Rent It Again? Incorporating Re-Rent Information for Generating Recommendations in the Clothing Rental Industry

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ABSTRACT

The fashion industry's significant contribution to global carbon emissions highlights the urgent need for sustainable alternatives to traditional clothing consumption. This study explores the potential of incorporating re-rent information to enhance recommendation systems within the clothing rental sector, using the "Vibrent Clothes Rental Dataset." By analyzing customer rental patterns and preferences, I investigate the effectiveness of "Buy It Again" recommendation methods, adapting them to the context of clothing rentals. My approach extends beyond conventional recommendation techniques by integrating the frequency of repeated rentals as a key factor in predicting customer preferences. The experiments involved re-splitting the dataset to include a validation set and tuning hyperparameters to optimize model performance. The results indicate that models accounting for re-rentals significantly improve recommendation quality across various metrics, including hit rate and precision. This suggests that leveraging repeat rental behavior can lead to more accurate and personalized recommendations. Furthermore, my investigation into content-based encoding methods reveals that incorporating repeat rental counts as a feature enhances recommendation accuracy, demonstrating the importance of feature engineering. This study underscores the value of integrating repeat rental information to refine recommendation systems, offering a pathway towards promoting sustainable consumption practices in the fashion industry.

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1 INTRODUCTION

Reports indicate that fashion production accounts for up to 10% of global carbon emissions, with 85% of textiles discarded annually [20]. The European Union reports that only 1% of used clothes are recycled into new garments, while in 2020, the average person's textile consumption within the EU resulted in a carbon footprint of 270 kg [8].

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One potential solution is to shift the fashion industry's business model from purchasing clothing to renting it. This concept led to the founding of Vibrent, a Norwegian company established in 2016 with the aim of offering consumers a sustainable way to enjoy fashion without the waste associated with buying new clothing [5].

In their 2024 study, Borgersen, et al. highlighted the lack of datasets for recommendation systems in the clothing rental industry. Consequently, they partnered with Vibrent to create a new dataset named the "Vibrent Clothes Rental Dataset" [2]. The objective of their study was to introduce this new dataset and establish basic recommendation methods as a baseline for future research. Upon reviewing their results, it is evident that recommending outfits previously rented by customers proved to be one of the most effective methods, with a Hit@10 score of 0.0546. This was second only to combining it with popular outfit recommendations, which achieved the best result, with a Hit@10 score of 0.0607. [3] (Note: these results were reported in the original paper and are not the baseline I will use, as I have re-split the training and test data).

In this work, I will present my attempts to improve upon the initial results from the original study. This includes implementing additional recommendation methods, such as Collaborative Filtering with Item-Based Nearest Neighbors, reporting results for methods that were initially implemented but not reported, and adding more evaluation metrics to provide a more comprehensive analysis.

Nonetheless, the primary goal of this article is to demonstrate the integration of re-rent information into various models by implementing "Buy It Again" methods on this dataset. As previously mentioned, recommending outfits that customers have already rented proves to be one of the most effective strategies. My exploration of the data (discussed in the Data section) further reveals that most customers tend to rent outfits they have rented before. In detail, I will integrate the frequency of repeated rentals as a key factor in predicting customer preferences, including both by reordering the recommendations and using it as a feature in content-based approaches. Additionally, I will explore using it as an implicit rating that the customer could assign to the outfit.

All code associated with the project have been made available at: NettaMendel/RecSys_Project_Rent_It_Again_Vibrent

2 RELATED WORK

Due to the limited research on fashion rental recommendation systems — where a search for relevant studies primarily leads to the work of Borgersen et al. — I will review several related domains. These include fashion retail recommendation systems, research in the field of fashion rental (encompassing business models, technology, and customer perspectives), recommendation systems in other rental-based industries, and the only other existing dataset in this field besides that of Borgersen et al., along with its limitations. Finally, I will discuss previous research on "Buy It Again" recommendation systems, which serve as the inspiration for my approach. Note that I will not revisit the work of Borgersen et al. in this section, as I have already reviewed it in the introduction and will continue the review in The Data section.

