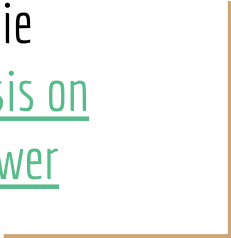




CareTracker


A win-win for
Tahoe Health Solutions
and its patients

Anthony Abercrombie
[Find my detailed analysis on
Jupyter Notebook Viewer](#)





Today's Presentation

1. Business Problem
 2. Data Context
 3. Solutions
 4. Proposal
 5. Next Steps
- 

In [01]: Business Problem



- ❖ 20% of all hospitalized medicare patients are readmitted within 30 days. 34% within 90 days.
- ❖ National annual cost of hospital readmissions is **\$17.4 billion.**
- ❖ Hospital Readmissions Reduction Program (HRRP) penalizes hospitals for readmissions with a fine.
- ❖ HRRP is monitoring readmissions for AMI, HF, and pneumonia. more to come....
- ❖ 18% of Tahoe Health System's (THS) medicare revenue comes from these three conditions. THS will lose **\$8,000 per readmitted patient.**

In [01]: Business Problem --- Last Year's Numbers

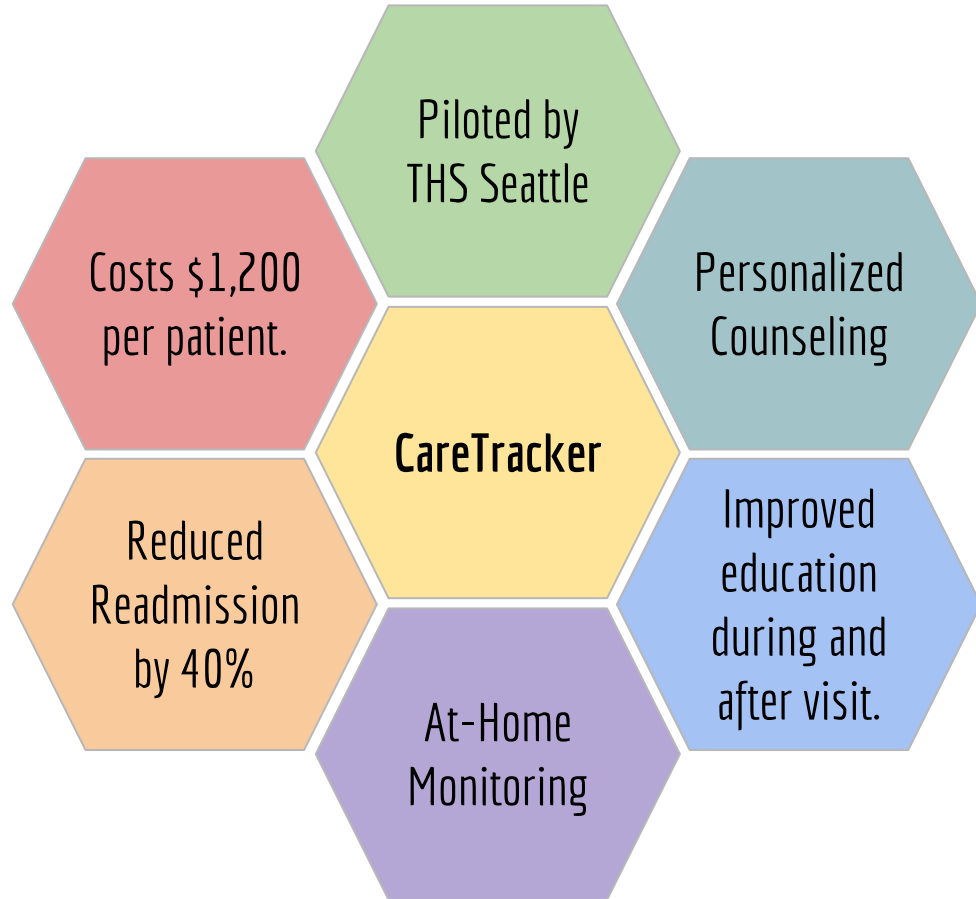
Assumptions:

- ❖ Per-patient readmission cost of \$8000.
- ❖ Patient data from the last year represents any given year (22.8% readmission rate).
- ❖ CareTracker reduces readmissions by 40%,
- ❖ ACA survives the current administration.
- ❖ HRRP expands list of conditions.

Implications:

- ❖ **\$7,984,000 annual loss to HRRP fines if THS does not take action.**

In [01]: Business Problem --- The Intervention



- ❖ Would cost \$5,258,400 if everyone got CareTracker.
- ❖ Combined cost of CareTracker for everyone + HRRP fines would be **\$10,048,000**.

In [01]: Business Problem --- A Saner Approach



**Extend CareTracker
intervention to
patients who need it.**

- Managerial Segmentation
- Machine Learning

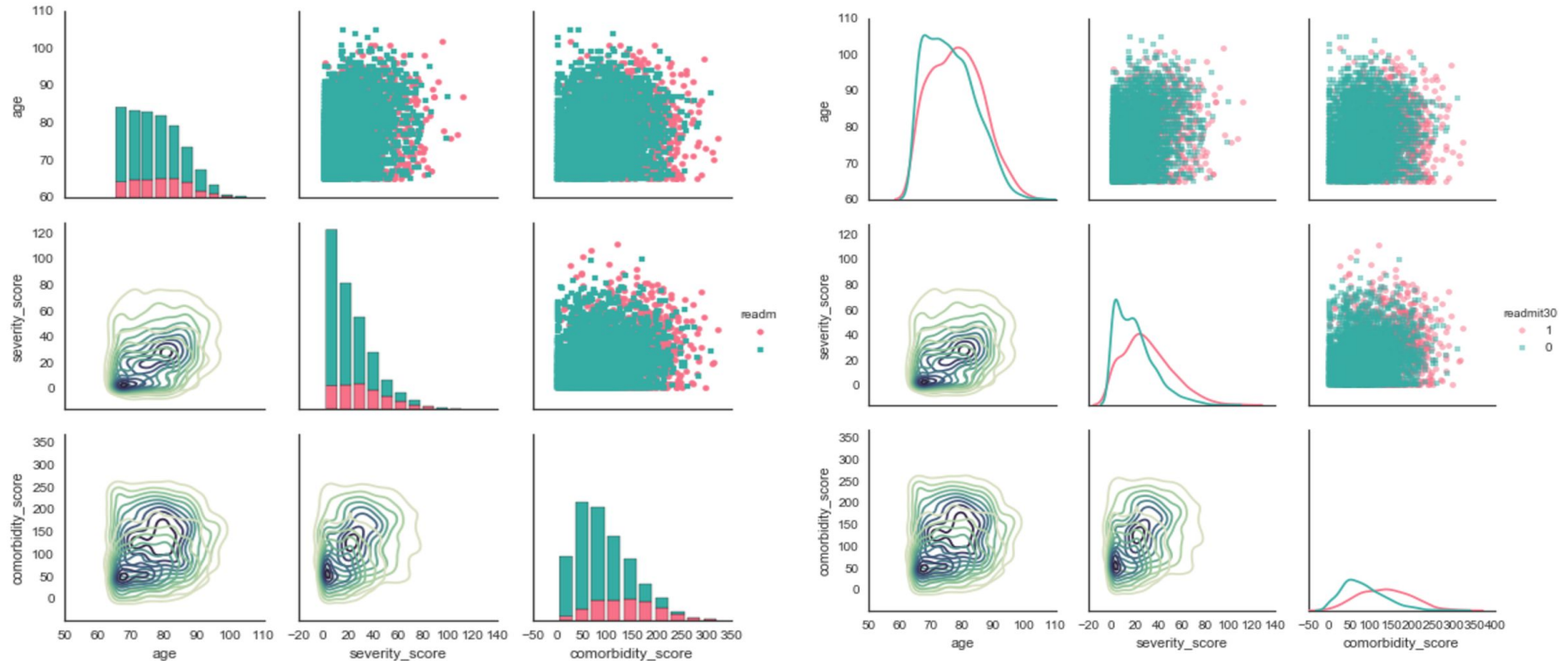


Data Context



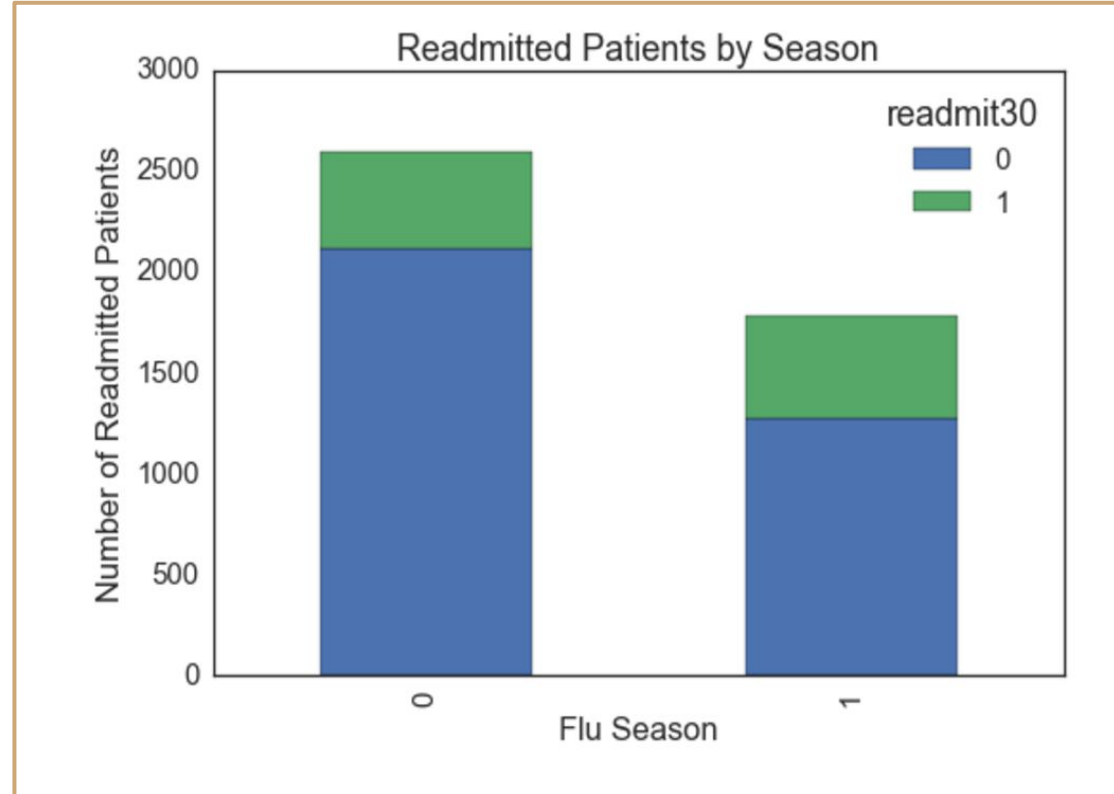
In [02]: Data Context --- State of Affairs

❖ Many patients who are readmitted have high **comorbidity** and **severity** scores.



