Abstract

One of the impediments in advancing actuarial research and developing open source assets for insurance analytics is the lack of realistic publicly available datasets. In this work, we develop a workflow for synthesizing insurance datasets leveraging current neural network techniques. We evaluate the predictive modeling efficacy of datasets synthesized from publicly available data in the domains of general insurance pricing and life insurance shock lapse modeling. The trained synthesizers are able to capture representative characteristics of the real datasets. This workflow is implemented via an R interface to promote adoption by researchers and data owners.

Keywords synthetic data · generative adversarial networks · actuarial science

1 Introduction

With the increased interest in applying machine learning (ML) and predictive modeling techniques across all fields of actuarial science in recent years, access to data is becoming more important. Having access to realistic data from insurers allows researchers to tackle more practical problems and validate newly developed methodologies. If the data is also publicly available, it allows researchers and companies to open source their methodologies, which encourages others to build upon existing work. Furthermore, having a common collection of datasets for each research question allows the community to define the state of the art, benchmark new workflows, and measure progress.

Of course, much of the data in the industry is confidential and proprietary. While there are publicly available datasets, new datasets are hard to come by. Even if data owners are willing to share anonymized datasets, the effort involved in obsfuscating the data and navigating beauracracy may prevent them from doing so. We posit that, if there is an easy way for data owners to create “fake”, or synthesized, data that have characteristics similar to the real data, it would reduce friction in data disclosure.

While synthetic data generation is an active area of research in the broader ML community, with many recent results (see, e.g., Choi et al. [4], Park et al. [15], and Xu et al. [19]), research on synthesizing insurance datasets in particular is scarce. One notable example is Gabrielli and Wüthrich [7], which describes a methodology for fitting neural networks to claims history data. The authors provide a fitted model for researchers to generate data, and the model has been implemented as an R package [1]. However, it does not provide an easy way for a data owner to develop a new data generator from a different portfolio of claims.

In this paper, we propose a workflow to train a neural network-based data synthesizer using confidential data and generate data from the trained synthesizer. We utilize the CTGAN architecture proposed by Xu et al. [19], which is based on generative adversarial networks (GAN) [8], and introduce modifications along with pre- and post-processing transformations specific to insurance datasets. We introduce an extension of the ML
efficacy evaluation methodology from the CTGAN paper utilizing cross-validation, and evaluate our workflow on two publicly available datasets using this methodology. To promote adoption, we provide an R package and code templates for researchers and data owners to use.

The remainder of the paper is organized as follows. Section 2 provides brief overviews of GAN and CTGAN and introduces our workflow, Section 3 applies the workflow to two publicly available datasets, describes our evaluation methodology for ML efficacy, and evaluates the synthesized datasets with it, Section 4 discusses the data disclosure workflow and data privacy considerations, and Section 5 concludes.

2 Methodology

Our workflow is based on the CTGAN architecture with some modifications. As of the writing of this paper, CTGAN represents the state-of-the-art for synthesizing tabular data [19]. In this section, we provide a brief overview of GANs, the extensions of GAN that CTGAN proposes in order to train quality generative models for tabular data, and modifications we introduce to adopt the architecture for insurance datasets. We remark that neural network rudiments have been discussed extensively in the actuarial literature (see, for example, the survey by Richman [16], the lecture notes by Wüthrich and Buser [17], and references therein) and will not be covered here.

2.1 GAN Overview

GAN is generative modeling technique based on neural networks. In a typical setup, a generator network, $G(Z)$, takes some noise vector (usually sampled from a spherical Gaussian) as input, and outputs an instance of interest (which, in our case, is a row of data). A discriminator, or critic, network, $C(X)$ takes an instance (again, a row in our case) and outputs a scalar score that represents how likely it thinks the instance comes from the real data distribution. The generator and critic then play a “game” in which the former tries to create more realistic instances while the latter tries to identify the “fake” instances, much like the relationship between an art forger and a curator, where the instances of interest are paintings. In fact, in its original formulation, GANs are a minimax game in the formal sense, and one can write

$$\min_G \max_C V(C, G) = \mathbb{E}_{x \sim p_{\text{data}}(x)}[\log C(x)] + \mathbb{E}_{z \sim p_{z}(z)}[\log(1 - C(G(z)))],$$

(1)

where $V(C, G)$ denotes the value function. Figure 1 illustrates the relationship between the generator and the critic.

