

Buy 'Til You Die - A Walkthrough

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1 Introduction

The BTYD package contains models to capture non-contractual purchasing behavior of customers—or, more simply, models that tell the story of people buying until they die (become inactive as customers). The main models presented in the package are the Pareto/NBD model and the BG/BB models, which describe scenario of the firm not being able to observe the exact time at which a customer drops out. We will cover each in turn. If you are unfamiliar with these models, Fader et al. (2005) provides a description of the Pareto/NBD model and Fader et al. (2010) provides a description of the BG/BB model.

2 Pareto/NBD

The Pareto/NBD model is used for non-contractual situations in which customers can make purchases at any time. Using four parameters, it describes the rate at which customers make purchases and the rate at which they drop out—allowing for heterogeneity in both regards, of course. We will walk through the Pareto/NBD functionality provided by the BTYD package using the CDNOW¹ dataset. As shown by figure 1, the Pareto/NBD model describes this dataset quite well.

2.1 Data Preparation

The data required to estimate Pareto/NBD model parameters is surprisingly little. The customer-by-customer approach of the model is retained, but we need only three pieces of information for every person: how many transactions they made in the calibration period (frequency), the time of their last transaction (recency), and the total time for which they were observed. A customer-by-sufficient-statistic matrix, as used by the BTYD package, is simply a matrix with a row for every customer and a column for each of the above-mentioned statistics.

¹Provided with the BTYD package and available at brucehardie.com. For more details, see the documentation of the `cdnowSummary` data included in the package.

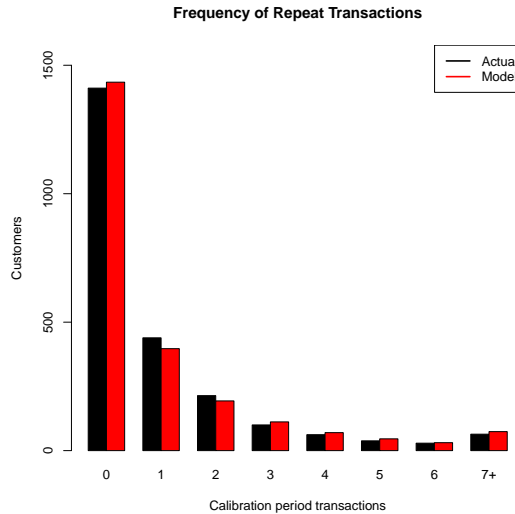


Figure 1: Calibration period fit of Pareto/NBD model to CDNOW dataset.

You may find yourself with the data available as an event log. This is a data structure which contains a row for every transaction, with a customer identifier, date of purchase, and (optionally) the amount of the transaction. `dc.ReadLines` is a function to convert an event log in a comma-delimited file to an data frame in R—you could use another function such as `read.csv` or `read.table` if desired, but `dc.ReadLines` simplifies things by only reading the data you require and giving the output appropriate column names. In the example below, we create an event log from the file “cdnowElog.csv”, which has customer IDs in the second column, dates in the third column and sales numbers in the fifth column.

```
cdnowElog <- system.file("data/cdnowElog.csv", package = "BTYD")
elog <- dc.ReadLines(cdnowElog, cust.idx = 2,
                    date.idx = 3, sales.idx = 5)

elog[1:3,]

#   cust    date sales
# 1    1 19970101 29.33
# 2    1 19970118 29.73
# 3    1 19970802 14.96
```

Note the formatting of the dates in the output above. `dc.Readlines` saves dates as characters, exactly as they appeared in the original comma-delimited file. For many of the data-conversion functions in BTYD, however, dates need to be compared to each other—and unless your years/months/days happen to be in the right order, you probably want them to be sorted chronologically and

not alphabetically. Therefore, we convert the dates in the event log to R Date objects:

```
eelog$date <- as.Date(eelog$date, "%Y%m%d")
eelog[1:3, ]

#   cust      date sales
# 1    1 1997-01-01  29.33
# 2    1 1997-01-18  29.73
# 3    1 1997-08-02  14.96
```

Our event log now has dates in the right format, but a bit more cleaning needs to be done. Transaction-flow models, such as the Pareto/NBD, is concerned with interpurchase time. Since our timing information is only accurate to the day, we should merge all transactions that occurred on the same day. For this, we use `dc.MergeTransactionsOnSameDate`. This function returns an event log with only one transaction per customer per day, with the total sum of their spending for that day as the sales number.

```
eelog <- dc.MergeTransactionsOnSameDate(eelog)
```

To validate that the model works, we need to divide the data up into a calibration period and a holdout period. This is relatively simple with either an event log or a customer-by-time matrix, which we are going to create soon. I am going to use 30 September 1997 as the cutoff date, as this point (39 weeks) divides the dataset in half. The reason for doing this split now will become evident when we are building a customer-by-sufficient-statistic matrix from the customer-by-time matrix—it requires a last transaction date, and we want to make sure that last transaction date is the last date in the calibration period and not in the total period.

```
end.of.cal.period <- as.Date("1997-09-30")
eelog.cal <- eelog[which(eelog$date <= end.of.cal.period), ]
```

