Using Machine Learning Models and Logistic Regression Analyses to Develop a Comprehensive Understanding of Extinction Risk For Marine Animal Phyla Across the Paleozoic

Adarsh Ambati[1], Theo Chiang[1], Anya Sengupta[1], Pedro Monarrez[1], Michael Pimentel-Galvan[1], Noel Heim[2], and Jonathan Payne[1]

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Abstract

Extinction within the Paleozoic era has been studied in the past, but there still lacks a comprehensive understanding of how extinction risk changed throughout it. Our research project aims to bridge this gap by exploring extinction risk in relation to major Paleozoic phyla and ecological characteristics. Using R, we analyzed the Stanford Earth Body Size dataset, which includes extensive data (n=8816) on Paleozoic marine animals. In Step 1, regression coefficients were formed, indicating whether being in one of the 6 phyla in each period of the Paleozoic era conferred greater or less extinction risk. In Step 2, the examined ecological characteristics included ocean acidification resilience, feeding patterns, body volume, length, surface area, motility, tiering, circulatory systems, and respiratory organ type. In Step 3, 6 binomial machine learning models were created using the traits from Step 2 to determine whether an individual genus went extinct in a particular period. Our Step 1 results confirm that within these timeframes, while certain phyla have greater extinction risk, extinction risk was not uniform across these groups. Our Step 2 results show certain traits provided advantages and disadvantages for an organism's extinction risk. One interesting pattern was that the only consistently non-significant traits were body length, area, and volume. Likewise with Step 1, extinction risk for each ecological characteristic varied across the Paleozoic. Finally, in Step 3, the results were largely successful. Most of the six models had an accuracy above 80% with the highest being 92% in the Cambrian. The areas under the Precision-Recall and the Receiver Operating Characteristic Curves were all in the acceptable (<0.6) range, demonstrating that the model has low false positive/ negative rates and is able to distinguish between what trait indicates extinction or survival for each period. Our research project identified phyla at risk of extinction in each period of the Paleozoic, determined which natural traits incited greater extinction risk, and demonstrated machine learning models trained on fossil descriptors can predict when an individual genus became extinct. Our results confirmed that extinction risk is not consistently dependent on a singular factor nor is it constant across every period of the Paleozoic era.

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Stanford
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Geological Sciences

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Abstract

Extinction within the Paleozoic era has been studied in the past, but there still lacks a comprehensive understanding of how extinction risk changed throughout it. Our research project aims to bridge this gap by exploring extinction risk in relation to major Paleozoic phyla and ecological characteristics.

Using R, we analyzed the Stanford Earth Body Size dataset, which includes extensive data (n=8816) on Paleozoic marine animals. In Step 1, regression coefficients were formed, indicating whether being in one of the 6 phyla in each period of the Paleozoic era conferred greater or less extinction risk. In Step 2, the examined ecological characteristics included ocean acidification resilience, feeding patterns, body volume, length, surface area, motility, tiering, circulatory systems, and respiratory organ type. In Step 3, 6 binomial machine learning models were created using the traits from Step 2 to determine whether an individual genus went extinct in a particular period. Our Step 1 results confirm that within these timeframes, while certain phyla have greater extinction risk, extinction risk was not uniform across these groups. Our Step 2 results show certain traits provided advantages and disadvantages for an organism's extinction risk. One interesting pattern was that the only consistently non-significant traits were body length, area, and volume. Likewise with Step 1, extinction risk for each ecological characteristic varied across the Paleozoic. Finally, in Step 3, the results were largely successful. Most of the six models had an accuracy above 80% with the highest being 92% in the Silurian. The areas under the Precision-Recall and the Receiver Operating Characteristic Curves were all in the acceptable (>0.6) range, demonstrating that the model has low false positive/ negative rates and is able to distinguish between what trait indicates extinction or survival for each period.

Our research project identified phyla at risk of extinction in each period of the Paleozoic, determined which natural traits incited greater extinction risk, and demonstrated machine learning models trained on fossil descriptors can predict when an individual genus became extinct. Our results confirmed that extinction risk is not consistently dependent on a singular factor nor is it constant across every period of the Paleozoic era.

Methodology

The dataset we used included nine biological and ecological traits, and it also includes taxonomic groupings and phyla. After making logistic regression models for each trait, we then made regularized regression models predicting extinction in each period based on these characteristics. Below are the Paleozoic periods that we are analyzing.

Cambrian
Ordovician
Silurian
Devonian
Carboniferous
Permian

All analyses and plots were made using the programming language R. During stages 1 and 2, the following were our categories of analysis.
1. Phyla - Echinodermata, Mollusca, Chordata, Arthropoda, Brachiopoda, Foraminifera (Taxonomic Group)
2. Descriptors - buffering, feeding patterns, motility, oceanic tiering, respiratory organ type, circulatory system type, length, surface area, volume

For Stage 3, we built regularized binomial regression models.

