Second Opinion: A Collaborative Online Game for Medical Diagnosis

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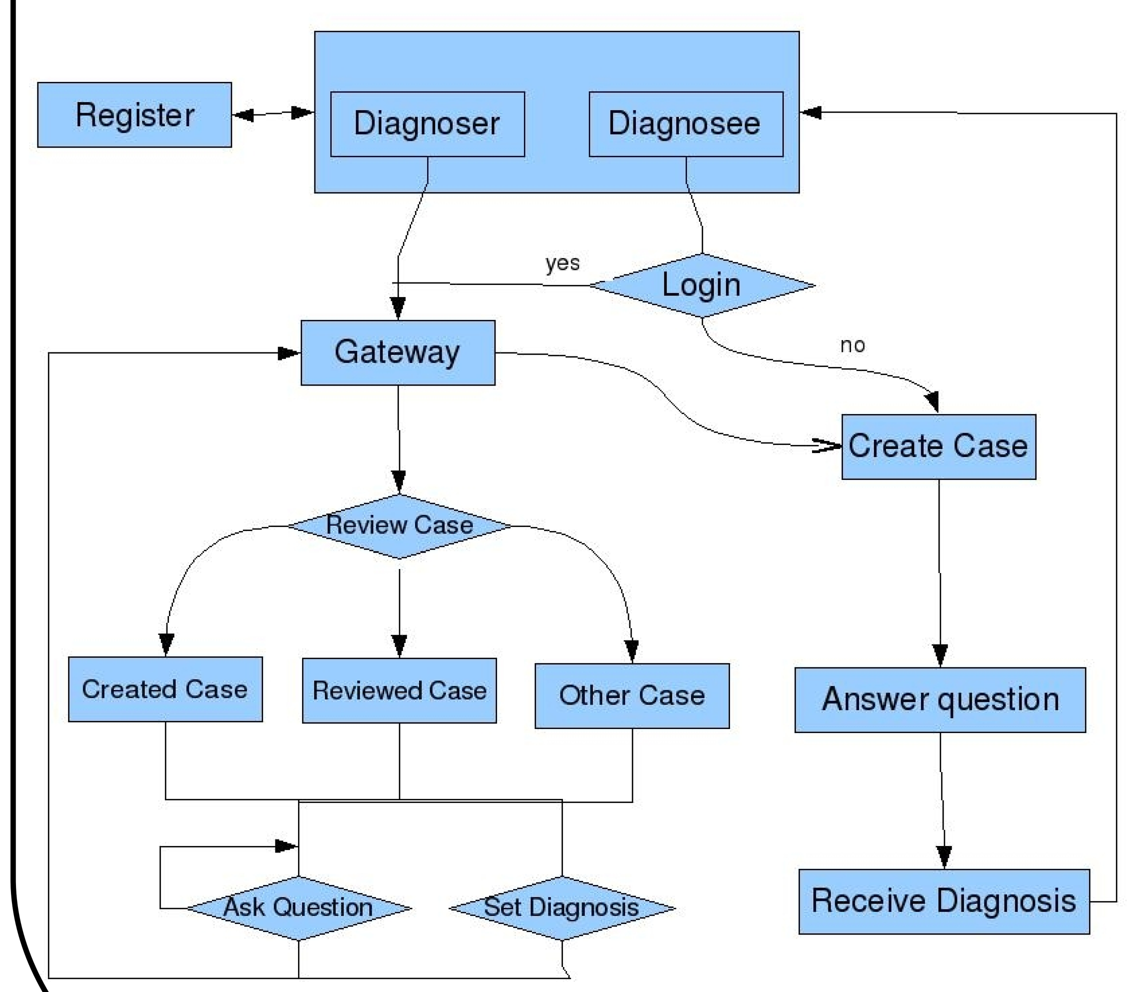
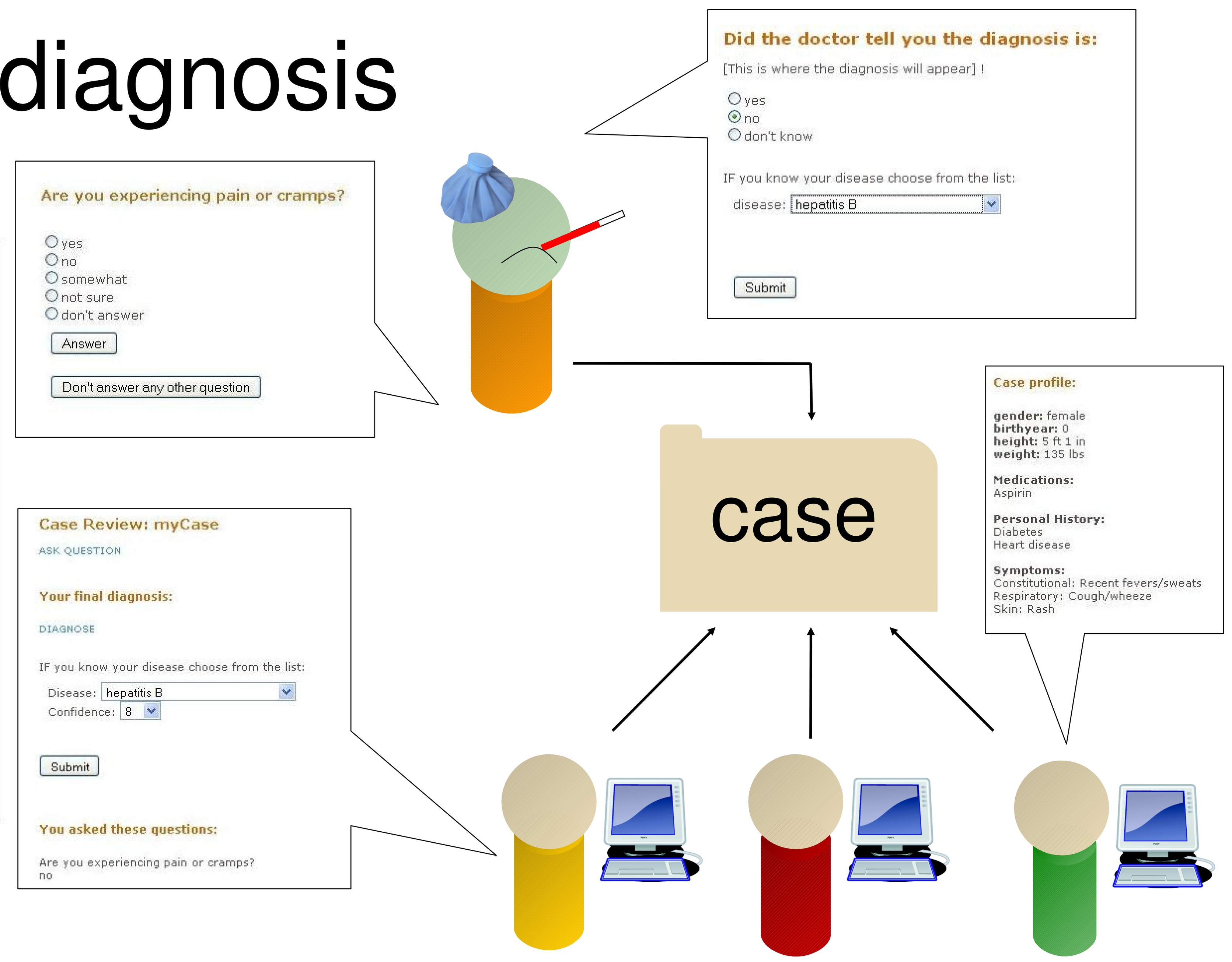
Applying the wisdom of crowds to medical diagnosis





