PFI-TT: Democratizing Deep Recommendation Systems for Small and Medium Restaurants' Digital Drive-Thru Transformation.

Proposal submission on FastLane.nsf.gov [DEADLINE: January 12, 2021.]

- ☐ Project Summary [One (1) page max].
- ☐ FastLane documentation
  - ☐ Collaborators and other affiliations
  - ☐ Current and pending support
  - ☐ Bio sketch
  - ☐ Budget
  - ☐ Data management
  - ☐ Equipment and facilities
  - ☐ Postdoctoral management plan

Project Description. -Fifteen (15) pages max-

- ☑ Executive Summary (no more than one page)
- ☑ From NSF Basic Research to Addressing a Market Opportunity (suggested length: 4 -5 pages)
- ☑ Technical Challenges and Applied Research Plan (suggested length: 5-7 pages)
- ☑ Achieving Societal Impact through the Realization of Commercial Potential (2-4 pages)
- ☑ Project Team (suggested length: 1-2 pages)
- ☑ Partnerships (suggested length: 1-2 pages)
- ☑ Training Future Leaders in Innovation and Entrepreneurship (suggested length: 1-2 pages)
- ☑ Broadening Participation (suggested length: up to 1 page)

Others

- ☑ Letter of support Visa
- ☑ Letter of support Lyft
- ☐ Letter of support Chi's Japanese Cuisine

Project summary -1 page

1 Overview

This project aims to build upon the NSF award (#1750074), CAREER: Human-Centric Big Network Embedding grant, to further translate the academic research and technologies in Automated Graph Neural Networks into advanced recommendation systems to help hospitality industry adopt advanced machine learning (ML) technologies, and particularly, the quick service restaurant (QSR) industry to embrace enterprise business analytics software. Many large restaurant chains can currently implement recommendation systems; however, existing approaches focus on heuristics to decide the optimal configuration of complex pipelines. The primary goal of this project is to develop a novel automated recommender system upon the NSF lineage's research fruits on automated and scalable graph neural networks. The product development will be based on the PI's leading automated machine learning project, i.e., AutoKeras. The PFI team will tailor the resulting automated recommender system to bridge the gap between machine learning expertise and software developments and reduce the requirements for software developers to launch ML-related services. This reduction in complexity and deployment cost can help QSR' driv thru operations leverage advanced ML technologies.

2 Intellectual merit

Modeling Complex User-Item Relationships with Efficient Deep Learning Solution: User-item relationship modeling has long been a critical factor for building a sound recommender system. Often, higher-order relationships between users and items are also the key information to discover the potential needs of customers. To tackle the problems above, one may leverage deep neural networks (DNN) and graph neural networks (GNN) to build a deep learning solution. However, the computational cost of DNN and GNNs is expensive, which may lead to an inefficient inference that damages the user experience. Furthermore, due to the over-expressive power of GNNs, current GNNs suffer from an over smoothing issue and, therefore, unable to model higher correlations between users and items effectively.

End-to-End Automated Recommender System: Typically, the development of an end-to-end recommender system pipeline requires intensive human efforts. The PI's previous efforts on AutoKeras provides neural architecture search which allows software engineers to conduct experiments on ML model without ML knowledge. Still, data processing is a heavy-duty job that requires domain experts to collaborate with data engineers to perform data processing tasks, which is expensive for small businesses. In addition, all of the existing AutoML solutions solely focus on ML model development, while data processing plays a key role in a successful recommender system. However, data processing automation is very challenging as the search space may be very large, which leads to a computational bottleneck. In addition, joint optimization of data processing and ML model is impossible without clearly identified application scenarios for shrinking search space.

3 Broader impacts

This PFI-TT project will expand the fundamental understanding and provide practical computational tools in dealing with an emerging and critical ML automation and interpretation problem for recommendation systems with significant applications in QSR's drive thrus. The proposed translational research's successful outcome will enable more QSR managers to build and deploy advanced recommendation system frameworks but at a fraction of current time and cost. Furthermore, the strong support from companies such as Visa and Lyft has been instrumental in search to commercialize the PI's lineage findings and ML technologies. Such industrial partnerships will be key when translating NSF-funded technologies to the PFI partners Chi's Japanese to effectively enhance the US QSR experience to simplify excessive amounts of data and offer more relevant products to consumers. Recommenders are essential online channels: they shape the media people consume and the products they seek; therefore, it is critical to allow its access to broader QSR in the US. By partnering with Chi's Japanese, Visa and Lyft, the PFI team effectively enhance partnerships between academia and industry in the US, which is key to drive innovation and economic prosperity in the country.

1 Executive summary

1.1 The societal need and the customer

The current US labor shortage in the restaurant industry is pushing small and medium businesses (SMB) to explore efficient ways to serve their customers. Experts estimate that about 60-70 percent of a restaurant's sales comes from a drive-thru, **if they have one** [1]. Quick service restaurants (QSR) in particular are currently looking to improve their drive-thru operations to serve a market shifting to buy in a fast, reliable and contact-less manner. In 2019, 39% of consumers reported they used the drive-thru more often than they did the year prior, and in particular, 74% of customers mentioned that an easy-to-read menu board is a top priority [2]. However, even though digital menus made drive-thrus speedier and more accurate, because of its complexity and cost, digital menus were present in less than 4% of SMB US restaurants [3]. In a segment with razor thin margins, providing access to the technology to make the drive-thru service easy and fast is crucial.

1.2 The value proposition

Our lineage work successfully reduces data overload by providing meaningful results to increase product-customer match accuracy and speed, while allowing managers forecast user demand. Our team has developed a proof-of-concept system [4, 5] to create recommendation systems at a fraction of current time and cost. Our proposed low-cost recommendation-system automation for drive-thru is designed **to help SMB understand their customers better**.

1.3 The innovation

This PFI project proposes AutoML (machine learning automation) to allow QSR managers to implement AI-aided drive-thru solutions. Our proposed framework learns the graph representation for any modal data to reveal the intrinsic relatedness of data at the feature or instance level. Our solution will be built upon *our highly praised open-source system, AutoKeras* [6], which has become one of the most used AutoML systems (with over 8,300 stars and 1,300 forks on Github).

To enable a seamless and easy-to-set-up data acquisition system by SMB, we propose to integrate around our **AutoML-based recommendation system** the needed building blocks to obtain user data from participants that decide to share their information. Such elements include **car-plate recognition capabilities**, **natural language processing** to help employees throughout the order taking and **active audio feedback** to assist customers ordering at the drive thru point.

1.4 The partnership

Our team has established a partnership with minority-owned **Chi's Japanese** restaurant which will become our pilot for our ML-aided drive-thru. Also, the company **Visa** is heavily investing in helping QSRs to digitize their commercial operations; therefore, their feedback and access to anonymized data will be key to this feasibility project as we aim to solve global-scale drive-thru challenges. In the same way, food delivery apps have disrupted the QSR industry. Particularly, the at-restaurant pick-up task still requires a faster interaction between the restaurant personnel and the person picking-up a food order. Thus, our partnership with **Lyft** presents a key opportunity to assess challenges for the click-and-collect (buy in app, pick-up in store) business segment.

1.5 Training and leadership development in innovation and entrepreneurship

We are proposing an educational plan for our postdoctoral researcher that leverages the entrepreneurial resources available at Rice Alliance for Entrepreneurship. Our on-campus incubator offers an intensive program designed to provide our postdoc with the training, network, and co-working space to validate the business hypothesis of this project. The entrepreneurial education plan includes proper training to help him submit a subsequent SBIR proposal, where our postdoc will receive mentoring from mentors, entrepreneurs, and investors.