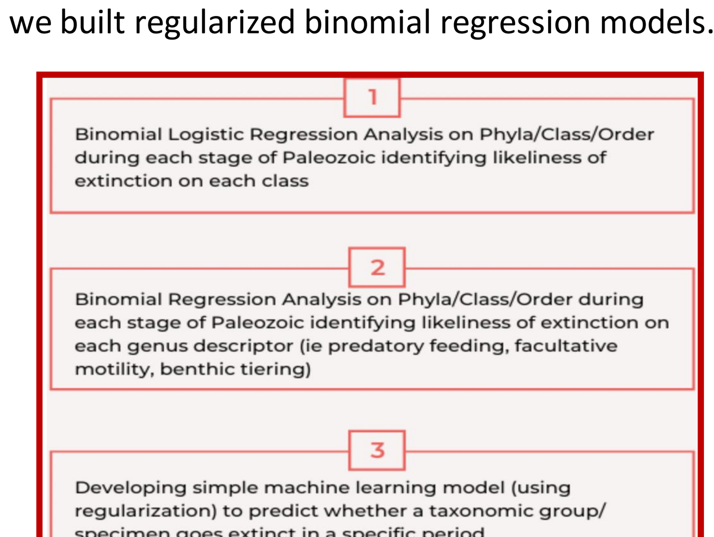

Figure 1: Summary of Analysis Stages

Figures

Figure 2

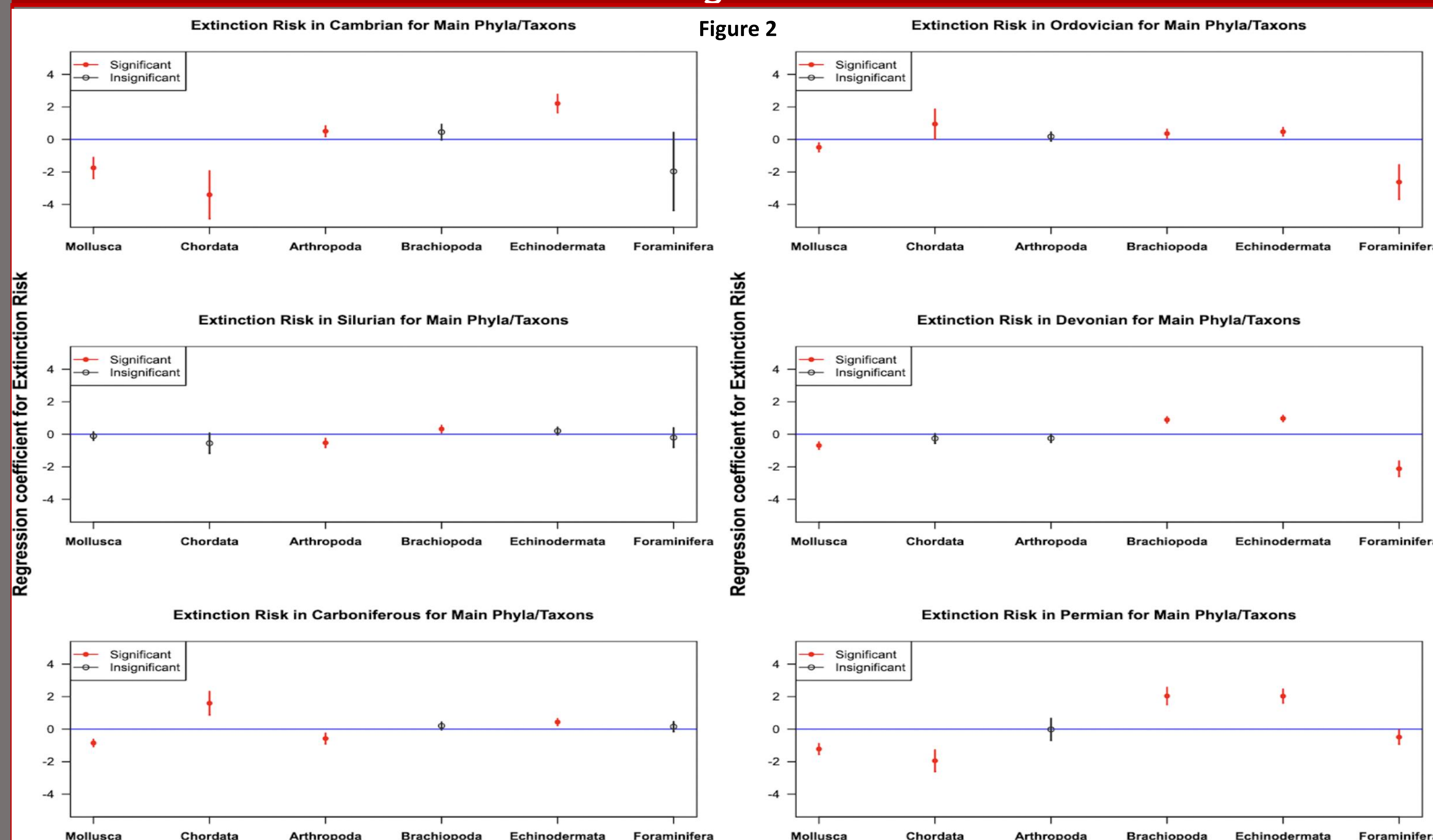

Figure 3

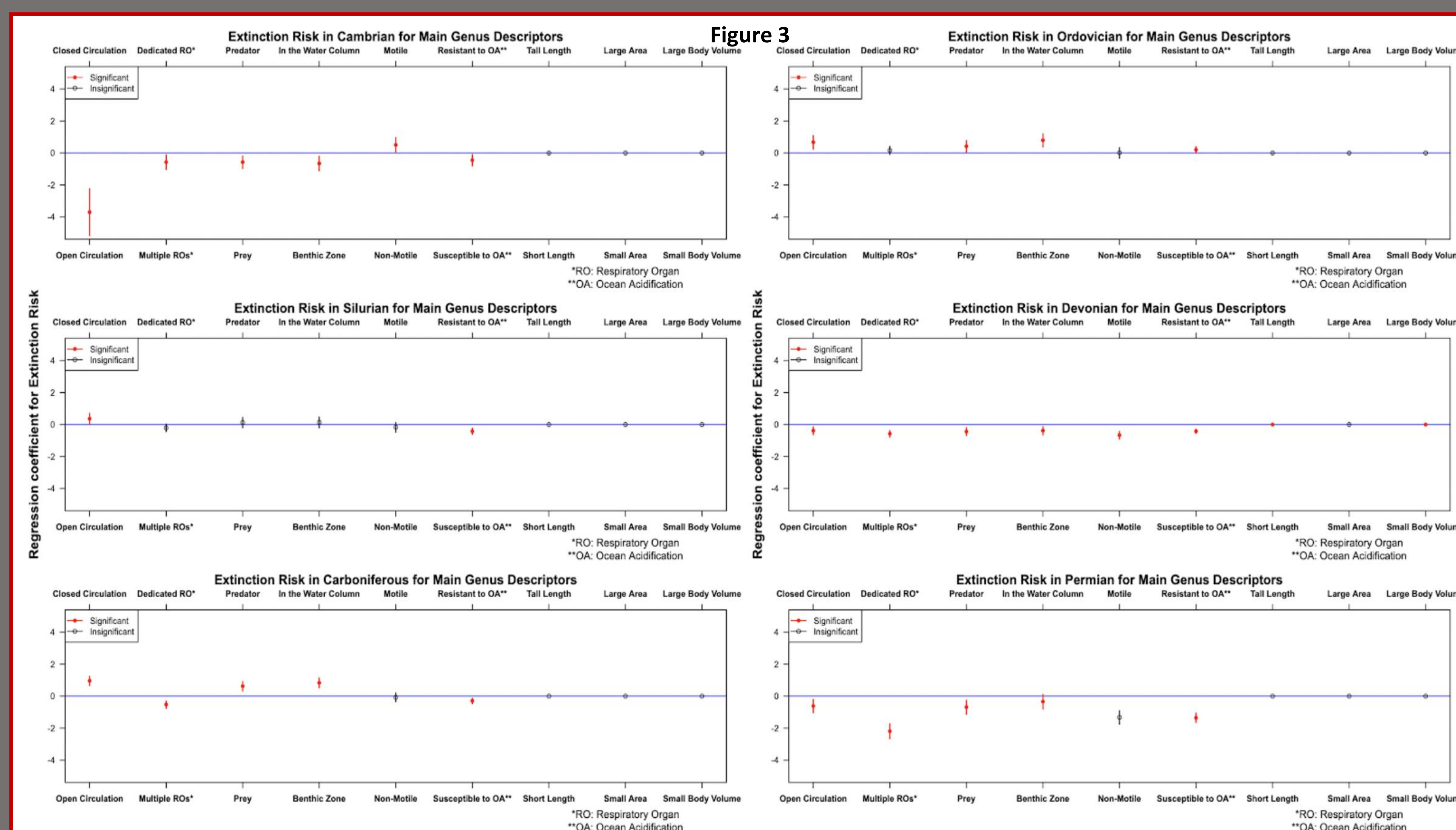

Figure 4

	Cambrian Model Features	Score
1	Circulation System	3.3422079
2	Motility	2.27727063
3	Ocean Acidification Resistance	1.12284708
4	Feeding Patterns	0.42942449
5	Respiratory Organ System	0.37019192
6	Tiering	0.02890546
7	Maximum Length	0.00479994
8	Maximum Area	4.23E-07
9	Calculated Maximum Volume	2.39E-09

	Ordovician Model Features	Score
1	Motility	1.06918333
2	Ocean Acidification Resistance	0.85323525
3	Tiering	0.33049509
4	Feeding Patterns	0.32654485
5	Respiratory Organ System	0.15505047
6	Circulation System	0.02294367
7	Maximum Length	0.00124485
8	Maximum Area	4.10E-06
9	Calculated Maximum Volume	1.08E-08

