# Paycheck Pathways

## Unveiling the Key Factors Shaping Early Career Earnings

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# Outline

# Background

- **Motivation:** Recent research has shown that where students attended college was a key factor into how much they made post-graduation
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- **Motivation:** Recent research has shown that where students attended college was a key factor into how much they made post-graduation
- But this research did not delve into what was associated with this discrepancy
- The natural question emerges:
  **What factors lead to differences in salary after graduation?**

# Why is this important?

- Allows us to see if this discrepancy is related to academics and/or socioeconomics
- Idea of the "Cycle of Poverty"
- Other factors may be university-specific

# The Dataset

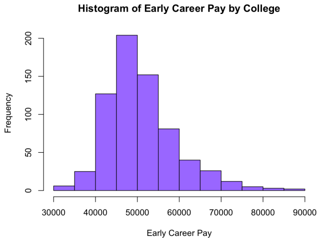
The data comes from the US Department of Education with 58 variables.

- University information: acceptance rate, average SAT score, region/locale
- Student Body information: diversity and domestic/international, socioeconomic status, % STEM and "Better World"
- Tuition/Financial Aid information: tuition revenue/cost of attendance, Pell Grants, etc.

# Distribution of Early Career Pay

Our response variable is early career pay, measured as an average across the alumni student body of each college.

1. Early career pay appears to follow some right-skewed and positive distribution, which indicates we need to transform our response variable, or fit a model with a positive response



# Response & Predictor Transformations

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1. Early career pay appears to follow some right-skewed and positive distribution, which indicates we need to transform our response variable, or fit a model with a positive response
2. As such, a log transformation will be considered for early career pay for our linear models
3. Predictor transformations include:
   - Admission rate: inverse transformation
   - Total enrollment: log transformation
   - % Domestic students: quartic transformation

# Linear Dependencies & Multicollinearity

- A few variables were linear combinations of one another – this caused linear dependencies to occur
- Some multicollinearity between some of the strongly correlated data:
  - → Multiple variables related to tuition (in-state, out-of-state, total costs, etc.)
  - → Certain diversity factors
  - → Economic factors such as median household income and poverty rate
- These predictors were dropped from consideration in all of our models in order to meet assumptions

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## Stepwise Selection

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1. We kept the same variable transformations as in OLS
2. Applied 10-fold CV to further reduce the risk of overfitting
3. Reduced number of terms from 53 to 8 (including intercept)

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| (Intercept) | 10.5680 | 0.1780 | 59.37 | $< 0.0001$ |
| Avg SAT Score | -1.564e-04 | 3.861e-05 | -4.05 | 0.0001 |
| % Students in STEM | 0.3241 | 0.0205 | 15.79 | $< 0.0001$ |
| Tuition Revenue per Student | 3.310e-06 | 4.807e-07 | 6.89 | $< 0.0001$ |
| Avg Faculty Salary | 2.256e-05 | 1.707e-06 | 13.21 | $< 0.0001$ |
| % Students with Pell Grants | -0.2935 | 0.0268 | -10.95 | $< 0.0001$ |
| % Domestic students | 0.5419 | 0.2727 | 1.99 | 0.0474 |
| $(\%\ \text{Domestic})^4$ | -0.3730 | 0.1068 | -3.49 | 0.0005 |

## LASSO

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| Variable | Coefficient |
|---|---|
| (Intercept) | 10.7034 |
| % World Better | 0.0391 |
| % Students in STEM | 0.2263 |
| Located in Rural Town | -0.0110 |
| Tuition Revenue per Student | 1.769e-06 |
| Avg Faculty Salary | 1.761e-05 |
| % Students on Pell Grants | -0.1957 |
| Graduation Rate | 0.0826 |
| % Households with Graduate Degree | 0.2248 |
| (% Domestic Students)^4* | -0.1143 |
| % Students identifying as Female | -0.0930 |
| % Students identifying as Asian | 0.0979 |

