**Arthur Charpentier**

charpentier.arthur@gmail.com

http://freakonometrics.hypotheses.org/

**Université de Rennes 1, January 2016**

# Welfare, Inequality & Poverty, # 2

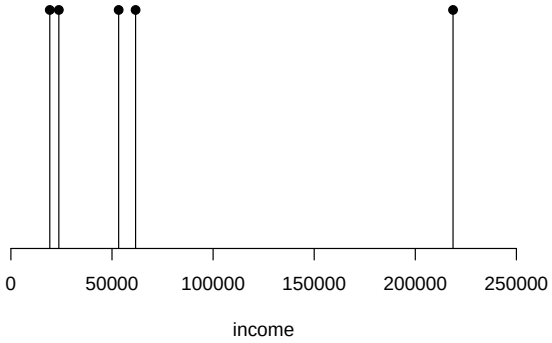
# Modeling Income Distribution

Let $\{x_1, \cdots, x_n\}$ denote some sample. Then

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i = \sum_{i=1}^{n} \frac{1}{n} x_i$$

This can be used when we have census data.

```
load(url("http://freakonometrics.free.fr/
    income_5.RData"))
income <- sort(income)
plot(1:5, income)
```




It is possible to use survey data. If $\pi_i$ denote the probability to be drawn, use weights

$$\omega_i \propto \frac{1}{n\pi_i}$$

The weighted average is then

$$\overline{x}_\omega = \sum_{i=1}^{n} \frac{\omega_i}{\omega} x_i$$

where $\omega = \sum \omega_i$. This is an unbaised estimator of the population mean.

Sometime, data are obtained from stratified samples: before sampling, members of the population are groupes in homogeneous subgroupes (called a strata). Given $S$ strata, such that the population in strata $s$ is $N_s$, then

$$\overline{x}_S = \sum_{s=1}^{S} \frac{N_s}{N} \overline{x}_s \text{ where } \overline{x}_s = \frac{1}{N_s} \sum_{i \in \mathcal{S}_s} x_i$$

# Statistical Tools Used to Describe the Distribution

Consider a sample $\{x_1, \cdots, x_n\}$. Usually, the order is not important. So let us order those values,

$$\underbrace{x_{1:n}}_{\min\{x_i\}} \leq x_{2:n} \leq \cdots \leq x_{n-1:n} \leq \underbrace{x_{n:n}}_{\max\{x_i\}}$$

As usual, assume that $x_i$'s were randomly drawn from an (unknown) distribution $F$.

If $F$ denotes the cumulative distribution function, $F(x) = \mathbb{P}(X \leq x)$, one can prove that

$$F(x_{i:n}) = \mathbb{P}(X \leq x_{i:n}) \sim \frac{i}{n}$$

The quantile function is defined as the inverse of the cumulative distribution function $F$,

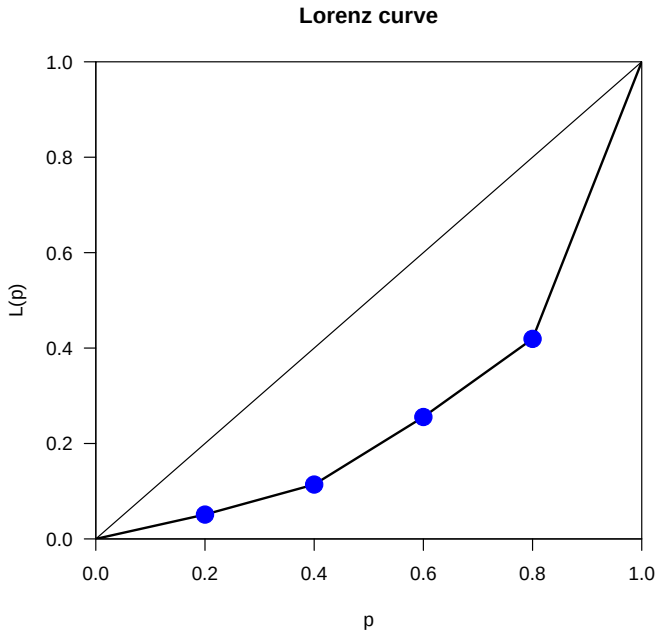
$$Q(u) = F^{-1}(u) \text{ or } F(Q(u)) = \mathbb{P}(X \leq Q(u)) = u$$

# Lorenz curve

The empirical version of Lorenz curve is

$$L = \left\{ \frac{i}{n}, \frac{1}{n\overline{x}} \sum_{j \leq i} x_{j:n} \right\}$$

```
> plot((0:5)/5,c(0,cumsum(income)/sum(income
    )))
```



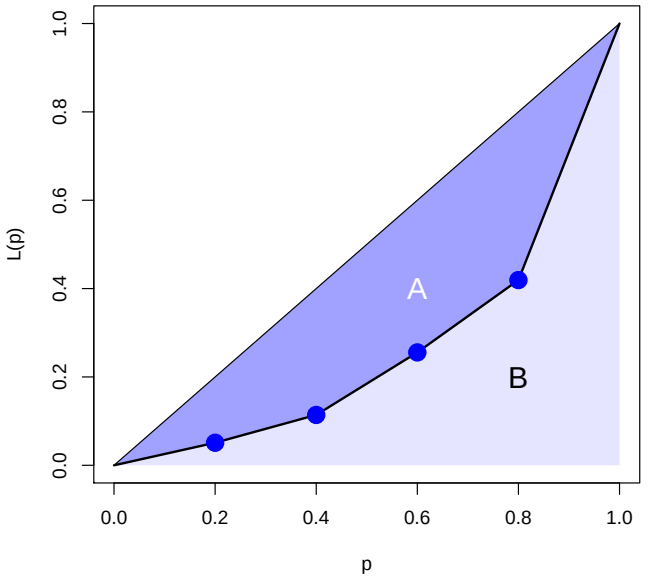
# Gini Coefficient

Gini coefficient is defined as the ratio of areas, $\frac{\mathsf{A}}{\mathsf{A}+\mathsf{B}}$.

