## CUTTING THROUGH THE HYPE: Comparing Predictive Scoring Vendors



# D & B Lattice

This eBook was originally written by Lattice Engines which was acquired by Dun & Bradstreet in 2019.

#### **INTRODUCTION**

If you're intrigued by the promise of using predictive marketing applications to gain new buyer insights, you're not alone. These applications help marketing and sales pros predict the likelihood of prospects and customers taking action, whether responding to an offer, message or interaction. Savvy marketers are using these apps to discover which leads and accounts are ready for sales and which need more nurturing.

However, not all predictive scoring models are created equal. Some applications were created to systematically spit out a number and have limited value in solving your business objectives. To be successful with predictive scoring, you have to think about it being more than just a number. At Lattice, we value our team's deep expertise in marketing and sales to help materialize that score into best practices and process changes that drive real impact for your company.

Furthermore, if you choose suboptimal technology or a vendor that doesn't address your requirements, it's impossible to drive the outcomes you're seeking from predictive scoring solutions. To avoid this trap, it's critical to first compare and test models, and then choose the one that will yield the desired results once you go live. Arriving at that decision requires that you prepare appropriately for the tests and follow a proven approach to testing.

This guide was designed to help you do just that. With it, you can compare and evaluate models enabled by different vendors and select the predictive scoring technology that will best suit your needs. In it, we lay out:

#### HOW TO PREPARE FOR A MODEL TEST

HOW TO MEASURE THE RESULTS OF THE TESTS

HOW TO COMPARE THE DIFFERENCES IN OUTCOMES

### **IDENTIFY THE GOAL**

#### PREDICTIVE SCORING CAN BE USED TO ANSWER A VARIETY OF QUESTIONS AND SOLVE A VARIETY OF PROBLEMS.

Before getting started, you should have a solid understanding of the goal you are trying to achieve. Are you interested in acquiring more customers, selling more to existing customers or retaining customers?

The following scenarios outline the data, modeling and scoring requirements for achieving each of these goals.

Once you understand the problem you want to solve, you should target vendors that support that scenario. Note that as your company grows, its needs may evolve quickly. Keep in mind the scenarios that are currently applicable, as well as those likely to be relevant over the next 12 to 24 months.



Predictive scoring solutions can predict the likelihood of a lead converting to a customer, an existing customer purchasing additional products or services, or an existing customer churning. You have to decide which problem(s) you are trying to solve and select a vendor supports those scenarios.





If you're focused on acquiring new customers, the model used scores the database contacts in your marketing automation system by propensity or likelihood to become a customer. It does not predict which product or set of products the contact might purchase or how much revenue you can expect from purchases.

If you want to focus on finding and prioritizing prospect companies rather than inbound leads, you can choose a similar, though slightly different, scoring model. This one scores accounts from your CRM system — rather than contacts in your marketing automation system — and assumes you've developed a large database of these over time.



### Sell More to Existing Customers

If you sell multiple products at a wide range of price points, you may consider a model that predicts which products your customers want to buy. It scores your database contacts by propensity to purchase specific products and the revenues you can expect from these purchases. Again, if you want to focus on accounts rather than specific contacts, you can use a similar, though slightly different, scoring model to score accounts from your CRM system.



#### **Retain Existing Customers**

Do you want to proactively discourage customer churn? Go for a model that scores accounts based on likelihood of attrition.

