# Internet of Things and Machine Learning Competencies in IS Curricula: Advocating for Incremental Evolution of Core Courses

Elahe Javadi
ejavadi@ilstu.edu
School of Information Technology
Illinois State University
Normal, IL, USA

Judith Gebauer
gebauerj@uncew.edu
Congdon School
University of North Carolina Wilmington
Wilmington, NC, USA

Matthew Tunberg
mjtunbe@ilstu.edu
Technology Solutions
Illinois State University
Normal, IL, USA

**ABSTRACT**

The Internet of Things (IoT) and Machine Learning (ML) are considered two important components of the current wave of digital transformation. Yet most IS curricula do not establish a consistent ground for students to develop related competencies through program-level plans. While the distinction between fads and fundamentals has long been a challenge for the constantly changing IS field, the discipline clearly must bear a portion of the responsibility to prepare students for new job roles in the 21st century. In the current paper, we advocate for an evolutionary approach to curriculum development that combines foundational knowledge with the skills required for roles in ML and IoT. We propose to evolve the typical IS-core courses and present an exemplary 4-week module to enhance the introductory database course by adding IoT and ML concepts and competencies. Based on the IS2020 curriculum (Leidig & Salmela, 2021), we identify areas where these two topics can be incorporated into the curriculum core competencies and place them within the framework of one of the accreditation bodies for computing programs.

**Keywords:** Machine Learning, Internet of Things, Core Competencies, Program Objectives

## 1. INTRODUCTION

Gartner has identified three Artificial Intelligence areas in the top 10 strategic technologies for 2023 (Groombridge, 2022). AI literacy has been proposed to be an essential dimension of public education in K-12 and beyond (Ng et al., 2021) and a few states (e.g., GA and FL) have established initiatives for including Artificial Intelligence learning outcomes in their K-12 curricula (Georgia's AI CTAE Frameworks). Similarly, Internet of Things applications are

 ISSN: 2473-4901
v9 n6041

increasingly becoming an integral part of consumer lives as well as business operations. Home security cameras, medical devices, and meteorological sensors are just a few examples of consumer-facing devices, with a lot more non-salient devices being present in agriculture, smart cities and vehicles, environmental monitoring, and wildlife preservation (Trelstad & Cao, 2022). The value of the global IoT market is expected to reach $1.6 trillion by 2025 with a projection of more than 25.4 billion active IoT devices by 2030. Specialized IoT and ML roles are created for different phases of the systems development life cycle, including IoT Strategist, IT Infrastructure Architect, IoT Software Developer, Machine Learning Engineer (Moderation), and Staff Software Engineer - Applied Machine Learning (LinkedIn Jobs). Both ML and the IoT have been posited as elements of the current wave of digital transformation with far-reaching implications for industry and society (Bodrozic & Adler, 2022). In addition, both technologies are interrelated in many ways. For instance, reinforcement learning models used in robots, drones, or autonomous vehicles rely on data that is collected and transmitted via IoT devices to tune their models (Mohammadi et al., 2017). ML and IoT also interrelate when massive environmental data are collected through IoT devices and intelligent analysis is applied to extract actionable insights from the data (Zhang et al., 2021). Considering the growing trend and the new job roles, it is necessary for IS curricula to evolve and actively foster ML and IoT literacy, education, and career readiness for IS graduates.

The IS domain continues to evolve over time (Dede, 1989); however, the realm of competencies has largely remained the same for decades covering foundations, data, technology, development, organizational domain, and integration (Leidig & Salmela, 2021). For instance, relative developments in analytics/big data and security have become part of the data and technology realms. Another recent example of IS core competencies evolving was when IS took an active role in training the future workforce in mobile technology and application development (Bélanger et al., 2019) and was added as a required competency to the IS2020 undergraduate model curriculum (Leidig & Salmela, 2020). In the IS2020 model curriculum, a competency is defined as "*an ability to apply knowledge, skills, and dispositions to effectively complete tasks*", whereby particular competency definitions must include specifications of all three dimensions. The recommended required competency areas in IS2020 are listed in Figure 1, which compared to IS2010 removed Enterprise Architecture (Leidig and Salmela 2020, p. 28). IS2020 competency areas seven through 10 were considered electives (7 & 8) or non-existent (9 & 10) in IS2010.

