# NUGGET MARKETS

## Secret Special Price Optimization

**UC Davis | MSBA | 443 – Analytical Decision Making | Team Paper**

**June 2nd, 2018**

*By Team Nugget – Crystal Liu, Daria Zhan, Mei Yang, Pallavi Sama, Sarah Gustafson*

# Table of Contents

# 1. Background

### *1.1 Nugget Markets*

Nugget Markets Inc. is an upscale grocery chain primarily located in the greater Sacramento area of Northern California. It is a family owned-and-operated business which has been recognized on FORTUNE's "100 Best Companies to Work For" for twelve straight years. The company places an emphasis on quality, competitive pricing, guest service, and excellent selection. Their specialty offerings include local & organic produce, organic & grass fed meat, large variety of cheese and wine with on-hand specialists, artisan bakeries and so on.

There are 16 operating stores associated with 4 different brands underneath the Nugget Markets parent company. They are Nugget Markets, Fork Lift by Nugget Markets, Food 4 Less, and the recently acquired Sonoma & Glen Ellen Village Markets. The variety of store brands allows Nugget Markets Inc. to provide the most competitive format for that store's particular target demographic. The size of business varies from location to location.

### *1.2 Secret Special Promotions*

The company launched a unique type of promotional offer called Secret Special in 2013. It is an exclusive promotional discount, valid for two days only (typically on Friday and Saturday), that is emailed weekly to subscribers and redeemed in-store. The Secret Special always is the same item and price at every store across all brands, despite variations in customer demographic. Since the Secret Special program originally launched 4.5 years ago, the growth has been dependably slow and steady. The primary objective of the partnership with the UC Davis MSBA program is to increase the sign-up and redemption rates of the Secret Special Coupon. However, as our team has been exploring their data, we have found a couple of potential business problems (pricing strategy, customer segmentation, etc.) that can be solved to maximize the impact of their promotions.

# 2. Business Problem

For our case study, we have chosen a "tactical" decision problem of pricing a product for the retailer. In the retail industry, pricing is equivalent to survival. If the prices are too low, you're leaving money on the table. If they're too high, buyers walk away empty-handed.

Adopting a successful price optimization strategy has become more important than ever to profitability — and even viability. As we have mentioned before, Nugget Markets does not employ any specific pricing strategy with regard to the Secret Special promotional items. There is a lot of potential in terms of the differences in store demographics and performance which can be leveraged to create a differential pricing strategy to maximize the overall profits.

Price optimization is the process of finding a sweet spot of price against customers' willingness to pay. Willingness to pay or WTP is the maximum amount of money a customer is willing to pay for a product. From the weekly transactional data available at store level, we have found that average prices for some categories of products vary across the 16 stores when the products are not on promotion. That is not the case when the products are offered on Secret Special promotion. However, demand varies across the different stores and there is a gap in the current pricing strategy. So, instead of having a single price strategy, we suggest Nugget Markets should look at an optimization problem at product level for designing a more effective Secret Special promotion. We shall look at the optimization problem for a single product across two stores. ***Our aim is to find an optimal pricing for the product – "Domaine Carneros Brut Sparkling Wine" across the stores – Glen Ellen Village Market and Nugget Markets in West Sacramento.***

## 3. Modeling Approach

At a high level, we approach the problem in two steps –

1. Break down the problem to identify the factors required to solve it
2. Match the specific real-world problem to a typical modeling problem so as to identify the generic solution framework that can be applied

### *3.1 Elements of the problem*

The key to solve a price optimization problem is to determine the below factors –

- **Demand of the Product in the market:** Demand can be estimated based on regression models using historical sales transactions and other factors. The important thing to keep in mind is that demand varies across markets and segments. The impact of prices on demand can be modeled using a price response function. We use historical data from 25 months of transactions from the two stores on 13 similar items from the Sparkling wine category to approximate the demand.

- **Customers' WTP for the product:** The data on WTP is usually collected through market surveys. We do not have survey data but we know that WTP of a customer for a product of a company depends on the price history of that product, prices currently charged for similar products by the company and prices currently charged for similar products by other companies. So, we explored the distributions of historical transactions on the product and the overall category across the two stores and consider the average and variance of the prices paid as the closest proxy for WTP.
- **Marginal Cost of the product:** We could either consider a markup of 15-20% based on common knowledge. We also confirmed our assumption with the client's operations team and found that the net cost paid per bottle is around $15.
- **Market size:** For market size for each segment (in our case each store), we looked at the demographics and the overall shoppers population based on the transactional data across the two stores. For the sake of simplicity, we assume that total market consists of only these two store populations.

