Impact of Property Features on

Property Pricing

April 2025

Glenn Barnes
Lan Dinh
Senkay Li

LGS Co.

DATA 3960 Capstone

Table *of* Contents

Introduction

Evaluation on how property features influence property pricing in Edmonton based upon neighbourhood, time, and property style segmentation

Abstract

This research investigates the impact of specific property features on residential housing prices in Edmonton, Alberta, using a comprehensive, segmented analytical approach that accounts for variations by neighbourhood, property style, and year of construction. Using an extensive dataset comprising over 300,000 property transaction records from 2000 to 2024, the study examines critical factors that influence home values, including the number of bedrooms and bathrooms, basement development, the presence of a garage, and neighbourhood crime rates. Advanced predictive modelling techniques, specifically Random Forest and XGBoost, were employed to quantify these impacts, revealing that features such as listing price per square foot, bathroom count, and property age significantly influence pricing decisions. Neighbourhood-level analysis further underscored the nuanced role of local crime, demonstrating its moderate negative correlation with property values. Among the models tested, Random Forest exhibited superior interpretability and robustness, achieving a high explanatory power with an R^2 score of approximately 0.92. These findings provide actionable insights for stakeholders, including homebuyers, sellers, real estate professionals, and urban planners, supporting informed decision-making in Edmonton's dynamic real estate market.

Introduction

Understanding real estate pricing is crucial for stakeholders including homebuyers, real estate professionals, and urban planners. The Edmonton housing market is influenced by a diverse array of property features, from physical characteristics like bathrooms, bedrooms and garages to contextual variables such as crime rates and neighborhood identity.

Introduction

1.1 Background and Motivation

Previous studies have demonstrated that housing prices are not determined solely by square footage or location, but also by micro-level features that reflect utility, safety, and aesthetic appeal. However, many studies rely on unsegmented data, overlooking how combinations of features operate differently depending on local context, property style, or age of construction.

1.2 Literature Review

Some relevance researches show that:

- Garage presence and finished basements consistently enhance property valuation, along with other characteristics such as square footage, number of bathrooms, and finished basements [Sirmans, G. S., MacDonald, L., Macpherson, D. A., & Zietz, E. N. (2006). Journal of Real Estate Finance and Economics].
- Multiple bathrooms and garage presence are positively associated with home valuation in Canada, contributing significant price premiums in urban housing markets [Steele, M., & Goy, R. (1996). Canada Mortgage and Housing Corporation].
- Estimates of the Impact of Crime Risk on Property Values from Megan's Laws. [Linden, L., & Rockoff, J. E. (2008). American Economic Review]

Summary of Current Knowledge and Research Gap: While much of the existing literature identifies the role of structural and locational features in price determination, few studies explore how these effects differ across time segments, property styles, or neighborhood. Specifically, there is a lack of real-world data-driven segmentation analyses in medium-sized Canadian cities like Edmonton that account for the joint influence of crime data, historical construction periods, and architectural typology.

Introduction

1.3 Research Objectives and Questions

This analysis project aims to:

- Quantify the effect of key property features on sale price.
- Examine how pricing differs across neighborhoods, year-built and styles segments.
- Assess the influence of local crime severity on pricing.

In detail, the key objective of this analysis project is to evaluate the factors that influence property pricing in Edmonton's real estate market. By analyzing property features such as number of bedrooms, number of bathrooms, basement development, presence of a garage, and neighbourhood crime, the project seeks to uncover trends and patterns that can be valuable for stakeholders. This analysis will help in understanding how these factors interact to influence pricing, ultimately enabling more informed decision-making in the real estate sector. To make the most sense out of the insights gathered from datasets, the evaluation of property pricing will be segmented based upon neighborhood regions, time of build year, and property style.

The data will be segmented into three key categories - neighborhood, year built, and property style - to provide a more comprehensive analysis of how each factor influences property pricing. This segmentation is essential because property pricing is impacted by a variety of factors and analyzing them in isolation could obscure the true influencers of pricing. By grouping properties based on neighborhood, year built, and property style, we ensure that comparisons are made between similar properties, leading to more accurate and meaningful insights. Without segmentation, comparing properties with vastly different features could distort pricing trends. In this way, segmentation allows for a more refined analysis, ensuring that comparisons are based on relevant similarities and providing a clearer understanding of which features have the greatest influence of property pricing in Edmonton.

Introduction

Neighborhood

- Based on neighborhood districts as outlined by the City of Edmonton
- A property's pricing will be compared to other properties in the same district

Year Built

- Grouped into 10-year intervals
- A property's pricing will be compared to other properties built within the same 10-year period

Property Style

- Based on property style classifications (e.g., bungalow, townhouse, etc.)
- A property's pricing will be compared to other properties of the same style

The findings from this analysis will primarily benefit homebuyers and real estate agents by enabling data-driven decision-making and enhancing market transparency. Homebuyers will gain a clearer understanding of how various features - such as number of bedrooms/bathrooms, basement development, presence of a garage, and neighbourhood crime - affect pricing in their desired areas. This will empower them to make more informed choices, reducing the risk of overpaying and improving the likelihood of finding properties that meet both their financial and lifestyle needs. For real estate agents, these insights can be leveraged to refine pricing strategies, optimize investment opportunities, and maximize returns for their clients. With a more granular understanding of how different property features impact market values, agents can confidently advise clients on the best time to buy or sell, which areas offer the most potential for value growth, and how to position a property competitively in the market. Furthermore, agents will be better equipped to guide negotiations effectively, helping clients secure favorable deals based on a deeper understanding of the market dynamics at play in Edmonton. From a business perspective, these insights could be used to attract and retain clients by offering data-driven expertise, improving customer satisfaction, and ultimately increasing sales volume. Real estate firms can enhance their market positioning by integrating these findings into their business models, offering a clear value proposition to both buyers and sellers and establishing themselves as trusted experts in the local market.

Introduction

Research Questions

To guide the analysis and uncover valuable insights, several key research questions will be explored. These questions are designed to investigate the various factors that influence property pricing in Edmonton's real estate market, with a focus on identifying patterns and trends that can benefit both buyers and real estate professionals. By examining the impact of property features, neighborhood dynamics, time-related factors, and property styles, the study aims to provide a comprehensive understanding of how these elements interact to affect market prices. The following research questions will drive the investigation and inform the practical applications of the findings.

1. How do property features such as number of bedrooms, number of bathrooms, basement development, presence of a garage and crime affect property pricing?
2. Which features add the most value to a property in Edmonton? How do these features rank?
3. Are there specific neighbourhood trends, time patterns, and property styles that influence pricing?
4. How can real estate professionals use these insights to improve decision-making and investment strategies?
5. How can buyers make informed decisions based on these insights?

