

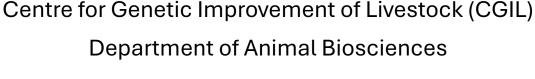
#### AMERICAN SOCIETY OF ANIMAL SCIENCE



# Python computational pipeline for predictive machine learning modelling of livestock data

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IMPROVE LIFE.



#### Summary



#### What you get from this workshop

- Some (hopefully functional) Python code ... for regression problems (due to time constraints)
  - The code relies on the Python scikit-learn library <a href="https://scikit-learn.org/">https://scikit-learn.org/</a>
- Some information and explanations of what the code does and why

#### Assumptions

- You know a bit about machine learning
  - If not, read this: Greener et al. (2021): A guide to machine learning for biologists

(https://www.nature.com/articles/s41580-021-00407-0)

You can operate a computer

# Warnings / Disclaimers



- Python code is not optimized or comprehensive
  - It is built to (hopefully) facilitate understanding
  - Sacrificed performance and best programming practices
- Input datasets are assumed to be ready and clean
  - Your job
- The code should only be used for good causes
- If you make money with this code my share is 10% (cash, check or plastic is fine)

### Python Use

• Follow the instructions provided in the "Python\_usage\_instructions.pdf" file

# Data formatting

- Expectations:
  - Tabular format
  - Last column contains the predictor variable
  - Data was cleaned prior to using the Python script
  - Data includes only numeric values

- Recommended reading:
  - Browman and Woo (2018) Data Organization in Spreadsheets (https://www.tandfonline.com/doi/full/10.1080/00031305.2017.1375989)

### Data sets (for this workshop)

2 subsets of the data from:

Marshall et al. (2023): A farmer-friendly tool for estimation of weights of pigs kept by smallholder farmers in Uganda

- Article: <a href="mailto:ttps://link.springer.com/article/10.1007/s11250-023-03561-z">ttps://link.springer.com/article/10.1007/s11250-023-03561-z</a>
- Data:

https://data.mel.cgiar.org/dataset.xhtml?persistentId=hdl:20.50 0.11766.1/FK2/IWXZQH

#### MarshallEtAl2023\_selected\_measurements.csv

#### • 4 input variables (all numeric):

- heartgirth
- height
- length
- body\_condition\_score

#### 1 output variable:

exact\_weight

#### MarshallEtAl2023\_selected\_measurements

heartgirth	height	length	body_condition_score	exact_weight
81	50.1	95	3	42.7
59	53	64	3	16
59	53	64	3	16
26	17	26	3	1.7
27	17	28	3	1.8
28	21	27.5	3	1.9
99	65	111	3	64.1
62	42	67	3	18.7
34	23	39	2	3.5
37	25	39	3	4.1
97	58	101	3	51.4
93	56	96	4	54.5
92	57	96	3	50.3
89	54	94	4	46.4

#### MarshallEtAl2023\_more\_selected\_measurements.csv

- 6 input variables (all numeric):
  - household id
  - age\_months
  - heartgirth
  - height
  - length
  - body\_condition\_score
- 1 output variable:
  - exact\_weight

#### MarshallEtAl2023\_more\_selected\_measurements

1	household_id	age_months	heartgirth	height	length	body_condition_score	exact_weight
2	PBM-KML-113	34	140	901	141	4	205
3	PBM-MSK-138	24	0	0	0	4	200
4	PBM-MSK-107	15	130	80	138	4	193.2
5	PBM-MSK-106	41	140	76	141	4	177.2
6	PBM-WKS-401	27	128	85	140	4	170
7	PBM-KML-106	30	121	72	140	4	160
8	PBM-MSK-137	19	124	76	142	4	148
9	PBM-WKS-401	24	122	81	136	3	137.7
10	PBM-MSK-139	18	134	89	147	3	134
11	PBM-MSK-102	20	117	81	149	4	132.9
12	PBM-MSK-142	13	121	80	140	4	131.5
13	PBM-WKS-416	43	120	72	145	3	131.1
14	PBM-HMA-240	12	113	90	137	3	129.5
15	PBM-MSK-107	12	112	78	136	4	127.3
16	PBM-MSK-102	20	122	77	135	4	126.5

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# Data cleaning



- Remove rows with missing values
- Remove duplicate rows
- Remove duplicate columns
- Remove single value columns
- Find and remove outliers (Z-score method)
- Change categorical columns to numeric
- Save cleaned dataset

