# The Drive to Healthcare 4.0 through Big Data and ML

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# Speakers for this Session

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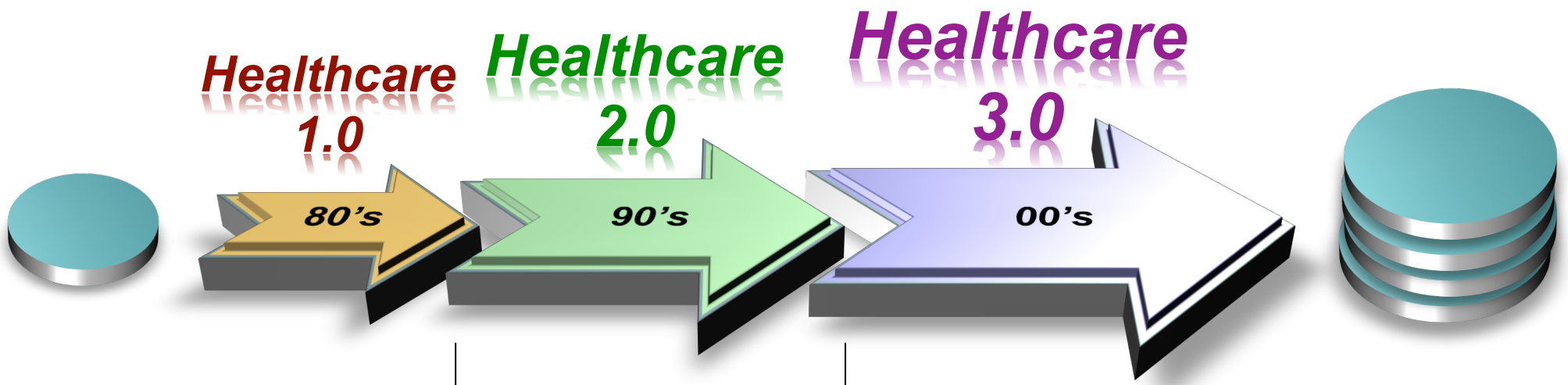
# Healthcare Tech Evolution – Last 30 Years