What are the benefits of this analysis & the real-world relevance?

This project is essential for uncovering the key factors that influence property pricing in Edmonton. By analyzing individual property features, such as basement development, parking options, and the number of bedrooms, we can identify which attributes add the most value to a home. The insights derived from this analysis will offer multiple benefits:

Data-Driven Decision Making: By quantifying the impact of specific property characteristics on pricing, this study provides actionable insights for buyers, homeowners, sellers, real estate agents, and investors.

Enhanced Market Transparency: Understanding pricing trends at both the property and neighborhood levels allows for greater transparency in real estate transactions, benefiting all market participants.

Introduction

This analysis is relevant to various stakeholders in the real estate market:

1. **Buyers can make well-informed purchasing decisions by understanding which property features contribute most to value, ensuring they get the best deal.**
2. **Homeowners can strategically invest in renovations that will maximize resale value, preventing unnecessary expenditures on low-impact upgrades.**
3. **Real Estate Agents gain an evidence-based approach to pricing recommendations, improving their ability to market and sell properties efficiently.**
4. **Investors can optimize property acquisitions and portfolio management by identifying trends that drive long-term appreciation.**

Value of this analysis:

- **This analysis will provide valuable insights on how specific property features impact pricing, helping buyers and investors identify which attributes add the most value. By understanding these key factors, they can make data-driven decisions to maximize returns, optimize investments, and negotiate more effectively.**
- **Additionally, insights into neighborhood trends will offer a broader context, allowing stakeholders to refine their strategies while focusing on property characteristics that drive the greatest financial impact.**

1.4 Statement of Purpose

In conclusion, this analysis aims to fill the gap by examining how the interaction of property features with neighborhood, year built, and property style affects pricing in Edmonton. Through this segmented approach, the research offers enhanced clarity on market drivers, enabling more accurate forecasting and valuation in localized real estate contexts.

Description of Data

The datasets used for the purposes of our study

1

Edmonton Property Sales Data

This dataset includes detailed transaction records for over 300,000 residential properties sold in Edmonton from 2000 to 2024. Key features captured are property price, year built, property style (e.g., bungalow, duplex), size attributes (number of bedrooms and bathrooms, lot size), basement development status, and garage availability. This dataset serves as the core component of the analysis, providing critical insights into property-specific factors influencing market values.

2

Neighborhood Crime Data

Comprising aggregated crime incident data at the neighborhood level, this dataset summarizes crime frequency and categories such as theft, burglary, and vehicle-related offenses. Crime statistics were normalized and integrated with property records to examine the impact of local safety concerns on property valuation.

3

Edmonton Neighborhood Metadat

This dataset contains geographic and city planning information for Edmonton neighborhoods, including boundary definitions, planning district categorization, and demographic context. Integrating neighborhood metadata with property transactions facilitated spatial analyses, enabling investigation into how geographic location and community characteristics shape residential pricing patterns.

Together, these datasets enabled a robust, multifaceted analysis of the factors driving housing prices within Edmonton's real estate market.

Methodology

This research aimed to predict residential property sale prices in Edmonton, Alberta, utilizing advanced machine learning methods and comprehensive predictive features. The methodological framework employed encompasses a rigorous multi-step approach, including data acquisition, preprocessing, integration, feature engineering, and predictive modeling.

Data Acquisition and Cleaning

The analysis leveraged three comprehensive datasets:

- Property Sales Data (sold_df): This dataset provided extensive details about over 300,000 residential transactions between 2000 and 2024, including the number of bedrooms and bathrooms, basement development, garage presence, and year built.
- Crime Data (crime_df): Compiled at the neighborhood level, this dataset included aggregated records of various crime categories, facilitating an analysis of safety as a determinant of property values.
- Neighborhood Metadata (neighbourhoods_df): This dataset included geographic and planning information, enabling a spatial dimension to the analysis.

Each dataset underwent rigorous data cleaning, which included standardization of column naming conventions, removal of irrelevant variables, and handling of missing values to ensure accuracy and consistency.

Data Integration

To manage data volume and ensure computational efficiency, crime data were aggregated at the neighborhood level. These aggregated crime statistics were then merged with property sales and neighborhood metadata datasets based on standardized neighborhood identifiers (neighbourdood_name) , resulting in a unified dataset containing 319,494 records.

Methodology

Feature Engineering

The analysis further involved the creation of additional derived variables aimed at enhancing predictive capability:

- Property age (property_age)
- Total rooms and bathroom-bedroom ratios (total_baths, full_baths)
- Crime rate normalized per capita (crime_rate_per_capita)
- Sale seasons and construction year categories

Categorical variables were transformed using one-hot encoding to facilitate their integration into predictive models.

Feature Selection and Preprocessing

A variance threshold of 0.01 was applied to remove low-variance features, reducing dimensionality while preserving predictive relevance. Numerical features underwent imputation and scaling, whereas categorical features were consistently encoded through structured pipelines using scikit-learn. The dataset was partitioned into training (80%; 255,595 records) and testing sets (20%; 63,899 records) to rigorously evaluate predictive models.

Modeling and Evaluation

Three regression models were applied and comparatively evaluated:

- Linear Regression (baseline)
- Random Forest Regressor
- XGBoost Regressor

Models were assessed based on Root Mean Squared Error (RMSE) and the coefficient of determination (R^2), providing clear indicators of predictive accuracy and explanatory power.

Findings

Individual Dataset Analysis

Property Sales Data: Structural attributes like property size, age, bathroom, and bedroom counts significantly impacted property valuations.

Crime Data: Neighborhood crime negatively correlated with property prices, though its effect was moderate.

Neighborhood Metadata: Geographic context substantially enriched the predictive insights, emphasizing the importance of location and spatial dynamics in determining market prices.

Combined Dataset Analysis

Integrating all datasets significantly enhanced predictive accuracy. Key influencing features included listing price per square foot, bathroom counts, bedrooms, property dimensions, age, architectural style, property classification, and neighborhood crime levels.

Model Performance Summary

Model	RMSE (CAD)	R^2 Score
Linear Regression	$76,340	0.79
Random Forest	$48,265	0.92
XGBoost	$48,522	0.92

Random Forest emerged as the best-performing model, characterized by the lowest RMSE and high R^2, effectively capturing complex non-linear relationships within the data.

