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The use of denoising autoencoders for categorical and continuous variables

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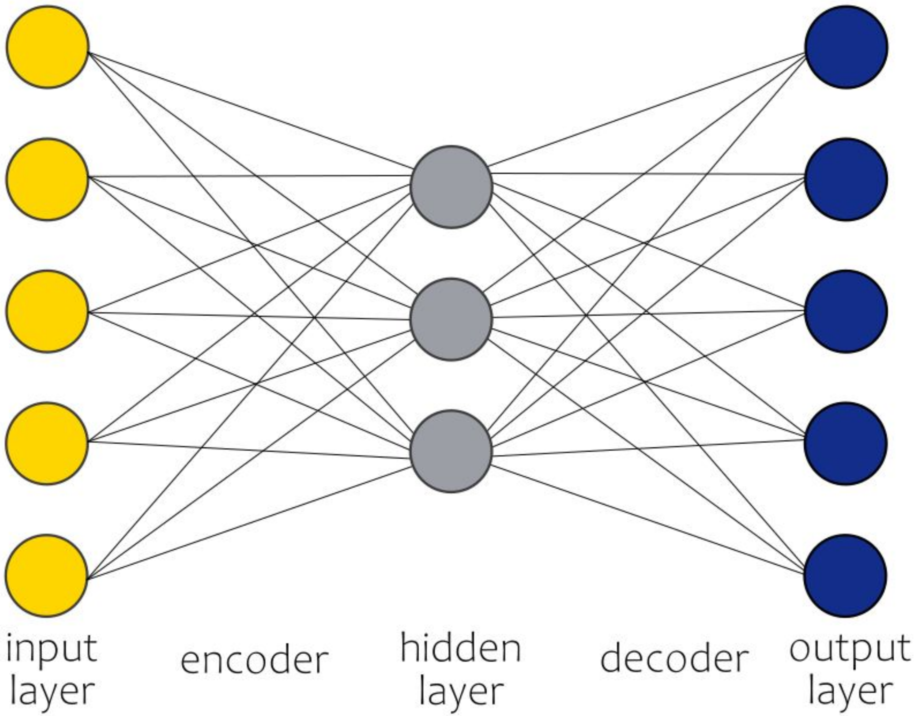
Test autoencoders on categorical variables, until now Entity Embedding has been used in the actuarial field.

Autoencoders



Benefits of using autoencoders

Erhan, Dumitru and Manzagol, Pierre-Antoine and Bengio, Y. and Bengio, S. and Vincent, Pascal . (2009). *The Difficulty of Training Deep Architectures and the Effect of Unsupervised Pre-Training.* Twelfth International Conference on Artificial Intelligence and Statistics

Vincent, Pascal and Larochelle, Hugo and Lajoie, Isabelle and Bengio, Y. and Manzagol, Pierre-Antoine. (2008). *Extracting and composing robust features with denoising autoencoders.* In ICML 2008: Proceedings of the Twenty-fifth International Conference on Machine Learning

Vincent, Pascal and Larochelle, Hugo and Lajoie, Isabelle and Bengio, Y. and Manzagol, Pierre-Antoine. (2010). *Stacked Denoising Autoencoders: Learning Useful Representations in a Deep Network with a Local Denoising Criterion.*, Journal of Machine Learning Research

Autoencoders for categorical variables

- autoencoder softmax all
- autoencoder softmax per variable

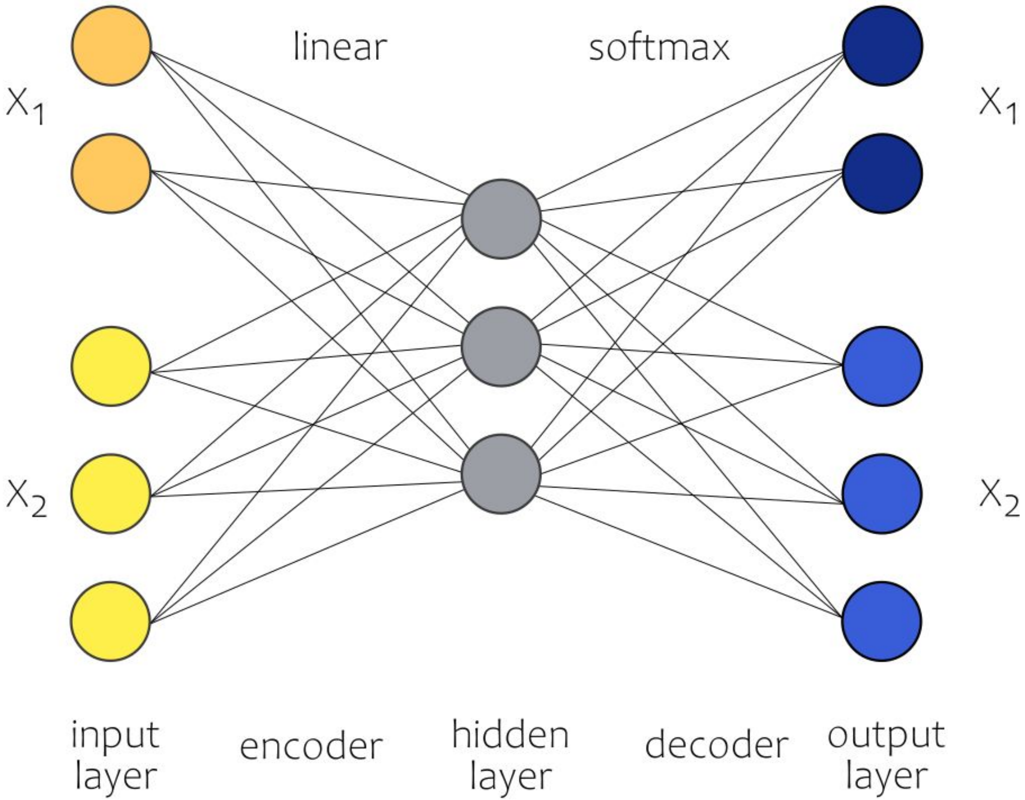
Categorical variables should be one-hot encoded before constructing the autoencoder.

