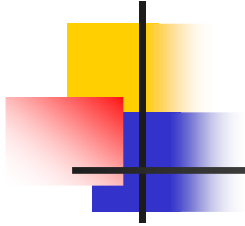




# Topics in Algorithms 2007

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Ramesh Hariharan



# Random Projections



# Solving High Dimensional Problems

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- How do we make the problem smaller?
- Sampling, Divide and Conquer, what else?



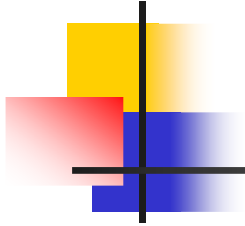
# Projections

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- Can  $n$  points in  $m$  dimensions be projected to  $d \ll m$  dimensions while maintaining geometry (pairwise distances)?
- Johnson-Lindenstrauss: YES

for  $d \sim \log n / \epsilon^2$ , each distance stretches/contracts by only an  $O(\epsilon)$  factor

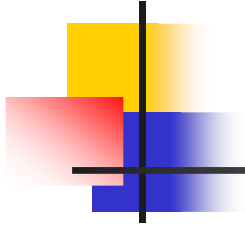
So an algorithm with running time  $f(n, d)$  now takes  $f(n, \log n)$  and results don't change very much (hopefully!)



# Which $d$ dimensions?

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- Any  $d$  coordinates?
- Random  $d$  coordinates?
- Random  $d$  dimensional subspace



## Random Subspaces

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- How is this defined/chosen computationally?
- How do we choose a random (spherically symmetric) line (1-d subspace)



# Random Subspaces

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- We need to choose  $m$  coordinates
- Choices:
  - Independent Uniform distributions on cartesian coordinates
    - Not defined: infinite ranges
    - Not spherically symmetric: different axis segments of the same length map surface patches with different surface areas
  - Independent Uniform distributions on polar coordinates
    - Works in 2d
    - Does not work in higher dimensions!! Why? for a 3d sphere, half and not one-third the area is located within 30 degrees



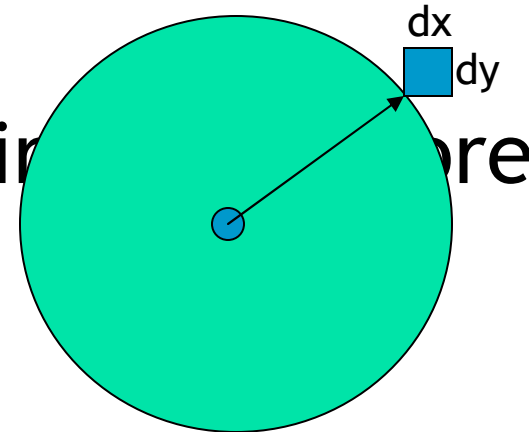
# Random Subspaces

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- What works?
- Normal distribution on cartesian coordinates
- Choose independent random variables  $X_1 \dots X_m$  each  $N(0,1)$

# Why do Normals work?

- Take 2d: Which points on the circle are more likely?



$$e^{-x^2/2} dx \times e^{-y^2/2} dy = e^{-x^2/2-y^2/2}$$

dydx



# A random d-dim subspace

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- How do we extend to d dimensions?
- Choose d random vectors

Choose independent random variables  $X_1^i \dots X_m^i$  each  $N(0,1)$ ,  $i=1..d$



# Distance preservation

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- There are  ${}^n\mathbf{C}_2$  distances
- What happens to each after projection?
- What happens to one after projection; consider single unit vector along x axis
- Length of projection  $\text{sqrt}\left[\left(x^1/l_1\right)^2 + \dots + \left(x^d/l_d\right)^2\right]$



# Orthogonality

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- Not exactly
- The random vectors aren't orthogonal
- How far away from orthogonal are they?
  
- In high dimensions, they are nearly orthogonal!!



# Assume Orthogonality

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- Assume orthogonality for the moment
- How do we determine bounds on the distribution of the projection length
$$\text{sqrt} \left[ \left( x_1^1 / l_1 \right)^2 + \dots + \left( x_1^d / l_d \right)^2 \right]$$
- Expected value of  $\left[ \left( x_1^1 \right)^2 + \dots + \left( x_1^d \right)^2 \right]$  is  $d$  (by linearity of expectation)
- Expected value of each  $l_i^2$  is  $m$  (by linearity of expectation)
- Roughly speaking, overall expectation is  $\text{sqrt}(d/m)$
- A distance scales by  $\text{sqrt}(d/m)$  after projection in the “expected” sense; how much does it depart from this value?



# What does Expectation give us

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- But  $E(A/B) \neq E(A)/E(B)$
- And even if it were, the distribution need not be tight around the expectation
- How do we determine tightness of a distribution?
- Tail Bounds for sums of independent random variables; summing gives concentration (unity gives strength!!)