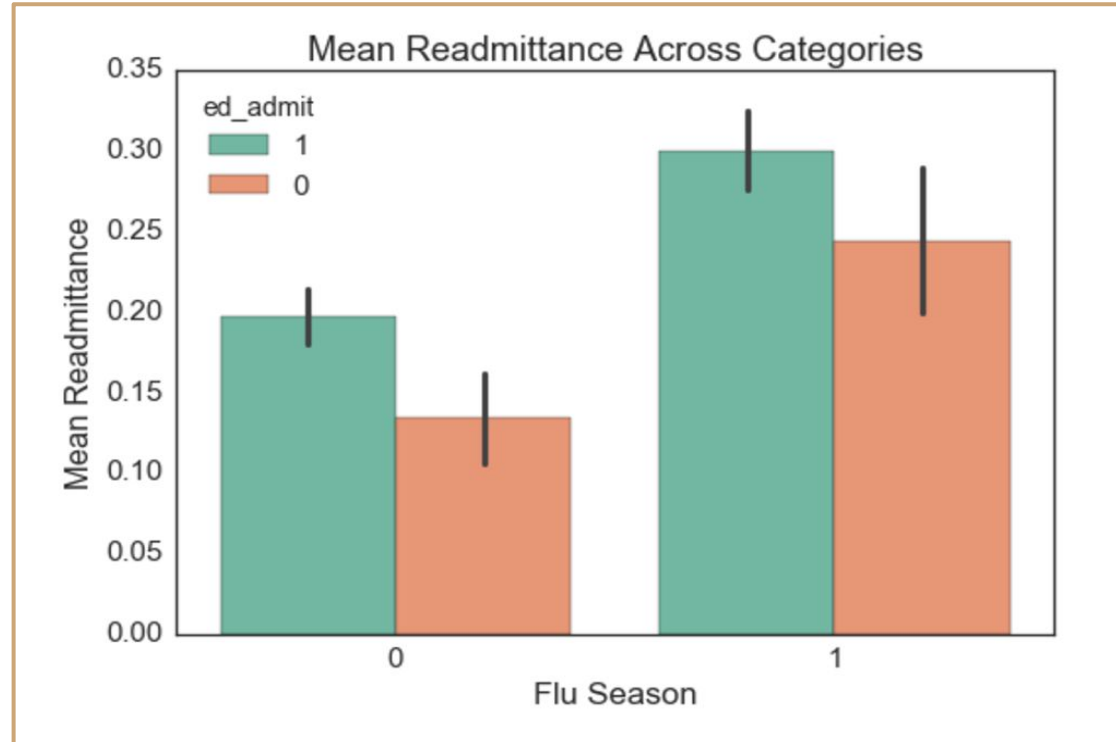
In [02]: Data Context --- State of Affairs

- ❖ **22.8%** of the sample size was readmitted within 30 days of the initial visit.
- ❖ **40.8%** of the sample size was admitted during flu season.

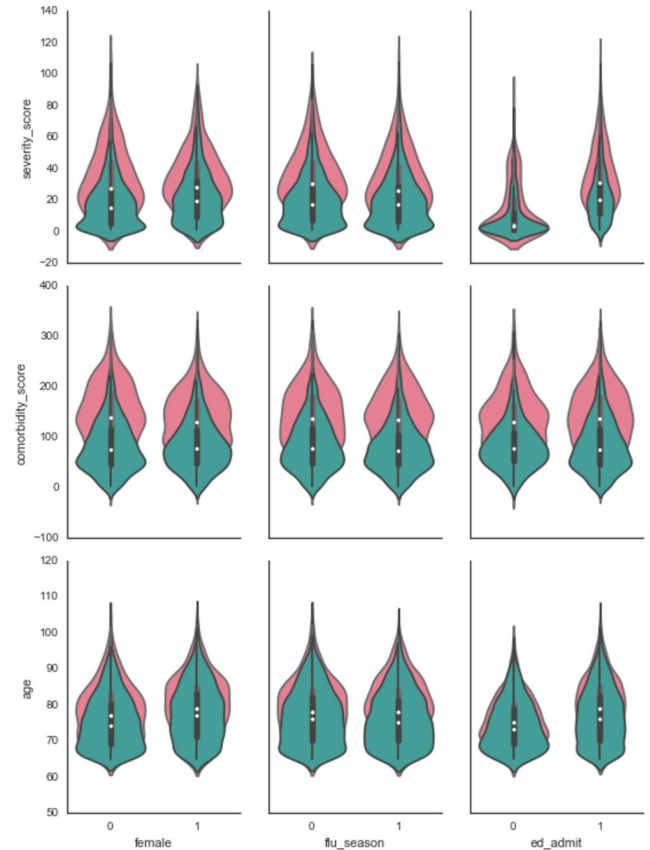
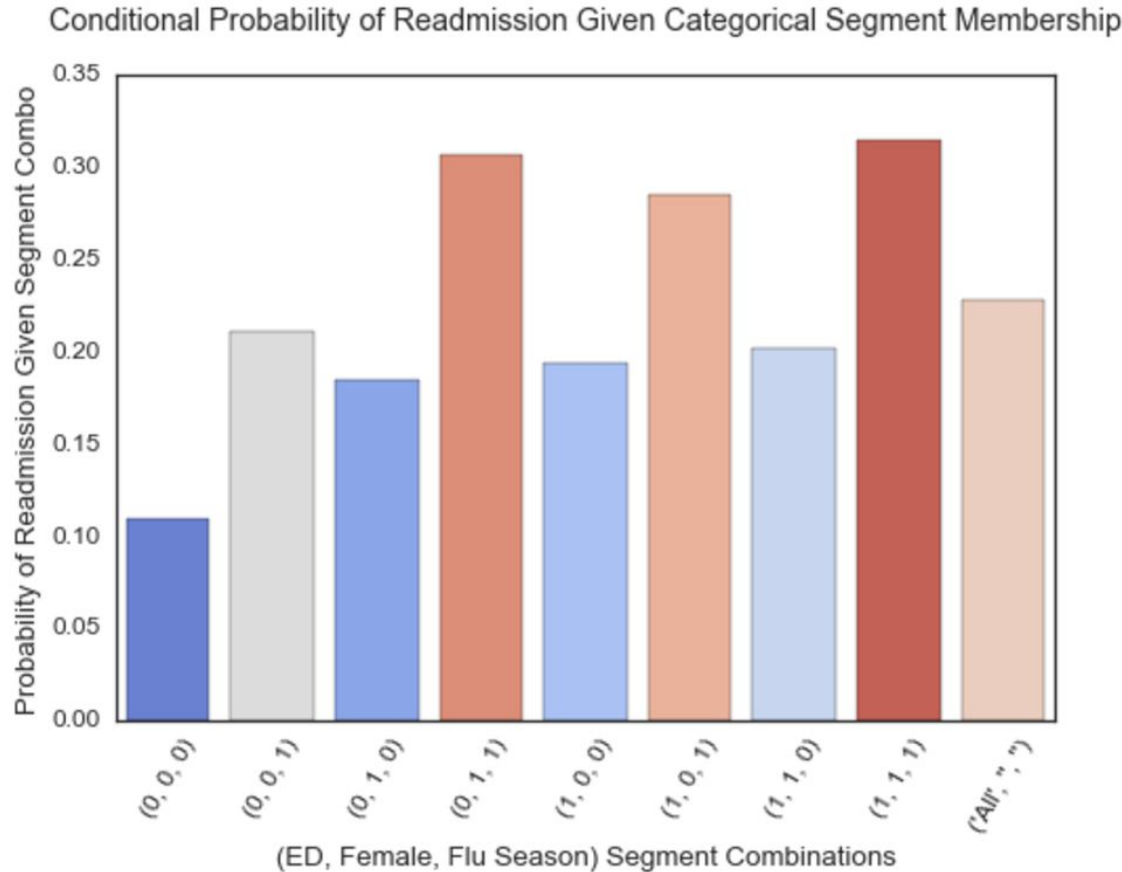


In [02]: Data Context --- State of Affairs

- ❖ **18.5%** of the non-flu-season visitors were readmitted within 30 days of their initial visit.
- ❖ **28.9%** of the flu-season visitors were readmitted within 30 days of their initial visit.



In [02]: Data Context --- Segmentation Opportunities



In [02]: Data Context --- The State of Affairs

Takeaways:

- ❖ Many patients who are readmitted have high comorbidity and severity scores.
- ❖ Patients who were admitted during flu season have greater readmission rates!
 - $p\text{-value} = 6.81e^{-16}$
- ❖ ED admission is not a significant factor within flu season segments.
- ❖ We can use this information to target at-risk patients with CareTracker.



