Uncovering the Latent Relationships in Food Inspection Records via Unsupervised Clustering

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Abstract

Regulatory food premises inspection records encode a structured profile of each establishment's operational characteristics, equipment inventory, and compliance history. However, the administrative risk categories assigned to food premises may not capture the full latent structure present in these records. We present the first machine learning study to leverage open food premises inspection data from Toronto Public Health (TPH), introducing a novel dataset of **20,055** records that has not previously been used in any machine learning or data-driven research. We develop an unsupervised clustering pipeline in which records are projected to 2-dimensions using **UMAP** and partitioned using **Gaussian Mixture Model (GMM)**, with the number of components k selected by minimizing the Bayesian Information Criterion (BIC) over $k \in \{2, \ldots, 10\}$. We selected $k = 5$ to balance statistical fit with interpretability. Cluster quality is assessed against the regulatory three-level risk label (Low, Medium, High) using Adjusted Rand Index (ARI) and Normalized Mutual Information (NMI). Post-hoc analysis reveals five operationally coherent establishment phenotypes, providing a complementary basis for inspection beyond rule-based risk scoring.

1. Introduction

Food safety inspections are a cornerstone of public health infrastructure, implemented by governments worldwide to reduce the incidence of foodborne illness (Barnes et al., 2024). In Ontario, Canada, food establishment inspections fall under the jurisdiction of local public health agencies (LPHAs) according to the Ontario Health Protection and Promotion Act. LPHAs conduct regulatory inspection programs, assessing the compliance of food premises with food safety requirements, including O. Reg. 493/17: Food Premises (Ministry of the Attorney General, 2017). Structured inspection records encode risk categorization, violations, and compliance actions. These records are summarized into a set of ordinal risk categories (e.g., High, Medium, Low) that determine inspection frequency, mandated by the provincial regulation.

The risk taxonomy is operationally convenient but is determined largely by rule-based assignment procedures developed in 2019 that do not exploit the full breadth of historical inspection records. A natural question follows: *does the full inspection history contain richer latent structure than the official risk taxonomy captures?* Answering this question requires an approach that bypasses the risk categorization labels during learning.

Unsupervised clustering has proven effective at revealing latent structure in public health data, including patient subphenotyping from electronic health records (Birkenbihl et al., 2023; Lu, 2025), behavioural risk profiling of youth substance use (Yang et al., 2022), and cardiovascular disease risk stratification (Khamis et al., 2025). Systematic review by Li et al. documented the rapid growth in machine learning (ML) applications across the food safety domain from 2014 to 2024. Zhang et al. further demonstrated the utility of clustering algorithms and their applications in food safety risk assessment. These precedents motivate our application of unsupervised clustering to food inspection records. Our contributions are as follows:

1. **A standardized preprocessing pipeline** for a structured inspection dataset, comprising feature selection, missingness imputation, and mixed-type data encoding.

2. **A UMAP + GMM clustering framework** with BIC-driven component selection, producing interpretable low-dimensional embeddings and probabilistic cluster assignments.

3. **Post-hoc facility-level analysis** linking cluster mem-

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bership to official risk categories, quantifying both agreement and divergence, with soft assignment confidence as an epistemic signal for ambiguous records.

2. Data and Preprocessing

2.1. Data Sources

The TPH Establishment List is a food inspection registry maintained by Toronto Public Health (TPH), comprising 20,055 records across 64 variables obtained under a data-sharing agreement with the City of Toronto. Each record corresponds to an active food premises as of February 6, 2026. Variables span establishment identity, operational characteristics, equipment inventory, staffing, licensing status, and hours of operation.

2.2. Feature Selection and Preprocessing

Three feature types were retained: categorical, binary, and numerical. Variables with greater than 20% missing values were excluded. Identifiers were also removed. This threshold eliminated 36 of 64 features, leaving 28 features available for downstream analysis (See Appendix A for details). The `Current Risk` (`Low`, `Medium`, `High`) is retained solely for post-hoc evaluation and is never seen during training. **Categorical Features.** Variables with more than 15 unique levels were treated as high-cardinality: the 15 most frequent levels were retained and remaining levels were mapped to "Other". All categorical variables were subsequently one-hot encoded with no reference level dropped. **Binary Features**. Free-text "Yes/No" responses were mapped to $\{1, 0\}$. Missing values were imputed as 0 ("No"), consistent with the assumption that absence of a recorded feature indicates its non-presence. **Numerical Features.** Missing values were imputed with the column median, then subsequently standardized to zero mean and unit variance.

