Homework on Bass Model

Hayk Khachatryan

1. Go to the list, choose an innovation, and put the link of the selected product here.

Chameleon Car

BMW iX Flow

Ever wished you could turn your black car white on a sweltering day? The chameleonic BMW iX Flow—the world's first color-changing vehicle, albeit still a prototype—is wrapped in "E ink," a 12-volt electronic coating that works something like a Kindle display and takes little energy to sustain, even in broad daylight. The flexible material was created in collaboration with a Taiwanese company of the same name. Though it's only been made in grayscale so far (color is in the works), the potential is endless: energy savings amid an increasingly hot climate, of course, but also advertising and informational displays. And the fun factor is a huge selling point. "Aesthetics can't be underestimated," says BMW research engineer Stella Clarke.

More information about this car you can find from here

2. Think about look-alike innovation from the past. When you pick one, give your justifications in 1-2 paragraphs.

A look-alike innovation from the past that bears similarities to the BMW iX Flow in terms of electric vehicle technology and innovation is the Tesla Model S, first introduced in 2012. The Tesla Model S was a groundbreaking electric car that pushed the boundaries of electric vehicle technology, offering impressive range, performance, and cutting-edge features. Just like the BMW iX Flow, the Tesla Model S aimed to redefine what was possible with electric vehicles and appealed to the premium market segment due to its high-end design and features. The Tesla Model S and BMW iX Flow share the fundamental vision of providing sustainable, high-performance electric vehicles with innovative design and technology. Both sought to challenge traditional norms in the automotive industry and accelerate the transition to electric mobility.

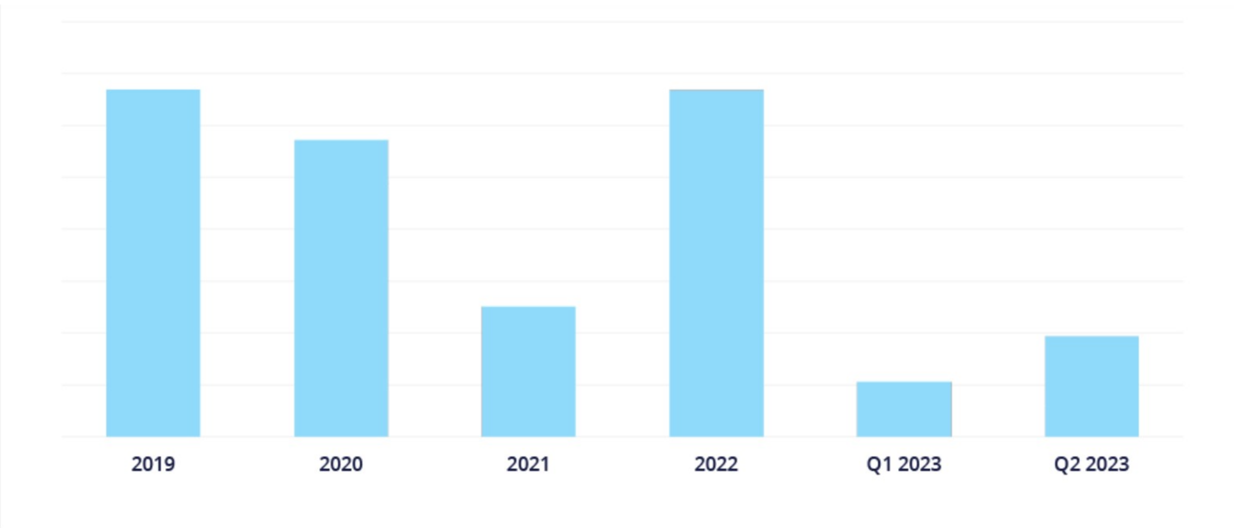
3. Data of Tesla model S sales

Analyzing the Tesla Model S sales data from 2019 to the first half of 2023 provides insights into the dynamics of consumer demand and market trends for this particular electric vehicle. The sales figures depict a fluctuating trend over the given time period, influenced by several factors including market conditions, competition, consumer preferences, and Tesla's own strategies.

