Grouping of Contracts in Life Insurance using Neural Networks

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What to expect?

Intention of our work

Improve the performance of ***K*-means clustering** when grouping term life insurance contracts

→ Numerical Concept

Relevance for Actuaries

Stay **up to date** with innovations

Potential for significant **time savings** in risk management

Agenda

I. Grouping of Contracts in Life Insurance

II. Basics of Neural Networks

III. Application of Neural Networks
   1. Prediction
   2. Grouping

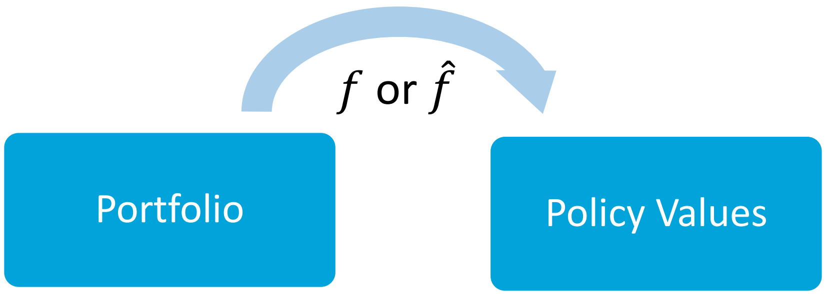
IV. Conclusion

Grouping of Contracts

- Problem — High computation times of extensive methods for insurance portfolios (e.g. SCR identification)
- Grouping — Reduce the complexity of the existing portfolio while (approximately) preserving some feature(s) of interest
- Benefit — Perform extensive method(s) on simplified portfolio
  → Lower computation times
- Example — Consider two contracts c_1, c_2 with policy values V_{x_1}, V_{x_2}. We are interested in finding one contract c, with V_x such that

$$2 \cdot V_x \approx V_{x_1} + V_{x_2}$$

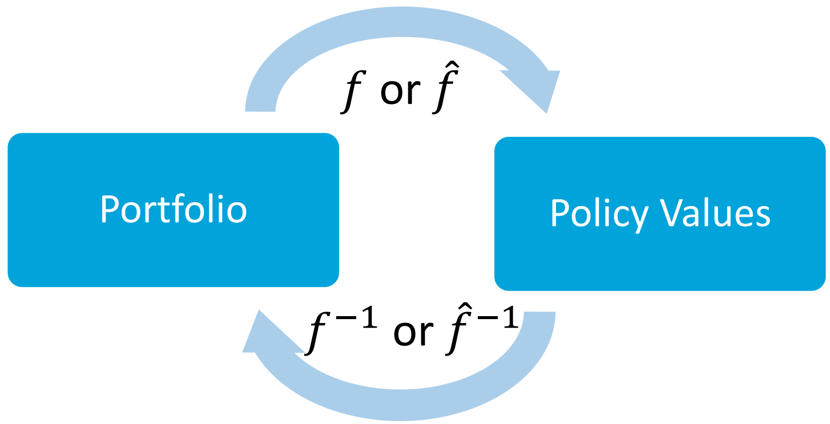
Grouping of Contracts – Our Concept (1/2)



- Step 1: Construct (approximative) computation f (resp. $\hat{f}$) of selected feature(s) of interest (e.g. policy values)

  - Input: Vector, representing an individual contract
  - Output: Vector, respresenting policy values (up to maturity) of an individual contract

Grouping of Contracts – Our Concept (2/2)



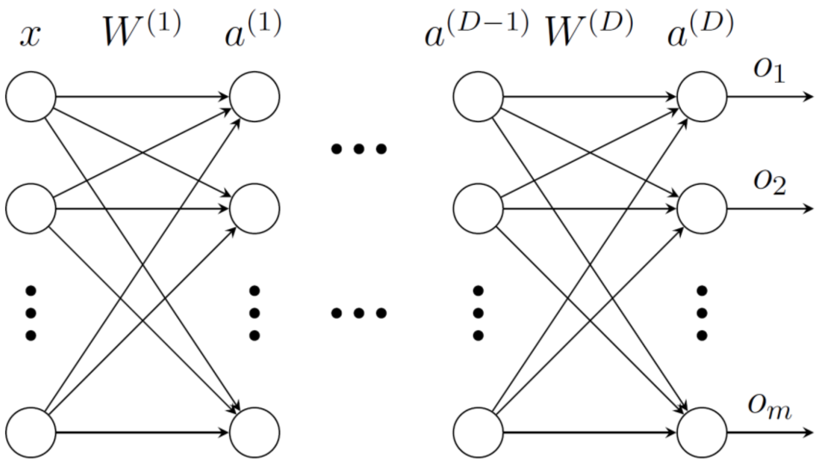
- Step 2: Find a simplified portfolio, which mirrors the feature(s) of interest (given by f, resp. $\hat{f}$)
  $\rightarrow$ Utilize f^{-1}, resp. $\hat{f}^{-1}$

