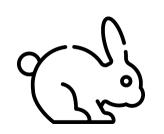
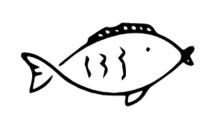
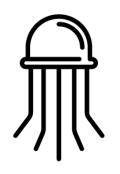
Get This Sea Snake Out of My Zoo!

Sam Ballerini Clarity Insights Case Study 2018





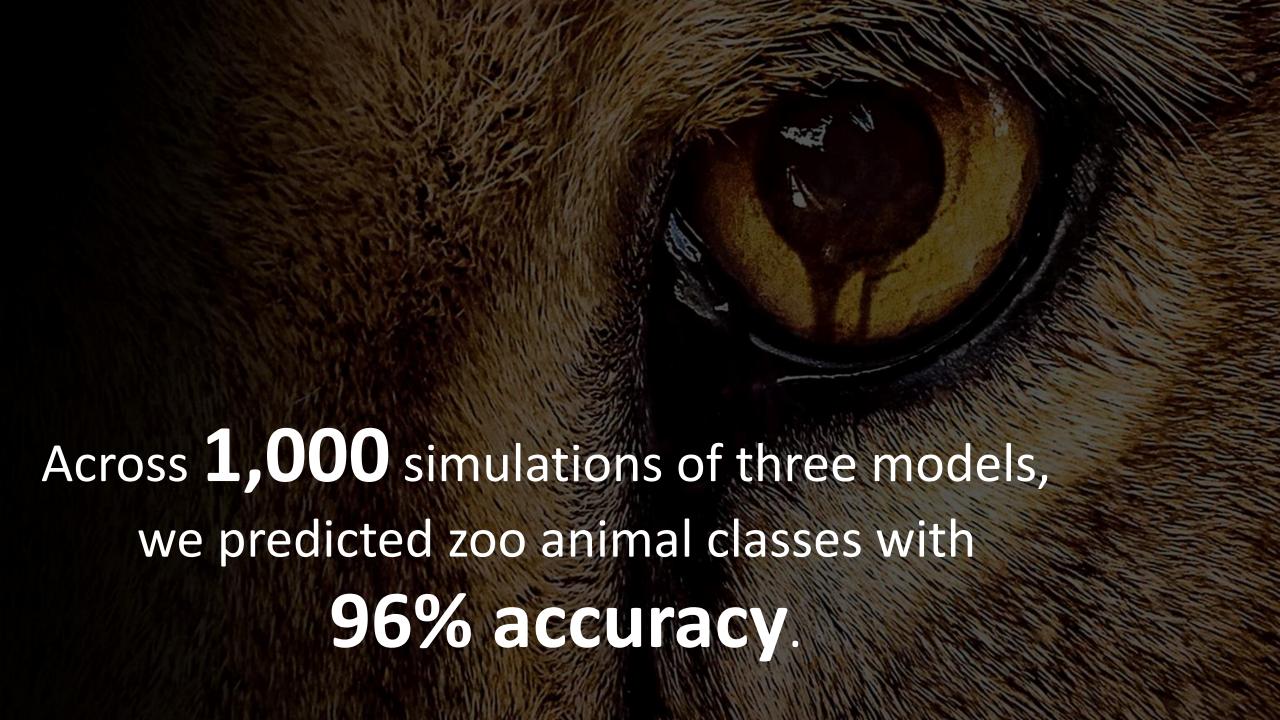










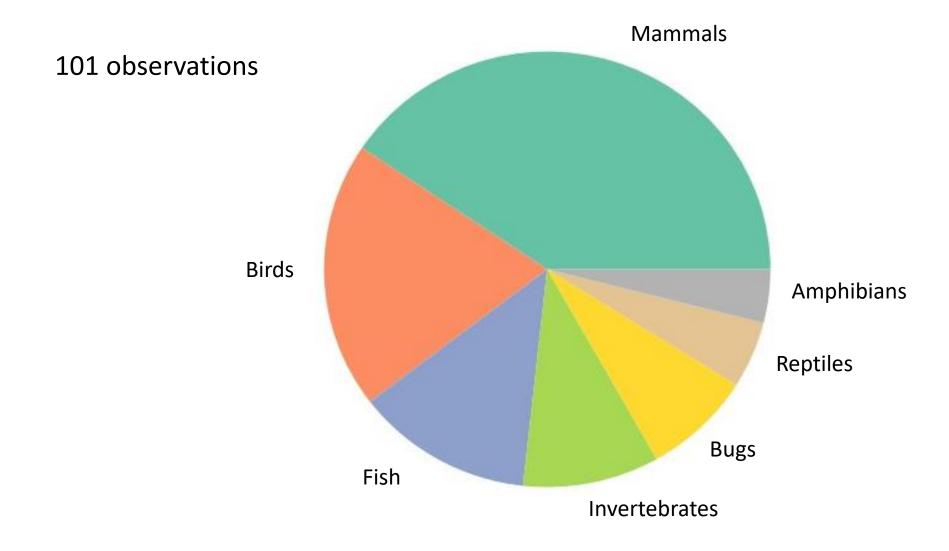


Agenda

- 1. Problem Overview
- 2. Data Exploration
- 3. Model Development
- 4. Model Evaluation



Class Breakdown



Initial Features

- 15 binary variables
- 1 categorical variable with
 6 levels (dummy coded)

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- 1 categorical variable with
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Transformed Features

