MovieLens Recommendation System (Collaborative Filtering)

In [18]:
```
from IPython.display import HTML
HTML("""
<style>
/* Tighten markdown spacing */
.rendered_html p { margin: 0.25em 0; }
.rendered_html ul { margin: 0.25em 0 0.25em 1.2em; }
.rendered_html li { margin: 0.1em 0; }
</style>
""")
```

Out[18]:

Business Understanding (stakeholder + problem + value)

Stakeholder: A movie streaming platform's product + personalization team.

Real-world problem: Users face choice overload; if they can't quickly find movies they enjoy, engagement drops and churn risk increases.

Project goal: Build a recommendation system that predicts how a user would rate unseen movies and returns Top-5 personalized recommendations.

How stakeholders would use it:

- Populate a "Recommended for You" row on the homepage
- Improve email/push recommendations
- Support content discovery and retention efforts

Success criteria:

- Low prediction error (RMSE/MAE) on held-out ratings
- Recommendations that are plausible and relevant for sample users

Data Understanding (dataset source, size, sparsity, limitations)

I use the MovieLens "latest small" dataset (ml-latest-small) from GroupLens. It contains 100,836 ratings and 3,683 tag applications across 9,742 movies from 610 users. Ratings use a 0.5–5.0 scale. These explicit ratings are well-suited to collaborative filtering.

Limitations that matter for this project:

- The user–movie matrix is sparse (most users rate only a small fraction of movies)
- Cold start exists for brand-new users and new movies
- No user demographics are included

Data Exporation

In [19]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

ratings = pd.read_csv("../data/ratings.csv")
movies  = pd.read_csv("../data/movies.csv")
links   = pd.read_csv("../data/links.csv")
tags    = pd.read_csv("../data/tags.csv")

ratings.head()
```

Out[19]:

	userId	movieId	rating	timestamp
0	1	1	4.0	964982703
1	1	3	4.0	964981247
2	1	6	4.0	964982224
3	1	47	5.0	964983815
4	1	50	5.0	964982931

In [20]:
```
# Basic dataset Facts
print("ratings shape:", ratings.shape)
print("movies shape:", movies.shape)
print("tags shape:", tags.shape)

print("Unique users:", ratings["userId"].nunique())
print("Unique movies rated:", ratings["movieId"].nunique())
print("Rating scale:", ratings["rating"].min(), "to", ratings["rating"].max())

ratings["rating"].describe()
```

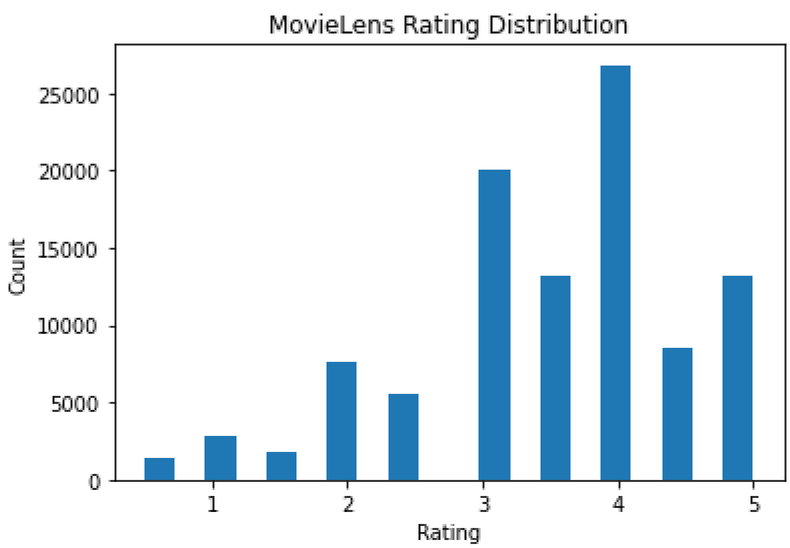
```
ratings shape: (100836, 4)
movies shape: (9742, 3)
tags shape: (3683, 4)
Unique users: 610
Unique movies rated: 9724
Rating scale: 0.5 to 5.0
```

Out[20]:
```
count    100836.000000
mean          3.501557
std           1.042529
min           0.500000
25%           3.000000
50%           3.500000
75%           4.000000
max           5.000000
Name: rating, dtype: float64
```

In [21]:
```
# Checking for data Sparsity
n_users = ratings["userId"].nunique()
n_items = ratings["movieId"].nunique()
n_obs = len(ratings)

density = n_obs / (n_users * n_items)
sparsity = 1 - density

print(f"Users: {n_users}, Movies: {n_items}, Ratings: {n_obs}")
print(f"Matrix density: {density:.6f}")
print(f"Matrix sparsity: {sparsity:.6f}")
```

