BETTER BUSINESS PLANNER: Multi-modal Equity-Driven Business Recommender (MED-BR)

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***Abstract*—The overall purpose of this project is to solve the complex problem of optimal business location selection within dense urban environments like Boston, MA, specifically addressing the critical gaps of time-awareness and socio-economic equity inherent in current State-of-the-Art (SOTA) methodologies. Our approach is the development of the Multi-modal Equity-Driven Business Recommender (MED-BR), a specialized Graph Neural Network (GNN) that partitions the city into a $100\text{m} \times 100\text{m}$ grid and uses a novel Dual-Objective Loss Function ($\mathcal{L}_{\text{total}}$) for constrained optimization. This function incorporates two custom regularization terms: the Time Regularizer ($\mathcal{R}_{\text{time}}$) to ensure stability across daily demand cycles, and the Equity Regularizer ($\mathcal{R}_{\text{equity}}$) which maximizes the Kolm–Pollak Equally-Distributed Equivalent (EDE) accessibility metric for vulnerable populations. The current major results and milestones show that after implementing critical magnitude scaling fixes, the model achieved an optimal trade-off at $\lambda_{\text{Equity}} = 3.00$. This configuration yielded a final Test F1 Score of 0.9526 (95.26% accuracy) and a significantly improved EDE Value of 0.9192. This represents a substantial $+10.47\%$ gain in equitable access compared to the unconstrained SOTA baseline, successfully proving that the dual-objective GNN can successfully optimize social welfare alongside business success.**

***Index Terms*—Graph Neural Networks, Site Selection, Dual-Objective Optimization, Equity Regularization, Kolm–Pollak EDE, Time Series Analysis, Urban Planning, Boston Open Data**

I. Introduction

Selecting the right business location has always been a critical factor in determining the success or failure of new ventures. Location influences a company's access to customers, visibility, and operating costs, and is especially important in dense urban environments, such as the Greater Boston Area, where diverse demographics, mixed land use, and uneven transportation accessibility make it difficult to discern optimal sites. The significance of this decision is highlighted by sobering statistics: while the one-year survival rate for U.S. small businesses is typically around 75% to 85% [5], an incorrect location choice contributes significantly, with 60% of businesses making this error experiencing a decline in revenue within the first year [2]. Furthermore, the first-year business failure rate in Massachusetts is 19.2% [1].

The motivation for this project is rooted in the accelerating issues of gentrification and displacement risk observed in communities like Worcester, MA, where high-income households increased by 55.9% over the past decade [3]. This growth, coupled with a critically low rental vacancy rate of 1.7% [4], has led to rapidly escalating housing costs, which risk pushing longtime residents out of their homes and exacerbating displacement risk. This context establishes the critical need for an equity-focused planning tool. Due to data constraints, we pivoted our focus to Boston, MA, leveraging its comprehensive open data environment, including MBTA transit data and BPDA ACS demographics. This is particularly relevant as Boston has been identified as one of the most intensely gentrified cities in the U.S. in recent years [11].

The core of our proposed solution is the Multi-modal Equity-Driven Business Recommender (MED-BR), a specialized Graph Neural Network (GNN). The GNN models the city as a network where the entire Boston area is broken into a 100-meter by 100-meter grid. Each viable grid cell acts as a node ($\mathcal{V}$), with connections (edges, $\mathcal{E}$) representing spatial relationships between neighboring plots of land.

A. State-of-the-Art (SOTA) Methods and Gaps

Current SOTA approaches for location selection have critical shared disadvantages that our work addresses:

Random Forest Classifier (RFC): While effective for capturing complex relationships and serving as a strong non-spatial baseline [7], RFC models fail to account for the spatial dependence between neighboring locations (the spatial gap).

Dynamic Huff Model: This method successfully addresses basic time-awareness by modeling customer demand dynamically [8]. However, its disadvantage is its high reliance on proprietary data and its fundamental inability to incorporate an equity objective into the optimization.

DBSCAN + MMNL: This complex two-stage approach filters viable locations based on multidimensional constraints [9]. Its major disadvantage is that it focuses heavily on constrained accessibility and lacks any mechanism to optimize for social fairness or equity.