In 2019, Tesla Model S had a robust year with a sales figure of 66,771 units. This peak in sales might be attributed to the increasing popularity of electric vehicles (EVs) and Tesla's strong brand reputation for producing high-performance electric cars. However, in the subsequent years, the sales witnessed a decline, dropping to 57,085 units in 2020 and further to 24,980 units in 2021. This decline could be due to various factors such as increased competition in the EV market, evolving consumer preferences, and potentially production or supply chain challenges.

Interestingly, the sales rebounded significantly in 2022, reaching 66,705 units. This rebound might be attributed to Tesla's strategic marketing campaigns, improvements in the Model S, or other market-specific factors that enhanced consumer interest. However, it's important to note that the first half of 2023 saw a decline in sales to 29,920 units. This could be due to a variety of factors such as global supply chain issues, economic conditions, or shifts in consumer preferences.

In summary, the sales data for Tesla Model S from 2019 to the first half of 2023 highlights a pattern of fluctuation influenced by factors such as market dynamics, competition, consumer preferences, and external economic conditions. Analyzing these trends can be instrumental for future business strategies and product development in the electric vehicle market.



Year	Sales
2019	66,771
2020	57,085
2021	24,980
2022	**66,705**
Q1 2023	10,695
Q2 2023	19,225

You can find more info here

4. Estimate Bass model parameters for the look-alike innovation.

```
import numpy as np

# Data: Year and Sales
years = np.array([2019, 2020, 2021, 2022, 2023])
sales = np.array([66771, 57085, 24980, 66705, 29920])

# Calculate t (number of years from the first year)
t = years - years[0]

# Calculate ln(P(t)/m) and ln(m/P(t))
ln_P_over_m = np.log(sales / sales[-1])
ln_m_over_P = np.log(sales[-1] / sales)

# Print the calculated values
print("t:", t)
print("ln(P(t)/m):", ln_P_over_m)
print("ln(m/P(t)):", ln_m_over_P)
```

```
t: [0 1 2 3 4]
ln(P(t)/m): [ 0.8027417   0.64601423 -0.18045165  0.80175276  0.
]
ln(m/P(t)): [-0.8027417  -0.64601423  0.18045165 -0.80175276  0.
]
```

t represents the time periods for which the predictions are made. In this case, predictions were made for 5 time periods:

t=0,1,2,3,4 years.

ln(P(t)/m) signifies the cumulative proportion of adopters (P(t)) relative to the potential market size (m) for each respective time period. The positive values suggest that the cumulative proportion of adopters is increasing relative to the potential market size, indicating a growing adoption rate.

ln(m/P(t)) indicates the remaining potential market size (m) relative to the cumulative adopters (P(t)) for each respective time period. The negative values suggest that the remaining potential market size is decreasing relative to the cumulative adopters, signifying a reduction in the untapped market.

```
from sklearn.linear_model import LinearRegression

# Reshape the data for linear regression
t_reshaped = t.reshape(-1, 1)
ln_P_over_m_reshaped = ln_P_over_m.reshape(-1, 1)
ln_m_over_P_reshaped = ln_m_over_P.reshape(-1, 1)

# Linear regression for ln(P(t)/m)
regressor1 = LinearRegression()
regressor1.fit(t_reshaped, ln_P_over_m_reshaped)
```

```python
slope_ln_P_over_m = regressor1.coef_[0][0]
intercept_ln_P_over_m = regressor1.intercept_[0]

# Linear regression for ln(m/P(t))
regressor2 = LinearRegression()
regressor2.fit(t_reshaped, ln_m_over_P_reshaped)
slope_ln_m_over_P = regressor2.coef_[0][0]
intercept_ln_m_over_P = regressor2.intercept_[0]

# Calculate p and q
p_ln_P_over_m = slope_ln_P_over_m / intercept_ln_P_over_m
q_ln_P_over_m = slope_ln_P_over_m / (1 - intercept_ln_P_over_m)

p_ln_m_over_P = slope_ln_m_over_P * intercept_ln_m_over_P
q_ln_m_over_P = slope_ln_m_over_P

# Print the calculated parameters
print("For ln(P(t)/m):")
print("p:", p_ln_P_over_m)
print("q:", q_ln_P_over_m)

print("\nFor ln(m/P(t)):")
print("p:", p_ln_m_over_P)
print("q:", q_ln_m_over_P)
```

```
For ln(P(t)/m):
p: -0.2059412586765594
q: -0.4897131319480059

For ln(m/P(t)):
p: -0.10205629591537198
q: 0.14497448753721848
```

