DS 3000: Introduction to Machine Learning

Canadian Households Coursework

Analysis of Canadian Household Demographics and Spending Patterns

Group 9

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1 Executive Summary

This project analyzes Canadian household data to identify patterns in demographic and economic behavior using clustering and dimensionality reduction, followed by predictive modeling of insurance and pension spending.

1. Clustering and Dimensionality Reduction

We began with data cleaning, removing 47 variables closely tied to the target to avoid leakage. Given the mismatch between metadata and dataset, variables not found were logged and the rest removed. Outliers were handled conservatively using IQR-based winsorization, chosen for its robustness in skewed data.

To uncover household clusters, we applied K-Means clustering. Elbow and Silhouette methods agreed that the optimal cluster number was likely 2 or 3, but both indicated weak clustering structure. We proceeded with $K = 3$ for further analysis.

PCA was used to reduce dimensionality. We compared results on scaled and unscaled data, choosing the scaled version for interpretability despite higher raw variance in the unscaled results. PC1 (67.9% variance) captured economic activity and household size; PC2 reflected immigrant presence versus native-established populations; PC3 related to household structure and living arrangements.

Cluster interpretation yielded:

- **Cluster 0:** Affluent immigrant families with high spending and traditional structures.
- **Cluster 1:** Low-spending, high-immigration, small households.
- **Cluster 2:** Native-born, mid-spending, non-traditional households.

UMAP was applied for further visualization using tuned hyperparameters. Manhattan distance with `n_neighbors=40` and `min_dist=1` showed best separation. UMAP produced clearer cluster boundaries than PCA, particularly highlighting differences in household composition and immigrant status.

2. Regression Modeling for Insurance & Pension Spending

The target variable was defined as the proportion of income spent on personal insurance and pensions. We excluded related features to prevent leakage and cleaned the dataset through imputation, low-variance feature removal, and IQR-based winsorization. The resulting features were standardized and categorical variables one-hot encoded.

Two models were developed:

- **Elastic Net Regression** achieved an R^2 of 0.8040 (95% CI: [0.8020, 0.8058]) with MSE of 0.1966. Top predictors included employment/unemployment rates, median age, and miscellaneous household spending. These captured macroeconomic and demographic signals, showing strong but linear effects.
- **XGBoost Regression** significantly outperformed Elastic Net, with R^2 of 0.9114 (95% CI: [0.9105, 0.9123]) and MSE of 0.0888. It captured non-linear patterns missed by Elastic Net, including threshold effects for housekeeper count and gift contributions.

SHAP analysis on the XGBoost model confirmed the importance of variables such as number of housekeepers, secondary mortgage, gift spending, median maintainer age, and childcare expenses. These insights emphasized the non-linear and interactive nature of the problem, supporting the use of XGBoost over linear models.

Recommendations

- Deploy XGBoost with SHAP-based monitoring for explainability.
- Segment users by key drivers (e.g., maintainer age, household support).
- Expand the dataset with behavioral variables for more granular targeting.
- Use A/B testing to measure impact of model-driven interventions.

2 Clustering and Dimensionality Reduction

In this section we outline the process and results of applying the K-Means Clustering algorithm, and the Principal Component Analysis (PCA) and the Uniform Manifold Approximation and Projection (UMAP) dimensionality reduction techniques to learn if there are segments or axes of grouping in our data that allow us to uncover meaningful patterns or characteristics and guide subsequent predictive modeling.

2.1 Data Preprocessing

To prepare the data for clustering and dimensionality reduction, we first merged the DemoStats and HouseholdSpend datasets using Dissemination Area (DA) identifiers, then dropped the identifier columns as they offered no predictive value.

We addressed missingness by identifying variables, mostly median age-related, with over 10% null values. Despite this, they showed meaningful correlation with the target variable, so we retained them and imputed missing values using the column medians.

To avoid information leakage into unsupervised learning, we removed 47 variables tied to our regression target, including those containing terms like income, insurance, pension, retirement, and tax. This prevented clustering from being influenced by features directly related to the dependent variable in the regression.

Given the skewed nature of our dataset, we handled outliers using IQR-based winsorization, capping extreme values at 1.5 the interquartile range. This method was preferred over z-score trimming, which would have reinforced distribution skewness.

Finally, we applied z-score normalization to all numeric features. As K-Means and PCA are scale-sensitive, standardization ensures fair comparison across features.

2.2 K-Means Clustering

Due to the datasets size, we applied the Elbow and Silhouette methods on a 10% sample to estimate an appropriate number of clusters for K-Means while minimizing compute overhead.

The Elbow method (Figure 1) shows a bend at $k = 4$, indicating diminishing returns in distortion reduction beyond this point.

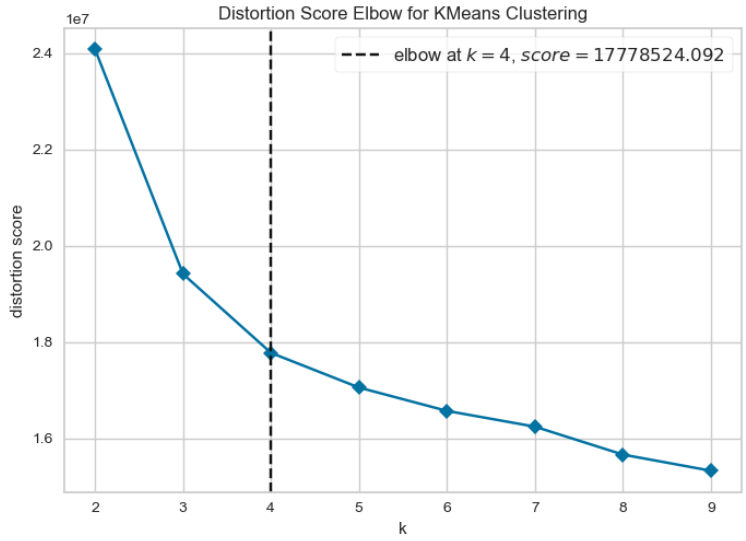


Figure 1: Distortion Score Elbow for KMeans Clustering

Silhouette plots for $k = 2$, $k = 3$, and $k = 4$ (Figures 24) illustrate a trade-off between cohesion and interpretability. $k = 2$ (Figure 2) yields the highest average score but produces overly broad clusters. $k = 3$

(Figure 3) shows clearer separation with moderate cohesion. At $k = 4$ (Figure 4), cohesion declines further with increased overlap.

