Response Summary - Short Quiz on Domain Adaptation

Total respondents: 172

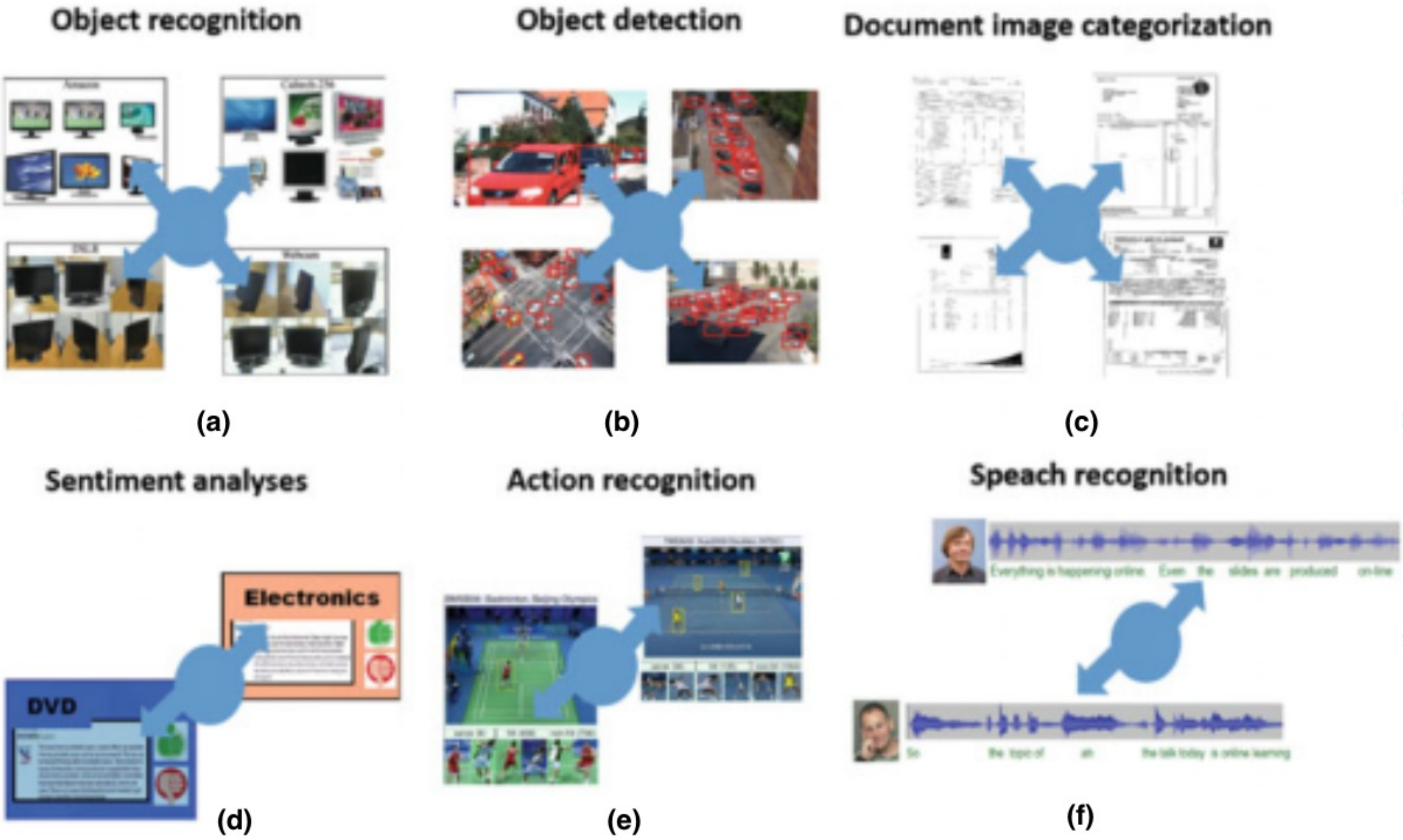
A domain $\mathcal{D}$ is composed of a d-dimensional feature space $\mathcal{X} \subset R^d$ and a marginal probability distribution $P(X)$ and task $\mathcal{T}$ is defined by a label space $\mathcal{Y}$ and conditional probability distribution $P(Y|X)$ where $X = \{x_1, \cdots, x_n\} \in \mathcal{X}$ and $Y = \{y_1, \cdots, y_n\} \in \mathcal{Y}$.

