Quantum Machine Learning

16.887/EM.427 Technology Roadmapping and Development
Fall 2023

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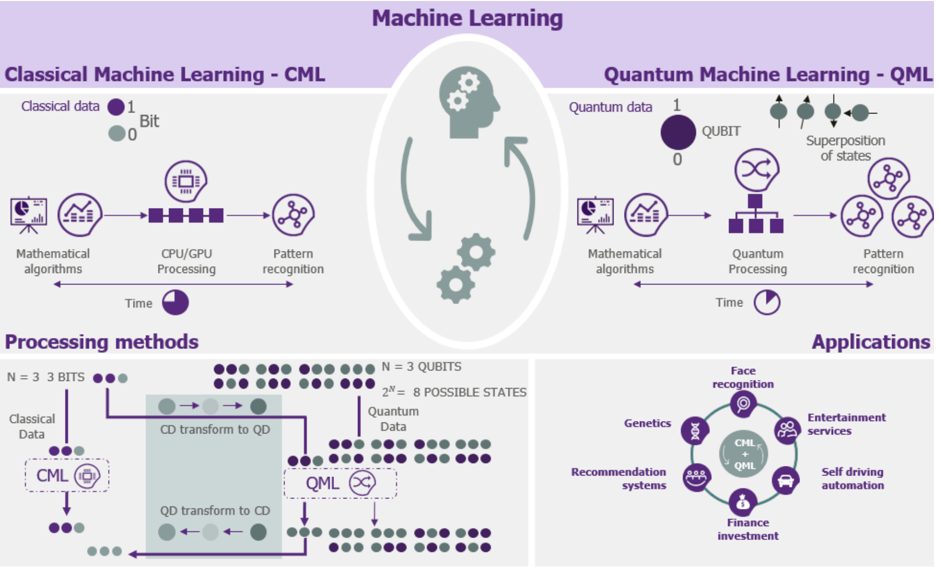
Roadmap Overview

Quantum Machine Learning (QML)

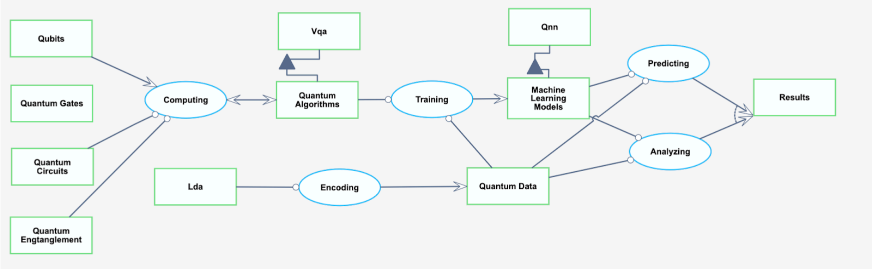
Technology classification: **Process Information**

- QML," which merges the high-speed data processing capabilities of "quantum computing" with "machine learning," is garnering attention for the future.



Quantum Machine Learning (QML) intertwines quantum computing and machine learning, presenting a novel approach to handling computational tasks and data processing. Quantum computers, utilizing quantum bits (qubits), operate fundamentally differently from classical computers, which use classical bits (Bit) that represent either "0" or "1". Qubits, on the other hand, can represent both "0" and "1" simultaneously through a phenomenon known as superposition. Various types of qubits, such as "superconducting qubits" and "optical qubits," achieve superposition differently, impacting the theory and apparatus used in calculations.

OPM



DSM Allocation (interdependencies with others roadmaps)

	Qubits	Quantum Gates	Quantum Data	Quantum Algorithms	ML Models	Results	Quantum Circuits	Quantum Entanglement	VQA	Quantum NN	LDA
Qubits	-	X	-	X	-	-	X	X	-	-	-
Quantum Gates	X	-	-	X	-	-	X	-	-	-	-
Quantum Data	-	-	-	X	X	-	-	-	-	-	-
Quantum Algorithms	X	X	X	-	X	X	X	-	X	X	-
ML Models	-	-	X	X	-	X	-	-	X	X	X
Results	-	-	-	X	X	-	-	-	-	-	-
Quantum Circuits	X	X	-	X	-	-	-	X	X	X	-
Quantum Entanglement	X	-	-	-	-	-	X	-	-	-	-
VQA	-	-	-	X	X	X	X	-	-	-	-
Quantum NN	-	-	-	X	X	X	X	-	-	-	-
LDA	-	-	X	-	X	X	-	-	-	-	-

