Facilitators and blockers for ML adoption in official statistics

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Introduction

There is a great degree of interest in Machine Learning (ML) from the Official Statistics community. This is due to the potential for ML to increase the ability of NSOs to:

- Leverage new data sources, by capturing and processing data that previously would have required large amounts of human labour. For example, classifying images such as clothing items captured from websites (see, for example Xu et al. (2022)) or vehicles captured in CCTV cameras (for example, applied to official statistics, Chen et al. (2021)).
- Increase the efficiency of operations, by increasing the number of manual processes that can be automated to cover ones that previously required a large degree of human interaction or repetitive effort.
- Increase the quality of statistical products, by providing an increased suite of techniques to tackle a given statistical or data problem.

Most literature on ML and AI capabilities focuses on the technical capabilities: how the models are trained, deployed and utilised. Therefore, we have a good understanding of areas such as the lifecycles of ML models, how these are deployed, best MLOps practices and ML roles (see Kreuzberger, Kühl & Hirschl, 2002). One of the less studied areas is understanding how ML / AI business capabilities are built, as well as what are the recommended patterns and antipatterns to avoid for building such capabilities.

In this paper we initially discuss frameworks that can help us to describe and understand the ML capabilities of an organisation. Then we use the framework to identify potential facilitators and blockers for the adoption of ML, followed by a set of preliminary recommendations on how to improve adoption and success.

Describing ML capabilities

An inherent difficulty of discussing ML capability and how it relates to its adoption is the lack of an accepted framework. Many of the existing ML frameworks are either technical in nature or focus on technical skills. What are the most important facets of Machine Learning that should be captured? One potential way to describe ML capabilities would be to describe them as TOGAF (The Open Group Architecture Framework) capabilities, which are defined as: “A business capability is a particular ability or capacity that a business may possess or exchange to achieve a specific purpose or outcome.” The capability consists of:

- People, such as roles, stakeholders, business units.
- Processes, such as business processes and workflows
- Information, such as reports, business data, statistical data, metrics.
- Resources, such as IT and applications, tools, or intellectual property.

An understanding of ML capabilities is important for understanding maturity as well as different patterns that NSOs might have adopted. An alternative framework is used by Statistics Sweden who use the AI Maturity Assessment tool by AI Sweden. This tool decomposes areas of interest for ML into data, technology, organisation, ecosystem, expertise and culture.

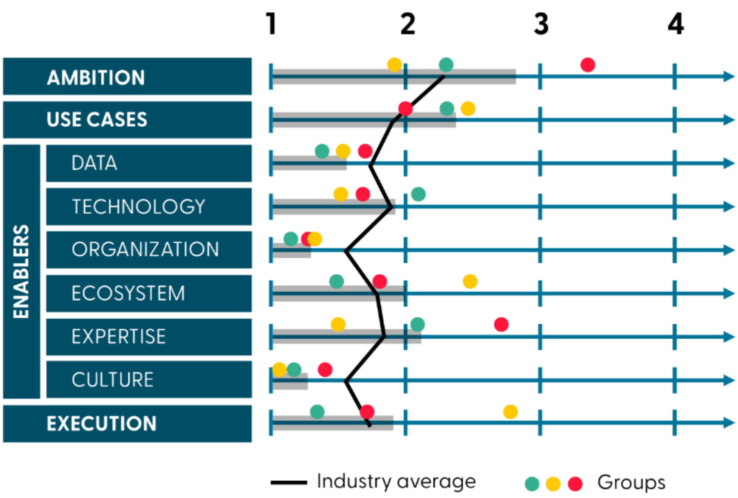

Figure 1. Example of AI Maturity Assessment by AI Sweden.

This is a useful breakdown as it provides a better opportunity to focus on some intangibles of NSOs with regards to ML capability: culture and expertise. The definition of 'information' of TOGAF is, however, more general than that of 'data', and will be used from here onwards. The resulting framework is simple and contains five domains as seen below.