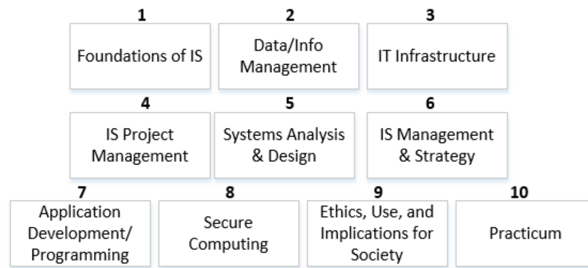


**Figure 1: IS2020 required competency areas (Leidig & Salmela 2020)**

IS2020 has AI and IoT both listed as elective competencies under the Data & Information Management (for AI) and Technology & Security (IoT) realms. IS programs in Business Schools, Computing & Engineering Schools, and Information Schools are approaching ML and IoT education in a variety of ways (Chen, 2022). Some IS programs cover IoT in hardware/software concept courses, others in cloud computing courses. Some programs address ML/IoT topics in business analytics courses while others offer applied data mining courses. The Accreditation Board for Engineering and Technology (ABET) which is an accreditation body for teaching-focused institutions has identified five outcome areas for computing programs. The high-level outcomes serve as guidelines for each institution to articulate detailed localized outcomes; the outcomes are listed in Appendix Table 4; ABET curriculum requirements also address techniques, skills, and tools necessary for computing practice, secure computing, and local and global societal impacts. The five high-level ABET outcomes and the curriculum requirements are consistent with the IS2020 competency realms and areas. There can be an accreditation-level effort to address IoT/ML gaps, but that is not our focus here.

We suggest that there are two general approaches to addressing skills gaps related to innovative technologies, such as ML and IoT: (1) Development of specialized elective courses that provide in-depth coverage of IoT and ML applications within specific domains of IS, such as AI in healthcare, AI in finance, ML for cybersecurity, or AI-driven business analytics. These specialized courses allow students to explore advanced topics and apply IoT and ML techniques in their chosen areas of interest (Chen, 2022). (2) Modification of existing courses and integration of ML/IoT across courses. This

 

ISSN: 2473-4901
v9 n6041

approach can be managed by each IS program individually, as long as there is consensus within the discipline about the expected higher-level competencies and the departments define desired objectives and specific student outcomes for each competency realm and area. Such objectives and outcomes are then established at the program level and implemented to develop skills at different levels of responsibility in the domain, from following instructions and steps to higher levels of setting strategies and policies (Brown, 2020). The Skills Framework for the Information Age (SFIA) levels of responsibility differ regarding the extent to which they require or allow autonomy, influence, complexity, knowledge, and business skills. The program-level approach would enable establishing clarity on expected objectives and outcomes; it would also enable creating competencies at different levels for future roles students may assume in the field, ranging from skilled team members to effective leaders in ML/IoT-focused areas of practice. Developing concept inventories and mapping program objectives and course outcomes would augment the transparency of a program-level initiative.

Programs can foster cross-course integration by encouraging faculty to incorporate subsets of agreed-upon AI/IoT concepts into their respective courses. For example, a course on the Foundations of IS may explore AI-powered data visualization techniques or ML algorithms for forecasting and predictive analytics. Application Development and Programming courses can incorporate learning experiences such as those interacting with prominent ML APIs such as OpenAI Gym. This approach ensures that ML/IoT competencies are not offered in silos but instead integrated throughout the program. There is also a practical reason because, with the advancement of technology, programs would need to regularly update course materials and adapt the curriculum to keep pace with the latest developments, and these updates are easier to implement when the responsibility to modify courses is distributed across many topics. The program-level approach can consist of evolving both elective (program-specific) and core courses.

In the current study, we focus on the potential for evolving the core courses in the IS curriculum and propose ways to integrate ML and IoT competencies. The goal of our work is to (1) point out ML and IoT competencies that are inherently IS competencies as opposed to belonging to other majors (e.g., computer science) and (2) provide a set of learning outcomes through which ML and IoT competencies may be integrated into established IS core courses. We also present examples of learning modules that can contribute to this incremental evolution of the IS curriculum. We believe that an evolutionary approach to IS curriculum development that is set up to include the foundations of new technologies, such as AI and IoT, into regular courses (Lightfoot, 1999) will be faster to adapt and can better prepare graduates for a variety of specialized roles.

## 2. Machine Learning Competencies

Intelligence is defined as the ability to accomplish complex goals (Tegmark, 2017). Artificial intelligence involves creating entities (e.g., information systems or robots) that have complex goals, pursue those goals, and refine their inner working when necessary (i.e., they learn). Intelligent entities include components for perception, representations and reasoning, learning, natural interaction, and societal impact. (Tourzekey, 2024). Machine learning is a specific component of AI, yet we use the two terms interchangeably for the purpose of the curriculum. The scarcity of AI/ML-related competencies among students is a challenge for adopting organizations (Anton et al., 2020). Organizational ML competencies depend on the collection of skills possessed by individual employees (Weber et al., 2022). Creating ML-enabled products and services has been formulated to require skills in different areas of the ML pipeline and many ML-related activities are fundamentally IS-related (as opposed to CS-, CE-, or ECE-related). C3.Ai, a lab that creates ML-based predictive maintenance systems that are used by the Air Force provides the following practice-oriented definition:

"*A machine learning pipeline is the end-to-end construct that orchestrates the flow of data into, and output from, a machine learning model (or set of multiple models). It includes raw data input, features, outputs, the machine learning model and model parameters, and prediction outputs*" (Simons & Gonzalez, 2018).

