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Data-Driven Recyclability Classification of Plastic Waste

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This work aims to propose a general data-driven plastic waste categorisation procedure that defines their recyclability based on classification into material recycling classes. The contamination in plastics, such as metal fillers or additives, is accumulated during the entire Life Cycle, which can be harmful to either mechanical or chemical recycling. The plastic polymers can also degrade during recycling due to weakened chemical bonds in the polymers. The diversity of plastic material types and products makes it necessary to use a data-driven quality-based definition of plastic waste properties to facilitate proper waste recycling and mitigation. This study demonstrates the use of Machine Learning tools that enable automated classification to analyse the plastic waste data and derive the indicators for plastic waste recyclability. Tree-based models such as the Decision Tree Model and Random Forest Algorithm are used as they produce interpretable if-then rules for plastic waste categorisation. The proposed method allows an analysis of the metal contamination and degradation data in a collection of plastic material samples or batches to derive a general categorisation rule for a polymer type – PE. The data-driven plastic categorisation could help in understanding the current waste practices and determining a proper recycling plan for local or even global plastic waste.

1. Introduction

The global annual production of plastics reached approximately 400 Mt by 2015 (Ritchie and Roser, 2018), and the trend is accelerating. Solving the issues of plastics recycling is of paramount importance for minimising the use of fossil fuel resources, the related Greenhouse Gas Footprint (Ritchie and Roser, 2017), and Plastic Waste Footprint (Klemeš et al., 2020). The overall recycling workflow is complex, and the decisions (Williams et al., 2018) depend on the simultaneous consideration of several factors – including mixing of plastics in the waste, the presence of contaminants (e.g. food, oils), and the condition of the base polymer of the plastic material.

There are several possible routes of plastic waste processing: product reuse, material reuse (mechanical recycling), chemical recycling, and final treatment/disposal. The degrees to which each of these options is applied depend on the batch composition, condition, and danger to the ecosystems and human health.

Geyer et al. (2017) have shown that in 2017, only approximately 18 % of the global plastic waste was recycled, 24 % - incinerated, and 58 % were disposed of. The major concern regarding plastic waste is the contamination of water bodies – rivers, lakes, oceans. A forecast (Jambeck et al., 2015) projects the amount of ocean plastic waste to reach about 150 Mt by the year 2025. It has been shown by Klemeš et al. (2020b) that during the COVID pandemic, plastic consumption has surged. They noted the increase of both packaging and medical waste. A further analysis (Klemeš et al., 2020a) has stressed the need for a proper recyclability evaluation method to enable the discourse on legislation and regulations that implement waste management.

Efficient plastic waste recycling practices are required to counter the high rate of plastic waste disposal. The concept of Circular Economy is developed to focus on recirculation of the materials and subsequently emphasising waste recycling (EC, 2015).

In terms of plastic waste categorisation, Huysman et al. (2017) have analysed the compatibility between polymers by studying the interfacial tension between the polymers. They defined the substitution ratio of

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recycled plastic, which is correlated to compatibility and derived a quality indicator. Eriksen et al. (2018) have explored various scenarios of the efficiencies of plastic recycling processes and qualitatively defined the plastic waste categorisation based on EU standards. They assessed the polymeric composition and other general polymer residues. Brouwer et al. (2019) studied plastic packaging waste in a Dutch recycling plant between 2014 and 2017. They reported that most of the recycled plastics are suited only for open-loop applications due to contamination. Vollmer et al. (2020) have comprehensively reviewed the routes for the chemical recycling of plastic waste. They analysed the scientific development in this area along with better recycling policy and platforms with all stakeholders are needed. Brouwer et al. (2020) proposed a categorisation of plastic package waste based on the degradation properties, chemical contaminations as well as physical strength values. The categorisation is intuitive, but it is qualitative in nature. It is ambiguous for policymakers to define a proper threshold for plastic waste categorisation.
Based on the above literature review, the following research gaps can be identified:

(i) There is a lack of data-driven and quantitative plastic waste classification methods for proper recycling.
(ii) Various properties, including chemical contaminations, metals or additive accumulations and degradation properties, are not considered in the plastic waste categorisation.

This work addresses the mentioned gaps by proposing a systematic plastic waste classification procedure based on several waste properties. This paper applies the well-known tree-based classification models, i.e. Decision Tree analysis and Random Forest algorithm (VanderPlas, 2016), to derive a set of interpretable 'if-then rules for quality patterns determination of the various plastic waste streams. This paper focuses on formulating a criterion for materials recyclability for a given batch of plastic material based on its condition. The criterion formulation is based on the evaluation of the rate of polymer degradation and the rate of leakage of fragments to the environment. The guiding principle for the decision is to prevent significant leakage that would damage ecosystems and humans. The paper is divided into Section 2 that defines the classes of material sources. Section 3 explains the data collection framework. Section 4 describes the example dataset used in the demonstration and the interpretation of the results.