# Tail Bounds

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- $P(|\sum^k X_i^2 - k| > \epsilon k) < 2e^{-\epsilon^2 k/4}$

$$\text{sqrt}[(x_1^1/l_1)^2 + \dots + (x_1^d/l_d)^2]$$

- Each  $l_i^2$  is within  $(1 \pm \epsilon)m$  with probability inverse exponential in  $\epsilon^2 m$
- $[(x_1^1)^2 + \dots + (x_1^d)^2]$  is within  $(1 \pm \epsilon)d$  with probability inverse exponential in  $\epsilon^2 d$
- $\text{sqrt}[(x_1^1/l_1)^2 + \dots + (x_1^d/l_d)^2]$  is within  $(1 \pm O(\epsilon)) \text{sqrt}(d/m)$  with probability inverse exponential in  $\epsilon^2 d$  (by the union bound)



# One distance to many distances

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- So one distance  $D$  has length  $D (1 \pm o(\epsilon)) \sqrt{d/m}$  after projection with probability inverse exponential in  $\epsilon^2 d$
- How about many distances (could some of them go astray?)
- There are  $\binom{n}{2}$  distances
- Each has inverse exponential in  $\epsilon^2 d$  probability of failure, i.e., stretching/compressing beyond  $(1 \pm o(\epsilon)) \sqrt{d/m}$
- What is the probability of no failure? Choose  $d$  so that  $e^{-\epsilon^2 d/4}$   
\*  $\binom{n}{2}$  is  $\ll 1$  (union bound again), so  $d$  is  $\Theta(\log n / \epsilon^2)$



# Orthogonality

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- What is the distribution of angles between two spherically symmetric vectors
- Tight around 90 degrees!!



# Orthogonality

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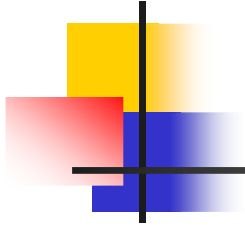
- Distribution for one vector  $X$  is  $e^{-\frac{X^T X}{2}} dx$
- Invariant to rotation
  - Rotation is multiplication by square matrix  $R$  where  $R^T R = I$
  - Take  $Y = RX$  so  $R^T Y = X$
  - Distribution of  $Y$  is  $e^{-\frac{(RY)^T (RY)}{2}} dy = e^{-\frac{Y^T Y}{2}} dy$
- $Y$  is sph sym in the  $n-1$  dim space ortho to  $X$ 
  - $Z = RX$  so that  $Z = 10000\dots$
  - $RX, RY$  are sph sym
  - So  $RY$  comprises  $n$  independent  $N(0,1)$ 's
  - The portion of  $RY$  orthogonal to  $RX$  has  $n-1$  independent  $N(0,1)$ 's



# Orthogonality

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- Start with  $v=10000\dots$
- Projection on first vector has length  $X/L$  where  $X$  is  $N(0,1)$  and  $L$  is sqrt of sum of squares of  $N(0,1)$
- Project  $v$  and all other vectors in the space ortho to the first vector
- Again rotate within this orthogonal space so  $v=\text{sqrt}[1- (X/L_1)^2] 0 0 0 0 0$
- All other vectors are still sph sym in this ortho space
- So projection of  $v$  on second vector has length  $X'/L' * \text{sqrt}[1- (X/L_1)^2]$
- And so on.. overall dampening is  $(\text{sqrt}[1- (X/L_1)^2])^d = (1- \log n/n)^{d/2}$  whp



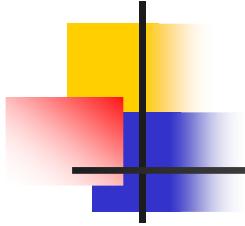
## Tail Bound Proof

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Show  $P(|\sum^k X_i^2 - k| > \epsilon k) < 2e^{-\epsilon^2 k/2}$

Two parts

- $P(\sum^k X_i^2 < (1-\epsilon)k) < e^{-\epsilon^2 k/2}$
- $P(\sum^k X_i^2 > (1+\epsilon)k) < e^{-\epsilon^2 k/2}$



# Tail Bound Proof

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$$P(\sum^k X_i^2 < (1-\epsilon)k) < e^{-\epsilon^2 k/4}$$

$$= P(e^{-t\sum X^2} > e^{-t(1-\epsilon)k}) \quad :t>0$$

$$\leq E(e^{-t\sum X^2}) / e^{-t(1-\epsilon)k} \quad : \text{Markov's}$$

$$\leq E(e^{-tX^2})^k e^{t(1-\epsilon)k} \quad : \text{Independence}$$

$$\leq (2t+1)^{-k/2} e^{t(1-\epsilon)k} \quad : \text{Why?}$$

Minimize for  $t$  and complete the proof??



# Exercises

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- Complete proof of tail bound
- Take a random walk in which you move left with prob  $p$  and right with prob  $1-p$ ; what can you say about your distance from the start after  $n$  steps?