Hasso Plattner Institut
IT Systems Engineering | Universität Potsdam

Clinical decision support system for acute kidney injury

Bastien Grasnick, Henriette Dinger

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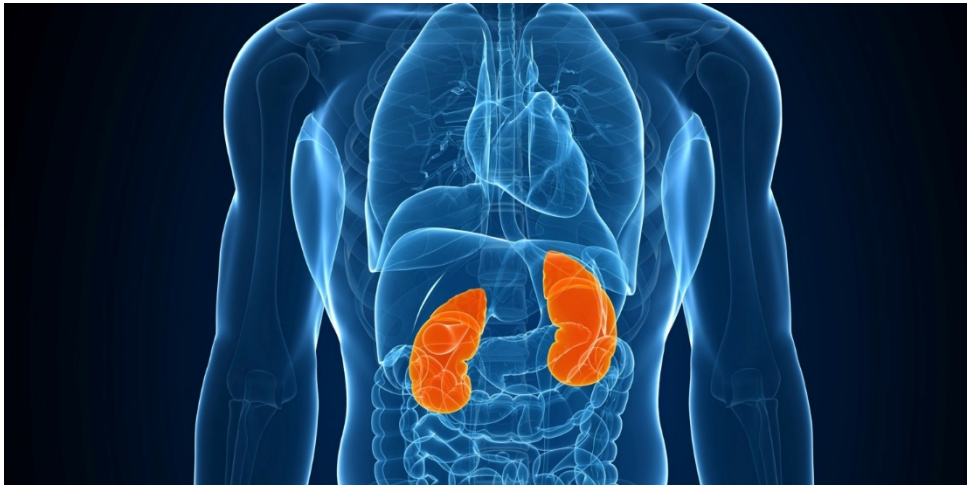
Outline

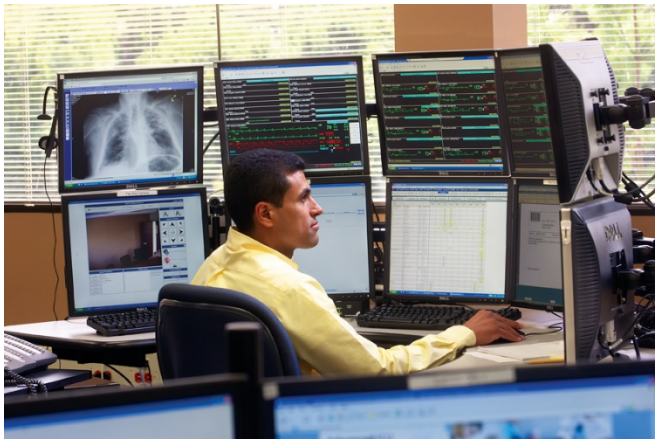
1. Background
2. Goal
3. Technology
4. Solution
5. Results
6. Further steps
7. Discussion



Background

Background
Problem

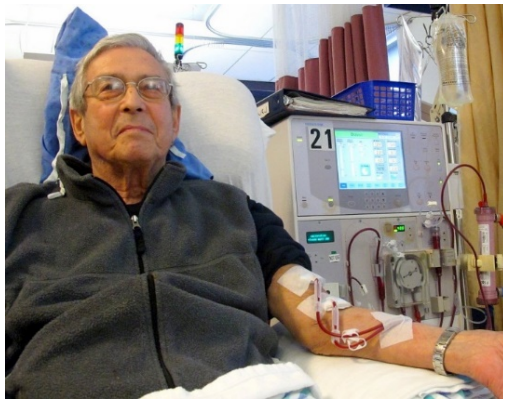
- Acute kidney injury (AKI):
  - Mostly asymptomatic
  - High risk of death
  - No trivial treatment



- Continuous monitoring of creatinine values required
  - High amount of data

Background
Significance

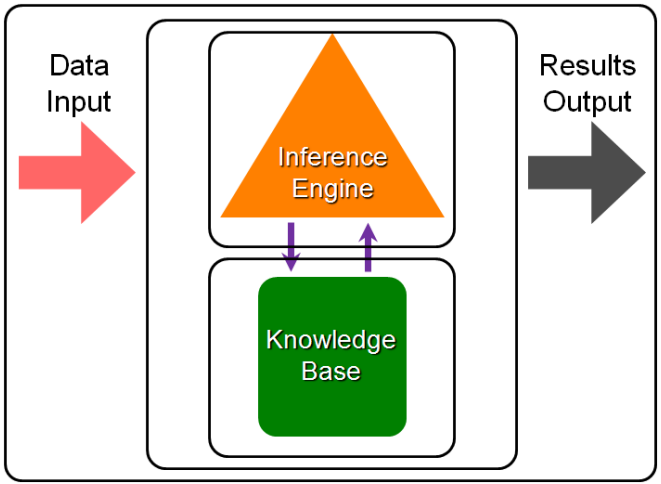
- Currently in Germany
  - 70.000 patients / 2,5 Mio. EUR p.a.
  - 100.000 patients by 2020
- High risk of mortality
- Very high medical costs for dialysis



Background
Clinical Decision Support System (CDSS)

"Clinical decision support systems (CDSS) provide clinicians, staff, patients, and other individuals with **knowledge** and **person-specific information**, intelligently filtered and presented at **appropriate times**, to enhance health and health care"

