Representation of Unsold Properties - The Biggest Problem You Don't Know You Have!

By Kevin Keene, Keene Mass Appraisal Consulting kevin@keenemac.com and Alex Raju, Modeling Supervisor, Office of Property Assessment, City of Philadelphia alex.raju@phila.gov

As mass appraisers, we attempt to estimate something unknown (the values of a universe of properties) based on the prices and attributes of properties that have sold. We use different methods, such as cost, comparable sales, sales and income in regression models and even AI models to estimate values. The basis of all of our techniques is the assumption that properties that have sold represent the properties that have not sold. Representation of unsold properties is one of the most common, yet least understood, problems that all assessors face.

A well-represented sales file is the foundation for reliable and effective mass appraisal. It enhances data quality, feature engineering and validation, ultimately leading to more accurate property value estimates.

Whenever we use ratio studies to analyze assessment performance, or use sales-based methods to estimate property value, we are assuming:

That properties that sell are similar to properties that do not sell

- AND -

That representation of unsold properties is proportionate to sales activity.

Is it safe or reasonable to make these assumptions?

How can we test the validity of these assumptions?

There are no standards, and very little in the body of knowledge that does more than hint at the magnitude of the issue. There are statistical tests to determine the degree of variation in a sales file, but no widely accepted methods for *directly* comparing the observations in the sales file to the wider universe of unsold properties.

In an efficient market, most or all types of properties in the inventory will be represented by sales, but markets are not equally efficient. In my experience, there is a great deal of variation in the degree of representation of unsold properties from one market to the next. Many properties in disadvantaged communities or properties that are not "typical" are not represented by sales, which can easily lead to errors in valuation and/or analysis. When properties are not directly represented by sales, our valuation processes have to generalize to estimate values, and the likelihood of error increases as the degree of generalization increases. In addition, our sales ratio studies tell us little or nothing about those properties that are not represented by sales. Can we truly draw valid conclusions about assessment performance and quality across the entire inventory if some or many properties are not represented?

It is important for all assessors to understand how well sales represent their respective inventories. Better yet, techniques that can *precisely* identify properties that are not represented by sales can be very helpful in improving assessment performance and equity. Properties that are not represented by sales present higher risks for overvaluation or undervaluation.

Some of the dimensions in which properties might not be represented by sales include neighborhoods, property types, condition of improvements, building or lot sizes, construction quality, age and even price class or value class.

Group Summary Method

The Group Summary Method assigns properties to groups using a common schema called a Group Identifier (Group ID). Every transaction in the sales file and every property in the inventory file will be assigned a Group ID.

Using these groups, we can summarize and present data about each group, and directly compare sales to the wider inventory. This is not a new technique. I built the first Group IDs in Philadelphia in the late 1990s. They have been used to great effect ever since.

Heuristic Measure of Representation (HMR)

The Heuristic Measure of Representation is similar to the Group Summary Method in that it assigns properties to groups. The primary difference is that the groups are defined by regression models, with a different schema for each model that is used to estimate values. The method derives a score for each property that reflects the degree of generalization from the model used to estimate value. This method is relatively new, and has yet to be comprehensively applied.

Both methods allow us to gain more precise insight into model and assessment performance, facilitate review of valuation projections and can identify submarkets or even specific properties that are not well served by the valuation process.

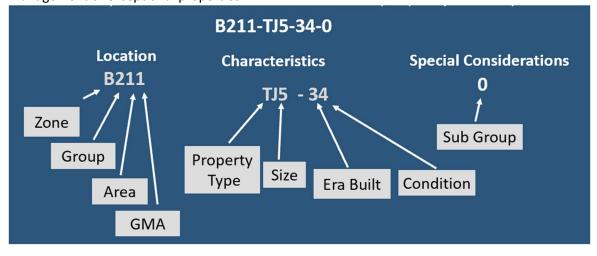
First, let's look at the Group Summary Method.

Why Use Grouping IDs? It is not particularly difficult to make good decisions in appraising properties. The hard part of mass appraisal is making sure that, when decisions are applied, they affect Every property that *should* be affected - and No properties that should *not* be affected.

Building Group IDs

Group IDs are built by identifying the five or six most important contributors to value. These are usually the attributes that determine comparability. These attributes are transformed into codes that are concatenated into a text string. Most categorical attributes are already in the CAMA system as codes, so transformation might not be necessary. Numeric attributes, such as building square footage or lot size, need to be transformed into categorical bins to which codes can be assigned. The important attributes may vary from market to market, and certainly from one property type to the next. Group IDs provide a 'snapshot' of a property, bringing together the most important elements that describe a property in one place.

