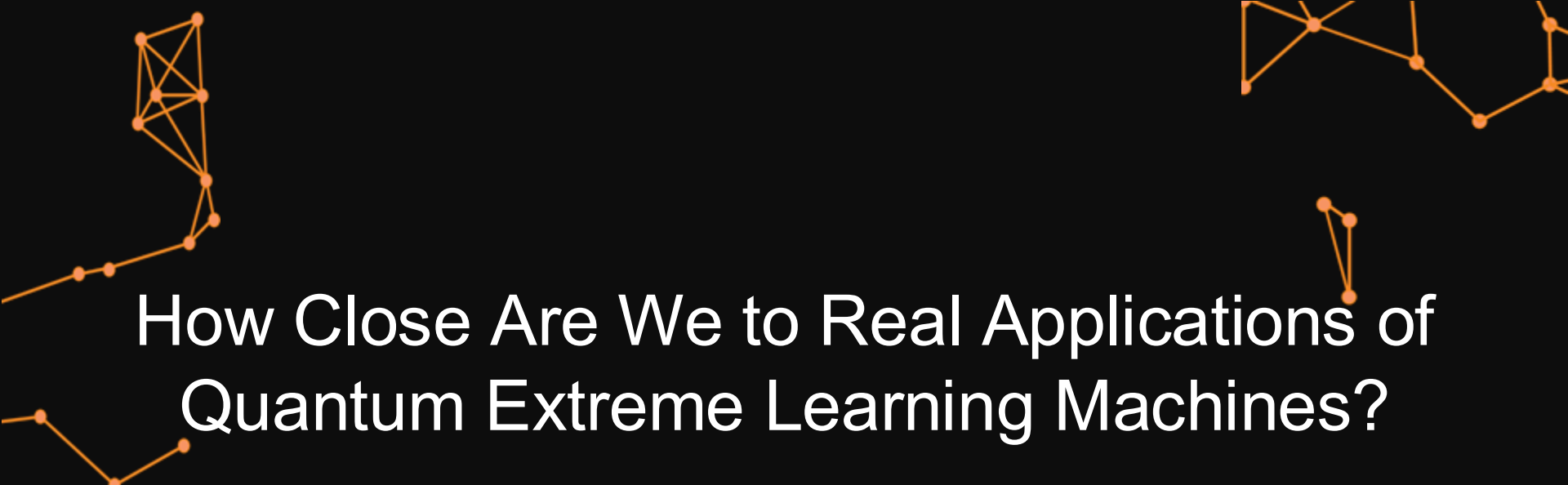




How Close Are We to Real Applications of Quantum Extreme Learning Machines?

Shaukat Ali

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Quantum Computing (QC)

QC promises to solve many complex problems, possibly together with classical computing.

Many technologies are being tried out to build quantum computers.

Superconducting

IBM
IQM
Google
Chalmers University

Quantum Annealers

D-Wave

Photonic

Xanadu
PsiQuantum
QuiX Quantum

Silicon

SemiQon
Equal 1

Trapped Ion

Quantinuum
IonQ

Neural Atom

PASQAL
Atom Computing
ColdQuanta
QuEra

Irrespective of technology, we need to program quantum computers.

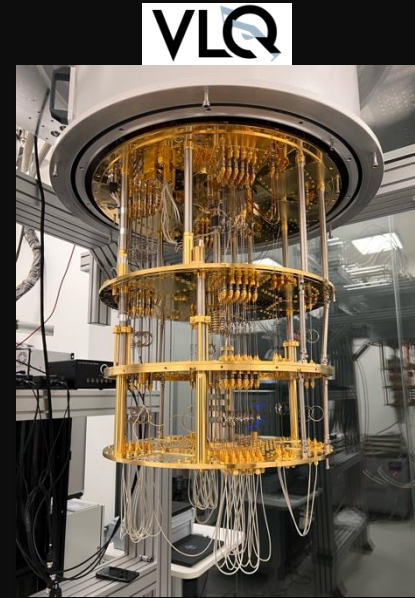
What is Quantum Software Engineering?

Quantum computers, irrespective of their technology, are programmed with quantum software.

Quantum software is at the core of the promised revolutionary QC applications, quantum communication, and sensing.

Software exists across all layers of the quantum computing stack

Quantum software engineering enables the cost-effective and scalable development of dependable quantum software.



VLQ Quantum computer
Technical University of Ostrava
Czech Republic
LUMI-Q EuroHPC Consortium

Quantum Software Engineering Challenges

Modeling and Analyses

High-level design methodologies for hybrid software systems

Scalable quantum software maintenance and evolution

Intelligent code generation and orchestration

Programming Paradigms

Complexity of circuit

Composable and reusable quantum software

Abstractions for quantum software

Testing and Debugging

Efficient test oracles

Test scalability

From simulators to real quantum computers

Test strategies

Software Development Process

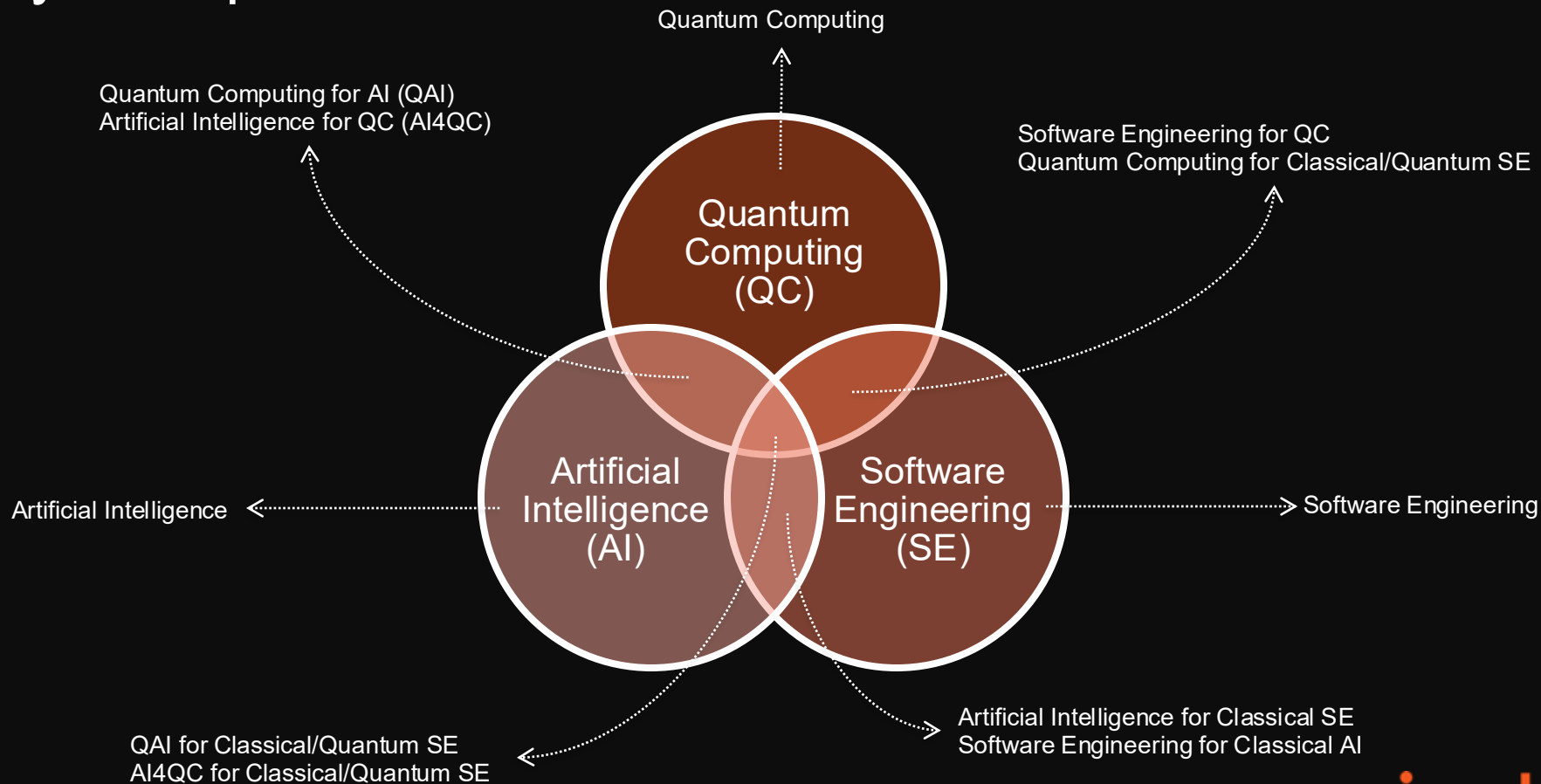
Managing iterative development

Risk management

Project management

Do we even need quantum software requirements engineering?

