

# EE382N.23: Embedded System Design and Modeling

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## Lecture 2 – Design Methodologies

Andreas Gerstlauer  
Electrical and Computer Engineering  
University of Texas at Austin  
gerstl@ece.utexas.edu



## Lecture 2: Outline

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- **Design methodologies**
  - Design process
  - Abstraction levels
  - Design models
  - System-level design flow
- **Design example**
  - Object recognition in smart camera network
  - Deep and convolutional neural networks (DNNs/CNNs)
  - Distributed CNN inference in IoT edge computing

## Design Process

- **Sequence of steps that transforms a set of requirements described informally into a detailed description that can be used for manufacturing**
  - Intermediate steps with transformation from a more abstract description to a more detailed one (*refinement*)
- **A designer can perform step-by-step refinement**
  - The “input” description is a *specification*
  - The final description of the design is an *implementation*
- **Take a model of the design at a level of abstraction and refine it to a lower one (level of detail ↑).**
  - Ensure that the **properties at the lower level of abstraction are verified**, and that the **performance indices are satisfactory**
  - Thus, refinement process involves **mapping constraints, performance indices and properties to the lower level**, so that they can be computed for the next level down

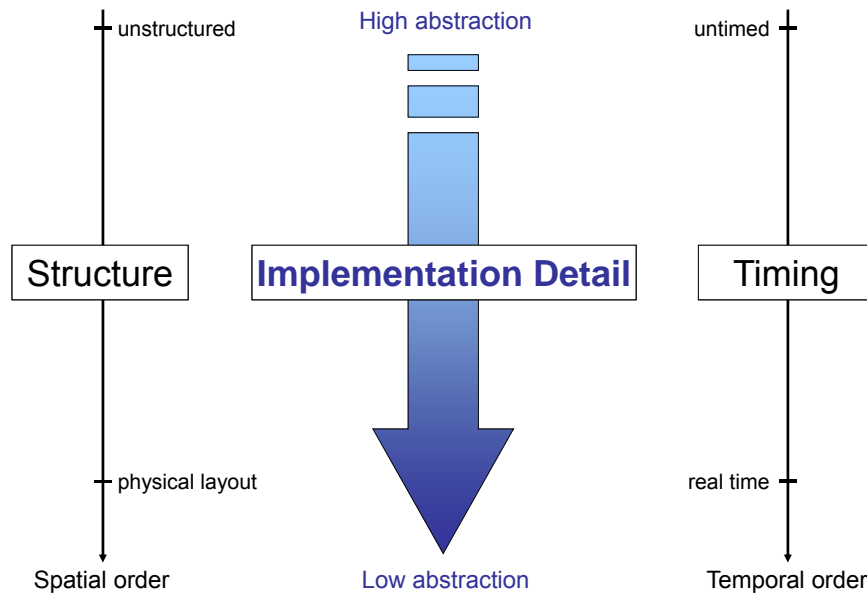
Source: M. Jacome, UT Austin

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## Abstraction Levels



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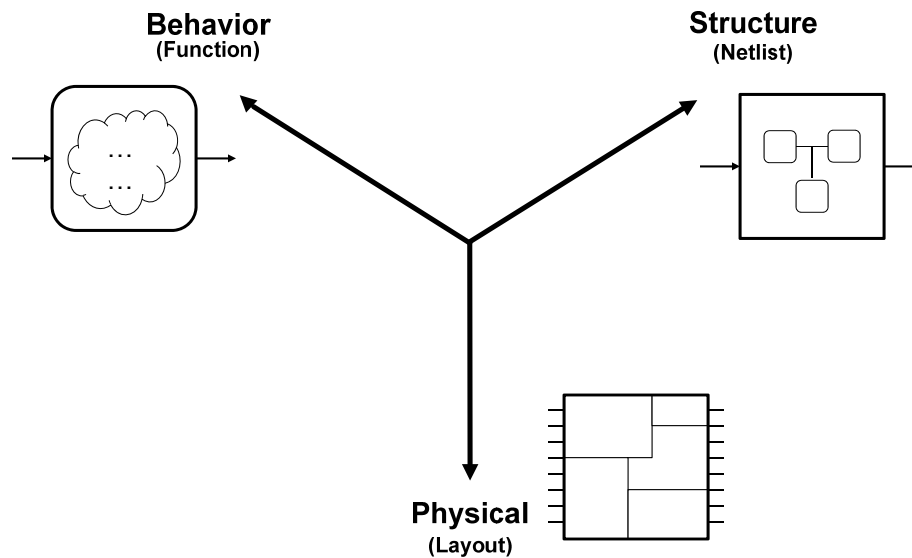
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## Design Methodology

