TikTok-Style Recommendation Analytics & A/B Experimentation

Import Required Libraries

```
# Core Data Handling

import numpy as np
import pandas as pd


# Visualization

import matplotlib.pyplot as plt
import seaborn as sns

# Machine Learning

from sklearn.decomposition import TruncatedSVD
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split


# Statistics & A/B Testing

from scipy.stats import ttest_ind


# Reproducibility

np.random.seed(42)


# Display Settings

pd.set_option("display.max_columns", 100)
sns.set(style="whitegrid")
```

Synthetic Dataset Generation

```
# Global parameters

N_USERS = 3000
N_VIDEOS = 1200
```

```
N_CREATORS = 300
N_TOPICS = 8
N_INTERACTIONS = 180_000

np.random.seed(42)

# Topics Name

topics = [

    "Comedy","Music", "Sports",
"Gaming","Education","Lifestyle","News","Tech"
]



# Users → Topic Preferences

user_prefs = np.random.dirichlet(alpha=[0.8] * N_TOPICS, size =
N_USERS)

# Videos → Topics + Length
video_topics = np.random.choice(N_TOPICS,N_VIDEOS)
video_lengths = np.random.randint(15,90,size = N_VIDEOS)

video_topics
```

```
array([3, 4, 7, ..., 0, 0, 2])
```

```
video_lengths
```

```
array([47, 44, 36, ..., 73, 73, 57])
```

```
# Creators → Specialization

creator_topics = np.random.choice(N_TOPICS, N_CREATORS)
video_creators = np.random.choice(N_CREATORS, N_VIDEOS)

# Generate Interactions


records = []

for _ in range(N_INTERACTIONS):
    user = np.random.randint(N_USERS)
    video = np.random.randint(N_VIDEOS)

    topic = video_topics[video]
    base_interest = user_prefs[user,topic]
```

```
    noise = np.random.normal(0,0.1)
    watch_fraction= np.clip(base_interest + noise, 0.05,1.0)

    watch_time = watch_fraction * video_lengths[video]


    records.append({

        "user_id" : user,
        "video_id": video,
        "creator_id": video_creators[video],
        "topic":topic,
        "video_length":video_lengths[video],
        "watch_time": watch_time,
        "completion_rate": watch_fraction,
        "likes": int(watch_fraction > 0.65),
        "shares": int(watch_fraction >0.8),
        "follows": int(watch_fraction > 0.9)


    })


records[0]
```

```
{'user_id': 2559,
 'video_id': 400,
 'creator_id': 252,
 'topic': 0,
 'video_length': 32,
 'watch_time': 1.6,
 'completion_rate': 0.05,
 'likes': 0,
 'shares': 0,
 'follows': 0}
```

```
df = pd.DataFrame(records)

df.head()
```

	user_id	video_id	creator_id	topic	video_length	watch_time	\
0	2559	400	252	0	32	1.600000	
1	1702	644	37	0	34	8.042061	
2	78	620	230	7	77	3.850000	
3	1566	460	270	3	86	11.870592	
4	1063	799	234	2	21	3.336751	

	completion_rate	likes	shares	follows
0	0.050000	0	0	0

```
1          0.236531      0       0         0
2          0.050000      0       0         0
3          0.138030      0       0         0
4          0.158893      0       0         0
```

