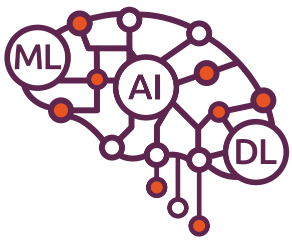
Getting Started With AI

June 2019

Executive Summary

Artificial intelligence (AI) and machine learning (ML) are beginning to transform business across almost every vertical. The healthcare, financial services, and automotive industries are leading the charge, but high-value use cases for AI are emerging in fields ranging from retail to energy, from utilities to manufacturing, and everywhere in between.



Artificial Intelligence vs Machine Learning vs Deep Learning

The terms 'artificial intelligence', 'machine learning' and 'deep learning' are often used interchangeably, but they do not mean the same thing. Artificial intelligence is an umbrella term for machines that are capable of mimicking human intelligence and behaviour. Machine learning, on the other hand, is a process used to achieve artificial intelligence. It involves designing algorithms that can learn from data to become more accurate and effective over time. Deep learning is a subfield of machine learning that draws inspiration from how the brain works. It involves using layers of artificial neural networks that create a human-like logic structure.

The business potential of AI is growing daily – especially as the technology moves beyond prediction and analysis towards true, autonomous decision-making – unlocking unprecedented levels of insights, knowledge, and innovation. Early adopters are already achieving immense value from AI programs, with benefits across many use cases - financial, security, customer churn reduction, fraud detection, website abandonment reduction, human engagement, employee retention, and robotics, to name a few. Gartner estimates that AI technology will generate $3.9 trillion in business value by 2022. We are rapidly approaching the point where companies that do not invest in AI risk falling behind competitively.

In this whitepaper, we will explore three fundamental steps in launching a successful and sustainable AI program. Each step highlights some of the key questions that should be answered:

1. Building your AI business case

This is sometimes referred to as 'start with the end in mind'. There are three key questions at this step - what problem are you trying to solve? Do you have realistic expectations? Do you have the right data?

2. Assessing your AI readiness

After identifying the business case, it is time to determine if you're ready for AI. The important questions here are: What are the blueprints for quickly identifying gaps in readiness? What are the key factors to consider? Are there hidden gaps in readiness? What are the common pitfalls to avoid? How can you ensure that your business has the infrastructure and expertise in place to succeed?

3. Creating your AI program

The outcomes from the previous steps are inputs into designing your AI program. With limited time and budget, the business case and gaps in AI readiness help focus and prioritise the scope of work. Some key questions: How do you go about implementing AI? Have you found the right gaps to fill and in the right order? Which gaps can be ignored and for how long? What are the blueprints for quickly achieving some initial value? What remains to be done for effective planning and governance of an AI program?

By following the steps highlighted in this whitepaper you should be able to establish a plan for your organisation to get started with AI. This proven methodology was established during a number of workshops, training and implementation projects by Canonical and our partners. It covers best practices and implementation guides that will deliver a structured program to help your organisation achieve its AI ambitions quickly, reliably, and cost-effectively.

Building your AI business case

AI is rapidly gaining popularity, but organisations should not adopt AI just to stay on trend. It is crucial to have a clear set of objectives, and to keep those objectives in focus throughout the project. Before you dive into AI establish the business rationale behind your AI project. It is easy to be carried away by the potential of AI and to apply it to a number of areas in your company. However, not all projects are suited to AI or economically solvable with AI in a certain timeframe.

Here are the key questions that you should ask of your business when considering your first AI projects.

Do you have realistic expectations?

Artificial intelligence and machine learning technologies can deliver tremendous cost savings and revenue growth, but the return on investment is not always immediate. AI can be one of the most resource-demanding technologies in use today, particularly in terms of compute and storage. While hardware is becoming more powerful and less expensive, if you have large amounts of data and anticipate large sets of deep learning experiments, you should expect relatively high upfront costs for your AI implementation. In this scenario, ROI might only be achieved in the long term as you refine and improve your solution, leaving you and your program in a potentially awkward position.

Resource requirements, data quality and volume, are just a few of the unknowns you'll want answered. There are more unknowns, covered in the AI readiness section below. Starting with a proof of concept might be your best option for uncovering all immediate unknowns since it will help you learn about the landscape - such as development velocity, risk areas, opportunity areas, data pipeline issues, and applicable machine learning models. The learnings will help you set realistic expectations - you will have gaps that need to be closed - and it will also help you accelerate time-to-value through improved focus. Further down in this paper we'll investigate what such a proof of concept could look like in the form of a design sprint.