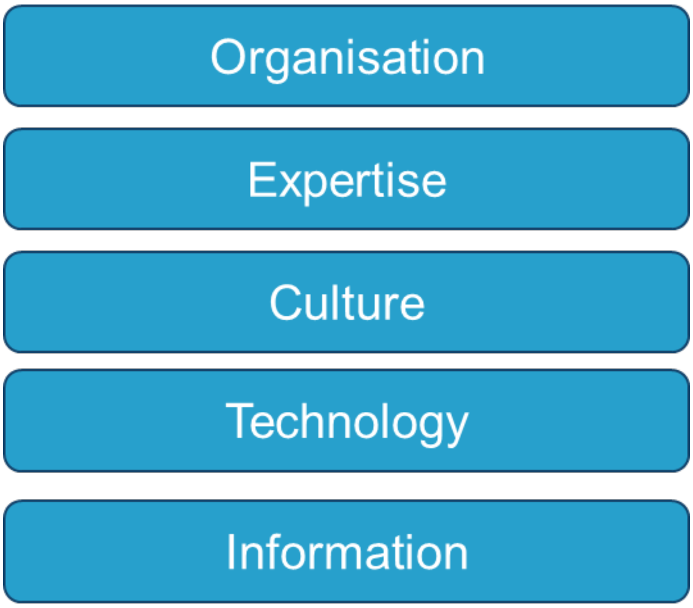

Figure 2. Framework to decompose machine learning capabilities used throughout this paper.

Facilitators and blockers

In this section we use the above framework to discuss facilitators and blockers for each one of the components of the machine learning capability of an NSO.

Organisation: Facilitators

Organisational facilitators are often structures or policies that allow ML practitioners to carry out their projects with greater ease. They tend to provide clarity, support as well as agency to the practitioners.

- Machine learning has a clear organisational function. The organisation has a clear goal with regards to ML, with areas of the organisation that deal with different issues involved in ML projects and business-as-usual. ML activities are publicised.
- Responsible owner and route of escalation. When ML capability or project issues arise, the organisation does have a senior responsible owner (or several) as well as being able to escalate issues through the line management in order to be solved.
- There are policies that govern and guide machine learning. There are agreed and available policies that govern the use of machine learning in the organisation. These policies govern the scope of projects, their initiation of projects and the best practices available within the organisation.
- Machine learning is visible in the organisation. ML activities are visible in the organisation and it is easy for any member of the organisation, regardless of business area or occupation to raise a ML request.
- There is an accepted organisational structure for machine learning. There is an accepted structure by which ML practitioners, topic knowledge experts and other business areas are organised. This often takes the form of a hub and spoke model, with a centre of expertise of ML and practitioners that are distributed in different business areas.

Organisation: Blockers

Organisational blockers tend to be the opposite of the facilitators: they drain the time of ML practitioners by requiring additional hurdles or make it difficult for staff to collaborate with ML practitioners. In the worst case scenarios, they involve they make ML progress impossible.

- Lack of leadership. There are no contacts or responsible owners for ML. Staff or areas that consider ML within specific projects have no way of turning their needs into active projects. There is no route to escalate issues if they arise and no support provided.
- No clarity on the status of machine learning. The organisation has no stated position on ML and it is unclear for staff whether they could or could not make use of ML techniques for their work.
- Inadequate or no policies on machine learning. There are no policies that support staff with ML projects.
- There’s no organisation of machine learning functions. The practitioners are spread across the NSO but unaware of other ML activities. There is no hub nor any hub and spoke. Projects are ad hoc.

Culture: Facilitators

Cultural facilitators often relate to how quickly expertise and knowledge can flow within the organisation, the attitude the risk, and the speed to which novel techniques can be adopted from other sectors.

- Existing expert groups that can establish and embed best practice. Communities and groups that allow the diffusion of best practice, development of policies and support learning and development speed up the adoption of ML.
- Links with external communities and forums. The interactions and collaborations with external groups and organisations such as academia, other government organisations and the private sector can help the acquisition of novel approaches.
- Established 'product delivery' or 'service delivery' approach. The NSO has experience with delivering 'products' or 'services' which can be repurposed to delivering ML models through their lifecycle rather than just 'projects' of which ML is a subservient part. Ultimately the models are managed as services or products that iterate through releases rather than projects with an established deadline.
- Trust & transparency. It is easy for staff to find out what ML has been delivered in the NSO and how it works. Practitioners are trusted with their time to deliver ML projects and the organisation is willing to incur some risks.

