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Automated Solution for Order-to-Invoice Mapping using NLP and DNN

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Dear Readers,

From the Editor's Desk

Greetings and welcome to the second volume of Feedforward, the flagship publication of the IEEE Computer Society, Santa Clara Valley chapter.

Our chapter holds the distinction of being the largest in the Silicon Valley Section of IEEE, with an impressive subscriber base of over 4,000 on our mailing list, more than 1,400 paid members, and a strong following of over 12,400 on Twitter. The proximity of our chapter to Silicon Valley, a leading innovation hub, positions us uniquely and gives us access to valuable expertise. We can play a crucial role in driving global economic and societal progress, and we are committed to doing so.

This volume features a cognitive solution for enterprise service providers to streamline the management and mapping of PO and invoice data. The method leverages a multi-task deep neural network and natural language processing to automate the search and mapping process, resulting in higher accuracy and efficiency compared to existing methods.

The articles in this volume of Feedforward reflect our international vision, featuring cutting-edge topics and authors from diverse geographic locations. We welcome submissions for future issues related to the IEEE Computer Society charter, with a preference for articles that relate to Silicon Valley. To submit your articles, please visit our website at https://r6.ieee.org/scv-cs/?p=2036

In addition to our flagship publication, we have organized and co-sponsored various events this year, with many more in the pipeline. To stay updated, you can find the list of upcoming events for March on our website at https://r6.ieee.org/scv-cs/?page_id=2030 . We encourage you to join our mailing list, follow us on social media, and participate in our events, as they often attract attendees from around the world, including from as far away as Thailand.

Networking is a vital aspect of professional societies, and we are committed to facilitating these connections. That's why we are planning to host an in-person chapter open-house and broadcast it live on YouTube and Zoom. You can view past events on IEEE.tv at https://ieeetv.ieee.org/search?search_q=scv-cs and on YouTube at https://www.youtube.com/playlist?list=PLLsxQYv4DdJlYcGPwqUJsnHmfqMtB3eSJ

Finally, we are seeking volunteers to help us in various roles, such as reviewing articles and papers, guest editing special issues, organizing conferences and events, and assisting with publicity. We invite you to join us and help make our chapter a success story. Please sign up at https://r6.ieee.org/scv-cs/?p=2039 . With the onset of the Spring season, let's move the chapter forward into a bright future. We appreciate your ongoing support, and we hope you enjoy reading this volume of Feedforward.

With every best wish,

Monday, March 28, 2023
Meenakshi Jindal San Jose, California, USA

Financial Services Data Extraction and Integration

Automated Solution for Order-to-Invoice Mapping using NLP and DNN

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Abstract—Enterprise service providers process thousands of contracts and purchase orders (POs) each year. A PO is a document that includes details of the sale of services or goods, total billing, PO validity period, and payment terms. Given the cost and effort involved in monitoring and mapping millions of PO records, many providers seek to streamline the process to efficiently manage PO and invoice data. However, there is a lack of uniformity in maintaining the data elements across departments and systems as business processes may be disconnected. Typically, these datasets are maintained by disintegrated systems which aren't connected to each other. Lastly, incorrect POs can be generated from expired contracts and duplicate invoices, thus creating obstacles to comprehensively mapping POs and invoices. Mapping POs and invoices help providers proactively perform dispute detection in the POs.

In this work, we develop a cognitive solution that automatically trims down the search space of invoices and maps them to corresponding POs. The method aims to group the large set of invoices into clusters and apply a multi-task Deep Neural Network (DNN) model for each cluster to further trim them down until finding one reasonably small set of invoices (or the invoice) with the highest matching probability of a single PO. Further, we utilize Natural Language Processing (NLP) to map the trimmed-down set of invoices to PO more accurately. We illustrate the method with an implementation from the toolset that we have built. The accuracy and efficiency of our method are reasonably higher than the existing prior art.

