Predictive Maintenance for Marine Engines using Machine Learning

Machine Learning in Business Analytics
Prof. Marc-Olivier Boldi
Ilia Azizi
2025

Group D:
Olivier Manthey,
Axel Lo Schiavo,
Salma Fourati

AGENDA

- Context & Problem Description
- Literature Review
- Data Base & Assumption
- Methodology
- Results
- Conclusion & Discussion
- References
- Q&A

Context & Problem Description

Problem Descritpion:

- Marine industry powers over 80% of international trade.
- Unexpected engine failure can lead to:
    - High costs
    - Safety risk
    - Delay in supply chain
- Traditional Maintenance
    - Reactive
    - Scheduled

  Limited efficiency
- Predictive Maintenance
    - Historical data
    - Real-time data

Goal of the project:

Explore whether ML can support a predictive maintenance approach.

Research Question:

How can machine learning models predict early signs of maintenance needs in marine engines using engine performance metrics, operational conditions, and failure modes data?

Literature Review

Predictive Maintenance → **Predictive Maintenance in Machine Learning**

Machine learning across different industries

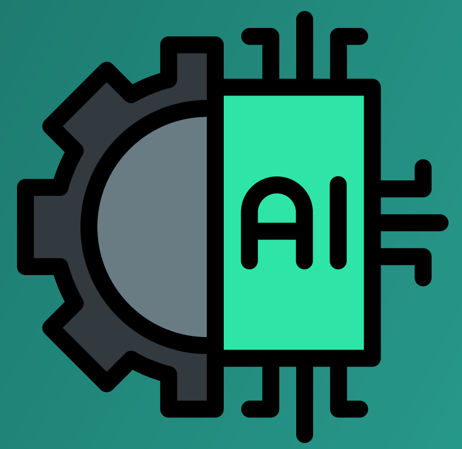
- Automotive: RF, SVM, ANN (Tessaro et al., 2020)
- Aerospace: Naïve Bayes, KNN (Adryan et al., 2021–22)

Hybrid Learning Approaches

- Combine unsupervised + supervised models
- Uncover patterns & anomalies to enhance models performance (Zhu et al., 2024)

Marine Engines: Our Approach

- Deep learning (CNNs) used with high accuracy but resource-heavy (Rehman et al., 2023)
- Investigation of a lighter alternative
- Efficient, interpretable, real-time solution



Data Base & Assumption

Data Base

- 50 engines
  - Weekly observation (2023-2024)

➡ Focus on Maintenance Status (Normal, Critical and Requires Maintenance)

Simplification

- Exlusion of time-series analysis.
- Treat each instance indepenently.

➡ Focus on relationship between sensor data and maintenance needs.

Methodology – Workflow Overview

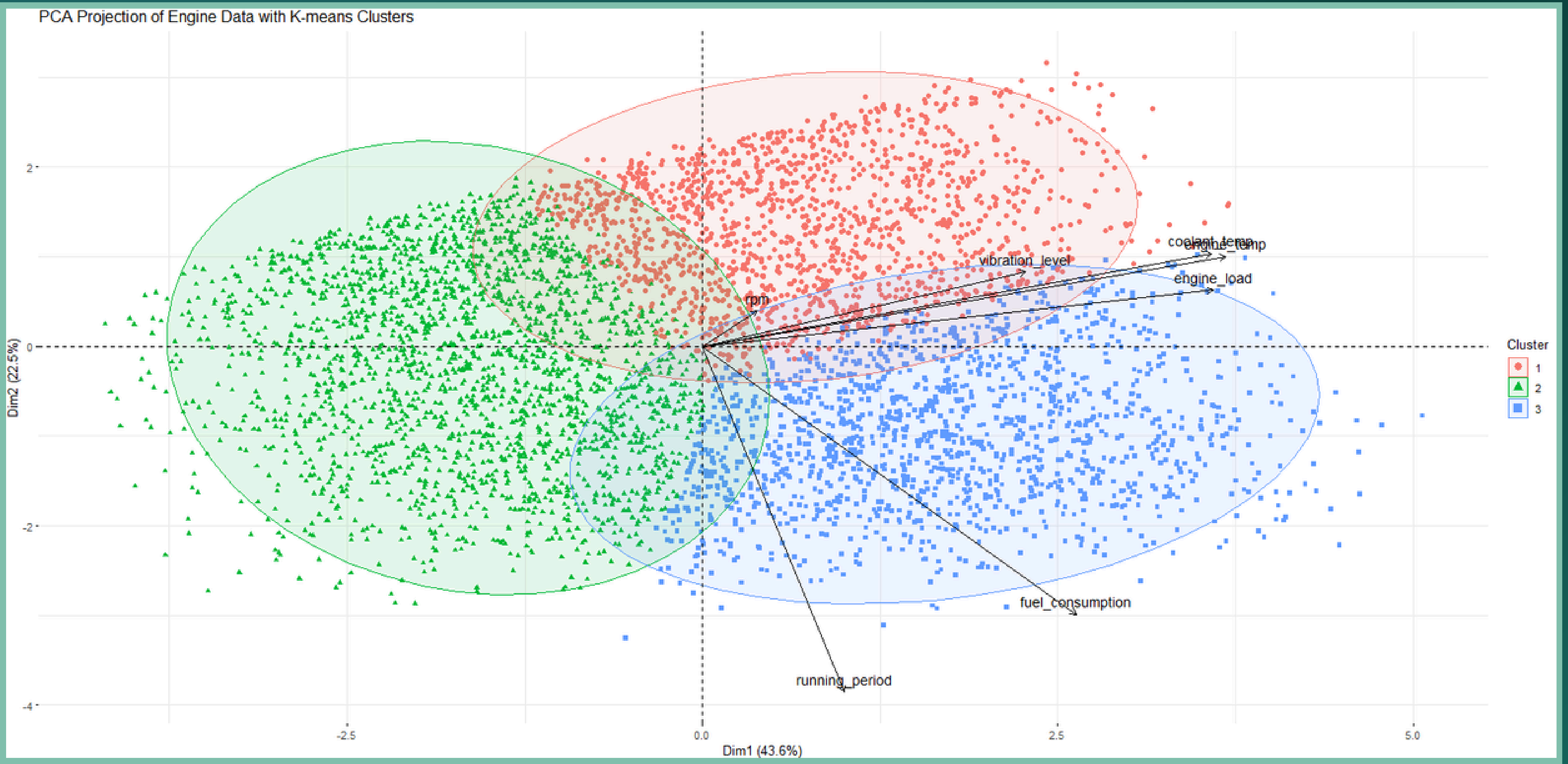
Exploratory Data Analysis (EDA)