ML FOMs and Technology Evolution

FOMs:

Computational Speedup [FLOPS]

Learning Efficiency (Loss Value) [%]

Model Accuracy [%]

Scalability [data per seconds]

Versatility [N]

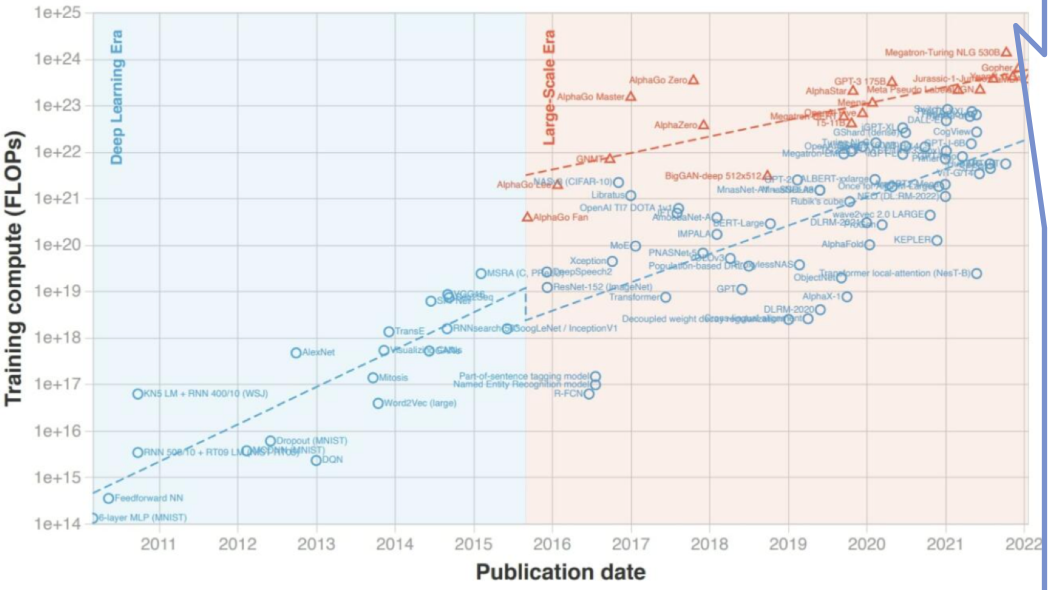
Generalization [%]

Resource Efficiency [Value]

CAPEX [USD]

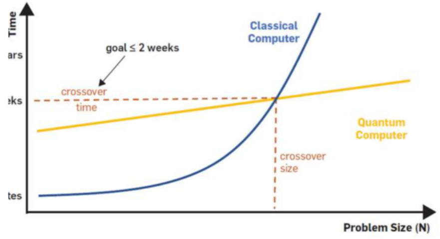
OPEX [USD]

[1] Machine learning needs more large scale data processing technology

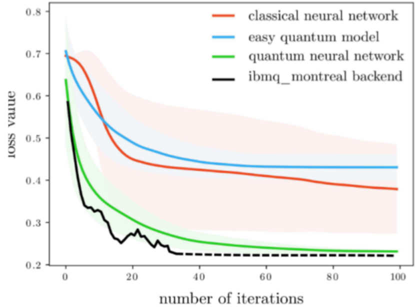


Quantum ML era is coming?

