Incremental Kernel Null Space based
Discriminant Analysis for Novelty Detection
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Novelty Detection and Null Space

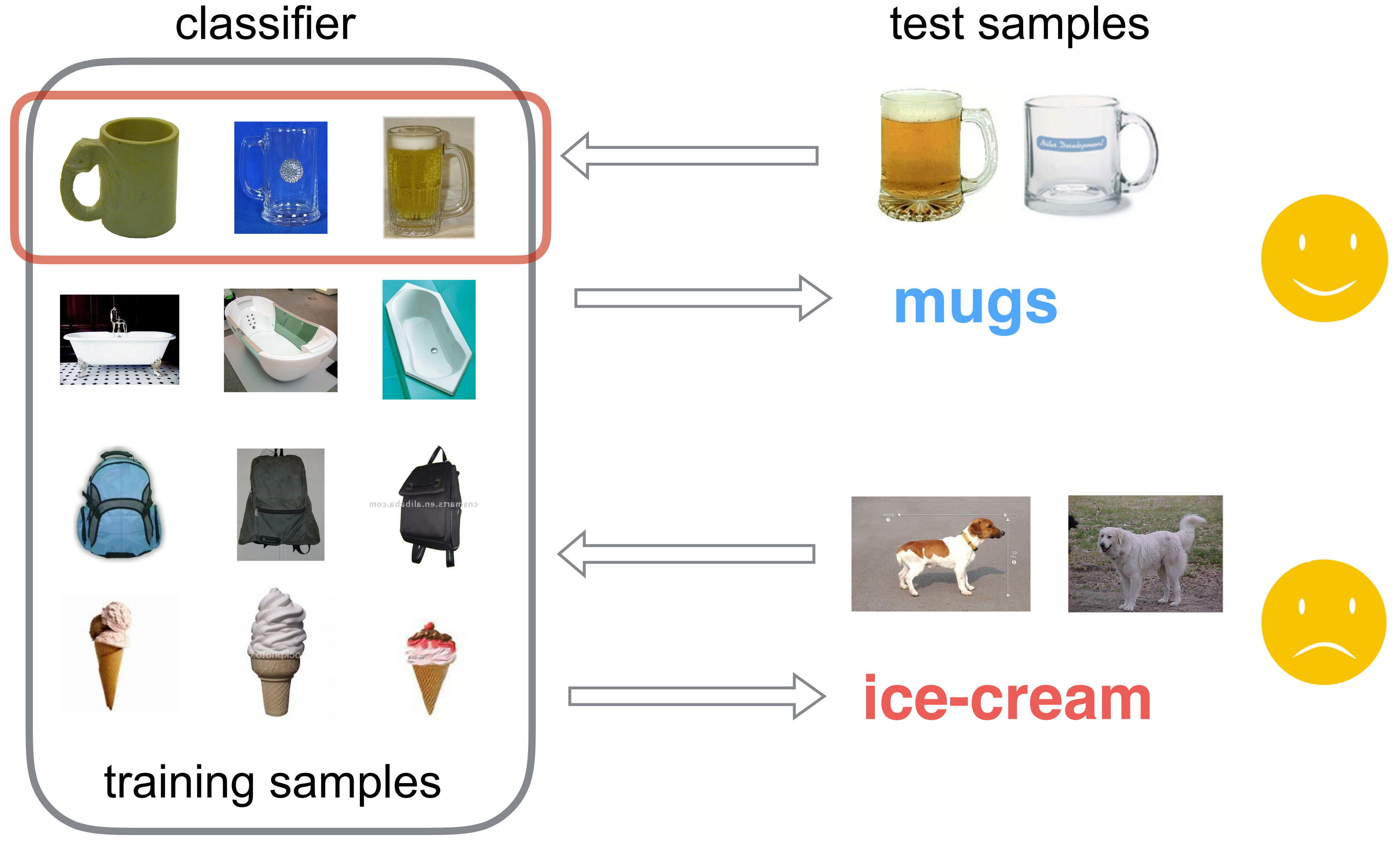


Fig1. Novelty detection.Novelty detection aims to identify new or unknown data that a system has not been trained with and was not previously aware of.

