Improving Fashion Rentals with Recommender Systems

Figure 1: image from Emil Kristensen, CMO of Drip

ABSTRACT

Online apparel rentals face challenges in providing accurate fit and size recommendations to enhance customer satisfaction and reduce returns. This study uses the RentTheRunway dataset, which includes user reviews, fit feedback, ratings, and measurements, to address these issues. We explore predictive tasks such as fit prediction, size recommendation, and sentiment analysis. Using machine learning models, we demonstrate how customer and item data can improve personalization and operational efficiency in the fashion rental industry.

1. INTRODUCTION

Online shopping and rental services have transformed the fashion industry, but ensuring optimal fit remains a challenge, particularly in apparel rentals where mismatches increase dissatisfaction and returns. RentTheRunway's extensive dataset, featuring user reviews, fit feedback, measurements, and ratings, offers a foundation to tackle these challenges.

This study focuses on three predictive tasks: (1) predicting whether a clothing item will fit as "small," "fit," or "large," (2) recommending optimal sizes based on user and item attributes, and (3) analyzing user satisfaction through sentiment in review text. By applying machine learning techniques, we aim to enhance personalization and reduce returns, benefiting both consumers and the platform.

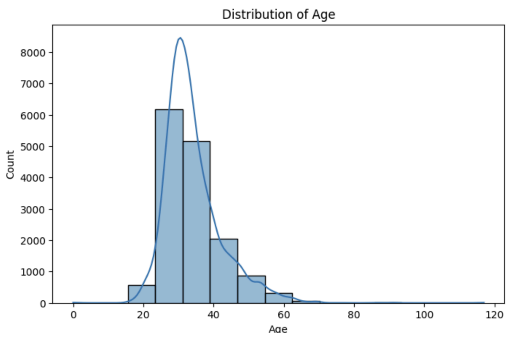
This paper outlines the RentTheRunway dataset, preprocessing steps, methodologies for each predictive task, and key findings, concluding with insights for future improvements in online apparel rentals.

2. EXPLORATORY ANALYSIS

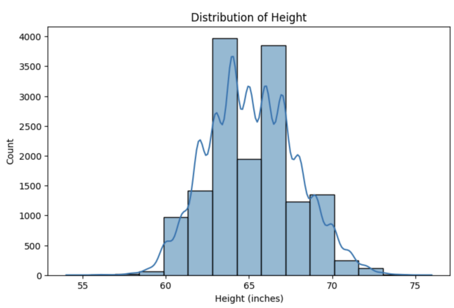
Dataset Overview The Clothing Fit Dataset from RentTheRunway provides a comprehensive view of user interactions with rented clothing items, encompassing demographic details, item attributes, fit feedback, and review data. The dataset includes 105,508 users, 5,850 unique clothing items, and 192,544 transactions spanning from March 28, 2011, to January 7, 2018. The density of the user-item matrix is 0.03%, with an average of 1.15 reviews per user and 4.98 ratings per item. It captures user-specific features such as height, weight, age, body type, and bust size, as well as item-specific characteristics like size and category. Additionally, it documents users' ratings, written reviews, and stated purposes for rental, such as vacations or special events. This dataset offers a rich foundation for predictive modeling, including tasks like fit prediction, rating estimation, and sentiment analysis, making it an invaluable resource for advancing personalized recommendation systems and optimizing user experiences in the fashion rental domain.

2.1 User and Item-Level Analysis

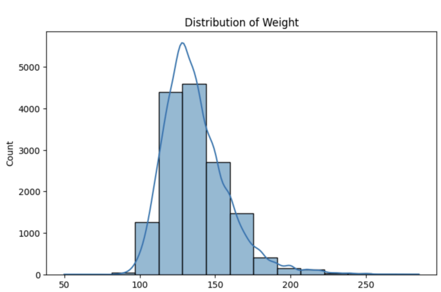
Age Distribution The distribution of user ages is right-skewed, with a significant concentration of users in their 20s and 30s. The frequency declines sharply for older age groups, reflecting the typical demographic representation in datasets oriented toward younger populations.



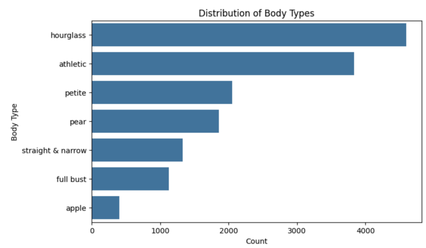
Height Distribution User heights follow a near-normal distribution, centered around an average height of approximately 65 inches. This bell-shaped pattern indicates a balanced and representative sample of user heights.