• 20 binary variables

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 6 levels (dummy coded)

Transformed Features

• 20 binary variables

Variable 1	Variable 2	Pearson Corr.	Counterexample
Milk	Hair	0.88	Dolphin
Feathers	2 Legs	0.82	Gorilla
Tail	Backbone	0.73	Toad

Initial Features

- 15 binary variables
- 1 categorical variable with
 6 levels (dummy coded)

Transformed Features

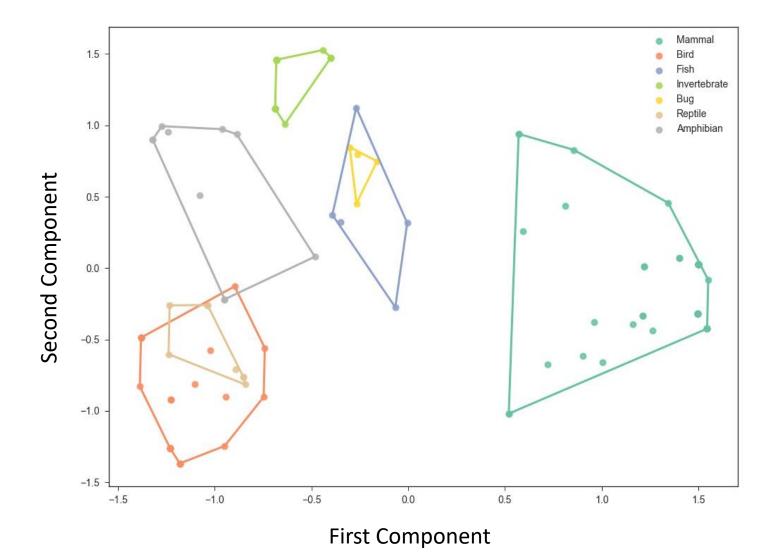
• 20 binary variables

Variable 1	Variable 2	Pearson Corr.	Counterexample
Milk	Hair	0.88	Dolphin
Feathers	2 Legs	0.82	Gorilla
Tail	Backbone	0.73	Toad
		_	
Toothed	Eggs	-0.64	Haddock
6 Legs	Backbone	-0.71	Worm (neither)
Milk	Eggs	-0.94	Platypus

