IBM Patient Care and Insights & Care Coordination

Webinar
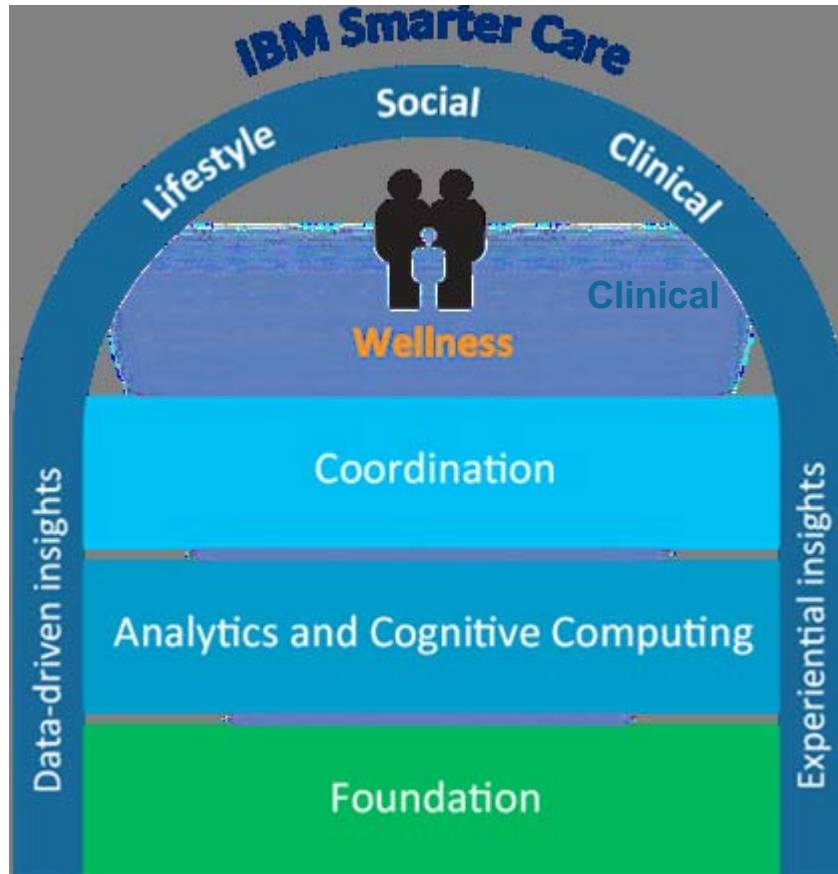
Paul Hake MSPA
IBM Software Solutions

Make healthcare smarter.

IBM Smarter Care uncovers valuable insights into **lifestyle choices**, **social determinants, clinical and financial factors** that effect the overall health of an individual …

Lifestyle

Choices have direct impact on an individual's mental and physical wellness.

Social

Demographic determinants such as where one is born, grows, lives, works and ages have direct impact on an individual's overall health, mental health and well-being.

Clinical

Factors such as specific medical symptoms, history, medications, diagnoses, etc are indicators of an individual's health.

Financial

Costs, insurance, reimbursement, incentive to modify behavior, new payment models, co-pays, etc. will pay a significant role.

IBM's integrated portfolio for Smarter Care

Disease and Cost of Care Progression

20% of People Generate 80% of Costs

Early Intervention Opportunities Identification

Health Status →

Healthy Low Risk

At Risk

High Risk

Early Clinical Symptoms

Active Disease

Health Care Spending →

Time

Early Intervention Opportunities Identification

70% of US Deaths from Chronic Diseases
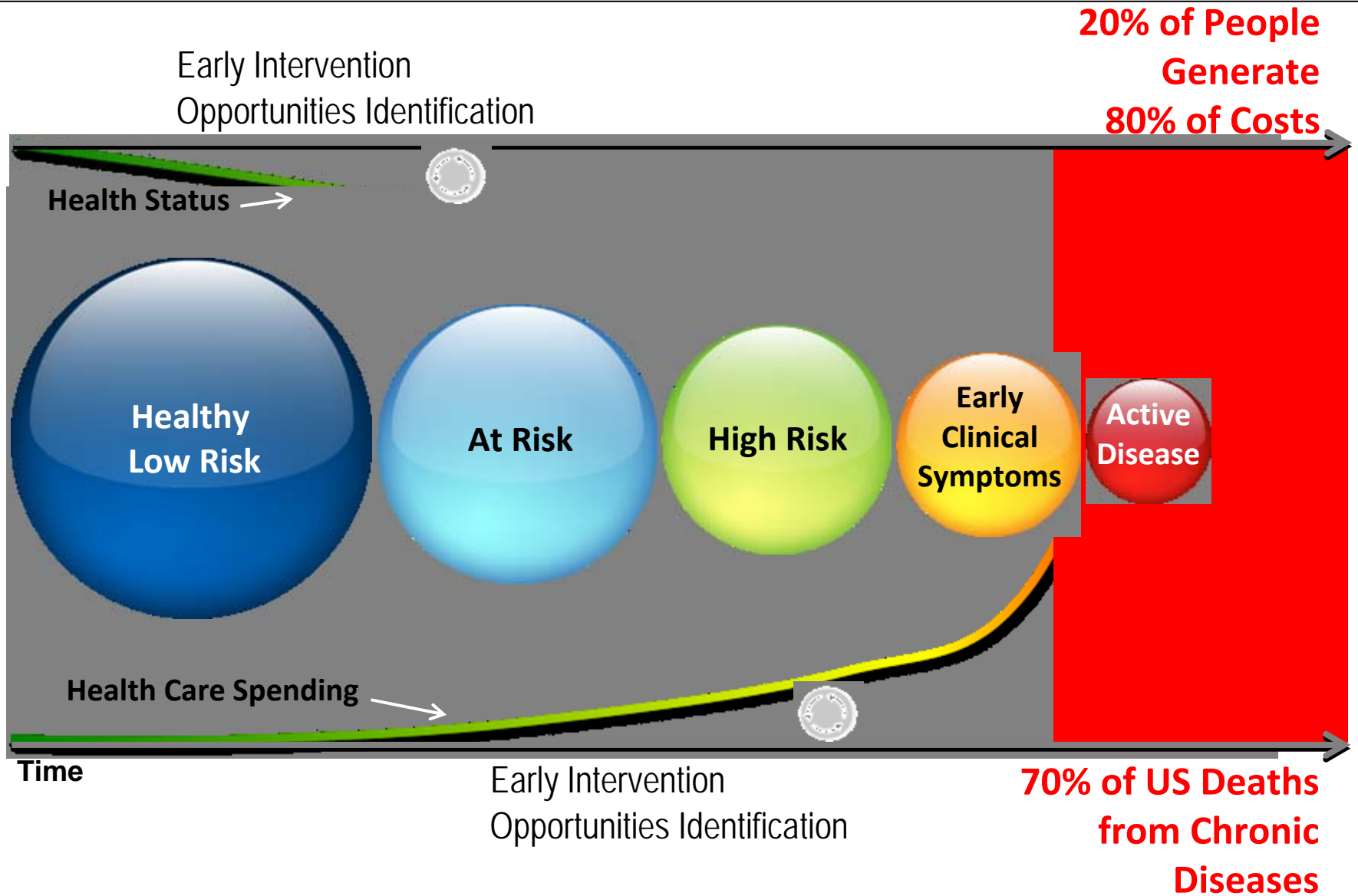
Information should aid us, not lie hidden and dormant

