

## Agenda

**Problem Statement** 

**Data Selection** 

**Data Analysis** 

**Model Training** 

**Conclusion** 

# What is the opportunity?

To predict the yield of wild blueberries based on a variety of complex variables

## The business case (economic value)

Wild blueberries far superior in taste and nutritional content, which can command higher market prices.

#### Data Question?

What variables will influence the yield of wild blueberries and how can we use these to predict future yields.

### **Data Selection**

- Source: kaggle [1]
- Synthetic data
- 18 columns
- No duplicates or null
- Target: Yield

#### DataFrame

Unit	Description	Variable / Features
m <sup>2</sup>	The average blueberry clone size in the field	Clone size (CS)
bees/m <sup>2</sup> /min	Honeybee (Apis mellifera (L.)) density in the field	Honeybee (HB)
bees/m <sup>2</sup> /min	Bumblebee (Bombus spp.) density in the field	Bumblebee (BB)
bees/m²/min	Andrena spp. bee density in the field	Andrena (AD)
bees/m <sup>2</sup> /min	Osmia spp. bee density in the field	Osmia (OS)
°F	The highest record of the upper band daily air temperature during the bloom season	MaxOfUpperTRange (MaxUTR)
°F	The lowest record of the upper band daily air temperature number	MinOfUpperTRange (MinUTR)
°F	The average of the upper band daily air temperature fare	AverageOfUpperTRange (AvUTR )
°F	The highest record of the lower band daily air temperature	MaxOfLowerTRange (MaxLTR)
°F	The lowest record of the lower band daily air temperature	MinOfLowerTRange (MinLTR)
°F	The average of the lower band daily air temperature	AverageOfLowerTRange (AvLTR)
Day	The total number of days during the bloom season, each of which has precipitation larger than zero	Raining Days (RD)
Day	The average of raining days of the entire bloom season	Average Raining Days (AvRD)
Ratio or %	The ratio of flowers that successfully develop into fruits	Fruitset
Ounces?	The average mass of a single fruit produced	Fruitmass
Count	The average number of seeds per fruit	Seeds
lb/m <sup>2</sup> ?	The total harvestable quantity of blueberries per unit area	Yield

## Data Analysis

What methods did you use in your experiment?