Neural Networks

1. Have a high capacity to approximate functions (Step 1)
2. Can be used to invert functions (Step 2)

Basics of Neural Networks – Feed Forward Network

- Architecture



- Computation

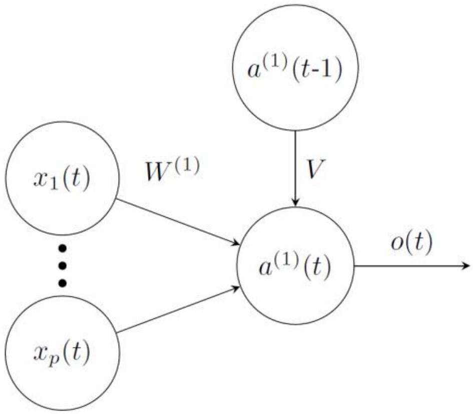
$$a^{(l)} \coloneqq \phi_{(l)}(W^{(l)} a^{(l-1)} + b^{(l)}) \qquad , \; l = 1, \dots, D$$

$$a^{(0)} \coloneqq x \text{ (input)}, \quad a^{(D)} = o \text{ (output)}$$

- Training SGD with (adaptive) stepsize and given loss function

Basics of Neural Networks – Recurrent Neural Network

- Architecture



- Computation

$$a^{(1)}(t) \coloneqq \phi_{(1)}(W^{(1)}x(t) + b^{(1)} + Va^{(1)}(t-1))$$

- Training Similar to Feed Forward Networks

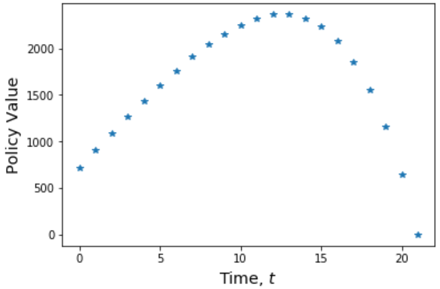
Application – Numerical Framework

- Data — Portfolio of $N = 100{,}000$ term life insurance contracts, each characterized by

Input

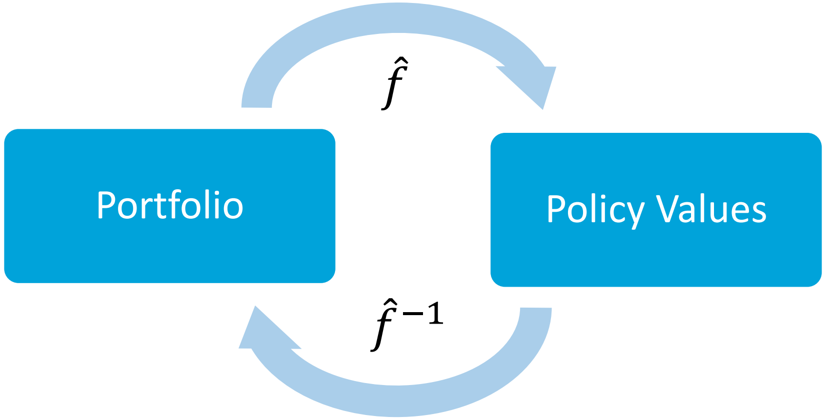
  - $x_1 \in \{25, \dots, 107\}$ – policyholder's current age
  - $x_2 \in \{10^3, \dots, 10^6\}$ – sum insured
  - $x_3 \in \{2, \dots, 40\}$ – duration of the contract
  - $x_4 \in \{0, \dots, 39\}$ – elapsed duration (since start)