```
Users: 610, Movies: 9724, Ratings: 100836
Matrix density: 0.017000
Matrix sparsity: 0.983000
```

In [22]:
```
# Rating distribution plot
ratings["rating"].plot(kind="hist", bins=20)
plt.title("MovieLens Rating Distribution")
plt.xlabel("Rating")
plt.ylabel("Count")
plt.show()
```



Data Preparation (Reproducible steps + leakage prevention)

To evaluate models fairly, I split ratings into:

- Training set (80%): model fitting + cross-validation (model selection)
- Holdout test set (20%): final evaluation only

This prevents leakage and estimates real-world performance on unseen ratings.

In [23]:
```
# Splitting strategy to prevent leakage

from sklearn.model_selection import train_test_split

train_df, test_df = train_test_split(
    ratings[["userId", "movieId", "rating"]],
    test_size=0.2,
    random_state=42
)

print("train_df:", train_df.shape, "test_df:", test_df.shape)
```

```
train_df: (80668, 3) test_df: (20168, 3)
```

In [24]:
```
# Suprise dataset objects

from surprise import Dataset, Reader

reader = Reader(rating_scale=(0.5, 5.0))

train_data = Dataset.load_from_df(train_df[["userId", "movieId", "rating"]], reac
# testset must be a list of (uid, iid, true_rating)
testset = list(test_df.itertuples(index=False, name=None))  # (userId, movieId, r
```

Modeling (Baseline → kNN → SVD, with justification)

Modeling (Iterative approach: Baseline → kNN → Matrix Factorization)

I follow an iterative modeling approach:

- 1. BaselineOnly: a simple benchmark that predicts ratings using global/user/movie biases.
- 2. KNNBaseline: neighborhood collaborative filtering using item-item similarity.
- 3. SVD (matrix factorization): learns latent factors representing user preferences and movie characteristics.
- 4. Tuned SVD: uses cross-validation to select hyperparameters for better generalization.

In [25]:
```
# Cross-validated model comparison on training data

from surprise.model_selection import cross_validate
from surprise import BaselineOnly, KNNBaseline, SVD

def cv_rmse_mae(algo, data, cv=3):
    results = cross_validate(algo, data, measures=["RMSE", "MAE"], cv=cv, verbose
    return np.mean(results["test_rmse"]), np.mean(results["test_mae"])

baseline_algo = BaselineOnly()
knn_algo = KNNBaseline(sim_options={"name": "pearson_baseline", "user_based": Fal
svd_algo = SVD(random_state=42)

baseline_rmse, baseline_mae = cv_rmse_mae(baseline_algo, train_data, cv=3)
knn_rmse, knn_mae = cv_rmse_mae(knn_algo, train_data, cv=3)
svd_rmse, svd_mae = cv_rmse_mae(svd_algo, train_data, cv=3)

print("CV Results (Train Only)")
print(f"BaselineOnly  RMSE={baseline_rmse:.4f}, MAE={baseline_mae:.4f}")
print(f"KNNBaseline   RMSE={knn_rmse:.4f}, MAE={knn_mae:.4f}")
print(f"SVD (default) RMSE={svd_rmse:.4f}, MAE={svd_mae:.4f}")
```