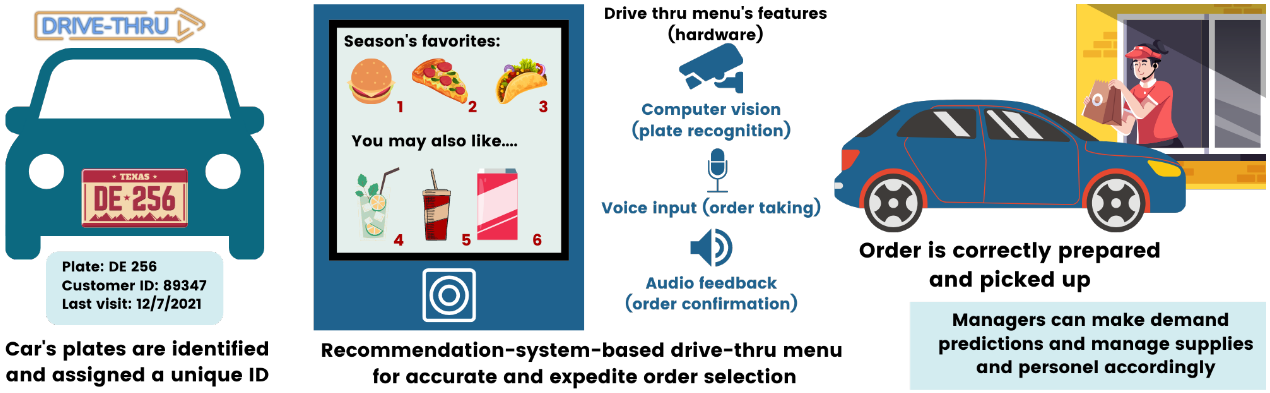

Figure 1: Overview of the proposed recommendation systems for SMB Restaurants' Digital Drive-Thru Transformation. (Left) The car-plate recognition capabilities will help SMB easily identify customers that decide to shsare their information. (Center) Our proposed recommendation-system-based drive thru menu is designed to expedite order selection by integrating natural language processing to help with order taking and active audio feedback to assist users ordering at the drive-thru-menu point. (Right) The benefits of our proposed integral systems extends beyond a fast and accurate order taking to allow restaurant owners to understand market demands and manage their supplies better.

2 From NSF basic research to addressing a market opportunity

2.1 NSF lineage

This proposed project develops from the NSF lineage work entitled *CAREER: Human-Centric Big Network Embedding, Award Number 1750074*. Network embedding is currently employed to learn a low-dimensional representation in recommendation systems to facilitate network analytics applications, including node classification and network visualization. This NSF lineage project has developed advanced graph neural networks to improve network embedding learning in various real-world applications, including social network and modular biochemical analysis. The lineage project also investigated a novel direction to explore how human beings could better understand the results. This multidisciplinary research's successful progress is currently leading to advances in enabling domain experts to interactively and quickly analyze big network data with human knowledge, thus positively impacting various information systems' online activity. During our lineage project, we recognized the missing computational elements to bridge the gap between sophisticated recommendation systems and the technologies tailored to assist SMB managers in taking full advantage of advanced ML tools in QSR.

Besides, the lineage project's results have helped develop a human-centric framework for modeling and incorporating human knowledge in network embedding, tackling data challenges in ML, and enabling interpretation and interaction of network embedding results. Our team has investigated multiview learning and deep structured frameworks to integrate three human knowledge types from the node-, edge- and community-level into a unified framework. Given that real-world online activity could contain heterogeneous, large-scale, and dynamic human knowledge, our research group has developed corresponding solutions to handle the problems. Our team also developed global and local interpretation algorithms to explain network embedding and interactive learning algorithms to integrate user feedback to facilitate the human understanding of our research results.

2.2 Relevant NSF lineage results and broader impact

Our lineage project has already shown promising results reported in [7], where we presented Auto-GNN (AutoGNN), a Neural Architecture Search of Graph Neural Networks, to find the optimal neural architecture given a node classification task. Our team designed the search space, RCNAS controller, and constrained parameter sharing strategy explicitly for the message-passing-based GNN. Our experiment results show that the discovered neural architectures achieve competitive performance on both transductive and inductive learning tasks. Furthermore, the proposed RCNAS controller searches the well-performed architectures more efficiently, and the shared weight could be effective in the offspring network under constraints. Thus, this technique can be applied to facilitate the network analytics tasks in recommender systems.

Personalized recommendation systems are ubiquitous and the primary source of revenue for many online services such as E-commerce, advertising, and social media. At its core, a recommendation system estimating how likely a user will adopt an item based on historical interactions like purchases and clicks. As such, collaborative filtering (CF), which focuses on exploiting the past user-item interactions to achieve the prediction, remains to be a fundamental task towards effective personalized recommendation. CF's most common paradigm is to learn latent features (a.k.a. embedding) to represent a user and an item and perform prediction based on the embedding vectors. Matrix factorization is an early model that directly projects the user's single ID to their embedding. Later on, several researchers found that augmenting user-ID with their interaction history as the input can improve embedding quality. Because of the user-item interaction graph, researchers could see these improvements from using the user's subgraph structure — more specifically, user's one-hop neighbors — to improve the embedding learning. Inspired by this, there is a surge of works recently that data scientists have proposed to model on such graph-structured data for practical user profiling. The essential idea behind them is to represent each user or item as a subgraph and then capture this subgraph's structure information by exploiting powerful graph neural networks GNNs.

2.3 Market analysis

SMB worldwide are currently looking to improve their online operations to serve a market shifting to buy in a a fast, reliable and contact-less manner, which is often an overlooked collateral effect of the current lookdowns and stay-at-home restrictions worldwide. Recommendation systems are a valuable tool for QSR drive-thrus because they reduce data overload by providing meaningful results to customers that increase the possibility of converting a sale. Allowing SMBs to build and deploy robust recommendation systems becomes more economically significant when knowing that only in the US, more than 49% of private-sector employment come from SMBs.

Business analytics tools for recommendation and demand forecasting for the hospitality industry are mainly composed of costly tailor-made and complex software systems, leaving an untapped market that demands more intuitive and accessible solutions. According to IBISWorld [8], the business analytics industry will generate $115.2 Billion US dollars in revenue in the US this year. Remarkably, the SMB in the hospitality industry as a whole can benefit highly from advances in hardware and software solutions as it represents more than $4.61 Billion of this market, as shown in Fig. 2, with a reported 13.5% average annual growth rate (AAGR) from 2016 to 2021.

Notably, the QSR industry relies heavily on business analytics tools for enterprise resource planning, customer relationship management, and performance management. From previous collaborations with Visa, we noticed that business analytics tools allow retailers to predict demand and understand better their customers to lower waste, maintenance costs, reduce employee downtime, and improve overall customer satisfaction.

Business analysts from IBISWorld also indicate that QSR are already heavy users of enterprise software. QSR with drive-thru capabilities are exceptionally prepared to adopt enterprise software because they already heavily use information technology as a core part of their business. On the one hand, we believe that our lineage project can reach a more mature commercialization potential with translational research that can build on top of our scientific research. To further lower the complexity of the production of less expensive production of tailor-made recommendation systems, we propose to apply AutoGNN to discover architectures for more applications such as graph classification and link prediction. By implementing more advanced graph convolution techniques in the search space to facilitate neural architecture search in different applications.

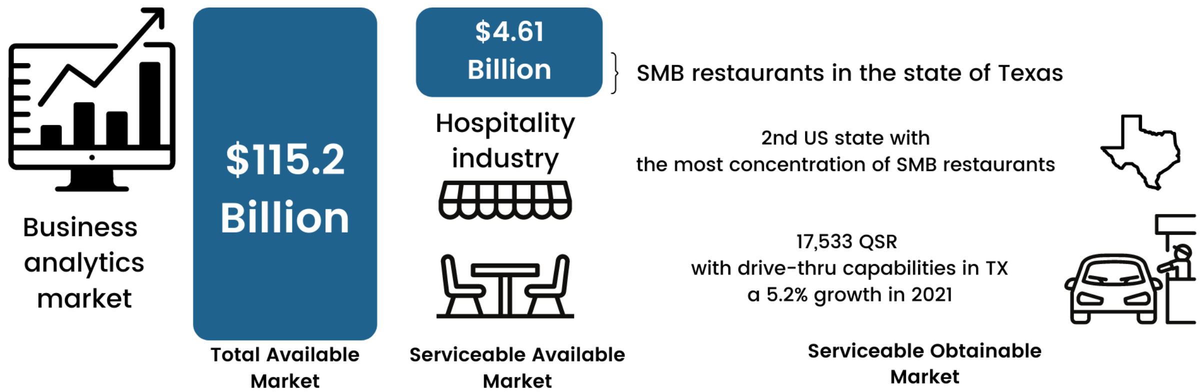

Figure 2: TAM, SAM and SOM of business analytics market and hospitality industry segment breakdown.

