Assessing model performance

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)verview



Holistic vs reductionist.

- keep in mind what your model is assuming and what it neglects
- it's the things you didn't know you didn't know that stab you in the back

model assessment is a testing of model assumptions

- hypothesis testing involves model comparisons, not comparisons between models and *reality*
- creative visualizations that best illustrate assessment
- relevant statistics
- avoid just listing and tallying scores
- descriptive vs inferential statistics
- identify structural errors in models

Visualization

- 1. Descriptive statistics of model outputs (mean, variance, histograms)
 - is the model behaving as expected?
 - plausible predictions for latent variables
- 2. Graphical comparisons of model and data
 - predicted vs observed plot
 - residuals vs predicted (process residuals vs observation error)
 - residuals vs time/space/aspect
 - Iooking for outliers in data and structural gaps in predictions

Revising model after step one is OK, revising model after step 2 and *re-assessing against same data* is suspect!

Statistical Analyses

- Visual analysis are subject to our hard-wiring to pick out patterns, even when none are there
- Statistics can insert some objectivity into patterns identified through visual analyses

$$\blacktriangleright \text{ RMSE } \sqrt{\frac{1}{n} \left(\text{Predicted} - \text{Observed} \right)}$$

correlation coefficients (deviations from Predicted = Observed)

model variance vs observation variance (SD ratios)

Taylor Diagrams

Null Models, Hierarchical Models, Nested Models

Remember we are not *ranking* models as good or bad, but assessing relative performance and identifying structural gaps Calibration versus Validation

Analysis of Residuals



residuals as observed — predicted



are residuals distributed as hypothesized?

look at residuals vs various aspects

- predicted
- time
- cofactors

residuals as likelihood of observed given model

quantiles of observed should be uniformly distributed