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ANTALYA, TÜRKİYE

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PREDICTIVE ANALYTICS

Tool of Providence or the End of Coincidence?

He who does not expect the unexpected will not find it out.

Unless you expect the unexpected you will ever find truth, for it is hard to discover and hard to attain.

Heraklit of Ephesus
(540 - 480 B.C.)



Who is your Presenter ?



Elmar Flamme s(trategic) CIO / s(enior) Consultant



Started working in healthcare as a nurse, spending 15 years on intensive care and emergency units

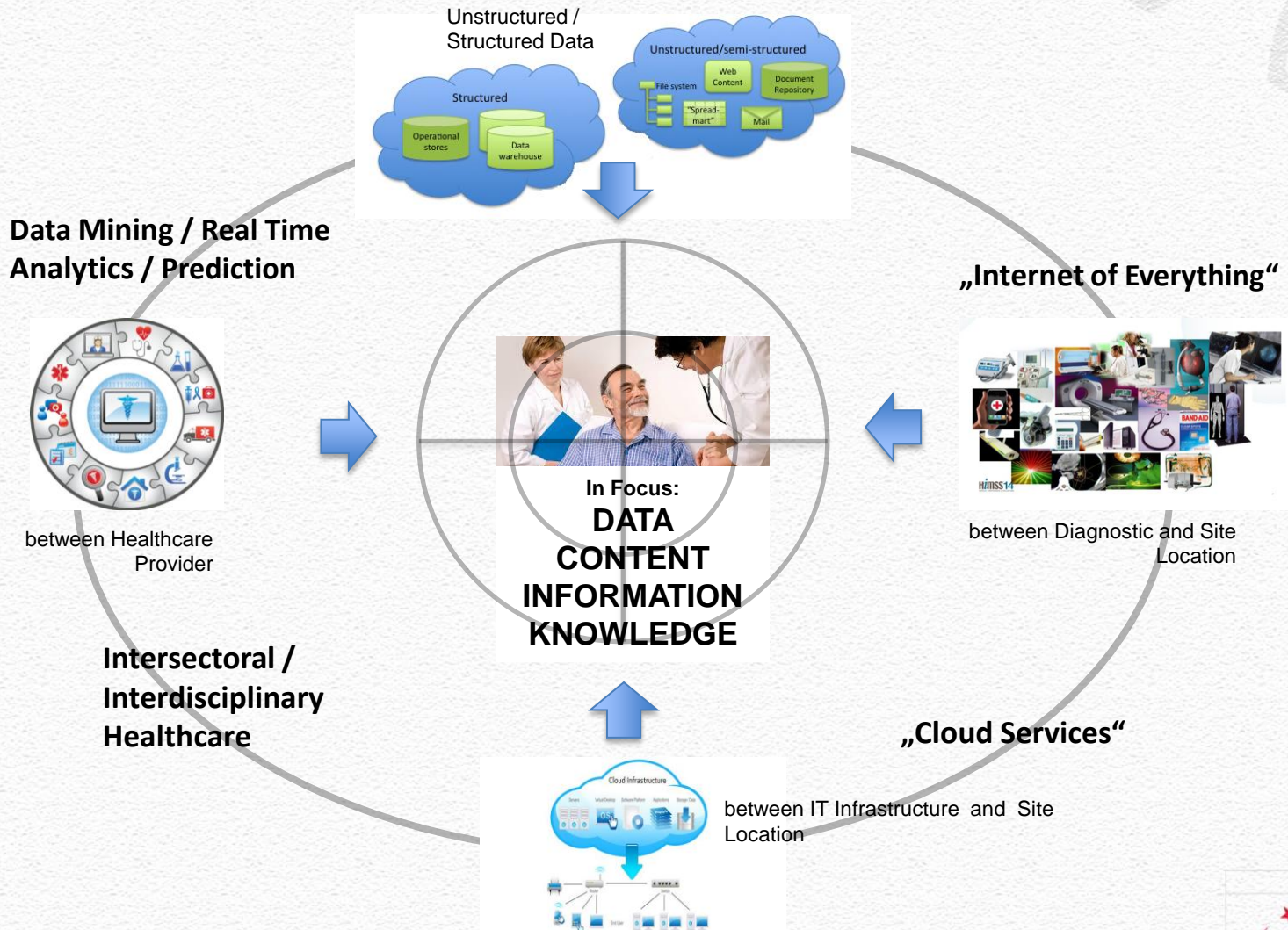
Currently **strategic CIO** for Klinikum Wels Grieskirchen, the biggest convent Hospital in Austria.