It can be tempting to jump right into a pilot project. Before diving in, define the success criteria. This will help crystallise expectations for the program. Starting with the end in mind - with the criteria that will be used to judge the effectiveness of the program - will pay dividends throughout the project. At the beginning it will help ensure the project team and the key stakeholders (project sponsors) agree on what the project must deliver. Throughout the execution phase, the success criteria can serve to reinforce the project milestones. The success criteria should include measurable increase in value to the business, paving the way for future AI investment. It is critical to do this before launching into the pilot project, before the team is consumed with exciting, shiny new toys.

What problem are you trying to solve?

Whatever business challenge you are trying to solve, ensure that you have a well-defined strategy that specifies why you are doing the project, and for whom. In our experience it is common to solve a few problems in parallel. The problems can be categorised as commercial, tactical and strategic.

The commercial category is the business driver for tackling AI. This area should be the primary motivation for leveraging AI and ensures the program is on solid footing for continued investment. The use cases for AI are broad and you most likely have specific business applications in mind. Examples of valuable AI use cases are abound in most sectors - financial services, retail, healthcare, manufacturing, robotics, energy, utilities, education, and government. The business driver could be sector specific or may be common across sectors, based on factors like functional area. Cross-sector examples include information systems, security, human resources, marketing and sales, quality control, and customer success.

The tactical category focuses on skills-based capabilities of the organisation to deliver on the commercial drivers. It is concerned with blocking and tackling issues related to project success. Example challenges to solve are - Where to start? What skills are needed? What infrastructure is needed? What data problems to solve? Do we have the right data? Is there 3rd party data which would be helpful? Which models are good starting points? Which models can be reused? The next section on AI readiness covers this area in more detail.

If you are unable to answer some of these questions, consider using the following as an example success criteria for the program: identify and train 4 people who will serve as the core of the AI team and who will be able to answer these questions.

As you answer these questions and prioritise the problems to solve, leverage the peak-to-peak principle - solve the problem associated with reaching the immediately visible peak before worrying about the next peak. This will keep you agile. Each path to the peak typically starts with a simple hello world example leveraging existing data and solutions, and then the team iterates on the solution until a commercial problem is resolved.

The strategic category is concerned with structuring the AI program in a way that leads to a virtuous cycle of successful AI model development and integration into your existing systems. The strategy generally includes a series of commercial and tactical solutions that are carefully orchestrated and prioritised to build upon each other. You can leverage the broadly understood ‘crawl, walk, run’ strategy:

1. Crawl - deliver one benefit to one business application, leveraging a small tiger team to eliminate risks and unknowns.

2. Walk - deliver multiple benefits by applying learnings across two business applications with the same tiger team.

3. Run - identify and deliver benefits across the entire business, including revenue generation and cost mitigation, by applying AI best practices to all relevant areas with an expanded team.

The AI program section below will provide a useful model for constructing this series of projects.

Do you have the right data?

All machine learning types require data. Your data will be the basis for teaching your models - they’ll learn to recognise patterns in the data and learn to identify relationships between those patterns and the outcomes you’re looking for. What kind of data do you have? Should you acquire data from other sources to train your models?

Examples of data and uses cases where your business may benefit:

- Sales and marketing - lead prioritisation, lifetime value prediction, sentiment analysis, behaviour analysis and prediction, customer engagement analysis, loss prevention, content generation, recommendation systems to increase engagement and share of wallet, demand forecasting

- Human resources and team productivity - hiring and ideal candidate identification and solicitation, top performer analysis and flight risk assessment, abnormal travel expenses, team productivity contributors, project risk management

- Security, failure and fraud - manufacturing and predictive maintenance, security and threat prevention, emerging threat identification, fraud prevention, general failure analysis and prediction, failure detection and prevention

- Education and customer engagement - customised learning paths, automated and intelligent customer service, customised user experiences based on history and cohort analysis

- Robotics - vision and motion, adaptive reasoning, distributed robotics and sensors, intelligent controllers for autonomous underwater vehicles.

However wide and varied the use cases for machine learning, the underpinnings are common - the need for data, the types of machine learning, the types of algorithms used. It's important to understand the requirements the machine learning algorithms will place on your data - completeness and quality in particular. These requirements will determine if additional data pipeline work is required before model training can start.

Regarding machine learning types, the algorithms generally fall into two types - supervised and unsupervised - with a third type gaining in popularity - reinforcement.

