A circularity accounting model for CO2: Artificial neural networks for estimating CO2 values in observation of planetary boundaries.

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Abstract

This paper explores the relevance of individual-based accountings in the operationalization of circular economy. It argues that to move toward a more sustainable way of consumption and production, it is necessary to develop individual-based accounting that can effectively track the environmental impact (in terms of CO2) of products and their alternatives. This may empower people by enabling more environmentally-aware decision-making. The study presents a proposal for the development and operationalization of a specific individual-based accounting model: the circularity accounting model. To that end, we methodologically explore the applicability of artificial neural networks in the development of a CO2 estimator and a CO2 production-consumption chain predictor, in order to re-assess the use of CO2 across global supply chains. Prior literature has pointed to the need for the advancement, development and operationalization of the circular economy. We present the potential of individual-based accounting as a means to achieving that goal under the lens of Latour views on promoting individual empowerment and action. In the view that the rise in CO2 emissions has been exponential, we engage the exponential growth of artificial intelligence models to work in concert with individual action, mediated by the circularity accounting model. A model architecture is developed and applied to a case study that involves measuring the movement toward CO2-related planetary boundaries, for one serving of breakfast in the UK.

Keywords: circular economy; climate change; artificial neural networks; individual based accountings, sustainability accounting.

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1. Introduction

In recent years it has become clear that excessive use of natural resources, the degradation of biosphere integrity and climate change are among the reasons why we urgently need to change patterns of production and consumption. Aware of planetary boundaries, the European Commission has recently published the EU Green Deal (European Commission, 2019) addressing the development of innovative research to foster the transition toward more sustainable ways of consumption and production. This proposal reiterates the importance attributed by the European Commission (European Commission, 2014; Schulze, 2016) to the use of the circular economy (CE) as a tool to guide the sustainable transition of all sectors.

The CE is widely recognized as a valuable alternative to the prevailing linear model and as a path forward (Ellen MacArthur Foundation, 2015a, 2015b; European Commission, 2020, 2015; Ogunmakinde, 2019). There is growing body of academic research on the CE, both at the macroeconomic level (Ghisellini et al., 2016; Kirchherr et al., 2017; Korhonen et al., 2018; Merli et al., 2018; Pomponi & Moncaster, 2017; Prieto-Sandoval et al., 2018; Urbinati et al., 2017) and the microeconomic level (ArandaUson et al., 2019; Katz Gerro & Lopez Sintas, 2019; Lewandowski, 2016), with scholars studying the role of firms in the development of the CE. To measure its introduction at the microeconomic level, specific approaches have been applied to products (De los Rios & Charnley, 2017; Di Maio & Rem, 2015; Linder et al., 2017; Niero & Kalbar, 2019) and consumers (Borrello et al., 2017). However, the study of the accounting implications of the CE is still in its early stages and the measurement of the scope of the CE from a sustainability accounting perspective remains underexplored (Rossi et al., 2020; Scarpellini et al., 2020). As such, there is a need for the accounting literature (Bebbington & Unerman, 2018) to include the CE in the research agenda. The majority of studies involving specific CE indicators have focused on end-of-life strategies (Di Maio & Rem, 2015), and eco-efficiency (Figge et al., 2018; Laner et al., 2017; Zhou et al.,

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2017) instead of environmental (Huysman et al., 2017), social (Geng et al., 2012) and overall sustainability (Corona et al., 2019). This is especially concerning, given that it has been noted that CE projects and processes need to be carefully analysed to improve global environmental sustainability performance (Korhonen et al., 2018).

Moreover, many of the existing indicators (and in general the models and approaches) proposed for a CE lack the computational tools needed to facilitate calculations, a practical interface for calculation, and examples for practical application (Rossi et al., 2020). In that respect, Jose et al. (2020) highlights the need for applications based on artificial intelligence (such as data mining, artificial neural networks) to help advance CE ideas, given their superior data processing capability. Against this background, this paper mobilizes ideas relating to planetary boundaries and Latour's practical "dis-hoping" (Latour, 2017) in order to develop an accounting model through the application of artificial neural networks. The proposed model advances CE assessment from a planetary boundaries accounting perspective. In so doing, the paper highlights the pivotal role of individuals in the fight against climate change. Individuals (among others, consumers) have agency to intervene in the course of social action. In that respect, York et al. (2021) explain that individual action and individual decisions (e.g., consumers' choices) are key to fostering the collective action needed for society to tackle compelling and complex sustainability challenges, such as climate change (see also United Nations Intergovernmental Panel on Climate Change reports[1] for further discussion). Indeed, some accounting researchers (Rodrigue & Romi, 2021) have pointed out that individuals can use their agency to act as a catalyst for the transformation needed to reduce CO2 emissions, which are one of the main drivers of climate change and have already exceeded some critical limits (Rockström et al., 2009). The literature presented in this introduction reveals that the indicators proposed to date do not provide information for sustainability accounting, or

[1] See https://www.ipcc.ch/

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describe the actual cost of material loop-closing. We take into consideration that some CE principles are not exclusively related to profitability criteria, as argued by Azevedo et al. (2017). Thus, it seems worthwhile to develop a circularity accounting model (CAM) that can turn individuals into active agents involved in measuring the CO2 in products they consume.

The contribution of this paper is threefold. First, it delves into the debate about the role of individual-based accounting in the operationalization of the CE, taking into account planetary boundaries (Rockström et al., 2009). Drawing on the concept of dis-hoping, we propose that individual-based accounting models, such as CAM, can play an active role in enabling improved decision making, and have the potential to become catalysts for environmental transformation (Rodrigue & Romi, 2021). As such, this study is aimed at exploring new perspectives to resolve the anthropogenic impact of economic systems on the natural environment (Bebbington et al., 2007; Bebbington & Larrinaga, 2014; Russell & Thomson, 2009; Fritz et al., 2016).

Second, this study develops and applies a case study of a CAM, expanding the scope of the CE from a sustainability accounting perspective (Rossi et al., 2020; Scarpellini et al., 2020), particularly in terms of stages at the microeconomic level, such as inputs, production, distribution, use and end-of-life (Schaltegger & Csutora, 2012), which are still underexplored from an accounting standpoint.

