Artificial Intelligence in Medicine

Peter Szolovits
Prof. of EECS, HST
CSAIL Clinical Decision Making Group
http://medg.csail.mit.edu

6.034
April 7, 2010

Massachusetts Institute of Technology

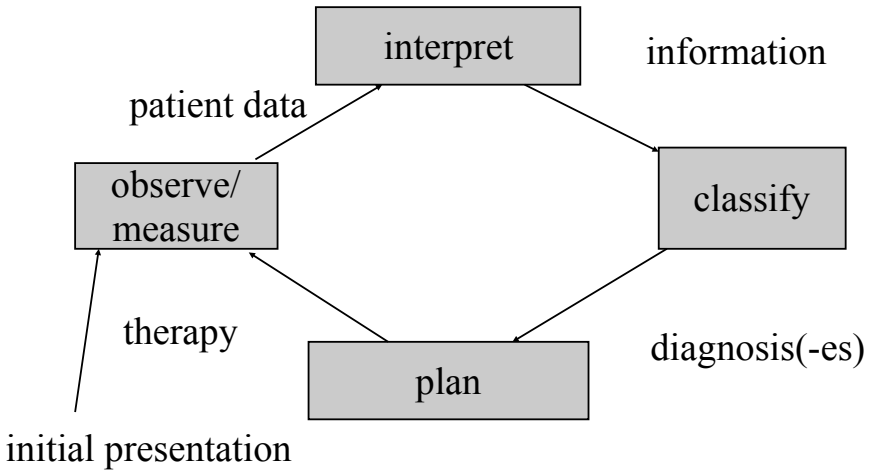
Personal History

- Interest in Knowledge Representation
  - How do you write down in a computer real-world knowledge that is useful for
    - inference
    - learning
    - consistency checking
  - Special types of knowledge
    - Likelihood
    - Time
    - Space
    - Belief

What do Doctors do?

- Three classical medical tasks
  - diagnosis
    - abduction: reasoning from effects to causes
  - prognosis
    - predictive models
  - therapy
    - choose actions, in light of diagnosis and prognosis
- Need to choose diagnostic tests makes it more like therapy
- Additional contemporary tasks
  - monitoring
  - prevention
  - public health and epidemiology
  - biomedical research

The Medical Cycle



The Meta-level Cycle

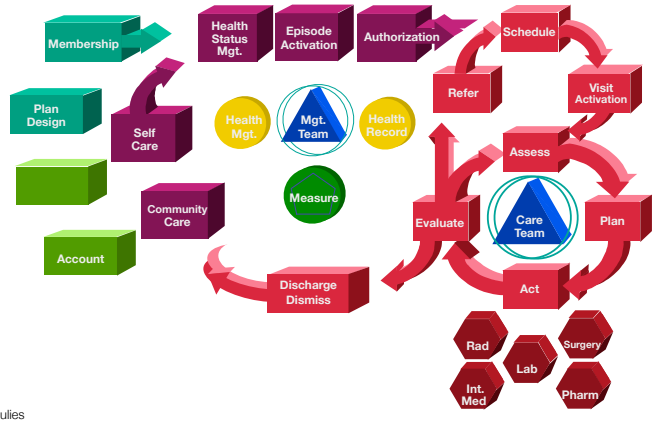
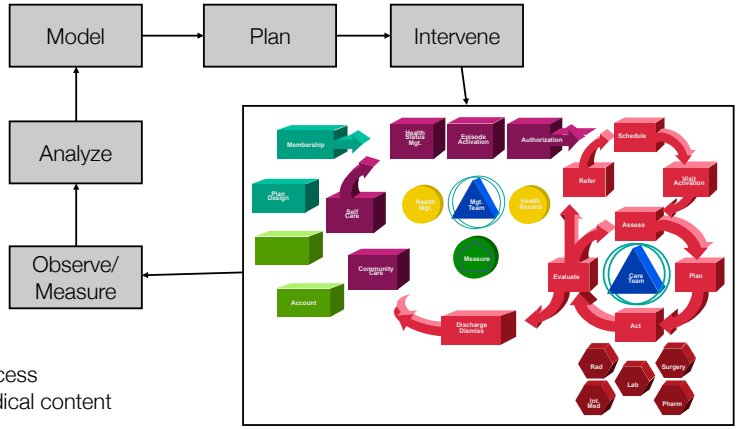


figure from David Margulies

The "Learning Health Care System"



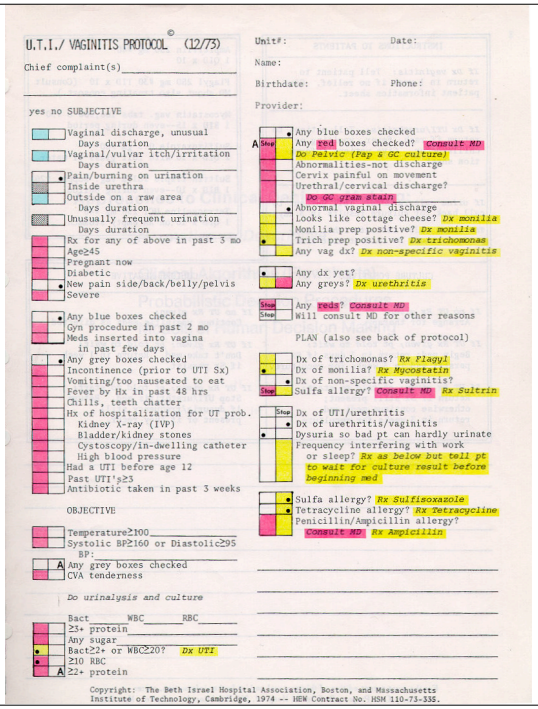
- Process
- Medical content

How can we emulate diagnosis?

