# Incremental Zero-Shot Learning Based on Attributes for Image Classification

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## ➢ Motivation

There are labeled samples in training phase for classification task

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Attributes as a connection of classes

color, shape, the presence or absence of a certain body part and so on.

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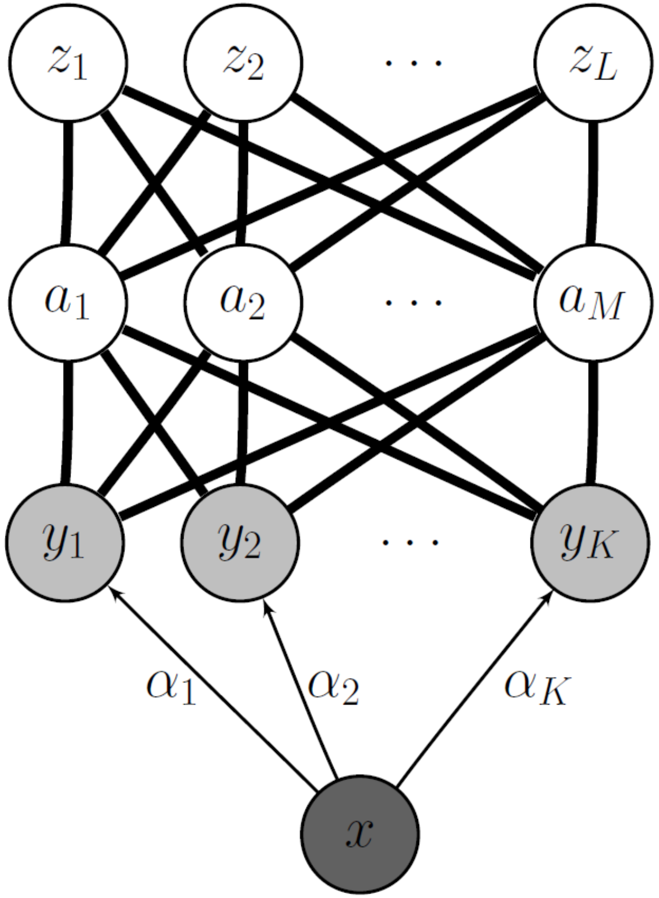
$$Y \cap Z = \emptyset$$




Indirect attribute prediction (IAP)

C.H. Lampert,et al.

[1] "Learning to detect unseen object classes by between-class attribute transfer" ,CVPR2009.

[2] "Attribute-based classification for zero-shot visual object categorization" , PAMI2014.

$$f(x) = \arg\max_{l=1,\ldots,L} p(z_l|x)$$

$$= \arg\max_{l=1,\ldots L} \prod_{m=1}^{M} \frac{\sum_{k=1}^{K} p\left(a_m^{z_l}|y_k\right) p(y_k|x)}{p\left(a_m^{z_l}\right)}$$

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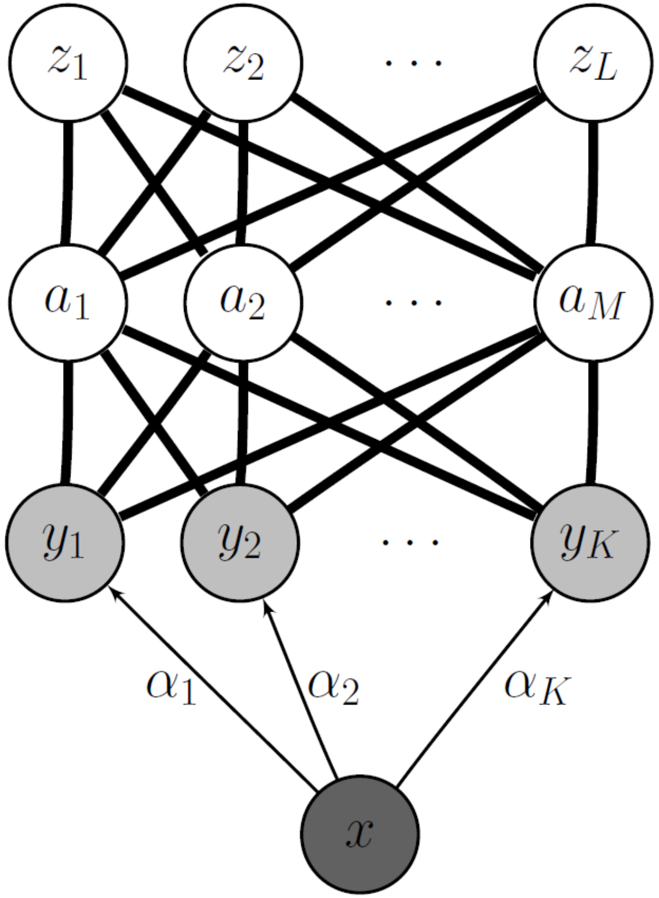


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- Combination of multiclass classification and statistical inference.

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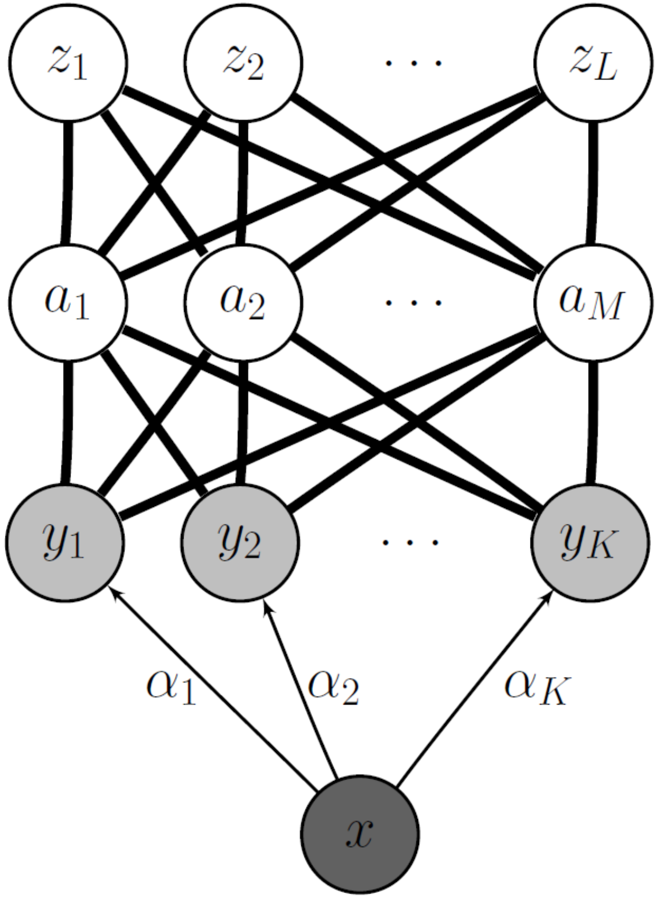


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Estimate $p(y_k|x)$

SVM

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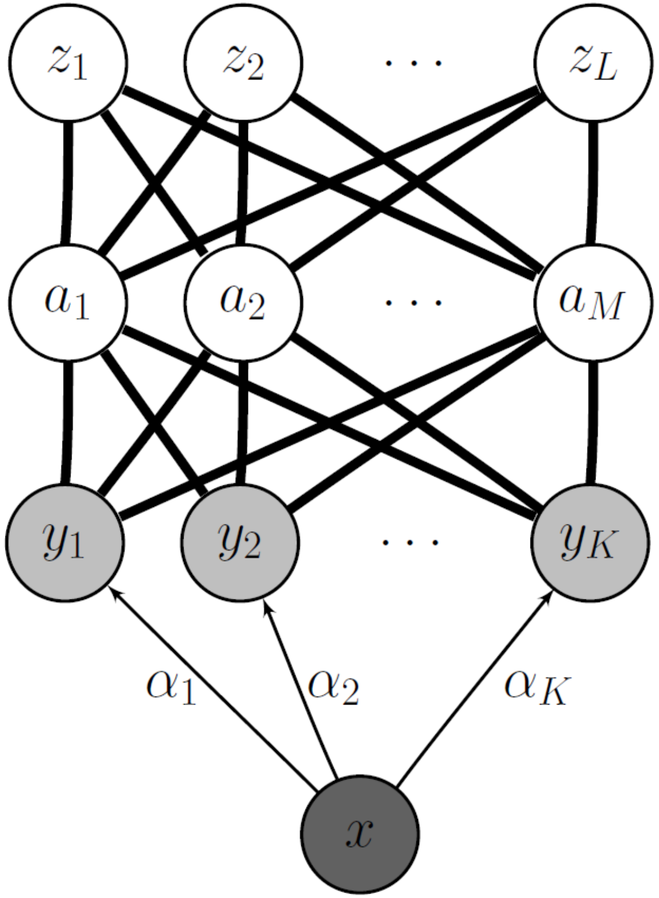


