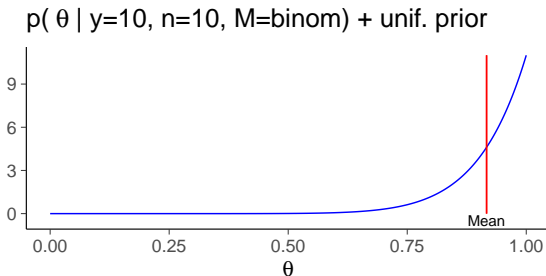


# Benefits of integration and prior

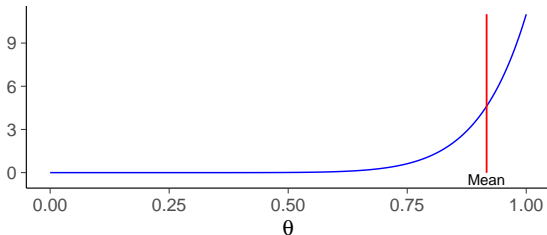
Example:  $n = 10, y = 10$  - uniform vs Beta(2,2) prior



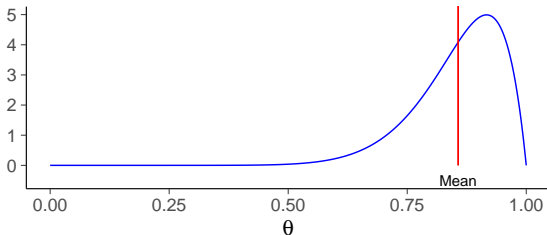
# Benefits of integration and prior

Example:  $n = 10, y = 10$  - uniform vs Beta(2,2) prior

$p(\theta | y=10, n=10, M=\text{binom}) + \text{unif. prior}$

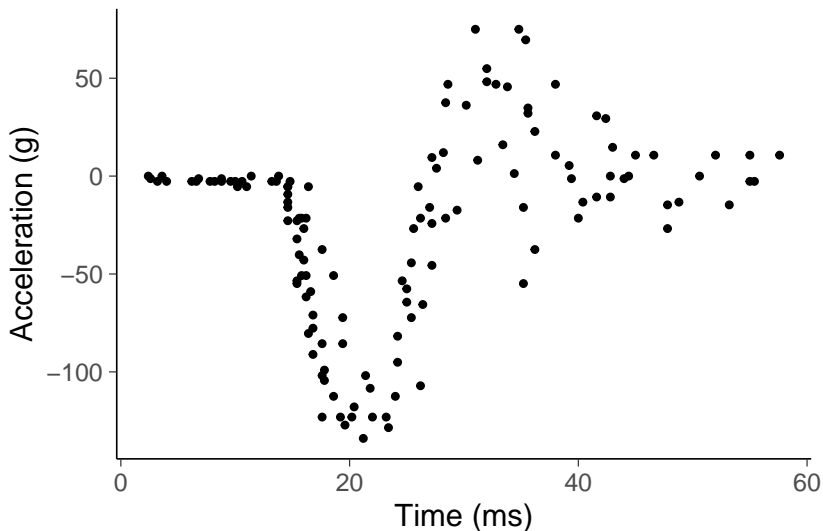


$p(\theta | y=10, n=10, M=\text{binom}) + \text{Beta}(2,2) \text{ prior}$



# Benefits of integration: Gaussian process example

Simulated data of  $g$  forces in a motorcycle accident



# Benefits of integration: Gaussian process example

- Gaussian process is a hierarchical normal model with multivariate normal population prior, where the off-diagonal covariances are determined by similarity measure (in this example distance)

