

# CopulaDTA: An R package for copula-based bivariate beta-binomial models for diagnostic test accuracy studies in Bayesian framework

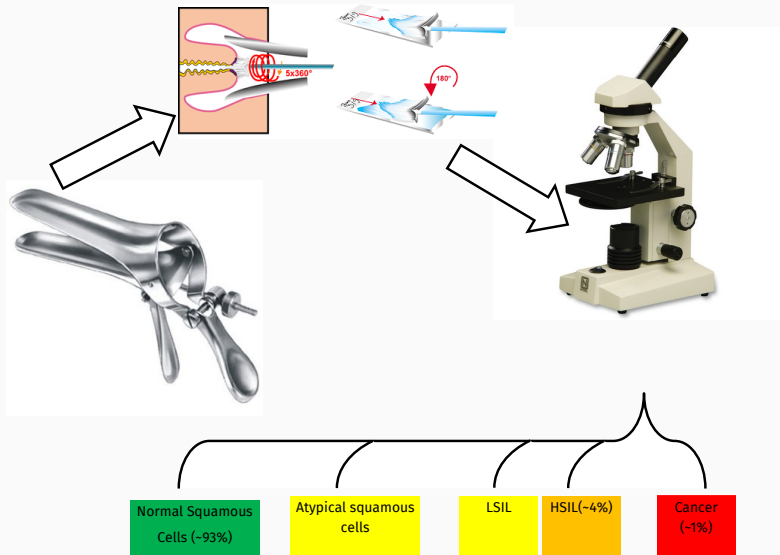
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# Introduction



# Introduction

Triage group	Management	Implication(s)
Normal Squamous Cells (~93%)	Routine check-up every 3 years	
Atypical squamous cells	?Repeat pap smear ? HPV DNA Testing ?HPV Mrna testing ?...	<ul style="list-style-type: none"><li>• Prediction on natural history difficult</li><li>• Spontaneous regression</li><li>◦ Anxiety</li><li>◦ Invasive treatment</li><li>◦ Financial burden</li><li>◦ Discomfort</li><li>◦ Overdiagnosis</li><li>◦ Overtreatment</li></ul>
LSIL		
HSIL(~4%)	Further exploration and treatment	Prevention
Cancer (~1%)	Surgery Radiotherapy ...	Increased survival

Diagnostic tests identifying women whose cervical lesions confer increased risk of cervical cancer.

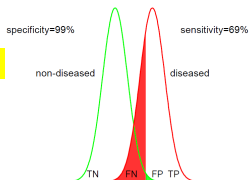
### **Arbyn et al. (2013)**

Among ASCUS triage group determine;

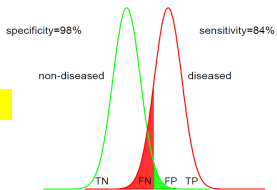
- Accuracy of
  1. HPV DNA Testing using HC2, and
  2. Repeat cytology in detecting CIN2+.
- Differences in accuracy between the two triage tests.

# Hypothetical data

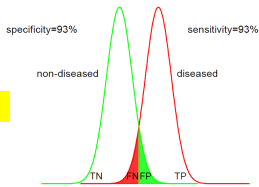
Study 1



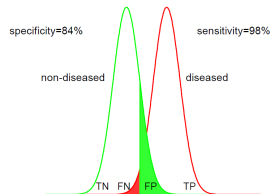
Study 2



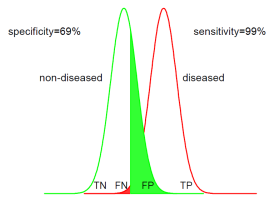
Study 3



Study 4



Study 5



... N

- Obtain population-averaged estimates.
- Account for the present intrinsic correlation between sensitivity and specificity.
- Obtain forest plots.

1. Bivariate normal vs. beta random-effects
2. The CopulaDTA package
3. Application

## Bivariate normal vs. beta random-effects

$$TP_i | se_i, \mathbf{x}_i \sim \text{bin}(se_i, Dis_i), i = 1, \dots, N,$$

$$TN_i | sp_i, \mathbf{x}_i \sim \text{bin}(sp_i, NonDis_i), i = 1, \dots, N.$$

### Normal distribution

$$\begin{pmatrix} \text{logit}(se_i) \\ \text{logit}(sp_i) \end{pmatrix} \sim N \left( \begin{pmatrix} \mu_{\text{logitse}} \\ \mu_{\text{logitsp}} \end{pmatrix}, \Sigma \right)$$

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}$$

### Beta distribution

$$\begin{pmatrix} se_i \\ sp_i \end{pmatrix} \sim f(se_i)f(sp_i)c(F(se_i), F(sp_i), \theta)$$

$$f(se_i) = \text{Beta}(\mu_{se}, \psi_{se}),$$

$$f(sp_i) = \text{Beta}(\mu_{sp}, \psi_{sp}),$$

$c(\cdot)$  = copula density: frank, gaussian, ...

