kaggle

Kaggle Winner Presentation (5th)

NeurIPS 2024 - Predict New Medicines with BELKA

https://www.kaggle.com/competitions/leash-BELKA

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Agenda



Agenda

- 1. Background
- 2. Summary
- 3. Feature selection & engineering
- 4. Training methods
- 5. Important findings
- 6. Simple model
- 7. Code review



Background



Background

- Contract computer vision and deep learning algorithm engineer.
 - identify fracture in x-ray images
 - implement visual slam for robotic navigation
 - finetune LLM models
- Familiar with deep learning and build deep models in my work.
- Experiences previous Kaggle competitions. Sequence modeling in molecule and medicine applications:
 - Bristol-Myers Squibb Molecular Translation
 - OpenVaccine: COVID-19 mRNA Vaccine Degradation Prediction



Summary

cnn1d net

SMILES token id (tokenised by character)



embedding (64)

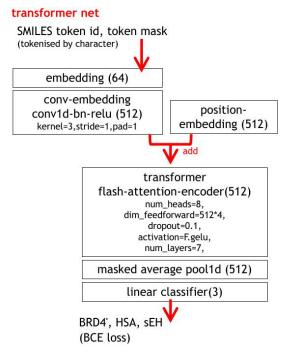
conv1d-bn-relu (128) kernel=3,stride=1,pad=1

conv1d-bn-relu (256) x4 kernel=3,stride=1,pad=1

average pool1d (256)

MLP classifier(3)

BRD4', HSA, sEH

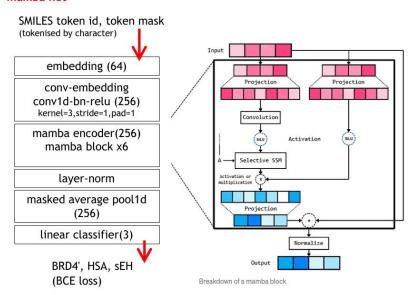


- ◆ To mitigate the effects of OOD (out-of-domain distribution), we use ensemble of different sequence models:
- 3-fold conv1d net
- 2-fold transformer net
- single-fold mamba (SSM, selective state machine)

◆ To handle 98 millions of training molecules efficiently, we use customized cuda kernel from open source flash attention[1] and mamba SSM[2] libraries



mamba net



- ◆ For training we have two Nvidia Ada A6000 / 48 GB Ampere GPUs. Time for training one fold with single GPU are:
- 7 hr for cnn1d,
- 28 hr for transformer,
- 36 hr for mamba.

					# keep sco	ore for the st	ubset, set ze	ero for other	S				
			all		keep-share #		keep-nonshare #		loc		cal CV (share)		
submission		fold	private	public	private	public	private	public	fold0	fold1	fold2	fold3	fold4
[1]+[2]+[3]	final-3fold-tx2a-mamba-fix.submit.csv		0.28557	0.46439	0.22761	0.34985	0.08320	0.10362	0.65976	0.66044	4	0.67601	
[1]	final-3fold-cnn1d.submit.csv	fold0,1,3	0.26615	0.41103	0.22693	0.34946	0.05424	0.08504					
[2]	final-2fold-transfomer.submit.csv	fold2,4	0.31236	0.42288	0.22613	0.34753	0.10124	0.09881			0.64041		0.64589
[3]	final-1fold-mamba.submit.csv	fold0	0.23905	0.43221	0.22404	0.34484	0.03002	0.11083	0.65559				
late subn	nission												
[2a]	final-2fold-cnn1d.submit.csv	fold2,4	0.26403	0.40879	0.22581	0.34814	0.05324	0.08411			0.63988		0.64613
[2b]	final-2fold-mamba.submit.csv	fold2,4	0.26361	0.41035	0.22712	0.34668	0.05150	0.08713			0.63848		0.64400



Features Selection/ Engineering



◆ Tokenization :

We tried several methods like character based, sentence piece, byte-pair-encoding (BPE), atom/smiles notation aware to break the SMILES strings. Surprisingly, the **simplest character** based tokenization performs the best across different net architecture

