Simulated GenProbe Data

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Simulating data with known correlation structure.

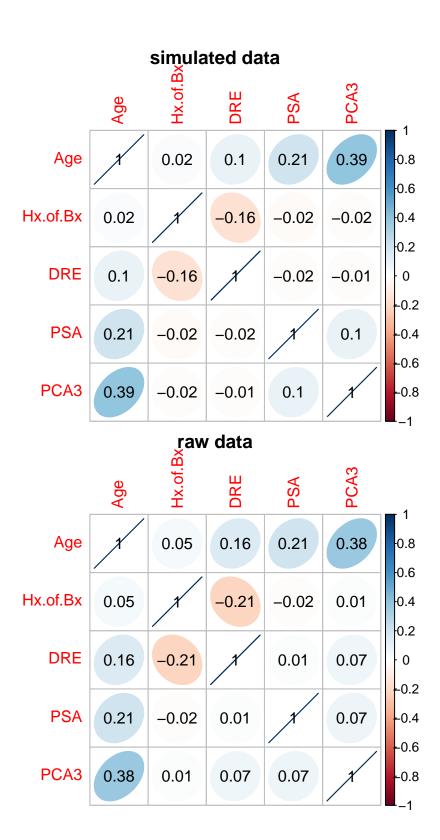
I use the method described here:

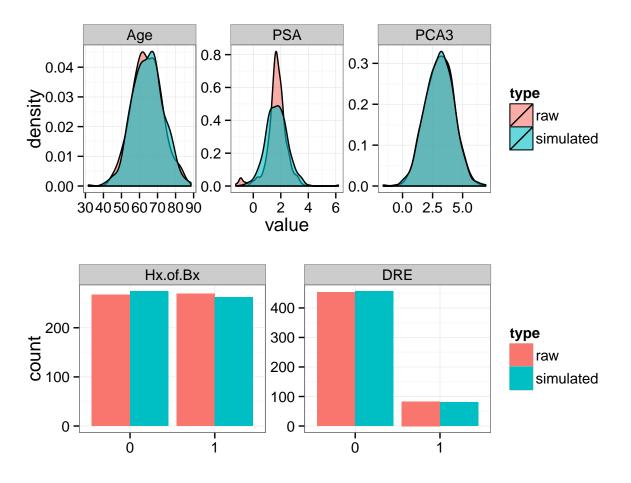
http://www.r-bloggers.com/easily-generate-correlated-variables-from-any-distribution-without-copulas/www.r-bloggers.com/easily-generate-correlated-variables-from-any-distribution-without-copulas/www.r-bloggers.com/easily-generate-correlated-variables-from-any-distribution-without-copulas/www.r-bloggers.com/easily-generate-correlated-variables-from-any-distribution-without-copulas/www.r-bloggers.com/easily-generate-correlated-variables-from-any-distribution-without-copulas/www.r-bloggers.com/easily-generate-correlated-variables-from-any-distribution-without-copulas/www.r-bloggers.com/easily-generate-correlated-variables-from-any-distribution-without-copulas/www.r-bloggers.com/easily-generate-correlated-variables-from-any-distribution-without-copulas/www.r-bloggers.com/easily-generate-correlated-variables-generate-correlated-variables-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-correlated-without-copulas/www.r-bloggers-generate-copulas/www.r-bloggers-generate-copulas/www.r-bloggers-generate-copulas/www.r-bloggers-generate-copulas/www.r-bloggers-generate-copulas/www.r-bloggers-generate-copulas/www.r-bloggers-generate-copulas/www.r-bloggers-genera

Assuming that the (scaled) continuous variables are approximately normal, we:

- 1. Draw variables from a joint normal distribution using the observed mean/covariance matrix estimated from the GenProbe data.
- Simulated Age, log(PSA), and log(PCA3) values are directly simulated from this multivariate normal distribution.
- 2. Apply the univariate normal CDF of variables to derive probabilities for binary variables 'suspicious DRE' and 'history of biopsy.'
- 3. Apply the inverse binomial CDF with $p = \hat{p}$ estimated from the raw data to simulate binary variables.
- This transformation reduces the amount of correlation among variables, but for this example the simulated variables follow pretty close to the observed correlation structure (see below).

Nex I show the correlation and marginal distributions in the raw vs. simulated data.





Simulating outcome

First I fit a logistic regression model using the raw data with age, DRE, history of biopsy, PSA and PCA3. I then simulate cancer outcome from a logistic model using the same coefficients from the model fit on the raw data.

```
## (Intercept) Age Hx.of.Bx DRE PSA PCA3
## obs.coef -2.748036 -0.005166188 -0.7954109 0.5796367 0.4158020 0.6464313
## new.coef -2.691541 -0.020114025 -0.4787605 0.7706856 0.5347999 0.8101323
```

Create plots for manuscript