The financial services data including purchase orders (POs) and contracts are maintained by service providers through various systems. The data contains information about the services or goods offered to customers. To efficiently manage and monitor this data, it is necessary to be able to match the orders to invoices billed and settled by the customer. Ideally, invoices generated for billing would be coupled with the PO data. They would be stored in the same data warehouse as POs and would have straightforward matching. However, we have observed different challenges for enterprise service providers in maintaining this ideal scenario. This article addresses these challenges by proposing an innovative methodology and shows its efficacy through its implementation. Section 1 discusses the background and challenges. Section 2 talks about the prior art and knowledge gaps. Section 3 introduces the overall methodology. In Section 4 we provide an example use case. We conclude this paper and present future work in Section 5.

1. BACKGROUND AND CHALLENGES

We define the challenges faced by enterprise service providers in their financial data below:

Firstly, PO data is typically maintained by different business teams in various data warehouses. They are maintained separately from the invoices billed and settled data. Second, as business units increase, key definitions of PO data may not be consistent across all organizations. The management of invoices data may digress from the PO data, wherein the billed information would rely on services usage by the customers and would not be aligned with the PO data. Third, the PO and invoice data maintenance and integration are costly and time-consuming. Even if one set of POs is mapped to invoices, the same mapping rules may not apply to another dataset. The fields in the datasets may change dynamically over time too. Hence, there is a need for an automated system that can analyze the features in the datasets to provide the mapping between them.

Mapping POs to invoices is critical for enterprise providers who need to manage their life cycle and avoid any risk of PO amount depletion before the end of the PO duration. The mapping process takes place during the online invoice approval process to ensure timely supplier payments, correct accounting of costs, and easy detection of fraudulent practices.[1] Additionally, with PO mapping controls, suppliers prevent fraudulent invoicing or duplicate invoicing for the receipt of the same goods.[2] This is a complex, high error rate, time-consuming, and resource-heavy task.

In the past few years, some processes have been streamlined to address some of these challenges. As stated in a multi-way matching method, once POs, receipt reports, and invoices are all in the system, 2-way matching, 3-way matching, and even 4-way matching will occur automatically.[2] If something does not line up, it will be flagged, and notify someone to review and solve the issue before making payment. If the multi- way matching process goes smoothly, the customer can take advantage of early payment options during invoicing. These positions the customers in such a way that they can leverage discounts to save money on future PO.

Despite the streamlined processes, the challenges that arise when dealing with invoices with missing data make mapping POs difficult, and the current state of the art does not address these gaps. First, the existing multi-way matching approach requires the prior knowledge of agents to know well of the terms in invoices and POs, so that they can define the “ways” or the common terms to match.

Second, as mentioned above, service providers usually manage PO data separately from invoices in the end-to-end order process. The supplier provides a PO to the customer for approval; however, an invoice is the payment request generated by the customer to the supplier after the order is delivered. Third, PO and invoice information is written in unstructured natural language texts that need to be extracted, parsed, and cleaned to structured data. Lastly, extracting significant and discriminating features from high dimensional dynamic PO and invoice data requires real-time computation to keep data up to date. In addition, most of the current works focus on building graph-based data matching and are harder to adopt by other supportive data warehouses.

We present a novel framework in the area of the financial services industry where we trimmed down the search space based on significant invoice features. Multi-task learning is used in which Deep Neural Network (DNN) models are trained with data from multiple tasks simultaneously, using shared representations to learn the common ideas between a collection of related tasks. These shared representations increase data efficiency and can potentially yield faster learning speed for related or downstream tasks. In this framework, we automate the PO and invoice mapping through multi- task learning of data features and then mapping tasks. Our proposed methodology comprises four key steps:

1) Apply the clustering algorithm to invoices for each line of business.
2) Construct the multi-task DNN on the set of invoices.
3) Construct the single-task DNN to map invoices to one PO.
4) Conduct text mining by Natural Language Processing (NLP) on item-level services in the PO and invoice.

