Discrete distributions

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Psych 6136

http://friendly.github.io/psy6136
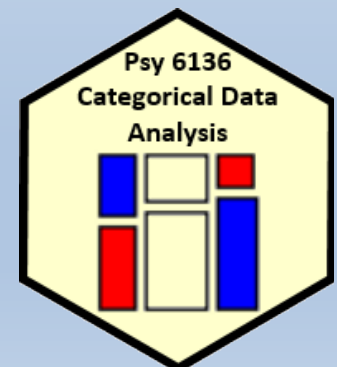
Discrete distributions: Basic ideas

- Quantitative data: often assumed Normal (μ, σ^2) – unreasonable for CDA

- Binomial, Poisson, Negative binomial, … are the building blocks for CDA

- Form the basis for modeling techniques
  - logistic regression, generalized linear models, Poisson regression

- Data:
  - outcome variable (k = 0, 1, 2, …)
  - counts of occurrences (n_k): accidents, words in text, males in families of size k
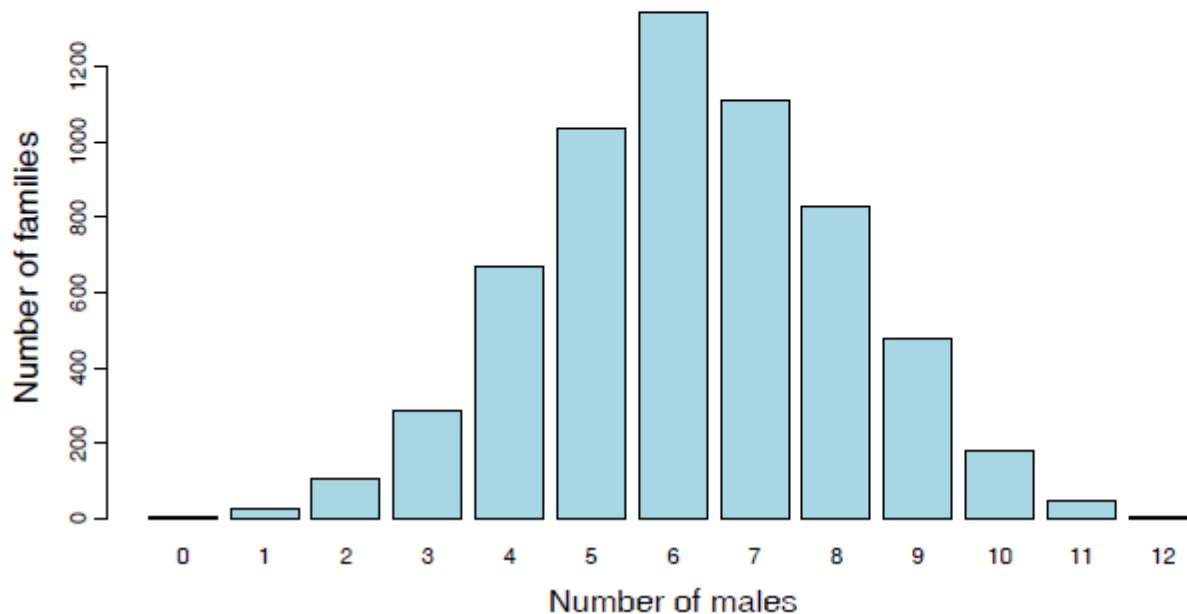
Examples: binomial

Human sex ratio (Geissler, 1889): Is there evidence that Pr(male) = 0.5?

Saxony families

Saxony families with 12 children having $k = 0, 1, \ldots 12$ sons.

| k	0	1	2	3	4	5	6	7	8	9	10	11	12
n_k	3	24	104	286	670	1033	1343	1112	829	478	181	45	7

Examples: Poisson

L. Von Bortkiewicz (1898) tallied the numbers of deaths by horse or mule kicks in 10 corps of the Prussian army over 20 years, $\rightarrow$ 200 corps-years
- In how many corps-years were there 0, 1, 2, … deaths?
- This is among the earliest examples of a Poisson distribution

```
> data(HorseKicks, package="vcd")
> HorseKicks
nDeaths
   0    1    2    3    4
 109   65   22    3    1
```
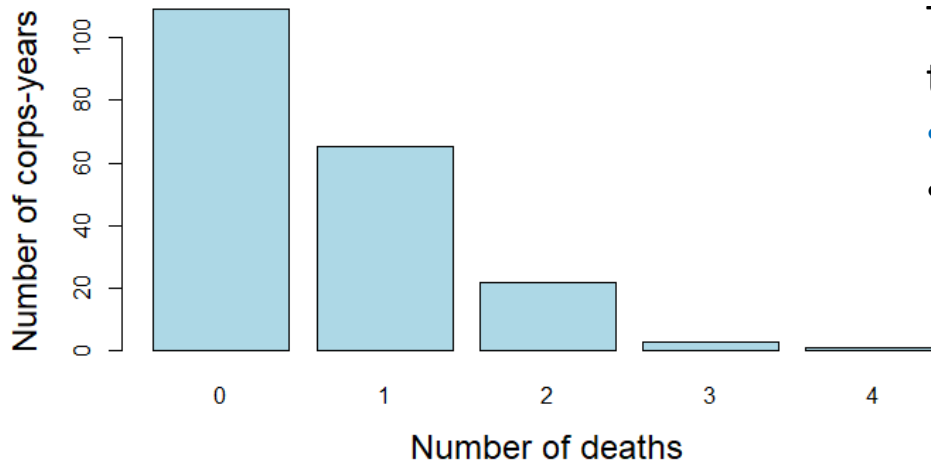

The Poisson distribution arises as that of the probability of 0, 1, 2, …
- Rare events, that
- Occur with constant probability

Examples: count data

Federalist papers: Disputed authorship

- 77 essays by Alexander Hamilton, John Jay, James Madison to persuade voters to ratify the US constitution, all signed with pseudonym "Publius"
  - Who wrote each?
  - 65 known, 12 disputed (H & M both claimed sole authorship)
- Mosteller & Wallace (1984): analysis of frequency dist^{n}s of key "marker" words: from, **may**, whilst, …
- e.g., blocks of 200 words: occurrences (k) of "may" in how many blocks (n_k)

```
> data(Federalist, package = "vcd")
> Federalist
nMay
  0   1   2   3   4   5   6
156  63  29   8   4   1   1
```

Count data: models
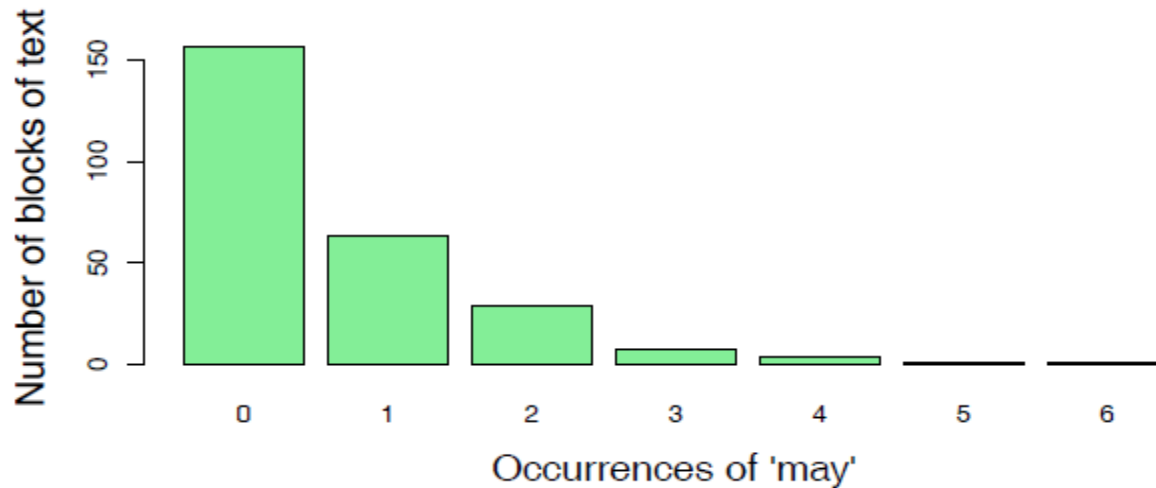
For each word ("from", "may", "whilst", …)
- Fit a probability model [Poisson(λ), NegBin(λ, p)]
- Estimate parameters (λ,p)
- $\rightarrow$ Calculate log Odds (Hamilton vs. Madison)
- $\rightarrow$ All 12 disputed papers most likely written by Madison

Example: Type-token distributions

- Basic count, k: number of "types"; frequency, n_k: number of instances observed
  - Frequencies of distinct words in a book or literary corpus
  - Number of subjects listing words as members of the semantic category "fruit"
  - Distinct species of animals caught in traps
- Differs from other distributions in that the frequency for $k = 0$ is *unobserved*
- Distribution is often extremely skewed (J-shaped)

Table: Number of butterfly species n_k for which k individuals were collected

| Individuals (k)	1	2	3	4	5	6	7	8	9	10	11	12	
Species (n_k)	118	74	44	24	29	22	20	19	20	15	12	14	
Individuals (k)	13	14	15	16	17	18	19	20	21	22	23	24	Su
Species (n_k)	6	12	6	9	9	6	10	10	11	5	3	3	5

```
data(Butterfly, package="vcd")
barplot(Butterfly,
        xlab = "Number of individuals",
        ylab = "Number of species",
        col = "pink",
        cex.lab = 1.5)
```

