

1 What is uncertainty?

Everything that is not certain. Analogy:

- What you know;
- What you don't know, and what you don't know that you don't know.

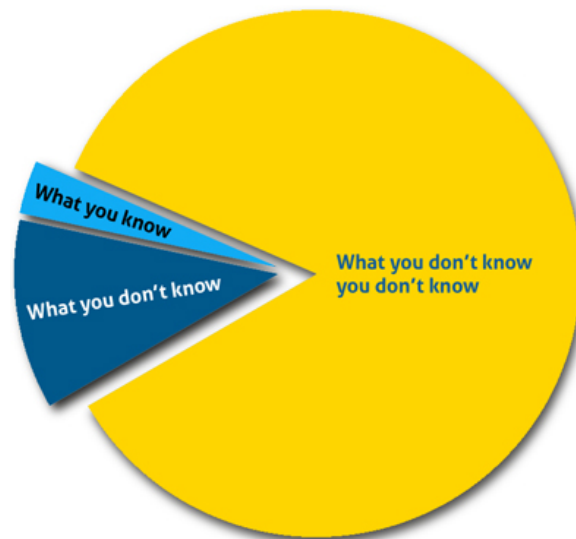


Figure 1: From <http://www.tecplot.com/wp-content/uploads/2012/09/dontknow.jpg>

The most widely used mathematical model for uncertainty uses probability.

1.1 Review of probability

- Probability space,
 - Set of outcomes Ω ,
 - Set of events \mathcal{F} containing subsets of Ω ,
 - A function (probability measure) $P : \mathcal{F} \rightarrow \mathbb{R}$.
- Random variables, distribution functions,

- Real-value random variable is a (measurable) function $X : \Omega \rightarrow \mathbb{R}$.
- Probability distribution function or cumulative distribution function: $F(x) = P(X \leq x)$ for all x .
- Probability density function, if it exists: $F(x) = \int_{-\infty}^x f(z)dz$.
- Examples (Bernoulli, Normal, Uniform, Exponential etc.),
 - Bernoulli with parameter p : $P(X = 1) = p, P(X = 0) = 1 - p$.
 - Exponential with rate λ : $F(x) = (1 - e^{-x})1_{[x \geq 0]}$ for all $x \in (-\infty, \infty)$.
 - Normal $N(0, 1)$: $f(x) = (2\pi)^{-1/2}e^{-x^2/2}$ for all $x \in (-\infty, \infty)$.
- Expectation,
 - Bernoulli: $\mathbb{E}X = p * 1 + (1 - p) * 0$

2 Newsboy solution

As seen last week, the (random) cost for the Newsboy problem is

$$g(s, D) = h \max(s - D, 0) + p \max(D - s, 0).$$

The expected cost $\mathbb{E}g(s, D)$ is

$$\begin{aligned} \bar{g}(s) \triangleq \mathbb{E}g(s, D) &= \int_0^\infty [h \max(s - z, 0) + p \max(z - s, 0)] f_D(z) dz \\ &= \int_0^s h(s - z) f_D(z) dz + \int_s^\infty p(z - s) f_D(z) dz. \end{aligned}$$

We are looking for that optimal value of s , so let's look at the first and second derivatives of $\mathbb{E}g(s, D)$.

$$\begin{aligned} \frac{d}{ds} \bar{g}(s) &= h \frac{d}{ds} s \int_0^s f_D(z) dz - h \frac{d}{ds} \int_0^s z f_D(z) dz + p \frac{d}{ds} \int_s^\infty z f_D(z) dz - p \frac{d}{ds} s \int_s^\infty f_D(z) dz \\ &= h \frac{d}{ds} s F_D(s) - p \frac{d}{ds} s (1 - F_D(s)) - h \frac{d}{ds} \int_0^s z f_D(z) dz + p \frac{d}{ds} \left(M - \int_0^s z f_D(z) dz \right), \end{aligned}$$

where M is the constant $\int_0^\infty z f_D(z) dz$, and we used the definition of F_D . Observe that

$$\frac{d}{ds} s F_D(s) = s F_D'(s) + F_D(s) = s f_D(s) + F_D(s)$$

and that¹

$$\frac{d}{ds} \int_0^s z f_D(z) dz = s f_D(s) - 0 f_D(0) + \int_0^s 0 dz = s f_D(s).$$

¹Use Leibniz's rule to move the derivative inside the integral: $\frac{d}{ds} (\int_{a(s)}^{b(s)} g(s, z) dz) = g(s, b(s)) b'(s) - g(s, a(s)) a'(s) + \int_{a(s)}^{b(s)} [\frac{d}{ds} g(s, z)] dz$.