### *3.2 Identifying the solution framework*

Next, we match the decision problem with the mathematical structure of the optimization problems and non-linear programming seems to be the most appropriate choice.

| Tool | Decision $x$ | Objective $f(.)$ | Constraint $g(.)$ |
|---|---|---|---|
| Linear Programming I | $x \in R^{+}$ | $c_1x_1 + c_2x_2$ | $a_1x_1 + a_2x_2 < b$ |
| Linear Programming II | $x = \{0,1\}$ | $c_1x_1 + c_2x_2$ | $a_1x_1 + a_2x_2 < b$ |
| Non-Linear Programming | $x \in R^{+}$ | $f'' \neq 0$ | $g(x)$ |
| Dynamic Optimization | $x_1, x_2, \dots x_T$ | $\Sigma_t \Pi_t(x_t)$ | $\Pi_t = g(\Pi_{t-1})$ |
| Stochastic Optimization | $x_1, x_2, \dots x_T$ | $\Sigma_t \mathbb{E}[\Pi_t(x_t)]$ | $\Pi_t = g(\Pi_{t-1}) + \epsilon$ |
| Game Theory and incentives Design | My decision $(x)$ vs. your decision $(y)$ | $f(x,y)$ | $g(x,y)$ |

So, we define the building blocks of the optimization problem as given below –

### *3.2.1 Decision Variables, x*

The optimal prices of the wine product for each store, a vector ***p = {$p_1$, $p_2$}*, where *p* ∈ *$R^+$***

### *3.2.2 Objective Function, f(.)*

Our primary goal is to maximize the profit given by the function below –

$$\Pi = d(p)\times(p-c)$$

where, p is the price, c is the marginal cost and d(p) is the demand at price p. For the sake of simplicity, we assume fixed costs to be zero.

Further, demand is given by the function –

$$d(p) = M\times\left[1-\Phi\left(\frac{p-\mu}{\sigma}\right)\right]$$

where M is the market size and Φ is the function representing willingness to pay (WTP) for the market which follows a normal distribution with mean μ and standard deviation σ. The probability distribution of the WTP function is given by –

$$\Phi\left(\frac{p-\mu}{\sigma}\right) = \frac{1}{2}\left[1+erf\left(\frac{p-\mu}{\sigma\sqrt{2}}\right)\right]$$

To make sure that the profit is maximum, we equate the first order derivative to zero and the second derivative should be less than zero.

### *3.2.3 Constraints, g(.)*

- Willingness to pay for each store's potential population follows a normal distribution,

$$WTP\sim N(\mu,\sigma^2)$$

- Total market size, M = 1, so if potential population of Glen Ellen village market = α, then potential population of Nugget Markets West Sacramento store = 1 – α.
- Non-negativity constraints on prices, ***$p_1$*, *$p_2$*** *≥ 0*
- Inventory limitations, if any *(We have not included any in our problem)*

Once we have identified the decision variables, objective function and constraints and gathered the required inputs, we can implement this approach by coding it in Python using the scipy optimization package *(See appendix for code).*

