Advanced Image Processing

CENTRE UNIVERSITAIRE D'INFORMATIQUE
UNIVERSITE DE GENEVE

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This course uses in part some materials from:

- A. K. Jain, Fundamentals of Digital Image Processing, Prentice-Hall,1989.
- P. Moulin, Lecture Notes, Advanced Image Processing ECE497PM, UIUC, 1998.
- M. Vetterli, Lecture Notes: Advanced Signal Processing: Wavelets and Applications, EPFL, 1999.
- M. Unser, Lecture Notes: Image Processing, EPFL.
- B. Girod, Lecture Notes: EE368: Digital Image Processing, Stanford, 2000.

Advanced Image Processing

Introduction

S. Voloshynovskiy

http://cui.unige.ch/~aip/

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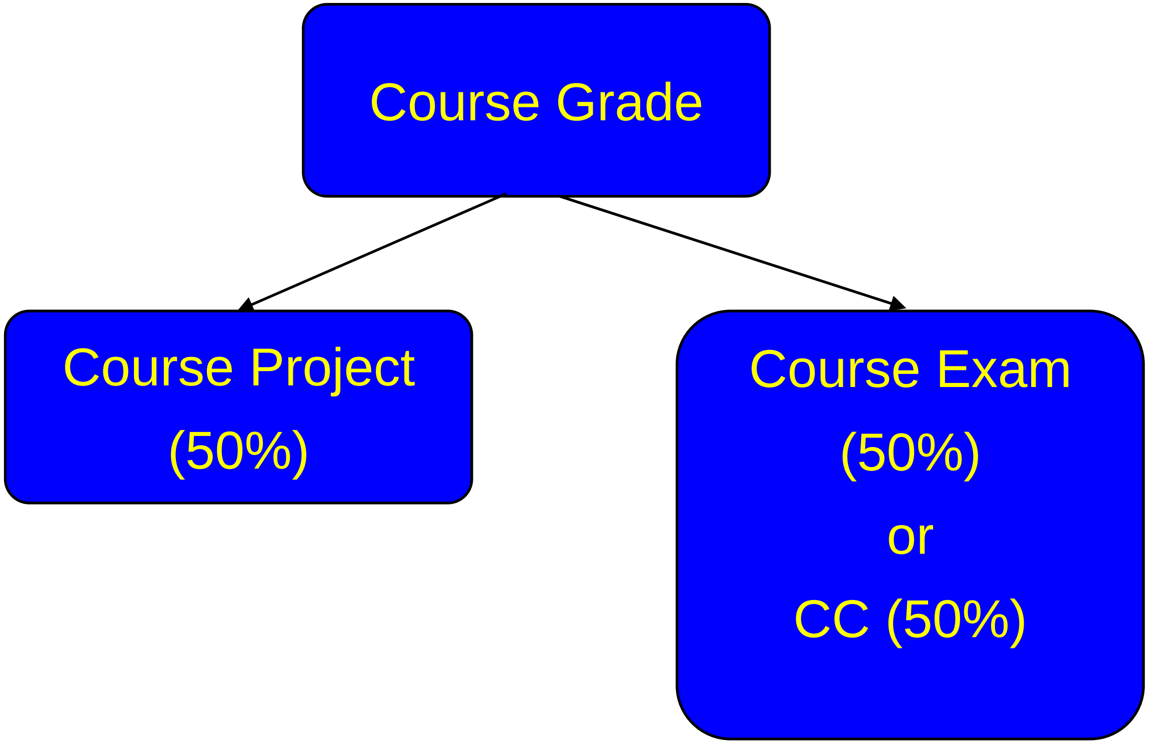
Grading Policy

The final grade will be determined based on a final course project and a final exam.