```
Estimating biases using als...
Estimating biases using als...
Estimating biases using als...
Estimating biases using als...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
Estimating biases using als...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
Estimating biases using als...
Computing the pearson_baseline similarity matrix...
Done computing similarity matrix.
CV Results (Train Only)
BaselineOnly  RMSE=0.8790, MAE=0.6797
KNNBaseline   RMSE=0.8758, MAE=0.6691
SVD (default) RMSE=0.8859, MAE=0.6829
```

Model change justification: kNN vs SVD

Why kNN vs Matrix Factorization?

kNN collaborative filtering is intuitive and interpretable: it recommends movies similar to those a user (or similar users) liked. However, MovieLens is sparse, and similarity methods can be limited when overlap is small.

Matrix factorization (SVD) learns compact latent representations of users and movies from all observed ratings, which often generalizes better in sparse settings. I therefore use kNN as a collaborative filtering baseline and SVD as the final candidate model.

Tuned SVD explanation

Tuned SVD (why tuning matters)
Tuning helps balance underfitting vs overfitting by adjusting:

- Model capacity (n_factors)
- Training duration (n_epochs)
- Regularization (reg_all)
- Learning rate (lr_all)

I tune SVD using cross-validation on training data, then evaluate the selected model once on a holdout test set.

In [26]:
```
# Tuned SVD
# Grid search SVD hyperparameters (train only)

from surprise.model_selection import GridSearchCV

param_grid = {
    "n_factors": [50, 100, 150],
    "n_epochs": [20, 30],
    "lr_all":   [0.002, 0.005],
    "reg_all":  [0.02, 0.05, 0.1]
}

gs = GridSearchCV(SVD, param_grid, measures=["rmse", "mae"], cv=3, joblib_verbose
gs.fit(train_data)

print("Best RMSE score:", gs.best_score["rmse"])
print("Best params:", gs.best_params["rmse"])
```

```
Best RMSE score: 0.8750858732518743
Best params: {'n_factors': 100, 'n_epochs': 30, 'lr_all': 0.005, 'reg_all': 0.
1}
```

Evaluation (RMSE/MAE, final model selection, holdout test)

Metrics justification + final test

Evaluation (Metrics, Final Model Selection, Holdout Test)
Metrics: RMSE and MAE are appropriate because the target is a numeric rating (0.5–5.0).

- RMSE penalizes large mistakes more heavily, which matters because extreme misrecommendations can reduce trust and engagement.
- MAE is more interpretable as the average number of “stars” the predictions are off.

Final model selection: I choose the final model based on cross-validated RMSE/MAE on training data and evaluate once on the holdout test set.

In [27]:
```
# Train best tuned SVD and evaluate on holdout test

from surprise import accuracy

best_params = gs.best_params["rmse"]
final_svd = SVD(**best_params, random_state=42)

# Fit on full training set
full_trainset = train_data.build_full_trainset()
final_svd.fit(full_trainset)

# Evaluate once on holdout test set
preds = final_svd.test(testset)
test_rmse = accuracy.rmse(preds, verbose=True)
test_mae  = accuracy.mae(preds, verbose=True)

(test_rmse, test_mae)
```

```
RMSE: 0.8754
MAE:  0.6700
```

Out[27]:
```
(0.8754193610148606, 0.6699772674176766)
```

Demo section: existing user you choose + new user simulation

Top-5 Recommendations Demo (Existing User + New User)

I demonstrate recommendations in two realistic scenarios:

- 1. Existing user with historical ratings (personalized recommendations)
- 2. New user: cold start handled by collecting a few initial ratings, then generating recommendations

In [28]:
```
# You choose an existing userID

# ---- YOU CHOOSE ----
CHOSEN_USER_ID = 599  # <-- replace with any existing userId you want
# --------------------

# Quick validation:
if CHOSEN_USER_ID not in set(ratings["userId"].unique()):
    raise ValueError(f"userId {CHOSEN_USER_ID} not found in dataset.")
else:
    print(f"Using existing userId: {CHOSEN_USER_ID}")
```

```
Using existing userId: 599
```

In [29]:
```
# Show what user already liked

def top_rated_by_user(user_id, ratings_df, movies_df, k=5):
    user_hist = ratings_df[ratings_df["userId"] == user_id].merge(movies_df, on='
    return user_hist.sort_values("rating", ascending=False)[["userId", "movieId",

print("User's top-rated movies (from available ratings):")
top_rated_by_user(CHOSEN_USER_ID, ratings, movies, k=5)
```