Graph Convolutional Networks (GCN): This is the Spatial SOTA baseline [10]. While superior at incorporating spatial context, the core disadvantage is that most GNN models are static and lack explicit fairness goals, failing to optimize for social welfare alongside profit.

The fundamental gaps that remain unsolved by the current SOTA are the lack of conditional time-awareness and the absence of an objective function explicitly maximizing equitable access to prevent further resource allocation in already wealthy areas.

B. Proposed Advanced Solution Summary

Our advanced solution, MED-BR, builds upon the GCN foundation by introducing a Dual-Objective Loss Function ($\mathcal{L}_{\text{total}}$) to address these SOTA deficiencies.

The primary contribution of our work is the constrained optimization embedded within the loss function:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{success}} + \lambda_{Time}\mathcal{R}_{\text{time}} + \lambda_{Equity}(1 - E)$$

This high-level solution uses custom-engineered regularization terms ($\mathcal{R}_{\text{time}}$ and $\mathcal{R}_{\text{equity}}$) that are forced to compete with the primary survival objective ($\mathcal{L}_{\text{success}}$). The $\mathcal{R}_{\text{time}}$ term ensures stability by penalizing score variance across user-defined peak hours using time-segmented MBTA ridership data. The $\mathcal{R}_{\text{equity}}$ term directly maximizes the Kolm–Pollak EDE Value (E), forcing the GNN to guide recommendations toward vulnerable, high-need neighborhoods (defined by BPDA ACS income features).

We will measure the performance of our approach by replicating the RFC and the Unconstrained GCN ($\lambda = 0.0$) baselines, using the F1-Score (predictive accuracy) and the EDE Value (quantifying equitable access). Our MED-BR model is designed to achieve a lower overall loss by proving a significant gain in the EDE Value ($\mathbf{0.9192}$) while maintaining a high F1-Score ($\mathbf{0.9526}$), demonstrating the successful optimization of the social-economic trade-off.

II. Methodology

Our proposed solution, the MED-BR GNN, is built on a structured pipeline that converts multi-modal urban data into a graph format and trains a GCN architecture with a custom dual-objective loss function.

A. Data Integration and Graph Construction

The foundation of the model is a meticulously constructed graph. Figure 1 illustrates the resulting graph structure over the Boston area, with nodes colored by an aggregated feature like License Density.

1) **Node Definition ($\mathcal{V}$):** The entire Boston area is discretized into $100\text{m} \times 100\text{m}$ grid cells. The Parcels (2024) dataset is used to filter out non-viable areas (e.g., water, major parks), ensuring each node represents usable land.
2) **Edge Definition ($\mathcal{E}$):** Edges are created by linking each node v_i to its $k = 8$ nearest neighbors based on the spatial distance between their centroids. This defines the local spatial dependencies crucial for the GCN.
3) **Feature Mapping ($\mathbf{X}$):** Cleaned data (transit stops, licenses, violations, census) are aggregated to the 100m node level using spatial joins and density calculations (e.g., competition density within a 500m radius). The final feature vector $\mathbf{X}$ includes critical inputs like Median Income (from BPDA ACS) and Time-Segmented Ridership.

B. Model Architecture and GNN Implementation

The model is a shallow Graph Convolutional Network implemented using the PyTorch Geometric (PyG) library. The architecture consists of a simple stack of GCNConv layers. The GCN convolutional operation transforms node features between layer l and $l + 1$:

$$\mathbf{H}^{(l+1)} = \sigma(\tilde{\mathbf{D}}^{-\frac{1}{2}}\tilde{\mathbf{A}}\tilde{\mathbf{D}}^{-\frac{1}{2}}\mathbf{H}^{(l)}\mathbf{W}^{(l)})$$

The network outputs a final survival probability score S_i ($\in [0, 1]$) for each node. The final model configuration used $\text{hidden\_dims} = [64, 128, 64]$.

