

An introduction to Gaussian Processes

github.com/andrewcparnell/intro_to_gaussian_processes

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Why learn about Gaussian Processes?

- They are a great introduction to thinking about the multivariate normal distribution
- They are widely used in spatial statistics and machine learning
- They are very flexible and extendable
- Some of you will be using them for your PhD

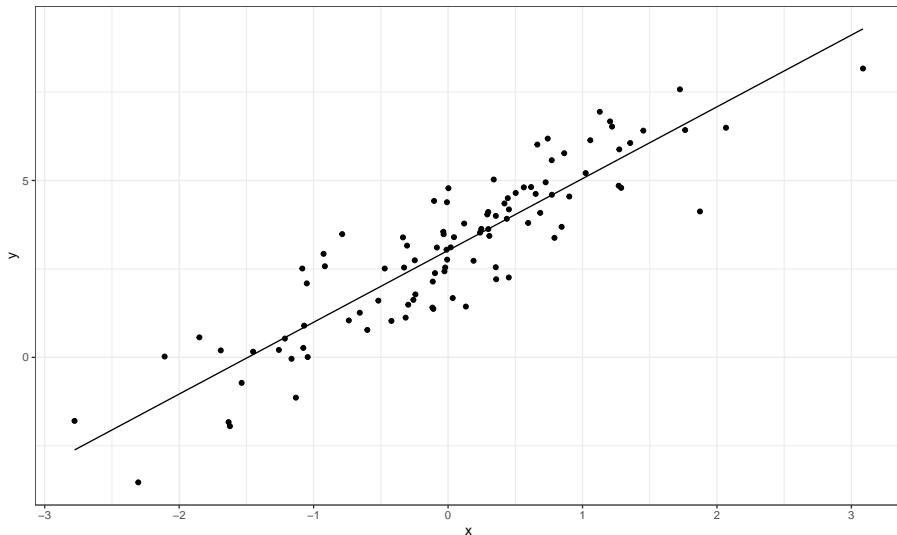
To follow this presentation you will need to understand linear regression and a bit of matrix algebra

Back to linear regression

```
lr_dat = tibble(  
  x = sort(rnorm(100)),  
  y = rnorm(100, 3 + 2 * x, 1),  
  fits = fitted(lm(y ~ x))  
)  
p = ggplot(lr_dat, aes(x, y)) +  
  geom_point() +  
  geom_line(aes(y = fits))
```

Linear regression plot

```
print(p)
```



We normally write this as:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i; \quad i = 1, \dots, n, \quad \epsilon_i \sim N(0, \sigma^2)$$

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Another way of writing this is:

$$y_i | x_i \sim N(\beta_0 + \beta_1 x_i, \sigma^2)$$

Linear regression in matrices

Suppose we write:

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, X = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \\ 1 & x_n \end{bmatrix}, \epsilon = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix}, \beta = \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}$$

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We can then write the model as:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \\ 1 & x_n \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix}$$

or

$$y = X\beta + \epsilon$$

One way to fit is to compute the (log) likelihood and maximise it:

$$\log L = \sum_{i=1}^n \log \left\{ \sqrt{\frac{1}{2\pi\sigma^2}} \exp \left[-\frac{1}{2\sigma^2} (y_i - \beta_0 - \beta_1 x_i)^2 \right] \right\}$$

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```
beta_0 = 0; beta_1 = 0; sigma = 1  
with(lr_dat, sum(dnorm(y, beta_0 + beta_1 * x, sd = sigma,  
                      log = TRUE)))
```

```
## [1] -820.2745
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## [1] -141.8936
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If you simplify the calculation on the previous slide you get:

$$\log L = -\frac{n}{2} \log(\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$$

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This can be re-written in matrix format

$$\log L = -\frac{1}{2} \log [\det(\Sigma)] - \frac{1}{2} (y - X\beta)^T \Sigma^{-1} (y - X\beta)$$

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This is the likelihood for a **multivariate normal distribution** written $y \sim \text{MVN}(X\beta, \Sigma)$

Fitting linear regressions using the multivariate normal

Two different ways to write the log likelihood:

```
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```
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```

```
library(mvtnorm)
Sigma = diag(sigma, nrow(lr_dat))
X = with(lr_dat, cbind(1,x))
beta = c(beta_0, beta_1)
with(lr_dat, dmvnorm(y, X%*%beta, Sigma,
                     log = TRUE))
```