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Estimate $p(y_k|x)$

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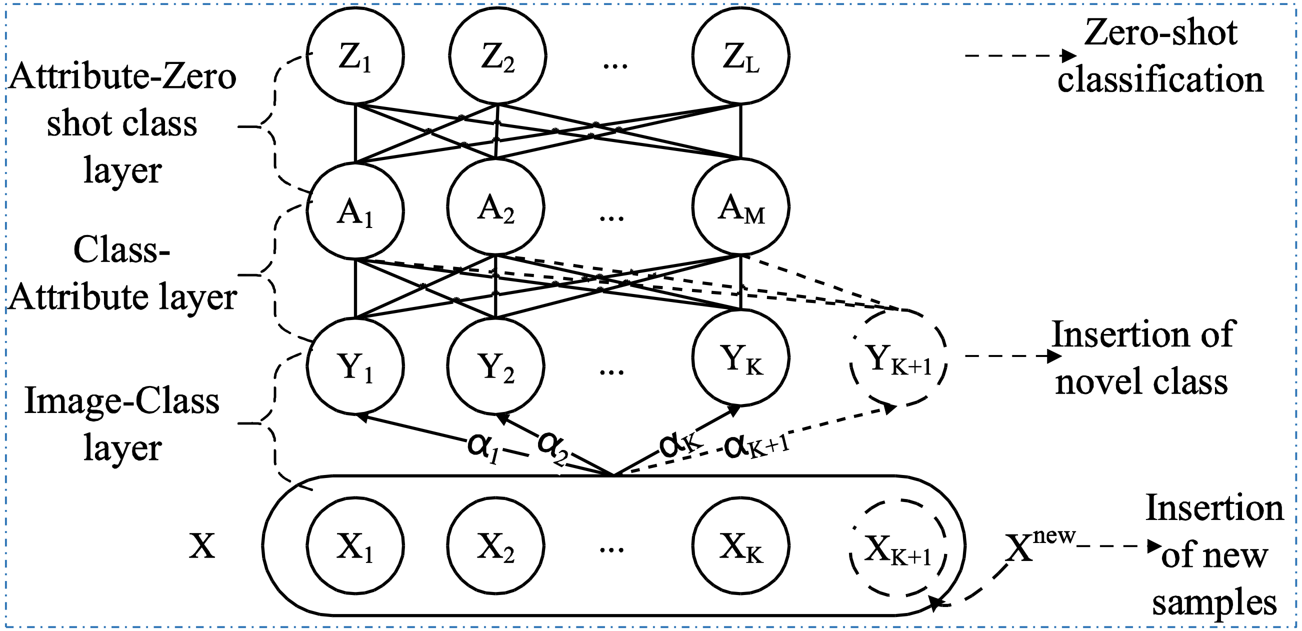
Problem:

- Small-sample-size(SSS)
- Unequal-sample-size(USS)
- Incremental learning

# ➢ Proposed Method

IIAP/QR Learning Model based on NLDA/QR[3] and IAP




IIAP/QR

[3] Delin Chu et al, “A new and fast implementation for null space based linear discriminant analysis,” Pattern Recognition2010.

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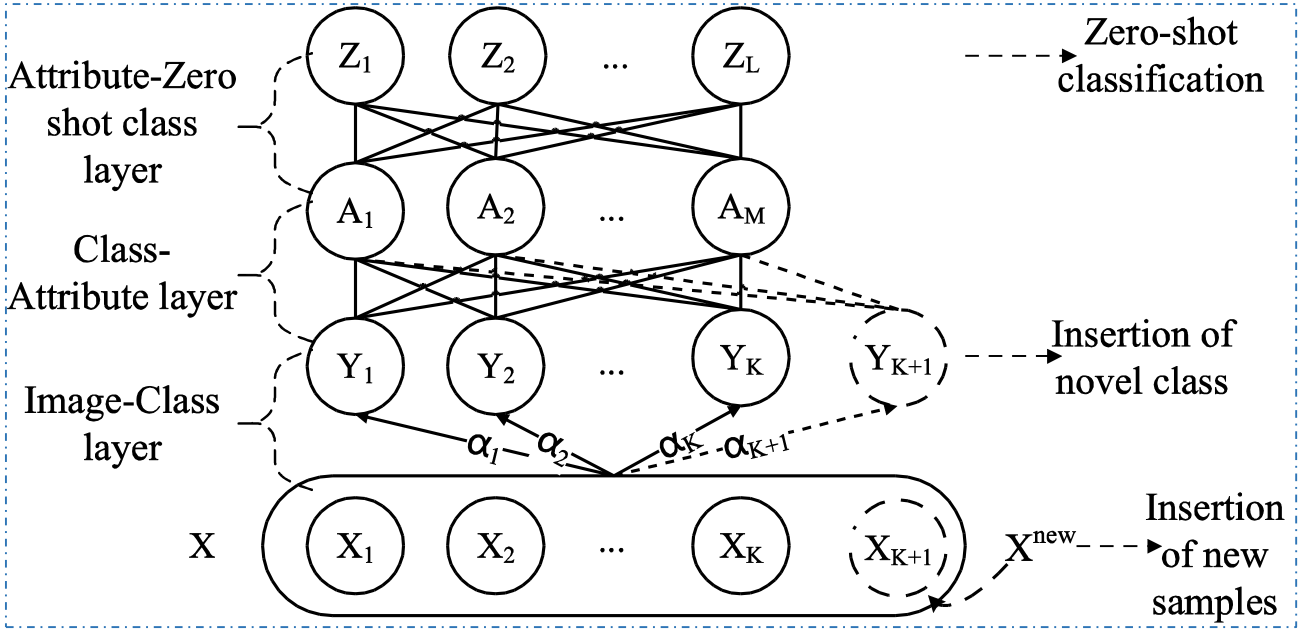


IIAP/QR

- The optimal projection matrix G
- KNN

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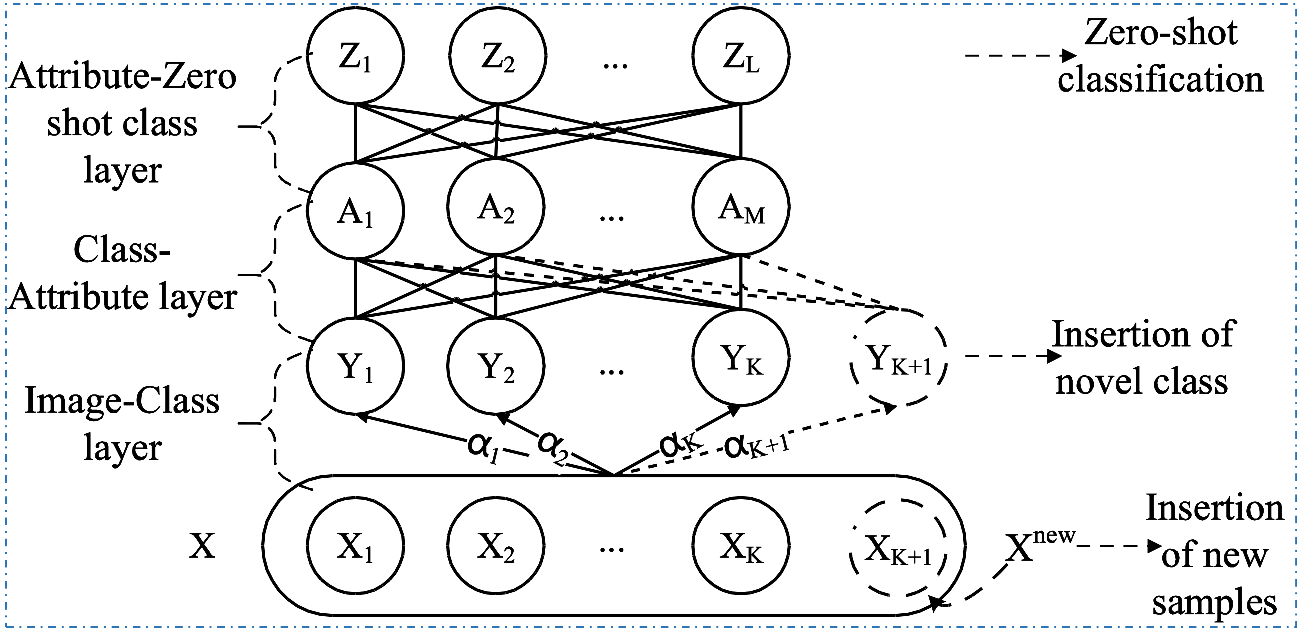


