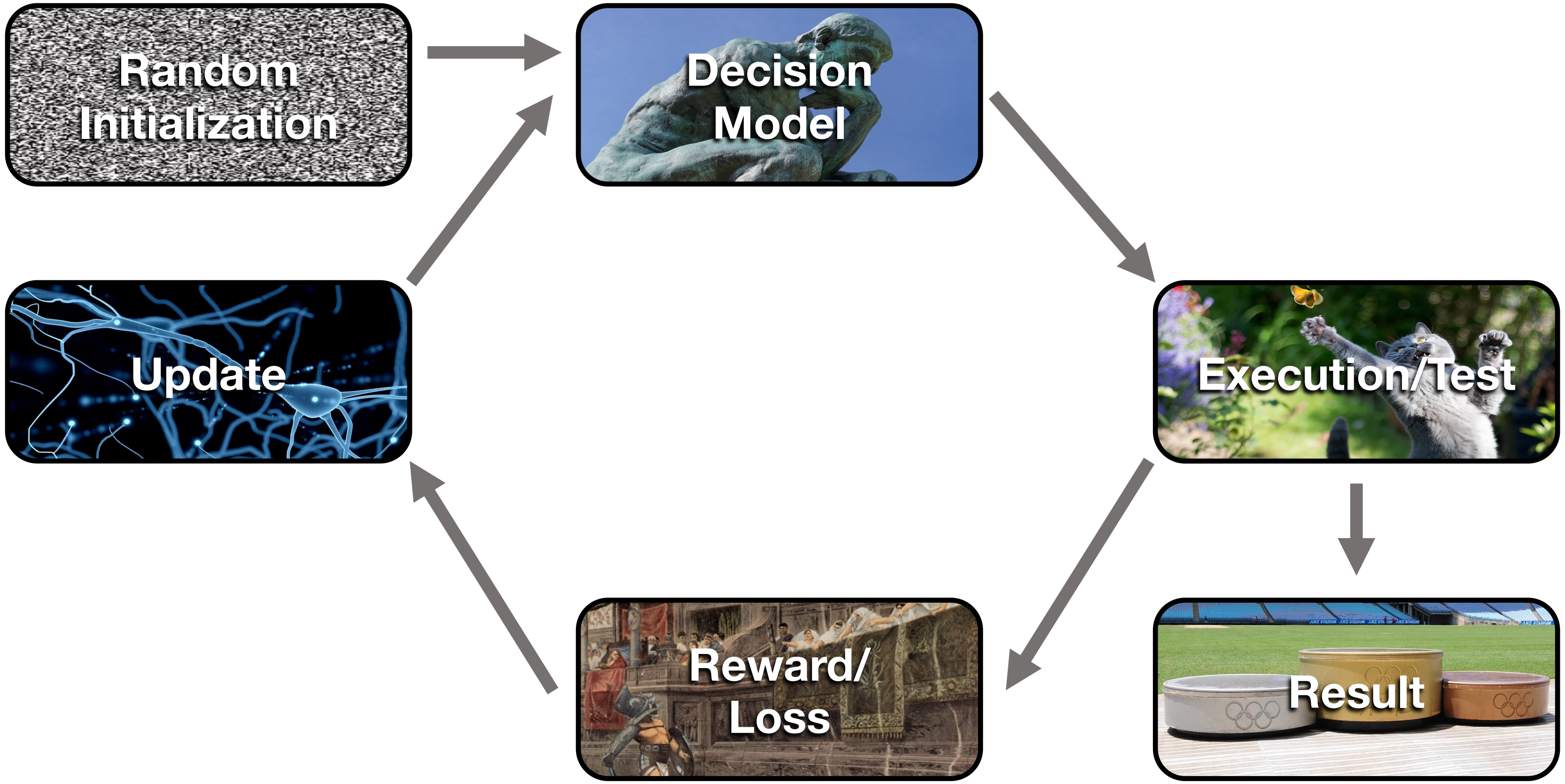
Towards Quantum Artificial Intelligence

Thomas Gabor

QAR-Lab, LMU Munich

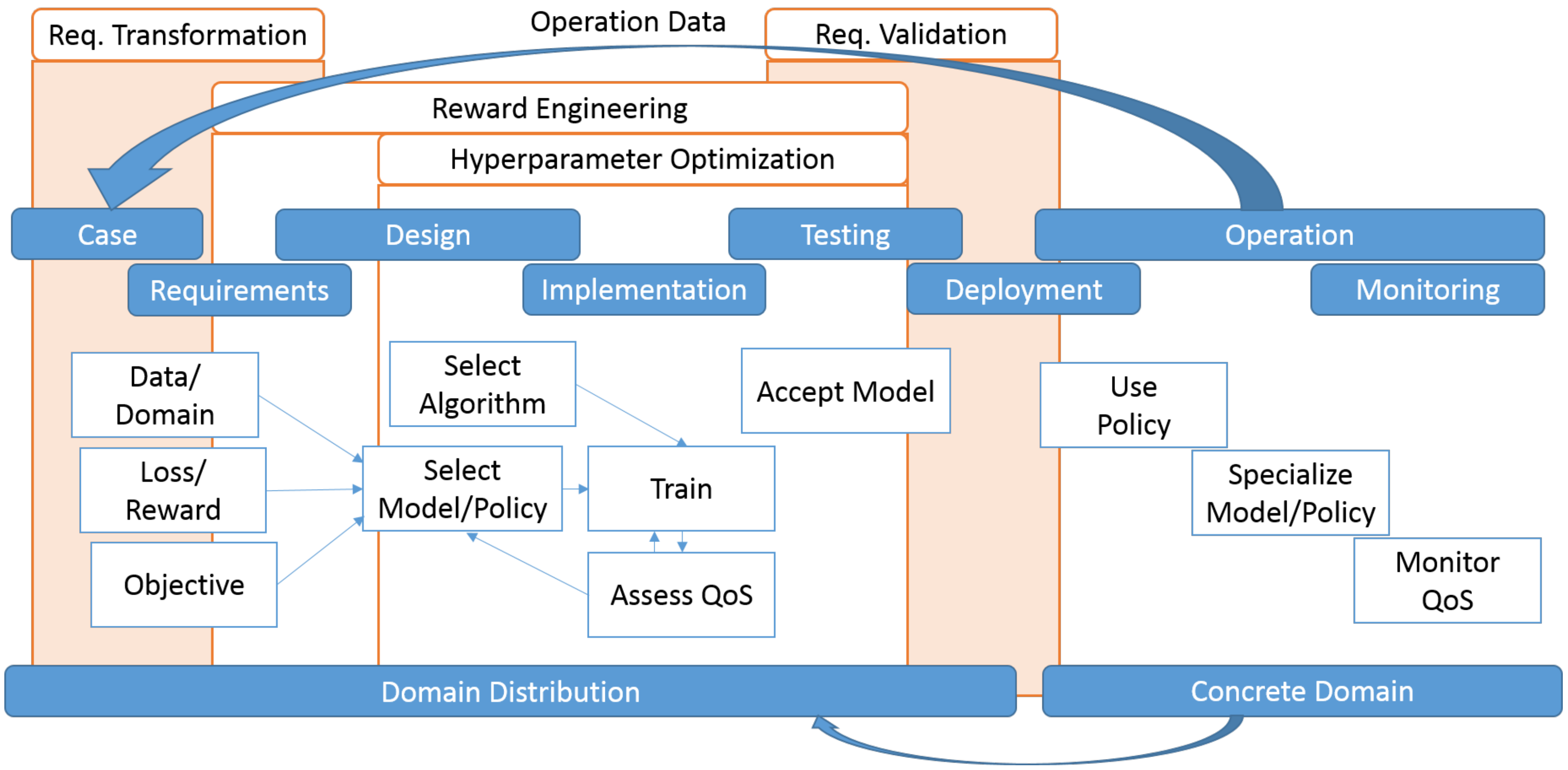
What is Artificial Intelligence?