As an example, in Philadelphia, we built Group IDs from Location (neighborhood); Building Design; The Relative Building Size code (building SF transformed into 5 categorical bins, ranging from smallest to largest); the year the property was built (transformed into seven categorical time periods); and the condition of the improvements. A sixth element allowed for recognition of any special circumstance that would make the property different in some way, which simplifies the management of exceptional properties.



Properties in the group B211-TJ5-34-0 would be similar, but not necessarily identical. Some might have garages; others not. Some might have central air conditioning. They could be on different size lots. But they would all be from the same neighborhood, have the same design, fall within a range of square footage that would allow them to be considered similar, have been built at around the same time period and would be in the same condition.

One of the advantages of the method is its great flexibility. I have built Group IDs for jurisdictions that used other attributes, such as Quality of Construction, the Number of Stories, or the class of the building or complex. Each market can define Group IDs in its own way. Group Ids can be built for all types of properties – from vacant land to Office Buildings to Condos.

There are many advantages to using Group Ids and Group summaries.

Group Ids allow us to designate properties as members of groups and *make decisions* at the group level. This ensures that all properties in the group are affected equally. It also allows us to have different methods, adjustment coefficients and techniques for different groups of properties. We can also keep aggregate or summarize data for all groups and easily publish that data to our constituents.

- Group Ids make databases much more efficient, avoiding multi-key joins between tables and simplifying retrieval
 of data through queries.
- Group IDs support direct comparison between sold and unsold properties.
- Group summaries can greatly improve our understanding of our markets and the performance of our assessments.
- Group IDs are very useful for reviewing market value estimates both within and between groups.
- Group IDs can greatly simplify identification and selection of comparable sales.
- Group IDs can be built for any sales and inventory file regardless of the valuation method used. Anyone can use this technique!

The Power of Persistent and Consistent Groups

Groups created by Group IDs are both consistent and persistent.

Consistent means that the group is always the same, no matter who accesses the data. Persistent means that the group, and data about the group, exists at all times.

Every account has a Group Id. There are around 59,000 distinct Group Ids in the Philadelphia data.

Every transaction has a SGroup Id (Group ID at time of sale). There are around 23,000 groups with 1 or more validated sales in the Philadelphia data.

Because the groups are both Consistent and Persistent, we can maintain data about Group IDs and SGroup IDs. Every account can be linked to the data about its Group ID and SGroup ID groups, including the number of accounts, number of valid sales, average size, market value or sale price per square foot, average sale price, median ratio of assessment, and many others.

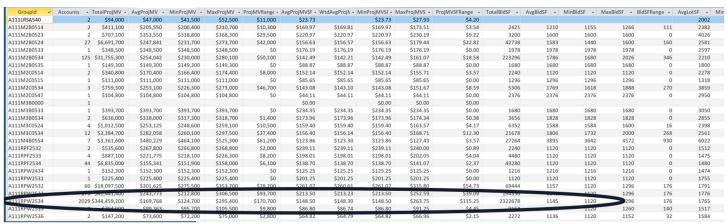
We can compare any given account to what is typical for the group, allowing us to find those that are at significant variance. How well does the sale price of a new transaction match what we know about what is typical for the group? How well does a specific value align with other properties in the group? These questions become easy to answer.

When we run a query, the result is a set of records that meet the parameters that were input. We can examine or analyze the records that were pulled, but we can't analyze the records that were not pulled. With Group ID summaries, we can also compare attributes of a set of records to attributes of records that are NOT in the dataset. This is called 'what is' to 'what is not' comparison.

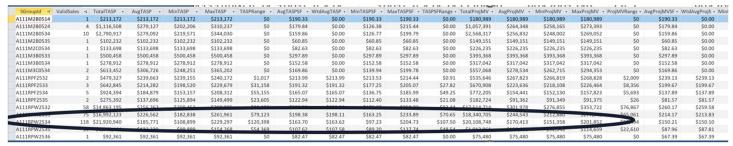
You can't do this if you don't group, or if you group 'on the fly'!