- Supervised learning - given a data set that includes input variables and an output, a model can learn the relationship between the input and the output. The output could be a classification, like yes or no, or it could be it could be continuous, like price prediction.

- Unsupervised learning - we can approach problems with little or no idea what the results should look like. Structure can be derived from the data, clustering results into groups which demonstrate the effect of the variables. An example is analysing a gene sequence to determine what role a gene plays in cancer development.

- Reinforcement learning - develops models by training itself using trial and error - a balance between exploration of uncharted territory and exploitation of current knowledge. The models can learn from external interactions and improve with time. Reinforcement learning is widely used in gaming, robotics and industrial automation for efficient adaptive control systems, text summarisation engines and dialogue agents, optimal treatment policies in healthcare, and online stock trading.

Assessing your AI readiness

Machine learning is a relatively new industry for most people – the skills, processes, tools, methodologies, and infrastructure required for a successful AI program may be new to your organisation. It is common for organisations that are just starting with AI to scale the program around a handful of motivated individuals once a business case has been established. That will help begin the discovery process and reduce the number of unknowns.

In this section we explore some of the key AI readiness questions you can ask to determine what gaps you may have.

Do you have in-house AI expertise?

AI programs rely on people with specialised skill sets to create the technology that will drive automation, experimentation, and business value.

Here is a simple list of the expertise you will need to get started:

- **Data Engineers** to ensure the quality and suitability of your data, and integrate it with your AI infrastructure.

- **Data Scientists and Machine Learning Engineers** to analyse the data, look for patterns, develop the AI models, algorithms, and neural networks that will consume your data, and to extract actionable insights.

- **DevOps Engineers** to deploy and manage your AI solutions in production.

More advanced AI scenarios require additional roles - examples include Infrastructure Engineers, Operations Engineers, Platform Engineers, Application Engineers, and managers of course.

Identify any gaps in your teams' capabilities, and ensure they are filled before beginning your AI journey. Shortage of specialised, in-house AI expertise emerged as one of the biggest pain points for CIOs in Gartner's 2018 survey. Therefore if you find that you have gaps in your team, it should not come as a surprise. While in some cases it can be viable to train existing employees to fill these functions, it is often more practical to bring in outside experts, especially for your first AI projects. Using these outside experts to train your team by collaborating on a joint project might be your best strategy to kickstart your program.

Do you have the hardware infrastructure?

Capacity planning is an important element of your AI initiative, from workstations to compute clusters. Workstations play a role in the discovery and development process, and could be all you need for training your models. Depending on the number of experiments and size of data, the data scientist or machine learning engineer can do a majority of their work locally. This work primarily involves data discovery, data analysis, and model prototyping or development.

Machine learning, and deep learning in particular, will place your infrastructure under additional strain. The reality for both types of learning is that careful analysis should be done to ensure throughput expectations are met. The primary factors that play a role in capacity planning are:

- How much data needs to be processed?
- What are the data access demands (IOPS, network bandwidth)?
- How many models need to be trained?
- How complex are the models (layers, computational)?
- What are the precision requirements for the models?
- What are your FLOPS capacity requirements?
- Will you employ continuous learning strategies?

The good news for those who can migrate some or all data to public clouds is that you can start your AI initiatives without detailed capacity planning and without detailed infrastructure build out plans. This lowers the barrier to entry for getting started. There are other benefits to leveraging the public cloud - you can leverage elastic infrastructure - using only what you need, when you need it, including GPU - and the public clouds can help you answer the capacity planning questions above, which will inform your hardware purchases. However, you should still go through some of the capacity exercises to better understand what your cloud costs will be.

For those who can't leverage a public cloud, or find the cost of public cloud to be too high, the capacity planning exercise is a hard requirement. Answering them will help ensure your hardware isn't a bottleneck, which would artificially constrain your learning pipeline. One of the choices you face in planning your infrastructure is whether to dedicate the infrastructure hardware for AI or to share the hardware across multiple types of workloads. Dedicated AI hardware makes sense for steady state learning, where 100% of the hardware is used all the time. Shared hardware allows for multiple workload types, which enables you to blend demand spikes and variations, minimising under-utilised hardware.

For each scenario above - public cloud, private cloud, on premise, shared or dedicated - you'll need software to manage the infrastructure. By combining Kubernetes and Kubeflow you'll have a powerful, open-source solution to manage hardware and software infrastructure. This will be discussed in greater detail in the next section.