Machine Learning

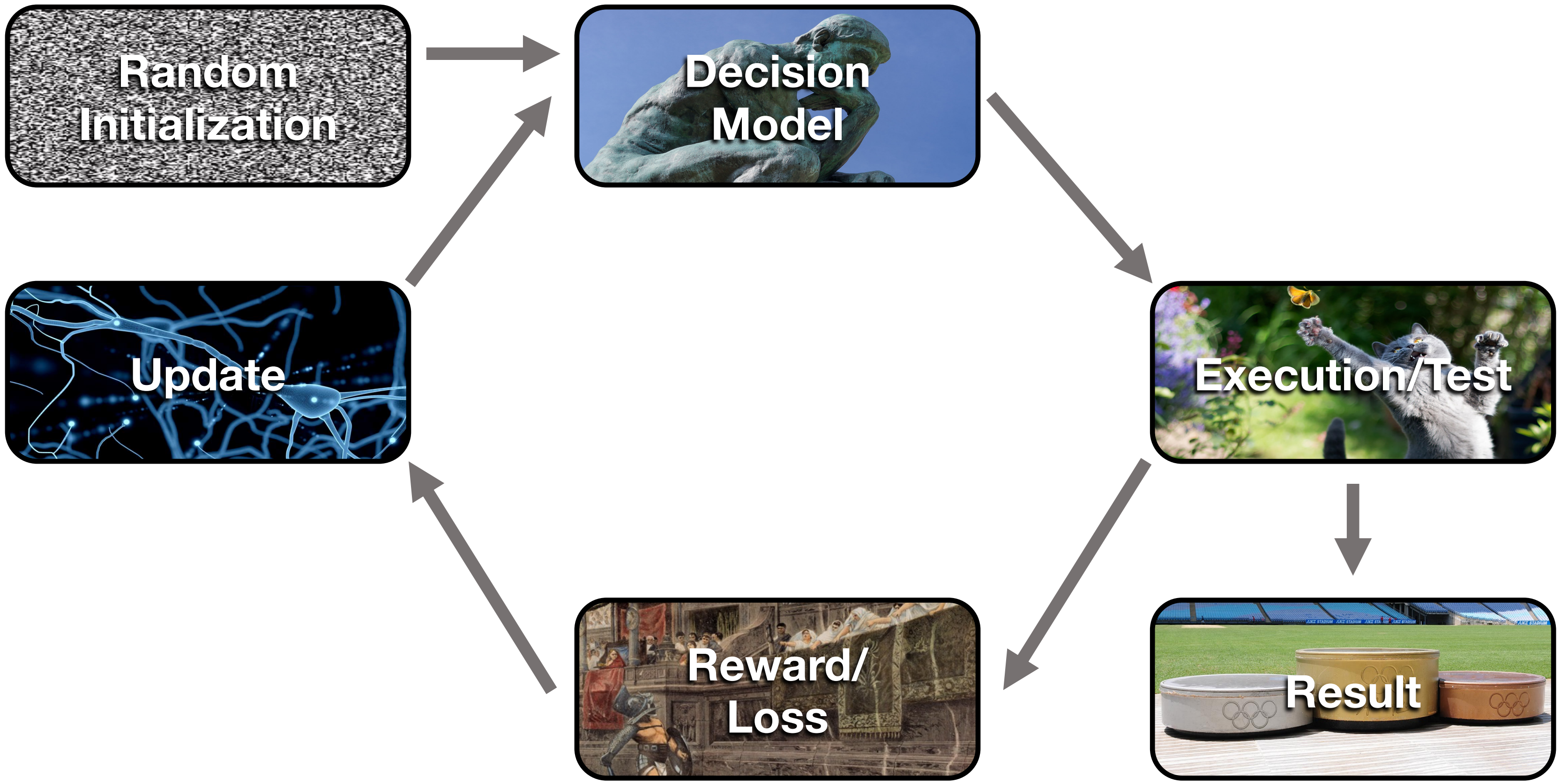


Machine Learning

Thomas Gabor et al.
The Scenario Coevolution Paradigm: Adaptive Quality Assurance for Adaptive Systems.
link.springer.com/content/pdf/10.1007/s10009-020-00560-5.pdf



Machine Learning



6 AI and the Compute Method

1) "AI researchers have often tried to **build knowledge** into their agents,
2) this always helps in the **short term**, and is personally satisfying to the researcher, but
3) in the long run it plateaus and even **inhibits further progress**, and
4) breakthrough progress eventually arrives by an opposing approach based on scaling computation by **search and learning**."

Rich Sutton.
The Bitter Lesson.
www.incompleteideas.net/IncIdeas/BitterLesson.html

7 AI and the Compute Method

1) "AI researchers have often tried to **build knowledge** into their agents,
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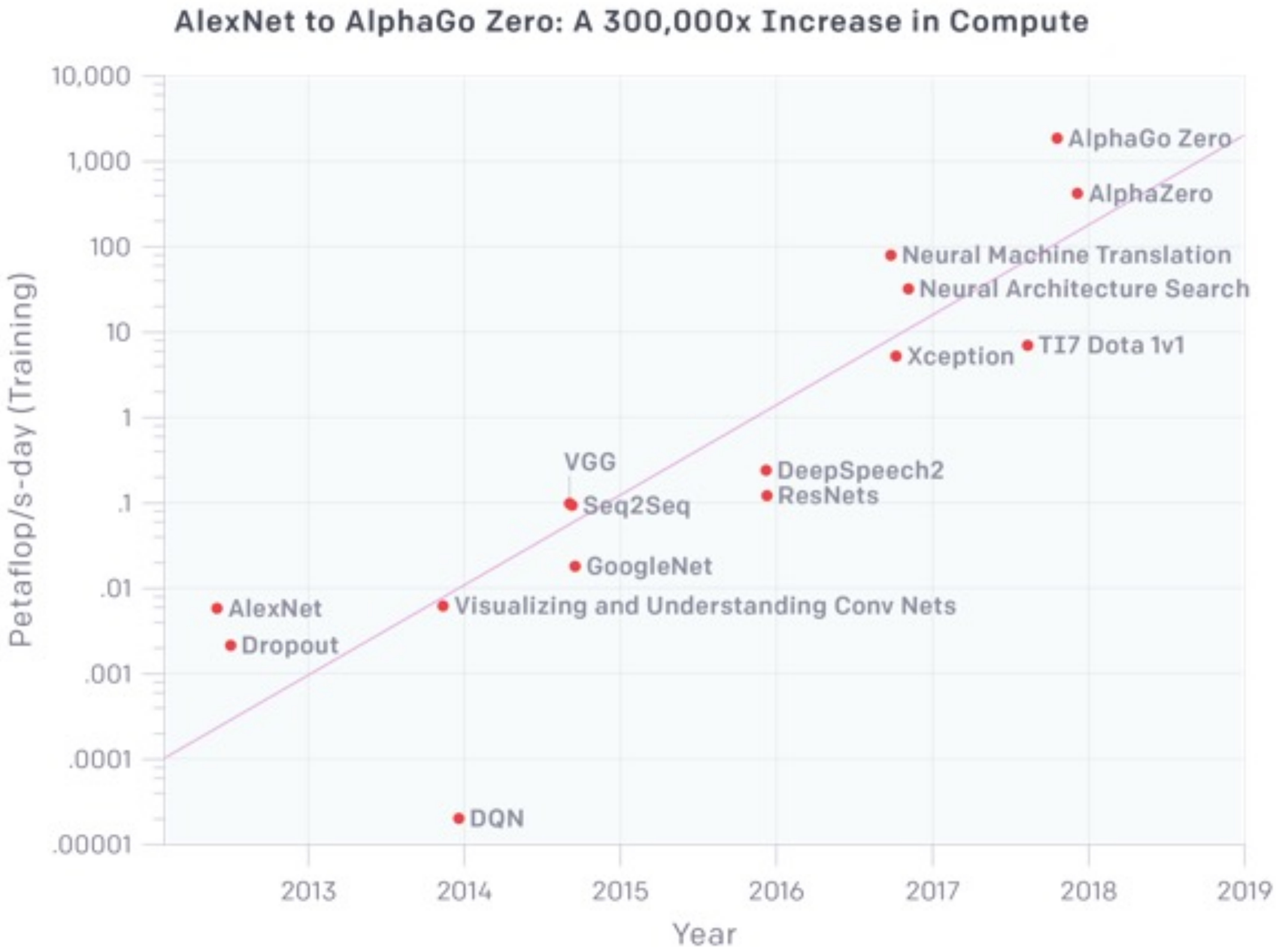
4) breakthrough progress eventually arrives by an opposing approach based on scaling computation by **search and learning**."