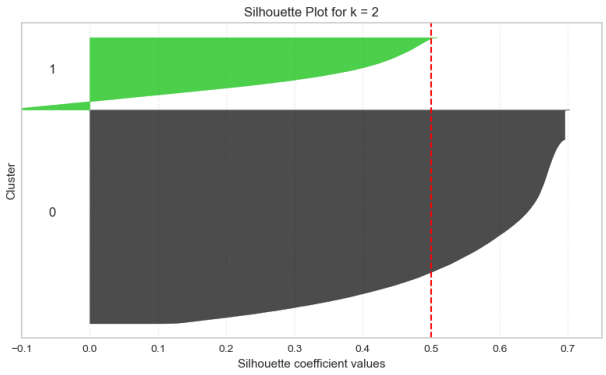


Figure 2: Silhouette Plot for $k = 2$

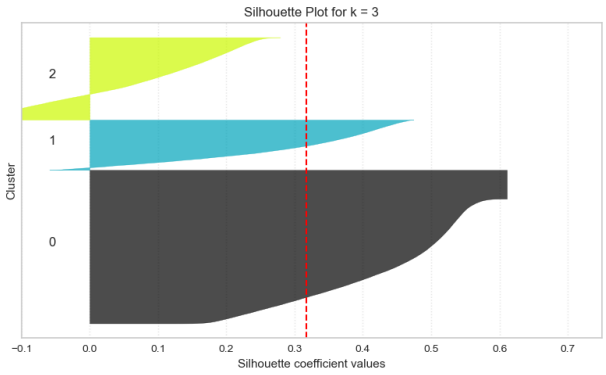


Figure 3: Silhouette Plot for $k = 3$

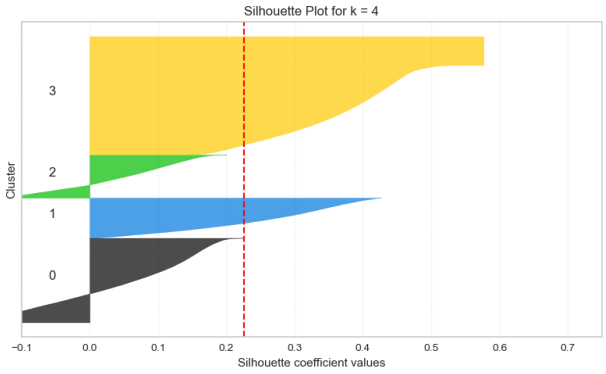


Figure 4: Silhouette Plot for $k = 4$

The Silhouette plot for $k = 5$ (Figure 13) and average Silhouette scores across $k = 2$ to $k = 5$ (Figure 14) are included in the appendix.

Given the interpretability and moderate separation at $k = 3$, we selected it as the final number of clusters. These labels were retained for dimensionality reduction and further analysis.

2.3 Principal Component Analysis

To explore latent structure in the data, we applied Principal Component Analysis (PCA), a linear dimensionality reduction technique. We compared results on both unscaled and standardized data. Although PCA on unscaled data yielded a first component that explains 98.8% of the variance, this result was driven largely by the presence of features with larger numeric scales. In contrast, the scaled version, where all variables are z-score normalized, produced a more balanced set of principal components, with the first three PCs explaining 67.9%, 3.7%, and 3.0% of the variance, respectively. Therefore, all PCA analyses moving forward are based on the scaled data.

Figure 5 illustrates 3D scatterplots of the first three principal components for both the unscaled and scaled data, coloured by the K-Means cluster labels ($k = 3$). The scaled data plot reveals broad, loosely separated regions aligned with the cluster assignments, though some overlap remains, suggesting that the clustering structure is not sharply defined but does capture some underlying gradients in the data.

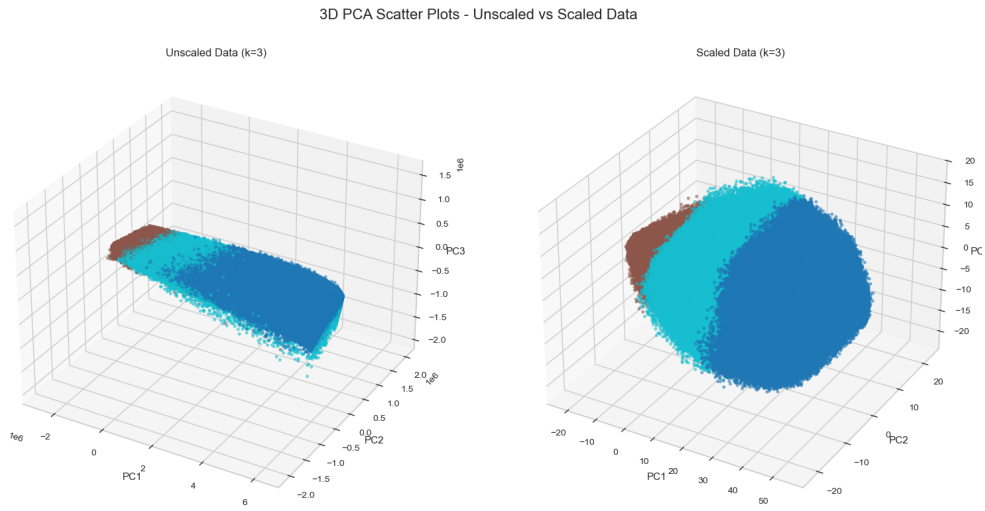


Figure 5: 3D PCA Scatter Plots Comparing Unscaled (Left) vs. Scaled (Right) Data

We calculated the top five positive and negative contributors to each of the first three principal components and grouped them by variable category for interpretability. The detailed variable-level contributions are presented in Appendix Tables 4–9.

PC1: Economic Activity and Household Presence. PC1 appears to capture a dimension tied to household economic activity and consumer behavior. The dominant contribution from the *Consumption* category (Figure 6) suggests that higher PC1 scores are associated with greater household spending. This is supported by additional contributions from population-related categories like *Total Household Population by Age*, indicating these are also demographically dense areas. Contributions from *Household Population 15+ by Industry* further reinforce the interpretation that PC1 reflects regions with economically active residents and a strong consumer presence.

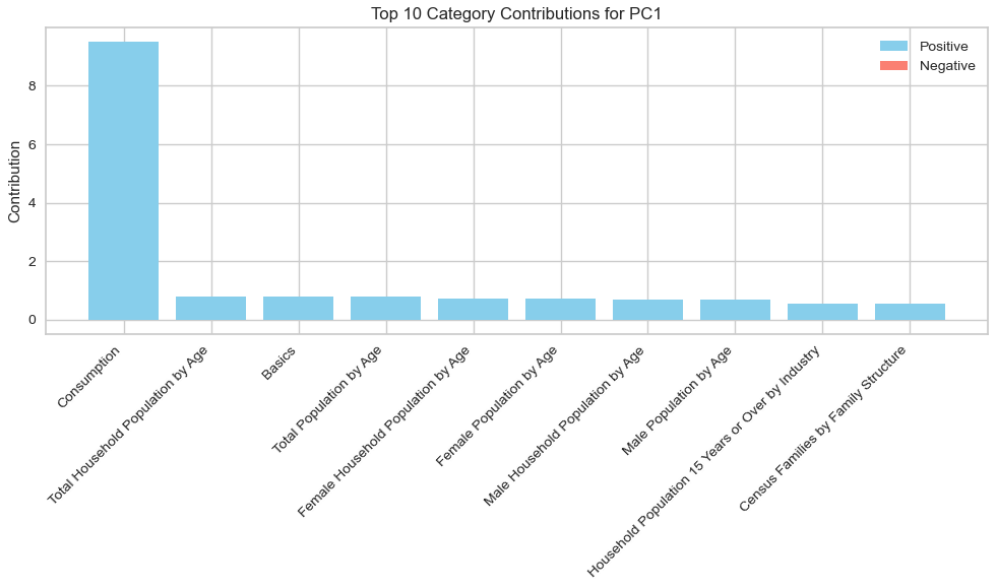


Figure 6: Top Contributing Categories to PC1

PC2: Immigrant Presence vs. Established Households. PC2 differentiates areas with high immigrant presence from those with more established populations (Figure 7). While *Consumption* remains a positive factor, the strongest negative contributions come from immigration-related categories such as *Total Immigrants and Place of Birth*, *Period of Immigration*, and *Age at Immigration*. High PC2 scores likely reflect long-established, non-immigrant populations with moderate spending, while lower scores correspond to recent immigrant-dense areas with distinct demographic structures.