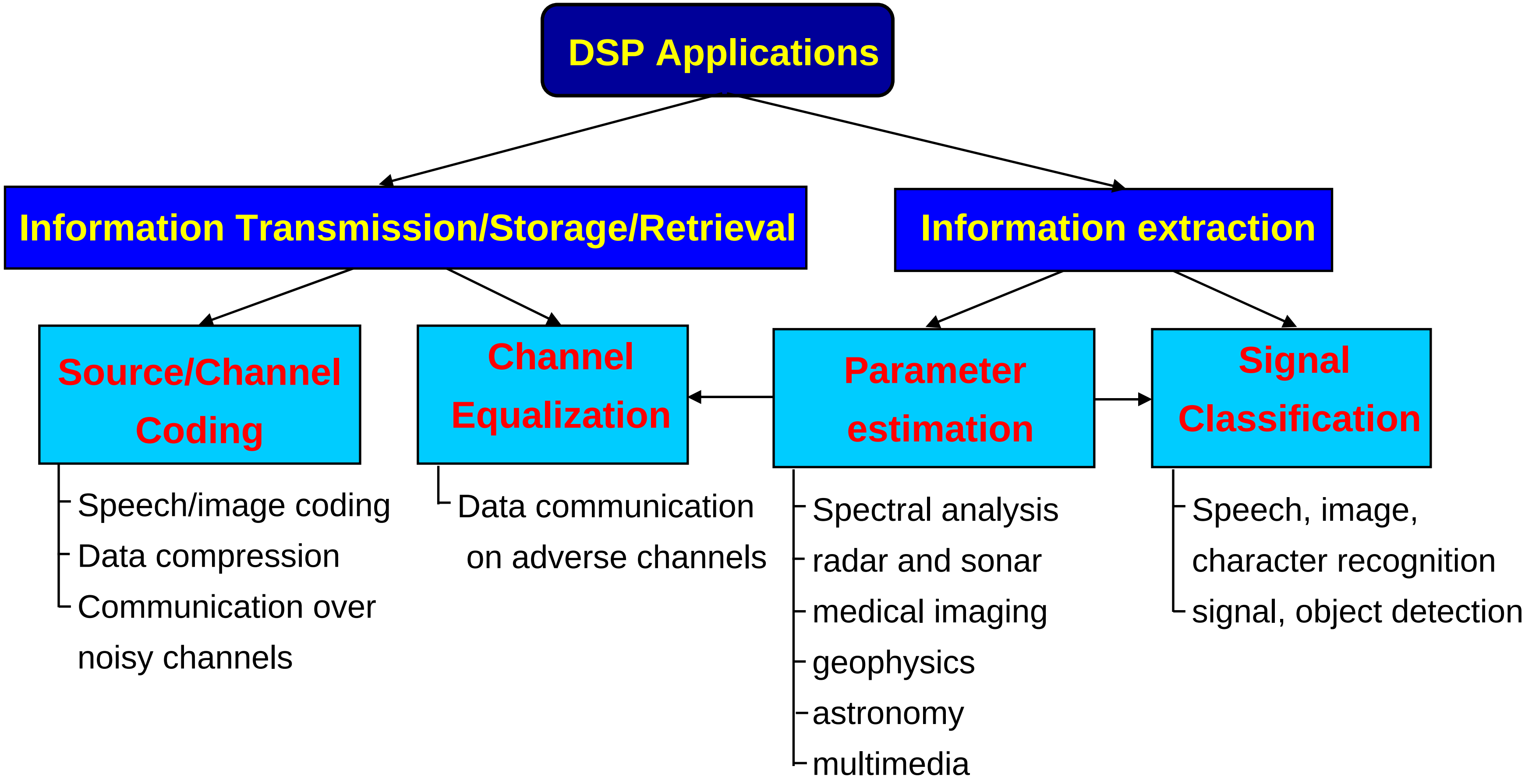
Course Outline

- Recall of Linear Algebra.
- Introduction. Human Visual System.
- Image Presentation: pyramids and wavelets.
- Random Signals.
- Image Modeling.
- Image Sensor Models. Noise Models.
- Image Denoising.
- Image Restoration.
- Image Compression.
- Video Modeling and Compression.
- Digital Data Hiding.