"The biggest lesson that can be read from 70 years of AI research is that general methods that **leverage computation** are ultimately the most effective, and by a large margin."

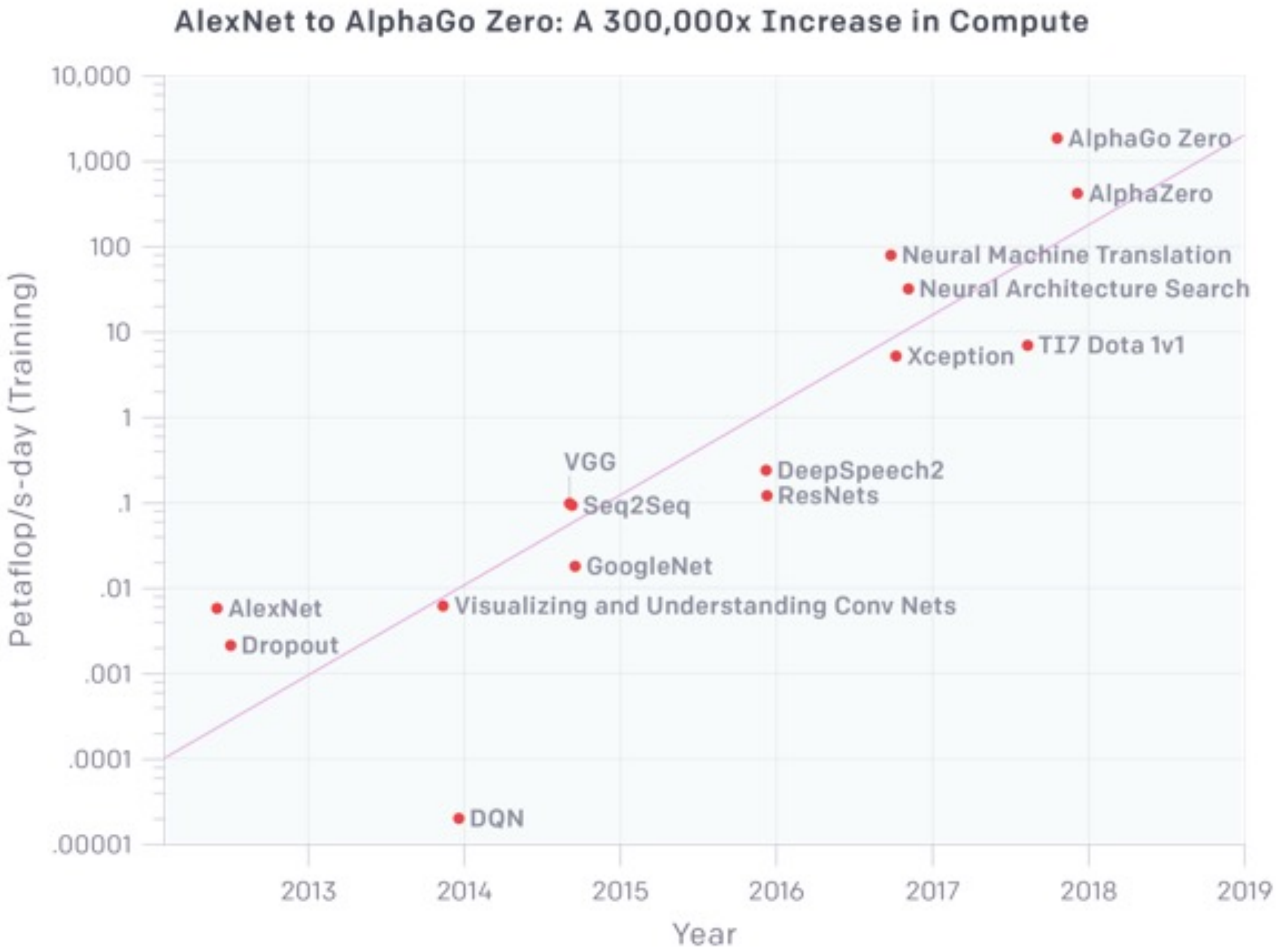
Rich Sutton.
The Bitter Lesson.
www.incompleteideas.net/IncIdeas/BitterLesson.html

8 The Power of Compute



Dario Amodei and Danny Hernandez.
AI and Compute.
openai.com/blog/ai-and-compute/

The Power of Compute



"Since 2012, the amount of compute used in the largest AI training runs has been increasing exponentially with a **3.5 month doubling time** (by comparison, Moore's Law had an 18 month doubling period)."

Dario Amodei and Danny Hernandez.
AI and Compute.
openai.com/blog/ai-and-compute/

Options for the Future of AI

Progress in AI research slows down.

AI research becomes exponentially more expensive.

New AI algorithms using less resources are developed.

New sources of computation power are discovered.

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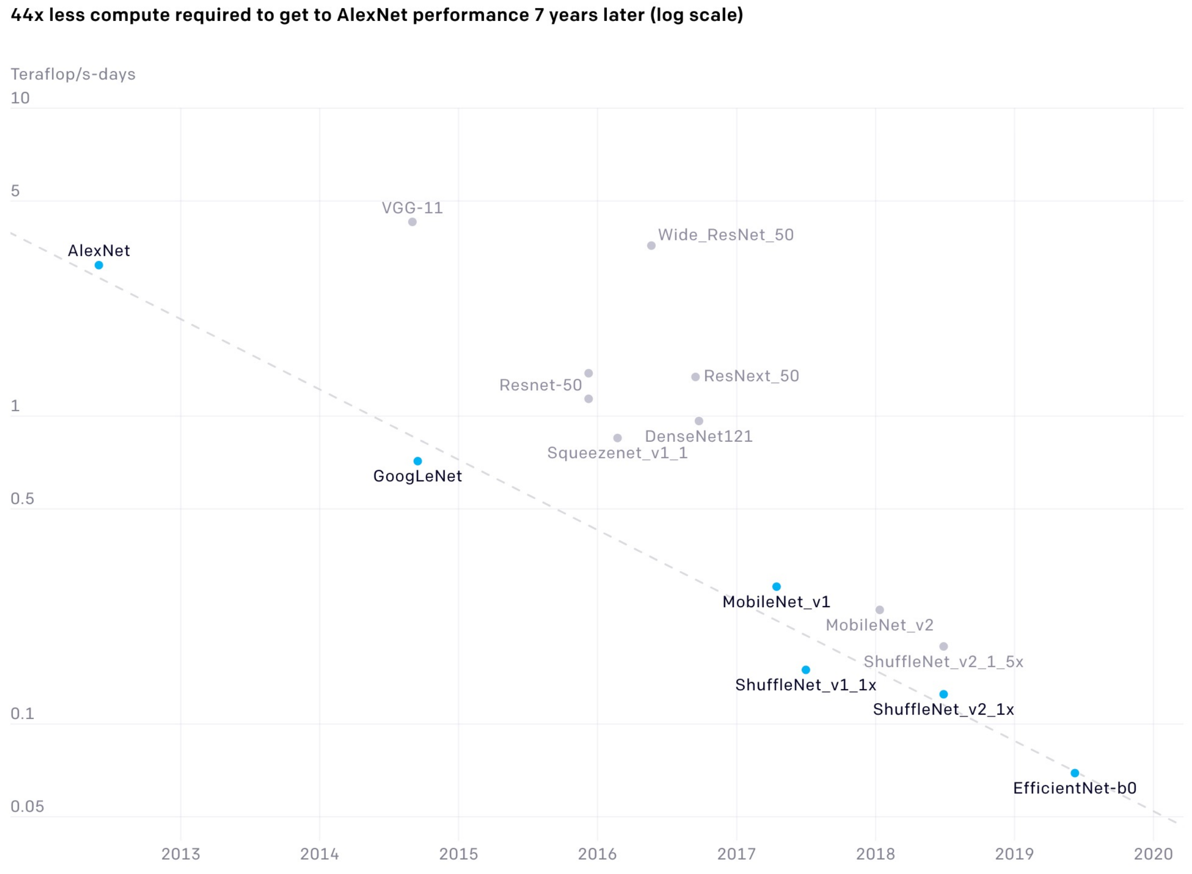
12 The Power of Efficiency



"Compared to 2012, it now takes 44 times less compute to train a neural network to the level of AlexNet (by contrast, Moore's Law would yield an 11x cost improvement over this period). Our results suggest that for AI tasks with high levels of recent investment, **algorithmic progress** has yielded more gains than classical hardware efficiency."

