



Feedforward neural networks from a statistical-modelling perspective

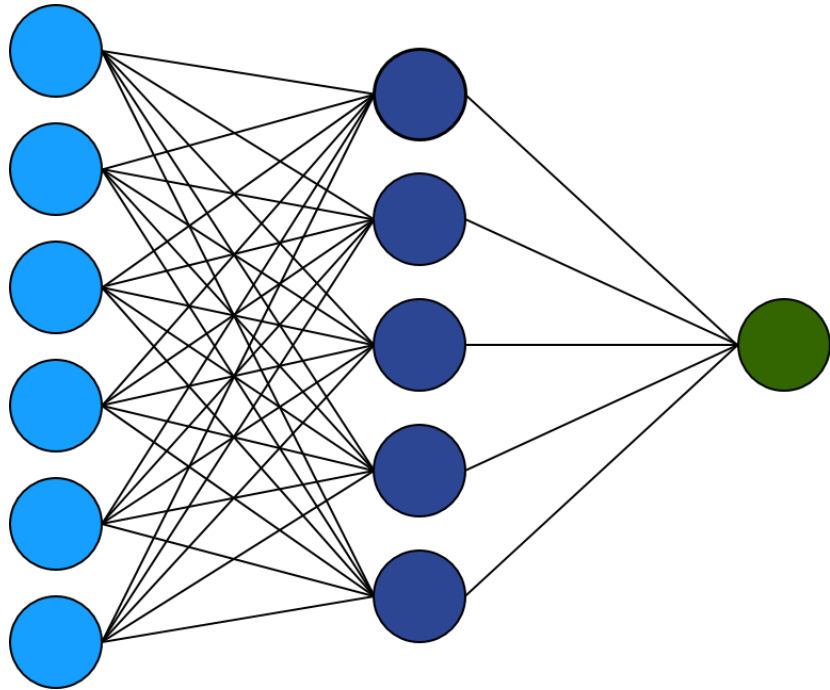
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Feedforward Neural Networks



$$\text{NN}(x_i) = \gamma_0 + \sum_{k=1}^q \gamma_k \phi \left(\sum_{j=0}^p \omega_{jk} x_{ji} \right)$$

Data Application

Insurance Data (Kaggle)

1,338 beneficiaries enrolled in an insurance plan

Response: `charges`

6 Explanatory Variables:

- `age`
- `sex`
- `bmi`
- `children`
- `smoker`
- `region`

R Implementation

Many packages available to fit neural networks in R.

Some popular packages are:

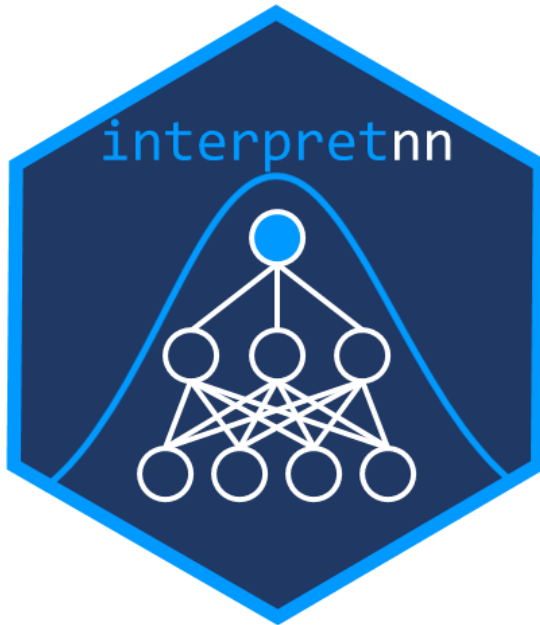
- `nnet`
- `neuralnet`
- `keras`
- `torch`

