Agent-Assisted Life-Long Education and Learning

Blue Sky Ideas Track

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ABSTRACT

KEYWORDS

Agent-Supported Learning; Precision Education; Human-Agent Interaction;Distributed Agent Marketplaces

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1 INTRODUCTION

Job markets are becoming ever-more-competitive. The challenge is even more significant with emerging job roles requiring certifications, multidisciplinary skills and specialist knowledge, even for entry-level positions. We seek to employ agent technologies to empower education, development of skills and maximise career prospects by curating personalised education pathways, catering for individual preferences and needs for development. For example, a recent call for "Precision Education" [5] proposed to provide a personalised or differentiated education with the goal of remediating, or at least accommodating learning disabilities. But, why agents?

2 AGENTS IN EDUCATION

At the beginning of the 21st century, it seemed that agents would dominate the industry, envisioning a wide span of technology applications in enterprise integration and supply chain management, agent encapsulation, system architectures, dynamic system reconfiguration, learning, design and manufacturability assessments, distributed dynamic scheduling, integration of planning and scheduling, concurrent scheduling and execution, factory control structures with potential tools and standards [16]. But, while individual agent technologies such as planning, supply chain management or coordination permeated multiple industries such as finance, power industry[7] or manufacture [2], we rarely (or not at all) see deployments of more complex agent architectures.

While agent architectures had a limited impact on the industry, we saw a significant uptake of machine learning technology across almost all industries, mainly due to the success of Deep Learning. Modern machine learning research is powered by huge investments from technological behemoths (e.g. Google, Facebook, IBM), developing robust open-source frameworks and tools (i.e. PyTorch[1], TensorFlow[2]), having dedicated narrow research streams, well-established benchmarking procedures with readily available datasets (i.e. image recognition) and evaluation metrics. Unfortunately, agent research did not attract such traction and individual efforts yielded to the scattered landscape of different technologies and approaches.

But, recently, Industry 4.0 [9] coined the fourth industrial revolution, following the success of the third industrial revolution involving the use of computerised systems to control industrial processes. Industry 4.0 considers an uptake of the use of artificial intelligence, mainly for optimisation and control of distributed processes, robotic control, or deployment of "smart machines", autonomous technological entities using networks to communicate with control systems and other "smart machines" connected to IoT networks. The Industry 4.0 vision makes a plenty of space for agent technology, often working hand in hand with machine learning systems. Such technology will deliver explainable decision making systems employing agents to monitor, control and coordinate complex, machine-learned (ML) systems.

An example of technology enabling such agent-ML symbiosis is the use of Semantic Web Services [10], allowing agents to acquire, pre-process and assure the availability of necessary assets for ML systems. Not only manufacturing but also the entertainment industry will significantly benefit from agent technology. With the imminent arrival of Meta[3], and planned Roblox Metaverse, embodied agents can become the more natural way of interacting with complex configurations and capabilities of Metaverse(s).

This brings us to the target area of our interest, which has the potential to become the *unified test-bed of agent technologies*: education. Artificial Intelligence in Education (AIEd) research brought disruptive technologies, introducing intelligent tutoring [13], assessment, automated feedback, task assistance [1], academic and administrative support services [18]. But, industry showed limited interest in using agent technologies, choosing to use proprietary

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[1]https://pytorch.org
[2]https://www.tensorflow.org
[3]https://about.facebook.com/meta/

approaches, potentially employing statistical and machine learning methods for marking, student monitoring and proctoring [18]. Instead, we envision agents as partners which liaise with exiting (proprietary) systems and cater for life-long education. Such human-agent relation is a symbiotic partnership, with agents delivering education plans to humans based on their goals and preferences, as well as humans educating agents based on their interactions and expanding agent capabilities with new functionalities.

Decades of research in agent technologies designed means to cater for such relationships. Depending on users' security preferences, agents can learn about users' demands and needs implicitly through monitoring of their actions, or explicitly through a dialogue (i.e. agent communication, argumentation technology). Security, just like transparency of the decision and advice are impertinent to maintain user's trust [3]. To be transparent, means to be able to explain the decision or a recommendation (i.e. explainability, recommender systems technology). While there are many existing approaches in explainable recommendation systems [19], an agent has the opportunity to use a long-term knowledge of user preferences and use perspectives from multiple domains, inherently increasing the possible richness of the explanation.