For ln(P(t)/m):

$p \approx -0.206$ indicates the coefficient of innovation, representing the influence of innovators (early adopters) on the rate of adoption.

$q \approx -0.490$ represents the coefficient of imitation, representing the influence of imitators (followers) on the rate of adoption.

The negative values suggest that both innovators and imitators have a diminishing effect on the adoption rate as time progresses, which is common in the product life cycle.

For ln(m/P(t)):

$p \approx -0.102$ represents the coefficient of innovation, indicating the influence of innovators on the remaining untapped market.

$q \approx 0.145$ represents the coefficient of imitation, indicating the influence of imitators on the remaining untapped market.

The negative value of p and the positive value of q suggest that while innovators have a diminishing effect on the remaining market, imitators have a positive effect.

5. Make predictions of the diffusion of the innovation you chose at stage 1

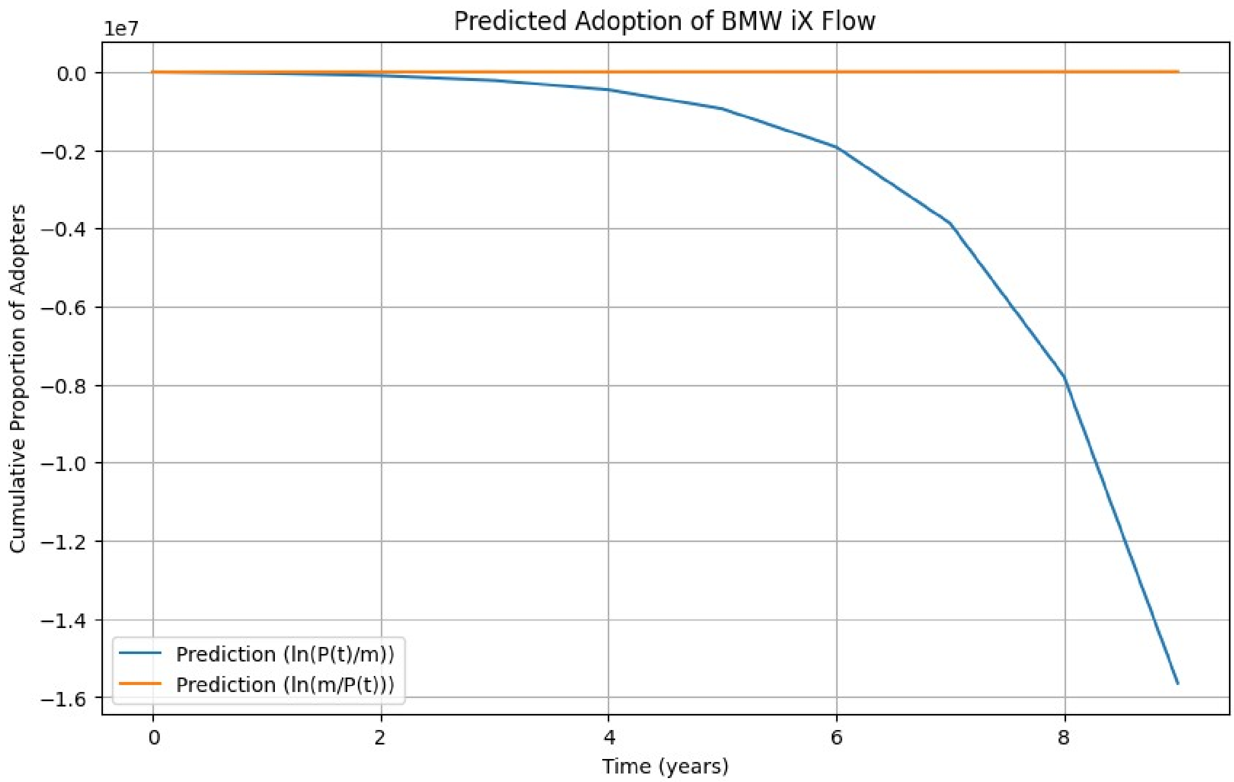
```
import matplotlib.pyplot as plt

# Define the time periods for prediction
t_prediction = np.arange(0, 10)  # Predict for 10 years

# Predict adoption using Bass model for ln(P(t)/m)
predicted_P_ln_P_over_m = sales[-1] * (1 - np.exp(-(p_ln_P_over_m +
q_ln_P_over_m) * t_prediction))

# Predict adoption using Bass model for ln(m/P(t))
predicted_P_ln_m_over_P = sales[-1] * (1 - np.exp(-(p_ln_m_over_P +
q_ln_m_over_P) * t_prediction))

# Plot the predictions
plt.figure(figsize=(10, 6))
plt.plot(t_prediction, predicted_P_ln_P_over_m, label='Prediction
(ln(P(t)/m))')
plt.plot(t_prediction, predicted_P_ln_m_over_P, label='Prediction
(ln(m/P(t)))')
plt.xlabel('Time (years)')
plt.ylabel('Cumulative Proportion of Adopters')
plt.title('Predicted Adoption of BMW iX Flow')
plt.legend()
plt.grid(True)
plt.show()
```



