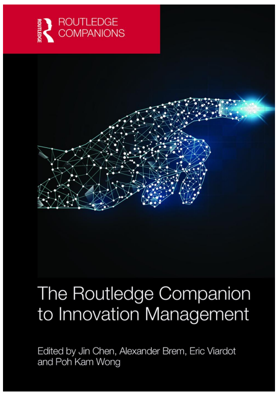

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SMART PROTOTYPING

Fei Yu and Bastian Enste

Introduction

Prototyping, as a central part of the innovation process (Rothwell, 1994), is one of the most critical activities in new product development (NPD) (Wall, Ulrich, and Flowers, 1992). It allows one to assess and to overcome uncertainties of future products (Wang, Guan, and Zhao, 2004; Zhang, Vonderembse, and Cao, 2009), and a good use of prototypes increases the speed to market of the products (Chen, Reilly, and Lynn, 2005). Today, many industries are facing the challenges of increasing competition, shorter product life cycles, changing customer demands and fast technology innovations (Liao and Tu, 2007). In such an environment, a highly efficient prototyping process is crucial to overcoming these challenges that could ensure the speed to market and increase successfulness (Tennyson, McCain, Hatten, and Eggert, 2006).

The modern NPD process is complicated and often requires cross-disciplinary collaboration, especially in prototyping, which contains intensive human-involved activities. It will be important and valuable to have a clearly described prototyping framework to support product design (Menold, Jablokow, and Simpson, 2017). There is often no common understanding of prototyping and the prototyping process. The use of prototypes and prototyping activities can be very different as well (Yu, Pasinelli, and Brem, 2017). The prototyping efforts in design are focused on learning and envisioning solutions (Lim, Stolterman, and Tenenberg, 2008), discovering new opportunities (Dow, Heddleston, and Klemmer, 2009), generating and refining design (Buxton, 2007), experiencing the tangible feeling and discussing with the users (Houde and Hill, 1997), and involving them in the NPD process (Hillgren, Seravalli, and Emilson, 2011). In a technical context, a prototype represents a preliminary version of a product or product component (Warfel, 2009). It focuses more on the product performance and quality, product life cycle, and manufacturability.

Artificial intelligence (AI) technology has gone through dramatic developments in recent years. Several companies have developed and provide platforms and tools for AI applications – for example, Google Tensorflow, Amazon AWS, and Microsoft Azure. The technology barriers have decreased significantly, which makes AI available for nonexperts.

In this chapter, we introduce a smart prototyping concept, which we define as an AI-based approach to support prototyping processes and activities. The chapter presents preliminary AI models to support smart prototyping based on prototyping criteria from previous prototyping literature (Filippi and Barattin, 2014). Four different machine learning algorithms are used in the model for data analysis. Workshops have been designed and used for data collection. By defining and prioritizing the prototyping criteria, the model can generate frameworks and suggestions for the selection of the prototyping process and activities. In the next section, we will present a brief overview of prototyping studies around the following three questions: What is a prototype? What are the materials, tools, and technologies used for prototyping? And what are the efforts related to smart prototyping? Then we introduce the methods used in this study and the development of the AI-based model. Conclusions and future research are presented in the following sections.

Brief overview of the literature

What is a prototype?

Prototypes are used in many fields. To answer this question, we need to know who are we asking of? The definition of a prototype varies among disciplines. The expectation of what a prototype is can be a foam model for industrial designers, a simulation of appearance and behavior for interaction designers, a test program for software developers (Houde and Hill, 1997), and a breadboard circuit for electronic engineers. These different definitions also have different levels of scope. Naumann and Jenkins (1982) state that a prototype system "captures the essential features of a later system" (p. 30). This is based on an engineering perspective that focuses on features and functions. This is in line with the definition by Warfel (2009), who states that a prototype represents a preliminary version of a product or product component. The purpose of a prototype is to gain information about the final product in terms of performance, quality, life cycle, and manufacturability (Warfel, 2009). Houde and Hill (1997) define a prototype as "any representation of a design idea – regardless of medium", and the authors further clarify that "designers are the people who create them – regardless of their job titles" (p. 3). It is a broad definition from the design perspective. Thus, the purpose of a prototype is not limited, but rather focuses on the front end of the process (i.e. represents an idea no matter if the idea leads to any products).

Another definition of a prototype is "an approximation of a product (or system) or its components in some form for a definite purpose in its implementation" (Chua, Leong, and Lim, 2010, p. 2). A prototype is not limited to a physical form. It could be a sketch, a CAD model, a mathematical model, or a functional or physical approximation. The use of a prototype is very flexible, but the authors emphasize that there should be a defined purpose. Prototypes also exist in software development to demonstrate concepts or to find new ways to solve problems (Sommerville, 2011). In contrast, Beaudouin-Lafon and Mackay (2003) define a prototype as "a concrete representation of a part or all of an interactive system" (p. 1007). In this definition, a prototype should be a tangible artifact that is used to envision and reflect on the final system.

Prototyping is then the process of realizing, analyzing, and testing these prototypes (Chua, Leong, and Lim, 2010). In a recent study, Menold, Jablokow, and Simpson (2017) asked 194 design students to define prototyping in their own words, which generated five categories: "Model to Link, Model to Test, Model to Communicate, Model to Decide, and Model to Interact" (p. 82). This reveals the different understandings and uses of a prototype in the same discipline. Thus, we need to understand and respect that prototyping is a complex process and there are differences in the purpose of a prototype.

Prototypes have a variable range of fidelity from low to high (McCurdy et al., 2006). The fidelity normally increases along with the progress of NPD (Exner, Damerau, and Stark, 2016), but there are also pieces of evidence showing the nonlinearity of the process; for example, lower-fidelity prototypes can also be used in the later prototyping phase where a number of high-fidelity prototypes have been developed and tested (Yu, Pasinelli, and Brem, 2017). Ulrich and Eppinger (2011) use alpha and beta prototypes to describe the early prototypes for testing whether the product works as designed and the later prototypes for testing the performance and the reliability, respectively. Depending on the context, prototypes are also called mock-ups, solid images, concepts, or models.

In this chapter, we use the broad definition in that there is no limitation on the form of a prototype, but the purpose of a prototype has to be clear (Chua, Leong, and Lim, 2010). We consider all the artifacts created during the process after the ideation and before the manufacturing (Rothwell, 1994) as prototypes. The study focuses on the development of prototypes for new physical products.

What are the prototyping materials, tools, and technologies?

There can be many different approaches and materials used for prototyping. Different tools and materials can be selected according to different prototyping phases (Yu, Pasinelli, and Brem, 2017). Low-fidelity materials, which are cheap, easy, or faster to handle, are often used in the early prototyping phases. Compared to complex prototypes, simple ones are often more successful (Yang, 2005). Designers are normally open to a wide range of low-fidelity materials (Yu, Pasinelli, and Brem, 2017), for example, clay, foam, or cardboard. They use the materials to quickly demonstrate and verify the physical forms of the prototype. There are a few examples that break the technology barrier between the disciplines. littleBits is a library of discrete electronic components pre-assembled in small circuit boards (Bdeir, 2009). After they were invented and launched in the market by Bdeir (2009), the early-phase prototyping process was disrupted. Developers with or without an electronic background can easily envision electronic features, which are normally developed in a later prototyping phase. This breaks the technology barrier that only engineers can make sophisticated circuits. Developers from other disciplines, and even users, can implement the electronic features in prototypes, and they can do it very quickly in the early phase. This disruptive technology makes it possible to test the features earlier, thus the prototyping speed is increased. Arduino is a well-known electronic platform based on easy-to-use hardware and software. It makes access to an embedded system much easier, although it still requires the developers to have a certain level of skill. For complicated tasks, a more powerful platform (Raspberry Pi) is often used by developers.

Digital tools, such as 3D computer-aided design (CAD) and simulation software, are adopted to flesh out the details and test the features. They are often applied in the middle phase. A virtual prototype is a computer simulation of the prototype in a digital version, which can be used for not only the evaluation of the physical form but also testing the functions (Yang, 2005). It can provide valuable feedback. The failures can be discovered before any expensive and time-intensive process is undertaken. It also helps the cross-disciplinary team members to have a better understanding of the product; thus, it improves the communication, efficiency, and productivity in the development process (Zorriassatine, Wykes, Parkin, and Gindy, 2003). The visual prototype can be used to evaluate the product for the manufacturing process. This can avoid poor planning in design and fabrication, which saves resources and reduces the amount of iterations of physical prototypes (Choi and Chan, 2004; Liu, Campbell, and Pei, 2013)

Generative design is "a designer driven, parametrically constrained design exploration process, operating on top of history based parametric CAD systems structured to support design as an emergent process"(Krish, 2011). It could produce efficient and buildable designs automatically based on the defined targets and constraints. With the adoption of topology optimization, generative designs can significantly reduce the complexity and the weight of the designed object. It frees the designers from the designing process, so they can focus more on creativity, as well as identifying the correct constraints (Jiang, Chen, Sadasivan, and Jiao, 2017). A number of studies have shown the value of a generative design approach in different disciplines. In the biomedical field, Jiang, Chen, Sadasivan, and Jiao (2017) used topology optimization for generative designs of personal aneurysm implants. Krish (2011) demonstrated the applications for consumer products. Troiano and Birtolo (2014) presented the genetic algorithms for supporting the generative design of user interfaces. Shea, Aish, and Gourtovaia (2005) combined a generative structural design system with an associative modeling system and applied it in the civil engineering field of designing an architectural structure. This is one of the first few attempts at generative design in academia. Today generative design functions are available in CAD software (e.g. AutoDesk Fusion 360 and Siemens NX). It becomes much easier to apply this approach in engineering design. Figure 12.1 shows an example of a generative design model. On the left image is an ordinary table we created in AutoDesk Fusion 360. By defining the constraint of the pressure on top and applying a generative design algorithm, the system generated a model as shown in the right image. Compared with the original table, the new one remains the same constraint but reduces the weight significantly. The generative design approach is a great step in smart prototyping with the adoption of computer-aided systems in prototyping activities. Applying it in combination with rapid prototyping technology will create a revolutionary impact on product development, manufacturing, and even changing consumer behavior.

