miRe2e: a full end-to-end deep model based on Transformers for prediction of pre-miRNAs

J. Raad, L. Bugnon, D.H. Milone and G. Stegmayer

Research Institute for Signals, Systems and Computational Intelligence sinc(i) (FICH-UNL/CONICET), Ciudad Universitaria, Santa Fe, Argentina.

Supplementary Material

PyTorch¹ was used to build and train the deep learning models. Our models were trained on a Nvidia Titan V GPU with 12 Gb of RAM. The architecture of the neural models are detailed in the following tables. We evaluated several loss functions, optimizers and learning rates on training data.

The selected loss functions were: Mean Squared Error (MSE) for the Structure prediction model and the MFE estimation model; and Focal Loss (FL) (Lin *et al.*, 2017) for the pre-miRNA classifier. The FL adds an extra factor to the standard cross entropy criterion, which allows reducing the relative loss for well-classified examples and puts more focus on hard, misclassified examples. The FL used here was

$$FL(p_{\tau}) = -\alpha (1 - p_{\tau})^{\gamma} \log(p_{\tau}), \qquad (1)$$

where p_{τ} is the predicted probability (output score) for the sequence under analysis, the parameter γ can be used to increase or reduce the weight given to those samples that are correctly classified, and α is a weighting factor to address class imbalance. We have used $\alpha = 1.0$ and $\gamma = 4.0$.

The optimizer selected was Stochastic Gradient Descent (SGD) with Nesterov momentum (Sutskever *et al.*, 2013), and a learning rate of 10^{-3} . Regarding the training process, each module was pre-trained separately and in cascade, using the outputs of the previous pre-trained model as inputs to the next model. No fine-tuning of the complete model was required. More implementation details are provided in the following tables and the source code².

¹https://pytorch.org/

²https://github.com/sinc-lab/miRe2e

Layer (type)	Output shape	Param #
ReLU-1	[4, 100]	0
BatchNorm1d-2	[4, 100]	8
Conv1d-3	[111, 100]	1,443
ReLU-4	[111, 100]	0
BatchNorm1d-5	[111, 100]	222
Conv1d-6	[111, 100]	37,074
ReLU-7	[111, 100]	0
BatchNorm1d-8	[111, 100]	222
Conv1d-9	[111, 100]	37,074
ResNet-10	[111, 100]	0
ReLU-11	[111, 100]	0
BatchNorm1d-12	[111, 100]	222
Conv1d-13	[111, 100]	37,074
ReLU-14	[111, 100]	0
BatchNorm1d-15	[111, 100]	222
Conv1d-16	[111, 100]	37,074
ResNet-17	[111, 100]	0
ReLU-18	[111, 100]	0
BatchNorm1d-19	[111, 100]	222
Conv1d-20	[111, 100]	37,074
ReLU-21	[111, 100]	0
BatchNorm1d-22	[-1, 111, 100]	222
Conv1d-23	[111, 100]	37,074
ResNet-24	[111, 100]	0
EncoderStr-25	[111, 100]	0
MultiheadAttention-26	[[2, 222], [100, 100]]	0
Dropout-27	[2, 222]	0
LayerNorm-28	[2, 222]	444
Linear-29	[2, 888]	198,024
Dropout-30	[2, 888]	0
Linear-31	[2, 222]	197,358
Dropout-32	[2, 222]	0
LayerNorm-33	[2, 222]	444
TransformerEncoderLayer-34	[2, 222]	0
MultiheadAttention-35	[[2, 222], [100, 100]]	0
Dropout-36	[2, 222]	0
LayerNorm-37	[2, 222]	444
Linear-38	[2, 888]	198,024
Dropout-39	[2, 888]	0
Linear-40	[2, 222]	197,358
Dropout-41	[2, 222]	0
LayerNorm-42	[2, 222]	444
TransformerEncoderLayer-43	[2, 222]	0
MultiheadAttention-44	[[2, 222], [100, 100]]	0
Dropout-45	[2, 222]	0
LayerNorm-46	[2, 222]	444
Linear-47	[2, 888]	198,024
Dropout-48	[2, 888]	0
Linear-49	[2, 222]	197,358
Dropout-50	[2, 222]	0
LayerNorm-51	[2, 222]	444
TransformerEncoderLayer-52	[2, 222]	0
MultiheadAttention-53	[[2, 222], [100, 100]]	0
Dropout-54	[2, 222]	0
LayerNorm-55	[2, 222]	444
Linear-56	[2, 888]	198,024
Dropout-57	[2, 888]	0
Linear-58	[2, 222]	197,358
Dropout-59	[2, 222]	0
LayerNorm-60	[2, 222]	444
TransformerEncoderLayer-61	[2, 222]	0
MultiheadAttention-62	[[2, 222], [100, 100]]	0
Dropout-63	[2, 222]	0
LayerNorm-64	[2, 222]	444
Linear-65	[2, 888]	198,024
Dropout-66	[2, 888]	0

Table 1: Structure predictor.