Source domain and task can be written as $\mathcal{D}^s = \{\mathcal{X}^s, P(X^s)\}$ and $\mathcal{T}^s = \{\mathcal{Y}^s, P(Y^s|X^s)\}$. Similarly, target domain and task can be written as $\mathcal{D}^t = \{\mathcal{X}^t, P(X^t)\}$ and $\mathcal{T}^t = \{\mathcal{Y}^t, P(Y^t|X^t)\}$. Choose the correct statements.

1. In **domain adaptation**, it is assumed that $\mathcal{T}^s = \mathcal{T}^t$ and $\mathcal{D}^s \neq \mathcal{D}^t$
2. In **domain adaptation**, it is assumed that $\mathcal{T}^s \neq \mathcal{T}^t$ and $\mathcal{D}^s = \mathcal{D}^t$
3. In **homogeneous domain adaptation**, it is assumed that $\mathcal{X}^s = \mathcal{X}^t$ and $\mathcal{T}^s = \mathcal{T}^t$
4. In **homogeneous domain adaptation**, it is assumed that $\mathcal{X}^s \neq \mathcal{X}^t$ and $\mathcal{T}^s = \mathcal{T}^t$
5. In **heterogenous domain adaptation**, it is assumed that $\mathcal{X}^s \neq \mathcal{X}^t$ and $\mathcal{T}^s \neq \mathcal{T}^t$
6. In **heterogenous domain adaptation**, it is assumed that $\mathcal{X}^s = \mathcal{X}^t$ and $\mathcal{T}^s = \mathcal{T}^t$

✔ **1,3**	**91 (54%)**
2,3	10 (6%)
1,3,6	23 (14%)
1,4,6	21 (12%)
2,5	25 (15%)

Which of the following can be cast as domain adaptation problems across the illustrated domains ?



Only {a,b,c}	12 (7%)
Only {a,b,c,d}	8 (5%)
✔ **Only {a,b,c,d,e,f}**	**117 (69%)**
Only {a,b,c,d,e}	15 (9%)
Only {a,b,d,e}	18 (11%)

Which of the following statements are true with respect to the domain adaptation model proposed in Adversarial discriminative domain adaptation (ADDA) [Link] ?

[1] Both the source and target encoder share the same set of weights in ADDA

[2] Both the source and target domain classifier share the same set of weights in ADDA

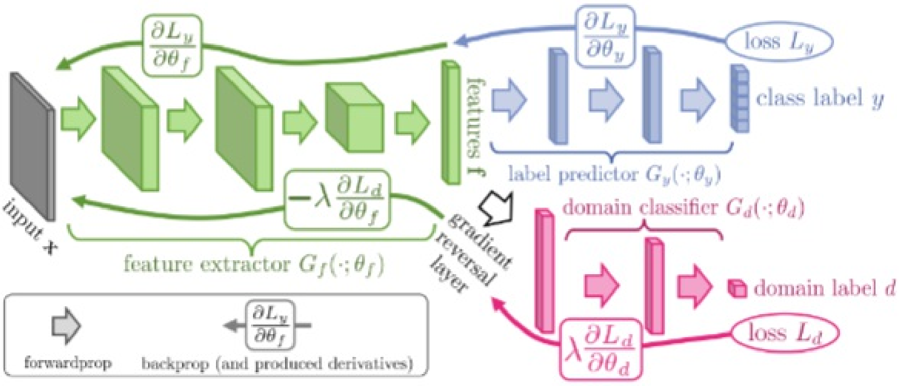
[3] The discriminator predicts the class label along with the domain label for both the source and target domains in ADDA

[4] The target domain samples are mapped from target domain space to source domain space in ADDA

[5] Target domain labels are required for ADDA to work

✔ **2,4**	**59 (35%)**
1,4	19 (11%)
1,3,4	39 (23%)
2,5	12 (7%)
1,3,5	17 (10%)
1,2,4	23 (14%)

In Domain Adversarial training of neural networks (DANN), authors propose the following architecture for domain finding domain invariant representations.



