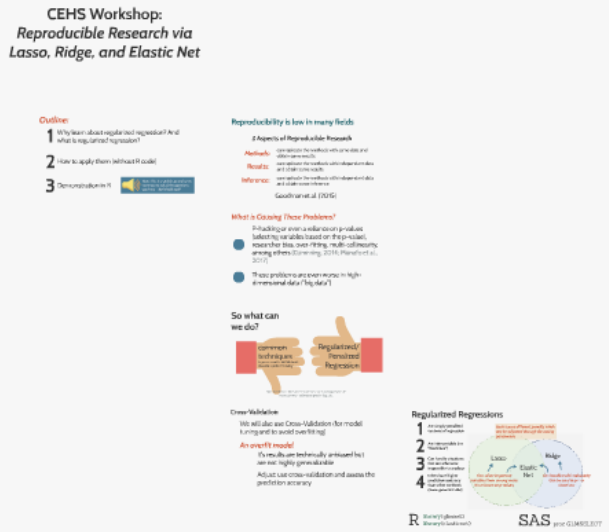
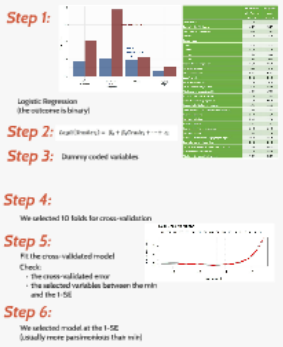
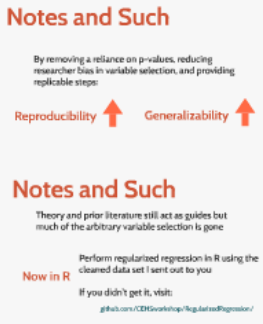
CEHS Workshop: *Reproducible Research via Lasso, Ridge, and Elastic Net*







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Outline:

1. Why learn about regularized regression? And what is regularized regression?

Reproduc

3 As

Outline:

1. Why learn about regularized regression? And what is regularized regression?

2. How to apply them (without R code)

3. Demonstration in R

Note: This is a workshop and so we want you to ask all the questions you have--don't hold back!

Reproducibility is low in many fields

3 Aspects of Reproducible Research

Methods: can replicate the methods with same data and obtain same results

Results: can replicate the methods with independent data and obtain same results

Inference: can replicate the methods with independent data and obtain same inference

Goodman et al. (2015)

What is Causing These Problems?

Goodman et al. (2015)

What is Causing These Problems?

- P-hacking or even a reliance on p-values (selecting variables based on the p-value), researcher bias, over-fitting, multi-collinearity, among others (Cumming, 2014; Munafo et al., 2017)
- These problems are even worse in high-dimensional data ("big data")

So what can we do?

Note that this is a bit extreme since there are great approaches to make common techniques great in big data

Cross-Validation

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Cross-Validation

We will also use Cross-Validation (for model tuning and to avoid overfitting)

