Reel Recommendations:

Leveraging Reinforcement Learning for Tailored LetterBoxd Recommendations

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Opportunity

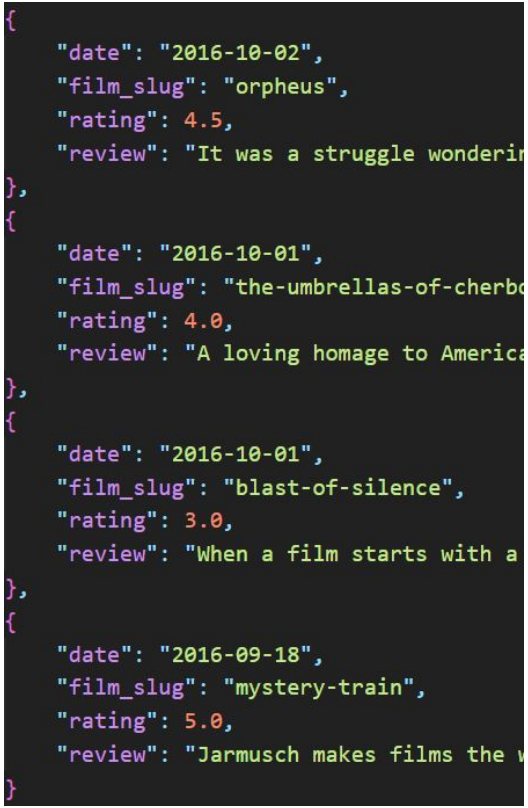
LetterBoxd, a popular movie logging / reviewing website, has extensive data and review text from users.

