Time series data

```r
require(ptLasso)
#> Loading required package: ptLasso
#> Loading required package: ggplot2
#> Loading required package: glmnet
#> Loading required package: Matrix
#> Loaded glmnet 4.1-8
#> Loading required package: gridExtra
```

We may have repeated measurements of X and y across time; for example, we may observe patients at two different points in time. We expect that the relationship between X and y will be different at time 1 and time 2, but not completely unrelated. Therefore, pretraining can be useful: we can use the model fitted at time 1 to inform the model for time 2.

`ptLasso` supports this setting, and below is an example. We first assume that X is constant across time, and y changes. Later, we will show an example where X changes across time.

To do pretraining with time series data, we:

1. fit a model for time 1 and extract its offset and support,
2. use the offset and support (the usual pretraining) to train a model for time 2.

We could continue this for k time points: after fitting a model for time 2, we would extract the offset and support. Now, the offset will include the offset from time 1 and the prediction from time 2; the support will be the *union* of supports from the first two models.

Example 1: covariates are constant over time

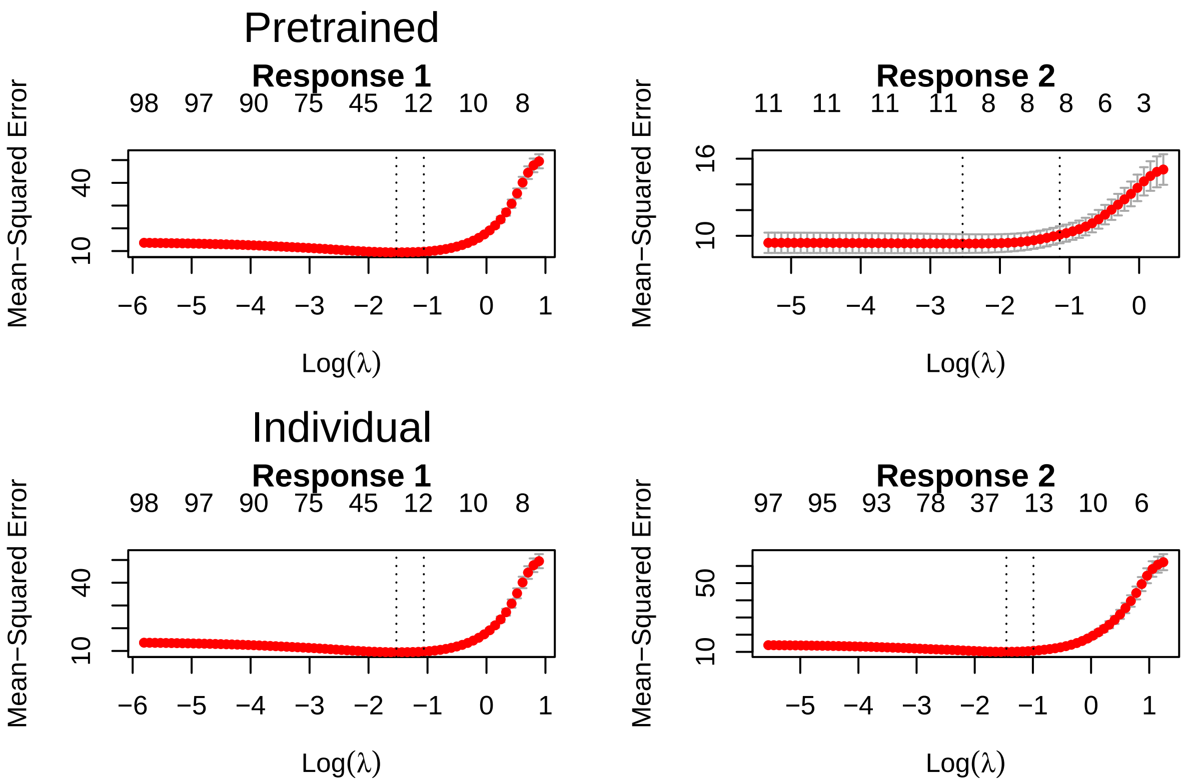
We'll start by simulating data – more details in the comments.

```r
set.seed(1234)

# Define constants
n = 600           # Total number of samples
ntrain = 300      # Number of training samples
p = 100           # Number of features
sigma = 3         # Standard deviation of noise

# Generate covariate matrix
x = matrix(rnorm(n * p), n, p)

# Define coefficients for time points 1 and 2
beta1 = c(rep(2, 10), rep(0, p - 10))  # Coefs at time 1
beta2 = runif(p, 0.5, 2) * beta1       # Coefs at time 2, shared support with time 1

# Generate response variables for times 1 and 2
y = cbind(
  x %*% beta1 + sigma * rnorm(n),
  x %*% beta2 + sigma * rnorm(n)
)
```

```r
# Split data into training and testing sets
xtest = x[-(1:ntrain), ]  # Test covariates
ytest = y[-(1:ntrain), ]  # Test response

x = x[1:ntrain, ]  # Train covariates
y = y[1:ntrain, ]  # Train response
```