$$y \sim \text{normal}(f(x), \sigma)$$

$$f \sim GP(0, K_1)$$

$$\sigma \sim \text{normal}^+(0, 1),$$

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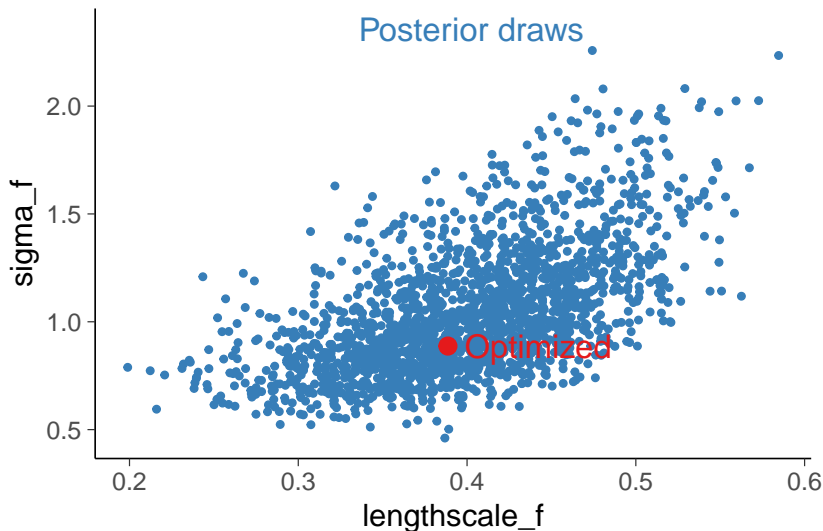
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- Latent values  $f$  can be integrated out analytically, and the remaining marginal posterior is 3 dimensional

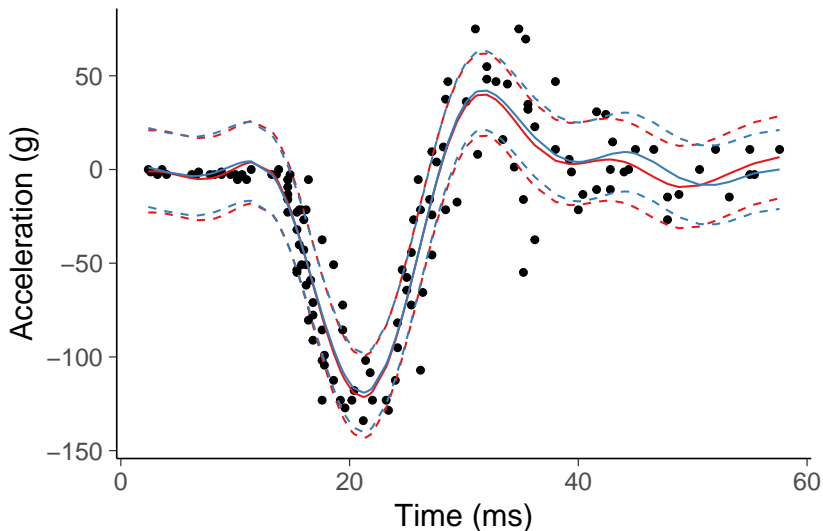
# Benefits of integration: Gaussian process example

Plenty of data: the mode of the posterior can be representative



# Benefits of integration: Gaussian process example

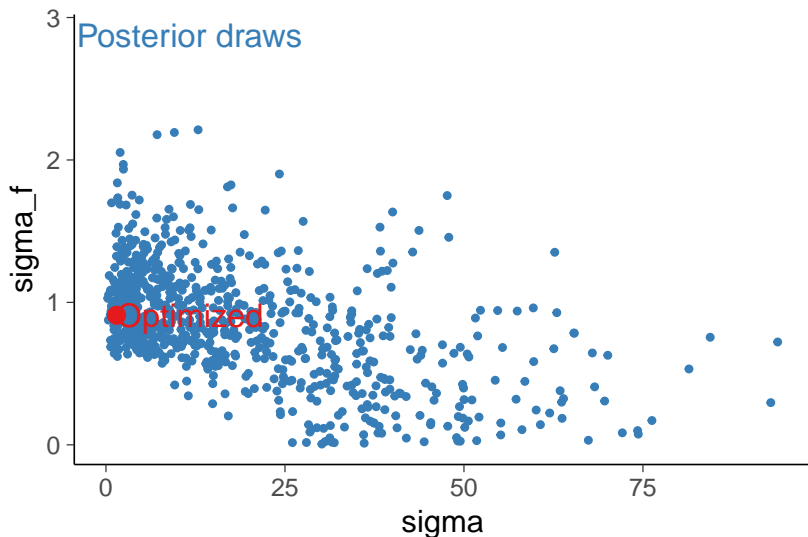
Plenty of data: the mode of the posterior can be representative