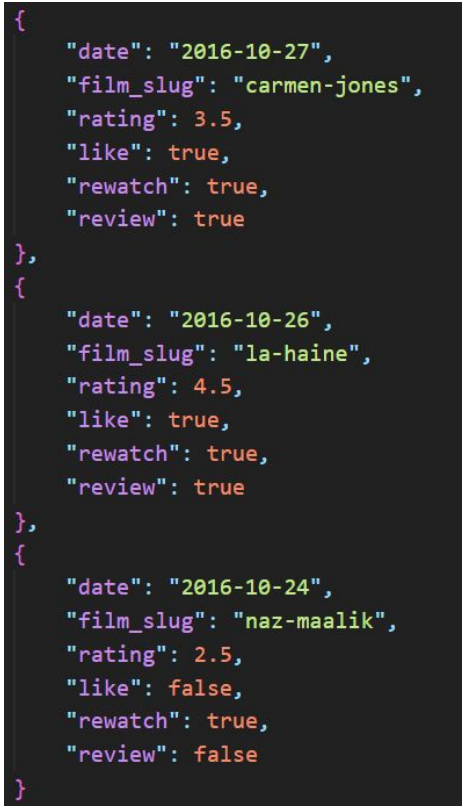
Solution

Leverage RL and Language Models to perform movie recommendations

Data

- LetterBoxd User Data
  - roughly 6500 top LetterBoxd users

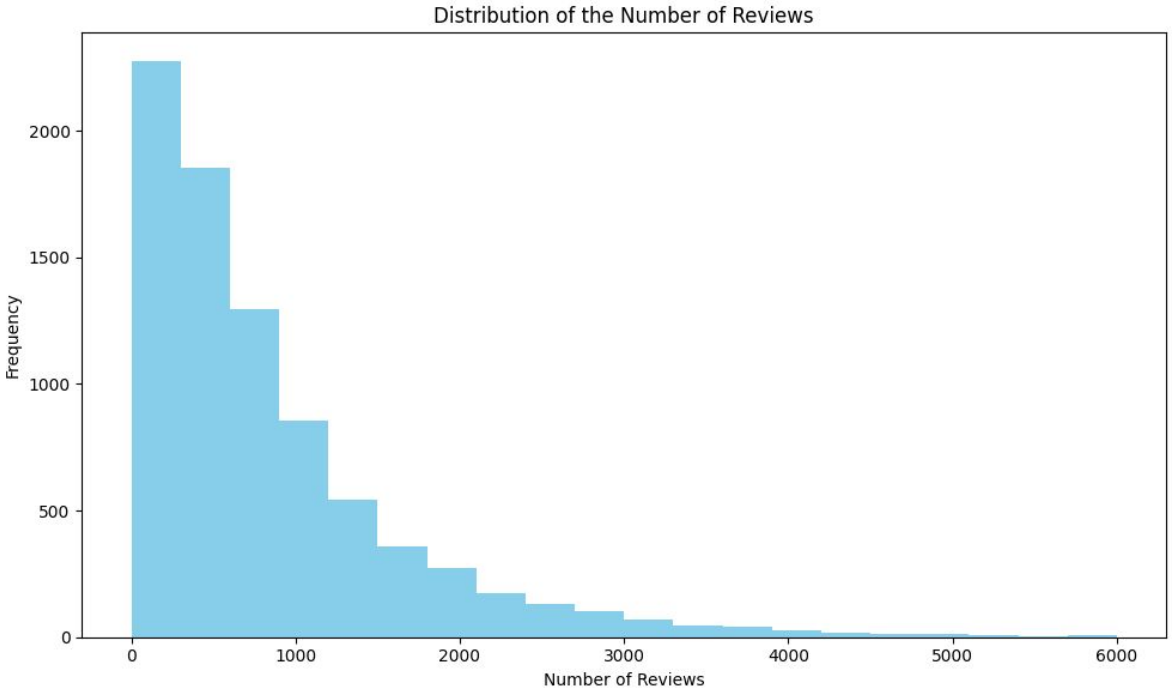




Data

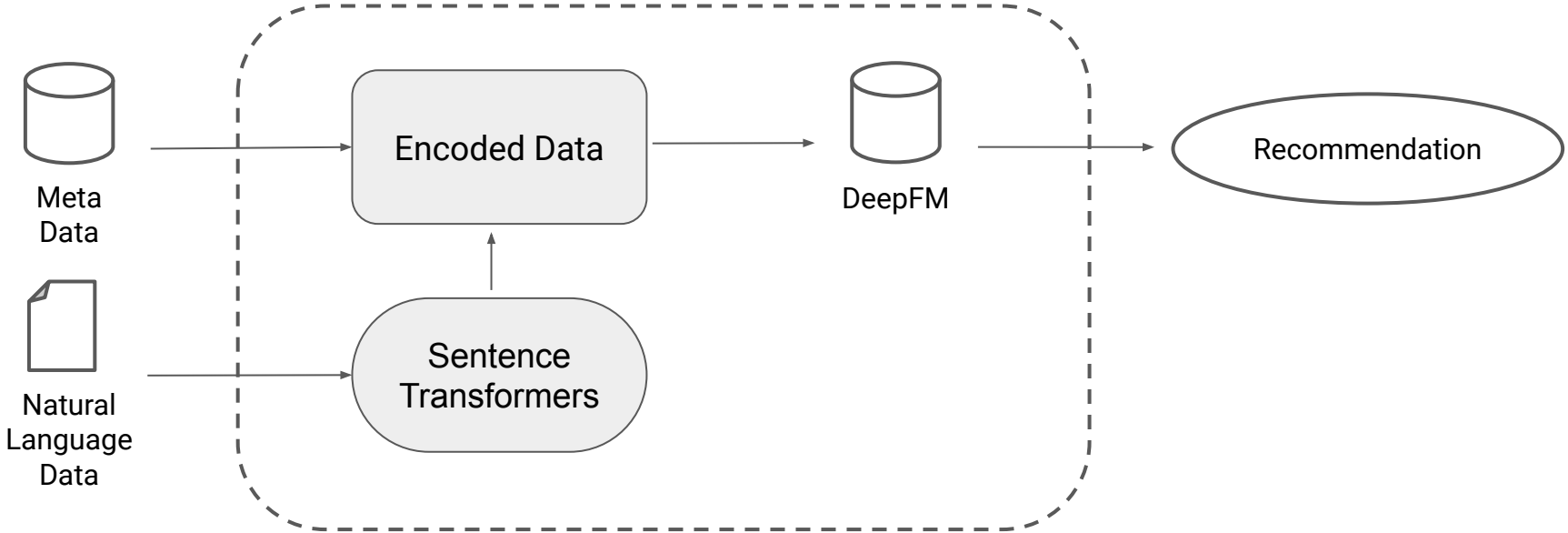
- LetterBoxd User Data
  - roughly 6500 top LetterBoxd users
- Movie Data
  - Kaggle Dataset (2022)
  - TMDB API