Culture: Blockers

Cultural blockers tend to relate to a lack of openness within the organisation and difficulty collaborating or investing time in projects.

- Machine learning expertise is embedded in silos. There are few forums for practitioners to interact within the NSO or to share experiences with external collaborators. Practitioners might have little agency to carry out ML projects and spend most of their time on other business area priorities.
- Machine learning is subordinate to the needs of the projects. The ML components are secondary to the main aims of business areas and their projects, with little thought given to how the models are implemented, how they fit the area and how they are maintained.
- Risk aversion. Given existing working practices or systems not being broken, there is no perceived benefit but an incurred risk on attempting new approaches, therefore the risk does not merit investigating ML solutions.

Expertise: Facilitators

Expertise facilitators relate to the recruitment, upskilling and retention of machine learning practitioners.

- The NSO has machine learning practitioners. Either through recruitment or upskilling, the organisation has sufficient staff with ML skills in order to carry out projects even if limited in scope.
- Machine learning is part of a recognised role. The NSO recognises ML either as a profession on itself or as a large subcomponent of another recognised profession or role. These staff can dedicate most of their working time to ML and expect to upskill on the role.
- There is access to training. Whether provided within the NSO, wider government or through third parties, staff and practitioners can have access to learning via training courses, dedicated project time or learning on the job.
- There is a history of undertaking big data, data science and machine learning projects. The NSO has been involved in similar skill and technology change projects over the years and it has the staff to support carrying out ML successfully. This includes ancillary roles, like an awareness amongst project managers, finance or methodologists on how such projects proceed.

Expertise: Blockers

Blockers relate to the difficulty developing and retaining machine learning talent.

- Machine learning projects are outsourced. When the entirety of ML projects is outsourced by bringing an external supplier, it can lead to no development of internal talent.
- No training is available. Although staff might be willing to learn and practice ML, the NSO provides very few learning opportunities or none at all.
- There is no recognition for machine learning roles. ML is carried out by staff on other roles who might be called to focus on other priorities at short notice, such as statisticians or IT practitioners. These staff are not recognised with regards to their work goals or training requirements.
- Uncompetitive salaries. Data science and ML are very competitive fields with regards to compensation, and although NSO and public sector work can have other benefits the salaries can make it difficult to attract and retain talent.

Technology: Facilitators

Technology facilitators relate to tooling and resources that make it easier to develop a machine learning capability.

- Staff have access to adequate hardware. ML hardware requirements are very high. Regular staff computers are hindrances for training of models as well as making it difficult later on in the process to deploy models in production environments. Access to specialised equipment like GPUs or cloud based equivalent greatly increases the performance of practitioners.
- Staff have access to adequate software. There is a wide array of available ML software a large proportion of which is open source in nature. Software can cover anything from programming languages to libraries, packages or other tools that support ML activities (like CI/CD tooling).
- Funding. Staff have adequate funding for hardware, tools or cloud services in order to carry out and maintain projects. In some cases this can have an impact on how finances are carried out in the organisation (i.e., is rental of cloud services a capital investment).
- Adequate open source policies. Considering the large proportion of ML models, software and packages that are released as open source, the organisation needs to have suitable policies and experience to use these.
- MLOps and DevOps tooling and practices. The NSO can benefit from the practices and tools that make it easier to develop and deploy models. DevOps often prepares the organisation for MLOps by breaking barriers between subject matter experts and IT practitioners.

Technology: Blockers

Technology blockers are often crucial: given the demands of bringing machine learning into production, blockers on this domain can quickly make projects untenable.

- Machine learning is carried out on regular staff devices. Staff laptops or generalist machines are very limited when carrying out machine learning projects, and in some instances can make model training impossible. In addition, not having access to cloud or dedicated environments can add an extra hurdle when handing over a model from training to deployment, or for replicating the training environment for other users.
- Software restrictions and delays. Difficulty and delays accessing suitable software and installing packages (which might be very out of date) can slow model development or make it unfeasible.

- Many handovers and hurdles from ideation to live deployment. Does one team develop a prototype, another strengthens it, and another deploy it in a live production environment with each team sending code and requirements to the next? You might have a problem. Each one of those handovers can increase uncertainty, likelihood and effort unless there is a certain degree of overlap between staff.