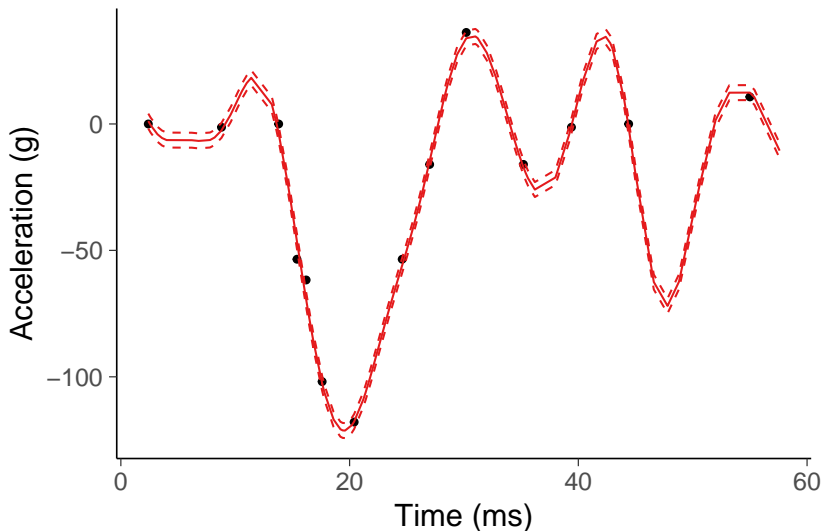
# Benefits of integration: Gaussian process example

Small data: the mode of the posterior is not representative



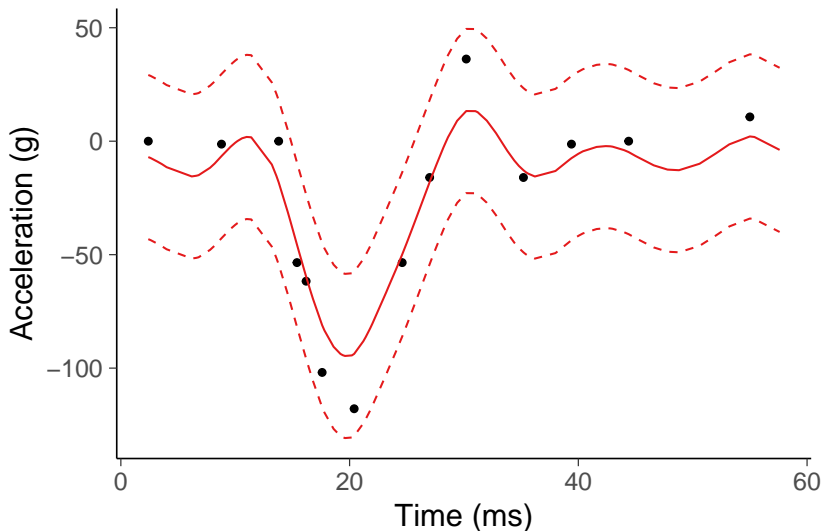
# Benefits of integration: Gaussian process example

Small data: the mode of the posterior is not representative



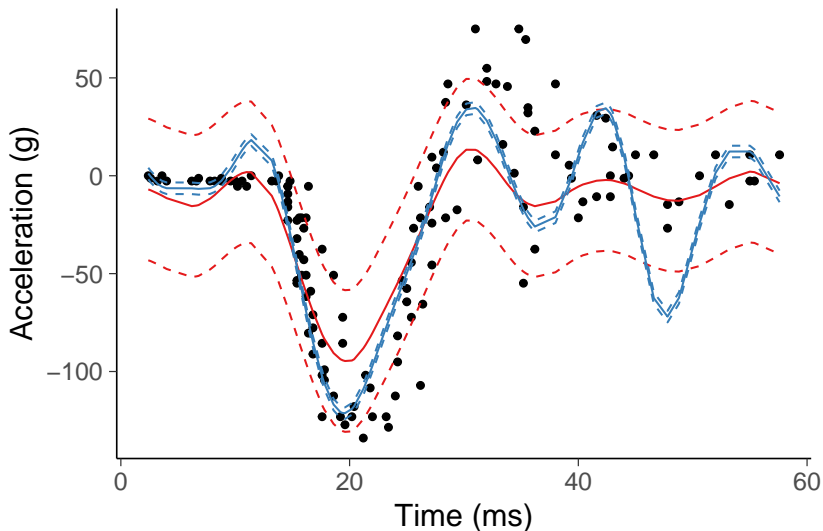
# Benefits of integration: Gaussian process example