Questions:
What is the total pop. of butterflies in Malaysia?
How many wolves remain in Canada NWT?
How many words did Shakespeare know?
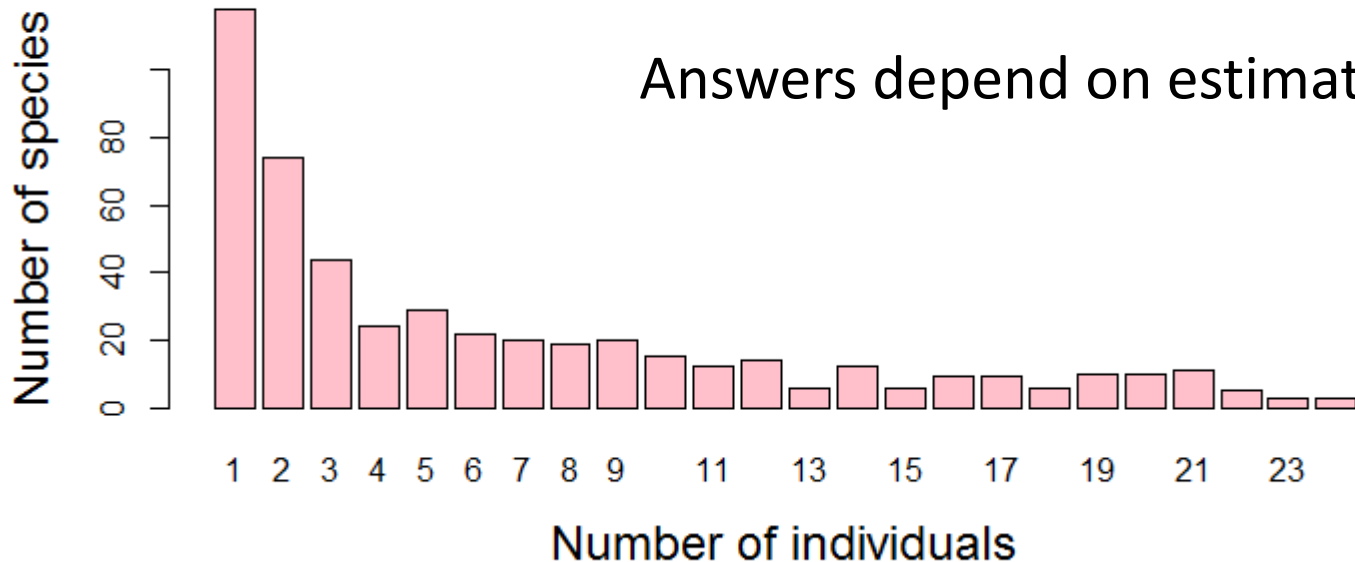
Answers depend on estimating Pr(k=0)

Discrete distributions: Questions

- General questions
  - What process gave rise to the distribution?
  - What is the form: uniform, binomial, Poisson, negative binomial, ... ?
  - $\rightarrow$ Fit & estimate parameters
    - Visualize goodness of fit
  - $\rightarrow$ Use in some larger context to tell a story
- Examples
  - *Families in Saxony*: might expect Bin(n=12, p); p=0.5?
  - *HorseKicks*: Poisson (λ); here, λ = mean = 0.61
  - *Federalist papers*: Perhaps Poisson(λ) or NegBin (λ, p)
  - *Butterfly data*: Perhaps a log-series distribution?

Fitting discrete distributions

Lack of fit:

- Lack of fit tells us something about the process giving rise to the data
- Poisson: assumes constant small probability of the basic event
- Binomial: assumes constant probability and independent trials
- Negative binomal: allows for *overdispersion*, relative to Poisson

Motivation:

- Models for more complex categorical data use these basic discrete distributions
- Binomial (with predictors) → logistic regression
- Poisson (with predictors) → poisson regression, loglinear models
- ⇒ many of these are special cases of *generalized linear models*

Common discrete distributions

Discrete distributions are characterized by a probability function, $\Pr(X = k) \equiv p(k)$, that the random variable X has value k.

- Common discrete distributions have the following forms:

Discrete distribution	Probability function, $p(k)$	Parameters
Binomial	$\binom{n}{k} p^k (1-p)^{n-k}$	$p = \Pr(\text{success})$; $n = \#$ trials
Poisson	$e^{-\lambda} \lambda^k / k!$	$\lambda = \text{mean}$
Negative binomial	$\binom{n+k-1}{k} p^n (1-p)^k$	p; $n = \#$ *successful* trials
Geometric	$p(1-p)^k$	p
Logarithmic series	$\theta^k / [-k \log(1-\theta)]$	θ

Discrete distributions: R

R functions: {d__, p__, q__, r__}

- d____ **d**ensity function, Pr(X=k) = p(k)
- p____ cumulative **p**robability, F(k) = $\sum_{X \leq k} p(k)$
- q____ **q**uantile function, find k = F^{-1} (p), smallest value such that $F(k) \geq p$
- r____ **r**andom number generator

Discrete distribution	Density (pmf) function	Cumulative (CDF)	Quantile CDF^{-1}	Random # generator
Binomial	dbinom()	pbinom()	qbinom()	rbinom()
Poisson	dpois()	ppois()	qpois()	rpois()
Negative binomial	dnbinom()	pnbinom()	qnbinom()	rnbinom()
Geometric	dgeom()	pgeom()	qgeom()	rgeom()
Logarithmic series	dlogseries()	plogseries()	qlogseries()	rlogseries()

What is "binomial"

Bi-no-mi-al /bīˈnōmēəl/

- **Taxonomy**: A two-part name, (genus, species) e.g., *Elephas maximus* for the Asian elephant

- **Mathematics**: An algebraic expression of a sum of two terms, (x + y) or expansion, $(x + y)^n$

$$(x+y)^0 = 1$$
$$(x+y)^1 = 1x + 1y$$
$$(x+y)^2 = 1x^2 + 2x^1y^1 + 1y^2$$
$$(x+y)^3 = 1x^3 + 3x^2y^1 + 3x^1y^2 + 1y^3$$
$$(x+y)^4 = 1x^4 + 4x^3y^1 + 6x^2y^2 + 4x^1y^3 + 1y^4$$
$$(x+y)^5 = 1x^5 + 5x^4y^1 + 10x^3y^2 + 10x^2y^3 + 5x^1y^4 + 1y^5$$

Coefficients of terms

$$C_k^n = \binom{n}{k} = \frac{n!}{k!(n-k)!}$$

Binomial distribution

The binomial distribution, $\mathrm{Bin}(n, p)$,

ways to get k out of n

Pr(k events)

Pr(n-k non-events)

$$\mathrm{Bin}(n, p) : \Pr\{X = k\} \equiv p(k) = \binom{n}{k} p^k (1 - p)^{n-k} \qquad k = 0, 1, \ldots, n , \quad (1)$$

arises as the distribution of the number of events of interest ("successes") which occur in n *independent trials* when the probability of the event on any one trial is the *constant* value $p = \Pr(\text{event})$.

Examples
- Toss 10 fair coins– how many heads?   Bin(10, ½)
- Toss 12 fair dice– how many 5s or 6s? Bin(12, 1/3)

Mean, variance, skewness:

Mean[X] = n p   MLE from data: $\hat{p} = \dfrac{\bar{x}}{n} = \dfrac{\sum_k k \times nk / \sum_k n_k}{n}$

  Var[X] = n p (1-p) = n p q

  Skew[X] = n p q (q-p)

Binomial distribution

Binomial distributions for k = 0, 1, 2, …, 12 successes in n=12 trials, for 4 values of p
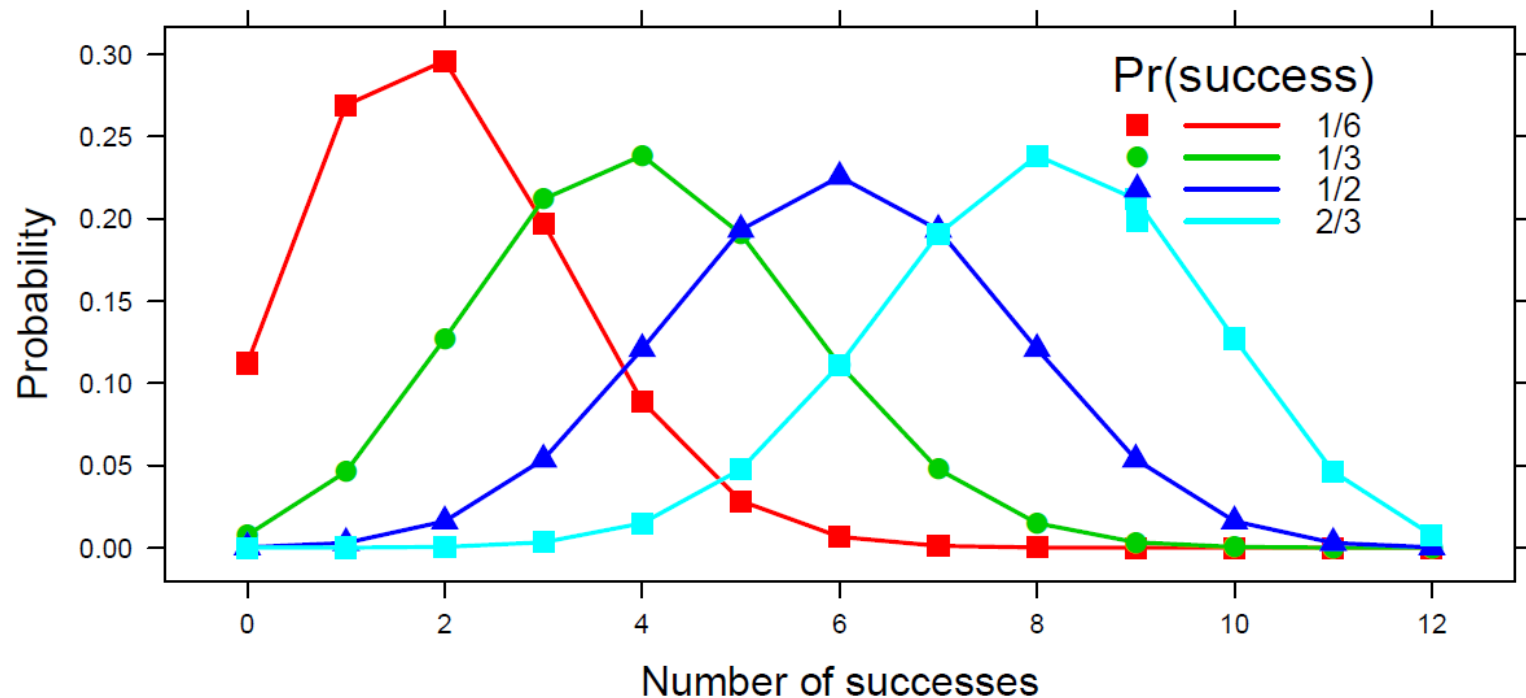
- Mean = n p
- Variance is maximum when p = ½
- Skewed when p ≠ ½

