Enhancing Computational Science Education Through Practical Applications: Leveraging Predictive Analytics in Box Meal Services

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Abstract. This paper presents a student project carried out in collaboration with a major industry partner, demonstrating the simultaneous novel application of predictive analytics, in particular machine learning (ML), in the domain of boxed meal services, and explores its implications for IT education. Drawing from a validated ML model trained on data collected from box meal companies, this study showcases how predictive analytics can accurately predict customer sociodemographic characteristics, thereby facilitating targeted marketing strategies and personalized service offerings. By elucidating the methodology and results of the ML model, this article demonstrates the practical utility of computational techniques in real-world electronic services. Moreover, it discusses the pedagogical implications of incorporating such case studies into computational science education, highlighting the opportunities for experiential learning, interdisciplinary collaboration, and industry relevance. Through this exploration, the article contributes to the discourse on innovative teaching methodologies in computational science, emphasizing the importance of bridging theory with practical applications to prepare students for diverse career pathways in the digital era.

Keywords: Computational Science Education· Predictive Analytics· Machine Learning · Box Meal Services · Experiential Learning · Interdisciplinary Collaboration · Industry Relevance

1 Introduction

The aim of this project was to create an IT system overseen by a staff member from an eminent IT company. Its purpose was to showcase genuine challenges

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DOI: 10.1007/978-3-031-63783-4_28

faced by users in practical scenarios, while also illustrating the intricacies and techniques involved in such operations. The project was meticulously chosen and managed to address real-world issues without compromising sensitive information or jeopardizing business affiliations.

Understanding the nutritional preferences of users, along with the freshness of the food offered and logistic efficiency, is a crucial aspect of the box catering service. Unlike customers ordering food in bars and restaurants, where the products can be seen and tasted, box catering customers rely solely on descriptions and images. Moreover, box catering typically involves ordering meals for multiple days, necessitating a deep understanding of customer preferences to ensure satisfaction over time [21]. The challenge lies in aligning the offered meal boxes with customer expectations to reduce service cancellations after the initial trial period.

To address this challenge, this study leveraged machine learning (ML) methods to infer customer sociodemographic characteristics based on their box selections and relevance to various service factors. The dataset utilized for this analysis, sourced from a survey conducted during the Covid-19 pandemic by a Polish meal box catering company and available on Kaggle, provided insights into customer behavior and preferences amidst changing circumstances. By employing ML techniques, the study aimed to classify and estimate customer profiles to enhance service personalization and customer satisfaction.

While previous research has explored customer profiling using artificial neural network techniques, few studies have comprehensively examined the impact of the Covid-19 pandemic on customer behavior in the context of box meal catering. Existing literature demonstrates the efficacy of ML models in profiling customers across various industries, including food tourism and online delivery services [22]. However, the specific application of ML in meal box customer profiling remains underexplored.

This study contributes to filling this gap by analyzing the factors influencing customers' choices in meal box services. By gaining insights into customer profiles and behaviors, businesses can tailor their services to better meet customer needs and preferences. Additionally, the findings shed light on the pedagogical implications of incorporating such case studies into computational science education, emphasizing the importance of bridging theory with practical applications to prepare students for diverse career pathways in the digital era. Through this exploration, the study aims to contribute to the discourse on innovative teaching methodologies in computational science and promote interdisciplinary collaboration between academia and industry.

2 Related Work

This section provides an overview of key research fields pertinent to the study, including meal box catering, customer profiling, and machine learning applications.

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DOI: 10.1007/978-3-031-63783-4_28

2.1 Meal Box Catering and Online Food Delivery

The food delivery market has experienced substantial growth, with online orders comprising a significant portion of all food deliveries [9]. Third-party delivery platforms such as GrubHub, UberEats, and DoorDash have played pivotal roles in expanding the scope of online food delivery services [17]. These platforms offer a wide range of meal options, including breakfasts, lunches, dinners, and all-day packages, catering to diverse customer preferences [17, 1]. The COVID-19 pandemic further accelerated the adoption of online food delivery services, particularly meal box subscriptions, as people sought convenient and safe meal solutions [21].

The proliferation of meal box catering services during the pandemic highlighted the importance of understanding customer preferences and tailoring services accordingly. This shift in consumer behaviour underscores the need for robust customer profiling strategies to enhance service personalization and satisfaction.