Looking into the operational side of ML, Kreuzberger and colleagues (2023) conducted mixed-method research to identify and describe its major principles, components, and the associated roles and architectures (Figure 2). The ML training infrastructure, model registry, feature stores, ML metadata stores, and model serving components support the following elements of the architecture: (1) MLOps project initiation, (2) Requirements for the feature engineering pipeline, (3) Feature engineering pipeline, and (4) Experimentation. Examples of associated careers and roles that might be attainable not only to CS or ECE but also IS graduates include ML Engineer/MLOps engineer, Backend Engineer,

ISSN: 2473-4901
v9 n6041

DevOps Engineer, Software Engineer, Data Engineer, and Data Scientist (Kreuzberger et al. 2023).

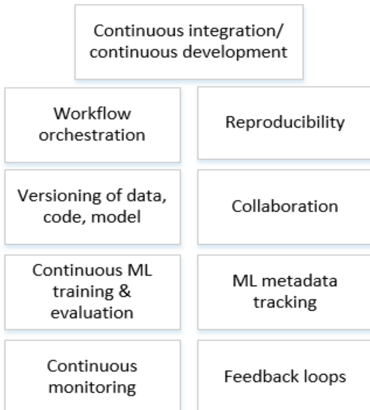


**Figure 2: Kreuzberger's Nine Principles of MLOPs (Kreuzberger et al., 2023)**

The efforts required to streamline and mature ML processes and services, so that they can be conducted with agility, maintained easily, and reproduced effectively are comparable to those practiced in the fields of software engineering and project management (Sugimura & Hartl, 2018). While the foundations are the same, contextual references, concepts and terms, and development frameworks and standards must evolve to include the knowledge and skills required to perform tasks in an ML pipeline. Google which made AI a priority in a move phrased as AI-first (McElhaney et al., 2023) frames ML pipeline activities as shown in Table 1.

**Table 1: Machine Learning Pipeline Activities by Google and their Connection to IS2020 Competency Areas (sources: Kreuzberger et al., 2023; Leidig and Salmela, 2021)**

| ML pipeline activity group (Google) | Targeted competency areas (IS2020) |
|---|---|
| Data collection, data verification, feature extraction | Data/information management, systems analysis & design, Ethics, use, and societal impacts |
| Model (s), model configurations, analysis tools | Foundations of IS, data/information management, IT infrastructure, Application development/programming |
| Machine resource management, serving infrastructure, configuration | IT infrastructure, IS management and strategy, systems analysis, and design, secure computing |
| Process management tools, monitoring | Foundations of IS, project management tools, Ethics, use, and societal impacts |

Researchers have formulated components of AI literacy in higher education (Ng et al., 2021), and K-12 special interest groups have formulated AI/ML outcomes. According to Sugimura and Hartl (2018), AI/ML-related skills needed for the workforce include foundations of data, data acquisition and transformation, feature engineering, models, algorithms, and hyperparameters thereof, as well as the interactions with the underlying platforms and hardware to manage performance and security. Given the developments and demands of industry practice and the wide impact of ML on society, adjusting the foundation courses to include ML flavors of the traditional core ideas is a timely change (Table 1). Because ML techniques are so pervasive, we posit that ML is no longer a choice of major or sequence, but ideally becomes a omnipresent component of all core courses. IS educators may create an ML concept inventory (Almstrum et al., 2006) that could allow a shared approach, yet would enable each specific IS program to evolve uniquely so long as those concepts and skills are adequately included. An example list is included in Table 2.

**Table 2. A sample non-exhaustive AI/ML concept inventory**

| Area | Concepts |
|---|---|
| Data and features | Data preprocessing, normalization, decoding, numerical, nominal, ordinal, factor analysis, clustering |
| Foundations | Supervised learning, unsupervised learning, reinforcement learning, transfer learning, bias, variance, training, test, learning rate, overfitting |
| Models | Neural networks, transformers, diffusion models, decision trees (random forests), logistic regression, naïve Bayes models, clustering, bagging, boosting |
| Model designs factors and parameters | NN layers, NN activation functions, regularization |
| Model selection and evaluation | Loss functions, metrics, cross-validation, performance metrics (e.g., accuracy), sensitivity, specificity, precision, error types |
| Model maintenance | Re-training, new data acquisition, model updating |
| Hardware | GPU, run-time considerations, platform configuration |

Using concept inventories and expected student outcomes, each program can engage in revisions by identifying and evolving courses that can best address these topics. A subset of the concepts listed in Table 2 fit into the courses listed in Table 1. For example, a traditional analytics course can be expanded to incorporate AI techniques for

 ISSN: 2473-4901
v9 n6041

analyzing and interpreting complex problems. Topics like regression, classification, clustering, and natural language processing can all be included in the toolkit with which students design solutions.

Finally, when educating the new generation of IT professionals, it is essential to leverage open-source tools to enable independent learning beyond the classroom and increase the possibility of society moving into a democratized decentralized deployment, application, and control of AI-enabled tools (Bodrozic & Adler, 2022).