Add a conv1d layer of kernel size=3, stride=1 to learned combinations of consecutive tokens (bi-grams, tri-grams) before passing them into cnn1d, transformer or mamba encoder.

```
#https://www.ascii-code.com/
MOLECULE_DICT = {
    'l': 1, 'y': 2, '@': 3, '3': 4, 'H': 5, 'S': 6, 'F': 7, 'C': 8, 'r': 9, 's': 10, '/': 11, 'c': 12, 'o': 13,
    '+': 14, 'I': 15, '5': 16, '(': 17, '2': 18, ')': 19, '9': 20, 'i': 21, '#': 22, '6': 23, '8': 24, '4': 25,
    '=': 26, '1': 27, '0': 28, '[': 29, 'D': 30, 'B': 31, ']': 32, 'N': 33, '7': 34, 'n': 35, '-': 36
}
MAX_MOLECULE_ID = np.max(list(MOLECULE_DICT.values()))
VOCAB_SIZE=MAX_MOLECULE_ID+3
UNK=255 #disallowed, will cause error
BOS=MAX_MOLECULE_ID+1
EOS=MAX_MOLECULE_ID+2
PAD=0
MAX_LENGTH=160
```



Features Selection/Engineering

♦ Batch normalization:

cnn1d model performance is sensitive to batch normalization. Different feature values for:

- in-distribution and out-distribution samples.
- +ve and -ve samples due to class imbalance (less than 1% +ve).

To alleviate the problem, we use high eps=5e-3 and low momentum=0.2



Training Methods



Training Methods

- binary cross entropy loss with ADAM optimizer.
 - step learning rate of 1e-3,1e-4,1e-5 for 6-12 epochs.
 - large batch size of 2000,2500,5000

Interesting, the best way to handle class imbalance is to do nothing (no up-sampling or undersampling of the class). Maybe because of the large batch size we used.



Important and Interesting Findings



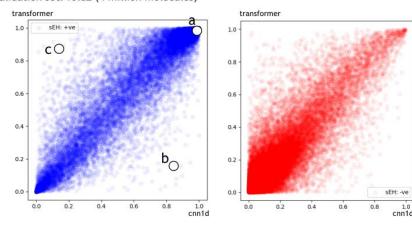
Important and Interesting Findings

◆ Transformer is the most robust

					# keep sco	re for the su	ıbset, set ze	ero for other	S				
			all		keep-share #		keep-nonshare #			local CV (share)		are)	
submission		fold	private	public	private	public	private	public	fold0	fold1	fold2	fold3	fold4
[1]+[2]+[3]	final-3fold-tx2a-mamba-fix.submit.csv		0.28557	0.46439	0.22761	0.34985	0.08320	0.10362	0.65976	0.66044		0.67601	
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[2a]	final-2fold-cnn1d.submit.csv	fold2,4	0.26403	0.40879	0.22581	0.34814	0.05324	0.08411			0.63988		0.64613
[2b]	final-2fold-mamba.submit.csv	fold2,4	0.26361	0.41035	0.22712	0.34668	0.05150	0.08713			0.63848		0.64400

◆ correlation of cnn1d and transformer predictions

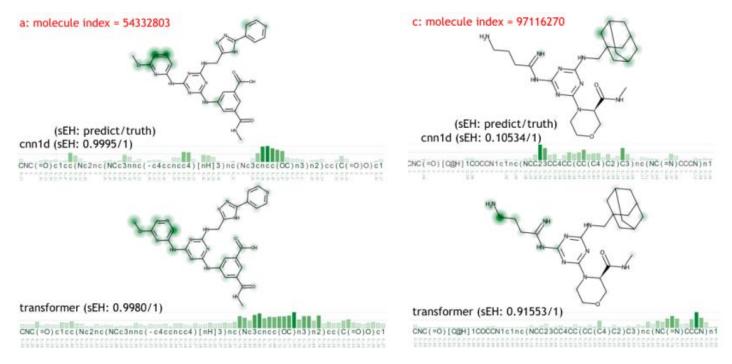
validation set: fold2 (4 million molecules)





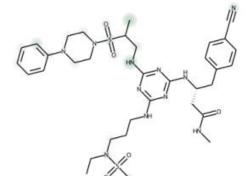
Important and Interesting Findings

◆ Generate the net prediction heatmap using GradCAM[3] and visualize it with XSMILES[4]. cnn1d has local activations, whereas transformer has more global ones.





b: molecule index = 21821828



(sEH: predict/truth) cnn1d (sEH: 0.9468/1)

CCN(CCCNc1nc(NCC(C)S(=O)(=O)N2CCN(c3cccc3)CC2)nc(N[OccH](CC(=O)NC)Cc2ccc(C#N)cc2)n1)S(C)(=O)=O

transformer (sEH: 0.1779/1)

heatmap is all zeros



Simple Model



Simple Model

◆ Just transformer alone is good enough!

