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Predictive Analytics in Child Welfare

An Introduction for Administrators and Policy Makers

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Executive Summary

Predictive analytics is increasingly seen as a technology that can improve child welfare outcomes, turning hindsight into insight and insight into value. Predictive analytics can be defined as analysis that uses data, statistics, and algorithms to answer the question "Given past behavior, what is likely to happen in the future?" This document walks through the different categories of advanced analytical techniques: descriptive, diagnostic, predictive, and prescriptive. While each technique is valuable in different ways, this document focuses on the benefits and challenges faced in using predictive analytics. Though each organization has a slightly different approach to applying predictive analytics, the key steps and decision points remain consistent. It is important to note that predictive analytics has the potential to produce benefits only when model results are used to intervene differentially based on the model output, leading to improvement on the outcome of interest.

A predictive analytics project can be broken down into two phases—before and after building a model—and during each phase several criteria can help an administrator understand the value and tradeoffs in continuing the project. The criteria below can help an organization to measure the ultimate success or failure of a predictive analytics effort; however, given that every potential project is different, the criteria may need to be adapted to fit each specific situation. Each criterion should be evaluated when building a predictive model and no single criterion alone can justify moving ahead to build the model. The failure of any single criterion below could be sufficient to halt the predictive analytics endeavor.

- **Data sufficiency**: The agency has access to the necessary breadth of information to build an accurate predictive model and key data elements used in the model are reasonably reliable.
- **Data quantity**: There is enough depth of data available to analyze a question adequately.
- **Identified implementation strategy**: The agency has a well-considered strategy to intervene differentially based on the model results and thereby create a measurable impact on the outcome the agency seeks to achieve.
- **Resource requirements**: The agency identifies and acquires necessary technical resources to carry out the effort, including skilled personnel and technical capacity (either in house or through external contracts) as well as resources to intervene differently based on analytical results.
- **Stakeholder support**: The predictive analytics process is sufficiently transparent to facilitate stakeholder support and provides enough insight into the effort to demonstrate that it has potential to achieve something of value.
- **Validation of the model:** The predictive analytics model algorithm is appropriate for the question. The model is validated using statistical methods, and the model results do not conflict with the intuition of the subject matter experts.
- **Accuracy of the model**: The predictive analytics model performance meets valid, predefined thresholds for accuracy and error rates. This includes both false positive and false negative results, with acceptable error rates depending on the consequences of each type of error in the process being modeled.
- **Precision of the model**: The predictive analytics model produces reliably consistent results.

What the reader will know by the end of the document:

- The different types of advanced analytics
- The types of child welfare questions to which child welfare agencies could apply predictive analytics
- Criteria that could help to assess whether predictive analytics is an appropriate tool for a given question or situation

Contents

Introduction to Predictive Analytics in Child Welfare

Predictive analytics is a set of advanced analytical methods that may enable child welfare agencies to leverage a range of case-level data about families' situations and turn hindsight into insight, and improve child welfare outcomes. These techniques are widely used in business and recently some social services agencies have begun considering their application in the child welfare context. A range of possible applications are being considered or implemented around the U.S, with a variety of possible benefits as well as potential pitfalls. Applications of predictive analytics in child welfare range from improving specific case outcomes to better understanding the system as a whole. Regardless of application, predictive analytics can provide additional tools for the caseworkers' decision-making processes, such as risk scores and pattern identification. In addition to supporting caseworkers, agencies can use predictive analytics to inform thinking around intervention strategies—sometimes involving multiple government agencies and stakeholder groups—to achieve the goal of providing a safe and supportive environment for children.

Predictive analytics can be defined as analysis that combines data and algorithms to answer the question "Given past behavior, what is likely to happen in the future?" Predictive analytics employs statistical techniques to discover patterns from data we have about the past and present to make inferences about future behavior or events.[1] Some child welfare agencies are currently implementing predictive analytics, though these efforts are in their infancy. Early adopters of these methods are experiencing many challenges while developing and implementing predictive analytics solutions, ranging from data quality to technical implementation to transparency in modeling efforts. For more information on efforts going on around the U.S., see *Predictive Analytics in Child Welfare: An Assessment of Current Efforts, Challenges and Opportunities*.[2]

This document builds on the previous paper and is intended as a guide to help child welfare administrators at the federal, state and local levels think strategically about when predictive analytics may be an appropriate tool to address certain types of questions.