```
## [1] -141.8936
```


The matrix Sigma currently looks like this:

$$\Sigma = \begin{bmatrix} \sigma^2 & 0 & \dots & 0 \\ 0 & \sigma^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma^2 \end{bmatrix}$$

What would happen if we changed the off-diagonal terms? These represent the covariances (or scaled correlations) between the y -values

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Gaussian processes

The *key idea* in Gaussian Processes is to change the off-diagonals of Σ so that the you get higher correlations between y_i and y_j when x_i and x_j are close.

Autocovariance functions

The most common autocovariance function (ACF):

$$\Sigma_{ij} = \tau^2 \exp \left[-\frac{(x_i - x_j)^2}{\theta} \right]$$

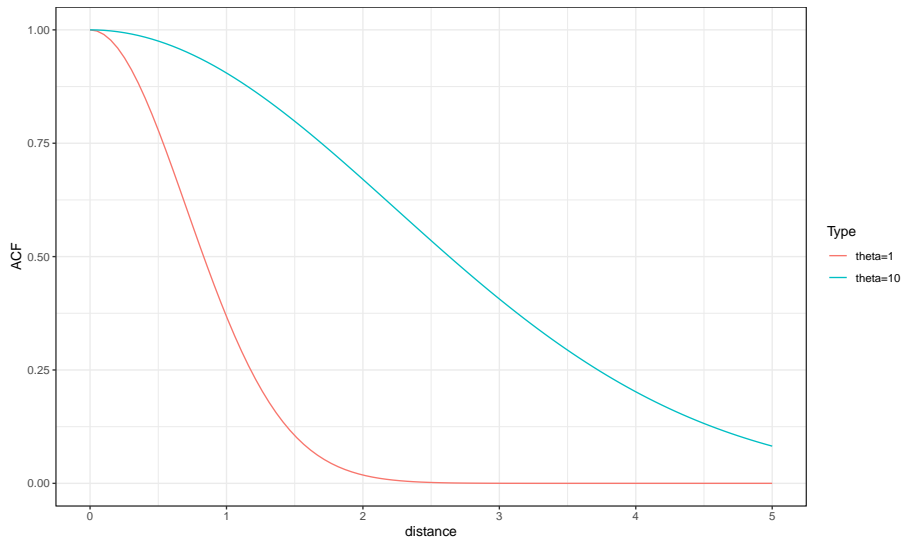
for $i \neq j$ with $\Sigma_{ii} = \tau^2 + \sigma^2$

This can be plotted:

```
sigma = 1; theta1 = 10; theta2 = 1
acv = tibble(
  distance = seq(0, 5, length = 100),
  `theta=10` = sigma^2 * exp(-(distance ^ 2) / theta1),
  `theta=1` = sigma^2 * exp(-(distance ^ 2) / theta2)
)
p = acv %>%
  gather(key = Type, value = ACF, -distance) %>%
  ggplot(aes(x = distance, y = ACF, colour = Type)) +
  geom_line()
```

Pictures of squared exponential covariance function

```
print(p)
```



Fitting a model via the MVN

We can fit this model in exactly the same way via the log-likelihood:

```
suppressPackageStartupMessages(library(fields))
sigma = 1; tau = 1
Sigma = with(lr_dat,
             diag(sigma^2, nrow(lr_dat)) +
             tau^2 * Exp.cov(x, x,
                             theta = theta2, p = 2))
round(Sigma[1:3,1:3], 3)
```

```
##      [,1] [,2] [,3]
## [1,] 2.000 0.799 0.638
## [2,] 0.799 2.000 0.962
## [3,] 0.638 0.962 2.000
```

```
with(lr_dat, dmvnorm(y, X%*%beta, Sigma,
                     log = TRUE))
```

```
## [1] -146.538
```

The magic GP formula

Suppose you want to predict some new y values for some given new x values. Write these as y_{new} and x_{new} , and set up the problem as:

$$\begin{bmatrix} y \\ y_{new} \end{bmatrix} \sim MVN \left(\begin{bmatrix} X\beta \\ X_{new}\beta \end{bmatrix}, \begin{bmatrix} \Sigma & \Sigma_{new} \\ \Sigma_{new}^T & \Sigma_{new,new} \end{bmatrix} \right)$$

where $\Sigma_{new,i,j} = \tau^2 \exp \left[-\frac{(x_i - x_{new,j})^2}{\theta} \right]$,

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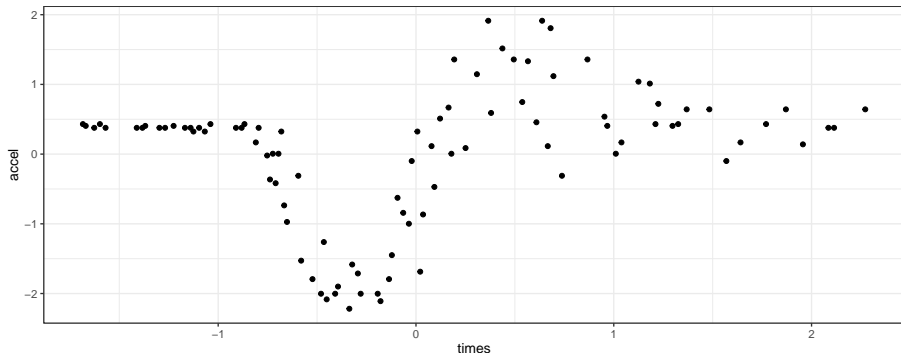
The magic formula gives you

$$y_{new}|y \sim MVN(X_{new}\beta + \Sigma_{new}^T \Sigma^{-1}(y - X\beta)), \Sigma_{new,new} - \Sigma_{new}^T \Sigma^{-1} \Sigma_{new})$$

This means that, once the parameters are estimated, we can produce instant predictions!

A new regression data set

