

Mining Healthcare Systems to Personalize Patient Care & Improve Clinical Decisions

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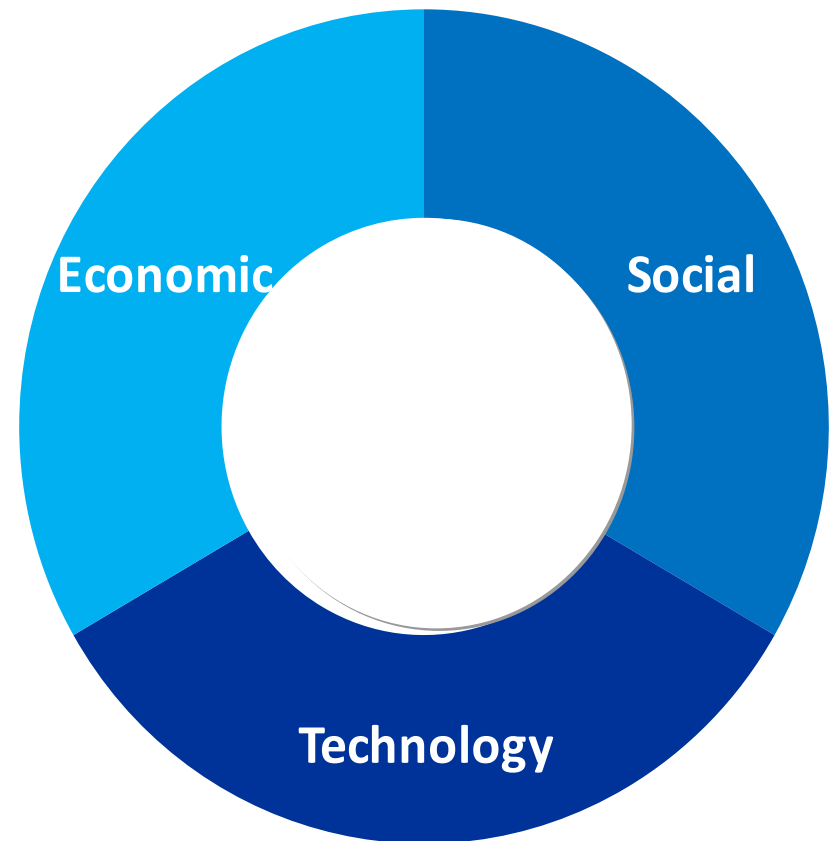
Outline

- Healthcare Challenges
- Knowledge-Based Medicine
- KBM in practice
 - Quality
 - Targeted decision support
 - Knowledge discovery
- Conclusion



Global Healthcare Market Trends

- Increasing Healthcare Costs (73% over the next 9 years)¹
- Increased consumerism & consumer awareness
- Knowledge explosion
 - Increased creation and dissemination of evidence based guidelines
- Data overload
 - Increased digitization of data
- New Technology
- Personalized Medicine



1: "National Health Expenditures... Calendar Years 2009—2018" - Centers for Medicare & Medicaid Services, Office of the Actuary