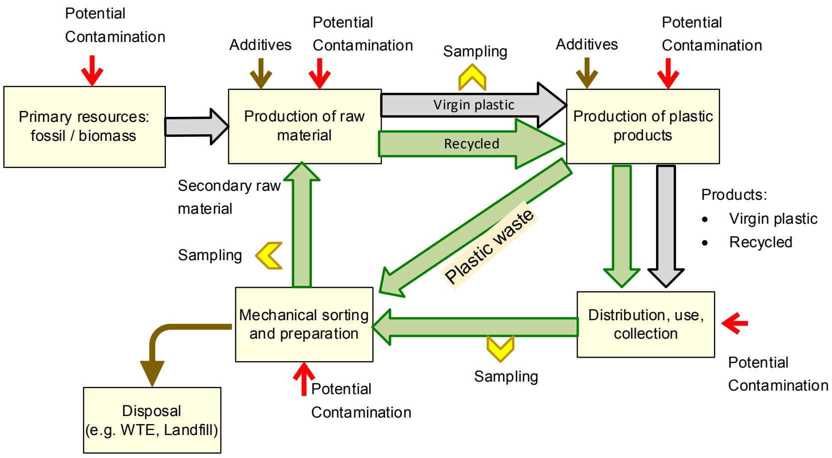

Figure 1: Plastic material flows, adapted from Eriksen et al. (2018)

2. Material sinks and classes of separation

The concept in this work stems from the general life cycle of plastic materials, as well as the established separation and recycling practices. A typical network of material flows for plastic products is shown in Figure 1, which is an adaptation of the flow diagram presented by Eriksen et al. (2018). The flow network starts the consideration from the extraction of primary resources and then includes the stages for raw material preparation, forming products, distribution/use of the products, waste separation and processing, recycling and landfilling.
In addition to that general flow pattern, it is also known that there are different applications for plastic materials (Grigore, 2017) – e.g. food and drink, household items, gardening items, building and interior items. Those applications define a set of material classes, which impose different quality and cleanliness requirements on the material sources. Taking a batch or a sample of waste plastics (termed a Source) and determining its future fate presents a classification problem. That can be modelled as a mapping of the source to a set of alternative sinks, as illustrated in Figure 2. In that figure, a set of sinks, which pose sufficiently close quality requirements, form a class of materials. Following that logic, the potential applications determine the classes of materials, and the potential source of secondary raw material has to be classified within one of those classes.

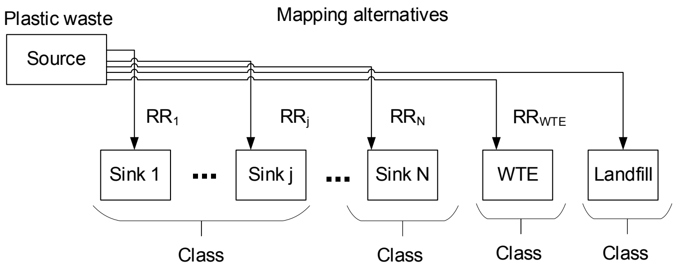

Figure 2: Sinks and classes of recycled materials

An important property of these classes is that they form a cascading hierarchy. Materials of a higher-quality class can be used as substitutes for the materials of any lower-quality classes, i.e. cascaded. For example, food-grade virgin plastic is perfectly safe for producing household or interior décor items, or even industrial plastic products, while industrial-grade plastic is typically not upgradable or usable as food-grade.

3. Data collection framework

It is first required to determine a data collection site to gather the properties data of the plastic waste streams. The quality data of the plastic waste streams can be collected from the entire plastic value chain (Figure 1). Based on Eriksen et al. (2018), the data on the plastic polymer types can be measured and collected from different origins- virgin plastics, industrial and household plastic wastes or reprocessed plastic waste streams. If necessary, the waste samples can be further divided into food-grade or non-food grade plastics as the chemicals added to the plastics are different and should comply with stricter legislation. Other plastic products can be more lenient in chemical contamination as long as they are within the utilisation standards.

