# SMAI Team Project

Team 18

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# **Project Name**

Scene Classification using Weak Supervision

### **Basic Ideas**

**Datasets** 

Low Level Representation

Semantic Theme Representation

Theme Vector Generation

**Scene Classification** 

### Collection of Datasets

#### **Corel Stock Photo**

We use the images from the Corel Stock photo Dataset.

#### 15-scene Category

15 scene categories are picked from MIT 67 Dataset.

#### Caltech 101

This dataset contains
101 object categories.
We will run this model on this dataset to compare its performance with other object classification algorithms.

### Low-Level Representation

#### Image Representation

At the low level, we represent the images as bags of 8 X 8 vectors of DCT coefficients sampled on a uniform grid. Only 36 (out of 64) top left coefficients are kept.



#### **Scene Categories**

Each image 'li' is labeled with a "Ground Truth" 'Si'. The image label 'Si' is considered to be an observation from a Semantic scene category 'S' defined on {S1, S2, ..., Sk}. This framework of lowlevel representation is similar to the "Bag-of-Visterms" representation.

### Semantic Theme Representation

#### Concept of Themes

To represent image by semantic themes the dataset is augmented by a vocabulary  $L = \{t1, t2, t3, ..., tL\}$  of semantic themes 'ti'. For example an image of "street" can have themes such as "road", "trees", "cars", "people" etc.

#### Theme Representation

Each image 'li' is labeled with a "Ground Truth" 'Si'. The image label 'Si' is considered to be an observation from a Semantic scene category S defined on {S1, S2, ..., Sk}.

#### **Casual Annotation**

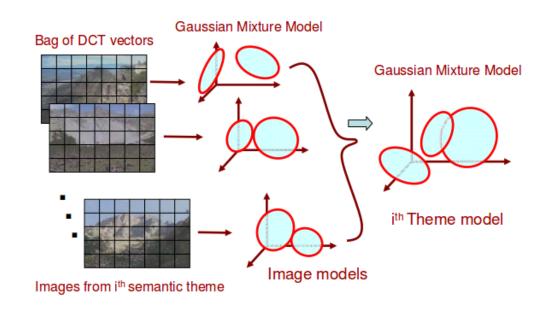
Usually theme annotations are absent in the training dataset. In such cases semantic theme categories serve as a proxy for the theme vocabulary. This is casual annotation and for this paper casual annotation is used.

## Semantic Theme Representation

#### Forming Theme Models

Now for all the images belonging to the same theme, the gaussian mixture model is estimated. Now using EM we estimate the Gaussian mixture model for the complete theme.

Hence we obtain  $P_{X|T}$ . Using this we will later estimate  $P_{T|X}$ .



## Generating Theme Vector

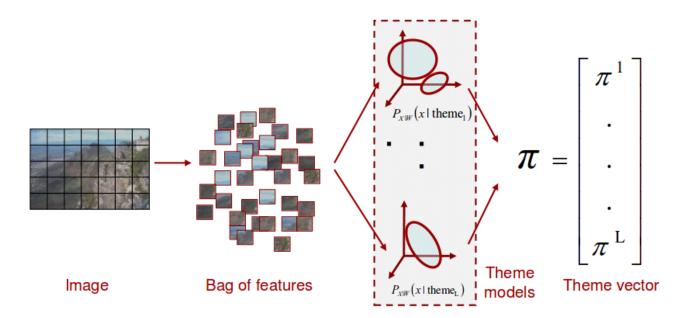
#### Why Not use Annotations?

Annotations seem to be good parameter for using as a feature vector. But we don' t use it because usually it's only available during training and if an image is not annotated with a particular theme then it doesn't necessarily mean that it doesn't have that theme.

#### Procedure

We will use theme vector as the feature vector of an image for learning. Feature vector ' $\Pi$ ' = { $\Pi_1$ , $\Pi_2$ ...., $\Pi_1$ } is a L-dimensional vector. Here ' $\pi_i$ ' represents the probability that the image feature vector is drawn from the ith theme. To calculate this we use Bayes rule as we already know  $P_{xit}$  and need  $P_{TIX.}$ 

## Generating Theme Vector



Here is the pictorial representation of the procedure.

### Scene Classification

#### Procedure

Till the previous step we learned the theme vector  $(\Pi)$  for each image.

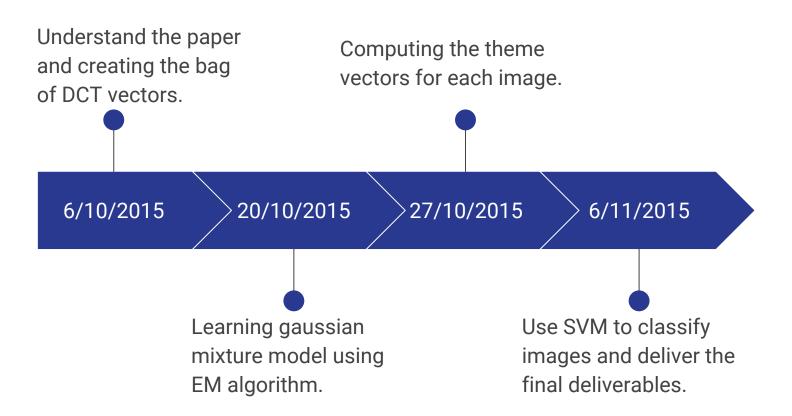
Now we will use a multi-class SVM using one-vs-all strategy with Gaussian kernel for classification, with the parameters obtained by 3-fold cross validation.

## Deliverables

Create a model that is able to classify images based on its semantic theme.

Also provide the theme vectors for each image which captures the different semantic meanings of the image.

### Timeline



# Thank You

Any Questions...?