5/29/2019 hmm homework

## Exercise

Session information

## hmm homework

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workflowr checks: (Click a bullet for more information)

• ▶ ✓ R Markdown file: up-to-date

• ► ✓ Environment: empty

• ► **√ Seed:** set.seed(20180411)

• ▶ ✓ Session information: recorded

▶ ✓ Repository version: 225f991
 (https://github.com/stephens999/stat34800/tree/225f991bff25554a3d7fae1b31f8917d1147696f)

**Expand here to see past versions:** 

Here we <u>simulate a simple HMM</u> with <u>two states</u>,  $Z_t \in \{1,2\}$  that <u>represent two different genetic populations</u>. The <u>data  $X_t$ </u> is <u>genetic data at locus (position) t</u>, which we will assume are <u>0 or 1</u>. So the <u>emission distribution</u> at <u>position t in state k is Bernoulli( $p_{kt}$ ) where  $p_{kt}$  is the <u>frequency</u> of the <u>1 allele at position t in population k.</u></u>

The transition matrix for the Markov chain is symmetric, with probability <u>0.9 of staying</u> in the same state, and <u>0.1 of switching</u> at each step.

Here is some code to simulate from this:

5/29/2019 hmm homework

```
set.seed(1)
T = 1000
K = 2
P = rbind(c(0.9, 0.1), c(0.1, 0.9))
# simulate the matrix of allele frequencies in each of the K populations at each
of T loci
p = matrix(runif(K*T),nrow=K,ncol=T)
# Simulate the latent (Hidden) Markov states
Z = rep(0,T)
Z[1] = 1
for(t in 1:(T-1)){
  Z[t+1] = sample(K, size=1, prob=P[Z[t],])
}
# Work out the corresponding bernoulli probability for each state
prob = rep(0,T)
for(i in 1:T){
  prob[i] = p[Z[i],i]
}
# Simulate the emitted/observed values
X= rbinom(n=T,size=1,prob=prob)
```

## Exercise

- Implement the forward and backwards algorithm to "decode" this HMM: that is to compute  $\Pr(Z_t = k | X_1, \dots, X_T)$  for each t. Note that because of the longer length of this Markov chain you will need to do some normalizing of the forwards and backwards probabilities to avoid numerical errors.
- Compute the error rate (compared with the truth) if you assign each  $Z_t$  to its most probable value.
- Now imagine you did not know the true values for Z. Explain how you would estimate the error rate directly from the output of the forward-backwards calculation. Compare this estimate with that obtained when you did know the truth. (Hint: this is a bit like estimating a False Discovery Rate from the Empirical Bayes Normal Means output)

## Session information

```
sessionInfo()
```

5/29/2019 hmm homework

```
R version 3.3.2 (2016-10-31)
Platform: x86_64-apple-darwin13.4.0 (64-bit)
Running under: OS X El Capitan 10.11.6
locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/c/en_US.UTF-8/en_US.UTF-8
attached base packages:
[1] stats
              graphics grDevices utils
                                            datasets methods
                                                                 base
loaded via a namespace (and not attached):
[1] workflowr_1.0.1
                       Rcpp 0.12.16
                                         digest_0.6.15
 [4] rprojroot_1.3-2
                       R.methodsS3_1.7.1 backports_1.1.2
[7] git2r_0.21.0
                       magrittr 1.5
                                         evaluate_0.10.1
[10] stringi_1.1.7
                       whisker_0.3-2
                                         R.oo_1.22.0
[13] R.utils_2.6.0
                       rmarkdown_1.9
                                         tools_3.3.2
[16] stringr_1.3.0
                       yaml_2.1.18
                                         htmltools_0.3.6
[19] knitr_1.20
```

This reproducible R Markdown (http://rmarkdown.rstudio.com) analysis was created with workflowr (https://github.com/jdblischak/workflowr) 1.0.1