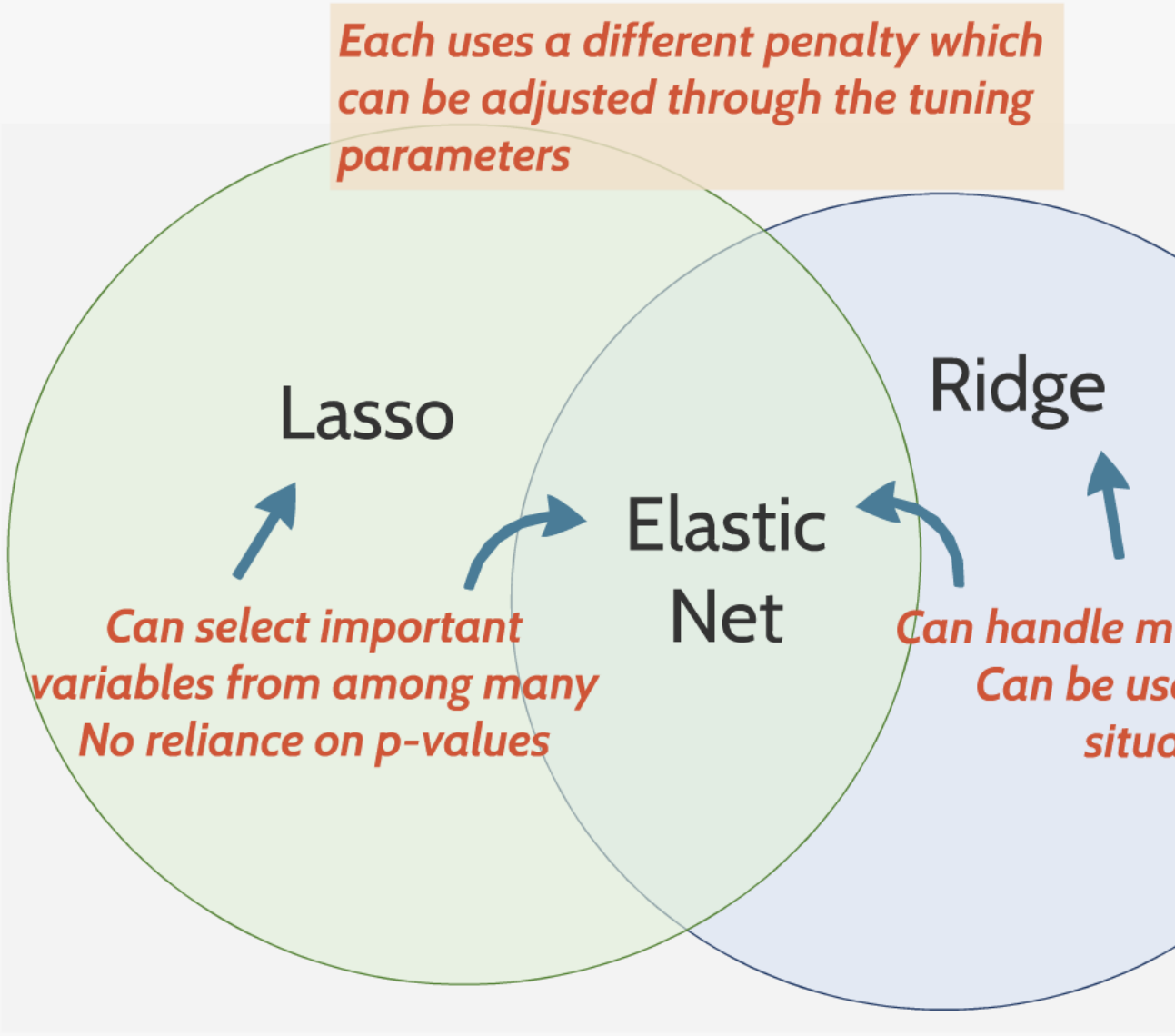
An overfit model

It's results are technically unbiased but are not highly generalizable

Adjust: use cross-validation and assess the prediction accuracy

Regularized Regressions

1. Are simply penalized versions of regression
2. Are interpretable (no "black box")
3. Can handle situations that are otherwise impossible to analyze
4. Often have higher prediction accuracy than other methods (more generalizable)



