Deep Learning for Clinical Decision Support System

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Outline of the Talk

- Introduction
- DL in NLP for Clinical Decision Support System (CDSS)
- DL with image processing (computer vision) for CDSS
- Challenges
- Issues
- Future research perspectives

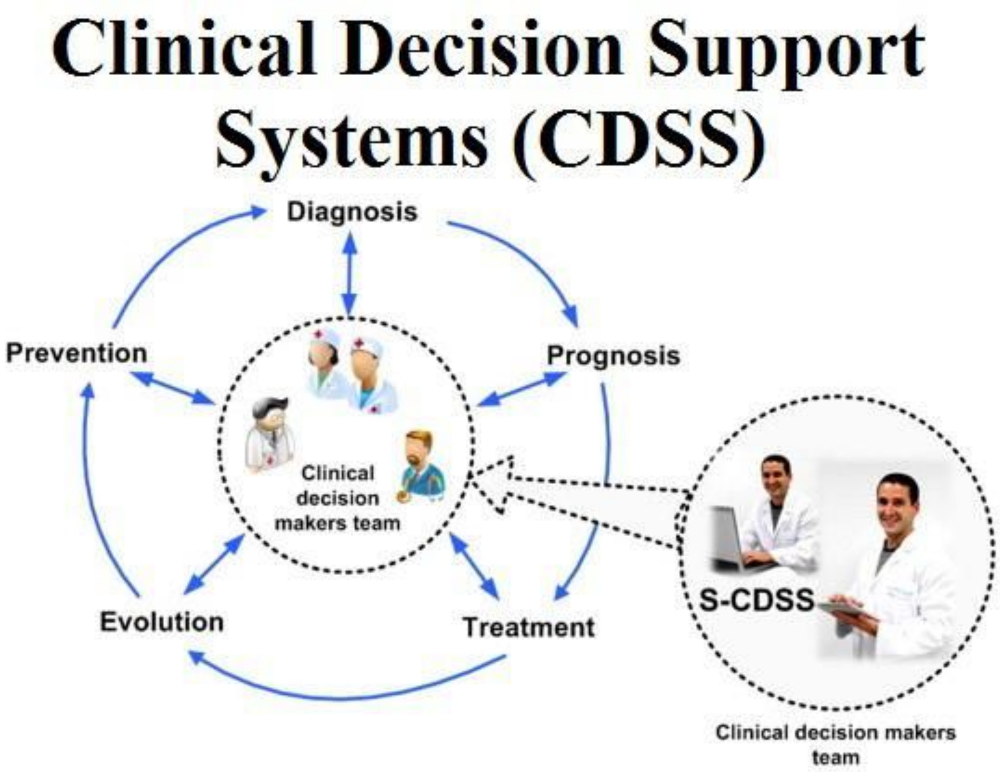
Introduction

- Decision support system
  - Clinical
    - diagnosis
    - therapy
    - treatment
    - medical prescription
  - non-clinical
    - resource allocation,
    - budgets,
    - strategic planning,