Solutions



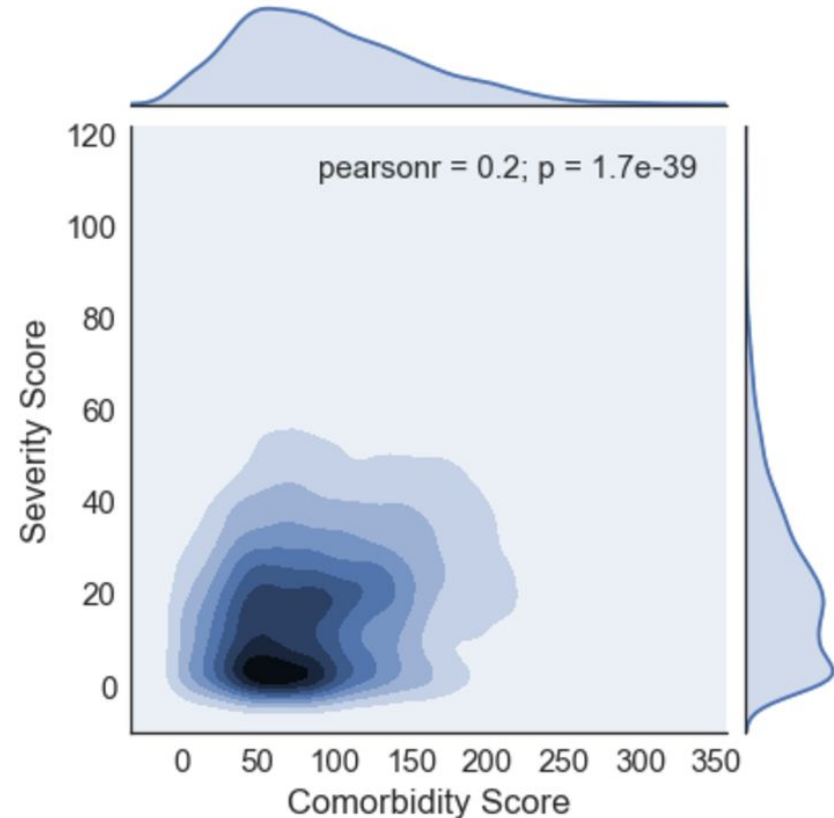
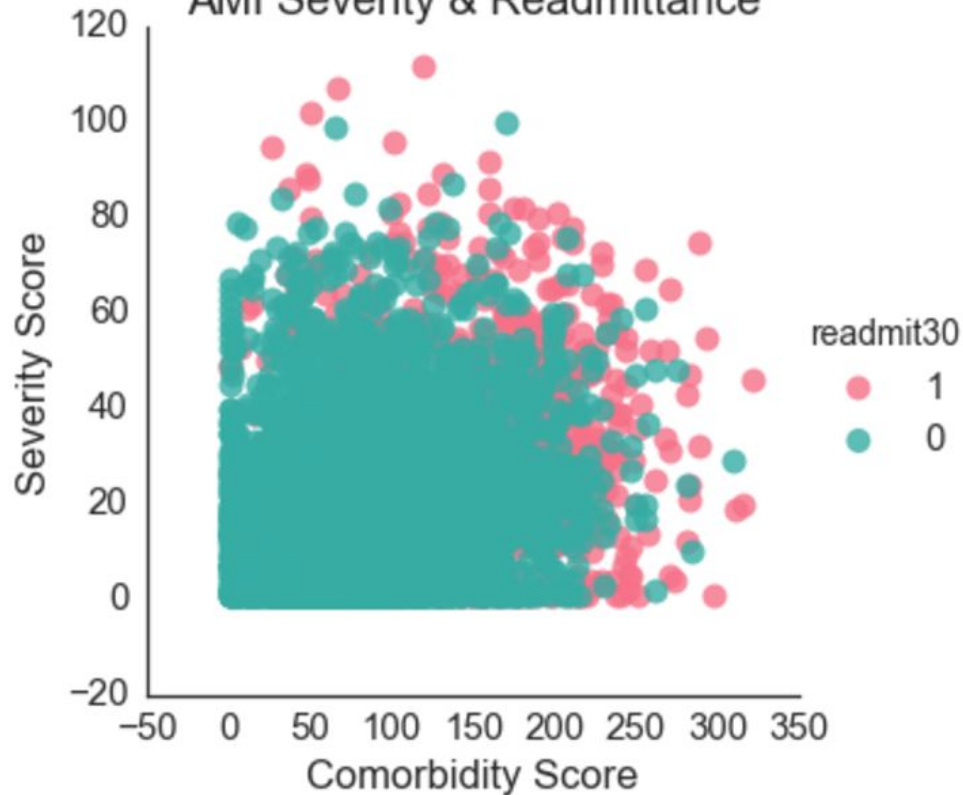
In [03]: Solutions --- Managerial Segmentation

The Concept:

- ❖ Define thresholds for Comorbidity and Severity Scores.
- ❖ Assign CareTracker to patients who surpass either of the thresholds.
- ❖ **Calculate savings.**

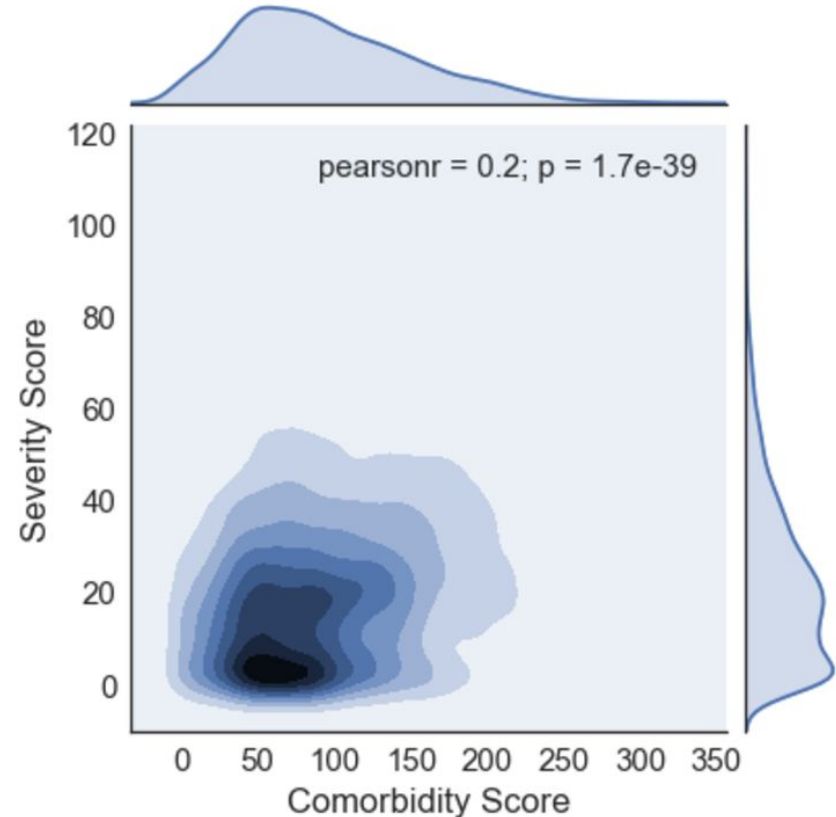
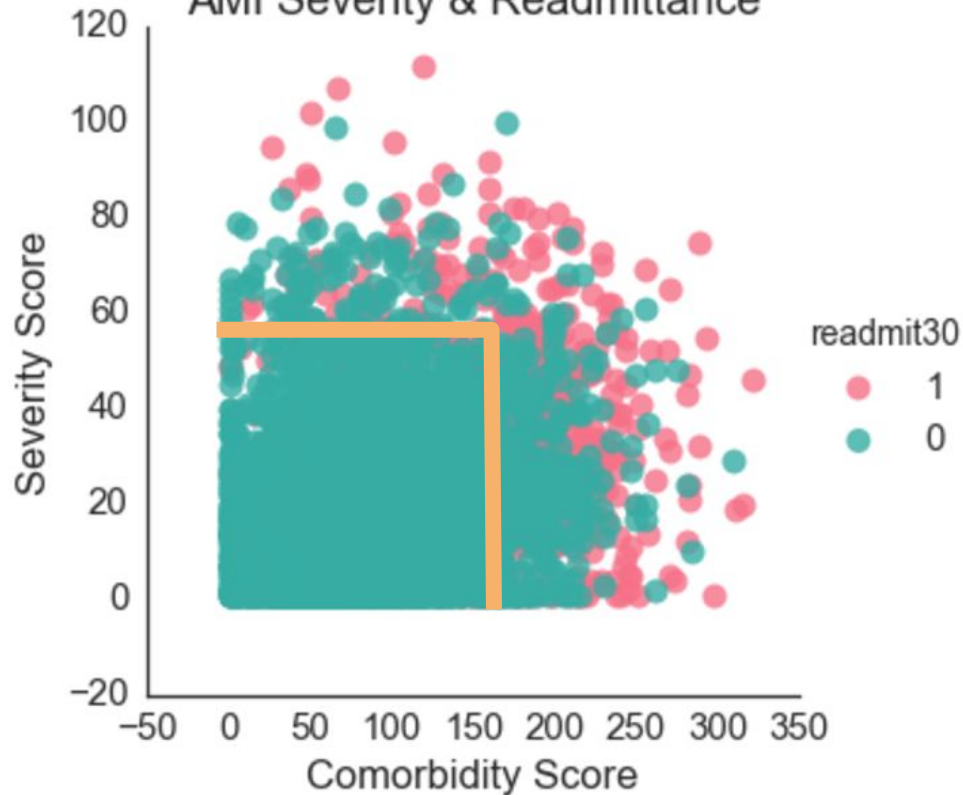
In [03]: Solutions --- Managerial Segmentation --- Drawing The Line