DDAR Fig 3.9, pp 76-77

Poisson distribution

The Poisson distribution, $\mathrm{Pois}(\lambda)$,

$$\mathrm{Pois}(\lambda) : \Pr\{X = k\} \equiv p(k) = \frac{e^{-\lambda}\lambda^k}{k!} \qquad k = 0, 1, \ldots \qquad (2)$$

gives the probability of an event occurring $k = 0, 1, 2, \ldots$ times over a *large number of independent* trials, when the probability, p, that the event occurs on any one trial (in time or space) is *small and constant*.
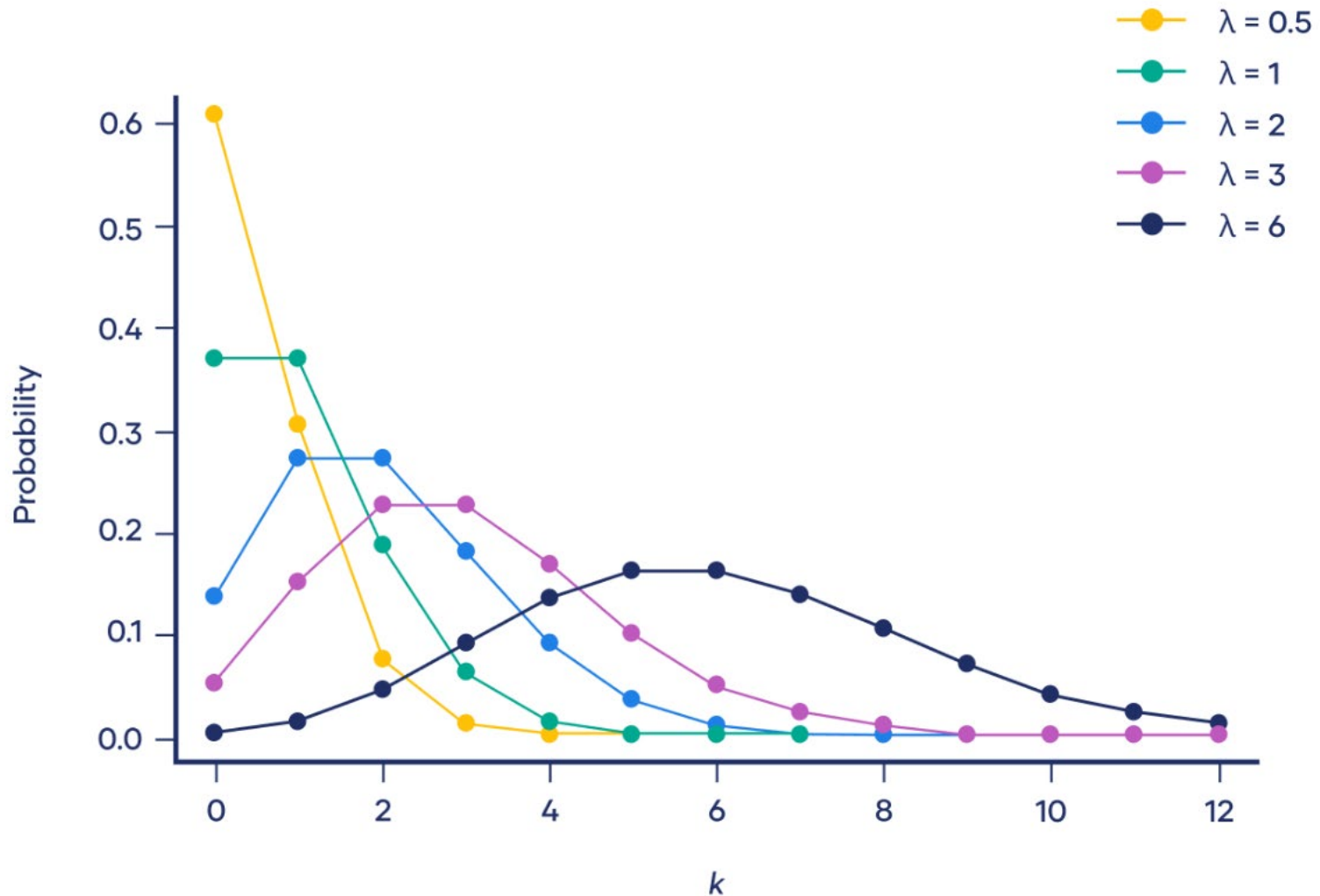Examples:

- Number of highway accidents at some given location
- Defects in a manufacturing process
- Number of goals scored in soccer games

Table: Total goals scored in 380 games in the Premier Football League, 1995/95 season

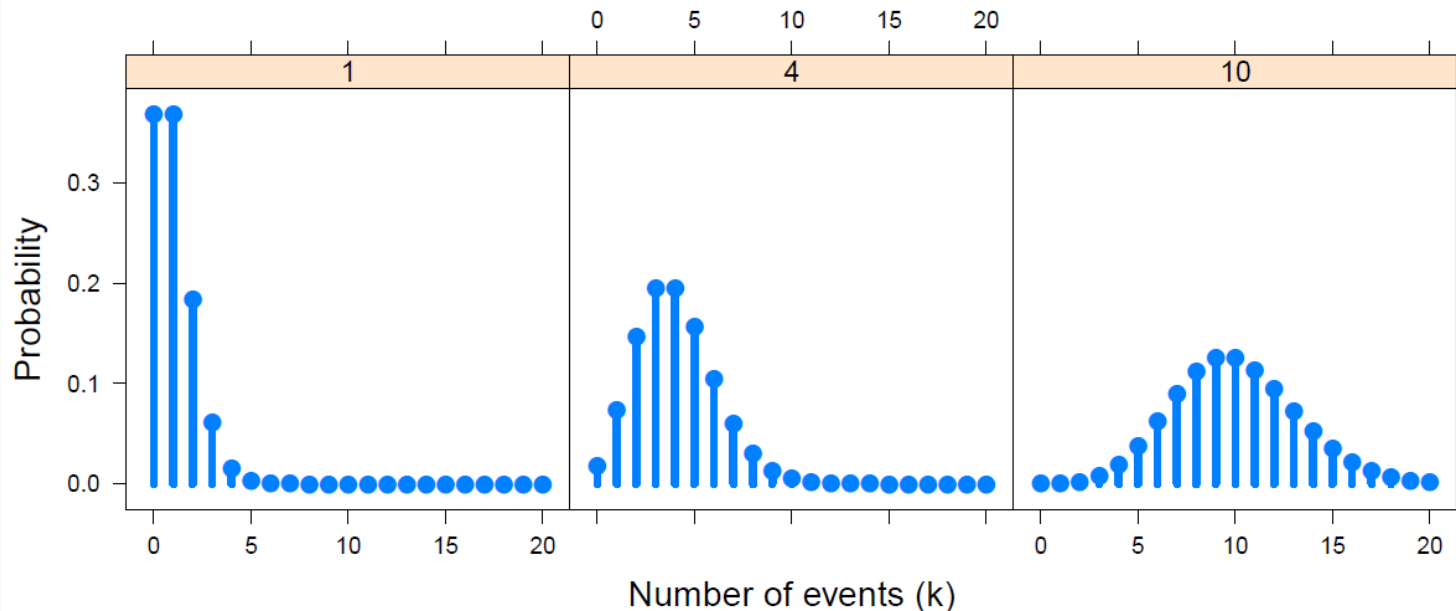| Total goals	0	1	2	3	4	5	6	7
Number of games	27	88	91	73	49	31	18	3

Poisson distribution

Poisson distributions for λ = ½, 1, 2, 3, 6

Poisson distribution

Poisson distributions for λ = 1, 4, 10

DDAR Fig 3.10, p 81

Mean, variance, skewness:

Mean[X] = λ

Var[X] = λ

Skew[X] = $\lambda^{-1/2}$

MLE: $\hat{\lambda} = \bar{x}$

Properties:

Sum of Pois (λ_1, λ_2, λ_3, …) = Pois($\sum \lambda_i$)

Approaches N(λ, λ) as n $\to$ ∞

Negative binomial distribution

The Negative binomial distribution, $\text{NBin}(n, p)$,

$$\text{NBin}(n, p) : \Pr\{X = k\} \equiv p(k) = \binom{n + k - 1}{k} p^n (1 - p)^k \qquad k = 0, 1, \ldots, \infty$$

is a waiting time distribution. It arises when n trials are observed with constant probability p of some event, and we ask how many non-events (failures), k, it takes to observe n successful events.

Example: Toss a coin; what is probability of getting $k = 0, 1, 2, \ldots$ tails before $n = 3$ heads?