*Denotes a variable that was also in Stepwise Selection

## Partial Least Squares

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| | Component 1 | Component 2 | Component 3 |
|---|---|---|---|
| % Students in STEM* | 0.0095 | 0.0264 | 0.0369 |
| log(total enrollment) | 0.0046 | 0.0148 | 0.0127 |
| Tuition Revenue per Student* | 0.0103 | 0.0088 | 0.0145 |
| Avg Faculty Salary* | 0.0128 | 0.0201 | 0.0233 |
| % Students on Pell Grants* | -0.0097 | -0.0174 | -0.0232 |
| Graduation Rate* | 0.0119 | 0.0137 | 0.0165 |
| % Households with Graduate Degree* | 0.0111 | 0.0093 | 0.0104 |
| % Students identifying as Female* | -0.0061 | -0.0202 | -0.0217 |
| % Students identifying as Asian* | 0.0095 | 0.0128 | 0.0147 |

Table of loadings of select predictors for the three loadings in the final PLS model. Predictors were included if there was a loading $\alpha$ that satisfied $|\alpha| > 0.015$ for any of the three components.
*Denotes a predictor that also appeared in the LASSO model.

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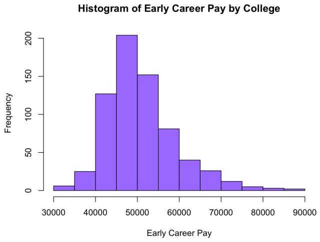
1. Financial data often follows a Gamma distribution - supports our earlier remarks about early career pay



# Why consider a Gamma GLM?

Note that the previous methods required a log-transformation of our response variable. It's natural to consider a Generalized Linear Model:

1. Financial data often follows a Gamma distribution - supports our earlier remarks about early career pay
2. There are benefits of working with a model that does not require further transformations.

# About the Gamma GLM

- A slightly different parameterization is used - with the shape parameter $\nu$ and then scale parameter $= \frac{\nu}{\mu}$
- A log-link $\log(\mu)$ was used (instead of the canonical link)
- When variance is small, the Gamma GLM with log-link performs rather similar to a Gaussian linear model with a log-transformed response.

# Predictors Included

We utilized the predictors that were screened from the stepwise regression model.

There is not variable selection or dimension reduction built-in.

# Our Results

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- The coefficients and standard errors were nearly exactly the same as those of the stepwise model w/ log transformation
- This is because the dispersion parameter - $1/\hat{\nu}$ - was small, and with large $\nu$ the Gamma distribution can be approximated by Normal
- But...the Analysis of Deviance test failed to reject the null model.

# Outline

BART: **B**ayesian **A**dditive **R**egression **T**rees

Notable questions answered in this presentation:

- What led us to consider a regression tree model?
  1. Non-parametric
  2. Capable of capturing nonlinear relationships
- Why *Bayesian* [additive] regression trees?

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- What led us to consider a regression tree model?
  1. Non-parametric
  2. Capable of capturing nonlinear relationships
  3. Trees are *weak learners*.
- Why *Bayesian* [additive] regression trees?
  1. Each tree intended to address *different* aspects of the prediction problem.
  2. No need for 'greedy growing' of each tree and subsequent pruning, as in CART models – see Ročková and Saha, 2018. Instead, a **prior** is used to combat overfitting.

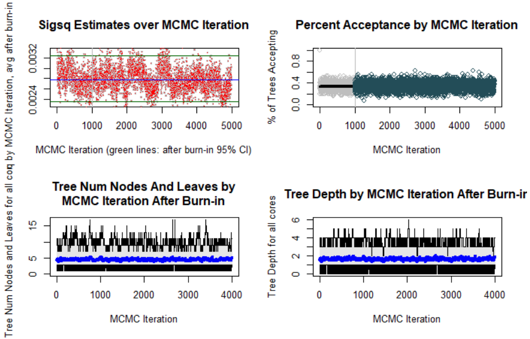
$$Y = \sum_{j=1}^{m} g(x; \underbrace{T_j, M_j}_{(2)}) + \epsilon \qquad \epsilon \sim N(0, \underbrace{\sigma^2}_{(1)})$$

1. **Variance of error term**: Errors are $\epsilon \sim N(0, \sigma^2)$ for mathematical tractability.
   - *Prior is inverse chi-squared* with scaling factor determined by hyperparameters on the *center* and *shape* of the distribution. $(\nu, q)$
2. **Pairs** of $(T_j, M_j)$ – $T_j$ are binary regression trees that split the range of predictors into subsets; $M_j$ are parameters of [terimal] nodes.
   - Prior includes factor of prior on $M_j | T_j$, affected by **depth** of a node and assigning high probability mass to the interval $(y_{\min}, y_{\max})$. $(k)$

Cross-validation chose hyperparameters $k = 5, \nu = 3, q = 0.90, m = 40$.

