

# Randomized Algorithms 2021A – Lecture 8 (second part)

## Oblivious Subspace Embedding\*

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### 1 Oblivious Subspace Embedding

**Embedding an entire subspace:** In some situations (like regression, as we will see soon), we want a guarantee for a whole subspace, which has infinitely many points.

Observe that a linear subspace  $V \subset \mathbb{R}^n$  of dimension  $d$  can be described as the column space of  $A \in \mathbb{R}^{n \times d}$ , i.e.,  $V = \{Ax : x \in \mathbb{R}^d\}$ .

A good way to think about the next definition is that we will solve a problem in  $\mathbb{R}^n$  involving an unknown  $d$ -dimensional subspace, by reducing the problem to dimension  $s = s(n, d, \epsilon, \delta)$ . Thus, we want  $s$  (the number of rows in  $S$ ) to be as small as possible.

**Definition:** A random matrix  $S \in \mathbb{R}^{s \times n}$  is called an  $(\epsilon, \delta, d)$ -Oblivious Subspace Embedding (OSE) if

$$\forall A \in \mathbb{R}^{n \times d}, \quad \Pr_S \left[ \forall x \in \mathbb{R}^d, \|SAx\| \in (1 \pm \epsilon)\|Ax\| \right] \geq 1 - \delta.$$

We next show that it is easy to construct OSE using JLT.

**Exer:** Show that the OSE property is preserved under right-multiplication by a matrix with orthonormal columns, as follows. If  $S \in \mathbb{R}^{s \times n}$  is an  $(\epsilon, \delta, d)$ -OSE matrix, and  $U \in \mathbb{R}^{n \times r}$  is a matrix with orthonormal columns, then  $SU$  is an  $(\epsilon, \delta, \min(r, d))$ -OSE matrix (for the space  $\mathbb{R}^r$ ).

**Theorem:** Let  $S \in \mathbb{R}^{s \times n}$  be an  $(\epsilon, \delta, b)$ -JLT for  $\epsilon < 1/4$ . Then  $S$  is also an  $(O(\epsilon), \delta, \frac{\ln b}{\ln(1/\epsilon)})$ -OSE.

Remark: To produce OSE for dimension  $d$ , we should set in this theorem  $d = \frac{\ln b}{\ln(1/\epsilon)}$ , i.e.,  $b = (1/\epsilon)^d$ , which we can achieve using a Gaussian matrix with  $s = O(\epsilon^{-2} \log(b/\delta)) = O(\epsilon^{-2}(d \log \frac{1}{\epsilon} + \log \frac{1}{\delta}))$  rows. A direct construction with sparse columns (and thus fast matrix-vector multiplication) was shown by [Cohen, 2016].

**Proof:** Was seen in class. The main idea is to use the JLT guarantee on a  $(3\epsilon)$ -net  $N$  of the unit sphere in  $\mathbb{R}^d$ , then represent arbitrary  $x \in \mathbb{R}^d$  as an infinite (but converging) sum  $x = \sum_{i=0}^{\infty} x_i$ ,

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\*These notes summarize the material covered in class, usually skipping proofs, details, examples and so forth, and possibly adding some remarks, or pointers. The exercises are for self-practice and need not be handed in. In the interest of brevity, most references and credits were omitted.

where each  $x_i$  is a (scalar) multiple of a net point, and finally use the triangle inequality. We used the next exercise, whose proof is based on volume arguments.

**Exer:** Show that one can construct a  $\gamma$ -net  $N$  of size  $|N| \leq (1 + 2/\gamma)^d \leq (3/\gamma)^d$ .

Hint: Let  $B_r$  be a ball of radius  $r > 0$  in  $\mathbb{R}^d$ . Then the volume of  $B_{2r}$  is bigger than that of  $B_r$  by a factor of  $2^d$ .

Remark: It is possible to get a better bound by employing a  $1/2$ -net (instead of  $\varepsilon$ -net) and expanding  $\|SAx\|^2$  including cross terms.