[1] Definition of predictive analytics adapted from Gartner, Inc. (2016). Available at: Online link.
[2] Available at: Online link.

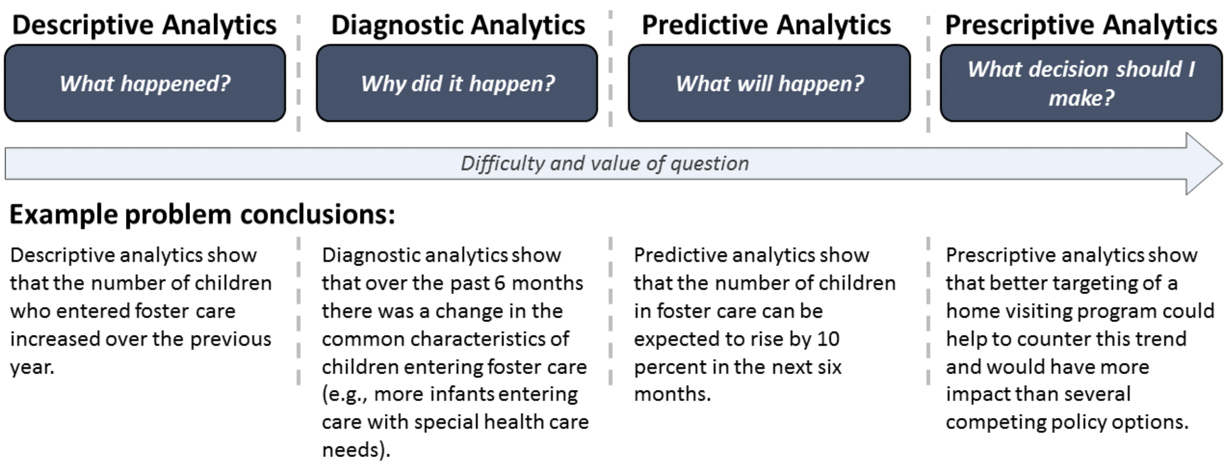
Determining When to Use Predictive Analytics

A predictive analytics project is a complex, time and resource-intensive process. For this reason, implementing a predictive analytics solution is not a task to be taken lightly. Like other techniques and strategies, this approach has both strengths and weaknesses. Agencies considering establishing capacity to conduct these analyses should carefully consider the benefits and challenges of these techniques and their applicability to the issue they are trying to address. The following section describes a process whereby child welfare leaders can begin to evaluate whether predictive analytics is an appropriate tool for a particular question (or range of questions) they seek to address.

Types of Analytics and Their Implementations

Before applying predictive analytics to a question, it is helpful to understand the types of questions that predictive analytics can solve. Figure 1, below, illustrates a progression of increasingly-challenging analytic problems, and answering each of these relies on different types of analytics. Solutions to these analytic problems vary in the amount of information they provide for decision making purposes. However, developing and implementing solutions that create greater value may be increasingly difficult and resource intensive.

Figure 1: Types of Analytics and the Questions They Can Answer



Each type of analytics can be applied to a specific class of question. Many child welfare agencies already routinely use administrative and other data to answer the question of "what happened?" with respect to families who come into contact with their agencies. Such efforts rely on **descriptive analytics** and are often the easiest questions to tackle, but these analyses are often of the least value because they only describe what has already occurred. For instance, many child welfare agencies routinely tally the number of children who enter and exit foster care and use descriptive analytics in this process. This information can be displayed in a dashboard of yearly totals and trends for caseworkers to use while out in the field or for administrators to use when explaining the reach and capability of their programs.

The next step in the analytic process is applying **diagnostic analytics** to answer the question, "why did it happen?" Analysts will often use techniques such as correlations and data mining to uncover patterns in data that can illuminate relationships between different variables. For example, applying diagnostic analytics to situations involving children entering the foster care system could entail determining what characteristics and circumstances are common among children who enter foster care. These factors could then be displayed alongside descriptive analytic tallies to add more value to the previous analysis.