- Distribution of numerical & categorical variables.
- Correlation analysis between interest variables.
- Outliers analysis → IQR Method

Unsupervised Learning Method

- K-Mean Clustering
  - Elbow Method (TWSS)
  - Slihouette Method

  → 3 clusters
- Principal Component Analysis (PCA)
  - Selection of 7 numerical variables preserving most of the variance.
  - Comparison with categorical variables.
    - Independence test (Chi-Squared)



- *engine_type vs. cluster*: $\chi^2 = 3.87$, df = 6, p = 0.6947
- *fuel_type vs. cluster*: $\chi^2 = 0.59$, df = 2, p = 0.7434
- *manufacturer vs. cluster*: $\chi^2 = 5.52$, df = 10, p = 0.8539
- *failure_mode vs. cluster*: $\chi^2 = 7.81$, df = 6, p = 0.253

→ **Exclude categorical variables**

Methodology - Methods Summary

Supervised Learning Models

Train/Test split: 80/20

Multinomial Logistic Regression (Baseline)

- Random Model
- Penalized MLR
  - LASSO
  - RIDGE

Coolant temperature, engine load, fuel consumption

Random Forest

- Random Model
- Hyperparameters tuning
  - ntree
  - mtry
  - nodesize
  - maxnode
- Variable importance

Coolant temperature, engine load, engine temperature

Support Vector Machine

- Random Model
  - Radial Kernel
- Hyperparameters tuning (CV)
  - Cost
  - Gamma

Vibration level, engine load, coolant temperature

Results

Model	F1 Score	Accuracy	Balanced Ac	Sens (N)	Sens (C)	Sens (RM)
MLR	**0.33**	0.3407	0.5044	0.1971	0.3448	0.4758
RF	0.285	0.3523	0.5150	0.0706	0.1983	0.7778
SVM	**0.33**	**0.3484**	0.5099	0.1588	0.3592	0.5214

RF

- Lowest F1 score
- Highest accuracy
- Low generalization

MLR

- “High” F1 score
- Median accuracy
- Good generalization

SVM

- Same F1 score as MLR
- Higher accuracy
- Good generalization

Poor results overall with low accuracy and low generalization across our models

Conclusion & Discussion

Limitations

- Synthetic dataset
- No time dimension
- Excluding categorical variables may have removed useful context

Findings

- Limited predictive power of features
- Certain features were helpful (fuel consumption, engine load, coolant temp)
- SVM showed relative strength

Futur Work

- Train on real-world sensor data
- Include more complex categorical variables
- Use time-series models

References:

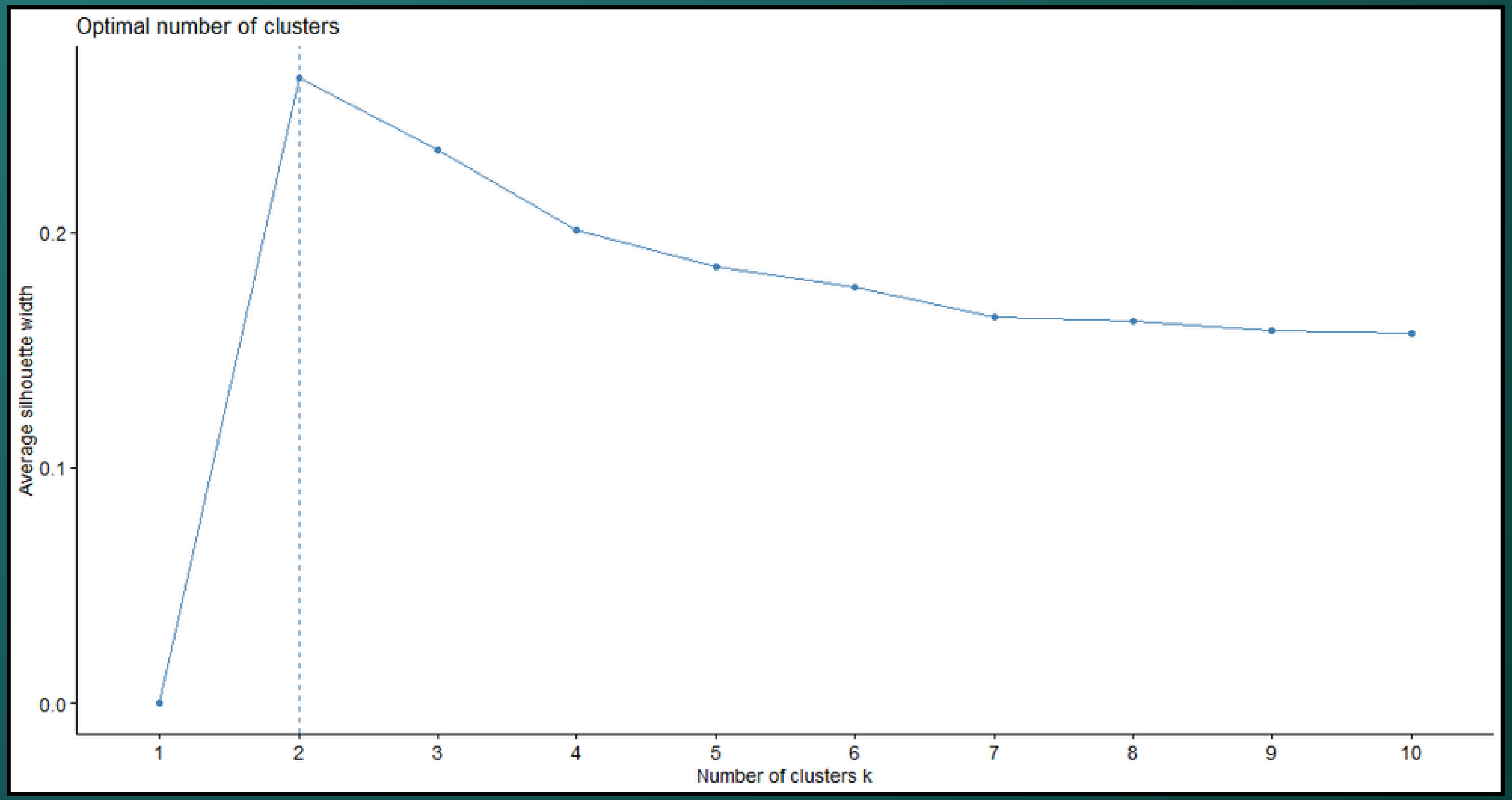
- Adryan, F. A., & Wijaya, S. K. (2022). Determining the method of predictive maintenance for aircraft engine using machine learning. *Journal of Computer Science and Technology Studies*, 4(1), 1–8.
- Jeleel, A. F. (2023). Preventive maintenance for marine engines [Data set]. Kaggle.
- Rehman, A., Khan, M. A., Saba, T., Tariq, U., & Alharbi, R. (2023). Energy-efficient fault detection framework for marine diesel engines using deep learning. *Energy, 281, 128676.*
- Tessaro, I., Mariani, V. C., & Coelho, L. d. S. (2020). Machine learning models applied to predictive maintenance in automotive engine components. *Proceedings, 64(1), 26*.
- Zhu, T., Ran, Y., Zhou, X., & Wen, Y. (2024). A survey of predictive maintenance: Systems, purposes and approaches. *arXiv preprint arXiv:1912.07383.*

Thank You for your time and attention !

