



AI in Actuarial Science

Ronald Richman

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Agenda

- *Introduction*
- Machine Learning
- Deep Learning
- Applications in Actuarial Science
- Discussion and Conclusion



Introduction

- This talk is about 3 things:
 - Provide context to understand deep learning
 - Discuss applications of deep learning in actuarial science
 - Provide code to experiment (see last slide)
- Inspiration of paper and talk:

"The future of insurance will be staffed by bots rather than brokers and AI in favor of actuaries"- Daniel Schreiber, CEO, Lemonade Inc.

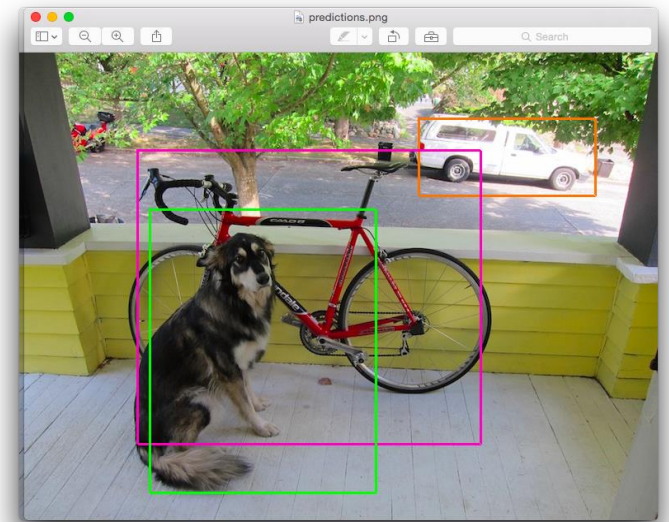
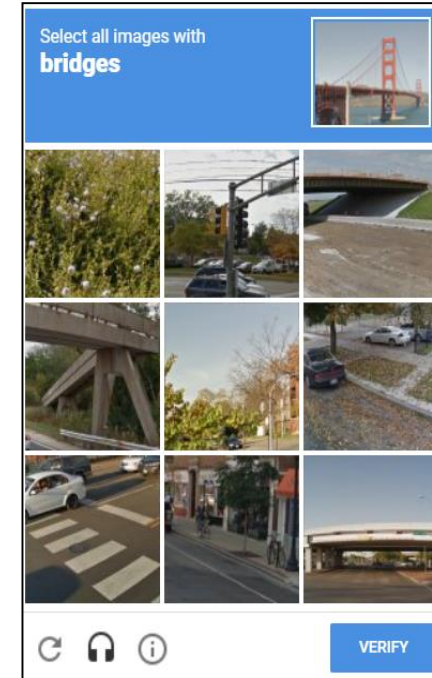


Deep Learning in the Wild

- We all use Deep Learning today:
 - Google/Apple/Facebook/Instagram/Pinterest...
 - ... and might use it more in the medium term (self-driving cars/medical applications)
- We help to train DL - Recaptcha
- DL is good enough to trick us
- But, are actuaries benefiting from Deep Learning?

Man from www.thispersondoesnotexist.com/

YOLO from <https://github.com/pjreddie/darknet/wiki/YOLO:-Real-Time-Object-Detection>



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Practical Successes of Deep Learning

- Computer vision starting with AlexNet architecture of Krizhevsky, Sutskever and Hinton (2012)
- Speech recognition (Hannun, Case, Casper et al. 2014).
- Natural language processing, e.g. Google's neural translation machine (Wu, Schuster, Chen et al. 2016)
- Winning method in 2018 M4 time series forecasting competition (Makridakis, Spiliotis and Assimakopoulos 2018a).
- Analysis of GPS data (Brébisson, Simon, Auvolat et al. 2015)
- Analysis of tabular data (Guo and Berkhahn 2016) (plus other Kaggle competitions)