Our partner Chi's Japanese Cuisine is a single-location and family-operated restaurant that provide food services to patrons who order via drive-thru or online for on-site pick-up in the city of Houston, TX. Our initial hypothesis is that the technology developed in this project will help SMBs accelerate their transition to a automated drive-thru technology. It is also important to mention that our partner is an example of the more than 17,533 QSR with drive-thru capabilities in Texas, a market segmend that has grown 5.2% over the past 12 months [9].

2.4 Competitive technologies analysis

ML is a disrupting force across many industries; Statista projects ML-solutions' demand to grow more than 50% year to year over the next five years [10]. **Commercial recommendation technologies** such as Recombee [11], Crossing Minds [12], ExpertRec [13], and Strands [14], respectively, are increasingly investing in ML automation techniques. We are looking to complement these efforts by further expanding our human-centered explainability technologies that are already visible in our published research and our popular open-sourced projects. We firmly believe that **our competitive advantage is our strong focus on ML automation, which we inherently combine with interpretable artificial intelligence (AI) to maximize human knowledge with intelligent machine support**. Specifically, our work in Auto-GNN can be used in interpretation because of the inherent user-item connection of GNN by knowing how two items are correlated, i.e., when a user has bought an item or shown a strong interest in a product, human experts can use the visual representation of such correlations to improve their recommendation systems.

On the other hand, our indirect competitors also include the **Open Source** libraries Keras [15–17] and Tensor Flow [18, 19]. While they offer elements to build recommendation systems, both libraries are not flexible for SMBs. Nevertheless, our goal is to push forward this effort by minimizing the business owners' learning curve and accelerating our recommendation system platform adoption. We do so by building proprietary software dedicated to ML automation on top of open-sourced neural architectures widely used by the AI community. Our vision is to use Automation and interpretation as key elements to make recommendation systems widely available for SMBs.

2.5 Intellectual property

Our team has already approached our IP office at Rice University to explore patenting different systems that our team will implement in this PFI project. **The preliminary United States Patent and Trademark Office (USPTO) patent search showed that there's no patent overlap with our proposed low-cost automated recommendation-system-based for drive-thru operation. This means that, to our knowledge, there is no existing IP that could block the commercialization of the innovation that we plan to pursue**. To be more specific, after this initial search our PFI-team is planning to submit a provisional patent for this PFI project upon start of the project for our initial platform version and a full patent after further validating AutoML functionalities.

Our team plans to protect the intellectual property generated in this project first via trade secret forms standard in enterprise solutions. Such practices include Non-Disclosure Agreements and non-compete clauses in the advent we have a spin-off startup, to name a few. In the same way, we plan to publish the advanced functions, such as automated machine learning, interpretable machine learning, and state-of-the-art recommendation modules, under the Berkeley Source Distribution (BSD) license, which forbidden users to develop their product based on these modules privately. Finally, our team has already approached our on-campus patent office to explore patenting different systems that our team will implement in this PFI project.

3 Technical challenges and applied research plan

Limitations of Current Practice. Current low-cost recommender system for drive thru is mainly deployed in the mobile app. Specifically, the users will login to the mobile app to order the items. Then the recommender system will recommend items to the customer within the app. While this solution is easy to deploy, it suffers from several key limitations. (1) First, some users may prefer to order the items from on-site instead of using mobile app. The traditional drive-thru solution cannot recommend items on-site. (2) Second, the user features within the mobile app can be limited, which will limit the performance of the recommender system. (3) Third, the model of traditional recommender system is often manually designed, which is laborious and could be sub-optimal. AutoML will be a promising solution to automatically design the model.

Overview of the proposed solution. To address the limitations of current practice, in this project, we propose to design and develop an automated drive thru recommender system to enable the automated deployment of recommender system on-site. Specifically, we first develop an AutoML enhanced deep recommender system by searching the optimal neural architectures for the recommendation task at hand. AutoML can liberate the human efforts and automatically discover the best model design in a data-driven manner. Then we propose an integrated system that deploys the recommender system in the drive thru system with extracted feature from the cars and customers. Our system can effectively recommend the items for the customers on-site.

Technical Challenges. The design of the integrated system is non-trivial. The main technical challenges are summarized as follows.

- □ **Challenge #1:** It is a challenging task to develop an effective recommender system that can well capture the complex interactions between users and items. In particular, users and items can have higher-order relations, which requires the model to capture the correlations multi-hop away.

- □ **Challenge #2:** It is difficult to design an efficient AuotML algorithm for recommender systems. Training a recommendation model often takes lots of time. We need to devise strategies to accelerate the AutoML search.

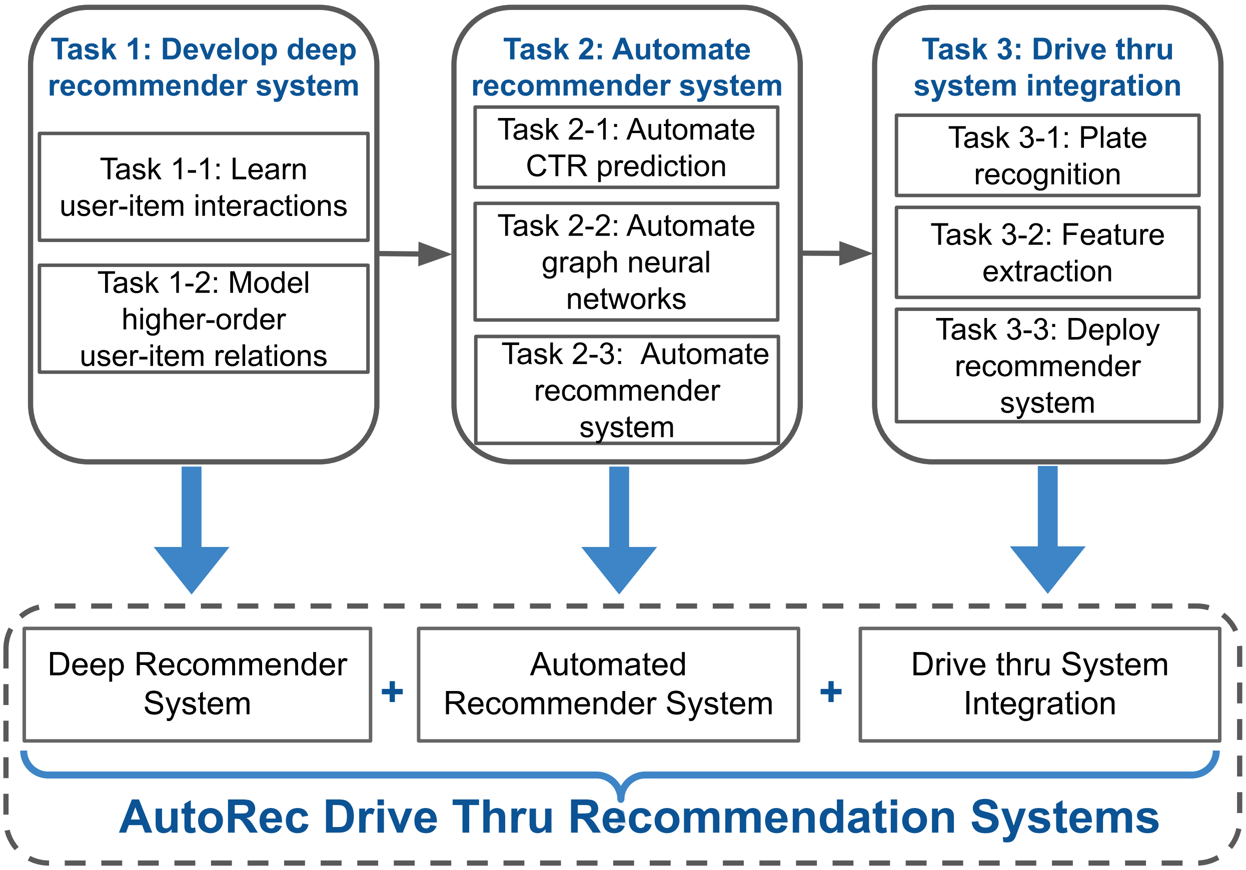

Figure 3: Overview of the PFI-TT project research plan.