- Target — Policy values of individual, active contracts for remaining duration



- Assumptions
  - No costs, profit repatriation or lapses
  - Constant discount rate
  - Parametric survival model

Application – Recall Motivation



- Step 1 Find Approximation $\hat{f}$ (Prediction Model)
- Step 2 Based on $\hat{f}^{-1}$, find simplified portfolio with similar (cumulative) policy values (Grouping)

Application – Prediction Model (Step 1)

Time Dependency
→ Recurrent Neural Network

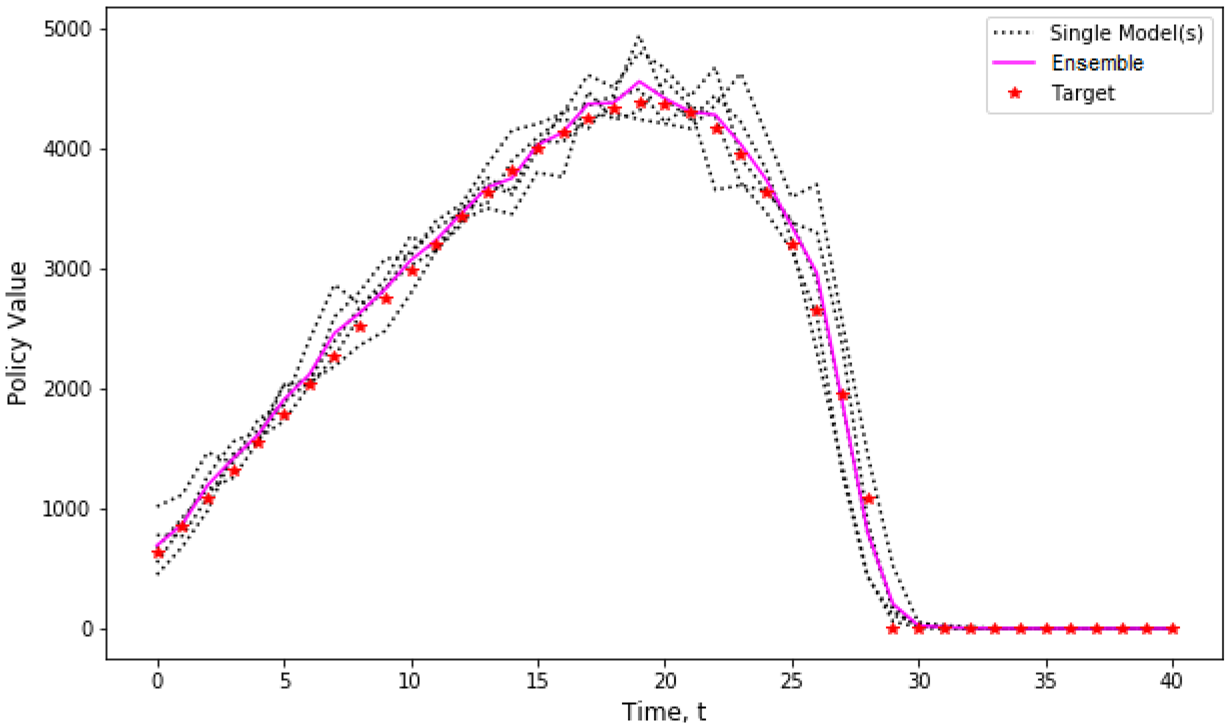
- Standard, actuarial computation

$$\left({}_{t}V_x + P - C\right)(1 + i) = q_{x+t}S + p_{x+t}\,{}_{t+1}V_x \qquad , t = 0, \dots , T - 1$$

- Design of neural network ($\widehat{f}$)
  - Scaled input $(x_1, x_2, x_3, x_4) \in [-1,1]^4$
  - Ensemble of neural networks, each with
    a. Two layers: 1x recurrent (LSTM), 1x feed-forward
    b. A final, deterministic re-scaling layer to reduce shift of parameters
  - Output: Mean of multiple policy value predictions
  - Regularization: Early Stopping

Application – Prediction Model (Step 2)

Exemplary Ensemble-Output for $x = (36, 270772, 32, 3)$



Application – Grouping (Step 2)

