Justification for the look-alike innovation

Both 3D cinemas and the Hologram Zoo are technological advancements that aim to enhance the visual experience of viewers by adding depth or lifelike experiences to what is traditionally a two-dimensional viewing space. They both represent leaps in how we consume visual media, transitioning from passive viewing to interactive experiences.

Justification for the data

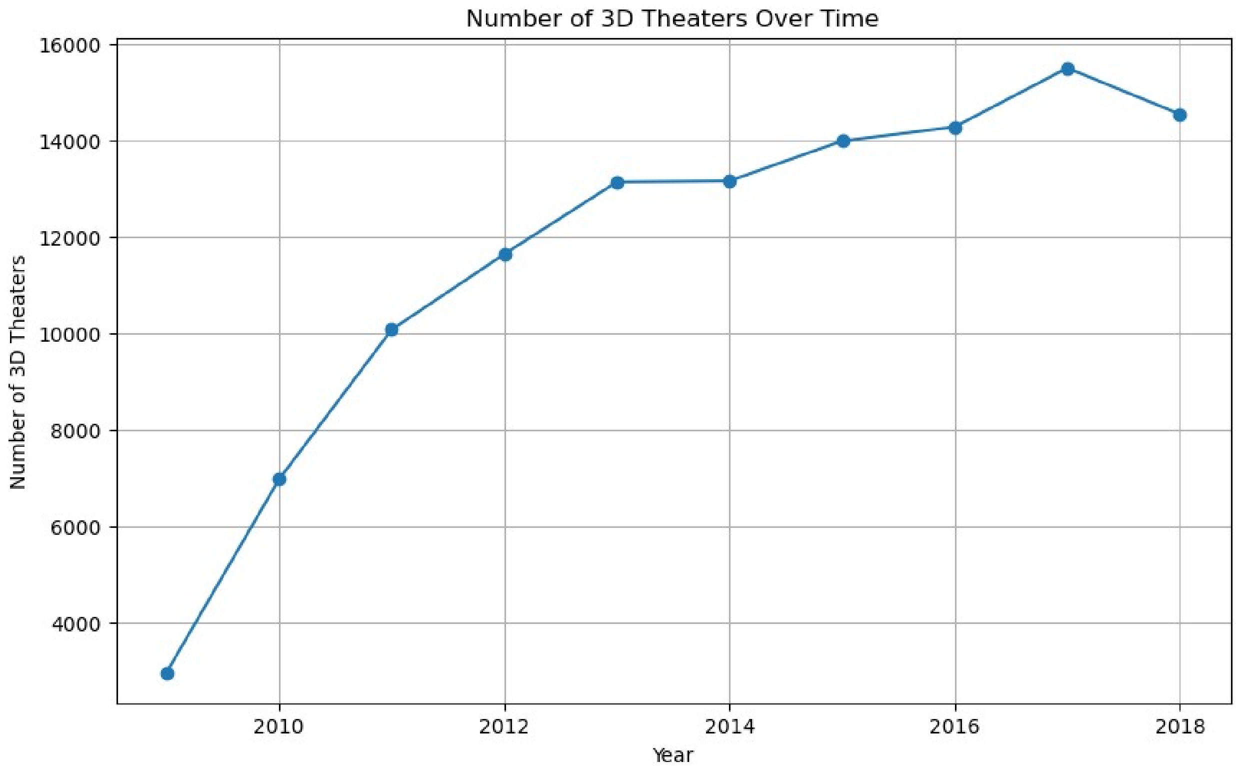
The data is taken from https://www.statista.com/statistics/440221/digital-3d-screens-in-european-countries/. The annual data of sales from 2009 to 2018 for 3D cinemas can serve as a good proxy for the initial adoption and growth phase of a similar entertainment technology.

Imports

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from scipy.optimize import curve_fit

df = pd.read_excel('cinema_data.xlsx')

print(df)
```

```
   Year  Count
0  2009   2961
1  2010   6968
2  2011  10073
3  2012  11639
4  2013  13136
5  2014  13158
6  2015  13985
7  2016  14278
8  2017  15499
9  2018  14543
```

```
plt.figure(figsize=(10, 6))
plt.plot(df['Year'], df['Count'], marker='o')
plt.title('Number of 3D Theaters Over Time')
plt.xlabel('Year')
plt.ylabel('Number of 3D Theaters')
plt.grid(True)
plt.show()
```