$$\mu_{\cdot} = \text{logit}^{-1}(\nu_{\cdot}) = \frac{\alpha_{\cdot}}{(\alpha_{\cdot} + \beta_{\cdot})}$$

$$\psi_{\cdot} = (\alpha_{\cdot} + \beta_{\cdot}) \text{ or } \frac{1}{1 + \alpha_{\cdot} + \beta_{\cdot}}$$



# Bivariate normal vs. beta random-effects

## Normal distribution

- Availability of software; SAS, R,...
- Approximative distribution:
  - Large sample size.

$$\begin{pmatrix} \mu_{logitse} \\ \mu_{logitsp} \end{pmatrix}$$

- Exit transformation

$$\begin{pmatrix} \mu_{se} | \epsilon_{logitse} = 0 \\ \mu_{sp} | \epsilon_{logitsp} = 0 \end{pmatrix}$$

$$\begin{pmatrix} \mu_{se} \\ \mu_{sp} \end{pmatrix} = \begin{pmatrix} E(\text{logit}^{-1}(\mu_{logitse} + \epsilon_{logitse})) \\ E(\text{logit}^{-1}(\mu_{logitsp} + \epsilon_{logitsp})) \end{pmatrix}$$

## Beta bistribution

- Programming skills needed: R, JAGS, **STAN**, ...
- Natural choice

$$\begin{pmatrix} \mu_{se} \\ \mu_{sp} \end{pmatrix}$$

## MCMC sampling engine

Stan

1. Easy to extend compared to JAGS(.dll).

**functions** {}

**data** {}

**transformed data** {}

**parameters** {}

**transformed parameters** {}

**model** {}

**generated quantities** {}

2. Faster convergence with fewer iteration even with poor initial values than with JAGS.

## Functions, objects and methods

- **cdtamodel function** → **cdtamodel object**

```
R > model <- cdtamodel(copula = 'fgm',  
+ modelargs=list(formula.se = StudyID ~ Test - 1,  
+ formula.sp = StudyID ~ Test - 1,  
+ formula.omega = StudyID ~ Test - 1,  
+ param=2,  
+ prior.lse='normal', par.lse1=0, par.lse2=5,  
+ prior.lsp='normal', par.lsp1=0, par.lsp2=5,...))
```

- **fit function** → **cdtafit object**

```
R > fitmodel <- fit(cdtamodel object, data, SID, cores=3,chains=3,  
+ iter=6000, warmup=1000,thin=10, ...)
```

- **Methods for cdtafit object: print, summary, plot, str**

## Package Installation

```
R> install.packages("CopulaDTA", dependencies = TRUE)
```

```
R> library(CopulaDTA)
```

## Data

```
R> data(ascus)
```

```
R> ascus
```

Test	StudyID	TP	FP	TN	FN
RepC	Anderson 2005	6	14	28	4
RepC	Bergeron 2000	8	28	71	4
RepC	Del Mistro 2010	20	191	483	7
.	.	.	.	.	.
HC2	Silverloo 2009	34	65	81	2
HC2	Solomon 2001	256	1050	984	11

## Model fitting

```
R> frank <- cdtamodel(copula = "frank",  
+ modelargs = list(formula.se = StudyID ~ Test + 0))  
R> fitfrank <- fit(frank,  
+ data = ascus,  
+ SID = "StudyID",  
+ iter = 19000,  
+ warmup = 1000,  
+ thin = 20,  
+ seed = 3)
```

## Posterior Estimates

```
R > print(fitfrank, digits=4)
```

```
Posterior marginal mean sensitivity and specificity
with 95% credible intervals
```

	Parameter	Mean	Lower	Upper	n_eff	Rhat
MUse[1]	Sensitivity	0.9097	0.8530	0.9441	384.26	1.000
MUse[2]	Sensitivity	0.7046	0.5701	0.7863	94.37	1.016
MUsp[1]	Specificity	0.5939	0.5102	0.6711	1187.25	1.000
MUsp[2]	Specificity	0.6736	0.5925	0.7497	680.34	1.007
RRse[1]	Sensitivity	1.0000	1.0000	1.0000	2700.00	NaN
RRse[2]	Sensitivity	0.7748	0.6312	0.8687	126.35	1.014
RRsp[1]	Specificity	1.0000	1.0000	1.0000	2700.00	NaN
RRsp[2]	Specificity	1.1392	0.9535	1.3558	1037.83	1.005
ktau[1]	Correlation	-0.5238	-0.8201	0.6067	2700.00	NaN
ktau[2]	Correlation	-0.7410	-0.8627	-0.3253	2700.00	NaN

Model characteristics

Copula function: frank, sampling algorithm: NUTS(diag\_e)