AMI Severity & Readmittance



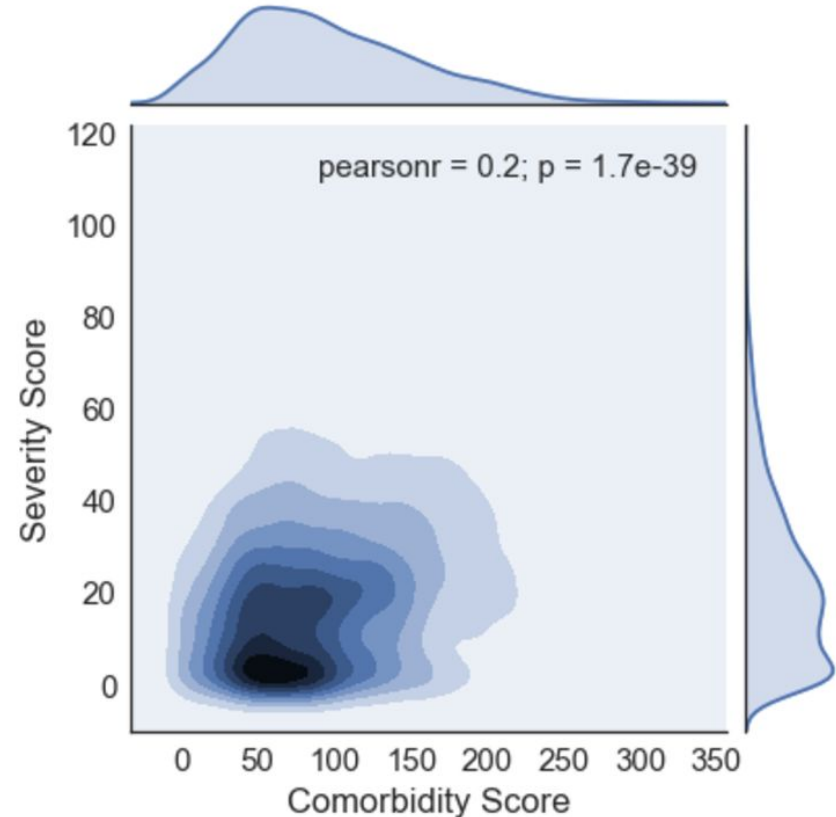
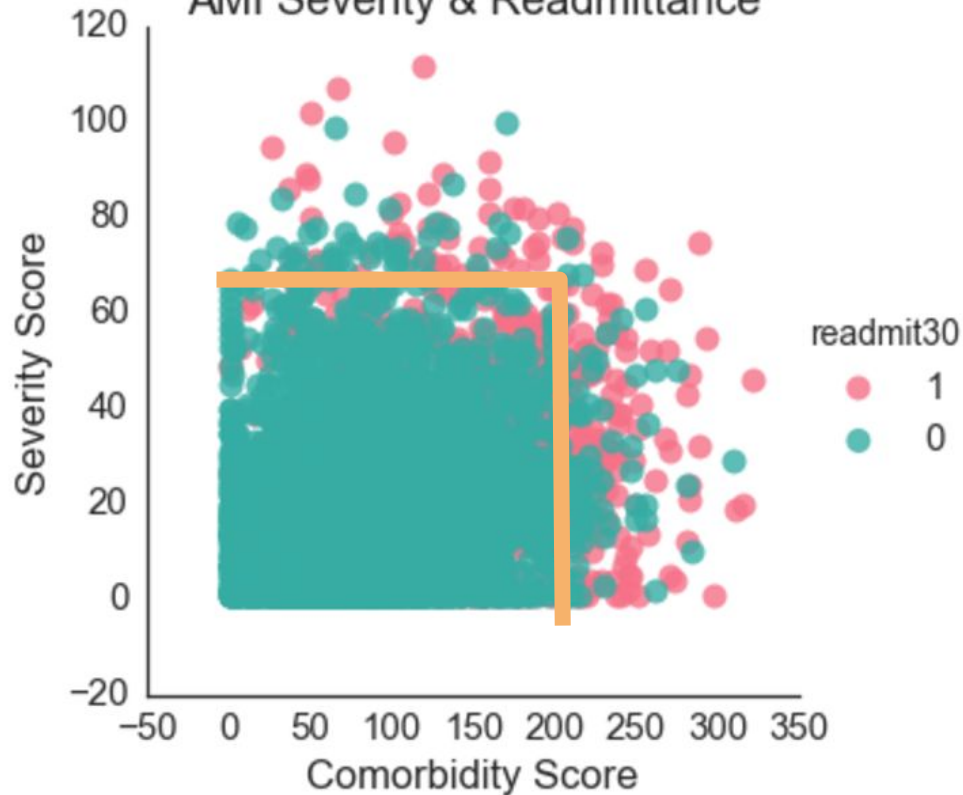
In [03]: Solutions --- Managerial Segmentation --- Drawing The Line

AMI Severity & Readmittance



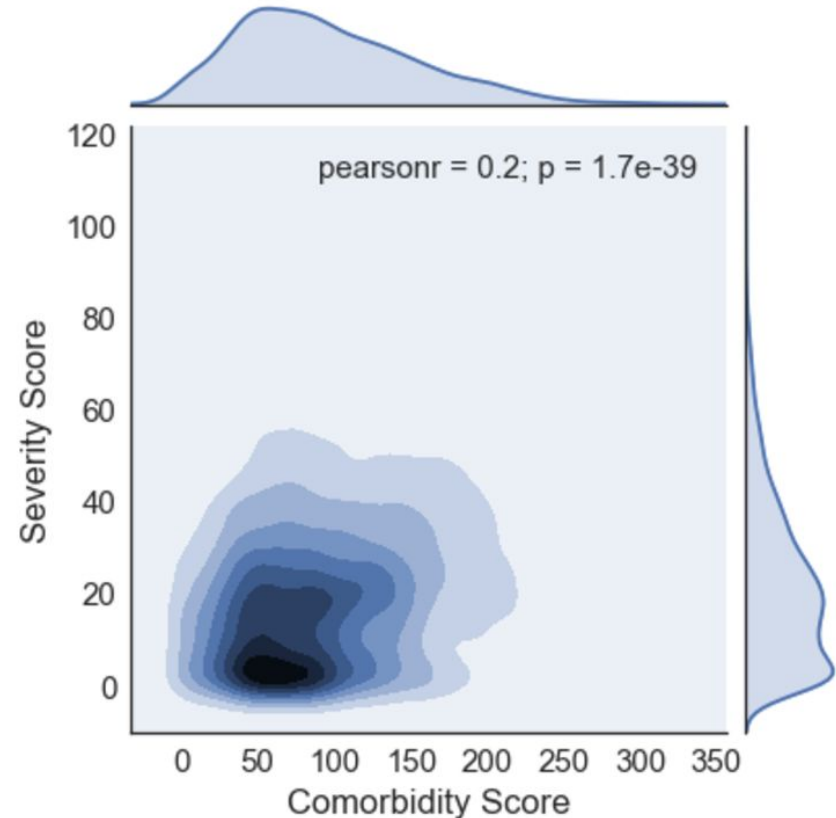
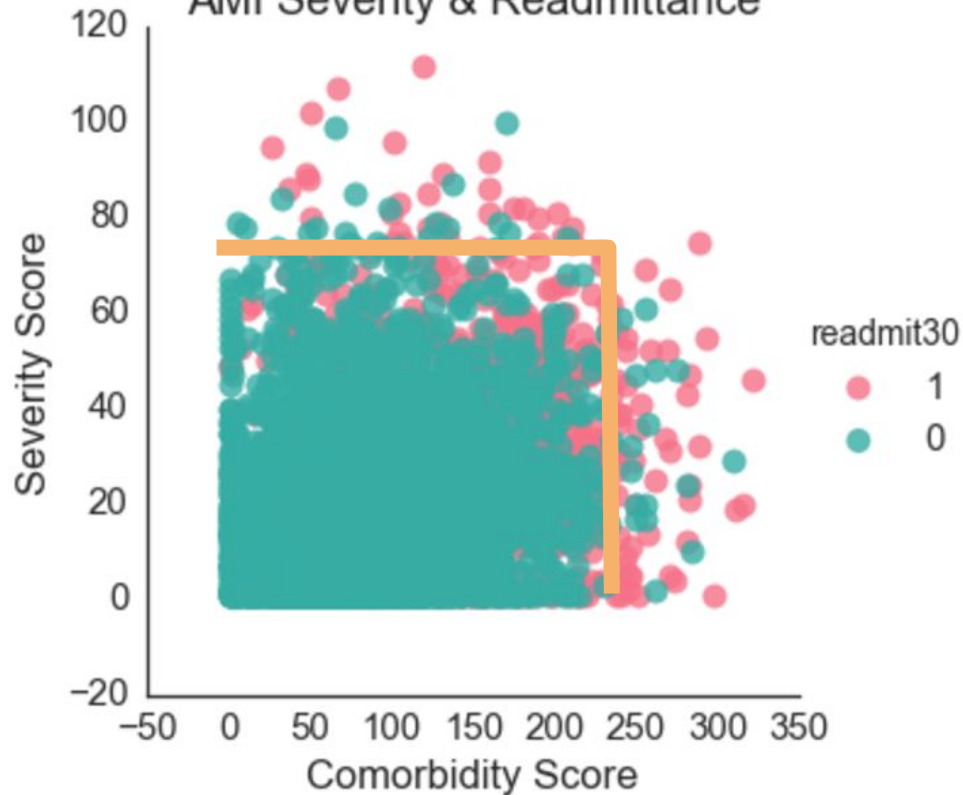
In [03]: Solutions --- Managerial Segmentation --- Drawing The Line

