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AI-Enabled Data Platforms for Automated Metrics Intelligence and Cloud-Based Enterprise Decision Support

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ABSTRACT

The enormous size of enterprise data in cloud, edge, and distributed information ecosystems have brought in an emergent need to use intelligent platforms that would convert heterogeneous data into feasible verdicts. The paper outlines an Automated Metrics Intelligence and Cloud Based Enterprise Decision Support with AI-Expected Data Platform that will aim to implement a unified AI-driven cloud infrastructure that will include data ingestion, intelligent tooling, metrics generation, predictive analytics and analytics visualization. Artificial intelligence methodologies based on machine learning on the proposed platform have automated the process of identifying, extracting, validating and interpreting the enterprise performance measures of both structured and semi-structured sources of data. An intelligent analytics layer identifies both trend, performance anomaly, correlation and new trend and a forecasting model will peg future intelligence to support operations and strategic planning. With dynamically scaling workloads and scalable computing and storage, which comes with cloud based, the platform will make it possible to store high volume enterprise data. The output of analytics and analysis is converted into actionable context(s) as advice, notifications, dashboards, and management metrics by a decision support layer. The framework focuses on automation, scalability, interoperability and real time intelligence and minimizes manualization of metrics preparation and disaggregated workflows in analytics. The proposed alternative provides the foundation to data-driven enterprise management that connects awakening organizational data to intelligence that all-time forms, is interpretable and decision-based.

Keywords: Artificial Intelligence, Data Platforms, Metrics Intelligence, Cloud Computing, Predictive Analytics, Enterprise Decision Support

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INTRODUCTION

The quicker process of digitizing these contemporary organizations has made the volume of data produced by enterprise applications, consumer contact, cloud computing, transactional frameworks, Internet of Things (IoT) gadgets and digital business procedures to widen remarkably. This data is becoming more and more important to organizations because of the need to keep track of operational performance, any emerging trends, resource optimization as well as aid strategic planning. But, there is no guarantee that a big, big quantity of data could be translated into effective decision-making. Heterogeneous systems, which have varying frequencies of update, exhibit different formats and terminologies, usually widely proliferate enterprise data. This then suggests that organizations will undergo continuous trials in terms of data integration, data quality, scale, semantic faithfulness, data analytics processing and real-time interpretation. This has led to heightened related strains that have strengthened the need to have intelligent data platform capable of transforming raw enterprise information into intelligible and usable intelligence.

The Big-data environments are marked by the tremendous possibilities in attaining the business value through exceptionally advanced analytical procedures. However, issues such as the volume, variety, speed,

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truthfulness, storage, data processing and analytical complexity can limit the ability of traditional data-management architecture [1]. Traditional enterprise reporting systems typically have a collection of pre-defined queries, ad hoc created datasets, and manual dashboards. These techniques can provide a good descriptive data but it may require a lot of human effort and it is incapable of identifying adequately the shifts in trends or how a performance unexpectedly changed. As the dynamism on the operations business keeps rising, there is a need to have analytical systems which can at all times crunch the data to produce the respective performance measures automatically.

Cloud computing is a good technological foundation towards fulfilling these requirements. The cloud based infrastructure also helps businesses to scale out its on-demand computing and storage infrastructure dynamically in response to workload demands and allows distributed processing of data, and centralized access to analytic service. Reporting automation as well as cloud migration proved that the development of metrics can be simplified and the number of individuals to work on manual reporting can be minimized [2]. However, a reporting system which is also hosted in the cloud and simply delegates existing workflows is rather more of a description system. An improved business platform must have artificial intelligence (AI) and machine learning to discern patterns, detect anomalies, retrospective predict and create situational expertise influenced by constantly evolving sizable amounts of data.

Data heterogeneity is also another big difficulty to enterprise intelligence. A data source can be considered as a relational database, enterprise resource planning system, customer relationship management system, spreadsheet, cloud repositories, APIs, sensor systems and unstructured documents. These sources are able to hold various schemes and semantic meanings to similar concepts of the business. Integration has since been researched and ontologies to govern development and interoperability of the big-data worlds [3]. Distributed frameworks based on ontologies on the same note can provide access, synthesis and reasoning on the information which is stored on various sources of data [4]. Such techniques can create an important foundation of shared intelligence of the business, bringing semantic network properties amongst otherwise unrelated datasets.

