Approximate Computing and Data Analysis

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Introduction

- Sometimes, computing the best possible output of some algorithm requires a significant amount of resources.
- For some applications, the best possible output is not actually needed, since minor degradations will possibly not even be recognized by users.
- This can be exploited in a resource-constrained environment in order to trade-off the quality of the output against resources.
- A certain deviation of the actual output is accepted, for example, for lossy audio, video and image encoding.
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This leads us to consider approximate computing.
An Example

slides from Sampson et al. 2013.

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It is essential to compare the best possible output (real) values $x_1, x_2, \ldots, x_n$ with the approximated output (signal) values $y_1, y_2, \ldots, y_n$, for $n$ samples.
Possible Metrics to Compare $\vec{x}$ and $\vec{y}$

**Definition**

The **Mean-Squared Error** (MSE) is defined as

$$MSE(\vec{x}, \vec{y}) = \frac{1}{n} \sum_{i=1}^{n} (x_i - y_i)^2$$
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The **Root-Mean-Squared Error (RMSE)** is defined as

$$RMSE(\vec{x}, \vec{y}) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - y_i)^2}$$
Definition

The Mean-Absolute Error (MAE) is defined as

$$MAE(\vec{x}, \vec{y}) = \frac{1}{n} \sum_{i=1}^{n} |x_i - y_i|$$

For identical deviations of the measured signal $y$ from real values $x$, the MAE is equal to the RMSE. However, the RMSE emphasizes large deviations between real and measured values (so-called outliers).
Peak Signal to Noise Ratio

**Definition**

The **Peak-Signal-to-Noise Ratio** (PSNR) is defined as

\[
PSNR(\vec{x}, \vec{y}) = 10 \log_{10} \left( \frac{x_{max}^2}{MSE(x, y)} \right) = 20 \log_{10} \left( \frac{x_{max}}{RMSE(x, y)} \right)
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where \(x_{max}\) is defined as the \(\max_{i=1}^{n} x_i\);
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- There are several other metrics, especially for images
- None of these metrics is really superior to others
- Several of these metrics should be computed and a careful comparison should be performed
Data Analysis in Approximating Computing

• For data analysis, classification of objects is a frequent goal
• Suppose that we restrict ourselves to binary classification
• Four cases are possible
  • True positives (TP): we classify some object as a cat and it is actually a cat
  • False positives (FP): we classify some object as a cat and it is not a cat
  • True negatives (TN): we classify some object as not a cat and it is actually not a cat
  • False negatives (FN): we classify some object as not a cat and it is actually a cat.
**Precision and Recall**

**Definition**

The *precision* is defined as 

\[
\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}
\]

**Definition**

The *recall* is defined as 

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\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}
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**Definition**

The **F1 score or F-measure** is defined as the harmonic mean of precision and recall.
## Accuracy and Specificity

### Definition

The **accuracy** is defined as:

\[
\frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{False Positives} + \text{True Negatives} + \text{False Negatives}}
\]

### Definition

The **specificity** is defined as:

\[
\frac{\text{True Negatives}}{\text{False Positives} + \text{True Negatives}}
\]
Approximate Computing: Some Examples

- Qualifiers of data types
  - \texttt{@approx} int \texttt{a := . . .} ;
  - \texttt{@precise} int \texttt{p := . . .} ;

- Variable \texttt{a} is not accurate and variable \texttt{p} is accurate

- Statements
  - \texttt{p := a;} (this is problematic)
  - \texttt{a := p;} (this is okay)

- Approximate Conditions
  \begin{verbatim}
  if (a = 10) { p :=2;}
  \end{verbatim} (this can be problematic, approximate bool)
Controlling Approximation

- Approximate should not interfere with precise
- Semantically, approximate results are unspecified best effort
- Only higher levels can measure quality, but application specific
- Lower (hardware or system software) levels can make monitoring convenient
- Offline: Profile, auto-tune
- Online: React, i.e., recompute or decrease the approximation level
Approximation-aware ISA

- An example (in MIPS ISA):
  lw r1, 0x04($0)
  lw r2, 0x08($0)
  add r3, r1, r2
  sw r3, 0x0c($0)

- An example (in Approximate MIPS ISA):
  lw r1, 0x04($0)
  lw r2, 0x08($0)
  add.a r3, r1, r2
  sw.a r3, 0x0c($0)

- add.a and sw.a need approximate ALU and approximate storage, respectively.
Floating-Point to Fixed-Point Conversion

- **Pros:**
  - Lower cost
  - Faster
  - Lower power consumption
  - Sufficient SNR, if properly used
  - Suitable for portable applications

- **Cons:**
  - Decreased dynamic range
  - Finite word-length effect, unless properly scaled
  - Overflow and excessive quantization noise
  - Extra programming effort
An Example: ADPCM

Cycles

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SNR (dB)

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Ki-II Kum, et al.