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Problem Statement



Chronic disease readmission is one of the leading cost drivers in US healthcare

By the Numbers



2017 Readmission Cost: **\$310M**
across top 10 health systems



Growth: **9.5-15%** Expected
CAGR from 2017-2022

Key Challenges



Readmission penalties



Expensive specialty
treatments



Resource allocation
challenges

Top Readmission Cases



Schizophrenia



Diabetes



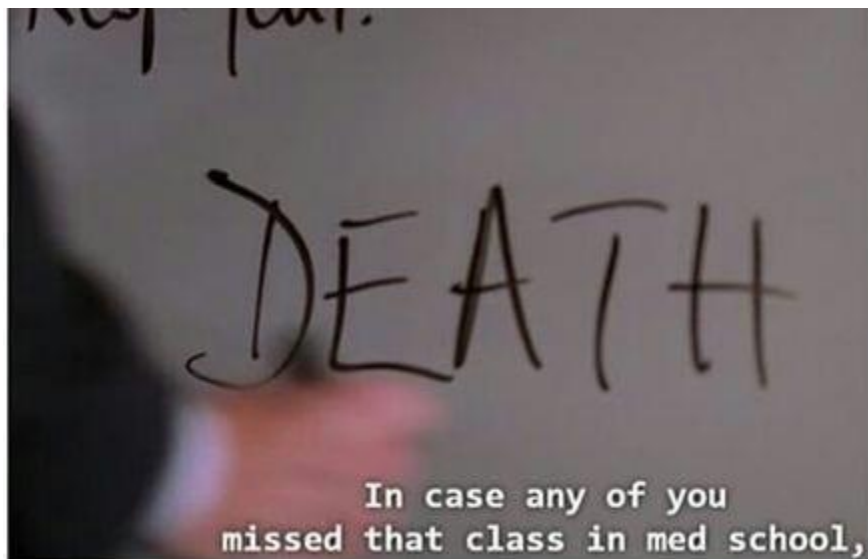
Surgical complications



In this study, we analyzed a patient dataset from 2001-2011 that contains demographic and treatment information for 100,000 diabetes cases, and built a classification model to predict whether or not a given patient would be readmitted within 30 days of discharge

Problem Statement (Cont.)

Identifying high-risk readmission cases is key to reducing mortality rates related to chronic health complications



Dataset, Assumptions, and Metrics



Dataset



Data was pulled from the UCLA medical learning library



101,776 Rows x 50 Columns



Messy: Contained missing values, string and number pairs, ambiguous features



Assumptions



Results from the dataset should only be generalized for patients with diabetes



Assumed data was accurate for a given patient



Assumed that dataset was pulled from a random sample of diabetes patients



Key Metrics

Model was evaluated against a **null model that predicted that the patient would not be readmitted for all cases**, because that is currently the industry standard.

