Dynamic pricing strategy and how we implement this model our games and A Brief Introduction and Economic Approach to this model

Dynamic pricing strategy is an approach aimed at determining the maximum demand for each price point and, in turn, maximizing profit.

In Classical and partially Keynesian economic models, the supply curve is positioned relative to demand, and efforts are made to reach an equilibrium point. The supply curve is typically viewed as upward sloping, meaning that as prices rise, producers are willing to supply more of a good or service, up to a certain point. However, in today's digital economic models, where the supply curve is often considered to have no inherent limit, applying a **demand-based approach** like dynamic pricing makes much more sense.

However, implementing and analyzing this model is challenging. Identifying the points at which maximum demand and profit occur depends on many variables, and these variables can change over time. Therefore, I will focus on two different approaches.

- One is an **A/B testing-based approach**, which is more suitable for applications with a smaller user base, where accurate analysis based on past data can be difficult.
- The other is a **profit maximization with marketing campaign model**, which is more applicable to applications with a large user base, focusing on predicting optimal pricing for maximum profit.

A/B testing-based approach

Separating the user base

User Demographics (for new users): Age, location, income level.

In this context, location and income level are the most prominent factors. Each country belongs to specific tiers based on various economic and demographic factors. For example, the US and the UK are considered Tier 1 countries, while India may be classified as Tier 3. These tiers play a crucial role in determining price points.

Price elasticity varies across these countries. Price elasticity refers to how demand changes in response to price fluctuations. Inelastic demand is less sensitive to price changes—these countries are typically Tier-1. On the other hand, elastic demand is highly responsive to price changes, which is often the case in low-income countries.

Age is another important factor. It makes sense to define price points that are appropriate for the target audience, but segmenting this by age can be more challenging.

Historical Data (for existing users): subscription upgrades/downgrades.

If our users do not renew their subscription during the renewal period, we can offer them a lower price point. Alternatively, if they have made 4-5 subscriptions at the same price, we could offer them a higher price point. However, we must consider the demographic factors mentioned earlier, as we need to analyze how sensitive these users are to price changes.

Usage Patterns: Frequency of use, feature engagement.

Determine Price Ranges

- Use the historical data to set a baseline.
- Consider a range of price points: e.g. (5%, 10%, 15%, 20%) above and below the baseline price.

Segment Users for Testing:

Country Tier	Subscription Status	Age Group	Segment Code
Tier-I	non-subscribe	young-mid	t1-ns-y
Tier-I	subscribe	young-mid	t1-s-y
Tier-I	non-subscribe	old	t1-ns-o
Tier-I	subscribe	old	t1-s-o
Tier-II	non-subscribe	young-mid	t2-ns-y
Tier-II	subscribe	young-mid	t2-s-y

Tier-II	non-subscribe	old	t2-ns-o
Tier-II	subscribe	old	t2-s-o
Tier-III	non-subscribe	young-mid	t2-ns-y
Tier-III	subscribe	young-mid	t2-s-y
Tier-III	non-subscribe	old	t2-ns-o
Tier-III	subscribe	old	t2-s-o

- **Country Tier**:
  - Tier 1 (e.g., US, UK, Germany)
  - Tier 2 (e.g., Brazil, Mexico, Turkey)
  - Tier 3 (e.g., India, Indonesia, Nigeria)
- **Subscription Status**:
  - Subscribed
  - Non-Subscribed
- **Age Group**:
  - Young (e.g., < 25 years)
  - Mid-Age (e.g., 25–40 years)
  - Old (e.g., > 40 years)

Ensure the cohorts are statistically significant.

As in the example above, this is a large-scale test, and it is crucial for the results to be statistically significant. Without this, the test could lead us in the wrong direction. If our budget cannot support testing so many groups, we will need to remove some parameters and conduct the test with a smaller subset.

Statistical significance is determined by the p-value:

- If $p < 0.05$ (common threshold), the result is considered statistically significant.

The sample size required for statistical significance depends on the desired confidence level, power, and expected effect size. Determine the minimum sample size for each cohort

$$n = \frac{2 \times (Z_{\alpha/2} + Z_{\beta})^2 \times \sigma^2}{(\mu_1 - \mu_2)^2}$$

$Z\alpha/2$: Z-value for the confidence level

$Z\beta$: Z-value for the desired power

σ: Standard deviation of the metric (e.g, conversion rate or revenue/user).

μ1,,μ2: Mean values of the metric for the two groups.

