ISSN 2473-4901
v7 5609

Infusing Artificial Intelligence in IS Curriculum through Service-Learning: A Summary of Pilot Programs

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Abstract

This manuscript presents an effort in which students in introductory and advanced information system courses were involved in an artificial intelligence-focused service-learning activity. Students' perception on AI tools and techniques were measured and the impact of the activity was assessed. Service-learning included running 3-session workshops for middle school and high school children through community partners of a public Midwestern university. Also, the service-learning included running AI workshops for non-IS major college students in general education IS courses.

Keywords: Artificial intelligence education, service-learning, bias

1. INTRODUCTION

Traditional Information Systems (IS) curriculum includes discussion of artificial intelligence (AI) topics in courses, such as decision support systems, expert systems, and sometimes in ethics and policy. In this manuscript we report how AI education can be infused and enhanced through service-learning. AI literacy is a key area of focus for IS/CS educators as more decisions are being made and/or supported with AI tools. While cybersecurity and data analytics curricula have been widely adopted in IS programs, AI education is not consistently included in the programs. Likewise, while computer science (CS) outcomes are now part of K-12 education in all states (example: all schools in the state of Indiana are to include CS in K12 curriculum by 2021), AI topics are not included in K-12 science (NGSS Lead States, 2013), mathematics (CCSS, 2010), or technology education (ITEA, 2000/2002/2007) learning standards. Most of the K-12 exposure to AI occurs in specialized afterschool or extra-curricular activities. Considering that AI-enabled systems are employed in many domains with potentially multi-faceted impacts on citizens' lives and work (Obermeyer 2019), it is fruitful to address the AI gap in IS education early through service-learning programs in K-12. The AI-focused service-learning program pilot detailed in this manuscript offers an impactful vessel through which IS students and community K-12 students together advance the understandings of AI concepts, techniques, and societal impacts.

It is anticipated that many IS and non-IS careers will require interaction with intelligent systems and/or robots (You & Robert 2019); therefore, knowledge of AI-enabled systems and how to interact with them will be an important part of any skillset. Furthermore, developing skills and self-efficacy in AI fields and promoting career-aspirations in AI will be essential for communities to grow and thrive in an AI-dominated era where many life-altering decisions may be made by or with the help of AI-enabled automated systems (Eubanks 2018; Samorani et al. 2019). The current project addresses this need by fostering AI literacy among both middle school children and future teachers.

2. AI LEARNING: PLUGGED AND UNPLUGGED ACTIVITIES

Many organizations at national, state, and local levels are working to enhance AI education in K-12 schools and in college. Examples of those programs are Google's Machine Learning crash course with TensorFlow playground, AI4K12 affiliated with the Association for Advancement of Artificial Intelligence, Code.org, AI4All, and MIT Media Lab. The AI workshop that was offered in the service-learning experience reported here builds upon the currently available AI curriculum to offer activities that broaden students' view to the world of AI.

Community Engagement and Service-Learning

The service-learning experience involved five distinct components that were related to each of the five big ideas of AI: perception, representation and reasoning, learning, human-AI interaction, and social impacts. Most of the activities in each component were based on original content and were complemented with external tools and ideas created by model programs listed in the previous section. We chose neural networks (NN) as the major model and learning context for the activities because open tools and resources for learning, experimenting, and coding with NN are readily available to support learning beyond the duration of the service-learning workshops. NNs applications span many areas, such as image recognition, voice recognition, and music creation which are familiar areas for college students and K-12 children. Also, many NN libraries, packages, and open-source projects and playgrounds are available for exploratory learning. Students who attended the workshops were given a daily list of exploratory exercises to guide their dependent learning. At the end of the workshop, students received a resource package that included all of the model curriculum resources.

Table 1: Example activities related to each of the five big ideas of AI

Area	Activities
Perception	(Appendix B, Figure 1)
Representation and reasoning	Feelings as finite state machines (Appendix A, Figure 3)
Learning	Learning fast, slow (Appendix B, Figure 2)
Human-AI interaction	Biases are contagious (Appendix A, Figure 2)
Social impacts	Algorithms & models make mistakes (Appendix A, Figure 1)

In-Workshop and Supplementary Activities

The service-learning series was completed over three weeks. In-workshop learning activities were complemented with learning activities outside the workshop, some of which are listed in Table 2.