Rapid prototyping (RP) keeps our attention in both the academia and the industry since the first commercial stereolithography was introduced by 3D Systems. It is a prototyping and manufacturing technique that refers to the fabrication of a physical model layer by layer based on a predesigned 3D CAD model. There are several commercially available PR technologies, such as stereolithography apparatus (SLA), laser engineered net shaping (LENS), selective laser sintering (SLS), three-dimensional printing (3DP), fused deposition modeling (FDM), and laminated object manufacturing (LOM) (Vimal, Vinodh, Brajesh, and Muralidharan, 2016). Depending on the technology, different raw materials can be applied for the 3D printing of the model, such as ABS (acrylonitrile butadiene styrene), PLA (polylactic acid), wood-based filaments, metal-filled filaments, and nylon. The form of the raw materials can be wire, powder, liquid, ink, or gas. According to the specification of the selected RP process, the printed prototypes have a variety of properties, and the production speed and cost can be very different as well.

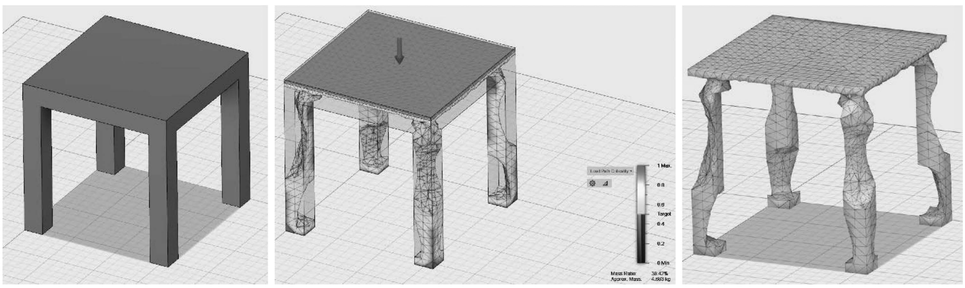

Figure 12.1 From left to right: Original design of the table; define constraint and apply generative design algorithm; generative design model

The RP process is a fast-growing technology that reduces prototyping and tool-making time (Drizo and Pegna, 2006). On one hand, new materials are tested and used for 3D printing. On the other hand, the quality of the models improves, while increasing production speed and lowering production cost. The use of RP is not only for developing prototypes but also as a production technique directly providing end-use products. Additive manufacturing (AM) evolved from RP with the focus on manufacturing and has been adopted by many industrial applications. Although AM is still being researched in most industries, this new processing technology has the potential of bringing a revolutionary change to the traditional manufacturing world due to its ability to build a freeform model – especially those models created by generative design that were not possible to be produced before, or at least at significantly higher cost.

What are the efforts related to smart prototyping?

There are numerous studies about prototyping frameworks, prototyping strategies, and selection of prototyping processes. The goal is to support prototyping processes and activities in terms of situation-based selection of the efficient prototyping process, increasing the effectiveness and efficiency of design teams, and increasing the desirability of products (Menold, Jablokow, and Simpson, 2017). To have a better understanding and holistic description of these efforts, we introduce a smart prototyping concept, defined as an AI-based approach to support prototyping processes and activities. In this section, we select a few outstanding examples that relate to smart prototyping.

Selection of RP process

One of the focused areas is the selection of the RP process. As presented in the previous section, many different RP approaches are available. How to select a proper RP process that fulfills the production requirements has been an interesting research area in prototyping studies for years. Several traditional constraints should be considered, including the use of materials, operating cost, post-processing requirements, speed, surface finish, etc. (Drizo and Pegna, 2006). In addition, environmental criteria like human health, environment, natural energy and resource, such as disposal of the wasted product, the toxicity of material, and energy consumption, are also applied in the selection algorithm (Vimal, Vinodh, Brajesh, and Muralidharan, 2016). A number of AI-based tools are used to select an RP process, for example, modified technique for order preference by similarity to an ideal solution (TOPSIS) (Byun and Lee, 2005), graph theory and matrix approach (Rao and Padmanabhan, 2007), analytic hierarchy process (AHP) (Armillotta, 2008), a rule-based expert system (Masood and Soo, 2002), and a rule-based expert system in combination with a fuzzy inference system (Munguia and Riba, 2008).

Byun and Lee (2006) use three factors to determine the optimal part-oriented RP process: surface quality, build time, and part cost. Surface quality is estimated according to the surface roughness and the contact area of support materials. Build time consists of three elements: data preparation time, part build time, and post-processing time. Part cost is calculated based on the labor time, build time, the volume of both, part material, and support material. Material loss is also considered. The simple additive weighting method is used for decision-making (Byun and Lee, 2006). Rao and Padmanabhan (2007) propose a "rapid prototyping process selection index" and use a matrix-based approach to evaluate and rank the RP processes, including SLA, SLS, FDM, LOM, Quadra, and 3DP. Traditional criteria, including dimensional accuracy of the part, surface roughness of the part, tensile strength, elongation, part cost, and build time, are considered in the algorithm (Rao and Padmanabhan, 2007). In another approach, the adaptive AHP decision model is applied to the RP process selection (Armillotta, 2008). The author provides 16 alternatives to tools and processes and considers 11 factors in the algorithm concerning final prototype properties, system usage, and process cost. In a recent study, Vimal, Vinodh, Brajesh, and Muralidharan (2016) present a conceptual model applying fuzzy analytic network process – TOPSIS-based hybrid methodology to compute criterion weights and use for process ranking. In addition to 16 traditional criteria, the authors select nine environmental criteria for the selection of RP processes. Furthermore, the authors develop a decision support system to save mathematical computation resources.

Prototyping framework

Compared to the numerous efforts on RP process selection, there are much fewer studies supporting general prototyping processes and activities. A possible reason could be the wide range of prototyping processes available – it is fuzzy to have one guideline to support prototyping activities across all disciplines. However, there is extraordinary work that attempts to provide systematic approaches to structure prototyping. Camburn et al. (2015) provide a systematic approach for design prototyping. By identifying the practices that improve prototyping, the authors found six key specific process variables: number of iterations, number of parallel concepts, use of scaling, use of subsystem isolation, use of requirement relaxation, and use of virtual prototypes. The method is correlated with improved outcome assessments, including prototype performance, time to build, cost, and adherence to suggested approach (Camburn et al., 2015). Menold, Jablokow, and Simpson (2017) introduce a holistic prototyping framework, Prototype for X. Based on a systematic review of prototyping research in many disciplines, the authors summarize three major functions of prototypes and four specifications for a holistic and structured prototyping framework. Figure 12.2 shows the Prototype for X structure. The first three goals (i.e. Prototyping for Feasibility, Prototyping for Viability, and Prototyping for Desirability) are designed to integrate human-centered design with a resource-, time-, and function-focused design (Menold, Jablokow, and Simpson, 2017). Filippi and Barattin (2014)

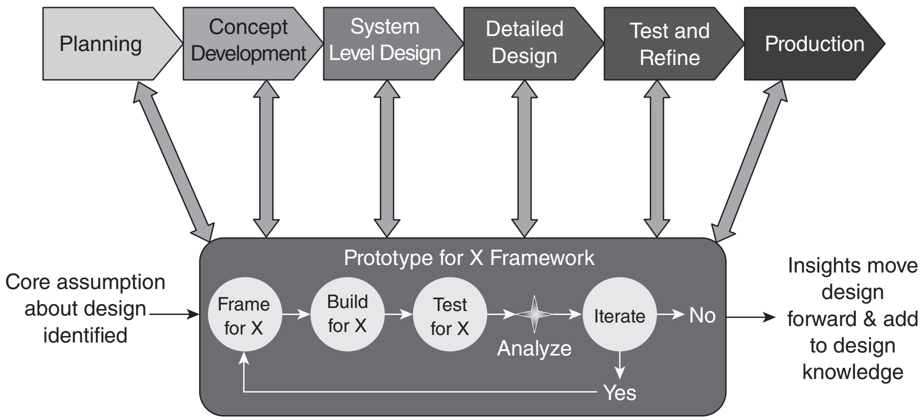

Figure 12.2 Prototyping for X structure and integration into the design process

Source: Menold, Jablokow, and Simpson (2017, p. 86) classify prototyping activities from a new perspective that five classes of prototyping activities are described in four dimensions (see Figure 12.3). The fifth dimension, time, is not presented in the figure to avoid time-dependent classification. The authors further suggest 11 prototyping situation indices to support the selection of prototyping activities, including direct interaction, physical feedback, total feedback, real environment, error recognition and recovery, functions required, prototype change flexibility, budget, time, human operators, and tolerances (Filippi and Barattin, 2014).