Summary Tables

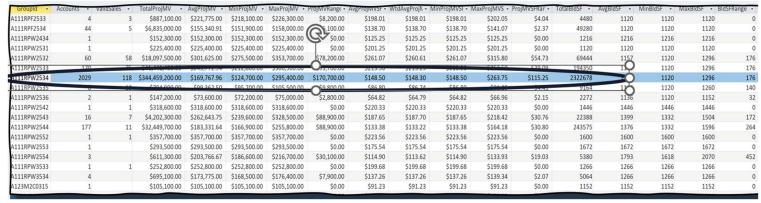
These tables store information about persistent groups. Every account can be linked to these tables by Group ID, so that any account can be compared to the summary data and all accounts in a group can be identified



This table summarizes property data by Group ID. Group A111RPW2534 contains 2029 properties.



This table summarizes sales data by Group ID. Group A111RPW2534 is represented by 118 sales.



This table combines sales and property data summaries into one table.

| GroupId - | Parcel_ID - | ParldNum + OPA_ACCOUI + | PROPID . | SEC_FLD | BLOCK_ID . | ADDRESS | → CENSUS_TRA → | CENSUS_BLO - | Zone | NBHD |
|-------------|-------------|-------------------------|------------|---------|------------|--------------------|----------------|--------------|------|------|
| 111RPW2534 | 1001483344 | 1001483344 344166100 | 7262007312 | 3257 | 7262007300 | 7312 SHERWOOD RD | 098 | 104 | A | A111 |
| A111RPW2534 | 1001675471 | 1001675471 343278700 | 8947001334 | 3257 | 8947001300 | 1334 N 75TH ST | 098 | 207 | A | A111 |
| A111RPW2534 | 1001675468 | 1001675468 343278400 | 8947001328 | 3257 | 8947001300 | 1328 N 75TH ST | 098 | 207 | A | A111 |
| A111RPW2534 | 1001675472 | 1001675472 343278800 | 8947001336 | 3257 | 8947001300 | 1336 N 75TH ST | 098 | 207 | A | A111 |
| A111RPW2534 | 1001675473 | 1001675473 343278900 | 8947001338 | 3257 | 8947001300 | 1338 N 75TH ST | 098 | 207 | A | A111 |
| A111RPW2534 | 1001675474 | 1001675474 343279000 | 8947001340 | 3257 | 8947001300 | 1340 N 75TH ST | 098 | 207 | A | A111 |
| A111RPW2534 | 1001675475 | 1001675475 343279100 | 8947001342 | 3257 | 8947001300 | 1342 N 75TH ST | 098 | 207 | A | A111 |
| A111RPW2534 | 1001675476 | 1001675476 343279200 | 8947001344 | 3257 | 8947001300 | 1344 N 75TH ST | 098 | 207 | A | A111 |
| A111RPW2534 | 1001675477 | 1001675477 343279300 | 8947001346 | 3257 | 8947001300 | 1346 N 75TH ST | 098 | 207 | A | A111 |
| A111RPW2534 | 1001675478 | 1001675478 343279400 | 8947001348 | 3257 | 8947001300 | 1348 N 75TH ST | 098 | 207 | A | A111 |
| A111RPW2534 | 1001106925 | 1001106925 343213100 | 1926007422 | 3257 | 1926007400 | 7422 BROOKHAVEN RD | 098 | 604 | A | A111 |
| A111RPW2534 | 1001106921 | 1001106921 343212800 | 1926007416 | 3257 | 1926007400 | 7416 BROOKHAVEN RD | 098 | 604 | A | A111 |
| A111RPW2534 | 1001099866 | 1001099866 343221700 | 1874007530 | 3257 | 1874007500 | 7530 BRENTWOOD RD | 098 | 606 | A | A111 |
| A111RPW2534 | 1001099868 | 1001099868 343221800 | 1874007532 | 3257 | 1874007500 | 7532 BRENTWOOD RD | 098 | 606 | A | A111 |
| A111RPW2534 | 1001675811 | 1001675811 343304500 | 8950001429 | 3257 | 8950001400 | 1429 N 76TH ST | 098 | 305 | A | A111 |
| A111RPW2534 | 1001675679 | 1001675679 343304800 | 8950001300 | 3257 | 8950001300 | 1300 N 76TH ST | 098 | 301 | A | A111 |
| A111RPW2534 | 1001675681 | 1001675681 343304900 | 8950001302 | 3257 | 8950001300 | 1302 N 76TH ST | 098 | 301 | A | A111 |
| A111RPW2534 | 1001675683 | 1001675683 343305000 | 8950001304 | 3257 | 8950001300 | 1304 N 76TH ST | 098 | 301 | A | A111 |
| A111RPW2534 | 1001675685 | 1001675685 343305100 | 8950001306 | 3257 | 8950001300 | 1306 N 76TH ST | 098 | 301 | A | A111 |

These are just some of the over 2,000 properties in Group A111RPW2534. They can be directly linked and compared to the summary tables.