3. Methodology

3.1. UMAP Dimensionality Reduction

Uniform Manifold Approximation and Projection (McInnes et al., 2020) is applied to project the 68 dimensional feature matrix X to 2 dimensions using hyperparameters $n_neighbors = 30$ and $min_dist = 0.1$. UMAP is preferred over PCA for this application because it preserves local topological structure while allowing a non-linear manifold discovery, which is well-suited to heterogeneous mixed-type data after one-hot encoding.

3.2. Gaussian Mixture Model Clustering

A Gaussian Mixture Model (Reynolds, 2009) with full covariance is fitted on the 2-D UMAP embedding for each $k \in \{2, 3, \ldots, 10\}$. The optimal k^* is selected by balancing the Bayesian Information Criterion (BIC) score and interpretability:

$$k^* = \arg\min_k \ \mathrm{BIC}(k) = \arg\min_k \left[-2 \ln \hat{L}_k + p_k \ln N \right], \tag{1}$$

where $\hat{L}_k$ is the maximized likelihood, p_k the number of free parameters, and N the sample size. GMMs are preferred over k-means because they produce soft probabilistic assignments, accommodate ellipsoidal clusters of varying shape and scale, and support principled model selection via BIC.

3.3. Evaluation

Cluster assignments are compared with the official risk label via:

- **Adjusted Rand Index (ARI)** (Santos & Embrechts, 2009) : measures pairwise agreement, corrected for chance; $\in [-1, 1]$.
- **Normalized Mutual Information (NMI)** (Strehl & Ghosh, 2002): measures shared information, normalized to $[0, 1]$.

Both metrics treat the risk label as an *external* reference. The clustering is strictly unsupervised (risk labels are never used as input).

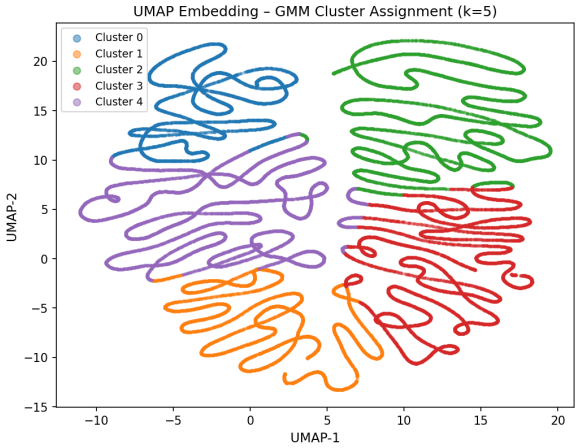
3.4. Post-hoc Analysis

For each cluster, we computed the prevalence of each feature, the distribution across establishment groups, and the composition of risk labels. To rank features by discriminative power across clusters, we applied **Pearson Chi-squared test** (χ^2) (Agresti, 2007) for binary and categorical features vs. cluster assignment and **One-way ANOVA F-test** for numerical features versus cluster assignment.

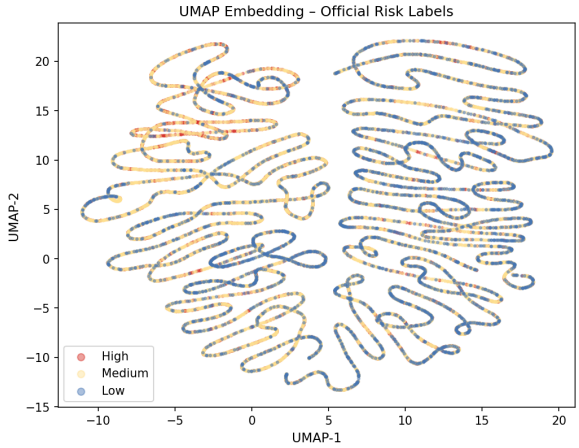
4. Experiments and Results

4.1. BIC Model Selection

BIC decreased monotonically from 275,758 at $k = 2$ to 270,956 at $k = 10$, with no inflection point (Appendix B). In the absence of a clear elbow, we selected $k = 5$ as the configuration as it produced additional cluster information than the regulatory three-level risk categorization, while generating a qualitatively distinct operational interpretation.



(a) GMM cluster assignment ($k = 5$).