## 3. IoT COMPETENCIES

Similar to ML/AI, IoT is also driving significant changes in society. Sensors are present in homes, agricultural settings, warehouses, and in many other areas of our lives as well as businesses. Again, the proliferation of connected devices in the IS ecosystems offers opportunities for a more comprehensive approach to core competencies that include IoT applications. In response to the ongoing trend and emerging job roles, IS curricula need to evolve and actively foster IoT literacy, education, and career readiness for IS graduates. IoT architecture consists of layers that include perception, networking, application, as well as business (Kumar & Mallick, 2018). IS graduates must attain foundational competencies to address the requirements of the work involved in designing, maintaining, and refining such architectures. Considering IoT devices' hardware specifications, their connectivity through the cloud, the type of data they produce (time series), the resource constraints they impose, and the focus on event-driven programming, we propose that they are best covered via the collective evolution of the IS core curricula as opposed to a dedicated elective course.

For instance, given the prominence of data as part of IoT applications, IoT-related data management can be an essential and timely addition to introductory database management courses. Most sensors in the IoT environment or on the equipment stream data that in many cases represent a time-series dataset. Students must gain foundational skills on the peculiarities of time series data. Topics specific to IoT data management such as handling streaming data from IoT devices and storing and retrieving IoT data efficiently can fit into multi-week modules. Students can also be exposed to schema design considerations specific to IoT environments.

Systems analysis and design courses may include models to demonstrate how SAD techniques can be applied to design, implement, and manage IoT solutions. This includes understanding the hardware and software components of IoT systems, integrating devices with the cloud platforms, collecting, and analyzing data from IoT devices, ensuring data security and privacy, and optimizing system performance and scalability. s
Project management students may investigate alternatives for managing the development and deployment of IoT solutions, considering project scope, resource allocation, and risk assessment specific to different types of equipment and choices for cloud platforms. Systems analysis and design courses can guide students to explore the unique challenges of IoT projects, such as integrating diverse IoT devices, handling data from multiple sources, and ensuring scalability and reliability.
Database management courses can include specific opportunities and requirements for time-series data processing.

Networking courses may include IoT networking protocols and communication standards, such as MQTT, alternative IoT network architecture, device connectivity factors, and interoperability between IoT network segments.
Cybersecurity courses may discuss IoT-specific security challenges, including device authentication, data encryption, secure firmware updates, and protection against IoT-based attacks.

Software Engineering courses may include IoT development platforms and frameworks; hardware & software concepts course currently offer Arduino, Raspberry Pi, or other popular IoT platforms.

**Table 3. Sample IoT Concepts and their Connections to IS2020 Competency areas**

| Concept | Potential competency areas |
|---|---|
| Things: microcontrollers, sensors, actuators, and gateways | IT infrastructure, Systems analysis & design, Secure computing |
| Network infrastructures: gateways, routers, aggregators, repeaters | IT infrastructure, Secure computing |
| Cloud infrastructure: storage and processing | Data/info management, IT infrastructure, Secure computing, IS management & strategy |

 ISSN: 2473-4901
v9 n6041

The focus of our work here is to showcase how we as a field can identify areas where these topics are closely related to those covered within core competencies.

## 4. ML and IoT COMPETENCIES and IS

As outlined in the previous sections, considering activities of typical ML pipelines and those involved in creating IoT architectures, IS core competencies and the corresponding courses are well suited to help improve the job readiness of the next generation of the technology workforce. ML and IoT overlap in many areas such as reinforcement learning when data from the environment is gathered through IoT devices in order to improve internal ML models, specifically in autonomous vehicles and robotics systems. Demands for individuals with expertise across various sectors are growing in different phases of requirements discovery, design, development, testing, deployment, and maintenance of new applications that involve ML or IoT. IoT- and ML-related understanding gained in the core courses can also bring about more diverse project opportunities for students in their capstone courses. This evolution is eventually beneficial for enhancing the likelihood of technology democratization (Bodrozic & Adler, 2022) and decentralization of future technologies as they impact more areas of life. A broader educational approach will enable a larger population of students to get involved in different areas of workforce, research, and development within these spheres. We believe that IS programs can take a more active role in education in areas where the skills are inherently IS-related. These suggestions provide a starting point for incorporating IoT competencies into core courses. However, it's important to note that the specific implementation will vary based on the program's structure and available resources. Faculty members should collaborate to identify the most appropriate topics and teaching methods to effectively integrate ML/IoT competencies into the information systems program.
Here we focus on the two curriculum governance bodies: ABET and IS2020. ABET outcomes cover areas such as problem-solving, technical skills, communication, teamwork, ethics, and lifelong learning. To infuse ML or IoT learning outcomes, we have identified the following set of ML outcomes as examples (Table 4).

**Insert Table 4 Here.**

Figure 3 summarizes our stipulations on the extent to which each competency area may need to evolve on a scale of 1-3. It shows the relative impact of ML and IT on the ICIS2020 areas based on the knowledge and competency areas of each of these fields. For instance, we anticipate the impact on Ethics and Societal impacts will be larger for ML compared to IoT and the impact on IT infrastructure will be larger for IoT compared to ML.