From the overview in the literature, we learn about the complexity of prototyping. The differences across disciplines are the definition of a prototype, the use of a prototype, and the approach and material for prototyping. There have been a lot of efforts to increase effectiveness and decrease uncertainty during the design process. AI-based techniques have been applied to support decision-making for the selection of RP processes, but they are not data-driven approaches, and an AI system is still missing that can support general prototyping processes and activities, even though great efforts have been made to provide holistic and systematic prototyping frameworks. This study attempts to develop an AI-based, data-driven system to support prototyping process and activity selections. In our preliminary setup, we use Filippi and Barattin's (2014) 11 prototyping situation indices as the prototyping parameters to determine the prototyping activities.

Research approach

This study is an attempt to deploy smart prototyping into a professional environment by developing an AI-based system that provides recommendations for selecting the most appropriate prototyping activity based on a given input. To achieve the goal, there are three major steps in the method. First, based on a literature survey, identify the key prototyping variables that can be used as the input to the system. Second, we need to collect data to train and validate the AI model. An experimental research was designed for data collection. 70 percent and 30 percent of the data were used for training and validation, respectively. The next section describes the data collection approach in detail. Then, we selected and applied four different AI models for the smart prototyping system. The performances of each model are analyzed and compared in the fifth section.

Data collection

Theory of experimental research

We chose experimental research as the approach for data collection. The aim of conducting experiments is to find causation, which we can use to predict phenomena in the future. Assuming the hypothesis is based on correct assumptions, a laboratory or artificial experiment makes it possible to carefully observe the effects of chosen independent variables while excluding external unwanted or irrelevant factors (Webster and Sell, 2014). The outcome of the study is thereby replicable and invites other researchers to adopt the research design to gather additional data that further support the research objective.

Further advantages that benefit the research are the ability to create very special environmental conditions while running the tests. This minimizes all eventual environmental variables that could normally influence the measurable outcome. The biggest potential disadvantage of conducting the research in the form of a laboratory experiment is the danger of generalization based on nonprobability samples (Cooper and Schindler, 2003).

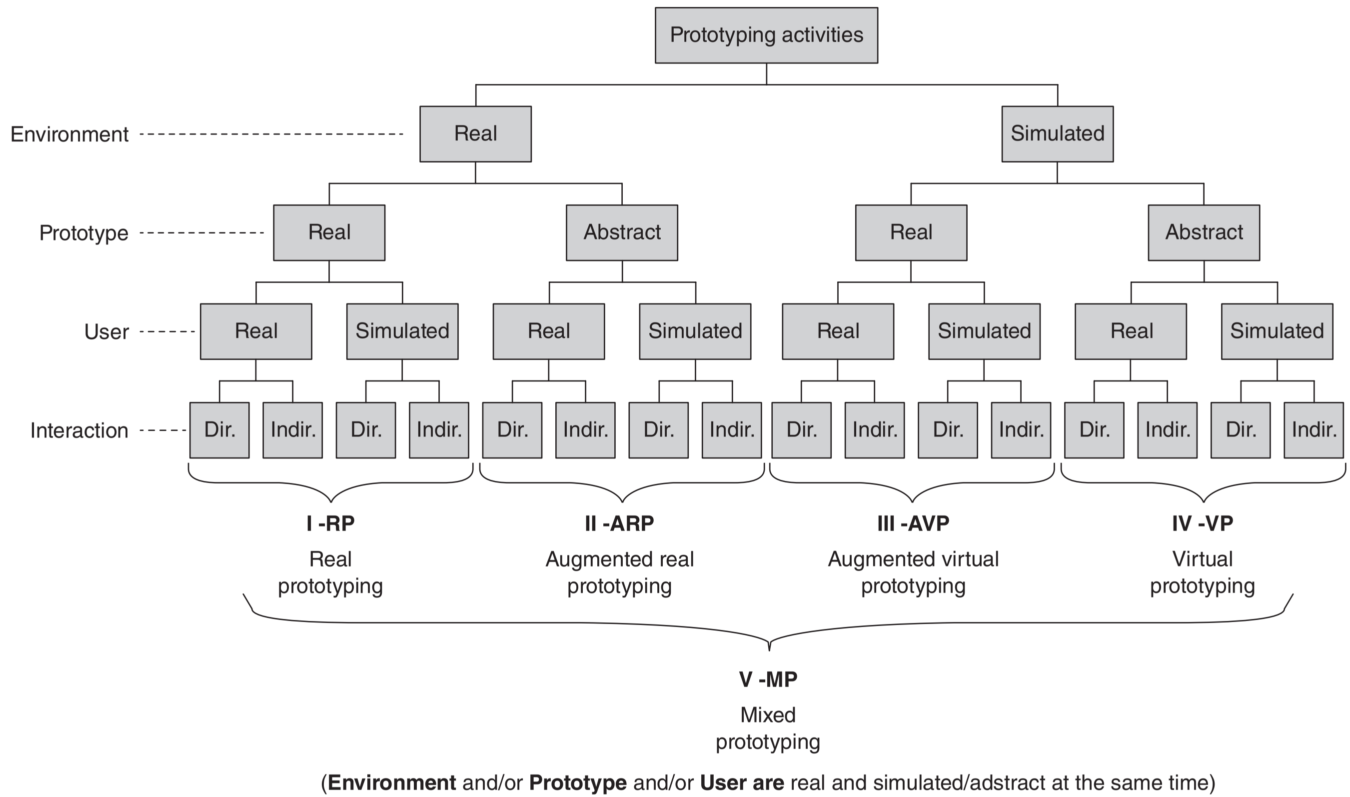

Figure 12.3 Classification of prototyping activities

Source: Filippi and Barattin (2014, p. 3)

For the research to capitalize on the advantages and minimize the disadvantages of the chosen method, the experiment must possess certain properties that are crucial to its success. It is necessary to wisely choose the participants for the experiment. While the participating groups should be as homogenous as possible regarding age, background, and education, as this fosters communication within the groups during the experiment, it is also important to eliminate people who are unlikely to contribute towards the discussion or may disrupt other participants (Greenbaum, 1997). Also, the facilities in which the experiment is conducted must be chosen wisely. The chosen room must offer enough space for all participants to work freely, while they must have equal access to given introductions and material (Greenbaum, 1997). This further supports the idea of minimizing the effects of external and environmental factors into the experiment.

To lower the chance of false generalization from the research's findings, randomization in the form of control groups is used to counteract a possible selection bias. Said bias can be entirely removed if the participants are randomly assigned into a treatment group, which is subject to the changing independent variable, and a control group which is not (Duflo, Glennerster, and Kremer, 2008). Doing this will eliminate as many confounding factors within the experiment as possible, that is, the problem of mixing the exposure of interest with other effects of external variables (Van Stralen, Dekker, Zoccali, and Jager, 2010). Lastly, the experiment is meticulously monitored and recorded by the facilitators so that all events can be analyzed by and shared with other researchers who want to comprehend or re-enact the observation.

Taking the previously made points into consideration, a fitting experimental design must be selected. Making an optimal choice here means keeping the balance between factors such as given constraints, making sure that changes in the dependent variables are truly due to changes within independent variables, and strengthening the generalizability of the study's results. Experiments put a further emphasis on matters such as randomization and control groups (Pruzan, 2016), which will highly influence the choice of the design, as can be seen in Figure 12.4.

The idea of the two-group simple randomized design is to randomly assign members of a sample of the population into either an experimental or a control group. The two groups are given different treatments of the chosen independent variable. The benefits can be seen in comparing them to the specifications declared earlier: the chosen design is simple, contains control groups, and therefore allows randomization of the individual differences between members of the sample. The limitations of this method lie mainly in the fact that external factors or influences of those conducting the research are not eliminated, which might influence the result of the experiment (Kothari, 2004).