2. PRIOR ART

An overview of criteria for the standard multi-way matching based on a small set of features has been done.[1] An extension has been done wherein it acquires the settlement invoices list, along with billed entry invoices, and matches them to orders based on a fixed set of features.[3] Bhatt et al. propose an automated framework that converts invoices into structured templates, organizes data as key-value pairs, and trains a machine learning-based duplicate detection algorithm to identify mapping duplicated invoices.[4] Similarly, Sun et al. propose a method utilizing image processing techniques to intelligently identify invoice information based on template matching.[5] Optical

Character Recognition (OCR) and computer vision are utilized to extract invoice information to match POs data.[6–7] Deep learning is a possible solution for realizing intelligent PO-to- Invoice mapping technology due to its many successful applications in many fields. For example, research work on automatic detection and faster extraction of features has been done.[8–10]

The framework we propose contributes to prior works in several ways: 1. the matching is based on top relevant features in invoices and POs; 2. utilizing DNN modeling method instead of OCR to match important, relevant features of invoices to PO, and the service level items being billed; 3. the models define the features to match according to historical data. Compared to the existing methods utilized in deep learning, our method extends the notion of in- voice feature extraction to matching based on different features. Block-chain-based solutions introduce invoice financing risk mitigation systems that provide transparency in invoice data. [11–12] However, this calls for a burgeoning scope to create a system leveraging different aspects of public, and private block-chain along with storing confidential, dynamic invoices data to create a more trusted PO-to-Invoice mapping process. Compared to this, our method is more efficient and has less overhead work required to prepare the end-to-end mapping.

3. METHODOLOGY

Overview of the Method

This method aims at providing a cognitive solution to trim down the search space of invoices for PO's. Inputs to our method are: 1) a set of invoices, 2) PO data, and 3) historical data maps (learning of data patterns, mapped elements, etc.). Note that the inputs may also include a different set of features pertaining to the use case. We cluster the invoices for each line of business and then utilize the multi-task DNN to cluster invoices into smaller sets of invoices. Next, we utilize the single-task DNN to perform the mapping between invoices to PO. Lastly, NLP-based text mining is leveraged to perform item-level services matching between PO and invoices. The output of our method is the matched order-to-invoice mapping. In the next section, we elaborate on the methodology.

Detailed Steps of the Method

In this section, we provide a detailed description of the four different steps of our method.

Perform clustering on invoices We receive invoice datasets including terms from the user (e.g., line of business, geography, customer type, and items in- voiced). The k-means clustering algorithm is leveraged to cluster invoice data into certain attributes which are user-defined, easily confused, and vary from the invoices by context.[13] For example, the geography of the supplier, and the geography of the billing address. In this step, we first specify k clusters to assign where k is randomly initialized. For each invoice, the invoice features are mapped based on the attribute and assigned to the closest centroid. To maximize the cluster, we compute a new centroid for each cluster until the centroid positions do not change. The k-means clustering algorithm frequently converges on clusters with centroid and the minimum number of m data points.

Construct the multi-task Deep Neural Network (DNN) Models In the next step, we build the multi-task DNN model on the dataset of invoices per cluster. The multi-task learning can help the DNN model focus its attention on those features that matter while further trimming down the searching space. The feature importance can be quantified by the "number of occurrences" or qualified by a unique "statement" from historical invoice data. The features can be, for example, the statement of country, brand, or services offering. Under each task, there are several feature layers for invoices. Some features are easy to learn from some tasks and some layers while being difficult to learn from the original invoice dataset. Therefore, we utilize multi-task learning on the original invoice features and then on the features defined from a trimmed or regrouped set of invoice data from the previous task.

In Figure 1, we see three tasks are the dense networks that take as inputs invoice data features, and we get a multi-task network with loss functions. Using the greedy search method, we start with a thin net- work and dynamically widen it greedily during training using a criterion that promotes the grouping of similar invoices. While searching from bottom to up, we adjust each layer's relative weight in the cost function by deriving a multi-task loss function with task-dependent uncertainty to quantify each model's performance. With the above multi-task DNN model, we get the output of trimmed-down sets of invoice data as shown in Figure 1.

Construct the single-task DNN to map invoices to PO Next, we import the PO dataset for layer-to-layer feature mapping of the trimmed-down sets of invoices.