The final cleanup step is a very important one. In the calibration period, the Pareto/NBD model is generally concerned with *repeat* transactions—that is, the first transaction is ignored. This is convenient for firms using the model in practice, since it is easier to keep track of all customers who have made at least one transaction (as opposed to trying to account for those who have not made any transactions at all). The one problem with simply getting rid of customers' first transactions is the following: We have to keep track of a “time zero” as a point of reference for recency and total time observed. For this reason, we use `dc.SplitUpElogForRepeatTrans`, which returns a filtered event log (`$repeat.trans.eelog`) as well as saving important information about each customer (`$cust.data`).

```
split.data <- dc.SplitUpElogForRepeatTrans(eelog.cal)
clean.eelog <- split.data$repeat.trans.eelog
```

The next step is to create a customer-by-time matrix. This is simply a matrix with a row for each customer and a column for each date. There are several different options for creating these matrices:

- Frequency—each matrix entry will contain the number of transactions made by that customer on that day. Use `dc.CreateFreqCBT`. If you have already used `dc.MergeTransactionsOnSameDate`, this will simply be a reach customer-by-time matrix.
- Reach—each matrix entry will contain a 1 if the customer made any transactions on that day, and 0 otherwise. Use `dc.CreateReachCBT`.
- Spend—each matrix entry will contain the amount spent by that customer on that day. Use `dc.CreateSpendCBT`. You can set whether to use total spend for each day or average spend for each day by changing the `is.avg.spend` parameter. In most cases, leaving `is.avg.spend` as `FALSE` is appropriate.

```
freq.cbt <- dc.CreateFreqCBT(clean.eelog)
freq.cbt[1:3, 1:5]
```

```
#      date
# cust 1997-01-08 1997-01-09 1997-01-10 1997-01-11 1997-01-12
#   1           0           0           0           0
#   2           0           0           0           0
#   6           0           0           0           1           0
```

There are two things to note from the output above:

1. Customers 3, 4, and 5 appear to be missing, and in fact they are. They did not make any repeat transactions and were removed when we used `dc.SplitUpElogForRepeatTrans`. Do not worry though—we will get them back into the data when we use `dc.MergeCustomers` (soon).
2. The columns start on January 8—this is because we removed all the first transactions (and nobody made 2 transactions withing the first week).

We have a small problem now—since we have deleted all the first transactions, the frequency customer-by-time matrix does not have any of the customers who made zero repeat transactions. These customers are still important; in fact, in most datasets, more customers make zero repeat transactions than any other number. Solving the problem is reasonably simple: we create a customer-by-time matrix using all transactions, and then merge the filtered CBT with this total CBT (using data from the filtered CBT and customer IDs from the total CBT).

```
tot.cbt <- dc.CreateFreqCBT(eelog)
cal.cbt <- dc.MergeCustomers(tot.cbt, freq.cbt)
```

From the calibration period customer-by-time matrix (and a bit of additional information we saved earlier), we can finally create the customer-by-sufficient-statistic matrix described earlier. The function we are going to use is `dc.BuildCBSFromCBTAndDates`, which requires a customer-by-time matrix, starting and ending dates for each customer, and the time of the end of the calibration period. It also requires a time period to use—in this case, we are choosing to use weeks. If we chose days instead, for example, the recency and total time observed columns in the customer-by-sufficient-statistic matrix would have gone up to 273 instead of 39, but it would be the same data in the end. This function could also be used for the holdout period by setting `cbt.is.during.cal.period` to `FALSE`. There are slight differences when this function is used for the holdout period—it requires different input dates (simply the start and end of the holdout period) and does not return a recency (which has little value in the holdout period).

```
birth.periods <- split.data$cust.data$birth.per
last.dates <- split.data$cust.data$last.date
cal.cbs.dates <- data.frame(birth.periods, last.dates,
                           end.of.cal.period)
cal.cbs <- dc.BuildCBSFromCBTAndDates(cal.cbt, cal.cbs.dates,
                                     per="week")
```

You'll be glad to hear that, for the process described above, the package contains a single function to do everything for you: `dc.ElogToCbsCbt`. However, it is good to be aware of the process above, as you might want to make small changes for different situations—for example, you may not want to remove customers' initial transactions, or your data may be available as a customer-by-time matrix and not as an event log. For most standard situations, however, `dc.ElogToCbsCbt` will do. Reading about its parameters and output in the package documentation will help you to understand the function well enough to use it for most purposes.

2.2 Parameter Estimation

Now that we have the data in the correct format, we can estimate model parameters. To estimate parameters, we use `pnbd.EstimateParameters`, which requires a calibration period customer-by-sufficient-statistic matrix and (optionally) starting parameters. `(1,1,1,1)` is used as default starting parameters if none are provided. The function which is maximized is `pnbd.cbs.LL`, which returns the log-likelihood of a given set of parameters for a customer-by-sufficient-statistic matrix.

```

params <- pnbld.EstimateParameters(cal.cbs)
params

# [1] 0.5534 10.5802 0.6061 11.6562

LL <- pnbld.cbs.LL(params, cal.cbs)
LL

# [1] -9595

```

As with any optimization, we should not be satisfied with the first output we get. Let's run it a couple more times, with its own output as a starting point, to see if it converges:

```

p.matrix <- c(params, LL)
for (i in 1:2) {
  params <- pnbld.EstimateParameters(cal.cbs, params)
  LL <- pnbld.cbs.LL(params, cal.cbs)
  p.matrix.row <- c(params, LL)
  p.matrix <- rbind(p.matrix, p.matrix.row)
}
colnames(p.matrix) <- c("r", "alpha", "s", "beta", "LL")
rownames(p.matrix) <- 1:3
p.matrix

#      r alpha      s  beta    LL
# 1 0.5534 10.58 0.6061 11.66 -9595
# 2 0.5534 10.58 0.6060 11.66 -9595
# 3 0.5534 10.58 0.6059 11.66 -9595

```

This estimation does converge. I am not going to demonstrate it here, but it is always a good idea to test the estimation function from several starting points.

