



Zero-Shot Transfer Learning for Cross-Industry BI Models

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ABSTRACT: Most Business Intelligence (BI) models are very industry specific and are thus hard to be reused in industries with divergent data models, business priorities and decision-making context. In this research article, Zero-Shot Transfer Learning of Cross-Industry BI Models, the authors discuss the application of the concept of zero-shot transfer learning that would allow BI systems to transfer knowledge in one field to another without the enormous volumes of labelled data in the target field. The suggested framework incorporates a trained base model, feature embedding without domain knowledge, semantic metadata embedding, prompt-based task-adaptation and cross-industry validity. The information in the source domain BI of retail, healthcare, financial, manufacturing and logistics is translated into a generic semantic representation in this model. The model then extends patterns learned to the unobservable scenarios in the industry based on the contextual embeddings and alignment of business ontology. This aids the system to implement the novel functions of demand forecasting, customer segmentation, risk prediction, anomaly detection and KPI recommendation with minimal retraining. The article finds the potential of zero-shot learning to reduce the cost of the model development, increase its scalability, and provide faster decision-making in a dynamic business environment. It also addresses important problems of domain shift, data heterogeneity, model interpretability, transfer of bias and trust of automated BI recommendations. The article concludes that zero-shot transfer learning can be an effective method to create flexible, reusable and intelligent BI models that can be used to cross-industry analytics. Future studies ought to concentrate on clarifiable transfer schemes, industry-specific assessment parameters, and the safe incorporation with enterprise BI systems.

KEYWORDS: Zero-Shot Learning; Transfer Learning; Business Intelligence; Cross-Industry Analytics; Foundation Models; Domain Adaptation; BI Automation.

I. INTRODUCTION

Business intelligence (BI) has been integrated as a critical part of the contemporary organisational managerial decision-making. The businesses in the industries use the BI systems to collect, process, analyse and visualise the information so that managers can make better strategic, operational and financial decisions [1] [2]. The traditional BI models are industry or business oriented. A retail BI model which can be used to examine customer buying behaviour, stock flow, seasonal sales, and sales forecast and a healthcare BI model which can examine patient flow, cost of treatment, resource utilisation and clinical risk factors are examples. In the same manner, the finance, manufacturing, logistics, education, energy, and e-commerce industries produce various types of data and demand the variety of types of analytical results. Due to this industry-specificity, BI models are usually narrow, with respect to the ability to transfer the knowledge in one industry to another [3].

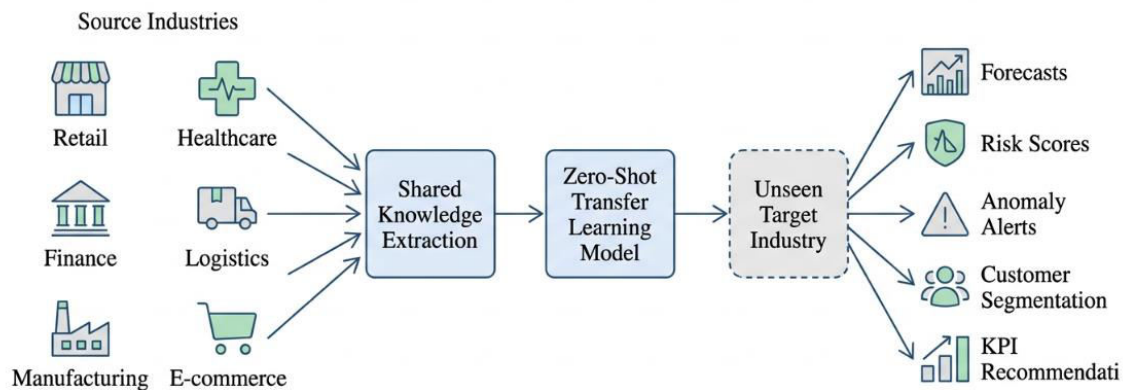


Figure 1: Conceptual Overview of Zero-Shot Transfer Learning for Cross-Industry BI Models

The past few years have seen organisations require BI systems which are scalable, adaptive and reusable in various spheres of business. The necessity to create BI models on a sector-by-sector basis is very expensive, time consuming and inefficient with the industries being more data driven. The classical BI model can often demand colossal amounts of labeled data, knowledge of the domain, data cleaning, feature engineering, model training, testing and deployment. This is an even more complex process when a business enters a new market, expands to a new industry or even when it is operating in multiple industries. In this instance the organisation might not have sufficient historical information in the target industry that would be able to produce a useful model. This poses a big challenge to cross industry analytics [4].