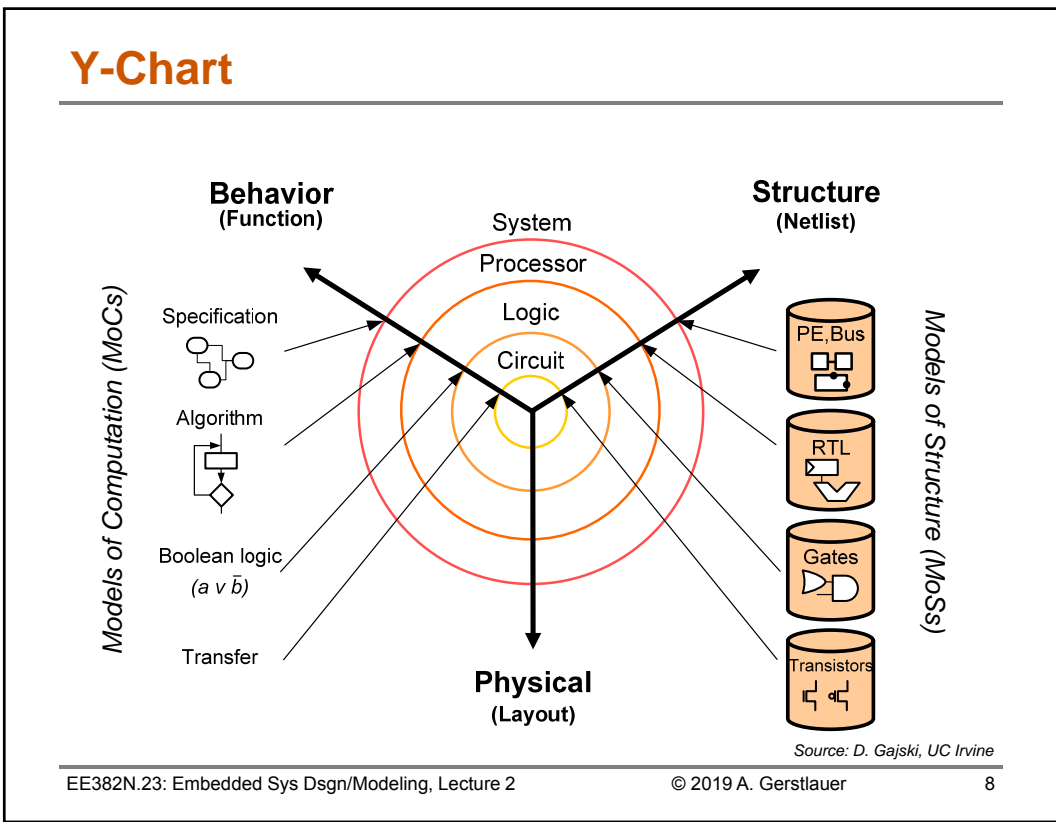
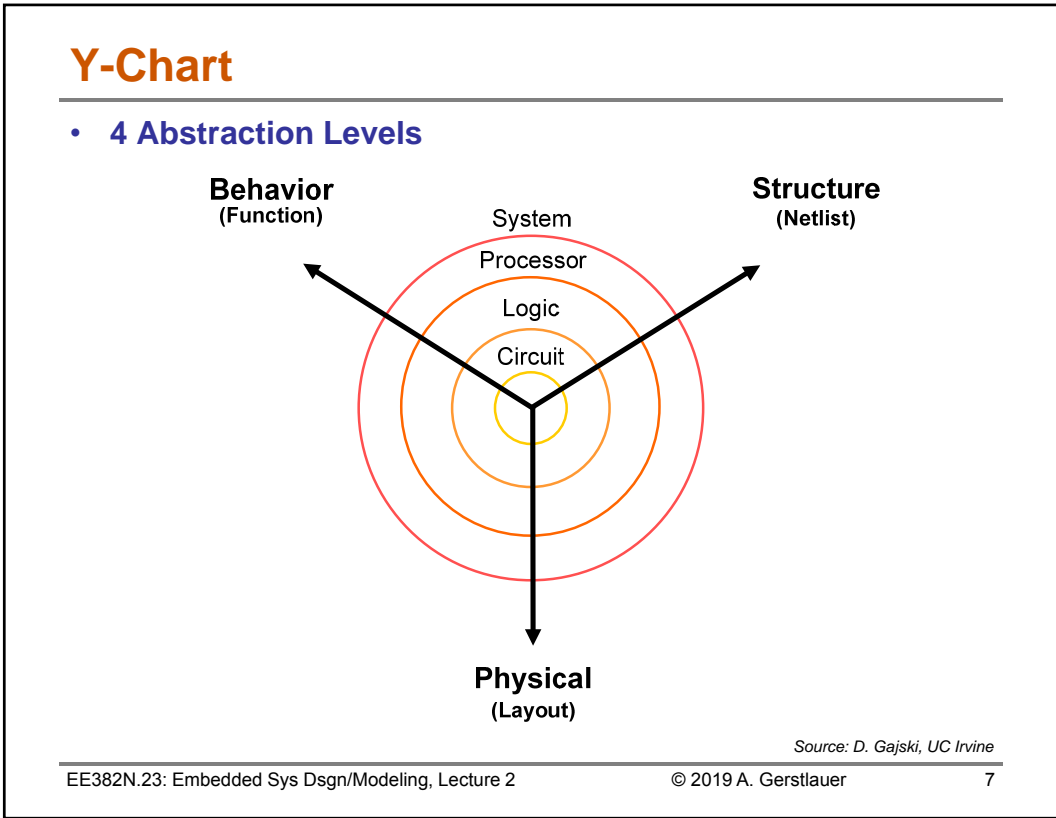
- **Set of Models**
  - Design representations
    - Specification and documentation at interface between steps
- **Set of Transformations**
  - Design decisions and design steps
    - Refine input model into an output model reflecting decisions
- **Formalization of a design flow**
  - Break into well-defined, repeatable steps
  - Automate