We noise all observations and one, two or three randomly selected columns per observation.

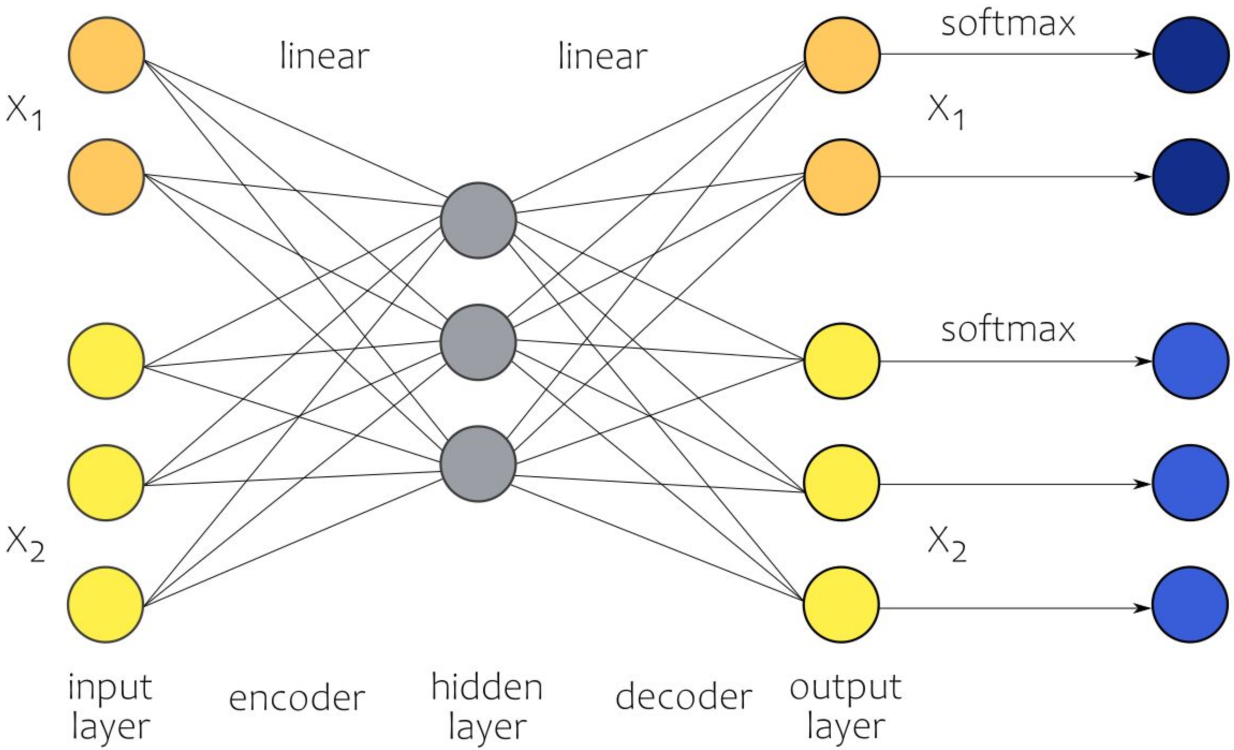
Each autoencoders we consider with noise. Types of noise:

- zeros 00100000 ⟶ 00000000
- sample 00100000 ⟶ 00000010

Autoencoder softmax all



Autoencoder softmax per variable



Autoencoders for numerical variables

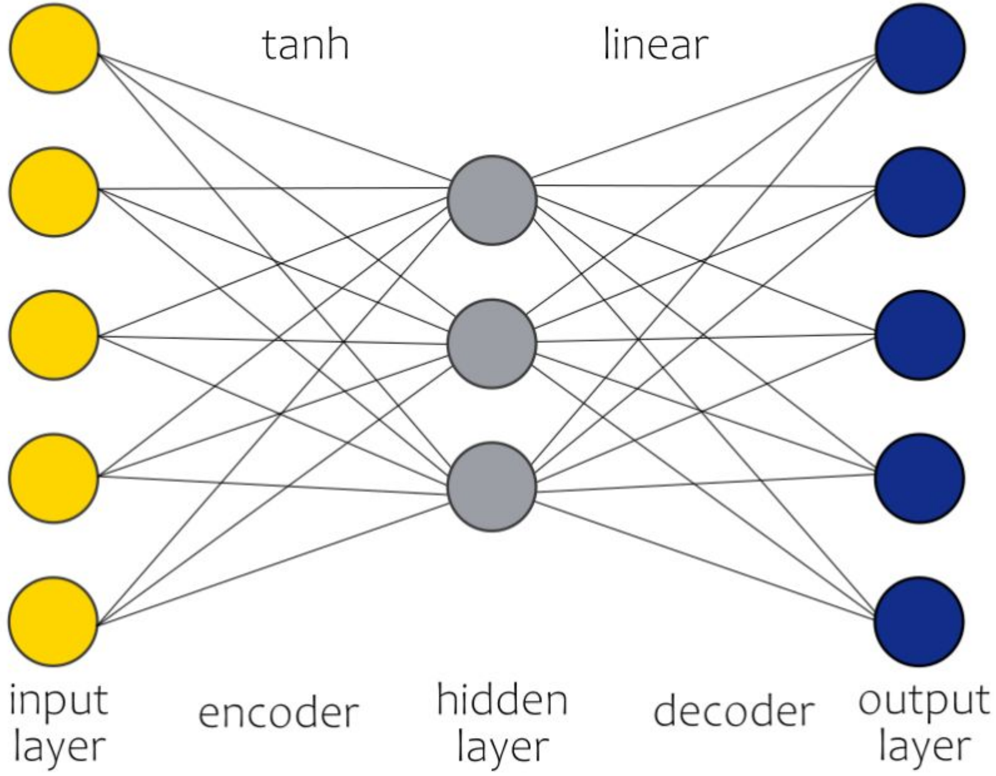
- autoencoder MSE

We noise all observations and one, two or three randomly selected columns per observation.

Each autoencoders we consider with noise. Types of noise:

- const - change value to zero
- sigma - change value to random value from normal distribution with expected value equal to the value from dataset and variance equal sigma square

Autoencoder for numerical variables



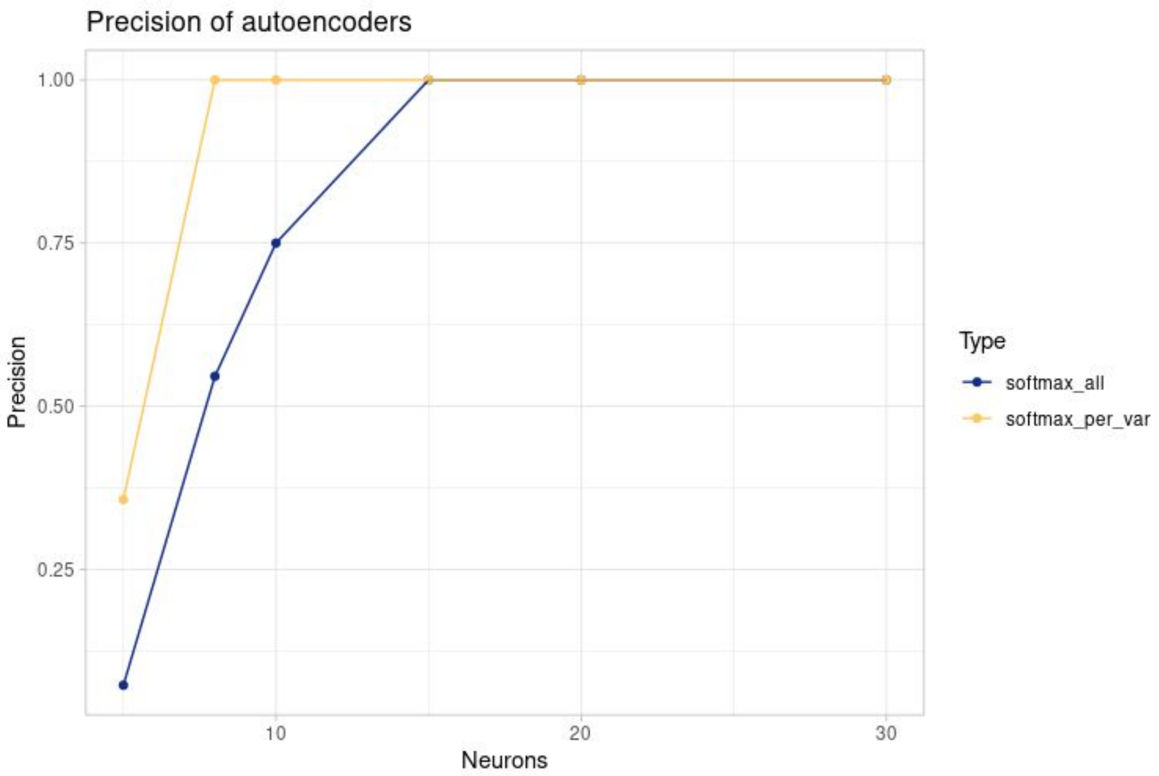
Dataset and experiments

Dataset: freMTPL2freq, select 100k observations by stratification
Categorical variable: Area, VehPower, VehAge, DrivAge, VehBrand, Region
Binary variable: VehGas
Numerical variable: BonusMalus, Density (log), Min-Max scaler

