Insights on Weld Quality using Unsupervised Learning: Clustering of MIG/MAG Process Signals

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Abstract. With the increasing complexity of gas metal arc welding (GMAW) processes, data-driven approaches for monitoring and understanding automated GMAW production lines are gaining increased prominence. In this work, welding process data recorded in a production environment is analysed using unsupervised learning methods. We describe a data processing pipeline for feature engineering and apply a state-of-the-art clustering method to gain more insights into the welding production process. The clustering results are compared with the results from the application of dimensional reduction techniques and discussed based on human-interpretable characteristics of the welding process.

1 Introduction

Gas metal arc welding (GMAW) is a key production process in metalworking industries. Modern arc welding processes are highly dynamic, with a multitude of different process variants available [1]. In addition, driven by market demands and automation, the complexity of modern welding systems is rapidly increasing [2]. For human operators, monitoring and optimizing the welding production process is becoming ever more challenging. With the advancing digitization of our world, modern information technologies are also finding their way into welding production lines [3]. Emerging technologies like big data and artificial intelligence (AI) may provide solutions to support process monitoring, prediction and control, as well as quality inspection [2].

In this context, the European project called Data and Metadata for Advanced Digitalization of Manufacturing Industrial Lines (metaFacturing) has the overall goal of establishing a more resilient production process by researching the development of an AI-based digital twin for metal part production, thereby reducing costly rework and scrap resulting from out-of-specification parts [4]. Line operators will be assisted by AI-based applications that will provide enhanced information about the manufacturing process. Leveraging the integration of diverse types of data, such as welding process data, visual inspection data, and quality control data from destructive testing, within metaFacturing we are creating the data environment required to determine whether defects in weld seams correlate to information hidden in the characteristics of the corresponding data.

Currently, we are building a foundation for predicting the weld seam quality from the welding process data, i.e., defects can be identified earlier (maybe even online) in the process. This converges with the overall goal of significantly reducing rework, scrap, machine downtime and energy spent, hence increasing material and process efficiency. Therefore, in this paper, production data obtained from welding seams is used for the development of an unsupervised machine learning (ML) model. In the first step of analysing the raw welding signals, we apply a clustering algorithm. Several approaches that could prove to be effective for this task are available, like Density-Based Spatial Clustering of Applications with Noise (DBSCAN), Hierarchical Clustering or k-means clustering. In this research, we focus on analysing the raw signals of electrical welding current and voltage in the form of time series by applying the k-means clustering method. In a follow-up step, clustering algorithms will be combined with feature extraction from the chosen welding signals, to enable the detection of anomalies and the assignment of an anomaly score for each weld seam.

Many studies on approaches to unsupervised GMAW process monitoring have been reported in the literature. Sumesh et al. (2017) established a statistical correlation between welding process signals and welding defects by comparison of probability density distributions of welding current and voltage [5]. Kirchner et al. (2020) applied a long short-term memory (LSTM) autoencoder to detect welding process instabilities in multivariate welding process signals from the reconstruction error and the latent space of the autoencoder. The reported anomalies were largely short circuits prevented by the process control unit of the welding system [6]. Some studies combine welding process data with additional sensor data, e.g. with video data recorded during welding [7]. Reisch et al. (2020) trained ML models too in the context of wire arc additive manufacturing (WAAM). They combined the outputs of the different models processing welding process data and video data, to calculate an overall anomaly score employing a Mahalanobis distance [8]. Other studies do not consider the analysis of welding process data (like current and voltage), but rely on acoustic signals for monitoring and anomaly detection [9, 10].

In many of the studies mentioned above, the data is often generated in a laboratory setting, with relatively small sample sizes. The present studies focus on the application of clustering methods on data recorded in an industrial production environment. The remainder of the paper is organised as follows. In Section 2, we present an overview of the welding process, the motivation and the challenges of this work, and we introduce the production data used for the analysis. In Section 3, we detail the methodology for analysing the welding signals. In Section 4, we present the results and the feedback received from the welding (domain) experts. Section 5 summarizes the content of the paper and discusses ideas for future work.