2.2 Customer Profiling

Customer profiling is a fundamental aspect of customer relationship management (CRM), enabling businesses to understand customer needs and behaviours [10]. By leveraging data mining techniques, companies can extract valuable insights from customer data to improve service offerings and enhance customer retention [2]. Effective customer profiling facilitates targeted marketing efforts and fosters customer engagement and loyalty [20].

2.3 Machine Learning and Artificial Neural Networks

Machine learning (ML) and artificial neural networks (ANNs) have emerged as powerful tools for analyzing complex datasets and making data-driven predictions [5].While machine learning is fueling technology that can help workers or open new possibilities for businesses, there are several things business leaders should know about machine learning and its limits. One is explainability, meaning what the machine learning models do and how they make decisions [7]. ANNs, inspired by the human nervous system, are particularly effective in solving pattern recognition and classification tasks [4].

The rapid advancement of ML techniques has led to their widespread adoption across various domains, including business, healthcare, and automotive industries [19, 24]. With the increasing complexity of ML algorithms and the availability of computational resources, these techniques are finding novel applications and fueling innovation across industries [23, 18].

3 Materials and Methods

This section describes the dataset's characteristics and how the raw data has been collected and utilized for this experiment. We built and tested various

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DOI: 10.1007/978-3-031-63783-4_28

machine learning models to learn and understand the feature importance and correlation between them. We have also experimented with these models to predict customer classification profiles using their characteristics and motivations in decision-making.

3.1 Dataset

The study is based on the publicly available dataset posted on Kaggle, and it contains available data reported by one of the meal box providers in Poland. The data was collected at the beginning of the 2020 COVID-19 pandemic. The available data set contains 842 records with 35 columns. Each column precisely describes the characteristics of the question it belongs to. Initially, the data was collected in Polish, but the dataset on Kaggle was translated into English. We can find 3 categories of the information collected. The first section provides social-demographics information like Age, Gender, Marital Status, Occupation, Monthly Income, Educational Qualifications, Place of Residence, Family size, Height, and Weight. The second section is focused on the box itself and type of delivery, payment preferences, special needs or requirements and physical activity profile. The third section is focused on the motivation and various factors of importance to choosing the meal box. The data collected in this third section is the most interesting because we know very little about this aspect and the role that fear of catching COVID-19 plays in the decision-making process, which factors influence this and what needs to be considered to properly understand consumer behavior.

3.2 Machine Learning Algorithms

We implemented an ML learning algorithm for customer classification in a meal box catering service. A training set (training data + answers) provided information about each client and his/her box for correct classification. The analyzed data set provides information about each client, including gender, age, education, income, profession, BMI-Body Mass Index, the type of food offered, and the importance they assign to various motivating factors that determine this choice. Responses to the following set of questions/features motivating the dietary decision allowed us to connect the sociodemographic characteristics of users to the type of answers given:

- Diet Type,
- For which period the order was placed,
- Motivation to choose a diet,
- Physical activity,
- Special needs,
- Do you find it cheaper than cooking at home?
- Do you find it easier and more convenient than preparing meals at home?
- Do you find it a time-saving alternative?
- What type of payment do you select?

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DOI: 10.1007/978-3-031-63783-4_28

- Do you value more diet offers and flexibility in changing them, and are you ready to pay for them?
- Is the food of the same or better quality as in the restaurant?
- Do you value a box diet from a health concern perspective?
- Do you see a problem with offered delivery times, and are you ready to pay for this?
- Do you value diversity in the menu, and are you ready to pay for this?
- Do you consider the quality and aesthetics of the packaging and the method of delivery important, and are you ready to pay for it?
- Do you value the possibility of replacing the meals, and are you ready to pay for this?
- How do you rate the safety of such a diet in terms of Covid 19 - no physical contact, no need to go shopping?
- How did you hear about this kind of service?
- Do you combine this diet with a special training program?
- Do you have a personalised diet created by a dietitian?
- How long are you going to use a diet,
- Are you going to extend it?
- Would you recommend this type of food to others?