Third, by applying artificial neural networks to operationalize the CAM, this research opens up new avenues for bridging the gap between disciplines (see Bebbington & Larrinaga, 2014), fostering transdisciplinary perspectives. Diverse competences are needed to effectively address the compelling and complex sustainability challenges that society faces (von Wehrden et al., 2019). The paper explores the application of artificial neural networks in the development of a CAM to frame accounting within planetary boundaries (Rockström et al., 2009),

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overcoming some of the shortcomings in ecological literacy and accounting (Whiteman et al., 2013).

The remainder of this paper is organized as follows: Section two outlines the theoretical basis of the study. Section three describes the architecture of the CAM. Section four presents the application of the CAM with a case study of breakfast cereal. Section five contains a discussion and concluding remarks.

2. The power of individual-based accounting to counter climate change

The presentation of the theoretical framework underpinning this study is organized into two subsections. The first subsection explores the relevance of individual-based accounting under the lens of promoting individual empowerment and action as a potential tool to solve climate change (Latour, 2017). This subsection introduces the concept of agency (human, machines and non-human agency) and its link to individual action. The second subsection hypothesizes that said agency and the leverage gained from the interaction between human, machine and non-human agency could be not only part of the anthropogenic cause of climate change but also part of the solution.

2.1 Dis-hoping and individual-based accounting

The relevance of individual action in finding a solution to climate change has been explored by many notable voices. Latour argued that a solution will come through action and not merely hoping for an instant solution (Latour, 2017). In his call for people to dis-hope, Latour proposes that individuals' actions are an essential part of the solution, arguing that their agency allows them to intervene in the course of social action such as the process to mitigate climate change.

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The concept of agency has been widely discussed in different fields (e.g., Giddens, 1984; Latour, 2017; Moravec, 1999; Nyholm, 2017; Wiener, 1961) and there is not a single approach to the concept of agency that is uniformly accepted among disciplines. Nevertheless, there is a relatively high level of agreement regarding the agency of decision making at the level of on/off or stop/go[2] , where agency can be described as the capacity for self-guided action. For example, a bacteria is self-guided, as is a computerized oil well or the movement of a robot. These are all agents, producing action from decisions. The only decision a simple oil well makes is perhaps to remain on or turn off, while a robot may make millions of different decisions each second. The literature distinguishes between three types of agency: human, machine and non-human (Contesse et al. 2021; Islam et al., 2019; Latour, 2014; for a critique see Králové, 1921).

Regarding climate change, if we expect humans (individuals) to take action against climate change, they must be provided with the necessary tools; namely, “instruments capable of tracing the loops that make the least of our actions react in response to its causes” (Latour, 2017, p. 252). As we approach limits of human cognitive and information acquisition capacity in contemporary environments, human agency alone cannot improve decision-making without additional information instruments or tools. Individual-based accounting with the application of non-human agency has the potential to provide with useful information to expose the environmental impact of alternative choices. Individual-based accounting can play an active role in enabling improved decision-making, and has the potential to become a catalyst for environmental transformation (Rodrigue & Romi, 2021). This is aligned with new research viewing accounting as an instrument that can raise the visibility of and accountability for

[2] Let us assume decisions measured in computational complexity (Bachmann, 1894), that objects are separable, and that decisions made by objects are equivalent at the Landauer limit (Landauer, 1961), measurable in units of physical action (information to mass: Herrera, 2014; entropy reduction to action: Brillouin, 1953).

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specific issues by creating new practices and evaluation instruments (e.g., Millo & MacKenzie, 2009; Revellino & Mouritsen, 2015). New accounting practices may play a mediating role in the implementation of sustainability and CE practices (Miller & O'Leary, 2007), for example in the United Nations Sustainable Development Goals (SDGs) (Bebbington & Larrinaga, 2014; Bebbington & Unerman, 2018). There are already some individual-based accounting initiatives being carried out by corporations (Patagonia[3], for further explanation: Rodrigue & Romi, 2021), as well as by national governments (Zero Waste Scotland, 2019-2021[4]) and transnational institutions (zero tolerance regime for unauthorised genetically modified crops, European Commission, 2011: European Commission Regulation (EU) 619/2011). In this regard, keystone actors such as corporations are needed to bring about an environmental transformation (Bebbington et al., 2019) because of their huge impact in terms of global emissions (Ekwurzel et al., 2017; Griffin & Heede, 2017; Heede, 2019), nevertheless individual action takes on a pivotal role in catalysing said environmental transformation (Latour, 2017). Clearly corporations would not survive if individuals stopped buying their products. Furthermore, action from individuals does not imply inaction from corporations; on the contrary, they are complementary (Berkes & Ross, 2013). This complementarity between the new forms of individual-based accounting carried out at different levels (corporate, individual, national) can be leveraged by the interaction between human, machine and non-human agency.

2.2. Recursive increase in the speed of exercising agency and individual-based accounting

Human agency (HA) is characterized by a natural physical limit that is slower than machine (MA) and non-human agency (Aur & Jog, 2007; Sabatini et al. 1999). While agency has been almost exclusively human in past centuries, machines are now complex enough to be capable

[3] See https://www.patagonia.com/home/
[4] See https://circulartayside.co.uk/zero-waste-scotlands-corporate-plan-2019-2023/

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of exercising a category of agency (Calvano et al. 2020). Such machines (including computers) can operate in a vast array of different domains: manufacturing, space, social media engines or in a national tax department. We can categorize the agency exercised through artificial neural networks as a type of non-human agency (NHA). With artificial neural networks (Jose et al., 2020), machines can accomplish many tasks which previously were performed only by humans: writing books, driving vehicles, managing accounting records. Its faster speed (actions per unit time (actions per unit time[5]) means that NHA has the potential to be stronger than both HA and MA when connected to systems which large action potentials. This is exemplified in the 2010 'flash crash' of the S&P 500 stock index futures market in the United States (Kirilenko et al., 2017), apparently caused by automatic trading systems. The activity of NHA may more quickly enable the creation of more NHA (Jin et al., 2020). For example, more mining allows more robots to be built, robots help assemble robots, and artificial neural networks may train artificial neural networks (Zhang et al. 2019). When successful, such agency can be recursive.

We propose that the recursive increases in the speed of exercising agency which enabled the physical impacts of the advanced production systems that characterize the Anthropocene era (Levy & Egan, 2003) can also be used to counteract those impacts.

