# **Promoter Sequence Classification**

using CNN, GRU, BERT based models

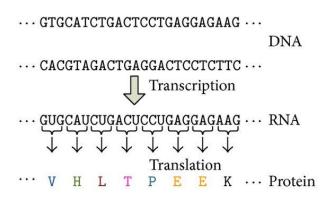
2019-13773 2018-18574 2018-12018

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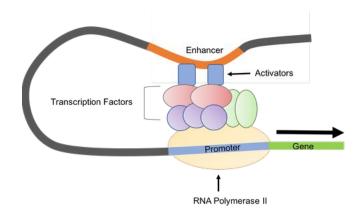
- 1. Motivation
- 2. Idea
- 3. Experiments
- 4. Results
- 5. Conclusion

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#### **Motivation**



Central Dogma



**Promoter Gene** 

- DNA, especially the non-coding region, indeed exhibits great similarity to human language, ranging from alphabets and lexicons to grammar and phonetics
- We chose promoter gene classification as a sample task

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### Idea

Task: Classifying the sequence whether it is a promoter gene

Models: CNN+GRU(baseline), CNN, GRU and BERT ... (+some variations)

Goal 1: To improve the accuracy by implementing other appropriate model

Goal 2: To practice applying various machine learning models into bioinformatic task

#### **Dataset**

- Sequences: same length (about 300)
- Label: 1: promotor gene, 0: non-promotor gene

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  - a. Baseline (CNN + GRU)
  - b. CNN
  - c. GRU
  - d. DNABERT + fine-tuning
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#### **Baseline: CNN+GRU**

- 2 CNN + 1 bidirectional GRU + 5 Linear
- Train 115 epoch with 100 minutes
  - Accuracy: 87.6%
  - o Precision: 86%
  - o Recall:89%

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### **CNN**

- Check the contribution of CNN part in Baseline
- Use only CNN layers and one more dense layer

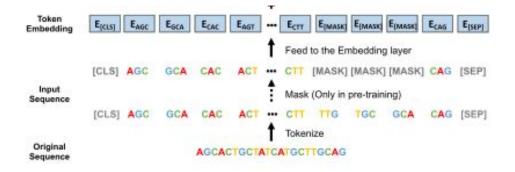
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# **GRU: only GRU**

- Check the contribution of GRU part in Baseline
- Use only Bidirectional GRU and Linear Layers

#### **GRU: Window + GRU**

- Idea of DNABERT
  - Window-based tokenization
- Wanted to replace CNN by
  Window-based tokenization



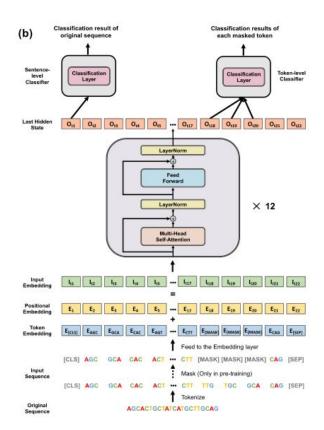
### **GRU: Result**

- Slow Train Speed
  - Limitation of RNN architecture
  - Long Input Sequence
  - only 40 epochs with 120 minutes
- Low Performance
  - only GRU accuracy: 82%
  - Window + GRU accuracy : 73%

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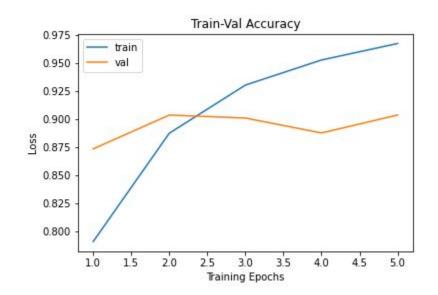
### **DNABERT** finetuning

- BERT pretrained with DNA sequences
- SOTA in DNA classification Area
- MLM with window-based tokenization



### **DNABERT + 1 Classification Layer**

- BERT + 1 Linear layer
- Finetuning with 5 epoch
  - o take about 180 minutes
- Good Performance, but Unstable

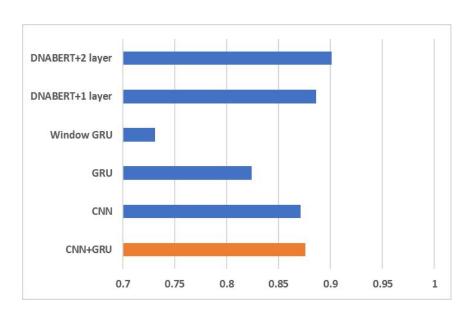


## **DNABERT + 2 Classification Layer**

- BERT + 2 Linear layer
- Better Performance
- Best Result
  - Accuracy: 90%

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### **Accuracy**



- DNABERT + 2 layers had the best result
- DNABERT + 1 layer also outperformed CNN + GRU
- Only CNN had slightly low performance than CNN+GRU

### **Model Size**

Model	Parameters
CNN+GRU	158,207
CNN	377,784
GRU	149,298
Window GRU	151,602
DNABERT + 1 layer	89,192,450
DNABERT + 2 layer	89,388,290

- DNABERT >> Others
- CNN > CNN+GRU > GRU

# **Training time**

- Training time
  - DNABERTs: 30min/epoch
  - CNN+GRU: 40s/epoch
  - GRUs: 3min/epoch
  - o CNN: 20s/epoch
- DNABERT models can be improved with more epochs

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#### Conclusion

- Pretrained Language Model can be applied on Promoter classification
  - Outperformed the baseline, and possibility for better results
- CNN itself has a nice performance
  - Good choice for limited computation source
- RNN structure is inappropriate
  - Slow training + Low performance
  - Low merit for combining with CNN

