

Process Mining and Management Project

Davide Donà - 264467 Andrea Blushi - 264468

January 2026

Contents

1	Introduction	1
2	Implementation	1
2.1	Encoding the Event Log	1
2.2	Training the Decision Tree Classifier	2
2.3	Optimizing the Classifier Hyperparameters	2
2.4	Generating Predictions	2
2.5	Extracting Recommendations	2
2.6	Evaluation of Recommendations	4
3	Evaluation	5
3.1	Hyperparameters	5
3.2	Decision Tree Structure	5
3.2.1	Evaluation Metrics	7
3.3	Recommendation Analysis	8
3.4	Performance by Prefix Length	10
4	Conclusion	11

1 Introduction

In modern business processes, predicting outcomes and providing recommendations based on historical data is crucial for improving efficiency and decision-making. In this project, we use process monitoring and machine learning techniques to analyze a real-life production log and predict whether a process instance will lead to a positive outcome (fast trace: $\text{cycle-time} < \text{avg-cycle-time}$) or a negative outcome (slow trace). When a negative outcome is predicted, we generate recommendations that suggest changes in the sequence of activities to steer the process towards a positive result. We then evaluate the effectiveness of our recommendation system by comparing the predicted outcomes with the actual outcomes in a test dataset.

2 Implementation

A recommendation system based on a decision tree classifier was implemented to analyze production event logs. The implementation was developed in Python, leveraging the *PM4Py* library for process mining tasks and the *scikit-learn* for machine learning functionality. The overall execution workflow is encapsulated in the *notebook.ipynb* file, which orchestrates the execution of all supporting utility functions.

2.1 Encoding the Event Log

The event log, provided in *XES* format, was imported using the *PM4Py* library and converted into a *PM4Py* event log object suitable for subsequent processing. A pruned version of the event log was then constructed by considering only trace prefixes. Specifically, each trace was truncated to a fixed number of events defined by the parameter *prefix.length*. Since ongoing traces in real-world scenarios are inherently incomplete, the classifier was trained exclusively on such prefixes.

Subsequently, the set of unique activity names was extracted from the complete event log and used to define the feature space. In addition to the activity-based features, each encoded trace included a trace identifier, the prefix length, and a ground truth label indicating whether the trace outcome was positive or negative.

To enable training with a decision tree classifier, the pruned traces were encoded using a *Boolean encoding* representation. For each unique activity, a binary feature was created indicating whether the activity occurred at least once within the trace prefix. This encoding scheme results in a fixed-dimensional feature space and avoids the need to pad traces to a uniform length. The final outcome of this step is a tabular *DataFrame* in which each row corresponds to a trace prefix and each feature column represents the presence or absence of a specific activity.

2.2 Training the Decision Tree Classifier

Following the encoding of the pruned event log, a decision tree classifier was trained using the *scikit-learn* library. The encoded dataset was partitioned into a feature matrix \mathbf{X} , obtained by excluding the trace identifier and label columns, and a label vector \mathbf{y} containing the ground truth outcomes. The original *XES* file provided a predefined split between training and test sets, which was preserved during this process.

After training the classifier, the learned decision rules were examined by visualizing the resulting decision tree using the visualization utilities provided by *scikit-learn*.

2.3 Optimizing the Classifier Hyperparameters

To improve classification performance, hyperparameter optimization was conducted using the *Hyperopt* library. This tool systematically explores a pre-defined search space, iteratively testing combinations of critical hyperparameters—such as *max_depth*, *max_features*, and the split criterion (e.g., *Gini* or *entropy*)—to identify the optimal configuration. For each configuration, the model was trained and evaluated using the *F₁*-score as the primary performance metric. The hyperparameter configuration yielding the highest *F₁*-score was selected as the final model.

To ensure reproducibility, a fixed random seed was set for all stochastic processes involved in the optimization and training phases.