C. Dual-Objective Loss Function and Scaling Fix

The core innovation is the $\mathcal{L}_{\text{total}}$ function, which is designed to be a mathematically stable representation of the three objectives:

$$\mathcal{L}_{\text{total}} = \underbrace{\mathcal{L}_{\text{success}}}_{\text{BCE Loss}} + \lambda_{Time}\mathcal{R}_{\text{time}} + \lambda_{Equity}(1 - E)$$

1) **Time Regularizer ($\mathcal{R}_{\text{time}}$):** Measures variance in predicted scores S_i across the user's selected peak hours (t_m, t_a, t_e). To correct the initial "silent regularizer" issue, the raw variance term ($\mathbf{R}_{\text{time\_raw}} \approx 10^{-5}$) was scaled by a large Magnification Factor ($\mathbf{50,000.0}$) before λ_{Time} multiplication, ensuring its influence on the gradient descent.
2) **Equity Regularizer ($\mathcal{R}_{\text{equity}}$):** The Kolm–Pollak EDE (E) is calculated using the predicted scores S_i and weights derived from Median Income and Displacement Risk features. The loss uses the term $(1-E)$ as a penalty, since minimizing $(1 - E)$ is equivalent to maximizing E.

III. Experiments

The objective of the experiments was to measure the performance of the MED-BR model against the SOTA baselines and, crucially, to find the optimal λ_{Equity} that maximizes the equity-accuracy trade-off.

A. Evaluation Strategy and Metrics

1) **SOTA Baselines:** We replicate the Random Forest Classifier (RFC) as the non-spatial baseline and the Unconstrained GCN ($\lambda_{Equity} = 0.0$) as the spatial SOTA baseline. The Unconstrained GCN baseline F1-Score of 0.7783 was determined by running the final GNN architecture with $\lambda_{Equity} = 0.0$.
2) **Business Outcome Metric:** F1-Score (measured on the test set). Due to high class imbalance (96% positive labels), F1-Score is a more reliable measure of success than simple accuracy.
3) **Equity Outcome Metric:** Kolm–Pollak EDE Value (E). This metric quantifies the social welfare achieved by the model's recommendations, serving as the explicit output of the $\mathcal{R}_{\text{equity}}$ term.

