Reference growth charts for Saudi Arabian children and adolescents

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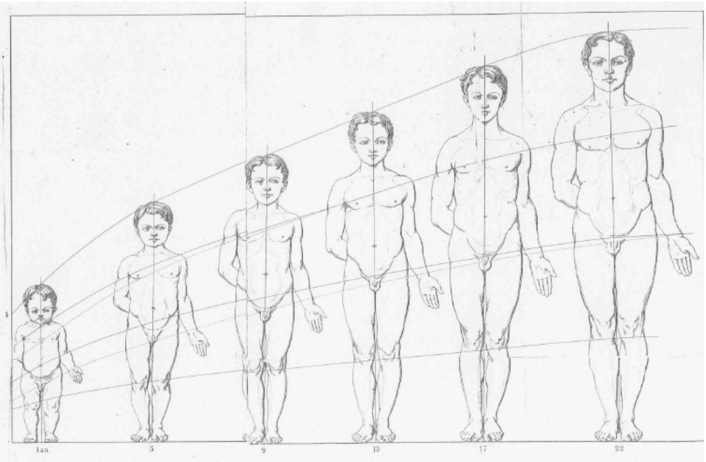
Quetelet's (1871) Growth Chart



Assumption about normality

The reference growth charts are based on normality assumptions for the data.

Age-specific mean $\mu(t)$ and standard deviation $\sigma(t)$ curves are estimated and chosen quantile curve for a $\alpha \in [0, 1]$ can then be constructed as:

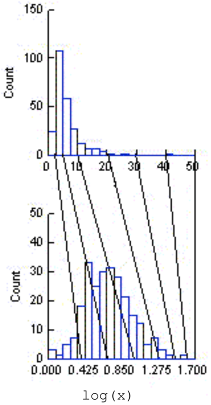
$$\hat{Q}\,(\alpha \mid t) = \hat{\mu}(t) + \hat{\sigma}(t)\Phi^{-1}(\alpha)$$

where $\Phi^{-1}(\alpha)$ denotes the inverse of the standard normal distribution function, in other words normal equivalent deviate of size α (corresponding to tail area).

Anthropometric data

Anthropometric data:

1. non-normally distributed,
2. tends to be right skewed rather than left, which is why a log transformation is often suggested to cope with it.



Penalised Maximum Likelihood Estimation

- Data: $\{Y\,(t_{i,j}) : j = 1, ..., J_i, \quad i = 1, ...n\}$
- Model: $Z(t) = \frac{[Y(t)/\mu(t)]^{\lambda(t)} - 1}{\lambda(t)\sigma(t)} \sim \mathcal{N}\,(0, 1)$
- Estimation:

$$\ell(\lambda, \mu, \sigma) = \sum_{i=0}^{n} [\lambda(t_i) \log \frac{Y(t_i)}{\mu(t_i)} - \log \sigma(t_i) - \frac{1}{2} Z^2(t_i)]$$

$$\max[\ell(\lambda, \mu, \sigma) - \nu_\lambda \int (\lambda''(t))^2 dt - \nu_\mu \int (\mu''(t))^2 dt - \nu_\sigma \int (\sigma''(t))^2 dt]$$

- Quantile: $Q\,(\alpha \mid t) = \mu(t)[1 + \lambda(t)\sigma(t)\Phi^{-1}(\alpha)]^{1/\lambda(t)}$

Data

SaudiR.csv

	A	B	C	D	E	F	G	H
1	REGION	IDNUMBER	SEX	WEIGHTOF	HEIGHTOF	HEADCIRC	AGEYEARS	AGEMON
2	1	1	1	.NA	.NA	.NA	.NA	.NA
3	1	1	2	.NA	.NA	.NA	.NA	.NA
4	1	1	2	64.5	148	59	17.9688	215.63
5	1	2	1	.NA	.NA	.NA	.NA	.NA
6	1	2	2	.NA	.NA	.NA	.NA	.NA
7	1	2	2	14.6	99	50	4.6525	55.83
8	1	3	1	.NA	.NA	.NA	.NA	.NA
9	1	3	2	.NA	.NA	.NA	.NA	.NA
10	1	3	1	8.5	74.5	49	0.914	10.97
11	1	3	2	9.5	82	48	1.3855	16.63
12	1	3	1	15.6	113	51	4.6197	55.44
13	1	3	2	29.5	129.5	55	7.6469	91.76
14	1	6	1	.NA	.NA	.NA	.NA	.NA
15	1	6	2	.NA	.NA	.NA	.NA	.NA
16	1	6	.NA	.NA	.NA	.NA	.NA	.NA
17	1	6	2	15.8	104	50	5.8009	69.61
18	1	6	1	35.2	130	51	9.6737	116.08
19	1	6	2	40	148	56	16.1846	194.21