R Implementation: nnet

```
library(nnet)
nn <- nnet(charges ~ ., data = insurance, size = 2, maxit = 2000,
           linout = TRUE)
summary(nn)
```

```
## a 8-2-1 network with 21 weights
##  b->h1 i1->h1 i2->h1 i3->h1 i4->h1 i5->h1 i6->h1 i7->h1 i8->h1
##  1.39 -0.43  0.08  0.03 -0.08 -3.16  0.07  0.11  0.15
##  b->h2 i1->h2 i2->h2 i3->h2 i4->h2 i5->h2 i6->h2 i7->h2 i8->h2
##  6.31  0.04  0.13  2.19 -0.11 -6.19  0.15  0.12  0.14
##  b->o h1->o h2->o
##  1.08 -4.82  2.45
##  [...]
```

Proposed Solution: interpretnn



```
# install.packages("devtools")  
library(devtools)  
install_github("andrew-mcinerney/interpretnn")
```

Statistical Perspective

$$y_i = \text{NN}(x_i) + \varepsilon_i,$$

where

$$\varepsilon_i \sim N(0, \sigma^2)$$

$$\ell(\theta, \sigma^2) = -\frac{n}{2} \log(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (y_i - \text{NN}(x_i))^2$$

Uncertainty Quantification

Then, as $n \rightarrow \infty$

$$\hat{\theta} \sim N[\theta, \Sigma = \mathcal{I}(\theta)^{-1}]$$

Estimate Σ using

$$\hat{\Sigma} = I_o(\hat{\theta})^{-1}$$

However, inverting $I_o(\hat{\theta})$ can be problematic in neural networks.

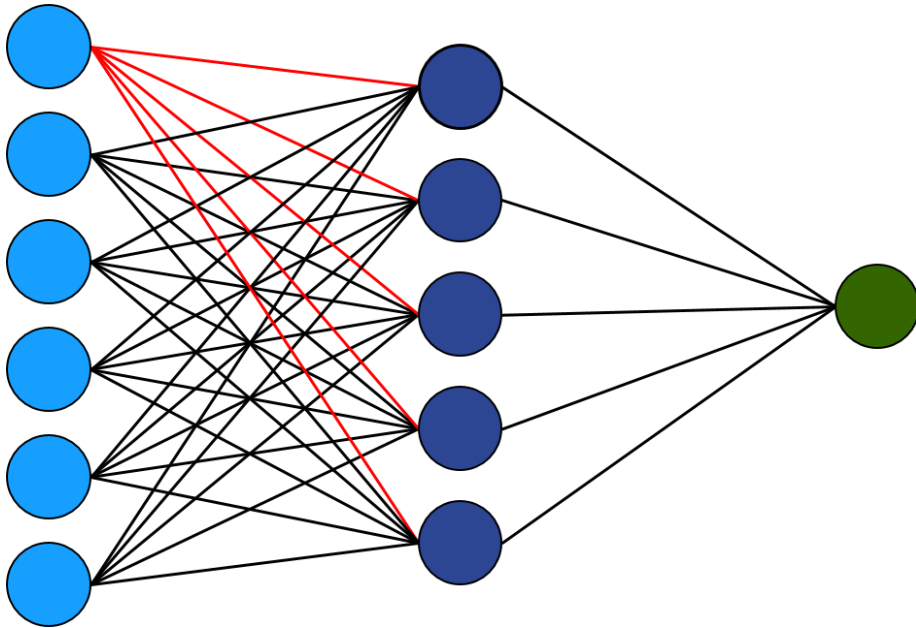
Redundancy

Redundant hidden nodes can lead to issues of unidentifiability for some of the parameters (Fukumizu 1996).

Redundant hidden nodes \implies Singular information matrix.

Trade-off between model flexibility and interpretability.

Significance Testing



Wald test:

$$\omega_j = (\omega_{j1}, \omega_{j2}, \dots, \omega_{jq})^T$$

$$H_0 : \omega_j = 0$$

$$(\hat{\omega}_j - \omega_j)^T \Sigma_{\hat{\omega}_j}^{-1} (\hat{\omega}_j - \omega_j) \sim \chi_q^2$$