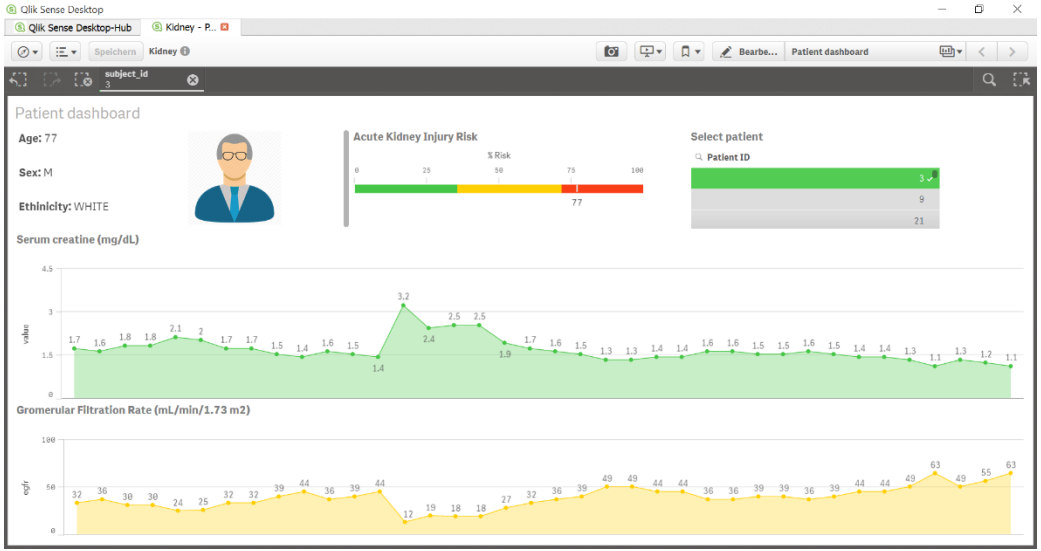
Berner (2009)



Goal

Goal

- Develop a proof of concept in form of a Bayesian network for the identification of AKI for future use in a clinical decision support system

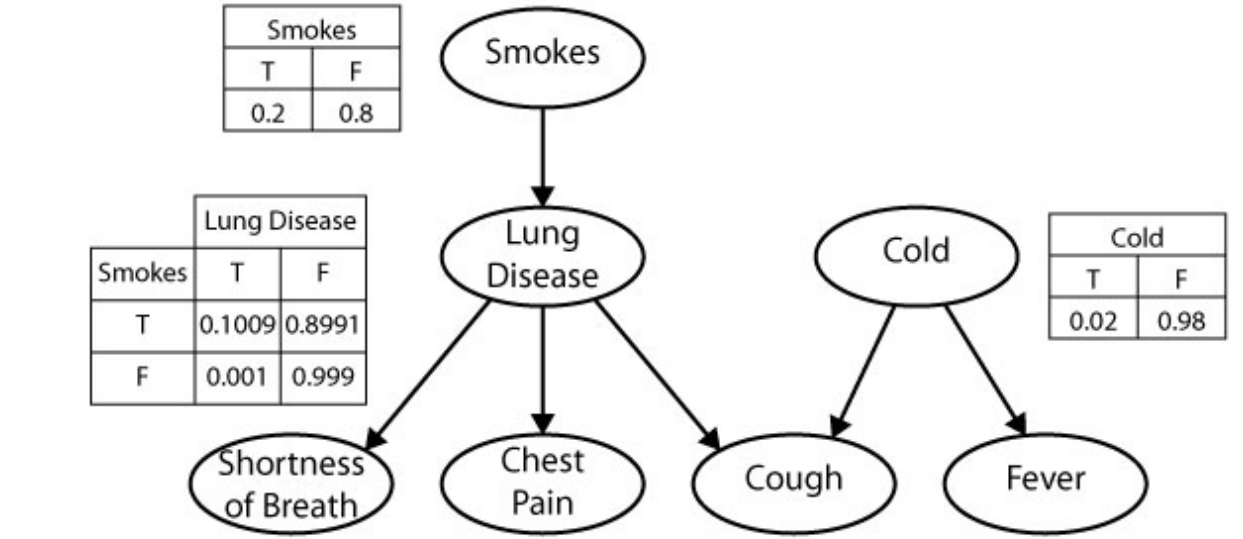


Technology

Bayesian Networks

- Directed acyclic graph representing multiple random variables and their conditional dependencies as probability functions

