Tensorized Feature Spaces for Feature Explosion

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Introduction

Hyperspectral Images(HSI):

- Images with hundreds of spectral bands at each pixel.
- Used in aerial land surveys with aircrafts or satellites.
- Each pixel has different features corresponding to spectral bands.

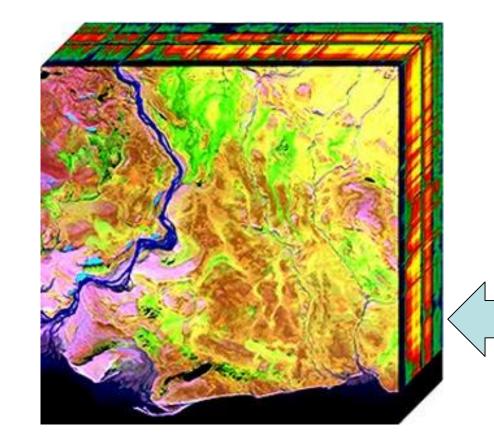
Experimental Evaluation

ORION is implemented using MATLAB and Python. We use the tensor toolbox⁴ for tensor completion, scikit-learn⁵ for classification tasks and Tensorly⁶ for tensor operations in python. All datasets used are publicly available. Code is available at <u>https://github.com/ravdeep003/ORION</u>.

Classification Accuracy

Classification accuracy of all the methods for 80-20 split

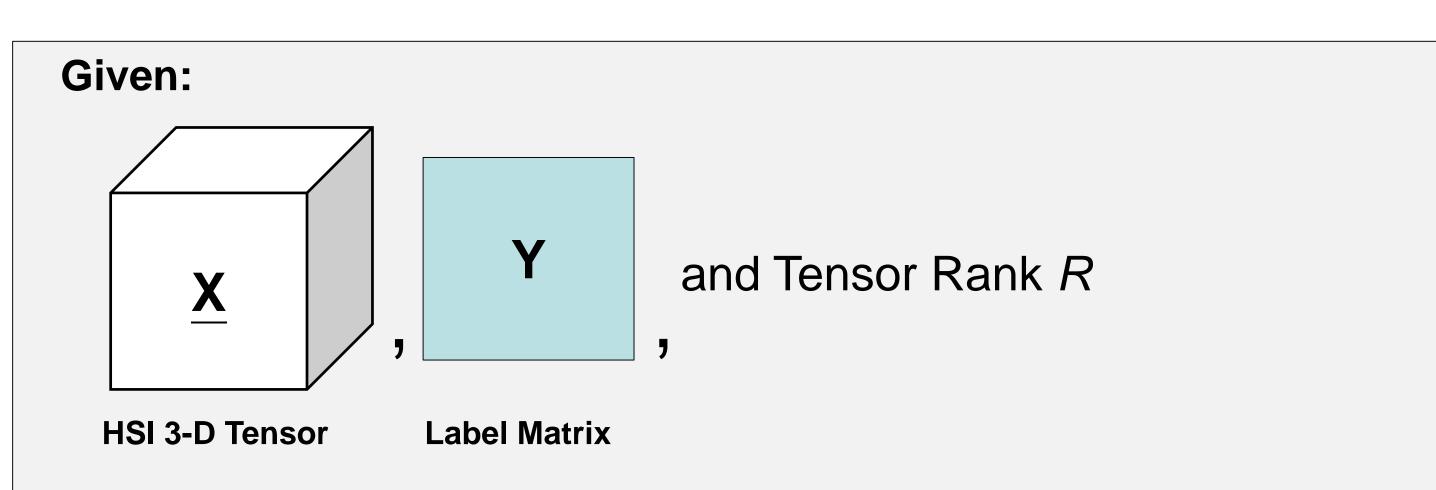
	Indian Pines	Pavia University	Salinas-A	Salinas
Linear SVM	0.8708 ± 0.0035	0.9176 ± 0.0017	0.9986 ± 0.0016	0.9339 ± 0.0014
Polynomial SVM	0.8979 ± 0.0054	0.9481 ± 0.0015	0.9978 ± 0.0015	0.9463 ± 0.0014
RBF SVM	0.9178 ± 0.0050	0.9622 ± 0.0020	0.9985 ± 0.0017	0.9620 ± 0.0024
MLP	0.9182 ± 0.0057	0.9635 ± 0.0041	0.9982 ± 0.0010	0.9629 ± 0.0045



Task: Assuming each pixel belongs to one class, classify all pixels in HSI.