```
User's top-rated movies (from available ratings):
```

Out[29]:

	userId	movieId	title	rating
1575	599	6874	Kill Bill: Vol. 1 (2003)	5.0
966	599	3160	Magnolia (1999)	5.0
340	599	951	His Girl Friday (1940)	5.0
285	599	741	Ghost in the Shell (Kôkaku kidôtai) (1995)	5.0
1547	599	6711	Lost in Translation (2003)	5.0

In [30]:
```
# Top-N recommender function + existing user recommendations

movie_id_to_title = dict(zip(movies["movieId"], movies["title"]))

def top_n_recs_for_user(algo, trainset, user_id_raw, n=5):
    inner_uid = trainset.to_inner_uid(user_id_raw)
    rated_inner_iids = {iid for (iid, _) in trainset.ur[inner_uid]}
    all_inner_iids = set(range(trainset.n_items))
    unseen_inner_iids = list(all_inner_iids - rated_inner_iids)

    scored = []
    for inner_iid in unseen_inner_iids:
        raw_iid = int(trainset.to_raw_iid(inner_iid))
        est = algo.predict(user_id_raw, raw_iid).est
        scored.append((raw_iid, est))

    scored.sort(key=lambda x: x[1], reverse=True)
    top = scored[:n]

    return pd.DataFrame([{
        "userId": int(user_id_raw),
        "movieId": mid,
        "title": movie_id_to_title.get(mid, "Unknown"),
        "predicted_rating": float(est)
    } for mid, est in top])

# pick a real user from training set
CHOSEN_USER_ID = int(train_df["userId"].iloc[0])
top_n_recs_for_user(final_svd, full_trainset, CHOSEN_USER_ID, n=5)
```

Out[30]:

	userId	movieId	title	predicted_rating
0	509	1223	Grand Day Out with Wallace and Gromit, A (1989)	4.061310
1	509	1104	Streetcar Named Desire, A (1951)	4.049562
2	509	318	Shawshank Redemption, The (1994)	4.034565
3	509	3468	Hustler, The (1961)	4.015110
4	509	1248	Touch of Evil (1958)	3.995758

New User Simulation (Cold Start)

Collaborative filtering cannot personalize recommendations for a brand-new user with zero ratings. A standard solution is to ask the user to rate a small number of popular movies to seed the model. I simulate this by creating a new user, adding 5 initial ratings, refitting the model on training data, and generating Top-5 recommendations.

In [31]:
```
# find good 'starter' movies for the new user to rate
# Use "popular" movies (lots of ratings) so the new user has overlap with the com

def popular_movies(ratings_df, movies_df, min_ratings=200, top_n=30):
    counts = ratings_df.groupby("movieId").size().rename("num_ratings")
    means = ratings_df.groupby("movieId")["rating"].mean().rename("avg_rating")
    pop = pd.concat([counts, means], axis=1).reset_index()
    pop = pop.merge(movies_df, on="movieId", how="left")
    pop = pop[pop["num_ratings"] >= min_ratings].sort_values(
        ["num_ratings", "avg_rating"], ascending=False
    )
    return pop[["movieId", "title", "num_ratings", "avg_rating"]].head(top_n)

starter_list = popular_movies(ratings, movies, min_ratings=200, top_n=30)
starter_list
```

Out[31]:

	movieId	title	num_ratings	avg_rating
314	356	Forrest Gump (1994)	329	4.164134
277	318	Shawshank Redemption, The (1994)	317	4.429022
257	296	Pulp Fiction (1994)	307	4.197068
510	593	Silence of the Lambs, The (1991)	279	4.161290
1938	2571	Matrix, The (1999)	278	4.192446
224	260	Star Wars: Episode IV - A New Hope (1977)	251	4.231076
418	480	Jurassic Park (1993)	238	3.750000
97	110	Braveheart (1995)	237	4.031646
507	589	Terminator 2: Judgment Day (1991)	224	3.970982
461	527	Schindler's List (1993)	220	4.225000
2224	2959	Fight Club (1999)	218	4.272936
0	1	Toy Story (1995)	215	3.920930
897	1196	Star Wars: Episode V - The Empire Strikes Back...	211	4.215640
46	50	Usual Suspects, The (1995)	204	4.237745
2144	2858	American Beauty (1999)	204	4.056373
43	47	Seven (a.k.a. Se7en) (1995)	203	3.975369
615	780	Independence Day (a.k.a. ID4) (1996)	202	3.445545
123	150	Apollo 13 (1995)	201	3.845771
899	1198	Raiders of the Lost Ark (Indiana Jones and the...	200	4.207500

In [32]:
```
# create a new user and enter a few ratings

