

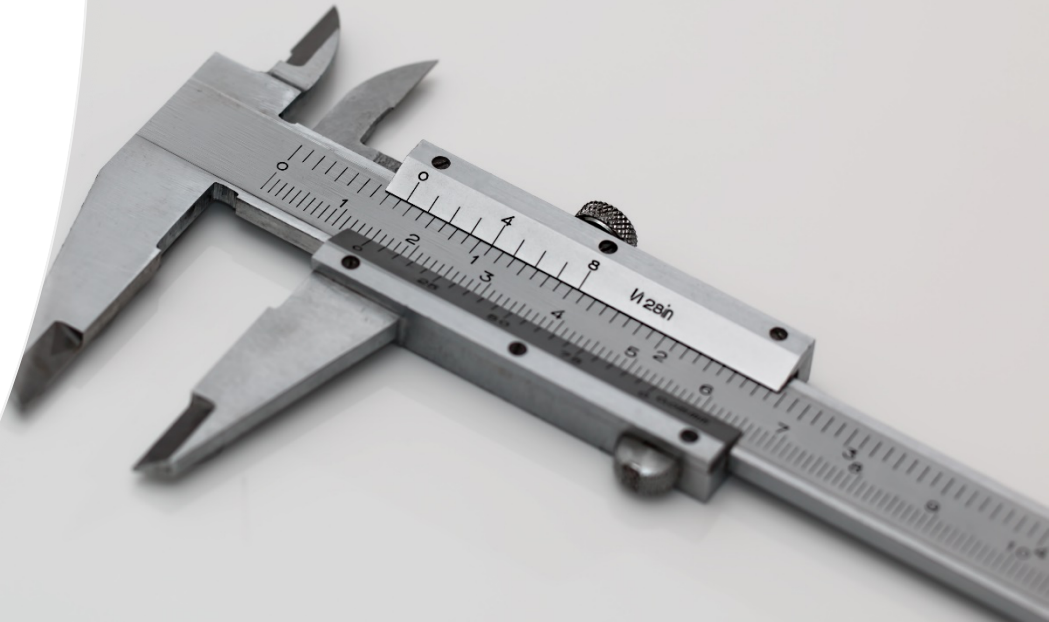
Measuring without Measurement

Applied AI Meets Applied Measurement

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Taking pictures is welcome!

- Some slides have references for more info. Do **feel free** to take pictures and follow for more detailed information.
- You can also use my slides, as long as you mention where it came from.



Talk Overview

- Measurement
- IEEE Instrumentation and Measurement Society
- Applied AI
- Applied AI for Measurement
 - Examples in Multimedia Systems and Networks

IEEE
INSTRUMENTATION
& MEASUREMENT
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SOCIETY®



PART 1

Measurement

What is Measurement?

- Formal definition:

the process of experimentally obtaining one or more quantity values that can reasonably be attributed to a quantity¹.

- Notes: Measurement does not apply to **nominal properties**. Measurement implies **comparison of quantities** and includes **counting** of entities.

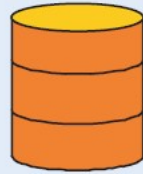
¹ International vocabulary of metrology — Basic and general concepts and associated terms, BIPM, JCGM 200:2008



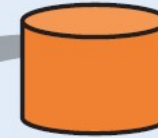
The 5 Agents in Measurement

The true quantity value is not only unknown, but is also unknowable.

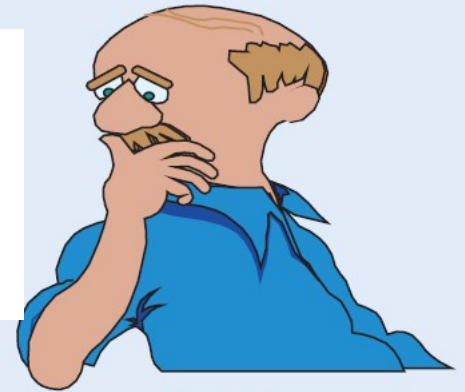
The Measurand



The Method



The Standard
The Measurement Unit



The Operator

Picture courtesy of "Measurement Uncertainty", IEEE I&M Magazine, June 2006.

- Measurement always has uncertainty from the “true” value of the measurand, due to the imperfectness of the 5 agents.
- **Measurand**: could change by the measurement method.
- **Standard**: only a (hopefully good) approximation.
- **Method**: based on the exploitation of a single physical phenomenon, while other phenomena may interfere
- **Instrument**: never perfect.
- **Operator**: insufficient training, incorrect reading, etc.

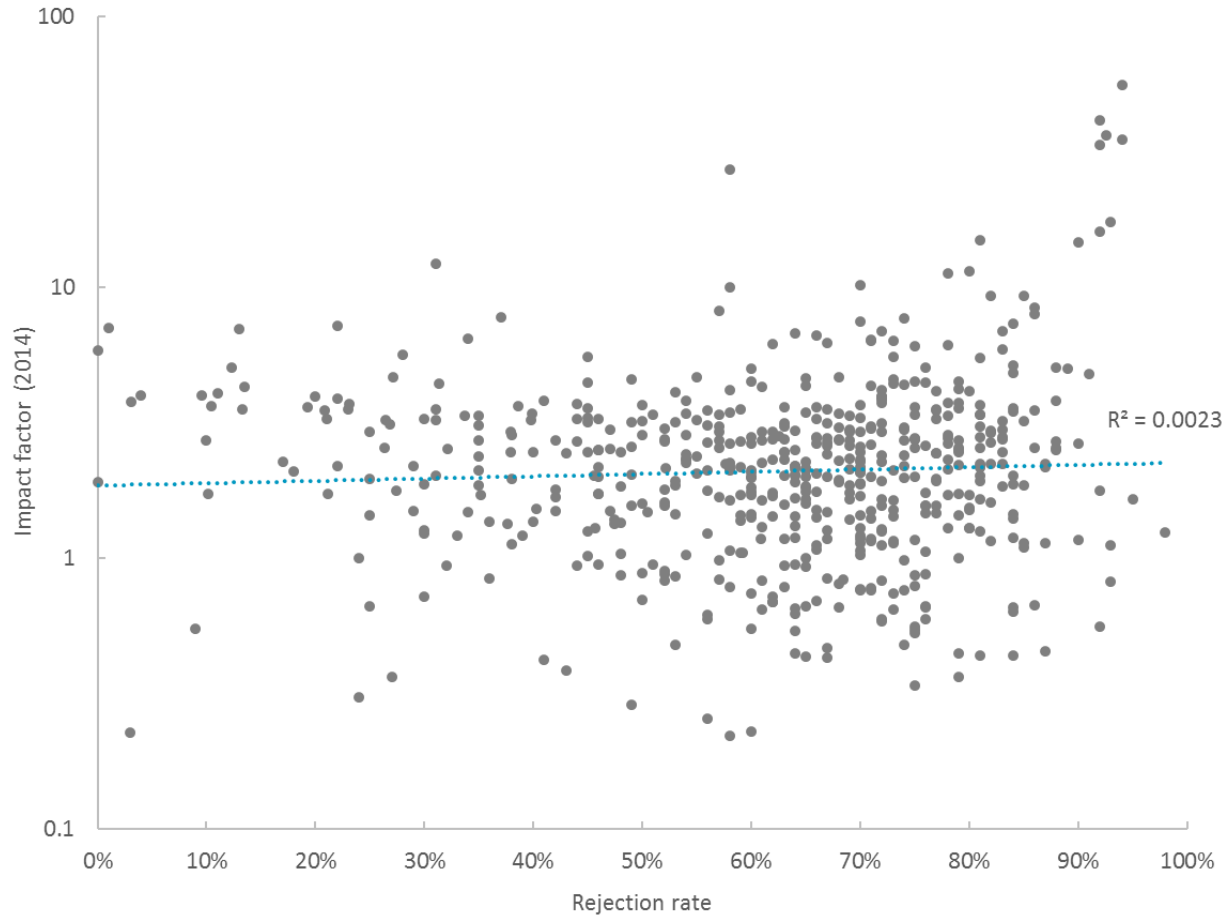


Uncertainty

- Formal definition:
non-negative parameter characterizing the dispersion of the quantity values being attributed to a measurand
- Can be **systematic**, or **random**.
- Systemic uncertainty must be corrected for as much as possible.
- Random uncertainty is hard, if not impossible in some applications, to eliminate.
- Uncertainty can be evaluated using **Type A** (standard deviation) or **Type B** (more complicated statistical methods)

Myth: Journals with higher rejection rate have higher Impact Factor.

Rejection rates for a sample of 570 journals with impact factors



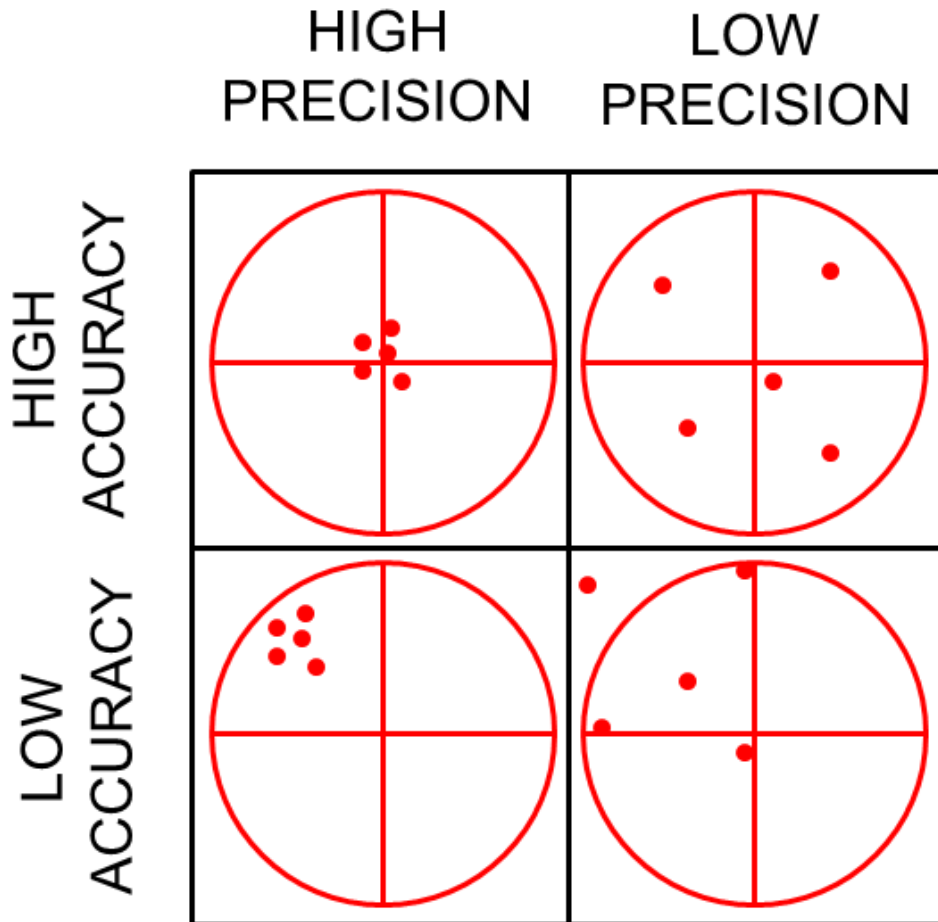
- Selecting for impact: new data debunks old beliefs, December 21 2015, *Open Science and Peer Review*, Top News.

Rejection Rate and Impact Factor



- New Data Debunks Old Beliefs: Part 2, March 4 2016, *Open Science and Peer Review*, Top News

Accuracy vs. Precision



In machine learning we refer to this as bias vs. variance.

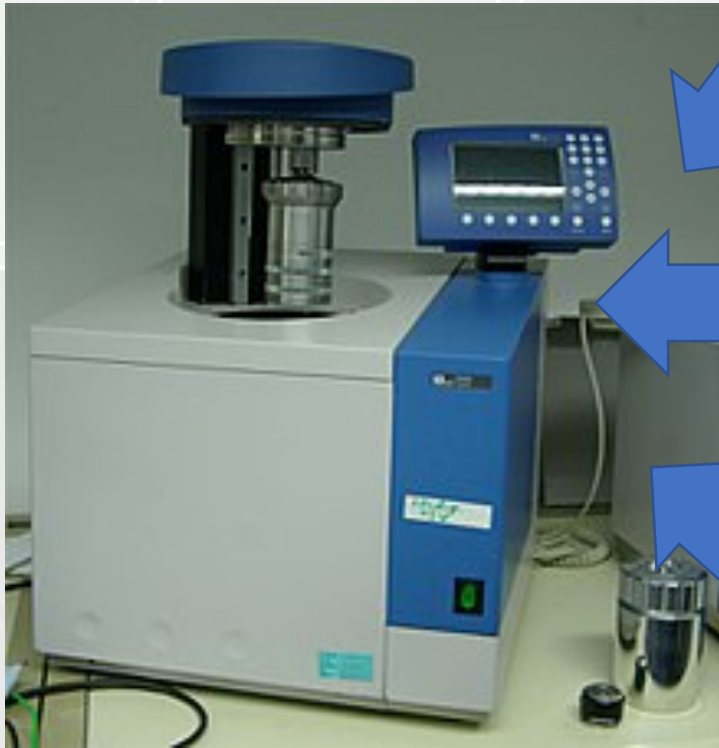
Measuring without Measurement?

