

Use of Machine Learning to Predict Diagnosis Codes for Nonalcoholic **Steatohepatitis in Administrative Healthcare Data**

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Background and Aims

Background

- The natural history of nonalcoholic steatohepatitis (NASH) is poorly understood
- Analysis of US administrative claims data to characterize the long-term consequences of NASH has been hampered by the grouping of NASH with other nonalcoholic fatty liver disease (NAFLD) in version 9 of the International Classification of Disease (ICD-9).
- In ICD-10 (adopted in the US in 01 Oct 2015), NASH has a unique diagnostic code
- Aims
- To use machine learning to identify ICD-9 NAFLD/NASH patients likely to have a claim for ICD-10 NASH based on claims observed in the ICD-9 era
- To create a cohort of NASH patients which spans ICD-9 and ICD10 claims as the expanded follow up time will enable a better understanding of the natural history of this condition

Methods

- Approach – Use the ensemble method Super Learner (SL) with leave one group out cross validation (LOGO CV) to create an algorithm which identifies ICD-9 NAFLD/NASH patients who would be likely to have a claim for ICD-10 NASH
- Apply this algorithm to cohorts of patients with claims in the ICD-9 era
- Data source:
- IQVIA PharMetrics Plus™ Claims dataset, including U.S. administrative claims for ~140M patient lives from 01 Jan 2006 to 30 Mar 2018
- Claims from 01 Jan 2006 30 Sep 2015 reported with ICD-9 codes
- Claims form 01 Oct 2015 30 Mar 2018 reported with ICD-10 codes

Data Set for Predictive Algorithm Creation

- Every patient included in the data set:
- had an ICD-9 claim for NAFLD/NASH (571.8)
- was at least 18 years of age on 01 Oct 2015 (index date)
- had continuous enrollment during the final 2 years of the ICD-9 era (01 Oct 2013 30 Sep 2015) ◆ NASH cohort patients (N=10,717) had a claim for NASH (K75.81) in the first year of the ICD-10
- era (01 Oct 2015 30 Sep 2016) ◆ <u>The Non-NASH cohort (N=90,214)</u> was comprised of a random ~30% sample of patients with
- no claim for ICD-10 NASH in any observation time in the ICD-10 era (starting 01 Oct 2015)

Data Set for Predictive Algorithm Creation NASH Cohort NASH Date: Observation End: Latest Enrollment Start Index Date First claim for NASH Earlier of 9/30/16 10/1/15 from 10/1/15 to 9/30/16 or last claim date 10/1/13 Censored ICD-10 era 2 years of claims prior to ICD-10 Era time N=10,717 ICD-9 NASH/NAFL Patids with ICD-10 NASH Non-NASH Cohort NASH Date **Observation End:** Latest Enrollment Start Earlier of 9/30/16 Index Date Blank; No claims evei 10/1/13 10/1/15 or last claim date for ICD-10 NASH Censored ~30% sample with 2 years of claims prior to ICD-10 ICD-10 era time era and no ICD-10 NASH claim N=90,214 ICD-9 NASH/NAFLD Patids with no claims for ICD-10 NASH

Claim Code Selection

- Identify all distinct ICD-9 diagnosis codes and GPI medication codes occurring during the 2 years of claims prior to the ICD-10 era (01 Oct 13 – 30 Sep 15)
- Create grouped variables to represent 10 pre-specified conditions known to be associated with NASH from
- 133 distinct diagnostic codes
- 78 distinct medication codes
- Any claim code not included in a pre-specified conditions is considered individually
- Create a 1/0 flag for each grouped or individual claim code that occurs during the 2 year observation prior to the ICD-10 era
- Final list of variables considered for NASH prediction:
- Age
- Sex