### $\rightarrow$ vendor requirements for building the models

In order to solve these three goals, vendors must be able to do the following when it comes to data integration, modeling and scoring:

|   | SELL MORE TO             |                       |                              |
|---|--------------------------|-----------------------|------------------------------|
|   | ACQUIRE NEW<br>CUSTOMERS | EXISTING<br>CUSTOMERS | RETAIN EXISTING<br>CUSTOMERS |
| DATA INTEGRATION  |                          |                       |                              |
| Securely and automatically retrieve contacts from marketing automation or CRM system.   | V                        |                       |                              |
| Append other internal and external data to database contacts or accounts.   | V                        |                       |                              |
| Securely and automatically retrieve product purchase data and correlate that to contacts or accounts.   |                          | V                     |                              |
| Append other internal data — including product usage details — and external data to accounts.   |                          |                       | V                            |
| MODELING  |                          |                       |                              |
| Only use contacts/accounts that are current customers and apply additional filtering criteria provided by the organization.   | V                        |                       |                              |
| Score contacts/accounts by propensity to become a customer or move to another desired state.  | V                        |                       |                              |
| Only use contacts/accounts that have purchased the desired product(s) and apply additional filtering criteria provided by the organization.                               |                          | V                     |                              |
| Score contacts/accounts by expected weighted revenue and other qualification criteria provided by the organization.   |                          | V                     |                              |
| When necessary, build a model that predicts the likelihood that a customer will purchase a bundle of products and services, rather than a stand-alone product or service. |                          | ٧                     |                              |
| Only use accounts that have churned in the past and apply additional filtering criteria provided by the organization.   |                          |                       | V                            |
| Score accounts by likelihood of attrition and other qualification criteria provided by the organization.  |                          |                       | V                            |
| SCORING   |                          |                       |                              |
| Provide flexible options for scoring contacts   |                          |                       |                              |
| • Option A: Score new contacts as they come in.   | V                        | V                     |                              |
| <ul> <li>Option B: Score existing contacts if they respond to marketing<br/>campaigns (i.e, click on an email link, download a white paper, etc.).</li> </ul>             | V                        | v                     |                              |
| <ul> <li>Option C: Score existing contacts if they display relevant business triggers</li> <li>(i.e, receive funding, post new jobs, etc.).</li> </ul>                    | V                        | V                     |                              |
| <ul> <li>Option D: Score all contacts regardless of activity or business events.</li> </ul>   | V                        | V                     |                              |
| Find accounts that were lost and/or not followed up with.   | V                        | V                     |                              |
| Only score accounts that are up for renewal in the next X # of days or have annual revenues over \$X.   |                          |                       | V                            |

### **KEY TAKEAWAYS**

IDENTIFY THE MOST PRESSING LEAD OR ACCOUNT SCORING GOAL(S) TO DETERMINE THE APPROPRIATE SCORING MODEL(S).



VALIDATE THAT THE VENDOR CAN SUPPORT ALL DATA INTEGRATION, MODELING AND SCORING CAPABILITIES ASSOCIATED WITH THE DESIRED SCORING MODEL.



## PREPARE YOUR DATA FOR MODELING

No matter the model, the insight you gain is only good as the data you put in. That means the quality of predictions from a scoring model depends heavily on the quality of data you provide to build it. The more high-quality data you can feed it, the better. While it may be tempting to take shortcuts in order to test and evaluate technologies quickly, we strongly discourage doing so. A lack of proper data preparation often leads to inconclusive results.

At the very least, we recommend that you do the following:

- $\rightarrow$  Leverage both internal and external data.
- $\rightarrow$  Determine how to segment leads.

#### LEVERAGE BOTH INTERNAL AND EXTERNAL DATA

The most effective scoring model takes into account both internal and external data. The truth is that the combined data provides a more full and accurate picture of contacts. Internal data is pulled from your CRM and marketing automation systems and refers to information observed or inferred through contacts, such as online behaviors. External data refers to information provided by the contact or that is somehow identifiable about the contact, such as company name or geographic location. It can include data scraped from websites or supplied by third-party data providers.

When comparing vendors, we strongly recommend providing as much internal data as the vendor can leverage. This will help determine the highest quality predictions a vendor's technology can provide, meaning you can compare all vendors based on a best-case scenario.