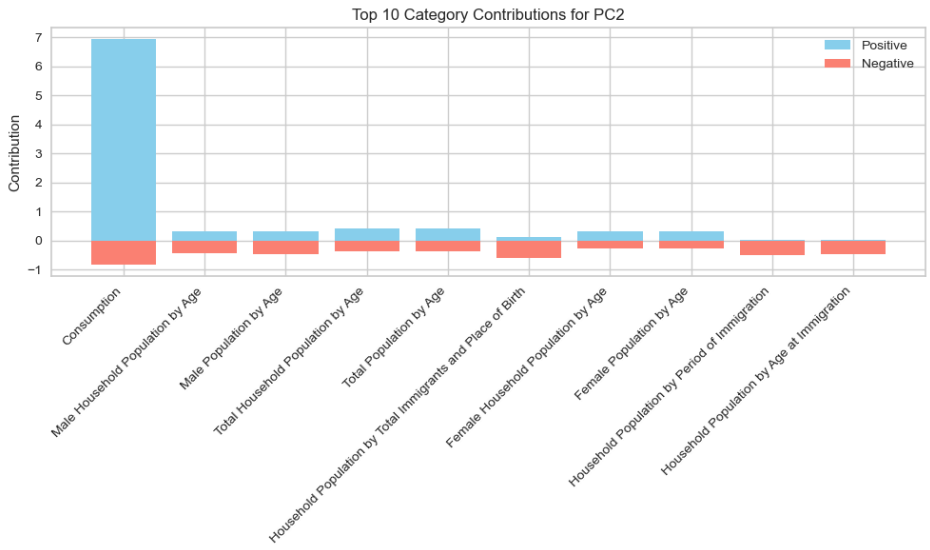


Figure 7: Top Contributing Categories to PC2

PC3: Household Composition and Structural Living. PC3 seems to reflect differences in household structure and housing type (Figure 8). Contributions are more muted from *Consumption*, while categories like *Census Family Households by Family Structure*, *Households by Household Type*, and *Occupied Private Dwellings by Structure Type* contribute negatively. This suggests that lower PC3 scores may represent non-traditional or smaller households in denser housing (e.g., apartments), whereas higher scores point to more traditional family units in larger dwellings.

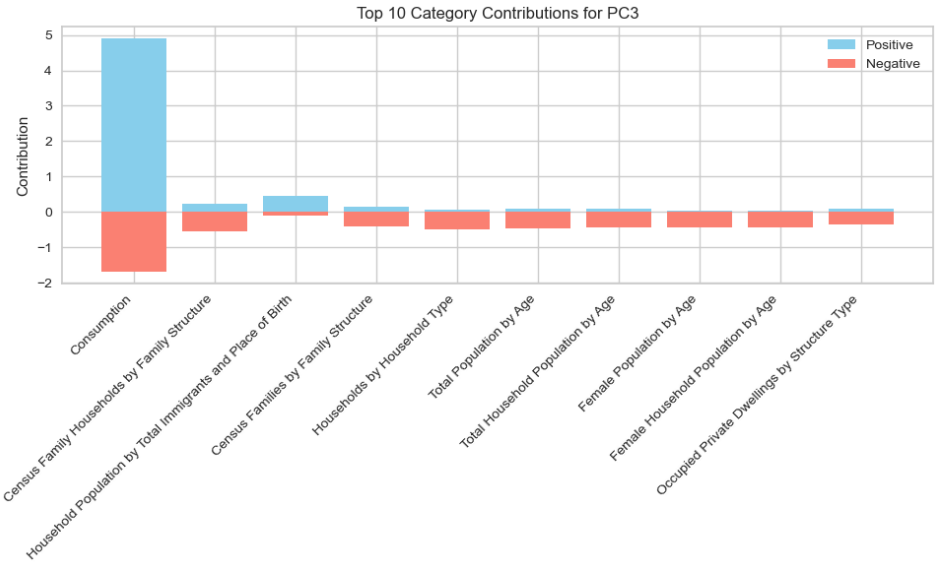


Figure 8: Top Contributing Categories to PC3

Overall, PCA revealed interpretable latent axes in the data related to economic activity, immigration patterns, and household structure. While clusters in the PCA-projected space are not strongly separable, the broad grouping captured by K-Means aligns with meaningful socioeconomic dimensions.

Cluster Profiling Based on Principal Components To better understand the characteristics of the clusters formed by K-Means ($k = 3$), we calculated the average values of the first three principal components within each cluster. Since PC1 explains a dominant 67.9% of the total variance, it serves as the primary basis for interpretation, while PC2 and PC3 (explaining 3.7% and 3.0%, respectively) provide additional nuance.

Table 1: Mean Principal Component Scores by Cluster

Cluster	PC1 Mean	PC2 Mean	PC3 Mean
0	37.89	-0.63	0.19
1	-15.13	-0.22	$\sim$0.00
2	5.19	0.80	-0.11

Cluster 0: Affluent, Traditional Immigrant Families. This cluster scores highest on PC1, indicating strong consumer activity and dense, demographically diverse households. The slightly negative PC2 score suggests a moderate immigrant presence, while a mildly positive PC3 implies more traditional household structures. These could be higher-income, family-oriented areas with a mix of native and immigrant populations.

Cluster 1: Low-Spending, High-Immigration, Small Households. Cluster 1 shows the lowest PC1 score, reflecting low household spending and smaller population centers. A modestly negative PC2 indicates relatively recent immigrant populations, and the near-zero PC3 score hints at non-traditional or smaller households. These may represent younger, immigrant-dominated areas with limited consumer capacity and less conventional living arrangements.

Cluster 2: Mid-Spending, Native, Non-Traditional Households. This group is moderate on PC1 (spending) and somewhat positive on PC2, suggesting a primarily native-born population. The slightly negative PC3 implies more non-traditional household setups, such as single-person or young professional units, possibly in urban or high-density housing contexts. These areas may be characterized by moderate economic activity and non-family household compositions.

These labels will be used in subsequent visualizations and interpretation.

2.4 Uniform Manifold Approximation and Projection

To further investigate latent structure, we applied UMAP to reduce the high-dimensional data to two dimensions for visualization. UMAP is a non-linear technique well-suited for preserving both local and global structure in complex datasets.

We conducted a grid search over key hyperparameters: `n_neighbors`, `min_dist`, and `spread`, using a low `n_epochs` of 100 for faster iteration. Three distance metrics (Euclidean, Manhattan, Cosine) were compared. Across all metrics and settings (Figures 15, 16, 17), Manhattan consistently yielded the most interpretable clusters.

The best configuration was found to be `n_neighbors=40`, `min_dist=1`, and `spread=1.5` using the Manhattan distance metric. This setup produced compact, well-separated clusters while maintaining a balance between local cohesion and global structure.

We then re-ran UMAP with this configuration and increased `n_epochs` to 1000 for improved convergence. The final embedding (Figure 9) revealed sharper boundaries between clusters and uncovered two additional tightly packed groups not visible in PCA. These distinct clusters suggest UMAP was able to capture non-linear structures missed by PCA, reinforcing its value for exploratory analysis.