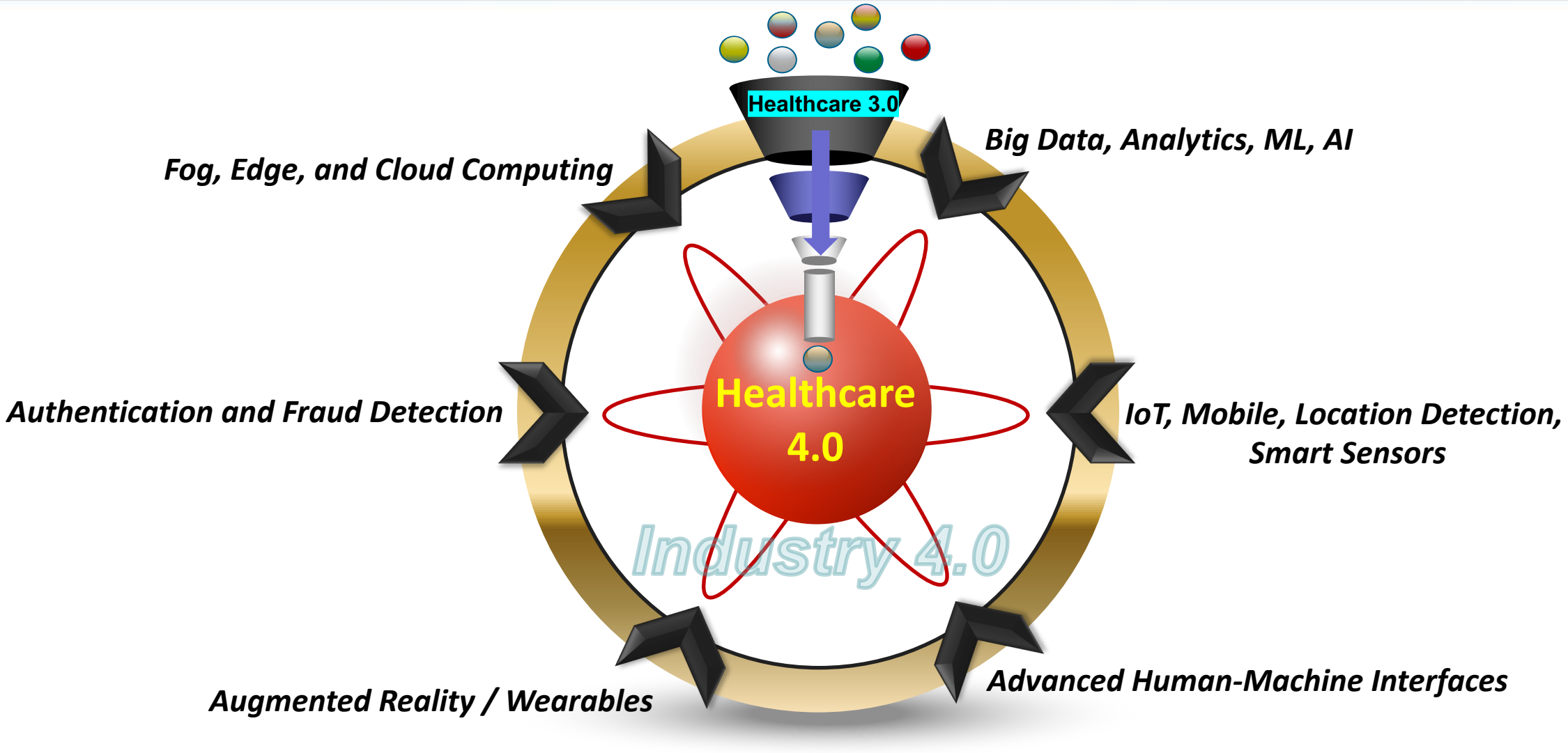



- Manual Medical and Clinical Processes
- Physical medical records
- Non-existent or limited Local Tech

- EMRs Emerge
- Integration and HIEs *(days to mins)*
- Disjunct Info and Patient experience
- Distributed and Networked Tech

- Standards, HIEs, EMRs, Clinical Modality Integration
- Merged Data and Single View of Patient
- Patient Experience Focus
- Transparency & Portals
- Analytics and Reporting
- High Performance and Resilient Tech