- □ **Challenge #3:** Developing an integrated system is a non-trial task. We need to develop algorithms to identify the plates of the cars and extract features from the customers. The feature design is crucial for developing an effective recommender system.

Overview of the Research Tasks. To tackle the above challenges, in this project, we propose three research tasks, summarized Figure 3. In **Task #1:** we propose to develop a deep recommender system to recommend the items by modeling the user-item interactions and higher-order user-item relations with graph neural networks. In **Task #2:** we automate the design of deep recommender system with neural architecture search. In **Task #3:** we integrate the deep recommender system into the drive thru system with plate recognition and tailored features extracted from the customers.

3.1 Research Task #1: Develop deep recommendation system

Task #1-1: Learn user-item interaction: The core idea of developing a data-driven recommender system is collaborative filtering, which models the direct interactions between users and items. Traditional models perform collaborative filtering on user-item matrix [20–23] and employ matrix factorization techniques [24–29] to learn the latent factors of users and items for further predicting the preferences of users to items. Matrix factorization-based methods leverage the inner product to model the interactions which combine the multiplication of latent factors of users and items linearly. However, assuming users and items are linearly correlated is insufficient for complex real-world data distribution.

To address the problem, we propose to leverage the strong expressive power of deep neural network [30] to model the direct relations between users and items. Specifically, we will focus on implicit feedback, which indirectly reflects users' preferences through behaviors like watching videos, purchasing products, and clicking items. Compared to explicit feedback (i.e., ratings and reviews), implicit feedback can be tracked automatically and is thus much easier to be collected by content providers.

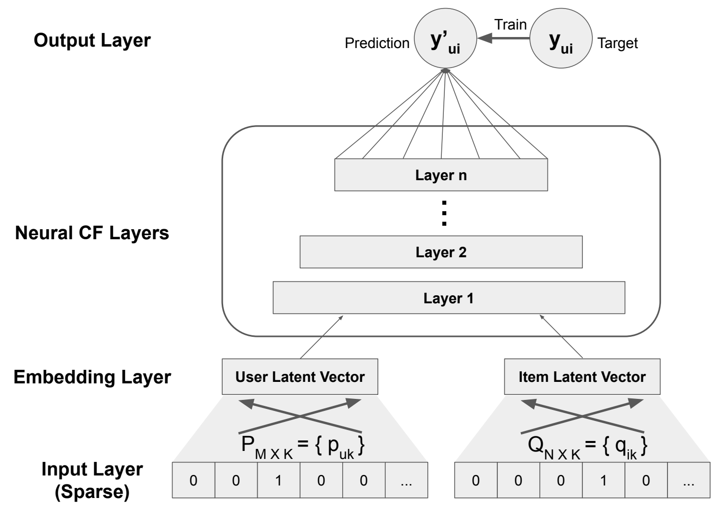

Figure 4: An overview of Neural Collaborative Filtering.

Figure 4 illustrates the neural collaborative filtering framework. The input of the framework is the sparse feature vector of a user/item. In this example, each entry representing whether the user/item has interacted with items/users. First, we will leverage a multi-layer perceptron to map the sparse feature vector into a dense user/item latent vector. Second, instead of leverage a simple inner product, we employ multiple deep neural network layers in Neural CF layers to model the non-linearity of the input user-item interaction. The neural architecture inside the Neural CF layers can be customized to discover certain structures of user-item interaction. Last but not least, the Neural CF layers pass the latent vector of interaction to the output layer for predicting the score y'_{ui} and compute the prediction error between the prediction y'_{ui} and the target y_{ui} to perform backpropagation and update the parameters of the framework. The framework's effectiveness has been validated [31] on various application scenarios, including movie recommendation and image recommendation.

Task #1-2: Modeling higher-order user-item relations: Following the recent success of deep learning on graph [32], graph neural networks (GNNs) have been widely adopted to recommendation problems, and various neural architectures [33–36] has been proposed to model deeper user-item relations to boost recommendation performances. By aggregating the neighborhood information for each node, GNNs learn the latent representation of nodes and perform downstream tasks such as node classification, link prediction, and recommendation. Furthermore, to model the higher-order correlation between users and items, GNNs extend the user-item matrix into a user-item bipartite adjacency matrix and form the bipartite graph where each node represents a user/item and each edge denoting the implicit/explicit feedback from the user to item. However, modern GNNs are suffered from several problems and over-smoothing problem [37] which lead to poor performance when capturing high order user-item relationships with deeper neural architecture. In addition, due to the computational complexity of the inference procedure, performing recommendations via classical GNNs will damage the efficiency of retrieving recommendation lists for users and, therefore, degrade the user experience.

To address the over-smoothing problem, we will develop our framework based on the previous research on group normalization technique [38]. Specifically, we relieved the over-smoothing issue from preserving group-structure characteristics and input features within node embeddings and proposed two over-smoothing metrics, i.e., group distance ratio and instance information gain. The group distance ratio measures the node embedding distances from different groups, which needs to be improved to separate the groups accompanied by various labels. The instance information gain measures the mutual information between input features and hidden node embeddings, which must be maintained to preserve the informative features for node classification. To optimize these two metrics, we developed a general module, called differentiable group normalization (DGN), applied between layers. It normalizes nodes within the same group independently and separates node distributions among different groups while keeping the input features during normalization. Experiments on real-world datasets demonstrate that DGN makes GNN models more robust to over-smoothing and achieves better performance with deeper GNNs.

Secondly, we address the retrieval efficiency based on our previous research, which learns a hash function for graph neural networks [39]. We investigate hashing with GNNs in this work and propose a simple yet effective discrete representation learning framework to learn continuous and discrete codes jointly. Our model consists of two components, a GNN encoder for extracting node representations and a hash layer for encoding representations to hash codes. A novel discrete optimization strategy based on a straight-through estimator (STE) with guidance is proposed to enable the hash layer differentiable and make our model is trained end-to-end. The principal idea is to avoid gradient magnification in the backpropagation of STE with continuous optimization guidance. Empirical results over several publicly available datasets demonstrated that our model can achieve comparable performance compared with its continuous counterpart and runs multiple times faster during inference.

3.2 Research Task #2: end-to-end automated deep recommender system

Task #2-1: Automated CTR Prediction: In terms of the application scenario, Click Through Rate (CTR) prediction is a crucial problem in many recommendation-related applications such as display advertising and search engine optimization. It drives the personalized experience for billions of users. Traditional solutions usually put effort into designing explicit feature interactions to capture the feature relationships and combine them with an MLP structure towards a two-tower model. However, the human-crafted architecture is often ad-hoc, and there lacks enough exploration on how to combine different types of explicit feature interactions with the implicit interactions learned from MLPs.

To address the problem, we will enable automated neural interaction discovery in our product based on our previous research on AutoCTR [40] to design a CTR prediction model automatically. It contains three key components to cope with three technical challenges. First, there are no dominant models in recommender systems such as the CNNs in CV tasks. We abstract and modularize simple yet representative operations in existing CTR prediction approaches to formulate a generalizable search space in AutoCTR. It also accommodates the heterogeneous and high-dimensional features in CTR prediction tasks. Second, since the designed search space is quite large, a good search algorithm is needed to provide an efficient exploration. We propose a hybrid search algorithm composed of an evolutionary algorithm and a learning-based algorithm based on a gradient-boosted tree. The algorithm provides a good balance between exploration and exploitation during the search process. It also utilizes a learning-to-rank loss, balancing the trade-off between different learning objectives and further enhancing search. Third, the CTR model is often learned on billions of data in practice. To further accelerate the search speed and reduce the space cost, AutoCTR involves a composited strategy of low-fidelity estimation, including data subsampling and hash size reduction. With abundant experiments on the three benchmark datasets, we empirically demonstrate the AutoCTR's effectiveness compared to human-crafted architectures and other classical NAS algorithms generalized from CV tasks. We also validate the generalizability and transferability of the discovered architecture across different datasets.

