Double hierarchical generalized linear models for micro-sensitivity in daily feed intake

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Introduction

> Analysis daily feed intake has focused on

- estimating genetic variation in feed intake curves
- possibilities to change feed intake curve by selection
- > early feed intake is strongly correlated to lean tissue growth

Modeling: Two-stage or random regression

Previous studies:

- genetic variation do exist along the trajectory
- opportunity for changing feed intake curve (Huisman et al., 2005; Bermejo et al., 2003)

Introduction

Pigs and environmental sensitivity

- Macro-environment
 - >Identifiable (e.g., temperature, housing, diets)
 - Linear-reaction norms models (Knap and Su, 2008; Hermesch et al., 2006)
- > Micro-environment
 - ➤ Undefined
- Genetic variance of micro-environmental sensitivity can be studied through genetic variance in residual variance (Hill and Mulder, 2010)
- h² for residual standard deviation of 0.46 (Eissen, 1999)

Introduction



- Residual variability in daily feed intake reflects (Hermesch et al., 2010)
 maintenance of metabolic homeostasis
 - response to micro-environmental challenges, e.g. air flow
 - Sub-clinical disease (Henryon et al., 2001)



Estimate breeding values for microenvironmental sensitivity (EBV_d) in daily feed intake, and variance components

Double hierarchical generalized linear model (DHGLM; Felleki et al., 2012)

Data

National test-station

- ▶ 2008 2012
- > 8,804 Duroc boars
- ➢ 65 records per pig, ranging from 40 to 77
- 570,901 daily feed intake records after editing

Pedigree traced back to 1st of Jan 1992
> 21,128 animals

Data



> Mean model $Y = X\beta + Z_1pe + Z_2p + Z_3a + e$

Fixed effects:

➤ Initial BW

2nd order legendre polynomials with barn*year*season (168 levels) specific coefficients

> Mean model $Y = X\beta + Z_1 pe + Z_2 p + Z_3 + e$

Random effects:

Legendre polynomials up to 2nd order
 Pen (571 levels)
 Non-genetic animal (8804 levels)
 Additive genetic (21128 levels)

Residuals

Mean model
 Y = Xβ + Z₁pe + Z₂p + Z₃a + e

 Residual dispersion model
 V(e) = exp(Xβ_d) + W₁p_d + W₂a_d)

 Fixed effects:
 Age classes (77 levels)



Estimation scheme

- > IRWLS algorithm (modified from Felleki et al., 2012)
 - 1) Initialize residual variance weights
 - $\mathbf{y} \sim N(\mathbf{X\beta} + \mathbf{Z_1pe} + \mathbf{Z_2p} + \mathbf{Z_3a}, \mathbf{I\sigma^2/w})$
 - 2) Compute $y_d = e^2/(1-h)$ and $w_d = (1-h)/2$
 - 3) Fit a Gamma GLMM with link log and weights (1-h)/2 to y_d
 - 4) Compute $\mathbf{w} = \text{diag}(E(\mathbf{y}_d)^{-1})$
 - 5) Run a bivariate normal-gamma model for **y** and **y**_d estimating
 - 6) Update \mathbf{y}_{d} and residual variance weights (\mathbf{w} and \mathbf{w}_{d}) in each iteration
 - 7) Repeat steps 5 and 6 until convergence

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Model selection

> 10 fold cross validation

- Exclude randomly 10 observations per pig
- Repeated 10 times

Measures of fit

Mean square prediction error

$$MSPE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

> Cor(observed, predicted)

Results

Model	MSPE	Correlation
Leg(1, 1)	0.2808 (0.002)	0.7858 (0.001)
Leg(2, 2)	0.2703 (0.002)	0.7975 (0.001)
Leg(1, 1, 1)	0.2797 (0.002)	0.7898 (0.001)
Leg(2, 2, 2)	0.2684 (0.002)	0.8008 (0.001)
Genetically structured		
Leg(1, 1)	0.2758 (0.002)	0.7977 (0.001)
Leg(Ø, 2, 2)	0.2683 (0.002)	0.8036 (0.001)
Leg(1, 1, 1)	0.2757 (0.002)	0.7978 (0.001)
Leg(2, 2, 2)	0.2633 (0.002)	0.8080 (0.001)

Results

Model		EBVI	EBVL	EBV _d	
DHGLM	EBV_{I}	0.038 (0.003)			
	EBV_L	0.47 (0.04)	0.033 (0.002)		
	EBV_d	0.51 (0.03)	0.92 (0.01)	0.023 (0.001)	
DHGLM sqrt-trans	EBV_{I}	0.0049 (0.0004)			
	EBV_L	-0.38 (0.04)	0.0032 (0.0002)		
	EBV_d	-0.43 (0.03)	0.92 (0.01)	0.024 (0.0008)	

Genetic coefficient of variation ~ 15%

Heritability of feed intake



Genetic correlations

	70	80	90	100	110	120	130	140
70	0.08							
80	0.97	0.08						
90	0.89	0.97	0.10					
100	0.78	0.90	0.98	0.10				
110	0.65	0.81	0.92	0.98	0.11			
120	0.53	0.71	0.86	0.95	0.99	0.12		
130	0.43	0.62	0.79	0.90	0.97	0.99	0.10	
140	0.34	0.55	0.73	0.86	0.94	0.98	0.99	0.08

Results

Pearson moment-correlations

EBVs for traits	EBV _d
Daily gain (30 to 100)	0.34
Meat percentage	-0.12
Feed conversion ratio	0.18

- Genetically correlated with fast, but relatively fat growing pigs
- Implications for feed efficiency?

Conclusion

- DHGLM RR-model was developed
- Heritability of FI: 0.08 0.12 (mean)
- Genetic variance in micro-environmental sensitivity was estimable
 - Genetic coefficient of variation of 15%
 - > EBV_d was positive strongly correlated to the mean trend
 - \succ EBV_d was correlated to production traits

How does micro-environmental sensitivity correlate to macro-environmental sensitivity?