AMI Severity & Readmittance



In [03]: Solutions --- Managerial Segmentation --- Drawing The Line

AMI Severity & Readmittance



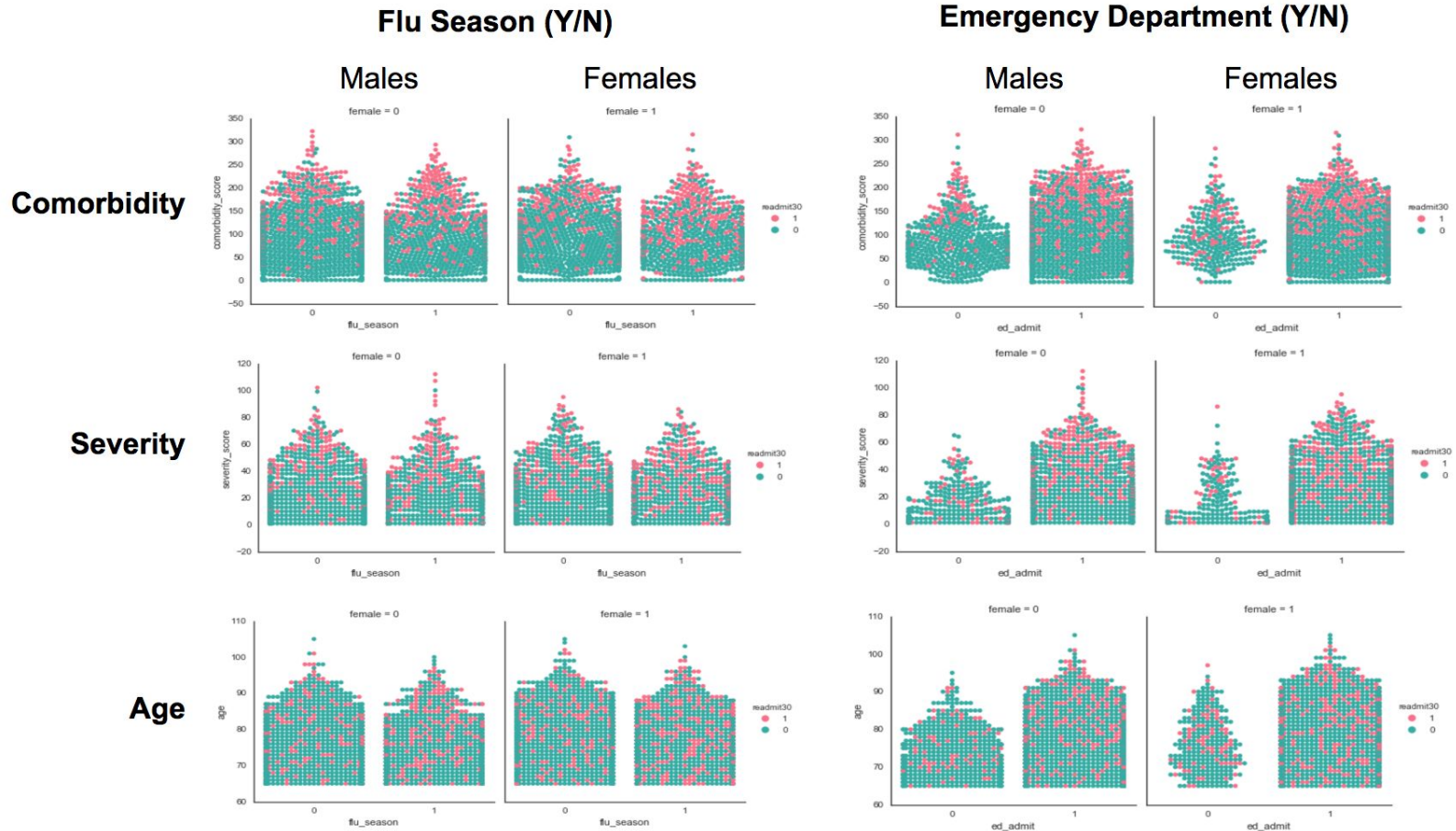
In [03]: Solutions --- Managerial Segmentation

Performance:

	Targeted	Not Targeted
Readmitted	652 (15%)	346 (8%)
Not Readmitted	858 (19%)	2526 (58%)

- ❖ Comorbidity Threshold:
 - 126.5
- ❖ Severity Threshold:
 - 43.7
- ❖ 1510 Targeted Patients (34%)
- ❖ Total Cost:
 - \$ 7,709,600.0
- ❖ F1 Score:
 - 0.32
- ❖ Improvement From Base Case:
 - \$ 274,400.0
 - ↑ 3%

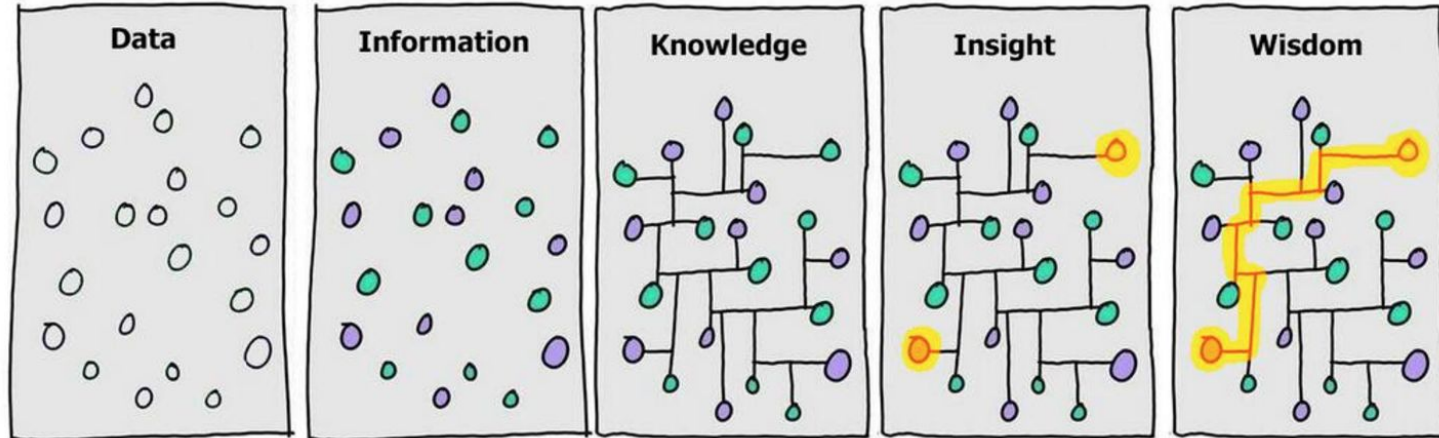
In [02]: Solutions --- Complexity at Play



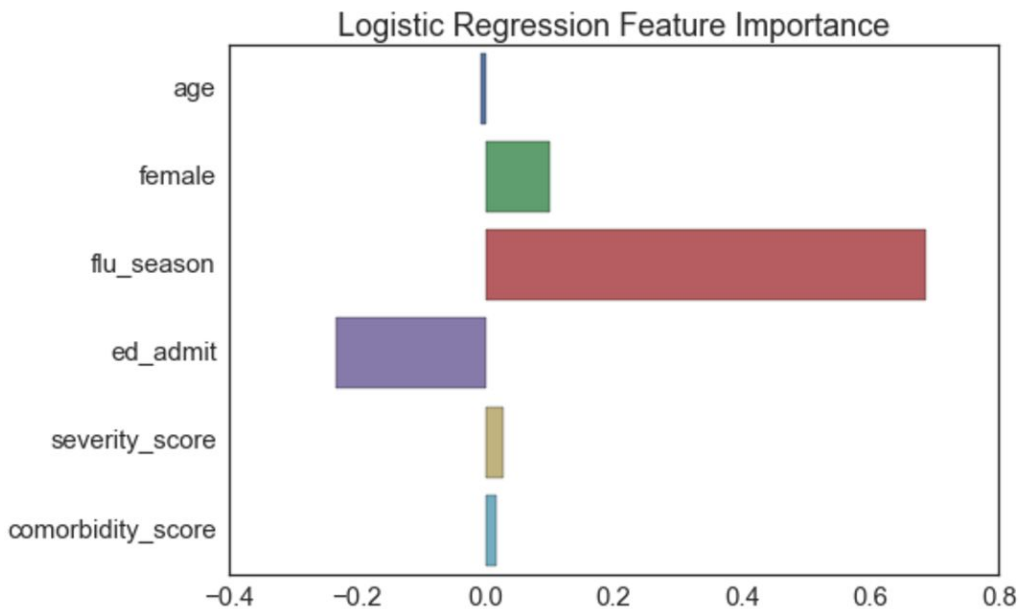
In [03]: Solutions --- Machine Learning

The Concept:

- ❖ Deploy algorithms to teach computers to learn patterns in our data.
- ❖ Train models on subsets of our data and then evaluate on a holdout test-set.
- ❖ Fit our entire dataset to the best model and predict whether patients are going to be readmitted.
- ❖ **Calculate savings.**



In [03]: Solutions --- Logistic Regression?



Logit Regression Results

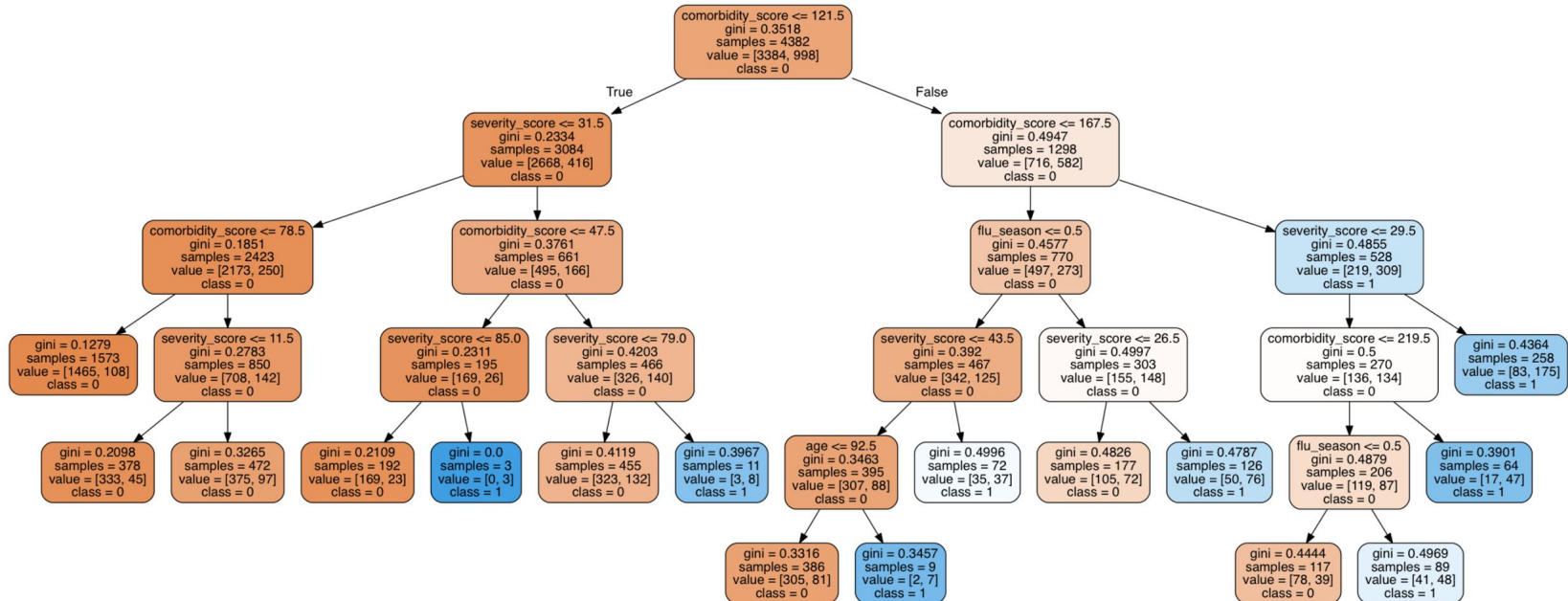
Dep. Variable:	readmit30	No. Observations:	4382
Model:	Logit	Df Residuals:	4377
Method:	MLE	Df Model:	4
Date:	Sat, 04 Mar 2017	Pseudo R-squ.:	0.1847
Time:	20:55:48	Log-Likelihood:	-1916.8
converged:	True	LL-Null:	-2351.1
		LLR p-value:	1.046e-186

	coef	std err	z	P> z	[0.025	0.975]
Intercept	-3.9849	0.128	-31.195	0.000	-4.235	-3.735
female	0.1840	0.081	2.264	0.024	0.025	0.343
flu_season	0.7439	0.082	9.081	0.000	0.583	0.904
severity_score	0.0259	0.002	11.993	0.000	0.022	0.030
comorbidity_score	0.0158	0.001	21.504	0.000	0.014	0.017