Task #2-2: Automated graph neural networks: As graph neural networks [41] have recently shown promise in various recommendation tasks [36, 42], we will automate the design of graph neural networks to enable better recommendation performance. Our system will focus on automation in two specific perspectives, including neural architecture design and aggregation opti-

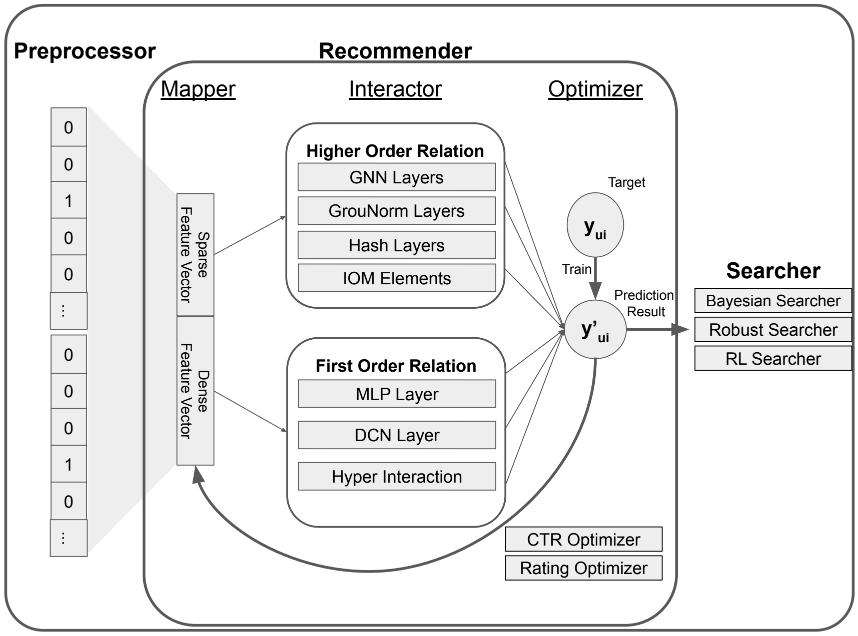

Figure 5: The structural diagram of the proposed automated recommender system.

mization.

First, we will develop automated graph neural networks (AGNN) [43], which aims to find an optimal GNN architecture within a predefined search space. In AGGN, we have defined a tailored search space from general GNN architecture composed of layers of message-passing-based graph convolutions. To improve the search speed, we have designed a more efficient controller by considering a key property of GNN architecture–the variation of representation learning capacity with slight architecture modification. We have also explored the heterogeneous GNN architectures in the context of parameter sharing to train the architecture more stable with shared weight. We have shown that the GNNs discovered in this way consistently outperform the existing state-of-the-art handcrafted models. Our team can adapt this technique to the context of recommender systems to enable more advanced GNN models automatically.

In addition to the search of neural architectures, we will adapt the aggregation strategy for different users and items based on our study of PolicyGNN [44]. Our study shows that other nodes in a graph often need a different number of iterations of aggregation to achieve the best performance. For example, in the context of the user-item graph, different users may share the interests of other users in different hops away. Our team can thus personalize the recommendation strategy to meet the needs of different users. In our product, we will optimize this aggregation strategy with deep reinforcement learning in a data-driven manner to improve the overall performance.

Task #2-3: Automated deep recommender system: AutoRec: A fundamental challenge of a recommender system is the engineering cost to adapt to new recommendation scenarios. Specifically, realistic recommender systems are required to have the capacity to adapt to the constantly evolving data and tasks quickly or to explore different models systematically. One of the most prominent examples of this is that Netflix has never deployed the champion recommendation model of their 1M contest due to its engineering cost and the business' shifting from movie recommendation (rating prediction) to video streaming (click-through-rate prediction). In addition, although recommender systems start to capitalize on the power of deep learning, they have yet been able to convert model depth into raw performance because of the proneness to overfit, which leads to severe online-offline mismatch. Therefore, most of the industry's active recommendation models are shallow compared to their CV counterpart [45]. This calls for a new approach of recommendation model development that emphasizes both flexibility and the systematic exploration of existing and new neural architectures alike.

In the industry, Most recommender systems are highly specialized in handling specific data and tasks. For example, NCF [31] takes user-item implicit feedback data as inputs for the rating prediction task; DeepFM [46] leverages both numerical and categorical data for the CTR prediction task. However, a high degree of specialization comes at the expense of model adaptability and tuning complexity. As recommendation tasks evolve and additional data types are collected, the initially apt model can either become obsolete or require tremendous tuning efforts.

To bridge the gap, we developed an open-source automated machine learning (AutoML) platform extended from the TensorFlow [24] ecosystem named AutoRec, which focuses on neural architecture search (NAS) for deep recommendation models. AutoRec supports a highly flexible pipeline that accommodates both sparse and dense inputs, rating prediction and click-through rate (CTR) prediction tasks, and an array of recommendation models. We will incorporate AutoRec into our product to enable automatic pipeline construction and neural architecture search in industrial recommendation tasks.

3.3 Research Task #3: Drive-through system integration

We will integrate the proposed end-to-end automated deep learning recommender system to the drive-through system to enable customers to enjoy personalized services. Our system will recommend items based on the features extracted from the customer and the items. The full system will consist of the following components:

Task #3-1: Plate recognition: We will develop algorithms to identify the plate number of each car. Then we can lookup the database to obtain customer information, such as historical orders and user profiles. These will serve as the features of the recommender system.

Task #3-2: Feature extraction: We will extract features for both customers and items. For customers, we will extract features based on historical orders and customer information, such as the model of the car, the color of the car etc. The item features will describe the characteristics of the items, such as the price, sales volume, etc. These features will serve as the inputs of our recommender systems.

Task #3-3: Recommendation: We will deploy our recommender systems and graph neural networks techniques to the drive through system. The system will recommend items based on the customer features, item features, and the purchase history, where each purchase will serve as an edge connection between a customer and an item. Then graph neural networks will be adopted to enhance the prediction of the the recommender systems. Our system will provide personalized items recommendation based on all the collected features.

3.4 Research and development plan

Our research and development will focus on an end-to-end, automated deep recommender system that our customers can readily adopt and deploy in real-world applications.

- □ **Developing deep recommender system.** We will build deep learning models to learn the complex interaction between users and items. We will also leverage the power of graph neural networks to model the higher-order user-item relations. Beyond the performance, we will develop interpretation functionalities to provide a better understanding of the models.

- □ **Automated deep recommender system.** Based on our deep learning models, we will enable automated CTR prediction with neural architecture search, and we will also automate the design of neural graph networks to capture the higher-order relationships efficiently.

□ **End-to-end robust deep recommender system.** We will wrap all of our models under the same framework with unified interfaces. We will also enhance the robustness of the system with robust loss functions.

3.5 Evaluation Plan and Success Metrics

Dataset. We will collect the data with through our partnership with Chi's Japanese Cuisine. We will set up hardware devices to collect the dataset with vehicle, customer voice and food information. Specifically, for each transaction, we will record the sentences that customer spoken, the license plate of vehicle, color of vehicle and the ordered food as well as the transaction timestamp. In addition, we will collect food ingredients from our partner for discovering customer patterns and train a detail-oriented machine learning model.

Baselines and Evaluation Metrics. We have specific evaluation metrics and baselines to validate the quality of our solutions on each of the proposed research tasks **(RT)**.

To evaluate RT #1, we will compare our deep learning framework with existing frameworks from academia and industry including our preliminary neural collaborative filtering [31], Google's Wide & Deep [47], and Facebook's DLRM [48]. We will evaluate the proposed framework on the collected datasets and follow the widely adopted metrics including precision, recall, mean average precision (MAP) and mean reciprocal rank (MRR).

To evaluate RT #2, we will compare our automated recommender system with industry automated machine learning solutions including Google's AutoML [49], Amazon's AutoGluon [50]. We will also compare with open-source machine learning systems including our preliminary work on AutoKeras [6], TPOT [51], and AutoSKlearn [52]. We will follow the evaluation protocol adopted by both industry and academia, including performance over time, performance over iteration and final performance. The aforementioned precision, recall, mean average precision and mean reciprocal rank will serve as the performance metrics during the evaluation.

