Introduction

Doug Gray

Unit 9

How to successfully apply analytics to your business to deliver economic impact and achieve strategic competitive advantage

Unit 9 Outline

Minimizing readmittance: minimizing discomfort and saving money

- Substance abuse rehabilitation readmission predictor
- Evidence-based medicine: spinal surgery predictor
- DR probe and predicting orthopedic surgery readmission

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Overview of Healthcare Industry

Doug Gray

Healthcare Industry

- $3 trillion U.S. industry (2015); about 20% GDP; $7 trillion globally; $8.7 trillion (2020)
- 25–30% of every dollar spent goes to administration
- Three primary goals for healthcare entities:
  1. Patient outcome and quality of life
  2. Patient quality of care
  3. Economic efficiency and financial performance (hospitals, insurance, pharma, etc.)
- Trend towards "evidence-based" medicine, e.g., stomach ulcer case
  - Based on data and data science, including AI, machine learning

Hospital Readmissions

- Readmissions are a particularly chronic problem today, top causes being:
  - Infection (sepsis), blood poisoning (septicemia)
  - Pneumonia
  - Congestive heart failure
  - Complications of surgical or medical care

https://www.verywellhealth.com/sepsis-and-septicemia-2615130

Hospital Readmissions

- The cost of all readmissions must now be borne by the hospital provider
  - In 2011, 3.3 million adult all-cause readmissions associated with $41.3 billion in hospital costs
    - *Medicare* patients' top three readmission conditions resulted in $4.3 billion in hospital costs
    - *Medicaid* patients' top three readmission conditions resulted in $839 million in hospital costs
    - *Privately insured* patients' top three readmission conditions resulted in $785 million in hospital costs

https://www.verywellhealth.com/sepsis-and-septicemia-2615130

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CIGNA Paper Discussion

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Cigna Collaborative Accountable Care

- Patient-centered medical home
- Accountable care organizations: quality, affordability, experience of care

Focus on the right care
Built on the principles of the IOM

- Safe
- Timely
- Efficient
- Effective
- Equitable
- Patient-centric

\+

Accountable for outcomes

Reward for improving the triple aim:

- Quality
- Cost efficiency
- Patient experience

\+

Achieved the right way
Guided by patient-centered medical home principles

- Personal physician
- Physician-directed practice
- Whole-person orientation
- Coordinated care
- Quality and safety
- Enhanced access

\+

Enabled by CIGNA resources

- Health advocacy integration
- Patient-specific actionable information
- Performance management reports

- Improve delivery of evidence-based care
- Improve patient engagement in care
- Improve care outcomes and overall health
- Reduce unnecessary care and costs

Cigna Solutions

CIGNA Solution			
Clinical programs	**Patient-specific information**	**Performance management reports**	**Client resources**
• Disease management • Case management • 24-hour health information line • Health assessment • Online coaching	• Readmission predictor • General predictor • Gaps in care	• Population-based • Episode-based • Focused trends	• Cigna field project management • Network engagement consultants • Clinical insights

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Substance Abuse Readmittance

Doug Gray

Case Analysis

Substance abuse rehabilitation

Readmissions Are a Huge Source of Costs for Hospitals and Insurers

According to the Agency for Healthcare Research and Quality (AHRQ):

- Hospitals spent $41.3 billion between January and November 2011 to treat patients readmitted within 30 days of discharge.
- 1.8 million readmissions cost the Medicare program $24 billion.
- 600,000 privately insured patient readmittance totaled $8.1 billion.
- 700,000 medicaid patient readmissions cost hospitals $7.6 billion.
- The 200,000 uninsured patients who were readmitted cost hospitals a relatively paltry $1.5 billion.

Causes of Readmissions

- Complications from surgery or treatment
- Infection
- Relapse of a physical malady or other condition
- Related (direct or indirect) health episode

Setting

For a project with a $2 billion U.S. Midwest healthcare insurer who wanted to look more closely at substance abuse patients who were readmitted versus those who were not

Goal

Identify and intercept those with a high propensity for readmissions and advise, treat, and counsel them accordingly.