IIAP/QR

NLDA/QR

- Twice QR factorizations
- Tackling SSS problem

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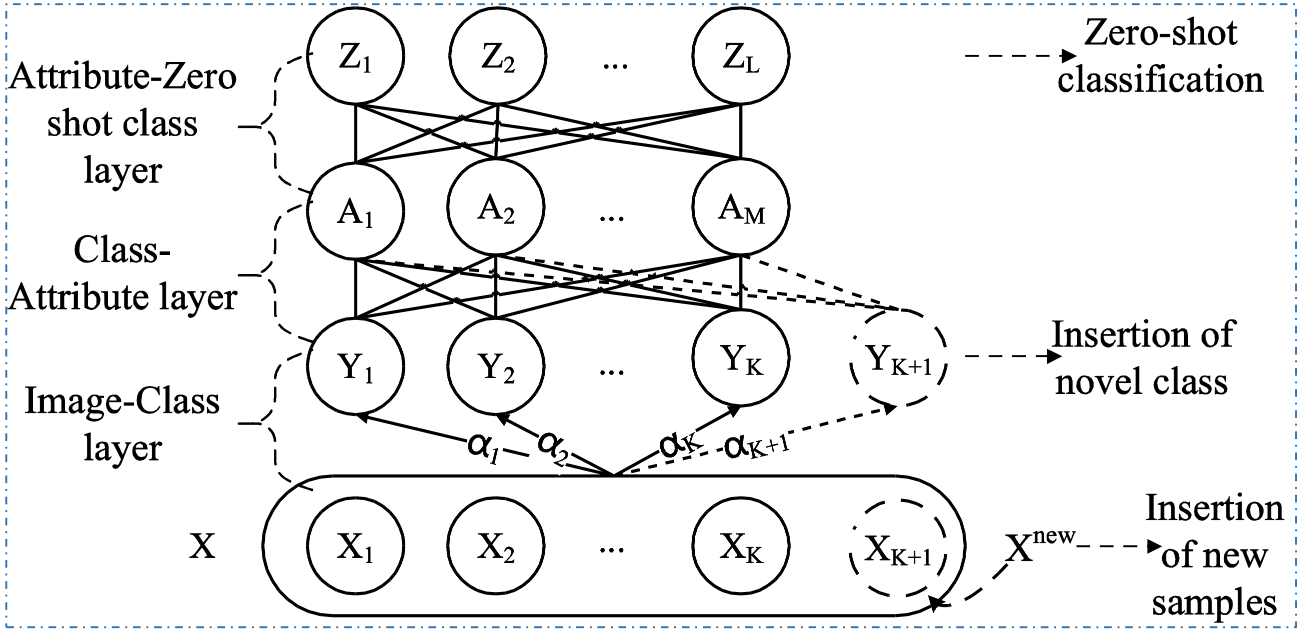


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Centroid matrix C as input

- Solving SSS problem
- Reduce computational complexity

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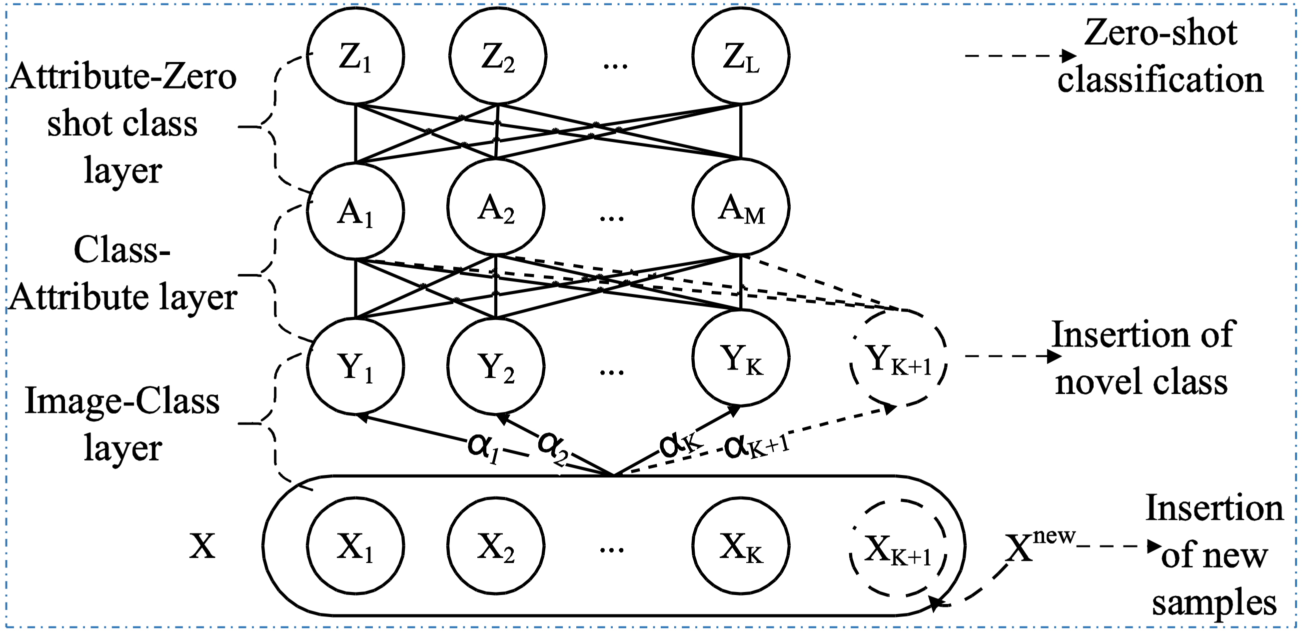


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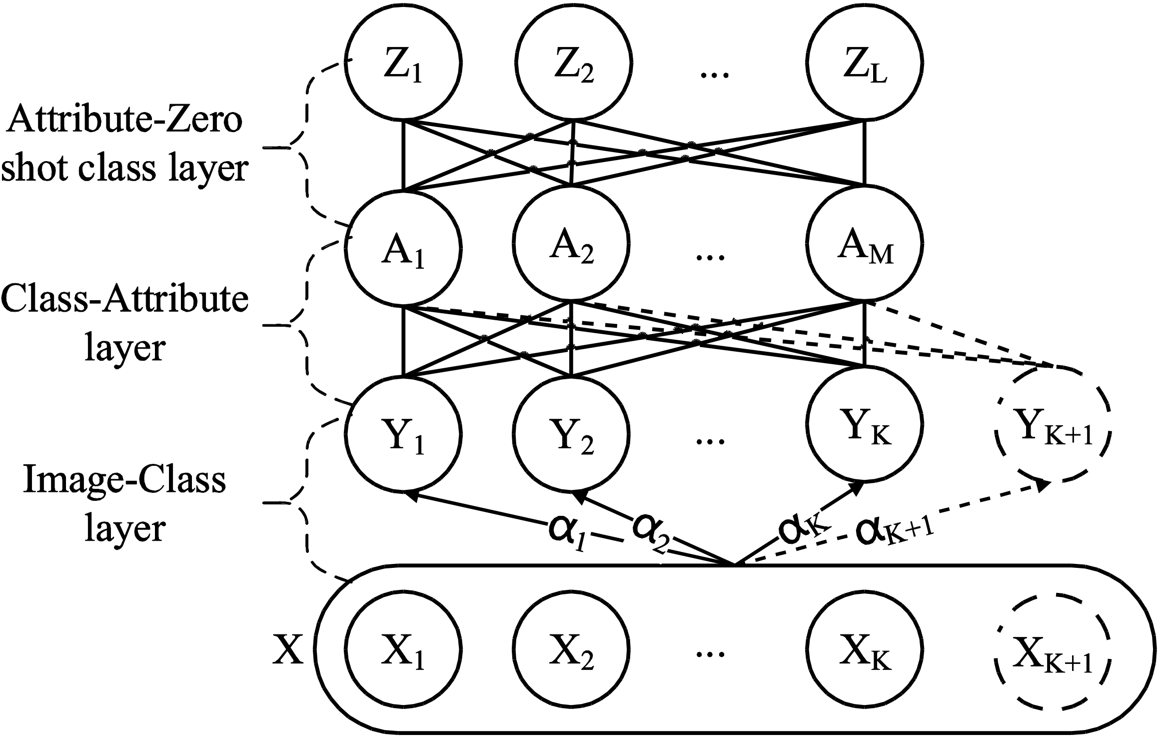
Incremental learning

- Adding novel classes
- Adding samples to existing classes
- Meeting quick updating need

# ➢ Incremental Learning

- Adding novel classes

$$X_{K+1} \in R^{d \times h}$$



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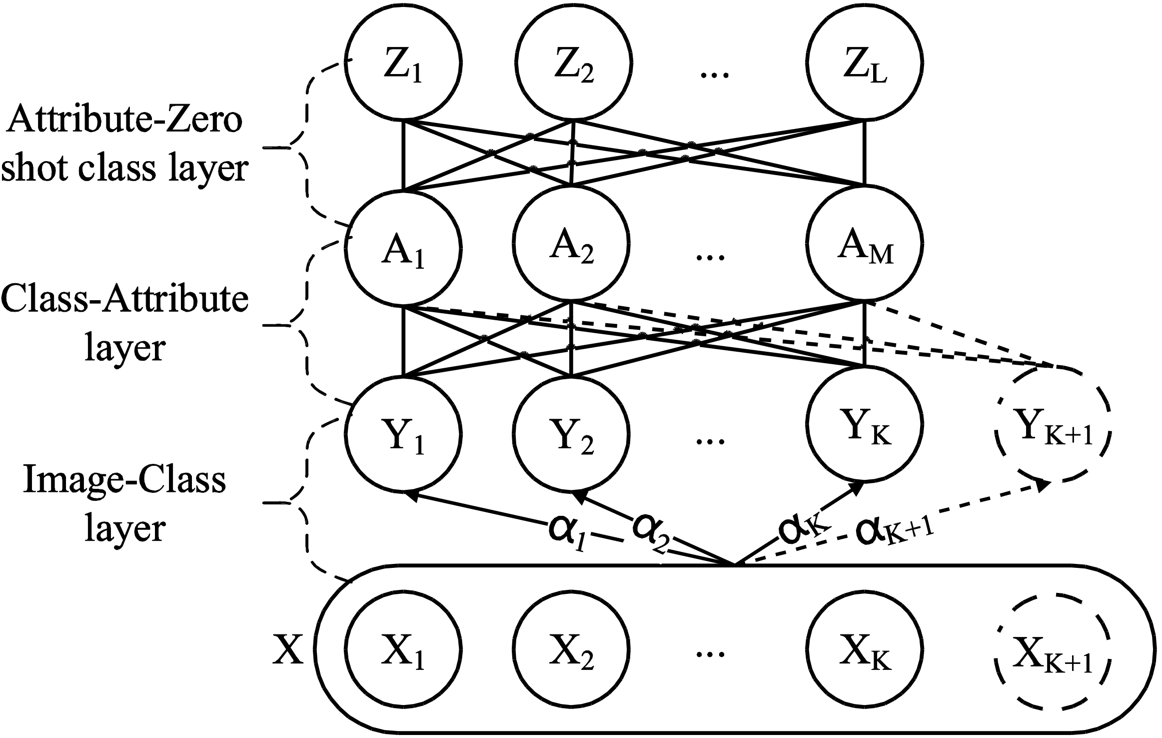
$$C = (C, C_h) = (QR, C_h)$$
$$= (Q, C_h)\begin{pmatrix} R & 0 \\ 0^T & 1 \end{pmatrix}$$



