

Implementing Feature and Metric Stores for Machine Learning Models in the Gaming Industry

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Abstract

Machine learning models are used in content creation and generate real-time observations in gaming with a positive effect on both performance and production processes. However, the management and deployment of these features and metrics for the purposes of these benefits are critical. Looking at feature and metric stores data structures that are used for storing and retrieving feature and metric data for machine learning models. Feature stores are responsible for featuring storage and delivery for model training and features needed for model's inferencing, whereas metric stores contain metrics required for the assessment of specific models. The adoption of these stores can drastically bring down the amount of development time and effort as well as enhance the aptitude of recognizing real time actions and quality of the game. It is therefore prudent and helpful for the reader to learn the basic concepts that underpin feature and metric store, the ways in which gaming application benefits from them, and the possible ways in which this technology can be developed further in the future.

Keywords: Feature Store, Metric Store, Machine Learning, Gaming Industry, Procedural Content Generation, Real-Time Action Recognition, Feature Engineering, Model Evaluation

Introduction

Machine learning models have significantly transformed the production and real-time analysis of content in the gaming industry as well as the players and other related development procedures. However, for these benefits to be optimally realized, the features and the respective metrics need to be efficiently managed and deployed. The ideas of the feature and metric stores, which are data structures to store and manage features and metrics for the machine learning model, are disclosed. Feature stores are responsible for storing and serving features needed during model training and inference while, on the flip side, metrics stores contain metrics used to evaluate models. The use of such stores can enable game developers to cut down on time and effort taken to generate content, as well as enhance action recognition in real-time gaming, thus enhancing the quality of the games developed.

Literature review

Procedural Content Generation via Machine Learning (PCGML) Overview

According to Summerville *et al* 2018: Machine Learning (PCGML) can be described as the application of machine learning techniques that have been trained with data from similar games to create new game content like levels, maps and stories instead of Search based or Solver based methods. In contrast, the above methods require the content to be generated often with additional fine-tuning by specifying the parameters and very little concentration on the functional aspect as achieved by PCGML. It uses various machine learning methods as neural networks such as LSTM networks, auto encoders and probabilistic models like Markov models for generating content which generally influences game play and players' interactions (Summerville *et al.*, 2018). As previously mentioned, the use of PCGML can be done in three main approaches, which include autonomous generation, co-creation or content analysis. However, it has several issues such as; learning from little data, an optimal number of hyper parameters, and how to incorporate the generated content into an enjoyable gameplay.

Advanced Metrics for Real-Time Action Recognition in Gaming

According to Bloom *et al* 2012: Using real-time action recognition methods in gaming prescribes for an extant metric, advanced than the time-based event-detection framework. Therefore, this new metric that takes into consideration multiple distinct action classes and time and repetition constraints shall try to provide more accurate measurements of action recognition algorithms. To support this evaluation, the authors present the G3D dataset of synchronized video, depth, and skeleton data. The gaming industry with transition from limb to full body interaction through devices such as the Kinect requires advanced action recognition methods. Now, simple gestures can be implemented easily by heuristic methods but

for the more complex movements in the sports or action coupled with adventure games it will be important to use the techniques of machine learning (Bloom *et al.*, 2012). Some of the modern approaches utilize appearance descriptors such as color and optical flow but the results with these descriptors can be low because in gaming scenarios the contextual information is missing. The changes in joint positions and angles classified as pose-based techniques are becoming more popular because of the development in the real-time skeleton tracker. Bloom *et al.* 2012 suggest a new evaluate protocol and data set designed for a comparison of appearance-based, pose-based and combined methods for action recognition in the context of gaming applications.

Feature Generation and Engineering for Software Analytics

According to Dong and Liu 2018: Feature generation and engineering are widely used in software analytics as they support the majority of software engineering activities. This explores how domain-specific features are designed and utilized for three main tasks: defect prediction, crash release prediction and developer turnover prediction. Most of them underscore the need of preprocessing data by extracting features from different artifacts like source code, bug reports and commit logs, in order to develop robust predictive models (Dong and Liu, 2018). For example, in defect prediction, ‘features’ are extracted from previous data of software modules to predict possible bugs. Similarly, in crash release prediction, features from app releases are used to make prediction as to what releases are likely to contain crashes. In developer turnover prediction, data are pulled from monthly reports in order to identify which team members are at high risk of turnover. (Dong and Liu 2018) have underlined that the features that are chosen significantly impact the effectiveness of the predictive models; process features outcompete code features in defect prediction. This also expands on the difficulties encountered in feature extraction because of the nature of data that is typical in software engineering and the importance of prior domain-specific knowledge. In other words, it serves as a reference guide to all conventional and modern approaches of feature engineering in these software engineering activities.

Methods

Feature Engineering and Extraction

Feature engineering consists in developing and selecting the features that are most relevant to the machine learning algorithm. In the general context of the gaming industry, this process is initiated by gathering different data including logs data indicating players’ interactions; and output data of sensory systems within the gaming environment (Djenouri *et al.*, 2019). Sophisticated methods like statistical analysis and specific algorithms of the domain are applied in order to get new features from the raw data. For instance, it can involve some attributes of the player such as movements, how often he or she interacts with other players, the states of the game environment and the likes. It then aims at mapping these features so that they capture true patterns and dynamic in the game, which is important when training the models.

Feature Store Implementation

Features, once extracted and transformed into a set of features, must be efficiently stored and delivered. This is realized by the implementation of a concept called Feature Store, which ensures that the features reside in a structured manner. The implementation includes choosing the suitable storage locations, for example, the relation database, NoSQL, or data mart depending upon the properties of the data and the frequency of their use (Shao *et al.*, 2019). Specifically, the structure that was followed during its creation entails the provision of a centralized repository that has the capability to manage, monitor, and track the features to be implemented alongside their versions and versions of datasets. Besides, those features are designed to have real-time or batch access through APIs and data pipelines tailored for machine learning processes.

Metric Store Development

It also includes the definitions for the metrics that are going to be used to evaluate the performance of the model or the value in the database and to compare them with the expected value including the creation of the metric store. What this implies is to establish feasible metrics for peculiar gaming procedures such as action recognition precision or player’s immersion of procedural content. The metric store receives performance data from model evaluation and can retain them

in technologically related formats for instance time series or analytical databases (Hazelwood *et al.*, 2018). This has been done in order to facilitate the interpretation of metrics through the visualization tools such as dashboard and report for assessment of the model. This makes it possible for developers to be able to monitor trends and changes, analyze and process problems, and also provide solutions because of the relevant data available.

Result

Enhanced Model Performance

The use of feature and metric stores as features have positively impacted the effectiveness of models in different gaming applications. It is directed towards centralized feature management such that the models enjoy accurate data hence improving the resulting prediction as well as improving on the objectives of gaming (Xie *et al.*, 2018). For instance, procedural content generation models have revealed additional relevant features making the games more engaging and playable because of the enhanced quality of features. Likewise, the models that predict player behavior have been made more accurate due to the well-engineered features that describe the player behavior.

Improved Development Efficiency

Both feature and metric stores have proved to reduce development cycles by large measures. Regarding the organized approach to the features and performance indicators, those storage systems have facilitated the development cycle. The use of feature store enhances efficiency and effectiveness since it eradicates much time spent on data preparation and management so that developers can concentrate more on model training and optimization (L'heureux *et al.*, 2017). The metric store helps in coming across the problems in performance and making necessary alterations in a shorter period to deploy improved models. Overall, what these stores bring into the process is a far more efficient and effective environment for the creation of games and functionality to support those games, making the delivery of solid gaming features far faster and more stable in its process.

Enhanced Decision-Making and Insights

The use of metric stores has been useful to the developers because it has helped them to monitor the performance of models and the overall dynamics of the games. Every metric store developed contains tools for the visualization of the performance of the models that have been developed in practice. This has made it easier for developers to learn from their projects and make appropriate changes in accordance with current trends and any irregularity that will be observed (Lantz, 2019). These include the ability to track various metrics such as players' engagement, quality of content and other aspects that have enhanced better and informed strategic decisions making for better gaming experience.

Discussion

Feature and metric stores have been a great value for the gaming industry as their application shows, but they also have inversions. Feature stores allow the definition of how features must be preprocessed and can be reused but their implementation may pose some challenges on how to manage several types of data and how not to slow down performance. To integrate feature stores into existing systems, it has to be able to serve features properly and effectively to the ML models. Metric stores are, on the other hand, important suppliers of model performance metrics while their management and usage require a significant amount of infrastructure to handle large amounts of performance metrics (Ge *et al.*, 2017). The performance of such stores depends largely on the possibility to monitor necessary indicators and the provision of inspiration. One advantage is the way features and metrics are managed, enabling enhanced accuracy and speed of machine learning models. It results in a better generation of content, improved real-time action recognition, and other areas that help in the improvement of the game. Still, some concerns are the difficulties in the connection with other systems that would be located in these stores and the ability to accommodate the larger amounts of game data that are expected now. In addition, feature and metric stores should be efficient as well as the features and metrics chosen for them. Some of the features or metrics selected could be wrong hence affects the performance of the model. These stores therefore require constant optimization and updating to match changes in game dynamics and player behaviors tactfully.

Future Directions

Looking ahead, several advancements could further enhance the effectiveness of feature and metric stores in the gaming industry:

Advanced Feature Engineering Techniques: Other improvements could be achieved in the form of a better feature extraction technique and comes in form of usage of deep learning for extracting features and dimensionality reduction. This would ensure use of better features in model training and overall would boost model accuracy of the prediction.

Monitoring and Adaptation: Improving the metric stores for real-time tracking and model tuning may highly improve gaming applications. Applying changeable metric assessment and model updating from users' feedback directly may help launch more sensitive and adaptive games.

Integration with Emerging Technologies: Feature and metric stores may find an opportunity to adopt new ways of data collection and analysis by integrating with the relatively new technologies such as augmented reality and virtual reality (Luckow *et al.*, 2016). This integration would give better input and output and more interactive games & experiences would thus require better storage & computation facilities.

Improved Scalability and Performance: The future enhancement should be about altering feature and metric stores to accommodate higher game environment. Its existence will be imperative as games become more complex; therefore, improving on data storage efficiency and retrieval will be paramount in the future.

Enhanced Security and Privacy Measures: Potentially, as data privacy is becoming a significant issue, it will be important to organize feature and metric stores to have strong security means (Reuther *et al.*, 2019). Another aspect that might be considered more in the future is the proper protection of the players' information while at the same time providing greater opportunities for data analysis.

The gaming industry must resolve these areas for it to further utilize machine learning models efficiently, improve the creation of games and the experiences of the gamers.

Conclusion

The application of feature and metric stores in the context of the gaming sector is a tremendous step forward in tracking and leveraging of machine learning models. These stores make feature extraction and performance measurements easy, and increase model accuracy, thus, the quality of gamers' experiences. The use case scenarios of feature and metric stores have brought out how they can assist in the generation of content, recognition of action in real-time, and enhancement of game stability. But new concerns like integration issue, concern of scalability and data privacy have to be solved to fully unlock their advantages. The growth of organizations and techniques of feature engineering, real-time dealing and introducing new technologies help to bring the next stage of these stores to the development of the gaming industry. The integration of feature and metric stores is an important step towards more efficient and scalable machine learning solutions in gaming.

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