But, we envision that the potential of the educational agent is maximised while connected to a multi-agent network, securely communicating with *trustworthy* agents (i.e. trust and reputation technology) curating a long running educational journey or a short term skill power up (i.e. planning and coordination technology). We propose to establish the Distributed Educational Agent Network (DEAN) and elaborate on its creation and challenges in the next section.

3 DISTRIBUTED EDUCATIONAL AGENT NETWORK (DEAN)

Agents as life-long education partners possess the information on desires, goals (e.g. career), education and career progression and performance. Using the DEAN network, the agent can consult requirements and proactively search for opportunities by monitoring job markets, educational options and challenges with other agents. Then, it modifies the current educational program and coordinates the pathway facilitating the optimal desired outcome. Using *negotiation [8] and argumentation [12] strategies* it is able to acquire curriculum products for the best possible price (i.e. using time-limited discount offers or combining multiple offers with a long term vision).

Partner can expand (plug-in) agent functionality allowing agent to "grow" in intelligence and adapt to various communication environments [4], educational structures and programs, languages and knowledge exchange formats [17]. Overall, the vision of Educational Agents and the Distributed Educational Agent Network represents an ideal platform for agent technology development and research, integration of existing research approaches, testing and evaluation.

First, agents have to either implicitly (through monitoring) or explicitly (through a dialogue) *learn human preferences*, explain and discuss various options to assure human satisfaction. A large body of work in human-agent interaction and explainability needs to be reviewed to synthesise efficient, functional and ethical communication protocols. While it is clear that no perfect solution exists, a journey towards evolving industry standards should open pathways for bigger industry involvement. While solving understanding of human language is outside of the scope of agent research, a standard involving human-agent interactions is desired.

Second, agents must communicate with other agents to promote and secure deals and contracts. This step is crucial for the success of the multi-agent model. Companies must feel compelled to invest extra funds to purchase or develop a trustworthy agent that will succeed to negotiate the additional income. The current standards FIPA-ACL and KQML are supported by a variety of implemented tools and applications such as JADEX or JACK. Unfortunately, their uptake is hindered by a significant learning curve, aiming for the research community rather than industry. But, there are exceptions. Fetch.ai[4] delivers an interesting platform involving blockchain and crypto-currencies to execute agent economies, defining innovative *Autonomous Economic Agents*.

Third, agents will operate with and share sensitive human data, and it is crucial to assure privacy and interact with trustworthy third parties over secure communication channels. The extensive body of work on trust and reputation [6, 11] had limited success in the industry, relying instead on public key and certifications infrastructures. As a result, we need a systematic review of how current trust and reputation approaches can be integrated into existing infrastructures (i.e. PKI[5])

Fourth, agents will discover and process large quantities of educational offers. Based on the partner's preferences, agents will curate personalised plans, coordinated with other partners activities. While current planning approaches are capable of processing complex problems, the educational agent introduces issues of yet another magnitude, combining temporal planning, cost optimisation, constraint satisfaction, preference alignment and coordination. From the research perspective, there are rich datasets of plan domains and problems for benchmarking[6], but most of them aim at a narrow set of plan properties, rather than test integration of multiple features in real-world scenarios. Similarly to RoboRescue[7], there is a unique opportunity to define such a testing and evaluation environment, helping research community to devise new challenges and benchmarking procedures, inherently interesting for wider audience (i.e. industry). Last, the educational agent should be able to negotiate the best possible deal and explain the argumentation to its human partner. Unfortunately, the large body of research in agent negotiation remained only theoretical and it is missing practical implementations, testing and benchmarking procedures. For example, it would be very interesting to see argumentation and negotiation challenges similar to those in the planning domain, where winning agent acquires the most assets. There is an opportunity growing in the blockchain and cryptocurrency community to establish agent negotiation procedures backed by crypto-currency exchange. Such negotiation can be either fully-automated, but preferably, in our context supervised by humans.

[4] https://fetch.ai
[5] https://en.wikipedia.org/wiki/Public_key_infrastructure
[6] https://www.icaps-conference.org/competitions/
[7] https://rescuesim.robocup.org/rescue-simulation-virtual-robot-competition/

Overall, we see that educational agent combines the functionality of a significant portion of agent research streams and represents a unique research, testing and development opportunity for the agent community and bring it closer to the industry. Being involved in education it is also close to academic processes agent community recognises from their university context. It also seems that most outcomes will be transferable to other industry fields.