Table 1: Properties to be measured and collected from the plastics value chain

Types	Properties	Description
Chemical	Polymeric composition	The composition of the targeted and non-targeted polymers in the waste stream
	Metals Concentrations	Amount of metals accumulated during wastes recycling
	Additive Concentrations	Amount of additives accumulated during wastes recycling
…	Residues Concentrations	Other non-plastic waste mixed with the plastic streams, e.g. paper, cardboard and etc.
Degradation	Melt flow index	Viscosity measures for the melted polymers (PE, PP, PS, etc.)
	Intrinsic viscosity (PET)	Viscosity measures for the melted polymers (PET)
Mechanical	Tensile strength (MPa)	Mechanical strength of the plastic wastes
Others	Colours	The colours in the plastic wastes affect its reusability

Depending on the treatment processes, the plastic polymers samples can be collected either before the pre-treatment or after the pre-treatment, such as washing. If the demands posed to the plastic polymers in the waste are not as strict, the plastic waste, even without pre-treatment, can be recycled, and its recyclability can be high. The collected data on the plastic waste streams tells a lot of information for the recyclability of the plastic waste streams. By investigating the data patterns on the plastic waste streams from different origins, the threshold of the properties can be determined so that the plastic waste streams can be distinguished from different origin classes. For example, by investigating the virgin plastic properties, one can determine the certain thresholds or limits of some properties, such as contamination levels, and it can be known whether the plastic streams are of high or low recyclability. Table 1 presents the example plastic wastes data that can be collected from the plastics value chain in Figure 1. Depending on the location or types of the plastic production processes, the collected properties of the plastic streams may differ but should not deviate significantly.

4. Case study demonstration

A case study is used to demonstrate how the Machine Learning-based classification method can define plastic waste recyclability. This study considers the metal concentrations of aluminium (Al) and the degradation properties of plastic polymers. The polymers degradation can be determined by measuring the viscosity of the melted plastic wastes. A degraded plastic waste is assumed to have a lower viscosity value due to its weakened chemical bonding in the polymers. The melt flow index for the polymers is in the range of 3 – 19 g/10 min – based on the samples in Danish plastic recycling plants (Eriksen et al., 2018).

Table 2: Dataset containing the properties of the plastic wastes streams in this case study. The metals contamination is obtained from Eriksen et al. (2018), and the degradation properties are estimated using the ranges of measured data from Eriksen et al. (2019). rIW: Reprocessed Industrial waste, rHHW: Reprocessed Household waste

Type	Polymer	Al Metal Concentration (ppm)	Degradation properties
			Melt flow index (g/10 min)
rHHW	PE	80.8	5.16
rHHW	PE	224	2.39
waste	PE	444	4.03
waste	PE	290	1.75
waste	PE	183	1.29
waste	PE	354	1.75
waste	PE	160	4.52
waste	PE	178	5.17
waste	PE	241	5.05
waste	PE	237	0.18
waste	PE	59.3	6.74
waste	PE	273	7.66
virgin	PE	28.4	8.12
virgin	PE	28.4	8.03
virgin	PE	28.4	8.77
rIW	PE	28.4	4.78
rIW	PE	12	1.08
rIW	PE	213	3.67
rIW	PE	122	1.72
rIW	PE	470	5.70
rIW	PE	145	1.94
rHHW	PE	345	5.26
virgin	PE	75.5	8.78
rIW	PE	118	5.68
rIW	PE	117	6.32
rIW	PE	28.4	0.49
virgin	PE	32.5	8.47
virgin	PE	85.4	7.90
virgin	PE	133	8.87
virgin	PE	108	8.92
rIW	PE	91.3	4.46
rIW	PE	147	5.15
rHHW	PE	195	4.22
rHHW	PE	272	5.51

Table 2 presents the illustrative dataset for PE polymer types that can be sampled from the plastic recycling system shown in Figure 1. The origins of the polymer are assumed to directly reflect the recyclability of the polymers. The virgin polymer samples have the highest recyclability, and the reprocessed streams are assumed to have medium recyclability, while the waste polymers streams have the lowest recyclability.
The open-source Python software (VanderPlas, 2016) with scikit-learn packages was used to apply the classification models to the dataset. The classification is obtained for each polymer type. For PE polymers, the Random Forest algorithm yields better accuracy than the Decision Tree method. Figure 3 illustrates the decision process with resulting 85.7 % accuracy. The confusion matrix is presented in Table 3. It shows the testing dataset is mostly correctly classified to the correct class, which only 1 ‘Household’ sample is classified to ‘Waste’ class. The top block represents the root node that has the split that yields the highest information gain, i.e. MFI $\leq$ 7.11 g/10 min. The left-branching (arrow) indicates this condition is fulfilled, while the right-branching (arrow) indicates the condition is not met. The blocks with no branching represent the leaf nodes and are the final

classification results that have zero entropies. For example, if a data sample has MFI ≥ 7.11 g/10 min, then the sample is classified as ‘Virgin’, which belongs to the highest recyclability class.