Bayesian Networks



Smokes	
T	F
0.2	0.8

	Lung Disease	
Smokes	T	F
T	0.1009	0.8991
F	0.001	0.999

Cold	
T	F
0.02	0.98

	Shortness of Breath	
Lung Disease	T	F
T	0.208	0.792
F	0.01	0.99

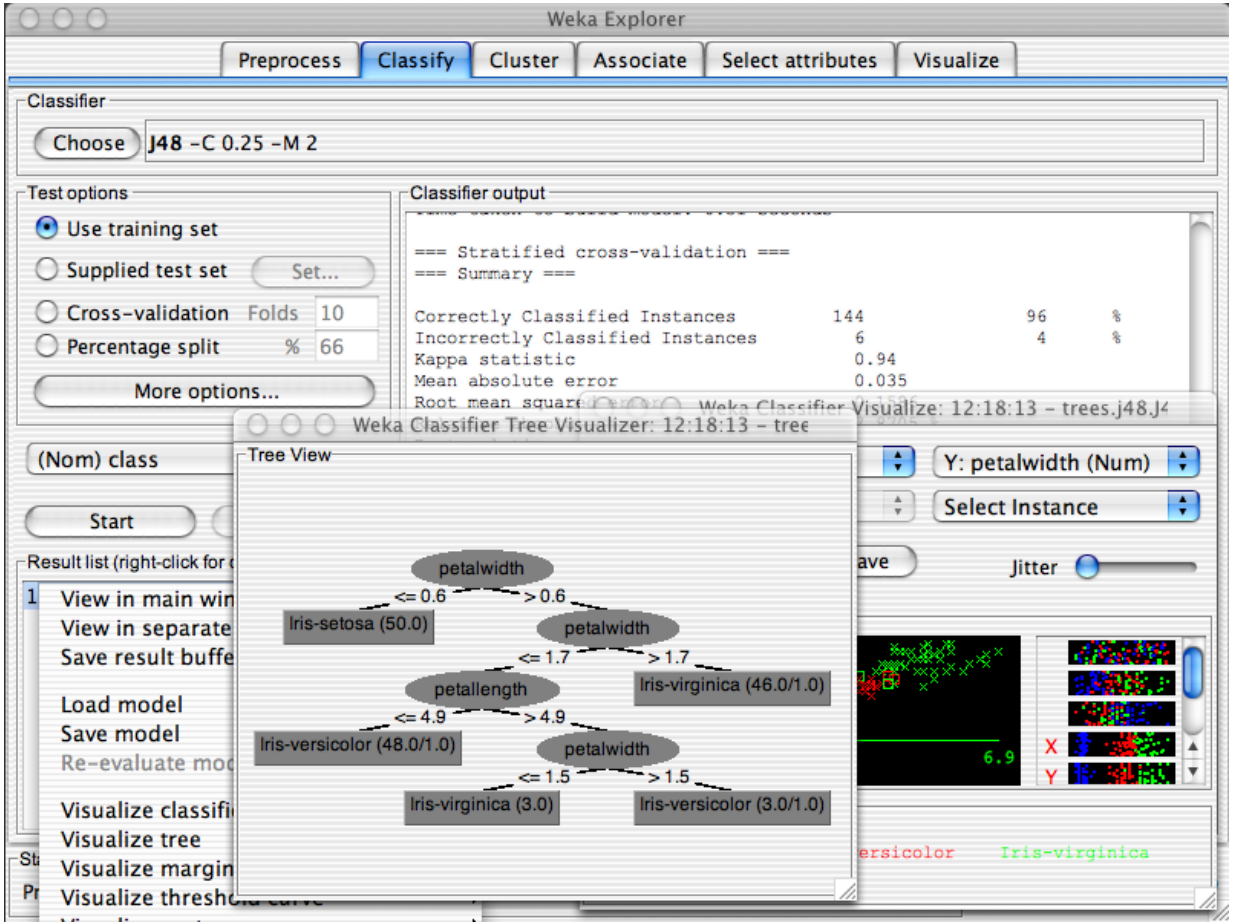
	Chest Pain	
Lung Disease	T	F
T	0.208	0.792
F	0.01	0.99

		Cough	
Lung Disease	Cold	T	F
T	T	0.7525	0.2475
T	F	0.505	0.495
F	T	0.505	0.495
F	F	0.01	0.99

	Fever	
Cold	T	F
T	0.307	0.693
F	0.01	0.99

[1] http://research.microsoft.com/apps/pubs/?id=69588

Tools
Weka


Weka Explorer
Preprocess
Classify
Cluster
Associate
Select attributes
Visualize
Classifier
Choose
J48 -C 0.25 -M 2
Test options
Use training set
Supplied test set
Set...
Cross-validation
Folds
10
Percentage split
%
66
More options...
Classifier output
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=== Summary ===
Correctly Classified Instances 144 96 %
Incorrectly Classified Instances 6 4 %
Kappa statistic 0.94
Mean absolute error 0.035
Weka Classifier Tree Visualizer: 12:18:13 - tree
Tree View
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> 0.6
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petalwidth
<= 1.7
> 1.7
petallength
Iris-virginica (46.0/1.0)
<= 4.9
> 4.9
Iris-versicolor (48.0/1.0)
petalwidth
<= 1.5
> 1.5
Iris-virginica (3.0)
Iris-versicolor (3.0/1.0)
(Nom) class
Y: petalwidth (Num)
Start
Select Instance
Jitter
Result list (right-click for
View in main win
View in separate
Save result buffe
Load model
Save model
Visualize tree
Visualize margin
Iris-virginica

Tools
GeNIe & SMILE

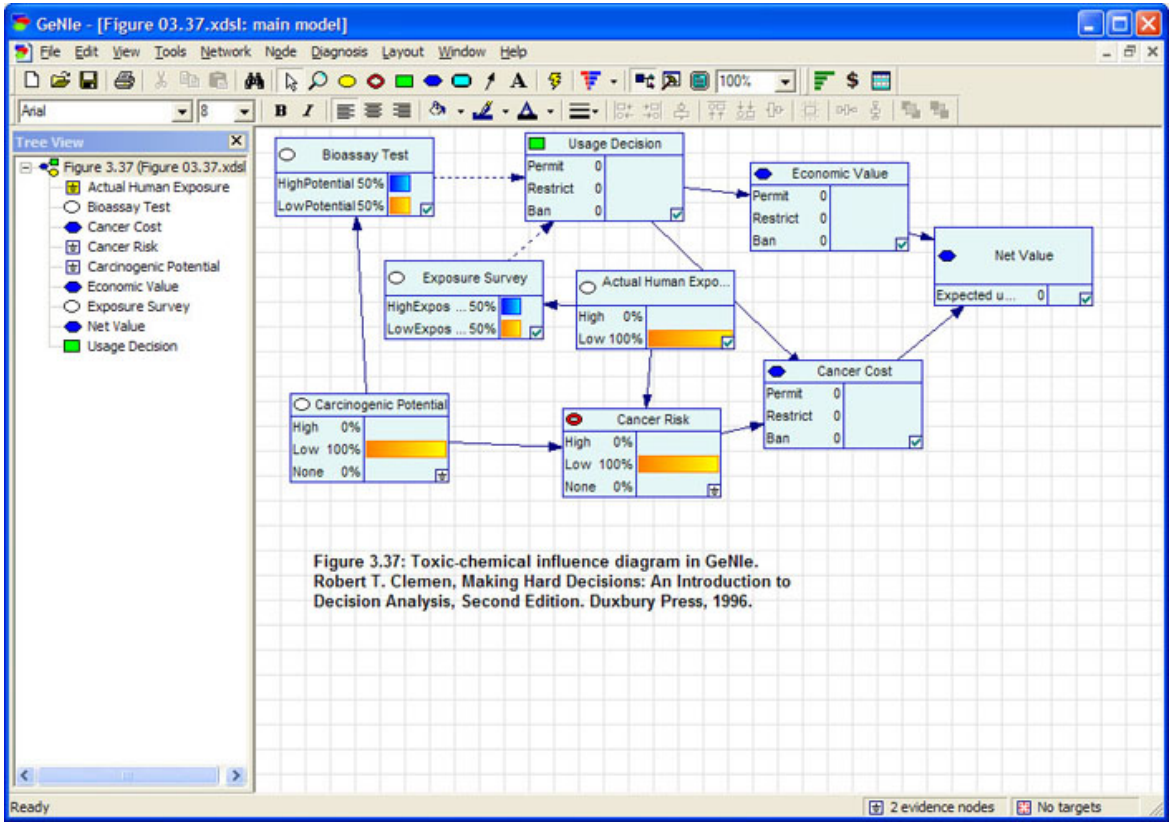

Figure 3.37: Toxic-chemical influence diagram in GeNIe. Robert T. Clemen, Making Hard Decisions: An Introduction to Decision Analysis, Second Edition. Duxbury Press, 1996.