Having simulated data, we are ready to call `ptLasso`; the call to `ptLasso` looks much the same as in all our other examples, only now (1) y is a matrix with one column for each time point and (2) we specify `use.case = "timeSeries"`. After fitting, a call to `plot` shows the models fitted for both of the time points with and without using pretraining.

```r
fit = ptLasso(x, y, use.case = "timeSeries", alpha = 0)
plot(fit)
```



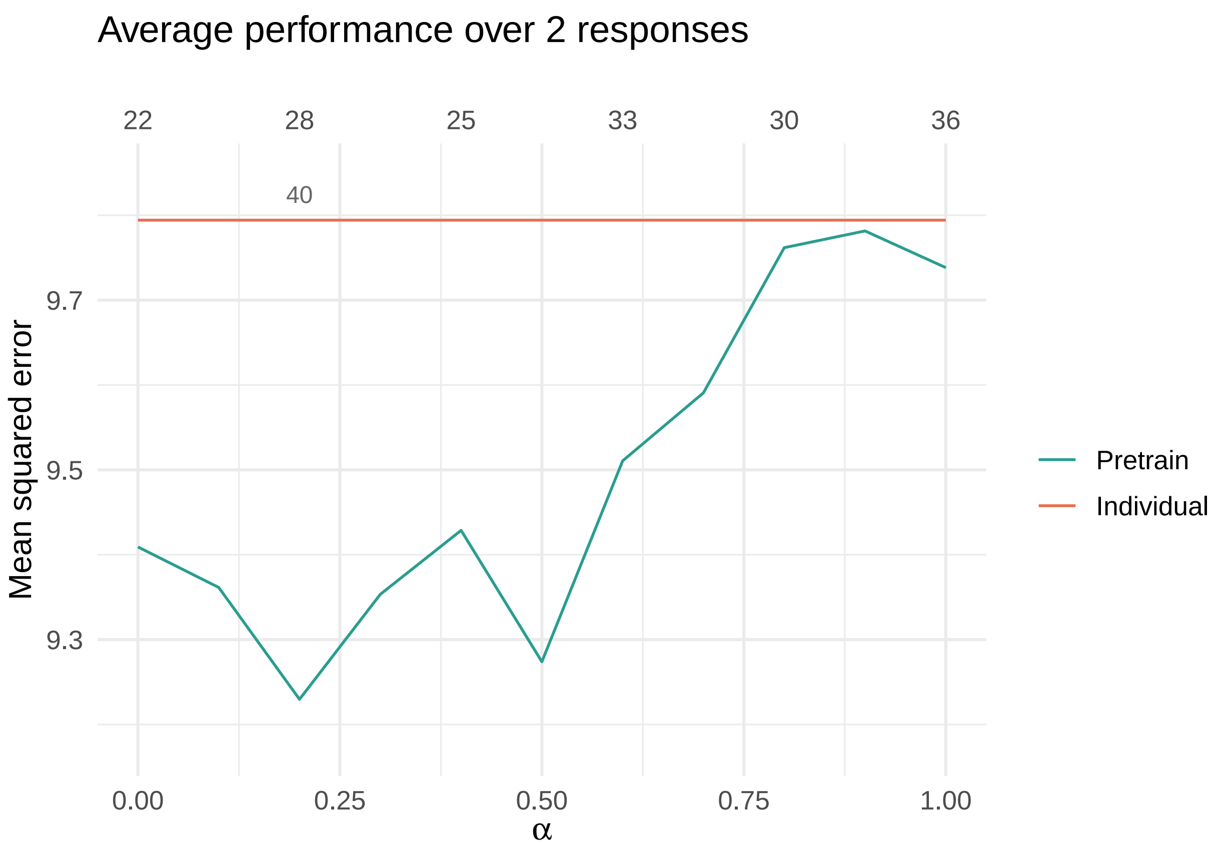
And as before, we can `predict` with `xtest`. In this example, pretraining helps performance: the two time points share the same support, and pretraining discovers and leverages this.

```r
preds = predict(fit, xtest, ytest = ytest)
preds
#>
#> Call:
#> predict.ptLasso(object = fit, xtest = xtest, ytest = ytest)
#>
#>
#>
#> alpha =  0
#>
#> Performance (Mean squared error):
#>
```

```
#>              mean response_1 response_2
#> Pretrain    9.604      10.78      8.428
#> Individual 10.428      10.78     10.076
#>
#> Support size:
#>
#> Pretrain   26 (10 common + 16 individual)
#> Individual 39
```

