An equivalent formulation of matrix kernels (II)

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1 Corrections to your section 1

Let $K(\cdot, \cdot)$ denote a usual kernel defined over vector pairs in \mathbb{R}^d . We use the shorthand $K(i, j) \stackrel{\text{def}}{=} K(X_i, X'_i)$ to denote the kernel value evaluated on the vector pair (X_i, X'_i) .

(Note: my definition of projection P seems to be the transpose of your definition of P.)

Proposition 1 (Rank-1 weights in Kernel). Define a kernel over matrix pairs, $\mathcal{K}(\boldsymbol{X}, \boldsymbol{X}') \stackrel{\text{def}}{=} \langle \boldsymbol{P}^T \Phi(\boldsymbol{X}) \boldsymbol{P}, \ \boldsymbol{P}^T \Phi(\boldsymbol{X}') \boldsymbol{P} \rangle$ for some rank-1 projection matrix $\boldsymbol{P} \in \mathbb{R}^{2 \times 1}$. Then, \mathcal{K} has an equivalent representation,

$$\mathcal{K}(\boldsymbol{X}, \boldsymbol{X}') = 2C \sum_{i,j} w_{ij} K(i,j),$$

where $\boldsymbol{W} = \boldsymbol{P}\boldsymbol{P}^T = [\![w_{ij}]\!]$ is a rank-1 weight matrix, and C>0 is a normalizing constant.

Proof. By definition,

$$\mathcal{K}(\boldsymbol{X}, \boldsymbol{X}') = \langle \boldsymbol{P}^T \Phi(\boldsymbol{X}) \boldsymbol{P}, \ \boldsymbol{P}^T \Phi(\boldsymbol{X}') \boldsymbol{P} \rangle$$

$$= \langle \underbrace{\boldsymbol{P} \boldsymbol{P}^T}_{=:\boldsymbol{W}}, \ \Phi^T(\boldsymbol{X}) \underbrace{\boldsymbol{P} \boldsymbol{P}^T}_{=:\boldsymbol{W}} \Phi(\boldsymbol{X}') \rangle$$
(1)

Both W and $\Phi^T(X)W\Phi(X')$ are d-by-d matrices. The (i,j)-th entry of $\Phi^T(X)W\Phi(X')$ is

$$[\Phi^{T}(\boldsymbol{X})\boldsymbol{W}\Phi(\boldsymbol{X}')]_{ij} = \sum_{s,s'} [\Phi^{T}(\boldsymbol{X})]_{is} [\boldsymbol{W}]_{ss'} [\Phi(\boldsymbol{X}')]_{s'j}$$

$$= \sum_{s,s'} w_{ss'} \langle (\phi(\boldsymbol{X}_{s:}), \phi(\boldsymbol{X}'_{i:})), (\phi(\boldsymbol{X}'_{s':}), \phi(\boldsymbol{X}'_{j:})) \rangle$$

$$= \sum_{s,s'} w_{ss'} (K(s,s') + K(i,j))$$

$$= CK(i,j) + \sum_{s,s'} w_{ss'} K(s,s'), \qquad (2)$$

where we have denoted the constant $C = \sum_{s,s'} w_{ss'} > 0$. Plugging (2) into (1) gives

$$\mathcal{K}(\boldsymbol{X}, \boldsymbol{X}') = \sum_{ij} w_{ij} [\Phi^{T}(\boldsymbol{X}) \boldsymbol{W} \Phi(\boldsymbol{X}')]_{ij}$$

$$= C \sum_{ij} w_{ij} K(i, j) + \left(\sum_{i,j} w_{ij} \right) \left(\sum_{s,s'} w_{ss'} K(s, s') \right)$$

$$= 2C \sum_{ij} w_{ij} K(i, j).$$

2 Commentary to your section 3

Proposition 2 (Isomorphic Mappings; From Mapping to Kernel). The following two mappings are isomorphic, in the sense that they induce the same kernel \mathcal{K} over matrix pairs.