Solution


Literature
Data
Model development
Expert consultation
Model improvement

Risk factors for AKI

- Many factors have an influence on AKI
  - Comorbidities, genetic predispositions, dehydration, demographic characteristics …
- Diagnosis with the help of analysis of urine output and/or serum creatinine
- Two main guidelines for the categorization of kidney injuries:
  - RIFLE & AKIN
  - AKIN is newer, thus more widespread

Data from MIMIC Database

- (Anonymized) Multiparameter Intelligent Monitoring in Intensive Care Database from PhysioNet contains:
  - Indications (code 584.9 for AKI)
  - Demographics
  - Lab results (most importantly creatinine values from blood/urine samples)
  - Comorbidities
  - (Medication)

Data from MIMIC Database

SELECT ICD9.SUBJECT_ID, D_PATIENTS.SEX, D_PATIENTS.DOB, D_PATIENTS.DOD, DEMOGRAPHIC_DETAIL.MARITAL_STATUS_DESCR, DEMOGRAPHIC_DETAIL.ETHNICITY_DESCR, DEMOGRAPHIC_DETAIL.OVERALL_PAYOR_GROUP_DESCR, DEMOGRAPHIC_DETAIL.RELIGION_DESCR, DEMOGRAPHIC_DETAIL.ADMISSION_TYPE_DESCR, DEMOGRAPHIC_DETAIL.ADMISSION_SOURCE_DESCR, MICROBIOLOGYEVENTS.DILUTION_AMOUNT, MICROBIOLOGYEVENTS.DILUTION_COMPARISON, MICROBIOLOGYEVENTS.INTERPRETATION, D_CODEDITEMS.CATEGORY AS CODEDITEMS_CATEGORY, D_CODEDITEMS.LABEL AS CODEDITEMS_LABEL, MICROBIOLOGYEVENTS.CHARTTIME AS MICRO_TIME, LABEVENTS.VALUE, LABEVENTS.VALUEUOM, LABEVENTS.FLAG, D_LABITEMS.TEST_NAME, D_LABITEMS.FLUID, D_LABITEMS.CATEGORY AS LAB_CATEGORY, LABEVENTS.CHARTTIME AS LAB_CHARTTIME, MEDEVENTS.DO SE, MEDEVENTS.DOSEUOM, MEDEVENTS.SOLVOLUME, MEDEVENTS.SOLUNITS, MEDEVENTS.ROUTE, D_MEDITEMS.LABEL AS MED_LABEL, MEDEVENTS.CHARTTIME AS MED_CHARTTIME, IOEVENTS.VOLUME, IOEVENTS.VOLUMEUOM, D_IOITEMS.LABEL AS IO_LABEL, D_IOITEMS.CATEGORY AS IO_CATEGORY, IOEVENTS.CHARTTIME AS IO_CHARTTIME, COMORBIDITY_SCORES.CATEGORY, COMORBIDITY_SCORES.CONGESTIVE_HEART_FAILURE, COMORBIDITY_SCORES.CARDIAC_ARRHYTHMIAS, COMORBIDITY_SCORES.VALVULAR_DISEASE, COMORBIDITY_SCORES.PULMONARY_CIRCULATION, COMORBIDITY_SCORES.PERIPHERAL_VASCULAR, COMORBIDITY_SCORES.HYPERTENSION, COMORBIDITY_SCORES.PARALYSIS, COMORBIDITY_SCORES.OTHER_NEUROLOGICAL, COMORBIDITY_SCORES.CHRONIC_PULMONARY, COMORBIDITY_SCORES.DIABETES_UNCOMPLICATED, COMORBIDITY_SCORES.DIABETES_COMPLICATED, COMORBIDITY_SCORES.HYPOTHYROIDISM, COMORBIDITY_SCORES.RENAL_FAILURE, COMORBIDITY_SCORES.LIVER_DISEASE, COMORBIDITY_SCORES.PEPTIC_ULCER, COMORBIDITY_SCORES.AIDS, COMORBIDITY_SCORES.LYMPHOMA, COMORBIDITY_SCORES.METASTATIC_CANCER, COMORBIDITY_SCORES.SOLID_TU MOR, COMORBIDITY_SCORES.RHEUMATOID_ARTHRITIS, COMORBIDITY_SCORES.COAGULOPATHY, COMORBIDITY_SCORES.OBESITY, COMORBIDITY_SCORES.WEIGHT_LOSS, COMORBIDITY_SCORES.FLUID_ELECTROLYTE, COMORBIDITY_SCORES.BLOOD_LOSS_ANEMIA, COMORBIDITY_SCORES.DEFICIENCY_ANEMIAS, COMORBIDITY_SCORES.ALCOHOL_ABUSE, COMORBIDITY_SCORES.DRUG_ABUSE, COMORBIDITY_SCORES.PSYCHOSES, COMORBIDITY_SCORES.DEPRESSION

