

Random Projections and Dimension Reduction

Rishi Advani¹ Madison Crim² Sean O'Hagan³

¹Cornell University

²Salisbury University

³University of Connecticut

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Introduction

During this talk, we will focus on the use of randomness in two main areas:

- low-rank approximation
- kernel methods



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- Johnson-Lindenstrauss Lemma
- Interpolative Decomposition
- Singular Value Decomposition
- SVD/ID Performance
- Eigenfaces

2 Kernel Methods

- Kernel Methods
- Kernel PCA
- Kernel SVM



Johnson-Lindenstrauss Lemma

If we have n data points in \mathbb{R}^d , there exists a linear map into \mathbb{R}^k , $k < d$, such that pairwise distances between data points can be preserved up to an ϵ tolerance, provided $k > C\epsilon^{-2} \log n$, where $C \approx 24$ [JL84]. The proof follows three steps [Mic09]:

- Define a random linear map $f: \mathbb{R}^d \rightarrow \mathbb{R}^k$ by $f(\mathbf{u}) = \frac{1}{\sqrt{k}} R \cdot \mathbf{u}$, where $R \in \mathbb{R}^{k \times d}$ is drawn elementwise from a standard normal distribution.
- If $\mathbf{u} \in \mathbb{R}^d$, show $\mathbb{E}[\|f(\mathbf{u})\|_2^2] = \|\mathbf{u}\|_2^2$.
- Show that the random variable $\|f(\mathbf{u})\|_2^2$ concentrates around $\|\mathbf{u}\|_2^2$, and construct a union bound over all pairwise distances.



Johnson-Lindenstrauss Lemma: Demonstration

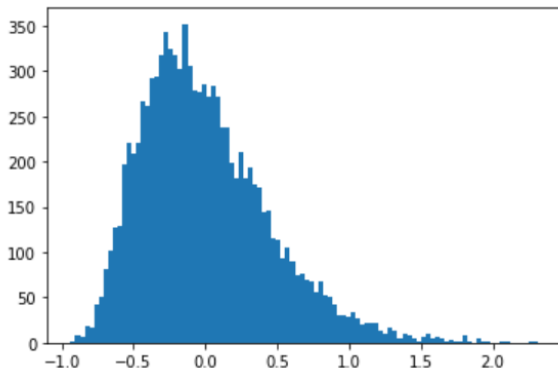


Figure: Histogram of $\|\mathbf{u}\|_2^2 - \|f(\mathbf{u})\|_2^2$ for a fixed $\mathbf{u} \in \mathbb{R}^{1000}$, $f(\mathbf{u}) \in \mathbb{R}^{10}$



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Deterministic Interpolative Decomposition

Given a matrix $A \in \mathbb{R}^{m \times n}$, we can compute an interpolative decomposition (ID), a low-rank matrix approximation that uses A 's own columns [Yin+18]. The ID can be computed using the column-pivoted QR factorization:

$$AP = QR.$$

To obtain our low-rank approximation, we form the submatrix Q_k using the first k columns of Q . We then have the approximation

$$A \approx Q_k Q_k^* A,$$

which gives us a particular rank- k projection of A .



Randomized Interpolative Decomposition

We introduce a new method to compute randomized ID, by taking a subset S of $p > k$ distinct, randomly-selected columns from the n columns of A . The algorithm then performs the column-pivoted QR factorization on the submatrix:

$$A_{(:,S)}P = QR$$

Accordingly we have the following rank k projection of A :

$$A \approx Q_k Q_k^* A,$$

where Q_k is the submatrix formed by the first k columns of Q .



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Deterministic Singular Value Decomposition

- Recall the singular value decomposition of a matrix [16],

$$A_{m \times n} = U_{m \times m} \Sigma_{m \times n} V_{n \times n}^*,$$

where U and V are orthogonal matrices, and Σ is a rectangular diagonal matrix with positive diagonal entries $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r$, where r is the rank of the matrix A .

- The σ_i s are called the singular values of A .



Randomized Singular Value Decomposition

Utilizing ideas from [HMT09], our algorithm executes the following steps to compute the randomized SVD:

- 1 Construct a $n \times k$ random Gaussian matrix Ω
- 2 Form $Y = A\Omega$
- 3 Construct a matrix Q whose columns form an orthonormal basis for the column space of Y
- 4 Set $B = Q^*A$
- 5 Compute the SVD: $B = U'\Sigma V^*$
- 6 Construct the SVD approximation: $A \approx QQ^*A = QB = QU'\Sigma V^*$



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Results - Testing 620×187500 Matrix