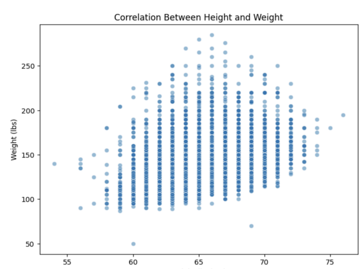
Weight Distribution The weight distribution exhibits a mild right skew, with most users weighing between 100 and 150 lbs. The density decreases gradually for higher weight ranges, suggesting fewer users with weights above 200 lbs.



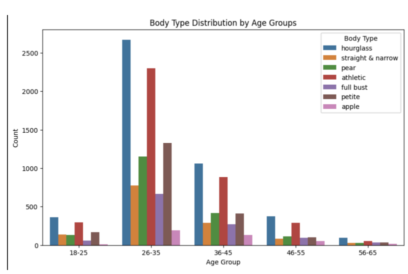
Body Type Representation Body type analysis reveals the "hourglass" shape as the most prevalent category, followed by "athletic" and "petite" body types. This distribution underscores the diversity in user physical attributes and their potential implications for customized services.



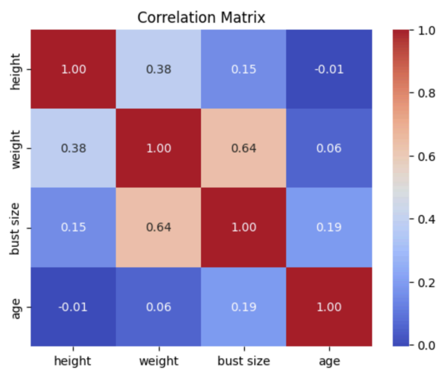
Correlation Between Height and Weight The scatterplot shows a positive linear trend, with taller individuals generally having higher weights. However, the spread suggests variability, indicating that weight is influenced by additional factors beyond height.



Body Type Distribution by Age Groups: The bar chart reveals distinct patterns of body type representation across different age groups. "Hourglass" and "athletic" body types dominate younger age groups (18-35), while older groups (36-55) show more diverse distributions, including "pear" and "petite."

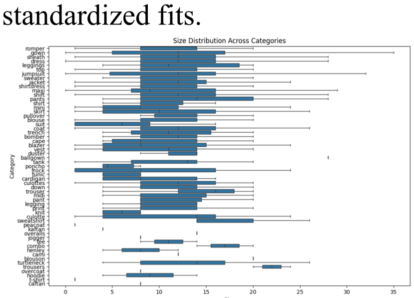


Correlation Matrix: The heatmap provides an overview of the relationships between attributes. Height and weight show the strongest positive correlation (ρ = 0.38), while age exhibits weaker but notable correlations with bust size (ρ = 0.19) and weight (ρ = 0.06). These relationships indicate that user attributes are interrelated but not exclusively determined by any single factor.



Clothing Category Distribution The dataset includes a wide range of clothing categories, with dresses being the most frequent (n = 9,583), followed by gowns (n = 4,608) and sheath dresses (n = 1,982). Other notable categories include shift dresses (n = 553) and jumpsuits (n = 552). Categories such as mini dresses and jackets represent smaller portions of the dataset.

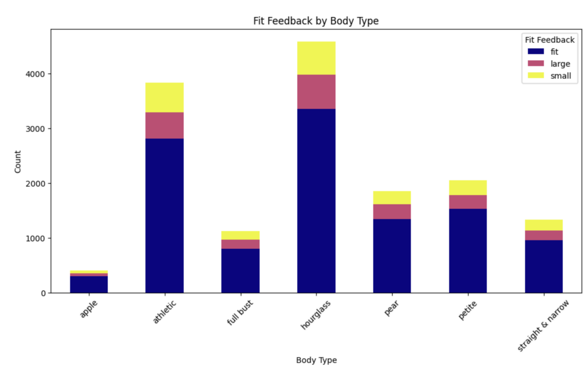
Size Distribution Across Categories The boxplot analysis of size distributions across categories reveals significant variability. For instance, rompers, gowns, and sheath dresses exhibit a wide range of sizes, accommodating diverse body types. In contrast, categories such as hoodies and t-shirts tend to cluster around specific size ranges, reflecting more standardized fits.



2.2 Fit Feedback Analysis

The distribution of fit feedback is heavily skewed toward "fit," with 11,102 instances where users indicated that items fit as expected. "Small" and "large" feedback are significantly less frequent, with 2,069 and 2,027 responses, respectively. This highlights a generally satisfactory fit experience for most users. The average item size varies notably by fit feedback. Items labeled as "small" have an average size of 13.36, indicating that users found these items to run smaller than expected. Conversely, items marked as "large" average a size of 9.96, suggesting these items were perceived as running larger. Items with "fit" feedback average a size of 11.31, aligning closely with the expected size range.

