Silverstone Partners

Asset Clustering – A Machine Learning Approach to Location Analytics

MARCH 2023

CAUTIONARY STATEMENT CONCERNING FORWARD LOOKING STATEMENTS

This document contains forward-looking statements. In addition, from time to time, we or our representatives may make forward-looking statements orally or in writing. We base these forward-looking statements on our expectations and projections about future events, which we derive from the information currently available to us. Such forward-looking statements relate to future events or our future performance, including: our financial performance and projections; our growth in revenue and earnings; and our business prospects and opportunities. You can identify forward-looking statements by those that are not historical in nature, particularly those that use terminology such as “may,” “should,” “expects,” “anticipates,” “contemplates,” “estimates,” “believes,” “plans,” “projected,” “predicts,” “potential,” or “hopes” or the negative of these or similar terms. In evaluating these forward-looking statements, you should consider various factors, including: our ability to change the direction of the Company; our ability to keep pace with new technology and changing market needs; and the competitive environment of our business. These and other factors may cause our actual results to differ materially from any forward-looking statement. Forward-looking statements are only predictions. The forward-looking events discussed in this document and other statements made from time to time by us or our representatives, may not occur, and actual events and results may differ materially and are subject to risks, uncertainties and assumptions about us. We are not obligated to publicly update or revise any forward-looking statement, whether as a result of uncertainties and assumptions, the forward-looking events discussed in this document and other statements made from time to time by us or our representatives might not occur.

SUMMARY OF RISK FACTORS

We face risks, which include, but are not limited to, the following:

- The availability of financing and attractiveness of its terms;
- Changes in economic conditions generally and the real estate market specifically;
- Changes in interest rates;
- Competition in the real estate industry generally and the apartment community sub-industry specifically;
- The supply and demand for properties in our target market areas;
- Our ability to successfully identify and acquire desirable properties;
- Our inability to efficiently manage our properties; and
- Legislative and regulatory changes.

Executive Summary

Location Analytics are a critical component of our investment process, where we strive to **identify the most attractive neighborhoods and segments of a market and understand the competitive dynamics influencing a particular property.** These factors have a significant impact on an individual property's performance and complement the overall market outlook. When combined, these considerations assist in arriving at an informed investment assessment and recommendation.

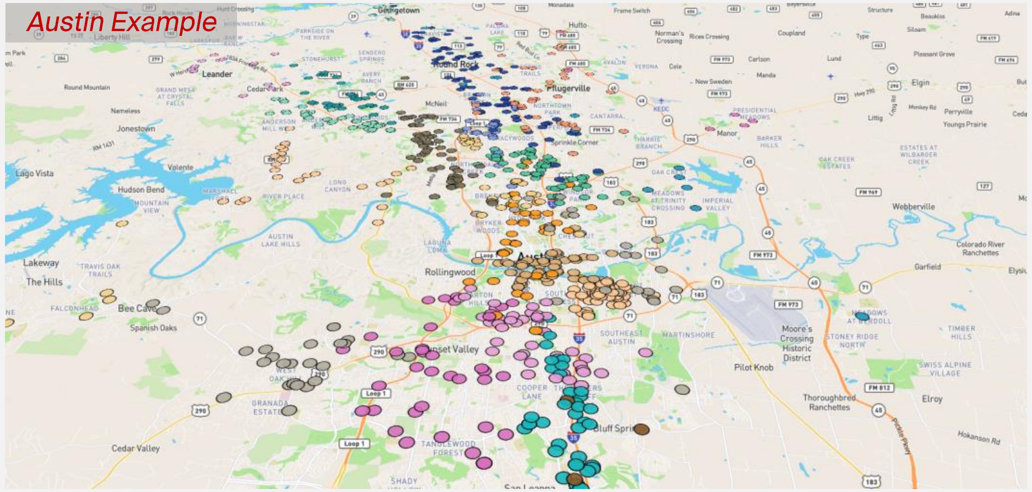
Our approach to Location Analytics and market segmentation is based on property "clustering" – a method of grouping similar properties together. This grouping is based on both traditional property information and demographics, as well as alternative data such as amenities, crime, transit connectivity and other measures of neighborhood quality. We employ machine learning algorithms that provide high performance but remain both flexible and adaptable, an approach that ultimately results in property groupings that meaningfully reflect a market's competitive dynamics. We have found this approach to be superior to the traditional approach of geographical submarket and asset class market segmentations.

This analysis provides three key actionable benefits:

1. Identification of attractive market segments and understand how they are currently positioned, allowing us to focus on specific parts of the market
2. Understanding of the importance of various factors and characteristics to performance, to tailor analysis and focus on those that are the most relevant
3. Support in evaluation of specific assets for underperformance or opportunities for value creation.