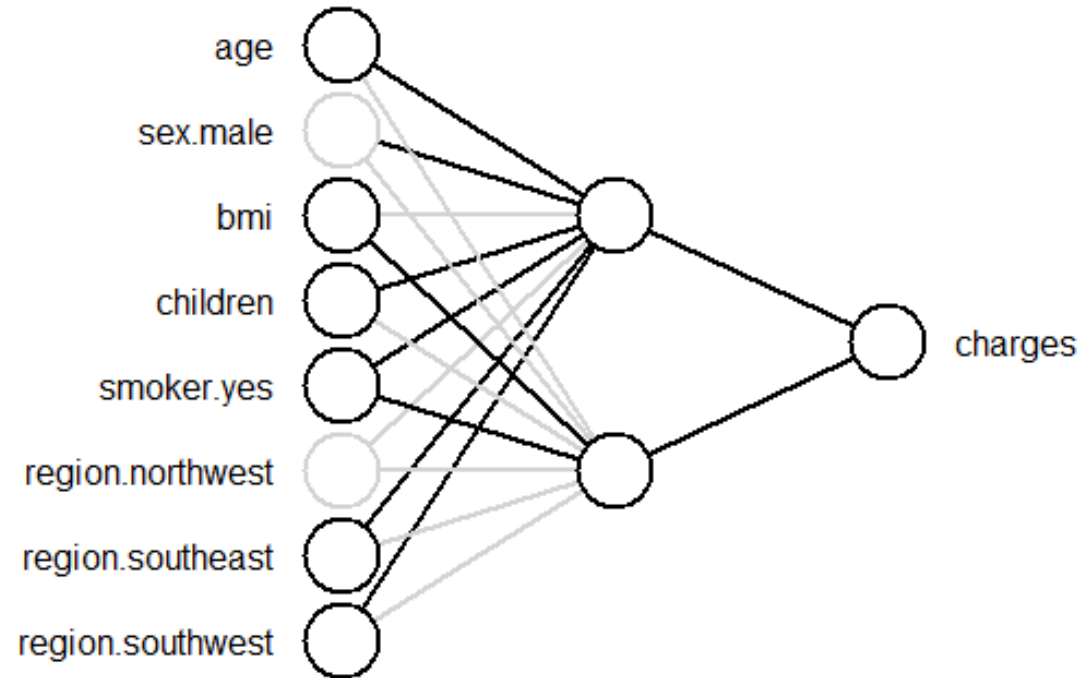
Insurance: Model Summary

```
intnn <- interpretnn(nn)
summary(intnn)
```

```
## Coefficients:
##
##              Weights |      X^2    Pr(> X^2)
##          age      (-0.43***, 0.04) |  41.4363 1.01e-09 ***
##    sex.male      (0.08*, 0.13) |   5.5055 6.38e-02 .
##          bmi      (0.03, 2.19***) | 105.6106 0.00e+00 ***
##    children  (-0.08***, -0.11.) |  19.0146 7.43e-05 ***
##    smoker.yes (-3.16***, -6.19***) | 250.6393 0.00e+00 ***
## region.northwest      (0.07., 0.15) |   2.8437 2.41e-01
## region.southeast      (0.11*, 0.12) |   6.2560 4.38e-02 *
## region.southwest      (0.15**, 0.14) |  10.8218 4.47e-03 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Insurance: Model Summary