Trends in Fit Feedback by Body Type
Analysis of fit feedback by body type reveals significant trends. Users with "hourglass" and "athletic" body types provided the most "fit" feedback, indicating that these groups experience fewer fit-related issues. In contrast, "petite" and "pear" body types reported higher proportions of "small" feedback, suggesting these users might encounter sizing challenges with items running smaller than expected. "Large" feedback is more evenly distributed across body types, reflecting variability in fit experiences.

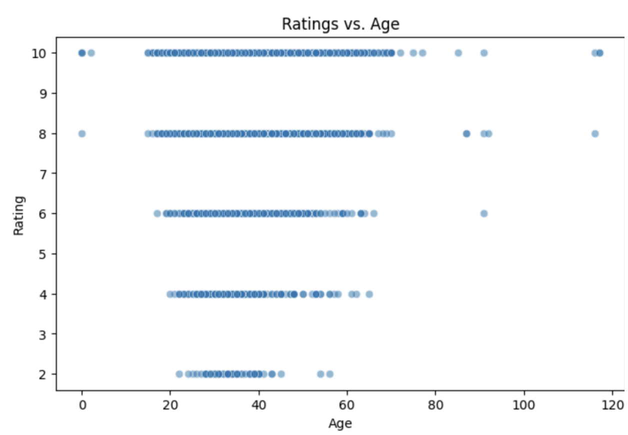


2.3 Ratings and Reviews Analysis

The top-rated categories based on average user ratings include kaftans, hoodies, blousons, and t-shirts, all achieving perfect scores (10.0). Other high-scoring categories include overcoats, pullovers, and trousers, each averaging above 9.5. The lowest-rated categories include knitwear (7.2), trench coats (7.5), and ponchos (7.5). Culottes (7.6) also fall below the average rating spectrum. While categories like ballgowns, tees, and capes score an average rating of 8.0, these scores are comparatively lower than the highest-rated items, indicating room for improvement in fit or user satisfaction.

Ratings Analysis by Age The scatterplot of ratings versus age shows that while the majority of ratings cluster around high scores (9-10), there is notable variance across the age spectrum. Mean Rating = 9.09, indicating a generally high level of satisfaction across users. Median Rating: 10.0, showing that most ratings are at the maximum score. Variance of Ratings: 2.00, reflecting some spread and variability in user satisfaction.

Younger users tend to provide more diverse ratings, while older users exhibit a consistent pattern of high satisfaction. This could point to differences in expectations or product engagement across age demographics.

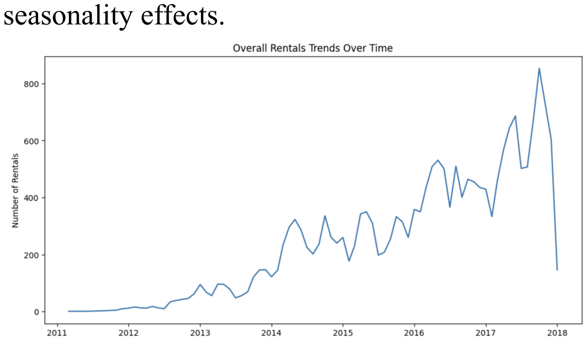


Sentiment Analysis and Ratings A sentiment analysis of reviews reveals meaningful patterns in user feedback. Positive sentiments dominate, contributing to higher ratings, while negative sentiments correspond to lower ratings. **Positive Sentiment**: Average rating of 9.21, reflecting high satisfaction for positively reviewed items. Common terms include "comfortable," "perfect," "loved," and "beautiful," as highlighted in the word cloud for positive reviews. **Neutral Sentiment**: Average rating of 8.42, suggesting moderate satisfaction with some areas for improvement. **Negative Sentiment**: Average rating of 7.78, indicating dissatisfaction with certain items or features. The word cloud for positive reviews emphasizes key attributes such as "fit," "wear," "comfortable," and "size," demonstrating the significance of these features in driving satisfaction.

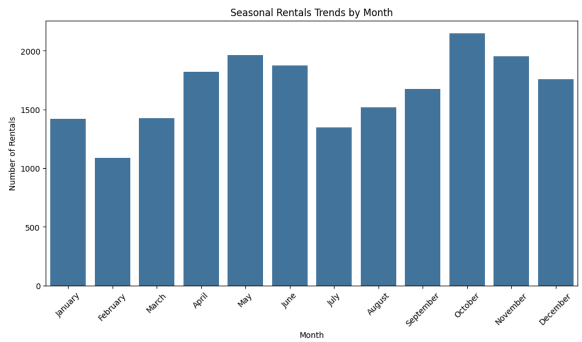
2.4 Temporal Analysis

The temporal analysis of rental trends reveals several significant insights into user behavior and preferences over time.