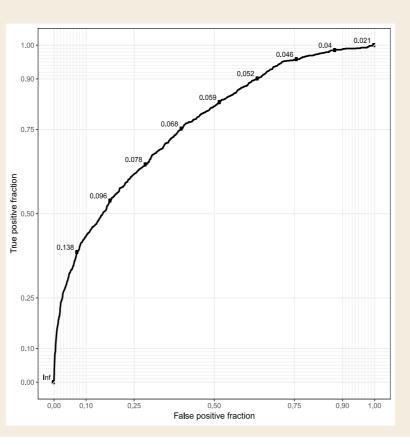
- 2,683 diagnosis codes
- 470 medication codes
- 10 pre-specified covariates

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Methods (cont'd)

Methods (cont'd							Results	(cont a)		
			Data Sets to which the	Predictive Algorithm	was Annlied					
10 Pre-Specified Covariates			 Data Sets to which the Predictive Algorithm was Applied Cohorts of patients were developed in a manner consistent with the development of the 				Selected NASH Outcomes			
	Pre-Specified NASH Covariates		predictor:	·		•	4 -			
Condition	ICD-9 COdes	GPI Codes	 Minimum of 2 years of c 2010, to 21 Aug 2015 	claims and an ICD-9 claim	n for NASH/NAFLD in the	e period from 01 Oct		Т		
Obesity	278.0x	07	2010 to 31 Aug 2015versions of ICD-9 clain	n codes prior to 01 Oct 201	0 did not include some co	des which were				Prediction Cut Points ◆ PPV 35%
Diabetes Metabolic Syndrome	C 277.7x	27x		tor as indicative of NASH			ervals	• 3.22	Т	■ PPV 20%
Hyperlipidemia	272.0x, 272.2x, 272.4x	39x	 The prediction algorithm 	produced a percent likelih	nood of NASH at the end	of 2 years of	8 - 5 - 5		• 2.74	– PPV 8% Youden Index
Hypertriglyceridemia	272.1x			ondition and medication cla			ıfiden			
Stroke	434.x		 Patients were required t ICD-9 era 	to have a minimum of 30 c	days for post-prediction of	observation in the	CO %		T	
Essential Hypertension Myocardial Infarction	410.x 410.x, 412.x		 Prediction thresholds sele 	ected based on algorithm	n performance in Valida	tion Test Set	- 2 - 2			
Coronary Atherosclerosis	414.0x, 414.3x, 414.4x, 429.2x		 Youden's index (sensit 				ios x		т	т
Smoking	305.1x, V15.82x		 Specific PPV threshold 				rd Rat	I.21	1.36	1.41
Note: here "x" refers to any subsequent dig	gits in the ICD-9 or GPI ontology		 Once a patient was predicted 	cted to have NASH, this	patient was removed fr	om future cohorts for	Handaria Han	L		0.96
			NASH prediction		finat O	evelleble eleime dete				± 0.70
Super Learner Ensemb	ble Method Setup		 If a patient was predicted and an additional year of 			-		₹ 0.26	± 0.38	
	raining Set (90%) and Validation	9%	was advanced forward or				0 +			1
Test set (10%)	9%	Validation Set							Outcomes Associated with NASH	
· · ·	earner run on 90% of Training	9%	Results					Liver Transplant <u>subjects</u> evts ptime(yrs)	HCC	Cardiac Events subjects evts ptime (yrs)
Set, validated using LOGO	<u>O CV (10-Fold)</u>	9%					Predicted: PPV: 35% Brodicted: PPV: 20%	9,990 385 14,613	9,986 352 14,715	6,955 741 9,943
Screen claims codes :	9%						Predicted: PPV: 20% Predicted: PPV: 8%	40,49258862,580214,520650347,326	40,28265562,405213,976922346,490	30,6072,12246,281170,0288,614267,745
 Utilize Bayesian Risk Ratio (BRR) for each code and select inclusion thresholds BRR > 1.47 OR BRR < 0.68 			Prediction Cohort sizes at different PPV Thresholds Prediction Threshold Number of patients				ICD-10 NASH Cohort	42,376 379 48,423	42,134 365 48,258	33,648 1,748 37,434
 Implement Sparsity Th 										
	on (Least Absolute Shrinkage and		Total elig		405,233				cs of Predicted NASH Cohort	(PPV 20%)