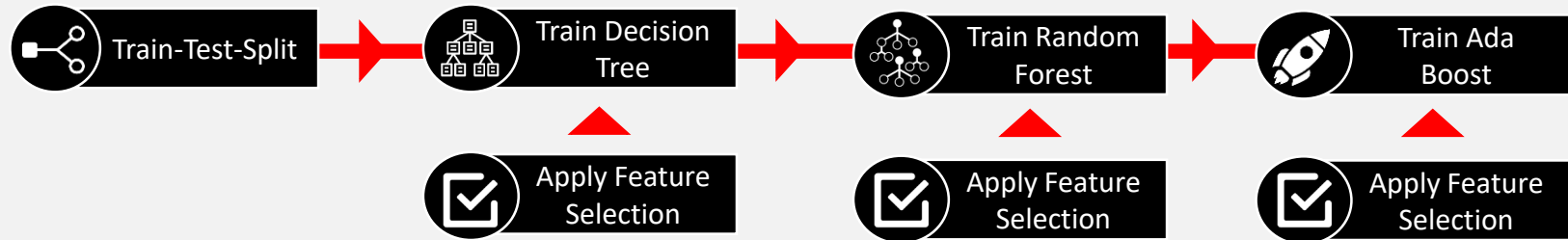
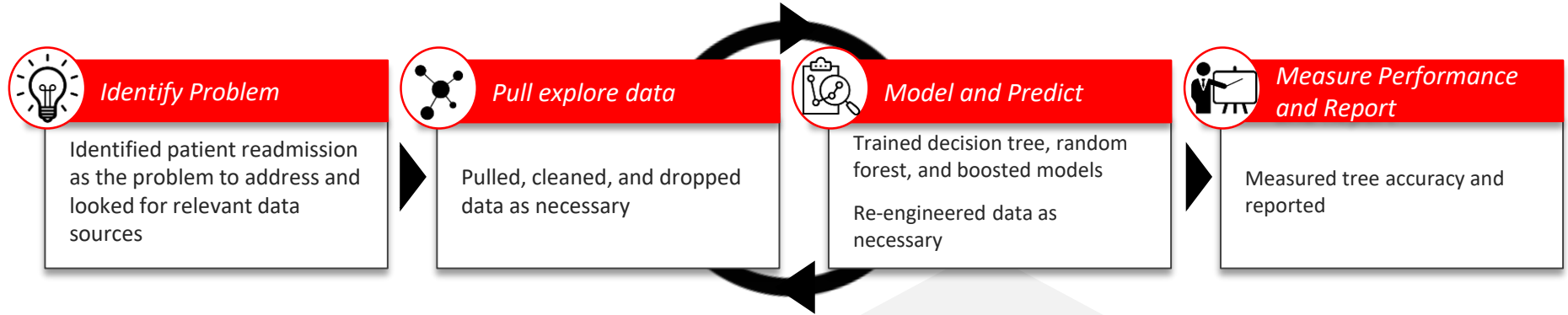
Goal: Outperform null model

Data

63768	1.15E+08	Caucasian Male	[70-80]	?		1	1	7	5 ?	?	73	0	12	0	0	0	428
12522	48330783	Caucasian Female	[80-90]	?		2	1	4	13 ?	?	68	2	28	0	0	0	398
15738	63555939	Caucasian Female	[90-100]	?		3	3	4	12 ?	InternalM	33	3	18	0	0	0	434
28236	89869032	AfricanAmr Female	[40-50]	?		1	1	7	9 ?	?	47	2	17	0	0	0	250.7
36900	77391171	AfricanAmr Male	[60-70]	?		2	1	4	7 ?	?	62	0	11	0	0	0	157
40926	85504905	Caucasian Female	[40-50]	?		1	3	7	7 ?	Family/Ge	60	0	15	0	1	0	428
42570	77586282	Caucasian Male	[80-90]	?		1	6	7	10 ?	Family/Ge	55	1	31	0	0	0	428
62256	49726791	AfricanAmr Female	[60-70]	?		3	1	2	1 ?	?	49	5	2	0	0	0	518
73578	86328819	AfricanAmr Male	[60-70]	?		1	3	7	12 ?	?	75	5	13	0	0	0	999
77076	92519352	AfricanAmr Female	[50-60]	?		1	1	7	4 ?	?	45	4	17	0	0	0	410
84222	1.09E+08	Caucasian Female	[50-60]	?		1	1	7	3 ?	Cardiology	29	0	11	0	0	0	682
89682	1.07E+08	AfricanAmr Male	[70-80]	?		1	1	7	5 ?	?	35	5	23	0	0	0	402
148530	69422211	Male	[70-80]	?		3	6	2	6 ?	?	42	2	23	0	0	0	737
150006	22864131	Female	[50-60]	?		2	1	4	2 ?	?	66	1	19	0	0	0	410
150048	21239181	Male	[60-70]	?		2	1	4	2 ?	?	36	2	11	0	0	0	572
182796	63000108	AfricanAmr Female	[70-80]	?		2	1	4	2 ?	?	47	0	12	0	0	0	410
183930	1.07E+08	Caucasian Female	[80-90]	?		2	6	1	11 ?	?	42	2	19	0	0	0	V57
216156	62718876	AfricanAmr Female	[70-80]	?		3	1	2	3 ?	?	19	4	18	0	0	0	189
221634	21861756	Other Female	[50-60]	?		1	1	7	1 ?	?	33	0	7	0	0	0	786
236316	40523301	Caucasian Male	[80-90]	?		1	3	7	6 ?	Cardiology	64	3	18	0	0	0	427
248916	1.15E+08	Caucasian Female	[50-60]	?		1	1	1	2 ?	Surgery-G	25	2	11	0	0	0	996
250872	41606064	Caucasian Male	[20-30]	?		2	1	2	10 ?	?	53	0	20	0	0	0	277