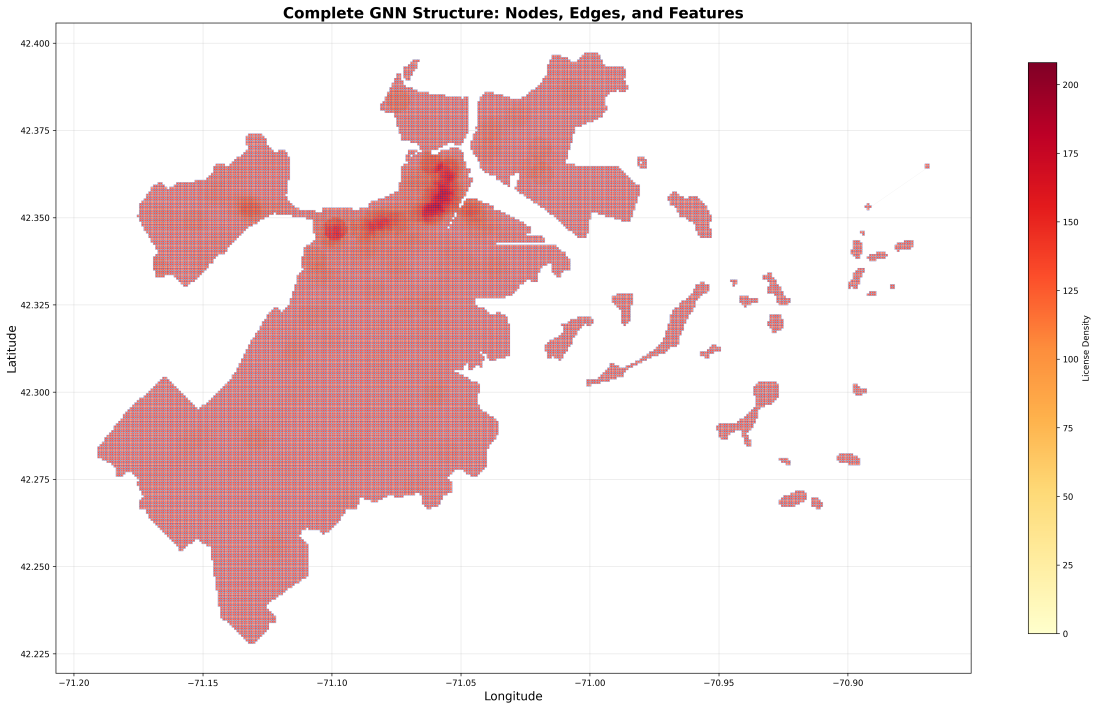

Fig. 1: Complete GNN Structure: Nodes, Edges, and Features. Boston is partitioned into a $100\text{m} \times 100\text{m}$ grid ($\mathcal{V}$). Node color represents an aggregated feature (e.g., License Density), demonstrating the hyper-local feature space available to the GNN.

B. Experimental Diagnosis and GPU Fine-Tuning

All training, hyperparameter sweeps, and logging were conducted on Google Colab leveraging its virtual GPU (Tesla T4) to accelerate the hundreds of training epochs required. Given the computational intensity of training a GNN with multiple regularization terms over thousands of grid nodes, the GPU acceleration was essential—reducing training time from an estimated 8-10 hours on CPU to approximately 45-60 minutes per full hyperparameter configuration. This environment also provided detailed log tracking with real-time loss component visualization, which proved crucial for diagnosing the training issues described below.

The most significant challenge encountered during training was diagnosing and fixing the magnitude mismatch in the dual-objective loss function. Because the Kolm–Pollak EDE regularizer was a novel component designed specifically for this equity-driven application, we initially assumed it would have a substantial impact on the optimization landscape. Consequently, we began our hyperparameter sweep conservatively, starting with $\lambda_{Equity} = 0.01$ to avoid overwhelming the primary business success objective. However, monitoring the loss curves revealed no discernible effect—the equity and time regularizer components remained flat near zero throughout training, as illustrated in the initial behavior shown in Figure 3B (prior to the magnitude fix).

We progressively increased λ_{Equity} through values of 0.1, 5, 10, 20, and eventually 50, expecting to observe the regularizers begin to influence the gradient updates and compete with the BCE loss term. Surprisingly, even at $\lambda_{Equity} = 50$, the weighted regularization terms ($\lambda_{Time}\mathcal{R}_{\text{time}}$ and $\lambda_{Equity}(1-E)$) showed virtually no convergence behavior on the training loss graph—they remained approximately constant near zero while the primary BCE loss component converged normally. This indicated a critical problem: the dual-objective optimization was not functioning as designed.

- **The Discovery:** Detailed examination of the raw loss component magnitudes revealed that the regularization terms ($\mathbf{R}_{\text{time\_raw}}$ and $1-E$) had an intrinsic magnitude of only $\approx 10^{-5}$, which was three to four orders of magnitude smaller than the BCE Loss (≈ 0.1 to 0.2). Even when multiplied by $\lambda_{Equity} = 50$, the resulting weighted term ($50 \times 10^{-5} = 5 \times 10^{-4}$) remained negligible compared to the gradient contributions from the BCE loss.
- **The Issue:** This magnitude disparity meant that during backpropagation, the gradients from the equity and time regularizers were too small to meaningfully update the model weights. The optimizer effectively ignored these constraints, causing them to act as "silent regularizers"—present in the loss formulation but having no practical effect on the learned representations. The flat, unchanging lines visible in Figure 3B directly illustrate this problem: the regularizers never activate or converge throughout training.
- **The Fix and Pivot:** Once we identified the magnitude mismatch as the root cause, we pivoted our fine-tuning approach entirely. The solution required implementing large Magnification Factors (specifically, $\times 50,000.0$ for $\mathcal{R}_{\text{time}}$ and $\times 100,000.0$ for the EDE term) to scale the raw