Two types of users

•**Diagnosee** create new medical cases for diagnosis
•**Diagnoser** can ask the patient a series of questions and provide a diagnosis

Creating cases

•Diagnosee can provide **general information** (medical history, current medications)
•System asks **questions** about the symptoms
•Questions' order is adapted based on the answers received
•System provides a **diagnosis** based on **previously** diagnosed cases
•Diagnosee **confirms** or corrects the diagnosis

Diagnosing cases

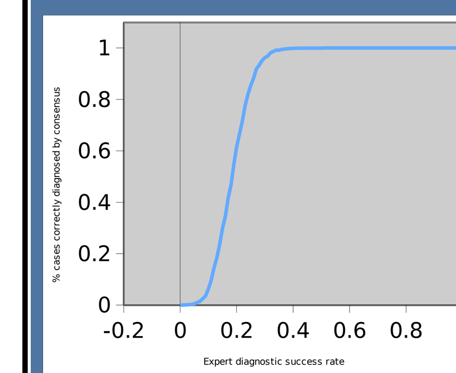
•Diagnosers can **review** cases
•They **ask questions** and receive the answer provided by the diagnosee
•They give diagnosis

Output

•A consensus is reached among diagnosers and a diagnosis is given based on all inputs

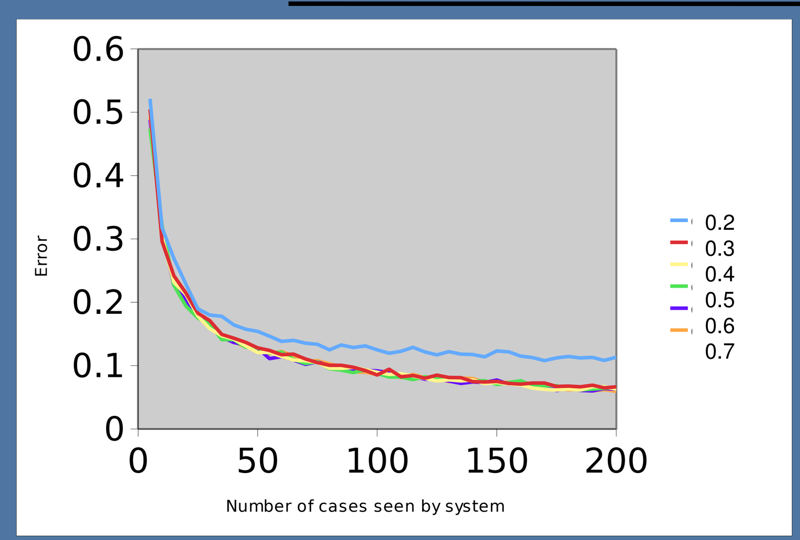
Simulation Results

Simulator that generates distribution for diseases, diagnoses, cases, diagnoser success rate

