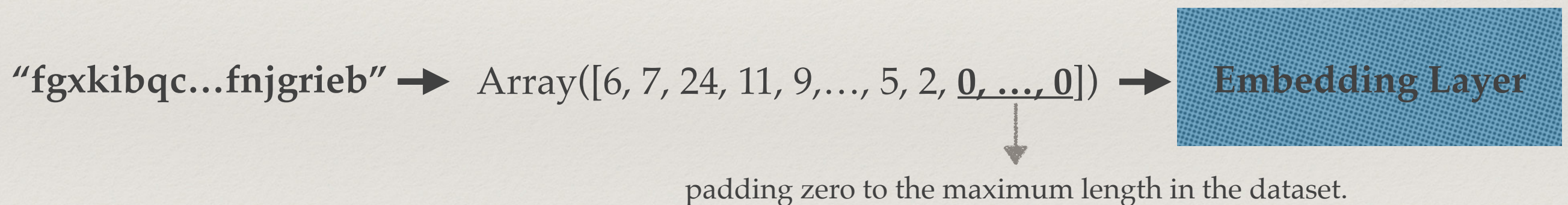


Data Note

- ❖ In the dataset, a single pair composed of:
INPUT: obfuscated text such as “fgxkibqc...fnjgrieb”, without any space
LABEL: totally 12 classes, distribution shown as below chart.

Class	0	1	2	3	4	5	6	7	8	9	10	11
Distribution	8.67%	22.5%	3.6%	9.5%	5.6%	5.5%	10.2%	12.3%	8.8%	2.4%	7.4%	3.4%

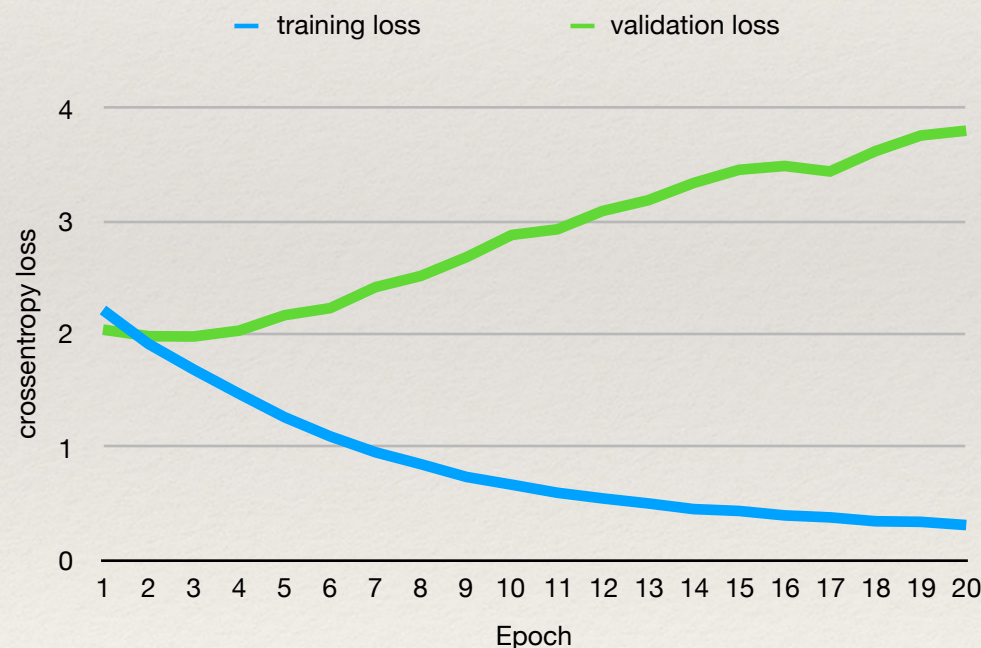
I can't share the dataset to public yet, but I believe similar tasks can share the experiment results here.



- ❖ The input Array[Integer] is expected to be stored as numpy memmap in my implementation.
- ❖ 20% of standalone validation set is split to judge the performance.

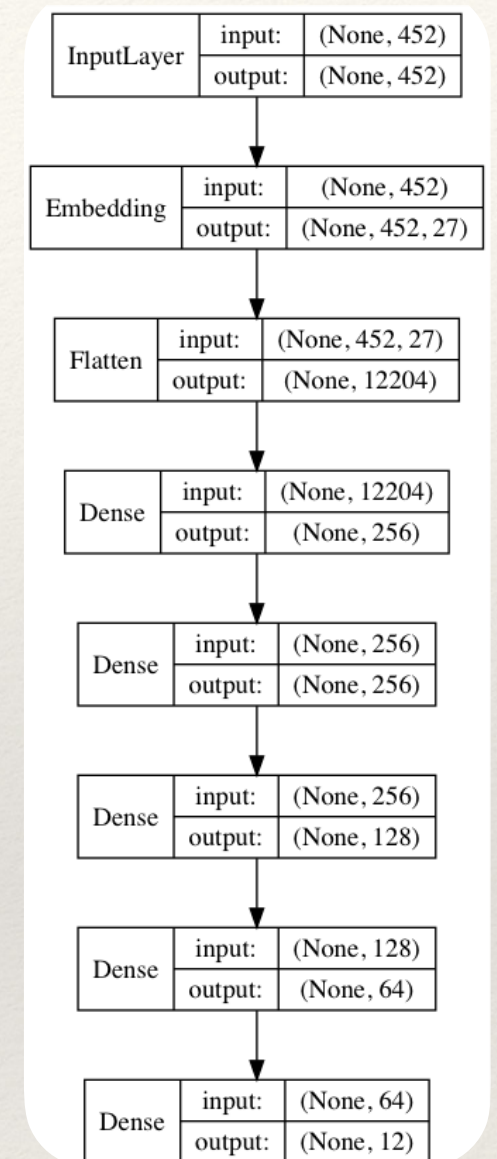
1_Baseline Model

- ❖ Expanding the full sequence vectors, pumped all in to a fully connected neural networks as a simple baseline. The neural network
- ❖ Best standalone validation accuracy: 32.45% (epoch 4)
- ❖ Overfitting start after epoch 4



Class	0	1	2	3	4	5	6	7	8	9	10	11
Precision	0.148	0.377	0.207	0.282	0.413	0.556	0.232	0.310	0.579	0.000	0.190	0.293
Recall	0.036	0.205	0.109	0.336	0.333	0.338	0.487	0.410	0.465	0.000	0.187	0.043

* All prediction based on best model (lowest validation loss), overall validation accuracy = 32.45%