2 Arc welding process (MIG/MAG)

2.1 Description and motivation

MIG- and MAG-welding are among the most common welding processes for steel and aluminium alloys. Both are jointly referred to as gas metal arc welding (GMAW) processes. GMAW is characterised by the electric arc which forms between the workpieces and the welding wire. This arc heats the joint while a protective gas (inert or active, thus metal inert gas (MIG) and metal active gas (MAG)) shields it from the environment. Using a robot, the welding torch is moved along the two workpieces' joints to create a weld seam with the desired length [1]. The quality of this joint is mainly given by the penetration of the created weld seam. It is a percentage of the workpiece thickness and a measure of the connection of both workpieces. A minimum penetration is an agreed quality feature between customers and suppliers of welded components to ensure the connection of both pieces for the expected life cycle.

For the determination of the penetration, destructive testing is broadly applied. Cutting a welded component perpendicular to the orientation of the weld seam gives an insight into the cross-section. The sample is then prepared by polishing and etching before the characteristics are measured visually. On the one hand, this procedure is fast and reliable, on the other hand, a part is destroyed and there is no data available other than for this sample.

A continuous control of the weld seam quality to estimate the penetration is our goal. This reduces the number of destroyed parts and can be applied to every single weld. Another benefit is early information on issues for the automatic or non-automatic optimisation of the process.

As a first step towards this goal, anomalous welds shall be isolated by the application of AI on the data from a welding power source.

2.2 Challenges

The weld penetration is dependent on many controlled and uncontrolled parameters. Considering the robot, the main parameters are the distance of the torch to the joint and the welding speed. Any changes in these parameters directly affect the arc-length, therefore the welding voltage, and the energy input per unit length of the weld seam. Since the process is dependent on the heat input from the arc, the robot thus has a significant influence on the quality [2].

The workpieces form a joint which is uneven along its length. The gap width, position, and contours vary between different parts and affect the heat distribution alongside the workpieces' heat treatment

(a) (b)

Figure 1: (a) Illustration of the cross-section and (b) photo of the weld seam.

before welding.

The greatest impact on the weld quality can be expected from the welding power source. These electronic devices contain sensors and complex control functions to ensure the weld quality by automatic means. Due to the direct exposure to the process, wear-off of the mechanics and electrics needs to be monitored. The wire feed mechanics and contact tip in the torch have to be thoroughly maintained.

Due to the dependency of the welding parameters on one another, it is expected that most information is contained in the signals of the power source. The analysis of these signals to deliver an approach for the decryption of quality information will be described in the following chapters.

2.3 Data recording

The dataset utilized in this article was generated by a Fronius TPS/i welding system, installed within the production line for welding sessions of the project partner BENTELER Automobiltechnik GmbH, as part of the metaFacturing project. For further analysis, a particular weld seam was selected. It is schematically illustrated in Figure 1a, showing a butt joint of two aluminium profiles. As a welding process, Fronius Pulse Multi Control (PMC) is used. Moreover, the option Fronius Synchro Pulse is enabled, resulting in the characteristic ripple effect of the weld seam surface, see Figure 1b.

The welding process data of the weld seam was recorded for many different parts, resulting in 1478 recorded data samples. The description of the recorded welding process signals, as well as challenges regarding the merging of time series signals recorded at different sampling frequencies, are described elsewhere [11]. The main signals used in the present analysis are the voltage, `welding_voltage`, and the current, `welding_current`, of the arc during welding, sampled at 10 kHz. Moreover, signals used for communication between the welding system and the robot, like `arc_on` and `welding_start`, are used to segment the welding signals into different regions of interest (see Section 3.1). These signals were sampled at 1 kHz. The different sampling rates at which the welding signals were recorded pose a challenge since any proper analysis of the welding activity will essentially require that all signals be sampled at the same sampling rate. In [11], we describe these challenges in detail and how they were resolved. In particular, the dataset utilised within this article results from the upsampling of the low 1 kHz frequency signals to 10 kHz with linear interpolation to fill out missing data.

3 Analysis of welding signals

3.1 Data preparation

This section delineates the data preprocessing pipeline, as depicted in Figure 3. For each dataset corresponding to a weld seam of the specified machine serial number, the process initiates as follows: filter out the dataset based on the designated seam number to generate a pool of datasets per weld seam. In this case, this step yielded 1478 weld seam datasets. Subsequently, we clean the data by removing datasets containing potential outliers. Incomplete welding sessions and welding sessions where an error code was raised by the welding system, are excluded, resulting in 1459 weld seam datasets.