- In conventional measurement, whether direct or indirect, the measurement method uses a physical phenomenon to measure the measurand.
- But what if a specific measurement application cannot afford to use the physical phenomenon?
 - Food Calorie measurement
 - Network latency measurement



Food Calorie Measurement

- Measuring the amount of Calories in an arbitrary food at a restaurant or at home.



Bomb Calorimeter

Atwater method: 4-9-4 = protein-fat-carbs



Network Latency Measurement

- **Network latency** plays an important role in large scale distributed applications: multiplayer online games, Content Distribution Networks, and peer-to-peer systems.
- Latency measurement is needed in determining performance, Quality of Service (QoS), and the level of scalability of these applications.
- However, explicit end-to-end delay measurements between every pair of nodes has $O(N^2)$ complexity, and leads to both **large computational overhead** and **large traffic overhead**.



Measurement Prediction & Measurement Guesstimation

- **Prediction** or **Forecast**: prediction of the quantity with the help of a mathematical model and using previous measurement.
- **Guestimate**: an estimate of the quantity based on a mixture of guesswork and mathematical modeling.
- Prediction and Guesstimation: not in the official vocabulary of metrology.
 - So they are not officially measurement.
- But in some applications direct measurement is not possible, so we need to predict/guesstimate it.
- So, we will be **measuring without measurement**.



guesstimation



PART 2



IEEE IMS

IEEE is the largest technical professional organization in the world.

<http://ieee-ims.org/>

- **IEEE I&M Society Vision:**
- Be the premier international professional Society in the Instrumentation and Measurement fields.
- **IEEE I&M Society Mission:**
- Provide the most comprehensive and high-quality services to our members and related professionals.
- Serve as the professional incubator for the growth of all (particularly younger) members.
- Be in the forefront of future I&M fundamental, technological, and application advances.
- Provide education in the field of instrumentation and measurement.

IMS Services



Publications

IEEE Trans. on I&M (Andy Chi Best Paper Award)
IEEE I&M Magazine



Conferences

I²MTC, MeMeA, SAS, AUTOTESTCON, IST (2020 Taiwan)



Education

DL, Graduate Fellowship Award, Faculty Course Development, Best I&M Application, Video Tutorials, Contests



Membership

Chapters, Events for Student, Young Professional, WIE



Technical Committees

22 TCs, 18 Standards; e.g., IEEE 1588, 18 PARs (Project Authorization Requests), Technical Activities



Awards

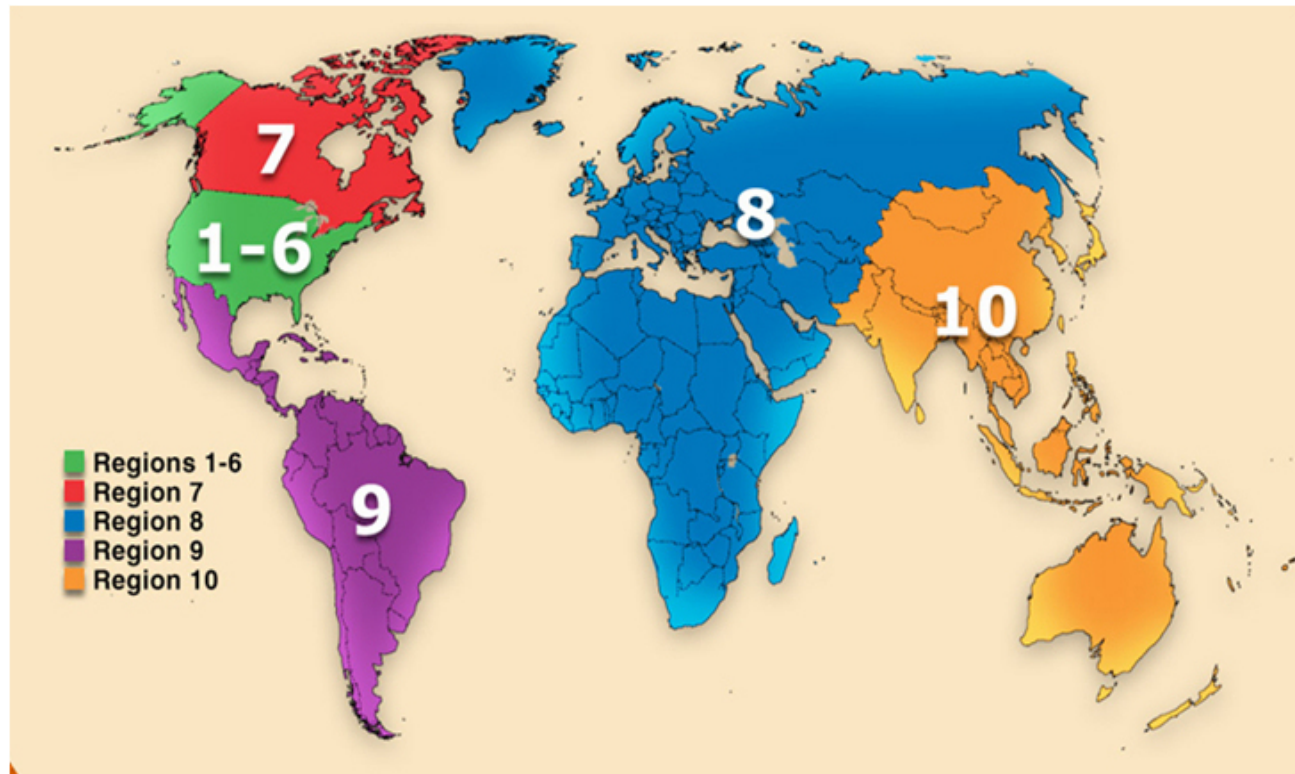
IEEE Joseph F. Keithley, J. Barry Oakes, Outstanding TC, Technical, Distinguished Service, Career Excellence, Outstanding Young Engineer.



IEEE Fellows Coordination

Chapters

Region	Chapters
1	4
2	1
3	1
4	2
5	2
6	1
7	6
8	19
9	6
10	9



IEEE TIM

IEEE TRANSACTIONS ON
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AND MEASUREMENT**

A PUBLICATION OF THE INSTRUMENTATION AND MEASUREMENT SOCIETY

<http://tim.ieee-ims.org/>

IEEE TIM considers papers that make contributions to:

1. methods or instruments for measurement, detection, tracking, monitoring, characterization, identification, estimation, or diagnosis of a physical phenomenon,
2. an application furthering the I&M fields, or
3. measurement theory including uncertainty, calibration, etc.

TIM: Number 1 general I&M journal

Number 1 in terms of:

- IF w/o Self Cites
- CiteScore
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IEEE Transactions on Instrumentation and Measurement (TIM) is the number 1 journal in the area of general Instrumentation and Measurement (I&M) in terms of Impact Factor without Self Cites, according to the 2018 Journal Citation Report, and in Quarter 1 (Q1) of the Instruments and Instrumentation category. In addition, according to the 2018 Scopus report, TIM is the number 1 journal in the area of general I&M with a CiteScore of 3.84 and SJR of 0.878. In terms of timeliness, TIM's average duration of submission-to-first-decision and submission-to-online-publication of 59 days and 26 weeks, respectively, are among the very best in all of IEEE journals.

In addition to regular papers, TIM also publishes short papers and survey/review



Submit:

- Regular paper
- Short paper
- Survey/review paper

Publish:

- Conventional
- Open Access

PART 3

Applied Artificial Intelligence



Let's start with a personal experience

Emergent Tech ▶ **Artificial Intelligence**

Network monitoring is hard... If only there was some kind of *machine* that could *learn* to do it

Pascal Monett 

Wednesday 22nd August 2018 22:11 GMT

[Report abuse](#)

Oh for God's sake

There is no AI. There is statistical analysis, and vast amounts of data, but we do not have a machine to which we can ask : "tell me what is working".

There are highly intelligent people who understand statistics and can fine-tune these statistical analysis machines, but AI it is not.

I would really like for the media to drop the "AI" in their articles, but that is obviously never going to happen because . . marketing. AI is sexy, and because we don't have it, it is the perfect fantasy.

↑ 6 ↓ 1

[Reply](#)

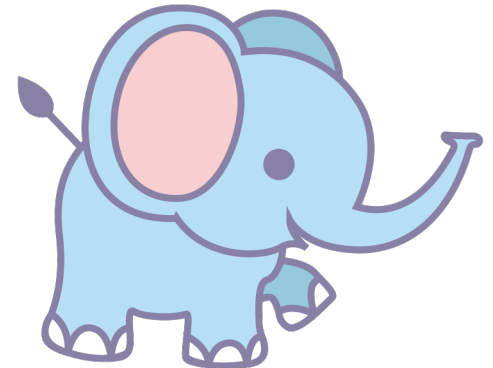
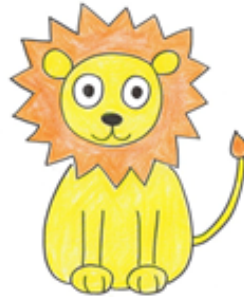
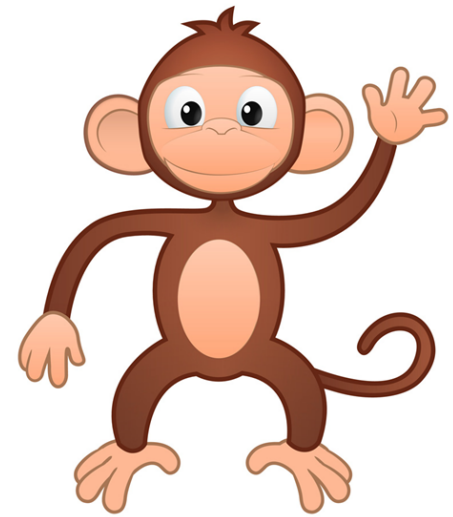
How did it get to this?

- Hollywood
- Marketing
- AI and ML are bad names for the public (OK for experts).



So, Let's get one thing out of the way first!

- Machine Learning is not really Learning.
- Artificial Intelligence is not really Intelligence.



Debunking myths about AI:

<https://www.youtube.com/watch?v=bSBbeGFEvgA>

Definition of Intelligence

- **Merriam Webster:**
 - The ability to learn or understand or to deal with new or trying situations.
 - also : the skilled use of reason.
 - The ability to apply knowledge to manipulate one's environment or to think abstractly as measured by objective criteria (such as tests.)
- **Oxford:**
 - The ability to acquire and apply knowledge and skills.
- **Dictionary.com:**
 - capacity for learning, reasoning, understanding, and similar forms of mental activity; aptitude in grasping truths, relationships, facts, meanings, etc.
 - manifestation of a high mental capacity.



Then, what is AI in today's Applied context?

- It's an **algorithm** for the **modeling** of systems in a **black box** fashion.
- It can be quite useful, and in many cases quite accurate for practical purposes, to model (complex) systems without complicated mathematics, and also to produce the desired results in those systems.
 - As long as we choose the right algorithm and train it with clean and sufficient data.
- It can be based on:
 - Logic
 - Decision making
 - Statistical inference, optimization (Machine Learning)
 - etc.



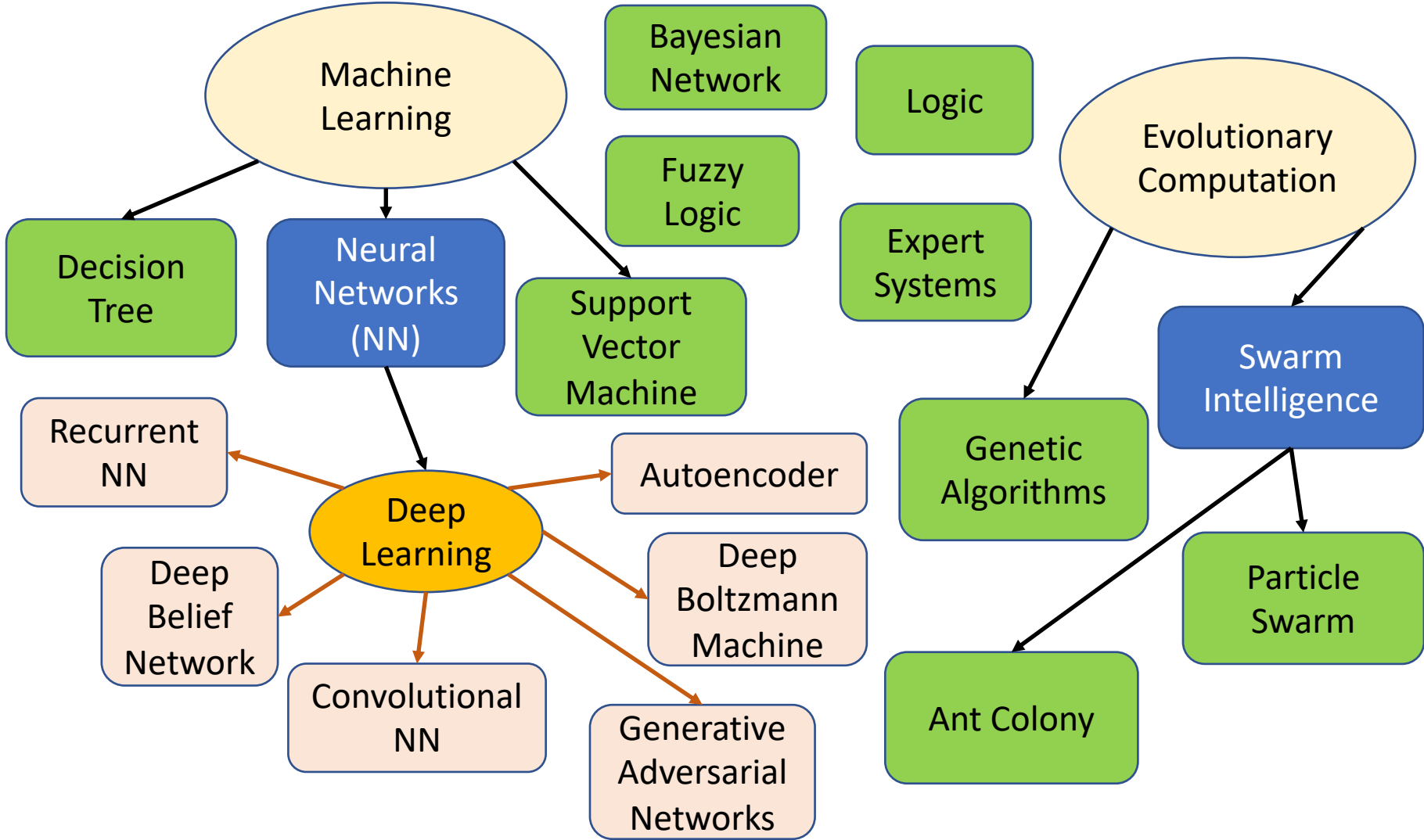
Normally inspired by how humans think and make decisions.

