Who Determines United States Healthcare Out-of-pocket Costs?

Factor Ranking and Selection Using Ensemble Learning

Chengcheng Zhang

Claremont Graduate University, Department of Economic Sciences

Yujia Ding, PhD

Claremont Graduate University, Institute of Mathematical Sciences

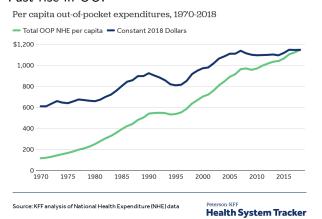
Qidi Peng, PhD

Claremont Graduate University, Institute of Mathematical Sciences

January 7-9, 2022

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- » Fast rise in OOP



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- » Our research goal is to fill this gap.

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- » Research Question:
 - Who determines OOP costs in the United States? Which factor is more important than the others when they are considered jointly?
- » Findings:
 - The selected top-ranking factors, in order of importance, are: insurance type, age, asthma, family size, race, and number of physician office visits.
 - The predictive models using these factors perform better.

Structure of the research

» 2016-17 MEPS Data

Demographic		Age Sex Race Race Region Family size Primary language not English English proficiency Marital status Born in the U.S. Years in the U.S. Year
Socioeconomic		Family income Individual's wage income Hourly wage level Employment status Self-employment status Occupation groups Purchased food stamps
Health status	Chronic condition	High blood pressure Coronary heart disease Stroke Bronchitis High cholesterol Cancer Diabetes Asthma Arthritis Joint pain
neath status	Functional limitation	Serious hearing difficulties Serious seeing difficulties Serious cognitive difficulties Cognitive limitation Physical functioning limitation Work/Housework/School limitation (Any limitation) Used assistive devices
	Self-reported health status	Perceived health status Perceived mental health status Number of physician office visits
Health insurance		Type of health insurance coverage

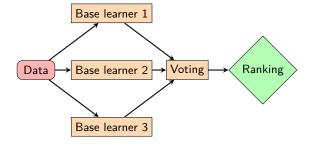
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- » 2016-17 MEPS Data
 - 18 64
 - 2016 2017
 - 39 predictors
- » Correlation detection
 - strong dependencies, yield inconsistent and misleading variable selection outputs
 - reduce collinearity
 - 13 variables are removed

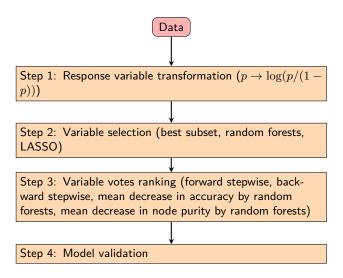
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- » 2016-17 MEPS Data
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 - strong dependencies, yield inconsistent and misleading variable selection outputs
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 - 13 variables are removed
- » Perform an ensemble learning for variable selection on the dataset obtained from correlation detection process.

Ensemble learning procedure



Ensemble learning procedure



Results

Table 5 Variable importance rankings.

	Ranking						Score			
Variable	Forward		d E	Backward			Mean decrease in accuracy		Mean decrease in node purity	
Type of insurance coverage	2	*	2		*	1	*	2	*	4
Age	3	*	3		*	6		3	*	3
Asthma	1	*	1		*	20		18		2
Family size	4	*	7	•		5	*	6		2
Race	6		5		*	2	*	8		2
Number of physician office visits	20		2	0		3	*	1	*	2
Family income	5	*	1	0		16		9		1
Primary language not English	7		4		*	12		10		1
Sex	10		9	•		4	*	12		1

* denotes the variable ranks among top five under the corresponding criterion.

Results

Table 6 Variables recommended by literature and data-driven solutions.

Recommended by Literature	Recommended by Data-driven Solutions
Type of insurance coverage	Type of insurance coverage
Age	Age
Sex	Asthma
Family income	Family size
Race	Race
Number of physician office visits	Number of physician office visits

Table 8 Comparison of the training MSE and test MSE.

Method	Recommended	by Literature	Recommended by Data-driven Solution		
	Training MSE	Test MSE	Training MSE	Test MSE	
Linear regression	0.456971	0.457194	0.371514	0.371977	
Random forests	0.339891	0.473549	0.311900	0.393755	
Ridge	0.458609	0.458814	0.375946	0.376285	
LASSO	0.459222	0.459375	0.384613	0.384935	

MSEs of the four models are calculated using variables (in Table 6) recommended by literature and data-driven solutions.

» data-driven recommended variables all result in lower training MSE and test MSE

Future study

- » examining how determinants influence OOP costs for individuals who have more healthcare needs.
 - different age groups
 - people have chronic diseases

Thank you!

Contact: chengcheng.zhang@cgu.edu

Publication version: https://doi.org/10.1007/s13755-021-00153-9

Source code: https://github.com/health-care-cost-data-

analysis/factor-ranking-and-selection