

Draft: 5/14/7/24/2019

As adopted by the Casualty Actuarial and Statistical (C) Task Force on XX/XX/XX

EXPOSURE NOTE: The drafting group are still considering comments on the 5/14/19 draft; no changes are yet made to the previously exposed sections of the paper. Two new sections are drafted in the paper and will be exposed for public comment at the Summer National Meeting: Part VIII Proposed Changes to the *Product Filing Review Handbook* and Part IX Proposed State Guidance. Please note that we expect changes from the comments on the 5/14 draft and any changes made will also be reflected in these two new sections.

Casualty Actuarial and Statistical (C) Task Force
Regulatory Review of Predictive Models

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I. INTRODUCTION

Insurers' use of predictive analytics along with big data has significant potential benefits to both consumers and insurers. Predictive analytics can reveal insights into the relationship between consumer behavior and the cost of insurance, lower the cost of insurance for many, and provide incentives for consumers to better control and mitigate loss. However, predictive analytic techniques are evolving rapidly and leaving many regulators without the necessary tools to effectively review insurers' use of predictive models in insurance applications.

When a rate plan is truly innovative, the insurer must anticipate or imagine the reviewers' interests because reviewers will respond with unanticipated questions and have unique educational needs. Insurers can learn from the questions, teach the reviewers, and so forth. When that back-and-forth learning is memorialized and retained, filing requirements and insurer presentations can be routinely organized to meet or exceed reviewers' needs and expectations. Hopefully, this paper helps bring more consistency and to the art of reviewing predictive models within a rate filing.

The Casualty Actuarial and Statistical (C) Task Force (CASTF) has been charged with identifying best practices to serve as a guide to state insurance departments in their review of predictive models¹ underlying rating plans. There were two charges given to CASTF by the Property and Casualty Insurance (C) Committee at the request of the Big Data (EX) Working Group:

- A. Draft and propose changes to the *Product Filing Review Handbook* to include best practices for review of predictive models and analytics filed by insurers to justify rates.
- B. Draft and propose state guidance (e.g., information, data) for rate filings that are based on complex predictive models.

This paper will identify best practices when reviewing predictive models and analytics filed by insurers with regulators to justify rates and provide state guidance for review of rate filings based on predictive models. Upon adoption of this paper by the Executive (EX) Committee and Plenary, the Task Force will evaluate how to incorporate these best practices into the *Product Filing Review Handbook* and will recommend such changes to the Speed to Market (EX) Working Group.

II. WHAT IS A "BEST PRACTICE?"

A best practice is a form of program evaluation in public policy. At its most basic level, a practice is a "tangible and visible behavior... [based on] an idea about how the actions... will solve a problem or achieve a goal"². Best practices are used to maintain quality as an alternative to mandatory legislated standards and can be based on self-assessment or benchmarking.³ Therefore, a best practice represents an effective method of problem solving. The "problem" regulators want to solve is probably better posed as seeking an answer to this question: How can regulators determine that predictive models, as used in rate filings, are compliant with state laws and regulations?

Key Regulatory Principles

In this paper, best practices are based on the following principles that promote a comprehensive and coordinated review of predictive models across states:

1. *State insurance regulators will maintain their current rate regulatory authority.*
2. *State insurance regulators will be able to share information to aid companies in getting insurance products to market more quickly.*
3. *State insurance regulators will share expertise and discuss technical issues regarding predictive models.*
4. *State insurance regulators will maintain confidentiality, where appropriate, regarding predictive models.*

In this paper, best practices are presented in the form of guidance to regulators who review predictive models and to insurance companies filing rating plans that incorporate predictive models. Guidance will identify specific information

¹ In this paper, references to "model" or "predictive model" are the same as "complex predictive model" unless qualified.

² Bardach, E. and Patashnik, E. (2016.) *A Practical Guide for Policy Analysis, The Eightfold Path to More Effective Problem Solving*. Thousand Oaks, CA: CQ Press. See Appendix A for an overview of Bardach's best-practice analysis.

³ Bogan, C.E. and English, M.J. (1994). *Benchmarking for Best Practices: Winning Through Innovative Adaptation*. New York: McGraw-Hill.

useful to a regulator in the review of a predictive model, comment on what might be important about that information and, where appropriate, provide insight as to when the information might identify an issue the regulator needs to be aware of or explore further.

III. DO REGULATORS NEED BEST PRACTICES TO REVIEW PREDICTIVE MODELS?

The term “predictive model” refers to a set of models that use statistics to predict outcomes⁴. When applied to insurance, the model is chosen to estimate the probability or expected value of an outcome given a set amount of input data; for example, models can predict the frequency of loss, the severity of loss, or the pure premium. The generalized linear model (GLM)⁵ is a commonly used predictive model in insurance applications, particularly in building an insurance product’s rating plan.

Depending on definitional boundaries, predictive modeling can sometimes overlap with the field of machine learning. In this modeling space, predictive modeling is often referred to as predictive analytics.

Before GLMs became vogue, rating plans were built using univariate methods. Univariate methods were considered intuitive and easy to demonstrate the relationship to costs (loss and/or expense). Today, many insurers consider univariate methods too simplistic since they do not take into account the interaction (or dependencies) of the selected input variables.

According to many in the insurance industry, GLMs introduce significant improvements over univariate-based rating plans by automatically adjusting for correlations among input variables. Today, the majority of predictive models used in private passenger automobile and homeowners’ rating plans are GLMs. However, GLM results are not always intuitive, and the relationship to costs may be difficult to explain. This is a primary reason regulators can benefit from best practices.

A GLM consists of three elements⁶:

- Each component of Y is independent and a probability distribution from the exponential family, or more generally, a selected variance function and dispersion parameter.
- A linear predictor $\eta = X\beta$.
- A link function g such that $E(Y) = \mu = g^{-1}(\eta)$.

As can be seen in the description of the three GLM components above, it may take more than a casual introduction to statistics to comprehend the construction of a GLM. As stated earlier, a downside to GLMs is that it is more challenging to interpret the GLMs output than with univariate models.

GLM software provides point estimates and allows the modeler to consider standard errors and confidence intervals. GLM output is typically assumed to be 100% credible no matter the size of the underlying data set. If some segments have little data, the resulting uncertainty would not be reflected in the GLM parameter estimates themselves (although it might be reflected in the standard errors, confidence intervals, etc.). Even though the process of selecting relativities often includes adjusting the raw GLM output, the resultant selections are not then credibility-weighted with any complement of credibility. Nevertheless, selected relativities based on GLM model output may differ from GLM point estimates.

Because of this presumption in credibility, which may or may not be valid in practice, the modeler and the regulator reviewing the model would need to engage in thoughtful consideration when incorporating GLM output into a rating plan to ensure that model predictiveness is not compromised by any lack of actual credibility. Therefore, to mitigate the risk that model credibility or predictiveness is lacking, a complete filing for a rating plan that incorporates GLM output should include validation evidence for the rating plan, not just the statistical model.

To further complicate regulatory review of models in the future, modeling methods are evolving rapidly and not limited just to GLMs. As computing power grows exponentially, it is opening up the modeling world to more sophisticated forms of data acquisition and data analysis. Insurance actuaries and data scientists seek increased predictiveness by using even more complex predictive modeling methods. Examples of these are predictive models utilizing random forests, decision

⁴ A more thorough exploration of different predictive models will be found in many statistics’ books, including Geisser, Seymour (September 2016). *Predictive Inference: An Introduction*. New York: Chapman & Hall.

⁵ The generalized linear model (GLM) is a flexible family of models that are unified under a single method. Types of GLM include logistic regression, Poisson regression, gamma regression and multinomial regression.

⁶ More information on model elements can be found in most statistics’ books.

trees, neural networks, or combinations of available modeling methods (often referred to as ensembles). These evolving techniques will make the regulators' understanding and oversight of filed rating plans incorporating predictive models even more challenging.

In addition to the growing complexity of predictive models, many state insurance departments do not have in-house actuarial support or have limited resources to contract out for support when reviewing rate filings that include use of predictive models. The Big Data (EX) Working Group identified the need to provide states with guidance and assistance when reviewing predictive models underlying filed rating plans.⁷ The Working Group circulated a proposal addressing aid to state insurance regulators in the review of predictive models as used in private passenger automobile and homeowners' insurance rate filings. This proposal was circulated to all of the Working Group members and interested parties on December 19, 2017, for a public comment period ending January 12, 2018.⁸ The Big Data Working Group effort resulted in the new CASTF charges (see the Introduction section) with identifying best practices that provide guidance to states in the review of predictive models.

So, to get to the question asked by the title of this section: Do regulators need best practices to review predictive models? It might be better to ask this question another way: Are best practices in the review of predictive models of value to regulators and insurance companies? The answer is "yes" to both questions. Best practices will aid regulatory reviewers by raising their level of model understanding. With regard to scorecard models and the model algorithm, there is often not sufficient support for relative weight, parameter values, or scores of each variable. Best practices can potentially aid in fixing this problem.

However, best practices are not intended to create standards for filings that include predictive models. Rather, best practices will assist the states in identifying the model elements they should be looking for in a filing that will aid the regulator in understanding why the company believes that the filed predictive model improves the company's rating plan, making that rating plan fairer to all consumers in the marketplace. To make this work, both regulators and industry need to recognize that:

- Best practices merely provide guidance to regulators in their essential and authoritative role over the rating plans in their state.
- All states may have a need to review predictive models whether that occurs with approval of rating plans or in a market conduct exam. Best practices help the regulator identify elements of a model that may influence the regulatory review as to whether modeled rates are appropriately justified. Each regulator needs to decide if the insurer's proposed rates are compliant with state laws and regulations and whether to act on that information.
- Best practices will lead to improved quality in predictive model reviews across states, aiding speed to market and competitiveness of the state marketplace.
- Best practices provide a framework for states to share knowledge and resources to facilitate the technical review of predictive models.
- Best practices aid training of new regulators and/or regulators new to reviewing predictive models. (This is especially useful for those regulators who do not actively participate in NAIC discussions related to the subject of predictive models.)
- Each regulator adopting best practices will be better able to identify the resources needed to assist their state in the review of predictive models.

Lastly, from this point on in this paper, best practices will be referred to as "guidance." This reference is in line with the intent of this paper to support individual state autonomy in the review of predictive models.

IV. SCOPE

The focus of this paper will be on GLMs used to create private passenger automobile and home insurance rating plans.

The knowledge needed to review predictive models, and guidance in this paper regarding GLMs for personal automobile and home insurance may be transferrable when the review involves GLMs applied to other lines of business. Modeling

⁷ Minutes of the Big Data (EX) Working Group, March 9, 2018: https://secure.naic.org/secure/minutes/2018_spring/ex_it_tf.pdf?59

⁸ All comments received by the end of January were posted to the NAIC website March 12 for review.

depends on context, so the GLM reviewer has to be alert for data challenges and business applications that differ from the most familiar personal lines. For example, compared to personal lines, modeling for rates in commercial lines is more likely to encounter low volumes of historical data, dependence on advisory loss costs, unique large accounts with some large deductibles and products that build policies from numerous line-of-business and coverage building blocks. Commercial lines commonly use individual risk modifications following experience, judgment, and/or expense considerations. A regulator may never see commercial excess and surplus lines filings. The legal and regulatory constraints (including state variations) are likely to be more evolved, and challenging, in personal lines. A GLM rate model for personal lines in 2019 is either an update or a late-adopter's defensive tactic. Adopting GLM for commercial lines has a shorter history.

