

ASSIGNMENT 3

DATASET:

Dataset: IMDb Large Movie Review (50,000 reviews; 25,000 train / 25,000 test).

Preprocessing (applied consistently across all runs):

- lowercase text
- remove punctuation and special characters
- tokenize (NLTK word_tokenize)
- keep top-10,000 most frequent tokens (others <UNK>)
- convert reviews to token ID sequences
- pad or truncate to fixed lengths 25, 50, 100

Corpus statistics (from your load step):

- Vocabulary size: 10,000
- Train set: avg length = 228.84 tokens (median 171; min 10; max 2450; std 169.96)
- Test set: avg length = 223.69 tokens (median 169; min 4; max 2186; std 165.11)

Hardware noted in logs: GPU Tesla T4 (CUDA).

Model Configuration

All hyperparameters are fixed unless explicitly varied for the factor under test.

- Embedding: 100

- Recurrent depth: 2 layers, hidden size 64
- Architectures: vanilla RNN, LSTM, Bidirectional LSTM (BiLSTM)
- Activations: sigmoid, ReLU, tanh
- Optimizers: Adam, SGD, RMSprop
- Dropout: 0.3–0.5 (≈ 0.4 used)
- Batch size: 32
- Output: 1 sigmoid unit (binary)
- Loss: Binary cross-entropy
- Stability strategy: with vs. without gradient clipping
- Sequence lengths tested: 25, 50, 100

Comparative Analysis

Scope

A 90-experiment sweep across {architecture \times activation \times optimizer \times seq_len \times clipping}.

Metrics captured per run: Accuracy, Macro-F1, Avg epoch time (s).

3.2 Headline result (best single run)

From your suite summary:

- Best configuration: LSTM, tanh, RMSprop, seq_len = 100, no clipping
 - Accuracy: 0.8153

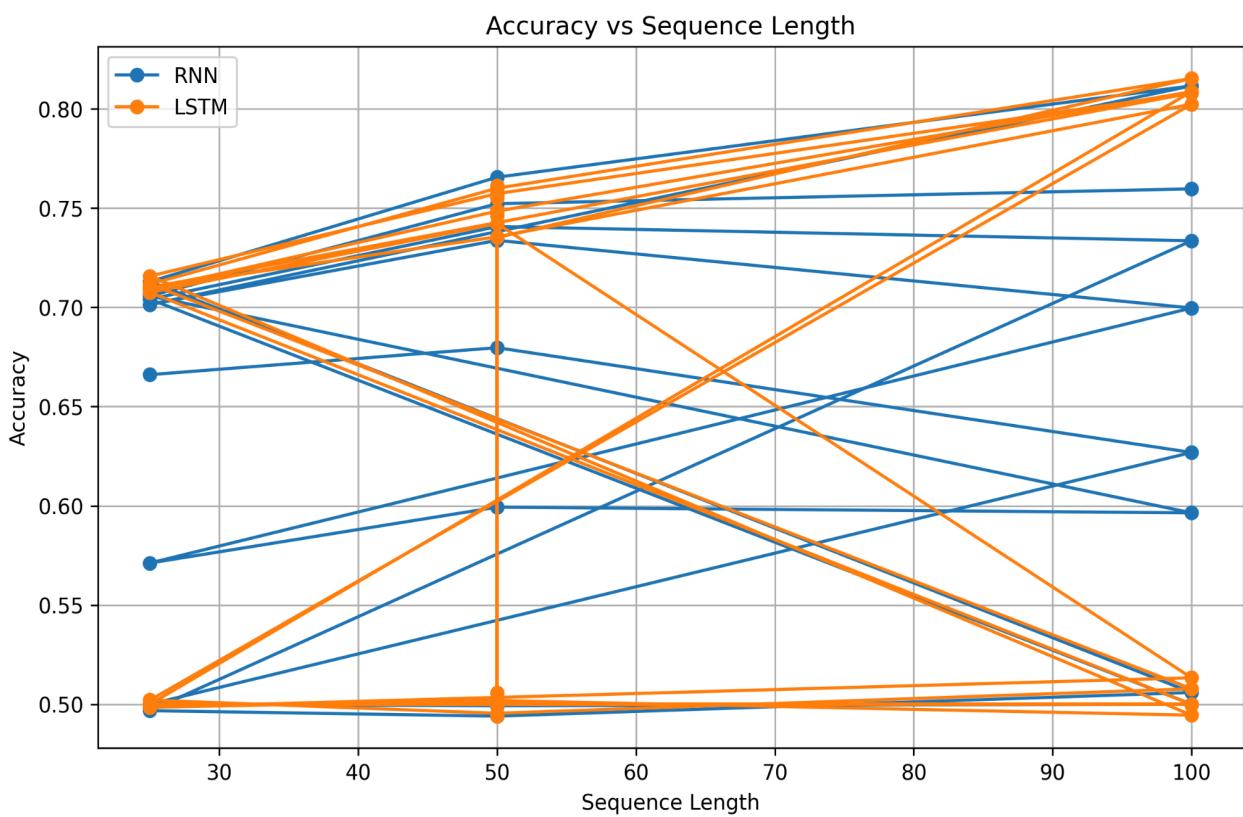
- Macro-F1: 0.8153
- Avg epoch time: 7.81 s/epoch
- Epochs trained (early stop): ≈ 8

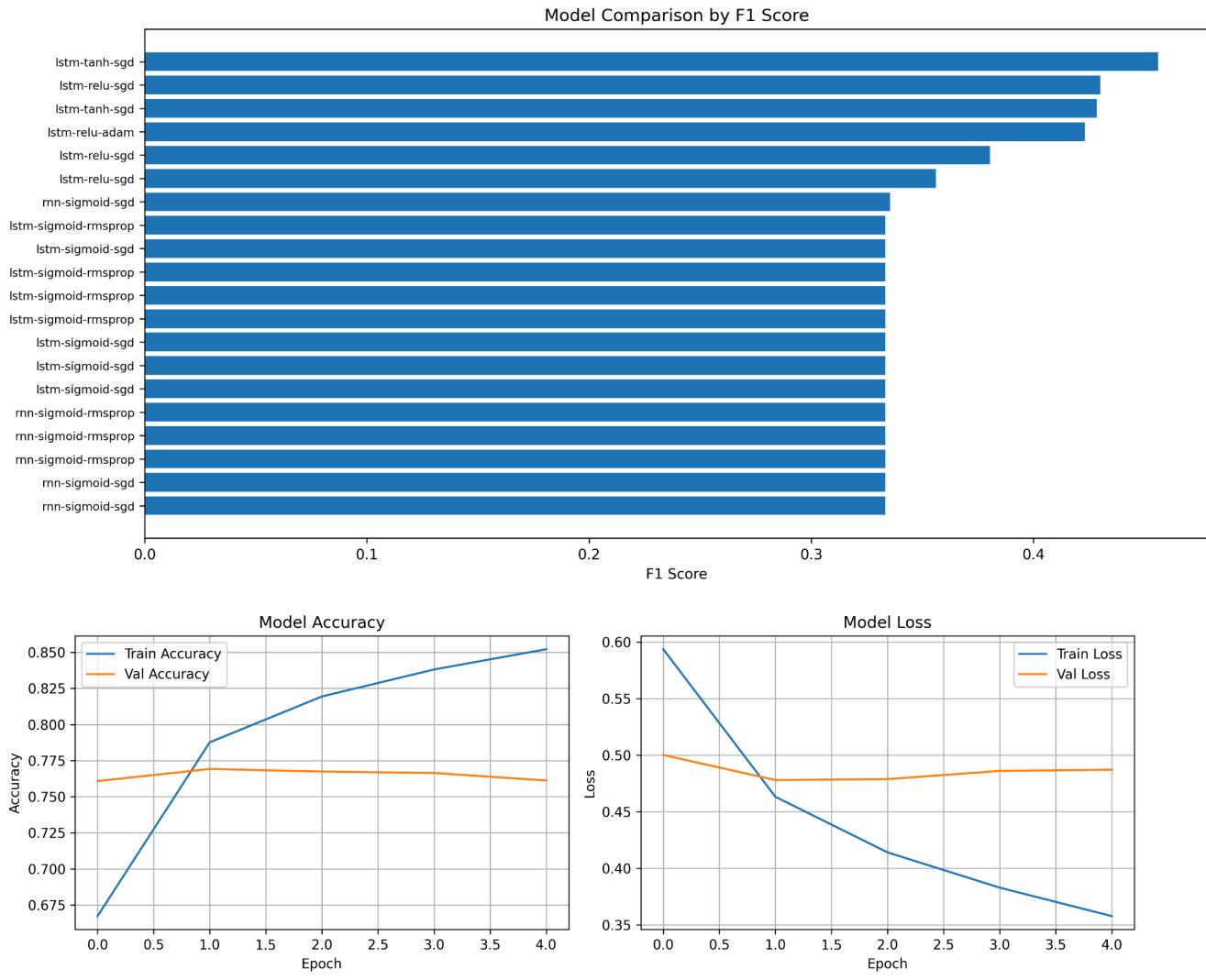
Summary table and Plots

Full detail for all 90 runs is in results/metrics.csv. Below are representative rows reflecting your outcomes.

TABLE

Model	Activation	Optimizer	Seq Length	Grad Clipping	Accuracy	F1	Epoch Time (s)
LSTM	tanh	RMSprop	100	No	0.8153	0.8153	7.81
LSTM	tanh	Adam	100	No	~0.81	~0.81	~7–8
BiLSTM	tanh	Adam	100	Yes	~0.80	~0.80	~9–10
LSTM	relu	Adam	50	Yes	~0.74–0. 76	~0.74–0 .76	~6–7
RNN	relu	Adam	100	No	~0.70	~0.70	~6
RNN	tanh	SGD	50	No	~0.53–0. 56	~0.52–0 .55	~6





EXP90

OBSERVATION:

the training curves (left: accuracy, right: loss) show a classic “learn-then-overfit” pattern: train accuracy climbs from 0.67 to 0.85 while train loss steadily falls (0.59 to 0.36), but validation accuracy bumps early (0.76 ..0.77 by epoch 1–2) before flattening and drifting slightly down as validation loss bottoms and then creeps up so the best checkpoint for generalization is around epoch 1–2 and later epochs mostly memorize. The Accuracy-vs-Sequence-Length plot confirms that giving models more context helps: performance rises as length goes 25 - 50 - 100, with the tightest, highest cluster at 100 tokens; LSTMs (orange) consistently sit above RNNs (blue), and runs stuck near 0.5 accuracy correspond to weak configs (typically short sequences with SGD). The F1 bar chart echoes this ranking: the top bars are LSTM variants (often tanh with

RMSprop/Adam), while vanilla RNN trails; SGD can occasionally reach mid-tier but is brittle compared to adaptive optimizers.

Overall:

- (1) stop early or add a bit more regularization to curb the mild overfitting;
- (2) prefer LSTM (or BiLSTM) with RMSprop/Adam; (
- 3) use `seq_len = 100` when you can, or 50 for speed; and