- Flowcharts
- Pattern matching
- Rules
- Probabilistic Networks

Flowchart

BI/Lincoln Labs
Clinical Protocols
1978


U.T.I./ VAGINITIS PROTOCOL (12/73)

Chief complaint(s)

yes no SUBJECTIVE

Vaginal discharge, unusual
Days duration
Vaginal/vulvar itch/irritation
Days duration
Pain/burning on urination
Inside urethra
Outside on a raw area
Days duration
Unusually frequent urination
Days duration
Rx for any of above in past 3 mo
Age≥45
Pregnant now
Diabetic
New pain side/back/belly/pelvis
Severe
Any blue boxes checked
Gyn procedure in past 2 mo
Meds inserted into vagina in past few days
Any grey boxes checked
Incontinence (prior to UTI Sx)
Vomiting/too nauseated to eat
Fever by Hx in past 48 hrs
Chills, teeth chatter
Hx of hospitalization for UT prob.
Kidney X-ray (IVP)
Bladder/kidney stones
Cystoscopy/in-dwelling catheter
High blood pressure
Had a UTI before age 12
Past UTI's≥3
Antibiotic taken in past 3 weeks

OBJECTIVE

Temperature≥100
Systolic BP≥160 or Diastolic≥95
BP:
Any grey boxes checked
CVA tenderness

Do urinalysis and culture

Bact WBC RBC
≥3+ protein
Any sugar
Bact≥2+ or WBC≥20? *Dx UTI*
≥10 RBC
≥2+ protein

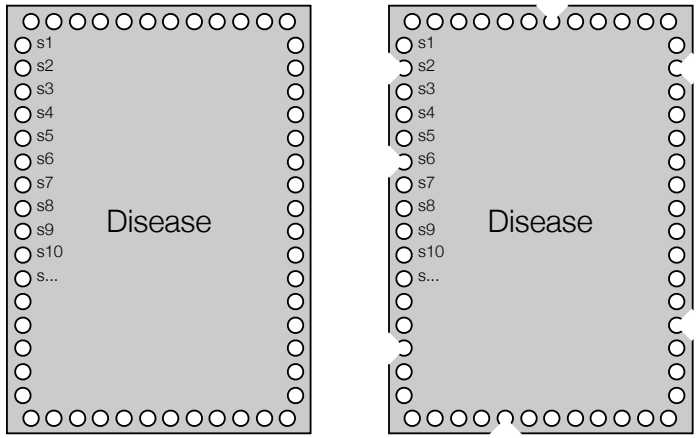
Unit#: Date:
Name:
Birthdate: Phone:
Provider:

Any blue boxes checked
Any red boxes checked? *Consult MD*
Do Pelvic (Pap & GC culture)
Abnormalities-not discharge
Cervix painful on movement
Urethral/cervical discharge?
Do GC gram stain
Abnormal vaginal discharge
Looks like cottage cheese? *Dx monilia*
Monilia prep positive? *Dx monilia*
Trich prep positive? *Dx trichomonas*
Any vag dx? *Dx non-specific vaginitis*
Any dx yet?
Any greys? *Dx urethritis*
Any reds? *Consult MD*
Will consult MD for other reasons

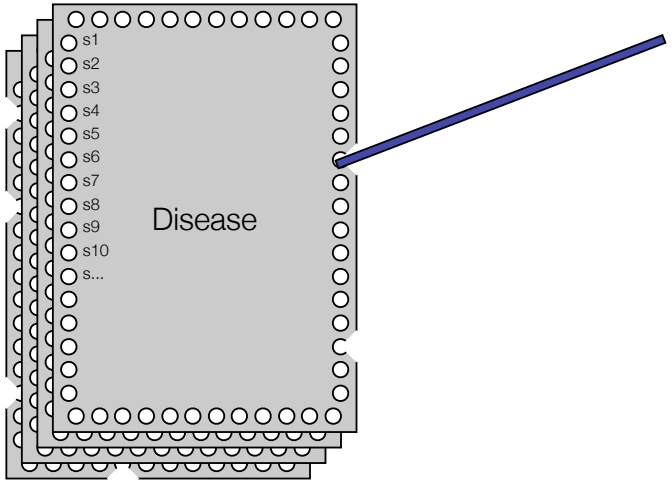
PLAN (also see back of protocol)

Dx of trichomonas? *Rx Flagyl*
Dx of monilia? *Rx Mycostatin*
Dx of non-specific vaginitis?
Sulfa allergy? *Consult MD* *Rx Sultrin*
Dx of UTI/urethritis
Dx of urethritis/vaginitis
Dysuria so bad pt can hardly urinate
Frequency interfering with work or sleep? *Rx as below but tell pt to wait for culture result before beginning med*
Sulfa allergy? *Rx Sulfisoxazole*
Tetracycline allergy? *Rx Tetracycline*
Penicillin/Ampicillin allergy?
Consult MD *Rx Ampicillin*

Simple Representation of Disease/Symptom Associations



Diagnosis by Card Selection

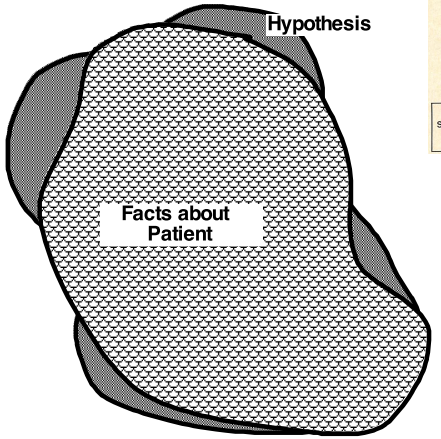


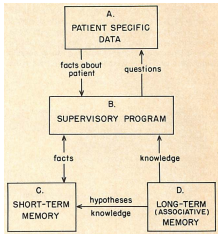
Diagnosis by Edge-Punched Cards

- Dx is intersection of sets of diseases that *may cause* all the observed symptoms
- Difficulties:
  - Uncertainty
  - Multiple diseases