Ratio of Variance Explained					
PC1	35%				
PC2	19%				
PC3	13%				
PC4	7%				

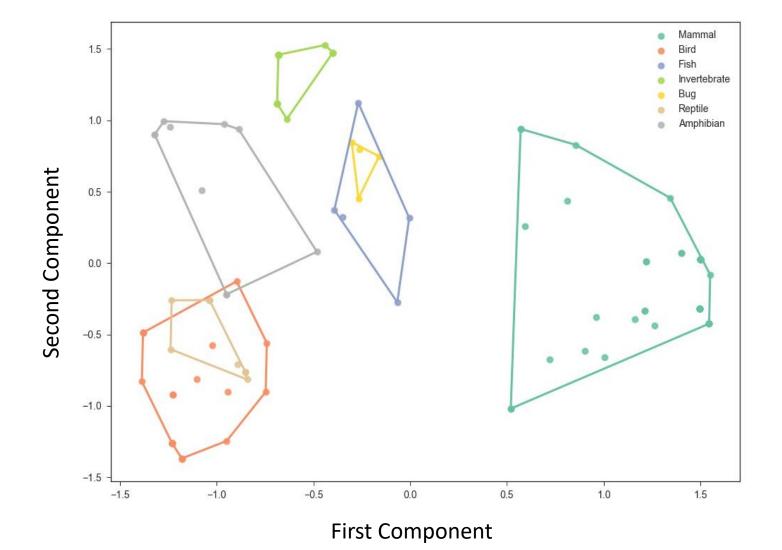
5%

PC5



Variable Loadings
on PC1

0111	-
Milk	0.42
4 Legs	0.35
Toothed	0.34
Eggs	-0.41

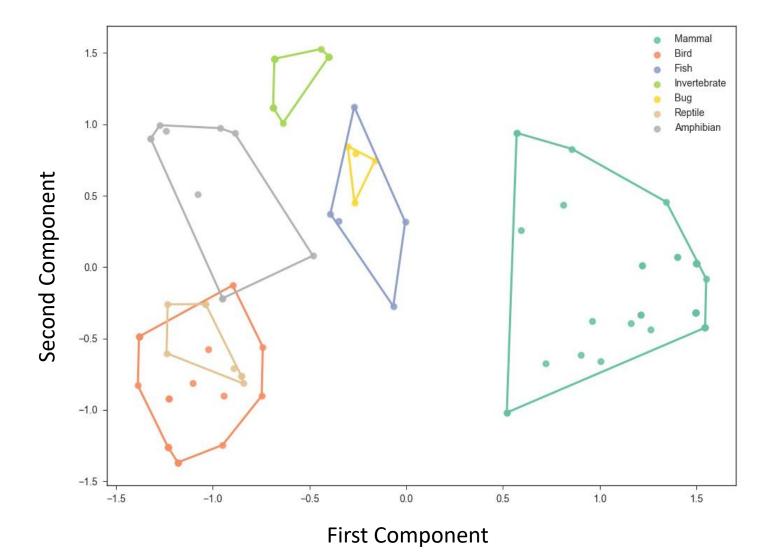


Variable Loadings
on PC2

Aquatic	0.43
Predator	0.34
Fins	0.32
Toothed	0.26
Breathes	-0.39
2 Legs	-0.35
Airborne	-0.34