Information integration based on ontology can also enhance the consistency of enterprise information and also increase its interpretability. Formalization of concepts and relation can be offered through ontology development techniques to help in integrating in heterogeneous data environments [5]. This can be extended to the intelligent matching of ontology that conform and exploit learning and optimization to discover matches between conceptual dissimilar arrangements [6]. Semantic modelling process can also offer the contextual representations that complement the interpretation and re-use of the complex data [7]. These are most especially significant to automated metrics intelligence since performance indicators not only require the numerical value, but also require their business context, relations, time dimension as well as their meaningway.

Such data engineering co-existing with smart thinking data approaches can present new alternatives of smart enterprise systems. Knowledge based frameworks have explained the interest between software engineering and data engineering and how we should continue to amalgamate data processing and knowledge management [8]. Similarly, the analysis of complex datasets can be aided by connecting and visualizing complex datasets with semantic information with the assistance of knowledge [9]. These trends indicate that the combination of interrelated capabilities of inter-semantic knowledge, analytical reasoning and interactive visualization needs to be included in the repertoire of enterprise decision-support systems not as a distinct stream of data but as inter-relationship capabilities.

This architecture can be supported by AI that can automate various phases of the intelligence lifecycle. Machine learning systems have the ability to recognize past trends, spot abnormalities, categorize the state of operation and produce forecasts. The processing of semi-structured and unstructured enterprise data could be employed to retrieve information using natural language processing and the results of analysis steps could be interpreted using generative AI. The expertise knowledge would also be in the form of rules and can be incorporated into the decision-support environment: as illustrated in interoperable knowledge-based decision-support systems [10]. Knowledge interoperability and reuse can also contribute towards the uniform use of organization knowledge in the process of analytical activities [11]. - It can then be converted into context sensitive recommendations by recommendation mechanisms that convert analytical results into those used to drive action in a decision support enterprise more than it is to operate in a monitoring capacity [12].

Upon this ground, this paper hypothesizes an AI based Data Platform onto Automated Metrics Intelligence and Cloud based Enterprise Decision Support. The proposed framework brings together heterogeneous data ingestion, semantic integration of data, automatic formation of metrics, AI-based analytics, processing on the cloud, visualization, and intelligent recommendations into a system into one natural architecture. It is meant to improve the efficiency of manually sunning analysis, relieve speed, consistency, expansion and portability of business know-how. Linking grimeys organization data to measure and choice oriented data which is continuously generated, the proposed platform should establish an overall foundation on data competent administration of a business.

Related Work

The increasing volume, nature and speed of business information have brought the requirement of the smart system which has the capability of merging the divergent information sources, coming up with useful measures and helping to make timely business decisions. Majority of current literature has discussed such barriers in various schools of thoughts such as big-data analytics, cloud-based reporting, semantic interoperability, ontology-based integration, intelligent matching, visualization and decision-support systems. Nevertheless, these areas of research are still fairly disorganized, which provides a chance of integrating an AI-based data platform.

This process by which organizational data can be turned into actionable information is based on the big-data analytics. The overall discussion is the challenges surrounding big-data report on the problem of data quality, data storage, data processing, data privacy, choices of data scaling and data analysis methodology [1]. The issues are particularly topical in the sphere of enterprises, when the flow of resulting data is endless and passes through a great number of activities and other digital interactions. Another point that is highlighted in the article is the applicability of the analytics tools to derive the business value based on large amounts and complex data. Nevertheless, the classical forms of big-data analytics traditionally require a lot of human input into data preparation, set-up and exposition of analytics. This also generates the necessity of automatic platforms able to continually generate meaningful performance metrics and decision oriented insights.

Mobility of the clouds and automation is a notable trend towards the further enhancement of the metric generation and reporting. cloud-based automation has been contemplated to automatize ROI measures and reporting towards the eradication of manual reports and refined provision of performance data [2]. Such a solution demonstrates the usefulness of the integration of cloud infrastructure and automated workflows of metric-processing. In case of enterprise decision support, automated reporting might not be enough. This requires a modern platform to outdone the existence of set indicators and execute a sense of recognizing patterns, aberrations, trends and associations and turn it into actionable intelligence.