It can be defined using order statistics as

$$G = \frac{2}{n(n-1)\overline{x}} \sum_{i=1}^{n} i \cdot x_{i:n} - \frac{n+1}{n-1}$$

```
> n <- length(income)
> mu <- mean(income)
> 2*sum((1:n)*sort(income))/ (mu*n*(n-1))-(n
    +1)/(n-1)
[1] 0.5800019
```



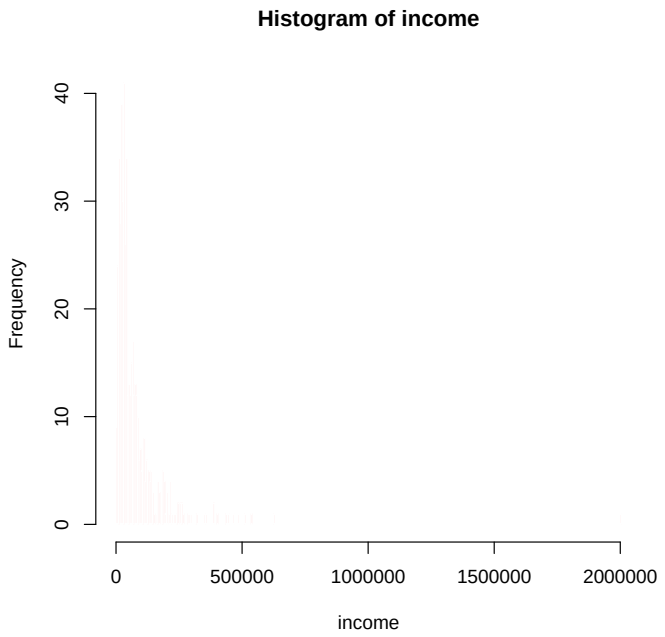
# Distribution Fitting

Assume that we now have more observations,

```
> load(url("http://freakonometrics.free.fr/income_500.RData"))
```

We can use some histogram to visualize the distribution of the income

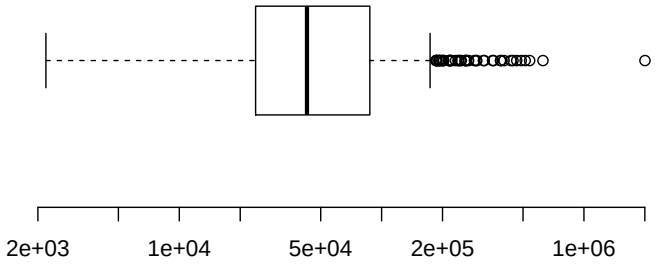
```
> summary(income)
   Min. 1st Qu.  Median    Mean 3rd Qu.
    Max.
   2191   23830   42750   77010   87430
 2003000
> sort(income)[495:500]
[1]  465354  489734  512231  539103  627292
 2003241
> hist(income,breaks=seq(0,2005000,by=5000))
```

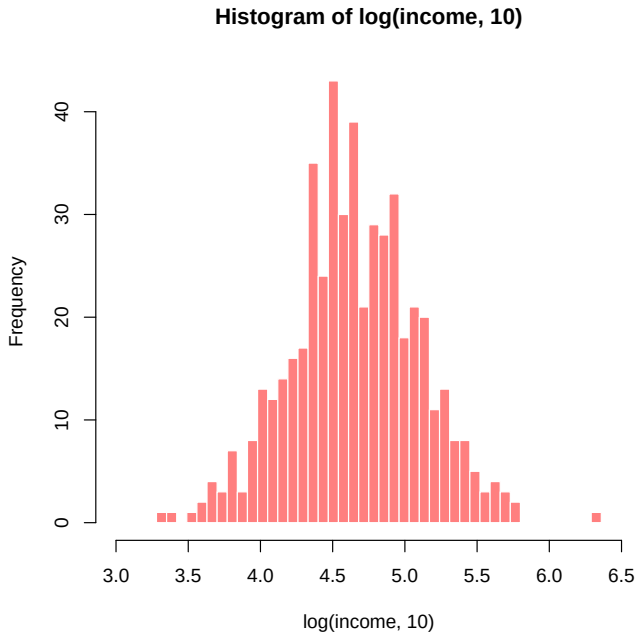


# Distribution Fitting

Because of the dispersion, look at the histogram of the logarithm of the data

```
> hist(log(income,10),breaks=seq(3,6.5,
    length=51))
> boxplot(income,horizontal=TRUE,log="x")
```

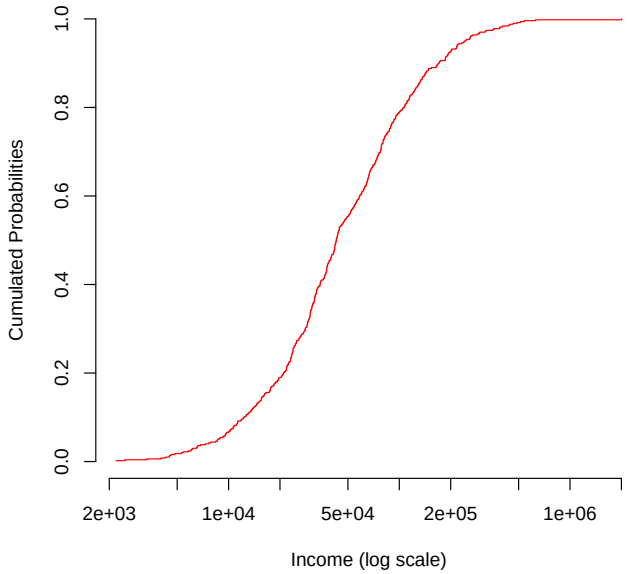


# Distribution Fitting

The cumulative distribution function (on the log of the income)

