Amazon Recommendation Systems: Comparison Analysis between Traditional Techniques and Neural Embedding

JeongWoo Ha [* 1 2] **Se Won Jang** [* 2] **Simon Kim** [* 2]

1. Motivation

Measuring similarities between two different items has been a focus of active research in the field of Recommender Systems. Specific designs of collaborative filtering systems differ greatly between industries and markets, but most of them share a common structure of Market-Basket Model, in which we make an assumption that with large volume of data, we can effectively recommend items based on basket co-occurrence.

A very common approach among such systems is to perform graph traversal techniques on a basket-to-item bipartite graph and generate a set of co-purchased candidates. However, this method has critical drawbacks to consider. First, graph traversal techniques are very sensitive to traversal hyperparameters. How far do we drift apart from the starting item? How many steps do we perform to find the right balance between exploration and exploitation? More importantly, how do we model the relational information between these items? These are all common challenges that such graph-traversal based recommender systems face.

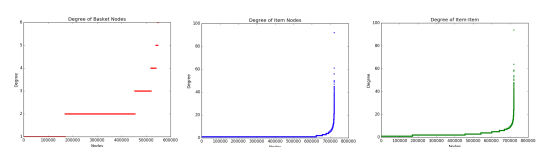
2. Related Works

Li[1] suggests a kernel-based recommendation approach that indirectly inspects customers and items related to user-item pair to predict whether an edge may exist between them. One limitation of this design, however, is that it can only work with nodes that are indirectly connected. To complement for the limitation, the model in the paper inspects structural commonalities of various parts of a network based on the examination of previous graph kernels. This graphical representation has been used for training the model on different graphs to devise a better recommendation system for predictions.

Mikolov et al[2] explore and evaluate a technique to embed natural language words in d-dimensional vector space, now commonly known as the word2vec model. The paper proposes multiple techniques to achieve this, which the paper describes as the CBOW (Continuous Bag of Words) model and the Skip-gram model. Although the two methods differ in the way the neural network is trained, they share the same philosophy in the sense that the neural network behaves as a form of autoencoder in which one of its layers, the weight matrix, represents a concatenation of vector representation of the natural language vocabulary. More importantly, this paper explores the capability of capturing word analogies. Certain relational properties between natural language words can be described as vector operations, such as (Men-Women) - (King-Queen), which can potentially provide interesting recommendations that traditional techniques cannot generate.

3. Data

We used the Amazon Product Co-Purchasing Network metadata provided by SNAP available at http://snap.stanford.edu/data/amazon-meta.html. This dataset holds a variety of product purchase metadata of 721,342 items, including product categories, reviews, and aggregated, filtered lists of co-purchased products ranging from books, music CDs, DVDs, and VHS video tapes. About 72% of the data is books, 3% are DVDs, 20% are music CDs, and 5% are videos. The lists of co-purchased products are not sampled from unique sessions, but is each an aggregation of co-purchase data across multiple user shopping sessions. This dataset does not contain any explicit definition of nodes and edges, and for the purpose of this project we have decided to generate two independent bipartite graphs.



4. Methods

4.1. Collaborative Filtering (CF)

Collaborative filtering (CF) has been a well-known algorithm for recommendation system. CF can be divided into two subcategories: memory-based and model-based CF. For the memory-based CF, the algorithm draws inferences about the

---

[*]Equal contribution [1]In CS229 [2]In CS224W. Correspondence to: JeongWoo Ha <jwha@stanford.edu>, Se Won Jang <swjang@stanford.edu>, Simon Kim <spkim@stanford.edu>.

relationship between different products based on which ones are purchased together. We create a ratings matrix where the rows represent the users and the columns represents the items. After filling up the matrix $R[i][j]$ with the ratings given by user i to the item j, we measure the similarity between any two pairs. Another approach is the model-based collaborative filtering, which is based on matrix factorization, an unsupervised learning method for latent variable decomposition and dimensionality reduction. It has advantages with scalability and sparsity of the matrix compared to the memory-based approach.

