Interpretability of Predictive Models in Underwriting

Malika Shahrawat
David Moore, FSA, MAAA
October 27, 2020
SOCIETY OF ACTUARIES
Antitrust Compliance Guidelines

Active participation in the Society of Actuaries is an important aspect of membership. While the positive contributions of professional societies and associations are well-recognized and encouraged, association activities are vulnerable to close antitrust scrutiny. By their very nature, associations bring together industry competitors and other market participants.

The United States antitrust laws aim to protect consumers by preserving the free economy and prohibiting anti-competitive business practices; they promote competition. There are both state and federal antitrust laws, although state antitrust laws closely follow federal law. The Sherman Act, is the primary U.S. antitrust law pertaining to association activities. The Sherman Act prohibits every contract, combination or conspiracy that places an unreasonable restraint on trade. There are, however, some activities that are illegal under all circumstances, such as price fixing, market allocation and collusive bidding.

There is no safe harbor under the antitrust law for professional association activities. Therefore, association meeting participants should refrain from discussing any activity that could potentially be construed as having an anti-competitive effect. Discussions relating to product or service pricing, market allocations, membership restrictions, product standardization or other conditions on trade could arguably be perceived as a restraint on trade and may expose the SOA and its members to antitrust enforcement procedures.

While participating in all SOA in person meetings, webinars, teleconferences or side discussions, you should avoid discussing competitively sensitive information with competitors and follow these guidelines:

• Do not discuss prices for services or products or anything else that might affect prices
• Do not discuss what you or other entities plan to do in a particular geographic or product markets or with particular customers.
• Do not speak on behalf of the SOA or any of its committees unless specifically authorized to do so.
• Do leave a meeting where any anticompetitive pricing or market allocation discussion occurs.
• Do alert SOA staff and/or legal counsel to any concerning discussions
• Do consult with legal counsel before raising any matter or making a statement that may involve competitively sensitive information.

Adherence to these guidelines involves not only avoidance of antitrust violations, but avoidance of behavior which might be so construed. These guidelines only provide an overview of prohibited activities. SOA legal counsel reviews meeting agenda and materials as deemed appropriate and any discussion that departs from the formal agenda should be scrutinized carefully. Antitrust compliance is everyone’s responsibility; however, please seek legal counsel if you have any questions or concerns.
Presentation Disclaimer

Presentations are intended for educational purposes only and do not replace independent professional judgment. Statements of fact and opinions expressed are those of the participants individually and, unless expressly stated to the contrary, are not the opinion or position of the Society of Actuaries, its cosponsors or its committees. The Society of Actuaries does not endorse or approve, and assumes no responsibility for, the content, accuracy or completeness of the information presented. Attendees should note that the sessions are audio-recorded and may be published in various media, including print, audio and video formats without further notice.
Predictive Models in Underwriting

• Predictive (or machine learning) models make predictions without explicitly being programmed to do so by learning a model
• Rule-based systems work well but have limitations
• Applications: risk selection, decline, misrepresentation, voice analysis, etc.
The What and the Why

• Models can quickly produce highly accurate results without human touch
The What and the Why

- Models can quickly produce highly accurate results without human touch
- But these decisions affect real people, do we only just care about the predictions?
The What and the Why

• Models can quickly produce highly accurate results without human touch

• But these decisions affect real people, do we only just care about the predictions?

• This is not a low risk environment, so we do want to know and understand the why

• Reasons behind predictions, underlying data trends, and where a predictive model shouldn’t be used or trusted
How can we achieve interpretability?

• The best performing models can be complex and often a black box
• Use less complex models forgoing high performance
• Or find ways to best understand the driving factors behind model predictions
Tools for Interpretability

- Model-agnostic allow for independence and flexibility
- Variable importance
- Partial Dependence Plots
- Tools such as SHAP and LIME
- Not inclusive!
Tools for Interpretability: PDPs

- Partial Dependence Plots (PDPs) show the marginal effect of one or two features on a prediction (global relationship)
- Intuitive and easy to interpret (and implement)
- Can realistically only interpret two features at a time and assumes independence
Tools for Interpretability: LIME

- LIME = Local interpretable model-agnostic explanations
- Uses local surrogate (more interpretable) models to approximate the predictions of the desired models and explain individual predictions
Tools for Interpretability: SHAP

- SHAP = SHapley Additive exPlanations
- Uses a game theory approach to explain a prediction of a data point by computing the contribution of each feature to the prediction
Building Trust

• We need to calibrate not only models but also trust
• Understanding predictive models’ capabilities and limits helps to understand where and when to use and trust the model
• Find the balance in transparency
Underwriter received standard prediction from model on a case

Underwriter is not convinced of the decision and has no explanation
Underwriter received standard prediction from model on a case

Underwriter is not convinced of the decision and has no explanation

Underwriter manually reviews the case

Underwriter looks through full case
Underwriter received standard prediction from model on a case