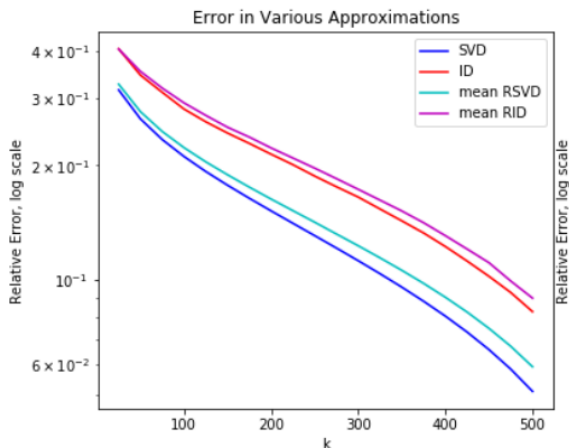


Figure: Error Relative to Original Data



Results - Testing 620×187500 Matrix

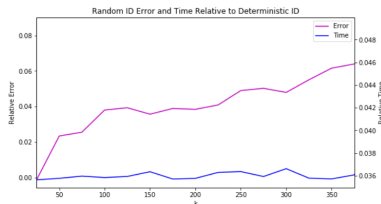


Figure: Random ID Error and Time Relative to Deterministic ID



Figure: Random SVD Error and Time Relative to Deterministic SVD



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Eigenfaces

- Using ideas from [BKP15], our eigenfaces experiment is based on the LFW dataset [Hua+07]. This dataset contains more than 13,000 RGB images of faces, where each image has dimensions 250×250 .
- We can flatten each image to represent it as vector of length $250 \cdot 250 \cdot 3 = 187500$.
- In our experiment we will only use 620 images from the LFW dataset. This gives us a data matrix A of size 187500×620 .
- We then can perform SVD on the mean-subtracted columns of A .

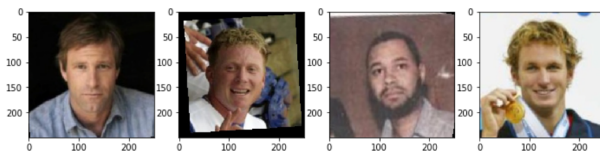


Figure: Original LFW Images



Image Results

We obtain the following eigenfaces from the columns of the matrix U :

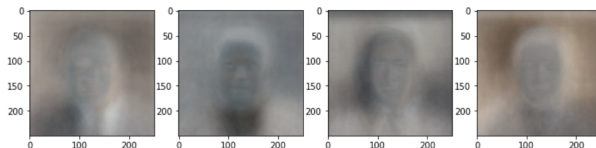


Figure: Eigenfaces Obtained using Deterministic SVD

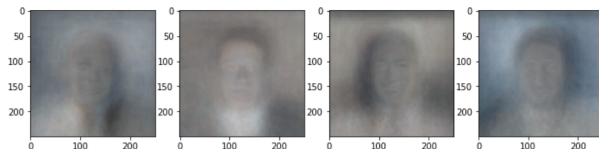


Figure: Eigenfaces Obtained using Randomized SVD



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- Kernel methods work by mapping the data into a high-dimensional space to add more structure and encourage linear separability.
- Suppose we have a feature map $\phi: \mathbb{R}^n \rightarrow \mathbb{R}^m$, $m > n$.
- The 'kernel trick' is based on the observation that we only need the inner products of vectors in the feature space, not the explicit high-dimensional mappings.

$$k(\mathbf{x}, \mathbf{y}) = \langle \phi(\mathbf{x}), \phi(\mathbf{y}) \rangle$$

- Ex. Gaussian/RBF Kernel: $k(\mathbf{x}, \mathbf{y}) = \exp(-\gamma \|\mathbf{x} - \mathbf{y}\|_2^2)$
- Kernel methods include kernel PCA, kernel SVM, and more.



Randomized Fourier Features Kernel

We can sample random Fourier features to approximate a kernel [RR08]. Let $k(\mathbf{x}, \mathbf{y})$ denote our kernel, and $p(\mathbf{w})$ the probability distribution corresponding to the inverse Fourier transform of k .

$$\begin{aligned} k(\mathbf{x}, \mathbf{y}) &= \int_{\mathbb{R}^d} p(\mathbf{w}) e^{-j\mathbf{w}^T(\mathbf{x}-\mathbf{y})} d\mathbf{w} \\ &\approx \frac{1}{m} \sum_{i=1}^m \cos(\mathbf{w}_i^T \mathbf{x} + b_i) \cos(\mathbf{w}_i^T \mathbf{y} + b_i), \end{aligned}$$

where $\mathbf{w}_i \sim p(\mathbf{w})$, $b_i \sim \text{Uniform}(0, 2\pi)$. For a given m , define

$$z(\mathbf{x}) = \sum_{i=1}^m \cos(\mathbf{w}_i^T \mathbf{x} + b_i)$$

to yield the approximation $k(\mathbf{x}, \mathbf{y}) \approx \frac{1}{m} z(\mathbf{x}) z(\mathbf{y})^T$ [Lop+14].