Findings

Exploring Alternative Models: Randomized CV and Neural Networks

To further improve the model's performance, we experimented with:

1. Randomized Cross-Validation (RandomizedSearchCV):
    a. Hyperparameter tuning was applied to the Random Forest model.
    b. Despite extensive tuning, the R^2 score did not improve significantly beyond the baseline Random Forest model.
2. Neural Networks:
    a. A feedforward neural network was implemented using TensorFlow/Keras.
    b. The model was trained with various architectures (e.g., hidden layers, activation functions) and hyperparameters (e.g., learning rate, batch size).
    c. However, the neural network struggled to outperform the Random Forest model, likely due to the tabular nature of the dataset and the relatively small size of the training data for deep learning.

Final Model Selection

Given the results, we chose to proceed with the Random Forest Model due to its:

1. High accuracy (R^2 = 0.92)
2. Robustness to overfitting
3. Interpretability (e.g., feature importance analysis)

Visualizations and Interpretations

Interpretation of Feature Importance and SHAP Analysis

The analysis leveraged feature importance metrics derived from two robust predictive models, Random Forest and XGBoost, augmented by SHAP (SHapley Additive exPlanations) values to interpret the predictive relationships and feature contributions within the housing market in Edmonton, Alberta. These visualizations not only quantify the relative importance of features but also illustrate their directionality and interactions, thus enhancing interpretability for stakeholders.

Random Forest Feature Importance Analysis:

- The Random Forest feature importance plot identified the most influential property attributes impacting price predictions. As depicted in Figure 1, the dominant feature emerged as the listing price per square foot (list_pr_/_sqft), significantly outperforming other predictors. This attribute's prominence underscores its role as a critical pricing benchmark within local market transactions. Other substantial features included the number of full and total bathrooms, number of bedrooms, and lot size (lot_sq_metres), reinforcing the importance of structural dimensions and facilities in market valuations. Moreover, age (property_age) and property styles (notably two-storey homes, style_ST2) significantly influenced property prices, reflecting market preferences for architectural attributes.

SHAP Summary and Dependency Analysis:

- SHAP summary plots (Figure 2) provided deeper insights into the distribution and directional impact of feature values on individual predictions. Confirming the findings from Random Forest importance rankings, list_pr_/_sqft exhibited substantial influence, with higher values consistently correlating positively with increased property prices. The SHAP values indicate both linear and non-linear relationships, clearly illustrating the complexity inherent within property valuation. Furthermore, features such as lot size and bathroom count displayed discernible patterns, reinforcing their fundamental impact on valuation predictions.

The SHAP dependence plot (Figure 3) further illustrated the nuanced interaction between list_pr_/_sqft and the number of full bathrooms (full_baths). Properties characterized by higher prices per square foot and increased bathroom counts exhibited notably positive SHAP values, signifying an amplified effect on predicted prices. Such feature interactions suggest that premium home buyers potentially prioritize both the quality (reflected in price per square foot) and utility (reflected in bathroom count) of properties.

Visualizations and Interpretations

Mean Absolute SHAP Value Analysis:

- The mean absolute SHAP value chart (Figure 4) aggregates the overall magnitude of feature impacts, highlighting the predominance of certain variables across the model. Consistent with prior plots, the highest mean impacts were attributed to list_pr_/_sqft, followed by lot_sq_metres and full_baths. This provides stakeholders with a consolidated view of predictive drivers, emphasizing critical features to consider during pricing evaluations, renovations, or market positioning.

XGBoost Feature Importance Analysis:

- The comparative analysis using XGBoost (Figure 5) corroborated many Random Forest insights but with distinct feature prioritizations. Full bathrooms (full_baths) and price per square foot remained top predictors; however, XGBoost notably elevated architectural style (style_ST2) and garage presence (garage_y/n_No) in importance rankings. This divergence indicates model-specific interpretations of the data, suggesting varying sensitivities toward certain housing characteristics. Such distinctions underscore the value of employing multiple analytical methodologies to capture the complex, multifaceted nature of real estate valuation.

Overall, this combined feature importance and SHAP value assessment provided comprehensive insights into the key determinants of property pricing in Edmonton. By clarifying the nuanced roles and interactions of individual property attributes, these analyses offer actionable guidance for real estate professionals, urban planners, and policymakers seeking strategic interventions within Edmonton’s housing market.

Discussions

Analysis of Research Questions

The analysis affirmed that non-linear models significantly outperform linear regression, underscoring the complexity inherent in real estate valuation. Key attributes like listing price per square foot, bathroom quantity, and property age emerged as consistent predictors. Crime negatively influenced prices but with less intensity than anticipated, suggesting a nuanced role within local market dynamics.

Evaluation of Approach and Limitations

The study demonstrated robust predictive accuracy and insightful interpretability, enhanced by comprehensive feature engineering. However, limitations included aggregated crime data lacking granular detail, absence of external socio-economic variables, and the lack of explicit temporal analysis, which could overlook evolving market trends.

Surprising Discoveries

The analysis revealed unexpected insights, such as the considerable influence of garages and specific architectural styles on home valuations. Additionally, the moderate impact of crime suggested buyers may prioritize other quality-of-life factors more heavily.

Recommendations for Future Work

Future analyses could benefit from incorporating additional granular data such as proximity to amenities, school ratings, and detailed demographic and economic indicators. Further exploration of advanced modeling techniques (LightGBM, CatBoost, ensemble stacking methods) and explicit temporal analyses could significantly enhance model precision and market insight.