SaudiR.csv
Ready
Sum=0

Codes and description of variables (health profile of Saudi children)

- Region: The ID number of the region. There are 13 regions in the Kingdom. All are covered in this survey.
- Id number: This is the id number of the household (family).
- Sex: 1=male, 2= female.
- Measure: The variables **weightof** (in Kg), **heightof** (in cm), **headcirc** (in cm), refer to the corresponding body measurements.
- Age: **Ageyears** and **agemon** refer to the date of measurement, recorded in Hijri calendar but subsequently converted to Gregorian.

Issues related to constructing the reference growth charts

- Detecting the **outliers**
- **Smoothing** the curves
- **Averaging** the overlapping period 2 to 3 years of age
- **Goodness-of-fit** of the centile curves
- **Comparison** between different geographical regions and between genders

Robust regression

R - a public domain language for data analysis

MASS package (contributed by W.N. Venables and B.D. Ripley)

```
> library(MASS)
> mp<-rlm(log(weight)~1+agey+I(agey^2)+I(agey^3), method="MM")
```

An object of class `rlm` inherited from `lm` is used to fit linear models and it can be used to carry out regression.

Using rlm fitting is done by iterated re-weighted least squares (IWLS).

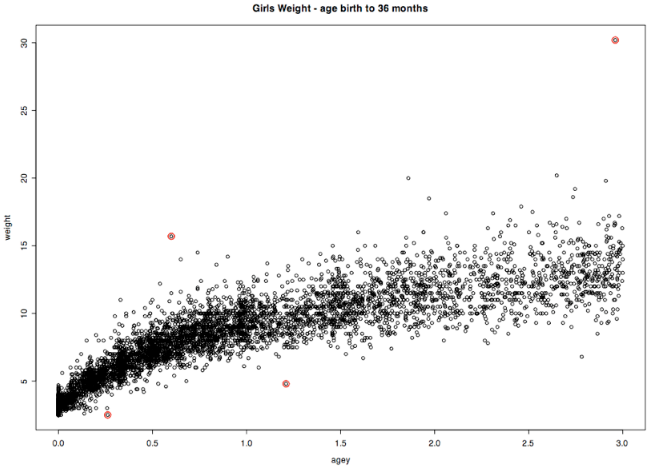
An additional component in `rlm` that is not in an `lm` object is:

`w` – the weights used in the IWLS process.

R Data Editor

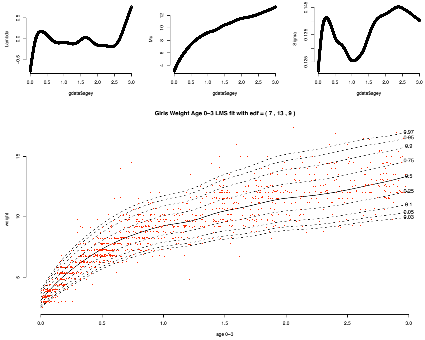
row.names	weight	agey	w
32	30.2	2.96	0
1676	4.8	1.21	0
2946	15.7	0.6	0
3979	2.5	0.2617	0
3776	11	0.33	0.002548249
186	6.8	2.7819	0.002738172
872	20	1.86	0.02485536
4361	8	0.15	0.02486028
3913	9.8	0.3	0.06277439
4141	8.4	0.2	0.06360341
2831	14	0.65	0.1121182
754	18.5	1.97	0.1242003
3985	3	0.259	0.1309745