(b) Official Current Risk label ($High$, $Medium$, Low).

Figure 1. UMAP embeddings comparison. (a) shows the hard assignment of cluster membership generated by GMM. It applies a winner-takes-all threshold: the point is assigned to whichever cluster achieves the highest posterior probability; (b) shows the current regulatory risk label being assigned to the food premises.

4.2. UMAP Visualization

The UMAP projection (Figure 1) of clusters appears as continuously connected, ribbon-like manifolds. This reveals that the underlying high-dimensional feature space has strong continuity. Food premises transition gradually along risk and infraction gradients rather than falling into discrete groups. Comparing panel (a) with (b), the official Current Risk labels do not align cleanly with any single GMM cluster. Medium and Low labels are interleaved across multiple clusters. This mismatch suggests the hand-assigned official risk categories may not fully capture the multivariate structure present in the inspection data.

4.3. Robustness of the Pipeline

A natural concern is that clustering after a non-linear projection manufactures clusters that do not exist in the source feature space, since UMAP preserves local structure while distorting global density on which the GMM likelihood depends. We therefore fit the GMM ($k = 5$, full covariance) in three representation spaces: (1) the original 28-D feature space, (2) a PCA space retaining 95% of variance, and (3) the 2-D UMAP embedding. Table 1 reports external agreement with the official risk categories (ARI, NMI) and internal cohesion (Silhouette score).

If UMAP were inventing spurious clusters, we would expect comparable or stronger label agreement in the original space. Instead, GMM in the original 28-D space produces ARI $= 0.024$ and a low silhouette (0.101), indicating poorly separated components. PCA retaining 95% variance still requires 25 of 28 components, and its performance is nearly identical to the original feature space. UMAP is the only space in which compact, well-separated components emerge (silhouette 0.429, roughly four times the original-space value), and its clusters also show the highest mutual information with an external label set the embedding never observed (NMI 0.183 vs. 0.027 and 0.039). We emphasize NMI and silhouette over ARI in this comparison because ARI is dominated by the large Medium stratum and is the least stable metric across embeddings, whereas the consistent ordering across all three measures is what supports the conclusion.

Table 1. GMM clustering ($k = 5$) across representation spaces. UMAP yields both the most cohesive clusters and the strongest alignment with regulatory labels; clustering in the original or PCA space recovers only weak structure.

Representation space	ARI	NMI	Silhouette
Original (28-D)	0.024	0.027	0.101
PCA (95% var, 25-D)	0.028	0.039	0.094
UMAP (2-D)	**0.089**	**0.183**	**0.429**

4.4. Feature Discriminability

Figure 2 presents the top-15 features ranked by cluster-discriminating power. Previous Risk level (Chi² statistic) is the single most informative feature, followed by equipment indicators: Commercial Dishwasher, Donair/Shawarma, 3-Compartment Sink, and Barbeque/Rotisserie. Day-of-week features (Saturday, Sunday) also rank highly, reflecting systematic differences in the operational schedules of distinct establishment types.

4.5. Cluster Profiles and Risk Alignment

Cross-tabulation of cluster membership against official risk labels (Figure 3) reveals highly differentiated cluster pro-