Asset Clustering Highlights

- We recommend a powerful method of segmenting properties within a market, using asset characteristics in addition to geographic location, and implementing a machine learning-based methodology.
- This exercise offers significant assistance in both formulating investment theses, as well as identifying under-performing and over-performing properties, thus uncovering compelling investment opportunities
- Our results indicate that our approach is superior to the traditional approach of submarkets, offering better performance across a host of dimensions



Introduction

Silverstone Partners' investment strategy is largely focused on multifamily properties in US markets, where we see clear evidence of supportive supply/demand fundamentals, a favorable macroeconomic backdrop, and an attractive long-term outlook. As part of this process, not only do we focus on markets and that we believe have a compelling outlook in both the near- and long-term, but we also strive to select properties we believe to be well-positioned to outperform within their markets.

While a property's behavior will of course be influenced by asset-specific factors as well as the dynamics of the aggregate market, performance will also be heavily influenced by its respective market segment, specifically similar properties with which it competes for tenants. Developing an understanding of how these segments behave, their cyclical positioning, as well as the positioning of a property within its segment will provide significant insight into a property's future prospects.

The conventional approach to grouping properties is a combination of location and asset quality – specifically defined geographic boundaries and asset class (A/B/C). We believe there are several shortcomings to this approach that can be addressed by including additional property and location-specific characteristics that are valuable indicators of a property's competitive dynamics and positioning, increasing the flexibility of the geographic definitions to allow overlap, and applying machine learning techniques to drive the analysis.

The ultimate objective is to create more meaningful groupings of properties within a market that more accurately reflect the competitive dynamics. This will provide a deeper understanding of market segmentation, allowing us to focus our investment efforts on the most desirable segments of the overall market, as well as identify properties that are underperforming their peer set. This makes up a critical piece of our location analytics, which complements our in-person assessments of the property and neighborhood upon which we make our final investment recommendations.

Approach to Location Analytics

Market Selection

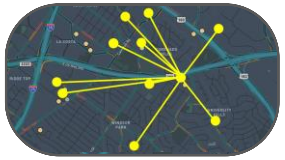
Identify markets with compelling near-term fundamentals and an attractive long-term outlook

Market Segmentation

Focus on the most attractive segments within a market, with emphasis on:
- Cyclical positioning
- Long-term supply/demand
- Segment characteristics
- Amenities / demographics

Focus of Asset Clustering Insights

Asset Location Dynamics



Evaluate a property's direct competitors with a thorough comparison of relative positioning, property amenities, etc.

Asset Clustering – Breaking Down a Market

After a market has been selected for investment, **identifying the best areas within the market and type of property** are the next critical decisions. While a property's performance will certainly be based on its individual characteristics (e.g. unit finishes, amenities, location), understanding the broader competitive dynamics is essential to understanding how individual assets will perform.

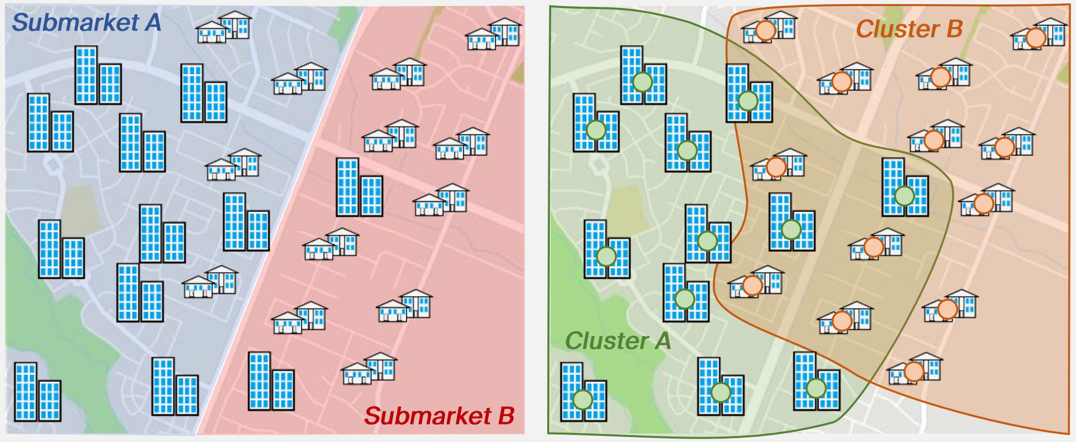
As an example, consider a recently constructed, fully-amenitized high-rise apartment building in the urban core. This property will compete with similar properties – i.e. nearby buildings of a comparable size and interior finish, as well as similar amenities and characteristics (e.g. close to transit). It would likely *not* compete with a similar asset located in the suburbs (as location is likely a primary consideration), nor would it compete with a nearby property that is older and less amenitized.

