# Workshop 8.3a: Non-independence part 1

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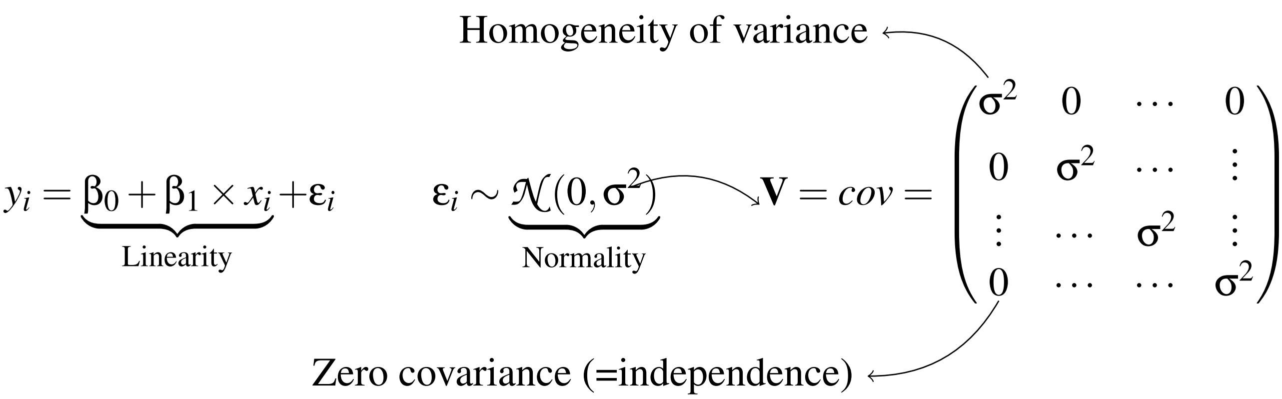
## 1. Linear modelling assumptions

### 1.1. Linear modelling assumptions

$$y_i = \beta_0 + \beta_1 \times x_i + \varepsilon_i$$
$$\epsilon_i \sim \mathcal{N}(0, \sigma^2)$$




### 1.2. Variance-covariance

$$\mathbf{V} = \underbrace{\begin{pmatrix} \sigma^2 & 0 & \cdots & 0 \\ 0 & \sigma^2 & \cdots & \vdots \\ \vdots & \cdots & \sigma^2 & \vdots \\ 0 & \cdots & \cdots & \sigma^2 \end{pmatrix}}_{\text{Variance-covariance matrix}}$$

### 1.3. Compound symmetry

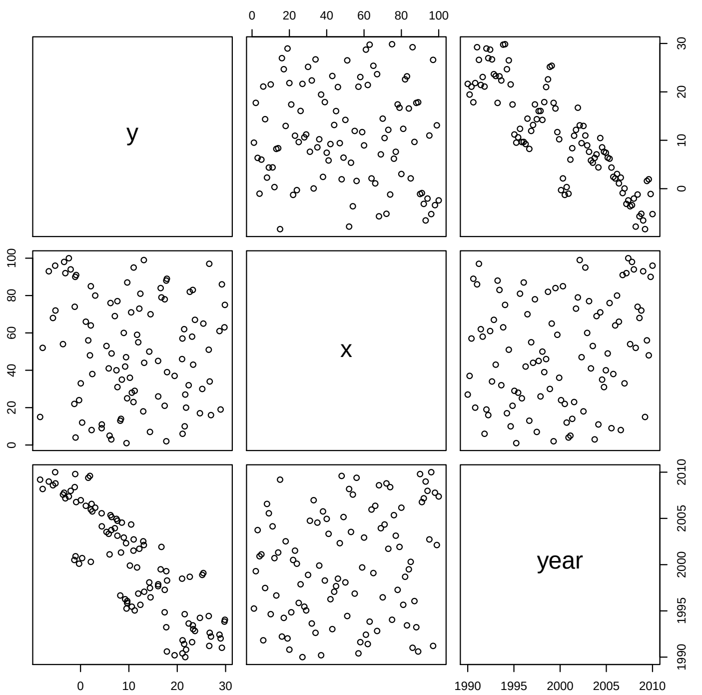
- constant correlation (and cov)
- **sphericity**

$$cor(\varepsilon) = \underbrace{\begin{pmatrix} 1 & \rho & \cdots & \rho \\ \rho & 1 & \cdots & \vdots \\ ... & \cdots & 1 & \vdots \\ \rho & \cdots & \cdots & 1 \end{pmatrix}}_{\text{Correlation matrix}}$$

$$\mathbf{V} = \underbrace{\begin{pmatrix} \theta + \sigma^2 & \theta & \cdots & \theta \\ \theta & \theta + \sigma^2 & \cdots & \vdots \\ \vdots & \cdots & \theta + \sigma^2 & \vdots \\ \theta & \cdots & \cdots & \theta + \sigma^2 \end{pmatrix}}_{\text{Variance-covariance matrix}}$$

## 1.4. *Temporal autocorrelation*

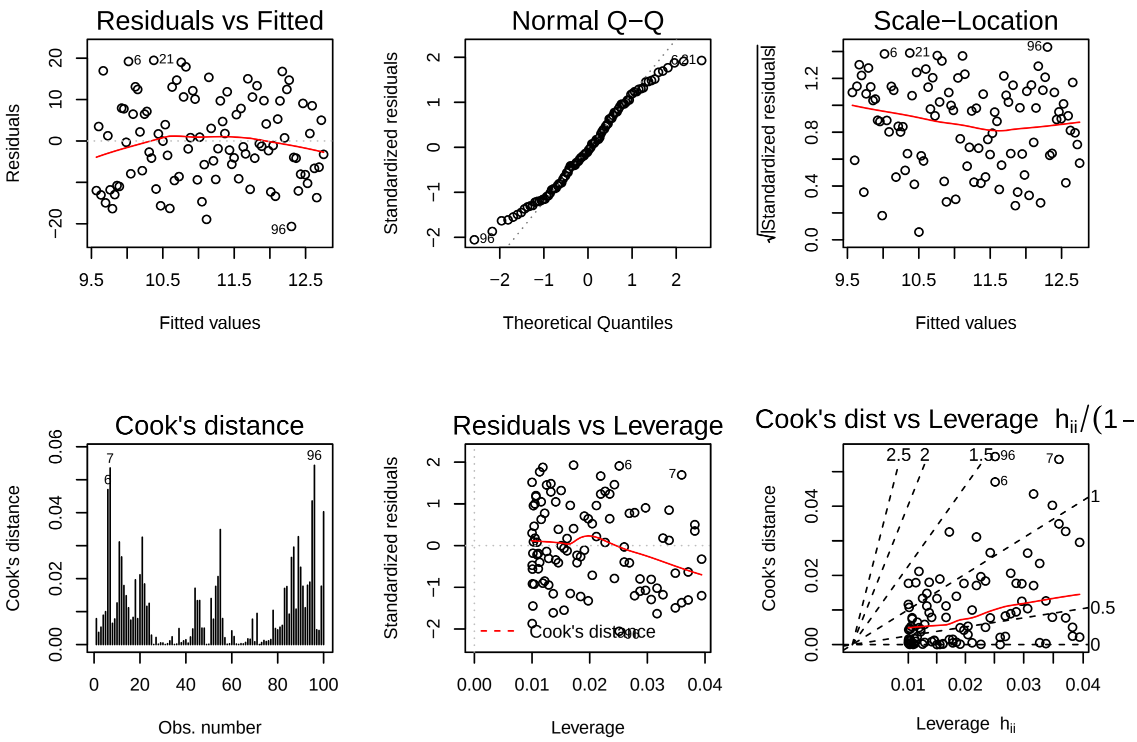
- correlation dependent on proximity
- **data.t**