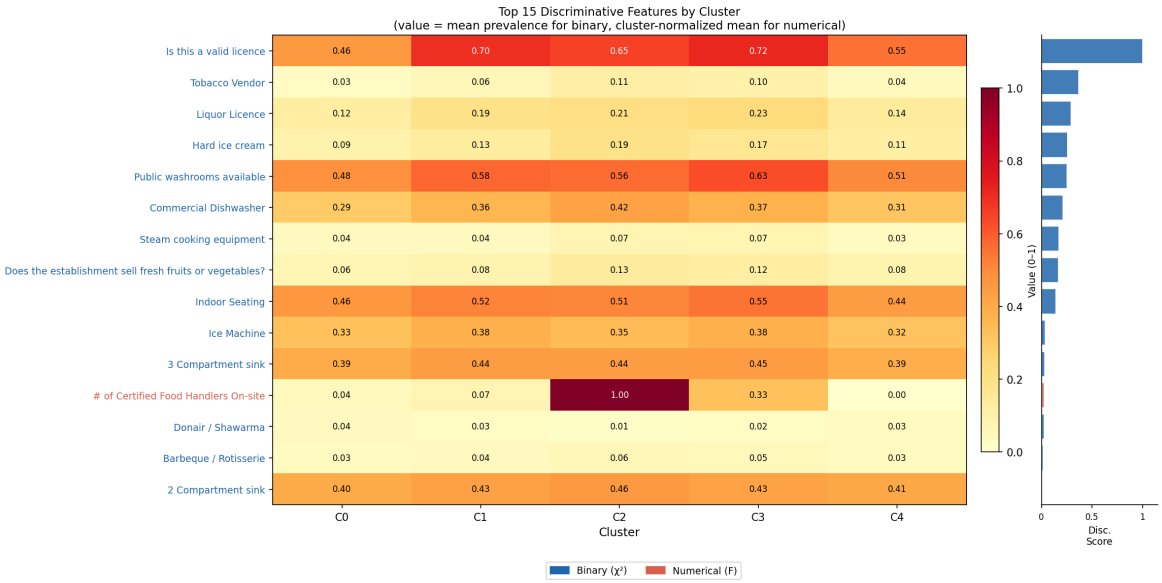


Figure 2. Top 15 discriminative features ranked jointly by normalized discriminability score (sidebar). Binary features (blue labels) are scored by Pearson χ^2 and displayed as cluster mean prevalence; numerical features (red labels) are scored by one-way ANOVA F-statistic and displayed as cluster-normalized means rescaled to $[0, 1]$. Cell values and colour intensity encode the per-cluster profile.

files. The alignment metrics yield ARI $= 0.09$ and NMI $= 0.18$, indicating modest but statistically meaningful correspondence. The relatively low values reflect that clustering is driven by operational and equipment features rather than by the risk label directly. Table 2 summarizes each cluster by its risk-label composition, and the binary/categorical features whose within-cluster prevalence deviates most from the global mean.

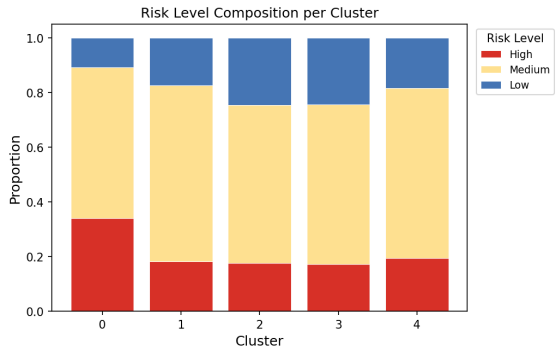


Figure 3. Row-normalized cross-tabulation of cluster membership vs. official risk level.

We then translate these "signature features" into interpretable food premises profiles:

- **Cluster 0 - Full-service restaurants**: High prevalence of commercial dishwashers, 3-compartment sinks, and liquor licences; predominantly full-service restaurants with High/Medium risk.

Table 2. The five discovered clusters. "Signature features" are those whose within-cluster prevalence most exceeds or falls below the global mean.

Cluster	Dominant risk (purity)	Signature features
C0	Medium/High (0.58)	high commercial-dishwasher use; many previously High-risk
C1	Medium (0.90)	service-type, previously Medium; the "standard restaurant" core
C2	Low (0.74)	retail, no indoor seating; minimal-prep, lowest handler need
C3	Low (0.85)	licensed retail, previously Low, no 3-compartment sink
C4	Medium (0.52)	unrated/NA prior risk; new or recently re-registered premises

- **Cluster 1 - Institutional kitchens**: Primarily weekday-only operations (Mon–Fri open, Sat–Sun closed); dominated by institutional catering (child care, cafeterias).

- **Cluster 2 - Retail convenience stores**: High tobacco vendor prevalence and convenience store features; predominantly Low risk retail establishments.

- **Cluster 3 - Take-out only outlets**: High takeout-only prevalence; limited equipment; Medium risk food take-out premises.

- **Cluster 4 - Seasonal and mobile vendors**: Mixed profile; seasonal flag elevated; includes outdoor vendors and food carts.

5. Discussion

The proposed pipeline recovers five interpretable establishment phenotypes from the TPH registry without access to risk labels during training. The moderate alignment with official risk tiers (ARI = 0.09, NMI = 0.18) indicates that operational and equipment profiles encode structural information beyond what the current three-class taxonomy captures. We highlight several actionable implications:

Medium risk is internally heterogeneous. Multiple clusters with predominantly Medium-risk membership exhibit substantially different equipment profiles. Stratifying the Medium tier by equipment complexity could enable more granular inspection scheduling.