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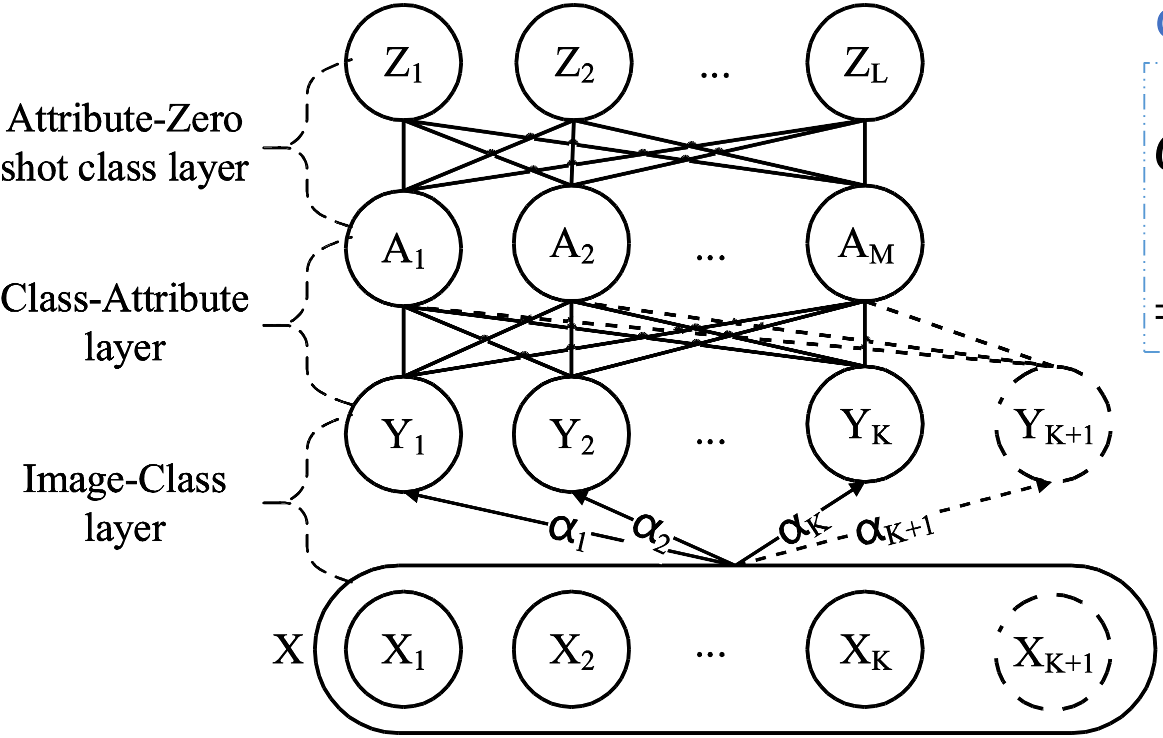


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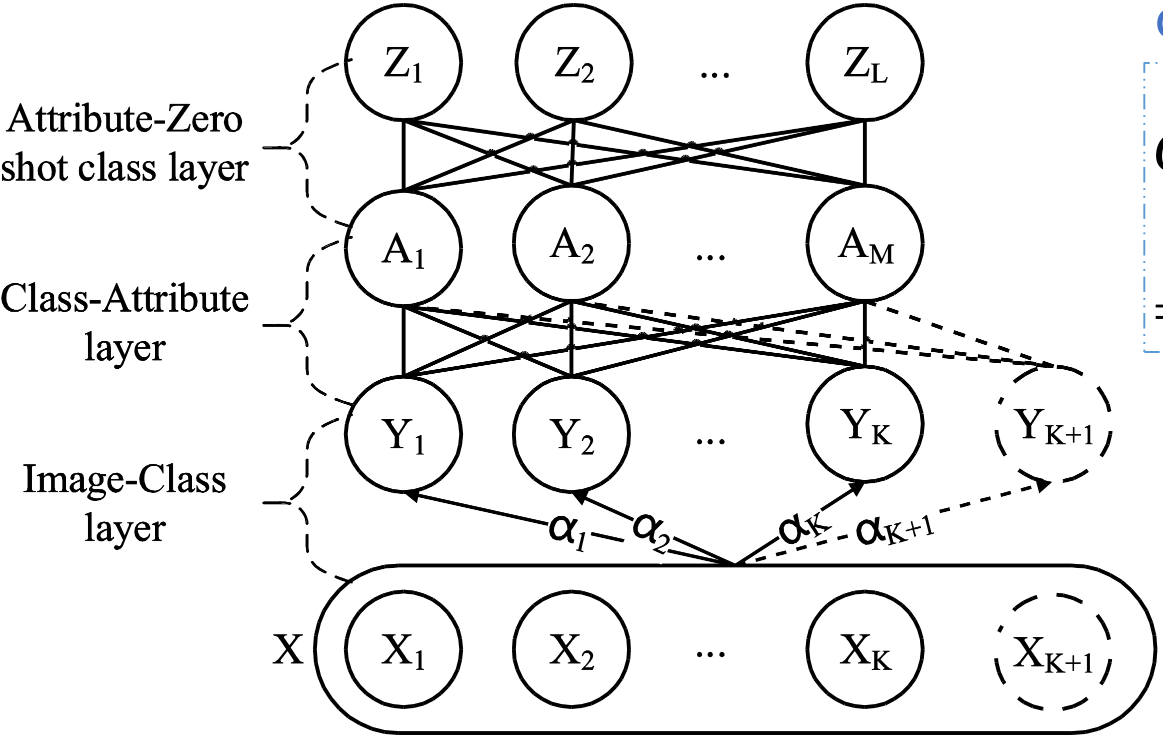


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$$H\overline{R} = H_{K,K+1}\cdots H_{K+h-1,K+h}\overline{R} \equiv R$$
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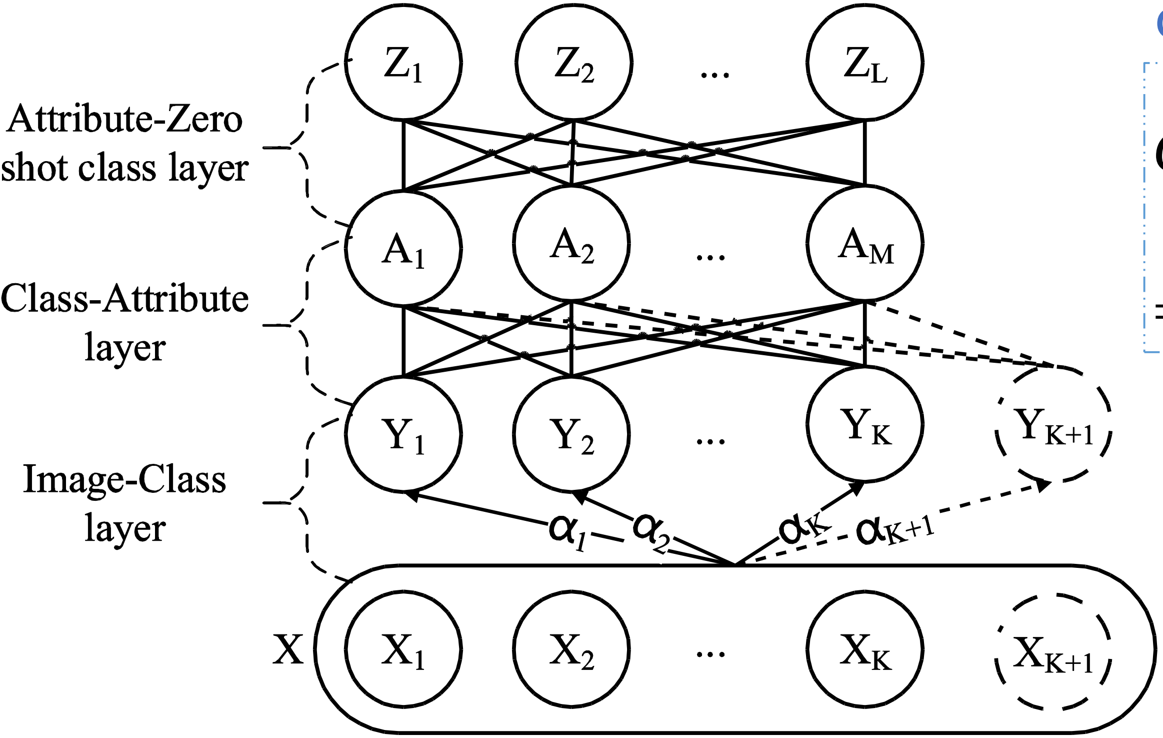