2.1 Fashion Retail Recommendation Systems

In contrast to the limited research on fashion rental recommendation systems, the broader field of fashion recommendation is well-established. Deldjoo et al. [6] conducted an extensive literature review on recommender systems for various aspects of clothing sales, covering feature generation methods, prediction algorithms, generative models, evaluation techniques, and existing datasets. Additionally, numerous datasets are available in this domain, including the H&M dataset [12]

2.2 Fashion Rental

Charnley et al. [4] conducted a survey on methods and technologies related to second-hand clothing stores. The Ellen MacArthur Foundation [7] analyzed how the structure of the fashion industry can be transformed into a more sustainable model — one that is economically, socially, and environmentally beneficial, rather than treating clothing as an almost disposable product. Lang, Li, and Zhao [17] explored user responses to fashion rentals using text mining techniques. Mukendi et al. [22] explored ways to develop a fashion rental business that meets the needs of current consumers, based on consumer perspectives of the fashion rental industry, extracted from interviews.

2.3 Rental Recommendation Systems

Rental recommendation systems exist in many domains, each with its own set of research approaches. First, I will mention the real estate rental field. For example, Gharahighehi et al. [11] surveyed this area; however, it is primarily focused on long-term rentals and addresses challenges more akin to those in the purchasing domain rather than renting, making it less relevant to my work.

A domain more similar to the focus of this study is library book rentals. For instance, Iqbal et al. [14] developed a recommendation system for a Korean library. Additionally, I will mention the work of Ismaeel et al. [15], who created a recommendation system for a general domain rental marketplace.

2.4 Existing Dataset

The only other existing dataset for fashion rentals is Rent the Runway [16], published in [21]. However, the limitation of this dataset is that it focuses on stock performance and does not include the customers who rented the outfits or any details about the clothing itself, unlike the dataset from Borgersen et al., Therefore, it is challenging to base a recommendation system on this dataset.

2.5 Repeat Purchase Recommender

Bhagat et al. [1] describe several models designed to ranking repeat purchase recommendations. Specifically, they present four models, all based on statistical analysis of customer data, leveraging different distributions of various data segments to predict when a customer is likely to repurchase the same product. These predictions are then used to generate and rank recommendations accordingly.

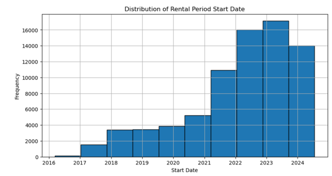

Figure 1: Distribution of Rental Start Time.

Park et al. [23] and Wang et al. [24] explore the application of the Hawkes process in repeat purchase recommendations, accounting for both short-term and long-term repurchase behaviors. The Hawkes process is a statistical model used to analyze event sequences, characterized by a self-exciting property — where the occurrence of an event increases the likelihood of subsequent events in the near future [18].

Ludewig et al. [19] take a different approach, focusing on recommending previously listened-to songs to users. Their model incorporates the number of times a user has listened to a particular song as a key feature, along with additional derived features.

3 THE DATA

The dataset contains **15.6K unique outfits**, grouped into **9.7K outfit groups**, with **7.4K anonymized users** and **50.1K outfit images**. It includes **77.1K transactions**, each specifying the customer, the rented outfit, and the rental period (start and end time). Each outfit is associated with multiple tags, categorized into **11 Categories**: *Brand, Gender, Length, Occasion, Seasons, Category, Details, Fit*, among others [3]. Notably, an outfit can have multiple tags within the same category, with a maximum of 12 different colors assigned to a single outfit.

The dataset spans orders from **2016 to 2024**, with the majority occurring between **2022 and 2024**, as illustrated in Figure 1. Most rentals last approximately **one month**, with a smaller portion lasting **one week** and only a few spanning **between one week and two months**, as shown in Figure 4 in the appendix.

When analyzing the categories, I observed that, except for **Gender** and **Length**, the number of outfits assigned to a specific tag closely matches the number of rental orders for that tag. Figure 3 in the appendix provides an example of this for the **Category** attribute. Additionally, the **average rental price per tag** remains relatively consistent across tags.

