Challenges to the Implementation of Artificial Intelligence

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Despite the vast potential of artificial intelligence, it hasn't caught hold in most industries. Sure, it has transformed consumer internet companies such as Google, Baidu, and Amazon — all massive and data- rich with hundreds of millions of users. But for projections that AI will create $13 trillion of value a year to come true, industries such as manufacturing, agriculture, and healthcare still need to find ways to make this technology work for them. Here's the problem: The playbook that these consumer internet companies use to build their AI systems — where a single one-size-fits-all AI system can serve massive numbers of users — won't work for these other industries.

Instead, these legacy industries will need a large number of bespoke solutions that are adapted to their many diverse use cases. This doesn't mean that AI won't work for these industries, however. It just means they need to take a different approach.

To bridge this gap and unleash AI's full potential, executives in all industries should adopt a new, data-centric approach to building AI. Specifically, they should aim to build AI systems with careful attention to ensuring that the data clearly conveys what they need the AI to learn. This requires focusing on data that covers important cases and is consistently labeled, so that the AI can learn from this data what it is supposed to do. In other words, the key to creating these valuable AI systems is that we need teams that can program with data rather than program with code.

Why adopting AI outside of tech can be so hard?

Why isn't AI widely used outside consumer internet companies? The top challenges facing AI adoption in other industries include:

1. **Small datasets.** In a consumer internet company with huge numbers of users, engineers have millions of data points that their AI can learn from. But in other industries, the dataset sizes are much smaller. For example, can you build an AI system that learns to detect a defective automotive component after seeing only 50 examples? Or to detect a rare disease after learning from just 100 diagnoses? Techniques built for 50 million data points don't work when you have only 50 data points.
2. **Cost of customization.** Consumer internet companies employ dozens or hundreds of skilled engineers to build and maintain monolithic AI systems that create tremendous value — say, an online ad system that generates more than $1 billion in revenue per year. But in other industries, there are numerous $1-5 million projects, each of which needs a custom AI system. For example, each factory manufacturing a different type of product might require a custom inspection system, and every hospital, with its own way of coding health records, might need its own AI to process its patient data. The aggregate value of these hundreds of thousands of these projects is massive.

3. **Gap between proof of concept and production.** Even when an AI system works in the lab, a massive amount of engineering is needed to deploy it in production. It is not unusual for teams to celebrate a successful proof of concept, only to realize that they still have another 12-24 months of work before the system can be deployed and maintained.

   For AI to realize its full potential, we need a systematic approach to solving these problems across all industries. The data-centric approach to AI, supported by tools designed for building, deploying, and maintaining AI applications — called machine learning operations (MLOps) platforms — will make this possible. Companies that adopt this approach faster will have a leg up relative to competitors.