Guidance offered here might be useful (with deeper adaptations) when starting to review different types of predictive models. If the model is not a GLM, some listed items might not apply. Not all predictive models generate p-values or F tests. Depending on the model type, other considerations might be important. When transferring guidance to other lines of business and other types of model, unique considerations may arise depending on the context in which a predictive model is proposed to be deployed, the uses to which it is proposed to be put, and the potential consequences for the insurer, its customers and its competitors. This paper does not delve into these possible considerations but regulators should be prepared to address them as they arise.

V. CONFIDENTIALITY

Regulatory reviewers are required to protect confidential information in accordance with applicable State law. However, insurers should be aware that a rate filing might become part of the public record. Each state determines the confidentiality of a rate filing, supplemental material to the filing, when filing information might become public, the procedure to request that filing information be held confidentially, and the procedure by which a public records request is made. It is incumbent on an insurer to be familiar with each state's laws regarding the confidentiality of information submitted with their rate filing.

VI. GUIDANCE FOR REGULATORY REVIEW OF PREDICTIVE MODELS (BEST PRACTICES)

Best practices will help the regulator understand if a predictive model is cost based, if the predictive model is compliant with state law, and how the model improves, the company's rating plan. Best practices can, also, make the regulator's review more consistent across states and more efficient, and assist companies in getting their products to market faster. With this in mind, the regulator's review of predictive models should:

1. Ensure that the factors developed based on the model produce rates that are not excessive, inadequate, or unfairly discriminatory.
 - a. Review the overall rate level impact of the revisions proposed based on the predictive model output in comparison to rate level indications provided by the filer.
 - b. Review the premium disruption for individual policyholders and how the disruptions can be explained to individual consumers.
 - c. Review the individual input characteristics to and output factors from the predictive model (and its sub-models), as well as, associated selected relativities to ensure they are not unfairly discriminatory.
2. Thoroughly review all aspects of the model including the source data, assumptions, adjustments, variables, and resulting output.
 - a. Determine that individual input characteristics to a predictive model are related to the expected loss or expense differences in risk. Each input characteristic should have an intuitive or demonstrable actual relationship to expected loss or expense.
 - b. Determine that the data used as input to the predictive model is accurate, including a clear understanding how missing values, erroneous values and outliers are handled.
 - c. Determine that any adjustments to the raw data are handled appropriately, including but not limited to, trending, development, capping, removal of catastrophes.
 - d. Determine that rating factors from a predictive model are related to expected loss or expense differences in risk. Each rating factor should have a demonstrable actual relationship to expected loss or expense.

- e. Obtain a clear understanding how often each risk characteristic, used as input to the model, is updated and whether the model is periodically rerun, so model output reflects changes to non-static risk characteristics.
3. Evaluate how the model interacts with and improves the rating plan.
 - a. Obtain a clear understanding of the characteristics that are input to a predictive model (and its sub-models), their relationship to each other and their relationship to non-modeled characteristics/variables used to calculate a risk's premium.
 - b. Obtain a clear understanding of how the selected predictive model was built and why the insurer believes this type of model works in a private passenger automobile or homeowner's insurance risk application.
 - c. Obtain a clear understanding of how model output interacts with non-modeled characteristics/variables used to calculate a risk's premium.
 - d. Obtain a clear understanding of how the predictive model was integrated into the insurer's state rating plan and how it improves that plan.
 - e. For predictive model refreshes, determine whether sufficient validation was performed to ensure the model is still a good fit.
4. Enable competition and innovation to promote the growth, financial stability, and efficiency of the insurance marketplace.
 - a. Enable innovation in the pricing of insurance through acceptance of predictive models, provided they are actuarially sound and in compliance with state laws.
 - b. Protect the confidentiality of filed predictive models and supporting information in accordance with state law.
 - c. Review predictive models in a timely manner to enable reasonable speed to market.

VII. PREDICTIVE MODELS – INFORMATION FOR REGULATORY REVIEW

This section of the paper identifies the information a regulator may need to review a predictive model used by an insurer to support a filed P/C insurance rating plan. The list is lengthy but not exhaustive. It is not intended to limit the authority of a regulator to request additional information in support of the model or filed rating plan. Nor is every item on the list intended to be a requirement for every filing. However, the items listed should help guide a regulator to obtain sufficient information to determine if the rating plan meets state specific filing and legal requirements.

Though the list seems long, the insurer should already have internal documentation on the model for more than half of the information listed. The remaining items on the list require either minimal analysis (approximately 25%) or deeper analysis to generate the information for a regulator (approximately 25%).

The "Importance to Regulator's Review" ranking of information a regulator may need to review is based on the following level criteria:

Level 1 - This information is necessary to begin the review of a predictive model. These data elements pertain to basic information about the type and structure of the model, the data and variables used, the assumptions made, and the goodness of fit. Ideally, this information would be included in the filing documentation with the initial submission of a filing made based on a predictive model.

Level 2 - This information is necessary to continue the review of all but the most basic models; such as those based only on the filer's internal data and only including variables that are in the filed rating plan. These data elements provide more detailed information about the model and address questions arising from review of the information in Level 1. Insurers concerned with speed to market may also want to include this information in the filing documentation.

Level 3 - This information is necessary to continue the review of a model where concerns have been raised and not resolved based on review of the information in Levels 1 and 2. These data elements address even more detailed aspects of the model including (to be listed after we assign levels). This information does not necessarily need to be included with the initial submission, unless specifically requested in a particular jurisdiction, as it is typically requested only if the reviewer has concerns that the model may not comply with state laws.

Level 4 - This information is necessary to continue the review of a model where concerns have been raised and not resolved based on the information in Levels 1, 2, and 3. This most granular level of detail is addressing the basic building blocks of the model and does not necessarily need to be included by the filer with the initial submission, unless specifically requested in a particular jurisdiction. It is typically requested only if the reviewer has serious concerns that the model produces rates or factors that are excessive, inadequate, or unfairly discriminatory.

A. Selecting Model Input

Section	Information Element	Level of Importance to the Regulator's Review	Comments
1. Available Data Sources			
A.1.a	Review the details of all data sources for input to the model (only need sources for filed input characteristics). For each source, obtain a list all data elements used as input to the model that came from that source.	1	Request details of all data sources. For insurance experience (policy or claim), determine whether calendar, accident, fiscal or policy year data and when it was last evaluated. For each data source, get a list all data elements used as input to the model that came from that source. For insurance data, get a list all companies whose data is included in the datasets. Request details of any non-insurance data used (customer-provided or other), including who owns this data, on how consumers can verify their data and correct errors, whether the data was collected by use of a questionnaire/checklist, whether data was voluntarily reported by the applicant, and whether any of the data is subject to the Fair Credit Reporting Act. If the data is from an outside source, find out what steps were taken to verify the data was accurate.
A.1.b	Reconcile raw insurance data and with available external insurance reports.	3	Accuracy of insurance data should be reviewed as well.
A.1.c	Review the geographic scope and geographic exposure distribution of the raw data for relevance to the state where the model is filed.	1	Evaluate whether the data is relevant to the loss potential for which it is being used. For example, verify that hurricane data is only used where hurricanes can occur.
A.1.d	Be aware of any non-insurance data used (customer-provided or other), including who owns this data, how consumers can verify their data and correct errors, whether the data was collected by use of a questionnaire/checklist, whether it was voluntarily reported by the applicant, and whether any of the variables are subject to the Fair Credit Reporting Act. If the data is from an outside source, determine the steps that were taken by the company to verify the data was accurate.	2	If the data is from a third-party source, the company should provide information on the source. Depending on the nature of the data, data should be documented and an overview of who owns it and the topic of consumer verification should be addressed.

2. Sub-Models			
A.2.a	Consider the relevance of (e.g., is there a bias) of overlapping data or variables used in the model and sub-models.	1	Check if the same variables/datasets were used in both the model, a submodel or as stand-alone rating characteristics. If so, verify there was no double-counting or redundancy.
A.2.b	Determine if sub-model output was used as input to the GLM; obtain the vendor name, and the name and version of the sub-model.	1	The regulator needs to know name of 3rd party vendor and contact whether model or sub-model. Examples of such sub-models include credit/financial scoring algorithms and household composite score models. Sub-models can be evaluated separately and in the same manner as the primary model under evaluation. A sub-model contact for additional information should be provided. SMEs on sub-model may need to be brought into the conversation with regulators (whether in-house or 3rd-party sub-models are used).
A.2.c	If using catastrophe model output, identify the vendor and the model settings/assumptions used when the model was run.	1	For example, it is important to know hurricane model settings for storm surge, demand surge, long/short-term views.
A.2.d	If using catastrophe model output (a sub-model) as input to the GLM under review, verify whether loss associated with the modeled output was removed from the loss experience datasets.	1	If a weather-based sub-model is input to the GLM under review, loss data used to develop the model should not include loss experience associated with the weather-based sub-model. Doing so could cause distortions in the modeled results by double counting such losses when determining relativities or loss loads in the filed rating plan. For example, redundant losses in the data may occur when non-hurricane wind losses are included in the data while also using a severe convective storm model in the actuarial indication. Such redundancy may also occur with the inclusion of fluvial or pluvial flood losses when using a flood model, inclusion of freeze losses when using a winter storm model or including demand surge caused by any catastrophic event.
A.2.e	If using output of any scoring algorithms, obtain a list of the variables used to determine the score and provide the source of the data used to calculate the score.	1	Any sub-model should be reviewed in the same manner as the primary model that uses the sub-model's output as input.
A.2.f	Determine if the sub-model was previously approved (or accepted) by the regulatory agency.	2	If the sub-model was previously approved, that may change the extent of the sub-model's review. If approved, verify when and that it was the same model currently under review.
3. Adjustments to Data			

A.3.a	Determine if premium, exposure, loss or expense data were adjusted (e.g., developed, trended, adjusted for catastrophe experience or capped) and, if so, how? Do the adjustments vary for different segments of the data and, if so, identify the segments and how was the data adjusted?	2	Look for anomalies in the data that should be addressed. For example, is there an extreme loss event in the data? If other processes were used to load rates for specific loss events, how is the impact of those losses considered? Examples of losses that can contribute to anomalies in the data are large losses, flood, hurricane or severe convective storm models for PPA comprehensive or home losses.
A.3.b	Identify adjustments that were made to raw data, e.g., transformations, binning and/or categorizations. If any, identify the name of the characteristic/variable and obtain a description of the adjustment.	1	
A.3.c	Ask for aggregated data (one data set of pre-adjusted/scrubbed data and one data set of post-adjusted/scrubbed data) that allows the regulator to focus on the univariate distributions and compare raw data to adjusted/binning/transformed/etc. data.	3	This is most relevant for variables that have been "scrubbed" or adjusted. Though most regulators may never ask for aggregated data and do not plan to rebuild any models, a regulator may ask for this aggregated data or subsets of it. It would be useful to the regulator if the percentage of exposures and premium for missing information from the model data by category were provided. This data can be displayed in either graphical or tabular formats.
A.3.d	Determine how missing data was handled.	1	
A.3.e	If duplicate records exist, determine how they were handled.	1	
A.3.f	Determine if there were any data outliers identified and subsequently adjusted during the scrubbing process. Get a list (with description) of the outliers and determine what adjustments were made to these outliers.	2	
4. Data Organization			
A.4.a	Obtain documentation on the methods used to compile and organize data, including procedures to merge data from different sources and a description of any preliminary analyses, data checks, and logical tests performed on the data and the results of those tests.	2	This should explain how data from separate sources was merged.