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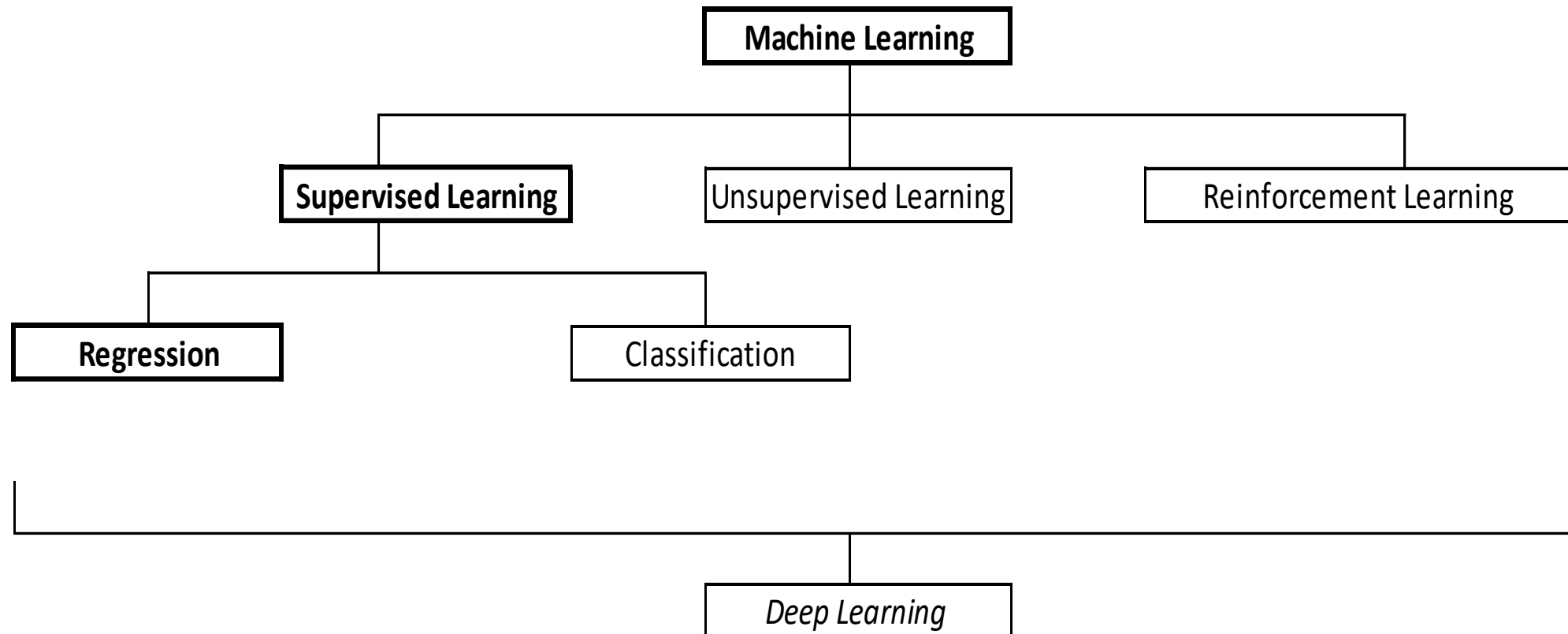


Machine Learning

- Machine Learning is concerned with “the study of algorithms that allow computer programs to automatically improve through experience” (Mitchell 1997)
 - Machine learning approach to AI - systems trained to recognize patterns within data to acquire knowledge (Goodfellow, Bengio and Courville 2016).
- Earlier attempts to build AI systems = hard code knowledge into knowledge bases
- But doesn't work for highly complex tasks e.g. image recognition, scene understanding and inferring semantic concepts (Bengio 2009)
- ML Paradigm – feed data to the machine and let it figure it out!



Map of Machine Learning





Supervised Learning

- Supervised learning = application of machine learning to datasets that contain features and outputs with the goal of predicting the outputs from the features (Friedman, Hastie and Tibshirani 2009).

y (outputs)			X (features)											
			IDpol	ClaimNb	Exposure	Area	VehPower	VehAge	DrivAge	BonusMalus	VehBrand	VehGas	Density	Region
1:	1	1	0.1000000000	D	5	0	55	50	B12	Regular	1217	R82		
2:	3	1	0.7700000000	D	5	0	55	50	B12	Regular	1217	R82		
3:	5	1	0.7500000000	B	6	2	52	50	B12	Diesel	54	R22		
4:	10	1	0.0900000000	B	7	0	46	50	B12	Diesel	76	R72		
5:	11	1	0.8400000000	B	7	0	46	50	B12	Diesel	76	R72		