Appendix

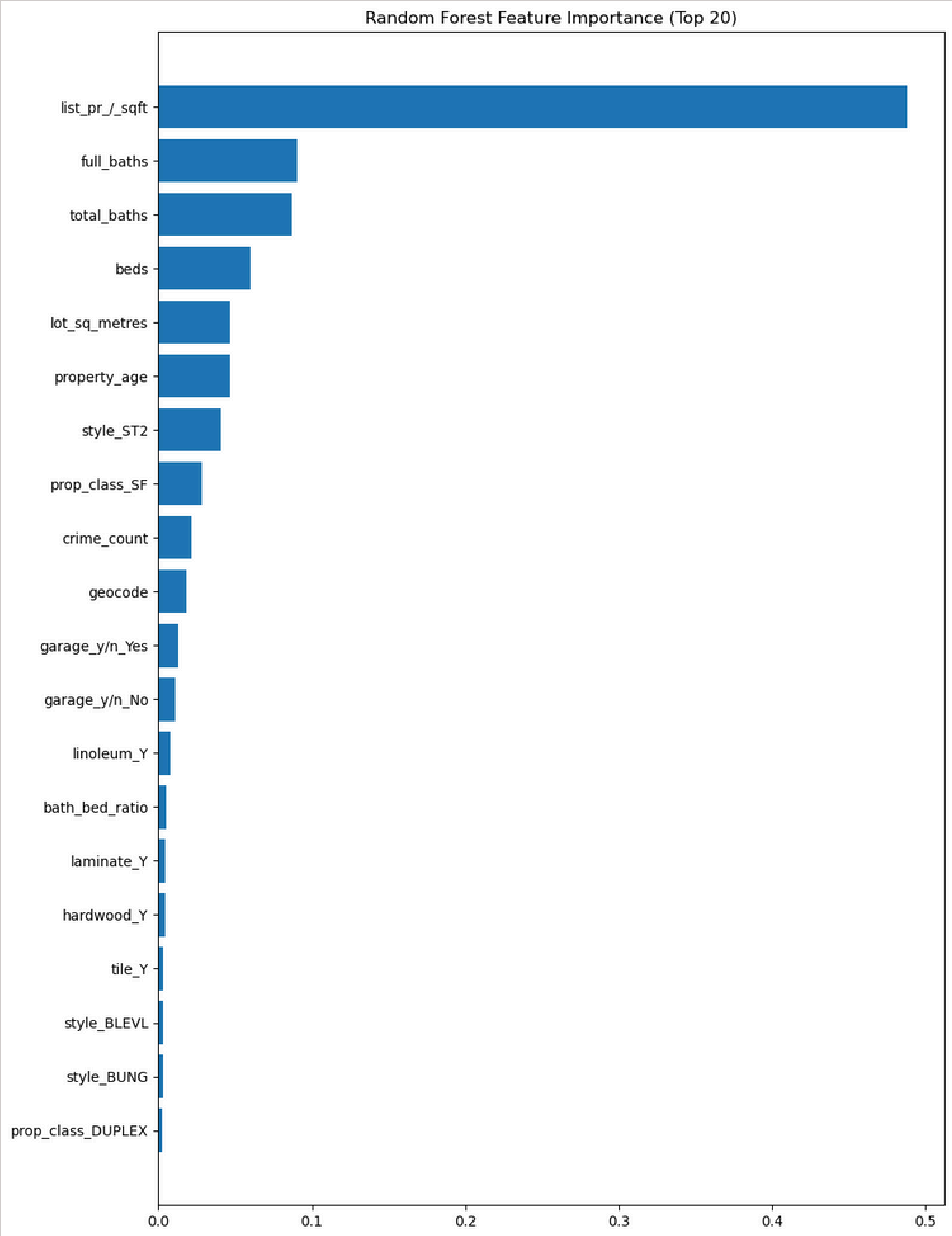


Figure 1

Appendix

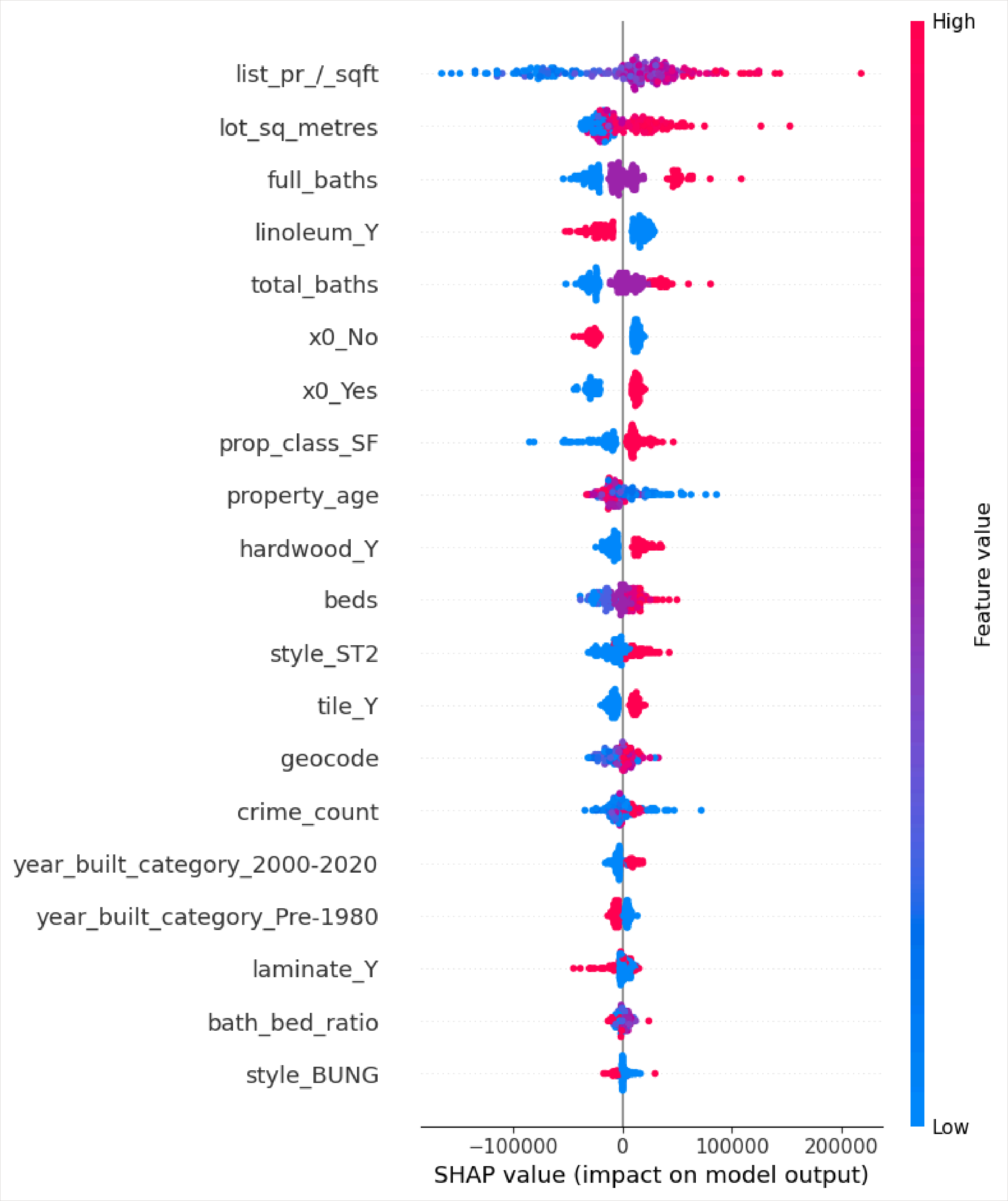


Figure 2

Appendix

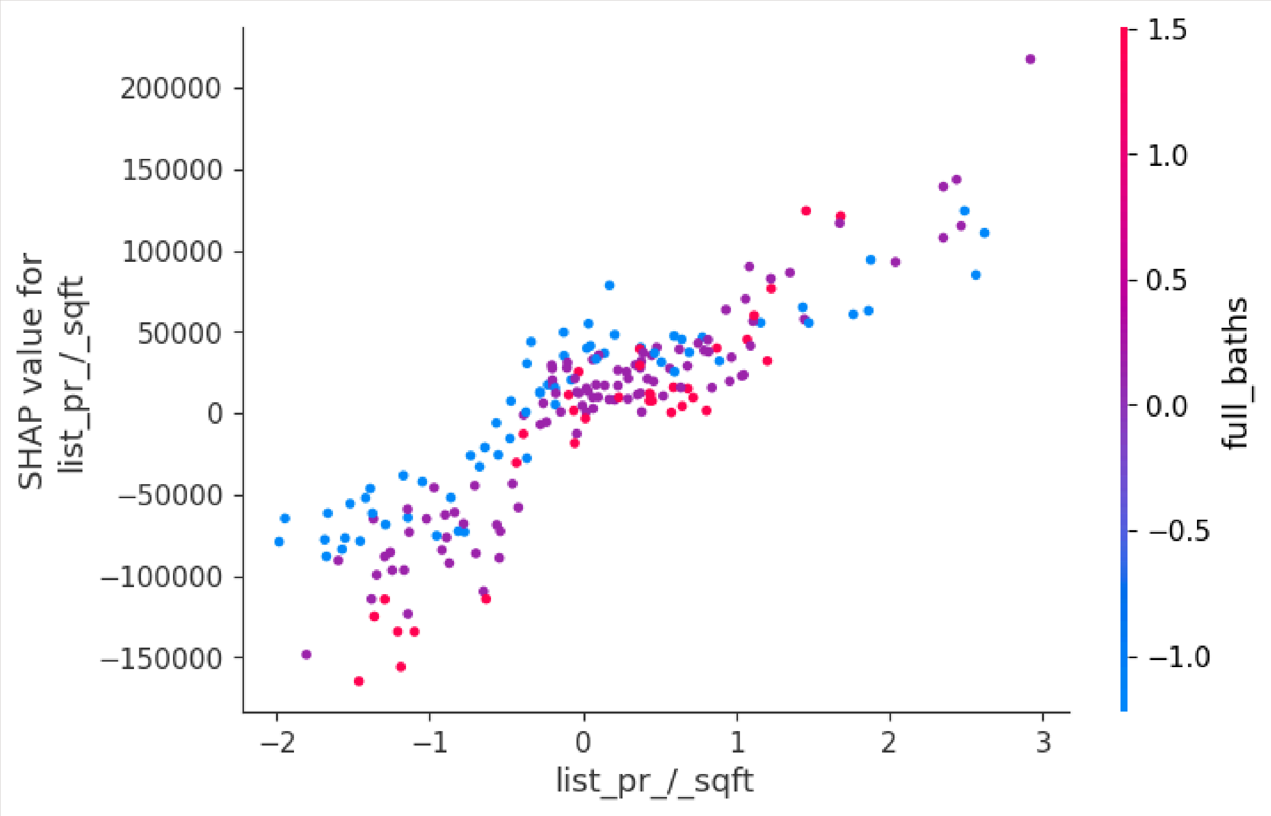


Figure 3

Appendix

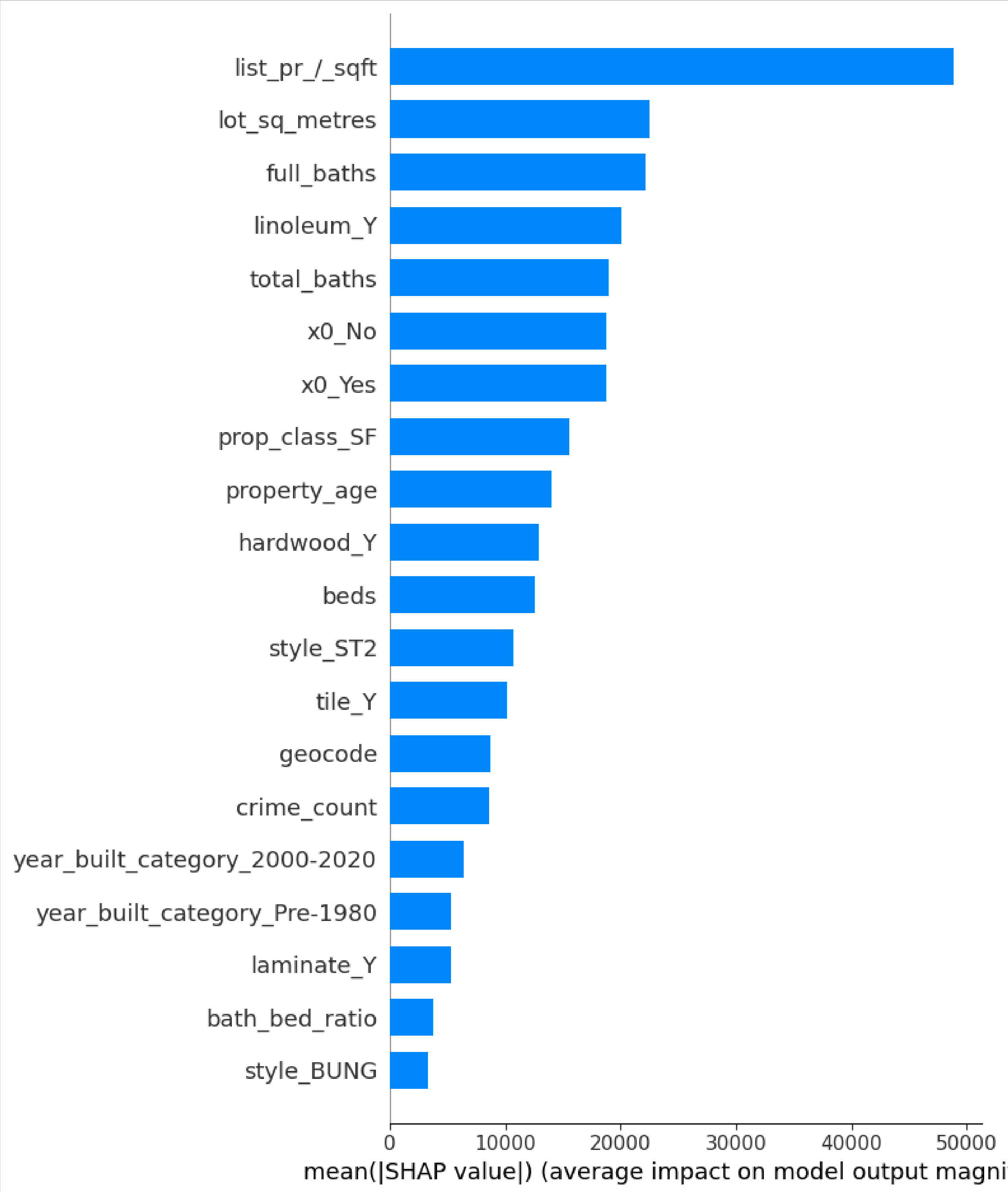


Figure 4

Appendix

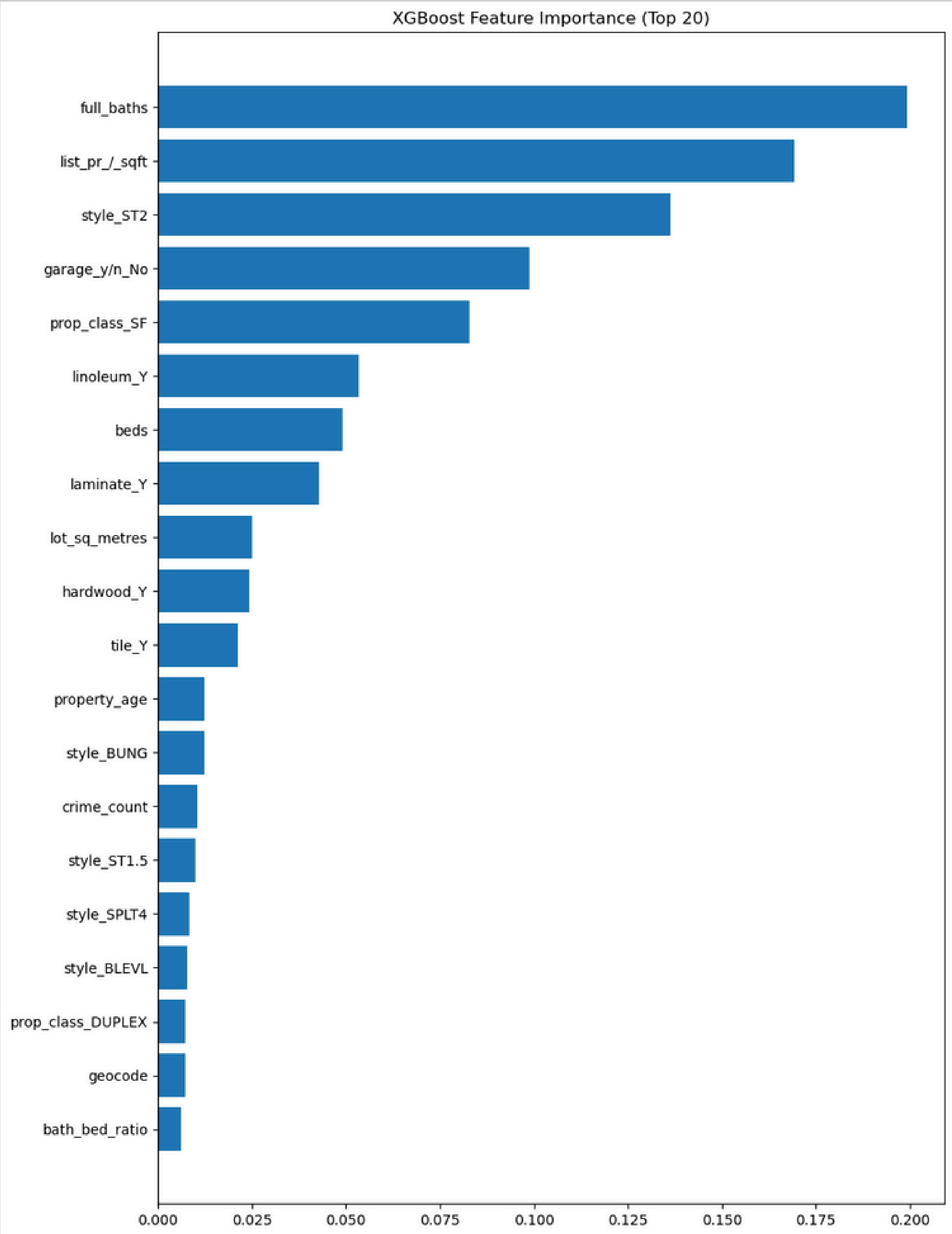


Figure 5

Appendix

Crime Classifications

Occurrence Category	Occurrence Group	Occurrence Type Group	
Disorder	Disputes/Disturbances	Dispute	1,783
		Disturbance	323
	General Disorder	Suspicious Person	787
		Suspicious Vehicle	315
		Trespassing	1,674
		Trouble with Person	5,816
	Mischief/Graffiti	Graffiti	258
		Mischief - Property	5,657