Identifying groups of similar assets can significantly increase our understanding of the behavior of both the market as well as an individual property, and uncover potential opportunities or risks. For instance:

- A group of properties in an up-and-coming part of town may be in high demand and have limited supply, creating attractive opportunities for organic rent growth
- A group of properties may have a high vacancy rate or is about to see an influx of new development, hurting future rental pricing power
- A property that is underperforming its peer group, possibly due to mismanagement, poor physical condition, or the absence of a key amenity or feature.
- An abundance of very similar assets within a group may be creating a negative competitive dynamic, representing a potential risk to an investment
- Recently renovated properties within a group may be identified to command a large rental premium – justifying renovation of other older properties within the group

While the conventional methodology of submarkets – a mostly geographical approach – is a useful starting point, there is an opportunity to improve on this by including other metrics and evolving the approach with advanced analytics.

Grouping assets into submarkets according to location vs intelligent clustering based on multiple property and neighborhood characteristics



A simplistic submarket approach to grouping properties

Including multiple factors allows for more intelligent clustering of properties

Shortcomings of the Traditional Market Segmentation Approach

There are **three primary shortcomings** to the traditional approach that can be improved upon by including additional metrics and applying advanced analytics techniques.

1. Overlooking Critical Information

The current approach of grouping properties relies almost exclusively on location (with submarket boundaries that do not overlap) and asset class. However, there now exists significantly more information about the characteristics and attributes of a property as well as its nearby location, including building type (high rise tower vs low rise garden style), nearby amenities (restaurants, grocery stores, nightlife, transit connectivity) and demographics, among many others.

These factors are sources of differentiation with different types of products catering to different types of tenants – ultimately driving the decision to rent and hence informative to grouping properties. An approach to grouping properties that includes these additional pieces of information will significantly enhance the understanding of market dynamics and how properties compete with one another.

2. Submarket Boundaries

When delineating submarkets, boundaries must be drawn – these are typically major streets, zip code boundaries, or some other familiar geographical metric. However, in many cases, certain assets which are in close proximity to each other (perhaps even on opposite sides of a street) may fall into two different submarkets, simply because a boundary line must be drawn somewhere. This may not be reflective of the true competitive dynamic that exists.

3. Neighborhood Variation within the Submarket

In many cases, submarkets can be defined to be quite large, and include very different parts of a market. One end of a submarket may be on the outskirts of an expanding urban core with high density and ample access to public transit, while the other end may be firmly in a suburban area surrounded by large single family homes. These different area characteristics may lead to very different property behavior, catering to different tenant bases.

Neighboring properties in the same submarket that are clearly very different in age, price and amenities, and cater to different tenant bases,

Property Clustering – A Machine Learning Approach

To more meaningfully group properties that have similar characteristics, we assemble several datapoints reflecting a property's characteristics and tenant appeal, including location, class (A+ to C) and age, as well as several demographic[1] and alternative data[2] metrics that characterize the neighborhood.

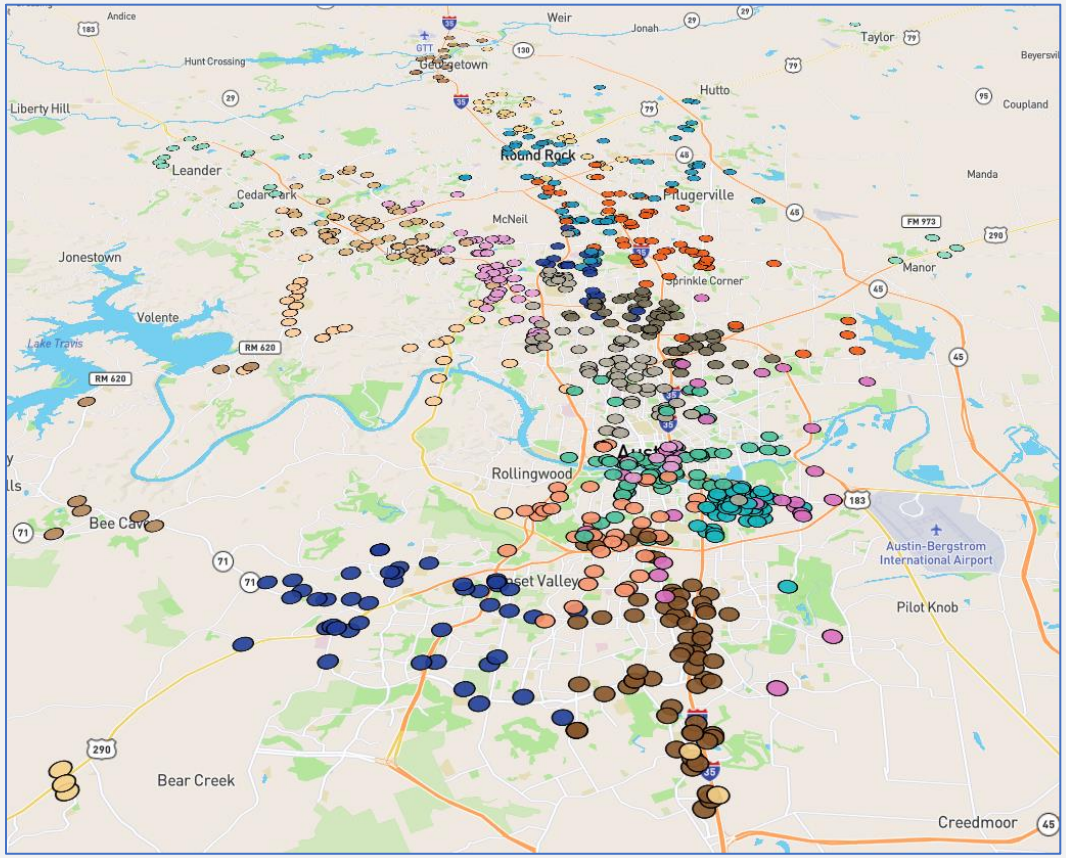
To effectively use this information to create groupings, we turn to machine learning and advanced analytics, specifically "clustering"– a type of analysis where the objective is to take in large amounts of datapoints (with associated characteristics) and create groupings, based on the similarity of the datapoints according to these characteristics[3].