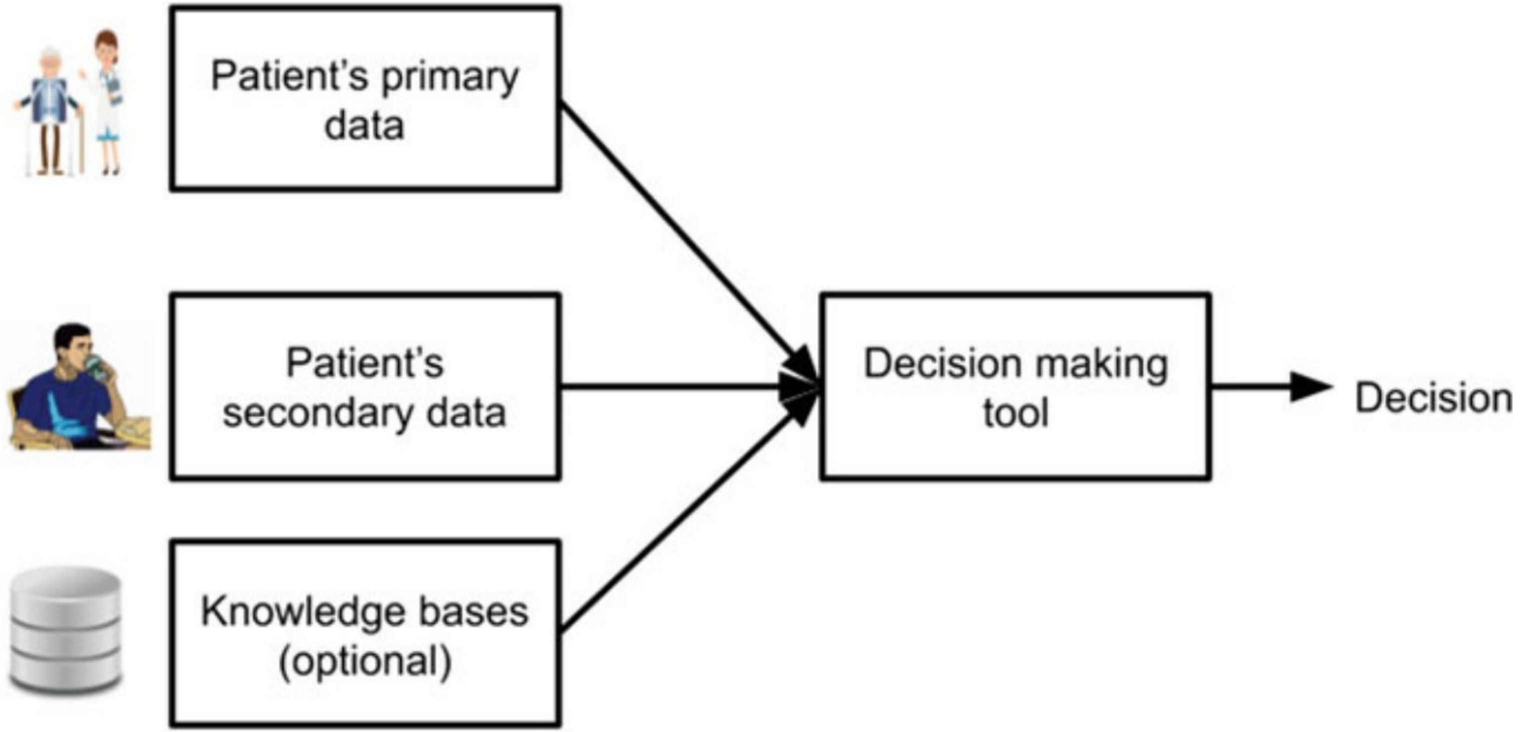
CDSS

- Clinical decisions are one among the many complex and challenging decision support systems, mainly because of the various measurable and non-measurable attributes involved in decision making and complex relations that exist between those attributes.
- The attributes include patients’ beliefs, lifestyles, experiences, education level, diagnostic reports, historical health records and so on.
- DL algorithms can serve as effective tools for supporting the decision making process, however the attributes input to the algorithms must be measurable and quantifiable.

CDSS


Clinical Decision Support Systems (CDSS)
Diagnosis
Prevention
Prognosis
Clinical decision makers team
Evolution
Treatment
S-CDSS
Clinical decision makers team

CDSS



Patient's primary data
Patient's secondary data
Knowledge bases (optional)
Decision making tool
Decision

Computing techniques used to create DSS

- Machine Learning and Adaptive Computing
  - Inductive Tree Methods
  - Case Based Reasoning
  - Artificial Neural Networks
- Expert Systems - Knowledge based Methods
  - Rule based Systems

Early AI/Decision Support Systems.

- De Dombal's system for acute abdominal pain (1972)
  - developed at Leeds University
  - decision making was based on the naive Bayesian approach
  - automated reasoning under uncertainty
  - designed to support the diagnosis of acute abdominal pain
  - The computing system's overall diagnostic accuracy (91-8%) was significantly higher than that of the most senior member of the clinical team to see each case (79 6%).
  -

Design Cycle for the development of a CDSS

- Planning Phase
- Research Phase
- System Analysis and conceptual phase
- Design Phase
- Construction phase
- Further Development phase
- Maintenance, documentation and adaptation

Early AI/Decision Support Systems.