A second dimension of research is the data integration. It is proposed to use a unifying ontology to be implemented in the change of the big-data ecosystems, to address the problem of maintaining interoperability to the heterogeneous data environments that are continually changing [3]. The ontology based governance can offer a shared semantic base on which different data of an enterprise can be described in the same manner. Likewise, an ontology based framework to access, integrate and reason about data created by multiple sources has also been developed (distributed) [4]. The approaches can be effectively applied to the enterprise systems because organizational data is typically distributed within databases, applications, cloud computing solutions, documents and off-site. The ontology-based methods are however more oriented towards integration and reasoning as compared to the end-to-end automated metrics intelligence.

The other has been creation of ontology as a tool of semantic consistency during data integration process [5]. Partnerships between heterogeneous data elements can be achieved via formal conceptual structures and allow knowledge to be reused across the different analytic processes. This is also extended to intelligent ontology matching where provision of learning and optimization services are employed to determine the correspondences among ontologies [6]. It is especially useful when it comes to automated platforms within an enterprise since data might use disparate terminology, schema and a description of what can be a similar business concept. Semantic based mappings can thereby reduce the amount of mappings that are manually configured.

Research on semantic modelling has also been scrutinized in the name of reflecting intricate district specific data and possessing the ability of performing more efficient interpretations to heterogeneous data [7]. These types of semantic representations have a significant place in the context of intelligent analytics since without putting raw data into context, higher-order insights cannot be created. A knowledge-based software engineering/data engineering paradigm has also brought insight into the need to intrude on knowledge management and data-oriented development processes [8]. This view advocates evolution of enterprise platforms where data engineering pipelines are linked with knowledge representation and smart analytical services instead of being separate parts.

Visualization is another aspect of data-driven intelligence that is significant. The ontology based approach has shown how knowledge-assisted visualization may be used to help in explaining complex mobility datasets [9]. It implies that not only appropriate data integration and analytics is the efficient decision support, but also that the instruments of making the results of the analytical results clear in a comprehensible form. Enterprise applications might need a dashboard, automated notifications, trend summaries and contextual visualizations, in which case, the managers are more directly presented with the information related to performance.

The other fields where acquisition and representation of expert knowledge has been studied are in the field of decision-support. Interoperable clinical decision-support systems have been suggested to be based on a lightweight mechanism to obtain expert rules [10]. These rule-based methods demonstrate how the domain knowledge can be taken advantage of boosting data-driven analytics in the presence of contextual limitations to decisions or expert-



imposed policies. Interoperability and reuse of knowledge has also been analysed using ontology based method of understanding with regards to the value of semantic knowledge reusable in the intelligent systems [11]. The overall implication of these studies is that machine-generated insights can become competent to provide enterprise decision-support capabilities when they are combined, in harmony with organized knowledge in organizations.

The other intelligence that can be used is the recommendation-oriented intelligence. The recommender systems have been integrated with semantic information and social information to offer relatively contextual information in terms of recommendations [12]. Despite the variations in the field of use, the general rule of heterogeneous information and smart inference can be employed to implement the automated enterprise recommendations. Such mechanisms can support transitioning to using other systems rather than descriptive dashboards that may suggest actions that can be taken based on the conditions that being identified.

COGNITIVE METRICS FABRIC: AN AI-ORCHESTRATED CLOUD FRAMEWORK FOR ENTERPRISE DECISION INTELLIGENCE

The suggested structure is called the Cognitive Metrics Fabric (CMF) and is intended to convert the various enterprise information into a continuous process of generating metrics, analytical knowledge and recommendation-driven feedback. Evidence of a pipeline between the data sources and semantic interpretation, automatic measurements intelligence, predictive analytics and enterprise decision support is clearly demonstrated in the proposed architecture as compared to the traditional business intelligence architecture where the current use of fixed stream of data and fixed uses of dashboards are considered to be in operation. The cloud-native data services, artificial intelligence, semantic modelling, machine learning, and visualization are combined in the architecture to create a dynamic analytical space. The total layout is composed of seven layers which are interactive and they are data acquisition, cloud data foundation, semantic harmonization, automated metrics intelligence, AI analytics, decision intelligence and visualization and feedback.