Danny Hernandez and Tom Brown. AI and Efficiency. openai.com/blog/ai-and-efficiency/

13 Options for the Future of AI

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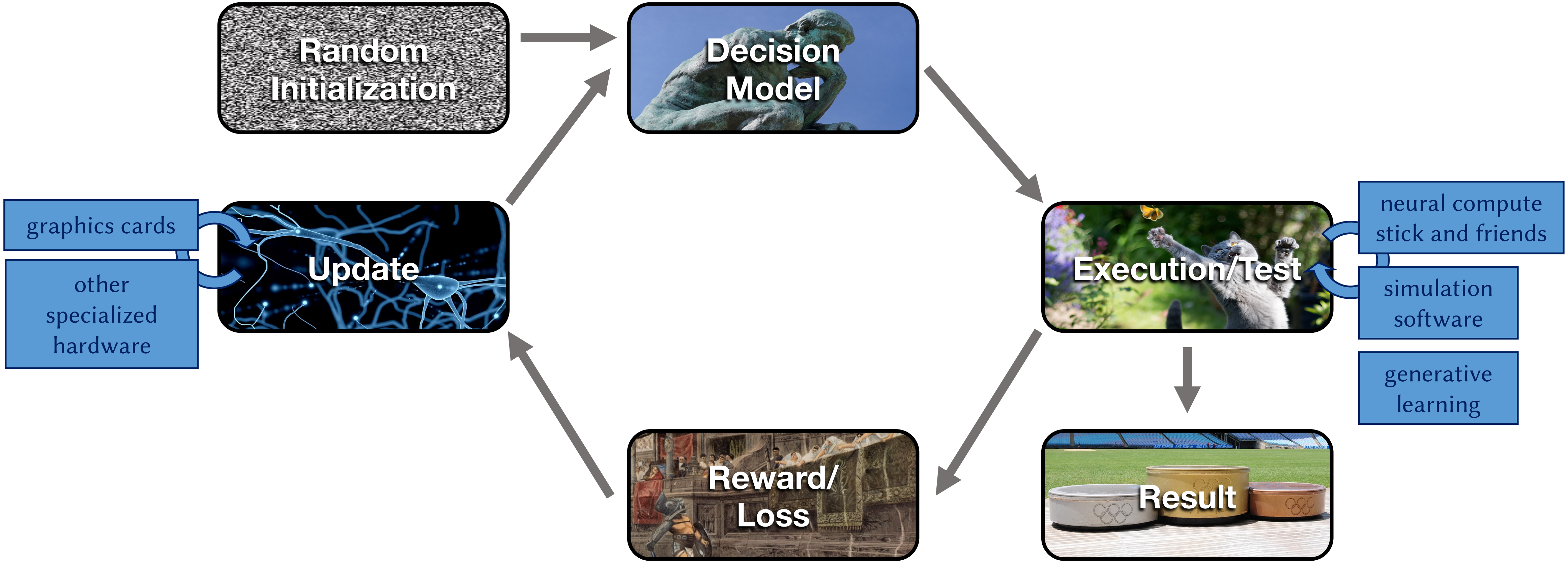
14 Machine Learning



Options for the Future of AI

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Why Quantum AI?

Quantum Computing and AI

Quantum Computing		Artificial Intelligence
could provide more computing power	→	always needs more computing power
noisy for the foreseeable future	→	needs randomness
can perform stochastic search (quantum annealing or QAOA)	→	uses stochastic search
circuits are hard to construct for new algorithms	←	can invent creative solutions for well-defined goals

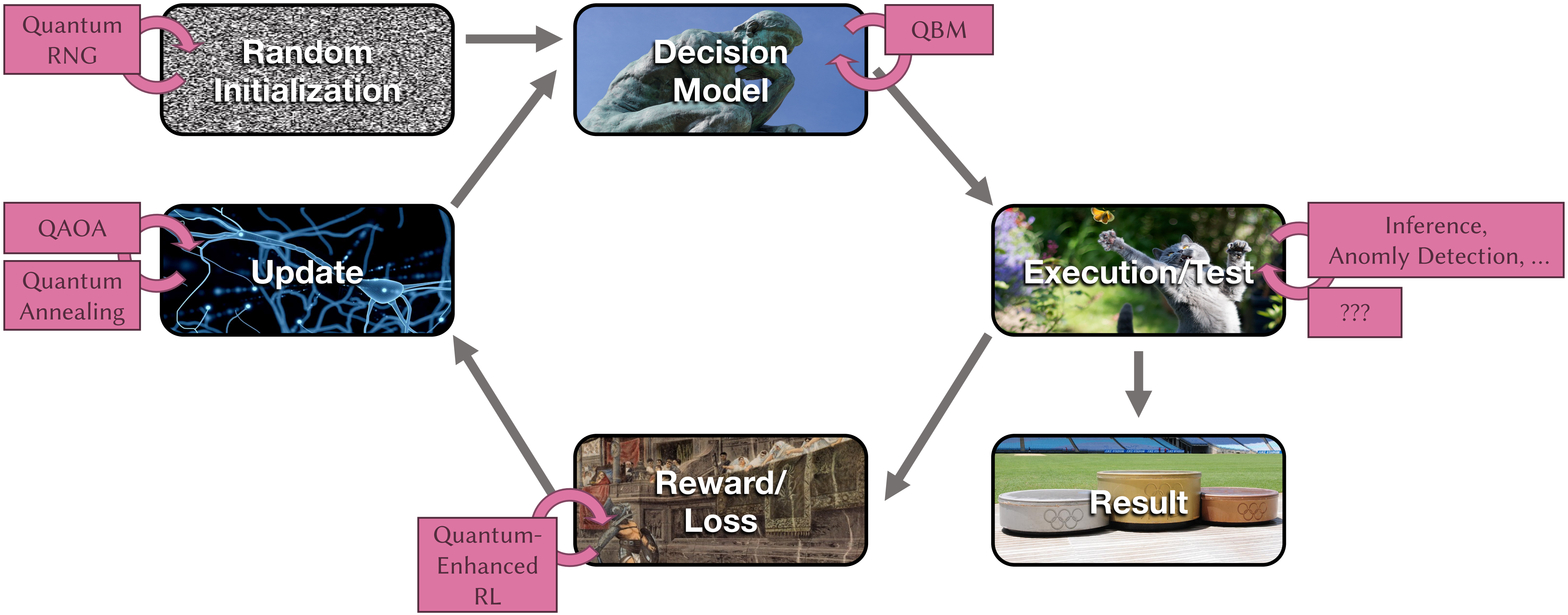
operates on a multitude of possibilties to
return a relatively short answer

