

Recommender System Project – Movielens100k

Data discription

- 根據 ml-100k 中 readme.md 的描述：

u.data 有 100000 筆資料, u1.base~u5.base 各有 80000 筆資料, u1.test~u5.test 各有 20000 筆資料。

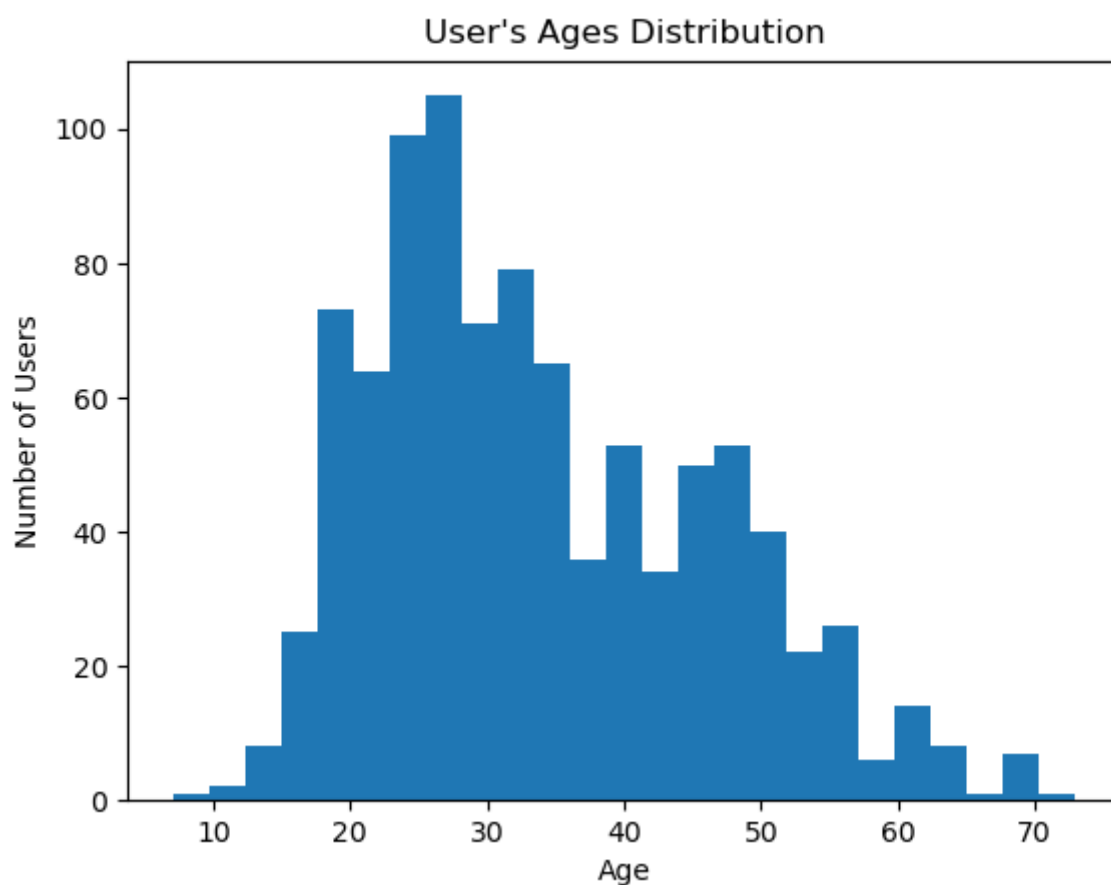
- u.data u1~u5 中都有 4 個 columns:

user id | item id | rating | timestamp

- u.user 中有 5 個 columns:

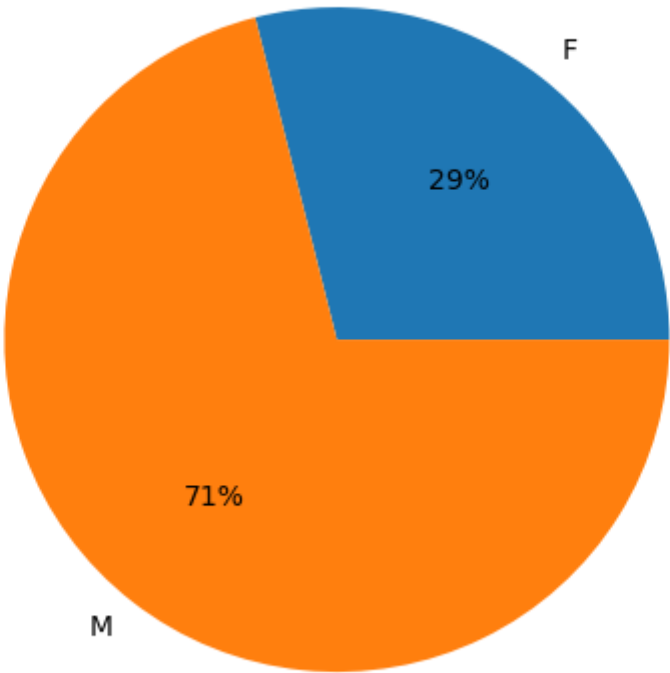
user id | age | gender | occupation | zip code