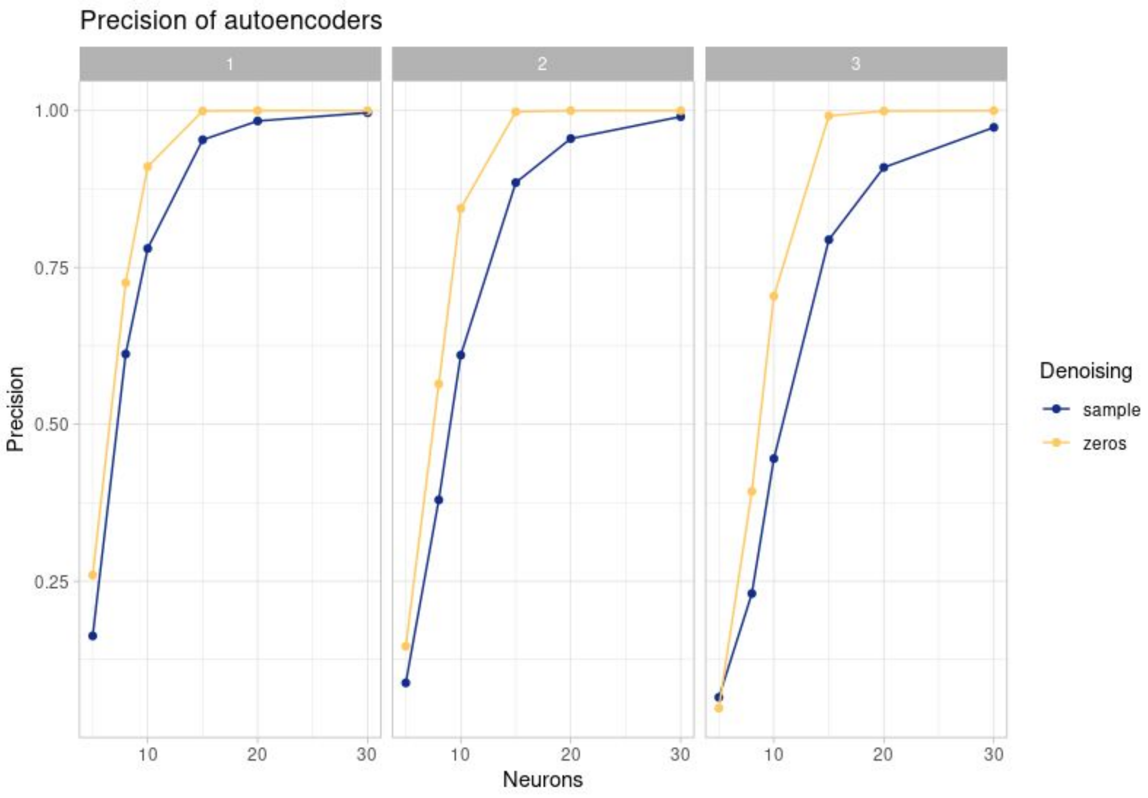
Experiments with autoencoder for categorical variables:

Parameter	Value
neurons	5, 8, 10, 15, 20, 30
epochs	500
batch size	1000
learning rate	0.001
min delta	0
patience	15
noise	zeros, sample