2.4 Generating Predictions

The optimized classifier was subsequently applied on the test set to generate predictions. The predicted labels were obtained by applying the model to the feature set derived from the encoded test log. Similar to the training phase, the features (\mathbf{X}_{test}) were constructed by removing the trace identifier and ground truth label columns. The classifier's performance was subsequently evaluated using standard scikit-learn metrics, including *Accuracy*, *Precision*, *Recall*, and the *F1-score*.

2.5 Extracting Recommendations

Due to the inherent interpretability of decision tree models, the trained classifier can be used to derive proactive recommendations for traces predicted to result in a negative outcome. The recommendation generation procedure consists of three main steps:

1. **Extracting Positive Paths:** identifying all distinct decision paths leading to leaf nodes associated with a positive outcome.

2. **Filtering Compliant Paths:** selecting, for a given negatively predicted trace prefix, those positive paths whose conditions are not violated by the activities already observed.
3. **Generating Recommendations:** choosing the compliant positive path with the highest confidence score and determining the activities required to complete that path.

It should be noted that the implemented function signature differs from the originally proposed one. In particular, the *class_values* parameter was removed to simplify the implementation, as the experimental setting is restricted to binary classification.

Extracting Positive Paths from the Decision Tree: To extract all positive paths from the decision tree, the decision tree is traversed from the root node using a *depth-first search* (DFS) strategy. At each internal node, the corresponding feature, comparison operator (e.g., \leq , $>$), and threshold value were recorded. Upon reaching a leaf node labeled with a positive outcome, the complete sequence of conditions along the path, together with its associated confidence score, was stored.

To prevent the selection of statistically unrepresentative paths, a weighted confidence score was employed. This weighting incorporates the number of samples reaching each leaf node, thereby penalizing paths that achieve high confidence based on only a small number of observations.

The Algorithm 2.5 formally defines the procedure for extracting positive paths from the decision tree.

Algorithm 1 Get Positive Paths

```

1: function GETPOSITIVEPATHS(node, current_path, positive_paths)
2:   if node is leaf then
3:     if node.label == positive then
4:       Add (current_path, node.confidence) to positive_paths
5:     end if
6:   else
7:     Append (node.feature,  $\leq$ , node.value) to current_path
8:     Call GetPositivePaths(node.left, current_path, positive_paths)
9:     Remove last element from current_path
10:
11:    Append (node.feature,  $>$ , node.value) to current_path
12:    Call GetPositivePaths(node.right, current_path, positive_paths)
13:    Remove last element from current_path
14:   end if
15: end function

```

Filtering Compliant Paths: For each trace prefix predicted as negative, the set of extracted positive paths was filtered to retain only those that are compliant with the observed activities. A path is defined as compliant if none of its feature conditions are violated along the path by the activities present in the trace prefix. Among all compliant paths, the one with the highest confidence score was selected. In case of a tie in confidence, the shortest path was chosen as a secondary selection criterion.

Generating Recommendations: Once the most suitable positive compliant path was identified, recommendations were generated by determining which activities needed to be added to the current trace in order to satisfy the conditions of that path. For each test-set prefix, the recommendation set is defined as follows:

- *None*, if the trace was already predicted to result in a positive outcome;
- the empty set, if no compliant positive path could be identified;
- otherwise, the set of activities corresponding to the unsatisfied conditions along the selected positive path.

2.6 Evaluation of Recommendations

The quality of the generated recommendations was evaluated by comparing them against the complete traces in the test set, which serve as ground truth. Each trace in the test set was matched with its corresponding prefix and the recommendation generated for that prefix.

Recommendations for which no action was required were excluded from the evaluation. Recommendations consisting of an empty set were considered *not followed*, reflecting the absence of a feasible corrective action. A recommendation was considered *followed* if and only if all Boolean conditions associated with the selected path were satisfied in the full trace. If any condition was violated, the recommendation was classified as *not followed*.