Once unrepresented properties are identified, we can use a variety of cluster or tabular analytics to better understand the relationships between properties that sell and those that do not.

Using Summaries to Understand Representation

Properties will not be proportionately represented by sales, as sales will represent different numbers of accounts. Some groups of properties may be represented by few or no sales, as illustrated in this sample from a Group summary report. You can directly compare time adjusted prices to values, examine variance in both price and value within the group and even see how well the properties that sold compare to the unsold properties in terms of building and lot size.

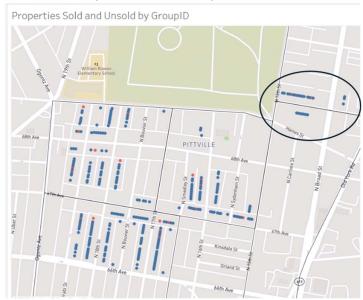
This report supports direct comparison of sold and unsold properties both *within* and *between* groups. There are no sales for the 30 properties in group M111RPW2454, but they are larger than the properties in group M111RPW2444. We would expect slightly higher values, but possibly lower MV per square foot rates in M111RPW2454 when compared to M111RPW244 – which is exactly the case. Comparing group M111RPW2445 (fair condition) to group M111RPW2444 (average condition), we can see if the adjustment coefficient from the model is producing the correct effect.

| GroupId | Accounts Valid Sales | Agv MV Agv TASP | Min MV MinTASP | Max MV MaxTASP | MVRange TASPRange | WtdAvgMVS WtdAvgTASPS | | | <i>Range</i> | AvgBldSF AvgSBldSF | AvgLotSF AvgSLotSF | ı |
|-------------|----------------------|------------------------|------------------------|------------------------|------------------------|--------------------------|----------------------|----------------------|---------------------|-----------------------|-----------------------|---|
| M111RPF2344 | 301 17 | \$165,418 \$170,057 | \$155,200 \$139,064 | \$185,900 \$191,300 | \$30,700 \$52,236 | \$117.22 \$116.82 | \$117.41 \$96.36 | \$130.34 \$131.19 | \$12.93 \$34.83 | 1,411 1,456 | 1,522 1,529 | |
| M612TOS3353 | 43 22 | \$531,742 \$500,055 | \$440,300 \$366,316 | \$816,700 \$658,954 | \$376,400 \$292,638 | | \$196.39 \$123.13 | \$242.49 \$272.45 | \$46.10 \$149.33 | 2,764 2,598 | 4,072 4,169 | |
| M621TOS3354 | 49 2 | \$473,682 \$463,211 | \$432,500 \$453,694 | \$603,400 \$472,728 | \$170,900 \$19,034 | | \$200.74 \$202.18 | \$216.00 \$206.61 | \$15.26 \$4.43 | 2,364 2,266 | 3,303 3,225 | |
| M111RPW2444 | 16 2 | \$179,244 \$176,882 | \$178,400 \$174,114 | \$179,300 \$179,650 | \$900 \$5,536 | | \$119.18 \$115.77 | \$119.22 \$119.45 | \$0.04 \$3.68 | 1,504 1,504 | 2,400 2,400 | |
| M111RPW2445 | 1 | \$111,100 \$109,275 | \$111,100 \$109,275 | \$111,100 \$109,275 | \$0 \$0 | \$73.87 \$72.66 | \$73.87 \$72.66 | \$73.87 \$72.66 | \$0.00 \$0.00 | 1,504 1,504 | 2,400 2,400 | |
| M111RPW2454 | 30 | \$187,770 | \$181,800 | \$204,700 | \$22,900 | \$112.57 | \$112.68 | \$120.30 | \$7.61 | 1,668 | 2,707 | |

This report presents inventory data on the top row and sales data for the same group on the bottom row.

