NLP-Android app Deep Neural Networks

Apostolos Papatheodrou



Presentation Index

- **❖** Android application
- ❖ Machine learning-NLP
 - > Dataset-Preprocessing
 - GRU/LSTM models for multiclass categorization
- Real Examples and Evaluation
- Summary



Client-Server architecture

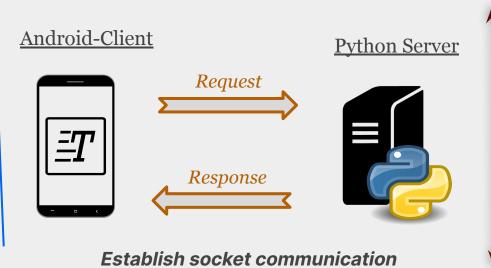
Android-Client



Python Server



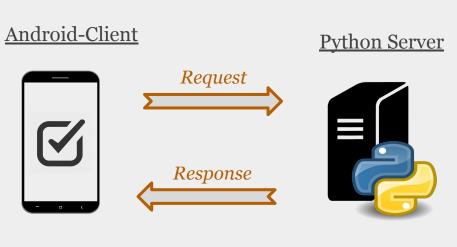
Client-Server architecture



Server-Side

- A. Approves the connection
- B. Process client's request
 - a. <u>Text classification</u> into four categories: science/tech., business, medicine, entertain.
 - b. <u>Summarize text</u> with the most important sentences in input-text (<u>Term Frequency</u> scores)
- C. Sends Response to user

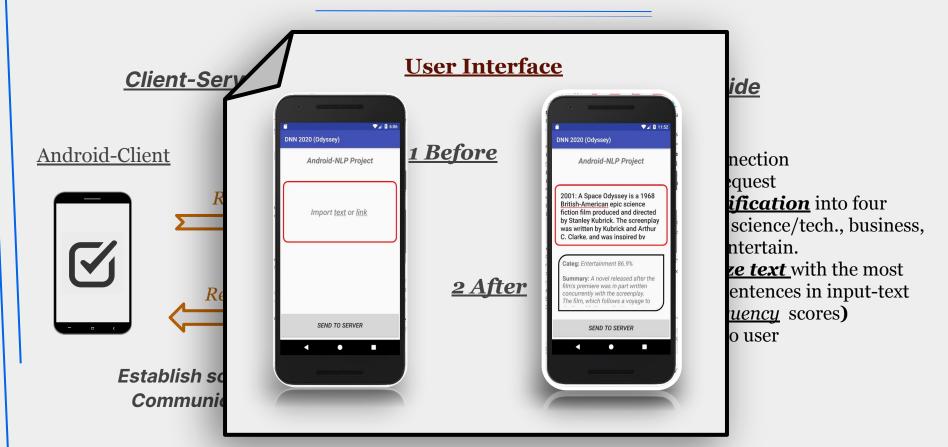
Client-Server architecture



Establish socket communication Communication is terminated

Server-Side

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News Aggregator dataset: News headlines collected by a web aggregator in 2014 (*UCI ML Repository*)

Data are splitted in 4 classes:

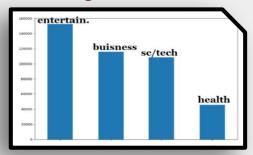
Medicine, Business, Science/tech and Entertainment



Dataset WordCLoud



Categ. distribution



News Aggregator dataset: News headlines collected by a web aggregator in 2014 (*UCI ML Repository*)

Data are splitted in 4 classes:

Medicine, Business, Science/tech and Entertainment



Science/tech



Medicine



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Preprocessing & Embeddings

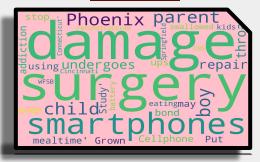
Preprocessing: Natural Text is unsuitable for learning

- Encode words with integers
- Padding sentences to a fixed length

Science/tech



Medicine



News Aggregator dataset: News headlines collected by a web aggregator in 2014 (*UCI ML Repository*)