Thinking about Big Data since developing and implementing a Clinical Meta Data Archive



The walls have been demolished



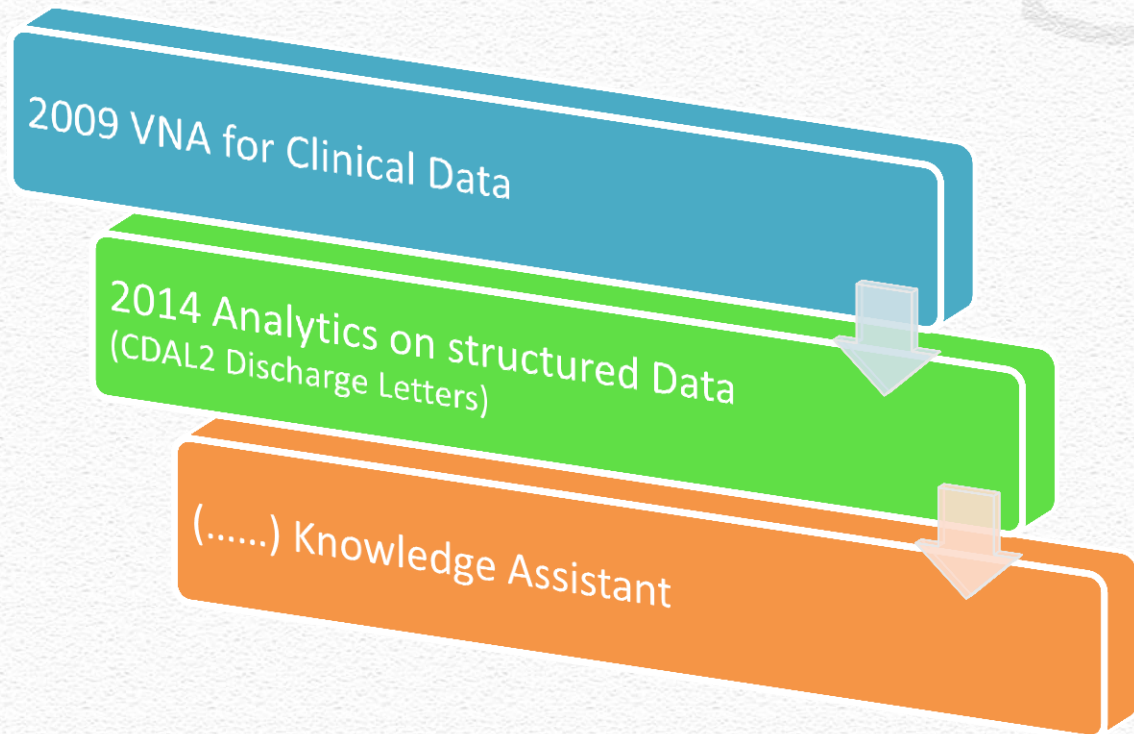
The Story behind the Story



Display relevant
Information



At the right time
At the right place
At the right device
In the right context
In the right role



Looking for solutions which help us to prevent the medical staff from being overwhelmed by information and to help them find the necessary content in the nightmare of information

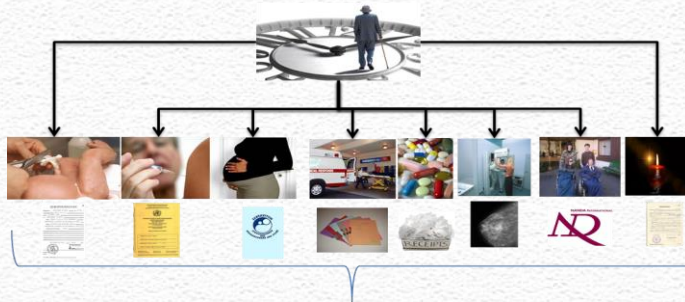


Big Data

Medical Data

Growing

of Sectors



from „Birth“ to „Death“

Personal, Health, Medical Data

- Is continuous Growing
- Is present in diff. Sectors
- Is present in diff. Data Forms

Decisions can be based on:

- A Single piece of Information
- A Summary of Information
- An Interpretation of all Information



Out of Big Data



only a specific information is important



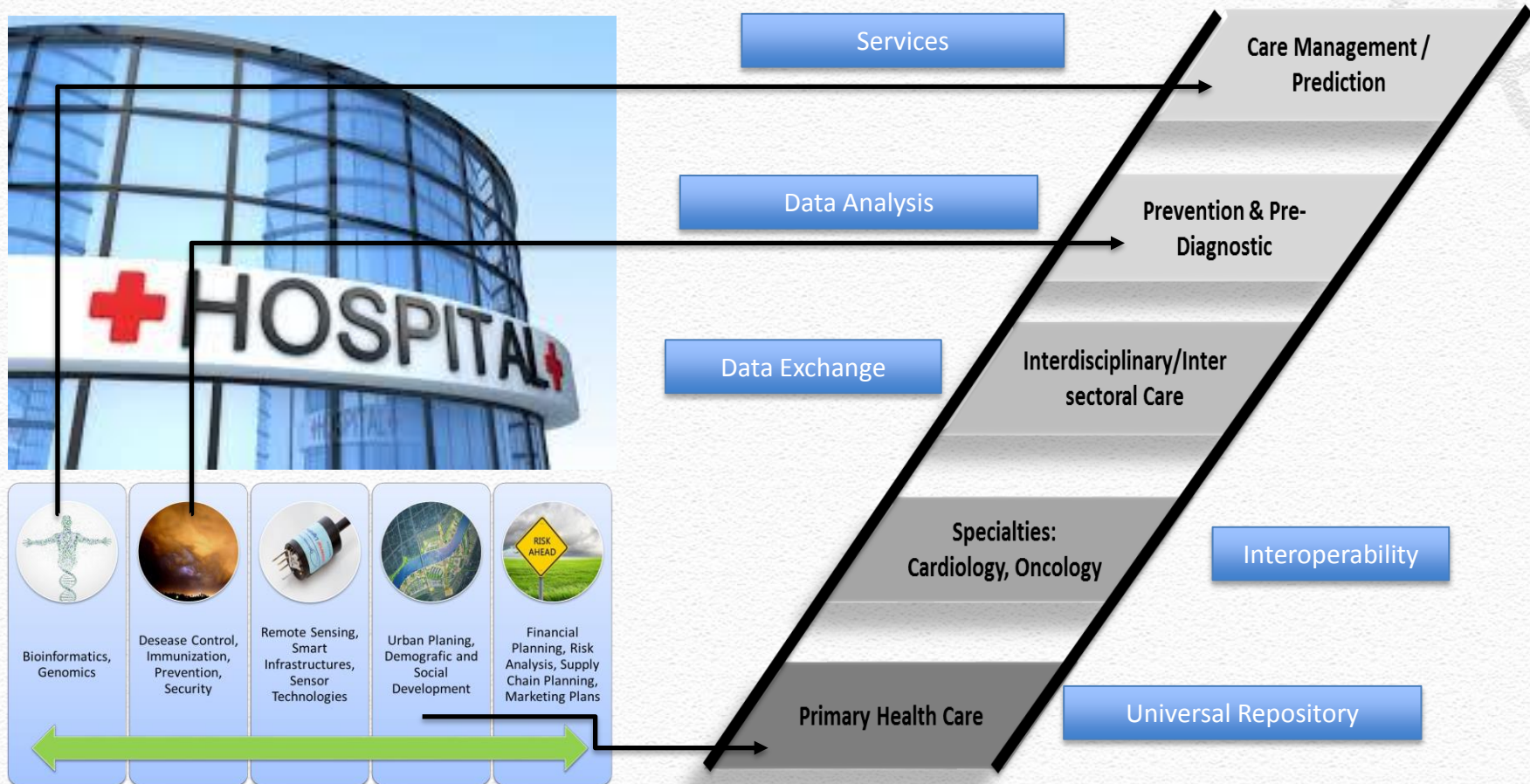
for the consumer in a
specific Situation



Dr. House Syndrom (whole Body Scan)

- Cause they're useless. Could probably scan every one of us and find five different doodads that look like cancer.

Healthcare Development and Challenges



„Demographic Data“ View in Time of Demographic Challenges, MEGA Cities, Economic Crisis, extreme Pollution / Climate Change)

Healthcare Providers



eHR / PHR Data
Cancer Prevention
Cronicle Disease Management
Immunization
Health Promotion

Demographic Data

Population Development
Income Distribution / Welfare / Property
Public and Health Infrastructure
Economic Infrastructure



Longterm Prediction for Strategy / Ressource Development / Social Development on Districts / Region / Countries

Benefits of (Predictive) Analytics

- **Disease management** – this can be used to drive a predictive risk of cost for each member in a healthcare plan by asking such questions as, “How probable is it that this person will be high risk, high cost?”
- **Enhancing patient care** – healthcare facilities can take a more proactive approach to treatment. For example, by more precisely predicting which patients will develop chronic conditions, or which ones will respond best to certain types of medications or therapies, healthcare organizations can focus not only on treating existing conditions, but also on preventing recurrences.
- **Optimizing resource utilization** – patterns and trends in patient admissions, bed utilization, length of stay, and other metrics can be analyzed and used to predict future volumes – particularly when peaks may occur. Hospitals can be more prepared and ensure there are enough resources on hand to provide superior care, thereby better allocating nurses, clinicians, diagnostic machinery, and other resources.
- **Fraud detection** – predictive analytics can help healthcare professionals determine claims that need additional review for fraud by increasing the likelihood of discovering fraudulent claims.
- **Improving clinical outcomes** – health care organizations can pull clinical data from large amounts of patient information to understand patient histories and predict future outcomes. By closely analyzing which treatments work best, providers can make more intelligent decisions about treatment plans, minimizing complications and patient readmissions.
- **Increasing income and revenue** – identify opportunities to collect missing income, including claims that are wrongfully rejected by payers or overdue monies from patients.

