Predicting Enrollment at University of Iowa

Using Adversarially Debiased Neural Networks and Ensemble Trees

ISIB Research Symposium

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July 17, 2025

Objectives & Motivations

- **Goal:** Properly predicting enrollment during application cycle
- **Motivations**
  - Used by Administrators, Housing, and Academic Advisors
  - Preparation for future class years

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- **Current Models**
  - Ensemble tree methods
    - Random Forests
    - Gradient Boosted Trees
  - Room for improvement

Data Overview

- Individual Data
  - Scholarship money
  - Distance from University of Iowa
  - Orientation Attendance
  - 90+ predictive variables
- Collected weekly during application cycles
- Six years of data
  - The tracked data varies by year
- Data Cleaning
  - Continuous: NAs set to 0; NA identification factor added
  - Categorical: NAs added as factor level

Data Used & Model Size

- Aligned Data
  - Data used from similar time in admission cycle in different years
  - Also uses 4 different years of data
  - Data presented is from middle of cycle
- Unaligned Data
  - Data collected from different periods in admission cycle
  - Data from 4 different years
- Model tested on data from years not in the training set

What is a Neural Network?

- Machine learning technique
- Models highly nonlinear relationships
  - Layers of linear and nonlinear functions
  - Sequential building of layers
- Increasing model complexity could lead to better predictions
- Many parameters to be learned
  - Very accurate results
  - Fear of overfitting
- Two model sizes
  - Small: 565,000 parameters
  - Large: 1,217,000 parameters

Neural Network Architecture

```{r}

net <- nn_module(
  initialize = function(d_in, d_hidden_1, d_hidden_2, d_out){
    self$net <- nn_sequential(
      nn_linear(d_in, d_hidden_1),
      nn_relu(),
      nn_linear(d_hidden_1, d_hidden_2),
      nn_relu(),
      nn_linear(d_hidden_2, d_out)
    )},
  forward = function(x){
    self$net(x)
  }
)


```

Figure 1: Neural Network using Torch [5]

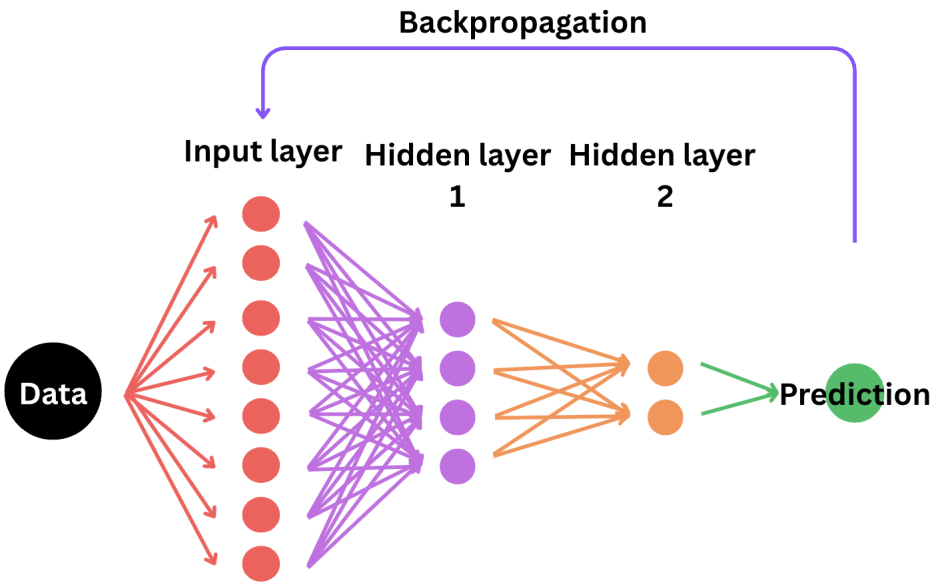

Figure 2: Network Architecture

Network Training

- Forward Pass
  Takes Inputs $\vec{X}$ and Predicts enrollment, Y

$$\hat{Y} = f(\vec{X}) = \sigma \circ T_3 \circ ReLU \circ ... \circ T_1(\vec{X})$$

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- Loss Function
  Quantifies Accuracy

$$L(\hat{y}, y) = -\frac{1}{n} \sum_{i=1}^{n} \sum_{k=1}^{2} \mathbb{I}\{y_i = k\} \cdot \log(P(y_i = k | x_i, \theta))$$

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- Backward Pass
  - Compute Gradients
  - Update Parameters
    - Stochastic Gradient Descent
    - ADAM Optimization Function
    - Variation of Learning Rate