To evaluate RT # 3, we will utilize widely adopted accuracy to evaluate the developed plate recognition algorithm. In addition, we will do ablation studies on each extracted features with the aforementioned precision, recall, MAP and MRR to evaluate the quality of extracted features.

3.6 Risk and mitigation plan

Our research and development will center on a recommendation system engine that our customers can readily adopt. The sections above discuss the technical challenges and proposed solutions. Still, two technical risks might be raised by our customers.

Risk #1, data quality might be a potential risk as target customers are small business which may not have sufficient or quality data to train an ML-based recommender system. In this case, we will first build a rule-based recommender system based on customers' domain expertise and collect the data. Then, based on the amount and quality of the collected data, we will build a hybrid recommender system that generate recommendation result based on domain expertise and ML models and gradually increase the portion of autoML model with increasing amount and quality of the data.

Risk #2, as the portion of autoML model increasing, customer may not trust the model as the whole operation is a black-box to our customer. To address their concern, we will provide a friendly interface to the customers to learn about the operation process of the model and visualize the data and recommendation outcome to allow customers to surveillance the whole process. In addition, interpretable machine learning techniques will be adopted to provide model interpretation in the interface to explain the complex interaction within the neural model to increase the credibility of the autoML model.

3.7 Timeline and milestones

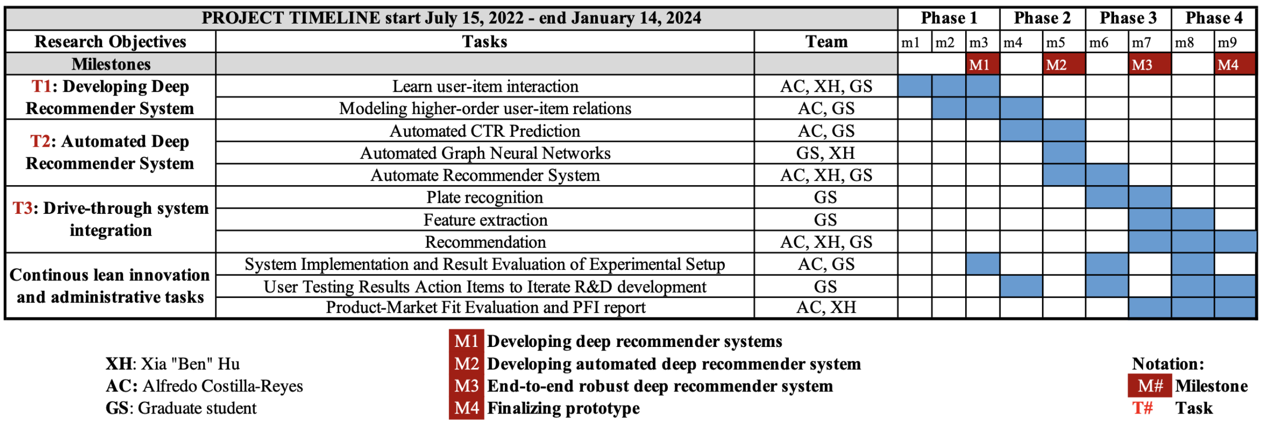

Figure 6: Recommendation system's PFI feasibility project timeline.

Overall, research and development will take 18 months. We will first start with implementing the system and then focus on enabling AutoML in our system. After that, we will spend half a year to polish and finalize our product based on the community's feedback. The milestone and timeline are summarized as follows.

Milestone #1: Developing deep recommender systems (6 months): We will evolve our product for commercial purposes. We will build upon our previous research lineage to develop an easy-to-use deep recommender system for a user-item recommendation.

Milestone #2: Developing automated deep recommender system (4 months): We will enable automated machine learning in a deep recommender system. The team will focus on neural architecture search for the automatic design of fully connected networks and graph neural networks. After that, we will apply the robust loss to improve the robustness of the system. Finally, we will test our AutoML product internally and run evaluations on cloud services.

Milestone #3: End-to-end robust deep recommender system (4 months): We will closely support end-users to try our AutoML system. We will collect some feedbacks and improve our product. In this period, our objective is to ensure we provide a human-friendly interface for end-users.

Milestone #4: Finalizing prototype (4 months): Based on the customer's feedback, we will complete our work with improved interfaces. We will present our product in two options based on the input. First, we will tentatively wrap the product as software installed on personal computers or servers. Alternatively, we could deploy our development as a cloud service with a web-based user interface. We will choose one of the above options (or both) based on the user feedback from the open-source version.

4 Achieving societal impact through the realization of commercial potential

4.1 Commercialization strategy

We believe that the first step in our go-to-market strategy is to heavily invest in customer discovery. In this regard, the open-source community has been an essential portion of our commercialization efforts. Notably, the demand of our popular open-source packages (i.e., AutoKeras), measured through downloads and reviews, has historically correlated to useful package features to the community. Releasing open-source packages serve two goals: first, it helps us gauge and understand download activity and user-feedback reviews to measure the success of our packages, and second, it is also a great way to build a community of programmers, researchers, and more importantly, other entrepreneurs that want to commercialize technologies in recommendation systems.

A way to fund further development is by actively seeking non-dilutive funding support from federal agencies such as the Small Business Innovation Research (SBIR) grant. We believe that our successful results in the CAREER: Human-Centric Big Network Embedding grant prepared us well to propose this PFI grant to seek to commercialize our research. To achieve this goal, our postdoc will receive the proper training to write a proper SBIR proposal throught the help of our Liu Idea Lab for Innovation and Entrepreneurship on-campus accelerator.

In addition, note that the technology commercialization office at Rice University will also be a valuable asset in our pursuit of technology commercialization. Mainly in two areas, their mentorship and entrepreneurial curriculum will be invaluable for our team, and secondly, they already possess a strong network of investors and domain experts. Finally, note that Rice University's incubator and accelerator, along with the customer discovery training provided by I-Corps, will be necessary for our commercialization strategy and the development of a spin-off company.

The NSF I-corps program will also help us gauge the success of our commercialization strategy. At this point, one of the business hypotheses we need to validate or invalidate is that our business model will follow conventional practices in the business intelligence industry, divided into non-recurring and recurring revenue streams. **Non-recurring revenue streams** involve setup infrastructure costs such as AI & ML model building, platform installation, operator training, deployment expenses, and data preprocessing. Our **recurring revenue streams** may follow standard models of cloud container companies [53] such as AWS®. They include ML deployment operation, license fees, data volume analysis, and extra premium features related to security and data encryption. The I-corps program and their business model canvas methodology can undoubtedly help us gauge the validity of our value proposition and product-market fit in our quest to translate academic research and technologies into commercial use rapidly.

5 Project team

This team comprises expertise from data mining and machine learning systems (Hu), entrepreneurship and, data science (Costilla Reyes), including faculty and graduate students with strong experience developing AutoRec from at the Data Lab at Rice University.

PI Dr. Xia "Ben" Hu is an Associate Professor at Rice University in the Department of Computer Science. He has published more than 100 papers in major data mining venues. His articles have received seven Best Paper Award (candidate), and he is the recipient of the JP Morgan AI Faculty Award, the Adobe Data Science Award, and the NSF CAREER Award. An open-source package developed by his group, namely AutoKeras, has become the most used automated deep learning system on Github (with over 8,000 stars and 1,200 forks). Dr. Hu's work on deep collaborative filtering, anomaly detection, and knowledge graphs is part of the TensorFlow package, Apple production system, and Bing production system. Hu's work has been cited more than 10,000 times, with an h-index of 41. He was the conference General Co-Chair for WSDM 2020.