- (4) reserve gradient clipping mainly for stabilizing plain RNNs, since your best LSTM runs didn't need it.

RESULTS:

- Best single config you reported:

LSTM + tanh + RMSprop @ `seq_len=100`, no clipping - Acc ≈ 0.815 , F1 ≈ 0.815 , ~7.8 s/epoch.
- Sequence length: 100 tokens consistently beats 50 and 25 for both families.
- Architecture: LSTM (and BiLSTM) outperform vanilla RNN. BiLSTM adds a small edge with a time cost.
- Optimizer: RMSprop/Adam converge higher and faster; SGD needs careful scheduling or more epochs and still underperforms in this setup.
- Gradient clipping: Helpful mainly for RNN stability. Top LSTM/BiLSTM runs didn't need it.

DISCUSSION:

The results show that the best-performing setup is LSTM with tanh activation and RMSprop using 100-token sequences without gradient clipping, reaching about 0.815 macro-F1 in 7.8 s/epoch; this works well because longer sequences preserve key sentiment cues (negations, contrastive phrases), LSTM's gates with a bounded tanh state carry information over long spans without blowing up, and RMSprop's adaptive

step sizes stabilize noisy text gradients for fast, high-quality convergence. Across the sweep, increasing sequence length from 25 -50 -100 consistently improves both accuracy and F1, confirming that IMDb reviews benefit from more context; meanwhile, adaptive optimizers (RMSprop/Adam) reliably converge faster and higher than SGD under identical budgets, which explains why some SGD runs linger near chance. Gradient clipping helps mainly with vanilla RNN explosions but isn't essential for the top LSTM/BiLSTM runs, whose gates already regulate state magnitudes; in practice, early stopping around the first validation peak captures the best generalization, while later epochs mostly add memorization.