The ML algorithm learns with the training set. When a new customer arrives at the E-Commerce portal and begins an order by answering questions, the algorithm can classify them based on the knowledge about sociological classification it has acquired. During our research phase, we built our machine learning models based on theoretical foundations for multiclass and multi-output algorithms. This classification joining method is known as multi-output and is also called multitask classification. We have experimented with and verified a few models for which we have used TensorFlow and ScikitLearn. Fundamentally, most classification algorithms aim to capture dependencies between input variables x_j and the output variables y_j. The prediction $y' = f(x)$ of a scoring classifier f is often regarded as an approximation of the conditional probability $P_r(y = y'/x)$, i.e., the probability that y' is the true label for the given instance x. In multi-output classification models, dependencies may exist between x and each target y_i and between the labels y_1 , ..., y_n themselves. Traditionally, a supervised multi-output learning paradigm simultaneously predicts multiple outcomes with one entry, which means much more complex decision problems. Compared to traditional single output learning, multi-output learning is multi-dimensional, and the results can be complex interactions that can only be handled by structured inference. Multi-output machine learning algorithms can be used in many ways in various fields [26] e.g.:

- binary output values - related to multi-label classification problems,
- nominal output values - related to multidimensional classification problems,
- ordinal output values - studied in label ranking problems,
- real-valued outputs - considered in multi-target regression problems.

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DOI: 10.1007/978-3-031-63783-4_28

Many studies have been conducted in the field of multi-output classification, and the same problem of funnel model and theory for understanding consumer decision-making and behavior has been discussed by many authors. Predicting consumer behavior becomes a prerequisite for marketing decision-making, and it is considered very important, especially in online shopping. In the work of Jungwon Lee [15], we can deeply analyze the suitable machine learning model for predicting online consumer behavior. This work analyzed 8 models comparing suitable machine learning algorithms and sampling methods in the context of online consumer behavior. Those models are:

- Classification tree (TREE);
- Artificial neural network (NNET);
- K-Nearest-Neighbor (KNN);
- Logistic Regression (LOGIT);
- Support vector machine with the linear kernel (SVML);
- Random forest (RF);
- Gradient Boosting Algorithm (GBM);
- eXtreme Gradient Boosting (XGB).

The authors validated some of them and proposed the best model adapted to the tested data. In our analysis, we looked at their solutions and employed the proposed algorithms in data analysis and model building in a customized fashion for our study. As mentioned earlier, in our study, we built a model capable of combining multi-output classification with multi-label classification. Ultimately, in our scenario, each multi-output class also utilizes multiple labels. In other words, our model classifies an object into different class categories simultaneously, giving them a specific label from the pool of available labels for a given class category. We have been building our multi-output neural network model utilizing TensorFlow framework, which has been used to classify our social-demographics items using 8 separate forks in the architecture:

- one fork is responsible for classifying the age of a given input;
- the second fork is responsible for classifying the gender;
- next fork classifies marital status;
- next fork occupation accuracy;
- next fork monthly income;
- next fork educational qualifications;
- next fork place of residence;
- the last fork is responsible for classifying family size.

Finally, we have trained the network to classify the training dataset and obtain the multi-output classification results.

4 Results

4.1 Environment setup

Using Jupyter Notebook, a seed has been initialized to ensure reproducibility in all experiments.

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DOI: 10.1007/978-3-031-63783-4_28

4.2 Data collection and structure

The data was collected from the Warsaw Concept company, which used catering services from miodmalina.eu, the collection period lasted from March 2020 to November 2020, and the data was published as a dataset on Kaggle.com. The dataset was cleaned before publication, and there are complete data and answered questions. From the data type perspective, we only have one data category in floating point format. This value was calculated as BMI, obtained from height and weight values, which are integers. Box calories are also in integer format. The remaining data represents the type of the data type object. All other data are not in numerical format but can be easily converted to a numeric scale assigned to a given response category. We have answered the questions and grouped them into sets 1 to 5 or 1 to 6 or 1 to 7, or 1 to 9 categories. Psychometric questions include "Do you value the possibility of replacing the meals and are you ready to pay for this?" These are typical Likert-type questions, ranging from 1 to 5 or 1 to 7, where 1 means "strongly disagree" and 5 "strongly agree". An example of the data categorization method is shown in Figure 1, which shows the age distribution of the studied dataset grouped into 6 categories. The count represents the number of users of the meal box services assigned to each age category group. After reading and cleaning the data, categorical variables have

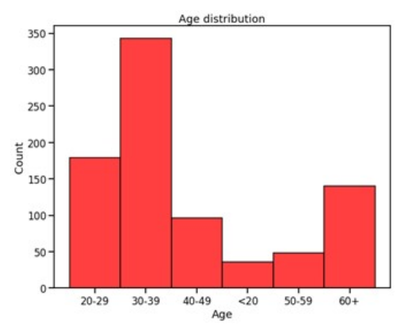

Fig. 1. Age distribution of the meal box catering users.