If we could only activate the relevant information to bring insights to the point of care when needed most …

Knowledge, Guidelines and Best Practice Measures			

Confirm what I think or suspect?

How many are being missed?

Identify Intervention Opportunities

Adapt Care to Changing Conditions and New Information

Longitudinal "Data Driven" Insights

Show me something new or unexpected?

How do we move faster and anticipate change?

Time once spent manually interpreting data … becomes time spent healing patients

- Aggregate, activate and enrich relevant patient information beyond what is known
- Surface new data driven insights that enable new intervention opportunities … earlier
- Adapt to changes and proactively deliver individualized patient centered care

IBM Patient Care and Insights Solution Overview

A *Configurable Solution* designed to surface evidence based insights from longitudinal data that enables advanced population analysis, personalized interventions and proactive care delivery in complex and costly disease scenarios. Supporting doctors treating patients in collaborative care models with process complexity, interventions and care transitions.

Configurable Solution Options

Advanced Care Insights Solution Models
- Readmission Prediction and Prevention
- Condition Onset or Deterioration Prediction and Prevention
- Drug Treatment Efficacy and Effectiveness
- Physician, Care Team or Resource Matching
- Resource Utilization Pattern and Anomaly Detection
- Risk Adjusted Scoring Improvement
- Care Pathways Adherence and Deviation
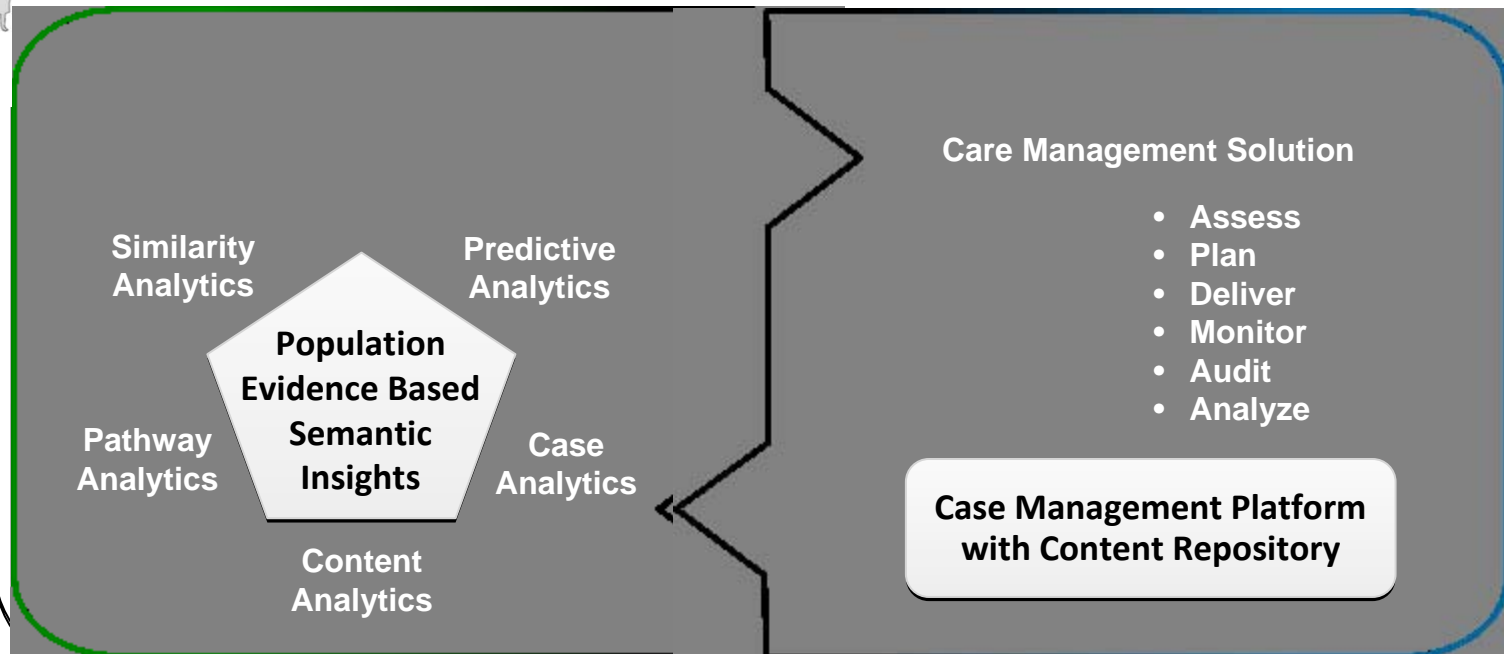
Advanced Care Management Solution Plans
- Disease and Scenario Specific Care Plans and Templates

Visualizations
- Care Pathway Flows
- Custom Population Analysis

User Experience, Dashboards and Reporting
- Case Performance Analysis and Monitoring
- Semantic Powered Search

Similarity Analytics

Predictive Analytics

Population Evidence Based Semantic Insights

Pathway Analytics

Case Analytics

Content Analytics

Care Management Solution

- **Assess**
- **Plan**
- **Deliver**
- **Monitor**
- **Audit**
- **Analyze**

Case Management Platform with Content Repository

Why Similarity Analytics ?