18 Quantum Computing and AI

Algorithm/Task	QC platform	Impl. available	NISQ	Quantum tasks in ML pipeline
Variational quantum eigensolver [43]	Gate model	PennyLane [41]	Yes	Data/Domain, Use Policy
HHL [24]	Gate model	Qiskit [1]	Unlikely [45]	Data/Domain, Train
Clustering [6]	Gate model	-	No?	Data/Domain, Use Policy
Clustering [32]	Gate model	-	Yes?	Data/Domain, Use Policy
Quantum nearest-neighbor [52]	Gate model	-	-	Data/Domain, Use Policy
Recommendation system [28]	Gate model	-	Unlikely [45]	Data/Domain, Use Policy
SVM [25]	Gate model	Qiskit [5]	Yes	Data/Domain, Use Policy
SVM [54]	Quantum annealing	-	-	Data/Domain, Use Policy
QAOA [19]	Gate model	PennyLane [2]	Yes	Train
QUBO / Ising spin glasses [23, 34]	Quantum annealing	D-WAVE [37]	Yes	Train
Quantum-assisted EA [30]	Quantum annealing	-	-	Train
Quantum BM [53]	Gate model	-	Yes	Train
Quantum BM [9]	Quantum annealing	-	-	Train
Autoencoder [47]	Gate model	[48]	Yes	Train
Autoencoder [29]	Quantum annealing	-	-	Train
Quantum GAN [17, 33]	Gate model	PennyLane [3]	Yes	Data/Domain
Quantum GAN [46]	Gate model	-	Yes	Data/Domain
Quantum GAN [56]	Gate model	Qiskit [4]	Yes	Data/Domain
Quantum-enhanced RL [39]	Quantum annealing	-	-	Train
Quantum RL [18]	Gate model	-	-	Train, Use Policy

Thomas Gabor et al.
The Holy Grail of Quantum Artificial Intelligence: Major Challenges in Accelerating the Machine Learning Pipeline.
Proceedings of the IEEE/ACM 42nd International Conference on Software Engineering Workshops. 2020.

Quantum Machine Learning



What is Quantum Annealing?

Quantum Annealing

Theory: Algorithm by Kadowaki and Nishimori

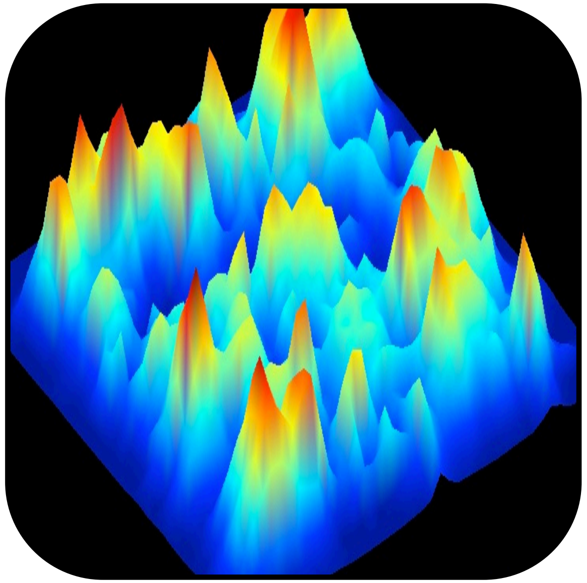
Implementation: Mainly D-Wave Systems

Tadashi Kadowaki and Hidetoshi Nishimori.
Quantum annealing in the transverse Ising model.
Physical Review E 58.5 (1998): 5355.

Mark W. Johnson et al.
Quantum annealing with manufactured spins.
Nature 473.7346 (2011): 194-198.

