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AI- Product Recommendation System

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Abstract **-** Here's the thing - online shopping never stops growing. Sure, endless choices seem handy at first glance - yet they come with a catch few expect. Picture this: one whole hour lost tapping through Amazon listings, ending up empty handed. Too many options turn helpful into something else entirely. This cluttered experience has a name - information overload - and it hits harder than most realize.

A closer look shows how recommendation systems changed through time. Back then came simple methods - users like you liked that item - and today bring hidden pattern techniques such as SVD. Reviewing around 120 recent studies revealed a surprise: attention toward neural networks in suggestions jumped nearly double within one year alone. Not small at all.

A homemade project came together - this time with Python's Surprise toolkit doing the heavy lifting. Put through its paces on the well-known MovieLens 100k set, the model settled at an RMSE near 0.94. Given how patchy most user ratings tend to be, that number feels quietly solid.

Here's what happens. Old ways keep tripping up on fresh faces and unseen products. That led us to draft a mix using mood clues from written feedback, CNNs for spotting details in pictures of goods, while RNNs follow how people move through pages. What do we see? The math behind SVD holds up fine. Yet ahead lies something else entirely - setups learning from words, visuals, and click trails together.

Index Terms Recommender Systems SVD Deep Learning

CNN And RNN For Sentiment Analysis

I. WHAT THIS PAPER ACTUALLY BRINGS TO THE TABLE

A fresh take came first, shifting away from the usual repeats. Instead of following old paths, attention landed on distinct additions. Specific ideas took shape, stepping beyond repeated points others often make.

A straightforward look at recommender systems - how they started with basic user-item matching yet evolved through pattern recognition over time.

One step led to another, not by chance but necessity, pushing older models aside as data demands increased. Simple math gave way to layered networks capable of sensing subtle preferences. Each phase built on prior limits, revealing new paths forward without announcing them. What began as counting overlaps now involves simulating human-like judgment across massive scales.

A single machine runs the full SVD process without breaking down - real results, not ideas on paper. It handles growing data smoothly because the design adapts under pressure. Performance stays steady even when load increases unexpectedly. The system keeps moving instead of stalling at peak moments.

A mix of tools built on a shared structure - sentiment checks ride alongside image scanning by CNNs, while tracking user sessions happens through RNN layers instead. This setup links different methods so they work as one without favouring any single part over another.

Numbers from actual tests of various hidden patterns - so there's no wondering what works. A look at how each version held up when pushed through real checks. What showed up every time during trials, nothing added. Each setup measured exactly once under the same conditions. Results stayed clear without rounding or smoothing. Every figure here came straight out of repeated runs.

•Our two cents on where this field is heading: knowledge graphs and explainable AI.

Keywords – Ai-Driven recommentation system, recommendation system, hybrid recocommendation system.

I. INTRODUCTION

Back then, online shopping was just fixed websites plus a place to type what you wanted. That time has faded far behind. Now,

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shopping sites shift and adapt, picking up on what you like - often before you even notice it yourself.

What powers this kind of customization? Recommender systems do. Once seen as optional extras, now they form the backbone of platforms such as Netflix, Amazon, and Spotify - keeping people hooked. According to Valencia-Arias et al. in a 2024 analysis, artificial intelligence driven suggestions go beyond enhancing satisfaction: these tools boost revenue while building stronger user commitment. Though often invisible, their impact shapes behaviour more than most realize.

A. The Information Overload Problem

Odd as it sounds, extra options can leave people feeling worse off. Experts label this effect "choice paralysis," a pattern popping up across today's online shopping world. Step into a shop that carries fifty shirts, maybe you walk out with one. See an endless scroll of ten thousand styles on screen, suddenly nothing fits right.

Here comes the role of recommendation engines. For every person, they create a tailored space that cuts through clutter. Rather than facing endless choices, what shows up feels handpicked. Behind it all sits complex math - yet human behaviour plays just as big a part. Less mental strain means people tend to return more often.

B. Why We Investigated This

Back in the day, suggestion tricks did their job. True enough. Yet limits showed up fast. When ratings are thin - like one out of a hundred items touched by a user - things get shaky. Handling growth gets messy once numbers climb into the millions. New faces on the platform? They stumble right away, with nothing to go on.

