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What Really Matters When Predicting Other Cause Mortality for Men with Prostate Cancer: A Machine Learning Approach to Variable Selection

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#### **Prostate Cancer**

#### Figure 3. Leading Sites of New Cancer Cases and Deaths – 2020 Estimates

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	Male			Female			
	Prostate	191,930	21%	Breast	276,480	30%	
Estimated New Cases	Lung & bronchus	116,300	13%	Lung & bronchus	112,520	12%	
	Colon & rectum	78,300	9%	Colon & rectum	69,650	8%	
	Urinary bladder	62,100	7%	Uterine corpus	65,620	7%	
	Melanoma of the skin	60,190	7%	Thyroid	40,170	4%	
	Kidney & renal pelvis	45,520	5%	Melanoma of the skin	40,160	4%	
ted	Non-Hodgkin lymphoma	42,380	5%	Non-Hodgkin lymphoma	34,860	4%	
na	Oral cavity & pharynx	38,380	4%	Kidney & renal pelvis	28,230	3%	
stii	Leukemia	35,470	4%	Pancreas	27,200	3%	
ш	Pancreas	30,400	3%	Leukemia	25,060	3%	
	All sites	893,660		All sites	912,930		
	Male			Female			
	Lung & bronchus	72,500	23%	Lung & bronchus	63,220	22%	
	Prostate	33,330	10%	Breast	42,170	15%	
	Colon & rectum	28,630	9%	Colon & rectum	24,570	9%	
ths	Pancreas	24,640	8%	Pancreas	22,410	8%	
Dea	Liver & intrahepatic bile duct	20,020	6%	Ovary	13,940	5%	
p	Leukemia	13,420	4%	Uterine corpus	12,590	4%	
Estimated Deaths	Esophagus	13,100	4%	Liver & intrahepatic bile duct	10,140	4%	
	Urinary bladder	13,050	4%	Leukemia	9,680	3%	
	Non-Hodgkin lymphoma	11,460	4%	Non-Hodgkin lymphoma	8,480	3%	
			20/	Brain & other nervous system	7 0 2 0	3%	
	Brain & other nervous system	10,190	3%	brain & other nervous system	7,830	370	

Estimates are rounded to the nearest 10, and cases exclude basal cell and squamous cell skin cancers and in situ carcinoma except urinary bladder. Estimates do not include Puerto Rico or other US territories. Ranking is based on modeled projections and may differ from the most recent observed data.

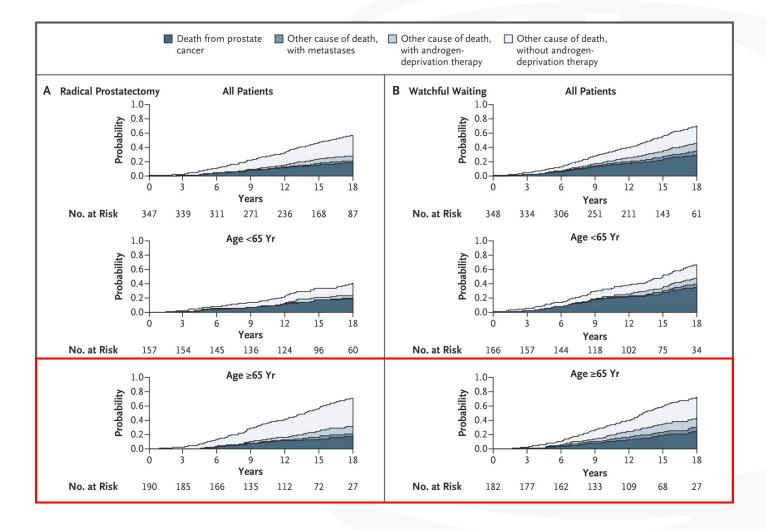
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#### What Do Prostate Cancer Patients Die Of?

OF

MEDICINE





#### **Current Tools to Evaluate Life Expectancy**

ТооІ	Year Variables		Number of Inputs
Cowen et al. <sup>3</sup>	2006	Age, Charlson Comorbidity Index, angina, systolic blood pressure, BMI, smoking, marital status, PSA, Gleason sum, clinical stage, treatment	27
Walz et al.4	2007	Age, Charlson comorbidity index, treatment type (radical prostatectomy vs external beam radiotherapy)	19
Hoffman et al. <sup>5</sup>	2015	Age, race, and patient-reported overall health	3
Daskivich et al. <sup>6</sup>	2015	Age, race, treatment, PSA, Gleason Score, cancer stage, and the Prostate Cancer-specific Comorbidity Index	30
Cho/Hawken s et al. <sup>7</sup>	2017	Age, race, Charlson Comorbidity Index	19

Only 23% of urologists report using life expectancy tools in practice.<sup>8</sup>



### Enthusiasm for Big Data

<u>Front Oncol</u> . 2016; 6: 149. Published online 2016 Jun 14. do	oi: <u>10.3389/fonc.2016.00149</u>	PMCID: PMC4905980 PMID: <u>27379211</u>				
Big Data Analytics for	Prostate Radiotherap	y				
James Coates, 1,* Luis Souhami,	<sup>2</sup> and <u>Issam El Naqa</u> <sup>3</sup>					
Author information > Article no	<u>J Am Med Inform Assoc</u> . 2015 No Published online 2015 Nov 9. doi		PMCID: PMC5009910 PMID: <u>26555016</u>			
	The NIH Big Data to F	Knowledge (BD2K) initiative				
<u>N C Med J</u> . Author manuscript; Published in final edited form as <u>N C Med J. 2014 Jul-Aug; 75</u>	Jennie Larkin, <sup>1</sup> and Beth Russell <sup>1</sup>					
•	on-Based Cancer Resource Section and Surveillance Section 2015					
Laura Green, MBA, project man	ch assistant professor, <u>Andrew F.</u> ager, <u>Adrian Meyer</u> , MS, director <u>Ethan Basch</u> , MD, MSc, director,	Big Data and Machine Learning in Health Care				
		PMID: 29532063 DOI: <u>10.1001/jama.2017.18391</u>				



## Aim of the Study

To identify the most influential variables for predicting other cause mortality for men newly diagnosed with prostate cancer.