Activation: LeakyReLU

Last Activ.: softmax

Loss: crossentropy

Optimizer: Adam

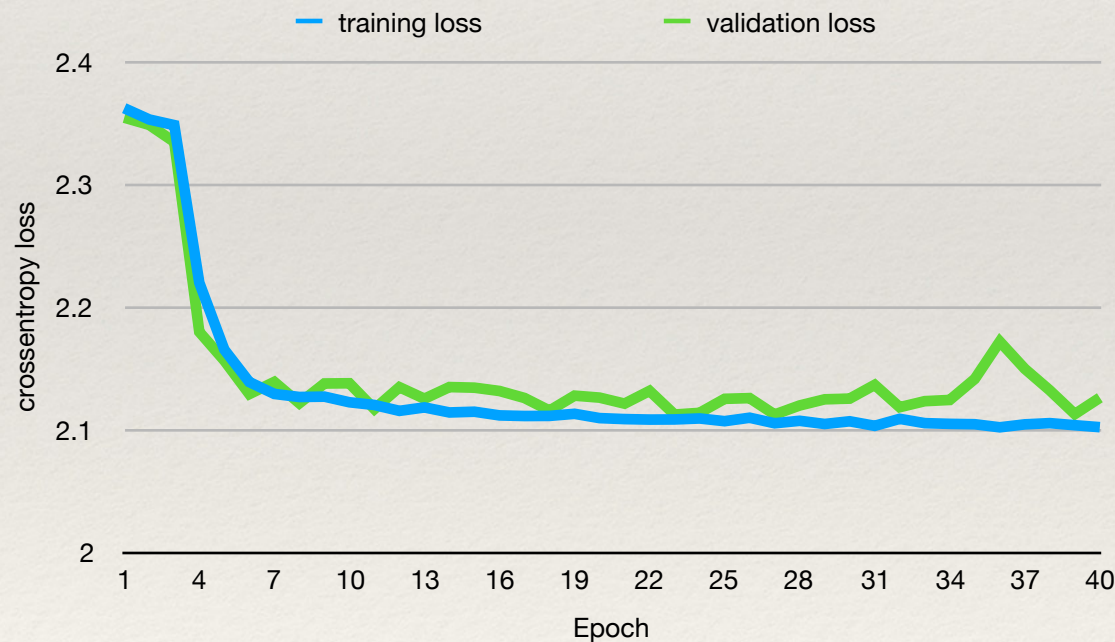
Batch size: 100

Dropout: 0.2

* Details please refer to
1_Baseline.py

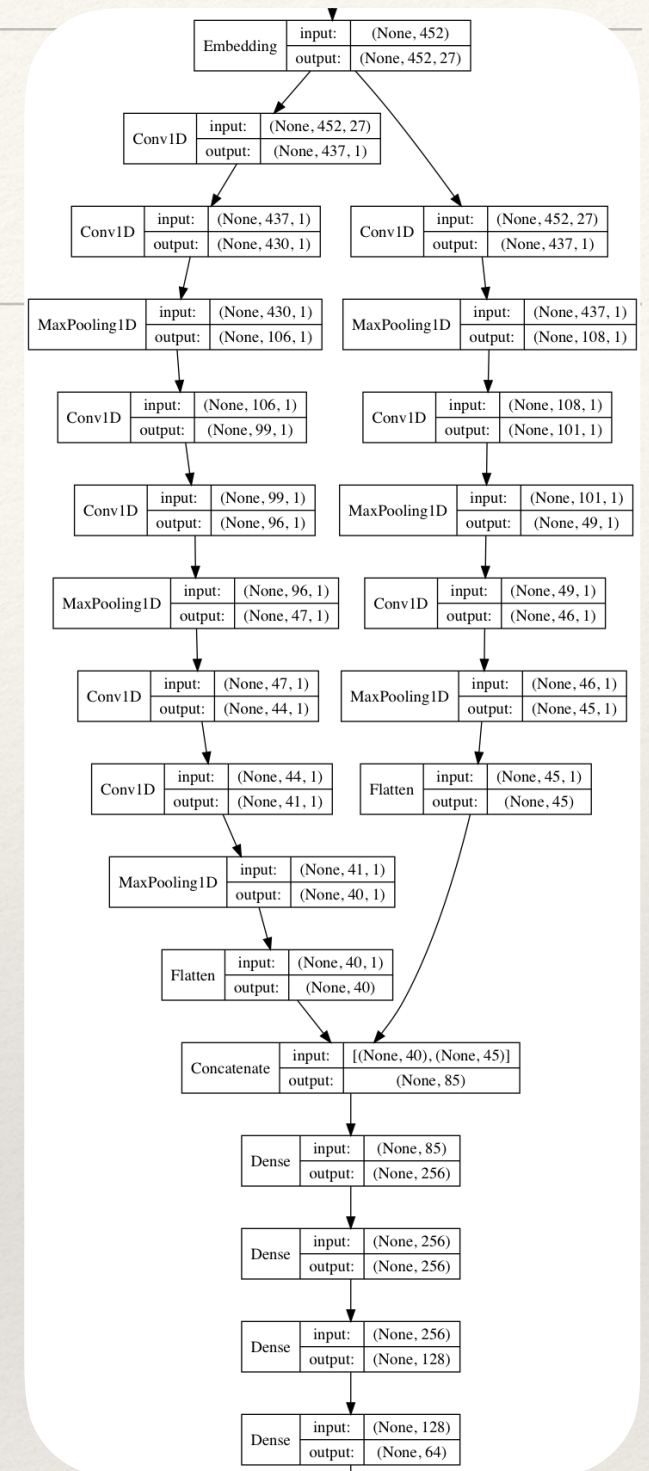
2_CNN Model

- ❖ Hypothesis here:
 1. Convolution serves as a special mask to quantify a sequence characters, here I choose 16.
 2. MaxPooling serves as choosing and filtering only the most possible “words”.
- ❖ According to above, right branch here assumes 16 characters form a words, 8 most possible words make a sentence, 4 sentences reside valuable info.
- ❖ Left branch mimics Pyramid-CNN which has proved to be affective dealing with character-level classifications. [8]
- ❖ Best standalone validation accuracy: 23.93% (epoch 23)



Class	0	1	2	3	4	5	6	7	8	9	10	11
Precision	0.000	0.389	0.000	0.000	0.000	0.000	0.372	0.183	0.919	0.000	0.000	0.000
Recall	0.000	0.084	0.000	0.000	0.000	0.000	0.262	0.997	0.384	0.000	0.000	0.000

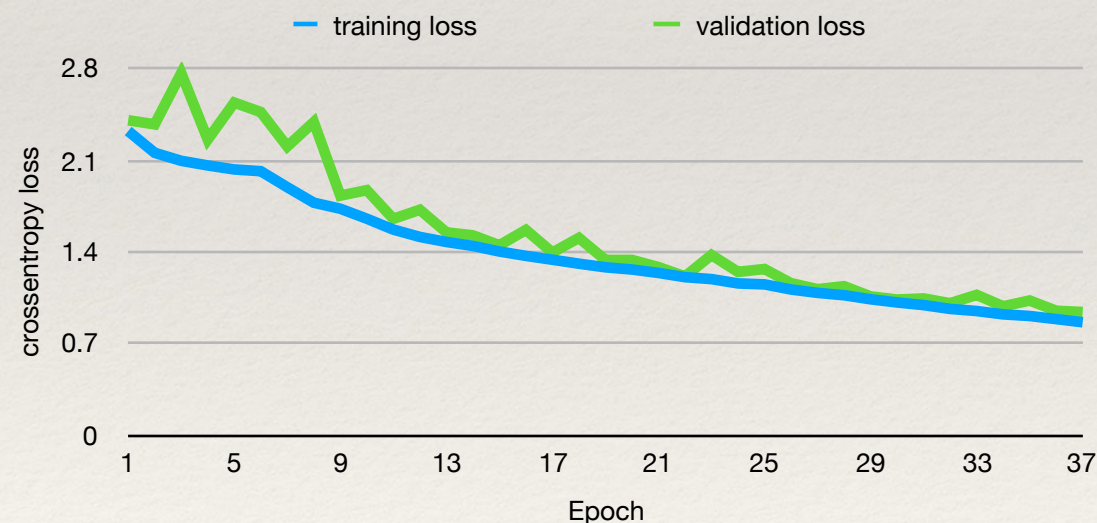
* All prediction based on best model (lowest validation loss), overall validation accuracy = 23.93%



CNN Activation: ReLU
 DNNActivation: LeakyReLU
 Last Activ.: softmax
 Loss: crossentropy
 Optimizer: Adam
 Batch size: 100
 Dropout: 0.2
 * Structure details please refer to 2_CNN.py

