BIG DATA AND ITS ROLE ON FOSTERING INNOVATION IN ASIA

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Abstract

Artificial intelligence is all about imbuing machines with a type of intelligence which is primarily attributed to humans. Extant literature coupled with the experiences of ours as practitioners suggests that while AI might not be completely ready to totally dominate very innovative things inside the development process, it shows promise as a major assistance to development supervisors. In this post, we broadly relate to the derivation of computer enabled, models, data-driven insights, and visualizations inside the development activity as innovation analytics. AI might play a vital role in the innovation activity by turning several factors of innovation analytics. We existing 4 case studies that are different of AI in motion based on the previous work of ours in the industry. We highlight limitations and benefits of utilizing AI in development and conclude with additional resources and strategic implications for development managers.

Keywords

Big data analytics; Data mining; Banking; Survey

JEL Classification

M43, M45

DOI: https://doi.org/10.14311/bit.2022.01.21

Introduction

Artificial intelligence is now a favorite subject of business and the application of its continues to be explored across disciplines by practitioners and academics. One recurring conclusion is the fact that AI will influence some company pursuits more than others, based on the degree of creativity natural to the exercise. The bigger the amount of imagination, the more difficult it is going to be for AI to add value [1]. This poses an intriguing dilemma for supervisors accountable for turning the procedure of development within firms: Can AI considerably help support the development method even though extremely innovative jobs can't be totally automated?

AI is all about imbuing machines with a type of intelligence which is primarily attributed to humans. Arguably, AI could play the job of creative partner and enabler of the innovation supervisor across the data driven innovation procedure [3]. Just like the main usage of AI in various other practical uses, significant worth could be shot using AI to automate tedious but effort intensive activities. Used more, data scientists are able to assist innovation managers leverage unstructured major data consisting of video which, sound, and text is ubiquitous in the development operation.

In this post, we explain just how AI could reasonably be deployed at the fuzzy front end of development. We talk about just how AI could allow innovation analytics, a phrase we utilize for describing the derivation of computer enabled, models, data-driven insights, and visualizations inside the innovation operation [2]. In order to frame the discussion of ours, we think about the innovation process like a double diamond design that spans the exploration as well as selection of concepts in the issue as well as solution space. We existing 4 case studies of AI in action one for every component of the originality process based on the previous work of ours in the industry. The project teams in these case studies consist not just of conventional innovation providers but additionally information experts which assist the teams unlock the possibility of AI, demonstrating just how AI enabled feature analytics are able to deliver richer insights in a cost effective fashion [4]. We determine with ramifications for innovation managers and highlight the advantages and the limits of using AI.

Literature Review

Computers frequently play a distinctly servile job within the development process, used predominantly to deal with things that innovation supervisors may perceive as arduous or monotonous too to do yourself. This kind of chores are able to entail regular information processing along predefined methods, replicating outcomes, and storing information in different file formats and databases. AI offers to essentially expand the job of technology in the development activity by elevating pcs from simple servants to partners, therefore empowering humans to additional exhibit inventive strengths values. Besides the abilities of' normal' pcs, AI powered pcs are able to perform deeper analyses of information, help make choices below uncertainty, and greatly improve over time by constantly incorporating external feedback. Information scientists with their potent and rare blend of AI relevant programming expertise, statistical knowhow, and then industrial acumen can help innovation managers unlock the possible value of AI in development tasks [5].

AI may considerably affect a minimum of 4 primary drivers of development analytics: specification of objectives, value capture and, modeling, preparation and data collection. These elements are reviewed in subsections.

The development process like a double diamond

The fuzzy front end of the development process requires a convergence-divergence dynamic which spans solutions and problems; this representation is usually known as the double diamond, made famous by a likewise named visible framework created by the U.K. Design Council. The double diamond captures a generic method which is commonly relevant to development methods and allows frame the subsequent discussion of ours. Crucially, the double diamond breaks down the development process into phases which could be exclusively mapped to various use cases of AI enabled innovation analytics [7].

