

**kk**

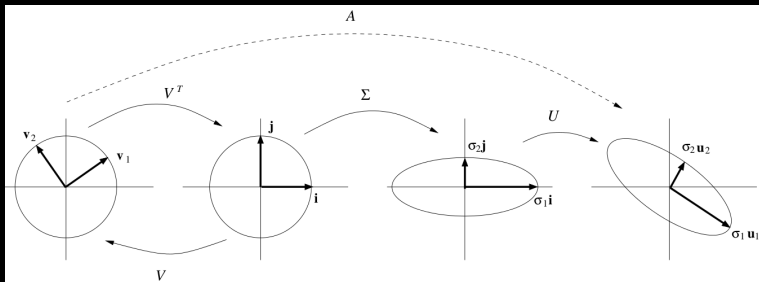
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# What does $A = U\Sigma V^T$ mean?

## Geometric interpretation

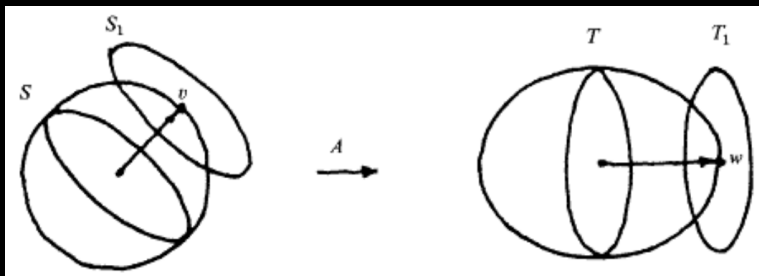


# Why SVD is possible? Geometrical insight

Is all about orthogonality

$$A = U\Sigma V^T \implies A\mathbf{v}_i = \sigma_i\mathbf{u}_i \quad \ni \quad i = 1 \dots \text{rank}(A)$$

What is special about  $\mathbf{v}$ ?



Got curious?

Check the report, it has the full proof.

# SVD as an Eigenproblem

## Algebraic Proof

Almost a whole chapter of the report, check it out!

The eigenproblem, solved for symmetric matrices

$$B^{n \times n} = Q \Lambda Q^T$$

$A^T A$  is symmetric!

$$A = U \Sigma V^T \iff A^T A = V \Sigma^2 V^T$$

$A A^T$  is symmetric too! (used in GenSim)

$$A = U \Sigma V^T \iff A A^T = U \Sigma^2 U^T$$

# Is SVD problem well conditioned?

A problem is well conditioned if ...

$$x \simeq (x + \delta) \implies f(x) \simeq f(x + \delta)$$

Weyl's Theorem

$$|\tilde{\sigma}_i - \sigma_i| \leq \|E\|_2 \quad \ni \quad \tilde{A} = A + E$$

Wedin's Theorem

The singular vectors subproblem is not well conditioned in theory, but it has bounds.

In practice we are fine

We do not need singular vectors by themselves ( $\mathbf{v} = \Sigma^{-1} U^T \mathbf{x}$ ).

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**Algorithm 1:** The Single-Vector Lanczos Algorithm

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**Input** : A matrix  $A^{m \times n}$  and a truncation factor  $k$

**Output:** The  $k$  singular values and its associated right singular vectors of  $A$ . Both are numeric approximations.

- 1 Use Lanczos Tridiagonalization Step to generate a family of  $c$  symmetric tridiagonal matrices  $\{T_j\}$  for  $A^T A$  ( $c > k$ )
  - 2 Compute the eigenvalues and eigenvectors of  $T_k$  using the (implicit) QL Method.
  - 3 For each computed  $\lambda_i$  of  $T_k$ , calculate the associated unit eigenvector  $\mathbf{z}_i$  such that  $T_k \mathbf{z}_i = \lambda_i \mathbf{z}_i$ .
  - 4 For each calculated eigenvector  $\mathbf{z}_i$  of  $T_k$ , compute the Ritz vectors  $\mathbf{v}_i = Q_c \mathbf{z}_i$  as an approximation to the  $i$ -th eigenvector of  $A^T A$ . Note that the matrix  $Q_c$  is a side product of the first step.
  - 5 return  $(\{\lambda_1, \lambda_2, \dots, \lambda_k\}, \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\})$
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**Algorithm 2:** Lanczos Tridiagonalization Step (sparse,2)