Source: Andrew Pearson, 2012, Qualex Asia Limited

Structured Data"

The diagram shows a 3D tensor of data, represented by a grid of small cubes. Two arrows point from this tensor to two different 3D representations. The top representation shows a 3D grid of cubes, while the bottom representation shows a 3D grid of vertical bars, indicating a transformation or processing step.

Predictive analytics encompasses a variety of statistical techniques from modeling, machine learning, and data mining that analyze current and historical facts to make predictions about future, or otherwise unknown, events

(Source: Wikipedia)

[illegible]




TC Sağlık Bakanlığı

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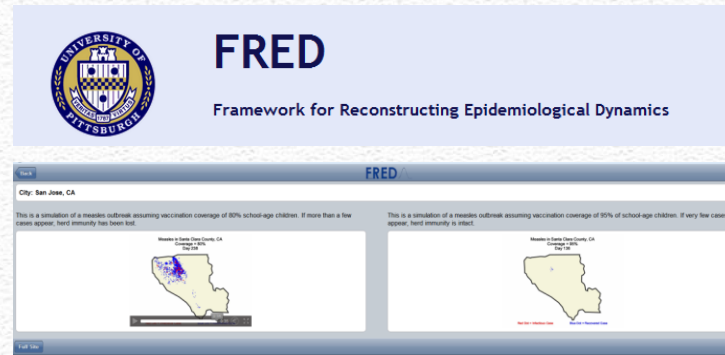
A1. Basic Analytics - FRED

Computer Simulation Models Measles Outbreaks

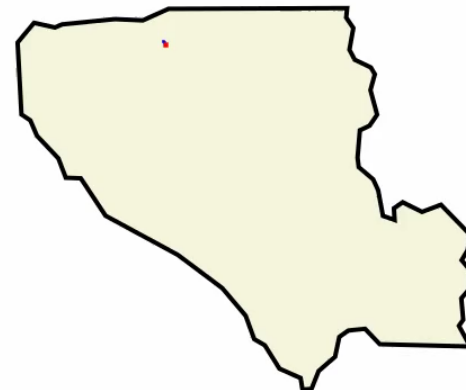
FRED supports research on the dynamics of infectious disease epidemics and the interacting effects of: mitigation strategies, viral evolution, and personal health behavior.

The system uses agent-based modeling based on census-based synthetic populations that capture the demographic and geographic distributions of the population, as well as detailed household, school, and workplace social networks. Multiple circulating and evolving strains can be simulated. Mitigation strategies in the framework include vaccination, anti-viral drugs, and school closure policies. FRED supports models of health behavior change to facilitate the study of critical personal health behaviors such as vaccine acceptance, personal hygiene and spontaneous social distancing.

FRED is available through open source in the hopes of making large-scale agent-based epidemic models more useful to the policy-making community, the research community, and as a teaching tool for students in public health.



Measles in Santa Clara County, CA
Coverage = 80%
Day 30



Red Dot = Infectious Case

Blue Dot = Recovered Case

A₂. Basic Analyze – MRSA

The screenshot shows the Similarity Explorer web application. The browser address bar displays 'healthcare.similarity.com'. The page title is 'similarity Explorer'. Below the title, a note states: 'This analysis is based upon data from the Nationwide Emergency Department Sample (NEDS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality.' There are tabs for 'Archetypes', 'Discoveries', and 'Dataset Summary'. The 'Archetypes' tab is active. On the left, there is a sidebar with a 'Use Filter Form' dropdown and a list of filters: Demographics, Hospital (selected), Visit, Procedure, Diagnosis, Disposition, Feature Types, and Misc. The 'Hospital' filter is expanded, showing options: Hospital Region - will be applied, Hospital Trauma Center Level, Hospital Urban/Rural Location, Hospital Teaching Status, and Hospital Control. Below the filters, there is a 'Start with an Empty Score' button. The main content area is divided into two sections: 'Archetypes' and 'Scores for Archetype 'Sterile Fail Ecodes''. The 'Archetypes' section shows a table with columns 'Owner' and 'Name'. It lists several archetypes: 'Sterile Fail Ecodes', 'Sterile Fail Ecodes Dos', 'Decubitus (Pressure) Ulcers', 'Septicemia', and 'Type II Diabetes'. The 'Scores for Archetype 'Sterile Fail Ecodes'' section shows a table with columns 'Owner' and 'Name'. It lists one archetype: 'Females in the Northeast'. The bottom of the page shows the browser's developer tools.

