THE DATA LAB GUIDE TO DATA TEAMS

From Storming to Norming

Building high impact data teams

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Modern technology has already made substantial changes to the modern workplace. The potential for high-value development based on these new data capabilities is already clear, but not all businesses are positioned to take advantage of these new capabilities. In particular, in-depth technical understanding is disproportionately concentrated in people who are at relatively early stages of their career, which can leave senior leaders unsure where to turn for guidance on the strategic and organisational changes needed to take advantage of these new possibilities.

This series of papers from The Data Lab offers some initial clarity and guidance on what is needed to build value-driven, sector-focused data science capabilities into an existing business.

The Data Lab would like to thank the organisations who attended the original round table and who contributed their expertise and case studies to this document.

Contents

Background

After an organisation has made its first one or two data scientist hires, it may seem that the most substantial challenges have been tackled. The first one or two projects have been delivered, perhaps to general acclaim within the organisation, and the new data team is beginning to understand the business. While these are indeed the first hurdles to overcome, there are further challenges to be faced at this stage.

To become an embedded part of an organisation, a team must be able to deliver consistently – and this is no different for a data science team. This stage can present new challenges to an organisation, such as:

- embedding the data professionals in their roles
- helping the business to become accustomed to calling on the team for support
- developing in a way which is sustainable within the wider organisation

Facing the challenge of scaling within a large organisation, Heineken and The Data Lab organised a round table to discuss challenges and the approaches that can work in this situation, as well as the mistakes to learn from. The attendees ranged from managers of large and established distributed teams, to large but still fairly-new teams and start-ups with only one or two data scientists in their team. The discussion was focused around key topics, and the learnings are presented here under the headings "Strategy and Ability to Execute" and "Data Team".

This document has been produced following the round table, to consolidate and formalise the outcomes of the round table, and to enable the key learnings to be circulated beyond the immediate attendees to other organisations in the same position.

In this document, the term "data team" is used generically to apply to any team embedded within an organisation with particular responsibility for making data useful and usable to the organisation. This may be an analytics function or a data science function, and can be made up of any set of data-related skills. Occasionally, parts of the document are particularly relevant to individuals or teams with particular "data science" aims or skills, such as data programming, algorithms or machine learning. In these cases "data science" is explicitly specified.

Additional resources and links are provided in the Appendix.

Strategy and Ability to Execute

In this section, the position of the data team within a broader organisation is considered. How can a data team be effectively integrated into an organisation? What practical steps can help a data team become an established part of an organisation, and what does that mean for the data team pipeline and prioritisation?

Summary

In this section we consider the context of an organisation, and how a data team will relate to its broader context. We consider how culture and leadership can enable a new data function to succeed. We discuss how team names and positioning can aid a data team to work effectively with other teams in an organisation, and we look into the creation and maintenance of a healthy pipeline of projects for a data team.

Key recommendations:

- Align data strategy across all strategic functions
- Have a champion in the leadership team to support key relationships between teams
- Manage expectations across the business through clear naming and structure
- Maintain a pipeline of achievable projects with an organisational champion and a clear route to value

Culture and Leadership

The challenge of creating a stable, embedded data team is ultimately one that encompasses both organisation culture and leadership. This is broadly true across organisations of all sizes, although the nature of the challenges faced may be different between small and large organisations.

Culture can be one of the most difficult things to change in an organisation, and it is certainly true that some cultures can be barriers to the successful of an embedded data capability. Conservative cultures that resist change, cultures that reward risky behaviour, or authoritarian leadership styles where admitting ignorance is discouraged can all make it harder to successfully embed a data-led culture.

Data-Led Culture

In many ways, embedding a data capability is similar to any other new function within an organisation – the new function needs a clear purpose, a place within the organisation, to hire people with the correct skillset, and so on. One key difference is that a data-led culture empowers other departments within the organisation to do things differently. It is not enough to simply enable the team and leave them to it; the rest of the organisation must also adapt to the new capability and absorb the new insights into their processes.

As well as other business teams, a new data capability also challenges the organisation's leadership to incorporate key findings in their strategies and decision-making. Leaders who are not accustomed to having the sort of tools data can provide may struggle to adapt their processes to this new capability, and worse, may resist investing in the tools, infrastructure and people which are required to fully enable the potential of data in an organisation. This can become a vicious circle: decisions cannot be based on data-led insight because the timescales for making the decisions are too fast, but investing in the data pipeline cannot be progressed because the leadership see such capability as fundamentally unnecessary.

Some leadership challenges are likely to have been sorted by this stage in adopting a data team. The organisational leadership is sufficiently bought-in to the prospect as to have hired the team and provided the relevant IT capability. It may be, however, that the practicalities of adopting the recommendations that emerge from the new data team are a barrier to some organisational leaders. Change is difficult, and convincing managers to adopt suggestions from a team outside the leadership team, particularly a new one or one which is not fully understood, can result in blockages. Senior leaders may wish to use the data team primarily as a badge of innovation and modern thinking, without being fully willing to adapt their decision-making processes to the new capability. The ability to use the team's capabilities to genuinely make things better can be a motivating factor for many data scientists, and there is a real risk that if the organisation is not seen to act on their recommendations that they will become disillusioned and leave. While this may be less of a risk for a mature and embedded team where there is strong organisational knowledge, for a new team just getting started much of the initial learnings are held by the people in the team and if they move on too soon that can be a great loss to both team and organisation.

Ultimately these challenges are part and parcel of navigating change in any organisation, and are not specific to a new data team. With time, and with the delivery of successful projects, the capabilities and potential of a data capability will be better understood by the leadership. It can be helpful to have one or two "champions" at a high level in the organisation to help push the individual and organisational change the new capability represents, and to be ready and able to spot areas where the leadership can benefit from data capabilities. If there are people within leadership positions who are particularly sceptical or resistant to change, it is often easier to work around them than to try to change them; such characters often create the most resistance to new ideas and will become gradually easier to work with as the ideas become familiar and the impact more evident.

Vision and Strategy

To create a data team, considerable thought may have had to be given to the overall purpose of the new team in order to sell the concept to the broader organisation. When it is time to consider how to embed a team in the organisation, that overall vision will need to be revisited in light of the new aims and in light of what has been achieved to date. The new vision should be aspirational and need not be rooted in practical considerations – that is what the strategy is for.

It is important that the vision and strategy for the team are shared, and that key stakeholders – team members, clients and management – are bought into and agree with the overall direction. People will not align with a strategy they are unaware of, and giving key stakeholders some ownership of their general direction is an important part of building an engaged team. The challenge of creating a vision and strategy is that of understanding what problem you are solving and how you can solve it. Without articulating this clearly to all stakeholders, effective management can feel more like firefighting others' flawed expectations.

Strategy ties back to organisational structure and can also tie in to performance objectives and team KPIs. It can also be a powerful tool for prioritising workload; with a clear and explicit strategy in place it can be considerably simpler to pick and choose the most appropriate projects from the pipeline. This all ties back to the team brand – the projects that are delivered for clients and the way they are handled reinforce the message of the overall team purpose. Together this can be a virtuous circle, reinforcing the desired purpose. Naturally, a corresponding vicious circle also exists where poor client expectations and a lack of strategy lead to a pipeline of unsuitable projects, the delivery of which contribute to the poor expectations.

The team can have a single strategy, but it is also valid to focus the strategy on different aspects of the role, such as recruitment, project adoption, staff induction or communication.

Case Study

The Data Lab has been running "Executive Education" sessions for organisational leaders for several years now. These courses focus on demystifying the capabilities of data, cutting through the hype and supporting leaders to identify where data and related capabilities can add value within their organisational context.