Using data driven clinical decision support for smarter care delivery

- Physicians have limited time and resources to focus on complex care dilemmas, yet many patients have multiple conditions

- Clinical trials and health research typically focus on single diseases

- Treatment guidelines are usually developed with "standardized" reference data

- Care delivery tends to be ad hoc in nature; care guidelines not followed 40% of the time

  83% of Medicaid patients have at least one chronic condition (almost 25% have at least 5 co-morbidities) [1]

  Medicare patients with 5 or more chronic conditions accounted for 76% of all Medicare expenditures [2]

Why not augment care delivery guidelines with population specific insights- including those derived from unstructured data- to enhance decision making?

1. *Projection of Chronic Illness Prevalence and Cost Inflation* from RAND Health. October 2000
2. *The Rise in Spending Among Medicare Beneficiaries: The Role of Chronic Disease Prevalence and Changes in Treatment Intensity* from Health Affairs, August 2006
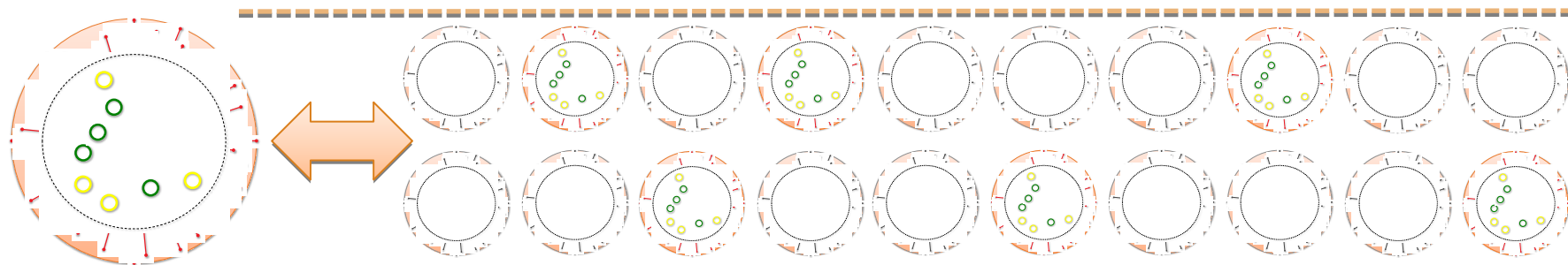
How Similarity Analytics Work, Part 1
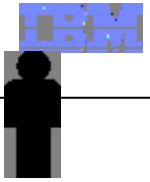
For this patient …

- Analyze longitudinal data to develop profile across 30,000+ possible points of comparison

- Determine the individual risk factors for this patient based on the desired outcome

