MACHINE LEARNING RUINED MY LYFE!!1!

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Methods Implemented

- SVD
- SVD++
- timeSVD++
- KNN
- RBM
- Blending
- Preprocessing with user mean normalization

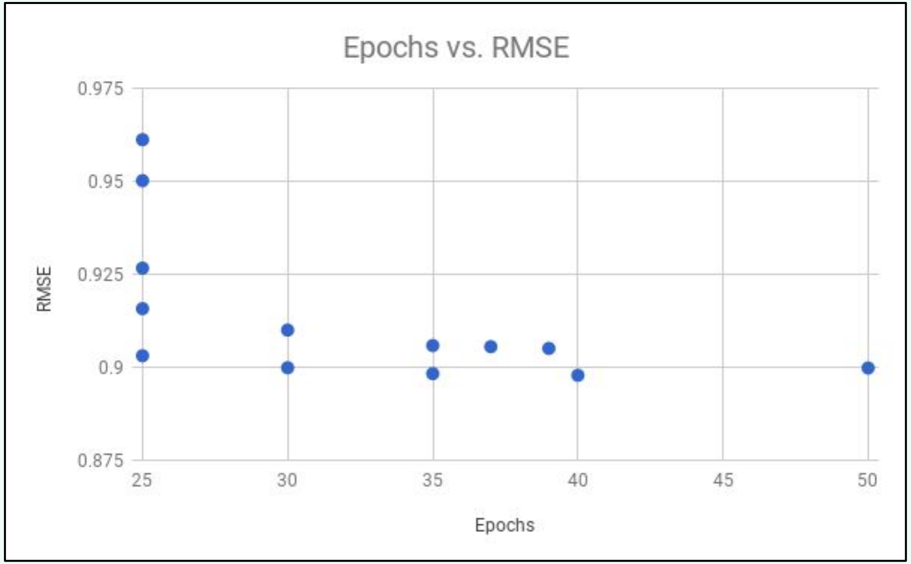
What Worked

- SVD
  - Resulted in highest score on leaderboard
  - Performed extensive parameter tuning to improve score
- SVD++, TimeSVD++
  - Did not have as good of results as SVD, parameters perhaps not tuned as well (~3.5% above water) due to longer running time
- Normalizing Data
  - normalizing scores by user mean (i.e. subtracting user mean from each rating) slightly improved performance
- Blending using linear regression and probe data
  - saw an average of +0.1% above water when blending results from the same model

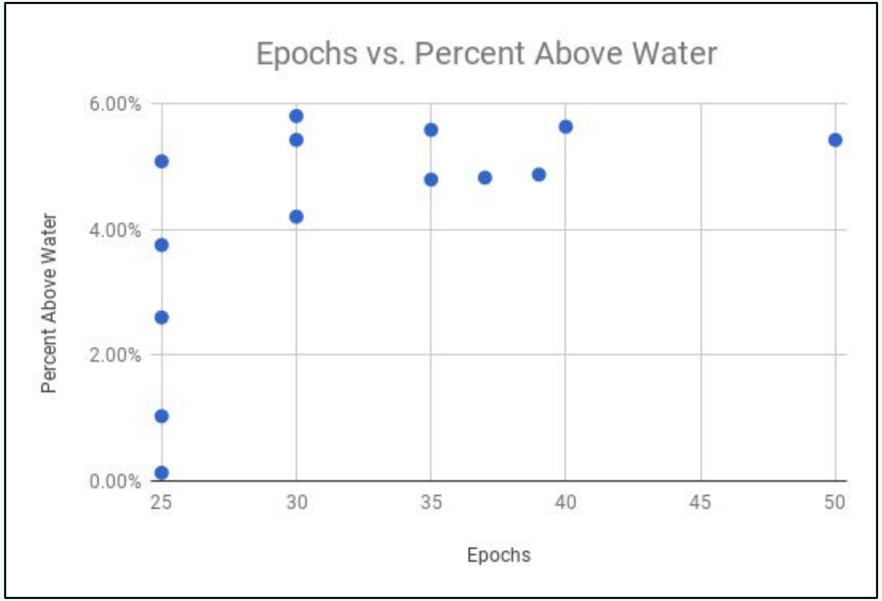
What Did Not Work

- Python
  - tried surprise library for SVD (too slow and performance not very good ~2.1% above water)
- SVD++ and TimeSVD++
  - many more parameters to train than SVD, and we were unable to find learning rates and regularization terms/bin numbers that performed better than SVD
- KNN
  - Runtime was too extensive (on the order of weeks to run)
  - Tried to improve runtime by changing training data structure, improved performance but not enough to run KNN in a feasible amount of time
- RBM
  - Used SkLearn to implement RBM
  - Did not produce good results, as many outputs were 1's.
  - Figured SVD related methods were better