Feathers

-0.29



Variable Loadings on PC3

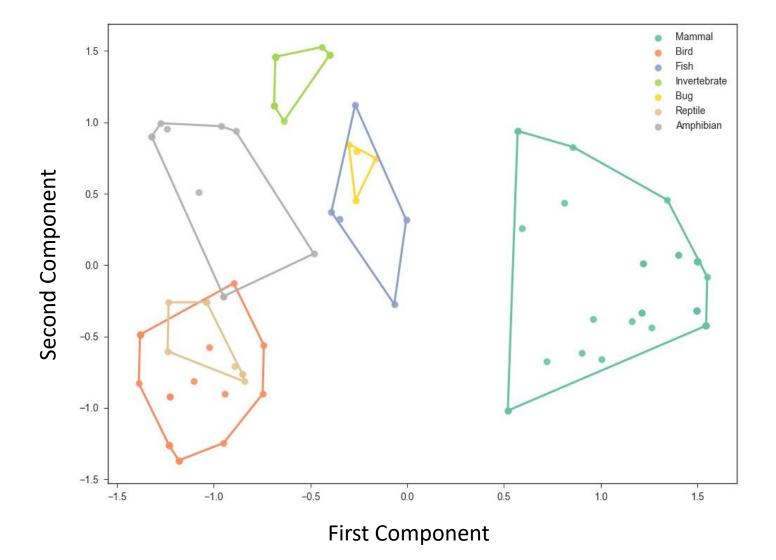
6 Legs 0.31

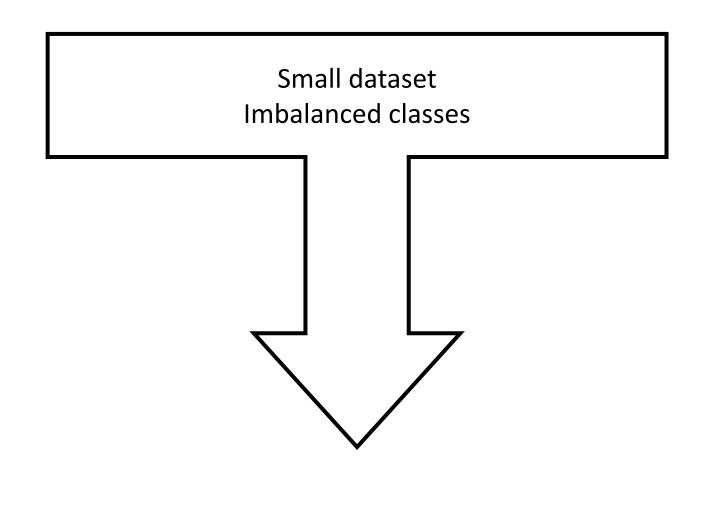
Tail -0.51

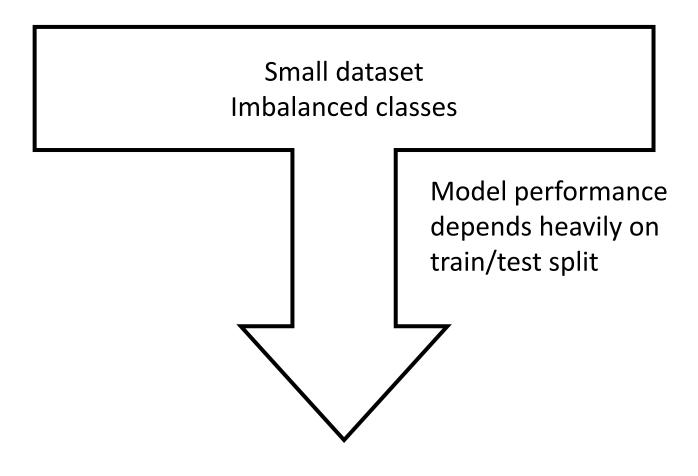
Backbone -0.46

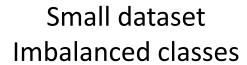
2 Legs -0.36

Feathers -0.32









Model performance depends heavily on train/test split

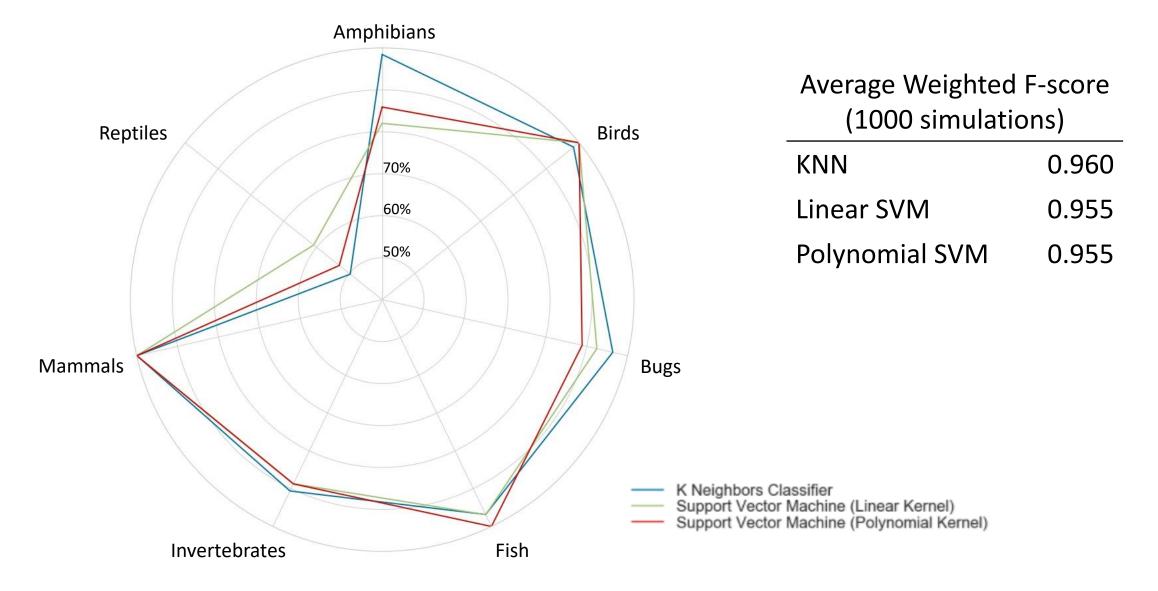
Simulate train/test splits for hyperparameter tuning and k-fold cross-validation

