

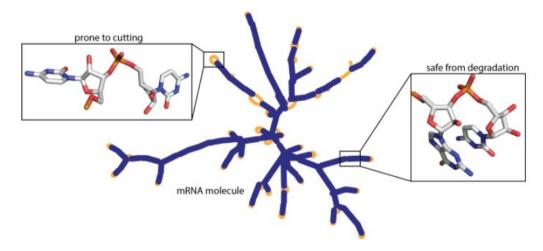
Final Project Presentation

COVID-19 mRNA Vaccine Degradation Prediction

CS7140 Advanced Machine Learning Rajesh Sakhamuru, Zhiyu Chen

Project Introduction

- With the attack of COVID-19 worldwide, scentific community is taking full effort to develope mRNA vacine.
- mRNA vaccine is unstable, depending on its sequence structure.
- Stanford-covid dataset provides the stability of some mRNA sequence.
- Our task is to predict stability of the unknown sequence.



Dataset Structure-Feature

sequence	structure	predicted_loop_type	signal_to_noise	SN_filter	seq length	seq_scored
string	string	string	float	int	int	int
107	107	107	>0.0	0 or 1	107	68

index	id	sequence	structure	predicted_loop_type	signal_to_noise	SN_filter	seq_length	seq_scored
0	id_001f94081	GGAAAAGCUCUAAUAACAGGAGACUAGGACUACGUAUUUCUAGGUA	((((((()))).)).((((EEEEESSSSSSHHHHHHHSSSSBSSXSSIIIIISSIISSSSSSSHHH	6.894	1	107	68
1	id_0049f53ba	GGAAAAAGCGCGCGCGGUUAGCGCGCGCUUUUGCGCGCGC	(((((((((((((((((((((((((((((((((((((((EEEEE888888888888888888888888888888888	0.193	0	107	68
2	id_006f36f57	GGAAAGUGCUCAGAUAAGCUAAGCUCGAAUAGCAAUCGAAUAGAAU	((((-((((((-((()))	EEEEESSSISSIIIIISSSSMSSSHHHHHSSSMMSSSSHHHHHHS	8.800	1	107	68

Dataset Structure-prediction

reactivity	float list	length:68
deg_Mg_pH10	float list	length:68
deg_pH10	float list	length: 68
deg_Mg_50C	float list	length: 68
deg_50C	float list	length: 68

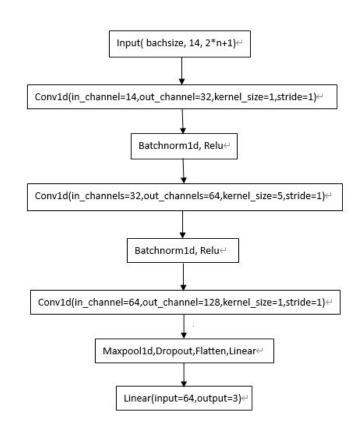
reactivity_error	float list	length:68
deg_error_Mg_pH10	float list	length:68
deg_error_pH10	float list	length:68
deg_error_Mg_50C	float list	length:68
deg_error_50C	float list	length:68

reactivity_error	deg_error_Mg_pH10	deg_error_pH10	deg_error_Mg_50C	deg_error_50C	reactivity	deg_Mg_pH10	deg_pH10	deg_Mg_50C	deg_50C
	[0.261300000000000003, 0.384200000000000004, 0.1	0.286000000000000003,		[0.2167, 0.34750000000000003, 0.188, 0.2124, 0	[0.3297, 1.5693000000000001, 1.1227, 0.8686, 0	[0.7556, 2.983, 0.2526, 1.3789, 0.6376000000000	[2.3375, 3.506000000000000002, 0.3008, 1.0108, 0	2.9683, 0.2589, 1.4552,	[0.6382, 3.4773, 0.9988, 1.3228, 0.78770000000
[2.8272, 2.8272, 2.8272, 4.7343, 2.5676, 2.567	[73705.3985, 73705.3985, 73705.3985, 73705.398	[10.1986, 9.2418, 5.0933, 5.0933, 5.0933, 5.0933,	[16.6174, 13.868, 8.1968, 8.1968, 8.1968, 8.19	[15.4857, 7.9596, 13.3957, 5.8777, 5.8777, 5.8	[0.0, 0.0, 0.0, 2.2965, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,	[0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0,	[4.947, 4.4523, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.		[7.6692, 0.0, 10.9561, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.
[0.0931, 0.132900000000000002, 0.11280000000000	[0.1365, 0.2237, 0.1812, 0.1333, 0.1148, 0.160	[0.170200000000000002, 0.178, 0.111, 0.091, 0.0	[0.1033, 0.1464, 0.1126, 0.0962000000000000001,	[0.149800000000000002, 0.1761, 0.1517, 0.116700	[0.44820000000000004, 1.4822, 1.1819, 0.743400	[0.2504, 1.4021, 0.9804, 0.496700000000000003,	[2.243, 2.9361, 1.0553, 0.721, 0.6396000000000	[0.5163, 1.6823000000000001, 1.0426, 0.7902, 0	[0.9501000000000001, 1.797499999999999, 1.499