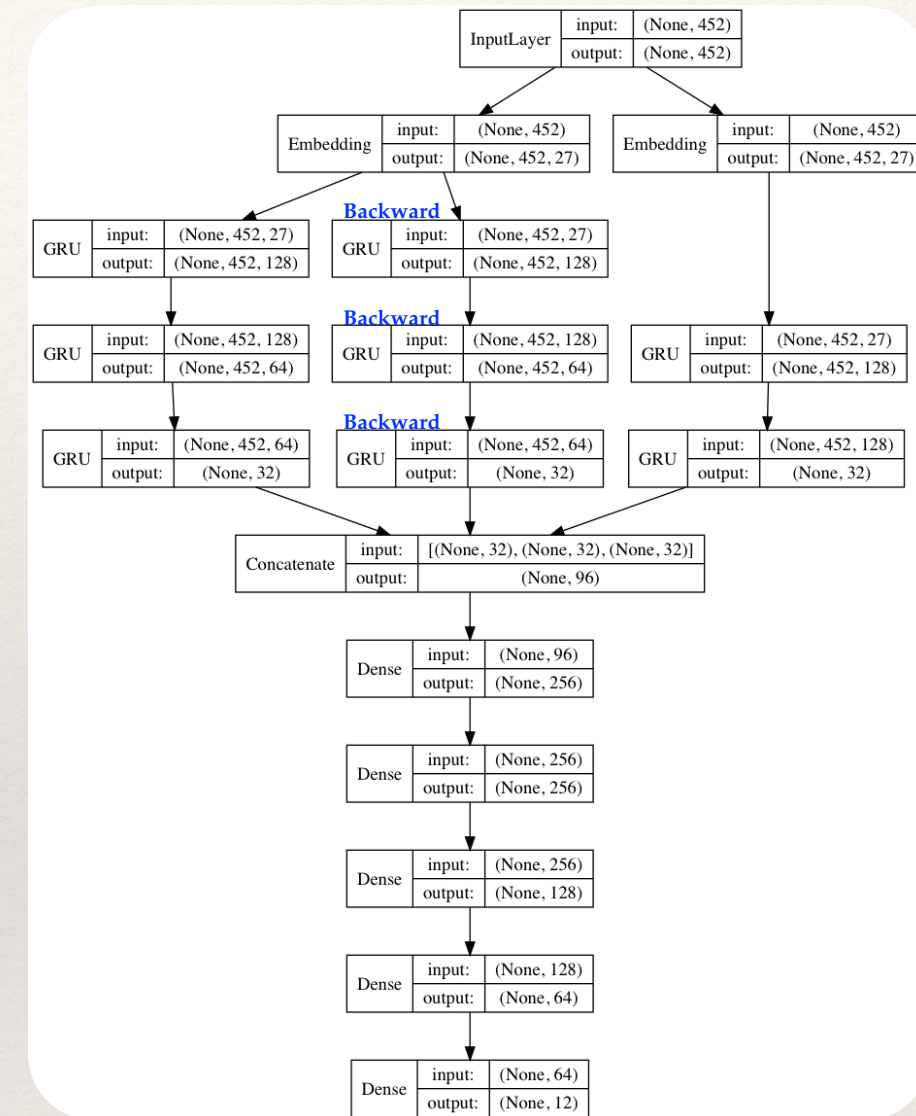
3_GRU Model

- ❖ Tested and validated that LSTM has same performance as GRU, choosing GRU due to its efficiency. Stacking GRU together to compose Pyramid-GRU, which proved to be powerful with seq2seq problem.
- ❖ A small Pyramid-GRU on the right validated to be essential to boost the accuracy up. And its embedding must be separate to interpret characters differently.
- ❖ Bidirectional GRU, the additional **Backward** branch here, gain no performance margin at all. But it only prove the backward reading is not informative in this specific obfuscation only, which might still works in another kind of obfuscation.
- ❖ Best standalone validation accuracy: 73.95% (epoch 32)
- ❖ Validation loss seems very promising. Would be valuable to keep training to test the real limit.



Class	0	1	2	3	4	5	6	7	8	9	10	11
Precision	0.815	0.697	0.766	0.729	0.891	0.898	0.695	0.746	0.858	0.760	0.620	0.508
Recall	0.682	0.757	0.562	0.727	0.741	0.869	0.764	0.812	0.797	0.477	0.622	0.657

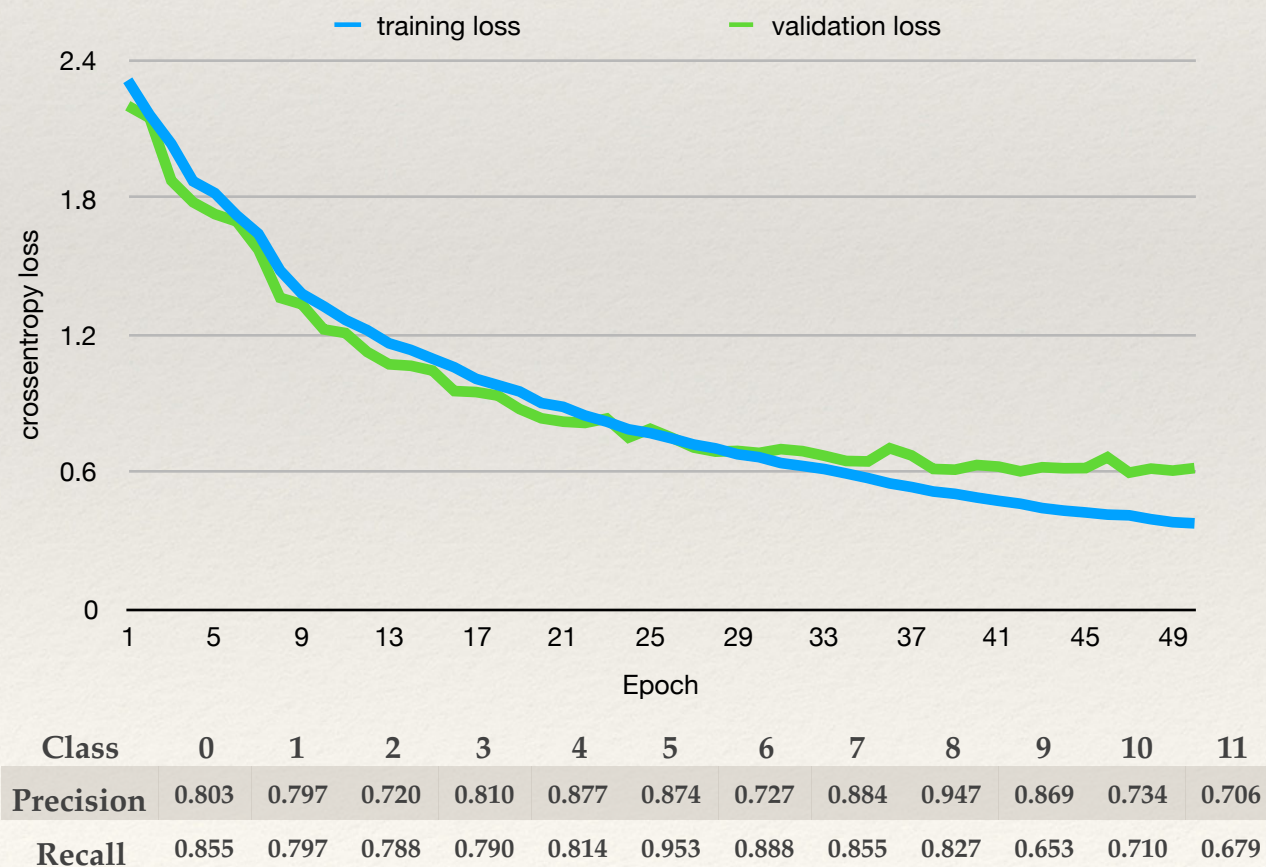
* All prediction based on best model (lowest validation loss), overall validation accuracy = 73.95%