Hence, we have

$$\begin{aligned}\frac{d}{ds}\bar{g}(s) &= (h+p)(sf_D(s) + F_D(s)) - p - (h+p)sf_D(s) + p \cdot 0 \\ &= (h+p)F_D(s) - p.\end{aligned}$$

The second derivative is

$$\frac{d^2}{ds^2}\bar{g}(s) = (h+p)f_D(s),$$

which is non-negative for all $s \geq 0$. Hence, \bar{g} is convex, and setting $\frac{d}{ds}\bar{g}(s) = 0$, we find that the value of s that minimizes expected cost is

$$s^* = F_D^{-1}\left(\frac{p}{h+p}\right),$$

where h is the cost per unit of excess inventory, and p is the cost per unit of inventory shortfall.

In summary, we have presented a solution to the newsboy problem that takes inputs h , p , and the distribution F_D , and outputs an optimal order size s^* . We assume that F_D is given; however, we can also estimate F_D from past observations of the demand.

Homework: How can we use the Newboy solution in beer game?

3 Forecasting

Forecasting is about time (past and future) and quantities (demand, inventory levels, etc.). In the context of supply chains, we are most interested in discrete time: $1, 2, \dots$. The quantities of interest in the supply chains are of the form X_1, X_2, \dots , taking values in \mathbb{R}^d . At time n , the time steps $1, \dots, n$ are in the past and the values X_1, \dots, X_n are observations already made, whereas the time steps $n+1, n+2, \dots$ are in the future and the values X_{n+1}, X_{n+2}, \dots are not yet seen. However, at time n , the decision-maker can make forecasts $\hat{X}_{n+1}, \hat{X}_{n+2}, \dots$ for these values. Later in the future, at time $n+2$ say, we can compare $\hat{X}_{n+1}, \hat{X}_{n+2}$ with the true values X_{n+1}, X_{n+2} .

3.1 Pitfalls

Weather forecasts are simple compared to supply chain forecasts: a forecast of 10mm of rain has little effect on the actual realization of rain.

- Ignoring important factors in our model
 - Demand and decisions made are interconnected,
 - Marketing campaign affects demand,
 - Other participants, competitors,
- Effect of forecast \hat{X}_{n+1} on the future realization,

- Actions taken in response to the forecasts,
- Positive reinforcement: self-fulfilling effect (meeting self-imposed targets),

Responsible forecast must incorporate all the above.

3.2 Bass model

In order to forecasts to make sense, we must first make reasonable assumptions to obtain a model of the system whose quantities X_1, X_2, \dots we want to forecast.

In the newsboy problem, we had the simplest model for demand: the same probability distribution F_D everyday. This is suitable for products that do not change over time: food, newspapers, etc. In this section, we consider a model for demand for products that are new. Consider a population of m customers $1, \dots, m$. For every customer i , we model the time of adoption (purchase) of the product by the customer by a random variable T taking values on $[0, \infty]$. Let T_1, \dots, T_m denote the times at which customers $1, \dots, m$ adopt a given new product. We assume that these random variables are independent and identically distributed according to F_T .

The probability distribution F_T has the following parameters: the coefficient of innovation p and the coefficient of imitation q . Let f_T denote the corresponding probability density. The density function at time t is model as

$$\frac{dF_T(t)}{dt} = f_T(t) = [p + qF_T(t)](1 - F_T(t)),$$

where $p + qF_T(t)$ is the density function conditioned on the event that the customer has not yet adopted at time t , and $1 - F_T(t)$ is the probability that it was not adopted already. Notice that the imitation term $qF_T(t)$ is proportional to the fraction $F_T(t)$ of customer who already adopted the product, whereas the innovation term is not. Solving this differential equation for F with the initial condition $F(0) = 0$, we obtain²

$$F_T(t) = \frac{1 - e^{-(p+q)t}}{1 + (q/p)e^{-(p+q)t}}, \quad \text{for all } t \geq 0.$$

This distribution is shown in Figure 3.2. It has a density as shown in Figure 3.2.