rosiglitazo	acarbose	miglitol	trogliator	tolazamid	examide	citogliptor	insulin	glyburide-	glipizide-n	glimepirid	metformir	metformir	change	diabetesM	readmitted
No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	NO
No	No	No	No	No	No	No	Up	No	No	No	No	No	Ch	Yes	>30
No	No	No	No	No	No	No	No	No	No	No	No	No	No	Yes	NO
No	No	No	No	No	No	No	Up	No	No	No	No	No	Ch	Yes	NO
No	No	No	No	No	No	No	Steady	No	No	No	No	No	Ch	Yes	NO
No	No	No	No	No	No	No	Steady	No	No	No	No	No	Ch	Yes	>30
No	No	No	No	No	No	No	Steady	No	No	No	No	No	Ch	Yes	NO
No	No	No	No	No	No	No	Steady	No	No	No	No	No	Ch	Yes	>30
No	No	No	No	No	No	No	Steady	No	No	No	No	No	Ch	Yes	<30
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No	No	No	No	No	No	No	Steady	No	No	No	No	No	No	Yes	NO
No	No	No	No	No	No	No	Steady	No	No	No	No	No	No	Yes	>30
No	No	No	No	No	No	No	Up	No	No	No	No	No	Ch	Yes	NO
No	No	No	No	No	No	No	Steady	No	No	No	No	No	Ch	Yes	<30
No	No	No	No	No	No	No	No	No	No	No	No	No	No	Yes	NO
No	No	No	No	No	No	No	Steady	No	No	No	No	No	No	Yes	>30
No	No	No	No	No	No	No	Steady	No	No	No	No	No	Ch	Yes	NO
No	No	No	No	No	No	No	Down	No	No	No	No	No	Ch	Yes	NO
No	No	No	No	No	No	No	Steady	No	No	No	No	No	Ch	Yes	NO
No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	NO
No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	>30

Approach



Model and Solution

Three classification models were trained using the patient dataset, and measured against a null model performance



Decision Tree



No max depth



No min-leaf size



SelectFromModel feature-selector was applied to isolate important features

Accuracy: 47.1%



Random Forest Classifier



100 decision trees



No max depth

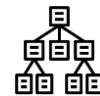


SelectFromModel feature-selector was applied to isolate important features

Accuracy: 57.6%



Ada Boost Classifier



100 decision trees



0.1 learning rate

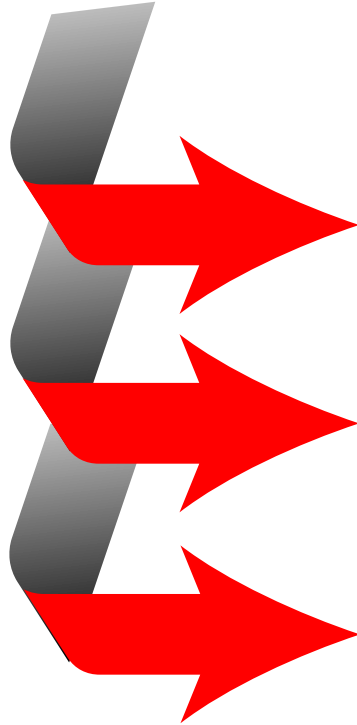


SelectFromModel feature-selector was applied to isolate important features

Accuracy: 59.1%

Null Model Performance: 51%

Retrospective



Spend more time up-front cleaning data

- Features and rows were dropped due to missing data or lack of interpretability, which reduced robustness of the model
- More effort in cleaning features would have increased accuracy

Train models with small `n_estimators` at first

- Due to high number of features, Random Forest and Ada boost classifiers took a longtime to run (~25-40 minutes) and yielded marginal improvements run-over-run

Incorporate more robust classifiers into ensemble

- Outside of Adaboost, I would have liked to implement XG Boost and potentially a deep learning classifier

Questions?