Figure 1 shows a trend of increasing CO2 emissions measured in parts-per-million (PPM), through several eras of agency depicted on a horizontal time axis. HA, MA, and NHA eras are drawn as approximate lines to show economic progression. A polynomial curve is fitted (Nordebo et al., 2020) to CO2 concentration data[6] from 1958 to 2020. The curve is

[5] measuring action as $h\nu \geqslant kT$, the output energy resulting from a decision which provides entropy reduction greater than $\Delta S = k \ln 2$ (Brillouin., 1953, eq. 29). h Planck, and k Boltzmann constants, v is quanta.
[6] CO2 PPM data is a set of monthly averages of CO2 measurements made at Mauna Loa Observatory, with one year containing 12 data points. Data begin from the 'Keeling curve', 1958 to 1974 (Keeling, 1974). After 1973, the data are from NOAA (2020). The curve is fitted as y=9.041-5 x2 + 0.00637 x + 314.53.

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extended on this plot until the year 2105. A grey bar marks the approximate location of a 1°C temperature anomaly (measured at 0.98°C in 2020; see NOAA, 2020), this temperature change is related with the planetary boundary of climate change, and correlated with the extinction of fauna species (Song et al., 2021). For context, in this simplified diagram the curve is marked with a CO2 PPM value of 600 around the year 2065, while the literature suggests some future scenarios of 600 PPM around 2075 (IPCC, 2000; 2001).

[Insert FIGURE 1 near here]

Caption

Figure 1. Eras plotted with atmospheric CO2 concentrations based on a polynomial curve fitted to data from 1958-2020 and extended past the year 2080.

Figure 1 depicts several economic eras, where an increase in the speed of agency is followed in each subsequent era by an increase in CO2 concentrations. CO2 concentrations coincident with human economic activity are plotted, and indications of planetary physical boundaries at the temperature threshold of 1°C are shown. The relationship we wish to present is the correlation between NHA activity and the increase in CO2 concentration. The first period covers a time when economic activity was primarily driven by HA and ends approximately with the steam age. The second period shows the beginning of the measurement of CO2 concentration and roughly coincides with the age of automobiles, when MA was integrated strongly into economic activity, amplifying human activity. The most recent period, which shows the arrival of NHA, is drawn when NHA actions were measured to have large economic impacts. We draw it around the era of networked computers. Through the second and third eras depicted, the increase in CO2 emissions becomes clearly exponential. Over this period, the

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digitization of economies has played a relevant role in increasing the speed of monetary flows, which became faster than physical flows (e.g., Leblanc 1990). Figure 1 depicts CO2 values over the course of the industrialization of economies in the 20th century, which may support the premise that faster economic systems produce CO2 at a higher rate[7].

At present, the financial economy, which is expressed in transactions of monetary units, and the physical economy, measured in movements of mass, can differ in size by orders of magnitude. The barriers imposed by the limited speed and volume of physical money were removed when money became encoded in electrons and photons as digital rather than a physical mass such as coins or paper (Leblanc, 1990). In today's economies the physical, operated via HA and MA, and the financial, operated via NHA, may be orders of magnitude different in terms of speed (see footnote 5). Here we can posit a central hypothesis: when faster economic activity causes a corresponding increase in a quantity of a physical activity, the speed of movement toward physical boundary conditions, thus planetary boundaries, may be increased.

Humans and machines have different boundary conditions; accordingly, economies based on HA, MA, or NHA activity have different speeds and capacities. The theoretical speed limits for machines (Prokopenko et al., 2014) are found in the quantum regime while milliseconds is standard for HA (the speed of neurons, Sabatini et al., 1999). The boundary conditions which concern HA are not the same boundaries which affect MA or NHA. Contemporary NHA is insensitive to the biological boundary conditions of temperature and various contaminants that may affect and even jeopardize HA. This study gives a CO2-related planetary boundary a relevant role in NHA architecture.

[7] This trend was developed on CO2 emitting energy sources, drawing on Keeling (1974).

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When testing the hypothesis that an economy which operates at a faster speed may more quickly reach planetary boundaries related to CO_2, we find recursive patterns of increase in MA and NHA. As increase in the speed of economic action drives growth of NHA; NHA becomes iteratively more capable of refining or developing new NHA. We should thus seek to direct this recursive pattern to counteract the problem of rising CO_2 concentrations. In this study, individual-based accounting allows individuals to make decisions which reduce CO_2 footprints. This individual-based accounting is based in the interaction between HA and NHA, mediated by a CAM. In turn, the CAM is implemented though artificial neural network models, an NHA designed to invert the correlation between increases in CO_2 emissions and the increase in the speed of agency in economies.

We develop the CAM from the perspective that agendas of change are operationalized by exercising agency, regardless of scale (individual to government). In developing the model, we do not propose assigning agendas to particular actors; rather, to ensure the practicality of the implementation, this work is accessible online to all actors. Our focus is on the actors who may implement the estimator and activate the potential of their agency, rather than assigning responsibility. The problematic privilege of assigning responsibility for change agendas (reducing CO_2) to actors (individual people, corporations, government) may be avoided by developing the estimator as a tool accessible to any actor. In this paper, it is packaged for individual people considering the relevance of individual action and individual-based accounting. The development, training and use of artificial neural network models of CO_2 in objects can be operationalized through the action of individuals. Indeed, individuals, organizations or administrative bodies may contribute to or use models individually at the small scale, or in aggregate for inference at the big-data scale. This follows an established pattern of open-source software development, which spans the range from individual contributors to implementation and use of open-source tools in national and international organizations.

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Drawing on these ideas, the next section presents the CAM, an individual-based accounting model to measure circularity through the application of artificial neural networks. The CAM is targeted at helping individuals to recognize and assess the results of their actions, thereby enabling and encouraging individual engagement in dealing with climate change and planetary boundaries.

3. Circularity accounting model & architecture

In this section, the main features of the model and its implementation architecture are presented separately in two subsections. The first subsection details the main features of the model. In the second subsection, we introduce the architecture designed to operationalize the CAM through the application of artificial neural networks. The CAM provides CO2 estimates and circularity predictions for objects. Making this information available for individual decision-makers provides them with evidence on which to base decisions. In so doing, the CAM creates a link between CO2 values and decision-making behaviour.

3.1 Circularity accounting model

Atmospheric CO2 is a container for entropy from human activity in at least the thermodynamic regime. While directing energy toward a goal is a process that attracts the attention of economic agents, its thermodynamic dual, the dissipation of entropy, is also of concern to living creatures. Divestiture of entropy outward is limited in closed systems, as with gas pressure, for example, when entropy production is encumbered by a container (Clapeyron, 1842). Economic activity can be modelled from the same physical principles (Marchettini et al., 2006) as it approaches planetary boundaries.