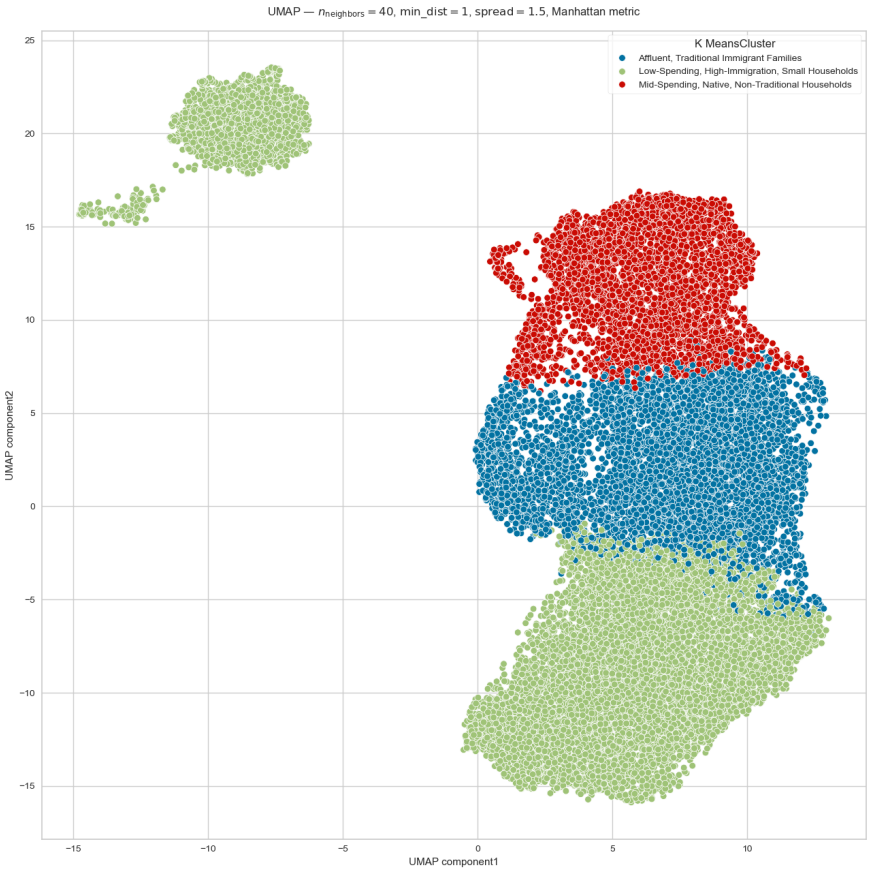


Figure 9: UMAP with Manhattan distance, `n_neighbors=40`, `min_dist=1`, `spread=1.5`, and 1000 epochs.

3 Regression

Target Definition & Feature Engineering

We define the target variable as the proportion of household income spent on personal insurance premiums and retirement/pension contributions. Concretely, if I denotes total insurance spending, P denotes pension contributions, and H denotes household income, then

$$y = \frac{I + P}{H}.$$

To prepare the data, we:

- Imputed missing values using column medians.
- Excluded 47 columns containing keywords ("income", "retirement", "pension", "income tax", "insurance") to avoid leakage.
- Dropped ∼300 near-constant features (low variance).
- Applied IQR-based winsorization to continuous predictors only, capping values at the 1.5×IQR bounds to mitigate the influence of extreme outliers.

We retained zerocontribution cases to capture non-working households. Using correlation heatmaps, we created interaction terms (e.g., household sizeinsurance spending). Continuous features were winsorized at 1.5IQR and standardized, and multi-level categoricals were one-hot encoded. This pipeline prepared the data for both linear and non-linear models.

3.1 Elastic Net Regression

An `ElasticNetCV` model was fit using a grid over regularization strength $\alpha \in \{0.01, 0.05, 0.1\}$ and mixing parameter ℓ_1 ratio $\in \{0.1, 0.3, 0.5\}$, with three-fold CV and up to 10,000 iterations for convergence. On the test set, the model achieved

$$\begin{aligned} \text{MSE} = 0.1966, \quad & 95\%\,\text{CI}\,[0.1948, 0.1983], \\ R^2 = 0.8040, \quad & 95\%\,\text{CI}\,[0.8020, 0.8058]. \end{aligned}$$

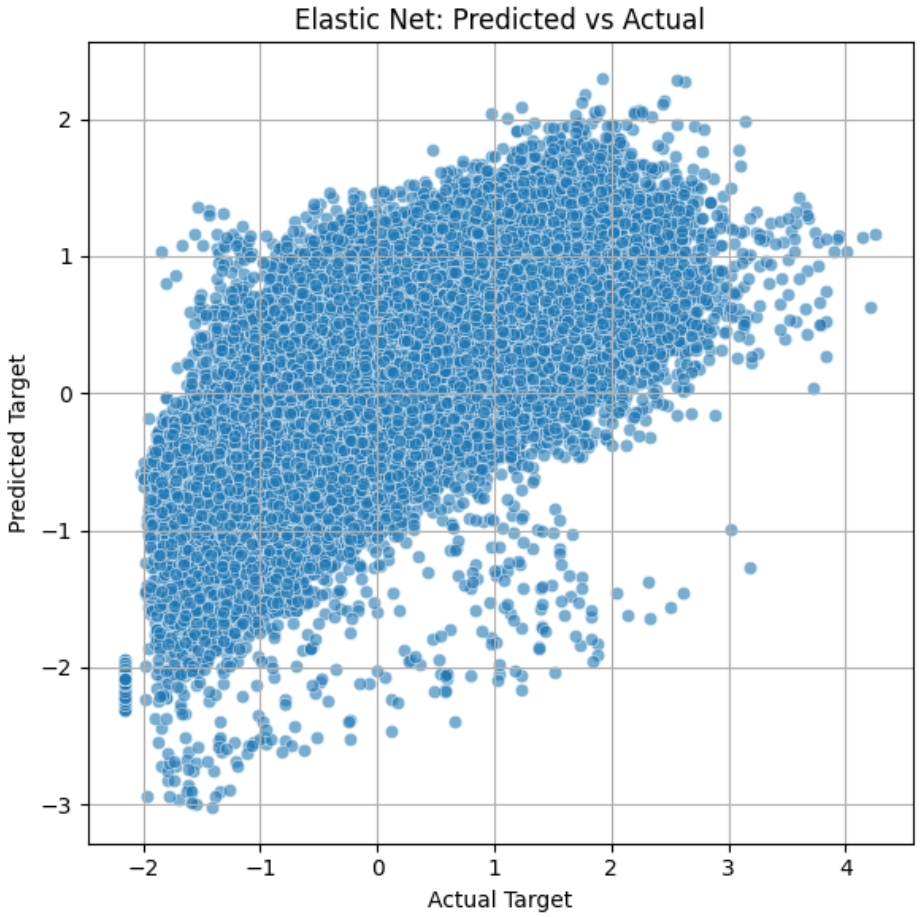


Figure 10: Elastic Net: Predicted vs. Actual Proportion on Test Set.

The top five coefficients (by magnitude) are shown in Table 2.

