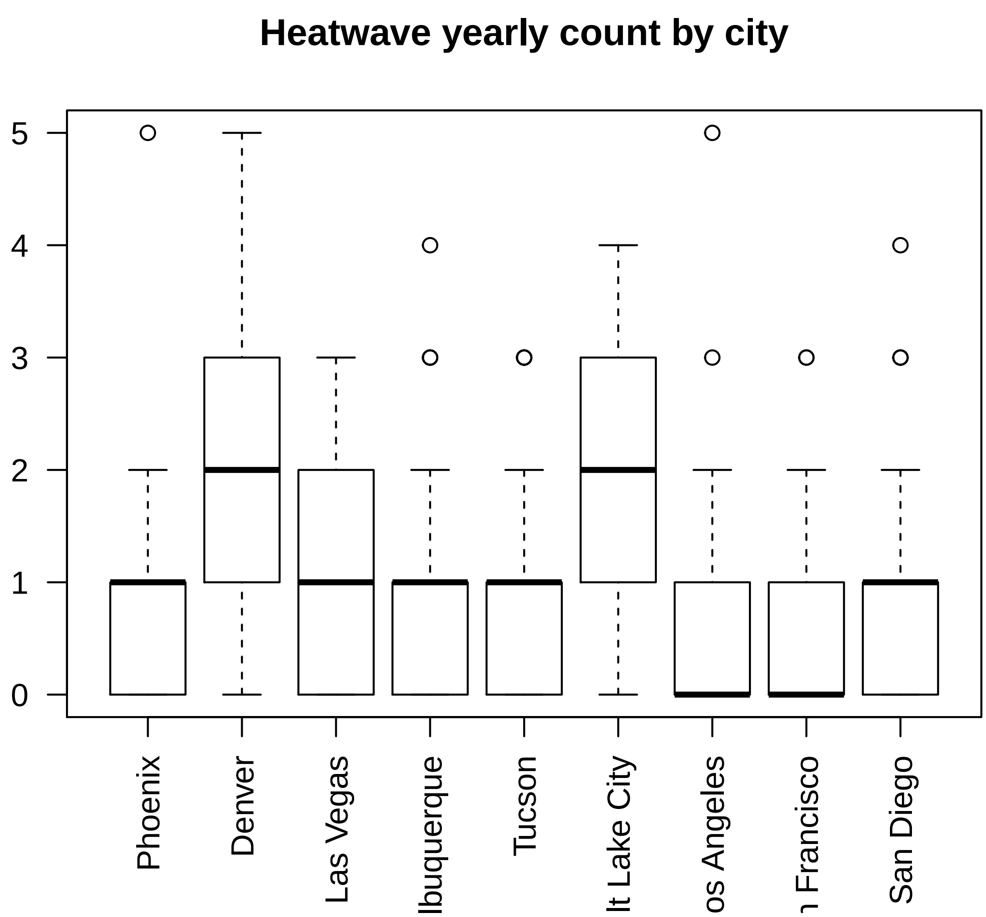
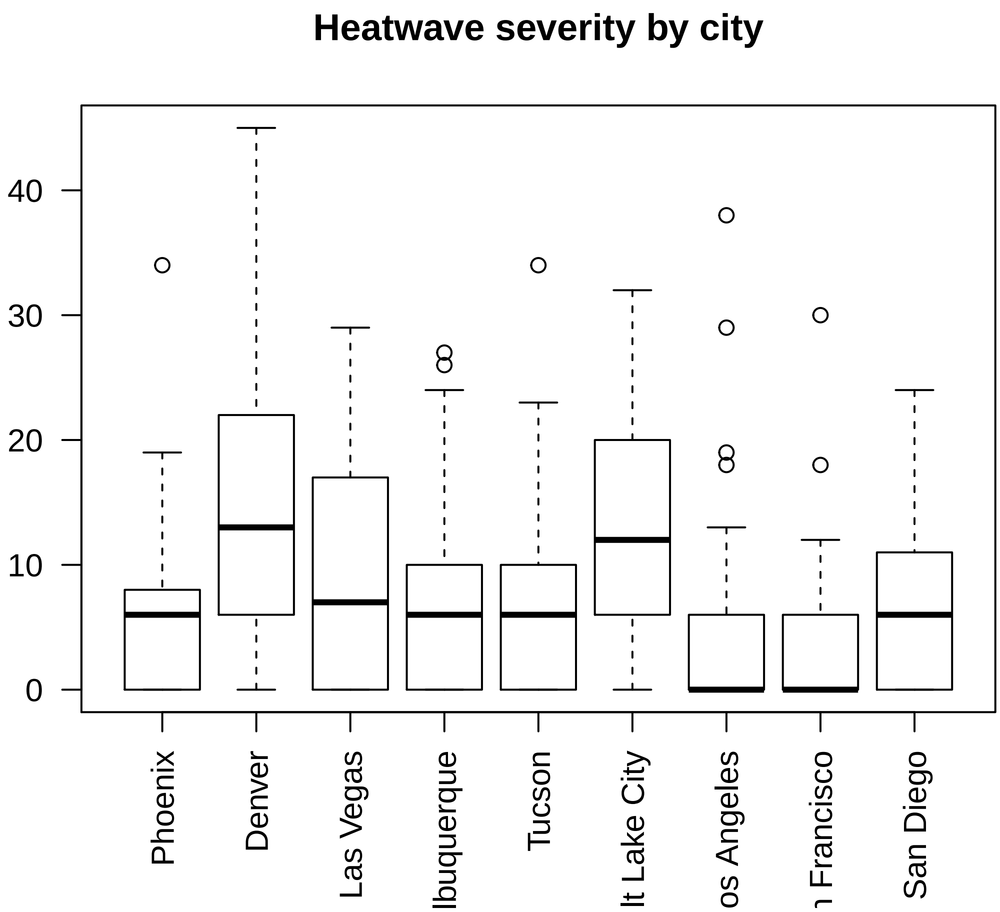
E3

```
rm(list = ls())
library(rjags)
library(coda)
library(pander)
setwd("c:/e/brucebcampbell-git/bayesian-learning-with-R/E3")
load("heatwaves.RData")
n.chains = 2
n.thin = 2
nSamples = 10000
load("HWD2.RData")

df <- data.frame(X.num)
colnames(df) <- city_names
boxplot(df, las = 2, main = "Heatwave yearly count by city")
```



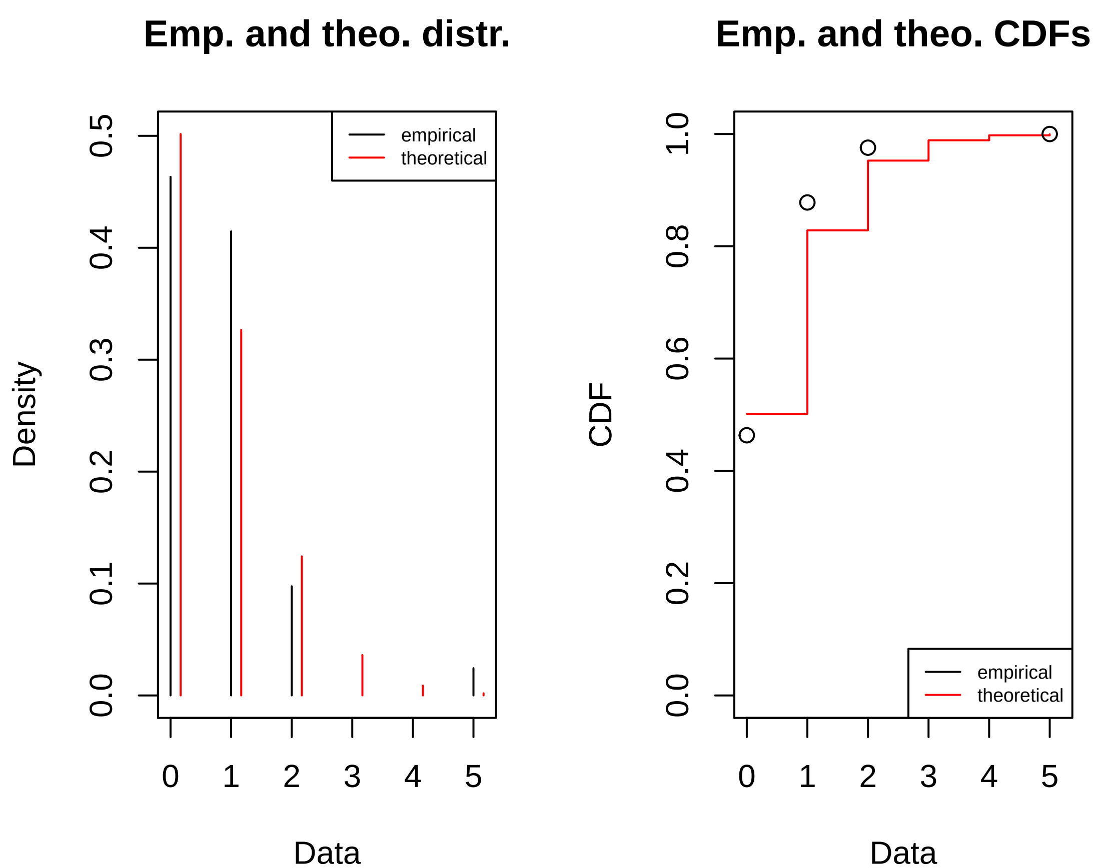

```
df <- data.frame(X.sev)
colnames(df) <- city_names
boxplot(df, las = 2, main = "Heatwave severity by city")
```

