Limitation of Content Based Recommendation using KNN

Content-based movie recommendation systems using K-Nearest Neighbours (KNN) offer valuable insights and recommendations based on the features of movies and the preferences of users. However, they come with their own set of **limitations that can affect its performance, impact the quality and effectiveness** of the recommendations.

- **Limited Serendipity**: Content-based recommendation using KNN tends to recommend items that are **similar to the ones a user has already interacted with**. This can lead to a lack of serendipity, as users may not be exposed to new or diverse items outside their established preferences.

- **Cold Start Problem**: Content-based KNN struggles when dealing with **new items that lack historical interaction data or feature information**. To overcome this challenge, hybrid models can incorporate collaborative filtering techniques during the cold start to make informed recommendations based on user or item similarities.

- **Curse of Dimensionality**: As the number of features (dimensions) in the dataset increases, the distance between data points becomes less meaningful, and the algorithm's **performance may degrade**. This is known as the curse of dimensionality.

- **Scalability:** Calculating item similarities for **a large number of items can be computationally intensive and time-consuming**. Strategies like dimensionality reduction, clustering, and the use of approximate nearest neighbours can help enhance the scalability of content-based KNN systems.

- **Memory Usage:** KNN needs to store the entire training dataset in memory, which can be a limitation when dealing with large datasets.

- **Limited Exploration**: Content-based systems **do not encourage exploration of entirely new or dissimilar content**, as they primarily rely on existing user preferences and item features.

Hybrid Approaches for Balanced Recommendations: One effective strategy to mitigate several of these limitations is the integration of content-based and collaborative filtering techniques. Hybrid models strike a balance between relevance and diversity, leveraging the strengths of both approaches. This combination enhances recommendation quality by providing a more comprehensive and adaptive user experience.

OUTPUT:

```
recommend('Batman Begins')
```

```
The Dark Knight
Batman
Batman
The Dark Knight Rises
Batman Returns
Batman v Superman: Dawn of Justice
Batman & Robin
10th & Wolf
Rockaway
```

```
recommend('Iron Man')
```

```
Iron Man 2
Iron Man 3
Avengers: Age of Ultron
Captain America: Civil War
The Avengers
Ant-Man
Guardians of the Galaxy
X-Men
X-Men Origins: Wolverine
```