Figure one presents one iteration of the double diamond, which could serve as the reference point of ours for the fuzzy front end of the development operation. The double diamond comprises of two primary dichotomies. For starters, we differentiate between solutions and problems. An issue could be described as the unmet need of a certain stakeholder. An answer is the intangible or tangible innovation which can fix a certain problem. Next, we differentiate between selection and exploration. Exploration captures the idea of producing as well as identifying new insights, while choice involves filtering as well as combining the insights. Mapping these dichotomies creates the 4 unique phases of the double diamond [6].

In the problem exploration stage, we need understanding the complete range of problems that are possible in our specified innovation context. The problem-selection stage whittles down the identified issue set to a far more tractable subset based on a few key elements related to company constraints, predefined strategic goals, and any other external influences. In the solution-exploration stage, the shortlist of issues acts like a reference point for producing brand new ways and discovering or reframing present answers which could be related [8]. The shortlist of issues concentrates and restricts the exploration of solutions; this's completely different from the situation in trouble exploration, in that the purpose of reference might be something even more abstract. Lastly, the solution selection phase picks out the most promising solutions being prepared more. Treatments are generally selected by a panel of subject matter experts as well as best executives, judging on areas including novelty, feasibility, and business viability.

Specification of objectives

The goals of working with innovation analytics in a certain circumstance could be mapped to concrete, AI enabled analyses, that could typically be divided into 4 types :

1. Descriptive examination is exploratory in nature and about summarizing visualizing historic data;

2. Diagnostic analysis utilizes past data to build links between various events or concepts, allowing the innovation director to drill down in to certain parts of the information and combine them to create as well as test hypotheses;

3. Predictive analysis synthesizes past as well as real time info to create designs which can forecast or even imagine the upcoming status of variables the feature supervisor might be curious in; and

4. Prescriptive analysis not just predicts the future though it's additionally opinionated in the sense it is able to suggest what you should do down the road and the way to do it.

Collection as well as preparing of data

Many data types could be collected from numerous sources throughout the innovation operation. Several of this's structured information, which can be nicely represented as tables of well defined rows as well as columns [9]. Structured information is definitely a staple of innovation analytics, along with numerous identified statistical techniques for regression as well as classification analyses rely on this kind of information. Nevertheless, a considerable level of unstructured data is collected throughout the development activity from textual, sound, and video solutions. Unstructured data has to be parsed as well as coded in a way to acquire fundamental nuggets of info. Up to now, the evaluation of unstructured details in innovation analysis has heavily different not totally relied on labor intensive, qualitative techniques. AI-based techniques for text mining provide a complementary strategy to analyzing unstructured information.

Modeling

To model the real life is a main inspiration behind employing AI for innovation analytics. Figure two shows a two-by-two matrix for planning typical algorithms and figuring out when you should utilize them. A dimension of the matrix distinguishes between regression as well as category algorithms. Regression algorithms are utilized to examine ordinal or continuous output data, while classification algorithms are hugely ideal for unordered categorical paper data [10]. The alternative dimension of the matrix differentiates between supervised plus unsupervised learning. For supervised learning, a data set that contains the mapping among input as well as output information is provided, as well as the job is deriving a mathematical feature which best approximates this particular mapping. In unsupervised learning, output information isn't labeled as a result, and the process would be to identify patterns in the information in an exploratory manner [12]. Supervised learning might be utilized to teach an unit on historic product sales information to foresee the achievements of new merchandise launches, whereas unsupervised learning could use clustering strategies to find anomalies and commonalities in the information.

Value capture

It's essential to capture the worth that is created using AI based innovation analytics. Worth is usually taken in the phases of AI output as well as the corresponding version, so that as the development staff reflects on the ramifications of the result of the model [13]. The paper of diagnostic and descriptive analyses are able to cover a selection of visualizations, from simple graphs and tables to network-based and tree-based diagrams of latent buildings in the data; the latter specifically stresses the valuation of AI. Meanwhile, in prescriptive and predictive analyses, crucial components of the paper can add the expected potential status, the quantity of confidence which is usually ascribed to this particular prediction, as well as the benefits or maybe weighting given to every one of the enter variables within deriving the prediction. Aside from the output, the product itself may be caught for potential analysis, that has a few advantages: The unit may be reused, critiqued, and shared with other people. Lastly, the feature staff also can record importance by looking at the insights of theirs to those created by the AI. Whereas the insights will probably overlap to some amount, the AI might also deliver insights which are brand new to the innovation group [11].

Case studies of AI based development analytics in practice

We existing 4 case studies, 1 for every stage at the innovation process found earlier in Figure one. Each emanates from the involvement of ours in relevant innovation tasks and was performed by cross-functional teams comprising of regular innovation analysts/managers and information experts with AI expertise. Instead of trying to make a deep dive of AI techniques inside the boundaries of these quite short case studies, the aim of ours is inspiring pretty traditional feature supervisors to think about working much more closely with information scientists as well as use the possible value of AI in development tasks [15].

Discovering customer requirements for personal care products

The very first case concerns a big German manufacturer of individual care products. In the quest for different blockbuster solutions, airers4you commissioned an innovation staff to perform an exhaustive evaluation of internet user generated information on customer must have [14]. The aim was to gain a set of key trouble areas within the body treatment part around which ideas for products that are new might be designed. Going through the massive amount of pertinent UGC involves a lot of hand-operated work, leading feature supervisors to restrict the scope of theirs of evaluation based on experience and time as well as resource restrictions. In this particular situation, the innovation group chose to investigate AI's potential to lessen analysis burden as well as enhance the quality of insights produced. 2 various goals have been specified: AI will be utilized to differentiate plausible customer requirements and the issues they imply from simple chatter along with other editorial content material, also to make a descriptive clustering of the determined requirements, which may later be enhanced by the development group. AI might therefore facilitate a far more extensive exploration of the issue domain compared to the purely hand tactic as well as leverage really the UGC related big information.

The staff started using its domain expertise to determine as well as search on the internet discussion boards regarding body treatment, yielding aproximatelly 1.75 million posts. The majority of the posts were up to three sentences in length [16]. Articles related to customer needs subsequently had to be recognized in this original haul of information. Such a binary category of articles demanded a subset of the articles being tagged as possibly a customer demand or perhaps not really a consumer need to be able to enable a supervised algorithm to classify the majority of the posts. In order to label the subset of articles, an instruction guide for qualitative coding was ready and a part of the project group marked aproximatelly 5,000 posts by hand. Lastly, using an automatic process, every one of the text in the raw textual details were encoded as special numerical vectors which may be given into the AI algorithms.

Data scientists on the staff developed the algorithm for determining consumer requires applying neural nets. Neural nets are able to decompose the process of learning about a big piece of textual details into many simpler things [18]. Upon classifying the UGC possibly as customer requires or otherwise customer needs, a descriptive clustering of the consumer needs information was conducted utilizing an unsupervised algorithm dependent on latent Dirichlet allocation. The LDA strategy deemed the whole range of community posts and supposed the presence of a particular number of topics consisting of a pair of relevant words that might be variously coupled generating every one of the forum posts. The LDA process will be to infer such a pair of subjects while ensuring a sense of balance in between the quantity of subjects and the text a subject. Crucially, the subject areas served as approximations of the themes contained in the UGC associated with customer must have [17].