A.4.b	Obtain documentation on the process for reviewing the appropriateness, reasonableness, consistency and comprehensiveness of the data, including a discussion of the intuitive relationship the data has to the predicted variable.	2	An example is when by-peril or by-coverage modeling is performed; the documentation should be for each peril/coverage and make intuitive sense. For example, if “murder” or “theft” data are used to predict the wind peril, provide support and an intuitive explanation of their use.
A.4.c	Identify material findings the company had during their data review and obtain an explanation of any potential material limitations, defects, bias or unresolved concerns found or believed to exist in the data. If issues or limitations in the data influenced modeling analysis and/or results, obtain a description of those concerns and an explanation how modeling analysis was adjusted and/or results were impacted.	1	

B. Building the Model

Section	Information Element	Level of Importance to Regulator's Review	Comments
1. High-Level Narrative for Building the Model			
B.1.a	Identify the type of model (e.g. Generalized Linear Model – GLM, decision tree, Bayesian Generalized Linear Model, Gradient-Boosting Machine, neural network, etc.). Understand the model's role in the rating system and provide the reasons why that type of model is an appropriate choice for that role.	1	There should be an explanation of why the model (using the variables included in it) is appropriate for the line of business. If by-peril or by-coverage modeling is used, the explanation should be by-peril/coverage.
B.1.b	Identify the software used for model development. Obtain the name of the software vendor/developer, software product and a software version reference.	2	
B.1.c	Obtain a description how the available data was divided between model training, test and validation datasets. The description should include an explanation why the selected approach was deemed most appropriate, and whether the company made any further subdivisions of available data and reasons for the subdivisions (e.g., a portion separated from training data to support testing of components during model building). Determine if the validation data was accessed before model training was completed and, if so, obtain an explanation how and why that came to occur.	1	
B.1.d	Obtain a brief description of the development process, from initial concept to final model and filed rating plan (in less than three pages of narrative).	1	The narrative should have the same scope as the filing.
B.1.e	Obtain a narrative on whether loss ratio, pure premium or frequency/severity analyses were performed and, if separate frequency/severity modeling was performed, how pure premiums were determined.	1	
B.1.f	Identify the model's target variable.	1	A clear description of the target variable is key to understanding the purpose of the model.

B.1.g	Obtain a detailed description of the variable selection process.	1	The narrative regarding the variable selection process may address matters such as the criteria upon which variables were selected or omitted, identification of the number of preliminary variables considered in developing the model versus the number of variables that remained, and any statutory or regulatory limitations that were taken into account when making the decisions regarding variable selection.
B.1.h	In conjunction with variable selection, obtain a narrative on how the Company determine the granularity of the rating variables during model development.	1	
B.1.i	Determine if model input data was segmented in any way, e.g., was modeling performed on a by-coverage, by-peril, or by-form basis. If so, obtain a description of data segmentation and the reasons for data segmentation.	1	The regulator would use this to follow the logic of the modeling process.
B.1.j	If adjustments to the model were made based on credibility considerations, obtain an explanation of the credibility considerations and how the adjustments were applied.	2	Adjustments may be needed given models do not explicitly consider the credibility of the input data or the model's resulting output; models take input data at face value and assume 100% credibility when producing modeled output.
2. Medium-Level Narrative for Building the Model			
B.2.a	At crucial points in model development, if selections were made among alternatives regarding model assumptions or techniques, obtain a narrative on the judgment used to make those selections.	2	
B.2.b	If post-model adjustments were made to the data and the model was rerun, obtain an explanation on the details and the rationale for those adjustments.	2	Evaluate the addition or removal of variables and the model fitting. It is not necessary for the company to discuss each iteration of adding and subtracting variables, but the regulator should gain a general understanding how these adjustments were done, including any statistical improvement measures relied upon.
B.2.c	Obtain a description of univariate balancing and testing performed during the model-building process, including an explanation of the thought processes involved.	2	Further elaboration from B.2.b.

B.2.d	Obtain a description of the 2-way balancing and testing that was performed during the model-building process, including an explanation of the thought processes of including (or not including) interaction terms.	2	Further elaboration from B.2.a and B.2.b.
B.2.e	For the GLM, identify the link function used. Identify which distribution was used for the model (e.g., Poisson, Gaussian, log-normal, Tweedie). Obtain an explanation why the link function and distribution were chosen. Obtain the formulas for the distribution and link functions, including specific numerical parameters of the distribution.	1	
B.2.f	Obtain a narrative on the formula relationship between the data and the model outputs, with a definition of each model input and output. The narrative should include all coefficients necessary to evaluate the predicted pure premium, relativity or other value, for any real or hypothetical set of inputs.	2	B.4.1 and B.4.m will show the mathematical functions involved and could be used to reproduce some model predictions.
B.2.g	If there were data situations in which GLM weights were used, obtain an explanation of how and why they were used.	3	Investigate whether identical records were combined to build the model.
3. Predictor Variables			
B.3.a	Obtain a complete data dictionary, including the names, types, definitions and uses of each predictor variable, offset variable, control variable, proxy variable, geographic variable, geodemographic variable and all other variables in the model (including sub-models and external models).	1	Types of variables might be continuous, discrete, Boolean, etc. Definitions should not use programming language or code. For any variable(s) intended to function as a control or offset, obtain an explanation of their rationale and impact.
B.3.b	Obtain a list of predictor variables considered but not used in the final model, and the rationale for their removal.	4	The rationale for this requirement is to identify variables that the company finds to be predictive but ultimately may reject for reasons other than loss-cost considerations (e.g., price optimization)
B.3.c	Obtain a correlation matrix for all predictor variables included in the model and sub-model(s).	2	While GLMs accommodate collinearity, the correlation matrix provides more information about the magnitude of correlation between variables.
B.3.d	Obtain an intuitive explanation for why an increase in each predictor variable should increase or decrease frequency, severity, loss costs, expenses, or any element or characteristic being predicted.	2	The explanation should go beyond demonstrating correlation. Considering possible causation is relevant, but proving causation is neither practical nor expected. If no intuitive explanation can be provided, greater scrutiny may be appropriate.

B.3.e	If the modeler made use of one or more dimensionality reduction techniques, such as a Principal Component Analysis (PCA), obtain a narrative about that process, an explanation why that technique was chosen, and a description of the step-by-step process used to transform observations (usually correlated) into a set of linearly uncorrelated variables. In each instance, obtain a list of the pre-transformation and post-transformation variable names, and an explanation how the results of the dimensionality reduction technique was used within the model.	2	
4. Adjusting Data, Model Validation and Goodness-of-Fit Measures			
B.4.a	Obtain a description of the methods used to assess the statistical significance/goodness of the fit of the model to validation data, such as lift charts and statistical tests. Compare the model's projected results to historical actual results and verify that modeled results are reasonably similar to actual results from validation data.	1	<p>For models that are built using multi-state data, validation data for some segments of risk is likely to have low credibility in individual states. Nevertheless, some regulators require model validation on State-only data, especially when analysis using state-only data contradicts the countrywide results. State-only data might be more applicable but could also be impacted by low credibility for some segments of risk.</p> <p>Look for geographic stability measures, e.g., across states or territories within state.</p>
B.4.b	Obtain a description of any adjustments that were made in the data with respect to scaling for discrete variables or binning the data.	2	A.3.f addresses pre-modeling adjustments to data. In the mid-level narrative context, B.2.a addresses judgments of any kind made during modeling. Only choices made at "crucial points in model development" need be discussed.
B.4.c	Obtain a description of any transformations made for continuous variables.	2	<p>A.3.f addresses pre-modeling transformations to data. In the mid-level narrative context, B.2.a addresses transformations of any kind made during modeling. Only choices made at "crucial points in model development" need be discussed.</p> <p>To build a unique model with acceptable goodness-of-fit to the training data, important steps have been taken. Such steps may have been numerous, and at least some of the judgments involved may be difficult to describe and explain. Nevertheless, neither the model filer nor the reviewer can assume these steps are immaterial, generally understood, or implied by the model's generic form. The model filer should anticipate regulatory concerns in its initial submission by identifying and explaining the model fitting steps it considers most important. If a reviewer has regulatory concerns not resolved by the initial submission, appropriate follow up inquiries are likely to depend on the particular circumstances.</p>

<p>B.4.d</p>	<p>For each discrete variable level, review the parameter value, confidence intervals, chi-square tests, p-values and any other relevant and material tests. Determine if model development data, validation data, test data or other data was used for these tests.</p>	<p>1</p>	<p>Typical p-values greater than 5% are large and should be questioned. Reasonable business judgment can sometimes provide legitimate support for high p-values. Reasonableness of the p-value threshold could also vary depending on the context of the model, e.g., the threshold might be lower when many candidate variables were evaluated for inclusion in the model.</p> <p>Overall lift charts and/or statistical tests using validation data may not provide enough of the picture. If there is concern about one or more individual variables, the reviewer may obtain, for each discrete variable level, the parameter value, confidence intervals, chi-square tests, p-values and any other relevant and material tests. For variables that are modeled continuously, it may be sufficient to obtain statistics around the modeled parameters; for example, confidence intervals around each level of an AOI curve might be more than what is needed.</p>
<p>B.4.e</p>	<p>Identify the threshold for statistical significance and explain why it was selected. Obtain a reasonable and appropriately supported explanation for keeping the variable for each discrete variable level where the p-values were not less than the chosen threshold.</p>	<p>1</p>	<p>Typical p-values greater than 5% are large and should be questioned. Reasonable business judgment can sometimes provide legitimate support for high p-values. Reasonableness of the p-value threshold could also vary depending on the context of the model, e.g., the threshold might be lower when many candidate variables were evaluated for inclusion in the model.</p> <p>Overall lift charts and/or statistical tests using validation data may not provide enough of the picture. If there is concern about one or more individual variables, the reviewer may obtain, for each discrete variable level, the parameter value, confidence intervals, chi-square tests, p-values and any other relevant and material tests. For variables that are modeled continuously, it may be sufficient to obtain statistics around the modeled parameters; for example, confidence intervals around each level of an AOI curve might be more than what is needed.</p>