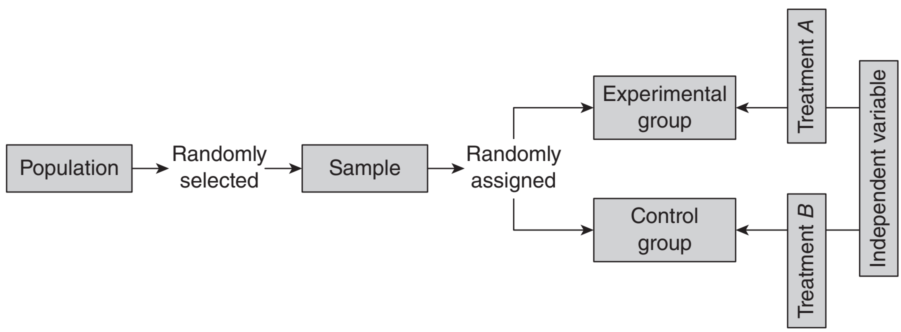

Figure 12.4 Two-group simple randomized experimental design (in diagram form)

The following subsection will explain the final setup of the experiment and how it meets all the previously given requirements.

Experimental setup

The following experimental setup was arranged according to the previously presented two-group simple randomized design. The following requirements must be fulfilled throughout the entire experimental process:

- All relevant results and outcomes must be documented.
- The group of participants is homogeneous and on the same knowledge level regarding the chosen activities.
- Control groups are created, and the experiment is randomized.
- Half of the exercises should be practical, while the other half should be theoretically studied.

The experiment as stated was held in the form of a prototyping workshop that lasted 120 minutes. The period is divided into three steps are described as follows.

1) All participants of the workshop were asked to fill out a questionnaire regarding their previous experiences with prototyping. The selected questions were:

    - How would you describe the experiences you have had regarding prototyping during past or current projects?
    - How much time have you spent on prototyping compared to the whole project duration?
    - Have you ever had problems with deciding on a prototyping activity within your group work?

    The written answers should be given rather quickly and, most importantly, truthfully. The gained information can be used to assess the general experience and knowledge of the contestants regarding prototyping.
2) All participants of the workshop cycle through nine individual stations in which they will experience individual prototyping activities in either a practical or theoretical way. The chosen activities are listed here, while the tasks can be found in the appendix:

    - Paper prototyping
    - Breadboard prototyping
    - Low-fidelity prototyping
    - Quick prototyping
    - Rapid prototyping
    - Augmented real prototyping
    - Augmented virtual prototyping
    - 3D/CAD prototyping
    - Generative design prototyping

After completing each individual task, the participants fill out a form in which they must assess each activity based on 11 descriptive parameters for prototyping activities (Filippi and Barattin, 2014) with values between 0 and 10. Figure 12.5 shows the prototyping activity assessment form. For the participants to rate the prototyping activities as precisely as possible,

Direct interaction between prototype and user	Physical feedback	Additional total feedback (visual, audio, etc.)	Real environment in which the prototype is placed	Error recognition and recovery implemented in the prototype	Functions required in the prototype	Change flexibility	Budget	Time	Human operators required for the prototype to function	Tolerances required in the prototype	Prototyping activity
											Paper prototyping
											Breadboard prototyping
											Low-fidelity prototyping (marshmallow, spaghetti, balloons, etc.)
											Quick prototyping (wood, foam, metal, plastic)
											Rapid prototyping
											Augmented real prototyping
											Augmented virtual prototyping
											CAD/3D prototyping
											Generative prototyping

Figure 12.5 Prototyping activity assessment form

it was necessary to agree on a description of each individual activity to align knowledge and previously gained experience. The initial focus of the chosen prototyping activities was on early product development stages in which the emphasis is on exploring and testing new features or designs. Therefore, the aim of all activities is a quick and easy implementation of ideas into physical or virtual models so that a direct interaction with users can provide valuable insights.

- **Paper prototyping** is an activity commonly used within the field of user-centered design in which the prototype or interface is created solely from painted paper or printed paper, all in 2D.
- **Breadboard prototyping** allows the user to quickly prototype features and functions of electrical systems on a breadboard without permanently tying them to each other.
- **Low-fidelity prototyping** is used in ideation or very early stages of product development to test possible and/or relevant features using cheap and easy-to-access materials. In this case, we provide materials such as balloons, straws, tape, etc.
- **Quick prototyping** is mainly used for design prototypes. Concept ideas or later designs are prototyped using materials such as foam, plastic, or wood, which are easy to form and adapt.
- **Rapid prototyping** utilizes additive manufacturing techniques such as 3D printing to quickly create prototypes previously designed in CAD software.
- **Augmented real prototyping** places an abstract or virtual prototype within a real environment.
- **Augmented virtual prototyping** places a real prototype within a virtual or computer-generated environment.
- **CAD/3D prototyping** creates a purely virtual and computer-generated prototype using CAD software such as Autodesk or Siemens NX.
- **Generative design prototyping** uses simulation abilities within CAD programs to generate designs that satisfy predefined constraints.

A control group that did not previously cycle through the activities was asked to assess the same activities based on 11 parameters. This had the purpose of seeing if the collected data are comparable to that collected during the workshop and if the experiment is transferable to a rather impersonal, survey-based approach for greater data collection. Furthermore, we hereby achieve a certain degree of randomization throughout the experiment, which was one of our requirements.

The second requirement, homogeneity within the participant base, must be fulfilled to minimize the effects of confounding within the experiment. All participants must fulfill the following requirements:

- Same age range
- Same educational background
- Same educational level
- Experience within group and project work

Figure 12.6 presents the general experimental research process. We recruited 17 engineering students with prototyping experience for the experiment. Eleven students were assigned randomly to participate in the workshop, while the remaining four students were in the control group.

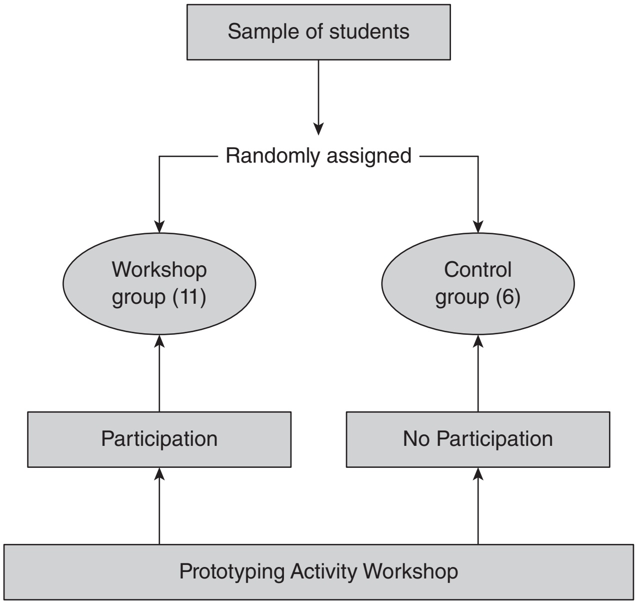

Figure 12.6 Chosen experimental design

Table 12.1 Experiment participant data

	Average age	*Average BIS-11*
Treatment group (11)	25.63	71.72
Control group (6)	22.66	69.33

For an initial assessment of the participant group, all participants were asked to fill out the Barrett Impulsiveness Scale (BIS-11) (Patton, Stanford, and Barratt, 1995) to assess their impulsiveness. Table 12.1 shows the average age and the BIS-11 results of both groups.

Findings

All participants of the study teamed up into smaller groups and accomplished all tasks mentioned in the nine stations of prototyping activity. Complex and abstract prototyping activities such as augmented real prototyping, augmented virtual prototyping, and generative design prototyping were not only hard to teach but also especially hard to understand and assess for the participants without the necessary technical setup and experience. Nevertheless, a mixture of the supplied material and efforts by the facilitator (see appendix) could make it accessible to the participants. Simpler and more practical activities such as paper prototyping, breadboard prototyping, and low-fidelity prototyping were much easier to assess for the participants since they could rely on the previous experiences from other projects or work, but also because the general interaction with the individual activity was more carefree and "fun".

After the workshop, all participants filled out the questionnaire regarding the assessment of prototyping activities. From the analysis of the gathered data, two conclusions could be drawn:

- The assessment of the treatment group and the control group, which was not present during the workshop, gave very similar values to each of the tested parameters of each prototyping activity. This means that upscaling the data collection to a survey is possible to shorten the data collection time.
- Table 12.2 shows all the gathered data from the 17 participants. A dataset of 153 samples was collected. For every prototyping activity, the arithmetic mean and the standard deviation were calculated and added to each row.

The two calculated and extracted values for each of the nine parameters of every prototyping activity are the respective mean and standard deviation. The arithmetic mean of each parameter provides insights into how the different activities differ from each other when examining them on a more in-depth level. This is used to give an understanding of why a certain prototyping activity is chosen over another one in specific cases and an idea of what the machine learning models will base their predictions on.

A small standard deviation hereby expresses homogeneity within the collected data, which will further improve the performance of the models, as rank-breaking values will lower their accuracy and make predictions more random.

Development of the AI-based system

Having the data gathered from the pilot study, the next step is to extract relevant information, insights, and knowledge. We follow the three steps of data science for data examination: exploration, visualization, and prediction.