Adversarial Neural Networks

- GAN - Generative Adversarial Networks [3]
  - Two networks: a generator creating simulated data and a discriminator trying to detect it
- Idea: One network, two predictions
  - Enrollment: Predict whether the student will enroll as accurately as possible
  - Year: Predict the year in which the student is applying as poorly as possible
- Input data strongly described by unimportant variable (Year)
- Two predictors are "Adversaries"
- Debiases Predictions [7]

Adversarially Debiased Architecture

```r
{r}
# Adversarial network
anet <- nn_module(
  initialize = function(d_in, d_hidden_1, d_hidden_2, d_out, num_classes_z){
    self$net <- nn_sequential(
      nn_linear(d_in, d_hidden_1),
      nn_relu(),
      nn_linear(d_hidden_1, d_hidden_2),
      nn_relu()
    )

    self$binary_head <- nn_sequential( nn_linear(d_hidden_2, d_out))
    self$multi_head <- nn_sequential( nn_linear(d_hidden_2, num_classes_z))
  },
  forward = function(x){
    features <- self$net(x)
    y_pred <- self$binary_head(features)
    z_pred <- self$multi_head(features)
    list(y_pred = y_pred, z_pred = z_pred)
  },

```

Figure 3: Adversarially Debiased Neural Net[5]

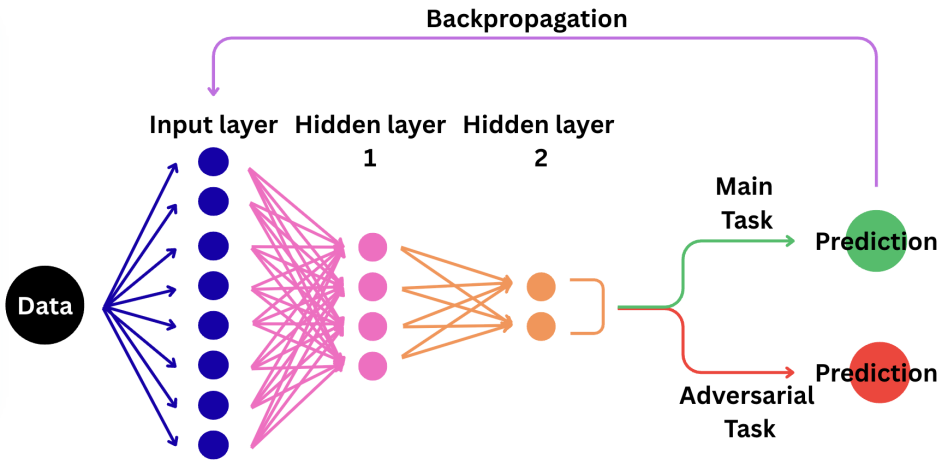

Figure 4: Network Architecture

Adversarially Debiased Loss Function

- Enrollment loss function: [4]

$$L_1(\hat{y}, y) = -\frac{1}{n}\sum_{i=1}^{n}\sum_{k=1}^{2}\mathbb{I}\{y_i = k\} \cdot \log(P(y_i = k|x_i, \theta))$$

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- Year loss function:

$$L_2(\hat{z}, z) = -\frac{1}{n}\sum_{i=1}^{n}\sum_{k=1}^{4}\mathbb{I}\{z_i = k\} \cdot \log(P(z_i = k|x_i, \theta))$$

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- Adversarial loss function:

$$L(\hat{y}, \hat{z}, y, z) = L_1(\hat{y}, y) - \lambda \cdot L_2(\hat{z}, z)$$

Experiment Results

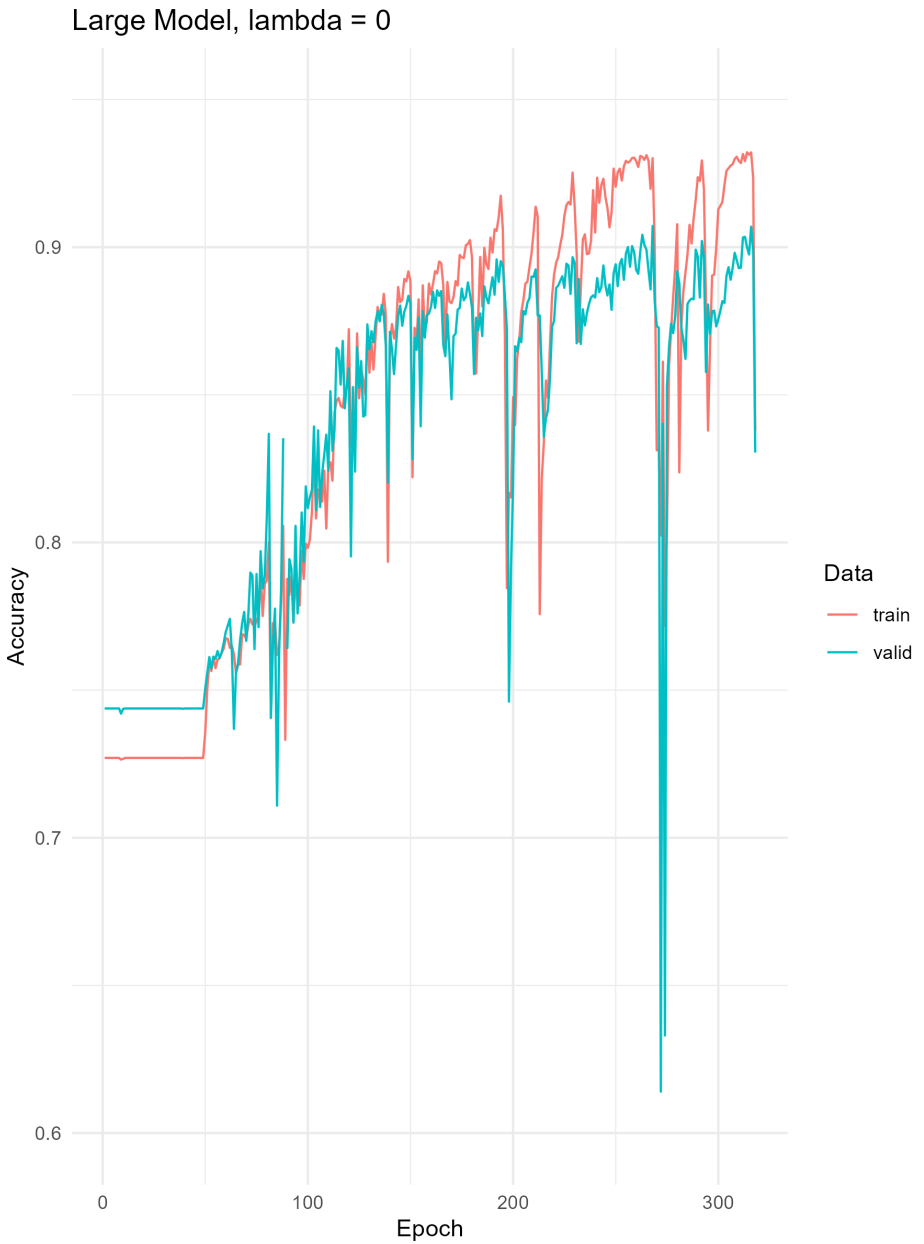
Model Size	$\lambda = 0$	$\lambda = 0.25$	$\lambda = 0.5$
Small	0.869	0.809	0.846
Large	0.867	0.750	0.858