Classifying and Predicting Patient Post-Discharge Behavior

- Classification, segmentation, propensity to re-admit
- Latent class modeling
- K-means clustering, CART/CHAID
- Logistic regression (odds of readmitting)
- Bayesian Inference (Multivariate)

Data

- Medical history data including pre-existing and current conditions
- Demographic and psychographic data from Acxiom
- Prior readmission history

Frame and Solve: Analytics Solution Approach

- Healthcare industry
- Healthcare insurer
- *“Substance abuse readmissions have increased 33% YOY”*
- *“Limited patient care staff cannot amply support all recently released patients”*

Frame and Solve: Analytics Solution Approach

"How can we focus patient care staff on the patients at highest risk of readmission?"

Predictive

*Identify **(predict)** patients who may be prone to substance abuse rehabilitation readmission and care for them to **reduce** their likelihood of readmission*

There are a dozen or more variables that can influence whether or not a patient will readmit after rehabilitation

Stochastic

Predicting readmission with certainty is not possible; predict the "probability" of a patient readmitting after rehabilitation

- *Probability: Bayesian Inference*
- *Odds or [p/(1-p)]: Logistic Regression*

Bayesian Inference Model

- The “Swiss Army Knife” of *modern* statistical predictive modeling

Breast Cancer Screening Indicator (BCSI) Test				
BCSI test result	**True cancer state**	**Patient has cancer**	**Patient has no cancer**	**Total number patients tested**
POS +		88	36	124
NEG -		16	37	55
Total		106	73	179
P(Patient has cancer/POS + test result) = 88 / 124 = 71%				
P(POS + test result/patient has no cancer) = 36 /73 = 49%				

$$P(M|E) = P(M) \cdot \frac{P(E|M)}{P(E)}$$

Modeling propensity of an outcome given *prior* information and *empirical* information

- Disease state given a test result
- Heart attack or stroke
- Hospital readmission
- Consumer behavior, e.g., product purchase, churn

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Spinal Injury

Pachinko, Logistic Regression, and Architecture

Doug Gray

Case Analysis

Spinal surgery predictor

Spinal Surgery Can Often Be Avoided or Postponed Indefinitely With

- Weight loss
- Exercise
- Physical therapy or occupational therapy
- Improved mechanics
- Medications

Goal

Goal: identify and intercept with a high propensity for spinal surgery and advise and counsel them with alternative non-invasive, non-surgical treatments

Methods: Classifying and Predicting Patient Propensity for Spinal Surgery

- Classification, segmentation, propensity to require spine surgery
- Latent class modeling
- K-means clustering, CART/CHAID
- Logistic regression (odds of requiring spinal surgery)

Data

- Medical history data including preexisting and current conditions
- Demographic and psychographic data from Acxiom
- Prior readmission history
- Work history

Frame and Solve: Analytics Solution Approach

- Healthcare industry
- Healthcare insurer
- *“Spinal surgery patients have increased 25% YOY”*
- *“Spinal surgery typically results in additional surgeries, creating risk”*

Frame and Solve: Analytics Solution Approach

"How can we prevent spinal surgeries from occurring?"

Predictive

*Identify **(predict)** patients who may be prone to spinal surgery and intercept and treat them **before** they undertake surgery*

There are a dozen or more variables that can influence whether or not a patient will require spinal surgery

Stochastic

Predicting spinal surgery with certainty is not possible; predict the "odds" or "probability" of a patient spinal surgery event

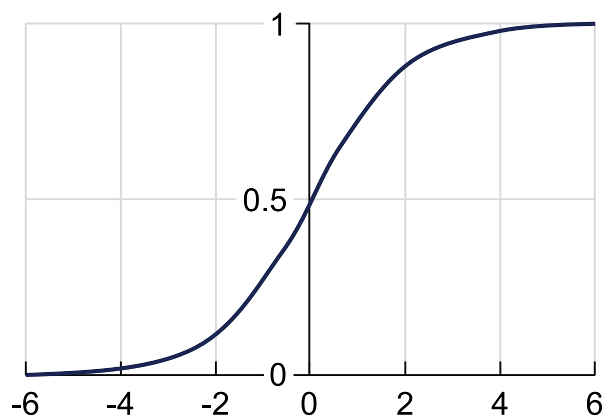
- *Odds or [p/(1-p)]: Logistic Regression*
- *Probability: Bayesian Inference*