- Pearson Correlation
- EDA
- Feature Selection

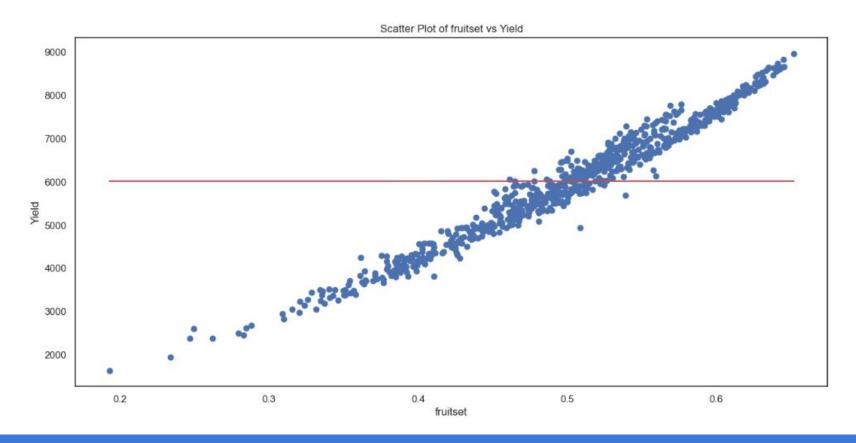
#### Pearson Correlation

											_						
						Pe	earsor	Corr	elatio	n of F	eatur	es					
donesize	1	0.12	0.0048	0.0085	-0.14	0.034	0.033	0.034	0.034	0.034	0.034	-0.022	-0.024	-0.56	-0.47	-0.5	-0.52
honeybee	0.12	1	-0.23	-0.13	-0.19	0.026	0.025	0.026	0.026	0.026	0.026	-0.074	-0.093	0.0094	-0.17	-0.17	-0.044
bumbles	0.0048	-0.23	1	0.011	0.29	-0.023	0.0058	0.016	-0.025	-0.017	-0.014	0.058	0.075	0.29	0.36	0.38	0.31
andrena	-0.0085	-0.13	0.011	1	0.39	-0.026	-0.024	-0.026	-0.027	-0.026	-0.025	0.035	0.044	0.1	0.092	0.089	0.14
osmia	-0.14	-0.19	0.29	0.39	1	-0.064	-0.043	-0.055	-0.066	-0.057	-0.053	0.084	0.1	0.33	0.34	0.35	0.38
MaxOfUpperTRange	0.034	0.026	-0.023	-0.026	0.064	1	0.99	1	1	1	1	0.0033	0.0057	-0.13	0.058	-0.034	-0.19
MinOfUpperTRange	0.033	0.025	0.0058	0.024	0.043	0.99	1	1	0.99	1:	1	0.0008	0.0019	-0.12	0.068	-0.024	-0.18
AverageOfUpperTRange	0.034	0.026	-0.016	-0.026	0.055	1	1	1	1	1	1	0.0023	0.0042	-0.13	0.064	-0.029	-0.18
MaxOfLowerTRange	0.034	0.026	-0.025	-0.027	0.066	1	0.99	1	1	1	1	0.0036	0.0061	-0.13	0.058	-0.035	-0.19
MinOfLowerTRange	0.034	0.026	-0.017	-0.026	0.057	1	1	1	1	1	1	0.0024	0.0043	-0.13	0.062	-0.031	-0.18
AverageOfLowerTRange	0.034	0.026	-0.014	-0.025	0.053	1	1	1	1	1	1	0.0019	0.0036	-0.12	0.064	-0.029	-0.18
RainingDays	-0.022	0.074	0.058	0.035	0.084	0.0033	0.0008	0.0023	0.0036	0.0024	0.0019	1	0.99	-0.48	-0.45	-0.48	-0.54
AverageRainingDays	0.024	-0.093	0.075	0.044	0.1	0.0057	0.0019	0.0042	0.0061	0.0043	0.0036	0.99	1	-0.49	-0.45	-0.47	-0.54
fruitset	-0.56	0.0094	0.29	0.1	0.33	-0.13	-0.12	-0.13	-0.13	-0.13	-0.12	-0.48	-0.49	1	0.95	0.97	0.98
fruitmass	-0.47	-0.17	0.36	0.092	0.34	0.058	0.068	0.064	0.058	0.062	0.064	-0.45	-0.45	0.95	1	0.99	0.93
seeds	-0.5	-0.17	0.38	0.089	0.35	0.034	0.024	0.029	-0.035	0.031	0.029	-0.48	-0.47	0.97	0.99	1	0.96
yield	-0.52	-0.044	0.31	0.14	0.38	-0.19	-0.18	-0.18	-0.19	-0.18	-0.18	-0.54	-0.54	0.98	0.93	0.96	1
	donesize	honeybee	pumples	andrena	osmia	pperTRange	pperTRange	pperTRange	owerTRange	owerTRange	owerTRange	RainingDays	RainingDays	fruitset	fruitmass	spees	yield

	Correlation
AverageRainingDays	-0.541215
RainingDays	-0.540069
clonesize	-0.518737
MaxOfLowerTRange	-0.187439
MaxOfUpperTRange	-0.187075
MinOfLowerTRange	-0.183339
AverageOfUpperTRange	-0.181774
AverageOfLowerTRange	-0.181293
MinOfUpperTRange	-0.175883
honeybee	-0.044250
andrena	0.140277
bumbles	0.309407
osmia	0.380892
fruitmass	0.930365
seeds	0.961249
fruitset	0.984081
yield	1.000000

- -0.2

#### EDA - Correlation between Fruitset & Yield



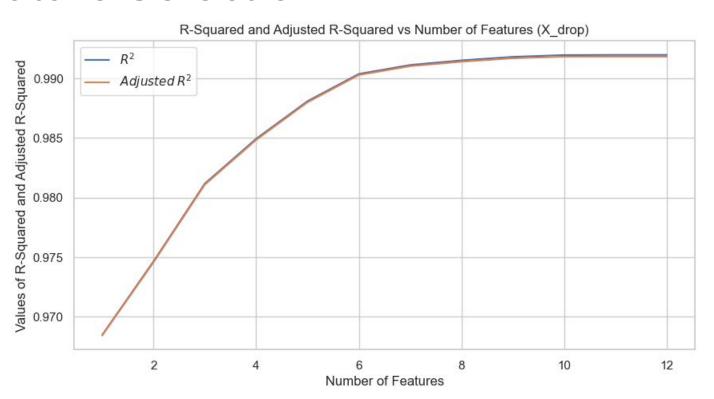
#### Feature Selection

#### Resulting features:

fruitset, RainingDays, osmia, AverageOfUpperTRange, seeds, fruitmass, andrena, honeybee, clonesize, AverageRainingDays, Average OfLowerTRange