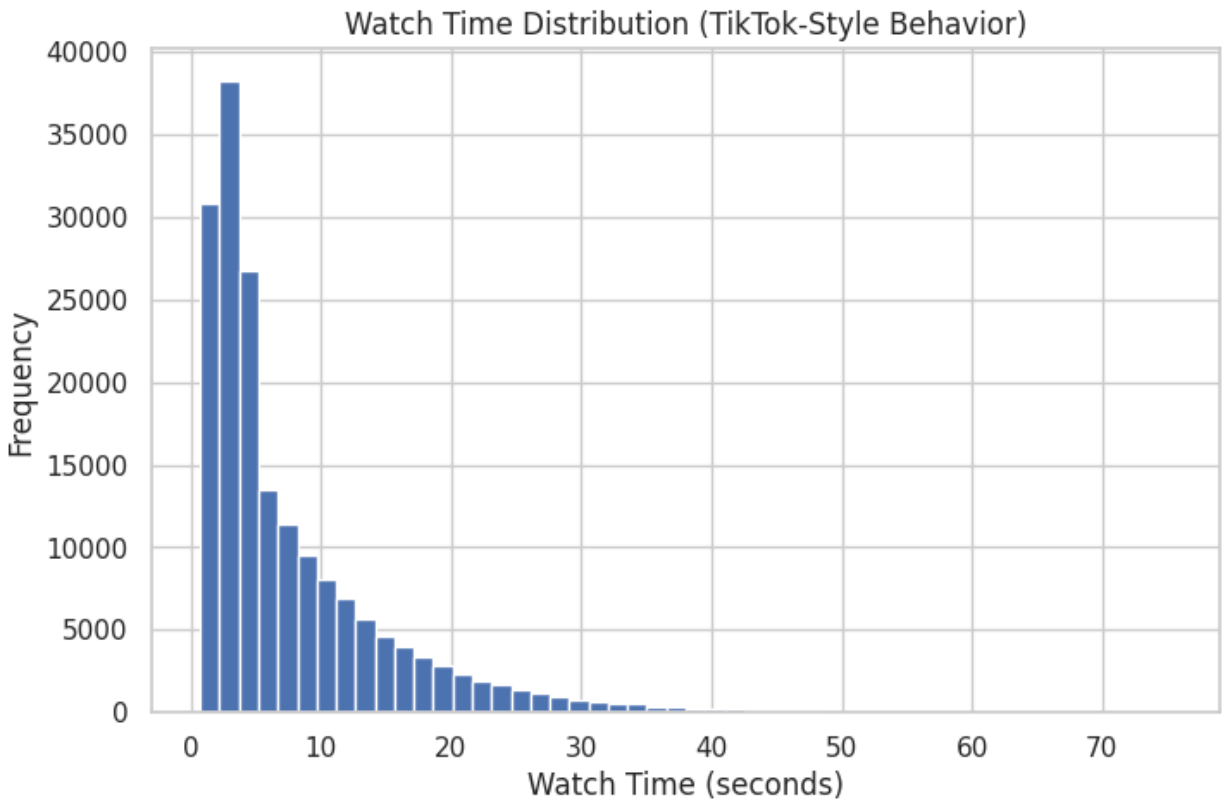
```
df.describe()
```

```
             user_id       video_id     creator_id          topic  \
count  180000.000000  180000.000000  180000.000000  180000.000000
mean     1497.038717     598.214533     147.786594       3.339956
std       865.920797     346.182453      86.330147       2.288610
min         0.000000       0.000000       0.000000       0.000000
25%       747.000000     298.000000      75.000000       1.000000
50%      1497.000000     598.000000     146.000000       3.000000
75%      2246.000000     897.000000     221.000000       5.000000
max      2999.000000    1199.000000     299.000000       7.000000

        video_length     watch_time  completion_rate          likes  \
count  180000.000000  180000.000000    180000.000000  180000.000000
mean       51.851767       7.882182         0.152159       0.003828
std        21.264201       7.738903         0.125722       0.061751
min        15.000000       0.750000         0.050000       0.000000
25%        34.000000       2.800000         0.050000       0.000000
50%        51.000000       4.625071         0.106806       0.000000
75%        70.000000      10.538150         0.213415       0.000000
max        89.000000      75.293587         1.000000       1.000000

              shares        follows
count  180000.000000  180000.000000
mean        0.000367       0.000044
std         0.019145       0.006667
min         0.000000       0.000000
25%         0.000000       0.000000
50%         0.000000       0.000000
75%         0.000000       0.000000
max         1.000000       1.000000
```

```
print("Unique users:", df.user_id.nunique())
print("Unique videos:", df.video_id.nunique())
print("Unique creators:", df.creator_id.nunique())
```

```
Unique users: 3000
Unique videos: 1200
Unique creators: 291
```

```
plt.figure(figsize=(8, 5))
plt.hist(df["watch_time"], bins=50)
plt.title("Watch Time Distribution (TikTok-Style Behavior)")
plt.xlabel("Watch Time (seconds)")
plt.ylabel("Frequency")
plt.show()
```



Engagement Score Engineering

- What Is an Engagement Score?

  A single number that represents how valuable an interaction was to the platform.