# Create a new userId not used in the dataset
new_user_id = int(ratings["userId"].max() + 1)

# Choose movieIds from starter_list and assign ratings
# Example seed ratings (edit these to your picks)
new_user_ratings = [
    (new_user_id, 1, 5.0),     # Toy Story (1995) usually movieId 1 in MovieLens
    (new_user_id, 2571, 4.5), # Matrix (1999) often 2571
    (new_user_id, 296, 4.0),  # Pulp Fiction (1994) often 296
    (new_user_id, 593, 4.5),  # Silence of the Lambs (1991) often 593
    (new_user_id, 318, 5.0),  # Shawshank Redemption (1994) often 318
]

new_user_ratings_df = pd.DataFrame(new_user_ratings, columns=["userId", "movieId"
new_user_ratings_df.merge(movies, on="movieId", how="left")[["userId","movieId",'
```

Out[32]:

	userId	movieId	title	rating
0	611	1	Toy Story (1995)	5.0
1	611	2571	Matrix, The (1999)	4.5
2	611	296	Pulp Fiction (1994)	4.0
3	611	593	Silence of the Lambs, The (1991)	4.5
4	611	318	Shawshank Redemption, The (1994)	5.0

In [33]:

```
### Train “final tuned SVD” including the new user (personalized cold-start resol
# append the new ratings to the training data and refit the tuned SVD.
# then recommend top-5

from surprise import Dataset, Reader
from surprise import SVD

# already have best_params from GridSearchCV earlier
# best_params = gs.best_params["rmse"]

reader = Reader(rating_scale=(0.5, 5.0))

# IMPORTANT: add new user's ratings to TRAIN ONLY (do not touch holdout test)
aug_train_df = pd.concat([train_df, new_user_ratings_df], ignore_index=True)

aug_train_data = Dataset.load_from_df(aug_train_df[["userId","movieId","rating"]]
aug_full_trainset = aug_train_data.build_full_trainset()

final_svd_new = SVD(**best_params, random_state=42)
final_svd_new.fit(aug_full_trainset)

# Recommend for the new user
top5_new_user = top_n_recs_for_user(final_svd_new, aug_full_trainset, new_user_ic
top5_new_user
```

Out[33]:

	userId	movieId	title	predicted_rating
0	611	3468	Hustler, The (1961)	4.640310
1	611	2318	Happiness (1998)	4.618084
2	611	898	Philadelphia Story, The (1940)	4.616641
3	611	1262	Great Escape, The (1963)	4.613325
4	611	1283	High Noon (1952)	4.609720

Cold-start fallback strategy

Cold-start fallback (true new user with 0 ratings)

If a user provides zero ratings, collaborative filtering cannot personalize. In that case, a practical fallback is to recommend movies that are both popular (many ratings) and highly rated (high average rating). This provides reasonable defaults until enough user feedback is collected.

In [34]:
```
# Fallback recommendations for 0-rating user

fallback_recs = popular_movies(ratings, movies, min_ratings=200, top_n=10)\
    .sort_values(["avg_rating","num_ratings"], ascending=False)\
    .head(5)[["movieId","title","num_ratings","avg_rating"]]

print("Fallback Top-5 for a true cold-start user (0 ratings):")
fallback_recs.reset_index(drop=True)
```