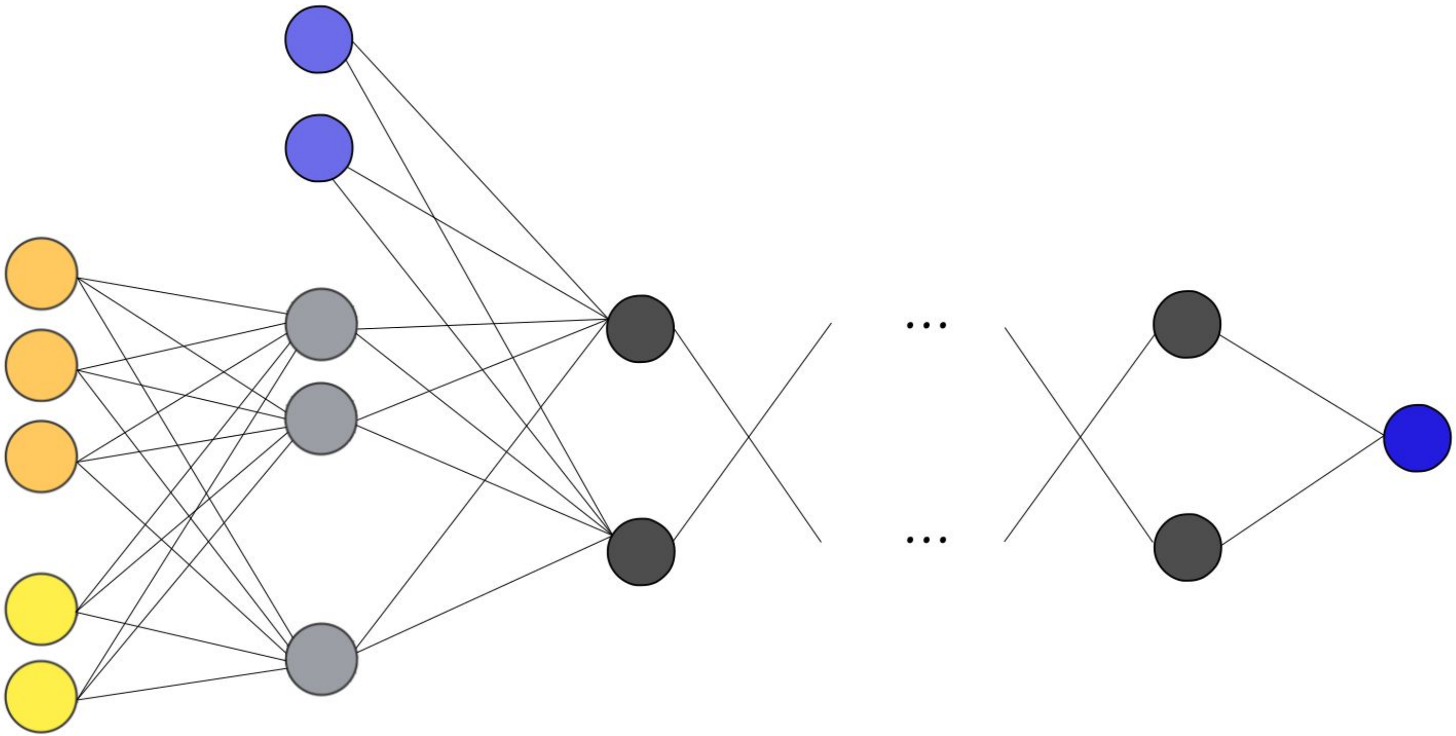
Results for autoencoders



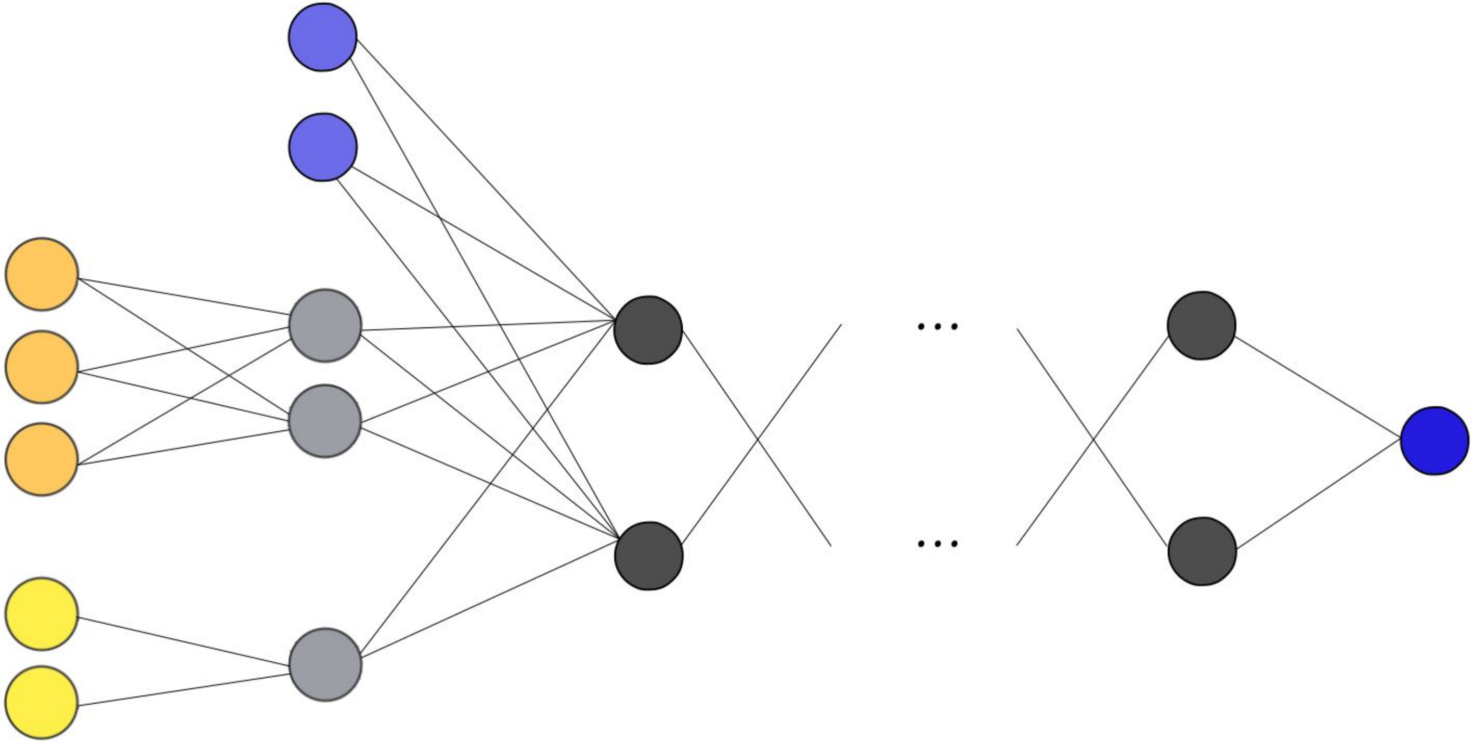
Results for autoencoder softmax per variable with denoising



Neural Networks with autoencoders



Neural Networks with Entity Embedding



Experiments

	With weight from autoencoder	
1 AE	epochs	15, 50, 100, 200, 300
	learning rate	5 * 10 ^ (-5), 5 * 10 ^ (-4), 5 * 10 ^ (-3)
	denoising	sample, zeros
	cols	1, 2, 3
2 AE	denoising	const, sigma
	sigma/feat noise	0, 0.1, 0.25, 0.5/ 0.1, 0.3, 0.5
	epochs	15, 50, 100, 200, 300
	learning rate	5 * 10 ^ (-5), 5 * 10 ^ (-4), 5 * 10 ^ (-3)
Neural Network	number layer	1, 3
	neurons layer	[20], [30], [50],[30, 30, 30], [30, 20, 10], [20, 15, 10]
	learning rate	10 ^(-4), 10 ^ (-3), 10 ^ (-2)