## 1.5. *Temporal autocorrelation*

- Relationship between Y and X

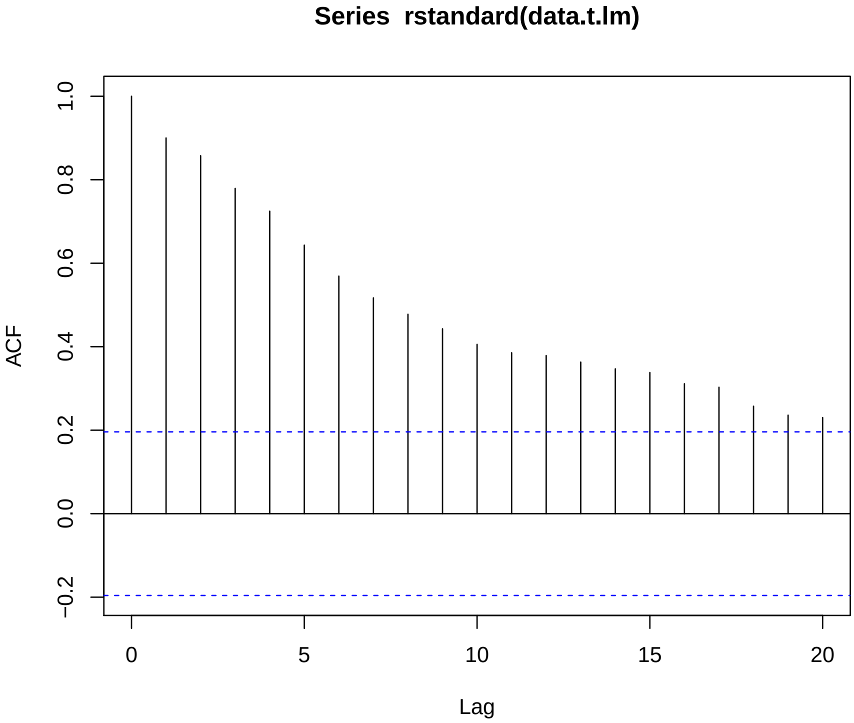
```
> data.t.lm <- lm(y~x, data=data.t)
> par(mfrow=c(2,3))
> plot(data.t.lm, which=1:6, ask=FALSE)
```




## 1.6. Temporal autocorrelation

- Relationship between Y and X

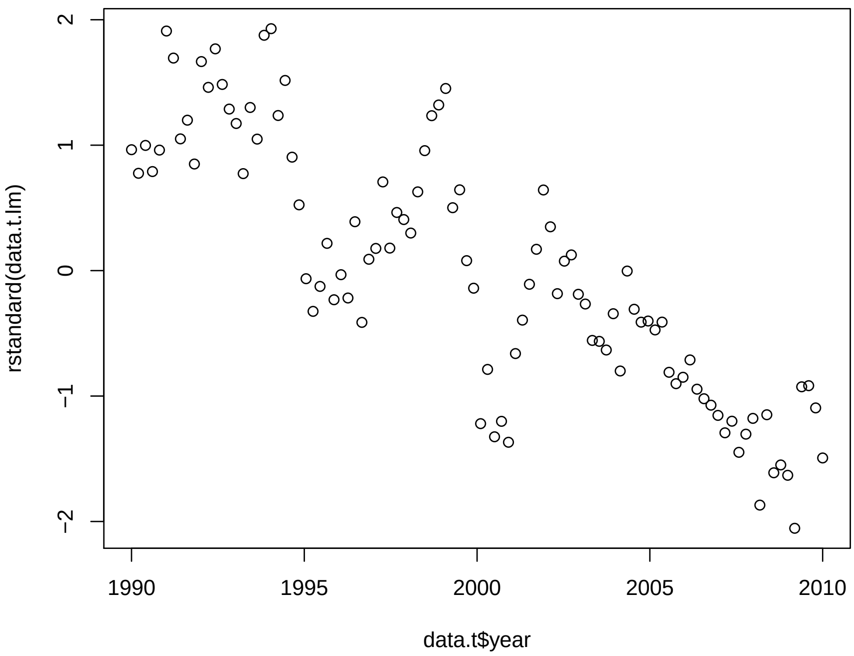
```
> acf(rstandard(data.t.lm))
```




## 1.7. Temporal autocorrelation

- can we partial out time

```
> plot(rstandard(data.t.lm)~data.t$year)
```



## 1.8. Temporal autocorrelation

- can we partial out time

```
> library(car)
> vif(lm(y~x+year, data=data.t))
```

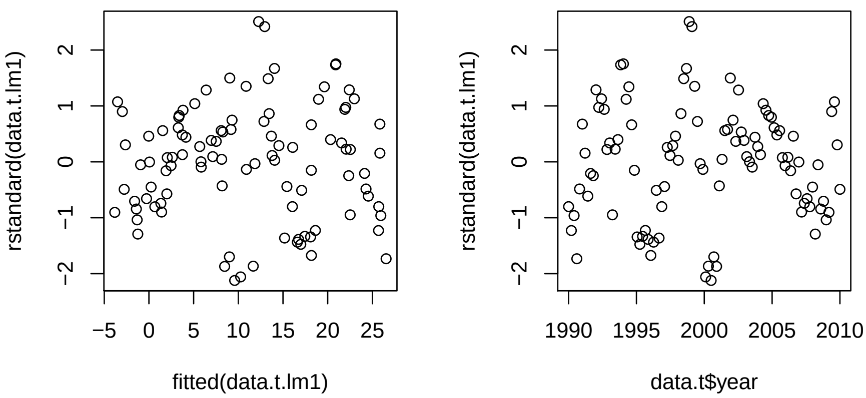
```
       x     year
1.040037 1.040037
```

```
> data.t.lm1 <- lm(y~x+year, data.t)
```