其中 age 的分佈爲：

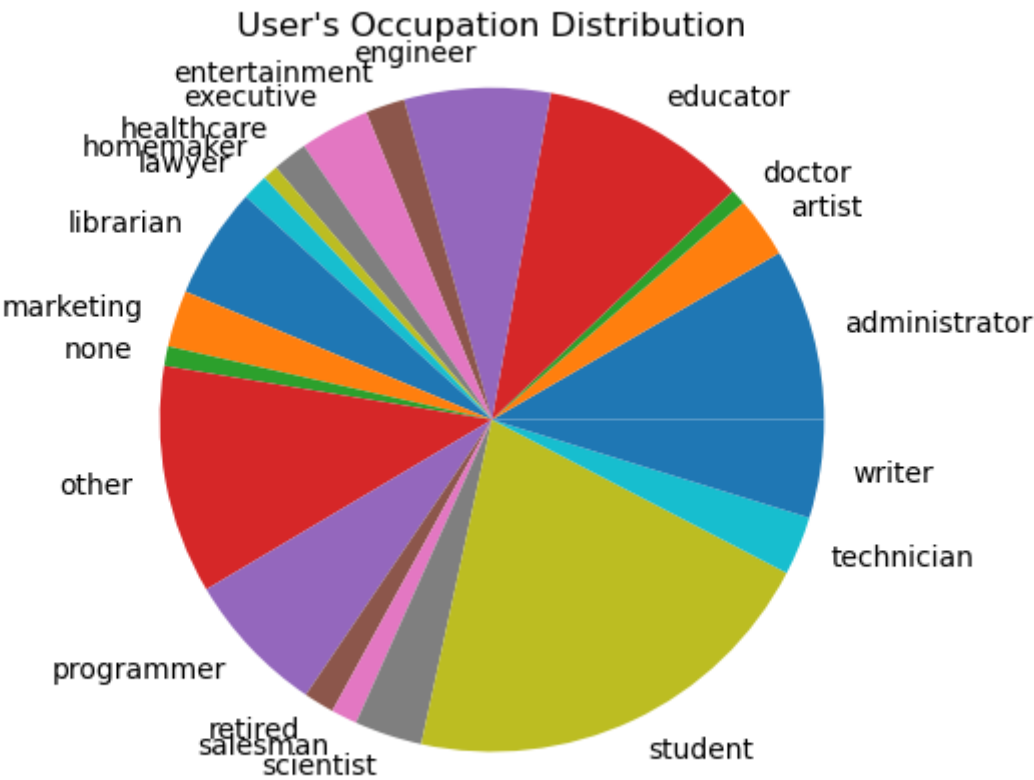


gender 的分佈爲：

User's Gender Distribution



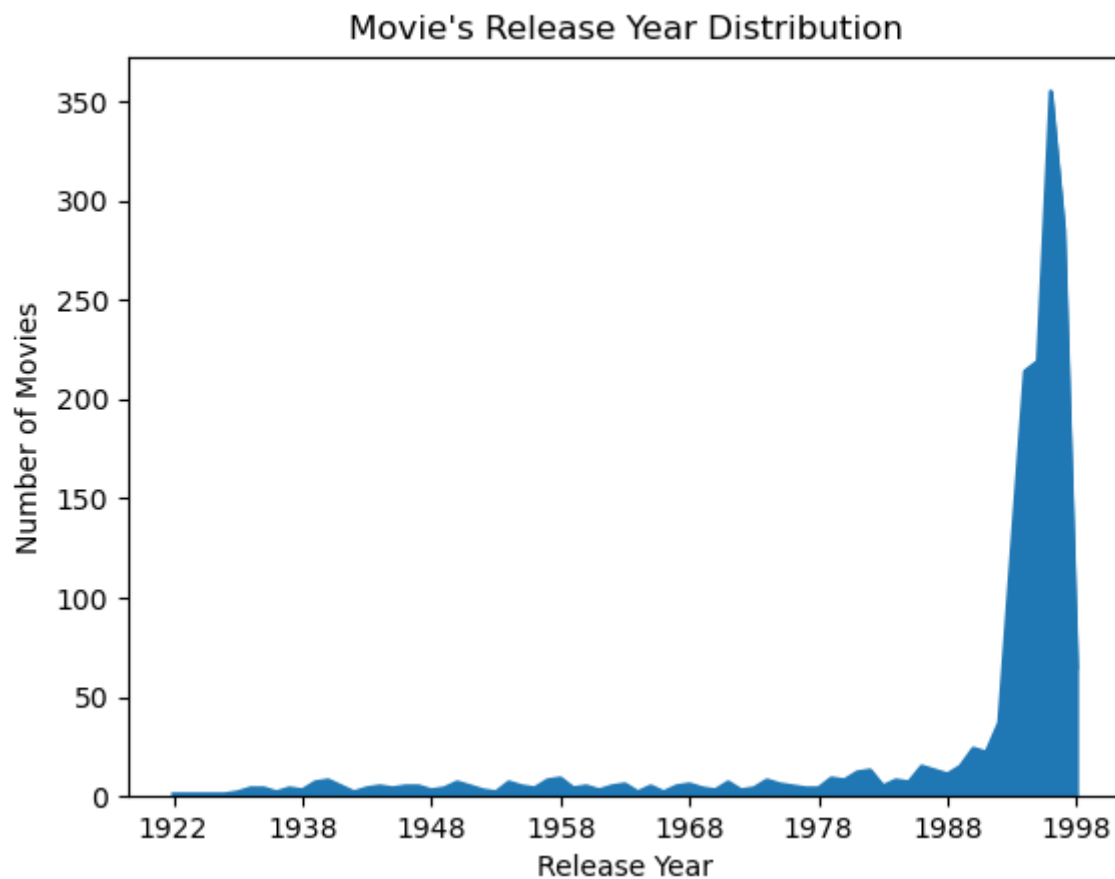
occupation 的分佈爲：



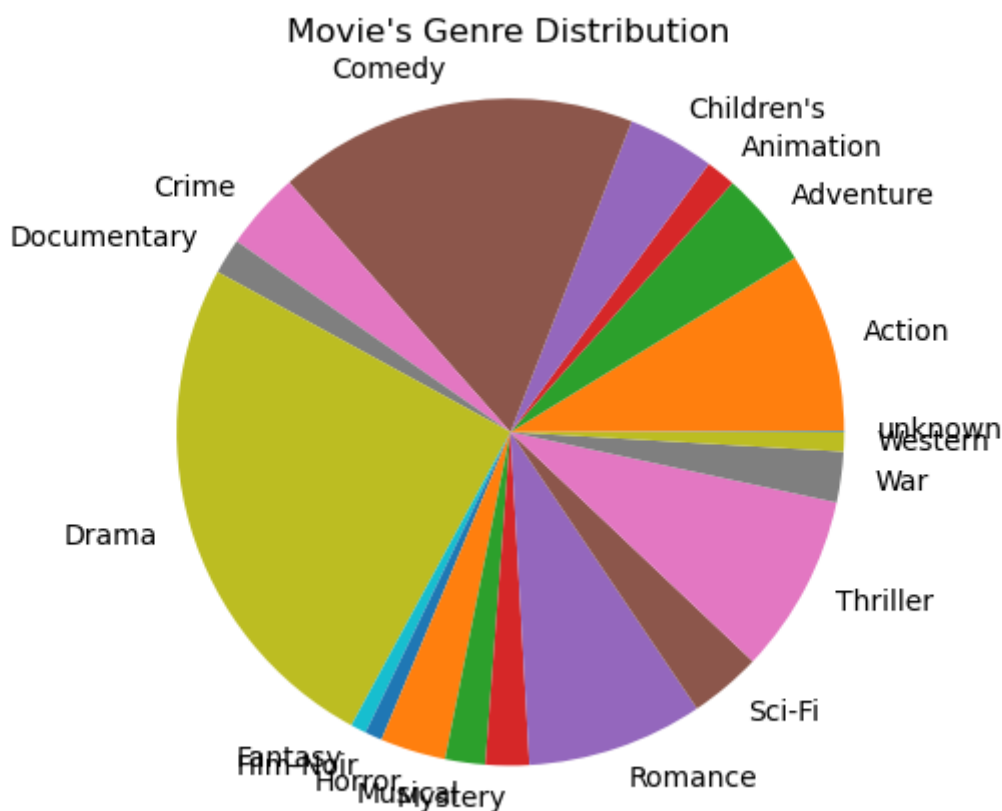
- u.item 中有 24 個 columns:

movie id | movie title | release date | video release date | IMDb URL | unknown | Action | Adventure | Animation | Children's | Comedy | Crime | Documentary | Drama | Fantasy | Film-Noir | Horror | Musical | Mystery | Romance | Sci-Fi | Thriller | War | Western