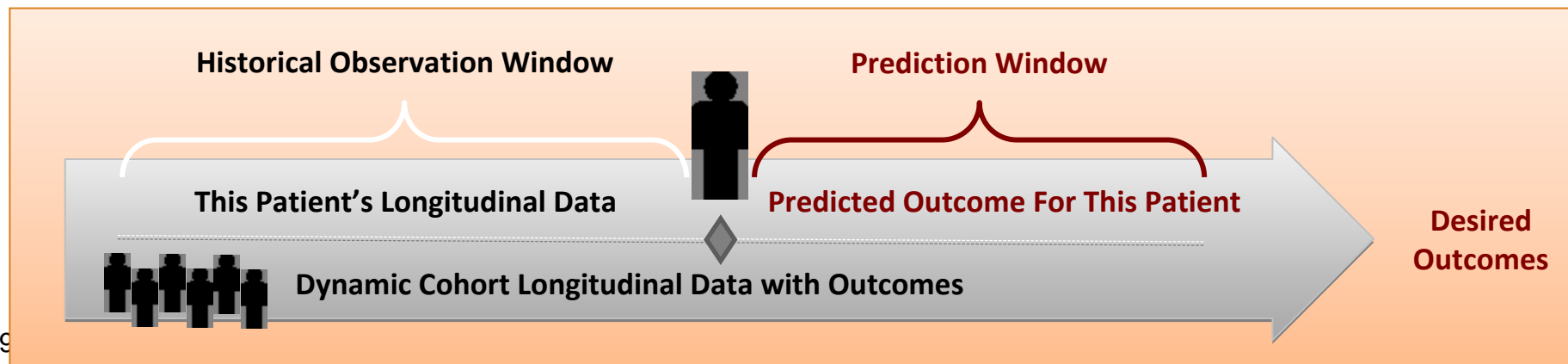- Create an outcomes based personalized profile for this patient
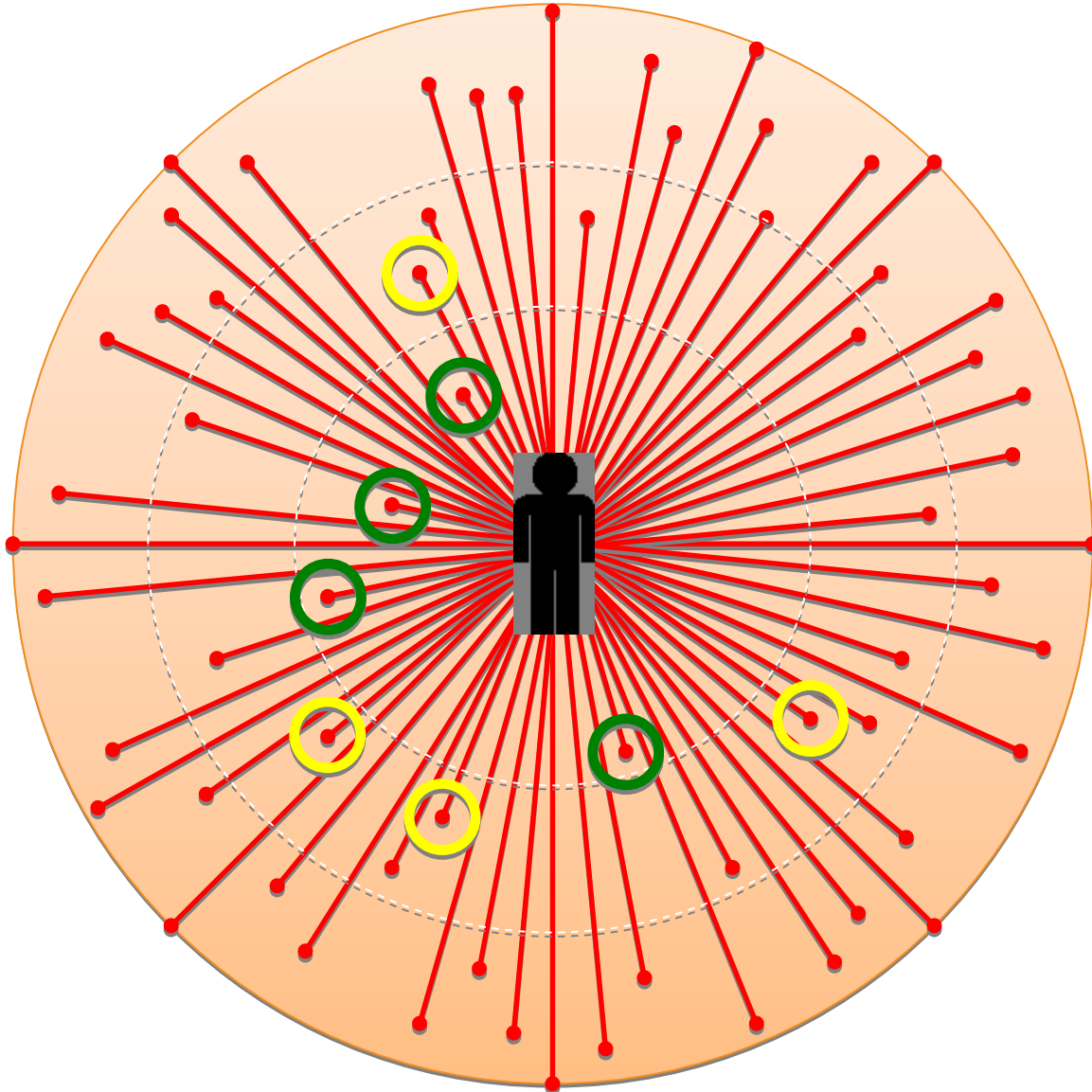
How Similarity Analytics Work, Part 2

Based on this personalized profile …

- Find the **most** similar patients (or **dynamic cohort**) from entire population

- Analyze the attributes and outcomes for this cohort (across 30,000+ dimensions)

- Predict the probability of the desired outcome for patient in question

- Suggest a personalized care plan based on the unique needs of this patient

Historical Observation Window

Prediction Window

This Patient's Longitudinal Data

Predicted Outcome For This Patient

Dynamic Cohort Longitudinal Data with Outcomes

Desired Outcomes

IBM.