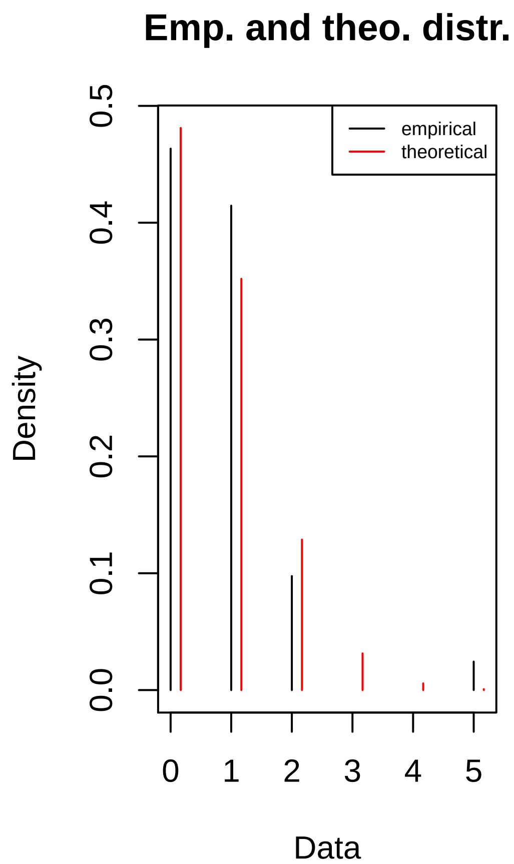


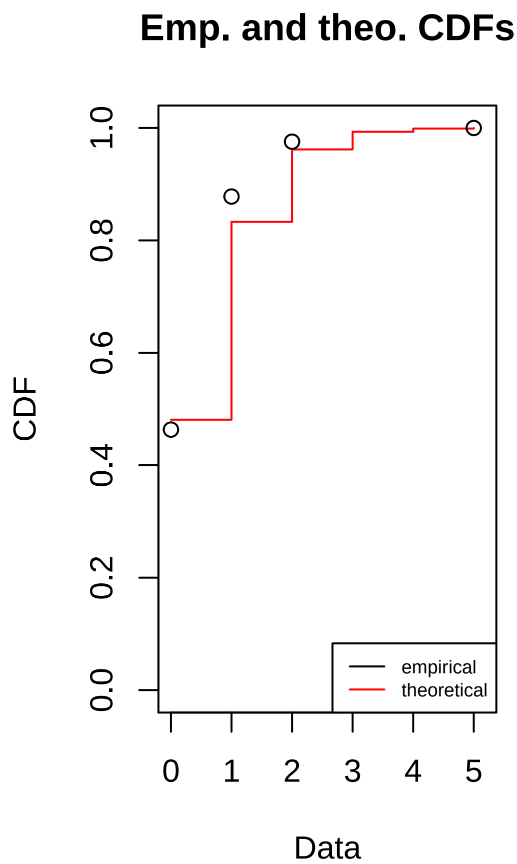

```
################################### Find MLE of fit to pois and negbinom,
################################### and fit glm's with time as predictor
mle.nb.params <- matrix(nrow = 9, ncol = 2)
mle.pois.params <- matrix(nrow = 9, ncol = 1)

mle.nb.glm.params <- matrix(nrow = 9, ncol = 8)
mle.pois.glm.params <- matrix(nrow = 9,
    ncol = 8)
library(fitdistrplus)
library(gamlss)

for (k in 1:9) {
    print(city_names[k])
    fit_nb <- fitdist(X.num[, k], "nbinom",
        start = list(mu = 3, size = 0.1))
    plot(fit_nb)
    # gofstat(fit_nb)

    mle.nb.params[k, 1] <- fit_nb$estimate[1]
    mle.nb.params[k, 2] <- fit_nb$estimate[2]

    fit_pois <- fitdist(X.num[, k], "pois",
        method = "mle")
```

```
    mle.pois.params[k, 1] <- fit_pois$estimate[1]
    plot(fit_pois)
    # gofstat(fit_pois)
}
```

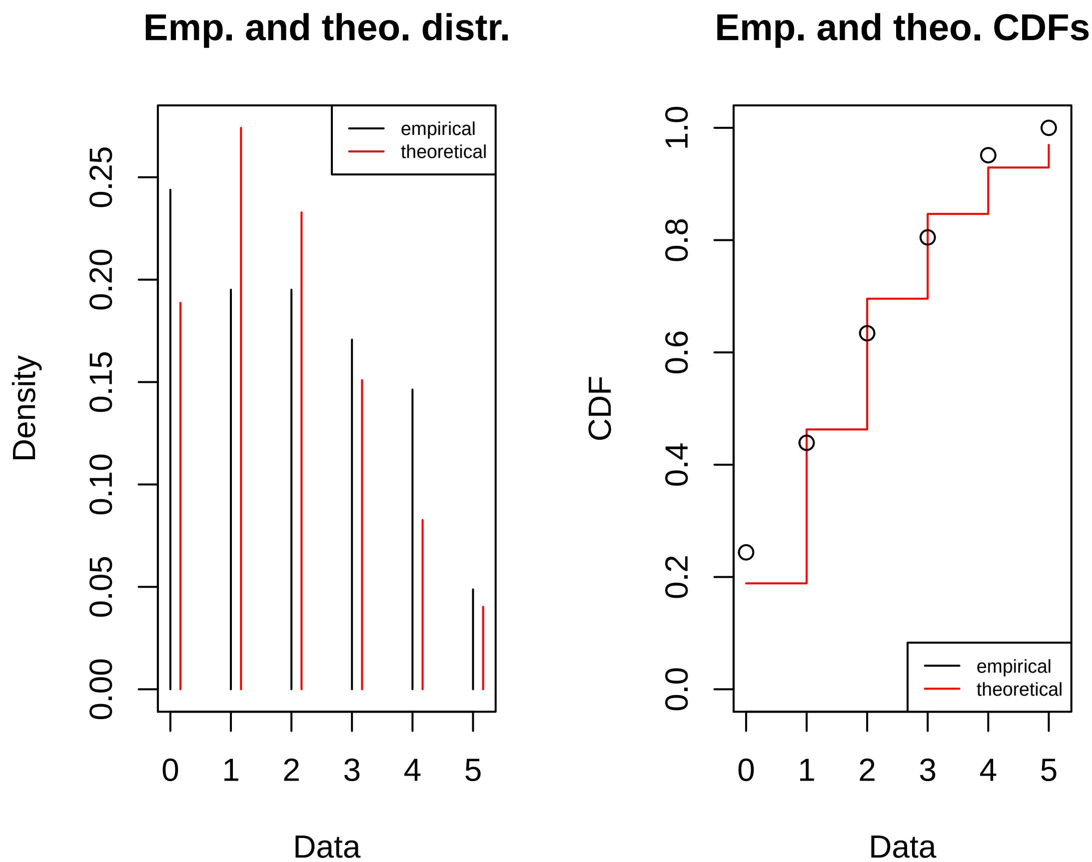
```
##      city
## "Phoenix"
```




Emp. and theo. distr.
empirical
theoretical
Density
0.0
0.1
0.2
0.3
0.4
0.5
0
1
2
3
4
5
Data


Emp. and theo. CDFs
empirical
theoretical
CDF
0.0
0.2
0.4
0.6
0.8
1.0
0
1
2
3
4
5
Data

```
##
## "Denver"
```


Emp. and theo. distr.
Density
Data
empirical
theoretical
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0.15
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0.25
0
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4
5
Emp. and theo. CDFs
CDF
Data
empirical
theoretical
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0.2
0.4
0.6
0.8
1.0
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1
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3
4
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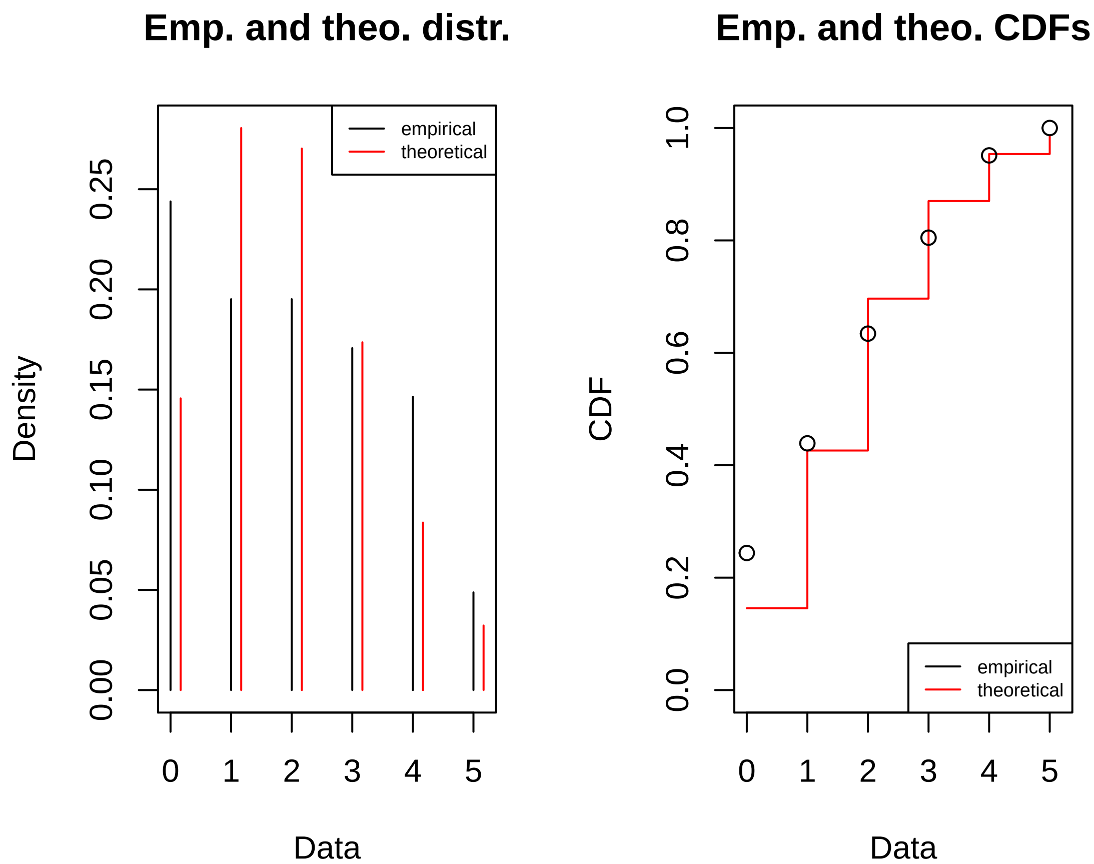