We specified `alpha = 0` in this example, but cross validation would advise us to choose $\alpha = 0.2$. Plotting shows us the average performance across the two time points. Importantly, at time 1, the individual model and the pretrained model are the same; we do not see the advantage of pretraining until time 2 (when we use information from time 1).

```r
cvfit = cv.ptLasso(x, y, use.case = "timeSeries")
plot(cvfit)
```




```r
predict(cvfit, xtest, ytest = ytest)
#>
#> Call:
#> predict.cv.ptLasso(object = cvfit, xtest = xtest, ytest = ytest)
#>
#>
#>
#> alpha =  0.2
#>
#> Performance (Mean squared error):
#>
```

```
#>             mean response_1 response_2
#> Pretrain   10.62      10.87      10.37
#> Individual 10.45      10.87      10.03
#> 
#> Support size:
#> 
#> Pretrain   28 (10 common + 18 individual)
#> Individual 40
```

Note that we could also have treated this as a *multireponse* problem, and ignored the time-ordering of the responses. See more in the section called "Multi-response data with Gaussian responses". (However, time ordering can be informative, and the multi-response approach does not make use of this.)

```
fit = ptLasso(x, y, use.case = "multiresponse")
```

Example 2: covariates change over time

Now, we'll repeat what we did above, but we'll simulate data where x changes with time. In this setting, ptLasso expects x to be a list with one covariate matrix for each time.

```
set.seed(1234)  # Set seed for reproducibility

# Define constants
n = 600          # Total number of samples
ntrain = 300     # Number of training samples
p = 100          # Number of features
sigma = 3        # Standard deviation of noise

# Covariates for times 1 and 2
x1 = matrix(rnorm(n * p), n, p)
x2 = x1 + matrix(0.2 * rnorm(n * p), n, p)  # Perturbed covariates for time 2
x = list(x1, x2)

# Define coefficients for time points 1 and 2
beta1 = c(rep(2, 10), rep(0, p - 10))  # Coefs at time 1
beta2 = runif(p, 0.5, 2) * beta1       # Coefs at time 2, shared support with time 1

# Response variables for times 1 and 2:
y = cbind(
  x[[1]] %*% beta1 + sigma * rnorm(n),
  x[[2]] %*% beta2 + sigma * rnorm(n)
)

# Split data into training and testing sets
xtest = lapply(x, function(xx) xx[-(1:ntrain), ])  # Test covariates
ytest = y[-(1:ntrain), ]  # Test response

x = lapply(x, function(xx) xx[1:ntrain, ])  # Train covariates
y = y[1:ntrain, ]  # Train response
```