Detecting the outliers

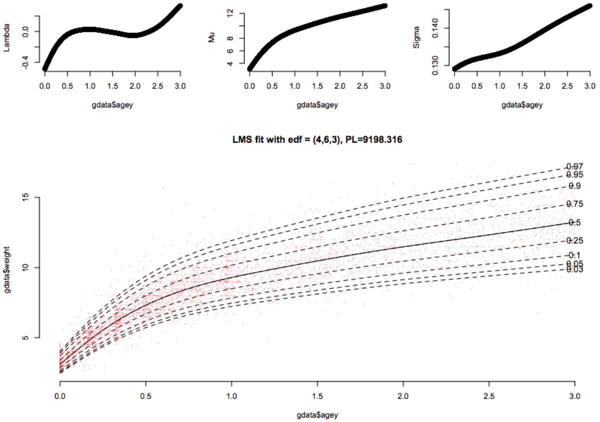


R package lmsqreg (contributed by V. J. Carry)

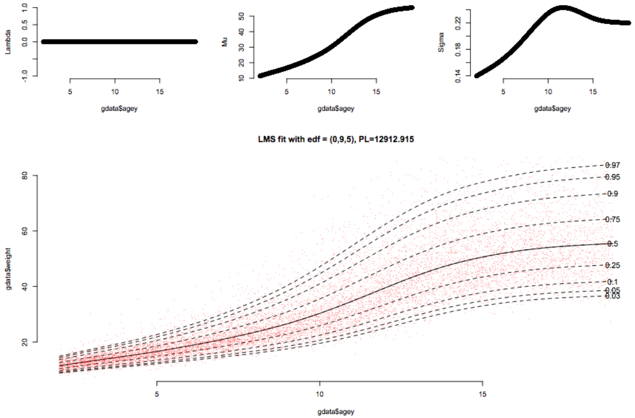
```
> library(lmsqreg)
> mw3<-lmsqreg.fit(gdata$weight, gdata$agey, edf=c(7, 13, 9),
pvec = c(0.03, 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95, 0.97))
```



Smoothing with edf(4, 6, 3)



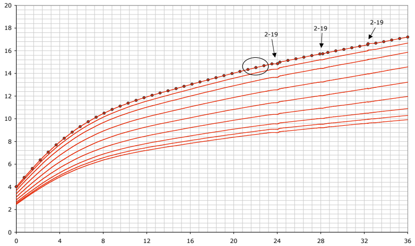
$\lambda = 0$

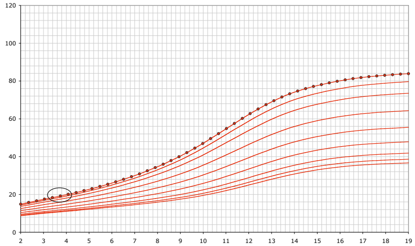

Lambda
gdata$agey
Mu
gdata$agey
Sigma
gdata$agey
LMS fit with edf = (0,9,5), PL=12912.915
gdata$weight
gdata$agey
0.97
0.95
0.9
0.75
0.5
0.25
0.1
0.05
0.03

Overlap for age 2 to 3 years

```
lmsqreg.fit(YY, TT, edf = c(3, 5, 3), targlen = 50, pvec = c(0.05, 0.1, 0.25, 0.5,
0.75, 0.9, 0.95))
```

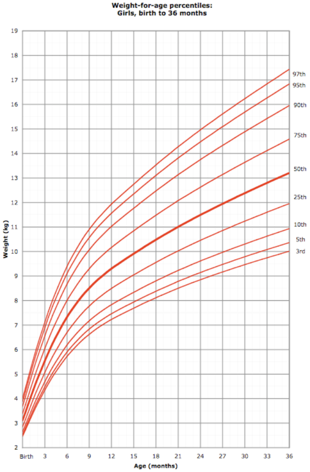
`targlen` - Number of points at which smooth estimates of L, M, S should be extracted for quantile plotting.