[2] QC Evolution improves ML performance



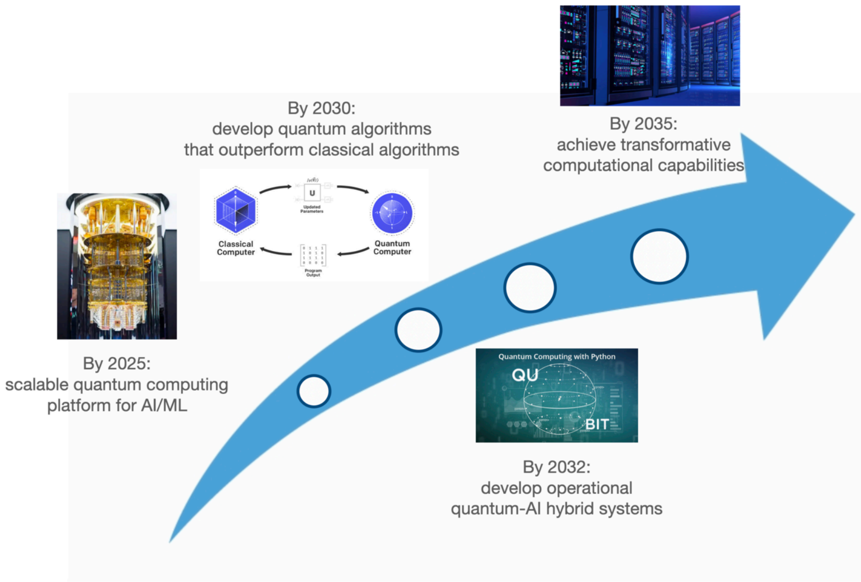
[3] Q Algorithm Evolution improves ML Efficiency



Reference:
[1] Brian Wang, Three Eras of Machine Learning and Predicting the Future of AI, Next BIG Future, 2022
[2] Florian Meyer, ETH Zurich , On Realistically Achieving Quantum Advantage, *Communications of the ACM* , 2023
[3] Hsin-Yuan Huang, et al. Power of data in quantum machine learning, Power of data in quantum machine learning, nature communications 2021

Technology Strategy Statement

Our goal is to lead in integrating Quantum Computing with Artificial Intelligence and Machine Learning, aiming for groundbreaking computational advances by 2035, utilizing quantum computers to tackle complex AI/ML challenges beyond the scope of classical computing.



- 1. Quantum Algorithm Development: Our focus is on crafting and improving AI/ML-centric quantum algorithms, targeting quantum machine learning, optimization, and pattern recognition, to surpass classical algorithms by 2030.

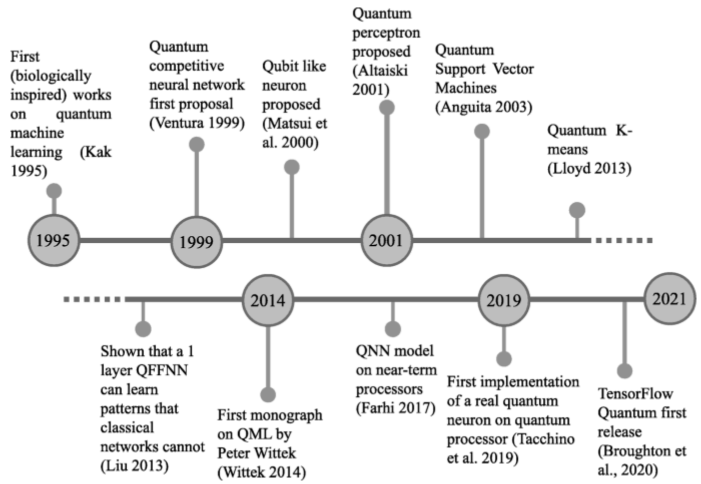
- 2. Quantum Hardware Advancement: In collaboration with quantum tech leaders, we aim to enhance quantum hardware, focusing on qubit coherence, error correction, and scalability, to achieve a robust quantum computing platform for AI/ML by 2025.

- 3. Quantum-AI Hybrid Systems: Given the emerging state of quantum computing, we're dedicated to developing hybrid quantum-classical systems, serving as an interim solution for AI/ML advancements and a step towards fully quantum solutions.

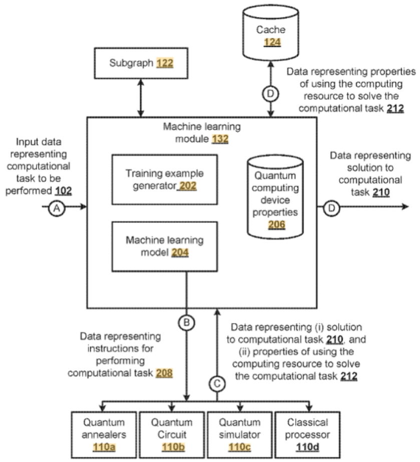
Key Publications & Patents for Basic Survey

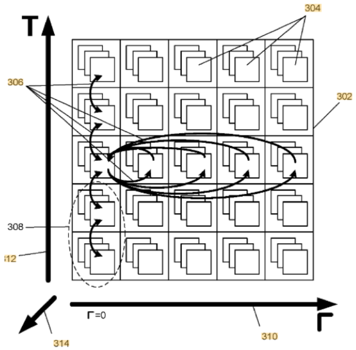
- Quantum machine learning (QML) explores synergies between machine learning and quantum computing, focusing on how quantum computing can advance intelligent data mining, despite facing development and application challenges.
- The evolution of quantum machine learning can be divided into two phases: initial model formulation from the mid-90s to 2007, and the current phase emphasizing implementation. Key developments include early biologically inspired quantum neural networks and recent advances like the release of Tensorflow Quantum in 2020, marking significant progress in the field.