been converted to one-hot encoding representation for all models (neural networks, trees, GBMs) except for Logistic Regression (the targets for regression have been encoded as integers). Next, we selected the target data columns. We have extracted the columns from the data set that can be used to do the sociodemographic characteristics of the clients of box catering services. From the entire dataset, we have selected the following data types that we use to categorize and predict users:

- Age;
- Gender;
- Marital Status;

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DOI: 10.1007/978-3-031-63783-4_28

- Occupation;
- Monthly Income;
- Educational Qualifications;
- Place of residence;
- Family size.

The next step was to divide the dataset into training and evaluation parts. The data has been split into training (631 records) and testing (211 records) sets.

4.3 Model Performance Evaluation

This section evaluates the performance of various machine learning models in predicting the sociodemographic characteristics of customers using box catering services based on their box selection behaviour. We first discuss the performance of a multi-label Multi-Layer Perceptron (MLP) model and then compare it with other classic machine learning algorithms.

Multi-Label Multi-Layer Perceptron (MLP) Model We initially constructed a multi-label MLP model to predict specific sociodemographic properties. The model was trained using a training dataset and validated using test data. Figure 2 illustrates the confusion matrix for the "Occupation" category, demonstrating the model's accuracy in predicting different occupations.

Fig. 2. Confusion matrix for the "Occupation" category

The MLP model exhibited commendable accuracy, particularly in predicting categories such as "Student" or "Small business," achieving over 90% accuracy for these categories.

Hyperparameter tuning played a crucial role in optimizing the model's performance. We manually tuned the hyperparameters, considering the dataset's

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DOI: 10.1007/978-3-031-63783-4_28

size and model complexity, resulting in satisfactory accuracy for real-world applications.

The topology of the MLP model, depicted in Figure 3, comprised hidden layers with ReLU activation and an output layer with softmax activation. The model achieved an accuracy of 0.8934 with a loss of 0.3123.