Small data: the mode of the posterior is not representative



# Benefits of integration: Gaussian process example

Small data: the mode of the posterior is not representative



# Benefits of integration: Gaussian process example

- More complex model, with time dependent residual variance  $\exp(g(x))$

$$y \sim \text{normal}(f(x), \exp(g(x)))$$

$$f \sim GP(0, K_1)$$

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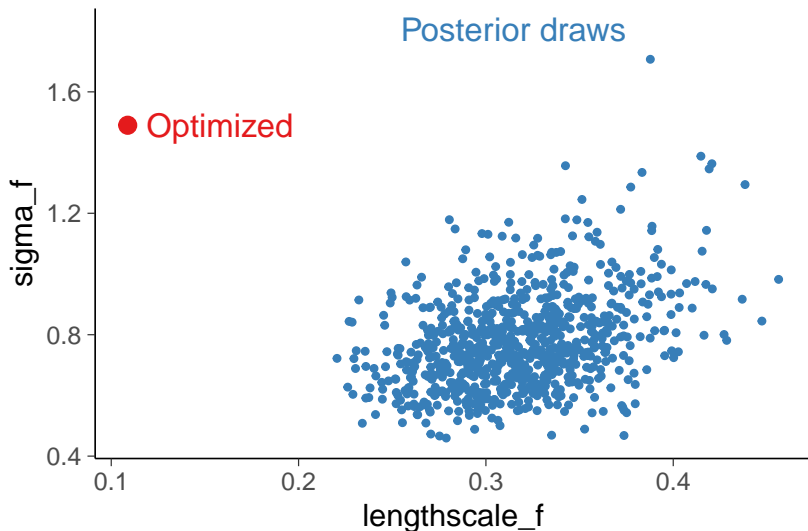
$$f \sim GP(0, K_1)$$

$$g \sim GP(0, K_2).$$

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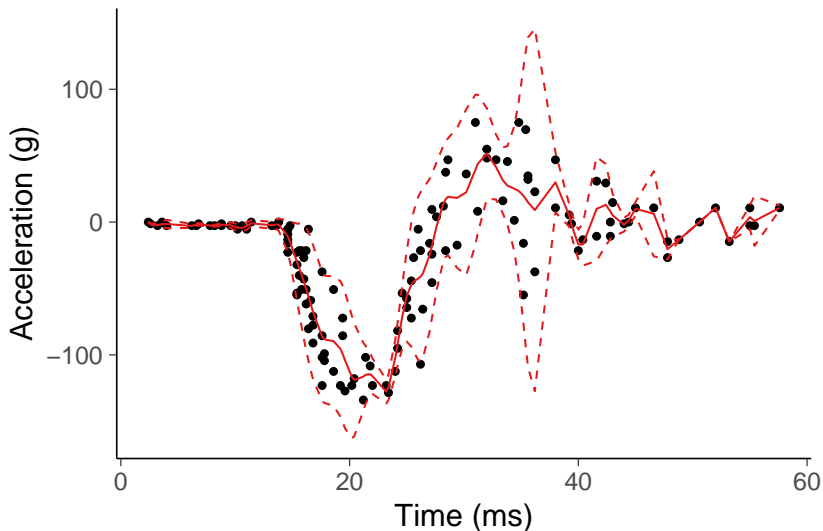
# Benefits of integration: Gaussian process example

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# Benefits of integration: Gaussian process example