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The CAM is an instrument for operationalizing the CE, implemented for CO2. Figure 2 shows a theoretical CAM diagram. The CAM diagram depicts a measurement of movement toward or away from planetary boundaries, as a gap between the beginning and end of the circumference. The CAM responds to the need for CE tools that can deal with thermodynamic limits and planetary boundaries (Korhonen et al., 2018).

In a theoretical scenario, levels of CO2 in the Earth's atmosphere present stimuli and limits to forms of activity which are affected at a certain concentration of CO2. Concentrations of CO2 can thus be seen as boundary conditions for activities, and the impact of such boundary conditions can be evaluated. CAM diagrams provide a means to describe the contribution of objects to the movement toward CO2-related planetary boundaries.

Considering the challenge of CO2 limits and the potential for individual reaction, the CAM measures the CO2 *circularity* of recognized objects, where a zero CO2 emissions object is circular.

From an accounting perspective, the model has the following characteristics: (i) In terms of capital to maintain and unit of measurement, it accounts for natural capital and uses the physical units of CO2 as the unit of measurement. In doing so, the CAM seeks to connect the data with the physical objects they proxy, instead of valuing all economic transactions according to market rules and in monetary units. If the accounting framework is to disclose the value of real flows of goods and services, the measuring system must be founded on physical flows of goods and services and not on their financial or monetary interpretation. (ii) In terms of scope of measurement, it encompasses both direct (scope 1) and indirect impacts (scopes 2, 3), as in the greenhouse gas (GHG) protocol (Word Resources Institute, 2004), and includes the stages of inputs, production, distribution, use and end-of-life (Schaltegger & Csutora, 2012). Additionally, the CAM is designed to measure both the emissions and sequestrations of

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these stages. (iii) Regarding the users of the information, the model operates through the combination of human agency and the NHA of artificial neural networks. The model outputs provide people with information enabling their cognitive processes and decision-making. As a source of information, the CAM has social agency. The goal is to provide humans with an NHA tool to support decision-making about objects which make up CO2 production-disposal chains.

[Insert FIGURE 2 near here]

Caption

Figure 2. Diagram of the CAM.

The heavy black circular line represents a cycle starting at a time = 0 point. The CO2 values along a production-to-disposal carbon chain are plotted in a counter-clockwise circular form, ending at disposal of the object. Positions (orange and green dots) A_1, A_2, … A_n , B_1, B_2, ... B_n represent measurements of CO2 values within the production segments, while points C_1, C_2, ... C_n and D_1, D_2, ... D_n represent measurements made in consumption and disposal.

The graph is segmented into named regions. We take four segments of the CO2 chain, *ABCD*. *A* plots the CO2 value of inputs and production; *B* plots the CO2 value of distribution; *C* plots the CO2 value of use, and *D* plots the CO2 value of end-of-life including waste management. The circle is divided in two regions: the left side, $A + B$, represents the production side, while the right side, $C + D$, represents the consumption side of the CO2 chain.

At each measurement in the chain, emissions are plotted as positive (outward) and sequestrations as negative (inward) in a counter-clockwise circular form. The diagram represents one *ABCD* cycle for one object and the 0 point represents both the beginning and end of the cycle. A theoretical object that has the same total of emissions and sequestrations along its cycle would be plotted as a closed form. In contrast, a manufactured product will have

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a variance from zero along its cycle as emissions or sequestrations in its chain, and so produced objects will end on a non-zero value. As non-zero endpoints result in a broken circle, through repetitions of cycles the diagram will display a spiral shape (see *Figure 4* in section 4). Variance from circularity may be measured as entropy introduced into the CO2 chain. The entropy of the chain is a measure of the chain's CO2 interaction with its surrounding environment. For objects, a life cycle inventory (e.g., Thomassen et al., 2008) can tell the story of their production and materials. It can also tell the story of their disposal. The process of reorganizing parts to create an object often involves chemical reactions; we might then look to simulations of chemical reactions for tools and make use of techniques employed in such simulations (Higham, 2008). The model of an object varies over the span of production, and we can identify the object only at measurable moments t. The measurements at a moment in time $t = 0$, $t = 1$, … can model an object in a simple way. We organize them as list, and this is a vector x of values, which we write as a state vector $x(t) = [\ x^1(t), x^2(t), \dots x^n(t)\ ]$; the length of x grows with the quantity of measurements of the object at t, which are stored as image files. In *Figure 2*, the positions marked with orange and green dots indicate the measured CO2 values in a production-disposal chain. We encode the CO2 values as a row vector named the *consumption vector* of the object. An object's CO2 impact is the sum of all values in the vector. Individual and aggregate CO2 consumption vectors are learned by modular artificial neural networks.

3.2 Architecture of the CO2 estimator: a modular structure to implement CAM with artificial neural networks

The CAM is implemented by a CO2 estimator, a CO2 chain predictor using a neural network architecture, and a database. From the recursive increase in the speed of agency which machine learning provides, the CAM also may also benefit from an increase in its speed and capacity.

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The artificial neural networks of the architecture are a perceptual tool to help individuals gain information that is not otherwise accessible. Reorganizing the networks into a different implementation may change their measurable strength of agency (section 2.1), as determined by the strength of their output action. The CO2 estimator performs carbon emission-sequestration estimation using neural network models in a process of: (i) building and training models of objects (such as products), (ii) obtaining their CO2 sequestration value from existing reports, and (iii) connecting models together. The first two items in this process require human involvement to acquire samples of data, such as visual images or video of the object to be estimated, and to assign CO2 values to the objects. In this way, consumers are no longer passive stakeholders but can also be part of the production of information. After acquiring sufficient training data and performing the training, the neural networks learn to make inferences about novel input, and become iteratively less dependent on new information. The outputs of the model provide feedback to consumers, giving them information on which to base their thought processes. The estimator is a software tool that takes sensor input data and processes it though an artificial neural network. The result is a classification of the object found in the data, into a category, which describes its CO2 value. The category is retrieved from a database that lists known objects, and each object is recognizable by a neural network which has been trained to recognize the object from its data. The CO2 chain of the object is then predicted.

In developing the CO2 estimator, we undertake an investigation into defining objects as an encoding in artificial neural networks, so that a network identifies objects and contains the definitive model of the object. Using neural network detectors for the definition of objects stands in contrast to previous approaches for defining objects, in which they are defined in terms of language, and entail human agency where a person physically creates a definition of an object, or through a social or legal framework that is enforced by human agency. For example, writing a label on a product. The CO2 estimator models the CO2 of things, acting to

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classify from observer independent definitions of objects which do not require the continuous intervention of human or social agency.

