

# Full House

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# Learning Objective

01

## Markov Random Field

To model the low level image processing tasks in this framework

02

## Conditional Random Field

To model the low level image processing tasks in this framework

03

## Hopfield Network

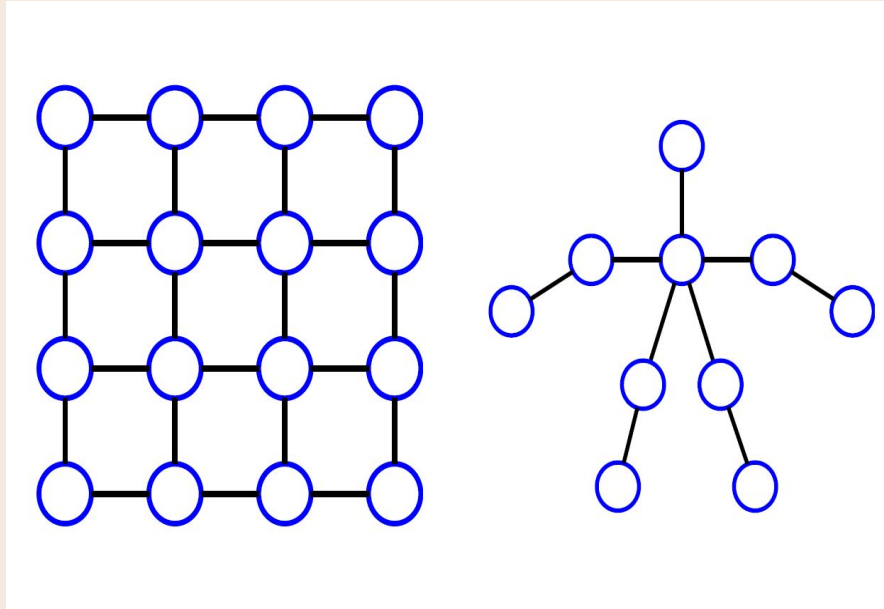
To use it for solving some interesting combinatorial problems

# MARKOV Random Field

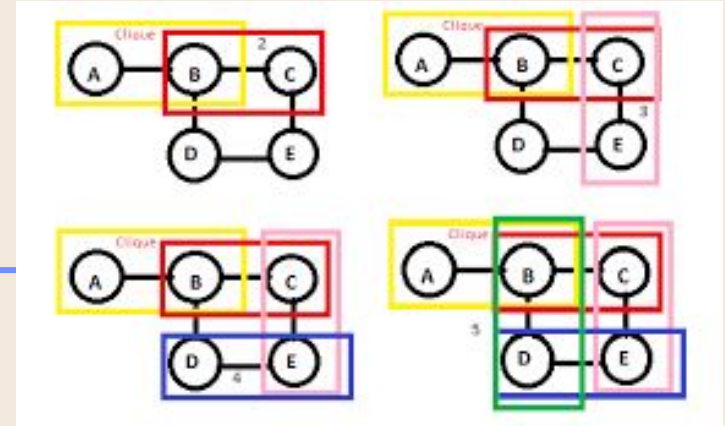
Smoothness  
Favouring Energy  
Function

Cliques

A Markov Random Field is a graph whose nodes model random variables, and whose edges model desired local influences among pairs of them. A natural MRF that models this has a node for each of the pixels. An edge connects two nodes that are adjacent (on the grid). The structure of this graph decides the dependence or independence between the random variables. A variable's neighboring nodes or variables are also called the Markov Blanket of that variable.



Grid or graph of nodes that can be represented in terms of pixels of image.



A clique in a graph is a set of nodes in which every pair is connected by an edge.



Example Image

# Markov Random Fields And Image Processing



## Image Restoration

Here we are given an image that is both noisy (i.e. some of its pixels have incorrect values) and incomplete (i.e., some of its pixels don't have a value).



## Image Segmentation

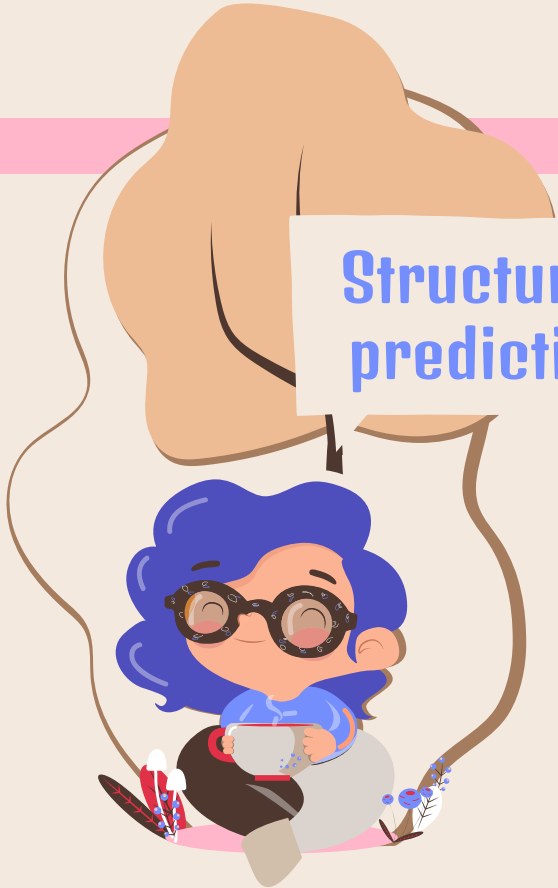
Image segmentation is a commonly used technique in digital image processing and analysis to partition an image into multiple parts or regions, often based on the characteristics of the pixels in the image.