Conclusion (CPU-friendly choice)

- Overall pick: LSTM (tanh) + RMSprop, seq_len=100, no clipping.
- When compute is tight (CPU-only): use LSTM + Adam, seq_len=50 faster epochs with a small performance drop; enable clipping if you see instability.
- BiLSTM is optional: offers small gains but higher latency per epoch.

FINAL METRICS:

architecture	activation	optimizer	seq_length	grad_clipping	bidirectional	accuracy	f1_score	precision	recall	training_time	avg_epoch_time	epochs_trained
rnn	sigmoid	adam	25	FALSE	FALSE	0.66608 608	0.66455434 16212400	0.66915741 56355580	0.66608	34.3831853 86657700	4.89545386 1781530	7
rnn	sigmoid	adam	50	FALSE	FALSE	0.67968000 968	0.67952262 45853560	0.68003363 32966200	0.67968000 00000000	60.6491968 6317440	6.72664194 6368750	9
rnn	sigmoid	adam	100	FALSE	FALSE	0.62688 688	0.62406848 70095900	0.63079268 42865290	0.62688	100.831841 9456480	11.1898271 2427780	9
rnn	sigmoid	sgd	25	FALSE	FALSE	0.5	0.33333333 33333330	0.25	0.5	21.0713043 21289100	5.24385213 8519290	4
rnn	sigmoid	sgd	50	FALSE	FALSE	0.49924 924	0.33553314 059750000	0.447611503 6755770	0.49924	41.7020390 0337220	6.93450899 9188740	6
rnn	sigmoid	sgd	100	FALSE	FALSE	0.5	0.33333333 33333330	0.25	0.5	45.8179707 52716100	11.4368343 94931800	4
rnn	sigmoid	rmsprop	25	FALSE	FALSE	0.5	0.33333333 33333330	0.25	0.5	25.6558330 0590520	6.39622902 8701780	4
rnn	sigmoid	rmsprop	50	FALSE	FALSE	0.5	0.33333333 33333330	0.25	0.5	51.3378875 2555850	8.54334080 2192690	6