This distribution is often used as an alternative to the Poisson when

- constant probability p or independence are violated
- variance is greater than the mean (overdispersion: $\text{Var}[X] > \text{Mean}[X]$)

$$
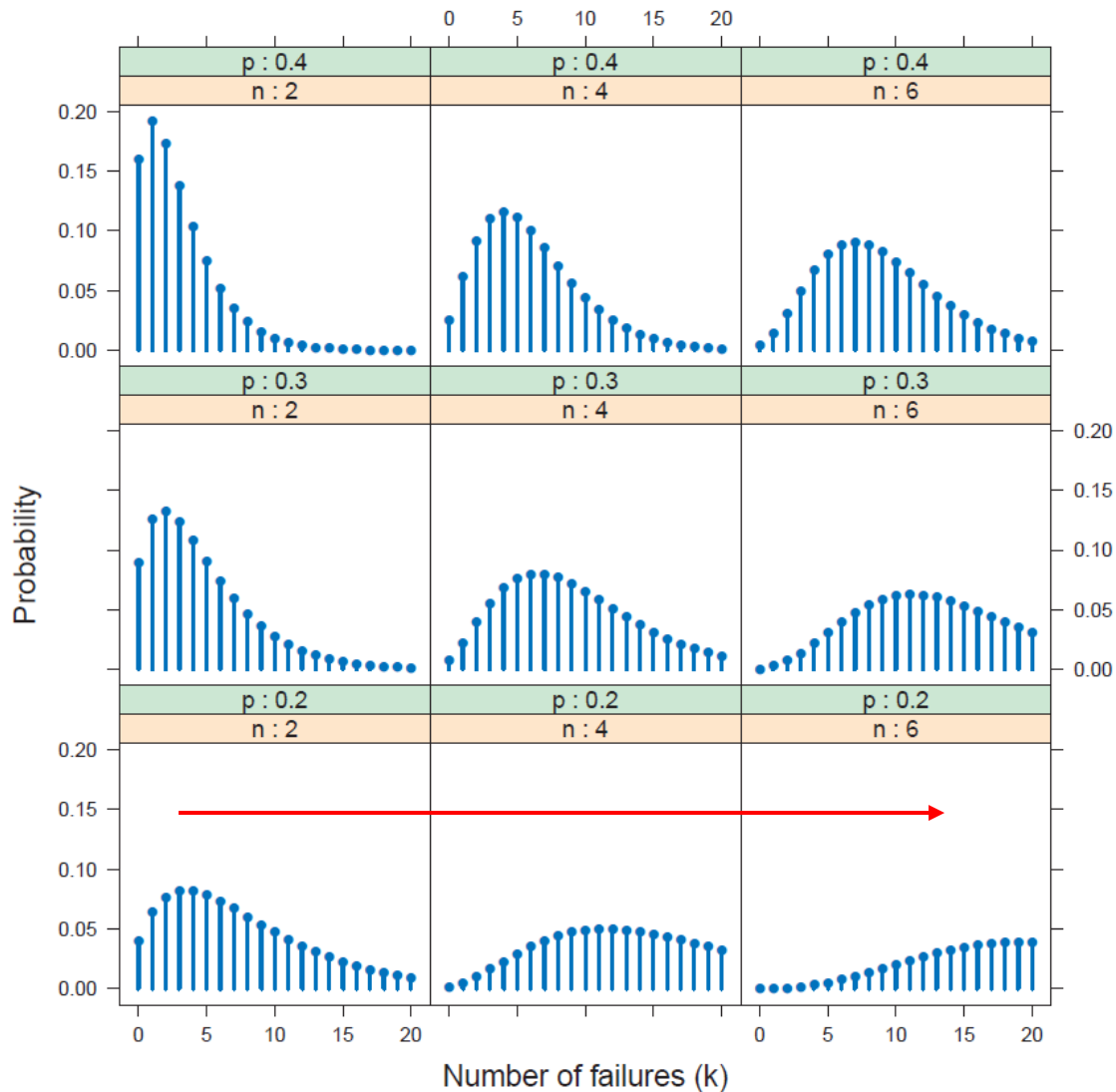\begin{aligned}
\text{Mean}(X) &= nq/p = \mu \\
\text{Var}(X) &= nq/p^2 \\
\text{Skew}(X) &= \frac{2 - p}{\sqrt{nq}},
\end{aligned}
$$

$$
\begin{aligned}
\text{Mean}(X) = \mu &= \frac{n(1 - p)}{p} \implies p = \frac{n}{n + \mu}, \\
\text{Var}(X) &= \frac{n(1 - p)}{p^2} \implies \text{Var}(X) = \mu + \frac{\mu^2}{n}.
\end{aligned}
$$

Negative binomial distributions for
n = 2, 4, 6
p = 0.2, 0.3, 0.4

Mean:
Increases with *n*
Decreases with *p*

DDAR Fig 3.13, p 85

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Fitting discrete distributions

Fitting a discrete distribution involves the following steps:

① Estimate the parameter(s) from the data, e.g., p for binomial, λ for Poisson, etc. Typically done using maximum likelihood, but some distributions have simple expressions:

- Binomial, $\hat{p} = \sum k n_k / (n \sum n_k) = \text{mean} / n$
- Poisson, $\hat{\lambda} = \sum k n_k / \sum n_k = \text{mean}$

② Calculate fitted probabilities, $\hat{p}(k)$ for the distribution, and then fitted frequencies, $N\hat{p}(k)$.

③ Assess Goodness of fit: Pearson X^2 or likelihood-ratio G^2

$$X^2 = \sum_{k=1}^{K} \frac{(n_k - N\hat{p}_k)^2}{N\hat{p}_k} \qquad G^2 = \sum_{k=1}^{K} n_k \log\left(\frac{n_k}{N\hat{p}_k}\right)$$

Both have asymptotic chisquare distributions, χ^2_{K-s} with s estimated parameters, under the hypothesis that the data follows the chosen distribution.

Fitting & graphing discrete distributions

In R, the vcd and vcdExtra packages provide functions to fit, visualize and diagnose discrete distributions

- **Fitting**: `goodfit()` 	fits uniform, binomial, Poisson, neg bin, geometric, logseries, ...
- **Graphing**: `rootogram()` 	assess departure between observed, fitted counts
- **Ord plot**: `Ordplot()` 	diagnose form of a discrete distribution
- **Robust plots**: `distplot()` 	handle problems with discrepant counts

Example: Saxony families

```
> data(Saxony, package="vcd")
> Saxony
nMales
   0    1    2    3    4    5    6    7    8    9   10   11   12
   3   24  104  286  670 1033 1343 1112  829  478  181   45    7
```

Use **goodfit()** to fit the binomial; test with **summary()**

```
> Sax.fit <- goodfit(Saxony, type = "binomial", par=list(size=12))
> summary(Sax.fit)

        Goodness-of-fit test for binomial distribution

              X^2 df P(> X^2)
Likelihood Ratio  97 11 6.98e-16
```

Example: Saxony families

The print() method for **goodfit** objects shows the details

```
> Sax.fit     # print

Observed and fitted values for binomial distribution
with parameters estimated by `ML'

 count observed    fitted pearson residual
    0         3     0.933             2.140
    1        24    12.089             3.426
    2       104    71.803             3.800
    3       286   258.475             1.712
    4       670   628.055             1.674
    5      1033  1085.211            -1.585
    6      1343  1367.279            -0.657
    7      1112  1265.630            -4.318
    8       829   854.247            -0.864
    9       478   410.013             3.358
   10       181   132.836             4.179
   11        45    26.082             3.704
   12         7     2.347             3.037
```

Pay attention to the pattern & magnitudes of residuals, d_k

Pearson $\chi^2 = \sum d_k^2$

Graphing discrete distributions
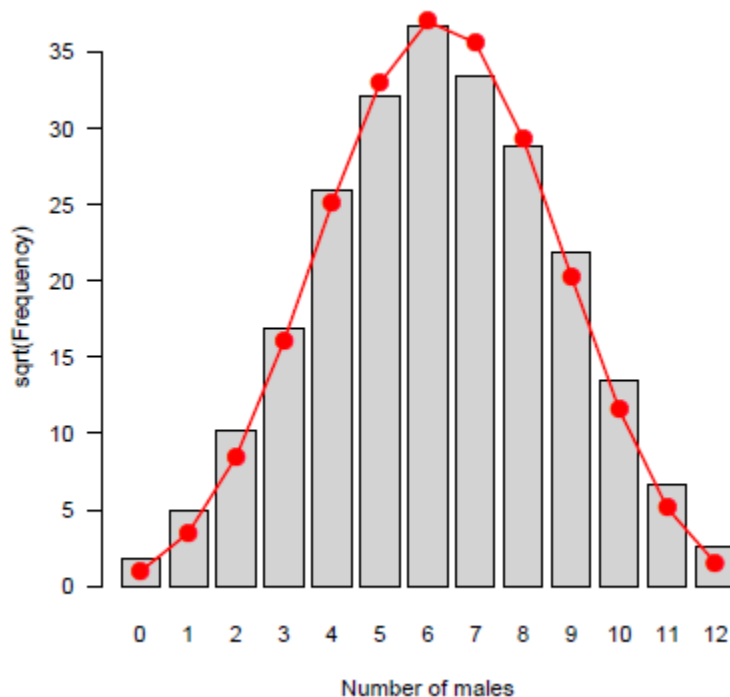
Rootograms
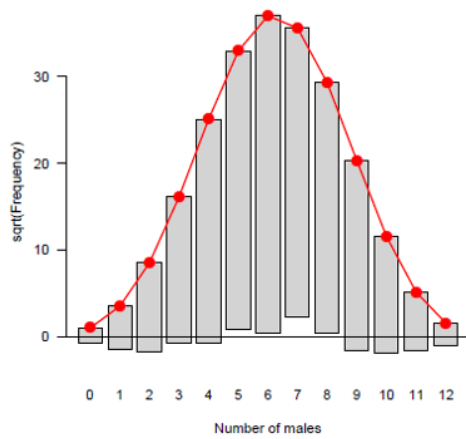
Ord plots
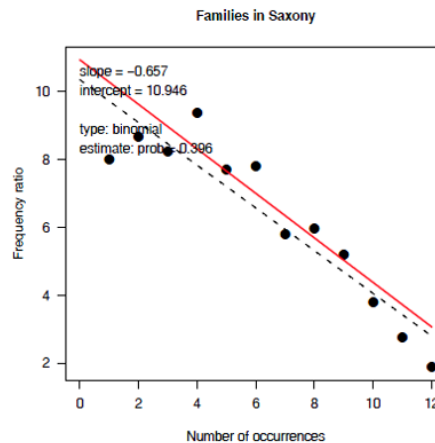
Robust distribution plots
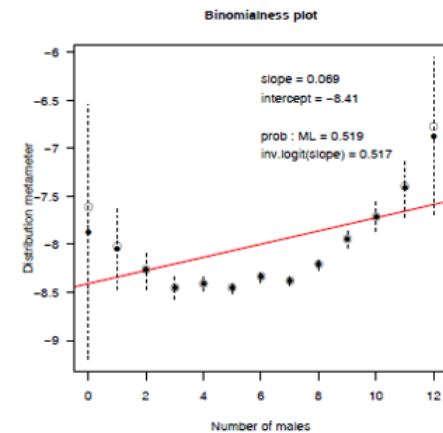
What's wrong with simple histograms?

