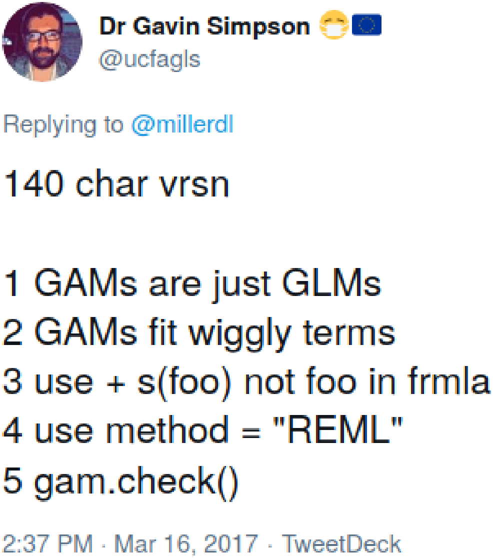
Generalized Additive Models (GAMs)

CMDA 4654 Project 2

Group 19: Brady Bolton, Eryk Jesse, Charles Lee, Dan Schlicht

Generalized Additive Models



Dr Gavin Simpson 😷🇪🇺
@ucfagls

Replying to @millerdl

140 char vrsn

1 GAMs are just GLMs
2 GAMs fit wiggly terms
3 use + s(foo) not foo in frmla
4 use method = "REML"
5 gam.check()

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Generalized Additive Models

- Type of generalized linear model
- Response variable depends on smooth functions $f_i(x_i)$
- General structure of a GAM:
  $g(\mathrm{E}(Y)) = \beta_0 + f_1(x_1) + f_2(x_2) + \cdots + f_n(x_n)$
- Smooth functions can be many different things (polynomials, splines, weighted means, etc)

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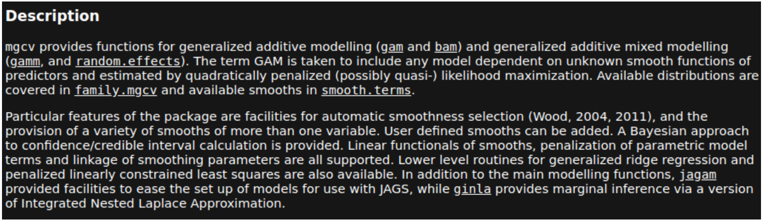
Generalized Additive Models in R

- Two options for packages, mgcv and gam
- mgcv is more commonly used and better supported



Description

mgcv provides functions for generalized additive modelling (gam and bam) and generalized additive mixed modelling (gamm, and random.effects). The term GAM is taken to include any model dependent on unknown smooth functions of predictors and estimated by quadratically penalized (possibly quasi-) likelihood maximization. Available distributions are covered in family.mgcv and available smooths in smooth.terms.

Particular features of the package are facilities for automatic smoothness selection (Wood, 2004, 2011), and the provision of a variety of smooths of more than one variable. User defined smooths can be added. A Bayesian approach to confidence/credible interval calculation is provided. Linear functionals of smooths, penalization of parametric model terms and linkage of smoothing parameters are all supported. Lower level routines for generalized ridge regression and penalized linearly constrained least squares are also available. In addition to the main modelling functions, jagam provided facilities to ease the set up of models for use with JAGS, while ginla provides marginal inference via a version of Integrated Nested Laplace Approximation.

Example - Simulated Data

```r
library(mgcv)
set.seed(0)
sim_data <- gamSim(1, n = 400, dist="normal", scale=2)
```

```
Gu & Wahba 4 term additive model
```

```r
head(sim_data)
```

```
          y        x0        x1         x2         x3         f        f0
1  5.114211 0.8966972 0.1478457 0.34826473 0.04572472  7.962274 0.6377368
2  2.175828 0.2655087 0.6588776 0.85868745 0.36652658  5.514517 1.4814113
3  6.334878 0.3721239 0.1850700 0.03443876 0.74139303  3.576406 1.8407682
4  6.853276 0.5728534 0.9543781 0.97099715 0.93350625  8.692625 1.9478442
5  7.743879 0.9082078 0.8978485 0.74511014 0.67320995  8.752859 0.5687870
6 13.920886 0.2016819 0.9436971 0.27325524 0.70135711 16.190349 1.1841037
        f1           f2 f3
1 1.344055 5.980482e+00  0
2 3.735028 2.980780e-01  0
3 1.447937 2.877006e-01  0
4 6.744695 8.611364e-05  0
5 6.023672 2.160400e+00  0
6 6.602142 8.404104e+00  0
```

