




LOCATION PREDICTION FOR TWEETS

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Aim : To develop a deep learning based solution to predict geographic information for tweets.

Motivation

The current approaches bear two major limitations-

- hard to model the long term information.
- hard to explain to the end users what the model learns.

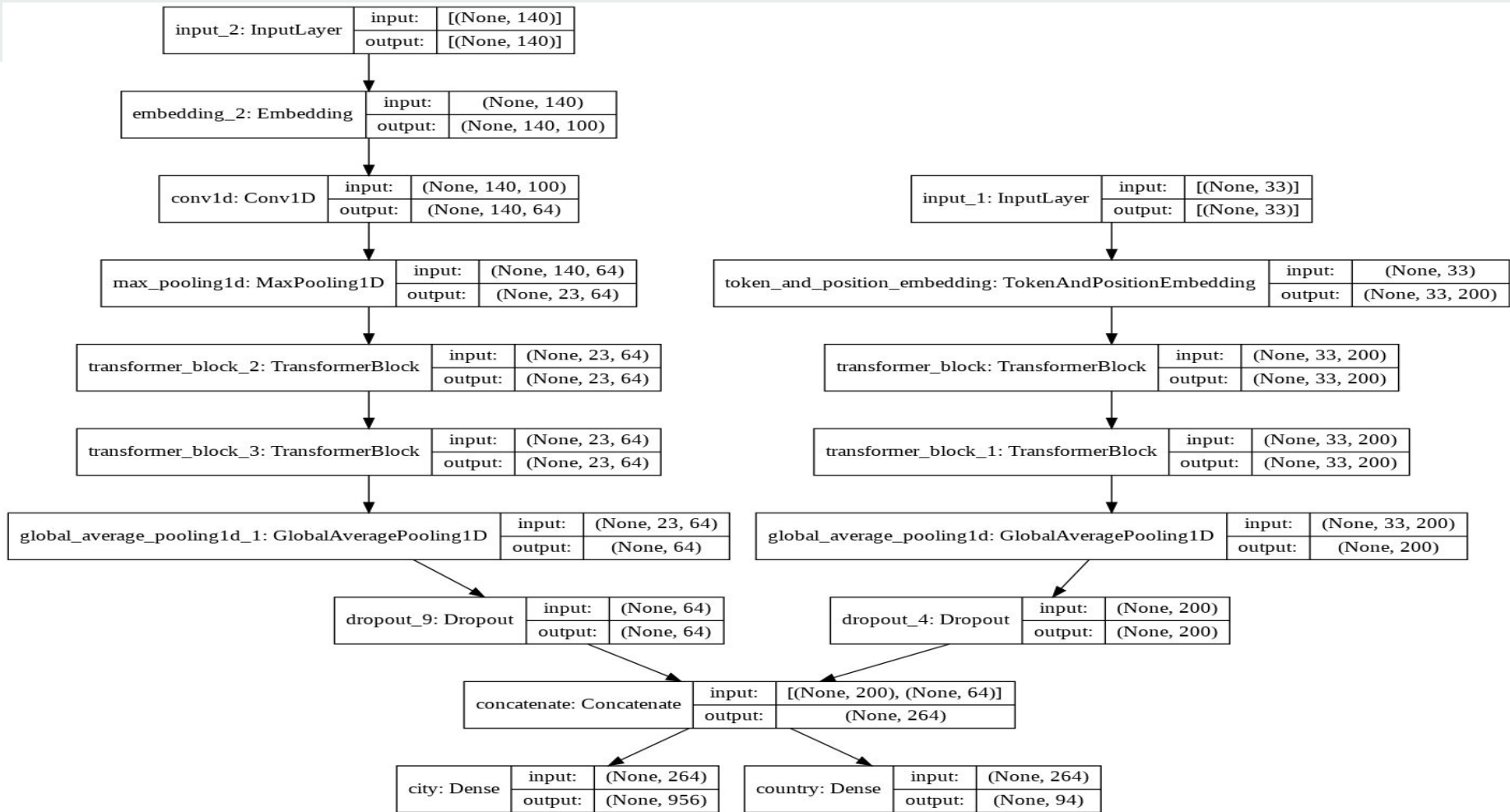
Applications

- Marketing Recommendation Systems
- Event Detection Systems



Methods Used

- Multi-head self Attention Mechanism
- Subword Feature
- Multitask Learning





Dataset

Training Example	5000
Testing Example	630
No of country	94
No of City	956

Testing Accuracy

Country Prediction	43.80 %
City Prediction	4.60 %

Training Accuracy

Country Prediction	58.80 %
City Prediction	7.02%



Additional Task Implemented

- Sandwich Transformer
- Early Stopping
- Adding Multihead Attention layer after Concatenation
- Adding a LSTM layer after Concatenation
- Having Multiple filters rather than single Convolution layer
- Hyperparameter Tuning

Sandwich Transformer



A horizontal bar representing a sequence of 20 sublayers. The bar is divided into 20 segments, each containing a letter. The letters alternate between 's' and 'f' in a repeating pattern: s, f, s, f, s, f, s, f, s, f, s, f, s, f, s, f, s, f, s, f. The segments are colored in a repeating pattern of green and purple.