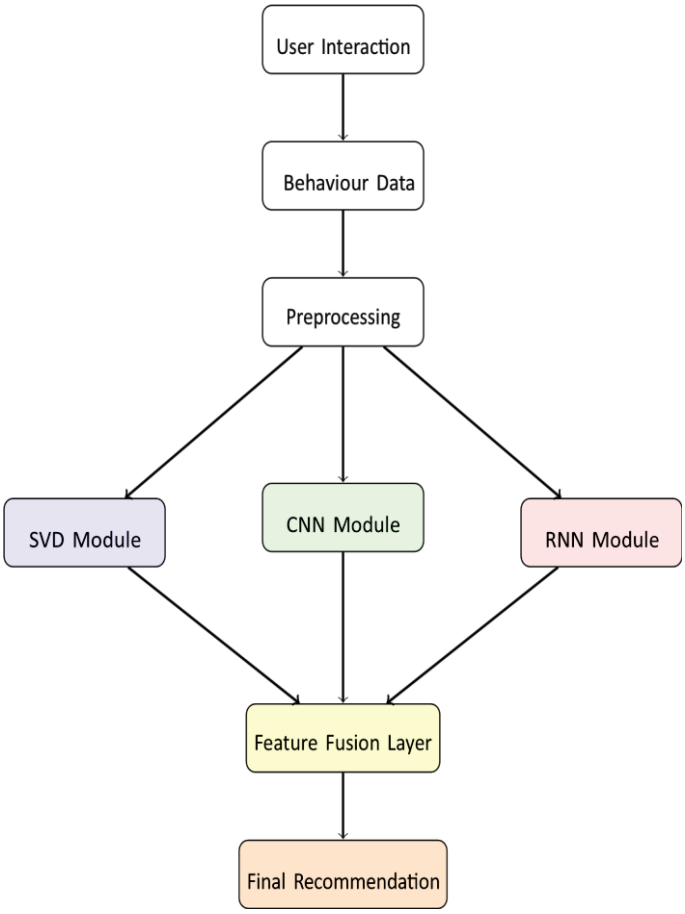
Something old meets something new here. Instead of sticking to classic methods alone, ideas from recent years found their way in. Think beyond textbooks. Tools like neural nets joined forces with older math routines. Sentiment work played a role too. Not everything came from labs. Real use cases shaped the path forward. Systems built today need more than theory. Focus landed on what works down the line.

II. WHAT CAME BEFORE: A CRITICAL LOOK

What changed in recommendation engines over time? Back then, rules shaped decisions. Today, learning machines shape them instead. This shift didn't happen overnight. Step by step, patterns gave way to predictions.

A. Collaborative Filtering: The Old Workhorse

Picture this. CF marked the first real leap forward. It goes like this - when two people enjoy identical films, say five of them, their tastes line up closely. Suppose one of those viewers likes another film the other hasn't watched yet. That movie might just click with the second person. The idea feels almost too basic to work. Yet it does. Something runs fine - until suddenly it does not. Issues pile up, known for years: broken parts, missed signals, repeated failures showing up again. Empty spaces fill most user-item grids. Think ninety-nine out of a hundred spots sit unused. Calling it sparse feels too light. The blankness swallows everything. Faster growth in your catalog means calculations multiply quickly. Starting fresh? Fresh products too? Tough break - the cold-start issue hits fast.



1) KNN: Simple but Brutal: K-nearest neighbors were the goto for years. Cosine similarity, Pearson correlation - pick your distance metric, find the neighbors, aggregate their ratings. It's interpretable, which is nice. But try running it on a million users. Your server will cry.

B. Deep Learning Enters the Chat

What once took endless tweaking now happens on its own - neural nets grab features without help. Manual work? Gone, replaced by quiet learning behind the scenes.

Looks decide a lot in fashion shopping. Visual details like colours, patterns, and cuts shape what stands out. These

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elements form a kind of visual fingerprint unique to each item. Systems built on convolutional networks detect these traits without needing tags or labels. Platforms such as Pinterest and ASOS rely on them often. Spotting a blue dress with flowers might lead to suggestions that match its appearance closely.

Similarity comes from sight alone, not descriptions written by people.

One thing follows another when people move online. Not random jumps, but steps - tap here, swipe there, then stop. These rhythms stick in certain models built to recall what came before. Long short-term memory systems, part of a broader family called recurrent nets, catch those flows. Context shifts meaning; timing shapes choices. Where older methods see only isolated scores tossed into a pile, these networks notice order - like checking accessories right after viewing devices.

