# CS461 – RECITATION 05 MACHINE LEARNING PRINCIPLES

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## TODAY'S CONTENT

- AdaBoost
- Quiz 02

### **ADABOOST**

#### Data:

- Iteratively reweight samples
- Misclassified ones get higher weight

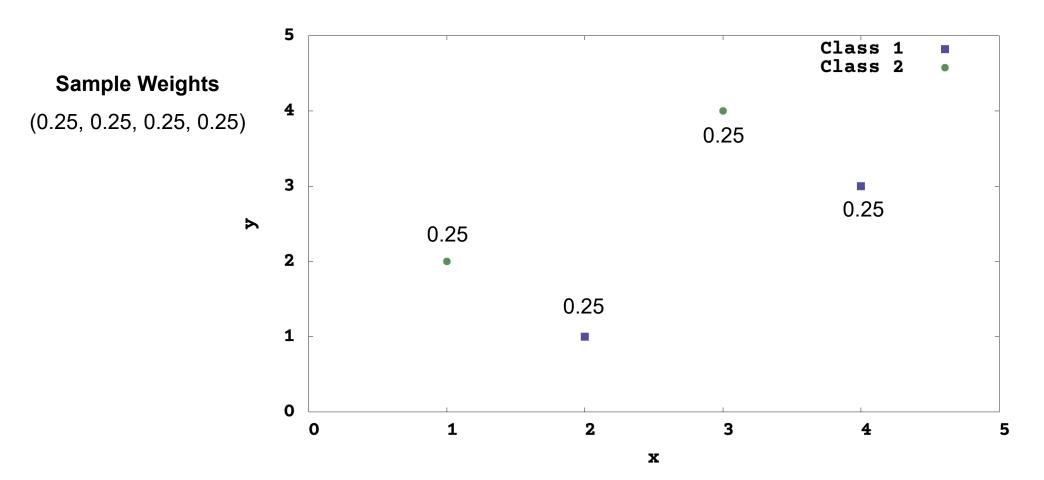
#### Model:

- Chain many weak learners (decision stumps)
- Weight each by its accuracy for final prediction

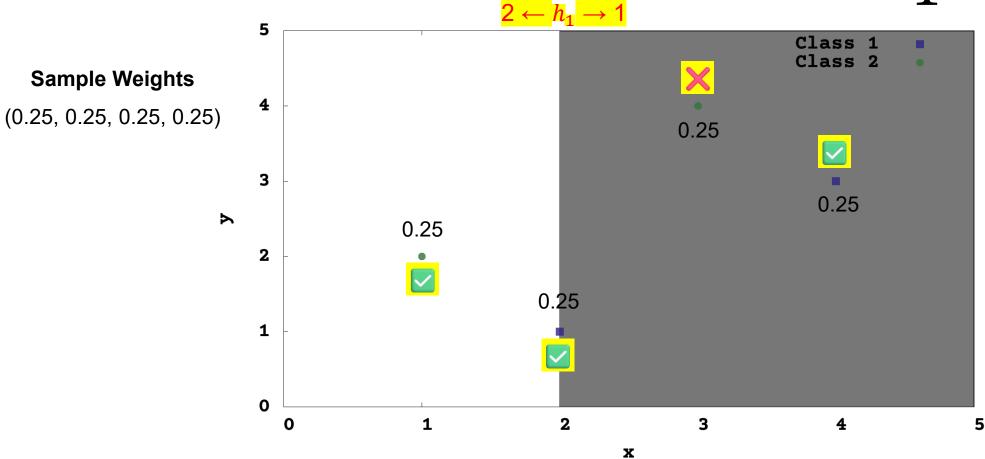
### **ADABOOST**

- 1. Initialize sample weights uniformly.
- 2. Repeat for *T* rounds:
  - a. Train a learner  $h_t$  on the weighted data.
  - b. Compute weighted error  $\epsilon_t$ .
  - c. Set learner weight  $\alpha_t = \frac{1}{2} \ln \frac{1 \epsilon_t}{\epsilon_t}$ .
  - d. Update and renormalize sample weights.
- 3. Predict *X* by sign( $\sum_{t=1}^{T} \alpha_t h_t(X)$ ).