## Y-Chart

- **3 Design Views**

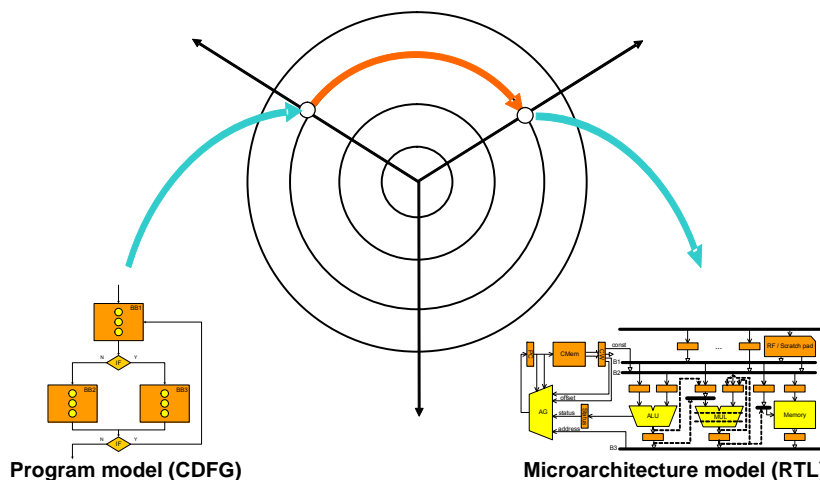


Source: D. Gajski, UC Irvine



## Processor Synthesis

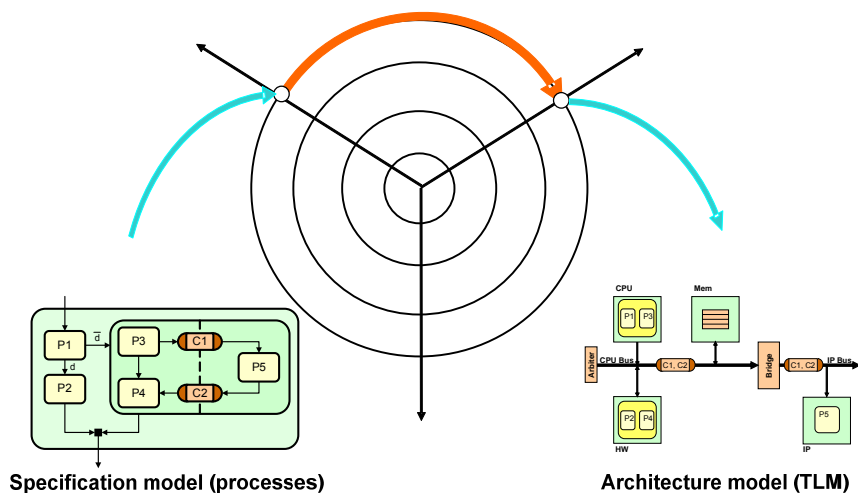
- **Software processor**
  - Compilation and linking
- **Hardware processor**
  - High-level synthesis