~ "Problem-Knowledge Coupler" of Weed

Taking the Present Illness: Diagnosis by Pattern Directed Matching



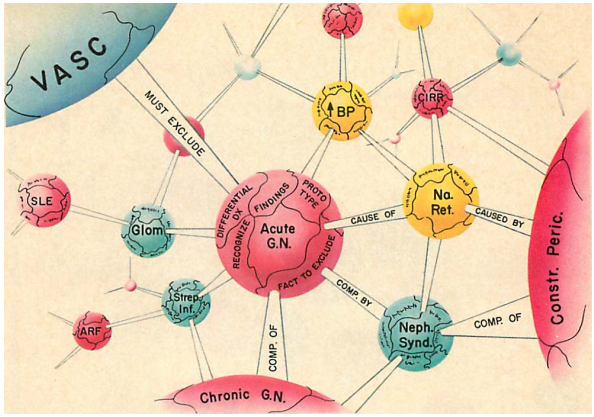


PIP's Theory of Diagnosis

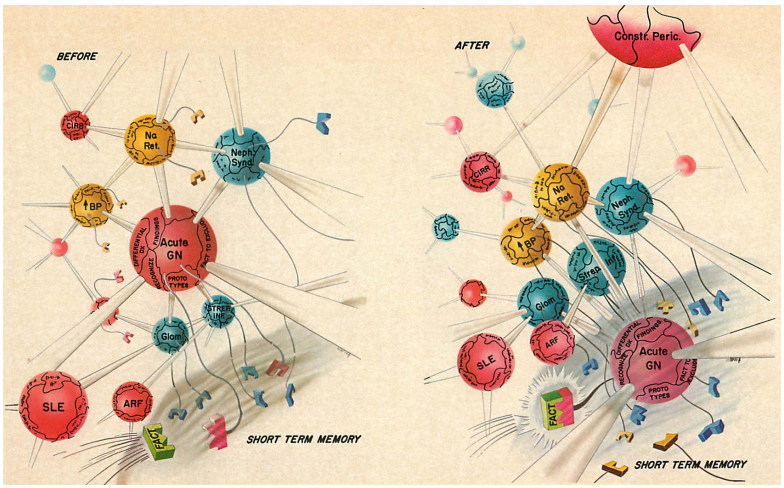
- **From initial complaints, *guess* suitable hypothesis.**
- **Use current active hypotheses to guide questioning**
- **Failure to satisfy expectations is the strongest clue to a better hypothesis; *differential diagnosis***
- **Hypotheses are *activated, de-activated, confirmed* or *rejected* based on**
  - **(1) logical criteria**
  - **(2) probabilities based on:**
    - **findings local to hypothesis**
    - **causal relations to other hypotheses**

The Scientific Method

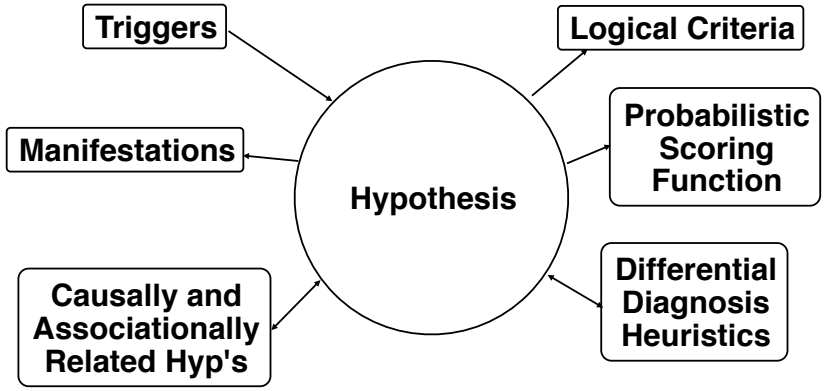
The Long-Term Memory:
Medical Knowledge of Diseases and Symptoms



The Short-Term Memory
Hypotheses about the Patient



Memory Structure in PIP



PIP's Model of Nephrotic Syndrome

NEPHROTIC SYNDROME, *a clinical state*
FINDINGS:
1* Low serum albumin concentration
2. Heavy proteinuria
3* >5 gm/day proteinuria
4* Massive symmetrical edema
5* Facial or peri-orbital symmetric edema
6. High serum cholesterol
7. Urine lipids present
IS-SUFFICIENT: **Massive pedal edema & >5 gm/day proteinuria**
MUST-NOT-HAVE: **Proteinuria absent**
SCORING . . .
MAY-BE-CAUSED-BY: **AGN, CGN, nephrotoxic drugs, insect bite, idiopathic nephrotic syndrome, lupus, diabetes mellitus**
MAY-BE-COMPLICATED-BY: **hypovolemia, cellulitis**
MAY-BE-CAUSE-OF: **sodium retention**
DIFFERENTIAL DIAGNOSIS:
neck veins elevated ➠ constrictive pericarditis
ascites present ➠ cirrhosis
pulmonary emboli present ➠ renal vein thrombosis

A Case of a Middle-Aged Woman with Pedal Edema (swollen feet)

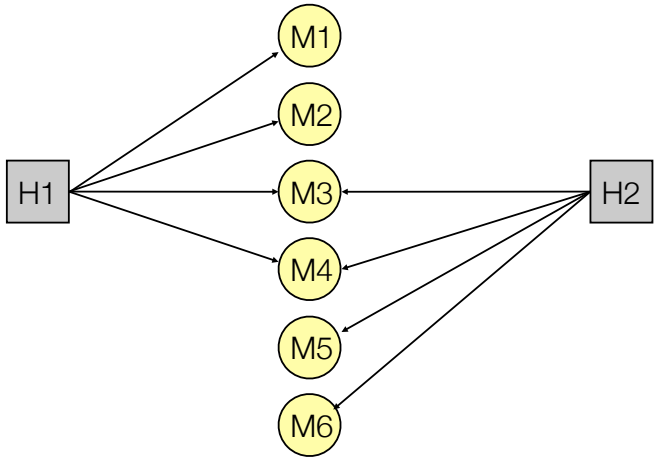
- PRESENTING PROBLEM: A MIDDLE AGED WOMAN WITH PEDAL EDEMA.
- THE CASE CAN BE SUMMARIZED AS FOLLOWS:
  - THIS IS A MIDDLE-AGED WOMAN, WHO HAS PEDAL EDEMA, WHICH IS NOT-PAINFUL, NOT-ERYTHEMATOUS, PITTING, SYMMETRICAL. 4+, WITHOUT-TEMPORAL-PATTERN, OCCASIONAL AND FOR-WEEKS. SHE DOES NOT HAVE DYSPNEA. SHE HAS HEAVY ALCOHOL CONSUMPTION. SHE HAS JAUNDICE. SHE HAS PAINFUL HEPATOMEGALY. SHE HAS SPLENOMEGALY. SHE HAS ASCITES. SHE HAS PALMAR ERYTHEMA. SHE HAS SPIDER ANGIOMATA. SHE DOES NOT HAVE PAROTID ENLARGEMENT. SHE HAS MODERATELY-ELEVATED. DIRECT-AND-INDIRECT BILIRUBIN. SHE HAS PROLONGED PROTHROMBIN TIME. SHE HAS MODERATELY-ELEVATED SGPT. SHE HAS MODERATELY-ELEVATED SGOT. SHE HAS MODERATELY-ELEVATED LDH. SHE HAS NOT-RECEIVED BLOOD TRANSFUSIONS. SHE HAS NOT-EATEN CLAMS. SHE DOES NOT HAVE ANOREXIA. SHE HAS MELENA. SHE DOES NOT HAVE HEMATEMESIS. SHE HAS LOW SERUM IRON. SHE HAS ESOPHAGEAL VARICES.
- DIAGNOSES THAT HAVE BEEN ACCEPTED ARE: ALCOHOLISM AND GI BLEEDING.
- THE LEADING HYPOTHESIS IS CIRRHOSIS.