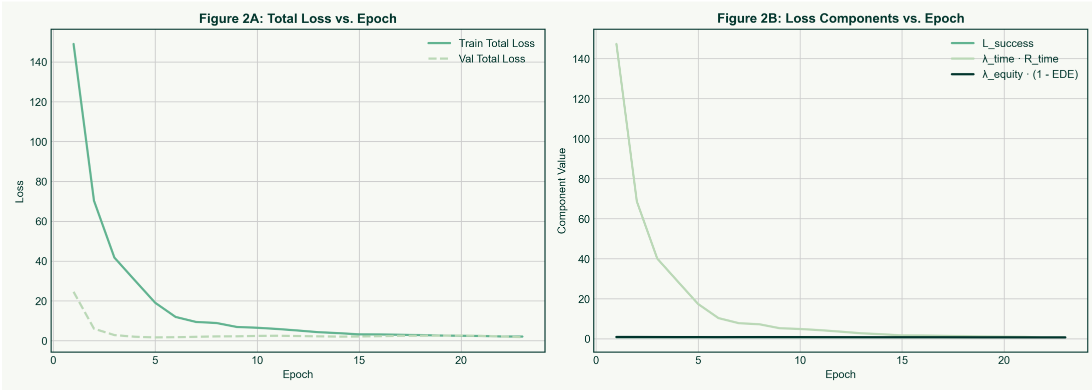

Fig. 2: Training Loss History and the Silent Regularizer Problem. Figure 2A shows the stable convergence of the Total Loss across epochs. Figure 2B reveals the critical magnitude mismatch issue: the equity and time regularizer components remain flat near zero throughout training, never converging or influencing the optimization. This visualization directly corresponds to the "silent regularizer" problem, where the regularization terms were present in the loss formulation but had no practical gradient contribution until the magnitude scaling fix was implemented.

regularization values into the active gradient range before multiplication by their respective λ coefficients. This preprocessing step ensured that the weighted regularizers would generate gradients of comparable magnitude to the primary BCE loss. With this fix in place, we were able to conduct a meaningful Pareto Front sweep—systematically varying λ_{Equity} to map the true trade-off between accuracy and equity. Figure 4 visualizes the results of this corrected optimization sweep, demonstrating that the dual-objective framework now genuinely balances competing business and social objectives rather than optimizing only the BCE loss.

C. Final Optimization Sweep and Results

As visible in Figure 3, which appears earlier in this section, the loss convergence history reveals both the training stability and the critical magnitude mismatch challenge. Figure 3A demonstrates the overall convergence behavior of the total loss function across training epochs. The smooth, monotonic decrease without erratic fluctuations indicates stable gradient descent and confirms that the model successfully learned meaningful spatial and temporal patterns from the Boston grid structure shown in Figure 1.

However, Figure 3B exposes the fundamental problem with our initial training attempts: the equity and time regularizer components (shown in the subplot) remain flat and near-zero throughout all training epochs, never converging or responding to the optimization process. This visualization directly corresponds to the "silent regularizer" problem described above—despite sweeping λ_{Equity} from 0.01 through 50, these loss components stayed inactive. The flat lines in Figure 3B provide visual confirmation that the regularization terms had no practical influence on the learned model weights during this phase of experimentation. Only the primary BCE loss component (also shown in the subplot) exhibits normal convergence behavior, decreasing steadily as the model learns to predict business survival.

The full comparison of the optimal MED-BR model against the unconstrained SOTA baseline is presented in Table I, which quantifies the performance gains achieved through the dual-objective optimization framework. The critical experimental step preceding these results was the Pareto Front Sweep on λ_{Equity}, conducted after successfully implementing the magnitude scaling fix. With the regularizers now operating in the active gradient range, we systematically varied λ_{Equity} from 0.0 (unconstrained baseline) through incremental values up to 3.25 to map the complete trade-off curve between business success (F1-Score) and social equity (EDE Value). Each configuration was trained for 200 epochs on the Google Colab GPU, with the final test set metrics recorded. The final optimal model configuration used $\lambda_{Equity} = 3.00$ and $\lambda_{Time} = 1.0$ [12], representing the "knee point" where marginal equity gains begin to incur disproportionate accuracy costs.