Example of Hyperspectral Image¹

Problem Definition



Generate a feature space for a classifier such that pixels in the image are classified into one of the given classes.

• **Khatri-Rao Product (KRP)** of two matrices $\mathbf{A} \in \mathbb{R}^{I \times R}$ and $\mathbf{B} \in \mathbb{R}^{J \times R}$ is a column-wise Kronecker product.

$$\mathbf{A} \odot \mathbf{B} = [a_1 \otimes b_1 a_2 \otimes b_2 \dots a_n \otimes b_n] \in \mathbb{R}^{IJ \times R}$$

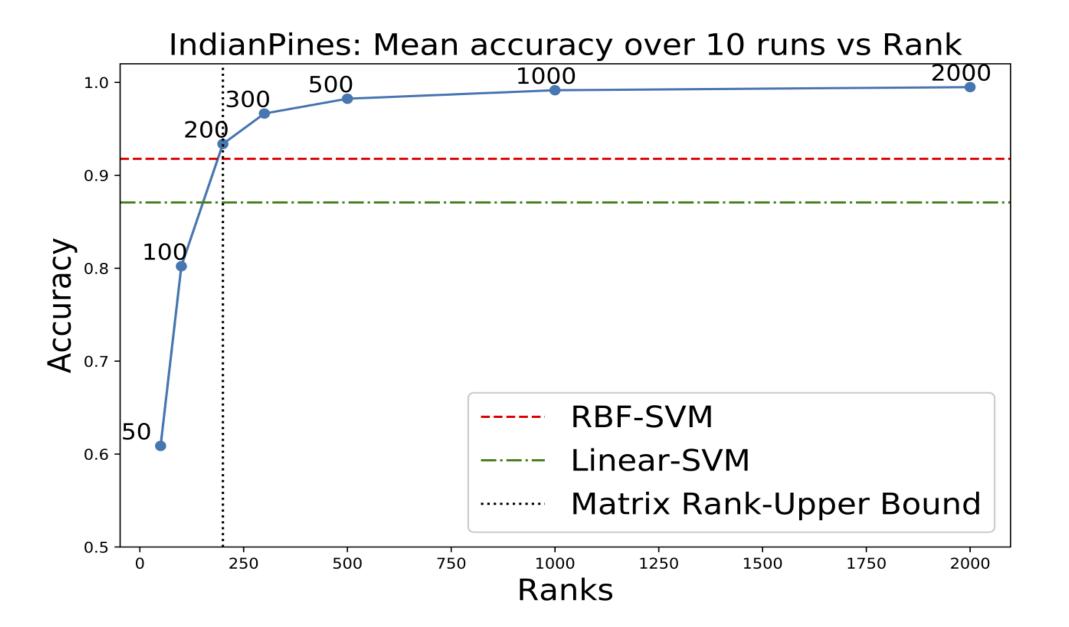
Orion -1000	0.9916 ± 0.0022	0.9502 ± 0.0032	0.9690 ± 0.0067	0.9927 ± 0.0010
Orion -2000	0.9949 ± 0.0022	$\textbf{0.9828} \pm \textbf{0.0030}$	0.9680 ± 0.0063	$\textbf{0.9954} \pm \textbf{0.0006}$

 In case of Indian Pines, Pavia University and Salinas datasets, ORION performs better than the baselines.