Source: D. Gajski, UC Irvine

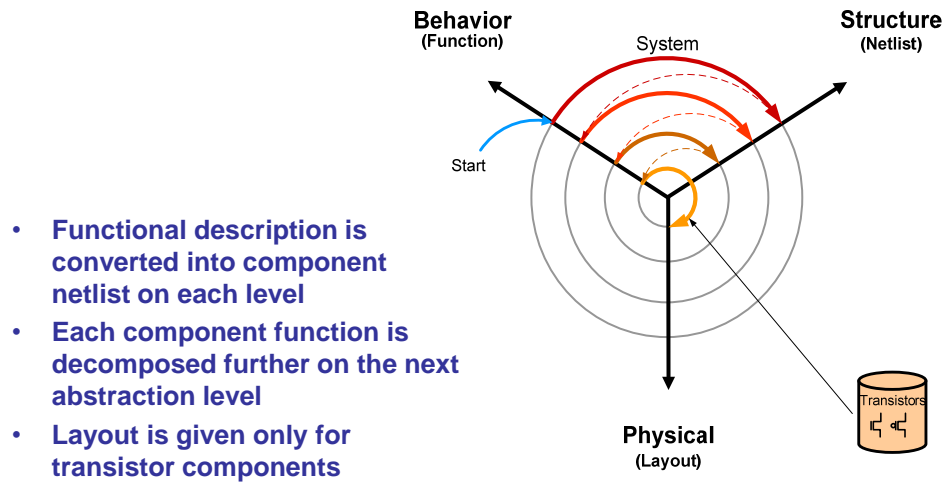
## System Synthesis

- **Structure**
  - Partitioning, mapping
- **Timing**
  - Scheduling



Source: D. Gajski, UC Irvine

## Top-down Methodology



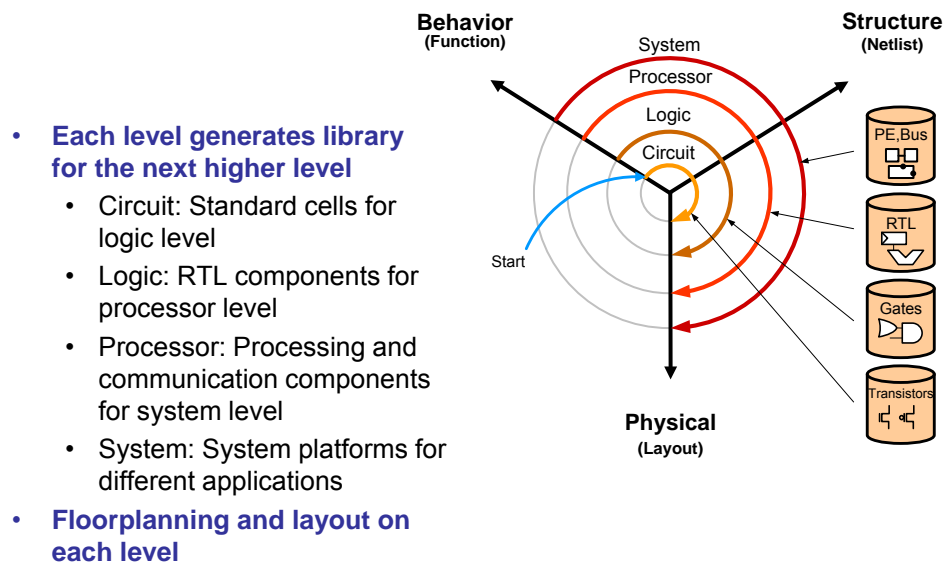
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## Bottom-Up Methodology



Source: D. Gajski, UC Irvine

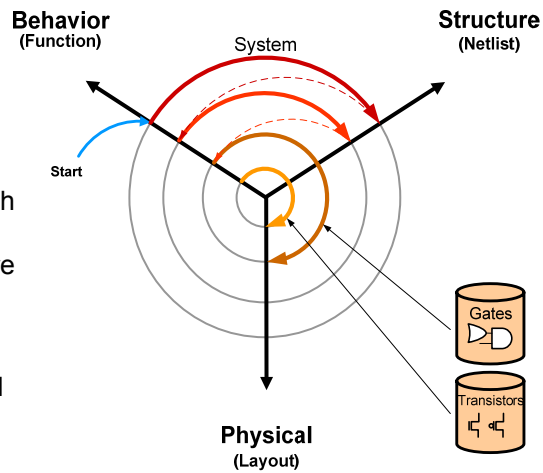
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## Meet-in-the-Middle Methodology

- **Gate netlist is hand-off**
- **Three levels of synthesis**
  - System is synthesized with processor components
  - Processor components are synthesized with RTL library
  - RTL components are synthesized with standard cells
- **Two levels of layout**
  - System layout is performed with standard cells
  - Standard cells layout with transistors



Source: D. Gajski, UC Irvine

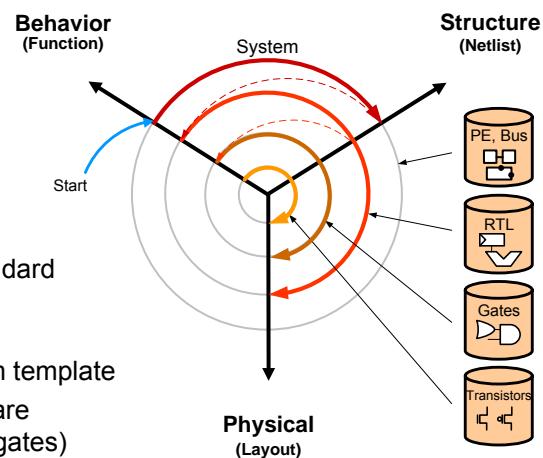
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## Platform-Based Design

- **Meet-in-the-middle at the system level**
  - System platform with standard components
  - System synthesis to map specification onto platform template
  - Some custom processor are synthesized (to RTL and gates)
  - Other (programmable) processors are pre-synthesized and just need software compilation
  - Layout and floorplanning at the SoC level