```
plotnn(intnn)
```



Covariate-Effect Plots

$$\widehat{\overline{\text{NN}}}_j(x) = \frac{1}{n} \sum_{i=1}^n \text{NN}(x_{i,1}, \dots, x_{i,j-1}, x, x_{i,j+1}, \dots)$$

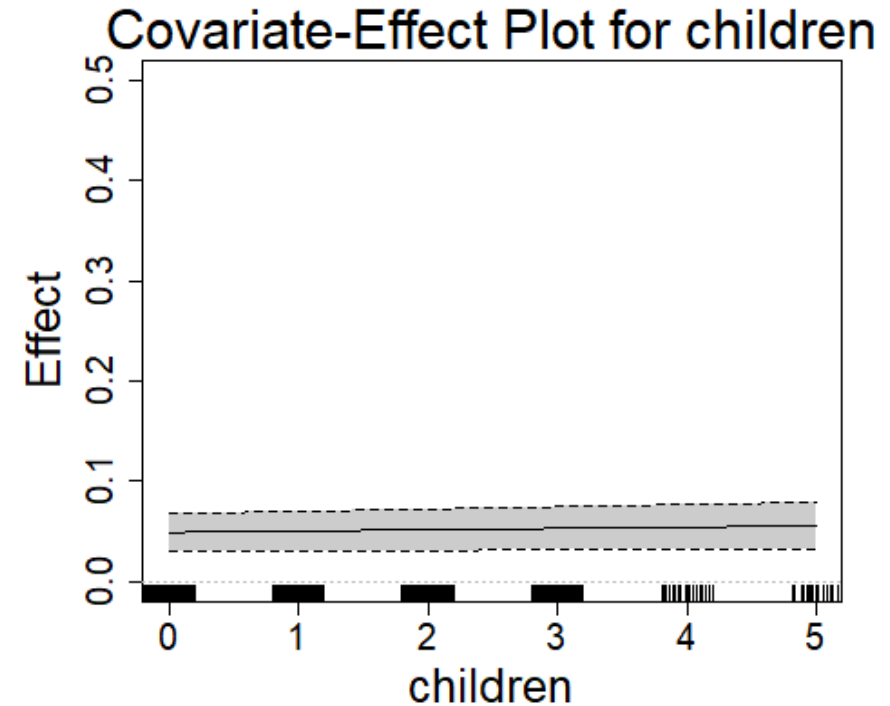
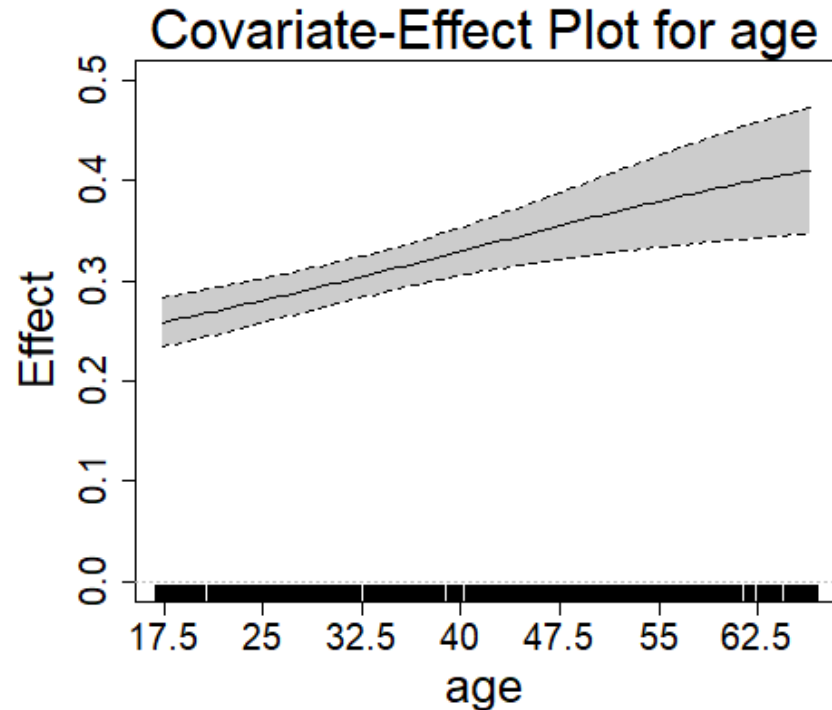
Propose covariate-effect plots of the following form:

$$\hat{\beta}_j(x, d) = \widehat{\overline{\text{NN}}}_j(x + d) - \widehat{\overline{\text{NN}}}_j(x)$$

Usually set $d = \text{SD}(x_j)$

Insurance: Covariate Effects

```
plot(intnn, conf_int = TRUE, which = c(1, 4))
```



References

- McInerney, A., & Burke, K. (2022). A statistically-based approach to feedforward neural network model selection. arXiv preprint arXiv:2207.04248.
- McInerney, A., & Burke, K. (2023). Interpreting feedforward neural networks as statistical models. In Preparation.

R Package

```
devtools::install_github("andrew-mcinerney/interpretnn")
```



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