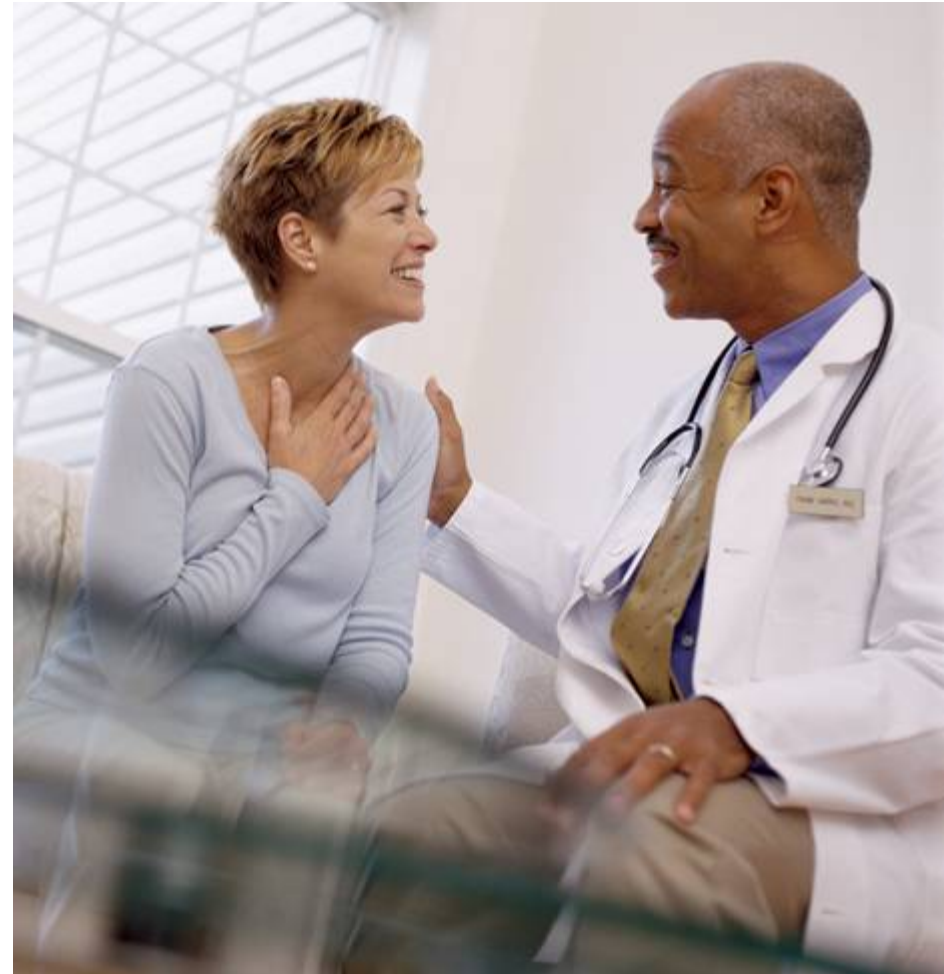
Clinical decisions are more complex



**Clinicians need support to manage these challenges.
Data mining and personalization of care can help.**

Outline

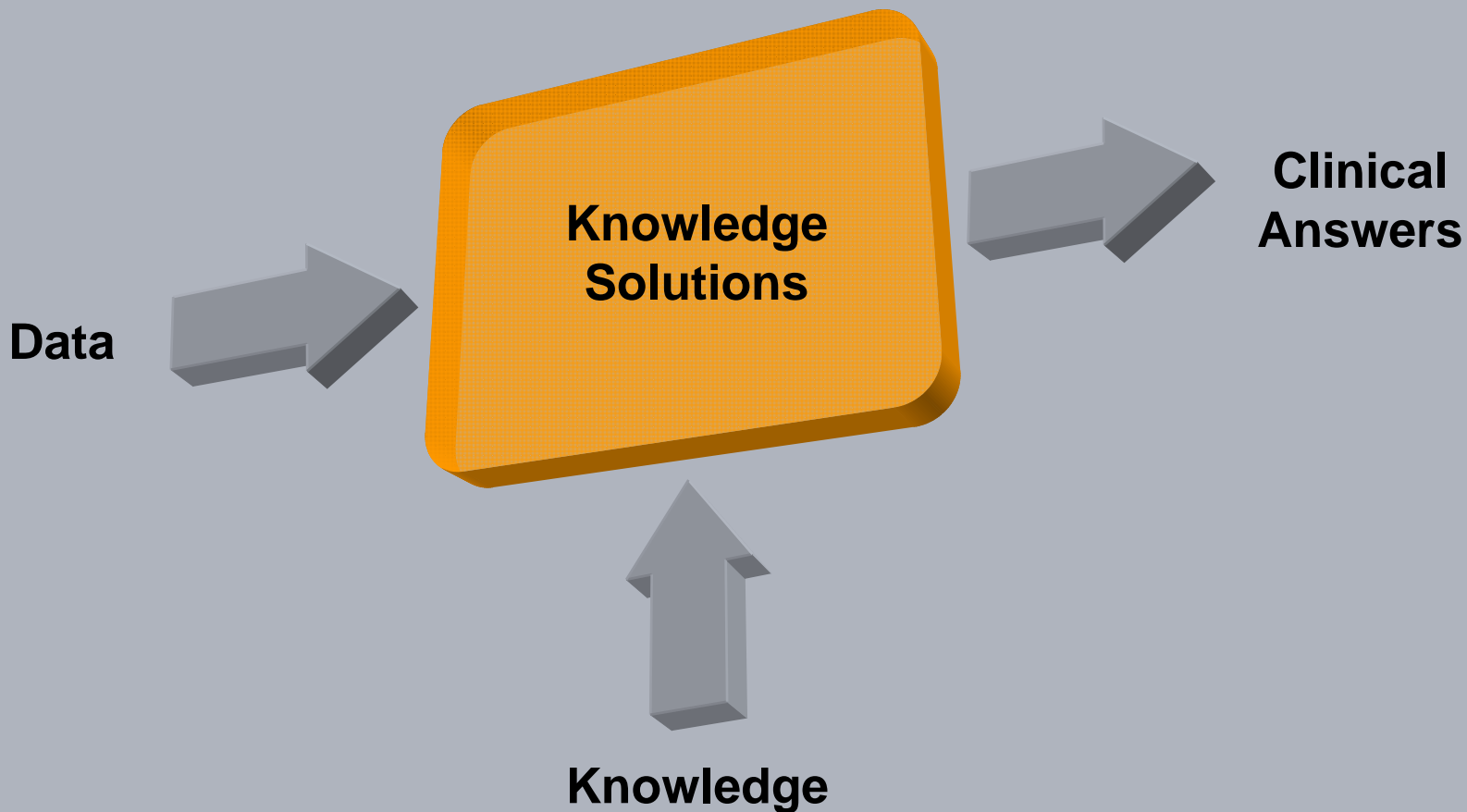
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Integrate patient data with medical knowledge to improve health outcomes.

- Access **existing patient data** from disparate sources
- Manage and integrate **knowledge** for decision support
- Impact workflow & **outcomes**

Impacting Clinical Workflow



Two aspects of Knowledge Based Medicine

- Knowledge Utilization
 - Knowledge-driven decision support
 - Data aggregation from disparate sources – **using existing data**
 - Inject knowledge (e.g., guidelines) via Probabilistic inference
 - Present conclusive findings

- Knowledge Discovery
 - Combine imaging, clinical, IVD and genetic information
 - Discover combined diagnostic signatures
 - ... from multi-institution data
 - Enable increasing personalization of care

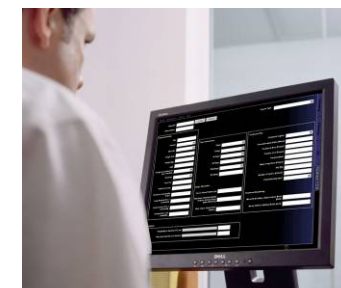
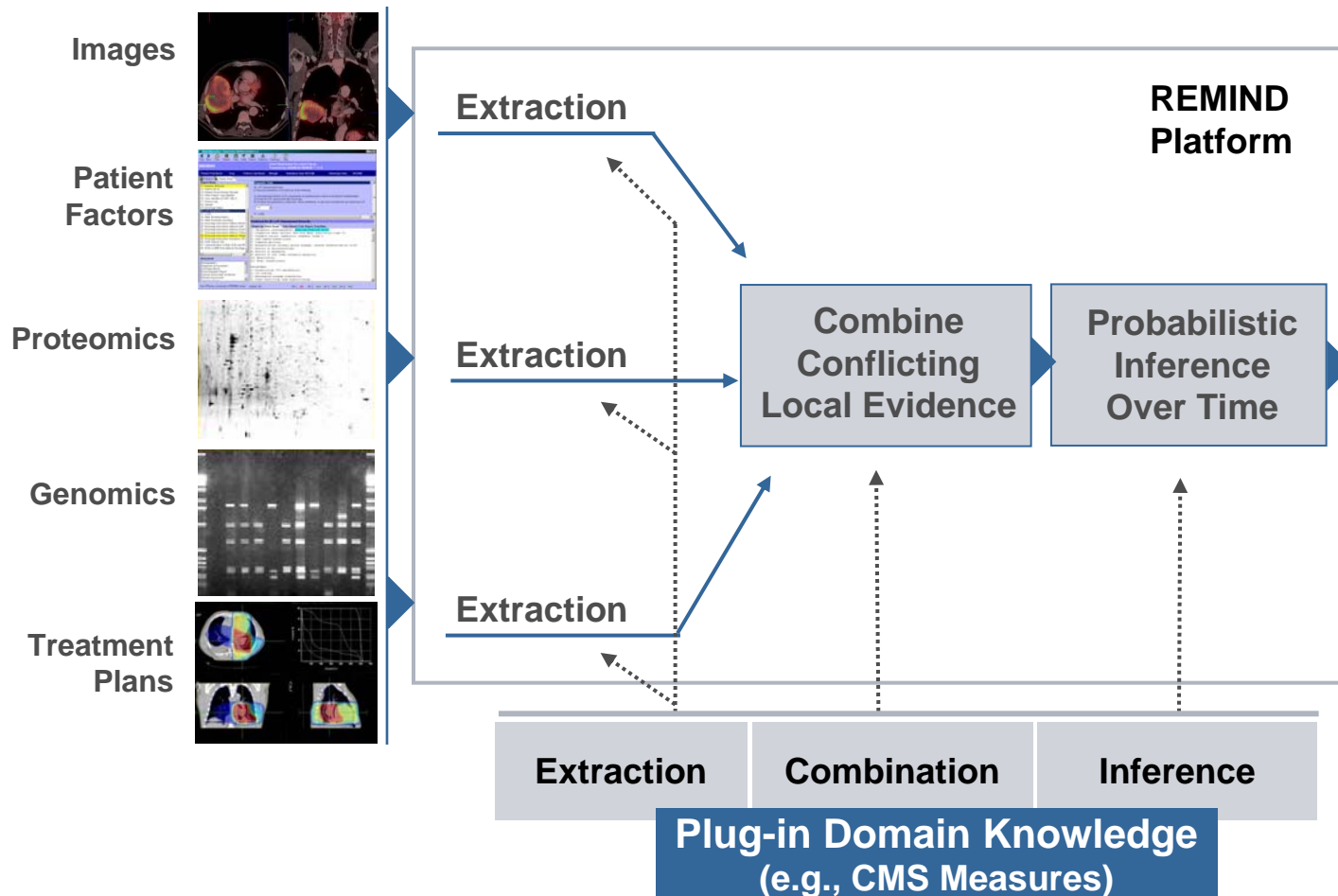


*Not considered a Medical device.

REMIND Knowledge Platform*: Architecture



Reliable Extraction & Meaningful Inferece from Nonstructured Data



Decision Support / Knowledge Discovery

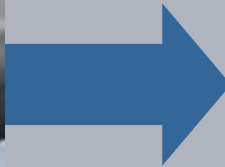
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Automated Quality Abstraction & Reporting



HEART FAILURE (HF) PAPER TOOL
(PLEASE PRINT)

DIAGNOSTIC TESTS

20. LVE Assessment
Is there documentation of at least one of the following?

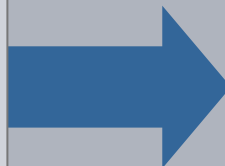
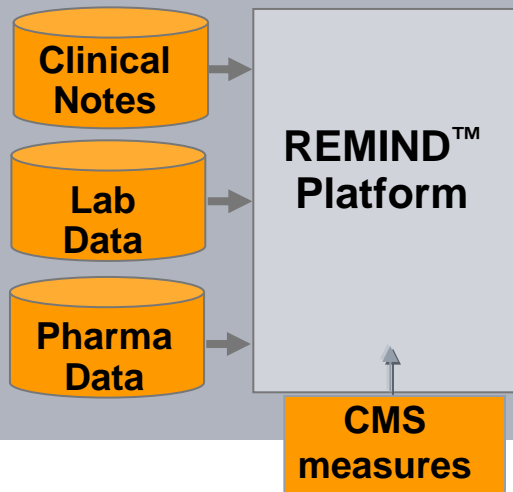
- Left Ventricular Function (LVF) assessment at anytime prior to arrival or during this hospital stay?
- A plan for LVF assessment after discharge
- A reason documented by a physician, nurse practitioner, or physician assistant for not assessing LVF

Yes
 No
Reason:

21. LVSD
Is the Left Ventricular Function (LVF) documented as an ejection fraction (EF) less than 40% or a narrative description consistent with moderate or severe systolic dysfunction?
If "No" or "Reason", OPTION "No" SHOULD BE MARKED HERE.