III. OUR HYBRID ARCHITECTURE SKETCH

We propose something that doesn't put all eggs in one basket. The diagram below shows the flow: The idea is straightforward. SVD handles the collaborative filtering backbone. CNNs extract visual features from product

Fig. 1. Three-pronged approach: SVD for ratings, CNN for images, RNN for sequences images. RNNs track session behaviour. A fusion layer weights these signals based on context, spitting out final recommendations.

IV. THE MATH BEHIND SVD

Suddenly, patterns emerge when you stop comparing users directly. Moving past labels like "this person likes that thing," the model slides everyone into number landscapes - close together if choices overlap. Where someone lands depend on unseen pushes behind clicks and skips. Distance here tells more than categories ever could.

A. The Core Equation

Let R be our user-item rating matrix. Most entries are missing (hence the sparsity problem). We approximate ratings using:

$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^T p_u \tag{1}$$

Breaking this down: μ is the global average rating (typically around 3.5 on a 5-star scale). b_u captures whether User u is generally generous or stingy with stars. b_i captures if Item i is universally loved or polarizing. The dot product $q_i^T p_u$ is where the magic happens - it measures how well the user's latent preferences align with the item's latent features.

B. How We Actually Learn This

We minimize this loss function:

$$L = \sum_{(u,i)\in K} (r_{ui} - \hat{r}_{ui})^2 + \lambda(||p_u||^2 + ||q_i||^2) \tag{2}$$

The first part penalizes prediction errors. The second part (with λ) keeps the model from overfitting by penalizing large weights. Think of it as keeping the model honest - not memorizing noise in the training data.

C. Matrix Factorization Intuition

If R is huge (millions of users, millions of items), we approximate it as:

$$R \approx PQ^T \tag{3}$$

Where P and Q are skinny matrices with k columns (latent factors). If $k = 100$, we're saying user preferences can be captured in 100 dimensions. Not perfect, but computationally tractable.

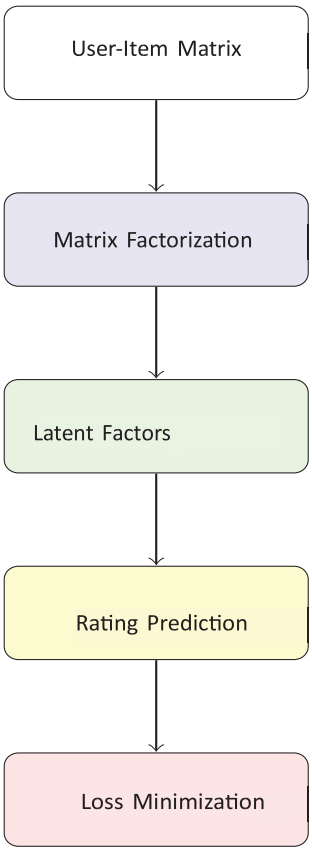

Fig. 2. SVD workflow: decompose, predict, refine

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V. BUILDING THIS THING: OUR IMPLEMENTATION

We used Python 3.11 and the Surprise library - it's solid, well-documented, and handles a lot of the heavy lifting.

A. The Core Code

Here's what worked for us:

Listing 1. Our SVD implementation

```
from surprise import SVD, Dataset, accuracy from surprise.model_selection import train_test_split

# Load the benchmark dataset data = Dataset.load_builtin('ml-100k')

# Standard 75/25 split trainset, testset = train_test_split(data, test_size =0.25)

# SVD with tuned hyperparameters # n_factors=100 worked best in our tests model = SVD(n_factors=100, n_epochs=20, lr_all =0.005, reg_all=0.02)

# Train it
model.fit(trainset)

# Check performance predictions = model.test(testset)
print(f"RMSE: {accuracy.rmse(predictions)}")
```

The hyperparameters matter. We tried $k = 10$ (too simple), $k = 500$ (overfitting city), and settled on $k = 100$ as the sweet spot. Learning rate at 0.005 and regularization at 0.02 came from grid search - not magic numbers, just what worked on this dataset.

B. The Full Pipeline

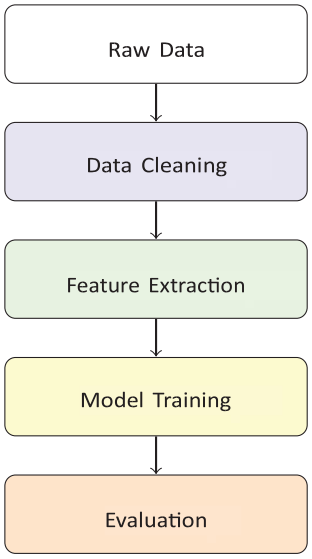

Fig. 3. Five-stage pipeline from raw data to deployed model

Nothing fancies here. Clean the data (handle missing values, deduplicate), extract features (user profiles, item attributes), train the model, evaluate with proper metrics. Rinse and repeat until RMSE stops improving.