- Goal: Optimize performance of K-means clustering

- Methodology
  1. Perform K-means clustering
     → Cluster assignment & centroids
  2. For each cluster (C) find representative contract $a^{(1)}$ such that

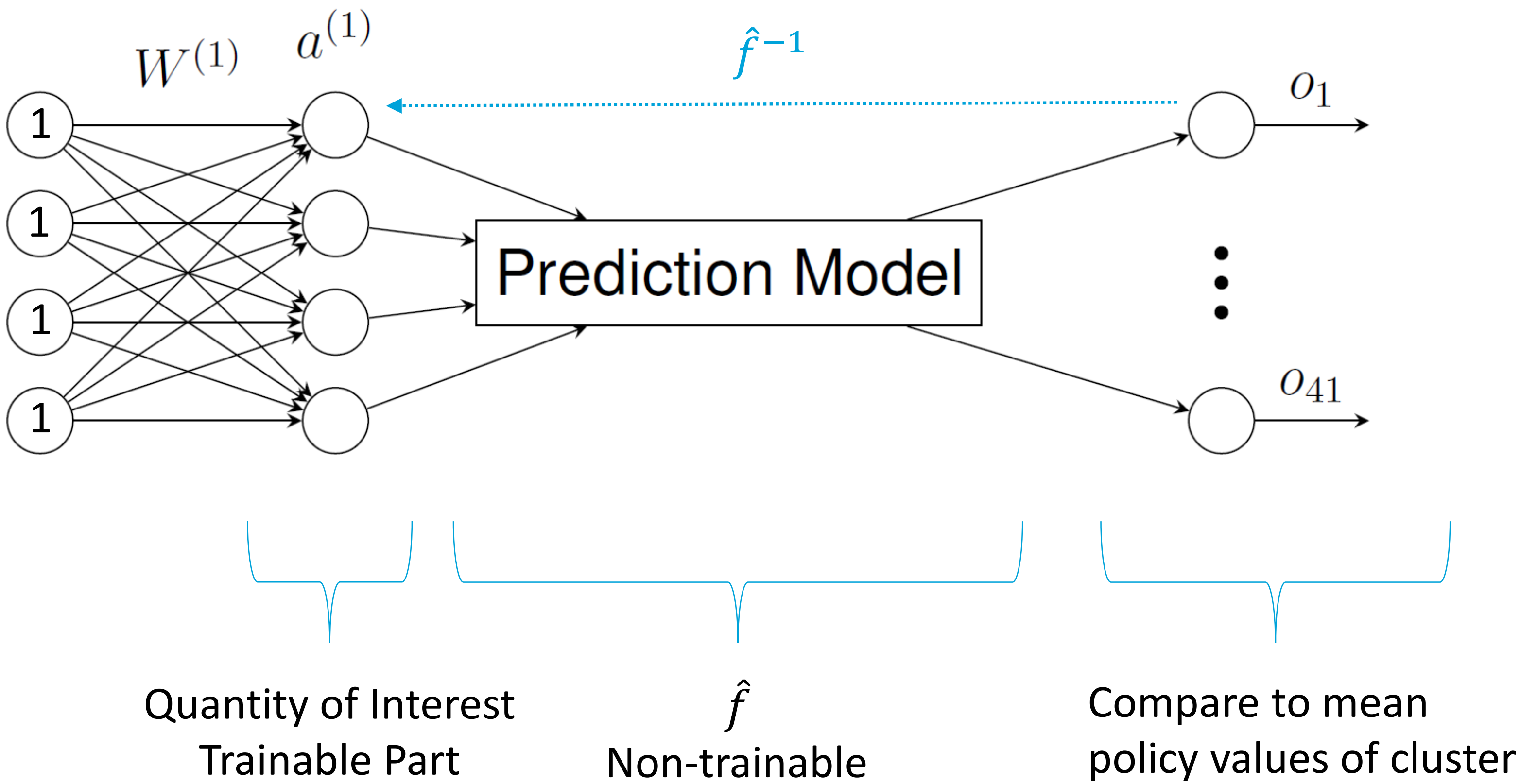
$$\hat{f}\left(a^{(1)}\right) - \frac{\sum_{\{x \in C\}} \hat{f}(x)}{|C|} \rightarrow \min$$