[1] Genealogy of Quantum Machine Learning Publications



[2] [3] Patents: Quantum computing machine learning module & Optimization



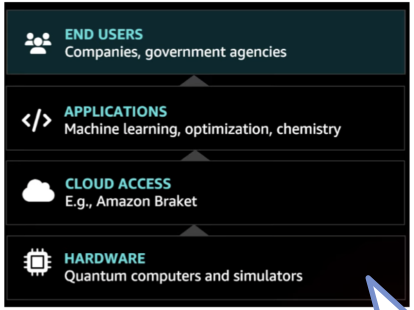


Reference:
[1] Leonardo Alchieri, et al. An introduction to quantum machine learning: from quantum logic to quantum deep learning, Quantum Machine Intelligence, 2021
[2] Quantum computing machine learning module, US10275721B2, Accenture Global, 2022
[3] Quantum assisted optimization, US11449760B2, Google, 2022

Alignment with Company Strategic Drivers

The 'Company' aims to launch a Quantum Machine Learning SaaS product, leveraging a mix of purchased and custom-developed Quantum Computing hardware to power advanced algorithms for diverse B2B applications

Quantum Machine Learning (QML) System Stack with HW FOMs



FOM	Description	Equation	Nominal Value
Number of Qubits	The fundamental unit of computation for a quantum computer. The more qubits in a quantum computer, the greater its processing power	N/A	433 (and improving)
Quantum Speed of computation	The speed of the time taken by a time taken by a quantum algorithm relies on the number of qubits and its quality, usually refers stable qubits	Stable Qubits = $N * Q$ N: number of qubits Q: average quality of qubits	128
Quantum Volume	A measure of the effective size and error rate of a quantum computer. It takes into account both the number of qubits and the quality of the operations on those qubits.	Volume = min (n, d^n) n= number of qubits d= number of gates	64
Quantum Error Rate	Represents the probability of an error occurring during a quantum operation.	Rate=$\frac{Number\ of\ Errors}{Total\ of\ Operations}$	< 5%
Quantum Gate Fidelity	Measures the accuracy of quantum gate operations. It's the probability that a quantum gate will produce the correct output state.	Fidelity=$\frac{Number\ of\ Correct}{Total\ of\ Operations}$	>99%