## 1.9. Testing for autocorrelation

### 1.9.1. Residual plot

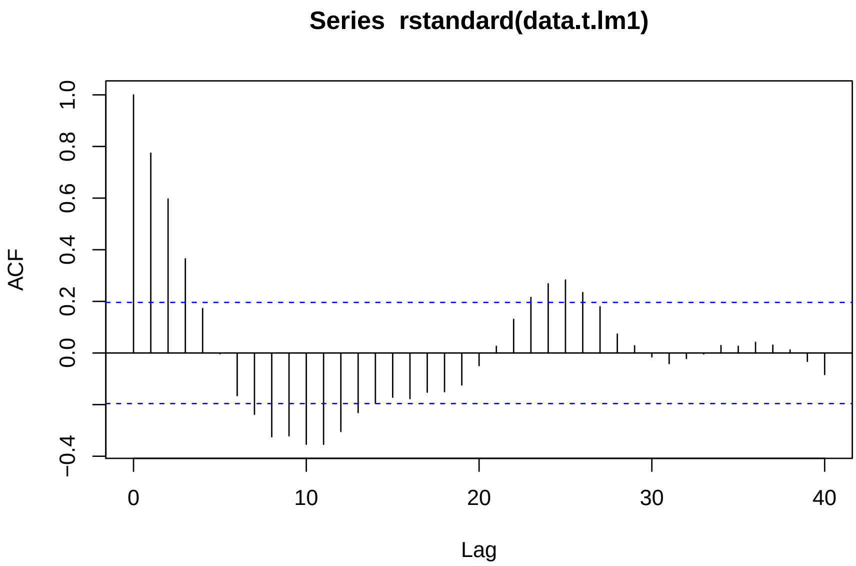
```
> par(mfrow=c(1,2))
> plot(rstandard(data.t.lm1)~fitted(data.t.lm1))
> plot(rstandard(data.t.lm1)~data.t$year)
```




## 1.10. Testing for autocorrelation

### 1.10.1. Autocorrelation (acf) plot

```
> acf(rstandard(data.t.lm1), lag=40)
```




## 1.11. First order autocorrelation (AR1)

$$cor(\varepsilon) = \underbrace{\begin{pmatrix} 1 & \rho & \cdots & \rho^{|t-s|} \\ \rho & 1 & \cdots & \vdots \\ \vdots & \cdots & 1 & \vdots \\ \rho^{|t-s|} & \cdots & \cdots & 1 \end{pmatrix}}_{\text{First order autoregressive correlation structure}}$$

where:

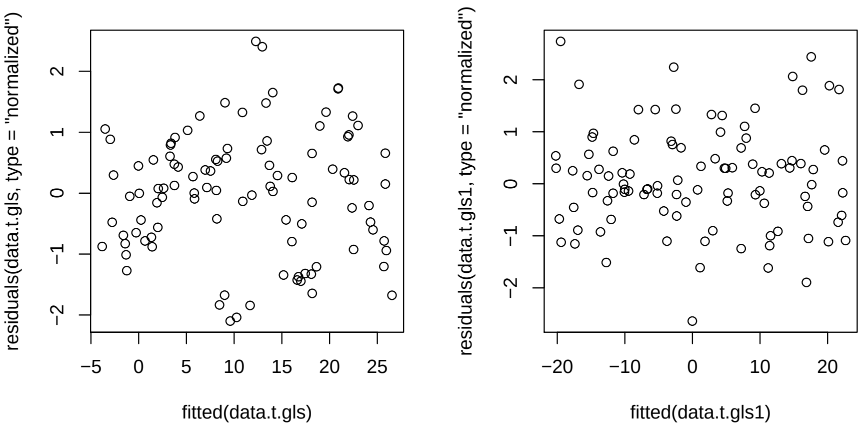
- $s$ and $t$ are the times.
- $s - t$ is the lag

## 1.12. First order auto-regressive (AR1)

```
> library(nlme)
> data.t.gls <- gls(y~x+year, data=data.t, method='REML')
> data.t.gls1 <- gls(y~x+year, data=data.t,
+         correlation=corAR1(form=~year),method='REML')
```

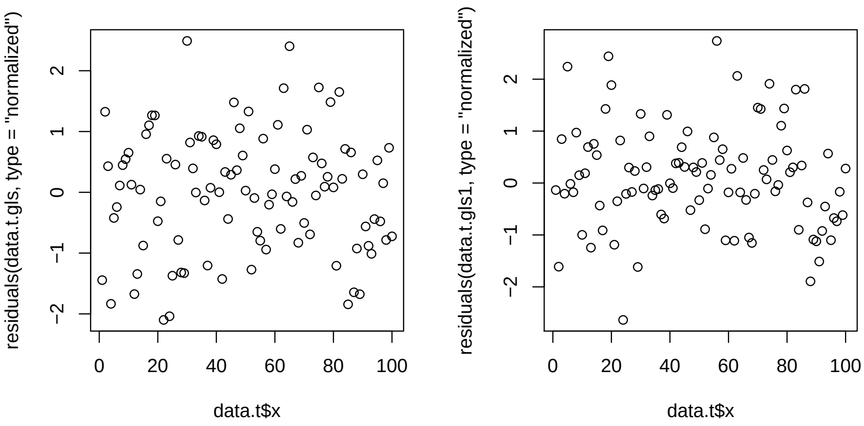
## 1.13. First order auto-regressive (AR1)

```
> par(mfrow=c(1,2))
> plot(residuals(data.t.gls, type="normalized")~
+      fitted(data.t.gls))
> plot(residuals(data.t.gls1, type="normalized")~
+      fitted(data.t.gls1))
```



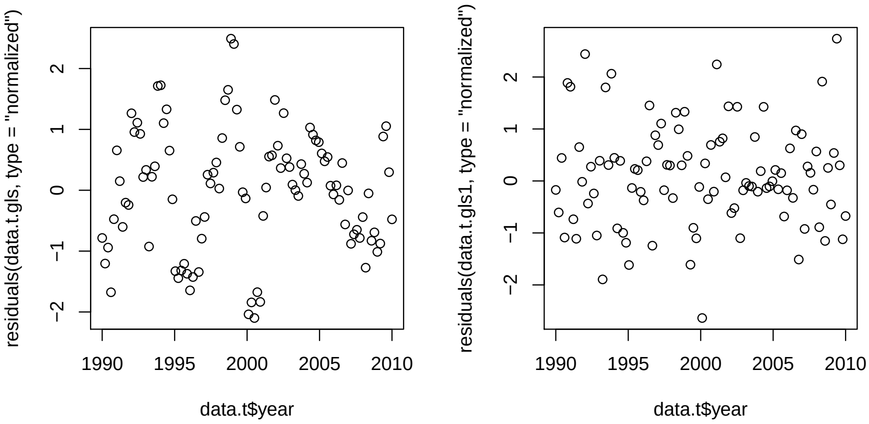

## 1.14. First order auto-regressive (AR1)

```
> par(mfrow=c(1,2))
> plot(residuals(data.t.gls, type="normalized")~
+       data.t$x)
> plot(residuals(data.t.gls1, type="normalized")~
+       data.t$x)
```