Overview | Patient List | Demographics

Smith, Judy | MRN: 7300021

Age: 52 | Gender: female | DOB: 01/01/1960 | Last updated 02/18/2012

Show:
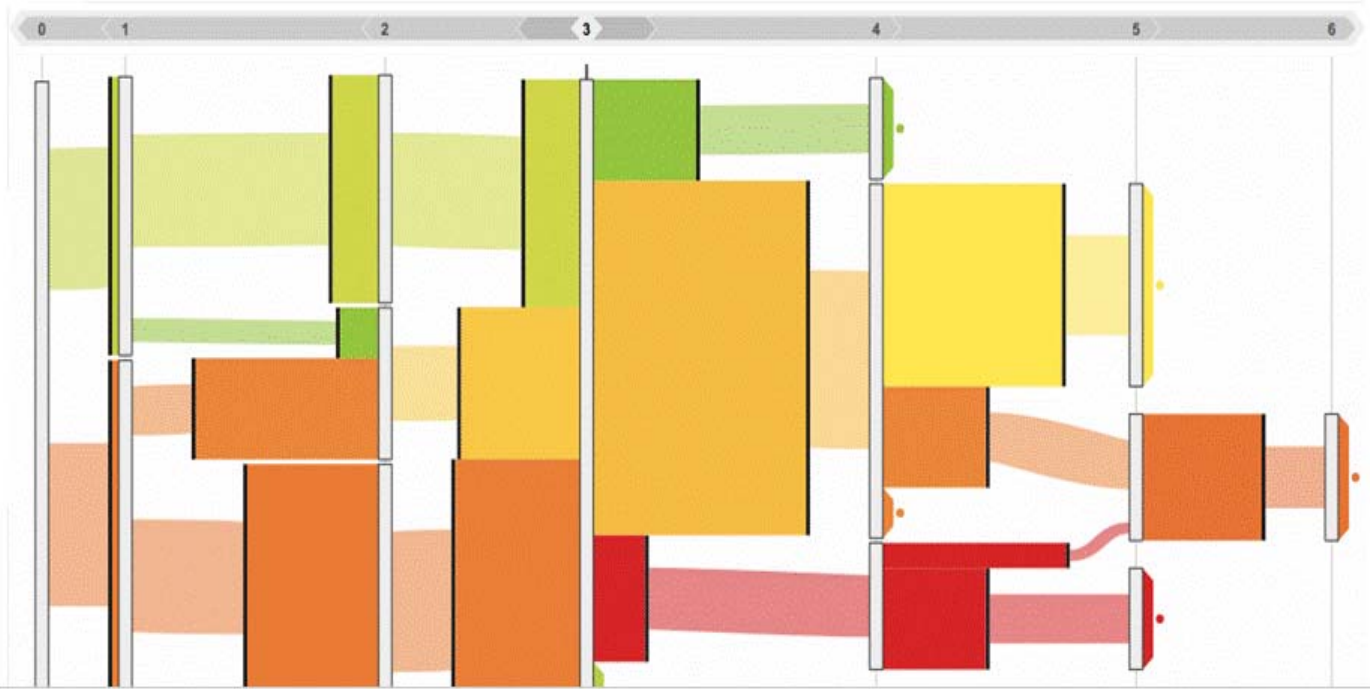
Groups

Risk for Kidney Disease Onset (24)
1 filter, modified 12:34 7/14/2012

CHF Onset (345)
1 filter, modified 12:34 6/30/2012

CHF Readmission (127)
1 filter, modified 12:34 6/30/2012

Utilization (63)
1 filter, modified 12:34 6/30/2012

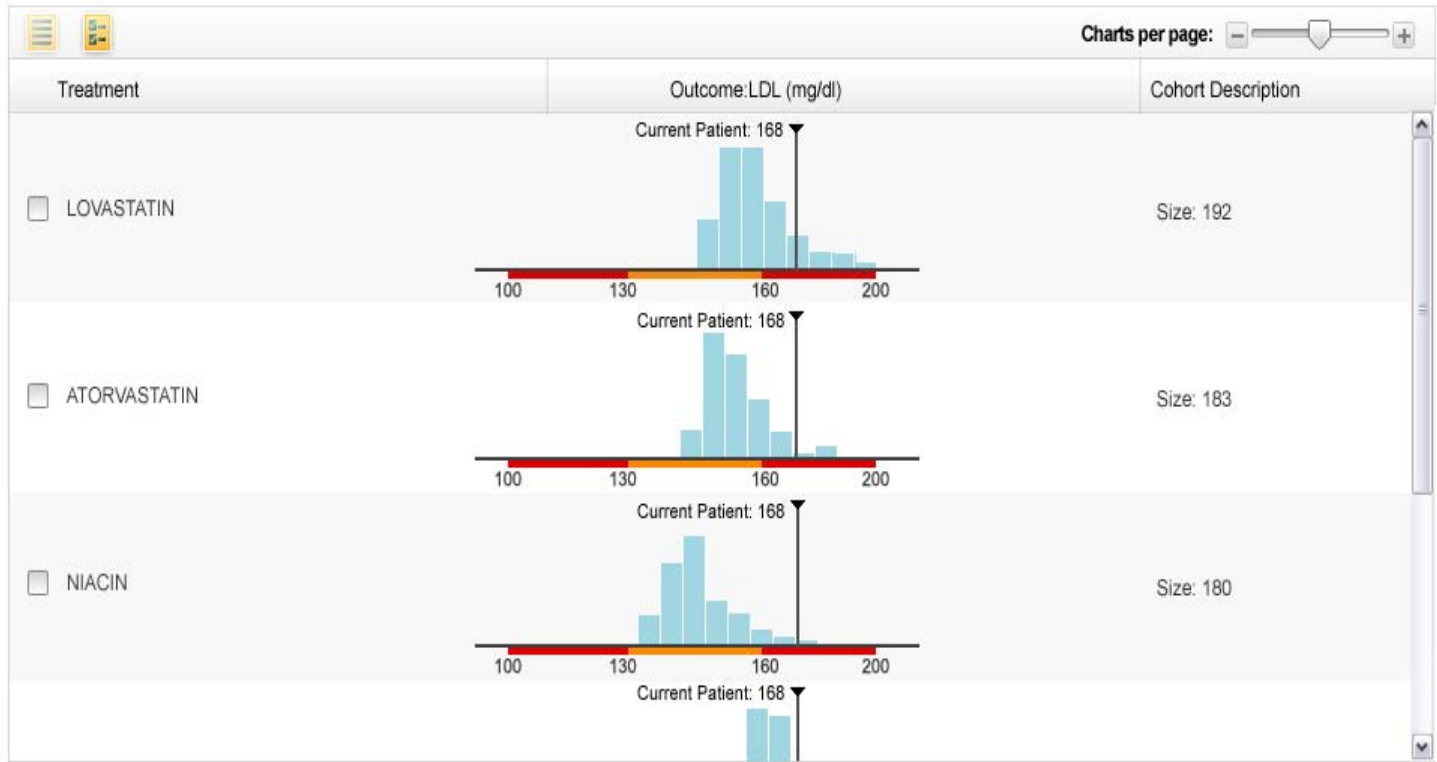Hyperlipidemia (13)
1 filter, modified 12:34 6/30/2012

CHF onset

! CHF onset risk score: 0.98

Predictive Factor	Predictive Weight
Ankle Edema	85%
Dispnea	34%
Rales	4%

Risk Assessment

0.0 ▬▬ 1.0
Outcome

0   1   2   3   4   5   6

Overview | **Patient List** | Demographics

Smith, Judy | MRN: 7300021

Show: 📁 🦠 (3) ➕ (3) 📊 🧪   👥

Age: 52 | Gender: female | DOB: 01/01/1960 | Last updated 02/18/2012

Hyperlipidemia

Hyperlipidemia Risk: 0.72   🟥

Charts per page: ─ ▭ ＋

Treatment	Outcome:LDL (mg/dl)	Cohort Description
☐ LOVASTATIN	Current Patient: 168	Size: 192
☐ ATORVASTATIN	Current Patient: 168	Size: 183
☐ NIACIN	Current Patient: 168	Size: 180
	Current Patient: 168	