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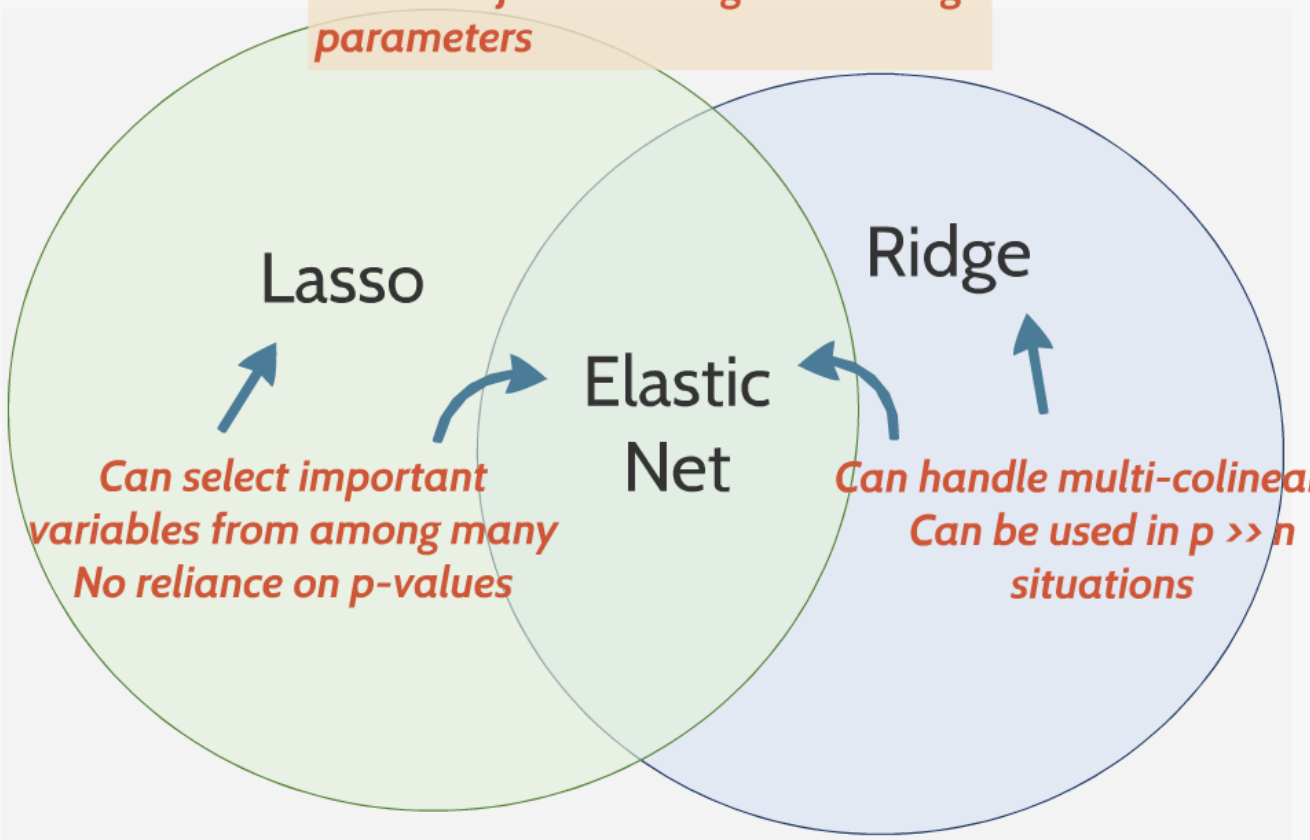
Each uses a different penalty which can be adjusted through the tuning parameters



R library(glmnet)
library(elasticnet)

SAS proc GLMSELE

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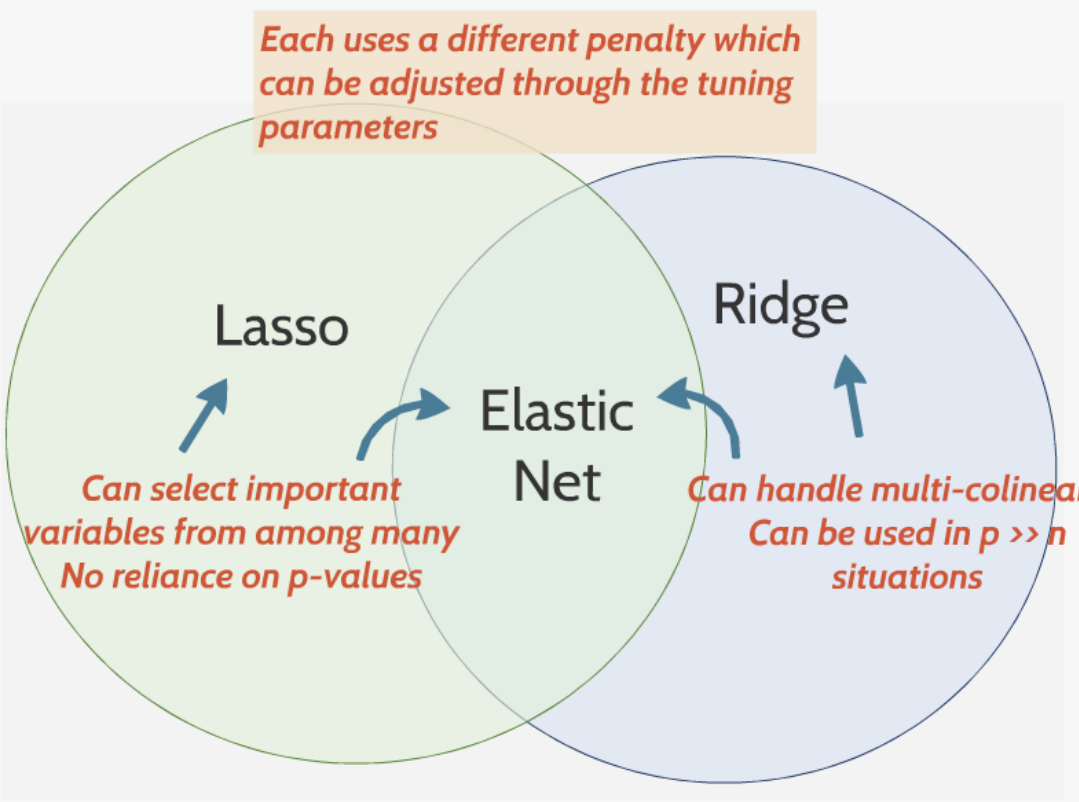