## STEP1: INITIALIZE SAMPLE WEIGHTS

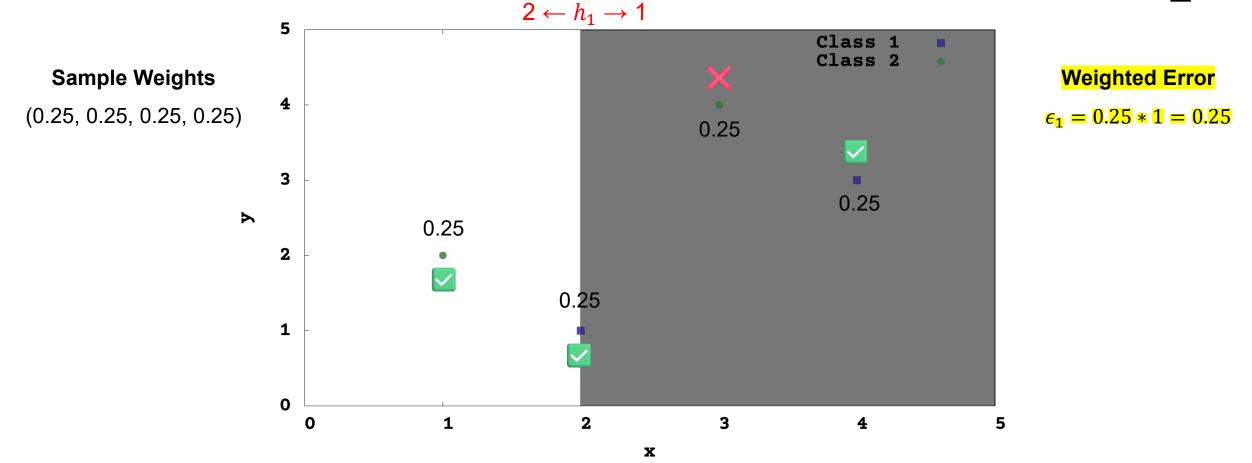


## STEP2-A: TRAIN LEARNER h<sub>1</sub>



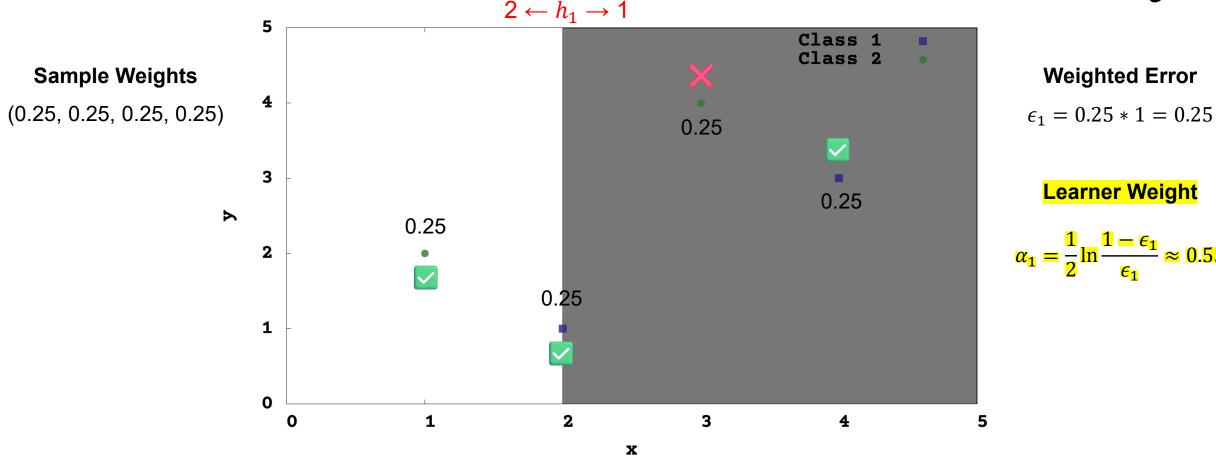
## STEP2-B:

## COMPUTE WEIGHTED ERROR $\epsilon_1$



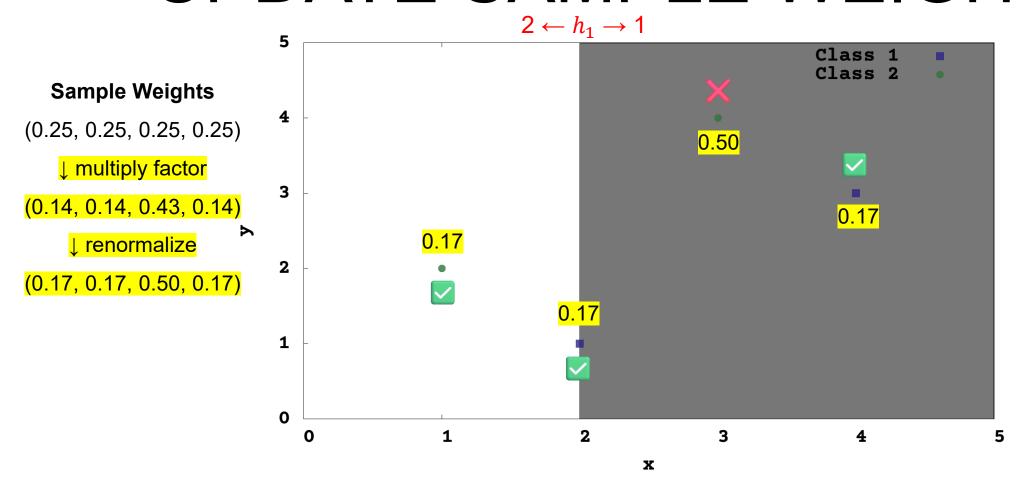
## STEP2-C:

## COMPUTE LEARNER WEIGHT $\alpha_t$



$$\alpha_1 = \frac{1}{2} \ln \frac{1 - \epsilon_1}{\epsilon_1} \approx 0.55$$

## STEP2-D: UPDATE SAMPLE WEIGHTS



#### **Weighted Error**

$$\epsilon_1 = 0.25 * 1 = 0.25$$

#### **Learner Weight**

$$\alpha_1 = \frac{1}{2} \ln \frac{1 - \epsilon_1}{\epsilon_1} \approx 0.55$$

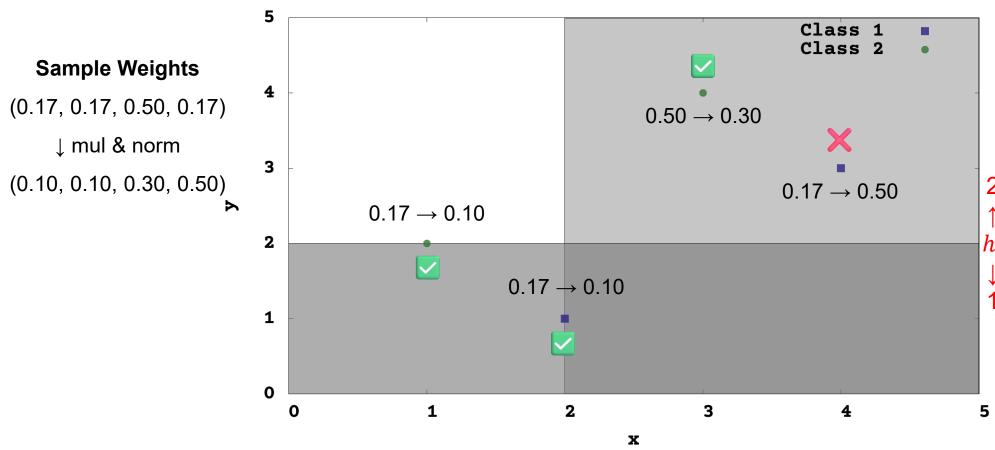
#### **Update Factor**

$$e^{-\alpha_1}$$



(0.58, 0.58, 1.73, 0.58)