Having a valid license is the strongest individual predictor of cluster membership. This finding validates the use of licence status in risk labelling but also suggests that establishments undergoing licence transitions may be systematically misallocated under the current scheme.

Day-of-week patterns differentiate clusters. Saturday and Sunday operations are statistically significant cluster discriminators, reflecting that weekend-only or daily operators present different food safety risk profiles even within the same risk tier.

5.1. Limitations

The monotonically decreasing BIC without a clear elbow makes k selection sensitive to range assumptions. $k = 5$ was selected for better interoperability. Missingness imputation as 0 for binary features may introduce noise for variables with systematic rather than random absence patterns. Additionally, the analysis is cross-sectional. Timestamps and geographical information were excluded in the study. Nevertheless, the clusters has demonstrated meaningful separation. Longitudinal modelling of risk trajectory would be a natural extension of this line of work.

Several further limitations qualify the present findings. Agreement with the official risk taxonomy is modest by construction. Our clustering is driven by operational and equipment features rather than the inspection outcomes that define the tiers. The characterization is descriptive and correlational. The discriminative features distinguish clusters but are not causally linked to inspection outcomes, making external and prospective validation necessary before any operational use.

6. Conclusion

To the best of our knowledge, this is the first application of unsupervised clustering to food premises inspection records, and the first use of TPH's open inspection dataset in any data-driven research context. Prior work on such data has relied primarily on statistical models (Howell et al., 2026; Cho, 2026), and much of the broader food safety ML literature has focused on upstream tasks such as microbial detection and supply chain optimization (Zhong et al., 2023; Revelou et al., 2025; Liu et al., 2024). Inspector-generated records are distinctive in that virtually all covered premises serve consumers directly, making them particularly relevant to public health practice.

This work demonstrates that unsupervised clustering can automatically discover latent structure within structured inspection records, recovering operationally coherent establishment phenotypes that partially diverge from the official risk taxonomy. The identified clusters and their risk compositions may inform new approaches to inspection scheduling and resource allocation. Moreover, the discriminative feature analysis provides a foundation for subsequent predictive risk modelling, with the potential to support more responsive, evidence-based food inspection system.

We are actively collaborating with the Local Public Health Agencies (LPHAs) under an integrated knowledge translation (IKT) model (Canadian Institutes of Health Research, 2012), in which inspection practitioners and public health stakeholders are engaged throughout the research process. The present study forms part of a larger effort to build an AI-enabled predictive system designed to integrate into existing inspection workflows rather than replace them. The unsupervised clustering reported here serves as an interpretable foundation, within which subsequent components can be developed and validated within the same practitioner-engaged framework.

Future work proceeds along three directions. First, we will expand the dataset and pipeline beyond the City of Toronto to additional LPHAs, testing whether the recovered phenotype structure generalizes across jurisdictions or is specific to a single registry. Second, we are building a standardized data dictionary, which harmonizes the heterogeneous inspection data across agencies. It is a prerequisite for any multi-jurisdiction predictive system and a contribution we intend to formalize. Third, we will explore a wider range of machine learning applications in food safety inspection, including supervised risk prediction,inspection-outcome forecasting, and resource-allocation optimization, each evaluated prospectively and in collaboration with the participating agencies.

7. Impact Statement

This paper presents work aimed at advancing the field of food safety inspection. Applications of this methodology could improve the efficiency of regulatory inspection programs and support more equitable allocation of public health resources. No specific ethical concerns are anticipated beyond those applicable to any use of administrative records under data-sharing agreements.

8. Acknowledgement

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A. Dataset Description and Preprocessing

Dataset Description. The dataset used in this study was drawn from the City of Toronto's municipal-level food premises inspection registry, with the original file name "Establishment List.xlsx". Each record within this file corresponds to a unique food premises and includes a curated set of operational and infrastructural attributes collected during routine inspections. For the official assigned risk classification, TPH originally assigned four ordinal levels (High, Medium, Low, and Super Low) instead of three (which is the provincial standard). Thus, for the purpose of standardization, we merged the class "Super Low" with "Low" (having an inspection frequency that's lower or equal to once per year). The raw dataset exhibits a moderate class imbalance, with "Medium" being the dominant group. Figure 4 shows the distribution of the risk categorization.

It should also be noted that the operational characteristics of the food premises would no longer be collected since Nov, 2025. The remaining features being monitored by the City of Toronto would be limited to only tobacco vendors, certified food handlers, and Toronto Business License.