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**Input** : A unit vector  $\mathbf{q}_1 \in \mathbb{R}^n$  and a symmetric matrix  $A^{n \times n}$

**Output:** The sequences  $\{\alpha_i\}$ ,  $\{\beta_i\}$  and matrix  $Q = [\mathbf{q}_1 | \mathbf{q}_2 | \cdots]$

```
1  $k \leftarrow 0, \beta_0 \leftarrow 1, \mathbf{q}_0 \leftarrow 0, r_0 \leftarrow \mathbf{q}_1$ 
2 while  $k = 0 \vee \beta_k \neq 0$  do
3    $\mathbf{q}_{k+1} \leftarrow \frac{\mathbf{r}_k}{B_k}$ 
4    $k \leftarrow k + 1$ 
5    $\alpha_k \leftarrow \mathbf{q}_k^T A \mathbf{q}_k$ 
6    $\mathbf{r}_k \leftarrow A \mathbf{q}_k - \alpha_k \mathbf{q}_k - \beta_{k-1} \mathbf{q}_{k-1}$ 
7    $\beta_k \leftarrow \|\mathbf{r}_k\|_2$ 
8 return  $(\{\alpha_i\}, \{\beta_i\}, Q = [\mathbf{q}_1 | \mathbf{q}_2 | \cdots])$ 
```

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## The $T_k$ from Lanczos Tridiagonalization Step

$$T_k = \begin{bmatrix} \alpha_1 & \beta_1 & \cdots & 0 \\ \beta_1 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \beta_{k-1} \\ 0 & \cdots & \beta_{k-1} & \alpha_k \end{bmatrix}$$



# Lanczos Algorithm Reality Check

## **Is it numerically stable?**

No, the tridiagonalization step needs to be rewritten (thanks Paige!).

## **Is orthogonality really guaranteed?**

No, it is lost precisely with the converged singular vectors (thanks again Paige!). Selective re-orthogonalization is required (thanks Parlett and Simon!).

## **What to do then?**

Berry's implementation, LASVD/LAS2, consider all aspects above; including performance (parallelization).

## LASVD/LAS2 Profiling by Berry

Routine	Library	Description
SPMXV	BLAS level 2	Sparse matrix-vector mult.
IMTQL2 / TRED2	EISPACK	Implicit QL Algorithm.
DAXPY	BLAS level 1	$\mathbf{x} \leftarrow \gamma \mathbf{x} + \mathbf{y}$
DAXPY	BLAS level 1	$\mathbf{x} \leftarrow \mathbf{y}$
DDOT	BLAS level 1	$\mathbf{x} \cdot \mathbf{y}$

	Alliant FX/80		Cray-2S/4-128	
Routine	Speedup	%CPU Time	Speedup	%CPU Time
SPMXV	3	27%	-	72%
IMTQL2	4.3	14%	-	12%
DAXPY	5	17%	-	-
DCOPY	3.6	20%	-	-
DDOT	7.7	2%	-	-

## SVDPACK $\implies$ SVDLIBC: lost parallelism

- Berry's SVDPACK LAS2: SPMXV (BLAS?), IMTQL2 (EISPACK)
- Berry ports to SVDPACKC: opa/opb (user), IMTQL2 (serial!)
- Rohde new skin of SVDLIBC: opa/opb (serial!), IMTQL2 (serial!).
- Radim's python wrapper SPARSESVd : same all
- Radim's GenSim uses a serial LAS2 routine!