Choose the correct options with respect to the paper mentioned above

1. Target and Source domain encoder share the same weights in the DANN architecture
2. The value of λ (represented in the Figure) must be negative to find a representation which is both discriminative and domain invariant
3. Maximum Mean Discrepency (MMD) between source and target domain samples is used to achieve invarience between the domains
4. Unlike in ADDA (Adversarial Discriminative Domain Adaptation), source and target representations are learned concurrently in DANN.

DANN (Link)

ADDA (Link)

✔ **1,2,4**	**41 (24%)**
1,2	14 (8%)
1,4	32 (19%)
2,4	20 (12%)
1,3,4	46 (27%)
1,3	18 (11%)

Consider a source domain $\mathcal{D}^s = \{\mathcal{X}^s, P(X^s)\}$ and task $\mathcal{T}^s = \{\mathcal{Y}^s, P(Y^s|X^s)\}$ along with the target domain and task $\mathcal{D}^t = \{\mathcal{X}^t, P(X^t)\}$ and $\mathcal{T}^t = \{\mathcal{Y}^t, P(Y^t|X^t)\}$. Given the following two scenarios :-

1. Scenario 1
   (a) Source domain samples $X^s = \{x_1^s, x_2^s, \cdots, x_n^s\}$ and labels $Y^s = \{y_1^s, y_2^s, \cdots, y_n^s\}$
   (b) Target domain samples $X^t = \{x_1^t, x_2^t, \cdots, x_n^t\}$ only
   (c) $\mathcal{X}^s = \mathcal{X}^t$
   (d) $\mathcal{Y}^s = \mathcal{Y}^t$
   (e) $P(X^s) \neq P(X^t)$
2. Scenario 2
   (a) Source domain samples $X^s = \{x_1^s, x_2^s, \cdots, x_n^s\}$ and labels $Y^s = \{y_1^s, y_2^s, \cdots, y_n^s\}$
   (b) Target domain samples $X^t = \{x_1^t, x_2^t, \cdots, x_n^t\}$ only
   (c) $\mathcal{X}^s = \mathcal{X}^t$
   (d) $\mathcal{Y}^s \neq \mathcal{Y}^t$
   (e) $P(X^s) \neq P(X^t)$

   Select the **most** appropriate option representing the scenarios.

✔ **Scenario 1 - Unsupervised Domain Adaptation, Scenario 2 - Unsupervised Transfer Learning**	**79 (46%)**
Scenario 1 - Unsupervised Transfer Learning, Scenario 2 - Unsupervised Domain Adaptation	24 (14%)
Scenario 1 - Semi-supervised Domain Adaptation, Scenario 2 - Unsupervised Domain Adaptation	30 (18%)
Scenario 1 - Unsupervised Domain Adaptation, Scenario 2 - Unsupervised Heterogenous Domain Adaptation	37 (22%)

Suppose we use the image (shown below) as a data sample [We have 1 million such samples] and the task requires us to classify each pixel of the image to a particular object class (such as a tree, bus, scooter etc.). In computer vision literature, this is called Semantic Segmentation problem.

In the **first scenario**, we make an annotator manually classify each pixel of the image before using it in training [shown below].

In the **second scenario**, we upload the image to Instagram and let people comment with appropriate tags [shown below] . Although the tags may not describe appropriate classes exactly, we use them to train the network for pixel-level classification.

#car, #india, #palmtrees, #indiancountryside, #travellinglove

Choose the **most appropriate** option -

✔ **Scenario 1 - Fully Supervised Learning, Scenario 2 - Weakly Supervised Learning**	**95 (56%)**
Scenario 1 - Fully Supervised Learning, Scenario 2 - Few-shot Learning	47 (27%)
Scenario 1 - Weakly Supervised Learning, Scenario 2 - Zero-shot Learning	12 (7%)
Scenario 1 - Semi-supervised Learning, Scenario 2 - Few-shot Learning	17 (10%)