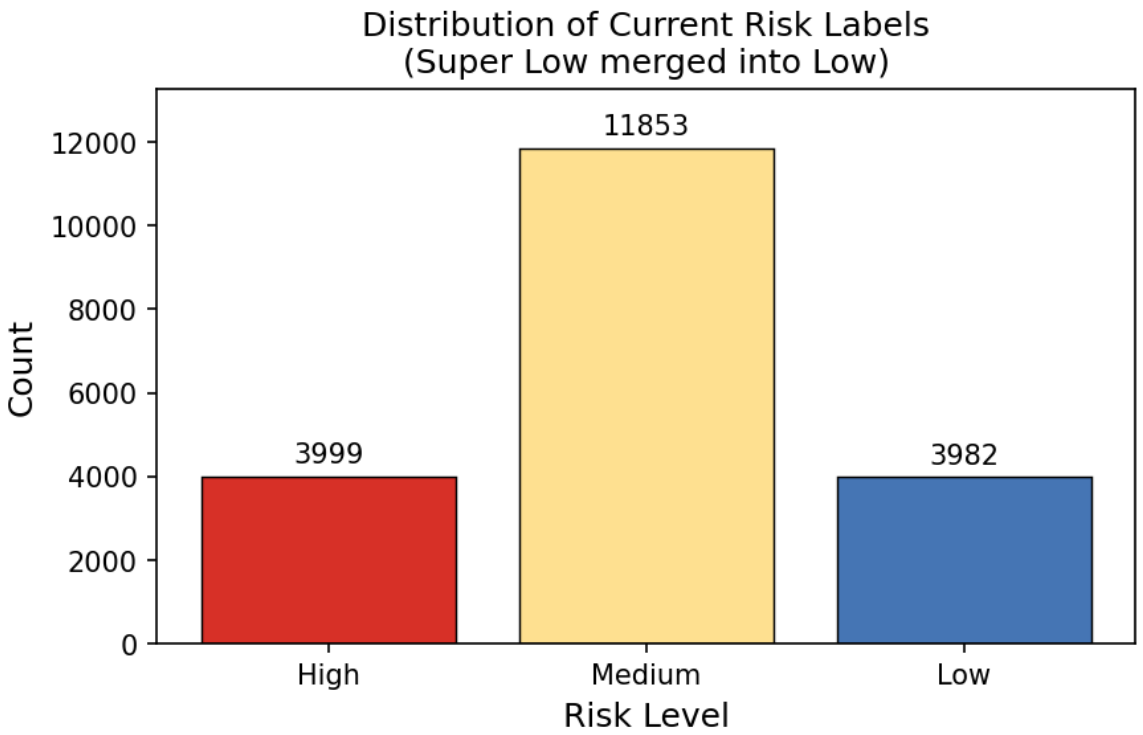

Figure 4. Risk classification distribution of the original file. The majority of food premises are classified as "Medium". The required inspection frequency for "Medium" is twice per year. The required inspection frequency for "High" is three times per year, and for "Low" is once per year.

Missingness Report. Features with higher than 20% missingness were excluded in the downstream analysis. Table 3 summarizes the features being dropped. The potential reasons for having a high value of missingness are 1) the field was not required to be filled during inspection; 2) administrative variables that might not be applicable to the majority of food premises;3) accidental omission during manual data entry and/or collection (human error).

Table 3. Variables excluded due to >20% missingness (top-20 shown).

Variable	Missing (%)
Date Permanently Closed	99.8%
Vehicle Plate Number	99.7%
Date Out of Business (OOB)	99.7%

Continued on next page

Table 3. Variables excluded due to >20% missingness (continued)

Variable	Missing (%)
Toronto Vehicle Licence	99.7%
Seasonal Month Open	95.9%
Seasonal Month Closed	95.9%
Food Preparation Location	94.8%
Approved Source of Food	86.0%
Start of Operation Date	77.2%
UNIT	74.4%
Regulated Food Premises	50.7%
Municipal Code Chapter 545 N/A	44.0%
Business Licence N/A	43.1%
Public washrooms location?	40.5%
Toronto Licence Expiry Date	36.8%
Sunday Closing	36.2%
Sunday Opening	36.0%
Number of staff washrooms	32.4%
Saturday Closing	31.8%
Saturday Opening	31.7%

Preprocessing Statistics. After filtering for missingness, the retained variables are presented in Table 4. For each weekday (Sunday through Saturday), a binary *Open* indicator was engineered: if both the opening and closing time fields are non-null and non-zero for a given day, the establishment is coded as open on that day ($= 1$); otherwise closed ($= 0$). This collapses 14 sparse time columns into 7 interpretable binary features. All features were standardized where appropriate prior to dimensionality reduction. UMAP was applied to the full feature matrix to produce a 2-dimensional embedding for visualization and downstream clustering. $ESTABLISHMENT$ is excluded for downstream analysis because it encodes for each establishment's id (an identifier, not a feature).