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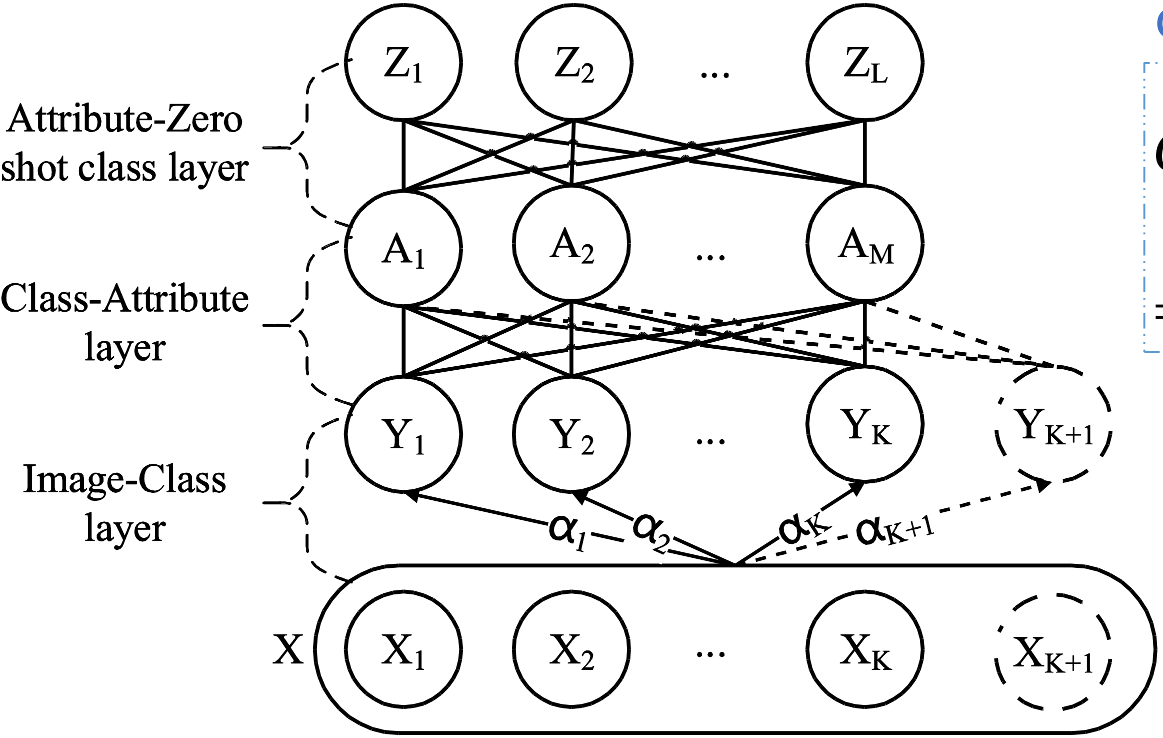


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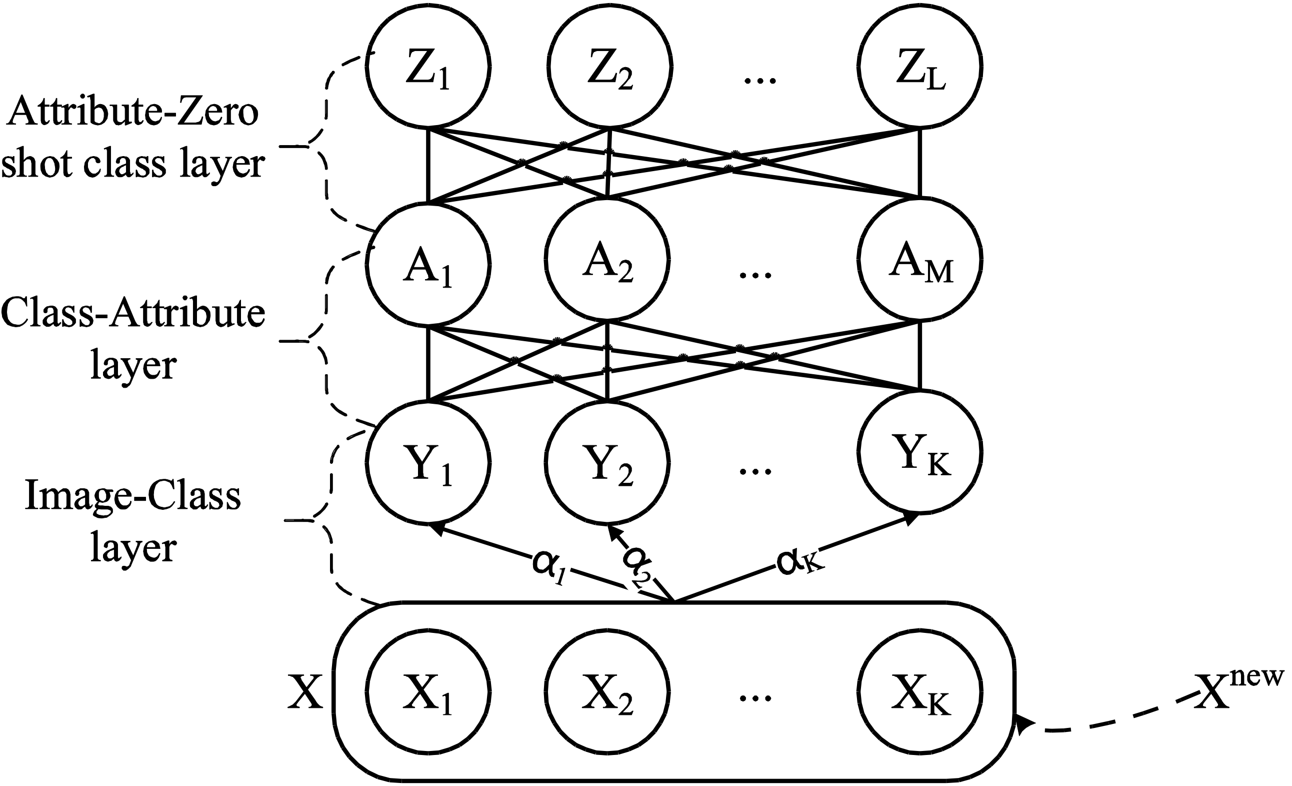
$$\tilde{C} = \tilde{Q}\tilde{R}$$

The second QR factorization

$$G$$

# ➢ Incremental Learning

- Adding new samples to existing classes



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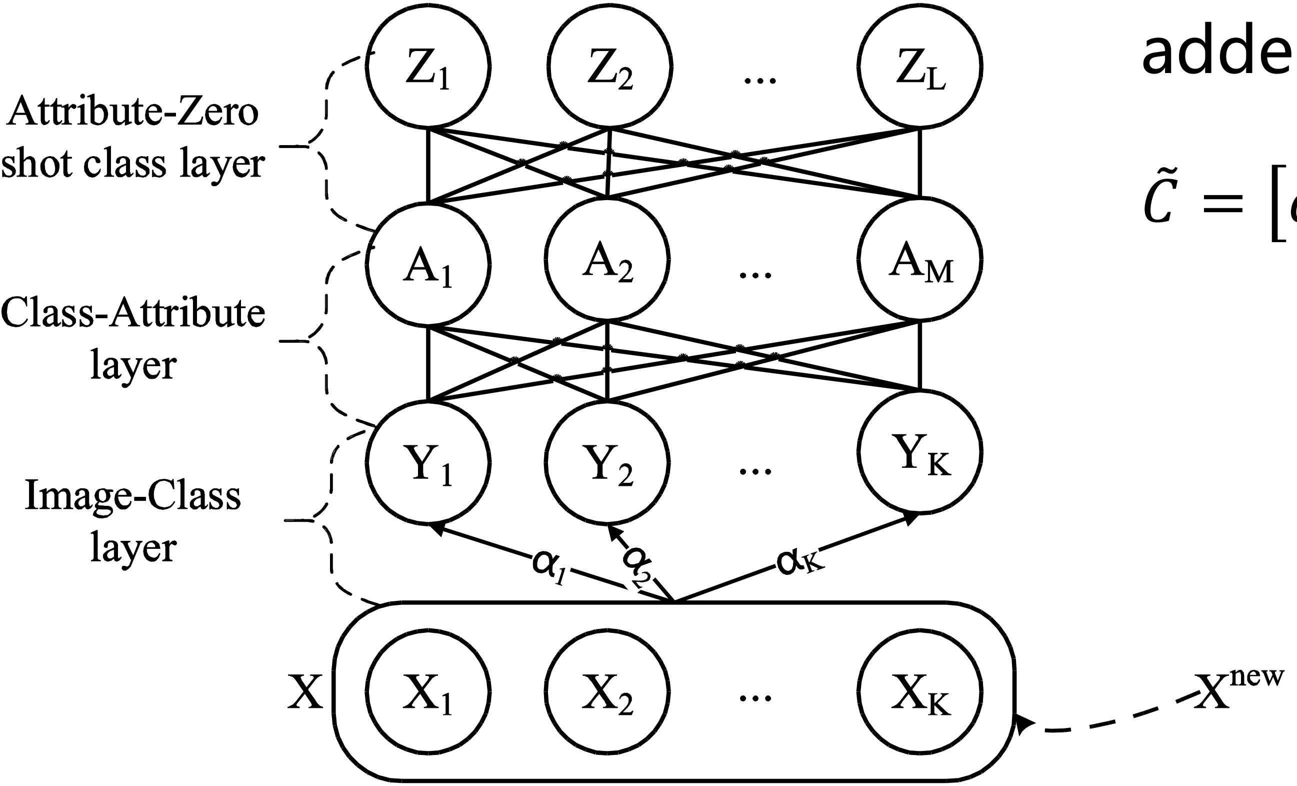