Yes
 No

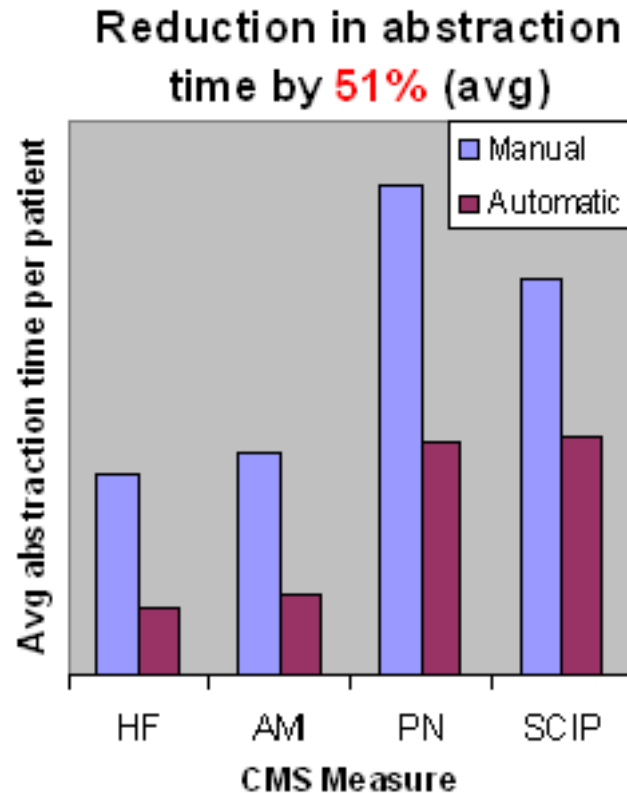
**Manual Chart
Abstraction**



**Quality Measures
enabled by the
REMIND Platform**

Quality Measurement & Improvement

Quality Measures

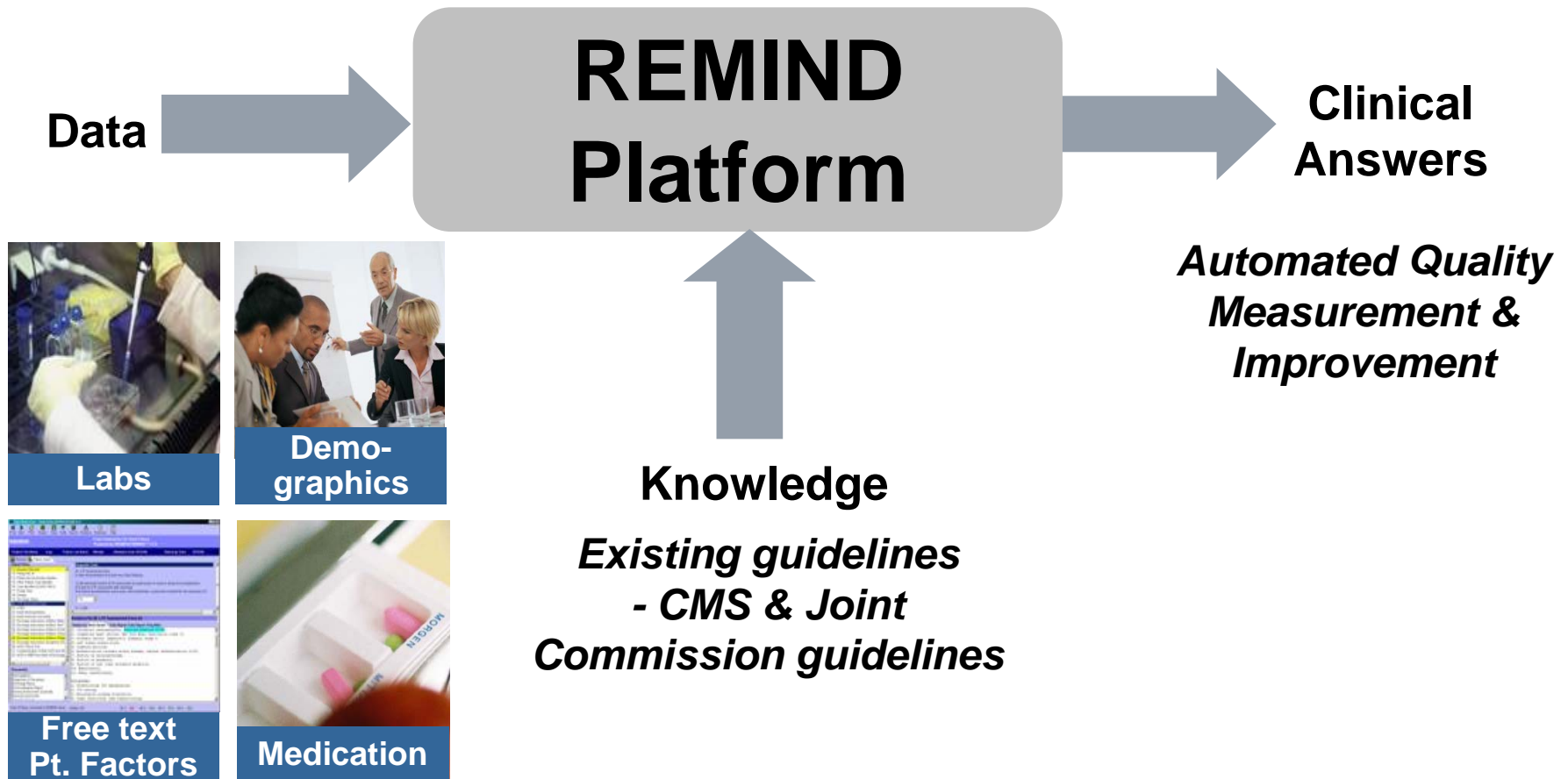


“Soarian Quality Measures is an essential, time-saving solution that automates the abstraction of critical patient data from both structured and unstructured free text from clinical narratives. It enables our teams to focus on providing the best quality of care possible.”