AI Black Box

- The model that an AI method creates is purely based on **matching input to output** (black box), unlike the **analytical model** that a domain expert creates (white box).
- For example, to create a system that detects skin cancer from the image of a patient's skin lesions, a biomedical engineer needs to develop an **analytical model** based on the skin lesions' shape, pattern, brightness, colour, concentration, area, and many other parameters, some of which are complicated to model, impossible to model, or simply unknown. This is very complex, especially if the model needs to be generalizable
- But AI, for example a machine learning algorithm, **can be trained** with a large-enough dataset of previously taken images of skin lesions with and without cancer. The method then **creates its own model** of how to match features in those images to whether or not cancer is present. This not only significantly reduces complexity, but also in some cases gives an even better result than an analytical model.
- Of course, the accuracy of AI depends on the **specific AI method** and the **quality of the provided dataset**.



AI Methods

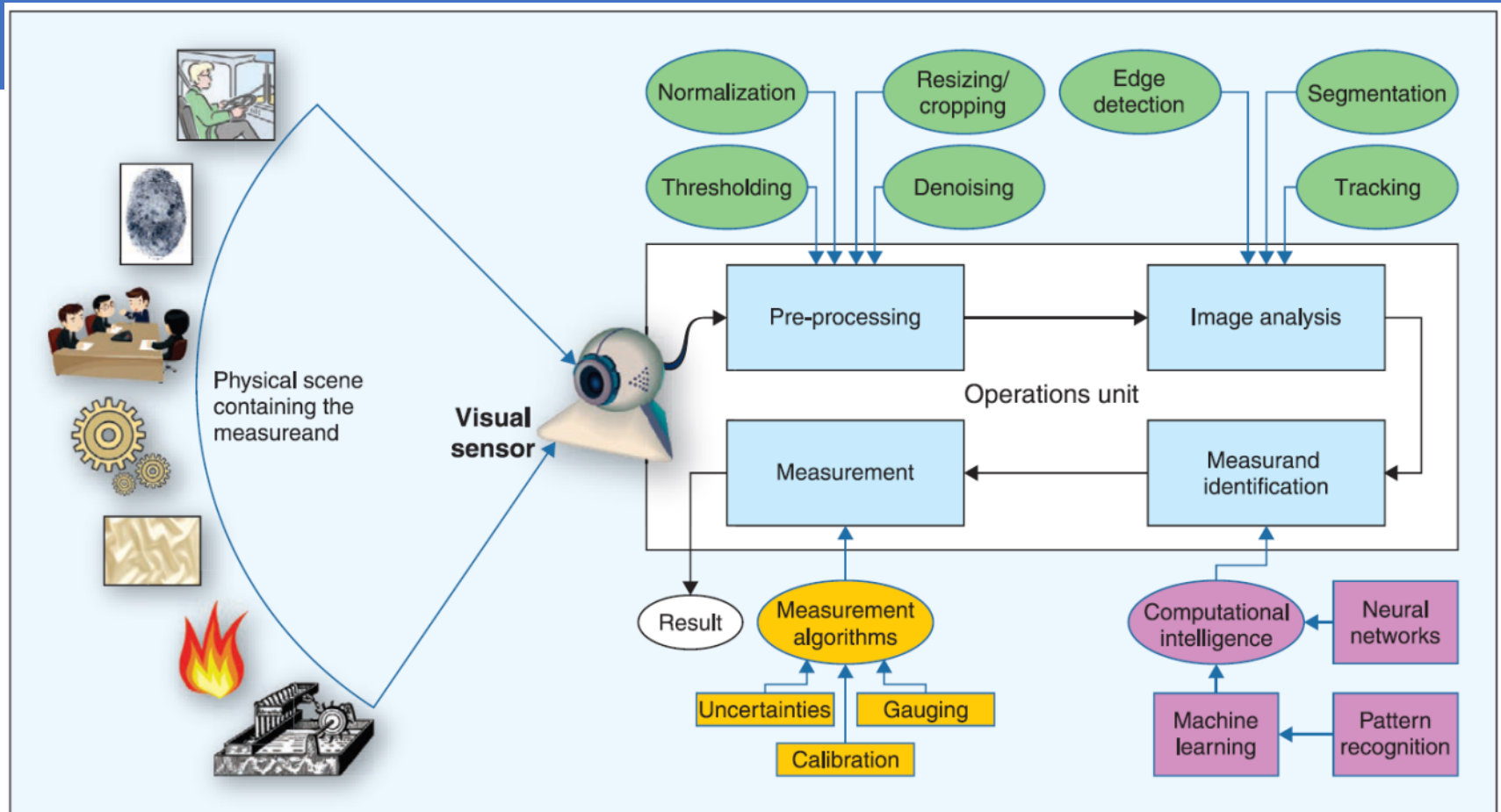


Uncertainty in AI-Based Measurement

- Measurement Applications vary in the **level of uncertainty** they can tolerate.
- E.g., we tolerate most Siri mistakes, but **critical applications** like autonomous driving or medical devices need much less uncertainty in their predictions.
- **Systematic uncertainty** occurs when the AI system is trained with input data that is not sufficiently comprehensive to cover the entire input domain.
- The following methods can quantify the uncertainty of AI prediction:
 - Monte-Carlo Dropout
 - Deep Ensembles (e.g., Distributional Parameter estimation or Ensemble Averaging)
 - Dropout Ensembles
 - Quantile Regression
 - Gaussian Process Inference

Vision Based Measurement

Among measurement applications, VBM is the most frequent user of AI.



S. Shirmohammadi and A. Ferrero, "Camera as the Instrument: The Rising Trend of Vision Based Measurement", *IEEE Instrumentation & Measurement Magazine*, Vol. 17, No. 3, June 2014, pp. 41-47.



PART 4

Examples from My Research

- Measurement Prediction
- Measurement Guesstimate

My Research Topic

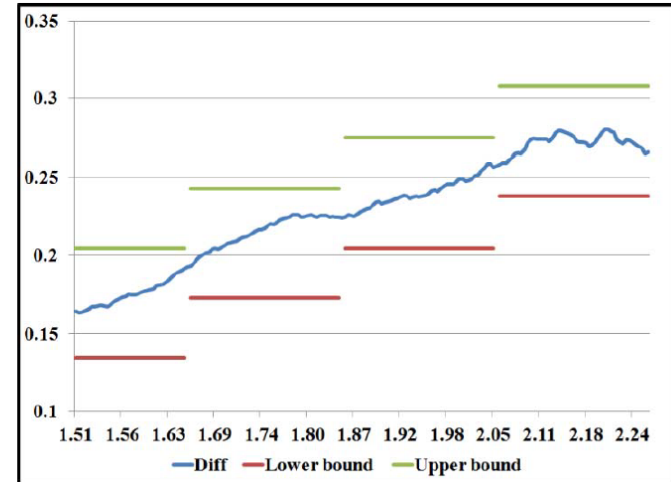
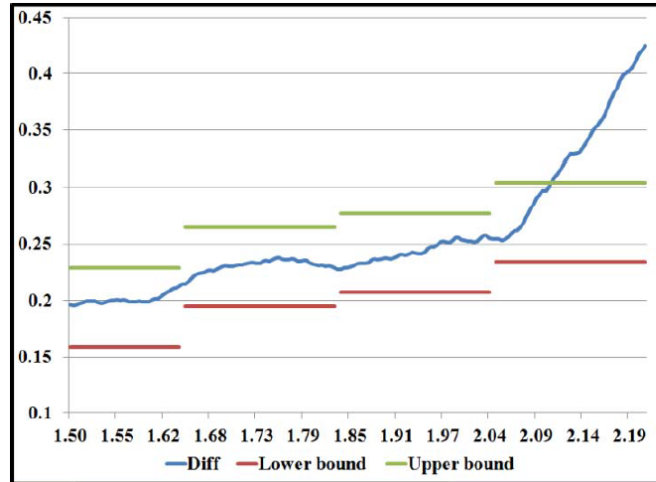
Private Sector



Public Sector



AVAILABLE BANDWIDTH CHANGE DETECTION



Magor

$$f(x|\rho, x_M) = \frac{\rho x_M^\rho}{x^{\rho+1}}, \quad x \geq x_M > 0, \quad \rho > 0$$

- A. Javadtalab, M. Semsarzadeh, A. Khanchi, S. Shirmohammadi, and A. Yassine, “Continuous One-Way Detection of Available Bandwidth Changes for Video Streaming over Best Effort Networks”, *IEEE Trans. on Instrumentation and Measurement*, Vol. 64, No. 1, January 2015, pp. 190-203.
- A. Khanchi, S. Shirmohammadi, M. Semsarzadeh, and A. Javadtalab. “Network Congestion Prediction”, US Patent 13/872,376 April 29 2013



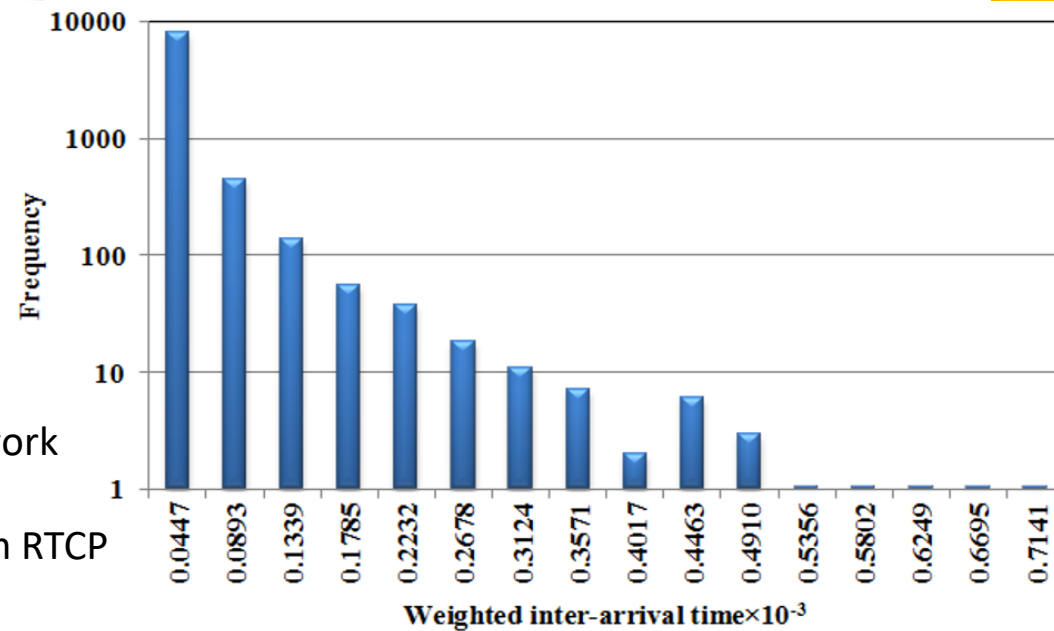
Requirements

- HDVC: need to know fast if bandwidth is about to go down or up.
 - Too late if we wait for bandwidth to go down and adjust the bitrate only then, because by then we will lose some packets and hence video quality will be unsatisfactory.
 - Also, once we have more bandwidth, we should use it to get maximum video quality
 - Maximum according to DRC algorithm.
- Method should have little to **no overhead**.
- This is Live video over RTP, not OTT Video over HTTP!

Modeling (1/2)

Logarithmic histogram of weighted inter-arrival time for video packets of a sample video trace.