In these sessions, the key components of a successful data strategy are identified as the following:

1. Source. What data does the organisation have, and where does it come from?
2. Trust. What do you need to do to or with your data to build trust in it?
3. Analysis. What questions will you ask of it, and which changes will you track?
4. Insight. How do you use and present your data and analysis?

The resulting data strategy has the best chance of success when it aligns clearly with the business strategy, and everyone knows what you are doing, when, and how it delivers value.

Positioning and Branding

Positioning and branding are some of the tools any team can use to set or manage expectations regarding team function. As each organisation is unique, there are no hard and fast rules as to how to effectively brand a data team. The most successful positioning and branding will support the team in identifying stakeholders, managing their expectations effectively, and identifying suitable projects for the pipeline.

What's in a name?

The name of a team is a key tool in managing expectations for the team's accountabilities and capabilities. Selecting an appropriate name can be challenging in an environment where technical terms can be poorly understood and where today's new thing quickly becomes tomorrow's old news. Some approaches to team names are outlined in Figure 1.

The success of a name can also be impacted by the organisation itself, in the sense that previous uses of a similar label can have historical baggage and can create a particular expectation in colleagues. Within the tech space, it is also necessary to be aware of the ebb and flow of fashionable terms, as this can change the expectations set up by particular terminology in the minds of the clients. What was once cutting edge can become stale or even misleading as usage rapidly changes.

In a large organisation, it is likely that there will be other teams delivering work that may be similar to your data team. There may be several teams of analysts working with particular areas of expertise; there may be a BI or MI team. The IT department may include people or teams of people with particular data-related skills. It is essential that a manager of a data team can be clear what capabilities and functions their particular team can provide, and it is considerably simpler to set the correct expectations from the start with a clear and descriptive name than it is to continually battle others' incorrect assumptions and expectations.

It is particularly difficult to overcome any name which is, in essence, just dull. If the team name says "we have a role so just leave us to it" or "you've worked with us in the past and regretted it" then building embedded capability and gaining acceptance of key clients will be all the harder. It may be wise to avoid being labelled "IT", as the organisation will have expectations of what an IT department can or cannot deliver which may not mesh with the data team's desired remit. In some cases even the term "data science" may not work, as in some contexts it may carry associations of isolated techies working in silence in a closed room rather than a collaborative resource for solving business problems.

Case Study

A team name is one way to set expectations within an organisation. Where expectations clash with the reality of what a team can deliver, this can become an obstacle to success.

Mudano works with many clients to support them in improving their data science and analytics capabilities. They use many techniques to do this. One of these is by setting up physical environments to challenges their clients' preconceptions.

This 'Obeya room' (from Japanese "large room" or "war room') format enables decision-makers to collectively interpret data and make faster evidence-based decisions through a collaborative way of working. This in turn leads to more successful adoption of projects from the top down.

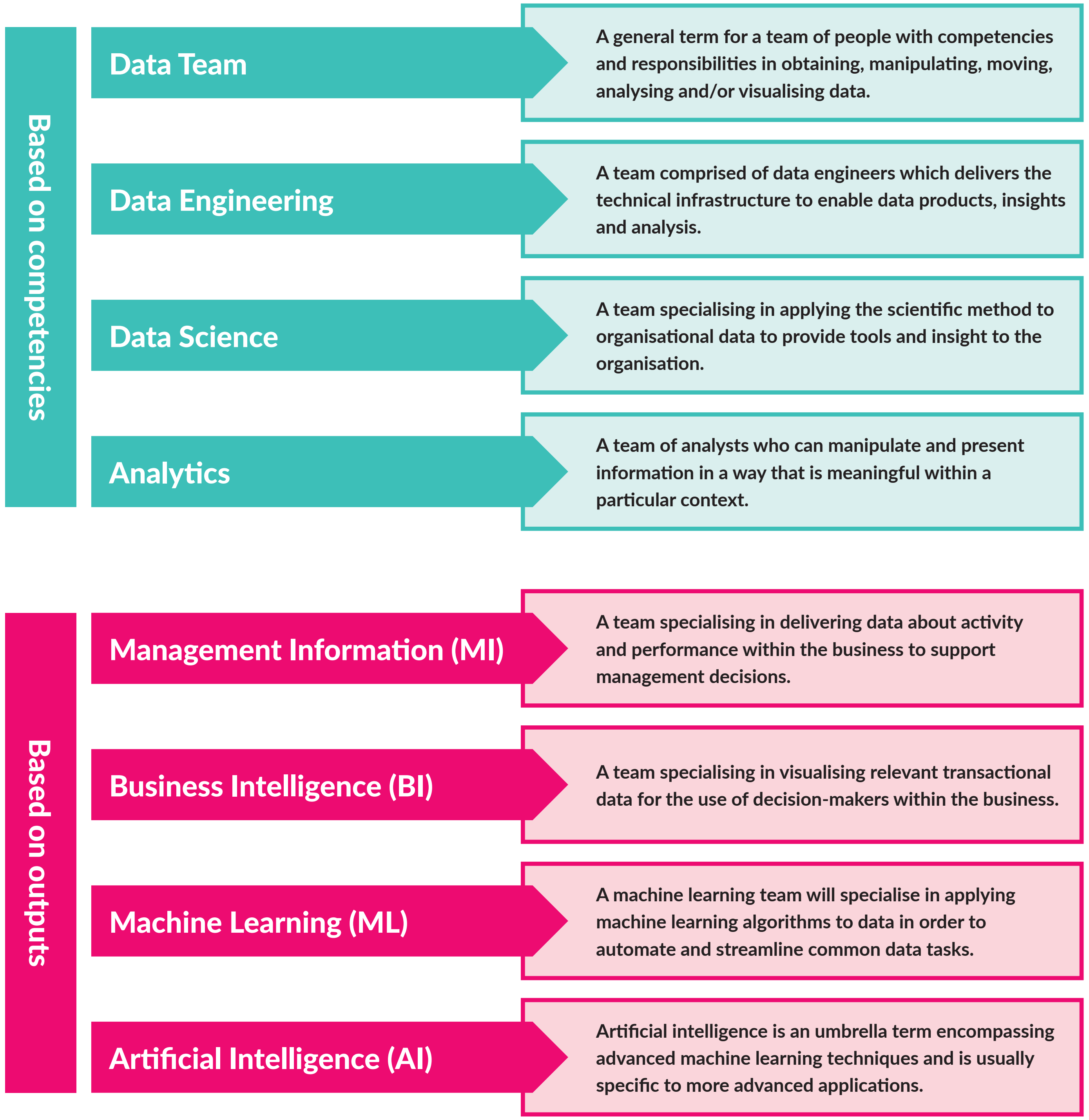

Figure 1: Naming teams based on either the team competencies or deliverables. What does your team name suggest about the team's capabilities, skillsets, and role within the organisation?

Organisation design

When growing a team from a few people to something more substantial, the location of the team within the broader organisation may become a more substantial challenge. It is worthwhile to spend some time considering where the team should sit.

Growing a data capability is about both embedding the capability within the existing organisation, and also about allowing the organisation to grow such that it takes advantage of this new capability. This means that the data team and the broader business should expect to evolve together, and the structure adopted should be designed to allow this. This means the organisation should expect two things to happen over time: the data team becomes more aware of the data techniques that are most suitable for the organisation's context, and the business starts to evolve day-to-day procedures to take into account the new capabilities.

A dedicated data team can be created within a business to enable data capability to expand, and this can work well in some contexts. However, it is also possible to build a team which leverages existing capabilities in other teams – a "matrix"-type structure. Data scientists may not sit in a shared team at all, but may sit entirely with their clients, with a much smaller centralised team coordinating their efforts and strategy. This is one way of building domain knowledge for the data scientists and for emphasising relationships with business teams.