678009:	6114326	0	0.002739726	E	4	0	54	50	B12	Regular	3317	R93		
678010:	6114327	0	0.002739726	E	4	0	41	95	B12	Regular	9850	R11		
678011:	6114328	0	0.002739726	D	6	2	45	50	B12	Diesel	1323	R82		
678012:	6114329	0	0.002739726	B	4	0	60	50	B12	Regular	95	R26		
678013:	6114330	0	0.002739726	B	7	6	29	54	B12	Diesel	65	R72		

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So, ML is just regression, right?

- Not exactly. ML relies on a different approach to building, parameterizing and testing statistical models, based on statistical learning theory. For other ideas – see Richman (2018)
- Distinction between tasks of predicting and explaining, see Shmueli (2010). Focus on predictive performance leads to:
 - Building algorithms to predict responses instead of specifying a stochastic data generating model (Breiman 2001)...
 - ... favouring models with good predictive performance at expense of interpretability.
 - Accepting bias in models if this is expected to reduce the overall prediction error.
 - Quantifying predictive error (i.e. out-of-sample error)



Unsupervised learning

- Unsupervised learning = application of machine learning to datasets containing only features to find structure within these datasets (Sutton and Barto 2018).
- Task of unsupervised learning is to find meaningful patterns using only the features.
- Recent examples:
 - modelling yield curves using Principal Components Analysis (PCA) for the Interest Rate SCR in SII
 - mortality modelling – Lee-Carter model uses PCA to reconstruct mortality curves



The ML Actuary

- Actuarial problems are often supervised regressions =>
- If an actuarial problem can be expressed as a regression, then machine and deep learning techniques can be applied:
 - P&C pricing
 - IBNR reserving
 - Experience analysis
 - Mortality modelling
 - Lite valuation models
- But don't forget about unsupervised learning either!

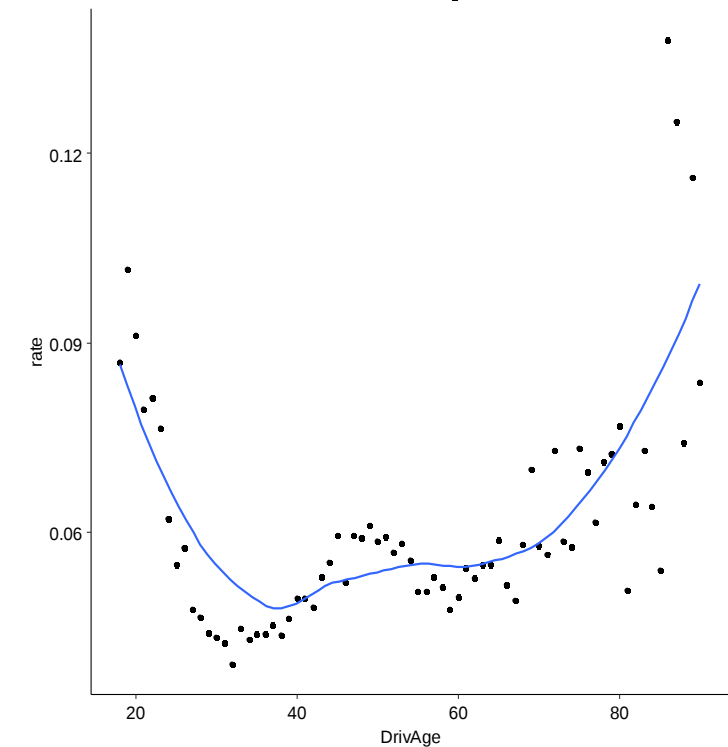


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Feature Engineering (Model Specification)

- Suppose we realize that Claims depends on $\text{Age}^2 \Rightarrow$ enlarge feature space by adding Age^2 to data. Other options – add interactions/basis functions e.g. splines