Table 4. Descriptive statistics for all retained features (raw, before scaling).

Feature	Type	Missing (%)	Mean	Std
Is this a valid licence	binary	7.950	0.625	0.484
Tobacco Vendor	binary	17.700	0.072	0.258
Seasonal	binary	0.120	0.039	0.193
Commercial Dishwasher	binary	14.330	0.357	0.479
2 Compartment sink	binary	16.040	0.426	0.494
3 Compartment sink	binary	15.760	0.424	0.494
Soft Serve Ice Cream	binary	12.750	0.035	0.182
Hard ice cream	binary	12.890	0.141	0.348
Barbeque / Rotisserie	binary	12.910	0.042	0.201
Ice Machine	binary	11.830	0.350	0.477
Cooking equip. for customers	binary	13.090	0.008	0.091
Steam cooking equipment	binary	13.180	0.054	0.225
Sous Vide Cooking	binary	13.130	0.014	0.118
Donair / Shawarma	binary	13.140	0.026	0.159
Indoor Seating	binary	12.340	0.499	0.500
Takeout only	binary	13.550	0.356	0.479
Public washrooms	binary	14.120	0.556	0.497
Sunday_Open	binary	0.000	0.000	0.000
Monday_Open	binary	0.000	0.000	0.000

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Table 4. Descriptive statistics for all retained features (continued)

Feature	Type	Missing (%)	Mean	Std
Tuesday_Open	binary	0.000	0.000	0.000
Wednesday_Open	binary	0.000	0.000	0.000
Thursday_Open	binary	0.000	0.000	0.000
Friday_Open	binary	0.000	0.000	0.000
Saturday_Open	binary	0.000	0.000	0.000
# of Cert. Food Handlers Req.	numerical	13.320	1.194	0.942
# of Cert. Food Handlers On-site	numerical	13.230	1.320	1.819
ESTABLISHMENT	categorical	0.010	—	—
POSTAL CODE	categorical	1.670	—	—
Establishment Group	categorical	0.120	—	—
Previous Risk	categorical	16.340	—	—

B. Gaussian Mixture Model Clustering

Gaussian Mixture Model (GMM) clustering was performed on the UMAP embeddings. The number of clusters/components was selected through the Bayesian information criterion (BIC) (Konishi & Kitagawa, 2008). We selected $k = 5$ as the operationally interpretable solution. It should be noted that $k = 5$ is not the minimal k within the sweeping range.

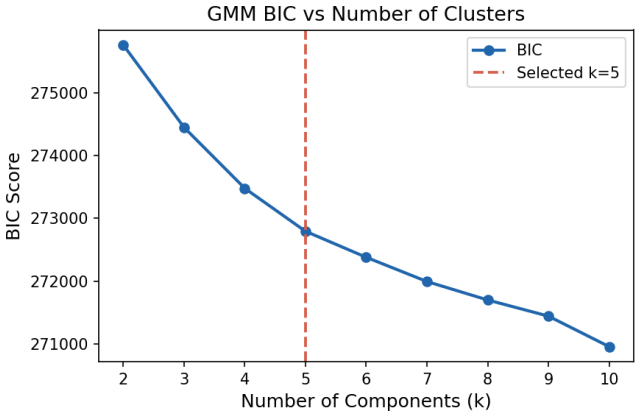

Figure 5. BIC score as a function of GMM components k. BIC is minimized at $k = 10$, the selected k is $k = 5$.

Table 5. GMM BIC and AIC scores for $k = 2$ to 10. Selected $k^* = 5$.

k	**BIC**
2	275,757.7
3	274,446.3
4	273,476.9
5	**272,792.3**
6	272,378.6
7	271,992.6
8	271,698.8
9	271,442.0
10	270,956.4