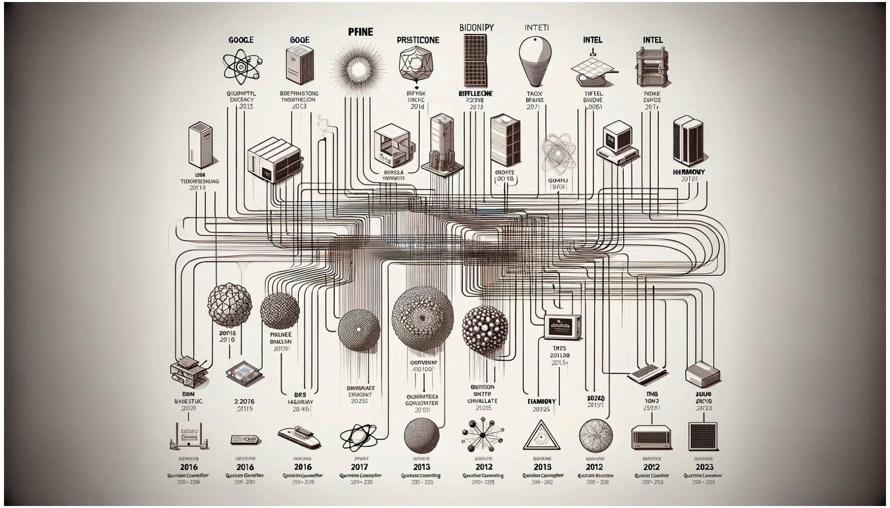
Company Strategic Drivers

Item	Company Strategic Driver	1QCAIML Target(s)	Alignment RAG Status
1	To secure the highest fidelity computing platform to deploy our Quantum Machine Learning algorithms for B2B customers	**> 16 Qubit machine: This is a primary consideration for evaluating the raw performance capability of our QC hardware**	Aligns
		> 99.9& Qubit fidelity: This is the more significant factor when evaluating the efficiency of our QC hardware	Aligns
2	To develop the best in class QML algorithms for our B2B customers to rely on for their critical business needs	**> 1% market share of machine learning SaaS business**: To secure enough revenue to capture a significant chunk of the nascent $1B QML market	At Risk
3	To secure the most cost-stable hardware for our nascent SaaS business	**< 25% variability in cost of hardware acquisition**: This is a key consideration in proving out our B2B offering of QML	Does not Align

R&D Projects, Company Positioning vs. Competition with FOMs

- Various architectures (Superconducting, ion, photons, etc.) are being explored by vendors, focusing on qubits count, fidelity, and Quantum Volume as key R&D metrics.”
- "Among these, Quantinuum's H1-1 aligns with our Strategic Driver requirements, standing out in a competitive field.

Correlation Map of Quantum Computer R&D Projects



Reference: Created the above correlation diagram in Open AI DALL-E 2 from a list of Circuit-based quantum processors <https://en.wikipedia.org/wiki/List_of_quantum_processors#Circuit-based_quantum_processors>

Positioning and Competitive Technology List

Quantum Hardware	Manufacturer	Error rate / Fidelity [%]	Physical Qubits [#]	Quantum Volume [#]	Release Year
Forte	IonQ	99.98 (1 qubit) 98.5-99.3 (2 qubit)[23]	32		2022
Maxwell	M Squared Lasers	99.5 (3-qubit gate) 99.1 (4-qubit gate)[28]	400		2022
H2	Quantinuum	99.997 (1 qubit) 99.8 (2 qubit)	32	65,536	2023
H1-1	Quantinuum	99.996 (1 qubit) 99.8 (2 qubit)	20	524,288	2022
H1-2	Quantinuum	99.996 (1 qubit) 99.7 (2 qubit)	12	4096	2022
Soprano	Quantware	99.9 (single-qubit gates)	5		2021
Contralto	Quantware	99.9 (single-qubit gates)	25		2022
Agave	Rigetti	96 (Single-qubit gates) 87 (Two-qubit gates)	8		2018
Acorn	Rigetti	98.63 (Single-qubit gates) 87.5 (Two-qubit gates)	19		2017
Aspen-1	Rigetti	93.23 (Single-qubit gates) 90.84 (Two-qubit gates)	16		2018
Aspen-4	Rigetti	99.88 (Single-qubit gates) 94.42 (Two-qubit gates)	13		2019
Aspen-7	Rigetti	99.23 (Single-qubit gates) 95.2 (Two-qubit gates)	28		2019
Aspen-8	Rigetti	99.22 (Single-qubit gates) 94.34 (Two-qubit gates)	31		2020
Aspen-9	Rigetti	99.39 (Single-qubit gates) 94.28 (Two-qubit gates)	32		2021
Aspen-10	Rigetti	99.37 (Single-qubit gates) 94.66 (Two-qubit gates)	32		2021
Aspen-11	Rigetti	99.8 (Single-qubit gates) 92.7 (Two-qubit gates CZ) 91.0 (Two-qubit gates XY)	40		2021
Aspen-M-1	Rigetti	99.8 (Single-qubit gates) 93.7 (Two-qubit gates CZ) 94.6 (Two-qubit gates XY)	80	8	2022
Aspen-M-2	Rigetti	99.8 (Single-qubit gates) 91.3 (Two-qubit gates CZ) 90.0 (Two-qubit gates XY)	80		2022
Aspen-M-3	Rigetti	99.9 (Single-qubit gates) 94.7 (Two-qubit gates CZ) 95.1 (Two-qubit gates XY)	80		2022