Discrete distributions are often graphed as histograms, with a theoretical fitted distribution superimposed
The plot() method for goodfit objects provides some alternatives

```
> plot(Sax.fit, type = "standing", xlab = "Number of males")
```
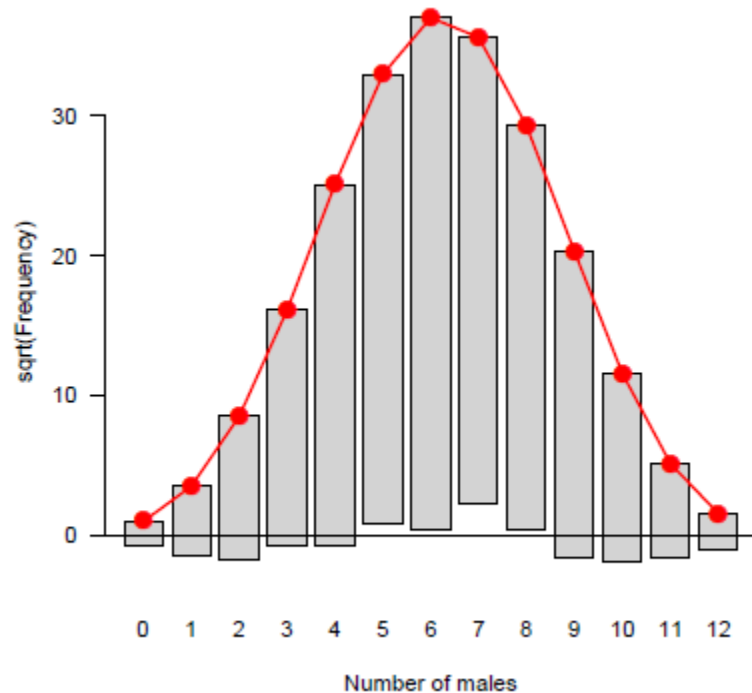

Problems:
- Largest frequencies dominate
- Must assess deviations vs. the fitted curve

Hanging rootograms

Tukey (1972, 1977):

- shift histogram bars to the fitted curve
- → judge deviations vs. horizontal line.
- plot $\sqrt{\text{freq}}$ → smaller frequencies are emphasized.

We can now see clearly where the binomial doesn't fit

Deviation rootograms

```
> plot(Sax.fit, type = "deviation", xlab = "Number of males")
```
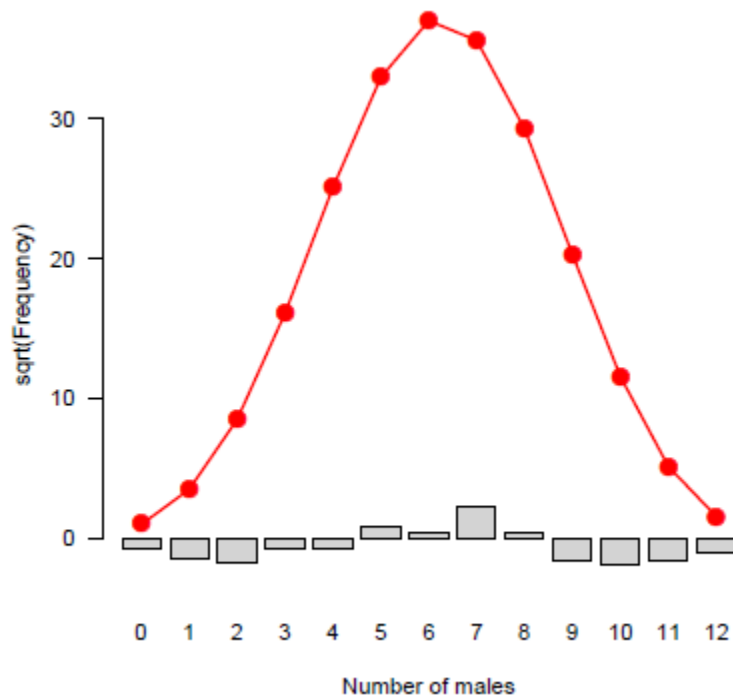

Deviation rootogram:

- emphasize differences between observed and fitted frequencies
- bars now show the residuals (gaps) directly

There are more families with very low or very high number of sons than the binomial predicts.
Q: Why is this so much better than the lack-of-fit test?

Example: Federalist papers

```
> data(Federalist, package="vcd")
> Federalist
nMay
  0   1   2   3   4   5   6
156  63  29   8   4   1   1
```

Fit the Poisson distribution

```
> Fed.fit0 <- goodfit(Federalist, type="poisson")
> summary(Fed.fit0)

        Goodness-of-fit test for poisson
distribution

                  X^2 df P(> X^2)
Likelihood Ratio 25.2  5 0.000125
```

This fits very poorly!

Example: Federalist papers

Try the Negative binomial distribution

```
> Fed.fit1<- goodfit(Federalist, type="nbinomial")
> summary(Fed.fit1)

        Goodness-of-fit test for nbinomial distribution

                 X^2 df P(> X^2)
Likelihood Ratio 1.96  4    0.742
```

This now fits very well, indeed! Why?

- Poisson assumes that the probability of a given word ("may") is constant across all blocks of text.
- Negative binomial allows the rate parameter λ to vary over blocks of text

Federalist papers: Rootograms

Hanging rootograms for the Federalist papers data, comparing Poisson and Negative binomial

```
> plot(Fed.fit0, main = "Poisson")
> plot(Fed.fit1, main = "Negative binomial")
```
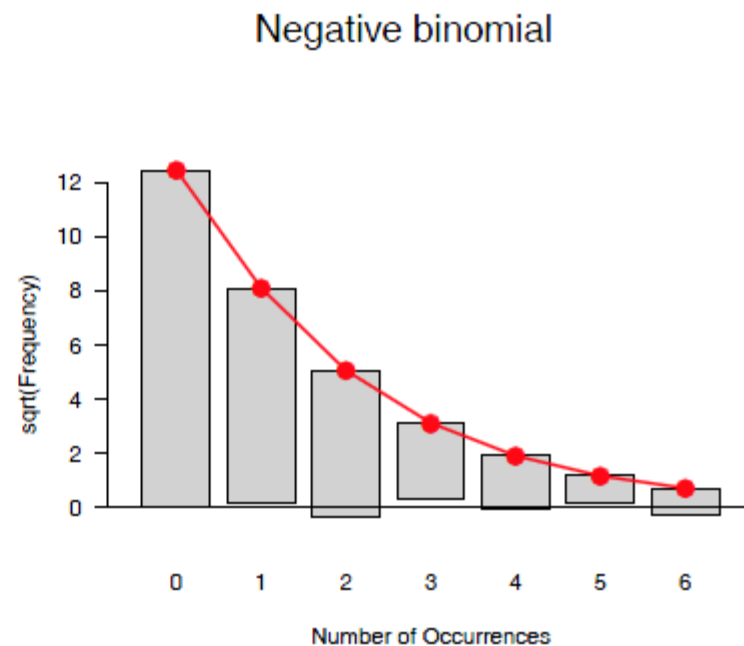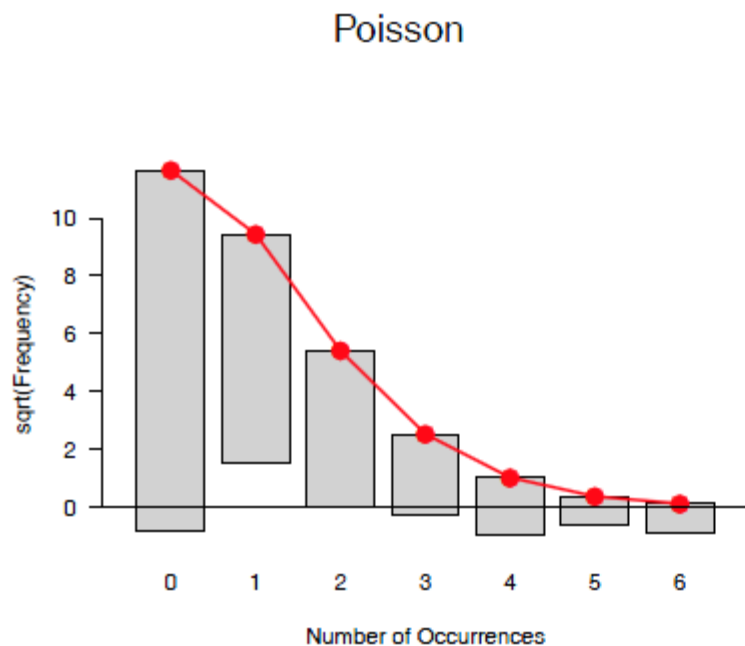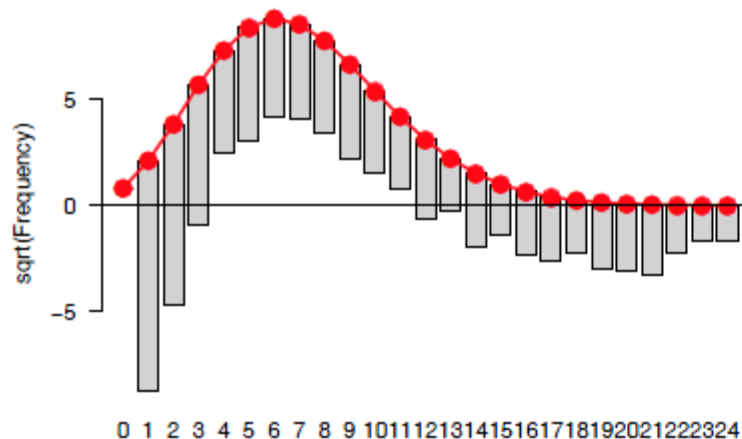
Butterfly data