The question of where a team sits and how it is are managed has implications for later strategy, particularly in terms of opportunities for advancement and development, and for building relationships with client teams. It may also have an impact on the data the team can access, particularly in strongly-legislated industries, such as utilities, where there are legal requirements against data sharing. The data experts within an organisation will benefit from the ability to share knowledge, in terms of general data capabilities and also the structures and capabilities in the wider organisation. If the team are managed in a distributed team, it may be necessary to take additional care with training and development to overcome their separation.

Case Study

In many cases the most obvious way to set up a new capability is to create a new team with a single reporting line. However, this is not always the most appropriate choice, and it can bring risks of becoming a silo within the business.

Skyscanner is a highly-successful Scottish business with a large data science team. The data scientists deliver value as part of multi-discipline teams throughout the business and across geographies. The data science leadership team put considerable effort into providing an environment which supported development of core skills, knowledge sharing and collaboration across the embedded data scientists.

Managing the pipeline

There are a number of potential project sources which can contribute to the team's pipeline. Projects may generally originate from the business; such projects can be valuable for building collaboration with business teams in the organisation.

These can be unsolicited or solicited, where either a client brings a known business challenge to the data team or where a meeting between client and data scientist results in project ideas. Projects can also come from the data team themselves, through new approaches or ideas or through data exploration, or can be follow-up work to previous projects. As the data team builds connections with other teams across the organisation, new project ideas can emerge.

A healthy pipeline should have a good mixture of simple but high-value jobs, longer-term projects and good technical challenges. If the pipeline looks a little dry, it may be time to reconnect with your key clients, meet new potential customers or revisit some previous work with fresh eyes. It is also true that a few successful projects can lead to high demand for the team's services. This can result in an overfull pipeline where highly valuable and necessary projects are lost in the general press of new ideas. If a pipeline is looking particularly full, there are two options for dealing with this. One option is to methodically assess the pipeline according to existing strategy and rank each project for challenge and value, enabling clear identification of priority projects. The other option is, of course, to grow the team to cope with high demand. These two options are not mutually exclusive, and in fact should generally be applied together – it is undesirable for a team to be grown in expectation of high demand only to discover that many of the suggested projects are low priority or technically unachievable.

Managers of data teams should remember that developing a project to the point where it is ready to execute can take time, and therefore part of the team's time should be spent working with key teams and clients to solicit ideas and develop project plans. To avoid an overly-full pipeline overwhelming capability, each idea should be effectively prioritised within the business context and with a realistic timescale in mind. These techniques will support a healthy long-term pipeline, will ensure projects remain tied to business value, and can help maintain strong links between the data team and the business.

Delivering a data science capability can also get stuck at the proof of concept stage if the IT and infrastructure support is not present to enable successful projects to be productionised. High-value data science projects – even more so than analytics or insight-driven projects – often rely on fast access to up-to-date information, and this means the data must be able to move quickly and efficiently to where it is needed. A healthy pipeline in data science projects will not achieve its potential value if the critical infrastructure is not in place. It is a key function of a successful data strategy to understand these dependencies and to act to enable the required progress, and if such interdependencies are frequent blockers the data strategy may need to be revisited to account for this.

KPIs for Data Scientists

Key Performance Indicators (KPIs) are a valuable tool in some organisations where it is necessary to quantify a team's delivery and alignment to company values. However, they are also a difficult thing to develop well. To be successful, KPIs must align well to the team's ability to deliver value and their overall strategy. The best KPIs directly measure concepts that are under the team's control to deliver; often too much focus on value-added is an unsuccessful strategy simply because the team only has control over this up to a point.

For a data team, one challenge can be that the team itself is in a support function, which means the team may not contribute value directly but through support given to other teams. If the client team fails to act on the data team recommendations, how far should that be reflected in their respective performance indicators? One solution may be to have project-specific KPIs which are aligned with the client team. This allows each project to be measured against its own aims, and encourages the data scientist to consider what will really add value to the client in their project. The risk here is that each individual data scientist and project will end up with near-unique measurable indicators, resulting in confusion over the whole team's performance.

In choosing the team's KPIs it is important to align the team with the business's strategy, and to include benchmarks for both core deliverables and for behaviours the team is expected to improve. The core team deliverables might include:

- number of projects delivered
- number of leads identified
- new teams targeted
- external clients engaged

Essentially, whatever is most suitable for the team's key role. For desirable behaviours, some indicators might include:

- a target for number of conversations with the business or the percentage of these which result in a follow-up project or proposal
- training delivered or attended
- time utilised on business-led projects
- targets related to good practices, such as number of policy documents updated or adoption of new team techniques

In many organisations, KPIs that measure against core values can be highly desirable and can provide a common structure across all teams. These also generally align well with business strategy. Company values can be very useful for target setting.

In general, the number of targets a team is being measured against should be carefully managed. Too many targets and it becomes unreasonably difficult for team members to retain their focus on their targets when considering their behaviours. Too few targets, and either the team will focus on their targets at the expense of other desirable behaviours or the KPI measurement itself will only account for some fraction of the team's time. As with all targets, the level should be set carefully. Too hard, and either the team become disengaged or they focus on that single outcome to the detriment of other necessary work ("teaching to the test"). Too easy, and the target becomes entirely irrelevant to the work undertaken by the team.

Some examples of KPIs for data teams are included in the Additional Resources: Strategy and Ability to Execute.

Case Study

Mudano takes a different approach to failure than other organisations. For Mudano, failure is seen as a necessary part of a wider process and therefore should be an expected part of a client's process. Mudano's "start now and prototype" mentality means that clients are able to readdress their relationship with failure by taking on risk in a controlled way to test an approach before delivering.

To do this, they establish a clear hypothesis across every project in the initial stages in order to condense their focus around a specific value goal. With one client, a large bank, they used this approach to test innovative ways of solving complex problems with an experimental approach. Each one of these experiments were run in quick one-week sprints, so they could be validated quickly and either prioritised or discarded early without large investment.

In this format, failure is ok, and even encouraged – as each hypothesis is ruled, they narrowed their focus to the core concepts the business needed, with the exit criteria of these rapid delivery cycles being a functional prototype which could then be taken into production with the wider business.

This enabled Mudano and its client to rapidly test more innovative, higher-risk methods to solve their problems, and resulted in a greater uptake of these novel approaches in core programmes, with the prototypes providing a concrete example of what is possible, and the pass/fail experiments giving an objective appraisal of the merits of each option.

Capacity to Execute

The overall capacity to execute for a data team is comprised of the team capabilities and the team context. In this section, we have discussed the team context:

- Leadership and culture can empower an organisation to connect with a data team and deliver value; strong leadership can enable change, align resources to support new capability, and form connections with enablers across the business
- Positioning and branding are part of communication and management of expectations across the business. A thoughtful approach to team structure and positioning can connect the team to the business and to enablers within leadership; strong branding can support the embedding of a new capability within an organisation by managing expectations and providing clarity on capabilities and responsibilities
- Managing the pipeline is about providing and prioritising projects which will support the data team to deliver value. A strong pipeline is the team's connection to the business; the projects within the pipeline represent opportunities, for the business to deliver value and for the data team to apply their skills. Pipeline management is part of demonstrating value, managing and acquiring resources, and providing opportunities to learn and grow within a team and within an organisation.

Context can be either empowering or disempowering. Blockers in any of these areas will reduce the ability of a data team to deliver on its potential. Time can be lost in correcting incorrect assumptions, winning over hostile leadership, or endlessly re-running manual approaches to projects which call for automation but which cannot be automated due to poor infrastructure or processes. Context, then, is a key part of a team's ability to deliver.