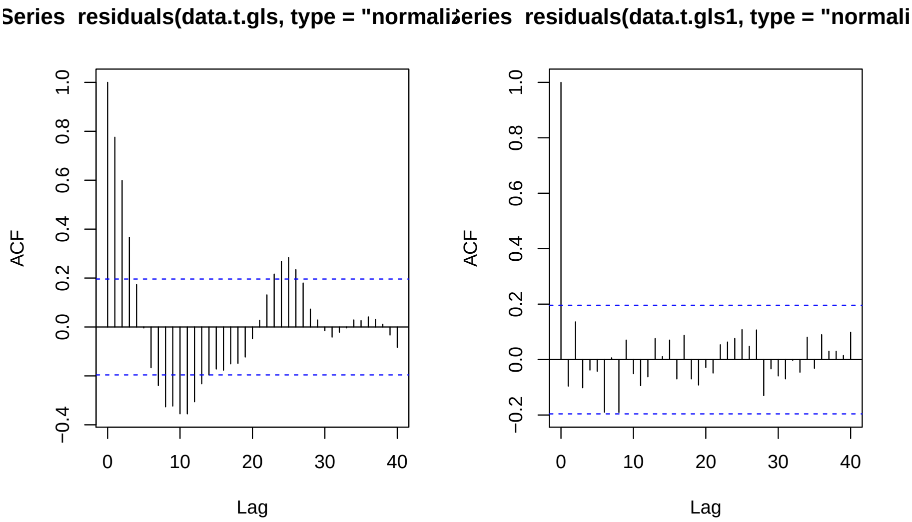

## 1.15. First order auto-regressive (AR1)

```
> par(mfrow=c(1,2))
> plot(residuals(data.t.gls, type="normalized")~
+       data.t$year)
> plot(residuals(data.t.gls1, type="normalized")~
+       data.t$year)
```




## 1.16. First order auto-regressive (AR1)

```
> par(mfrow=c(1,2))
> acf(residuals(data.t.gls, type='normalized'), lag=40)
> acf(residuals(data.t.gls1, type='normalized'), lag=40)
```




## 1.17. First order auto-regressive (AR1)

```
> AIC(data.t.gls, data.t.gls1)
```

```
            df      AIC
data.t.gls   4 626.3283
data.t.gls1  5 536.7467
```

```
> anova(data.t.gls, data.t.gls1)
```

```
            Model df      AIC      BIC    logLik   Test  L.Ratio p-value
data.t.gls      1  4 626.3283 636.6271 -309.1642
data.t.gls1     2  5 536.7467 549.6203 -263.3734 1 vs 2 91.58158  <.0001
```

### 1.18. Auto-regressive moving average (ARMA)

```
> data.t.gls2 <- update(data.t.gls,
+     correlation=corARMA(form=~year,p=2,q=0))
> data.t.gls3 <- update(data.t.gls,
+     correlation=corARMA(form=~year,p=3,q=0))
> AIC(data.t.gls, data.t.gls1, data.t.gls2, data.t.gls3)
```

```
            df      AIC
data.t.gls   4 626.3283
data.t.gls1  5 536.7467
data.t.gls2  6 538.1032
data.t.gls3  7 538.8376
```

### 1.19. Summarize model

```
> summary(data.t.gls1)
```

```
Generalized least squares fit by REML
  Model: y ~ x + year
  Data: data.t
       AIC      BIC    logLik
  536.7467 549.6203 -263.3734

Correlation Structure: ARMA(1,0)
 Formula: ~year
 Parameter estimate(s):
     Phi1
0.9126603

Coefficients:
               Value Std.Error   t-value p-value
(Intercept) 4388.568 1232.6129  3.560378  0.0006
x              0.028    0.0086  3.296648  0.0014
year          -2.195    0.6189 -3.545955  0.0006

 Correlation:
     (Intr) x
x     0.009
year -1.000 -0.010

Standardized residuals:
      Min         Q1        Med         Q3        Max
-1.423389  1.710551  3.377925  4.372772  6.624381

Residual standard error: 3.37516
Degrees of freedom: 100 total; 97 residual
```

## 2. Spatial autocorrelation

### 2.1. Spatial autocorrelation

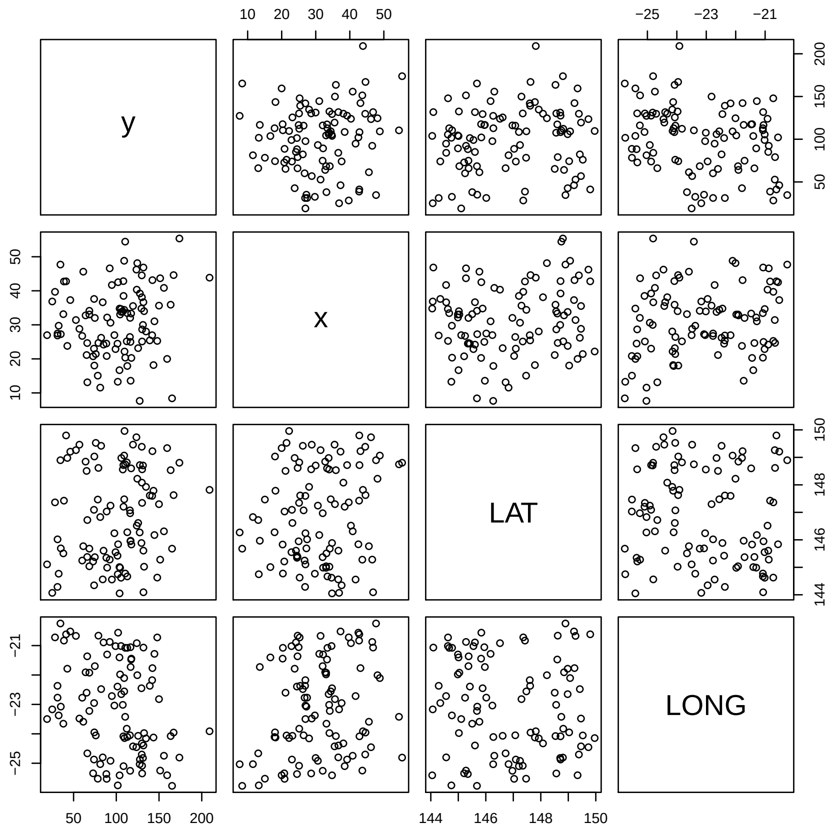
- similar, yet dependency is 2d
- 2d Euclidean dissimilarity

- **Exponential** decay

$$cor(\varepsilon) = \underbrace{\begin{pmatrix} 1 & e^{-\delta} & \cdots & e^{-\delta D} \\ e^{-\delta} & 1 & \cdots & \vdots \\ \vdots & \cdots & 1 & \vdots \\ e^{-\delta D} & \cdots & \cdots & 1 \end{pmatrix}}_{\text{Exponential autoregressive correlation structure}}$$