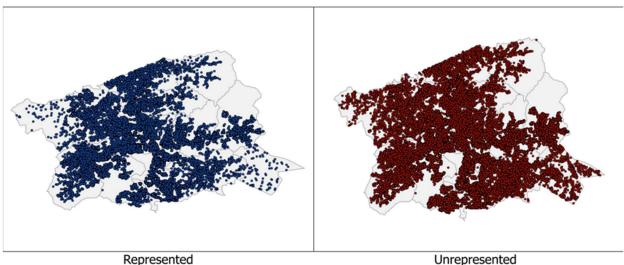
Mapping Representation

We can use maps to examine Groups.



All of these properties are in the same Group. Blue dots are unsold properties, while sales are represented by red dots. The circled cluster has no sales, but all of these properties are comparable.

Buncombe County Represented vs Unrepresented Properties



This map shows the locations of all properties that are in groups that are represented by at least one sale juxtaposed with properties that are in group that are not represented by any sales. In many cases, they are interspersed with each other, but we can see that there are some neighborhoods in the county where there are no sales.

Representation Summary

Here's a sample breakdown of representation by groups of similar properties. There is a lot of information in this table, but perhaps the most telling is that there are 21,000 groups representing almost 60,000 properties that are not represented by any sales – 14% of the inventory - in this dataset. I have worked with datasets where the percentage of unrepresented accounts is closer to 50%.

We can identify every property that is in any of these groups.

| | Groups | Accts | Sales | Pct of Groups | Pct of Accts | Pct of Sales | Representation Pct |
|-------------------|--------|---------|--------|---------------|--------------|--------------|--------------------|
| SF Total | 35,233 | 422,996 | 54,966 | | | | 13% |
| 1 account | 15,708 | 15,708 | 4,094 | 45% | 4% | 7% | 26% |
| Lt 5 Accounts | 25,245 | 40,836 | 10,905 | 72% | 10% | 20% | 27% |
| 100 or more Accts | 845 | 201,453 | 16,030 | 2% | 48% | 29% | 8% |
| 500 or more Accts | 65 | 47,401 | 3,530 | 0.2% | 11% | 6% | 7% |
| No Sales | 20,951 | 59,763 | - | 59% | 14% | 0% | 0% |
| At least 1 sale | 14,282 | 363,233 | 54,966 | 41% | 86% | 100% | 15% |
| At least 3 sales | 5,002 | 291,239 | 43,126 | 14% | 69% | 78% | 15% |
| Less than 3 sales | 30,231 | 131,757 | 11,840 | 86% | 31% | 22% | 9% |
| 10 or more sales | 1,141 | 172,065 | 24,895 | 3% | 41% | 45% | 14% |
| Condition 7 | 1,337 | 3,715 | 745 | 4% | 1% | 1% | 20% |
| Condition 6 | 1,088 | 2,094 | 954 | 3% | 0% | 2% | 46% |
| Condition 5 | 3,234 | 11,889 | 4,044 | 9% | 3% | 7% | 34% |
| Condition 4 | 18,109 | 352,270 | 26,092 | 51% | 83% | 47% | 7% |
| Condition 3 | 6,902 | 31,406 | 10,861 | 20% | 7% | 20% | 35% |
| Condition 2 | 3,625 | 14,007 | 8,552 | 10% | 3% | 16% | 61% |
| Condition 1 | 898 | 7,572 | 3,718 | 3% | 2% | 7% | 49% |

This table examines representation by value class. We can easily see how relatively underrepresented are the lower value classes.

ValueClass * Represented2 Crosstabulation

| | | | Represe | | |
|------------|--------------|---------------------|---------|-------|--------|
| | | | No | Yes | Total |
| ValueClass | Below 120k | Count | 7288 | 2777 | 10065 |
| | | % within ValueClass | 72.4% | 27.6% | 100.0% |
| | 120k to 175k | Count | 6123 | 3648 | 9771 |
| | | % within ValueClass | 62.7% | 37.3% | 100.0% |
| | 175k to 215k | Count | 4963 | 5088 | 10051 |
| | | % within ValueClass | 49.4% | 50.6% | 100.0% |
| | 215k to 250k | Count | 4651 | 5866 | 10517 |
| | | % within ValueClass | 44.2% | 55.8% | 100.0% |
| | 250k to 282k | Count | 3883 | 5585 | 9468 |
| | | % within ValueClass | 41.0% | 59.0% | 100.0% |
| | 282k to 322k | Count | 4363 | 5833 | 10196 |
| | | % within ValueClass | 42.8% | 57.2% | 100.0% |
| | 322k to 374k | Count | 4643 | 5329 | 9972 |
| | | % within ValueClass | 46.6% | 53.4% | 100.0% |
| | 374k to 460k | Count | 4791 | 5289 | 10080 |
| | | % within ValueClass | 47.5% | 52.5% | 100.0% |
| | 460k to 640k | Count | 4820 | 5063 | 9883 |
| | | % within ValueClass | 48.8% | 51.2% | 100.0% |
| | 640k+ | Count | 4504 | 3670 | 8174 |
| | | % within ValueClass | 55.1% | 44.9% | 100.0% |
| Total | | Count | 50029 | 48148 | 98177 |
| | | % within ValueClass | 51.0% | 49.0% | 100.0% |