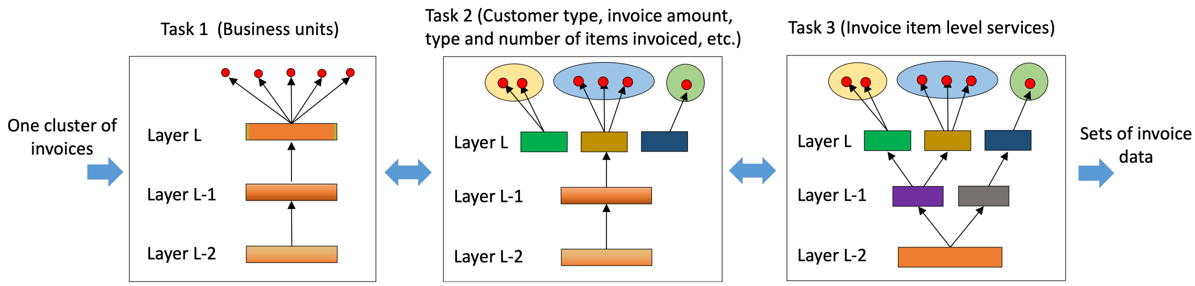

FIGURE 1. Training the multi-task DNN models on clusters of invoices. The three related tasks are learned simultaneously layer by layer of the shared features.

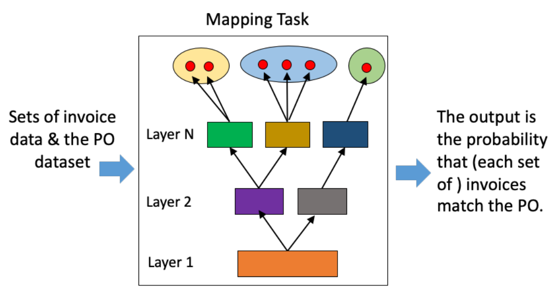

FIGURE 2. Training the single-task DNN model to match invoice(s) to PO.

PO features include i.e., PO duration, status (whether active, draft, expired, etc.), PO Line of business, and billing frequency. The PO features are ranked based on the historical feature importance ranking. The task-dependent uncertainty function is now employed in a DNN model as the reference of PO-to-Invoice mapping. Figure 2 shows the task outline trained using the DNN. The output is the probability of each invoice (set of invoices) matches the PO. Usually, the set of invoices or the invoice with the highest matching probability will be picked.

Perform text mining on item-level services in an invoice and PO Sometimes, we find more than a single invoice match to the PO from the previous step. We resolve this matching by working at the item-level services level for the set of invoices. POs and invoices have item-level services or goods in a textual format that can be used for more accurate matching. To be able to do better matching, we can utilize a rule-based NLP model to parse the item-level services on both datasets. Note that our system utilizes training data from the products and services catalog, in order to get the item-level services that are provided to customers through orders. The rules used to parse and match item-level services include three key steps:

1) Straightforward matching strings of item-level services between PO and invoices.
2) Using Wordnet to annotate specific items that are billed and map them to the product catalog.[14]
3) Text categorization to automatically assign extracted item-level services to predefined product categories.

The output of this rule-based mapping leads to a further trimmed-down mapping of invoices to PO. Table 1 provides examples of the products and item-level services that are mapped. The final output of the system is the matched PO and invoices, driven by the data features.

4. IMPLEMENTATION

In this section, we describe the implementation of our method. We start by explaining our real-world application Global Purchase Order (GPO) tool. The tool provided PO monitoring and management as well as invoices. Our goal is to trim down the search space for matching POs to invoices. The tool used real-world PO and invoice data from one of the world's biggest IT service providers. Our objective is to apply our method to the active ongoing PO and invoice data. We next present the evaluation setup and share the results of our evaluation.

Evaluation Setup

For our implementation, we selected a set of 7,763 POs from the PO dataset which included records between year 2011 and year 2022. The structured PO data contained attributes i.e., PO number, customer name, contract number, PO start and end date, and geography. Additionally, we obtained 50,000 invoice records in that time duration. The structured invoice

TABLE 1. Examples of Product catalog and item level-services keywords.