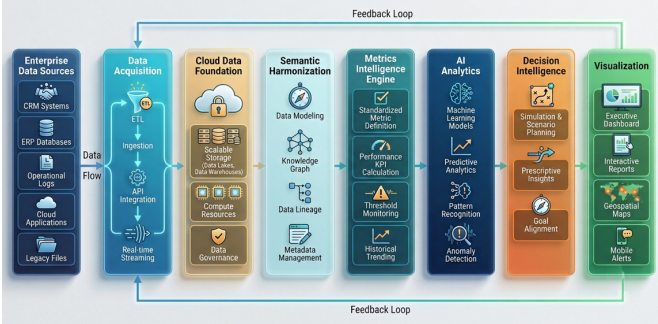


Figure 1: Overall Cognitive Metrics Fabric Architecture

Heterogeneous Enterprise Data Acquisition Layer

The latter layer assembles the data on the different sources of enterprises. These sources can consist of enterprise resource planning systems, customer relationship management systems, financial applications, human-resource systems, production databases, spreadsheets, cloud applications, and APIs, IoT devices, and document repositories. The framework allows delivering structured and semi-structured data to support situations where organizations are not obliged to have distinct analytical realms with different data styles.

A collection of activities that receive data which still flows in via batch and near time processes are referred to as data acquisition services. Incoming datasets are accompanied by metadata, the identity of sources, time and type of incoming data are presented, the frequency of update and ownership are also given. The missing values, duplication, inconsistent format, and abnormal entries, are checked, subsequently, by automated validation mechanisms. This early-age intelligence provides solid ground to rely on, where intelligence in the downstream will be constructed on.

Cloud-Native Data Foundation

Scalable cloud-based computing and storage infrastructure will be in the second layer. Depending on the type of a dataset, a hybrid data architecture can encompass such types of data structures as relational databases, data warehouses, data lakes, or object-based cloud storage. Scalable cloud environments have the ability to store operation information, which is needed most often and large data volumes and data history can be stored in optimally repositories.

Cloud Orchestration is dynamic in the way it allocates a computation resource to work of a given analysis. This will enable this platform to be scaled to growth or a downsizing of the size enterprise data without full provisioning the system to scale. The data processing services carry out data transformation, cleaning and aggregation steps and preparing of data and later transfer of information to the analysis components. The cloud foundation has security mechanisms, such as authentication, authorization,

encryption, access policies, and audit trails, to safeguard enterprise information.

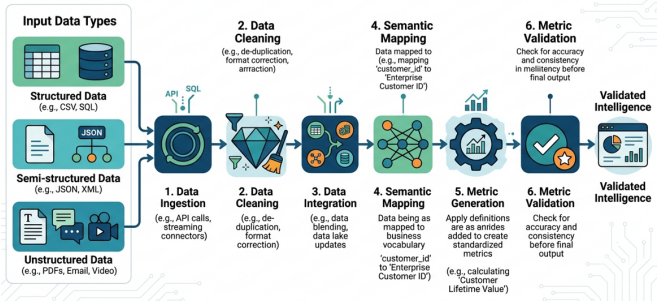


Figure 2: Automated Enterprise Data-to-Intelligence Pipeline

Semantic Harmonization and Knowledge Layer

One of the key aspects of the proposed framework is the semantic harmonization layer. Enterprise systems tend to be variant when it comes to names, format and definition of similar concepts. Indicatively, organizational systems might possess dissimilar expression of revenue, value of sales, customer value and value of transactions. Fully automatic measures may produce the incorrect meanings without the congruence in semantics to differentiate the meanings.

The framework maintains an enterprise knowledge model which has business ideas, qualities, associations, definition of measures that are applicable, business dimensions and contextual metadata. Ontology-based techniques build up relationships between the heterogeneous schemas, and support the semantic mapping. Based on the source attribute, and preexisting enterprise concepts, automated matching mechanisms can be used to determine similarities, which makes it unnecessary to map manually.

metric definitions and dependencies are also kept in the knowledge layer. The measures will be linked to every source data, business meaning, aggregation need and time based quality in terms of its nature and the dimensions related to a particular organization. This would enable the platform to distinguish between similar values that are different in the definition of the business but values of similar kinds in reality.