· /	help with variable selection and regularization		Youden Index	(8% PPV)	216,180)		and Claime	ed ICD-10 NASH Cohort	
 Run each of 19 selected prediction algorithms (base learners) individually to identify those that contribute to the final model 			20% PF	PV	41,912		Variable			
			35% PF	PV	10,771			10.24 \	(N=41,912) N(%)	(N=42,744) N(%)
Step 2: Meta-Learner run	on full Training Set		Salastad Outsemaal Dr	ediated NACH Cabor	two Claimed ICD 1			18-34 y 35-44 y	2,263 (5.40) 5,172 (12.34)	3,655 (8.55) 6,887 (16.11)
 Repeat BRR calculation 	n, sparsity measures, and LASSO		Selected Outcomes: Pr	edicted NASH Conor	rt vs. Claimed ICD-10	UNASH Conort	A	45-54 y	11,974 (28.57)	12,262 (28.69)
 Run Super Learner 			Methods:				Age Group	55-64 y	17,647 (42.10)	15,747 (36.84)
	learners found to be significant when run in		 Data source: IQVIA Pharl 	Metrics Plus™ Claims da	ataset, including US adr	ministrative claims for		65-74 y	4,189 (9.99)	3,713 (8.69)
- Final model is a weigh	nted combination of results from individual b	base learners	~140M patient-lives from	01 Jan 2006 to 30 Mar 2	2018			75+ y Female	667 (1.59)	480 (1.12)
			Index date: predicted NAS	SH date (in predicted col	hort) or first ICD-10 NA	SH claim (in claimed	Sex	Male	21,409 (51.08) 20,503 (48.92)	22,260 (52.08) 20,484 (47.92)
19 base learners for t	the machine learning library in	Super Learner	ICD-10 NASH cohort)					Mean (SD)	1.56 (0.94)	1.15 (0.71)
19 Ba	ase Learners with Super Learner-Assigned Weigh	nts	 Age ≥18 years on index of 	late with no prior claims	for the outcome of inter	rest	FO Time (years)	Mean (SD) Median (Q1, Q3)	1.33 (0.74, 2.23)	1.06 (0.52, 1.75)
Base Learner	Weight Base Learner	Weight	 End of follow-up for all pa 	·				Obesity	16,947 (40.43)	19,369 (45.31)
			 Date of first claim for ou 					Diabetes Metabolic Syndrome	22,556 (53.82) 3,024 (7.22)	19,128 (44.75) 2,217 (5.19)
Generalized Linear Model (GLM)	0.077 Flexible Discriminant Analysis	0.038						Hyperlipidemia	28,781 (68.67)	28,101 (65.74)
Bayesian GLM0.076Classification and Regression Trees (CART)0.000			 Date of last claim in data set End of data (30 Sep 2015 for predicted cohort, 30 Mar 2018 for ICD-10 NASH cohort) Hazard ratios (HRs) and corresponding 95% confidence intervals (CIs) calculated using Cox 				Baseline Conditions	Hypertriglyceridemia	2,480 (5.92)	2,589 (6.06)
Elastic-Net Regularized GLM 0.077 Multivar. Adaptive Regression Splines (Param Set 1) 0.011								Essential Hypertension	33,092 (78.96)	31,547 (73.81)
Boosted GLM	0.021 Multivar. Adaptive Regression Spli	nes (Param Set 2) 0.015			ifidence intervals (CIs) o	calculated using Cox		Stroke Myocardial Infarction	942 (2.25) 1,787 (4.26)	648 (1.52) 1,334 (3.12)
Penalized Multinomial Regression	n 0.080 Penalized Discriminant Analysis (F	Param Set 1) 0.066	proportional hazards met	hods				Coronary Atherosclerosis	5,981 (14.27)	4,400 (10.29)
Boosted Logistic Regression	0.041 Penalized Discriminant Analysis (Param Set 2) 0.035	 Time-to-event analysis 					Smoking	8,702 (20.76)	8,488 (19.86)