## 4. Recommendations

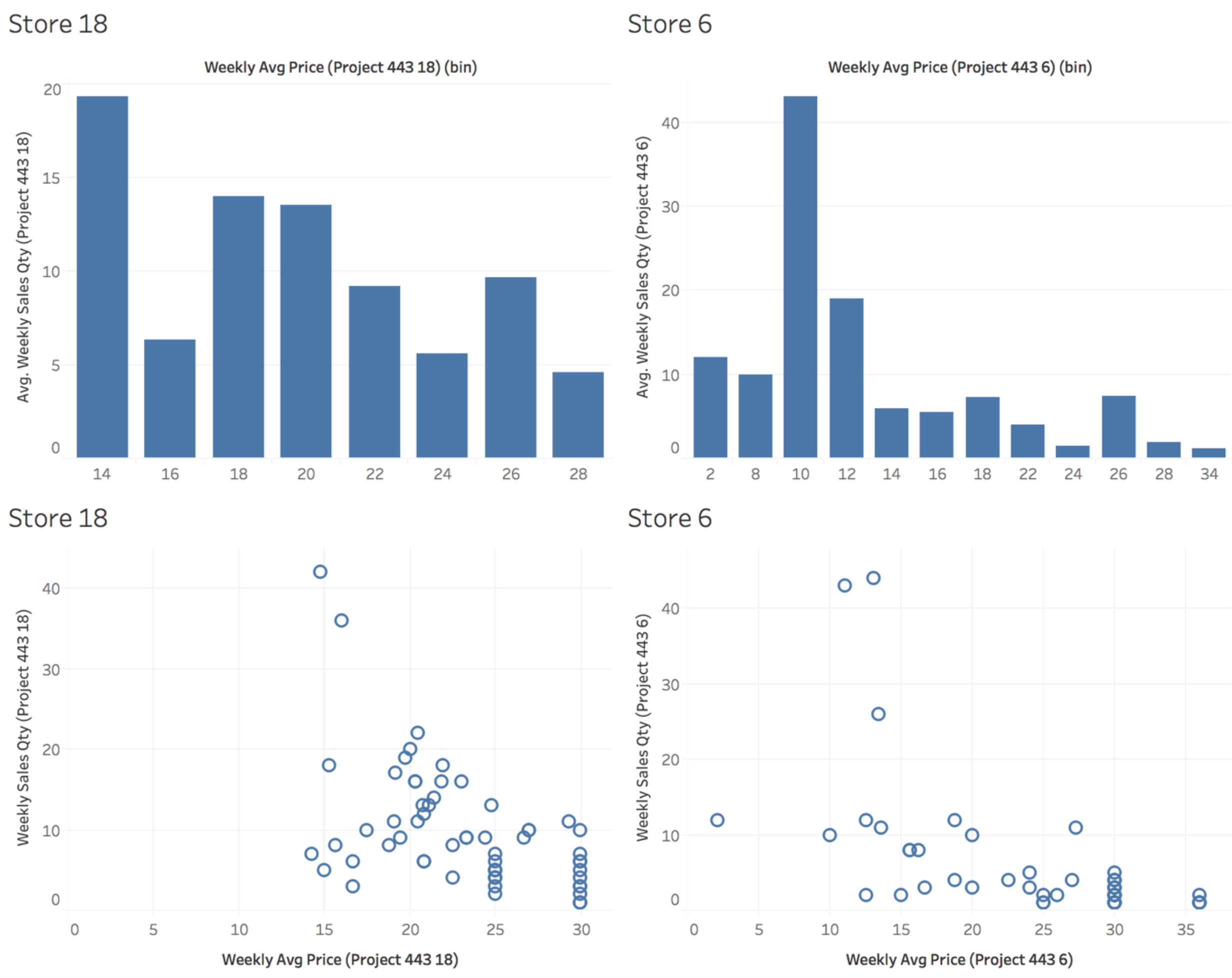
Firstly, we would recommend Nugget Markets to conduct market surveys to get a better idea of the willingness to pay for the potential customers. They could create surveys online on the website for the customers who subscribe for the weekly Secret Special promotions or they could also have in-store surveys. WTP can be managed by explaining the value of a product to the customers regarding their attributes (brand, size, flavor, etc.) and assessing their preferences. This could involve performing a conjoint analysis. Another important concept is the reference price which is shaped by the factors that affect the WTP – price history, price of similar products, price of competitor's products, value of the product.

Demand is a very important factor for setting the optimal price of a product, but predicting demand accurately is another challenge which retailers face. So, we also recommend them to invest in a demand prediction model, and then based on the WTP understand how sensitive demand is at various price points.

Once they have the understood your demand and WTP, they can feed these factors into an optimization model as discussed above to get the optimal prices. From our implementation, the optimal prices for the two stores are - $23.20 for Glen Ellen Village market and $17.96 for the West Sacramento Nugget Markets store with a profit margin of $2.64. The price for the Glen Ellen Village market is very close to the average WTP of its customers, but for the West Sacramento store it's much higher than the average WTP. However, since the product is a premium brand, it could be a charged little higher than the overall category. The pricing manager will have to select the prices very carefully keeping in mind that customers will buy the product only if the posted retail price is lower than their willingness to pay.