The recommendation outcome (followed or not followed) was then compared with the ground truth label of the trace to derive an approximate confusion matrix defined as follows:

- **True Positives:** the recommendation was followed in the actual trace and the ground truth outcome is positive.
- **False Positives:** the recommendation was followed in the actual trace but the ground truth outcome is negative.
- **True Negatives:** the recommendation was not followed in the actual trace and the ground truth outcome is negative.

- **False Negatives:** the recommendation was not followed in the actual trace but the ground truth outcome is positive.

Based on this confusion matrix, we computed standard evaluation metrics, such as accuracy, precision, recall, and F1-score, to assess the effectiveness of the generated recommendations.

3 Evaluation

In this section, we present the evaluation results for both $\text{prefix_length} = 5$ and $\text{prefix_length} = 11$ of the decision tree classifier and the recommendation system built on top of it.

3.1 Hyperparameters

Tables 1 and 2 show the optimized hyperparameters obtained through *Hyperopt* for both prefix lengths.

For $\text{prefix_length} = 5$, the optimizer selects a shallow tree with a maximum depth of 3 and a small number of features considered at each split. This choice limits overfitting in a setting where only partial information about the trace is available, while still allowing the model to exploit the most informative activities. The use of the entropy criterion leads to more balanced and interpretable decision paths.

For $\text{prefix_length} = 11$, the optimal configuration still constrains the maximum depth to 3, confirming that deeper trees do not provide additional benefits even when more information is available. However, the maximum number of features increases, indicating that longer prefixes allow the model to effectively leverage a richer set of activities. In this case, the Gini criterion is selected, suggesting that it better captures class separation when more contextual information is present.

Hyperparameter	Value
Criterion	Entropy
Max Depth	3
Max Features	2

Table 1: Optimized hyperparameters for the decision tree classifier for $\text{prefix_length} = 5$.

Hyperparameter	Value
Criterion	Gini
Max Depth	3
Max Features	3

Table 2: Optimized hyperparameters for the decision tree classifier for $\text{prefix_length} = 11$.

3.2 Decision Tree Structure

Figures 1 and 2 illustrate the structure of the trained decision trees. The color-coded leaf nodes (blue for positive outcomes, orange for negative outcomes)

clearly show the distribution of predictions across different decision paths. Both trees maintain interpretability thanks to their depth, as the controlled *max_depth* and *max_features* parameters prevent excessive branching. The tree structures provide valuable insights into which activities are most discriminative for predicting case outcomes, making the model transparent.

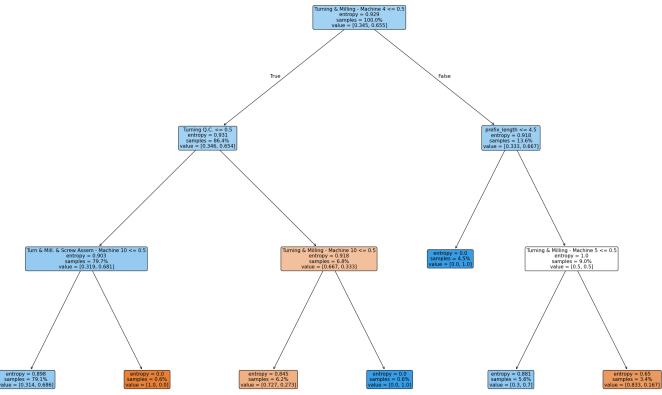


Figure 1: Visualization of the trained decision tree classifier for *prefix_length* = 5. Each node represents a decision based on the presence or absence of specific activities, leading to recommendations at the leaf nodes.