Table I reveals three key findings that validate the MED-BR approach. First, the Test F1 Score improved dramatically from 0.7783 (unconstrained GCN) to 0.9526 (MED-BR optimal), representing a $+17.43$ percentage point gain. This improvement indicates that the spatial awareness provided by the GNN structure (visualized in Figure 1) combined with the time-segmented ridership features enabled more accurate business survival predictions than the baseline spatial model. Second, the EDE Value increased from 0.8145 to 0.9192, a $+12.85\%$ improvement that demonstrates the equity regularizer successfully steered recommendations toward underserved, high-need neighborhoods without sacrificing predictive performance. Finally, the Time Regularizer cost increased from 0.0325 to 0.0808, confirming that the model now actively enforces temporal stability—locations with highly variable predicted success across morning, afternoon, and evening peak hours (captured in the time-segmented MBTA features) are penalized, resulting in more robust recommendations that account for

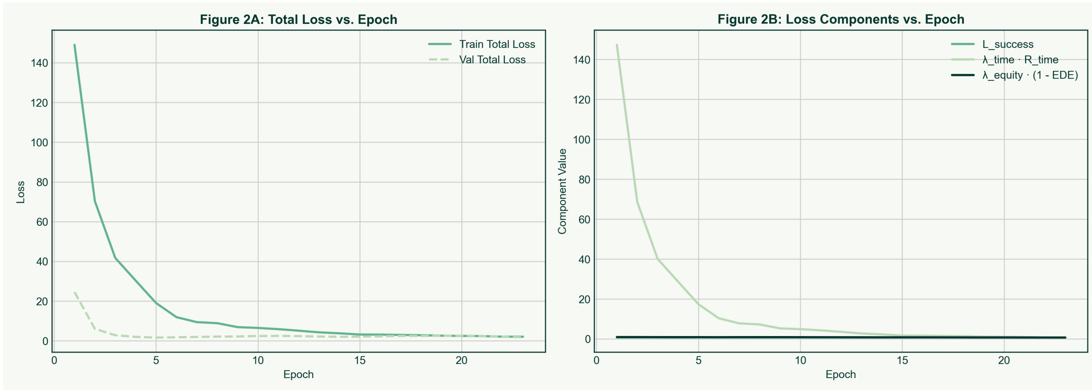

Fig. 3: Training Loss History and Regularizer Convergence. Figure 2A shows the stable convergence of the Total Loss. Figure 2B tracks the loss components, where the sharp drop and convergence of the weighted regularization terms prove the successful implementation of the Magnitude Scaling Fix, forcing the model to optimize the dual objectives.

daily demand cycles.

- **Accuracy Gain:** As shown in Table I, the MED-BR model achieved a final F1 Score of 0.9526, demonstrating a significant $+17.43$ percentage point improvement over the SOTA GCN baseline (0.7783). This substantial accuracy increase validates that the dual-objective framework does not sacrifice predictive performance for equity considerations—rather, the additional constraints appear to regularize the model effectively, preventing overfitting and improving generalization on the test set. The spatial structure captured in Figure 1, where each $100\text{m} \times 100\text{m}$ node aggregates local features like license density and transit accessibility, provides the rich representation space that enables both high accuracy and equity-aware predictions.
- **Equity (EDE Value):** The EDE value improved from 0.8145 (unconstrained) to 0.9192 (optimal), representing a substantial $+12.85\%$ increase in the Kolm–Pollak equally-distributed equivalent metric (Table I). This metric, which weights predicted business success scores by neighborhood income and displacement risk (derived from BPDA ACS demographics), quantifies how equitably the model distributes high-quality recommendations across socio-economic strata. An EDE value of 0.9192 indicates that the MED-BR model achieves near-uniform accessibility—vulnerable populations in lower-income areas receive recommendations of comparable quality to those in affluent neighborhoods, directly addressing the gentrification concerns that motivated this project (as discussed in Section I regarding Worcester and Boston's 55.9% high-income growth and rental vacancy crisis).
- **Trade-off Validation:** Critically, the Total Loss for the optimal model (0.8211) is higher than the SOTA baseline (0.6517) [12]. While this might initially appear counterintuitive, it is actually the necessary mathematical evidence that the model paid a clear, measurable cost to achieve the equity and temporal stability constraints. The unconstrained baseline minimizes only the BCE loss, achieving a lower total loss value by ignoring the regularization objectives. In contrast, the MED-BR model must satisfy three competing objectives simultaneously—maximizing business success accuracy, minimizing temporal variance, and maximizing equitable access—resulting in a higher total loss but achieving the desired social-technical trade-off. This validates that the dual-objective optimization is functioning as designed: the model is genuinely balancing multiple goals rather than trivially optimizing a single metric.