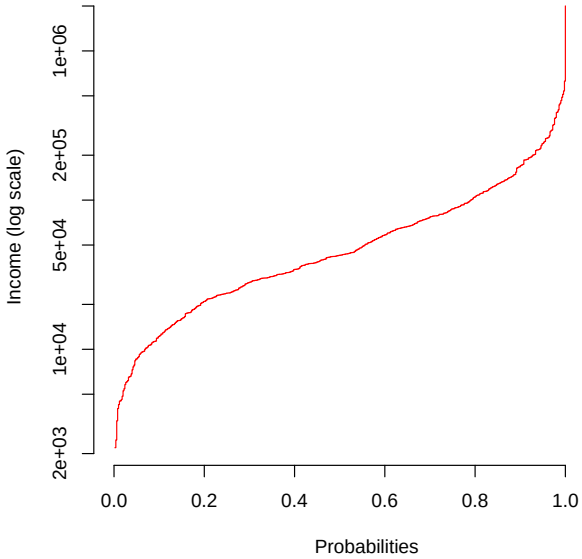
```
> u <- sort(income)
> v <- (1:500)/500
> plot(u,v,type="s",log="x")
```



# Distribution Fitting

If we invert that graph, we have the quantile function

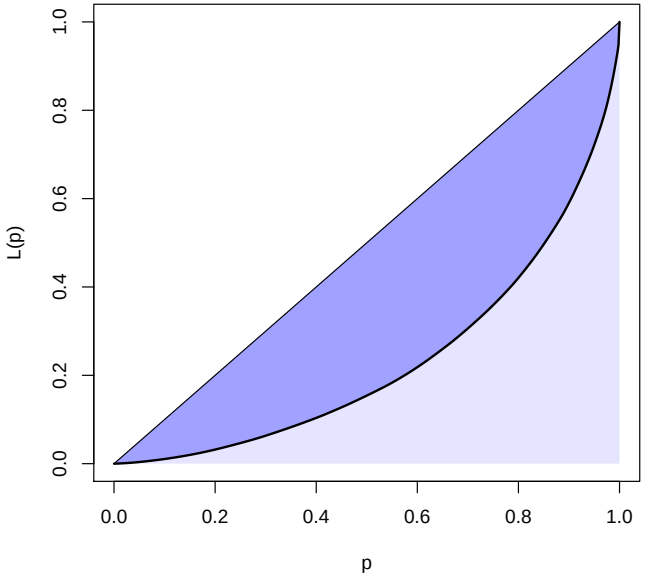
```
> plot(v,u,type="s",col="red",log="y")
```



# Distribution Fitting

On that dataset, Lorenz curve is

```
> plot((0:500)/500,c(0,cumsum(income)/sum(
    income)))
```



## Distribution and Confidence Intervals

There are two techniques to get the distribution of an estimator $\widehat{\theta}$,

- a parametric one, based on some assumptions on the underlying distribution,
- a nonparametric one, based on sampling techniques

If $X_i$'s have a $\mathcal{N}(\mu, \sigma^2)$ distribution, then $\overline{X} \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right)$

But sometimes, distribution can only be obtained as an approximation, because of asymptotic properties.

From the central limit theorem, $\overline{X} \to \mathcal{N}\left(\mu, \frac{\sigma^2}{n}\right)$ as $n \to \infty$.

In the nonparametric case, the idea is to generate pseudo-samples of size $n$, by resampling from the original distribution.

## Bootstraping

Consider a sample $\boldsymbol{x} = \{x_1, \cdots, x_n\}$. At step $b = 1, 2, \cdots, B$, generate a pseudo sample $\boldsymbol{x}^b$ by sampling (with replacement) within sample $\boldsymbol{x}$. Then compute any statistic $\widehat{\theta}(\boldsymbol{x}^b)$

```
> boot <- function(sample,f,b=500){
+ F <- rep(NA,b)
+ n <- length(sample)
+ for(i in 1:b){
+ idx <- sample(1:n,size=n,replace=TRUE)
+ F[i] <- f(sample[idx])}
+ return(F)}
```

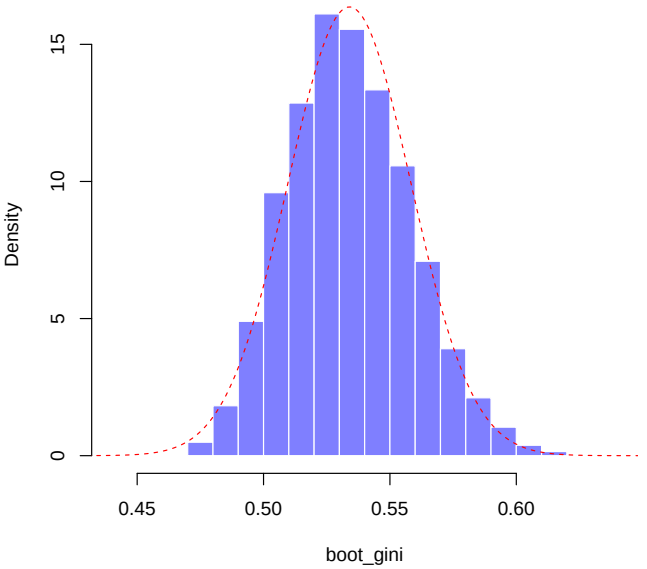
# Bootstraping

Let us generate 10,000 bootstraped sample, and compute Gini index on those

```
>boot_gini <- boot(income,gini,1e4)
```

