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Machine Learning to better understand and optimize cheese production

Manon Perrignon¹, Mathieu Emily², Romain Jeantet¹ and Thomas Croguennec¹

¹ L'Institut Agro, INRAE, STLO (Science et Technologie du Lait et de l'œuf), Rennes, France

² L'Institut Agro, Université de Rennes, CNRS, IRMAR (Institut de Recherche Mathématique de Rennes)-UMR 6625, Rennes, France



CONTEXT

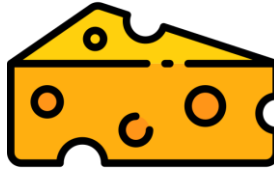
Cheese production and monitoring:



Milk
standardisation

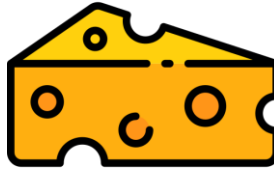
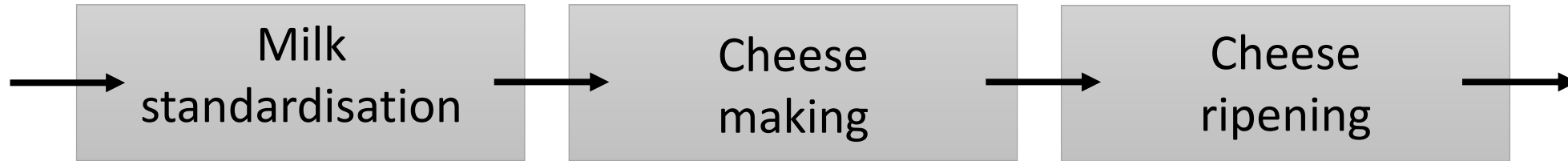
Cheese
making

Cheese
ripening



Dry matter
Yield
Quality
...

Cheese production and monitoring:



Dry matter
Yield
Quality
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- **Complex** process
 - Many sources of **variability** (process , ingredient,..)
 - Many process **parameters** to monitor (manual, automatic)
- **Large amount of data** collected during daily cheese process

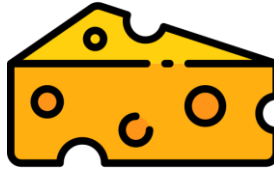
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How to improve dry matter by adopting a holistic view of the process and associated data ?

Dry matter optimization (target value) at present:

Guinee TP (2021) International Dairy Journal **121**: 105095
Kern C et al. (2019) Food Research International **121**: 471–478

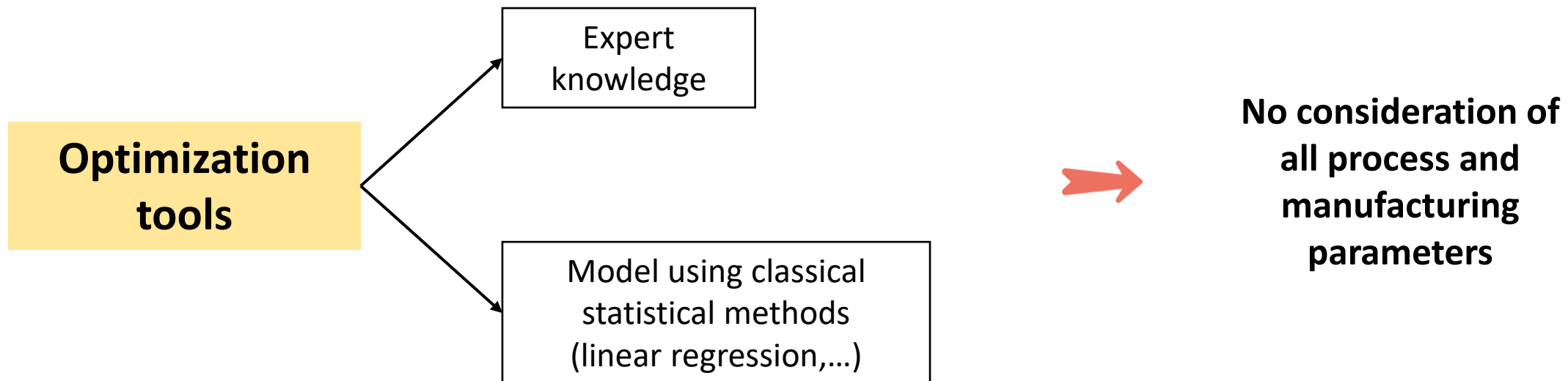
- Modification of standardisation parameters (casein micelle content,...)
- Modification of process parameters (stirring time/speed,...)

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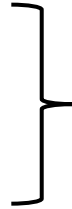
→ Modification of standardisation parameters (casein micelle content,...)

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Methodology for modelling dry matter:

- Complex process
- No global equation
- Huge amount of data

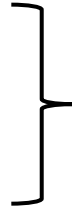


Need an appropriate and data-driven method

Methodology for modelling dry matter:

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(Generalized) Linear Regression



→ Known function

→ Additivity of effects

→ Easy interpretation

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→ Black box: difficult interpretation

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How to implement a Machine Learning approach to optimize dry matter ?