Assess model performance with leave-one-out cross-validation

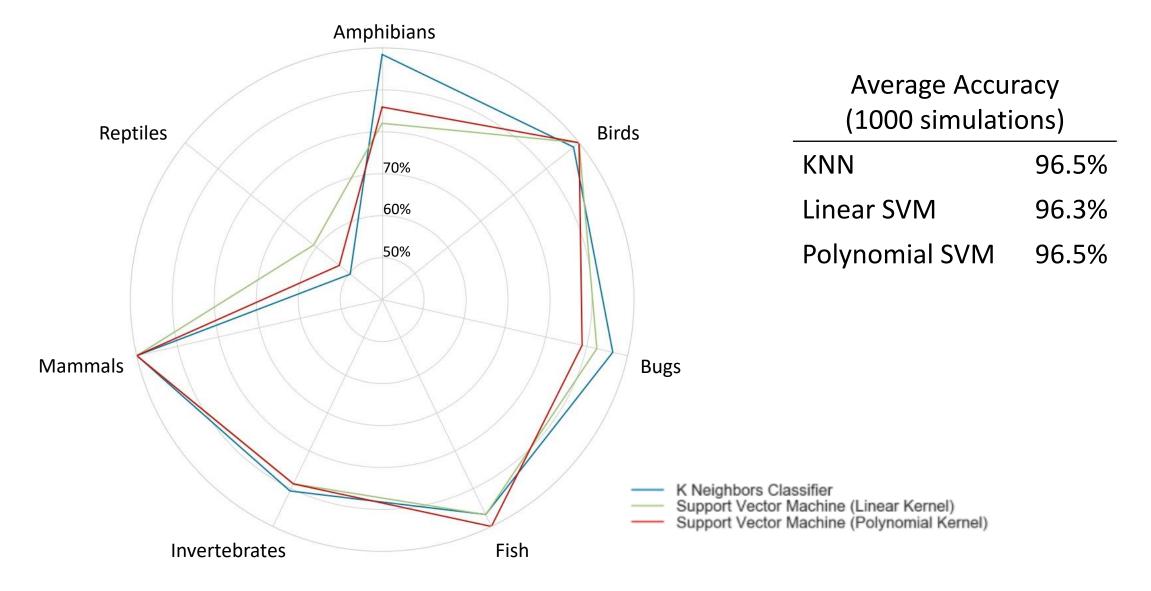
Models

- KNN
 - Jaccard distance
 - K = 3
 - Neighbors are weighted by distance to the observation of interest.
- Support Vector Machine
 - Linear kernel, C=1
 - Polynomial kernel, C=0.01, Gamma = 1

Average F-Score by Class and Model



Average F-Score by Class and Model



			Animal	Predicted Class	Actual Class
			Sea Snake	Fish	Reptile
		KNN	Scorpion	Reptile	Invertebrate
Average A	ccuracy		Tortoise	Bird	Reptile
KNN	97%				

			Animal	Predicted Class	Actual Class
		-	Sea Snake	Fish	Reptile
		KNN	Scorpion	Reptile	Invertebrate
Average Accuracy			Tortoise	Bird	Reptile
KNN	97%		Sea Snake	Fish	Reptile
Linear SVM	97%	Linear SVM	Scorpion	Reptile	Invertebrate
			Newt	Reptile	Amphibian

			Animal	Predicted Class	Actual Class
			Sea Snake	Fish	Reptile
		KNN	Scorpion	Reptile	Invertebrate
Average Accuracy			Tortoise	Bird	Reptile
KNN	97%		Sea Snake	Fish	Reptile
Linear SVM	97%	Linear SVM	Scorpion	Reptile	Invertebrate
Polynomial SVM	97%		Newt	Reptile	Amphibian
			Sea Snake	Invertebrate	Reptile
		Polynomial SVM	Newt	Reptile	Amphibian
			Tortoise	Invertebrate	Reptile

Recursive Feature Elimination w/ a Linear SVM

20 features

Airborne Aquatic Predator Toothed Backbone Breathes Venomous **Fins** Tail Domestic Catsize 2 Legs 4 Legs 5 Legs 6 Legs 8 Legs

Hair Feathers

> Eggs Milk

Recursive Feature Elimination w/ a Linear SVM

Predator
Toothed
Backbone
Breathes
Venomou
Fins
Tail
Domestic
Catsize
2 Legs
4 Legs
5 Legs
6 Legs