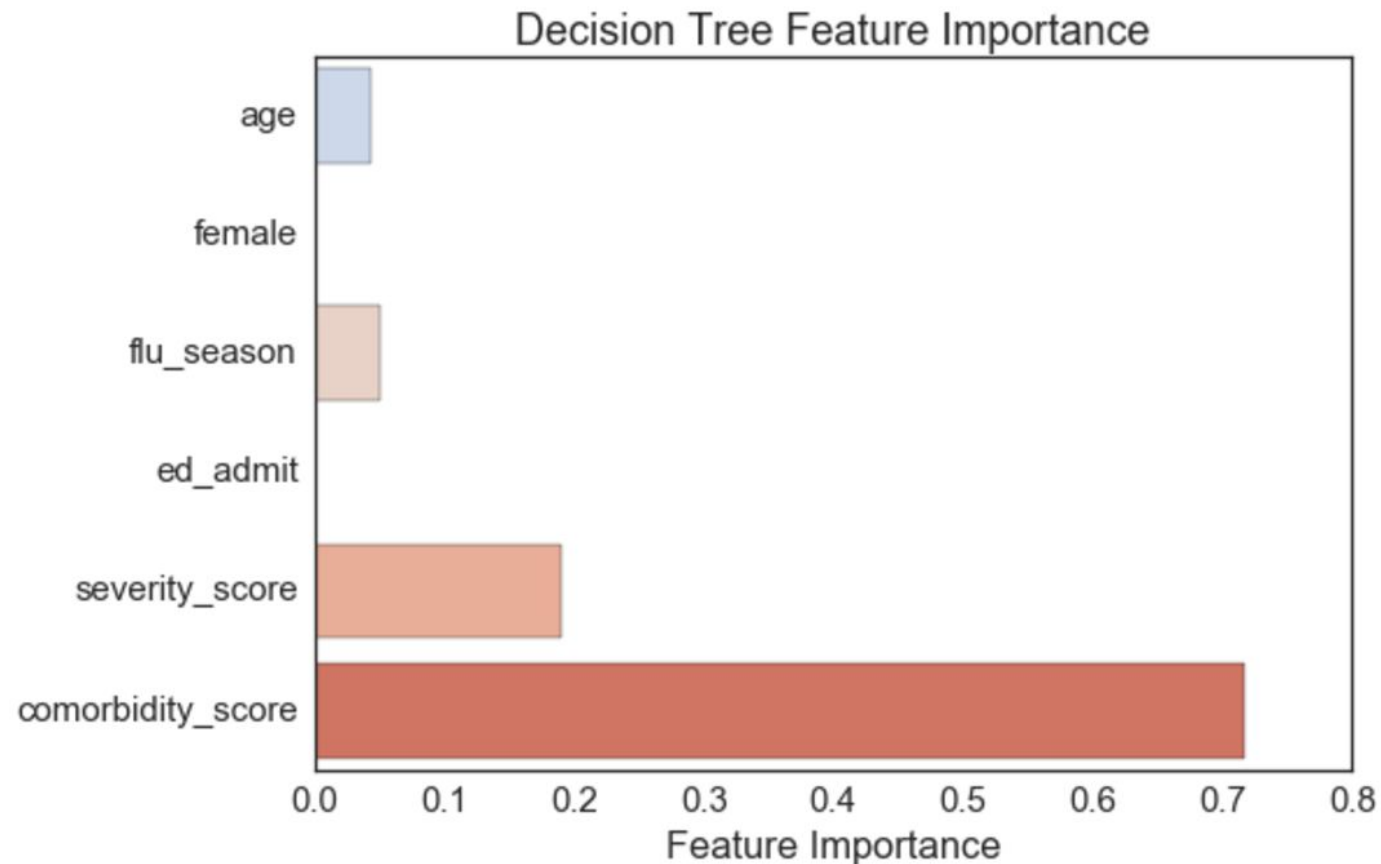
In [03]: Solutions --- Decision Tree

“One bit of advice: it is important to view knowledge as sort of a semantic tree -- make sure you understand the fundamental principles, ie the trunk and big branches, before you get into the leaves/details or there is nothing for them to hang on to.”

- [Elon Musk, Reddit AMA](#)