	Silurian Model Features	Score
1	Motility	1.32779174
2	Circulation System	1.06206068
3	Respiratory Organ System	0.70851463
4	Feeding Patterns	0.6192809
5	Ocean Acidification Resistance	0.59558913
6	Tiering	0.59509338
7	Maximum Length	0.00258455
8	Maximum Area	3.22E-06
9	Calculated Maximum Volume	3.32E-08

	Devonian Model Features	Score
1	Ocean Acidification Resistance	0.70835892
2	Respiratory Organ System	0.45876009
3	Motility	0.22309167
4	Circulation System	0.06226351
5	Maximum Length	0.00555858
6	Maximum Area	2.00E-05
7	Calculated Maximum Volume	4.32E-08
8	Feeding Patterns	0
9	Tiering	0

	Carboniferous Model Features	Score
1	Circulation System	2.32544688
2	Ocean Acidification Resistance	0.73146419
3	Respiratory Organ System	0.65025381
4	Maximum Length	0.00189793
5	Feeding Patterns	0
6	Tiering	0
7	Motility	0
8	Maximum Area	0
9	Calculated Maximum Volume	0

	Permian Model Features	Score
1	Circulation System	2.18390017
2	Respiratory Organ System	1.04694225
3	Ocean Acidification Resistance	0.93551679
4	Feeding Patterns	0.86094481
5	Tiering	0.74849748
6	Motility	0.70993468
7	Maximum Length	0.000241
8	Calculated Maximum Volume	2.56E-08
9	Maximum Area	0

Figure 5

Period	Alpha Value	Lambda Value	Accuracy	AUROC	AUPR
Cambrian	0	0.01	0.92	0.93	0.8
Cambrian	0.1	0.01	0.92	0.93	0.8
Cambrian	0.2	0.01	0.92	0.93	0.8
Cambrian	0.3	0.01	0.92	0.93	0.8
Cambrian	0.4	0.01	0.92	0.93	0.8
Cambrian	0.5	0.01	0.92	0.93	0.8
Cambrian	0.6	0.01	0.92	0.93	0.8
Cambrian	0.7	0.01	0.92	0.93	0.8
Cambrian	0.8	0.01	0.92	0.93	0.8
Cambrian	0.9	0.01	0.08	0.5	0.79
Cambrian	1	0.01	0.91	0.5	0

Period	Alpha Value	Lambda Value	Accuracy	AUROC	AUPR
Ordovician	0	0.012589254	0.83	0.67	0.73
Ordovician	0.1	0.01	0.83	0.68	0.73
Ordovician	0.2	0.012589254	0.83	0.67	0.73
Ordovician	0.3	0.01	0.83	0.67	0.73
Ordovician	0.4	0.01	0.83	0.67	0.73
Ordovician	0.5	0.01	0.83	0.66	0.73
Ordovician	0.6	0.01	0.82	0.66	0.73
Ordovician	0.7	0.01	0.82	0.66	0.73
Ordovician	0.8	0.01	0.82	0.66	0.74
Ordovician	0.9	0.01	0.82	0.61	0.74
Ordovician	1	0.01	0.82	0.61	0.75

Period	Alpha Value	Lambda Value	Accuracy	AUROC	AUPR
Silurian	0	0.005416508	0.91	0.6	0.89
Silurian	0.1	0.001219581	0.91	0.6	0.89
Silurian	0.2	0.000578704	0.91	0.6	0.89
Silurian	0.3	0.000578704	0.91	0.6	0.89
Silurian	0.4	0.000578704	0.91	0.6	0.89
Silurian	0.5	0.000578704	0.91	0.6	0.89
Silurian	0.6	0.000578704	0.91	0.6	0.89
Silurian	0.7	0.000578704	0.91	0.6	0.89
Silurian	0.8	0.000578704	0.91	0.6	0.89
Silurian	0.9	0.000578704	0.91	0.6	0.89
Silurian	1	0.000578704	0.91	0.6	0.89

Period	Alpha Value	Lambda Value	Accuracy	AUROC	AUPR
Devonian	0	0.025118864	0.79	0.64	0.75
Devonian	0.1	0.015848932	0.79	0.64	0.75
Devonian	0.2	0.019952623	0.79	0.64	0.75
Devonian	0.3	0.006309573	0.79	0.64	0.75
Devonian	0.4	0.003981072	0.79	0.64	0.75
Devonian	0.5	0.003981072	0.79	0.64	0.75
Devonian	0.6	0.003162278	0.79	0.64	0.75
Devonian	0.7	0.001584893	0.79	0.64	0.75
Devonian	0.8	0.002511886	0.79	0.64	0.75
Devonian	0.9	0.001995262	0.79	0.64	0.75
Devonian	1	0.003162278	0.79	0.64	0.75

Period	Alpha Value	Lambda Value	Accuracy	AUROC	AUPR
Carboniferous	0	0.003541732	0.83	0.6	0.77
Carboniferous	0.1	0.002915452	0.83	0.6	0.77
Carboniferous	0.2	0.011383466	0.83	0.6	0.77
Carboniferous	0.3	0.002915452	0.83	0.6	0.77
Carboniferous	0.4	0.002915452	0.83	0.6	0.77
Carboniferous	0.5	0.002915452	0.83	0.6	0.77
Carboniferous	0.6	0.003541732	0.83	0.6	0.77
Carboniferous	0.7	0.002915452	0.83	0.6	0.77
Carboniferous	0.8	0.002915452	0.83	0.6	0.77
Carboniferous	0.9	0.002915452	0.83	0.6	0.77
Carboniferous	1	0.002915452	0.83	0.6	0.77

Period	Alpha Value	Lambda Value	Accuracy	AUROC	AUPR
Permian	0	0.002915452	0.84	0.62	0.79
Permian	0.1	0.002915452	0.84	0.62	0.79
Permian	0.2	0.002915452	0.84	0.63	0.78
Permian	0.3	0.002915452	0.84	0.62	0.79
Permian	0.4	0.002915452	0.84	0.56	0.82
Permian	0.5	0.002915452	0.84	0.56	0.82
Permian	0.6	0.002915452	0.84	0.56	0.82
Permian	0.7	0.002915452	0.84	0.56	0.82
Permian	0.8	0.002915452	0.84	0.45	0.83
Permian	0.9	0.002915452	0.84	0.46	0.83
Permian	1	0.002915452	0.84	0.46	0.83

Results / Discussion

In Stage One, we conducted logistic regression analyses for each stage of the Paleozoic era for each of the major phyla. The goal was to identify the phyla that have a predilection for extinction during each stage. As evident in Figure 2, we came across some impressive results as 23 of the 36 data points had a significant regression coefficient. 12 data points had a significantly greater extinction risk while 11 were significantly selected for survival. Among various phyla, coefficient values were high in magnitude, but no groups were consistently significant across all periods. However, specifically, Mollusca was generally selected for survival while Echinodermata was generally selected for extinction. For Brachiopoda, you may notice the relatively low coefficients in background periods but a significant extinction risk during the major extinction events in Devonian and Permian. This is in line with the understanding that these extinction events devastated Brachiopoda populations.

In Stage Two, we conducted a logistic regression analysis and binomial test to determine which natural traits incited greater evolutionary selection. The examined factors included ocean acidification resilience (buffering), predatory nature, body volume, length, surface area, motility, tiering, circulatory systems, and respiratory organ type. The largest coefficient value was around -3.9 which demonstrated a high susceptibility of organisms with open circulatory systems for extinction during the Cambrian period. The majority of the data points were significant,30 of 54. Among these, the only consistently insignificant characteristics were factors associated with body size. This shows that body size had little impact on the extinction risk of organisms. Surprisingly, two descriptors out of nine were significant across the board, circulatory systems, and buffering. Although the type of circulation and amount of buffering that was selected for extinction varied across the Paleozoic.