B.4.f	For overall discrete variables, review type 3 chi-square tests, p-values, F tests and any other relevant and material test. Determine if model development data, validation data, test data or other data was used for these tests.	2	<p>Typical p-values greater than 5% are large and should be questioned. Reasonable business judgment can sometimes provide legitimate support for high p-values. Reasonableness of the p-value threshold could also vary depending on the context of the model, e.g., the threshold might be lower when many candidate variables were evaluated for inclusion in the model.</p> <p>Overall lift charts and/or statistical tests using validation data may not provide enough of the picture. If there is concern about one or more individual variables, the reviewer may obtain, for each discrete variable level, the parameter value, confidence intervals, chi-square tests, p-values and any other relevant and material tests. For variables that are modeled continuously, it may be sufficient to obtain statistics around the modeled parameters; for example, confidence intervals around each level of an AOI curve might be more than what is needed.</p>
B.4.g	Obtain evidence that the model fits the training data well, for individual variables, for any relevant combinations of variables and for, the overall model.	2	<p>For a GLM, such evidence may be available using chi-square tests, p-values, F tests and/or other means.</p> <p>The steps taken during modeling to achieve goodness-of-fit are likely to be numerous and laborious to describe, but they contribute much of what is generalized about GLM. We should not assume we know what they did and ask "how?" Instead, we should ask what they did and be prepared to ask follow up questions.</p>
B.4.h	For continuous variables, provide confidence intervals, chi-square tests, p-values and any other relevant and material test. Determine if model development data, validation data, test data or other data was used for these tests.	2	<p>Typical p-values greater than 5% are large and should be questioned. Reasonable business judgment can sometimes provide legitimate support for high p-values. Reasonableness of the p-value threshold could also vary depending on the context of the model, e.g., the threshold might be lower when many candidate variables were evaluated for inclusion in the model.</p> <p>Overall lift charts and/or statistical tests using validation data may not provide enough of the picture. If there is concern about one or more individual variables, the reviewer may obtain, for each discrete variable level, the parameter value, confidence intervals, chi-square tests, p-values and any other relevant and material tests. For variables that are modeled continuously, it may be sufficient to obtain statistics around the modeled parameters; for example, confidence intervals around each level of an AOI curve might be more than what is needed.</p>

B.4.i	Obtain a description how the model was tested for stability over time.	2	<p>Evaluate the build/test/validation datasets for potential model distortions (e.g., a winter storm in year 3 of 5 can distort the model in both the testing and validation datasets).</p> <p>Obsolescence over time is a model risk. If a model being introduced now is based on losses from years ago, the reviewer should be interested in knowing whether that model would be predictive in the proposed context. Validation using recent data from the proposed context might be requested. Obsolescence is a risk even for a new model based on recent and relevant loss data. What steps, if any, were taken during modeling to prevent or delay obsolescence? What controls will exist to measure the rate of obsolescence? What is the plan and timeline for updating and ultimately replacing the model?</p>
B.4.j	Obtain a narrative on how were potential concerns with overfitting were addressed.	2	
B.4.k	Obtain support demonstrating that the GLM assumptions are appropriate.	2	<p>Visual review of plots of actual errors is usually sufficient.</p> <p>The reviewer should look for a conceptual narrative covering these topics: How does this particular GLM work? Why did the rate filer do what it did? Why employ this design instead of alternatives? Why choose this particular distribution function and this particular link function?</p>
B.4.l	Obtain 5-10 sample records with corresponding output from the model for those records.	3	
5. "Old Model" Versus "New Model"			
B.5.a	<p>Obtain an explanation why this model is an improvement to the current rating plan.</p> <p>If it replaces a previous model, find out why it is better than the one it is replacing; determine how the company reached that conclusion and identify metrics relied on in reaching that conclusion. Look for an explanation of any changes in calculations, assumptions, parameters, and data used to build this model from the previous model.</p>	1	Regulators should expect to see improvement in the new class plan's predictive ability or other sufficient reason for the change.
B.5.b	Determine if two Gini coefficients were compared and obtain a narrative on the conclusion drawn from this comparison.	3	One example of a comparison might be sufficient.
B.5.c	Determine if double lift charts analyzed and what conclusion was drawn from this analysis?	2	One example of a comparison might be sufficient.

B.5.d	<p>If replacing an existing model, obtain a list of any predictor variables used in the old model that are not used in the new model. Obtain an explanation why these variables were dropped from the new model.</p> <p>Obtain a list of all new predictor variables in the model that were not in the prior model.</p>	2	Useful to differentiate between old and new variables so the regulator can prioritize more time on factors not yet reviewed.
6. Modeler Software			
B.6.a	Request access to SMEs (e.g., modelers) who led the project, compiled the data, built the model, and/or performed peer review.	3	The filing should contain a contact that can put the regulator in touch with appropriate SMEs to discuss the model.

C. The Filed Rating Plan

Section	Information Element	Level of Importance to Regulator's Review	Comments
1. General Impact of Model on Rating Algorithm			
C.1.a	In the actuarial memorandum or explanatory memorandum, for each model and sub-model (including external models), look for a narrative that explains each model and its role in the rating system.	1	This item is particularly important, if the role of the model cannot be immediately discerned by the reviewer from a quick review of the rate and/or rule pages. (Importance is dependent on state requirements and ease of identification by the first layer of review and escalation to the appropriate review staff.)
C.1.b	Obtain an explanation of how the model was used to adjust the rating algorithm.	1	Models are often used to produce factor-based indications, which are then used as the basis for the selected changes to the rating plan. It is the changes to the rating plan that create impacts. Consider asking for an explanation of how the model was used to adjust the rating algorithm.
C.1.c	Obtain a complete list of characteristics/variables used in the proposed rating plan, including those used as input to the model (including sub-models and composite variables) and all other characteristics/variables (not input to the model) used to calculate a premium. For each characteristic/variable, determine if it is only input to the model, whether it is only a separate univariate rating characteristic, or whether it is both input to the model and a separate univariate rating characteristic. The list should include transparent descriptions (in plain language) of each listed characteristic/variable.	1	Examples of variables used as inputs to the model and used as separate univariate rating characteristics might be criteria used to determine a rating tier or household composite characteristic.
2. Relevance of Variables and Relationship to Risk of Loss			
C.2.a	Obtain a narrative how the characteristics/rating variables, included in the filed rating plan, logically and intuitively relate to the risk of insurance loss (or expense) for the type of insurance product being priced.	2	The narrative should include a discussion of the relevance each characteristic/rating variable has on consumer behavior that would lead to a difference in risk of loss (or expense). The narrative should include a logical and intuitive relationship to cost, and model results should be consistent with the expected direction of the relationship. This explanation would not be needed if the connection between variables and risk of loss (or expense) has already been illustrated.

3. Comparison of Model Outputs to Current and Selected Rating Factors			
C.3.a	Compare relativities indicated by the model to both current relativities and the insurer's selected relativities for each risk characteristic/variable in the rating plan.	1	“Significant difference” may vary based on the risk characteristic/variable and context. However, the movement of a selected relativity should be in the direction of the indicated relativity; if not, an explanation is necessary as to why the movement is logical.
C.3.b	Obtain documentation and support for all calculations, judgments, or adjustments that connect the model's indicated values to the selected values.	1	The documentation should include explanations for the necessity of any such adjustments and explain each significant difference between the model's indicated values and the selected values. This applies even to models that produce scores, tiers, or ranges of values for which indications can be derived. This information is especially important if differences between model indicated values and selected values are material and/or impact one consumer population more than another.
C.3.c	For each characteristic/variable used as both input to the model (including sub-models and composite variables) and as a separate univariate rating characteristic, obtain a narrative how each was tempered or adjusted to account for possible overlap or redundancy in what the characteristic/variable measures.	2	Modeling loss ratio with these characteristics/variables as control variables would account for possible overlap. The insurer should address this possibility or other considerations, e.g., tier placement models often use risk characteristics/variables that are also used elsewhere in the rating plan. One way to do this would be to model the loss ratios resulting from a process that already uses univariate rating variables. Then the model/composite variables would be attempting to explain the residuals.
4. Responses to Data, Credibility and Granularity Issues			
C.4.a	Determine what, if any, consideration was given to the credibility of the output data.	2	At what level of granularity is credibility applied. If modeling was by-coverage, by-form or by-peril, explain how these were handled when there was not enough credible data by coverage, form or peril to model.
C.4.b	If the rating plan is less granular than the model, obtain an explanation why.	2	This is applicable if the insurer had to combine modeled output in order to reduce the granularity of the rating plan.
C.4.c	If the rating plan is more granular than the model, obtain an explanation why.	2	A more granular rating plan implies that the insurer had to extrapolate certain rating treatments, especially at the tails of a distribution of attributes, in a manner not specified by the model indications.

5. Definitions of Rating Variables			
C.5.a	Obtain a narrative on adjustments made to raw data, e.g., transformations, binning and/or categorizations. If adjustments were made, obtain the name of the characteristic/variable and a description of the adjustment.	2	
C.5.b	Obtain a complete list and description of any rating tiers or other intermediate rating categories that translate the model outputs into some other structure that is then presented within the rate and/or rule pages.	1	
6. Supporting Data			
C.6.a	Obtain aggregated state-specific, book-of-business-specific univariate historical experience data, separately for each year included in the model, consisting of, at minimum, earned exposures, earned premiums, incurred losses, loss ratios and loss ratio relativities for each category of model output(s) proposed to be used within the rating plan. For each data element, obtain an explanation whether it is raw or adjusted and, if the latter, obtain a detailed explanation for the adjustments.	3	For example, were losses developed/undeveloped, trended/untrended, capped/uncapped, etc? Univariate indications should not necessarily be used to override more sophisticated multivariate indications. However, they do provide additional context and may serve as a useful reference.
C.6.b	Obtain an explanation of any material (especially directional) differences between model indications and state-specific univariate indications.	3	Multivariate indications may be reasonable as refinements to univariate indications, but possibly not for bringing about significant reversals of those indications. For instance, if the univariate indicated relativity for an attribute is 1.5 and the multivariate indicated relativity is 1.25, this is potentially a plausible application of the multivariate techniques. If, however, the univariate indicated relativity is 0.7 and the multivariate indicated relativity is 1.25, a regulator may question whether the attribute in question is negatively correlated with other determinants of risk. Credibility of state data should be considered when state indications differ from modeled results based on a broader data set. However, the relevance of the broader data set to the risks being priced should also be considered. Borderline reversals are not of as much concern.

7. Consumer Impacts			
C.7.a	Obtain a listing of the top five rating variables that contribute the most to large swings in premium, both as increases and decreases.	2	These rating variables may represent changes to rate relativities, be newly introduced to the rating plan, or have been removed from the rating plan.
C.7.b	Determine if the insurer performed sensitivity testing to identify significant changes in premium due to small or incremental change in a single risk characteristic. If such testing was performed, obtain a narrative that discusses the testing and provides the results of that testing.	3	One way to see sensitivity is to analyze a graph of each risk characteristic's/variable's possible relativities. Look for significant variation between adjacent relativities and evaluate if such variation is reasonable and credible.
C.7.c	For the proposed filing, obtain the impacts on expiring policies and describe the process used by management, if any, to mitigate those impacts.	2	Some mitigation efforts may substantially weaken the connection between premium and expected loss and expense, and hence may be viewed as unfairly discriminatory by some states.
C.7.d	Obtain a rate disruption/dislocation analysis, demonstrating the distribution of percentage impacts on renewal business (create by rerating the current book of business).	2	<p>The analysis should include the largest dollar and percentage impacts arising from the filing, including the impacts arising specifically from the adoption of the model or changes to the model as they translate into the proposed rating plan.</p> <p>While the default request would typically be for the distribution/dislocation of impacts at the overall filing level, the regulator may need to delve into the more granular variable-specific effects of rate changes if there is concern about particular variables having extreme or disproportionate impacts, or significant impacts that have otherwise yet to be substantiated.</p> <p>See Appendix C for an example of a disruption analysis.</p>
C.7.e	Obtain exposure distributions for the model's output variables and show the effects of rate changes at granular and summary levels.	3	See Appendix C for an example of an exposure distribution.