Emp. and theo. distr.
empirical
theoretical
Density
0.00
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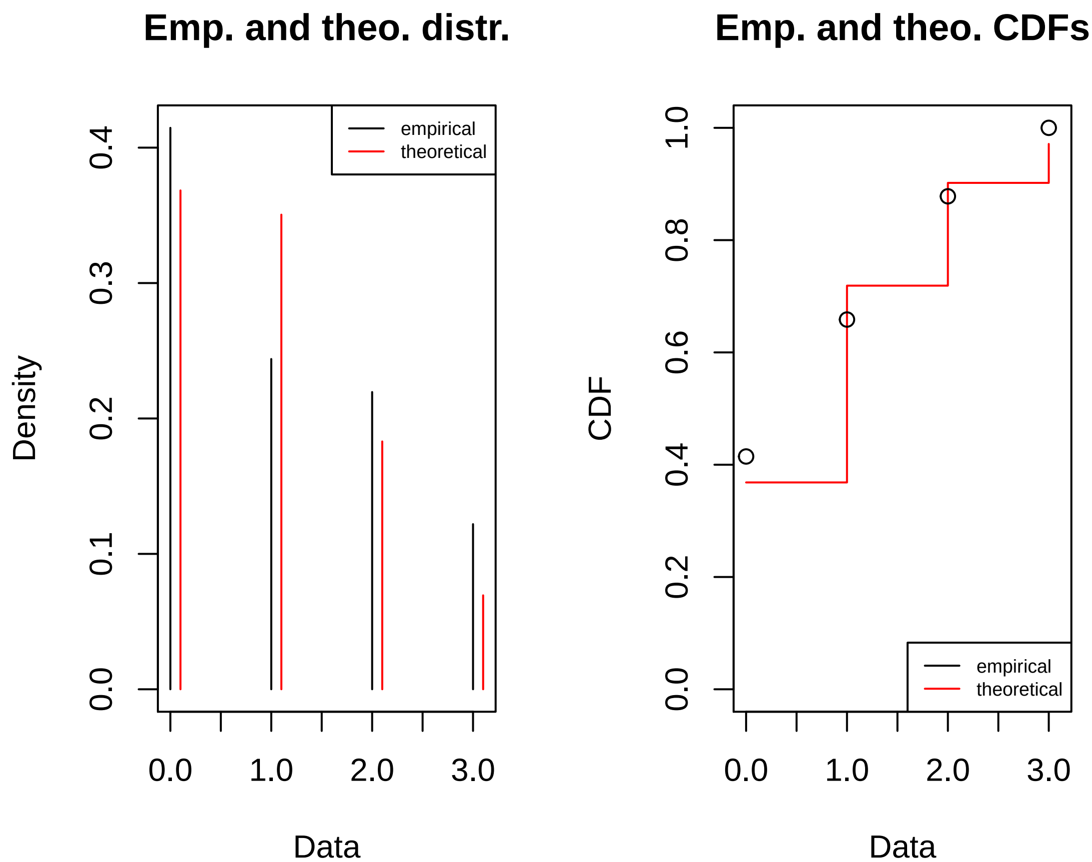
0.10
0.15
0.20
0.25
0 1 2 3 4 5
Data
Emp. and theo. CDFs
CDF
0.0
0.2
0.4
0.6
0.8
1.0
empirical
theoretical
0 1 2 3 4 5
Data


```
##
## "Las Vegas"
```


Emp. and theo. distr.
empirical
theoretical
Density
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0.2
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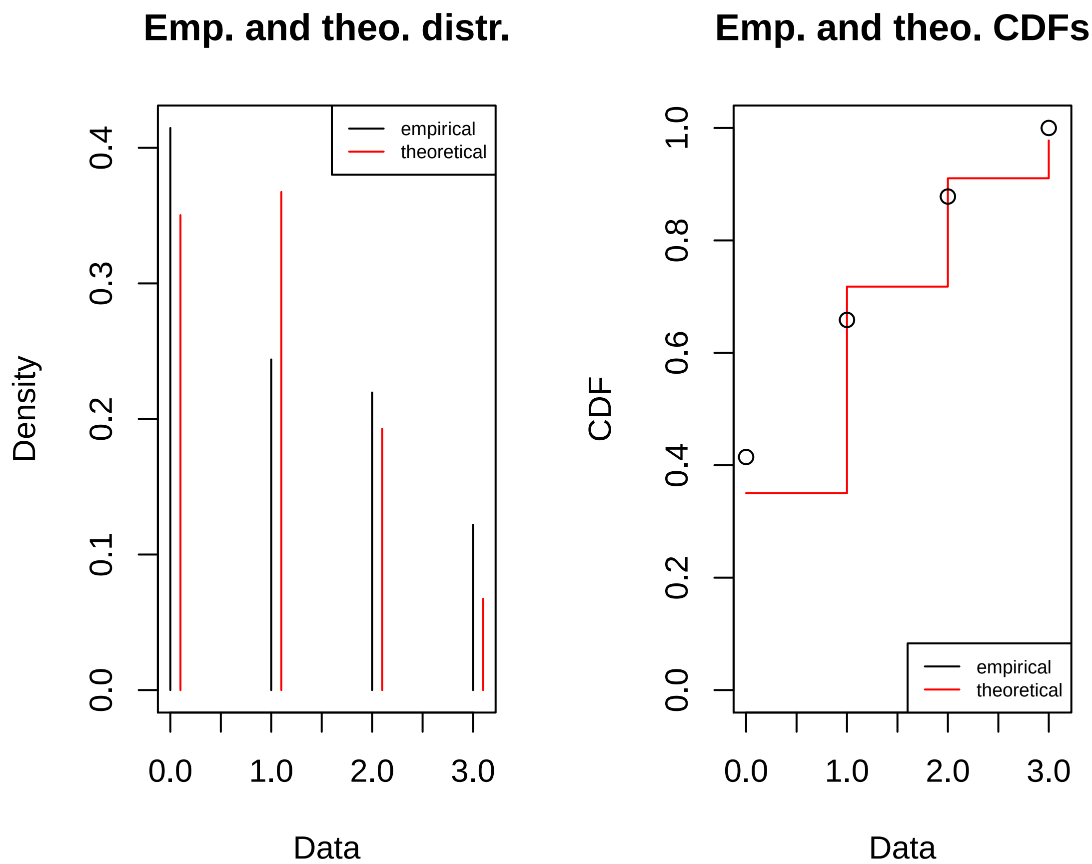
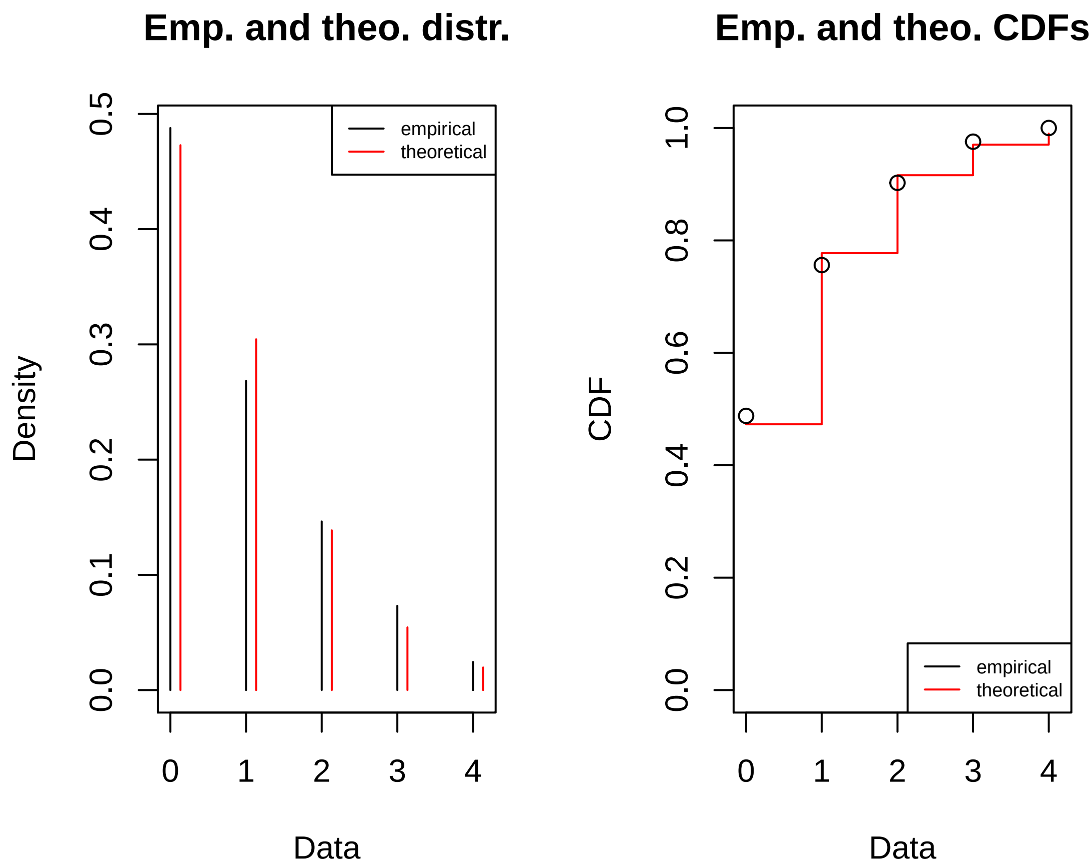
Data
Emp. and theo. CDFs
CDF
0.0
0.2
0.4
0.6
0.8
1.0
empirical
theoretical
0.0
1.0
2.0
3.0
Data




```
##
## "Albuquerque"
```