## 2.2. Spatial autocorrelation

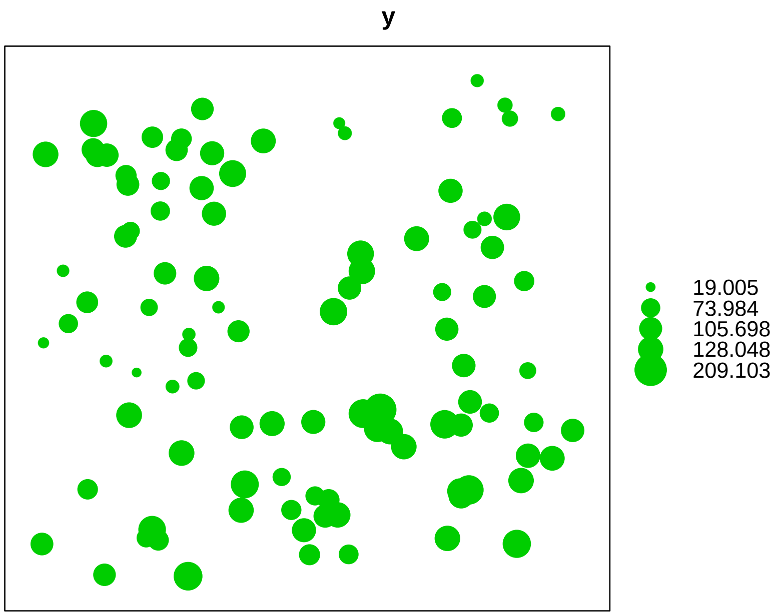
- **data.s**




## 2.3. Spatial autocorrelation

- Spatial arrangement of Y

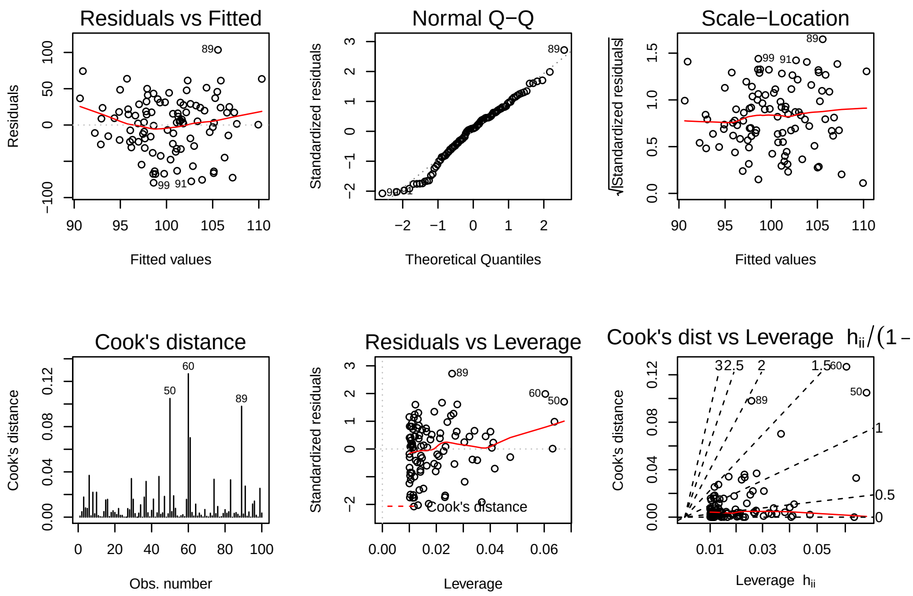
```
> library(sp)
> coordinates(data.s) <- ~LAT+LONG
> bubble(data.s,'y')
```




## 2.4. Spatial autocorrelation

- Relationship between Y and X

```
> data.s.lm <- lm(y~x, data=data.s)
> par(mfrow=c(2,3))
> plot(data.s.lm, which=1:6, ask=FALSE)
```

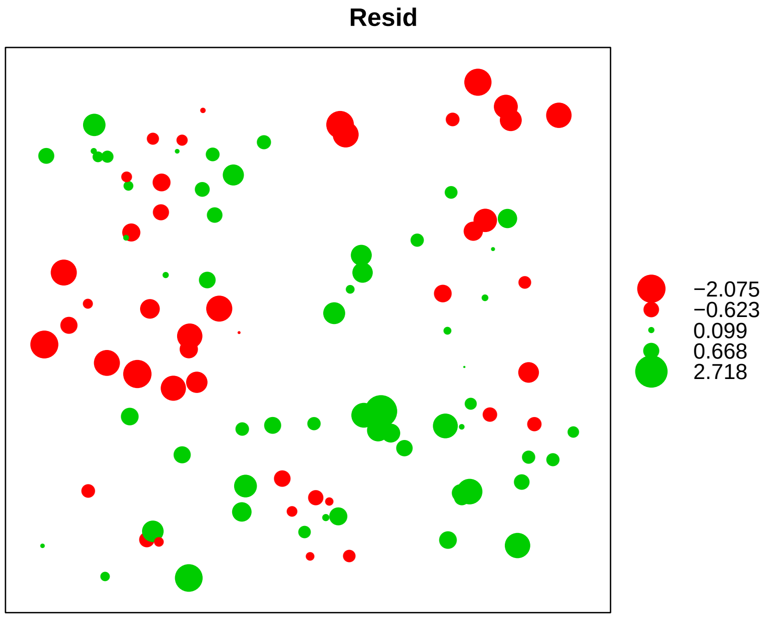



## 2.5. Detecting spatial autocorrelation

- bubble plot
- semi-variogram

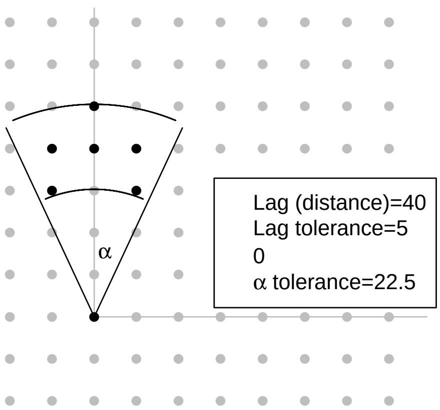
## 2.6. Bubble plot

```
> data.s$Resid <- rstandard(data.s.lm)
> library(sp)
> #coordinates(data.s) <- ~LAT+LONG
> bubble(data.s,'Resid')
```




## 2.7. Semi-variogram

- **semivariance** = similarity (of residuals) between pairs at specific distances
- distances 'binned' according to distance and orientation (N)