Regarding **Gender**, the dataset includes **only 62 outfits for men**, making comparisons between gender-based tags less meaningful. Moreover, men's outfits were rented very infrequently. As for **Length**, while the distribution of outfits and rentals is similar, it is worth noting that **longer garments tend to have higher rental prices**, as depicted in Figure 5 in the appendix..

When examining repeat rentals, the data shows that **16.03% of customers** rented the **same outfit** more than once, while **15.13% of orders** were repeat rentals. Additionally, **29.91% of outfits** were rented more than once by the same customer. At the **group level**, **17.26% of customers** rented from the **same outfit group** more

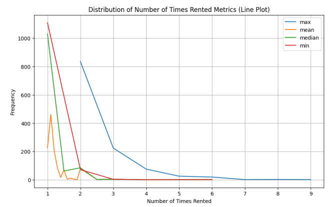

Figure 2: Distribution of Number of Times Rented Metrics

than once, and **18.06% of orders** were for a rental from a previously rented group. Furthermore, **39.69% of groups** were rented more than once by the same customer. Figure 2 illustrates the distribution of the **mean, maximum, minimum, and median** number of times a customer rented an outfit. *(Note: In this plot, customers who rented each outfit only once were filtered out.)*

Given that most orders were placed between **2022 and 2024**, I examined the effect of filtering out earlier orders. When excluding rentals before **January 1, 2020**, the percentage of customers who rented an outfit more than once increased to **30.13%**, while the percentage of repeat orders remained nearly the same at **15.43%**. Filtering further to exclude rentals before **January 1, 2021**, the percentage of repeat customers rose to **36.69%**, and for orders placed after **January 1, 2022**, this percentage further increased to **38.40%**. However, the percentage of repeat orders remained relatively stable at **15.51%** and **15.40%**, respectively.

4 THE METHOD

All the following methods were applied to both individual outfit prediction and group prediction.

In Borgersen et al. [3], several basic recommendation methods have already been implemented. I will not explain them in detail but will briefly mention them. For a detailed explanation, please refer to their work.

They categorize the methods into three types:

- **Baseline**
  - **Most Popular**
  - **Previous Rental** – Recommends outfits that the customer has previously rented.
  - **Previous Rental + Most Popular** – A combination of the two previous methods.
  - **Random** – Implemented by them but not reported in the article.
- **Collaborative Filtering**
  - ALS
  - BPR

  Both are Matrix Factorization-based methods.
- **Content-Based**
  - **Tag Encoding** – Multi-label encoding of the categories.
  - **Picture Embedding** – Based on embeddings extracted by an auto-encoder from outfit images.
  - **Combined Embedding** – Uses embeddings extracted by an auto-encoder, combining picture embeddings and tag encoding (implemented by them but not reported in the article).
  - **Concatenate** – Creates a single vector by concatenating picture embeddings and tag encoding(implemented by them but not reported in the article).

  For all these methods, they use Nearest Neighbor techniques to generate recommendations.

To these, I add a few more basic methods:

- **Collaborative Filtering**
  - Logistic Matrix Factorization
  - Item-Based Nearest Neighbor
  - BM25 Nearest Neighbor

Based on insights gained from my data exploration, I developed my own encoding method. Table 1 presents the columns I used and the possible values for each. Most of the values are binary, with each outfit being tagged according to the categories it belongs to. For the price feature, I opted to use the monthly rate, as the majority of orders spanned this period. For size and length, which have an inherent order, I converted them to numerical values. It is important to note that the length encoding is based on [13], while the size was originally represented in two different sizing systems. I unified them into a single system based on [10]. (will be refred as my encoding)

4.1 Repeat Rent

In this section, I implemented a few approaches.