Zero-shot transfer learning is one way to get out of this dilemma. Zero-shot learning is a term that is used to refer to the capability of a model to be trained on a novel or unseen domain without being trained on particular samples on the domain to learn that domain. Transfer learning on the other enables the transfer of the learning in one task or field to another related field. With a BI model, zero-shot transfer learning can be used to transfer the learned knowledge in one or more source industries and convert it to a new target industry with minimal or no target-domain training data. The strategy is useful particularly in BI application since most of the business issues of the industries have some common percentage of similarities though the data structure and environment of operation in each application may vary [5].

The examples are demand forecasting in retail, patient admission forecasting in health care and production requirement forecasting in manufacturing all of which need the ability to forecast the future needs in relation to the previous trends, external influences and scarce resources. In line with this, customer churn prediction in telecommunication, patient dropout prediction in health care programmes, client attrition prediction in financial services are all busy in trying to discover behavioural patterns which are indicative of the risk of disengagement. The data sets and terms, which can be implemented in any industry, can be different, however, the analysis can be logical. With the help of zero-shot transfer learning that enables the semantic understanding, domain mapping and contextual representation, these general patterns can be detected and transferred to new business cases [6] [7].

The increasing application of artificial intelligence, machine learning, natural language processing, and foundation models has opened up new opportunities to cross-industry BI systems. Existing AIs have the capability to learn general representations by being trained on a large and varied set of data. These images can explain relationships between business concepts, performance indicators, customer behaviour, business risks and decision results. Zero-shot BI models accomplish this by using features that are domain-invariant and semantic embeddings to eliminate such strong industry-specific designs and permit more flexible analytics. This means that a BI system that has a training on diverse industries can bully new business problems via the deciphering of metadata, business description, KPI definitions, and context [8] [9].

The concept of cross-industry BI models applies as the modern business is hardly able to operate in closed industries. A big company can be running a retail, logistics, finance, supply chain, customer service and digital platform simultaneously. Likewise, healthcare organisations have the ability to conduct financial analytics, supply chain analytics, workforce analytics and patient experience analytics at the same time. The traditional BI systems tend to look at the areas separately, thus creating data silos and duplication of models. These limitations can be mitigated by zero-



shot transfer learning by creating reusable intelligence layers, which can be transferred to diverse business processes and in industry contexts [10].

Nonetheless, there are difficulties in implementing zero-shot transfer learning to BI. One of the significant issues is domain shift. The content of any of the industries can be different in form, sense, size, quality and value to business. What in one side of the industry would be a very important attribute, would not be a very important attribute in the other. The use of conversion rate in e-commerce where it can be used to imply online purchases as compared to the healthcare where it can imply patient appointment or treatment enrolment. Similarly, financial risk can be perceived to mean credit default, but could mean equipment failure or production delay in a manufacturing. Therefore, the most optimal zero-shot BI models ought to have exceptional business ontology semantic mapping and semantic alignment.

The other key challenge is interpretability. BI systems are utilized by managers, analysts and executives as they need to understand why a model has arrived at a certain insight or recommendation. In case a zero-shot model is applied to a new industry, they should be able to examine the logic that was transferred to the new environment in terms of its applicability. Such inability to explain it may lead to non-reliability of the output to the decision-makers, especially in sensitive fields, such as healthcare, banking, insurance, or government services. Thus, to render predictions, recommendations, and KPI interpretable and credible, zero-shot BI systems must incorporate explainable AI techniques [11].

Other important issues are the absence of data privacy and governance. Cross industry BI models can be trained/adapted based on the data of more than one industry and some of the industries might be business information of hidden nature or personal sensitive information. No exclusive information or transfer discriminative patterns within one area to the other should be involved in the transfer of knowledge to the structure. To support this, even though the customer segmentation patterns of a given industry might be trained using biased patterns, the forecast will be erroneous or biased in another industry. Therefore, good governance, security and fairness are an ingredient that should be considered in the development and analysis of models [12].

