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Impact of Data Preprocessing on Neural Network Performance: A Comparative Analysis

Saverio Mattia **Merenda**
saveriomattia.merenda@studenti.unipr.it

Fondamenti di Intelligenza Artificiale
[2024-2025]

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Overview

- **Objective:** Study how neural network effectiveness varies when using clean datasets and unfiltered datasets

- **Presentation Overview:**

  - Context and motivations for data preprocessing

  - Preprocessing pipeline architecture

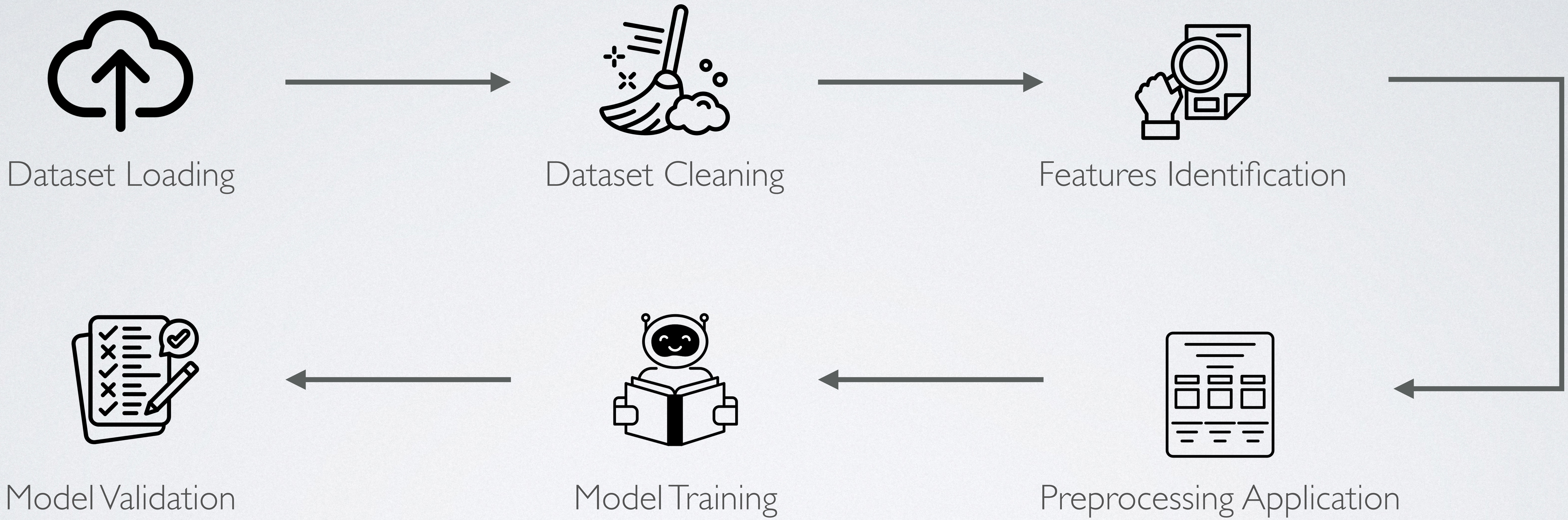
  - Different preprocessing scenarios

  - Comparative results

Why Data Quality Matters?

- **Data preprocessing** is a crucial step that directly impacts neural network performance.
- **Poor quality data can lead to:**
  - Reduced Accuracy: Inconsistent and noisy data leads to poor model predictions
  - Training Instability: Missing values and outliers cause convergence issues
  - Bias Introduction: Improper handling of data can create systematic biases
- **Common Dataset Problems:**
  - Missing Values: "?", "nan", "NaN", empty cells
  - Outliers: Extreme values that skew distributions
  - Inconsistent Scaling: Features with different ranges

Pipeline Workflow



Scenario: NaN Values Removal

- **Advantages:**
    - Simple and straightforward approach
    - No assumptions about missing data patterns
    - Clean dataset with complete information
- **Disadvantages:**
    - Potential significant data loss
    - May introduce bias if missingness is not random
    - Reduced statistical power

Scenarios: NaN Imputation Strategies

- **Three Imputation Methods:**
  - Mean Imputation
  - Mode Imputation
  - Median Imputation
- **Advantages:**
  - Maintains dataset size with multiple imputation options
- **Disadvantages:**
  - Can introduce bias and affect variance

Scenario: Outlier Removal

- Isolation Forest method with various thresholds [1%, 3%, 5%]
- **Advantages:**
  - Improves model stability by removing extreme outliers
- **Disadvantages:**
  - May remove valuable data if the method is too aggressive

Scenarios: Normalization and Transformation

- Descriptions of **z-score** normalization and **quantile** transformation
- **Advantages:**
  - Normalizes and transforms data for optimal training performance
- **Disadvantages:**
  - Could alter inherent characteristics of the original data