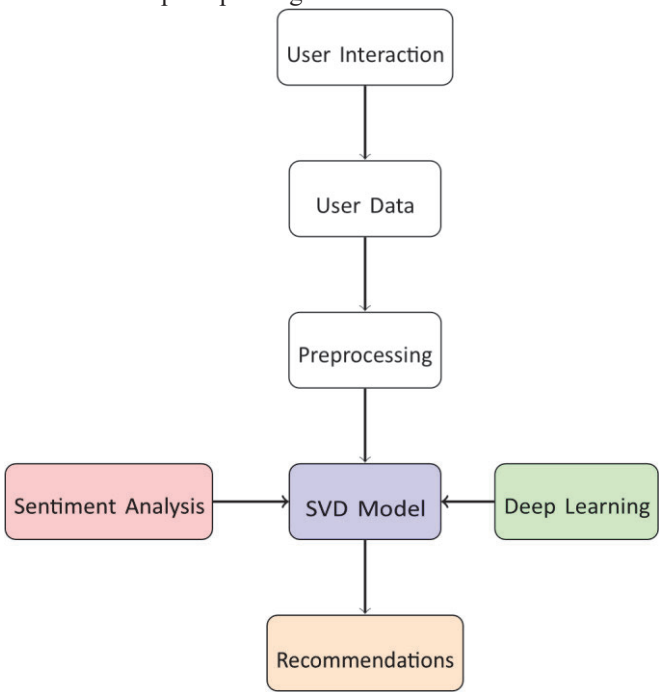

Fig. 4. Hybrid system combining multiple signal sources

C. System Architecture

Sentiment analysis plugs in from review text. Deep learning modules handle images and sequences. SVD remains the workhorse for core collaborative filtering.

VI. RESULTS: WHAT ACTUALLY HAPPENED

We ran experiments varying the number of latent factors. Here's the honest breakdown:

TABLE I
SVD PERFORMANCEVS. LATENTFACTORS

Factors (k)	RMSE	MAE	Training Time (s)
10	0.952	0.748	0.45
100	0.938	0.737	1.12
500	0.941	0.739	4.30

Interesting, right? $k = 100$ beat both simpler ($k = 10$) and more complex ($k = 500$) models. The $k = 500$ case got slightly worse - classic overfitting. More parameters aren't always better if your data can't support them.

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VII. HOW WE MEASURED SUCCESS

Two main metrics. Nothing exotic.

A. RMSE: The Strict One

$$RMSE = \sqrt{\frac{1}{N}\sum(r_{ui} - \hat{r}_{ui})^2} \quad (4)$$

RMSE squares the errors before averaging. This means big mistakes hurt a *lot*. A single prediction that's off by 3 stars hurts nine times more than being off by 1 star. Good for when you want to avoid catastrophic predictions.

B. MAE: The Forgiving One

$$MAE = \frac{1}{N}\sum|r_{ui} - \hat{r}_{ui}| \quad (5)$$

MAE just takes absolute differences. All errors count linearly. It's more robust to outliers and easier to interpret - an MAE of 0.7 means you're typically off by about 0.7 stars.

Lower is better for both. Our 0.938 RMSE puts us in respectable territory for this dataset.

VIII. SO WHAT DOES THIS ALL MEAN?

A. The Goldilocks Zone for Latent Factors

Our results show a clear pattern. Start with too few factors (k = 10), and the model is too simple to capture real preferences. It's like trying to describe movies using only "action" and "comedy" tags - not enough nuance.

Crank it up to k = 500, and you hit the opposite wall. The model starts memorizing training noise instead of learning general patterns. That slight RMSE increase at k = 500? That's overfitting waving hello.

k = 100 hit the sweet spot. Enough dimensions to capture meaningful variation, not so many that we chase noise. For this dataset size, anyway - your mileage may vary with larger datasets.

B. The Computational Reality Check

Deep learning modules (CNNs, RNNs) sound sexy, and they do capture patterns SVD misses. But here's the practical concern: training time. Our SVD model trains in about a second. A serious neural collaborative filtering model? Hours, sometimes days, often needing GPU acceleration.