To visualize the distribution of the index

```
> hist(boot_gini,probability=TRUE)
> u <- seq(.4,.7,length=251)
> v <- dnorm(u,mean(boot_gini),sd(boot_gini)
    )
> lines(u,v,col="red",lty=2)
```



## Continuous Versions

The empirical cumulative distribution function

$$\widehat{F}_n(x) = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}(x_i \leq x)$$

Observe that

$$\widehat{F}_n(x_{j:n}) = \frac{j}{n}$$

If $F$ is absolutely continuous,

$$F(x) = \int_0^x f(t)dt \text{ i.e. } f(x) = \frac{dF(x)}{dx}.$$

Then

$$\mathbb{P}(x \in [a,b]) = \int_a^b f(t)dt = F(b) - F(a).$$

## Continuous Versions

One can define quantiles as

$$x = Q(p) = F^{-1}(p)$$

The expected value is

$$\mu = \int_0^\infty xf(x)dx = \int_0^\infty [1 - F(x)]dx = \int_0^1 Q(p)dp.$$

We can compute the average standard of living of the group below $z$. This is equivalent to the expectation of a truncated distribution.

$$\mu_z^- = \frac{1}{F(z)} \int_0^z xf(x)dx = \int_0^\infty \left[1 - \frac{F(x)}{F(z)}\right] fx$$

## Continuous Versions

Lorenz curve is $p \mapsto L(p)$ with

$$L(p) = \frac{1}{\mu} \int_0^{Q(p)} x f(x) dx$$

Gastwirth (1971) proved that

$$L(p) = \frac{1}{\mu} \int_0^p Q(u) du = \frac{\int_0^p Q(u) du}{\int_0^1 Q(u) du}$$

The numerator sums the incomes of the bottom p proportion of the population. The denominator sums the incomes of all the population.

$L$ is a $[0,1] \to [0,1]$ function, continuous if $F$ is continuous. Observe that $L$ is increasing, since

$$\frac{dL(p)}{dp} = \frac{Q(p)}{\mu}$$

Further, $L$ is convex

The sample case

$$L\left(\frac{i}{n}\right) = \frac{\sum_{j=1}^{i} x_{j:n}}{\sum_{j=1}^{n} x_{j:n}}$$

The points $\{i/n, L(i/n)\}$ are then linearly interpolated to complete the corresponding Lorenz curve.

The continuous distribution case

$$L(p) = \frac{\int_0^{F^{-1}(p)} y dF(y)}{\int_0^{\infty} y dF(y)} = \frac{1}{\mathbb{E}(X)} \int_0^p F^{-1}(u) du$$

with $p \in (0, 1)$.

Let $L$ be a continuous function on $[0, 1]$, then $L$ is a Lorenz curve if and only if

$$L(0) = 0,\ L(1) = 1,\ L'(0^+) \geq 0 \text{ and } L''(p) \geq 0 \text{ on } [0, 1].$$

## From Lorenz to Bonferroni

The Bonferroni curve is

$$B(p) = \frac{L(p)}{p}$$

and the Bonferroni index is

$$BI = 1 - \int_0^1 B(p)dp.$$

Define

$$P_i = \frac{i}{n} \text{ and } Q_i = \frac{1}{n\overline{x}} \sum_{j=1}^{i} x_j$$

then

$$B = \frac{1}{n-1} \sum_{i=1}^{n-1} \left( \frac{P_i - Q_i}{P_i} \right)$$

## Gini and Pietra indices

The Gini index is defined as twice the area between the egalitarian line and the Lorenz curve

$$G = 2\int_0^1 [p - L(p)]dp = 1 - 2\int_0^1 L(p)dp$$

which can also be writen

$$1 - \frac{1}{\mathbb{E}(X)}\int_0^\infty [1 - F(x)]^2 dx$$

Pietra index is defined as the maximal vertical deviation between the Lorenz curve and the egalitarian line

$$P = \max_{p\in(0,1)}\{p - L(p)\} = \frac{\mathbb{E}(|X - \mathbb{E}(X)|)}{2\mathbb{E}(X)}$$

if $F$ is strictly increasing (the maximum is reached in $p^\star = F(\mathbb{E}(X))$)

# Examples

E.g. consider the uniform distribution

$$F(x) = \min\{1, \frac{x-a}{b-a}\mathbf{1}(x \geq a)\}$$

Then

$$L(p) = \frac{2ap + (b-a)^2p^2}{a+b}$$

and Gini index is

$$G = \frac{b-a}{3(a+b)}$$

E.g. consider a Pareto distribution,

$$F(x) = 1 - \left(\frac{x_0}{x}\right)^{\alpha}, \ x \geq x_0,$$

with shape parameter $\alpha > 0$. Then

$$F^{-1}(u) = \frac{x_0}{(1-u)^{\frac{1}{\alpha}}}$$

and

$$L(p) = 1 - [1-p]^{1-\frac{1}{\alpha}} \ p \in (0,1).$$

and Gini index is

$$G = \frac{1}{2\alpha - 1}$$

while Pietra index is, if $\alpha > 1$

$$P = \frac{(\alpha-1)^{\alpha-1}}{\alpha^{\alpha}}$$

E.g. consider the lognormal distribution,

$$F(x) = \Phi\left(\frac{\log x - \mu}{\sigma}\right)$$

then

$$L(p) = \Phi(\Phi^{-1}(p) - \sigma) \ p \in (0,1).$$

and Gini index is

$$G = 2\Phi\left(\frac{\sigma}{\sqrt{2}}\right) - 1$$

# Fitting a Distribution

The standard technique is based on maximum likelihood estimation, provided by

```
> library(MASS)
> fitdistr(income,"lognormal")
     meanlog          sdlog
  10.72264538     1.01091329
 ( 0.04520942) ( 0.03196789)
```