Information: Facilitators

Information facilitators mainly involve the ease of accessing and using data.

- Data required for machine learning can be easily accessed. Data access and the suitability of linking different data sets varies by topic and NSO. Those NSOs that have greater ease of reusing or acquiring data for ML use cases have an advantage over those which are (often by law) very restricted on doing so.
- Availability of metadata and business rules. Metadata is sufficiently comprehensive, and information is available about how data is acquired and processed to reduce undue research on sources.
- Secure environments are available. The NSO possesses environments that meet data security and privacy requirements from data suppliers or citizens.

Information: Blockers

Blockers on this field relate to the difficulty of making data available for machine learning.

- Data can't be accessed, acquired, or merged. Due to legislation, unavailability of secure environments or any other reason, the NSO can't access or merge data of use for ML. Limiting ML to only open or public data can be a strong limiting factor on adoption.
- Strong legal or privacy-based restrictions. On some instances the exploration of data using ML might be more restrictive than its use for stated statistical purposes.

Recommendations

Based on the discussed facilitators and blockers, many of them drawn from discussions with other NSOs and prior experience, here are some recommendations that can help with machine learning adoption. As these are proven or disproven, they can be built into a maturity model, to complement other maturity models such as those focused on ML infrastructure or MLOps (such as Google's [MLOps: Continuous delivery and automation pipelines in machine learning]).

Organisation

- Establish a named lead or Senior Responsible Owner who is responsible for machine learning in the organisation. Ensure there is a means of escalating issues and risks to this lead and that they have means of taking action within the organisation.
- Clarify the status of machine learning in your organisation by publishing and disseminating a clear set of policies. Policies do not need to be exhaustive initially and can grow and iterate as the organisation matures its practices.
- Provide teams that are initiating machine learning projects sufficient room to fail. Much of the time spent on initial projects at an NSO is focused on learning and upskilling, as well as integrating the new practices into the organisation.
- Don't fully focus machine learning on innovation or expanding the field of published statistics. Some of the established processes and practices of the NSO (for example, administrative or backroom processes) could be low hanging fruit.

Culture

- Create internal networks for knowledge sharing, presentations, mentoring and for the professional development of staff interested in machine learning. In addition to this, identify external networks of practitioners that staff are invited to participate in.
- Be open and transparent about machine learning in the organisation – publicise activities and achievements internally as well as externally. Make it easy for staff to find out what works, what doesn't work and how to participate.
- Treat critical machine learning models and services as products on their own right. These products or services need to be managed throughout their lifecycle with dedicated staff to develop, maintain and retire them. The needs of the users (which could be multiple internal business areas and external users) need to be evaluated on a regular basis.

Expertise

- Recognise machine learning and data science roles. Such roles should be recognised with their own requirements, goals and training opportunities alongside statistical and IT roles. Staff should not spend undue time combining multiple roles.
- Provide sufficient opportunities to carry out projects. Too often practitioners find that projects are not ready to be initiated: data can't be accessed, environments are not ready, requirements have not been gathered. When projects could be carried out, these might be additional to their work rather than the staff being dedicated to them.
- Provide access to training. A combination of internal and external training, whether in person or online is needed both to upskill staff as well as to continue their professional development.

Technology

- Don't expect a single tool or solution to solve everything. Some flexibility on hardware and software is needed to implement machine learning solutions in different topics.
- Consider hardware requirements. Either on premises or by using cloud services, ML practitioners will need access to GPUs for training. Even when training schedules are not particularly heavy, better access to memory, computing power and storage can greatly improve efficiency.
- Review your open source policies. A lot of ML solutions and the programming languages they are written on are open source. Some consideration needs to be given to how packages and libraries are managed.
- Consider MLOps. Some thought has to be given to how ML practitioners can bring their solutions all the way to live environments and how do they integrate and enhance the IT practices of the NSO. Deploying, scaling and interfacing with ML services produced by the NSO can't be an afterthought.

Information

- Target the data you can leverage with machine learning. Take into account the legal, data sharing and privacy laws of your country, and the available platforms and systems. Consider whether new data products can be developed from existing open data, or whether more secure handling of data is required.
- Ensure your platforms and environments are fit for purpose. ML has high requirements of storage, speed and, in the case of some datasets, security.

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