Case, continued

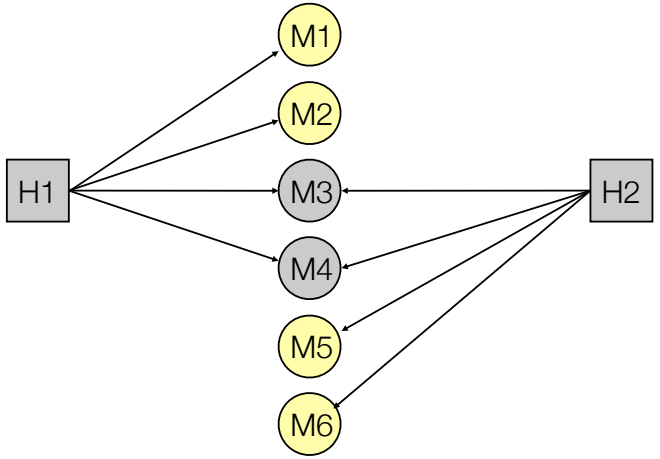
- HYPOTHESES BEING CONSIDERED:

Hypothesis	fit of case to hypothesis	fraction of finding explained	average score
CIRRHOSIS	0.72	0.78	0.75
HEPATITIS PORTAL	0.75	0.30	0.53
HYPERTENSION	0.72	0.17	0.45
CONSTRICTIVE PERICARDITIS	0.17	0.13	0.15

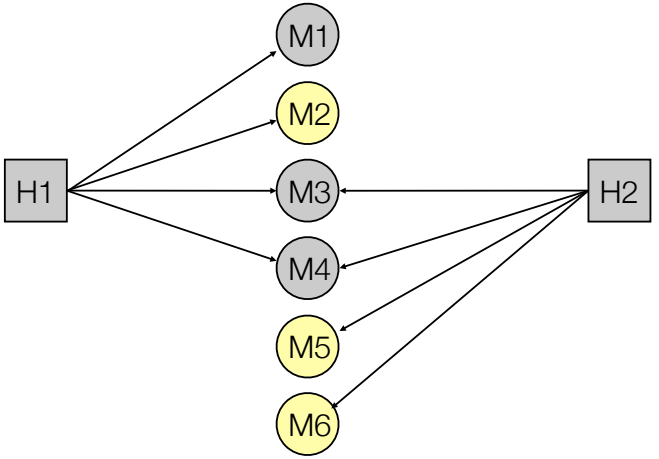
QMR Partitioning



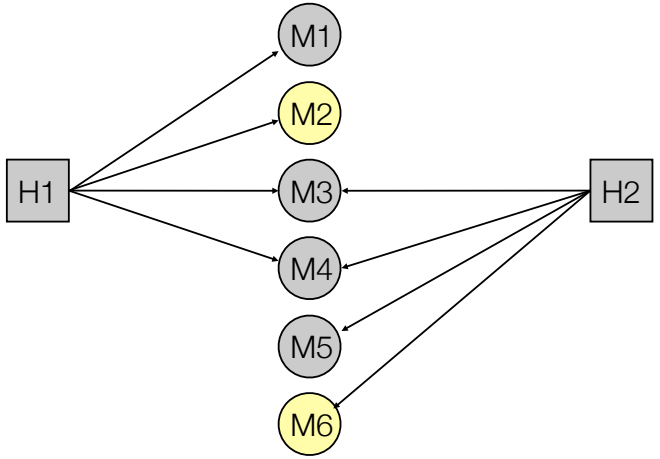
Competitors



Still Competitors



Probably Complementary



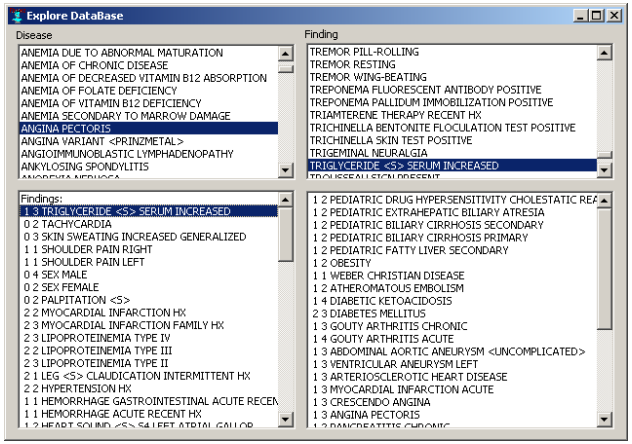
Multi-Hypothesis Diagnosis

- Set aside complementary hypotheses
- … and manifestations predicted by them
- Solve diagnostic problem among competitors
- Eliminate confirmed hypotheses and manifestations explained by them
- Repeat as long as there are coherent problems among the remaining data

Internist/QMR

- Knowledge Base:
  - 956 hypotheses
  - 4090 manifestations (about 75/hypothesis)
  - *Evocation* like P(H|M)
  - *Frequency* like P(M|H)
  - *Importance* of each M
  - *Causal relations* between H's
- Diagnostic Strategy:
  - Scoring function
  - Partitioning
  - Several questioning strategies