Artificial neural networks which can successfully detect, recognize, and describe real world objects, locations and features model a neural network information processor. The successful process will result in the detection or recognition of objects or features, from incoming data.

[Insert FIGURE 3 near here]

Caption

Figure 3. Architecture of the CO2 estimator.

The CO2 estimator and CO2 chain predictor architecture (Figure 3) is built from three modules. We use an ensemble of different detectors and recognizers to obtain an identity for an object, and a separate group of models to convert the identified object to its CO2 consumption vector. This allows a modular structure so that models can be changed without affecting the architecture while it is in use.

1. An object classifier detects, recognizes and classifies objects (*Figure 3a* to *3d*). Video and image data (*Figure 3.a*) are used to train single-shot-detector (SSD) models and autoencoder models. The models are trained on wavelength (colour), spatial structure, and other features. Networks may also learn from features such as audio, or spatial position and environment. CO2 sequestration of detected objects is computed by matching the detected objects with a database of reported data for products and reported physical estimates. For this task, a general *ImageNet* image classifier (*Figure 3.b*) is used to select appropriate SSD models *Figure 3.c*). The image is passed to the class of autoencoder models (*Figure 3.d*), one of which may encode the definitive model of the object perceived in the incoming image data. Objects to be analysed are sensed through

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video that is broken into images, each of which is treated as a multidimensional surface of data mapped to a matrix. An object is a set of data for which an agenda for investigation is followed in an architecture of detectors and classifiers, and a specialized recognizer. Popular model architectures in the last decade include those trained on ImageNet (Deng et al., 2010), which classifies incoming images; SSD (Liu et al., 2016), which detects objects in incoming images; and autoencoders (Li et al., 2019; Nourmohammadi-Khiarak et al., 2018; Sundermeyer et al., 2018), which can recognize the visual details of objects.

2. An *object database* lists CO2 values for objects that may be detected (*Figure 3.e*). A database module acting as a library contains CO2-sequestration data for classes of objects (*Figure 3.e*). This database allows public contribution of the CO2 values for objects; thus, consumers are no longer passive stakeholders but can be part of the production of information. This carbon cost data may be learned by the models (*Figure 3.d*) and obviate a database. Disuse of a database will lead to a more autonomous system, at the cost of removing an important avenue for participating in the action of the system.

The database connects object identity, data about the object, and models which encode the object's details. Its function is to connect an object detected by a network to its CO2 value and related data. The database is an information-processing structure, and an entry point for community participation in developing CO2 consumption vectors for objects.

Incoming classified objects are represented by symbols, and these symbols are used to identify the object through all the processes in the architecture, and as labels for the position of the object in CO2 chains. The database stores and encodes a limited universe of symbols, which represent objects and production-consumption chains. The data in the database can be deterministically input and edited by participants. The limited domain of the database allows

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the architecture to accomplish the mapping of a source object to a target CO2 chain. The CO2 chain predictor is trained using these data. The deterministic mapping in the database is unlike the detector and CO2 chain models, which are trained on its data and then operate through probabilistic inference.

3. A *CO2 chain predictor* lists the CO2 contributions in the production and disposal chain for an object. (*Figure 3.f &g*)**.** Modelling or predicting a supply and disposal chain from sparse samples (a sample of one object) requires a pre-existing model of the chain, which we build from reported descriptions of the chain. Prediction of precedence and subsequence in symbol sequences are supported by research in generative and translational neural network models such as seq2seq (Sutskever, 2014) and transformer models (Vaswani et al., 2017).

We use seq2seq to provide the estimator with a means to encode supply-disposal chains (*Figure 3.g*) and to predict more complete chains from single samples (single positions in the chain). seq2seq is more generally known for its use in neural machine translation (Britz et al., 2017). The task of predicting CO2 chains is similar to translating between languages: both tasks require two sets of nodes, for which the connections between the nodes are learned for each group, and then mapped. We are interested in finding the (non-branching) vector which describes the CO2 values for the production-disposal sequence. This process begins with a tree graph, which should be reduced to 0 branches, and pruning the possibilities to one per step creates the linear sequence that is our CO2 consumption vector.

The use of artificial neural networks to assist analysis or action on atmospheric CO2 is a topic that has received a great deal of attention in recent years. Research has focused on issues such as carbon capture (Chan & Chan, 2017; Rahimi et al., 2021; Sipöcz et al., 2011), sequestration (CO2 storage: Koperna et al., 2020; soil: Cheshmberah et al., 2020; saline

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aquifers: Song et al., 2020; oil recovery: Thanh et al., 2020), and emission prediction (Jin, 2021). This is a first attempt to use the present approach and architecture to operationalize an individual-based accounting model to improve consumers' decision-making. This architecture gives information about CO2 values which may influence people's cognitive and behavioural processes. Harnessing human agency in participation may endow the technical implementation with social agency, and the participatory aspect transforms passive users of information into participants and providers of data.

4. Case study of an application of CAM: One serving of breakfast in the UK

A case study of an application of the CAM is organized into two subsections. The first subsection presents the application of the CAM to one serving of breakfast cereals in UK. In the second subsection, we introduce the architecture needed to operationalize the CAM with real data from the case study.

The CAM is implemented in an architecture of artificial neural networks, which after training, does not require human intervention for operation. It predicts the value of CO2 from objects and with training can learn to make increasingly accurate predictions and broaden its scope to new types of input. The initial training stage of a network is usually the organization and curation of training data. The data in this case study was deterministically input by two participants of the research team. For small datasets, the network quickly learns the data exactly and enters a local minima. With tiny datasets, it is necessary to train the network with every permutation to obtain the capability to produce a complete prediction of the CO2 consumption vector from a complete production-disposal dataset. With a larger training set, the object detector and CO2 chain predictor will make inferences from the training data. An alpha stage interface to contribute training data is at entropynetwork.com/circularity.