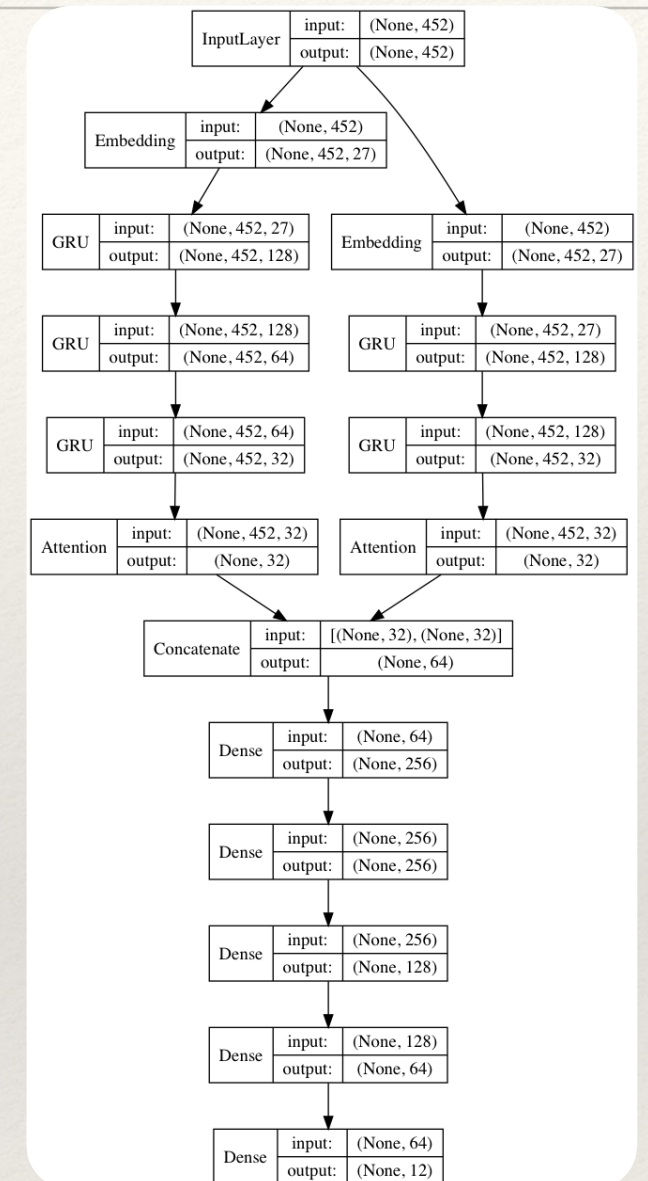
GRU Activation: tanh
DNN Activation: LeakyReLU
Last Activ.: softmax
Loss: crossentropy
Optimizer: Adam
Batch size: 100
Dropout: 0.2
* Structure details please refer to 3_GRU.py

4_GRU_Attention Model

- ❖ The attention used here is Hierarchical Attention Networks proposed by Zichao Yang et. al. [9]
- ❖ The attention proved to be a big breakthrough. And the pyramid-GRU (stacking GRU that still returning time sequences) proved to be critical too. However, the model can be further simplified as the next page shown.
- ❖ Best standalone validation accuracy: 81.59% (epoch 47)



* All prediction based on best model (lowest validation loss), overall validation accuracy = 81.59%

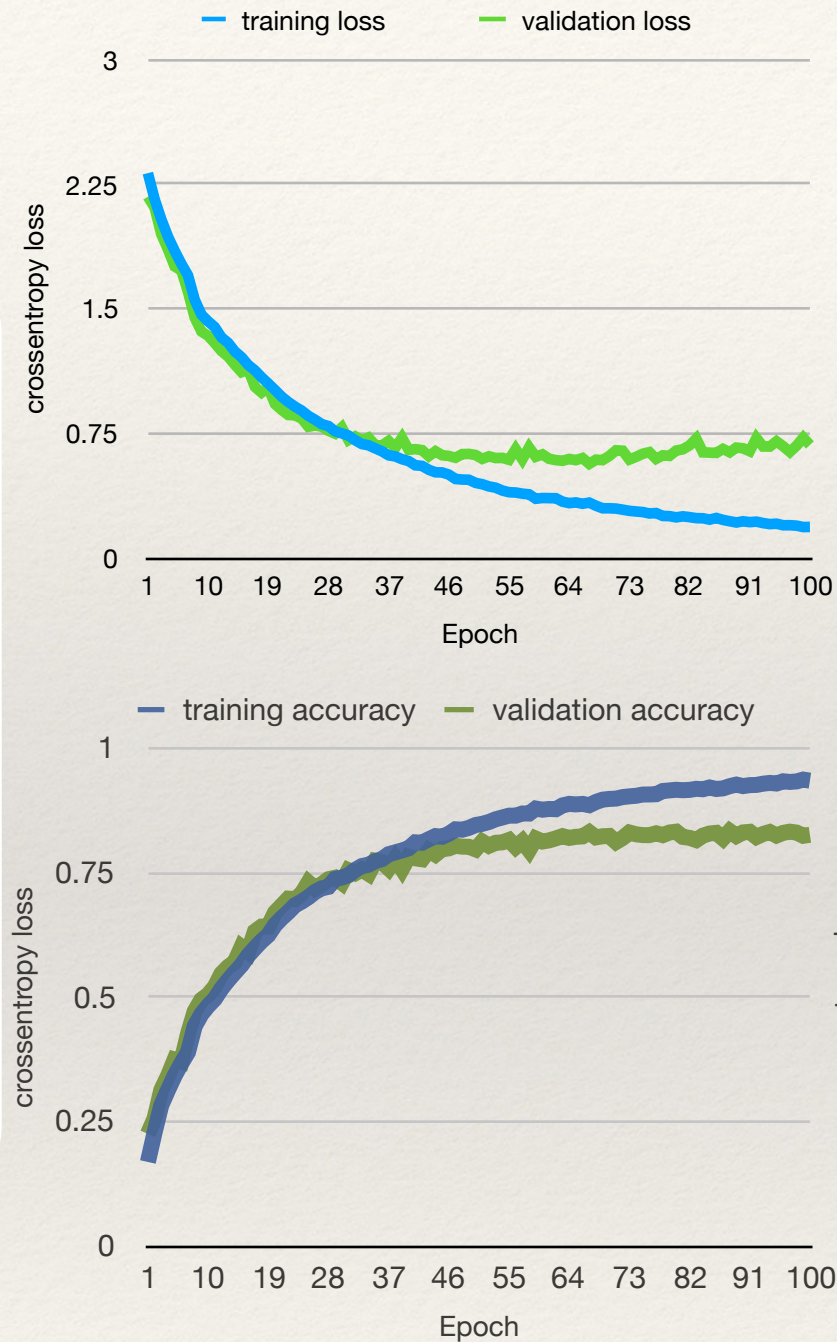
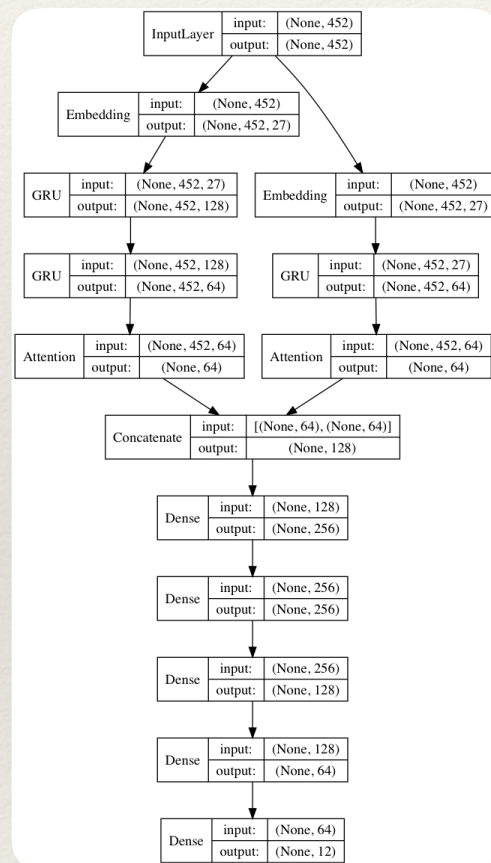