The team's ability to deliver will also depend on the team capabilities. The team must have a good mix between technical capability and business skills. Where the infrastructure is becoming a blockage, the team will require either the skills and resources to work this out themselves, or the ability and authority to work with other teams to resolve the blockage. Strong and relevant project prioritisation and management processes can support the effective delivery of value from data capability. Communication skills are essential to support effective client and expectation management, to share learnings as projects develop and are delivered, and to ensure the value provided by the team is communicated to the broader organisation.

Taken together, context and capabilities can be a very powerful combination, where the team's ongoing capability to deliver high value builds trust in the team, awareness of the team's value and skillset, and supports the formation of a strong brand. This in turn can nurture a healthy pipeline of suitable and high-value projects.

We will consider the team capabilities in detail in the next section.

Data Team

In this section, some of the challenges associated with building and managing a sustainable data team are considered. How do we ensure a data team includes the required mix of technical and business knowledge? What tools and techniques can we use to ensure the team works effectively? What makes for an environment where data professionals can grow and thrive in their career?

Summary:

In this section we consider the nuts and bolts of running a data or data science team. We consider technical and soft skillsets that could be necessary, and how different personalities and career stages can combine to create a strong team. We consider effective ways of working in terms of maintaining expertise and project management techniques, and we look into routes for development and training that work well for a data team.

Recommendations:

- Consider hiring people with distinct skillsets to form a team with the right broad mix of skills
- Ensure opportunities for development and progressions within the team
- Experiment with project management techniques to provide a supportive structure without overloading on bureaucracy

Building a “Purple” team

One way of conceptualising the building of an effective data team originally introduced by Deloitte , is to think of hard technical or mathematical skills as “blue” and business skills as “red”. The aim is to build a purple team. One way to do this would be to only to hire people who are already purple, but in practice such people are harder to find than the blues and the reds. This is simply because people are generally trained and developed in either data or business skills, meaning that “red” or “blue” heads can be more easily identified than “purple”. A team made up of a few purple people, a few reds and a few blues will provide the same benefits, but will be easier to recruit.

A methodical assessment of the skills present in the team and the skills required to fulfil the strategy and vision allows for a gap analysis which can support recruitment. One approach to a gap analysis often used in The Data Lab’s Executive Education sessions, is shown in Figure 2. Such an assessment can be periodically repeated, allowing for the requirements for the team to evolve over time alongside the organisation’s structure and strategy, and ensuring that the team continues to attract the right mix of talent over the long term.

A similar model can work for other groups of skills, such as data scientists and data engineers, or even technical skillsets and project management skillsets. In Figure 3, some data-related job titles and their technical skillsets and capabilities are outlined.

Key team skills		Desired level of expertise					
		Beginner	Learner	Fully competent	Differentiating	Expert	Thought leader
Business	Business Knowledge			P.1			
Business	Communication			P.1			
Business	Ethics			P.1			
Technical	Coding			P.2			
Technical	Machine learning		P.2				
Technical	Data wrangling		P.3	GAP			
Analytical	Visualisation		P.3	GAP			
Analytical	Hypothesis & modeling			P.4			
Analytical	Curious & creative mind			P.4			

Figure 2: In this gap analysis, the desired key skills and level have been assessed, and the competencies of existing team members have been included. The identified gap suggests the key capabilities and level the next hire should have.

Further reading: https://www2.deloitte.com/ca/en/pages/deloitte-analytics/articles/people-dimension-of-analytics.html

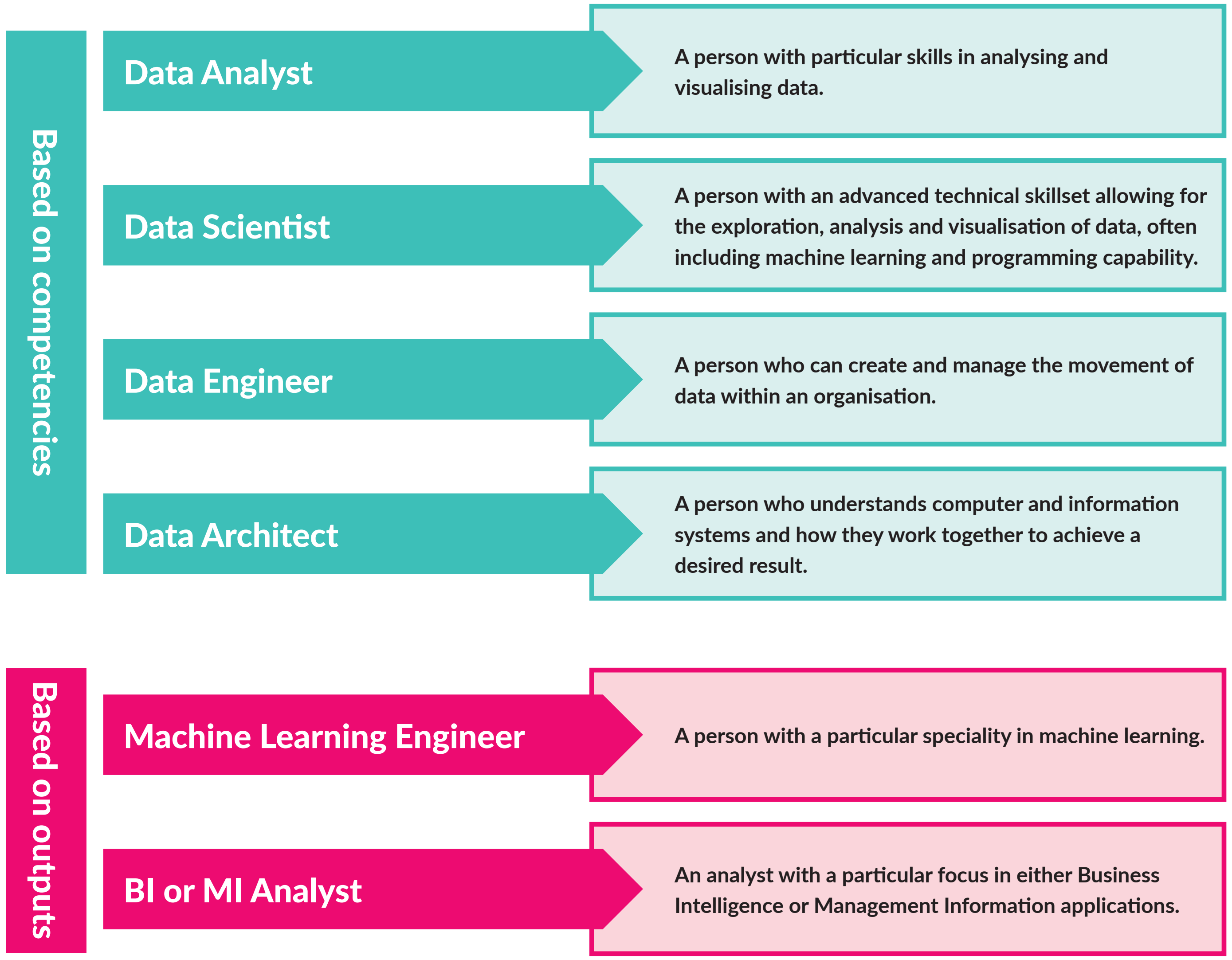

Figure 3: Job titles imply a lot about a person's competencies, responsibilities and skillsets, and this can be important to get right from the moment of specifying a new hire.