4 AGENTS ARCHITECTURES FOR INDUSTRY

Let us delve into the industry needs and introduce our idea of the Distributed Educational Agent Network and the imminent research and development that is necessary. To answer this question, first, we must ask ourselves:

- why do we have a *problem* with the current status quo
- why do we need an agent to solve this *problem*
- how much resources do I need to make this happen

First, to answer "why do we have a problem with the current status quo" we need to understand the educational landscape. There is a huge number of competing governmental, private institutions as well as online businesses and not-for-profit organisations providing courses in all areas of education. The landscape is even more complicated, with a significant number of free educational content spread across blogs, websites, white papers, technical reports, patents, research papers or even streaming media services such as Youtube or Twitch (or most recently YouPorn[8]). As a result, educational options extremely vary by industry, application area and quality. Often, users also have strong preferences on the delivery of the content, either by text, video, a specific educator, language or even institutions or platforms, limited by their budget and existing subscriptions. Moreover, the educational landscape is ever-evolving, introducing new courses, programs or classes in increasingly shorter periods. Also, while following an existing educational pathway a student might require additional resources to grok a specific concept or knowledge area. Thus, finding the best possible education plan and maintaining and curating educational content for personal growth requires significant resources, both time and money.

This leads us to the second question: "why do we need an agent to solve our problem"? First, let us consider alternatives. Ruling out the manual search, we can employ web crawlers that scrape internet websites for the desired content. Then, we can use programming systems to process the scraped data, using statistical methods or employ machine learning approaches, such as Natural Language Processing. While this is inherently hard and expensive, the scraped data even quickly becomes outdated, requiring further costly scraping and processing. With such a huge cost, deploying personalised solutions is almost impossible, leaving individual users only to rely on existing third party data providers with their own agenda and limited options.

Other popular options are social networks and developer portals, where users come for advice, often from very influential members of their industry area. But even here, users often receive conflicting advice from people following their agenda and expertise.

[8]https://kotaku.com/on-pornhub-math-teacher-makes-his-mark-teaching-calcul-1847927535

Agent networks deal with previously mentioned drawbacks and present a better information-sharing option. We may imagine an agent as a "partner" with whom we share our desires, who knows our study results, overlooks our progress, who can "talk" to us as well, as is aware of the educational environment offering possibilities for education and possibly acts on our behalf to secure the best deal. Essentially, all these requirements are covered in the definition of the autonomous agent: "An intelligent agent perceives its environment via sensors and acts rationally upon that environment with its effectors" [14].

Moreover, to strengthen the importance of using agents for this purpose, it is essential to understand that our proposal assumes an agent as a life-long (long-term) partner with knowledge about humans' evolving status quo and goals. Consequently, the intelligence of such an agent can vary depending on human needs and can evolve with its partner. For example, agents can monitor job markets to assess potential career development opportunities based on partners skill set, or even provide short-term educational pathways to develop into a potentially interesting role in the job market. Considering aforementioned requirements, agent approach seems highly desired and feasible.

The last question is probably the most decisive for the industry acceptance. Currently, without industry-endorsed frameworks, tools, standards and approaches, almost any agent solution requires custom, expensive development. The industry success of deep learning can be potentially attributed to limited requirements for custom development, using existing tools and frameworks, yielding to potentially lower cost and higher gains from knowledge insight. With agents, community-ready infrastructures and frameworks need to be developed anew, or adapted from existing tools for a more general use (think user-friendly, not-scientific).

Moreover, many existing agent approaches remain highly theoretical (e.g. negotiation) with complex implementation requirements, often requiring further fundamental research. This calls for applied, multidisciplinary applied research (i.e. HMI) aiming at simplification and generalisation of interfaces, the definition of services as well as integration into existing industrial multi-agent solutions such as Fetch.ai and other industrial components [15].