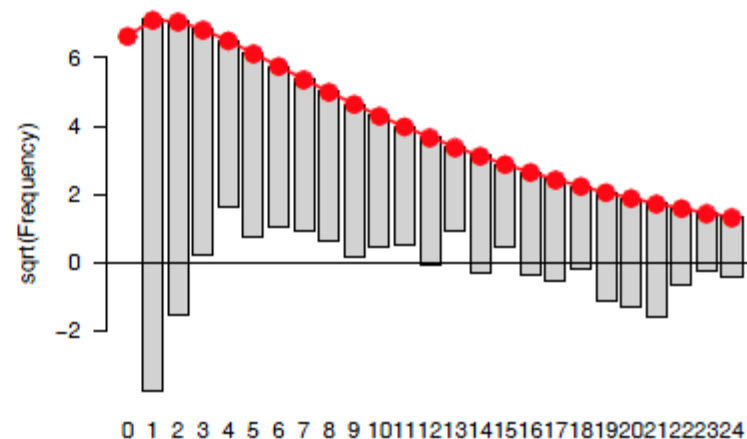Both Poisson and Negative binomial are terrible fits!   What to do??

```
But.fit1 <- goodfit(Butterfly, type="poisson")
But.fit2 <- goodfit(Butterfly, type="nbinomial")
plot(But.fit1, main="Poisson")
plot(But.fit2, main="Negative binomial")
```


Poisson

Negative binomial

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Ord plots: Diagnose form of distribution

How to tell which discrete distributions are likely candidates?

- Ord (1967): for each of Poisson, Binomial, Negative binomial, and Logarithmic series distributions,
    - plot of kp_k/p_{k-1} against k is linear
    - signs of intercept and slope $\rightarrow$ determine the form, give rough estimates of parameters

Slope (b)	Intercept (a)	Distribution (parameter)	Parameter estimate
0	+	Poisson (λ)	$\lambda = a$
−	+	Binomial (n, p)	$p = b/(b-1)$
+	+	Neg. binomial (n,p)	$p = 1-b$
+	−	Log. series (θ)	$\theta = b$
			$\theta = -a$

- Fit line by WLS, using $\sqrt{n_k - 1}$ as weights
- A heuristic method: doesn't always work, but often a good start.

Butterfly data: The slope and intercept correctly diagnoses the log-series distribution

```
> Ord_plot(Butterfly,
        main = "Butterfly species collected in Malaya",
        gp=gpar(cex=1), pch=16)
```
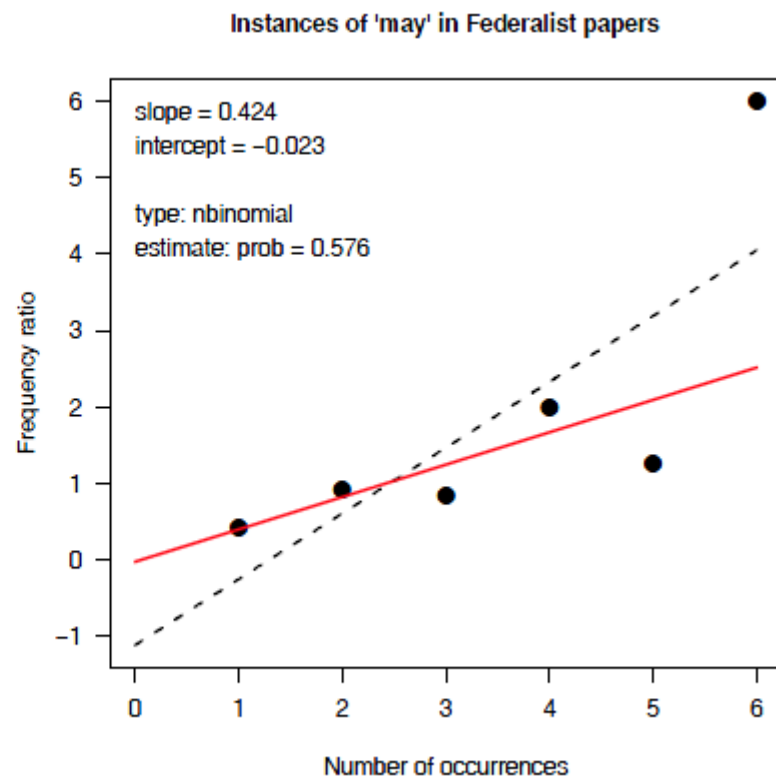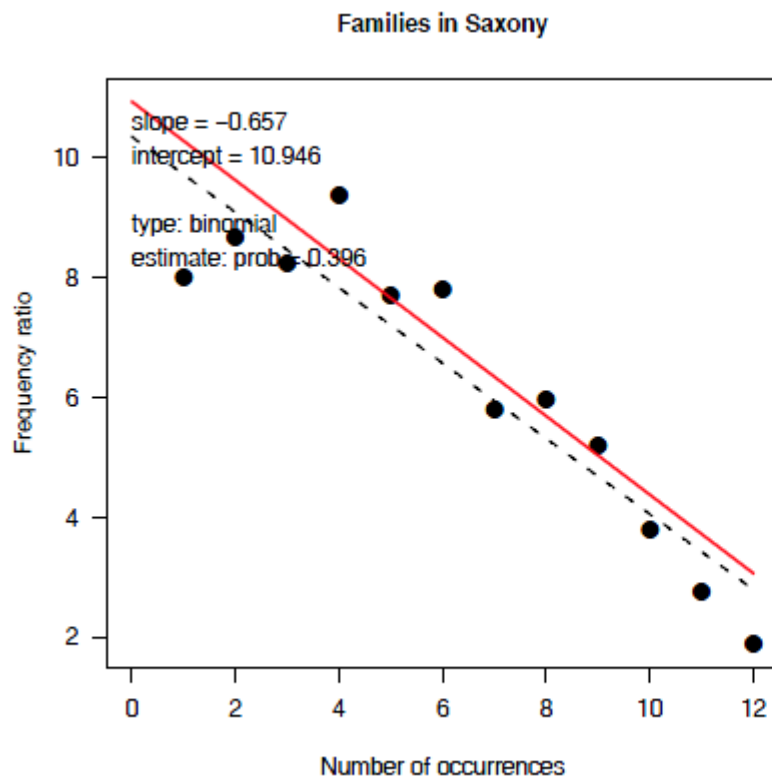
Butterfly species collected in Malaya

slope = 1.061
intercept = -0.709

type: log-series
estimate: theta = 1.061
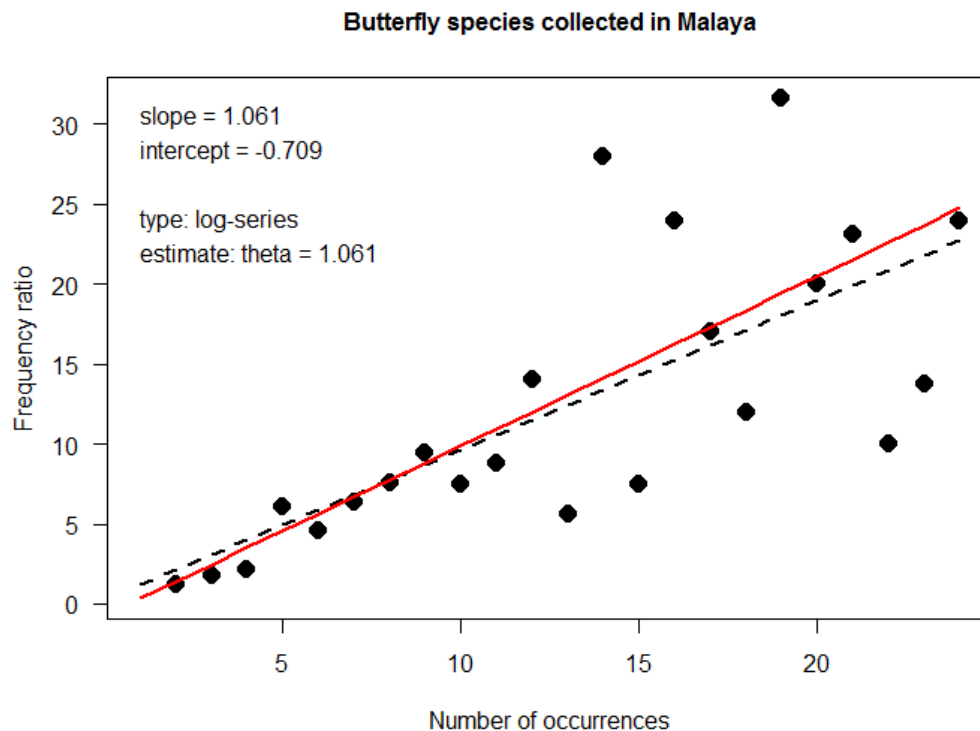
+ slope
- intercept
→ log-series