Automated Metrics Intelligence Engine

The fourth layer is most basic metrics intelligence engine. It does so in an effort to automatically calculate, monitor, identify and define enterprise performance indicators, to authenticate and place them in context. The engine does not need manually-configured dashboards; it has a constantly growing list of organizational measures.

The semantic layer provides the engine with standardized data that constitutes the operational, financial, customer, productivity, quality and resource related indicators based on the organizational requirements. Majority of the common features such as attributes and relationships can be automatically identified via metric discovery that can be used to create new indicators. Usually, metric validation services query the data availability, data consistency and data temporality and suggest anomalous changes to data, prior to the release of the metrics.

Dynamic monitoring of metrics is also carried out by the engine. The current values are compared to the historical values in a bid to determine the existence of any significant changes, new trend, aberrant variations and performance trends. Scales, consequently, may be distinguished with regard to their current level and business environment.

AI-Driven Analytical Intelligence Layer

Machine learning and AI on the generated measurements and existing enterprise data are the fifth level. Descriptive analytics provides a summary on the last and existing performance as compared to, diagnostic analytics seeks to explore association and potential reasons why changes have been noted. Predictive models make predictions of future metric behaviour based on previous patterns and the environmental variables.

Anomaly-detection models call attention to abnormal metric behaviour that might not be determined by pre-determined threshold conditions. The classification models can be applied to create similarities among the customers, business units, transactions or performance trends by classification and also the clustering approach can be applied to create similarities among transactions or between similar performance trends. Time-series models assist in predicting the demand, revenue, workload, resource usage and other measures, which vary with time.

Natural language processing can also be used to locate business information within the textual documents as a part of the framework. Other applications of generative AI may also include the generation of summaries of analytic results in natural-language, and presenting the user with a perspective of why a measure has changed and what causes of change should be explored by the non-technical user. Interestingly, produced AI works are linked with metrics and metadata, which would further traceability.

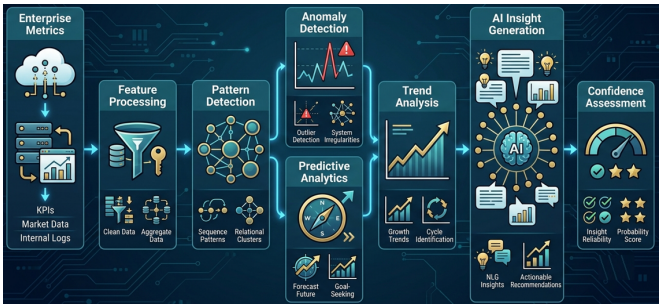


Figure 3: AI-Driven Metrics Intelligence Workflow

Enterprise Decision Intelligence Layer

The decision intelligence layer transforms the findings of the analytical process to information that can be consumed in

the enterprise. This layer does not show isolated numbers to managers, but the conditions of measures, predictive outcomes, presence of an organizational climate and established business regulations as relative to each other.

A recommendation engine provides context sensitive recommendations on the perception of trends, anomaly, forecast and organization policy. An example here would be the reduction trend in one of the operating measures that can prompt an investigation workflow, or a speeding up of work being scheduled can lead to a resource-planning suggestion. In such situations, the rule-based reasoning can be used to augment any machine-learning model, which means that organizational policies or domain constraints should be able to be captured by machine-learning models.

The confidence indicators and supporting evidence of AI-generated recommendations are also a part of the system. This will enable the deciders to differentiate among the observed items, model-generated forecasts, and the item generated on recommendation. To accept, amend or discard the recommendations is a question of human decision-makers hence the framework is supportive but not the entirely independent process of decision making.