My Group's Focus

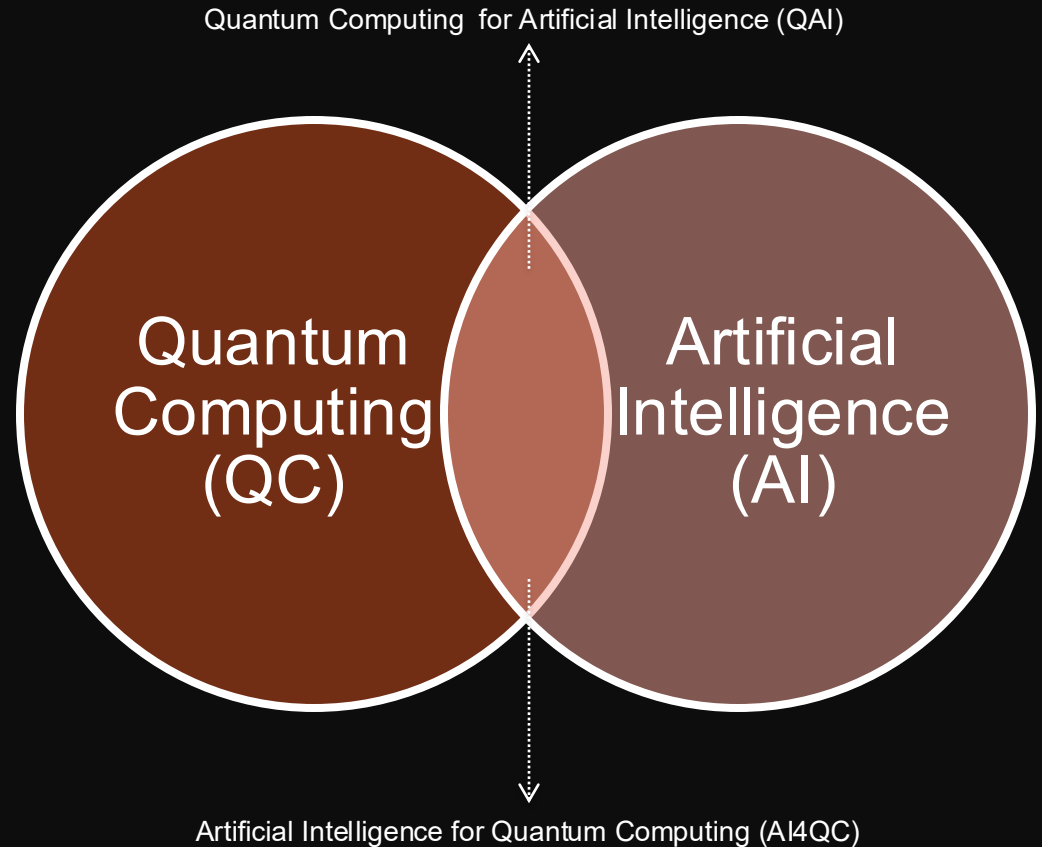


QAI enhances classical AI techniques:

- 1) “Quantize” a part of classical AI
- 2) Fully quantum AI

QAI examples:

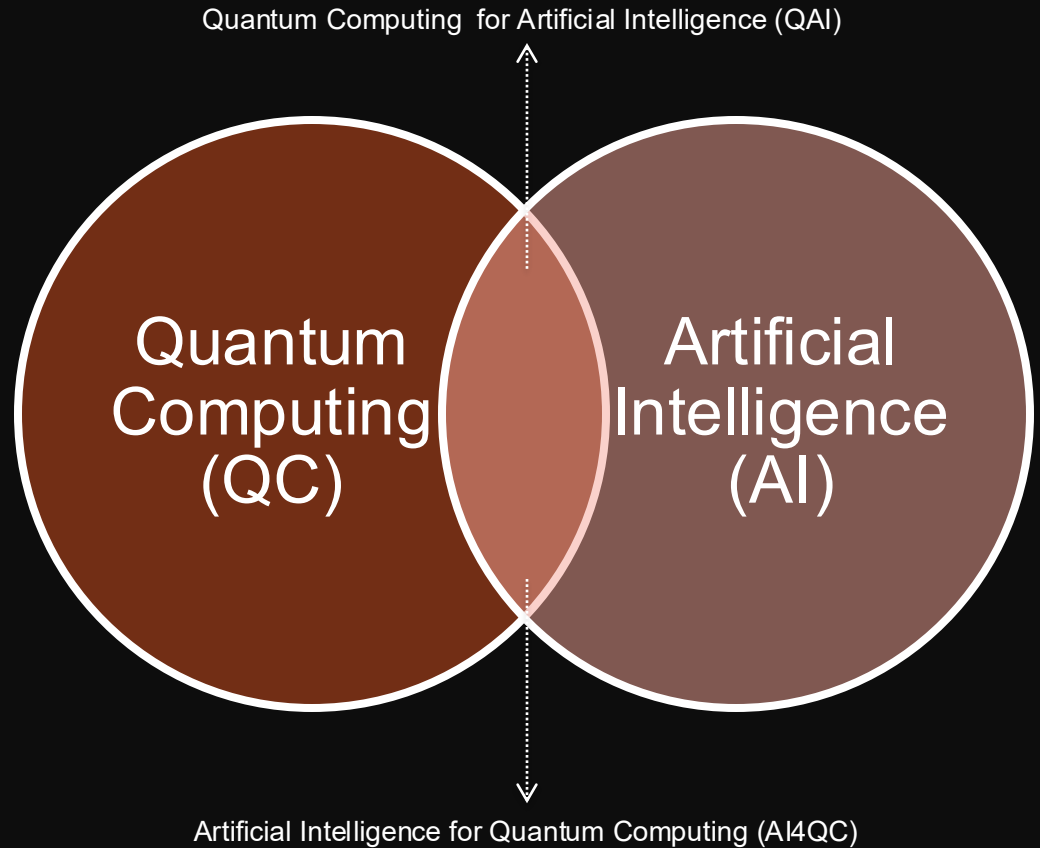
- 1) Quantum annealing and quantum approximate optimization algorithms
- 2) Quantum reservoir
- 3) Quantum diffusion models

