

Medical Diagnosis

- **Diseases** with probability of happening.
- Tests with costs.
- Each test has +/- outcome for each disease.

- We want to identify the disease of the patient by taking tests one by one, and observing each test outcome before choosing the next one. **Goal:** minimizing expected cost of diagnosis.

\$=billions) 2000-2015, projected



. Census: MGI analysis: McKinsey & Co., genetic testing

edcaremag.com/archives/2009/5/managing-cost-diagnosis

Optimal Decision Tree

- Hypotheses with a distribution, based on which one of them (i*) has happened.
- Decisions with costs and +/- outcomes on hypotheses.
- We make decisions one by one, and observe the feedback, before the next one.
- **Goal:** minimizing expected cost of identifying the hypothesis that has happened.

Toxic Chemicals Identification

- Missing Data
- Device Errors
- Inconsistent behaviors



* specifies an unknown outcome.

Noise Model

- We can model unknown outcomes to be + or with probability $\frac{1}{2}$ each.
- Extension to other probabilities
- Persistent Noise

Example: In table above if $i^* = 2$ and we run test 3, then we observe + w.p. $\frac{1}{2}$ or - w.p. $\frac{1}{2}$. While we always observe - if we run test 2.



Optimal Decision Tree with Noisy Outcomes Su Jia, Fatemeh Navidi, Viswanath Nagarajan, R. Ravi

Adaptive vs Non-Adaptive

- In adaptive model we observe the feedback after each test.
- In non-adaptive model:
- No observed feedback
- The same sequence for every chosen hypothesis
- Can be used for batch-mode testing
- No real-time processing time

Bayesian Active Learning

- A set of data points, each has an unknown label
- A set of linear classifiers, under each the data points have specific labels
- One classifier has happened based on a distribution
- We want to query labels of data points one by one until we identify the classifiers Threshold
- Noisy labels when data is within
- a threshold of classifiers boundaries
- Minimizing the number of queries

Our Results

- Adaptive: $O(\log m + \min(r, h))$ -approximation algorithm
- *m*: number of hypothesis
- r: maximum number of unknowns for each test
- h: maximum number of unknowns for each hypothesis
- Adaptive for sparse case: $O(\log m)$ -approximation algorithm
- Non-adaptive: $O(\log m)$ -approximation algorithm.
- First result that handles any number of unknown outcomes.
- Tight result for adaptive case if either r or h are $O(\log m)$, and for non-adaptive case with any number of unknowns.





Adaptive Algorithms

- Simple greedy style algorithms
- Repeatedly selecting a test that maximizes a combination of:
- The expected number of eliminated hypotheses
- The minimum probability of eliminated hypotheses
- Updating the set of compatible hypotheses based on observed feedback

Non-Adaptive Algorithms

The non-adaptive algorithm comes in two phases:

- the approximation fails and we need to run all tests.

Experiments

- Information Theoretic Lower Bound (Entropy)
- Low Adaptive
- Our Algorithms: Non-Adaptive, ODTN-r and ODTN-h



> In phase 1, using sampling we run an algorithm by [Azar, Gamzu'11] for Submodular Function Ranking problem on our instance, to estimate a score for each element. \succ In phase 2, we choose the test with maximum score. If it is smaller than a threshold,