- Consider that Video Data is:
 - Heavy-tailed
 - Infinite mean
 - Infinite variance
 - Self-similar
 - Long-range dependent
- Video is transferred over an unreliable network with RTP
 - Limited network parameters exist from RTCP
- Assume D = normalized inter-arrival time of subsequent packets
 - $D(n) = \{\text{Arrival}(n) - \text{Arrival}(n - 1)\} / \text{packet_size}$
- D is heavy-tailed
- Candidate: Pareto distribution



Confirmed

Modeling (2/2)

- Probability density of a **Pareto** distribution with parameters ρ (shape parameter) and x_M (minimum possible value):

$$f(x | \rho, x_M) = \frac{\rho x_M^\rho}{x^{\rho+1}}, \quad x \geq x_M > 0, \rho > 0,$$

- 1) $\rho > 1$: finite average;
- 2) $\rho > 2$: finite variance;
- 3) $\rho > 3$: finite skewness;
- 4) $\rho > 4$: finite kurtosis.

- Most Internet data with Pareto distribution have $\rho < 2$ and consequently **slight chance for the existence of statistical mean and variance**. So, developing any method based on these parameters will lead to unreliable solutions.
- In addition, Internet data exhibits **self-similarity, burstiness, and long-range dependence**, whereas having a fixed shape parameter does not address these characteristics.
- Hence, considering a fixed value for ρ will not help us understand the behavior of bandwidth variations.

Bayesian Algorithm (1/2)

- Fix x_m from previous experience.
- Shape parameter ρ follows a Gamma(a, b) distribution
 - Gamma, so that as we dynamically update the information according to weighted interarrival times, the distribution of ρ does not alter.
- Prior information: $\rho \sim \text{Gamma}(a, b)$ with mean ab and variance ab^2
- After the arrival of two packets, J_1 is calculated, where packet numbering has started from zero. The likelihood function of $L(\rho | J_1)$, proportional to ρ , is shown in

$$L(\rho | J_1) = \begin{cases} \frac{\rho x_M^\rho}{J_1^{\rho+1}} & \text{if } J_1 > x_M \\ 0 & \end{cases}$$

- Therefore, the posterior distribution of the shape parameter based on the observed data, J_1 , is:

$$G\left(a_0 + 1, \left[\frac{1}{b_0} + \ln \frac{J_1}{x_M}\right]^{-1}\right)$$

Bayesian Algorithm (2/2)

- As a result, based on the numerical value of J_1 , ρ follows a gamma distribution with the average presented in

$$E(\rho) = (a_0 + 1) \left[\frac{1}{b_0} + \ln \frac{J_1}{x_M} \right]^{-1}$$

- Once the next packet arrives and J_2 is calculated, it will be used to obtain a new estimation of the Pareto shape parameter, and its corresponding average, shown in next two equations:

$$\rho \sim G \left(a_1 + 1, \left[\frac{1}{b_1} + \ln \frac{J_2}{x_M} \right]^{-1} \right)$$

$$E(\rho) = (a_1 + 1) \left[\frac{1}{b_1} + \ln \frac{J_2}{x_M} \right]^{-1}$$

- This scheme will be continued and after each packet arrival the expectation of the shape parameter is calculated, which will provide us with a sequence of mathematical expectations of the shape parameters.

Decision

- We propose to generate a numerical sequence of differences of the last moving averages of orders n_1 and n_2 ($n_1 < n_2$) following each packet arrival. When the i^{th} packet arrives ($i > n_2$), the difference is determined as shown here:

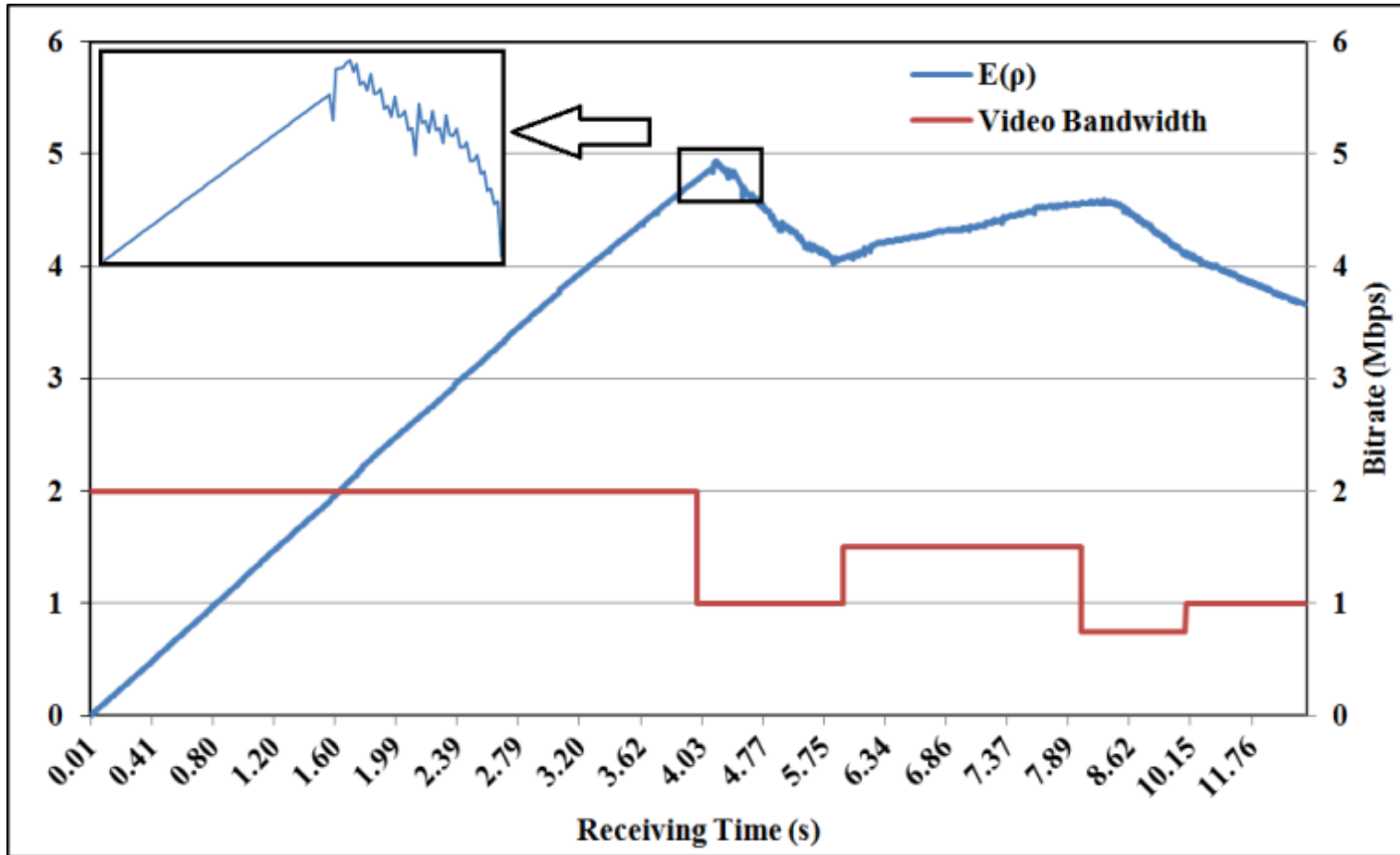
$$Diff_i = MA_i(n_1) - MA_i(n_2),$$

where

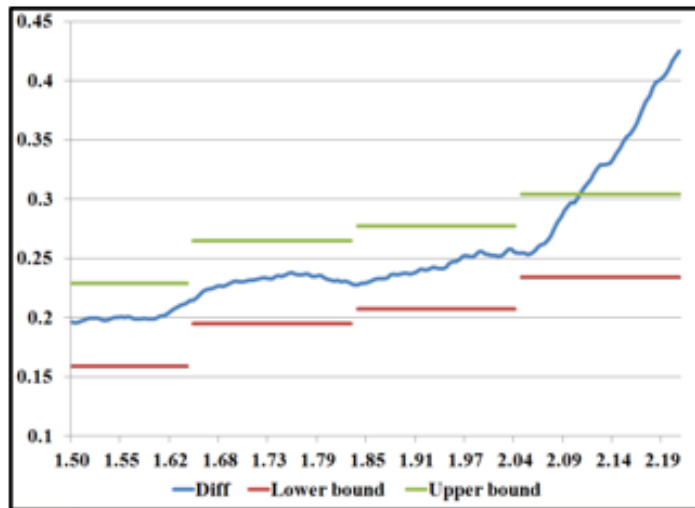
$$MA_i(n) = \frac{\sum_{k=i-n+1}^i E_k}{n}, i \geq n$$

- An acute decline in the value of *Diff* indicates a decrease in the available bandwidth and, analogously, a rise in *Diff* shows an increase.

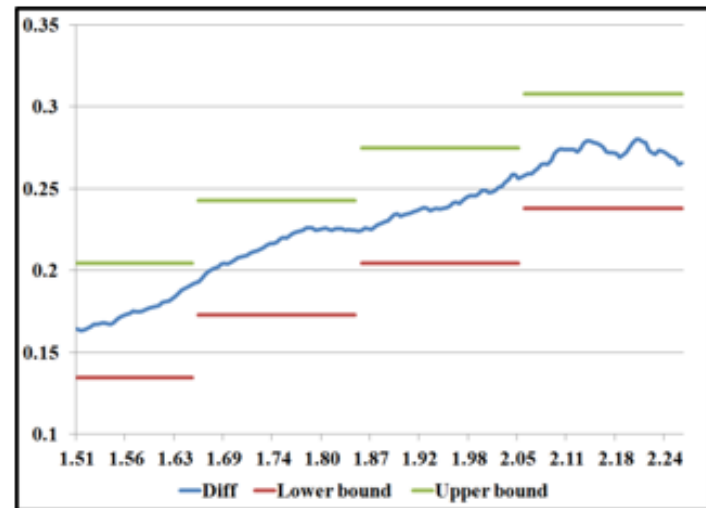
Why Moving Average?



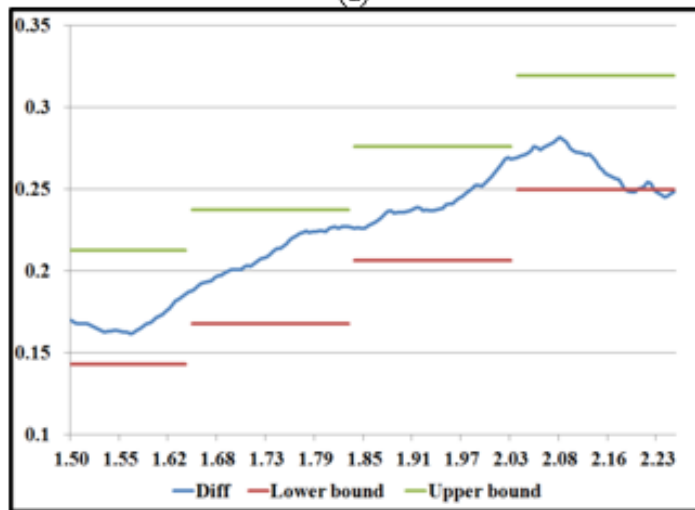
Results



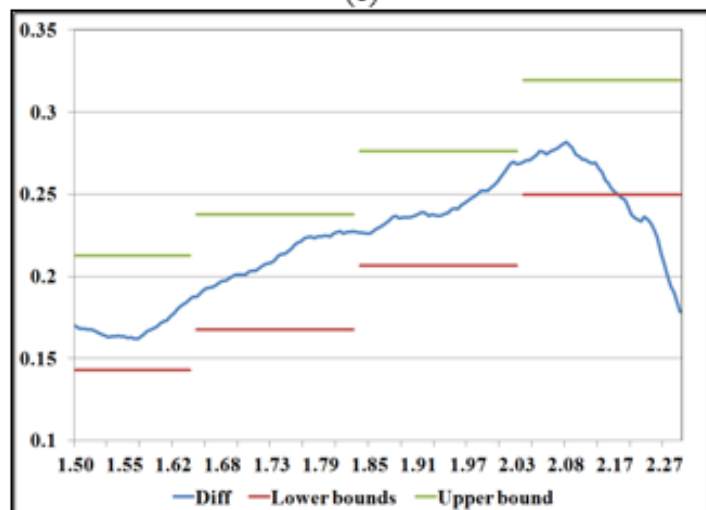
(a)



(b)



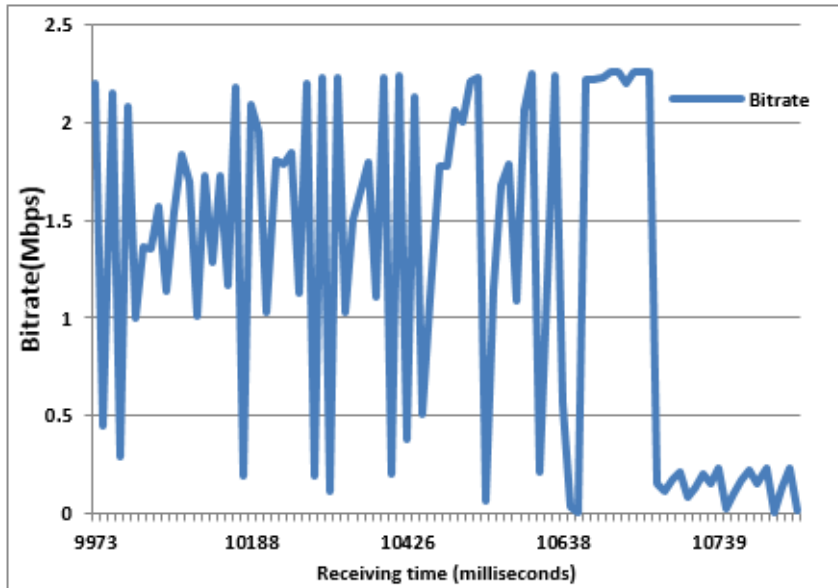
(c)