Again, in Equation (1), the critic $C$ aims to maximize the score it assigns to instances from the real data samples, while the generator $G$ maximize the score given by the critic to the samples it generates. In practice, we alternately optimize the two networks, fixing one while training the other. Once the generator and critic networks have been trained, one can input samples of $Z$ into the generator $G$ to obtain synthesized instances.

2.2 CTGAN

CTGAN, whose architecture we illustrate in Figure 2, proposes two novel techniques to improve tabular data generation: mode-specific normalization and conditional training-by-sampling.

Mode-specific normalization is designed to address the difficulty vanilla GAN has with modeling multi-modal distributions in numeric columns. It uses variational Gaussian mixture (VGM) modeling [11] to determine the number of modes for each column and normalize the values accordingly. During training, these encoded values are used in place of the original data; upon obtaining a synthesized dataset, the values are transformed back to the original scale.
To address imbalanced factor level frequencies in categorical columns, CTGAN employs a conditional training approach. In this scheme, the random selection of a column and one of its levels is encoded into a condition vector. This condition vector is used both as an input to the generator and a filtering condition for sampling from the real data distribution. To ensure that rare categorical levels are sampled evenly, the authors choose to sample according to the log-frequency of the categories; in other words, the frequency of each category is logged and then normalized.

In addition to these extensions, CTGAN also leverages recent advances in GAN training such as Wasserstein GAN with gradient penalty [9] and PacGAN [13], which improve learning stability and help avoid mode collapse, a scenario where the generator repeatedly generates similar instances without diversity.

2.3 Modifications for Insurance Datasets

We make one key modification to the CTGAN implementation to accommodate our domain specific datasets. During sampling of categories, we use the true data frequency rather than the log-frequency. We find that using log-frequency causes the synthesizer to unrealistically oversample rare categories.

To complete our workflow, we perform dataset-specific transformations before training the synthesizer and after the generated dataset is obtained. For insurance datasets, these include ensuring that numerical columns with few unique values are properly learned and that events and exposures are internally consistent. In the next section, we provide specific examples of these transformations.

3 Application Examples

We evaluate our methodology on two publicly available datasets: the first is the French Third-Party Liability (TPL) claim frequency dataset, which is a well studied pricing dataset first introduced in Charpentier [2]; the second is a dataset for life insurance shock lapse modeling originally provided as part of a Society of Actuaries (SOA) experience study [12]. Both of these datasets are available for download online. In the remainder of this section, we describe in detail our evaluation methodology, apply it to the two datasets, and discuss the results.

3.1 Evaluation of Predictive Modeling Efficacy

Our evaluation scheme extends the ML efficacy definition, described in Xu et al. [19] and first introduced by Esteban et al. [6], by introducing a cross-validation component. The process, illustrated in Figure 3, is as follows. First, we set up 10-fold cross validation on the modeling dataset, which we denote as $D$; in other words, we randomly split the dataset into 10 subsets of approximately equal size, which are referred to as folds $D^k$, $k = 1, \ldots, 10$. We define each $T^k_{\text{assessment}} := D^k$ as the assessment set, and the complement $T^k_{\text{analysis}} = D \setminus D^k$ as the analysis set. For each $k$, we train a generative model $G^k$ using $T^k_{\text{analysis}}$, and use it to generate a table $T^k_{\text{syn}}$, which has the same number of records as $T^k_{\text{analysis}}$. Then, we train two predictive models on $T^k_{\text{syn}}$ and $T^k_{\text{analysis}}$, obtaining models $M^k_{\text{syn}}$ and $M^k_{\text{analysis}}$, respectively. Each of the predictive models is then used to score $D^k$ to obtain an out-of-sample performance metric. Finally, we inspect these metrics to see how much worse the model trained from the synthetic data performs. For both examples, we

---

3.1 Evaluation of Predictive Modeling Efficacy

Our evaluation scheme extends the ML efficacy definition, described in Xu et al. [19] and first introduced by Esteban et al. [6], by introducing a cross-validation component. The process, illustrated in Figure 3, is as follows. First, we set up 10-fold cross validation on the modeling dataset, which we denote as $D$; in other words, we randomly split the dataset into 10 subsets of approximately equal size, which are referred to as folds $D^k$, $k = 1, \ldots, 10$. We define each $T^k_{\text{assessment}} := D^k$ as the assessment set, and the complement $T^k_{\text{analysis}} = D \setminus D^k$ as the analysis set. For each $k$, we train a generative model $G^k$ using $T^k_{\text{analysis}}$, and use it to generate a table $T^k_{\text{syn}}$, which has the same number of records as $T^k_{\text{analysis}}$. Then, we train two predictive models on $T^k_{\text{syn}}$ and $T^k_{\text{analysis}}$, obtaining models $M^k_{\text{syn}}$ and $M^k_{\text{analysis}}$, respectively. Each of the predictive models is then used to score $D^k$ to obtain an out-of-sample performance metric. Finally, we inspect these metrics to see how much worse the model trained from the synthetic data performs. For both examples, we