(a) Interleaved Transformer



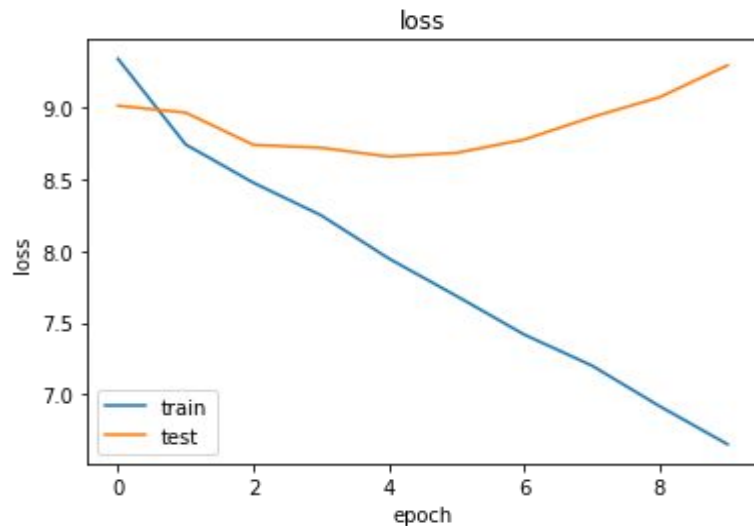
A horizontal bar representing a sequence of 20 sublayers. The bar is divided into 20 segments, each containing a letter. The sequence starts with 8 's' characters, followed by 8 'f' characters, and ends with 4 'f' characters. The segments are colored in a repeating pattern of green and purple.

(b) Sandwich Transformer

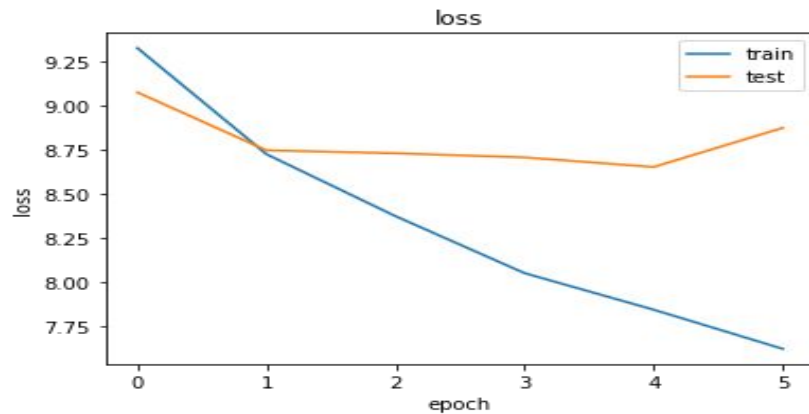
[Improving Transformer Models by Reordering their Sublayers](#)