```
Fallback Top-5 for a true cold-start user (0 ratings):
```

Out[34]:

	movieId	title	num_ratings	avg_rating
0	318	Shawshank Redemption, The (1994)	317	4.429022
1	260	Star Wars: Episode IV - A New Hope (1977)	251	4.231076
2	527	Schindler's List (1993)	220	4.225000
3	296	Pulp Fiction (1994)	307	4.197068
4	2571	Matrix, The (1999)	278	4.192446

Results Summary (Cross-Validation + Holdout Test)

The table below summarizes performance across models. Cross-validation (CV) scores are computed on the training data only. The holdout test scores are reported once for the final selected model to estimate real-world generalization performance.

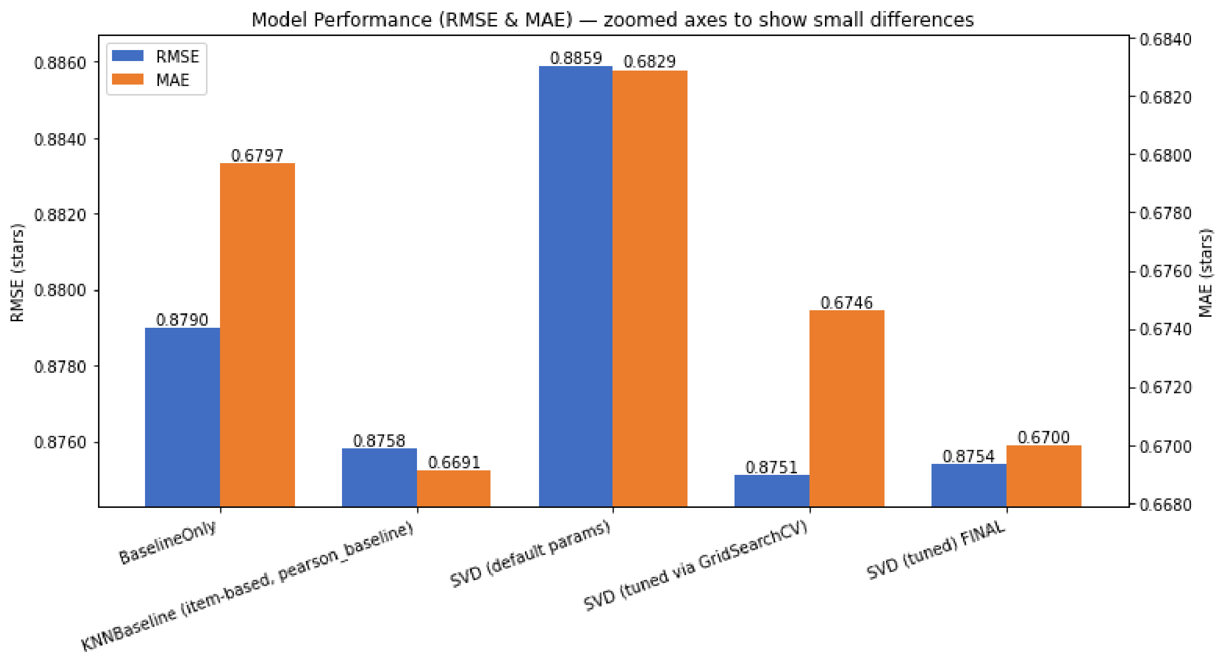
In [35]:
```python
# Results summary table (CV + Holdout)

results_summary = pd.DataFrame([
    {
        "Model": "BaselineOnly",
        "Validation Method": "3-Fold CV (train only)",
        "RMSE": baseline_rmse,
        "MAE": baseline_mae
    },
    {
        "Model": "KNNBaseline (item-based, pearson_baseline)",
        "Validation Method": "3-Fold CV (train only)",
        "RMSE": knn_rmse,
        "MAE": knn_mae
    },
    {
        "Model": "SVD (default params)",
        "Validation Method": "3-Fold CV (train only)",
        "RMSE": svd_rmse,
        "MAE": svd_mae
    },
    {
        "Model": "SVD (tuned via GridSearchCV)",
        "Validation Method": "3-Fold CV (train only)",
        "RMSE": gs.best_score["rmse"],
        "MAE": gs.best_score["mae"]
    },
    {
        "Model": "SVD (tuned) FINAL",
        "Validation Method": "Holdout Test (20%)",
        "RMSE": test_rmse,
        "MAE": test_mae
    }
])