Inflection Points

Inflection points in this context is intended to refer to trigger points where it becomes clear that a new stage in the journey has been reached. The first of these obviously centres around the initial formation of the data team and the initial project or projects. There may be more than one inflection point in the first year or so of a new team within an organisation, with growth from no team to a small team of maybe four data scientists and a number of concurrent projects happening fairly rapidly, especially in a company which already has a large amount of data.

Generally speaking, groups of up to five or so sit fairly naturally within a single team. Depending on the policies within the organisation, larger teams can be managed by a single person, but particularly for a team with a varied, technically-demanding pipeline of projects it is likely to be necessary to include a team structure, with sub-team leads and/or senior/junior delineation, as the team grows. Separating people and technical management can reduce the load on individuals and can provide opportunities for people with varied skillsets to develop effectively. Such substructure in a larger team has several beneficial side effects:

- The team is easier to manage, with sensibly-delegated authority
- There is more opportunity to develop within the team
- A broader and more structured team encourages team members to take risks, step outside their comfort zone, and can support members as they gain skills

As the pipeline demands more time and additional headcount, an inflection point will be reached where the team will move from a simple team structure with a single manager, to something with more internal structure and potentially with varied roles within the team.

It is important to note that there is no one-size-fits-all approach to building a data team. The focus should not be on matching a template for a successful data team, but in building a sustainable group with a good mix of skills who work well within the organisation and its culture.

Spock Vs Bones

In the original Star Trek television series, the character Spock was a Vulcan: highly logical, devoted to science and lacking in emotional connection. The character Dr McCoy, known as Bones, was an emotionally-driven doctor who worked on intuition and distrusted Spock's logical approach. In this context, a "Spock" might be a person dedicated to the craft of data science, who wishes to work on datasets and algorithms for the majority of their time. A "Bones" is more connected to the people and processes in the organisation, aware of the inevitable politics and able to connect with its clients.

In the real world, most people are to some extent a mix of both types. With a small team, a single manager can perhaps take the lead in team outreach, leaving the data scientists to focus near-exclusively on project delivery. This is particularly effective if the talent has been drawn from new graduates or from academia, and hence has minimal exposure to navigating organisations. As the team grows, it can handle more and bigger projects, and the need to engage with the business becomes more demanding for a single person to handle. It becomes necessary to build a team that includes business acumen, communication, and client management skills alongside data expertise. This can happen through investment in the skills and development of the existing team members, through mentoring, stretch assignments, or formal training. If the team is scaling more rapidly or the skills need to be included on a shorter timescale then hiring talent with the desired mix of skills may be the more appropriate solution.

As the team grows, the effort required to keep it centred within the organisation is higher and that the team must be resourced with this effort in mind. Too many Spocks, and the team becomes isolated from the wider organisation, opportunities stop arising from the business and business teams lose interest in delivering the changes that provide the value in data projects. Too many Bones, and the team may find it cannot effectively build or maintain the expertise to deliver varied data projects. The optimal ratio will vary depending on the types of tasks taken on by the team, and even within a particular organisation the demand for each skill type may vary over time; a good manager will maintain awareness of the team's changing context and business priorities to maintain the required balance.

There are other skills which are core to delivering strong data capabilities, and the team may choose to build these within the team or to connect to outside capabilities. This can include IT-based skills in data engineering, architecture, experts in key systems, or software engineers. It can also include people with softer skills, such as project managers, communication experts, admin support, or change managers. Different organisations will produce different pipelines and will require a different mix of skillsets, behaviours and priorities to effectively manage and deliver that pipeline.

Case Study

A key part of scaling a team is empowering staff to take more responsibility, supported by investment in their development through a combination of mentoring, training and feedback.

For example, Skyscanner recruited an entry-level data analyst who focused on producing the monthly KPI report for the leadership team. Typically, in this situation the analyst who produces a report passes it up a chain of command and wouldn't be present at the review meeting. However, in this case, the analyst's line manager worked with her to develop across a number of areas including:

1. Technical understanding: Having a deep knowledge of the KPIs, their composition, history and characteristics
2. Engagement: The ability to present the report to senior management and engage in the discussion taking onboard feedback
3. Confidence: Self-belief, that as the producer of the metrics, the analyst can take responsibility to present
4. Transitioning: Having a staged plan to take ownership, including observing management meetings when her manager presented the report

The deep technical understanding is a foundation: the ability to confidently engage and commit to a transition plan were the key elements to succeeding in this situation. It was the manager's skill in developing these three areas that led to the successful outcome.

Effective Ways of Working

Building a team is ultimately about finding ways of working that deliver for the organisation, that work for the team, and that are ultimately sustainable. Within a data team environment, such ways of working need to combine the flexibility to change with the organisation's needs, with the constancy to provide measurable progress. Similarly, within job roles, each individual should be able to both deliver high-quality work and also step outside their comfort zone to develop new skillsets and capability. All of these are part of the process of both building and evolving a purple team.

An Innovation Culture

Data science is the application of the scientific method to data, and people who are drawn to this type of endeavour tend to be explorative, creative and innovative. In fact, a culture of innovation and learning from failure is the only effective route to building a team where the value inherent in data is uncovered and mined.

To allow for this it is wise to minimise the overall cost of failure to the organisation by promoting an innovation culture. This can be challenging, but done well it provides job satisfaction, allows for gains in efficiency, and reduces the risk of the team stagnating. Effective ways of working should be evaluated based on whether the resulting team is capable, able to experiment, able to work together, and empowered to deliver. While there are a number of ways that an innovation culture may be defined, in this context the two key pillars of innovation are considered to be collaboration and experimentation.

A data team relies on collaboration, both internally and externally. Collaborating with colleagues supports shared learning and the development of technical capability; it can also encourage new approaches and support team members in broadening their technical practice. Collaboration with other teams in an organisation builds value by identifying opportunities for projects, effectively aligning capability with desirability. To function effectively, the data team must maintain good links to teams within the organisation that can provide and enable suitable projects, and must ensure their deliverables are crafted to effectively target the value the organisation's needs.

Some barriers to innovation can stem from a more rigid culture in which experimentation is considered risky, resources may be hoarded until results are certain, and team members spend all of their time working on high priority business as usual tasks. Cultural change can be a challenge, but there are concrete actions which can be used to combat such ideas and allow team members to apply their creativity in their role. Some are suggested in the table below.

Cultural barriers to innovation	How do we change?
Punishing failures	Allow for experimentation
No learning from mistakes	Plan for "positive failures": what can we learn?
Culture of pessimism	Celebrate the attempts, not only the successes
No resource without results	Have a budget for new ideas.
Too much high priority Business As Usual	Allow time for own development and ideas.

Experimentation is a key part of data science. At its simplest, within a data project experimenting with a given dataset allows a data scientist to be led by the data and can suggest new approaches and ideas. Experimenting with the types of projects and approaches can be a fruitful way to identify new high-value ideas.

Innovation, by definition, offers the promise of new ways of working, and these new ways can be highly valuable. By fostering experimentation and collaboration, creativity can flourish and innovative ideas can be nurtured until they are ready to deliver their potential. Data teams thrive on creativity, but innovation culture has value beyond its impact on a data team, if an organisation as a whole can learn to foster collaboration and experimentation.

Managing Projects

The approaches and capabilities needed to deliver a data project can be very variable, particularly when a project is driven by the data itself. This can lead data professionals to believe that only the full flexibility of working entirely without oversight can work for data projects. In practice, this is not only not the case but can be counterproductive. Without at least some oversight or governance, projects are likely to suffer from continued scope-creep, resulting in a perceived lack of progress and an inability to deliver on promised value. In this section, some basic information is provided about approaches to project management, which may prove useful in setting some governance and procedures in place.