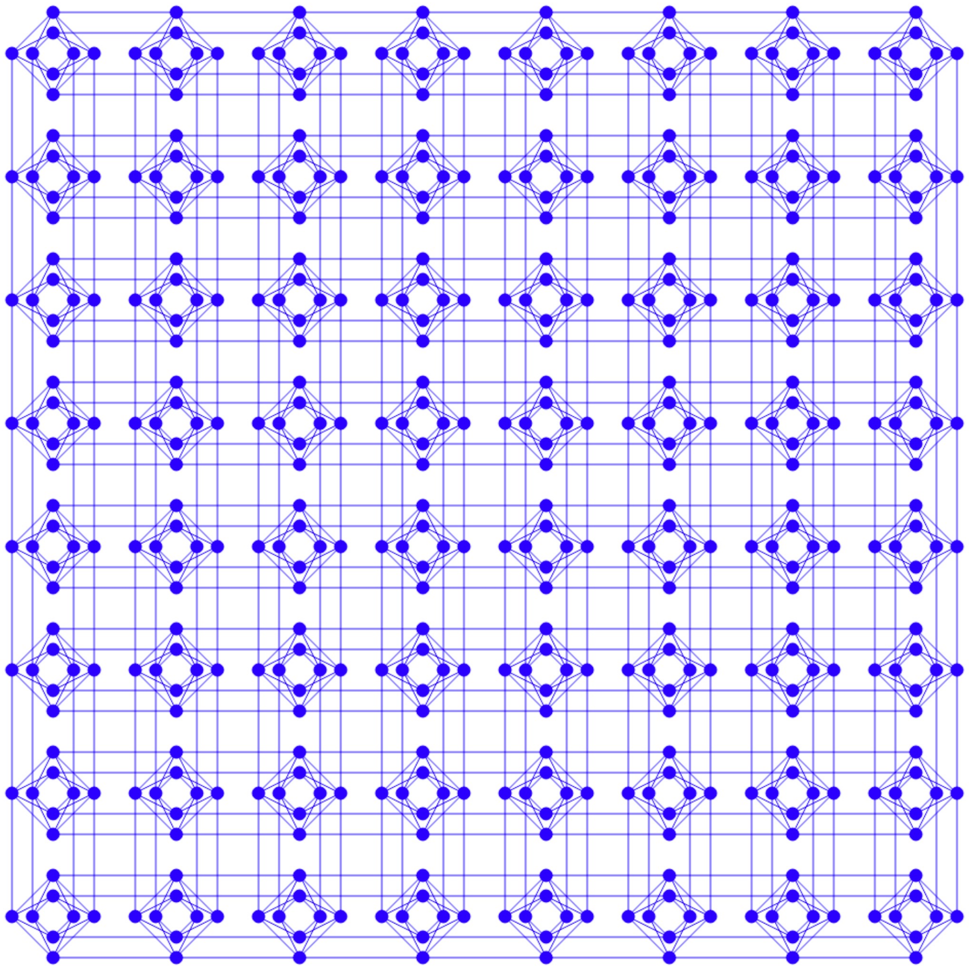
Specialized Hardware

Using
Quantum(-ish) Effects



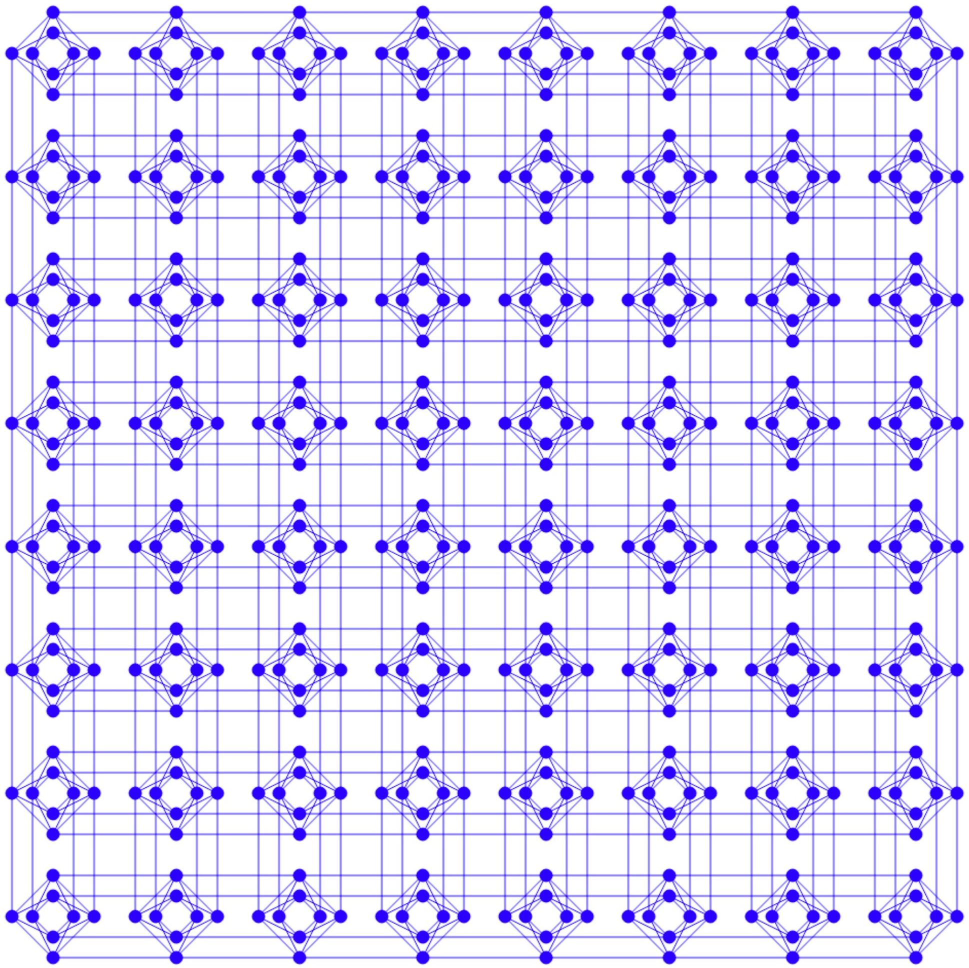
To Solve
Optimization Problems

22 Quantum Annealing



Quantum Annealing

1) apply field strength
   to single qubits
2) apply coupling strength
   to couples of qubits
3) the universe minimizes total energy
4) measure
5) qubits assume state that minimizes
   total energy



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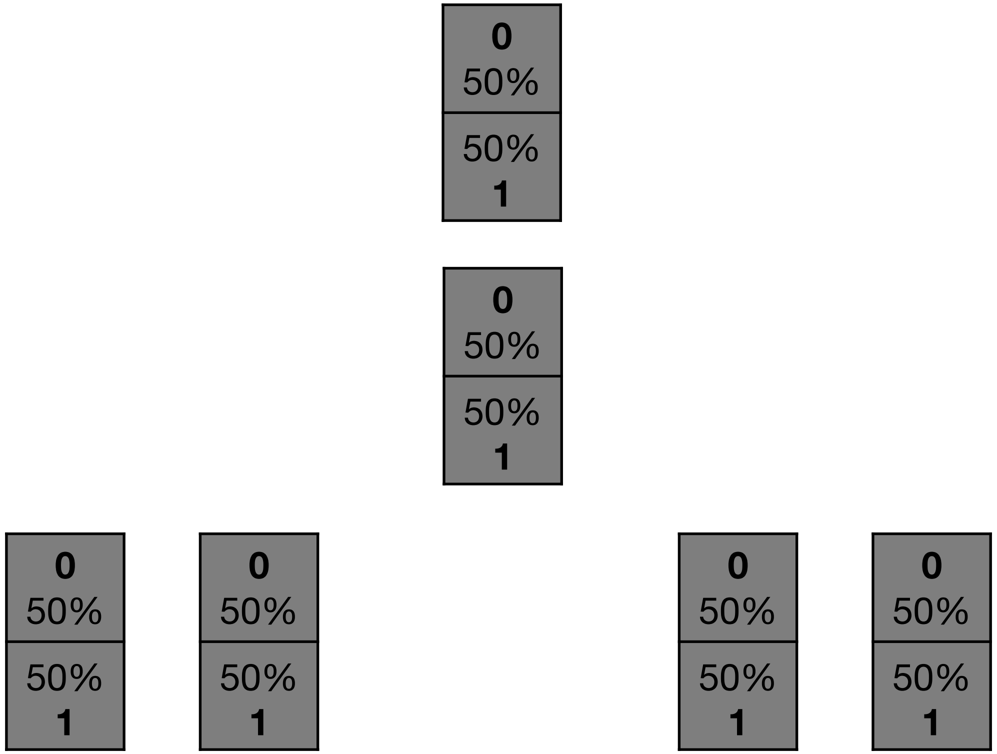

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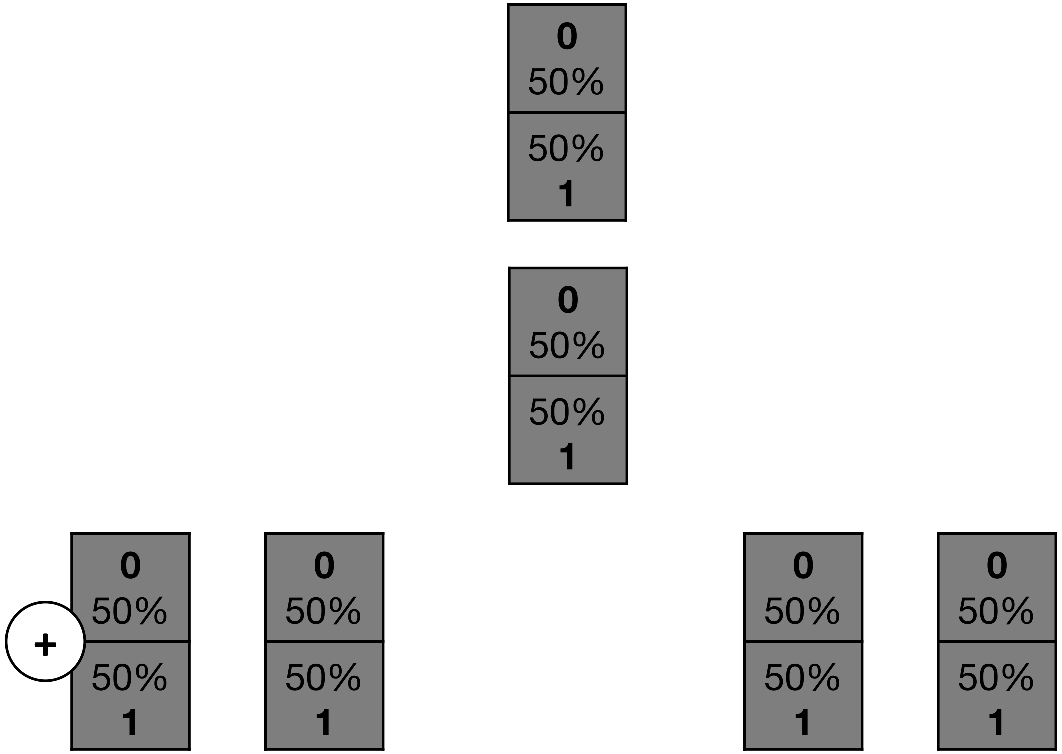