Emp. and theo. distr.
Density
Data
empirical
theoretical
0.0
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0.3
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4
Emp. and theo. CDFs
CDF
Data
empirical
theoretical
0.0
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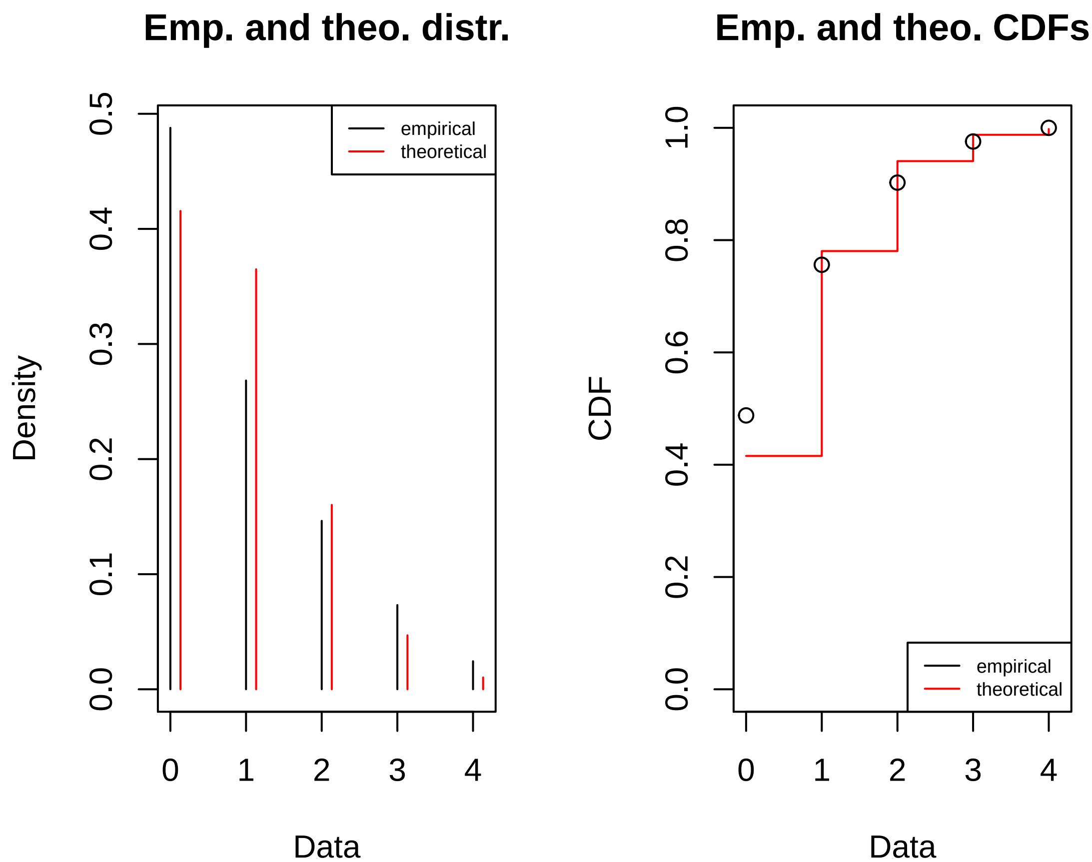
Emp. and theo. distr.
Density
0.0
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0.5
empirical
theoretical
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Data
Emp. and theo. CDFs
CDF
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0.2
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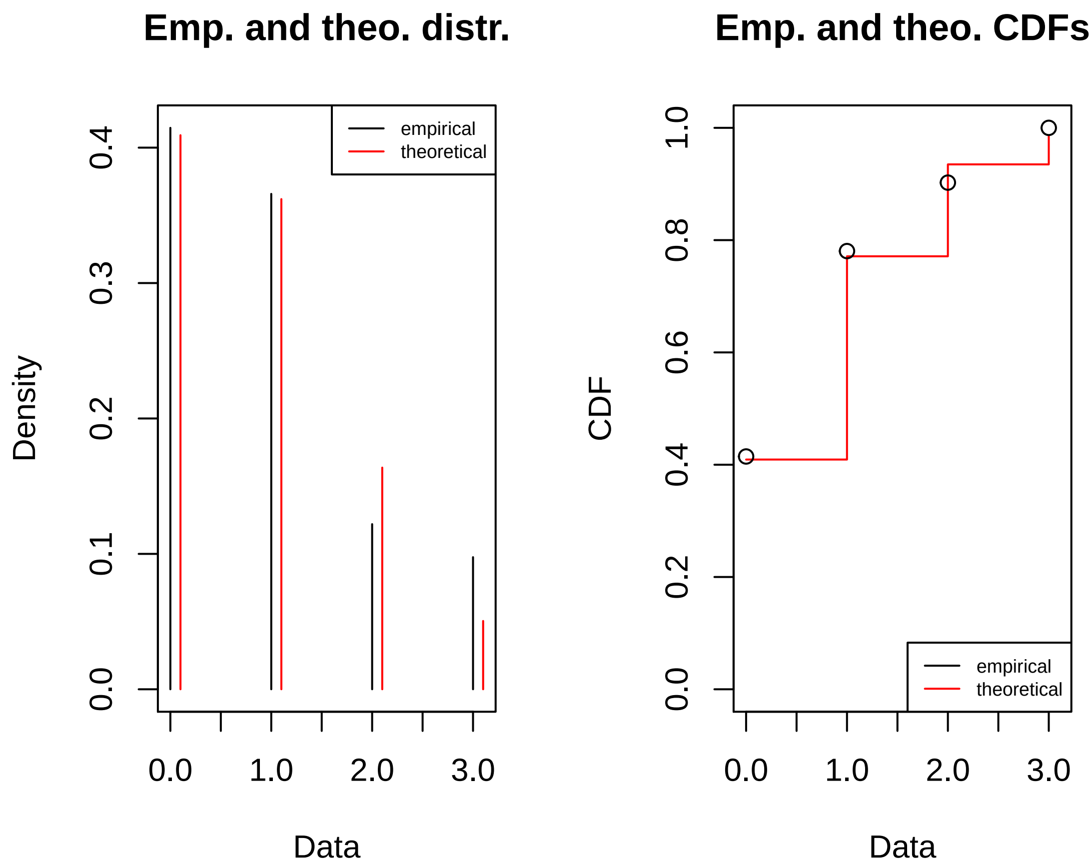
0.6
0.8
1.0
empirical
theoretical
0
1
2
3
4
Data

```
##
## "Tucson"
```