Identify Risk of „MRSA“ Infection within 30sec

Choose: Region / Healthcare Provider

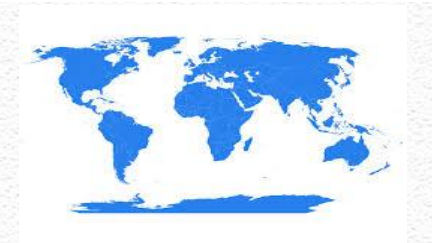
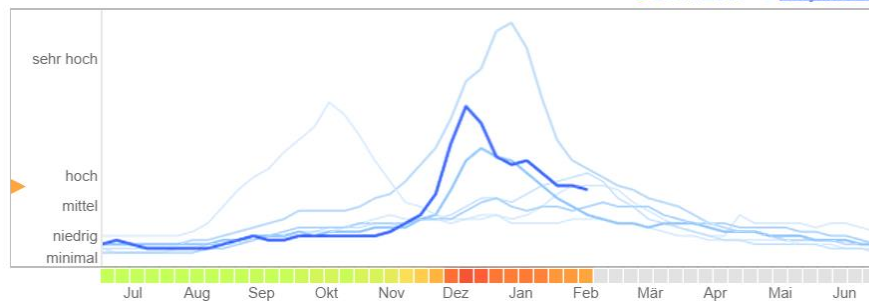
Search: MRSA

Get: Predictive Archetype Result

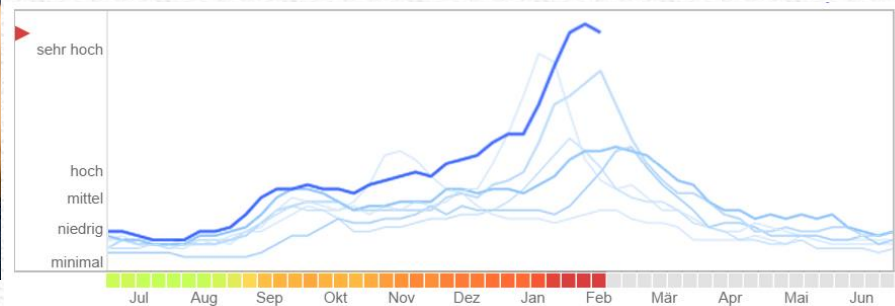
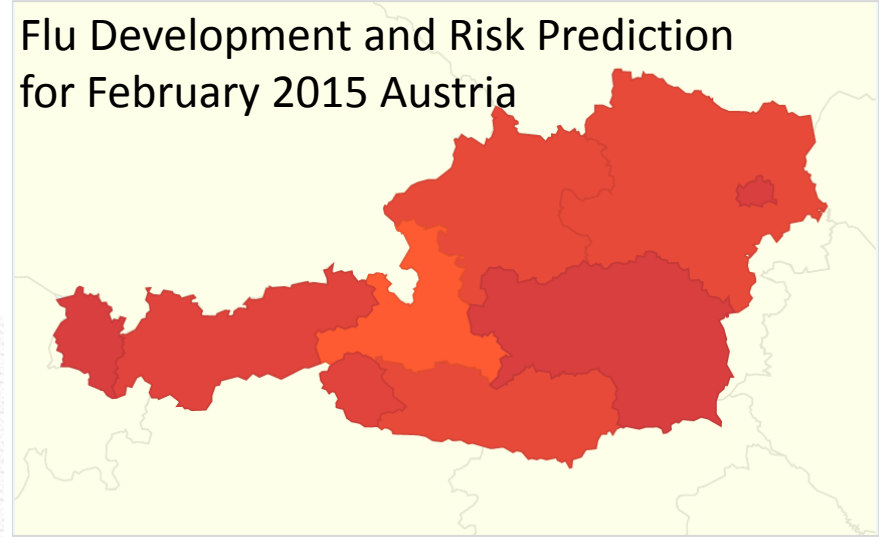
Set: Filter to Identify the possible affected

....Drill Down to the PHR after 30 sec ...

B₁. Predictive Analytics – Google Flu



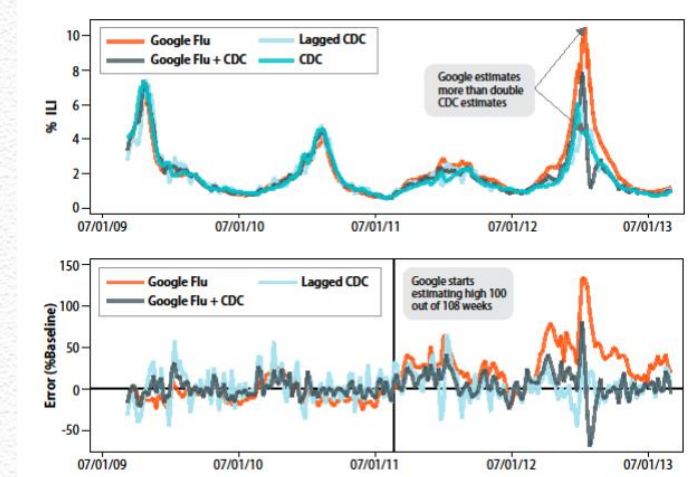
Prevention
Immunisation



B₂. Google Flu in (short) Detail

- Tracking Data since 2009
- Monitoring millions of users' health tracking behaviors online
- Google also implemented the policy to anonymize IP address in their search logs after 9 months
- The initial Google paper stated that the Google Flu Trends predictions were 97% accurate comparing with CDC data
- However subsequent reports asserted that Google Flu Trends' predictions have sometimes been very inaccurate—especially over the interval 2011-2013, when it consistently overestimated flu prevalence, and over one interval in the 2012-2013 flu season predicted twice as many doctors' visits as the CDC recorded.