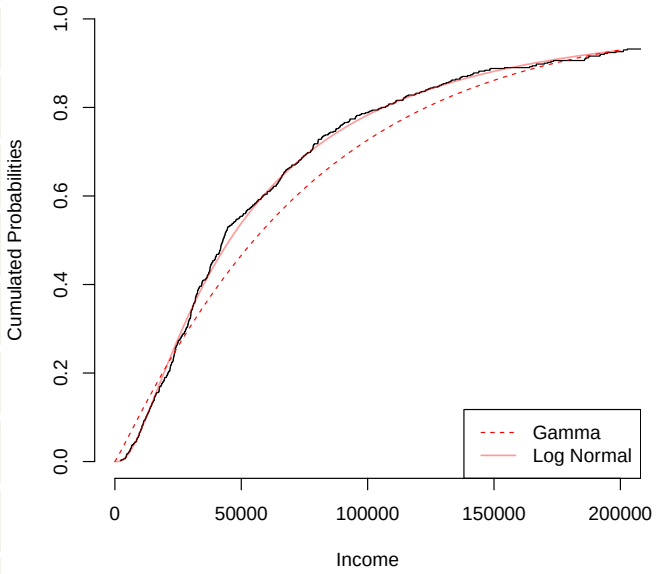
For other distribution (such as the Gamma distribution), we might have to rescale

```
> (fit_g <- fitdistr(income/1e2,"gamma"))
      shape             rate
  1.0812757769   0.0014040438
 (0.0473722529) (0.0000544185)
> (fit_ln <- fitdistr(income/1e2,"lognormal"))
    meanlog          sdlog
  6.11747519     1.01091329
 (0.04520942) (0.03196789)
```

# Fitting a Distribution

We can compare the densities

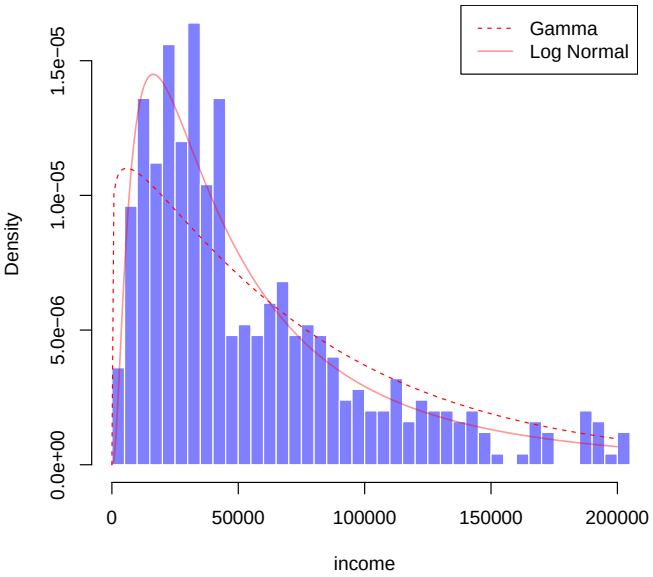
```
> u=seq(0,2e5,length=251)
> hist(income,breaks=seq(0,2005000,by=5000),
    col=rgb(0,0,1,.5),border="white",xlim=c
    (0,2e5),probability=TRUE)
> v_g <- dgamma(u/1e2, fit_g$estimate[1],fit
    _g$estimate[2])/1e2
> v_ln <- dlnorm(u/1e2, fit_ln$estimate[1],
    fit_ln$estimate[2])/1e2
> lines(u,v_g,col="red",lty=2)
> lines(u,v_ln,col=rgb(1,0,0,.4))
```



# Fitting a Distribution

or the cumuluative distributions

```
x <- sort(income)
y <- (1:500)/500
plot(x,y,type="s",col="black")
v_g <- pgamma(u/1e2, fit_g$estimate[1],fit_g
    $estimate[2])
v_ln <- plnorm(u/1e2, fit_ln$estimate[1],fit
    _ln$estimate[2])
lines(u,v_g,col="red",lty=2)
lines(u,v_ln,col=rgb(1,0,0,.4))
```



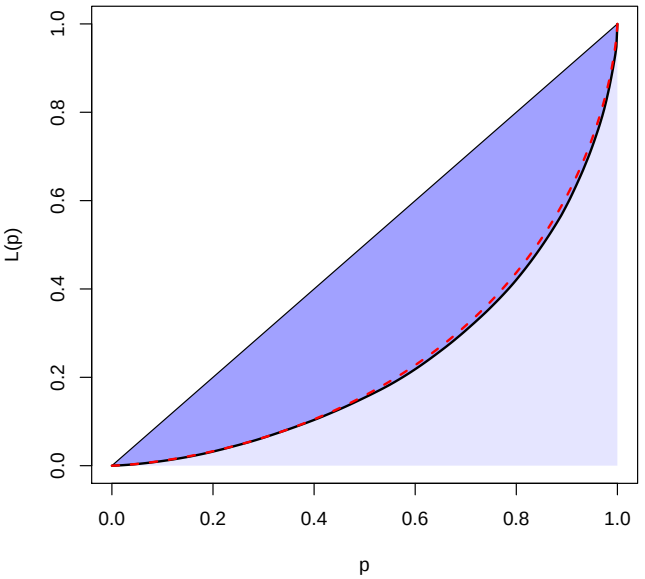

One might consider the parametric version of Lorenz curve, to confirm the goodness of fit, e.g. a lognormal distribution with $\sigma = 1$ since

```
> fitdistr(income,"lognormal")
      meanlog          sdlog
   10.72264538     1.01091329
```

