JL Lemma, Dimensionality Reduction, and Subspace Embeddings

Lecture 11

September 29, 2022

F_2 estimation in turnstile setting

AMS-ℓ_2-Estimate:

```
Let Y_1, Y_2, ..., Y_n be {-1, +1} random variables that are
    4-wise independent
z ← 0
While (stream is not empty) do
    a_j = (i_j, Δ_j) is current update
    z ← z + Δ_j Y_{i_j}
endWhile
Output z^2
```

Claim: Output estimates $||x||_2^2$ where x is the vector at end of stream of updates.

Analysis

$Z = \sum_{i=1}^{n} x_i Y_i$ and output is Z^2

$$Z^2 = \sum_i x_i^2 Y_i^2 + 2 \sum_{i \neq j} x_i x_j Y_i Y_j$$

and hence

$$\mathrm{E}\left[Z^2\right] = \sum_i x_i^2 = ||x||_2^2.$$

One can show that $Var(Z^2) \leq 2(\mathrm{E}[Z^2])^2$.

Linear Sketching View

Recall that we take average of independent estimators and take median to reduce error. Can we view all this as a sketch?

AMS-ℓ_2-Sketch:
    $k = c\log(1/\delta)/\epsilon^2$
    Let M be a $k \times n$ matrix with entries in $\{-1, 1\}$ s.t
        (i) rows are independent and
        (ii) in each row entries are 4-wise independent
    z is a $\ell \times 1$ vector initialized to 0
    While (stream is not empty) do
        $a_j = (i_j, \Delta_j)$ is current update
        $z \leftarrow z + \Delta_j M e_{i_j}$
    endWhile
    Output vector z as sketch.

M is compactly represented via k hash functions, one per row, independently chosen from 4-wise independent hash family.

Geometric Interpretation

Given vector $x \in \mathbb{R}^n$ let M the random map $z = Mx$ has the following features

- $\mathrm{E}[z_i] = 0$ and $\mathrm{E}\left[z_i^2\right] = \|x\|_2^2$ for each $1 \leq i \leq k$ where k is number of rows of M
- Thus each z_i^2 is an estimate of length of x in Euclidean norm
- When $k = \Theta(\frac{1}{\epsilon^2}\log(1/\delta))$ one can obtain an $(1 \pm \epsilon)$ estimate of $\|x\|_2$ by averaging and median ideas

Thus we are able to compress x into k-dimensional vector z such that z contains information to estimate $\|x\|_2$ accurately

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Question: Do we need median trick? Will averaging do?

Distributional JL Lemma

Lemma (Distributional JL Lemma)

Fix vector $x \in \mathbb{R}^d$ *and let* $\Pi \in \mathbb{R}^{k \times d}$ *matrix where each entry* Π_{ij} *is chosen independently according to standard normal distribution* $\mathcal{N}(0, 1)$ *distribution. If* $k = \Omega(\frac{1}{\epsilon^2} \log(1/\delta))$*, then with probability* $(1 - \delta)$

$$\|\frac{1}{\sqrt{k}} \Pi x\|_2 = (1 \pm \epsilon)\|x\|_2.$$

Can choose entries from $\{-1, 1\}$ as well.
Note: unlike ℓ_2 estimation, entries of Π are independent.

Letting $z = \frac{1}{\sqrt{k}} \Pi x$ we have projected x from d dimensions to $k = O(\frac{1}{\epsilon^2} \log(1/\delta))$ dimensions while preserving length to within $(1 \pm \epsilon)$-factor.

Dimensionality reduction

Theorem (Metric JL Lemma)

Let $v_1, v_2, \ldots, v_n$ be any n points/vectors in $\mathbb{R}^d$. For any $\epsilon \in (0, 1/2)$, there is linear map $f : \mathbb{R}^d \rightarrow \mathbb{R}^k$ where $k \leq 8 \ln n/\epsilon^2$ such that for all $1 \leq i < j \leq n$,

$$(1 - \epsilon)||v_i - v_j||_2 \leq ||f(v_i) - f(v_j)||_2 \leq ||v_i - v_j||_2.$$

Moreover f can be obtained in randomized polynomial-time.

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Moreover f *can be obtained in randomized polynomial-time.*

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Proof.