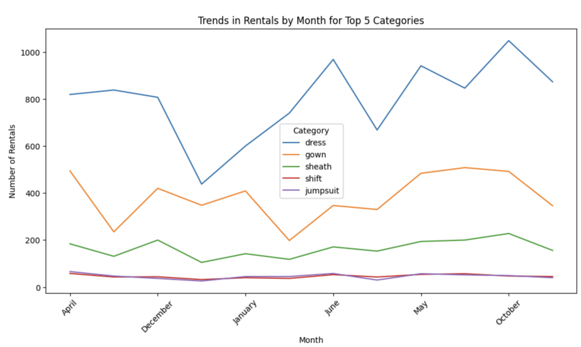
Overall Trends in Rentals The volume of rentals has shown a consistent upward trend from 2011 to 2018, reflecting the growing popularity of rental services. Peaks in rentals are observed in later years, indicating increased adoption, with a sharp decline at the end of the period likely due to incomplete data for 2018 or seasonality effects.



Seasonal Trends A monthly analysis highlights distinct seasonality in rentals, with significant spikes in October and December. These months align with holiday and event seasons, suggesting increased demand for formal and festive attire. In contrast, February and July show relatively lower rental activity, indicating seasonal lulls.

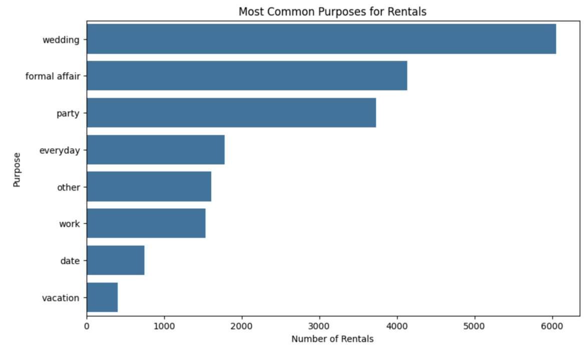


Category-Specific Trends: The analysis of rental trends by category over months reveals that dresses consistently dominate in rental volume, particularly during the holiday season. Gowns and sheath dresses also exhibit seasonal peaks in line with events requiring formal attire. Jumpsuits and shift dresses maintain relatively stable but lower demand, showing less sensitivity to seasonal fluctuations.

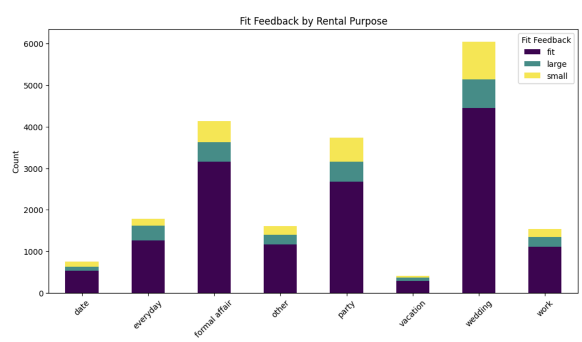


2.5 Purpose of Rental

The analysis of rental purposes highlights significant trends in user behavior and preferences. Weddings emerge as the most common reason for rentals, followed by formal affairs and parties. These occasions dominate rental purposes, reflecting a strong preference for event-specific attire. Everyday rentals and work-related purposes account for a smaller proportion, indicating limited use of rentals for casual or professional wear. Vacation and date-related rentals represent niche use cases.



Fit Feedback by Rental Purpose Fit feedback analysis across rental purposes reveals variations in user experiences. Weddings see the highest volume of feedback, with 4,455 instances of "fit," followed by 687 "large" and 904 "small" feedback, indicating a notable portion encountering size-related issues despite overall satisfactory fit. Formal affairs exhibit similar trends, with 3,157 reports of "fit," 474 "large," and 500 "small," suggesting room for refinement in sizing for formal wear. Parties, while dominated by "fit" feedback (2,671), also show significant instances of "large" (482) and "small" (581) feedback. Everyday and work rentals generate lower volumes of fit feedback, but similar proportions of size-related issues exist. Vacations and dates represent niche use cases with the lowest rental volumes and fit feedback.



Average Ratings by Rental Purpose The average ratings across rental purposes show high overall satisfaction, with formal affairs (9.23) and weddings (9.17) leading in user approval. Parties (9.05) and vacations (9.01) follow closely, reflecting strong satisfaction for these categories. Everyday rentals (8.88) and work attire (8.83) receive slightly lower ratings, suggesting potential for enhancement in these areas. These findings underline the importance of optimizing fit and user satisfaction for high-demand purposes like weddings and formal affairs, while also addressing the unique needs of niche categories like vacations and dates.