These 11 features would give the best prediction

#### Feature Selection



## Modelling

- Multiple Linear Regression
- Ridge Regression
- Lasso Regression

#### Results

```
Multiple Linear Regression for 11 features Metrics:
R-squared (R<sup>2</sup>): 0.9919746420219046

Ridge Regression for 11 features Metrics:
R-squared (R<sup>2</sup>): 0.9906832500974772

Lasso Regression for 11 features Metrics:
```

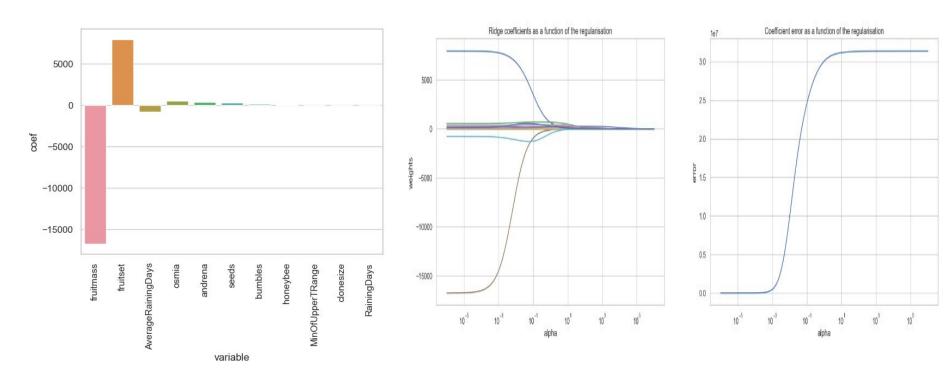
R-squared (R2): 0.9908032850488285

```
Multiple Linear Regression for all 16 features Metrics: R-squared (R^2): 0.9913733793291577
```

R-squared (Fruitset)

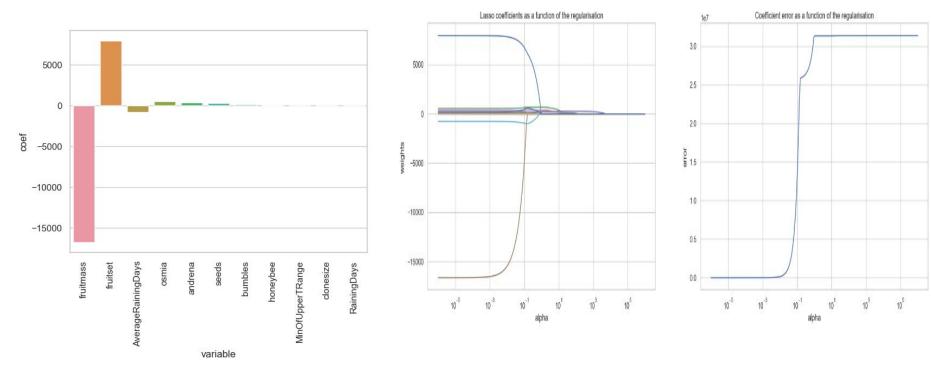
0.9684132908271317

#### Ridge Regression [3]



Influence of each variable on the model's predictions

#### Lasso Regression [4]



Influence of each variable on the model's predictions

#### Conclusion

Linear regression is marginally better the Ridge & Lasso

Fruitset as a predictor is ok, using 11 features gives best result

Can **predict** the yield of wildberries using regression models:

#### **Yield Prediction**

```
AverageRainingDays = 1
RainingDays = 15
clonesize = 10
fruitmass = 0.384646
seeds = 0.392303
fruitset = 29.742583
# Create a dictionary
data_features = {'AverageRainingDays': [AverageRainingDays],
        'RainingDays': [RainingDays],
        'clonesize': [clonesize],
        'fruitmass': [fruitmass],
        'seeds': [seeds],
        'fruitset': [fruitset]}
# Convert the dictionary to a DataFrame
x features = pd.DataFrame(data features)
# Make a prediction
Ypred features = linreg features.predict(x_features)
print('Predicted yield: ', Ypred features[0])
# Predicted yield: 344300.1975937406
```

### Next Steps?

- Use other variables (soil temp)
- Compare to cultivated blueberries
- Other models (Tree-Based)



#### References

[6] Chat GPT and Microsoft Copilot

https://www.kaggle.com/datasets/shashwatwork/wild-blueberry-yield-prediction-dataset
Linear Regression Scikit-Learn: https://scikit-learn.org/stable/modules/generated/sklearn.linear\_model.LinearRegression.html
Ridge Regression Scikit-learn: https://scikit-learn.org/stable/modules/linear\_model.html#ridge-regression-and-classification
Lasso Regression Scikit-learn: https://scikit-learn.org/stable/modules/linear\_model.html#lasso
IOD Labs 4

## Questions?