Emp. and theo. distr.
empirical
theoretical
Density
0.0
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Data
Emp. and theo. CDFs
CDF
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theoretical
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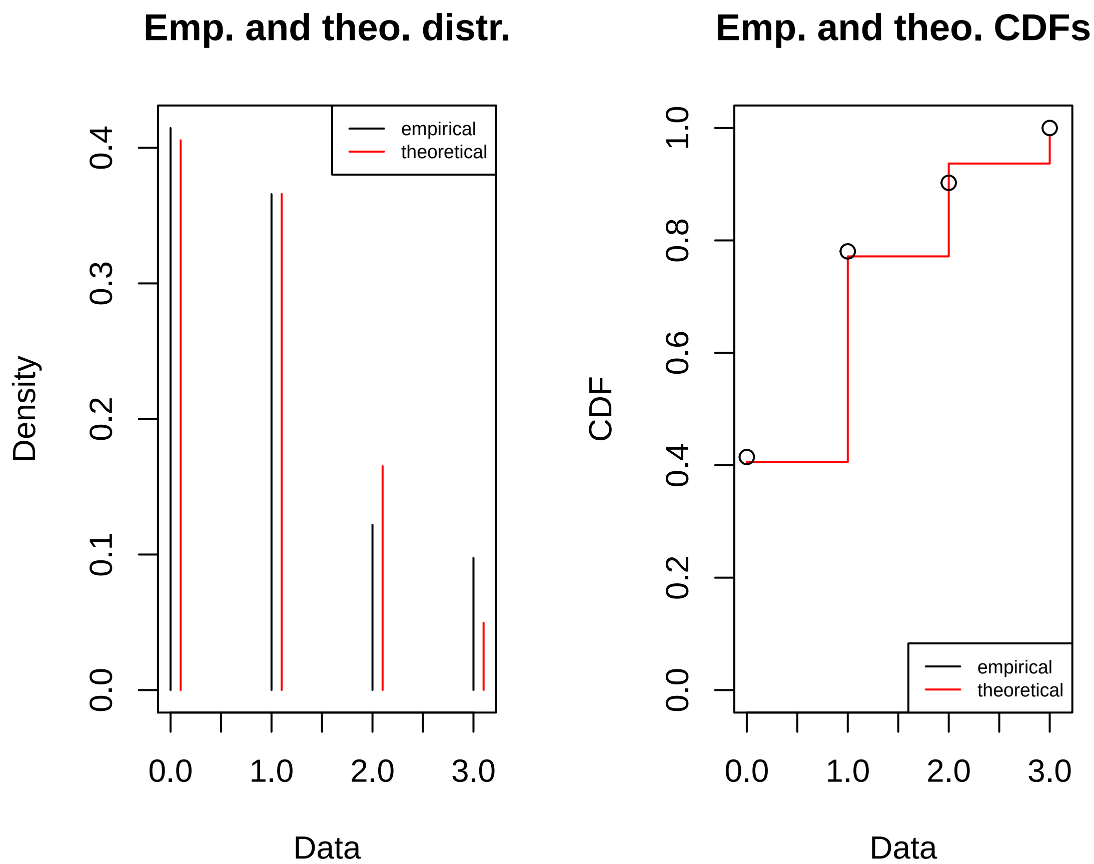
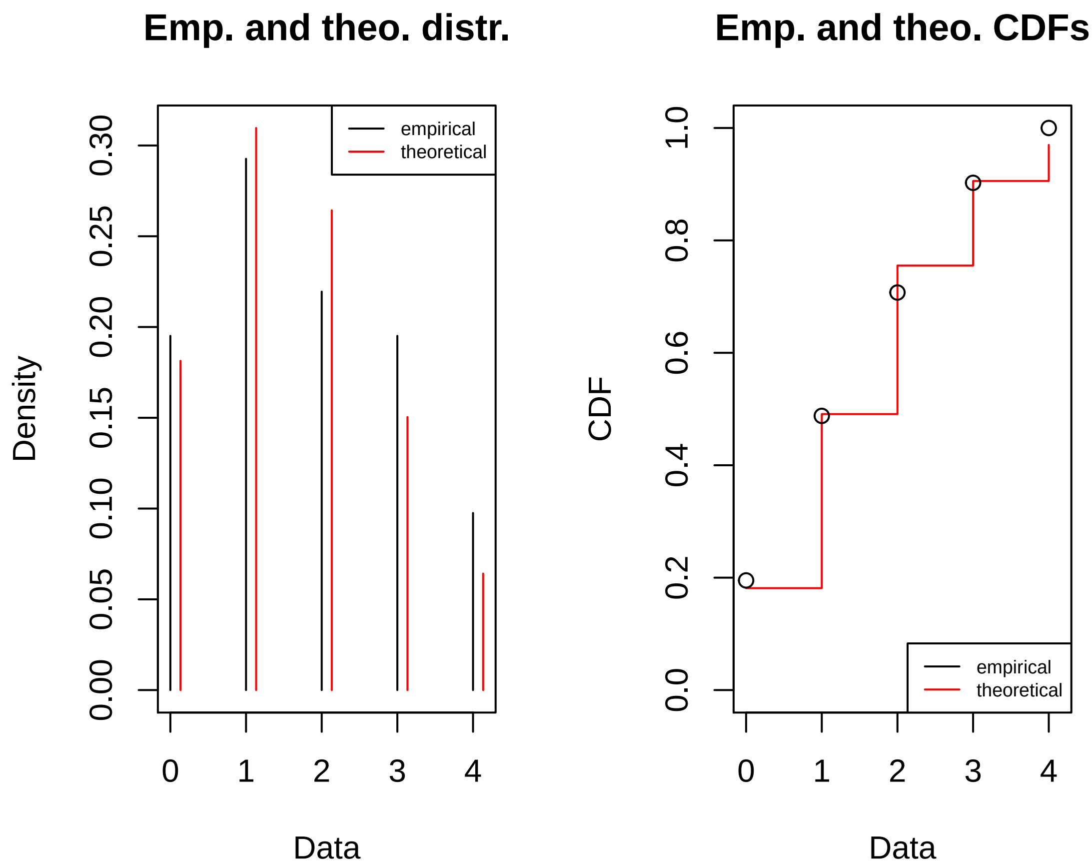
Data




```
##
## "Salt Lake City"
```


Emp. and theo. distr.
empirical
theoretical
Density
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Data
Emp. and theo. CDFs
CDF
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0.2
0.4
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0.8
1.0
empirical
theoretical
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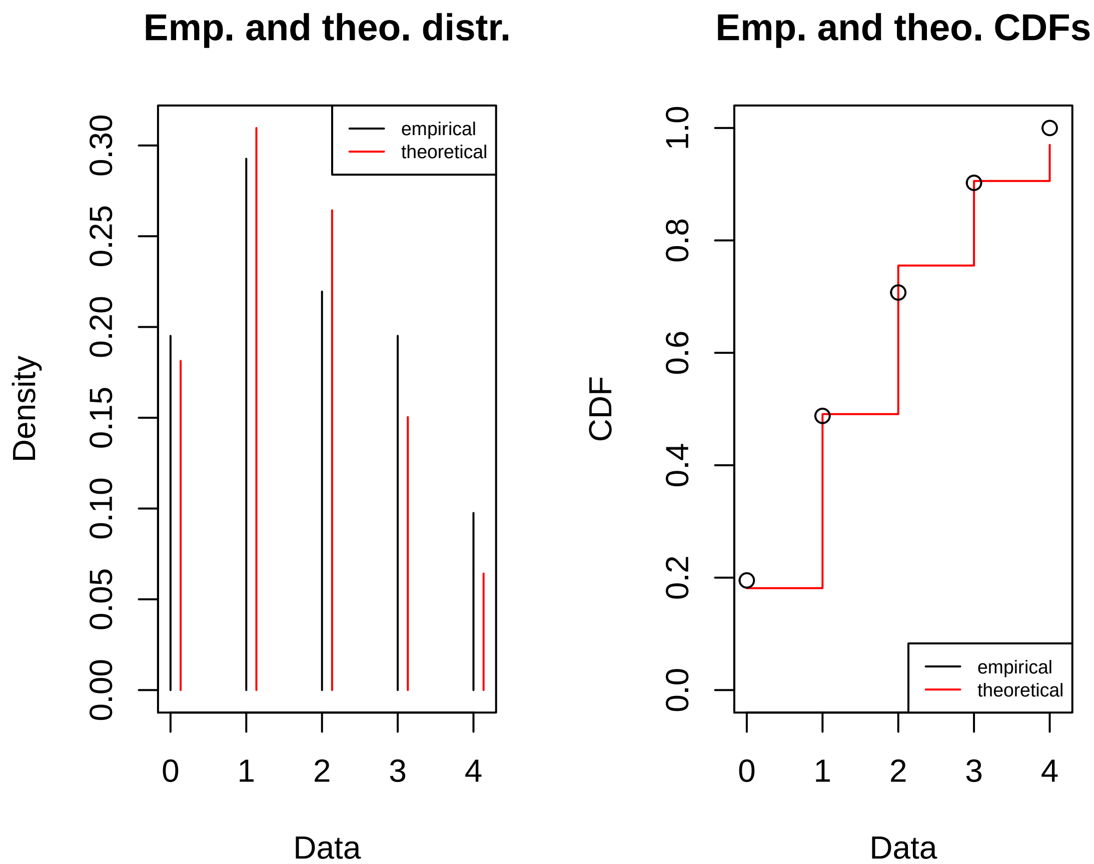
Data