Finally, in Stage Three, we built machine learning models for each period of the Paleozoic using the ecological factors that we tested in Stage Two. In the Cambrian, the model with the highest accuracy was 92%. In chronological order, the remaining periods had a model with the highest accuracies of 83%, 91%, 79%, 83%, and 84%. As evident, the Devonian appeared to have the lowest accuracy. We believe that with increased data and testing out alternative models, this accuracy can increase greatly.

Major Take-aways:
- Extinction Risk is not uniform across both geologic history or across taxonomic groups
- Certain traits can act as indicators for higher extinction risk; however, these too vary across geologic history
- These traits can even be used to create relatively accurate predictive models.

Future Research:
For future developments, we believe that completing analysis across the rest of geologic history could allow us to identify patterns of how extinction risk changes for each phylum and each trait across every period in Earth's history. This could allow us to know how anoxic conditions affect extinction risk for each phyla/trait or how mass extinctions affect extinction risk for each phyla/trait.

For the machine learning model, we would like to test out Decision Tree or Random Forest Regression Models to predict the exact first and last appearance in geologic history for each genus. Finally, we will look into Building Neural Nets for this type of prediction

Acknowledgements

Thank you to Stanford post-doctoral scholar Dr. Pedro Monarrez, Stanford Graduate Student Michael Pimentel, and Director of Education outreach, Dr. Jennifer Saltzmann for helping direct and lead the Stanford Earth Biodiversity program. Thanks also to Professor Jonathan Payne for helping make the program possible by hosting it within the Payne Paleobiology Lab.

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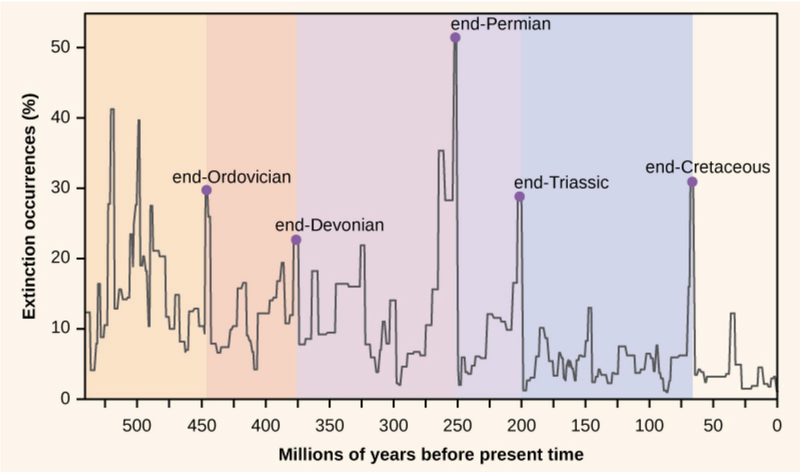
Basic Info/Background

- ➢ Extinction is volatile and relies on many ecological and biological variables
- ➢ Nature of extinction risk varies across geologic time; we focus on the Paleozoic Era



542 mya — **Cambrian**
Cambrian Explosion

488 mya — **Ordovician**
Late Ordovician Mass Extinction

444 mya — **Silurian**

416 mya — **Devonian**
The Devonian Mass Extinction

359 mya — **Carboniferous**

299 mya — **Permian**
End Permian Mass Extinction -

252 mya

Questions

1. Were certain taxonomic groups of organisms preferentially selected for extinction during the Paleozoic era?

2. Were certain types of organisms preferentially selected for extinction during the Paleozoic era?

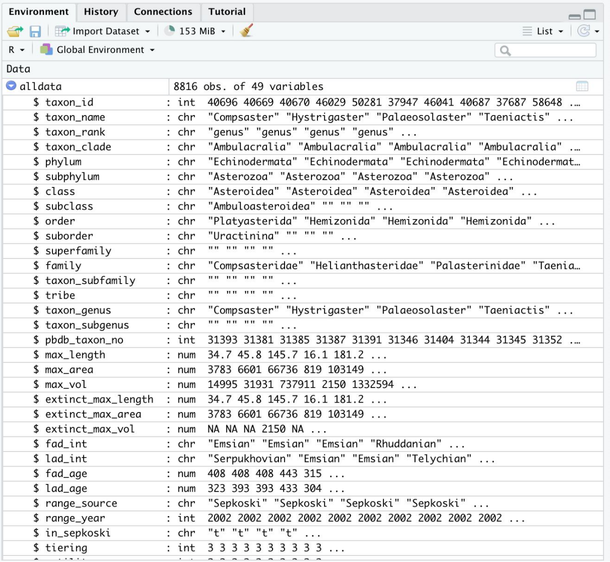
3. Is it possible to predict when a particular genus goes extinct during the Paleozoic using characteristics/descriptors?

Methodology

- ➢ Phyla - Echinodermata, Mollusca, Chordata, Arthropoda, Brachiopoda

- ➢ Descriptors - buffering, feeding patterns, motility, oceanic tiering, respiratory organ type, circulatory system type, length, surface area, volume

- ➢ Regularized binomial regression models(Step 3) + logistic binomial regression(Step 1/2)
  - ➢ Built Using R
  - ➢ Uses Stanford Earth Body Size Dataset (n=8816)



Methodology Cont.