4.1.1. Latent Factor Model SVD

The biggest challenge with this model was the size and sparsity ($R^{1.5M \times 400k}$, sparsity$< 0.01\%$). Also, it is important to note that the ratings are influenced by latent factors (e.g. cost, personal preferences, etc.). Thus, we've decided map the user/item features to the latent feature space, and using root mean squared error (RMSE) to minimize the loss. First, using SVD, which decomposes the matrix into three different matrices U, Σ, and V^T, where $R^{m\times n}$, $U^{m\times k}$, $\Sigma^{k\times k}$, $V^{Tk\times n}$, we train k, the number of latent features. Then, with the given k, we train $Q = U$ and $P^T = \Sigma V^T$, using stochastic gradient descent. To address overfitting and improve the accuracy, we add regularization and biases for each user/item feature.

$$\min_{P,Q} \sum_{(u,i\in R)} \left(r_{ui} - q_i \cdot p_u^T \right)^2 + \lambda_1 \sum_u \|p_u\|^2 + \lambda_2 \sum_i \|q_i\|^2$$

and the SGD will be for each r_{ui}

$$\epsilon_{ui} = 2(r_{ui} - q_i \cdot p_u^T)$$

$$q_i := q_i + \mu_1(\epsilon_{ui} p_u - 2\lambda_2 q_i)$$

$$p_u := p_u + \mu_2(\epsilon_{ui} q_i - 2\lambda_1 p_u)$$

4.2. Random Walk

We have a bipartite graph with item nodes on one side and the basket nodes on the other. To get the similarities between two items, it is too costly to iteratively walk through all nodes exhaustively to find the distance between two items. An alternative method to heuristically determine similarity between two items is to perform random walks on two items and find the Jaccard similarity between all the item nodes both walks have landed on.

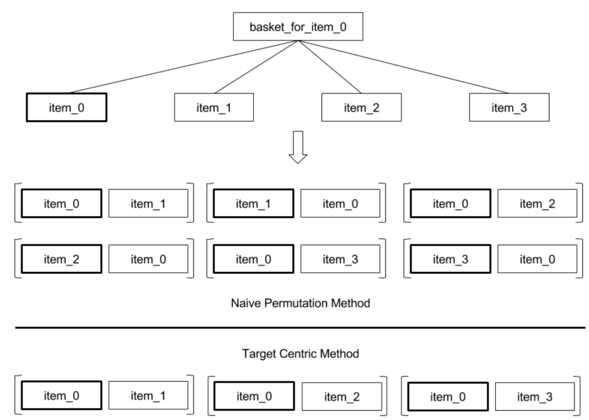
We have three parameters: α, k, and iterations. α determines the probability of the current node of the random walk to be teleported back to the original item; k determines how many steps to walk from the original node; value of iterations determines the number of such k steps to take to be summed to a counter of all the nodes each iteration has finished on. One of the goals of training this model is to perform hyperparameter tuning to find the optimal composition of these parameters.

The end of a random walk on each node will create a counter of nodes it has produced. To heuristically determine the relatedness of two items, we performed the length of the intersection of two counters over the length of the union. As higher values of alpha would teleport the walk back to the origin node, we were aware that the Jaccard similarity values of any pair of nodes would be significantly lower as alpha probability of the final nodes will be the origin node.

4.3. Neural Embeddings Candidate Generation

We explore the effectiveness of Neural Embeddings as a means of co-purchase candidate generation. More specifically, given a co-purchase bipartite graph of baskets and items where each basket holds a flattened representation of multiple user shopping-cart sessions, we analyze the explorative properties of Neural embeddings learned per item.

To do so, we first extract training data from the given bipartite graph with which a word2vec model is trained. Then, upon assigning each item node with its learned high dimensional vector, we run k nearest neighbors over the entire embeddings space to generate the top k candidates.



4.3.1. Training Data Generation

Since the product co-purchase information was aggregated from multiple user sessions, and hence does not capture temporal co-purchase information, our basket-item graph inherently has a low item to item degree distribution. This means that normal skip-gram word2vec model will not perform well, due to the lack of training data. This required us to implement two different train data generation techniques.

First, given a set of co-purchased items for a basket, we apply binary permutation on the set, acquiring the set $(0, 1), (1, 0), (0, 2), ..., (n, n-1)$. The reason that we generate permutation instead of combination is because no autoencoders are guaranteed to be symmetric by nature. This means that the model may learn to successfully output 1 given 0, but not the other way round. Second, we applied a different technique where for each basket a target item was chosen. This is a direct reflection of the property of our dataset, where each co-purchase list was generated for a specific item. Given a target item, and a set of co-purchased items, we generate bi-directional tuples between the target item and each co-purchased item.