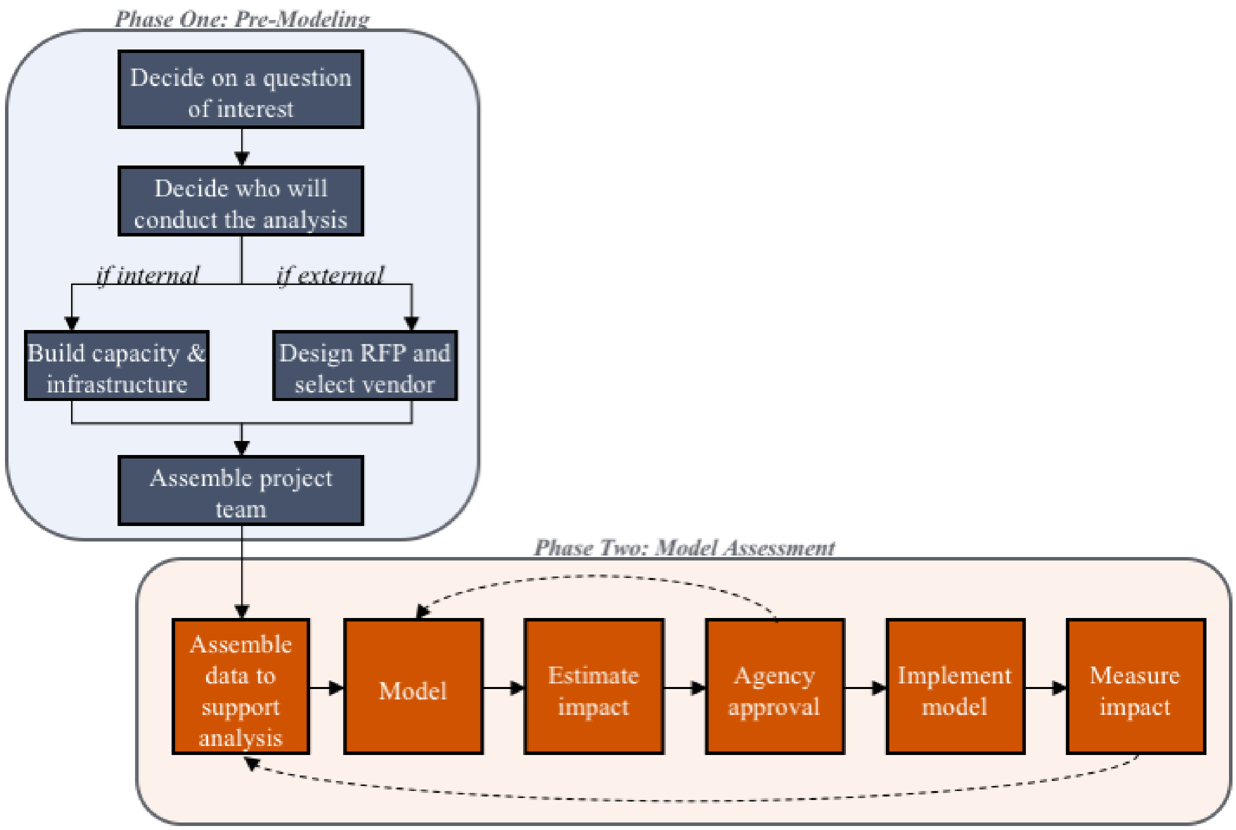
Predictive analytics takes the conclusions from descriptive and diagnostic analytics one step further and uses historical information to estimate the likelihood of a future event. Predictive analytics algorithms generally fall into two different categories: predicting a category (classification) and predicting a quantity (regression); however, both types of predictive algorithms have similar difficulties when predicting certain events. Relatively rare events, such as the risk of a child maltreatment fatality, are more difficult to model or predict due to small datasets that result in relatively unique characteristics for each child. Conversely, the risk of repeated maltreatment, which occurs more frequently, would likely be easier to model or predict due to larger sample sizes and the resulting common features that describe a child's circumstances through information routinely collected by case workers during the course of a case. Applying predictive analytics to the previous foster care system example could result in the addition of estimating the number of children who are likely to enter the foster care system during the next six months, based on patterns uncovered through the prior descriptive and diagnostic steps.