As an illustrative example, we apply these techniques to Austin, with the results shown on the right. We ultimately define 29 different clusters with each dot representing a property, and the color representing its cluster. The influence of both geography as well as other metrics can be clearly seen, given the close proximity of the properties within a given cluster, but also the frequent overlap between clusters as other metrics are factored into the analysis.

These clusters are a better representation of the market's competitive dynamics compared to a purely geographical (i.e. submarket) approach, allowing us to focus on clusters where we not only see opportunities for the cluster as a whole, but also for individual assets within that cluster that are either mispriced or underperforming.

Methodology Notes: *Several clustering algorithms were evaluated, including K-means, HDBScan, and Spectral. Gaussian Mixture clustering was ultimately selected as the most suitable for this analysis, providing the best results. Results were optimized by manual evaluation, supplemented with the Silhouette, Calinski-Harabasz and Davies-Bouldin Cluster scores.*

Austin Clusters



[1] Primarily sourced from ArcGIS
[2] We utilize Location Scores from [Local Logic](), which provide numerical ratings that evaluate different aspects of a location along a host of dimensions.
[3] More detail on clustering techniques can be found in the Appendix

Evaluating Clusters Quality

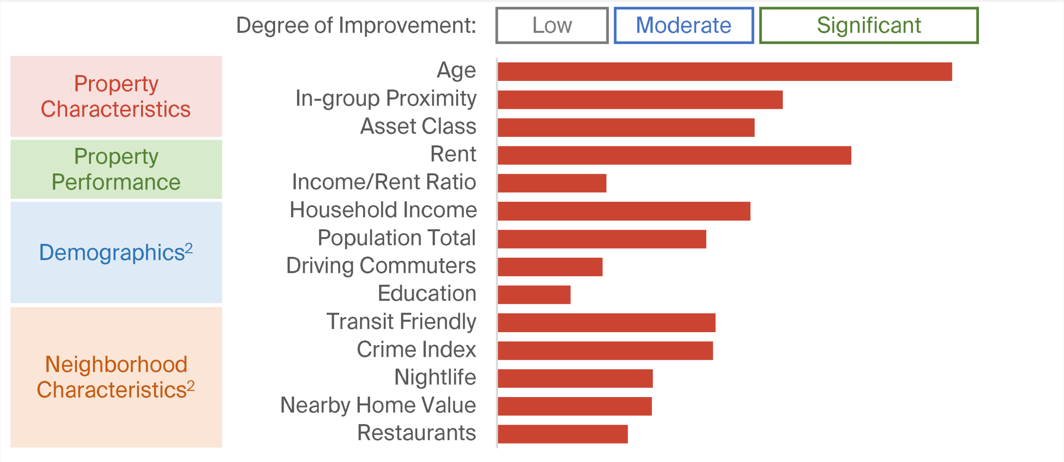
The results can be qualified by measuring whether properties within a cluster are in fact more similar to one another, when compared to the traditional approach.

As can be seen below, there is a higher degree of similarity[1] of properties within the clusters, compared to property groupings using the traditional approach, across several key metrics of **property characteristics, property performance, demographics**[2] and **neighborhood characteristics**[2]. For instance, building age typically varies +/- 15 years on either side of the submarket average[3], versus clustering, where this variation drops to +/- 8 years – a vast improvement. Notable improvements are also seen in rent level, asset class, household incomes, population density and transit connectivity.