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#### Overall look at the data

- Check the size of the dataset
  - Number of records (rows)
  - Number of variables/features (columns)
- Look at the first few records

- Look at descriptive statistics
  - Check for obvious outliers or extreme values

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# Explore the data visually first

If feasible/applicable

- Check the distribution of the variables
  - Histograms
  - Scatter-plots
- Check correlations among variables/features

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# Prepare data for modelling

- Separate data into training (80%) and testing (20%)
  - The percentages depend on data size, available time, goals
- Training set:
  - Model construction
  - Model validation
  - Hyper-parameter optimization
- Testing set:
  - Testing the final models

#### **Golden Rule of Machine Learning**

**NEVER EVER** use the testing set during the construction/validation/optimization stage of a model.

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# Scaling your data

- How
  - Transform data to a standardized range
  - StandardScaler, MinMaxScaler, RobustScaler
- Why
  - Reduces the impact of extreme values
    - ... for algorithms sensitive to outliers or for those relying on normality assumptions
  - Reduces differences in value scales among variables
    - Speeds up convergence and provides equal opportunities for features to influence the outcome variable
  - Helps making more robust models

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#### ML Models

- Select models from different categories
  - Tree-based: Decision Tree, AdaBoost, Random Forest
  - Artificial Neural Networks: Multi Layer Perceptron
  - Lazy estimators: K-Nearest Neighbour
  - Linear: Linear Model, LASSO, Ridge
  - Gradient-based: Gradient Boost
- Select more than 2 models
  - Different strengths and weaknesses
  - Different data representations

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#### Model evaluation strategies

- K-fold cross-validation
  - Choose K as a function of data size and computing time
    - High K values: small-medium datasets
    - Low K values: large datasets
- Choose your measures/"metrics"
  - Regression
    - Errors: MAE, MSE, RMSE, MAPE, ...
    - Correlation coefficients: Pearson, Spearman, Kendal, Concordance (CCC)
    - R<sup>2</sup>
  - Classification
    - Confusion matrix-based: F1-score, precision, recall (TPR, sensitivity), accuracy, ... [NOT USED IN THE CURRENT CODE -- NA]

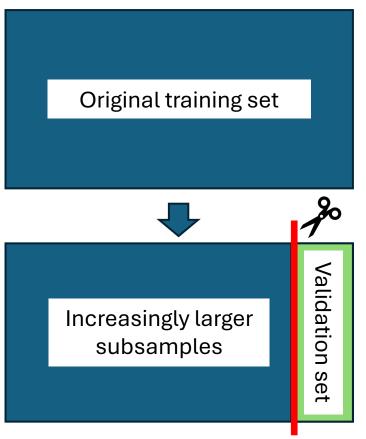
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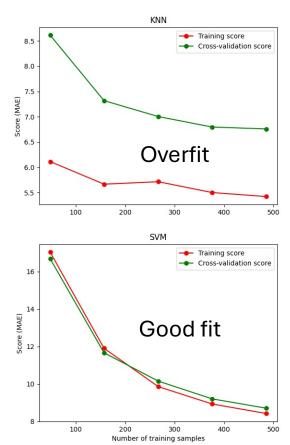
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# Overfitting analysis

- Use learning curves
  - training vs. validation scores for increasing training set sizes





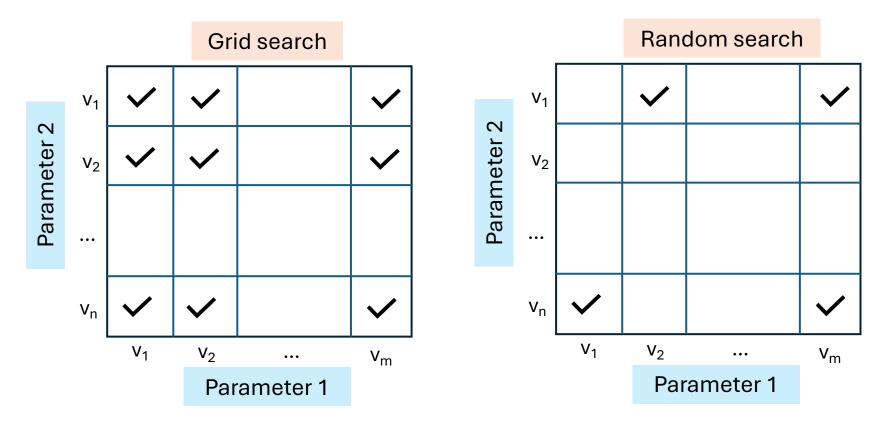
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# Hyper-parameter optimization