The last category of questions, making a decision and understanding the impact of that decision, can be solved with **prescriptive analytics**. This branch of analytics is dedicated to answering high-impact and high-difficulty questions like "how do I get to a particular outcome?" or "what decision should I make?" For example, the previous analytic steps could identify a set of children who are likely to enter the foster care system in the next six months. Prescriptive analytics could be used to determine the best intervention strategy to reduce the risk of removing the child from his/her family and placing them in congregate care. Such an analysis would evaluate the family's circumstances, the availability of services that might prevent the need for placement, the fit of a caseworker to a family, any tradeoffs within a caseworker's caseload, and any other objectives the child welfare agency would want to consider, and provide a recommended approach.

When applying analytic techniques to child welfare, most agencies are currently focused on predicting an undesirable event so that services can be better delivered before that event escalates. Such a situation would involve applying predictive analytics, though as described earlier, predictive analytics itself relies on applications of both descriptive and diagnostic analytics. Child welfare agencies may apply some form of prescriptive analytics, but in discussions with stakeholders at child welfare agencies, it seems that they rely more on the significant expertise of caseworkers and administrators to make decisions, using analytics as support in this process.

Though each organization might have a slightly different approach to applying predictive analytics, the key steps and decision points remain consistent. As depicted in Figure 2, this process is broken into two parts. The first phase, shown in blue, represents initial activities necessary for the predictive analytics project and involves identifying and allocating resources. The second phase, in orange, represents the process of model-building and implementation. The initial path through this process is sequential; however, the last part should be repeated over time to ensure model accuracy and effectiveness. Key steps include determining a question of interest, assembling a team, gathering significant amounts of data to be used for each event to be modeled, building models, implementing and assessing impact, and repeating, as necessary.

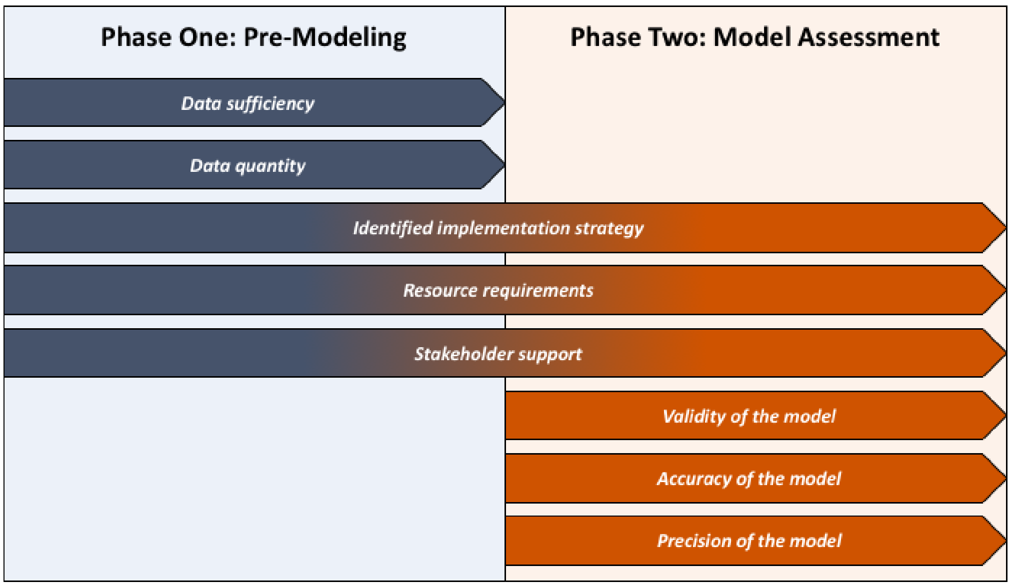
Figure 2: Flow Chart of Key Decision Points



Two-Phase Approach to Applying Criteria

There are many topics within a child welfare agency to which predictive analytics could be applied. However, the agency will need to determine where to focus its attention and resources. Child welfare administrators and their data scientists—whether employed by the child welfare agency or an external partner—can use the criteria described below to determine whether a predictive analytics project would be in the best interest of a child welfare agency, in terms of probability of success, benefit and risk. These criteria can be broken down into two phases, as shown in Figure 3, below. The first phase, conducted before a model is built, determines if the necessary conditions for a successful implementation exist. The second phase, conducted after the model is built, determines if the model developed has sufficient validity and predictive performance such that it is worthwhile to fully implement the model and incorporate it into the operations of the agency. Criteria in the first phase are more strategically focused—e.g., is the initiative clearly defined or do we understand how the model output would be used? Criteria used in the second phase are focused on technical performance, including accuracy and precision of the model. Some criteria—such as resource requirements and stakeholder support—need to be continually applied and assessed throughout the project.