Number	Products or services catalog	Item-level services keywords from Orders dataset	Item-level services keywords from invoices dataset
1	Cloud	AWS, Azure, GCP tec	Amazon Web Services, Elastic search etc.
2	Servers	Mac OS	Linux OS
3	Networks	Wireless	WIFI
4	Security	Authentication	security encryption
5	Software platform	Java	Java SDK
6	Malware	security	secure data

data included attributes i.e., the line of business, geography, customer type, items billed, settlement of invoices, and billing dates. From the invoice datasets, multiple smaller sets of invoices are evaluated together in the next section.

Clustering Invoices and Building the Multi-task DNN

In order to better find out the common characteristics of invoices, the k-means clustering model is trained on the invoices data. The termination condition of the algorithm is that the objective function is less than a threshold or the difference between two consecutive centroids is less than a threshold. For the dataset of 50,000 invoices, we segregated and clustered invoices into 8-10 cluster sets. Figure 3 provides examples of invoices clustered together based on centroids-like countries. The k-means clustering algorithm showed better accuracy (p-values « 0.05) over other similar algorithms.

Each cluster of invoices was then trained over the multi-task DNN. We used to mini-batch-base stochastic gradient descent (SGD) to learn the features of our model (i.e., the features of all task-specific layers) as shown in Figure 1. In each epoch, a mini-batch was selected, and the model was updated according to the task-specific objective for the task. This approximately optimized the sum of all multi-task objectives. We constructed the multi-task DNN (MT DNN) model on the cluster of invoices to trim down and regroup the "matched" invoices into three sets for task-specific objectives, to achieve the best "matching" to terms of "Supplier Name", "Tech Service", and "Billing Date after Dec 10th, 2021". By then, we got the sets of invoices that best matched the three-task objectives. We compare the MT-DNN with existing state-of-the- art models including BERT and demonstrate its effectiveness in Table 2. Less than 5% of invoices were removed from the sets of invoices because they had invalid or null data.

TABLE 2. Comparison of MT-DNN with existing state-of-the-art.

Model	#of training data points	Accuracy (%)
MT DNN	23000 (Cluster group 1)	88.1
	5214 (Cluster group 2)	95.7
BERT	23000 (Cluster group 1)	82.9
	5214 (Cluster group 2)	93.9

TABLE 3. Comparison of single-task DNN with existing state-of-the-art.

Cluster group #	Mapping Techniques	Accuracy
1	Single task DNN	0.79
	2-way, 3-way matching	0.34
2	Single task DNN	0.85
	2-way, 3-way matching	0.56
3	Single task DNN	0.87
	2-way, 3-way matching	0.63

Single-task DNN to Map Invoices to PO and Text Mining

To trim down search space for invoices to map to POs, the single-task DNN was used. It used the same model architecture as multi-task DNN but for a single-task objective. The output of this model is the probability for each invoice (or each set of invoices) matching to the PO. This step was enforced with rule-based matching that augmented the mapping task. The layers selected were the top features of PO, calculated using python's inbuilt feature importance function. The accuracy of this single-task DNN was higher than compared to the existing state-of-the-art PO-invoice mapping techniques like 2-way, and 3-way matching. Table 3 provides a result of accuracy comparison.

Lastly, in large cluster sets, more than a single invoice was matching to the PO. Hence using rule-based NLP, the item-level services were parsed using the rules from Section 3.

Invoice ID	Line of Business	Items billed	Country
123	Cloud	Cloud servers, security	USA
234	Semiconductors	Chip perf	Japan
345	Cloud	Cloud servers, security	UK
456	Banking	Financial service	USA
567	AI	ML model	UK

Invoice ID	Line of Business	Items billed	Country	Cluster group
123	Cloud	Cloud servers, security	USA	1
234	Semiconductors	Chip perf	Japan	2
345	Cloud	Cloud servers, security	UK	3
456	Banking	Financial service	USA	1
567	AI	ML model	UK	2

FIGURE 3. Examples of the clustered invoices.

We picked the ones with the highest matching probability to the PO for further textual analysis by the rule-based NLP model. Table 4 shows examples of item-level services, extracted keywords, and categorization of text that mapped the PO to invoice data.