Next, the dataset undergoes further processing through either **Pipeline A** or **Pipeline B**, as illustrated in Figure 3. Within **Pipeline A**, the dataset is subjected to two distinct transformations. The first transformation selects the signals `welding_current` and `welding_voltage` for each dataset. The second transformation calculates the power spectral density (PSD) of the `welding_current` and `welding_voltage` using SciPy's Welch[1] function [12], producing two feature vectors per weld seam, each with dimensions $(1, n)$, where n is the number of frequencies. Merging the feature vectors sequentially by their respective production time results in 2 feature matrices, each with dimensions (m, n), where $m = 1459$, the number of weld seams. Finally, we merge these 2 feature matrices, which result in a tensor of dimensions $(m, n, 2)$.

[1] Documentation of SciPy `welch` function

Within **Pipeline B**, each dataset per weld seam is initially divided into three distinct phases using the low-frequency signals, `arc_on` and `welding_start`, which were upsampled with expert knowledge from Fronius. Figure 2 illustrates these phases, which are further described below:

- **Phase I** is the *start phase* at the beginning of the weld seam. In this phase, the arc is ignited, and the base material is heated.
- **Phase II** is the *main phase*, where welding is usually carried out at a constant welding speed.
- **Phase III** is the *end phase*, where the crater at the end of the weld seam is finished.

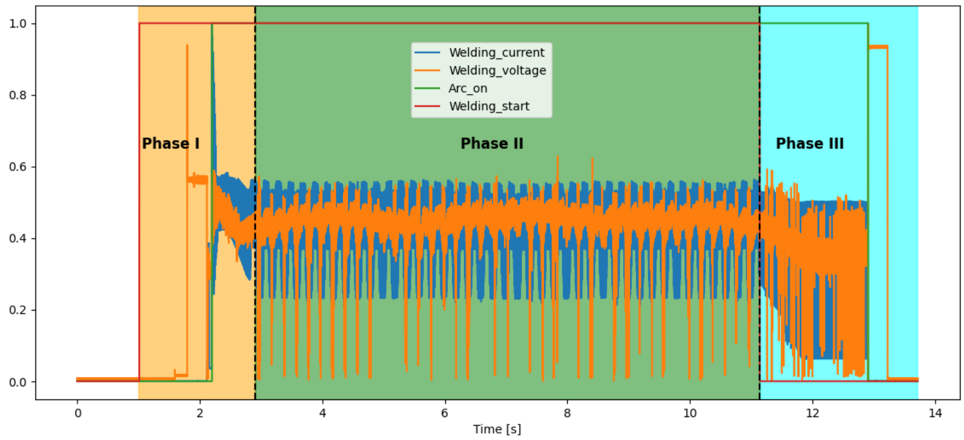


Figure 2: Separation of the welding data into three different phases. For illustration purposes, the depicted signals were normalized to the range between 0 and 1.

In this research work, we restrict the analysis activities that are described in the next subsection, to **Pipeline A** and Phase II (the main phase) of **Pipeline B**. As demonstrated in Figure 3 below, the Phase II dataset, generated for each weld seam, undergoes the exact transformation as described earlier for **Pipeline A** to obtain the feature tensor of dimension $(m, n, 2)$.

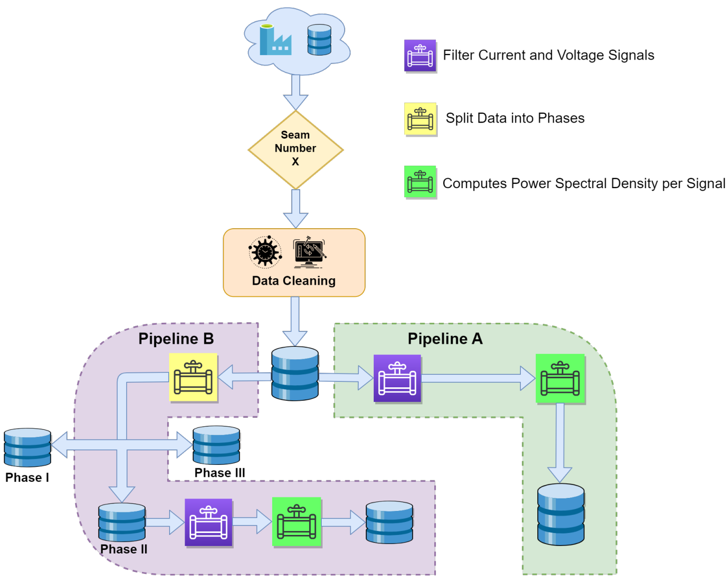


Figure 3: Data preprocessing and feature extraction pipeline.