Logistic Regression Model

The "Swiss Army Knife" of *classical* statistical predictive modeling

$$f(z) = \frac{e^{\approx}}{e^{\approx} + 1} = \frac{1}{1 + e^{-\approx}}$$

Nonlinear: No closed form equations for model parameters; must be solved using maximum likelihood estimation (MLE)



$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k$$

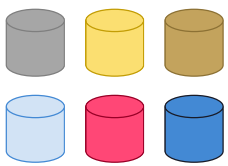
Modeling propensity of an outcome

- Heart attack or stroke
- Hospital readmission
- Consumer behavior, e.g., product purchase, churn

Solve using MS excel solver (GRG) for nonlinear programming or MATLAB

Analytics Architecture Flow

Enterprise systems



44 Source systems

Business problems or questions

IBM DB2 UDB

ETL

Enterprise data warehouse

Analytics data warehouse

TERADATA

MicroStrategy

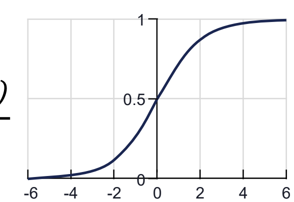
IBM SPSS

Cloud hosting

$$f(z) = \frac{e^{\approx}}{e^{\approx} + 1} = \frac{1}{1 + e^{-\approx}}$$

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots + \beta_k x_k$$

$$P(M|E) = P(M) \cdot \frac{P(E|M)}{P(E)}$$



Analytical models

Patient risk profiles

Patient outcome predictions

Patient outcome likelihoods

Decision makers

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Orthopedic Surgery (Hip, Knee) Re-admission Predictor

Final Project

Predicting

Hospital

→ Readmissions ←

Following Joint Replacement Surgery

Meet... Jim & John

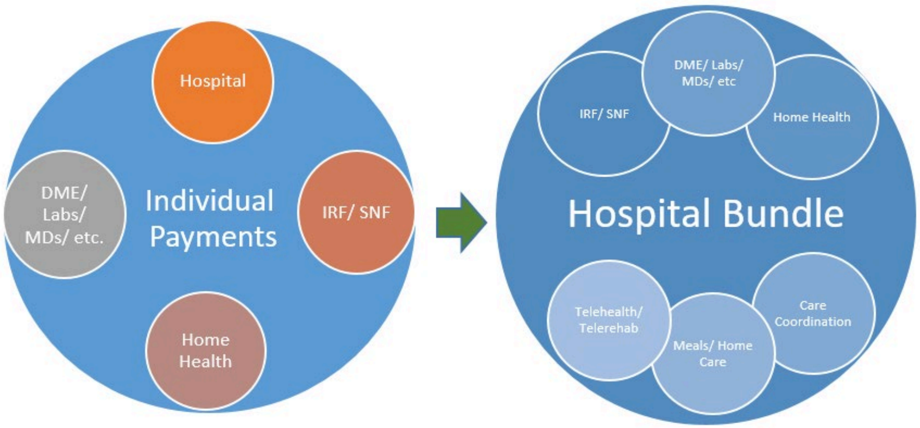
- **Jim**
  - Total Hip Replacement Surgery
  - Not Readmitted
- **John**
  - Total Hip Replacement Surgery
  - Readmitted

WHY... focus on Joint Replacement ???

- By **80 years** of age
  - **6%** will have an → **artificial hip**
  - **10%** will have an → **artificial knee**
- **Growth rate**
  - Hips **7.4%** CAGR
  - Knees **15.7%** CAGR
- **Average cost:** total knee customer
- **$28,184** US
- **$6,687** Spain

Evolution of Medicare Payments

- Medicare created........................1965
- Inpatient prospective payment...........1984
  - DRG (diagnosis related groups)
  - MS-DRGs
  - APR-DRGs
- <u>Optional</u> **Bundled Payment....................2013**
- Pilot <u>Mandatory</u> **Bundled Payment…………………2016**



Bundles: Reimbursement Future?

