Predicting Divorce from Demographic Traits

Helen Skinner

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- Uses, shortcomings and further work
- Acknowledgements

Purpose and justification

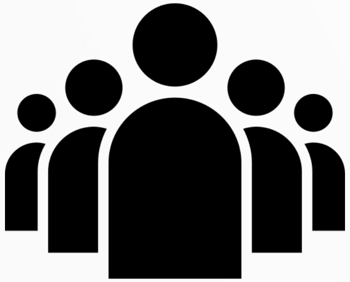
Purpose: Is it possible to predict whether an individual has ever been divorced based on demographic traits?

Justification:

- Commercial uses
- Intervention targeting and potential prevention
- General interest

Data – Overview

General Social Survey 2012



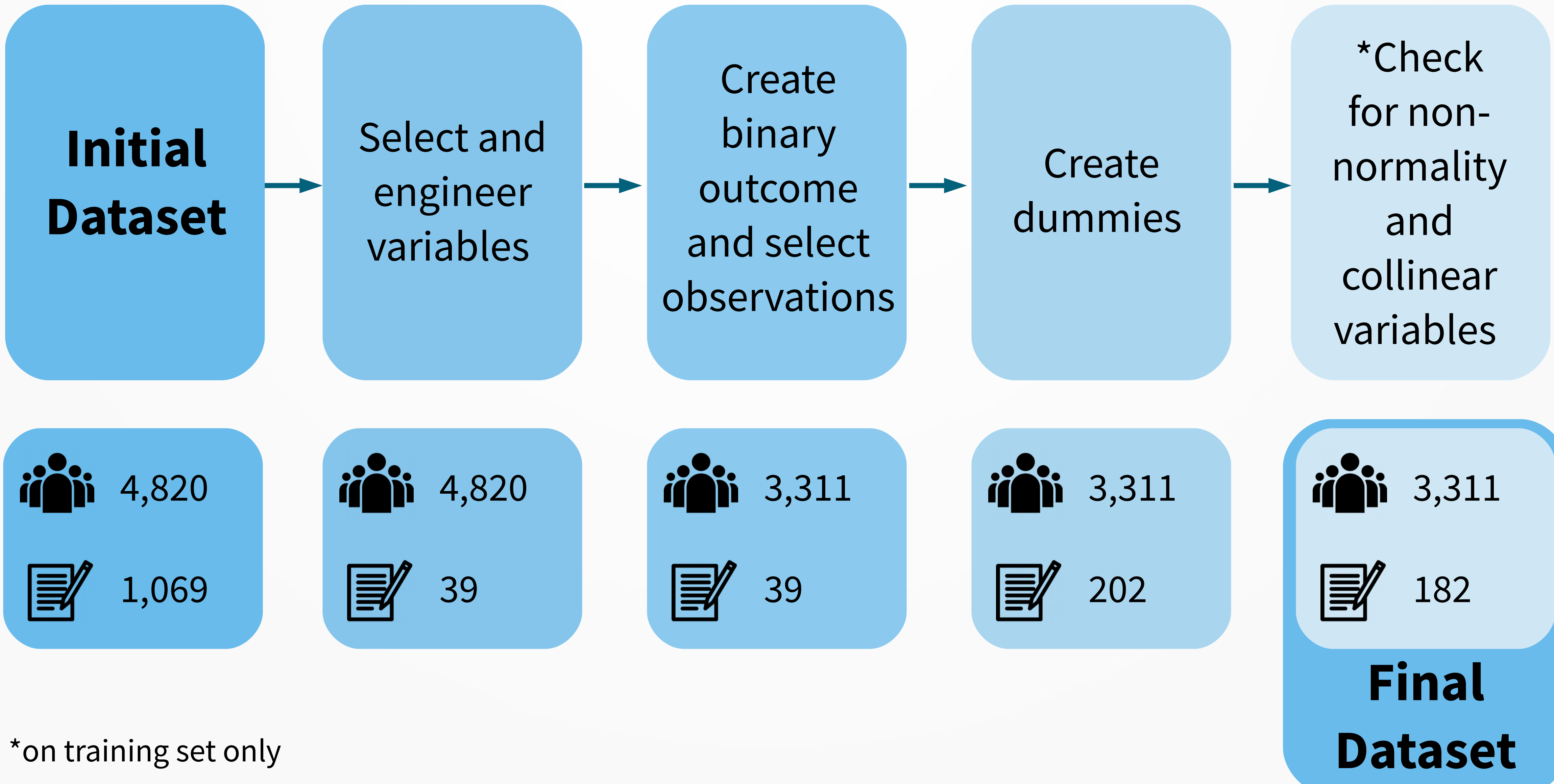
4,820 respondents

1,069 variables

Significant data preprocessing required:

- Respondents did not answer every question
- Inconsistent coding for ‘inapplicable’, ‘don’t know’ and ‘no answer’
- Potential for label leakage

Data – Preprocessing workflow



*on training set only

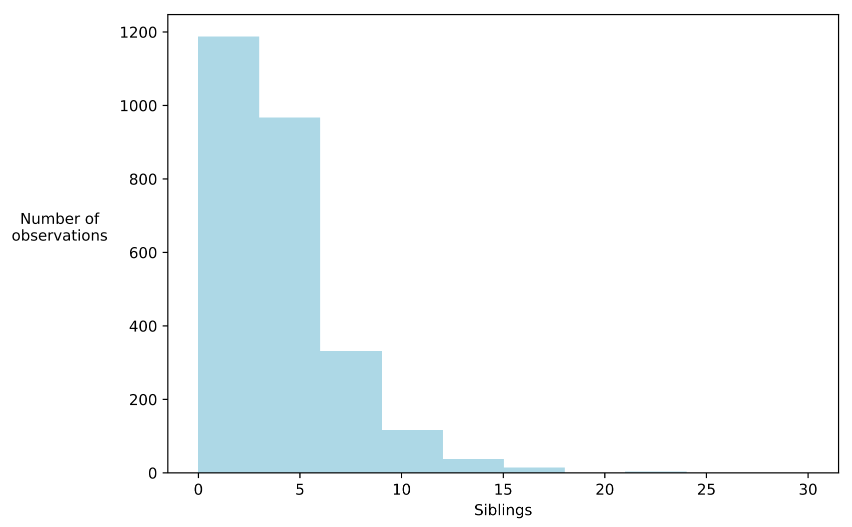
Data – Select and engineer variables

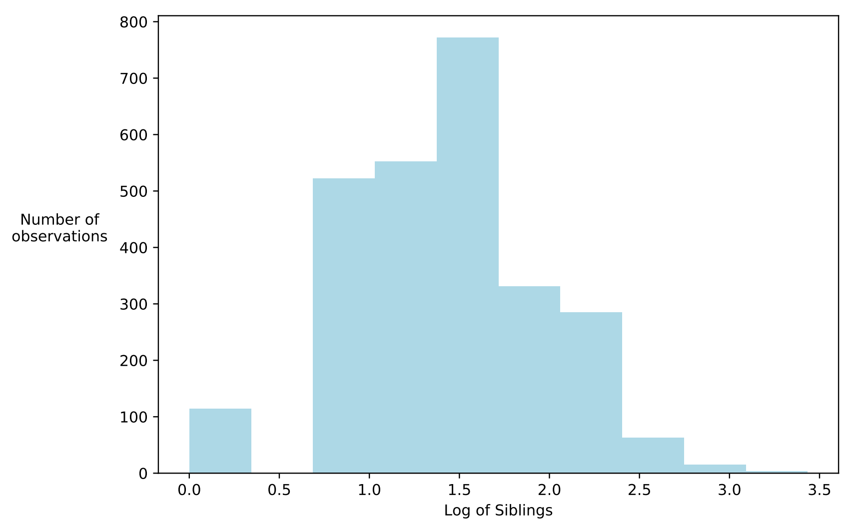
Dropping	• Low response rates • Label leakage • Manual selection required	e.g. Most opinion questions e.g. Dwelling type
Grouping	• Reduce noise • Reduce overfitting	e.g. Religion e.g. Occupation
Imputing	• Potentially important but some missing data • Sensible method available	e.g. Income using logical rules