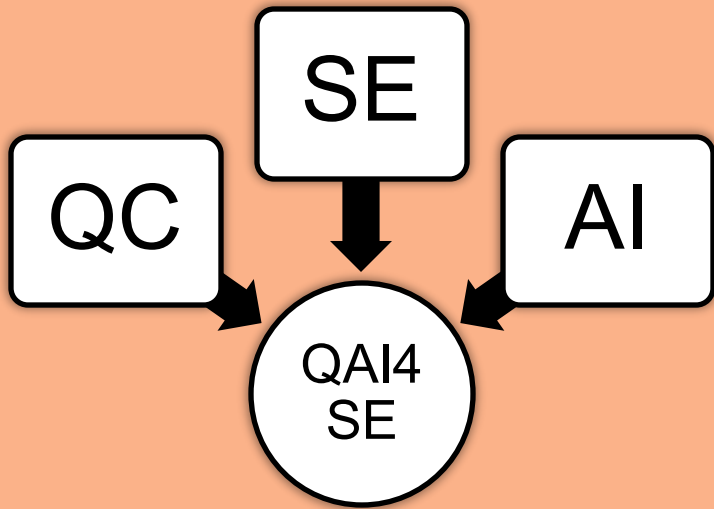


AI4QC applies classical AI techniques to enhance some QC activity

AI4QC examples:

- 1) Noise reduction
- 2) Quantum software engineering
- 3) Circuit design with large language models





Quantum Extreme Learning Machines for Testing Industrial Elevator Software

(QUELL)



Industrial Context: Orona, Spain

Orona

- Develop and maintain elevators
- Software in the loop testing, hardware in the loop testing, etc



Elevator attributes

- Safety
- Quality of service (QoS)
- ...

Elevate

- Performance analysis
- Simulation with visual display
- Building, elevator and passenger data

ELEVATE						
Time (hrs:min:sec)	00:02:43	Direction	-	-	^	^
AWT (s)	8.8	Position (m)	0.00	22.80	0.02	
ATT (s)	18.8	Speed (m/s)	0.00	0.00	0.13	
		Load (kg)	0	0	0	
Floor Name	People Waiting	Landing Calls	Car 1	Car 2	Car 3	
Level 8	0					
Level 7	0					
Level 6	0					
Level 5	0					
Level 4	0					
Level 3	0					
Level 2	1	▲				
Level 1	0					

Application Context

- Elevator software testing
- Classical machine learning-based approach

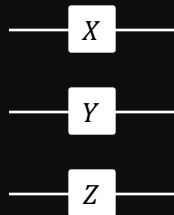
Study quantum machine learning in this context

simula

Background - Quantum Gates

Pauli gates:

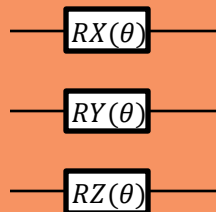
It rotates a qubit around x , y , or z axis with π radians



Encoding

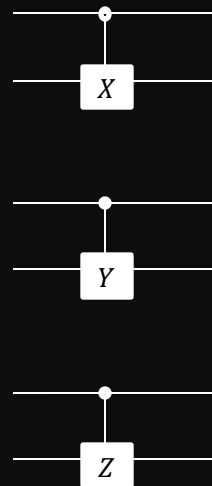
Rotation gates:

It rotates a qubit around x , y , or z axis with θ radians



Control gates:

If the control qubit is $|1\rangle$, the target qubit rotates around x , y , or z axis with π radians



QUELL – Encoder Types

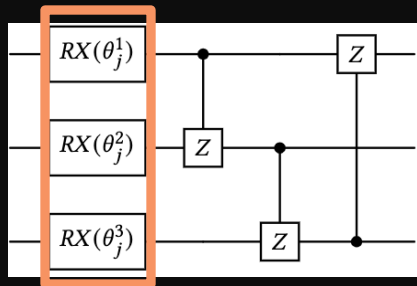
Passenger Traffic Data

Features, e.g.,
number of upward
calls

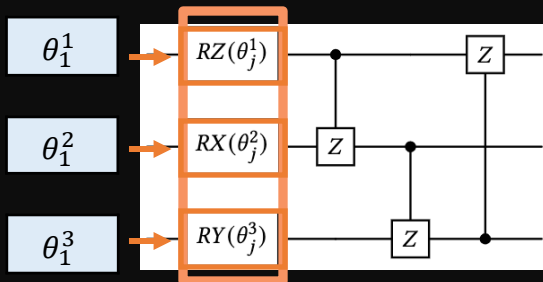
Time	F_1	F_2	F_3
tw_1	s_1^1	s_1^2	s_1^3
...	...	...	...
tw_p	s_p^1	s_p^2	s_p^3

Time
window of 5
min

Time	F_1	F_2	F_3
tw_1	θ_1^1	θ_1^2	θ_1^3
...	...	...	...
tw_p	θ_p^1	θ_p^2	θ_p^3



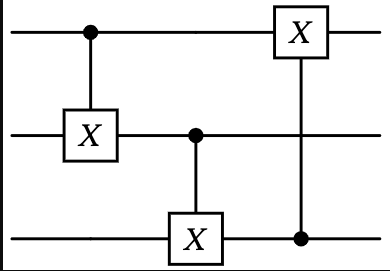
Determined hardware efficient
(DHE) encoder



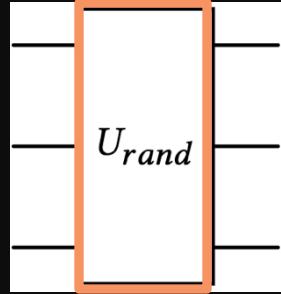
Randomized hardware efficient
(RHE) encoder

- Encoders process input data by parameterizing the **Rotation Gate**.
- To avoid multiple values being encoded in the same state, min-max **normalization** is used to scale feature values to a range of **0 to π radians**.
- Feed normalized feature values of **each time window** into the quantum encoder.

QUELL – Reservoir Types

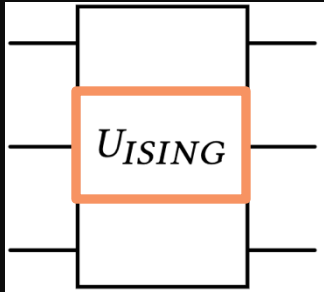


CNOT reservoir

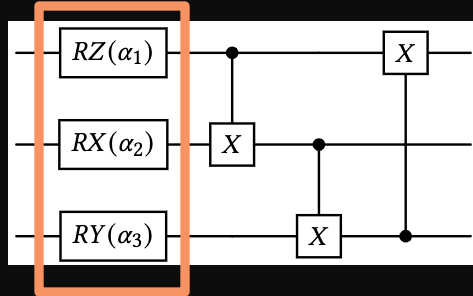


Harr random (Harr) reservoir

- Gate angles and coefficients are randomly assigned.