Each program may initiate the discussion by placing each of these areas on a given scale across different core courses and derive decisions about the extent of the revisions. For instance, we have examined each of the first nine IS2020 competencies (excluding practicum) because practicum is typically for reinforcement of the competencies gained previously through coursework and drafted a sample list of ML-and IoT- specific competencies for each of the nine areas.

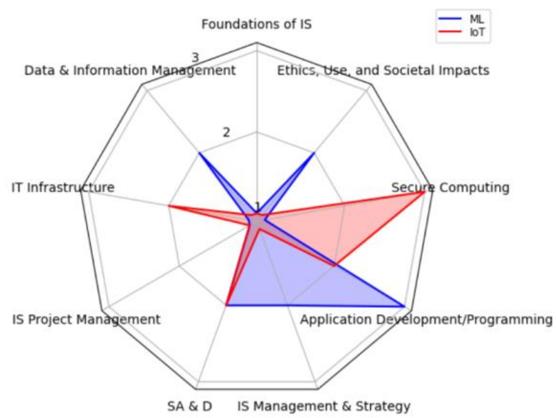


**Figure 3: A view of the extent of the evolution of ICIS2020 core competencies on a 1-3 scale**

**Insert Table 5 Here.**

The competencies for ML are listed according to the competency realms and the competency areas (Figure 5).

## 5. LEARNING MODULE EXAMPLES

In this section, we introduce two learning modules that allow students to explore the ML/IoT topics in an introductory Database course. The following sections focus on the IoT module followed by a shorter ML module. The IoT module is expected to take up to three 75-minute class meetings, and the ML module up to two 75-minute class meetings. The IoT module requires more work with the setup and orientations of students in order to include a hardware component.

### *IoT LEARNING MODULE*

Most information systems programs have a course in which hardware and software concepts are discussed. Ideally, these courses involve a project, and most commonly Raspberry Pi[1] or Aruduino[2] kits are used for student projects. Both of these project boards have plenty of documentation and extensive communities built around them, so they both support independent learning. Students can create projects to monitor temperature, humidity, heart bit rate, and control cameras or motors. To transmit and store data to the cloud, WiFi-enabled boards are preferred because newer generations of Raspberry Pi (e.g., 3B, Zero W) and Arduino (e.g., Arduino Uno WiFi, Arduino Yùn) are WiFi-enabled. Older generations of both devices can be WiFi-enabled using external modules (e.g, ESP8266 Serial Wifi Module ESP-01) or data can be received via serial ports and then sent to the cloud. In practice, the communication between IoT devices and the cloud is typically wireless, which means that communication security is an important topic that connects this work to the encryption technology mentioned above. Table 1 lists the learning objectives of the IoT learning module.

**Table 6: learning objectives for the IoT data management module**

| Topic | Learning objectives |
|---|---|
| IoT | Experiment with connecting IoT sensors to the project board.<br>Assess if the connection has been established correctly.<br>Optional: Monitor and evaluate information received via serial ports. |
| Cloud database setup | Setup database and tables in the cloud platform.<br>Experiment with creating tokens (or API keys) needed for communicating. with the cloud database. |
| Data acquisition & management | Experiment with libraries that enable cloud communication<br>Create and test a connection to write to the cloud database.<br>Create and evaluate queries on time-series data. |

#### *Part 1: Arduino and temperature sensor setup*

Part 1 of the learning module focuses on the two IoT-related learning objectives (Table 1). While Arduino or Raspberry Pi (or comparable boards) with WiFi capability are preferable, we set up our experiment with an older generation of Arduino and Raspberry Pi devices and established communication through serial ports. The reason was the availability and affordability of the older generations of the boards for the database course (the department had many older generation boards in inventory). The work required by students included working with Arduino IDE (C++ programming) and coding in Python to establish communication with the cloud platform. If Raspberry Pi is used students will use Python scripting only to interact with the IoT device and establish communication with the cloud. Consequently, the learning scope is smaller (and more manageable) when Raspberry Pi is used.
Typically, the project boards are small, and the circuits are very easy to create on a small desk space that is typically available in computer labs. Students will set up the connection and specify the port and start reading the information on the serial port.

#### *Part 2: Cloud database and API setup*

The second part of the learning module addresses the two learning objectives related to the cloud database setup (Table 1). From open-source time-series cloud-based database platforms, Prometheus and InfluxDB were shortlisted and explored. We decided on InfluxDB[3] because of easy access for the students, as it provides a free 50 GB cloud instance for individuals to use. In addition, InfluxDB integrates easily with Grafana, an open-source data visualization service, and it provides very good documentation; while influxDB was used here for this specific module, all other cloud platforms have components to support IoT connections.