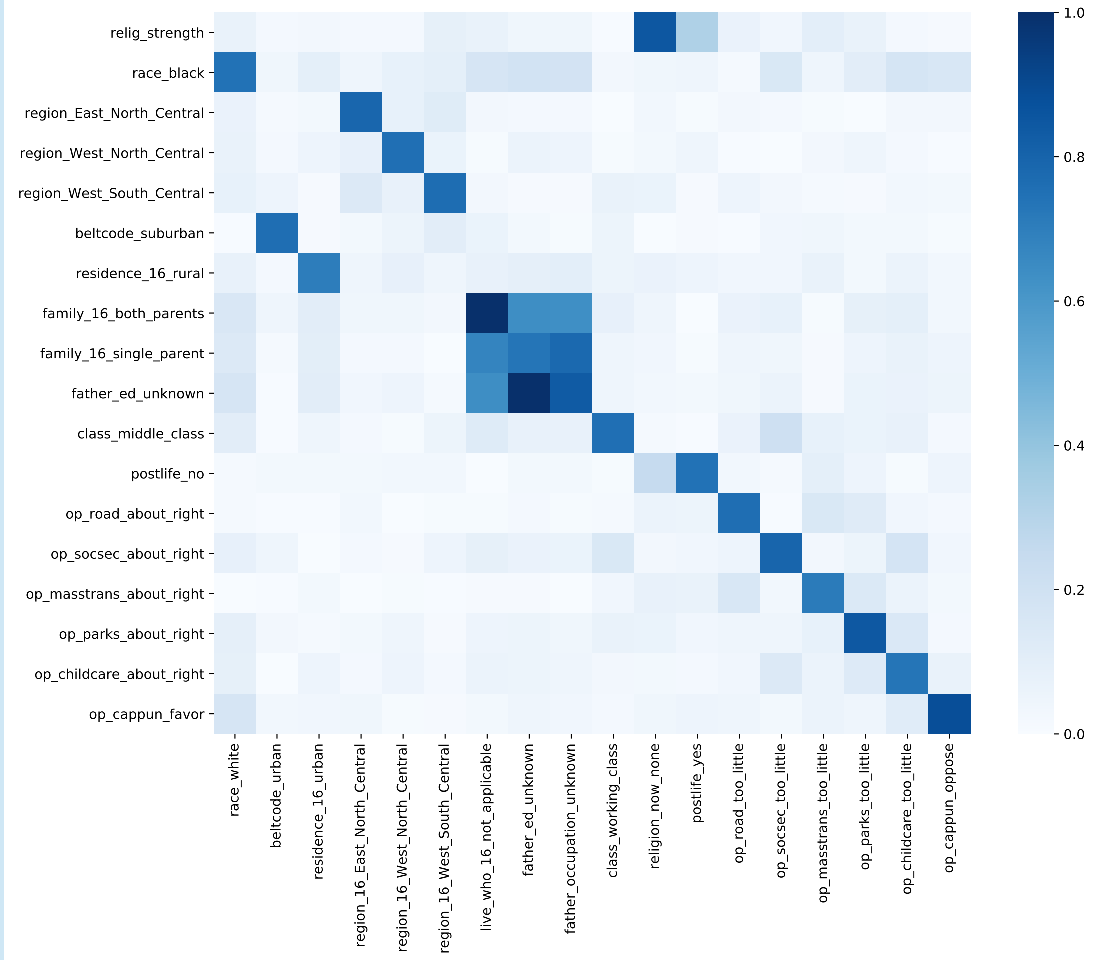
Data – Create binary outcome and select observations

Binarizing 01 10	• Compare “not divorced / separated” vs “divorced / separated” • Remove all single people as not applicable • Previously divorced and now remarried counts as “divorced / separated” • Widowed counts as “not divorced / separated”
Dropping	• Remove single people as not applicable • Remove observations with missing data