First, Borgersen et al. [3] applied Collaborative Filtering based solely on whether a customer rented an outfit, without considering the frequency of repeated rentals. However, since many customers repeatedly rented the same outfit, this behavior indicates a strong preference for those items. Therefore, I extended the Collaborative Filtering approach by incorporating this information. Specifically, I treated the number of times a customer rented an outfit as their implicit "rating" of it. I recommend outfits with a rating of 2 or higher.

To implement this approach, I experimented with the following methods:

- Nearest Neighbor - both item based and user based (will be refred as NN_rating)
- SVD (will be refred as SVD_rating)
- SVD++ (will be refred as SVD++_rating)
- Non-negative Matrix Factorization (will be refred as NMF_rating)

In the second approach, I examined whether changing the order of recommendations could have a positive effect. To achieve this, I modified the *Previous Rental* and *Previous Rental + Most Popular* methods by reordering the recommendations based on the number of times a customer had rented each outfit in the training and validation sets. These modified methods will be referred to as *Previous Rental with Order* and *Previous Rental + Most Popular with Order*.

In the third approach, I considered the number of times a customer rented an outfit as a feature. I incorporated this feature into the various encodings described in the content-based approach of the original study, as well as into my encoding. However, I could not add this feature to any other content-based implementation—essentially, to any model that actively learns—because the feature would always have a value of 1 or more for positive samples and 0 for the generated negative examples. These modified

Column	Outfit_id	Norm. Price Per Month	Spring	Summer	Winter	Fall	Brand_1	…	Brand_n
Values		0-1	0/1	0/1	0/1	0/1	0/1		0/1
Color_1	…	Color_n	Fit_1	…	Fit_n	Female	Male	Material_1	…
0/1		0/1	0/1		0/1	0/1	0/1	0/1	
Material_n	Occasion_1	…	Occasion_n	Size	Length				
0/1	0/1		0/1	1-10	0/0.5/1				

Table 1: An example of my encoding, showing the possible values for each column.

approaches will be referred to as *Tag Encoding with Repeat Count*, *Picture Embedding with Repeat Count*, *Combined Embedding with Repeat Count*, *Concatenate with Repeat Count*, and *My Encoding with Repeat Count*.

5 EXPERIMENTS AND EVALUATION

For my experiments, I re-split the data to include a validation set in addition to the original train and test sets. As a result, I adjusted the proportions of each set to 20% for testing, 10% for validation, and the remaining 70% for training. The split was performed chronologically: the training set contained the customer's oldest orders, the validation set included more recent orders, and the test set comprised the newest orders. I chose this approach to ensure that newer orders were not used to predict older ones. This methodology is similar to the approach taken by Borgersen et al. [3], except that they split the data into only training (70%) and test (30%) sets.

I excluded customers who had only a single order, as they were stored in a separate table in the original dataset. Additionally, if a customer did not have enough orders to be included in all three sets, I prioritized the test and training sets over the validation set.

I also incorporated hyperparameter tuning into all Collaborative Filtering methods, including my rating-based approach. However, I did not apply hyperparameter tuning to the content-based method using k-NN, as its only hyperparameter is the number of nearest neighbors, which was already determined by the number of outfits used for evaluation.

In the Results section, I will report the hyperparameters that produced the best results during the tuning process. These hyperparameters are as follows:

- **ALS**:
  - **test_factors**: 48
  - **test_regularization**: 0.005
- **BPR**:
  - **test_factors**: 216
  - **test_regularization**: 0.02
  - **test_learning_rate**: 0.005
- **LMF**:
  - **test_factors**: 64
  - **test_regularization**: 0.01
  - **test_learning_rate**: 0.005
- **NN**:
  - **k**: 10
- **BM25**:
  - **k**: 10
  - **k1**: 100
  - **b**: 0.9
- **KNN_rating outfits**:
  - **k**: 5
  - **name**: 'cosine'
  - **min_support**: 1
  - **user_based**: False
- **Group**:
  - **k**: 5
  - **name**: 'cosine'
  - **min_support**: 1
  - **user_based**: False
- **SVD_rating outfits**:
  - **n_factors**: 50
  - **n_epochs**: 10
  - **lr_all**: 0.01
  - **reg_all**: 0.05
- **Group**:
  - **n_factors**: 50
  - **n_epochs**: 10
  - **lr_all**: 0.01
  - **reg_all**: 0.05
- **SVD++_rating outfits**:
  - **n_factors**: 50
  - **n_epochs**: 10
  - **lr_all**: 0.01
  - **reg_all**: 0.05
- **Group**:
  - **n_factors**: 50
  - **n_epochs**: 10
  - **lr_all**: 0.01
  - **reg_all**: 0.05
- **NMF_rating outfits**:
  - **n_factors**: 10
  - **n_epochs**: 50
  - **reg_pu**: 0.06
  - **reg_qi**: 0.06
- **Group**:
  - **n_factors**: 10
  - **n_epochs**: 50
  - **reg_pu**: 0.06
  - **reg_qi**: 0.06