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Data for Kernel PCA Experiments

To test kernel PCA methods, we use a dataset that is not linearly separable — a cloud of points surrounded by a circle:

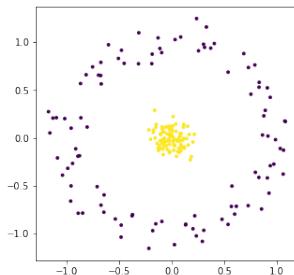


Figure: Data used to test kernel PCA methods



Randomized Kernel PCA Results

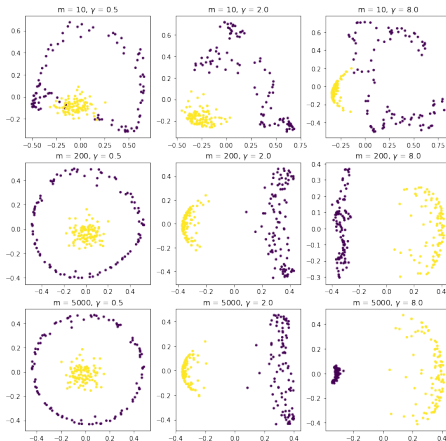


Figure: Random Fourier features KPCA results



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- We may also use kernel methods for support vector machines (SVM).
- The goal of an SVM is to find the $(d - 1)$ -hyperplane that best separates two clusters of d -dimensional data points.
- In two dimensions, this is a line separating two clusters of points in a plane.
- Using the kernel trick, we can project inseparable points into a higher dimension and run an SVM algorithm on the resulting points.



Randomized Kernel SVM

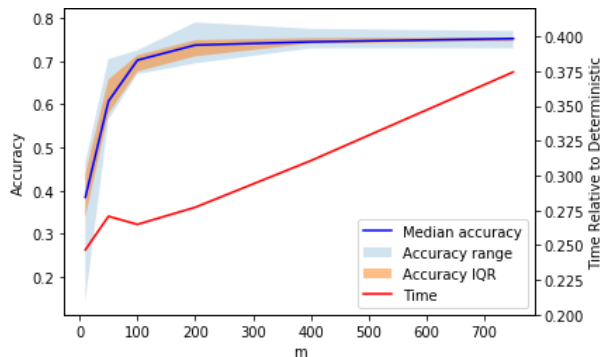


Figure: Randomized Kernel SVM Accuracy and time results as m varies



Comparison of Deterministic and Randomized Kernel SVM

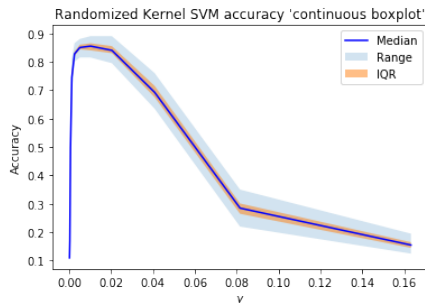
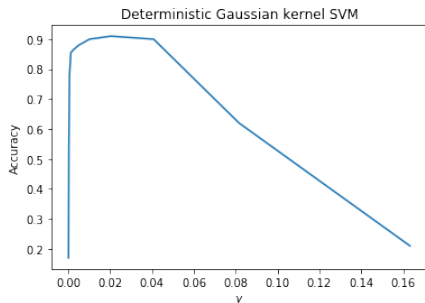
Using the MNIST dataset [LC10] we test 10000 images (784 features), for a **fixed** γ :

- Deterministic Kernel
 - Accuracy: 0.9195
 - Time: 37.99s
- Randomized Kernel
 - Accuracy: Mean: 0.891, St. dev. 0.0042
Min: 0.881, Max: 0.9005
 - Mean Time: 2.14s



Comparison of Deterministic and Randomized Kernel SVM

On 1000 MNIST images, we plot the accuracies of the deterministic and random kernel SVMs as γ varies:



Application of Randomized Kernel SVM: Grid Search

Testing 100 γ values to identify the best one:

- Deterministic Kernel, Series: 133.03s
- Randomized Kernel, Series: 78.97s
- Randomize Kernel, Parallel: 41.18s
- Best γ value obtained from randomized method corresponds with either best or second best deterministic γ (3 trials)

$$\hat{\mathbf{K}} = \frac{1}{m} \mathbf{z}(\mathbf{X}) \mathbf{z}(\mathbf{X})^T$$



Takeaways

- When using large datasets, randomized algorithms are able to maintain most of the accuracy of their deterministic counterpart, while offering a huge reduction in computational cost
- These algorithms are useful for matrix factorization/decomposition as well as for kernel approximation



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To explore more visit our website at the following link:
<https://rishi1999.github.io/random-projections/>