GRU Activation: tanh
 DNN Activation: LeakyReLU
 Last Activ.: softmax
 Loss: crossentropy
 Optimizer: Adam
 Batch size: 100
 Dropout: 0.2

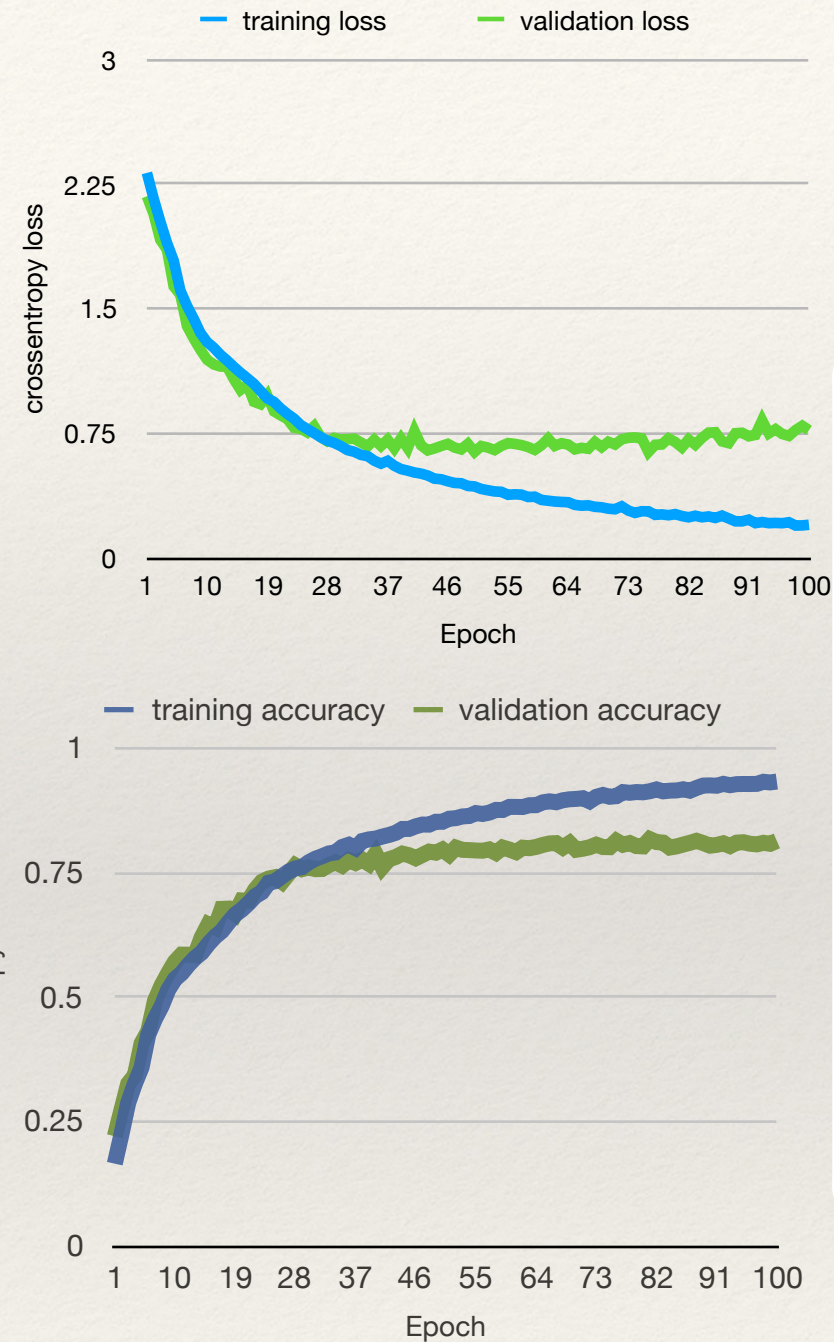
* Structure details please refer to 4_GRU_Attention.py