R library(glmnet)
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SAS proc GLMSELECT

Simple Steps to Use Elastic Net, Lasso or Ridge

Step 1

Understand your data
Select type of model
(linear, logistic, etc.)

Step 2

Specify the model (just like specifying regression)

Step 3

Dummy code
categorical variables

Step 4

Number of "folds" in
cross-validation

Step 5

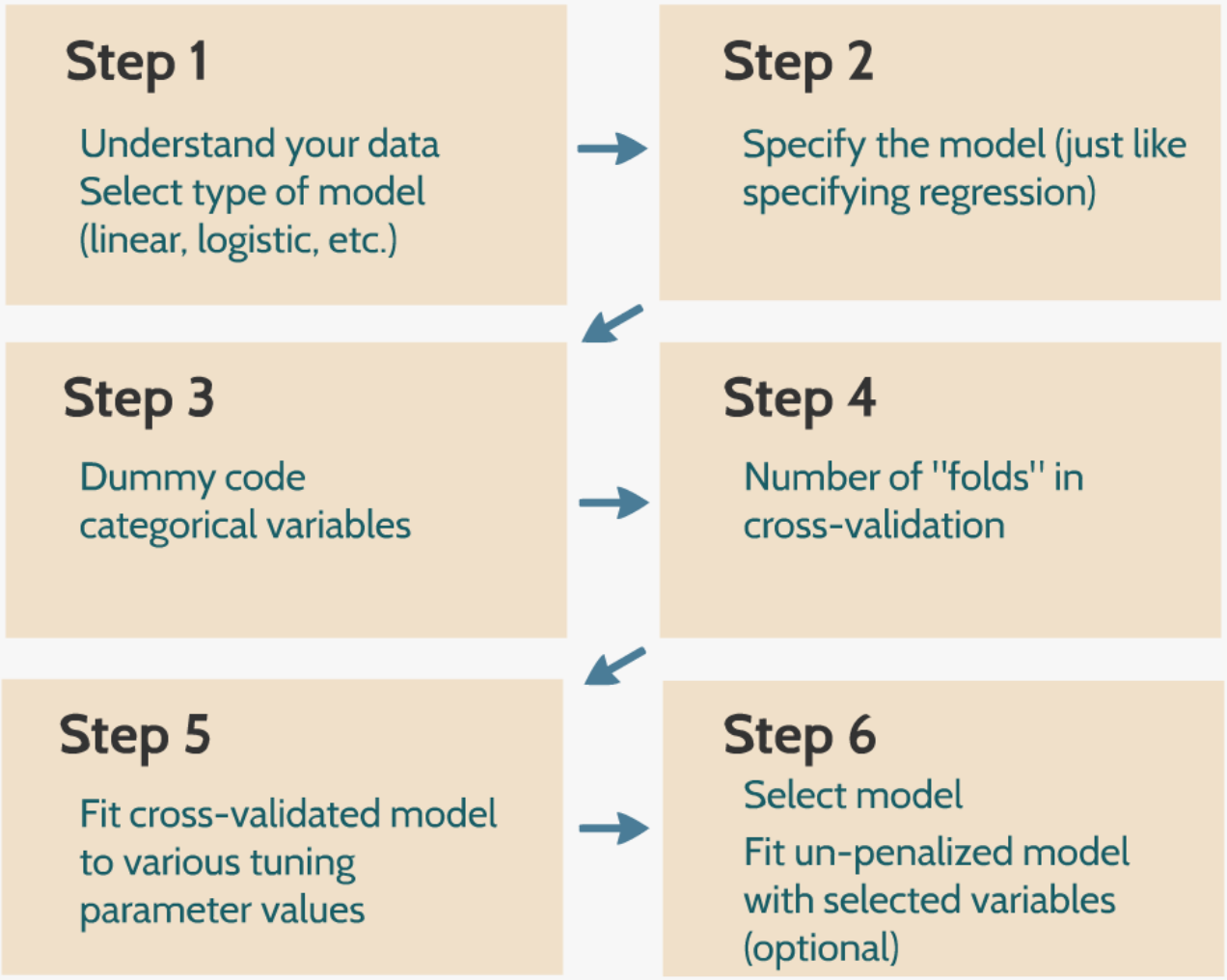
Fit cross-validated model

Step 6

Select model

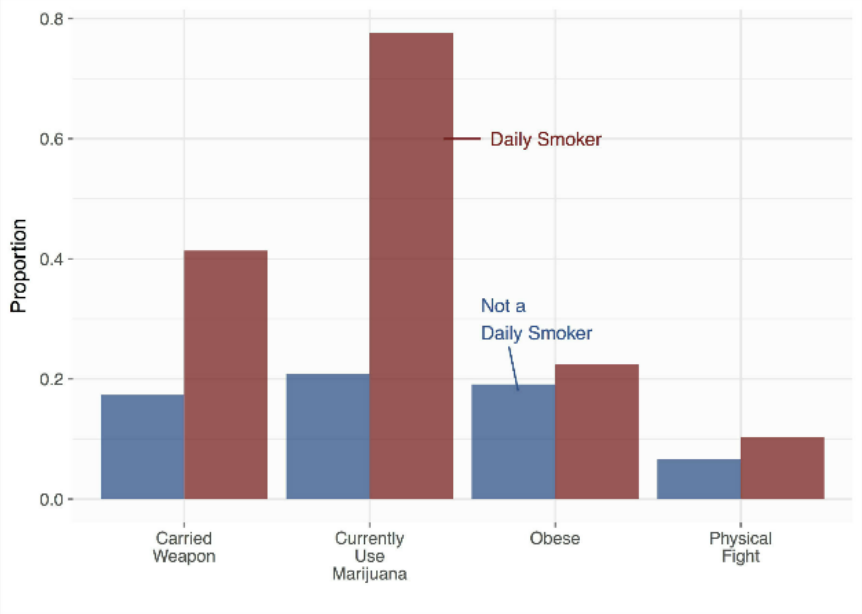
Let's
example
using ci
adolesce

Simple Steps to Use Elastic Net, Lasso or Ridge



Let's go through an example about the risk of using cigarettes among adolescents with asthma

Step 1:



	Total Sample with Asthma n = 1856	Marijuana Users n = 803
Used Marijuana	43.2%	-
Currently Use Marijuana	22.6%	52.2%
Used Synthetic Marijuana	10.8%	24.9%
Female	52.9%	53.3%
School grade		
9th	26.4%	23.0%
10th	23.3%	16.7%
11th	25.2%	29.4%
12th	25.1%	30.9%
Rode with drinking driver	21.6%	32.0%
Carried a weapon	18.1%	24.8%
Weapon at school	4.9%	8.0%
Unsafe at school	5.3%	6.2%
Were bullied at school	23.3%	26.3%
Were electronically bullied	19.0%	23.3%
Made plan to commit suicide	19.9%	27.5%
Smoked cigarette before age 13	7.5%	14.8%
Used electronic vapor products	48.0%	80.0%
Drank alcohol before age 13 years	18.6%	29.4%
Drank five or more drinks of alcohol in a row	21.2%	41.2%
Ever used cocaine	5.1%	11.5%
Ever used inhalants	7.8%	12.6%
Ever used heroin	0.9%	2.0%
Ever used methamphetamines	2.3%	5.2%
Ever used ecstasy	5.6%	12.8%
Ever took prescription drugs (no prescription)	20.7%	38.2%
Ever injected any illegal drug	0.9%	1.9%
Offered/sold/given an illegal drug at school	24.8%	35.5%
Ever had sexual intercourse	45.8%	73.8%
Made mostly A's or B's in school	70.3%	61.6%