Technical Model: Morphological Matrix and Sensitivity Analysis with FOMs

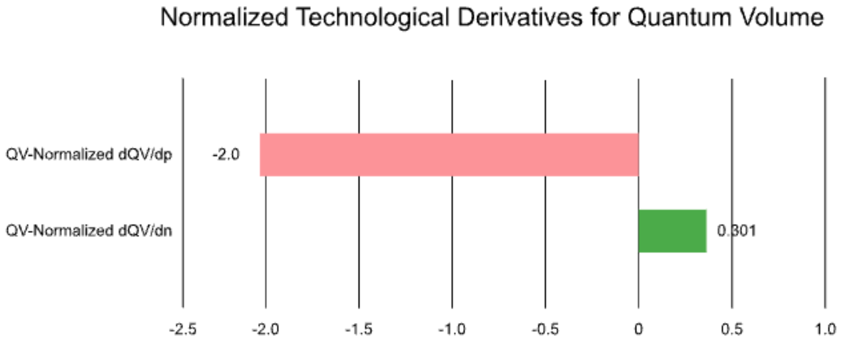
- Our selection of the H1-1 device, with its superior Quantum Volume, is based on a detailed morphological matrix comparison.
- Quantum Volume (QV), a balance of qubit count and error rate, is the primary metric for evaluating quantum computer performance.

Morphological Matrix

Variable	Unit	Description	Option		
			1 (H2)	2 (H1-1)	3 (H1-2)
n	[]	Number of qubits in the machine	32	20	12
p	[%]	Error rate of qubits (sometimes expressed as fidelity=1-p)	0.003-0.2	0.004-0.2	0.004-0.3
Quantum Volume	[]	A measure of the effective size and error rate of a quantum computer	2^16	2^19	2^12

Sensitivity Analysis

Number of Qubits (n)	Error Rate (p)	Quantum Volume (QV)	dQVdn = dQV/dn	dQVdp = dQv/dp	Norm(dQVdn)	Norm(dQVdp)
64	0.001	1.84099E+19	5.54192E+18	-3.68566E+19	0.3010	-2.0020
64	0.005	1.82627E+19	5.49763E+18	-3.6709E+19	0.3010	-2.0101
64	0.01	1.80797E+19	5.44252E+18	-3.65246E+19	0.3010	-2.0202
64	0.05	1.66482E+19	5.0116E+18	-3.50488E+19	0.3010	-2.1053
64	0.1	1.49419E+19	4.49795E+18	-3.32041E+19	0.3010	-2.2222
128	0.001	3.39602E+38	1.0223E+38	-6.79884E+38	0.3010	-2.0020
128	0.005	3.36888E+38	1.01413E+38	-6.77162E+38	0.3010	-2.0101
128	0.01	3.33511E+38	1.00397E+38	-6.73759E+38	0.3010	-2.0202
128	0.05	3.07105E+38	9.24478E+37	-6.46536E+38	0.3010	-2.1053
128	0.1	2.75629E+38	8.29725E+37	-6.12508E+38	0.3010	-2.2222
256	0.001	1.15561E+77	3.47872E+76	-2.31353E+77	0.3010	-2.0020
256	0.005	1.14637E+77	3.45092E+76	-2.30426E+77	0.3010	-2.0101
256	0.01	1.13488E+77	3.41632E+76	-2.29268E+77	0.3010	-2.0202
256	0.05	1.04502E+77	3.14583E+76	-2.20005E+77	0.3010	-2.1053
256	0.1	9.37916E+76	2.82341E+76	-2.08426E+77	0.3010	-2.2222



*Where n is number of qubits, and p is the quantum error rate (FOMs)

*Taking a nominal design point of n=128 Qubits and p=5%;

$$\frac{dQ_v}{dn} = 2^n log(2)(1-p)^2 \rightarrow \frac{dQ_v}{dn} = 2.128689 \times 10^{38}$$

$$\frac{dQ_v}{dp} = -2^{n+1}(1-p) \rightarrow \frac{dQ_v}{dp} = -6.465364 \times 10^{38}$$

*Normalization equations

$$\frac{\frac{dQ_v}{dn}}{Q_v} = log(2) = 0.301$$

$$\frac{\frac{dQ_v}{dp}}{Q_v} = -\frac{2}{1-p} \approx -2$$

Financial Model

- ➢ The Quantum Machine Learning market, while currently crowded and competitive, is expected to consolidate, leaving **a few dominant players with an estimated 34.8% market share by 2035**.
- ➢ Our analysis projects these target companies to follow investment trends akin to today's ML giants, resulting in a **Net Present Value (NPV) of $32,211 million**, as detailed in the following simulation results.