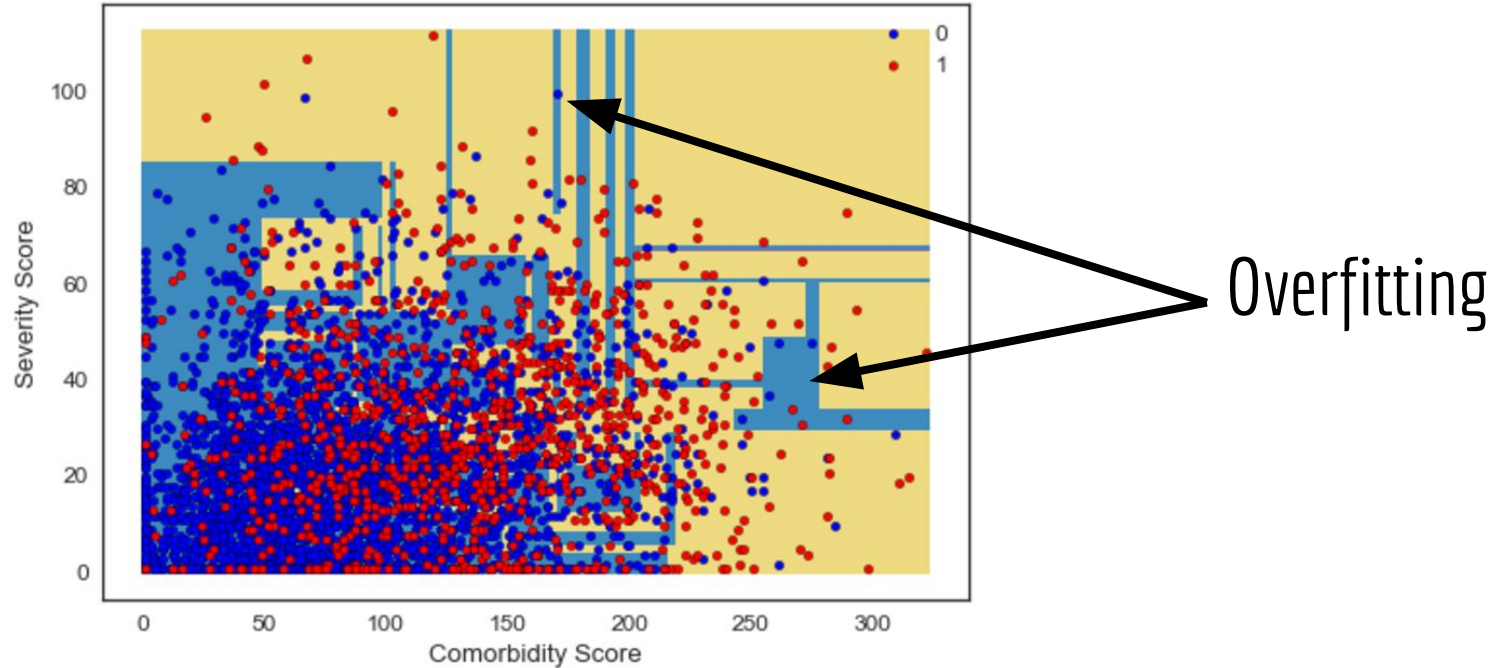


In [03]: Solutions --- Decision Tree



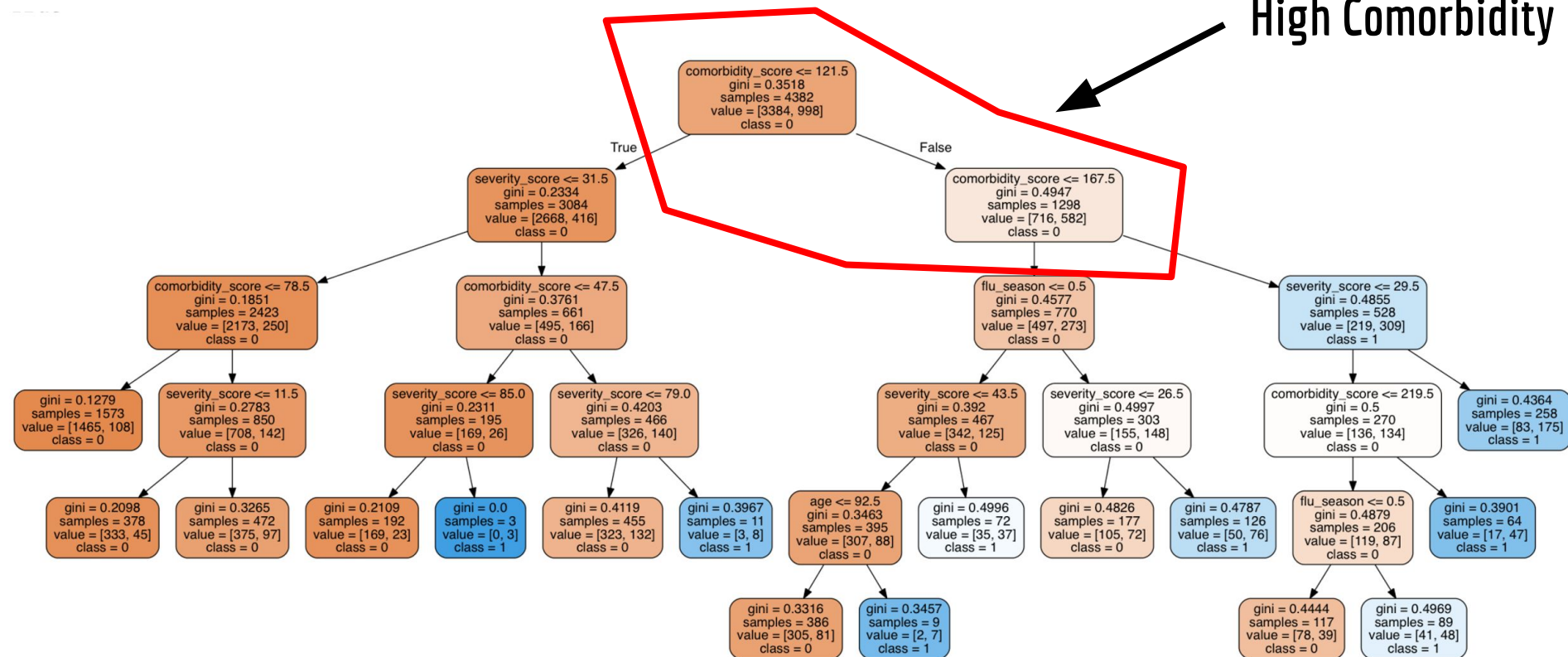
In [03]: Solutions --- Decision Tree

Decision Surface Of Decision Tree Trained On Comorbidity and Severity Score Features