# Ord plots: Examples

Ord plots for the Saxony and Federalist data

> Ord_plot(Saxony, main = "Families in Saxony", gp=gpar(cex=1), pch=16)
> Ord_plot(Federalist, main = "Instances of 'may' in Federalist papers", gp=gpar(cex=1), pch=16)

Robust distribution plots

- Ord plots lack robustness
  - one discrepant freqency, n_k affects points for both k and $k + 1$
  - the use of WLS to fit the line is a small attempt to minimize this
- Robust plots for Poisson distribution (Hoaglin and Tukey, 1985)
  - For Poisson, plot **count metameter** $= \phi(n_k) = \log_e(k!\, n_k/N)$ vs. k
  - Linear relation $\Rightarrow$ Poisson, slope gives $\hat{\lambda}$
  - CI for points, diagnostic (influence) plot
  - Implemented in `distplot()` in the vcd package

For the Poisson distribution, this is called a "poissonness plot"

Poissoness plot

slope = 0.228
intercept = -1.53

lambda : ML = 0.656
exp(slope) = 1.256

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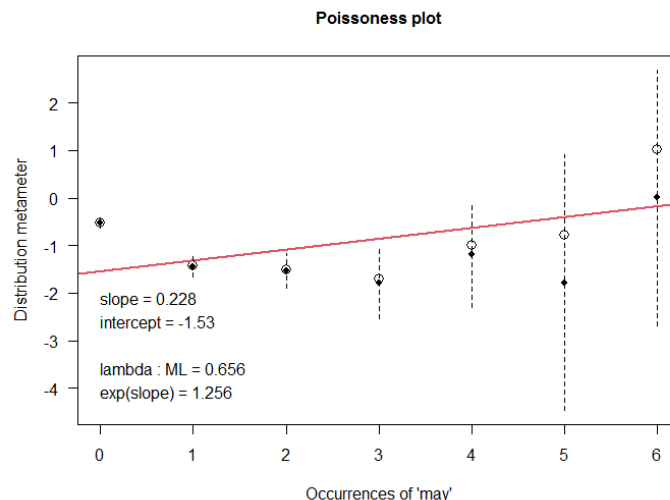
Poissonness plot: Details

- If the distribution of n_k is Poisson(λ) for some fixed λ, then each observed frequency, $n_k \approx m_k = Np_k$.

- Then, setting $n_k = Np_k = e^{-\lambda} \lambda^k / k!$, and taking logs of both sides gives

$$\log(n_k) = \log N - \lambda + k \log \lambda - \log k!$$

which can be rearranged to

$$\phi(n_k) \equiv \log\left(\frac{k! \, n_k}{N}\right) = \boxed{-\lambda + (\log \lambda) \, k}$$

- $\Rightarrow$ if the distribution is Poisson, plotting $\phi(n_k)$ vs. k should give a line with
  - intercept $= -\lambda$
  - slope $= \log \lambda$

- Nonlinear relation $\rightarrow$ distribution is *not* Poisson

- Hoaglin and Tukey (1985) give details on calculation of confidence intervals and influence measures.
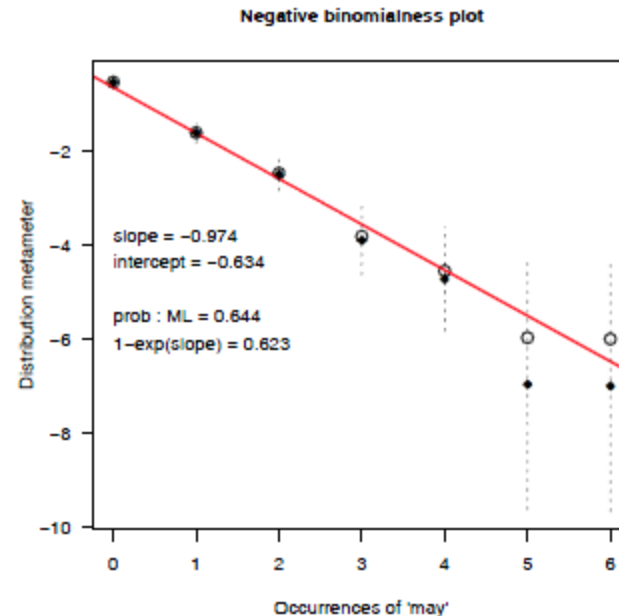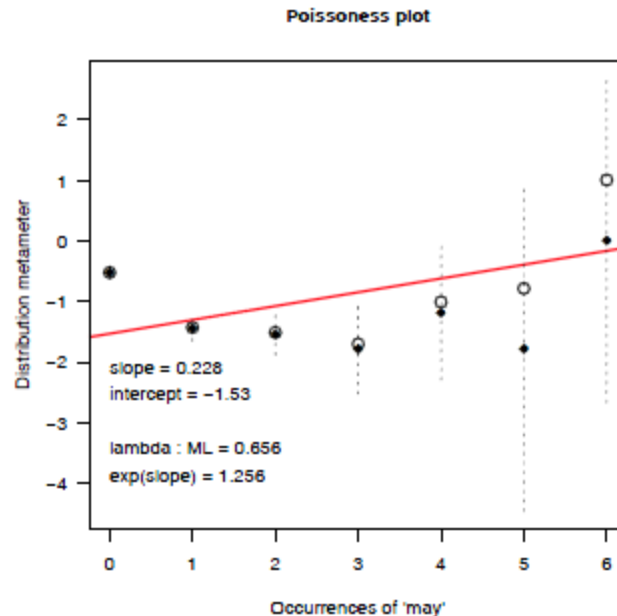
Other distributions

This idea extends readily to other discrete data distributions:

- The binomial, Poisson, negative binomial, geometric and logseries distributions are all members of a general power series family of discrete distributions. See: *DDAR*, Table 3.10 for details.

- This allows all of these to be represented in a plot of a suitable count metameter, $\phi(n_k)$ vs. k. See: *DDAR*, Table 3.12 for details.

- In these plots, a straight line confirms that the data follow the given distribution.

- Confidence intervals around the points indicate uncertainty for the count metameter.

- The slope and intercept of the line give estimates of the distribution parameters.

distplot: Federalist

Try both Poisson & Negative binomial

```
distplot(Federalist, type="poisson", xlab="Occurrences of 'may'")
distplot(Federalist, type="nbinomial", xlab="Occurrences of 'may'")
```


Poissoness plot

slope = 0.228
intercept = −1.53

lambda : ML = 0.656
exp(slope) = 1.256

Negative binomialness plot

slope = −0.974
intercept = −0.634

prob : ML = 0.644
1−exp(slope) = 0.623

Again, the Poisson distribution is seen not to fit, while the Negative binomial appears reasonable.

distplot: Saxony

For purported binomial distributions, the result is a "binomialness" plot

```
plot(goodfit(Saxony, type="binomial", par=list(size=12)))
distplot(Saxony, type="binomial", size=12, xlab="Number of males")
```
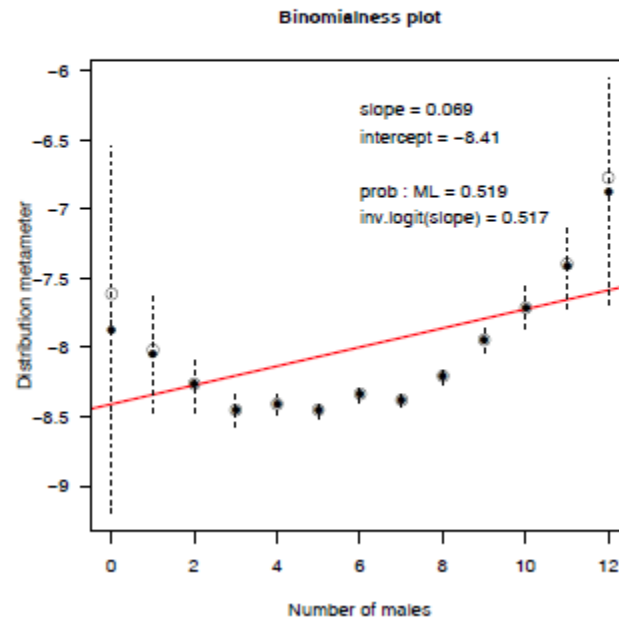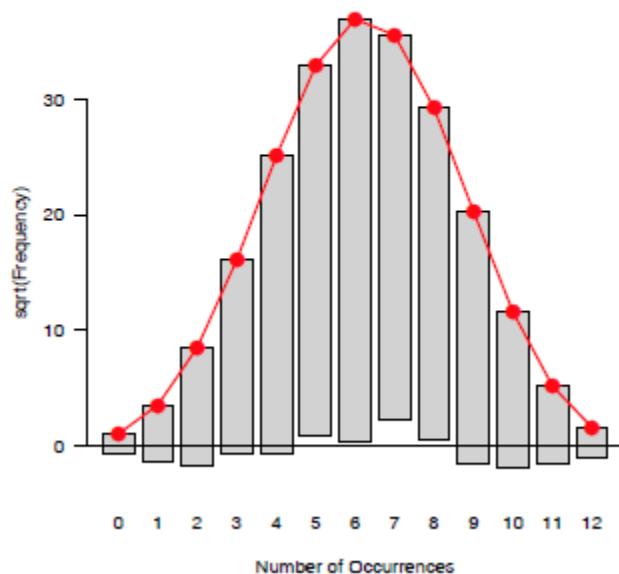

Both plots show heavier tails than the binomial distribution. distplot() is more sensitive in diagnosing this

What have we learned?

