CREATIVE INSPIRATION: MORAL CONVICTIONS OF HUMANS AS TABULATION OF LARGE NUMBERS OF BIASED COIN TOSSES

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1. Speculative Scenario for Human Moral Convictions

We seek the suspension of disbelief of our dear readers and imagine that for each human being on Earth, when the curtains are raised from their inner hearts, we find a Stochastic Conviction Apparatus.

The Stochastic Conviction Apparatus is operated as follows. Each person, in his private heart has a coin that is heavily biased, with probability of heads being 96-100% and probability of tails being 0-4%.

On a given moral issue, the person goes into his private heart and lays down on the table a long vector of 250 slots. Then he flips the biased coin 250 times and records a string of 0 for head and 1 for tail.

Then he tallies the heads and tails. Then for the moral question at hand, he uses the formula:

$$a = 10\frac{n_t}{n_h + n_t}$$

The probability he uses for p_{tails} is the same as all other humans dependent on the question.

2. The Model Here is a Serious Scientific Model

There might be arbitrary set of things going on with the person that determine the flipping and recording process. I will not worry about those connections.

I will simplify all other issues and concentrate on whether the measured data supports this sort of model well.

3. Fitting Q179

```
lgchoose<-function(n,k){
  out<- log( n/(sqrt(2*pi)*k*(n-k))) +
    n*log(n/exp(1)) - k*log(k/exp(1)) - (n-k)*log((n-k)/exp(1))
  out
}

binom<-function(p,n,k){
  exp(lgchoose(n,k)+k*log(p)+(n-k)*log(1-p))
}
```

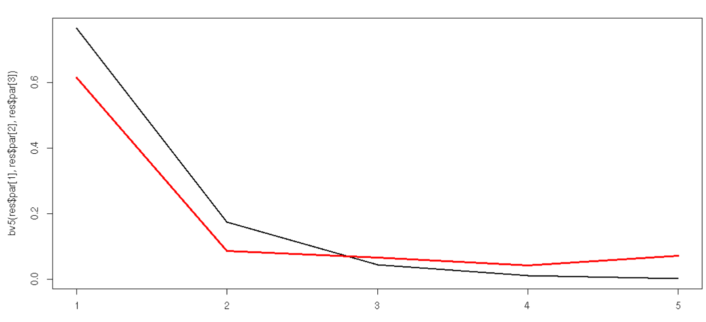
Date: May 25, 2021.

```
bv<-function(p,n,alpha){
  z<-rep(0,10)
  for (k in 1:10){
    z[k] <- binom(p*alpha,n,k*alpha)
  }
  nrm(z)
}

bv5<-function(p,n,alpha){
  z<-rep(0,5)
  for (k in 1:5){
    z[k] <- binom(p,n*alpha,k*alpha)
  }
  nrm(z)
}


binom.err<-function( theta ){
  p <- theta[1]
  n <- theta[2]
  alpha <- theta[3]
  y <- bv5(p,n,alpha)
  print(y)
  norm( y - nrm(z[1:5]), type="2")
}
res<-optim(c(0.003,50,0.31),fn=binom.err,lower=c(0.00001,10,0.1),method="L-BFGS-B")

> res$par
[1]  0.002664301 49.999943988  0.329579448
```



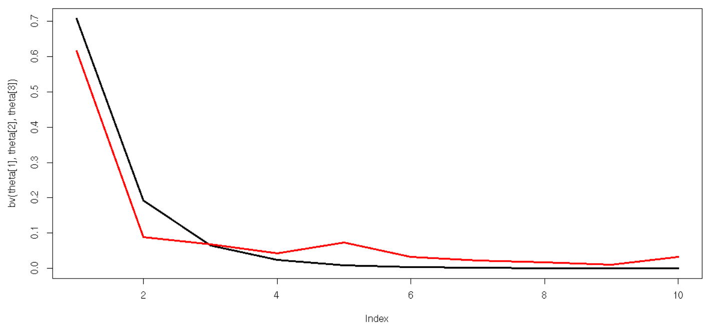
This is quite imperfect but has some nice virtues: the parameters are reasonable. Unfortunately the optimiser is not sensitive enough to estimate the parameters without assistance.

4. This Approach Will Work: Return to Understanding Process

It's quite clear that this approach will yield good results after some work. Now how can we demystify the locus of the biased coin flips? Well, I would stretch out the process to two million years roughly in our evolutionary history.