Classification accuracy of all the methods for 30-70 split

	Indian Pines	Pavia University	Salinas-A	Salinas
Linear SVM	0.8371 ± 0.0034	0.9134 ± 0.0015	0.9965 ± 0.0010	0.9322 ± 0.0007
Polynomial SVM	0.8511 ± 0.0042	0.9367 ± 0.0010	0.9941 ± 0.0017	0.9406 ± 0.0009
RBF SVM	0.8739 ± 0.0041	0.9546 ± 0.0007	0.9966 ± 0.0011	0.9515 ± 0.0012
MLP	0.8693 ± 0.0098	0.9556 ± 0.0029	0.9931 ± 0.0029	0.9475 ± 0.0041
Orion -1000	0.9725 ± 0.0032	0.9119 ± 0.0015	0.8607 ± 0.0146	0.9662 ± 0.0013
Orion -2000	0.9806 ± 0.0031	0.9544 ± 0.0021	0.8982 ± 0.0073	0.9832 ± 0.0013

- One of the challenges in HSI pixel classification is limited labelled data. We split the data into 30% training and 70% testing.
- In case of Indian Pines and Salinas ORION performs better than baselines.
- In both cases, baselines perform better in Salinas-A. A probable explanation for this behavior is Salinas-A, which is a subscene of Salinas, has a linearly separable structure. We shall investigate this in future work.



- $\mathbf{M} \bigcirc \mathbf{D} \quad [m_1 \oslash p_1 m_2 \oslash p_2 \dots m_R \oslash p_R] \subset \mathbf{M}$
- **CP/PARAFAC Decomposition** of a 3-mode tensor of size $I \times J \times K$ for a particular rank *R* is given by sum of *R* rank-one tensors:

 $\mathbf{\underline{X}} pprox \sum_{r=1}^{R} \mathbf{A}\left(:,r
ight) \circ \mathbf{B}\left(:,r
ight) \circ \mathbf{C}\left(:,r
ight)$

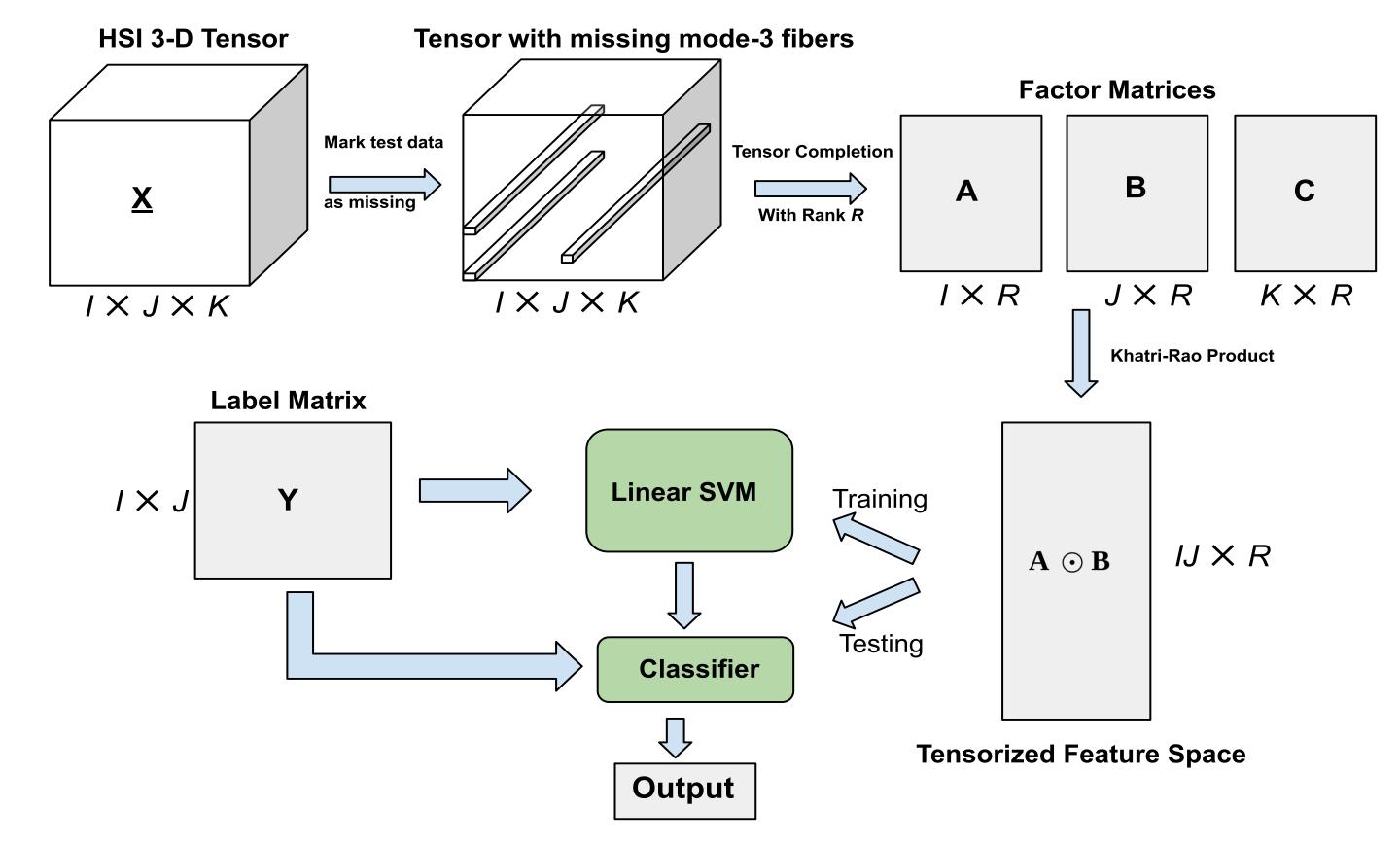
Where $\mathbf{A} \in \mathbb{R}^{I \times R}$, $\mathbf{B} \in \mathbb{R}^{J \times R}$ and $\mathbf{C} \in \mathbb{R}^{K \times R}$ are factor matrices. • denotes the three-way outer product.