- INTERNIST-I (1974)
  - rule-based expert system designed at the University of Pittsburgh
  - diagnosis of complex problems in general internal medicine
  - It uses patient observations to deduce a list of compatible disease states
  - used as a basis for successor systems including CADUCEUS and Quick Medical Reference (QMR)

Example: Decision Tree 1

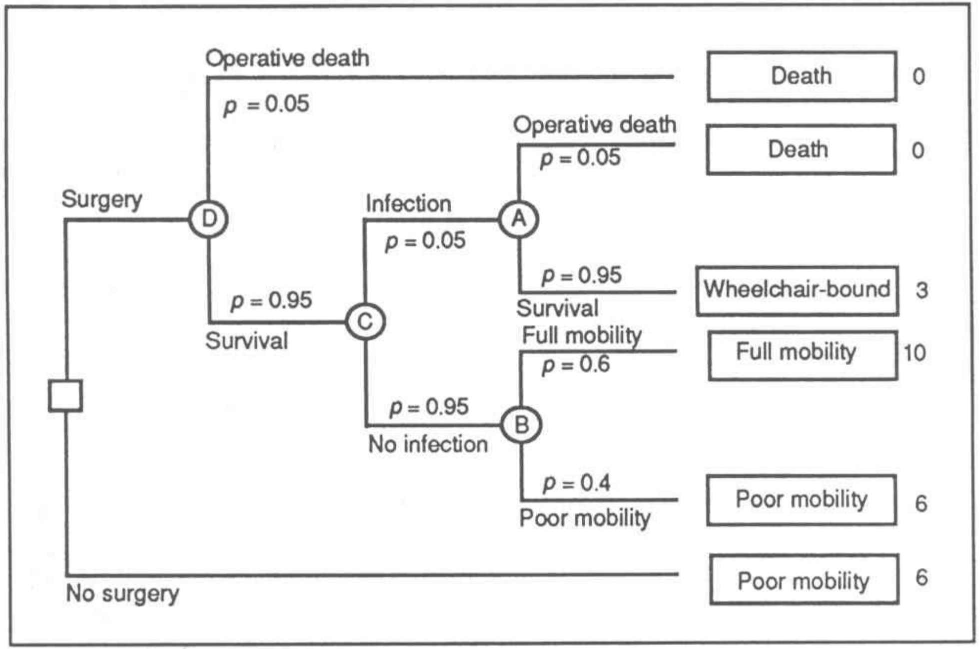


FIGURE 3.10. Decision tree for knee-replacement surgery. Probabilities have been assigned to each branch of each chance node. The patient's valuations of outcomes (measured in years of perfect mobility) are assigned to the tips of each branch of the tree.