• Mapping 1

$$\Phi_1: \mathbb{R}^{d_1 \times d_2} \to \mathcal{H}_r^{d_1} \times \mathcal{H}_c^{d_2}$$

$$\boldsymbol{X} \mapsto (\Phi_r(\boldsymbol{X}), \Phi_c(\boldsymbol{X})) \stackrel{\text{def}}{=} (\phi_r(\boldsymbol{X}_{1:}), \dots, \phi_r(\boldsymbol{X}_{d_1:}), \phi_c(\boldsymbol{X}_{:1}), \dots, \phi_c(\boldsymbol{X}_{:d_2}))$$

• Mapping 2

$$\Phi_2: \mathbb{R}^{d_1 \times d_2} \to (\mathcal{H}_r \times \mathcal{H}_c)^{d_1 \times d_2}$$

$$\boldsymbol{X} \mapsto [\Phi_2(\boldsymbol{X})_{ij}], \quad \text{where } \Phi_2(\boldsymbol{X})_{ij} \stackrel{\text{def}}{=} (\phi_c(\boldsymbol{X}_{i:}), \ \phi_r(\boldsymbol{X}_{:j}))$$

Proof. Using the similar argument in Proposition 1, we show that the kernel induced by (mapping 2 + low-rank coefficients) is

$$\mathcal{K} \colon \mathbb{R}^{d_1 \times d_2} \times \mathbb{R}^{d_1 \times d_2} \to \mathbb{R}$$

$$\mathcal{K}(\boldsymbol{X}, \boldsymbol{X}') \mapsto \sum_{i,j \in [d_1]} w_{ij}^{\text{row}} K_r(i,j) + \sum_{i,j \in [d_2]} w_{ij}^{\text{col}} K_c(i,j), \tag{3}$$

where $\boldsymbol{W}^{\mathrm{row}} = [\![w_{ij}^{\mathrm{row}}]\!] = \frac{1}{c_1} \boldsymbol{P}_r \boldsymbol{P}_r^T$, $\boldsymbol{W}^{\mathrm{col}} = [\![w_{ij}^{\mathrm{col}}]\!] = \frac{1}{c_2} \boldsymbol{P}_c \boldsymbol{P}_c^T$ are some p.s.d. low-rank matrices, and $c_1 = \|\boldsymbol{1}_{d_1}^T \boldsymbol{P}_r\|_2^2 > 0$, $c_2 = \|\boldsymbol{1}_{d_2}^T \boldsymbol{P}_c\|_2^2 > 0$ are two normalizing constants.

Now, we consider the kernel induced by (mapping 1 + low-rank coefficients),

$$\mathcal{K}(\boldsymbol{X}, \boldsymbol{X}') = \langle \Phi_r(\boldsymbol{X}) \boldsymbol{P}_r, \ \Phi_r(\boldsymbol{X}') \boldsymbol{P}_r \rangle + \langle \Phi_c(\boldsymbol{X}) \boldsymbol{P}_c, \ \Phi_c(\boldsymbol{X}') \boldsymbol{P}_c \rangle
= \sum_{i,j \in [d_1]} w_{ij}^{\text{row}} K_r(i,j) + \sum_{i,j \in [d_2]} w_{ij}^{\text{col}} K_c(i,j),$$
(4)

where $\boldsymbol{W}^{\mathrm{row}} = [\![w_{ij}^{\mathrm{row}}]\!]$, $\boldsymbol{W}^{\mathrm{col}} = [\![w_{ij}^{\mathrm{col}}]\!]$ are some p.s.d. low-rank matrices.

Two important properties in the induced kernels (3) and (4):

- 1. [Additivity] The new kernel is a linear combination of regular row and column kernels;
- 2. [Low-rank p.s.d.] The weight matrices W^{row} , W^{col} are p.s.d. + low-rank.

Conjecture 1 (From Kernel to Mapping). Let $\mathcal{K}(\cdot,\cdot)$ be a function that maps a pair of matrices to a real-value. Suppose $\mathcal{K}(\cdot,\cdot)$ satisfies the above two properties. Then, the kernel \mathcal{K} induces a decomposable feature mapping in that $\Phi(\mathbf{X}) = \Phi_r(\mathbf{X}) + \Phi_c(\mathbf{X})$, where, informally speaking, $\Phi_r(\cdot)$, $\Phi_c(\cdot)$ are the row- and column-wise mappings, respectively.

The decomposable mapping means the effects from rows and columns are additive/separable. Similar to an ANOVA model $Y_{ij} = \mu_i + \mu_j$ with marginal effects only. Additivity is a common assumption for matrix-based network analysis; see [1].

References

[1] Peter D Hoff. Additive and multiplicative effects network models. To appear in Statistical Science, arXiv preprint arXiv:1807.08038, 2018.