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4.1 The CAM of breakfast cereal: Comparison between two products

The case study was applied to one serving of breakfast cereals in the UK. We obtained the preliminary CO2 data to train the artificial neural networks from the CCaLC project (2021). This project contains the CO2 footprint data of a vast array of products for the stages of materials, energy, transport, packaging, and waste. We selected the *Food and Drink* section, which is a macro-scale analysis of food and drink systems in the UK, to identify carbon footprints in supply chains. We selected the two sets of "Breakfast cereal" which provided the most comprehensive data to use in this example. The two sets are *cereal with milk* and *cereal without milk*. Their supply chains include stages of raw material processing, food and drink production, storage, consumption, transport and waste management. The main raw materials are corn grain, malted barley, milk, corn syrup, sodium chloride and sugar. The CCaLC data is measured in functional units of kg, while the CAM (estimator and CO2 chain predictor) is trained with expected standard units and sizes: one serving of breakfast cereal (with milk) is 37 grams (SmartLabel, 2021), the estimator must multiply this value by the functional unit. Other sizes and units can be trained as required, and a more developed estimator should provide an indication of the quantity present.

We refer to the breakfast cereal with milk as "BC_milk" and to breakfast cereal without milk as "BC_nomilk". Milk refers to semi-skimmed cow milk.

[Insert FIGURE 4 near here]

Caption

Figure 4. CAM with data from BC_milk and BC_nomilk.

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All figures are expressed in kg CO2. The first measurement in the inputs stage is 6.62 for BC_milk and 0.46 for BC_nomilk. In the subsequent stages of production, storage, use, transport (transport in several points of the supply chain) and waste production BC_milk has [0.21, 1.03, 0.03, 0.09, 0, 0.44, 0.04, 0] whereas BC_nomilk has [0.11, 1.03, 0.03, 0.09, 0, 0.44, 0.04, 0]. At the end of one cycle, the estimator output for BC_milk is 8.46 kg CO2, and 2.20 kg CO2 for BC_nomilk (see appendix 1 for further details). This final total is the sum of all measurements in the CO2 chain. Given that the information in the database was expressed in kgs, these figures must be multiplied by the serving size of 37 grams. After this calculation, each serving of cereal with milk moves 0.31302 kg CO2 toward planetary boundaries, and 0.0814 kg CO2 for cereals without milk. In other words, cereals with milk represent an environmental burden that is 284% greater than that of cereals without milk. Circularity is 0 emissions. A closed loop is not necessarily circular. A closed loop can have 0 net emissions but not have 0 emissions/sequestrations along the cycle. Anything that is not 0 emissions will draw a spiral. In our case study, both options are broken circles tending to a spiral; however, cereal without milk is a better choice from a CO2 boundary perspective.

4.2 Details of the estimation for BC_milk and BC_nomilk

We obtained CO2 data for production-disposal chains from the CCaLC project (2021) and made predictions of the CO2 consumption vector for two objects. The first prediction is shown in detail in Figure 5. (*5.f*) shows a consumption vector of CO2 values, while below it is a beam search graph. In this graph, the first line below each circle is the CO2 label then the node number, and the second line is the mean error. (*5.g*) sums the CO2 consumption vector.

[Insert FIGURE 5 near here]

Caption

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Figure 5. Detection and prediction.

4.2.1 Object classifier

Video images were acquired from a video stream captured on a mobile phone. ImageNet detected class *n02998003*, which was matched to database symbol *storage1_breakfast-with-milk*, and no further recognition was undertaken. This symbol was added to a session record. The next data frames were skipped. ImageNet then detected class *n02997910*, which was matched to symbol *use1_breakfast-with-milk*, and no further recognition was undertaken.

A refined autoencoder for specific or exact objects could be used as a final classification stage but was not needed for BC_milk/nomilk. We trained SSD models to detect particular classes from images that we collected in the field. However, a detector trained generally, for example on MSCOCO (Lin et al., 2014) or other datasets, could be helpful for coverage of other objects.

4.2.2 Object database

The symbol *use1_breakfast-with-milk* is an entry in a database, which allows detected objects to be linked to positions in CO2 chains. The symbol is stored in the database with its CO2 chain as a graph. During preparation and training, the CO2 chains for BC_milk and BC_nomilk were given as training data to seq2seq models, which learned the chains.

4.2.3 CO2 chain predictor

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On prompting the models with the detected object *use1_breakfast-with-milk*, the forward and backward production chain sequences were recovered, and their corresponding CO2 chain was inferred by the seq2seq model. *use1_breakfast-with-milk* was found to have a CO2 value of 0.44 kg CO2 at position 7 in its chain. The entire CO2 chain was then inferred as [6.62, 0.21, 1.03, 0.03, 0.09, 0, 0.44, 0.04, 0]. The precision in this test case is only 2 significant figures after the decimal due to training data input; however, the model may express an arbitrary quantity of significant figures.

With training on additional object data and CO2 chains, we can present other breakfast cereals or other objects to the estimator to infer a chain of CO2 values (of input *A,* through *BCD* disposal) showing deviation from circularity.

5. Concluding remarks

The paper discusses the need for individual-based accounting and presents an individual accounting model. A review of the literature suggests that environmental accounting is still underdeveloped when it comes to operationalizing the CE. Current operationalization initiatives have focused on end-of-life strategies (Di Maio & Rem, 2015), and eco-efficiency (Laner et al., 2017; Zhou et al., 2017) instead of environmental (Huysman et al., 2017) and social aspects (Geng et al., 2012).

From a theoretical standpoint, this paper explores the relevance of individual-based accounting as a tool in the fight against climate change. Based on Latour’s views on dis-hoping, we argue that in order to move towards a more sustainable way of consumption and production, individuals must be provided with tools to enable them to become active users of climate change information. In the implementation of CE practices, it is vital to provide individuals (e.g., consumers) with indicators that allow them to improve their decision-making (Rodrigue

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& Romi, 2021). In this regard, this paper proposes that the recursive increase in the speed of exercising agency of artificial neural networks could offer potential for operationalizing the individual-based accounting model, CAM, proposed in this paper.

From a practical standpoint, this paper proposes a novel perspective on the development of CAM, an individual-based accounting grounded in sustainability accounting. For example, it accounts for natural capital and takes physical units of CO2 as the unit of measurement, while its scope of measurement encompasses both direct (scope 1) and indirect impacts (scopes 2, 3) and includes the stages of inputs, production, distribution, use and end-of-life (Schaltegger & Csutora, 2012). The CAM is developed through the application of artificial neural networks. Thus, the proposed accounting model fosters the use of innovative technologies to value the secondary resources contained in waste streams. Through the development of the model and its operationalization, this study adds to previous literature (Rossi et al., 2020; Scarpellini et al., 2020), highlighting the need for analysis of the accounting implications of CE from an sustainability/environmental accounting perspective. In particular, it underscores the need to study micro-level indicators for the stages of inputs, production, distribution, use and end-of-life (Schaltegger & Csutora, 2012).