C.7.f	Identify policy characteristics, used as input to a model or sub-model, that remain "static" over a policy's lifetime versus those that will be updated periodically. Obtain a narrative on how the company handles policy characteristics that are listed as "static," yet change over time.	3	<p>Some examples of "static" policy characteristics are prior carrier tenure, prior carrier type, prior liability limits, claim history over past X years, or lapse of coverage. These are specific policy characteristics usually set at the time new business is written, used to create an insurance score or to place the business in a rating/underwriting tier, and often fixed for the life of the policy. The reviewer should be aware, and possibly concerned, how the company treats an insured over time when the insured's risk profile based on "static" variables changes over time but the rate charged, based on a new business insurance score or tier assignment, no longer reflect the insured's true and current risk profile.</p> <p>A few examples of "non-static" policy characteristics are age of driver, driving record and credit information (FCRA related). These are updated automatically by the company on a periodic basis, usually at renewal, with or without the policyholder explicitly informing the company.</p>
C.7.g	Obtain a means to calculate the rate charged a consumer.	3	The filed rating plan should contain enough information for a regulator to be able to validate policy premium. However, for a complex model or rating plan, a score or premium calculator via Excel or similar means would be ideal, but this could be elicited on a case-by-case basis. Ability to calculate the rate charged could allow the regulator to perform sensitivity testing when there are small changes to a risk characteristic/variable. Note that this information may be proprietary.
8. Accurate Translation of Model into a Rating Plan			
C.8.a	Obtain sufficient information to understand how the model outputs are used within the rating system and to verify that the rating plan, in fact, reflects the model output and any adjustments made to the model output.	1	

VIII. PROPOSED CHANGES TO THE *PRODUCT FILING REVIEW HANDBOOK*

~~TBD—placeholder to include best practices for review of predictive models and analytics filed by insurers to justify rates~~

The Task Force was charged to propose modifications to the 2016 *Product Filing Review Handbook* to reflect best practices for the regulatory review of predictive analytics. The following are the titled sections in Chapter Three “The Basics of Property and Casualty Rate Regulation.” Proposed changes are shown as tracked changes.

Product Filing Review Handbook, August 2016 CHAPTER THREE The Basics of Property and Casualty Rate Regulation

No changes are proposed to the following sections at the beginning of Chapter Three: **Introduction; Rating Laws; Rate Standards; Rate Justification and Supporting Data; Number of Years of Historical Data; Segregation of Data; Data Adjustments; Premium Adjustments; Losses and LAE (perhaps just DCC) Adjustments; Catastrophe or Large Loss Provisions; Loss Adjustment Expenses; Data Quality; Rate Justification: Overall Rate Level; Contingency Provision; Credibility; Calculation of Overall Rate Level Need; Methods (Pure Premium and Loss Ratio Methods); Rate Justification: Rating Factors; Calculation of Deductible Rating Factors; Calculation of Increased Limit Factors; and Credibility for Rating Factors.**

Interaction between Rating Variables (Multivariate Analysis)

If the pricing of rating variables is evaluated separately for each rating variable, there is potential to miss the interaction between rating variables. Care should be taken to have a multivariate analysis when practical. In some instances, a multivariate analysis is not possible. But, with computing power growing exponentially, insurers are finding many ways to improve their operations and competitiveness through use of often very complex predictive models in all areas of their insurance business.

Approval of Classification Systems

With rate changes, companies sometimes propose revisions to their classification system. Because the changes to classification plans can be significant and have large impacts on the consumers’ rates, regulators should focus on these changes.

Some items of proposed classification can sometimes be deemed to be against public policy, such as the use of education or occupation. You should be aware of your state’s laws and regulations regarding which rating factors are allowed. Finding rating or underwriting characteristics that may violate public policy is becoming more difficult for regulators with the increasing and innovative ways insurers use predictive models.

Rating Tiers

Some states allow an insurer to have multiple rate levels, or rating tiers, within a single company. These rating tiers are another way of classifying risks for rating purposes. Typically, there are requirements for rating tiers: the underwriting rules for each tier should be mutually exclusive, clear, and objective; there should be a distinction between the expected losses or expenses for each tier; and the placement process should be auditable. Tiers within a company are mainly seen in personal lines products.

One particular concern with rating tiers would be the analyses of whether a plan produces unfair discrimination. Questions arise around the time-sensitive aspects of the underwriting criteria and any related re-evaluation of the tiers upon renewal. For example, consider two tiers where the insured is placed in the “high” tier because of a lapse of insurance in the prior 12 months. The question is: What happens upon renewal after there has no longer been a lapse of insurance for 12 months? Does the insured get slotted in the “low” tier as he would if he was new business? Some statutes limit the amount of time that violations, loss history, or insurance scores can be used, and some statutes might only allow credit history to be used for re-

Commented [DK1]: EXPOSURE NOTE: Comments are being considered on the 5/14/19 draft of the white paper. Please note that we expect to make changes to the 5/14 draft in consideration of written comments. Many of those changes will also need to be consistently made in this section of the paper.

Commented [DK2]: The most recent Product Filing Review Handbook can be found at this link: https://www.naic.org/documents/prod_serv_marketreg_pfr_hdb.pdf

Commented [DK3]: Should review this section; seems outdated.

Commented [DK4]: page 30 of Handbook

Commented [DK5]: page 30 of Handbook

Commented [DK6]: - page 30 of Handbook (no changes are proposed)

rating at the policyholder's request. Regulators should consider the acceptability of differences in rates between existing and new policyholders when they have the same current risk profile.

Insurers also can create different rating levels by having separate companies within a group. While regulators should examine rating tiers within an insurer to a high degree of regulatory scrutiny, there tends to be less scrutiny with differences in rates that exist between affiliated companies. Workers' compensation insurers are more likely to obtain rating tiers using separate companies.

Rate Justification: New Products – (No change is proposed.)

Predictive Modeling

Commented [DK7]: -- page 32 of Handbook

The ability of computers to process massive amounts of data has led to the expansion of the use of predictive modeling in insurance ratemaking. Predictive models have enabled insurers to build rating, marketing, underwriting and claim models with significant segmentation predictive power and are increasingly being applied in such areas as claims modeling and used in helping insurers to price risks more effectively.

Key new rating variables that are being incorporated into insurers' predictive models include homeowners' rates by peril, homeowners rating by building characteristics, vehicle history, usage-based auto insurance, and credit characteristics.

Data quality within and communication about models are of key importance with predictive modeling. Depending on definitional boundaries, predictive modeling can sometimes overlap with the field of machine learning. In the modeling space, predictive modeling is often referred to as predictive analytics.

Insurers' use of predictive analytics along with big data has significant potential benefits to both consumers and insurers. Predictive analytics can reveal insights into the relationship between consumer behavior and the cost of insurance, lower the cost of insurance for many, and provide incentives for consumers to better control and mitigate loss. However, predictive analytic techniques are evolving rapidly and leaving many regulators without the necessary tools to effectively review insurers' use of predictive models in insurance applications. To aid the regulator in the review of predictive models, best practices have been developed along with specific information that will aid the regulator in their review of predictive models (specifically generalized linear models or "GLMs") for private passenger automobile and homeowners' insurance applications.

The term "predictive model" refers to a set of models that use statistics to predict outcomes. Then applied to insurance, the model is chosen to estimate the probability or expected value of an outcome given a set amount of input data; for example, models can predict the frequency of loss, the severity of loss, or the pure premium.

To further complicate regulatory review of models in the future, modeling methods are evolving rapidly and not limited just to GLMs. As computing power grows exponentially, it is opening up the modeling world to more sophisticated forms of data acquisition and data analysis. Insurance actuaries and data scientists seek increased predictiveness by using even more complex predictive modeling methods. Examples of these are predictive models utilizing random forests, decision trees, neural networks, or combinations of available modeling methods (often referred to as ensembles). These evolving techniques will make the regulators' understanding and oversight of filed rating plans incorporating predictive models even more challenging.

A. Generalized Linear Models

The generalized linear model (GLM) is a commonly used predictive model in insurance applications, particularly in building an insurance product's rating plan. Because of this and the fact most Property and Casualty regulators are most concerned about personal lines, NAIC has developed a white paper for guidance⁹ in reviewing GLMs for Home and private passenger automobile insurance.

Before GLMs became vogue, rating plans were built using univariate methods. Univariate methods were considered rational and easy to demonstrate the relationship to costs (loss and/or expense). However, many consider univariate methods too simplistic since they do not take into account the interaction (or dependencies) of the selected input variables. GLMs introduce significant improvements over univariate-based rating plans by automatically adjusting for correlations among

⁹ Refer to NAIC's white paper titled Regulatory Review of Predictive Models, found at the NAIC website.

input variables. Today, the majority of predictive models used in private passenger automobile and home insurance rating plans are GLMs. But, GLM results are not always rational and the relationship to costs may be difficult to explain.

A GLM consists of three elements:

- Each component of Y is independent and a probability distribution from the exponential family, or more generally, a selected variance function and dispersion parameter.
- A linear predictor $\eta = X\beta$.
- A link function g such that $E(Y) = \mu = g^{-1}(\eta)$.

As can be seen in the description of the three GLM components above, it may take more than a casual introduction to statistics to comprehend the construction of a GLM. As stated earlier, a downside to GLMs is that it is more challenging to interpret the GLMs output than with univariate models.

B. Credibility of Model Output

GLM software provides point estimates and allows the modeler to consider standard errors and confidence intervals. GLM output is typically assumed to be 100% credible no matter the size of the underlying data set. If some segments have little data, the resulting uncertainty would not be reflected in the GLM parameter estimates themselves (although it might be reflected in the standard errors, confidence intervals, etc.). Even though the process of selecting relativities often includes adjusting the raw GLM output, the resultant selections are not then credibility-weighted with any complement of credibility. Nevertheless, selected relativities based on GLM model output may differ from GLM point estimates.

Because of this presumption in credibility, which may or may not be valid in practice, the modeler and the regulator reviewing the model would need to engage in thoughtful consideration when incorporating GLM output into a rating plan to ensure that model predictiveness is not compromised by any lack of actual credibility. Therefore, to mitigate the risk that model credibility or predictiveness is lacking, a complete filing for a rating plan that incorporates GLM output should include validation evidence for the rating plan, not just the statistical model.