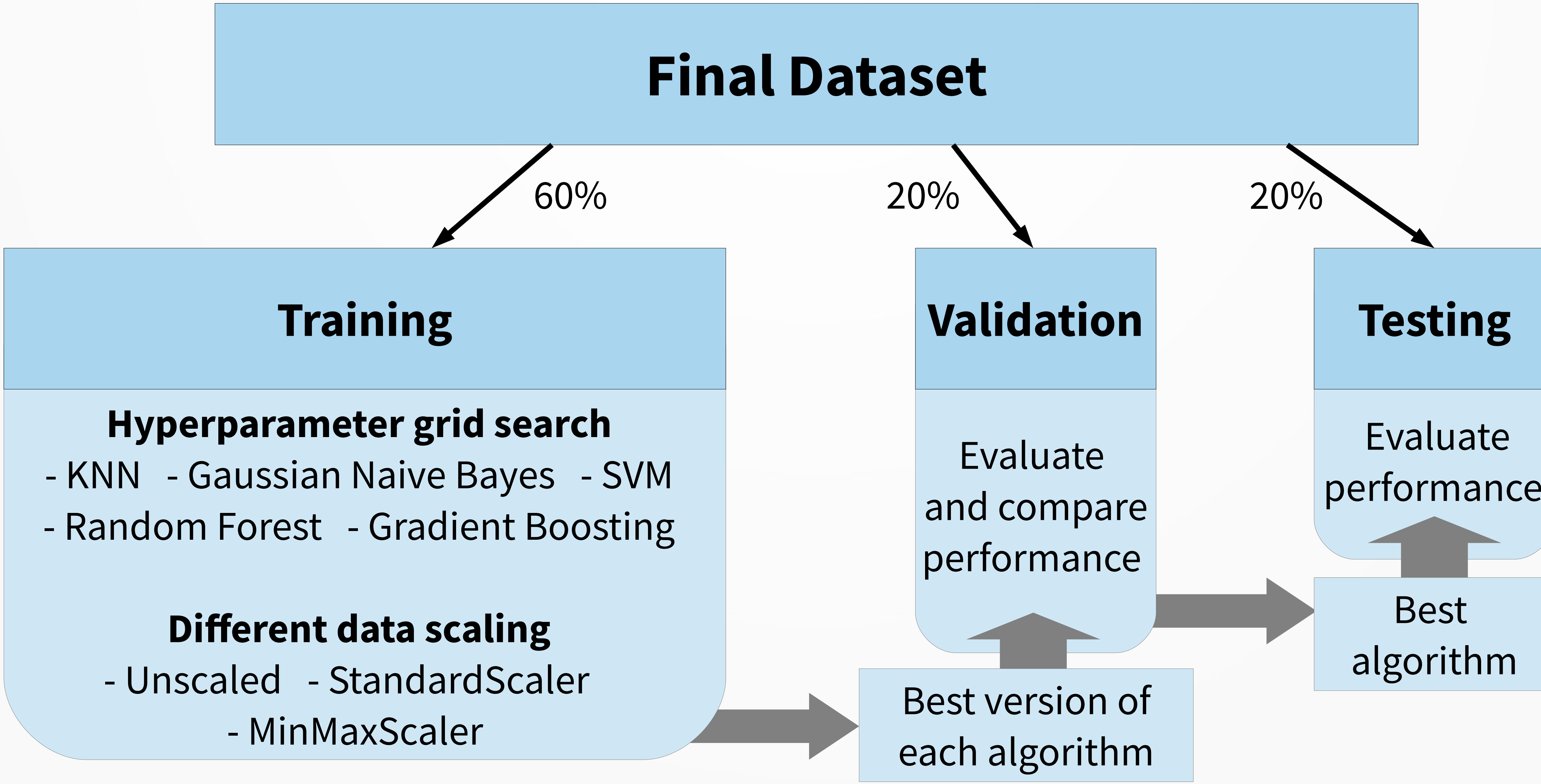
Data – Non-normality and collinearity







Modeling – Selection pathway



Modeling – Training strategy

Algorithm	Tuned hyperparameters
KNN	• n_neighbors • weights
Gaussian Naive Bayes	• var_smoothing
Random Forest	• n_estimators • criterion • max_depth • max_features
Gradient Boosting	• loss • learning_rate • max_depth • max_features
SVM	• C • gamma

- Aim to find best version of each algorithm
- Tune each algorithm to find
  - Best hyperparameters
  - Best data scaling
- Use f1 score to assess
- All algorithms trained on:
  - Unscaled data
  - StandardScaler
  - MinMaxScaler

Modeling – Training results

Algorithm	Best hyperparameters	Best data scaling
KNN	• n_neighbors = 18 • weights = distance	Unscaled
Gaussian Naive Bayes	• var_smoothing = 1e-09	StandardScaler
Random Forest	• n_estimators = 100 • criterion = entropy • max_depth = 4 • max_features = None	No difference
Gradient Boosting	• loss = exponential • learning_rate = 0.1 • max_depth = 4 • max_features = None	No difference
SVM	• C = 10 • gamma = 0.0005	Unscaled

To get the best performance from each algorithm:

- Use data scaled in this way
- Use these hyperparameters

Modeling – Validation results

KNN

Predicted \ Actual	0	1
0	68%	48%
1	32%	52%

f1: 0.546 Accuracy: 0.610

G. Naive Bayes

Predicted \ Actual	0	1
0	7%	3%
1	93%	97%

f1: 0.621 Accuracy: 0.470

Random Forest

Predicted \ Actual	0	1
0	51%	23%
1	49%	77%

f1: 0.649 Accuracy: 0.627

Gradient Boosting

Predicted \ Actual	0	1
0	73%	47%
1	27%	53%

f1: 0.570 Accuracy: 0.642

SVM

Predicted \ Actual	0	1
0	73%	44%
1	27%	56%

f1: 0.589 Accuracy: 0.653

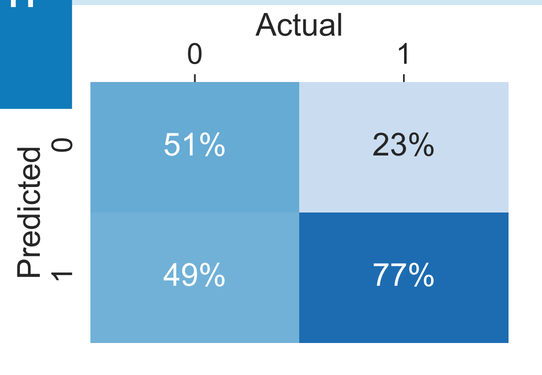
Guessing

Predicted \ Actual	0	1
0	100%	100%
1	0%	0%

f1: N/A Accuracy: 0.551

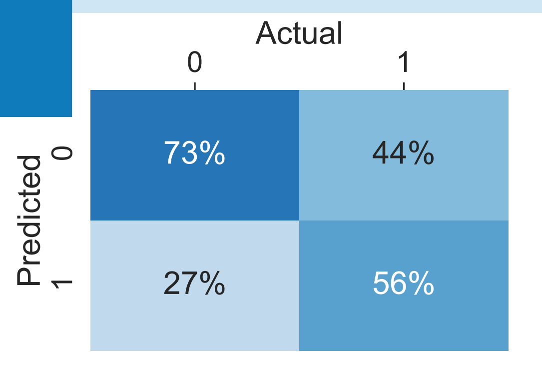
Modeling – Validation results

Random Forest



f1: 0.649   Accuracy: 0.627

SVM



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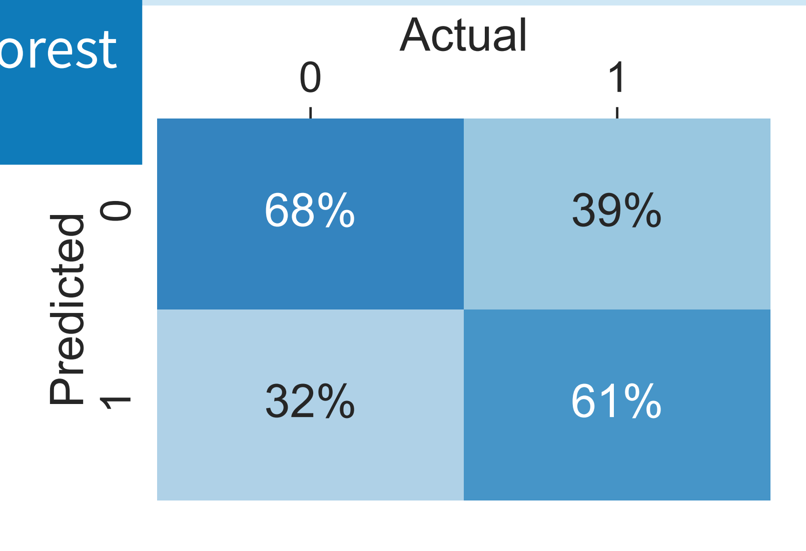
Average of Random Forest and SVM