Assuming 1 sample of each classes are added into the model,

$$\tilde{C} = \left[c'^{(1)}, \ldots, c'^{(K)}\right], c'^{(i)} = \frac{c^{(i)} n_i + x^{(i)}}{n_i + 1}$$

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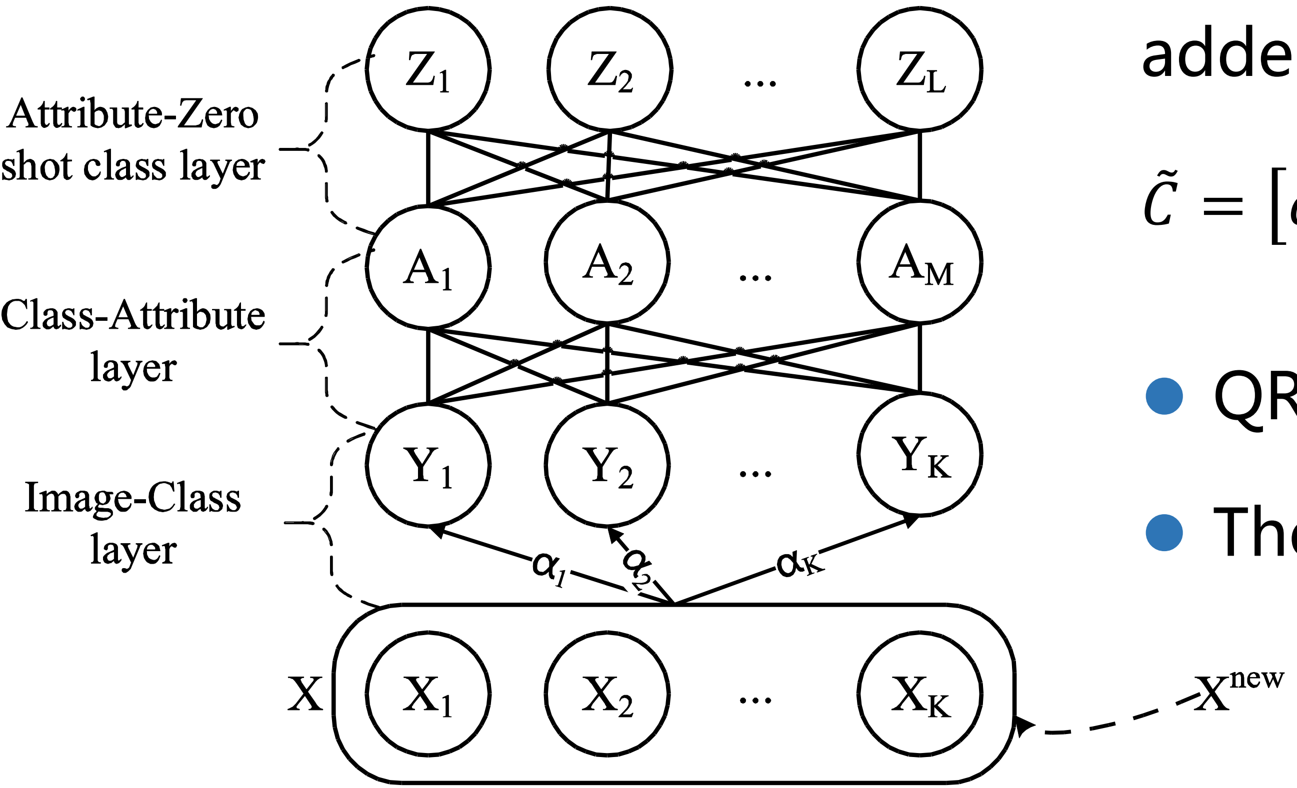


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- QR factorization of $\tilde{C}$
- The second QR factorization

# Experiments

**Dataset** (TPAMI2014)

- AWA, 85 attributes,50 different kinds of animals. We choose ‘cq’, ‘decaf’, ‘vgg19’ feature representations.
- aPascal, 20 classes with 64 attributes.

| | AWA | aPascal |
|---|---|---|
| Number of initial training classes | 30 | 10 |
| Number of zero-shot classes | 10 | 5 |
| Number of incremental classes | 10 | 5 |

| | cq | decaf | vgg19 | aPascal |
|---|---|---|---|---|
| Dimension | 2688 | 4096 | 4096 | 9751 |
| Sample number of each training class | 40 | 70 | 70 | 80 |
| Sample number of each zero-shot class as test | 30 | 40 | 40 | 70 |
| Sample number of each initial training class | 20 | 50 | 50 | 60 |

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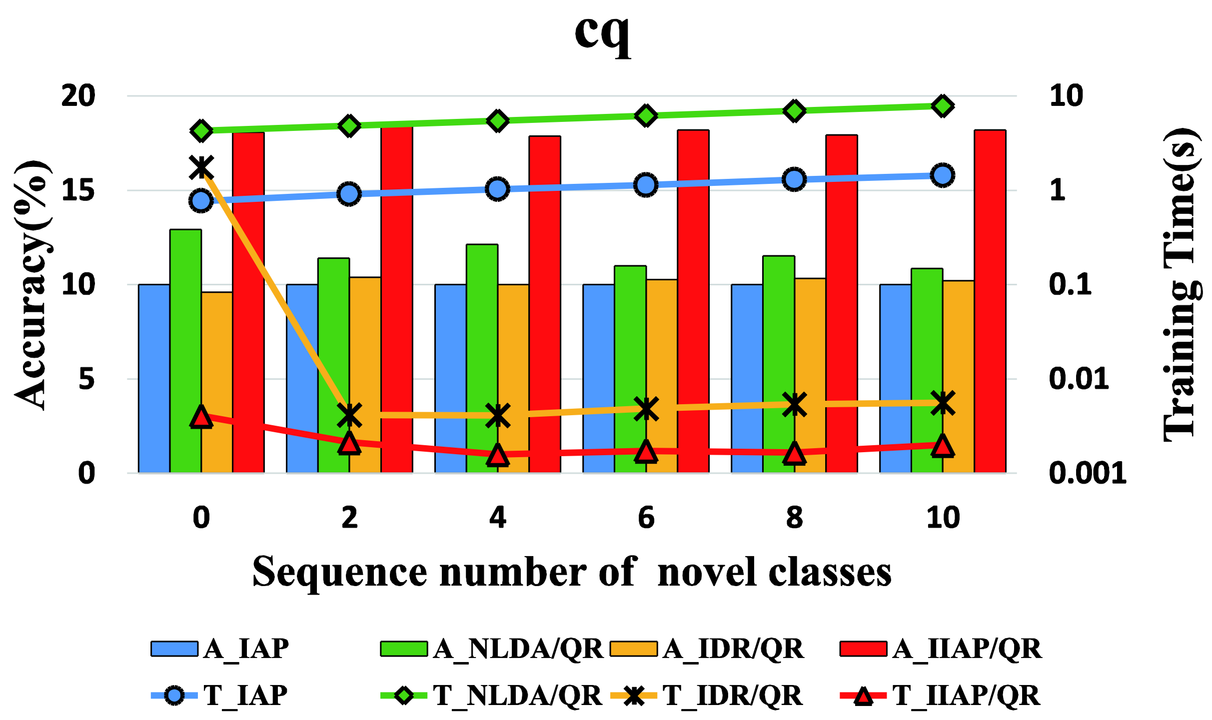
- Insertion of novel classes




- The bar : recognition rate
- The line : training time
- IAP: retraining of PAMI2014
- NLDA/QR: retraining of PR2010
- IDR/QR: incremental learning of TKDE2005
- IIAP/QR: ours