Now that we have the parameters, the BTYD package provides functions to interpret them. As we know, r and α describe the gamma mixing distribution of the NBD transaction process. We can see this gamma distribution in figure 2, plotted using `pnbld.PlotTransactionRateHeterogeneity(params)`. We also know that s and β describe the gamma mixing distribution of the Pareto (or gamma exponential) dropout process. We can see this gamma distribution in figure 3, plotted using `pnbld.PlotDropoutHeterogeneity(params)`.

From these, we can already tell something about our customers: they are more likely to have low values for their individual poisson transaction process parameters, and more likely to have low values for their individual exponential dropout process parameters.

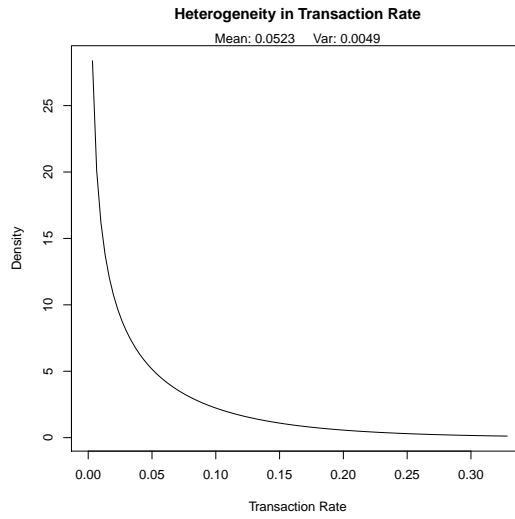


Figure 2: Transaction rate heterogeneity of estimated parameters.

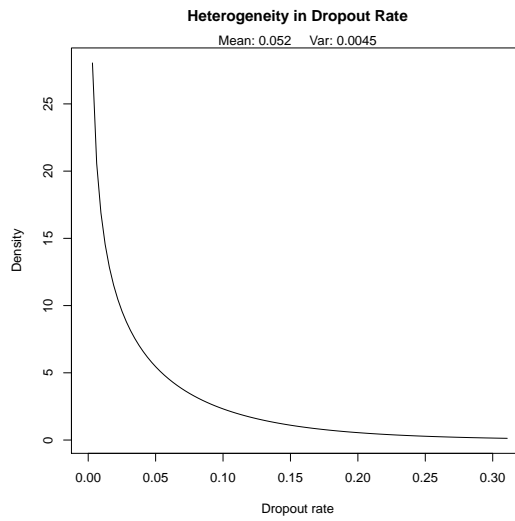


Figure 3: Dropout rate heterogeneity of estimated parameters.

2.3 Individual Level Estimations

Now that we have parameters for the population, we can make estimations for customers on the individual level.

First, we can estimate the number of transactions we expect a newly acquired customer to make in a given time period. Let's say, for example, that we are interested in the number of repeat transactions a newly acquired customer will make in a time period of one year. Note that we use 52 weeks to represent one year, not 12 months, 365 days, or 1 year. This is because our parameters were estimated using weekly data.

```
pnbd.Expectation(params, t = 52)

# [1] 1.473
```

We can also obtain expected characteristics for a specific customer, conditional on their purchasing behavior during the calibration period. The first of these is `pnbd.ConditionalExpectedTransactions`, which gives the number of transactions we expect a customer to make in the holdout period. The second is `pnbd.PAlive`, which gives the probability that a customer is still alive at the end of the calibration period. As above, the time periods used depend on which time period was used to estimate the parameters.

```
cal.cbs["1516",]

#      x    t.x T.cal
# 26.00 30.86 31.00

x <- cal.cbs["1516", "x"]
t.x <- cal.cbs["1516", "t.x"]
T.cal <- cal.cbs["1516", "T.cal"]
pnbd.ConditionalExpectedTransactions(params, T.star = 52,
                                     x, t.x, T.cal)

# [1] 25.46

pnbd.PAlive(params, x, t.x, T.cal)

# [1] 0.9979
```

There is one more point to note here—using the conditional expectation function, we can see the “increasing frequency paradox” in action:

```
for (i in seq(10, 25, 5)){
  cond.expectation <- pnbd.ConditionalExpectedTransactions(
    params, T.star = 52, x = i,
    t.x = 20, T.cal = 39)
```



```

cat ("x:",i,"\t Expectation:",cond.expectation, fill = TRUE)
}

# x: 10    Expectation: 0.7062
# x: 15    Expectation: 0.1442
# x: 20    Expectation: 0.02251
# x: 25    Expectation: 0.003093

```

2.4 Plotting/ Goodness-of-fit

We would like to be able to do more than make inferences about individual customers. The BTYD package provides functions to plot expected customer behavior against actual customer behaviour in the both the calibration and holdout periods.