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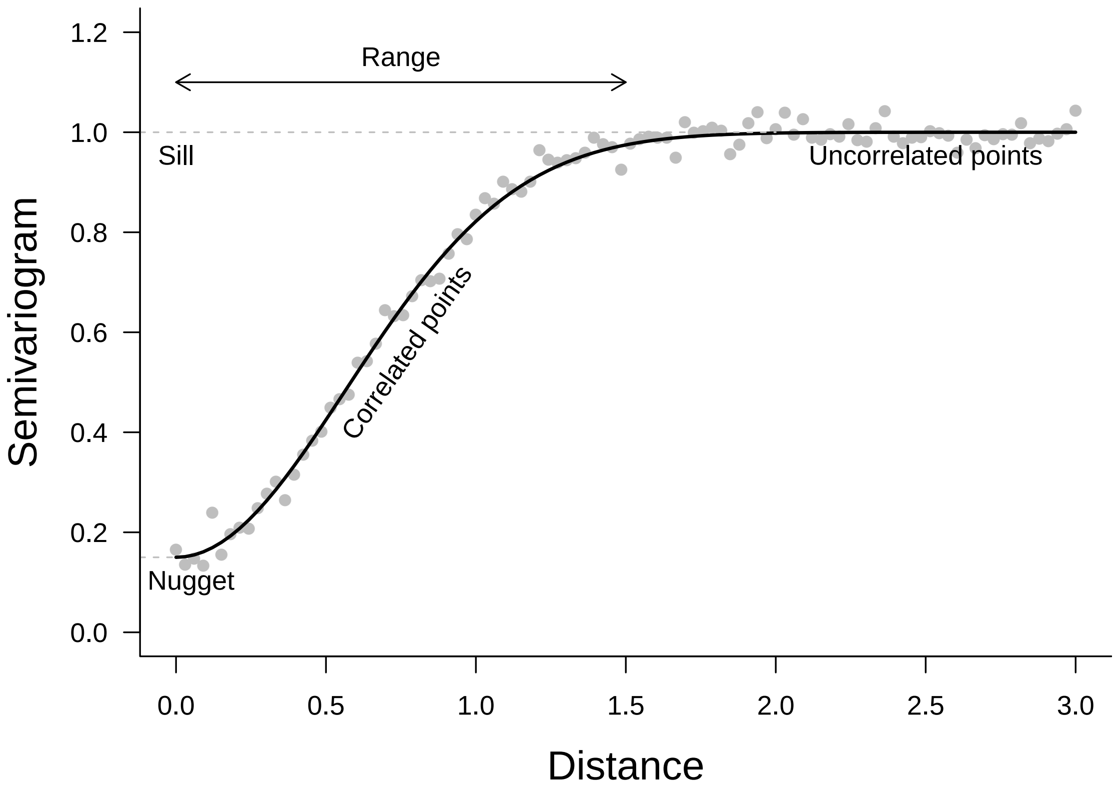
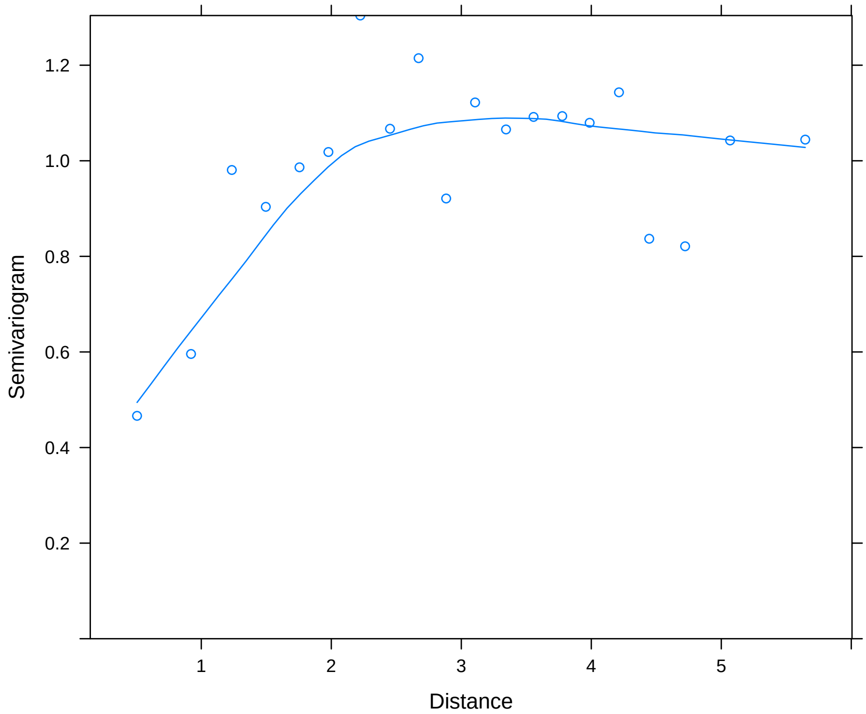
35 Stirling Highway, Crawley WA 6009
Tel: (08) 6369 4000
Fax: (08) 6488 4585

## 2.8. Semi-variogram



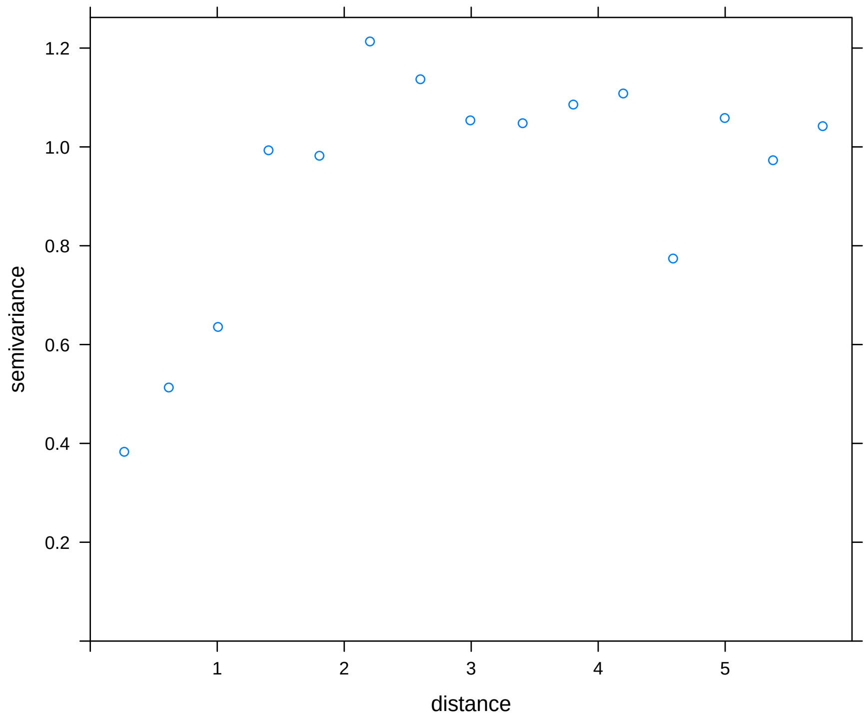

## 2.9. Semi-variogram

```
> library(nlme)
> data.s.gls <- gls(y~x, data.s, method='REML')
> plot(nlme:::Variogram(data.s.gls, form=~LAT+LONG,
+        resType="normalized"))
```



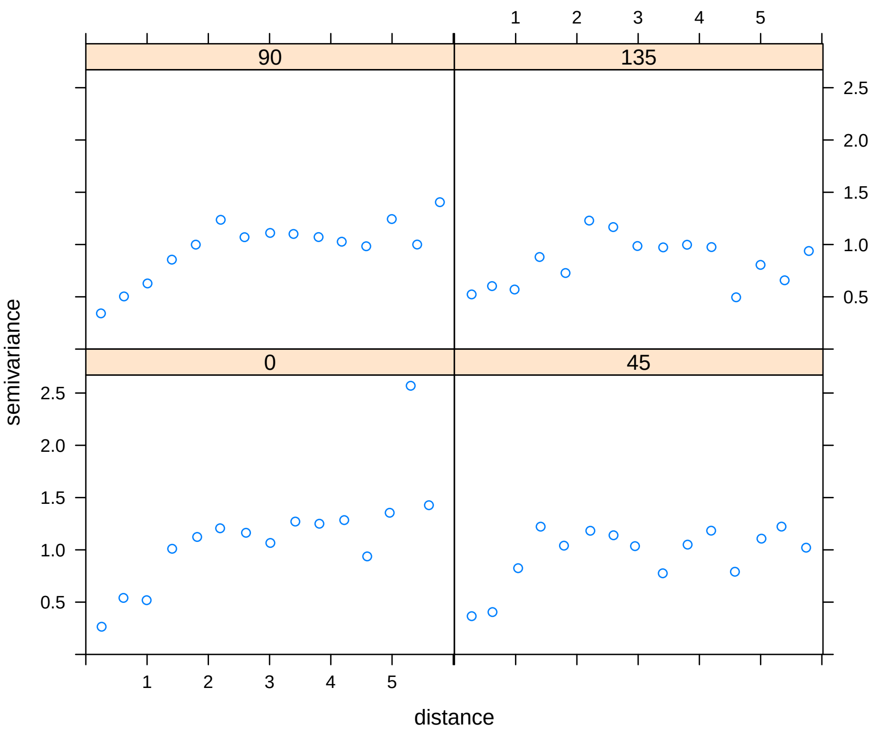

## 2.10. Semi-variogram

```
> library(gstat)
> plot(variogram(residuals(data.s.gls,"normalized")~1,
+       data=data.s, cutoff=6))
```