# Fitting a Distribution

We can use functions of R

```
library(ineq)
Lc.sim <- Lc(income)
plot(0:1,0:1,xlab="p",ylab="L(p)",col="white")
polygon(c(0,1,1,0),c(0,0,1,0),col=rgb(0,0,1,.1),border=NA)
polygon(Lc.sim$p,Lc.sim$L,col=rgb(0,0,1,.3),border=NA)
lines(Lc.sim)
segments(0,0,1,1)
lines(Lc.lognorm, parameter=1,lty=2)
```



# Standard Parametric Distribution

For those distributions, we mention the R names in the gamlss package. Inference can be done using

```
fit <-gamlss(y~1, family=LNO)
```

- **log normal**

$$f(x) = \frac{1}{x\sigma\sqrt{2\pi}}\, e^{-\frac{(\ln x-\mu)^2}{2\sigma^2}},\ x \geq 0$$

with mean $e^{\mu+\sigma^2/2}$, median $e^{\mu}$, and variance $(e^{\sigma^2}-1)e^{2\mu+\sigma^2}$

```
LNO(mu.link = "identity", sigma.link = "log")
dLNO(x, mu = 1, sigma = 0.1, nu = 0, log = FALSE)
```

- **gamma**

$$f(x) = \frac{x^{1/\sigma^2-1}\exp[-x/(\sigma^2\mu)]}{(\sigma^2\mu)^{1/\sigma^2}\Gamma(1/\sigma^2)},\ x \geq 0$$

with mean $\mu$ and variance $\sigma^2$

```
GA(mu.link = "log", sigma.link ="log")
dGA(x, mu = 1, sigma = 1, log = FALSE)
```

- **Pareto**

$$f(x) = \frac{\alpha\, x_{\mathrm{m}}^{\alpha}}{x^{\alpha+1}} \text{ for } x \geq x_m$$

with cumulated distribution

$$F(x) = 1 - \left(\frac{x_{\mathrm{m}}}{x}\right)^{\alpha} \text{ for } x \geq x_m$$

with mean $\dfrac{\alpha x_m}{(\alpha-1)}$ if $\alpha > 1$, and variance $\dfrac{x_{\mathrm{m}}^2\alpha}{(\alpha-1)^2(\alpha-2)}$ if $\alpha > 2$.

```
PARETO2(mu.link = "log", sigma.link = "log")
dPARETO2(x, mu = 1, sigma = 0.5, log = FALSE)
```

# Larger Families

- **GB1** - generalized Beta type 1

$$f(x) = \frac{|a|x^{ap-1}(1-(x/b)^a)^{q-1}}{b^{ap}B(p,q)},\ 0 < x^a < b^a$$

where $b$ , $p$ , and $q$ are positive

```
GB1(mu.link = "logit", sigma.link = "logit", nu.link = "log",tau.link
    = "log")
dGB1(x, mu = 0.5, sigma = 0.4, nu = 1, tau = 1, log = FALSE)
```

The GB1 family includes the generalized gamma(GG), and Pareto as special cases.

- **GB2** - generalized Beta type 2

$$f(x) = \frac{|a|x^{ap-1}}{b^{ap}B(p,q)(1+(x/b)^a)^{p+q}}$$

```
GB2(mu.link = "log", sigma.link = "identity", nu.link = "log", tau.
    link = "log")
dGB2(x, mu = 1, sigma = 1, nu = 1, tau = 0.5, log = FALSE)
```

The GB2 nests common distributions such as the generalized gamma (GG), Burr, lognormal, Weibull, Gamma, Rayleigh, Chi-square, Exponential, and the log-logistic.

- Generalized Gamma

$$f(x) = \frac{(p/a^d)x^{d-1}e^{-(x/a)^p}}{\Gamma(d/p)},$$

# Dealing with Binned Data

```
> load(url("http://freakonometrics.free.fr/income_binned.RData"))
> head(income_binned)
     low   high number   mean std_err
1      0   4999     95   3606     964
2   5000   9999    267   7686    1439
3  10000  14999    373  12505    1471
4  15000  19999    350  17408    1368
5  20000  24999    329  22558    1428
6  25000  29999    337  27584    1520
> tail(income_binned)
       low    high number    mean std_err
46  225000  229999     10  228374    1197
47  230000  234999     13  232920    1370
48  235000  239999     11  236341    1157
49  240000  244999     14  242359    1474
50  245000  249999     11  247782    1487
51  250000     Inf    228  395459  189032
```

# Dealing with Binned Data

There is a dedicated package to work with such datasets,

```
> library(binequality)
```

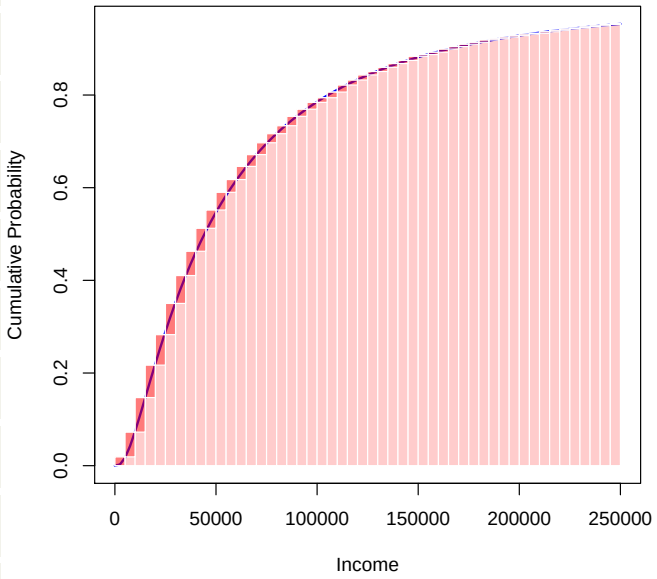
To fit a parametric distribution, e.g. a log-normal distribution, use functions of R

```
> n <- nrow(income_binned)
> fit_LN <- fitFunc(ID=rep("Fake Data",n), hb=income_binned[,"number"
    ], bin_min=income_binned[,"low"], bin_max=income_binned[,"high"],
    obs_mean=income_binned[,"mean"], ID_name="Country", distribution=
    LNO, distName="LNO")
Time difference of 0.09900618 secs
for LNO fit across 1 distributions
```