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Modeling – Testing results

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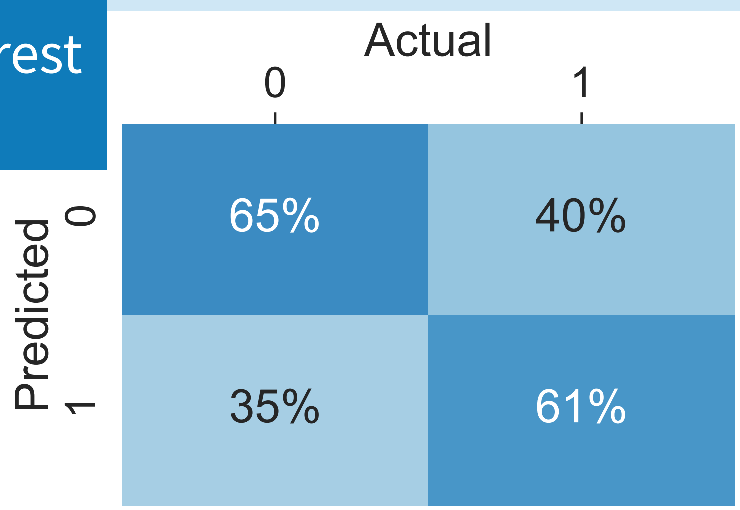
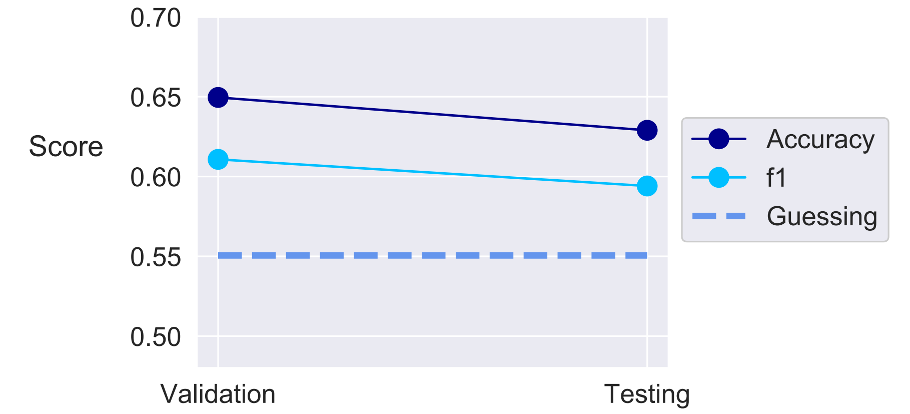


f1: 0.594 Accuracy: 0.629



- Small reduction in accuracy on test set compared to validation
- Still more accurate than guessing all not divorced

Practical uses of the model

- Advertising or actuarial
  - Counseling or legal services via social media to at risk groups
  - Insurance implications
- Intervention
  - Support or help for at risk groups
  - Charity or governmental
- General interest
  - Individuals may be interested to know personal probability
  - Either for decision-making or not

Weak points of the model

- Accuracy
  - Approximately 8 percentage points better than guessing
- Feature importances
  - Difficult to extract due to use of SVM
- Scaling
  - Run time of 11.2 seconds for training set with 2,648 observations and testing set with 663 observations
  - Estimated run time of over 24 hours for datasets over ~5 million

Further work

Test on alternative data

- Other years of GSS available
- Would require significant data preprocessing

Try using PCA

- Decrease computing time
- Increase difficulty in extracting feature importances

Different data

- More observations
- Additional variables about marital information e.g. age married

Investigate feature importances

- Straightforward for Random Forest
- Not so straightforward for SVM

Further feature engineering

- Lower collinearity threshold
- Categorize occupations differently

Different model

- Try non-binary classification
- Similar but different predictions e.g. whether someone has children

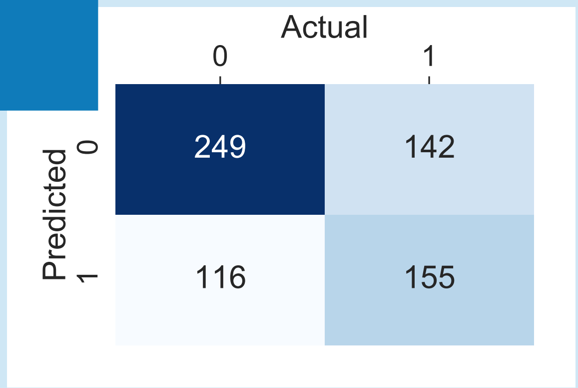
Acknowledgements

- Technical advice and support gratefully received from
  - Jenny Yu
  - Tom Nickson
  - Technical Coaching and peer group via Slack
- Icons
  - Icons made by OCHA and Freepik from www.flaticon.com

Appendix
Additional slides for information purposes

Modeling – Validation results

KNN



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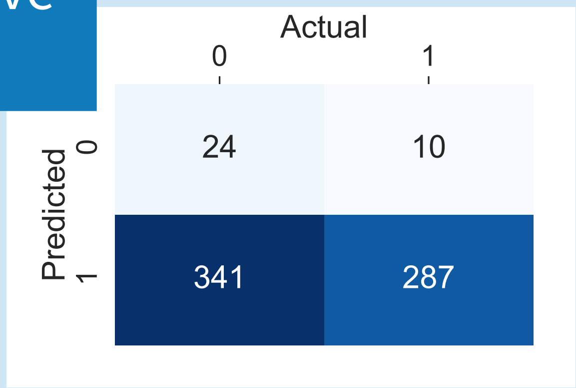