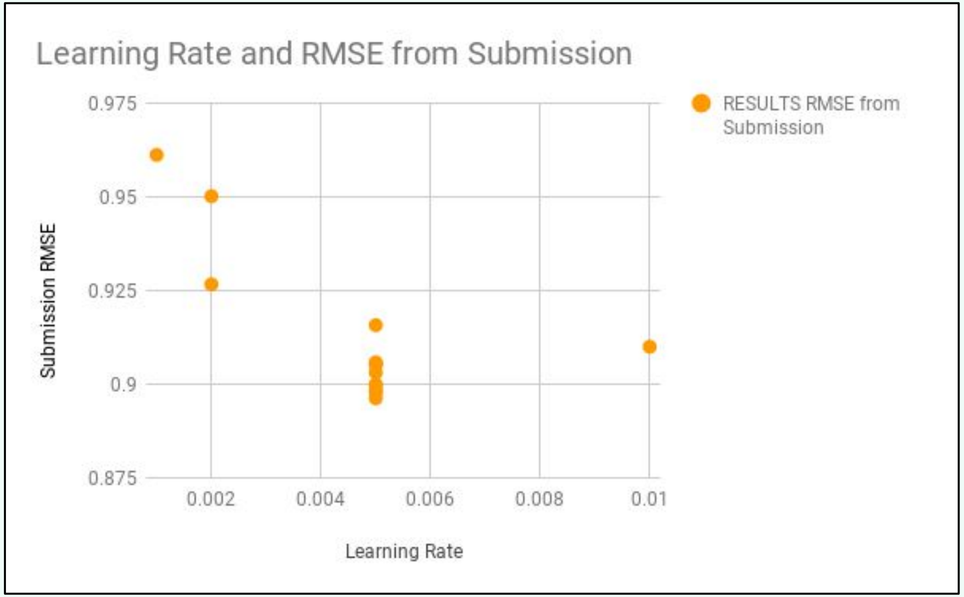
Results: Epochs vs. RMSE for SVD

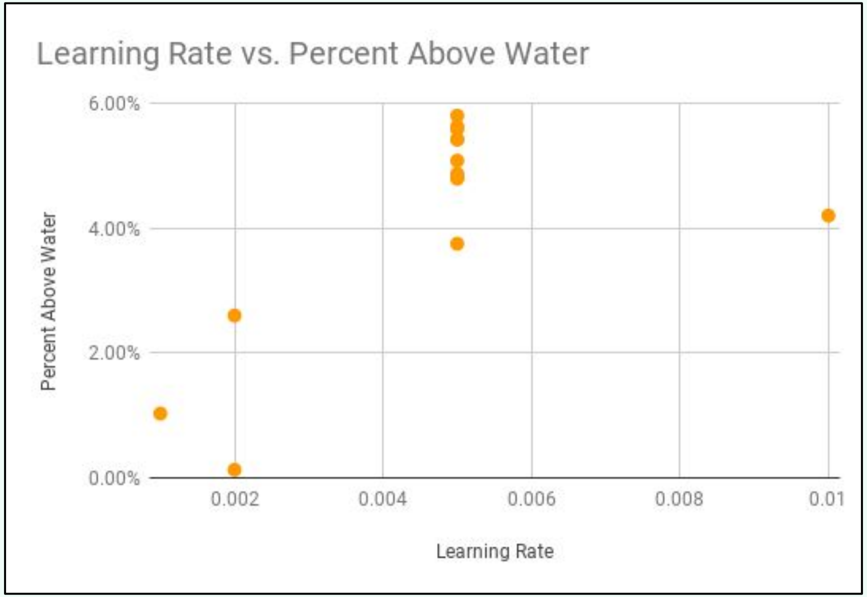


- Note: Dots within the same # of epochs represent different parameter combinations