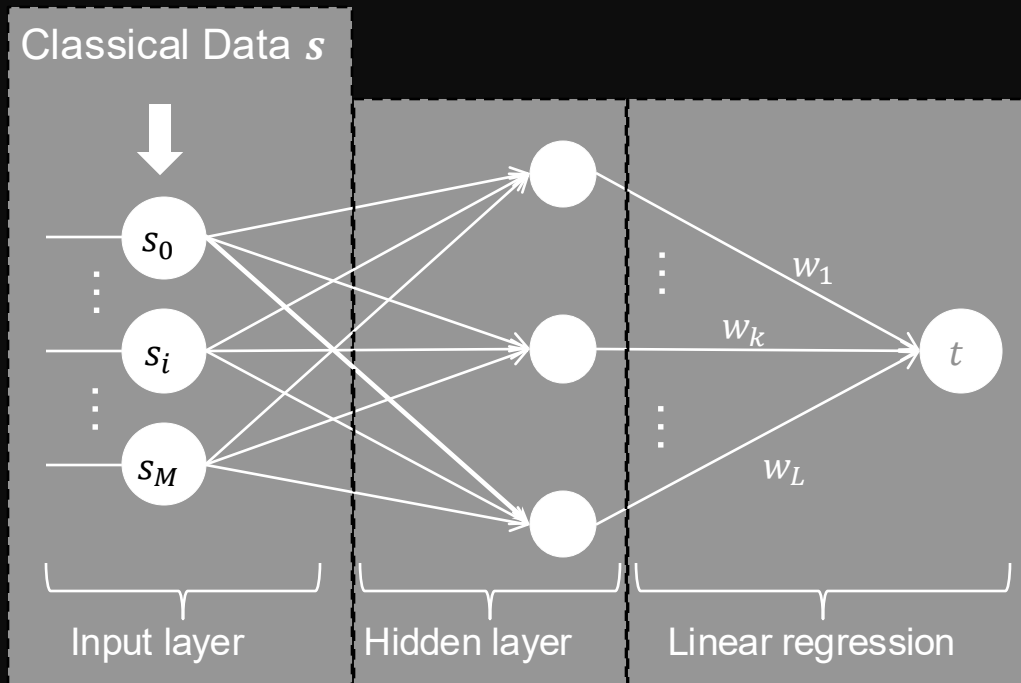


Ising Mag Traverse (ISING) reservoir



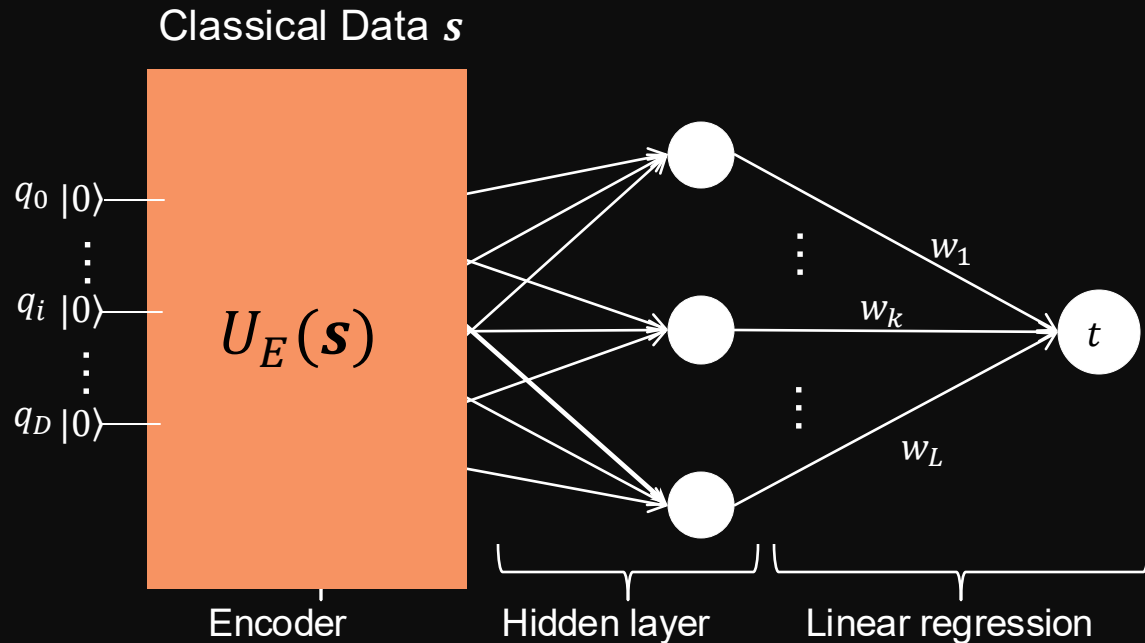
Rotation reservoir

Classical Extreme Learning Machines



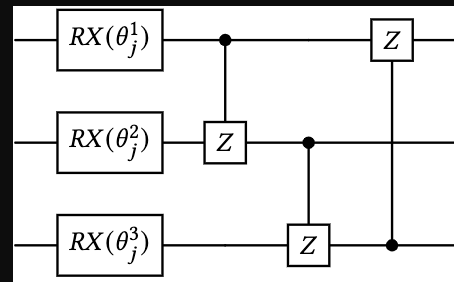
- Feedforward neural network
- Classical data into the input layer
- Hidden layer: **fixed** and **randomly** assigned weights and biases
- Train the **linear regression model** on the output layer's weights to predict the target value

Classical to Quantum Extreme Learning Machines



Encoder

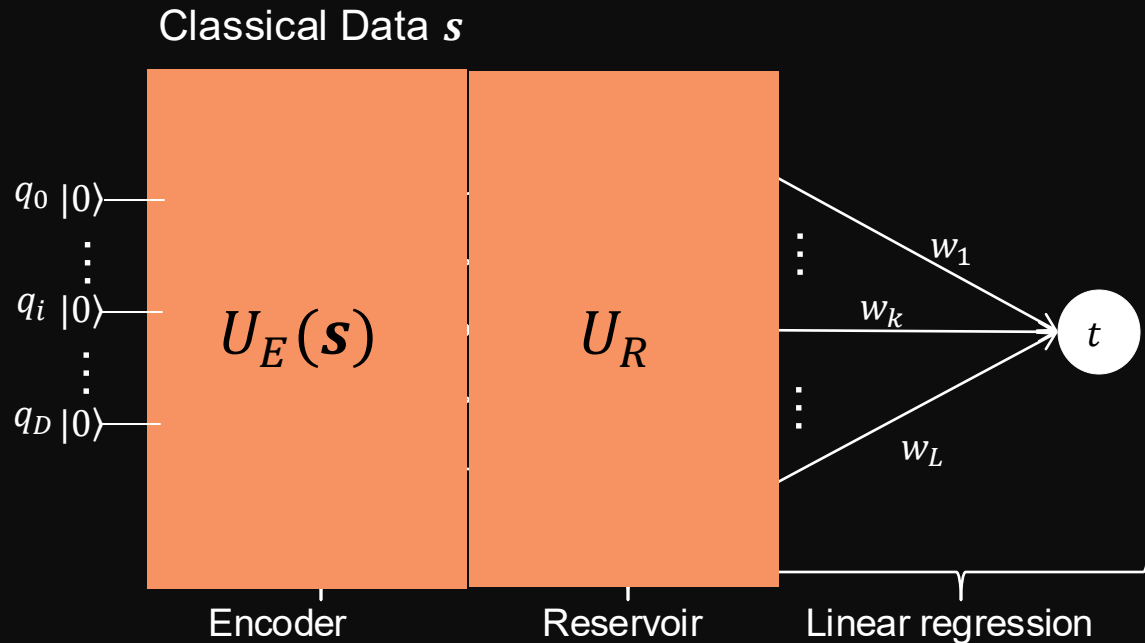
Maps classical data into high dimensional quantum states