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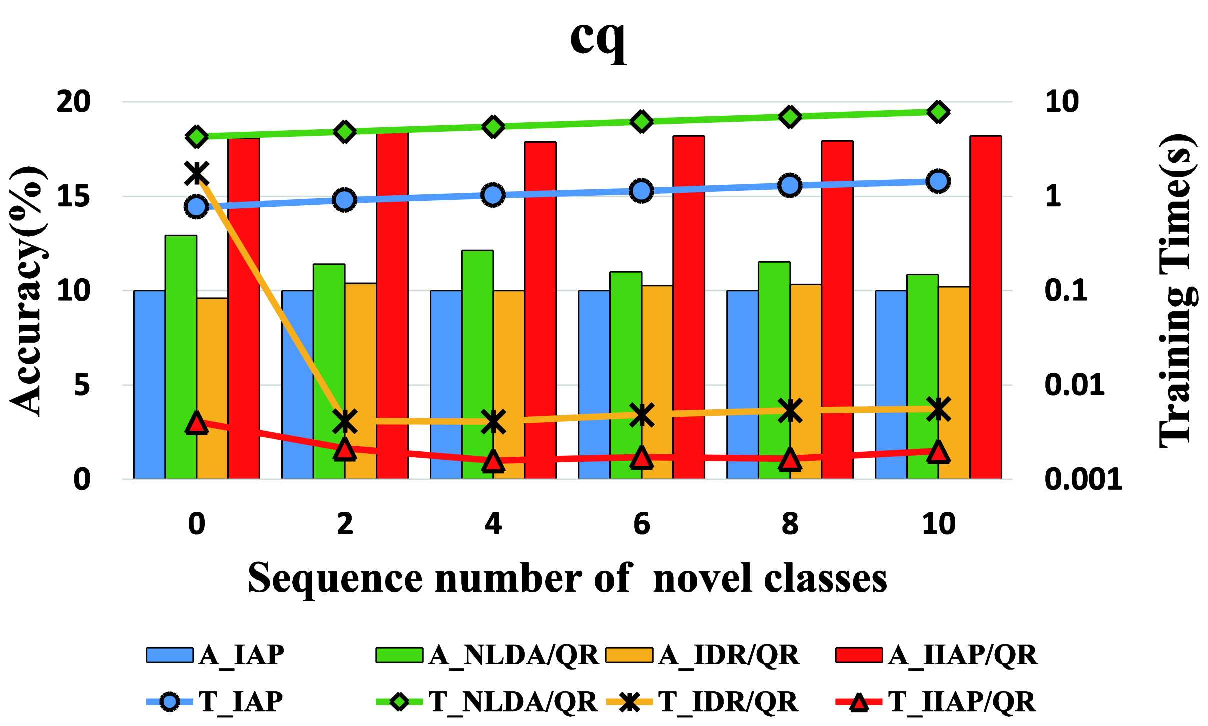


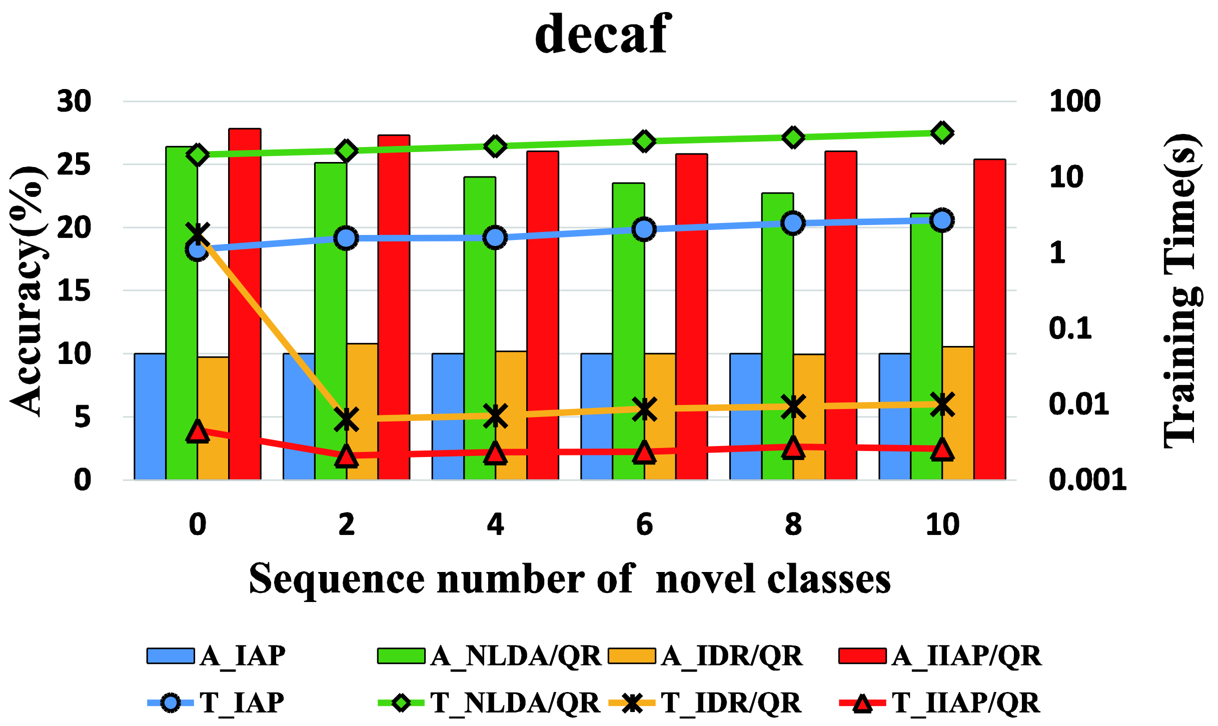

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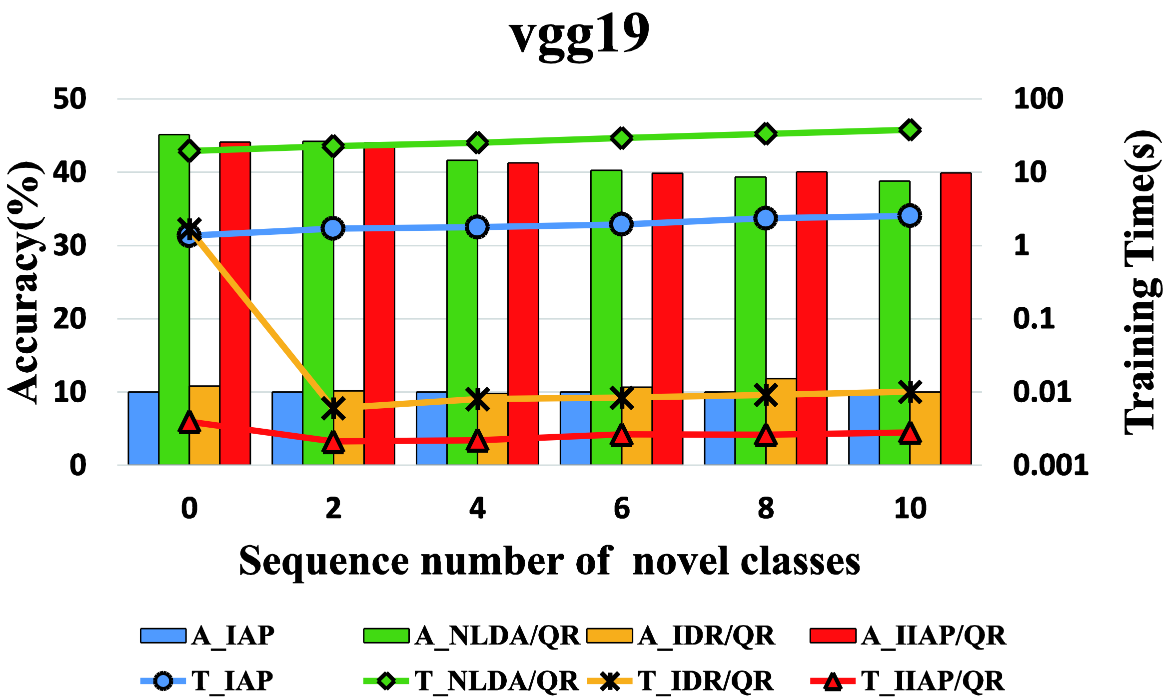


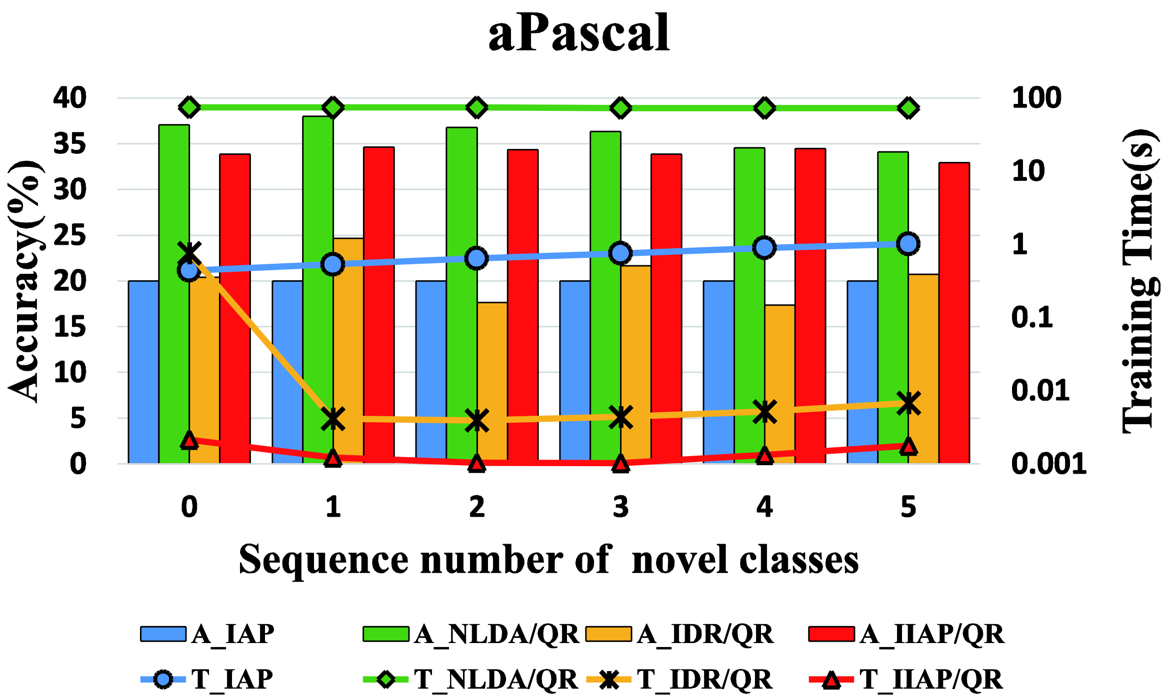


Accuracy: raise 8%-25% or comparable

Batch time: improve 2-3 orders of magnitude(centroid matrix)

