Session 4

Multi-test, multi-population models

Matt Denwood 2021-06-29

Why stop at two tests?

NOTE: THIS MATERIAL IS NOT YET FINALISED, PLEASE CHECK BACK SOON!

In *traditional* diagnostic test evaluation, one test is assumed to be a gold standard from which all other tests are evaluated

 So it makes no difference if you assess one test at a time or do multiple tests at the same time

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Using a latent class model each new test adds new information - so we should analyse all available test results in the same model

Simulating data: simple example

Simulating data using an arbitrary number of independent tests is quite straightforward:

```
# Parameter values to simulate:
N < -200
sensitivity \leftarrow c(0.8, 0.9, 0.95)
specificity \leftarrow c(0.95, 0.99, 0.95)
Populations <- 2
prevalence \leftarrow c(0.25,0.5)
data <- tibble(Population = sample(seq len(Populations), N,

    replace=TRUE)) %>%

 mutate(Status = rbinom(N, 1, prevalence[Population])) %>%
 mutate(Test1 = rbinom(N, 1, sensitivity[1]*Status +
 mutate(Test2 = rbinom(N, 1, sensitivity[2]*Status +
 mutate(Test3 = rbinom(N, 1, sensitivity[3]*Status +
 select(-Status)
```

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```
Tally[1:8,p] ~ dmulti(prob[1:8,p], TotalTests[p])
# Probability of observing Test1- Test2- Test3-
prob[1,p] \leftarrow prev[p] * ((1-se[1])*(1-se[2])*(1-se[3]) +
              (1-prev[p]) * (sp[1]*sp[2]*sp[3])
# Probability of observing Test1+ Test2- Test3-
prob[2,p] \leftarrow prev[p] * (se[1]*(1-se[2])*(1-se[3])) +
              (1-prev[p]) * ((1-sp[1])*sp[2]*sp[3])
## snip ##
# Probability of observing Test1+ Test2+ Test3+
prob[3,p] <- prev[p] * (se[1]*se[2]*se[3]) +
              (1-prev[p]) * ((1-sp[1])*(1-sp[2])*(1-sp[3]))
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```

• We need to take extreme care with these equations, and the multinomial tabulation!!!

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- Example: we test people for COVID using an antigen test on a nasal swab, a PCR test on a throat swab, and the same antigen test on the same throat swab
 - The virus may be present in the throat, nose, neither, or both
 - But we use the same antigen test twice
 - Might it cross-react with the same non-target virus?

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 - Might it cross-react with the same non-target virus?
- In both situations we have pairwise correlation between some of the tests

Dealing with correlation: Covid example

TODO: add DAG showing blocking path

TODO: refer back to this from session 5

It helps to consider the data simulation as a (simplified) biological process (where my parameters are not representative of real life!):

```
# The probability of infection with COVID in two populations:
prevalence <- c(0.01, 0.05)
# The probability of shedding COVID in the nose conditional on
\hookrightarrow infection:
nose shedding <- 0.8
# The probability of shedding COVID in the throat conditional on

    infection:

throat shedding <- 0.8
# The probability of detecting virus with the antigen test:
antigen_detection <- 0.75
# The probability of detecting virus with the PCR test:
pcr detection <- 0.999
# The probability of random cross-reaction with the antiqen test:
antigen_crossreact <- 0.05
# The probability of random cross-reaction with the PCR test:
```

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# The probability of random cross-reaction with the PCR test:
```

Simulating latent states:

Simulating test results:

```
covid data <- covid data %>%
  ## The nose swab antigen test may be false or true positive:
 mutate(NoseAG = case when(
   Nose == 1 ~ rbinom(N, 1, antigen_detection),
   Nose == 0 ~ rbinom(N, 1, antigen_crossreact)
 )) %>%
 ## The throat swab antigen test may be false or true positive:
 mutate(ThroatAG = case when(
   Throat == 1 ~ rbinom(N, 1, antigen_detection),
   Throat == 0 ~ rbinom(N, 1, antigen crossreact)
 )) %>%
  ## The PCR test may be false or true positive:
 mutate(ThroatPCR = case_when(
   Throat == 1 ~ rbinom(N, 1, pcr_detection),
   Throat == 0 \sim rbinom(N, 1, pcr crossreact)
 ))
```

The overall sensitivity of the tests can be calculated as follows:

The overall specificity of the tests is more straightforward:

```
covid_specificity <- c(
    # Nose antigen:
    1 - antigen_crossreact,
    # Throat antigen:
    1 - antigen_crossreact,
    # Throat PCR:
    1 - pcr_crossreact
)
covid_specificity
## [1] 0.95 0.95 0.99</pre>
```

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## [1] 0.95 0.95 0.99</pre>
```

However: this assumes that cross-reactions are independent!

TODO: show formulation as proportion of possible correlation

```
prob[1,p] <- prev[p] * ((1-se[1])*(1-se[2])*(1-se[3])
                         +covse12 +covse13 +covse23) +
              (1-prev[p]) * (sp[1]*sp[2]*sp[3]
                              +covsp12 +covsp13 +covsp23)
prob[2,p] \leftarrow prev[p] * (se[1]*(1-se[2])*(1-se[3])
                            -covse12 -covse13 +covse23) +
               (1-prev[p]) * ((1-sp[1])*sp[2]*sp[3]
                               -covsp12 -covsp13 +covsp23)
## snip ##
# Covariance in sensitivity between tests 1 and 2:
covse12 ~ dunif( (se[1]-1)*(1-se[2]) ,
                     min(se[1], se[2]) - se[1]*se[2])
# Covariance in specificity between tests 1 and 2:
covsp12 \sim dunif((sp[1]-1)*(1-sp[2]),
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                     min(sp[1], sp[2]) - sp[1]*sp[2])
```

It is quite easy to get the terms slightly wrong!

Template Hui-Walter

The model code and data format for an arbitrary number of populations (and tests) can be determined automatically using the template_huiwalter function from the runjags package:

```
template_huiwalter(
  covid_data %>% select(Population, NoseAG, ThroatAG, ThroatPCR),
  outfile = 'covidmodel.txt')
```

This generates self-contained model/data/initial values etc

```
model{
    ## Observation layer:
    # Complete observations (N=20000):
    for(p in 1:Populations){
        Tally_RRR[1:8,p] ~ dmulti(prob_RRR[1:8,p], N_RRR[p])
        prob_RRR[1:8,p] <- se_prob[1:8,p] + sp_prob[1:8,p]</pre>
    }
    ## Observation probabilities:
    for(p in 1:Populations){
        # Probability of observing NoseAG- ThroatAG- ThroatPCR- from a
        \hookrightarrow true positive::
        se_{prob}[1,p] \leftarrow prev[p] * ((1-se[1])*(1-se[2])*(1-se[3])
        \hookrightarrow +covse12 +covse13 +covse23)
        # Probability of observing NoseAG- ThroatAG- ThroatPCR- from a
        sp_prob[1,p] \leftarrow (1-prev[p]) * (sp[1]*sp[2]*sp[3] +covsp12
        \hookrightarrow +covsp13 +covsp23)
        # Probability of observing NoseAG+ ThroatAG- ThroatPCR- from a
```