---

https://cellar.kasa.ai
use the default hyperparameters specified in the CTGAN paper. The code for the experiments in this section is available on GitHub.

3.2 TPL Claim Frequency Modeling

The TPL dataset consists of 678,013 records, each representing a motor insurance policy in a single year. The dataset contains various policy characteristics, exposures, and the claim counts associated with each policy. The modeling problem we consider is predicting the number of claims filed on each policy, i.e., the frequency component of a frequency-severity model. Prior to cross-validation, we employ pre-processing steps as outlined in Noll et al. [14] to address data quality issues and perform binning of variables. The variables and their transformations are listed in Table 1.

| Column     | Original type | Pre-processing               | Post-processing     |
|------------|---------------|------------------------------|---------------------|
| Claim count| Integer       | Upper bound by four, convert to categorical | Convert to Integer |
| Vehicle power | Categorical     | Bin                          | —                   |
| Vehicle age  | Numeric        | Bin                          | —                   |
| Bonus/malus | Numeric        | Bin                          | —                   |
| Vehicle brand| Categorical    | —                            | —                   |
| Vehicle gas  | Categorical    | —                            | —                   |
| Density     | Numeric        | Log                          | —                   |
| Exposure    | Numeric        | Upper bound by one           | —                   |

During training of the synthesizer, we treat the claim count variable, which takes five different values (0, 1, 2, 3, and 4) as a categorical variable. We find that this treatment allows the synthesizer to learn a more realistic distribution. When we treat the variable as numeric, the synthesized samples underrepresent policies with more than one claim.

In order to constrain training time, we take a subset of the analysis data in each fold by randomly sampling 100,000 rows. This results in training time of approximately 10 minutes, which we feel is reasonable for users to experiment with. During training, we use a minibatch size of 10,000.

After obtaining generated data from the trained synthesizer, we lower bound the exposure at one day (1/365), since the synthesizer may generate values less than zero.

A generalized linear model (GLM) is fit to the training data in each of the cross validation splits. The error distribution assumed is Poisson with the canonical log link function, and log policy exposures are used as the

\[ \text{https://github.com/kasaai/gen-syn} \]
offset term. Root mean squared error (RMSE) is used as the performance metric for comparing models. We remark that no variable selection or penalized regression techniques are employed, as our purpose is not to fine-tune a predictive model.

3.3 Shock Lapse Modeling

For the other example, we employ the data released with the SOA 2014 Post Level Term Lapse & Mortality Report [12]. This dataset contains aggregated experience from various companies for term life products from 2000 to 2012. Each row in the dataset represents a unique combination of study year, cell, and duration. Here, each cell represents a unique combination of policy and policyholder characteristics, including gender, issue age, and face amount, among others.

In level premium term life insurance, policyholders pay fixed premiums for a period of time (ten years in our case study) agreed upon at contract inception. At the end of the level term, these contracts usually convert to annually renewable term (ART), which means the premiums increase, typically significantly, year after year. The increase in premiums results in a phenomenon known as shock lapse, wherein insurers experience a higher lapse rate than during the level term, leading to decreased cashflows and a shift towards higher risk policyholders. Being able to forecast which policyholders are likely to lapse aids with risk management and assumptions setting at insurers, which motivates this example. The predictive modeling problem we consider involves predicting the number of policies that lapse at durations after the level term, using policy characteristics as predictors.

Following Kueker et al. [12], we perform further grouping of some categorical variables and convert some ordinal categorical variables, such as issue age and premium jump ratio, to numeric. The full list of predictors and their pre-processing transformations can be found in Table 2.