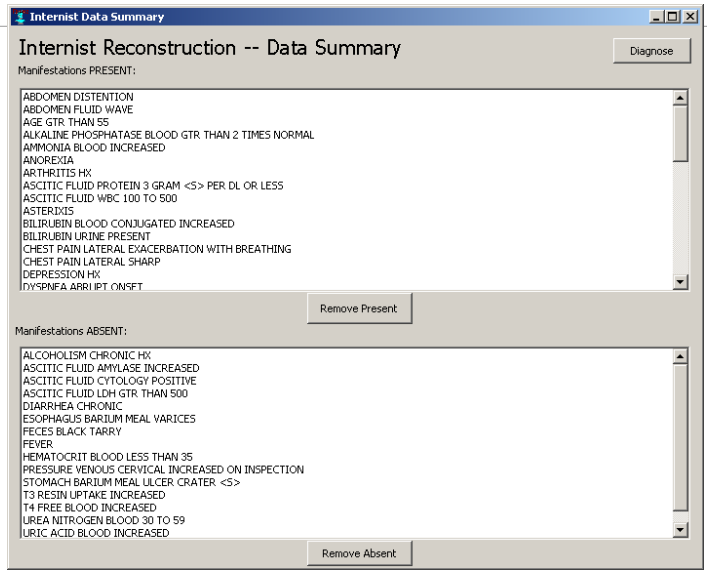
QMR Database



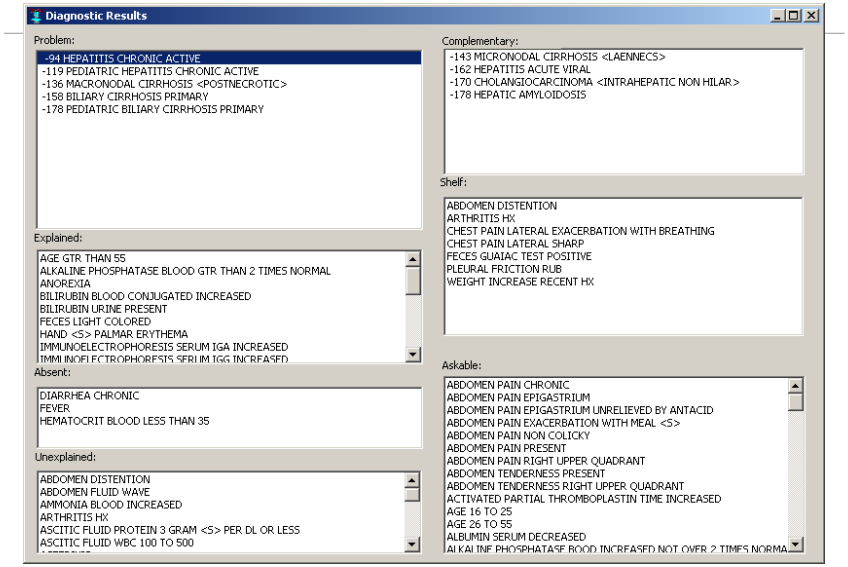
QMR Scoring

- Positive Factors
  - Evoking strength of observed Manifestations
  - Scaled Frequency of causal links from confirmed Hypotheses
- Negative Factors
  - Frequency of predicted but absent Manifestations
  - Importance of unexplained Manifestations
- Various scaling parameters (roughly exponential)

Example Case



Initial Solution



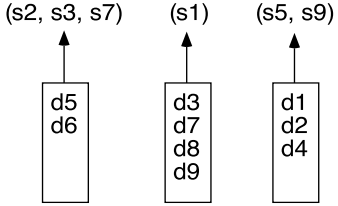
Symptom Clustering for Multi-Disorder Diagnosis

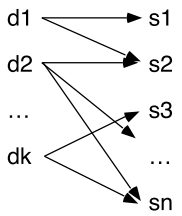
— Tom Wu, Ph.D. 1991

Assume a bipartite graph representation of diseases/symptoms

Given a set of symptoms, how to proceed?

If we could "guess" an appropriate clustering of the symptoms so that each cluster has a single cause …





… then the solution is (d5, d6) x (d3, d7, d8, d9) x (d1, d2, d4)

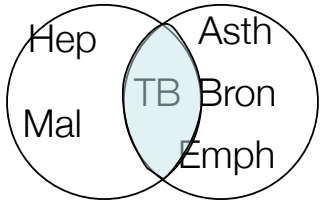
Clustering Alternatives

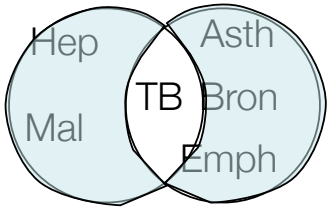
Symptom	Possible Causes
Fever	TB, Hepatitis, Malaria
Cough	TB, Asthma, Bronchitis, Emphysema

H1 H2

Fever, Cough
TB

Fever	Cough
Hep Mal	Asth Bron Emph





Synopsis in Renal Disease

- Diseases
  - Hypertension (HTN)
  - Acute glomerulonephritis (AGN)
  - IgA nephropathy (IgA)
  - Prerenal azotemia (PRA)
  - Hepatorenal syndrome (HRS)
  - Renal vasculitis (RV)
  - Congestive heart failure (CHF)
  - Aldosteronism (Aldo)
  - Constrictive pericarditis (Peri)
  - Diabetic ketoacidosis (DKA)
  - Analgesic nephropathy (AN)
  - Hypokalemic nephropathy (HKN)
  - Chronic renal failure (CRF)
  - Renal tubular acidosis (RTA)
- Symptoms
  - High urine osmolality (Osm↑)
  - High urine specific gravity (Sg↑)
  - Low urine sodium (Na↓)
  - Low urine pH (pH↓)

	HTN	AGN	IgA	PRA	HRS	RV	CHF	Aldo	Peri	DKA	AN	HKN	CRF	RTA
Osm↑	X	X	X	X	X	X								
Sg↑	X	X	X	X	X	X	X							
Na↓				X	X		X	X	X					
pH↓		X		X						X	X	X	X	X

After Osm↑

Osm↑
HTN AGN IgA PRA HRS RV

	HTN	AGN	IgA	PRA	HRS	RV	CHF	Aldo	Peri	DKA	AN	HKN	CRF	RTA
Osm↑	X	X	X	X	X	X								
Sg↑	X	X	X	X	X	X	X							
Na↓				X	X		X	X	X					
pH↓		X		X						X	X	X	X	X

Add Sg↑

Cover

Osm↑, Sg↑
HTN AGN IgA PRA HRS RV

	HTN	AGN	IgA	PRA	HRS	RV	CHF	Aldo	Peri	DKA	AN	HKN	CRF	RTA
Osm↑	X	X	X	X	X	X								
Sg↑	X	X	X	X	X	X	X							
Na↓				X	X		X	X	X					
pH↓		X		X						X	X	X	X	X