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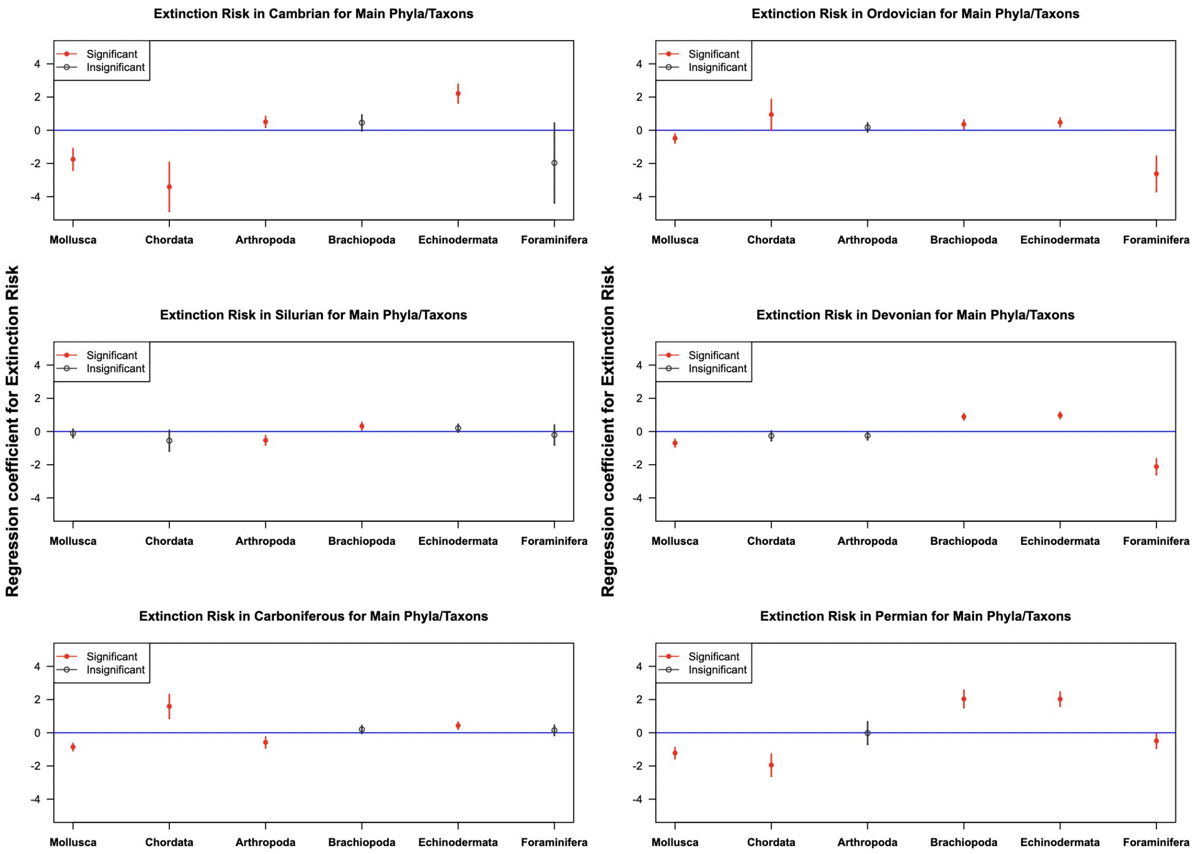
$ chordata         : num  0 0 0 0 0 0 0 0 0 0 ...
$ arthropoda       : num  0 0 0 0 0 0 0 0 0 0 ...
$ brachiopoda      : num  0 0 0 0 0 0 0 0 0 0 ...
$ echinodermata    : num  1 1 1 1 1 1 1 1 1 1 ...
$ foraminifera     : num  0 0 0 0 0 0 0 0 0 0 ...
$ expermian        : num  0 0 0 0 0 0 0 0 0 0 ...
$ excarboniferous  : num  1 0 0 0 1 0 1 0 0 0 ...
$ exdevonian       : num  0 1 1 0 0 0 0 1 0 0 ...
$ exsilurian       : num  0 0 0 1 0 1 0 0 0 1 ...
$ exordovician     : num  0 0 0 0 0 0 0 0 1 0 ...
$ excambrian       : num  0 0 0 0 0 0 0 0 0 0 ...
```

- ➢ Step 1: Binomial Logistic Regression Analysis on Phyla/Class/Order during each stage of Paleozoic identifying likeliness of extinction on each class

- ➢ Step 2: Binomial Regression Analysis on Phyla/Class/Order during each stage of Paleozoic identifying likeliness of extinction on each genus descriptor (ie predatory feeding, facultative motility, benthic tiering)

- ➢ Step 3: Developing simple machine learning model (using regularization) to predict whether a taxonomic group/specimen goes extinct in a specific period

Step 1:

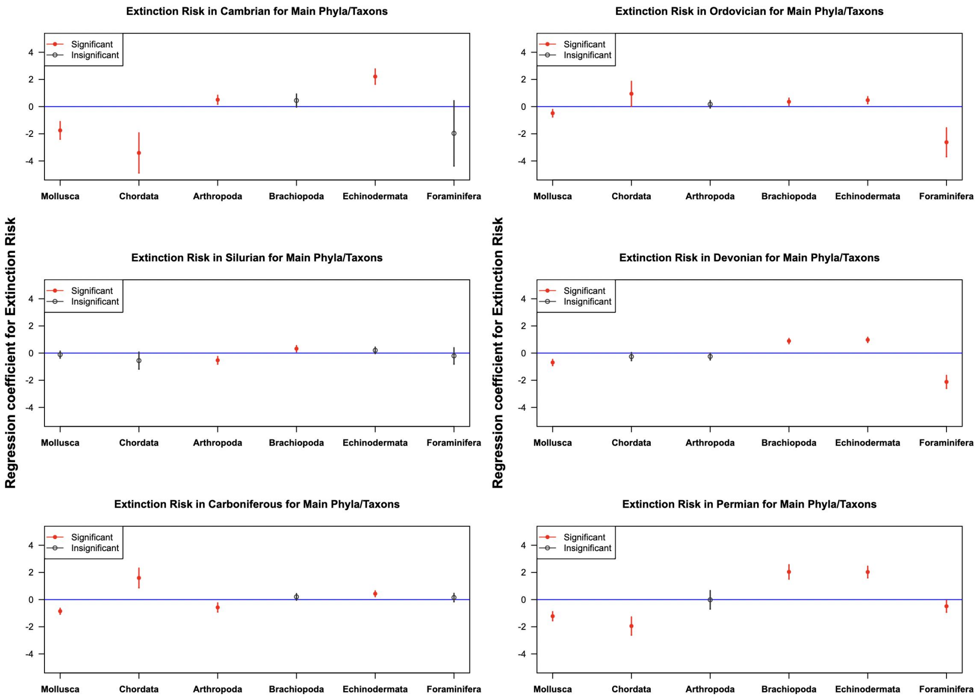

Extinction Risk in Cambrian for Main Phyla/Taxons
Extinction Risk in Ordovician for Main Phyla/Taxons
Extinction Risk in Silurian for Main Phyla/Taxons
Extinction Risk in Devonian for Main Phyla/Taxons
Extinction Risk in Carboniferous for Main Phyla/Taxons
Extinction Risk in Permian for Main Phyla/Taxons
Significant
Insignificant
Regression coefficient for Extinction Risk
4
2
0
-2
-4
Mollusca
Chordata
Arthropoda
Brachiopoda
Echinodermata
Foraminifera

Step 1: Key Findings

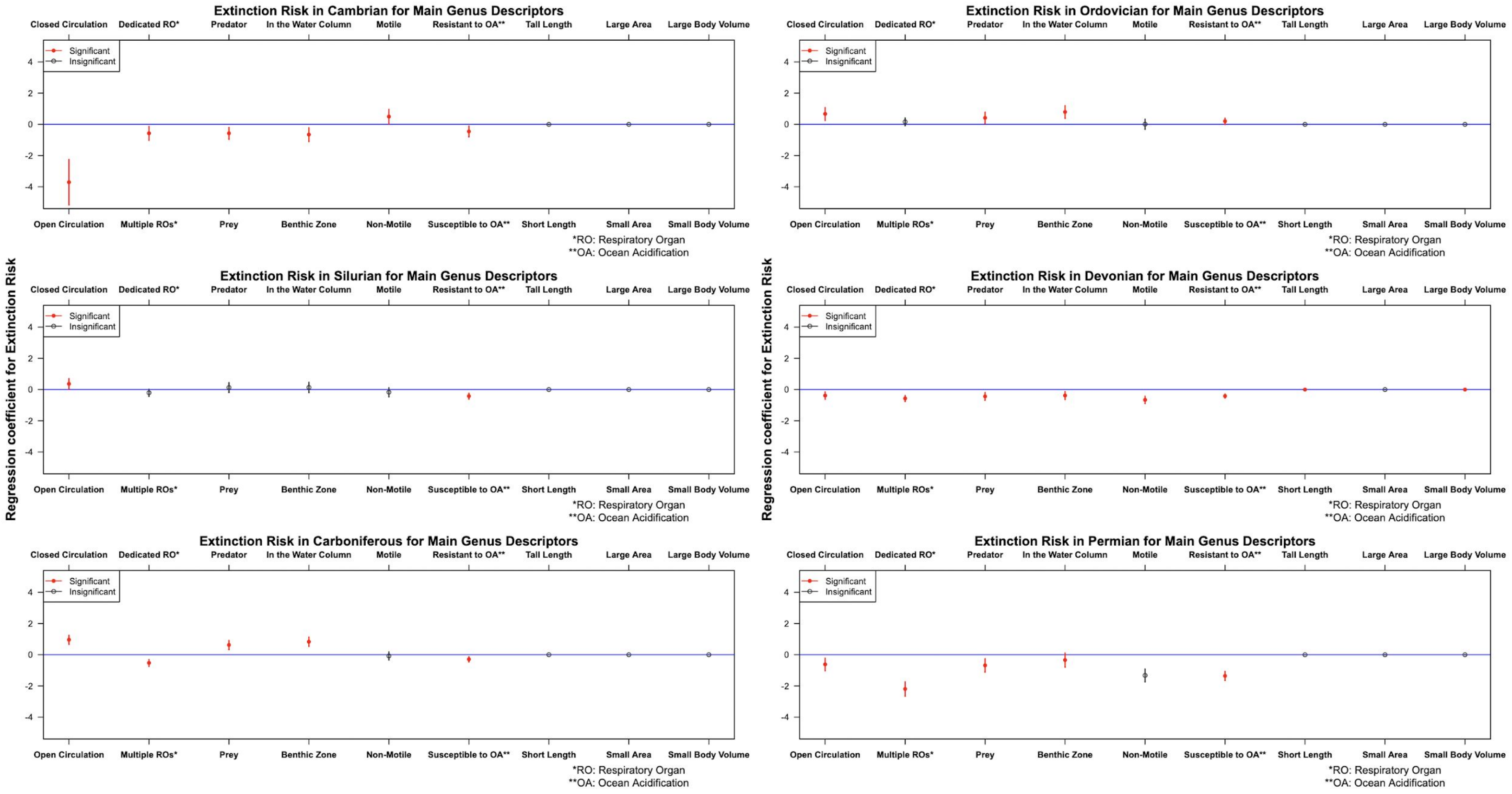
- **23** of **36** data points were significant
  - **12** data points had a significant greater extinction risk
  - **11** data points were significantly selected for survival.

- Patterns
  - Mollusca — consistently selected for survival
  - Brachiopoda— (major extinction events in Devonian and Permian, reflected in graphs)
  - Echinodermata — consistently selected for extinction

- **Extinction Risk was not uniformly felt across all major phyla in the Paleozoic**



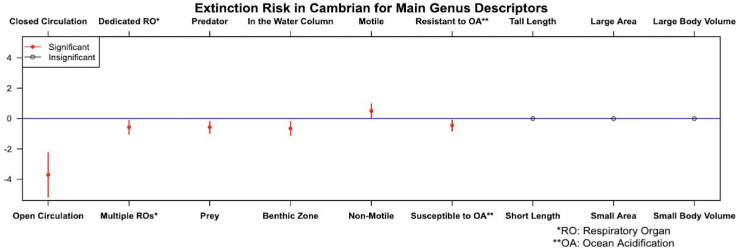
Step 2:

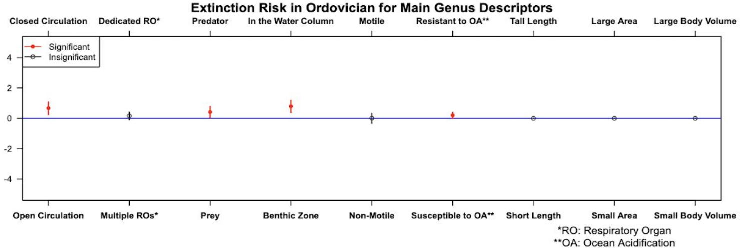


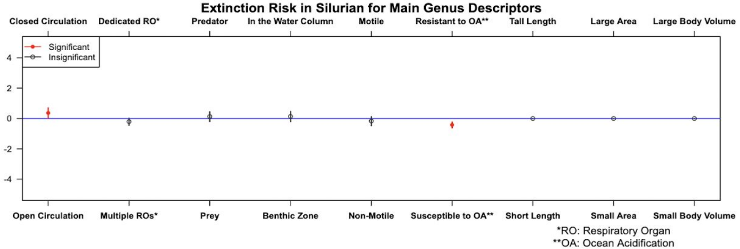
Extinction Risk in Cambrian for Main Genus Descriptors
Extinction Risk in Ordovician for Main Genus Descriptors
Extinction Risk in Silurian for Main Genus Descriptors
Extinction Risk in Devonian for Main Genus Descriptors
Extinction Risk in Carboniferous for Main Genus Descriptors
Extinction Risk in Permian for Main Genus Descriptors
Closed Circulation
Dedicated RO*
Predator
In the Water Column
Motile
Resistant to OA**
Tall Length
Large Area
Large Body Volume
Open Circulation
Multiple ROs*
Prey
Benthic Zone
Non-Motile
Susceptible to OA**