METHOD

Data obtained from one cheese company over a one year period:

Classical pre-processing of data = obtain the database suitable for analysis



In collaboration with industrial experts

- Remove **redundant variables**
- Remove **outliers**
- Remove **missing data**

Selection of Machine Learning methods:

Breiman L (2001)
Friedman JH (1999)
Boser et al. (1992)

RANDOM FOREST (2001)

➔ Uses a set of decision trees built on random sub-samples of the training data

GRADIENT BOOSTING (1999)

➔ Builds decision trees sequentially, with each new tree correcting the errors of the previous ones

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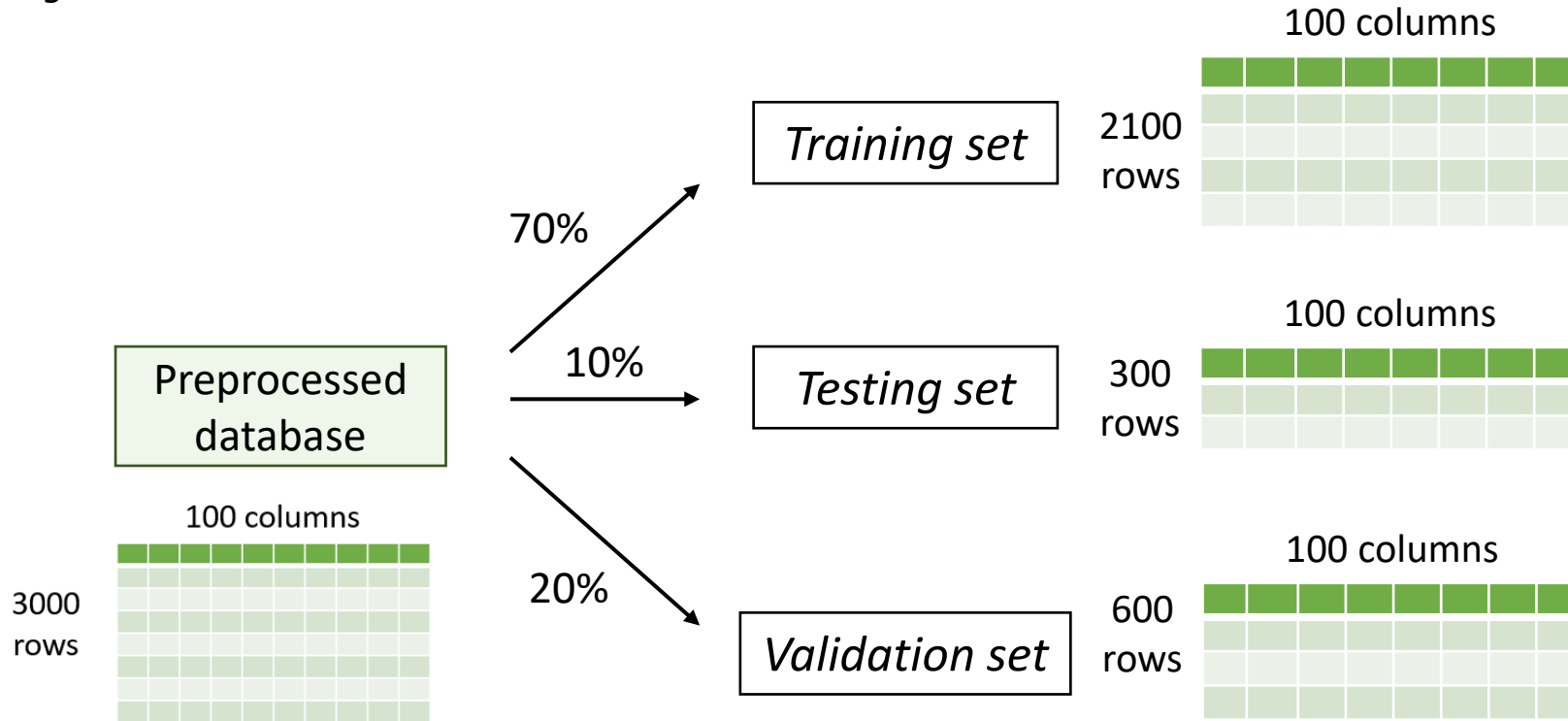
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SUPPORT VECTOR MACHINE (SVM) (1992)

➔ Find the optimal hyperplane that separates or fits the data

Comparison of Machine Learning methods:

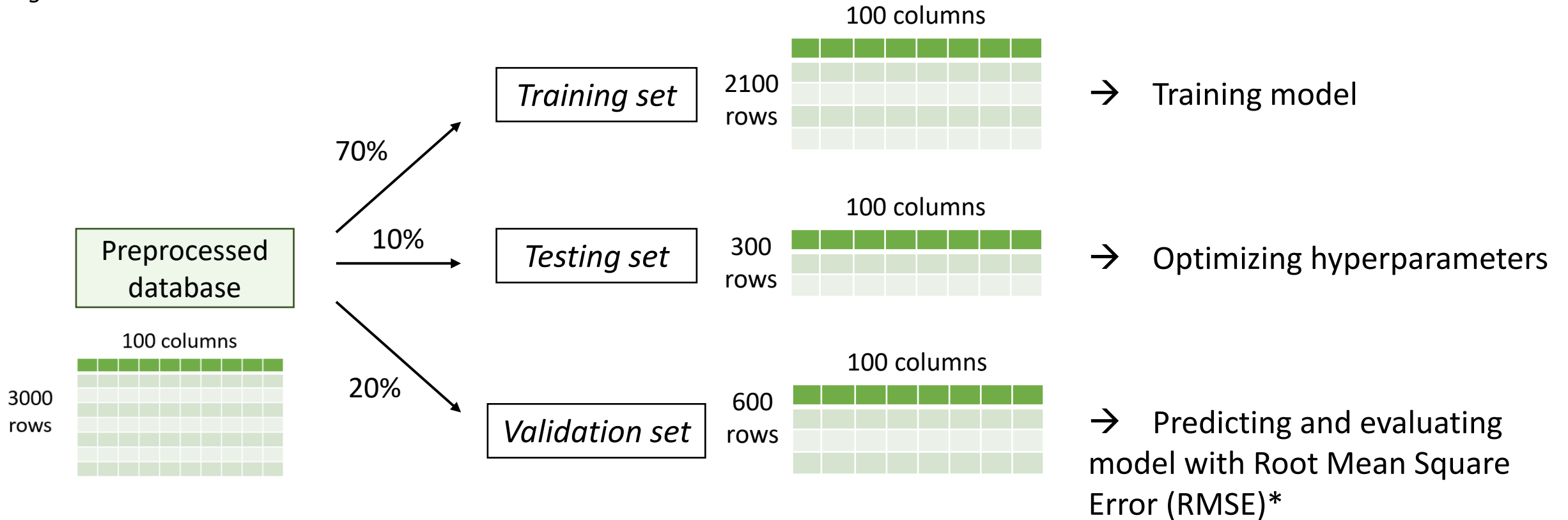
Using R



Comparison of Machine Learning methods:

Using R

*RMSE (Root mean square error) = Standard deviation of the residuals (prediction error)



→ Resampling techniques (cross-validation, bootstrap, out-of-bag) can be used to optimize hyperparameters

Interpretation of Machine Learning models:

Breiman L (2001) Machine Learning
Lundberg SM et al. (2018) Computer Science, Mathematics

Importance of variables in model:

Using R

Principle: Calculate the importance of variables in the model for predicting dry matter

 Rank variables according to their importance in predicting the variability of the target

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Shapley value:

Using Python

Principle: modify one variable at a time, keeping all others constant, to assess its impact on dry matter

➔ Assess the single effect of a variable

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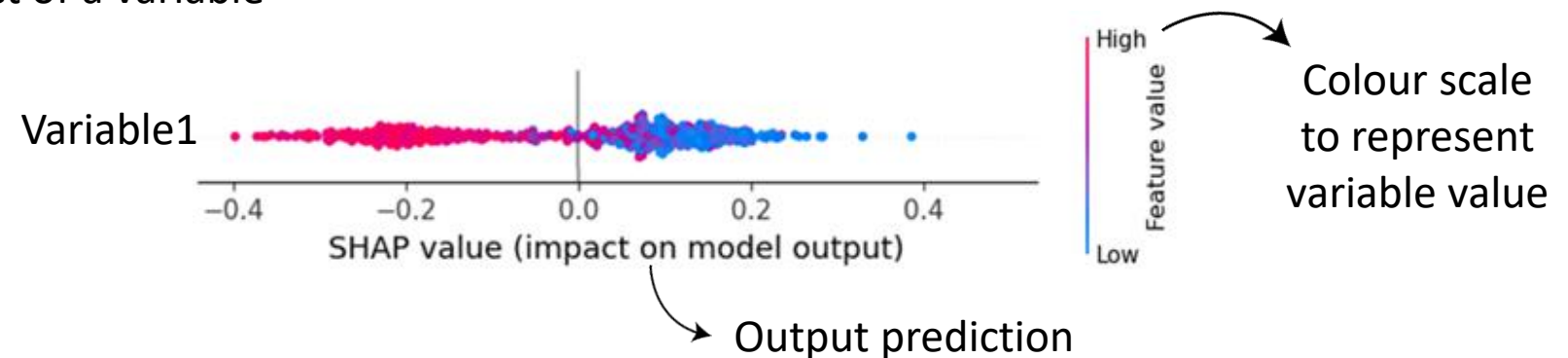
Using Python

Principle: modify one variable at a time, keeping all others constant, to assess its impact on dry matter

➔ Assess the single effect of a variable

Results example:

One point = one prediction



RESULTS

Comparison of methods:

- 3 machine learning methods and 1 classical statistical method
- For each method: model training, hyperparameter optimization, model evaluation

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Method	RMSE
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Linear Regression	0.37
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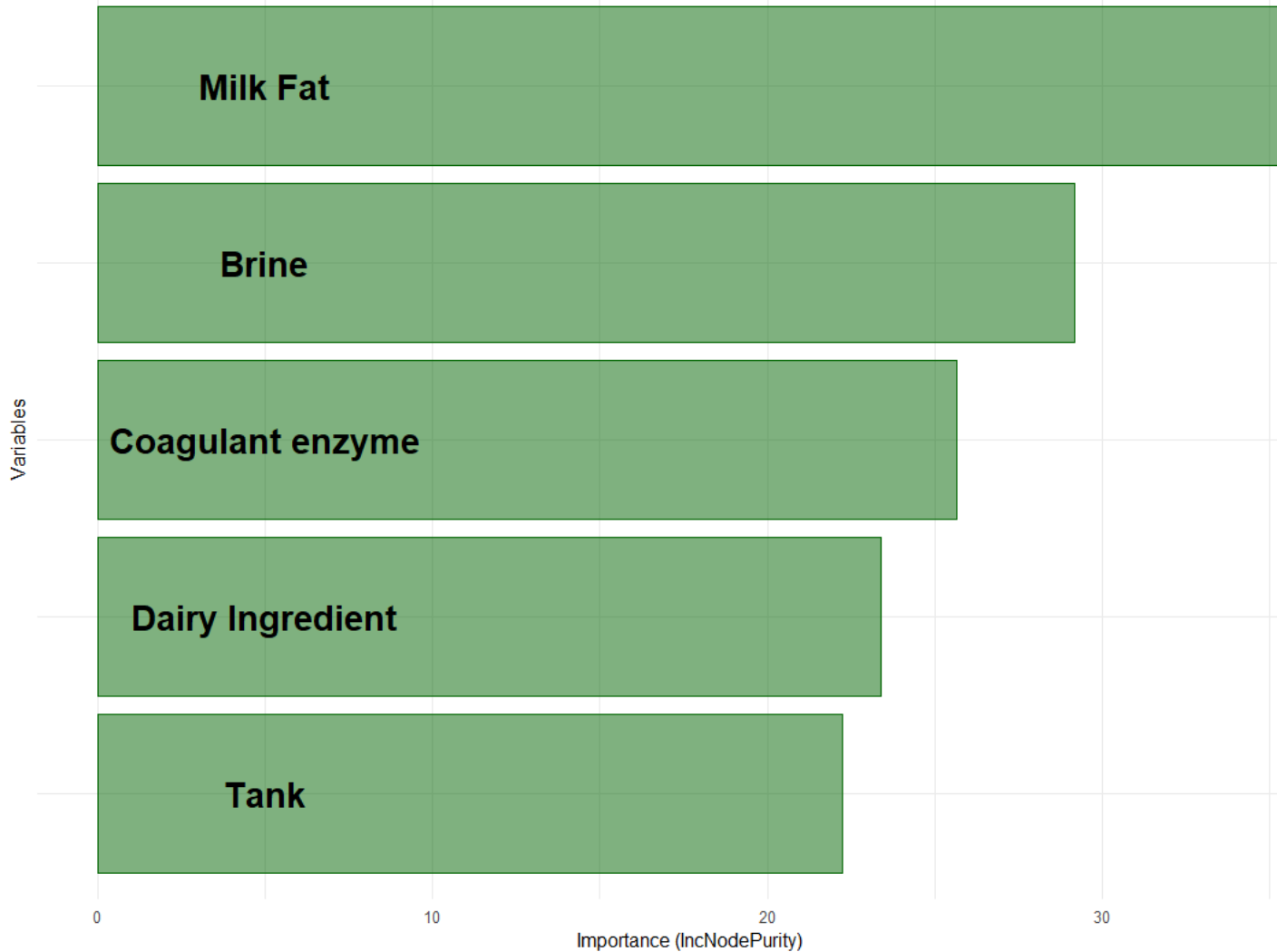
Selection of Random Forest to model dry matter

