

# weekly report: amino acid seq

Jitian Zhao

University of Wisconsin Madison

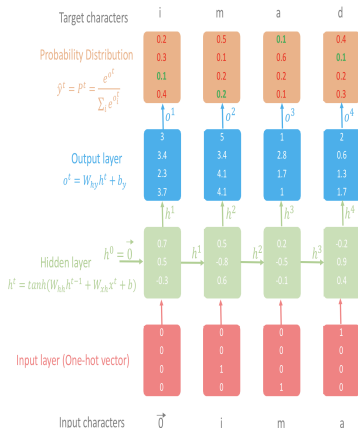
September 23, 2019

# Outline

- low performance of Char-RNN
- code modification of Transformer

# char-RNN:recap

- training:  $\hat{X}_n = \text{sample}(P(X_n|X_1, \dots, X_{n-1}))$
- generating:  $\hat{X}_n = \text{sample}(P(X_n|\hat{X}_1, \dots, X_{n-1}))$



Source: <https://towardsdatascience.com/character-level-language-model-1439f5dd87fe>

## low performance of Char-RNN

- low reconstruction accuracy for test dataset: 33%
- low accuracy was not due to error propagation
- model insensitive to the given information

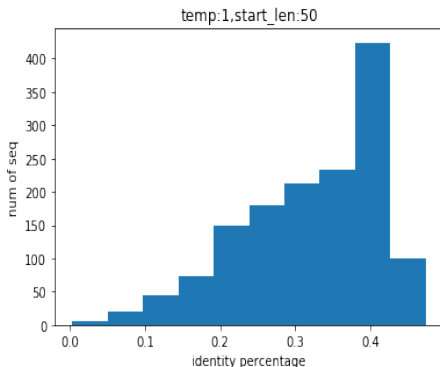


Figure: reconstruction accuracy

## possible reasons of why it doesn't work

- simple structure: 1 gru layer + 1 fc layer
- does not learn from the position
- sequence diversity or data clustering
- ...

# Transformer

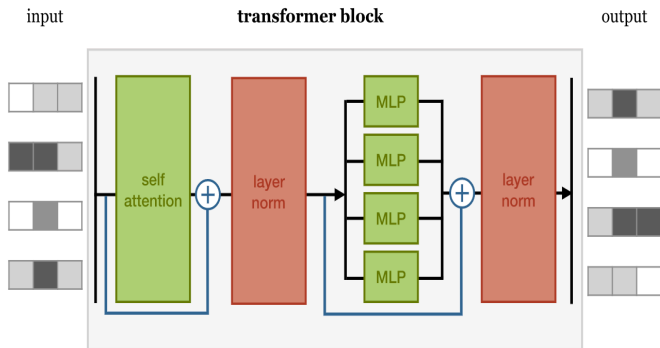


Figure: structure of transformer

Source: <http://peterbloem.nl/blog/transformers>

# self-attention mechanism

- input:  $X_1, \dots, X_t$
- output:  $Y_i = \sum_j w_{ij} X_j$
- weight:  $w_{ij} = \text{softmax}(w'_{ij}), w'_{ij} = X_i^T X_j$
- one input vector  $X_i$  serves 3 needs: contribute to its own weight (query), other inputs weight (key), final weighted sum (value)

## catch the position information : multi-head attention

- example: 'mary', 'gives', 'jane', 'a', 'flower'
- neighbor matters!
- different attention heads have different sets of matrices, which gives it power of discriminating neighbors.

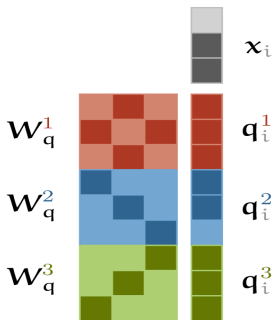


Figure: multi-head attention

Source: <http://peterbloem.nl/blog/transformers>



## tailored modification for a.a. seq

- sequence padding
- random trunk → randomly choose one sequence
- word encoding: different vocabulary