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_63 (Dense)             (None, 128)               12672
_________________________________________________________________
dense_64 (Dense)             (None, 32)                4128
_________________________________________________________________
dropout_5 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_65 (Dense)             (None, 8)                 264
=================================================================
Total params: 17,064
Trainable params: 17,064
Non-trainable params: 0
```

Fig. 3. Single output multi-label MLP model summary

Multi-Output Neural Network Model to obtain a comprehensive understanding and analyze correlations between multiple output scenarios, we developed a multi-output neural network model using TensorFlow with Keras API. The model comprised eight branches, each dedicated to predicting a specific sociodemographic feature.

The model architecture consisted of dense layers with ReLU activation feeding into each branch. We monitored training using validation data and compiled the model using categorical cross-entropy loss and the Adam optimizer.

The achieved accuracy for individual categories and the mean absolute loss functions are summarized in Table 1. The model exhibited an impressive coefficient of accuracy across all features, with an average accuracy of 0.8933.

Table 1. Accuracy and loss for multi-output classification

Feature	Accuracy	Loss
Age	0.9289	0.1939
Gender	0.9242	0.1929
Marital Status	0.9005	0.2447
Occupation	0.8768	0.5240
Monthly Income	0.8341	0.3685
Educational Qualifications	0.8910	0.2904
Place of Residence	0.9100	0.2929
Family Size	0.8815	0.3899

Comparison with Classic Machine Learning Algorithms We compared the performance of our neural network models with several classic machine learning

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DOI: 10.1007/978-3-031-63783-4_28

algorithms, including Decision Trees, Random Forest, eXtreme Gradient Boosting (XGB), Support Vector Machines (SVM), and Logistic Regression.

The results, presented in Table 2, highlight the superior accuracy achieved by our models compared to those discussed in prior studies [15]. Notably, our multi-output MLP model outperformed other algorithms, achieving an accuracy of 0.8934.

Table 2. Comparison of accuracy with classic ML algorithms

Model	Accuracy (Our Experiment)	Accuracy (Prior Study)
MLP	0.8934	0.8367
Decision Trees	0.8524	0.8133
Random Forest	0.8750	0.8544
XGB	0.8728	0.8643
SVM	0.8181	0.8318
Logistic Regression	0.8833	0.7386

Our experiments demonstrate the effectiveness of neural network models, particularly multi-output MLP, in predicting the sociodemographic characteristics of box catering service customers. These models outperformed classic machine learning algorithms and provided valuable insights for targeted marketing and customer profiling in the food service industry

5 Discussion

In this section, we will explore how this student's project is making an impact on computational science education, highlighting experiential learning opportunities, interdisciplinary collaboration and relevance to industry.

5.1 Experiential Learning Opportunities

Applying Kolb's Experiential Learning Cycle to educational practices in computational science, such as machine learning, offers a structured framework for understanding how students engage with and internalize complex concepts [13]. Kolb's model delineates four stages: concrete experiences, reflective observation, abstract conceptualization, and active experimentation. In this discussion, we explore how each stage aligns with the hands-on activities involved in teaching machine learning and computational science, drawing from existing literature to support our argument.

Concrete Experiences: Engaging students in hands-on activities, such as building and evaluating machine learning models, serves as the foundation for concrete experiences in Kolb's model. This aligns with Kim et al., who advocate for experiential learning in computational science education [6]. By actively

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DOI: 10.1007/978-3-031-63783-4_28

participating in tasks like data preprocessing, model selection, hyperparameter tuning, and performance evaluation, students directly interact with real-world datasets and algorithms. This hands-on approach not only enhances understanding but also allows students to grasp the practical implications of theoretical concepts.

Following concrete experiences, students engage in reflective observation, a stage characterized by introspection and analysis of one's experiences. Larson and Keiper emphasize the importance of reflection in experiential learning, highlighting how it enables learners to identify patterns and connections within their experiences [14]. In the context of machine learning education, students reflect on their data preprocessing strategies, model selection criteria, and the outcomes of their experiments. This reflective process encourages deeper comprehension and facilitates the transition from concrete experiences to abstract conceptualization.

Abstract conceptualization involves synthesizing observations and experiences to develop theoretical frameworks or mental models. Through reflection, students internalize concepts and principles underlying machine learning algorithms and methodologies. They begin to generalize their experiences, recognizing recurring patterns and principles that govern the behavior of computational systems. This aligns with Kolb's notion of abstract conceptualization and underscores the transformative potential of experiential learning in computational science education.

Active experimentation represents the culmination of the learning cycle, wherein students apply their newfound understanding to solve real-world problems or explore novel scenarios. By deploying machine learning models on authentic datasets or designing computational experiments, students demonstrate mastery of concepts and techniques learned throughout the learning process. This iterative approach to learning reinforces understanding and fosters innovation, as students refine their skills through repeated cycles of experimentation and reflection.

Applying Kolb's Experiential Learning Cycle to machine learning education facilitates a comprehensive and iterative approach to skill development and conceptual understanding. By providing students with opportunities for hands-on experimentation, reflection, conceptualization, and application, educators, especially those with deep knowledge and experience in industry, can foster deep learning experiences that prepare students to tackle the complexities of computational science effectively. This pedagogical approach not only enhances students' technical proficiency but also cultivates critical thinking abilities essential for success in data-driven fields.

5.2 Interdisciplinary Collaboration

Leveraging Vygotsky's Social Development Theory posits that learning is inherently social and occurs through interactions with more knowledgeable peers or mentors [3]. In the context of computational science education, interdisciplinary collaboration with the top expert from an international IT company mirrors

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DOI: 10.1007/978-3-031-63783-4_28

this social learning process, enabling students to benefit from diverse perspectives and deep expertise knowledge [11].