Emp. and theo. distr.
Density
0.00
0.05
0.10
0.15
0.20
0.25
0.30
empirical
theoretical
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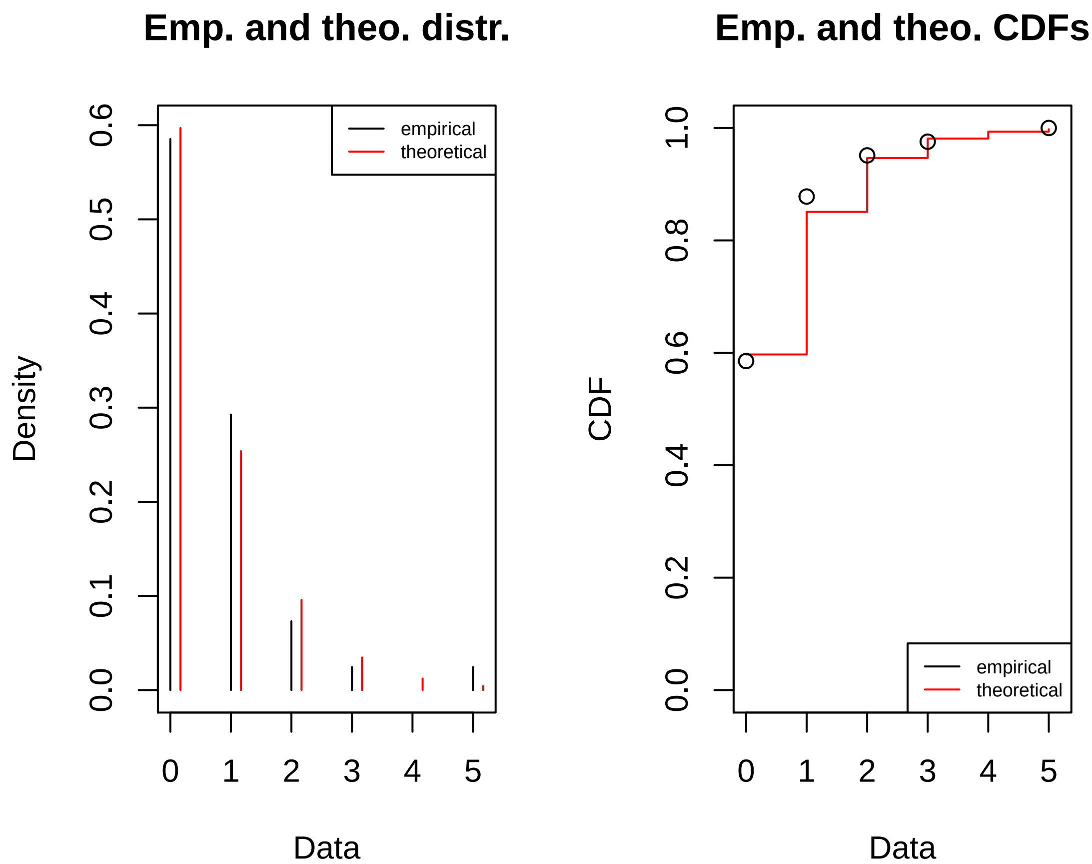
4
Data
Emp. and theo. CDFs
CDF
0.0
0.2
0.4
0.6
0.8
1.0
empirical
theoretical
0
1
2
3
4
Data

```
##
## "Los Angeles"
```


Emp. and theo. distr.
Density
Data
empirical
theoretical
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5
Emp. and theo. CDFs
CDF
Data
empirical
theoretical
0.0
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0.4
0.6
0.8
1.0
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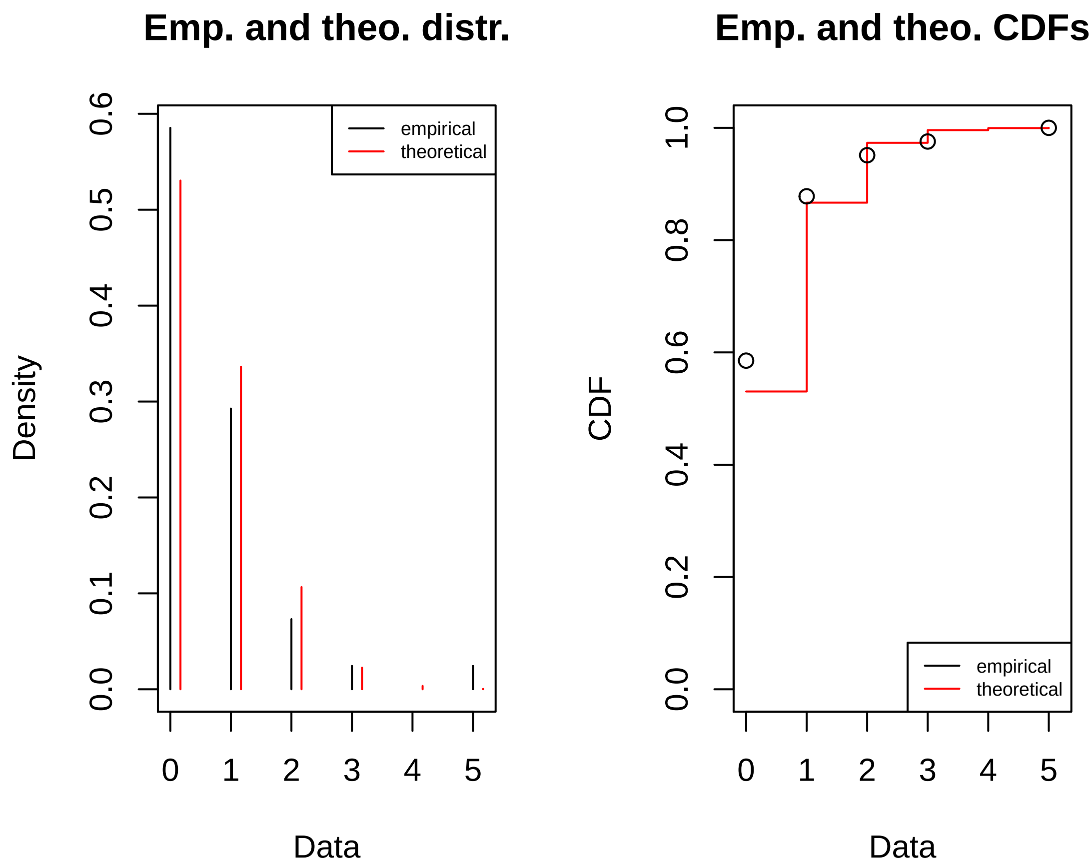
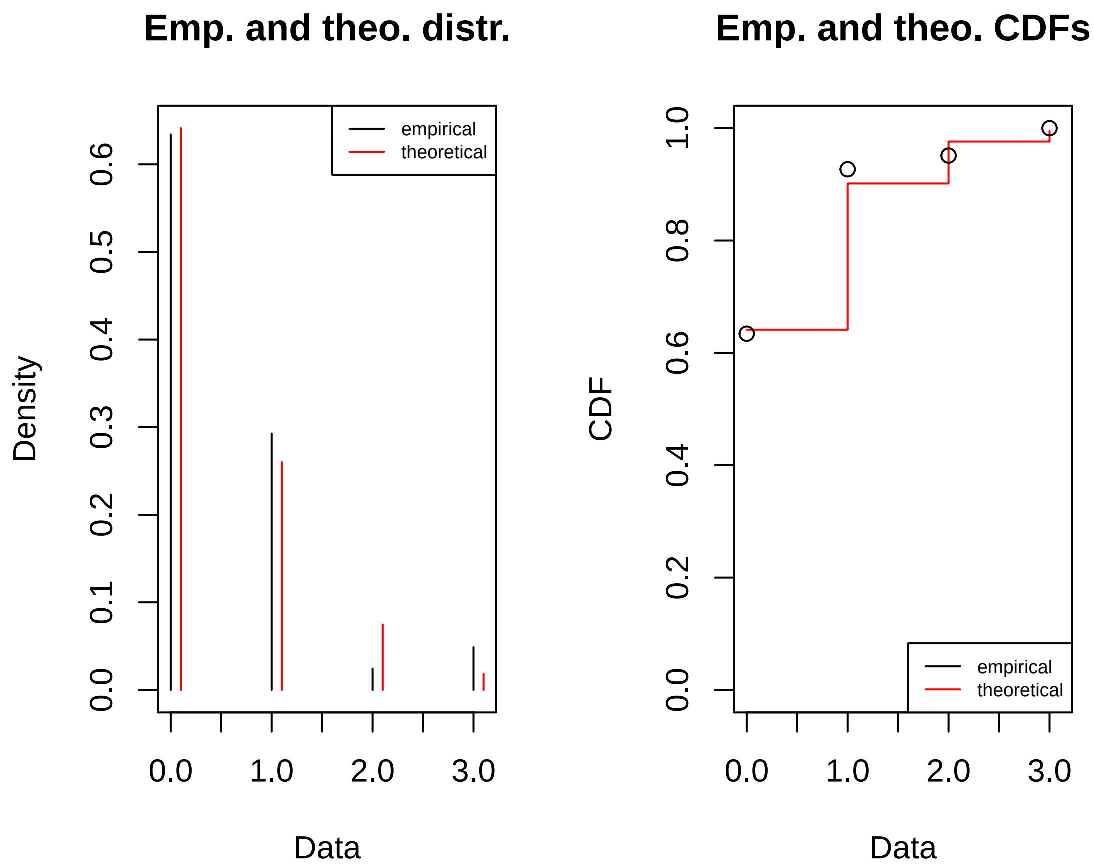
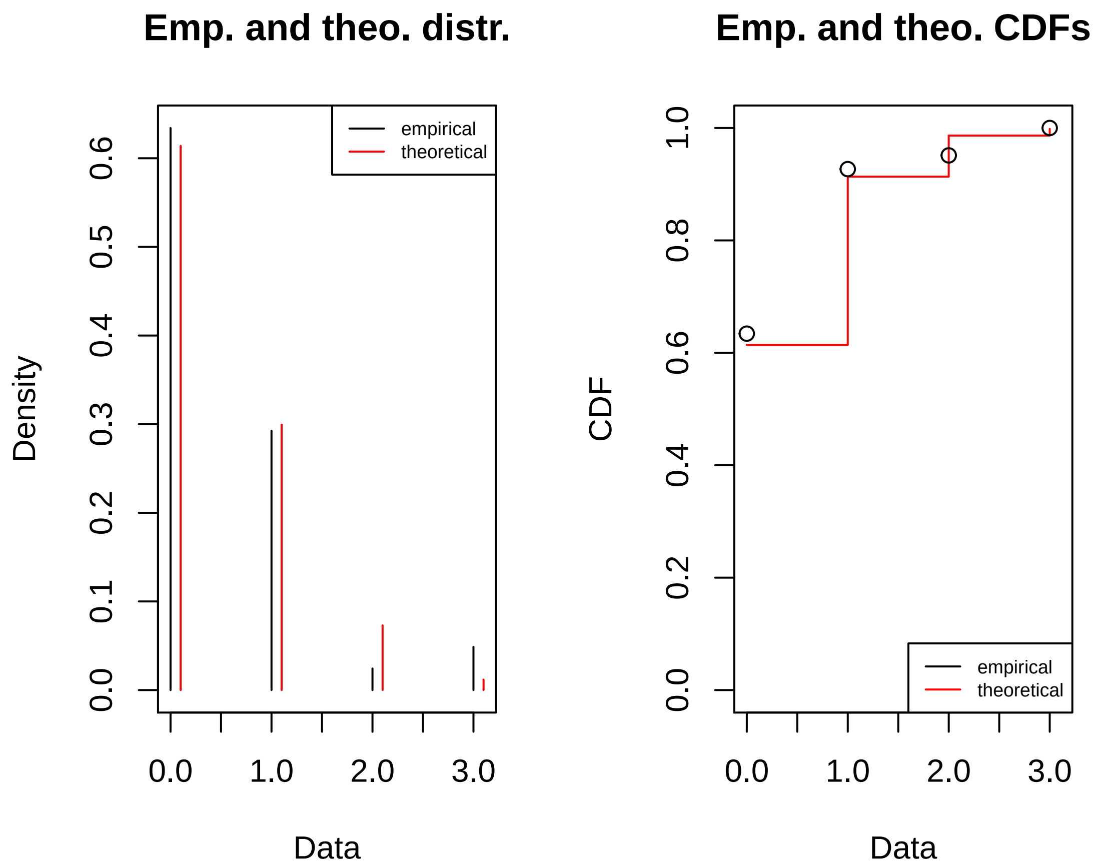
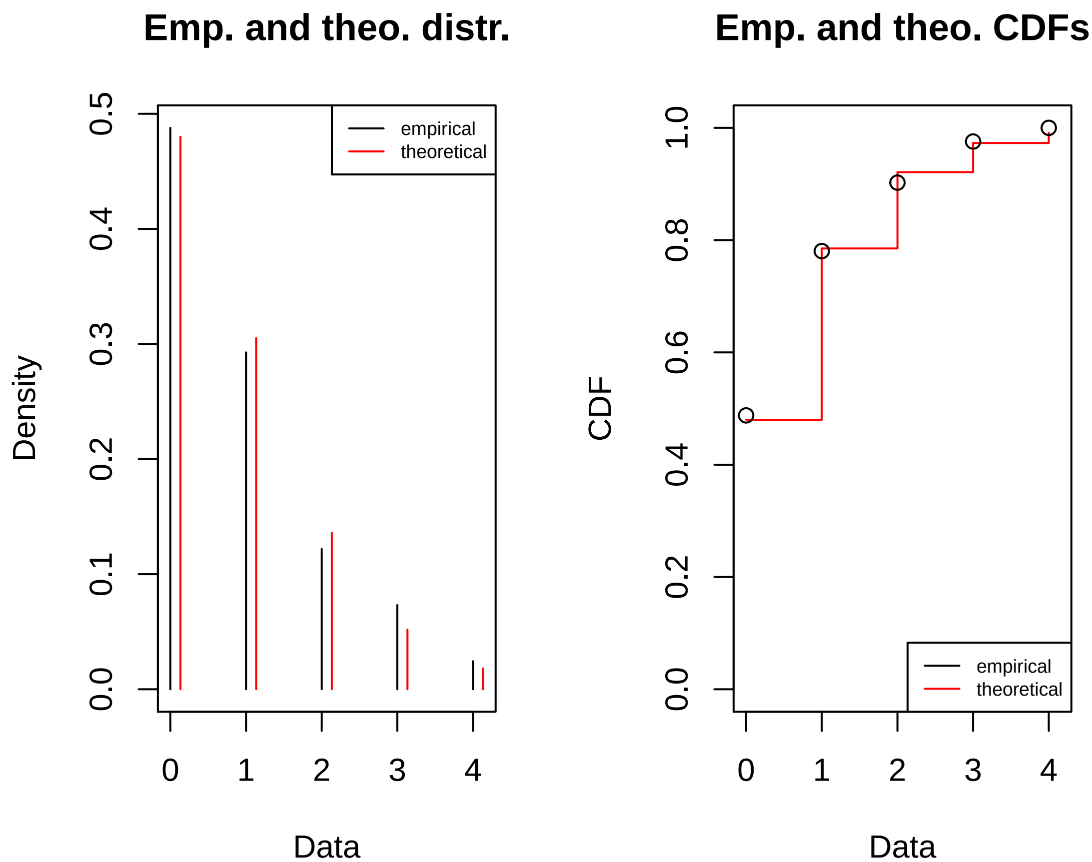



```
##
## "San Francisco"
```

