Assessing Feature Importance in Non-Linear Regression: An Ecology Perspective

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Motivation:

- For years, linear regression has been used by ecologists to study and quantify observed ecological relationships.
- These tools have been useful in understanding ecological mechanism, but our societal mandate to **predict future ecological state** requires models which offer more predictive power than a simple linear method can (there's reason to believe many relationships are nonlinear).
- To maintain scientific and practical credibility, these models must be at least to some extent *interpretable* to both researchers and the users of their predictions.
- Simple methods to capture the nonlinearities of many ecological relationships with provable properties are kernel regression and SVMs.

Key Question: What methods exist to extract variable importance from a non-linear regression, and how do the results therein compare to coefficients from a standard linear regression model? **Do the non-linear methods still capture theoretically-rigorous biology?**

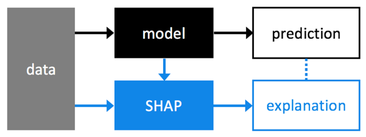
Data:

- **Angert et al. 2011** gathered **functional trait data** for Swiss alpine plants ($N = 133$, **Holzinger et al. 2008**) and computed the *observed elevational range shift* from historical records (i.e: how much has the maximum elevation at which these plants are observed shifted in the past century?). There are $d = 32$ observed traits.
- This is one of two datasets analyzed.

Methods:

- We compare **Ordinary Least Squares' coefficient values** to :
  - Kernel Regression (RBF, Polynomial) coefficients
  - Ridge Regression coefficients
  - Random Forest Gini Scores
  - **Shapley Values[1]** for SVM (RBF, Polynomial)

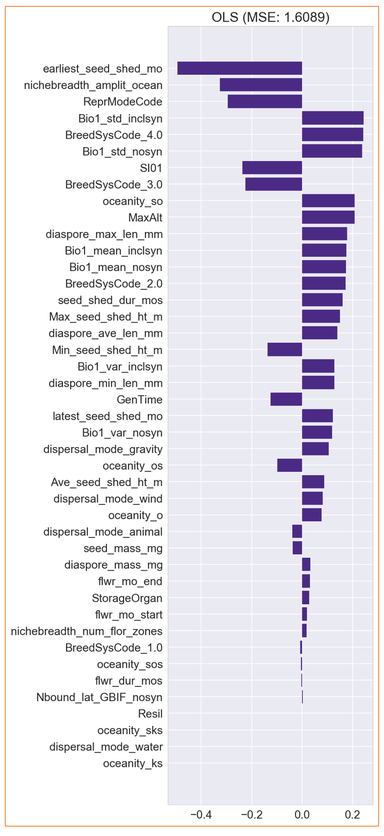
1: The Shapley additive feature importance measure, defined in **Lundberg and Lee 2017**, from cooperative game theory.



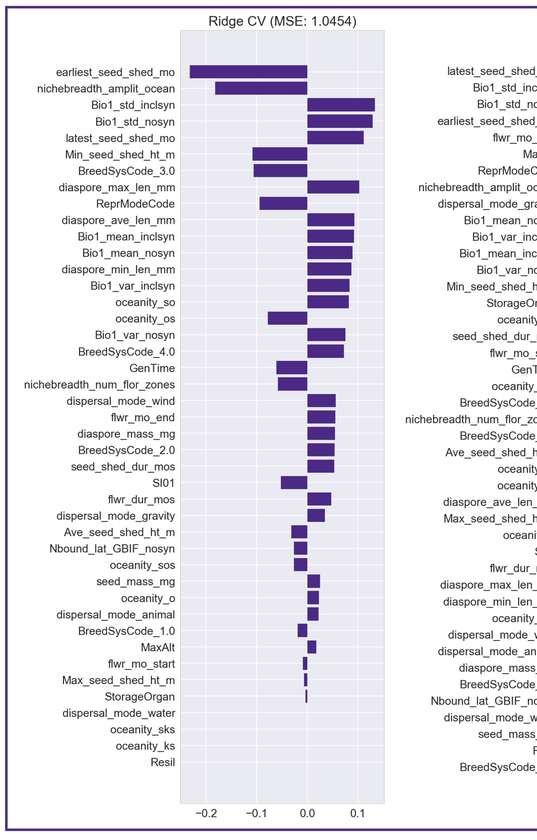
Implementation:

- We remove samples (i.e., plant species) which are missing any feature data, which brings us to $N = 20$.
- We one-hot encode categorical features, $d = 43$.
- We center the numeric features with 0 mean and unit variance for regression.