- Higher score → better recommendation signal.

```
print(
    "Signal            Why it matters\n"
    "Watch Time        Strong indicator of user interest\n"
    "Completion Rate   Reflects content quality\n"
    "Shares            Measures virality and reach\n"
    "Likes             Weak but useful explicit signal\n"
    "Follows           Indicates long-term user value"
)
```

```
Signal            Why it matters
Watch Time        Strong indicator of user interest
Completion Rate   Reflects content quality
Shares            Measures virality and reach
```

```
Likes             Weak but useful explicit signal
Follows           Indicates long-term user value
```

Normalize Watch Time

```
df.columns
```

```
Index(['user_id', 'video_id', 'creator_id', 'topic', 'video_length',
       'watch_time', 'completion_rate', 'likes', 'shares', 'follows'],
      dtype='object')
```

```
df.watch_time
```

```
0          1.600000
1          8.042061
2          3.850000
3         11.870592
4          3.336751
             ...
179995     1.700000
179996    14.454122
179997     1.350000
179998    11.733004
179999     3.907845
Name: watch_time, Length: 180000, dtype: float64
```

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()


df['watch_time_norm'] = scaler.fit_transform(df[['watch_time']])
```

```
df.watch_time_norm
```

```
0         0.011403
1         0.097823
2         0.041586
3         0.149182
4         0.034701
              ...
179995    0.012744
179996    0.183840
179997    0.008049
179998    0.147337
179999    0.042362
Name: watch_time_norm, Length: 180000, dtype: float64
```

Define Engagement Weight

```
W_WATCH = 0.45
W_COMPLETION = 0.30
W_SHARE = 0.15
W_LIKE = 0.10
```

`Why These Weights?`

- Watch time dominates revenue
- Completion reflects content strength
- Shares > likes (virality > vanity)
- Likes are weakest`

```
df['engagement_scores'] = (

    W_WATCH * df["watch_time_norm"] +
    W_COMPLETION * df['completion_rate'] +
    W_SHARE * df['shares'] +
    W_LIKE * df['likes']
)

df["engagement_scores"].describe()
```

```
count    180000.000000
mean          0.089141
std           0.083270
min           0.015000
25%           0.029488
50%           0.058379
75%           0.124147
max           0.977858
Name: engagement_scores, dtype: float64
```

Interaction Matrix → Apply SVD

```
interaction_matrix = df.pivot_table(

    index = "user_id",
    columns= "video_id",
    values = "watch_time",
    aggfunc= "mean",
    fill_value = 0

)
```

```
interaction_matrix

video_id  0     1         2         3     4     5          6
7     \
user_id

0          0.0   0.0  0.000000  0.000000   0.0   0.0   0.000000
0.000000
1          0.0   0.0  0.000000  0.000000   0.0   0.0   0.000000
0.000000
2          0.0   0.0  0.000000  7.583277   0.0   0.0   0.000000
0.000000
3          0.0   0.0  7.754404  0.000000   0.0   0.0   0.000000
0.000000
4          0.0   0.0  0.000000  0.000000   0.0   0.0   0.000000
0.000000
...        ...   ...       ...       ...   ...   ...        ...
...
2995       0.0   0.0  0.000000  0.000000   0.0   0.0   0.000000
0.000000
2996       0.0   0.0  0.000000  0.000000   0.0   0.0  14.790461
15.953241
2997       0.0   0.0  0.000000  0.000000   0.0   0.0   0.000000
0.000000
2998       0.0   0.0  0.000000  0.000000   0.0   0.0   4.450000
0.000000
2999       0.0   2.2  0.000000  0.000000   0.0   0.0   0.000000
0.000000

video_id  8     9     10    11        12        13    14    15    16
17    \
user_id

0          0.0   0.0   0.0   0.0  0.000000  8.96553   0.0  0.00   0.0
0.0
1          0.0   0.0   0.0   0.0  0.000000  0.00000   0.0  0.00   0.0
0.0
2          0.0   0.0   0.0   0.0  0.000000  0.00000   0.0  0.00   0.0
0.0
3          0.0   0.0   0.0   0.0  0.000000  0.00000   0.0  0.00   0.0
0.0
4          0.0   0.0   0.0   0.0  0.000000  0.00000   0.0  2.75   0.0
0.0
...        ...   ...   ...   ...       ...      ...   ...   ...   ...
...
2995       0.0   0.0   0.0   0.0  0.000000  0.00000   0.0  0.00   0.0
0.0
2996       0.0   0.0   4.1   0.0  0.000000  0.00000   0.0  0.00   0.0
0.0
2997       0.0   0.0   0.0   0.0  0.000000  0.00000   0.0  0.00   0.0
```