Dimension	Epochs	Learning Rate	Loss	Optimization	Negative Sample
128	20	0.03 ~ 0.0001 decayed exponentially by 0.95	Nce loss	Stochastic Gradient Descent	128

4.3.2. Model and Candidate Generation

For the neural embeddings model, we have adopted the word2vec model with noise-contrastive estimation. This is because the vocabulary size of all Amazon products can be much larger than that of a natural language vocabulary. Applying softmax over several hundreds of thousands of multinomial classes can be extremely inefficient. By modifying the multinomial classification problem into a binomial one allows us to train the model much faster.

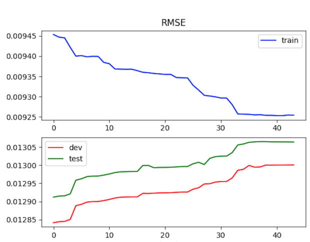
Once we train the object embeddings, we generate recommended candidates by running k-nearest neighbors search on the 128 dimensional space, in terms of cosine similarity. This is a very expensive process, and will likely be very hard to push to a real-time serving system without applying LSH techniques or a large distributed cluster. For the sake of this project however, we simply normalized the embeddings matrix so that each row has norm of 1.0, and ran batched dot product between rows to compute cosine similarities, and generate top 50 candidates.

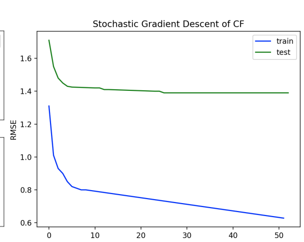
5. Results

5.1. Collaborative Filtering

5.1.1. Paramter Tuning through SVD and SGD

We first use SVD to obtain the value k, which is the number of latent features, that minimizes the loss between the decomposed matrices and the actual ratings matrix. We noticed that for $k > 40$, the change in error for all train, dev, and test dataset was negligible, so we chose $k = 50$ for the number of latent features. With this value, we trained the model Q and P^T with SGD that minimizes the loss. The final set of optimal parameters was $k = 50$, $\mu = 0.04$, and $\lambda_1 = 0.07$, $\lambda_2 = 0.12$.





5.1.2. Distance and Reachability Metrics

	Total queries	Fully reachable	Partially reachable	Not reachable	Mean Distance	Std Distance	Max Distance	Min Distance
Naive	721342	0	562	720780	8.231	15.736	89	1
Targeted	721342	0	703	720639	7.939	12.102	53	1

The results show that the collaborative filtering model has a high maximum distance and standard deviation. This implies that the model could potentially recommend items that Random Walk model cannot. However, it could also mean that the CF model is not as accurate as the Neural Embedding or Random Walk models, especially when the ratings matrix is very large and sparse. Out of 721342 nodes, only 562 and 703 candidate sets were partially reachable from the query item, which shows that over 99.9% of all candidate sets had no reachable nodes from the query node. Thus, this result shows that the CF model may provide insightful recommendations that Random Walk model can't easily, yet the size and sparsity of the given data makes it difficult to always accurately provide appropriate recommendations.

5.1.3. Examples of Qualitative Analysis

The table of qualitative analysis shows some good cases of appropriate recommendations and some bad. From the first row, we can see that although there are some unrelated ones such as 'Seabiscuit,' many of the recommended books are in the scope of some social issues or historical events that are related to social movements. Also, it was pleasing to see that for the second query, the resulting recommendation included almost all books related to some sort of guide. However, many of the recommendations was also very unhelpful like the last row; this shows the crucial weak point of SVD leveraged CF, which is that it could provide bad recommendations due to the significant reduction in the matrix dimension.

Query	1	2	3	4	5
A Cruel Paradise: Journals of an International Relief Worker, Group [Book]	Lords of the Lake: The Naval War on Lake Ontario, 1812-1814 [Book]	Open Society and Its Enemies (Vol 1) [Book]	PLACE AT THE TABLE: THE GAY INDIVIDUAL IN AMERICAN SOCIETY: [Book]	Seabiscuit: An American Legend [Book]	Defying Male Civilization: Women in the Spanish Civil War [Book]
Leopard and Fat-Tailed Geckos: Reptile Keeper's Guide (Reptile Guidebook Series) [Book]	Kitchens: A Design Sourcebook [Book]	Taking Up Riding as an Adult (Horse-Wise Guides Series) [Book]	Poetry As Prayer, Emily Dickinson (The Poetry As Prayer Series) [Book]	Complete Guide to Lock Picking [Book]	Insight Guide Puerto Rico (Puerto Rico, 3rd ed) [Book]
Science As Inquiry: Active Assessment Strategies to Enhance Student Learning [Book]	The Art of Living: The Classic Manual on Virtue, Happiness, and Effectiveness [Book]	Becoming a Chief Home Officer [Book]	Always & Forever: The Classics [Music]	Devotion [Music]	The Opal (Studies in Austrian Literature, Culture, and Thought Translation Series) [Book]

5.2. Random Walk

5.2.1. Hyperparameter Tuning

To observe the effects of changing α, weve initially fixed k to be 10 and performed 100,000 iterations with varying alpha. The resulting distances of two candidate nodes are as follows. Note that weve removed pairs with distance 0.

alpha	Total queries	Mean Distance	Std Distance	Max Distance	Min Distance
0.05	721342	8.02	3.02	10	1
0.1	721342	6.52	3.41	10	1
0.25	721342	3.78	2.77	10	1
0.5	721342	1.99	1.39	10	1
0.8	721342	1.25	0.56	9	1

k	Total queries	Mean Distance	Std Distance	Max Distance	Min Distance
1	721342	1	0	1	1
5	721342	4.09	1.41	5	1
10	721342	6.51	3.41	10	1
100	721342	9.99	9.49	100	1

You can see that α sets the boundary random walks can explore out to. Higher α values prevent the walker from exploring far, and thus the candidates are likely to conservatively explore closer nodes more than further ones.

To observe the effects of changing k, weve fixed α to be 0.1 and performed 100,000 iterations for each value of k. As k increases, the runtime cost rises exponentially because each step increases the number of travelled nodes exponentially.

As k increases, you can see the value approaches $\frac{1}{\alpha}$, which is as expected. Therefore, we can see that k determines how conservative the model should be within the boundary set by α. By setting $k = 100$, we could insure two distant nodes have a higher chance of being selected as candidates for similar items, but because we have around 720k nodes the runtime cost was far too costly for the model to be run with $k = 100$. As a result, for the purpose of this paper weve set the value of k to be 10.

The graph had an average of 2.93 degree in item-to-item relations. The above tables show the effects of changing different parameters. As will be discussed below, recommendations by random-walk are limited to only nodes that are directly reachable from the origin node. This prevents the recommendation from suggesting items that are not directly connected, but still are similar. Below, this paper will show why Neural Embeddings, a non-traditional method, is more successful in specific cases.

5.2.2. Examples of Qualitative Analysis

These qualitative analysis show clearly the strengths and limitations of random walk model. From positive results we can see it is successful in selecting candidates that are in close distance from the origin item node. For items with sufficient neighboring item-item degrees, the random walk can generate candidates with visible similarities between the pairs.

Query	1	2	3	4	5
Prettybelle (1974 Original Cast)	That Travelin' Two-Beat/Sings the Great Country Hits	Beethoven: Symphony No. 9 "Choral"	Passtrak Series 7: General Securities Representation	The Best of Natalie Cole [EMI-Capitol Special Markets]	These Twelve Days: A Family Guide to After-Christmas Celebrations
Guitar Country/ More of That Guitar Country	Finger Style Guitar/ Stringin' Along with Chet Atkins	Hum & Strum / Other Chet Atkins	Most Popular Guitar/Down Home	Mister Guitar/Chet Atkins in Three Dimensions	Essential [Music]
Making Bread: The Taste of Traditional Home-Baking	That Travelin' Two-Beats/Sings the Great Country Hits	Jewish Family and Life : Traditions, Holidays, and Values for Today's Parents and Children	Mathematics of the Securities Industry	The Best of Natalie Cole [EMI-Capitol Special Markets]	These Twelve Days: A Family Guide to After-Christmas Celebrations
World War II Allied Fighter Planes Trading Cards	That Travelin' Two-Beat/Sings the Great Country Hits	Beethoven: Symphonies Nos. 3 "Eroica" & 8	Mathematics of the Securities Industry	The Best of Natalie Cole [EMI-Capitol Special Markets]	These Twelve Days: A Family Guide to After-Christmas Celebrations
Brittas Empire (Vols. 4-6)	Brittas Empire (Vols. 1-3)	That Travelin' Two-Beat/Sings the Great Country Hits	Beethoven: Symphonies Nos. 3 "Eroica" & 8	The Best of Natalie Cole [EMI-Capitol Special Markets]	These Twelve Days: A Family Guide to After-Christmas Celebrations

However, the clustering effect can bring detrimental results to random walks. If an item has no associated items such that it is connected to a single basket, and the basket is also connected only to the origin item node, then regardless of how the random walk is progressed it will not yield significant results, as seen by the first two negative results. The third negative result also shows the limitations of random walk. This is the case where the two books Brittas Empire (Vols. 4-6) and Brittas Empire (Vols. 1-3) are mutually connected via single basket, and these two items are the only ones directly connected. With no teleportation to random nodes, the random walks will be trapped in the cluster of these wo items, and thus apart from recommending one another it will not yield any significant results, as seen from the top candidates. This shows that for network with sparse item-item network, random walk is not the best model to generate similar candidates. This is why this paper suggests Neural Embeddings, as shown below.

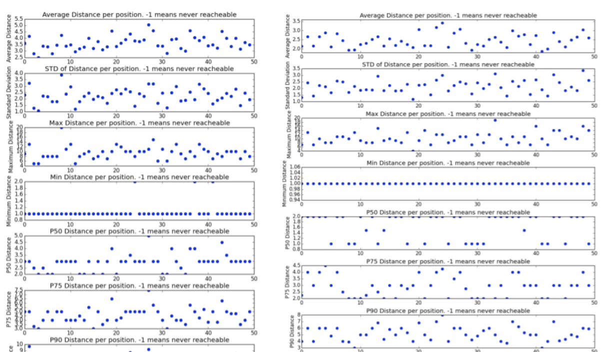
5.3. Neural Embeddings Candidate Generation

5.3.1. Distance and Reachability Metrics

The evaluation results show that Neural Embeddings trained from the two training sampling methods are capable of generating candidates that are unreachable from the query node on the basket-item graph. Out of 721342 total items, only 1102 and 1728 candidate sets contained candidates that were reachable from the query item node. There were 0 candidate set where all of the candidates were reachable from the query node, and over 99.5% of all candidate sets had absolutely none of its candidates reachable from the query node. Even considering the fact that this dataset includes some partial information (some items are only mentioned in the co-purchase list), this is an extremely high number. These numbers suggest that using word2vec embeddings and cosine similarity as the comparator function allows us to capture some complex information that is invisible from the graph structure. In other words, it may be capable of encoding proximity and similarity information that cannot be captured by traditional graph analysis techniques.

	Total queries	Fully reachable	Partially reachable	Not reachable	Mean Distance	Std Distance	Max Distance	Min Distance
Naive	21342	0	1102	7202240	3.637	2.396	20	1
Targeted	721342	0	1728	719614	2.533	2.329	19	1

Only looking at candidates that were reachable on the graph, the distribution of candidate distances per position looks quite uniform throughout the position indices (top 50 candidates), with average distance around $2.5 \sim 3.6$ and standard deviation of 2.3. There are two interesting things to note from this data. First, the distance distribution is not uniform across distances. Second, the distance distribution is quite uniform across candidate positions, at around 3.5 hops from the query node. This means that the word2vec model does not completely ignore the distances between nodes on the graph, but is in fact capable of capturing the proximity of two items on the bipartite graph. If the word2vec model had failed to learn meaningful information, this distribution would have shown uniform-like distribution (BFS tree depth per node for this graph can be over 150).



Left : On-graph distribution per position for naive training sampling method.
Right : On-graph distribution per position for targeted training sampling method

Query	1	2	3	4	5
Creative Thinking in Photoshop [Book - Design]	Dragons: A Book of Designs [Book - Design]	Resonant Power Converters [Book - Engineering]	Security Analysis on Wall Street [Book - Finance]	Construction Qa/Qc Systems that Work [Book - Engineering]	The Self as Agent [Book - Self motivation]
Spanish Complete Course : Basic-Intermediate , Complete Compact Edition [Book - Education]	Crazy in Alabama [Book - Crime]	Tutorials in Introductory Physics and Homework Package [Book - Education]	A Cat in the garden 2002 calendar [Book - Calendar]	Great Expectations [Book - Classics]	The Canoe - A Living Tradition [Book - Education / Nonfiction]
Muslim Rulers and Rebels [Book - History]	Kanzi - the ape at the brink of human mind [Book - Anthropology]	Why the Frog has Big Eyes [Book - Childrens]	Greatest Hits [Music]	Meaning and Mental Representation [Book-Nonfiction]	One Hundred Years of Collectible Jewelry [Book - Antiques]
Air Pollution Engineering Manual [Book - Engineering]	The Complete Guide to Editing Your Fiction [Book - Reference]	The Roses - Pierre-Joseph Redoute [Book - Arts]	Equine Dentistry [Book - Medicine]	Benjamin Smoke [DVD - Documentary]	Life is a Dream [Book]
The Donna Summer Anthology [Music - Disco,Pop,R&B]	Frida Kahlo [Book - Autobiography]	Ian Anderson: Divinities - Twelve Dances with God [Music - Rock]	The Addams Family [Video - Fantasy]	Employee's Entrance [Video - Drama]	Wireless Video Communications [Book - Engineering]