Figure 3: Suggested Criteria for Assessing the Use of Predictive Analytics in Child Welfare



It is worth defining the term "success" as it applies to a predictive analytics project. In the context of this document, a successful project is defined as a project that has a measurable positive impact on the surrounding child welfare ecosystem—the children and families served and the agencies and/or courts that interact with them—at an acceptable cost and minimal level of risk. A successful predictive analytics project will also enhance the agency's ability to achieve its mission. The criteria below can help to measure an organization's ultimate success or failure when implementing predictive analytics; however, given that every potential project is different, the criteria may need to be adapted to fit each specific situation.

Phase One: Pre-Modeling

Criteria used before building a model are generally strategically focused to determine if the necessary conditions exist for a successful application of predictive analytics. Such criteria can help a child welfare agency to determine the initial feasibility and scope of a project before embarking on any specific data modeling or analysis. The criteria below are presented not in an order of importance but rather in a way intended to show how the criteria can relate to each other.

Data Sufficiency

Is there sufficient, available quality data that is relevant to the chosen question? Does the data capture attributes of the child and perpetrator environment that can explain the question? Is there data on the prediction outcomes, both positive and negative?

Before building a predictive analytics model, an agency needs to determine whether it has the breadth of data required to analyze the question. Breadth of data is described as the extent to which a particular dataset provides a complete picture of a child, their environment, and the particular outcomes being analyzed for this question. To start, child welfare agency employees should conduct a preliminary examination based on the research literature and practice experience of what attributes could impact outcomes, which could serve as the initial set of data required to analyze the question. This should be informed by a review of the emerging literature on both predictive analytics in child welfare and the topic addressed by the predictive analytics implementation, as well as early lessons learned by agencies that have begun working with predictive analytics (see Predictive Analytics in *Child Welfare: An Assessment of Current Efforts, Challenges and Opportunities*[3]).

EXAMPLE APPLICATION

Over the past five years, a local Department of Children and Families averages about ten fatality cases each year. This past year has seen twenty child fatalities which inspires administrators to focus on preventing future fatalities. While DCF has robust information about the children, there is limited data available on the alleged perpetrators and their behavior leading up to the incidents. Because factors related to a fatality are more likely to relate to the perpetrator than the child, statisticians advise that DCF acquires more robust historical data on the adults before proceeding with the project.

Finally, an agency should consult with the data owners to ensure that the data meets certain quality standards. Just because a data element exists does not mean that the element is worth using; if the data are not up to certain quality standards, they could incorrectly influence a predictive analytics model. This is usually referenced through the saying, “Garbage in, garbage out” to reflect that poor-quality data inputs result in poor-quality model outputs.

This preliminary examination will help agencies determine whether they need to look further to identify whether there are other factors that may have been overlooked initially. The greater the breadth of data that are available, the more likely it is that useful models can be built. If every desired variable cannot be included in the final dataset, analysts can still build predictive models; however, administrators need to understand that model results are only as accurate as the data that is used to feed the model. If key factors related to the outcome of interest are not available, the agency should proceed cautiously—it is possible that the missing factors do not convey useful information, but it is also possible that the inability to include key variables will significantly reduce the model’s accuracy. Despite missing information, the exercise of building a model may still be valuable given the correct interpretation and understanding of the model’s

[3] Available at: Online link.

shortcomings. Child welfare administrators should discuss the available data with their data scientists to determine if they have sufficient data to proceed.

Data Quantity

Is there enough data, that is, an ample number of observations of the event you are trying to predict, to provide an adequate base of information on which to build a model(s)?