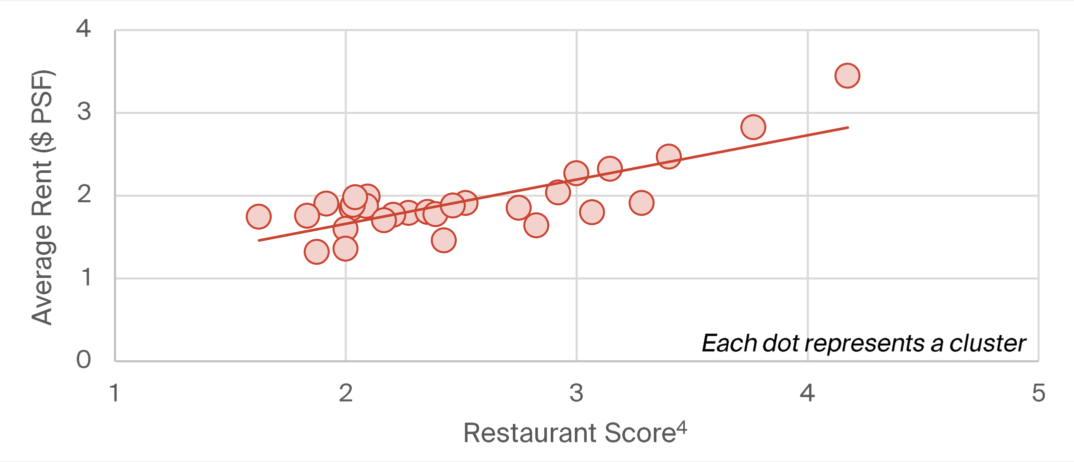
The result is clusters of properties that are more representative of the different segments of the market, when compared to the traditional approach. This allows for easier identification of outliers, potential mispricings or underperforming assets that represent opportunities.

Valuable observations can also be made by examining cluster behavior. For example, the relationship between average rent within a cluster and the Restaurant score[1] of the cluster can clearly be seen below. While there are undoubtedly other factors at play, this helps quantify the value of this amenity, and potentially factor this into an estimate of the rent potential and value of a property.

Improvement in Property Similarity within Clusters (vs Submarket Approach)[1]



Average Restaurant Score vs Average Rent



[1] Improvement is measured as the average reduction in standard deviation of a given metric within each cluster
[2] Based on 0.5 mile radius; data from Local Logic and ArcGIS
[3] Measured as the one standard deviation above and below the average
[4] Data from Local Logic

Asset Clustering – Bringing Relevance to Investment Decisions

This clustering approach is directly relevant to how markets can be segmented and assessed, supporting the identification and evaluation of individual opportunities. By including both traditional and alternative data sources in a meaningful framework, we uncover key actionable insights with direct relevance to our investment strategy and process. Key benefits of this approach include:

1. **Efficiently Identify Attractive Clusters:** Properties within a cluster will generally exhibit similar behavior, and often compete with one another directly. Identifying clusters that generally have more attractive characteristics or are better positioned in their cycle allows investment efforts to be more refined and focused.
2. **Understand Factor Relevance:** The importance of various asset and neighborhood characteristics can be directly observed. Where these factors are strongest or weakest, as well as where they are changing, is an important factor in the assessment of an individual opportunity.
3. **Evaluate and Screen for Specific Properties:** Within clusters, the characteristics and performance of individual properties can be evaluated, providing an opportunity to identify a "short list" of properties that meet certain investment criteria. For instance, properties that will benefit from future improvements in transit infrastructure, or properties that are underperforming their peer set for identifiable reasons that can be remedied.
4. **Standardized and Scalable Approach:** The approach has been designed to be easily replicable across markets, with an efficient assessment of both the quality of the results and extraction of key insights, without sacrificing the flexibility of the analysis to reflect market-specific factors.

As an example of one critical dimension that offers insight into performance, the strong relationship between rent growth and average occupancy from 2014-2019[1] amongst the clusters within Austin can be clearly observed, with a 300 bps difference in annual rent growth between the top and bottom performing clusters. Those clusters with the highest average occupancy generally experienced the strongest rent growth. Looking forward, favoring clusters that currently have a high level of occupancy and little expected new supply are better positioned for success.

