Deep self-normalizing network for credit risk assessment

Lovre Mrčela[1], Andro Merćep[1], Karmela Ljubičić[1], Matija Birov[2], and Zvonko Kostanjčar[1]

[1] *Laboratory for Financial and Risk Analytics, Faculty of Electrical Engineering and Computing, University of Zagreb, Croatia*

`http://lafra.fer.hr`

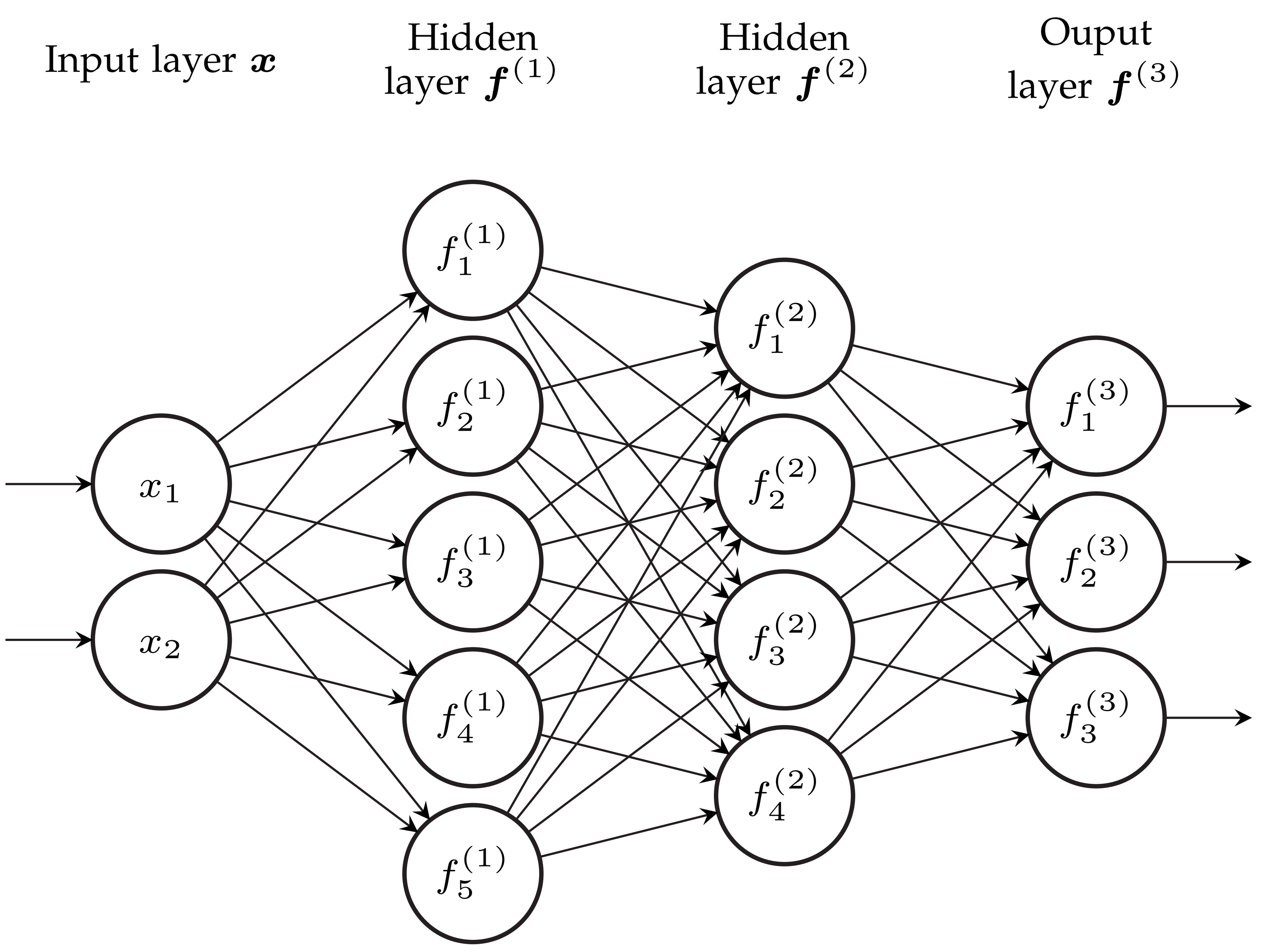
[2] *Privredna Banka Zagreb, Member of Intesa Sanpaolo Group, Zagreb, Croatia*

Introduction

- Behavioral models are used in the credit monitoring phase; they are usually logistic regression based (generalized linear models).
- We propose a deep self-normalizing network that can capture non-linear relationships between inputs and target values.

Methods

- Feedforward neural network: information flows from the input nodes, through hidden layers, to the output nodes.