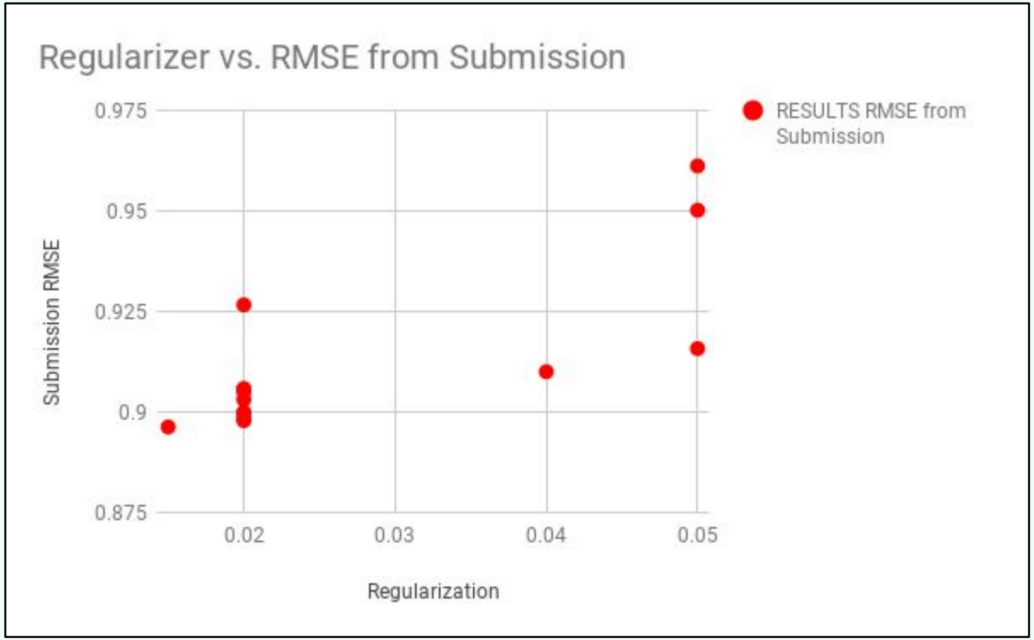


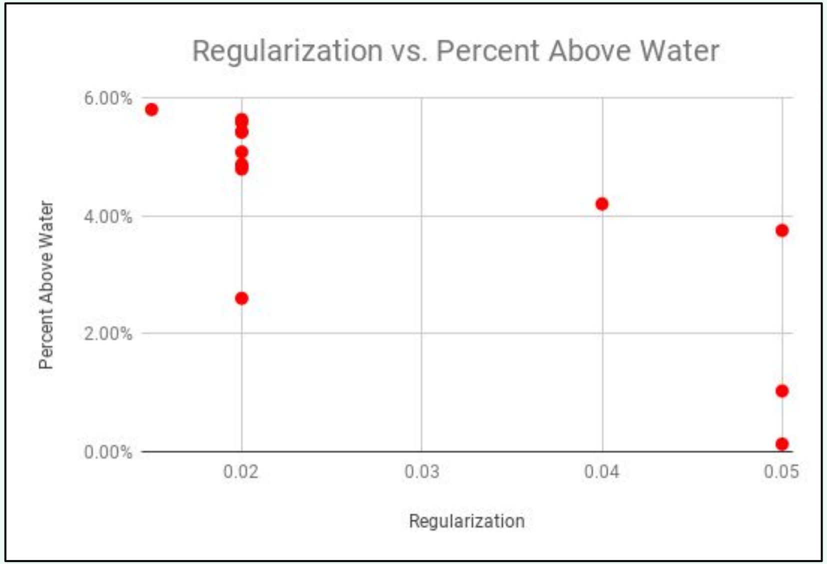
Results: Learning Rate vs. RMSE for SVD



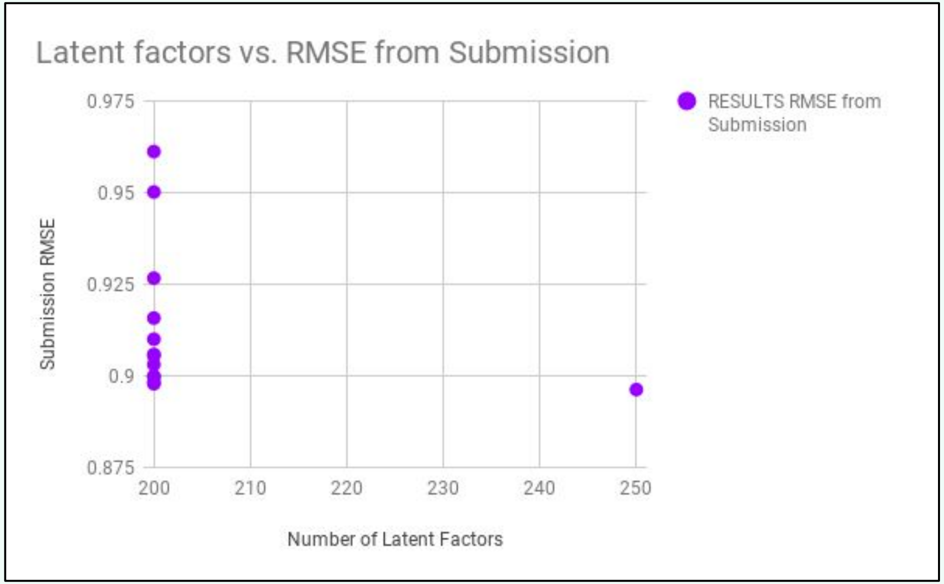


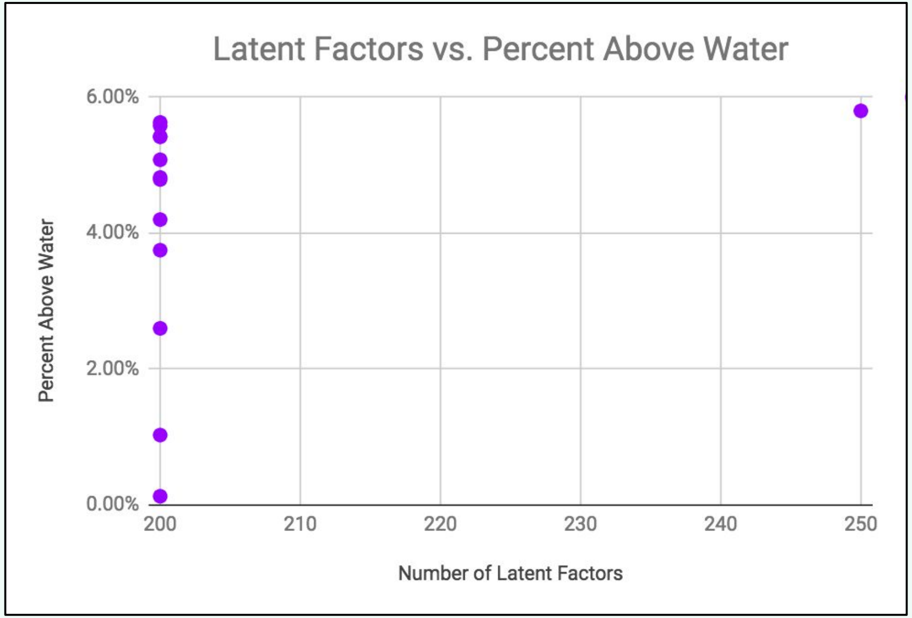