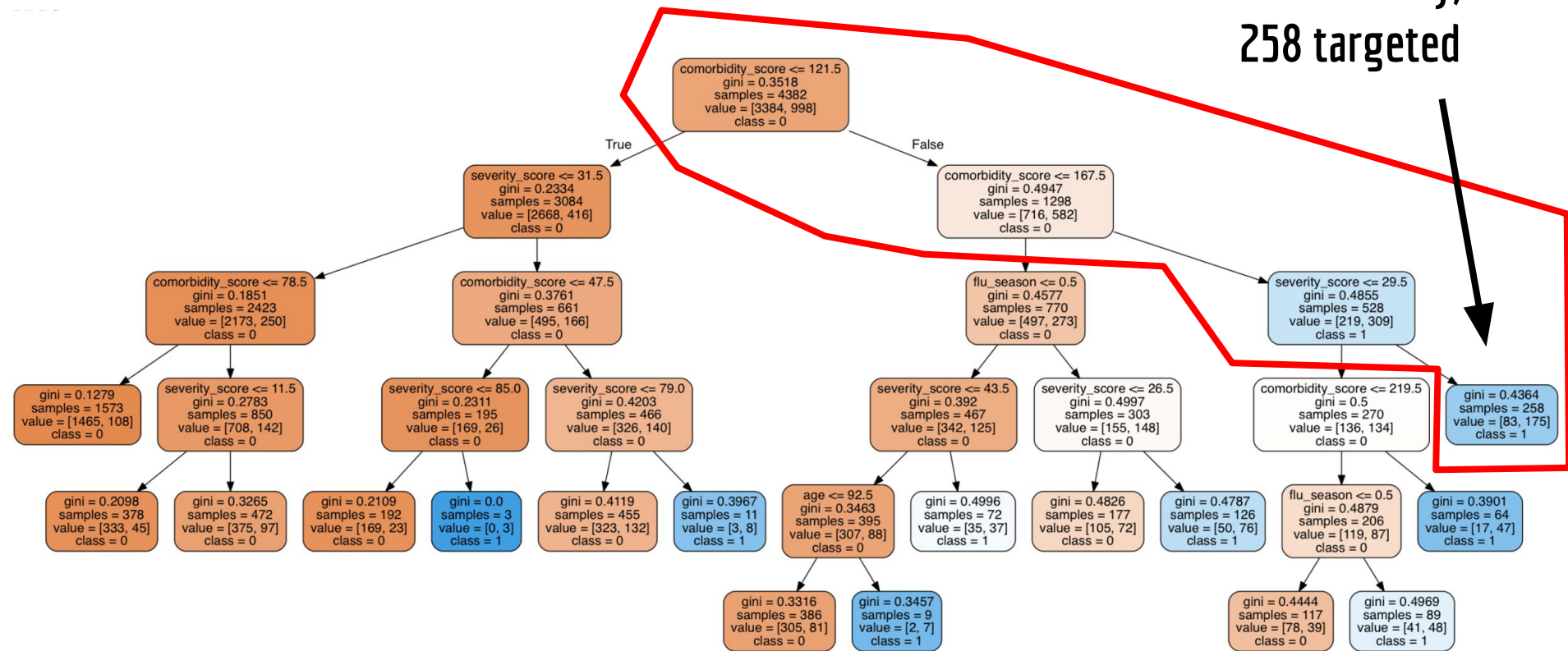
In [03]: Solutions --- Decision Tree

High Comorbidity



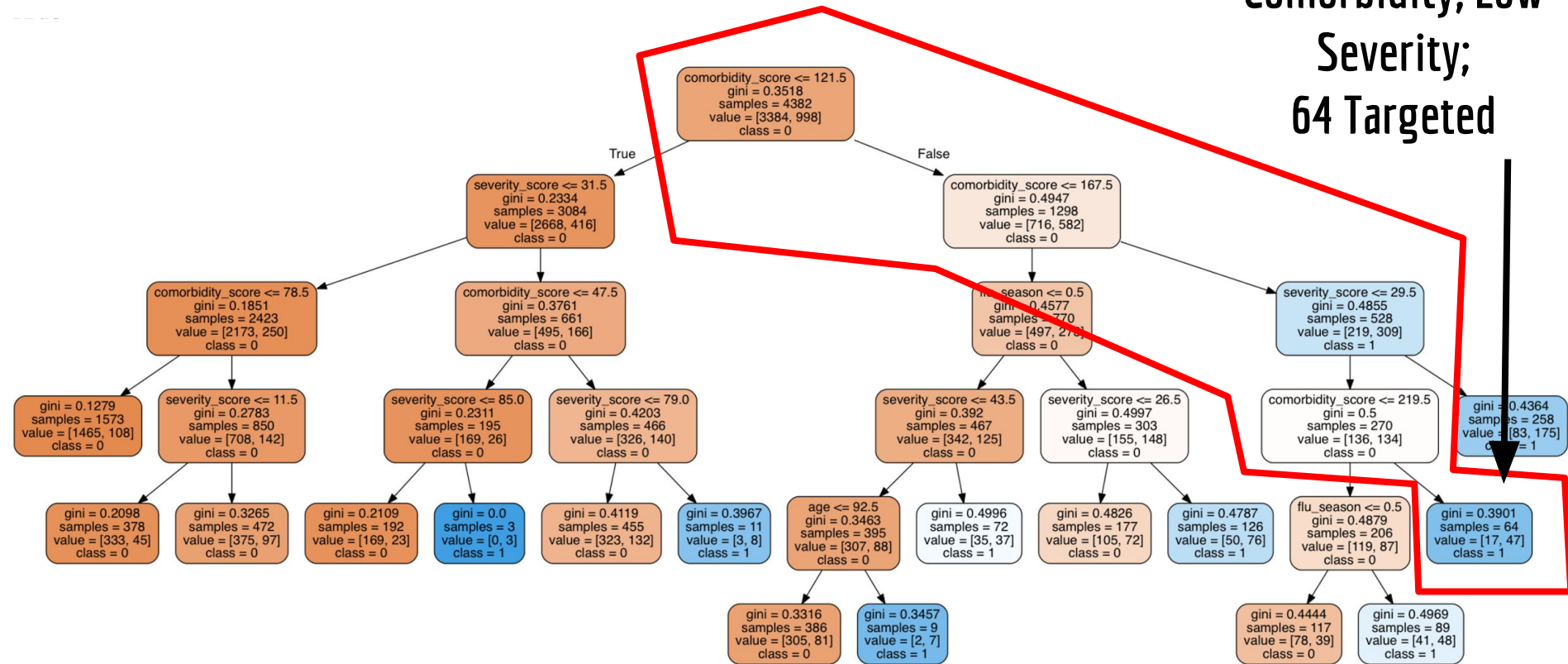
In [03]: Solutions --- Decision Tree

High Comorbidity
and Severity;
258 targeted



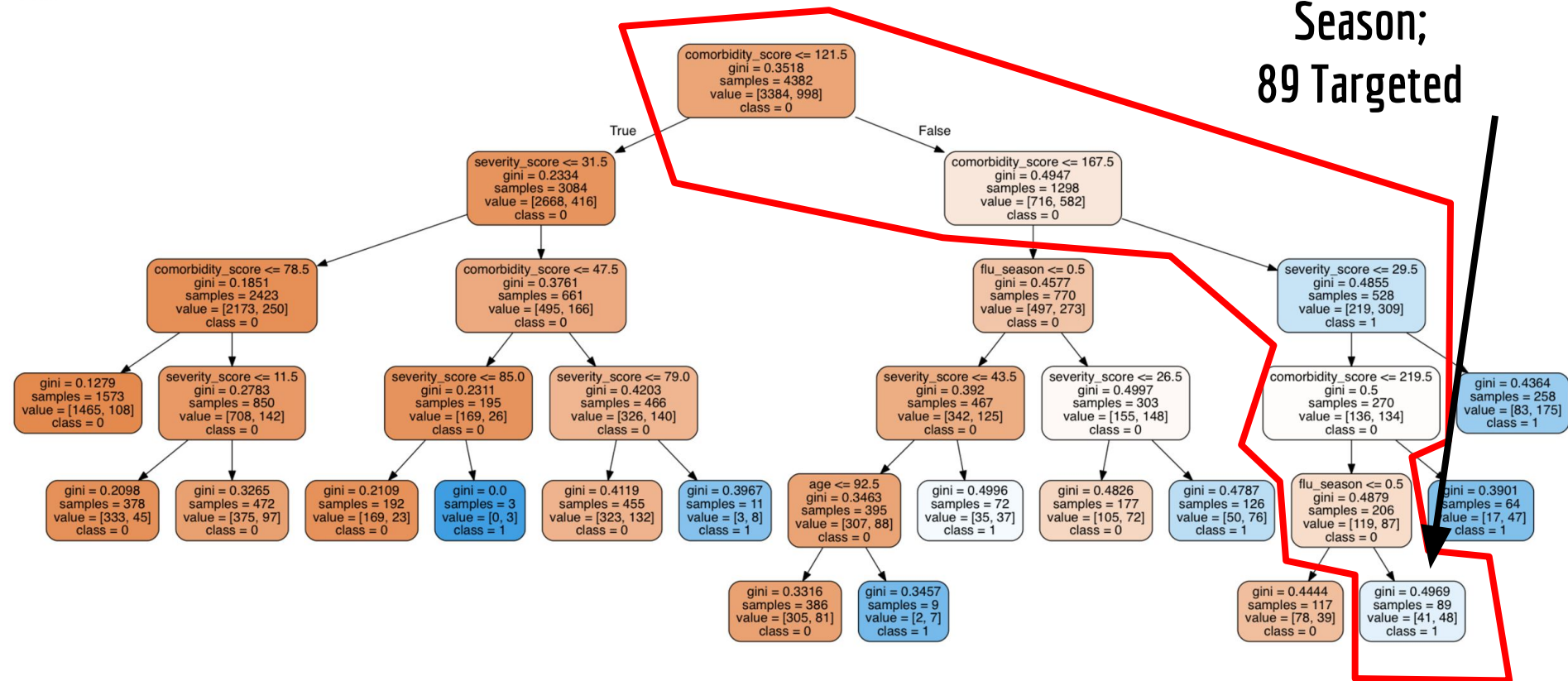
In [03]: Solutions --- Decision Tree

Really High
Comorbidity, Low
Severity;
64 Targeted



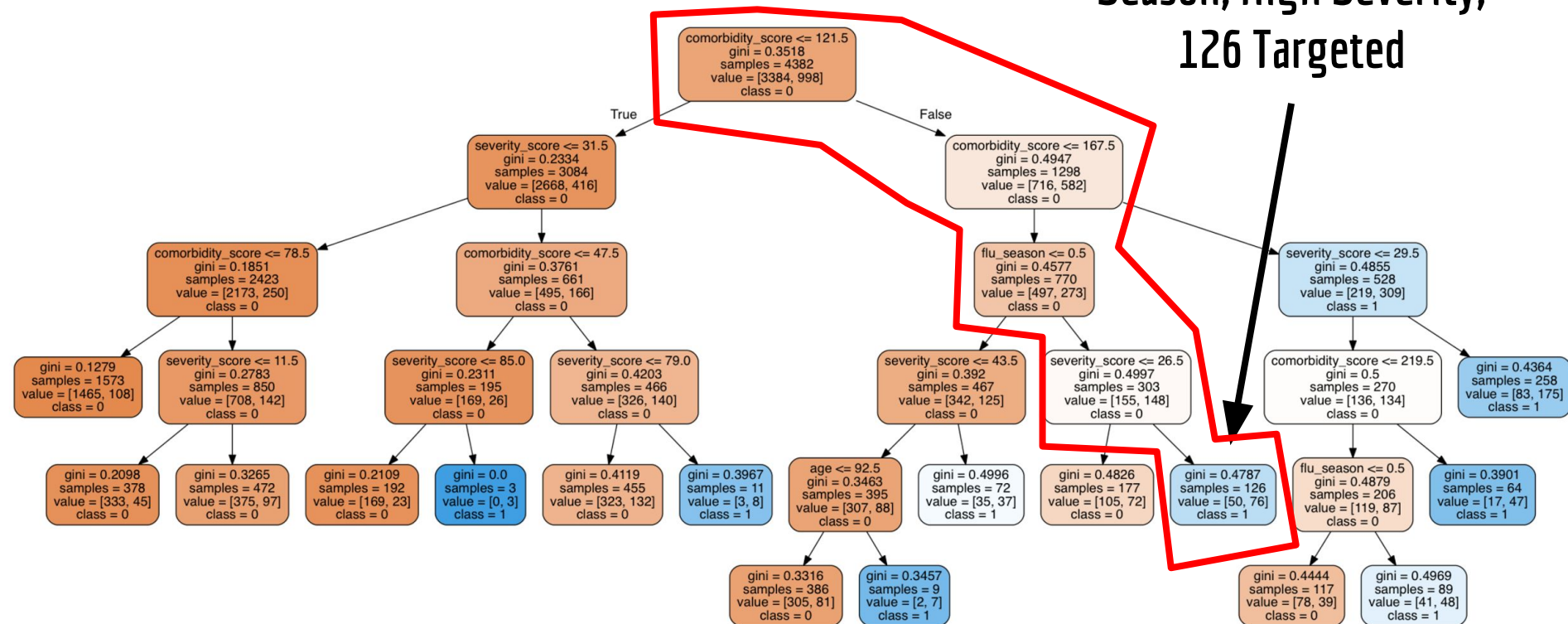
In [03]: Solutions --- Decision Tree

High Comorbidity,
Low Severity, Flu
Season;
89 Targeted



In [03]: Solutions --- Decision Tree

High Comorbidity, Not Flu
Season, High Severity;
126 Targeted



In [03]: Solutions --- Decision Tree

Performance:

	Targeted	Not Targeted
Readmitted	470 (11%)	528 (12%)
Not Readmitted	209 (5%)	3175 (72%)

- ❖ 1510 Targeted Patients (34%)
- ❖ Total Cost:
 - \$ 7,294,800
- ❖ F1 Score:
 - 0.56
- ❖ Improvement From Base Case:
 - \$ 689,200
 - ↑ 9%



Proposal



In [04]: Proposal

Policy	Cost	Savings	% Savings
Do Nothing	\$ 7,984,000	\$ 0	0 %
CareTracker For All	\$ 10,048,800	-\$2,064,800	-0.26
Managerial Segmentation	\$ 7,709,600	\$ 274,400	3 %
Decision Tree	\$ 7,294,800	\$ 689,200	9 %

In [04]: Proposal

Impact:

"The journey of a thousand miles begins with a single step."

- Lao Tzu

- ❖ Saves THS ~ **\$689,200** a year.
- ❖ Improves patient experience and well-being.
- ❖ Improves our reputation.
- ❖ Transition to data-driven precision medicine.

Limitations:

- ❖ **CareTracker seems effective, but is not proven.**
 - Geographic context
 - Piloted in Seattle
 - Temporal context
 - No longitudinal study
 - 40% readmission reduction claim is a broad generalization.

- ❖ **Model Validity**
 - Best F1 score: 0.56
 - Health care regulations will change, this model will not endure.
 - Issues of overfitting and regularization.
 - The model was trained solely on AMI cases.
 - Every medical condition has its own readmission patterns.

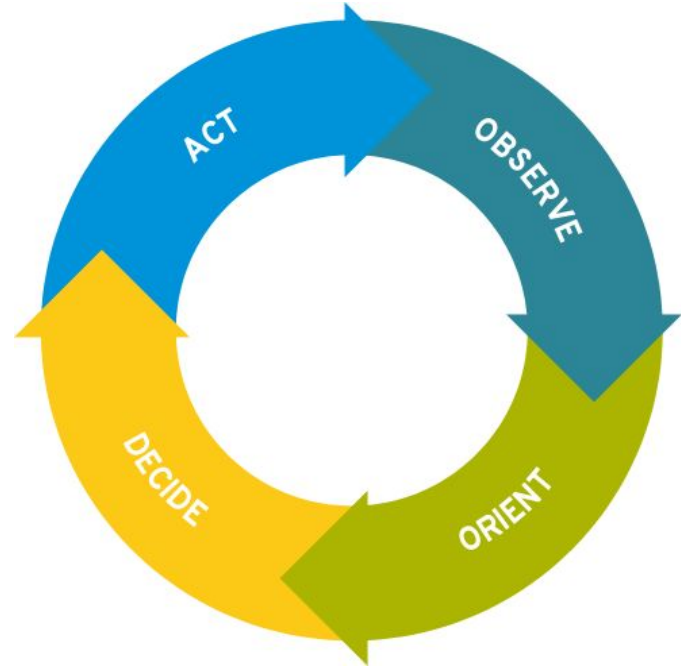
- ❖ **Human Element**
 - Patients may react adversely to being "Targeted."
 - Demands on practitioners and infrastructure.
 - Ethical issues around patient confidentiality.

Next Steps



In [05]: Next Steps

- ❖ Begin “online” targeting of at-risk patients for CareTracker.
 - Retrain readmission model iteratively by comparing predictions with outcomes.
- ❖ Implement CareTracker in hospitals with high readmission rates.
 - Monitor readmission reduction rates over time.
 - Bayesian A/B testing
- ❖ Develop and implement models for all major conditions.
- ❖ Collect more patient data and engineer better features for each condition.
 - Hospital locations
 - Admission and readmission dates
 - Medical history



In [06]:

```
C:\Users\Scott\Anaconda2\lib\site-packages\scipy\signal\filter_design.py in <module>()
    12 from numpy import mintypecode
    13 import numpy as np
--> 14 from scipy import special, optimize
    15 from scipy.special import comb
    16

C:\Users\Scott\Anaconda2\lib\site-packages\scipy\optimize\__init__.py in <module>()
    220
    221 from .optimize import *
--> 222 from ._minimize import *
    223 from ._root import *
    224 from .minpack import *

C:\Users\Scott\Anaconda2\lib\site-packages\scipy\optimize\_minimize.py in <module>()
    29 # constrained minimization
    30 from .lbfgsb import _minimize_lbfgsb
--> 31 from .tnc import _minimize_tnc
    32 from .cobyla import _minimize_cobyla
    33 from .slsqp import _minimize_slsqp

C:\Users\Scott\Anaconda2\lib\site-packages\scipy\optimize\tnc.py in <module>()
    35 from __future__ import division, print_function, absolute_import
    36
--> 37 from scipy.optimize import moduleTNC, approx_fprime
    38 from .optim import sizeResult, _check_unknown_options
    39 from numpy import int, array, zeros, asfarray

ImportError: cannot import name moduleTNC
```

Questions?