(d)

Figure 7 Graphs for our proposed approach for the Rush hour video for various decreasing cases a) Case 3 (2 Mbps to 2.25 Mbps), b) Case 4 (2 Mbps to 1.75 Mbps), c) Case 5 (2 Mbps to 1.5 Mbps) and d) Case 6 (2 Mbps to 1 Mbps)

Comparison with TFRC



Detects bandwidth change in less than 200 msec

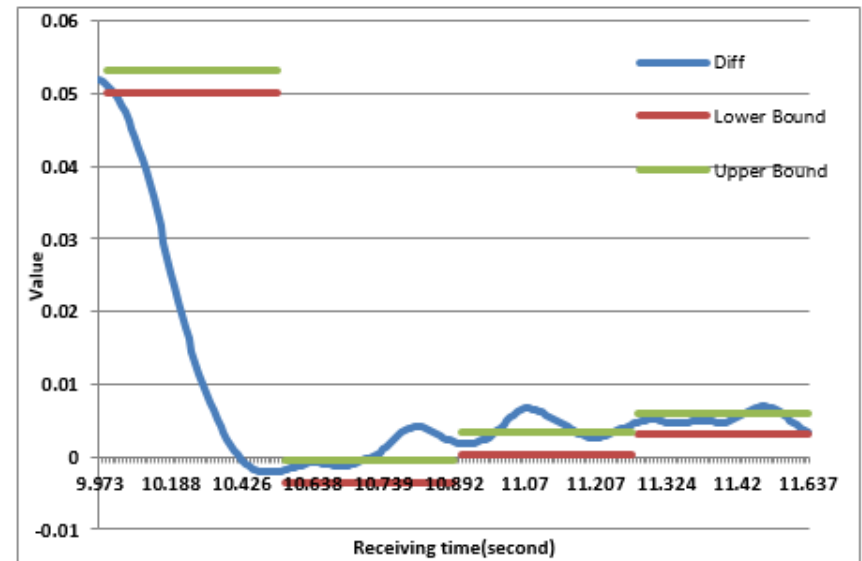
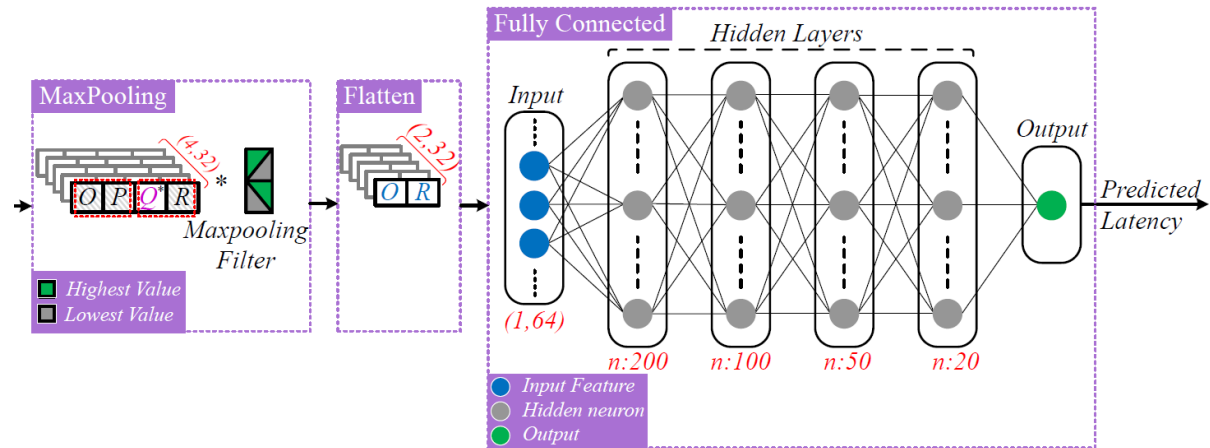


Figure 18 A real trace of the proposed method over the Internet

A. Javadtalab, M. Semsarzadeh, A. Khanchi, S. Shirmohammadi, and A. Yassine, "Continuous One-Way Detection of Available Bandwidth Changes for Video Streaming over Best Effort Networks", *IEEE Transactions on Instrumentation and Measurement*, Vol. 64, No. 1, January 2015, pp. 190-203.

AI-BASED DISTRIBUTED DELAY MEASUREMENT



S.A. Mohammed, S. Shirmohammadi, and S. Altamimi, “A Multimodal Deep Learning Based Distributed Network Latency Measurement System”, *IEEE Trans. on Instrumentation and Measurement*, January 20 2020, 8 pages.

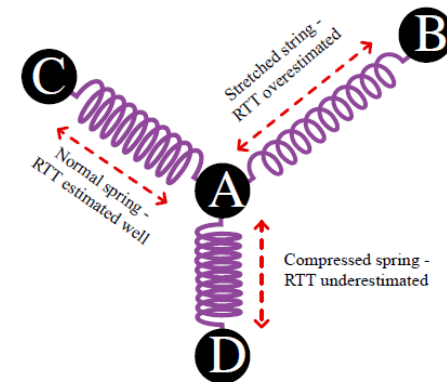
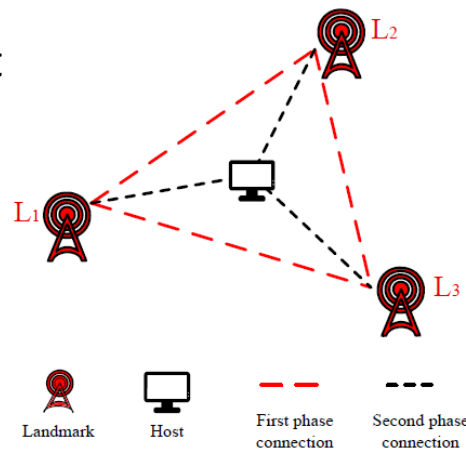
Network Latency Measurement

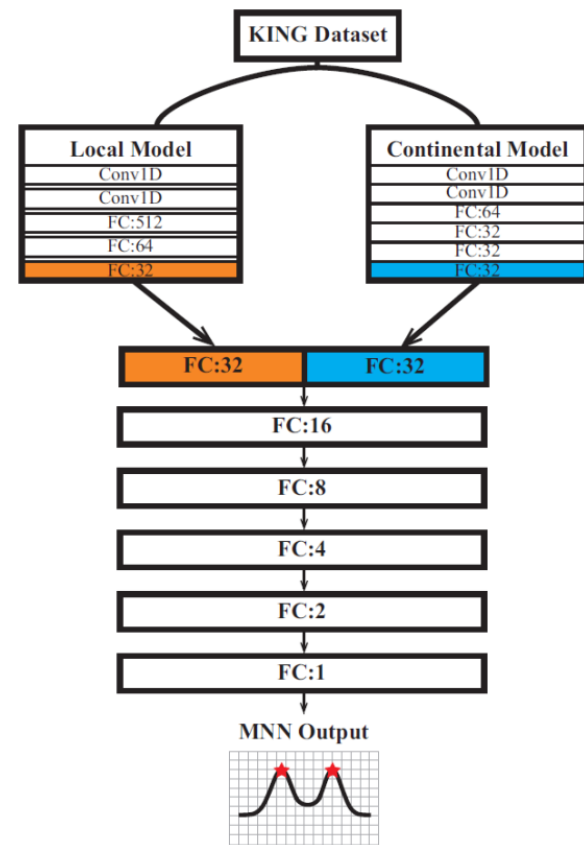
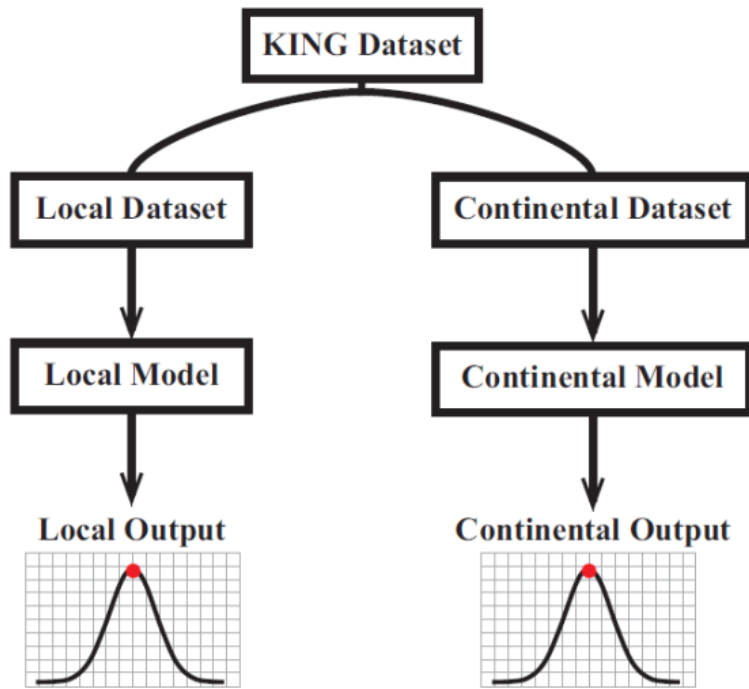
- **Network latency** plays an important role in large scale distributed applications: multiplayer online games, Content Distribution Networks, and peer-to-peer systems.
- Latency measurement is needed in determining performance, Quality of Service (QoS), and the level of scalability of these applications.
- However, explicit end-to-end delay measurements between every pair of nodes has $O(N^2)$ complexity, and leads to both **large computational overhead and large overhead traffic**.
- Typical solutions are based on **Network Coordinates Systems (NCS)**, which estimate the RTT between any pair of network nodes even without prior RTT measurement between them.
 - NCS works by explicitly **measuring only a few sets of RTT**. Then, it **predicts the rest of the network latencies** between any pair of network nodes.
- There are two major models for implementing the NCS: **Euclidean Distance Model** e.g., Vivaldi or GNP, and **Matrix Factorization**.



Problems with existing work

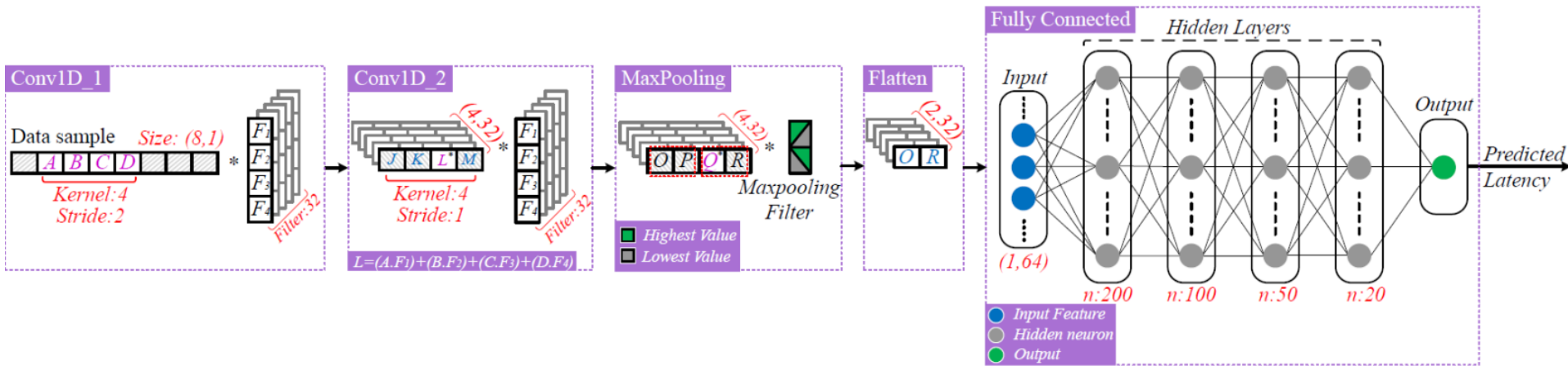
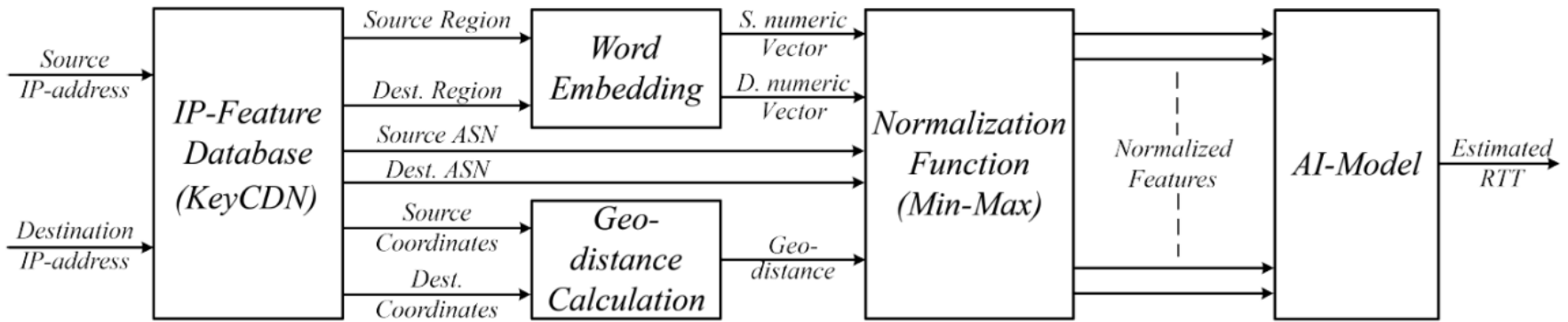
- The Euclidean Distance-based Model assumes that the distance between two network nodes is symmetric, which is not always correct
- The Matrix Factorization Model does not consider the geographical distances between hosts that introduce constant propagation delays.
- In addition, it is hard to know the exact rank of the true latency matrix from noisy measurements.
- Both approaches require an initial time to converge which is proportional to the number of network nodes. This time can be long and is not trivial in practical situations.