# Pretty formatting
results_summary["RMSE"] = results_summary["RMSE"].astype(float).round(4)
results_summary["MAE"]  = results_summary["MAE"].astype(float).round(4)

results_summary
```

Out[35]:

	Model	Validation Method	RMSE	MAE
0	BaselineOnly	3-Fold CV (train only)	0.8790	0.6797
1	KNNBaseline (item-based, pearson_baseline)	3-Fold CV (train only)	0.8758	0.6691
2	SVD (default params)	3-Fold CV (train only)	0.8859	0.6829
3	SVD (tuned via GridSearchCV)	3-Fold CV (train only)	0.8751	0.6746
4	SVD (tuned) FINAL	Holdout Test (20%)	0.8754	0.6700

In [43]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

# --- Build a plotting dataframe from your results_summary table ---
order = [
    "BaselineOnly",
    "KNNBaseline (item-based, pearson_baseline)",
    "SVD (default params)",
    "SVD (tuned via GridSearchCV)",
    "SVD (tuned) FINAL"
]

plot_df = results_summary.copy()
plot_df = plot_df[plot_df["Model"].isin(order)].copy()
plot_df["Model"] = pd.Categorical(plot_df["Model"], categories=order, ordered=Tru
plot_df = plot_df.sort_values("Model")

labels = plot_df["Model"].astype(str).tolist()
rmse = plot_df["RMSE"].astype(float).values
mae  = plot_df["MAE"].astype(float).values

x = np.arange(len(labels))
width = 0.38

# --- Zoom ranges (separately for RMSE and MAE) ---
rmse_min, rmse_max = rmse.min(), rmse.max()
mae_min, mae_max   = mae.min(), mae.max()

rmse_pad = 0.0008
mae_pad  = 0.0012

# We'll use the RMSE range as the plotted axis, and draw MAE on a secondary axis
# so BOTH can be zoomed appropriately and remain readable.
fig, ax1 = plt.subplots(figsize=(11, 6))

# RMSE bars (left axis)
bars1 = ax1.bar(x - width/2, rmse, width, label="RMSE", color= "#4472C4")
ax1.set_ylabel("RMSE (stars)")
ax1.set_ylim(rmse_min - rmse_pad, rmse_max + rmse_pad)
ax1.yaxis.set_major_formatter(lambda v, pos: f"{v:.4f}")

# MAE bars (right axis)
ax2 = ax1.twinx()
bars2 = ax2.bar(x + width/2, mae, width, label="MAE", color= "#ED7D31")
ax2.set_ylabel("MAE (stars)")
ax2.set_ylim(mae_min - mae_pad, mae_max + mae_pad)
ax2.yaxis.set_major_formatter(lambda v, pos: f"{v:.4f}")

# X labels / title
ax1.set_title("Model Performance (RMSE & MAE) — zoomed axes to show small differe
ax1.set_xticks(x)
ax1.set_xticklabels(labels, rotation=20, ha="right")

# Value labels on bars (4 decimals)
for b, v in zip(bars1, rmse):
    ax1.text(b.get_x() + b.get_width()/2, v, f"{v:.4f}", ha="center", va="bottom'
```

```
for b, v in zip(bars2, mae):
    ax2.text(b.get_x() + b.get_width()/2, v, f"{v:.4f}", ha="center", va="bottom"

# Combined Legend
handles1, labels1 = ax1.get_legend_handles_labels()
handles2, labels2 = ax2.get_legend_handles_labels()
ax1.legend(handles1 + handles2, labels1 + labels2, loc="upper left")

plt.tight_layout()
plt.show()

print("Note: RMSE and MAE use separate (zoomed) y-axes so small differences are e
```




```
Note: RMSE and MAE use separate (zoomed) y-axes so small differences are easier
to see.
```

Conclusion & Next Steps

Summary of results

I compared a baseline model, neighborhood collaborative filtering (kNN), and matrix factorization (SVD).

Hyperparameter tuning improved SVD’s cross-validated performance and produced strong holdout test results (RMSE/MAE).

The system generates Top-5 recommendations for existing users and can handle new users via seeded ratings or popularity-based fallback.

On the holdout test set, the tuned SVD achieved RMSE ≈ 0.88, meaning predictions are typically within about ~0.9 stars of the true rating.

Business implications

Personalized recommendations can reduce choice overload and improve engagement and retention.

A cold-start strategy is necessary for new users and new content.

Limitations

Sparse rating matrix limits personalization for low-activity users

No user demographics or rich item metadata

Offline RMSE/MAE does not fully capture business KPIs (e.g., click-through, watch-time)

Next steps

Add a simple hybrid (content + CF) using genres/tags for cold-start

Evaluate with ranking metrics (Precision@K / Recall@K) and online A/B testing

Incorporate implicit feedback (clicks, watch-time) for production use

In [ ]:

```
```