Determined hardware
efficient **encoder**

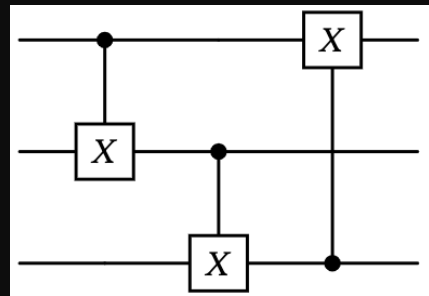
simula

Classical to Quantum Extreme Learning Machines



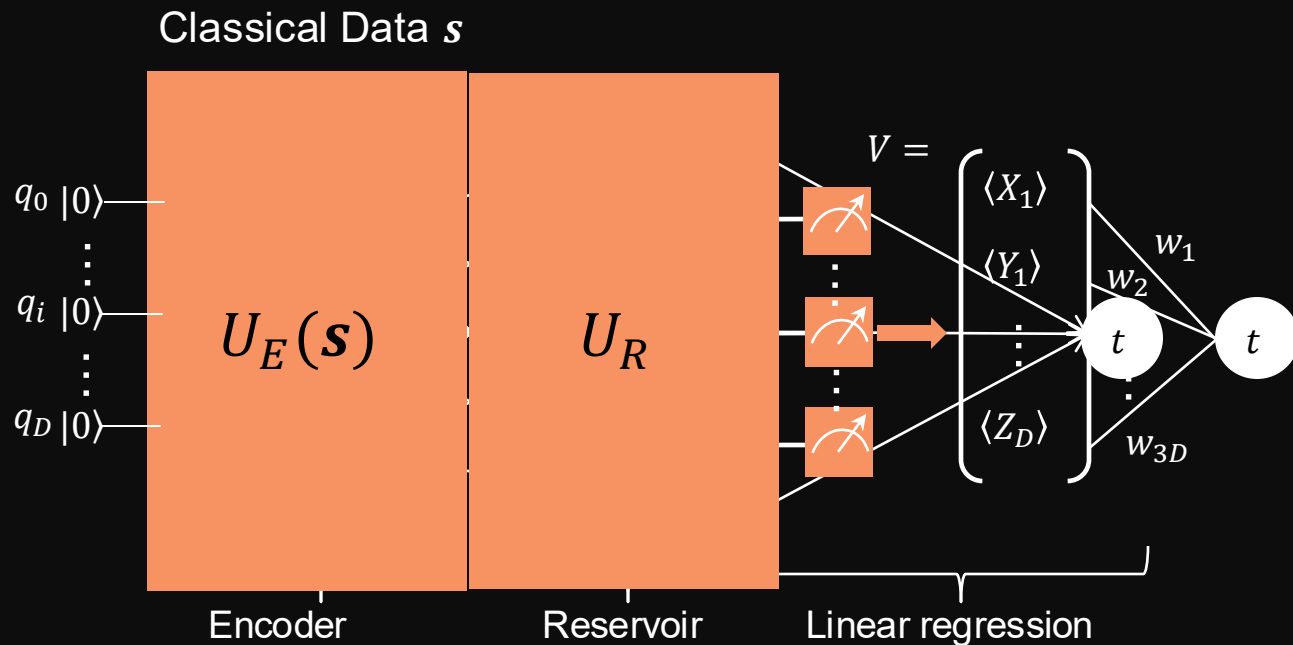
Quantum Reservoir

Processes the encoded quantum state



CNOT reservoir

Classical to Quantum Extreme Learning Machines



Training

Read qubits

Apply linear regression

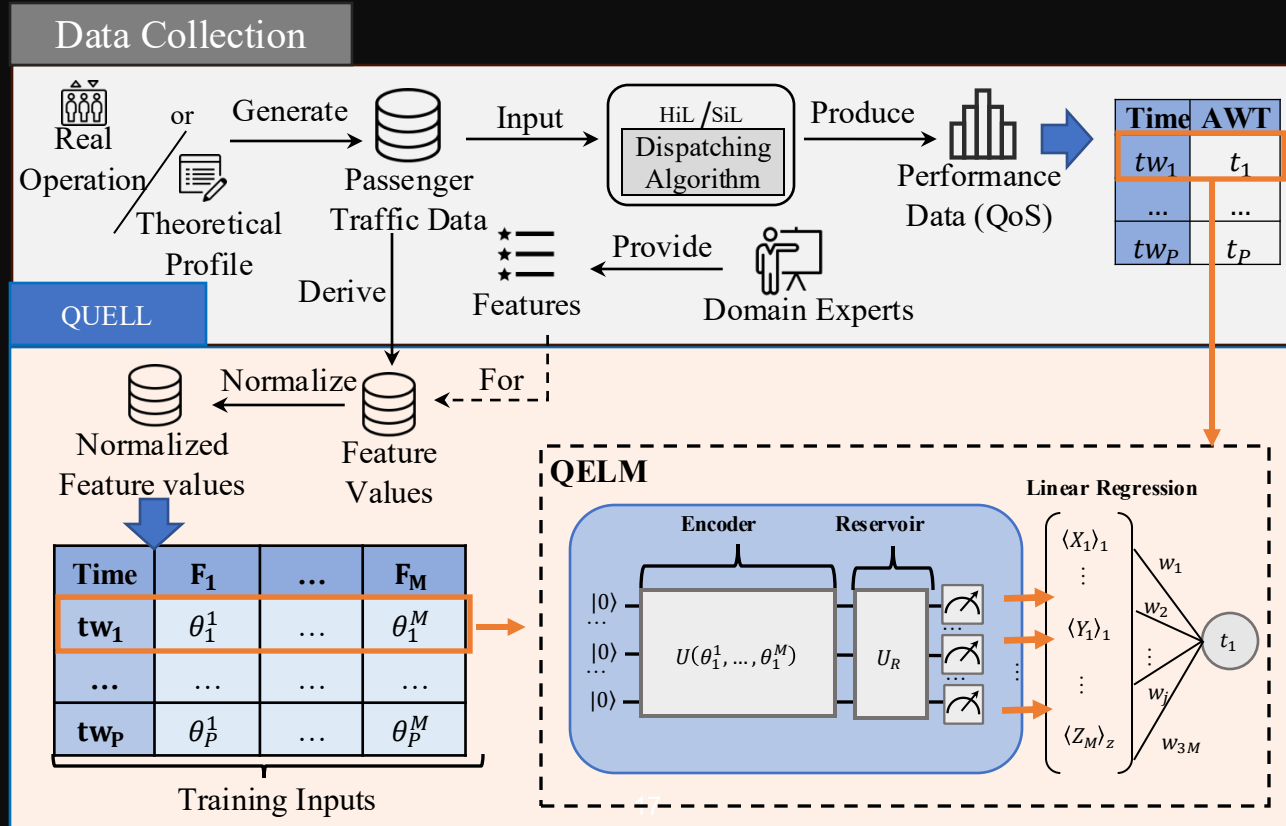
Benefits

Efficient linear regression training with fewer features while maintaining good prediction quality.

Enables applications that require predictions in real-time

simula

Overall Approach



Key Results and Findings

Results

Evaluation with real operational data and existing classical machine learning techniques at Orona

QUELL with few features outperforms QUELL with the maximum number of features (10 in our context)

For the same prediction task in our industrial context, QUELL outperforms classical machine-learning approaches

Applications

Runtime predictions during elevators' real operation

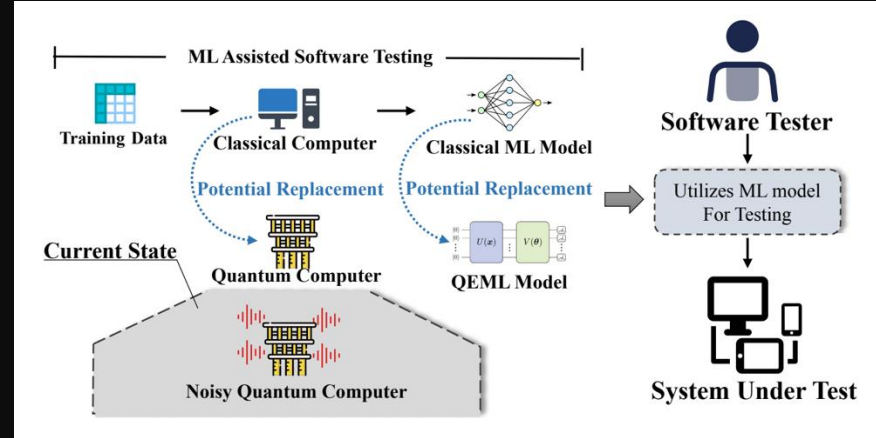
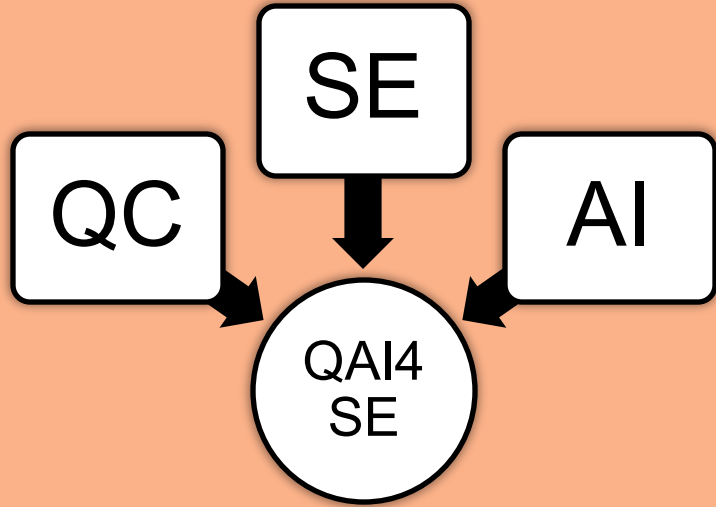
Integration into existing digital twins of elevators