```
0.0
2998       0.0   0.0   0.0   0.0  5.588256  0.00000   0.0  0.00   0.0
0.0
2999       0.0   0.0   0.0   0.0  0.000000  0.00000   0.0  0.00   0.0
0.0

video_id  18    19    20    21    22    23    24    25        26    27
\
user_id

0          0.0  0.00   0.0   0.0   0.0   0.0   0.0   0.0  3.378324
0.00
1          0.0  0.00   0.0   0.0   0.0   0.0   0.0   0.0  0.000000
0.00
2          0.0  4.05   0.0   0.0   0.0   0.0   0.0   0.0  0.000000
0.00
3          0.0  0.00   0.0   0.0   0.0   0.0   0.0   0.0  0.000000
0.00
4          0.0  0.00   0.0   0.0   0.0   0.0   0.0   0.0  0.000000
0.00
...        ...   ...   ...   ...   ...   ...   ...   ...       ...   .
..
2995       0.0  0.00   0.0   0.0   0.0   0.0   2.9   0.0  0.000000
0.00
2996       0.0  0.00   0.0   0.0   0.0   0.0   0.0   0.0  0.000000
0.00
2997       0.0  0.00   0.0   0.0   0.0   0.0   0.0   0.0  0.000000
0.00
2998       0.0  0.00   0.0   0.0   0.0   0.0   0.0   0.0  0.000000
0.00
2999       0.0  0.00   0.0   0.0   0.0   0.0   0.0   0.0  0.000000
1.95

video_id  28    29        30    31    32    33         34    35    36
37    \
user_id

0          0.0   0.0  0.000000   0.0  0.00   0.0   0.000000   0.0
0.0   0.0
1          0.0   0.0  0.000000   0.0  0.00   0.0   0.000000   0.0
0.0   0.0
2          0.0   0.0  0.000000   0.0  0.00   0.0   0.000000   0.0
0.0   0.0
3          0.0   0.0  6.620115   0.0  0.00   0.0   0.000000   0.0
0.0   0.0
4          0.0   0.0  0.000000   0.0  0.00   0.0   0.000000   0.0
0.0   0.0
...        ...   ...       ...   ...   ...   ...        ...   ...   ..
.   ...
2995       0.0   0.0  0.000000   0.0  3.85   0.0   0.000000   0.0
```

```
0.0   0.0
2996       0.0   0.0  0.000000   0.0  0.00   0.0  15.684871   0.0
0.0   0.0
2997       0.0   0.0  0.000000   0.0  0.00   0.0   0.000000   0.0
0.0   0.0
2998       0.0   0.0  0.000000   0.0  0.00   0.0   0.000000   0.0
0.0   0.0
2999       0.0   0.0  0.000000   0.0  0.00   0.0   0.000000   0.0
0.0   0.0

video_id  38    39       40        41        42       43    44
45    \
user_id

0          0.0   0.0  0.00000   0.00000  0.000000  0.00000   0.0
3.405985
1          0.0   0.0  0.00000   0.00000  0.000000  0.00000   0.0
0.000000
2          0.0   0.0  0.00000   0.00000  0.000000  0.00000   0.0
0.000000
3          0.0   0.0  0.00000   0.00000  0.000000  6.91515   0.0
0.000000
4          0.0   0.0  0.00000   0.00000  0.000000  0.00000   0.0
0.000000
...        ...   ...      ...       ...       ...      ...   ...
...
2995       0.0   0.0  2.02191   0.00000  8.365606  0.00000   0.0
0.000000
2996       0.0   0.0  0.00000   0.00000  0.000000  0.00000   0.0
0.000000
2997       0.0   0.0  0.00000   0.00000  0.000000  0.00000   0.0
0.000000
2998       0.0   0.0  0.00000  19.22286  0.000000  0.00000   0.0
23.682213
2999       0.0   0.0  0.00000   0.00000  0.000000  3.10000   0.0
0.000000

video_id  46         47    48        49    ...       1150  1151  1152
1153  \
user_id                                    ...

0          0.0   0.000000   0.0  0.000000  ...   0.000000   0.0   0.0
0.0
1          0.0   0.000000   0.0  0.000000  ...   0.000000   0.0   0.0
0.0
2          0.0   0.000000   0.0  0.000000  ...   0.000000   0.0   0.0
0.0
3          0.0  22.934576   0.0  0.000000  ...   0.000000   0.0   0.0
0.0
4          0.0   0.000000   0.0  0.000000  ...   0.000000   0.0   4.3
```

```
0.0
...         ...         ...   ...       ...  ...         ...   ...   ...
...
2995        0.0   0.000000   0.0  3.742672  ...   0.000000   0.0   0.0
0.0
2996        0.0   0.000000   0.0  0.000000  ...   0.000000   0.0   0.0
0.0
2997        0.0   0.000000   0.0  0.000000  ...  28.477744   0.0   0.0
0.0
2998        0.0   0.000000   0.0  0.000000  ...   0.000000   0.0   0.0
0.0
2999        0.0   0.000000   0.0  0.000000  ...   0.000000   0.0   0.0
0.0

video_id  1154  1155       1156      1157  1158      1159
1160  \
user_id

0           0.0   0.0   0.000000  0.000000   0.0  0.000000   0.000000

1           0.0   0.0  15.605155  3.153752   0.0  0.000000   0.000000

2           0.0   0.0   0.000000  0.000000   0.0  0.000000   0.000000

3           0.0   0.0   0.000000  0.000000   0.0  0.000000   0.000000

4           0.0   0.0   0.000000  0.000000   0.0  0.000000   0.000000

...         ...   ...         ...       ...   ...       ...         ...