FROM ICD9 INNER JOIN MICROBIOLOGYEVENTS ON ICD9.SUBJECT_ID=MICROBIOLOGYEVENTS.SUBJECT_ID INNER JOIN D_CODEDITEMS ON MICROBIOLOGYEVENTS.SPEC_ITEMID=D_CODEDITEMS.ITEMID OR MICROBIOLOGYEVENTS.ORG_ITEMID=D_CODEDITEMS.ITEMID OR MICROBIOLOGYEVENTS.AB_ITEMID=D_CODEDITEMS.ITEMID INNER JOIN D_PATIENTS ON ICD9.SUBJECT_ID=D_PATIENTS.SUBJECT_ID INNER JOIN DEMOGRAPHIC_DETAIL ON ICD9.SUBJECT_ID=DEMOGRAPHIC_DETAIL.SUBJECT_ID INNER JOIN COMORBIDITY_SCORES ON ICD9.SUBJECT_ID=COMORBIDITY_SCORES.SUBJECT_ID INNER JOIN IOEVENTS ON ICD9.SUBJECT_ID=IOEVENTS.SUBJECT_ID INNER JOIN D_IOITEMS ON IOEVENTS.ITEMID=D_IOITEMS.ITEMID INNER JOIN MEDEVENTS ON ICD9.SUBJECT_ID=MEDEVENTS.SUBJECT_ID INNER JOIN D_MEDITEMS ON MEDEVENTS.ITEMID=D_MEDITEMS.ITEMID INNER J OIN LABEVENTS ON ICD9.SUBJECT_ID=LABEVENTS.SUBJECT_ID INNER JOIN D_LABITEMS ON LABEVENTS.ITEMID=D_LABITEMS.ITEMID **WHERE** ICD9.CODE = '584.9'