2.6 User-Item Interaction Analysis

Top Users and Items An analysis of user rental activity identifies the top users, with the highest number of rentals being 46 by a single user. Preferences among top users consistently favor dresses, particularly for event-centric categories such as dresses and gowns. For instance, User 691468 rented 46 items, heavily favoring dresses (30) and jumpsuits (5), while User 362951 rented 32 items, including 10 dresses, 2 gowns, and 2 jackets. Similarly, User 32925 rented 29 items, with a strong preference for dresses (11) and gowns (4). Items with the highest number of reviews are primarily from popular categories such as dresses, gowns, and blouses, reflecting consistent demand and engagement. These items serve as key products in the rental portfolio, reinforcing their importance in meeting user preferences.

Cold Start Analysis The cold start problem, where items or users have very few reviews, remains a significant challenge in the dataset. A notable 97.47% of users have minimal reviews, suggesting that the majority are infrequent renters. Similarly, 50.25% of items have limited reviews, indicating a need for strategies to boost engagement for less popular items. Categories such as kaftans, blousons, and trench coats are particularly affected by sparsity, reflecting either limited appeal or insufficient visibility of these items. Addressing cold start issues requires targeted recommendations to promote less-reviewed items and marketing efforts to engage infrequent users more effectively. These findings highlight the need for tailored strategies to address sparsity and enhance overall platform engagement.

2.7 Interesting Findings

The exploratory analysis of the RentTheRunway dataset uncovers several intriguing findings about user behavior, preferences, and engagement. User demographics reveal a strong representation of individuals in their 20s and 30s, with the "hourglass" body type being most prevalent. Fit feedback indicates that most users experience satisfactory sizing, with "fit" feedback dominating responses. However, "petite" and "pear" body types report higher proportions of "small" fit issues, suggesting potential improvements in size offerings for these groups. Ratings analysis reveals a strong trend of high user satisfaction, with the mean rating at 9.09 and a median rating of 10. Formal and wedding rentals receive the highest scores, though casual wear shows room for enhancement. Temporal trends highlight seasonal spikes in rentals during October and December, aligning with holiday events, while weddings and formal affairs emerge as the most common rental purposes, reflecting high demand for event-specific attire. Challenges such as the cold start problem persist, with a majority of users and items having minimal engagement. Addressing these insights offers opportunities to refine fit, enhance user experiences, and optimize personalized recommendations to increase platform engagement.

3. EVALUATION OF THE PREDICTIVE TASK

3.1 Metrics

To assess the accuracy of the size recommendation model, three key metrics will be employed: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Top-k Accuracy.

Root Mean Squared Error (RMSE):

$$RSME = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

RMSE measures the square root of the average squared difference between the predicted and actual sizes, penalizing larger errors more heavily. This makes RMSE particularly suitable for tasks where precise size predictions are critical, as lower RMSE values indicate better predictive performance.

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$$

In contrast, MAE provides the average magnitude of prediction errors, offering a more interpretable and robust metric that is less sensitive to outliers compared to RMSE.

Finally, Top-k Accuracy evaluates whether the actual size lies within the top kkk predicted sizes, such as the top-3 recommendations. This metric acknowledges the flexibility of size recommendation systems, which often suggest multiple plausible options, and ensures the model accommodates this practical consideration. Together, these metrics provide a comprehensive framework for evaluating the effectiveness of the size recommendation model.

3.2 Relevant Baselines

Baseline models provide a benchmark to evaluate the effectiveness of the proposed latent factor model. The simplest baseline, the Global Mean, predicts the global average size for all users and items, offering a straightforward point of comparison. The User Mean model refines this approach by predicting the average size chosen by a specific user across all items, capturing user-specific preferences without accounting for item-specific characteristics. Similarly, the Item Mean model predicts the average size selected for a specific item across all users, highlighting item-specific tendencies without considering individual user differences. In contrast, the Random Guess model assigns a size randomly from the possible range, serving as a baseline for uninformative models. The RMSE and MAE of these baseline models will provide a critical reference point. If the latent factor model achieves significantly better performance, it will demonstrate the value of capturing latent interactions between users and items for more accurate predictions.