Janene Yeater, Vice President of Quality and Planning MedCentral Health System - July 2009

N. Chopra, F. Farooq, B. Krishnapuram, J. Yeater, “Automatic Abstraction for CMS Quality Measures,” IHI 2009

Quality Measurement & Improvement



Outline

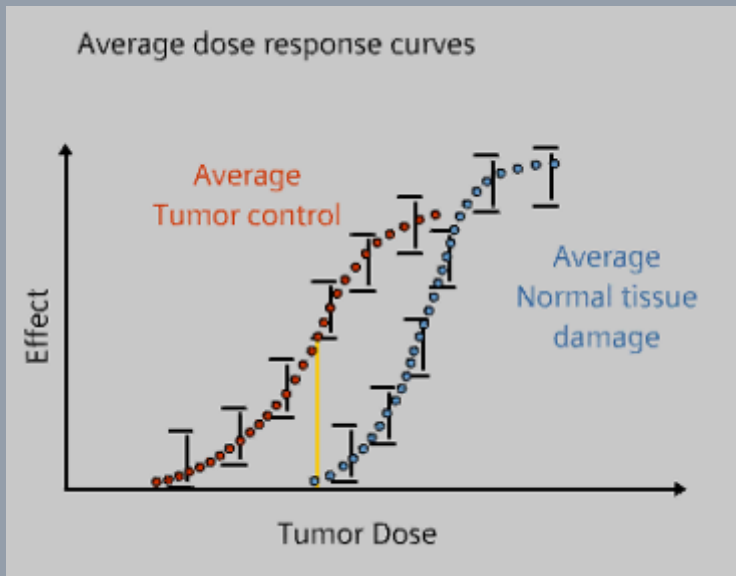
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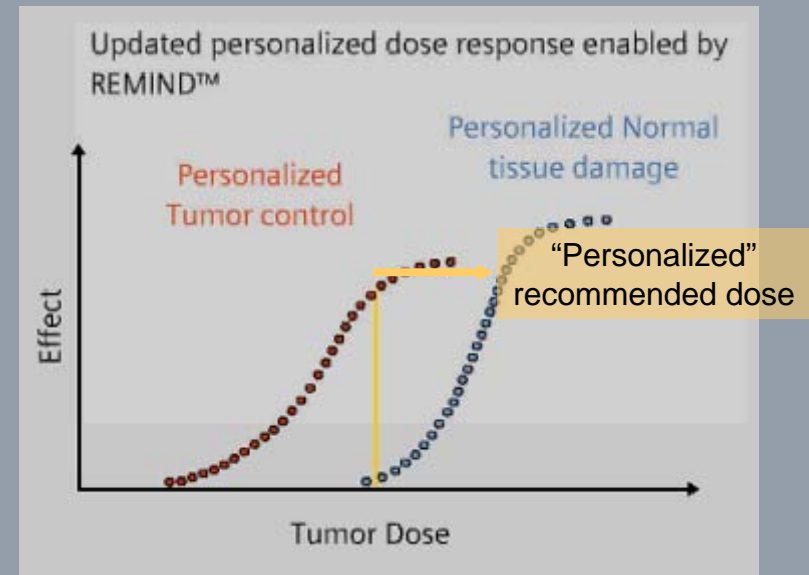
Personalized dose recommendation

Non Small-Cell Lung Cancer

REMIND Platform: Prediction models for lung cancer patients: www.predictcancer.org



Current plans based on “average dose response curves” appropriate for a population



Create personalized dose response rate for individual patients for models created by mining large database of patient data and external medical knowledge

*This information about this product is preliminary. The product is under development and not commercially available for sale in the U.S. and its future availability cannot be ensured.

REMIND Platform Clinical Decision Support (CDS)

Viewing

3D

REMIND CDS

OIS

Patient Information

Age: 66

Gender: female

Height (cm): 179.00

Weight (kg): 72.00

BMI: 22.47

Weight loss (during the last 3 months): stable

Smoking: current smoker

Pack Yrs:

WHO Perf Scale: 1.00

Charlson Comorbidity Index: 0.00

Lung function FEV₁ second (ltr):

Lung function FEV₁ second (%):

Hemoglobin level (mmol/l): 7.70

Patient clinical factors

Tumor Information

Stage: IIIb

T-Stage: T4

N-Stage: N3

M-Stage: M0

Pathology:

Histology: squamous cell ca.

Image Information

Gross Tumor Volume (cc): 83.76

Maximum Standard Uptake Value, primary tumor (from FDG-PET): 133.00

Num. of pos. lymph node stations: 1.00

Load

Cancer Type: Lung (Non Small Cell)

Treatment Plan

Patient treatment factors

Mean Lung Dose (Gray): 15.82

V20 (%): 24.00

Treatment regime: sequential before RT

Overall treatment time (days): 41.00

Treatment dose (Gray): 60.00

Fraction size (Gray): 2.00

Fractions/day: 1.00

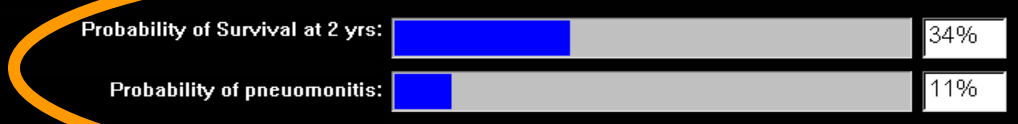
Number of cycles (chemo): 3.00

Chemotherapy type:

Mean % deviation of given dose (from plan):

Mean shift of radiation fields (mm):

Prediction



Prediction of survival outcomes and side effects

REMIND Platform CDS

Viewing

3D

REMIND CDS

OIS

Patient Information

Age:
 Gender:
 Height (cm):
 Weight (kg):
 BMI:
 Weight loss (during the last 3 months):
 Smoking:
 Pack Yrs:
 WHO Perf Scale:
 Charlson Comorbidity Index:
 Lung function FEV, 1 second (ltr):
 Lung Function FEV, 1 second (%):
 Hemoglobin Level (mmol/ltr):

PatientID:
 Patient Name:

Cancer Type:

Tumor Information

Stage:
 T-Stage:
 N-Stage:
 M-Stage:
 Pathology:
 Histology:

Image Information

Gross Tumor Volume (cc):
 Maximum Standard Uptake Value, primary tumor (from FDG-PET):
 Num. of pos. lymph node stations:

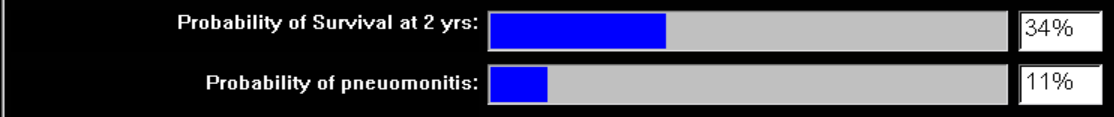
Treatment Plan

Mean Lung Dose (Gray):
 V20 (%):
 Treatment regime:
 Overall treatment time (days):
 Treatment dose (Gray):
 Fraction size (Gray):
 Fractions/day:
 Number of cycles (chemo):
 Chemotherapy type:

Treatment Monitoring

Mean % deviation of given dose (from plan):
 Mean shift of radiation fields (mm):

Prediction



REMIND Platform CDS

Viewing

3D

REMIND CDS

OIS

Patient Information

Age: 66

Gender: female

Height (cm): 179.00

Weight (kg): 72.00

BMI: 22.47

Weight loss (during the last 3 months): stable

Smoking: current smoker

Pack Yrs:

WHO Perf Scale: 1.00

Charlson Comorbidity Index: 0

Lung function FEV₁ second (ltr):

Lung Function FEV₁ second (%):

Hemoglobin Level (mmol/ltr): 7.70

PatientID: 1 Load

Cancer Type: Lung (Non Small Cell)

Patient Name:

Tumor Information

Stage: IIIb

T-Stage: T4

N-Stage: N3

M-Stage: M0

Pathology:

Histology: squamous cell ca.