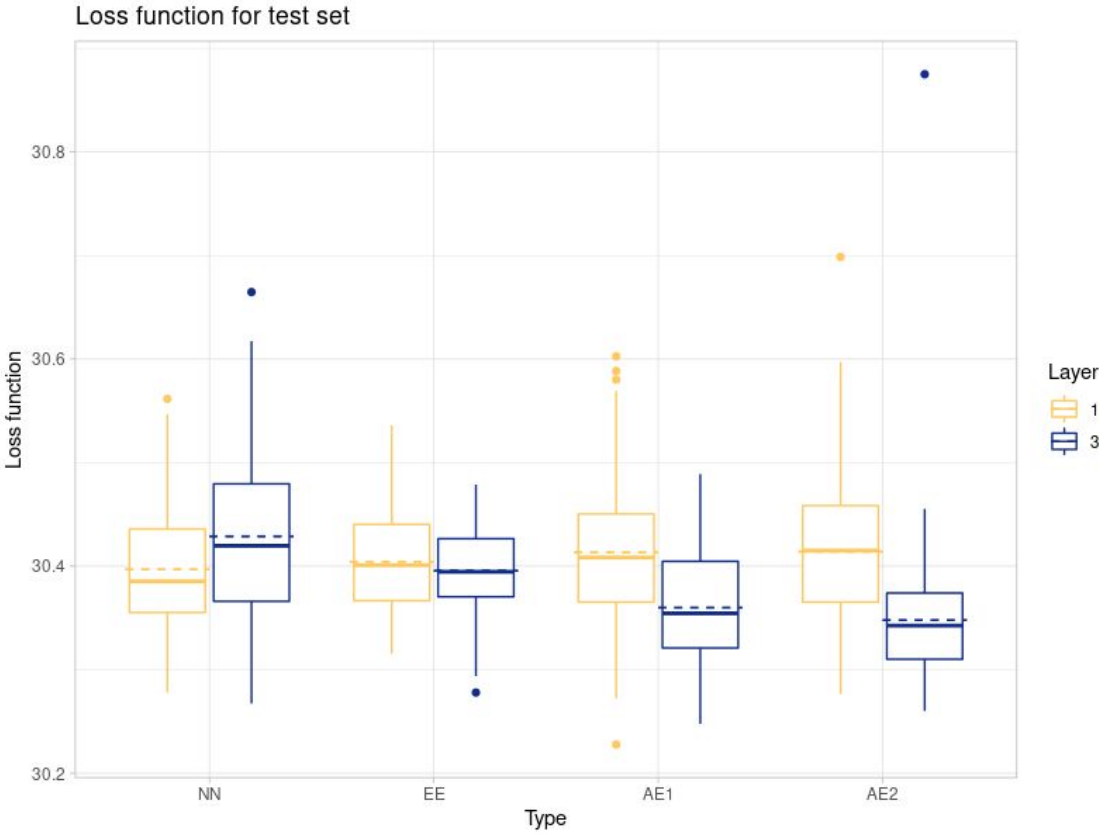
Without weight from autoencoder	
number layer	1, 3
neurons layer	[20], [30], [50],[30, 30, 30], [30, 20, 10], [20, 15, 10]
learning rate	10 ^ (-4), 10 ^ (-3), 10 ^ (-2)

Entity Embedding	
number layer	1, 3
neurons layer	[47], [57], [77], [25, 20, 11], [35, 24, 10], [33, 32, 32]
learning rate	10 ^ (-4), 10 ^ (-3), 10 ^ (-2)

Models chosen with 5 fold cv

neurons number	neurons_layer	number layer	learning rate AE	learinig rate	epochs	type	test
8	[20]	1	0.00005	0.01	100	2 AE	31,088
8	[50, 35, 20]	3	0.005	0.0001	15	2 AE	31,043
8	[20, 15, 10]	3	0.005	0.0001	200	2 AE	31,061
8	[50]	1	0.005	0.01	50	2 AE	31,100
8	[20]	1	0.00005	0.0001	15	1 AE	31,081
8	[20]	1	0.005	0.01	200	1 AE	31,081
8	[50]	1	0.0005	0.01	100	1 AE	31,083
8	[20, 15, 10]	3	0.0005	0.0001	100	1 AE	31,069
8	[50, 35, 20]	3	0.005	0.0001	15	1 AE	31,056
8	[50, 35, 20]	3	0.005	0.001	15	1 AE	31,061
8	[25, 20, 11]	3		0.001		EE	31,104
8	[50, 35, 20]	3		0.0001		NN	31,127
8	[30]	1		0.001		NN	31,097
8	[57]	1		0.01		EE	31,124

Results on test set - loss functions



Results on test set - loss functions

One layer

	EE	NN	AE1	AE2
1st Q	30,370	30,360	30,370	30,370
mean	**30,400**	**30,400**	**30,410**	**30,410**
3rd Q	30,440	30,440	30,450	30,460
sd	0,052	0,057	0,070	0,072

Three layer

	EE	NN	AE1	AE2
1st Q	30,370	30,370	30,320	30,310
mean	**30,400**	**30,430**	**30,360**	**30,350**
3rd Q	30,430	30,480	30,400	30,370
sd	0,040	0,083	0,053	0,068