Hair Feathers

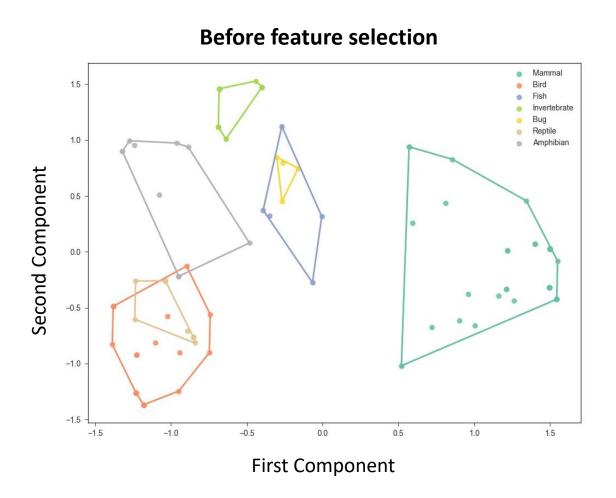
8 Legs

Eggs Milk Airborne Aquatic **Predator** Backbone Breathes **Venomous Domestic**

Feathers
Eggs
Milk
Airborne
Aquatic
Toothed
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Fins
Tail
2 Legs
4 Legs
6 Legs

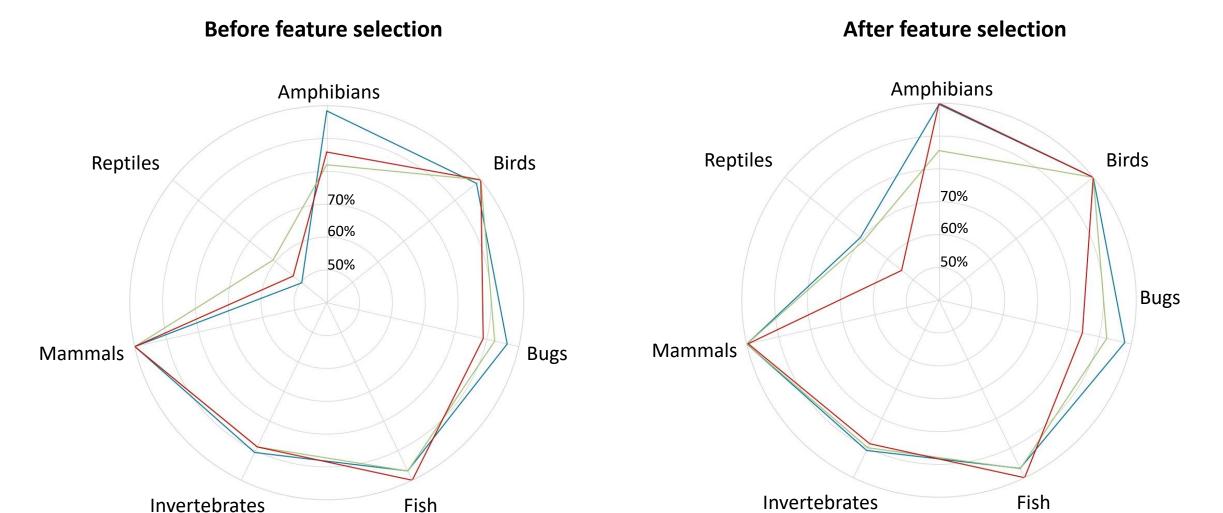
Hair

14 features



After feature selection Invertebrate 1.0 Reptile Amphibian Second Component -1.0 -1.0 0.0 0.5 1.0 1.5 First Component

Average F-Score by Class and Model



	Befor	Before Feature Elimination			er Feature Elimir	nation
	Animal	Predicted Class	Actual Class	Animal	Predicted Class	Actual Class
	Sea Snake	Fish	Reptile			
KNN	Tortoise	Bird	Reptile			
	Scorpion	Reptile	Invertebrate			

	Befor	Before Feature Elimination			r Feature Elimir	nation
	Animal	Predicted Class	Actual Class	Animal	Predicted Class	Actual Class
	Sea Snake	Fish	Reptile	Sea Snake	Fish	Reptile
KNN	Tortoise	Bird	Reptile	Tortoise	Bird	Reptile
	Scorpion	Reptile	Invertebrate			

	Betoi	re Feature Elim	nination	Afte	r Feature Elimir	nation
	Animal	Predicted Class	Actual Class	Animal	Predicted Class	Actual Class
	Sea Snake	Fish	Reptile	Sea Snake	Fish	Reptile
KNN	Tortoise	Bird	Reptile	Tortoise	Bird	Reptile
	Scorpion	Reptile	Invertebrate			
	Sea Snake	Fish	Reptile			
Linear SVM	Scorpion	Reptile	Invertebrate			
	Newt	Reptile	Amphibian			