$m = 40$ was highest considered value – runs with higher $m$ led to intractability when visualizing trees.

Other notable parameters: 1000 iterations for burn-in; 4000 iterations after burn-in concluded.



Two R packages – BARTMAN (BART **M**odel **An**alysis) and BARTMACHINE (running BART).

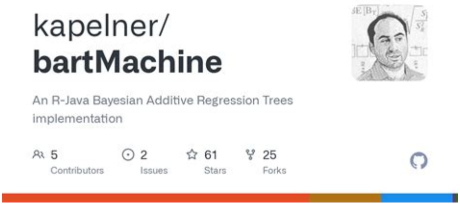



Figure: Profile of bartMachine package repository

Figure: "Bartman," alternate persona of Bart Simpson

To *run BART* is not a computational challenge on a laptop (tech-lab computers did not have Java :( ); to *visualize* the $\approx$ 1.6 million trees, however, took $\approx$ 5 hours and all but 4 MB of 15.8 GB of available RAM.

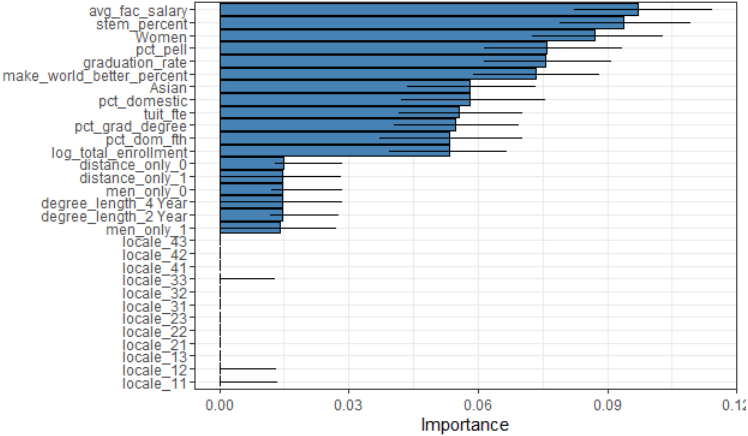



Figure: Variable Importance for BART

# Outline

| | OLS | Stepwise | LASSO | PLS | GLM | BART |
|---|---|---|---|---|---|---|
| RMSE (Train) | 0.0557 | 0.0639 | 0.0634 | 0.0605 | 0.0639 | **0.0465** |
| RMSE (Test) | 0.0760 | 0.0775 | 0.0775 | 0.0726 | 0.0774 | **0.0655** |
| Difference | 0.0203 | 0.0136 | 0.0141 | **0.0121** | 0.0135 | 0.0190 |
| Num. Terms | 53 | 8 | 15 | **3***  | 8 | – |

* number of components retained

Table: Summary of various comparison methods for our models. Note the errors are presented on the log-scale.

# Answering our Research Question

**What factors lead to differences in salary after graduation?**

| Important for both PLS and BART | Is only important in BART |
|---|---|
| % of Students in STEM | % Make World Better |
| Average Faculty Salary | % Domestic Students |
| log(total enrollment) | (% Domestic Students)^4 |
| Tuition Revenue per Student | Distance Only |
| % of Students on Pell Grants | Men Only |
| Graduation Rate | Locale |
| % Students identifying as Female | Degree Length |
| % Students identifying as Asian | |
| % Households with Graduate Degree | |

Predictors in red had negative relationship with early career pay (PLS).
Note: We can only determine correlation, not causation

# Questions?

Any and all questions are welcome!
If you are curious, our paper can be obtained by the QR code below: