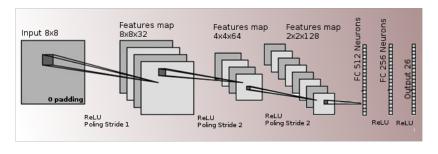


Figure 5: Architecture of convolution neural network

Model Complexity

Layer	Size	Memory	Weights	Bias
Input	8x8x1	64	0	0
CONV	8x8x32	8x8x32 = 2048	$2x2x1 \times 32 = 128$	32
POOL	8x8x32	8x8x32 = 2048	0	0
CONV	8x8x64	$8 \times 8 \times 64 = 4096$	2x2x1 * 64 = 256	64
POOL	4x4x64	$4 \times 4 \times 64 = 512$	0	0
CONV	4x4x128	4x4x128 = 2048	2x2x1 * 128 = 512	128
POOL	2x2x128	2x2x128 = 512	0	0
FC	1×512	512	2x2x128x512 = 262144	512
FC	1×256	256	$512 \times 256 = 131072$	256
OUT	1×26	26	$26 \times 256 = 6656$	26
FC	1×256	256	$512 \times 256 = 131072$	

Total memory = 413908×4 bytes (*float32*) x 2 (back propagation) = 3311264 = 3.1 Megabytes

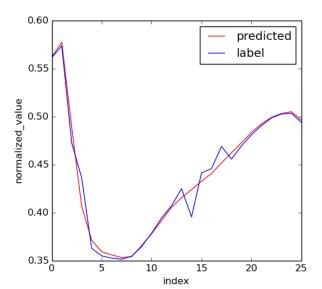
Evaluation Setup

- Training data set size 300,000 (75%).
- ► Test data set size 100,000 (25%).
- ▶ Inputs are normalized using max-min scaling

 - $\blacktriangleright \ \, \mathsf{X_s} = \left(\mathsf{X} \text{ Input}_{\mathsf{mean}}\right) \, / \, \left(\text{ Input}_{\mathsf{std}} \, \right)$
- Learning Rate 0.001
- Dropout 0.95
- ▶ Max number of Epochs 120000
- ▶ Batch Size 3
- ▶ Weights were randomly initialized such that the random numbers had mean=0.1 and stddev=0.3
- ▶ Bias were also randomly initialized such that the random numbers had mean=0 and stddev=0.03

Results

▶ MSE drops to 0.003 but the network failed to predict the spikes



Dying ReLU Problem

"ReLU units can be fragile during training and can "die". For example, a large gradient flowing through a ReLU neuron could cause the weights to update in such a way that the neuron will never activate on any datapoint again."

¹http://cs231n.github.io/neural-networks-1/

Solution Leaky ReLU

- Use a Leaky ReLU
 - ▶ Slop 0.001

Mean Square Error of the CNN Model

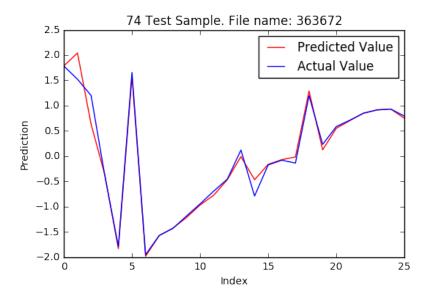


Figure 7: Mean Square Error of the CNN Model

Questions ?