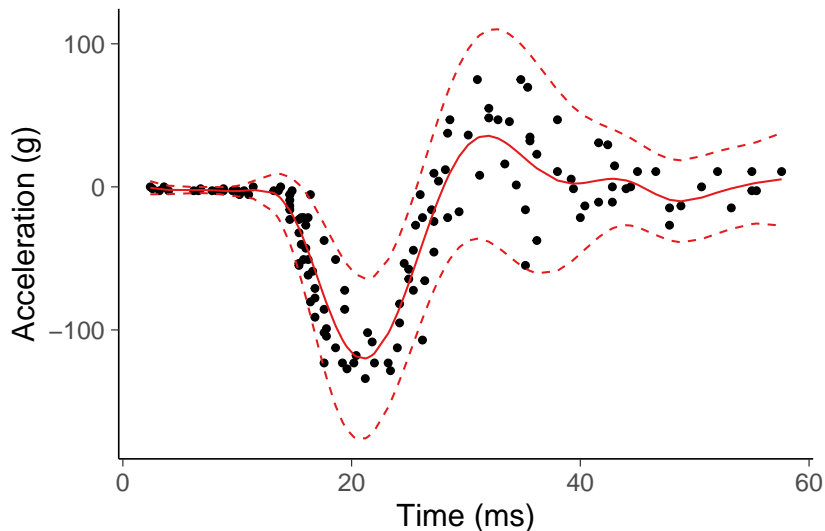
Optimization overfits





# Benefits of integration: Gaussian process example

Integration works well



## Benefits of better priors: logistic regression

$$y \sim \text{Bernoulli} \left( \text{logit}^{-1}(\alpha + \beta X) \right)$$

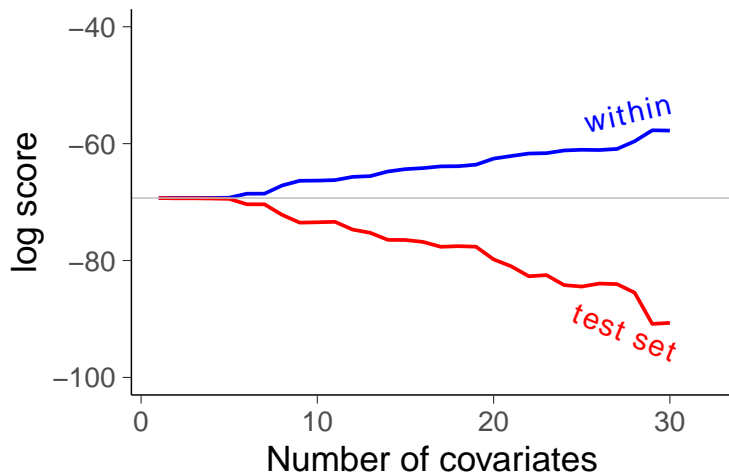
where  $\alpha$  is a scalar intercept,  
and  $\beta$  is a vector of coefficients

## Model selection is needed to avoid overfitting?

logistic regression: 30 **completely irrelevant** variables,  
100 observations

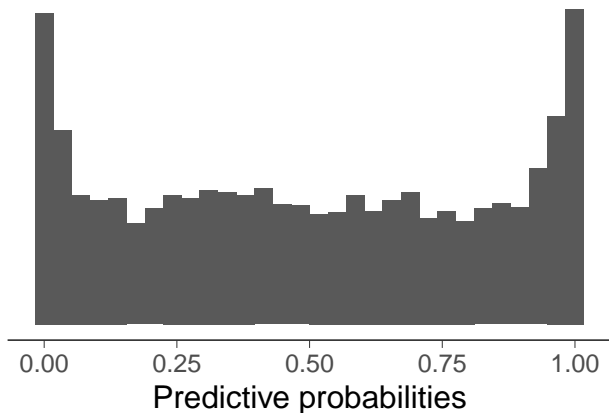
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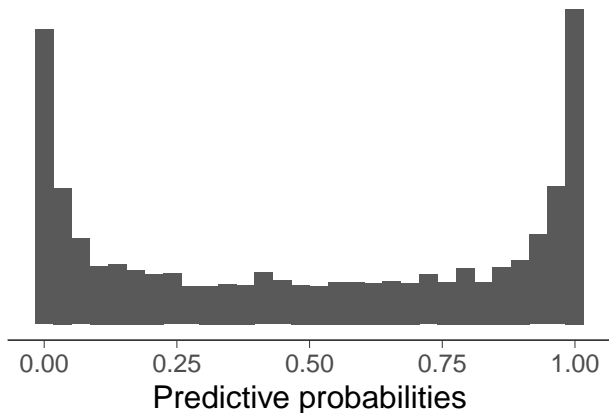
# Prior on parameters vs predictions