2995        0.0   0.0   0.000000  0.000000   0.0  0.000000   0.000000

2996        0.0   0.0   0.000000  0.000000   0.0  9.415112  23.860116

2997        0.0   0.0   0.000000  0.000000   0.0  0.000000   0.000000

2998        0.0   0.0   0.000000  0.000000   0.0  0.000000   0.000000

2999        0.0   0.0   0.000000  0.000000   0.0  0.000000   0.000000


video_id       1161  1162       1163  1164      1165  1166  1167  1168
\
user_id

0          16.773660   0.0  19.286271   0.0  0.000000  0.00   0.0   0.0

1           0.000000   0.0   0.000000   0.0  0.000000  0.00   0.0   0.0

2           0.000000   0.0   0.000000   0.0  0.000000  0.00   0.0   0.0
```

```
3          0.000000   0.0   0.000000   0.0  0.000000  0.00   0.0   0.0

4          0.000000   0.0   0.000000   0.0  0.000000  0.00   0.0   0.0

...             ...   ...        ...   ...       ...   ...   ...   ...

2995       0.000000   0.0   0.000000   0.0  0.000000  0.00   0.0   0.0

2996       0.000000   0.0   0.000000   0.0  0.000000  0.00   0.0   0.0

2997       0.000000   0.0   0.000000   0.0  6.975872  0.00   0.0   0.0

2998       3.263552   0.0   0.000000   0.0  0.000000  0.00   0.0   0.0

2999       0.000000   0.0   0.000000   0.0  0.000000  1.75   0.0   0.0


video_id      1169  1170       1171       1172  1173  1174  1175  1176
1177  \
user_id

0          0.000000   0.0   0.000000   0.000000   0.0   0.0   0.0   0.0
0.0
1          3.084997   0.0   0.000000   0.000000   0.0   0.0   0.0   0.0
0.0
2          0.000000   0.0   0.000000   0.000000   0.0   0.0   0.0   0.0
0.0
3          0.000000   0.0   0.000000   0.000000   0.0   0.0   3.0   0.0
0.0
4          0.000000   0.0   0.000000   0.000000   0.0   0.0   3.0   0.0
0.0
...             ...   ...        ...        ...   ...   ...   ...   ...
...
2995       0.000000   0.0   0.000000   0.000000   0.0   0.0   0.0   0.0
0.0
2996       0.000000   0.0   0.000000  23.291644   0.0   0.0   0.0   0.0
0.0
2997       0.000000   0.0   0.000000   0.000000   0.0   0.0   0.0   0.0
0.0
2998       0.000000   0.0   0.000000   0.000000   0.0   0.0   0.0   0.0
0.0
2999       0.000000   0.0  14.214455   0.000000   0.0   0.0   0.0   0.0
0.0

video_id       1178  1179  1180       1181  1182  1183  1184  1185
1186  \
user_id

0          0.000000   0.0  0.00   0.000000  0.00   0.0   0.0   0.0
0.0
```

```
1          0.000000   0.0  0.00   0.000000  0.00   0.0   0.0   0.0
0.0
2          0.000000   0.0  0.00   0.000000  0.00   0.0   0.0   0.0
0.0
3          0.000000   0.0  0.00   0.000000  3.35   0.0   0.0   0.0
0.0
4          0.000000   0.0  0.00  19.390712  3.35   0.0   0.0   0.0
0.0
...             ...   ...   ...        ...   ...   ...   ...   ...   .
..
2995       0.000000   0.0  0.00   0.000000  0.00   0.0   0.0   0.0
0.0
2996       0.000000   0.0  0.00   5.263990  0.00   0.0   2.5   2.4
0.0
2997       0.000000   0.0  2.95   0.000000  0.00   0.0   0.0   0.0
0.0
2998      24.918864   0.0  0.00   0.000000  0.00   0.0   0.0   0.0
0.0
2999       0.000000   0.0  0.00   0.000000  0.00   0.0   0.0   0.0
0.0

video_id  1187  1188  1189  1190  1191      1192  1193  1194  1195
1196  \
user_id

