# Distributional word representations: dimensionality reduction 

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CS 244U: Natural language understanding


## Goals

- Eliminate correlations
- Improve similarity measures


## Guiding intuitions



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## Latent Semantics Analayis (LSA)

## Singular value decomposition

For any matrix of real numbers $A$ of dimension $(m \times n)$ there exists a factorization into matrices $T, S, D$ such that

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$$
\begin{aligned}
\left(\begin{array}{cccc}
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot
\end{array}\right) & =\left(\begin{array}{lll}
\cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot
\end{array}\right)\left(\begin{array}{lll}
\cdot & \\
& \cdot \\
& \\
& A_{3 \times 4} & \\
& T_{3 \times 3} \quad\left(\begin{array}{lll}
\cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot
\end{array}\right)^{T} \\
S_{3 \times 3} & D_{4 \times 3}^{T}
\end{array}\right.
\end{aligned}
$$

## Example

|  | d1 d2 d3 d4 d5 d6 |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
| gnarly | 10 | 1 | 0 | 0 | 0 |
| wicked | 01 | 0 |  | 0 |  |
| awesome | 11 | 1 | 1 | 0 | 0 |
| lame | 00 | 0 | 0 | 1 | 1 |
| terrible | 00 | 0 | 0 | 0 |  |

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Distance from gnarly

1. gnarly
2. awesome
3. terrible
4. wicked
5. lame

## Example



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## Comparisons before and after LSA with $\mathrm{k}=100$

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PMI with LSA ( $k=100$ ), word $x$ word


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## Comparisons before and after LSA with $\mathrm{k}=100$

## PMI, word x word



PMI with LSA ( $k=100$ ), word $x$ word


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For more: Turney and Pantel 2010, 'From frequency to meaning', p. 160.