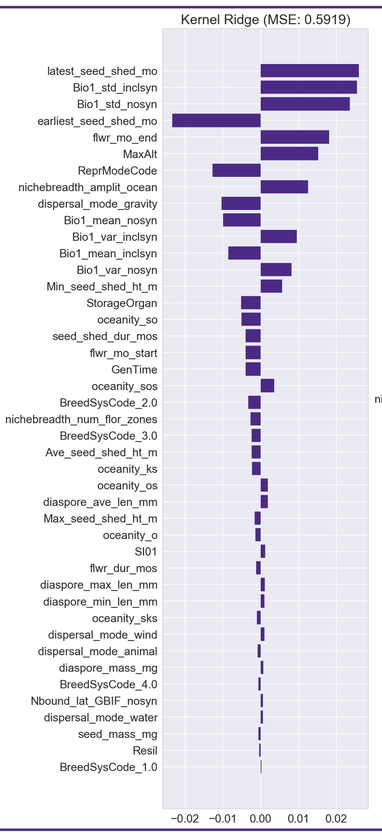
References:
Angert, A. et al., 2011. "Do species' traits predict recent shifts at expanding range edges?" *Ecology Letters*, **14**: 677–689.
Holzinger, B. et al., 2008. "Changes in plant species richness over the last century in the eastern Swiss Alps: elevational gradient, bedrock effects and migration rates." *Plant Ecol.*, **195**, 179–196.
Lundberg, S. and Lee, S., 2017. "A unified approach to interpreting model predictions" *NIPS 2017. arXiv:1705.07874*



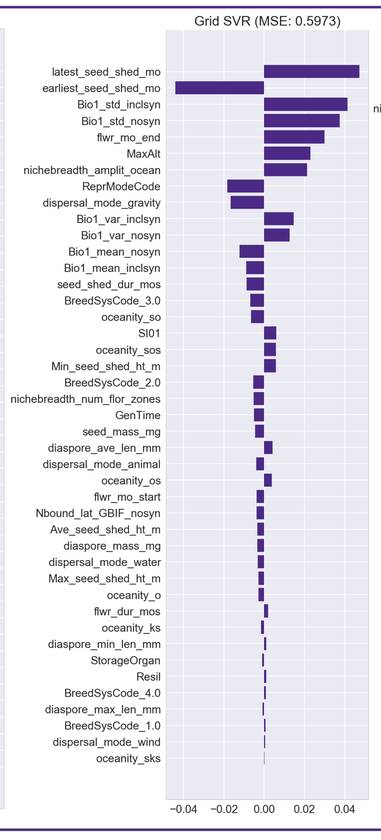
OLS Coefficients



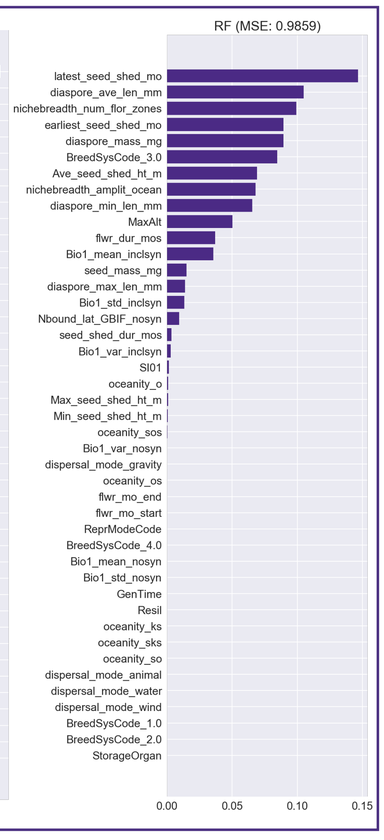
Ridge Regression Coefs.