- Each neuron has its own parameters $\boldsymbol{w}$ and b; its output is equal to $f = \phi(\boldsymbol{w}^\top \boldsymbol{x} + b)$, where ϕ denotes the activation function.
- Self-normalizing neural networks (SNN) introduce neurons whose outputs automatically converge towards zero mean and unit variance.
- They use scaled exponential linear unit as activation function

$$\mathrm{SELU}(x) = \lambda \begin{cases} x & \text{if } x > 0 \\ \alpha e^x - \alpha & \text{otherwise} \end{cases},$$

  where α and λ are predetermined coefficients.
- Alpha-dropout regularization randomly sets activations to α' where

$$\lim_{x \to -\infty} \mathrm{SELU}\,(x) = -\lambda\alpha = \alpha'.$$

Dataset

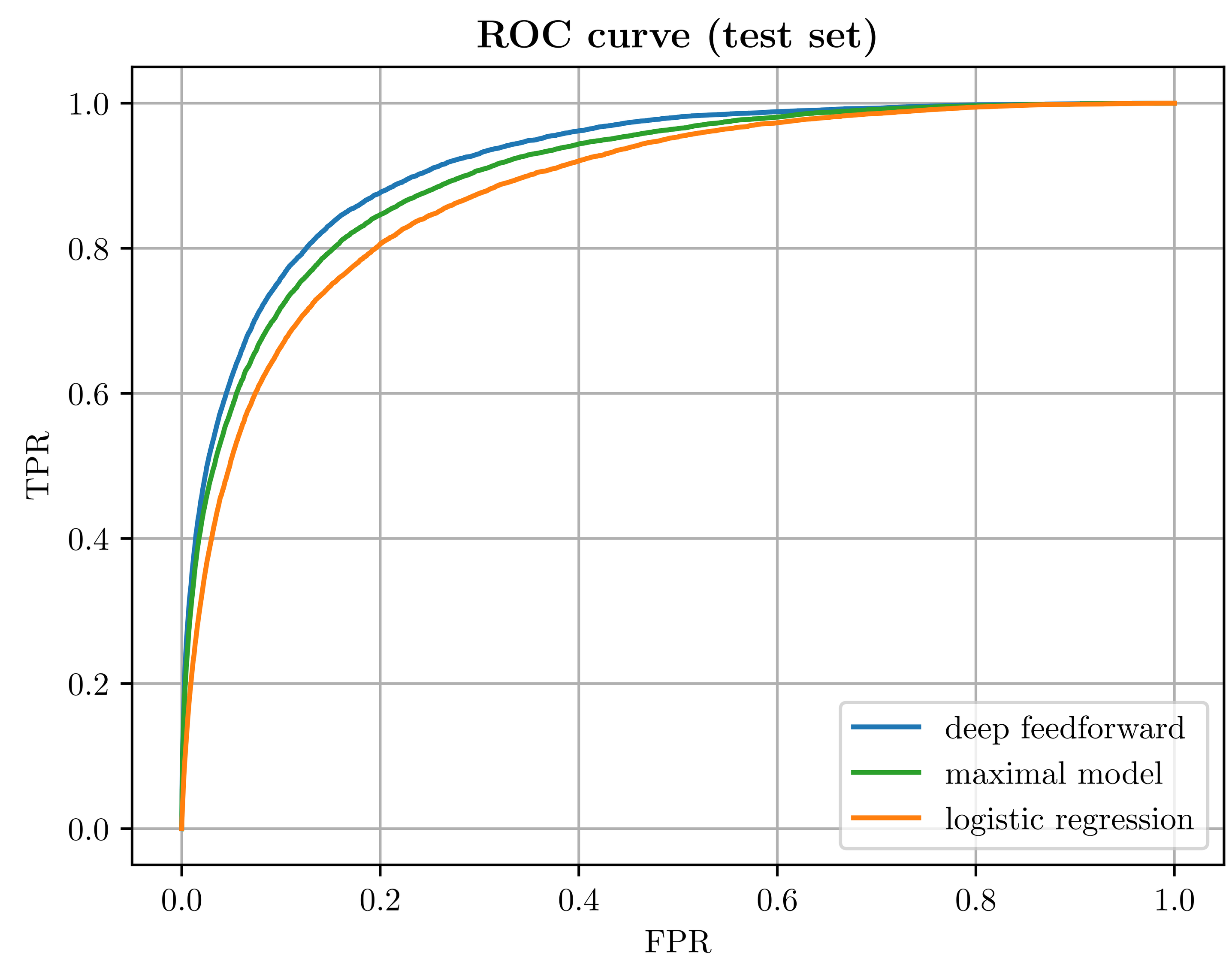
- We use a behavioral retail credit risk dataset that contains end-of-year snapshots between 2009 and 2013.
- Each example has 125 features monitored during the 12 month observation period that precedes the snapshot date.
- Default event – debtor is past due more than 90 days on any credit obligation within the performance period (12 months after the snapshot date).
- The dataset contains 1 281 436 examples, with 49 856 defaulted contracts (3.089% default rate).