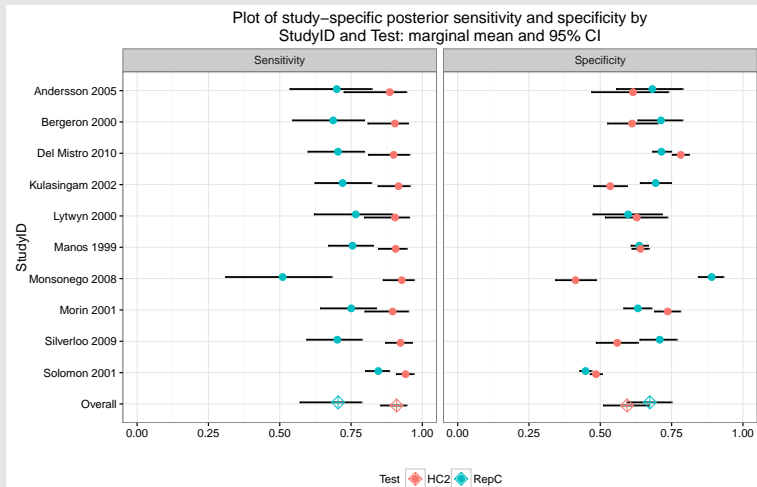
Formula(1): MUse ~ Test + 0  
Formula(2): MUsp ~ Test + 0  
Formula(3): Omega ~ Test + 0  
3 chain(s)each with iter=19000; warm-up=1000; thin=20.  
post-warmup draws per chain=900;total post-warmup draws=2700.

Predictive accuracy of the model

Log point-wise predictive density (LPPD): -2660.0999  
Effective number of parameters: 16.4699  
Watanabe-Akaike information Criterion (WAIC): 5353.1396

## Forest Plot




```
R > plot(fitfrank)
```



- Repeat cytology less sensitive than HC2 in diagnosing cervical precancer in women with equivocal pap smear.
- Marginal as well as study-specific estimates.
- Parameters with natural interpretation.



## References

-  Arbyn M, Roelens J, Simoens C, Buntinx F, Paraskevaidis E, Martin-Hirsch PP, Prendiville WJ (2013).  
**“Human Papillomavirus Testing Versus Repeat Cytology for Triage of Minor Cytological Cervical Lesions.”**  
*Cochrane Database of Systematic Reviews*, 31–201.
-  Reitsma JB, Glas AS, Rutjes AW, Scholten RJ, Bossuyt PM, Zwinderman AH (2005).  
**“Bivariate Analysis of Sensitivity And Specificity Produces Informative Summary Measures in Diagnostic Reviews.”**  
*Journal of Clinical Epidemiology*, **58**(10), 982–990.
-  Nyaga VN (2015).  
**CopulaDTA: Copula Based Bivariate Beta-Binomial Model for Diagnostic Test Accuracy Studies.**  
R package version 0.0.2,  
URL <http://CRAN.R-project.org/package=CopulaDTA>.

**Good evening  
&  
Enlightening conference**

# Comparison

Parameter	Arbyn et al.(2013)*	Bayesian BRMA	BB (frank)
Sensitivity(HC2)	0.91[0.86, 0.94]	0.90[0.84, 0.95]	0.91[0.85, 0.94]
Specificity(HC2)	0.61[0.54, 0.68]	0.60[0.47, 0.72]	0.59[0.51, 0.67]
Sensitivity(RepC)	0.72[0.63, 0.79]	0.71[0.59, 0.80]	0.70[0.57, 0.79]
Specificity(RepC)	0.68[0.60, 0.76]	0.66[0.53, 0.78]	0.67[0.59, 0.75]

## Posterior Estimates

Inference for Stan model: a502b880df243c0c4d60042c0ff01f04.

3 chains, each with iter=5000; warmup=1000; thin=10;

post-warmup draws per chain=400, total post-warmup draws=1200.

	mean	se_mean	sd	2.5%	97.5%	n_eff	Rhat
betamu[1,1]	2.3892	0.0090	0.2509	1.8846	2.8868	770	1.0014
betamu[1,2]	0.4404	0.0070	0.2063	0.0128	0.8608	865	1.0011
betamu[2,1]	0.9399	0.0073	0.2179	0.5022	1.3593	882	1.0013
betamu[2,2]	0.7649	0.0069	0.2088	0.3555	1.1983	914	0.9987
mu[1,1]	0.9140	0.0007	0.0199	0.8681	0.9472	764	1.0018
mu[1,2]	0.6073	0.0016	0.0487	0.5032	0.7028	871	1.0011
mu[2,1]	0.7170	0.0015	0.0441	0.6230	0.7957	884	1.0013
mu[2,2]	0.6807	0.0015	0.0449	0.5880	0.7682	925	0.9986
MU[1,1]	0.9033	0.0010	0.0273	0.8374	0.9446	723	1.0021
MU[1,2]	0.6008	0.0023	0.0619	0.4722	0.7193	756	1.0029
MU[2,1]	0.7076	0.0019	0.0544	0.5884	0.8017	837	0.9980
MU[2,2]	0.6644	0.0024	0.0618	0.5302	0.7753	683	1.0017

Samples were drawn using NUTS(diag\_e) at Sat Jan 16 14:16:42 2016.

For each parameter, n\_eff is a crude measure of effective sample size, and Rhat is the potential scale reduction factor on split chains (at convergence, Rhat=1).