The most common project management methodologies are generally categorised as Waterfall or Agile in type. A Waterfall-type project methodology is characterised by a series of stages or "gates" at which projects are held to particular standards. As the project progresses, the project is held to higher standards of specification and governance, and each gate passed will unlock more resources for the next stage in developing the project. This type of project approach is useful for efforts where design precedes construction and where construction is a single one-off effort, such as building large capital projects.

Agile project methodology has a reputation for being light on bureaucracy and governance although this is only the case in comparison to Waterfall type projects. Agile is designed for software development teams, and has considerable advantages in that format. The aim of an Agile project is to iteratively design a product through a series of time-restricted "sprints", in which user requirements are allowed to evolve over time as the project aim is better understood, and where the overall aim is that there should be a working prototype or product at the end of each sprint.

For data projects, an Agile approach offers some real improvements as compared to design-heavy Waterfall systems. It can still be challenging to work in pure Agile projects, particularly since the amount of effort or time needed to uncover meaningful value in a data project can be highly variable, and the regular sprints in Agile can leave data professionals feeling dispirited when they cannot report progress. To work effectively for a data team some tweaks to standard Agile methodology are likely to be needed, and a team should experiment to find ways that work within their context and organisation.

With a small team and only a handful of delivered projects, a project management framework may not be necessary, although alignment in approach between team members will always be beneficial. As a team matures, some form of framework becomes invaluable, not just to support the process from specification to delivery but also to enable the governance of a suite of projects and strategic decisions regarding how and where to best use the available capabilities. So instead of providing a detailed list of steps which must be followed, build a framework which can support a flexible approach to projects but which provides the core support where necessary.

In contrast to a software development team, a data project rarely progresses gradually from initial idea to finished project. Instead it is much more common to require a two-stage approach with initial proof-of-concept stage followed by a distinct project to productionise. Organisations with a well-established data infrastructure may find such a distinction unnecessary, as the proof of concept can be designed with the production methodologies firmly in place, but for organisations where the infrastructure is still being developed it is common to find a new approach is needed when a proof of concept is carried forward into the production stage. When choosing a project management structure, such concepts can be helpful in assessing where projects begin and end, and how they can progress.

Examples of project management approaches have been collated in the Links and Additional Resources section Data Team.

Case Study

Many project management frameworks exist. However, it may require some experimentation to identify which particular techniques will be the most successful within an organisation. Pure waterfall, agile or other approaches are optimised for particular types of project and may not adapt well to the needs of a data team.

Mallzee uses a hybrid approach to the development and data science workflow. Specifically, data science projects undergo a research phase, where the business problem is contextualised and starting ideas are collected, followed by an inception phase where multiple possibilities are trialled and the existing literature on approaches is analysed. Only after these initial stages does a cycle of prototype building and testing start, which leads to the generation of code solving the problem at hand, evaluated via quality assurance (QA) metrics. After a satisfactory prototype is built, the code is put into production in the engineering phase, becoming useable software.

Sharing Knowledge

Part of enabling innovation through managed failure is to ensure you have good processes in place to allow for knowledge sharing between team members. Training and development is clearly also relevant here, however sharing knowledge is not only about the individual learning; knowledge sharing is about embedding learning in an organisation, and can support the evolution of best practice. It is therefore as much about sustainability and growing expertise as it is about individual development.

There are many ways to encourage knowledge sharing in a team. These can include:

- Regular, structured and collaborative team meetings
- Formalised policies and procedures
- Pairing up team members on particular tasks, as is used in software development in "pair programming"
- A formal failure record or procedure, which may involve, for example, sharing learnings with the client as well as with the data team.

Modern tools, such as a team wiki or collaboration tools such as Microsoft Teams, can support the creation of a formal or informal record of learnings and can be valuable approaches, especially in a distributed team. Projects can also be leveraged as a development tool for a data team member by providing opportunities that challenge their existing capabilities. Pairing junior or less experienced team members with more senior colleagues can reduce the risk of failure when working outside core capabilities, and ensures knowledge is passed from more experienced to less experienced members. In this way, less experienced colleagues build skills, more experienced colleagues gain mentoring and coaching experience, and the risks of losing more experienced people start to be mitigated.

Although the benefits of knowledge sharing in an organisation are clear, there can also be barriers. Individuals can derive worth and status by their possession of particular pieces of information; people can be embarrassed to admit their mistakes; or people who are highly skilled in a particular context may lack the patience or capability to support others in building skills. A knowledge-sharing culture can go a long way to overcoming these barriers. Embarrassment is less acute when managers and peers have shown themselves willing to share their mistakes for the benefit of the team. Those who are not teachers by nature will build skills through the examples of their peers and the techniques used by the team. And in a culture of knowledge-sharing, prestige can be built by helping others gain skills, not by hoarding expertise. It is not easy to build a knowledge-sharing culture, but it can be grown and encouraged over time.

In this way, effective ways of working can be helped to evolve from the team's capabilities, skills, and learnings over time.

Case Study

The Data Lab funds 155 students per year through Masters-level courses in a variety of data topics across 11 Scottish universities. Working with universities, students and employers over four years, The Data Lab has created additional elements to prepare students for using their skills in the workplace. These include:

1. Employability skills training, enabling students to gain confidence and techniques in interviewing and being part of a work place
2. An Innovation Week focused on design thinking and soft skills to understand problems and explore solutions before applying technical methods
3. A placement programme that enables students to work with industry/public/third sector organisations
4. Data Talent Scotland, a recruitment event bringing together companies recruiting data talent with the students seeking employment
5. Ethics training: The Data Lab are collaborating with University of Edinburgh to create an online data ethics primer which will be compulsory for all sponsored students to complete.

These additional elements enable students to confidently transition into the world of work. For example, through Innovation Week, students begin to understand that soft skills are an important element enabling them to be able to perform and present technical work, whilst student placements enable both students and employers to gain an initial understanding of what it is like to work as/ with a post-graduate level data scientist".

Development and progression

Any professional career must offer opportunities for development and progression if it wants to keep team members motivated as their skills develop. Building a team from the early stages into a sustainable capability within an organisation requires an ongoing effort not just to hire high-quality people but to provide an environment where they can continue to learn and develop. Data professionals are generally highly-skilled and curious people, and are therefore motivated by opportunities to learn. There can be tension between what a data professional wants to spend their time learning and what an organisation needs to develop in their data team, and this must be managed carefully. But in general progression routes are highly desirable for team members and for an organisation, and it is worth spending time to create these opportunities.

New Professionals

Data science, and data more generally, are fairly new capabilities, and many of the people who have come through the university pipeline in data-related topics are fairly young. It is therefore worthwhile to consider the particular challenges, expectations and requirements that are likely to be presented when hiring new data professionals fresh from their university experience.

The expectations of new professionals in terms of problem definition are likely to present issues. In an academic setting, data problems are presented very clearly and with relatively clean datasets; as a result a student can spend most of their time using their skills to manipulate the data and present a solution. This is generally unusual in a non-academic environment. Problems can be poorly defined: rather than "Can you use the data from this system to predict X and display the prediction on the monitor?" the problem is more likely to be presented as "we think we could do something with the data from this system, but we're not sure what".

New professionals will need to adjust their expectations to the reality that defining data problems is a key part of their role, and the best way to create value using data.

There is likely to be a disconnect between the learning expectations of new professionals, who may have recently left full-time education, and more seasoned members with more experience in the team and business environment. Graduates can place more weight on highly-formalised learning environments, such as in-person training courses and certifications, while those with more experience in the workplace may be better equipped to recognise the value of less formalised on-the-job learning opportunities.