Groups

📁 **Risk for Kidney Disease Onset (24)** ≫
   1 filter, modified 12:34 7/14/2012

📁 **CHF Onset (345)** ≫
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   1 filter, modified 12:34 6/30/2012

📁 **Hyperlipidemia (13)** ≫
   1 filter, modified 12:34 6/30/2012

Changes were applied to the Kidney Disease Group

Dr Troy

Overview | Patient List | Demographics

Smith, Judy | MRN: 7300021

Age: 52 | Gender: female | DOB: 01/01/1960 | Last updated 02/18/2012

Show:

Physician Match

Physician Name	Match Score
Closest Nephrologist: **Mercado, Venus**	**55**
Troy, Helen	*95*
Hilt, Lauren	*95*
Hernandez, Magee	*94*
Keller, Channing	*92*
Duke, Emi	*90*
Ochoa, Grady	*88*
Miranda, Raphael	*88*
Gibbs, Isadora	*87*
Todd, Tatyana	*86*
Dotson, Jamilia	*85*
Johns, Olivia	*85*
gav, Melodie	*84*

Groups

Risk for Kidney Disease Onset (24)
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CHF Onset (345)
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Overview   Patient List   Demographics

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Show:

Utilization

Overall Risk: 1.0

6 Month Utilization Profile

Visit Type	Frequency	
↑ Emergency Room & Urgent Care Visit	Actual: 3 Expected: 0.66	
Independent Lab Visit	Actual: 7 Expected: 7.05	
Inpatient Hospital Visit	Actual: 1 Expected: 1.05	
↓ Other (Specialist) Visit in Doctor's Office	Actual: 0 Expected: 1.80	
↓ Other Visit	Actual: 0 Expected: 1.00	
↓ Outpatient Hospital Visit	Actual: 3 Expected: 3.27	
PCP Visit in Doctor's Office	Actual: 4 Expected: 4.28	
Patient's home	Actual: 5 Expected: 5.47	

12 Month Utilization Profile

Overall Utilization Profile

Groups

Risk for Kidney Disease Onset (24)
1 filter, modified 12:34 7/14/2012

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IBM Natural Language Processing Annotator technology …

- Annotators are used to identify valuable facts in unstructured documents (e.g. clinician notes, consult reports, free text fields in EMRs) and convert to a structured form

- Annotators execute in a sequence called the UIMA or Unstructured Information Management Architecture pipeline

- IBM Patient Care and Insights Annotators use UMLS to normalize discovered facts to coding systems

- Excellent application training services / annotators can be developed in IBM Content Studio

Unstructured Information Management Architecture
An Apache Project.

Unified Medical Language System

Healthcare Annotators example

- Problems
  - Result of a series of interim annotations that identify diseases, symptoms, and disorders
  - Normalize to standard terms and standard coding systems including SNOMED CT, ICD-9, HCC, CCS
  - Capture timeframes of the problem
    - determine if past or current problem
  - Determine confidence
    - Positive, Negative, Rule Out, etc.
    - Negation example
      - "abdominal pain"

```
HEENT: History of blurry vision and hearing impaired. No glaucoma.
CARDIOVASCULAR: Shortness of breath, congestive heart failure, and arrhythmia. Prior history of chest pain.
RESPIRATORY: Bronchitis and pneumonia. No valley fever.
GASTROINTESTINAL: No nausea, vomiting, hematemesis, melena, or abdominal pain.
UROLOGICAL: No frequency or urgency.
MUSCULOSKELETAL: No arthritis or muscle weakness.
SKIN: Non-significant.
NEUROLOGICAL: No TIA. No CVA or seizure disorder.
ENDOCRINE: Non-significant.
HEMATOLOGICAL: Non-significant.
PSYCHOLOGICAL: Anxiety. No depression.
PHYSICAL EXAMINATION:
```

Problems | Properties

roperty	Value
conceptid	21522001
confidence	negative
Covered text	abdominal pain
hccCode	empty
icd9	789.00
modifiers	
normalized	abdominal pain
origin	symptom

Annotator Content...

- **Problems**
  - Result of a series of interim annotations that identify diseases, symptoms, and disorders
  - Normalize to standard terms and standard coding systems including SNOMED CT, ICD-9, HCC, CCS
  - Capture timeframes of the problem
    - determine if past or current problem
  - Determine confidence
    - Positive, Negative, Rule Out
    - Negation example
      - "abdominal pain"

- **Procedures**
  - Identify compound procedures
    - example: direct extensive adhesiolysis and enterolysis left side
  - Normalize to standard terms and standard coding systems including SNOMED CT, CCS, CPT
  - Capture timeframes of the procedure

- **Medications**
  - Result of a series of interim annotations that identify drugs, administrations, measurements
  - Normalize to standard terms and can normalize to RxNorm

- **Demographic and Social**
  - Patient Age
  - Living Arrangement
  - Employment status
  - Smoking status
  - Alcohol use

- **Compliance & Noncompliance**
  - Patient's history of medication compliance with directions such as "take all doses, even if you feel better earlier"
  - Noncompliance - Patient's history of medication noncompliance with directions.

- **Labs results**
  - Type of lab test performed, unit of measure, result value

- **Ejection Fraction** – in support of CHF use cases

- **Coding Systems –** can identify these codes
  - CPT
  - CCS
  - HCC
  - NDC (National Drug Codes)
    - Breaks out by components - example, Lortab 5 contains 5 mg of hydrocodone and 500 mg acetaminophen. This would result in 2 Ndc Code annotations.