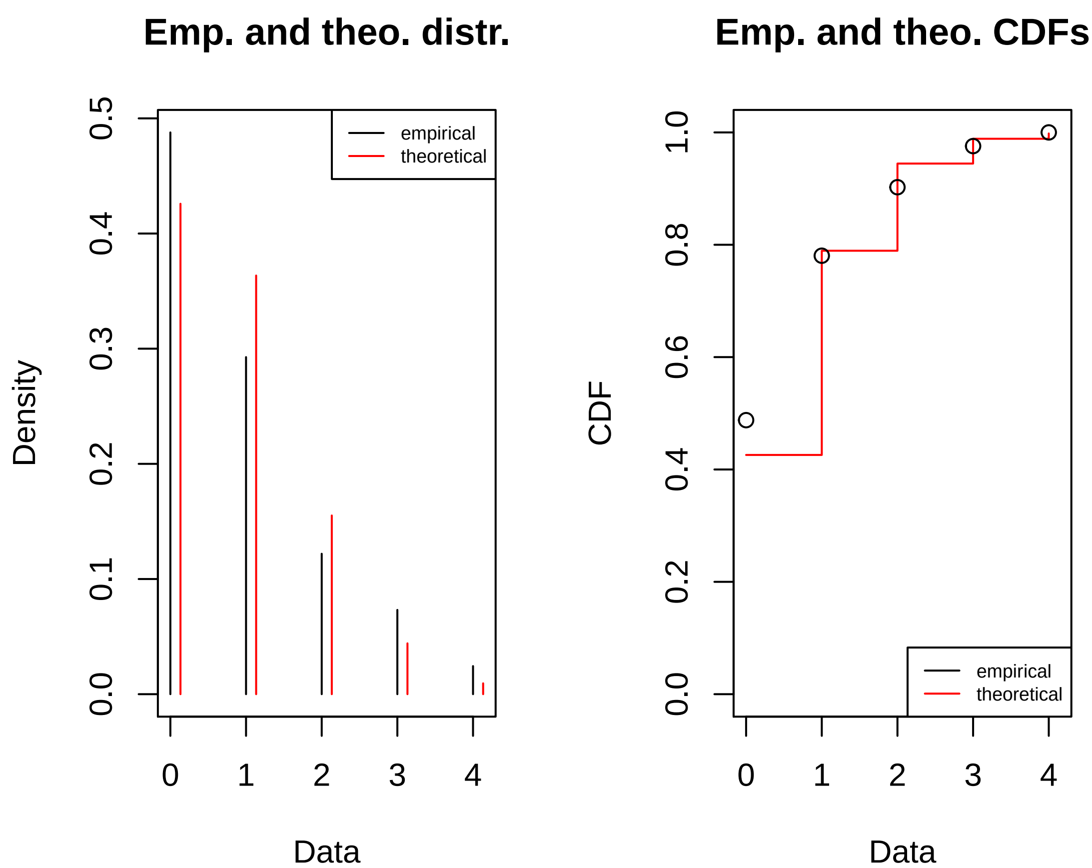

Emp. and theo. distr.
Density
Data
empirical
theoretical
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.0
1.0
2.0
3.0
Emp. and theo. CDFs
CDF
Data
empirical
theoretical
0.0
0.2
0.4
0.6
0.8
1.0
0.0
1.0
2.0
3.0


Emp. and theo. distr.
empirical
theoretical
Density
Data
Emp. and theo. CDFs
empirical
theoretical
CDF
Data

```
##
## "San Diego"
```