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Preprocessing & Embeddings

Preprocessing: Natural Text is unsuitable for learning

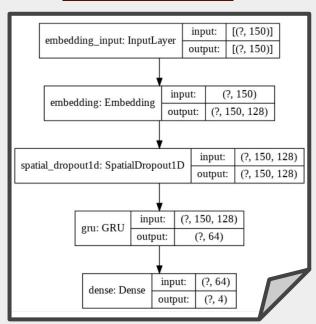
- Encode words with integers
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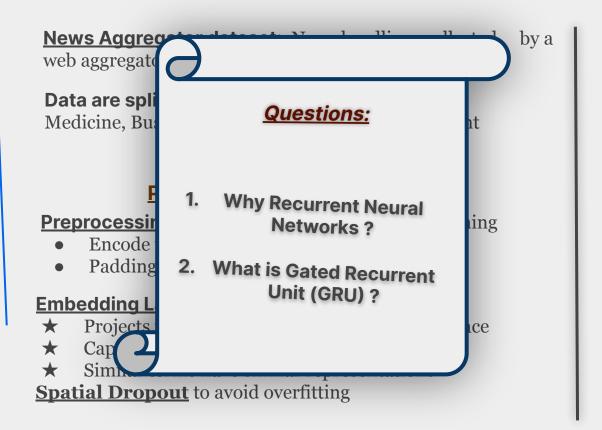
Embedding Layer:

- ★ Projects the words into a continuous vector space
- ★ Captures the relationships between words
- ★ Similar terms have similar representations

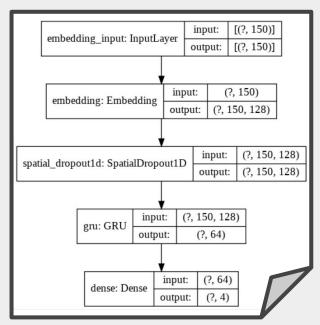
Spatial Dropout to avoid overfitting

Model's structure





Model's structure



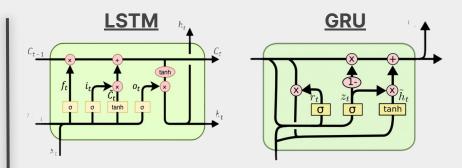
RNNs

Vanilla RNNs

- ☐ Capture sequential information in input data (e.g. correlations between words)
- At each step the output is calculated based on the new input and the hidden state
- ☐ When the gap between relevant worlds is small they can learn to use past information
- ☐ (hidden state signifies past knowledge)

Drawbacks

- Suffer from vanishing gradient and exploding gradient problems
- ☐ LSTM/GRU solve the vanishing gradient problem and can learning long term dependencies



LSTM(1997) & GRU(2014)

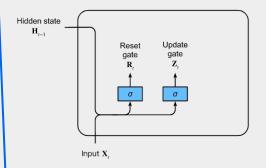
LSTM and GRU both use gated mechanisms to regulate the memory in hidden state (ht)

- ➤ LSTM: Cell, Input, Output and Forget gates
- GRU Update and Reset gates

They can keep information for long time without washing it out and remove it if needed

GRU is considered a variation of LSTM

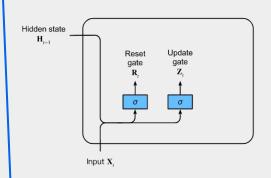
Gated Recurrent Unit



Reset Gate: How much of the past information to forgot (what flows out of the memory)

Update Gate: How much the new state is copy of the old state (what flows into the memory)

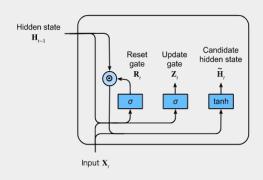
Gated Recurrent Unit



Reset what flows out **Update** what flows in

$$egin{aligned} \mathbf{R}_t &= \sigma(\mathbf{X}_t\mathbf{W}_{xr} + \mathbf{H}_{t-1}\mathbf{W}_{hr} + \mathbf{b}_r), \ \mathbf{Z}_t &= \sigma(\mathbf{X}_t\mathbf{W}_{xz} + \mathbf{H}_{t-1}\mathbf{W}_{hz} + \mathbf{b}_z). \end{aligned}$$

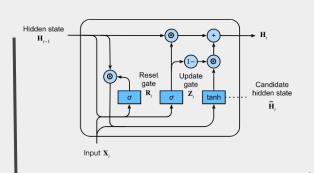
σ((n*d)*(d*h)+(n*h)*(h*h))
X_t (n*d), h_t-1:(n*h)
Wxr,Wxz:(d*h), Whr,Whz:(h*h)