Recommended books

- A. K. Jain, Fundamentals of Digital Image Processing, Prentice-Hall, 1989.
- A. Bovik, Handbook of Image & Video Processing, Academic Press, 2000.
- H. Stark and J. W. Woods, Probability, Random Processes, and Estimation Theory for Engineers, Prentice-Hall, 1994.
- A. Gersho and R. M. Gray, Vector Quantization and Signal Compression, Kluwer, 1992.
- M. Vetterli and J. Kovacevic, Wavelets and Subband Coding, Prentice-Hall, 1995.

Introduction: Digital Signal Processing (DSP)

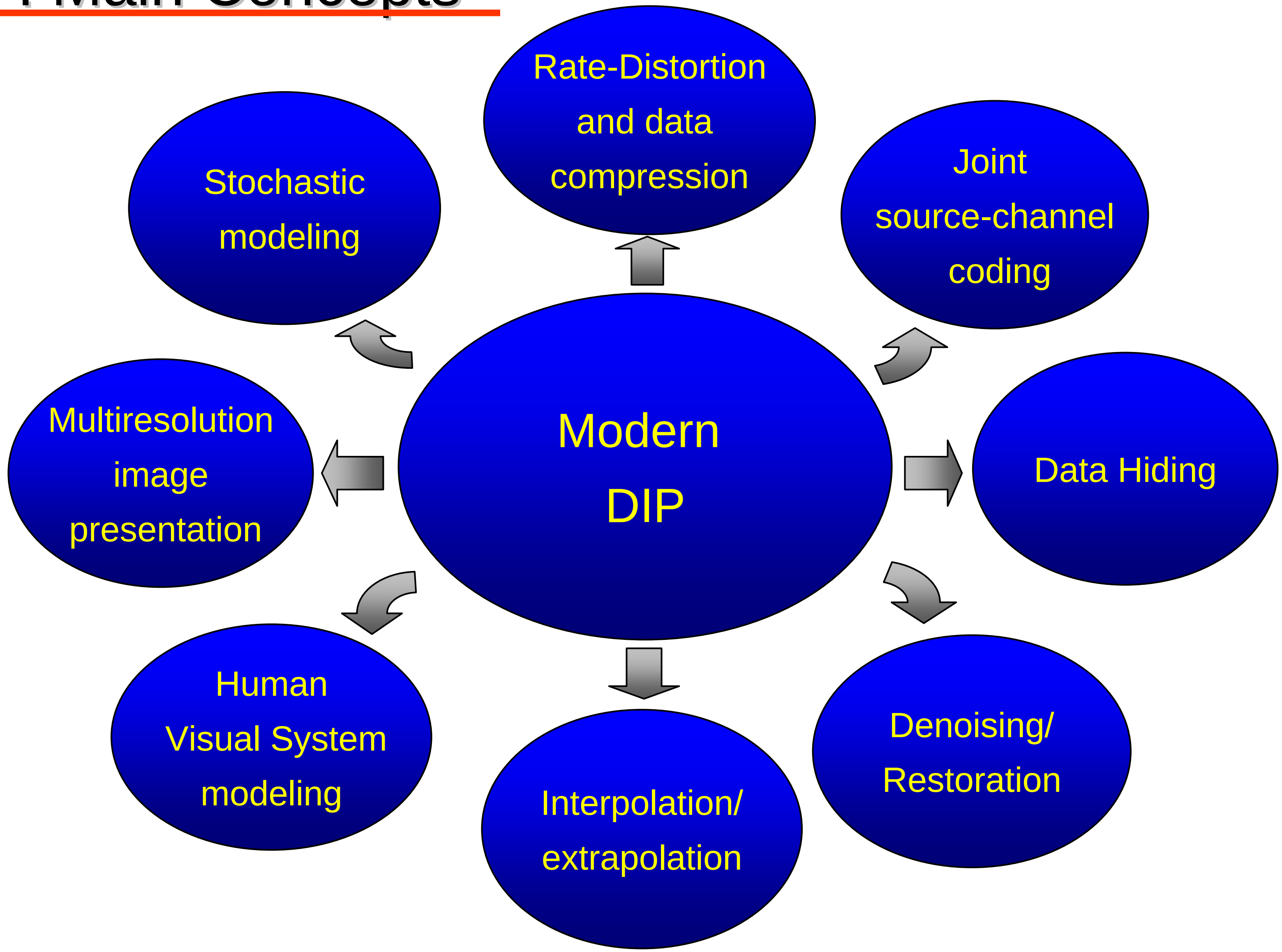


Introduction: Digital Image Processing (DIP)