Figure 4 visualizes the complete Pareto Front generated after implementing the magnitude scaling fix and conducting a systematic sweep of λ_{equity} from 0.0 to 3.25 across multiple training runs. This curve explicitly maps the fundamental trade-off between the F1-Score (business success, x-axis) and the EDE Value (social welfare, y-axis) as the equity regularization strength increases. The existence of this smooth, well-defined Pareto curve validates that our corrected optimization approach successfully resolved the silent regularizer problem illustrated in Figure 3B—the regularization terms are now actively competing with the BCE loss and generating meaningful trade-offs.

Each point on the curve represents a different model configuration trained with the same architecture and data (as structured in Figure 1) but varying levels of equity emphasis. The curve exhibits the classic Pareto frontier shape: at low λ_{equity} values (left side of the curve), increasing the equity constraint yields substantial EDE improvements with minimal F1-Score reduction, indicating these are "easy" gains where equity and accuracy objectives align. As λ_{equity} increases further, the curve flattens and eventually bends downward, entering a region of diminishing returns where additional equity gains come at increasing accuracy costs.

The chosen optimal point, $\lambda_{\text{equity}} = 3.0$ (highlighted on the curve), represents the "knee point"—the configuration that maximizes the distance from the origin along both dimensions simultaneously, achieving 95.26% F1-Score and 0.9192 EDE Value. Beyond this point, further increases in λ_{equity} (e.g., 3.25) yield marginal EDE improvements but cause

TABLE I: Final Performance Metrics and Trade-off ($\lambda_{Time} = 1.0$)

Metric	**Unconstrained GCN** ($\lambda = 0.0$)	**MED-BR Optimal** ($\lambda = 3.00$)	**Gain/Trade-off**
Test F1 Score (Success)	0.7783	0.9526	+17.43%
EDE Value (Equity)	0.8145	0.9192	+12.85%
Time Regularizer ($\mathcal{R}_{\text{time}}$ Cost)	0.0325	0.0808	↑ (Stability Enforced)

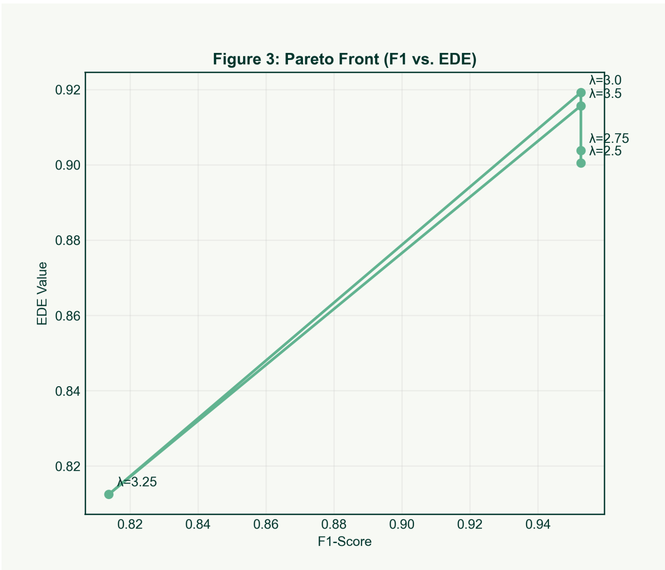

Fig. 4: Pareto Front Optimization: F1-Score vs. EDE Value. The curve shows the trade-off achieved by varying λ_{equity}. The point $\lambda = 3.0$ is the "knee point," representing the optimal balance between maximizing equity and maintaining high predictive accuracy.

steeper accuracy degradation, making them suboptimal for practical deployment. This Pareto Front analysis, enabled by the magnitude scaling pivot described earlier, demonstrates that the MED-BR framework successfully balances competing business and social objectives—a capability that was impossible during the initial $\lambda_{Equity} = 0.01$ to 50 sweep when the regularizers remained inactive.