					# keep sco	ore for the su	ubset, set ze	ero for other	S				
			all		keep-share #		keep-nonshare #		loc		cal CV (share)		
submission		fold	private	public	private	public	private	public	fold0	fold1	fold2	fold3	fold4
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Code Review



https://github.com/hengck23/solution-leash-BELKA

Kaggle Competition Solution (5th)

NeurIPS 2024 - Predict New Medicines with BELKA

https://www.kaggle.com/competitions/leash-BELKA

For discussion, please refer to:

https://www.kaggle.com/competitions/leash-BELKA/discussion/456084

1. Hardware

- · GPU: 2x Nvidia Ada A6000 (Ampere), each with VRAM 48 GB
- CPU: Intel® Xeon(R) w7-3455 CPU @ 2.5GHz, 24 cores, 48 threads
- Memory: 256 GB RAM

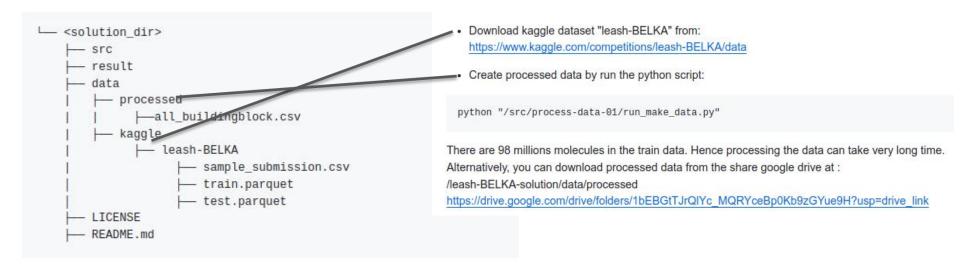
2. OS

ubuntu 22.04.4 LTS

20

3. Set Up Environment

- Install Python >=3.10.9
- Install requirements.txt in the python environment
- Set up the directory structure as shown below.



Modify the path setting by editing "/src/third_party/_current_dir_.py"

```
# please use full path
KAGGLE_DATA_DIR = '<solution_dir>/data/kaggle'
PROCESSED_DATA_DIR = '<solution_dir>/data/processed'
RESULT_DIR = '<solution_dir>/result'
```

tion Template 21

4. Training the model

Warning !!! training output will be overwritten to the "/result" folder

Please run the following python scripts to learn the model files

```
python "/src/cnn1d-nonshare-05-mean-layer5-bn/run train.py"
output model:
/result/cnn1d-mean-pool-ly5-bn-01/fold-0/checkpoint/00400000.pth
- /result/cnn1d-mean-pool-ly5-bn-01/fold-1/checkpoint/00550000.pth
/result/cnn1d-mean-pool-ly5-bn-01/fold-3/checkpoint/00415000.pth
python "/src/transformer-fa-03/run train.py"
output model:
- /result/transfomer-fa-03/fold-2/checkpoint/00264000.pth

    /result/transfomer-fa-03/fold-4/checkpoint/00264000.pth

python "/src/mamba-03/run_train.py"
output model:
- /result/mamba-03/checkpoint/00255000.pth
```

If you want to do local validation, you can run the scripts:

```
python "/src/cnn1d-nonshare-05-mean-layer5-bn/run_valid.py"
python "/src/transformer-fa-03/run_valid.py"
python "/src/mamba-03/run_valid.py"
```



5. Submission csv

Please run the following scripts:

```
python "/src/cnn1d-nonshare-05-mean-layer5-bn/run_submit.py"
python "/src/transformer-fa-03/run_submit.py"
python "/src/mamba-03/run_submit.py"
python "/src/run_ensemble.py"
output file:
- /result/final-3fold-tx2a-mamba-fix.submit.csv
```

		# keep score for the subset, set zero for others										
		ě	all	keep-sha	are only #	keep-nonshare only						
		private	public	private	public	private	public					
	final-3fold-tx2a-mamba-fix.submit.csv	0.28557	0.46439	0.22761	0.34985	0.08320	0.10362					
fold0,1,3	final-3fold-cnn1d.submit.csv	0.26615	0.41103	0.22693	0.34946	0.05424	0.08504					
fold2,4	final-2fold-transfomer.submit.csv	0.31236	0.42288	0.22613	0.34753	0.10124	0.09881					
fold0	final-1fold-mamba.submit.csv	0.23905	0.43221	0.22404	0.34484	0.03002	0.11083					

6. Reference trained models and validation results

Reference results can also be found in the share google drive at:
 //eash-BELKA-solution/result
 https://drive.google.com/drive/folders/1bEBGtTJrQIYc_MQRYceBp0Kb9zGYue9H?usp=drive_link



· It includes the weight files, train/validation logs.

Authors

https://www.kaggle.com/hengck23

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Acknowledgement

"We extend our thanks to HP for providing the Z8 Fury-G5 Data Science Workstation, which empowered our deep learning experiments. The high computational power and large GPU memory enabled us to design our models swiftly."



Question and Answer





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