Apply DJL with $\delta = 1/n^2$ and apply union bound to $\binom{n}{2}$ vectors $(v_i - v_j)$, $i \neq j$. □

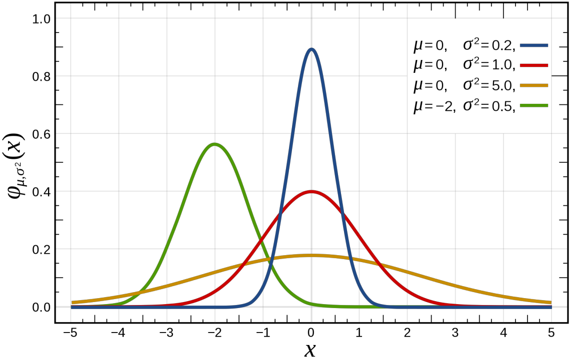
DJL and Metric JL

Key advantage: mapping is *oblivious* to data!

Normal Distribution

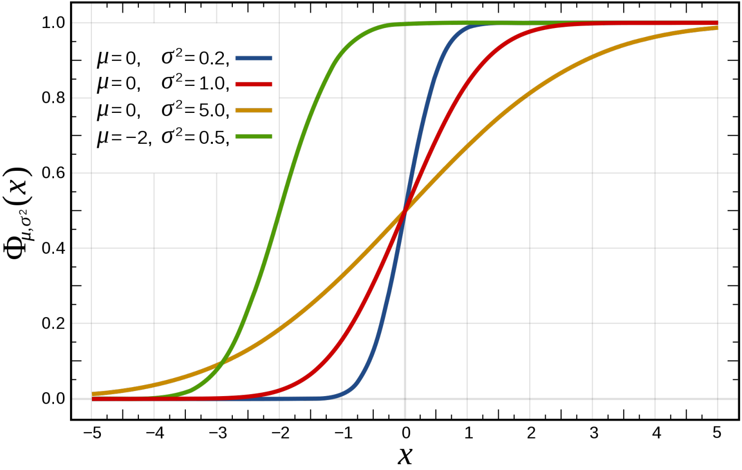
Density function: $f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

Standard normal: $\mathcal{N}(0, 1)$ is when $\mu = 0, \sigma = 1$



Normal Distribution

Cumulative density function for standard normal:
$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{\infty}^{t} e^{-t^2/2}$ (no closed form)



Sum of independent Normally distributed variables

Lemma

Let X and Y be independent random variables. Suppose $X \sim \mathcal{N}(\mu_X, \sigma_X^2)$ and $Y \sim \mathcal{N}(\mu_Y, \sigma_Y^2)$. Let $Z = X + Y$. Then $Z \sim \mathcal{N}(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2)$.

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Corollary

Let X and Y be independent random variables. Suppose $X \sim \mathcal{N}(0, 1)$ and $Y \sim \mathcal{N}(0, 1)$. Let $Z = aX + bY$ where a, b are arbitrary real numbers. Then $Z \sim \mathcal{N}(0, a^2 + b^2)$.

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Normal distribution is a *stable* distributions: adding two independent random variables within the same class gives a distribution inside the class. Others exist and useful in F_p estimation for $p \in (0, 2)$.

Random Guassian vector

One can consider higher dimensional normal distributions, also called multivariate Guassian (or Normal) distributions. Here we consider one such.

Fix some dimension $k \geq 1$. A real random vector $Z = (Z_1, Z_2, \ldots, Z_k)$ is a *standard* normal random vector if $Z_i \sim \mathcal{N}(0, 1)$ for each i and $Z_1, \ldots, Z_k$ are independent.

Some observations about Z:

- Density function is $f(y_1, y_2, \ldots, y_k) = (\frac{1}{\sqrt{2\pi}})^k e^{-(y_1^2+\ldots+y_k^2)/2}$. Hence distribution is centrally symmetric. Can be used to generate a random unit vector in $\mathbb{R}^k$
- Euclidean length: $\mathrm{E}\left[\|Z\|_2^2\right] = \sum_i \mathrm{E}\left[Z_i^2\right] = k$. Will see that the length is concentrated.

Concentration of sum of squares of normally distributed variables

$\chi^2(k)$ distribution: distribution of sum of *squares* of k independent standard normally distributed variables
$Y = \sum_{i=1}^{k} Z_i^2$ where each $Z_i \simeq \mathcal{N}(0, 1)$.

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$\mathrm{E}\left[Z_i^2\right] = 1$ hence $\mathrm{E}[Y] = k$.