Table 2: Columns of the Lapse Study dataset and their transformations.

| Column       | Original type | Pre-processing            | Post-processing                                      |
|--------------|---------------|----------------------------|------------------------------------------------------|
| Lapse count  | Integer       | Divide by exposure         | Bound to [0, 1], multiply by exposure, and round    |
| Risk class   | Categorical   | Bin                        | —                                                    |
| Face amount  | Categorical   | —                          | —                                                    |
| Issue age    | Categorical   | Convert to numeric         | —                                                    |
| Premium jump ratio | Categorical       | Convert to numeric         | —                                                    |
| Duration     | Categorical   | —                          | —                                                    |
| Exposure     | Integer       | —                          | Lower bound by one                                  |

Recall that each row of the dataset represents a cell rather than an individual policy, which means they have a wide range of exposures and lapse counts. Also, each exposure can lapse at most once, which differs from the previous TPL case study. To accommodate these specifics, we introduce the following scheme for data generation. Prior to fitting the synthesizer, we compute the lapse rate, defined as the number of lapses divided by the number of policies, and use it in place of the actual lapse count. Once we have the synthesized dataset, we bound the lapse rate column below by zero and above by one. The lapse rate is then multiplied by the generated exposures (number of policies) and rounded to obtain an integer lapse count.

Similar to the TPL example, we use a Poisson GLM, and the (log) number of policies is used in the offset. RMSE is used as the performance metric.

3.4 Results & Discussion

In Figure 4 and Table 3, we exhibit the cross-validation performance of models built on synthetic and real data for the two case studies. We see that the models trained using the synthetic datasets perform similarly to those trained using the real datasets.
Figure 4: Box plots of cross-validated performance of models trained on real and synthetic data for the two case studies.

Table 3: Average cross-validated metrics of models trained on real and synthetic data.

| Dataset        | Mean RMSE (Real Data) | Mean RMSE (Synthetic Data) | Relative Difference |
|----------------|-----------------------|----------------------------|---------------------|
| TPL Frequency  | 0.2367                | 0.2419                     | 2.21%               |
| Shock Lapse    | 4.0038                | 4.0203                     | 0.41%               |

4 Workflow and Privacy

To encourage usage, we implement an R interface to the original Python implementation in the form of an open source package, ctgan\footnote{https://github.com/kasaai/ctgan}. We envisage this package to appeal to a variety of personas in the field. As examples, companies who are looking to crowd-source insights into their data gain an option for data disclosure, and researchers working with confidential data can release reproducible workflows along with a sample dataset. Depending on the use case, one can decide whether to share a single sample dataset, or release a trained synthesizer, containing the generator only, for users to generate data on demand. In the latter case, one can further choose whether to make available the generator’s parameters, or to expose the generator through a Web service, while keeping the model parameters private.

Assuming one has identified the dataset and performed necessary anonymization and pre-processing, an example workflow for data disclosure is as follows:

1. Train a synthesizer using ctgan
2. Sample a dataset using the synthesizer
3. Perform post-processing on the generated dataset
4. Share the data

In the case where one wishes to release the synthesizer itself, the steps would resemble the following:

1. Train a synthesizer using ctgan
2. Save the synthesizer model files
3. One of
a. Share the models files, along with post-processing code  
b. Provide access to a Web service that returns generated and post-processed datasets

The mode of data disclosure depends on the goals of the data owner and the degree to which the training data is already anonymized. The threat model we are interested in is that of membership inference attacks. Specifically, consider the case where an adversary has actual, but incomplete, information of an individual claim (e.g., a subset of claim characteristic variables), and also access to the data synthesizer. Would this adversary be able to reconstruct, with high confidence, the full information on that specific claim? If so, one may consider the event a privacy breach.

Data privacy with respect to GAN is an active area of research. Chen et al. [3] proposes a taxonomy of different extents of model disclosure and perform experiments on the efficacies of membership inference attacks on various architectures. Hayes et al. [10] and Hilprecht et al. [11] propose attacks on GANs for images to attempt to recover images used in training. Defenses to these attacks have also been proposed, such as PATE-GAN [20] and DPGAN [18], by making the discriminator differentially private [5].

While CTGAN, as implemented, is not differentially private, it can be extended to be so. We remark that, even without formal privacy guarantees, one can still avoid exposing personally identifiable information by removing unnecessary data, such as social security numbers and birth dates of claimants, before training. For an impactful attack to be theoretically possible, the adversary would need to obtain information on an individual through other means, and have access to the generator—either the model parameters or a sufficient number of queries to the Web service. The generator would also have to have been trained on granular enough data. In many cases, publishing a sampled dataset may suffice for the goals of the data provider; without the generator, vulnerabilities are minimized, and the provider can inspect the dataset prior to release to further ensure nothing confidential is exposed.

