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

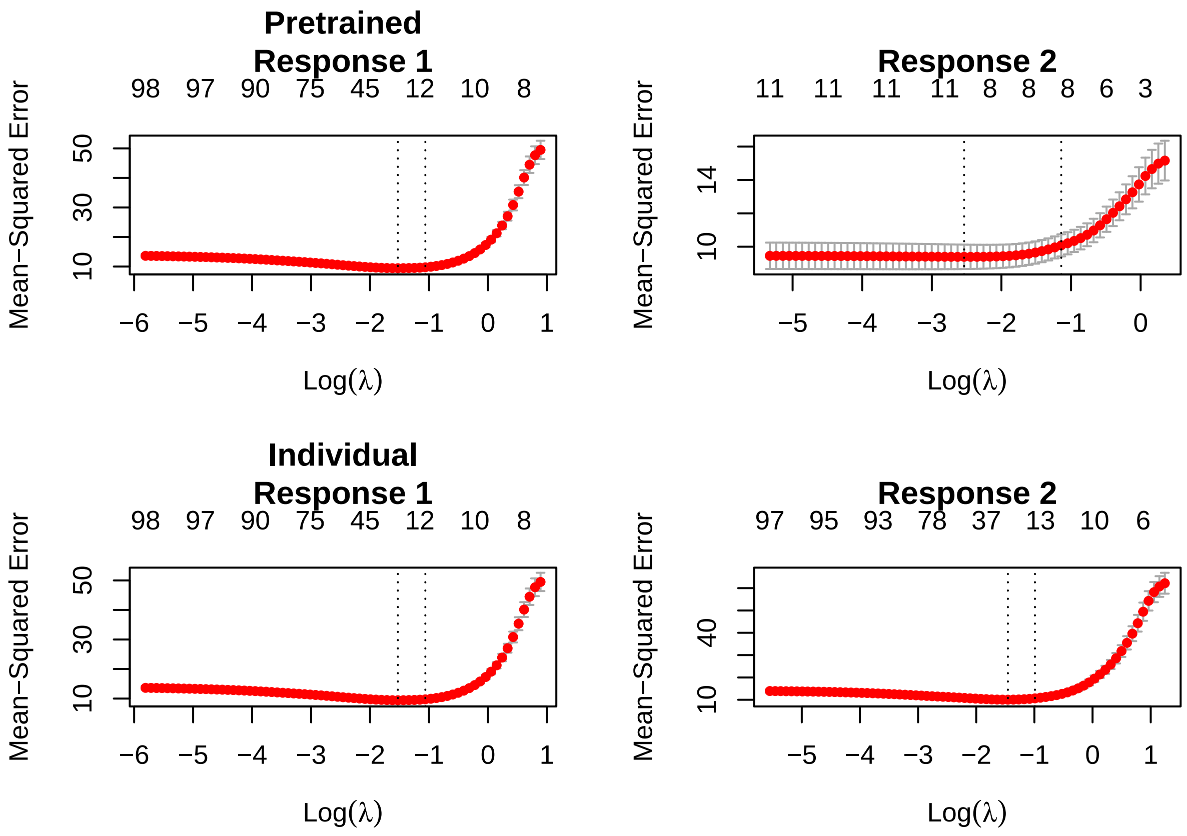
We'll start by simulating data – more details in the comments.

```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)
```



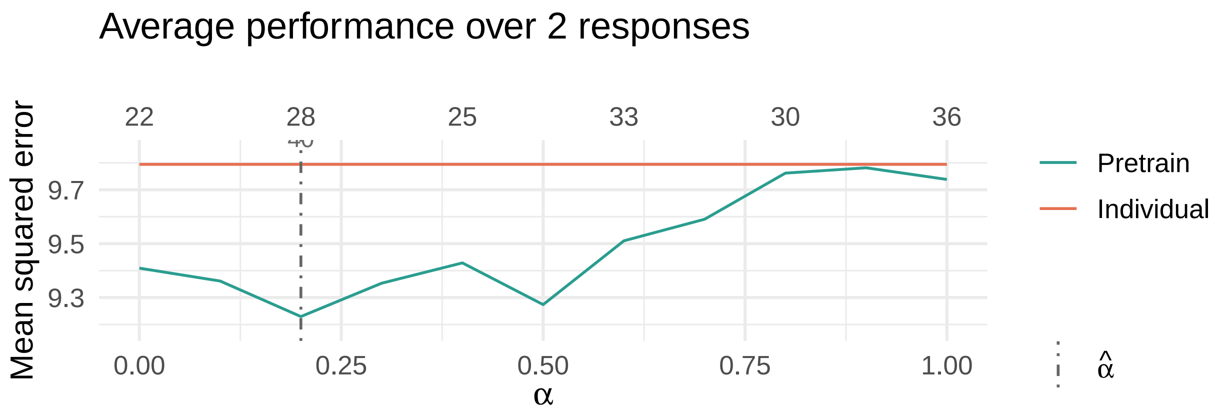
And as before, we can `predict` with `xtest`. In this example, pretraining helps performance: the two time points share the same support, and pretraining discovers and leverages this.