To illustrate the application of CAM with real data, it was applied to a case study measuring the movement toward CO2-related planetary boundaries, for one serving of breakfast cereals in the UK. By doing so, this study makes the application of an accounting perspective in the CE more accessible to society, and particularly to consumers.

Finally, it is worth highlighting the use of artificial intelligence to operationalize CAM, which encourages the essential interconnection of disciplines needed to resolve environmental issues (von Wehrden et al., 2019). The exchange of knowledge between multiple disciplines

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can generate fruitful conversations, helping to address shortcomings in ecological literacy and accounting (Whiteman et al., 2013).

The developments presented in this study have important implications for both consumers and policy-makers. The estimator represents an open tool that empowers consumers, so that they are not merely passive receivers of information but can also become providers of information to improve decision-making. Thus, the model can potentially function as a springboard for a transition to a circular economy, allowing consumers to demand products with a higher degree of circularity and encouraging manufacturers to engage in material recirculation activities. It also has potential utility as a key performance indicator for benchmarking and comparing products, companies and industries. To this end, a range of business stakeholders can leverage different types of resources with the aim of promoting circularity within the private sector (Geng et al. 2012). This model also has important implications for policy-makers, who find in the CE a way of tackling the current environmental crisis (European Commission, 2019). Hence, the proposed model provides a feasible tool for measuring circularity, which can help operationalize the CE from an accounting perspective.

To conclude, we hope that the evidence presented in this paper will encourage the accounting academia to conduct more research with a particular focus on linking accounting to CE. The CAM will be trained with different products in order to improve the reliability of the model and its adequacy for CE measurement. Collaborative research (Correa & Larrinaga, 2015) based on engaging a plurality of actors potentially related to the CAM (e.g., consumers, firms, policy-makers) can contribute to its subsequent application across industries, as well as helping to legitimize (and consequently standardize) the model. Lastly, further studies exploring CAM from the consumers' perspective, analysing whether and how the information derived from the CAM influences their decision-making could yield useful insights (in line

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with e.g., Grunert et al., 2014; see also de-Magistris et al., 2017 for further discussion of consumers' decision-making).

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Colonialism statement:

The University of Washington stands on the land of the Coast Salish peoples; we acknowledge the Coast Salish peoples of the land which touches the shared waters of all tribes and bands within the Duwamish, Puyallup, Suquamish, Tulalip and Muckleshoot nations.

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CO2 generation and power consumption:

Deep learning models were trained in Beijing using an estimated 1008kWh generating 980.2 kg CO_2 from coal (5.65%), petroleum (33.8%), natural gas (31.8%), external transmitted electricity (25.99%), and others (2.77%); and in Seattle using a measured 25kWh generating 24.75 kg CO_2 from hydro (84%), unknown (6%), nuclear (5%), wind (4%), biogas (1%).

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Appendix 1:

(kg CO2 eq./f.u.)	Difference	breakfast with milk	breakfast without milk
rawmaterials	6.16	6.62	0.46
trans7	0.10	0.21	0.11
production		1.03	1.03
trans6		0.03	0.03
storage		0.09	0.09
trans5		0	0
use		0.44	0.44
trans4		0.04	0.04
wastefinal			
wasterawmaterials			
w1, 2, 3…			
trans2		0.00459	0.00459
wasteproduction			
trans3			
wastestorage			
Total	6.26	8.46459	2.20459

Source: CCaLC database

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Figures

Figure 1. Eras of agency.

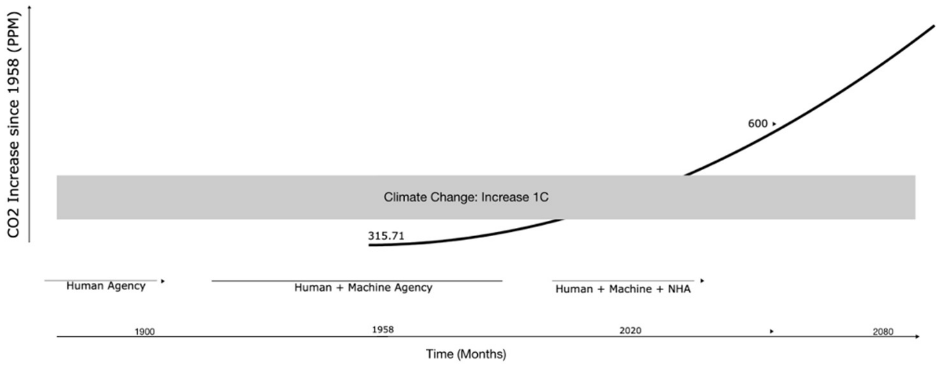

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Figure 2. Circularity accounting model.