#### *Part 3: Connecting to the cloud and recording data*
The third session is focused on connecting to the cloud and recording the data observed on the serial port, this part addresses the three learning objectives related to data acquisition and management (Table 1). A script would need to parse the received data and format it in a way that is compatible with InfluxDB. This involves converting the data format and possibly adding timestamps to the data. A Python script can use the InfluxDB Python library to send the formatted data to InfluxDB. The data is then stored in InfluxDB in a time-series format and organized by timestamps for later retrieval. Depending on the cloud platform and the IoT device, this part of the work will change. More details of the InfluxDB

[1] *https://www.raspberrypi.org/*
[2] *https://www.arduino.cc/*
[3] *https://cloud2.influxdata.com/*

connection in Python is shared in the Appendix.

***Part 4: Exploration, extension, and Reflection***

During the final part of the learning module, students are encouraged to explore visualization tools provided by InfluxDB. They can add sensors to receive more data and create new buckets for collecting the added data. They can practice modifying the Python script to send different data to their buckets. Another possibility is to use Grafana for visualization. Simple scripts can create connections to the Grafana API to create visualizations in Grafana.

***ML LEARNING MODULE***

**Table 7: Learning objectives for the ML data management module**

| Topic | Learning objectives |
|---|---|
| Prelude | Recognize requirements of supervised models with numerical or categorical targets (labels), change the scale of numerical predictors, encode categorical targets, split data into train and test subsets |
| Model parameters | Define an estimation and classification problem (e.g., penguin body mass, or species), its input, and the target |
| Model evaluations & comparisons | Write GoogleSQL queries to evaluate and compare model Identify evaluation metrics appropriate for a given model (e.g., estimation) |

Many database management systems including now offer in-database machine learning. Adding an ML module, therefore, to a database course does not change the foundations of the work but extends the focus areas only. In this one-week module students will start learning about the machine learning operations and pipeline and be introduced to the currently available ML features of typical databases, we propose the following list of objectives. We used Google BigQuery in this module for the availability of practice datasets, educational access privileges to the platform (an instructor can obtain credits and distribute or students can apply for credits individually), and training modules provided by Google that can support learning outside the class. Palmer Archipelago Penguins dataset (Horst et al. 2022) consists of information about three species of penguins and includes 344 records of three species of penguins living on three islands. The data has seven fields including those denoting species, island, and sex, and the other four are numerical. The dataset has gained popularity for teaching purposes and it has been included in the BigQuery training. The reason we chose this data is because of the small size, ease of access, and availability on the Google Cloud for running ML queries.

***Part 1: Research Questions, Data Requirements, and Model Foundations***

In the first part of this module, students will explore different activities of the Machine Learning Pipeline shown in Figure 1. Students will also learn about supervised and unsupervised learning models as well as train, validation, and test datasets and their purposes. Students can learn a few foundational supervised and unsupervised models such as decision trees (or linear/logistic regression), and K-meaning (or hierarchical clustering). The choices of the models may change depending on the datasets that instructors have access to but it's recommended that two alternatives are introduced for each problem.

***Part 2: Model Parameters, ML Queries***

Students write the first ML Query. In this example, we used Google's BigQuery because the platform allows students to experiment with the tools through students' credit and learning paths and provide details of step.

***Part 3: Create Model and Evaluate Models***

*BigQuery Penguin weight estimation examples provide a good starting example for creating and evaluating models by writing BigQuery.*

```
CREATE OR REPLACE MODEL `ML_in_DB.penguins_model`
OPTIONS
  (model_type='linear_reg',
  input_label_cols=['body_mass_g']) AS
SELECT
  *
FROM
  `bigquery-public-data.ml_datasets.penguins`
WHERE
  body_mass_g IS NOT NULL
```

**Figure 4: Google's BigQuery Penguin Weight Estimation Model**

***Part 3: Model Evaluation & Societal Impacts***

Students can examine evaluation metrics (e.g., mean squared error for estimation models), schema, and training details. In this example, students will examine metrics that are related to those they have seen in their introductory

ISSN: 2473-4901
v9 n6041

statistics or econometric courses. However, it's important for students to experiment with and evaluate classification models where metrics such as sensitivity, precision, and specificity are relevant; these measures may have a distinct impact on machine learning models' stakeholders and may lend themselves to fruitful discussions on equity and model impact assessment.

## 6. CONCLUSIONS

The short learning IoT and ML data management modules presented in this study enrich the introductory database course and the IS curriculum; this incremental approach can be extended to include other features and concepts. An example of a successful project completed in the authors' school is an IoT Long Range (LoRa) weather mesh network that allowed devices to connect and share telemetry data over long distances. The premise of this work is to evolve the core curriculum by defining new competencies, expected outcomes, and a common standard concept inventory for the current disruptive technologies instead of or in addition to creating new majors or sequences.

## 9. REFERENCES

ABET (2020), *Criteria for Accrediting Engineering Programs, 2021 – 2022*, Retrieved05.07.2022, from http://www.abet.org.