Incremental phase time: faster 4-5 times than IDR/QR

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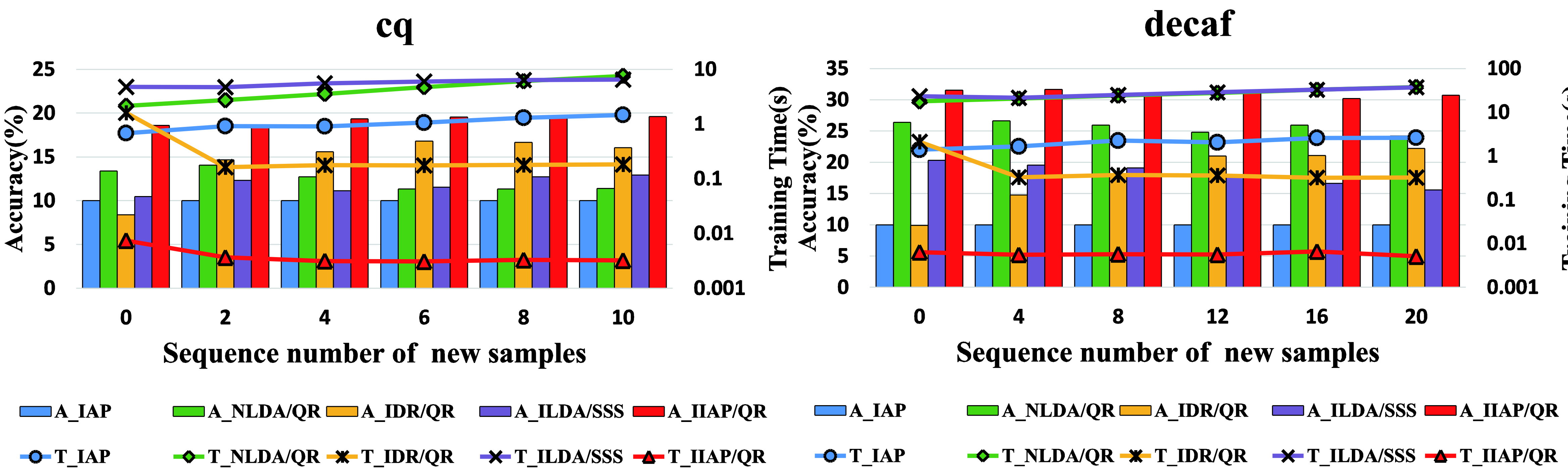
- Insertion of new samples to existing classes




ILDA/SSS: incremental learning of CVPR07

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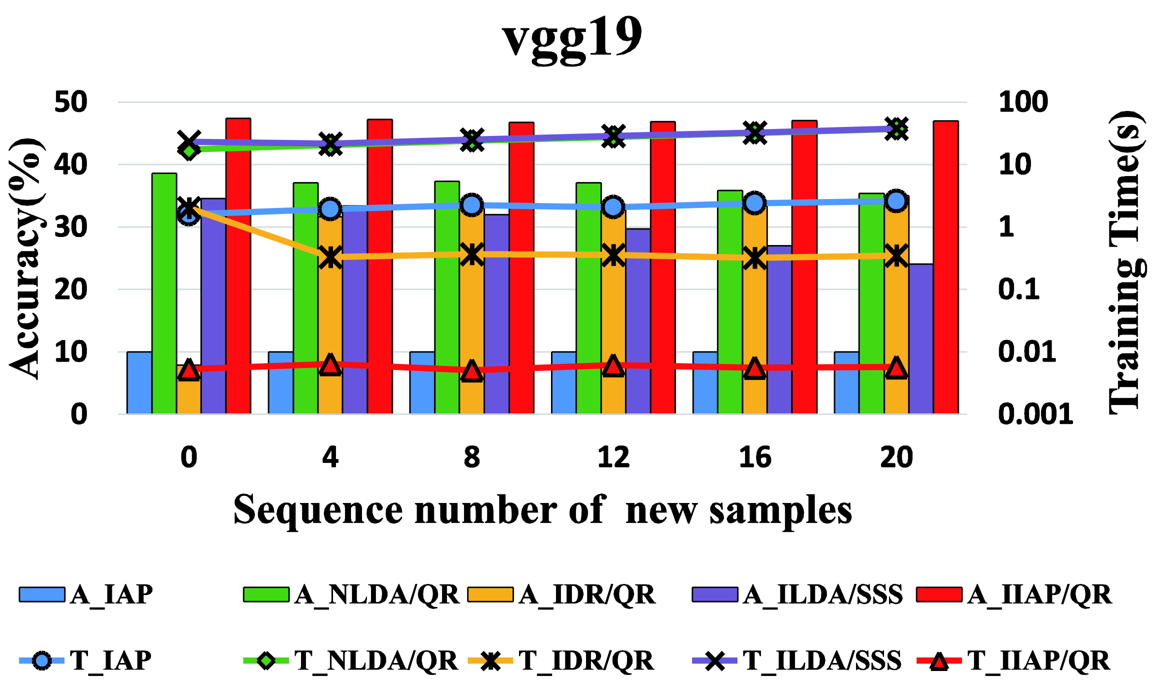


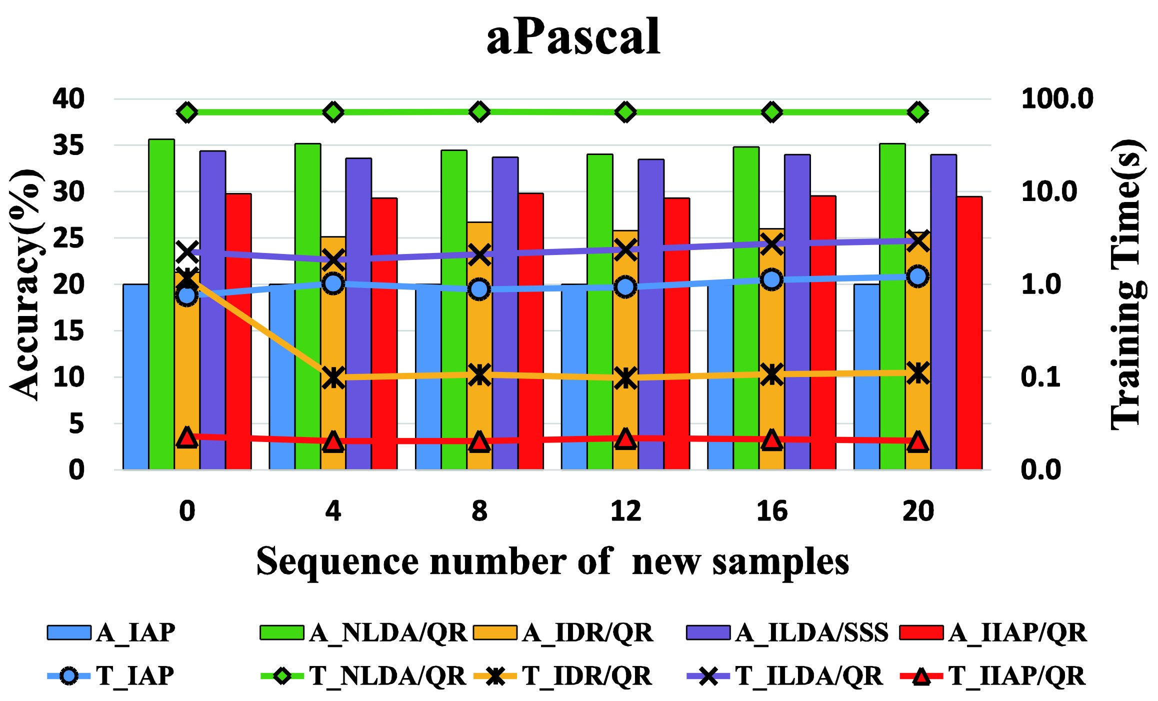


Accuracy: raise 3%-12% or comparable

Time: improve 1-4 orders of magnitude(centroid matrix)

# ➢ Conclusion

- Solve small-sample-size and unequal-sample-size problems
- Comparable recognition accuracy
- Online learning with quick updating

# Thanks!