Source: en Wikipedia 2015



The Parable of Google Flu: Traps in Big Data Analysis David Lazer, 1,2*
Ryan Kennedy, 1,3,4 Gary King, 3 Alessandro Vespignani5

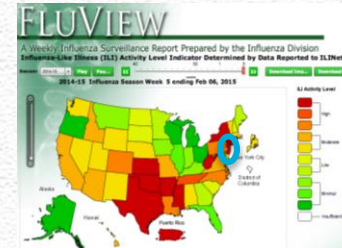
C. NDA PoC: US Healthcare Provider CA



Clinical Admit

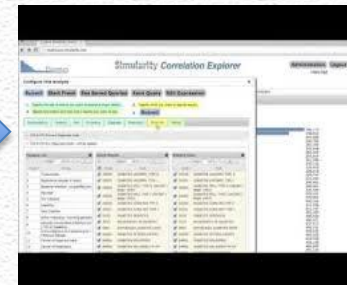


Medical Examination



Summary:

- Patient comes into hospital
- Patient ID bracelet includes QR code
- When doctor scans patient bracelet QR code, patient's clinical history (including COPD, which puts patient at higher risk of Influenza complications) is combined with current flu outbreak data based on location.
- If patient is at high risk of complications and in an outbreak location, the patient record on the smart phone includes an alert indicating high risk of complications, and why.



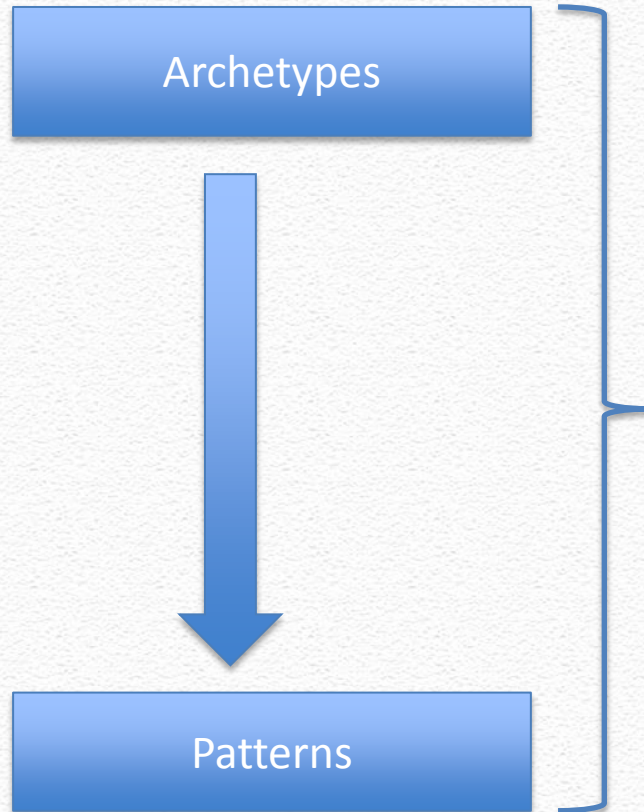
Correlation



Warning

Example: Step 1 – What you are looking for ?

Predictive Analytics Tools



RISK Ratio on Patients based on:

General Indicators


- Patients in my Enterprise Area possible affected by Influenza - Source based national empiric Data (CDC)
- Finding general Exposures (Age, Gender, Health Status,)


Patient / Healthcare Provider Centrific Indicators


- (Expected) Numbers of Patients which could be affected by Influenza cause by patient history (PHR)
- Unexpected Numbers of Patients affected by Influenza caused by the possibility to get it through main illness and possible complications


Example: Reconstruction – Step 1


This analysis is based upon data from the Nationwide Emergency Department Sample (NEDS), Healthcare Cost and Utilization Project (HCUP), Agency for Healthcare Research and Quality.


 Start with an Empty Archetype

 Start with an Empty Score

 Close


 Process, See Now


 Save


 Edit Expression


Use Filter Form


☒ Exclude Archetype Events

 Start with an Empty Score

 Close


 Process, See Now

 Save

 Edit Expression

Use Filter Form

☒ Exclude Archetype Events

**Parameters for Archetype 'Risk of Influenza'**

Page 1 of 1 25 View 1 - 7 of 7

Verb	Value
▢ Diagnosis	
is	(0415) H. INFLUENZAE INFECT NOS
is	(4802) PARINFLUENZA VIRAL PNEUM
is	(4822) H.INFLUENZAE PNEUMONIA
is	(4870) INFLUENZA WITH PNEUMONIA
▢ Feature Types	
is one of	Admission month, Age Range, Diagnosis, Median household income national quartile for patient ZIP Code, Patient Location: NCHS Urban-Rural Code (V2006), Region of hospital
▢ Significance	
is	5
▢ Metric for Feature Selection	
is	(log_likelihood) Log-likelihood Ratio