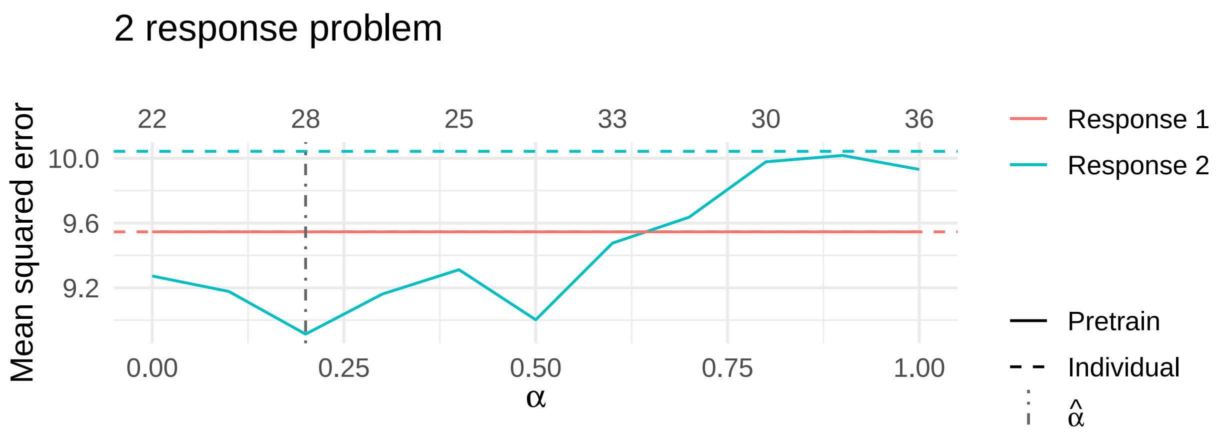
```r
preds = predict(fit, xtest, ytest = ytest)
preds
#>
#> Call:
#> predict.ptLasso(object = fit, xtest = xtest, ytest = ytest)
#>
#>
#>
#> alpha =  0
#>
```

```
#> 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 as well as the performance for each time point. Note that, at time 1, the 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).

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





```
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
```

A minor detail: 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, we recommend using the time ordering!)

```
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.