Feature	Coefficient	Interpretation
ECYACTER	+0.606	Employment rate increases spending ratio
ECYACTUR	+0.398	Unemployment rate increases proportion
ECYMTNMED	−0.224	Higher median age reduces ratio
ECYMTNAVG	−0.206	Higher average maintainer age reduces ratio
HSME001S	+0.174	Miscellaneous spending increases ratio

Table 2: Top five Elastic Net coefficients.

We observed that $\alpha = 0.01$ and ℓ_1 ratio=0.3 were consistently selected, balancing sparsity and shrinkage. The model converged in under 2,500 iterations. All VIF scores were below 5, and residuals showed ho-

moscedasticity and near-normality. Coefficient paths against α confirmed that uninformative features were quickly shrunk to zero, demonstrating effective regularization.

3.2 XGBoost Regression

We trained an XGBoost model using `GridSearchCV` (3-fold) over learning rate $\in \{0.05, 0.1, 0.2\}$, max depth $\in \{3, 5, 7\}$, and n_estimators $\in \{100, 200, 300\}$. The optimal parameters were

$$\text{learning\_rate} = 0.1, \quad \text{max\_depth} = 5, \quad n\_\text{estimators} = 200.$$

Test performance improved substantially:

$$\begin{aligned} \text{MSE} &\approx 0.0888, \quad 95\%\,\text{CI}[0.0880, 0.0896], \\ R^2 &\approx 0.9114, \quad 95\%\,\text{CI}[0.9105, 0.9123]. \end{aligned}$$

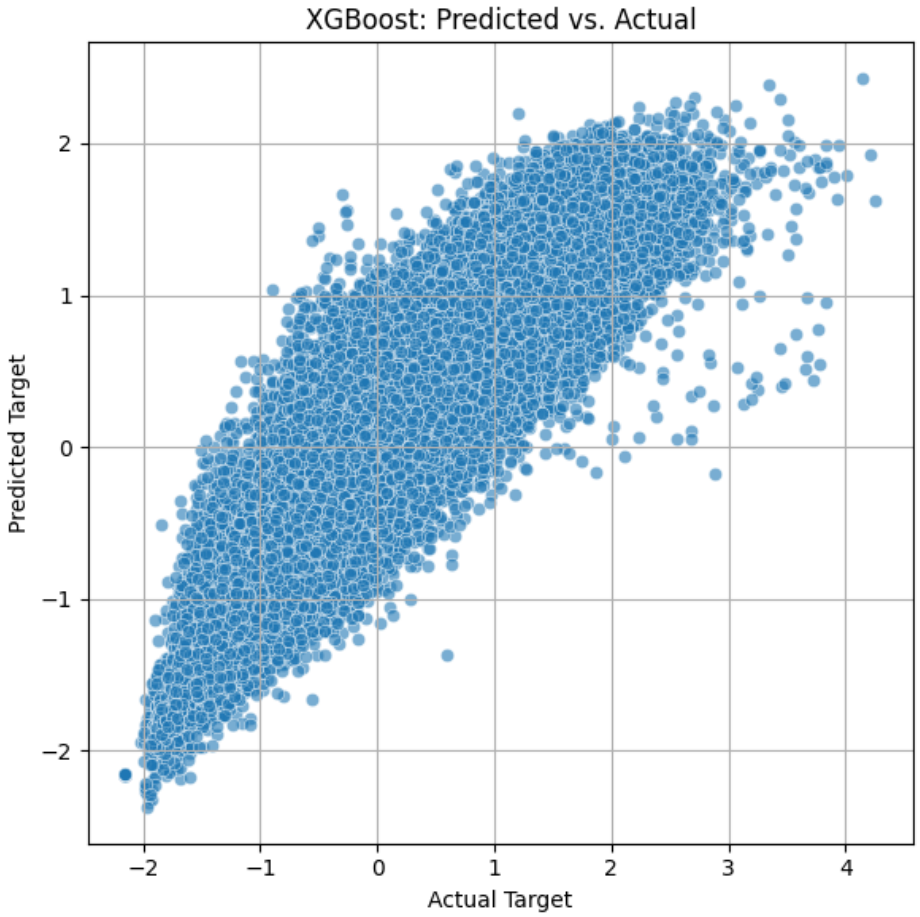


Figure 11: XGBoost: Predicted vs. Actual Proportion on Test Set.

We used early stopping (50 rounds) to prevent overfitting. Feature importance (gain and cover) matched SHAP rankings. Partial dependence plots for `HSHO002` and `ECYMTNMED` showed non-linear threshold effects. Sensitivity tests confirmed that `max_depth`=5 balanced interaction capture and variance. These findings highlight XGBoosts ability to model complex patterns beyond linear methods.

3.3 SHAP-Based Interpretation

We computed SHAP values on the test set to quantify feature contributions. Table 3 shows the top five features by mean |SHAP|, and Figure 12 displays the dependence plot for `HSHO002`.

Table 3: Top five features by mean —SHAP— (XGBoost)

Feature	**Description**	$\overline{\lvert\text{SHAP}\rvert}$
HSHO002	Number of housekeepers employed	0.137
HSSH042	Mortgage on secondary residences	0.129
HSMG001S	Total money gifts and contributions	0.125
ECYMTNMED	Median maintainer age	0.101
HSCC002	Childcare outside the home	0.083

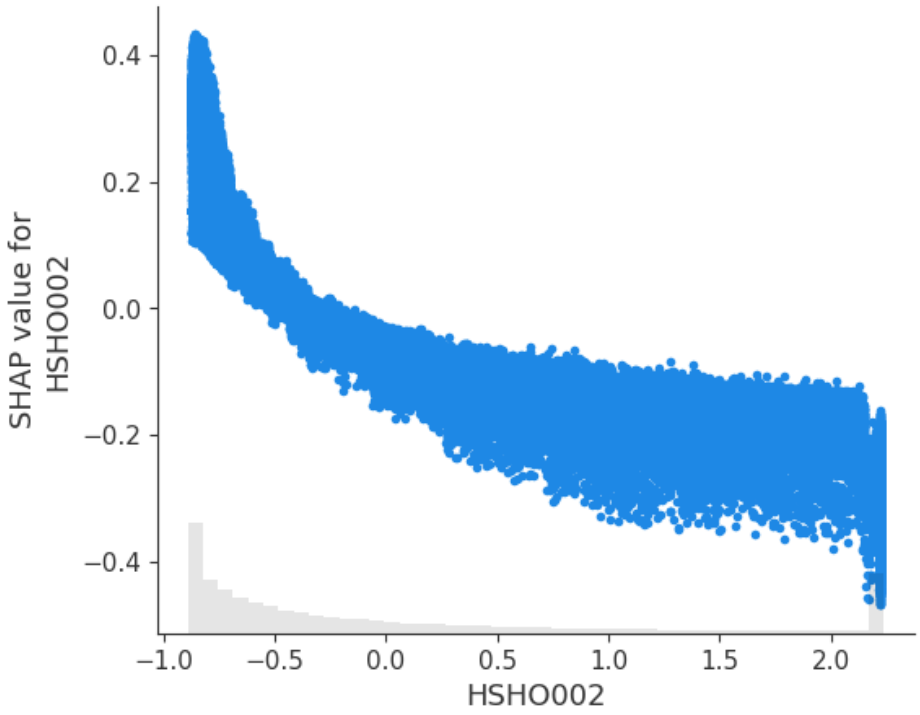


Figure 12: SHAP dependence plot for `HSHO002`.