I used grid search to optimize the hyperparameters, selecting the best configuration based on the validation set. The evaluation criterion for hyperparameter selection was hit@10. However, I did not use cross-validation for grid search.

The final model performance was evaluated using the following metrics [9]:

- Hit rate at 10 – Measures the proportion of users who receive at least one relevant recommendation.
- Precision at 10 – Measures the proportion of relevant items among the top 10 recommendations.
- Recall at 10 – Measures the coverage of relevant items within the top 10 recommendations.
- F1 score (at 10) – A metric that balances Precision and Recall.

I selected k=10 because I wanted a relatively small number of recommendations that a customer would still have patience to review.

6 RESULTS

Table 2 presents the results for individual outfit prediction. When comparing the baseline methods with and without ordering by the number of times an outfit was re-rented, it is evident that ordering improves both the hit rate and precision. However, it does not enhance recall or the F1 score.

When comparing the content-based encodings with and without the repeat rent count, the inclusion of this feature generally led to equal or better results across all encoding methods and evaluation metrics—except for my encoding. In general, my encoding did not perform well, particularly in comparison to the original tag encoding. However, when the repeat rent count was incorporated, it improved the hit rate and precision but did not enhance recall or the F1 score.

For methods that treated the re-rent count as a rating, the performance remained consistent across all metrics. This is likely because the predicted "ratings" did not differ significantly, and after filtering to determine recommendations, the final results remained the same. Overall, these methods achieved good precision but performed poorly in the other evaluation metrics.

Table 3 presents the results for group prediction. In general, these results closely resemble those for individual outfit prediction, with some instances where the first and second places switched, such as in recall. The only notable difference is in the F1 score, where Previous Rental + Most Popular with Order emerged as the best-performing method.

7 DISCUSSION AND FUTURE WORK

In general, addressing re-rent cases has a positive effect on the model. Models that accounted for re-rent cases in some way achieved the best performance across all metrics for group prediction. For individual outfit prediction, this was also true for all metrics except the F1 score, where the second-best model still incorporated re-rent information. This suggests that future research should further explore how to effectively integrate re-rent cases into recommendation models.

For instance, I attempted to use the Hawkes process, as done by Park et al. [23] and Wang et al. [24], but was unable to do so due to resource limitations.

Another important direction for future research is evaluating whether an outfit was available when the customer intended to rent it. I attempted to explore this but found very little literature on the subject. This lack of prior work prevented meaningful contributions in this area, mainly due to challenges in evaluation. Specifically, the dataset only includes completed orders—meaning that only outfits available at the time of the customer's order are recorded. As a result, the potential impact of availability-based approaches cannot be observed in the results.

The results also show that tag and content-based encodings outperformed picture and outfit embeddings. This may suggest that the embeddings generated by the autoencoders could be improved. In my work, I did not attempt to refine this aspect and instead used the embeddings and autoencoder configurations exactly as they were in the original study. However, I did notice that the autoencoder used for outfit embedding had only two layers for encoding and two for decoding, with a very small number of training epochs. Adjusting these parameters might yield better performance. Another possible improvement could be replacing the autoencoder-based approach (which is later used with a k-NN model) with a fully neural network-based recommendation process.