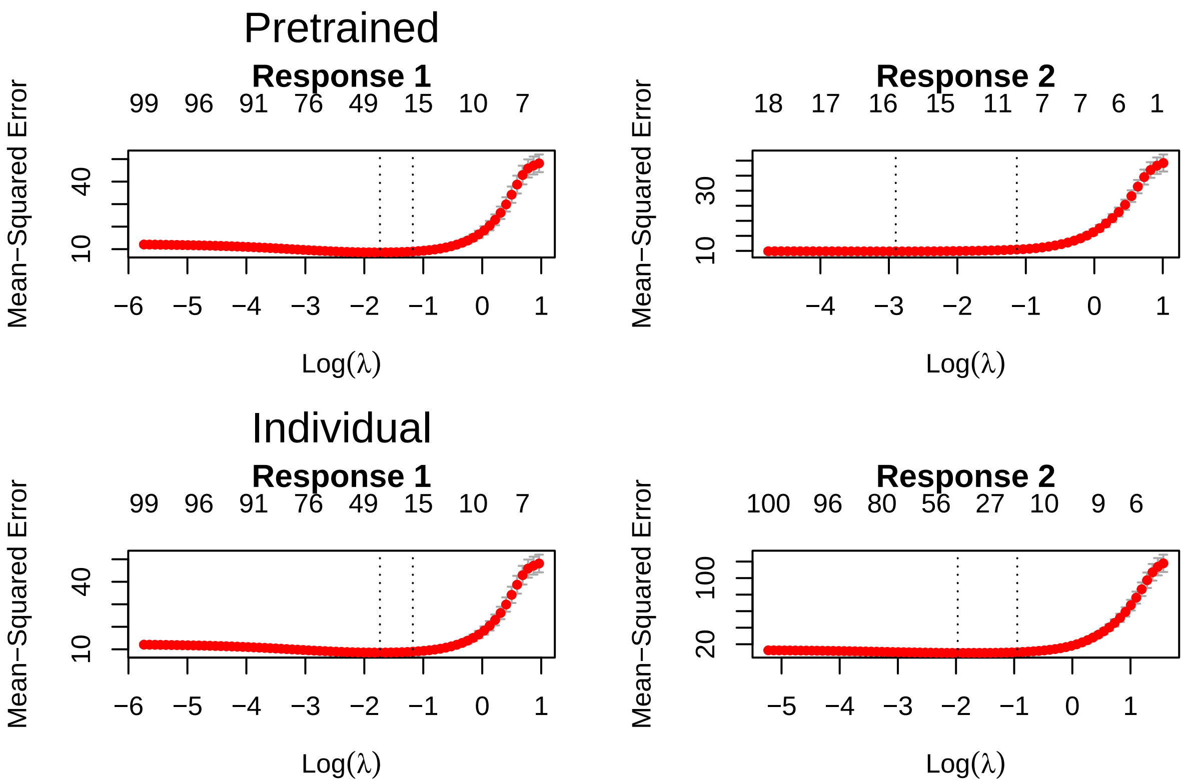
Now, x is a list of length two:

```
str(x)
#> List of 2
#>  $ : num [1:300, 1:100] -1.207 0.277 1.084 -2.346 0.429 ...
```