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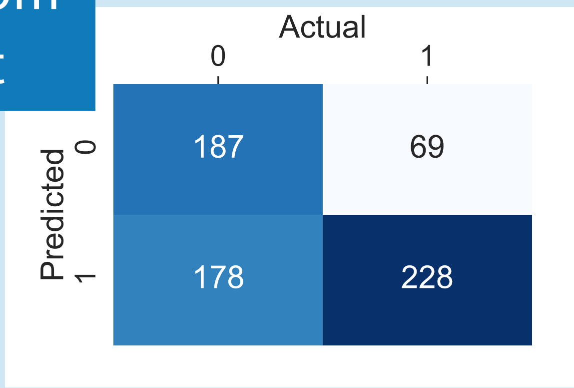
Random Forest



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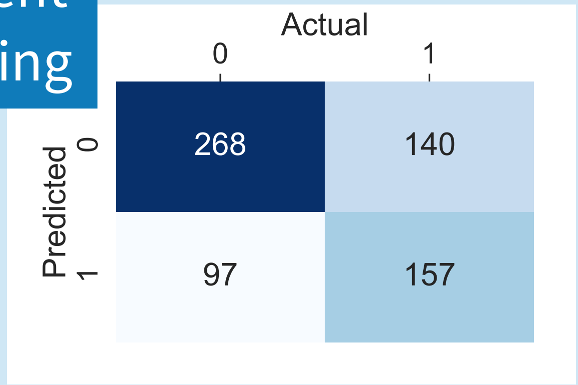
Gradient Boosting



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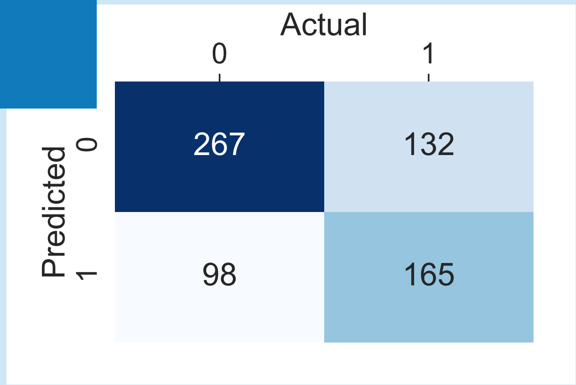

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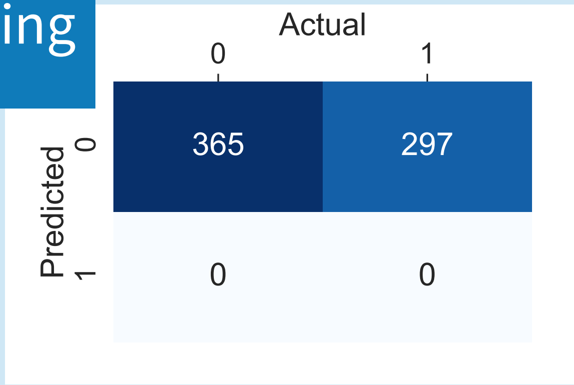
Guessing



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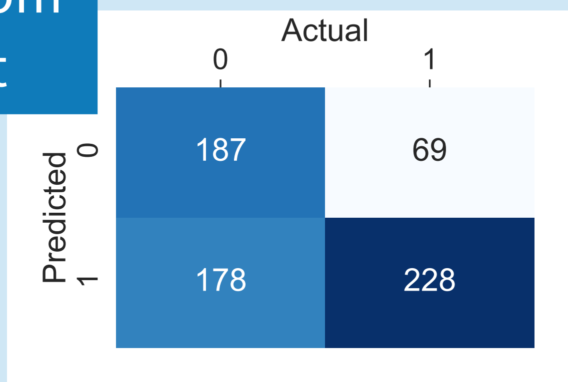
Modeling – Validation results

Random Forest



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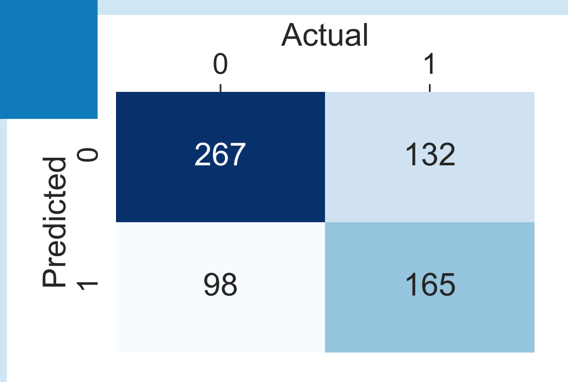