Short Length
Small Area
Small Body Volume
Significant
Insignificant
Regression coefficient for Extinction Risk
4
2
0
-2
-4
*RO: Respiratory Organ
**OA: Ocean Acidification

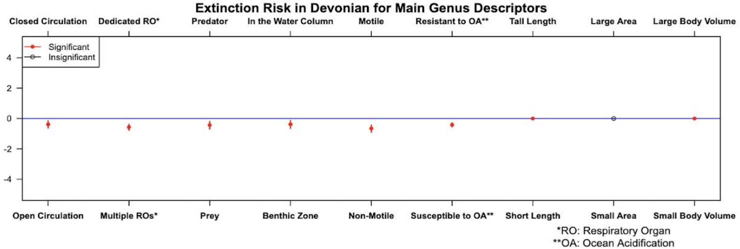
Step 2: Key Findings

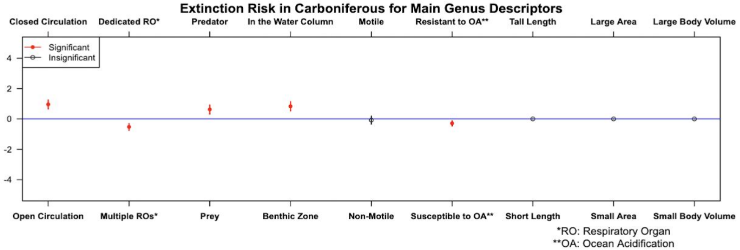
- **30** of **54** data points were significant
- Patterns
  - **Body Size**
  - Circulatory Systems (very volatile)
  - Respiratory Organ Type

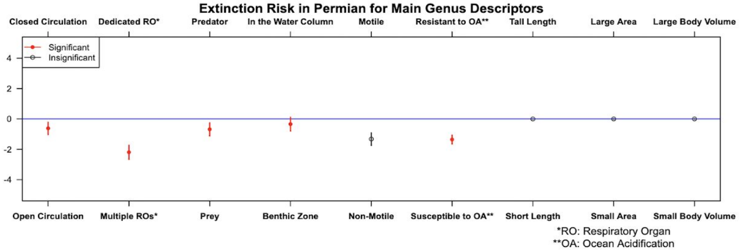












Step 3: Machine Learning Model

- 6 binomial regression models with regularization for each period
  - Regularization is helps in two major ways:
    - Reducing the variance of the model so as to not cause it to become overfit to the training data
    - Helps determine the features that causes the model to increase in variance and removes or shrinks their contribution to the model. (Essentially, features that do not predict have their coefficients reduced)
- Features:
  - Circulatory systems
  - Type of Respiratory Organ
  - Feeding (Predator or Prey)
  - Tiering (Water Column or Benthic)
  - Motility (Freely Moving or Non-motile)
  - Ability to withstand Ocean Acidification
  - Maximum length
  - Maximum Area
  - Maximum Volume
- **Predicting Outcome:** whether or not a genus went extinct in a particular period

Step 3: Machine Learning Model

Three types of regression models (lasso, elastic net, and ridge regression) were tested:

- **Lasso:** Focused on Feature Elimination (penalizes by removing)
- **Ridge Regression:** Focused on Feature Coefficient Reduction (penalizes by shrinking)
- **Elastic Net:** middle of both
- Nomenclature: Lasso : $\alpha = 1$; Ridge : $\alpha = 0$; Elastic net: $0 < \alpha < 1$
- The best model identified by running the program for α values between 0-1

Step 3: Machine Learning Model

circc	respOrgan	feeding	tiering	motility	oceanacidificationwithstand	max_length	max_area	calc_max_vol	excambrian
0	0	1	0	1	0	34.700000	3782.7603	1.499532e+04	0
0	0	1	0	1	0	181.200000	103149.2939	1.332594e+06	0
0	0	1	0	1	0	18.232000	1044.2837	2.613302e+03	0
0	0	1	0	1	0	55.450000	9659.4628	5.353129e+04	0
0	0	1	0	1	0	64.057376	12891.0460	7.920197e+04	0
0	0	1	0	1	0	37.300395	4370.9591	1.824551e+04	0
0	0	0	0	1	0	37.269746	4363.7789	1.820484e+04	0
0	0	0	0	1	0	40.702486	5204.6525	2.312418e+04	0
0	0	0	0	1	0	91.940000	26555.7700	2.112418e+05	0
0	0	0	0	1	0	41.897815	5514.8362	2.501452e+04	0
0	0	0	0	1	0	43.493046	5942.7783	2.768527e+04	0
0	0	0	0	1	0	10.141566	323.1171	5.316888e+02	0
0	0	0	0	1	0	45.810729	6593.0184	3.187570e+04	0
0	0	1	0	1	0	46.668914	6842.3497	3.352294e+04	0
0	0	0	0	0	0	27.050000	2298.7112	3.482660e+04	0

Period	Alpha Value	Lambda Value	Accuracy	AUROC	AUPR
Cambrian	0	0.01	0.92	0.93	0.8
Cambrian	0.1	0.01	0.92	0.93	0.8
Cambrian	0.2	0.01	0.92	0.93	0.8
Cambrian	0.3	0.01	0.92	0.93	0.8
Cambrian	0.4	0.01	0.92	0.93	0.8
Cambrian	0.5	0.01	0.92	0.93	0.8
Cambrian	0.6	0.01	0.92	0.93	0.8