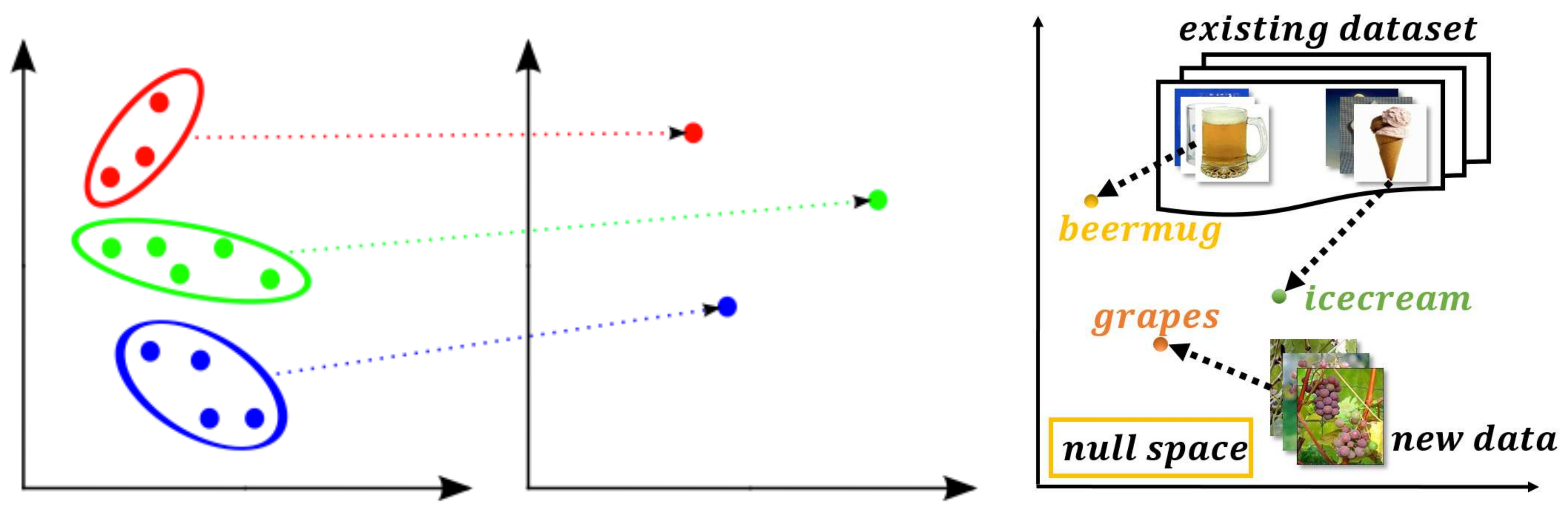


Fig2. Null Space DA.Novelty detection aims to identify new or unknown data that a system has not been trained with and was not previously aware of.

Make it Incremental !

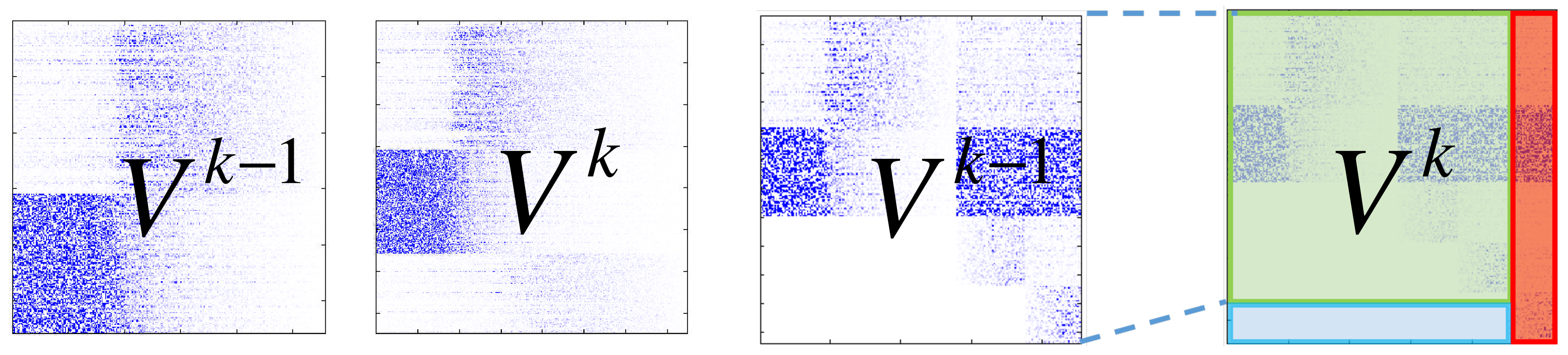


Fig3. An illustrative comparison of the batch KNDA with our IKNDA algorithm. The batch method computes bases without taking advantage of previously computed matrix Vk−1. While, our approach extracts new bases Vnew from novel classes, marked in red square, then integrates with previously obtained information Vk−1 (marked in green square).