Kernel Regression SHAP



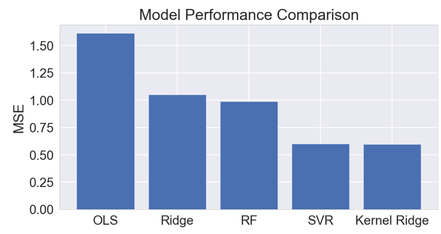
SVM SHAP



Random Forest Gini Scores

	OLS	Ridge	Kernel Ridge	RF	SVR	mean
earliest_seed_shed_mo	0.0	0.0	3.0	3.0	1.0	1.4
Bio1_std_inclsyn	3.0	2.0	1.0	14.0	2.0	4.4
nichebreadth_amplit_ocean	1.0	1.0	7.0	7.0	6.0	4.4
latest_seed_shed_mo	21.0	4.0	0.0	0.0	0.0	5.0
Bio1_std_nosyn	5.0	3.0	2.0	31.0	3.0	8.8
ReprModeCode	2.0	8.0	6.0	28.0	7.0	10.2
BreedSysCode_3.0	7.0	6.0	22.0	5.0	14.0	10.8
Bio1_mean_inclsyn	11.0	10.0	11.0	11.0	12.0	11.0
MaxAlt	9.0	35.0	5.0	9.0	5.0	12.6
Bio1_var_inclsyn	18.0	13.0	10.0	17.0	9.0	13.4
Bio1_mean_nosyn	12.0	11.0	9.0	30.0	11.0	14.6
Min_seed_shed_ht_m	17.0	5.0	13.0	21.0	18.0	14.8
diaspore_ave_len_mm	16.0	9.0	26.0	1.0	23.0	15.0
seed_shed_dur_mos	14.0	24.0	16.0	16.0	13.0	16.6
Bio1_var_nosyn	22.0	16.0	12.0	23.0	10.0	16.6
flwr_mo_end	31.0	21.0	4.0	26.0	4.0	17.2
oceanity_so	8.0	14.0	15.0	36.0	15.0	17.6
dispersal_mode_gravity	23.0	27.0	8.0	24.0	8.0	18.0
SI01	6.0	25.0	29.0	18.0	16.0	18.8
nichebreadth_num_flor_zones	34.0	19.0	21.0	2.0	20.0	19.2
diaspore_max_len_mm	10.0	7.0	31.0	13.0	39.0	20.0
diaspore_min_len_mm	19.0	12.0	32.0	8.0	35.0	21.2
GenTime	20.0	18.0	18.0	32.0	21.0	21.8
Ave_seed_shed_ht_m	25.0	28.0	23.0	6.0	28.0	22.0
oceanity_os	24.0	15.0	25.0	25.0	25.0	22.8
BreedSysCode_2.0	13.0	23.0	20.0	41.0	19.0	23.2
diaspore_mass_mg	30.0	22.0	36.0	4.0	29.0	24.2
oceanity_sos	36.0	30.0	19.0	22.0	17.0	24.8
BreedSysCode_4.0	4.0	17.0	37.0	29.0	38.0	25.0
Max_seed_shed_ht_m	15.0	37.0	27.0	20.0	31.0	26.0
seed_mass_mg	29.0	31.0	40.0	12.0	22.0	26.8
flwr_dur_mos	37.0	26.0	30.0	10.0	33.0	27.2
oceanity_o	27.0	32.0	28.0	19.0	32.0	27.6
flwr_mo_start	33.0	36.0	17.0	27.0	26.0	27.8
Nbound_lat_GBIF_nosyn	38.0	29.0	38.0	15.0	27.0	29.4
dispersal_mode_animal	28.0	33.0	35.0	37.0	24.0	31.4
dispersal_mode_wind	26.0	20.0	34.0	39.0	41.0	32.0
StorageOrgan	32.0	38.0	14.0	42.0	36.0	32.4
oceanity_ks	42.0	41.0	24.0	34.0	34.0	35.0
dispersal_mode_water	41.0	39.0	39.0	38.0	30.0	37.4
oceanity_sks	40.0	40.0	33.0	35.0	42.0	38.0
BreedSysCode_1.0	35.0	34.0	42.0	40.0	40.0	38.2
Resil	39.0	42.0	41.0	33.0	37.0	38.4

Feature Importance Rank per Method, and Averaged Across Methods.



Results | Discussion | Conclusions:

- Across these methods, **dispersal-related traits** like `{latest_seed_shed_mo, earliest_seed_shed_mo}` consistently rank highest in importance across these methods, as measured by the absolute value of the coefficients. For all methods except for the Ridge and OLS, `latest_seed_shed_mo` across was the variable with the highest importance.
- These results are consistent with Angert et al.'s 2011 analysis, wherein seed dispersal period duration was the most important predictor variable.
- This result indicates that the predictive performance gains (see MSE figure above) from the SVM/Kernel Ridge regression maintain their theoretical biological underpinnings while better representing nonlinearities in the relationship between species range shift and trait values.

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