This table examines representation by condition of improvements. Notice the low percentages of representation in less than normal condition properties.

| Condition * Represented2 Crosstabulation | | | | | | | | | |
|--|-----------|---------|-------|--------|--|--|--|--|--|
| | | Represe | | | | | | | |
| | | No | Yes | Total | | | | | |
| Condition | Fair | 2775 | 201 | 2976 | | | | | |
| | | 93.2% | 6.8% | 100.0% | | | | | |
| | Good | 4923 | 5871 | 10794 | | | | | |
| | | 45.6% | 54.4% | 100.0% | | | | | |
| | Normal | 36784 | 39281 | 76065 | | | | | |
| | | 48.4% | 51.6% | 100.0% | | | | | |
| | Poor | 1102 | 52 | 1154 | | | | | |
| | | 95.5% | 4.5% | 100.0% | | | | | |
| | Renovated | 3020 | 2737 | 5757 | | | | | |
| | | 52.5% | 47.5% | 100.0% | | | | | |
| | Unsound | 260 | 6 | 266 | | | | | |
| | | 97.7% | 2.3% | 100.0% | | | | | |
| Total | | 50029 | 48148 | 98177 | | | | | |
| | | 51.0% | 49.0% | 100.0% | | | | | |

Group Ids are a good way to understand representation. They are easy to implement and can help you better understand your market.

Now let's look at another way to measure and understand representation.

Heuristic Measure of Representation (HMR)

Multiple Regression Analysis (MRA) is used in many jurisdictions to develop Models for Mass Appraisal. Ratio Study metrics are used to measure performance such as Uniformity and Equity. Seldom does one check if the data used to build models are representative of the population that we are trying to model. In the world of (re)assessment, for any given year the Population (Master Roll) for any jurisdiction is fixed. The following is an effort to measure / quantify representation of your data used in your model to the population that you are trying to model - <u>A Heuristic Measure of Representation (HMR)</u>.

In a multiple regression model, continuous variables always develop adjustment coefficients. What happens to binary or categorical variables that do not develop coefficients? They get treated like the base. The contributory value is generalized for that attribute. Why does this happen? The variable is under-represented or unrepresented in the data whereby it does not develop a coefficient with significance. If we can identify and quantify the degrees of generalization, we can formulate a metric to measure / quantify representation.

In the simplest form, the scoring algorithm can be:

- Identify the base binaries for each categorical variable.
- Identify the binaries that developed coefficients.
- Assign a score for each binary variable in the Population that is
 - NOT used as the base

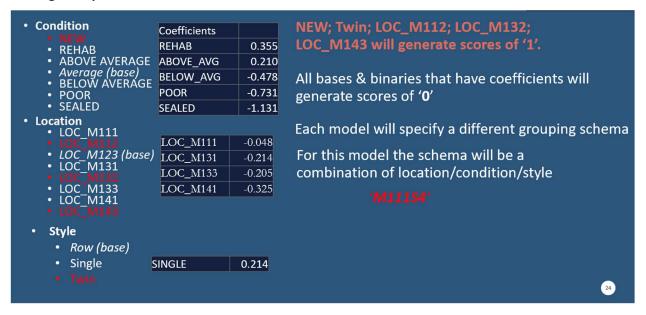
AND

- o DID NOT generate a coefficient.
- Tally scores for each case

The Final Score = Degree of Generalization

Each parcel to which the model is applied will get a score. Scores will range from "0" to "n", where n is the number of unrepresented binary or categorical attributes. A group of properties with the same characteristics will have the same score. Higher the score, higher the degree of generalization which indicates a **lower degree of representation** in the model and possibly lower degrees of accuracy in the estimates.