		Public Mischief	113
	Provincial Statute Violations	Intoxicated Person	1,622
Drugs	Drug Violation	Drugs	9
	Drug Violations	Drugs	1,103
Non-Violent	Abandoned/Recovered/Seized Vehicles	Abandoned Vehicle	172
		Recovered Motor Vehicle	1,502
	Counterfeiting/Gaming and Betting	Counterfeit Money	90
	Property	Break and Enter Commercial	2,222
		Break and Enter Residential	3,439
		Fire Arson	415
		Fraud - Financial	2,099
		Fraud General	1,182
		Fraud Personal	827
		Internet Fraud	1,762
		Possession Stolen Property	1,167
		Property Damage	52
		Technology/Internet Crime	17
		Theft of Motor Vehicle	4,128
		Theft Over $5000	1,290
		Theft Under $5000	22,743
Other	Provincial Statute Violations	Liquor Act	90
	Workplace/Labour Violations	Labour Dispute	3
		Workplace Accident	2
Traffic	Criminal Flights/Impaired Operation/Escape Lawful	Criminal Flight Event	547
		Impaired Driving	1,329
Violent	Personal Violence	Assault	6,207
		Homicide	36
		Robbery Commercial	295
		Robbery Personal	795
	Sexual Violations	Indecent Act	135
Weapons	Explosives/Dangerous Goods	Bomb Threat	19
		Dangerous Condition	11
	Weapons Violations	Weapons Complaint	930
		Weapons Complaint Firearm	482

Count of Date Reported broken down by Occurrence Category, Occurrence Group and Occurrence Type Group.