Representation learning

- In many domains, including actuarial science, traditional approach to designing machine learning systems relies on humans for feature engineering. But:
 - designing features is time consuming/tedious
 - relies on expert knowledge that may not be transferable to a new domain
 - becomes difficult with very high dimensional data
- Representation Learning = ML technique where algorithms automatically design features that are optimal for a particular task. Traditional examples are PCA (unsupervised) and PLS (supervised)
- Simple/naive RL approaches often fail when applied to high dimensional data



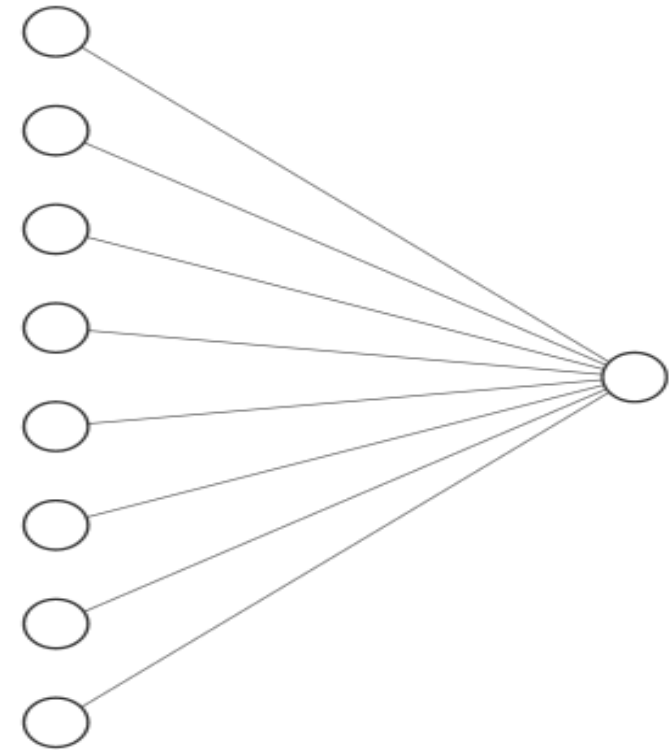
Deep Learning

- Deep Learning = representation learning technique that automatically constructs hierarchies of complex features
- Modern example of deep learning is feed-forward neural networks, which are multi-layered machine learning models, where each layer learns a new representation of the features.
- The principle: Provide data to the network and let it figure out what and how to learn.
- Desiderata for AI by Bengio (2009):
 - *“Ability to learn with little human input the low-level, intermediate, and high-level abstractions that would be useful to represent the kind of complex functions needed for AI tasks.”*



Single Layer NN = Linear Regression

- Single layer neural network
- Circles = variables
- Lines = connections between inputs and outputs
- Input layer holds the variables that are input to the network...
- ... multiplied by weights (coefficients) to get to result
- Single layer neural network is a linear regression!