Results

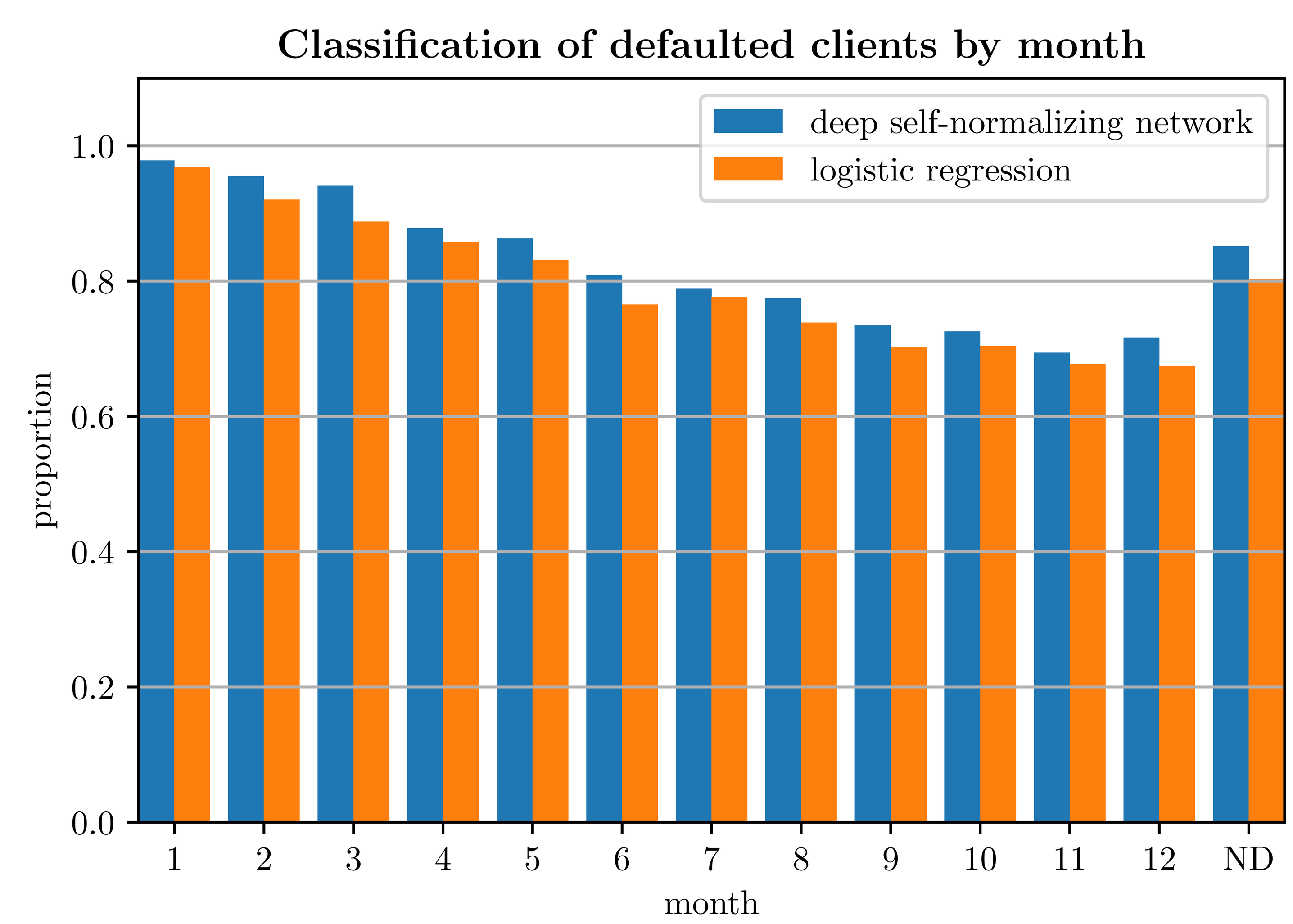
- We use a deep SNN with three hidden layers:
  - Network configuration $125 \times 600 \times 200 \times 10 \times 1$
  - Dropout inclusion probability: 0.9 for input, 0.8 for hidden layers
  - L^2 norm penalty with regularization factor $\alpha = 10^{-4}$
- We compare the deep model to two benchmark models:
  - Reference logistic regression based scoring model (uses 16 features)
  - Maximal logistic regression model (uses all 125 features)

	Train Somers' D	Test Somers' D
Logistic	76.02%	75.39%
Maximal	80.69%	80.91%
Deep SNN	**86.20%**	**84.08%**

- ROC curve comparison:



- Comparison of classification accuracy by months of default:



Conclusion

- Proposed deep SNN model demonstrated higher predictive power in comparison to benchmark models.
- Deep learning architectures are a promising new method of credit risk assessment due to their ability to capture highly non-linear dependencies.

University of Zagreb

Laboratory for Financial and Risk Analytics