% of variability explained

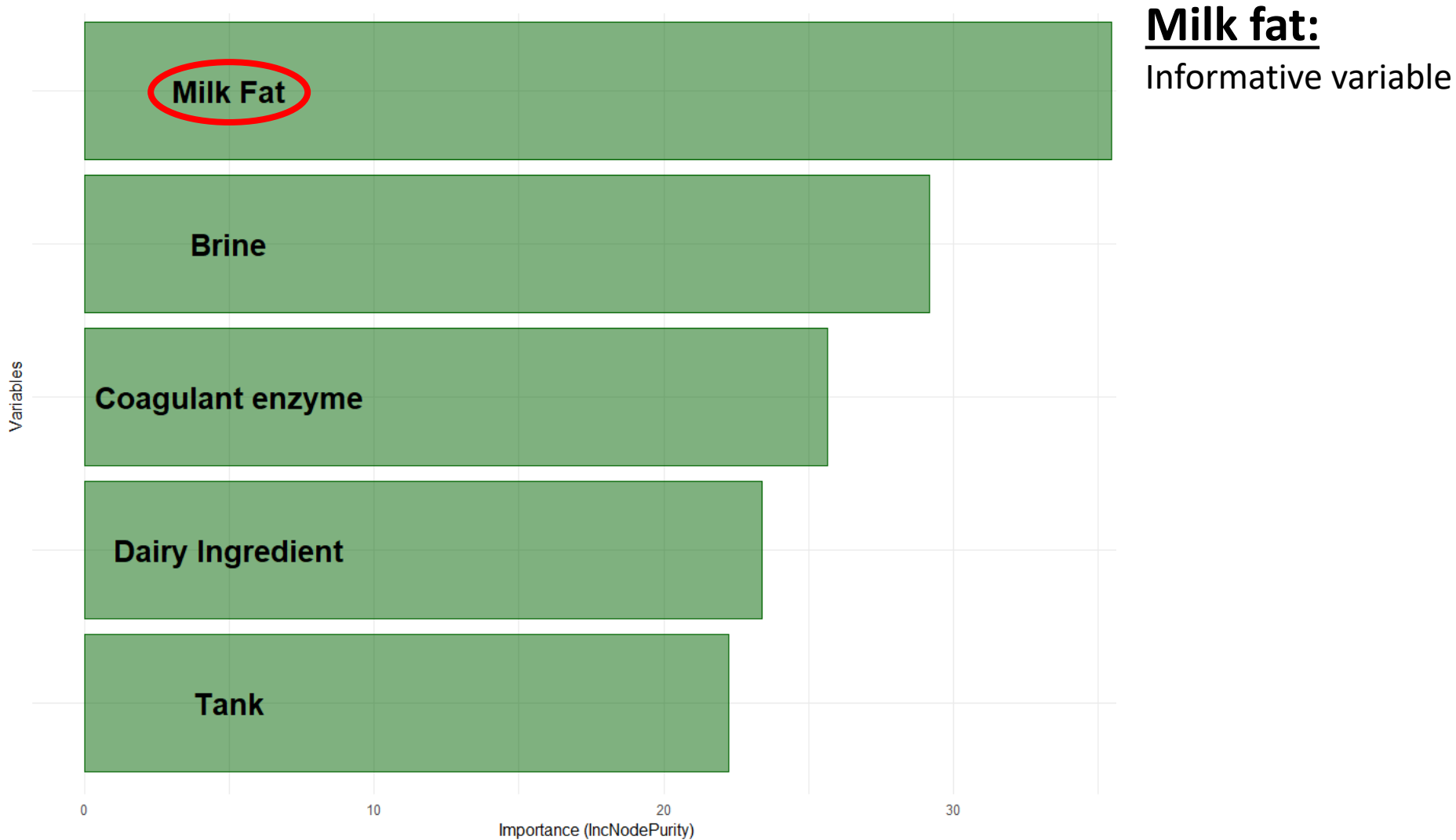
66.6

- Additional data could enhance this measurement and the accuracy of the model

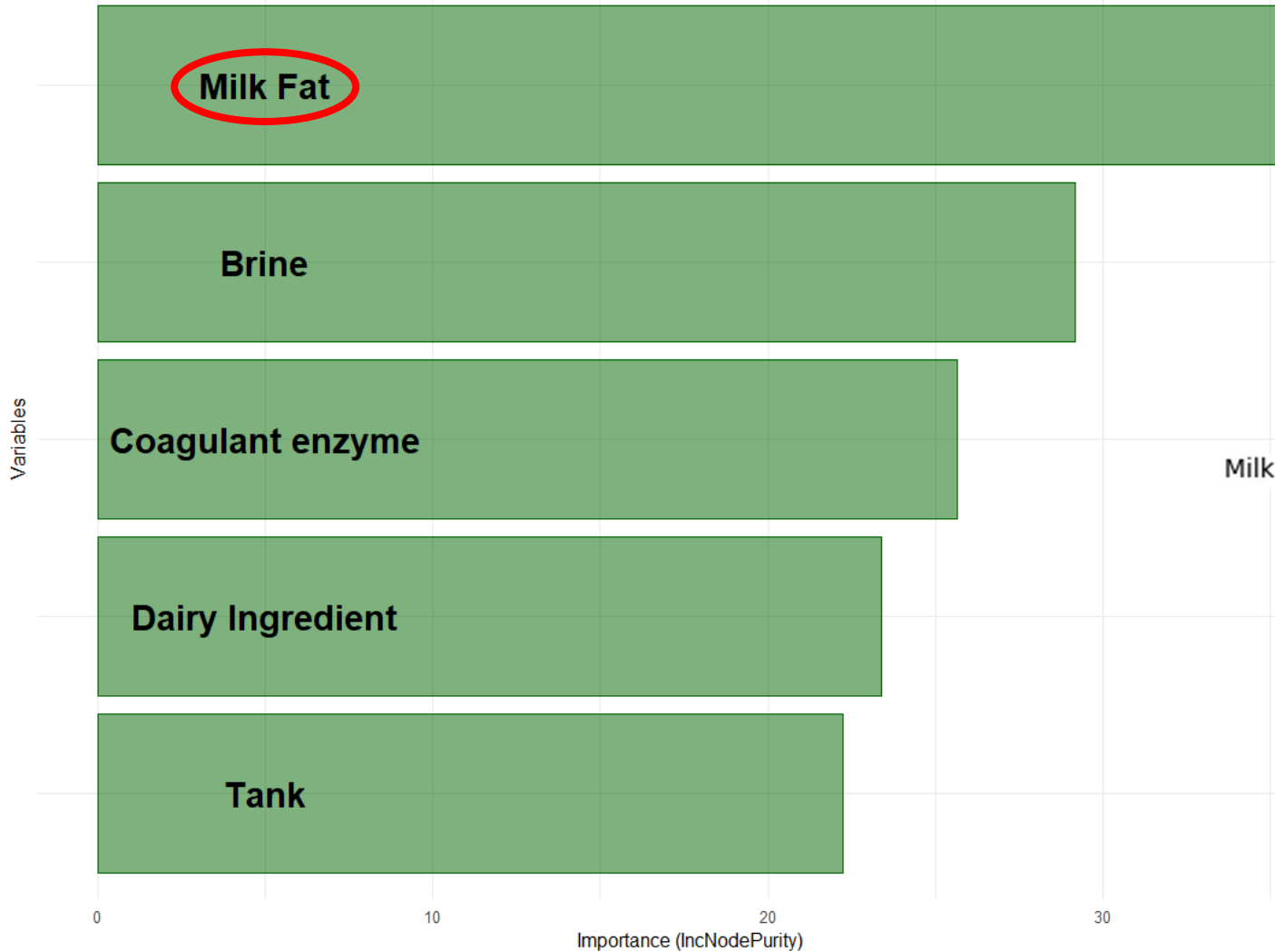
Importance of variables on dry matter with Random Forest:



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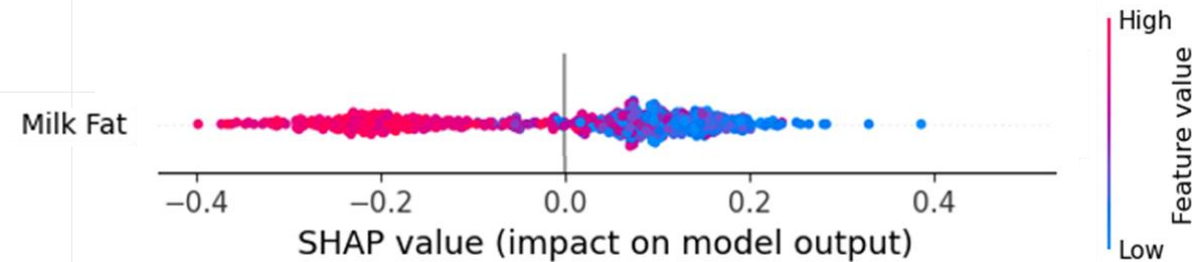
Milk fat:

Informative variable

How does this variable affect dry matter ?