By working collaboratively on projects involving data scientists, domain experts, and industry practitioners, students engage in peer-to-peer learning that enhances their cognitive development and problem-solving abilities [11]. Through shared experiences and collective problem-solving, students co-construct knowledge and develop critical thinking skills essential for success in computational science and beyond [16].

5.3 Industry Relevance

Integrating Bloom's taxonomy of learning domains provides a structured framework for categorizing educational objectives into cognitive, affective, and psychomotor domains [8]. This study primarily focuses on cognitive objectives within the context of computational science education, aligning with revision of Bloom's Taxonomy.

By infusing industry-relevant case studies, datasets, and projects into the curriculum, educators elevate learning experiences to higher levels of cognitive complexity. This approach enables students not only to acquire knowledge but also to comprehend, apply, analyze, synthesize, and evaluate information within the context of real-world problems. McKendree et al. emphasize the importance of authentic tasks in promoting deep learning, as they challenge students to engage in higher-order cognitive processes [25].

Through active engagement with industry-relevant challenges, students develop critical thinking skills essential for success in data-driven fields. Koedinger and many others advocate for project-based learning approaches that immerse students in authentic problem-solving contexts, allowing them to develop domain expertise while honing their analytical and evaluative abilities [12].

In the context of machine learning projects, students are tasked with analyzing datasets, selecting appropriate algorithms, optimizing model performance, and interpreting results. By navigating these complex tasks, students engage in cognitive processes spanning the spectrum of Bloom's Taxonomy. They not only acquire theoretical knowledge but also apply it to practical scenarios, analyze data to extract meaningful insights, synthesize findings to inform decision-making, and evaluate the effectiveness of their solutions.

Moreover, exposure to industry-relevant projects equips students with transferable skills that are highly valued in data science, machine learning, and related fields. By tackling authentic challenges, students develop resilience, adaptability, and problem-solving abilities that are crucial for success in dynamic professional environments.

Integrating Bloom's Taxonomy into machine learning education enhances the cognitive rigor of learning experiences, fostering the development of critical thinking skills and domain expertise. By immersing students in authentic problem-solving contexts and challenging them to engage with real-world datasets and scenarios, educators prepare students for the demands of careers in

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DOI: 10.1007/978-3-031-63783-4_28

data science and computational science. This approach not only enriches learning but also empowers students to make meaningful contributions to the field of machine learning and beyond.

6 Conclusion

In conclusion, this study not only contributes to advancements in machine learning and business analytics but also underscores the transformative potential of computational science education in fostering innovative teaching and learning practices. By leveraging machine learning algorithms to analyze sociodemographic characteristics and motivations of customers in the catering box services industry, we have demonstrated the practical utility of computational methodologies in informing business strategies and catering service offerings.

However, beyond the technical contributions of our study, it is essential to emphasize the educational innovations and pedagogical insights gained throughout the research process. Our project served as a compelling educational case study, providing students with hands-on experience in data analysis, model development, and interdisciplinary collaboration. The collaboration between industry instructors and students was instrumental in bridging the gap between academic theory and real-world application, providing students with valuable insights into industry practices and challenges.

By integrating real-world projects like the one presented in this study into curricula, we have created experiential learning opportunities that not only bridge the gap between theory and practice but also foster collaboration and knowledge exchange between academia and industry. This cooperative approach not only enhances the relevance and applicability of educational experiences but also prepares students for seamless transitions into the workforce.

Moreover, our study highlights the importance of feedback loops between research findings, industry practices, and the teaching and learning process. Through reflection on our experiences and insights gained from the project, we can identify areas for curriculum enhancement, pedagogical innovation, and student engagement. By embracing educational feedback loops and fostering a culture of collaboration, we can continuously refine our educational approach and adapt to the evolving needs of students and industries.

In terms of our contribution to educational innovation, it is essential to highlight the novel approach employed in integrating machine learning projects into computational science education. By emphasizing hands-on, experiential learning opportunities and fostering collaboration between industry instructors and students, we have created a dynamic learning environment that equips students with the skills and knowledge needed to thrive in an increasingly data-driven world.

Moving forward, future research directions should focus on further refining our educational approach, incorporating larger and more diverse datasets, and exploring the broader implications of machine learning in computational science education. By continuing to prioritize educational innovation and fostering col-

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DOI: 10.1007/978-3-031-63783-4_28

laboration between academia and industry, we can ensure that computational science education remains at the forefront of preparing students for the demands of the modern workforce.

In summary, while our study contributes to advancements in machine learning and business analytics, it also underscores the transformative potential of computational science education in fostering educational innovation and empowering students. By embracing feedback loops, prioritizing experiential learning opportunities, and fostering collaboration between academia and industry, we can cultivate a dynamic learning environment that prepares students to excel in the digital age.

Acknowledgements This paper and the research behind it would not have been possible without the exceptional support of Graphcore Customer Engineering and Software Engineering team. We would like to express our very great appreciation to Hubert Chrzaniuk, Krzysztof Góreczny and Grzegorz Andrejczuk for their valuable and constructive suggestions connected to testing our algorithms and developing this research work. This research was partly supported by PLGrid Infrastructure at ACK Cyfronet AGH, Krakow, Poland.

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ICCS Camera Ready Version 2024
To cite this paper please use the final published version:
DOI: 10.1007/978-3-031-63783-4_28