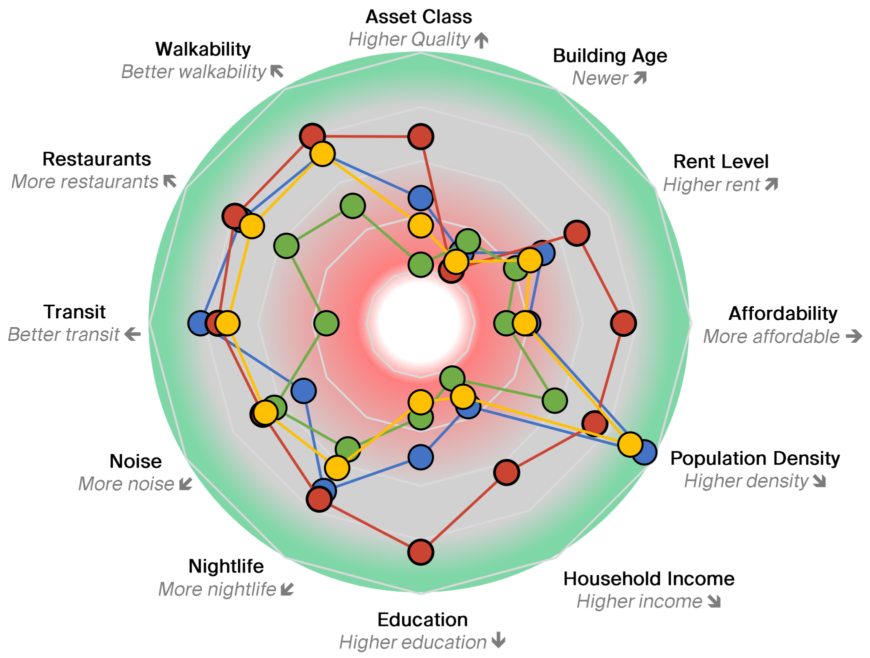
Historical (5Y) Cluster Average Rent Growth vs Average Occupancy

[1] *Covid years excluded due to the significant volatility and noise within the market*

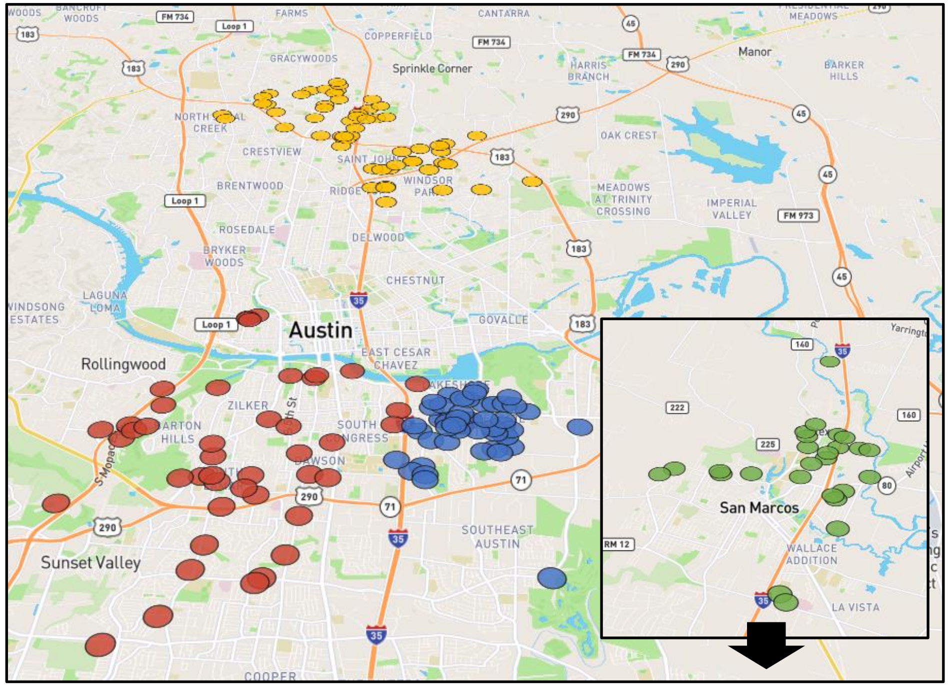
Asset Clustering – Identifying Opportunities within Austin

As an example of how this technique can be applied, four clusters of properties within Austin can be identified that currently screen as attractive. These properties are in relatively high demand and offer potential for future above-market rent growth given current supply / demand dynamics. Focusing efforts on identifying specific properties within these clusters, that meet additional criteria, is the next step.

These results generally support the thesis of pursuing well-located Class B properties in desirable neighborhoods that are either near major employers or offer access to major thoroughfares for easy commutes. An abundance of nearby amenities is also a desirable feature.



- Class A & B properties of older vintage in the Barton Hills, Bouldin and Travis Heights neighborhoods offering walkable and energetic nodes with little new supply
- Class B & C properties in the intensifying, dense Riverside neighborhood, with ample amenities and lower rents
- Class B and C properties in northern Austin offering affordable housing in close proximity to several high-growth job centers
- Older Class B & C properties in San Marcos, a desirable suburban community south of Austin proper



Conclusions

Clustering properties according to their characteristics, the neighborhood attributes, as well as location offers significant advantages over the more traditional submarket approach. These factors are not only more representative of the tenant's perspective, but also result in greater consistency of the segment's operational and investment performance. The approach itself is also highly flexible and adaptable, providing an overall better "definition" of the market segments.