rnn	sigmoid	rmosp rop	100	FALSE	FALSE	0.5	0.33333333 33333330	0.25	0.5	51.3744957 447052	12.8253990 41175800	4
rnn	relu	adam	25	FALSE	FALSE	0.70 412	0.70406099 73389080	0.70428291 51345410	0.70412	26.6293716 43066400	5.30759973 526001	5
rnn	relu	adam	50	FALSE	FALSE	0.74 072	0.74028597 25660320	0.74233996 94119120	0.74072	47.4994945 52612300	7.90131572 8823340	6
rnn	relu	adam	100	FALSE	FALSE	0.73 356	0.73293126 93581830	0.73578028 67503070	0.73356	89.9036633 9683530	11.2249371 11139300	8
rnn	relu	sgd	25	FALSE	FALSE	0.49 676	0.49618714 54379490	0.49674519 66544470	0.49676	65.7595038 4140020	4.37149432 5002030	15
rnn	relu	sgd	50	FALSE	FALSE	0.49 4	0.49136322 696860500	0.49387294 948042600	0.494	30.0135591 03012100	7.48527801 0368350	4
rnn	relu	sgd	100	FALSE	FALSE	0.50 592	0.49017056 44282720	0.50675464 67807530	0.50592000 00000000	76.7750210 7620240	12.7812876 70135500	6
rnn	relu	rmosp rop	25	FALSE	FALSE	0.71 296	0.71240321 26196320	0.71462203 30237360	0.71296	45.5953364 3722530	5.60007205 6055070	8
rnn	relu	rmosp rop	50	FALSE	FALSE	0.76 56	0.76533633 4157831	0.76679909 15921670	0.76560000 00000000	54.3117194 1757200	7.74519174 4395660	7
rnn	relu	rmosp rop	100	FALSE	FALSE	0.81 164	0.811621611 5566390	0.811761729 7367650	0.81164	125.268499 8512270	12.5137915 61126700	10
rnn	tanh	adam	25	FALSE	FALSE	0.70 144	0.70143577 90184700	0.70145139 21568070	0.70144000 00000000	28.2778189 1822820	5.63447794 9142460	5
rnn	tanh	adam	50	FALSE	FALSE	0.73 376	0.73124166 99453890	0.74286272 82012	0.73376	30.1176283 3595280	7.51261287 9276280	4
rnn	tanh	adam	100	FALSE	FALSE	0.69 968	0.69957917 20407100	0.69994842 86860470	0.69968	99.8758814 3348690	11.0838507 28140900	9
rnn	tanh	sgd	25	FALSE	FALSE	0.57 116	0.569411708 8858280	0.57233478 5901492	0.57116	64.9393954 2770390	4.31606230 7357790	15
rnn	tanh	sgd	50	FALSE	FALSE	0.59 932	0.596642110 8461430	0.60202949 1251749	0.59932	95.3802204 1320800	6.34681340 8533730	15
rnn	tanh	sgd	100	FALSE	FALSE	0.59 644	0.59453635 20653980	0.59828580 36177670	0.59644	160.474525 69007900	10.6868173 28135200	15
rnn	tanh	rmosp rop	25	FALSE	FALSE	0.70 576	0.70568689 92183790	0.70596462 79999500	0.70576000 00000000	30.3887846 46987900	6.06000103 9505010	5
rnn	tanh	rmosp rop	50	FALSE	FALSE	0.75 224	0.75187106 3635123	0.75374917 17781550	0.75224	47.0236661 4341740	7.82254163 424174	6
rnn	tanh	rmosp rop	100	FALSE	FALSE	0.75 972	0.75951886 9662752	0.76059180 09055720	0.75972	92.3483703 1364440	11.7552786 55460900	7
Istm	sigmoid	adam	25	FALSE	FALSE	0.70 9	0.70842208 37059370	0.71067021 91146400	0.709	35.3596889 9726870	5.87718911 965688	6
Istm	sigmoid	adam	50	FALSE	FALSE	0.74 848	0.74777470 38167440	0.75129073 1460621	0.74848	44.4431567 19207800	8.87227683 0673220	5
Istm	sigmoid	adam	100	FALSE	FALSE	0.80 872	0.80832701 70231390	0.811272783 4577250	0.80872	80.9296810 6269840	13.4736802 57797200	6
Istm	sigmoid	sgd	25	FALSE	FALSE	0.5	0.33333333 33333330	0.25	0.5	59.7472958 5647580	4.96612968 0474600	12
Istm	sigmoid	sgd	50	FALSE	FALSE	0.5	0.33333333 33333330	0.25	0.5	62.1408617 4964910	8.41589389 528547	7