Comparable Companies Analysis

Machine Learning Industry Comparables

Competitors (figures in $ thousands)	Sales	Sales of ML %	ML Revenue	Market Share	Fixed Assets (TA-CA)	Fixed Assets /Sales	WC	WC /Sales	EBITDA	EBITDA /Sales	- CapEx	-CapEx /Sales	R&D	R&D/Sales
NVIDIA	$26,974,000.00	20%	$5,394,800.00	3.41%	$20,758,000.00	77.0%	$24,494,000.00	90.8%	$ 5,987,000.00	22.2%	$ 10,946,000.00	40.6%	$7,812,000.00	29%
IBM	$61,171,000.00	5%	$3,058,550.00	1.94%	$97,755,000.00	159.8%	-$2,387,000.00	-3.9%	$ 14,139,000.00	23.1%	$ 72,893,000.00	119.2%	$6,567,000.00	10.74%
Microsoft	$211,915,000.00	5%	$10,595,750.00	6.71%	$362,421,000.00	171.0%	$95,495,000.00	45.1%	$ 102,384,000.00	48.3%	$ 253,460,000.00	119.6%	$27,195,000.00	12.83%
Google	$297,132,000.00	15%	$44,569,800.00	28.21%	$220,401,000.00	74.2%	$90,000.00	0.0%	$ 93,365,000.00	31.4%	$ 270,845,000.00	91.2%	$43,581,000.00	14.67%
Average	**$149,298,000.0**	**11.25%**	**$15,904,725.0**	**10.07%**	**$175,333,750.0**	**120.49%**	**$29,423,000.0**	**33.00%**	**$53,968,750.0**	**31.26%**	**$152,036,000.0**	**92.63%**	**$21,288,750.0**	**16.80%**