Figure 6

Appendix

Neighbourhood Classifications

District Plan

Central	Ellerslie	Horse Hill	Jasper Place	Mill Woods ..	North Central	Northe..	Northw..	Rabbit Hill	Scona	Southe..	Southw..	West Ed monton	West Henday	Whitem..
BOYLE	ALCES	ANTHO..	ALBERTA	ANTHO..	ABBOT..	ANTHO..	ALBANY	EDMON..	ALLEND..	AVONM..	ALLARD	ALDER..	ANTHO..	ANTHO..
STREET	CHARLE..	ANTHO..	PARK	ASTER	ALBERTA	ANTHO..	ANTHO..	EDMON..	ARGYLL	BONNIE	AMBLE..	BELME..	ANTHO..	ANTHO..
CENTRAL	DECOTE..	EDMON..	INDUST..	BISSET	AVENUE	BALWIN	ANTHO..		BELGRA..	DOON	ANTHO..	CALLIN..	BRECKE..	ASPEN
MCDOU..	EDMON..	EVERG..	ANTHO..	CRAWF..	BEACON	BANNE..	ANTHO..		CALGARY	CAPILA..	BLACKB..	CALLIN..	EDGEM..	GARDE..
DOVER..	EDMON..	MARQU..	ARMST..	DALY	HEIGHTS	BELMO..	ATHLO..		TRAIL	CLOVER..	BLACK..	CAMER..	GLASTO..	BEARS..
DOWNT..	ELLERS..	QUARRY	BONAV..	GROVE	BELLEV..	BELVED..	BARAN..		NORTH	CORON..	CALLAG..	DECHE..	GRANVI..	BLACK..
GLENO..	ELLERS..	RIDGE	BRITAN..	EDMON..	BERGM..	BRINTN..	BATUR..		CPR	CORON..	CASHM..	DONSD..	HAWKS	BLUE
INGLE..	MATTS..	RURAL	BROWN	EKOTA	BEVERLY	CANON	BEAUM..		IRVINE	DAVIES	CAVAN..	GARIEPY	RIDGE	QUILL
MCCAU..	MELTW..	NORTH	INDUST..	GREEN..	HEIGHTS	RIDGE	BELLE		EMPIRE	INDUST..	CHAPP..	JAMIES..	KINGLET	BLUE
NORTH	RURAL	EAST	CANORA	HILLVIE..	BLATCH..	CASSEL..	RIVE		PARK	DAVIES	DESRO..	LA PERLE	GARDE..	QUILL
GLENO..	SOUTH	HORSE	CARLET..	JACKSO..	CROMD..	CLAREV..	CAERN..		GARNE..	INDUST..	GLENRI..	LYMBU..	LEWIS	ESTATES
OLIVER	EAST	HILL	CREST..	KAMEY..	DELTON	CLOVER	CALDER		GRAND..	EASTGA..	GLENRI..	OLESKIW	FARMS	BRAND..
PRINCE	SUMME..	RURAL	DOMINI..	KINISKI	EASTW..	BAR	CANOS..		HAZELD..	FOREST	GRAYD..	ORMSBY	INDUST..	BROOK..
CHARLES	THE	NORTH	EDMIST..	GARDE..	EDMON..	AREA	CARLIS..		LANSD..	HEIGHTS	HAYS	PLACE	PINTAIL	BULYEA
PRINCE	ORCHA..	EAST	ELMWO..	LARKSP..	ELMWO..	CRYSTA..	CARLTO..		LENDR..	FULTON	RIDGE	PLACE	LANDING	HEIGHTS
RUPERT	WALKER	SOUTH	GAGNON	LAUREL	HIGHLA..	CRYSTA..	CHAMB..		MALMO	PLACE	AREA	LARUE	POTTER	CALGARY
QUEEN		STURG..	ESTATE	LEE	MONTR..	CY	CUMBE..		PLAINS	GAINER	HERITA..	RIVER	GREENS	TRAIL
MARY			INDUST..	RIDGE	NEWTON	BECKER	DUNLU..		MCKER..	INDUST..	HERITA..	VALLEY	RIVER'S	SOUTH
PARK			GARSIDE	MAPLE	PARKD..	DELWO..	EAUX		MILL	GIRARD	KESWICK	CAMER..	EDGE	CARTER
RIVER			INDUST..	MENISA	RIVER	EBBERS	CLAIRES		CREEK	INDUST..	MACEW..	RIVER	RIVERV..	CREST
VALLEY			GLENW..	MEYOK..	VALLEY	FRASER	ELSINO..		RAVINE	GOLD	PAISLEY	VALLEY	ROSEN..	DUGGAN
GLENO..			GROVE..	MEYON..	HIGHLA..	GORMA..	EVANS..		SOUTH	BAR	RICHFO..	LESSARD	SECORD	ERMIN..
RIVER			HAWIN	MICHA..	RIVER	HAIRSI..	GLENG..		PARKAL..	HOLYR..	RIVER	NORTH	STARLI..	FALCON..
VALLEY			PARK	MILL	VALLEY	HOLLIC..	GOODR..		PLEASA..	IDYLWY..	VALLEY	RIVER	STEWA..	GREEN..
VICTOR..			ESTATE	WOODS	KINNAI..	HOMES..	GRIESB..		QUEEN	KENILW..	WINDE..	VALLEY	STILLW..	HADDO..
RIVERD..			INDUST..	GOLF	RIVER	INDUST..	HAGMA..		ALEXAN..	KING	RUTHE..	OLESKIW	SUDER	HENDE..
ROSSD..			HIGH	COURSE	VALLEY	KENNE..	HUDSON		RITCHIE	EDWARD	WINDE..	SUMME..	GREENS	HODGS..
SHERB..			PARK	MILL	RUNDLE	KERNO..	KENSIN..		RIVER	PARK	WINDE..	TERRA	THE	KEHEE..
WESTM..			HIGH	WOODS	RUNDLE	KILDARE	KILLAR..		VALLEY	LAMBT..		LOSA	HAMPT..	LEGER
WOODC..			PARK	PARK	HEIGHTS	KILKEN..	KLARVA..		MAYFAIR	MAPLE		THORN..	THE	MACTA..
			INDUST..	MILL	SPRUCE	KIRKNE..	LAGO		RIVER	RIDGE		WEDGE..	UPLAN..	MAGRA..
			HUFF	WOODS	AVENUE	MATT	LINDO		VALLEY	MAPLE		WESTRI..	TRUMP..	OGILVIE
			BREMN..	TOWN	VIRGINI..	BERRY	LAUDE..		WALTE..	RIDGE			WEBBER	RIDGE
			JASPER	CENTRE	WESTW..	MAYLIE..	LORELEI		⋯	INDUST..			GREENS	RAMSAY
			PARK	MINCH..	YELLO..	MCCON..	MCART..			⋯			WESTVI..	HEIGHTS
			⋯	⋯	YELLO..	⋯	⋯						⋯	⋯

Neighbourhood Name broken down by District Plan.