Do you have modern software infrastructure that leverages available hardware?

The benefits of a robust Kubernetes cluster are not limited to AI. Migrating other workloads – especially corporate production workloads – to Kubernetes can unlock significant additional savings, and it can accelerate the transformation of your business applications.

Whether you have your own hardware or you leverage hardware from the cloud, machine learning at any scale requires effective use of the underlying hardware. Hardware accelerators like GPUs are expensive and therefore need to be used efficiently across users. You'll need software that makes effective use of what's available. Additionally, you'll want a portable solution that gives you the flexibility to train models on-prem or in the cloud, enabling hybrid and multi-cloud infrastructure strategies. It is for these reasons that Kubernetes has proven to be the right infrastructure automation solution for AI. Kubernetes can efficiently use your physical resources, sharing them amongst your users, and works equally well across multiple types of infrastructure - private or public, bare-metal, VMware, OpenStack, AWS, GCP, Azure, etc.

Originally developed by Google, Kubernetes is an open-source container-orchestration system that automates deployment, scaling and management of containerised applications. Kubernetes enables users to deploy complex workloads in a way that is simple and repeatable. In addition to supporting applications and workloads, Kubernetes excels at managing containerised jobs, which have proven to be effective for machine learning model training and experiments. Kubernetes also provides a solid foundation for most technologies used in data engineering as well, as highlighted in the Cloud Native Compute Foundation's (CNCF) landscape diagram. It is for these reasons that Kubernetes is the infrastructure automation of choice for AI.

If your organisation has plans for either multi-cloud deployments or hybrid deployments, the default Kubernetes for Ubuntu is known as the Charmed Distribution of Kubernetes (CDK), by Canonical and works across the broadest set of private and public infrastructure, as well as the broadest set of CPU architectures. CDK is pure upstream Kubernetes - the source code and binaries published by Kubernetes are used in CDK, which allows users to benefit from all upstream innovations without any vendor lock-in. In addition to CDK being pure upstream Kubernetes, CDK follows the open-source Kubernetes project closely - often releasing within a week of the latest upstream release, ensuring users are current with the latest innovations.

For developers looking to get started locally, on a laptop or workstation, Microk8s is a simple, single-node kubernetes solutions that installs in seconds with a single command. For enterprise deployments to support an entire team of developers, Charmed Kubernetes will satisfy your needs.

Kubernetes itself provides a solid platform for containerised applications and jobs. You still need an AI application or platform that can deploy onto Kubernetes and work with it to provide the right end-to-end solutions for machine learning. Kubeflow is the ideal for this, as discussed in the next section.

Do you have a modern software stack that leverages the latest machine learning innovations?

Some organisations operate DIY technology stacks for their AI programs, built and maintained by in-house specialists. If a key stakeholder who runs one of these 'snowflake' (unique and fragile) stacks leaves, it can put the business in a particularly difficult situation. Moving to a standardised deployment eliminates this risk.

The AI world moves fast. There's a continuous stream of innovations across the entire landscape, from improving productivity to democratising AI, making it easier for beginners to produce powerful solutions. It's important to understand these innovations and leverage those relevant to your team and problem domain. This presents a few problems beyond simple awareness of the innovations: How can your organisation take advantage of the latest software and achieve high levels of productivity? How can your organisation ensure new versions of software platforms can be rolled out safely, without impacting production devops pipelines? How can you leverage multiple versions of components in your technology stack?

There are a few logistics problems that occur at scale as well: How to leverage all your hardware, achieving close to 100% utilisation if necessary? How to compare experiments at scale? How to leverage and re-use best practices in model creation and model training? Is there a way to ensure all engineers follow the same workflow, from training to production (think corporate standards)?

Software frameworks and platforms help in these areas. Specifically, for AI, Kubeflow addresses all of these questions. Kubeflow is a Kubernetes-native, standardised machine learning solution that comes with pre-built machine learning technology stacks, including the ability to define your own. Kubeflow makes it easy to deploy your preferred machine learning frameworks, libraries and tools on the hardware of your choice. Examples of popular components include Tensorflow, TFX, JupyterHub, PyTorch, XGBoost, Pachyderm and Seldon, but there are many more, and you can extend Kubeflow with your own components as well. Kubeflow's rapid release cadence will allow you to consume innovations in these components at predictable intervals, accelerating your AI team's velocity.