Great was taken out of the use of AI in a few ways. For starters, the algorithms identified needs related posts with seventy five % accuracy. The LDA strategy generated subjects that seemed plausible enough the innovation team saw really serious potential in using AI far more regularly in future projects as a means to decrease the mechanical burden at the original phases of data analysis. Far from replacing conventional innovation practitioners, nonetheless, the usage of AI exhibited a means to redefine the role of theirs within the analytical procedure [19]. Providers are able to move far from the monotonous job of coding text and producing original subject clusters and toward orchestrating as well as enhancing the interpretation procedure in cooperation with information scientists. The visualization of the paper produced the internal functions of the AI algorithms more transparent, further helping the development team's comprehension of the raw textual information. Lastly, one staff member with domain expertise independently performed a qualitative evaluation of the book to gain possible trouble areas for people discovered the AI output mostly validated the insights of her. She did produce fewer original issue or maybe topic clusters compared to the LDA based strategy, nonetheless, and was therefore in the position to bring on the automated AI output to improve the manual findings of her.

Implications for innovation managers

AI might play a crucial role in the development process, out of the exploration of issues on the number of strategies. As underscored by the real life case studies of ours, AI can considerably drive innovation analytics. From the research of ours, we found 3 major implications for how AI could fundamentally alter the way innovation managers consider leveraging technology that is such of the innovation process [20]. For starters, AI draws a lot of worth out of BDA; feature teams could leverage huge volumes of information and carry out informative analyses that are replicable and scalable highly. Though there's still much space to improve the sophistication of algorithms supposed to parse unstructured details, the resources now available could discuss a selection of low hanging fruits of all the usage cases in the development operation. Next, AI could empower feature managers to work directly with data scientists to assign things of higher resourceful complexity to the computer; the case studies of ours from the area claim that AI can frequently assist validate resourceful insights and reduce the creative blind spots of ours [21]. Last, AI can enable those interested in the development process to better respond pre-existing and additionally to question much better questions based on AI models which account for a selection of complex interactions between variables; such variants may additionally be utilized to inductively derive brand new questions or hypotheses concerning the originality situation.

The utilization of AI in innovation additionally comes with the challenges of its. Conventional innovation teams might not have the know-how to construct and use AI models and can therefore need to collaborate strongly with data scientists, preferably making them core staff from the beginning. Additionally, present technical limitations imply that, at minimum in the temporary, the paper of AI might not be as contextually nuanced as analyses ready by humans. Any efforts from AI must be examined significantly and complemented by the development staff as necessary. Additionally, AI techniques, which usually cope with correlations, don't obviate the demand for controlled experiments to build causal consequences [22]. From the book Prediction Machines of theirs, Gans, Agrawal, along with Goldfarb reported that "everyone has experienced and will quickly get an AI moment," that is basically recognized by the realization that AI is not simply an additional technology but something essentially much deeper that causes us to reexamine the understanding of ours of becoming human. For all those engaged in the development process, these kinds of a realization can come when dealing with AI to find insights that neither human or pc might achieve by yourself [23]. To this conclusion, we created a set of materials for getting started with AI in training. The materials are by no means exhaustive but deal with a selection of basic learning materials as well as open source resources, with short notes on the application of theirs to innovation analytics. We hope these materials are of specific value to conventional innovation providers that want to collaborate much more closely with information scientists to utilize AI throughout the course of innovation tasks down the road.

References

1. AKTER, J. S., & Haque, S. M. (2022). Innovation Management: Is Big Data Necessarily Better Data. *Management of Sustainable Development*, *14*(2), 27-33.
2. JACOB, E.K., “Classification and Categorization: A Difference that Makes a Difference”, Library Trends 52(3), 2004, pp. 515–540.
3. JAHAN, S. A., & Candidate, M. B. A. (2022). Factors Affecting The Adoption Of Financial Technology Among The Banking Customers In Emerging Economies. *Financial Studies*, *39*.
4. JAHAN, S. A., & Sazu, M. H. (2022). Role of IoTs and Analytics in Efficient Sustainable Manufacturing of Consumer Electronics. *International Journal of Computing Sciences Research*, *6*.
5. JAHAN, S. A., & Sazu, M. H. (2022). The Impact of Data Analytics on High Efficiency Supply Chain Management. *CECCAR Business Review*, *3*(7), 62-72.
6. JOHNSON, M.W., C.M. Christensen, and H. Kagermann, “Reinventing Your Business Model”, Harvard Business Review, 2008. https://hbr.org/2008/12/reinventing-your-business-model
7. KOLLWITZ, C., M.P. Mengual, and B. Dinter, “Cross-Disciplinary Collaboration for Designing Data-Driven Products and Services”, 2018 Pre-ICIS SIGDSA Symposium on Decision Analytics Connecting People, Data & Things, 2018, pp. 1–15.
8. LAVALLE, S., E. Lesser, R. Shockley, M.S. Hopkins, and N. Kruschwitz, “Big Data, Analytics and the Path From Insights to Value”, MIT Sloan Management Review Winter issue 2011, 2011.