Image Processing covers:

- denoising
- restoration
- interpolation/extrapolation
- compression
- detection
- recognition
- data hiding
- data retrieval

DIP: Main Concepts



Goal of the course

Despite different applications, existing solutions and used particular methods, there are a few powerful, basic principles that can be used to guide the design of image processing algorithms.

The goal of this course is to introduce these concepts and to investigate their applicability to Image Processing.

Goal of the course

In the scope of the course we will:

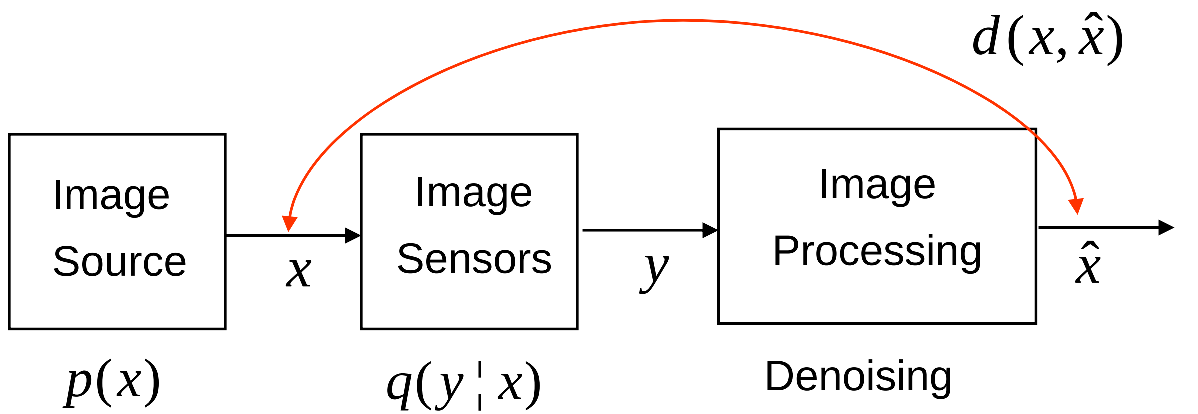
- study optimal processing techniques;

- learn how to recognize the implicit assumptions that lie behind suboptimal techniques;

- understand the fundamental connections between optimal techniques in apparently unrelated areas such as image restoration and interpolation/extrapolation, image denoising and lossy image compression.

Analytical Framework

Analytical framework



- Denoising
- Interpolation
- Restoration
- Compression
- Image Analysis
- Detection
- Recognition