Early Stopping

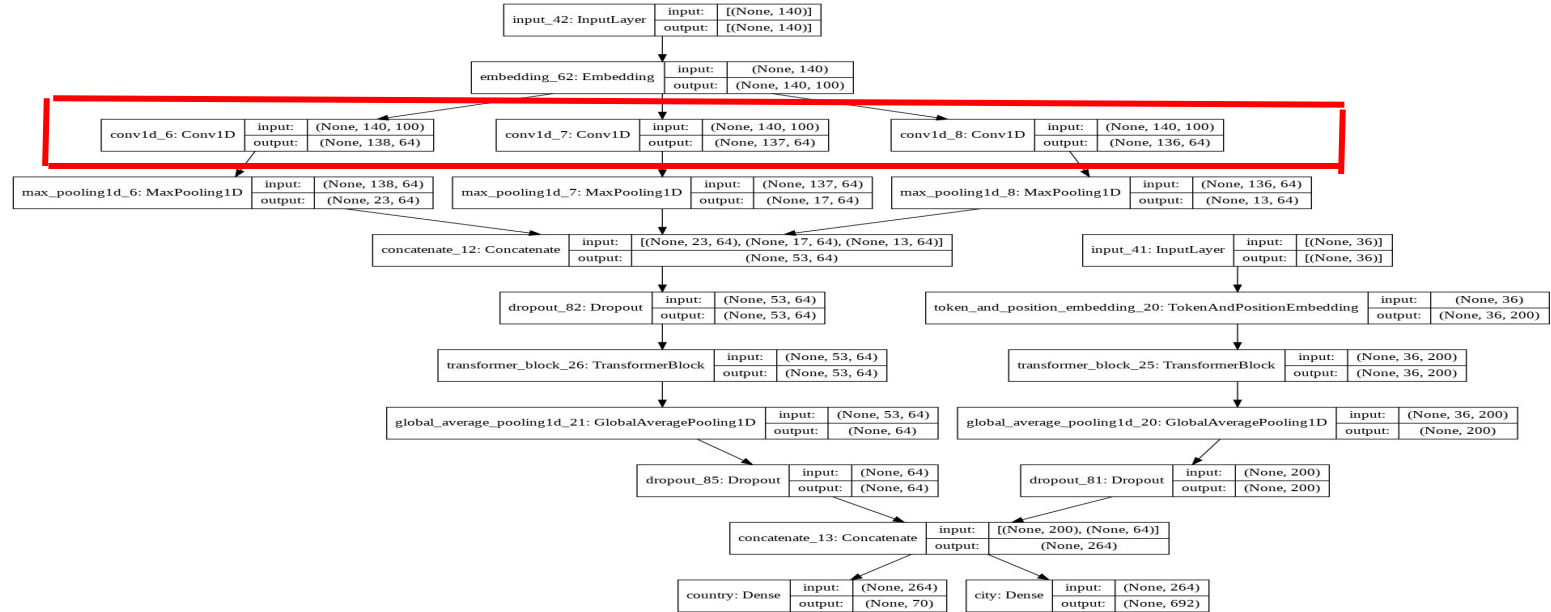
Without Early Stopping



With Early Stopping

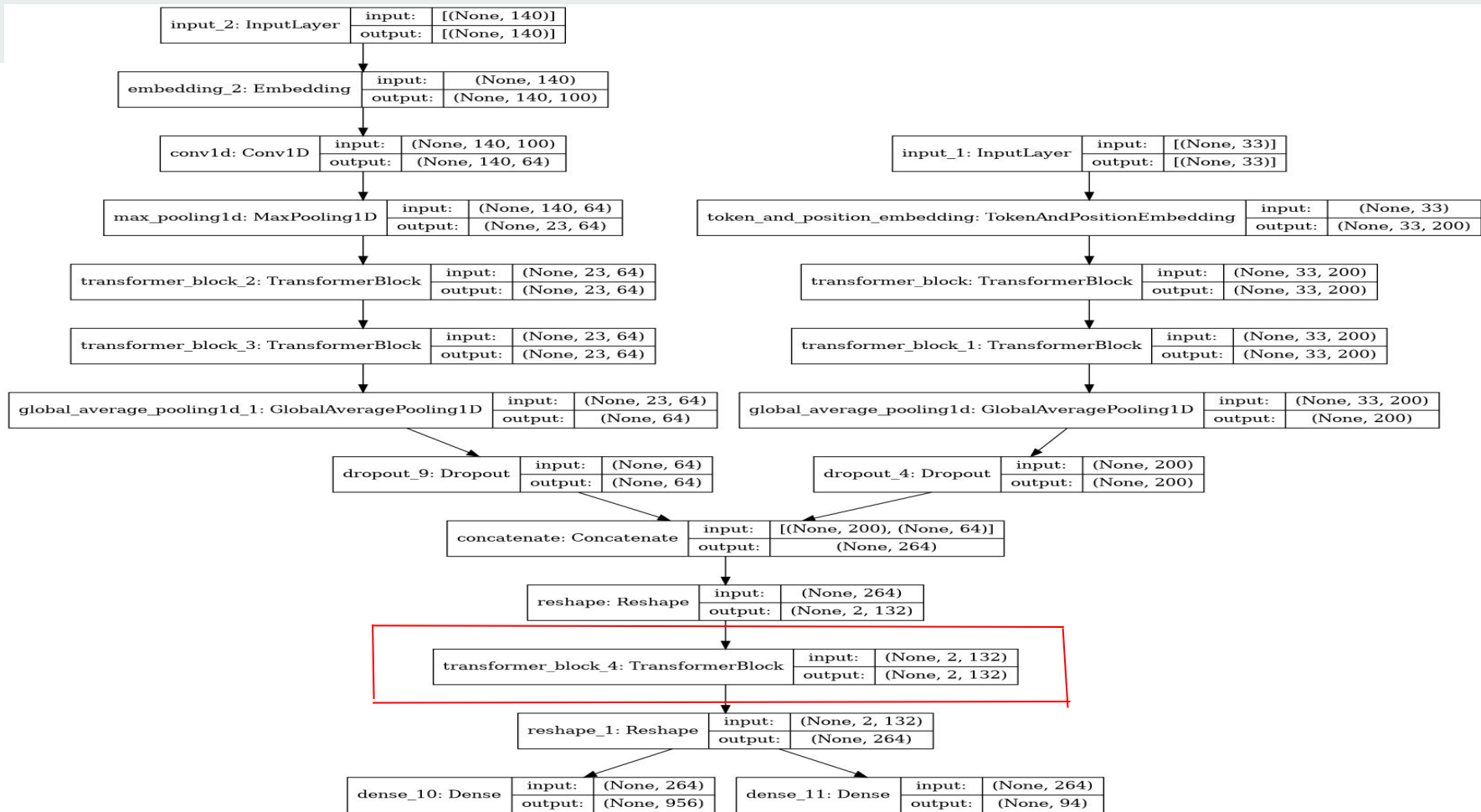


Having Multiple Parallel convolution layer with different filter sizes rather than single Convolution layer





Adding LSTM Layer / Multihead Attention Layer after Concatenation





Other Types of model

input_5: InputLayer	input:	[(None, 33)]
	output:	[(None, 33)]