Underwriter is not convinced of the decision and has no explanation

Underwriter manually reviews the case

Underwriter looks through full case

Underwriter ultimately changes decision

Underwriter’s loses some trust in the model
Underwriter received standard prediction from model on a case

Underwriter is not convinced of the decision and has no explanation

Underwriter manually reviews the case

Underwriter looks through full case

Underwriter ultimately changes decision

Underwriter’s loses some trust in the model
<table>
<thead>
<tr>
<th>Underwriter received standard prediction from model on a case</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underwriter is not convinced of the decision and has no explanation</td>
</tr>
</tbody>
</table>

**With interpretability**

<table>
<thead>
<tr>
<th>Underwriter manually reviews the case</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underwriter looks through full case</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Underwriter ultimately changes decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underwriter’s loses some trust in the model</td>
</tr>
</tbody>
</table>
Building Trust

Underwriter ultimately changes decision

Underwriter's loses some trust in the model

Underwriter received standard prediction from model on a case

Underwriter is not convinced of the decision and has no explanation

Underwriter is not convinced of the decision but notes the explanation

Underwriter manually reviews the case

Underwriter looks through full case

Underwriter directly pinpoints reason behind model’s decision

With interpretability
Underwriter received standard prediction from model on a case

| Underwriter is not convinced of the decision and has no explanation | Underwriter is not convinced of the decision but notes the explanation |

**Underwriter manually reviews the case**

| Underwriter looks through full case | Underwriter directly pinpoints reason behind model’s decision |

**Underwriter ultimately changes decision**

| Underwriter’s loses some trust in the model | Underwriter understands the limitations of the model |
Predictive Model Interpretability

- What is the perspective of
  - Actuary
  - Business Leaders
  - Senior Management

- Transparency and challenges
Interpretability Defined:
Interpretability Defined:

There is NO mathematical definition of interpretability
The Rashomon Effect

- Four people, from different vantage points, witness an incident
- When they come to testify in court, they all report the same facts, but their stories of what happened are very different
- The Rashomon Effect is that there is often a multitude of different descriptions \([\text{equations } f(x)]\) in a class of functions giving about the same minimum error rate

Leo Breiman, Statistical Modeling : The Two Cultures, Statistical Science 2001, V16 #3
The Occam Dilemma

• Accuracy generally requires more complex prediction methods
• Simple and interpretable functions do not make the most accurate predictors

Leo Breiman, Statistical Modeling: The Two Cultures, Statistical Science 2001, V16 #3
Which means...

• A large data set will likely be able to produce several models that are very close in terms of accuracy
• The best models will be difficult to explain
Interpretability in the eyes of different stakeholders

• Many people are anchored in interpretable models:
  • Linear Regression
  • Logistic Regression
  • Decision Trees

• Data availability and computing powers mean we don’t need to be constrained to use easily interpretable techniques, however we need to be aware on the needs of the model users and stakeholders
Interpretability Challenges

• Regulatory view: If the model is a black box, how do we know what contributes to a decision or score? Is the model biased?
• Management view: Typically want high level summary of data, with the ability to dive deeper as needed. As models become more advanced, provided an accurate summarization can be challenging
• IT view: Can we just use automated machine learning
• Underwriter view: There is a lack of trust in model decisions, need more context to go along with decision from the model
Underwriting Case Study

- Underwriter is typically anchored in the existing or ‘traditional’ underwriting process
  - Requires model output that aligns with their way of thinking about the risk
  - Needs specific reasons to understand model output/decision, or else there is a lack of trust
Credit based model (TRL or LNRC)

High Risk

Medical based model (Part B questions, Rx data, etc.)

Low Risk
Interpreting Variable Importance

Illustrative Variable Importance Chart
Underwriting Case Study

• Model interpretation needs to be very specific to the circumstances of the case

• Data availability and computing powers mean we don’t need to be constrained to use easily interpretable techniques, however we need to be aware on the needs of the end user

• Even with precision, the interpretation can create mistrust
Underwriting Case Study

Using Rules in combination with models

• To bridge the traditional underwriting to the models, rules allow us to set boundaries that provide trust to end users
  • i.e. No one with a BMI over 33 can pass the model

• This can be a safe harbor, or provide additional security to the underwriting process

• Ideally, experience data can show many of the rules are not necessary
Discussion

• How can model development be altered to make predictive models easier to interpret, and therefore lead to a better business process?
Audience Questions?
Suggested Resources

• Interpretable Machine Learning: A Guide for Making Black Box Models Explainable, Christoph Molnar

• Statistical Modeling: The Two Cultures Leo Breiman
  http://www2.math.uu.se/~thulin/mm/breiman.pdf

• People + AI Guidebook: Explainability + Trust
  https://pair.withgoogle.com/chapter/explainability-trust/
Suggested Tools

• SHAP https://github.com/slundberg/shap
• LIME https://homes.cs.washington.edu/~marcotcr/blog/lime/
SOA
2020 VIRTUAL ANNUAL MEETING & EXHIBIT