Dr. Alfredo Costilla-Reyes, is a postdoctoral associate at Rice University in the Department of Computer Sciences. He is also **a first-generation graduate** with an Entrepreneurship and Technology Commercialization program at Mays Business School and a doctorate in Electrical Engineering, both from Texas A&M University. **Dr. Alfredo has been a recipient of the NSF I-Corps Site, 2017-2018 Kirchner, Silicon Labs and the Rice Innovation Fellowships, and the**

prestigious Mexico's National Award, presented by the president of Mexico for his contributions in science, technology, and entrepreneurship. Specifically, Dr. Alfredo has led projects regarding embedded software and systems for future agriculture, battery-less wearable consumer electronics, application-specific integrated circuits, and wireless systems for IoT applications. His research and entrepreneurial endeavors have participated in YCombinator's YC120 event, Silicon Valley Bank Trek, and Rice University's OwlSpark accelerator.

The team has established long-term collaboration, co-authored publications, and worked together on active DARPA and NSF projects to conduct fundamental research in developing interpretable and automated machine learning systems. In addition, our past collaborations have provided a solid ground for the technology commercialization of our NSF lineage technologies. We want to highlight that we are investing in developing more entrepreneurial talent in our group. This is important for this project because a graduate student from our highly competitive group will be invited to participate in this project, our goal is to invite one of our female students to join us in our mission in democratizing deep recommendation systems for small and medium restaurants' digital drive-thru transformation.

6 Partnerships

Pilot partner

Supporting partners

Our **pilot partner**, the restaurant Chi's Japanese Cuisine is a great representative example of the target market we believe will benefit the most from this project. This key participant will help us gather information and understand the most urgent problems that business owners in the hospitality industry regularly face in their daily activities. Chi's Japanese Cuisine will facilitate an actual establishment where our smart drive-thru system will be installed and the resulting data analyzed. Chi's Japanese Cuisine participation will be vital in attracting other restaurants.

The team has collaborated with the SMB mentioned above and established methods for data-sharing through direct access with their establishment. The purpose of this partnerships is to demonstrate the applicability and effectiveness of the proposed system on real-world data and solve problems that matter to business owners.

Outcomes of the proposed project will facilitate an automated recommender system in QSR applications by providing a more effective ranked list of items/products automatically. To better understand user needs and commercialization opportunities, as well as evaluate the effectiveness and efficiency of the developed systems on real-world datasets, PI Hu and the team will actively collaborate with corresponding domain experts from leading companies, including Lyft and Visa, through funded joint research and development. The **supporting partners** Lyft and Visa are critical in pursuing our current technologies' commercialization. Notably, as the leading payment processor, Visa is very well positioned to push forward our efforts, and their experience with real-world problems will help us deliver better solutions tailored to small QSRs around the globe. Moreover, we have collaborated extensively with Lyft AI team, which has provided vital specific problem needs, collaborative data curation, evaluation platforms, performance metrics, and feedback. Both partnerships are key for our commercialization strategy moving forward.

7 Training future leaders in innovation and entrepreneurship

The Rice Alliance for Technology and Entrepreneurship office at Rice University has supported our endeavors with different entrepreneurial and leadership tools available at Rice University that we will continue implementing in this PFI proposal to enable our postdoctoral researcher and graduate students to develop the skills needed for the successful commercialization of our NSF-funded research in engineering. The following programs were offered by the Rice Alliance for Technology and Entrepreneurship office at Rice University. First, the OwlSpark Accelerator is an intense, immersive 12-week summer program that will provide our team members with firsthand experience launching a tech startup. OwlSpark delivers entrepreneurship education throughout the summer, teaches relevant business fundamentals, pairs teams with knowledgeable mentors and industry experts, features office hours with successful entrepreneurs, and yields key connections. **The assessment plan of this accelerator includes evaluating the outcomes and impact of this training program with the Bayou Startup Showcase, a pitch presentation to the Houston startup community, and the university accelerator mentors.** An excellent opportunity for our team to showcase the PFI outputs of this proposal. OwlSpark has the resources and collaboration to provide us with exposure and direct access to the local entrepreneurial ecosystem, increasing the probability of continued success beyond the proposed PFI project.

Second, the Liu Idea Lab for Innovation and Entrepreneurship (Lilie) is the home of experiential learning and co-curricular activities in entrepreneurship and innovation at Rice University. For this PFI project, Dr. Alfredo Costilla has been invited to be a Rice Innovation Fellow and benefit from co-curricular offerings at the curricular level. Such courses include fundamentals in entrepreneurship to management and accounting classes.

Finally, we would like to take this proposal's opportunity to empower our team, including faculty members, postdoctoral researchers, and Ph.D. students, by harnessing the opportunity to learn and grow our entrepreneurial talent. We particularly plan to invest in training our team by using courses and material such as Disciplined Entrepreneurship: 24 Steps to a Successful Startup [54] developed at MIT, consisting of a series of lessons and methodology to formulate and test business assumptions. Another tool we will use in this project is The Startup Owner's Manual [55], an Step-By-Step Guide for Building a Great Company developed by Steve Blank, which is a method highly recognized for its replicable product-market fit testing process.

8 Broadening participation

We firmly believe in being a driver of diversity, excellence and innovation among our research members and third-party collaborations. Particularly, Mexico's presidential-award recipient, postdoctoral researcher Alfredo Costilla-Reyes, brings a unique entrepreneurial approach to challenges that has helped him recognize different opportunities and embrace them through his engineering projects. We are confident that Dr. Costilla's strong technical and entrepreneurial acumen will further contribute to having an exceptional inclusive, equitable, and diverse PFI research partnership for many other students and collaborators at MSU. **We want to highlight that knowing that almost one in five Americans is identified as Hispanic, it is important for us to serve as an example to other Latino entrepreneurs in the US and inspire them to become leaders in the tech industry**.

Finally, our pledge is to add at least one female member to this PFI project. We plan to do so by developing female talent at our research group as well as increasing reaching out to more graduate-student applicants self-identified as women or person with disabilities.

9 Broader Impacts

The Broader Impacts of this proposed PFI project are detailed in prior sections of the Project Description.

References

[1] David Yaffe-Bellany. *Drive-Throughs, a Lifeline for Fast-Food Chains*, 2020 (Accessed January 4, 2022). Retrieved from NPG group database.

[2] SeeLevel HX and King-Casey. *2019 Manuboard survey report*, 2019 (Accessed January 4, 2022).

[3] FoodserviceResults team and QSR magazine. *The 2021 QSR magazine Drive-Thru Study: Digital Menuboard*, July 2021.

[4] Ting-Hsiang Wang, Xia Hu, Haifeng Jin, Qingquan Song, Xiaotian Han, and Zirui Liu. Autorec: An automated recommender system. In *Fourteenth ACM Conference on Recommender Systems*, pages 582–584, 2020.

[5] DATA (Data Analytics at Texas AM) Lab. *AutoRec, an open-source automated machine learning (AutoML) platform extended from the TensorFlow ecosystem*, 2020 (Accessed February 9, 2021). https://autorec.ai/.

[6] Haifeng Jin, Qingquan Song, and Xia Hu. Auto-keras: An efficient neural architecture search system. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 1946–1956, 2019.

[7] Kaixiong Zhou, Qingquan Song, Xiao Huang, and Xia Hu. Auto-gnn: Neural architecture search of graph neural networks. *CoRR*, abs/1909.03184, 2019.

[8] Dan Cook. *IBISWorld US Industry (NAICS) Report 51121C. Business Analytics Enterprise Software Publishing in the US*, March 2021. Retrieved from IBISWorld database.

[9] IBISWorld. *US Industry Fast Food Restaurants in Texas - Number of Businesses*, January 20212. Retrieved from IBISWorld database.

[10] Tractica. *Revenues from the artificial intelligence software market worldwide from 2018 to 2025, by region (in billion U.S. dollars) [Graph]*, April 22, 2019 (Accessed October 6, 2020). https://www.statista.com/statistics/721747/worldwide-artificial-intelligence-market-by-region/.

[11] PitchBook Data. *Recombee | Private Company Profile*, February 2021. Retrieved from PitchBook database.

[12] PitchBook Data. *Crossing Minds | Private Company Profile*, February 2021. Retrieved from PitchBook database.

[13] PitchBook Data. *ExpertRec | Private Company Profile*, February 2021. Retrieved from PitchBook database.

[14] PitchBook Data. *Strands | Private Company Profile*, February 2021. Retrieved from PitchBook database.

