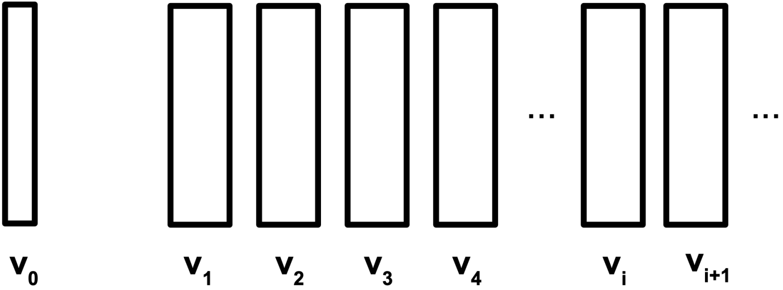
2nd Place @ ML Challenge #2
or:
How I ran out of Parameters

Daniel Lersch

November 20, 2019

The Second ML Challenge

- GlueX **F**orward **D**rift **C**hamber (**FDC**)
  - 24 planes
  - Each plane: $\vec{v}_i = \begin{pmatrix} x \\ y \\ z \\ p_x \\ p_y \\ p_z \end{pmatrix}$
- **Goal:** Reconstruct particle in plane $i+1$, when all previous planes fired



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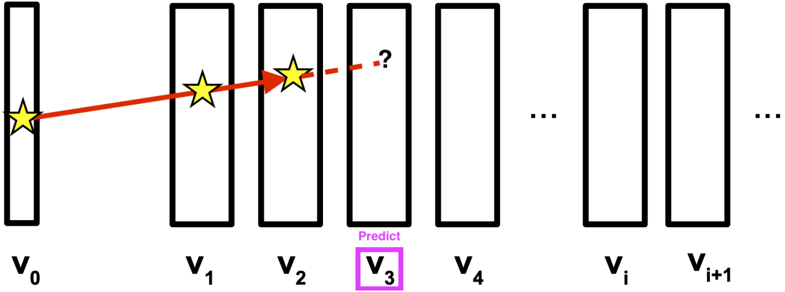

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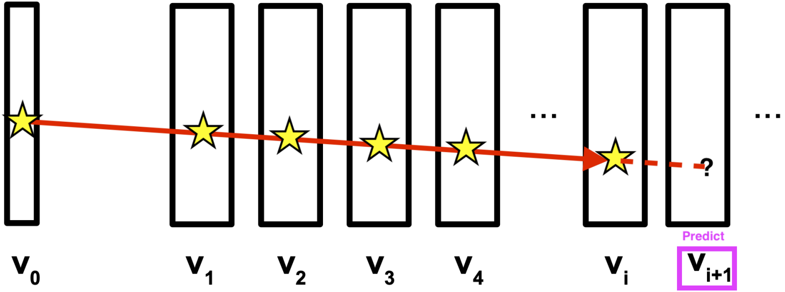

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- with:

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- This is dangerous! $\Rightarrow$ Vanishing gradient!

Model Selection

- After a few test runs, decided to run with the following models:

$$M_1(n, u_0, u_1, .., u_{n-1}) = L_{lstm}(u_0) + \sum_{i=1}^{n-1} L_{dense}(u_i) + L_{dense}(6) \tag{4}$$

$$M_2(n, u_0, u_1, .., u_{n-1}) = L_{dense}(u_0) + \sum_{i=1}^{n-1} L_{dense}(u_i) + L_{dense}(6) \tag{5}$$

- with:

Variable	Meaning
L_{lstm}	LSTM recursive network layer
L_{dense}	Dense network layer
n	Number of hidden layers
u_i	Number of neurons in layer i

- NOTE: Input layer is not shown here
- Activation functions:
  - Output layer: Linear $\Rightarrow$ Want to regress the data
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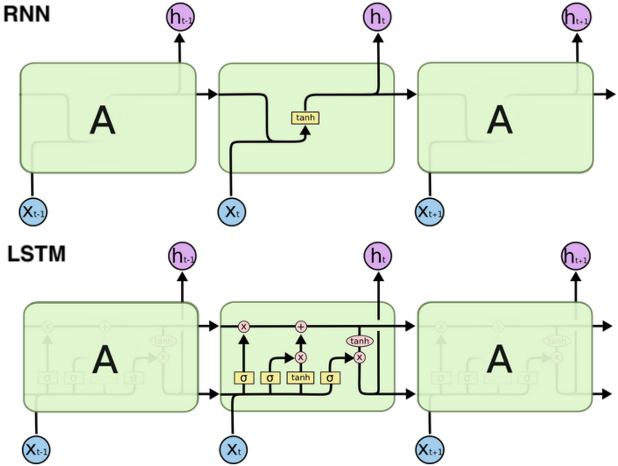
Short Reminder: RNN vs. LSTM

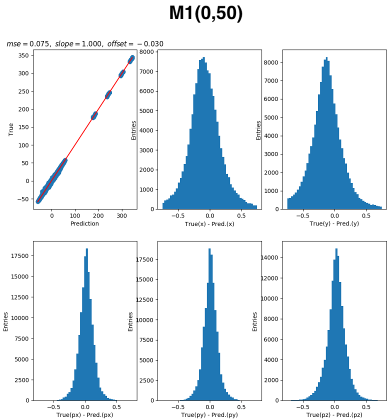


Also tested RNN, but LSTM showed better performance

Pictures taken from here (good explanation)