## STEP2: REPEAT UNTIL CONVERGENCE



#### **Weighted Error**

$$\epsilon_2 = 0.17 * 1 = 0.17$$

#### Learner Weight

$$\alpha_2 = \frac{1}{2} \ln \frac{1 - \epsilon_2}{\epsilon_2} \approx 0.80$$

#### **Update Factor**

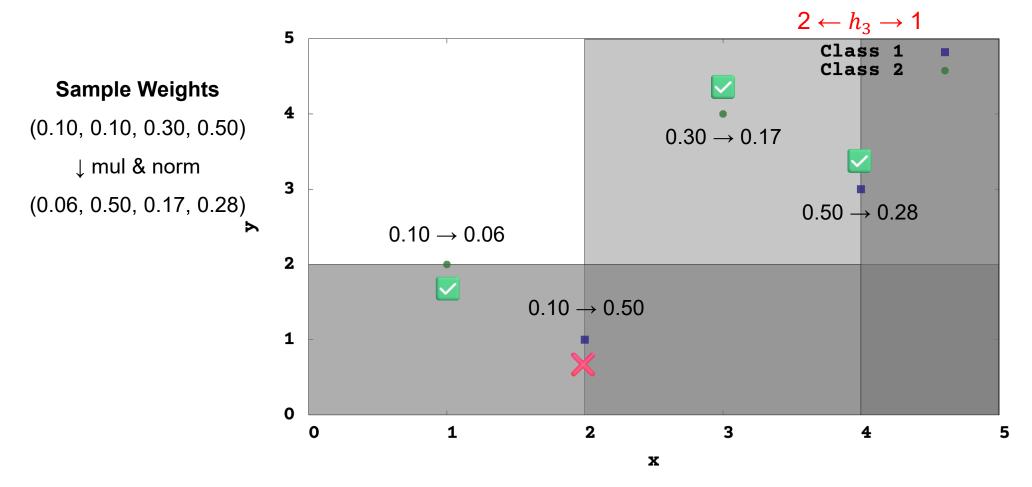
$$\sim$$
:  $e^{-\alpha_2}$ 

$$\times : e^{\alpha_2}$$

(0.45, 0.45, 0.45, 2.24)

### STEP2:

## REPEAT UNTIL CONVERGENCE



#### **Weighted Error**

$$\epsilon_3 = 0.10 * 1 = 0.10$$

#### **Learner Weight**

$$\alpha_3 = \frac{1}{2} \ln \frac{1 - \epsilon_3}{\epsilon_3} \approx 1.10$$

#### **Update Factor**

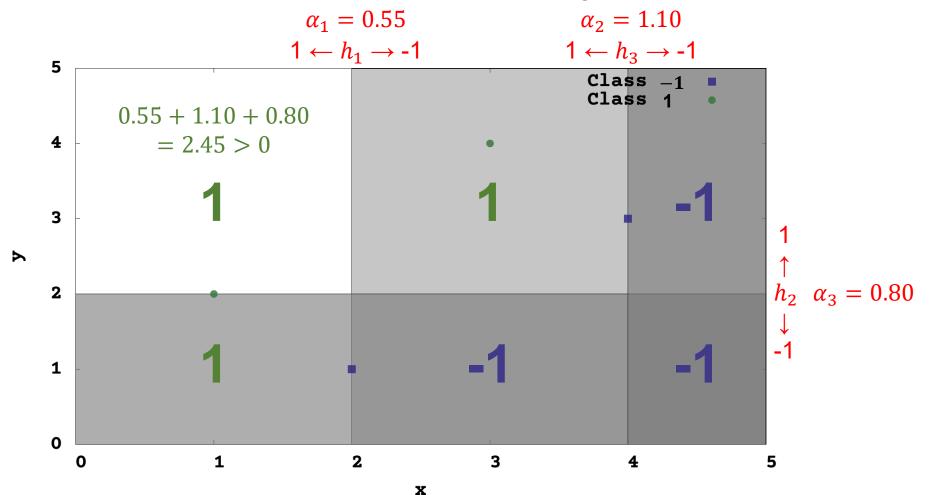
$$\sim$$
:  $e^{-\alpha_3}$ 

$$\times : e^{\alpha_3}$$

(0.33, 3.00, 0.33, 0.33)

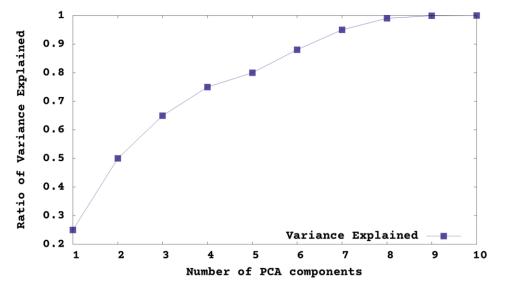
## STEP3:

## PREDICT X BY $sign(\sum_{t=1}^{T} \alpha_t h_t(X))$



Α	В	С	D	
3	1	14	3	

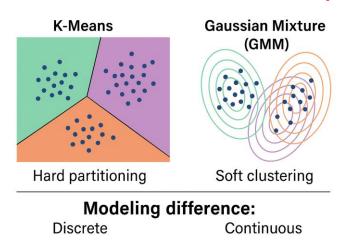
- 1) When preprocessing data using principal component analysis with eigenvalues, which of the following statements is false?
- (a) The eigenvalue from the first component is the largest.
- (b) The first two components explain about half of the dataset variance.
- (c) The first components explain the most variance. They should be dropped.
- (d) The last components explain the least variance. They should be dropped.