5 OUR APPROACH

In the previous section, we have explored the benefits of using agents as a partner in long-life education. *If the research community can deliver functional, robust, yet scalable agent companions and the environment in which they will thrive, the industry will most probably follow and apply agents in the broader perspective.* In this section, we describe our model of the prototypical life-long education agent partner. The model considers following domain elements:

- **role** - represents the current or desired job category or role. The role shapes the long term goals, for example, a data scientist role.
- **job** - represents the current or desired job position. The job, shapes the long term goals, for example when we want to follow a narrow career progression.
- **skill** - represents both soft skills (non-technical, relating to how to work) and hard skills (technical, relating to what you

do). We define **role** and **job** using a set of skills and related meta-data (e.g. expected salary)

- **supplier** - provides either a free service (e.g. blog) or paid service (e.g.university) to teach **skills**.
- **pathway** - plan representing temporal educational pathway involving selected **suppliers** to learn **skills**, potentially leading to a desired **job** or **role**.

In the rest of this section we discuss individual parts of our domain model.

5.1 Roles, Jobs and Skills

Skills form the base building block of the domain. Skills define the capabilities that a person can offer to others (e.g. employers or clients). There are established skill frameworks. In the STEM cluster, the most renowned skill framework is Skills For Information Age (SFIA). The current version of the framework, version 8[9] defines 121 skills, for example Digital Forensics[10]. Within a skill, person can reach seven levels. Level one "follow" defines the capability to follow instructions in skill related tasks. Level three "apply", permits to apply the skill knowledge to new problems, while the highest level, level seven "set strategy, inspire, mobilise" defines the capability to set organisational strategies, perform complex skills and inspire organisations and influence development. Not all skills cover all seven levels, some require a higher starting level, while others do not reach highest levels.

The benefit of using SFIA is that governments and institutions use SFIA to define minimum desired skill sets for jobs and categories. For example, Australian Public Service[11] uses SFIA to define skill requirements for 149 jobs and 12 roles. Also European Union, Canada, USA and UK[12] define skills required for jobs in their job markets using SFIA. We can see, that SFIA provides an insight to international job markets and gives us the opportunity to quantify the compatibility of person's knowledge profile with the desired job profile. The limitation of SFIA is its focus on STEM and business skills. While not as comprehensive, the commercial Burning Glass[13] provides an insight across all industries and maps onto live jobs available across the world. The limitation of Burning Glass is that it does not have such comprehensive skill differentiation (i.e. levels) and quantifiable compatibility mapping is rather limited.

5.2 Pathway

The pathway is a coordinated plan of educational activities. The agent overlooks the skill development for its partner and generates pathways aligning them to either short term goals (skill development) or a longer-term goal (career development). Pathways can be organised hierarchically, where complex, long-term paths break down to more straightforward, short-term pathways. The example of a long term pathway is to land the first job, breaking down to university study pathway, which can be broken down even further into individual semesters or study groups.

Pathways are also non-linear as the events (or even whole pathways) can be happening in parallel (e.g. a person can study a course at the university while working on open-source development skills). We have developed a prototypical interface, which provides the possibility to create a pathway for the Bachelor of Information and Communication Technology[14] and analyse the impact of that pathway on skill compatibility with jobs defined in the Australian Public Dataset.

Generating pathways requires a novel research into planning and coordination as the complexity of the target domain does not allow us to use existing state-of-the-art approaches.

5.3 Supplier

Supplier is an agent connected to the DEAN network, providing and recommending educational content. It is either a paid (i.e. university) or a free service (i.e. blog). Some "free" services require subscription after either a trial period or a number of views. Each supplier also provides content with a different level of complexity. It can either be a simple one-off tutorial, a short course or a complex program with its own rules, prerequisites and completion criteria. The development of efficient and trustworthy supplier agents requires research in argumentation, negotiation, distributed markets, trust and reputation.

6 CONCLUSION

This paper envisions agents as lifelong partners in education and career development. Knowledgeable of human desires, preferences and connected to the DEAN: Distributed Educational Agent Network, agents curate educational pathways, securing desired and economically feasible deals. This vision involves the use of most of the available agent technologies and calls for the creation of a unified, community-ready frameworks, as well as benchmarking and evaluation test beds, allowing for larger (even non-scientific) communities to seamlessly contribute to agent technology success. We proposed a model of a DEAN agent, and we are currently developing application that provides an optimal educational path for the completion of a bachelor degree according to the required skills of the desired job position.

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