User Review Data Distribution

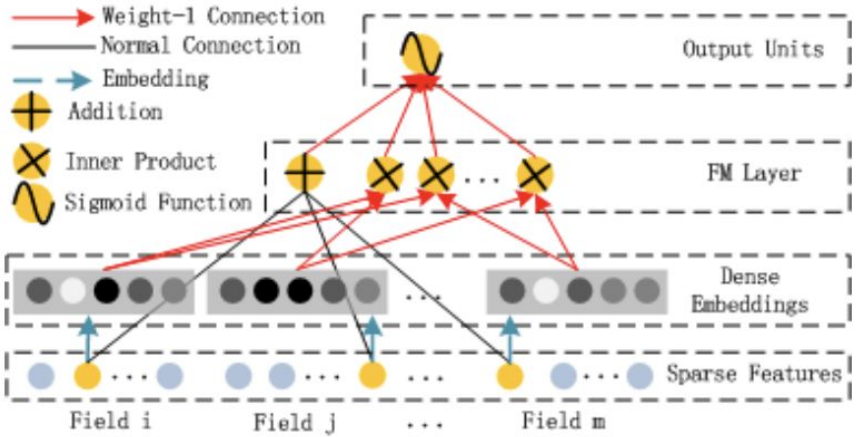


	Ratings Pages	Reviews
count	4747	8139
mean	32.8	868
std	35.2	979
min	1	0
25%	15	267
50%	25	588
75%	42	1130
max	1208	17184

Approach: Overview



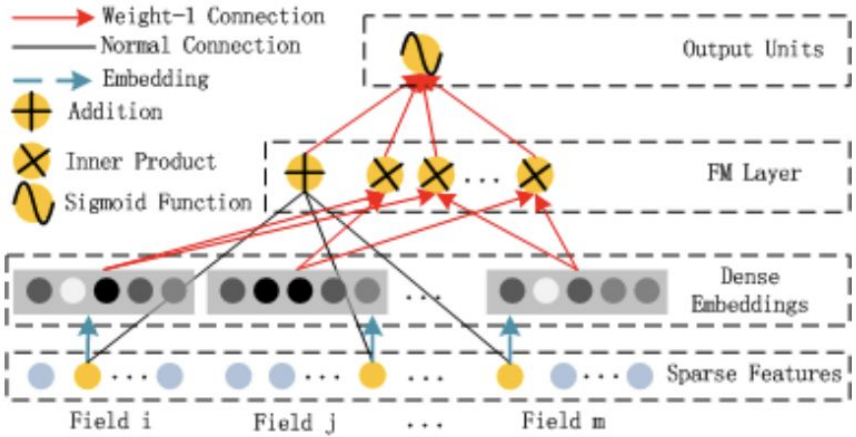
Approach 1: Recommendations with DeepFM[1]



- Dense features constructed by sparse features.

1. Guo et al. 2017 "DeepFM: a factorization-machine based neural network for CTR prediction."

Approach 1: Recommendations with DeepFM[1]



- Dense features constructed by sparse features.
- Trained User Vectors given a set of Movie Vectors
  - Movie Vectors were generated during our preprocessing

1. Guo et al. 2017 "DeepFM: a factorization-machine based neural network for CTR prediction."

Experiment 1: Results (Raw Prediction)

Split	Acc. (No Personalization)	100 Epoch Acc. (train)	200 Epoch Acc. (train)	100 Epoch Acc. (test)	200 Epoch Acc. (test)
30 train, 0 test	0.7106	0.9040	0.9889	-	-
500 train, 100 test	0.769	0.7860	0.8430	0.5695	0.5732
1000, 150 test	0.745	0.6030 (degrad.)	0.9040	0.5170	0.5369
9000 train, 1000 test	0.7322	0.8437	0.8878	0.5641	0.5662