Workflow definition and execution is an exciting area of Kubeflow for most users. Kubeflow helps you capture best practices and standardise machine learning workflows through its Pipelines framework. You'll be able to streamline the process of building, training, evaluating, and deploying machine learning models. You can define the steps in the workflow, including things like bias detection, compliance processes, and performance gates. Pipelines accomplish this by enabling you to define reusable workflows that will help promote your models from development to production with predefined steps that are important to you.

In the multi-cloud AI world, where AI practitioners leverage multiple environments, portability requirements surface rather quickly. We consider each environment, from laptop to workstation to compute cluster, to be different and in need of the ability to define a repeatable machine learning stack. Repeatability means the machine learning stack can be deployed to any environment. And it means that the development and training can be done on any environment as well. Without a well-supported Kubeflow and Kubernetes implementation, connecting and managing all of the components that make up your AI ecosystem will be enormously time-consuming. What's more, moving your AI models between environments could require considerable re-architecture, making it difficult to transition from development to testing and production.

Are you aware of common pitfalls?

Artificial intelligence, and machine learning in particular, have many pitfalls that you'll want to avoid – we'll go over some of them here. While discussing the solutions to each of these pitfalls is beyond the scope of this whitepaper, readers should understand that a lot of benefit can be derived from tribal knowledge. It is highly useful to draw on the experience of people who have been down this road already and can help you overcome these hurdles quickly and easily.

The pitfalls can be categorised as:

- **Data pitfalls –** data sources, data quality, missing data, data leakage, data splitting, sampling bias, data privacy and appropriate use
- **Model pitfalls –** feature selection, mis-calculated features, algorithm selection, black boxes, failure to explore new techniques
- **Evaluation pitfalls –** statistical errors, correlation vs causation, neglecting outliers, evaluation criteria, overfitting
- **Operational pitfalls –** ineffective performance KPIs, incomplete testing, data quality drift, data bias drift
- **Project pitfalls –** time to value, scope and minimum viable product (MVP) selection, team diversity (human bias), technical debt from DIY
- **Business pitfalls –** developing trust in AI, deployment costs vs ROI, PoC vs pilots, lack of use case exploration and growth, problem discovery and definition
- **Ethics and bias pitfalls –** bias in large datasets, bias in model development, ethical reasoning skills, embedded values and assumptions

Knowing these exist is the first step to avoiding them. They should form part of your project execution checklist and be used as part of your project governance. Let's explore a few of these pitfalls in more detail.

#1: What are the common data pitfalls?

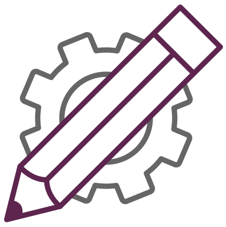
Data quality, including missing data, is one of the most common data pitfalls that need to be addressed before machine learning can be used. Initial data exploration will often find gaps in quality and content, and it'll highlight how large a task is in front of the team. It's possible that considerable effort is necessary to get the data into a state that is useful for machine learning. Otherwise you'll experience 'garbage-in garbage-out' first hand.

To supplement traditional data quality control methods, which are typically based on user experience and manual processes, we can utilise machine learning with advanced techniques to overcome these challenges and provide greater value to users. Machine learning leverages computing resources, rather than human resources, to overcome limits in performance and desirable accuracy from previously established business rules. Machine learning and rules-based data quality inspections continuously monitor the data for quality, completeness, and formatting. Scoring the data along these axis allows for automated exceptions, sending alerts to data owners and end users about the issues.

#2: Are we able to identify, monitor, and explain bias in trained models?

It is hard, maybe impossible, to completely eliminate bias in the models that are trained and used in decision making applications. If you have really large data sets, you might not even realise that the data are slightly biased on gender, race, age or whatever you're analysing. With AI in production and constantly making predictions, it is essential to understand that the model can be out-of-step with reality. The model may have been trained with data that doesn't match well with the data the model sees in production. Depending on what the model does, this may not be a big problem. For example, is it identifying profitable customers, or is it trying to find the best candidates to hire? Those are very different ethical scenarios. You AI team should understand the gravity of the problems they are solving with their AI models and ask normative questions, ie; bias awareness.

There are a few steps one can take to help monitor or alleviate this type of pitfall. First, it is important to think about how technologies embed particular values and assumptions which lead to bias, and how that bias leads to ethical challenges. Most of these ethical challenges have no single right answer, so it's important for the team to learn fundamental ethical-reasoning skills, and understand that in everything the AI team designs there are always going to be normative questions. Second, look at the algorithms themselves and ensure that nothing about the way they are coded perpetuates bias. Third, find ways to expose the decision making process - which model, which training data, which input data. Finally, consider ways in which AI itself can help to mitigate against the risk of biased data or algorithms.