Main points:

- Discrete distributions involve basic *counts* of occurrences of some event occurring with varying *frequency*.

- The ideas and methods for one-way tables are building blocks for analysis of more complex data.

- Commonly used discrete distributions include the binomial, Poisson, negative binomial, and logarithmic series distributions, all members of a *power series* family.

- Fitting observed data to a distribution $\rightarrow$ fitted frequencies, $N\hat{p}_k$, $\rightarrow$ goodness-of-fit tests (Pearson X^2, LR G^2)

- R: `goodfit()` provides `print()`, `summary()` and `plot()` methods.
- Plotting with rootograms, Ord plots and generalized distribution plots can reveal *how* or *where* a distribution does not fit.

What have we learned?

Some explantions:

- The Saxony data were part of a much larger data set from Geissler (1889) (`Geissler` in `vcdExtra`).
  - For the binomial, with families of size $n = 12$, our analyses give $\hat{p} = \Pr(male) = 0.52$.
  - Other analyses (using more complex models) conclude that p varies among families with the same size.
  - One explanation is that family decisions to have another child are influenced by the boy–girl ratio in earlier children.

- As suggested earlier, the lack of fit of the Poisson distribution for words in the Federalist papers can be explained by *context* of the writing:
  - Given "marker" words appear more or less often over time and subject than predicted by constant rates (λ) for a given author (Madison or Hamilton)
  - The negative binomial distribution fit much better.
  - The estimated parameters for these texts allowed assigning all 12 disputed papers to Madison.

Looking ahead: PhdPubs data

Example 3.24 in DDAR gives data on the number of publications by PhD candidates in the last 3 years of study

```
data("PhdPubs", package = "vcdExtra")
table(PhdPubs$articles)

##
##    0    1    2    3    4    5    6    7    8    9   10   11   12   16   19
##  275  246  178   84   67   27   17   12    1    2    1    1    2    1    1
```
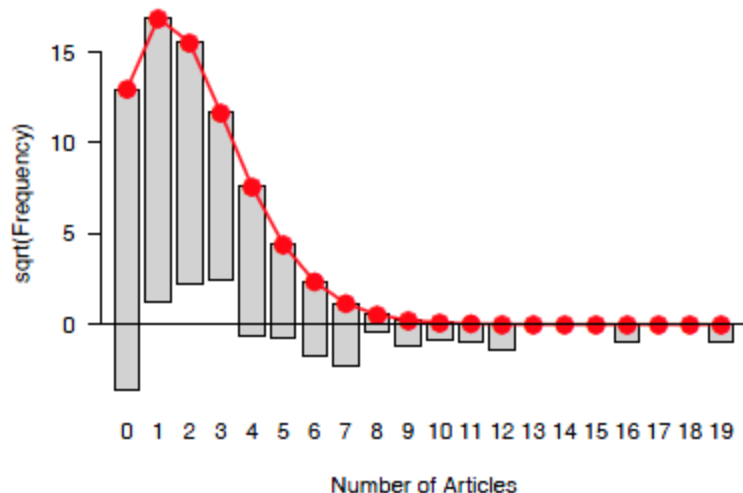
- There are predictors: gender, marital status, number of children, prestige of dept., # pubs by student's mentor
- We fit such models with glm(), but need to specify the form of the distribution
- Ignoring the predictors for now, a baseline model could be

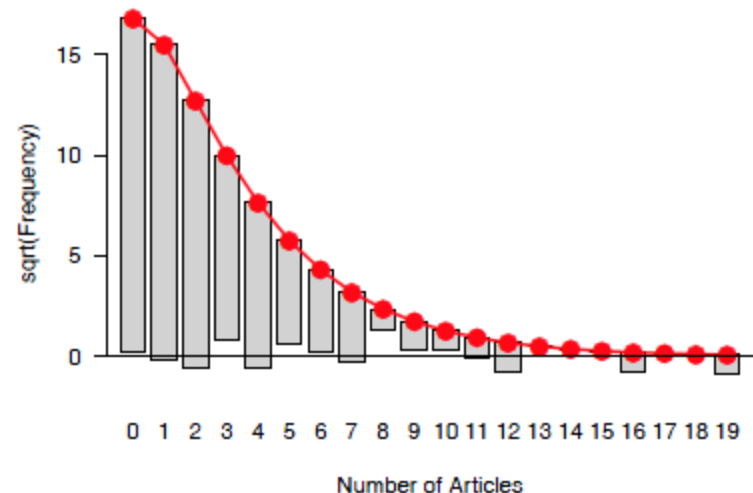   glm(articles ~ 1, data=PhdPubs, family = "poisson")

Looking ahead: PhdPubs

```
plot(goodfit(PhdPubs$articles), xlab = "Number of Articles",
     main = "Poisson")
plot(goodfit(PhdPubs$articles, type = "nbinomial"),
     xlab = "Number of Articles", main = "Negative binomial")
```


Poisson doesn't fit: Need to account for excess 0s (some never published)
Neg binomial: Sort of OK, but should take predictors into account

Looking ahead: Count data models

Count data regression models (DDAR Ch 11)
- Include predictors
- Allow different distributions for unexplained variation
- Provide tests of one model vs. another
- Special models handle the problems of excess zeros: zeroinlf(), hurdle()

```
# predictors: female, married, kid5, phdprestige, mentor
phd.pois  <- glm(articles ~ ., data=PhdPubs, family=poisson)
phd.nbin  <- glm.nb(articles ~ ., data=PhdPubs)

LRstats(phd.pois, phd.nbin)

## Likelihood summary table:
##            AIC   BIC LR Chisq  Df Pr(>Chisq)
## phd.pois 3313  3342     1634  909     <2e-16 ***
## phd.nbin 3135  3169     1004  909      0.015 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Effect plots show the predicted values for each term in a model, averaging over all other factors.
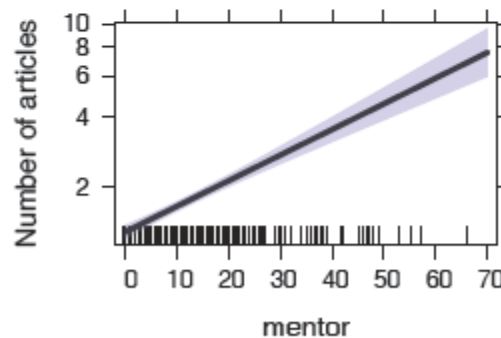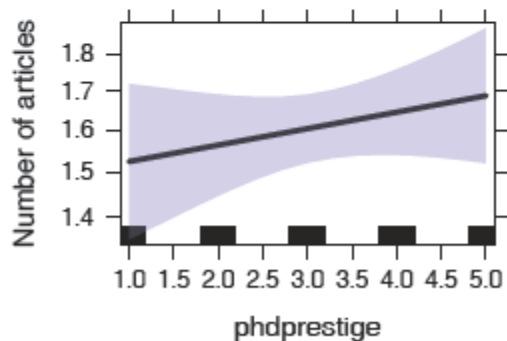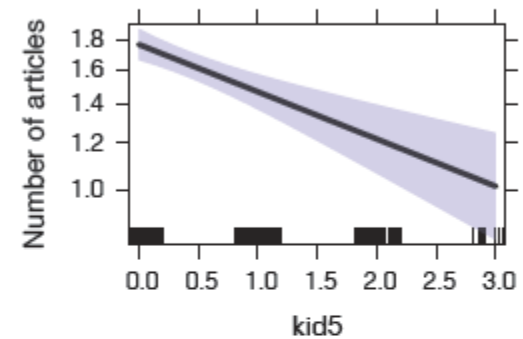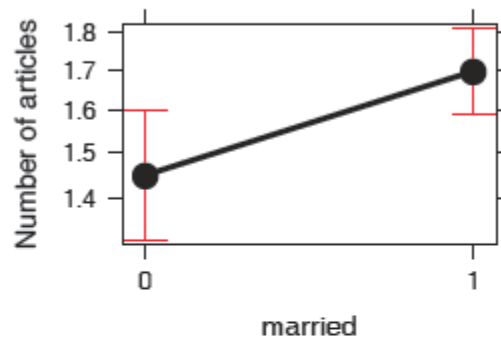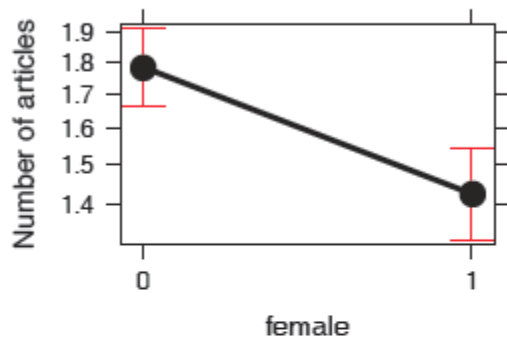
These are better visual summaries for a model than a table of coefficients.

Summary

- Discrete distributions are the building blocks for categorical data analysis
  - Typically consist of basic counts of occurrences, with varying frequencies
  - Most common: binomial, Poisson, negative binomial
  - Others: geometric, log-series
- Fit with goodfit(); plot with rootogram()
  - Diagnostic plots: Ord_plot(), distplot()
- Models with predictors
  - Binomial $\rightarrow$ logistic regression
  - Poisson $\rightarrow$ poisson regression; logliner models
  - These are special cases of generalized linear models