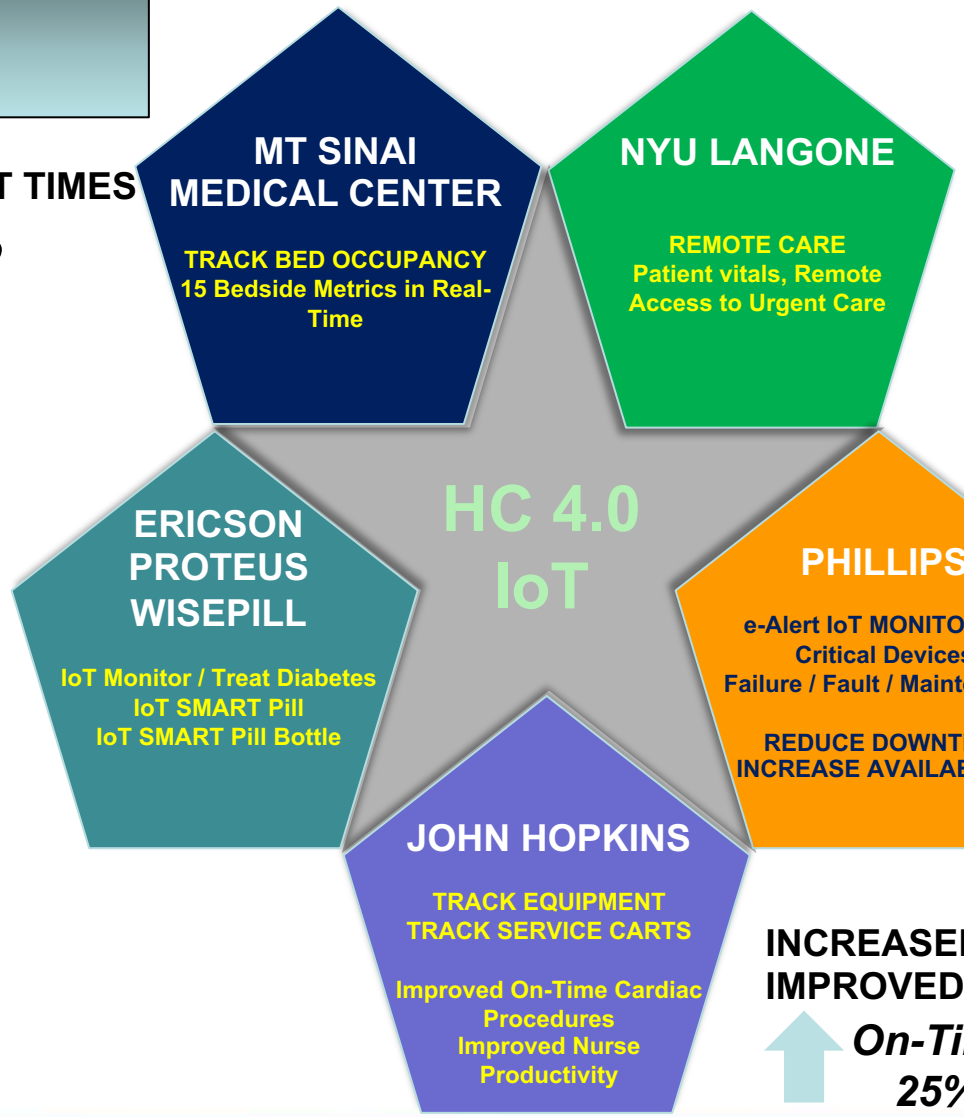
# Healthcare Tech Today – Healthcare 4.0 Emerges



# Prevalent HC 4.0 Use Cases

## IoT and Mobility

*Most Prevalent HC 4.0 Adoption*




**REDUCED ER WAIT TIMES**

***50%***

**IMPROVED SPEED / ACCESS TO CARE**
**REDUCED COST**

***SPEED 75-100%***

***COST 50+%***

**IMPROVED MEDICATION ADHERENCE**

***75%***

**REDUCED CRITICAL EQUIPMENT DOWNTIME**

***30-40%***

**INCREASED ON-TIME PROCEDURES, IMPROVED PRODUCTIVITY**

***On-Time 25%***

***Productivity 100%***

# HEALTHCARE 4.0 – Big Data (BD) and ML - *ANALYSIS*

- **Motivation:** Accelerate Value-based Care, Improve Patient life style & experience, Enable cost optimization for Healthcare providers, Reduce delinquent payments
- **Method:** Surveys, Interviews, Discussions with U.S. Hospitals – Examine their Roadmaps for Value-based Care while suggesting and evaluating up to top 10 use cases
- **Sample size:** 10 U.S. Hospitals
- **2 Use Cases Prioritized:** (2 out of 10) of primary interest to ALL
  - Patient Readmission and Emergency Department Congestion Predictions
- **Status:** Machine Learning models designed, trained, tested, & validated with preliminary results
- **Next Steps:** Additional patient/hospital data into Machine Learning models to improve accuracy. Observe influential factors, and comprehend correlations

# HC 4.0 BD/ML *CASE STUDY 1*

## *Emergency department congestion prediction*

**Business Challenges**

**Predict Crowding of ER**

**Help Director of Emergency Dept plan staff, equipment, and space needs to reduce crowding and wait time**

**Solution Highlights**

**Use Big Data / ML to Capacity and Resource Plan**

**Model analyzing: staff attributes (years of experience, recommendations, academic institution, degree type, type of training(s), certification(s)), vacation, equipment, infrastructure, influenza heatmap, weather, events, conferences, travel patterns, construction, & demographics**