Future Directions

Dealing with noise

Build new quantum encoder and reservoir types

Assessing Quantum Extreme Learning Machines for Software Testing in Practice



Cancer Registry of Norway

- Population-based, national coverage
- Covers 5.5 million people
- Compulsory reporting of cancer since 1952
- 38,265 incident cancer cases in 2020
- 1.7 million individuals with cancer in the database
- Personal identification number – ensures correct:
 - Cancer counts
 - Cancer rates (rate per 100,000 men and women per year)
 - Linkage with other sources and registries
 - Follow up of patients for survival analysis
- Completeness 98.6% of all cancer cases registered



Cancer in Norway 2022

Cancer incidence, mortality, survival and prevalence in Norway

Cancer in Norway 2022

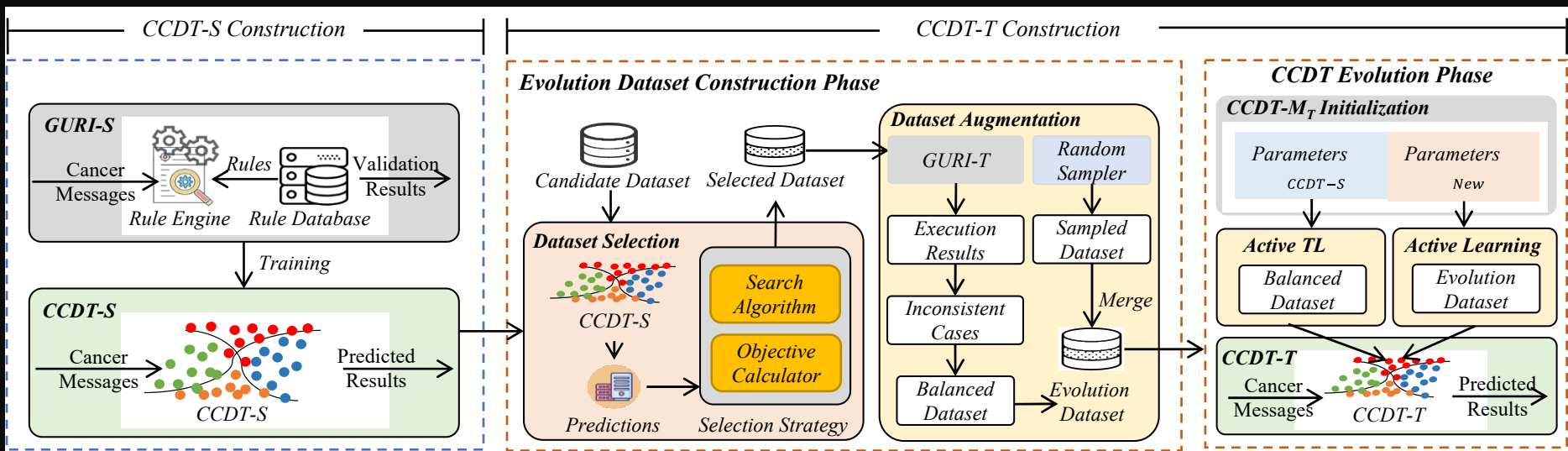
Table S.1: Number and age-standardised rates of new cases by primary site and sex, 2022

ICD-10	Site	Cases			Age-standardised rates			
		Males	Females	Total	Norwegian std.		World std.	
					Males	Females	Males	Females
C00-96	All sites	20 487	17 778	38 265	708.1	574.7	360.2	325.9
C00-14	Mouth, pharynx	469	227	696	16.2	7.3	9.0	4.1
C00	Lip	50	41	91	1.7	1.3	0.7	0.5
C02-06	Oral cavity	134	98	232	4.7	3.1	2.5	1.7
C07-08	Salivary glands	37	28	65	1.4	0.9	0.6	0.6
C09-10, C01, C14	Oropharynx	205	50	255	6.9	1.6	4.2	1.0
C11	Nasopharynx	19	4	23	0.6	0.1	0.4	0.1
C12-13	Hypopharynx	24	6	30	0.8	0.2	0.4	0.1
C15-26	Digestive organs	4 169	3 522	7 691	144.4	109.9	71.0	55.3
C15	Oesophagus	274	89	363	9.4	2.7	4.6	1.3
C16	Stomach	298	196	494	10.4	6.2	5.0	3.3
C17	Small intestine	144	107	251	5.1	3.4	2.8	1.9
C18	Colon	1 603	1 649	3 252	55.5	50.8	26.7	24.5
C19-20	Rectum, rectosigmoid	886	607	1 493	30.5	19.6	15.9	10.9
C21	Anus	28	63	91	0.9	2.1	0.5	1.2
C22	Liver	242	149	391	8.3	4.7	4.1	2.5
C23-24	Gallbladder, bile ducts	94	96	190	3.3	3.0	1.6	1.6
C25	Pancreas	523	503	1 026	18.2	15.4	8.5	7.4
C26	Other digestive organs	77	63	140	2.7	1.9	1.3	0.8
C30-34, C38	Respiratory organs	1 907	1 778	3 685	64.7	54.7	30.3	27.0
C30-31	Nose, sinuses	30	19	49	1.1	0.6	0.7	0.4
C32	Larynx, epiglottis	66	25	91	2.2	0.8	1.1	0.4
C33-34	Lung, trachea	1 804	1 730	3 534	61.2	53.1	28.3	26.1
C38	Heart, mediastinum and pleura	7	4	11	0.3	0.1	0.2	0.1
C40-41	Bone	31	36	67	1.1	1.3	1.0	1.2
C43	Melanoma of the skin	1 462	1 449	2 911	51.1	47.8	27.3	29.0
C44	Skin, non-melanoma	1 686	1 375	3 061	62.6	40.9	22.6	16.1
C45	Mesothelioma	72	22	94	2.5	0.7	0.9	0.4
C47	Autonomic nervous system	8	7	15	0.3	0.3	0.5	0.4
C48-49	Soft tissues	87	72	159	3.1	2.4	1.9	1.5
C50	Breast	23	4 224	4 247	0.8	144.1	0.4	91.6
C51-58	Female genital organs		1 770			58.3		34.9
C51-52, C57.3-9	Other female genital		136			4.3		2.1
C53	Cervix uteri		302			10.8		8.4
C54	Corpus uteri		817			26.1		14.3
C55	Uterus, other		7			0.2		0.1
C56, C57.0-4, C48.2	Ovary etc.		506			16.7		10.0
C58	Placenta		2			0.1		0.1
C60-63	Male genital organs	5 844		5 844	196.9		105.2	
C61	Prostate	5 474		5 474	183.6		94.1	
C62	Testis	286		286	10.4		9.6	
C60, C63	Other male genital	84		84	2.9		1.4	
C64-68	Urinary organs	2 015	775	2 790	69.3	24.6	34.4	13.3
C64	Kidney (incl. renal pelvis)	627	310	937	21.3	10.1	12.8	6.3
C65-68	Urinary tract	1 388	465	1 853	48.0	14.4	21.6	7.0
C69	Eye	64	27	91	2.3	0.9	1.4	0.7
C70-72	Central nervous system	456	532	988	16.0	17.8	11.0	12.2
C73	Thyroid gland	158	321	479	5.6	11.4	3.7	8.7
C74-75	Other endocrine glands	59	47	106	2.1	1.6	1.4	1.0
C76, C80	Other or unspecified	172	200	372	6.3	6.0	2.6	2.3
C81-96	Lymphoid/haematopoietic tissue	1 805	1 394	3 199	63.0	44.6	35.6	26.2
C81	Hodgkin lymphoma	85	68	153	3.0	2.4	2.4	2.2
C82-86, C96	Non-Hodgkin lymphoma	617	465	1 082	21.3	14.8	12.1	8.0
C88	Immunoproliferative disease	41	43	84	1.4	1.3	0.6	0.6
C90	Multiple myeloma	318	260	578	11.1	8.1	5.3	4.0
C91-95	Leukaemia	744	558	1 302	26.2	18.1	15.2	11.4