4_GRU_Attention Model

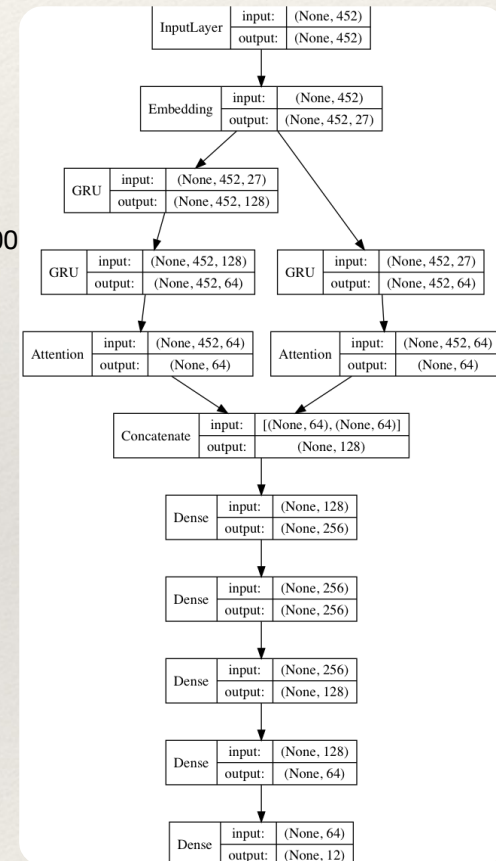
Compare single v.s. multiple embedding



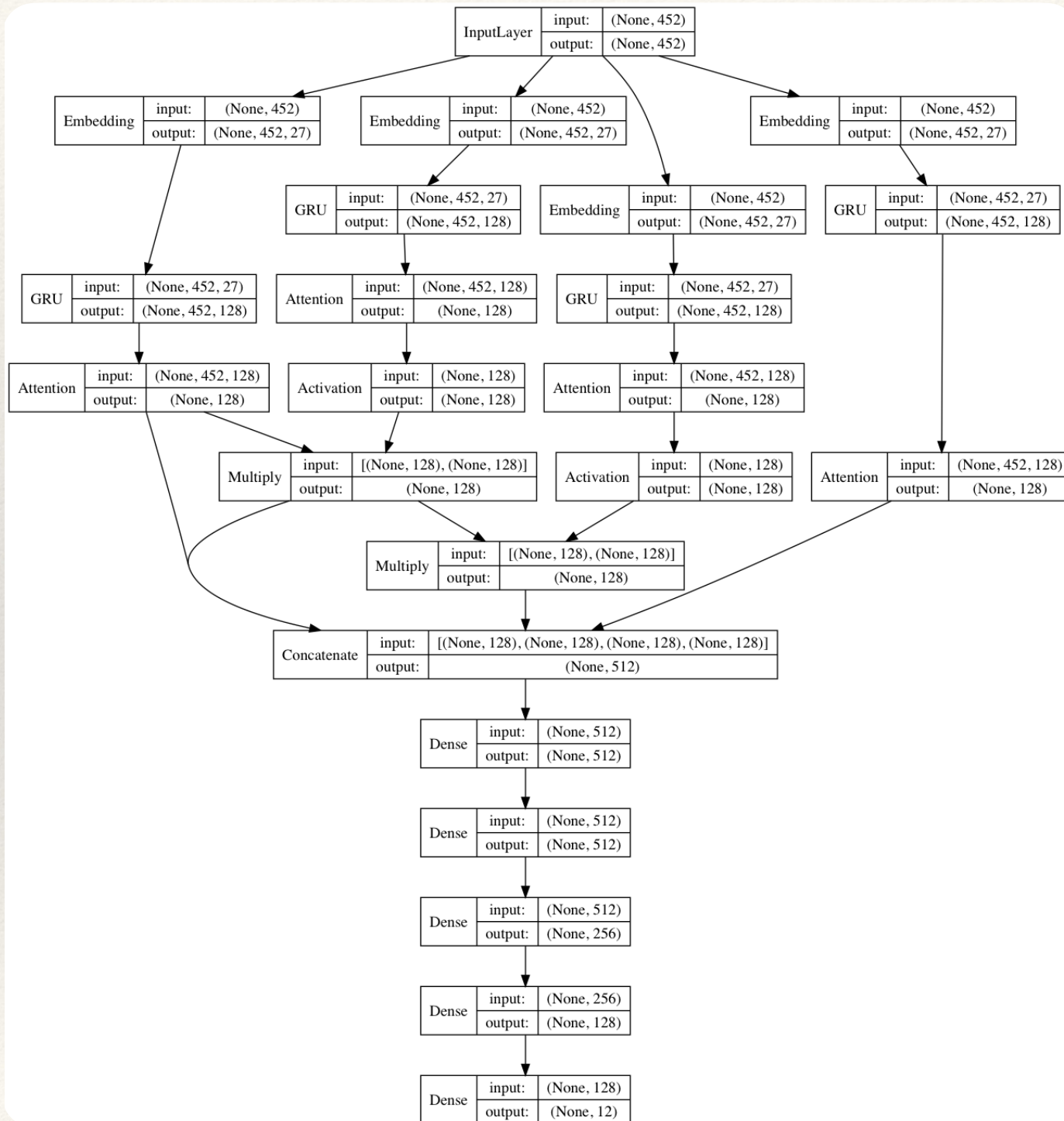
* Standalone validation accuracy = **83.12%** (epoch 67)



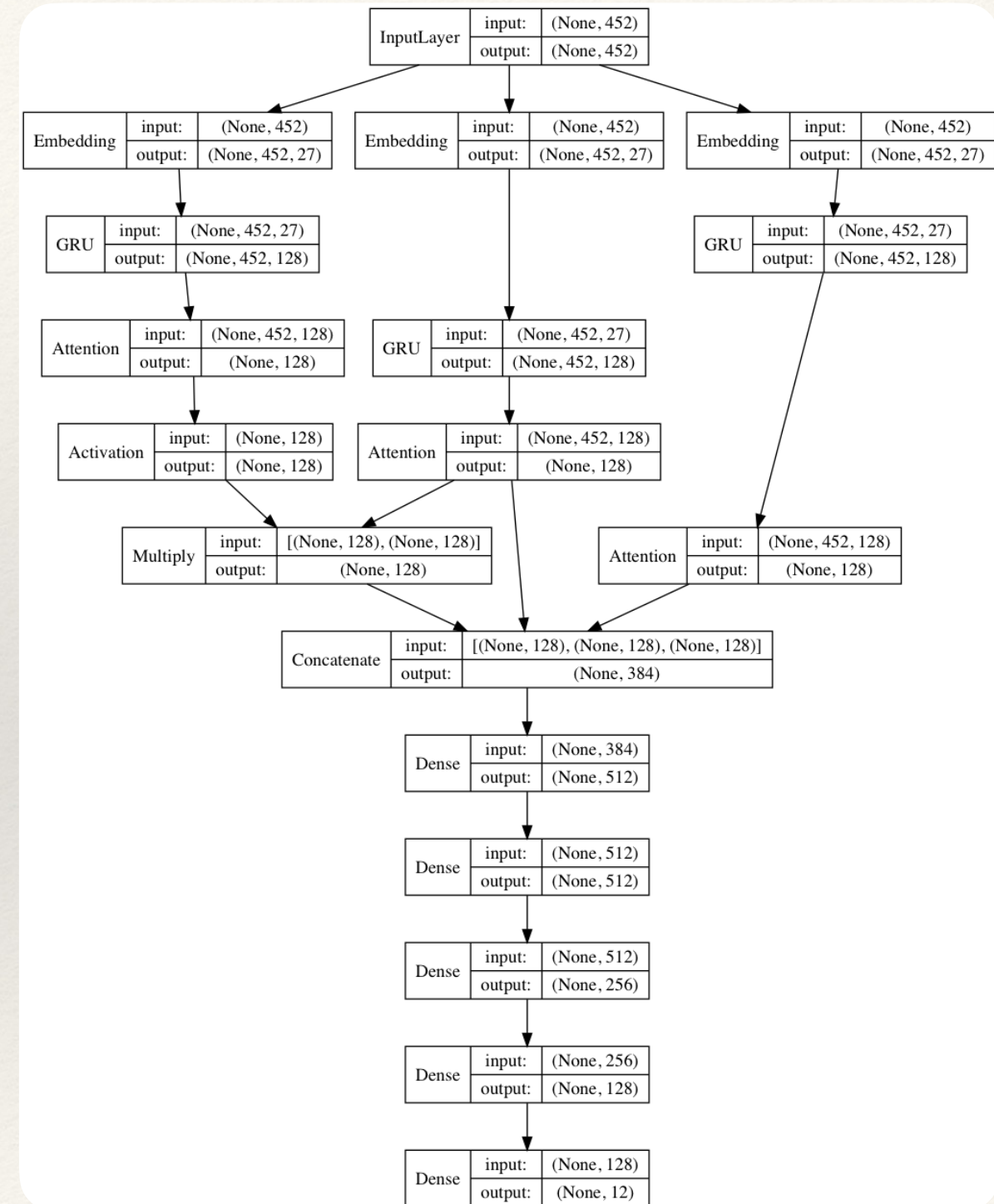
* Standalone validation accuracy = 81.39% (epoch 76)



4_GRU_Attention_Multihop Model



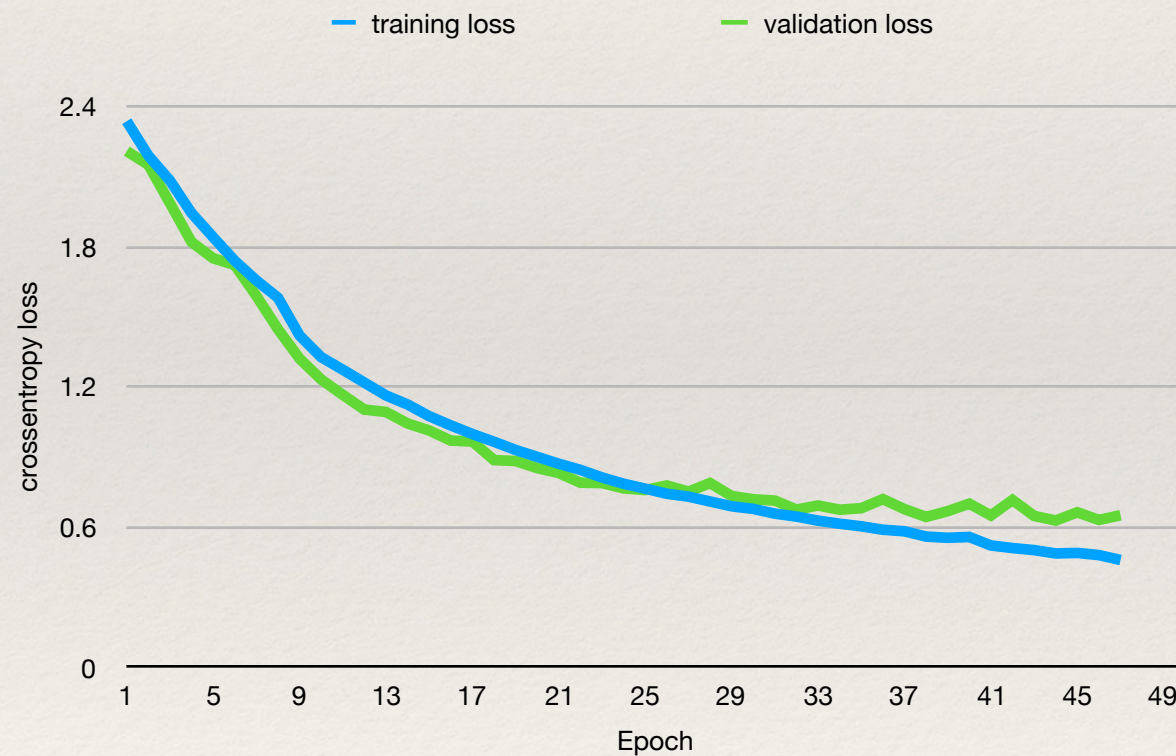
* Standalone validation accuracy = 73.81% (epoch 24)