- We found the null space problem has a very elegant structure, the new matrix can be augmented by the old one. Therefore the new null space can be updated in an efficient way:

$$D = \begin{pmatrix} D_0 & D_1 \\ 0 & D_2 \end{pmatrix} \qquad D^T\beta = \begin{pmatrix} D_0^T & 0 \\ D_1^T & D_2^T \end{pmatrix}\begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} = 0$$

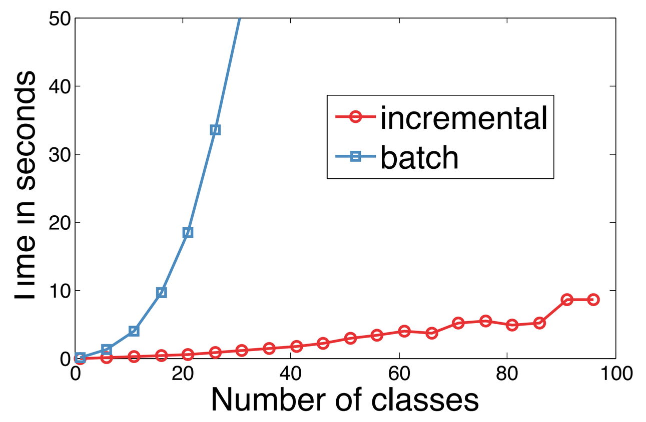
- The incremental null space problem can be boiled down to the following formula:

$$\begin{pmatrix} D_1^T\beta_0 & D_2^T \end{pmatrix}\begin{pmatrix} \alpha \\ \beta_2 \end{pmatrix} = 0$$

$$s.t. \quad \alpha^T\alpha + \beta_2^T\beta_2 = I$$

- Asymptotic complexity of IKNDA and the batch mode KNDA in terms of a, l, and N, where l is the incremental size.

	IKNDA	KNDA	SRKDA
time	$O(l^3 + alN)$	$O((l+N)^3)$	$O(N^2(l/2+c))$
space	$O(Nl)$	$O((l+N)^2)$	$O(Nl)$



Let's see how it works

- we carry out experiments to evaluate performance of novelty detection methods on the two publicly-available datasets: FounderType-200 (new font detection) and Caltech-256 (new class detection).
- To simulate the on-line updating process, we incrementally inject one class in every iteration. To perform novelty detection, we first map the test sample x to the null space as a single point x∗, and the corresponding novelty score is calculated as the smallest distance (Euclidean distance) between the point and all training class centers.