In the initial step of exploration, it is important to get familiar with the collected data. While accessing the overall amount, it is hereby key to only select features that are beneficial for predicting our outputs. A deeper understanding, especially for external observers and interested parties, is generated and transferred by visualizing the data and their correlations in a graphical way. By doing this, predictions can often already be made with the naked eye. The final step is the application of different machine and/or deep learning algorithms that gradually learn from the data, which gives them the ability to make predictions for future inputs.

Data exploration

The information that can be gathered in the exploration phase is mostly about the data's composition. A sample from the dataset describes an individual prototyping activity using only integer values between 0 and 10. Table 12.2 further tells us that the standard deviation for each of the parameters is small compared to the overall interval of 10. It shows that the gathered data are homogeneous and not entirely random, as we would not have any possibility for prediction based on randomness.

Early in the analysis process, the examination of the correlation between each of the nine parameters can be a very insightful and helpful step. The correlation of two attributes is a measure of their linear relation. A value close to 1 or -1 signalizes a completely positive or negative

Table 12.2 Arithmetic mean and standard deviation of 17 observations after the experiment

	Phy. feedback	*Add. feedback*	*Environment*	*Error*	*Functions*	*Change*	*Budget*	*Time*	*Tolerances*	*Activity*
Mean	1.82	1.59	4.35	1.65	1.82	8.76	0.41	1.94	1.47	Paper Prototyping
StDev	0.95	1.58	3.14	1.22	1.63	0.97	0.51	1.14	1.01	
Mean	7.65	8.06	4.24	6.94	7.94	8.41	3.29	4.00	2.41	Breadboard Prototyping
StDev	2.71	1.64	2.95	3.01	1.14	2.74	2.14	1.94	2.24	
Mean	8.18	2.82	6.47	2.00	2.47	8.82	1.24	1.82	1.18	Low-Fidelity Prototyping
StDev	1.24	1.13	1.33	1.12	1.07	0.95	0.75	1.01	1.01	
Mean	8.24	2.47	7.76	7.00	2.47	7.18	4.82	6.65	5.82	Quick Prototyping
StDev	1.15	1.42	1.20	1.54	1.07	1.33	1.29	1.66	1.74	
Mean	9.06	2.82	8.06	7.88	6.18	7.06	6.59	5.47	8.47	Rapid Prototyping
StDev	0.97	1.70	1.03	1.05	1.24	1.20	1.80	1.18	1.07	
Mean	1.18	4.12	8.82	7.24	2.71	8.06	3.41	4.35	2.41	Augmented Real Prototyping
StDev	1.67	1.36	0.73	1.09	1.21	1.82	1.06	1.22	1.80	
Mean	1.88	3.29	0.88	5.06	6.53	2.76	7.88	7.00	7.06	Augmented Virtual Prototyping
StDev	2.34	1.61	0.78	1.34	1.50	1.25	1.87	1.77	2.41	
Mean	0.94	4.88	0.76	8.35	7.59	9.47	3.47	6.65	9.12	3D/CAD Prototyping
StDev	1.09	2.39	0.90	1.50	1.54	0.87	1.07	1.50	1.90	
Mean	1.41	4.82	1.41	8.82	8.06	9.06	3.76	7.06	9.47	Generative Design Prototyping
StDev	1.23	3.32	1.18	0.95	1.30	1.30	1.15	2.08	0.72	

linear relation, whereas a value close to 0 indicates no linear correlation. A common formula used to calculate the Pearson correlation is given with (Allen, 2018)

$$r = \frac{\sum XY - \frac{\sum X \sum Y}{N}}{\sqrt{\left(\sum X^2 - \frac{\left(\sum X\right)^2}{N}\right)\left(\sum Y^2 - \frac{\left(\sum Y\right)^2}{N}\right)}}$$

with r being the correlation coefficient, N the number of samples, and X and Y the two variables.

A strong correlation of several parameters can be seen in Table 12.3. With a value of 0.581, the parameters "Budget" and "Time" are highly correlated, which means that higher financial investments in activities cause a direct increase in time investment. Other highly correlated values are:

- Time <-> Tolerances 0.630
- Additional total feedback <-> Functions required −0.489

Higher negative values signalize an inverse correlation between parameters. Looking at "Real environment" and "Functions required", which carry a value of −0.489, shows that putting higher awareness onto a real environment reduces functions required and implemented into the prototype.

Lastly, values around 0 such as for "Physical feedback" and "Additional total feedback" or "Budget" and "Additional total feedback" can imply independency between two parameters, which needs to be explored further.

Data visualization

The second step of visualizing the data is used to make the collected data more understandable and comprehensible for external viewers. Many of the patterns and relationships of the different parameters which will later be used by the machine learning models can be identified with visualization techniques using different chart or graph types. A promising initial approach to a new and unknown dataset is the creation of a pair plot. The result is a grid showing a coordinate system making comparisons of every feature. By color-coding each individual prototyping activity, the observer can recognize features that clearly separate prototyping activities from others. This helps with understanding the decision-making process happening later in the machine learning section.

Figure 12.7 shows an extract of four plots mapping the features "Change flexibility", "Budget", "Physical feedback", and "Additional feedback". Looking at the plot in the top-left corner of "Change flexibility" – "Physical feedback", we can see the separation of the light-grey squares belonging to "Augmented virtual prototyping". The understanding gained from just this step alone would be enough to make the decision for an activity without the use of advanced machine learning models just based on this simple visualization.

A very interesting feature is the "Budget" constraint, as financial investments in the early stages of product development can be crucial. Figure 12.8 shows the distribution plot of the budget feature, which shows how the feature is distributed within the interval of 0 to 10. As the graph shows, the nine chosen prototyping activities were mostly evaluated within the lower half of the spectrum. This further supports that the choice of activities when focusing on early product development stages is backed by the evaluation of the participants. Prototyping activities used so early on should not and cannot produce high financial investments.

Table 12.3 Prototyping data correlation matrix

	Physical feedback	*Additional total feedback*	*Real environment*	*Error recognition*	*Functions required*	*Change flexibility*	*Budget*	*Time*	*Tolerances required*
Physical feedback	1.00000	−0.00324	0.41712	−0.03567	−0.09296	−0.04815	0.08272	−0.14829	−0.16270
Additional feedback	−0.00324	1.00000	−0.14845	0.28520	0.45995	0.11186	0.00160	0.14246	0.02679
Real environment	0.41712	−0.14845	1.00000	−0.07759	−0.48874	0.07983	−0.05771	−0.31624	−0.36323
Error recognition	−0.03567	0.28520	−0.07759	1.00000	0.53908	0.06482	0.40622	0.56797	0.59734
Functions required	−0.09296	0.45995	−0.48874	0.53908	1.00000	−0.02957	0.36394	0.43868	0.54121
Change flexibility	−0.05815	0.11186	0.07983	0.06482	−0.02957	1.00000	−0.59031	−0.21991	−0.11504
Budget	0.08272	0.00160	−0.05771	0.40621	0.36394	−0.59031	1.00000	0.58126	0.51576
Time	0.14829	0.14246	−0.31624	0.56797	0.43868	−0.21991	0.58126	1.00000	0.63009
Tolerances required	−0.16270	0.02679	−0.36323	0.59734	0.54121	−0.11504	0.51576	0.63009	1.00000