Data from MIMIC Database

Literature | Data | Model development | Expert consultation | Model improvement

```
D_LABITEMS.TEST_NAME,
D_LABITEMS.FLUID,
D_LABITEMS.CATEGORY AS LAB_CATEGORY,
LABEVENTS.CHARTTIME AS LAB_CHARTTIME,

FIRST_VALUE(LABEVENTS.VALUE) OVER (PARTITION BY (ADMISSIONS.HADM_ID, D_PATIENTS.SUBJECT_ID) ORDER BY

MIN(LABEVENTS.VALUE) OVER (PARTITION BY (ADMISSIONS.HADM_ID, D_PATIENTS.SUBJECT_ID) ORDER BY LABEVEN

CASE WHEN ((FIRST_VALUE(LABEVENTS.VALUE) OVER (PARTITION BY (ADMISSIONS.HADM_ID, D_PATIENTS.SUBJECT_
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--CASE WHEN ((MIN(LABEVENTS.VALUE) OVER (PARTITION BY (ADMISSIONS.HADM_ID, D_PATIENTS.SUBJECT_ID) OR
--(ROUND ((MIN(LABEVENTS.VALUE) OVER (PARTITION BY (ADMISSIONS.HADM_ID, D_PATIENTS.SUBJECT_ID) ORDER

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    ROUND( (LABEVENTS.VALUE::numeric - LAG(LABEVENTS.VALUE) OVER (PARTITION BY LABEVENTS.SUBJECT_ID
ELSE 0 END  AS CREAT_INCREASE,

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    CASE
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            THEN ROUND (175 * POWER(LABEVENTS.VALUE::numeric , -1.514) * POWER(EXTRACT (EPOCH from (
        WHEN (D_PATIENTS.SEX = 'F' AND DEMOGRAPHIC_DETAIL.ETHNICITY_DESCR = 'BLACK/AFRICAN AMERICAN'
            THEN ROUND (175 * POWER(LABEVENTS.VALUE::numeric, -1.514) * POWER(EXTRACT (EPOCH from (M
        WHEN (D_PATIENTS.SEX <> 'F' AND DEMOGRAPHIC_DETAIL.ETHNICITY_DESCR <> 'BLACK/AFRICAN AMERICA