Let's say $n = 200$ biased independent coin flips determine our conviction about some topic T, here we are looking at stealing. We can distribute the coin flipping in two million years so that the recorded coin flips are in our genome for say 90% or 80% of the $n = 200$ and leave the rest to actual brain and social development of individuals, including development of emotions, social understanding, and other psychological functions.

5. NLOpt Fit Full Vector




```
lgchoose<-function(n,k){
  out<- log( n/(sqrt(2*pi)*k*(n-k))) +
    n*log(n/exp(1)) - k*log(k/exp(1)) - (n-k)*log((n-k)/exp(1))
  out
}

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  exp(lgchoose(n,k)+k*log(p)+(n-k)*log(1-p))
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  nrm(z)
}

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  z<-rep(0,5)
  for (k in 1:5){
    z[k] <- binom(p,n*alpha,k*alpha)
  }
  nrm(z)
```
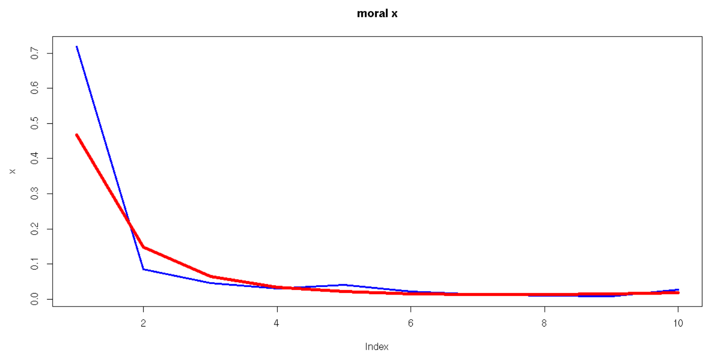

```
}


binom.err<-function( theta ){
  p <- theta[1]
  n <- theta[2]
  alpha <- theta[3]
  y <- bv5(p,n,alpha)
  print(y)
  norm( y - nrm(z[1:5]), type="2")
}

binom.err2<-function( theta ){
  p <- theta[1]
  n <- theta[2]
  alpha <- theta[3]
  y <- bv(p,n,alpha)
  #print(y)
  norm( y - nrm(z), type="2")
}
res<-nloptr(theta0,binom.err2,lb=lb0,
            opts=list("algorithm"="NLOPT_LN_NELDERMEAD",
                      "xtol_rel"=1.0e-6,
                      "maxeval"=5000,
                      "print_level"=1))

theta<-res$solution
plot(bv(theta[1],theta[2],theta[3]),type='l',lwd=3)
lines(as.numeric(y)[1:5], col='red',lwd=3)
> res

Call:

nloptr(x0 = theta0, eval_f = binom.err2, lb = lb0, opts = list(algorithm = "NLOPT_LN_NELDERME
    xtol_rel = 1e-16, maxeval = 5000, print_level = 1))


Minimization using NLopt version 2.4.2

NLopt solver status: 4 ( NLOPT_XTOL_REACHED: Optimization stopped because
xtol_rel or xtol_abs (above) was reached. )

Number of Iterations....: 434
Termination conditions:  xtol_rel: 1e-16 maxeval: 5000
Number of inequality constraints:  0
Number of equality constraints:    0
Optimal value of objective function:  0.103779375754603
Optimal value of controls: 1e-04 5 0.08003433
```

6. Scaled Binomial Log-Quadratic Model




```
lgchoose<-function(n,k){
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    n*log(n/exp(1)) - k*log(k/exp(1)) - (n-k)*log((n-k)/exp(1))
  out
}

binom<-function(p,n,k){
  exp(lgchoose(n,k)+k*log(p)+(n-k)*log(1-p))
}

bv<-function(p,n,alpha){
  z<-rep(0,10)
  for (k in 1:10){
    z[k] <- binom(p*alpha,n,k*alpha)
  }
  nrm(z)
}

bv5<-function(p,n,alpha){
  z<-rep(0,5)
  for (k in 1:5){
    z[k] <- binom(p,n*alpha,k*alpha)
  }
  nrm(z)
}


binom.err<-function( theta ){
  p <- theta[1]
  n <- theta[2]
  alpha <- theta[3]
  y <- bv5(p,n,alpha)
  print(y)
```

```
  norm( y - nrm(z[1:5]), type="2")
}

binom.err2<-function( theta, z){
  p <- theta[1]
  n <- theta[2]
  alpha <- theta[3]
  y <- bv(p,n,alpha)
  #print(y)
  norm( y - nrm(z), type="2")
}


fit.binom.quad<-function( z, theta0){

  f<-function(theta){
    binom.err2(theta,z)
  }

  res<-nloptr(theta0,f,lb=lb0,
              opts=list("algorithm"="NLOPT_LN_NELDERMEAD",
                        "xtol_rel"=1.0e-6,
                        "maxeval"=5000,
                        "print_level"=1))

  theta<-res$solution
  y<-bv( theta[1], theta[2], theta[3])

  qmod<-lm( log(z) ~ poly(log(y),2))
  print(summary(qmod))
  yp<-exp(predict(qmod))
  yp<-nrm(yp)
  yp
}

> 1- sum((y-x)^2)/sum(x^2)
[1] 0.8715459
```