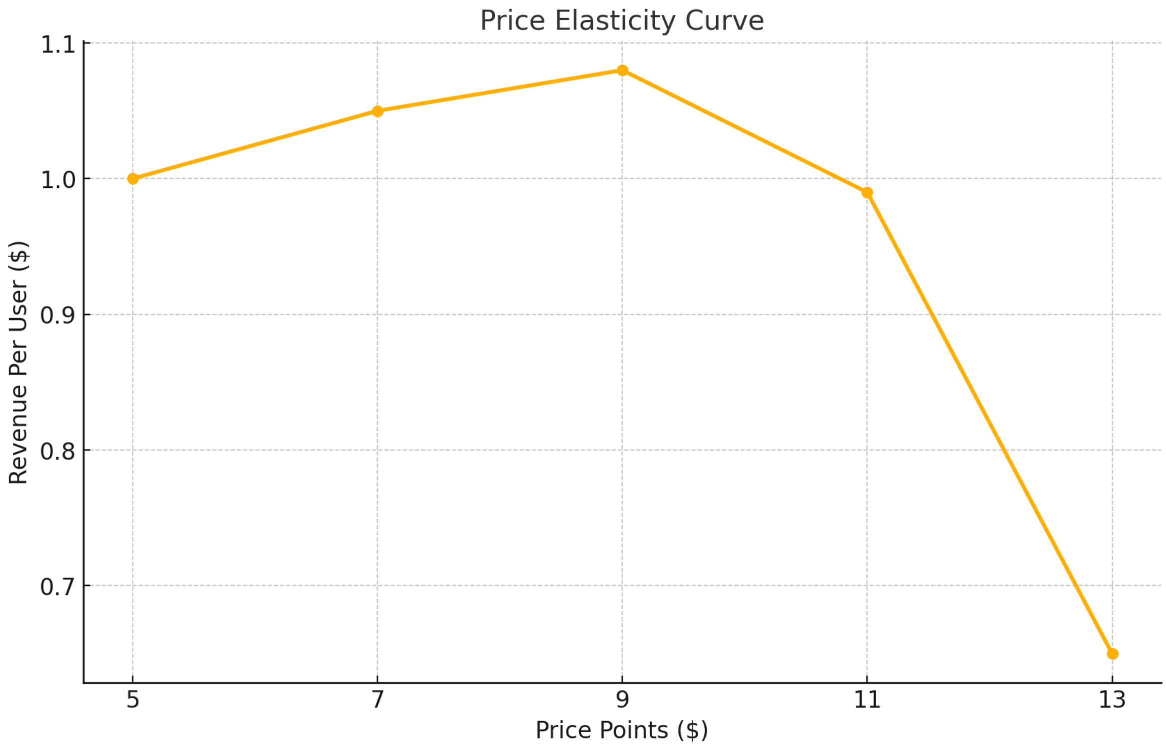
!! We can use the statsmodel package in python.

Elasticity of Price Points: Example Curve

Price elasticity measures how sensitive the demand for a subscription is to changes in price. Here's an example of how to interpret elasticity:

1. **Elastic Demand**: A small price increase leads to a significant drop in demand.
2. **Inelastic Demand**: Demand changes little with price changes.

Let’s assume we test price points: $5, $7, $9, $11, and $13.



The curve illustrates how revenue per user changes with different price points. The peak revenue occurs around $9, suggesting this price point balances conversion and revenue effectively. Beyond $9, higher prices reduce user uptake significantly, highlighting elastic demand in this range.

Features and Data to Consider After Testing

Monetization data:

- **Conversion Rate:** Percentage of users subscribing at each price point.
- **Churn Rate:** Retention trends for users subscribed under different price points.
- **Revenue Per User (RPU):** Revenue generated per user at each price level.
- **LTV:** Predicted revenue from a user during their subscription.

Behavioral and inn-app data:

- Time spent in-app and engagement levels after subscription
- Cancellation count per user

Determining Price Points with Marketing Campaigns Approach

(I apologize for the naming convention I came up with, but I will try to explain what I meant.)

We can leverage **marketing channels** to predict optimal price points and dynamically adjust them based on user behavior and acquisition sources. This approach involves using data from marketing platforms to identify high-value users and tailor pricing strategies accordingly.

For example, we can run targeted marketing campaigns based on the **lifetime** of our product. For instance, when we launch a **D30 ROAS campaign**, we optimize it to acquire users who are most likely to make purchases in the app within 30 days of downloading, based on the return on ad spend (ROAS) target you've set.