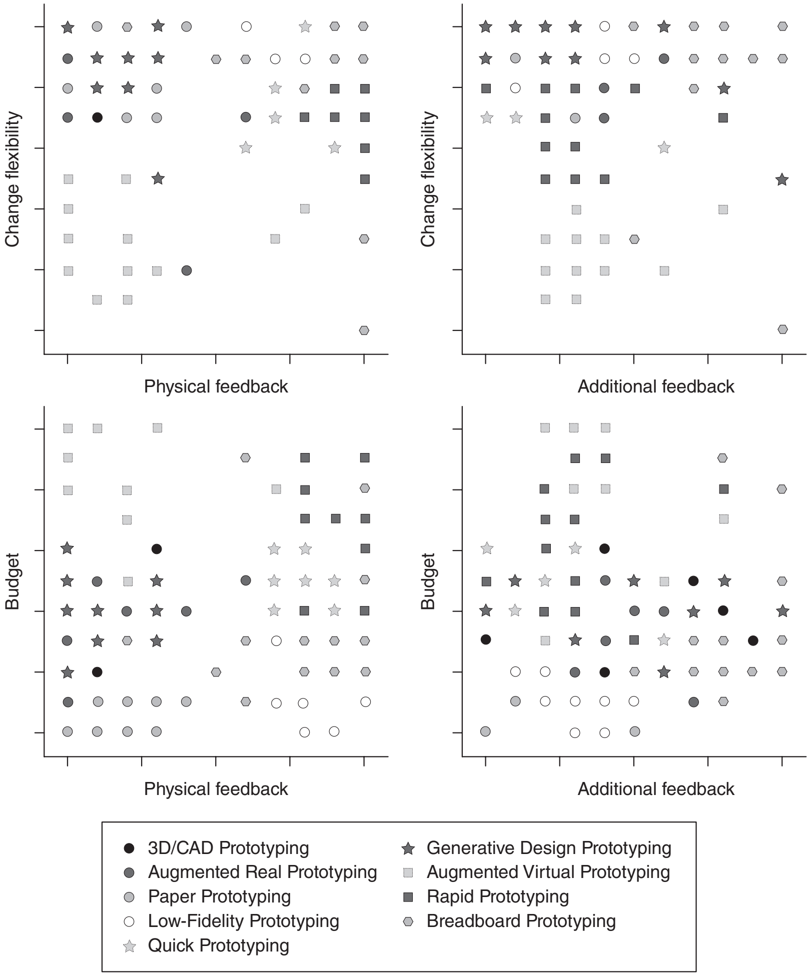

Figure 12.7 Extract of the pair plot of the collected data

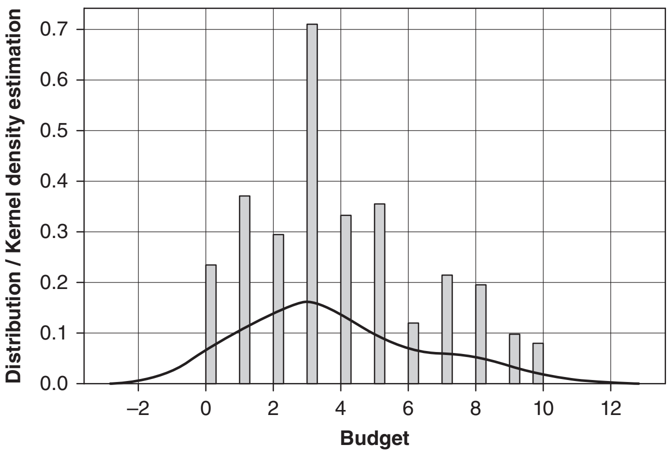

Figure 12.8 Distribution plot of the data

The count plot (Figure 12.9) examines this behavior even more. The count of appearance of every prototyping activity is listed in the graph according to its evaluation based on the "Budget" feature. While the new insights overlap with the ones from the previous graph, it can now be determined which activities were evaluated as outliers in high budget regions and should therefore be excluded from the early development process.

Machine learning algorithms

There is a long list of machine learning algorithms that could be used for this classification problem. With 153 samples gathered, it becomes clear that in particular algorithms that work better with a smaller number of samples such as decision trees or logistic regression might perform very well in the prediction part. To allow an easy approach to the topic, the chosen models are straightforward. The following four algorithms were chosen:

- Decision tree
- *K*-nearest neighbors
- Logistic regression
- Artificial neural network

Decision trees and *K*-nearest neighbors models are that are simple to understand and interpret since they resemble the human decision-making process. With them, it is possible to not just view the algorithm as a black box, but rather comprehend how the model performs predictions. Logistic regression utilizes a linear approach by gradually changing variables to model the desired outcome at the best possible rate. Neural networks within the area of deep learning gradually become more and more popular within every application of artificial intelligence, which is why a comparison with traditional algorithms is of interest.

Decision tree

Using the decision tree algorithm for classification purposes is probably one of the most direct approaches in machine learning for labeling data according to its class affiliation. A decision tree consists of several levels, each of which consists of several branches, so-called decision nodes. At each node, the data are split based on certain conditions.

The "smart" component within this algorithm is deciding which parameter is used to split the data. This decision is made based on the information gain that can be acquired from each split. The information gain is a measure of enhancing the entropy or purity of the dataset by splitting and slowly reaching the goal of an accurate prediction (Provost and Fawcett, 2013). The advantages of applying the decision tree algorithm to machine learning problems are diverse. The created models can be applied to classification and regression problems and thus perform well with both small and large datasets (James, Witten, Hastie, and Tibshirani, 2013).

K-nearest neighbors

A secondary simple and intuitive approach is the utilization of the *K*-nearest neighbors algorithm. *K*-nearest neighbors is an algorithm that estimates the conditional distribution of all possible classes given the different features and further classifies the observation to the class with the highest probability (James, Witten, Hastie, and Tibshirani, 2013).

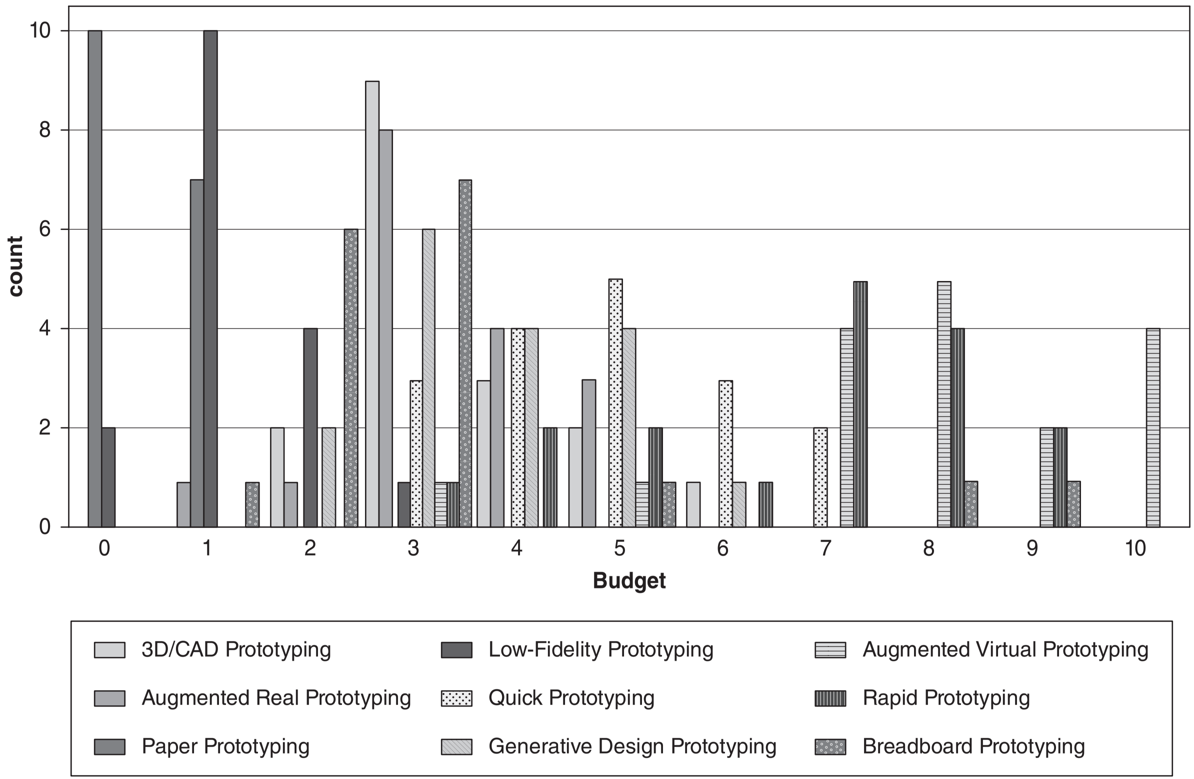

Figure 12.9 Count plot of the given data

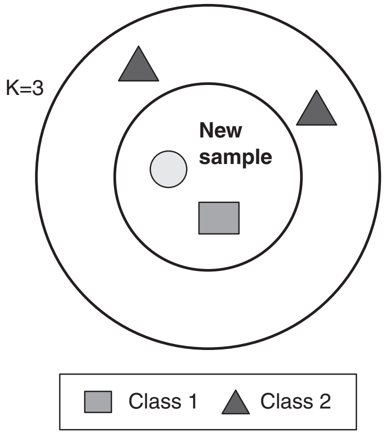

Figure 12.10 *K*-nearest neighbor classification

After training the model with a chosen integer value for K, the algorithm assigns every new observation O to the class with the biggest resemblance to O. If K is larger than 1, O is assigned to the class that has the most representative data points in the near vicinity, as can be seen in Figure 12.10. It is advisable to iterate through different ascending values for K and choose the value that returns the smallest error on known test data (Cover and Hart, 1967).

Logistic regression

Different from linear regression, in which continuous values are predicted, logistic regression can be used to model the probability of an observation belonging to a particular class. The probability is computed by calculating the log-odds or logit for each observation (Provost and Fawcett, 2013; James, Witten, Hastie, and Tibshirani, 2013):

$$log\left(\frac{p(X)}{1-p(x)}\right)=\beta_0+\beta_1X_1+\ldots+\beta_nX_n$$

After the beta-coefficients have been computed from the training data, methods such as maximum likelihood analysis can be used so that a new observation will return its class dependency according to the probability given with the formula

$$\hat{p}(X)=\frac{e^{\beta_0+\beta_1X_1+\ldots+\beta_nX_n}}{1+e^{\beta_0+\beta_1X_1+\ldots+\beta_nX_n}}$$

The graph of the logistic regression curve displays the probability distribution of the data, as the outcome or dependent variable can only take a limited number of possible values between 0 and 1.