# Dealing with Binned Data

To visualize the cumulated distribution function, use

```
> N <- income_binned$number
> y1 <- cumsum(N)/sum(N)
> u <- seq(min(income_binned$low),max(income
    _binned$low),length=101)
> v <- plnorm(u,fit_LN$parameters[1],fit_LN$
    parameters[2])
> plot(u,v,col="blue",type="l",lwd=2,xlab="
    Income",ylab="Cumulative Probability")
> for(i in 1:(n-1)) rect(income_binned$low[i
    ],0,income_binned$high[i],y1[i],col=rgb
    (1,0,0,.2))
> for(i in 1:(n-1)) rect(income_binned$low[i
    ],y1[i],income_binned$high[i],c(0,y1)[i
    ],col=rgb(1,0,0,.4))
```

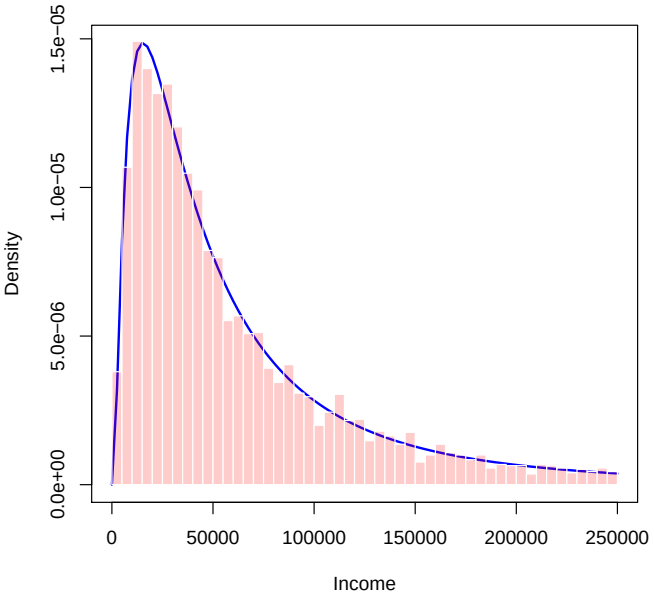


# Dealing with Binned Data

and to visualize the cumulated distribution function,

use

```
> N=income_binned$number
> y2=N/sum(N)/diff(income_binned$low)
> u=seq(min(income_binned$low),max(income_
    binned$low),length=101)
> v=dlnorm(u,fit_LN$parameters[1],fit_LN$
    parameters[2])
> plot(u,v,col="blue",type="l",lwd=2,xlab="
    Income",ylab="Density")
> for(i in 1:(n-1)) rect(income_binned$low[i
    ],0,income_binned$high[i],y2[i],col=rgb
    (1,0,0,.2),border="white")
```



# Dealing with Binned Data

But it is also possible to estimate *all* GB-distributions at once,

```
> fits=run_GB_family(ID=rep("Fake Data",n),hb=income_binned[,"number"
    ],bin_min=income_binned[,"low"],bin_max=income_binned[,"high"],obs
    _mean=income_binned[,"mean"],
+ ID_name="Country")
Time difference of 0.03800201 secs
for GB2 fit across 1 distributions

Time difference of 0.3090181 secs
for GG fit across 1 distributions

Time difference of 0.864049 secs
for BETA2 fit across 1 distributions
```

...

```
Time difference of 0.04900193 secs
```

```
for LOGLOG fit across 1 distributions

Time difference of 1.865106 secs
for PARETO2 fit across 1 distributions
```

```
> fits$fit.filter[,c("gini","aic","bic")]
       gini       aic       bic
1        NA        NA        NA
2  5.054377  34344.87  34364.43
3  5.110104  34352.93  34372.48
4        NA  53638.39  53657.94
5  4.892090  34845.87  34865.43
6  5.087506  34343.08  34356.11
7  4.702194  34819.55  34832.59
8  4.557867  34766.38  34779.41
9        NA  58259.42  58272.45
10 5.244332  34805.70  34818.73
```

```
> fits$best_model$aic
```

```
     Country obsMean distribution  estMean         var
1 Fake Data      NA          LNO 72328.86 6969188937
         cv    cv_sqr      gini      theil       MLD
1 1.154196 1.332168 5.087506 0.4638252 0.4851275
        aic       bic didConverge logLikelihood nparams
1 34343.08 34356.11         TRUE      -17169.54       2
    median        sd
1 44400.23 83481.67
```

That was easy, those were simulated data...