For each of the top five features, key SHAP-based behaviors include:

- **HSHO002**: Values below approximately two housekeepers drive strong positive contributions, while higher counts reverse to negative impacts, indicating threshold-like effects (Fig. 12).
- **HSSH042**: Negative contributions intensify for large secondary mortgage values, consistent with heightened budget constraints under elevated debt loads.
- **HSMG001S**: Small to moderate gift and contribution amounts yield positive effects, but marginal impact diminishes at higher values, suggesting diminishing returns.
- **ECYMTNMED**: Consistently negative impact on predicted spending, with a sharper decline at extreme ages, highlighting accelerated non-linear aging effects.

- **HSCC002**: Low levels of childcare outside the home contribute positively and steeply, then plateau, reflecting interplay with total household support expenditures.

We used SHAP interaction values to detect pairwise effects, notably between `HSHO002` and `HSCC002`. Individual explanations showed how feature contributions sum to predictions. A summary dot plot (not shown) revealed variability for extreme `HSMG001S` values. However, correlated features can share attribution. Overall, SHAP provides reliable global and local insights for policy decisions.

Conclusions and Recommendations

We predicted insurance and pension spending accurately with both methods. Elastic Net ($R^2 = 0.8040$) highlighted key macroeconomic and demographic drivers. XGBoost ($R^2 \approx 0.9114$) captured non-linear, threshold effects (e.g. housekeeper counts, gift contributions) that Elastic Net missed. SHAP confirmed these non-linear patterns and provided actionable global and local insights.

- **Deploy the XGBoost model in production**, with routine monitoring of predictive performance and recalibration every quarter. Leverage early-stopping and validation-based retraining to guard against concept drift.
- **Integrate SHAP-driven alerts** into decision workflows. For example, flag households with extreme SHAP values on `HSHO002` or `HSMG001S` to target outreach or adjust product offerings.
- **Segment the customer base** by key drivers uncovered (e.g. median maintainer age, household support expenditures). Tailor marketing and education campaignsfor younger households, emphasize pension benefits; for high secondary-mortgage clients, highlight insurance products that mitigate debt risk.
- **Expand data coverage** to include behavioral and psychographic variables (e.g. online engagement, risk tolerance surveys) to refine model granularity and support personalized recommendations.
- **Establish a governance framework** for model explainability and fairness. Regularly audit feature importances and SHAP interactions to ensure no adverse or biased effects on underserved groups (e.g. unemployed or non-working-age segments).
- **Conduct A/B tests** to quantify the lift from model-driven interventions versus standard strategies, using metrics such as contribution rate uplift and retention.

Appendix

A Experiment Notebooks

The Jupyter Notebooks in which our experiments and analysis were conducted are provided alongside this report. The work related to Clustering and Principal Component Analysis can be found in `Clustering_and_PCA.ipynb`. UMAP related works are provided in `UMAP.ipynb`, and all regression related work is in `Part_2.ipynb`.

B Extra Silhouette Plots

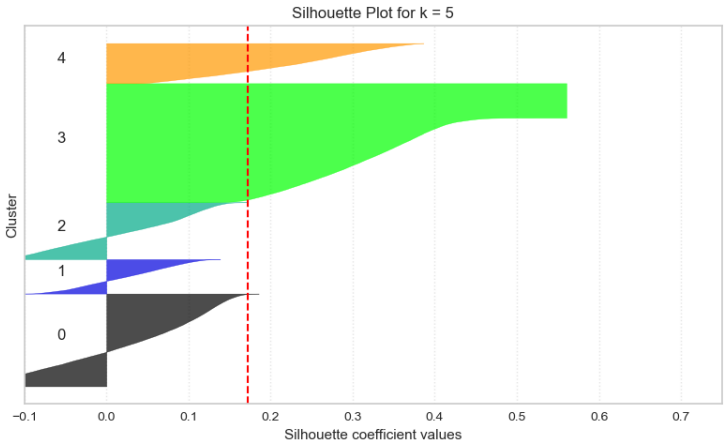


Figure 13: Silhouette Plot for $k = 5$

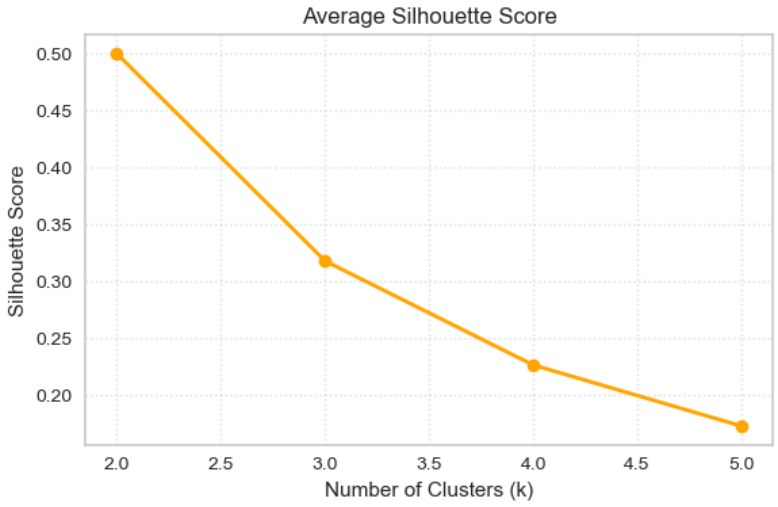


Figure 14: Average Silhouette Scores for $k = 2$ to $k = 5$

C PCA Component Loadings

The following tables show the top five positive and negative variable loadings for each of the first three principal components (PC1PC3). These values were used to interpret the latent dimensions of the PCA results. HHS refers to the HouseholdSpend dataset.

Table 4: Top Positive Loadings for PC1

Variable	HHS Description	HHS Type	DemoStats Category	Loading
ECYHOMSING	-	-	Language Spoken Most Often At Home	0.04791
ECYMOTSING	-	-	Mother Tongue	0.04789
ECYMOBHPOP	-	-	5-Year Mobility	0.04789
ECYAIDHPOP	-	-	Indigenous Identity	0.04788
ECYRIMHPOP	-	-	Recent Immigrants (2017Present)	0.04788

Table 5: Top Negative Loadings for PC1

Variable	HHS Description	HHS Type	DemoStats Category	Loading
ECYMTNMED	-	-	Maintainer Age	-0.00437
ECYPFAMED	-	-	Female Population by Age	-0.00413
ECYHFAMED	-	-	Female Household Population by Age	-0.00348
ECYPMAMED	-	-	Male Population by Age	-0.00348
ECYHMAMED	-	-	Male Household Population by Age	-0.00282

Table 6: Top Positive Loadings for PC2

Variable	HHS Description	HHS Type	DemoStats Category	Loading
HSSH037A	Wood/Fuel for Heating	Consumption	-	0.11518
ECYHTAMED	-	-	Household Pop. by Age	0.11505
ECYPTAMED	-	-	Total Population by Age	0.11242
ECYHMAMED	-	-	Male Household Population by Age	0.10444
HSSH034	Other Fuel	Consumption	-	0.10254