Results on test set - claim intensities

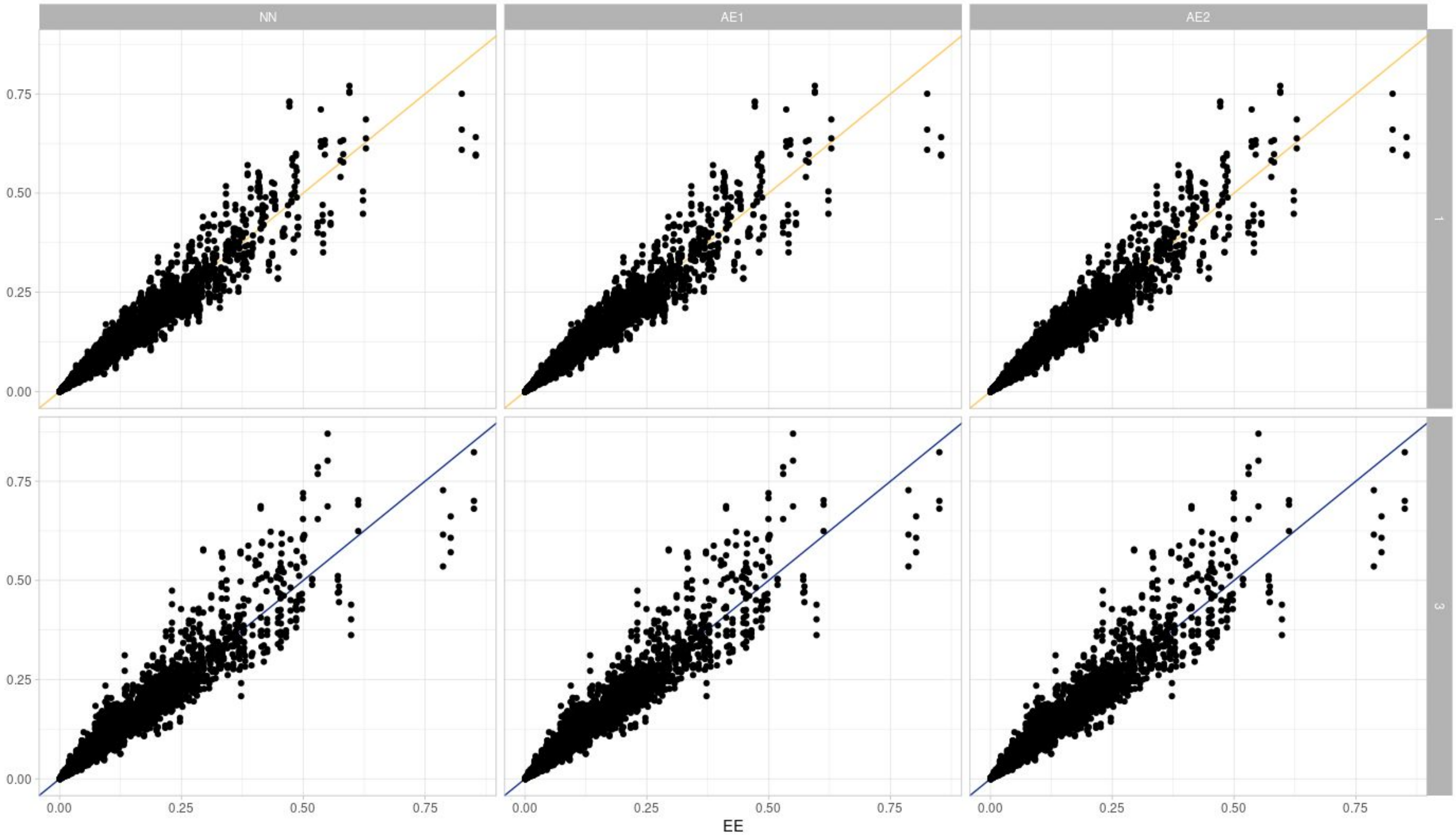
One layer

	NN	EE	AE1	AE2
1st Q	4,996	4,923	4,948	4,907
mean	**5,071**	**5,044**	**5,086**	**5,063**
3rd Q	5,157	5,17	5,236	5,178
sd	0,102	0,170	0,189	0,224
y mean	**5,105**	**5,105**	**5,105**	**5,105**