Accumulative values

Α	В	С	D	
1	2	0	18	

- 2) Which is true about soft clustering?
- (a) Soft clustering is used in K-Means.
- (b) Soft clustering is used in K Nearest Neighbors.
- (c) Soft clustering is used when making final cluster assignments after training, but not during training.
- (d) Soft clustering allows a point's likelihood to be explained by multiple clusters.



K-Means: hard

GMM: soft

Α	В	С	D	
2	15	4	0	

- 3) Which of the following is a supervised technique?
- (a) Guassian Mixture Models
- (b) Logistic Regression
- (c) Hierarchical Agglomerative Clustering
- (d) Principal Component Analysis

All clusterings are un-supervised.

Α	В	С	D	
2	15	4	0	

- 4) Which statement about the K-Means algorithm is true?
- (a) K-Means deals well with overlapping clusters of different classes.
- (b) K-Means can be improved by choosing initial cluster centers that are far apart.
- (c) K-Means is guaranteed to converge on the best cluster split.
- (d) K-Means works well when clusters are not spherical.

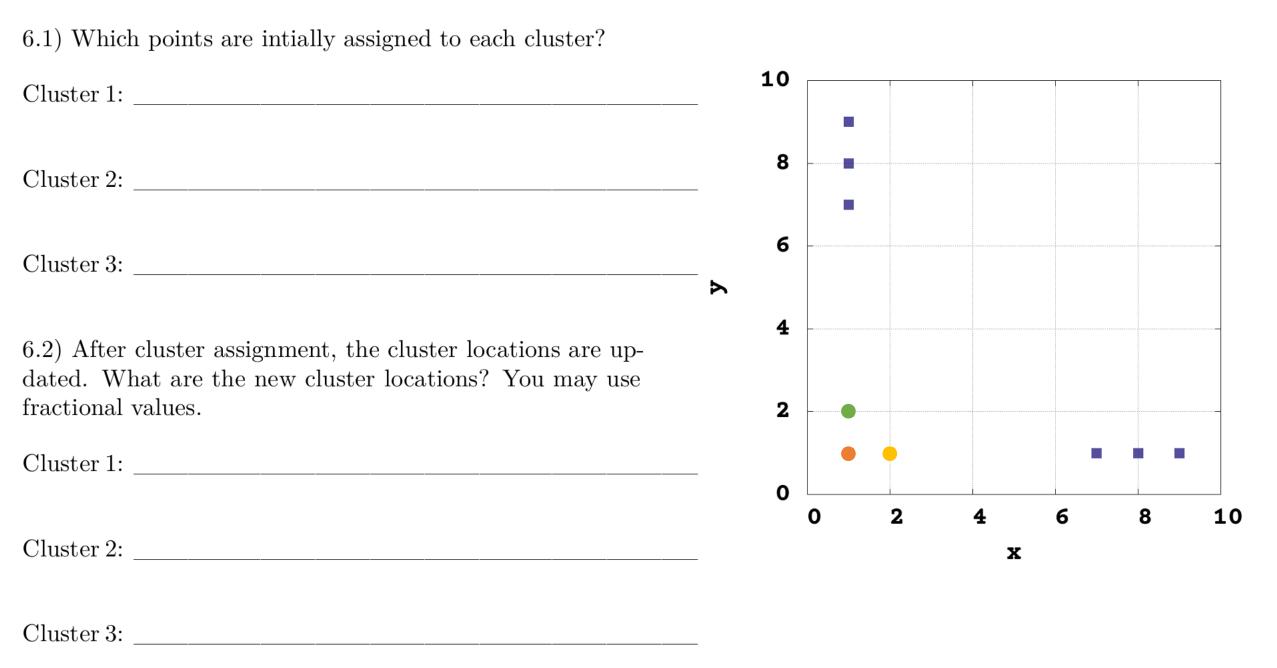
Α	В	С	D	
3	12	3	3	

- 5) Which of the following statements about decision boundaries is false?
- (a) Decision boundaries in decision trees are noisy because small changes in the dataset can lead to large changes in pivot choices.
- (b) Linear regression creates a complicated decision boundary that is known to easily overfit to the individual data samples.
- (c) The decision boundaries in a Gaussian Mixture Model cluster assignment consider the cluster variance.