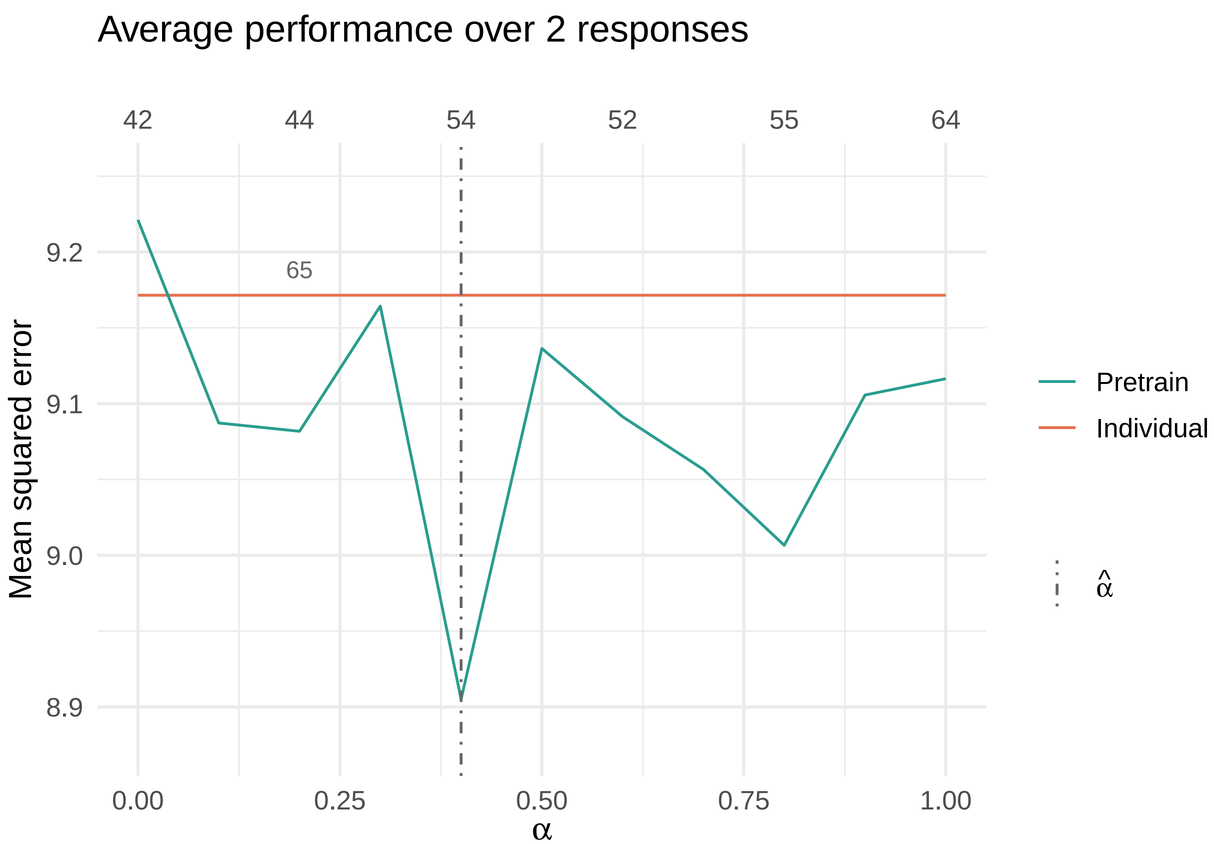
```
#>  $ : num [1:300, 1:100] -1.493 0.303 1.172 -2.316 0.224 ...
```

We can call ptLasso, cv.ptLasso, plot and predict just as before:

```r
fit = ptLasso(x, y, use.case = "timeSeries", alpha = 0)
plot(fit)   # Plot the fitted model
```




```r
predict(fit, xtest, ytest = ytest)  # Predict using the fitted model
#> 
#> Call:
#> predict.ptLasso(object = fit, xtest = xtest, ytest = ytest)
#> 
#> 
#> 
#> alpha =  0
#> 
#> Performance (Mean squared error):
#> 
#>                mean response_1 response_2
#> Pretrain   11.92        12.1      11.75
#> Individual 11.46        12.1      10.82
#> 
#> Support size:
#> 
#> Pretrain   36 (16 common + 20 individual)
#> Individual 61

# With cross validation:
cvfit = cv.ptLasso(x, y, use.case = "timeSeries")
plot(cvfit, plot.alphahat = TRUE)  # Plot cross-validated model
```




```
predict(cvfit, xtest, ytest = ytest)  # Predict using cross-validated model
#>
#> Call:
#> predict.cv.ptLasso(object = cvfit, xtest = xtest, ytest = ytest)
#>
#>
#>
#> alpha =  0.4
#>
#> Performance (Mean squared error):
#>
#>             mean response_1 response_2
#> Pretrain   15.73      12.11      19.35
#> Individual 11.53      12.11      10.96
#>
#> Support size:
#>
#> Pretrain   54 (19 common + 35 individual)
#> Individual 65
```