Neural Network Architecture

- The neural network used is a **feed-forward network** configured with **3 hidden layers**:
  - First hidden layer: `size = max(64, input_size * 2)`
  - Second hidden layer: `size = max(32, input_size)`
  - Third hidden layer: `size = max(16, input_size // 2)`
- Each layer incorporates **Batch Normalization**, **ReLU activation**, and **Dropout**
- **Advantages:**
  - Adapts to the number of features and enhances training stability
- **Disadvantages:**
  - Fixed architecture that might not be optimal for every dataset

Used Datasets

- Trained for 100 epochs
- **Classification:**
  - Census Income (48k instances): [archive.ics.uci.edu]
  - Bank Marketing (45k instances): [archive.ics.uci.edu]
- **Regression:**
  - Bike Sharing (17k instances): [archive.ics.uci.edu]
  - House Pricing (168k instances): [kaggle.com]

Classification Metrics

- **Accuracy:** Proportion of correct predictions
- **Precision:** Ratio of true positives to all positive predictions
- **Recall (Sensitivity):** Ability to identify all actual positive cases
- **F1 Score:** Harmonic mean of precision and recall

Regression Metrics

- **Mean Absolute Error (MAE):** The average absolute difference between actual and predicted values
- **Mean Squared Error (MSE):** The average of squared differences between actual and predictions
- **R Squared (R^2):** Represents the proportion of variance explained by the model

Census Income Results

Method	Accuracy	Precision	Recall	F1
01_without_NaN	0.8513	0.8454	0.8513	0.8465
02_imputed_mean	0.8530	0.8476	0.8530	0.8492
03_imputed_mode	0.8552	0.8499	0.8552	0.8514
04_imputed_median	0.8550	0.8496	0.8550	0.8510
05_no_outliers_0.01	0.8535	0.8489	0.8535	0.8504
05_no_outliers_0.03	0.8525	0.8489	0.8525	0.8503
05_no_outliers_0.05	0.8507	0.8466	0.8507	0.8481
06_normalized	0.8511	0.8474	0.8511	0.8488
07_transformed	0.8462	0.8430	0.8462	0.8443
08_normalized_transformed	0.8452	0.8417	0.8452	0.8431
(AutoML) Light Gradient Boosting Machine	**0.8737**	**0.8737**	**0.8694**	**0.8700**

Bank Marketing Results

Method	Accuracy	Precision	Recall	F1
01_without_NaN	0.7461	0.7255	0.7461	0.6929
05_no_outliers_0.01	0.7519	0.7313	0.7519	0.7086
05_no_outliers_0.03	0.7524	0.7304	0.7524	0.7111
05_no_outliers_0.05	0.7542	0.7325	0.7542	0.7106
06_normalized	0.7526	0.7327	0.7526	0.7096
07_transformed	0.7497	0.7289	0.7497	0.7033
08_normalized_transformed	0.7530	0.7325	0.7530	0.7096
(AutoML) Gradient Boosting Classifier	**0.9451**	**0.9451**	**0.9361**	**0.9384**

Bike Sharing Results

Method	MSE	MAE	R^2
01_without_NaN	732.0428	17.9583	0.9849
05_no_outliers_0.01	1262.5328	25.7145	0.9740
05_no_outliers_0.03	1323.4792	24.9745	0.9727
05_no_outliers_0.05	1737.3779	28.8209	0.9640
06_normalized	11559.1484	83.1329	0.7615
07_transformed	12692.0869	85.6862	0.7381
08_normalized_transformed	15285.6006	95.9158	0.6843
(AutoML) Linear Regression	**0.0**	**0.0**	**1.0**

House Pricing Results

Method	MSE	MAE	R^2
01_without_NaN	9.893339e+14	1.444670e+07	-0.2592
05_no_outliers_0.01	7.572025e+14	1.376704e+07	-0.3129
05_no_outliers_0.03	6.610446e+14	1.334692e+07	-0.3506
05_no_outliers_0.05	6.028811e+14	1.296907e+07	-0.3639
06_normalized	4.179000e-01	2.709000e-01	0.5519
07_transformed	**1.296000e-01**	**2.722000e-01**	**0.8705**
08_normalized_transformed	1.501000e-01	2.942000e-01	0.8509
(AutoML) Light Gradient Boosting Machine	1.143050e+14	3.591056e+06	0.8545

Key Findings

- **Most Effective Techniques**
  - Mode/Median Imputation: Better than mean imputation
  - Moderate Outlier Removal: 3-5% thresholds optimal
  - Quantile Transformations: Essential for skewed data
- **Less Effective Techniques**
  - Simple Normalization: Often degraded performance
  - Complex Combinations: No guaranteed improvements
  - Aggressive Preprocessing: Can remove valuable patterns

AutoML & Future Research

- **AutoML Growing Adoption**
  - Industry-wide adoption: Major cloud providers (AWS, Google, Azure) integrate AutoML
  - Democratization of ML: Non-experts can now build effective models
  - Preprocessing automation: Growing focus on automated data preparation pipelines
- **Future Research Directions**
  - Adaptive preprocessing: Automatic technique selection based on data characteristics
  - Intelligent quality assessment: Automated metrics for preprocessing necessity
  - Context-aware pipelines: Real-time adaptation to dataset patterns

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github.com/merendamattia/neural-network-performance-by-data-quality

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