Results: Regularizer vs. RMSE for SVD



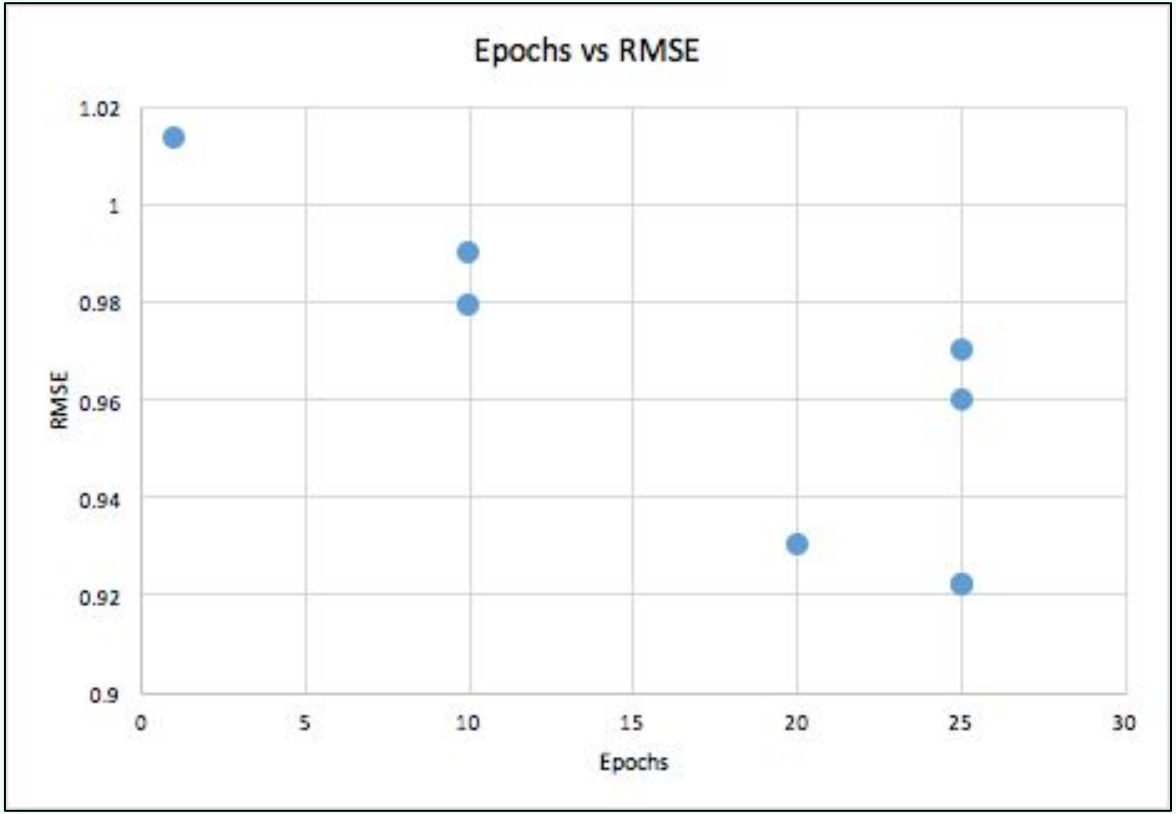


Results: Latent Factors vs. RMSE for SVD





Epochs vs. RMSE for TimeSVD++



Final Model Parameters

The final model parameters for the submitted model with 5.8% above water result were:

- 250 latent factors
- 30 epochs
- 0.005 learning rate
- 0.015 regularization

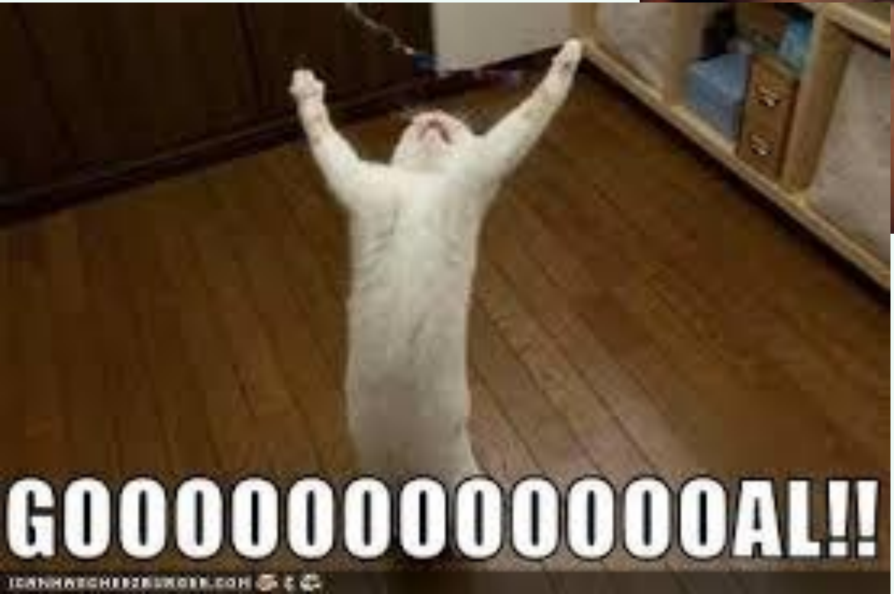
Final Scoreboard Results

CS156B: Welcome to the FINAL RESULTS scoreboard!