The first such function is the obvious starting point: a comparison of actual and expected frequencies within the calibration period. This is figure 1, which was generated using the following code:

```
pnbd.PlotFrequencyInCalibration(params, cal.cbs, 7)
```

This function obviously needs to be able to generate expected data (from estimated parameters) and requires the actual data (the calibration period customer-by-sufficient-statistic). It also requires another number, called the censor number. The histogram that is plotted is right-censored; after a certain number, all frequencies are binned together. The number provided as a censor number determines where the data is cut off.

Unfortunately, the only thing we can tell from comparing calibration period frequencies is that the fit between our model and the data isn't awful. We need to verify that the fit of the model holds into the holdout period. Firstly, however, we are going to need to get information for holdout period. `dc.ElogToCbsCbt` produces both a calibration period customer-by-sufficient-statistic matrix and a holdout period customer-by-sufficient-statistic matrix, which could be combined in order to find the number of transactions each customer made in the holdout period. However, since we did not use `dc.ElogToCbsCbt`, I am going to get the information directly from the event log. Note that I subtract the number of repeat transactions in the calibration period from the total number of transactions. We remove the initial transactions first as we are not concerned with them.

```

elog <- dc.SplitUpElogForRepeatTrans(elog)$repeat.trans.elog
x.star <- rep(0, nrow(cal.cbs))
cal.cbs <- cbind(cal.cbs, x.star)
elog.custs <- elog$cust
for (i in 1:nrow(cal.cbs)) {
  current.cust <- rownames(cal.cbs)[i]

```

```

    tot.cust.trans <- length(which(elog.custs == current.cust))
    cal.trans <- cal.cbs[i, "x"]
    cal.cbs[i, "x.star"] <- tot.cust.trans - cal.trans
  }
cal.cbs[1:3, ]

#   x    t.x T.cal x.star
# 1 2 30.429 38.86      1
# 2 1  1.714 38.86      0
# 3 0  0.000 38.86      0

```

Now we can see how well our model does in the holdout period. Figure 4 shows the output produced by the code below. It divides the customers up into bins according to calibration period frequencies and plots actual and conditional expected holdout period frequencies for these bins.

```

T.star <- 39 # length of the holdout period
censor <- 7  # This censor serves the same purpose described above
x.star <- cal.cbs[, "x.star"]
comp <- pnbd.PlotFreqVsConditionalExpectedFrequency(params, T.star,
                                                    cal.cbs, x.star, censor)

rownames(comp) <- c("act", "exp", "bin")
comp

#      freq.0  freq.1  freq.2  freq.3  freq.4  freq.5  freq.6  freq.7+
# act    0.2367  0.6970  1.393   1.560   2.532   2.947   3.862   6.359
# exp    0.1385  0.5996  1.196   1.714   2.399   2.907   3.819   6.403
# bin 1411.0000 439.0000 214.000 100.000 62.000  38.000  29.000  64.000

```

As you can see above, the graph also produces a matrix output. Most plotting functions in the BTYD package produce output like this. They are often worth looking at because they contain additional information not presented in the graph—the size of each bin in the graph. In this graph, for example, this information is important because the bin sizes show that the gap at zero means a lot more than the precision at 6 or 7 transactions. Despite this, this graph shows that the model fits the data very well in the holdout period.

Aggregation by calibration period frequency is just one way to do it. BTYD also provides plotting functions which aggregate by several other measures. The other one I will demonstrate here is aggregation by time—how well does our model predict how many transactions will occur in each week?

The first step, once again, is going to be to collect the data we need to compare the model to. The customer-by-time matrix has already collected the data for us by time period; so we'll use that to gather the total transactions per day. Then we convert the daily tracking data to weekly data.

```

tot.cbt <- dc.CreateFreqCBT(elog)

# ...Completed Freq CBT

```

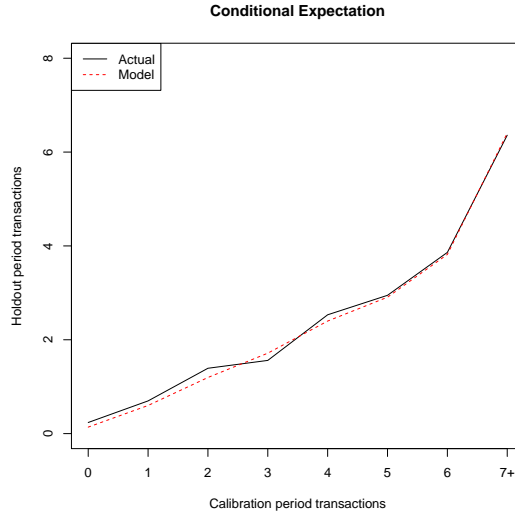


Figure 4: Actual vs. conditional expected transactions in the holdout period.

```
d.track.data <- rep(0, 7 * 78)
origin <- as.Date("1997-01-01")
for (i in colnames(tot.cbt)) {
  date.index <- difftime(as.Date(i), origin) + 1
  d.track.data[date.index] <- sum(tot.cbt[, i])
}
w.track.data <- rep(0, 78)
for (j in 1:78) {
  w.track.data[j] <- sum(d.track.data[(j * 7 - 6):(j * 7)])
}
```

Now, we can make a plot comparing the actual number of transactions to the expected number of transactions on a weekly basis, as shown in figure 5. Note that we set `n.periods.final` to 78. This is to show that we are working with weekly data. If our tracking data was daily, we would use 546 here—the function would plot our daily tracking data against expected daily transactions, instead of plotting our weekly tracking data against expected weekly transactions. This concept may be a bit tricky, but is explained in the documentation for `pnbd.PlotTrackingInc`. The reason there are two numbers for the total period (`T.tot` and `n.periods.final`) is that your customer-by-sufficient-statistic matrix and your tracking data may be in different time periods.