Cambrian	0.7	0.01	0.92	0.93	0.8
Cambrian	0.8	0.01	0.92	0.93	0.8
Cambrian	0.9	0.01	0.08	0.5	0.79
Cambrian	1	0.01	0.91	0.5	0

Period	Alpha Value	Lambda Value	Accuracy	AUROC	AUPR
Ordovician	0	0.012589254	0.83	0.67	0.73
Ordovician	0.1	0.01	0.83	0.68	0.73
Ordovician	0.2	0.012589254	0.83	0.67	0.73
Ordovician	0.3	0.01	0.83	0.67	0.73
Ordovician	0.4	0.01	0.83	0.67	0.73
Ordovician	0.5	0.01	0.83	0.66	0.73
Ordovician	0.6	0.01	0.82	0.66	0.73
Ordovician	0.7	0.01	0.82	0.66	0.73
Ordovician	0.8	0.01	0.82	0.66	0.74
Ordovician	0.9	0.01	0.82	0.61	0.74
Ordovician	1	0.01	0.82	0.61	0.75

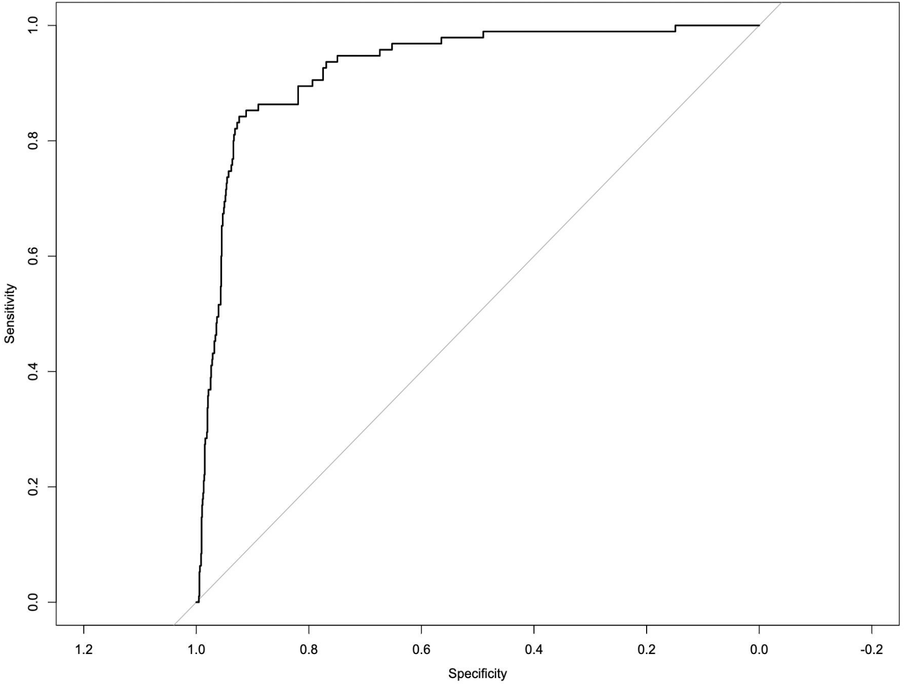
Period	Alpha Value	Lambda Value	Accuracy	AUROC	AUPR
Silurian	0	0.005416508	0.91	0.6	0.89
Silurian	0.1	0.001219581	0.91	0.6	0.89
Silurian	0.2	0.000578704	0.91	0.6	0.89
Silurian	0.3	0.000578704	0.91	0.6	0.89
Silurian	0.4	0.000578704	0.91	0.6	0.89
Silurian	0.5	0.000578704	0.91	0.6	0.89
Silurian	0.6	0.000578704	0.91	0.6	0.89
Silurian	0.7	0.000578704	0.91	0.6	0.89
Silurian	0.8	0.000578704	0.91	0.6	0.89
Silurian	0.9	0.000578704	0.91	0.6	0.89
Silurian	1	0.000578704	0.91	0.6	0.89

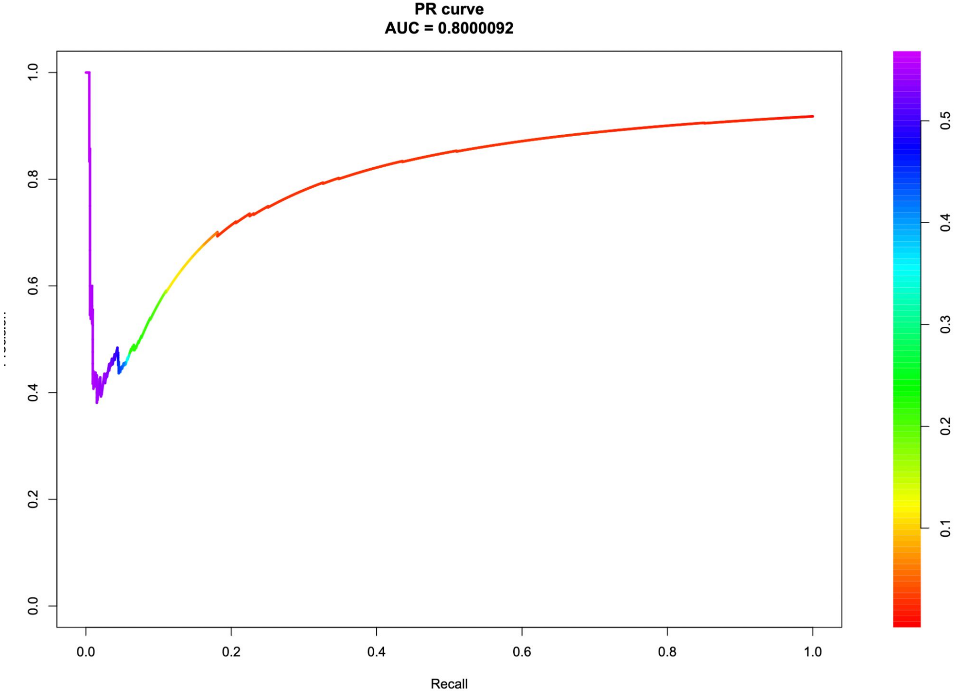
Period	Alpha Value	Lambda Value	Accuracy	AUROC	AUPR
Devonian	0	0.025118864	0.79	0.64	0.75
Devonian	0.1	0.015848932	0.79	0.64	0.75
Devonian	0.2	0.019952623	0.79	0.64	0.75
Devonian	0.3	0.006309573	0.79	0.64	0.75
Devonian	0.4	0.003981072	0.79	0.64	0.75
Devonian	0.5	0.003981072	0.79	0.64	0.75
Devonian	0.6	0.003162278	0.79	0.64	0.75
Devonian	0.7	0.001584893	0.79	0.64	0.75
Devonian	0.8	0.002511886	0.79	0.64	0.75
Devonian	0.9	0.001995262	0.79	0.64	0.75
Devonian	1	0.003162278	0.79	0.64	0.75

Period	Alpha Value	Lambda Value	Accuracy	AUROC	AUPR
Carboniferous	0	0.003541732	0.83	0.6	0.77
Carboniferous	0.1	0.002915452	0.83	0.6	0.77
Carboniferous	0.2	0.011383466	0.83	0.6	0.77
Carboniferous	0.3	0.002915452	0.83	0.6	0.77
Carboniferous	0.4	0.002915452	0.83	0.6	0.77
Carboniferous	0.5	0.002915452	0.83	0.6	0.77
Carboniferous	0.6	0.003541732	0.83	0.6	0.77
Carboniferous	0.7	0.002915452	0.83	0.6	0.77
Carboniferous	0.8	0.002915452	0.83	0.6	0.77
Carboniferous	0.9	0.002915452	0.83	0.6	0.77
Carboniferous	1	0.002915452	0.83	0.6	0.77

Period	Alpha Value	Lambda Value	Accuracy	AUROC	AUPR
Permian	0	0.002915452	0.84	0.62	0.79
Permian	0.1	0.002915452	0.84	0.62	0.79
Permian	0.2	0.002915452	0.84	0.63	0.78
Permian	0.3	0.002915452	0.84	0.62	0.79
Permian	0.4	0.002915452	0.84	0.56	0.82
Permian	0.5	0.002915452	0.84	0.56	0.82
Permian	0.6	0.002915452	0.84	0.56	0.82
Permian	0.7	0.002915452	0.84	0.56	0.82
Permian	0.8	0.002915452	0.84	0.45	0.83
Permian	0.9	0.002915452	0.84	0.46	0.83
Permian	1	0.002915452	0.84	0.46	0.83

Step 3: Machine Learning Model Results





Area under ROC Curve of **0.93** (ability to distinguish extinction and survival) and Area under PR Curve of **0.80** (fewer prediction errors)

Step 3: Machine Learning Model Results

	Cambrian Model Features	Score