Candidate h'_t

$$ilde{\mathbf{H}}_t = anh(\mathbf{X}_t\mathbf{W}_{xh} + (\mathbf{R}_t\odot\mathbf{H}_{t-1})\,\mathbf{W}_{hh} + \mathbf{b}_h)$$

Reduce the influence/Forget the previous hidden state (incorporate update gate)



Output h_t

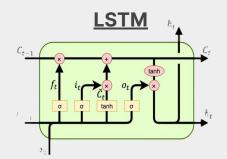
$$\mathbf{H}_t = \mathbf{Z}_t \odot \mathbf{H}_{t-1} + (1 - \mathbf{Z}_t) \odot \tilde{\mathbf{H}}_t.$$

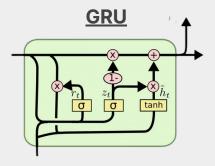
The extent to which the output is the old state h_t-1 and how much of the candidate state is used

GRU & LSTM

Generally:

- GRU and LSTM are varintas of classical RNN
- > They capable to deal with Long term dependencies
- LSTM has more gates than GRU
- GRU has less parameters for training
- > GRU can achieve better results in small datasets
- > In general lstm is strictly better than gru





Evaluation

Accuracy

GRU: Train: 0.9206, Test: 0.9234 LSTM: Train: 0.9270, Test: 0.9256







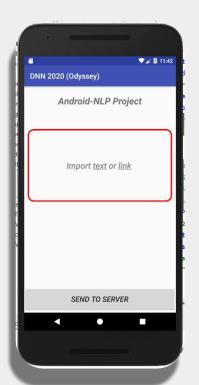
Evaluation

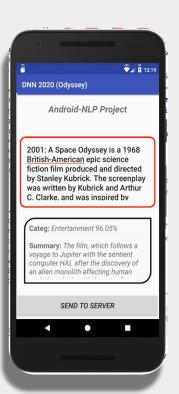
Accuracy

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<u>GRU</u>	precision	Recall	F1-score
Entertain.	0.95	0.95	0.95
Business	0.90	0.90	0.90
science	0.90	0.91	0.91
Medicine	0.94	0.94	0.94



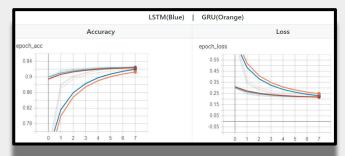


Space-Odyssey(wiki) => <u>Entertain. 96.05%</u> All_predictions [[0.96, 0.003, 0.033, 0.004]]

Evaluation

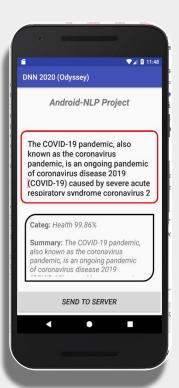
Accuracy

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<u>LSTM</u>	precision	Recall	F1-score
Entertain.	0.95	0.95	0.95
Business	0.90	0.90	0.90
science	0.90	0.90	0.91
Medicine	0.94	0.94	0.94





Covid-19(wiki) => <u>Health 99.9%</u> All_predictions [[0, 0.01, 0, 0.999]]

Presentation Summary



- An NLP-Android Application for text categorization
- ❖ An android client sends request to a python server
- ❖ The server uses RNN models which
 - ➤ Are trained on a dataset from news headlines
 - Make use of Gated Recurrent Units & Long short Term Memory units to solve the vanishing gradient problem
- Examples & Results



Questions?





Thanks for your time

Relevant Sources

Project:

https://github.com/PapApostolos/NLP-Android

Sources

Embeddings:

https://www.tensorflow.org/tutorials/text/word_embeddings
https://aylien.com/blog/overview-word-embeddings-history-word2vec-cbow-glove

RNN:

https://colah.github.io/posts/2015-08-Understanding-LSTMs/ https://theaisummer.com/understanding-lstm/#lstm-long-short-term-memory-cells

GRU:

https://d2l.ai/chapter_recurrent-modern/gru.html https://towardsdatascience.com/understanding-gru-networks-2ef37df6c9be