$$\hat{Y} = X\left[X'X\right]^{-1}X'Y$$

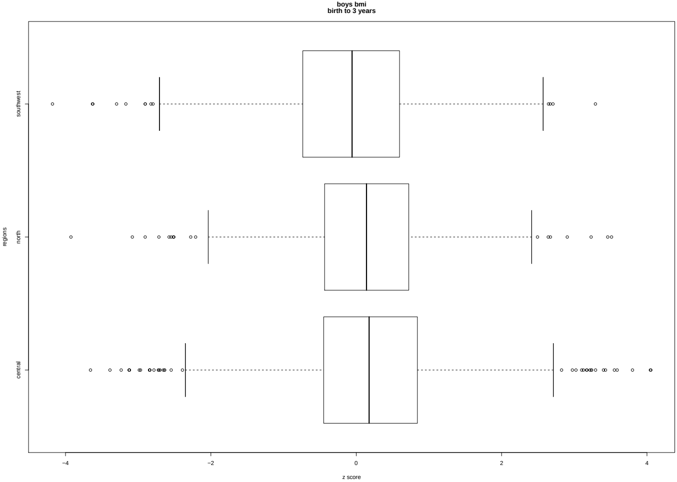
Averaged Chart



R package lmsqreg (mw3)

```
> mw3

lms quantile regression, version , fit date Thu Jun  4 14:37:52 2009

Dependent variable: gdata$weight , independent variable: gdata$agey
The fit converged with EDF=( 4,6,3 ), PL= 9198.316

nominal percentile   0.030 0.050 0.10 0.25 0.500 0.750 0.900 0.95 0.970
estimated percentile 0.025 0.052 0.09 0.24 0.506 0.755 0.905 0.95 0.972

KS tests: (intervals in gdata$agey //p-values)
   (-0.001,0]      (0,0.348] (0.348,0.802]  (0.802,1.54]       (1.54,3]        Overall
        0.000          0.000          0.271          0.324          0.676          0.001

t tests: (intervals in gdata$agey //p-values)
   (-0.001,0]      (0,0.348] (0.348,0.802]  (0.802,1.54]       (1.54,3]        Overall
        0.006          0.000          0.562          0.369          0.568          0.810

X2 tests (unit variance): (intervals in gdata$agey //p-values)
   (-0.001,0]      (0,0.348] (0.348,0.802]  (0.802,1.54]       (1.54,3]        Overall
        0.000          0.000          0.717          0.050          0.462          0.979
```

BoxPlots of mean SD scores of the three geographical regressions



R analysis of variance (ANOVA)

```
> summary(fm<-aov(z~group))
              Df Sum Sq Mean Sq F value    Pr(>F)
group          2   69.4    34.7  37.589 < 2.2e-16 ***
Residuals   3941 3640.0     0.9
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

> TukeyHSD(fm)
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = z ~ group)

$group
                        diff        lwr         upr     p adj
north-central    -0.01495461 -0.1000653  0.07015605 0.9107089
southwest-central -0.33239976 -0.4255862 -0.23921328 0.0000000
southwest-north   -0.31744515 -0.4224195 -0.21247080 0.0000000
```

Procedure for using ANCOVA to compare the growth standards between the regions

1. STEP 1: Find the best fitting polynomials having the lowest possible common degree for each of the three regions.

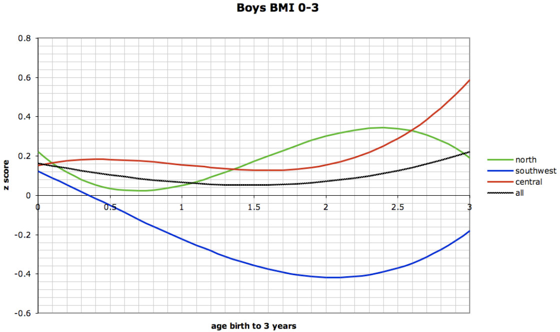
2. STEP 2: We want to answer the question "Is a common polynomial of the same degree as found in STEP 1 appropriate for all three regions or do the polynomials vary with region?" ie. for a particular measurement, sex and age group we want to test:

   $H_0 : E\left[z \mid age\right] = \beta_0 + ... + \beta_q age^q$ for each region, where $q \leq 3$ is the degree of the common best fitting polynomial.

   vs. H_1 : The polynomial for at least two regions differ.