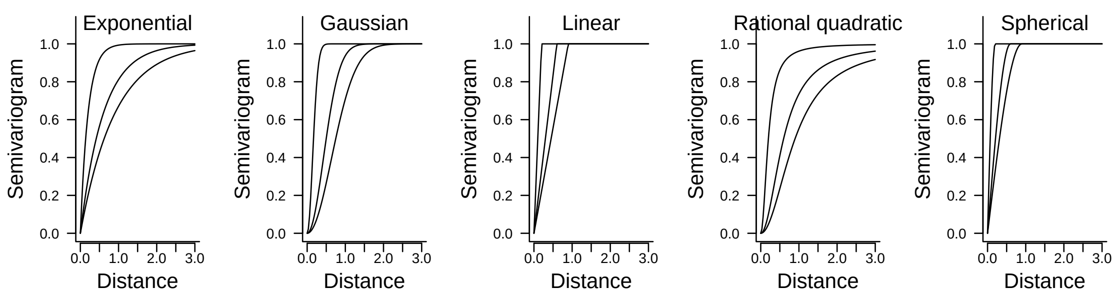
## 2.11. Semi-variogram

```
> library(gstat)
> plot(variogram(residuals(data.s.gls,"normalized")~1,
+     data=data.s, cutoff=6,alpha=c(0,45,90,135)))
```




## 2.12. Accommodating spatial autocorrelation

| Correlation function | Correlation structure | Description |
|---|---|---|
| `corExp(form= lat+long)` | Exponential | $\Phi = 1 - e^{-D/\rho}$ |
| `varGaus(form= lat+long)` | Gaussian | $\Phi = 1 - e^{-(D/\rho)^2}$ |
| `varLin(form= lat+long)` | Linear | $\Phi = 1 - (1 - D/\rho)I(d < \rho)$ |
| `varRatio(form= lat+long)` | Rational quadratic | $\Phi = (d/\rho)^2/(1 + (d/\rho)2)$ |
| `varSpher(form= lat+long)` | Spherical | $\Phi = 1 - (1 - 1.5(d/\rho) + 0.5(d/\rho)^3)I(d < \rho)$ |



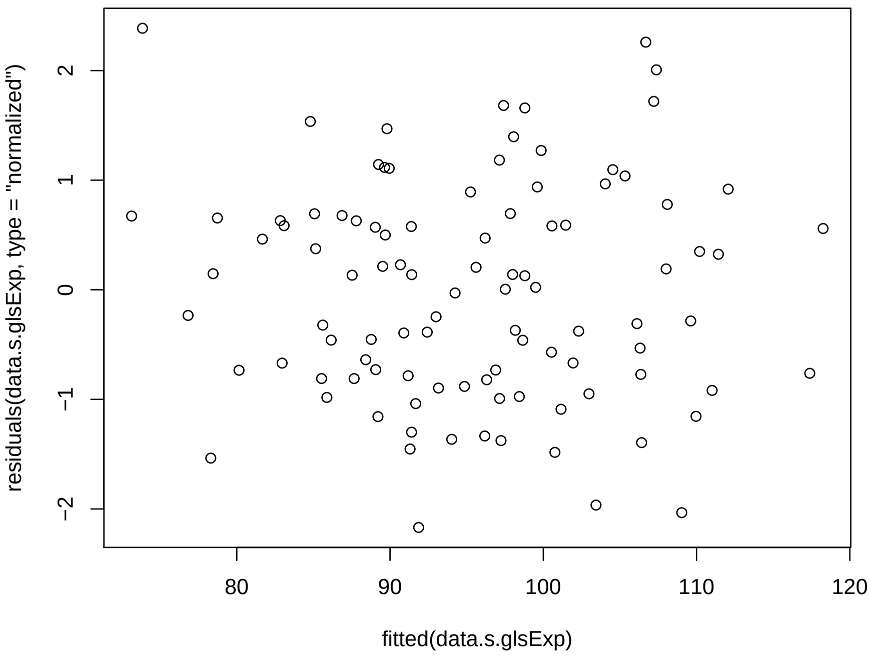
## 2.13. Accommodating spatial autocorrelation

```
> data.s.glsExp <- update(data.s.gls,
+     correlation=corExp(form=~LAT+LONG, nugget=TRUE))
> data.s.glsGaus <- update(data.s.gls,
+    correlation=corGaus(form=~LAT+LONG, nugget=TRUE))
> #data.s.glsLin <- update(data.s/gls,
> #   correlation=corLin(form=~LAT+LONG, nugget=TRUE))
> data.s.glsRatio <- update(data.s.gls,
+    correlation=corRatio(form=~LAT+LONG, nugget=TRUE))
> data.s.glsSpher <- update(data.s.gls,
+    correlation=corSpher(form=~LAT+LONG, nugget=TRUE))
>
> AIC(data.s.gls, data.s.glsExp, data.s.glsGaus, data.s.glsRatio, data.s.glsSpher)
```

```
                df       AIC
data.s.gls       3 1013.9439
data.s.glsExp    5  974.3235
data.s.glsGaus   5  976.4422
data.s.glsRatio  5  974.7862
data.s.glsSpher  5  975.5244
```