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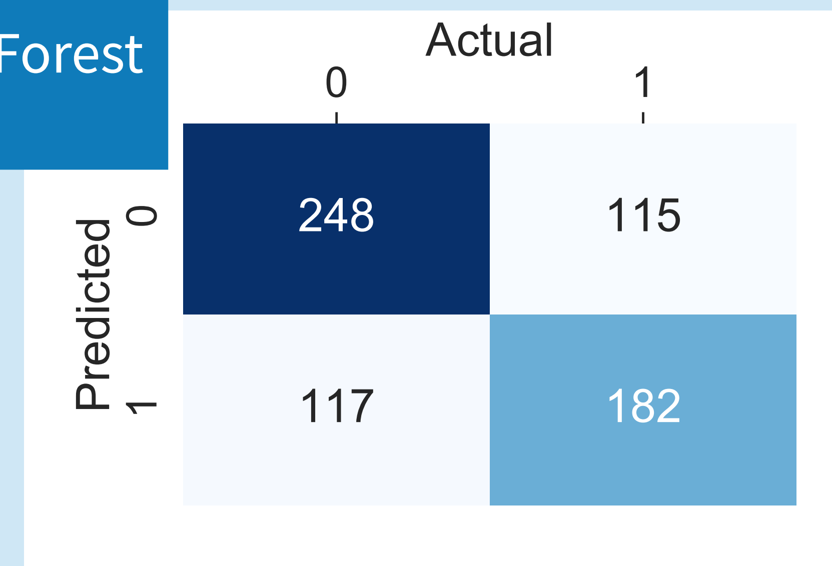
Average of Random Forest and SVM



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Modeling – Testing results

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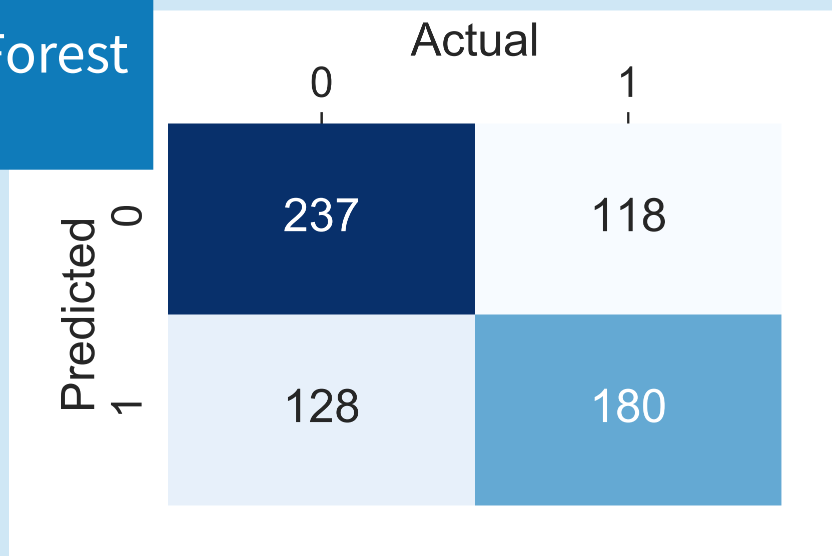

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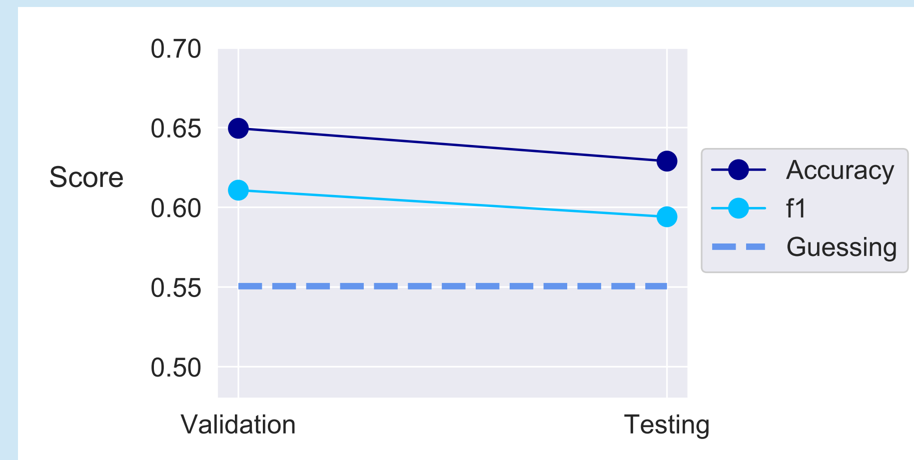

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