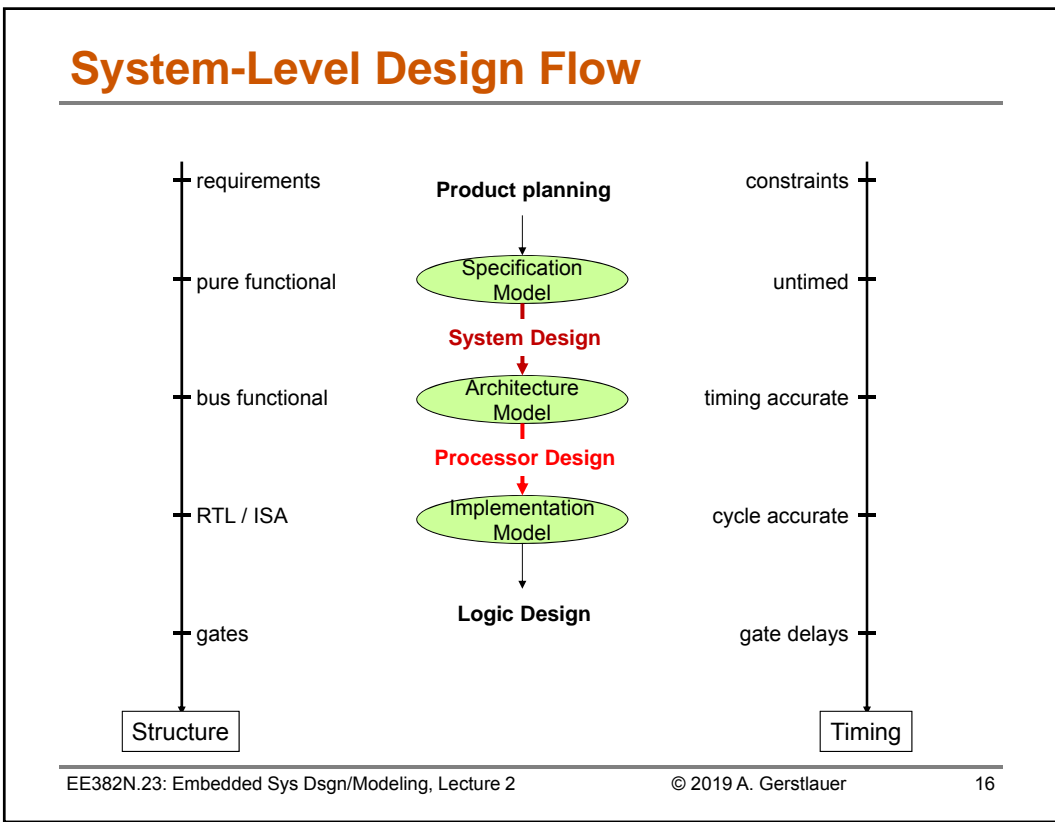
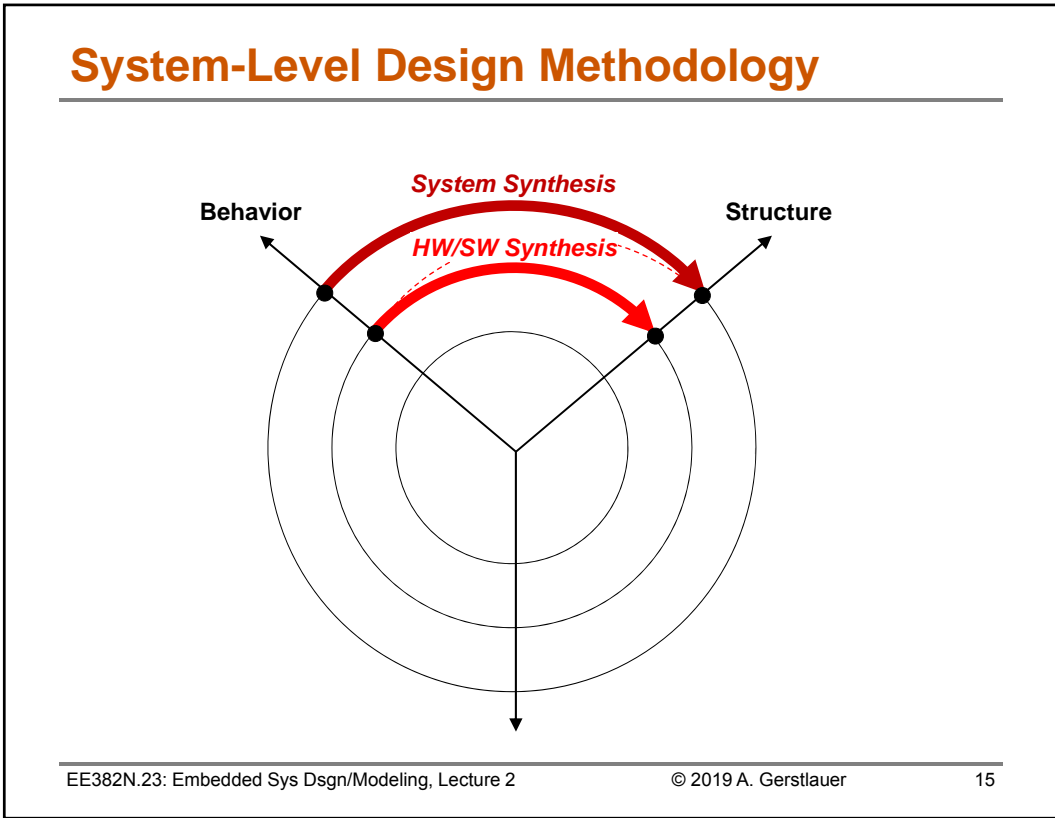