Logistic Regression
(the outcome is binary)

Step 2:

$$Logit(Smoker_i) = \beta_0 + \beta_1 Grade_i + \cdots + \varepsilon_i$$

Step 3:

Dummy coded variables

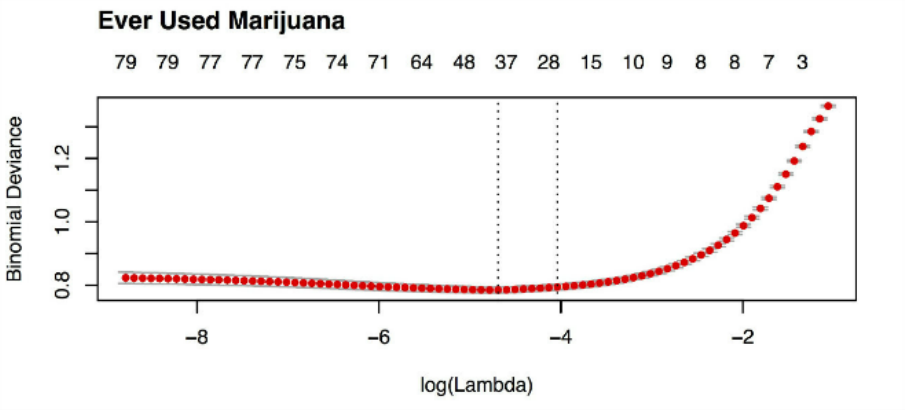
Step 4:

Step 3: Dummy coded variables

Ever had sexual intercourse	45.8%	73.8%
Made mostly A's or B's in school	70.3%	61.6%

Step 4:

We selected 10 folds for cross-validation



Step 5:

Fit the cross-validated model

Check:

- the cross-validated error
- the selected variables between the min and the 1-SE

Step 6:

We selected model at the 1-SE
(usually more parsimonious than min)

Notes and Such

By removing a reliance on p-values, reducing researcher bias in variable selection, and providing replicable steps:

Reproducibility 

Generalizability 

Notes and Such

Notes and Such

Theory and prior literature still act as guides but much of the arbitrary variable selection is gone

Now in R

Perform regularized regression in R using the cleaned data set I sent out to you

If you didn't get it, visit:

github.com/CEHSworkshop/RegularizedRegression/

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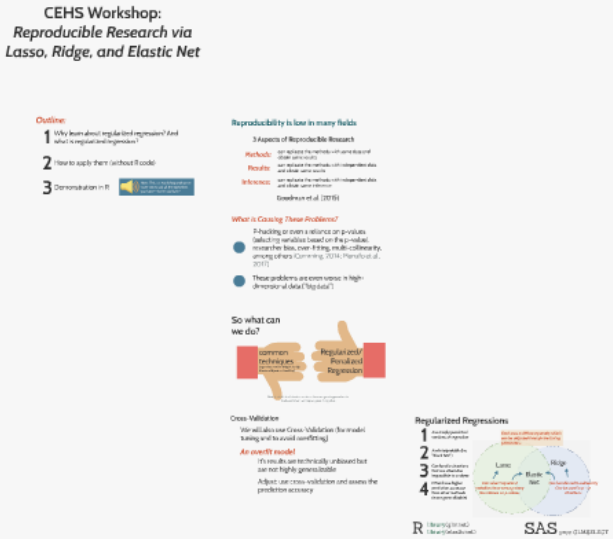

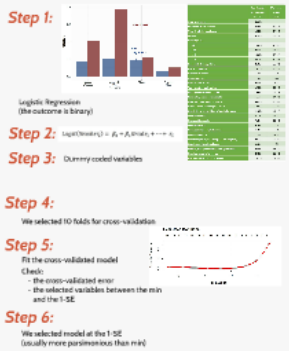

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