Finally, another crucial direction for future exploration is implementing different model types for the content-based approach, beyond k-NN. I attempted to use both CatBoost and gradient boosting but obtained a score of zero across all evaluation metrics. This suggests that there was an issue with my implementation, but I was unable to identify the exact cause.

8 CONCLUSION

In this study, I explored the impact of incorporating repeat rental information into a recommendation system for a clothing rental platform. My approach was not to introduce entirely new methodologies but to refine and enhance existing recommendation techniques. This involved adapting "Buy It Again" methods to the clothing rental sector, leveraging the frequency with which customers re-rented items as a key indicator of preference.

The results of my experiments demonstrate that accounting for re-rentals can indeed improve recommendation quality. Specifically, models that considered re-rentals, such as the "Previous Rental with Order" and "Previous Rental + Most Popular with Order" methods, showed enhanced performance across various evaluation metrics. This suggests that even subtle adjustments, like reordering recommendations based on rental frequency or treating repeat rentals as implicit ratings, can lead to significant improvements in recommendation accuracy.

Furthermore, my investigation into different encoding methods, particularly the content-based approaches, revealed that incorporating repeat rental counts as a feature generally led to better results. This highlights the importance of feature engineering and the potential benefits of leveraging existing data in nuanced ways.

In conclusion, this study underscores the value of integrating repeat rental information into recommendation systems. It highlights that significant improvements can often be achieved through incremental refinements of existing methods.

9 ACKNOWLEDGMENTS

I would like to express my sincere gratitude to Dr. Adir Solomon for his guidance throughout this work, both in understanding the methods used and in helping to identify promising directions for exploration in this study.

Method Type	Method	outfit hit rate@10	outfit precision@10	outfit recall@10	outfit f1 score@10
Baseline	Previous rental + Most popular	0.04874	0.00513	0.02492	**0.00716**
	Previous rental	0.04284	0.00454	0.01914	0.00609
	Most popular	0.01744	0.00185	0.00950	0.00264
	Random	0.00282	0.00028	0.00095	0.00031
Baseline With Order	Previous rental + Most popular with order	**0.05003**	0.00528	0.02451	0.00711
	Previous rental with order	0.04464	0.00475	0.01912	0.00613
Collaborative Filtering	ALS	0.02950	0.00310	0.01055	0.00396
	BPR	0.02617	0.00262	0.01110	0.00340
	NN	0.02335	0.00236	0.01228	0.00332
	BM25	0.01052	0.00108	0.00675	0.00156
	LMF	0.00180	0.00018	0.00053	0.00023
Collaborative Filtering - Rating Based	KNN rating	0.02540	**0.00680**	0.00371	0.00437
	NMF rating	0.02540	**0.00680**	0.00371	0.00437
	SVD rating	0.02540	**0.00680**	0.00371	0.00437
	SVD++ rating	0.02540	**0.00680**	0.00371	0.00437
Content-Based	Tag encoding	0.04669	0.00482	0.02790	0.00688
	concatenated embeddings	0.04438	0.00459	**0.03076**	0.00702
	picture embeddings	0.02950	0.00295	0.02435	0.00488
	outfit embeddings	0.02771	0.00277	0.02008	0.00438
	my encoding	0.02488	0.00254	0.02234	0.00431
Content-Based With Repeat Count	Tag encoding with repeat count	0.04823	0.00498	0.02882	0.00711
	concatenated embeddings with repeat count	0.04438	0.00459	**0.03076**	0.00702
	picture embeddings with repeat count	0.02950	0.00295	0.02435	0.00488
	outfit embeddings with repeat count	0.02771	0.00277	0.02008	0.00438
	my encoding with repeat count	0.02463	0.00251	0.02232	0.00428

Table 2: The results for individual outfit prediction.