Example: Decision Tree 2

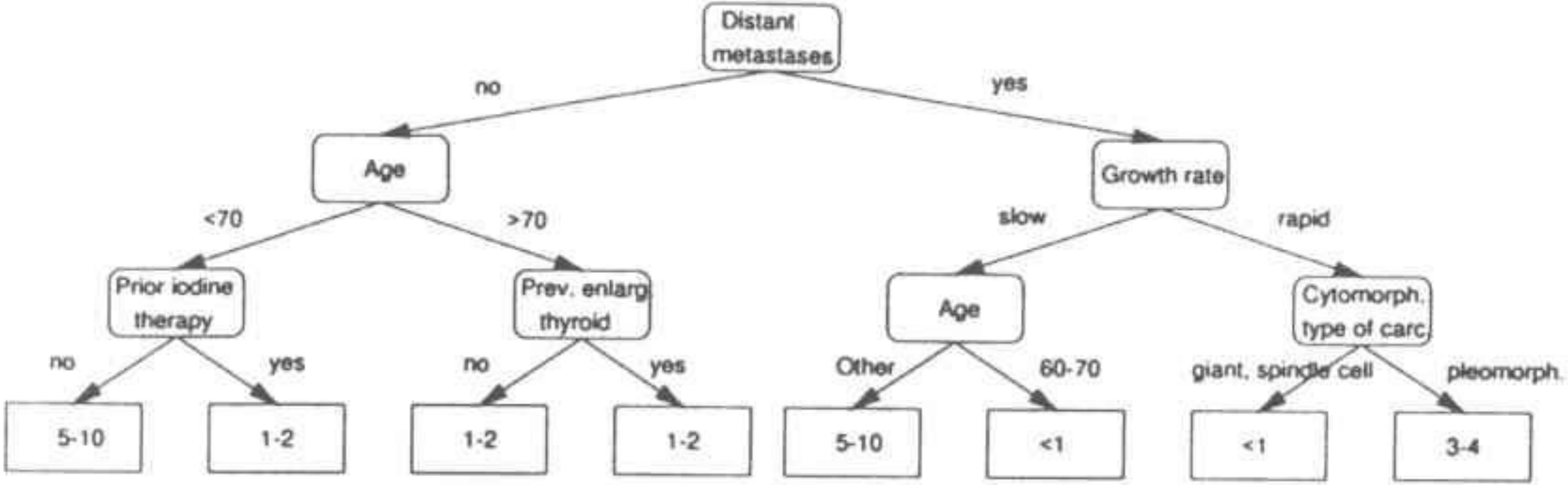


Figure 7.2 Decision tree generated by Assistant-I.

Traditional AI based CDSS

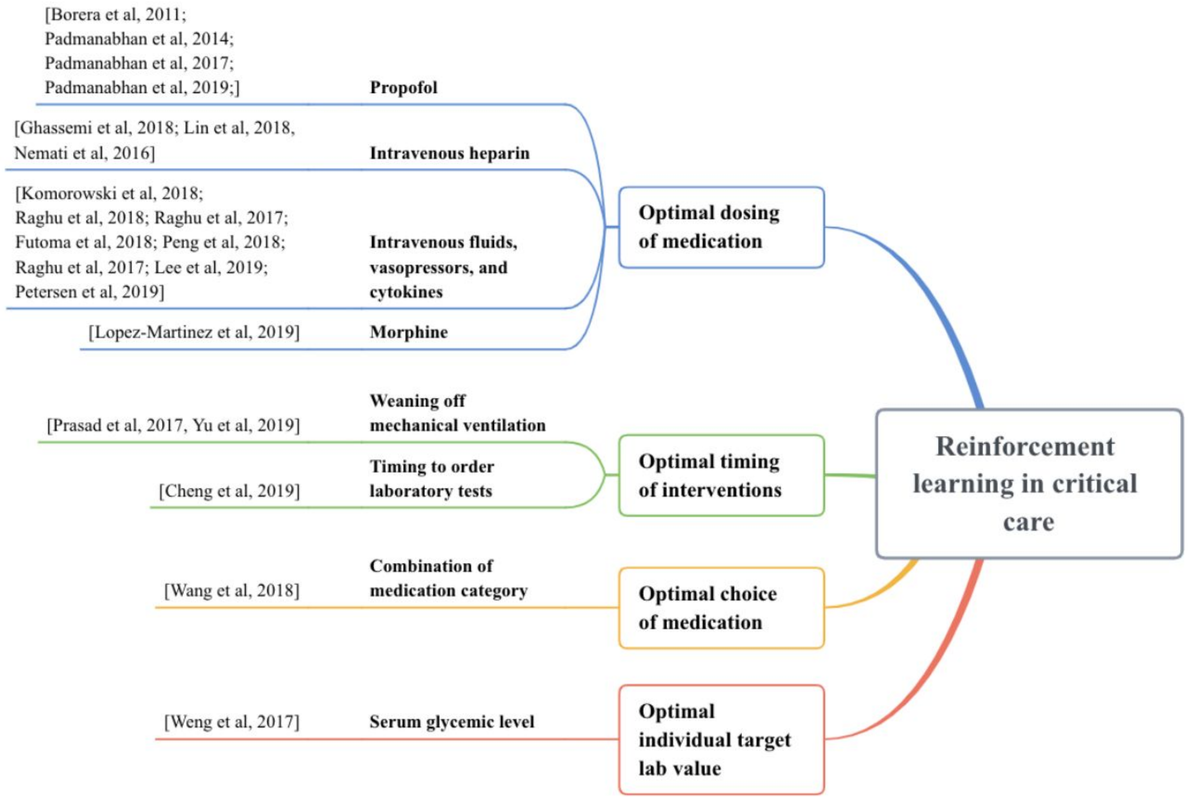
- MYCIN (1976)
  - rule-based expert system designed to diagnose and recommend treatment for certain blood infections (extended to handle other infectious diseases)
  - Clinical knowledge in MYCIN is represented as a set of IF-THEN rules with certainty factors attached to diagnoses