## Image Denoising

Image noise is random variation of brightness or color information in images, and is usually an aspect of electronic noise. Removing noise from imagery.

# Conditional Random Fields



## Structured prediction

For a moment, let us assume a Markov Random Field and divide it into two sets of random variables  $Y$  and  $X$  respectively. Conditional Random Field is a special case of Markov Random field wherein the graph satisfies the property : "When we condition the graph on  $X$  globally i.e. when the values of random variables in  $X$  is fixed or given, all the random variables in set  $Y$  follow the Markov property  $p(Y_u/X, Y_v, u \neq v) = p(Y_u/X, Y_x, Y_u \sim Y_x)$ , where  $Y_u \sim Y_x$  signifies that  $Y_u$  and  $Y_x$  are neighbors in the graph."

# Hopfield Network

## Associative Memory



A Hopfield network is a single-layered and recurrent network in which the neurons are entirely connected, i.e., each neuron is associated with other neurons. If there are two neurons  $i$  and  $j$ , then there is a connectivity weight  $w_{ij}$  lies between them which is symmetric  $w_{ij} = w_{ji}$ .



# Hopfield network and combinatorial problems



## Discrete Hopfield Network

It is a fully interconnected neural network where each unit is connected to every other unit. It behaves in a discrete manner, i.e. it gives finite distinct output. The weights associated with this network is symmetric.



## Continuous Hopfield Network:

Here the time parameter is treated as a continuous variable. So, instead of getting binary/bipolar outputs, we can obtain values that lie between 0 and 1. It can be used to solve constrained optimization and associative memory problems.

## Testing Algorithm of Discrete Hopfield Net

**Step 0:** Initialize the weights to store patterns, i.e., weights obtained from training algorithm using Hebb rule.

**Step 1:** When the activations of the net are not converged, then perform Steps 2-8.

**Step 2:** Perform Steps 3-7 for each input vector X.

**Step 3:** Make the initial activations of the net equal to the external input vector X:

$$y_i = x_i \text{ for } i = 1 \text{ to } n$$

**Step 4:** Perform Steps 5-7 for each unit  $y_i$ . (Here, the units are updated in random order.)

**Step 5:** Calculate the net input of the network:

$$y_{ini} = x_i + \sum_j y_j w_{ji}$$

It is a symmetrically weighted network i.e.,  $w_{ii} = 0$  and  $w_{ij} = w_{ji}$ .

**Step 6:** Apply the activations over the net input to calculate the output:

$$y_i = \begin{cases} 1 & \text{if } y_{ini} > \theta_i \\ y_i & \text{if } y_{ini} = \theta_i \\ 0 & \text{if } y_{ini} < \theta_i \end{cases}$$

where  $\theta_i$  is the threshold and is normally taken as zero.

**Step 7:** Now feed back the obtained output  $y_i$  to all other units. Thus, the activation vectors are updated.

**Step 8:** Finally, test the network for convergence.

# What is Hopfield Again...

- **Neuron**
- **Weight**
- **Energy**
- **Connections**
- **Memory**
- **Type**
- **Goal**



# Hopfield Network Again

## Neuron

In this problem we consider the cities as the neurons

## Weight

We will make a distance matrix and use it as a weight

## Energy

The energy function contains various sections that represent the patterns stored in the network. The input pattern of the network, represents a particular point in the energy landscape.

## Connections

In Tsp all cities are connected to each other and as a neurone they will store the feedback.

**Code**

# RESOURCES

- <https://cgi.luddy.indiana.edu/~natarasr/Courses/I590/Papers/MRF.pdf>
- <https://towardsdatascience.com/markov-random-fields-and-image-processing-20fb4cf7e10d#:~:text=A%20Markov%20Random%20Field%20is,image%20on%20a%20rectangular%20grid>
- <https://towardsdatascience.com/conditional-random-fields-explained-e5b8256da776>
- <http://www.inference.org.uk/mackay/itila/>
- [http://www.cs.toronto.edu/~fleet/research/Papers/BMVC\\_denoise.pdf](http://www.cs.toronto.edu/~fleet/research/Papers/BMVC_denoise.pdf)