Linear-67	[2, 222]	197,358
Dropout-68	[2, 222]	0
LayerNorm-69	2, 222	444
TransformerEncoderLayer-70	[2, 222]	0
MultiheadAttention-71	[[2, 222], [100, 100]]	0
Dropout-72	[2, 222]	0
LayerNorm-73	[2, 222]	444
Linear-74	[2, 888]	198,024
Dropout-75	[2, 888]	0
Linear-76	[2, 222]	197,358
Dropout-77	[2, 222]	0
LayerNorm-78	[2, 222]	444
TransformerEncoderLayer-79	[2, 222]	0
TransformerEncoder-80	[2, 222]	0
Dropout-81	[100, 222]	0
Linear-82	[100, 100]	22,300
ELU-83	[100, 100]	0
Dropout-84	[100, 100]	0
Linear-85	[100, 10]	1,010
ELU-86	[100, 10]	0
Linear-87	[100, 1]	11
Tanh-88	[100, 1]	0

Table 2: MFE estimation model.

Layer (type)	Output shape	Param $#$
ReLU-1	[5, 100]	0
BatchNorm1d-2	[5, 100]	10
Conv1d-3	[64, 100]	1,024
ReLU-4	[64, 100]	0
BatchNorm1d-5	[64, 100]	128
Conv1d-6	[64, 100]	12,352
ReLU-7	[64, 100]	0
BatchNorm1d-8	[64, 100]	128
Conv1d-9	[64, 100]	12,352
ResNet-10	[64, 100]	0
AvgPool1d-11	[64, 50]	0
ReLU-12	[64, 50]	0
BatchNorm1d-13	[64, 50]	128
Conv1d-14	[64, 50]	12,352
ReLU-15	[64, 50]	0
BatchNorm1d-16	[64, 50]	128
Conv1d-17	[64, 50]	12,352
ResNet-18	[64, 50]	0
AvgPool1d-19	[64, 25]	0
ReLU-20	[64, 25]	0
BatchNorm1d-21	[64, 25]	128
Conv1d-22	[64, 25]	12,352
ReLU-23	[64, 25]	0
BatchNorm1d-24	[64, 25]	128
Conv1d-25	[64, 25]	12,352
ResNet-26	[64, 25]	0
AvgPool1d-27	[64, 12]	0
Encoder-28	[64, 12]	0
Linear-29	[100]	76,900
ELU-30	[100]	0
BatchNorm1d-31	[100]	200
Linear-32	[30]	3,030
ELU-33	[30]	0
BatchNorm1d-34	[30]	60
Linear-35	[1]	31
ELU-36	[1]	0

Layer (type)	Output shape	Param #
ReLU-1	[5, 100]	0
BatchNorm1d-2	[5, 100]	10
Conv1d-3	[64, 100]	1,024
ReLU-4	[64, 100]	0
BatchNorm1d-5	[64, 100]	128
Conv1d-6	[64, 100]	12,352
ReLU-7	[64, 100]	0
BatchNorm1d-8	[64, 100]	128
Convld-9	[64, 100]	12,352
ResNet-10	[64, 100]	0
ReLU-II	[64, 100]	0
BatchNorm1d-12	[64, 100]	128
Convid-13	[64, 100]	12,352
DetabNorm1d 15	[64, 100]	128
Convid 16	[64, 100]	120
BesNet-17	[64, 100]	12,552
BeLU-18	[64, 100]	0
BatchNorm1d-19	[64, 100]	128
Conv1d-20	[64, 100]	12.352
ReLU-21	[64, 100]	12,002
BatchNorm1d-22	[64, 100]	128
Conv1d-23	[64, 100]	12.352
ResNet-24	[64, 100]	0
AvgPool1d-25	[64, 50]	0
ReLU-26	[64, 50]	0
BatchNorm1d-27	[64, 50]	128
Conv1d-28	[64, 50]	12,352
ReLU-29	[64, 50]	0
BatchNorm1d-30	[64, 50]	128
Conv1d-31	[64, 50]	12,352
ResNet-32	[64, 50]	0
ReLU-33	[64, 50]	0
BatchNorm1d-34	[64, 50]	128
Conv1d-35	[64, 50]	12,352
ReLU-36	[64, 50]	0
BatchNorm1d-37	[64, 50]	128
Conv1d-38	[64, 50]	12,352
ResNet-39	[64, 50]	0
ReLU-40 Datab Name 1d 41	[64, 50]	100
Carrild 42	[04, 50]	120
DoI U 42	[64, 50]	12,552
BatchNorm1d 44	[64, 50]	128
Copy1d-45	[64, 50]	12 352
BesNet-46	[64, 50]	12,002
AvgPool1d-47	[64, 25]	0
ReLU-48	[64, 25]	Ő
BatchNorm1d-49	[64, 25]	128
Conv1d-50	[64, 25]	12.352
ReLU-51	[64, 25]	0
BatchNorm1d-52	[64, 25]	128
Conv1d-53	[64, 25]	12,352
ResNet-54	[64, 25]	0
ReLU-55	[64, 25]	0
BatchNorm1d-56	[64, 25]	128
Conv1d-57	[64, 25]	12,352
ReLU-58	[64, 25]	0
BatchNorm1d-59	[64, 25]	128
Conv1d-60	[64, 25]	12,352
ResNet-61	[64, 25]	0
ReLU-62	[64, 25]	0
BatchNorm1d-63	[64, 25]	128
Convid-64	[64, 25]	12,352
ReLU-05 Detab News 1 d CC	[04, 25]	100
BatchNorm1d-66	[04, 25]	128