Rule507

IF:	1)	The infection which requires therapy is meningitis,
	2)	Organisms were not seen on the stain of the culture,
	3)	The type of infection is bacterial,
	4)	The patient does not have a head injury defect, and
	5)	The age of the patient is between 15 years and 55 years
THEN:	The organisms that might be causing the infection are diplococcus-pneumoniae and neisseria-meningitidis	

FIGURE 16.1. A typical rule from the MYCIN system. Rules are conditional statements that indicate what conclusions can be reached or actions taken *if* a specified set of conditions is found to be true. In this rule, MYCIN is able to conclude probable bacterial causes of infection if the five conditions in the premise are all found to be true for a specific patient. Not shown are the measures of uncertainty that are also associated with inference in the MYCIN system.

ML/DL/RL based CDSS



Source: https://www.jmir.org/2020/7/e18477/pdf

ML/DL/RL based CDSS

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1. Optimal Individualized Target Laboratory Value

Weng et al's RL model is as follows:

- First, they represented the patient]s states from 128 variables.
- These variables included patient demographics, comorbid conditions, vital sign changes, and laboratory value changes.
- They used a spare autoencoder to reduce the high dimensionality of the raw features (128 dimensions) to only 32 dimensions so that the RL model could be trained more efficiently with limited observational data.
- Second, they chose to act upon 1 of 11 discrete ranges of serum glucose at each time step.

Optimal Individualized Target Laboratory Value

- Third, they designed the reward function so that the RL agent could recommend an hourly target glucose level to optimize long-term survival.
- A positive 100 was assigned to the end state if patients survived 90 days after admission, and a negative 100 was assigned if the patients died.
- For each state-action pair, the value of the pair was iteratively estimated using the reward from the training data.

2. Optimal Choice of Medications

- Apart from some clinical decision support systems, commonly used systems such as computerized prescriber order entry and bar-coded medication administration lack personalized recommendations to optimize medication effectiveness and minimize side effects.
- Wang et al applied a deep learning network based on RL to exploit medication recommendations with a data-driven strategy.
- Their approach accounted for individual patient demographics, laboratory values, vital signs, and diagnoses from the MIMIC III database.

contd...

- The authors defined RL action as the medication combinations from the 180 drug categories.
- They adopted an actor-critic RL agent that suggested a daily medication prescription set, and aimed to improve patients' hospital survival.
- For each patient's ICU day, the actor network would recommend one medication combination by considering state variables such as demographics, laboratory results, and vital signs.
- A reward value of positive 15 would be given to the end state if a patient survived until hospital discharge and negative 15 if the patient died.

contd...

- The reward was designated as 0 for all other time steps.
- To counterbalance the actor network, the critic network was applied to evaluate the consistency of actual physician prescriptions and the RL agent's recommendations.
- The net effect of the actor-critic RL agent was to optimize the long-term outcomes of patients (hospital mortality) while minimizing deviations of RL-recommended actions from actual prescription patterns.
- In addition to the actor-critic network, the authors also applied LSTM to represent a patient's current state by incorporating the long sequence of all historical states.
- They suggested that hospital mortality would be reduced by 4.4% if clinicians adhered to the RL agent's recommendations.

Issues

- Privacy concerns/laws.
  - No code shared with EMR/CIS/HIS.
  - Patient identity not shared with DSS system.
- Tremendous amount of data and rules must be incorporated into system.
  - National Health Information Technology Coordinator created in 2004 to encourage/fund electronic health initiatives.
- Resistance/job fears of clinicians
  - Goal is to assist clinicians, not replace them.

Issues

- Clinical Trial Hurdles.
  - Make recommendations, not diagnoses.
  - Disclaimers regarding use.
- All past efforts have failed to achieve common usage.
  - Include end users (physicians, nurses, schedulers, IT departments) in the design decisions and testing.
  - Iterative design approach (i.e. modify based on feedback.)