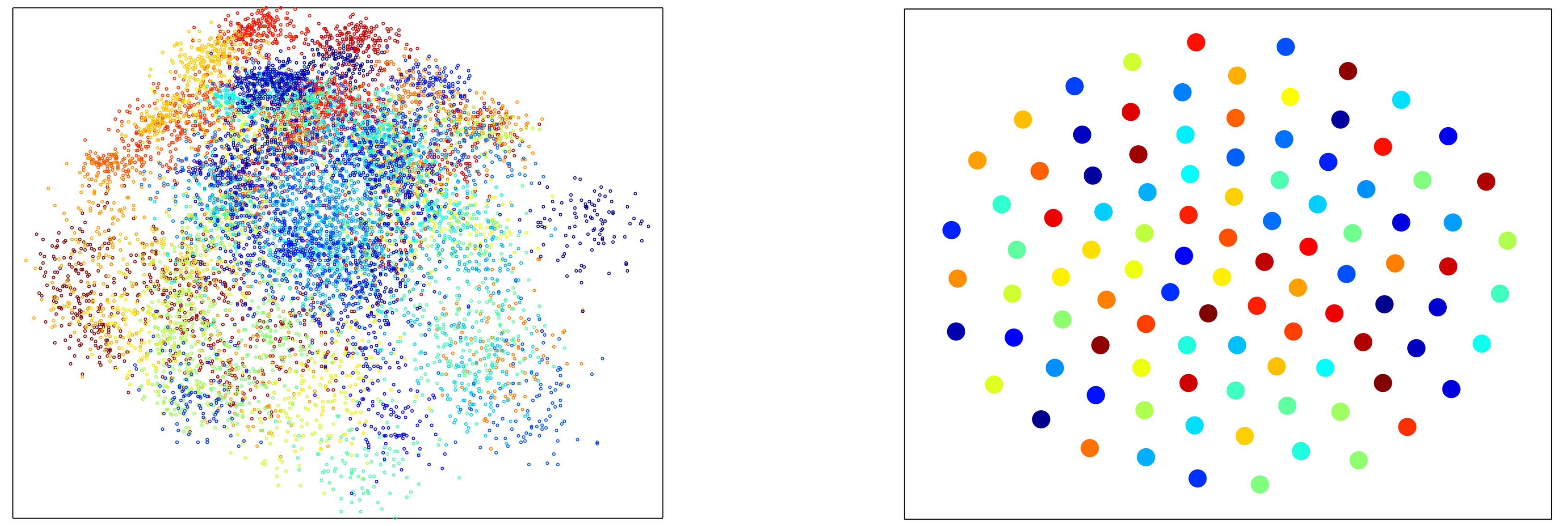


Fig4. Joint null space of 100 classes in the FounderType-200 dataset. Each class is mapped to a single point null space (visualized by t-SNE). Left: original CNN features. Right: Mapped joint null space.

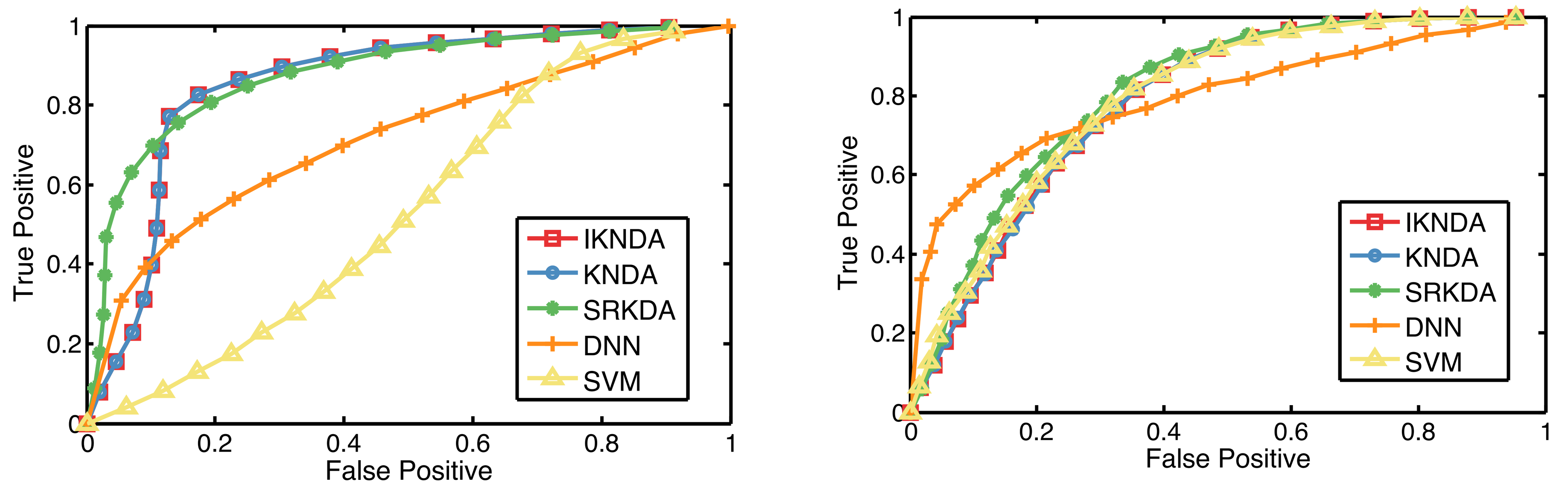


Fig5. ROC curves of five novelty detection methods evaluated on the FounderType-200 dataset (left) and Caltech-256 (right).