Feel free to work with other students, but make sure you write up the homework and code on your own (no copying homework *or* code; no pair programming). Feel free to ask students or instructors for help debugging code or whatever else, though.

- **1** (Murphy 12.5 Deriving the Residual Error for PCA) It may be helpful to reference section 12.2.2 of Murphy.
- (a) Prove that

$$\left\|\mathbf{x}_i - \sum_{j=1}^k z_{ij} \mathbf{v}_j\right\|^2 = \mathbf{x}_i^\top \mathbf{x}_i - \sum_{j=1}^k \mathbf{v}_j^\top \mathbf{x}_i \mathbf{x}_i^\top \mathbf{v}_j.$$

Hint: first consider the case when k = 2. Use the fact that $\mathbf{v}_i^{\top} \mathbf{v}_j$ is 1 if i = j and 0 otherwise. Recall that $z_{ij} = \mathbf{x}_i^{\top} \mathbf{v}_j$.

(b) Now show that

$$J_k = \frac{1}{n} \sum_{i=1}^n \left(\mathbf{x}_i^\top \mathbf{x}_i - \sum_{i=1}^k \mathbf{v}_j^\top \mathbf{x}_i \mathbf{x}_i^\top \mathbf{v}_j \right) = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i^\top \mathbf{x}_i - \sum_{i=1}^k \lambda_j.$$

Hint: recall that $\mathbf{v}_j^{\top} \mathbf{\Sigma} \mathbf{v}_j = \lambda_j \mathbf{v}_j^{\top} \mathbf{v}_j = \lambda_j$.

(c) If k = d there is no truncation, so $J_d = 0$. Use this to show that the error from only using k < d terms is given by

$$J_k = \sum_{j=k+1}^d \lambda_j.$$

Hint: partition the sum $\sum_{j=1}^{d} \lambda_j$ into $\sum_{j=1}^{k} \lambda_j$ and $\sum_{j=k+1}^{d} \lambda_j$.

a) I had to look at the solution for this one. Again, I'll summarize:

$$\left\|\mathbf{x}_i - \sum_{j=1}^k z_{ij} \mathbf{v}_j\right\|^2 = (\mathbf{x}_i - \sum_{j=1}^k z_{ij} \mathbf{v}_j)^T (\mathbf{x}_i - \sum_{j=1}^k z_{ij} \mathbf{v}_j)$$

Simplify by bringing \mathbf{x}_{i}^{T} into the sum, and since $\mathbf{v}_{i}^{T}\mathbf{v}_{j}=1$ if and only if i=j, we finally get:

$$\mathbf{x}_{\mathbf{i}}^{T}\mathbf{x}_{\mathbf{i}} - \sum_{j=1}^{k} \mathbf{v}_{\mathbf{j}}^{T}\mathbf{x}_{\mathbf{i}}\mathbf{x}_{\mathbf{i}}^{T}\mathbf{v}_{\mathbf{j}}$$

as desired

b)

$$J_k = \frac{1}{n} \sum_{i=1}^n (\mathbf{x}_i^T \mathbf{x}_i - \sum_{j=1}^K \mathbf{v}_j^T \mathbf{x}_i \mathbf{x}_i^T \mathbf{v}_j)$$

$$= \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i^T \mathbf{x}_i - \sum_{j=1}^k \mathbf{v}_j^T \Sigma \mathbf{v}_j$$

$$= \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i^T \mathbf{x}_i - \sum_{j=1}^k \lambda_j$$

c) Looked at the solutions for reference for this one. We know that:

$$J_k = \frac{1}{n} \sum_{i=1}^n \mathbf{x}_i^T \mathbf{x}_i - \sum_{j=1}^d \lambda_j + \sum_{j=k+1}^d \lambda_j = \sum_{j=k+1}^d \lambda_j$$

As Prof Gu mentioned during lecture, the sum of the unused eigenvalues is equal to the reconstruction error of a PCA projection.

2 (ℓ_1 -Regularization) Consider the ℓ_1 norm of a vector $\mathbf{x} \in \mathbb{R}^n$:

$$\|\mathbf{x}\|_1 = \sum_i |\mathbf{x}_i|.$$

Draw the norm-ball $B_k = \{\mathbf{x} : \|\mathbf{x}\|_1 \le k\}$ for k = 1. On the same graph, draw the Euclidean norm-ball $A_k = \{\mathbf{x} : \|\mathbf{x}\|_2 \le k\}$ for k = 1 behind the first plot. (Do not need to write any code, draw the graph by hand).

Show that the optimization problem

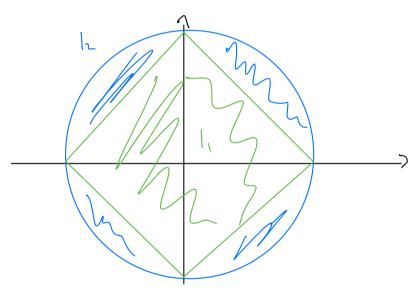
minimize: $f(\mathbf{x})$ subj. to: $\|\mathbf{x}\|_p \le k$

is equivalent to

minimize: $f(\mathbf{x}) + \lambda ||\mathbf{x}||_p$

(hint: create the Lagrangian). With this knowledge, and the plots given above, argue why using ℓ_1 regularization (adding a $\lambda \|\mathbf{x}\|_1$ term to the objective) will give sparser solutions than using ℓ_2 regularization for suitably large λ .

Graph:



Per the class notes,

$$infsupL(\mathbf{x}, \lambda) = infsupf(\mathbf{x}) + \lambda(||\mathbf{x}||_p - k)$$

Now, referring to the solution guide, we can flip the inf and the sup because it is in its dual, such that:

$$infsupf(\mathbf{x}) + \lambda(||\mathbf{x}||_p - k) = supg(\lambda)$$

By optimizing x, we will solve the minimization of $f(\mathbf{x}) + \lambda ||\mathbf{x}||_p$ for some value of $\lambda >= 0$. After looking at the solution, I still don't quite understand what is going on. I will be sure to ask Prof Gu either during class or I will set up an appointment with her.

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