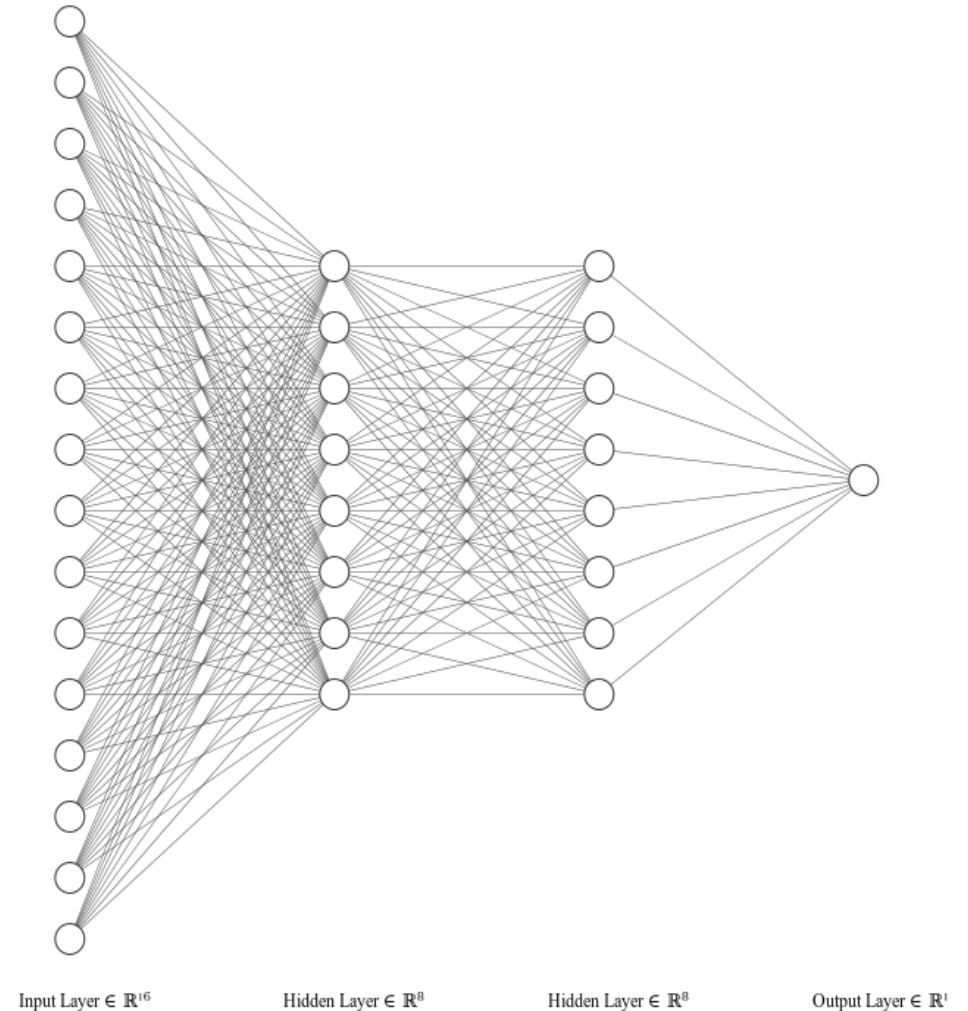


Input Layer $\in \mathbb{R}^8$



Deep Feedforward Net

- Deep = multiple layers
- Feedforward = data travels from left to right
- Fully connected network = all neurons in layer connected to all neurons in previous layer
- More complicated representations of input data learned in hidden layers
- Subsequent layers represent regressions on the variables in hidden layers





Embedding layers

- Several specialized types of neural networks depending on purpose
- Embedding layer learns dense vector transformation of sparse input vectors and clusters similar categories together; see Section 3.3 in Richman (2018)
- Embeddings often capture actuarially meaningful relationships in categorical data – can be interpreted as relativities

	Actuary	Accountant	Quant	Statistician	Economist	Underwriter
Actuary	1	0	0	0	0	0
Accountant	0	1	0	0	0	0
Quant	0	0	1	0	0	0
Statistician	0	0	0	1	0	0
Economist	0	0	0	0	1	0
Underwriter	0	0	0	0	0	1

	Finance	Math	Statistics	Liabilities
Actuary	0.5	0.25	0.5	0.5
Accountant	0.5	0	0	0
Quant	0.75	0.25	0.25	0
Statistician	0	0.5	0.85	0
Economist	0.5	0.25	0.5	0
Underwriter	0	0.1	0.05	0.75



Summary of architectures

- Key principle - Use architecture that expresses useful priors about the data => major performance gains:
- Deep feedforward network – structured (tabular) data
- Embedding layers – categorical data (or real values restructured as categorical data)
- Deep autoencoder (non-linear PCA) – unsupervised learning
- Convolutional neural network – data with spatial/temporal dimension e.g. images and time series
- Recurrent neural network – data with temporal structure



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Recent Papers applying DL

- Searches within actuarial literature confined to articles written after 2006, when current resurgence of interest in neural networks began (Goodfellow, Bengio and Courville 2016).
 - Pricing of non-life insurance (Noll, Salzmann and Wüthrich 2018; Wüthrich and Buser 2018) **X**
 - IBNR Reserving (Kuo 2018b; Wüthrich 2018b; Zarkadoulas 2017) **X**
 - Analysis of telematics data (Gao, Meng and Wüthrich 2018; Gao and Wüthrich 2017; Wüthrich and Buser 2018; Wüthrich 2017) **X**
 - Mortality forecasting (Hainaut 2018; Richman and Wüthrich 2018)
 - Approximating nested stochastic simulations (Hejazi and Jackson 2016, 2017)
 - Forecasting financial markets (Smith, Beyers and De Villiers 2016)