token_and_position_embedding_1: TokenAndPositionEmbedding	input:	(None, 33)
	output:	(None, 33, 200)



transformer_block_4: TransformerBlock	input:	(None, 33, 200)
	output:	(None, 33, 200)



transformer_block_5: TransformerBlock	input:	(None, 33, 200)
	output:	(None, 33, 200)



global_average_pooling1d_2: GlobalAveragePooling1D	input:	(None, 33, 200)
	output:	(None, 200)

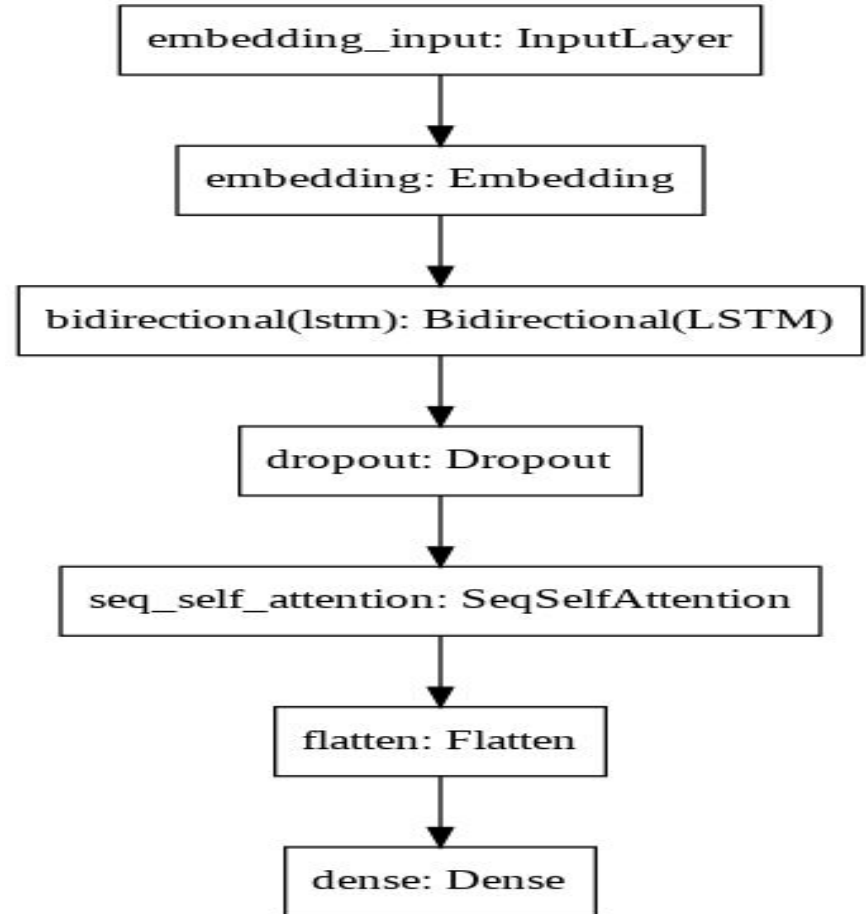


dropout_18: Dropout	input:	(None, 200)
	output:	(None, 200)