[15] Nikhil Ketkar. Introduction to keras. In *Deep learning with Python*, pages 97–111. Springer, 2017.

[16] Antonio Gulli and Sujit Pal. *Deep learning with Keras*. Packt Publishing Ltd, 2017.

[17] Jojo Moolayil, Jojo Moolayil, and Suresh John. *Learn Keras for Deep Neural Networks*. Springer, 2019.

[18] Nishant Shukla. *Machine learning with TensorFlow*. Manning Publications Co., 2018.

[19] Joshua V Dillon, Ian Langmore, Dustin Tran, Eugene Brevdo, Srinivas Vasudevan, Dave Moore, Brian Patton, Alex Alemi, Matt Hoffman, and Rif A Saurous. Tensorflow distributions. *arXiv preprint arXiv:1711.10604*, 2017.

[20] Jonathan L Herlocker, Joseph A Konstan, Loren G Terveen, and John T Riedl. Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems (TOIS)*, 22(1):5–53, 2004.

[21] J Ben Schafer, Dan Frankowski, Jon Herlocker, and Shilad Sen. Collaborative filtering recommender systems. In *The adaptive web*, pages 291–324. Springer, 2007.

[22] Robin Burke. Hybrid recommender systems: Survey and experiments. *User modeling and user-adapted interaction*, 12(4):331–370, 2002.

[23] Gediminas Adomavicius and Alexander Tuzhilin. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE transactions on knowledge and data engineering*, 17(6):734–749, 2005.

[24] Yehuda Koren, Robert Bell, and Chris Volinsky. Matrix factorization techniques for recommender systems. *Computer*, 42(8):30–37, 2009.

[25] Andriy Mnih and Russ R Salakhutdinov. Probabilistic matrix factorization. *Advances in neural information processing systems*, 20:1257–1264, 2007.

[26] Ruslan Salakhutdinov and Andriy Mnih. Bayesian probabilistic matrix factorization using markov chain monte carlo. In *Proceedings of the 25th international conference on Machine learning*, pages 880–887, 2008.

[27] Xiangnan He, Hanwang Zhang, Min-Yen Kan, and Tat-Seng Chua. Fast matrix factorization for online recommendation with implicit feedback. In *Proceedings of the 39th International ACM SIGIR conference on Research and Development in Information Retrieval*, pages 549–558, 2016.

[28] Steffen Rendle. Factorization machines. In *2010 IEEE International Conference on Data Mining*, pages 995–1000. IEEE, 2010.

[29] Yehuda Koren. Factorization meets the neighborhood: a multifaceted collaborative filtering model. In *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 426–434, 2008.

[30] Maithra Raghu, Ben Poole, Jon Kleinberg, Surya Ganguli, and Jascha Sohl-Dickstein. On the expressive power of deep neural networks. In *international conference on machine learning*, pages 2847–2854. PMLR, 2017.

[31] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. Neural collaborative filtering. In *Proceedings of the 26th international conference on world wide web*, pages 173–182, 2017.

[32] Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and S Yu Philip. A comprehensive survey on graph neural networks. *IEEE Transactions on Neural Networks and Learning Systems*, 2020.

[33] Rianne van den Berg, Thomas N Kipf, and Max Welling. Graph convolutional matrix completion. *arXiv preprint arXiv:1706.02263*, 2017.

[34] Jiani Zhang, Xingjian Shi, Shenglin Zhao, and Irwin King. Star-gcn: Stacked and reconstructed graph convolutional networks for recommender systems. *arXiv preprint arXiv:1905.13129*, 2019.

[35] Xiang Wang, Xiangnan He, Meng Wang, Fuli Feng, and Tat-Seng Chua. Neural graph collaborative filtering. In *Proceedings of the 42nd international ACM SIGIR conference on Research and development in Information Retrieval*, pages 165–174, 2019.

[36] Rex Ying, Ruining He, Kaifeng Chen, Pong Eksombatchai, William L Hamilton, and Jure Leskovec. Graph convolutional neural networks for web-scale recommender systems. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 974–983, 2018.

[37] Deli Chen, Yankai Lin, Wei Li, Peng Li, Jie Zhou, and Xu Sun. Measuring and relieving the over-smoothing problem for graph neural networks from the topological view.

[38] Kaixiong Zhou, Xiao Huang, Yuening Li, Daochen Zha, Rui Chen, and Xia Hu. Towards deeper graph neural networks with differentiable group normalization. *Advances in Neural Information Processing Systems*, 33, 2020.

[39] Qiaoyu Tan, Ninghao Liu, Xing Zhao, Hongxia Yang, Jingren Zhou, and Xia Hu. Learning to hash with graph neural networks for recommender systems. In *Proceedings of The Web Conference 2020*, pages 1988–1998, 2020.

[40] Qingquan Song, Dehua Cheng, Hanning Zhou, Jiyan Yang, Yuandong Tian, and Xia Hu. Towards automated neural interaction discovery for click-through rate prediction. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 945–955, 2020.

[41] Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*, 2016.

[42] Wenqi Fan, Yao Ma, Qing Li, Yuan He, Eric Zhao, Jiliang Tang, and Dawei Yin. Graph neural networks for social recommendation. In *The World Wide Web Conference*, pages 417–426, 2019.

[43] Kaixiong Zhou, Qingquan Song, Xiao Huang, and Xia Hu. Auto-gnn: Neural architecture search of graph neural networks. *arXiv preprint arXiv:1909.03184*, 2019.

[44] Kwei-Herng Lai, Daochen Zha, Kaixiong Zhou, and Xia Hu. Policy-gnn: Aggregation optimization for graph neural networks. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 461–471, 2020.

[45] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[46] Huifeng Guo, Ruiming Tang, Yunming Ye, Zhenguo Li, and Xiuqiang He. Deepfm: a factorization-machine based neural network for ctr prediction. In *Proceedings of the 26th International Joint Conference on Artificial Intelligence*, pages 1725–1731, 2017.

[47] Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, and Mustafa Ispir. Wide & deep learning for recommender systems. In *Proceedings of the 1st workshop on deep learning for recommender systems*, pages 7–10, 2016.

[48] Maxim Naumov, Dheevatsa Mudigere, Hao-Jun Michael Shi, Jianyu Huang, Narayanan Sundaraman, Jongsoo Park, Xiaodong Wang, Udit Gupta, Carole-Jean Wu, Alisson G. Azzolini, Dmytro Dzhulgakov, Andrey Mallevich, Ilia Cherniavskii, Yinghai Lu, Raghuraman Krishnamoorthi, Ansha Yu, Volodymyr Kondratenko, Stephanie Pereira, Xianjie Chen, Wenlin Chen, Vijay Rao, Bill Jia, Liang Xiong, and Misha Smelyanskiy. Deep learning recommendation model for personalization and recommendation systems. *CoRR*, abs/1906.00091, 2019.

[49] Google. Automl. https://github.com/google/automl.

[50] Nick Erickson, Jonas Mueller, Alexander Shirkov, Hang Zhang, Pedro Larroy, Mu Li, and Alexander Smola. Autogluon-tabular: Robust and accurate automl for structured data. *arXiv preprint arXiv:2003.06505*, 2020.

[51] Trang T Le, Weixuan Fu, and Jason H Moore. Scaling tree-based automated machine learning to biomedical big data with a feature set selector. *Bioinformatics*, 36(1):250–256, 2020.

[52] Matthias Feurer, Aaron Klein, Katharina Eggensperger, Jost Tobias Springenberg, Manuel Blum, and Frank Hutter. Auto-sklearn: efficient and robust automated machine learning. In *Automated Machine Learning*, pages 113–134. Springer, Cham, 2019.

[53] Donna L Hoffman and Thomas P Novak. A conceptual framework for considering web-based business models and potential revenue streams. *International Journal of Marketing Education*, 1(1):7–34, 2005.

[54] Bill Aulet. *Disciplined entrepreneurship: 24 steps to a successful startup*. John Wiley & Sons, 2013.

[55] Steve Blank and Bob Dorf. *The startup owner's manual: The step-by-step guide for building a great company*. John Wiley & Sons, 2020.