```
def bass_model(t, p, q, m):
    """
    Bass model function
    p: Coefficient of innovation
    q: Coefficient of imitation
    m: Potential market size
    t: Time period
    """
    adoption = m * (((p + q)**2 / p) * np.exp(-(p + q) * t) / ((1 + (q
/ p) * np.exp(-(p + q) * t))**2))
    return adoption

# Subtract the smallest year from all years to create a time series
starting at 0
t = np.array(df['Year'] - df['Year'].min())

# Convert the 'Count' column to an array for use in modeling
N = np.array(df['Count'])

# Set initial guesses for the Bass model parameters
guess = [0.03, 0.38, max(N)]  # p (innovation), q (imitation), m
(market size)

# Fit the Bass model to the data using curve_fit, with the initial
parameter guess
params, covariance = curve_fit(bass_model, t, N, p0=guess,
```

```
maxfev=10000)

# Extract the fitted parameters p, q, and m from the output
p, q, m = params

print(f'Estimated Coefficient of Innovation (p): {p}')
print(f'Estimated Coefficient of Imitation (q): {q}')
print(f'Estimated Potential Market Size (m): {m}')
```

```
Estimated Coefficient of Innovation (p): 0.03103119042294525
Estimated Coefficient of Imitation (q): 0.2782770103485192
Estimated Potential Market Size (m): 177636.67683359515
```

```
def predict_adopters(bass_params, years_to_predict, start_year):
    # Unpack the Bass model parameters: p (innovation), q (imitation),
m (market size)
    p, q, m = bass_params

    # Initialize the list to store predicted adoptions starting with 0
(no adopters at start)
    adoption = [0]

    # Calculate cumulative adoption for each year in the prediction
period
    for t in range(1, years_to_predict + 1):
        adoption.append(bass_model(t, p, q, m))

    # The initial number of adopters before the prediction starts
    initial_adopters = adoption[-1]

    # Calculate the predicted adoption for each year and subtract
initial adopters to get annual adoption
    predicted_adoption = [initial_adopters + bass_model(t, p, q, m)
for t in range(1, years_to_predict + 1)]

    # Return the annual predicted adoption
    return np.array(predicted_adoption) - initial_adopters

# Set the number of years to predict into the future
years_to_predict = 10

# Determine the start year for predictions by taking the maximum year
in the dataset and adding 1
start_year = df['Year'].max() + 1

# Call the predict_adopters function with the Bass model parameters
and the number of years to predict
# This function returns the predicted number of adopters for each year
in the future
```

```python
predicted_adopters = predict_adopters((p, q, m), years_to_predict,
start_year)

df_predictions = pd.DataFrame({
    'Year': np.arange(start_year, start_year + years_to_predict),
    'Predicted_Adopters': predicted_adopters.cumsum()
})

print(df_predictions)
```

```
   Year  Predicted_Adopters
0  2019         6992.552495
1  2020        15670.203233
2  2021        26149.867743
3  2022        38397.062051
4  2023        52171.956824
5  2024        67012.481508
6  2025        82277.249521
7  2026        97247.972632
8  2027       111259.996381
9  2028       123813.067173
```

```python
df_combined = pd.concat([
    df.rename(columns={'Adopters':
'Adopters_Cumulative'}).assign(Type='Actual'),
    df_predictions.rename(columns={'Predicted_Adopters':
'Adopters_Cumulative'}).assign(Type='Predicted')
])

# Plot the actual and predicted adopters
plt.figure(figsize=(14, 7))

# Plot actual data
plt.plot(df['Year'], df['Count'], label='Actual Adopters',
color='blue', marker='o')

# Plot predicted data
plt.plot(df_predictions['Year'], df_predictions['Predicted_Adopters'],
label='Predicted Adopters', color='red', linestyle='--', marker='x')

# Annotations for the last actual and predicted points
plt.annotate(f"{df['Count'].iloc[-1]}",
             (df['Year'].iloc[-1], df['Count'].iloc[-1]),
             textcoords="offset points", xytext=(-15,10), ha='center')
plt.annotate(f"{int(df_predictions['Predicted_Adopters'].iloc[-1])}",
             (df_predictions['Year'].iloc[-1],
df_predictions['Predicted_Adopters'].iloc[-1]),
             textcoords="offset points", xytext=(-15,10), ha='center')

# Plot details
plt.title('Historical and Predicted Adoption of 3D Cinemas and
```

```
Hologram Zoo')
plt.xlabel('Year')
plt.ylabel('Cumulative Number of Adopters')
plt.legend()
plt.grid(True)
plt.show()
```