Source:Yahoo Finance (2023), Statista, macrotrends

Technical Value Analysis

(USD in millions) Year	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035	Assumptions
Market Size	613.00	796.90	1,035.97	1,346.76	1,750.79	2,276.03	2,958.83	3,846.48	5,000.43	6,500.56	7,800.67	9,360.80	11,232.96	12,917.91	Source Statista
% growth	30%	30%	30%	30%	30%	30%	30%	30%	30%	20%	20%	20%	15%	15%	SourceStatista
Market Share	10.1%	11.1%	12.2%	13.4%	14.7%	16.2%	17.8%	19.6%	21.6%	23.7%	26.1%	28.7%	31.6%	34.8%	From Industry Average
% growth	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	5.0%	Sales -> industry average, constant growth rate
Revenues	$62	$88	$126	$181	$258	$369	$528	$755	$1,079	$1,544	$2,037	$2,689	$3,550	$4,491	
EBITDA	$22	$32	$46	$65	$93	$133	$191	$272	$390	$557	$736	$971	$1,282	$1,621	
% of Sales	*36.1%*	*36.1%*	*36.1%*	*36.1%*	*36.1%*	*36.1%*	*36.1%*	*36.1%*	*36.1%*	*36.1%*	*36.1%*	*36.1%*	*36.1%*	*36.1%*	*EBITDA/sales ->steady state (e.g., industry average), linearly*
Depreciation & Amortization	$6	$9	$13	$18	$26	$37	$53	$75	$108	$154	$204	$269	$355	$449	
% of Sales	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	10.0%	Target 10% of amortized sales for tax deductions when performance (sales)
EBIT	$16	$23	$33	$47	$67	$96	$138	$197	$282	$403	$532	$702	$927	$1,172	
% of Sales	26.1%	26.1%	26.1%	26.1%	26.1%	26.1%	26.1%	26.1%	26.1%	26.1%	26.1%	26.1%	26.1%	26.1%	
WC (= CA-CL)	$12	$17	$25	$36	$51	$73	$104	$149	$213	$304	$401	$530	$699	$885	industry average relative to sales, linearly
% of Sales	19.7%	19.7%	19.7%	19.7%	19.7%	19.7%	19.7%	19.7%	19.7%	19.7%	19.7%	19.7%	19.7%	19.7%	
Fixed Assets (= TA - CA)	$74	$106	$152	$217	$311	$445	$636	$909	$1,301	$1,860	$2,455	$3,241	$4,277	$5,411	TA includes R&D stock and equipment for production as intangible assets
Fixed Assets / Sales	120.49%	120.49%	120.49%	120.49%	120.49%	120.49%	120.49%	120.49%	120.49%	120.49%	120.49%	120.49%	120.49%	120.49%	Fixed asset/sales -> industry average, linearly
Depr./Fixed Assets	*#REF!*	*11.9%*	*11.9%*	*11.9%*	*11.9%*	*11.9%*	*11.9%*	*11.9%*	*11.9%*	*11.9%*	*11.0%*	*11.0%*	*11.0%*	*10.5%*	*Depreciation = 0 x Fixed Assets*
-ΔWC	($4)	($9)	($17)	($28)	($43)	($65)	($96)	($141)	($205)	($296)	($393)	($522)	($691)	($877)	
% of Sales	-	-10.6%	-13.4%	-15.3%	-16.6%	-17.5%	-18.2%	-18.6%	-19.0%	-19.2%	-19.3%	-19.4%	-19.5%	-19.5%	Capex (t) = Fixed assets (t) - (1 - dep rate)x Fixed assets (t-1) = Δ Fixed
-CapEx	$57	$82	$117	$167	$239	$342	$489	$699	$1,000	$1,430	$1,887	$2,491	$3,288	$4,160	
% of Sales	92.6%	92.6%	92.6%	92.6%	92.6%	92.6%	92.6%	92.6%	92.6%	92.6%	92.6%	92.6%	92.6%	92.6%	
-(ΔWC + CapEx)	$53	$72	$100	$140	$196	$277	$393	$558	$795	$1,134	$1,494	$1,969	$2,597	$3,283	
% of Sales	85.9%	82.0%	79.3%	77.4%	76.0%	75.1%	74.4%	74.0%	73.7%	73.4%	73.3%	73.2%	73.2%	73.1%	
After Tax EBITDA	$18	$25	$36	$51	$74	$105	$151	$215	$308	$440	$581	$767	$1,012	$1,281	
-(ΔWC + CapEx)	$53	$72	$100	$140	$196	$277	$393	$558	$795	$1,134	$1,494	$1,969	$2,597	$3,283	
tau * Depreciation	$1	$2	$3	$4	$5	$8	$11	$16	$23	$32	$43	$56	$75	$94	
t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
CF	$72	$99	$139	$195	$275	$390	$555	$790	$1,126	$1,606	$2,118	$2,793	$3,684	$4,658	
Terminal value													$93,164		Terminal Value
Total	$72	$99	$139	$195	$275	$390	$555	$790	$1,126	$1,606	$2,118	$2,793	$96,848		
(1+r)^(-t)	0.909	0.826	0.751	0.683	0.621	0.564	0.513	0.467	0.424	0.386	0.350	0.319	0.290		
Discounted CF	$65	$82	$104	$133	$171	$220	$285	$368	$477	$619	$742	$890	$28,053		
Total PV								$32,211					$26,986		

Tax rate	21.0%
Discount rate	10.0%
Final growth rate	5.0%

Assumption

- ✓ Our NPV stands at $32,211M, inclusive of a $26,986M Terminal Value in 2035.
- ✓ Market growth is projected at 30% until 2030, slowing to 20% through 2035 (Virtue Market Research).
- ✓ We anticipate a steady 10% annual growth in sales.
- ✓ The discount rate is set at 10%, with R&D capital costs funded via equity and debt (r= E/(E+D)* re + D/(D+E)*rd)
- ✓ Cash Flow (CF) parameters are derived from Comparable Companies Analysis:
- ✓ $CF = 1 - \tau \times EBITDA + \tau \times Depreciation - CapEx - Change\ in\ WC$
- ✓ $CapEx\ t = Fixed\ Assets\ t - Fixed\ Assets\ t{-}1 + Depreciation(t)$
- ✓ WC = Inventory + Accounts Receivable − Accounts Payable
- ✓ CF formula: Net of taxes, EBITDA, depreciation, capital expenditure, and working capital changes.
- ✓ Capital Expenditure (CapEx) calculation reflects current fixed assets, previous year adjustments, and depreciation. Working Capital (WC) comprises inventory and receivables minus payables.
- ✓ R&D is conventionally a sunk cost but can be capitalized as an intangible asset for amortization over its useful life, aligning expenses with the expected benefits