The research paper targets exploring the possibilities of zero-shot transfer learning to develop cross-industry analytics in the form of reusable BI models. It also proposes a model that is an amalgamation of pre-trained models, semantic metadata mapping, domain-invariance aspects of feature extraction, business ontology matching, prompt-based adaptation and performance validation. It is hoped to explore how knowledge can be generalised across industries and support decision making in the context of the invisible industry using the BI models. The research adds to the emerging area of intelligent BI by overcoming the shortcomings of the conventional domain-specific analytics and offering a more adaptable way of future enterprise decision systems.

Overall, zero-shot transfer learning can revolutionize the process of developing BI models by making them less dependent on big labelled datasets, cheaper to implement, more scalable, and quicker to deploy analytics to industries. As organisations compete in more and more complex, data-rich and dynamic environments, cross-industry BI models can offer a truly formidable platform of flexible and smart decision-making. This kind of introduction generates the need of such models and the basis on which a further discourse of the provided framework, methodology, evaluation, challenges and directions of research are to be introduced.

II. BACKGROUND

2.1 Evolution of Business Intelligence Models

The Business Intelligence has now become more advanced than the mere reporting systems in that it can carry out intelligent decision-support services on the structured and unstructured data in large amounts. The past BI systems were majorly focused on dashboards, historical reports and descriptive analytics. Such systems assisted organisations to know what had taken place in the past like the levels of sales, customer behaviour, efficiency in production or even financial trends. However, BI has developed to predictive and prescriptive analytics with the growing popularity of the artificial intelligence and machine learning. The existing BI models can predict the demand, risk detection, prescriptions, anomalies and aid in the strategic planning.

This is despite the fact that, as of now, most of the BI models are business industry or business specific models. The model created to predict retail sales would not necessarily be used in the healthcare resource planning or manufacturing risk analysis since data format, terminologies, performance measures and decision rules in the two industries are



different. This will also introduce a necessity of having more flexible BI systems that can tap into the knowledge of industries.

2.2 Limitations of Industry-Specific BI Models

The traditional BI model construction is based on feature engineering which is a feature engineering that is directed by domain specific data and expert-managed feature engineering. In the case of any new industry the organisations usually have to gather all historical data, clean, label, train the model, verify its accuracy and customize the model to the needs of the business. It is a process that is time consuming and requires technical knowledge, investment and maintenance.

The problem is even more severe when an organisation gets in a new industry or even a new market where one cannot find many labelled data. One case of the scenario is that as a logistics company enters into the healthcare supply chains, it may have insufficient information on the issues that are unique to the healthcare to apply it in training an effective BI model. Likewise, insurance, retail or education might not fit into a financial analytics model without significant modification. This has helped to achieve low reusability, low scalability and low speed of deployment of industry specific BI models.

2.3 Concept of Zero-Shot Transfer Learning

Zero-shot transfer learning provides this solution as the models can be applied to address unseen domain problems even without being trained on particular examples of that domain. In this method the model gets acquainted with more general patterns in the source domains and generalizes them in a new domain with assistance of semantic comprehension, contextual embeddings and task descriptions. Zero-shot models utilise the learned correlations between concepts in comparison to using labelled data only.

It can be applied to the BI context in that a trained model based on business patterns in other businesses like retail, finance, manufacturing or logistics can be applicable to a new industry by finding similar decision structures. The example is the customer churn, patient dropout, supplier failure and employee attrition could be in any industry, but all of it comes with risk prediction that is based on behavioural or operational indicators.

2.4 Need for Cross-Industry BI Models

The value of cross-industry BI models is increasing as the contemporary business establishments are interconnected with each other. One company can be selling/financing/controlling supply chain/customer support/managing workforce/digital, all at the same time. It is more cumbersome and expensive since individual models are developed in regions.

Zero-shot transfer learning would also become useful in creation of reusable BI intelligence that would be applicable in other industries. By mapping business-specific information onto a common semantic space, the model can learn about the common business problems, and be used to create valuable information in novel situations. It makes BI systems more flexible, economical and can be applicable in dynamic business environments where quick decision-making is critical.