5.3.2. Examples of Qualitative Analysis

Its very hard to measure the quality of a recommender system without a way to measure the online performance. So in this paper, we provide a few good and bad examples to demonstrate the type of recommendations that this model makes. These samples were chosen from top 10 candidate sets in terms of their distances away from the query item. Here, the average distance from the query items are between 10 and 20 ($10 \sim 20$ random hops away from the query item). We can say however, that they are well beyond the discovery scope of traditional graph recommender technique.

5.4. Analysis

Random-walk algorithm is limited for sparse graph structures, as seen above. It is limited to suggesting candidates that are directly connected by edges, and also cannot travel to nodes that are further away in distance yet still may be similar. Also, it is vulnerable to clustering effects. If a basket only contains two items, and each of the items is only connected to one another, the random-walk algorithm will be limited to suggesting only each other as the most similar candidate and fail to explore to look at others.

Collaborative filtering is more successful in attempting to capture similarities of two items that are not necessarily connected, as seen by the results above. However, we can see that this model is vulnerable to sparse dataset. If the ratings matrix is too sparse, then even with the SVD the model will be unsuccessful in capturing meaningful similarities between two items due to enormous amount of noise that arise.

From the results we can see that the neural embeddings model is successful in capturing similarities between two items that are not directly connected to each other. The distance between the target item and the candidate nodes are significantly small enough to suggest meaningful similarities, as seen by our qualitative analysis of the results. In addition, it is successful in capturing similarities between partially reachable item nodes as well. Therefore, we can conclude that for dataset with sparse ratings matrix, a significant number of disconnected nodes, and clustering effects, neural embeddings model can perform better than the traditional models.

6. Conclusion

This paper looked into traditional recommender system models, such as Collaborative Filtering and Random-Walk algorithms. We could see that for sparse datasets, these models are not successful in capturing similarities of items that are not directly connected by graph structures. As a result, we have looked into an alternative to recommender systems - Neural Embeddings, which we could see is more successful in capturing embedded similarities between items that are not directly connected. We believe this paper will be a stepping stone to providing an alternative model to traditional models.

Acknowledgements

Project TA Lucio Dery has provided some great insights to improve our CF model. Since our dataset was too big, we were stuck in terms of how to calculate the similarity matrix for the ratings. Lucio guided us to look through various optimized CF models to help solve the challenges.

References

[1] Li, X. & Chen, H. (2013). Recommendation as link prediction in bipartite graphs: A graph kernel-based machine learning approach. *Decision Support Systems*, 54(2), 880-890.

[2] Mikolov, Tomas, et al. (2013). Efficient Estimation of Word Representations in Vector Space. [1301.3781]

[3] Videla-Cavieres, Ivan F., and Sebastian A. Rios. (2014). Extending market basket analysis with graph mining techniques: A real case. *Expert Systems with Applications*, 41(4), 1928-1936.

[4] Gutmann, M. & Hyvarinen, A. (2010). Noise-contrastive estimation: A new estimation principle for unnormalized statistical models. *PMLR*, 9:297-304.

[5] Zhou, Y., et al. (2008). Large-Scale Parallel Collaborative Filtering for the Netflix Prize. *AAIM*, 5034:337-348.

Contributions

We all came up together with the methods to tackle the recommender systems. After many brainstorming sessions and initial tests, we came up with three different approaches.

JeongWoo Ha worked on the Collaborative Filtering. He parsed the data and created framework to run various methods of CF. He ran the initial experiments using PCA to reduce matrix dimensionality. He also modeled SVD in our dataset and designed SGD methods with biases for optimization. He discussed potential pitfalls and challenges with projects TAs. He also contributed in creating testing classes for the result. He contributed in writing the paper.

Se Won Jang worked on the Neural Embedding part. He designed the framework for leveraging word2vec model in this setting. He created the bipartite graph models to analyze the basket-item model that we are implementing. He also contributed in creating testing classes for the result. He also contributed in writing the paper.

Simon Kim worked on Random Walk algorithm. He wrote the parser to organize raw data, and created algorithms for RW. Simon also worked on the preliminary work on graph traversal to calculate the distance (similarity) between items. He also contributed in writing the paper.