3.2 Unsupervised learning – Clustering

This subsection details the machine learning methodology employed to analyse the dataset generated in Subsection 3.1. For an analysis focused on the quality statuses of the weld seams, it would necessitate the availability of target labels defining their quality, thereby indicating a supervised machine learning approach. However, due to the unavailability of quality data for the weld seams at the time of analysis, we adopted an unsupervised machine learning approach.

Specifically, we utilized the k-means clustering algorithm, as implemented in [13, 14], to cluster weld seams based on their PSD features. A primary challenge with the k-means algorithm is determining the optimal number of clusters. Generally, minimizing the cost function alone is not effective, as this approach tends to favour a larger number of clusters, given that increasing the number of clusters typically reduces the cost function. Hence, choosing the value of k solely to minimize the cost function is not a suitable method.

4 Results and discussion

Our approach to determining the number of clusters was experimental. We executed the k-means clustering algorithm, with the number of clusters ranging from 2 to 50. For each specified number of clusters, the algorithm was run with 50 random initialisations of the cluster centroids. The model with the minimum distortion cost for each chosen number of clusters was selected as the best model. Additionally, we computed the mean silhouette score for each chosen number of clusters, to evaluate the quality of clustering. The silhouette score measures how similar an object is to its own cluster compared to other clusters, ranging from -1 to 1, where a higher value indicates better clustering performance.

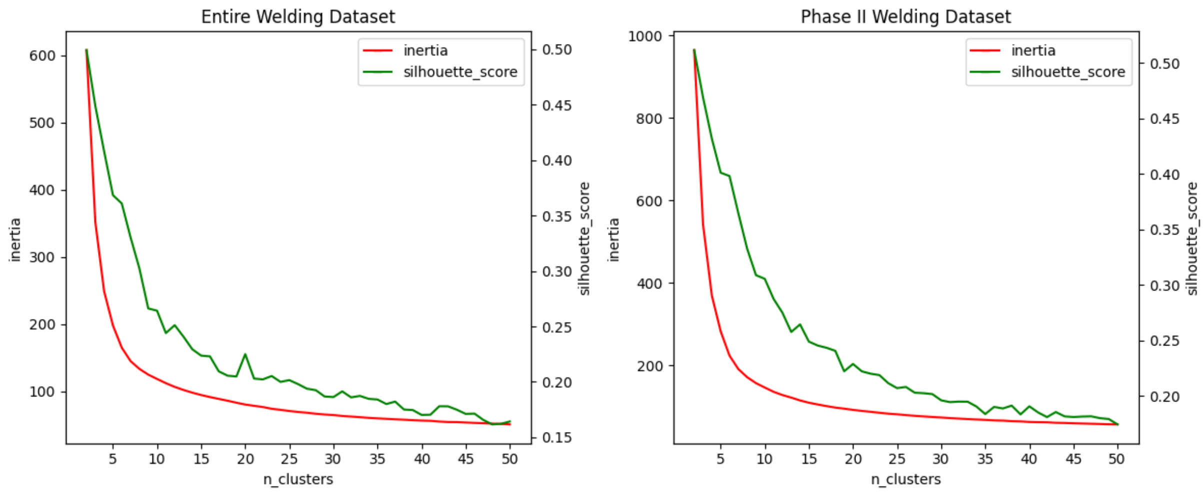


Figure 4: Number of clusters against inertia and silhouette score.

Figure 4 illustrates the experimental results for the datasets generated by **Pipeline A** over the entire duration of the welding session and by **Pipeline B**, which is confined to the *main welding phase* (Phase II). From Figure 4, it is evident that the silhouette scores indicate a decrease in clustering quality as the number of clusters increases. Consequently, we limited our analysis to 2 and 3 clusters.

