Intelligent Systems Master's Degree in Informatics Engineering



Coordinator: Mariano Garralda

Academic Year: 2024-2025

Work Package 1 (WP1)

Supervised Machine Learning Pipeline

EDA, Feature Engineering, and Model Development



Overview

In this work package, your task is to carry out a complete supervised machine learning project on a dataset of your choice. You will follow the typical machine learning pipeline, including problem understanding, EDA, preprocessing, feature engineering, model development, evaluation, and selection. This exercise will provide hands-on experience in building predictive models and understanding the intricacies of the machine learning workflow.

Main Points

Your submission should address the following steps:

1. Dataset Selection & Problem Definition (5%)

- Dataset Selection: Choose a dataset suitable for a supervised learning problem (classification or regression). Possible sources include Kaggle, UCI Machine Learning Repository, or any reputable open data source.
- **Domain Context**: Provide background information on the domain or industry the data represents.
- **Problem Statement**: Clearly define the problem you aim to solve. Specify the input features and the target variable.
- Objectives: Outline the objectives of your analysis and model development.

2. Exploratory Data Analysis (EDA) (15%)

• **Data Overview**: Describe the dataset structure, including the number of samples, features, and data types.

• Univariate Analysis:

- Analyze the distribution of individual features and the target variable using statistical summaries and visualizations.
- Discuss any observations or patterns found in the distributions.

• Correlation Analysis:

- Compute correlation coefficients between features.
- Use correlation matrices and heatmaps to visualize relationships.
- Discuss any strong correlations or multicollinearity issues found.

• Bivariate Analysis:



- Examine relationships between features and the target variable using appropriate plots (e.g., scatter plots for regression, box plots for classification).
- Identify significant predictors.

• Multivariate Analysis:

- Explore interactions among multiple features.
- Use correlation matrices, heatmaps, or pair plots to identify multicollinearity.

• Initial Findings:

- Summarize the key findings from your EDA.
- Relate the findings back to your problem statement and objectives.

3. Data Preprocessing (10%)

• Data Cleaning:

- Handle missing values based on insights from EDA.
- Correct data inconsistencies and handle duplicates.

• Outliers Handling:

- Use findings from EDA to identify outliers.
- Decide on appropriate strategies to handle outliers (e.g., removal, transformation).

• Data Transformation:

- Apply necessary transformations (e.g., scaling, normalization) to prepare data for modeling.
- Justify why these transformations are appropriate.

4. Feature Engineering (15%)

• Feature Creation:

- Create new features that could enhance model performance.
- $-\,$ Explain the rationale behind each new feature.

• Feature Encoding:

- Convert categorical variables into numerical formats using techniques like one-hot encoding, label encoding, etc.
- Discuss any challenges faced during encoding.



• Feature Selection:

- Use methods such as correlation analysis, variance thresholding, or feature importance to select relevant features.
- Address any issues related to multicollinearity.

5. Model Development (20%)

• Model Selection:

- Choose appropriate machine learning algorithms for your problem (e.g., linear regression, decision trees, SVM, etc.).
- Justify your choice of algorithms.

• Training and Validation:

- Split the data into training and validation sets using appropriate methods (e.g., train-test split, cross-validation).
- Explain your strategy for model validation.

• Model Training:

- Train your models using the prepared data.
- Ensure reproducibility by setting random seeds where applicable.

6. Model Evaluation (20%)

• Performance Metrics:

- Select appropriate metrics for evaluating your models (e.g., accuracy, precision, recall, F1-score for classification; RMSE, MAE for regression).
- Justify why these metrics are suitable for your problem.

• Evaluation Results:

- Present the performance of your models using the selected metrics.
- Use visualizations like ROC curves, confusion matrices, or residual plots as appropriate.

• Model Comparison:

- Compare the performance of different models.
- Discuss which model performs best and why.

• Cross-Validation:

- Implement cross-validation to assess the robustness of your model.
- Report cross-validation scores and analyze the variance.



7. Conclusions & Recommendations (10%)

• Summary:

- Summarize the overall process, key findings, and the performance of your final model.
- Reflect on the effectiveness of your feature engineering and model selection.

• Future Work:

- Suggest potential improvements or next steps for further enhancing the model.
- Discuss any limitations faced during the project.

Assessment (Grading Breakdown)

- Dataset Selection & Problem Definition: 5%

- Exploratory Data Analysis (EDA): 15%

Data Preprocessing: 10%
Feature Engineering: 10%
Model Development: 25%
Model Evaluation: 25%

- Conclusions & Recommendations: 10%

Submission Guidelines

- Submit a well-documented **Jupyter Notebook** containing your code, analysis, visualizations, and explanations.
 - Ensure that your notebook is organized with clear headings and follows a logical flow.
 - Include all code outputs and make sure the notebook runs from start to finish without errors.
 - Any external data files used should be accessible or instructions provided on how to obtain them.
- Submit a **report** containing your conclusions, recommendations, and any additional insights not covered in the notebook.
- The submission (zip file) should be made via the **Campus Virtual** platform.
- **Note**: You may be requested to provide clarifications or answer questions regarding your submitted work.



Deadline

• Submission deadline: 15th December 2024