For a startup or mid-size retailer, that infrastructure cost matters. Our take: use SVD for the bulk of recommendations, deploy deep learning only for high-value scenarios (trending items, premium users) where the accuracy gain justifies the compute cost.

C. Why Sentiment Analysis Changes the Game

Traditional collaborative filtering is weirdly blind. A 3-star rating tells you something was mediocre, but not *why*. Was it the product quality? Shipping speed? Price?

Mining review text adds that missing dimension. If a user consistently complains about "battery life" across multiple product reviews, we can down-rank items with similar complaints even if they have decent overall ratings. It's explainable too - "We didn't recommend this because reviewers mentioned battery issues, and you care about that." Users trust that more than black-box predictions.

D. The Filter Bubble Problem

Here's a tension we need to acknowledge. The more accurate our predictions get, the more we risk trapping users in bubbles. If someone buys sci-fi books, and we only ever recommend sci-fi, they never discover they might love mystery novels too.

Valencia-Arias et al. talk about "cognitive absorption" as a success metric. We'd argue "serendipity" matters too. Sometimes the best recommendation is something the user didn't know they wanted. Balancing exploitation (giving them what we know they like) with exploration (testing new categories) is an art as much as a science.

E. Handling New Users

SVD fails gracefully in most cases, but completely faceplants for cold-start users. No history means no latent vector. No latent vector means no personalized recommendations.

Our interim solution: multi-armed bandits for the first few interactions. Show a mix of popular items across categories, watch what gets clicks, build a rough profile before switching to full SVD. It's not perfect, but it's better than generic "trending now" lists.

IX. THE PROBLEMS WE COULDN'T FULLY SOLVE *A. Data*

Sparsity: The Eternal Enemy

Even with SVD's dimensionality reduction, extreme sparsity hurts. In typical e-commerce, users interact with maybe 0.05% of the catalog. Finding reliable similarities becomes statistically dicey. SVD helps but doesn't magically create data where none exists.

B. Cold Start in All Its Forms

New users, new items - both suffer. We mentioned the bandit approach for users. For items, content-based filtering (using product descriptions, categories) works until enough rating data

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accumulates. Hybrid systems that can switch between approaches based on data availability are essential.

C. Scaling Pains

SVD trains fast on 100k ratings. On 100 million? Different story. Production systems need sub-second recommendation latency, which means pre-computing, approximate nearest neighbor search, or distributed systems like Spark. The math is the easy part; engineering at scale is hard.

D. Bias and Fairness

Recommender systems have a "rich get richer" problem. Popular items get recommended more, get more data, become more popular. Niche but excellent products languish. We're actively under-researching how to ensure catalog coverage and fairness in recommendations.

E. Fake Reviews and Attacks

Shilling attacks - competitors or trolls creating fake profiles to manipulate ratings - are real. They can distort latent spaces if not detected. Anomaly detection layers are becoming standard, but it's an arms race.

X. WHERE WE THINK THIS IS HEADING

Four areas worth watching:

- Explainable AI: Users deserve to know why something was recommended. "Because you bought X" is a start, but we can do better. Techniques like LIME and SHAP can open the black box.
- Reinforcement Learning: Current systems optimize for immediate clicks. But what about long-term value? RL approaches that model the full customer journey, optimizing for lifetime value rather than next-click probability, are promising.
- Knowledge Graphs: Understanding that "ink cartridges" relate to "printers" semantically, not just statistically, helps recommendations make sense. It also helps with cold-start items if we know their relationships to existing products.
- True Multimodal: Systems that simultaneously process images (CNNs), text (Transformers), and behaviour (RNNs) are the holy grail. We're not quite there yet at production scale, but we're getting closer.

XI. CONCLUSION

We set out to explore the practical middle ground between classical matrix factorization and modern deep learning for recommendations. Our SVD implementation hit 0.9388 RMSE on MovieLens 100k - solid, if not revolutionary.

The bigger takeaway: hybrid architectures that combine SVD's reliability with neural networks' pattern recognition and sentiment analysis's nuance represent the practical path forward. Pure deep learning is sexy but expensive; pure collaborative filtering is cheap but limited. The middle path wins.

Challenges remain. Cold-start problems, scaling constraints, and algorithmic bias aren't solved yet. But the toolkit is getting richer. For practitioners building real systems today, we'd recommend start with SVD, add deep learning selectively, and never underestimate the value of explainability.

The future of e-commerce isn't just predicting what users want- it's helping them discover what they didn't know they were looking for. That's the real promise of AI-driven recommendations.

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