Architecture

- The Dataset is split into two sets and fed into two different CNN models.
- The Two CNN Models are frozen, their outputs are concatenated and followed by fully connected layers.

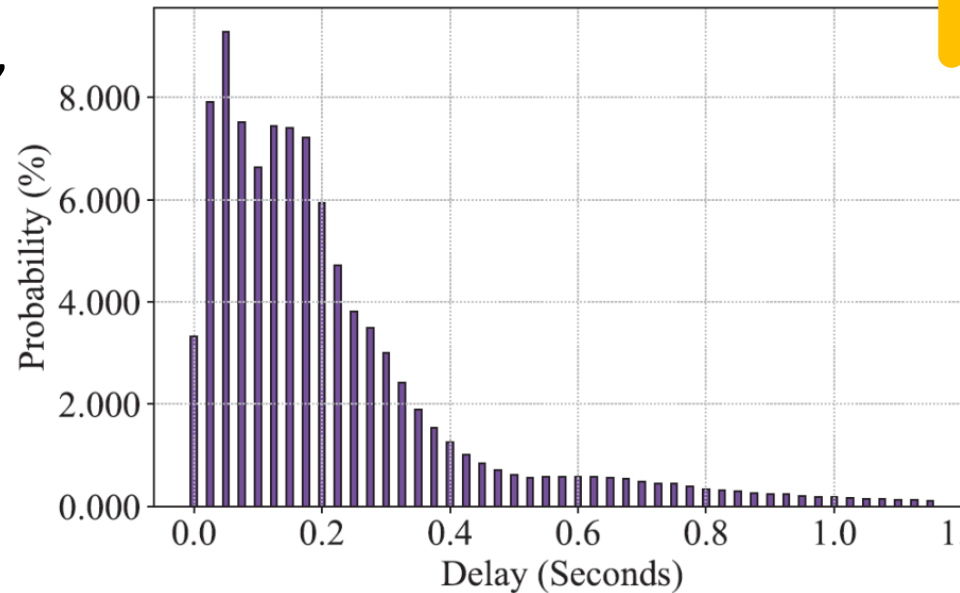


System Design

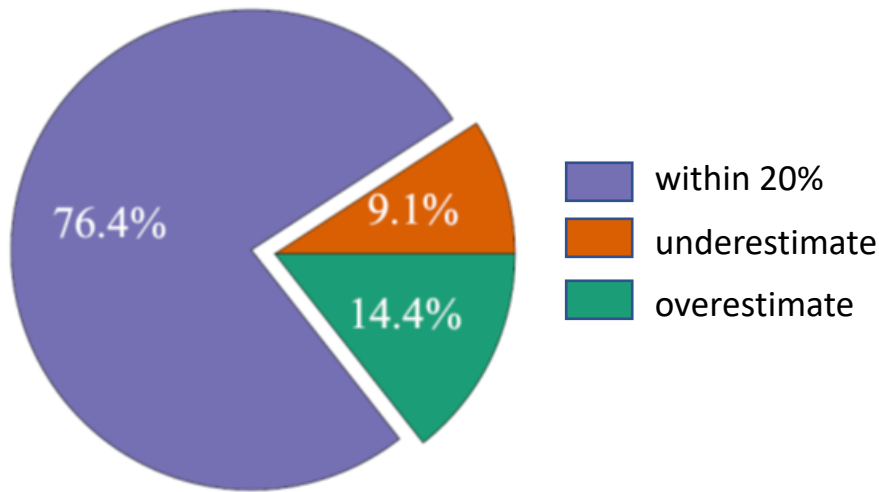
- KeyCDN is used to extract features of an IP address, including geo-location, autonomous system, DNS, region, and VPN.
- We train (60%), validate (10%) and test (30%) our model using the KING dataset.
- For the AI subsystem, we tested *Linear regression (LR)*, *Support Vector Machine (SVM)*, deep learning-based *Convolutional Neural Network (CNN)* and *Multimodal DL Networks (MDN)*.

Dataset Peculiarities

- The distribution does not have a single density. In addition, even after removing the outliers (>3 sec), it has a **long tail** that is challenging for DL algorithms since they consider such tails as additional data outliers that either need to be clipped or removed.
- However, in KING's case, the **tail measurements represents actual delay measurements** between different continents, i.e. two far nodes in the network. These measurements are therefore **valid** and can neither be clipped nor removed.
- This made it challenging for us to properly model the system with DL.



Results



Estimation distribution

AVERAGE ACCURACY FOR AI APPROACHES AND STATE OF THE ART ALGORITHMS IN TERMS OF PERCENTAGE.

MDN	96.1%	Vivaldi	90.6%	DMF	92.8%
CNN	94.7%	IDES	92.3%	Phoenix	93.5%

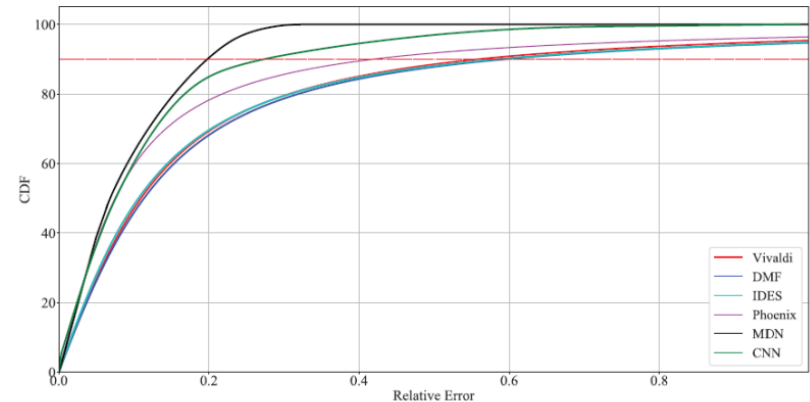
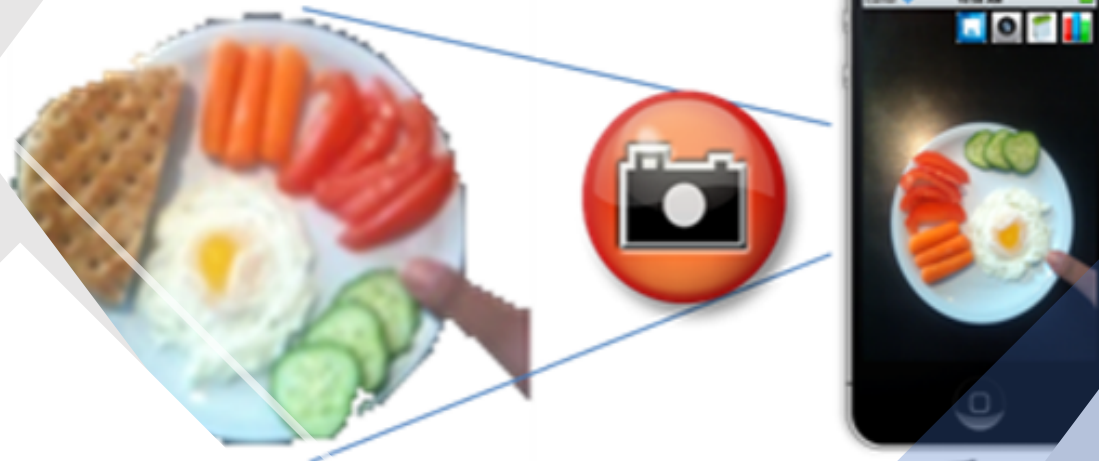


Fig. 8. Cumulative distribution function (CDF) of relative errors (RE).

S.A. Mohammed, S. Shirmohammadi, and S. Altamimi, “A Multimodal Deep Learning Based Distributed Network Latency Measurement System”, *IEEE Trans. on Instrumentation and Measurement*, January 20 2020, 8 pages.

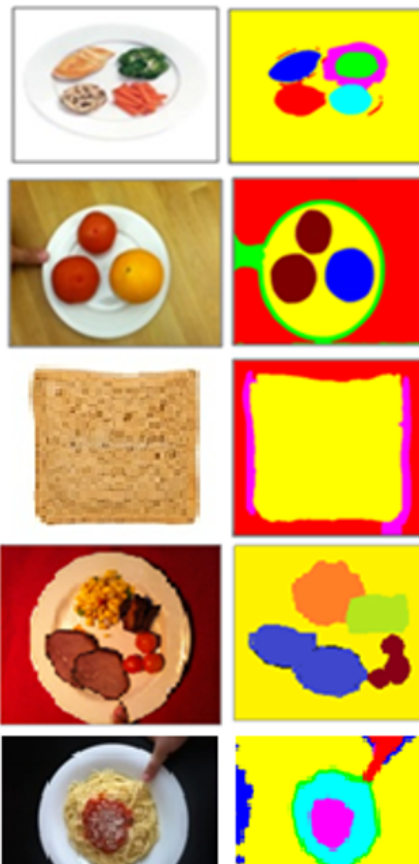
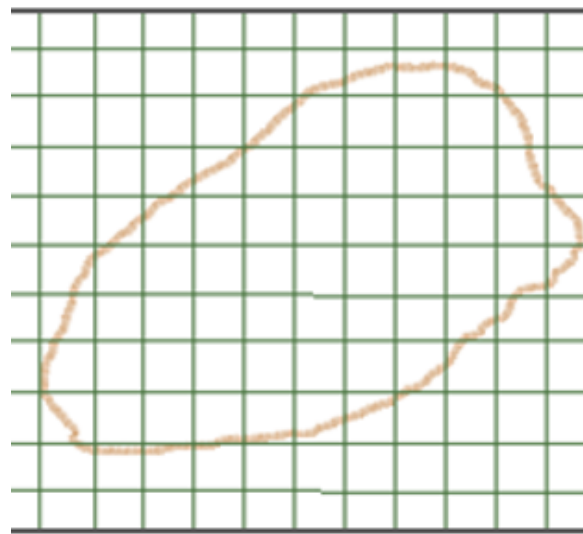
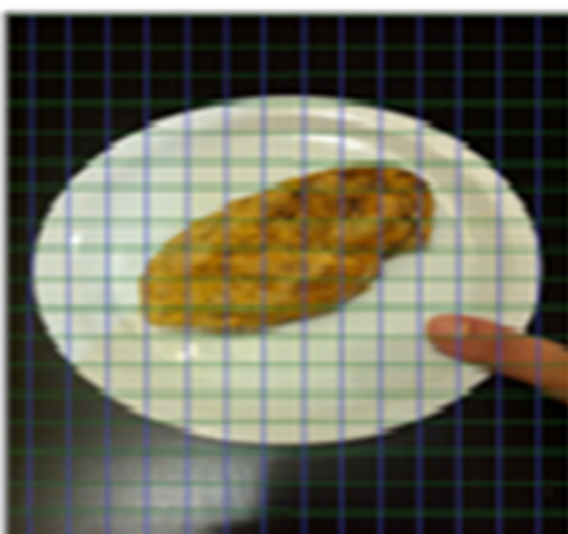
Food Calorie Measurement



Food
Image

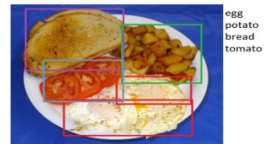
Food Portion
Volume
Measurement

- P. Pouladzadeh and S. Shirmohammadi, “**Mobile Multi-Food Recognition Using Deep Learning**”, *ACM Trans. on Multimedia Computing, Communications, and Applications*, Volume 13, Issue 3s, August 2017, Article 36, 23 pages.
- P. Pouladzadeh, S. Shirmohammadi, and R. Almaghrabi, “**Measuring Calorie and Nutrition from Food Image**”, *IEEE Trans. on Instrumentation and Measurement*, Vol. 63, Issue 8, August 2014, pp. 1947-1956.