其中 release date (modified to release year) 的分佈爲:



各個 genre 的分佈爲:



Program discription

Item Base Collaborative Filtering Model

實作方法：

1. 使用 pandas 的 pivot 將 rating data 轉換成 item-to-user 的稀疏矩陣。
2. 使用 sklearn 的 NearestNeighbors 由 item-to-user 矩陣取得 k-neighbor's cosine similarity 還有 k-neighbor's indices。
3. 照公式 $\widehat{rate} = \frac{\sum (similarity \times rate)}{\sum similarity}$ 得出預測的 rating 的值。
4. 計算 RMSE 衡量預測值的誤差。

Code 如下：

```
class Item_Base_CF:
    def __init__(self, n_neighbors=3) -> None:
        self.item_user = np.empty((1682, 943))
        self.n = n_neighbors
        self.knn = NearestNeighbors(n_neighbors=self.n, metric="cosine")
        self.distances, self.indices = np.empty((1682, self.n)),
        np.empty((1682, self.n))
        self.similarities = np.empty((1682, self.n))

    def fit(self, data):
        self.item_user = data.pivot(index="item_id", columns="user_id",
```

```

values="rating")
    # Fail to adjust item-to-user matrix with mean of user-ratings
    # self.item_user =
self.item_user.subtract(self.item_user.mean(axis=1), axis = 0).fillna(0)
    self.item_user = self.item_user.reindex(index=np.arange(1,1683),
fill_value=0).fillna(0)
    # Use sklearn NearestNeighbors to find n similar item's indices &
cosine similarities
    self.knn.fit(self.item_user)
    self.distances, self.indices =
self.knn.kneighbors(n_neighbors=self.n)
    self.similarities = 1 - self.distances

def predict(self, item_id, user_id, epsilon=1e-8):
    # Function to predict rating via item_id & user_id
    # Using formula in 01_Neighborhood-
based_collaborative_filtering.pptx page 32
    pred_r = self.item_user.iloc[item_id-1,user_id-1]
    sim, ind = self.similarities[item_id-1], self.indices[item_id-1]
    product = 1
    product_sum = 0
    if self.item_user.iloc[item_id-1,user_id-1]!=0:
        return pred_r
    else:
        for i in range(len(ind)):
            product = self.item_user.iloc[ind[i],user_id-1] * sim[i]
            product_sum += product
        pred_r = product_sum / (np.sum(sim)+epsilon)
    return pred_r

def rmse(self, data):
    # Function to calculate RMSE of predicted rating & actual rating
    x = data[["item_id", "user_id"]].to_numpy()
    y = data[["rating"]].to_numpy()
    losses = []
    for i in range(len(x)):
        losses.append((self.predict(x[i][0], x[i][1]) - y[i]).item())
    return sqrt(np.nanmean(np.square(losses)))

```

輸出結果：

```

# Number of neighbors set
k = [2, 4, 8]

```

使用 u1~u5 的資料集進行 5 次 RMSE 輸出，計算其平均值。

已知若使用所有預測值皆為 0 的 model，其 5 次的 RMSE 輸出將會落在 3.6, 3.7 左右，相較之下 Item Base CF 的誤差值有顯著的減少。

```
-----2-neighbors-----  
u1.test RMSE : 2.8520523211052926  
u2.test RMSE : 2.687808126654529  
u3.test RMSE : 2.603465358260204  
u4.test RMSE : 2.647911007490916  
u5.test RMSE : 2.7360450020224687  
mean : 2.705456363106682  
-----4-neighbors-----  
u1.test RMSE : 2.7258851793259886  
u2.test RMSE : 2.5596291495946533  
u3.test RMSE : 2.4705296126894747  
u4.test RMSE : 2.526707312903369  
u5.test RMSE : 2.62215865725013  
mean : 2.580981982352723  
-----8-neighbors-----  
u1.test RMSE : 2.6828780812337185  
u2.test RMSE : 2.500036414134187  
u3.test RMSE : 2.425303738135374  
u4.test RMSE : 2.4748264591987574  
u5.test RMSE : 2.575107201472646  
mean : 2.5316303788349366
```