**Deep Learning for Actuaries**

**Introduction**

Recent breakthroughs in artificial intelligence (AI) have been largely driven by neural networks, particularly deep learning frameworks. These techniques have revolutionized fields such as image recognition, natural language processing, and predictive analytics.

However, it can be difficult to apply neural networks in actuarial settings. First, neural networks are often considered "black boxes" because of their complex structure with thousands of parameters. Actuaries usually produce rating structures that clearly show how premiums and risk behave over different variables, as transparency and interpretability are crucial in actuarial work. Neural networks though only return a single prediction which makes it much more difficult to interpret model results and provide explanations to stakeholders. Second, most actuarial datasets have a tabular structure, consisting of structured numerical and categorical variables. It has been shown that neural networks and deep learning mainly excel in tasks such as image recognition and language processing <reference>. On tabular data, traditional models such as Generalized Linear Models (GLM) or tree-based models (e.g. Random Forest, GBM) usually perform better.

Recognizing these challenges, deep learning frameworks suited for actuarial problems and tabular data have been developed in the academic community. In this article, we discuss three of these frameworks: the Combined Actuarial Neural Network (CANN), LocalGLMNet and TabNet. We briefly explain the workings of these models and the pros and cons of each method.

**A brief intro to Neural Networks**

A neural network is a model inspired by the structure of the human brain. It consists of multiple layers of interconnected nodes (neurons) that process the data and aim to learn the relationships in the data. The three main components of a neural network are:

* **Input layer**: This is the layer that processes the input data. Each neuron in this layer represents a feature in the dataset (e.g., policyholder age, claim history, insured amount).
* **Hidden layers**: The hidden layers perform complex transformations on the data. Each neuron in a hidden layer takes inputs from the previous layer, applies a transformation and weighting, and then passes the result through an activation function.
* **Output layer**: The output layer produces the final prediction for the problem at hand.

Neural networks are usually trained ‘supervised’, meaning that we give the true labels of our problem to the model. So in a classification problem for example, we will provide the true labels which the model can compare to the predicted labels in a loss function. The neural network then learns by adjusting the weights of connections between the neurons to optimize the loss function.

**The Combined Actuarial Neural Network (CANN)**

The CANN model, as proposed by Wüthrich & Merz (2019) combines a GLM with a neural network. By using the GLM predictions, the neural network part aims to capture additional patterns that were not captured by the GLM. In the output layer, the final CANN prediction is then obtained by combining the GLM prediction (that arrives via a ‘skip connection’) with the neural network prediction. In this way, CANN retains the interpretability of GLMs while improving predictive performance.

**LocalGLMNet**

LocalGLMNet is another hybrid model designed for actuarial applications that was developed by Richman & Wüthrich (2023). Instead of producing a single set of fixed coefficients like a traditional GLM, it learns for each data record a distribution of local coefficients. For this the model uses attention weights, which are used in a neural network to determine the importance of different parts of the input data. By multiplying the attention weights with the input data, the structure of a GLM is maintained while allowing for more complex interactions. Furthermore, the attention weights can be used to generate local explanations that can help actuaries to explain results.

**TabNet**

Mention that there is increase in complexity: CANN/LocalGLMNet/TabNet

**Performance**

To evaluate these models, we applied them to an open source dataset for car insurance frequency. The results show that both CANN and LocalGLMNet outperform traditional GLMs in predictive accuracy while maintaining interpretability.

A comparison of model performance is provided in the following figure (to be added). Additionally, a GitHub repository will be linked for readers who want to explore the implementation in detail.

Show pros/cons from these models in a table?

**Conclusion**

Deep learning with neural networks has transformed many industries, but adoption in the actuarial field could be limited due to concerns about interpretability and suitability for tabular data. Models such as CANN, LocalGLMNet and TabNet aim to overcome these concerns by either combining the strengths of GLMs and neural networks or by specifically focusing on deep learning for tabular data. Our results demonstrate that these models have great potential to improve predictive performance while maintaining interpretability. Therefore, these techniques show a promising direction for actuaries that aim to leverage deep learning in their work.

**References**

Ronald Richman and Mario V. Wüthrich. 2023. LocalGLMnet: interpretable deep learning for tabular data. *\*Scandinavian Actuarial Journal\** 2023(1), 71–95.

Mario V. Wüthrich and Michael Merz. 2019. EDITORIAL: YES, WE CANN! *\*ASTIN Bulletin\** 49(1), 1-3.