Creating your AI program

Like most engineering endeavours, there is a common set of macro-phases that can be used to guide and govern your AI program. It is helpful to identify success criteria for each phase and use that as a gate for the next phase. This helps ensure the team stays focused and that key stakeholder expectations continue to be met. Like most agile practices, communication and having a clear understanding of progress are critical for successful projects.

Macro-phases

The macro-phases are:

- **Discovery –** start with a mile wide and an inch deep analysis, capturing essentials.
- **Assessment –** employ qualitative reasoning to the discovery artifacts.
- **Design –** iteratively solve for the highest risk areas first, before well understood areas.
- **Implementation –** follow the plan and work on operational scenarios.
- **Operation –** ensure your reliability and operations teams are prepared.

Each of these phases can span weeks or months. By answering the questions in the previous sections on business case and AI readiness, you have already started down the discovery and assessment phases. The gap-closure plan will straddle assessment and design.

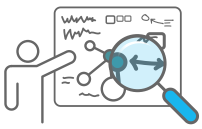
The macro-phases are presented in a waterfall manner, where each phase is done to exhaustion before moving to the next phase. This works well for small projects - less than a few man months of effort. For large projects, you should follow an iterative, agile methodology, which places emphasis on early feedback and risk mitigation.

As soon as possible, particularly for those just starting and for those who are stuck, it is imperative to understand the complete picture - going from idea to production deployment. It is for this reason we recommend pursuing a one week AI design sprint, which is detailed in the next section. The design sprint will give you a clear view into what is possible, which will facilitate setting expectations on timeline, features and quality.

AI Design Sprint

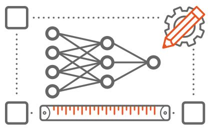
A one-week design sprint will help introduce your entire team to modern AI technologies and methodologies. Tackle a real business challenge and achieve tangible results. This will serve as a proof-of-concept for your AI innovations.

The key outcomes that you should expect from this week are a baseline architecture for iterative solution development – which includes a working continuous integration pipeline – and a high level strategy that addresses your AI transformation journey. Please note: this week typically relies on having the right hardware and software infrastructure in place to support the AI technology stack. The physical infrastructure can be on-premise or in a public cloud, and it must have access to the data to be used for model training. A Kubernetes cluster should be created on this physical infrastructure, with sufficient hardware to train models in the desired timeframe.

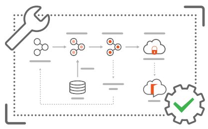


❶ **DISCOVERY:**
Goals, challenges, knowledge, sprint target

❷ **ASSESSMENT:**
Data, workflows, gaps, ideas, users



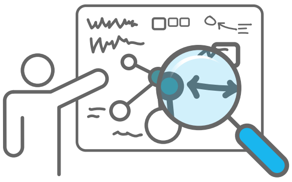
❸ **DESIGN:**
Prototypes, algorithms, tests, data



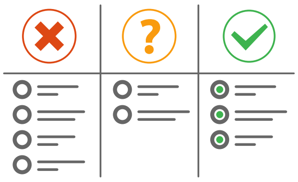
❹ **IMPLEMENTATION:**
Models, pipelines, integrations

❺ **OPERATION AND FEEDBACK:**
Deploy, operate, evaluate

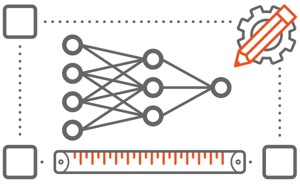
Here, we take a closer look at the life-cycle for an initial design sprint. The specific steps for each phase should be adjusted based on your particular needs:



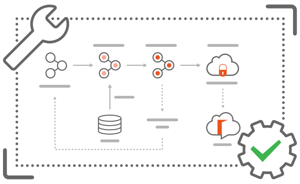
Day One - Discovery: Following a pre-kickoff (discussed below), gather the AI team for this structured conversation, which will create a path for the week. Start with the long-term goal, map out the challenge, ask your domain experts to share their knowledge, and pick a target for the sprint (sprint goal) - an ambitious yet manageable piece of the problem that can be solved this week. The mapped out challenge should include your business requirements, expected outcomes, data sources, deployment scenarios, potential opportunities and risks.