What Really Causes Readmissions at Seton?
The value of adding unstructured Data

The Data We Thought Would Be Useful … Wasn't

- Structured data not available, not accurate enough, without the unstructured data - which was more trustworthy

What We Thought Was Causing 30 Day Readmissions … Wasn't

- 113 possible candidate predictors expanded and changed after mining the data for hidden insights

New Hidden Indicators Emerged … Readmissions is a Highly Predictive Model

- 18 accurate indicators or predictors (see next slide)

97% at 80th percentile

49% at 20th percentile
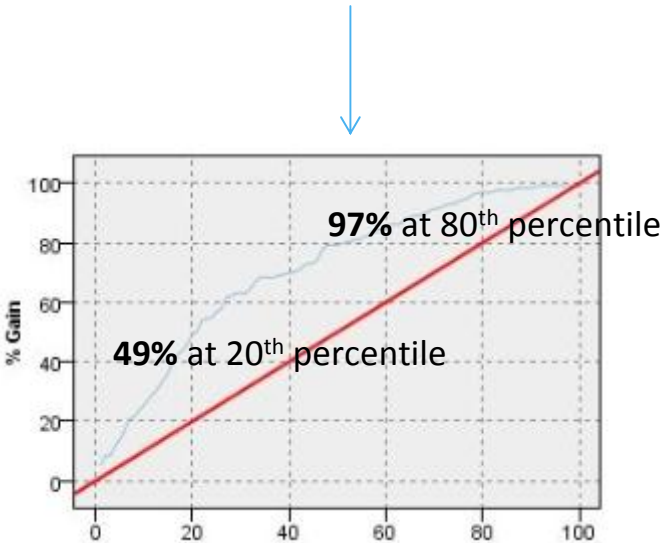
| Predictor Analysis	% Encounters Structured Data	% Encounters Unstructured Data
Ejection Fraction (LVEF)	2%	74%
Smoking Indicator	35% (65% Accurate)	81% (95% Accurate)
Living Arrangements	<1%	73% (100% Accurate)
Drug and Alcohol Abuse	16%	81%
Assisted Living	0%	13%

Top 18 Indicators

New Insights Uncovered by Combining Content and Predictive Analytics

- Top indicator JVDI not on the original list of 113 - as well as several others

- Assisted Living and Drug and Alcohol Abuse emerged as key predictors - only found in unstructured data

- LVEF and Smoking are significant indicators of CHF but not readmissions

- A combination of actionable and non-actionable factors cause readmissions
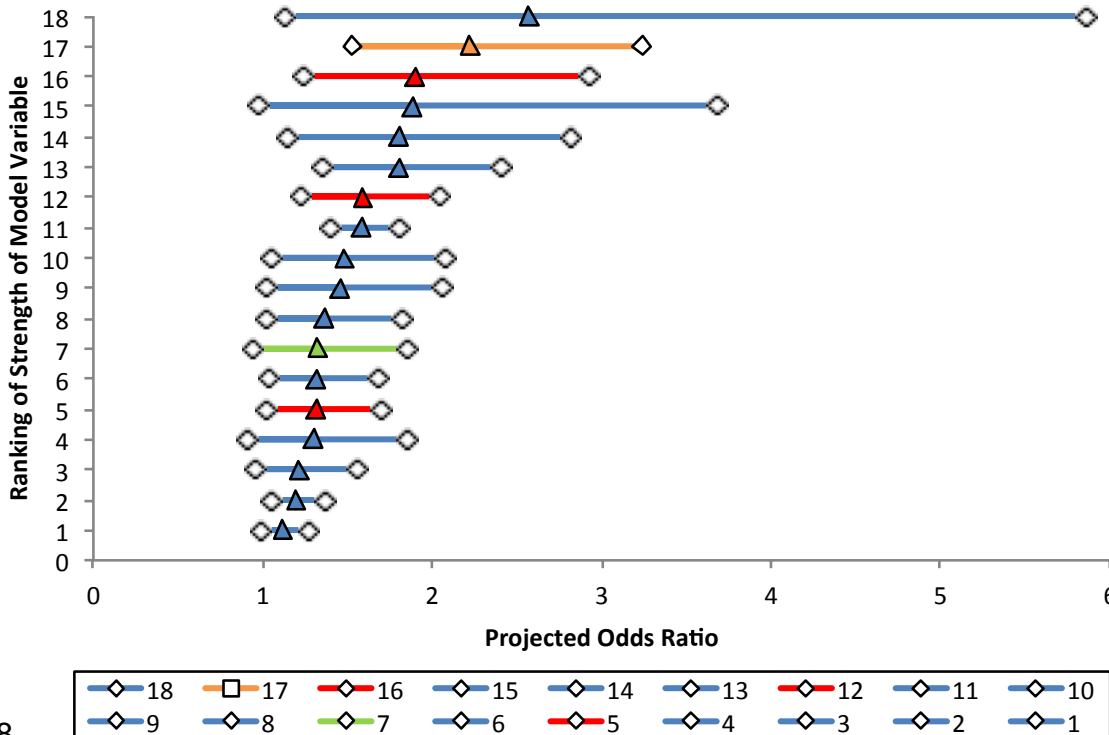
1. **Jugular Venous Distention Indicator**
2. Paid by Medicaid Indicator
3. Immunity Disorder Disease Indicator
4. Cardiac Rehab Admit Diagnosis with CHF Indicator
5. Lack of Emotion Support Indicator
6. Self COPD Moderate Limit Health History Indicator
7. With Genitourinary System and Endocrine Disorders
8. Heart Failure History
9. High BNP Indicator
10. Low Hemoglobin Indicator
11. Low Sodium Level Indicator
12. **Assisted Living**
13. High Cholesterol History
14. Presence of Blood Diseases in Diagnosis History
15. High Blood Pressure Health History
16. **Self Alcohol / Drug Use Indicator**
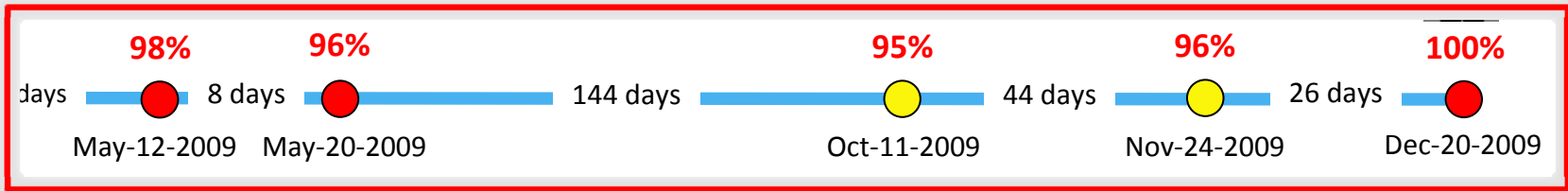17. Heart Attack History
18. Heart Disease History