Interpretation and Training Strategy

- **Model 1:** Recurrent + regressor ⇒ Learn series (encoded in pattern) and fit data
- **Model 2:** Simple regressor ⇒ Simply fit the data, including the "0" pattern
- **Training strategy:**
  i) Train (and evaluate) several models on subset of training data ⇒ Save time
  ii) Re-train (and re-evaluate) "best" model on full training (validation) data

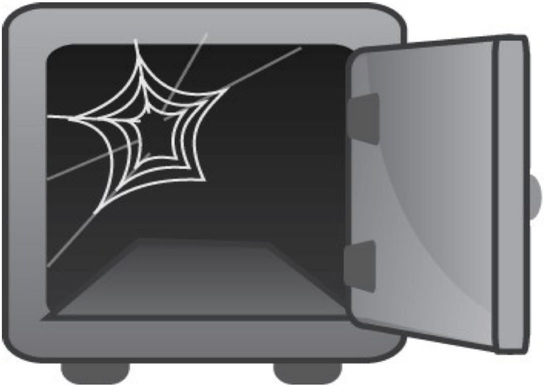


The Night before the Submission Deadline...

Everything was setup to train a deep neural net,

The Night before the Submission Deadline...

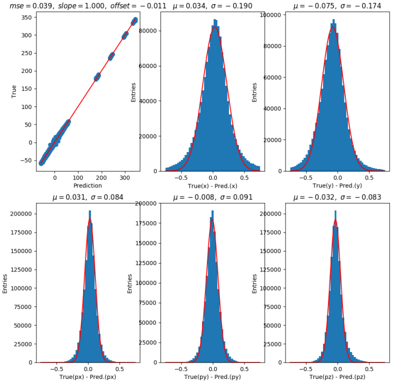
but...



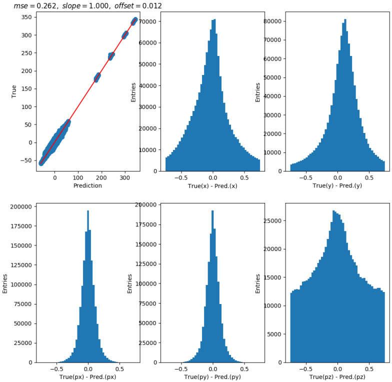
Final Configuration(s)

- $M_1 = L_{lstm}(50) + 2 \cdot L_{dense}(50) + L_{dense}(6)$ with $16.8\,\mathrm{k}$ parameters **(left)**
- $M_2 = 3 \cdot L_{dense}(50) + L_{dense}(6)$ with $10.4\,\mathrm{k}$ parameters **(right)**

M1



M2



Ideas and Tests that did not work out...

Picture taken from: http://screenrant.com/things-you-did-not-know-about-wile-e-coyote/

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- Introduced random noise $n_{k,i} = \mathcal{N}(0.0, \sigma_{k,i}) \neq 0$ to training data:

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- And many more...

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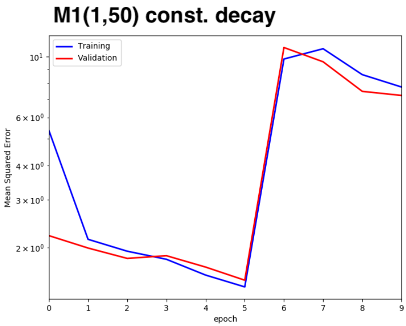

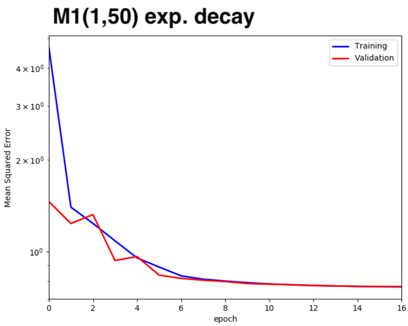

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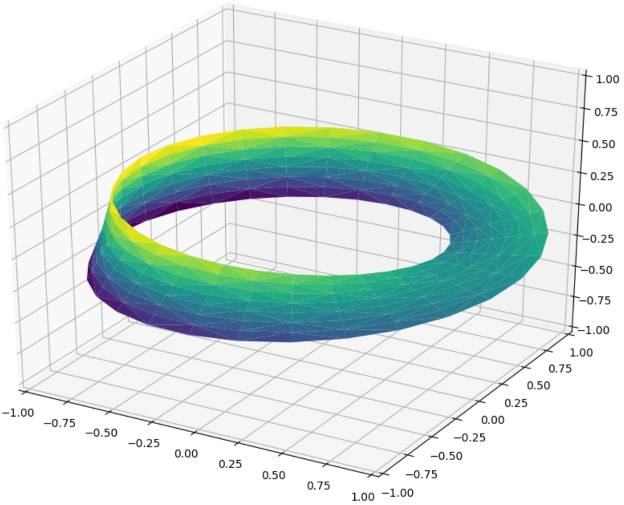

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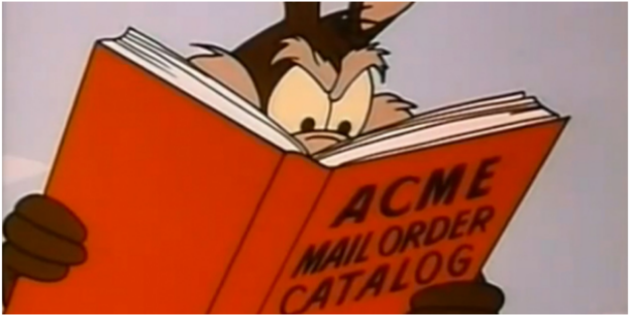

Picture taken from **here**

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- Do not be afraid to push your model to the limits