5 Conclusion

In this paper, we adopt a recent methodology, CTGAN, for synthesizing tabular data, to insurance datasets. We show that, with appropriate modifications, datasets generated using this methodology can achieve high ML efficacy on representative insurance datasets. To promote adoption within the insurance industry, we implement an open source R interface to utilize the technique.

While this paper focuses on generating datasets with scalar values, future work may include using generative modeling techniques to synthesize sequential data. Sequential data generation is particularly interesting for claims reserving research, where the instances of interest are cash flows over time. Related to data synthesis are privacy requirements in data disclosure. On this subject, interesting questions include what degree of privacy is needed for various types of data, and whether differential privacy is warranted in different scenarios.

References

[1] C. M. Bishop. Pattern recognition and machine learning. Springer Science+ Business Media, 2006.  
[2] A. Charpentier. Computational Actuarial Science with R. CRC Press, Aug. 2014. ISBN 978-1-4665-9260-5.  
[3] D. Chen, N. Yu, Y. Zhang, and M. Fritz. Gan-leaks: A taxonomy of membership inference attacks against gans. arXiv preprint arXiv:1909.03935, 2019.  
[4] E. Choi, S. Biswal, B. Malin, J. Duke, W. F. Stewart, and J. Sun. Generating multi-label discrete patient records using generative adversarial networks, 2017.  
[5] C. Dwork, A. Roth, et al. The algorithmic foundations of differential privacy. Foundations and Trends® in Theoretical Computer Science, 9(3–4):211–407, 2014.  
[6] C. Esteban, S. L. Hyland, and G. Rätsch. Real-valued (medical) time series generation with recurrent conditional gans, 2017.  
[7] A. Gabrielli and M. V. Wüthrich. An individual claims history simulation machine. Risks, 6(2):29, 2018.  
[8] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative adversarial nets. In Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, editors, Advances in Neural Information Processing Systems 27, pages 2672–2680. Curran Associates, Inc., 2014. URL http://papers.nips.cc/paper/5423-generative-adversarial-nets.pdf
[9] I. Gulrajani, F. Ahmed, M. Arjovsky, V. Dumoulin, and A. Courville. Improved training of wasserstein gans, 2017.

[10] J. Hayes, L. Melis, G. Danezis, and E. D. Cristofaro. Logan: Membership inference attacks against generative models, 2017.

[11] B. Hilprecht, M. Härterich, and D. Bernau. Reconstruction and membership inference attacks against generative models, 2019.

[12] D. Kueker, T. Rozar, M. Cusumano, S. Willeat, and R. Xu. Report on the lapse and mortality experience of post-level premium period term plans. Technical report, Society of Actuaries, May 2014. URL https://www.soa.org/resources/experience-studies/2014/research-2014-post-level-shock/.

[13] Z. Lin, A. Khetan, G. Fanti, and S. Oh. Pacgan: The power of two samples in generative adversarial networks, 2017.

[14] A. Noll, R. Salzmann, and M. V. Wuthrich. Case Study: French Motor Third-Party Liability Claims. SSRN Scholarly Paper ID 3164764, Social Science Research Network, Rochester, NY, Nov. 2018.

[15] N. Park, M. Mohammadi, K. Gorde, S. Jajodia, H. Park, and Y. Kim. Data synthesis based on generative adversarial networks. Proceedings of the VLDB Endowment, 11(10):1071–1083, Jun 2018. ISSN 2150-8097. doi: 10.14778/3231751.3231757. URL http://dx.doi.org/10.14778/3231751.3231757.

[16] R. Richman. Ai in actuarial science. 2018.

[17] M. V. Wüthrich and C. Buser. Data analytics for non-life insurance pricing. Swiss Finance Institute Research Paper, (16-68), 2019.

[18] L. Xie, K. Lin, S. Wang, F. Wang, and J. Zhou. Differentially private generative adversarial network. arXiv preprint arXiv:1802.06739, 2018.

[19] L. Xu, M. Skoulardou, A. Cuesta-Infante, and K. Veeramachaneni. Modeling Tabular data using Conditional GAN. arXiv:1907.00503 [cs, stat], June 2019.

[20] J. Yoon, J. Jordon, and M. van der Schaar. PATE-GAN: Generating synthetic data with differential privacy guarantees. In International Conference on Learning Representations, 2019. URL https://openreview.net/forum?id=S1zk9iRqF7.