- Bundled Payment for Care Improvement (BPCI)
  - Volunteer Program Started in October 2013
  - 48 Episode Types Made Up Of DRG "Families"
  - Account for 70% of Total Medicare Spend
  - Most Volunteered for by Participants - Major Joint Replacement, Congestive Heart Failure, Simple Pneumonia, COPD & Sepsis
- Joints (CJR) First BPCI to be Mandated
  - ***Hospitals held responsible*** for ***Costs*** and ***Quality*** for lower extremity joint replacement (LEJR) procedures – DRGs 469 & 470 – includes fractures
    - Costs: **All Part A and B costs** of care during stay plus Medicare costs for surgery plus **90 days post hospital discharge** w/very **few exclusions**
    - Quality: RSCR, HCAHPS & Patient Reported Outcomes (PRO)
- **Average Cost** of **Each Readmission:**

→ *$19,000 ABOVE…* (Original $28,184 Care)

Back to... Jim & John

	Jim	John
SAME: **Procedure**	Total Hip Replacement Surgery	Total Hip Replacement Surgery
SAME: **Age**	65 years old	65 years old
SAME: **Length of Stay**	3 Days in Hospital post-op	3 Days in Hospital post-op
SAME: **Discharge Type**	Home Health	Home Health
DIFFERENT OUTCOME	Not Readmitted	Readmitted

SO THEN...
WHY does John readmit and Jim doesn't ?

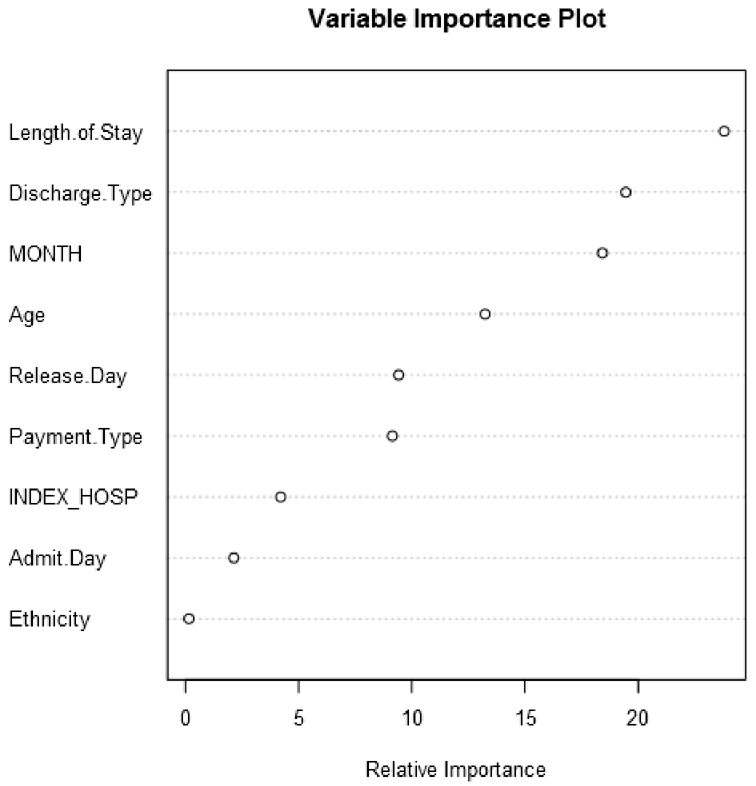
The Data

- July 2014 – June 2016 (2 years)
- 7192 hip and knee replacements
- 341 Readmissions
- Variable
  - Age, Race, Ethnicity, Payment Type, Discharge Date, Length of Stay, Discharge Instructions, Hospital System, and MORE.