III. FRAMEWORK FOR ZERO-SHOT TRANSFER LEARNING FOR CROSS-INDUSTRY BI MODELS

3.1 Overview of the Framework

The suggested system of Zero-Shot Transfer Learning of Cross-Industry Business Intelligence Models will allow transfer of knowledge of analytical tasks between industries to BI systems without having to provide huge quantities of labelled data on the target domain. The classical BI models are typically trained in a predetermined industry set up in which the information structure, key performance measures, business rules and decision objectives are predefined. In cross-industry contexts, however, the model has to obtain foreign terms of business, new data forms, new terms of work and hidden work of analysis. The proposed framework is used to solve the problem by means of the incorporation of pre-trained foundation models, semantic data representation, domain independent feature extraction, business ontology alignment, prompt based task adaptation, and performance validation.

The principle behind the framework is that on the surface, various industries might seem dissimilar to each other, but in actuality the business intelligence issues that might be involved are usually alike. An example is the customer churn in telecommunications, patient dropout in healthcare, loan default in finance and supplier failure in manufacturing all prediction problems, which require the risk identification. Likewise, sales forecasting, inventory forecasting, patient admissions forecasting and production planning are also interested in predicting the demand in the future. The



framework thus tries to find shared patterns in analytical activities throughout industries and apply them to new areas via semantic cognition as opposed to explicit supervised learning.

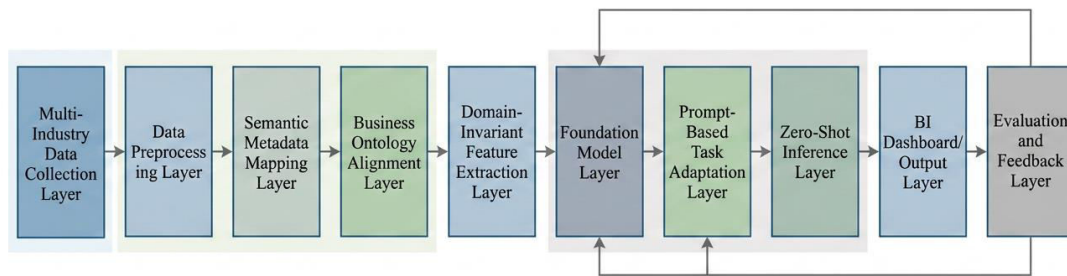


Figure 2: Framework Architecture

3.2 Source Industry Data Collection Layer

The initial layer in the framework is the source industry data collection layer. It is a layer containing historical BI data of various industries like retail, health care, finance, logistics, manufacturing, education and e-commerce. Such datasets can include the sales records, customer transactions, the supply chain records, financial risk indicators, records of hospital resource utilisation, production records, records of operational performance.

The objective of the multiple source industries is to subject the model to the different business conditions. The model lacks the skills in one area, and develops an overall understanding of the business processes, decision variables and performance outcomes. The data in the source can either be structured, semi-structured or unstructured. The formatted data are in numerical tables, transaction data and KPI dashboard. Semi-structured data are XML files, JSON records, system logs. The unstructured data is the business reports, customer feedback, support tickets, management notes and text description of business problems.

Prior to the data being used to learn, it undergoes cleaning and standardisation. The values that are missing, duplicated and discrepancy in units are handled, noisy data and irrelevant features are eliminated at the stage. It does not deal with transforming all the industries into a similar format but by allowing them to be learnt by semantically mapping and representing them.

3.3 Semantic Metadata Mapping Layer

The semantic metadata mapping layer is the second layer. It is also one of the most crucial sections of the framework since the column names or the raw feature labels cannot be used as the basis of the cross-industry BI models. The same idea can be manifested in various industries by various names. An example of customer retention in retail industry is the same as patient retention in the medical industry or subscriber retention in the telecommunication industry. Equally, retail inventory delay could be associated with either manufacturing supply shortage or inventory logistics risk.

In this case, the industry specific variables are mapped on a generic semantic model. Conceptual similarities are identified by metadata like column descriptions, KPI definitions, business glossary words, process description, and domain labels. It is combined with the models and natural language processing methods to convert business terms to semantic vectors. These vectors help the system to be aware that different terms can be used to refer to similar business functions.