Artificial neural network

Artificial neural networks are machine learning models that are modeled after biological neural networks within the human brain. These neural networks consist of several stacked layers with at least one input and output layer and, in the case of deep neural networks, several hidden layers in between, as shown in Figure 12.11.

In each of the individual nodes, all of the input signals are multiplied by individual weights and summed and altered by an activation function such as the sigmoid function to account for nonlinearity (Kröse and Smagt, 1996). The output of a given node for a given input *x* can hereby be expressed with:

$$O_1 = \sigma\left(\beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n\right) = \frac{1}{1 + e^{-\left(\beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n\right)}}$$

By using this design, neural networks are able to compute any given function, no matter the complexity (Cybenko, 1989; Hornik, Stinchcombe, and White, 1989). Neural networks learn by using a process called backpropagation (LeCun et al., 1989). As for every given observation the given input and desired output are known, the beta-weights as shown in the equation can be altered and changed, minimizing the error between model output and desired, real output.

The performance of the models

The first step before applying the different machine learning algorithms is splitting the dataset into a training set and a testing set. Seventy percent of the data are randomly selected for training the models, while the model's accuracy is tested on the remaining 30 percent. This is possible since we know the affiliation of each of the samples in the test set.

Applying the first three machine learning algorithms of decision tree, *K*-nearest neighbors, and logistic regression is simple, as they are part of the scikit-learn library. Importing the relevant model, fitting it to the data, and generating predictions can therefore be achieved with just four lines of code. Figure 12.12 shows an extract of the code for the decision tree classifier.

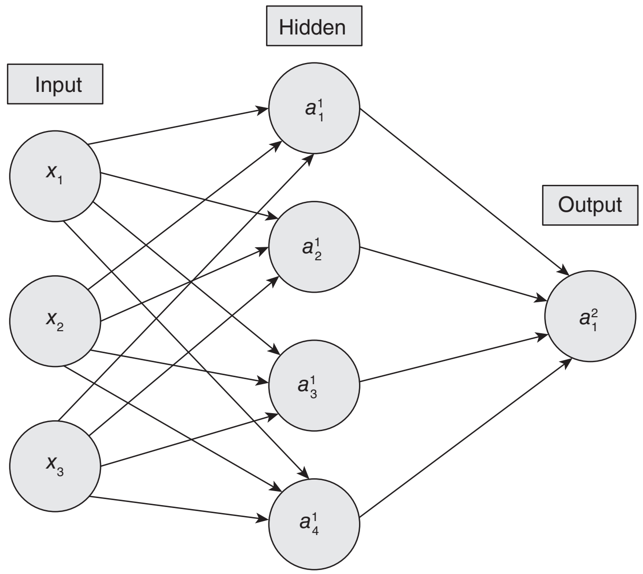

Figure 12.11 Artificial neural network

```
In [8]:  from sklearn.tree import DecisionTreeClassifier

In [9]:  dtree = DecisionTreeClassifier()

In [10]: dtree.fit(X_train,y_train)

Out[10]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                     max_features=None, max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, presort=False, random_state=None,
                     splitter='best')

In [11]: predictions = dtree.predict(X_test)
```

Figure 12.12 Process of importing and fitting the model and generating predictions

The neural network model requires the implementation of additional libraries (Keras and Tensorflow) to make the creation of the network structure more accessible. Keras offers such drastic simplifications that the creation of a multilayer deep network is done by just stacking layer after layer on top of each other. Furthermore, Keras offers tools for hyperparameter optimization, which optimizes the accuracy of the generated predictions.

Certain models even offer an understandable visualization, which helps the human facilitator understand how each individual decision is made. The visualization of the decision tree classifier, shown in Figure 12.13, makes it possible to retrace its decision-making process.

Table 12.4 contains the performance of all four chosen machine learning algorithms. The relevant information is given in a confusion matrix, the classification report and the first five predictions of observations in the testing set.

The tests showed that after applying all four machine learning algorithms, *K*-nearest neighbors performed best on the chosen testing set with precision and recall values of 92 percent and 91 percent, respectively. This good performance is due to the homogeneity of the collected data samples during the workshop. All chosen observations were very close to others of the same class, which explains this behavior.

Having trained several different models, it is now possible to utilize them for prediction purposes. In our case, we can simply create a new list of parameters that we plug into the model. A possible application might be a web application in which the user inputs their desired parameters and the algorithm will suggest the most fitting prototyping activity. Examples are shown in Table 12.5

Discussion and conclusion

Many efforts have focused on the selection of RP processes (Armillotta, 2008; Byun and Lee, 2005; Masood and Soo, 2002; Munguia and Riba, 2008; Rao and Padmanabhan, 2007). Different models have been developed and applied to RP process selection according to predefined criteria. But none of these studies have focused on general prototyping activities. Furthermore, these approaches are not applying data-driven models, that is, the new dataset is not used for training the models to further improve their quality.

Prototyping for X, an outstanding work presented by Menold, Jablokow, and Simpson (2017), is a holistic framework that can help to structure prototyping. It provides different prototyping

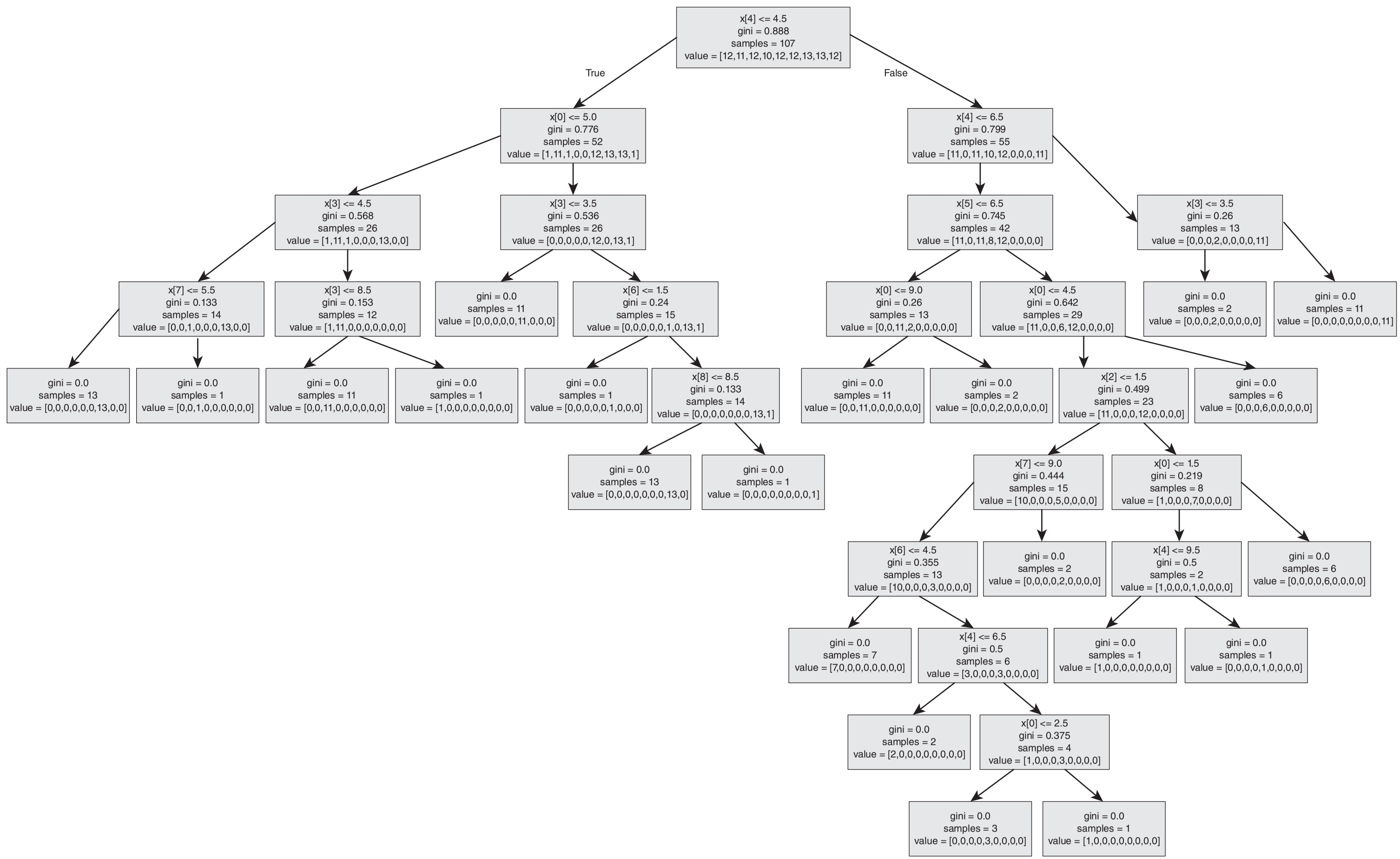

Figure 12.13 Visualization of the decision tree classifier

Table 12.4 Performance of the four machine learning algorithms on the testing set