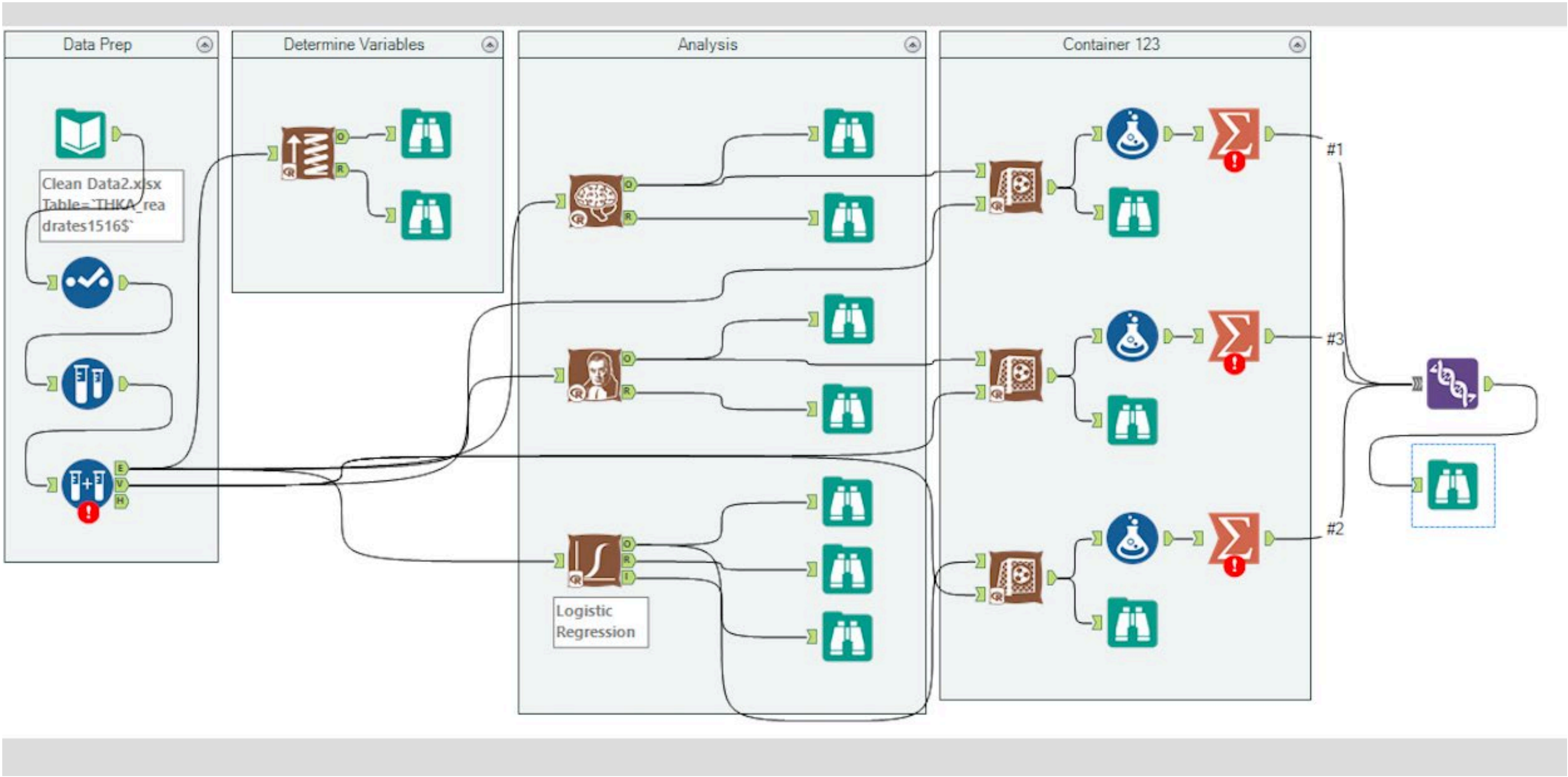
	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	
1	RandomID	LOCATION	METRIC_CODE	TYPE	HOSP_	PAT_	HOME_	RACE	ETHNICITY	PRINCIPAL_PAYER_	PRIMARY_I	INDEX_FAC	INDEX_	INDEX	INDE	INDEX_DISPD	INDEX_DIA	INDEX_PI	READMISSI	R
2	1001	GRP	THKA_FY16	THKA	3	33	76177	2	2	MANAGED CARE	HUMANA/(	GRP	1	6	0	DSCH./TRFD./HOME HEALTH	73342	8151	0	
3	1002	TMP	THKA_FY16	THKA		63	76528	4	2	SELF/UNKNOWN		TMP	1		N	Home with Home Health	71536	8154	0	
4	1003	PLA	THKA_FY16	THKA	15	72	75042	4	2	MANAGED CARE	BLUE CROS	PLA	2	6	0	D/C-TRANS W/HOME HEALTH	71516	8154	1	P
5	1004	PLA	THKA_FY16	THKA	15	78	75024	4	2	MEDICARE	MEDICARE	PLA	2	1	0	DSCHG HOME	71515	8151	0	
6	1005	MCK	THKA_FY16	THKA	17	90	75407	4	2	MEDICARE	MEDICARE	MCK	5	3	0	DSCH./TRFD.TO SNF	71535	8151	0	
7	1006	PLA	THKA_FY16	THKA	15	66	75075	4	2	MEDICARE	MEDICARE	PLA	2	1	0	DSCHG HOME	71516	8154	0	
8	1007	PLA	THKA_FY16	THKA	15	68	75069	3	2	MEDICARE	MEDICARE	PLA	2	6	0	D/C-TRANS W/HOME HEALTH	71515	8151	0	
9	1008	TMP	THKA_FY16	THKA		49	76549	4	2	SCOTT & WHITE	SWHP	TMP	2		N	Home or Self Care	71535	8151	0	
10	1009	TMP	THKA_FY16	THKA		75	76579	4	2	MEDICARE	MEDICARE	TMP	2		N	Home with Home Health	71536	8154	0	
11	1010	RND	THKA_FY16	THKA		60	76634	4	2	Commercial	AETNA	RND	2		N	Home or Self Care	71535	8151	0	