Add Na↓

Restrict

Osm↑, Sg↑, Na↓
PRA HRS

or

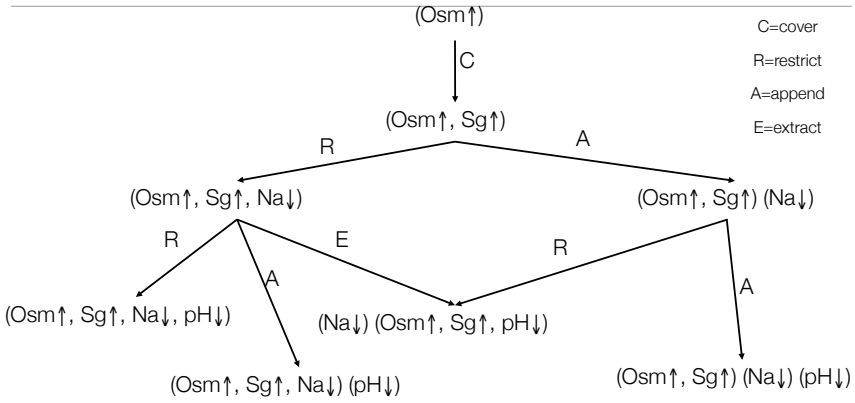
Append

Osm↑, Sg↑
HTN AGN IgA RV

Na↓
Aldo CHF Peri

	HTN	AGN	IgA	PRA	HRS	RV	CHF	Aldo	Peri	DKA	AN	HKN	CRF	RTA
Osm↑	X	X	X	X	X	X								
Sg↑	X	X	X	X	X	X	X							
Na↓				X	X		X	X	X					
pH↓		X		X						X	X	X	X	X

Search Space



	HTN	AGN	IgA	PRA	HRS	RV	CHF	Aldo	Peri	DKA	AN	HKN	CRF	RTA
Osm↑	X	X	X	X	X	X								
Sg↑	X	X	X	X	X	X	X							
Na↓				X	X		X	X	X					
pH↓		X		X						X	X	X	X	X

Symptom Clustering is Efficient

- Like in any "planning island" approach, reducing an exponential problem to several smaller exponential problems vastly improves efficiency, if it captures some insight into the problem.
- Wu's algorithm (SYNOPSIS) will keep a compact encoding even if it overgenerates slightly.
  - E.g., suppose that of the set of diseases represented by (d5, d6) x (d3, d7, d8, d9) x (d1, d2, d4), d6 x d8 x d1 is not a candidate. To represent this precisely would require enumerating the 23 valid candidates. Instead, the factored representation is kept.

In a diagnostic problem drawn from a small subset of the Internist database, it is a power of 3 faster and a power of 5 more compact than standard symptom clustering.

Guide search via probabilities, if we have a reasonable model(!)

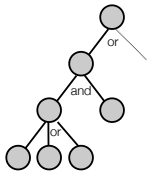
Reasoning Using Rules

- Mycin used *backward chaining* (from conclusions back to facts) with a collection of <1000 rules
  - Domain: bacterial infections
- E.g., RULE037
  - If the organism
    - stains grampos
    - has coccus shape
    - grows in chains
  - Then there is suggestive evidence (.7) that it is streptococcus.

How Mycin Works

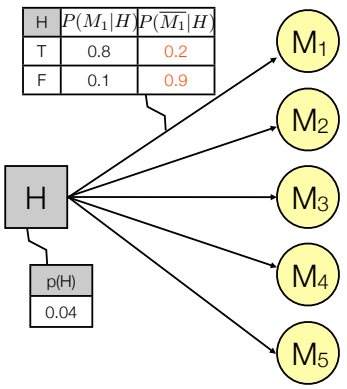
- To find out a fact
  - If there are rules that can conclude it, try them
  - Ask the user
- To "run" a rule
  - Try to find out if the facts in the premises are true
  - If they all are, then assert the conclusion(s), with a suitable certainty
- Backward chaining from goal to given facts

- *Dynamically traces out behavior of (what might be) a flowchart*
- *Information used everywhere appropriate*
- *Single expression of any piece of knowledge*



Probabilistic View

H	$P(M_1\|H)$	$P(\overline{M_1}\|H)$
T	0.8	0.2
F	0.1	0.9



Condition probability:

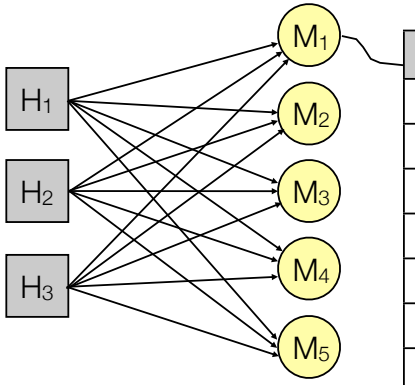
$$P(M|H) = P(M\&H)/P(H)$$

$$P(H|M_1,\ldots,M_5) \propto P(H) \times P(M_1|H) \times \cdots \times P(M_5|H)$$

Naive Bayes or Bayesian Classifier

$$\begin{aligned} O(H) &= P(H)/(1-P(H)) \\ L(M_i|H) &= P(M_i|H)/P(M_i|\overline{H}) \\ O(H|M_1,\ldots,M_5) &= O(H) \times L(M_1|H) \times \cdots \times L(M_5|H) \\ \log O(H|M_1,\ldots,M_5) &= \log O(H) + \log L(M_1|H) + \cdots + \log L(M_5|H) \\ W(H|M_1,\ldots,M_5) &= W(H) + W(M_1|H) + \cdots + W(M_5|H) \end{aligned}$$

Bipartite Graph with Probabilities

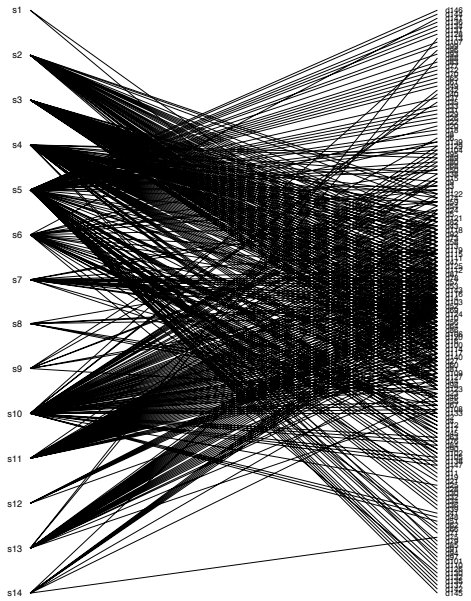


H_1	H_2	H_3	P(M1| H1,H2,H3)	P(¬M1| H1,H2,H3)
F	F	F	0.001	0.999
F	F	T	0.01	0.99
F	T	F	0.007	0.993
F	T	T	0.2	0.8
T	F	F	0.1	0.9
T	F	T	0.15	0.85
T	T	F	0.2	0.8
T	T	T	0.7	0.3

- Bayesian Network
- Computation cost exponential in number of "loops"

A Realistic Bipartite Graph

- Symptoms of prerenal azotemia, and their alternative causes (Tom Wu PhD 1992)



What to do with Tons of Data?