Treatment Plan

Increase treatment dose

V20 (%): 24.00

Treatment regime: sequential before RT

Overall treatment time (days): 41.00

Treatment dose (Gray): 65.00

Fraction size (Gy): 2.00

Fractions/day: 1.00

Number of cycles (chemo): 3.00

Chemotherapy type:

Increasing treatment dose increases the probability of survival, but also increases likelihood of side effects

Value, primary tumor (from FDG-PET): 133.00

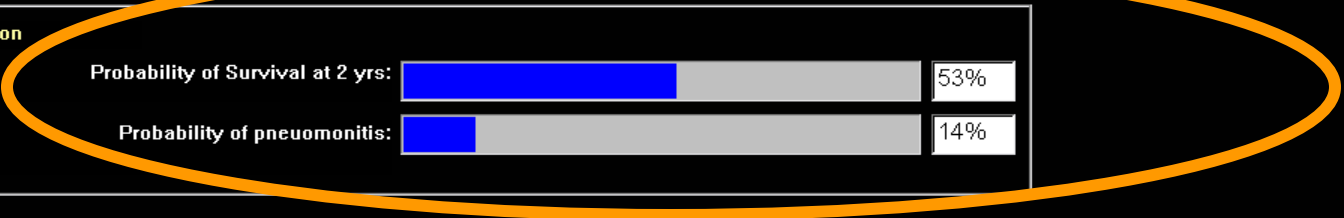
Num. of pos. lymph node stations: 1.00

Treatment Monitoring

Mean % deviation of given dose (from plan):

Mean shift of radiation fields (mm):

Prediction



REMIND Platform CDS

Viewing

3D

REMIND CDS

OIS

Patient Information

Age: 66

Gender: female

Height (cm): 179.00

Weight (kg): 72.00

BMI: 22.47

Weight loss (during the last 3 months): stable

Smoking: current smoker

Pack Yrs:

WHO Perf Scale: 1.00

Charlson Comorbidity Index: 0

Lung function FEV₁ second (ltr):

Lung Function FEV₁ second (%):

Hemoglobin Level (mmol/ltr): 7.70

PatientID: 1 Load

Cancer Type: Lung (Non Small Cell)

Patient Name:

Tumor Information

Stage: IIIb

T-Stage: T4

N-Stage: N3

M-Stage: M0

Pathology:

Histology: squamous cell ca.

Treatment Plan

V20 (%): 24.00

Treatment regime: sequential before RT

Overall treatment time (days): 41.00

Treatment dose (Gray): 70.00

Fraction size (Gray): 2.00

Fractions/day: 1.00

Number of cycles (chemo): 3.00

Chemotherapy type:

Further increase treatment dose

Further increasing treatment dose increases likelihood of side effects, but does not improve probability of survival.

Value, primary tumor (from FDG-PET): 133.00

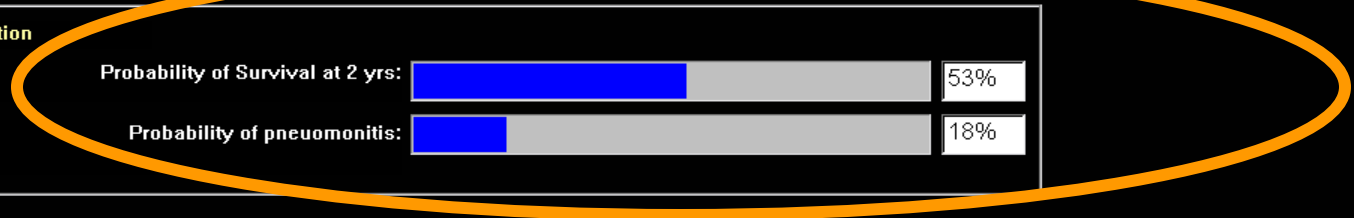
Num. of positive lymph node stations: 1.00

Treatment Monitoring

Mean % deviation of given dose (from plan):

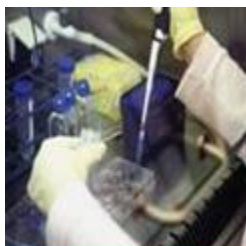
Mean shift of radiation fields (mm):

Prediction

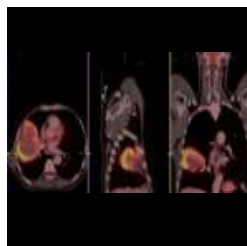


Targeted Decision Support at Point of Care

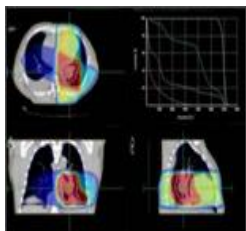
Personalized therapy selection for Lung cancer



Labs



Images



Treatment Plans



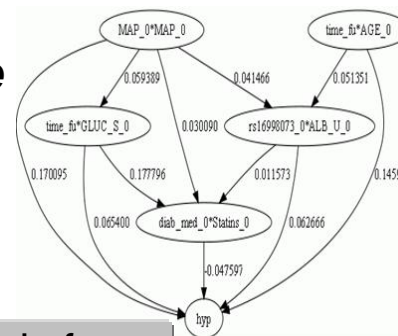
Genomics

Knowledge

Existing guidelines

*Learned knowledge
- Predictive models
discovered from
patient data)*

*Treatment impact
- Adjust dose based
on outcomes & side
effects*



REMIND Platform: Prediction models for lung cancer patients: www.predictcancer.org

Outline

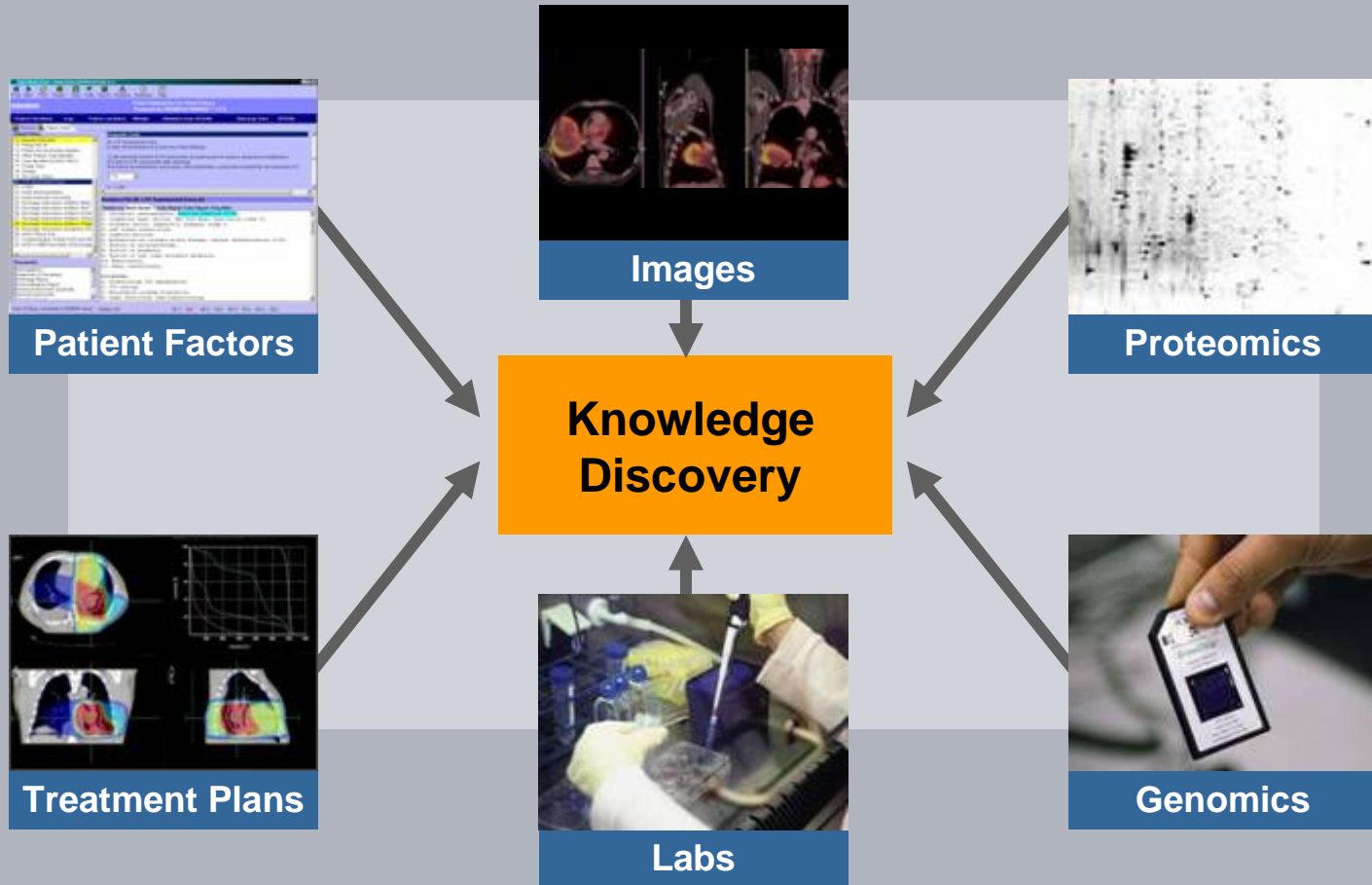
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Discover Combined Diagnostics

