Space Bounded Randomized Complexity Classes

one-sided error, log space bounded classes handy techniques for probabilistic reasoning

- A language L is in RLP if there is an log-space *and poly-time* PTM M such that
 - if $x \in L$ then Pr[M accepts x] $\ge 2/3$ and
 - if x ∉ L then Pr[M accepts x] = 0

 UPATH = { (G,s,t) | node t can be reached from node s in an *undirected* graph G} UPATH Algorithm:

- On input (G,s,t), follow a random path from s
 - If t is reached at some step, halt and accept
 - If t is not reached within 6e(n-1) steps, halt and reject
- The algorithm is correct if t is not reachable from s, since it must reject
- What if t is reachable from s?

- Let T(G,s,t) be the number of edges of G that are traversed on a random walk from s to t
- Claim: Expected value of $T(G,s,t) \le 2e(n-1)$
- We can use the claim and Markov's inequality to show that the random walk algorithm accepts yes instances of UPATH with probability at least 2/3

- Markov's Inequality: If X is a nonnegative random variable and k is a positive real then
 Prob[X ≥ k E[X]] ≤ 1/k
- Let X be T(G,s,t), i.e., the number of edges of G that are traversed on a random walk from s to t
- Since the expected value of T(G,s,t) ≤ 2e(n-1), then the probability that a random walk from s takes at least 6e(n-1) steps to reach t is at most 1/3

- Let T(G,s,t) be the number of edges of G that are traversed on a random walk from s to t
- We still need to prove the claim that the expected value of T(G,s,t) ≤ 2e(n-1)
- We need some background on *Markov Chains*

A finite *Markov chain* with discrete time and stationary transition probabilities is an infinite sequence of random variables over some state space S

X₀, X₁, X₂, ...,

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such that for all i, j in S, $Prob[X_k = j | X_{k-1} = i] = P_{ij}$, where P_{ij} may depend on i and j but not on k

The matrix P is called the *transition matrix*

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P_{ij}^m is the probability of reaching j from i in exactly m steps (there is an easy proof by induction on m)

A Markov Chain is *irreducible* if for all states i and j, there exists k such that $Prob[X_k = j | X_0 = i] > 0$

Theorem: Let P be the transition matrix of an irreducible Markov Chain. Then π P = π has a unique solution π up to constant multiplicative factors

If $\sum_{i} \pi_{i} = 1$, π is sometimes referred to as the stationary distribution of the Markov chain

Markov Chains and Random Walks on Graphs

- For an undirected connected graph G = (V,E), let
 N(u) be the set of neighbours of node u
 - d(u) = |N(u)| be the degree of node u
- A random walk on G is an irreducible Markov chain with state space equal to V and with

$$-$$
 Puv = 1/d(u), if {u,v} is in E

- Puv = 0, if {u,v} is not in E
- The stationary distribution π of this random walk is such that $\pi_u = d(u)/2e$

A *random commute* from i to j in G is a random walk starting at i that ends the first time it returns to i after having at some point visited j

Let θ_{ijuv} be the expected number of times edge $\{u,v\}$ is visited from u to v on a random commute from i to j

Analysis of UPATH: Random Commutes

Claim: θijuv is independent of v: for all v' in N(u), θijuv = θijuv'

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Proof follows from fact that each time u is visited, it is equally likely that v or v' is visited next

Analysis of UPATH: Random Commutes

Claim: Let θ_{iju} be θ_{ijuv} for any v. Then θ_{iju} is independent of u.

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Proof: The following identity holds for any u in V:

$$d(u) \ \theta_{iju} = \sum_{v \in N(u)} \theta_{ijv}$$

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$$= \sum_{v \in N(u)} d(v) \ \theta_{ijv} \ 1/d((v))$$

expected number of times a random commute from i to j leaves u

expected number of times a random commute from i to j enters u

Proof: The following identity holds for any u in V:

$$\begin{array}{ll} \mathsf{d}(\mathsf{u}) \ \theta_{ij\mathsf{u}} &= \sum_{\mathsf{v} \ \in \ \mathsf{N}(\mathsf{u})} \theta_{ij\mathsf{v}} \\ &= \sum_{\mathsf{v} \ \in \ \mathsf{N}(\mathsf{u})} d(\mathsf{v}) \ \theta_{ij\mathsf{v}} \ 1/d((\mathsf{v})) \\ &= \sum_{\mathsf{v} \ \in \ \mathsf{v}} d(\mathsf{v}) \ \theta_{ij\mathsf{v}} \ \mathsf{P}_{\mathsf{v}\mathsf{u}} \end{array}$$

expected number of times a random commute from i to j leaves u

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So, the vector of terms $d(u) \theta_{iju}$ is a constant times the stationary distribution π , where the constant is independent of u (but depends on i and j). For an edge {i,j} of G, let T_{ij} be the expected time to reach j from i on a random walk starting at i

Claim:
$$T_{ij} \le 2e$$
.
Proof: $T_{ij} \le \sum_{\{u,v\} \in E} (\theta_{ijuv} + \theta_{ijvu}) = 2e \theta_{ijij} \le 2e$

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Finally: if p is a path of length at most n-1 from s to t, then $T(G,s,t) \le \sum_{\{i,j\} \in p} T_{ij} \le 2e(n-1)$

Summary



In fact, UPATH is in Log Space: Shown by Omer Reingold, 2004.

Summary

- Many conjecture that
 - BPP = P
 - RLP = L (here L is "log space", see Reingold, Trevisan,
 Vadhan 2004)
- Reingold's proof uses theory of graph expanders
- There's an extensive body of work on pseudorandom generators, motivated in part by the goal of resolving these conjectures (see appendix of Arora-Barak)