Given the distribution F_T , we can also model other interesting quantities. The number $N_{a,b}$ of customers adopting the product between time instants a and b is

$$N_{a,b} = \sum_{i=1}^m 1_{[a < T_i < b]},$$

where $1_{[a < T_i < b]}$ is a Bernoulli random variable with parameters $\mathbb{P}(a < T_i < b) = F_T(b) - F_T(a)$. Finally, we conclude that the random variable $N_{a,b}$ has a binomial distribution (cf. Figure 3.2) with the following density:

$$\mathbb{P}(N_{a,b} = k) = \binom{m}{k} \left(F_T(b) - F_T(a) \right)^k \left(1 - F_T(b) + F_T(a) \right)^{m-k}.$$

²Homework: check this.

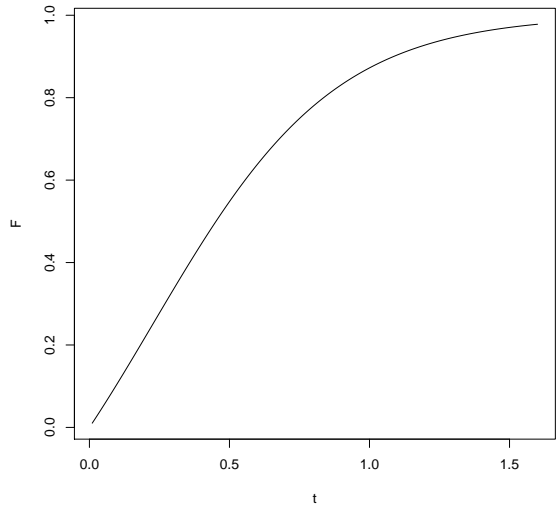


Figure 2: The distribution F_T .

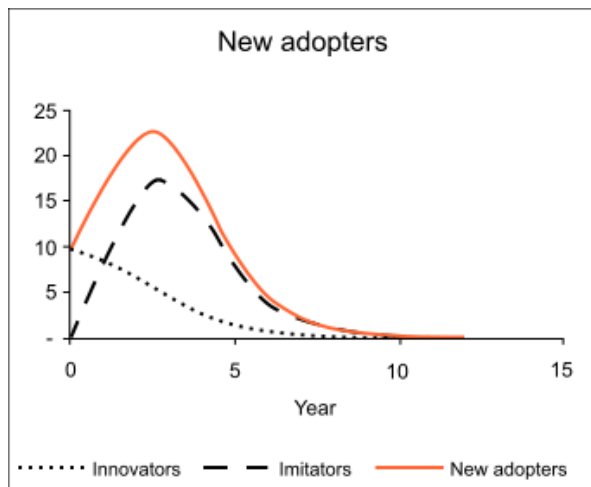


Figure 3: From https://upload.wikimedia.org/wikipedia/commons/thumb/d/d0/Bass_new_adopters.svg/339px-Bass_new_adopters.svg.png

Remark 1. From the above density, we can obtain the cumulative distribution function F_N for the demand of the new product over the time interval $[a, b]$. This F_N in turn can be used as input to a newsboy problem to find the optimal number of new products to produce or order.