```
suppressPackageStartupMessages(library(boot))
scale2 = function(x) (x - mean(x))/sd(x)
motor2 = motor %>% mutate_all(scale2)
motor2 %>%
  ggplot(aes(x = times, y = accel)) +
  geom_point()
```




```
nll = function(par) {  
  tau = par[1]  
  sigma = par[2]  
  theta = par[3]  
  Sigma = with(motor2,  
               diag(sigma^2, nrow(motor2)) +  
               tau^2 * Exp.cov(times, times,  
                               theta = theta, p = 2))  
  with(motor2, -dmvnorm(accel,  
                       cbind(1, times)%*%beta,  
                       sigma = Sigma, log = TRUE))  
}  
nll(c(1,1,1))  
  
## [1] 138.4153
```

Optimising the parameters

```
library(optimx)
answer = optimx(par = c(1,1,1),
                fn = nll,
                method = 'BFGS')
print(answer)
```

```
##           p1           p2           p3    value fevals gevals n
## BFGS 3.441868 -0.4365699 0.7728277 81.24886      57      12
##      kkt1 kkt2 xtime
## BFGS TRUE TRUE 0.109
```

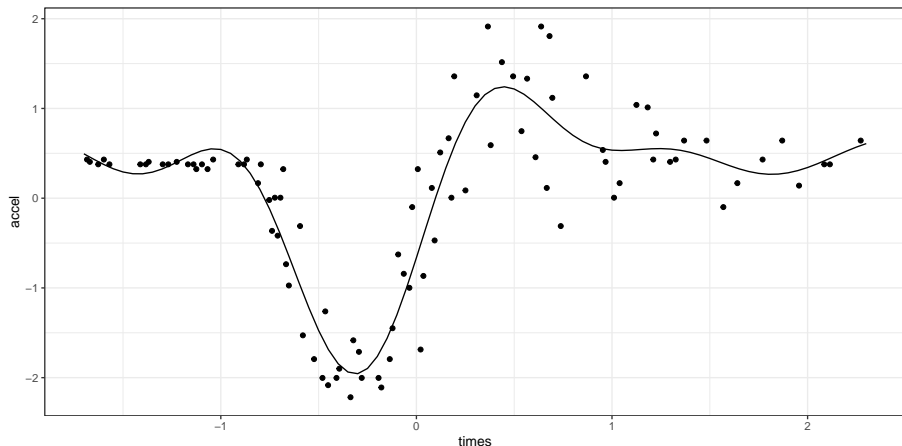
Making predictions using GPs

Now use the magic formula to predict for new x values:

```
tau = answer$p1
sigma = answer$p2
theta = answer$p3
x_new = pretty(motor2$times, n = 100)
Sigma_new = with(motor2,
                  tau^2 * Exp.cov(times, x_new,
                                   theta = theta, p = 2))
Sigma = with(motor2,
             diag(sigma^2, nrow(motor2)) + tau^2 * Exp.cov(times,
                                                             x_new,
                                                             theta = theta, p = 2))
GP_pred = tibble(
  x_new = x_new,
  mu_pred = t(Sigma_new) %*% solve(Sigma) %*% motor2$accel
)
```

Plot of predictions

```
ggplot(motor2, aes(x = times, y = accel)) +  
  geom_point() +  
  geom_line(data = GP_pred, aes(x = x_new, y = mu_pred))
```



Shiny app

andrewcparnell.shinyapps.io/GP_explore

or

is.gd/gp_play

What else can you do with GPs?

- You can put the linear regression terms back in to the mean if you want
- If you drop the σ^2 off the diagonal you can perform interpolation rather than smoothing
- The x values don't have to be one dimensional. Provided you can create a univariate distance between them you can run a GP. This is the foundation for spatial statistics and Kriging
- Lots of work on clever covariance functions
- Easy to make Bayesian by putting priors on parameters
- Big road block is calculation of Σ^{-1}

- You have now seen that a Gaussian Process is just a multivariate normal distribution
- The first clever trick is to make the observations correlated to each other by an autocovariance function
- The second clever trick is to use the magic multivariate normal formula to get instant access to predictions (and confidence intervals)

Thanks, and enjoy using Gaussian Processes!