# **EEL6935 Course Project Final Report**

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# **Sentiment Analysis**

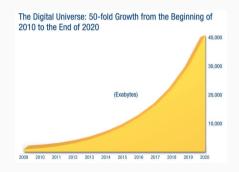
Goal: assign sentiment labels to a sentence.

$$f:\mathcal{D}\to\mathcal{L}$$

- $\mathcal{D} = \{d_0, d_1, \dots, d_{n-1}\}$  is the set of sentence
- $\mathcal{L} = \{l_0, l_1, \dots, l_{k-1}\}$  is the set of labels.

Movie review is ideal for sentiment analysis

- Most dataset of movie review are already associated with scores
- The scores in dataset are reliable



<sup>&</sup>lt;sup>1</sup>Gantz, J., & Reinsel, D. (2012). The digital universe in 2020: Big data, bigger digital shadows, and biggest growth in the far east. IDC iView: IDC Analyze the future, 2007(2012), 1-16.

## **Text Encoding**

• Define the collection of text documents to be

$$\mathcal{D} = \{d_1, d_2, \dots, d_D\}$$

Define vocabulary to be

$$\mathcal{V} = \{v_0, v_1, \dots, v_{m-1}\}$$

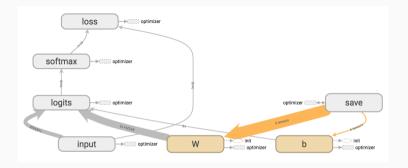
• The notation of frequency of a word  $v \in \mathcal{V}$  occurred in document  $d \in \mathcal{D}$  is  $f_d(v)$ , hence a document can be represented as a vector

$$\bar{d} = \{f_d(v_1), f_d(v_2), \ldots\}$$

ullet Define total number of documents  $d\in\mathcal{D}$  containing the word w is represented as

$$f_{\mathcal{D}}(v)$$

# Backend: Logistic Regression



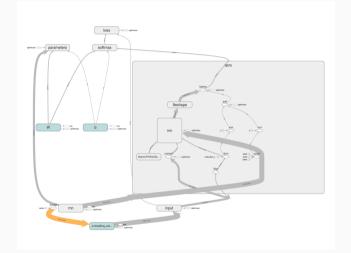
- Multiply input vectors by W, add b
- Convert output into probabilities with Softmax
- pick  $i = argmax(\hat{y}_i)$
- Train the model using Adam Optimizer
- Common baseline model and simple to implement

#### Backend: LSTM Model

Given a word sequence  $S = \{v_0, v_1, \dots, v_{l-1}\}$  with length l, the states of LSTM are updated as:

$$\begin{bmatrix} i_t \\ f_t \\ o_t \\ c_t \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{bmatrix} S[h_{t-1}, x_t]$$

- $c_t = f_t \circ c_{t-1} + i_t \circ \hat{c_t}$
- $h_t = o_t \circ \tanh c_t$



#### **Backend: LSTM Model**

To build our LSTM model:

Define a dictionary

$$D = [w_1, w_2...w_N]$$

to contain the set of all words representable by our LSTM network

• The *i*-th input to our LSTM is a vector

$$v_i = [\pi_{i1}, \pi_{i2}...\pi_{iL}]$$

corresponding to a movie review  $r_i$  of length L, where  $\pi_{ij}$  is the dictionary index of the j-th word of r

• D = [cat, dog, meow]

$$r = [\mathsf{dog}, \mathsf{dog}, \mathsf{cat}, \mathsf{meow}] \Rightarrow v = [1, 1, 0, 2]$$

## Simulation Platform Specs

- Training based on Stanford Large Movie Review Dataset
  - 50,000 highly polar movie reviews
  - 25,000 for training, 25,000 for testing
- Code in Python with Tensorflow/Scikit-Learn
- simulations will be conducted on computers with
  - 3.1GHz Intel Core i7 CPU with 8MB cache
  - nVidia GTX 1050 GPU with 4GB Memory
  - 16GB RAM
  - Ubuntu 14.04 LTS

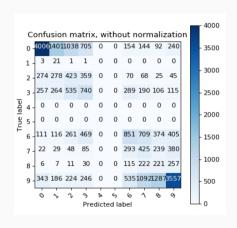


 Table 1: System Performance

Method	Epochs	Binomial Training	Binomial Testing	Multinomial Training	Multinomial Testing
scikit-learn LR	N/A	0.9981	0.8697	N/A	N/A
tensorflow LR	20	0.8670	0.8583	0.9982	0.3734
larger LSTM	8	N/A	N/A	0.6693	0.3657
smaller LSTM	2	N/A	0.8507	0.5622	0.4098

#### Front End: Flask Web App

- Web App via Flask
- Allow model selection
- Accept text input and sentiment analysis output
- Hosted on low spec VM
  - Ubuntu 16.04 LTS
  - Single Core CPU
  - 2GB RAM
  - No standalone GPU





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# Thank You!

Questions?