$N(0,3)$  prior on each coefficient  
1 variable



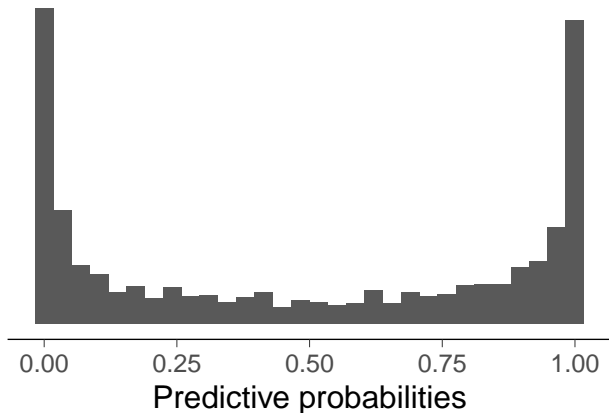
# Prior on parameters vs predictions

$N(0,3)$  prior on each coefficient  
2 variables



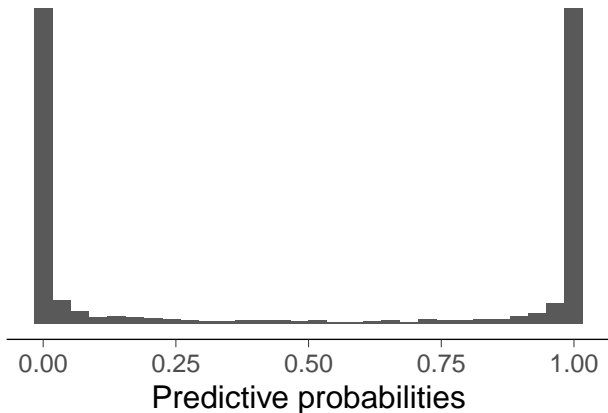
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# Prior on parameters vs predictions

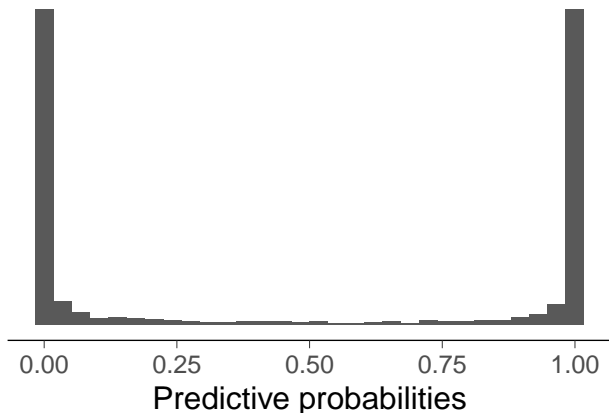
$N(0,3)$  prior on each coefficient  
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# Prior on parameters vs predictions

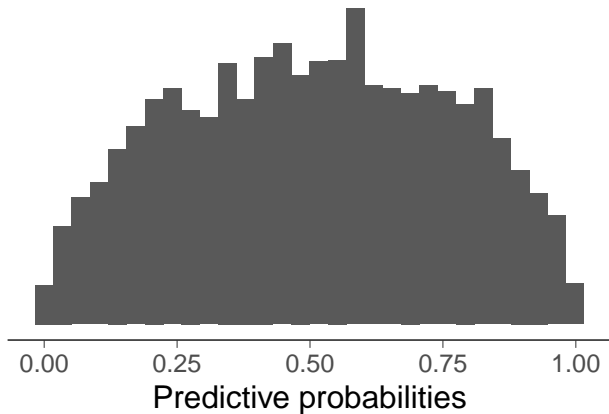
$N(0,3)$  prior on each coefficient  
30 variables