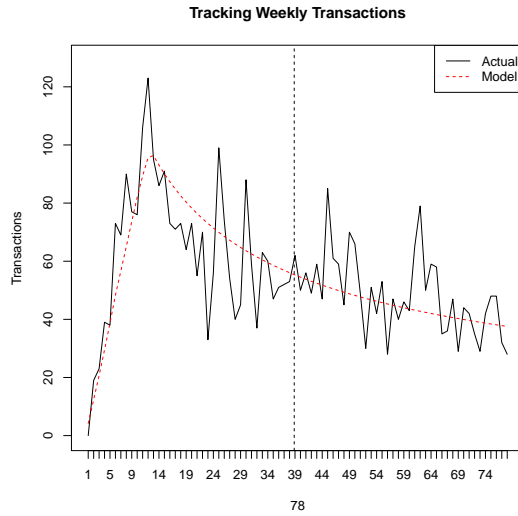


Figure 5: Actual vs. expected incremental purchasing behaviour.

```
T.cal <- cal.cbs["T.cal"]
T.tot <- 78
n.periods.final <- 78
inc.tracking <- pnbd.PlotTrackingInc(params, T.cal,
                                     T.tot, w.track.data,
                                     n.periods.final)

inc.tracking[,20:25]

#           [,1] [,2] [,3] [,4] [,5] [,6]
# actual    73.00 55.00 70.00 33.00 56.00 99.00
# expected  78.31 76.42 74.65 72.98 71.41 69.93
```

Although figure 5 shows that the model is definitely capturing the trend of customer purchases over time, it is very messy and may not convince skeptics. Furthermore, the matrix, of which a sample is shown, does not really convey much information since purchases can vary so much from one week to the next. For these reasons, we may need to smooth the data out by cumulating it over time, as shown in figure 6.

```
cum.tracking.data <- cumsum(w.track.data)
cum.tracking <- pnbd.PlotTrackingCum(params, T.cal,
                                     T.tot, cum.tracking.data,
                                     n.periods.final)

cum.tracking[,20:25]
```

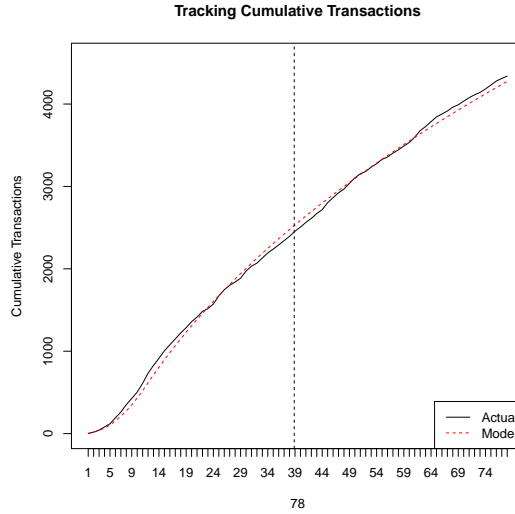


Figure 6: Actual vs. expected cumulative purchasing behaviour.

#	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]
# actual	1359	1414	1484	1517	1573	1672
# expected	1309	1385	1460	1533	1604	1674

3 BG/BB

The BG/BB model is also used for non-contractual settings. In many regards, it is very similar to the Pareto/NBD model—it also uses four parameters to describe a purchasing process and a dropout process. The difference between the models is that the BG/BB is used to describe situations in which customers have discrete transaction opportunities, rather than being able to make transactions at any time. For this section, we will be using donation data presented in Fader et. al. (2010). Figure 7 shows that this model also fits the right type of data well.

3.1 Data Preparation

Luckily, preparing data to be used by the BTYD package BG/BB functions is going to be very easy if you understood how to set up the data for the Pareto/NBD package. The BG/BB model uses exactly the same data as the Pareto/NBD model, but since it is discrete we can go one step further and create a recency-frequency matrix from our customer-by-sufficient-statistic matrix. We are able

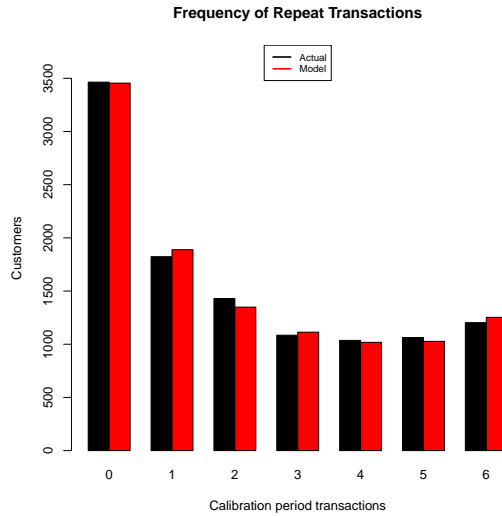


Figure 7: Calibration period fit of BG/BB model to the donations dataset.

to do this because the data is discrete—a recency-frequency matrix consists of a row for every possible calibration period recency/frequency combination, and contains the total number of customers which had that particular combination of recency and frequency. While this is not strictly necessary, it greatly reduces the amount of space required to store the data and makes parameter estimation much faster—for the donation data, for example, there is a reduction from 11,104 rows (number of customers) down to 22.