Non-life pricing (1)

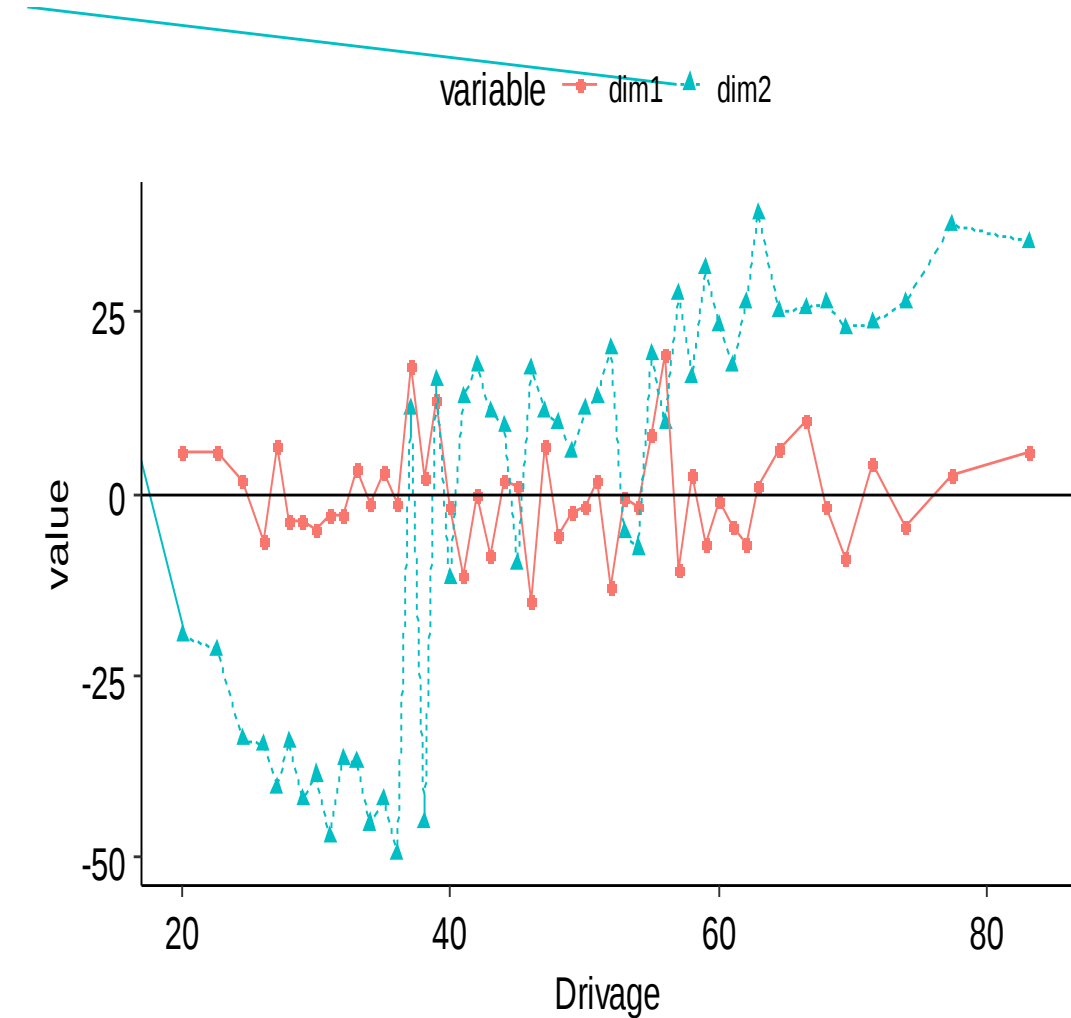
- Non-life Pricing (tabular data fit with GLMs) seems like obvious application of ML/DL
- Noll, Salzmann and Wüthrich (2018) is tutorial paper (with code) in which apply GLMs, regression trees, boosting and (shallow) neural networks to French TPL dataset to model frequency
 - ML approaches outperform GLM
 - Boosted tree performs about as well as neural network...
 -mainly because ML approaches capture some interactions automatically
 - In own analysis, found that surprisingly, off the shelf approaches do not perform particularly well on frequency models.
 - These include XGBoost and 'vanilla' deep networks