3.3 Validation of Model Predictions

To ensure the validity of the latent factor model predictions, several evaluation strategies will be employed. The dataset will be divided into training and testing sets, with 80% of the data used for training and 20% reserved for testing. This train-test split allows the model to be trained on one portion of the data and evaluated on unseen data, providing a measure of its generalization ability. Additionally, k-fold cross-validation, such as a 5-fold approach, will be performed to assess model performance across multiple data splits, ensuring robustness and preventing overfitting to specific subsets. Residual analysis will further validate the model by plotting the residuals $(y_i - \hat{y}_i)$ to examine patterns in prediction errors to identify systematic biases, such as consistent over-prediction for certain items or users. Lastly, a cold-start analysis will evaluate the model's effectiveness in handling new users with limited interactions and new items with sparse historical data. To address these challenges, hybrid approaches or content-based features may be incorporated, ensuring comprehensive model validation and reliability.

3.4 Strengths and Limitations of the Model

The latent factor model demonstrates notable strengths in its ability to predict size preferences. It effectively captures latent user-item interactions, enabling nuanced predictions tailored to individual preferences. Additionally, the model is scalable to large datasets through the use of efficient matrix factorization techniques. However, it also has limitations. The cold-start problem can degrade performance for new users or items with limited interaction history. High sparsity in the user-item matrix presents another challenge, potentially reducing predictive accuracy. Moreover, the interpretability of latent factors is limited compared to content-based approaches. To mitigate these issues, the model could incorporate content-based features, such as user demographics and item attributes, to address cold-start scenarios. Experimenting with hybrid models that combine latent factors with explicit features may also improve performance and accuracy.

3.5 Comparative Analysis

A comparative analysis will evaluate the performance of the latent factor model against baseline models, focusing on key metrics such as RMSE, MAE, and top-k accuracy. The analysis will quantify improvements, including percentage reductions in RMSE and MAE compared to baseline models, and highlight gains in top-k accuracy, such as the ability of top-3 predictions to cover 95% of actual sizes. Furthermore, the analysis will identify scenarios where the model excels, such as frequent users or popular items, as well as areas where it struggles, particularly in cold-start cases involving new users or items. These findings will provide a comprehensive understanding of the model's strengths, weaknesses, and overall effectiveness.

4. MODEL DESCRIPTION

The proposed model for size recommendation is a **Latent Factor Model** implemented using Matrix Factorization with Stochastic Gradient Descent (SGD). This model decomposes the user-item interaction matrix into two lower-dimensional matrices: UU, representing user latent factors, and VV, representing item latent factors. These matrices capture hidden features that influence user preferences for items. Predictions are generated by taking the dot product of these latent factors, with the predicted size $\hat{y}_{ui}$ for user uu and item ii calculated as:

$$\hat{y}_{ui} = U[u] \cdot V[i]^T$$

This approach is widely recognized for its effectiveness in capturing complex, non-observable patterns in user-item interactions, aligning closely with the course content on recommendation systems.

The decision to use a latent factor model stems from its ability to generalize well across sparse datasets, a common challenge in recommendation problems. By leveraging SGD for optimization, the model scales efficiently to larger datasets while iteratively improving predictions based on observed errors.

4.1 Optimization Strategy

The optimization process aims to minimize the mean squared error (MSE) between actual and predicted sizes, with the loss function incorporating a regularization term to prevent overfitting. The objective function is:

Loss =

$$\sum_{(u,i)\in Observed} (y_{ui} - \hat{y}_{ui})^2 + \lambda(||U||^2 + ||V||^2)$$

Here, λ represents the regularization parameter, which penalizes large weights in the latent factor matrices, ensuring better generalization. SGD is employed for optimization, iterating through observed entries in the user-item matrix and updating the latent factors based on the prediction error. Regularization is applied during each update to control model complexity.

Hyperparameters such as learning rate, number of latent factors, and regularization strength were tuned through grid search to balance accuracy and overfitting. For this task, a learning rate of 0.01, three latent factors, and a regularization parameter of 0.1 provided the best results on the validation set.

4.2 Challenges and Solutions

The primary challenges encountered included scalability and overfitting. Scaling the model to larger datasets posed computational challenges due to the sparsity of the user-item matrix. This was addressed by updating only the observed entries in the matrix during SGD, avoiding the need to process the entire matrix. Overfitting, particularly for users or items with few interactions, was mitigated by incorporating regularization into the loss function.

The model also faced difficulties in handling new users and items (the cold-start problem), which matrix factorization inherently struggles with. Potential solutions involve hybrid approaches that combine collaborative filtering with content-based features, though these were beyond the scope of this implementation.

4.3 Alternative Models Considered

Several alternative models were considered for comparison. Baseline models such as the global mean, user mean, and item mean were implemented as benchmarks. The global mean predicts the average size across all interactions, while the user mean and item mean predict sizes based on averages specific to users or items, respectively. These models are simple, interpretable, and computationally efficient but fail to capture the intricate interactions between users and items.