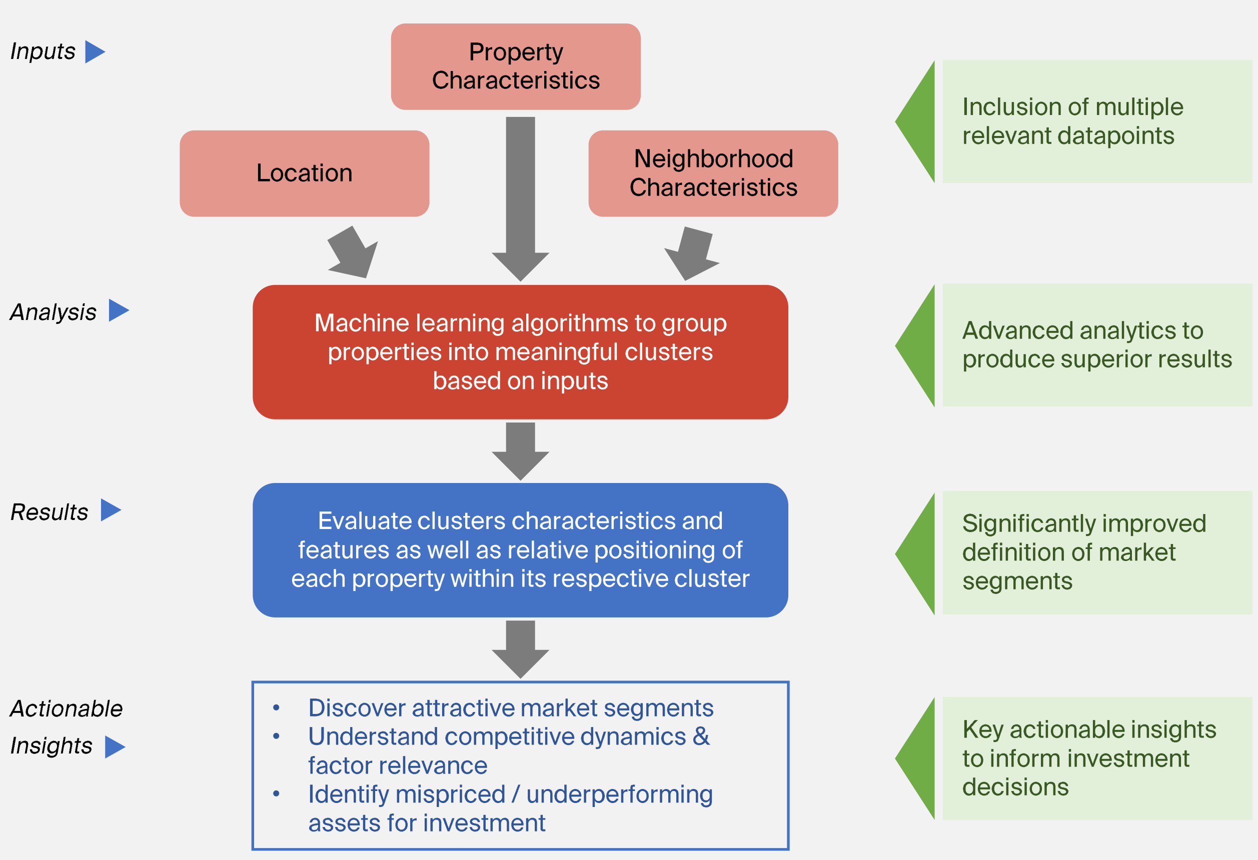
The key, actionable benefits of this clustering process are to:

- More easily and confidently discover attractive segments of the market and better understand competitive dynamics within these segments
- Identify the factors most relevant to cluster and property performance
- Identify mispriced or underperforming properties within clusters

In our Austin example, we found ~300 bps of annual rental growth differential between the top- and bottom-performing market clusters over a five-year period (see chart on Page 8). Understanding what drove this performance differential and what future prospects are help us (a) target the segments that currently offer the most attractive outlook, and (b) focus investment efforts on specific properties within these segments that have desirable characteristics and are attractively positioned.

This approach marks a significant step forward in leveraging advanced analytics and alternative data to inform superior real estate investment decisions, which is combined with conventional analytics and our established approach to investment and asset management.

Summary of Approach and Benefits



Appendix: What is Clustering?

Clustering is a type of machine learning algorithm where the objective is to identify and form natural groups (or "clusters") of datapoints, where the datapoints in any given group have a high degree of similarity to each other.

This type of analysis is useful for situations where descriptive information across multiple categories are available for specific datapoints, and one wishes to form a number of groupings of these datapoints based on those categories. In particular, the analysis lends itself well to segmentation of customers, companies, tenants, or other datasets for which descriptive statistics exist and play a role in "defining" the datapoints. If meaningful clusters can be found, the data can be more effectively interpreted and characterized, facilitating a better understanding of the information.