Since I don't have access to the original event log for the donation data, I am going to demonstrate the data preparation process with simulated data (included in the package):

```
simElog <- system.file("data/discreteSimElog.csv",
                      package = "BTYD")
elog <- dc.ReadLines(simElog, cust.idx = 1, date.idx = 2)
elog[1:3,]

#   cust      date
# 1    1 1970-01-01
# 2    1 1975-01-01
# 3    1 1977-01-01

elog$date <- as.Date(elog$date, "%Y-%m-%d")
max(elog$date);
```

```

# [1] "1983-01-01"

min(eolog$date);

# [1] "1970-01-01"

# let's make the calibration period end somewhere in-between
T.cal <- as.Date("1977-01-01")

simData <- dc.ElogToCbsCbt(eolog, per="year", T.cal)
cal.cbs <- simData$cal$cbs

freq<- cal.cbs[, "x"]
rec <- cal.cbs[, "t.x"]
trans.opp <- 7 # transaction opportunities
cal.rf.matrix <- dc.MakeRFmatrixCal(freq, rec, trans.opp)
cal.rf.matrix[1:5,]

#      x t.x n.cal custs
# [1,] 0  0     7  2900
# [2,] 1  1     7   933
# [3,] 1  2     7   218
# [4,] 2  2     7   489
# [5,] 1  3     7    95

```

3.2 Parameter Estimation

Estimating BG/BB parameters is very similar to estimating Pareto/NBD parameters. The same rules apply—we use `bgbg.EstimateParameters`, which also uses (1,1,1,1) as default starting parameters. Once again, we should run the estimation several times with its own output as starting parameters, to make sure that our estimation converges. One should also test the estimation from different starting points, but I am not going to do that here.

```

data(donationsSummary)
rf.matrix <- donationsSummary$rf.matrix
params <- bgbb.EstimateParameters(rf.matrix)
LL <- bgbb.rf.matrix.LL(params, rf.matrix)
p.matrix <- c(params, LL)
for (i in 1:2) {
  params <- bgbb.EstimateParameters(rf.matrix, params)
  LL <- bgbb.rf.matrix.LL(params, rf.matrix)
  p.matrix.row <- c(params, LL)
  p.matrix <- rbind(p.matrix, p.matrix.row)
}

```

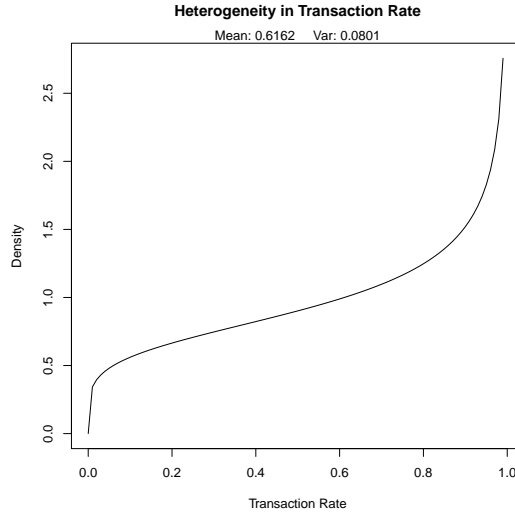


Figure 8: Transaction rate heterogeneity of estimated parameters.

```
colnames(p.matrix) <- c("alpha", "beta", "gamma", "delta", "LL")
rownames(p.matrix) <- 1:3
p.matrix

#   alpha  beta  gamma delta   LL
# 1 1.204 0.7498 0.6568 2.784 -33226
# 2 1.204 0.7497 0.6568 2.784 -33226
# 3 1.204 0.7497 0.6568 2.784 -33226
```

The parameter estimation converges very quickly. It is much easier, and faster, to estimate BG/BB parameters than it is to estimate Pareto/NBD parameters, because there are fewer calculations involved.

We can interpret these parameters by plotting the mixing distributions. Alpha and beta describe the beta mixing distribution of the beta-Bernoulli transaction process. We can see the beta distribution with parameters alpha and beta in figure 8, plotted using `bgbb.PlotTransactionRateHeterogeneity(params)`. Gamma and Delta describe the beta mixing distribution of the beta-geometric dropout process. We can see the beta distribution with parameters gamma and delta in figure 9, plotted using `bgbb.PlotDropoutHeterogeneity(params)`. The story told by these plots describes the type of customers most firms would want—their transaction parameters are more likely to be high, and their dropout parameters are more likely to be low.

