Checklist to evaluate your readiness for Machine Learning

11 questions to ask yourself before applying Machine Learning to your business

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Introduction

Machine Learning (ML) algorithms are changing nearly every industry. They're increasing productivity, boosting sales and helping us make more informed decisions. Many organizations are either already leveraging the power of ML, or have it laid out in their roadmap as an opportunity worth pursuing.

Trouble is, ML is complex and you might ask yourself whether your business is ready for it or not. Asking that question is absolutely right! Before jumping on a ML endeavor, you should make sure your organization fulfills certain requirements.

That's why we've put together an interactive checklist with **11 questions to ask yourself before applying Machine Learning to your business.** They refer to your organization's **strategy, resources** as well as to the **data** and should bring you one step further in your decision-making process.

You can answer each question with "absolutely", "mostly" or "not at all". The more questions you answer in the affirmative, the readier you are for a ML project. Your organization seems to be far from ready? Don't worry! Take a step back, get support from industry experts if needed and retake the questionnaire. **Good luck!**

Disclaimer: The questions apply to companies where Machine Learning is not the core business.

Alan Descoins
CTO & Partner

Strategy

	Not at all	Mostly	Absolutely

1. Does your organization have clear business goals?

Even if ML is started as an experiment, there should always be an end business goal that actually matters and which can be impacted by ML. The success criteria of ML algorithms should not be a certain % in accuracy, but a business metric. For example, imagine you're in the retail space and your main focus now is to reduce costs. A specific business goal could be to reduce warehouse costs by 10% at the end of H2. One way to fulfill this could be via optimizations derived from ML algorithms

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2. Have you defined whether ML should reduce costs or increase revenue?

A successful ML project will either reduce costs or increase revenue (or both!) and you should define in which you are going to focus on. Only this way will ML have a major impact on the organization and its growth.

3. Do you have a clear and realistic way of measuring the success of your ML initiative?

Each ML project is different and you need to define a success metric that makes sense for that specific project and which you'll be able to measure. Examples of these metrics are: number of items sold, hours spent on a task times the cost of one hour, or user engagement (hours spent in the app) . Once that metric is set, it needs to be accepted by business people and data scientists alike.

4. Is your company able to handle the risk of a ML initiative failing?

As with all innovations, there is a chance that the results of the ML initiative do not turn out as expected because of several factors. Maybe you discover that you need much more data to get a meaningful result or that the data was simply not good enough. Maybe the problem is just too complex or there are many variables which you hadn't accounted for. Maybe, after months of work, you discover that the final solution would be far too costly. In any case, there is some uncertainty in ML projects, which cannot be completely avoided and for which you should be prepared.

Culture / Resources

Not at all Mostly Absolutely

5. Do you have a clear high level understanding of what ML is?

Don't just use ML because you want to follow the hype. Make sure you understand different use cases, what input ML algorithms need and when they can't be applied. You should conceptually understand what ML brings to the picture, either by doing some research or talking to the right people.

6. Is the access to information guaranteed?

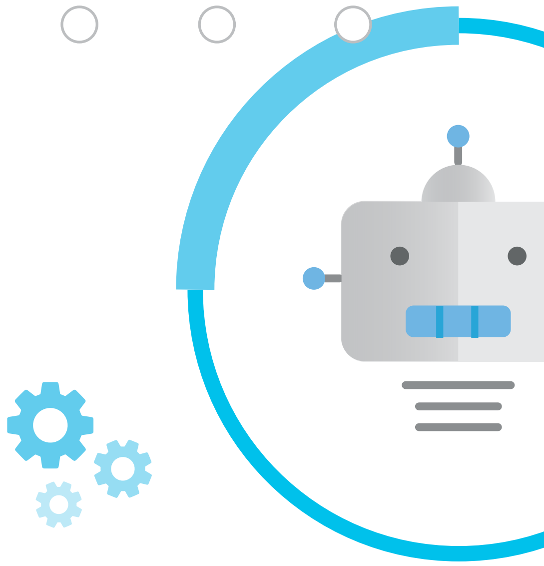
When starting ML initiatives, data scientists need to have easy access to information. They will need to work together with key people, possibly from different departments (not just IT!). Those people need to support the project with business knowledge of some sorts and internal bureaucracy would be a main constraint. Ideally and in time, ML and data science should be transversal to the whole organization, just like the accounting department is.

7. Can your organization attract the right talent or is it ready to outsource?

There is a very high market demand for ML expertise, and this fierce competition makes it challenging to acquire. Hiring and building a quality in-house team is going to prove difficult for nearly every company – unless you are somehow very competitive both in salaries and in challenging problems your company poses. Especially when timing is important and you want to improve your business metrics sooner rather than later, outsourcing can be a good alternative that allows you to access people with the right ML skills.

8. Is your organization on a stage that can invest for mid-term results?

Results from ML initiatives take time and you'll not be able to prove success over night. This requires your organization's financial ability to invest in a mid-term project. In the software development world, time estimations have always been troublesome. This problem is augmented in the case of ML development, because the process itself has even more uncertainty. Sometimes, you can be stagnated and a simple breakthrough can completely turn things around. Normally, it can take several months of work until you get the desired results.



Data

Not at all | Mostly | Absolutely

9. Is your organization collecting the right data?

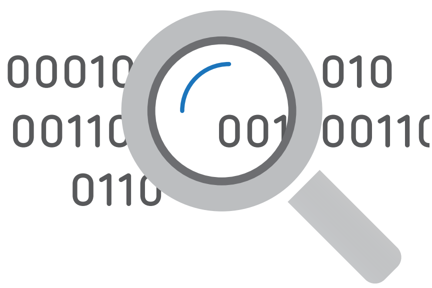
Machine Learning algorithms are no magic. They need data to work, and they can only be as good as the data you feed in. If there's no data provided, there's no use for ML and you'd need to go some steps back and actually start collecting the data that matters.

10. Is your organization collecting the data in the right format?

It's not only about the amount or type of data, but also about its format. Imagine you have taken thousands of perfect pictures of smartphones (good resolution and white background) in order to train a computer vision model to detect them in images. Then you discover that it won't work, because the actual use case was detecting people holding smartphones in various lighting/contrasts/backgrounds, and not the smartphones by themselves . Your past data collection effort would be nearly worthless, and you'll need to start over. Moreover, you'll need to understand if bias exists in the data being collected, because ML algorithms will learn that bias.

11. Can your organization afford the human labeling of data, if necessary?

Depending on the project, the ML solution can be based on supervised algorithms. These algorithms require the collected data to be labeled, ie. a human would need to specify what the expected outcome is for each example that we have collected, so the algorithm can learn from these insights. Ensure that your organization is able to afford the costs for people building such a (potentially large) dataset for the ML experiment.



About Tryolabs

Tryolabs is a Machine Learning consulting shop that helps companies leverage their data to improve KPIs. By using the latest techniques in Deep Learning, Computer Vision and Natural Language Processing, Tryolabs is bridging the gap between academic research and the industry.

Learn more about Tryolabs and current projects at tryolabs.com.

Ask the expert

Do you feel your organization is ready for Machine Learning and want to share your ideas with an industry expert? **We're curious!** Schedule a 15 minutes free call, and tell us a little bit about it!

SCHEDULE CALL