Figure 7.1, 7.2

Appendix

Property Style Classifications

Style (group)	Style	
Apartment	APART	48,898
	APRTM	2,117
Bilevel	BLEVL	20,061
Bungalow	BUNG	81,723
	BUNGH	275
	BUNGR	1,394
Split-level	BK-SP	205
	HL-SP	9
	SPLT2	997
	SPLT3	1,553
	SPLT4	15,156
	SPLT5	1,056
Storey	ST1.5	8,131
	ST2	135,013
	ST2.5	1,233
	ST3	2,376
Other	LOFT	872
	MOBLD	24
	MOBLS	77
	MODUL	10
	PENTH	695
	STUDI	73
	VILLA	1

Count of Listing ID # broken down by Style (group) and Style.

Figure 8

Appendix

References

Sirmans, G. S., MacDonald, L., Macpherson, D. A., & Zietz, E. N. (2006). The Value of Housing Characteristics: A Meta Analysis. The Journal of Real Estate Finance and Economics, 33(3), 215–240.
https://www.researchgate.net/publication/5151851_The_Value_of_Housing_Characteristics_A_Meta_Analysis

Steele, M., & Goy, R. (1996). Hedonic Price Indexes and Multiple Listing Service Average Prices for Canadian Census Metropolitan Areas, 1990 to 1993. Canada Mortgage and Housing Corporation. Retrieved from
https://publications.gc.ca/collections/collection_2018/schl-cmhc/nh15/NH15-832-1996-eng.pdf

Linden, L., & Rockoff, J. E. (2008). Estimates of the impact of crime risk on property values from Megan's laws. American Economic Review, 98(3), 1103–1127.
https://www.aeaweb.org/articles?id=10.1257/aer.98.3.1103

https://www.edmonton.ca/sites/default/files/public-files/assets/Districts-and-Neighbourhoods.pdf (map of districts)

https://www.edmonton.ca/sites/default/files/public-files/District-Policy.pdf (district policy, shows how the city is split)

https://www.edmonton.ca/city_government/urban_planning_and_design/plans-in-effect (plans, where to get district documentation)

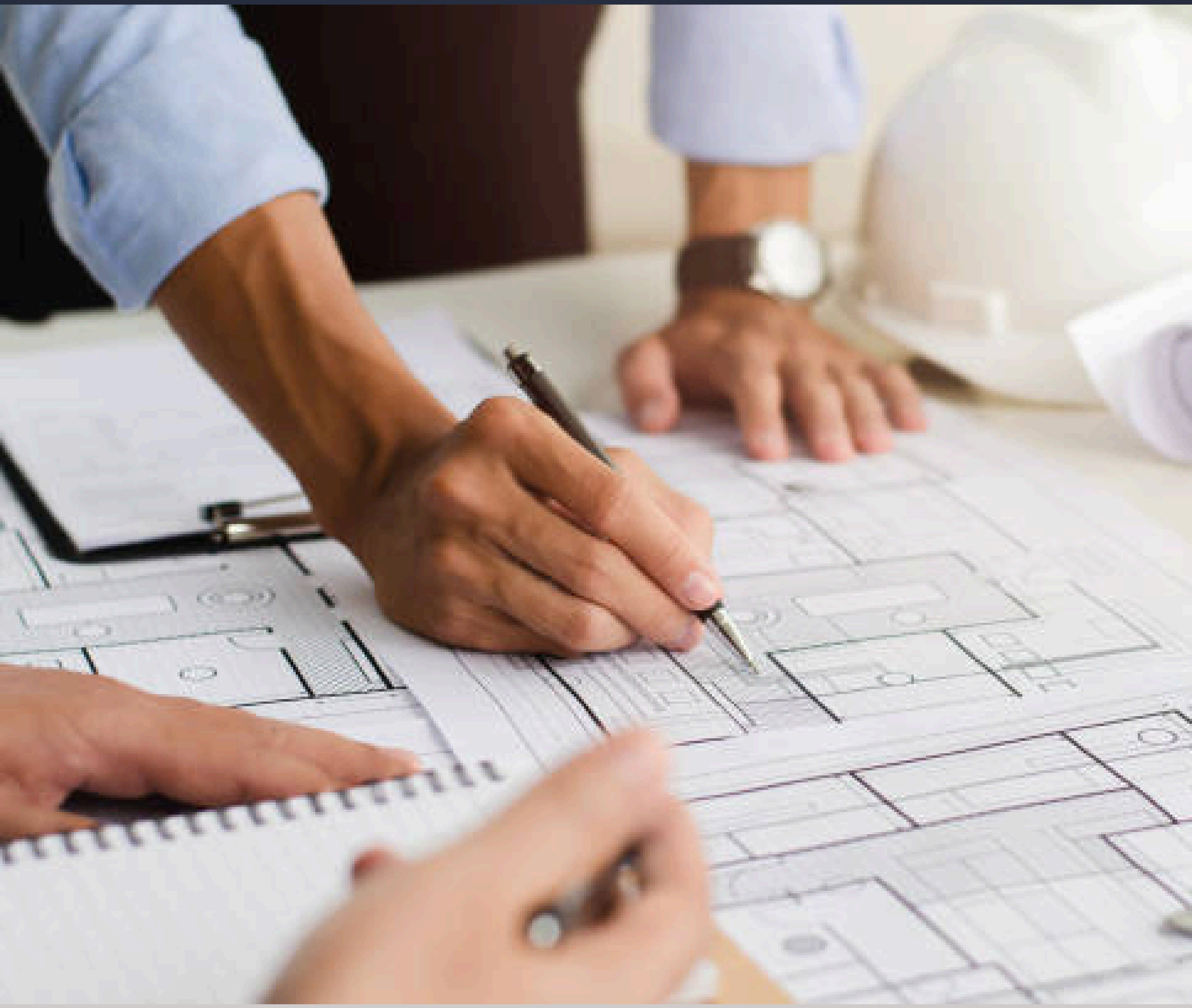
https://cosspp.fsu.edu/dmc/wp-content/uploads/sites/8/2020/09/02.2009-Crime-and-Housing-Prices.pdf (crime and price literature)

Images

https://www.voyagerpacific.com/wp-content/uploads/2021/08/single-family-home.jpg

https://media.istockphoto.com/id/1358582944/fr/photo/gros-plan-dun-ing%C3%A9nieur-planifiant-une-conception-dessin%C3%A9e-%C3%A0-la-main-avec-des-%C3%A9quipements.jpg?s=612x612&w=0&k=20&c=yqJE_bRQdJwJa5UeVRwTvn1s0Ph0WgjhfxZVgyreqPk=

Contact us for *further inquiries*



LGS Co.

www.LGS.com
aboutus@LGS.com
780.123.3960