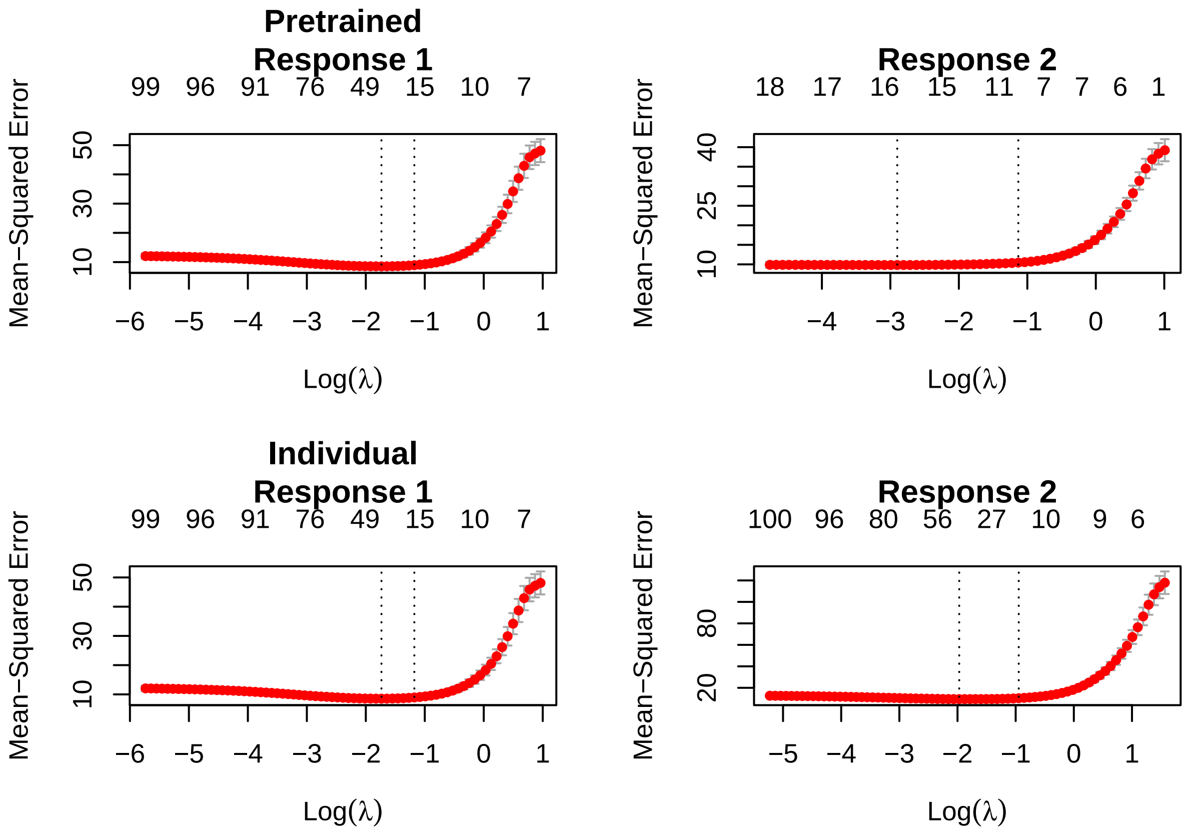
```
set.seed(1234)  # Set seed for reproducibility

# 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:

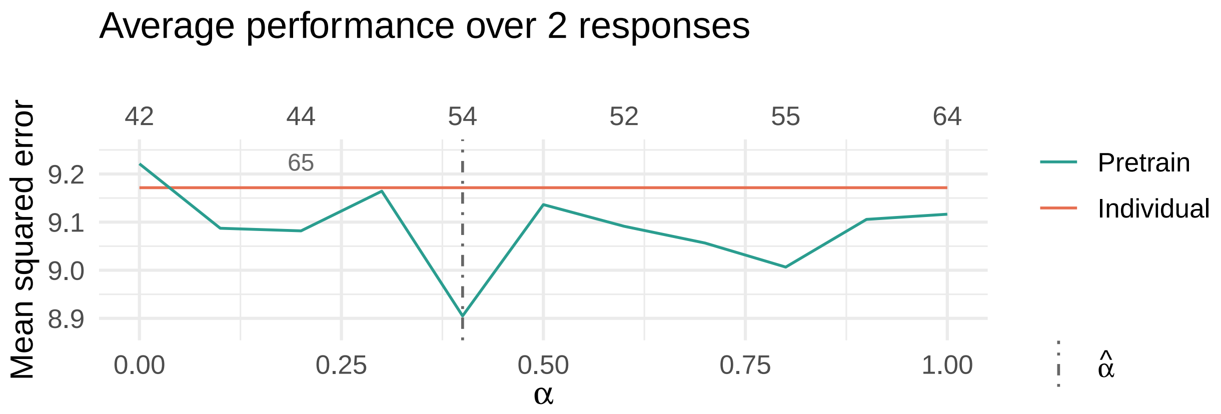
```
str(x)
#> List of 2
#>  $ : num [1:300, 1:100] -1.207 0.277 1.084 -2.346 0.429 ...
#>  $ : num [1:300, 1:100] -1.493 0.303 1.172 -2.316 0.224 ...
```

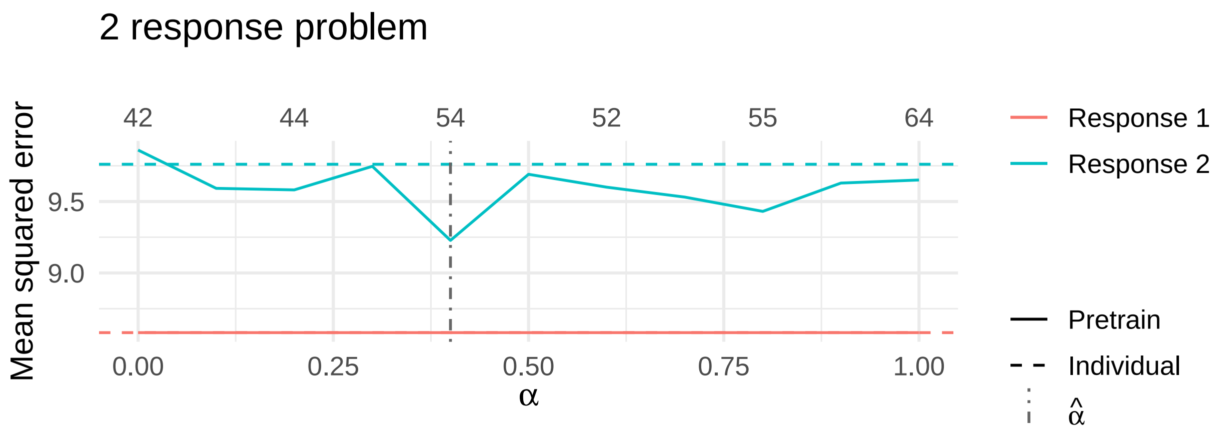
We can call `ptLasso`, `cv.ptLasso`, `plot` and `predict` just as before:

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



```
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
```