In our experience, behavioral data from marketing automation has proven to improve the quality of predictions by as much as 200 percent. This is good news for you. After all, you're producing engaging content and running terrific campaigns to better connect with — and learn more about — prospective buyers. You certainly want to put all that hard work to good use! So make sure the vendor you're considering can ingest both internal and external data to build its model. Most vendors leverage contacts, leads, and account- and opportunity-related data from an organization's internal systems. However, many can't leverage behavioral data, such as web visits, event attendance and content downloads from a marketing automation solution.

#### **SEGMENT LEADS**

If your business operates globally or in a wide variety of industries, it may make sense to segment your data prior to conducting any scoring test. Specifically, segment leads to reflect major characteristics of your business and make sure the technologies chosen for evaluation can support multiple models. Otherwise, it is highly likely that the predictive scoring model will not demonstrate ROI.

#### A BEST PRACTICE FOR TEST CRITERIA

We've found that the best way to conduct a lead scoring test is to use a training set of 100,000 leads. At least one percent of those 100,000 should have converted (i.e., either closed/won or closed/lost). The test set should be at least 20 percent of the size of the set used to train the algorithm. Keep the outcome to yourself and put the models to the test. Each vendor should have access to the same amount of data and develop models to predict which out of the 100,000 leads became customers.

WHETHER IT'S TRADITIONAL OR PREDICTIVE, THE MOST EFFECTIVE LEAD SCORING TAKES INTO ACCOUNT BOTH INTERNAL AND EXTERNAL DATA

### **KEY TAKEAWAYS**



A COMBINATION OF INTERNAL AND EXTERNAL DATA PROVIDES A FULL AND MORE ACCURATE PICTURE OF LEADS AND ACCOUNTS.

THE MORE INTERNAL DATA A SCORING MODEL LEVERAGES, THE HIGHER THE QUALITY OF ITS LEAD PREDICTIONS.

IF LEAD CHARACTERISTICS VARY BY SEGMENT, MAKE SURE THE VENDOR'S TECHNOLOGY CAN SUPPORT MULTIPLE SCORING MODELS.



**CUTTING THROUGH THE HYPE: COMPARING PREDICTIVE SCORING VENDORS** 

## ASSESSING YOUR READINESS FOR PREDICTIVE LEAD SCORING

Most marketing and sales leaders think of lift measurement when comparing the performance of two prediction models. While lift is ideal for segmenting good leads from bad, it is not a good approach for comparing two scoring models.

Ideally you want to focus on success criteria specific to the goal at hand. For instance, if you are trying to sell to more customers, train the test measurement on an increase in revenue rather than an increase in leads. After all, it's possible that a single customer could generate a significant increase in revenue; your focus should be on identifying the leads with that potential.

On the other hand, if you want to acquire new customers, specific revenues are irrelevant. In that case, you need to understand how many leads are required to land the desired number of new customers, so the focus should be on lead conversion rate.

Once you have decided on your success criteria, it's important to measure the testing results the same way for each vendor. Keep in mind that prediction models can use a number of different machine learning techniques, including neural networks, decision trees and logistic regression to name a few. However, as long as the models are trained and tested on the same data sets and are built to predict the same event, you can use the same criteria to measure their performance.

If you're not familiar with the concept and methodology behind lift measurement, review the short overview in the appendix. Otherwise, read on. IN MATHEMATICAL TERMS, THE LIFT MEASURES THE CHANGE IN CONCENTRATION OF A PARTICULAR CLASS WHEN THE PREDICTION MODEL IS USED TO SELECT A GROUP FROM THE GENERAL POPULATION

## **DEFINE SUCCESS CRITERIA**

#### THE RIGHT APPROACH FOR MEASURING MODEL PERFORMANCE

While lift measure is a standard for determining lead cutoff, it is not very useful for comparing performance of lead scoring models. Consider the following table comparing lift for two models.

