Robust topics

- Median
- MAD
- Spearman
- Wilcoxon rank test
- Weighted least squares
- Cook's distance
- M-estimators

Robust topics

- Median => middle
- MAD => spread
- Spearman => association
- Wilcoxon rank test => group diffs
- Weighted least squares
- Cook's distance => observation influence
- M-estimators => framework for estimation

What do we mean by robust?

- "robust to outliers"
- "robust to misspecification of the model"

- Low variance ("precise"), low bias ("accurate")
- Accuracy (TP+TN/total), precision (1-FDR), sensitivity (TPR), specificity (1-FPR)

What do we mean by outlier?



- Technical error?
- Data entry error?
- Unaccounted for tail of data distribution?

How do most statistics work

Median

```
dat <- matrix(rnorm(5*1e5),ncol=5)
means <- rowMeans(dat)
medians <- apply(dat,1,median)</pre>
```



Efficiency

sd(medians)/sd(means)

[1] 1.197183

Median for non-normal data



Trimmed mean for non-normal data



MAD: median absolute deviation



Median absolute deviation & SD



Efficiency of MAD

```
dat <- matrix(rnorm(20*1e5),ncol=20)
sds <- apply(dat,1,sd)
mads <- apply(dat,1,mad)</pre>
```



MAD with outliers



+ less sensitive to outliers

- all subregions of range count equally



pearson spearman 0.9932279 0.9879952



pearson spearman 0.69943398 -0.03404562

- Drug resistance in cell lines
- Gene expression



pearson spearman 0.9977304 0.1939154

Wilcoxon / Mann-Whitney rank test



W <- 0
for (i in seq_along(x)) {
 W <- W + sum(y <= x[i])
}
print(W)</pre>

[1] 211

Wilcoxon vs t-test p distribution (n=20)



Wilcoxon vs t-test sensitivity (SD=1, n=4)



Wilcoxon for small sample size

```
wilcox.test(x=101:103, y=1:3)
```

```
Wilcoxon rank sum test
data: 101:103 and 1:3
W = 9, p-value = 0.1
alternative hypothesis: true location shift is
not equal to 0
```

Weighted least squares



Weighted least squares



Cook's distance





Cook's distance

```
dfbeta(fit1)[1, "x"]
```

[1] 0.654628

coef(fit1)[2] - coef(fit2)[2]

x 0.654628

Cook's distance

cooksD <- cooks.distance(fit1)</pre>



M-estimators



M-estimators

- M-estimators are a generalized framework for estimation
- M for Maximum likelihood-type estimation
- Least squares is a maximum likelihood estimate for data with normally-distributed error.

MLE reminder

theta <- seq(-5,5,.1)
plot(theta, dnorm(theta,log=TRUE))</pre>



Theory of estimation

It is interesting to look back to the very origin of the theory of estimation, namely to Gauss and his theory of least squares. Gauss was fully aware that his main reason for assuming an underlying normal distribution and a quadratic loss function was mathematical, i.e., **computational, convenience**. In later times, this was often forgotten, partly because of the central limit theorem.

Theory of estimation

However, if one wants to be honest, the central limit theorem can at most explain why many distributions occurring in practice are approximately normal. The stress is on the word "approximately." This raises a question which could have been asked already by Gauss, but which was, as far as I know, only raised a few years ago (notably by Tukey): What happens if the true distribution deviates slightly from the assumed normal one?

M-estimators



M-estimators

library(MASS)
rob.fit <- rlm(y ~ x)</pre>



Links on robust statistics in genomics

- **SAMseq**'s implementation of rank test
 - sequencing depth
 - noise of low counts
 - false discovery rate
- voom weighted linear model
- edgeR and limma-voom sample quality weights
- **DESeq2** use of Cook's distance