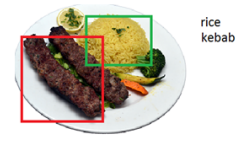


Automated Food Log

First VBM System for Automatic Food Identification, Calibration, and Calorie Measurement



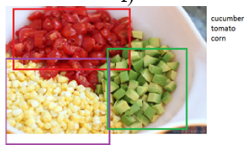
e)



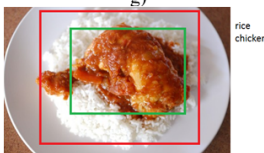
f)



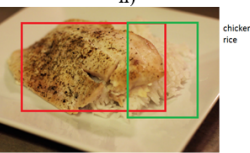
g)



h)

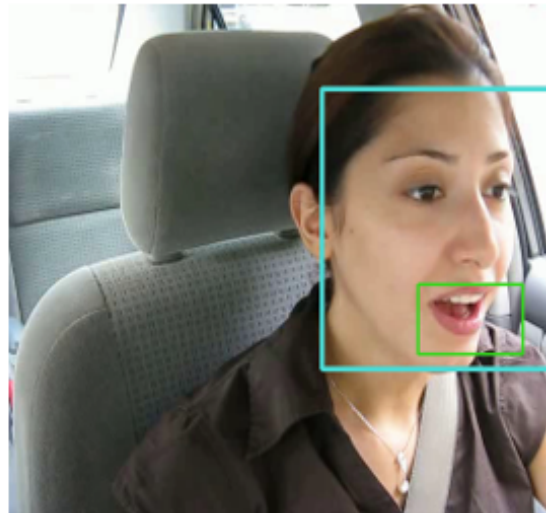
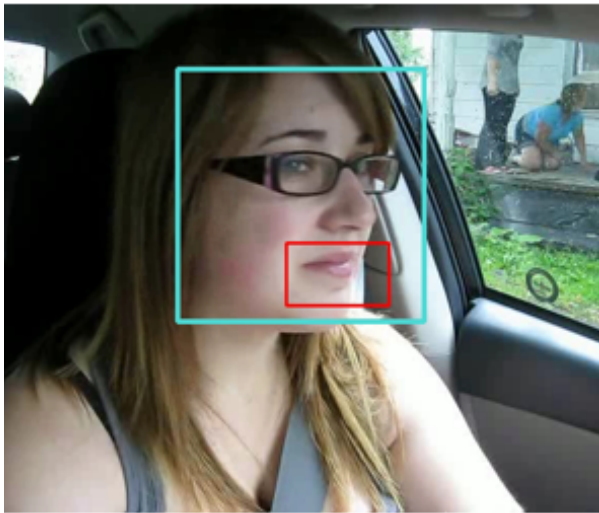
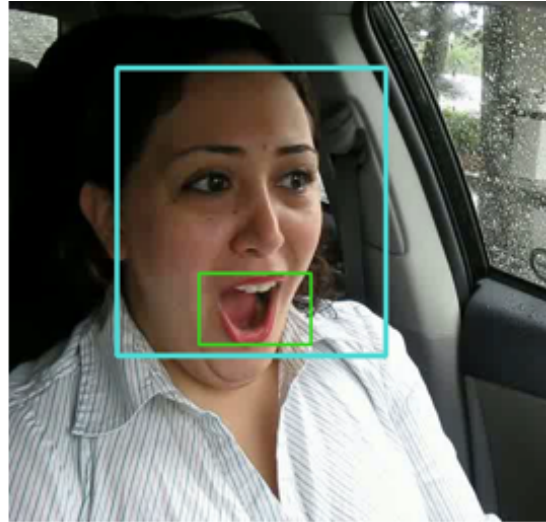
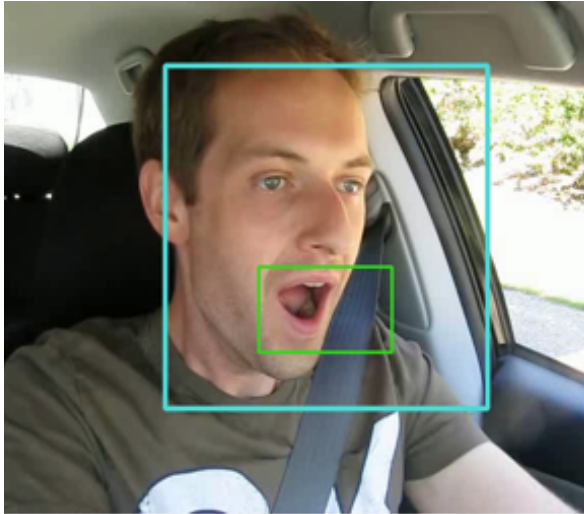


i)



j)

		Recognition Rate (%)		
N	Food items	Recall	Precision	Accuracy
1	Red Apple	93.64	96	96
2	Orange	95.59	97.5	98
3	Corn	84.85	80	85
4	Tomato	89.56	97	96
5	Carrot	93.25	98	98
6	Bread	98.39	89	90
7	Pasta	94.75	98	98
8	Sauce	88.78	92	93
9	Chicken	86.55	89	88
10	Egg	81.22	87	90
11	Cheese	95.12	97	97
12	Meat	95.73	96	96.5
13	Onion	89.99	93	95
14	Beans	98.68	95	97
15	Fish	77.7	85	88
16	Banana	97.65	97	97
17	Green Apple	97.99	97	97
18	Cucumber	97.65	98	98
19	Lettuce	77.55	85	88
20	Grapes	95.7	95	95
21	Potato	88.56	89	91
22	Tangerine	97.59	99	99
23	Chocolate Cake	88.19	85	90
24	Caramel Cake	85.29	85	88
25	Rice	94.85	94	94
26	Green Pepper	97.99	98	98
27	Strawberry	85	95	97
28	Cooked Vegetable	92.62	96	96
29	Cabbage	80	91	92
30	Blueberry	89	98	98
Total average		90.98	93.05	94.11



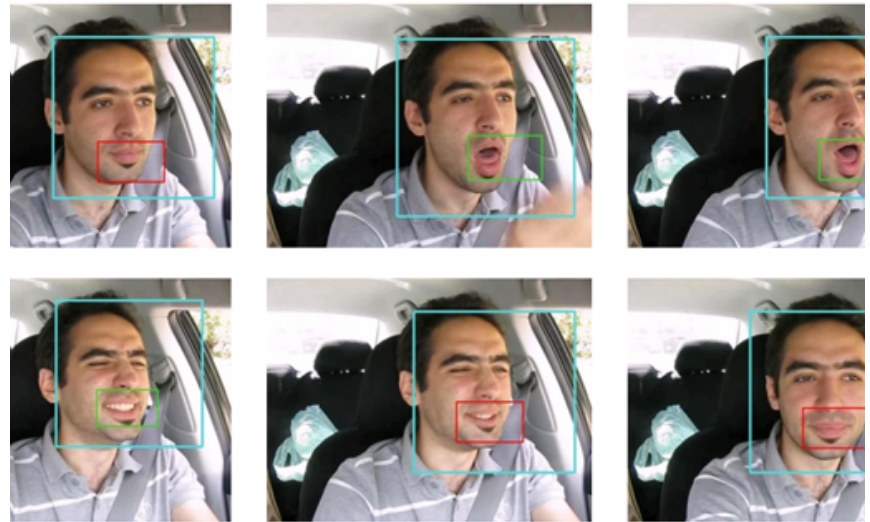
Applied AI for Driving Safety



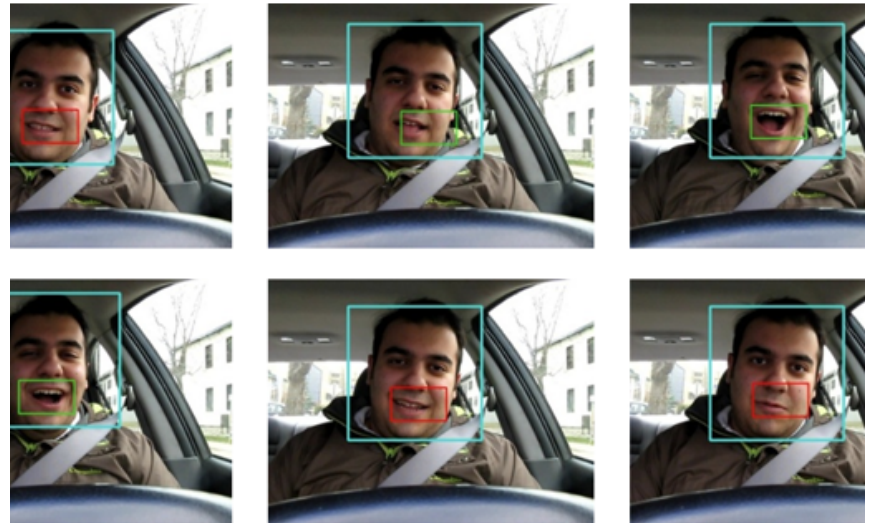
M. Omidyeganeh, S. Shirmohammadi, S. Abtahi, A. Khurshid, M. Farhan, J. Scharcanski, B. Hariri, D. Laroche, and L. Martel, “[Yawning Detection Using Embedded Smart Cameras](#)”, *IEEE Trans. on Instrumentation and Measurement*, Vol. 65, Issue 3, March 2016, pp. 570-582.

Driver Yawning Detection

- Part of fatigue detection.
- Can we detect yawning, and distinguish it from singing or talking?
- Successfully doing so could lead to fewer accidents.



(a) Camera installed under the front mirror

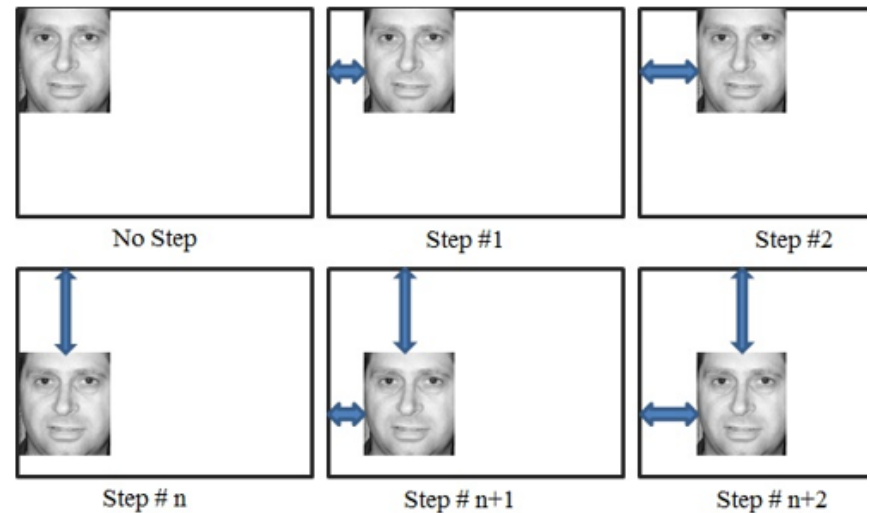


Smart Camera Limitations

- CogniVue APEX platform: Image Cognition Processors (ICP) consisting of an ARM 926EJTM 350MHz master processor, 34B Ops/sec low-power DSP subsystem using patented massively parallel Array Processor Unit (APU), a second 350MHz ARM 926 processor, H/W acceleration blocks, wide-bandwidth stream DMAs, internal dual 64-bit AXI data buses to/from all blocks, 16Mbyte DDR SDRAM, and 1Gbit NAND Flash. The platform does not support floating point operations, divisions, or numbers larger than 16 digits.



Fig. 6. Search for the face in a larger scale.



Results

- Technology was licensed to CogniVue Corp.
- It was as a showcase of their APEX platform in their customer demos.
- Also had significant impact as a key contributing factor to the development of CogniVue's next generation APEX processors.
- Company was bought by NXP Semiconductors, still offering the platform.

M. Omidyeganeh, S. Shirmohammadi, S. Abtahi, A. Khurshid, M. Farhan, J. Scharcanski, B. Hariri, D. Laroche, and L. Martel, "Yawning Detection Using Embedded Smart Cameras", *IEEE Trans. on Instrumentation and Measurement*, Vol. 65, Issue 3, March 2016, pp. 570-582.

DETECTION RESULTS

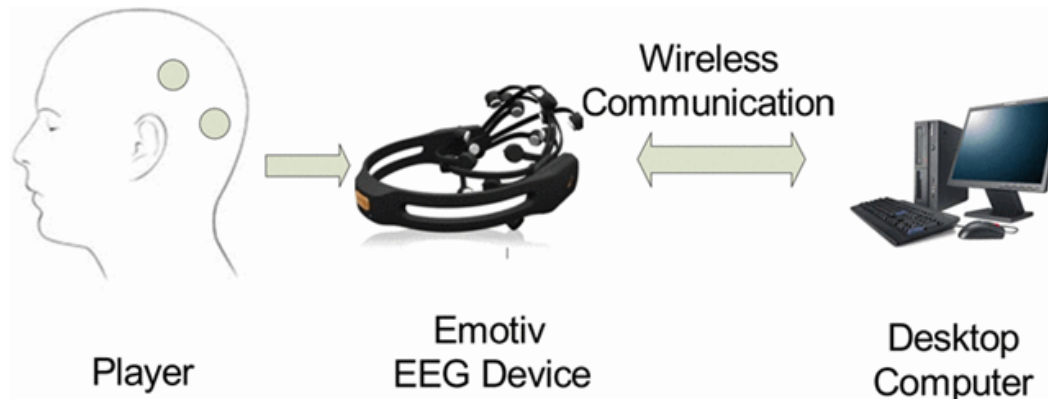
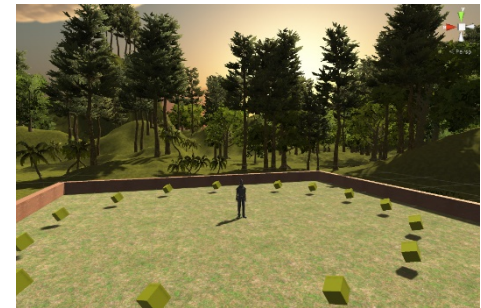
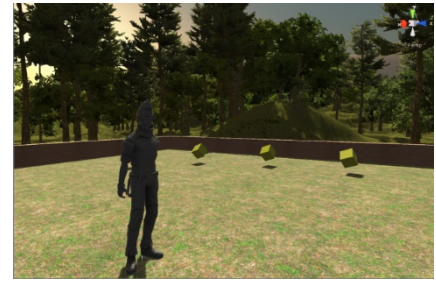
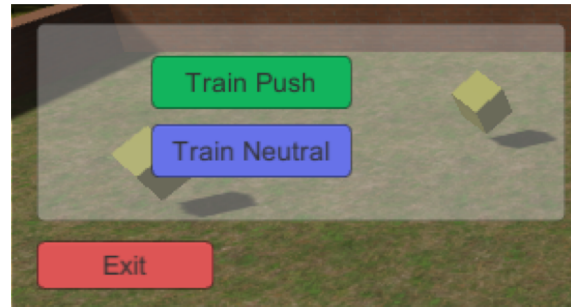
	Face detection CASE I	Mouth detection CASE I	Yawning detection CASE I	Face detection CASE II	Mouth detection CASE II	Yawning detection (RCD) CASE II
OpenCV	61%	48%	18%	85%	57%	20%
[20]	89%	68%	54%	94%	79%	67%
[21]	69%	52%	13%	78%	59%	19%
Proposed method	89%	68%	65%	94%	79%	75%