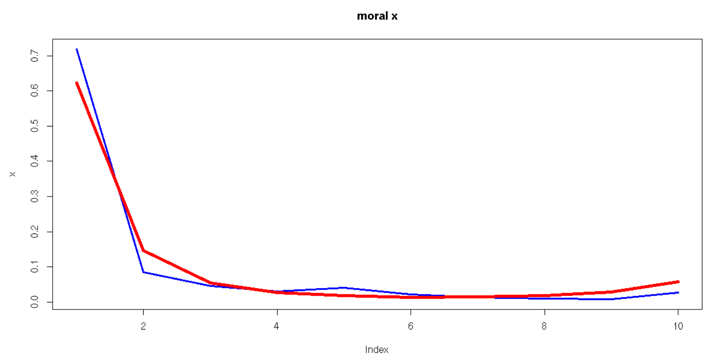
The R-squared of 0.87 is pretty good.

7. Weighted Least Squares For Quadratic

```
lgchoose<-function(n,k){
  out<- log( n/(sqrt(2*pi)*k*(n-k))) +
    n*log(n/exp(1)) - k*log(k/exp(1)) - (n-k)*log((n-k)/exp(1))
  out
}

binom<-function(p,n,k){
```

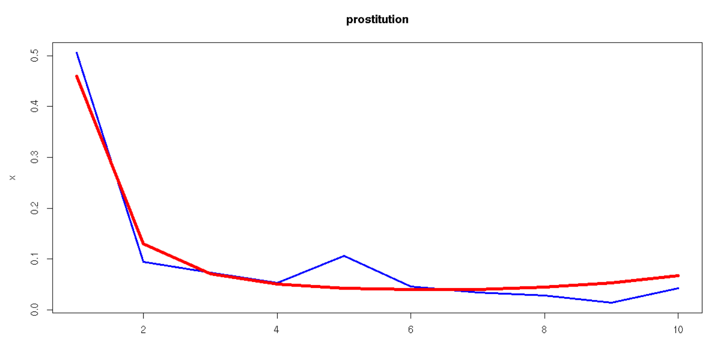
```
  exp(lgchoose(n,k)+k*log(p)+(n-k)*log(1-p))
}

bv<-function(p,n,alpha){
  z<-rep(0,10)
  for (k in 1:10){
    z[k] <- binom(p*alpha,n,k*alpha)
  }
  nrm(z)
}

bv5<-function(p,n,alpha){
  z<-rep(0,5)
  for (k in 1:5){
    z[k] <- binom(p,n*alpha,k*alpha)
  }
  nrm(z)
}


binom.err<-function( theta ){
  p <- theta[1]
  n <- theta[2]
  alpha <- theta[3]
  y <- bv5(p,n,alpha)
  print(y)
  norm( y - nrm(z[1:5]), type="2")
}

binom.err2<-function( theta, z){
  p <- theta[1]
  n <- theta[2]
  alpha <- theta[3]
  y <- bv(p,n,alpha)
  #print(y)
  norm( y - nrm(z), type="2")
}


fit.binom.quad<-function( z, theta0){

  f<-function(theta){
    binom.err2(theta,z)
  }

  res<-nloptr(theta0,f,lb=lb0,
              opts=list("algorithm"="NLOPT_LN_NELDERMEAD",
                      "xtol_rel"=1.0e-6,
```

```
                            "maxeval"=5000,
                            "print_level"=1))

  theta<-res$solution
  y<-bv( theta[1], theta[2], theta[3])

  s<-1:10
  weights<-exp(-s/2)
  weights<-nrm(weights)
  qmod<-lm( log(z) ~ poly(log(y),2), weights=weights)
  print(summary(qmod))
  yp<-exp(predict(qmod))
  yp<-nrm(yp)
  yp
}
```



8. Flawless Test on New Data

I tested on Q183, Prostitution.



Our R-squared was 0.967. This is a great success!