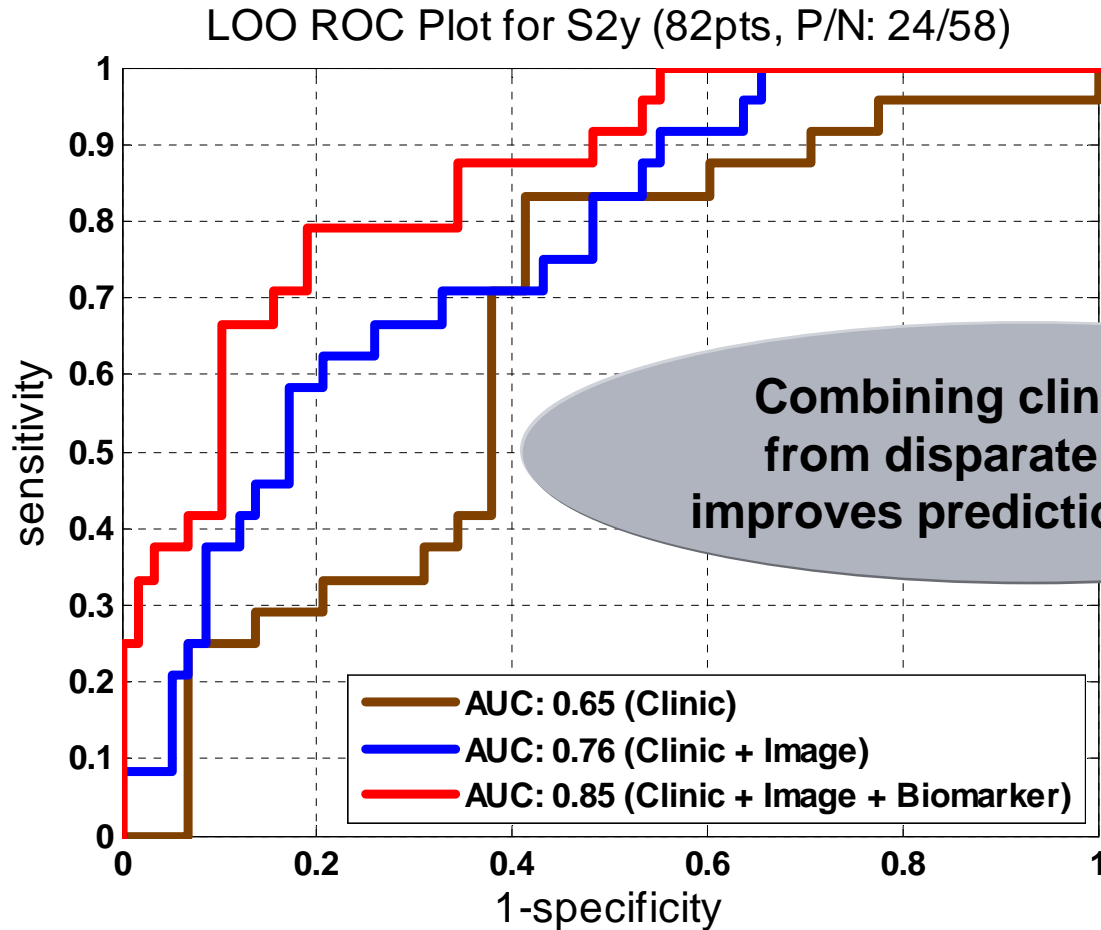
SIEMENS

Models that span Imaging, IVD, Genomic, Molecular & Clinical Biomarkers



Knowledge Discovery: Learning Combined Diagnostics **SIEMENS**

Does incorporating more data help? (Collaboration with MAASTRO)



S. Yu, C. Dehing-Oberije, D. De Ruyscher, K. van Beek, Y. Lievens, J. Van Meerbeeck, W. De Neve, G. Fung, B. Rao, P. Lambin, "Development, External Validation and further Improvement of a Prediction Model for Survival of Non-Small Cell Lung Cancer Patients treated with (Chemo) Radiotherapy," ASTRO 2008

What about data from multiple institutions?

SIEMENS

Predicting 2 year Lung Cancer Survival

- 455 inoperable NSCLC patients, stage I-IIIb, referred to the MAASTRO clinic (Netherlands) to be treated with (chemo)radiotherapy
- 112 patients from Gent hospital (Belgium)
- 40 patients from Leuven hospital (Belgium)

**How do we use data
from different institutions while
preserving patient privacy?**

Example: Cox Regression for Survival Analysis

- **Cox regression**, or the **Cox proportional-hazards model**, is one of the most popular algorithms for survival analysis
 - Defines a semi-parametric model to directly relate the predictive variables with the real outcome (i.e. the survival time)
 - Assumes a linear model for the log-hazard:

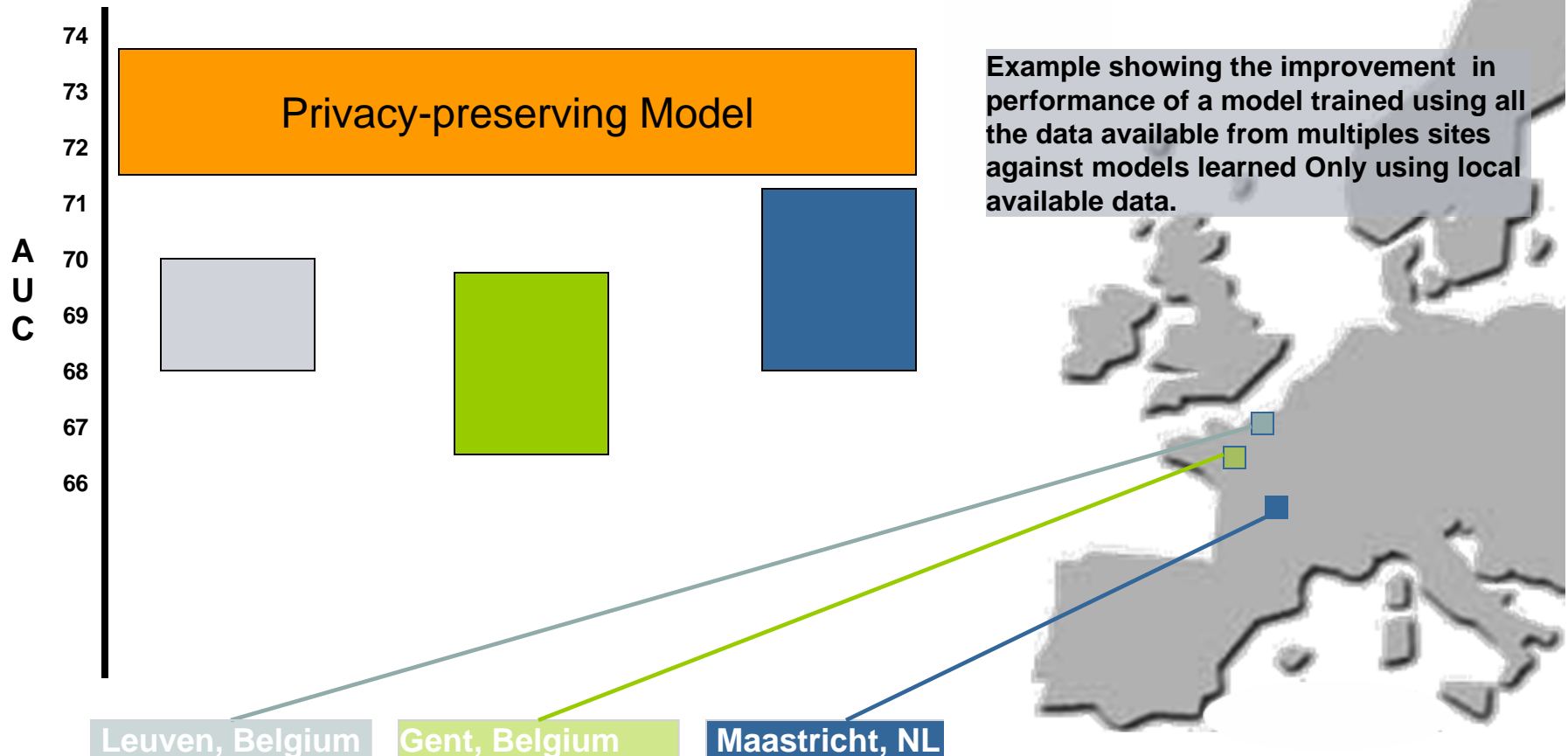
$$\lambda(t|\mathbf{x}_i) = \lambda_0(t) \exp[\mathbf{w}^\top \mathbf{x}_i]$$