Day Two - Assessment: Domain experts should provide initial feedback based on the Discovery phase. They will report on the data and make solution recommendations. They will discuss building a strategy roadmap for the project based on your specific business case. Any changes to your infrastructure should be highlighted during this step.



Day Three - Design: Prototype several solutions to the sprint goal and identify a candidate solution that seems to be the best fit. Data engineers should prepare the data. Data scientists should discuss and select appropriate features and machine learning algorithms. Machine Learning engineers should design, build and perform preliminary tests on your prototype neural network. Time permitting, start the iterative process of design and discovery on the data and the neural network model.



Day Four - Implementation: Complete the design process and begin training and testing your AI model until it reaches the desired accuracy threshold. Build a pipeline that will put your model into a suitable environment for testing and feedback from additional stakeholders. Domain experts should offer guidance on assessing machine learning predictions and putting discovered insights into action.

Day Five - Operation and feedback: This may include UI development, technical documentation, and hands-on knowledge transfer between development and operations teams to ensure they can operate the solution. It is important to discuss production deployment options – for example, a dark launch or an integration with a prototypical business application. During this step, elicit feedback from key stakeholders, covering the baseline architecture and model.

This five day, five step program relies on a couple of extra 'days' to ensure a successful experience:

1. Day Zero is a pre-kickoff. This involves getting enough of the preliminary information, data, stakeholders, and systems ready for Day One. That includes preliminary discovery and assessment with a small set of domain experts who are capable of delivering the key artifacts for these phase. These artifacts serve as input for the team attending Day One.

2. Day Six is a post-mortem. It is a longer followup to Day Five. The key output from day six is the set of lessons learned during the sprint week, and the AI program. Example questions - What was learned during the AI Design Sprint? What are the implications for the preliminary plan that was created for the broader program? What action is recommended and presented to project sponsors? What worked well? What didn't work well? These lessons serve as input into the AI program and contributes to creating a virtuous cycle.

It’s time to start

This whitepaper has outlined a simple yet effective strategy for getting your AI initiative on the right track. We have covered the three main steps to getting started in AI. The three steps are:

1. Build your AI business case.
2. Assessing your AI readiness.
3. Creating your AI program.

If you’ve read this whitepaper before starting with AI, then the business case development and AI readiness can form part of your AI program. Each step, as described above, comes with a set of key questions that should be answered and a set of expectations that define success. Now it is time to get started. You can leverage this checklist to guide your efforts:

- Plan:
  Develop a program charter, which includes:
    - Scope of program
    - Program success criteria
    - Program budget
    - Broad timeline for the design sprint and a pilot

- Organise:
  Create a small team to tackle pre-kickoff tasks:
    - Planning and analysis skeletons
    - Project management methodology
    - Reporting frequency and medium
    - Decide on any other project meetings required by your organisation.
    - Preliminary discovery and assessment (AI readiness)
        - Assess depth of in-house AI expertise
        - Hardware and software infrastructure
        - If there are existing AI assets, assess pitfall areas
    - Determine if outside experts are desired

- Execute:
  Engage the core team, key stakeholders, and deliver results:
    - Schedule kickoff meeting
    - Schedule design sprint
    - Assess design sprint results
    - Report on results and desired next steps
    - Schedule pilot project to continue momentum

Start! Sometimes this is the hardest part. And as part of starting, determine if outside help is desired. And if you’re looking for help...look no further.

AI with Canonical

If the AI Design Sprint seems daunting, or if you've identified gaps in the team that you'd like to close quickly, reach out to Canonical. While Canonical takes care of your infrastructure, our partners provide the data science and engineering expertise to get your AI project started. Together, we can help deliver the five-day/five-step AI Design sprint with your analytics and infrastructure teams. At the end of the engagement you will have a pattern for productive developer workstations, a machine learning infrastructure (in the cloud or on-premises), and AI applications delivering daily insights, powered by your data.

It may not be obvious upfront, but the expertise and tooling requirements can be a formidable barrier to entry for AI newcomers. Re-platforming, recruitment, and training are potentially lengthy and expensive processes that can delay time to value and negatively impact productivity. For those adventurous organisations that take a do-it-yourself approach, it may be difficult to grow beyond the developed system, even when the pain points are well understood.

With our structured program, we can approach any situation and provide the infrastructure and capabilities that your business needs. Proven best practices mean that we can take the guesswork and experimentation out of your AI adoption, and fast-track you to value without breaking your budget.