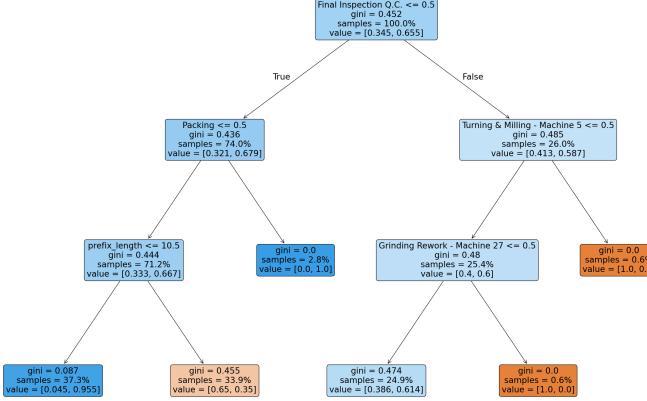


Figure 2: Visualization of the trained decision tree classifier for *prefix_length* = 11.

3.2.1 Evaluation Metrics

The classification results in Tables 3 and 4 demonstrate the predictive performance of our decision tree models.

For $\text{prefix_length} = 5$, these results indicate reasonably balanced performance when only a limited portion of each trace is available. In this setting, the model is already able to capture meaningful patterns, but the reduced amount of information limits its power.

The performance further improves for $\text{prefix_length} = 11$, where the results suggest that longer prefixes provide more informative context, enabling the model to make more confident positive predictions. Overall, the results confirm that increasing the prefix_length has a positive impact on outcome prediction, as more activities contribute to defining the case trajectory.

The confusion matrices in Figures 3 and 4 provide further insight into the distribution of predictions and misclassifications.

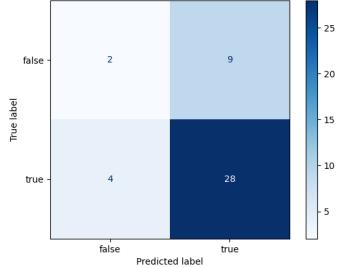


Figure 3: Confusion matrix of predictions in the test set ($\text{prefix_length} = 5$).

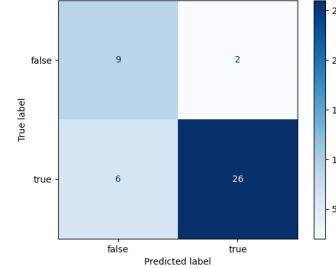


Figure 4: Confusion matrix of predictions in the test set ($\text{prefix_length} = 11$).

Metric	Value
Accuracy	69.77%
Precision	64.84%
Recall	69.77%
F1-Score	66.42%

Table 3: Evaluation metrics for the decision tree classifier on the test set for $\text{prefix_length} = 5$.

Metric	Value
Accuracy	81.40%
Precision	84.45%
Recall	81.40%
F1-Score	82.21%

Table 4: Evaluation metrics for the decision tree classifier on the test set for $\text{prefix_length} = 11$.

3.3 Recommendation Analysis

Recommendation Generation For the sake of simplicity in explaining the recommendation extraction process, we chose to consider the tree in Figure 5.

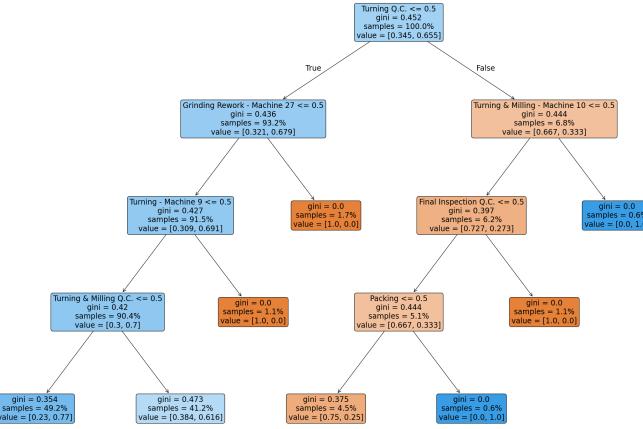


Figure 5: Simplified decision tree used to illustrate the recommendation extraction process. Given a node, the left child branch is taken if the condition is true (activity is absent in the trace), while the right child branch is taken if the condition is false (activity is present in the trace).