- We propose privacy-preserving Cox regression (PPCox) which is based on **random projection**
 - Provides accurate classification
 - Does not reveal private information

$$\lambda_{\text{HPPCox}}(t|\mathbf{x}_i) = \lambda_0(t) \exp[\mathbf{w}^\top \mathbf{B}^\top \mathbf{x}_i]$$

Developing Privacy Preserving Models for Survival

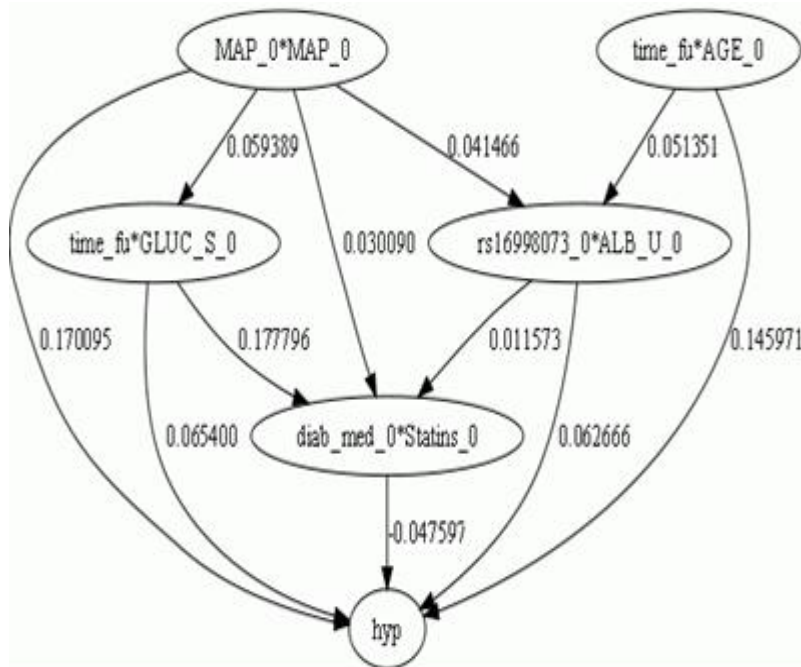
- We are using real data from several institutions across Europe to build models for survival prediction for non-small-cell lung cancer patients while addressing the potential privacy preserving issues



Which asymptomatic patients will develop hypertension within 5 years?

Collaboration with Univ of Greifswald

SIEMENS



- Based on data from large study, >4000 patients over 10 years
 - Genetic (SNPs), clinical, lab, imaging, ...
- Analyzed 100s of potential predictive variables to identify the most informative subset
- Learned a Bayesian Network
 - predicts patients who are at high risk to become hypertensive (AUC >0.85).

Creating Medical Knowledge

Mining large patient databases from multiple institutions

Data



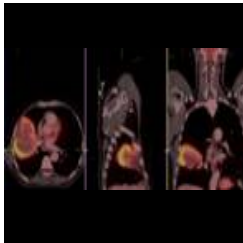
REMIND Platform



Predictive Models



Labs



Images



Medication

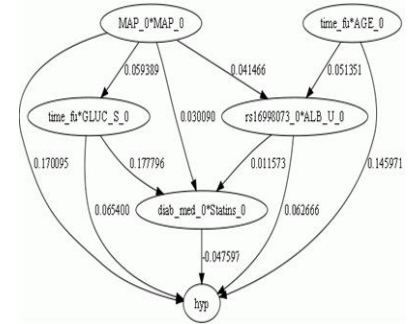


Knowledge

Existing guidelines for cancer therapy

Learned knowledge - Predictive models discovered from patient data

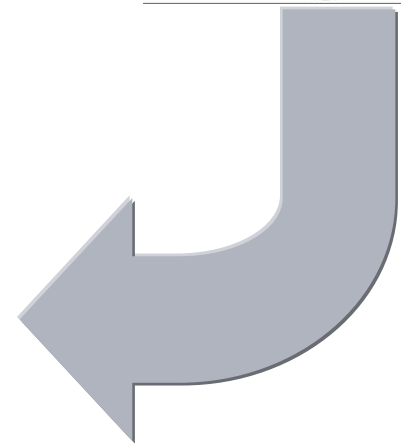
Learned knowledge - Predictive models discovered from patient data



Patient Factors



Genomics



Automated Identification of Patients for Clinical Trials**



Knowledge Discovery can accelerate and improve the selection process of appropriate patients for clinical studies**



Greatly Reducing Research Nurse Time

Manual (current methodology)

- 1 eligible patient found per **3 hours** of nurse time
- 1 patient enrolled per **75 hours** of nurse time

Using REMIND SmartTrials

- 1 eligible patient found per **12 minutes** of nurse time
- 1 patient enrolled per **3 hours** of nurse time

Greatly Reducing Elapsed Time

Manual (current methodology)

- 7 patients enrolled in 9 months

Using REMIND SmartTrials

- **3 patients enrolled in 1 week**

* This solution is not considered a medical device. Sale in the U.S. and its future availability cannot be ensured.

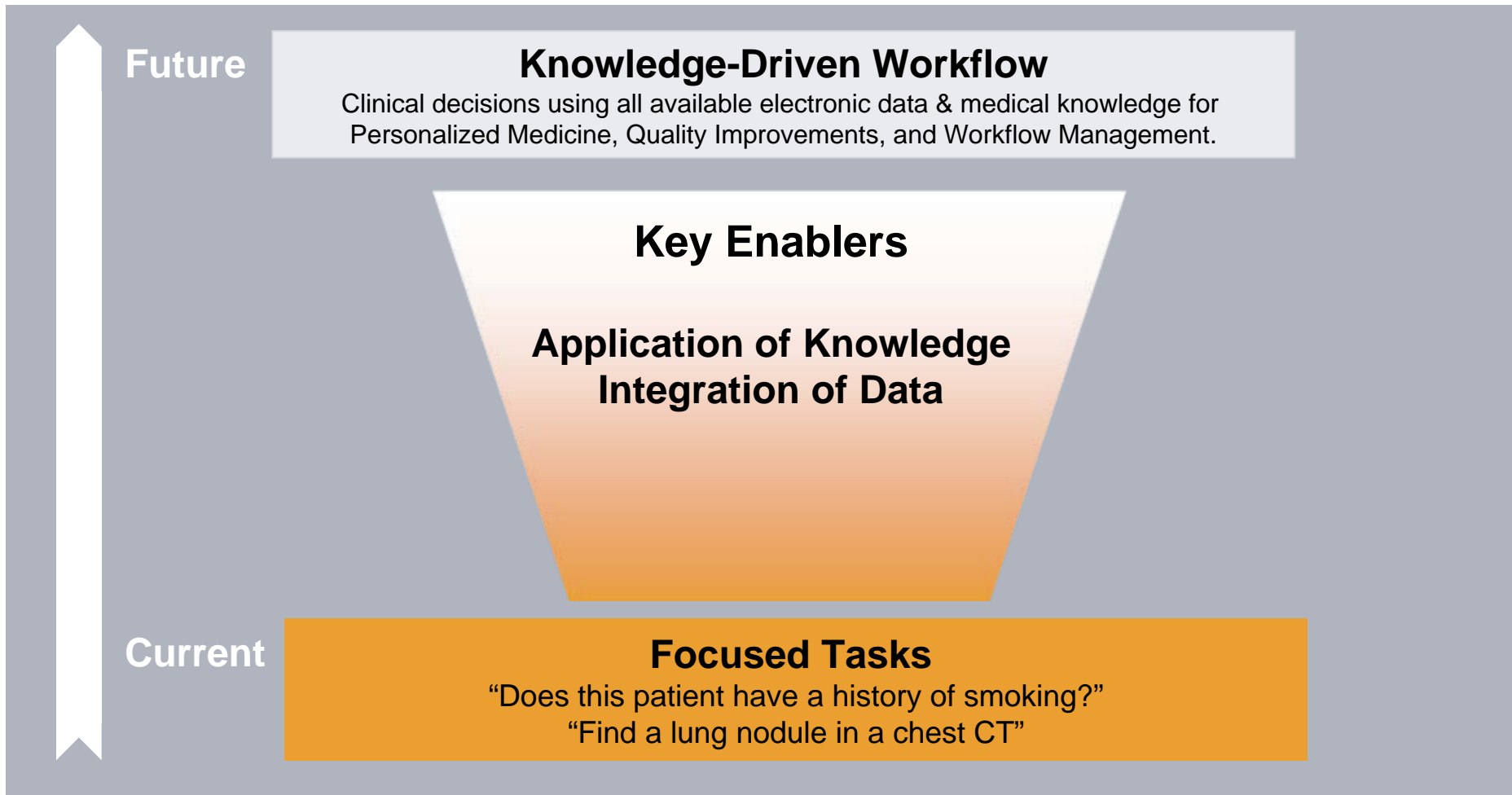
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The Road to Personalized Medicine