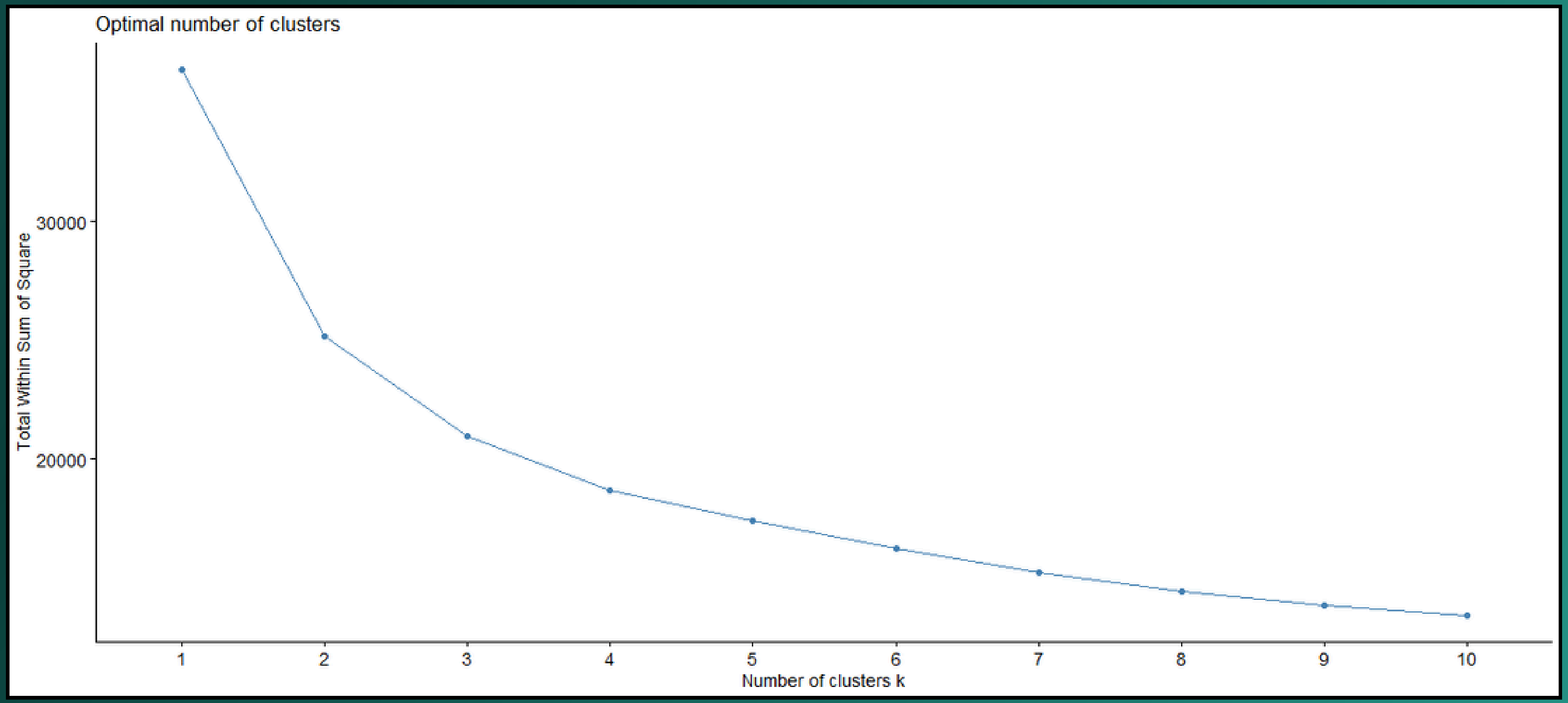
Do you have any questions ?