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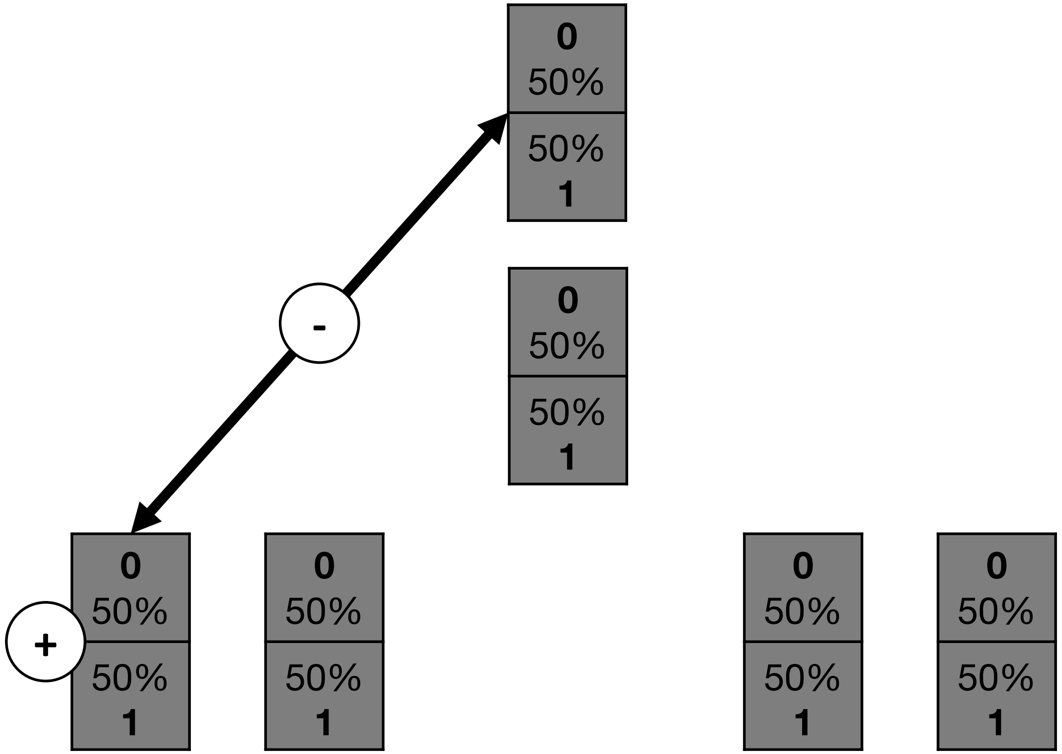

27 Quantum Annealing

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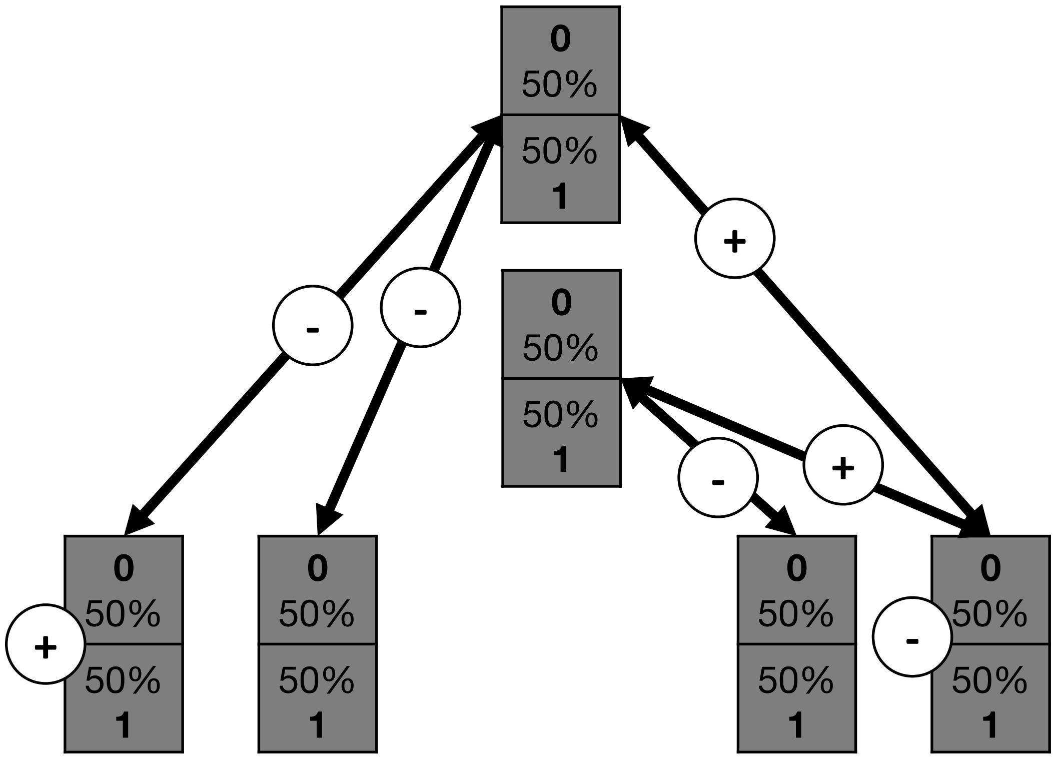

28 Quantum Annealing

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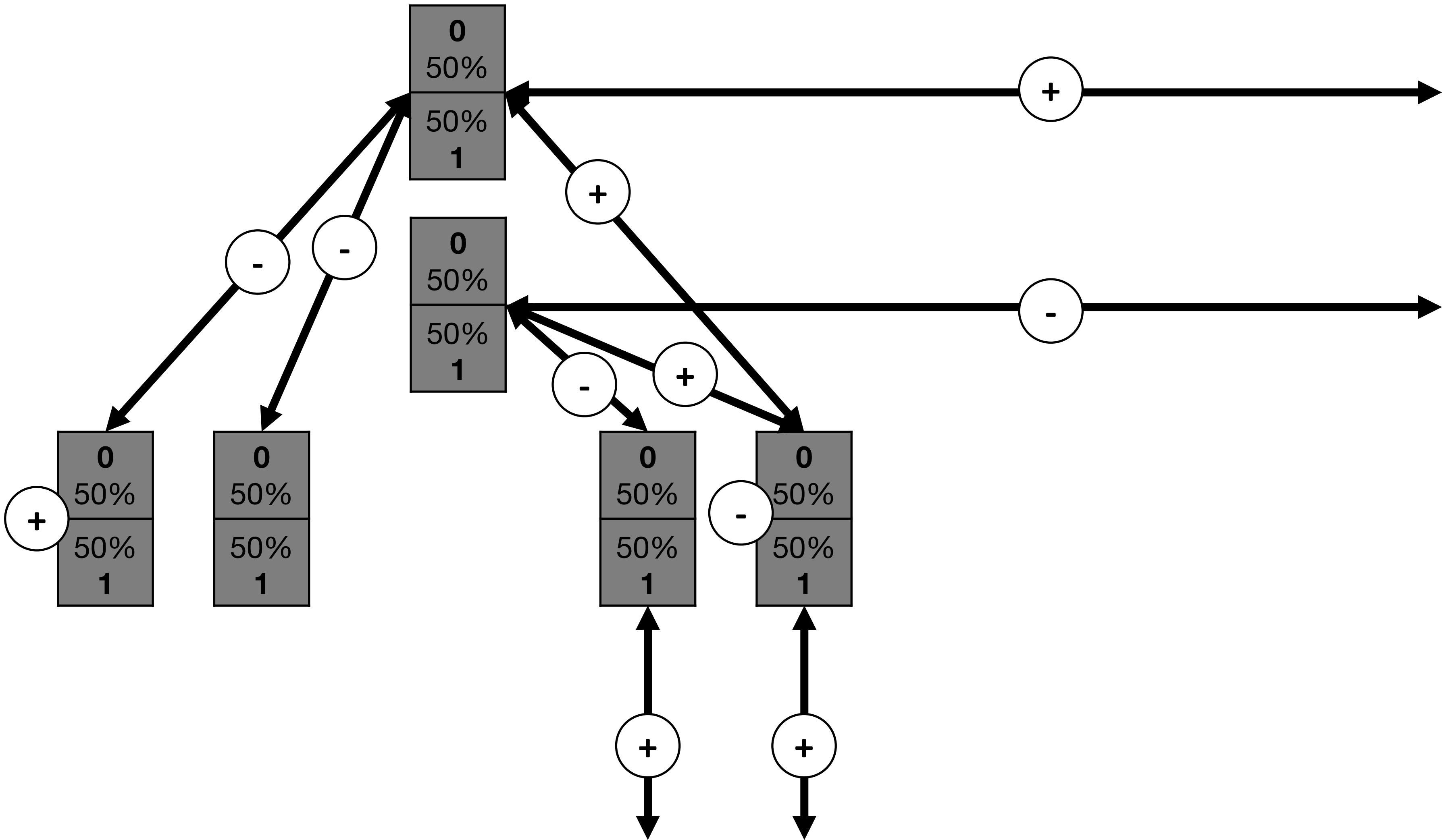