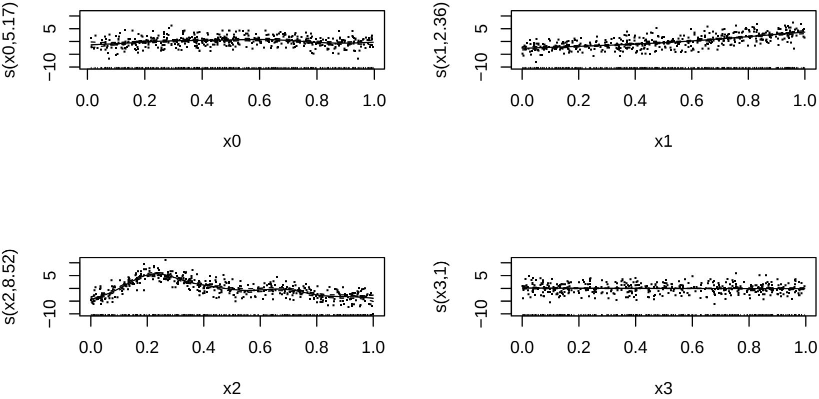
Example - Simulated Data

```
fit <- gam(y ~ s(x0) + s(x1) + s(x2) + s(x3), data = sim_data)
summary(fit)
```

```
Family: gaussian
Link function: identity

Formula:
y ~ s(x0) + s(x1) + s(x2) + s(x3)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   7.9150     0.1049   75.44   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
        edf Ref.df       F  p-value
s(x0) 5.173  6.287   4.564 0.000138 ***
s(x1) 2.357  2.927 103.053  < 2e-16 ***
s(x2) 8.517  8.931  84.308  < 2e-16 ***
s(x3) 1.000  1.000   0.441 0.506929
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.726   Deviance explained = 73.7%
GCV =  4.611  Scale est. = 4.4029    n = 400
```

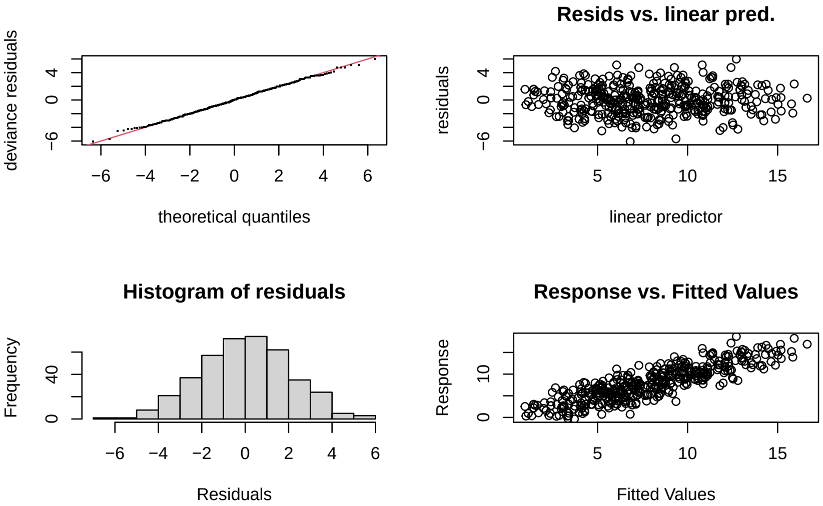
Example - Simulated Data

```
plot(fit, pages=1, residuals=TRUE)
```