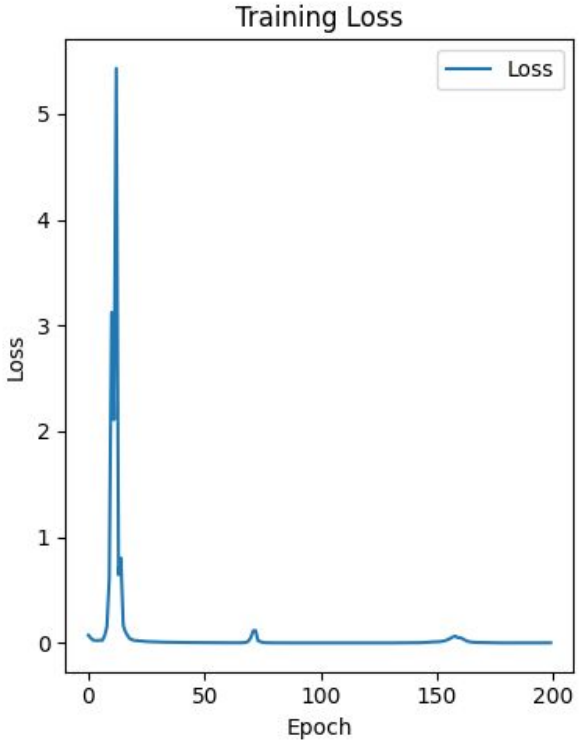
Future Work

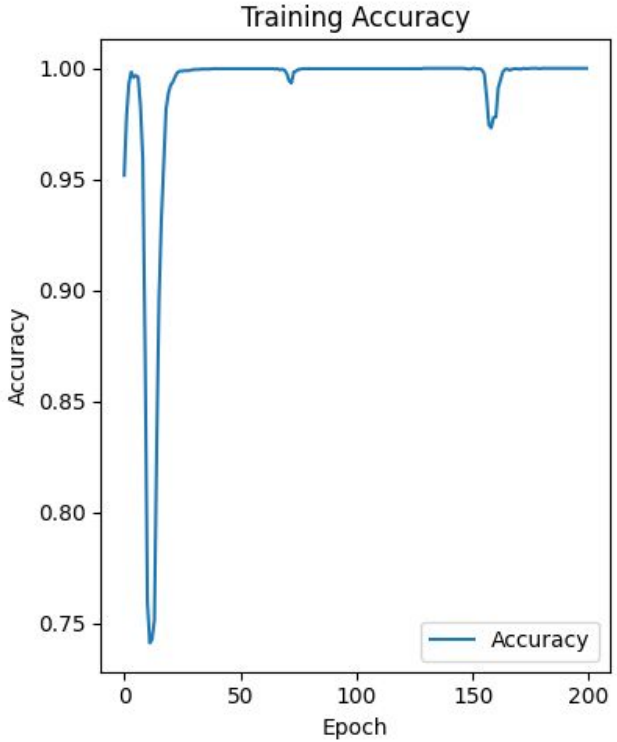
- Residual Exp. 1 Predictions
- Train GPT-2 for AutoReg. Score Prediction
- TBD: Using review text in pipeline

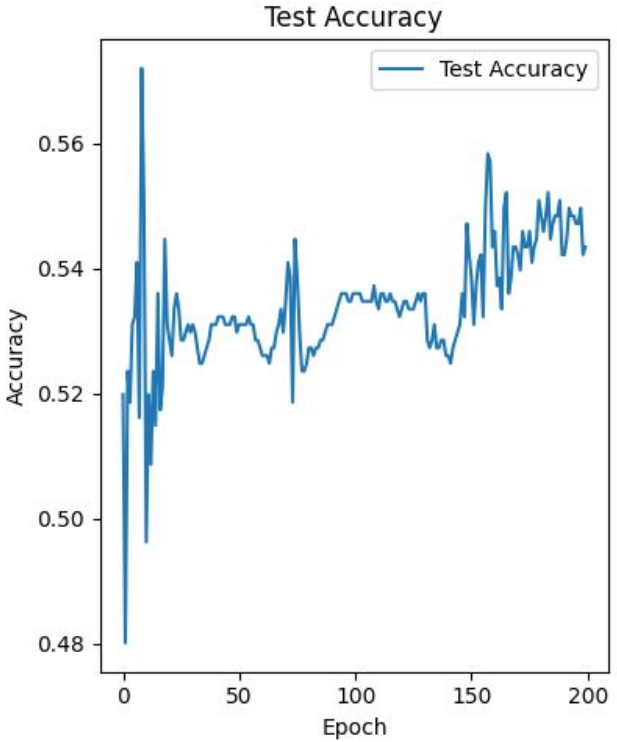
Questions?

References

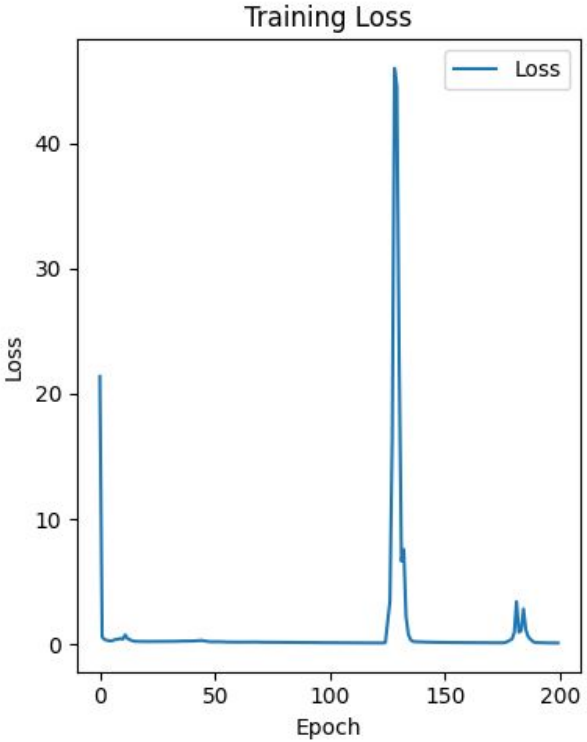
1. Guo, Huifeng, et al. "DeepFM: a factorization-machine based neural network for CTR prediction." arXiv preprint arXiv:1703.04247 (2017).