An example of using the framework is that there is a variable, abandonment rate of treatment, in a target industry, which can be used with the framework to correlate the notion with an already-learned notion, like which is customer churn, service cancellation or program dropout. This kind of semantic mapping allows the model to induct knowledge on the new yet related concepts with the aid of the familiar concepts.

3.4 Business Ontology Alignment Layer

The framework uses business ontology alignment layer following semantic mapping. A business ontology is the structured business concepts, relationships, entities and processes. It provides a spelling of the relationship between the concepts of customer, product, service, risk, demand, revenue, cost, resource and performance to each other.

In this framework, ontology alignment helps to overcome the gap that exists among industries. It can be used to speak about the fact that a customer is a type of service receiver, a patient is a type of service receiver, a client is a type of service consumer and a subscriber is a type of service consumer in case of retail using the ontology. Similarly, the product demand, the number of beds occupied, the number of loan applications and the amount of the shipment can be put as the subordinates of the umbrella term of resource demand.

This layer enhances transfer learning since the model does not merely compare the fields of raw data. Instead, it is aware of the connection between business organizations and processes. It is also easy to explain ontology alignment as it demonstrates the reasons why the knowledge in one industry can be transferred to another industry. To illustrate, the framework can be applied to explain the fact that a task in healthcare resource prediction is related to retail demand forecasting as they are both time-based demand forecasting, resource planning, capacity management.

3.5 Domain-Invariant Feature Extraction Layer

The domain-invariant feature extraction layer is the next layer. This layer is supposed to discover features that can be utilized within the industries. The traditional BI models can be very domain specific. However, inter-industry transfer presupposes similarities which are the description of similar business trends.

Examples of domain-invariant features are trend direction, seasonality, frequency of interaction, delay patterns, risk signals, transaction intensity, resource utilisation rate, growth rate, volatility, anomaly score and behavioural change indicators. As an example, it is possible to mention the speedy decline in the purchases rate in retail and the speedy decline in the attendance rate in the healthcare as the indications of the threat of disengagement. Similarly, non-periodic behaviour on payment in finance and non-periodic behaviour on delivery in manufacturing might either be indicators of risk of reliability.

These general features are extracted by the framework on the basis of the data of the source industry and stored in a common representation space. The similarities between datasets are found with machine learning and deep learning models. This is to minimise the application of labels which are industry specific and optimize the generalisation of the model to the unknown regions.

3.6 Foundation Model and Representation Learning Layer

A foundation model and a representation learning layer are then employed using the framework. The foundation model is a model which is pre-trained and is the source of intelligence of the system. It is conditioned on the corpus of large business, numerical, textual and operational data in a way that it is able to learn patterns in various industries.

This layer converts data, metadata and business descriptions into contextual embeddings. These embeddings refer to mathematical models of meaning of business variables, tasks and relationships. E.g. the model can be trained to know that the forecasting tasks can be of different types such as predict next month sales, forecast hospital bed demand and estimate production requirement.

Representation learning enables the model to cluster like business problems near each other in the embedding space. This makes zero-shot transfer possible. Problems in a new target-industry are all injected into the model and a new task representation is compared with the existing source domain representations and the most transferable knowledge is used to solve the problem.

3.7 Prompt-Based Task Adaptation Layer

The task layer is easily adapted and the model can be utilized to complete BI tasks in new industries without being re-trained. Instead of labelling examples to re-train the model, the user simply provides the description of the task,



business scenario, the variables available and expected results, and trains the model. This information is used in the model to comprehend the objective of analysis.

The next prompt can be a sample of what can be typed by a user: Predict the risk of patient non-attendance to appointment based on demographic, appointment history, and communication data. This healthcare task might not have been explicitly trained on this healthcare task by the model, but it can be related to related source-domain issues such as customer churn, non-use of services or cancellation of subscriptions.

Prompt-based adaptation can be of particular help to BI since business users can tend to formulate problems using natural language. Some of the questions that the managers might ask include: What customers are prone to cease purchase? Who will be able to delay the supply of a supplier? Which department is able to exceed its budget? The structure translates these prompts into machine comprehensible representation of the task and compares it to the knowledge that is learned.