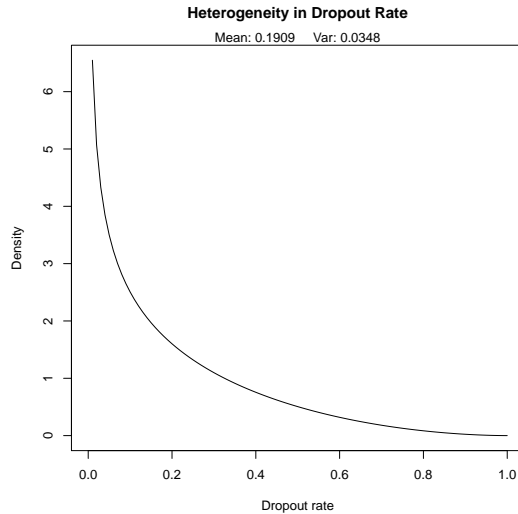


Figure 9: Dropout rate heterogeneity of estimated parameters.

3.3 Individual Level Estimations

We can estimate the number of transactions we expect a newly acquired customer to make in a given time period, just as with the Pareto/NBD model. For this example, let's say we are interested in estimating the number of repeat transactions we expect a newly-acquired customer to make in a period of 10 years. The same rules that we used for Pareto/NBD functions also apply to BG/BB functions: since we used years to estimate the parameters, we stick to years to represent time periods.

```
bgbg.Expectation(params, n = 10)
# [1] 3.18
```

But we want to be able to say something about our existing customers, not just about a hypothetical customer to be acquired in the future. Once again, we use conditional expectations for a holdout period of 10 years. I am going to do this for 2 customers: A, who made 0 transactions in the calibration period; and B, who made 4 transactions in the calibration period, with the last transaction occurring in the 5th year.

```
# customer A
n.cal = 6
n.star = 10
x = 0
```

```

t.x = 0
bgbb.ConditionalExpectedTransactions(params, n.cal,
                                     n.star, x, t.x)

# [1] 0.1302

# customer B
x = 4
t.x = 5
bgbb.ConditionalExpectedTransactions(params, n.cal,
                                     n.star, x, t.x)

# [1] 3.628

```

As expected, B's conditional expectation is much higher than A's. The point I am trying to make, however, is that there are 3464 A's in this dataset and only 284 B's—you should never ignore the zeroes in these models.

3.4 Plotting/ Goodness-of-fit

Figure 1, is the first plot to test the goodness-of-fit: a simple calibration period histogram.

```
bgbb.PlotFrequencyInCalibration(params, rf.matrix)
```

As with the equivalent Pareto/NBD plot, keep in mind that this plot is only useful for an initial verification that the fit of the BG/BB model is not terrible.

The next step is to see how well the model performs in the holdout period. When we used `dc.ElogToCbsCbt` earlier, we ignored a lot of the data it generated. It is easy to get the holdout period frequencies from that data:

```

holdout.cbs <- simData$holdout$cbs
x.star <- holdout.cbs[, "x.star"]

```

At this point, we can switch from simulated data to the real discrete data (donation data) provided with the package. The holdout period frequencies for the donations data is included in the package. Using this information, we can generate figure 10, which compares actual and conditional expected transactions in the holdout period. It bins customers according to calibration period frequencies.

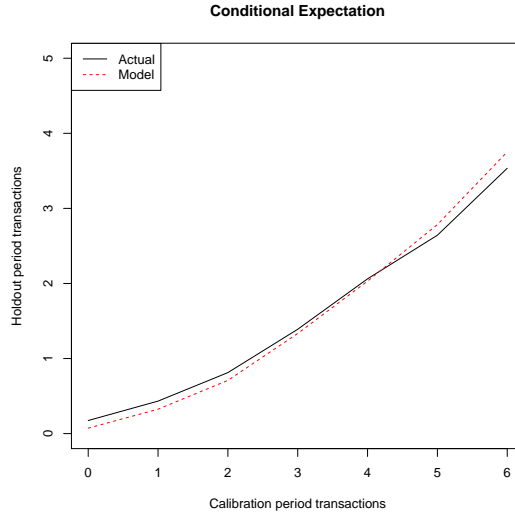


Figure 10: Actual vs. conditional expected transactions in the holdout period, binned by calibration period frequency.

```
n.star <- 5 # length of the holdout period
x.star <- donationsSummary$x.star
comp <- bgbb.PlotFreqVsConditionalExpectedFrequency(params, n.star,
                                                    rf.matrix, x.star)
rownames(comp) <- c("act", "exp", "bin")
comp
```

	freq.0	freq.1	freq.2	freq.3	freq.4	freq.5	freq.6
# act	1.744e-01	0.4328	0.8126	1.390	2.062	2.643	3.534
# exp	7.286e-02	0.3249	0.7089	1.334	2.031	2.784	3.753
# bin	3.464e+03	1823.0000	1430.0000	1085.000	1036.000	1063.000	1203.000

Since the BG/BB model uses discrete data, we can also bin customers by recency. Figure 11 shows the fit of holdout period frequencies, with customers binned in this manner.

```
comp <- bgbb.PlotRecVsConditionalExpectedFrequency(params, n.star,
                                                    rf.matrix, x.star)
rownames(comp) <- c("act", "exp", "bin")
comp
```

	rec.0	rec.1	rec.2	rec.3	rec.4	rec.5	rec.6
# act	1.744e-01	2.181e-01	0.3899	0.4873	0.8089	1.652	2.947
# exp	7.286e-02	8.569e-02	0.1798	0.4041	0.8511	1.726	3.027
# bin	3.464e+03	1.091e+03	890.0000	706.0000	654.0000	1136.000	3163.000