Integrate existing patient data with medical knowledge to improve health outcomes.

- Key components
 - Access **existing patient data** from disparate sources
 - Manage and integrate **knowledge** for decision support
 - Impact workflow & **outcomes**
- Healthcare Impact
 - Improve quality of care
 - Support personalization of care via targeted decision support
 - Continuous improvement by learning new medical knowledge

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Thank You

R. Bharat Rao

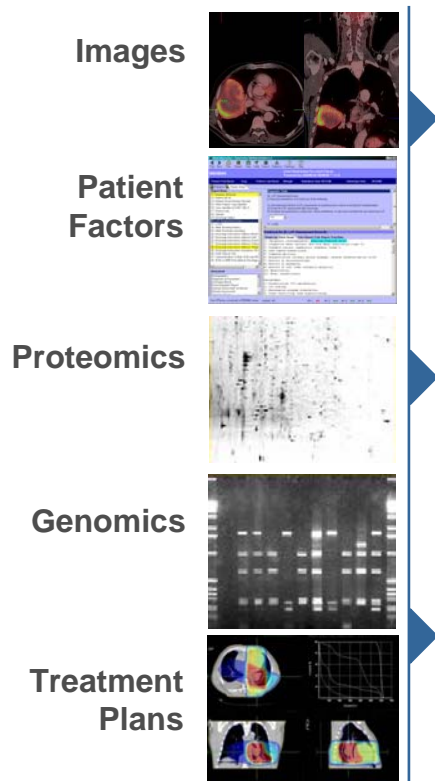
bharat.rao@siemens.com

Knowledge Solutions

Siemens Healthcare



Patient Identification for Clinical Trials enabled by the REMIND Platform



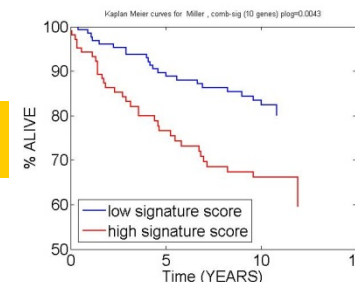
Computerized Patient Data



Clinical Decision Support



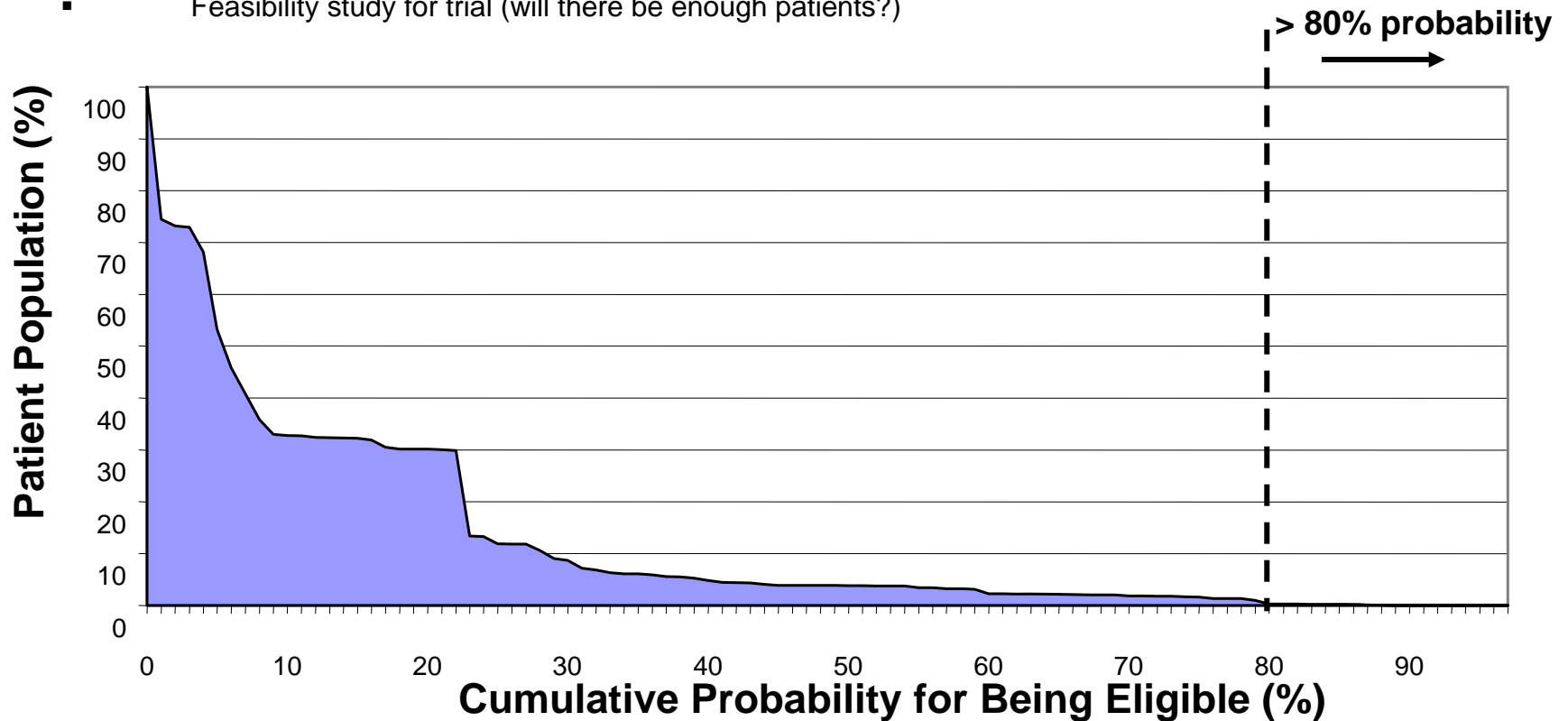
Knowledge Discovery



Patient Identification for Clinical Trials enabled by the REMIND Platform



- Two use cases
 - Clinician: Assess what clinical trials for which current patient is eligible
 - Researcher: Assess which patients are eligible for trial
 - Contact clinicians or patients to consider trial
 - Feasibility study for trial (will there be enough patients?)



Automated Identification of Patients for Clinical Trials**



REMIND SmartTrials* accelerates and improves the selection process of appropriate patients for clinical studies**



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