3. STEP 3: After finding a significant result in STEP 2 carry out pairwise comparisons between the regions.

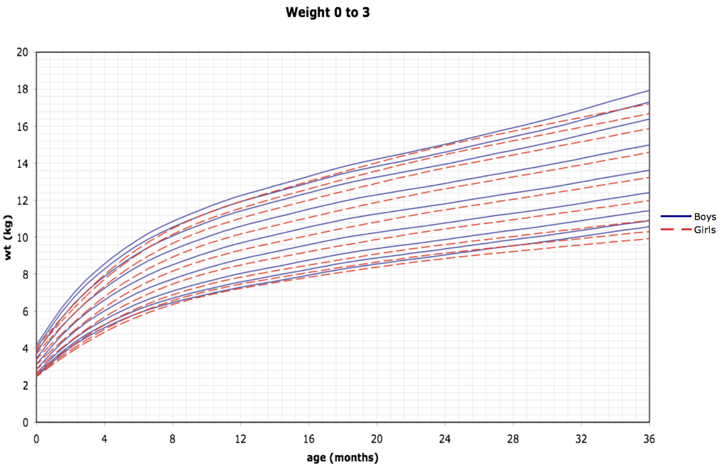
SD score regression models



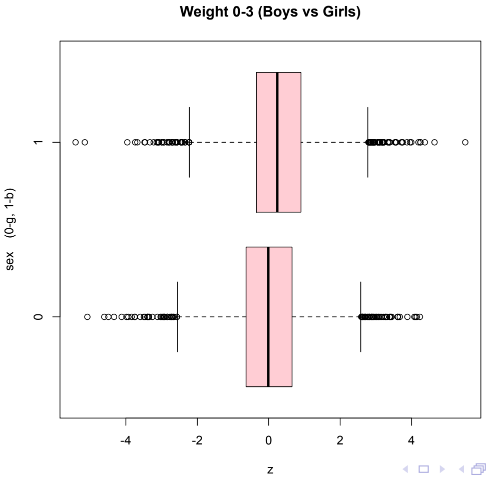
sex:male, age: birth to 36 moths

body mass index	
	p
north-central	0.061050
southwest-central	0.000000
southwest-north	0.000000

Weight, age birth to 36 months



Box Plots



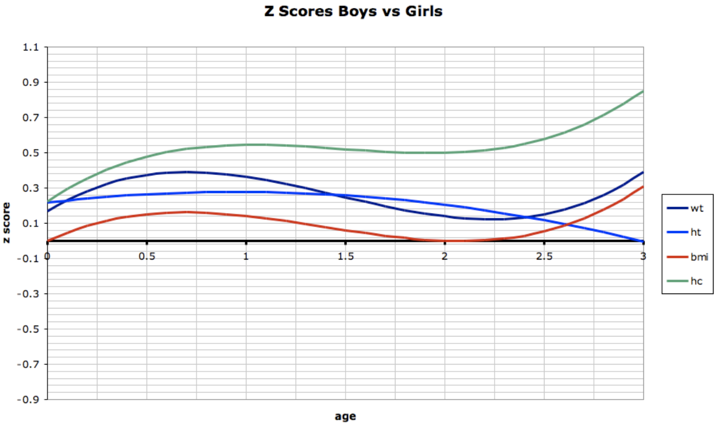
t-test

```
> t.test(z~sex)

Welch Two Sample t-test

data:  z by sex
t = -14.4148, df = 12473.99, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.2958223 -0.2249998
sample estimates:
mean in group 0 mean in group 1
    0.003078598     0.263489639
```

lm function used to fit linear models

```
> m<-lm(z~sex+sex*x+sex*I(x^2)+sex*I(x^3))
> summary(m)

Call:
lm(formula = z ~ sex + sex * x + sex * I(x^2) + sex * I(x^3))

Residuals:
      Min        1Q    Median        3Q       Max
-5.727730 -0.642032 -0.002139  0.649591  5.140159

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.0003369  0.0234113  -0.014 0.988518
sex1         0.1680739  0.0326333   5.150 2.64e-07 ***
x            0.1004580  0.1011812   0.993 0.320801
I(x^2)      -0.1245990  0.0993347  -1.254 0.209744
I(x^3)       0.0325240  0.0248738   1.308 0.191047
sex1:x       0.6006027  0.1418117   4.235 2.30e-05 ***
sex1:I(x^2) -0.5300762  0.1395383  -3.799 0.000146 ***
sex1:I(x^3)  0.1160172  0.0350394   3.311 0.000932 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 1.007 on 12473 degrees of freedom
Multiple R-Squared: 0.02064, Adjusted R-squared: 0.02009
F-statistic: 37.56 on 7 and 12473 DF,  p-value: < 2.2e-16
```

Boys vs Girls, age birth to 3 years



Things to do

1. Assessing the difference in fits of quantiles fitted by a parametric function and by a smooth non-parametric curve.
2. Test for a significant difference between the curves for the overlapping period with the original estimations.

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