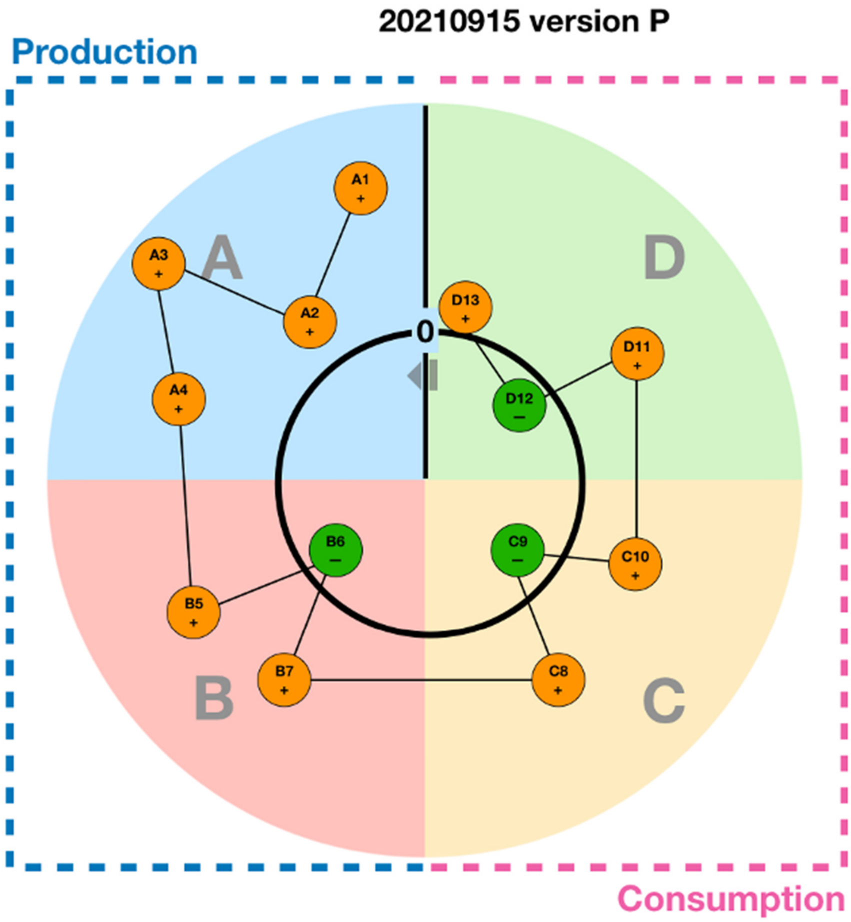

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Figure 3. Architecture of the CO2 estimator

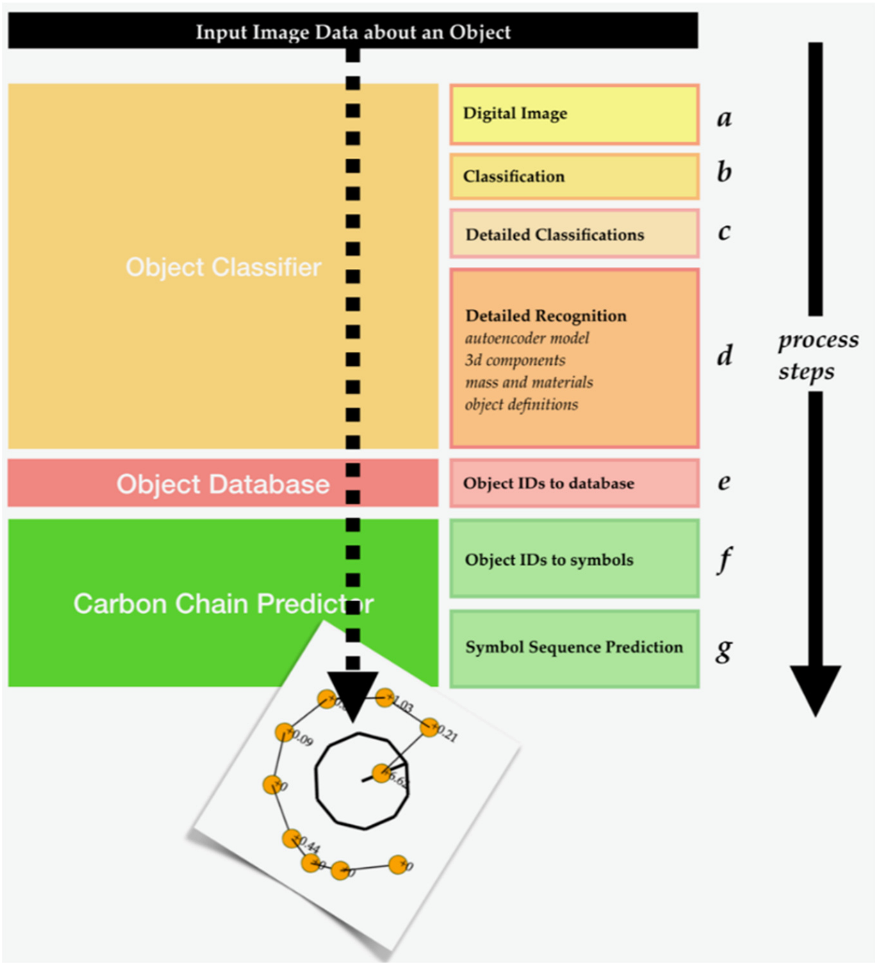

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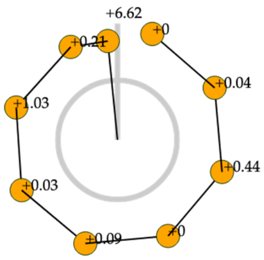
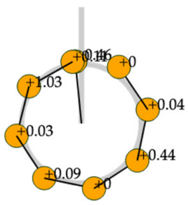
Figure 4. CAM: Circularity Diagram Comparison two sets of breakfast cereals



BC_milk



BC_nomilk

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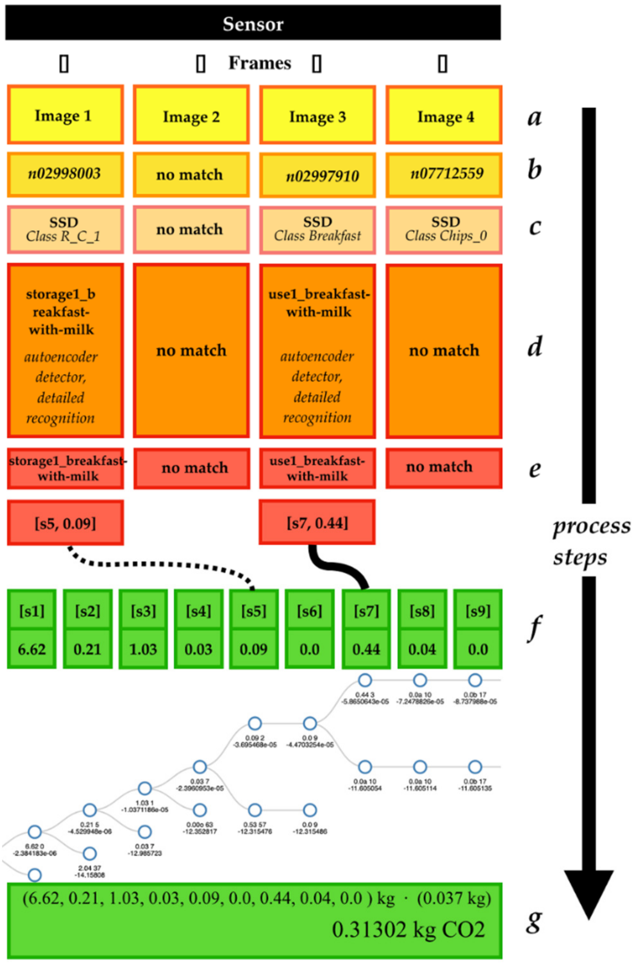
Figure 5. Architecture of the model with data from BC_milk



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