Example: Reconstruction – Step 3



My Analysis

Sort ☐ by Label, or ☒ by Value, and ☐ Ascending, or ☒ Descending

307434801	51.8144
303846881	51.4217
305074669	50.8019
303541275	50.7505
304359458	50.5926
307390392	50.5801
311780456	50.4670
309726133	50.4591
309342774	50.3628
311817337	50.3422
307120874	50.1427
302698695	50.1262
305636401	50.0566
308550822	50.0566
308141664	49.8016
302152856	49.7179
301047099	49.7058
300262189	49.5526
311748424	49.4244
300417409	49.3869
304971696	49.3435
310707034	49.3268
309097628	49.2877
309119142	49.1780
305325020	49.0527
311853167	48.9980
303831342	48.9918
303602918	48.9535
307182023	48.9396
301910912	48.9128
310959759	48.7772
306396993	48.7754
302974142	48.7496
307256388	48.6985
306710650	48.6677
310341386	48.5781
310493354	48.5753
306794138	48.5362
301206599	48.4870
309182734	48.3914



Risk of Influenza

Sort ☐ by Label, or ☒ by Number of Events, and ☐ Ascending, or ☒ Descending

VIRAL PNEUMONIA NEC (Dia...(1)	1,086.6943
H. INFLUENAE SEPTICEMIA ...(2)	780.5105
VIRAL PNEUMONIA NOS (Dia...(3)	208.9127
INFECT NOS-ANTEPARTUM (D...(4)	88.6695
BACTERIAL PNEUMONIA NOS ...(5)	84.1108
Flu dt iden H1N1 virus ...(6)	69.9603
PERINATAL CHR RESP DIS ...(7)	69.1093
STAPH AUREUS PNEUMON (Be...(8)	67.1427
PNEUMOCOCCAL PNEUMONIA ...(9)	60.7917
VENTLTR ASSOC PNEUMONIA ...(10)	57.2743
MYCOPLASMA PNEUMONIA (Be...(11)	42.4295
PROPHYLACTIC ISOLATION ...(12)	42.4119
CONGENITAL QUADRIPLEGIA ...(13)	40.0221
OTH GRAM NEG PNEUMONIA ...(14)	34.4117
K. PNEUMONIAE PNEUMONIA ...(15)	34.0700
BRONCOPNEUMONIA ORG NOS ...(16)	33.4001
PSEUDOMONAL PNEUMONIA (D...(17)	30.5411
OTHER PULMONARY INSUFF ...(18)	27.5265
METH RES PNEU D/T STAPH ...(19)	26.3443
EMPYEMA W/O FISTULA (Dia...(20)	24.7236
ASTHMA W/ STATUS ASTHMA...(21)	24.2232
HYPOXEMIA (Begin 2005) ...(22)	23.6148
RESPIRATOR DEPEND STATUS...(23)	23.0921
RESPIRATORY FAILURE (Beg...(24)	21.7976
MIXED ACID-BASE BAL DIS ...(25)	19.6548
AC AND CHR RESP FAILURE ...(26)	19.4607
LACK NORM PHYSIOL DEVELO...(27)	19.4175
SEPTIC SHOCK (Begin 2003...(28)	18.7136
POST TRAUM PULM INSUFFIC...(29)	18.4334
SYS INFLAM / INFECTI W O...(30)	17.2829
SEC DM WO CMP NT ST UNCN...(31)	15.5011
DOWN-s SYNDROME (Diagnosis)	15.0699
HEMOPTYSIS (end 2010) (D...(33)	14.5779
SEPTICEMIA NOS (Diagnosis)	14.2989
BACTEREMIA NOS (Diagnosis)	14.2072
ALKALOSIS (Diagnosis)	13.7334
TRACHEOSTOMY STATUS (Dia...(37)	13.5735
LOWER NEPHRON NEPHROSIS ...(38)	12.9762
LEUKOCYTOPENIA NOS (Beg...(39)	12.6727
GASTROSTOMY STATUS (Diag...(40)	12.6687
ANOXIC BRAIN DAMAGE (Dia...(41)	12.2799
CH OB ASTHMA W/ACUTE EXA...(42)	11.4366
CEREBRAL PALSY NOS (Diag...(43)	11.2539
OBS CHR BRONC W AC BRONC...(44)	11.0183

Must have`s for the future

- **Analytics Easy to Use for Healthcare Staff:** Analytics executed by Physician and Nurses as Part of Daily Work and Daily Information Management
- **Analytics without being a statistician or Data Scientist:** Analytics no longer reserved only to data specialists and their special knowledge
- **Analytics as part of Clinical Application:** Analytics not only reserved for complex, expensive and limited Data Warehouse Systems
- **Analytics as part of Daily Decision Support:** Real Time Access and Results without extensive preparations on top of Knowledge Assis
- **Analytics on Demand as Service on Smart Platforms:** Independent from “Hardware Battles”, affordable in Invest and Maintenance and without Core/CPU license woes