Method Type	Method	group hit rate@10	group precision@10	group recall@10	group f1 score@10
Baseline	Previous rental + Most popular	0.05849	0.00641	0.02561	0.00837
	Previous rental	0.05644	0.00621	0.02369	0.00800
	Most popular	0.02950	0.00321	0.00755	0.00347
	Random	0.00667	0.00072	0.00120	0.00067
Baseline With Order	Previous rental + Most popular with order	**0.06311**	0.00708	0.02510	**0.00857**
	Previous rental with order	0.06183	0.00698	0.02383	0.00835
Collaborative Filtering	ALS	0.04284	0.00475	0.01387	0.00560
	BPR	0.03181	0.00331	0.01267	0.00422
	NN	0.03874	0.00403	0.01881	0.00549
	BM25	0.01411	0.00141	0.00914	0.00210
	LMF	0.00334	0.00033	0.00103	0.00039
Collaborative Filtering - Rating Based	KNN rating	0.04233	**0.01249**	0.00797	0.00853
	NMF rating	0.04233	**0.01249**	0.00797	0.00853
	SVD rating	0.04233	**0.01249**	0.00797	0.00853
	SVD++ rating	0.04233	**0.01249**	0.00797	0.00853
Content-Based	Tag encoding	0.05362	0.00557	0.03149	0.00796
	concatenated embeddings	0.04720	0.00487	0.03261	0.00747
	picture embeddings	0.03181	0.00318	0.02587	0.00524
	outfit embeddings	0.03027	0.00303	0.02108	0.00469
	my encoding	0.03771	0.00382	0.02624	0.00584
Content-Based With Repeat Count	Tag encoding with repeat count	0.05387	0.00559	**0.03261**	0.00808
	concatenated embeddings with repeat count	0.04720	0.00487	0.03261	0.00747
	picture embeddings with repeat count	0.03181	0.00318	0.02587	0.00524
	outfit embeddings with repeat count	0.03027	0.00303	0.02108	0.00469
	my encoding with repeat count	0.03771	0.00382	0.02624	0.00584

Table 3: The results for group prediction.

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A DECLARATION OF TOOLS AND RESOURCES USED DURING THE STUDY

I, **Neta Mendelbaum**, hereby declare that during the course of my study, I utilized the following tools and resources:

- **ChatGPT** – Primarily for linguistic editing and improving the clarity and academic quality of my writing.
- **Microsoft Copilot** – For code creation and modification to support the development and refinement of my implementation.
- **Publicly Available GitHub Repositories** – Including, but not limited to, the code of Borgersen et al. and other open-source resources relevant to my research.
- **Online Search Resources** – Information obtained through searches using Google and Google Scholar, as referenced in the study.
- **Google Gemini** – Used for the creation of the abstract and conclusion of the study.
- **Google Colab** – For code editing and AI-generated code completion recommendations.
- **sklearn** – Used for machine learning algorithms and preprocessing.
- **torch** – For neural network model implementation.
- **surprise** – For building recommendation systems.
- **implicit** – Used for collaborative filtering in recommendation systems.

All sources and tools have been used in accordance with ethical guidelines, and appropriate citations have been provided where applicable.

Neta Mendelbaum 02/2025

B EXPLORATION

Comparison of Rentals per Tag with Outfits per Tag - Category: Category

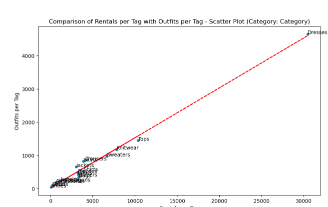

Figure 3: Comparison of Rentals per Tag with Outfits per Tag - Category: Category

Distribution of Rental Period

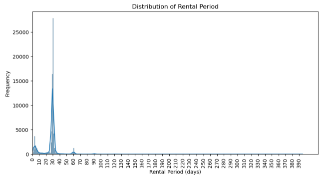

Figure 4: Distribution of Rental Period

Average Prices for Each Tag (Length)

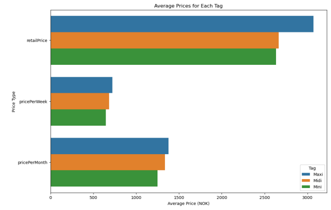

Figure 5: Average Prices for Each Tag (Length)