# Dealing with Binned Data

Consider now some real data,

```
> data = read.table("http://freakonometrics.free.fr/us_income.txt",
    sep=",",header=TRUE)
> head(data)
    low   high number_1000s   mean std_err
1     0   4999          4245   1249      50
2  5000   9999          5128   7923      30
3 10000  14999          7149  12389      28
4 15000  19999          7370  17278      26
> tail(data)
       low     high number_1000s    mean std_err
39  190000   194999          361  192031     115
40  195000   199999          291  197120     135
41  200000   249999         2160  219379     437
42  250000  9999999         2498  398233    6519
```

## Dealing with Binned Data

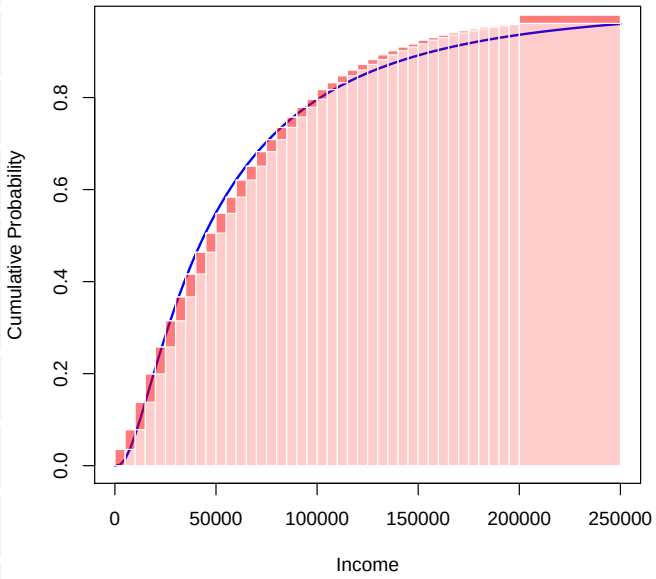
To fit a parametric distribution, e.g. a log-normal distribution, use

```
> n <- nrow(data)
> fit_LN <- fitFunc(ID=rep("US",n), hb=data[,"number_1000s"], bin_min
    =data[,"low"], bin_max=data[,"high"], obs_mean=data[,"mean"], ID_
    name="Country", distribution=LNO, distName="LNO")
Time difference of 0.1040058 secs
for LNO fit across 1 distributions
```

# Dealing with Binned Data

To visualize the cumulated distribution function, use

```
> N <- income_binned$number
> y1 <- cumsum(N)/sum(N)
> u <- seq(min(income_binned$low),max(income
    _binned$low),length=101)
> v <- plnorm(u,fit_LN$parameters[1],fit_LN$
    parameters[2])
> plot(u,v,col="blue",type="l",lwd=2,xlab="
    Income",ylab="Cumulative Probability")
> for(i in 1:(n-1)) rect(income_binned$low[i
    ],0,income_binned$high[i],y1[i],col=rgb
    (1,0,0,.2))
> for(i in 1:(n-1)) rect(income_binned$low[i
    ],y1[i],income_binned$high[i],c(0,y1)[i
    ],col=rgb(1,0,0,.4))
```

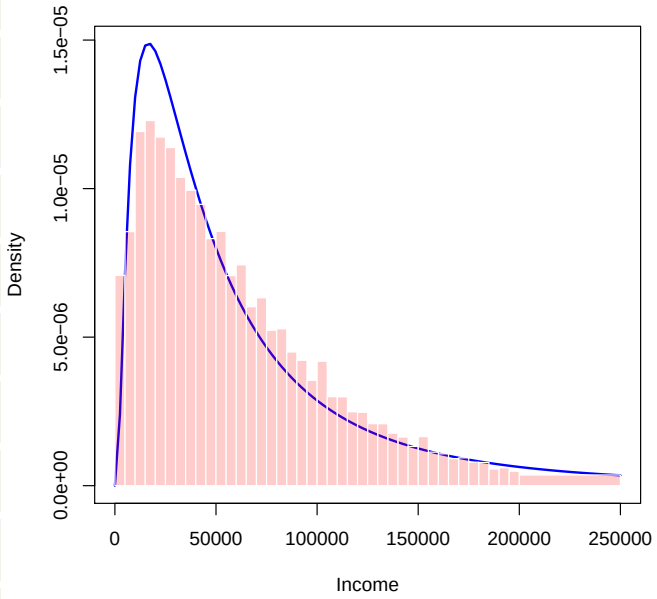


# Dealing with Binned Data

and to visualize the cumulated distribution function,

use

```
> N=income_binned$number
> y2=N/sum(N)/diff(income_binned$low)
> u=seq(min(income_binned$low),max(income_
    binned$low),length=101)
> v=dlnorm(u,fit_LN$parameters[1],fit_LN$
    parameters[2])
> plot(u,v,col="blue",type="l",lwd=2,xlab="
    Income",ylab="Density")
> for(i in 1:(n-1)) rect(income_binned$low[i
    ],0,income_binned$high[i],y2[i],col=rgb
    (1,0,0,.2),border="white")
```



# Dealing with Binned Data

And the winner is....

```
> fits$fit.filter[,c("gini","aic","bic")]
       gini       aic       bic
1  4.413411 825368.7 825407.4
2  4.395078 825598.8 825627.9
3  4.455112 825502.4 825531.5
4  4.480844 825881.5 825910.6
5  4.413282 825315.3 825344.4
6  4.922123 832408.2 832427.6
7  4.341085 827065.2 827084.6
8  4.318694 826112.9 826132.2
9        NA 831054.2 831073.6
10       NA       NA       NA
```

```
> fits$best_model$aic
  Country obsMean distribution  estMean        var
1      US      NA           GG 65147.54 3152161910
```

```
          cv     cv_sqr      gini      theil       MLD
1 0.8617995 0.7426984 4.395078 0.3251443 0.3904942
        aic       bic didConverge logLikelihood nparams
1 825598.8 825627.9         TRUE     -412796.4       3
    median        sd
1 48953.6 56144.12
```