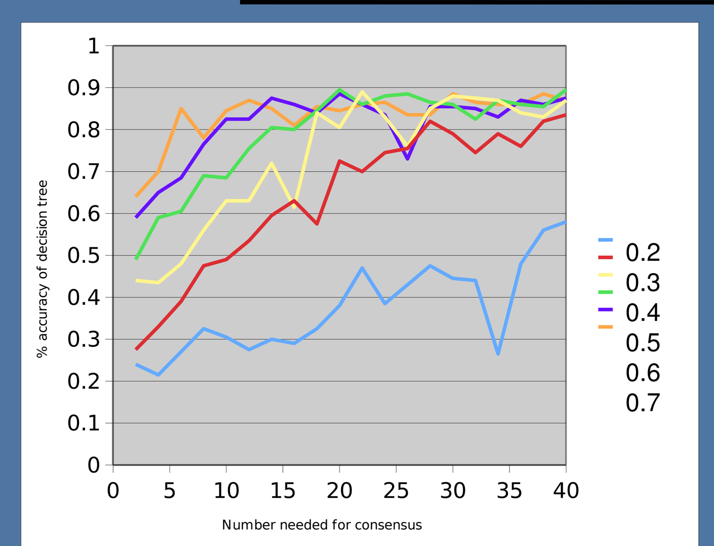


Accuracy of classification based on diagnoser success rate

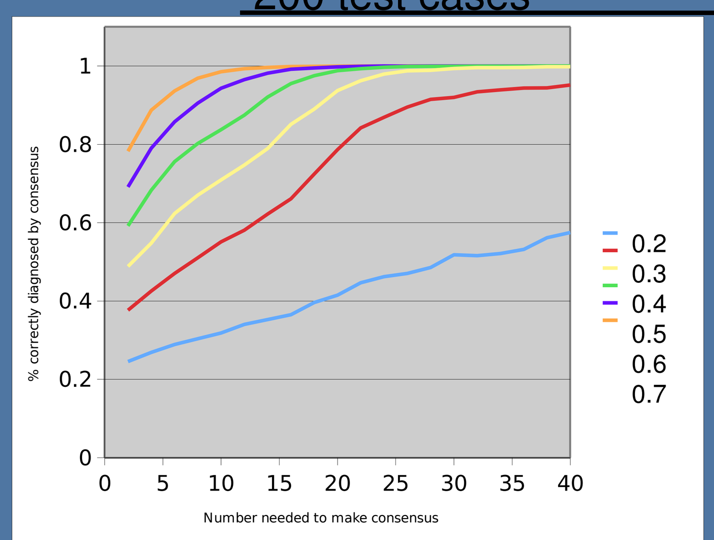
Param:500 cases,100 runs/succ. rate



Distance between estimated and real diagnosis based on success rate of diagnosers. Param:200cases,100 runs per number of cases



Accuracy of decision tree based on how many diagnosers it takes to have a consensus. Param:1800 training cases, 200 test cases



Correctly diagnosed cases based on how many diagnosers it takes to make a consensus Param:200 cases,100 trials

Parameters: 10 disease, 50 symptoms, 200 diagnosers, 40 diagnoses to close a case (success rate and number of cases is variable)

Decision Tree Learning

- Provide a diagnosis based on the training data present in the database

$$D \textit{ diseases random variable with values in } \{d_1, \ldots, d_n\}$$
$$\{S_1, \ldots, S_m\} \textit{ set of symptoms}$$

- **Information entropy** as a measure of uncertainty associated with D
  - •**A** high entropy gives more uncertainty to the diagnosis

$$H(D) = -\sum_{i=1}^{n} Pr(D = d_i) \log_2 Pr(D = d_i)$$

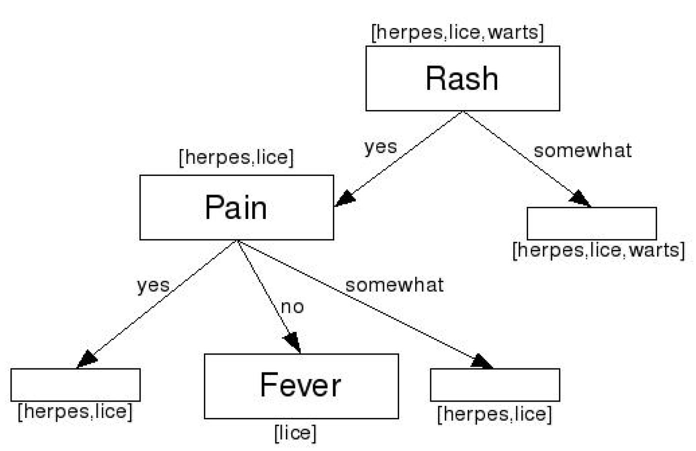
- **Information gain** gives the change in information entropy after associating a new symptom to the disease

$$IG(D; S) = H(D) - H(D|S)$$

•The decision tree is build by considering the set of symptoms that characterize the current case

$$IG(D^k; S_0, \ldots, S_k, S_\alpha) = H(D^k|S_0, \ldots, S_k) - H(D^k|S_0, \ldots, S_k, S_\alpha)$$

•Information gain help build the shortest decision tree



Learning from the wisdom of crowds

Reaching a Consensus

•Several diagnosis are voted by users

$$\textit{diagnoses for the current case} : \{\gamma_1, \ldots, \gamma_p\}$$
$$\textit{Diagnoser success rate } \{w_1, \ldots, w_p\}$$

•How to weight the opinions of the diagnosers to obtain the most likely diagnosis

$$\bar{d}_i = \sum_{i=1}^{p} \gamma_i * w_i \qquad \bar{d} = argmax_i d_i$$

Adjusting the weights of diagnosers

•The opinion of diagnosers is weighted based on their success rate

•After a case they voted in is closed, their weight is adjusted based on their match with the consensus

Successful num diagnosis / total num diagnosis

Real life application

•Provide diagnosis for Sexually transmitted diseases

•Highly symptomatic diseases (good for testing)

•Sensitive topic, people turn to the internet for information

Future work

•Release the online model of the system

•Providing users with a distribution of diagnosis

•Distinguish between user success rate in different classes of diagnoses

•Create incentives to attract people to play the game and return to the system

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