Expand the dataset

- ***Boosted model*** ran to determine key variables in dataset
- ***Expected importance***:
  - Length of Stay
  - Discharge Type
  - Age
- ***Unexpected***
  - **Release Month**
  - **Release Day of Week**
  - **Payment Type**



Alteryx Model



Test Batch Results

Logistic Regression → (Most False Positives X)

	Suc-Obs	Fail-Obs	
Suc-Pred	171	299	470
Fail-Pred	101	565	666
	272	864	1136
Accuracy	62.87%	65.39%	64.79%

Naïve Bayes

	Suc-Obs	Fail-Obs	
Suc-Pred	33	50	83
Fail-Pred	239	814	1053
	272	864	1136
Accuracy	12.13%	94.21%	74.56%

Neural Network → (Most Accurate!!!)

	Suc-Obs	Fail-Obs	
Suc-Pred	86	43	129
Fail-Pred	186	821	1007
	272	864	1136
Accuracy	31.62%	95.02%	79.84%

Sensitivity, Specificity and Predictive Value

	Logistic Regression	Naïve Bayes	Neural Network
True Positive	171	33	86
False Negative	101	239	186
False Positive	299	50	43
True Negative	565	814	821
Sensitivity	62.87%	12.13%	31.62%
Specificity	65.39%	94.21%	95.02%
Positive Predictive Value	36.38%	39.76%	66.67%

Sensitivity – The ability to determine the MAXIMUM number of POSITIVES
Specificity – The ability to determine the MAXIMUM number of NEGATIVES
Predictive Value - How accurate is the POSITIVE prediction