9. LIM, C., K.-H. Kim, M.-J. Kim, J.-Y. Heo, K.-J. Kim, and P.P. Maglio, "From data to value: A nine-factor framework for data-based value creation in information-intensive services", International Journal of Information Management 39, 2018, pp. 121–135.
10. LOEBBECKE, C., and A. Picot, "Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda", The Journal of Strategic Information Systems 24(3), 2015, pp. 149–157.
11. LUSCH, R.F., and S. Nambisan, "Service Innovation: A Service-Dominant Logic Perspective", MIS Quarterly 39(1), 2015, pp. 155–175.
12. MCLOUGHLIN, S., A. Puvvala, G. Maccani, and B. Donnellan, "A Framework for understanding & classifying Urban Data Business Models", Proceedings of the 52nd Hawaii International Conference on System Sciences, (2019).
13. MEIERHOFER, J., T. Stadelmann, and M. Cieliebak, "Data Products", In M. Braschler, T. Stadelmann and K. Stockinger, eds., Applied Data Science. Springer International Publishing, Cham, 2019, 47–61.
14. MIKALEF, P., I.O. Pappas, J. Krogstie, and M. Giannakos, "Big data analytics capabilities: a systematic literature review and research agenda", Information Systems and e-Business Management 16(3), 2018, pp. 547–578.
15. NAOUS, D., J. Schwarz, and C. Legner, "Analytics as a service: Cloud computing and the transformation of business analytics business models and ecosystems", Proceedings of the 25th European Conference on Information Systems, (2017), 487–501.
16. NEWELL, S., and M. Marabelli, "Strategic opportunities (and challenges) of algorithmic decision-making: A call for action on the long-term societal effects of 'datification'", The Journal of Strategic Information Systems 24(1), 2015, pp. 3–14.
17. SAZU, M. H. (2022). Does Big Data Drive Innovation In E-Commerce: A Global Perspective?. *SEISENSE Business Review*, *2*(1), 55-66.
18. SAZU, M. H., & Jahan, S. A. (2022). Can big data analytics improve the quality of decision-making in businesses?. *Iberoamerican Business Journal*, *6*(1), 04-27.
19. SAZU, M. H., & Jahan, S. A. (2022). HIGH EFFICIENCY PUBLIC TRANSPORTATION SYSTEM: ROLE OF BIG DATA IN MAKING RECOMMENDATIONS. *Journal of process management and new technologies*, *10*(3-4), 9-21.
20. KÜHNE, B., and T. Böhmann, "Data-driven business models - Building the bridge between data and value", Proceedings of the 27th European Conference on Information Systems, (2020).
21. SAZU, M. H., & Jahan, S. A. (2022). How Analytics Can Improve Logistics And Supply Chain In Multinational Companies: Perspectives From Europe And America. *Business Excellence and Management*, *12*(3), 91-107.
22. SAZU, M. H., & Jahan, S. A. (2022). Impact of big data analytics on business performance. *International Research Journal of Modernization in Engineering Technology and Science*, *4*(03), 367-378.
23. NICKERSON, R.C., U. Varshney, and J. Muntermann, "A method for taxonomy development and its application in information systems", European Journal of Information Systems 22(3), 2013, pp. 336–359. [49] OECD, Data-Driven Innovation, OECD Publishing, Paris, 2015.