Table 7: Top Negative Loadings for PC2

Variable	HHS Description	HHS Type	DemoStats Category	Loading
ECYNCA_18P	-	-	Citizenship	-0.09457
ECYVISVM	-	-	Visible Minority Status	-0.09315
ECYHOMNOFF	-	-	Language Spoken Most Often At Home	-0.09130
ECYNCANCIT	-	-	Citizenship	-0.09076
ECYPIM1621	-	-	Period of Immigration	-0.08743

Table 8: Top Positive Loadings for PC3

Variable	HHS Description	HHS Type	DemoStats Category	Loading
HSWH040S	Net Purchase Price of Residences	Consumption	-	0.13164
HSTE001ZBS	Non-current Consumption	Consumption	-	0.12020
HSSH033A	Natural Gas (Owned Residence)	Consumption	-	0.11436
HSSH033	Natural Gas	Consumption	-	0.10837
ECYCHAHHCH	-	-	Children at Home by Age	0.10319

Table 9: Top Negative Loadings for PC3

Variable	HHS Description	HHS Type	DemoStats Category	Loading
ECYSTYAPU5	-	-	Structure Type	-0.13074
ECYMOTFREN	-	-	Mother Tongue	-0.12838
ECYSTYAPT	-	-	Structure Type	-0.12515
ECYHOMFREN	-	-	Language Spoken Most Often At Home	-0.12314

D Varying UMAP Distance Metric Plots

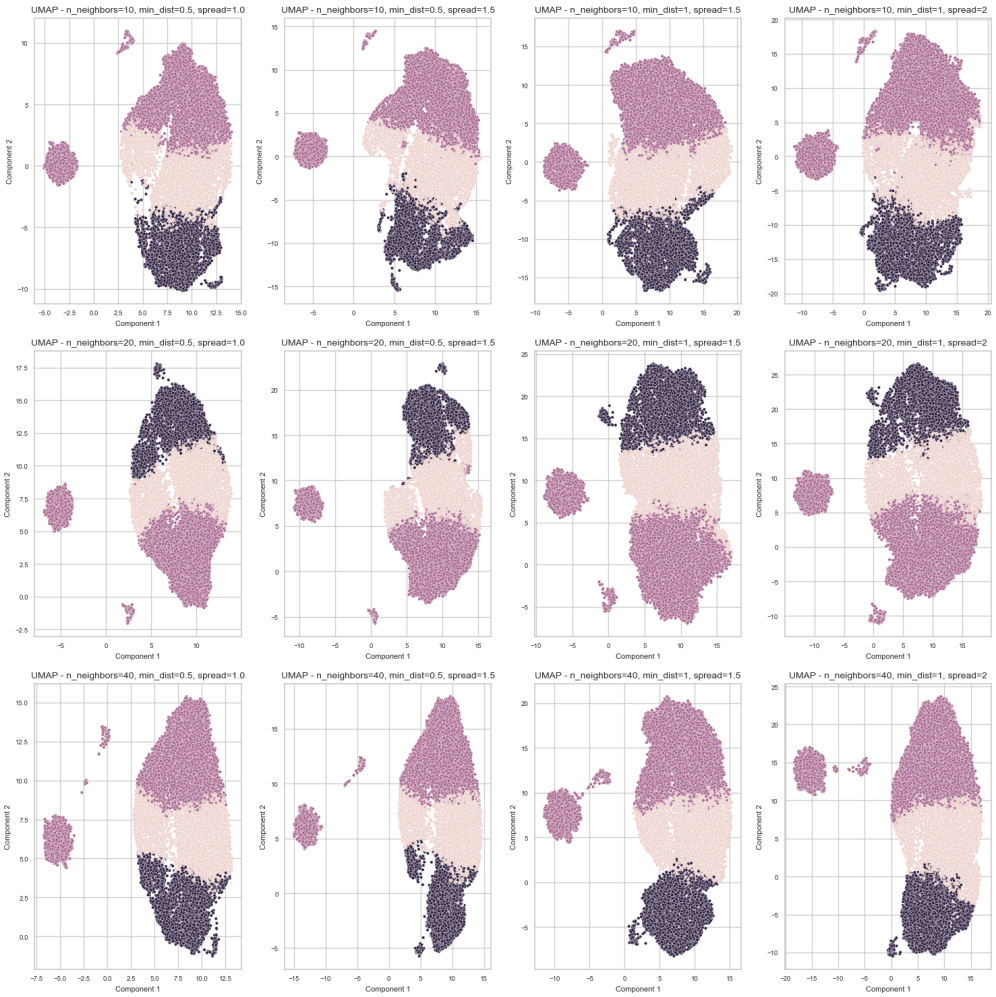


Figure 15: UMAP with euclidean distance metric and different values of n_neighbors, min_dist and spread.

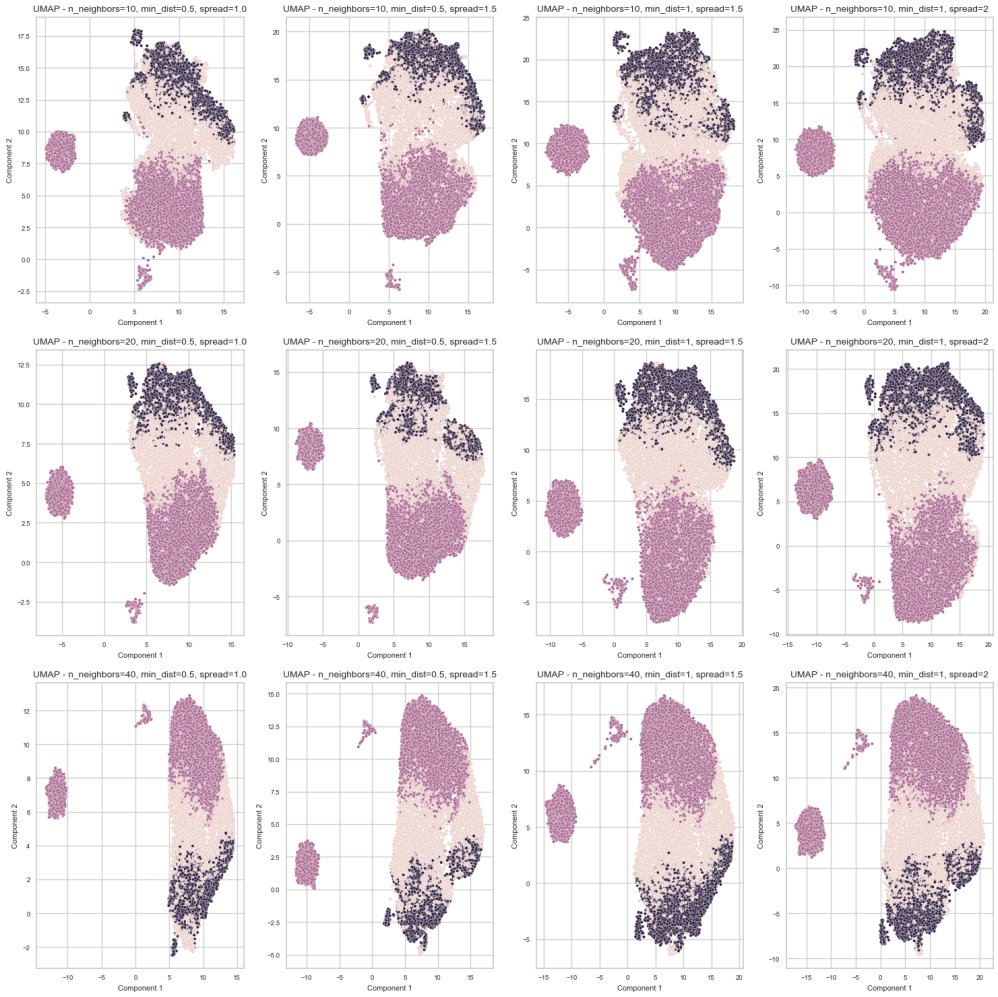


Figure 16: UMAP with cosine distance metric and different values of n_neighbors, min_dist and spread.