	Befor	re Feature Elim	nination	After Feature Elimination				
	Animal	Predicted Class	Actual Class	Animal	Predicted Class	Actual Class		
	Sea Snake	Fish	Reptile	Sea Snake	Fish	Reptile		
KNN	Tortoise	Bird	Reptile	Tortoise	Bird	Reptile		
	Scorpion	Reptile	Invertebrate					
	Sea Snake	Fish	Reptile	Sea Snake	Fish	Reptile		
Linear SVM	Scorpion	Reptile	Invertebrate	Platypus	Amphibian	Mammal		
	Newt	Reptile	Amphibian					

Refere Feature Elimination

	ветоі	re Feature Ellm	ilnation	After Feature Elimination					
	Animal	Predicted Class	Actual Class	Animal	Predicted Class	Actual Class			
	Sea Snake	Fish	Reptile	Sea Snake	Fish	Reptile			
KNN	Tortoise	Bird	Reptile	Tortoise	Bird	Reptile			
	Scorpion	Reptile	Invertebrate						
	Sea Snake	Fish	Reptile	Sea Snake	Fish	Reptile			
Linear SVM	Scorpion	Reptile	Invertebrate	Platypus	Amphibian	Mammal			
	Newt	Reptile	Amphibian						
	Sea Snake	Invertebrate	Reptile						
Polynomial SVM	Newt	Reptile	Amphibian						
	Tortoise	Invertebrate	Reptile						

After Feature Elimination

	Befor	re Feature Elim	nination	Afte	After Feature Elimination				
	Animal	Predicted Class	Actual Class	Animal	Predicted Class	Actual Class			
	Sea Snake	Fish	Reptile	Sea Snake	Fish	Reptile			
KNN	Tortoise	Bird	Reptile	Tortoise	Bird	Reptile			
	Scorpion	Reptile	Invertebrate						
	Sea Snake	Fish	Reptile	Sea Snake	Fish	Reptile			
Linear SVM	Scorpion	Reptile	Invertebrate	Platypus	Amphibian	Mammal			
	Newt	Reptile	Amphibian						
	Sea Snake	Invertebrate	Reptile	Sea Snake	Invertebrate	Reptile			
Polynomial SVM	Newt	Reptile	Amphibian	Platypus	Amphibian	Mammal			
	Tortoise	Invertebrate	Reptile	Tortoise	Invertebrate	Reptile			
				Tuatara	Amphibian	Reptile			

Average Accuracy Before
Feature Elimination

KNN	97%
Linear SVM	97%
Polynomial SVM	97%

Average Accuracy Feature Elimina			Average Accuracy After Feature Elimination				
KNN	97%	KNN	98%				
Linear SVM	97%	Linear SVM	98%				
Polynomial SVM	97%	Polynomial SVM	96%				

Why can't we get the sea snake right?!

• The reptile data is too small and too diverse











So what makes a sea snake anyways?



- Live the majority of their lives in the water
- Have developed tails for better swimming
- Some species lay eggs on land, but the majority have live births
- Need air regularly as they do not have gills

So what makes a sea snake anyways?



- Live the majority of their lives in the water
- Have developed tails for better swimming
- Some species lay eggs on land, but the majority have live births
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Wait a second...

hair	feathers	eggs	milk	airborne	aquatic	toothed	backbone	breathes	fins	tail	2 legs	4 legs	6 legs
0	0	0	0	0	1	1	1	0	0	1	0	0	0

Wait a second...

hair							backbone						
0	0	0	0	0	1	1	1	0	0	1	0	0	0

The dataset is WRONG!





Appendix

Problem Description

Given 101 observations of 20 binary characteristics, can we predict an animals classification in the Animalia kingdom? If so, how well can we do it, and how can we ensure model stability with such a small amount of data?

Data Cleaning

Renaming frog labels as 'frog1' and 'frog2'

Feature Engineering

- Encoding the *legs* variable
- Recursive feature elimination with a support vector machine

Python Tools and Packages

```
Data Manipulation

pandas, numpy

Graphing

matplotlib, seaborn, yellowbrick, pylab

Modeling

scikit-learn, scipy
```