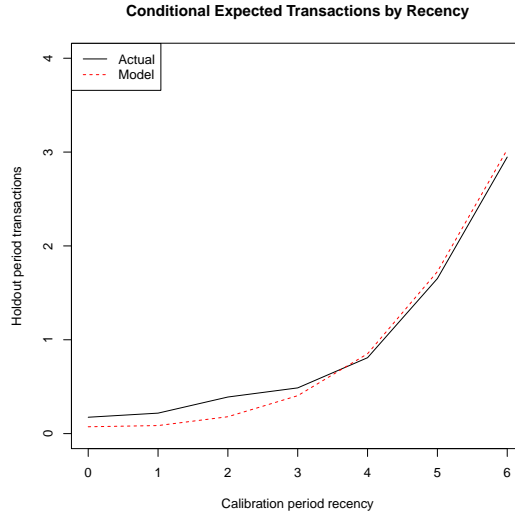


Figure 11: Actual vs. conditional expected transactions in the holdout period, binned by calibration period recency.

Another plotting function provided by the BTYD package is the tracking function—binning the data according to which time period transactions occurred in. Since we do not have the granular data available, we once again cannot get the required data from the event log; however, the process will be exactly the same as described in section 2.4. The annual transaction data is provided by the package.

```
inc.track.data <- donationsSummary$annual.trans
n.cal <- 6
xtickmarks <- 1996:2006
inc.tracking <- bgbb.PlotTrackingInc(params, rf.matrix,
                                     inc.track.data,
                                     xticklab = xtickmarks)
rownames(inc.tracking) <- c("act", "exp")
inc.tracking
```

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]	[,8]	[,9]	[,10]	[,11]
act	5652	4674	4019	3552	3555	3163	3110	2938	2703	2573	1936
exp	5536	4717	4148	3725	3396	3132	2914	2730	2574	2438	2319

Figure 12 shows remarkable fit, but we can smooth it out for a cleaner graph by making it cumulative (as shown in figure 13).

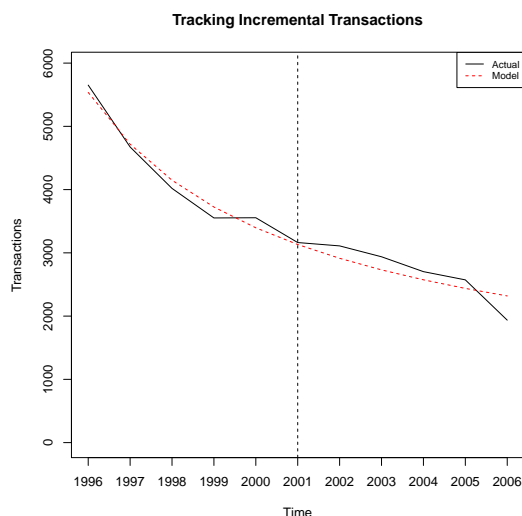


Figure 12: Actual vs. expected incremental purchasing behaviour.

```
cum.track.data <- cumsum(inc.track.data)
cum.tracking <- bgbb.PlotTrackingCum(params, rf.matrix, cum.track.data,
                                     xticklab = xtickmarks)
rownames(cum.tracking) <- c("act", "exp")
cum.tracking
```

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]	[,8]	[,9]	[,10]	[,11]
act	5652	10326	14345	17897	21452	24615	27725	30663	33366	35939	37875
exp	5536	10253	14401	18125	21521	24653	27566	30297	32871	35309	37627

4 Further analysis

The package functionality I highlighted above is just a starting point for working with these models. There are additional tools, such as functions for discounted expected residual transactions (the present value of the remaining transactions we expect a customer to make) and an implementation of the gamma-gamma spend model, which may come in useful for customer analysis. Hopefully you now have an idea of how to start working with the BTYD package - from here, you should be able to use the package's additional functions, and may even want to implement some of your own. Enjoy!

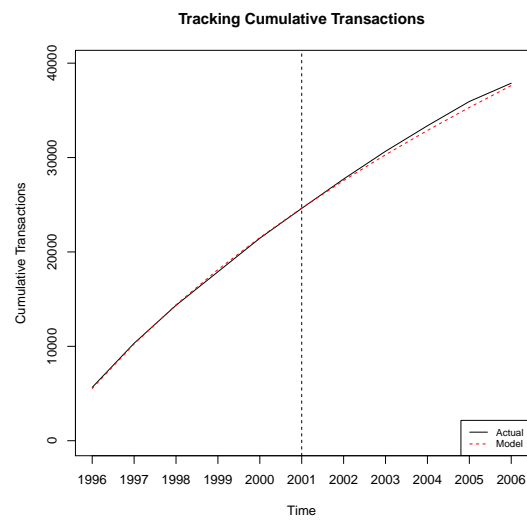


Figure 13: Actual vs. expected cumulative purchasing behaviour.

References

Fader, Peter S., and Bruce G.S. Hardie. “A Note on Deriving the Pareto/NBD Model and Related Expressions.” November. 2005. Web.
<<http://www.brucehardie.com/notes/008/>>

Fader, Peter S., Bruce G.S. Hardie, and Jen Shang. “Customer-Base Analysis in a Discrete-Time Noncontractual Setting.” *Marketing Science*, **29(6)**, pp. 1086-1108. 2010. INFORMS.
<<http://www.brucehardie.com/papers/020/>>