Restoration, Denoising and Enhancement

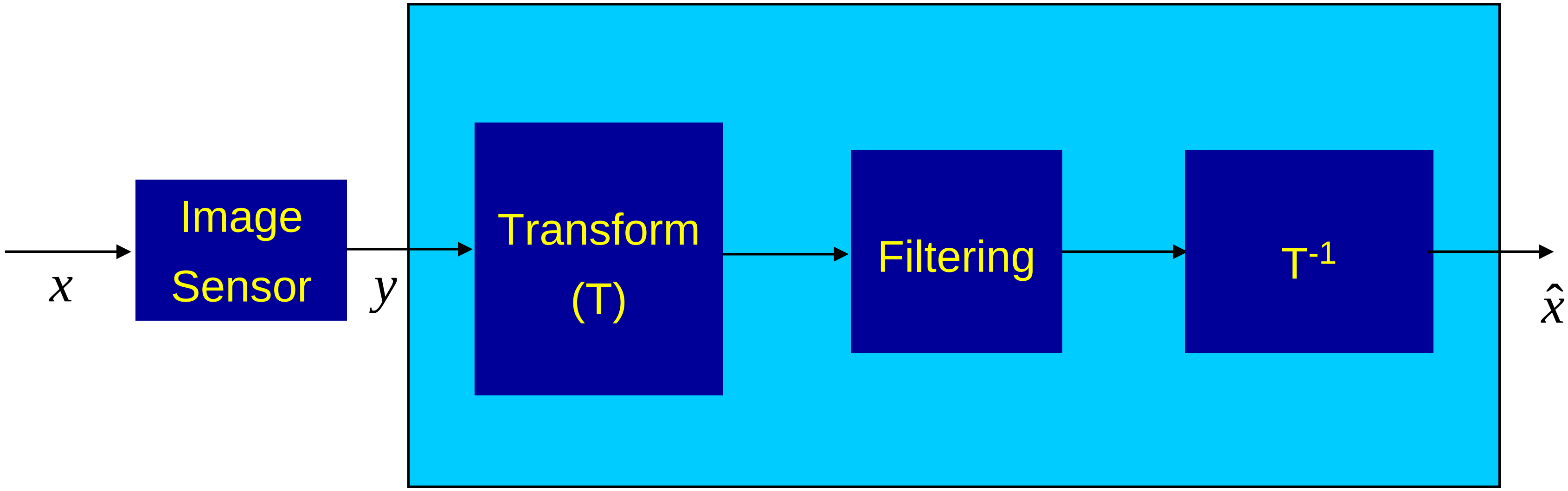


Image Restoration/Denoising

There is some uncertainty about the image x of interest, given the measurements y . This uncertainty is typically due to thermal noise or photon noise, or blurring introduced by the sensors.

This relationship can be modeled by a conditional probability distribution $q(y \mid x)$.

<u>Image restoration/denoising</u>: Compute $\hat{x}$ that minimizes the expected distortion $Ed\left(x,\hat{x}\right)$.

Image Compression

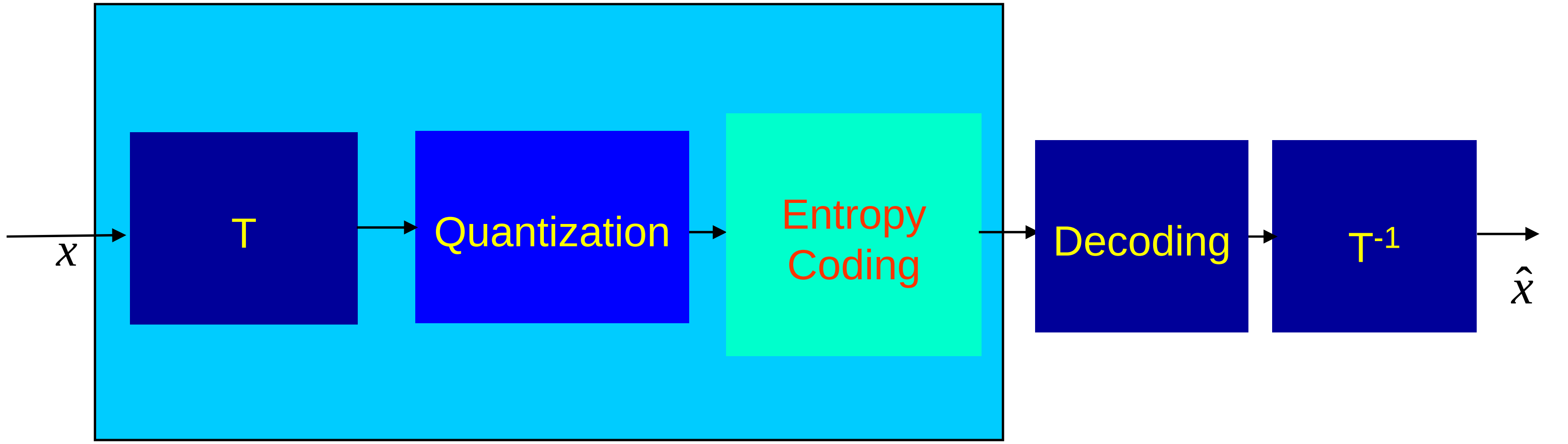


Image Compression

As well, there is a great variability among the possible images x .