- **Tensor Completion** is the task of predicting missing values in a tensor using tensor decomposition.
- As the Tensor rank increases, accuracy increases until a certain point. As we conjecture this increase in rank results in explosion of feature space which resembles how kernel method works.

Proposed Method: ORION

- Intuition: Map the input space to higher dimensional space by exploiting multi-linear structure of tensors.
- CP decomposition of a 3-D tensor <u>X</u> yields 3-factor matrices A, B and C.
- Tensorized Feature Space: Khatri-Rao Product of matrices A and B. $A \odot B \in \mathbb{R}^{IJ \times R}$

Overview of ORION



Conclusions

- Introduced tensorized feature space based on factors generated from tensor decomposition.
- Demonstrated effectiveness of our methods against traditional linear and non-linear supervised learning methods.

References

[1] J. M. Bioucas-Dias, A. Plaza, G. Camps-Valls, P. Scheunders, N. Nasrabadi, and J. Chanussot, "Hyperspectral remote sensing data analysis and future challenges," IEEE Geoscience and remote sensing magazine, vol. 1, no. 2, pp. 6–36, 2013. [2] N. D. Sidiropoulos, L. De Lathauwer, X. Fu, K. Huang, E. E. Papalexakis, and C. Faloutsos, "Tensor decomposition for signal processing and machine learning," IEEE Transactions on Signal Processing, vol. 65, no. 13, pp. 3551–3582, 2017. [3] E. Acar, D. M. Dunlavy, T. G. Kolda, and M. Mørup, "Scalable tensor factorizations for incomplete data," Chemometrics and Intelligent Laboratory Systems, vol. 106, no. 1, pp. 41–56, 2011. [4] Bader, B.W., Kolda, T.G., et al.: Matlab tensor toolbox version 2.6. Available online (February 2015) [5] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011 [6] J. Kossaifi, Y. Panagakis, A. Anandkumar, and M. Pantic, "Tensorly: Tensor learning in python," Journal of Machine Learning Research(JMLR), vol. 20, no. 26, 2019.







¹ Image from: https://en.wikipedia.org/wiki/Hyperspectral_imaging