Non-life pricing (2)

- Deep neural network applied to raw data (i.e. no feature engineering) did not perform well
- Embedding layers provide significant gain in performance over GLM and other NN architectures
- Layers learn a (multi-dimensional) schedule of relativities at each age (shown after applying t-SNE)
- Transfer learning – can boost performance of GLM

<u>Model</u>	<u>OutOfSample</u>
<i>GLM</i>	0.3217
<i>GLM_Keras</i>	0.3217
<i>NN_shallow</i>	0.3150
<i>NN_no_FE</i>	0.3258
<i>NN_embed</i>	0.3068
<i>GLM_embed</i>	0.3194
<i>NN_learned_embed</i>	0.2925





IBNR Reserving

- IBNR Reserving boils down to regression of future reported claim amounts on past => good potential for ML/DL approaches
 - Granular reserving for claim type/property damaged/region/age etc difficult with normal chain-ladder approach as too much data to derive LDFs judgementally
 - Wüthrich (2018b) (who provides code + data) extends chain-ladder as a regression model to incorporate features into derivation of LDF

$$\hat{C}_{i,j+1} = f(X).C_{i,j}$$

- DeepTriangle of Kuo (2018b) is less traditional approach. Joint prediction of Paid + Outstanding claims using Recurrent Neural Networks and Embedding Layers
- Better performance than CL/GLM/Bayesian techniques on Schedule P data from USA



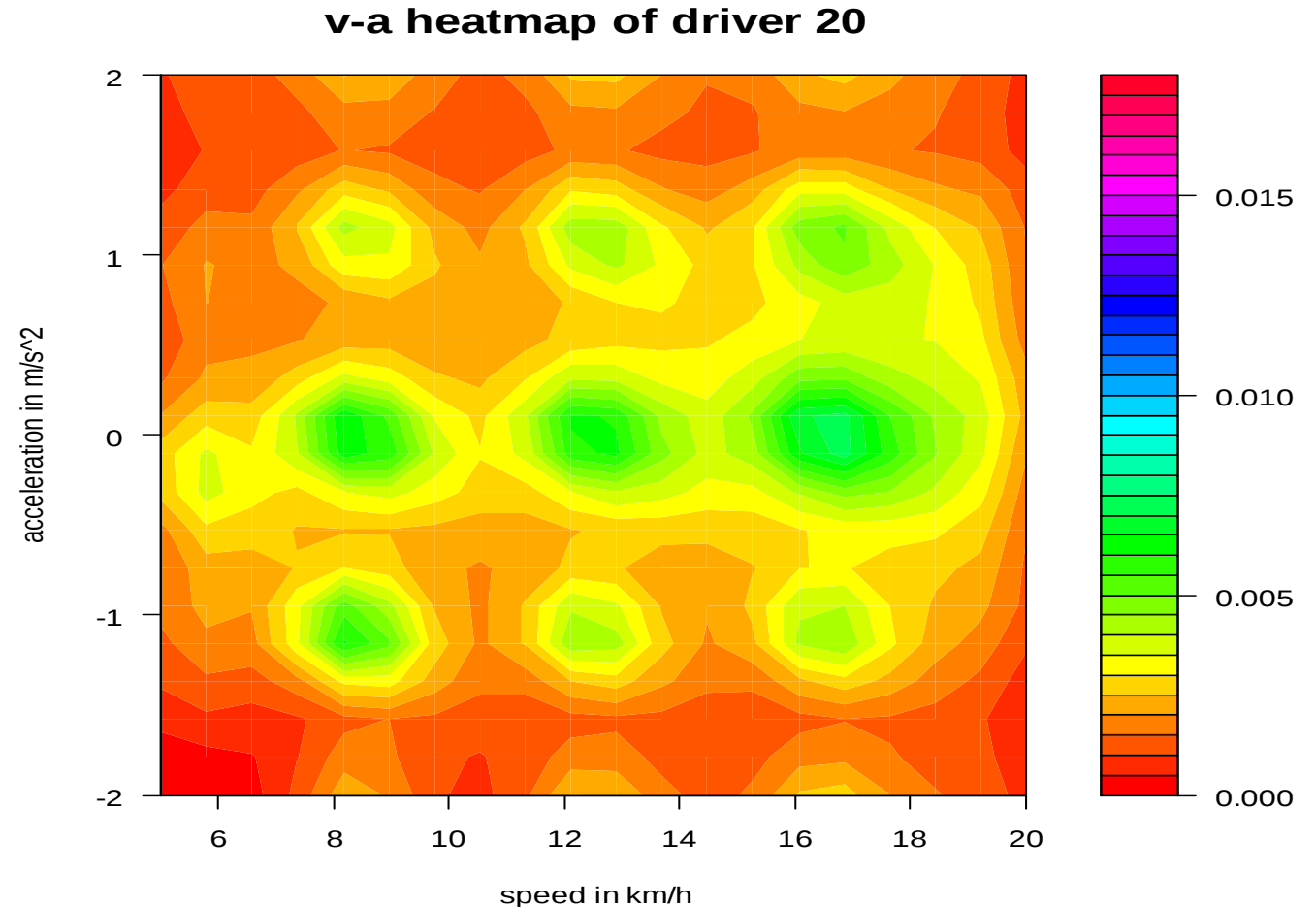
Telematics data (1)