Example - Simulated Data

```
gam.check(fit)
```



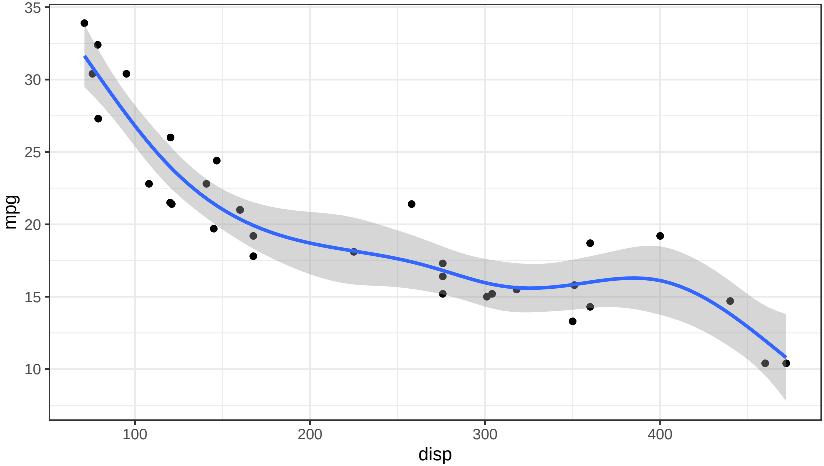
Example - mtcars

```r
data("mtcars")
mtcars_gam <-
  gam(mpg ~ s(disp), data = mtcars, method = "REML")
summary(mtcars_gam)
```

```
Family: gaussian
Link function: identity

Formula:
mpg ~ s(disp)

Parametric coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  20.0906     0.3788   53.04   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Approximate significance of smooth terms:
          edf Ref.df    F p-value
s(disp) 4.884  5.904 36.3  <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.874   Deviance explained = 89.4%
-REML = 74.101  Scale est. = 4.5918    n = 32
```

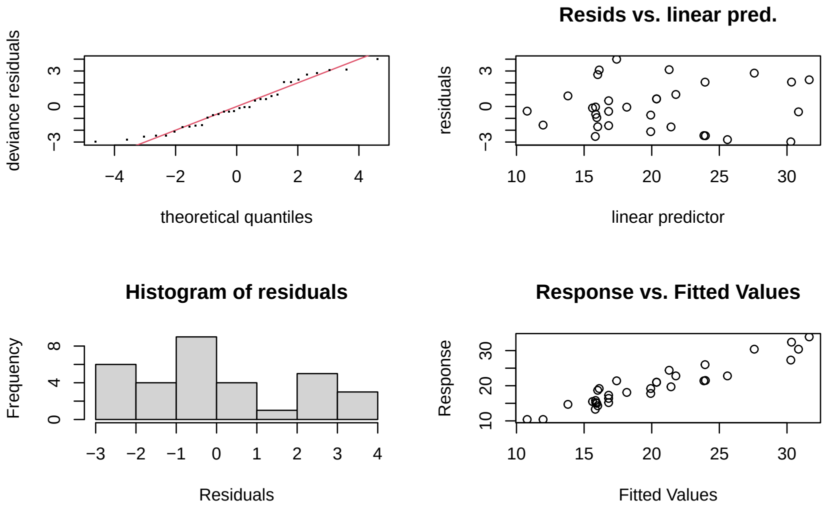
Example - mtcars

```r
library(ggplot2)
ggplot(data = mtcars, aes(x = disp, y = mpg)) +
  theme_bw() + geom_point() +
  geom_smooth(method = "gam", formula = y ~ s(x))
```



Example - mtcars

```
gam.check(mtcars_gam)
```



Example - mtcars

Example - iris

```r
data("iris")
```

Example - iris

Example - iris

Example - iris

Example - Health Data

```
# df <- read.csv('health_data.csv')
 # show the data
```

Example - Health Data

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Example - Health Data

Conclusion

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References