* Standalone validation accuracy = 76.75% (epoch 33)

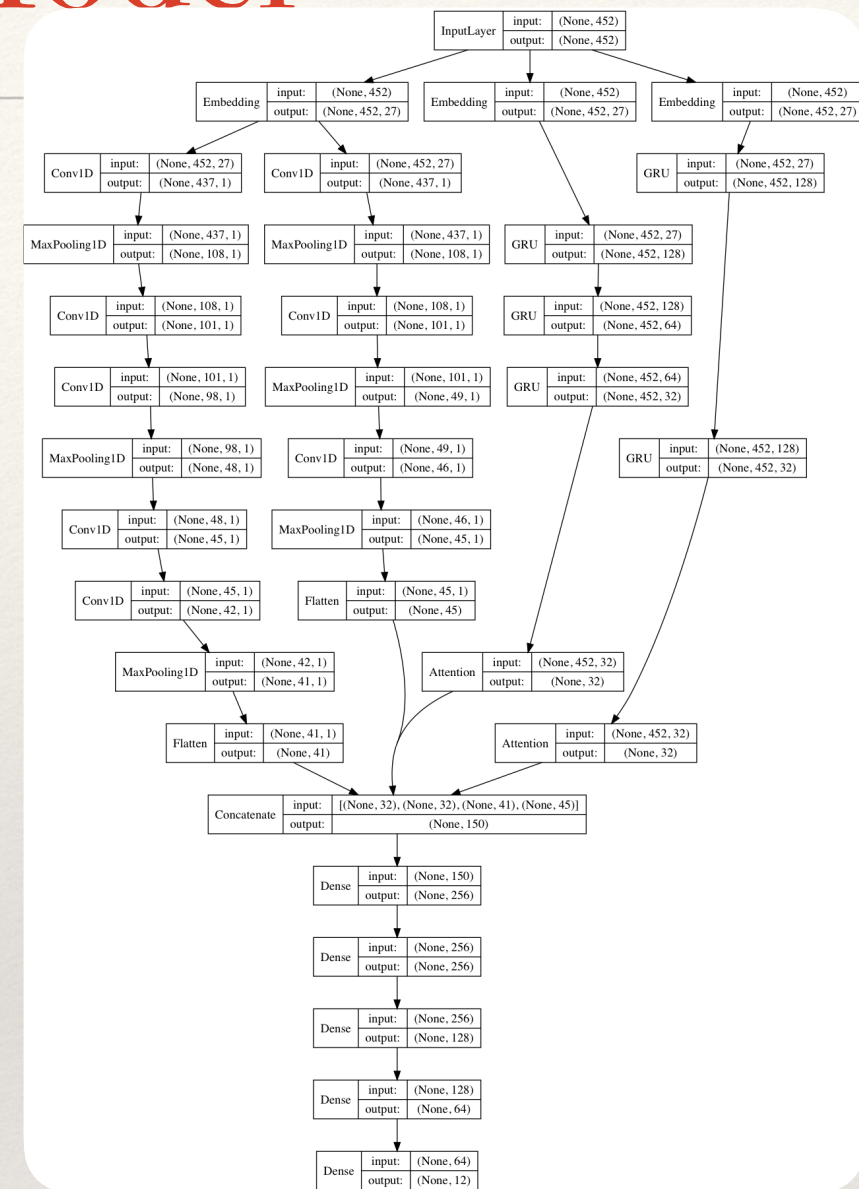
5_Hybrid_Parrallel Model

- ❖ CNN here is not helping as expected. More study and tuning need to boost this up.
- ❖ Best standalone validation accuracy: 80.07% (epoch 44)
- ❖ The more is not necessarily better.



Class	0	1	2	3	4	5	6	7	8	9	10	11
Precision	0.840	0.778	0.810	0.806	0.933	0.880	0.755	0.802	0.832	0.794	0.712	0.718
Recall	0.809	0.763	0.686	0.791	0.766	0.920	0.837	0.889	0.884	0.699	0.655	0.629

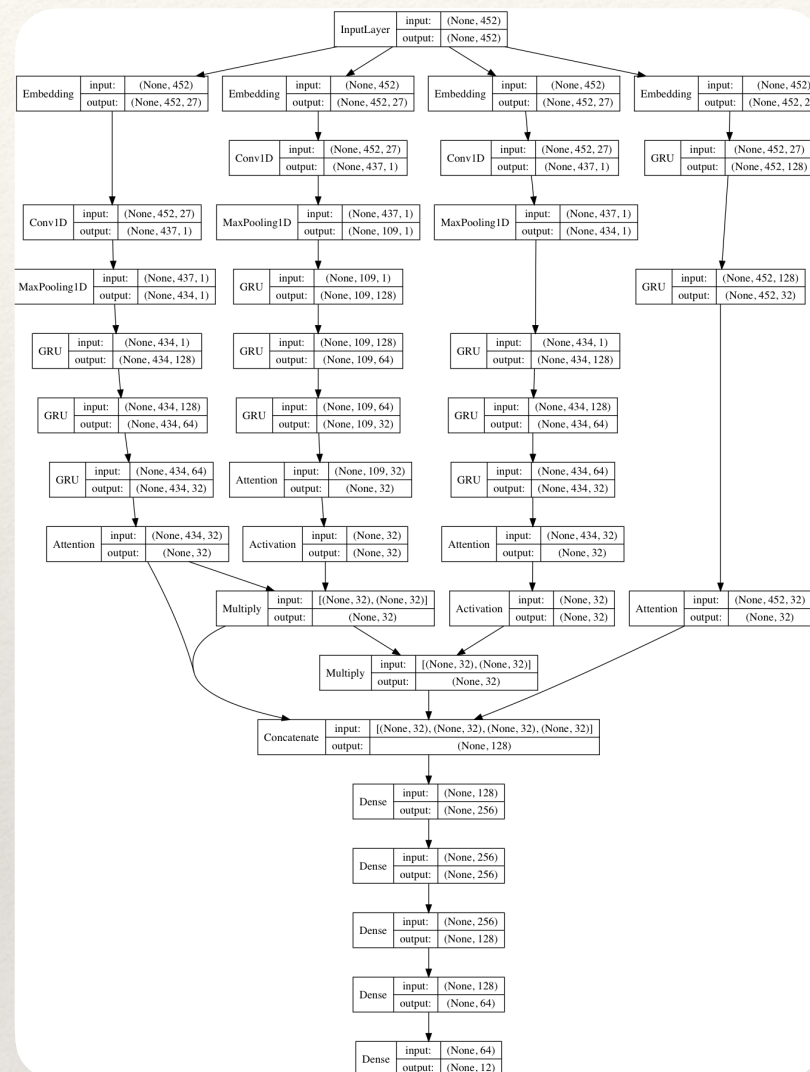
* All prediction based on best model (lowest validation loss), overall validation accuracy = 80.07%