Table 2: Sample of in-workshop and at home activities

Mode	Explorative & Experimental activities
In-workshop explorative	Ice breakers: Spot AI around you! Spot NN around you! AI systems as interpreter for Rap live concerts! Activities: Appendix A, Figures 1-3 CNN exploratory activity: Appendix B, Figures 2.
In-workshop experimental	Plugged activities: Gesture training with Google teachable machine NN training with TensorFlow playground Learning rate experiments with TensorFlow playground (Appendix B. Figure 1) Overfitting experiment with Google Teachable Machine
At home explorative	Human biases exercise Algorithmic Justice League Algorithmic Accountability Act of 2019 DeepFakes by Alan Zucconi
At home experimental	Overfitting experiment with TensorFlow playground Regularization methods Experimentation with TensorFlow playground

For instance, students completed an image processing training experiment with Google Teachable Machine during the workshop and were then asked to design and conduct additional experiments at home to investigate how lighting, background patterns, distance, and possibly other factors impacted the training process and the performance of the created model. Students were encouraged to read relevant articles and/or documents to further clarify concepts, techniques, and impact of the technology on daily life. In one activity, students were asked to read, analyze, and summarize the Algorithmic Accountability Act of 2019, watch the documentary Coded Bias, and play with simulations tools, such as object detection tools based on Tensorflow (https://tensorflow-js-object-detection.glitch.me/).

5. PILOT PROGAM AND DISCOVERIES

The pilot programs were completed before and during the pandemic. Before the pandemic, the pilot was run in person in one section of an advanced IS course and two sections of an introductory IS course. During the pandemic, the pilot was run online in two sections of an introductory IS course. The difference in format allowed the researcher to observe and experiment with modalities: While most of the structure and material stayed intact, modifications were made to the way the sessions were facilitated by the instructor and the extent to which interaction occurred among learners. The current paper reports the results from the three sections held before the pandemic, as authorized by the institutional review board.

Procedures

Students were trained during two 75-minute class sessions on the topics covered in the service-learning workshops. The topics were put into broader context as they relate to IS professionals. In addition, students were asked to use tools to complete specific experimentations independently outside the training sessions. The students were also asked to participate and co-facilitate service-learning workshops either for college students in a general education IT course or for K-12 kids signed up for the workshops via community partners (e.g., Boys and Girls Club).
Before and after the workshops, questionnaires were used to collect information about students' perceptions of AI system goals and stakeholders, as well as on input, algorithms, and decisions. Each questionnaire consisted of 12 questions with 5-level Likert scale answers, as included below.

Part 1. Reflect on artificial intelligent systems' goals and stakeholders (those who have a stake in the outcomes of or decisions made by the AI-enabled systems) and share your opinion about the following statements (1: strongly disagree, 5: strongly agree):

1. *Artificial intelligent systems are fundamentally neutral.*
2. *Humans decide the goals of the intelligent systems that they create. Advertised goals for intelligent systems may be different from true goals.*
3. *Different groups of stakeholders may have conflicting/opposing goals for the intelligent systems.*
4. *AI systems' predictions may impact different stakeholders in different ways.*
5. *AI systems may produce inaccurate, unfair, biased, or discriminatory decisions impacting individuals.*

Part 2. Reflect on artificial intelligent systems' input data, algorithms, and predictions and share your opinion about the following statements (1: strongly disagree, 5: strongly agree):

1. *Quantity of the training data impacts the accuracy and robustness of a supervised learning model.*
2. *Sampling bias can lead to inaccurate or meaningless predictions.*
3. *Quality and composition of the training dataset impacts the quality of the prediction.*
4. *Algorithmic bias may lead to inconsistent predictions across clusters of data that are essentially similar with respect to sought-after outcome (e.g., people with similar credit history and jobs get different results on their loan applications b/c they live in different zip codes).*
5. *Type I (false positive) and Type II (false negative) may lead to different consequences for different groups of stakeholders.*
6. *Some algorithms are riskier because of the nature of the data that they examine, how they examine the data, and the predictions they make using the data.*

All of the survey questions refer to specific topics that were covered at least once in plugged or unplugged activities during the workshop. We only administered the survey to IS students who participated in the service-learning process. K-12 students were not involved in any data collection activities. Answers were given on a 1-5 Likert scale, and were averaged for each question in before- and after- questionnaires. The averages then were used for a mean comparison t-test analysis. All answers were used as-is except for the first question that was recoded for analysis (5-value).

Table 3: Pilot Groups and Before & After Questionnaire Means Comparisons

Group	Sample size	Means Before & after
1	19	3.89 vs. 4.76 p= 0.07
2	26	3.57 vs 4.39 p=0.052
3	16	3.83 vs 4.72 p= 0.021

Pilot test groups and sizes are listed in Table 3.