Canonical provides a complete technology stack for AI, starting from the operating system (OS). Ubuntu is the default OS for Kubernetes, leveraged by leading enterprises around the world for their AI projects – including Google, Amazon, and IBM. We deliver a Kubernetes distribution on Ubuntu that delivers the latest container capabilities in modern kernels. And that is why so many companies rely on Ubuntu for their AI projects.

Just as Ubuntu runs in every environment – offering a consistent, familiar experience across workstations, racks, cloud, and IoT – Canonical's distribution of Kubernetes and Kubeflow can be deployed on any hardware, even on laptops. This flexibility boosts productivity and enables businesses to move seamlessly between model development, training, and production.

As a company, Canonical can design and implement an optimised, production-grade Kubernetes cluster in your environment of choice. We also offer on-site training for your Kubernetes operators as they onboard your new AI workloads. Alternatively if you would rather focus on your core business workloads, Canonical offers a fully managed service for your cluster and infrastructure.

Partners

Canonical works with leading data science consultancies to give our customers access to the very best AI expertise. Following a successful design sprint with one of these partners, the next step may be to continue working with your chosen partner to scale up your team and help you deliver on a more complex AI project. The strategy you developed during the design sprint will be applied to the challenges and opportunities within your business. Visit our website to see the latest list of our global partners.

Each partner can be engaged for long-running projects that tackle more difficult problems, and the engagement will typically follow the same structure as the design sprint. Learn more about some of our partners:

MANCEPS

Manceps is a machine learning solutions provider specialising in augmenting human capabilities with artificial intelligence. Manceps combines state-of-the-art deep learning, cloud, and big data technologies with extensive industry expertise to help clients gain and maintain competitive advantages.

From its headquarters in North America, Manceps collaborates with a global network of innovation labs, universities, and data scientists to share knowledge and new ideas. While protecting its customers' IP, Manceps is committed to open-sourcing all of its work in order to help the AI industry develop as a whole.

Discover more about how Manceps can help your business unlock new opportunities with AI at manceps.com

"Canonical shares our core values and commitment to the open source community, and we are excited to have them as a strategic infrastructure partner. Not only do they offer a popular enterprise OS and a proven private cloud infrastructure, they also make deploying and managing ML stacks on Kubernetes simple, scalable and portable with Kubeflow"

Al Kari, CEO, Manceps

deepsense.ai is a team of business-oriented problem solvers. We use our outstanding technical proficiency to identify, analyse and solve problems with AI-powered solutions.

Our data scientists and business team take a company's weaknesses and reforge them into strengths. We help our clients optimise spending, augment business processes and maximise performance. With an approach developed through extensive research and numerous commercial projects for international customers – including the United Nations, Intel, and NVIDIA – we use our proven methodology to help organisations at all stages of data science maturity. deepsense.ai delivers AI-based end-to-end solutions, with a focus on computer vision, predictive analytics and natural language processing.

deepsense.ai is helping to pioneer the field of reinforcement learning, where AI models learn by interacting with their environment rather than from existing data.

For additional information on deepsense.ai's expertise and services, visit deepsense.ai/

"As a machine learning-centric company, we value Canonical's expertise in delivering the infrastructure to power AI-based solutions. We leverage the flexibility and reliability of Kubeflow in our reinforcement learning projects. Kubeflow delivers a convenient and effective way to run MPI jobs on a Kubernetes cluster. It is currently the technology of choice enabling our team to connect these environments and deliver RL-based models faster, supporting both our commercial and scientific works"

Pawel Osterreicher, Director of Strategy and Business Development, deepsense.ai

Take the first step

Now that you know the fundamentals of a successful AI program, all that remains is to take the plunge and start your own AI journey. The sooner you begin, the sooner your business can begin reaping the benefits.

When taking your first steps with AI, there is no substitute for first-hand experience, which is why Canonical and our partners have teamed up to offer one-week design sprint workshops. Work with expert consultants to explore use cases, take an initial look at costs and ROI, and develop an AI roadmap – all while gaining hands-on experience and real business benefit. To book your design sprint, visit ubuntu.com/ai/consulting.

Further reading:

For a more detailed look into the artificial intelligence and machine learning landscape – including a deep dive into the core concepts, tools, and use cases – check out some of our webinars:

- AI, ML, & Ubuntu: Everything you need to know
- Getting Started with DevOps best practices: CICD
- How to build and deploy your fist AI/ML model on Ubuntu

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