- Partners Healthcare has ~4M records of previously-treated patients
- Mayo Clinic has ~60M discharge summaries
- We have 30K detailed records on patients in the ICU (Intensive Care Unit)
- Surely, these must be useful for ***something***!
- $State_k(patient_i)=f_k(features_{patient_i})$
  - We can learn f_k from data
  - Use it to predict $State_k$ for future patients
- What are useful $State_k$?
  - Death
  - Specific diseases
  - Effectiveness of particular therapies
  - Optimal timing of various interventions
  - ...

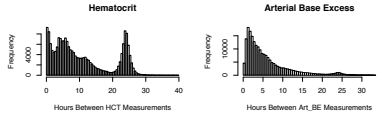
Using MIMIC data to build predictive models

- Mortality
  - Comparison to SAPS II
  - Stationary Daily Acuity Score
  - Daily Acuity Scores (one for each day *n* of ICU stay)
  - Real-time Acuity Scores
- Secondary Outcomes
  - Weaning from Vasopressors
  - Weaning from Intraortic Balloon Pump
  - Onset of Septic Shock
  - Acute Kidney Injury
  - Weaning from Mechanical Ventilator
  - Tracheotomy Insertion
  - First response to Vasopressor Reduction

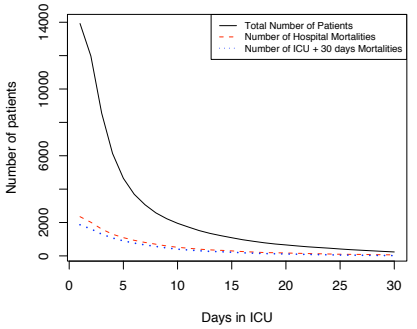
Caleb Hug, PhD 2009
http://dspace.mit.edu/handle/1721.1/46690

Cleaning the data—half the research time

- Missing values
  - Some values are not measured for some clinical situations
  - Failures in data capture process
- Episodically measured variables
- Unclear/undefined clinical states
- Imprecise timing of meds, ...
- Partially measured i/o
- Proxies: e.g., which ICU⇒what disease
- Derived variables: integrals, slopes, ranges, frequencies, etc.
- Transformed variables: square root, log, etc.
- Select subset of data with enough data!



Outcomes



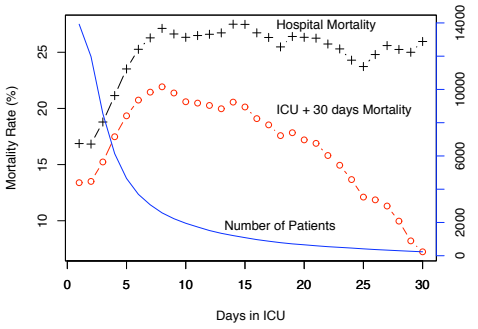


Table 3.15: Preprocessed Data

Number of Patients	10,066
Number of Rows	1,044,982
Number of Features	438

SAPS II

Table 4.1: SAPS II Variables

Variable	Max Points
Age	18
Heart rate	11
Systolic BP	13
Body temperature	3
PaO2:FiO2 (if ventilated or continuous positive airway pressure)	11
Urinary output	11
Serum urea nitrogen level	10
WBC count	12
Serum potassium	3
Serum sodium level	5
Serum bicarbonate level	6
Bilirubin level	9
Glasgow Coma Score[a]	26
Chronic diseases	17
Type of admission	8

[a]If the patient is sedated, the estimated GCS prior to sedation

Many univariate analyses

Model 5.1 SDAS Model for Fold 2 with 30 Covariates

Obs	Max Deriv	Model L.R.	d.f.	P	C	Dxy
20172	1e-09	5415.11	30	0	0.893	0.785
Gamma	Tau-a	R2	Brier			
0.787	0.176	0.439	0.076			

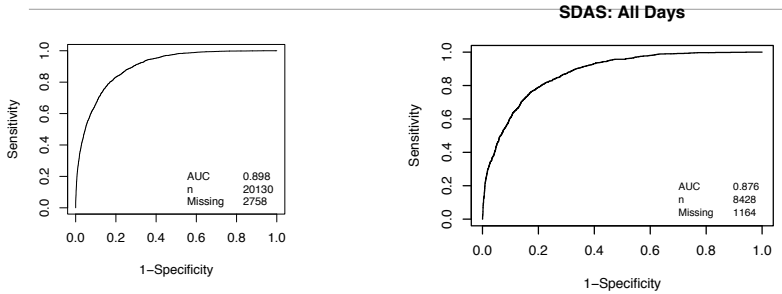
	Coef	S.E.	Wald Z	P
INR_mean_i	-1.795e+00	1.423e-01	-12.61	0.0000
GCS_max_sq	-7.485e-03	6.000e-04	-12.47	0.0000
OutputB_60_mean_sqrt	-6.561e-02	6.885e-03	-9.53	0.0000
pacemkr_max	-1.084e+00	1.183e-01	-9.16	0.0000
svCSRU_max	-9.516e-01	1.208e-01	-7.88	0.0000
GCSrdv_mean	-1.138e-01	1.528e-02	-7.45	0.0000
pressD01_mean_am	-2.774e+00	3.893e-01	-7.13	0.0000
Platelets_Slope_1680_min	-5.493e+00	8.615e-01	-6.38	0.0000
pressD01_sd_sq	-5.085e+00	8.678e-01	-5.86	0.0000
sedatives_mean_sq	-4.375e-01	8.455e-02	-5.17	0.0000
Bal24_max	-4.493e-05	1.222e-05	-3.68	0.0002
CV_HRrng_max	-3.267e-03	1.083e-03	-3.02	0.0026
Intercept	4.292e-01	4.085e-01	1.05	0.2934
Milrinone_perKg_min_sq	3.523e+00	1.113e+00	3.17	0.0015
LOSBal_max	2.247e-05	5.703e-06	3.94	0.0001
hrmVA_max	3.410e-01	6.767e-02	5.04	0.0000
MBPm.pr_min_am	1.904e+00	3.711e-01	5.13	0.0000
Mg_min_sq	1.067e-01	1.798e-02	5.93	0.0000
beta.Blocking_agent_mean_lam	2.418e-01	3.955e-02	6.11	0.0000
Na_mean_am	5.214e-02	8.415e-03	6.20	0.0000
mechVent_mean_sq	7.183e-01	1.047e-01	6.86	0.0000
RESP_mean_sq	9.226e-04	1.293e-04	7.13	0.0000
Platelets_mean_i	2.512e+01	3.512e+00	7.15	0.0000
Lasix_max_lam	2.550e-01	3.457e-02	7.38	0.0000
CO2_mean_i	2.038e+01	2.741e+00	7.43	0.0000
jaundiceSkin_mean_la	1.523e-01	2.014e-02	7.56	0.0000
hospTime_min_sqrt	6.860e-03	7.939e-04	8.64	0.0000
pressorSum.std_mean_sqrt	7.758e-01	7.225e-02	10.74	0.0000
SpO2.oor30.t_mean_sqrt	4.929e-01	4.095e-02	12.04	0.0000
BUNtoCr_min_sqrt	2.867e-01	2.323e-02	12.34	0.0000
Age_min_sq	2.258e-04	1.450e-05	15.57	0.0000