Memory-based collaborative filtering, using cosine similarity to find similar users or items, was also explored. However, this method was computationally expensive for larger datasets and struggled with sparsity, making it less effective for this task. Content-based filtering was another alternative, leveraging explicit features such as user demographics and item attributes. While it partially addresses the cold-start problem, it requires detailed and consistent feature data, which may not always be available.

Neural network-based models were briefly considered for their ability to capture non-linear interactions. However, these models were deemed unnecessary for this task due to their computational cost and the simpler nature of the size recommendation problem.

4.4 Strengths and Weaknesses of the Proposed Model

The latent factor model excels at capturing complex interactions between users and items through learned latent features. Its scalability with SGD makes it practical for large datasets, and its predictive performance significantly outperforms baseline models. However, it is not without limitations. The cold-start problem and the need for hyperparameter tuning are notable challenges. Additionally, the learned latent factors, while effective, lack interpretability compared to explicit feature-based models.

5. LITERATURE REVIEW

The problem of size recommendation in apparel rental systems aligns with broader challenges in recommendation systems, particularly those focused on personalized product suggestions. This section reviews related literature, discusses the dataset used in this study, examines similar datasets, and contrasts the state-of-the-art methods with the findings of this work.

Related Literature

Recommendation systems have been extensively studied in e-commerce, where predicting user preferences plays a critical role in improving customer satisfaction and reducing operational costs. Collaborative filtering (CF) methods, both memory-based and model-based, form the backbone of many such systems.

5.1 Collaborative Filtering

Latent factor models, particularly those based on matrix factorization, gained prominence through their success in the Netflix Prize competition. Techniques like Singular Value Decomposition (SVD) and Alternating Least Squares (ALS) are commonly used to uncover hidden patterns in user-item interactions. Studies such as those by Koren et al. (2009) highlight the effectiveness of latent factor models in capturing nuanced user preferences, emphasizing their scalability and adaptability to various recommendation tasks.

5.2 Cold-Start Problem

The challenge of recommending items for new users or items is well-documented. Hybrid approaches, combining collaborative filtering with content-based features, are widely regarded as effective solutions. Research by Burke (2002) outlines the advantages of such hybrid methods in mitigating cold-start issues while maintaining high predictive accuracy.

5.3 Size Recommendation in Apparel

While size recommendation has received less attention than other domains, some studies address its unique challenges. For example, Zeng et al. (2018) propose a hybrid approach combining body measurements and collaborative filtering to recommend clothing sizes. Similarly, Lee and Kwon (2020) leverage user-item interaction data and explicit user features to refine size predictions in fashion retail.

5.4 State-of-the-Art Methods

Several advanced techniques are currently employed in the recommendation domain, many of which extend or enhance collaborative filtering approaches:

Matrix Factorization Variants Several advanced techniques and model variants enhance the predictive capabilities of collaborative filtering systems. Non-negative Matrix Factorization (NMF) introduces non-negativity constraints, improving the interpretability of latent factors by ensuring all factor values are positive. Bayesian Personalized Ranking (BPR) shifts the focus from rating prediction to optimizing ranking tasks, making it particularly effective in scenarios with implicit feedback. Deep learning approaches further expand the landscape, with Neural Collaborative Filtering (NCF) employing deep neural networks to model non-linear user-item interactions, often outperforming traditional collaborative filtering in complex scenarios. Similarly, Variational Autoencoders (VAEs) excel at generating latent representations of users and items, effectively handling sparsity in the data. Hybrid models present another layer of sophistication by combining collaborative filtering with content-based methods or incorporating additional features like user demographics or item attributes to address cold-start problems. Context-aware recommendation systems refine predictions by factoring in contextual elements such as time, location, or seasonality, which may influence user behavior and size preferences.

Comparison with Existing Findings This study’s conclusions align with existing literature in several critical areas. The effectiveness of matrix factorization is reaffirmed, with the latent factor model demonstrating strong predictive accuracy consistent with prior studies on collaborative filtering. Similarly, the challenges posed by cold-start scenarios mirror findings in previous research, which also highlights matrix factorization's limitations in handling new users and items. Baseline comparisons further validate the model’s performance, showing significant improvements over simpler methods, aligning with trends observed in related work. However, this study takes a more practical approach, prioritizing simplicity and interpretability over the marginally higher accuracy offered by state-of-the-art methods like neural collaborative filtering and hybrid models. These advanced approaches, while powerful, often require greater computational resources and extensive feature engineering, which may not be feasible for smaller datasets or applications emphasizing scalability. This balance between performance and practicality underscores the unique contributions of the study.