Because predictive analytics depend on statistical properties of data to predict and classify, the more data available for a given event, the more likely the model will be useful. Additional observations typically help to obscure randomness and enable more accurate predictions. While there is no standard for minimum number of observations, most data scientists agree that having as many observations as possible to describe the outcomes is preferable[4]. In the case of predicting categorical outcomes (such as the type of response made to an abuse hotline call), enough data should be captured on each outcome to describe differences between them. Child welfare administrators should make sure to discuss the available data with their data scientists to determine if they have enough observations to run the desired predictive modeling algorithms. This criterion functions as a question-defining criterion, to help hone in on whether the desired outcome is the best application of predictive analytics given a child welfare agency's limited resources and risk tolerance for producing a useful model.

Identified Implementation Strategy

Is there an effective implementation strategy identified for use once the predictive analytics have been completed? Can the predictive model results be used in such a way that has a measurable, positive impact on the child welfare system?

Predictive analytics has the potential to produce benefits only when model results are used to intervene differentially based on the model output. It is imperative that the agency be clear about what it would do differently to intervene with families and have a strong theory of change (or better yet, research evidence) demonstrating how the differentiated intervention would lead to improvement on the outcome of interest. In general, a set of implementation strategies should be identified that would allow the child welfare agency to take action through direct use of the model results or by informing policy changes. The child welfare agency needs to have both a policy-related plan for using model results and a technical-related plan for integrating predictive results into existing IT systems (e.g., dashboards, flags in a screening tool, etc.). The plan should also provide for the continual assessment and, as needed, revision of the implementation plan as the model is put into production.

[4] Hyndman, R. J., & Kostenko A. V. (2007). Minimum sample size requirements for seasonal forecasting models. Foresight, 9 (6), pp. 12-15.

EXAMPLE APPLICATION

The local Department of Children, Youth, and Families (DCYF) is beginning a project to use predictive analytics to identify risk factors for a fatality that can be used to implement targeted interventions. Because the agency can only intervene with children already in the child welfare system, administrators have devised an implementation strategy that involves partnering with external agencies—such as Early Head Start—to engage high-risk families identified by predictive analytics in preventive strategies before the situation escalates. To enable this, administrators establish a partnership with those external agencies to focus on the goal of reducing child fatalities.

For any effort to be worthwhile, successful implementation should have a measurable impact on the children and families served by the child welfare system. Outputs of these models should be useful and actionable, not simply "nice to know." A child welfare agency might also be able to use the results in such a way to inform policy decisions to improve efficiency and allocation of resources. An agency would need to consider the spectrum of impact these results have before deciding if the model is worth the investment. In the context of assessing this criterion, the agency needs to decide what metrics they will use to measure impact. What outcomes does the agency want to achieve by implementing the model? Before building a predictive model, the data scientist will work with subject matter experts to determine what level of performance on specified metrics is acceptable enough to proceed.

Resource Requirements

Can the predictive analytics efforts be completed at a cost that is projected to be less than the perceived benefit after implementation?

As with any large project, cost and resource availability is a limiting factor that can dictate the project's success or failure. Predictive analytics require considerable expertise and technical infrastructure to succeed, and there are significant risks involved. For the endeavor to be worthwhile, the expected benefit to child welfare must justify the investment. This criterion transcends both the pre-modeling and model assessment phases and needs to be continually revisited throughout the entire duration of a predictive analytics project.

When considering available staff resources, recognize that subject matter experts most likely already have full workloads and, consequently, limited availability to contribute to new initiatives surrounding predictive analytics. Furthermore, many child welfare agencies do not have access to experienced data scientists or analysts, so hiring for new positions or contracting with external organizations to conduct the predictive analytics work is an added cost that needs to be considered.

Technological resources also need consideration under resource requirements—does the child welfare agency have access to the specialized technological tools required to implement predictive analytics? When choosing which software to utilize, a child welfare agency will often have a choice between an open source or proprietary solution to support their project. Each comes with advantages and disadvantages that should be discussed before selecting the software. Regardless of the chosen type of software, a child welfare agency also needs to have access to adequate hardware resources—such as servers, virtual machines, etc.—that provide enough computational power to run the software's algorithms. All of this investment has associated cost in terms of budget, as well as human resources to implement and maintain.

Lastly, in assessing the resources required for a predictive analytics project, an agency needs to consider the full timeline required to complete the project. Figure 2, above, also describes the typical process for a project and its iterative nature to ensure the model is ready for implementation. A predictive analytics project is often a lengthy endeavor that cannot be completed in a few short days.