Almstrum V. M., Henderson P. B., Harvey V., Heeren C., Marion W., Riedesel C., Soh L-K, & Allison Tew E. (2006). Concept inventories in computer science for the topic discrete mathematics. *SIGCSE Bull.* 38 (4):132-145. DOI: https://doi.org/10.1145/1189136.1189182

Anton, E., Behne, A., & Teuteberg, F. (2020), The Humans Behind Artificial Intelligence–An Operationalisation of AI Competencies. In *Proceedings of the 28th European Conference on Information Systems* (ECIS).

Schleiss, J., Bieber, M., Manukjan, A., Kellner, L., & Stober, S. (2022). *An interdisciplinary competence profile for AI in engineering*. In Towards a new future in engineering education, new scenarios that European alliances of tech universities open up (pp. 1601-1609). Universitat Politècnica de Catalunya.

van de Wetering, R., de Weerd-Nederhof, P., Bagheri, S., & Bons, R. (2023, July). Architecting Agility: Unraveling the Impact of AI Capability on Organizational Change and Competitive Advantage. In *International Symposium on Business Modeling and Software Design* (pp. 203-213). Cham: Springer Nature Switzerland.

Babb, J. S., Abdullat, A. (2012). The Need for Mobile Application Development in IS Curricula: An Innovation and Disruptive Technologies Perspective. I*nformation Systems Education Journal*, 10(1) pp 61-74.

Bélanger, F., Van Slyke, C. and Crossler, R. (2019) Information Systems for Business: An Experiential Approach, Edition 3.0. eISBN-13: 9781943153466

Bower, J. L., & Christensen, C. M. (1995). Disruptive Technologies: Catching the Wave. *Harvard Business Review*, 43-53.

Brown, J. (2020). An examination of the Skills Framework for the Information Age (SFIA) version 7. International Journal of Information Management, 51. https://doi.org/10.1016/j.ijinfomgt.2019.102058

Brynjolfsson E, McAfee A. Artificial intelligence, for real. *Harvard Business Review*. 2017.

Daugherty, P.R., & Wilson, H.J. (2018). *Human+ machine: Reimagining work in the age of AI*. HarvardBusiness Press.

Dede, C. (1989). The Evolution of Information Technology: *Implications for Curriculum. Educational Leadership*, 7, 23-26.

Dunn, P., & Miller, R. E. (2022). Teaching Case Widgets-R-Us: Using IoT to Monitor Part Levels. *Journal of Information Systems Education*, 33(3), 229-231.

McElhaney, K.A., Smith. G., Rustgagi, I., & Growth, O. (2022). *Responsible A.I.: Tackling Tech's Largest Corporate Governance Challenges*. Haas School of Business, University of California Berkeley. Retrieved from Harvard Business School Publishing.

Fountaine T., McCarthy B., & Saleh T. (2019). Building the AI-powered organization. *Harvard Business Review*. 97(4):62-73.

Groombridge D. (2022, October 17). Gartner Identifies the Top 10 Strategic Technologies for 2023. Retrieved July 4, 2023, from https://www.gartner.com/en/articles/gartner-top-10-strategic-technology-trends-for-2023

Horst, A.M., A.P. Hill, and K.B. Gorman (2022). Palmer Archipelago Penguins Data in the Palmerpenguins R Package - An Alternative to

Anderson's Irises. The R Journal. https://journal.r-project.org/articles/RJ-2022-020/.

Iansiti M., & Lakhani, K.R. (2020). Competing in the age of AI: strategy and leadership when algorithms and networks run the world. *Harvard Business Press* (25).

Kocielnik,, R., Amershi, S., & Bennett, P. N. (2019). Will you accept an imperfect AI?: Exploring designs for adju*sting end-user expectations of AI systems, Proc. CHI Conf. Hum. Factors Comput. Syst.*, pp. 1–14.

Kreuzberger D., Kühl N., and S. Hirschl (2023), Machine Learning Operations (MLOps): Overview, Definition, and Architecture, I*EEE Access*, vol. 11, pp. 31866-31879. doi: 10.1109/ACCESS.2023.3262138.

Kumar, N.M., & Mallick, P.K. (2018). The Internet of Things: Insights into the building blocks, component interactions, and architecture layers. *Procedia Comput. Sci.*, 132, pp. 109-117.

Leidig, P. M., & Salmela, H. (2022). The ACM/AIS IS2020 Competency Model for Undergraduate Programs in Information Systems: A Joint ACM/AIS Task Force Report. *Communications of the Association for Information Systems*, *50*(1), 25.

Lightfoot, J. M. (1999). Fads versus Fundamentals: The Dilemma for Information Systems Curriculum Design. Journal of Education for Business, 75(1), 43-50.

Mohammadi, M., Al-Fuqaha, A., Guizani, M., & Oh, J. S. (2017). Semisupervised deep reinforcement learning in support of IoT and smart city services. *IEEE Internet of Things Journal*, 5(2), 624-635.

Ng D. T. K., Leung J. K. L., Chu S. K. W., Qiao M. S. (2021), Conceptualizing AI literacy: An exploratory review, Computers and Education: Artificial Intelligence, Vol. 2, 100041, ISSN 2666-920X,

Noll, C. L., & Wilkins, M. (2002). Critical Skills of IS Professionals: A Model for Curriculum Development. Journal of Information Systems Education, 1(3), 143-154.