A weak prior on parameters can be a strong prior on predictions

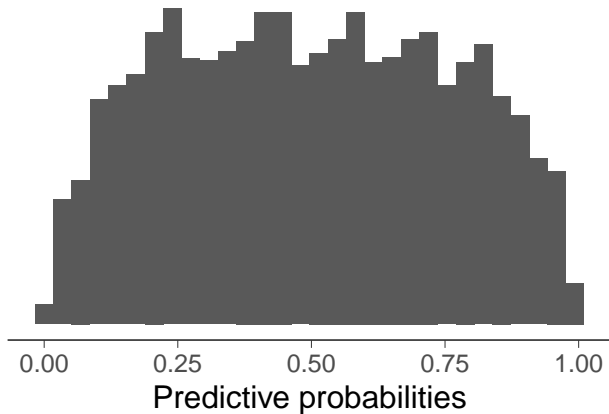
## Better priors

$N(0, \frac{1}{\sqrt{p}})$  prior on each coefficient  
1 variable



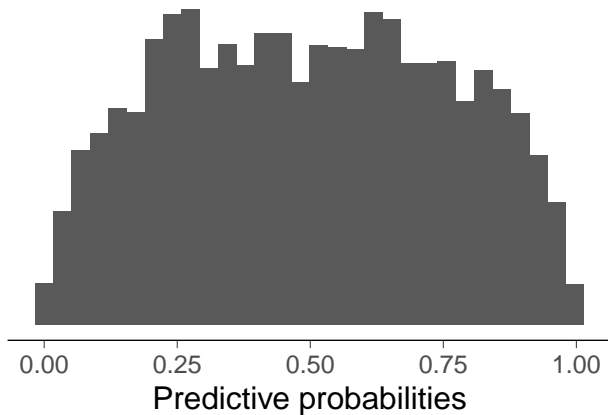
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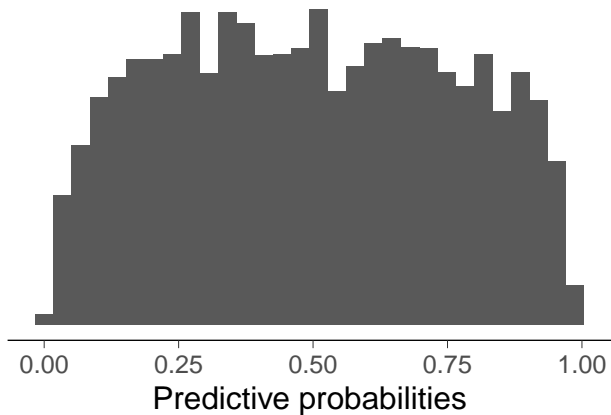
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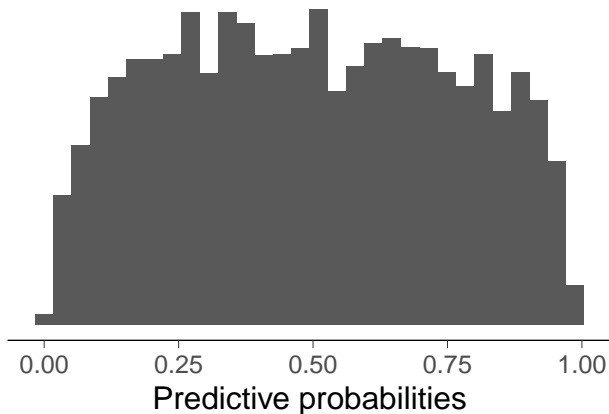
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## Better priors

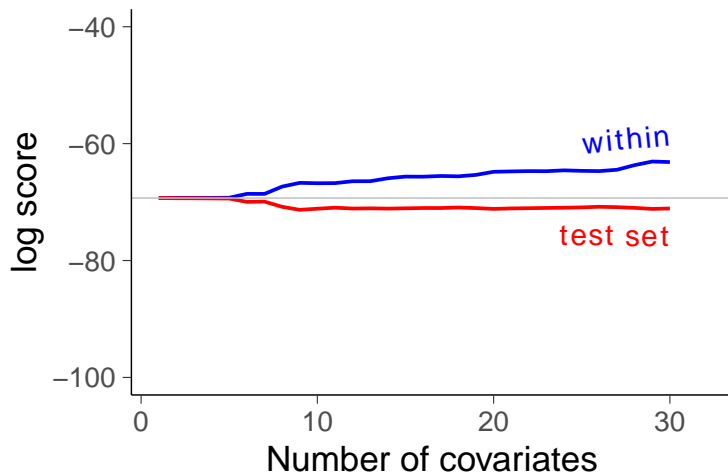
$N(0, \frac{1}{\sqrt{p}})$  prior on each coefficient  
30 variables



Prior on predictions (almost) fixed when the model gets bigger

## Better priors, no overfitting

logistic regression: 30 **completely irrelevant** variables,  
100 observations



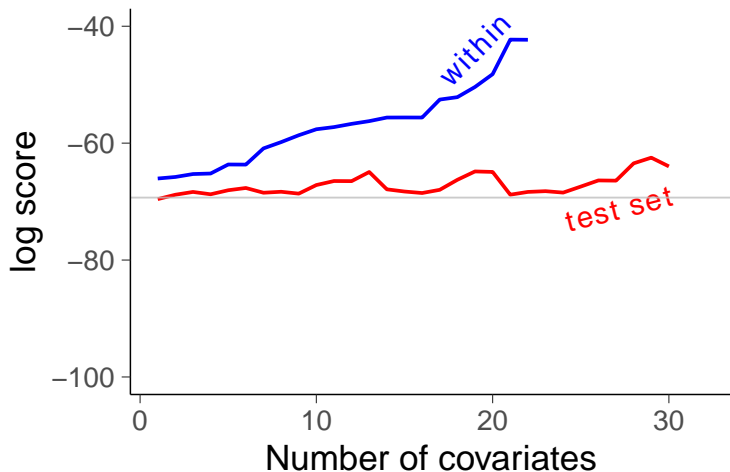
## Many weak effects, wide prior on parameters

logistic regression: 30 **weakly relevant** variables,  
100 observations, wide prior