Stakeholder Support

Is there enough approval—within the child welfare agency, the government at large, and among key stakeholders—to support the implementation of the predictive analytics effort? Is the agency prepared to be transparent about the data used, the analytics process, and the results?

The child welfare agency needs to be able to obtain the support of its stakeholders on the usefulness of the predictive analytics, and obtain agreement that such an investment is worth the cost and any associated risks. The agency must adequately address any ethical concerns surrounding the use of child welfare data for predicting a potential future outcome. While predictive analytics are widely used across industries, the potential implications are much more significant in child welfare. The consequence of incorrectly identifying abuse that is not present, or missing abuse is far higher than incorrectly identifying a consumer's movie preference. For more information on ethical concerns behind predictive analytics projects in child welfare, see *Predictive Analytics in Child Welfare: An Assessment of Current Efforts, Challenges and Opportunities*.[5]

Given the potential of implementing predictive analytics in child welfare, instilling public confidence in the predictive models and being transparent about the process is crucial. Without stakeholder and public buy-in for a predictive analytics project, barriers to success, ranging from political opposition to difficulty obtaining data sharing agreements and implementing findings, will likely increase. If not addressed, these barriers could evolve into legal situations: for example, if a removal decision based on a predictive model is challenged, the logic and process of predictive analytics–based decisions must be defended in open court. While there will always be concerned parties, a successful predictive analytics project will likely have multiple stakeholders intimately involved in the process, from data sharing to model building to model implementation. If a predictive analytics project does not consider stakeholder input, there is potential for the project to be shut down or stopped before implementation despite its potential usefulness. This criterion transcends the planning and implementation phases and needs to be continually assessed throughout the potential predictive analytics project.

Phase Two: Model Assessment

After a predictive model is built, it must be assessed to determine if it can technically perform to requirements. In this second phase, the predictive model must be validated and its results judged for

[5] Available at: Online link.

accuracy and precision. As these additional feasibility criteria are added and evaluated, consideration of the previous criteria related to the required resources and the stakeholder engagement should remain ongoing.

Validity of the Model

Is the modeling process rigorous and appropriate for the chosen question? Does the model accurately represent the real world? Do subject matter experts approve of the model results?

The 20th century statistician George E.P. Box famously said, "All models are wrong but some are useful."[6] Because the real world is random and unpredictable, no predictive models will be perfect; however, some models will be better than others at approximating behavior. Immediately after running a modeling process, data scientists need to put the model through a validation process to understand how well this particular model approximates the real world. Child welfare administrators should discuss the model validation—including the items described below—with their data scientists before implementing a predictive model.

The first step to model validation is assessing if you have chosen an appropriate algorithm. Does the algorithm predict categories or quantities, and is this consistent with your question? Does the data satisfy any necessary conditions to produce reliable results? Once the model algorithm and assumptions have been validated, the data scientists will likely turn to the model results and compute measures of accuracy, precision, and other metrics that can describe how good the model might be.

A final important step to model validation is looking at the important features as suggested by the modeling output and how they interact to predict the desired outcome. Do the variables make sense with the subject matter expert's intuition and expertise? While not all important features may be known ahead of running the predictive model, the chosen features should not be antithetical to knowledge about the question or how the child welfare system works. If a feature is important and yet unexplainable, this could be a sign that something failed in predictive modeling process or a fault in the underlying data.

[6] Box, George E.P. (1979, May). Robustness in the strategy of scientific model building (MRC Technical Summary Report #1954). Mathematics Research Center, University of Wisconsin-Madison.

Accuracy of the Model

To what extent does your model correctly predict the outcome of interest? Are the false positive and false negative rates within the risk tolerance for the agency?

Model accuracy is typically the most commonly discussed criteria when evaluating predictive analytics. Accuracy is defined as the ability for the model to predict the true value given a set of inputs, either in terms of classifying something in a category or predicting a value. This is often done by withholding a set of historical data that the model has not seen before and comparing model predictions with known, historical outcomes. In terms of predicting a categorical value, the model should minimize rates of false positives (e.g., incorrectly identifying risk where it doesn't exist) and false negatives (e.g., failing to identify risk where it exists). However, no model can simultaneously optimize in both directions, and there will always be a trade-off between minimizing false positives and false negatives. For models predicting a quantity, data scientists can help to calculate various metrics that assess how well that model fits your data. These metrics are used to describe the model's overall accuracy but can also describe how well it performs in extreme cases.

