Using RandomFields for genomic prediction

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RandomFields

The R-package RandomFields of Martin Schlather – a flexible tool for:

- estimation of variance components in arbitrary linear mixed models
- performing BLUP based on geostatistical models

Genomic Selection

Standard model:

```
phenotype = fixed effect + (random effect) + GV
+ environmental effect
```

- Assumption: GV depending on pedigree- and SNP-information
- · Aim: prediction of GV

Genomic Selection with Kriging

- Idea: use geostatistical kriging method for genomic selection
- Assumption: GV is realization of a Gaussian random field with parameterized covariance function

- Use geostatistical covariance functions to display covariance structures
- Use SNPs as coordinates at which random field is observed

Kriging

Kriging consists of two steps:

- Estimation of the unknown parameters and variables (e.g. via maximum-likelihood-methods)
 - → use fitvario of R-package RandomFields for parameter estimation
 - → use CovarianceFct of R-package RandomFields to calculate covariance structures for given parameters
- 2. Prediction via BLUP using the estimated covariance structures

Example: Statistical Model

$$\mathbf{y} = \mathbf{W}\boldsymbol{\beta} + \mathbf{Z}\mathbf{u} + g(\mathbf{X}) + \mathbf{e},$$

with

- y phenotypes,
- \beta \text{vector of fixed effects,}
- W and Z incidence matrices,
- $\mathbf{u} \sim \mathcal{N}(0, \sigma_u^2 \mathbf{A})$ with \mathbf{A} being the additive relationship matrix,
- \mathbf{x}_i a vector of SNPs observed on individual i (genotype), $\mathbf{X} = (\mathbf{x}_1, \dots, \mathbf{x}_n)^T$
- $g(\cdot)$ a Gaussian random field with $\mathbb{E}(g(\mathbf{x}_i)) = 0$ and $\operatorname{Cov}(g(\mathbf{x}_i), g(\mathbf{x}_j)) = K(\mathbf{x}_i, \mathbf{x}_j)$, with K being a covariance function depending on different parameters
- $\mathbf{e} \sim \mathcal{N}(\mathbf{0}, \sigma_e \mathbf{I})$ a vector of residual effects

aim: prediction of GV $\mathbf{z}_0^T \mathbf{u} + g(\mathbf{x}_0)$

Possible covariance functions

e.g.

- Matérn covariance function
- Exponential covariance function
- Gaussian covariance function
- . . .

Universal Kriging

Recall: $\mathbf{y} = \mathbf{W}\boldsymbol{\beta} + \mathbf{Z}\mathbf{u} + g(\mathbf{X}) + \mathbf{e}$

Steps:

- 1. Estimation of all parameters of K via ML, considering the density function of \mathbf{y} using fitvario
- 2. BLUP-approach for $g(\mathbf{x}_0)$: minimize $\mathbb{E}(\hat{g}(\mathbf{x}_0) - g(\mathbf{x}_0))^2$ with $\hat{g}(\mathbf{x}_0) = \mathbf{a}_q^T \mathbf{y}$ and $\mathbf{a}_q^T \mathbf{W} = 0$
- 3. Solution:

$$\begin{bmatrix} \mathbf{W} & \sigma_u^2 \mathbf{Z} \mathbf{A} \mathbf{Z}^T + \mathbf{K} + \sigma_e^2 \mathbf{I} \\ \mathbf{0} & \mathbf{W}^T \end{bmatrix} \cdot \begin{bmatrix} \boldsymbol{\lambda} \\ \mathbf{a_g} \end{bmatrix} = \begin{bmatrix} \mathbf{K}_0 \\ \mathbf{0} \end{bmatrix}$$

- → use CovarianceFct to calculate K
- 4. analogously for $\mathbf{z}_0^T \mathbf{u}$, finally: $\widehat{\mathsf{GV}} = \hat{g}(\mathbf{x}_0) + \widehat{\mathbf{z}_0^T \mathbf{u}}$

Code (I)

```
# load package
library(RandomFields)
# specify model
model <- list("+",
              list("X", X=Z, cov=list("$", var=NA,
                   list("const", M=A))),
              list("$", scale=NA, var=NA,
                   list("matern", nu=NA)),
              list("$", var=NA, list("nugget"))
# use SNP-data to estimate parameters
fit <- fitvario(x=SNPs, data=v, model=model,
                 trend=NA, mle.methods="ml")
```

```
Code (II)
```

```
# ...or use distance-matrix to estimate parameters
UKfit <- fitvario (Distances=distances, data=y,
                   model=model, trend=NA,
                   truedim=n.SNPs, mle.methods="ml")
# extract parameters
UK <- fit$table
sigma2.e.est <- UK["nug.var", "ml"]
sigma2.k.est <- UK["mat.var", "ml"]
nu.est <- UK["mat.nu", "ml"]</pre>
scale.est <- UK["mat.s", "ml"]</pre>
sigma2.u.est <- UK["con.var", "ml"]
# build covariance matrix
K <- CovarianceFct(x=distances, model="matern",</pre>
                    param=c (mean=0, nu=nu.est,
                            variance=sigma2.k.est,
                            scale=scale.est, nugget=0))
```

Code (III)

```
# Prediction via BLUP
KK <- K[idx,idx]
K \ 0 \ \leftarrow \ K[idx, -idx]
W <- matrix(rep(1, n.est))
D up <- cbind(W, sigma2.u.est*A[idx,idx]+KK+
               sigma2.e.est*diag(n.est))
D_{down} \leftarrow cbind(0, t(W))
D <- rbind(D up, D down)
Diny <- solve(D)
a.g <- (Dinv**rbind(K_0,0))[-1,]
g.est <- t(a.g)%*%v
a.u <- (Dinv**rbind(sigma2.u.est*A[idx,-idx],0))[-1,]
u.est <- t(a.u) %*%v
GV <- q.est + u.est
```

Possible contributions to Synbreed-R-package

Implement genomic selection using RandomFields:

- automatic call for RandomFields
- flexible model building and model selection (GBLUP; mixed linear models with geostatistical components)
- ML-estimation of variance-components for mixed linear models using fitvario
 - (→ fitvario as an alternative to "ASReml")