## 5. Appendix (Implementation)

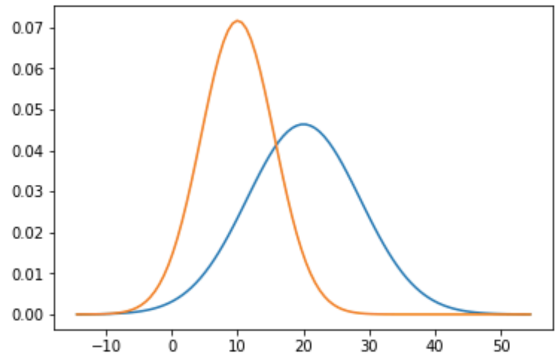
Below are some of the charts created in Tableau for our exploratory analysis performed on the data to get a sense of the distribution of average prices and sales. Store 18 is the Glen Ellen Village market and store 6 is the West Sacramento Nugget Markets.




The distribution is slightly right skewed but still supports our assumption of considering mean/median of the prices.

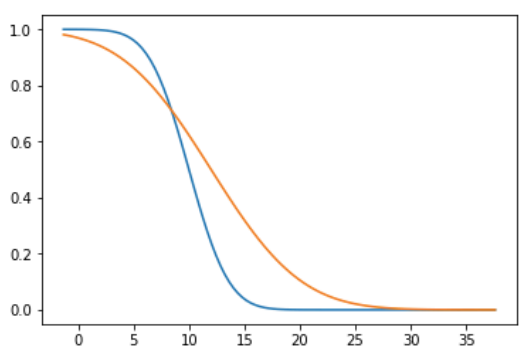
Based on the above assumption, we plot the distribution of the willingness to pay across the two stores.

In [10]:
```
# WTP for all sparkling wine category
import matplotlib.pyplot as plt
import numpy as np
import matplotlib.mlab as mlab
%matplotlib inline
import math

mu1, mu2 = 20, 10
variance1,variance2 = 74, 31
sigma1 = math.sqrt(variance1)
sigma2 = math.sqrt(variance2)
x = np.linspace(mu1 - 4*sigma1, mu1 + 4*sigma1, 100)
plt.plot(x,mlab.normpdf(x, mu1, sigma1))
plt.plot(x,mlab.normpdf(x, mu2, sigma2))
plt.show()
```




Next, we plot the demand curves for the two stores based on the average and variances of the historical transactions for the overall category of products.

In [6]:
```
# Demand function for the product from 2 years historical sales - separate for 2 stores
import matplotlib.pyplot as plt
import numpy as np
import matplotlib.mlab as mlab
import math
import scipy
from math import *
%matplotlib inline

mu1,mu2 = 10,12
variance1,variance2 = 8,41
sigma1 = math.sqrt(variance1)
sigma2 = math.sqrt(variance2)
x = np.linspace(mu1 - 4*sigma1, mu2 + 4*sigma2, 100)
plt.plot(x,(1-0.5*(1+scipy.special.erf((x-mu1)/(sigma1*math.sqrt(2))))))
plt.plot(x,(1-0.5*(1+scipy.special.erf((x-mu2)/(sigma2*math.sqrt(2))))))
plt.show()
```



Finally, we use the BFGS optimization technique to get the optimal prices and profit.

```
In [11]: #There are two populations of proportion alpha and 1-alpha,
         #with wtp that are normally distributed with vector mu and sigma
         import math
         import numpy as np
         from math import *
         from scipy.optimize import minimize_scalar
         from scipy.optimize import minimize
         mu=np.array([mu1,mu2]) # make sure to use the relevant mu values here
         sigma=np.array([math.sqrt(variance1),math.sqrt(variance2)]) # same as above
         M=1
         alpha=.9
         c=15 # Marginal Cost
         def profit(p):
             """Profit """
             return -alpha*((1-0.5*(1+erf((p[0]-mu[0])/(sigma[0]*math.sqrt(2)))))*\
                            (p[0]-c))-\
                            (1-alpha)*((1-0.5*(1+erf((p[1]-mu[1])/(sigma[1]*math.sqrt(2)))))*\
                            (p[1]-c))
         sol=minimize(profit, [0.1, 0.1], method="BFGS")
         print("Optimal Profit from the optimization is:",-sol.fun)
         print("OPtimal prices for the item across stores:",sol.x)

         Optimal Profit from the optimization is: 2.6421420716738853
         OPtimal prices for the item across stores: [23.20124414 17.96287991]
```

## 6. References


- Bodea and Ferguson. Segmentation, Revenue Management and Pricing Analytics. 2014
- https://docs.scipy.org/doc/scipy/reference/generated/scipy.optimize.minimize.html
- https://blog.blackcurve.com/what-is-price-optimisation
- https://www.utdallas.edu/~metin/Or6377/SolvExer/basicproEx.pdf