Source: D. Gajski, UC Irvine

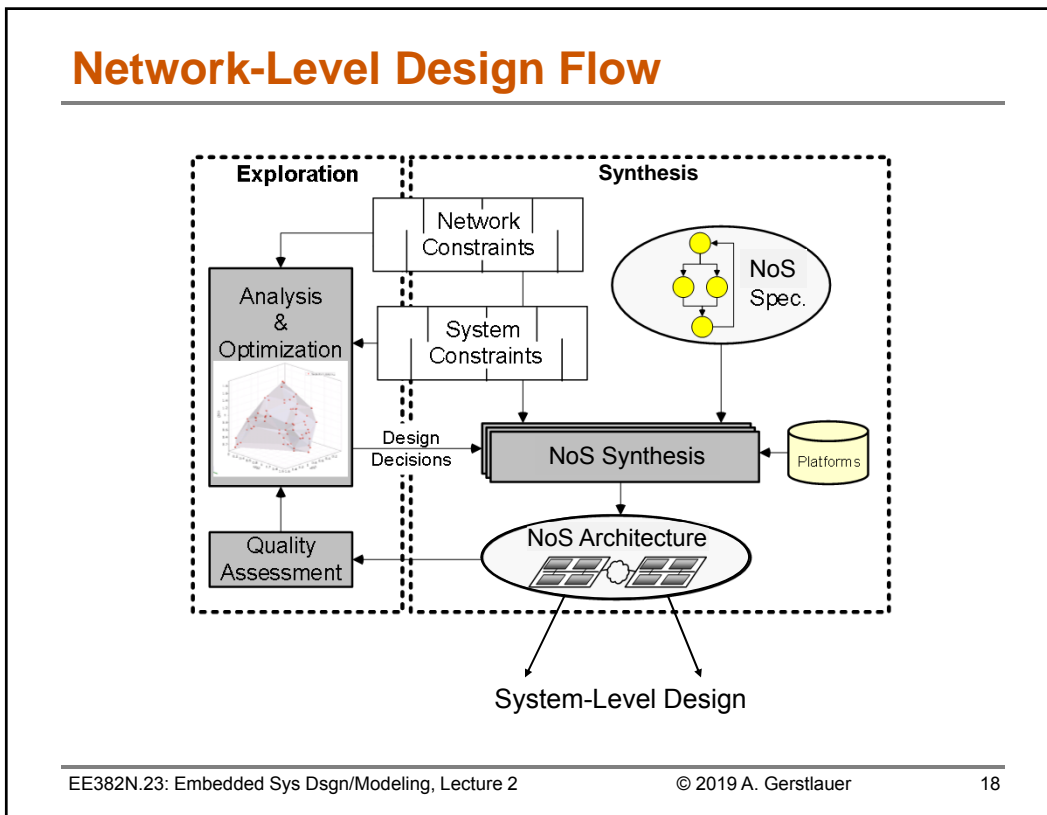
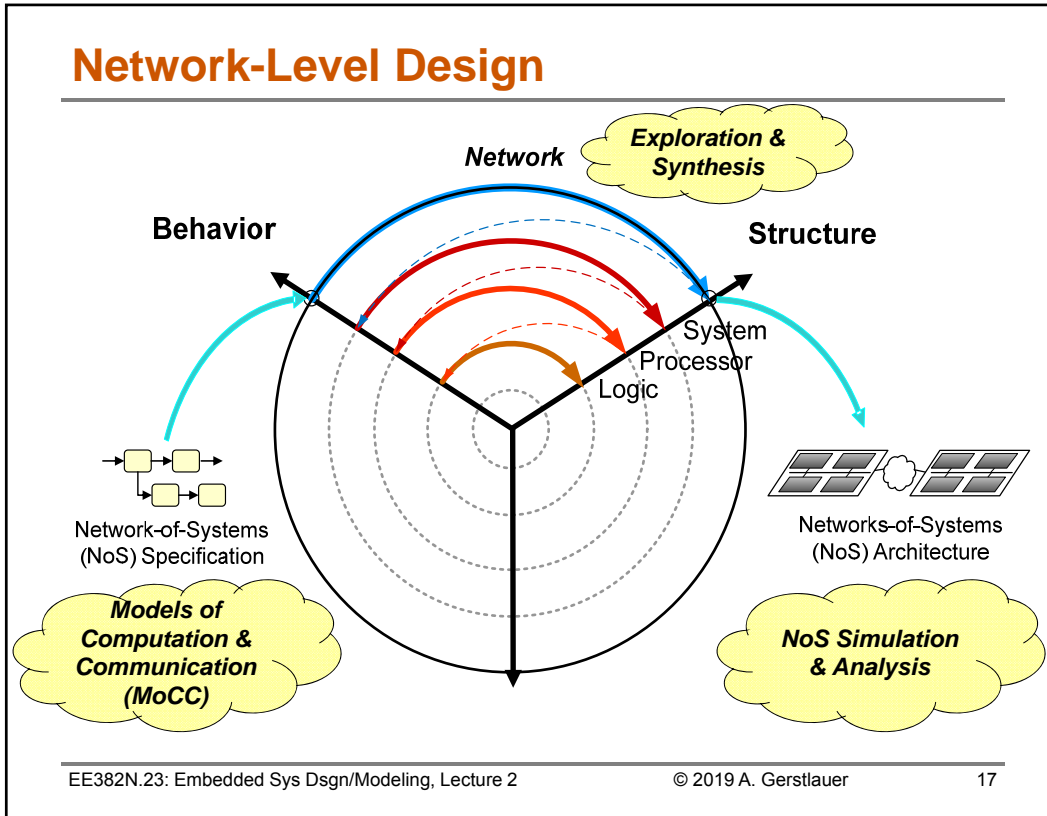
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## Lecture 2: Outline

### ✓ Design methodologies

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- ✓ System-level design flow

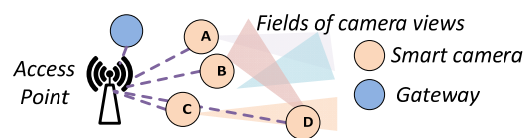
### • Design example

- Object recognition in smart camera network
- Deep and convolutional neural networks (DNNs/CNNs)
- Distributed CNN inference in IoT edge computing

## IoT System Design Example

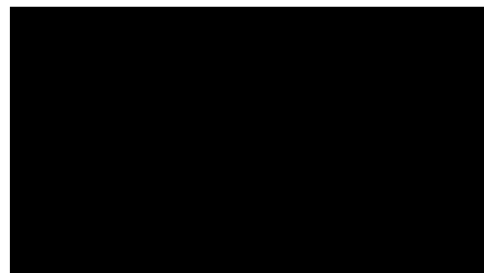
### • Smart camera network

- Smart city
- Smart homes
- ...