Clustering

K-Mean Clustering - Number of Cluster

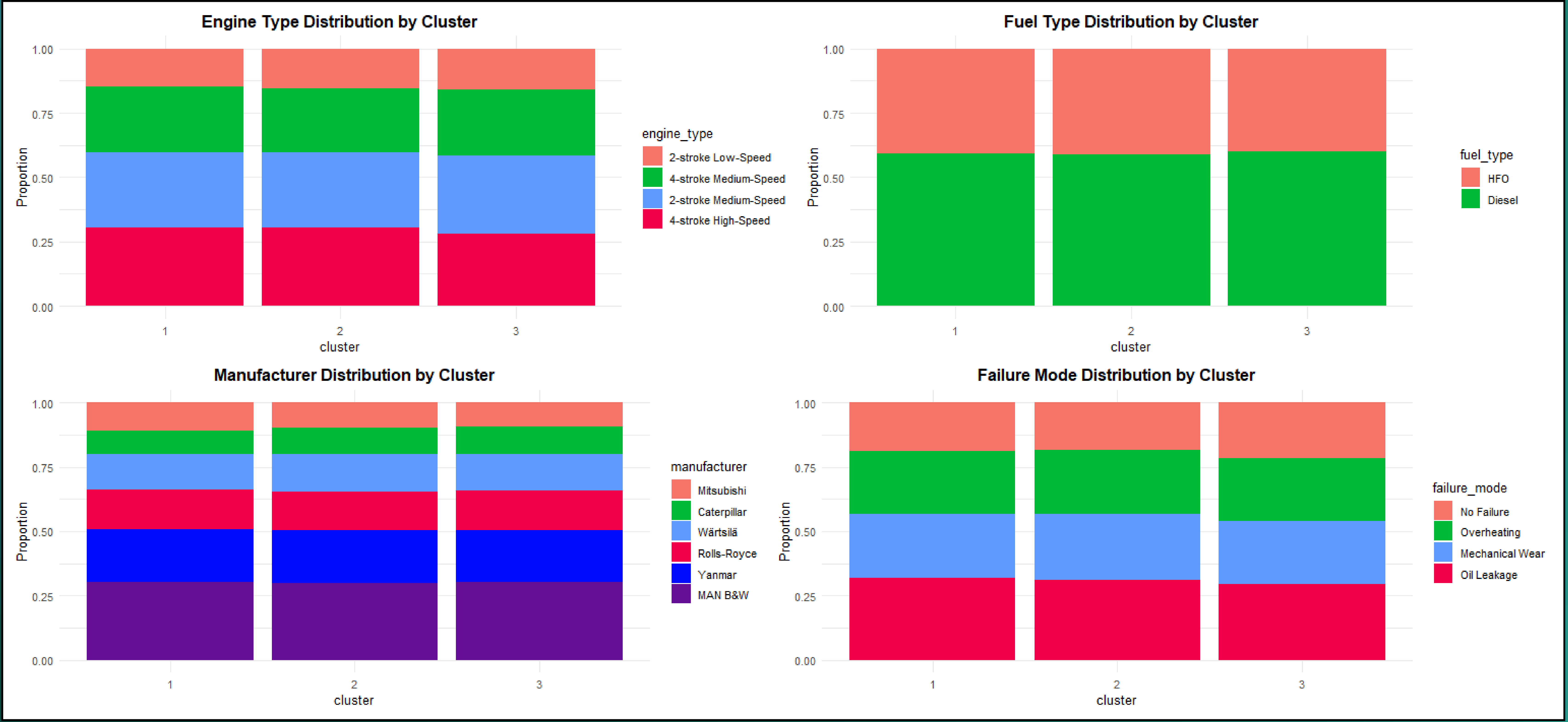


Silhouette Method



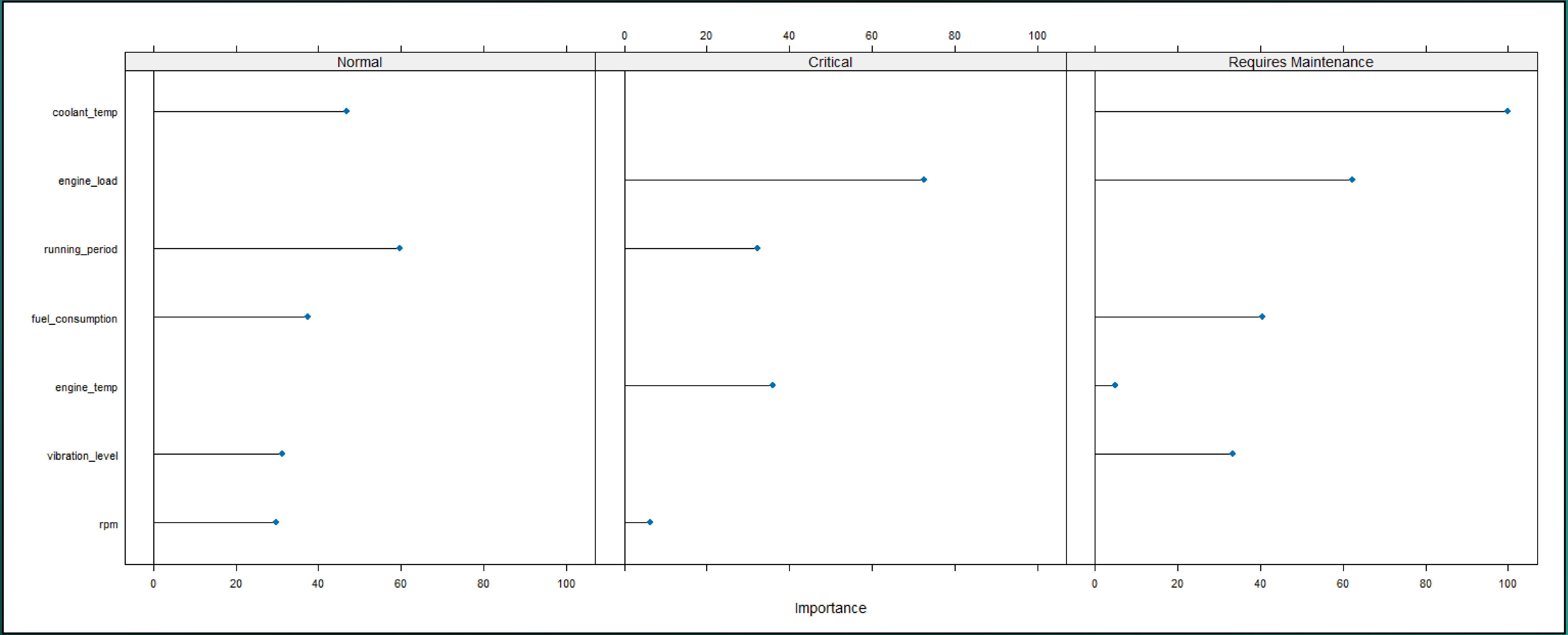
Elbow Method (TWSS)