This situation has some consequences:

- **CPI** (Cost Per Install) increase.
- As a result, we may not be able to acquire as many users as we would like through broad installs.

Because of this, we may not have the chance or luxury to conduct **statistically significant A/B tests** with a large enough user base.

Disadvantages of this approach:

- If the analysis is not done correctly, it could lead to significant negative outcomes. It is difficult to conduct accurate analysis.
- Marketing channels must be properly trained.
- The right marketing channel must be selected.
- Results may take longer to achieve, depending on our objectives.

Advantages of this approach:

- This could provide us with a new way to bypass the **sandbox** and the **iOS ATT** . This is very important for the new marketing era **.**

- With proper analysis, it can provide results faster than A/B testing.
- If marketing channels are correctly optimized, precise predictions can lead to increased profits.

Example:

I will provide a slightly different example from the one above. **Marketing channels** are already very successful in the targeting phase and can bring us the type of players we want. However, in this case, we can create our own criteria and, based on the behaviors within our application, assess the value of users. We can then make selections based on those values.

I wanted to conduct this analysis using **SKAdNetwork (SKAN)** because, with the newer iOS versions, it has become impossible to track data for users beyond 1 day.

During the user's first 24 hours (not just D0, but their first full day of app use), gather the following KPIs:

1. **Session Length**: Total time spent in the app.
2. **Session Count**: Total number of sessions.
3. **Total IAP (In-App Purchases)**: Total amount spent on in-app purchases.

Normalize the KPIs into a single score, **PlayerValue**, using the formula:

$$PlayerValue = \frac{(SessionLength \times a) + (SessionCount \times b) + (TotalIAP \times c) + k}{m}$$

Where:

- a, b, and c: Weights assigned to each KPI.
- k: A constant to adjust the baseline.
- m: A normalization factor ensuring PlayerValue is on a consistent scale.

Compare the calculated **PlayerValue** to predefined **SKAN Ranges**:

- RangeMin and RangeMax values correspond to different predicted user value bands.

Identify the range where **PlayerValue** falls, representing the user's potential value.

1.

Player value threshold	Range min	Range max
0	install	install
1000	0.01	0.015
2000	0.015	0.025
3000	0.035	0.045
4000	0.045	0.055
5000	0.055	0.065

Different countries have varying spending potential. Adjust the initial range using a **Country Tier Multiplier**:

AdjustedRange=OriginalRange×TierMultiplierAdjustedRange
TierMultiplierAdjustedRange=OriginalRange×TierMultiplier

Where:

- **Tier 1**: TierMultiplier1 (e.g., 1.2)
- **Tier 2**: TierMultiplier2 (e.g., 1.0)
- **Tier 3**: TierMultiplier3 (e.g., 0.8)

The **AdjustedRange** reflects the country-specific potential and places the user into the final value tier.

Once the **AdjustedRange** is calculated, marketing channels will use this value to dynamically adjust price points:

2. **Identify Price Point**:
    - High PlayerValue → Assign a higher price tier.
    - Low PlayerValue → Assign a lower price tier or offer discounts.

For example,

PlayerValue = 4250 and **Country** = Tier1

PlayerValue Threshold = 4000

SKAN Range = 0.045 - 0.055

TierMultiplier → Tier 1 = 1.2

With TierMultiplier = 0.054 - 0.066

Median = 0.06

In this case, it will return **RangeMin/Max** as if the **PlayerValue** were at 5000 threshold.

After a player is scored based on their value, they are then re-scored according to the value of the country they belong to, which gives their adjusted score. As a result, the category they fall into may change.

Dynamic Pricing with Country Tier:

Player value range	Country tier	Adjusted range	Price Point ($)
80-100	Tier 1(1.2)	96-120	12
60-80	Tier 2(1)	60-80	9
40-60	Tier 3(0.8)	32-48	6
0-40	Tier 4(0.6)	0-24	3

$$Price = BasePrice \times (1 + \gamma \times \text{PlayerValue})$$

Marketing channels will collect users who meet specific PlayerValue thresholds and serve dynamic pricing:

- Example: Users with PlayerValue > 80 will see premium subscription pricing, while users with PlayerValue < 60 might receive discount offers.

Advantages:

1. **Early and Accurate Predictions**: PlayerValue allows rapid identification of high-value users.
2. **Dynamic and Adaptive Pricing**: Personalized price points maximize conversion and profit.
3. **Improved Efficiency**: With the correct marketing channel targeting, profit can be optimized more quickly than traditional A/B testing.