Emp. and theo. distr.
Density
Data
empirical
theoretical
Emp. and theo. CDFs
CDF
Data
empirical
theoretical




```
################################### Find MLE of fit to pois and negbinom,
################################### and fit glm's with time as predictor
library(fitdistrplus)
library(gamlss)

for (k in 1:9) {
    print(city_names[k])

    df <- data.frame(t = seq(1:41), Y = X.num[,
        k])
    model.pois <- glm(Y ~ t, family = poisson,
        df)
    print(summary(model.pois))
    # print(model.pois)
    model.nb <- glm.nb(Y ~ t, data = df)
    print(summary(model.nb))
    # print(model.nb)
}
```

```
##      city
## "Phoenix"
##
## Call:
## glm(formula = Y ~ t, family = poisson, data = df)
```

```
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3896  -1.1577   0.0779   0.4388   3.2686
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.02045    0.34717  -0.059    0.953
## t           -0.01461    0.01557  -0.938    0.348
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 45.927  on 40  degrees of freedom
## Residual deviance: 45.039  on 39  degrees of freedom
## AIC: 96.974
##
## Number of Fisher Scoring iterations: 5
##
##
## Call:
## glm.nb(formula = Y ~ t, data = df, init.theta = 6.569842379,
##     link = log)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.34785  -1.12816   0.06597   0.42033   2.92727
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.01112    0.36828  -0.030    0.976
## t           -0.01508    0.01642  -0.918    0.359
##
## (Dispersion parameter for Negative Binomial(6.5698) family taken to be 1)
##
##     Null deviance: 41.370  on 40  degrees of freedom
## Residual deviance: 40.546  on 39  degrees of freedom
## AIC: 98.61
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  6.6
##           Std. Err.:  12.6
##
##  2 x log-likelihood:  -92.61
##
## "Denver"
##
## Call:
## glm(formula = Y ~ t, family = poisson, data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.5238  -1.3488  -0.0556   0.7895   1.6489
```

```
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) 0.018566   0.268288   0.069  0.94483
## t           0.027799   0.009817   2.832  0.00463 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 63.425  on 40  degrees of freedom
## Residual deviance: 55.146  on 39  degrees of freedom
## AIC: 143.55
##
## Number of Fisher Scoring iterations: 5
##
##
## Call:
## glm.nb(formula = Y ~ t, data = df, init.theta = 29.54988736,
##     link = log)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.46484  -1.30665  -0.06017   0.75007   1.57034
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.01262    0.27544   0.046  0.96344
## t            0.02806    0.01014   2.767  0.00566 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Negative Binomial(29.5499) family taken to be 1)
##
##     Null deviance: 60.362  on 40  degrees of freedom
## Residual deviance: 52.528  on 39  degrees of freedom
## AIC: 145.49
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  30
##           Std. Err.:  123
##
##  2 x log-likelihood:  -139.492
##
## "Las Vegas"
##
## Call:
## glm(formula = Y ~ t, family = poisson, data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6099  -1.3725  -0.1646   0.8341   1.6159
```

```
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.19184    0.32935  -0.582    0.560
## t            0.01100    0.01295   0.849    0.396
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 53.816  on 40  degrees of freedom
## Residual deviance: 53.091  on 39  degrees of freedom
## AIC: 115.57
##
## Number of Fisher Scoring iterations: 5
##
##
## Call:
## glm.nb(formula = Y ~ t, data = df, init.theta = 12.83604237,
##     link = log)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5746  -1.3469  -0.1602   0.7945   1.5289
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.19674    0.34161  -0.576    0.565
## t            0.01123    0.01348   0.833    0.405
##
## (Dispersion parameter for Negative Binomial(12.836) family taken to be 1)
##
##     Null deviance: 50.547  on 40  degrees of freedom
## Residual deviance: 49.864  on 39  degrees of freedom
## AIC: 117.49
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  12.8
##           Std. Err.:  46.3
##
##  2 x log-likelihood:  -111.487
##
## "Albuquerque"
##
## Call:
## glm(formula = Y ~ t, family = poisson, data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.6742  -1.1840  -0.2167   0.5390   2.1822
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.36313    0.30289   1.199   0.2306
```

```
## t           -0.02566    0.01447  -1.773   0.0763 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 56.865  on 40  degrees of freedom
## Residual deviance: 53.636  on 39  degrees of freedom
## AIC: 107.56
##
## Number of Fisher Scoring iterations: 5
##
##
## Call:
## glm.nb(formula = Y ~ t, data = df, init.theta = 3.2366733, link = log)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5455  -1.1190  -0.2060   0.4152   1.7435
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.39505    0.35058   1.127    0.260
## t           -0.02732    0.01637  -1.670    0.095 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Negative Binomial(3.2367) family taken to be 1)
##
##     Null deviance: 46.332  on 40  degrees of freedom
## Residual deviance: 43.633  on 39  degrees of freedom
## AIC: 108.53
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  3.24
##           Std. Err.:  3.89
##
##  2 x log-likelihood:  -102.529
##
## "Tucson"
##
## Call:
## glm(formula = Y ~ t, family = poisson, data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0369  -0.9135  -0.4620   0.6784   1.9942
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.32520    0.45391  -2.919  0.00351 **
## t            0.05012    0.01535   3.266  0.00109 **
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 47.826  on 40  degrees of freedom
## Residual deviance: 36.050  on 39  degrees of freedom
## AIC: 95.086
##
## Number of Fisher Scoring iterations: 5
##
##
## Call:
## glm.nb(formula = Y ~ t, data = df, init.theta = 13616.87733,
##     link = log)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0368  -0.9135  -0.4620   0.6784   1.9941
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.32522    0.45393  -2.919  0.00351 **
## t            0.05012    0.01535   3.266  0.00109 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Negative Binomial(13616.88) family taken to be 1)
##
##     Null deviance: 47.823  on 40  degrees of freedom
## Residual deviance: 36.048  on 39  degrees of freedom
## AIC: 97.087
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  13617
##           Std. Err.:  303952
## Warning while fitting theta: iteration limit reached
##
##  2 x log-likelihood:  -91.087
##
## "Salt Lake City"
##
## Call:
## glm(formula = Y ~ t, family = poisson, data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0678  -0.6042  -0.1133   0.6129   1.5083
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.26378    0.26016   1.014    0.311
```

```
## t            0.01240    0.01017   1.220    0.223
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 47.159  on 40  degrees of freedom
## Residual deviance: 45.662  on 39  degrees of freedom
## AIC: 134.18
##
## Number of Fisher Scoring iterations: 5
##
##
## Call:
## glm.nb(formula = Y ~ t, data = df, init.theta = 25023.24315,
##     link = log)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0677  -0.6041  -0.1133   0.6129   1.5083
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.26378    0.26017   1.014    0.311
## t            0.01240    0.01017   1.220    0.223
##
## (Dispersion parameter for Negative Binomial(25023.24) family taken to be 1)
##
##     Null deviance: 47.156  on 40  degrees of freedom
## Residual deviance: 45.659  on 39  degrees of freedom
## AIC: 136.18
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  25023
##           Std. Err.:  758018
## Warning while fitting theta: iteration limit reached
##
##  2 x log-likelihood:  -130.183
##
## "Los Angeles"
##
## Call:
## glm(formula = Y ~ t, family = poisson, data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.4101  -1.1028  -0.9516   0.5010   3.0566
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.01881    0.35789   0.053    0.958
## t           -0.02458    0.01700  -1.446    0.148
##
## (Dispersion parameter for poisson family taken to be 1)
```

```
##
##     Null deviance: 54.689  on 40  degrees of freedom
## Residual deviance: 52.543  on 39  degrees of freedom
## AIC: 94.857
##
## Number of Fisher Scoring iterations: 6
##
##
## Call:
## glm.nb(formula = Y ~ t, data = df, init.theta = 1.499263905,
##     link = log)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.2396  -1.0099  -0.8866   0.4151   2.1002
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.02877    0.44404   0.065    0.948
## t           -0.02511    0.02028  -1.238    0.216
##
## (Dispersion parameter for Negative Binomial(1.4993) family taken to be 1)
##
##     Null deviance: 38.996  on 40  degrees of freedom
## Residual deviance: 37.461  on 39  degrees of freedom
## AIC: 93.878
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  1.50
##           Std. Err.:  1.27
##
##  2 x log-likelihood:  -87.878
##
## "San Francisco"
##
## Call:
## glm(formula = Y ~ t, family = poisson, data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.1241  -1.0165  -0.9061   0.6642   2.4088
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.03398    0.49216  -2.101   0.0356 *
## t            0.01437    0.01906   0.754   0.4510
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 44.670  on 40  degrees of freedom
```

```
## Residual deviance: 44.096  on 39  degrees of freedom
## AIC: 80.694
##
## Number of Fisher Scoring iterations: 6
##
##
## Call:
## glm.nb(formula = Y ~ t, data = df, init.theta = 2.635591131,
##     link = log)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.0641  -0.9714  -0.8736   0.5973   2.0460
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.03374    0.53031  -1.949   0.0513 .
## t            0.01436    0.02075   0.692   0.4891
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for Negative Binomial(2.6356) family taken to be 1)
##
##     Null deviance: 37.728  on 40  degrees of freedom
## Residual deviance: 37.245  on 39  degrees of freedom
## AIC: 82.088
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  2.64
##           Std. Err.:  4.11
##
##  2 x log-likelihood:  -76.088
##
## "San Diego"
##
## Call:
## glm(formula = Y ~ t, family = poisson, data = df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5230  -1.2635  -0.1349   0.3499   2.4859
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.51769    0.37604  -1.377    0.169
## t            0.01624    0.01444   1.124    0.261
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 55.804  on 40  degrees of freedom
## Residual deviance: 54.526  on 39  degrees of freedom
## AIC: 107.84
```

```
##
## Number of Fisher Scoring iterations: 5
##
##
## Call:
## glm.nb(formula = Y ~ t, data = df, init.theta = 2.787336147,
##     link = log)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.4027  -1.1829  -0.1285   0.3186   1.9989
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.53768    0.42408  -1.268    0.205
## t            0.01715    0.01652   1.038    0.299
##
## (Dispersion parameter for Negative Binomial(2.7873) family taken to be 1)
##
##     Null deviance: 44.360  on 40  degrees of freedom
## Residual deviance: 43.327  on 39  degrees of freedom
## AIC: 108.54
##
## Number of Fisher Scoring iterations: 1
##
##
##               Theta:  2.79
##           Std. Err.:  3.06
##
##  2 x log-likelihood:  -102.541
```