Clustering
Categorical Variables Comparison



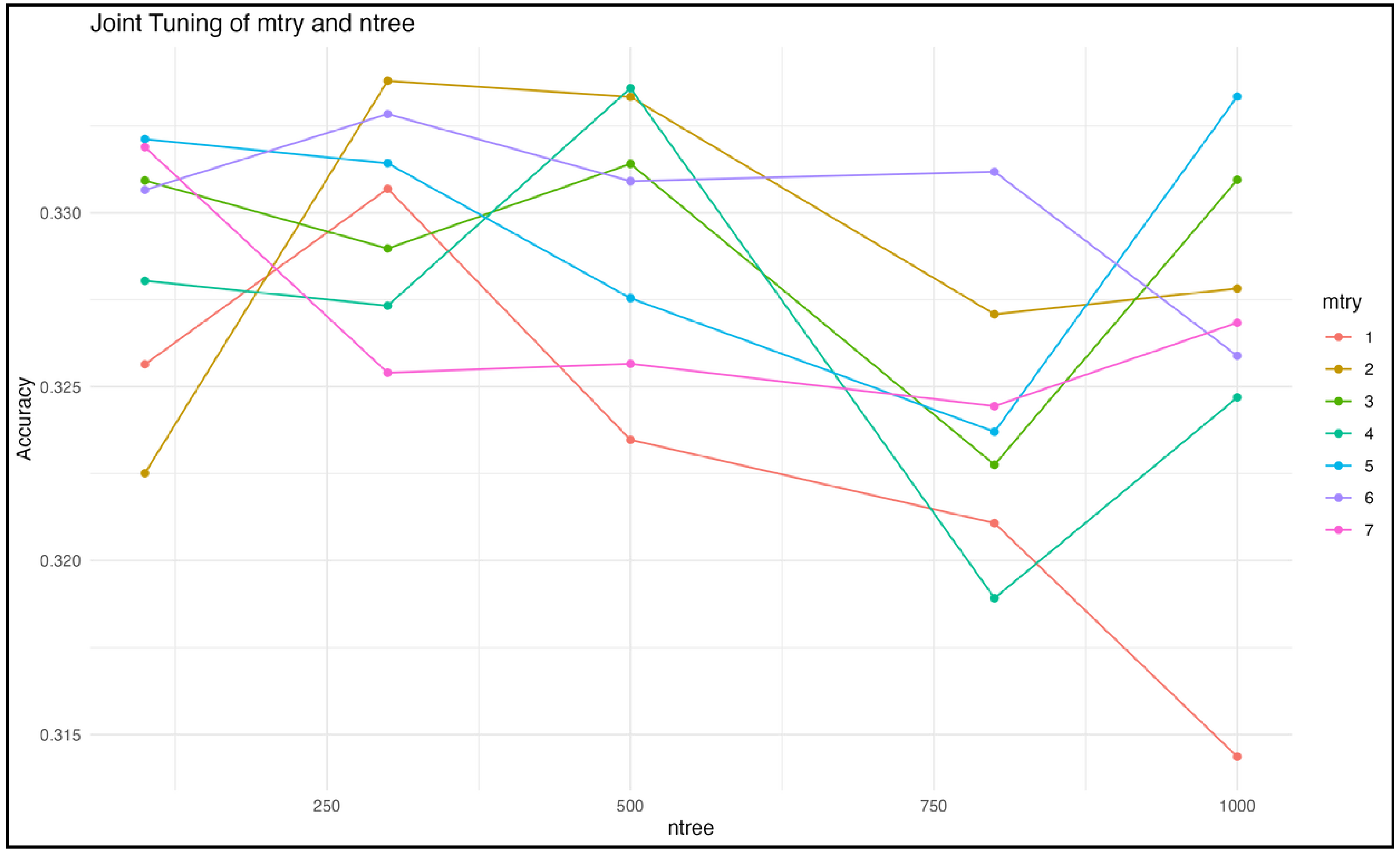
Multinomial Logistic Regression

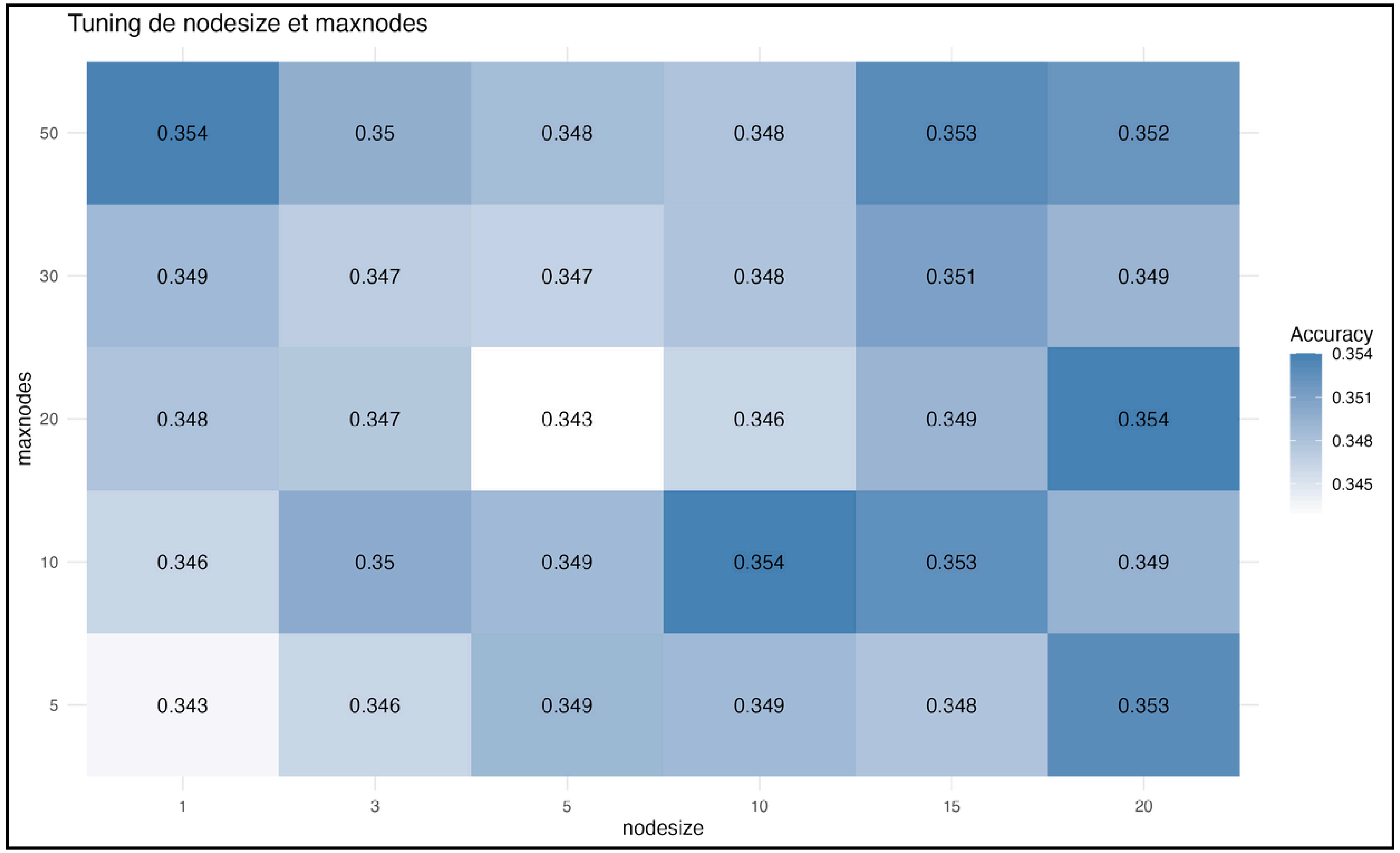
Features Importance



Random Forest

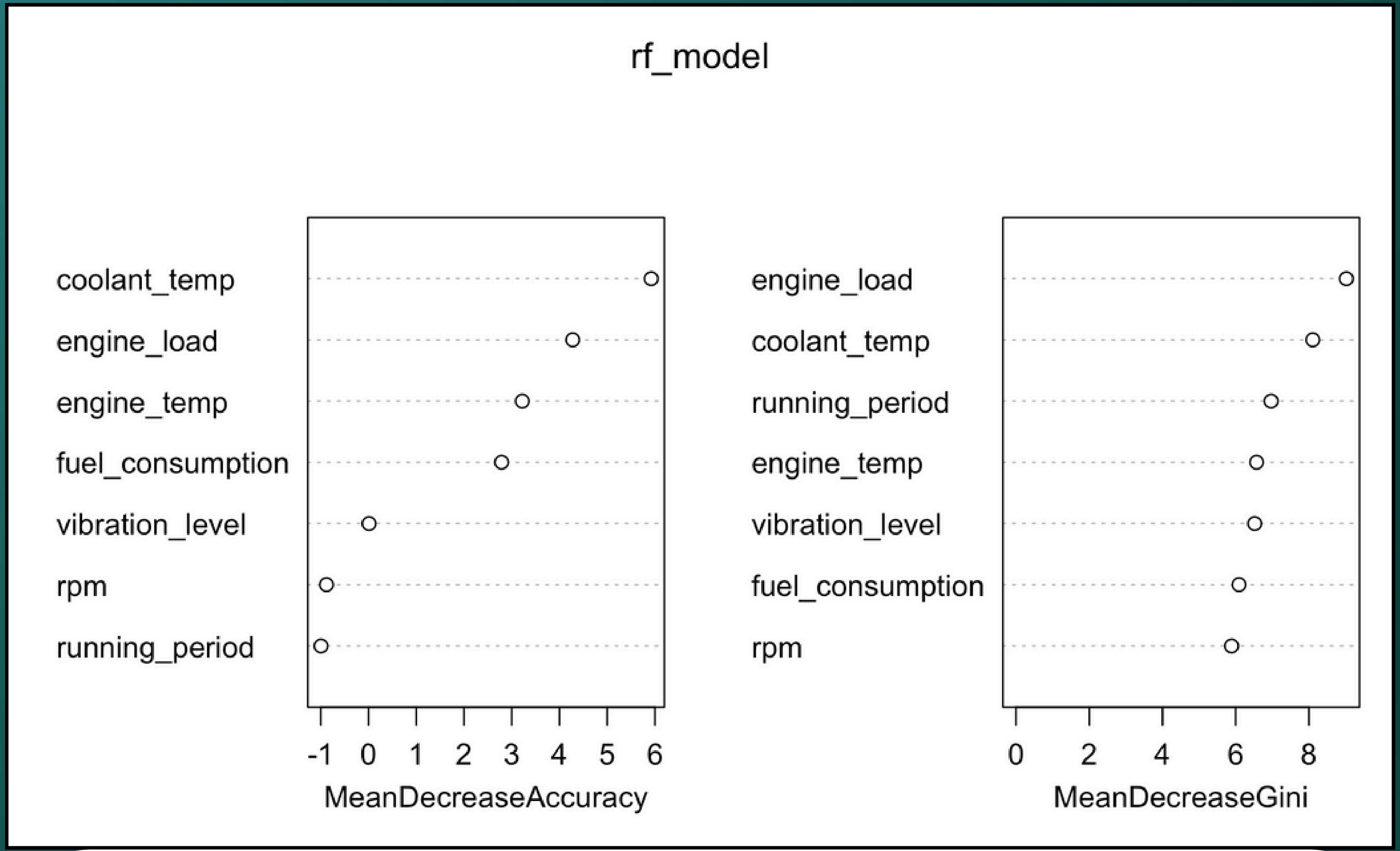