Model 5.2 Final SDAS model

Obs	Max Deriv	Model L.R.	d.f.	P	C	Dxy
20130	3e-10	5619.28	35	0	0.898	0.797
Gamma	Tau-a	R2	Brier			
0.798	0.177	0.456	0.074			

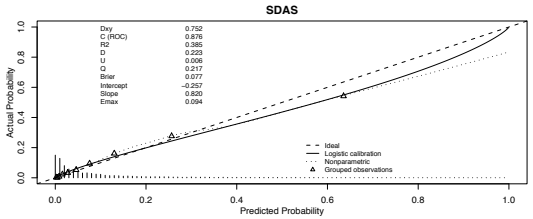
	Coef	S.E.	Wald Z	P
GCS_max_sq	-0.0064668	5.032e-04	-12.85	0.0000
INR_mean_i	-1.8734049	1.458e-01	-12.85	0.0000
pacemkr_max	-0.9337190	1.179e-01	-7.92	0.0000
svCSRU_max	-0.9137522	1.250e-01	-7.31	0.0000
RikerSAS_mean	-0.3430971	5.151e-02	-6.66	0.0000
Platelets_Slope_1680_min	-5.8856843	8.839e-01	-6.66	0.0000
urineByHr_mean_sqrt	-0.0584113	9.453e-03	-6.18	0.0000
GCSrdv_mean	-0.0902717	1.552e-02	-5.82	0.0000
GCSrng_min_am	-0.0812232	1.459e-02	-5.57	0.0000
pressD01_mean_am	-1.6132643	3.005e-01	-5.37	0.0000
CV_HRrng_max	-0.0061979	1.216e-03	-5.10	0.0000
Insulin_sd_sq	-2.1686950	4.372e-01	-4.96	0.0000
alloutput_max_la	-0.0890330	2.265e-02	-3.93	0.0001
MetCarcinoma_min	0.4468763	1.567e-01	2.85	0.0043
WBC_mean_am	0.0147036	5.149e-03	2.86	0.0043
AIDS_min	0.5954305	1.991e-01	2.99	0.0028
Intercept	1.5314512	4.529e-01	3.38	0.0007
MBPm.pr_min_am	1.4601630	3.518e-01	4.15	0.0000
HemMalig_min	0.6032027	1.212e-01	4.98	0.0000
RESP_mean_sq	0.0006615	1.324e-04	5.00	0.0000
hrmVA_max	0.3520834	6.823e-02	5.16	0.0000
PaO2toFiO2_mean	0.2672376	4.336e-02	6.16	0.0000
Na_mean_am	0.0549066	8.506e-03	6.45	0.0000
Mg_min_sq	0.1173220	1.815e-02	6.46	0.0000
ShockIdx_max	0.5742182	8.853e-02	6.49	0.0000
Platelets_mean_i	24.0719462	3.560e+00	6.76	0.0000
hospTime_min_sqrt	0.0057514	8.158e-04	7.05	0.0000
day_min_sq	0.0170075	2.372e-03	7.17	0.0000
jaundiceSkin_mean_la	0.1469141	2.045e-02	7.18	0.0000
CO2_mean_i	19.3845272	2.682e+00	7.23	0.0000
Lasix_max_lam	0.2523702	3.444e-02	7.33	0.0000
beta.Blocking_agent_mean_lam	0.2918077	3.923e-02	7.44	0.0000
Sympathomimetic_agent_min	0.8576883	9.254e-02	9.27	0.0000
SpO2.oor30.t_mean_sqrt	0.4059329	4.128e-02	9.83	0.0000
BUNtoCr_min_sqrt	0.2829088	2.348e-02	12.05	0.0000
Age_min_sq	0.0002601	1.495e-05	17.40	0.0000

Evaluating the models

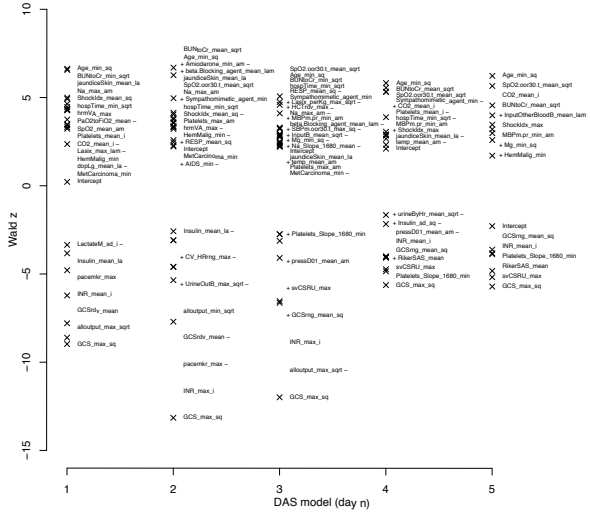


Devel

Validation



Selected features for each day of ICU stay



Evaluation of Survival Models

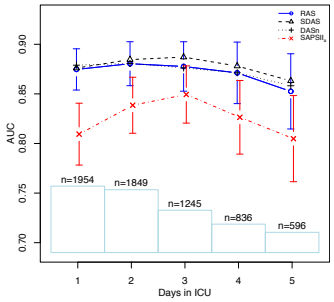


Figure 5-25: AUC versus day, first 5 ICU days (validation data). The 95% confidence intervals are shown for the RAS and SAPSII$_\alpha$ performances.

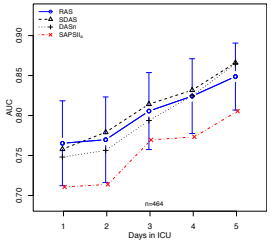


Figure 5-27: AUC versus day, patients with ICU stays $\geq$ 5 days (validation data). The 95% confidence intervals are shown for the RAS performances.

"There's Gold in Them Thar Hills"

- Federal investment of ~$45B in healthcare IT
- Strong pressures to make healthcare more efficient