0          0.0   0.0  0.00   0.0   0.0  0.000000   0.0   0.0   0.0
0.0
1          0.0   0.0  0.00   0.0   0.0  0.000000   0.0   0.0   0.0
0.0
2          1.0   0.0  2.35   0.0   0.0  0.000000   0.0   0.0   0.0
0.0
3          0.0   0.0  0.00   0.0   0.0  0.000000   0.0   0.0   0.0
0.0
4          0.0   0.0  0.00   0.0   0.0  0.000000   0.0   0.0   0.0
0.0
...        ...   ...   ...   ...   ...       ...   ...   ...   ...   .
..
2995       0.0   0.0  0.00   0.0   0.0  3.478793   0.0   0.0   0.0
0.0
2996       0.0   0.0  2.35   0.0   0.0  0.000000   0.0   0.0   0.0
0.0
2997       0.0   0.0  0.00   0.0   0.0  0.000000   0.0   0.0   0.0
0.0
2998       0.0   0.0  0.00   0.0   0.0  0.000000   0.0   0.0   0.0
0.0
2999       0.0   0.0  0.00   0.0   0.0  0.000000   0.0   0.0   0.0
0.0

video_id       1197  1198       1199
user_id
```

```
0           0.000000   0.0   0.000000
1          13.228794   0.0   0.000000
2           0.000000   0.0   0.000000
3           0.000000   0.0   0.000000
4           0.000000   0.0   0.000000
...              ...   ...        ...
2995        0.000000   0.0   0.000000
2996        0.000000   0.0   0.000000
2997        0.000000   0.0   0.000000
2998        0.000000   0.0   0.000000
2999        0.000000   0.0  17.343571

[3000 rows x 1200 columns]
```

```
interaction_matrix.shape
```

```
(3000, 1200)
```

```
# checking spacity

(interaction_matrix > 0).mean().mean()
```

```
0.048759166666666666
```

Truncated SVD

```
from sklearn.decomposition import TruncatedSVD

svd = TruncatedSVD(
    n_components = 30,
    random_state = 42
)

user_embeddings = svd.fit_transform(interaction_matrix)
video_embeddings = svd.components_.T

# Generate Personalized Score
import numpy as np
score_matrix = np.dot(user_embeddings, video_embeddings.T)
```

Recomend Top k Videos for user

```
def recommend_videos(user_id,k = 10):
    scores = score_matrix[user_id]
    top_videos = np.argsort(scores)[-k:][::-1]
    return top_videos

recommend_videos(user_id = 42, k = 5)
```

```
array([762, 293,  90,  43, 781])
```

A/B Experiment Setup

Control (A): Popularity-Based Feed

```
popular_videos = (

    df.groupby("video_id")['watch_time']
                .mean()
                 .sort_values(ascending = False)
                 .index
                 .values

)

def recommend_control(k = 10):
    return popular_videos[:k]
```

Treatment (B): Personalized SVD Feed

```
def recommend_treatment(user_id, k = 10):
    scores = score_matrix[user_id]
    return scores.argsort()[-k:][::-1]
```

Randomly Assign Users to A/B Groups

```
users = interaction_matrix.index.values

np.random.shuffle(users)

split = int(0.5 * len(users))
control_users = users[:split]
treatment_users = users[split:]
```

Simulate Feed Exposure

```
def simulate_feed(user_id, group, k = 10):
    if group == 'control':
        return recommend_control(k)
    else:
        return recommend_treatment(user_id, k)
```

Measure Metrics

```
def average_watch_time(user_ids, group):
    watch_times = []

    for u in user_ids:
        recs= simulate_feed(u,group)
        wt = df[
            (df.user_id == u) & (df.video_id.isin(recs))
        ]["watch_time"].mean()
        watch_times.append(wt)

    return np.nanmean(watch_times)
```

Compute A/B Results

```
control_wt = average_watch_time(control_users,"control")
treatment_wt = average_watch_time(treatment_users, "treatment")

uplift = (treatment_wt - control_wt) / control_wt * 100

control_wt, treatment_wt , uplift
```

```
(14.734923704109082, 22.347761777615077, 51.66526971146125)
```

Statistical Significance (t-test)