C. What is a “Best Practice”?

A best practice is a form of program evaluation in public policy. At its most basic level, a practice is a “tangible and visible behavior... [based on] an idea about how the actions... will solve a problem or achieve a goal”¹⁰. Best practices can maintain quality as an alternative to mandatory legislated standards and can be based on self-assessment or benchmarking.¹¹ Therefore, a best practice represents an effective method of problem solving. The “problem” regulators want to solve is probably better posed as seeking an answer to this question: How can regulators determine that predictive models, as used in rate filings, are compliant with state laws and regulations? However, best practices are not intended to create standards for filings that include predictive models.

Best practices are based on the following principles that promote a comprehensive and coordinated review of predictive models across states:

- State insurance regulators will maintain their current rate regulatory authority.
- State insurance regulators will be able to share information to aid companies in getting insurance products to market more quickly.
- State insurance regulators will share expertise and discuss technical issues regarding predictive models.
- State insurance regulators will maintain confidentiality, where appropriate, regarding predictive models.

D. Regulatory Review of Predictive Models

The knowledge needed to review predictive models, and guidance regarding GLMs for personal automobile and home insurance may be transferrable when the review involves GLMs applied to other lines of business. Modeling depends on context, so the GLM reviewer has to be alert for data challenges and business applications that differ from the most familiar personal lines. For example, compared to personal lines, modeling for rates in commercial lines is more likely to encounter

¹⁰ Bardach, E. and Patashnik, E. (2016.) *A Practical Guide for Policy Analysis, The Eightfold Path to More Effective Problem Solving*. Thousand Oaks, CA: CQ Press. See Appendix A for an overview of Bardach’s best-practice analysis.

¹¹ Bogan, C.E. and English, M.J. (1994). *Benchmarking for Best Practices: Winning Through Innovative Adaptation*. New York: McGraw-Hill.

low volumes of historical data, dependence on advisory loss costs, unique large accounts with some large deductibles and products that build policies from numerous line-of-business and coverage building blocks. Commercial lines commonly use individual risk modifications following experience, judgment, and/or expense considerations. A regulator may never see commercial excess and surplus lines filings. The legal and regulatory constraints (including state variations) are likely to be more evolved, and challenging, in personal lines. A GLM rate model for personal lines in 2019 is either an update or a late-adopter's defensive tactic. Adopting GLM for commercial lines has a shorter history.

Guidance offered here might be useful (with deeper adaptations) when starting to review different types of predictive models. If the model is not a GLM, some listed items might not apply. Not all predictive models generate p-values or F tests. Depending on the model type, other considerations might be important. When transferring guidance to other lines of business and other types of model, unique considerations may arise depending on the context in which a predictive model is proposed to be deployed, the uses to which it is proposed to be put, and the potential consequences for the insurer, its customers and its competitors. This guidance does not delve into these possible considerations but regulators should be prepared to address them as they arise.

Best practices will help the regulator understand if a predictive model is cost based, if the predictive model is compliant with state law, and how the model improves the company's rating plan. Best practices can, also, make the regulator's review more consistent across states and more efficient, and assist companies in getting their products to market faster. With this in mind, the regulator's review of predictive models should:

1. Ensure that the factors developed based on the model produce rates that are not excessive, inadequate, or unfairly discriminatory.
 - a. Review the overall rate level impact of the revisions proposed based on the predictive model output in comparison to rate level indications provided by the filer.
 - b. Review the premium disruption for individual policyholders and how the disruptions can be explained to individual consumers.
 - c. Review the individual input characteristics to and output factors from the predictive model (and its sub-models), as well as, associated selected relativities to ensure they are not unfairly discriminatory.
2. Thoroughly review all aspects of the model including the source data, assumptions, adjustments, variables, and resulting output.
 - a. Determine that individual input characteristics to a predictive model are related to the expected loss or expense differences in risk. Each input characteristic should have an intuitive or demonstrable actual relationship to expected loss or expense.
 - b. Determine that the data used as input to the predictive model is accurate, including a clear understanding how missing values, erroneous values and outliers are handled.
 - c. Determine that any adjustments to the raw data are handled appropriately, including but not limited to, trending, development, capping, removal of catastrophes.
 - d. Determine that rating factors from a predictive model are related to expected loss or expense differences in risk. Each rating factor should have a demonstrable actual relationship to expected loss or expense.
 - e. Obtain a clear understanding how often each risk characteristic, used as input to the model, is updated and whether the model is periodically rerun, so model output reflects changes to non-static risk characteristics.
3. Evaluate how the model interacts with and improves the rating plan.
 - a. Obtain a clear understanding of the characteristics that are input to a predictive model (and its sub-models), their relationship to each other and their relationship to non-modeled characteristics/variables used to calculate a risk's premium.
 - b. Obtain a clear understanding of how the selected predictive model was built and why the insurer believes this type of model works in a private passenger automobile or homeowner's insurance risk application.
 - c. Obtain a clear understanding of how model output interacts with non-modeled characteristics/variables used to calculate a risk's premium.
 - d. Obtain a clear understanding of how the predictive model was integrated into the insurer's state rating plan and how it improves that plan.
 - e. For predictive model refreshes, determine whether sufficient validation was performed to ensure the model is still a good fit.

4. Enable competition and innovation to promote the growth, financial stability, and efficiency of the insurance marketplace.

a. Enable innovation in the pricing of insurance through acceptance of predictive models, provided they are actuarially sound and in compliance with state laws.

b. Protect the confidentiality of filed predictive models and supporting information in accordance with state law.

c. Review predictive models in a timely manner to enable reasonable speed to market.

E. Information Needed to Follow Best Practices

To assist the regulator in following each best practice, the Casualty Actuarial and Statistical Task Force created a white paper titled *Regulatory Review of Predictive Models*. The paper contains a list of information elements and considerations that should be useful during the review of a model underlying a rating plan. To further assist the regulator, the information elements were mapped into the best practices listed above in Section XV of the paper.

F. Confidentiality

Regulatory reviewers are required to protect confidential information in accordance with applicable State law. However, insurers should be aware that a rate filing might become part of the public record. Each state determines the confidentiality of a rate filing, supplemental material to the filing, when filing information might become public, the procedure to request that filing information be held confidentially, and the procedure by which a public records request is made. It is incumbent on an insurer to be familiar with each state's laws regarding the confidentiality of information submitted with their rate filing.

Advisory Organizations – (No change is proposed.)

Workers' Compensation Special Rules – (No change is proposed.)

Premium Selection Decisions

Commented [DK8]: – Pages 34-35 of Handbook

➤ Indicated Rate Change vs. Selected Rate Change

After applying credibility, the indicated rate change should reflect the company's best estimate of their premium needs given their current or expected book of business. However, insurance companies also have other business considerations including competition, marketing, legal concerns, impact of the rate change on retention, etc. A company might wish to deviate from their indicated rate change and should justify those decisions, within the constraints of the law.

➤ Capping and Transition Rules

With advances in technology, it is possible for companies to introduce capping of rates on individual policies with an aim toward gradually increasing policyholders' rates, rather than making large modifications all at one time. Similarly, premiums are often proposed to be modified when an insurer acquires another company's book of business or decides to move from or to an advisory organization's plan. These types of proposed capping are sometimes called "renewal premium capping," "rate capping," "a rate stability program," or "transition rules."

Transition rules for individual policyholders can get quite complex and you need to be aware of your state's positions on premium capping rules. Any premium capping and transition rules require weighing the pros and cons of the potential for unfair discrimination (with some customers not paying the rate commensurate with the risks they have) vs. rate stability for existing policyholders.

If premium capping or transition rules are allowed, additional decisions will need to be made:

- ⇒ Which rates should get capped?
- ⇒ Do rate decreases get capped? If so, what is the impact if the policyholder asks to be quoted as new business?
- ⇒ Do all rate increases get capped or only above a certain percentage?
- ⇒ How much time will lapse or how many renewal cycles will occur before the new rates are in place or different rating plans are merged?
- ⇒ Should the insured be told what the final premium will be once no more capping is applied?
- ⇒ How would exposure change be addressed? If the policyholder buys a new car or changes their liability limits, what is the impact on their rate capping?

⇒ How many rate-capping rules can be implemented at any given time?

When premium capping or transition rules have been incorporated, future indicated rate changes and rating factor analyses need to properly reflect the fully approved rate changes. If the overall approved rate change was +10%, yet capping resulted in only 8% being implemented in the first year, the remaining amount to recognize the full 10% should be reflected in the premium on-level adjustment. Otherwise, the indicated rate would be redundant.

Some states encourage more frequent filing of rate changes that can help to avoid the need of premium capping and transition rules. Some states might prefer capping of individual rating variables, rather than capping for individual policyholders.

Installment Plans – (No change is proposed.)

Policy Fees – (No change is proposed.)

Potential Questions to Ask Oneself as a Regulator

Commented [DK9]: – Page 35 of the Handbook

Every filing will be different and will result in different regulatory analyses. But the following are some questions the regulator might ask oneself in a rate filing review:

1. Regarding data:
 - a. Is the data submitted with the filing enough information for a regulatory review?
 - b. Is the number of years of experience appropriate?
 - c. Did the company sufficiently analyze and control their quality of data?
2. Regarding the support and justification of rates:
 - a. Did they propose rate changes without justification?
 - b. Are proposals based on judgment or competitive analysis? If so, are the results reasonable and acceptable? Are there inappropriate marketing practices?
 - c. Are the assumptions (loss development, trend, expense load, profit provision, credibility etc.) used to develop the rate indication appropriate? Are they supported with data and are deviations from data results sufficiently explained?
 - d. Is the weighting of data by year (or credibility) properly justified or does it appear random?
 - Is there more weight being placed on data in one year solely because it produces a higher indicated rate change?
 - If there are two indications being weighted together and one is for a rate increase and one is a rate decrease, is the weighting justified?
 - e. Is there satisfactory explanation about why a proposed rate change deviates from the indicated rate change?
3. Regarding differences in assumptions from previous filings:
 - a. Have methodologies changed significantly?
 - b. Are assumptions for the weighting of years or credibility significantly different? Or does there appear to be some manipulation to the rate indication?
4. Is there unfair discrimination?
 - a. Do classifications comply with state requirements?
 - b. Are proposed rates established so that different classes will produce the same underwriting results?

- c. [If predictive models are used in the rating plan, are there concerns related to input variables that are prohibited or proxies for prohibited variables?](#)
5. What do you need to communicate?
 - a. Can you explain why you are taking a specific action on the filing?
 - b. What do you need to tell the Consumer Services Department?
 - Can you explain the impact of the rate change on current business? How big is the company and how much of the market is impacted?
 - What are the biggest changes in the filing (and the ones on which consumer calls might be expected)?
 - What is the maximum rate change impact on any one policyholder?

Questions to Ask a Company

If you remain unsatisfied that the company has satisfactorily justified the rate change, then consider asking additional questions of the company. Questions should be asked of the company when they have not satisfied statutory or regulatory requirements in the state or when any current justification is inadequate and could have an impact on the rate change approval or the amount of the approval.

If there are additional items of concern, the company can be notified so they will make appropriate modifications in future filings.