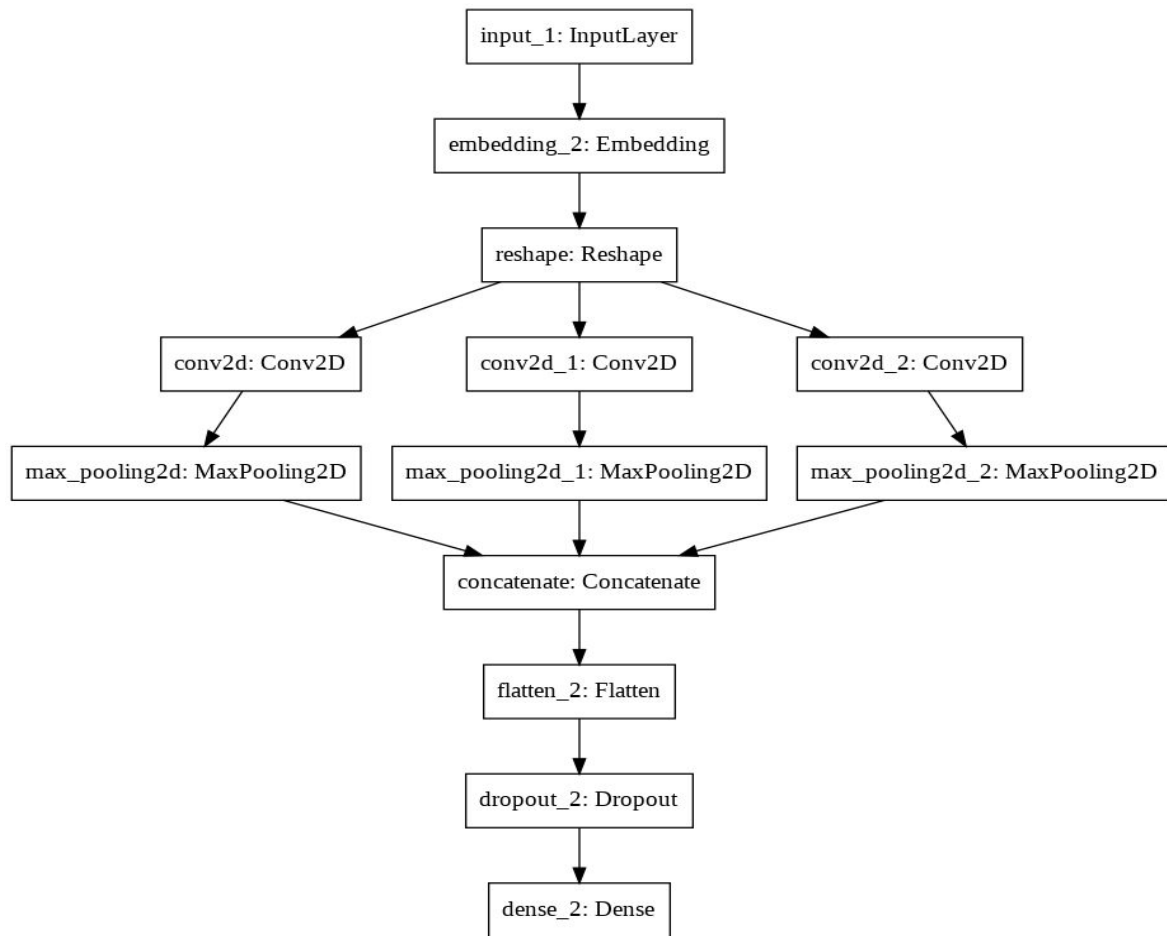


dense_18: Dense	input:	(None, 200)
	output:	(None, 94)

LSTM + Self Attention



CNN





Accuracy

	Country Prediction (trained on 5000 examples)	City Prediction (trained on 5000 examples)	Country Prediction (trained on 30,000 examples)	City Prediction (trained on 30,000 examples)
Without any modification	43.80 %	4.60%	48%	6.7%
Sandwich Transformer	44.44%	3.9%	48.3%	5.93%
Extra transformer block after concatenation	45.55%	4.92%	49.03%	5.50%
Extra transformer layer after concatenation + multiple convolution parallel layer	44.8%	5.8%	50.22%	6.3%
LSTM + self attention	40%	4.76%	46.19%	6.14%
CNN	43.17%	3.49%	49.45%	5.54%
Only word embedding of the given model used (right part only)	45.08%	2.7%	46.24%	5.41%



Thanks!