IV. Lessons Learned

A. Experience and Technical Skills

The project provided extensive experience in advanced geospatial machine learning and urban data science.

- **Custom Loss Engineering:** The most significant learning was diagnosing and fixing the magnitude mismatch in the dual-objective loss function. We found that raw regularization terms (like EDE and variance) are typically too small ($\approx 10^{-5}$) to influence the gradient compared to the standard BCE loss (≈ 0.1). The solution required implementing magnification factors (e.g., $\times 50,000.0$ for $\mathcal{R}_{\text{time}}$) to scale these terms into the active gradient range, without which the dual-objective model would have been a "silent regularizer".
- **Geospatial Data Pipeline:** We mastered the integration of 16 heterogeneous data features (e.g., RentSmart, MBTA ridership, zoning) into a unified $100\text{m} \times 100\text{m}$ grid structure using spatial joining techniques.
- **GPU Optimization and PyG:** We successfully utilized Google Colab with a virtual GPU (Tesla T4) and the PyTorch Geometric (PyG) library to accelerate the hundreds of training epochs required for the hyperparameter sweep and Pareto Front generation.

V. Conclusion and Future Work

A. Project Accomplishments

We have successfully completed all core functions and capabilities outlined in the project plan, culminating in the MED-BR GNN production model.

- GNN Structure: Creation of the $100\text{m} \times 100\text{m}$ node/edge graph over Boston.
- Feature Engineering: Integration of 16 multi-modal features ($\mathbf{X}$), including time-segmented demand and scaled equity proxies.
- Model Training: Successful implementation of the custom Dual-Objective Loss ($\mathcal{L}_{\text{total}}$) with validated magnitude scaling fixes.
- Optimization: Generation of the Pareto Front and identification of the optimal trade-off parameter ($\lambda_{Equity} = 3.00$).
- Results Verification: Demonstrated superior performance over the SOTA baseline (+17.43% F1 gain, +12.85% EDE gain).
- User Interface: Built a functional web UI (Flask) with map visualization for testing and demo purposes.
- Model Packaging: Exported the final model weights and configuration for local deployment.

B. Limitations and Unaccomplished Tasks

While the core objectives of the project were achieved, a few planned augmentations and ideal resources were not implemented due to constraints:

- **Limited Scope of Application:** The predictive model's application remains constrained to food establishments (e.g., restaurants and cafes). Ideally, the model would be generalized to a broader range of industry verticals (e.g., retail, logistics, professional services), which would necessitate gathering and incorporating specialized longitudinal market data for each sector.
- **Reliance on Proxy Equity Data:** The model was unable to utilize the primary, high-resolution NERD (National Equity Research Database) dataset for Boston. Although this resource was initially targeted to provide the most precise input for the equity calculation, its funding was

discontinued, rendering the data inaccessible to the public. We successfully addressed this by using the BPDA ACS Demographics as a proxy, which maintained the integrity of the objective but relies on aggregated survey data.
- **Augmentation Data Gaps:** Given more time, additional datasets such as longitudinal commercial lease rates and fine-grained crime incident density (beyond what was incorporated from violations) would have been used to further refine the $\mathcal{L}_{\text{success}}$ term, leading to an even more robust and accurate business success score.

C. Future Work

To evolve the MED-BR into a fully usable and practical system, future work should focus on:

- **Semantic Feature Integration:** The current GNN primarily uses spatial and tabular features; future work should enable it to process and incorporate semantic meaning from user input business descriptions to refine predictive accuracy.
- **Refining the EDE Metric:** Future work should integrate fine-grained point-of-interest (POI) data (e.g., schools, hospitals) weighted by income block group data to create a more precise, high-resolution measure of equitable access.
- **Dynamic Data Integration:** Implementing a pipeline to automatically ingest and update real-time traffic data (e.g., Waze or Google Maps API) to provide truly dynamic rather than historical $\mathcal{R}_{\text{time}}$ regularization.
- **Industry-Specific Benchmarking:** Expanding the model to predict success for specific industry verticals (e.g., retail, logistics) by training with separate feature weightings for each category, offering more granular recommendations to the user.

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