When comparing the results of the surveys before and after the workshops, it appears that the understanding about the nature and limits of AI increased for all groups, as indicated by greater agreements with the statements that were included in the questionnaires. However, we also note differences between the groups: In Group 1, the area that showed the greatest increase in agreement from before to after the service-learning workshops was related to stakeholders: "*AI systems' predictions may impact different stakeholders in different ways*." In Group 2, that area was unfairness and bias: "*AI systems may produce inaccurate, unfair, biased, or discriminatory decisions impacting individuals*." In Group 3, the highest improvement was related to data: "*Quality and composition of the training dataset impacts the quality of the prediction*". The variation noticed here, while not statistically significant when the groups are compared, appears to signify the inconsistencies that are inherent in the different groups of IS students. While the same instructor facilitated all of the workshops and ensured that the list of activities and times allocated to each activity stayed constant between the groups, within-group brainstorming and discussions varied depending on the learning guides' and learners' interest and engagement. The level of rapport that was established between the learning guides and learners also varied which in turn impacted the learning process and outcomes for both learners and learning guides.

7. SUMMARY AND CONCLUSION

AI literacy is fast becoming an important skill because the technology has significant impacts on every-day life, as well as on jobs and careers. For example, automated decision systems can impact the legal rights of individuals by collecting, aggregating, processing, and storing sensitive (e.g., work performance, race) and publicly available data (e.g., address, court records) (Eubanks 2018). Transparency and explainability (New & Castro 2018) tend to be difficult for complicated AI-enabled techniques, and formal assessment of their impact is better left to regulatory bodies (e.g., Algorithmic Accountability Act of 2019). However, individuals and communities are key players in identifying AI-enabled injustice and engaging in actions that alleviate the injustice (Angwin et al. 2017; Benjamin 2019).

The sample curriculum and pilot programs summarized in the current paper provide a starting point to develop AI literacy. But they also highlight an area of knowledge that requires more curriculum development and research on curriculum effectiveness within the IS field. AI concepts, techniques, and tools can be tackled in many ways. For example, they can be incorporated in other sequences, such as cybersecurity or analytics, or they can be addressed through service-learning with college or K-12 students. Future iterations of the current

ISSN 2473-4901
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work will measure learning outcomes among K-12 students as well as college students. In addition, we plan to administer service-learning activities that foster and enhance self-efficacy and career aspirations in AI-related fields among middle school children, as well as IS students.

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ISSN 2473-4901
v7 5609

Appendices and Annexures

Appendix A: Example of unplugged activities

Personal Opinions & Biases are Contagious, Computers Get them from Their Human Designers

Imagine that for a few years you have been organizing kids in the neighborhood for a basketball tournament (or your favorite sports or board game). Imagine that you are known for being really good at organizing exciting tournaments by the way you put kids into teams. Now you're off to college and younger kids in the neighborhood are asking you to leave them with few words of wisdom. You tell the neighborhood kids that you will be creating a computer-based model that will help them to create teams for future basketball tournament in the neighborhood.

1. What characteristics of the neighborhood kids would you use as input to your model?
2. Would you think there are any personal opinions or biases that you may have about basketball games, teams, players that you may inadvertently code into the computer and spread? Add items to the table below that show some part of the model will be your opinion solely and not a general rule.

Personal Opinions or Biases Are Not as Obvious When Coded into Computerized Models

If you were just to write a tournament rules documents to share your 'way' of doing tournaments, it'll be easy for future neighborhood kids to see different rules and analyze them or change them. But imagine they'll just use the model to run future tournaments and don't get a chance to look inside the code; see the following questions about salience of personal opinion, discuss, and add a few more examples that you can think of.

Input characteristics	Your opinions	Opinions' salience
Kids' height, weight, overall fitness for the game?	How do you define 'good players?	Do you think your personal opinions (or biases) are more salient when you share your experiences verbally or when you code them in a computerized model?
Kids' previous game stats	How do you define 'good teams'?	Would future neighborhood kids who will use your program investigate inside your model to change it or remove?
	Are there multiple versions of the good player or teams? Do you think that you see all 'good' versions in the same way?	

Figure 1: Human vs. algorithm biases (created by: Javadi & Gebauer 2019)

ISSN 2473-4901
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Algorithms & Models Make Mistakes

Remember what we discussed one reality vs. Algorithms' decisions or models' predictions. When the AI model says something true and, and in reality, it isn't, that's false positive and if the reverse happens it's a false negative. True positive and true negatives are when the model's prediction matches reality.

Imagine you or someone you know visited the COVID clinic; reflect on the impact of mistakes by the test (false positive, false negative); use a scale that shows positive, neutral, and negative impact, example:(-5, -4, -3, -2, -1, 0, +1, +2, +3, +4, +5).

- Who will be sad, happy, or indifferent?
- Would it be different for people of different ages? Job title? Would it be different for mother vs. Father in a family?
- Do you think we should other people or entities to the list?
- Should we separate family members or friends leaving with the individual?