Table 3: Pre-miRNA classifier.

Conv1d-67	[64 25]	12 352
D - N - CO	[01, 20]	12,002
ResNet-08	[04, 25]	0
AvgPool1d-69	[64, 12]	0
ReLU-70	[64, 12]	0
BatchNorm1d-71	[64, 12]	128
Conv1d-72	[64 12]	12 352
D.11179	[04, 12]	12,352
ReLU-73	[64, 12]	0
BatchNorm1d-74	[64, 12]	128
Conv1d-75	[64, 12]	12.352
BesNet-76	64 12	, 0
Del U 77	[64, 19]	Ő
ReLU-11	[04, 12]	0
BatchNorm1d-78	[64, 12]	128
Conv1d-79	[64, 12]	12,352
ReLU-80	[64, 12]	0
BatchNorm1d 81	[64, 12]	198
	[04, 12]	10.250
Collv1d-82	[04, 12]	12,332
ResNet-83	[64, 12]	0
ReLU-84	[64, 12]	0
BatchNorm1d-85	64. 12	128
Convld-86	[64, 12]	12 352
D.LU.97	[04, 12]	12,002
ReLU-8/	[04, 12]	0
BatchNorm1d-88	[64, 12]	128
Conv1d-89	[64, 12]	12,352
BesNet-90	64 12	, O
AvgPool1d 01	[64, 6]	Ő
Avgi oonu-si	[04, 0]	0
Encoder-92	[64, 6]	0
PositionalEncoder-93	[6, 64]	0
MultiheadAttention-94	[[2, 64], [6, 6]]	0
Dropout-95	[2, 64]	0
LaverNorm-96	2 64	128
Linear-97	[2, 256]	16 64
Dropout 08	[2, 256]	10,01
Lincon 00	[2, 200]	16 449
Linear-99	[2, 04]	10,448
Dropout-100	[2, 64]	0
LayerNorm-101	[2, 64]	128
TransformerEncoderLayer-102	[2, 64]	0
MultiheadAttention-103	[2, 64], [6, 6]]	0
Dropout-104	[2 64]	0
LoverNorm 105	[2, 64]	100
LayerNorm-105	[2, 04]	120
Linear-106	[2, 250]	10,04
Dropout-107	[2, 256]	0
Linear-108	[2, 64]	16,448
Dropout-109	[2, 64]	0
LaverNorm-110	2 64	128
TransformerEncoderLaver-111	[2, 64]	0
Multility dAttention 110	[[0, c,4], [c, c]]	0
MultineadAttention-112	[[2, 04], [0, 0]]	0
Dropout-113	[2, 64]	0
LayerNorm-114	[2, 64]	128
Linear-115	[2, 256]	16,64
Dropout-116	[2, 256]	0
Linear-117	2 64	16 448
Dropout 118	[2, 64]	10,110
Diopoul-118	[2, 04]	100
LayerNorm-119	[2, 64]	128
TransformerEncoderLayer-120	[2, 64]	0
TransformerEncoder-121	[2, 64]	0
BatchNorm1d-122	[385]	770
Linear-123	[1000]	386
FLU-124	[1000]	0
DatahNamp1d 195	[1000]	0
Datchivorin1d-125	[1000]	2
Dropout-126	[1000]	0
Linear-127	[1000]	1,001,000
Linear-128	[1000]	1,001,000
Linear-129	[2]	2,002
Softmax-130	2	0

References

- Lin, T.-Y. et al. (2017). Focal loss for dense object detection. In Proceedings of the IEEE International Conference on Computer Vision, pages 2980–2988.
- Sutskever, I. et al. (2013). On the importance of initialization and momentum in deep learning. In Proceedings of the 30th International Conference on Machine Learning, volume 28, pages 1139–1147.