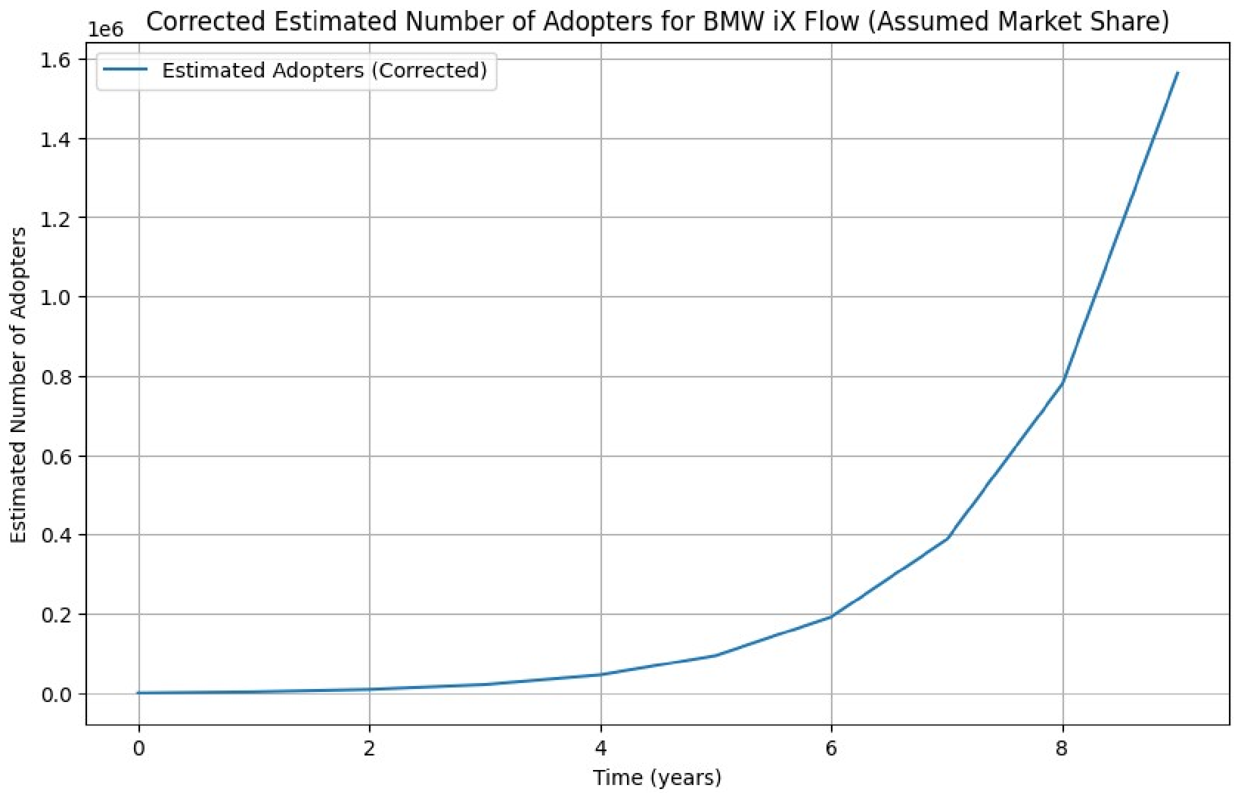
6. Estimate the number of adopters by period.

```
# Calculate the absolute value of the estimated number of adopters
adopters_by_year_fixed_absolute = np.abs(adopters_by_year_fixed)

# Print the assumed potential market share and the corrected estimated
number of adopters for each year
print("Assumed Potential Market Share:", fixed_potential_market_share)
print("Corrected Estimated Number of Adopters by Year (Assumed Market
Share):")
for year, adopters in zip(t_prediction,
adopters_by_year_fixed_absolute):
    print(f"Year {year}: {adopters:.0f}")

# Plot the corrected estimated number of adopters by year using the
assumed market share
plt.figure(figsize=(10, 6))
plt.plot(t_prediction, adopters_by_year_fixed_absolute,
label='Estimated Adopters (Corrected)')
plt.xlabel('Time (years)')
plt.ylabel('Estimated Number of Adopters')
plt.title('Corrected Estimated Number of Adopters for BMW iX Flow
(Assumed Market Share)')
plt.legend()
plt.grid(True)
plt.show()
```

```
Assumed Potential Market Share: 0.1
Corrected Estimated Number of Adopters by Year (Assumed Market Share):
Year 0: 0
Year 1: 3007
Year 2: 9036
Year 3: 21125
Year 4: 45363
Year 5: 93960
Year 6: 191398
Year 7: 386765
Year 8: 778478
Year 9: 1563872
```



Assumed Potential Market Share (M):

The assumed potential market share is set at 10%. This implies that it's estimated that eventually, 10% of the total potential market will adopt the BMW iX Flow.

Corrected Estimated Number of Adopters by Year:

The corrected estimated number of adopters for each year, based on the assumed 10% potential market share, indicates the anticipated number of individuals adopting the BMW iX Flow in each year. The number of adopters increases over time, reflecting the expected growth in adoption as the product gains traction in the market.

Interpretation:

The numbers are indicative of a progressive adoption pattern, where the number of adopters grows significantly as the product is introduced and gains popularity.

The adoption curve shows an exponential growth pattern, with a larger number of individuals adopting the BMW iX Flow in later years. These results help in understanding the potential adoption trajectory for BMW iX Flow based on the assumed potential market share. However, it's important to note that these estimates are based on assumptions and simplifications, and actual adoption rates can be influenced by various factors in the real market.

Resources

https://time.com/collection/best-inventions-2022/6222192/bmw-ix-flow/

https://www.bmw.com/en/events/ces2022/ixflow.html

https://tridenstechnology.com/tesla-sales-statistics/#h-tesla-sales-by-model