**Business Benefits**

- **Improve patient experience delivering value based care**
- **Reduced wait times**
- **Reduce mortality**
- **Optimized patient flow**
- **Mitigate financial risks**

*Email, Mobile, Tablet*

**VISUALIZATION**

*PyTorch, TensorFlow;*
*Random Forest, SVM, XGBoost,*

**MACHINE LEARNING**

*Cassandra, HBase, HDFS, SQL DW*

**STORAGE & ANALYSIS**

*Map Reduce, NiFi, Pig, Spark;*
*AirFlow, DVC, Luigi*

**DATA PROCESSING**

*FLUME, HUE, KAFKA, SQOOP*

**DATA**

*CDC*

*Census*

*EHR*

*ERP*

*Health Data.gov*

*NOAA*

*Social*

**DATA SOURCES**

# HC 4.0 BD/ML *CASE STUDY 2*

## Patient Readmission (within 30 days)

**Business Challenges**

Healthcare Provider Seeking Reduction in Patient Readmission (within 30 days)

**Solution Highlights**

Use Big Data / ML to find Readmission Candidates

Examine patient's in-hospital complications, such as hospital-acquired infections (HAIs), and their stability during discharge affecting their risk of 30-day readmissions. Common risk factors, such as C. difficile infection, vital sign instability upon discharge, and longer length of stay in the hospital were positively correlated with an unplanned 30-day readmission

**Business Benefits**

- Improve patient experience delivering value based care
- Potential increase in life expectancy
- Elevate brand awareness
- Mitigate financial risks

**VISUALIZATION**

*Email, Mobile, Tablet*

**MACHINE LEARNING**

*PyTorch, TensorFlow; Random Forest, SVM, XGBoost,*

**STORAGE & ANALYSIS**

*Cassandra, HBase, HDFS, SQL DW*

**DATA PROCESSING**

*Map Reduce, NiFi, Pig, Spark; AirFlow, DVC, Luigi*

**DATA**

*FLUME, HUE, KAFKA, SQOOP*

**DATA SOURCES**

*CDC* | *Census* | *EHR* | *ERP* | *Health Data.gov* | *NOAA* | *Social*

# HC 4.0 BD/ML *CASE STUDY 2 -* IMPACT

mAdvisor

D demo

SIGNALS

APPS

DATA

OVERVIEW | KEY DRIVERS | PREDICTION | IMPACT

| 783050 | 5579500 | 9382 | 27 | 468 Hrs 4 Mins | 12010.4X |
|---|---|---|---|---|---|
| Total Data Points | Number of Queries | Number of Analysis | Total Pages | Total Time Saved | Impact on Productivity |

Data Analyst

468 Hrs 12 Mins

0 Hrs *8* Mins

WOW!

*Great Job !!!* You have analysed the dataset that contains 50 variables after executing about ***5579500*** analytics queries and ***9382*** Statistical and ML analysis in parallel. Using mAdvisor, you have completed the analysis within ***0 Hrs 8 Mins*** which would have required around ***468 Hrs 12 Mins***.