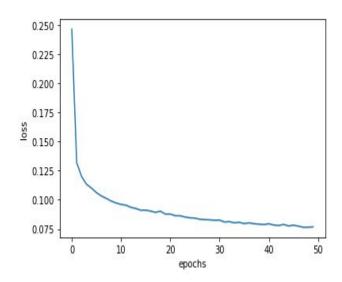
Test sequence length: 107 or 130; Prediction score length: 68 for public, 91 for private.

CNN model

- Assume stability of current base is only dependent on n previous and n afterwards bases
- Use one-hot encoding to encode current base
- Convolute 1d on sequence dimension
- Flatten and then use Dense layer to do prediction



Result and Improvement



- Clean the data, only use high sign to noise data to train the model
- Learning embedding of for each sequence symbol, rather than use one-hot encoding
- Slight improvement likely due to the removal of noisy data for training.
- Embedding has the similiar effect of one-hot encoding

Submission and Description	Private Score	Public Score	
CNNSubmissionCONVPOOL (3).csv	0.42497	0.32104	
- formando and by Balant Calibration			

Emb_Clean_CNNSubmission.csv	
a few seconds ago by Rajesh Sakhamuru	

Submission and Description

CNN with Embedding and de-noised data

a lew seconds ago by Rajesh bakhamo

CNN Model Submission

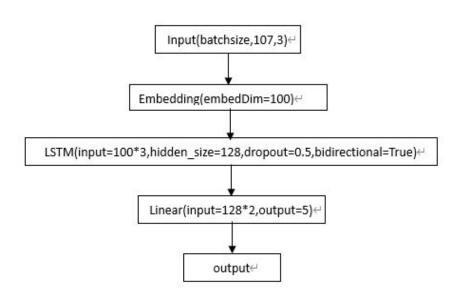
Private Score Public Score

0.32056

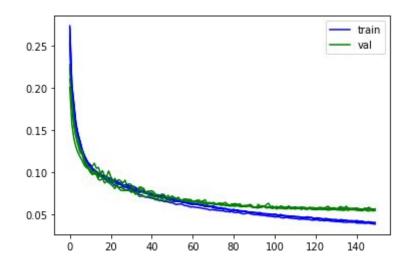
0.41448

LSTM Model

- Assume mRNA as time sequence sequence data
- The performance of mRNA base is affected by both its previous bases and afterwards bases.
- Use the hidden layer of each base to predict the performance
- Split train and validation mutliple time to train multiple model to average prediction



Result and improvement



- Bi-directional LSTM model performed significantly better than the CNN model.
- Has the ability to extract complex relationships at sequence locations to left and right of each nucleotide.
- One issue could be that the training data only has 68 predictions, the weights to predict after 68th prediction might not be updated in the training process.

Attempted Improvement:

- Add one more attention layer which could learn the affection weight of each time step to current time step.
- However, the result does not improve.

Submission and Description	Private Score	Public Score	Submission and Description	Private Score	Public Score
LSTMSubmission.csv a few seconds ago by Rajesh Sakhamuru	0.38448	0.27012	ATT_LSTMSubmission.csv a few seconds ago by jackychen718	0.38316	0.29657
LSTM Model			add submission details		

Reference

https://www.kaggle.com/c/stanford-covid-vaccine