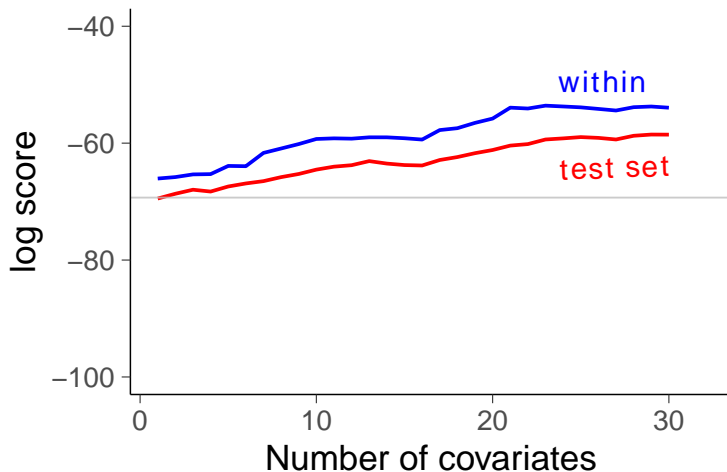
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# Many weak effects, better prior

logistic regression: 30 **weakly relevant** variables,  
100 observations, better prior

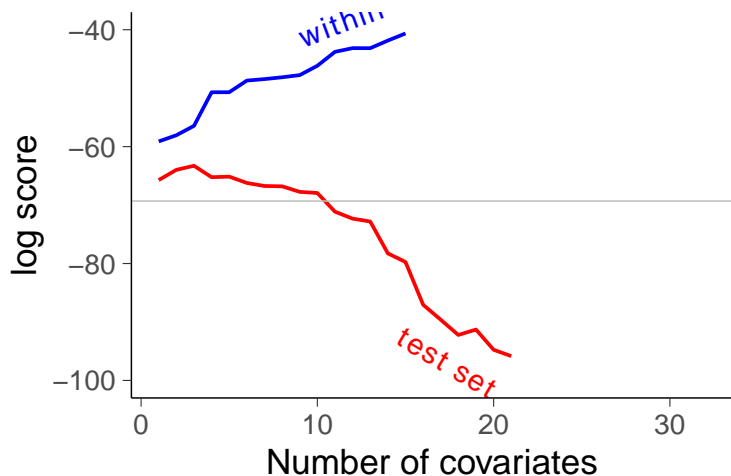


## Correlating variables, wide prior on parameters

logistic regression: 30 **correlating relevant** variables,  
100 observations

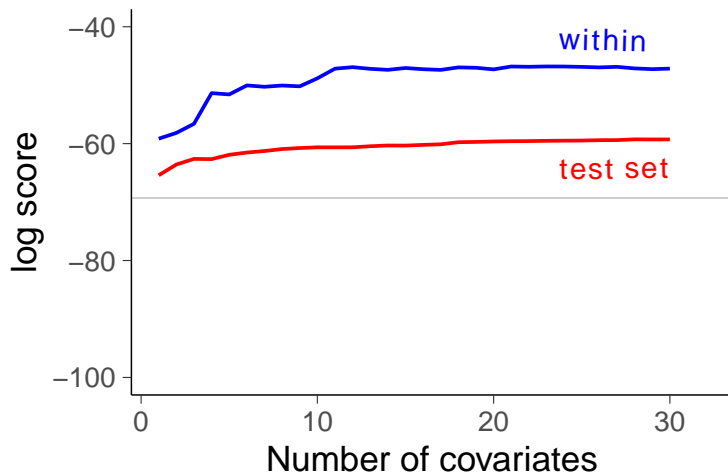
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logistic regression: 30 **correlating relevant** variables,  
100 observations



# Correlating variables, better prior

logistic regression: 30 **correlating relevant** variables,  
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# Benefits of integration and prior

- Integration helps to avoid overfitting
- Integration is not able to counter bad priors