Mean policy values of cluster

  3. Compare performance based on
     a. K-means centroids
     b. Optimized representative $a^{(1)}$

Application - Grouping (Step 2)

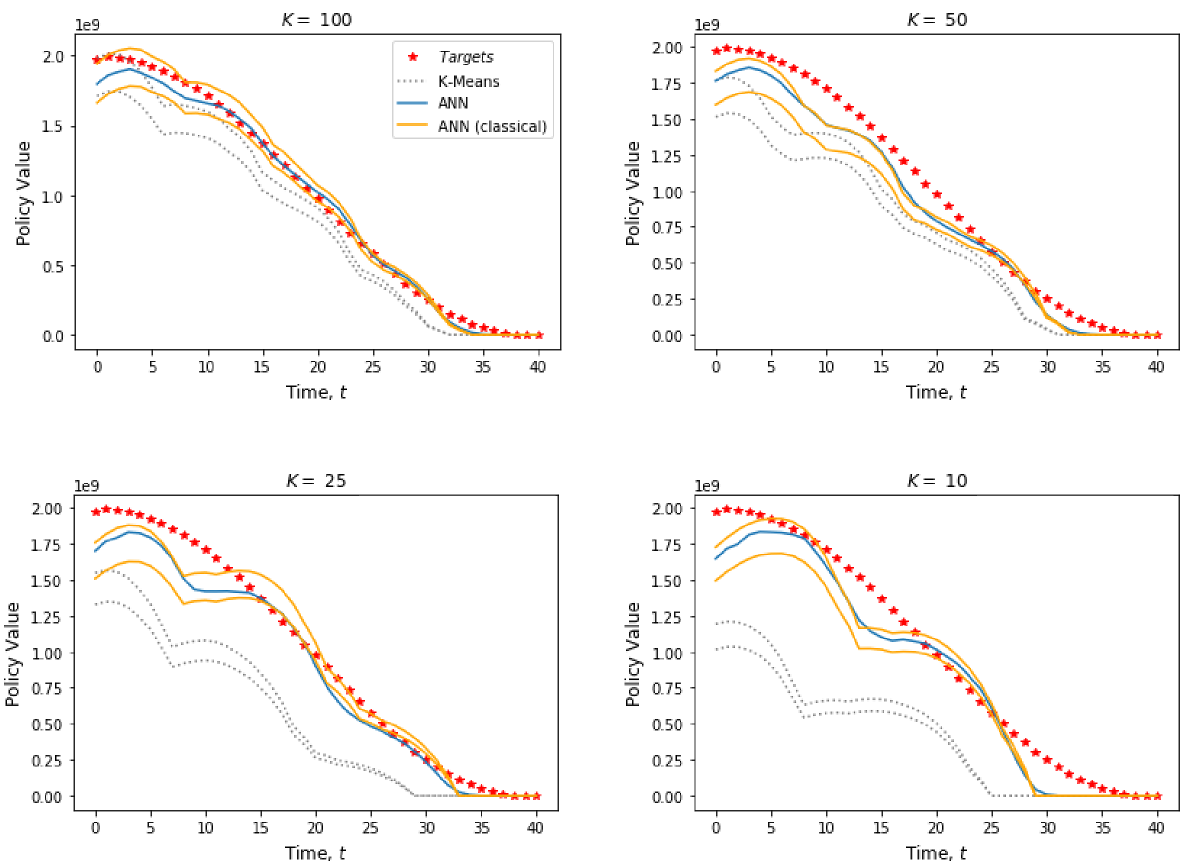
- Implementation using a neural network (for given cluster C)



Application - Grouping (Step 2)

Effect on policy values when grouping of $N = 100{,}000$ to K contracts using

- K-means centroid & classical, actuarial calculation
- Representatives $a^{(1)}$ & prediction $\hat{f}$ or classical, actuarial calculation



Neural Network **stabilizes** the **quality** of grouping!

Conclusion

- Results suggest significant improvements over K-means baseline

- Approach combines
  - Computation of a feature (policy values)
  - Control for the respective feature in grouping

- Further generalization are required/ of interest

- Takeaway for Actuaries
  - Neural Networks have the potential to improve grouping
  - The construction of appropriate network architectures requires actuarial expertise

Thank you for your Attention!

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A Selection of Relevant Literature

Grouping

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