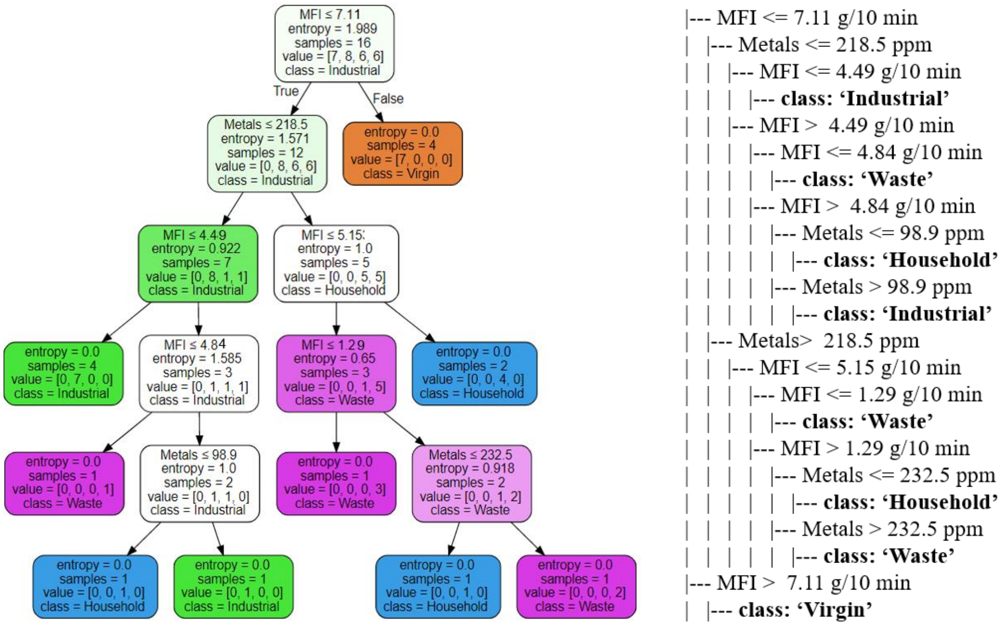

Figure 3: Decision tree obtained for PE polymers using Random Forest Algorithm (Test size = 0.2, random state =25, number of trees = 100). Accuracy is 85.7 %

Table 3: Confusion matrix of the classification model

Classes	Virgin	Industrial	Household	Waste
Virgin	2	0	0	0
Industrial	0	1	0	0
Household	0	0	0	0
Waste	0	0	1	3

Interpreting the decision rules from Figure 3, it seems that MFI is the key property that dominates the plastic waste categorisation. Higher MFI indicates the plastic wastes have better recyclability. It also can be observed in the dataset that metal contamination in virgin plastics is generally lower than the other types. ‘Industrial’ waste has lower MFI that classify them directly to the correct class (MFI ≤ 4.49 g/10 min), and compared to ‘Household’ waste, it has higher Al metal concentration (98.9 ppm ≤Metals ≤ 218.5 ppm, when MFI ≤ 4.49 g/10 min). However, only one sample in each ‘Industrial’ and ‘Household’ class are classified to this rule, and this rule requires further validation.

When the condition (Metals ≤ 218.5 ppm and 5.15 g/10 min ≤MFI ≤ 7.11 g/10 min) is met, the waste samples are directly assigned to the class ‘Household’. This suggests that the degradation in household plastic waste is milder as compared to industrial waste. This might be due to the thermal degradation of the industrial wastes during reprocessing. For ‘Waste’ samples, they have been classified when MFI ≤ 1.29 g/10 min and Metals ≥ 218.5 ppm, which indicates the waste streams that are highly contaminated with Al metal and degraded. When MFI ≥ 1.29 g/10 min, the data samples also show that ‘Household’ plastic wastes have lower metals concentration than ‘Waste’ (218.5 ppm ≤ Metals ≤ 232.5 ppm).

5. Conclusion

This work has presented a possible quantitative framework for defining the recyclability of the plastic waste streams that could facilitate a more accurate and informed recycling planning. The data for various polymers types can be sampled from different origins in the plastic value chain, including the virgin plastic stream, industrial or household wastes or landfilled wastes. The measurable data on the plastic waste properties can be used as the plastic waste categorisation using interpretable Machine Learning methods, which are responsible for identifying the threshold values for each property. An illustrative case study on PE polymer is used to demonstrate how the plastic waste can be categorised using the proposed method, and considerable high accuracy (85.7 %) is achieved. However, the main limitation is that the available data sample is too low (only 34 samples), for which the final categorisation rules could not be generalised for any PE polymer waste. This suggests that more data is needed, and the problem of a low dataset should be solved. Future works could include practical issues such as imbalanced class dataset, data uncertainties, more properties and heterogeneity of the polymers streams should be incorporated as well.

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