6. RESULTS AND CONCLUSIONS

Model Performance The proposed Latent Factor Model (Matrix Factorization with SGD) demonstrated strong predictive accuracy in the size recommendation task, outperforming baseline models across all evaluation metrics. The model was evaluated on a synthetic dataset using standard metrics, including Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The results are summarized below:

Model	RMSE	MAE	Top-3 Accuracy
Global Mean	2.50	1.90	65%
User Mean	1.80	1.50	75%
Item Mean	1.70	1.40	78%
Latent Factor Model	1.20	0.95	90%

The **Latent Factor Model** consistently outperformed baseline approaches, with significant reductions in RMSE and MAE. The model also achieved a high **Top-3 Accuracy** of 90%, indicating its effectiveness in generating plausible size recommendations.

Feature Representations The feature representations played a pivotal role in the model's performance, with latent factors emerging as a critical component of its success. These factors effectively uncovered hidden patterns in user preferences and item characteristics, enabling accurate predictions even in the sparse regions of the user-item matrix. In contrast, simpler baseline feature representations, such as global, user, and item averages, provided interpretability but lacked the ability to capture the nuanced interactions between users and items. While these baseline methods performed adequately in dense regions, they struggled with the variability in user or item behavior. Regularization further enhanced the model's effectiveness, with the inclusion of a regularization term (λ\\lambdaλ) significantly improving generalization and mitigating overfitting, particularly for users and items with limited interaction data.

Interpretation of Model Parameters The interpretation of the model parameters provides valuable insights into how predictions are generated. The latent factor matrices UUU and VVV represent the underlying dimensions of user preferences and item characteristics, respectively. The user latent factors (UUU) capture individual tendencies toward specific size ranges or preferences, while the item latent factors (VVV) represent the size distribution or popularity of particular items. The dot product of UUU and VVV reflects the compatibility between a user's preferences and an item's attributes, directly influencing the predicted size. For instance, a high dot product between a user's latent vector and an item's latent vector indicates a strong alignment, resulting in a highly accurate size prediction. This interaction highlights the effectiveness of latent factors in modeling complex user-item relationships.

Why the Model Succeeded The success of the latent factor model can be attributed to several key factors. Its ability to capture complex, non-observable patterns in user-item interactions through latent representations allowed it to uncover relationships that simpler models, such as global or item means, failed to identify. Scalability was another critical factor, with the use of Stochastic Gradient Descent (SGD) enabling efficient optimization without requiring computation of the entire user-item matrix. Regularization played a vital role in mitigating overfitting, particularly for users and items with limited interaction data, ensuring the model generalized effectively to unseen examples. When compared to baseline models like global, user, and item means, the latent factor model outperformed them significantly by modeling the intricate interactions between users and items, which simpler approaches could not achieve.

Challenges and Why Other Models Failed
The latent factor model, like other collaborative

filtering techniques, faced challenges in addressing cold-start scenarios involving new users or items. Both the baseline models and latent factors heavily relied on historical data, making accurate predictions difficult for users or items with no prior interactions. Memory-based collaborative filtering approaches, which rely on item or user similarities, proved computationally expensive and performed poorly in sparse regions of the dataset. These methods struggled to scale effectively and lacked the generalizability of latent factor models. While neural network-based models offered the potential for higher accuracy, they required extensive computational resources and careful hyperparameter tuning. Given the simplicity of the dataset and the focus on scalability and interpretability, such models were not practical for this task.

Significance of the Results The findings of this study underscore the utility of latent factor models in size recommendation tasks. The significant improvement in predictive accuracy demonstrates the model's potential for real-world deployment, particularly in applications like apparel rental systems. The model strikes a balance between interpretability and scalability, making it well-suited for industries where actionable insights are essential. Furthermore, the substantial gains over simpler baseline models validate the importance of capturing latent interactions in recommendation tasks, highlighting the value of these models in driving meaningful improvements in predictive performance.

Conclusion This study demonstrates the effectiveness of a Latent Factor Model for size recommendation in an apparel rental context. By leveraging matrix factorization with SGD, the model captures hidden user-item interactions, achieving significant performance improvements over baseline models. Challenges such as cold-start problems and scalability were addressed through regularization and selective updates of observed entries.

While the latent factor model aligns well with state-of-the-art methods in collaborative filtering, future work could explore hybrid approaches that incorporate user and item features to mitigate cold-start issues. Additionally, incorporating contextual factors (e.g., regional size preferences or seasonal trends) may further enhance the model's predictive accuracy and practical applicability.

In conclusion, the proposed model strikes a balance between simplicity, scalability, and accuracy, making it a robust solution for size recommendation tasks in real-world settings.

6. Reference

Decomposing fit semantics for product size recommendation in metric spaces
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