            THEN ROUND (175 * POWER(LABEVENTS.VALUE::numeric, -1.514) * POWER(EXTRACT (EPOCH from (M
        ELSE '0' END
ELSE '0' END AS eGFR,
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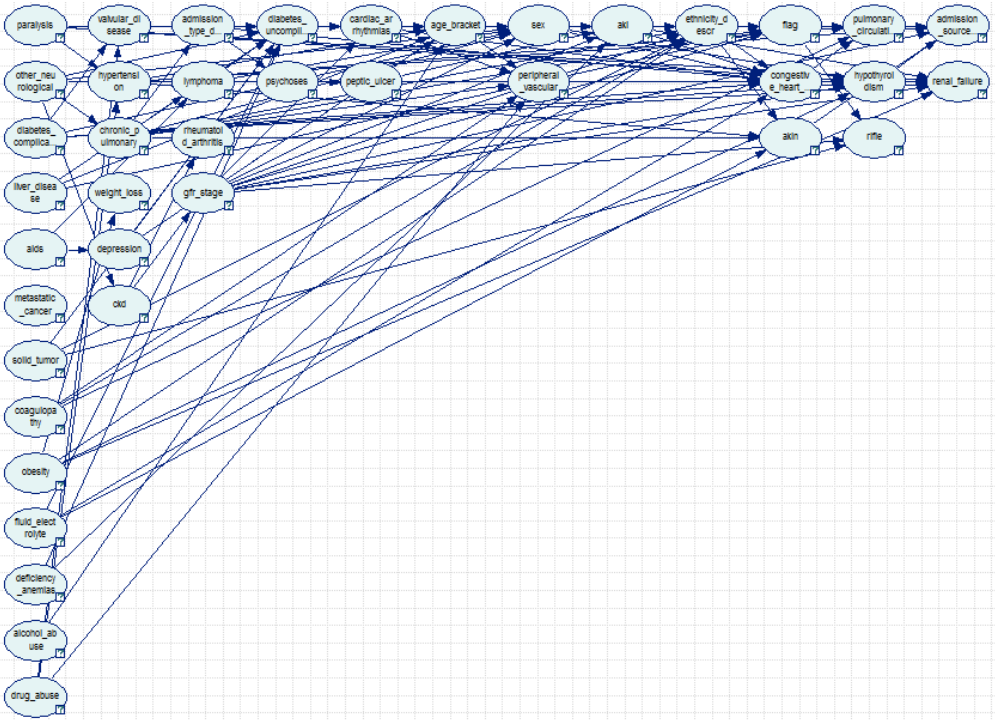
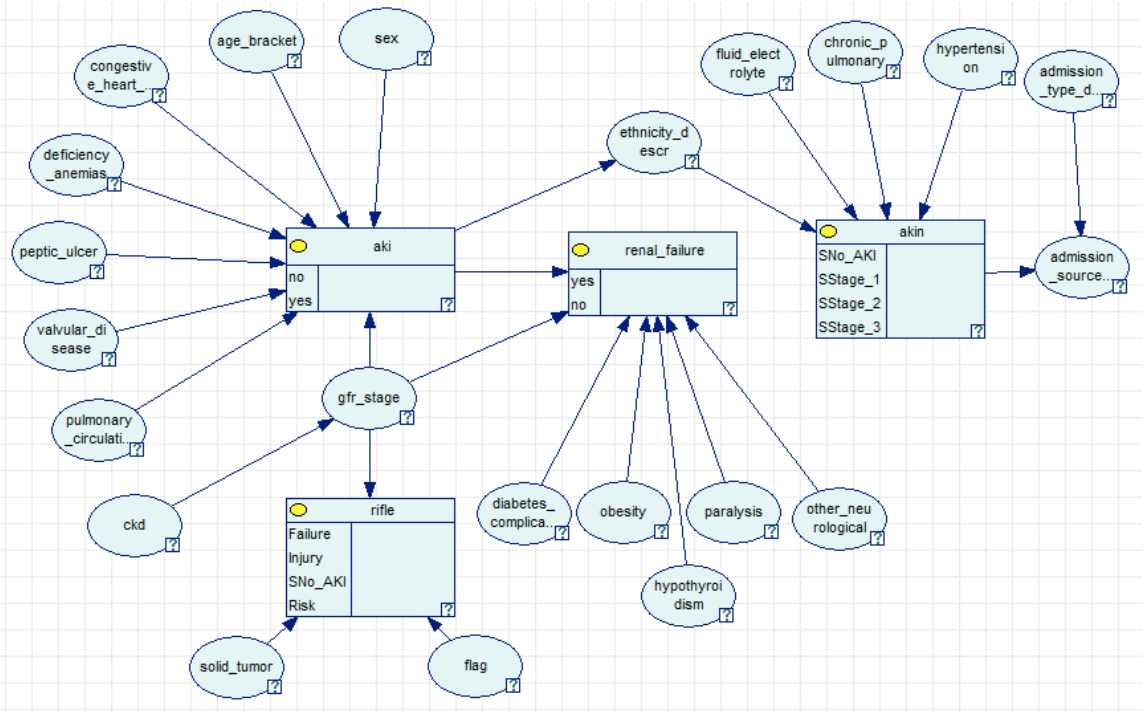
Model

Literature | Data | **Model development** | Expert consultation | Model improvement



Model

Literature | Data | Model development | Expert consultation | Model improvement



Model - Statistics

- Two data sets for training and evaluation:
  - 6000 entries (50% AKIN (Stage 1,2 or 3), 50% no AKIN)
  - 9000 entries (33% AKIN (Stage 1,2 or 3), 67% no AKIN)

Model - Statistics

Accuracy for correct measured AKIN:

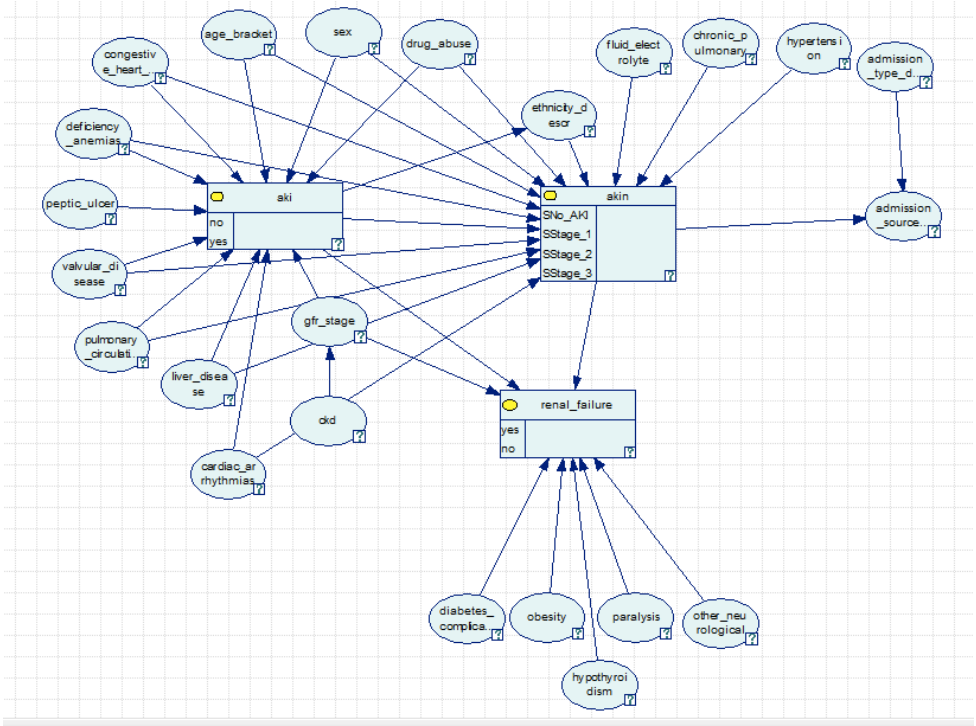
	GeNIe	Weka
6000	67%	58%
9000	73%	72%

Expert consultation

- Meeting at Charité with nephrologists (kidney experts)
- Discussion of the model and the dependencies
- Main insights:
  - New influencing factors: e.g. weight, urethitis or medication history
  - Time of comorbidities
  - AKIN guideline is an improved version of RIFLE and can be omitted

Improved model

Literature → Data → Model development → Expert consultation → **Model improvement**



Improved model - Satistics

Accuracy for correct measured AKIN:

	GeNIe	Weka
6000	83%	76%
9000	86%	83%

Results

Results

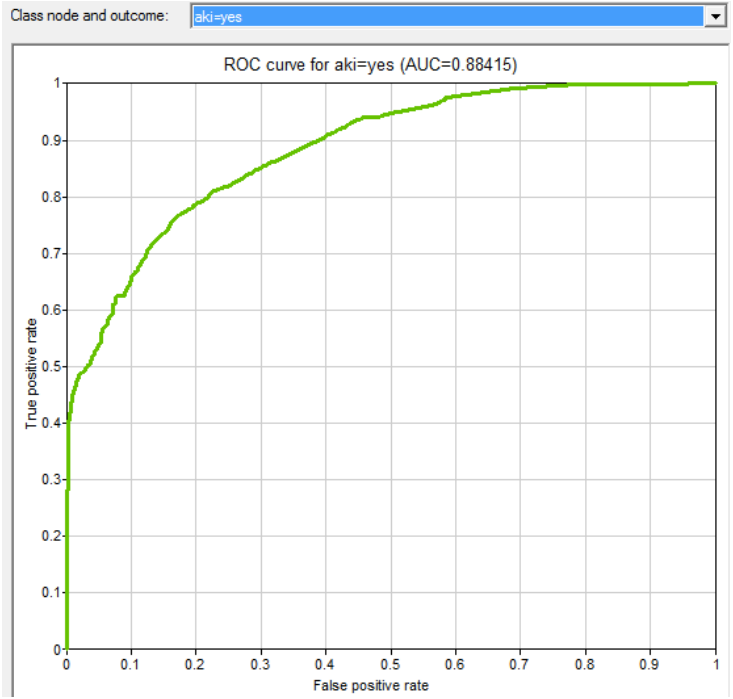
Accuracy before expert consultation:

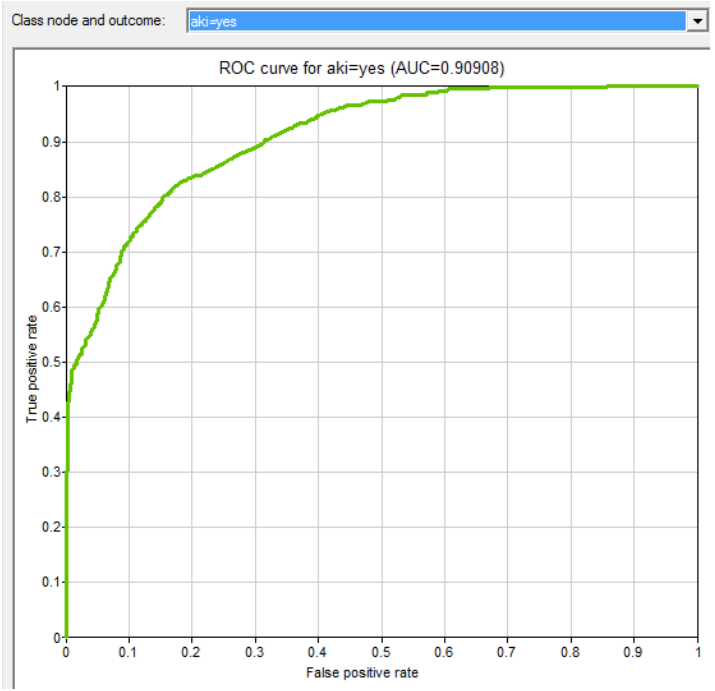
	GeNIe	Weka
6000	67%	58%
9000	73%	72%

Accuracy after expert consultation:

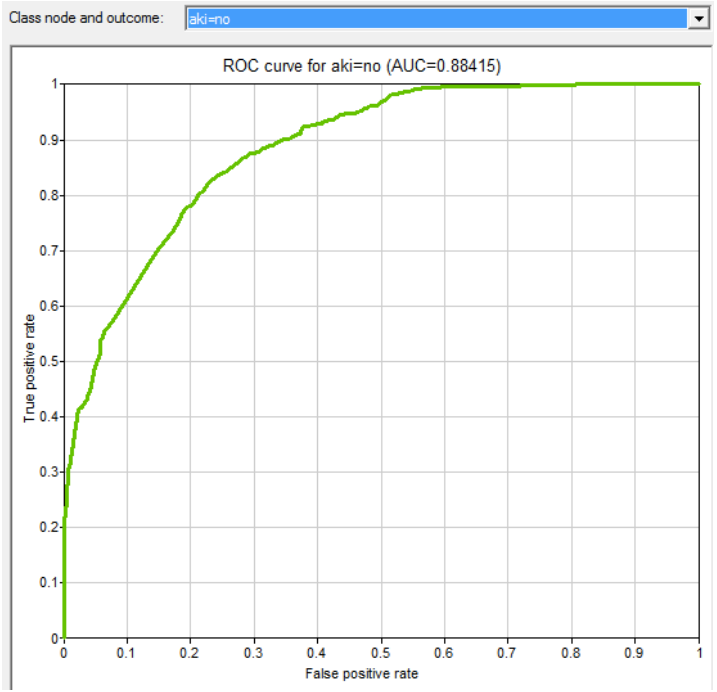
	GeNIe	Weka
6000	83%	76%
9000	86%	83%

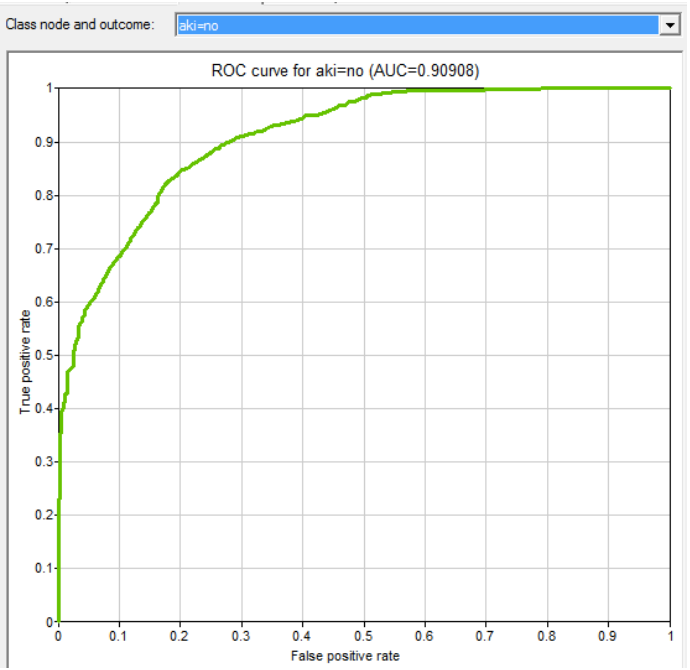
Results – ROC curve
AKI





Results – ROC curve
No AKI





Results

- Physicians welcome such projects in general, but are skeptical at first
- They would use a CDSS if proven helpful
- The system should be as unobtrusive as possible
- Nephrologists don’t really need such a system since they recognize AKI because of their experience
- A better use case is the intensive care unit where no specialists are working

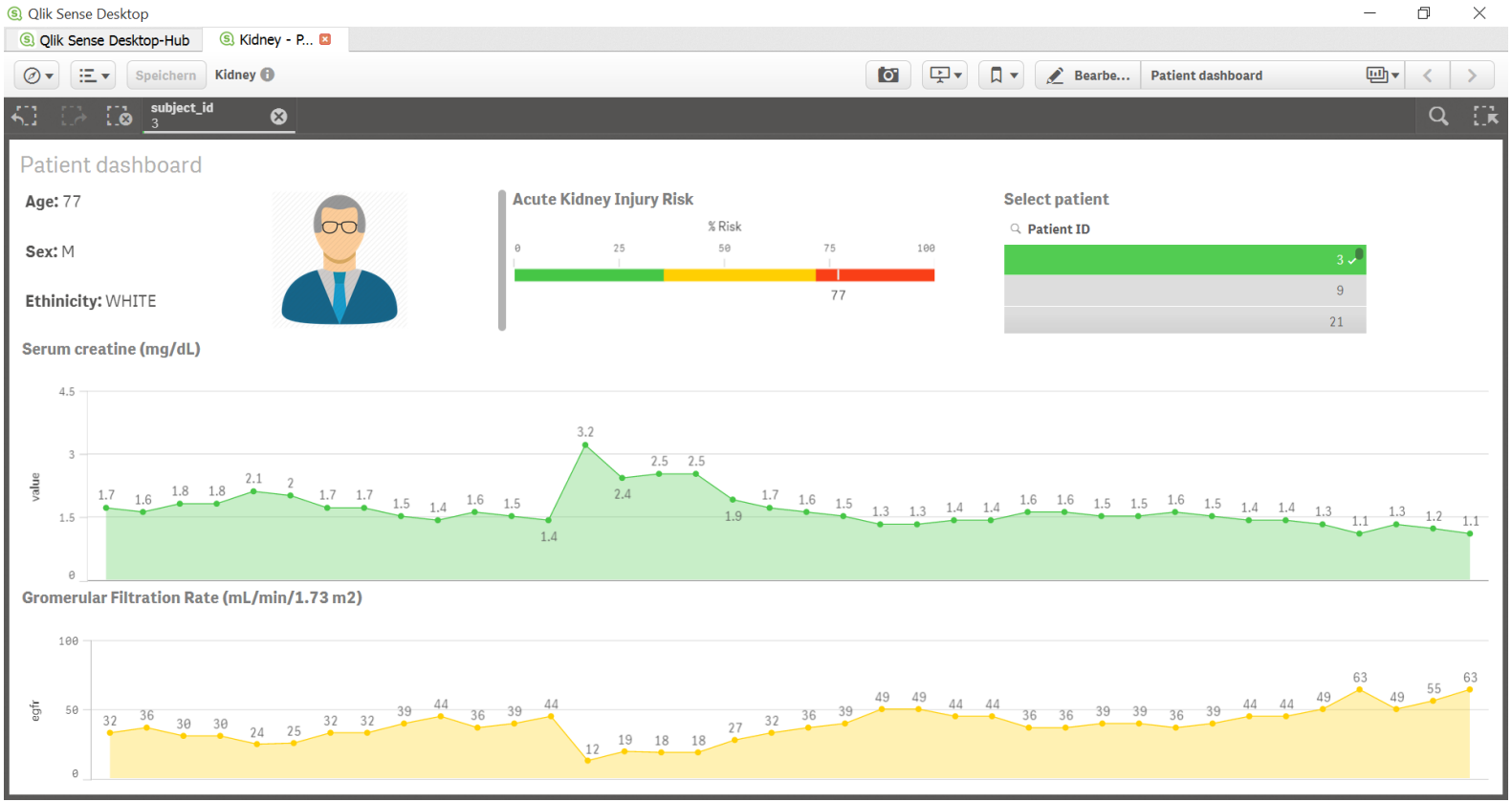
Further steps

Further steps

- Test in practice (e.g. Charité)
  - Model validation
  - Train with another, bigger data set

    with possibly different risk factors

- Build multiple user friendly frontends for different use cases
- Compare with other models (neural networks, trees, SVM, …)


Qlik Sense Desktop
Qlik Sense Desktop-Hub
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3
Patient dashboard
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Sex: M
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75
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Demo with GeNIe

Questions

Questions

- How many AKI patients will there possibly be in 2020?
- What are factors for AKI?
- What are the two main guidelines for AKI?

Discussion

Discussion

- To what extent can intelligent machines be useful in healthcare?

- Who will be responsible if the CDSS makes a wrong prediction and a patient dies because of it?