[The CASTF white paper, *Regulatory Review of Predictive Models*, documents questions that a regular may want to ask when reviewing a model. These questions are listed in the Predictive Model – Information for Regulatory Review section of the white paper. Note that although the white paper focuses on GLMs for home and private passenger auto insurance, some of the concepts may be transferable to other types of models and/or other lines of business.](#)

Additional Ratemaking Information

The Casualty Actuarial Society (CAS) ~~has an~~ [and the Society of Actuaries \(SOA\) has](#) extensive examination syllabi ~~syllabus~~ that contains a significant amount of ratemaking information, on both the basic topics covered in this chapter and on advanced ratemaking topics. The CAS ~~and SOA~~ websites contains links to many of the papers included in the syllabi. Recommended reading is the *Foundations of Casualty Actuarial Science*, which contains chapters on ratemaking, risk classification, and individual risk rating.

Other Reading

Some additional background reading is recommended:

- *Foundations of Casualty Actuarial Science*, Fourth Edition (2001):
 - Chapter 1: Introduction
 - Chapter 3: Ratemaking
 - Chapter 6: Risk Classification
 - Chapter 9: Investment Issues in Property-Liability Insurance
 - Chapter 10: Only the section on Regulating an Insurance Company, pp. 777–787
- Casualty Actuarial Society (CAS) Statements of Principles, especially regarding property and casualty ratemaking.
- Casualty Actuarial Society (www.casact.org): “Basic Ratemaking.”
- American Institute for Chartered Property Casualty Underwriters: “Insurance Operations, Regulation, and Statutory Accounting,” Chapter Eight.
- Association of Insurance Compliance Professionals: “Ratemaking—What the State Filer Needs to Know.”
- Review of filings and approval of insurance company rates.
- [NAIC’s Casualty Actuarial and Statistical Task Force white paper: “Regulatory Review of Predictive Models.”](#)

Summary

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Commented [DK11]: -----REFERENCES INCLUDED IN THE WHITE PAPER WILL BE ADDED

Commented [DK12]: – Page 37 of the Handbook

Rate regulation for property/casualty lines of business requires significant knowledge of state rating laws, rating standards, actuarial science, statistical modeling and many data concepts.

- Rating laws vary by state, but the rating laws are usually grouped into prior approval, file and use or use and file (competitive), no file (open competition), and flex rating.
- Rate standards typically included in the state rating laws require that “Rates shall not be inadequate, excessive, or unfairly discriminatory.”
- A company will likely determine their indicated rate change by starting with historical years of underwriting data (earned premiums, incurred loss and loss adjustment expenses, general expenses) and adjusting that data to reflect the anticipated ultimate level of costs for the future time period covered by the policies. Numerous adjustments are made to the data. Common premium adjustments are on-level premium, audit, and trend. Common loss adjustments are trend, loss development, Catastrophe/large loss provisions, and an adjusting and other (A&O) loss adjustment expense provision. A profit/contingency provision is also calculated to determine the indicated rate change.
- Once an overall rate level is determined, the rate change gets allocated to the classifications and other rating factors.
- Individual risk rating allows manual rates to be modified by an individual policyholder’s own experience.
- Advisory organizations provide the underlying loss costs for companies to be able to add their own expenses and profit provisions (with loss cost multipliers) to calculate their insurance rates.
- Casualty Actuarial Society’s *Statement of Principles Regarding Property and Casualty Insurance Ratemaking* provides guidance and guidelines for the numerous actuarial decisions and standards employed during the development of rates.
- NAIC model laws also include special provisions for workers’ compensation business, penalties for not complying with laws, and competitive market analysis to determine whether rates should be subject to prior approval provisions.
- Best practices for reviewing predictive models are provided the CASTF white paper titled *Regulatory Review of Predictive Models*. Although the white paper focuses on GLMs for home and private passenger automobile insurance, some of the concepts may be transferrable to other types of models and/or other lines of insurance.

While this chapter provides an overview of the rate determination/actuarial process and regulatory review, state statutory or administrative rule may require the examiner to adopt different standards or guidelines than the ones described.

No additional changes are proposed to the *Product Filing Review Handbook*.

IX. PROPOSED STATE GUIDANCE

~~TBD placeholder for guidance for rate filings that are based on predictive model~~

This paper acknowledges that different states will apply the guidance within it differently, based on variations in the legal environment pertaining to insurance regulation in those states, as well as the extent of available resources, including staff members with actuarial and/or statistical expertise, the workloads of those staff members, and the time that can be reasonably allocated to predictive-model reviews. States with prior-approval authority over personal-lines rate filings often already require answers in connection with many of the information elements expressed in this paper. However, states – including those with and without prior-approval authority – may also use the guidance in this paper to choose which model elements to focus on in their reviews and/or to train new reviewers, as well as to gain an enhanced understanding of how predictive models are developed, supported, and deployed in their markets. Ultimately, the insurance regulators within each state will decide how best to tailor the guidance within this paper to achieve the most effective and successful implementation, subject to the framework of statutes, regulations, precedents, and processes that comprise the insurance regulatory framework in that state.

X. OTHER CONSIDERATIONS

During the development of this guidance, topics arose that are not addressed in this paper. These topics may need addressing during the regulator’s review of a predictive model. A few of these issues may be discussed elsewhere within NAIC. All of these issues, if addressed, will be handled by each state on a case-by-case basis. A sampling of topics for consideration in this section include:

- TBD: When are rating variables or rating plans too granular? How is granularity handled during the development of the model and during the selection of rate relativities file in a rating plan supported by a model?
- TBD: Discuss the scientific mindset of open inquiry and its relevance to the best practice white paper.
- TBD: Discuss correlation vs causality in general and in relation to ASOP 12.
- TBD: Will following guidance provided in this white paper increase or pressure state regulatory budgets adversely?
- TBD: Discussion of data mining being in conflict with standard scientific model and increase in "false positives."
- TBD: Explain how the insurer will help educate consumers to mitigate their risk.
- TBD: Identify sources to be used at "point of sale" to place individual risks within the matrix of rating system classifications. How can a consumer verify their own "point-of-sale" data and correct any errors?
- TBD: Discuss cost to filing company and state to have expertise and resources adequate to document and review all knowledge elements identified in this white paper.
- Other TBDs

XI. RECOMMENDATIONS GOING FORWARD

The following are examples of topics that may be included in the recommendations:

- TBD: Discuss confidentiality as it relates to filings submitted via SERFF
- TBD: Discuss confidentiality as it relates to state statutes and regulations.
- TBD: Discuss policyholder disclosure when complex predictive model underlies a rating plan.
- TBD: Discuss the need for NAIC to update and strengthen information-sharing platforms and protocols.
- TBD: Determine the means available to a consumer to correct or contest individual data input values that may be in error.
- TBD: Given an insurer's rating plan relies on a predictive model and knowing all characteristics of a risk, discuss a regulator's ability/need to audit/calculate the risk's premium without consultation with the insurer.
- Other TBDs

XII. APPENDIX A – BEST PRACTICE DEVELOPMENT

Best-practices development is a method for reviewing public policy processes that have been effective in addressing particular issues and could be applied to a current problem. This process relies on the assumptions that top performance is a result of good practices and these practices may be adapted and emulated by others to improve results¹².

The term “best practice” can be a misleading one due to the slippery nature of the word “best”. When proceeding with policy research of this kind, it may be more helpful to frame the project as a way of identifying practices or processes that have worked exceptionally well and the underlying reasons for their success. This allows for a mix-and-match approach for making recommendations that might encompass pieces of many good practices¹³.

Researchers have found that successful best-practice analysis projects share five common phases:

A. Scope

The focus of an effective analysis is narrow, precise and clearly articulated to stakeholders. A project with a broader focus becomes unwieldy and impractical. Furthermore, Bardach urges the importance of realistic expectations in order to avoid improperly attributing results to a best practice without taking into account internal validity problems.

B. Identify Top Performers

Identify outstanding performers in this area to partner with and learn from. In this phase, it is key to recall that a best practice is a tangible behavior or process designed to solve a problem or achieve a goal (i.e. reviewing predictive models contributes to insurance rates that are not unfairly discriminatory). Therefore, top performers are those who are particularly effective at solving a specific problem or regularly achieve desired results in the area of focus.

C. Analyze Best Practices

Once successful practices are identified, analysts will begin to observe, gather information and identify the distinctive elements that contribute to their superior performance. Bardach suggests it is important at this stage to distill the successful elements of the process down to their most essential idea. This allows for flexibility once the practice is adapted for a new organization or location.

D. Adapt

Analyze and adapt the core elements of the practice for application in a new environment. This may require changing some aspects to account for organizational or environmental differences while retaining the foundational concept or idea. This is also the time to identify potential vulnerabilities of the new practice and build in safeguards to minimize risk.

E. Implementation and evaluation

The final step is to implement the new process and carefully monitor the results. It may be necessary to make adjustments, so it is likely prudent to allow time and resources for this. Once implementation is complete, continued evaluation is important to ensure the practice remains effective.

¹² Ammons, D. N. and Roenigk, D. J. 2014. Benchmarking and Interorganizational Learning in Local Government. *Journal of Public Administration Research and Theory*, Volume 25, Issue 1. P 309-335. <https://doi.org/10.1093/jopart/muu014>

¹³ Bardach, E. and Patashnik, E. 2016. *A Practical Guide for Policy Analysis: The Eightfold Path to More Effective Problem Solving*. Thousand Oaks, CA. CQ Press.

XIII. APPENDIX B -- GLOSSARY OF TERMS

Adjusting Data - TBD

Control Factor - TBD

Data source - TBD

Double-lift chart - TBD

Exponential Family - TBD

Fair Credit Reporting Act – The Fair Credit Reporting Act (FCRA), 15 U.S.C. § 1681 (FCRA) is U.S. Federal Government legislation enacted to promote the accuracy, fairness and privacy of consumer information contained in the files of consumer reporting agencies. It was intended to protect consumers from the willful and/or negligent inclusion of inaccurate information in their credit reports. To that end, the FCRA regulates the collection, dissemination and use of consumer information, including consumer credit information.¹⁴ Together with the Fair Debt Collection Practices Act (FDCPA), the FCRA forms the foundation of consumer rights law in the United States. It was originally passed in 1970 and is enforced by the US Federal Trade Commission, the Consumer Financial Protection Bureau and private litigants.

Generalized Linear Model - TBD

Geodemographic - Geodemographic segmentation (or analysis) is a multivariate statistical classification technique for discovering whether the individuals of a population fall into different groups by making quantitative comparisons of multiple characteristics with the assumption that the differences within any group should be less than the differences between groups. Geodemographic segmentation is based on two principles:

Home Insurance – TBD

Insurance Data - TBD

Linear Predictor - TBD

Link Function - TBD

Non-Insurance Data - TBD

Offset Factor– TBD

Overfitting - TBD

1. People who live in the same neighborhood are more likely to have similar characteristics than are two people chosen at random.
2. Neighborhoods can be categorized in terms of the characteristics of the population that they contain. Any two neighborhoods can be placed in the same category, i.e., they contain similar types of people, even though they are widely separated.