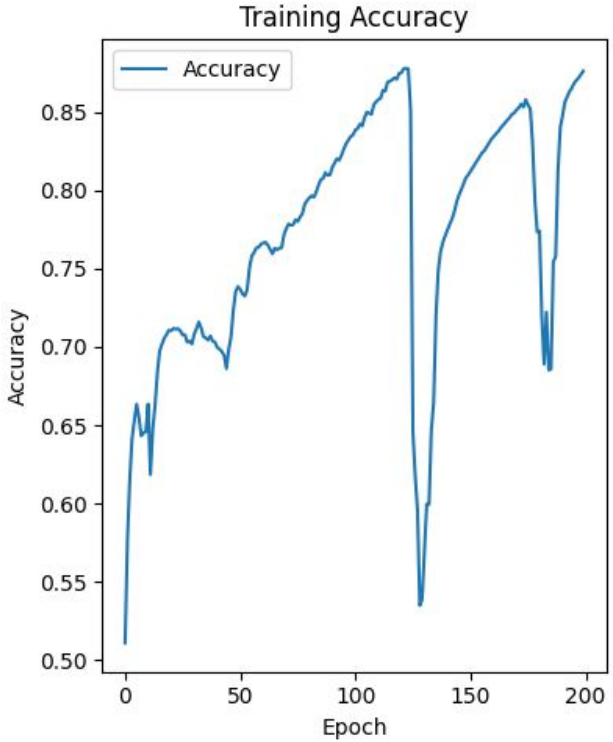

Training Loss
Loss
Loss
Epoch
0
50
100
150
200
0
1
2
3
4
5


Training Accuracy
Accuracy
Accuracy
Epoch
0
50
100
150
200
0.75
0.80
0.85
0.90
0.95
1.00


Test Accuracy
Test Accuracy
Accuracy
Epoch
0
50
100
150
200
0.48
0.50
0.52
0.54
0.56

N = 500


Training Loss
Loss
Loss
Epoch
0
10
20
30
40
0
50
100
150
200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Accuracy
Accuracy
Epoch
0.50
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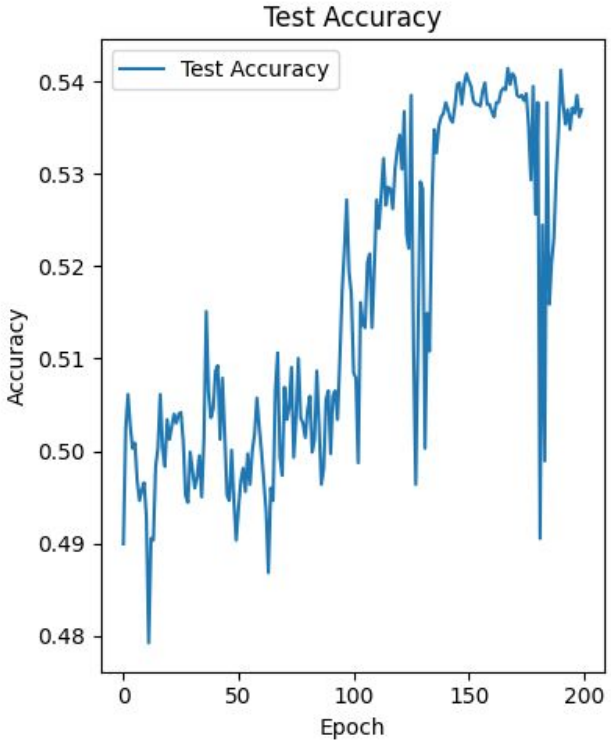
0.75
0.80
0.85
0
50
100
150
200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Accuracy
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0.48
0.49
0.50
0.51
0.52
0.53
0.54
0
50
100
150
200

N = 1000