Naïve Bayes	0.056 Single C5.0 Rule-Based Models	0.058								
Nearest Shrunken Centroids	0.027 Single C5.0 Decision Tree Models		Selected Outcomes	s: Predicted NASH	Cohort vs. Claime	ed ICD-10	Euturo D	irections		
Shrinkage Discriminant Analysis	0.066 Conditional Inference Tree	0.000	NASH Cohort				Future D	nections		
		0.000	Variable Definitions		Codes		Further develo	pment of NASH predi	ictor	
Stochastic Gradient Boosting	0.136		Outcome:	ICD-9-CM	ICD-10-CM	CPT/HCPCS			such as the inclusion of	f procedure codes
*Tuning parameters were selected with 5-fold	d cross validation	0.04 0.021			C22.0x, C22.2x, C22.3x,		Explore valida	ation in external cohort	S	•
	0.90	0.046	НСС	155.0x, 155.2x	C22.4x, C22.7x, C22.8x,		Euturo applica	tions of NASH cohort		
 Final Predictive Algorithm 17 of the 19 base learner 	rs (those with non-zero weights)	0.059			C22.9x				to permit extension of	follow up time (5+ year
 – 17 of the 19 base learner – 371 ICD and GPI codes 	C	0.078	Cardiac Events (Acute and	410.X (except with a 5th	I20.x (except I20.1x),		• •	to allow the examination	•	
 211 pre-specified, base 		0.096	Chronic ischemic heart disease, Angina pectoris,	digit of 2), 411.x, 413.x (except 413.1x), 414.x	121.x, 122.x, 124.x, 125.x					
	ected codes, based on BRR	8	Cardiomyopathy, Heart	(except 414.1x), 425.x,	(except l25.2x, l25.3x, l25.4x), l42.x, l50.x		Abbrevia	tions		
– Age	0.25		Failure)	428.x			 AUC– area under (receive 	er operating characteristic) curve	 LASSO – least absolute shr 	inkage and selection operator
 – Sex Final AUC = 0.76 			Liver Transplant	V42.7x	z94.4	47135, 47136, 505, 505.1, 505.9, 0093,	 BRR– Bayesian risk ratio CPT – Current procedura 		 LOGO CV – leave one grou NAFLD – nonalcoholic fatty 	ip out cross validation method
	0.10 0.00 Inf			VIZ.IA	201.1	0FY00Z0	 ESLD - End stage liver di 		 NASH – nonalcoholic steato PPV – Positive Predictive V 	ohepatitis
	0.00	0.10 0.25 0.50 0.75 0.90 1.00 False positive fraction						ational Classification of Diseases, 9th		
	Presented a	t the International Liver Cong	gress (EASL), 10-14 April 2019, Vier	nna, Austria					© 2019 G	Gilead Sciences, Inc. All rights reser

Base Learner	Weight	Base Learner	Weight
Generalized Linear Model (GLM)	0.077	Flexible Discriminant Analysis	0.038
Bayesian GLM	0.076	Classification and Regression Trees (CART)	0.000
Elastic-Net Regularized GLM	0.077	Multivar. Adaptive Regression Splines (Param Set 1)	0.011
Boosted GLM	0.021	Multivar. Adaptive Regression Splines (Param Set 2)	0.015
Penalized Multinomial Regression	0.080	Penalized Discriminant Analysis (Param Set 1)	0.066
Boosted Logistic Regression	0.041	Penalized Discriminant Analysis (Param Set 2)	0.035
Naïve Bayes	0.056	Single C5.0 Rule-Based Models	0.058
Nearest Shrunken Centroids	0.027	Single C5.0 Decision Tree Models	0.119
Shrinkage Discriminant Analysis	0.066	Conditional Inference Tree	0.000
Stochastic Gradient Boosting	0.136		







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Results (cont'd)