Simons R. & Golzalez, G. (2019). *C3.ai-Driven to Succeed*. Harvard Business School Publishing.

Sugimura, P., & Hartl, F. (2018). Building a Reproducible Machine Learning Pipeline. ArXiv. /abs/1810.04570

Topi, H., Valacich, J. S., Wright, R. T., Kaiser, K., Nunamaker, J. F., Sipior, J. C., et al. (2010). IS 2010: Curriculum Guidelines for Undergraduate Degree Programs in Information. Communications of the Association for Information Systems, 26(18).

Touretzky, D., Gardner-McCune, C., & Seehorn, D. (in press). Machine learning and the five big ideas in AI. International Journal of Artificial Intelligence in Education. https://par.nsf.gov/biblio/10357450

Trelstad B. & Cao B. Y. (2022). SMART: AI and ML for Wildlife Conservation. *Harvard Business Publishing*, NO 9: 323-326.

Weber M., Engert M., Schaffer N., Weking J., Krcmar H. (2022). Organizational Capabilities for AI implementation—Coping with Inscrutability and Data Dependency in AI. Information Systems Frontiers. 2022:1-21.

Liao, H-T & Wang, Z. & Wu, X. (2019). Developing a Minimum Viable Product for Big Data and AI Education*:* Action Research Based on a Two-Year Reform of an Undergraduate Program of Internet and New Media. *ICBDC: Proceedings of the 2019 4th International Conference on Big Data and Computing*, 42-47. 10.1145/3335484.3335509.

Weinberg, A. E., Basile, C. G., & Albright, L. (2011). The effect of an experiential learning program on middle school students' motivation toward mathematics and science. *RMLE Online*, 35(3), 1-12.

Williams R., Park H. W., & Breazeal C. (2019). A is for Artificial Intelligence: The Impact of Artificial Intelligence Activities on Young Children's Perceptions of Robots. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA, 447: 1-11. DOI: https://doi.org/10.1145/3290605.3300677

 ISSN: 2473-4901
v9 n6041

# Appendices

**Table 4: ABET general students' outcome and examples of corresponding ML outcomes**

| | |
|---|---|
| ABET outcome 1 ML outcome 1 | Analyze a complex computing problem and to apply principles of computing and other relevant disciplines to identify solutions. |
| | Identify contexts within which machine learning models may help analyze the problem or be included in designing and solving complex problems related to information systems. |
| ABET outcome 2 ML outcome 2 | Design, implement and evaluate a computing-based solution to meet a given set of computing requirements in the context of the program's discipline. |
| | Evaluate and select appropriate machine learning techniques for specific problem domains. |
| ABET outcome 3 ML outcome 3 | Communicate effectively in a variety of professional contexts. |
| | Communicate orally or in written form different processes and tasks required to complete an ML/IoT project that solves problems. |
| ABET outcome 4 ML outcome 4 | Recognize professional responsibilities and make informed judgments in computing practice based on legal and ethical principles. |
| | Identify societal trade-offs, ethical considerations, and potential adverse impacts associated with machine learning algorithms and models and explore ways to mitigate them. |
| ABET outcome 5 ML outcome 5 | Function effectively as a member or leader of a team engaged in activities appropriate to the program's discipline. |
| | Identify machine learning tools, libraries, and platforms for data analysis, modeling, and prediction that would enable effective continuous learning and professional development in this area. |

**Table 5: IS2020 competencies and the corresponding ML competencies**

| Competency realm | Competency area | ML competency |
|---|---|---|
| Foundations | Foundations of information systems | FOUN.FOIS. 8 Competency area: Identify major phases of machine learning pipelines and explain core activities related to each phase |
| Data | Data/Info management | DATA.MGMT.7: Write machine learning queries |
| Technology | IT Infrastructure | TECH.INFR. 10: Explain key infrastructural components of an organizational-level ML pipeline |
| | Security computing | TECH.SECU.9: Analyze privacy and security concerns at data preprocessing, deployment, and maintenance phasing of the ML pipeline |
| Development | Systems Analysis and Design | DEVP.SADN. 9: Describe supervised, unsupervised, and reinforcement machine learning models |
| | Application Development and Programming | Area: DEVP.ADEP.17: Identify data requirements and model alternatives for developing an ML pipeline that will solve a given business problem |
| Organizational Domain | Ethics, use, and societal impacts | ORGD.ETHS.10: Evaluate biases in different phases of the ML pipeline (e.g., datasets) and assess the impacts of the model on different stakeholders subject to the model's outcomes |
| | IS Management & Strategy | ORGD.ISMS.12: Establish internal auditing policies and procedures for the ML model's impact assessment |
| Integration | IS Project Management | INTG.ISPM16: Identify and implement appropriate model re-training and maintenance plans |
| | IS Practicum | INTG.ISPT.12: Utilize machine learning models and evaluate their performance |

 