```
def user_watch_time_on_feed(user_id, group):
    recs = simulate_feed(user_id, group)
    return df[
        (df.user_id == user_id) &
        (df.video_id.isin(recs))
    ]["watch_time"].mean()

control_vals = [
    user_watch_time_on_feed(u, "control")
    for u in control_users
]

treatment_vals = [
    user_watch_time_on_feed(u, "treatment")
    for u in treatment_users
]

from scipy.stats import ttest_ind
```

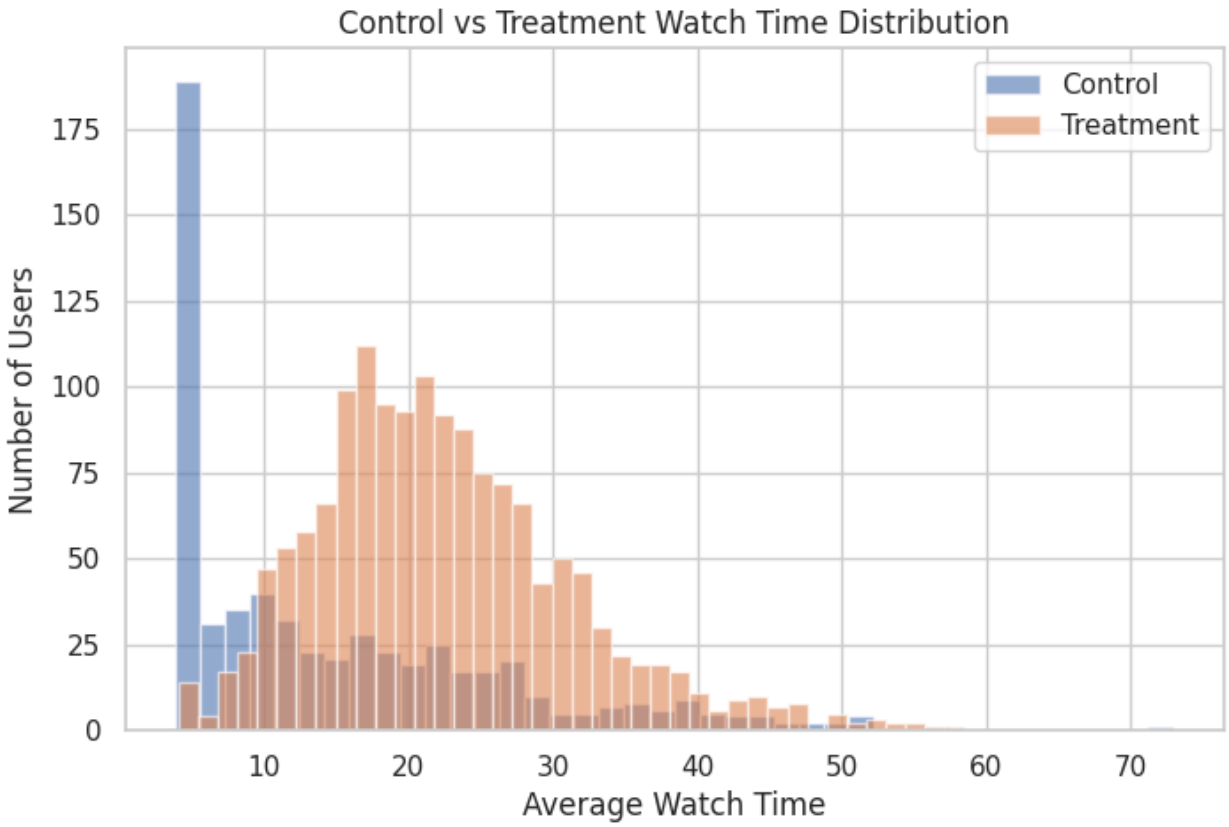
```
t_stat, p_value = ttest_ind(
    treatment_vals,
    control_vals,
    nan_policy="omit"
)