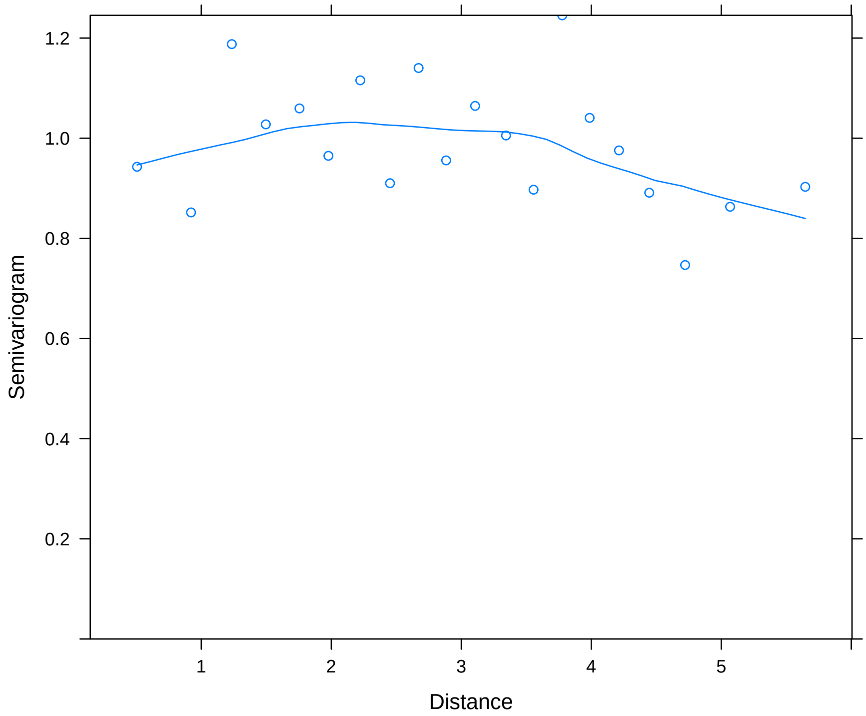
## 2.14. Accommodating spatial autocorrelation

```
> plot(residuals(data.s.glsExp, type="normalized")~
+      fitted(data.s.glsExp))
```




## 2.15. Accommodating spatial autocorrelation

```
> plot(nlme:::Variogram(data.s.glsExp, form=~LAT+LONG,
+      resType="normalized"))
```




## 2.16. Summarize model

```
> summary(data.s.glsExp)
```

```
Generalized least squares fit by REML
  Model: y ~ x
  Data: data.s
       AIC      BIC    logLik
  974.3235 987.2484 -482.1618

Correlation Structure: Exponential spatial correlation
 Formula: ~LAT + LONG
 Parameter estimate(s):
    range    nugget
1.6956723 0.1280655

Coefficients:
               Value Std.Error  t-value p-value
(Intercept) 65.90018 21.824752 3.019516  0.0032
x            0.94572  0.286245 3.303886  0.0013

 Correlation:
  (Intr)
x -0.418

Standardized residuals:
       Min         Q1        Med         Q3        Max
-1.6019483 -0.3507695  0.1608776  0.6451751  2.1331505
```

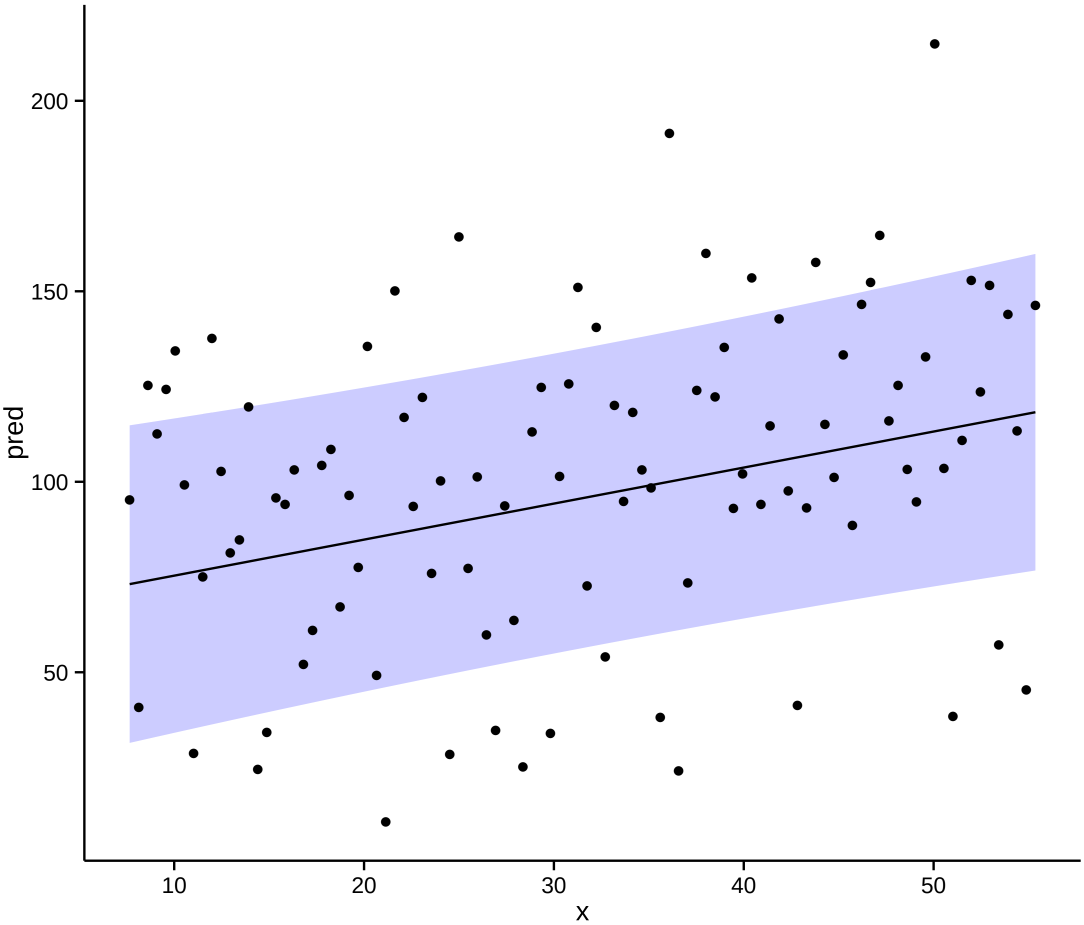
```
Residual standard error: 47.68716
Degrees of freedom: 100 total; 98 residual
```

```
> anova(data.s.glsExp)
```

```
Denom. DF: 98
            numDF  F-value p-value
(Intercept)     1 23.45923  <.0001
x               1 10.91566  0.0013
```

## 2.17. Summarize model

```
> xs <- seq(min(data.s$x), max(data.s$x), l=100)
> xmat <- model.matrix(~x, data.frame(x=xs))
>
> mpred <- function(model, xmat, data.s) {
+   pred <- as.vector(coef(model) %*% t(xmat))
+   (se<-sqrt(diag(xmat %*% vcov(model) %*% t(xmat))))
+   ci <- data.frame(pred+outer(se,qt(df=nrow(data.s)-2,c(.025,.975))))
+   colnames(ci) <- c('lwr','upr')
+   data.s.sum<-data.frame(pred, x=xs,se,ci)
+   data.s.sum
+ }
>
> data.s.sum<-mpred(data.s.glsExp, xmat, data.s)
> data.s.sum$resid <- data.s.sum$pred+residuals(data.s.glsExp)
>
> library(ggplot2)
> ggplot(data.s.sum, aes(y=pred, x=x))+
+     geom_ribbon(aes(ymin=lwr, ymax=upr), fill='blue', alpha=0.2) +
+     geom_line()+geom_point(aes(y=resid)) + theme_classic()
```



```
> #plot(pred~x, ylim=c(min(lwr), max(upr)), data.s.sum, type="l")
> #lines(lwr~x, data.s.sum)
> #lines(upr~x, data.s.sum)
> #points(pred+residuals(data.s.glsExp)~x, data.s.sum)
>
> #newdata <- data.frame(x=xs)[1,]
```

## 2.18. Summarize model