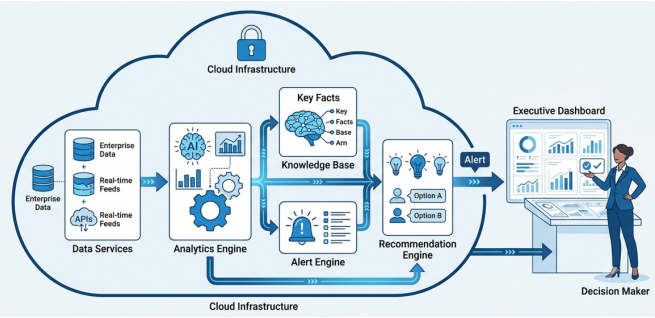


Figure 4: Cloud-Based Enterprise Decision Support Architecture

Visualization, Alerting, and Interaction Layer

The final interface layer provides natural-language analytical summaries, dashboards, metric cards, trend visualizations, alerts, reporting, and reports. Different positions in an organization will have an individualized view according to their positions. Detailed real-time indicators might be needed by the operational users, as compared to aggregated strategic metrics and forecasts that are required by the senior management.

A smart alarm system will focus on meaningful deviations and not show any notifications in the event of each measure being varied. An indicator on an organizational level can be further broken down to details on departments, processes or source datasets or past observations. Natural-language querying is also capable of supporting a user querying the information in business language as opposed to including database syntax.

Continuous Learning and Feedback Loop

Feedback with the analytics and metrics layers connects the decision layer to the other layers. The user-user interactions, product recommendation acceptance, and the business outcomes can give feedback on the definition of metrics, anomaly threshold, predictive models, the quality of recommendations further. Model monitoring services carry out frequent analyses of the model performance and determine the possible deterioration of the model.

Intelligence Validation and Enterprise-Scale Performance Assessment

The proposed Cognitive Metrics Fabric should be systematically tested in order to understand whether the given strategy would be able to transform the heterogeneous enterprise data to be converted into the appropriate metrics, analytical and decision support which can be translated into the practical actions. Measured performance in terms of the traditional measures should not be regarded alone, but in addition, the quality of data integration, significance of metrics employed, scalability to extreme scale, response, explainability and decision support effectiveness. This framework can then be assessed and determined by a mixture of scenario experimenting and quantifiable performance analyzes within an enterprise.

Data Integration and Semantic Consistency

A first evaluation dimension is the fact that the platform allows the combination of heterogeneous enterprise datasets. It is possible to add various datasets that have different schemas, format, naming convention as well as completeness on the platform. Measuring the success of integration can be achieved using schema-matching accuracy, semantic mapping accuracy, duplicate detection rate and missing-value handling and success rate of integration.

Semantic layer evaluation is combined with business alignment of semantically similar notions that are appropriately aligned in the various sources. The analysis is also able to determine the time taken to configure new sources of data as compared to the use of the previously manually configured integration pipelines. That the framework takes care of the interoperability issues would be a better automation of the mapping and less configuration work.

Automated Metrics Reliability

The metrics intelligence engine will be gauged on the ability to deliver effective and reliable performance indicators. A reference set is comprised of a set of checked enterprise metrics, which are manually checked. These reference values

may be compared to the automatically generated metrics with the various datasets and time periods.

It needs to be quantified with respect to metric accuracy, completeness, consistency and freshness and generation latency. Particular attention should be paid to the fact whether the platform can identify the data sources and what business dimensions it should generate measurements. It is also desirable to test on the system to understand whether the metric definitions will proceed in the face of any changes to the metrics before any enterprise processes can change.

AI Analytics and Anomaly Detection

Representative historical enterprise data on the normal and aberrant operating conditions can be used to assess the AI layer. Predictive models can be tested using appropriate measures of forecasting and classification and precision, recall and detection accuracy can be used to test the results of anomaly-detection.

The suggested AI-based approach has to be contrasted to the classic statistical surveillance and manually-designed thresholding mechanisms in experiments. The analysis would reveal how the AI-based analysis would detect certain deviations, which cannot be detected under predetermined thresholds of analysis. Another application of experiments in forecasting to obtain performance at different prediction horizons and levels of workload is possible. Incomplete, noisy and changing data should be considered as data model robustness.

Cloud Scalability and Processing Efficiency

Performance in clouds is highly important as the amount of enterprise data and workloads of analytics can increase dramatically. Such a schematic then needs to be tested about scaled amount of datasets as well as a few workloads of concurrent analysis. The most important indicators are processing time, response latency, throughput, resource utilization and scalability.