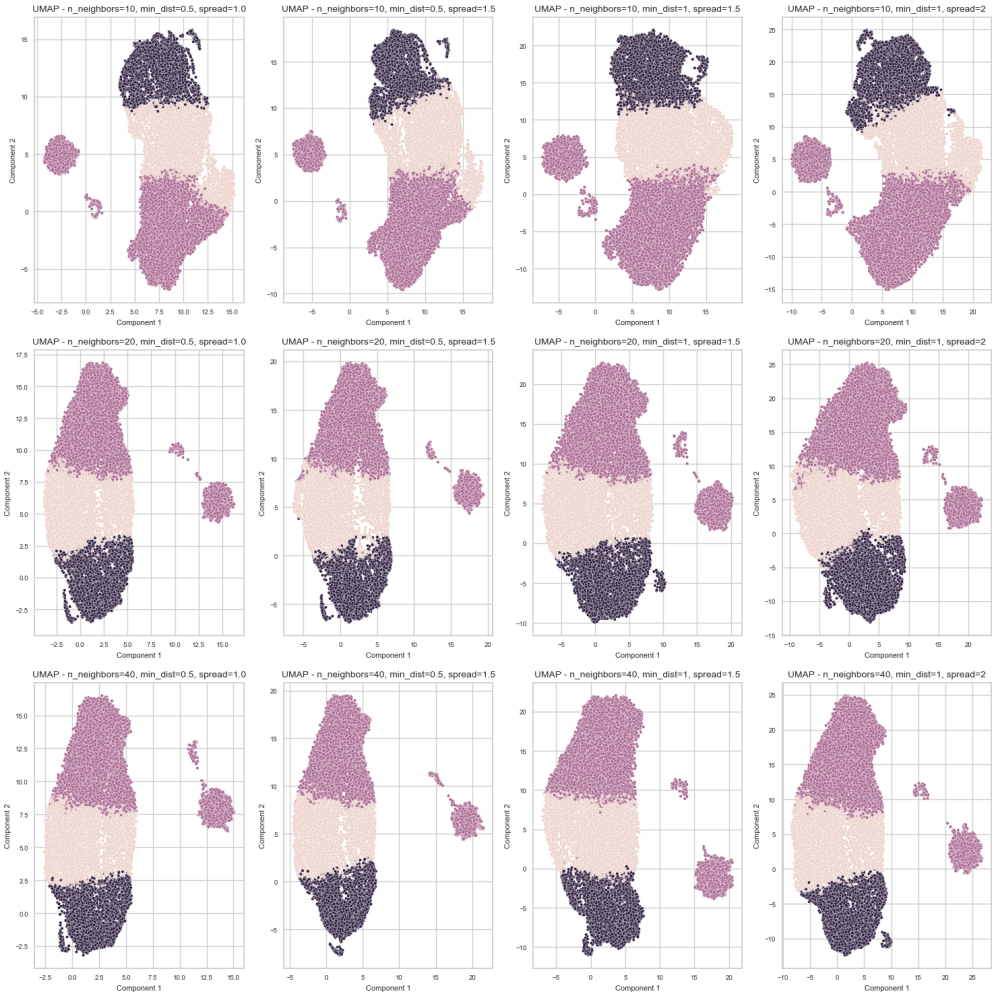
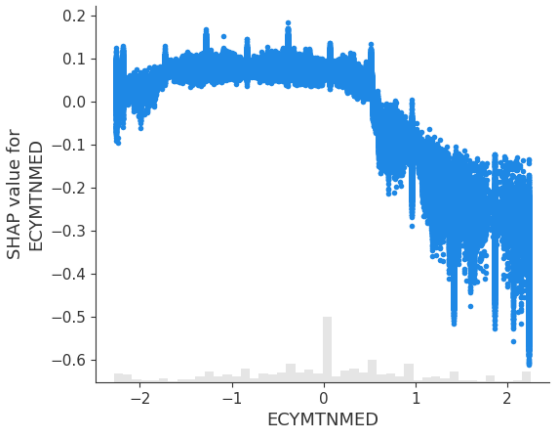
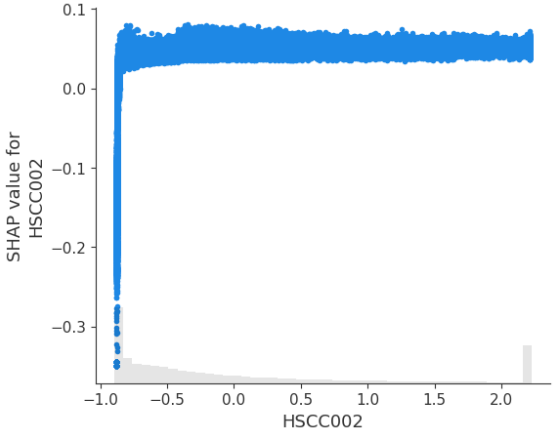


Figure 17: UMAP with manhattan distance metric and different values of n_neighbors, min_dist and spread.

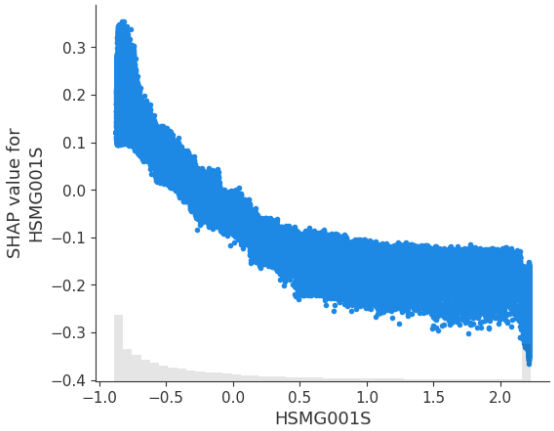
E SHAP Plots for Additional Variables



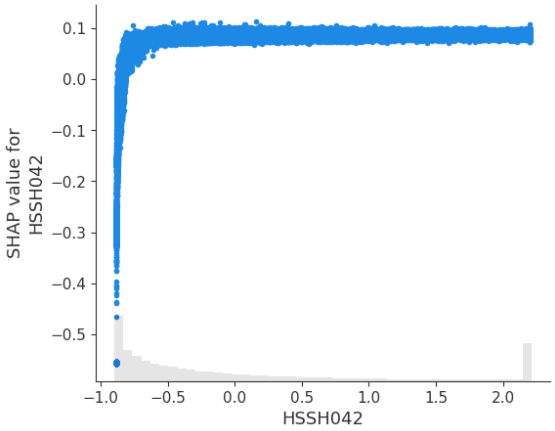
(a) SHAP for ECYMTNMED



(b) SHAP for HSCC002



(c) SHAP for HSMG001S



(d) SHAP for HSSH042

Figure 18: SHAP Value Graphs for Additional Variables