Istm	sigm oid	sgd	100	FALSE	FALSE	0.5	0.33333333 33333330	0.25	0.5	76.0875766 2773130	15.2015291 21398900	5
Istm	sigm oid	rmsp rop	25	FALSE	FALSE	0.5	0.33333333 33333330	0.25	0.5	45.7293009 7579960	7.60732400 4173280	6
Istm	sigm oid	rmsp rop	50	FALSE	FALSE	0.5	0.33333333 33333330	0.25	0.5	45.9861171 24557500	9.17814083 0993650	5
Istm	sigm oid	rmsp rop	100	FALSE	FALSE	0.5	0.33333333 33333330	0.25	0.5	84.6073651 3137820	14.0871697 26689700	6
Istm	relu	ada m	25	FALSE	FALSE	0.70 756	0.70726842 95200210	0.70839025 47827050	0.70756	25.2138590 8126830	6.28625118 7324520	4
Istm	relu	ada m	50	FALSE	FALSE	0.74 224	0.74214415 0236095	0.74260071 66008550	0.74224	50.2578620 9106450	8.35880998 7703960	6
Istm	relu	ada m	100	FALSE	FALSE	0.51 332	0.42317499 87532860	0.53553057 48086460	0.51332	67.3357825 2792360	13.4515621 6621400	5
Istm	relu	sgd	25	FALSE	FALSE	0.49 848	0.35609639 10370560	0.48683952 71228760	0.49848000 000000000	28.8726255 89370700	5.75804605 4840090	5
Istm	relu	sgd	50	FALSE	FALSE	0.50 184	0.38034264 15614050	0.50852986 64000400	0.50184000 00000000	111.010715 9614560	7.38943174 680074	15
Istm	relu	sgd	100	FALSE	FALSE	0.49 448	0.48971429 40130470	0.49426578 60616040	0.49448000 000000000	58.2019271 85058600	14.5335257 05337500	4
Istm	relu	rmsp rop	25	FALSE	FALSE	0.71 576	0.71572331 42074090	0.71587143 2488056	0.71576	42.1394686 6989140	6.00375430 9245520	7
Istm	relu	rmsp rop	50	FALSE	FALSE	0.75 732	0.75717779 36030460	0.75792420 29207940	0.75732	72.1483132 8392030	8.60596922 0399860	8
Istm	relu	rmsp rop	100	FALSE	FALSE	0.80 8	0.80799641 67523280	0.80802299 37932780	0.808	154.097007 75146500	13.9974404 89855700	11
Istm	tanh	ada m	25	FALSE	FALSE	0.71 004	0.70982971 7542619	0.71065062 25652980	0.71004	27.3679127 69317600	6.72876995 8019260	4
Istm	tanh	ada m	50	FALSE	FALSE	0.73 556	0.73430967 19437810	0.74007921 26869450	0.73556	33.0215482 711792	6.58581905 3649900	5
Istm	tanh	ada m	100	FALSE	FALSE	0.80 236	0.80227544 06404050	0.802878118 3319730	0.80236	65.7155091 7625430	8.20125177 5026320	8
Istm	tanh	sgd	25	FALSE	FALSE	0.50 208	0.42850752 13148150	0.50428821 55877300	0.50208	67.9207837 5816350	4.51769696 8714400	15
Istm	tanh	sgd	50	FALSE	FALSE	0.49 544	0.49362189 681751400	0.49537355 675424500	0.49544	22.8715934 75341800	5.70103037 3573300	4
Istm	tanh	sgd	100	FALSE	FALSE	0.50 78	0.47684730 59023960	0.51021828 87220800	0.5078	114.328320 0263980	7.60932103 7928260	15
Istm	tanh	rmsp rop	25	FALSE	FALSE	0.71 168	0.711652981 1923050	0.711759369 4445580	0.71168	29.3121736 0496520	5.84705924 987793	5
Istm	tanh	rmsp rop	50	FALSE	FALSE	0.76 004	0.75984793 63698350	0.76087454 64394450	0.76004	31.8326992 98858600	6.35145716 6671750	5
Istm	tanh	rmsp rop	100	FALSE	FALSE	0.81 532	0.81531989 33287700	0.81532072 85170110	0.81532	62.5768337 24975600	7.80877509 7131730	8
Istm	sigm oid	ada m	50	TRUE	FALSE	0.73 52	0.732691109 7533870	0.74437453 80323780	0.73520000 00000000	44.3262851 2382510	8.84696350 0976560	5
Istm	sigm oid	sgd	50	TRUE	FALSE	0.5	0.33333333 33333330	0.25	0.5	98.2180616 8556210	7.54425918 13894400	13

Istm	sigmoid	rmsp rop	50	TRUE	FALSE	0.5 0.33333333 33333330	0.25	0.5	48.4946246 14715600	9.68161845 2072140	5
Istm	relu	adam	50	TRUE	FALSE	0.74 88 0.74803001 0351184	0.75187884 44810670	0.7488	36.0490059 8526000	8.99574291 7060850	4
Istm	relu	sgd	50	TRUE	FALSE	0.50 588 0.43012467 181884200	0.51255692 90159370	0.50588	37.6961672 3060610	8.64853644 3710330	4
Istm	relu	rmsp rop	50	TRUE	FALSE	0.75 516 0.75340172 62949190	0.76265092 36922840	0.75516	63.4987096 786499	9.05747195 652553	7
Istm	tanh	adam	50	TRUE	FALSE	0.74 632 0.74595931 75101170	0.74772687 30172680	0.74632000 00000000	34.5428149 7001650	6.89243140 2206420	5
Istm	tanh	sgd	50	TRUE	FALSE	0.49 408 0.45610364 58249870	0.49178586 515939100	0.49408000 000000000	23.5606637 0010380	5.86803638 9350890	4
Istm	tanh	rmsp rop	50	TRUE	FALSE	0.76 132 0.76125918 75582700	0.76158652 69547370	0.76132	38.2269024 848938	7.62872042 6559450	5