Back to..... Jim & John

Score
.3572

Neural Network Predicts NEGATIVE Readmission

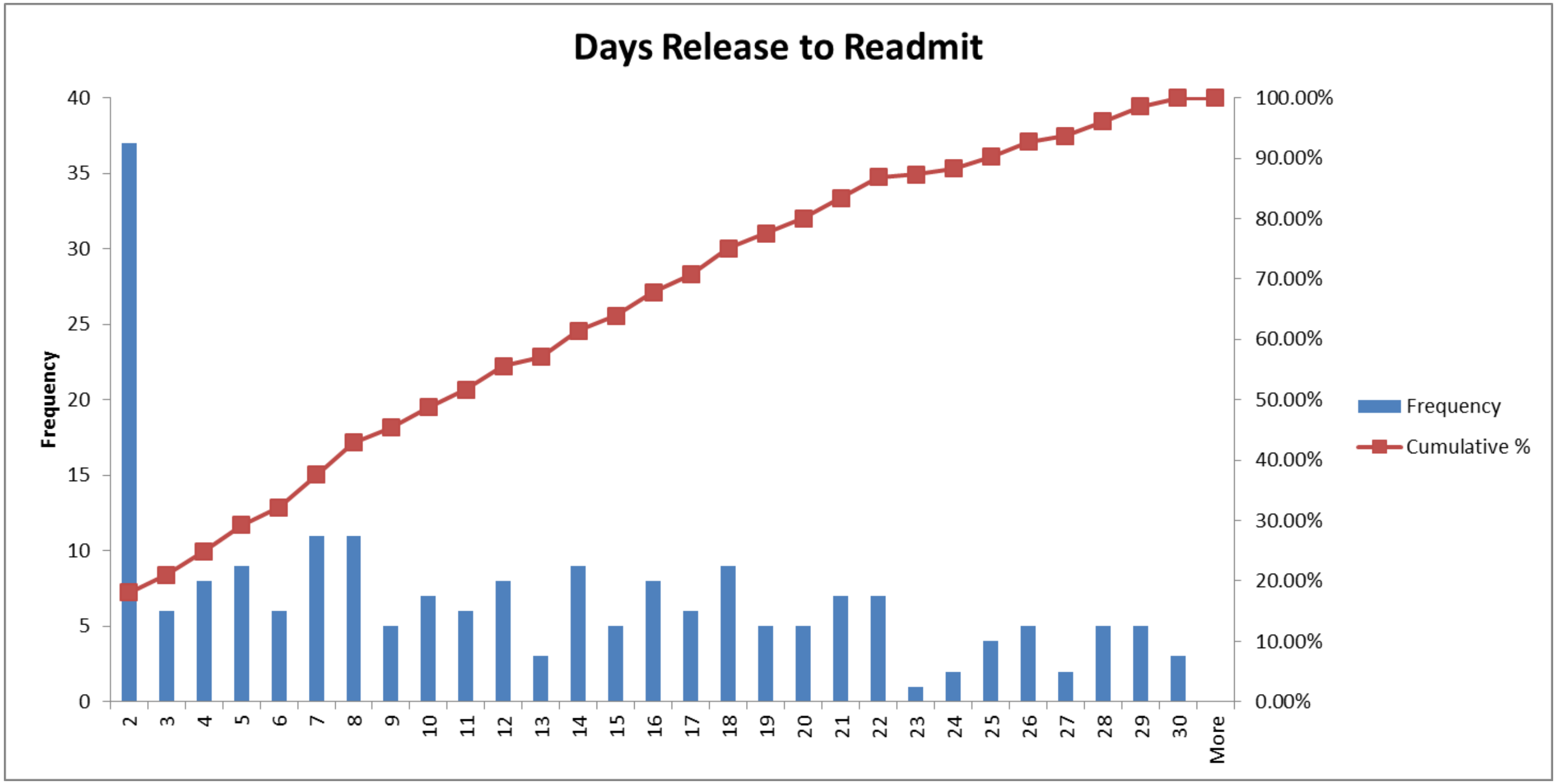
- Jim (Not Readmitted)
  - May Surgery
  - Released on Sunday
  - Medicare
  - Hospital = TMP
  - Not Hispanic

- John (readmitted)
  - August Surgery
  - Released on Thursday
  - Medicare
  - Hospital = WAX
  - Not Hispanic

Score
.7104

Neural Network Predicts POSITIVE Readmission

Histogram of Data Set



→ 18.05% of dataset readmitted within 2 days of release from hospital ←

Estimated **cost** of each **readmission**: **$19,000**

2 Prong Medical Intervention:

- ❑ Day 1
  "WEARABLE"VITALS

vitalconnect

* Temperature
* SPO2
* HR
* Respiratory Rate
* Posture
* Steps

✓ DAILY RECORDINGS
✓ DIGITALLY DELIVERED

- ❑ Day 3-4
  Internal Medicine Doctor Visit

ECONOMICS

[1] Preventative Cost Measures /Patient

- $100 Monitoring System [+]
- $250 Dr. Visit
- x81 Patients with high risk

→$28,350 / annual cost←

[2] To Prevent **54** Readmissions saving

$ 19,000 / Patient

TOTAL SAVINGS →$513 K

NET SAVINGS $484,650 / Year

→ Assuming a 50% success rate for preventative measures ←

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