3.8 Zero-Shot Inference and BI Output Layer

The model is made at the zero-shot inference layer to make predictions, classifications, recommendations or insights to the target industry. Since the model is not premised on the labelled target-domain training data on which it depends on semantic similarity, ontology relations and acquired domain-invariant features to find the most plausible outcome.

Output can consist of demand forecasts, risk scores, anomaly alerts, customer or user segments, KPI recommendations, operational alerts and decision support recommendations. The system will be in a position to detect the potential risk of shipment delay in a new logistics company on a pattern of manufacturing disruptions, retail stockouts and bottlenecks within the supply chain.

BI output layer is the presentation of the output as dashboards, reports, visual analysis and decision support summaries. The outputs should be simple to read and comprehend and actionable as the users of BI may not be technical professionals. The system should not only have to make a prediction but it should further give the most significant reasons as to why it made a prediction.

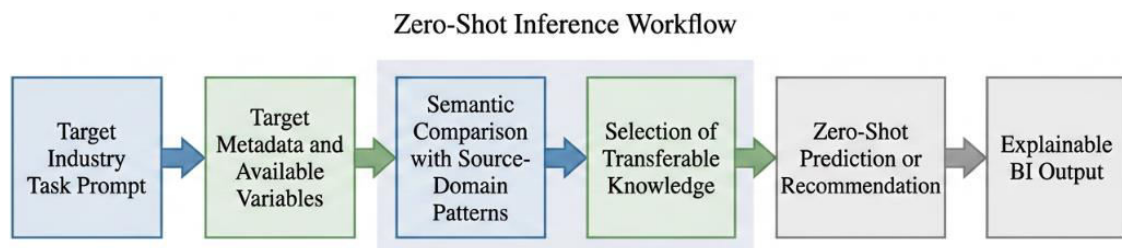


Figure 3: Zero-Shot Inference Workflow

3.9 Explainability and Trust Layer

Explainability is one of the significant considerations of the framework. Cross industry BI models can be viewed with skepticism in the possibility that the users are not acquainted with how the knowledge has been relayed in a different industry. By so doing, the framework will be supported by an explainability and trust layer to be able to give articulate explanations on model results.

These answers to the question where the patterns of the source domain had been applied, what target-domain variables had been matched and why were to be found in this layer. In order to demonstrate this, a model that forecasts patient dropout using the patterns with which it has learned to engage with the customer should clearly indicate that the two processes are, frequency reduced engagement, delayed response, missed interaction and declining engagement.

Explainability enhances the degree of user trust, managerial decision-making, and minimizes the risk of uninformed trust of automated outputs. It particularly applies in sensitive areas like healthcare, banking, insurance, public services and education.



3.10 Evaluation and Feedback Layer

The last layer is called evaluation and feedback layer. Although the early phases of zero-shot models do not involve any labelled target-domain data, it also needs to be monitored once deployed. As data of the target-domain are made available, the system can be utilized to verify the accuracy of prediction, relevance, equity and business usefulness.

Task-specific metrics like accuracy, precision, recall, F1-score, mean absolute error, root mean square error, anomaly detection rate and business impact indicators can be used to measure performance. Manager and analysts feedback is also received to enable it to make future recommendations better. In the long-term, the model can be adapted to few or continuous learning and the target domain may have a small population of examples to optimize the performance.

IV. PERFORMANCE EVALUATION

4.1 Evaluation Objective

The suggested Zero-Shot Transfer Learning of Cross-Industry BI Models framework is discussed in relation to the performance of the model transferring the knowledge between the industries that cannot be observed, but do not require labelled training data on the target domain. That the overall objective of the framework is cross-industry generalisation implies that the analysis will not be premised on the accuracy only. It should also decide the adaptability, interpretability, reliability and the usefulness to the business. The evaluation procedure will ensure that the model is able to comprehend industry-specific vocabulary appropriately, analogous corporate issues in various industries and produce useful BI outputs like forecasts, risk ratings, anomaly alerts and segmentation outcomes, and KPI propositions.