SHAPLEY VALUE

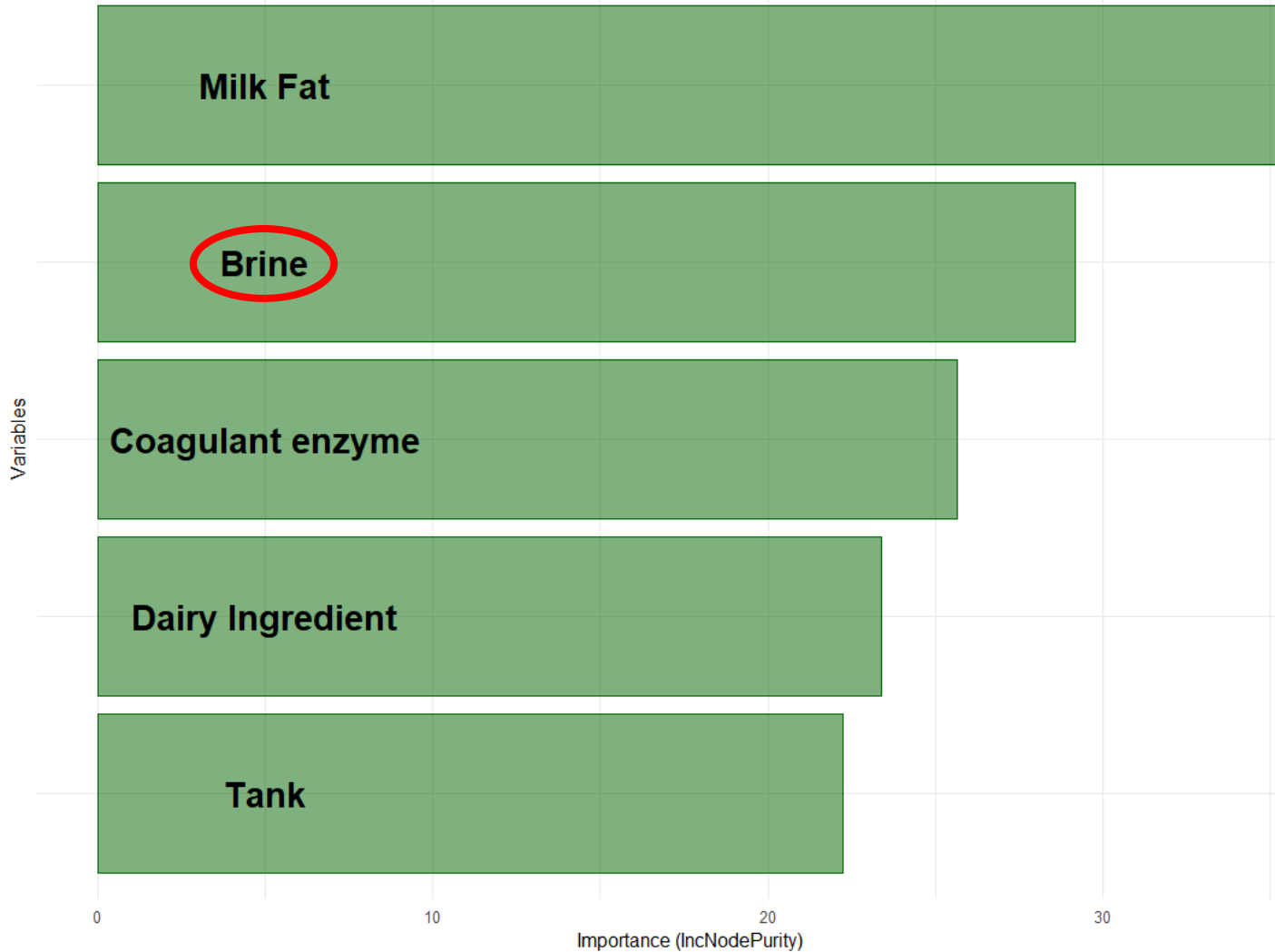


→ Higher milk fat leads to lower dry matter

Potential challenge for industrial process:

- How to adapt process to a given milk composition

Importance of variables on dry matter:

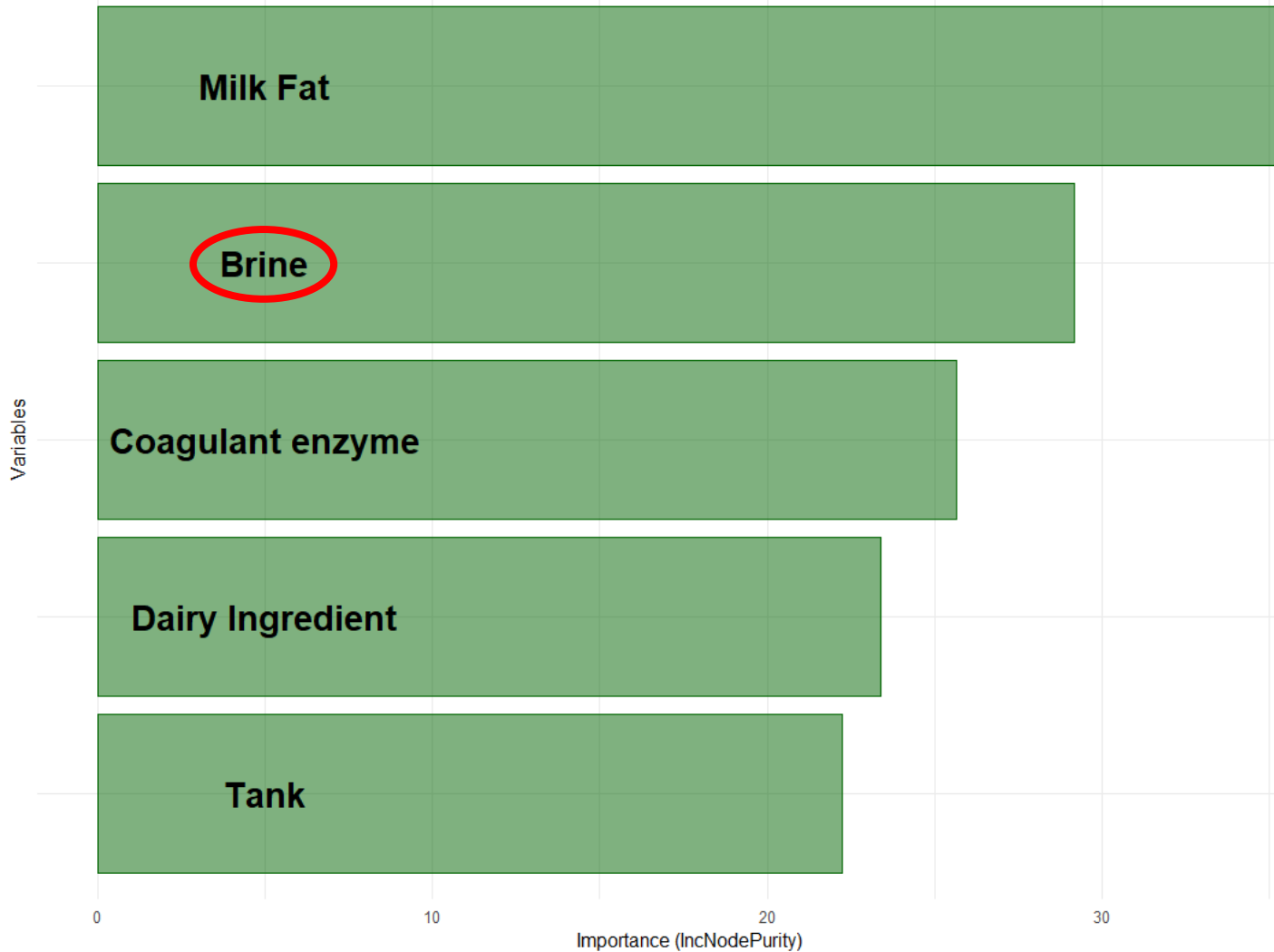


Brine:

Cheese position in the brine pool

Informative variable

Importance of variables on dry matter:



Brine:

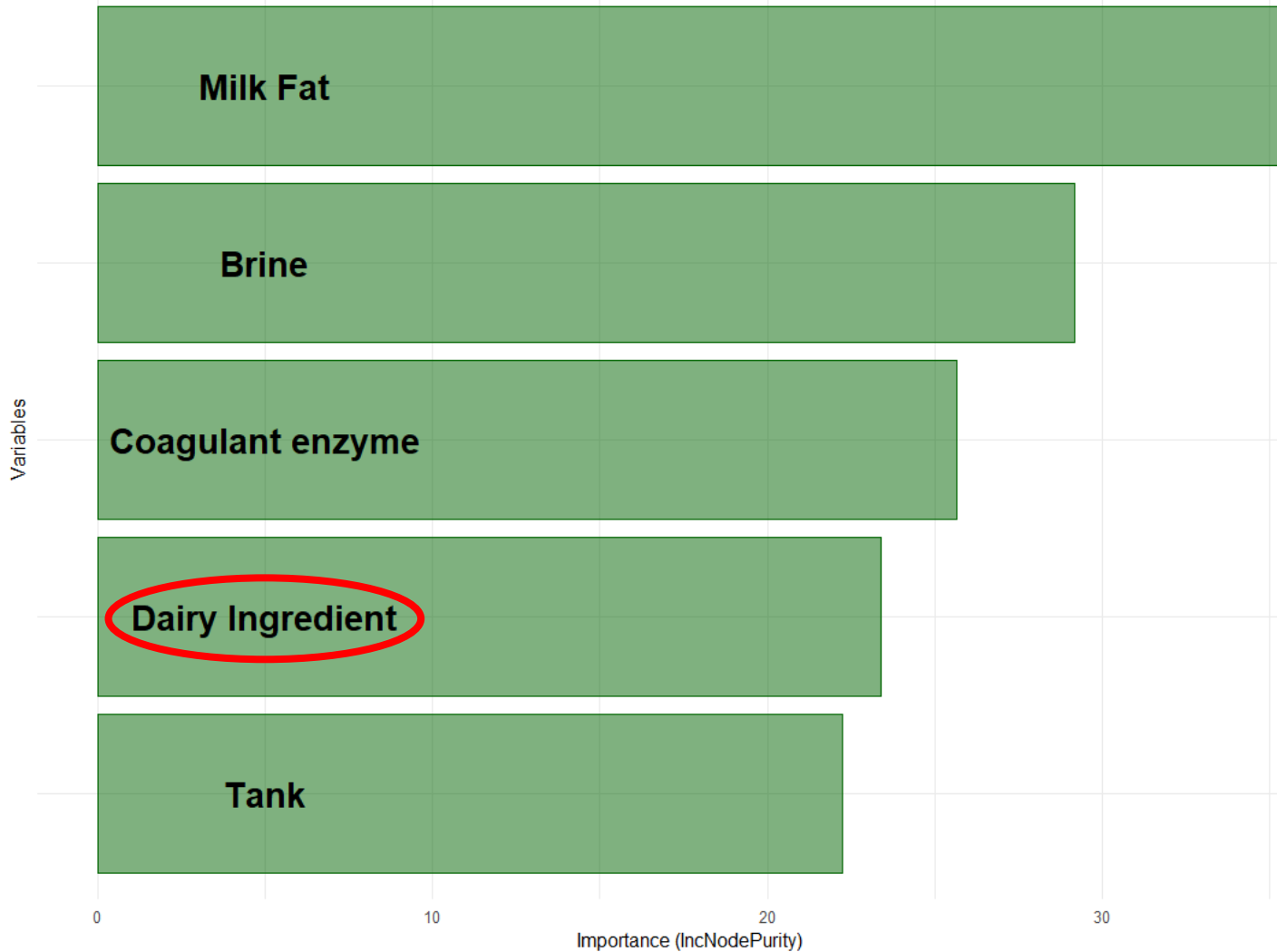
Cheese position in the brine pool

Informative variable

Potential challenge for industrial process:

- Checking information with experts
- Measuring new data

Importance of variables on dry matter:

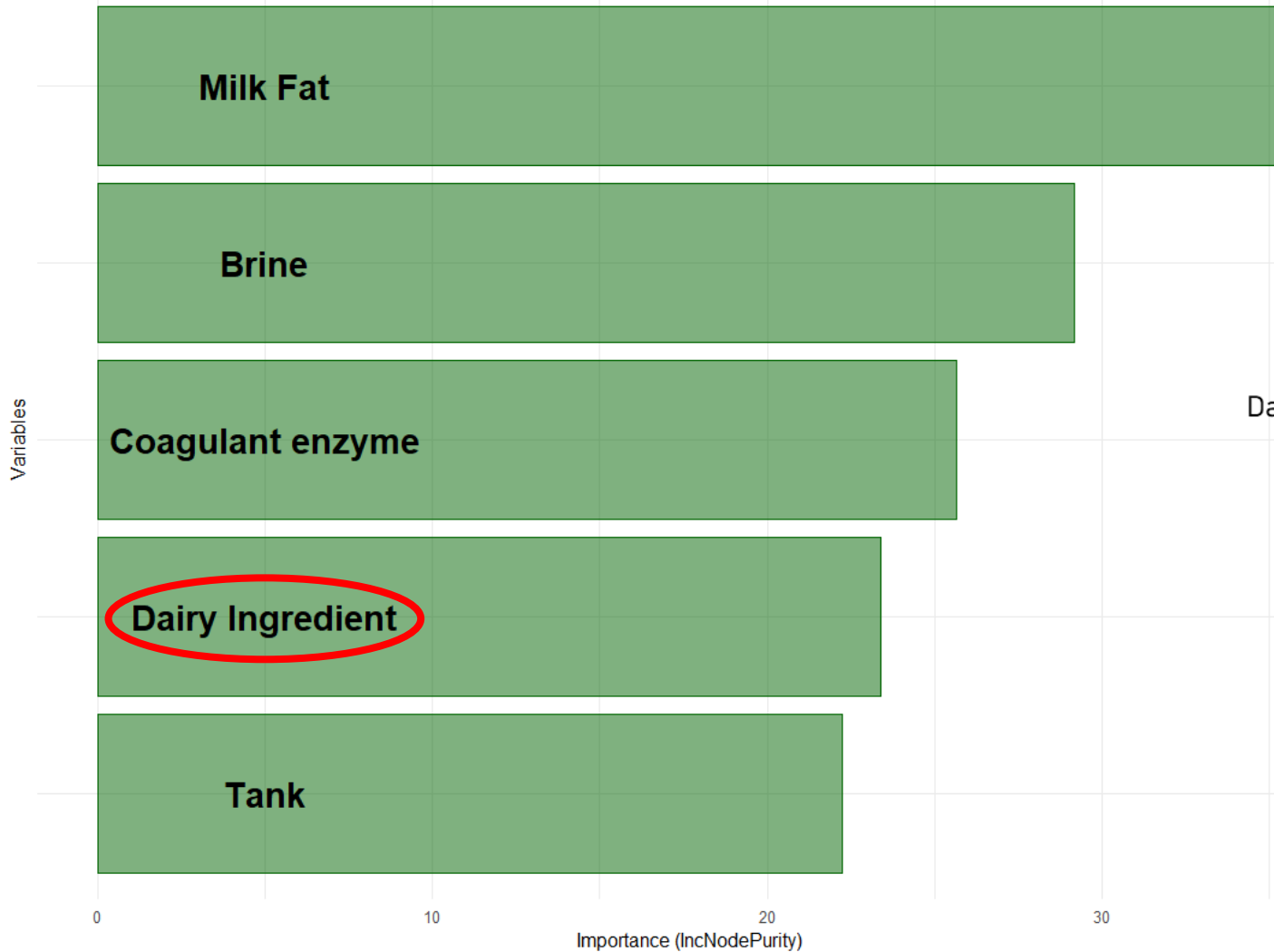


Dairy ingredient:

Quantity of dairy ingredient incorporated for standardization

Actionable variable

Importance of variables on dry matter:

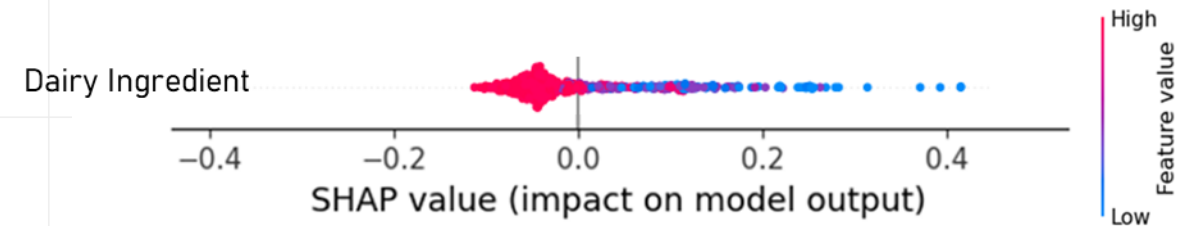


Dairy ingredient:

Quantity of dairy ingredient incorporated for standardization

Actionable variable

SHAPLEY VALUE:



→ Higher amount of dairy ingredient leads to lower dry matter

Potential challenge for industrial process:

- Understand the impact of this ingredient to better adapt standardisation

CONCLUSION AND PERSPECTIVES

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- Machine Learning establish **complex relationships** between process parameters and dry matter
- Essential **collaboration** with experts to understand output of the model and overall data
- Need for a large database to implement machine learning methods

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PERSPECTIVES

- Cheese production defined by **several performance indicators**
- Machine learning methods learn from data: **industrial trials** can provide new information
- **Known equation** could be integrated into modelling: hybrid model

IDF Cheese Science & Technology Symposium



Thanks for your
attention !

Contact : manon.perrignon@agrocampus-ouest.fr