For each specified number of clusters, we concatenated the feature matrices of the `welding_current` and `welding_voltage` from both **Pipeline A** and **Pipeline B**. We then performed Principal Component Analysis (PCA), reducing the dimensionality of the frequency feature space from 1025 to 2. The visualization of this dimensionality reduction, grouped by their respective clusters, is presented in Figure 5. For all shown cases, the two principal components together account for more than 95 % of the variance in the dataset, with frequencies ranging between 170 to 278 Hz as part of the top 10 frequencies having higher contribution scores to both components. Consequently, these frequencies contribute significantly to the variance captured within each of the principal components.

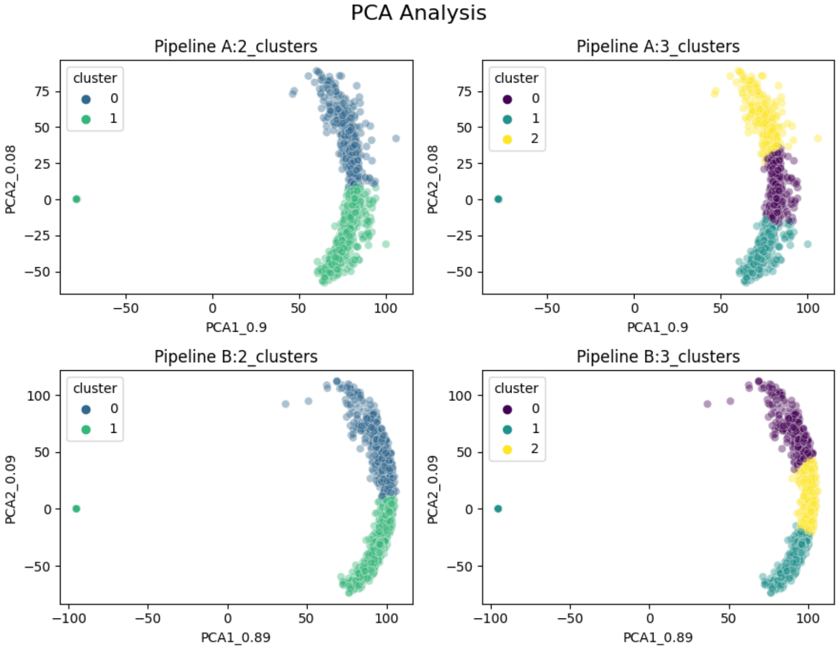


Figure 5: Downward projection of feature matrices using PCA and categorised based on their cluster values. The numeric values associated with the axis labels denote the explained variance ratio attributed to the respective principal component.

The cluster assignments predicted by the k-means clustering algorithm for each weld seam were used as target labels to train a classifier. The purpose of this classifier was to identify the frequencies that significantly influence the predicted clusters. Specifically, we employed the XGBoost classifier [15] to determine which frequencies are most critical in predicting the various clusters. The results, shown in Figure 6, highlight the top 10 frequencies for each of the k-clusters, with $k = 2, 3$, in the datasets generated by **Pipeline A** and **Pipeline B**.

The analysis reveals that, across all results, the most important frequencies fall within the range of 170 to 200 Hz. This finding is expected, as the welding pulse frequency, and therefore the frequency of droplet detachment, for the investigated weld seam lie within this range. Notably, for the welding current and the scenario involving 3 clusters (`psd_welding_current:3_clusters`), both pipelines indicate that the most important frequency is 366 Hz. This frequency likely represents a higher harmonic of the welding pulse frequency.