Hyperparameters tunning

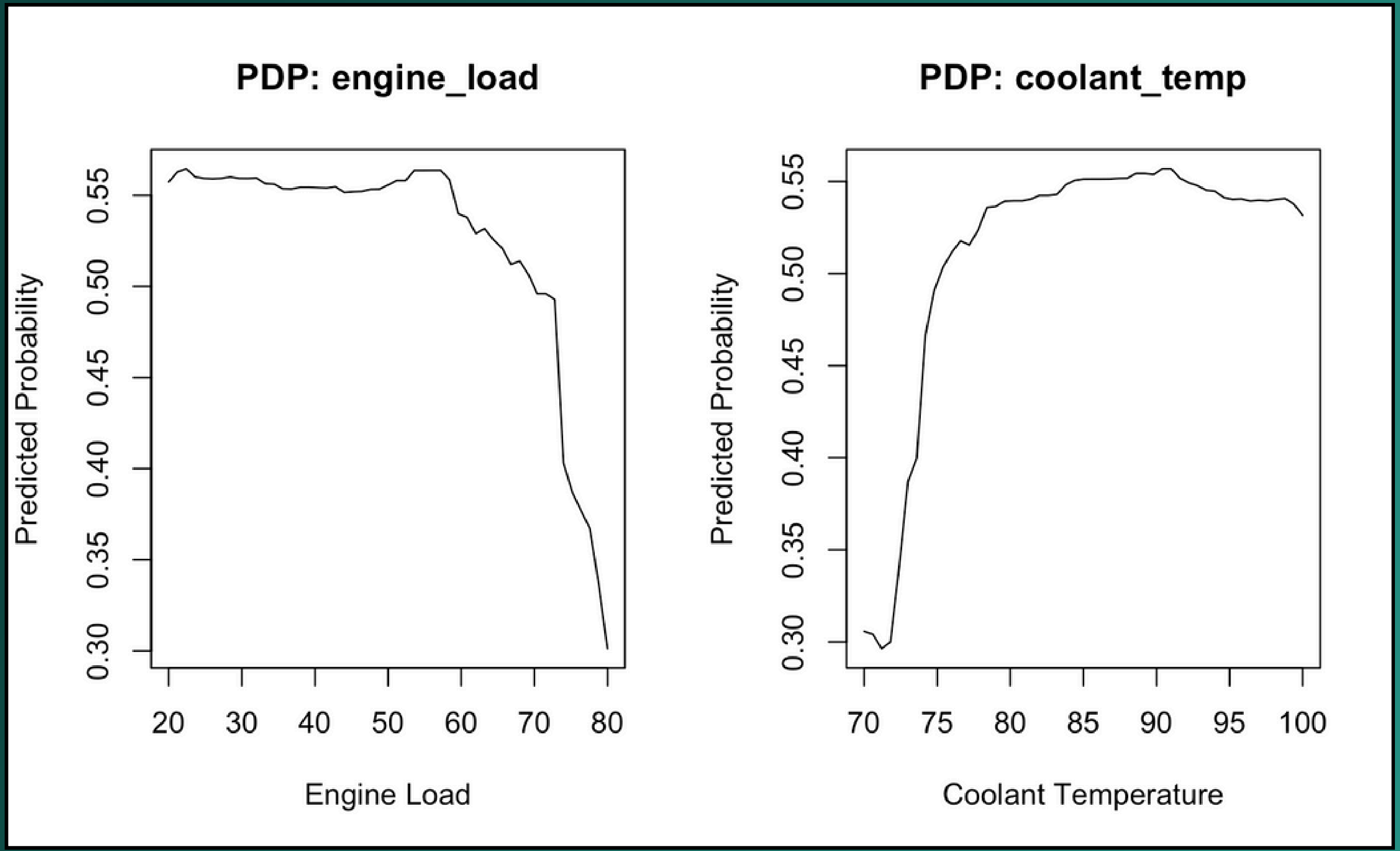




Optimal hyperparamters: ntree = 300, mtry = 2, nodesize = 10, maxnodes = 10

Random Forest
Variable Importance





Coolant temperature, engine load, engine temperature

Engine load: probability of predicting RM reamins high at moderate levels then drops with higher levels
Coolant temperature: probability of predicting RM increase with higher temperatures

Support Vector Machine

Cross-Validation - Hyperparameter tuning