- (d) With most techniques, poor decision boundaries can be improved with additional data, especially if it is near the decision boundary

6) Consider the table of initial distances and figure below. K-Means is initialized with three clusters, with starting points (1,1), (1,2), and (2,1).

Cluster	1	2	3
Start	(1,1)	(1,2)	(2,1)

Distance	1,1	1,2	2,1	1,7	1,8	1,9	7,1	8,1	9,1
Cluster 1	0	1	1	6	7	8	6	7	8
Cluster 2	1	0	1.41	5	6	7	6.08	7.07	8.06
Cluster 3	1	1.41	0	6.08	7.07	8.06	5	6	7



6.1) Which points are intially assigned to each cluster?

Cluster 1: (1,1)

Cluster 2: (1,2) (1,7) (1,8) (1,9)

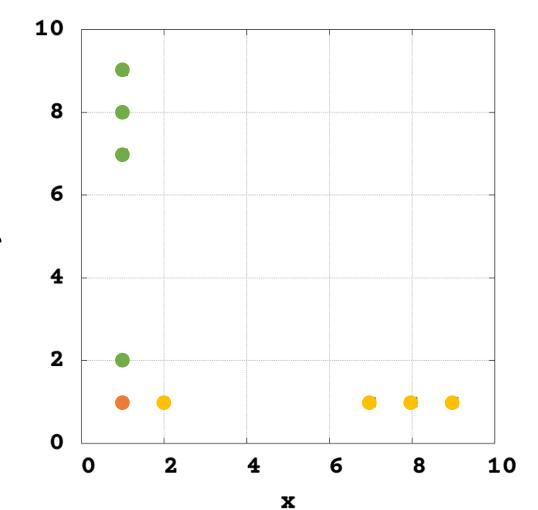
Cluster 3: (2,1) (7,1) (8,1) (9,1)

6.2) After cluster assignment, the cluster locations are updated. What are the new cluster locations? You may use fractional values.

Cluster 1:

Cluster 2: \_\_\_\_\_

Cluster 3: \_\_\_\_\_



6.1) Which points are intially assigned to each cluster?

Cluster 1: (1,1)

Cluster 2: (1,2) (1,7) (1,8) (1,9)

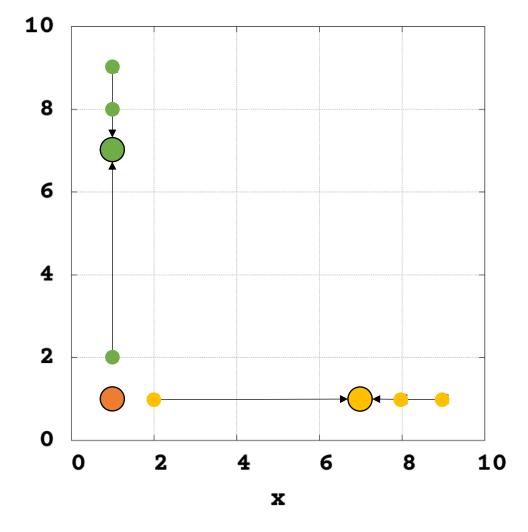
Cluster 3: (2,1) (7,1) (8,1) (9,1)

6.2) After cluster assignment, the cluster locations are updated. What are the new cluster locations? You may use fractional values.

Cluster 1: (1,1)

Cluster 2: 
$$\frac{\left(\frac{1+1+1+1}{4}, \frac{2+7+8+9}{4}\right) \rightarrow \left(1, \frac{13}{2}\right)}{}$$

Cluster 3: 
$$\left(\frac{2+7+8+9}{4}, \frac{1+1+1+1}{4}\right) \to \left(\frac{13}{2}, 1\right)$$



## Q&A