If you want to identify the top 100 leads, you'd choose Model 1 because it yielded the highest lift. However, if your goal is to identify more than 100 leads — or multiple segments — you'll see that Model 2 outperforms Model 1. Similarly, for the top 300 leads, Model 1 outperforms Model 2, but for the top 500 leads, Model 2 outperforms Model 1. In other words, looking at lift individually for each segment doesn't give you an accurate picture of which model is better.

| Α                  | В   | С   | D                    | E   | F                     |  |
|--------------------|---|---|----------------------|---|-----------------------|--|
| NUMBER OF<br>LEADS | CONVERSION /<br>SEGMENT<br>WHEN NOT<br>SCORED | CONVERSION /<br>SEGMENT<br>WHEN SCORED<br>(MODEL 1) | LIFT (%)<br>(MODEL1) | CONVERSION /<br>SEGMENT<br>WHEN SCORED<br>(MODEL 2) | LIFT (%)<br>(MODEL 2) |  |
| TOP 100            | 10  | 40  | 300%                 | 30  | 200%                  |  |
| <b>TOP 200</b>     | 11  | 18  | 63%                  | 16  | 63%                   |  |
| TOP 300            | 9   | 15  | 66%                  | 12  | 66%                   |  |
| <b>TOP 400</b>     | 11  | 8   | 27%                  | 20  | 81%                   |  |
| <b>TOP 500</b>     | 9   | 5   | 44%                  | 20  | 122%                  |  |
| TOP 600            | 11  | 3   | 73%                  | 1   | 90%                   |  |
| <b>TOP 700</b>     | 9   | 4   | -                    | 1   | -                     |  |
| <b>TOP 800</b>     | 11  | 4   | -                    | 0   | -                     |  |
| TOP 900            | 9   | 3   | -                    | 0   | -                     |  |
| <b>TOP 1000</b>    | 10  | 0   | -                    | 0   | -                     |  |



With that in mind, a better way to compare the models would be to compare the cumulative conversions (columns D and F) (rather than the lift of individual segments) as shown in the table below.

|                  | A                  | В   | С   | D                                     | E   | F                                     |
|------------------|--------------------|---|---|---------------------------------------|---|---------------------------------------|
| LEAD<br>SEGMENTS | NUMBER OF<br>LEADS | CONVERSION /<br>SEGMENT<br>WHEN NOT<br>SCORED | CONVERSION /<br>SEGMENT<br>WHEN SCORED<br>(MODEL 1) | CUMULATIVE<br>CONVERSION<br>(MODEL 1) | CONVERSION /<br>SEGMENT<br>WHEN SCORED<br>(MODEL 2) | CUMULATIVE<br>CONVERSION<br>(MODEL 2) |
| 1                | 100                | 10  | 40  | 40                                    | 30  | 30                                    |
| 2                | 200                | 11  | 18  | 58                                    | 16  | 46                                    |
| 3                | 300                | 9   | 15  | 73                                    | 12  | 58                                    |
| 4                | 400                | 11  | 8   | 81                                    | 20  | 78                                    |
| 5                | 500                | 9   | 5   | 86                                    | 20  | 98                                    |
| 6                | 600                | 11  | 3   | 89                                    | 1   | 99                                    |
| 7                | 700                | 9   | 4   | 93                                    | 1   | 100                                   |
| 8                | 800                | 11  | 4   | 97                                    | 0   | 100                                   |
| 9                | 900                | 9   | 3   | 100                                   | 0   | 100                                   |
| 10               | 1000               | 10  | 0   | 100                                   | 0   | 100                                   |

Using this approach, you can clearly see which model is better for your needs. If your goal is to pass 200 leads to the sales team, Model 1 is the better choice because it yields more conversions. If, on the other hand, your goal is to pass 500 leads, you would choose Model 2.

### **KEY TAKEAWAYS**

When comparing multiple models:

SET A CUTOFF GOAL PRIOR TO EVALUATING PREDICTIVE MODELS.

KEEP VENDORS INFORMED OF THE GOALS, AS MANY CAN TWEAK THE MODEL ACCORDINGLY TO YIELD THE BEST POSSIBLE PERFORMANCE.