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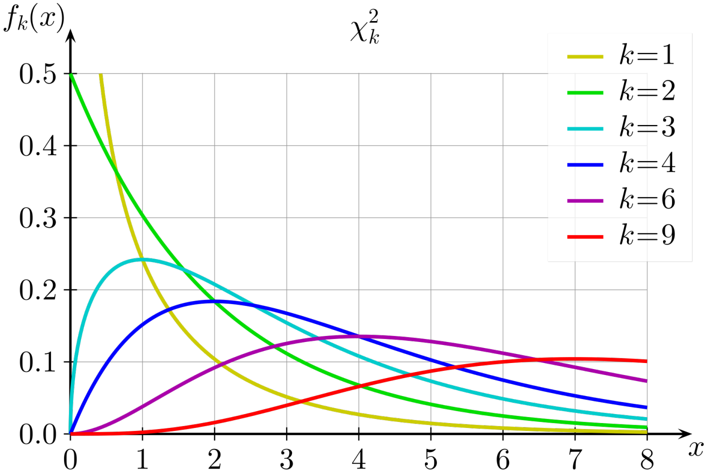
Lemma

Let $Z_1, Z_2, \ldots, Z_k$ be independent $\mathcal{N}(0,1)$ random variables and let $Y = \sum_i Z_i^2$. Then, for $\epsilon \in (0, 1/2)$, there is a constant c such that,

$$\Pr[(1-\epsilon)^2 k \le Y \le (1+\epsilon)^2 k] \ge 1 - 2e^{c\epsilon^2 k}.$$

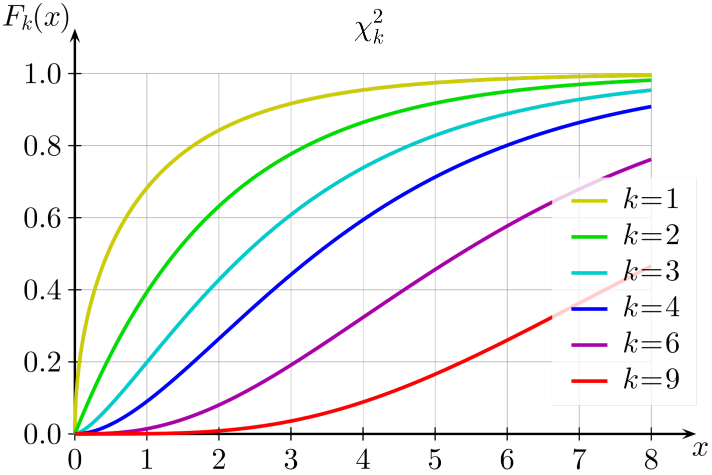
χ^2 distribution

Density function



χ^2 distribution

Cumulative density function



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Recall Chernoff-Hoeffding bound for *bounded* independent non-negative random variables. Z_i^2 is not bounded, however Chernoff-Hoeffding bounds extend to sums of random variables with exponentially decaying tails.

Random Guassian vector again

A real random vector $Z = (Z_1, Z_2, \ldots, Z_k)$ is a *standard* normal random vector if $Z_i \sim \mathcal{N}(0,1)$ for each i and $Z_1, \ldots, Z_k$ are independent.

Euclidean length: $\mathrm{E}\left[\|Z\|_2^2\right] = \sum_i \mathrm{E}\left[Z_i^2\right] = k$.

Thus, the Euclidean length of Z is concentrated around $\sqrt{k}$.

Proof of DJL Lemma

Without loss of generality assume $\|x\|_2 = 1$ (unit vector)

$Z_i = \sum_{j=1}^{n} \Pi_{ij} x_i$

- $Z_i \sim \mathcal{N}(0, 1)$ for each i

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- Hence $\Pr[(1-\epsilon)^2 k \leq Y \leq (1+\epsilon)^2 k] \geq 1 - 2e^{c\epsilon^2 k}$
- Since $k = \Omega(\frac{1}{\epsilon^2}\log(1/\delta))$ we have $\Pr[(1-\epsilon)^2 k \leq Y \leq (1+\epsilon)^2 k] \geq 1 - \delta$

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- Since $k = \Omega(\frac{1}{\epsilon^2} \log(1/\delta))$ we have $\Pr[(1-\epsilon)^2 k \leq Y \leq (1+\epsilon)^2 k] \geq 1 - \delta$
- Therefore $\|z\|_2 = \sqrt{Y/k}$ has the property that with probability $(1-\delta)$, $\|z\|_2 = (1 \pm \epsilon)\|x\|_2$.

JL lower bounds

Question: Are the bounds achieved by the lemmas tight or can we do better? How about non-linear maps?

Essentially optimal modulo constant factors for worst-case point sets.

Fast JL and Sparse JL

Projection matrix Π is dense and hence Πx takes $\Theta(kd)$ time.