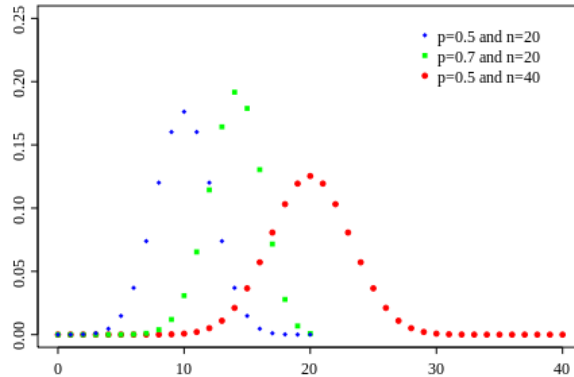


Figure 4: From https://en.wikipedia.org/wiki/Binomial_distribution

3.3 Linear regression forecast



Figure 5: From <http://www.cbsolution.net/>

In regression, we have a sequence of n observations $(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)$, where each $X_j \in \mathbb{R}^d$ is a sample (e.g., number of students registered for courses 1 to d) and $Y_j \in \mathbb{R}$ is an associated quantity (e.g., how many copies of the FOSCT textbook to order). The problem is as follows: given $(X_1, Y_1), (X_2, Y_2), \dots, (X_n, Y_n)$ and X_{n+1} as input, forecast Y_{n+1} .

Suppose that for all $j = 1, \dots, n$:

$$Y_j = g(X_j) + \nu_j,$$

where $\{\nu_i\}$ are noise random variables that are independent and have zero mean. The function g is unknown. The regression problem is to find a function \hat{g}_n using $X_1, Y_1, \dots, X_n, Y_n$ in order to estimate g .

The linear regression problem is a special case, where we assume additionally that there exists an (unknown) $\theta \in \mathbb{R}^d$ such that $g(z) = \theta^T z^3$. In this case, the assumption on Y_j becomes:

$$Y_j = \theta^T X_j + \nu_j, \quad j = 1, \dots, n, \quad (1)$$

so that the problem becomes estimating θ by $\hat{\theta}_n$. Once we have $\hat{\theta}_n$, we can forecast Y_{n+1} with $\hat{Y}_{n+1} = \hat{\theta}_n^T X_{n+1}$.

3.3.1 Least-squares approach

The *least-squares* estimate of the parameter θ is

$$\hat{\theta}_n = \arg \min_{\omega \in \mathbb{R}^d} \sum_{j=1}^n (Y_j - X_j^T \omega)^2,$$

where

$$h(\omega) = \sum_{j=1}^n (Y_j - X_j^T \omega)^2$$

is convex and non-negative.

For $\hat{\theta}_n$ to be a minimum, we must have the first derivative equal to zero:

$$\frac{dh}{d\omega^i}(\hat{\theta}_n) = 0, \quad \text{for all } i = 1, \dots, d.$$

This is the derivative of a scalar function h by a vector⁴; hence, by the properties of the derivative⁵, we obtain:

$$2 \sum_{j=1}^n X_j (Y_j - X_j^T \omega) = 0. \quad (2)$$

Letting

$$B \triangleq \sum_{j=1}^n X_j X_j^T,$$

³This denotes an inner product.

⁴See https://en.wikipedia.org/wiki/Matrix_calculus#Scalar-by-vector

⁵See https://en.wikipedia.org/wiki/Matrix_calculus#Scalar-by-vector_identities

the above (2) becomes

$$\sum_{j=1}^n X_j Y_j = B \hat{\theta}_n.$$

Hence, if B is an invertible matrix, then we have

$$\hat{\theta}_n = B^{-1} \sum_{j=1}^n X_j Y_j. \quad (3)$$

3.4 Moving average forecast

There is a sequence of demand values y_1, y_2, \dots with the positive integers as time indices. At time t , we have observed y_1, \dots, y_{t-1} and wish to forecast the unseen value y_t . For $N < t$, the N -th order moving average forecast is

$$\hat{y}_t = \frac{1}{N} \sum_{i=t-N}^{t-1} y_i.$$

Homework: for what assumptions and models does this work?

3.5 Exponential smoothing forecast

For $\alpha \in [0, 1]$, the exponential smoothing forecast is

$$\hat{y}_t = \alpha y_{t-1} + (1 - \alpha) \hat{y}_{t-1} = \sum_{i=0}^{\infty} \alpha (1 - \alpha)^i y_{t-i-1} * 1_{[t-i-1 > 0]}.$$

Homework: for what assumptions and models does this work?

4 Reading material

Books:

- FOSCT Section 4.4.2 and Wikipedia for Newsboy.
- For Bass model: “Why the Bass model fits without decision variables⁶” by Bass, Krishnan, and Jain, *Marketing Science*, 13(3), 1994.

⁶PDF