Applying the extraction of positive paths (Algorithm 2.5) to this tree, we obtain the following positive paths with their confidence scores:

- Path 1: *Turning Q.C. = F \wedge Grinding Rework - Machine 27 = F \wedge Turning - Machine 9 = F \wedge Turning & Milling Q.C. = F* with confidence 0.77;
- Path 2: *Turning Q.C. = F \wedge Grinding Rework - Machine 27 = F \wedge Turning - Machine 9 = T* with confidence 0.80;
- Path 3: *Turning Q.C. = T \wedge Turning & Milling - Machine 10 = F \wedge Final Inspection Q.C. = F \wedge Packing = T* with confidence 1.0;
- Path 4: *Turning Q.C. = T \wedge Turning & Milling - Machine 10 = T* with confidence 1.0;

Now, suppose a prefix trace that has the following activities: *{Final Inspection Q.C.: True, Packing: True, Grinding Rework - Machine 27: True}*, represented by the orange path in Figure 5, is predicted as false. To find the recommendations for this trace, we first filter the positive paths to find the compliant ones.

- Path 1 and Path 2 are not compliant because they require *Grinding Rework - Machine 27 = F*, which is violated by the trace;
- Path 3 is compliant because none of its conditions are violated by the trace;
- Path 4 is also not compliant because it requires *Final Inspection Q.C. = F*, which is violated by the trace.

Given this, we can derive the recommendations for the given prefix trace as the activities that need to be added to follow Path 3. Since both *Turning Q.C.* and *Turning & Milling - Machine 10* need to be true to follow Path 3, the recommended activities will be those. This is illustrated in Figure 6, with the green dotted nodes.

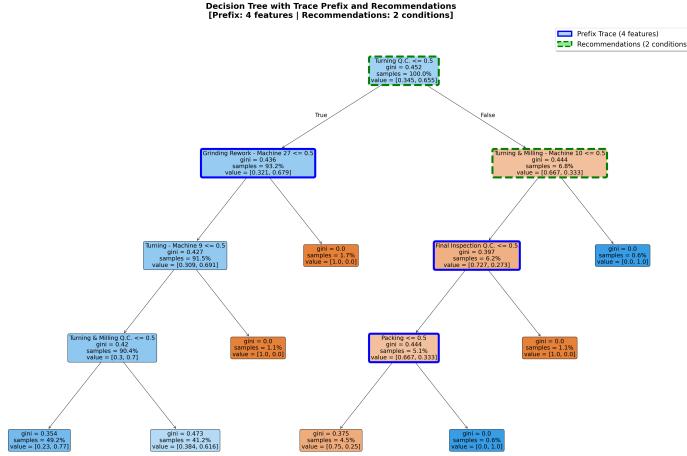


Figure 6: The blue squared nodes represent the activities present in the given prefix trace. The green highlighted nodes represent the recommended activities.

Recommendations Quality Tables 5 and 6 present the evaluation of our recommendation system. These values have to be considered as an approximation, since the ground truth is based on actual traces rather than hypothetical scenarios where recommendations were followed.

Overall, the results indicate that the limited size of the test dataset influences the number of recommendations and, consequently, their statistics.

For $\text{prefix_length} = 5$, we can see that we achieve 0% across all metrics, and the few recommendations generated were considered not followed. This outcome suggests that with very short prefixes, the system struggles to provide effective recommendations, likely due to insufficient context about the trace.

They then consistently failed to align with the actual trace outcomes. At this early stage of process execution, the activities observed may not yet be discriminative enough to distinguish between successful and unsuccessful process paths, resulting in recommendations that, while structurally valid according to the decision tree, do not reflect the actual dynamics of successful traces.