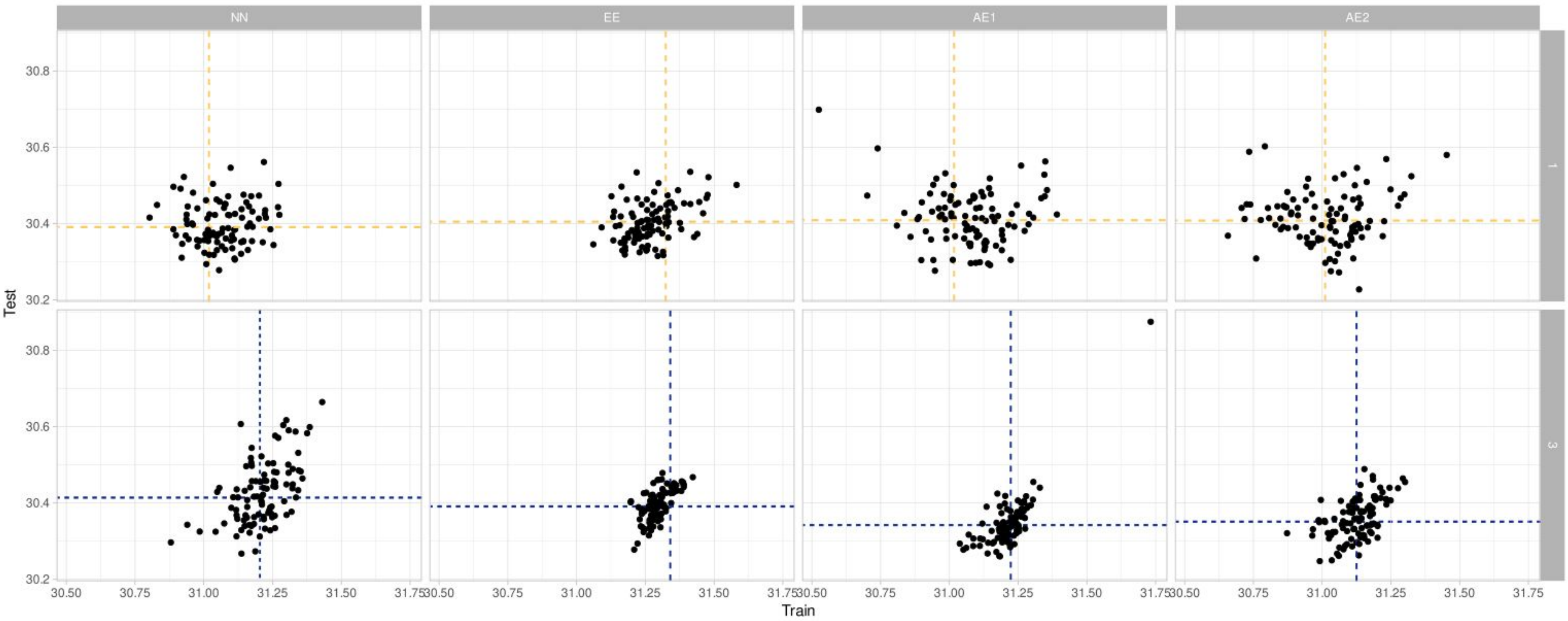
Three layer

	NN	EE	AE1	AE2
1st Q	5,099	4,981	5,141	5,234
mean	**5,149**	**5,054**	**5,183**	**5,262**
3rd Q	5,207	5,142	5,221	5,288
sd	0,068	0,114	0,060	0,039
y mean	**5,105**	**5,105**	**5,105**	**5,105**

Results on test set - claim intensities



Results on train and test sets - loss functions



What improvement comes with adding autoencoder?

AE	Loss function	Difference
0	30,408	
1	30,380	0,028
2	30,348	0,032

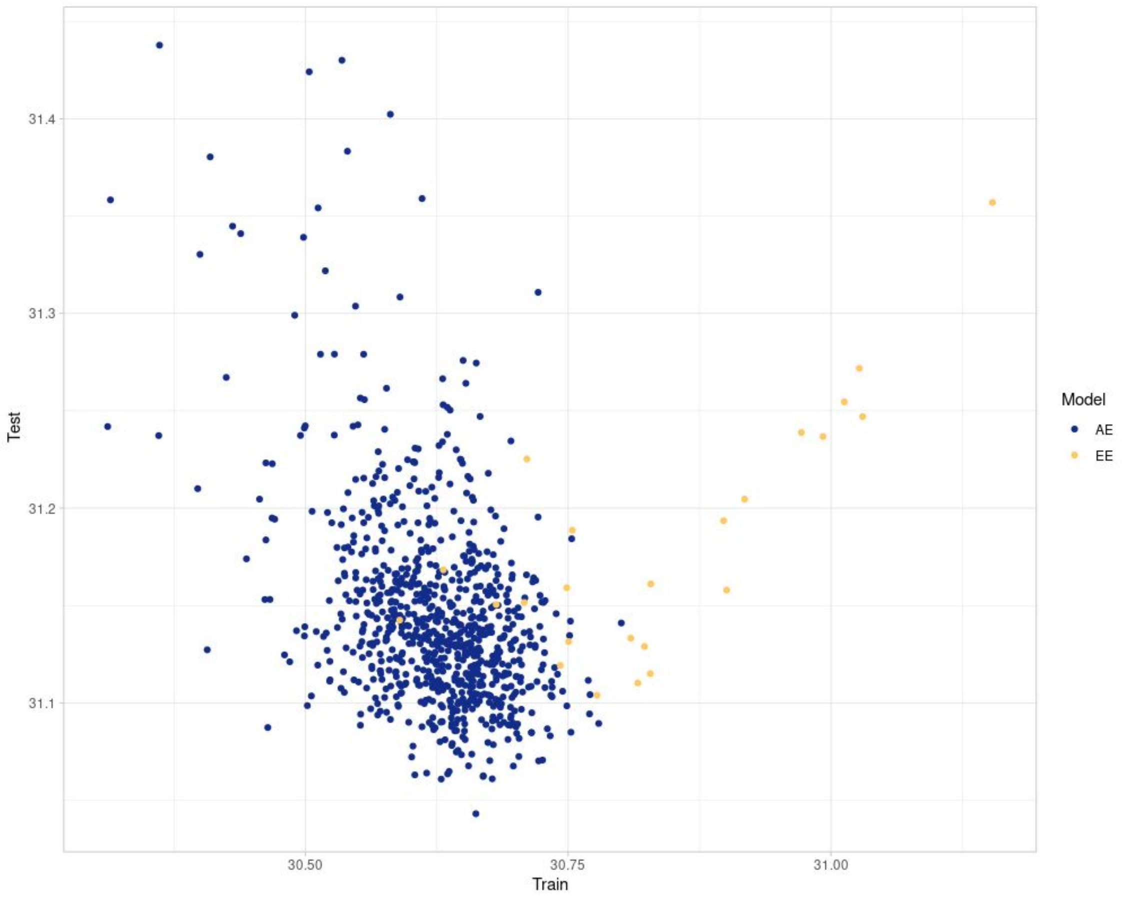
What improvement comes with adding autoencoder?

AE	Scaled weights	Loss function	Difference
1	No	30,674	
1	Yes	30,380	0,294

What improvement comes with adding autoencoder?

AE	Scaled weights	Neurons	Loss function	Difference
2	Yes	8	30,348	
2	Yes	11	30,336	0,012

Results on train and test sets - loss functions



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Thank you for your attention!