Our results were analyzed qualitatively by financial services experts and service providers in order to validate the accuracy of text mining and mapping PO to invoices. Since the trained models can be reused over vast datasets, the time effort required in mapping PO-invoices was reduced by a few days for the above datasets. The overall Order-to-invoice mapping had a mean accuracy of 0.85 and provided better results than existing state-of-the-art.

TABLE 4. Examples of extracted keywords and matching of data.

Rule based technique used	Keywords extracted	Example of matching
Straightforward matching strings	cloud, Cloud, authentication, auth	cloud <–>Cloud, authentication <–>auth
Items annotation	Cloud servers, AWS	Cloud <–>Cloud servers, AWS
Text categorization	AI, machine learning, NLP	AI product <–> {machine learning, NLP}

5. CONCLUSION AND FUTURE WORK

In this work, we showed a cognitive solution of PO- to-Invoice mapping based on vast invoice and PO datasets. We discussed the steps of our method and illustrate its utility with a use case. We successfully demonstrated an end-to-end method with clustering invoices and trimming down the search space for mapping to POs using DNNs.

Our future work includes building a more robust model for a contract-level data structure. We also would like to expand our dataset to other financial services datasets, and to other similar datasets in other industries.

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New Frontiers in Computing 2023

Quantum Computing Is Coming! What Can It Do?

Source: https://www.forbes.com/sites/bernardmarr/2021/10/04/the-5-biggest-data-science-trends-in-2022/?sh=6632dc2940d3

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Jointly organized by North America Taiwanese Engineering and Science Association (NATEA), Silicon Valley Chapter and IEEE Computer Society, SCV Chapter, this conference is in its 24th year. The first conference was organized in the year 1999.

Program

Time (PST)	Presentation Title	Speaker
4:00 – 4:20 PM	Registration and Networking	
4:20 – 4:30 PM	Opening Remarks	PC Chairs (NATEA and IEEE-CS)
4:30 – 5:15 PM	**Quantum computing startups in advancing health care and Pharmacy** (including Q&A)	Nardo Manaloto, managing partner of Qubits Ventures.
5:15 – 6:00 PM	**Industry use cases and potential application of different quantum technologies** (including Q&A)	Ankur Jindal, VP, Global head venturing, technology and innovation, Tata Communications.
6:00 – 6:30 PM	**Race to quantum security and standards** (including Q&A)	Prakash Ramchandran, SME in Telecom Standards and Nominations Committee Chair of IEEE Computer Society, SCV Chapter
6:30 – 7:30 PM	Break for dinner and networking	
7:30 – 8:15 PM	**Introduction to quantum computing hardware** (including Q&A)	Dr. Hiu-Yung Wong, associate professor, and Silicon Valley AMDT endowed chair in electrical engineering at San Jose State University.
8:15 – 9:00 PM	**Quantum Computing: Ecosystem, Services and Investment** (including Q&A) (online speech)	Dr. Kuang-Tase (KT) Huang, chair professor at sAsia University in Taichung City, Taiwan.
9:00 – 9:10 PM	Closing Remarks	PC Chairs (NATEA and IEEE-CS)

Since 2020, the Silicon Valley cybersecurity conference supported by SVCSI (Silicon Valley Cybersecurity Institute), a nonprofit organization, has hosted a cybersecurity research and education forum for sharing innovative developments in cybersecurity for academia and industry. SVCSI will host the 4th conference with IEEE including various programs: research forums, tutorials, a cybersecurity competition, and an industry exhibition to bring together researchers, practitioners, educators, underrepresented communities, and others interested in the latest advances in the security of computer systems and networks.

The 4th Silicon Valley Cybersecurity Conference (SVCC) will take place on **May 17-19, 2023,** at the Embassy Suites by Hilton San Francisco Airport Waterfront in Burlingame, CA. It is located 5.9 mi from Crystal Springs Golf Course and 6.6 mi from San Mateo County Event Center. This hotel is 11 mi (17.7 km) from Cow Palace and 15.9 mi (25.6 km) from Oracle Park.

For more details visit https://www.svcc2023.svcsi.org

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