YAWNING DETECTION STATISTICS USING OUR METHOD

	# Frames	#Real Yawning Frames	%True Positives	%True Negatives	%False Negatives	%False Positives
Average	560	100	70%	81%	33%	7%
Maximum	2443	376	80%	94%	78%	22%
Minimum	76	41	45%	72%	19%	3%

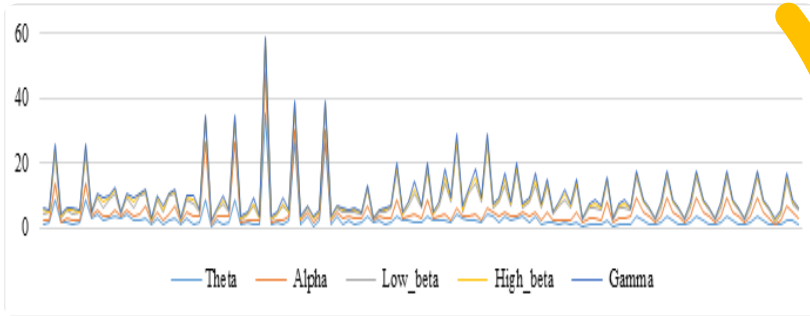
Serious Game with EEG

- Game is controlled by thought.
- The objective is to move the avatar by thought, to collect all cubes in the shortest time.

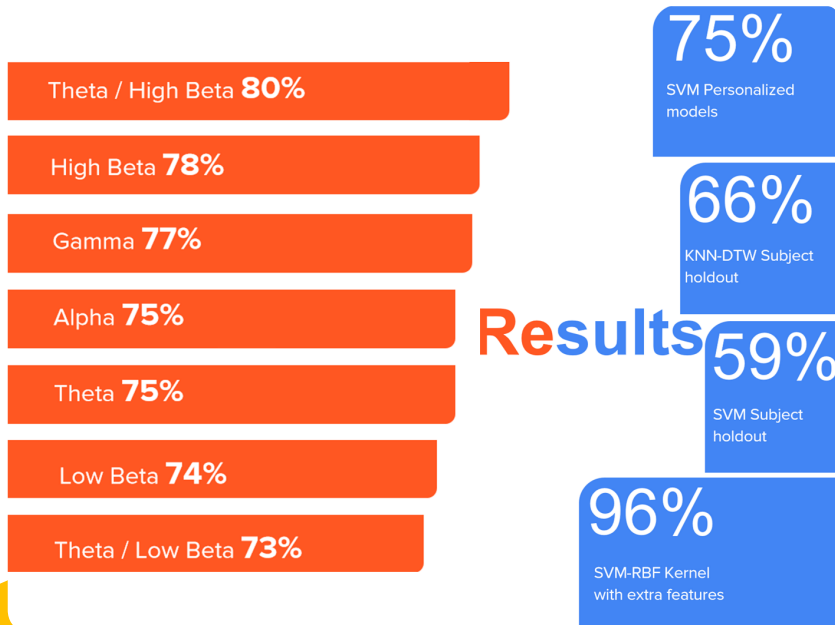


Results

- Testing was done with 5 healthy subjects and 4 subjects suffering from ADHD.
- Different classifiers were trained to detect ADHD recorded EEG signals. Results are shown below.
- The results show an average improvement of 10.25% in engagement and 8.25% in focus.



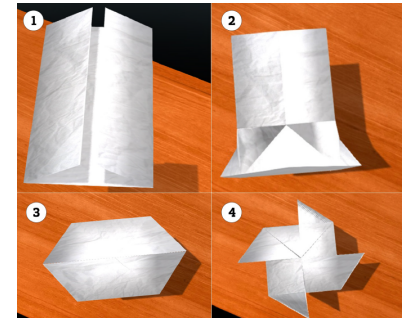
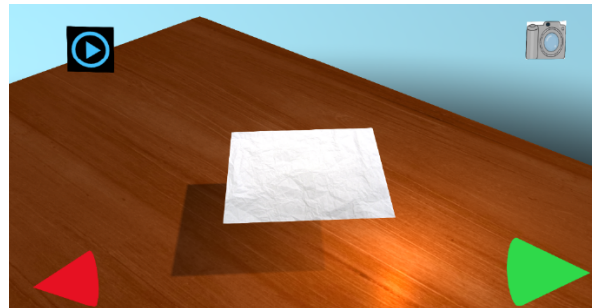
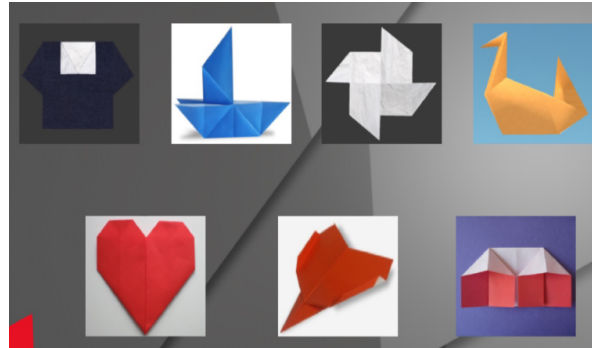
F1 score for various models



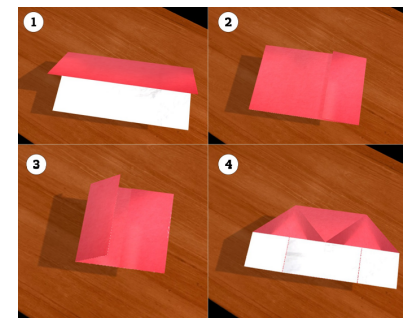
A.E. Alchalabi, S. Shirmohammadi, A. Nour Eddin, and M. Elsharnouby, “**FOCUS: Detecting ADHD Patients by An EEG-Based Serious Game**”, *IEEE Trans. on Instrumentation and Measurement*, Volume 67, Issue 7, July 2018, pp. 1512-1520.

Digital Origami

- Child sees the digital instructions, and can play digitally or with paper.
- Able to diagnose **Visual Sequential Memory Deficit**: reduced competency of remembering letters, numbers, objects or shapes in the correct order.
- Used clinical reference methods for comparison:
 - The Knox Cube Imitation Test
 - The Corsi Block-Tapping Test



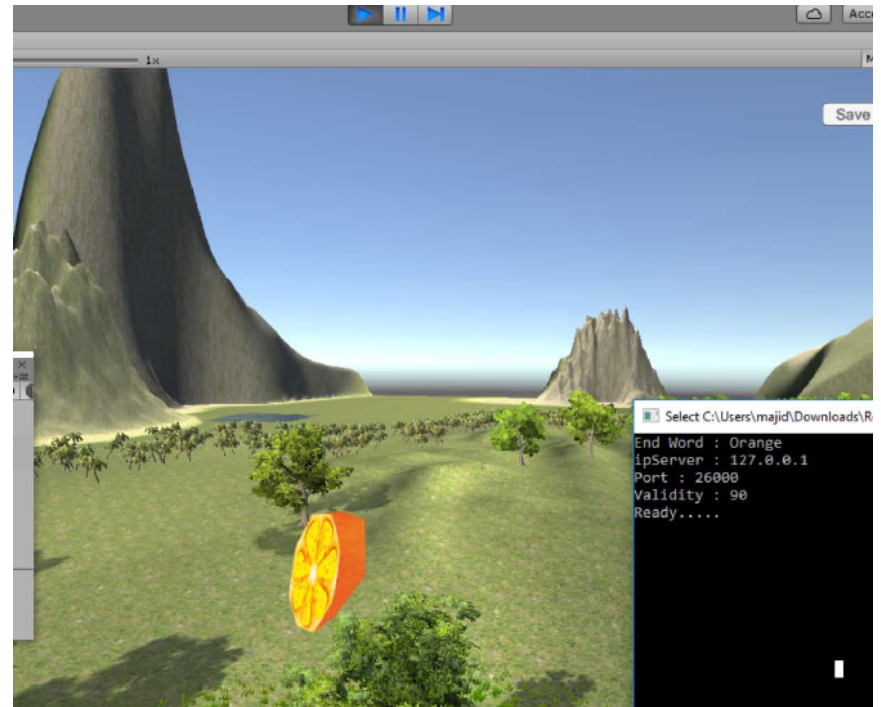
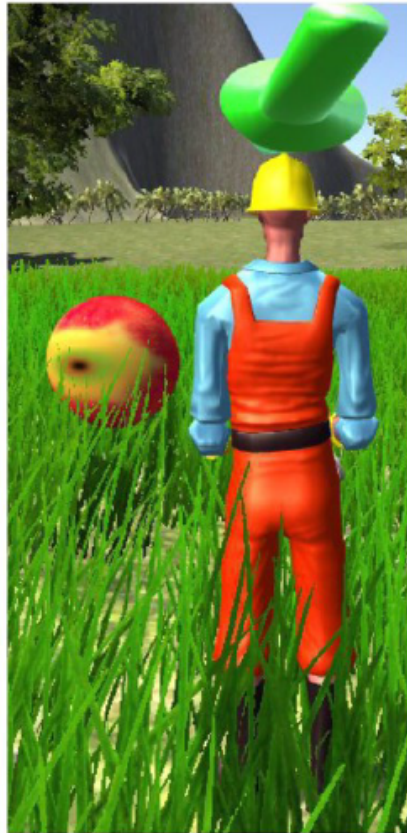
Therapy: whole animation or step by step.



Diagnosis: whole animation n times, then test.

Into the Forrest

A serious game for the therapy of children with speech disorder or hearing problems



Can move avatar by voice or keyboard.

Your options

Orange
Apple
BAnana
Speak Now!
volume:

Your results

Orange
Missed: None
Mispronounced: None
Score: 100
Speed: 80

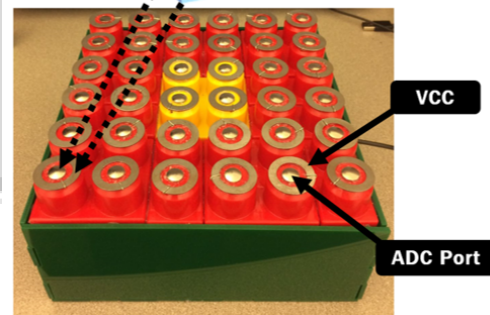
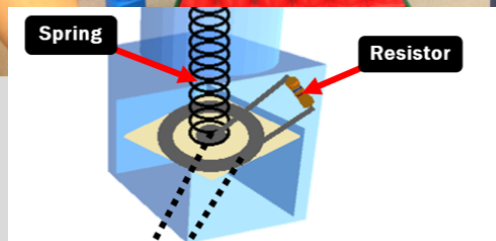


Assessment

- Pronunciation is measured by comparing the **phonemes** of the child's input with several possible valid references.
- By pitch tracking, we can record the child's **intonation** which are separated by spaces.
- Speed measurement shows how many phonemes have been uttered by the child in ten seconds.

Social Tangible UI Game

- Improving social skills for children with Autism.
- We recruited 9 ASD kids from *Children at Risk*, a community organization in Ottawa that provides services to families of children diagnosed with ASD.



Evaluation

- On Day 1, for the first phase of the experiment, Team A was assigned to play with a non-computer game and Team B was assigned to play with the computer game. They were given 15 minutes to play.
- For the second phase of the experiment, the teams switched games and they were given 15 minutes to play.
- On Day 2, the same procedure was repeated for Team C and Team D.

- *Social interaction*: Number of initiated social interactions between the participants.
- *Solitary play*: Time the participant spent playing alone.
- *Collaborative play*: Time the participant spent playing with other participants.
- *Engagement in other activities*: Time the participant was not engaged in the game.
- *Performance*: Number of mini levels (i.e. models) they successfully completed.

Variable	Non-Computer game		Computer game	
	Mean	σ	Mean	σ
<i>Social interaction a</i>	1.11	1.27	3.55	1.74
<i>Solitary play b</i>	45.6%	34.55	25.5%	20.19
<i>Collaborative play a</i>	26.07%	42.13	56%	27.68
<i>Engagement in other activities</i>	28.29%	29.01	18.5%	21.37
<i>Performance a</i>	2.44	2.35	6.11	4.70

^{a.} $p < 0.005$

^{b.} $p < 0.05$

Thank you!



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- For more information, please visit:

<http://www.discover.uottawa.ca/>

- or contact shervin@ieee.org