

CPSC 340: Machine Learning and Data Mining

PCA: fit

Bonus slides

PCA Computation: SVD

- How do we fit with normalization/orthogonality/sequential-fitting?
 - It can be done with the “singular value decomposition” (SVD).
 - Take CPSC 302.
- 4 lines of Julia code:
 - `mu = mean(X,1)`
 - `X -= repmat(mu,n,1)`
 - `(U,S,V) = svd(X)`
 - `W = V[:,1:k]'`

Computing \tilde{Z} is cheaper now:

$$\tilde{Z} = \tilde{X} W^T (W W^T)^{-1} = \tilde{X} W^T$$
$$W W^T = \begin{bmatrix} -w_1- \\ -w_2- \\ \vdots \\ -w_k- \end{bmatrix} \begin{bmatrix} | & | & \dots & | \\ w_1^T & w_2^T & \dots & w_k^T \\ | & | & \dots & | \end{bmatrix}$$
$$= \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & 1 \end{bmatrix} = I$$

Making PCA Unique

- PCA implementations add **constraints to make solution unique**:
 - **Normalization**: we enforce that $\|w_c\| = 1$.
 - **Orthogonality**: we enforce that $w_c^T w_{c'} = 0$ for all $c \neq c'$.
 - **Sequential fitting**: We **first fit w_1** (“first principal component”) giving a line.
 - **Then fit w_2 given w_1** (“second principal component”) giving a plane.
 - **Then we fit w_3 given w_1 and w_2** (“third principal component”) giving a space.
 - ...
- Even with all this, the solution is **only unique up to sign changes**:
 - I can still replace any w_c by $-w_c$:
 - $-w_c$ is normalized, is orthogonal to the other $w_{c'}$, and spans the same space.
 - Possible fix: **require that first non-zero element of each w_c is positive**.
 - And this is assuming you don’t have repeated singular values.
 - In that case you can rotate the repeated ones within the same plane.