DO NOT USE LIFT TO EVALUATE PERFORMANCE OF PREDICTION MODELS. INSTEAD, COMPARE THE TOTAL CONVERSION EXPECTED FROM A SET OF LEADS DETERMINED BY THE CUTOFF GOAL.



## COMPARE DIFFERENCES IN MODEL OUTCOMES

Once the vendors provide output from their predictive models, you will need to determine if the difference in performance is statistically significant.

Let's suppose a test set of 250,000 leads — with 5,000 converted leads — was created to compare the performance of two models. The performance of each model is shown below. Looking at the first three rows, one might conclude that Model 1 is better than Model 2 because Model 1 has more converted leads in the top 25,000 and 50,000.

| LEADS       | MODEL 1:<br>CONVERTED<br>LEADS | MODEL 2:<br>CONVERTED<br>LEADS |
|-------------|--------------------------------|--------------------------------|
| TOP 25,000  | 1,500                          | 1,450                          |
| TOP 50,000  | 2,500                          | 2,400                          |
| TOP 75,000  | 3,000                          | 3,075                          |
| TOP 100,000 | 3,000                          | 3,600                          |
| TOP 125,000 | 3,250                          | 3,750                          |
| TOP 150,000 | 3,450                          | 3,900                          |
| TOP 175,000 | 3,325                          | 3,920                          |
| TOP 200,000 | 3,600                          | 3,958                          |
| TOP 225,000 | 3,825                          | 3,983                          |
| ALL 250,000 | 5,000                          | 5,000                          |

However, keep in mind that the same model may produce different results each time it is used to score leads. The difference in performance is typically called "variance" and can be determined by well-known statistical sampling and measurement methods. If you're not a statistician, a simple rule is to take the square root of the sample result.

For example, the top 25,000 leads scored by Model 1 resulted in 1,500 converted leads (first row). The variance range for this segment can be estimated by taking the square root of 1,500, which is 39 (38.72 to be precise). So, if the top 25,000 leads were selected from another batch of 250,000 scored by Model 1, it is possible that between 1,461 and 1,539 (1,500 +/- 39) would convert. This variance in conversion rate is shown in the table below for each segment. With that in mind, you can see that Model 1 is better for scoring the top 25,000 and 50,000 leads, but not for scoring the top 75,000. Because there is significant overlap between the expected conversion range of the two models, there is no clear winner for the 75,000-lead tier. Interestingly, Model 2 performs better for scoring the top 100,000 leads and up to the top 225,000 leads.

| LEADS       | MODEL 1:<br>EXPECTED<br>CONVERSION<br>RANGE | MODEL 2:<br>EXPECTED<br>CONVERSION<br>RANGE | WHICH MODEL<br>IS BETTER? |
|-------------|---|---|---------------------------|
| TOP 25,000  | 5.85: 6.15%                                 | 5.65: 5.95%                                 | Model 1                   |
| TOP 50,000  | 4.90: 5.10%                                 | 4.70: 4.90%                                 | Model 1                   |
| TOP 75,000  | 3.93: 4.07%                                 | 4.03: 4.17%                                 | Both are same             |
| TOP 100,000 | 2.95: 3.05%                                 | 3.54: 3.66%                                 | Model 2                   |
| TOP 125,000 | 2.55: 2.65%                                 | 2.95: 3.05%                                 | Model 2                   |
| TOP 150,000 | 2.26: 2.34%                                 | 2.56: 2.64%                                 | Model 2                   |
| TOP 175,000 | 1.87: 1.93%                                 | 2.20: 2.28%                                 | Model 2                   |
| TOP 200,000 | 1.77: 1.83%                                 | 1.95: 2.01%                                 | Model 2                   |
| TOP 225,000 | 1.67: 1.73%                                 | 1.74: 1.80%                                 | Model 2                   |
| ALL 250,000 | 1.97: 2.03%                                 | 1.97: 2.03%                                 | Both are same             |