When taking on a number of recent graduates into a relatively new team, particularly in the absence of any existing corporate graduate training scheme, it is likely to be necessary to manage expectations from the beginning regarding what career development opportunities are likely to look like in practice. During a university course, learning outcomes and goals are not only well specified, they are also the primary purpose of most of a trainee's efforts. Within an organisation, only a minority of learning is likely to be formalised in this manner, and for some new graduates this change can be challenging.

The third space where new professionals may need additional support is in their general business awareness and soft skills. Academic courses in data can be both broad in scope and intensive; nonetheless their key aim is to develop technical skillsets, and this can leave graduates with the impression that technical skills are the most important. While technical skills are - of course - important, soft skills are equally so, including abilities such as:

- working with colleagues across disciplines
- selling ideas and results to decision makers
- showing true insight into the values and purpose of business efforts

Such skills are hugely valuable to organisations and are worth cultivating. It may take time for some new professionals to understand the value of such soft skills, and there may be resistance to development in these areas. Nevertheless, these are high-value skillsets and any data team should be incorporating these into their training and progression planning.

New professionals are generally a boon to any team. Their knowledge is both fresh and recent, and their technical skills can be excellent. They often bring creativity and enthusiasm to their role, and these can be infectious and can support more established team members in re-thinking their approaches. They will need support to develop their skillsets to support the needs of the organisation, but with a little planning and foresight a manager can work with them to build on their strengths and cultivate the skills that will enable the team to succeed.

Training

Learning has to be a priority within a data team. Data professionals are generally highly skilled and working in a space where approaches and technologies are changing rapidly; this means they are keen to learn and require time to assess new capabilities and approaches. If a team or organisation seems to be lacking opportunities to learn, staff can become disillusioned and bored, and this can lead to churn. However, opportunities for learning need not only be managerial or technical in nature, and a creative mind can often find challenge through better understanding the context of an organisation.

Formalised learning may not be the most desirable way to support this, although it can be valuable in some circumstances. Other options for training and development may be:

- Allow a buffer time within and between projects for reading and training on new approaches related to that project
- Team knowledge-sharing on lessons learned within projects: within team meetings, as a team show-and-tell session, or perhaps through channels like an internal blog post
- Opportunities to participate in the wider community through conferences, hackathons, meetups and other such events
- Space within the week to pursue personal projects
- Pairing with other business functions to support wider appreciation of the organisation's key strengths

There is also generally scope for learning on-the-job, through taking on projects which stretch a team member's existing skillset, perhaps in partnership with a more experienced colleague. A mentoring approach may also be beneficial for non-technical skills, such as providing opportunities in aspects of project management or other business-related skills.

Considering progression more formally, a single path to progression through management roles can be very limiting for certain people. Management requires a particular set of aptitudes and ambitions which are not always shared by high-quality people. Those who are particularly motivated by technical excellence may not find the management progression route acceptable, but such people are also likely to appreciate having their capabilities and values recognised. It is therefore particularly important to consider progression opportunities outside the management chain, such as technical lead positions and even routes into other aspects of the business.

For data roles in particular, developing a full relationship with business clients based on shared understanding of goals is a key aspect of development. This means that developing business understanding can be an important development goal for a data team. Understanding what the business strategies are and how the organisation builds value can lead to better prioritisation of resources and more high-value projects, which in turn builds stakeholder buy-in and hence a stronger pipeline. More business-focused data scientists, while they may not make up the majority of a team, can therefore drive a virtuous cycle within the organisation where serving the needs of the clients builds a great pipeline of projects.

The Challenge of Churn

Churn is what happens when an organisation has a relatively high number of employees leaving the organisation. It can happen gradually, or occasionally a number of team members can leave in a short timeframe, leaving the team exposed to lost capabilities. As hiring can be a lengthy process and developing organisational knowledge in a new hire can also take time, churn can have a high impact on an organisation or a team.

There are many reasons why employees may move on, but ongoing churn can be particularly destabilising for a team and can reduce the ability of a team to deliver for the organisation. Reasons can also vary depending on the career stage of the team members. New professionals may leave because the skills gained in the first year or two in an organisation can lead to opportunities for new roles, or because the expectations between an organisation and a new professional can be misaligned leading to a lack of engagement from the new professional. More experienced hires may move on when they feel their opportunities for progression within an organisation have been exhausted.

Although it can be troublesome and expensive, some churn is generally desirable. Graduates and new hires can have fresh and up-to-date technical knowledge; they have recent experience of techniques that may be new to more experienced colleagues. Both can lead to more effective and even innovative approaches within a team. Similarly, new faces from other sectors or organisations can provide new capabilities and approaches that can add value.

Mitigating the challenge of churn can be divided into two approaches. The overall impact of team members moving on is reduced if the team has systems and policies in place to embed knowledge across the team. Hiring practices can also be optimised to reduce the risk of people moving on earlier than expected. One approach could be to hire based more on aptitude than either qualifications or experience. This maximises the chance that the new hire will be challenged by their new position, giving them room to grow within their new role. Hiring a mix of new professionals and more experienced hires can reduce the risk of a number of team members moving on in a similar timeframe.

Providing effective ways of working which continually challenge the team, as well as providing opportunities to develop, can also give employees reasons to stay.

Case Study

Heineken took an initial strategy of employing high potential, higher degree (ie MSc, PhD) candidates, straight from university. They invested heavily in recruitment time, onboarding, business immersion and business skills development, but lost employees as they were lured to more established data science teams in other organisations. A strategy change was implemented to build a core of tenured data scientists to support the development needs of graduate hires. Striking the right balance of experience versus graduate potential is key to forming a stable team with a mix of skills and abilities.

Summary

Although data teams are a relatively new phenomenon within a modern organisation, many of the challenges of embedding a team are very similar to other functions. The team should have a clear purpose, communicate with its stakeholders, and support the goals of the organisation. Within the team, a balance of skills will be needed and this can be cultivated through a mix of hiring practices, training and development opportunities and judicious prioritisation of projects.

There are also key challenges particular to a data team. Since data science is a new field, many data scientists have limited business experience, which can lead to challenges with their organisational knowledge and leadership ability. On the other hand, technical problems, and their solutions, are not generally understood by an organisation, which can mean considerable effort is needed across disciplines to build understanding of what a good data project looks like and what it can deliver. Data science is a discipline which connects data to business value, but can stall in the absence of well-managed data infrastructure, something which is also not generally well understood and which can be neglected by well-meaning organisations.

A key additional challenge for a data team is that it is generally very much a support function – meaning that a data team will not, in most cases, directly generate value but will instead connect with other teams and support those teams in creating or increasing value to the organisation. In that sense, the KPIs for a data team can be strongly reliant on having good relationships with clients, who will have the ultimate responsibility for taking a data project and building it into something which has value for the organisation. This is an additional level of risk which is not present for teams in more direct function spaces, where competence is more directly tied to the requirements of the job. Further, highly-trained data professionals with limited business experience can struggle to understand how best to support the business through their work, and this can be a common barrier to achieving data value.

Like so many challenges in this area, the answer in general is to focus on the value and be willing to learn from failures. Each organisation is unique and there will not be a one-size-fits-all answer to how to embed a successful data team in a given organisation. At this stage in growing a team, then, it is necessary to have a flexible approach to team strategy and ways of working, and to be ready to discard any experiments that are not producing the desired effect. In the end, the team will become sustainable when it can identify and encourage virtuous cycles, which support a healthy project pipeline, strong in-team and intra-team relationships, and well-understood and explored routes to value.