Benefit from Cyber-Cyber Digital Twins

- Cyber-cyber digital twins: complete malleability, true twins, simulation hierarchy*
 - Simulates socio-technical behaviours of medical coders, hospital professionals, labs, policymakers
 - Digital twin reduces interactions with the real system and facilitates various experiments without intervening the operation of the real system
- Coevolution of digital twin and the system

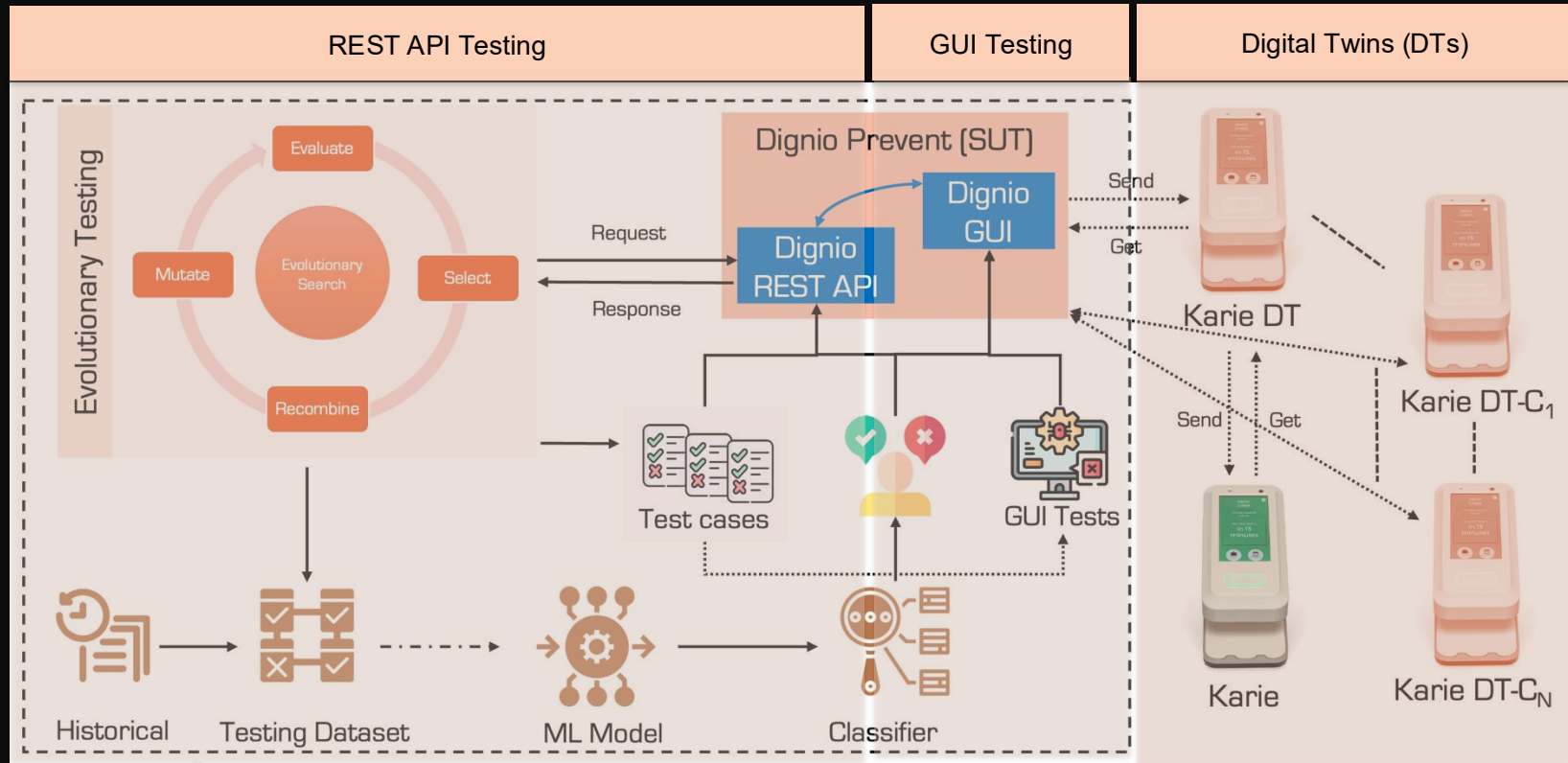
*John Ahlgren, Kinga Bojarczuk, Sophia Drossopoulou, Inna Dvortsova, Johann George, Natalija Gucevska, Mark Harman, Maria Lomeli, Simon MM Lucas, Erik Meijer, et al. 2021. Facebook's cyber-cyber and cyber-physical digital twins. In Evaluation and Assessment in Software Engineering. 1–9.



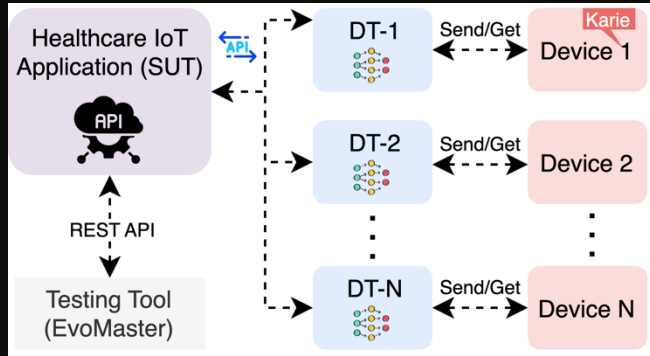
Oslo Kommune Healthcare Department

- **Objective:** Improve the software testing practice at City of Oslo (CoO)
 - Automated, systematic, and cost-effective testing
 - Reduce manual effort required for testing
 - Improve the quality of the current and future Welfare Technology Solutions (WTSs)

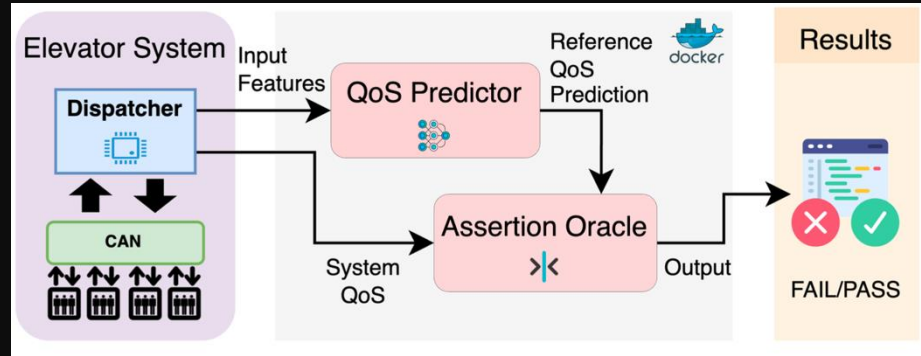
Digital Twin-based Testing Infrastructure for Oslo Kommune