IN MATHEMATICAL TERMS, THE LIFT MEASURES THE CHANGE IN CONCENTRATION OF A PARTICULAR CLASS WHEN THE PREDICTION MODEL IS USED TO SELECT A GROUP FROM THE GENERAL POPULATION



### **KEY TAKEAWAYS**

When comparing multiple models:



PREDICTIVE MODELS HAVE A BUILT-IN MARGIN FOR ERROR, SO IT'S POSSIBLE TO GET A SLIGHTLY DIFFERENT RESULT EVERY TIME THE MODEL IS APPLIED.

YOU NEED A STATISTICALLY SIGNIFICANT DIFFERENCE BETWEEN RESULTS TO CONCLUDE THAT ONE MODEL IS BETTER THAN ANOTHER.



## CONCLUSION

Predictive analytics carries enormous potential to immediately and significantly improve the way that you achieve your lead and account prioritization goals. That said, though they may look similar on the surface, predictive scoring models could yield quite different results. By adhering to the best practices and recommendations outlined in this guide, you can effectively assess each vendor's capabilities and choose the most fitting vendor and model for your business.

## **APPENDIX:** WHAT IS LIFT?

Let's assume you have a database of 1,000 leads and know which 100 of those leads converted. You randomly create 10 buckets of 100 leads each and determine the conversion rate of each (column B in the table below). While this approach shows a conversion lift, a better approach is to score leads using machine algorithms and predictive lead scoring to determine the additional and true conversion potential of leads.

|                  | A                  | В                          | С   | D               | E        |
|------------------|--------------------|----------------------------|---|-----------------|----------|
| LEAD<br>SEGMENTS | NUMBER OF<br>LEADS | CONVERSIONS<br>PER SEGMENT | CONVERSION PER<br>SEGMENT WITH<br>PREDICTION<br>MODEL | LIFT<br>(COUNT) | LIFT (%) |
| Segment 1        | 100                | 10                         | 40  | 30              | 300%     |
| Segment 2        | 100                | 11                         | 18  | 8               | 63%      |
| Segment 3        | 100                | 9                          | 15  | 6               | 66%      |
| Segment 4        | 100                | 11                         | 8   | -               | -        |
| Segment 5        | 100                | 9                          | 5   | -               | -        |
| Segment 6        | 100                | 11                         | 3   | -               | -        |
| Segment 7        | 100                | 9                          | 4   | -               | -        |
| Segment 8        | 100                | 11                         | 4   | -               | -        |
| Segment 9        | 100                | 9                          | 3   | -               | -        |
| Segment 10       | 100                | 10                         | 0   | _               | -        |



## **APPENDIX:** WHAT IS LIFT?

Next, let's suppose the leads are scored using a prediction model and sorted from the highest to lowest score, and then segmented into 10 buckets with 100 leads in each. In the table below, the number of conversions in each bucket is shown in column C.

The number of converted leads (column C) for top segments is much higher when the leads are scored as compared to when leads are not scored (column B). For example, Segment 1 yields 40 converted leads when they are scored and only 10 when they are not scored. This means that by scoring the leads and focusing on the top 100, you can increase the total conversions by 30 (column D) or 300 percent (column E). In other words, the prediction model yields a 300-percent lift for Segment 1. Similarly, the lift for Segment 2 is 63 percent and so on.

This method allows you to determine the right cutoff for salesready leads versus nurture-and-junk leads. For example, you may choose to send leads in Segments 1, 2 and 3 to sales; 4, 5 and 6 to the nurture program; and discard the rest as junk. Ready to pinpoint which leads are most sales-ready and which need more nurturing? REQUEST A DEMO OF LATTICE PREDICTIVE LEAD SCORING.







This eBook was originally written by Lattice Engines which was acquired by Dun & Bradstreet in 2019. Learn more about D&B Lattice, our market-leading Customer Data Platform, by visiting dnb.com.

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