PCA Approach (Principal Component Analysis) –The method creates multiple new variables from correlated groups of predictors. Those new variables exhibit little or no correlation between them—thereby making them potentially more useful in a GLM. A PCA in a filing can be described as “a GLM within a GLM.” One of the more common applications of PCA is geodemographic analysis, where many attributes are used to modify territorial differentials on, for example, a census block level.

Private Passenger Automobile Insurance – TBD

Probability Distribution - TBD

Rating Algorithm – TBD

¹⁴ Dlabay, Les R.; Burrow, James L.; Brad, Brad (2009). Intro to Business. Mason, Ohio: South-Western Cengage Learning. p. 471. ISBN 978-0-538-44561-0.

| Draft: ~~5/14~~7/24/2019

As adopted by the Casualty Actuarial and Statistical (C) Task Force on XX/XX/XX

Rating Plan – TBD

Rating System – TBD

Scrubbing data - TBD

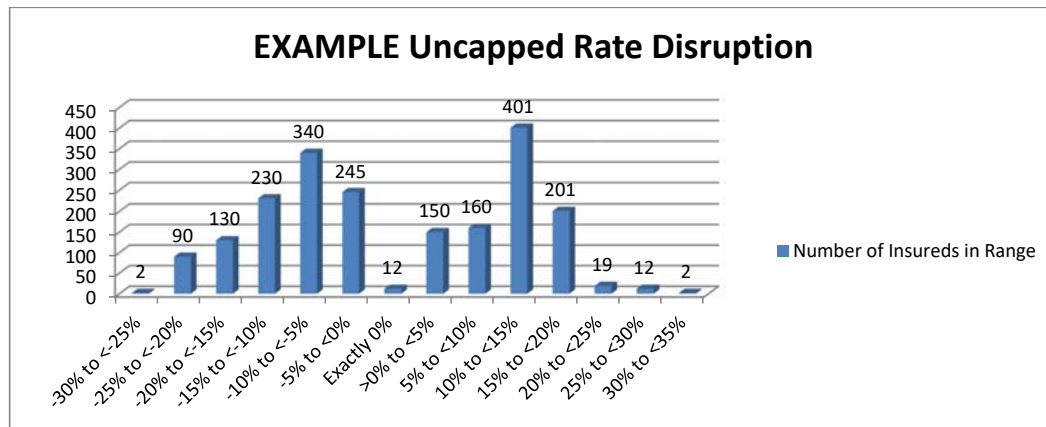
Sub-Model - any model that provides input into another model.

Univariate Model - TBD

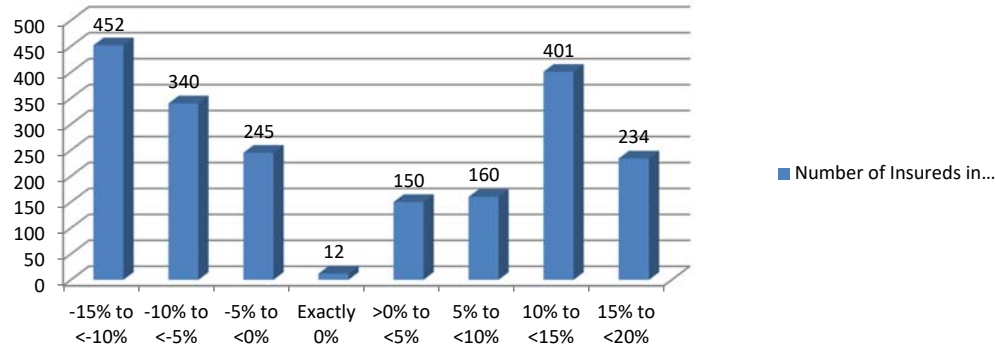
Etc.

XIV. APPENDIX C – SAMPLE RATE-DISRUPTION TEMPLATE

State Division of Insurance - EXAMPLE for Rate Disruption		<i>Template Updated October 2018</i>	
<ul style="list-style-type: none"> • First, fill in the boxes for minimum and maximum individual impacts, shaded in light blue. Default values in the cells are examples only. • The appropriate percent-change ranges will then be generated based on the maximum/minimum changes. • For every box shaded in light green, replace "ENTER VALUE" with the number of affected insureds within the corresponding change range. • Once all values are filled in, use the "Charts" feature in Excel to generate a histogram to visually display the spread of impacts. 			
NOTE: Values of Minimum % Change, Maximum % Change, and Total Number of Insureds must reconcile to the Rate/Rule Schedule in SERFF.			
	Uncapped		Capped (If Applicable)
Minimum % Change	-30.000%	Minimum % Change	-15.000%
Maximum % Change	30.000%	Maximum % Change	15.000%
Total Number of Insureds (Auto-Calculated)	1994	Total Number of Insureds (Auto-Calculated)	1994
	Uncapped Rate Disruption		Capped Rate Disruption (If Applicable)
Percent-Change Range	Number of Insureds in Range	Percent-Change Range	Number of Insureds in Range
-30% to <-25%	2	-15% to <-10%	452
-25% to <-20%	90	-10% to <-5%	340
-20% to <-15%	130	-5% to <0%	245
-15% to <-10%	230	Exactly 0%	12
-10% to <-5%	340	>0% to <5%	150
-5% to <0%	245	5% to <10%	160
Exactly 0%	12	10% to <15%	401
>0% to <5%	150	15% to <20%	234
5% to <10%	160		
10% to <15%	401		
15% to <20%	201		
20% to <25%	19		
25% to <30%	12		
30% to <35%	2		



EXAMPLE Capped Rate Disruption



State Division of Insurance - EXAMPLE for Largest Percentage Increase				Template Updated October 2018		
• Fill in fields highlighted in light green. Fields highlighted in red are imported from the Template for Rate Disruption.						
Largest Percentage Increase			Corresponding Dollar Increase (for Insured Receiving Largest Percentage Increase)			
Uncapped Change	30.00%	Uncapped Dollar Change	\$165.00	Current Premium	\$550.00	
Capped Change (if Applicable)	15.00%	Capped \$ Change (if Applicable)	\$82.50	Proposed Premium	\$632.50	
Characteristics of Policy (Fill in Below)						
• For Auto Insurance: At minimum, identify the age and gender of each named insured, limits by coverage, territory, make / model of vehicle(s), prior accident / violation history, and any other key attributes whose treatments are affected by this filing.						
• For Home Insurance: At minimum, identify age and gender of each named insured, amount of insurance, territory, construction type, protection class, any prior loss history, and any other key attributes whose treatments are affected by this filing.						
Automobile policy: Three insureds - Male (Age 54), Female (Age 49), and Male (Age 25). Territory: Las Vegas, ZIP Code 89105.						
Vehicle:	BI Limits:	PD Limits:	UM/UIM Limits:	MED Limits:	COMP Deductible:	COLL Deductible:
2009 Ford Focus	\$50,000 / \$100,000	\$25,000	\$50,000 / \$100,000	\$5,000	\$500	\$1,000
2003 Honda Accord	\$25,000 / \$50,000	\$10,000	\$25,000 / \$50,000	\$1,000	\$500	\$1,000
No prior accidents, 1 prior speeding conviction for 25-year-old male. Policy receives EFT discount and loyalty discount.						
Primary impacts are the increases to the relativities for the age of insured, ZIP Code 89105, COLL Deductible of \$1,000, and symbol for 2003 Honda Accord.						
Most Significant Impacts to This Policy (Identify attributes - e.g., base-rate change or changes to individual rating variables)						
NOTE: If capping is proposed to apply for this policy, include the impact of capping at the end, after displaying uncapped impacts by attribute. Add rows as needed. Total percent and dollar impacts should reconcile to the values presented above in this exhibit.						
Attribute	% Impact (Uncapped)	Dollar Impact (Uncapped)	What lengths of policy terms does the insurer offer in this book of business?			
Insured Age (M/25)	12.00%	\$66.00	Check all options that apply below. <input type="checkbox"/> 12-Month Policies <input checked="" type="checkbox"/> 6-Month Policies <input type="checkbox"/> 3-Month Policies <input type="checkbox"/> Other (SPECIFY)			
COLL Deductible (\$1,000)	10.00%	\$61.60				
Territory (89105)	4.00%	\$27.10				
Vehicle Symbol (2003 Honda Accord)	1.46%	\$10.29				
Effect of Capping	-11.54%	-\$82.50				
TOTAL	15.00%	\$82.50				

State Division of Insurance - EXAMPLE for Largest Dollar Increase				Template Updated October 2018		
• Fill in fields highlighted in light green.						
Largest Dollar Increase		Corresponding Percentage Increase (for Insured Receiving Largest Dollar Increase)				
Uncapped Change	\$306.60	Current Premium	\$2,555.00	Uncapped Percent Change	12.00%	
Capped Change (if Applicable)	\$306.60	Proposed Premium	\$2,861.60	Capped % Change (if Applicable)	12.00%	
Characteristics of Policy (Fill in Below)						
<ul style="list-style-type: none"> • For Auto Insurance: At minimum, identify the age and gender of each named insured, limits by coverage, territory, make / model of vehicle(s), prior accident / violation history, and any other key attributes whose treatments are affected by this filing. • For Home Insurance: At minimum, identify age and gender of each named insured, amount of insurance, territory, construction type, protection class, any prior loss history, and any other key attributes whose treatments are affected by this filing. 						
Automobile policy: Two insureds - Male (Age 33), Female (Age 32). Territory: Reno, ZIP Code 89504.						
Vehicle:	BI Limits:	PD Limits:	UM/UIM Limits:	MED Limits:	COMP Deductible:	COLL Deductible:
2016 Tesla Model S	\$200,000 / \$600,000	\$50,000	\$200,000 / \$600,000	\$10,000	\$2,500	\$2,500
2015 Mercedes-Benz C-Class (W205)	\$200,000 / \$600,000	\$50,000	\$200,000 / \$600,000	\$10,000	\$2,500	\$2,500
1 prior at-fault accident for 32-year-old female. Policy receives EFT discount and loyalty discount.						
Primary impacts are the increases to the relativities for the age of insured, symbol for 2015 Mercedes-Benz C-Class, and increased-limit factors for Property Damage and Medical Payments coverages.						
Most Significant Impacts to This Policy (Identify attributes - e.g., base-rate change or changes to individual rating variables)						
NOTE: If capping is proposed to apply for this policy, include the impact of capping at the end, after displaying uncapped impacts by attribute. Add rows as needed. Total percent and dollar impacts should reconcile to the values presented above in this exhibit.						
Attribute	% Impact (Uncapped)	Dollar Impact (Uncapped)				
Insured Age (M/33)	3.15%	\$80.48				
Insured Age (F/32)	3.23%	\$85.13				
Vehicle Symbol (2015 Mercedes-Benz C-Class)	2.45%	\$66.65				
Increased-Limit Factor for PD	1.55%	\$43.20				
Increased-Limit Factor for MED	1.10%	\$31.14				
TOTAL	12.00%	\$306.60				

XV. APPENDIX D – INFORMATION NEEDED BY REGULATOR MAPPED INTO BEST PRACTICES

TBD

XVI. APPENDIX E – REFERENCES

TBD