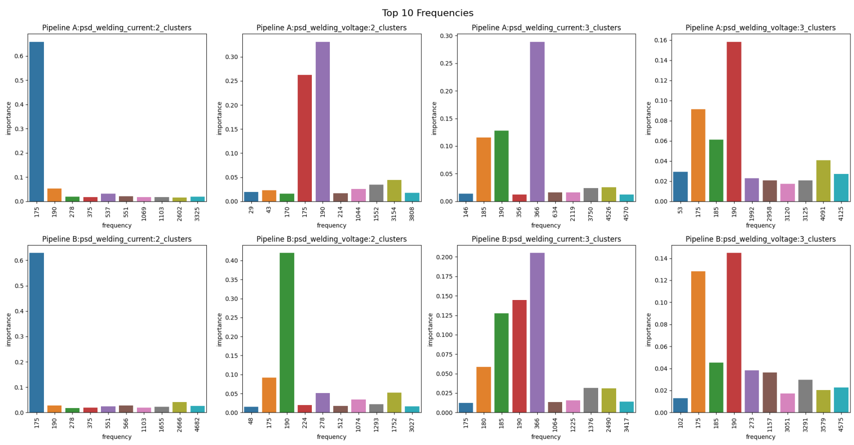
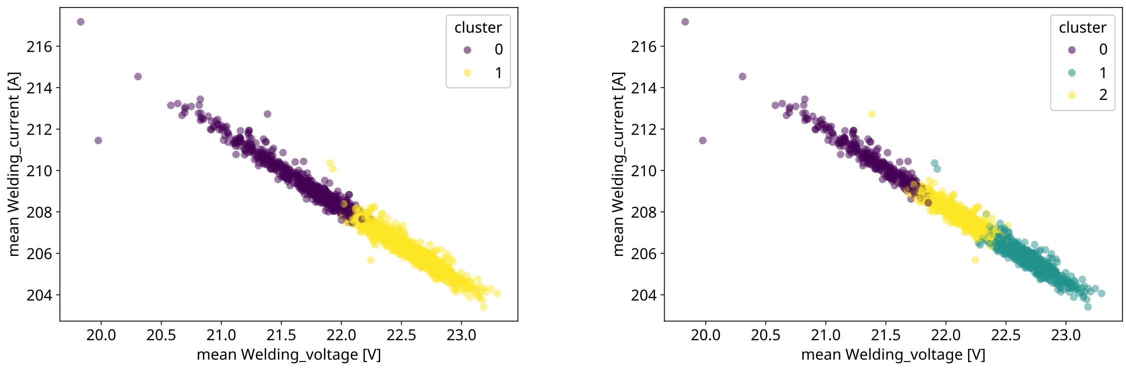


Figure 6: Top 10 frequencies obtained by a classifier predicting the cluster membership.

Figure 7 illustrates two scatter plots of the mean `welding_current` and mean `welding_voltage`, with each weld seam colour-coded according to its respective cluster. Here, we only focus on **Pipeline B** (scatter plots for **Pipeline A** are not shown). The mean current and voltage for each weld seam were calculated during active welding, specifically when the signal `arc_on` equals 1 (refer to Figure 2 above). It is evident that the differences between clusters are relatively well-demonstrated in the scatter plots in Figure 7. The clusters are primarily distinguished by varying values of welding current and voltage. This observation aligns with the PCA presented earlier (see Figure 5), where only two principal components account for the majority of the variance in the dataset, effectively separating the different clusters.



(a) (b)

Figure 7: Scatter plots of mean `welding_current` and mean `welding_voltage` for **Pipeline B**: Results for (a) two clusters and (b) three clusters.

5 Conclusion and future work

The analysis presented in this study demonstrates the application of unsupervised learning techniques, specifically k-means clustering, to identify patterns in welding process signals. The primary focus was on analysing the electrical signals of welding current and voltage recorded from a Fronius TPS/i welding system. The clustering results, based on power spectral density (PSD) features of these signals, revealed significant insights into the welding process quality and identified key frequency ranges that are most likely to influence weld seam quality.

Further analysis using principal component analysis (PCA) and feature importance analysis revealed that specific frequency bands, particularly those around the welding pulse frequency, in the range of 170 to 200 Hz, contribute significantly to the clustering results. The study's experimental approach to determining the optimal number of clusters provided valuable feedback from domain experts, indicating that a smaller number of clusters (two or three) is most likely to distinguish between different weld quality levels.

The successful application of unsupervised learning to industrial welding data in this study highlights the potential for such methods to improve process monitoring and quality control in real-world manufacturing environments. By identifying anomalies in weld seams, this approach can reduce the need for destructive testing, thereby saving time and resources while enhancing overall production efficiency.

Future work will focus on refining this approach by incorporating additional features and exploring different clustering algorithms. Furthermore, correlating the identified clusters with actual weld quality measurements will be crucial to validate the findings and establish a reliable anomaly detection system. Additionally, investigating the use of deep learning techniques for feature extraction and clustering could potentially improve the performance of the anomaly detection model. By continuously refining the approach and incorporating feedback from domain experts, we aim to develop a robust and effective tool for monitoring and improving welding process quality.

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