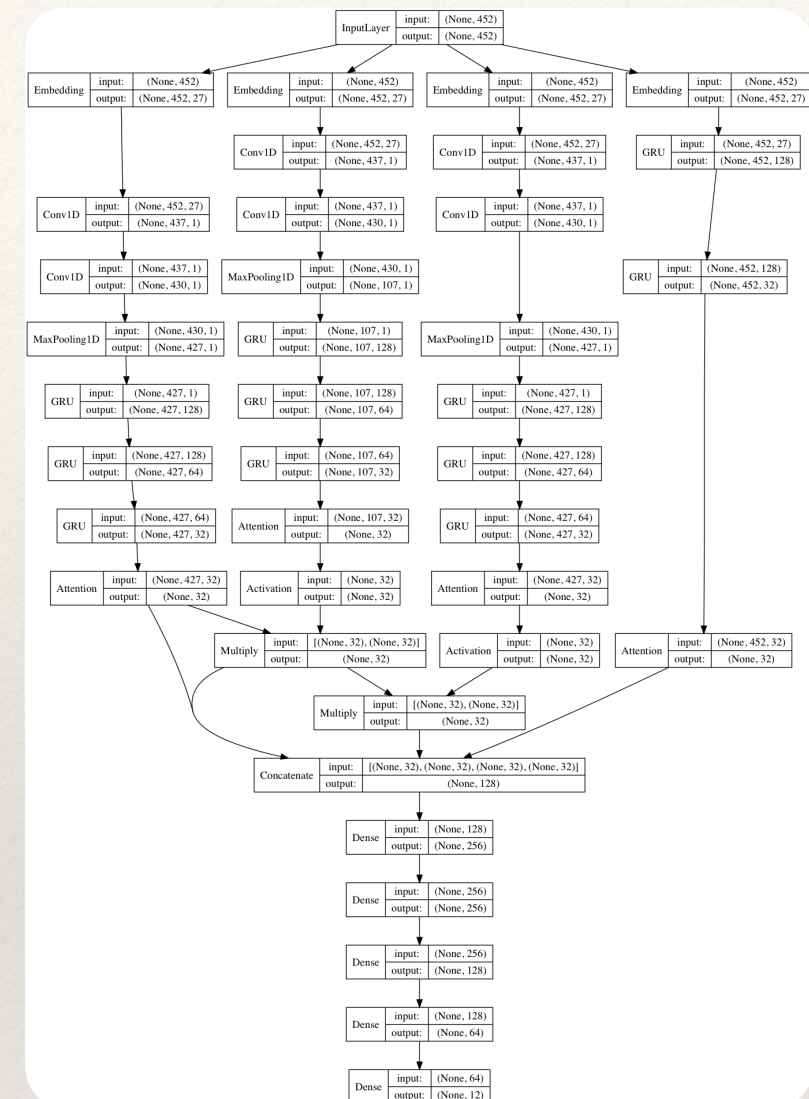
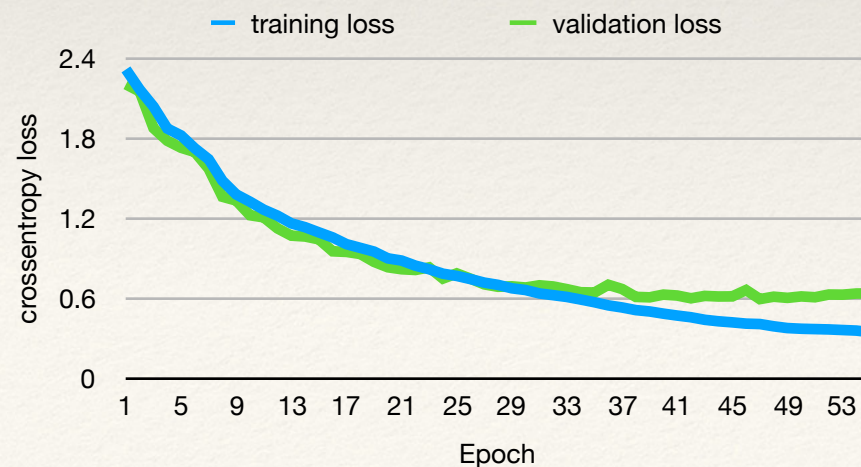
GRU Activation: tanh
 CNN Activation: ReLU
 DNN Activation: LeakyReLU
 Last Activ.: softmax
 Loss: crosentropy
 Optimizer: Adam
 Batch size: 100
 Dropout: 0.2

* Structure details please refer to 5_Hybrid.py

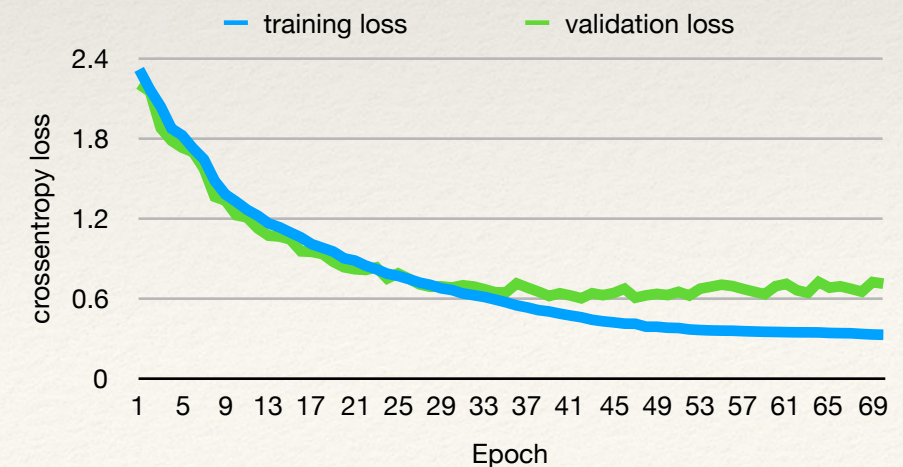
6_Hybrid_Concat Model



* Standalone validation accuracy = 78.39% (epoch 51)



* Standalone validation accuracy = 77.04% (epoch 63)



References

- (1) Attention layer is modified from:
<https://github.com/richliao/textClassifier/blob/master/textClassifierHATT.py>
- (2) Inspirations of trying CNN on raw character sequences:
<https://arxiv.org/pdf/1502.01710.pdf>
- (3) Normal dropout v.s. recurrent dropout on RNN:
<https://arxiv.org/pdf/1512.05287.pdf>
- (4) GRU v.s. LSTM:
<https://arxiv.org/pdf/1412.3555.pdf>
- (5) seq2seq using Attention:
<https://arxiv.org/pdf/1508.04025.pdf>
<https://www.cs.cmu.edu/%7Ediyy/docs/naacl16.pdf>
<https://arxiv.org/pdf/1706.03762.pdf>
- (6) CNN parameter tuning: How to choose filter size, kernel size, strides and pooling
<https://arxiv.org/pdf/1510.03820.pdf>
- (7) CNN dropout location:
<https://arxiv.org/pdf/1512.01400.pdf>
- (8) Pyramid-CNN
<http://ai.tencent.com/ailab/media/publications/ACL3-Brady.pdf>
- (9) Hierarchical Attention Networks
<https://www.cs.cmu.edu/%7Ediyy/docs/naacl16.pdf>

Tools & Environment

- ❖ Python 2.7.13
- ❖ Keras (2.1.3), TensorFlow (1.5.0), Theano (1.0.1),
numpy (1.14.0), scikit-learn (0.19.1)