- Telematics produces high dimensional data (position, velocity, acceleration, road type, time of day) at high frequencies – not immediately obvious how to incorporate into pricing
 - Sophisticated approaches to analysing telematics data from outside actuarial literature using recurrent neural networks plus embedding layers such as Dong, Li, Yao et al. (2016), Dong, Yuan, Yang et al. (2017) and Wijnands, Thompson, Aschwanden et al. (2018)
 - Within actuarial literature, series of papers by Wüthrich (2017), Gao and Wüthrich (2017) and Gao, Meng and Wüthrich (2018) discuss analysis of velocity and acceleration information from telematics data feed
 - Focus on v-a heatmaps which capture velocity and acceleration profile of driver but these are also high dimensional



Telematics data (2)

- Heatmap generated using code in Wüthrich (2018c)
- Shows density i.e. probability that driver is found at location in heatmap
- Wüthrich (2017) and Gao and Wüthrich (2017) apply unsupervised learning methods to summarize v-a heat-maps:
- K-means, PCA and shallow auto-encoders
- Stunning result = continuous features are highly predictive
- Why? Goodfellow, Bengio and Courville (2016) : “basic idea is features useful for the unsupervised task also be useful for the supervised learning task”





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Discussion

- Emphasis on predictive performance and potential gains of moving from traditional actuarial and statistical methods to machine and deep learning approaches.
- Measurement framework utilized within machine learning – focus on testing predictive performance => focus on measurable improvements in predictive performance led to refinements and enhancements of deep learning architectures
- Learned representations from deep neural networks often have readily interpretable meaning
- Very useful for high-frequency and high-dimensional data



Conclusion

- Deep learning can enhance the predictive power of models built by actuaries
- Application of deep learning techniques to actuarial problems seems to be rapidly emerging field within actuarial science => appears reasonable to predict more advances in the near-term.
- Deep learning is not a panacea for all modelling issues - applied to the wrong domain, deep learning will not produce better or more useful results than other techniques.
- Winter might be coming – if actuaries do not take the lead in applying deep learning, someone else will.



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Get involved

- Insurance Data Science conference - 14 June 2019
- ETH Zurich
- <https://insurancedatascience.org/>
- Amazing line-up of papers, presentations and speakers!
- [Kasa.ai](https://kasa.ai) – launching soon, led by Kevin Kuo of Rstudio
- An open research group encouraging innovation in insurance analytics
- Some interesting projects planned



Thanks for listening - Any questions?

Paper: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3218082

Contact: ron@ronaldrichman.co.za



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