Question: Can we find Π to improve time bound?

Two scenarios: x is dense and x is sparse

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Known results:

- Choose Π_{ij} to be $\{-1, 0, 1\}$ with probability $1/6, 1/3, 1/6$. Also works. Roughly $1/3$ entries are 0
- Fast JL: Choose Π in a dependent way to ensure Πx can be computed in $O(d \log d + k^2)$ time. For dense x.
- Sparse JL: Choose Π such that each column is s-sparse. The best known is $s = O(\frac{1}{\epsilon} \log(1/\delta))$. Helps in sparse x.

Part I

(Oblivious) Subspace Embeddings

Subspace Embedding

Question: Suppose we have linear subspace E of $\mathbb{R}^n$ of dimension d. Can we find a projection $\Pi : \mathbb{R}^n \rightarrow \mathbb{R}^k$ such that for *every* $x \in E$, $\|\Pi x\|_2 = (1 \pm \epsilon)\|x\|_2$?

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- Possible if $k = d$. Why?

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What we really want: *Oblivious* subspace embedding ala JL based on random projections

Oblivious Supspace Embedding

Theorem

Suppose $\boldsymbol{E}$ is a linear subspace of $\mathbb{R}^{\boldsymbol{n}}$ of dimension $\boldsymbol{d}$. Let Π be a DJL matrix $\Pi \in \mathbb{R}^{\boldsymbol{k} \times \boldsymbol{n}}$ with $\boldsymbol{k} = \boldsymbol{O}(\frac{\boldsymbol{d}}{\epsilon^2} \log(1/\delta))$ rows. Then with probability $(1 - \delta)$ for every $\boldsymbol{x} \in \boldsymbol{E}$,

$$\|\frac{1}{\sqrt{\boldsymbol{k}}}\Pi \boldsymbol{x}\|_2 = (1 \pm \epsilon)\|\boldsymbol{x}\|_2.$$

In other words JL Lemma extends from one dimension to arbitrary number of dimensions in a graceful way.

Proof Idea

How do we prove that Π works for *all* $x \in E$ which is an infinite set?

Several proofs but one useful argument that is often a starting hammer is the "net argument"

- Choose a large but finite set of vectors T carefully (the net)
- Prove that Π preserves lengths of vectors in T (via naive union bound)
- Argue that *any* vector $x \in E$ is sufficiently close to a vector in T and hence Π also preserves length of x

Net argument

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Claim: There is a net T of size $e^{O(d)}$ such that preserving lengths of vectors in T suffices.

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Claim: There is a net T of size $e^{O(d)}$ such that preserving lengths of vectors in T suffices.

Assuming claim: use DJL with $k = O(\frac{d}{\epsilon^2}\log(1/\delta))$ and union bound to show that all vectors in T are preserved in length up to $(1 \pm \epsilon)$ factor.

Net argument

Sufficient to focus on unit vectors in E.

Also assume wlog and ease of notation that E is the subspace formed by the first d coordinates in standard basis.

A weaker net:

- Consider the box $[-1, 1]^d$ and make a grid with side length ϵ/d
- Number of grid vertices is $(2d/\epsilon)^d$
- Sufficient to take T to be the grid vertices
- Gives a weaker bound of $O(\frac{1}{\epsilon^2} d \log(d/\epsilon))$ dimensions
- A more careful net argument gives tight bound

Net argument: analysis

Fix any $x \in E$ such that $\|x\|_2 = 1$ (unit vector)
There is grid point y such that $\|y\|_2 \leq 1$ and x is close to y
Let $z = x - y$. We have $|z_i| \leq \epsilon/d$ for $1 \leq i \leq i \leq d$ and $z_i = 0$ for $i > d$

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$$\begin{aligned} \|\Pi x\| = \|\Pi y + \Pi z\| &\leq \|\Pi y\| + \|\Pi z\| \\ &\leq (1+\epsilon) + (1+\epsilon)\sum_{i=1}^{d} |z_i| \\ &\leq (1+\epsilon) + \epsilon(1+\epsilon) \leq 1 + 3\epsilon \end{aligned}$$

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Similarly $\|\Pi x\| \geq 1 - O(\epsilon)$.

Application of Subspace Embeddings

Faster algorithms for approximate

- matrix multiplication
- regression
- SVD

Basic idea: Want to perform operations on matrix A with n data columns (say in large dimension $\mathbb{R}^h$) with small effective rank d. Want to reduce to a matrix of size roughly $\mathbb{R}^{d \times d}$ by spending time proportional to $\text{nnz}(A)$.

Later in course.