### ➤ Edge computing

- Detect, locate and classify objects in video stream
  - Bounding boxes
  - Types of objects
- Directly on cameras
  - Privacy
  - Real-time



## Objection Detection using Deep Learning

- **Classification vs. detection**

Image classification, global feature



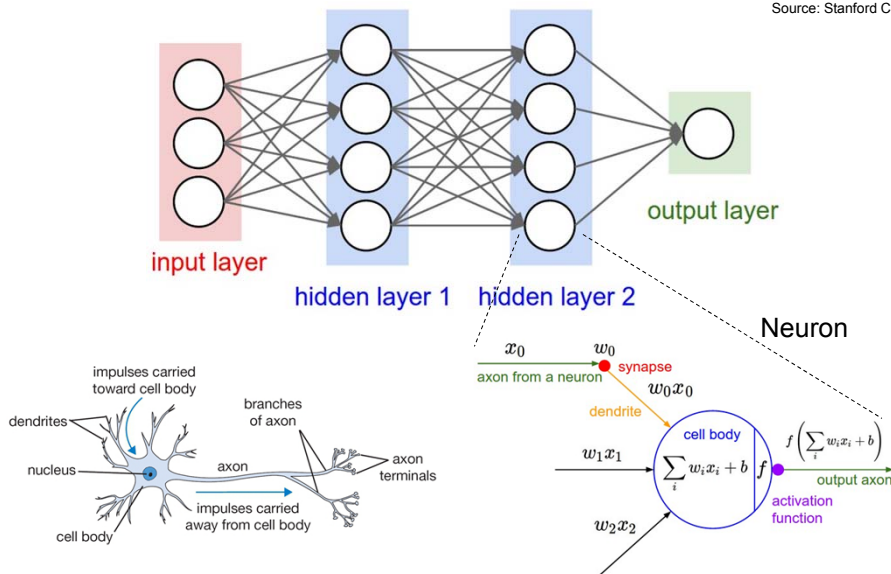
Object detection, classification + localization



- Convolutional neural networks (CNNs) widely used for image classification
- Sliding windows of different size/shape + CNN-based classification for brute-force, naïve object detection

## Traditional Neural Networks

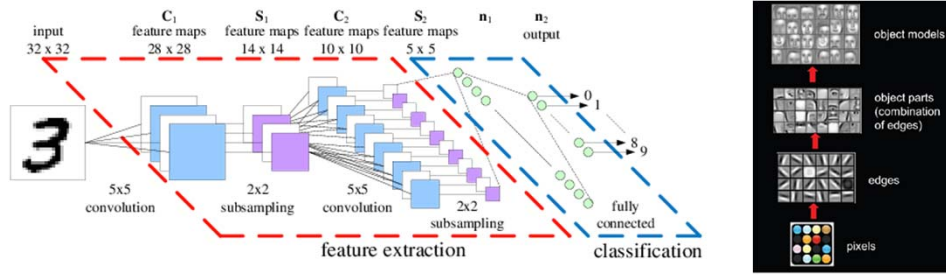
Source: Stanford CS231n



➤ **Deep Neural Networks (DNNs) with many hidden layers**

## Convolutional Neural Networks (CNNs)

- **Different types of layers**
    - Convolutional: 2D convolutions with trainable filters
    - Rectified linear units (ReLU): elementwise function
    - Pooling: non-linear down-sampling
    - Fully connected: traditional neural networks
- } usually combined



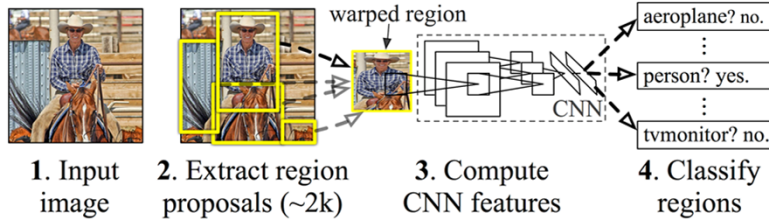
Digit recognition CNN (image classification)

➤ **Fully convolutional network (FCN): no fully connected layer**

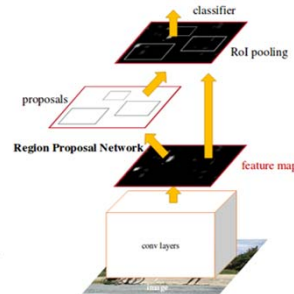
## Object Recognition (1)