Hyper-parameter = user-tunable parameter

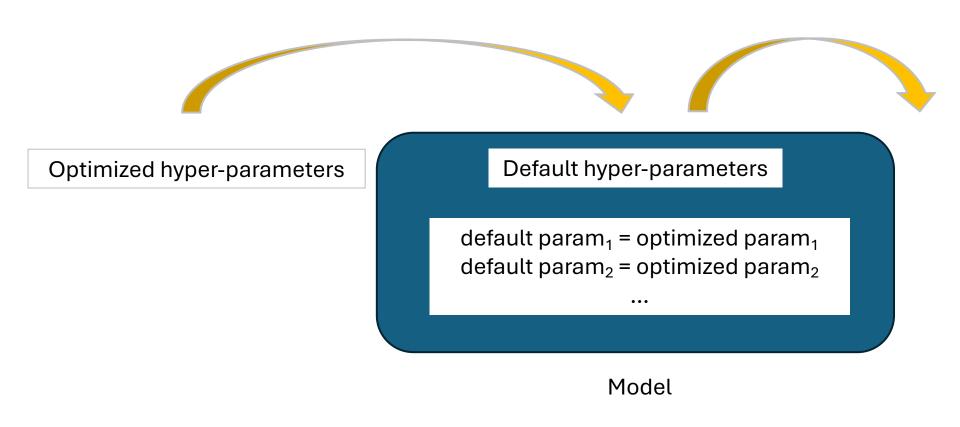


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### Hyper-parameters' update



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# Model evaluation (same as for 7)

- K-fold cross-validation
  - Choose K as a function of data size and computing time
    - High K values: small-medium datasets
    - Low K values: large datasets
- Choose your measures/"metrics"
  - Regression
    - Errors: MAE, MSE, RMSE, MAPE, ...
    - Correlation coefficients: Pearson, Spearman, Kendal, Concordance (CCC)
    - R<sup>2</sup>
  - Classification
    - Confusion matrix-based: F1-score, precision, recall (TPR, sensitivity), accuracy, ... [NOT USED IN THE CURRENT CODE -- NA]

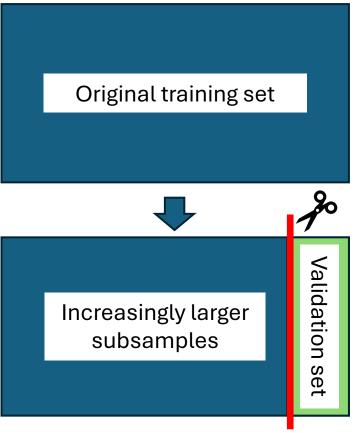
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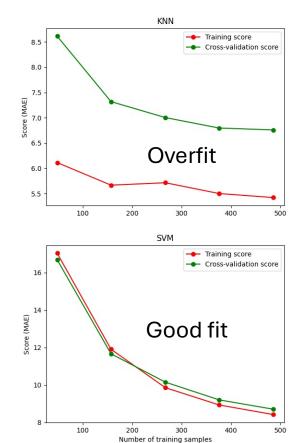
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# Overfitting analysis (same as for 8)

- Use learning curves
  - training vs. validation scores for increasing training set sizes





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#### Saving models

- Backup all optimized models
- Can be used later for deployment
- Save time on re-training and re-optimizing hyper-parameters

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#### Feature importance

- Use a model-agnostic process
- Permutation Feature Importance (PFI)
  - Shuffle one variable at a time
  - Evaluate each algorithm
  - Idea: if an important variable is shuffled it would hurt the model significantly (poor predictions)
- Other options: <u>SHAPley values</u>

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#### Model evaluation on test sets

- Use various evaluation measures
  - Error-based: MAE, MSE, RMSE, MAPE
  - Correlations: Pearson Product-Moment, Concordance, Spearman
  - (Adjusted) Coefficient of determination

Note: no single evaluation measure captures everything

- Use visual analysis, too
  - Scatter plots (predicted versus true values)
  - QQ plots for prediction errors

# Thank you