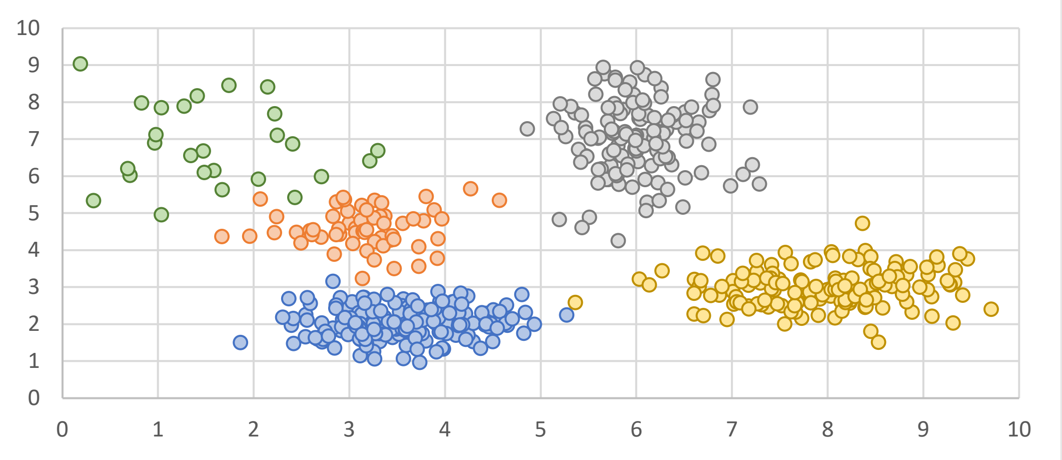
For example, a marketing firm may be interested in identifying distinct groups of customers for whom they are looking to create advertising campaigns, where customer information is readily available (e.g. age, income, marital status, location, spending habits). Typical groups might include "young single professionals living downtown", "affluent suburban families", or "recently retired couples". Although these groupings will never be perfect and many individuals may fit well into multiple groups, they can form the basis for targeted advertising campaigns.

As it relates to clustering of apartment properties, a property's location is only one of its important characteristics. Many other factors, including the specific characteristics of the property (e.g. age, physical condition, rent), the demographics of the surrounding area, and the nearby amenities are also relevant characteristics. These variables can all be incorporated into the analysis. While the concept of distance is straightforward for geographical location, it can easily be extended to other characteristics.

For instance, a Class B+ property is considered "closer" to a Class A property, and "further away" from a Class C- property. A property with a Walkability score of 4 (out of 5) is considered "closer" to a property with a score of 4.5, compared to one with a score of 2.0.

The concept of clustering can be easily visualized in two dimensions (i.e. two factors only) in the graph below, where there are five easily identifiable clusters. In application, multiple dimensions can be employed to identify these distinct clusters of similar properties.

Basic Example of Clustering in Two Dimensions



About Us

Real estate investing, innovated.

Silverstone Partners is a thematic investment manager focused on equity and debt opportunities in commercial real estate. With robust execution capabilities across the investment value chain, we seek to generate superior risk-adjusted returns for our investors through thoughtful market and asset selection, followed through with high-touch asset management. Silverstone is built on several foundational principles, including creating value at the asset level through direct involvement in operations, promoting a culture of data-driven decision making and operating with unwavering integrity and transparency in all aspects of our business.

Silverstone is currently focused on the residential sector, under two specific investment themes. The first theme is focused on acquiring underperforming core-plus and value-add assets in markets that exhibit strong evidence of supportive supply-demand fundamentals, with an opportunity to improve the operational and financial performance of the asset. The second theme is centered on opportunistic assets, where Silverstone can unlock additional value through asset repositionings and capital structure modifications.

Adam Brueckner

Managing Principal

Adam has more than 13 years of experience in real estate and capital management, with a focus on capital allocation, investment analysis, research and investment risk. Prior to co-founding Silverstone Partners in 2021, Adam served as VP of Global Portfolio Management and Investment Risk at a $50 billion global real estate fund. Key responsibilities included development and oversight of the firm's strategic capital allocation function, as well as leadership of the global research (forecasting for 80+ markets globally) and investment risk groups.

Adam holds a BASc in Systems Design Engineering from the University of Waterloo, an MASc and MBA from the University of Toronto, and is a CFA Charterholder.

Manoj Ramprakash

Managing Principal

Manoj has over 11 years of real estate investment experience including direct equity and credit investment, development and asset management. Prior to co-founding Silverstone Partners in 2021, Manoj was a senior member of the investment team for a $50 billion global real estate fund. Key responsibilities included leadership of multifamily investments for several US sunbelt states, oversight of the development of a 1.3 million square foot office building in Manhattan, and the deployment of over $6.0 billion across equity and credit investments.

Manoj holds an HBA from the Ivey Business School at Western University. Manoj is actively involved with the Pension Real Estate Association (PREA) and currently serves on its Rising Leaders Committee.