- **Region based (Fast/Faster/Mask R-CNN)**

### R-CNN: Regions with CNN features

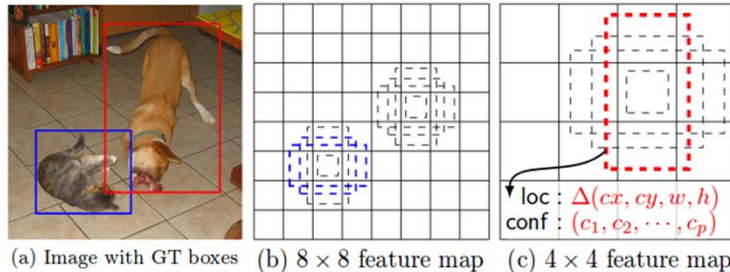


- Fast versions by sharing convolutional layers
- Common feature extraction for region proposal and classification



## Object Recognition (2)

- **Single Shot Multibox Detector (SSD)**

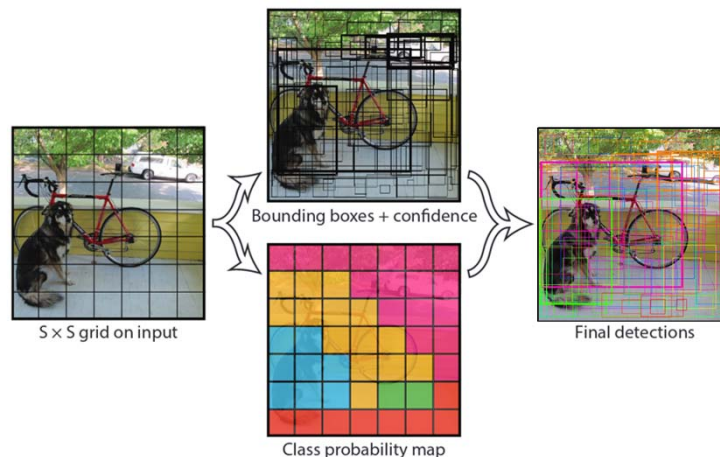


- Slide window of fixed size and shape
- Detect both bounding box and class within window
- Predict likelihood of different box/class combinations

## Object Detection (3)

- **You Only Look Once (YOLO)**

- Don't slide window, predict for all possible boxes/classes



## You Only Look Once (YOLO)



- **Default implementation on top of Darknet**
  - General open-source CNN framework/library in C
- **Also available for other deep learning frameworks**
  - PyTorch, Caffe2 [Facebook], TensorFlow [Google]

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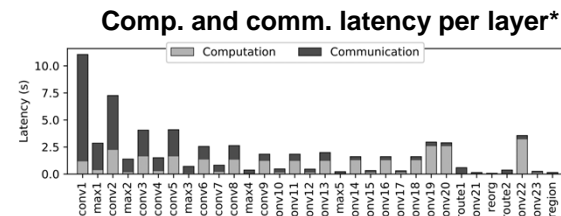
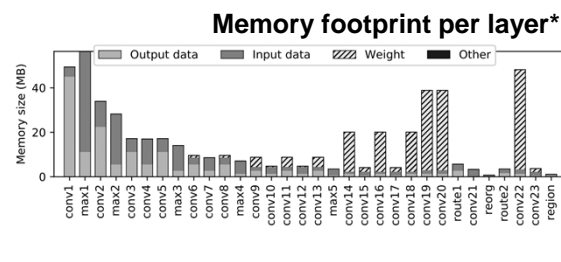
## CNN Mapping (1)

### • CNN inference resource demands

- Memory footprint
  - Early layers: data dominant
  - Later layers: weight dominant
- Comm. overhead
  - Decreasing with number of layers

### ➤ Distribute among edge cluster

- Collaborative processing
- Accelerate in edge devices



\*Profiling data is collected based on the single-core performance of a Raspberry Pi 3 running YOLOv2.

Source: Z. Zhao, K. Mirzazad, A. Gerstlauer, "DeepThings: Distributed Adaptive Deep Learning Inference on Resource-Constrained IoT Edge Clusters," IEEE TCAD, 2018

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## CNN Mapping (2)

- **Convolutional operation**

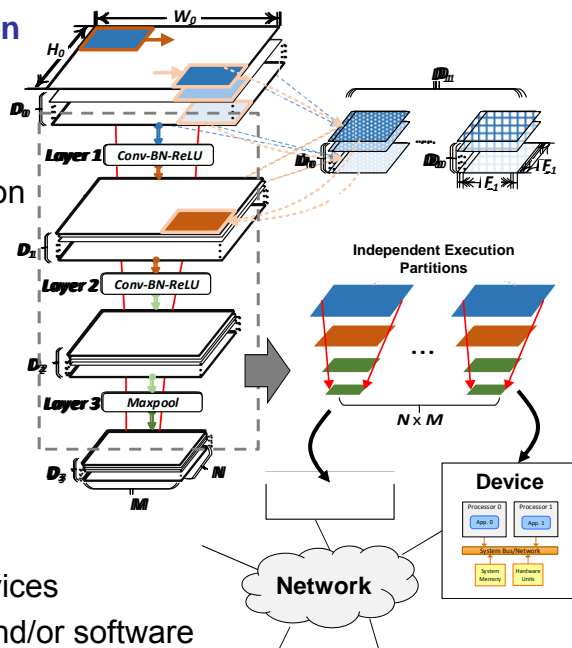
- Locality between consecutive layers
- Tile partitioning with boundary consideration

- **Chain of multiple convolutional layers**

- Large amount of intermediate data
- Synchronization overhead per layer
- Layer fusion

- **Independent tasks**

- Distribute among devices
- Map into hardware and/or software



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