Regardless, the model must outperform tolerances established by the agency for both types of errors to be considered successful. If a model is not highly accurate, it could lead to missing abuse that is present, or incorrectly identifying abuse that is not present. Tolerances for such errors will depend on the consequences for the child, family and agency and the implications of false positive and false negative results given the planned differential intervention and the outcome being modeled. Child welfare administrators should review the accuracy of a predictive model with their data scientists to understand how the model performs relative to other predictive models.

EXAMPLE APPLICATION

The local Department of Human Services has started a predictive analytics project focused on predicting child fatalities from historical data. The model has high accuracy, correctly predicting 99% of the fatalities. This model minimizes false negatives, meaning that it is overly cautious on predicting which children are at risk for a fatality. However, the model also incorrectly categorizes 10,000 children as high-risk for a fatality, a false positive rate that is extremely high. Administrators determine that intervening with so many families is too costly an intervention given that so many children may not experience the outcome and decide to not proceed with the model in its current form.

Precision of the Model

Can the model reliably predict accurate results for multiple cases? Does the model have enough consistency with its predictions to be implemented in the field?

A model may be able to predict the correct outcome, e.g. have high accuracy or validity, but it may not reliably repeat that correct prediction. This idea is known as the precision of a model. A model may be accurate and not precise, precise and not accurate, or any combination of the two. When a model is accurate and precise, the model predicts the correct outcome a large percentage of the time. Conversely, when a model is accurate but not precise, it can predict the correct outcome, but there is a lot of variation that can result in inconsistent predictions. When implementing a model, the agency needs to assess the ability of the model to consistently predict accurate results and determine if this rate is within their desired risk tolerance. Like with model validity and accuracy, child welfare administrators need to review model precision with their data scientists to better understand the performance of the predictive model.

EXAMPLE APPLICATION

The local Child Welfare Agency has started a predictive analytics project to predict the workload for a caseworker in the next 12 months to ultimately allocate resources more efficiently. The data scientists look at both accuracy and precision when evaluating the model. Assume that the 'correct' number of cases for this type of caseworker is 100. If the model is accurate but not precise, the model will predict a large range of cases centered on 100 (e.g., 50-150). Conversely, a precise but not accurate model will get a small range not centered around 100 (e.g., 50-70). The best model, one that is both accurate and precise, predicts a small range centered on 100 cases (e.g., 90-110).

Closing Thoughts

Predictive analytics is a powerful toolset capable of great benefit that should be applied in situations where it can provide legitimate value in the context of its costs and risks. These models are best applied in situations where the likelihood that something will happen at some point in the future—such as a placement disruption or foster care re-entry—and will occur frequently enough that statistical models, within acceptable tolerances, can be built. Even when predictive analytics can be applied to a specific question from a technical perspective, other attributes of the project—such as cost, implementation strategy, population size, and model accuracy—may steer an agency away from pursuing it. The criteria presented here can help a child welfare agency determine whether predictive analytics is an appropriate tool for a given question. While each criterion should be evaluated when building a predictive model, no single criterion should be used to authorize building the model. However, if any one criterion fails, that could halt the predictive analytics project.

Other fields—including criminal justice and marketing– use similar criteria for establishing the use of predictive analytics for their questions. If a model is built to predict the likelihood of someone opening a marketing email, there is little consequence if that person does not open the email. But in criminal justice, an incorrect prediction that a convict will not violate the conditions of his or her parole can have significant impact on the convict's life, or the lives of his/her friends, family, and potential victims.[7] Some child welfare applications, such as predicting the likelihood of future abuse of a child, have significant consequences if the model is wrong, similar to the criminal justice example. If a prediction has the potential for significant negative impact, then a conservative approach should be used for developing the predictive analytics model and the criteria should be applied very stringently. Ultimately, an agency needs to balance their own objectives among the relevant criteria to determine whether predictive analytics should become part of its strategy to improve the overall well-being of children and their families.

[7] Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016, May 23). Machine Bias: There's software used across the country to predict future criminals. And it's biased against blacks. Retrieved from ProPublica: Machine Bias

NOTICE