Movie Recommendation System(Deliverable-2)

My movies dataset consists of users and the movies they have watched. Each user has mentioned five favorite movies. Since the dataset is textual and not visual, I applied **text-specific preprocessing techniques** instead of image-based ones.

Preprocessing Steps Applied:

Lowercasing

All movie titles were converted to lowercase to avoid mismatches due to capitalization (e.g., "Inception" vs "inception").

• Whitespace Removal

Leading and trailing whitespace was stripped from each movie title to ensure consistency.

• Typo Fixing and Normalization

A dictionary of common typos and alternate titles was created to standardize movie names.

Example fixes:

- o "muna bhi mbbs" \rightarrow "munna bhai mbbs"
- o "top gun" \rightarrow "top gun maverick"

```
# 3. Fixing typos from dataset
fixes = {
    "interstellars": "interstellar",
    "top gun": "top gun maverick",
    "muna bhi mbbs": "munna bhai mbbs",
    "bhjrngi bhai jan": "bajrangi bhaijaan",
    "money hiest korean": "money heist",
    "mission impossible series": "mission impossible",
    "the heirs": "heirs",
    "matrix": "the matrix",
    "cars": "cars (2006)",
    "tron": "tron legacy",
}

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def fix_title(title):
    return fixes.get(title, title)

df[movie_cols] = df[movie_cols].applymap(fix_title)
```

• Duplicate Removal

If a user listed the same movie multiple times, duplicates were removed using Python's set function.

```
user_movies = {}
for i, row in df.iterrows():
    name = row['Name'].strip().lower()
    movies = [row[col] for col in movie_cols if pd.notna(row[col])]
    user_movies[name] = list(set(movies))  # remove duplicates per user
```

These steps were essential for preparing the dataset for clustering and recommendation without semantic conflicts.

Cross-Correlation Analysis

To mimic a cross-correlation analysis, I calculated the pairwise similarity between users based on their movie choices.