	False Positive	**False Negative**
patient		
Relative & friends		
Workplace colleagues/staff/boss		
Primary care provider		
Insurance company		
Health department		

Figure 2: Algorithms make mistakes

 ISSN 2473-4901
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"…Today we reflect on the 'think' component of an autonomous vehicle that will simulate work of a human brain. Particularly, we're going to discuss a commonly used model for visualizing working of our brain (Figure X). The model is called finite state machine diagram and is a commonly used model for visualizing working of our brain. Using state machine diagrams, we can see how our design impacts the next action that an autonomous vehicle performs. How many of you have ever seen a parent or a care-provider help a youth help to deal with their emotions? They'll often sit with their child and label the current feeling and try to direct child's attention to possible actions that may help them feel a less intense or less painful or different feeling: "I see that you feel hurt now, can we go for a walk and discuss possible things you or I can do so that you feel less hurt." And the idea is that a young person will learn different emotional states by labeling them and over time the child learns techniques and ideas on how to change from an emotional state to another (Figure Y). We're going to discuss different ways in which we can create state machine models …'

States	Obstacle: block in sight Sound: sound audible
Events	Recognize blocks Recognize sound
Actions	Move straight Change direction Say something

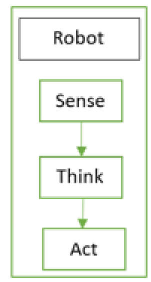

Figure X: Finite State Machines Parts

Emotional States	Hurt Sad Happy Neutral
Events	Someone acts mean or bullies Hears a friend's empathetic note Sees a friendly face in hallway Receives a positive comment Blames oneself with no grounds Stays put
Actions	Leaves the negative environment Responds and reasons Looks at the bully puzzled & shocked

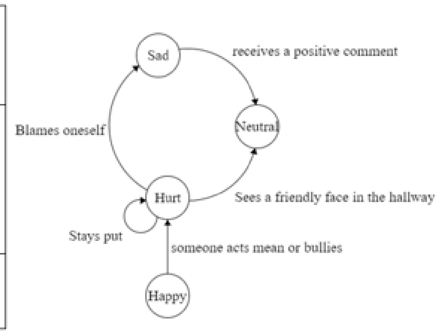

Figure Y: Finite State Machines for modeling emotional states

Figure 3: Feelings as Finite State Machines (created by: Javadi, Meyer & Darner 2019)

ISSN 2473-4901
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Appendix B: Example of plugged activities

Learning, Fast, Slow, or Somewhere in the Middle

Think about first time you rode a bike, drove a car, or played golf. Or think of similar experience you may have had playing video games. Think of your goal to stay on the bike lane, in your care lane, or get the golf ball in the hole. Now think of realizing that you are getting away from your goal, how much do you steer the wheel or change the direction and force by which you use the club. Depending on your situations, you may choose to steer the wheel strongly or moderately in the opposite direction or change the direction and the force you apply to the club. Now visit https://playground.tensorflow.org/, pick dataset, create your neural network model, pay attention to the learning rate. For a given neural network model that you create, try running it with three distinct values for learning rate: low, medium, high.

How many epochs does it take the model to converge?

How does the model performance change?

What can you state about learning rate for your model when applied to your selected dataset?

Would you think your findings will be different for other networks or datasets?

Figure 1: Learning Rate Experiment with TensorFlow Playground

Features of an Image and Convolutional Network

Explore: Try Quick Draw, play a few times to get a sense of how it works. Then play 5 times and record some of the guesses by the machine. Write those after each game so you won't forget them.

Trial	Target (name of the thing you're drawing)	Guesses
1		
2		
3		
4		
5		

Carefully examine your trials and the guesses machine made for each drawing. Discuss with a partner why a machine would guess wrong; what are some features of your drawing that it could get mistaken with something else? Are there lines/curves, dark/transparent, or any other peculiarities in the picture that make them get mistaken? Also, look at the data and find your trials' data. What do you think are the top 3 features of the images resembling the same thing? Sharp corners, square in the middle, curves at the top, dark circles on right, or some other characteristics that you can identify.

Convolutional Networks are Neural Networks (CNN) that are widely used in image processing; they help extract features that make classifying images much easier based on some major features. In this activity you will work with the CNN demo tool and explainer by Wang et al. Pick an input and make a network just like you did in the TensorFlow playground. Run and observe the performance carefully at each Convolution layer of the network. What happens? Note the activation function ReLU that you experimented with at home when you trained your model with TensorFlow Playground. Carefully examine the interplay between coevolution and activation. Write your observation and connect back to the ideas you discussed in your Quick Draw experiments.

At home discussion:

Play Quick Draw with a younger sibling, friend, neighbor, or a cousin and discuss these questions with them:

Would Quick, Draw be a fair judge of a drawing competition? Why or why not?

Do you think there will be any bias in the dataset that comes out of the quick draw images? Why or why not?

Look back at drawings available in data

Pick a picture, what kind of features of the picture do you think the computer picks up for future predictions?

Figure 2: Convolutional Networks Explorations (created by: Javadi & Gebauer, 2019)