Machine learning model	*Decision trees*	*K-nearest neighbors (K = 3)*	*Logistic regression*	*Neural network*
Confusion matrix	[[4 0 0 0 1 0 0 0 0] [0 4 0 0 0 0 0 1 1] [0 0 4 0 1 0 0 0 0] [0 0 0 6 0 0 0 0 1] [3 0 0 0 2 0 0 0 0] [0 0 0 0 0 5 0 0 0] [0 0 0 0 0 0 3 0 1] [0 0 0 0 0 1 0 3 0] [0 0 0 0 0 0 0 0 5]]	[[3 0 0 0 2 0 0 0 0] [0 5 0 0 0 0 0 1 0] [0 0 5 0 0 0 0 0 0] [0 0 0 7 0 0 0 0 1] [1 0 0 0 4 0 0 0 0] [0 0 0 0 0 5 0 0 0] [0 0 0 0 0 0 4 0 0] [0 0 0 0 0 0 0 4 0] [0 0 0 0 0 0 0 0 5]]	[[1 0 0 0 4 0 0 0 0] [0 5 0 0 0 0 0 1 0] [0 0 4 0 0 0 0 0 1] [0 0 0 7 0 0 0 0 0] [4 0 0 0 1 0 0 0 0] [0 0 0 0 0 5 0 0 0] [0 0 0 0 0 0 4 0 0] [0 0 0 0 0 0 0 4 0] [0 0 0 0 0 0 0 1 4]]	[[2 0 0 0 4 0 0 0 0] [0 5 0 0 0 0 0 0 0] [0 0 5 0 0 0 0 0 0] [0 0 0 6 0 0 0 0 0] [3 0 0 0 1 0 0 0 0] [0 0 0 1 0 5 0 0 0] [0 0 0 0 0 0 4 0 0] [0 1 0 0 0 0 0 3 1] [0 0 0 0 0 0 0 1 4]]
Classification report	precision recall 3D/CAD Prototyping 0.57 0.80 Augmented Real Prototyping 1.00 0.67 Augmented Virtual Prototyping 1.00 0.80 Breadboard Prototyping 1.00 0.86 Generative Design Prototyping 0.50 0.40 Low-Fidelity Prototyping 0.83 1.00 Paper Prototyping 1.00 0.75 Quick Prototyping 0.75 0.75 Rapid Prototyping 0.62 1.00 avg / total 0.82 0.78	precision recall 3D/CAD Prototyping 0.75 0.60 Augmented Real Prototyping 1.00 0.83 Augmented Virtual Prototyping 1.00 1.00 Breadboard Prototyping 1.00 1.00 Generative Design Prototyping 0.67 0.80 Low-Fidelity Prototyping 1.00 1.00 Paper Prototyping 1.00 1.00 Quick Prototyping 0.80 1.00 Rapid Prototyping 1.00 1.00 avg / total 0.92 0.91	precision recall 3D/CAD Prototyping 0.20 0.20 Augmented Real Prototyping 1.00 0.83 Augmented Virtual Prototyping 1.00 0.80 Breadboard Prototyping 1.00 1.00 Generative Design Prototyping 0.20 0.20 Low-Fidelity Prototyping 1.00 1.00 Paper Prototyping 1.00 1.00 Quick Prototyping 0.67 1.00 Rapid Prototyping 0.80 0.80 avg / total 0.78 0.76	precision recall 3D/CAD Prototyping 0.40 0.33 Augmented Real Prototyping 0.83 1.00 Augmented Virtual Prototyping 1.00 1.00 Breadboard Prototyping 0.86 1.00 Generative Design Prototyping 0.20 0.25 Low-Fidelity Prototyping 1.00 0.83 Paper Prototyping 1.00 1.00 Quick Prototyping 0.75 0.60 Rapid Prototyping 0.80 0.80 avg / total 0.77 0.76
First five predictions	• Rapid Prototyping • Generative Design Prototyping • Breadboard Prototyping • 3D/CAD Prototyping • Low-Fidelity Prototyping	• Rapid Prototyping • Generative Design Prototyping • Breadboard Prototyping • Generative Design Prototyping • Low-Fidelity Prototyping	• Rapid Prototyping • Generative Design Prototyping • Breadboard Prototyping • 3D/CAD Prototyping • Low-Fidelity Prototyping	• Rapid Prototyping • Generative Design Prototyping • Breadboard Prototyping • 3D/CAD Prototyping • Low-Fidelity Prototyping

Table 12.5 Made predictions using the *K*-nearest neighbors algorithm

Phy. feedback	*Add. feedback*	*Environment*	*Error*	*Functions*	*Change*	*Budget*	*Time*	*Tolerances*	*Activity*
10	3	6	4	3	9	6	6	7	Quick Prototyping
2	4	8	7	2	7	3	3	3	Augmented Real Prototyping
2	2	8	2	2	9	1	2	2	Paper Prototyping

strategies and guiding methods for a variety of purposes. This is in line with our study. The main motivation behind the study is to explain the different uses of prototypes and provide suggestions to support prototyping processes. Instead of creating a holistic framework that covers the overall process, our study aims at developing a smart approach for the selection of prototyping activities.

Camburn et al. (2015) formed a methodology for designing a prototyping strategy based on six key specific process variables that improve prototyping performance. Instead of focusing on the strategy level, our study pays more attention to the best practice of prototyping activities. We chose the criteria suggested by Filippi and Barattin (2014) in our models and further adopted four different AI-based approaches to generate suggestions for prototyping activities. The models are applied and tested for the selection of prototyping activities in the early phase. The beauty of this approach is the improvement of the models with a rising number of applications (i.e. training with new datasets). Our study fills the gap of missing an AI-based system to support the selection of general prototyping activities. More and more efforts on prototyping studies will adopt and benefit from AI technologies.

Limitations and further research

The major limitation of this research effort is the size and quality of the examined dataset. The data exploration, visualization, and predictive modeling discussed earlier is only based on 17 individual observations of engineering students. The participants were mostly subjected to a prior workshop or at least an introductory explanation. The collected dataset was homogenous and from novice engineers, which limits the performance of the model. Further research should investigate a bigger participant group to see if data-gathering efforts based on the questionnaire without a workshop would create comparably good and homogeneous results. Then a much bigger and higher-quality dataset can be collected via questionnaires from more experienced prototype developers. An increased use of the model by experts improves the quality of suggestions provided by the model.

A further approach is the expansion of the dataset with the application of smarter or more effective data mining techniques. By extending the dataset, more complex machine learning models can be applied.

In addition, prototyping activities considered in the pilot study are focused on the early phase of product development. Many more prototyping techniques and activities that were not subject to this study should be included and examined in future studies.

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Appendix

Note: Figures, which are used to explain the prototyping activities, are not included here.

Prototyping activity 1

Paper prototyping

You and your design team were instructed to supply a possible design for an app that operates within the topic of a "smart classroom".

During your ideation process, you are asked to supply two designs containing different measured parameters from the classroom and options on how you could display those to the students (energy use, CO_2 level, etc.).

Materials:

- Paper
- Markers

Prototyping activity 2

Breadboard prototyping

For one of your projects, you want to prototype the functionality of one of the components first before implementing it into the final product.

Prototype the following circuit and ensure yourself of its functionality.

Materials:

- Arduino Uno and breadboard
- Cables
- LED
- Button
- 220Ω and 10KΩ resistor

Prototyping activity 3

Low-fidelity prototyping

Using the materials supplied, design a prototype that protects the eggs from breaking when being dropped from a 1-meter height. Be creative!

Materials:

- Balloons
- Straws
- Tape
- Cups
- Toothpicks
- Eggs
- Ribbon

Prototyping activity 4

Quick prototyping

Discuss the intentions of designing and manufacturing prototypes that present a current or future design or a product without actually implementing any further features.

Prototyping activity 5

Rapid prototyping

Assess the steps of design and manufacturing, quality, and tolerances of the provided prototype. Can you notice any limitations or failures of this type of additive manufacturing? If possible, compare it to the prototype examples created earlier.

Materials:

- 3D printed prototypes from previous projects

Prototyping activity 6

Augmented-real prototyping

This prototyping activity involves placing a virtual prototype within a real environment. A very simple implementation of this technique can be achieved with various AR apps available for different smartphones.

Prototyping activity 7

Augmented-virtual prototyping

This prototyping activity involves placing a real prototype within a virtual or computer-generated environment. This technique is especially often used in the automobile industry when cars are exhibited to display weather, aerodynamic behaviour or other influences.

Prototyping activity 8

3D/CAD prototyping

In your first semester and in your semester projects, you should have had some insights into the creation of virtual or 3D prototypes. Discuss possible advantages or disadvantages of these types compared to real prototypes. Also think about what further benefits the virtual aspect brings to the table.

Materials:

- 3D virtual prototype

Prototyping activity 9

Generative design prototyping

Play around with the 3D design on the computer and see what happens to the prototype when you use the slider. Try to describe the generated model compared to a model you might have designed yourself and discuss the advantages of it.

Materials:

- Autodesk simulation showing the design and offering possibilities to make changes