CLINICAL META DATA REPOSITORIES



Physician / Nurses



Specialized Department



MedController



Data Analysts

BIG DATA Analytics needs Reliability and Responsibility



Predictive Analytics do not solve any Healthcare insufficiency

Predictive Analytics in Healthcare needs Human Interpretation

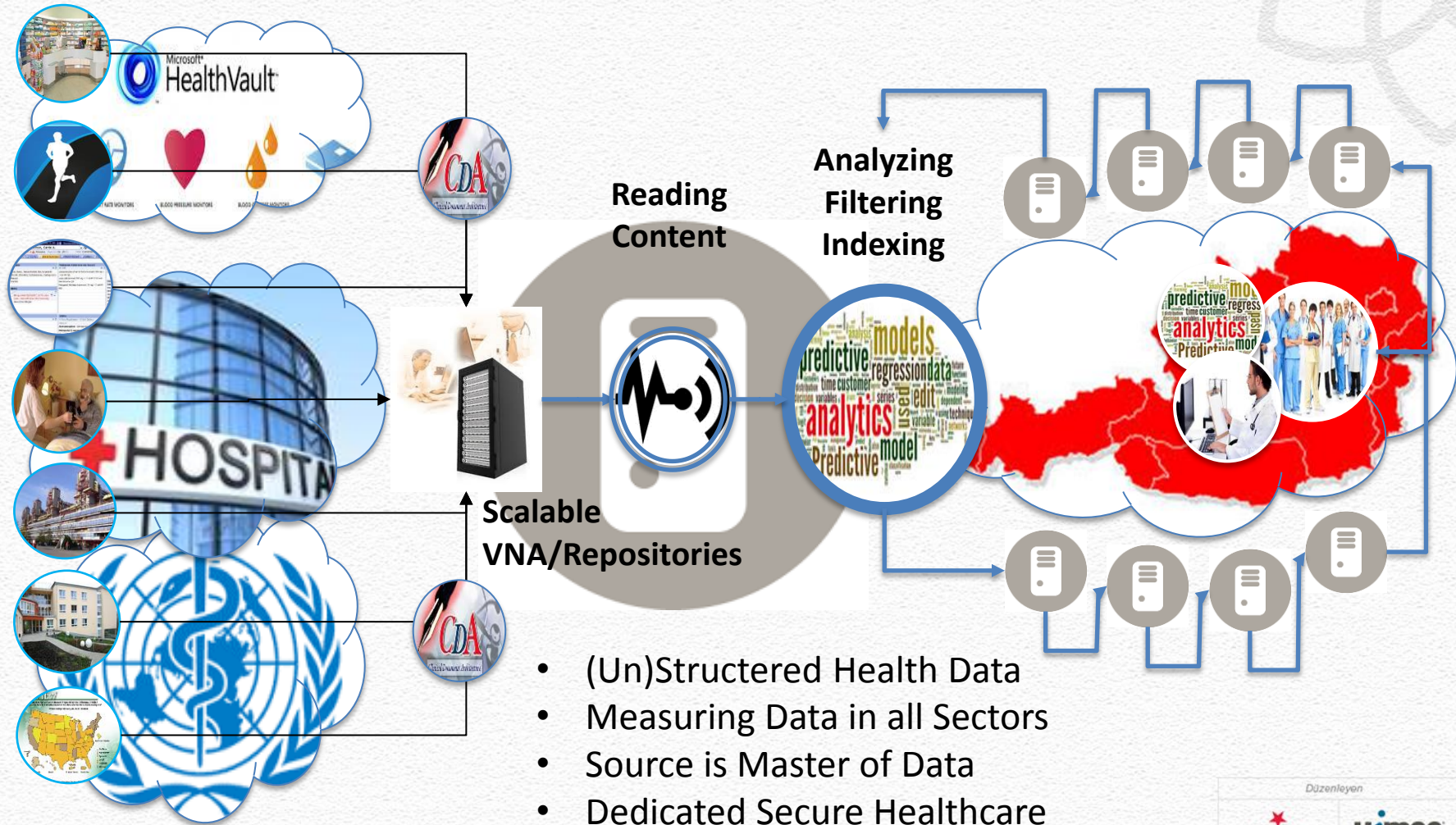


Predictive Analytics needs assistant measurement in legal regulation and data privacy



The Success of implementing Predictive Analytics in Healthcare depends on the acceptance by Patients / Clinicians / Public

A Vision for the Future



- (Un)Structured Health Data
- Measuring Data in all Sectors
- Source is Master of Data
- Dedicated Secure Healthcare Clouds

Dikkatiniz için
teşekkürler!

Thank you
For your
Audiance !

INFORMATION AND CONTACT

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