#### Methods

- Study Sample: SEER-CAHPS data
  - » Men 65 years and older diagnosed with prostate cancer from 2004 to 2013.
- Primary Outcome: Defined as expired from causes other than prostate cancer.
- Potential Predictive Variables (76 total): Included patient demographics (7), cancer information (4), claims-based measures (60), and patient-reported health measures (5).



# LASSO Regression

- Applied LASSO regression to identify the core set of variables from 76 potential inputs that minimize prediction error for other-cause mortality.
- LASSO regression is often used in machine learning
  - » Uses a shrinkage and variable selection method to identify subset of predictive variables that minimize prediction error

Passing Grade = y interecept + [slope1 x Study Time] + [slope2 x Sleep] + [slope3 x Sign] + [slope4 x Mile Pace]

If slope3 +  $\lambda$ (slope3) = 0 and slope4 +  $\lambda$ (slope4) = 0

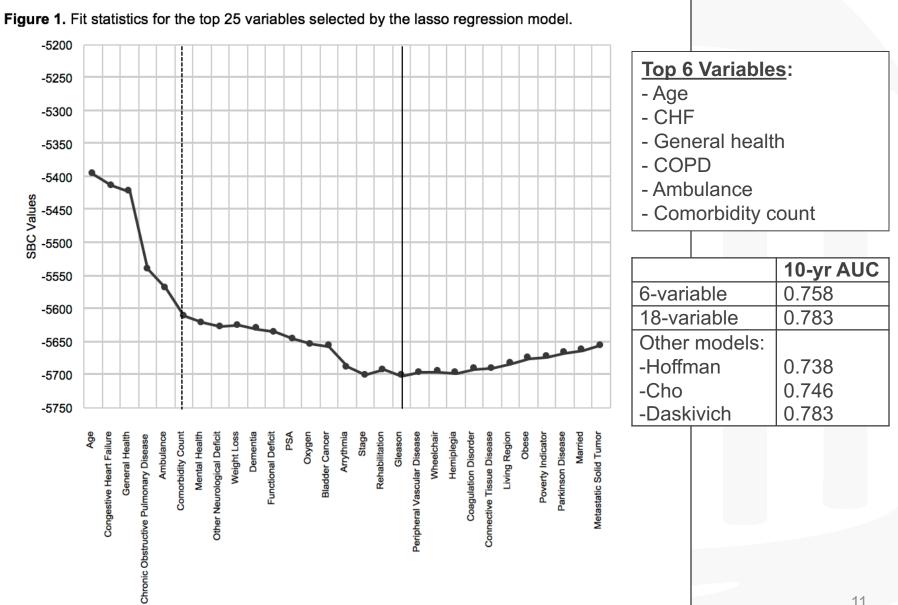
Passing Grade = y interecept + [slope1 x Study Time] + [slope2 x Sleep] + [0 x Sign] + [0 x Mile Pace]



### Results

- Among 3,240 men diagnosed with prostate cancer, 246 (7.62%) died of prostate cancer and 631 (19.48%) died of other causes.
- LASSO regression identified an 18-variable model:
  - » 1 demographic variable
  - » 3 cancer variables
  - » 10 claims-based variables
  - » 4 patient-reported variables



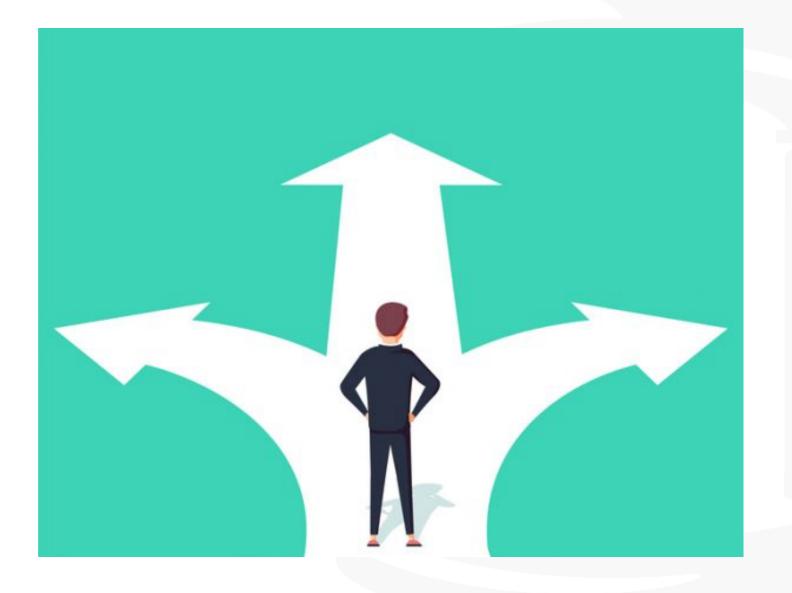




#### Conclusions

- Estimating other-cause mortality in men with prostate cancer can be accurately accomplished by using relatively few data inputs.
- Incorporating different types of data in combination with novel machine learning techniques may produce more parsimonious tools that facilitate usability.







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