Scoring Example



| ID | ADDR | Locale | Condition | Style | PredMV | L_Score | C_Score | S_Score | TOT_SCORE |
|------------|---------------------|--------|-----------|-------|---------------|---------|---------|---------|-----------|
| 8386000300 | 322 WINONA ST | M111 | 3 | P | \$ 280,000.00 | 0 | 0 | 0 | 0 |
| 5136000600 | 607 LOCUST AVE | M112 | 5 | Т | \$ 110,000.00 | 1 | 0 | 1 | 2 |
| 2390000100 | 126 E CLIVEDEN ST | M113 | 3 | 5 | \$ 229,900.00 | 1 | 0 | 0 | 1 |
| 1746007400 | 7426 BEVERLY RD | M131 | 1 | S | \$ 245,000.00 | 0 | 1 | 0 | 1 |
| 3108001800 | 1825 W ELEANOR ST | M132 | 3 | R | \$ 140,000.00 | 1 | 0 | 0 | 1 |
| 8196001400 | 1412 E WEAVER ST | M133 | 4 | R | \$ 115,000.00 | 0 | 0 | 0 | 0 |
| 2296005500 | 5518 CHEW AVE | M141 | 4 | Т | \$ 131,500.00 | 0 | 0 | 1 | 1 |
| 3666006300 | 6375 GERMANTOWN AVE | M143 | 1 | R | \$ 242,500.00 | 1 | 1 | 0 | 2 |
| 2330000000 | 65 E CLAPIER ST | M143 | 4 | R | \$ 275,000.00 | 1 | 0 | 0 | 1 |
| 1650006400 | 6415 N BEECHWOOD ST | M132 | 4 | Т | \$ 149,900.00 | 1 | 0 | 1 | 2 |
| 2366006200 | 6215 CLEARVIEW ST | M133 | 3 | R | \$ 70,000.00 | 0 | 0 | 0 | 0 |
| 5136000600 | 617 LOCUST AVE | M131 | 5 | Т | \$ 104,000.00 | 0 | 0 | 1 | 0 |
| 2532000100 | 151 E COULTER ST | M132 | 3 | S | \$ 272,000.00 | 1 | 0 | 0 | 1 |
| 5180001500 | 1518 W LOUDON ST | M133 | 5 | S | \$ 50,000.00 | 0 | 0 | 0 | 0 |
| 8817005900 | 5986 N 20TH ST | M141 | 1 | R | \$ 235,000.00 | 0 | 1 | 0 | 1 |
| 8817007300 | 7347 N 20TH ST | M141 | 4 | R | \$ 179,900.00 | 0 | 0 | 0 | 0 |
| 7308004500 | 4514 N SMEDLEY ST | M123 | 4 | Т | \$ 129,900.00 | 0 | 0 | 1 | 1 |

There are three unrepresented attributes – Condition, Location and Style – in this model. Scores will range from "0" to "3". M1125T generates a score of "2". All properties in that group will have the same score, and the same degree of generalization in the model.

Additionally, scoring can be scaled or weighted based on variable importance, adapted for different machine learning model types. Furthermore, continuous variables can be binned and scored as an additional facet. Scoring can be used in both feedback & feedforward pipeline to improve models. Scores and related groups may be used to transplant baked in

intelligence into (e.g.: Comparable Engine; Neighborhood Definitions etc.). Ratio studies and other performance metrics can be run on binned groups of HMR scores to get additional insights.

HMR scoring allows us to:

- Recognize parcel groups in the population that are under-represented or unrepresented in the data used to create the model.
- Respecify / recalibrate your variables to improve your models.
- Identify parcel groups that may need additional review before finalization.
- Gain more precise insight into model and assessment performance
- Identify submarkets that are not well served by your valuation process
- Better understand representation through maps and visualizations

Conclusions

The founding fathers of mass appraisal devised some great tools and methods for modern practitioners. IAAO standards and education have promoted use of these tools, established best practices and helped improve assessment performance in many jurisdictions. Understanding the degree to which sales represent unsold properties is critical in improving and validating assessment performance, and represents a significant blind spot in our body of knowledge. Any study of assessment equity should include analysis of representation. In some markets, it may be appropriate to use alternative methods of estimating values for sub-markets, groups or clusters of properties that are not represented by sales and about which sales tell us little or nothing.

Beyond the methods presented in this article, other methods and techniques should be discussed, developed and used to advance the understanding of representation in the industry. The authors encourage further engagement and discussion.