Chart: Ranking of Strength of Model Variable (y-axis, 0–18) vs Projected Odds Ratio (x-axis, 0–6)
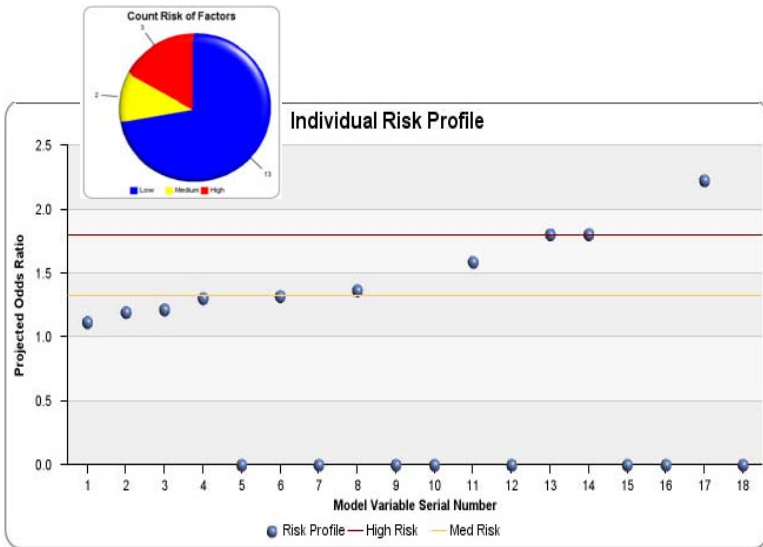
18

CHF Patient X – What Happened?

Admit / Readmission

30-Day Readmission

Patient X was hospitalized **6 times** over an **8 month period**. The same basic information was available at each encounter and Patient X's readmission prediction score never dropped below **95%** (out of possible 100%)

98%	98%	96%	95%	96%	100%
	2 days	8 days	144 days	44 days	26 days
Apr-18-2009	May-12-2009	May-20-2009	Oct-11-2009	Nov-24-2009	Dec-20-2009

Individual Patient Data at Each Encounter (Patient X @ Dec 20, 2009)

Count Risk of Factors

Individual Risk Profile

Projected Odds Ratio

Model Variable Serial Number

Risk Profile — High Risk — Med Risk

Description of Model Serial Number

18. Jugular Venous Distention Indicator

16. Immunity Disorder Disease Indicator
15. Cardiac Rehab Admit Diagnosis with CHF Indicator

12. With genitourinary system & Endocrine disorders

10. High BNP Indicator
9. Low Hemoglobin Indicator

7. Assisted Living from ICA Extract
6. High Cholesterol History
5. Presence of diseases of the blood in diagnosis history
4. High Blood Pressure Health History
3. Self Alcohol/Drug Use Indicator (Cerner + ICA)
2. Heart Attack History
1. Heart Disease History

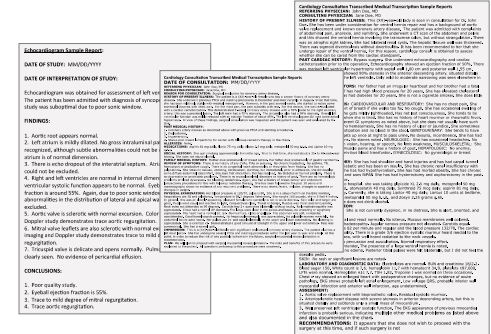Patient Population Monitoring Clinical and Operational Data

19

Structured Data is Not Enough

- Unstructured data significantly increases the richness and accuracy of analysis and decision making … including paper / faxes

Today's Care Guidelines Only Get You So Far

- Not granular enough to deliver on the promise of personalized medicine with data driven insights [1, 2]
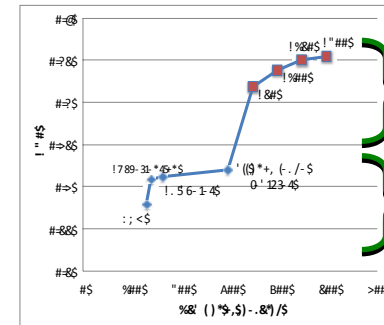
Manual Processes and Traditional Workflow Approaches Don't Work

- Process complexity increases with disease complexity … changing conditions require process adaptability [3]

Data Driven Insights

Knowledge and Guidelines

1. Dijun Luo, Fie Wang, Jimeng Sun, Marianthi Markatou, Jianying Hu, Shahram Ebadollahi, SOR: ScalableOrthogonal Regression for Low-Redundancy Feature Selection and its Healthcare Applications. SDM'12
2. Jimeng Sun, Jianying Hu, Dijun Luo, Marianthi Markatou, Fei Wang, Shahram Edabollahi, Steven E. Steinhubl, Zahra Daar, Walter F. Stewart. Combining Knowledge and Data Driven Insights for Identifying Risk Factors using Electronic Health Records. Under submission at AMIA'12
3. Blind Surgeon Metaphor Problem - W.M.P. van der Aalst, M. Weske, and D. Grünbauer. Case Handling: A New Paradigm for Business Process Support. Data and Knowledge Engineering, 53(2):129-162, 2005

➤ Advanced Care Insights

Thank you for attending!

Submit your questions in the Q&A box on the
lower right hand side of your screen

phake@us.ibm.com