Aggregate class performance: 9.0178% above water

Place	Team Name	Test RMSE	% Above Water	Novelty (BP)	Quiz RMSE	% Above Water	Total Submissions	Record Date
1	ROC #1	0.86711	**8.8596**	**68.2523**	0.86592	8.9847	2897	May 28, 2018, 9:54 p.m.
2	BBRW	0.87700	**7.8201**	**7.5641**	0.87598	7.9273	64	May 28, 2018, 4:24 p.m.
3	Taco Tuesday	0.87904	**7.6056**	**1.2320**	0.87819	7.695	156	May 28, 2018, 9:55 p.m.
4	Machine Forgetting	0.87916	**7.593**	**0.3977**	0.87840	7.6729	93	May 28, 2018, 8:03 p.m.
5	Jess Angels	0.87946	**7.5615**	**0.0075**	0.87860	7.6519	70	May 28, 2018, 6:57 p.m.
6	mLIsmYPasSiOn	0.87974	**7.5321**	**0.0000**	0.87878	7.633	169	May 28, 2018, 9:56 p.m.
7	Redacted	0.88212	**7.2819**	**0.0029**	0.88126	7.3723	159	May 27, 2018, 11:19 p.m.
8	YasersStatisticallySignificantOther	0.88428	**7.0549**	**0.0006**	0.88326	7.1621	579	May 28, 2018, 9:39 p.m.
9	Netboost(TM)	0.88559	**6.9172**	**1.1992**	0.88466	7.0149	49	May 28, 2018, 5:18 p.m.
10	Three neurons	0.88642	**6.8299**	**0.0000**	0.88558	6.9182	206	May 28, 2018, 9:58 p.m.
11	MACHINE LEARNING RUINED MY LYFE!1!	0.89662	**5.7578**	**0.0000**	0.89605	5.8177	99	May 28, 2018, 9:59 p.m.
12	SVDs Get Degrees	0.89979	**5.4246**	**0.6531**	0.89927	5.4793	115	May 27, 2018, 4:16 p.m.
13	The Blend and Snap	0.90216	**5.1755**	**0.5293**	0.90128	5.268	79	May 28, 2018, 9:59 p.m.
14	Math Dot Random	0.90531	**4.8444**	**1.0921**	0.90423	4.958	71	May 28, 2018, 9:51 p.m.
15	treading water	0.90615	**4.7561**	**0.0000**	0.90522	4.8539	186	May 28, 2018, 8:12 p.m.
16	Lonely at the Bottom	0.90881	**4.4766**	**0.0088**	0.90806	4.5554	251	May 28, 2018, 9:52 p.m.
17	Pumpkin	0.91048	**4.301**	**0.2131**	0.90992	4.3599	36	April 21, 2018, 11:17 a.m.
18	bonbons	0.92564	**2.7076**	**0.0317**	0.92458	2.819	47	May 28, 2018, 4:02 p.m.
19	choutap4	0.92729	**2.5342**	**0.9813**	0.92640	2.6277	20	May 22, 2018, 9:17 a.m.


1ST ROUND GAME 2
BOS 20
NY 23
1ST
00.0
TNT


GOOOOOOOOOOOOAL!!

Analysis and Observations

- Increasing number of latent factors in SVD, SVD++, timeSVD++ always decreased the RMSE when all other parameters are the same
- Initialization of decomposed matrices in SVD and related models matters a lot
  - SVD: best performance when initialized to small random numbers [0, 1/sqrt(k)]
- Loading all user x movie size matrices (C++ code) in the first pass dramatically sped up training
- Replacing all 5's and above with 4.9 improved score marginally
- timeSVD++ and SVD++ (with the same number of latent factors as SVD) took 3 times longer to run per epoch, compared to SVD
- Using probe data for blending results from the same model gave worse performance than training on blend data

Conclusions

- Parameter tuning is just as important as model selection
- SVD and its more complicated variations are very effective
    - increasing latent factors decreases RMSE
- Runtime was our biggest challenge.

Things We Would Change

- Test additional parameter combinations to optimize them as best as possible
  - Time taken per epoch was a major obstacle during testing (up to 25 min per epoch)
- Use more powerful machines to test faster
- Spent more time tuning SVD++ and timeSVD++
- Create own models instead of using well-known/existing ones

UPDATE: OUR LIVES ARE FYNE!!1!