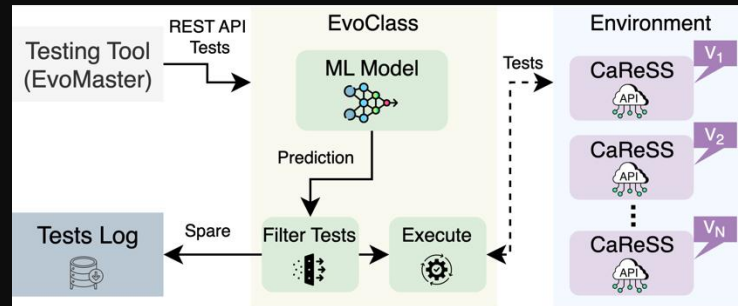
Software Testing Setup in Three Real-world Contexts



Oslo Kommune

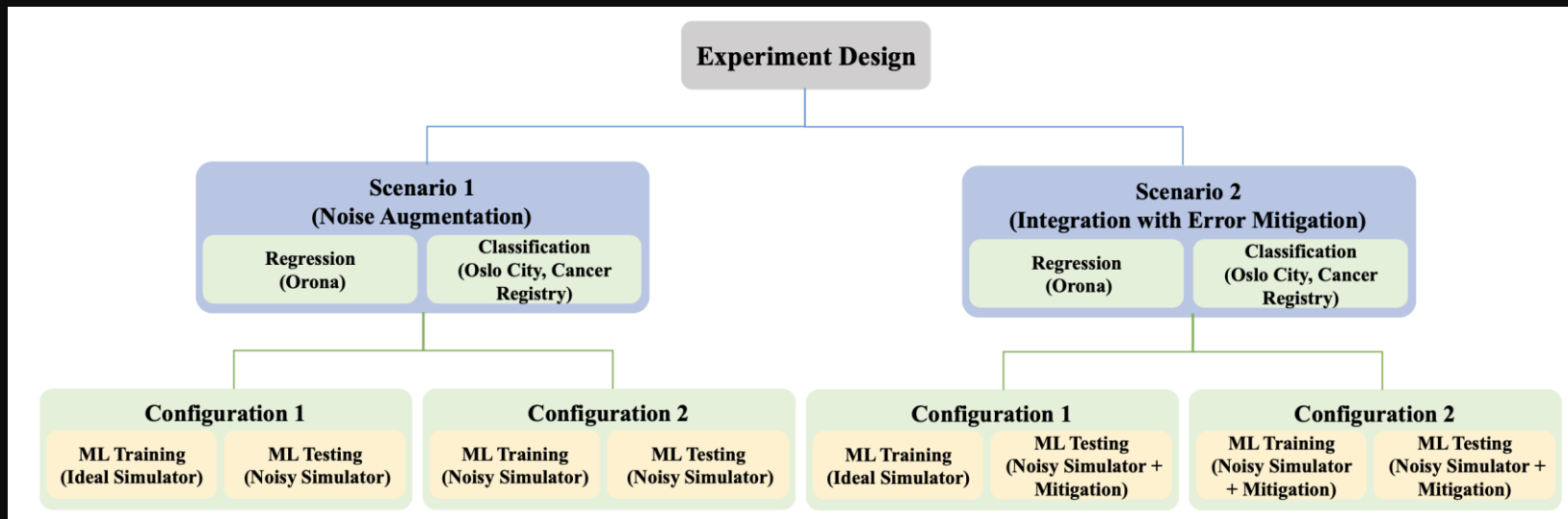


Orona



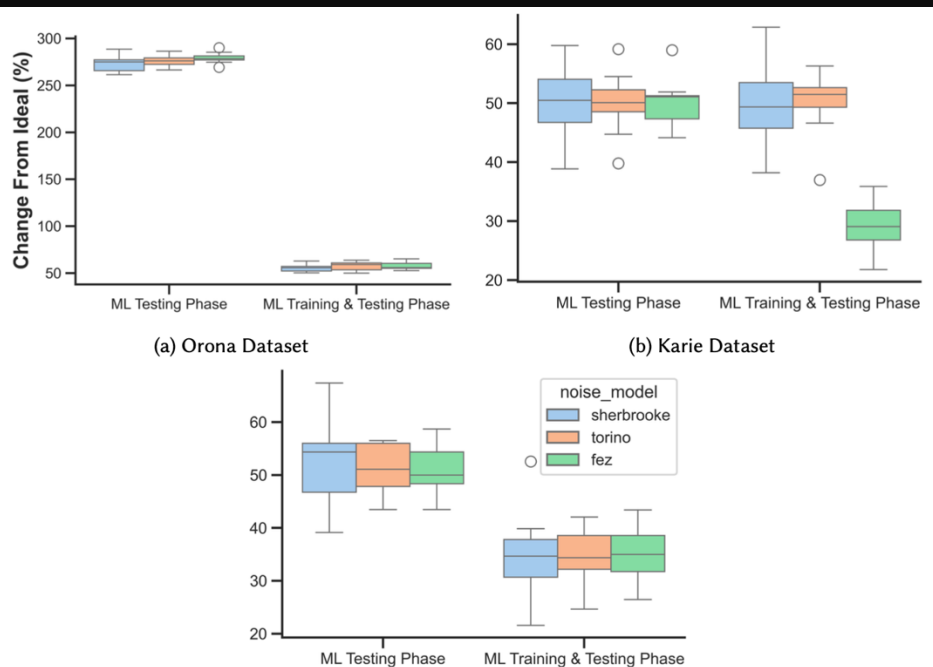
Cancer Registry

Setup of the Experiment



- (1) Picked the best encoder and reservoir from previous work
- (2) Tested Linear Regression, Logistic Regression, and Decision Tree Classifier

Results of Scenario 1



(1) QELMs struggle with noise

(2) Noise in the training and testing phases reduces its impact on model performance. However, the deviation from the ideal remains too large for practical use

(3) Uncertainty in prediction increases with the increase in qubits

Results of Scenario 2

(a) Integration with ZNE error mitigation

Dataset	Sherbrooke		Torino		Fez	
	T_N	TT_N	T_N	TT_N	T_N	TT_N
Orona	271.8	10.3	271.6	11.4	271.2	1.79
Karie	50.0	50.0	50.0	50.0	50.0	4.0
CaReSS	56.5	34.78	56.5	34.78	56.5	34.78

(b) Integration with Q-LEAR error mitigation

Dataset	Sherbrooke		Torino		Fez	
	T_N	TT_N	T_N	TT_N	T_N	TT_N
Orona	307.3	18.7	301.4	22.3	310.0	40.2
Karie	50.0	3.0	50.0	3.0	34.0	3.0
CaReSS	50.0	4.3	56.0	4.3	1.0	0.0

(1) Integrating error mitigation methods enhances the noise resistance of QELM

(2) Non-ML-based methods like ZNE are constrained by qubit size and noise models

(3) ML-based methods like Q-LEAR excel in classification tasks but struggle with regression

(4) Need tailored error mitigation strategies to optimize the performance of QELM models for real-world applications

Conclusions and Way Forward

- Opportunities exist to speed up classical search and optimization and AI techniques with quantum computing.
- Applying classical search and optimization and AI techniques to quantum computing, including quantum circuit design and noise learning, is promising.
- Quantum extreme learning machines (QELMs) work well with ideal simulators but struggle on real quantum computers.
- Research is needed to improve QELM performance under noise to enable practical applications.