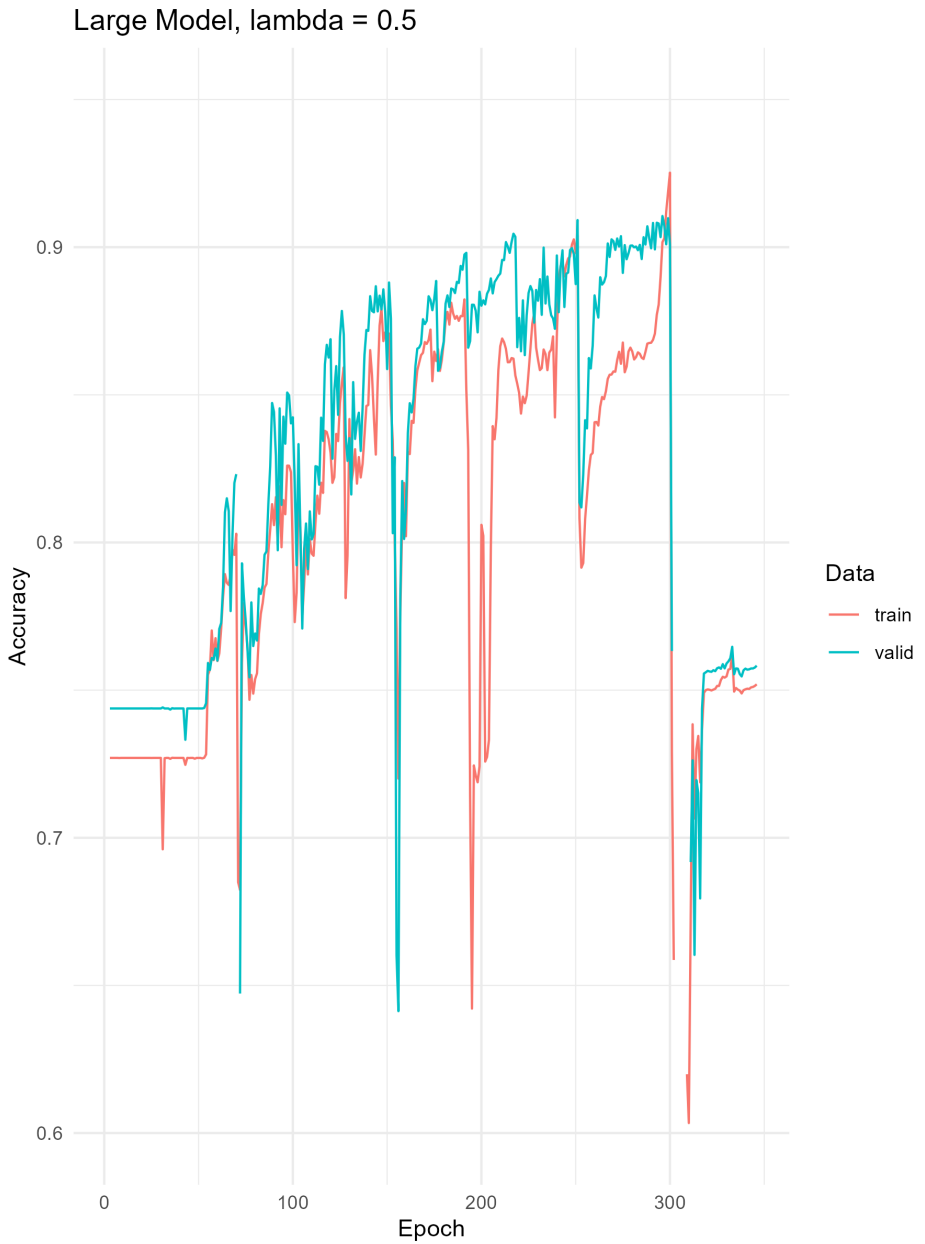
Table 1: Unaligned Data

Model Size	$\lambda = 0$	$\lambda = 0.25$	$\lambda = 0.5$
Small	0.743	0.910	0.898
Large	0.907	0.740	0.911

Table 2: Aligned Data, Middle of Cycle

Comparison Plot





Random Forest Model

- Builds and combines multiple decision trees in training using bagging [6]
- Randomness introduced in the creation of new trees
- Outputs the majority vote for classification tasks

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- Randomness introduced in the creation of new trees
- Outputs the majority vote for classification tasks
- Unaligned accuracy of: 0.864
- Aligned accuracy of: 0.922
- Run time of 1-2 minutes

XGBoost Model

- Makes predictions by combining outputs of many decision trees built sequentially [2]
- Each new tree is trained to correct the errors of the previous ones
- Uses gradient boosting to minimize a loss function based on residuals of the previous tree [1]

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- Makes predictions by combining outputs of many decision trees built sequentially [2]
- Each new tree is trained to correct the errors of the previous ones
- Uses gradient boosting to minimize a loss function based on residuals of the previous tree [1]
- Unaligned accuracy of: 0.906
- Aligned accuracy of: 0.922
- Runtime: 10-15 seconds

Model Comparisons

	Neural Net.	XGBoost	Random Forest
Unaligned Data	0.867	0.906	0.864
Aligned Data	0.911	0.922	0.922

Table 3: Accuracy Model Comparison Aligned

	Neural Net.	XGBoost	Random Forest
Sensitivity	0.967	0.960	0.525
Specificity	0.808	0.712	0.981

Table 4: Unaligned Data: Sensitivity & Specificity

	Neural Net.	XGBoost	Random Forest
Sensitivity	0.962	0.980	0.753
Specificity	0.860	0.753	0.981

Table 5: Aligned Data: Sensitivity & Specificity

Overall Conclusions

- Should the University Admissions Cycle team adopt our model?
- Additional investment into an Adversarial Debiasing Network may prove to be successful but cumbersome
- Inconsistency in the training process makes a current commitment to neural networks impractical
- While Neural Networks may not be the best way to predict enrollment, adversarial debiasing is a promising direction to continue exploring

References I

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[2] Tianqi Chen et al. *xgboost: Extreme Gradient Boosting*. R package version 1.7.7.1. 2024. URL: `https://CRAN.R-project.org/package=xgboost`.

[3] Antonia Creswell et al. "Generative adversarial networks: An overview". In: *IEEE signal processing magazine* 35.1 (2018), pp. 53–65.

[4] Daniel Falbel and Javier Luraschi. *torch: Tensors and Neural Networks with 'GPU' Acceleration*. R package version 0.14.2. 2025. URL: `https://CRAN.R-project.org/package=torch`.

[5] Sigrid Keydana. *Deep Learning and Scientific Computing with R torch*. Chapman and Hall/CRC, 2023.

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[7] Han Xu et al. “To be robust or to be fair: Towards fairness in adversarial training”. In: *Proceedings of Machine Learning Research* (2021).

Thank You!

ISIB Program sponsored by the National Heart Lung and Blood Institute

Grant HL161716-01.

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