Appendix: Links and Additional Resources

http://radar.oreilly.com/2011/09/building-data-science-teams.html -- overview of learnings from building data science capabilities at Facebook and LinkedIn.

https://econsultancy.com/a-beginner-s-guide-to-building-a-data-science-team/ - beginners guide to data science teams, covering definitions, purpose and recruitment.

Strategy and Ability to Execute

CULTURE AND LEADERSHIP: ADDITIONAL RESOURCES

Change Management

General change management: https://hbr.org/topic/change-management

About culture: https://www.thebalancecareers.com/culture-your-environment-for-people-at-work-1918809

For senior managers: https://www.shrm.org/resourcesandtools/hr-topics/employee-relations/pages/10-tips-for-changing-your-companys-culture%E2%80%94and-making-it-stick.aspx

Orchestrating change from the bottom up: https://hbr.org/2019/02/how-to-orchestrate-change-from-the-bottom-up

Building Management/Leadership Support

Convincing management that change is needed: https://blog.kevineikenberry.com/personal-professional-development/convincing-senior-management-change-needed/

Case study on building management support: https://real-leaders.com/smart-people-fail-4-steps-convincing-leaders-change/

POSITIONING AND BRANDING: ADDITIONAL RESOURCES

What's in a name

Branding the Blue Apron Analytics Team: https://medium.com/@roody/branding-the-blue-apron-analytics-team-whats-in-a-name-de04b8580ef

Organisation design

Building an effective analytics organisation: https://www.mckinsey.com/industries/financial-services/our-insights/building-an-effective-analytics-organization

What should be the Analytics Organisation Structure? https://medium.com/analytics-and-data/what-should-be-the-analytics-organization-structure-a8b54d5ff1d1

Data Science and Organisational Structure: https://adamdrake.com/data-science-and-organizational-structure.html

How to build your virtual centre of excellence: https://www.simonstapleton.com/wordpress/2008/06/16/how-to-build-your-virtual-center-of-excellence/

Vision and Strategy

What does a data team really do? A case study and example: https://towardsdatascience.com/what-does-a-data-team-really-do-12484482e683

Gartner 2017 data and analytics leadership strategy: https://www.gartner.com/binaries/content/assets/events/keywords/business-intelligence/bie18i/gartner_data-analytics_research-note_da-leadership-vision_2016.pdf

SAS: A practical guide to developing a data strategy https://support.sas.com/resources/papers/proceedings17/0830-2017.pdf

MANAGING THE PIPELINE: ADDITIONAL RESOURCES

KPIs for Data Scientists

Measuring data science business value: https://blog.dominodatalab.com/measuring-data-science-business-value/

Defining KPIs for business intelligence: https://www.sisense.com/blog/how-to-define-kpis-for-successful-business-intelligence/

17 suggested KPIs for data scientists: https://www.klipfolio.com/blog/17-kpi-management-data-driven-manager

4 things to remember when defining KPIs https://www.datascience.com/blog/4-things-to-remember-when-defining-kpis

Capacity to Execute

Data science for production and value: https://blog.dataiku.com/want-to-make-your-data-science-team-efficient-focus-on-production

General project pipeline management: http://ppmexecution.com/project-pipeline-management/

Data Team

BUILDING A PURPLE TEAM: ADDITIONAL RESOURCES

Building a Purple Team

The people dimension of analytics: https://www2.deloitte.com/ca/en/pages/deloitte-analytics/articles/people-dimension-of-analytics.html

Inflection Points

How to structure a data science team:

Creating a Data-Driven Organisation by Carl Anderson: Chapter 4, The analyst organisation: https://www.oreilly.com/library/view/creating-a-data-driven/9781491916902/ch04.html

What is the most effective way to structure a data science team? https://towardsdatascience.com/what-is-the-most-effective-way-to-structure-a-data-science-team-498041b88dae

How to structure data science team: key models and roles: https://www.altexsoft.com/blog/datascience/how-to-structure-data-science-team-key-models-and-roles/

Managing data science teams: https://www.dominodatalab.com/resources/field-guide/managing-data-science-teams/

Structuring teams generally:

Team structure: https://blog.udemy.com/team-structure/

What organisational structure should my team use? http://gusto.com/blog/people-management/what-organizational-structure-should-my-team-use

Scaling:

How management changes as your company grows: https://activecollab.com/blog/growth/how-management-changes-as-your-company-grows-greiner-growth-model

How to scale up your team to greatness: http://fortune.com/2014/04/10/how-to-scale-up-your-team-to-greatness/

The organized chaos approach to scaling a team: https://blog.trello.com/organized-chaos-approach-to-scaling-a-team

Lessons learned from scaling a team: https://www.intercom.com/blog/videos/lessons-learned-from-scaling-a-team/

Building a team in a tech start-up:

How to build an effective data science team for a tech start-up: https://www.itproportal.com/features/how-to-build-an-effective-data-science-team-for-a-tech-startup/?platform=hootsuite

Spock vs Bones

Ode to the Type A data scientist: https://towardsdatascience.com/ode-to-the-type-a-data-scientist-78d11456019

Do I need a data engineer? https://blog.fishtownanalytics.com/does-my-startup-data-team-need-a-data-engineer-b6f4d68d7da9

EFFECTIVE WAYS OF WORKING: ADDITIONAL RESOURCES

Innovation Culture

Collaboration between teams:

https://www.pmi.org/learning/library/collaborative-creative-business-analysis-9397

https://www.viqtordavis.com/blog/why-is-effective-collaboration-between-it-and-business-teams-so-difficult-to-achieve/

Innovation Culture

https://www.lead-innovation.com/english-blog/what-is-innovation-culture

https://talentculture.com/6-ways-leaders-can-build-a-culture-of-innovation/

Managing Projects

Overview of Agile project management:

https://www.apm.org.uk/blog/agile-project-management-the-what-and-the-why/

https://www.atlassian.com/agile/project-management

5 papers about project management for data science: https://www.thinkingondata.com/5-papers-about-data-science-project-management/

What works and what doesn't in Agile for data science: https://towardsdatascience.com/agiledatascience-3b7ca65278a4

A new agile event to assess the consequences of technology. (Included as an example of ways agile PM can be adapted to what a team needs to do): https://medium.com/doteveryone/an-agile-approach-to-designing-for-the-consequences-of-technology-18a229de763b

Sharing Knowledge

Collaboration to aid learning and skill sharing: https://towardsdatascience.com/better-collaborative-data-science-d2006b9c0d39

Tools to help data scientists share knowledge: https://www.ibm.com/blogs/bluemix/2017/11/sharing-knowledge-finding-right-tools-help-data-scientists-communicate-business/

DEVELOPMENT AND PROGRESSION: ADDITIONAL RESOURCES

Training

How to create a high-learning team: https://www.ccl.org/articles/leading-effectively-articles/how-to-create-a-high-learning-team/

Ways to encourage employee development: https://www.forbes.com/sites/williamcraig/2018/03/13/successful-ways-to-encourage-employee-development-and-strengthen-your-team/#4d5bb0dc1300

How and why to continue developing as a data scientist: https://www.mbnsolutions.com/uncategorized/how-and-why-to-develop-as-a-data-scientist/#

The challenge of churn

General definition: https://whatis.techtarget.com/definition/employee-churn

Combatting churn: https://www.fieldaware.com/blog/posts/7-keys-to-combating-employee-churn/

Churn in data science teams: https://campbell-north.com/blog/08-october-2018/churn-data-science-teams-%E2%80%93-why-and-how-prevent-it

Best Practice for managing turnover in data science groups, teams, and labs: https://osf.io/preprints/socarxiv/wsxru/

THE DATA LAB
value from data

Innovation Centres
Supported by The Scottish Funding Council, Highlands and Islands Enterprise and Scottish Enterprise.

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