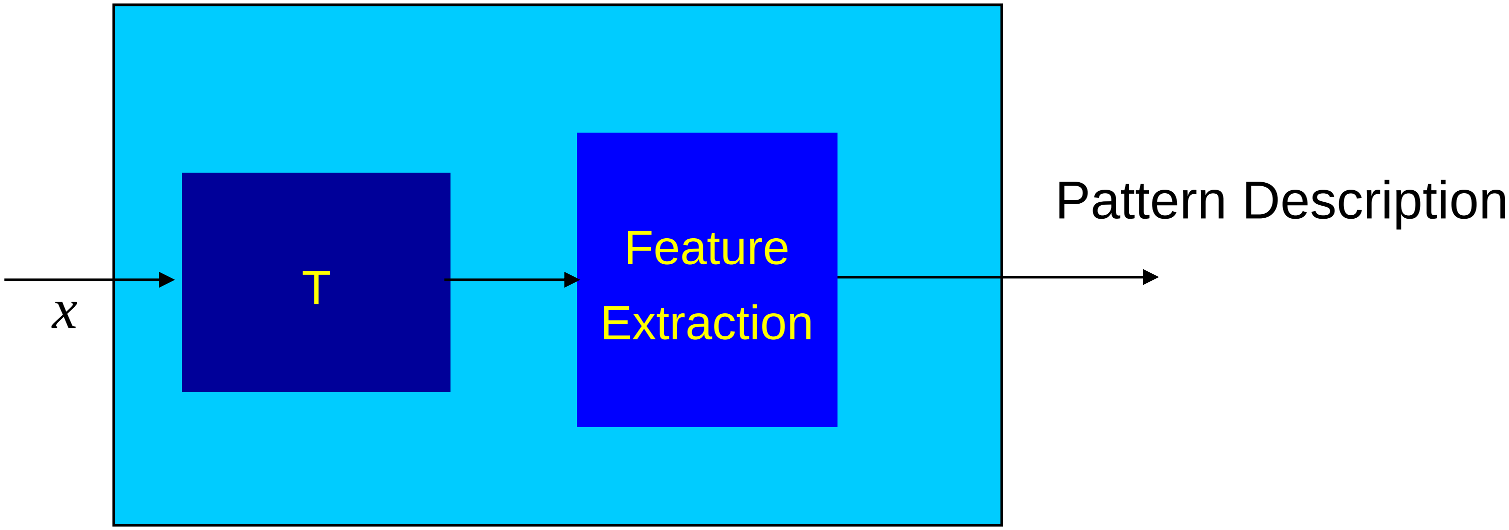
Consider the compression problem, assuming perfect sensor data for simplicity $(y = x)$.

Then $E\ell(\hat{x})$ represents an average over all possible input images x.

To evaluate $E\ell(\hat{x})$, we need a model with a <u>prior</u> distribution $p(x)$.

<u>Image compression:</u> Compute $\hat{x}$ that minimizes the expected distortion $Ed(x, \hat{x})$ subject to rate $E\ell(\hat{x}) \leq R$ constraint, where $\ell(\hat{x})$ is the length of the code word used to encode $\hat{x}$.

Image Analysis



Stochastic DIP

Once $p(x)$, $q(y|x)$ and $d(x,\hat{x})$ are specified, optimal solutions can <u>in principle</u> be obtained as the solution to an optimization problem.

The primary difficulty consists in identifying realistic models for $p(x)$ and $q(y|x)$ and $d(x,\hat{x})$ in making the optimization problem <u>tractable</u> (this introduces practical constrains on the possible models $p(x)$, $q(y|x)$ and $d(x,\hat{x})$).

Stochastic DIP

<u>Practical motivation</u>:

- Modeling of $p(x)$ is a difficult theoretical/practical problem.
- The physics of the sensors determine $q(y \mid x)$.
- The choice of a suitable $d(x, \hat{x})$ requires some knowledge of the Human Visual System.

Conclusions

A solid training in random processes is needed to formulate, understand and analyze statistical models.

Some familiarity with Image Processing is necessary to develop the necessary intuition about the design of statistical models.