p_value
```

```
2.4049013695309344e-55
```

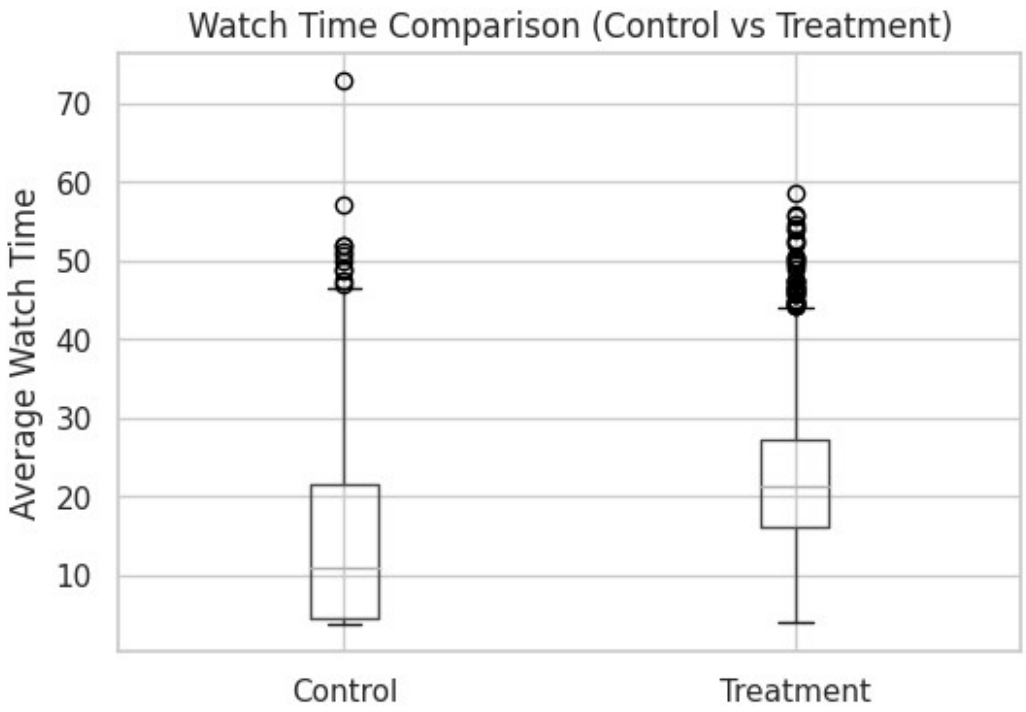
Visualize A/B Results (Control vs Treatment)

Prepare Per-User Metrics (Same as t-test)

```
control_vals = [
    user_watch_time_on_feed(u, "control")
    for u in control_users
]

treatment_vals = [
    user_watch_time_on_feed(u, "treatment")
    for u in treatment_users
]



plt.figure(figsize=(8, 5))
plt.hist(control_vals, bins=40, alpha=0.6, label="Control")
plt.hist(treatment_vals, bins=40, alpha=0.6, label="Treatment")
plt.xlabel("Average Watch Time")
plt.ylabel("Number of Users")
plt.title("Control vs Treatment Watch Time Distribution")
plt.legend()
plt.show()
```




```
box_df = pd.DataFrame({
    "Control": control_vals,
    "Treatment": treatment_vals
})

box_df.boxplot(figsize=(6, 4))
plt.ylabel("Average Watch Time")
plt.title("Watch Time Comparison (Control vs Treatment)")
plt.show()
```



Fairness Analysis (Creator Exposure)

Video → Creator Mapping

```
video_creator_map = (
    df[["video_id", "creator_id"]]
    .drop_duplicates()
)

def collect_creator_exposure(user_ids, group, k=10):
    exposure = []

    for u in user_ids:
        recs = simulate_feed(u, group, k)
        exposure.extend(recs)

    exposure_df = pd.DataFrame({"video_id": exposure})
    exposure_df = exposure_df.merge(
        video_creator_map,
        on="video_id",
        how="left"
    )
```

```
    return (
        exposure_df
        .groupby("creator_id")
        .size()
        .reset_index(name="exposure")
    )

control_exposure = collect_creator_exposure(
    control_users, "control"
)

treatment_exposure = collect_creator_exposure(
    treatment_users, "treatment"
)



import numpy as np

def gini(x):
    x = np.array(x)
    if np.sum(x) == 0:
        return 0
    x = np.sort(x)
    n = len(x)
    return (2 * np.sum((np.arange(1, n + 1) * x))) / (n * np.sum(x)) -
(n + 1) / n

gini_control = gini(control_exposure["exposure"])
gini_treatment = gini(treatment_exposure["exposure"])

gini_control, gini_treatment
```

```
(0.0, 0.5445474074074075)
```

Long-Tail Coverage (Very Important)

```
def long_tail_share(exposure_df):
    threshold = exposure_df["exposure"].quantile(0.8)
    return (
        exposure_df[exposure_df["exposure"] < threshold]
["exposure"].sum()
        / exposure_df["exposure"].sum()
    )

lt_control = long_tail_share(control_exposure)
lt_treatment = long_tail_share(treatment_exposure)
```

```
lt_control, lt_treatment
```

```
(0.0, 0.4592)
```

```
plt.figure(figsize=(7, 4))
plt.hist(
    control_exposure["exposure"],
    bins=50,
    alpha=0.6,
    label="Control"
)
plt.hist(
    treatment_exposure["exposure"],
    bins=50,
    alpha=0.6,
    label="Treatment"
)
plt.xlabel("Creator Exposure Count")
plt.ylabel("Number of Creators")
plt.title("Creator Exposure Distribution")
plt.legend()
plt.show()
```