# HC 4.0 BD/ML *CASE STUDY 2* – SIGNIFICANT CONTRIBUTORS

mAdvisor

demo

SIGNALS

APPS

DATA

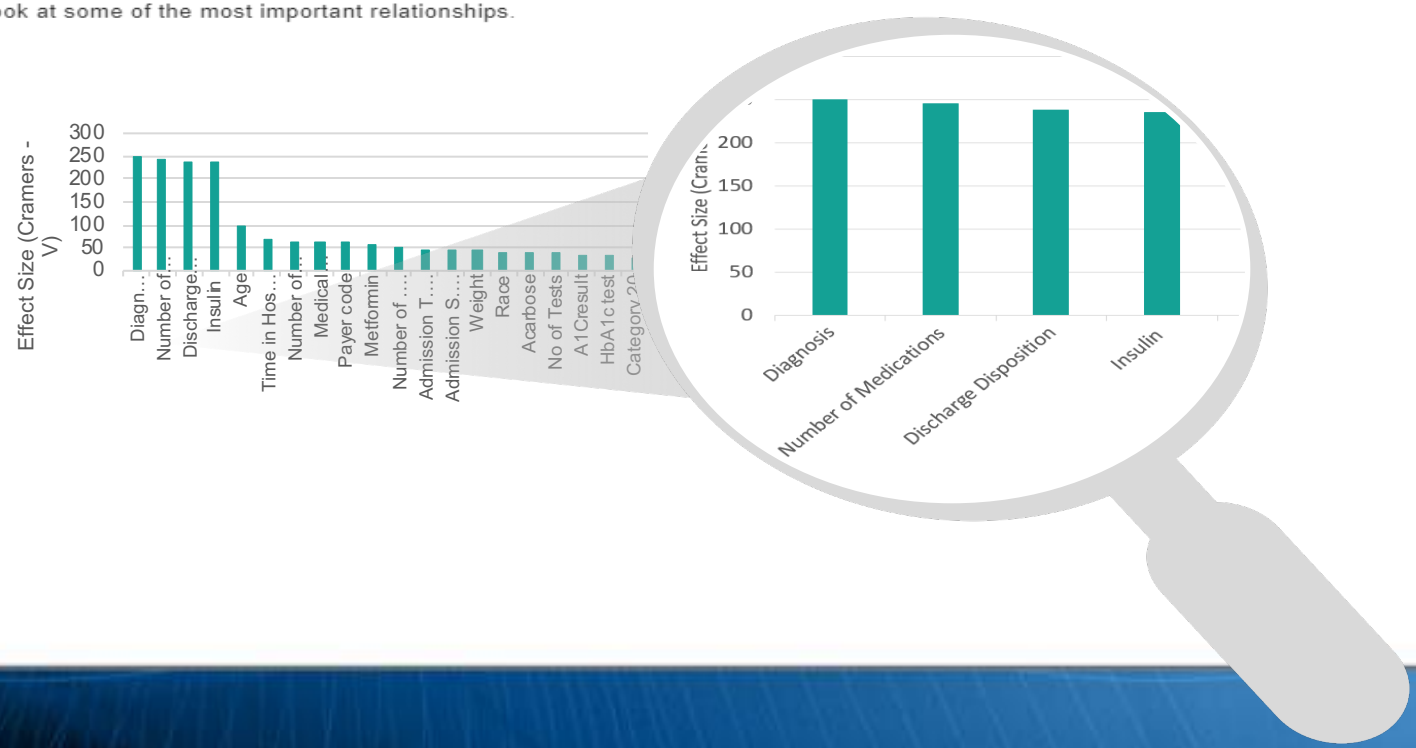
Signals/Readmission/Key Drivers

## Readmission

OVERVIEW | KEY DRIVERS | PREDICTION | IMPACT

### Key Factors that drive readmitted

There are **40 factors** in the dataset and **22 of them** (including diag_1, diag_3) have **significant association** with readmitted. It implies that specific categories within each of the dimensions show **considerable amount of variation** in distribution of readmitted categories. The chart below displays the **impact of key dimensions** on readmitted, as measured by effect size. Let us take a deeper look at some of the most important relationships.




https://madvisor.marlabsai.com

# HC 4.0 BD/ML *CASE STUDY 2* – BEST ALGORITHM

# QUESTIONS?

thank you
danke
謝謝
ngiyabonga
teşekkür ederim
gracias
merci
obrigado
bedankt
dziękuję
go raibh maith agat
mochchakkeram
sukriya
kop khun krap
terima kasih
grazie
arigatô
dakujem
takk
tapadh leat
спасибо
Баярлалаа
рахмат
dank je
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vinaka
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diolch
dhanyavadagalu
shukriya
mercé
мерси
trugarez
xièxie
ευχαριστώ
감사합니다
তোমাকে ধন্যবাদ