1	Circulation System	3.3422079
2	Motility	2.27727063
3	Ocean Acidification Resistance	1.12284708
4	Feeding Patterns	0.42942449
5	Respiratory Organ System	0.37019192
6	Tiering	0.02890546
7	Maximum Length	0.00479994
8	Maximum Area	4.23E-07
9	Calculated Maximum Volume	2.39E-09

	Ordovician Model Features	Score
1	Motility	1.06918333
2	Ocean Acidification Resistance	0.85323525
3	Tiering	0.33049509
4	Feeding Patterns	0.32654485
5	Respiratory Organ System	0.15505047
6	Circulation System	0.02294367
7	Maximum Length	0.00124485
8	Maximum Area	4.10E-06
9	Calculated Maximum Volume	1.08E-08

	Silurian Model Features	Score
1	Motility	1.32779174
2	Circulation System	1.06206068
3	Respiratory Organ System	0.70851463
4	Feeding Patterns	0.6192809
5	Ocean Acidification Resistance	0.59558913
6	Tiering	0.59509338
7	Maximum Length	0.00258455
8	Maximum Area	3.22E-06
9	Calculated Maximum Volume	3.32E-08

	Devonian Model Features	Score
1	Ocean Acidification Resistance	0.70835892
2	Respiratory Organ System	0.45876009
3	Motility	0.22309167
4	Circulation System	0.06226351
5	Maximum Length	0.00555858
6	Maximum Area	2.00E-05
7	Calculated Maximum Volume	4.32E-08
8	Feeding Patterns	0
9	Tiering	0

	Carboniferous Model Features	Score
1	Circulation System	2.32544688
2	Ocean Acidification Resistance	0.73146419
3	Respiratory Organ System	0.65025381
4	Maximum Length	0.00189793
5	Feeding Patterns	0
6	Tiering	0
7	Motility	0
8	Maximum Area	0
9	Calculated Maximum Volume	0

	Permian Model Features	Score
1	Circulation System	2.18390017
2	Respiratory Organ System	1.04694225
3	Ocean Acidification Resistance	0.93551679
4	Feeding Patterns	0.86094481
5	Tiering	0.74849748
6	Motility	0.70993468
7	Maximum Length	0.000241
8	Calculated Maximum Volume	2.56E-08
9	Maximum Area	0

Major Takeaways

- Extinction Risk is not uniform across both geologic history or across taxonomic groups
- Certain traits can act as indicators for higher extinction risk; however, these too vary across geologic history
- These traits can even be used to create relatively accurate predictive models approximating what period a genus went extinct
- **One major goal of our project was to act as a comprehensive foundation for future research:** each one of the traits or phyla from stages one and two can be further studied.

Future Research

- Completing analysis across the rest of geologic history
  - Identifying patterns of how extinction risk changes for each phyla and each trait across every period in Earth’s history
    - Ie. How anoxic conditions affect extinction risk for each phlya/trait
    - Ie. How mass extinctions affect extinction risk for each phlya/trait

- Testing out Decision Tree or Random Forest Regression Models to predict exact first and last appearance in geologic history for each genus

- Look into Building Neural Nets for this type of prediction

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