4.2 Evaluation Dataset and Experimental Setup

Data sets of other industries sources (retail, healthcare, finance, logistics, manufacturing, and e-commerce) can be assessed using the framework. The invisible target in both experiments and the other industries are considered as the source domains. The model could be pre-adapted or trained on retail, finance and logistics data and trained on healthcare data without target-domain labelled training as an example. It is possible to use this mapping to approximate the real transfer of the model in zero-shot.

The only data tested and validated is the target-domain data. The model is fed with business variables, metadata description, definitions of KPI and task prompts are given in a way that the model can draw inferences based on semantic mapping and features that are domain-invariant. This design makes sure that the performance of the model is based on its capability to generalise, as opposed to memorising industry-specific patterns.

4.3 Evaluation Metrics

The evaluation measures of various BI activities are different. These metrics, accuracy, precision, recall, F1-score and ROC area under the curve, may be useful measures to apply in tasks based on classification, e.g. churn prediction, risk detection, or anomaly classification. Mean Absolute Error, Root Mean Square Error and Mean Absolute Percentage Error are metrics that should be used when it comes to predicting such activities as demand forecasting, sales projection or resource planning.

The statistical measures will also be taken into account along with the business performance indicators. These might be a faster decision making, reduction in the number of manual analyses, risk identification in time, predictability of generated forecasts and applicability of generated recommendations. Improved business value since in practice the BI models support the decision of the manager, the performance of numerical models is equally important.

4.4 Baseline Comparison

The suggested framework will be compared with the traditional industry-specific BI models, rule-based BI systems, and the traditional transfer learning models. The classic model which is supervised can be helpful in cases where there are many labelled target-domain data, but not in situations where there are few target-domain data. Conversely, zero-shot framework ought to excel in new or data-sparse companies because it makes use of semantic knowledge transfer and ontology alignment.

Comparing it with the base would help in finding out whether the framework is actually improving the scalability, flexibility and successfully deploying it.



4.5 Interpretability and Feedback Evaluation

Testability of models can be done by testing the ability of the system to provide clear-cut explanations on how a given source-domain pattern was applied in the target industry. The user can get a feedback on the clarity, trustworthiness and actionability of outputs demonstrated by the BI analysts, managers and domain experts.

Overall, it can be said that performance evaluation should show that the framework is technically valid and reliable as well as transparent and cross-industrial business decisions.

V. CONCLUSION

The authors highlight the importance of zero-shot transfer learning as a potential approach to develop reusable cross-industrial Business Intelligence (BI) models in this research article. The classical BI systems will most likely be limited with the utilization of industry-specific data, labeled training samples and manually-defined features. The models, however, are difficult to navigate in and out of the industries especially when organisations are shifting to new markets or when organisations are operating in the world of data. In order to address this weakness, the proposed strategy will allow the BI models to utilize the knowledge gained about the source industries in the unobservable target industries without necessarily going through numerous retraining processes.

The analysis shows that the majority of business problems in the different industries are similarly analyzed. An example of such an aspect is that the customer churn, patient dropout, supplier failure, credit risk and employee attrition can be different at the domain level but all of them are where the risk is forecasted based on behavioural or operational indicators. Similarly in the retailing, the production forecasting in manufacturing and the resource planning in health care, the demand forecasting, resource planning and production forecasting are similar in their pattern of decision. Semantic metadata mapping, ontology alignment, and domain-invariant feature extraction and prompt-based adaptation can be used to learn such common structures in zero-shot transfer learning.

The framework suggested gives a structured procedure of the way to develop cross industry BI models. It integrates the source industry data collection, semantic representation, learning in the foundation model, zero-shot inference, explainability and feedback-based evaluation. This makes the framework useful in making forecasts, risk scores, anomaly alerts, KPI recommendations and decision-support insights in new business environments. It also helps in saving time to develop the models, minimises the implementation cost and maximises scalability.

However, the most crucial issues, which need to be resolved to make it work are the domain shift, data heterogeneity, interpretability, privacy, and transfer of bias. Before using the model to make strategic decisions, its users need to be in a position to comprehend and trust the model results. As a result, the emerging lines of the future research are explainable zero-shot learning, data governance, industry-specific benchmark datasets, and continuous feedback. Combined, zero-shot transfer learning can make the next-generation BI systems more flexible, intelligent and helpful in a much greater scale.

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