At $\text{prefix.length} = 11$, the recommendation system demonstrates substantial improvement across all metrics compared to shorter prefix lengths. The improved performance at this prefix length confirms that the recommendation system requires substantial contextual information to reliably identify patterns that distinguish successful from unsuccessful process executions and translate them into actionable recommendations. The higher number of recommendations followed indicates that the system is better able to suggest changes that align with actual successful outcomes in the traces.

Metric	Value
Accuracy	0.00%
Precision	0.00%
Recall	0.00%
F1-Score	0.00%

Table 5: Evaluation metrics for the recommendation system on the test set for $\text{prefix.length} = 5$.

Metric	Value
Accuracy	46.67%
Precision	60.00%
Recall	33.33%
F1-Score	42.86%

Table 6: Evaluation metrics for the recommendation system on the test set for $\text{prefix.length} = 11$.

For a more detailed understanding of the system’s performance, we present the confusion matrices in Figures 7 and 8.

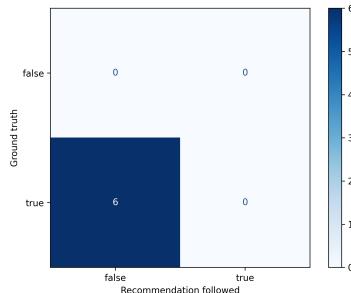


Figure 7: Confusion matrix of recommendations ($\text{prefix.length} = 5$).

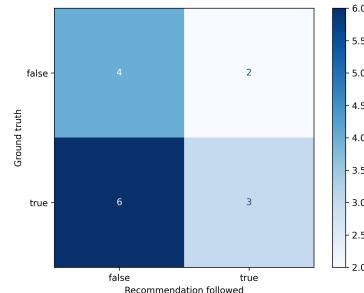


Figure 8: Confusion matrix of recommendations ($\text{prefix.length} = 11$).

3.4 Performance by Prefix Length

As shown in Figure 9, the F1-score for the decision tree classifier remains relatively stable across different prefix lengths, while the recommendation system

shows a more pronounced improvement as the prefix length increases. This trend reveals a fundamental difference between the two components: while the classifier can maintain consistent predictive performance regardless of prefix length, the recommendation system requires a minimum threshold of contextual information before it can generate meaningful recommendations.

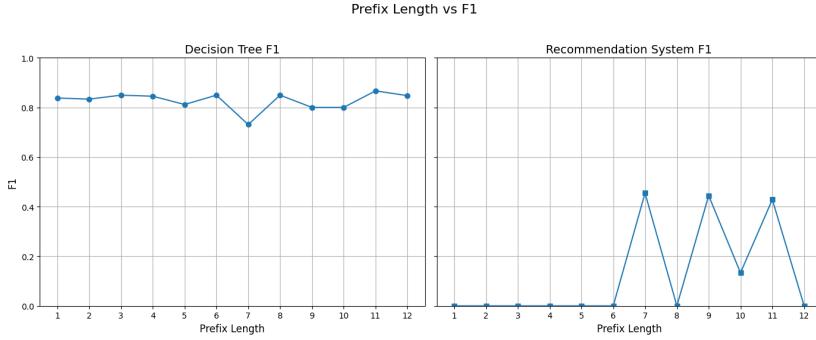


Figure 9: The box plots illustrate the distribution of F1-scores across different prefix lengths for both the decision tree classifier and the recommendation system.

4 Conclusion

Given the limited number of samples in our dataset, the results should be considered preliminary. Nevertheless, they are promising and suggest that, with the availability of more data, the proposed recommendation system could become a valuable tool for process improvement. Our evaluation indicates that the effectiveness of recommendations is highly dependent on the amount of process context available. Longer prefixes capture more detailed information about the process execution, enabling the recommendation system to generate more accurate and relevant suggestions.

Overall, this project demonstrates the feasibility of combining process mining and machine learning techniques to predict process outcomes and generate actionable recommendations. With further refinement and larger datasets, such systems have the potential to significantly enhance business process management and optimization.