They might be performed in small (or smaller) workloads, medium (or smaller) workloads and large (or larger) workloads to find out how performance with processing would be in an environment where records size and analytic requests size are inflated. Elastic resource allocation also can be analyzed with regard to the consumption of resources in the times of low and high demand. The tests can identify the viability of the cloud architecture to be rolled out in an enterprise.

Decision-Support Effectiveness and Explainability

The last assessment aspect looks at the content of whether or not generated intelligence enhances the usefulness and interpretability of enterprise decision support. Performance degradation, the fluctuation of demand, resource constraint, and uncertainty in operations can be used to simulate representative business scenarios. The decision-makers can analyze the system-generated dashboards, alerts, explanations, predictions and recommendations.

The specific criteria of evaluation may be applicability of the proposed recommendation, alert penetration, flow of action and user satisfaction and expression articulation. To comprehend the human participants whether the contextualized metrics, along with the artificial intelligence-produced explanations, can be comprehended more quickly, the participants will be given an opportunity to compare the current traditionally employed reporting with the proposed intelligent platform. It is worthy of mentioning that the appraisal has to create a boundary between objective measuring output of the system and perceptions as perceived by the users.

Ablation and Comparative Evaluation

The value of separate items of the framework can be successfully tested using ablation test as well. They can be disabled allowing semantic harmonization because they can be, they can be created as they can be, they can be spotted as they can be, they can make predictions as they can and they can be counseled as they can. Differences in performance could inform the most powerful forces of the effectiveness of the overall platform.

The thing is all even supposed to be compared to report with identical datasets and workloads with the help of commonsense business intelligence pipelines and cloud-based. This sort of comparative analysis can reveal the existence of a quantifiable benefit of integrating semantic data management, automated metrics intelligence, AI analytics, and decision support in comparison to individual parts of the analytic system. A combination of these experiments offers a rich foundation of validating the accuracy, scalability, adaptability and usefulness of the framework by enterprise value.

Conclusion and Future Research Directions

Conclusion

This paper introduced a Cognitive Metrics Fabric a cloud-computing program of AI to convert all forms of enterprise data to autonomous metrics wisdom and decision-biased information. Architecture will incorporate data internalization and information processing and repository, which are supported by clouds, semantic harmonization, workflow to generate automated metrics, analytics through AI power, decision intelligence, visualization, and constant feedback, to form an efficient mechanism. Relationships among such functions have aided the solution in question overcome the shortcomings of enterprise reporting systems, in particular, automatic compilation of Data sets, a priori measures, fragmented analysis processes and rigid dashboard. Semantic layer allows them to have a standard

interpretation of the different enterprise data and metrics engine allows to continue its generation of organisational performances measures and monitor them. The AI-based analysis services which identify anomalies, provide predictive analysis, detect patterns and generate contextual insights are also backing the framework. Such analytical results are then converted into alerts, explanations and recommendations by the decision support layer which can assist organizational users to make operational and strategic decisions. Cloud core offers dynamism which is needed in order to dynamically manipulate the enterprise workload. The proposed framework is usually a down-sized way of relating the raw data of the business to the finalized information that by-turn signifies the bedrock of more mechanized, scaleable and responsive information-driven management.

Future Work

The suggested framework has several prospects to get extended. Future research can be done on generative AI and large language models to interface with enterprise metrics and enable people to query their organization performance by talking to their conversational interfaces. It is federated and can be privacy-preserving trained to assist analytics in an environment with geographically spread companies and it does not require full access to sensitive data. Continuous generated IoOT, transaction and operational data can also be experimented on real time stream processing in the future. Future research should engage automated discovery of metrics, where algorithms would continue learning measures of possibly useful performance metrics on changing organizational objectives and data. The explainable AI processes can be cemented to provide a clear illustration of the forecasts and suggestions. Finally, high-scale longitudinal experiments can be carried out in large volumes in high numbers of industries to test the framework at scale, with variable workloads and under different conditions of business and compare the accuracy, scalability, latency, resource usage and performance to facilitate decision-making to existing enterprise analytics platforms.

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