[29] Quantum Annealing

1) apply field strength to single qubits
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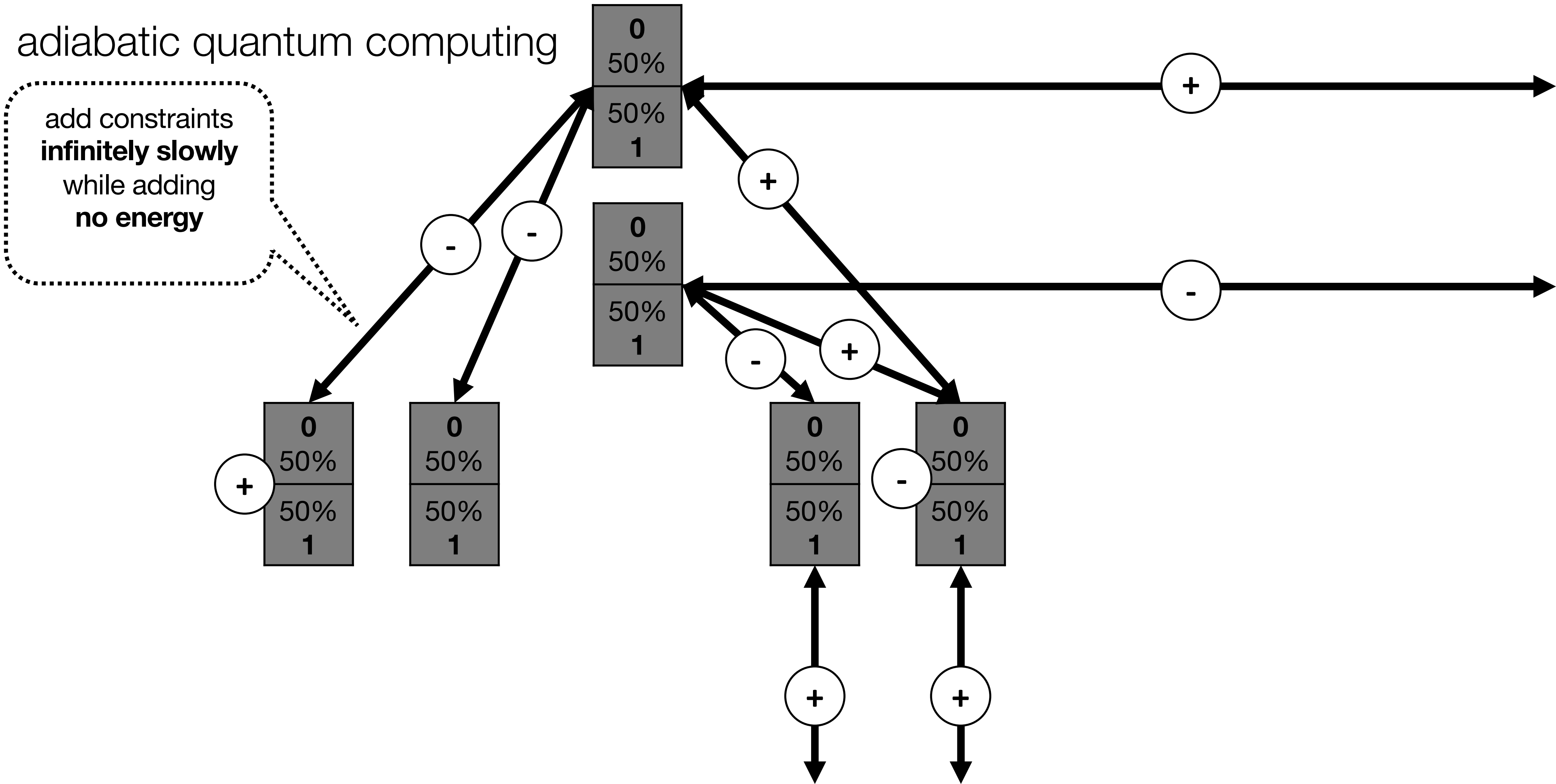
adiabatic quantum computing



Quantum Annealing

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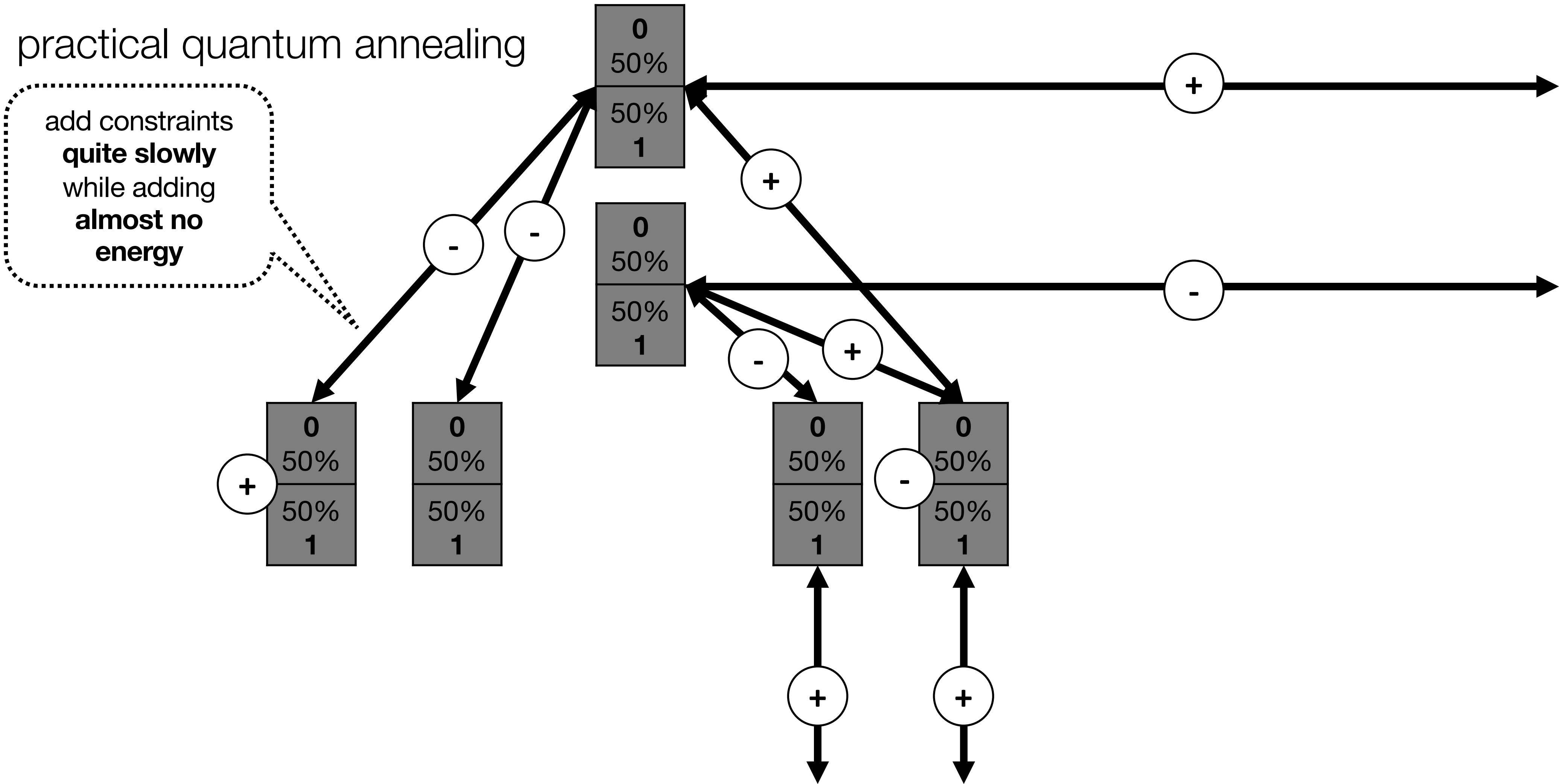
practical quantum annealing



31 Quantum Annealing

1) apply field strength to single qubits
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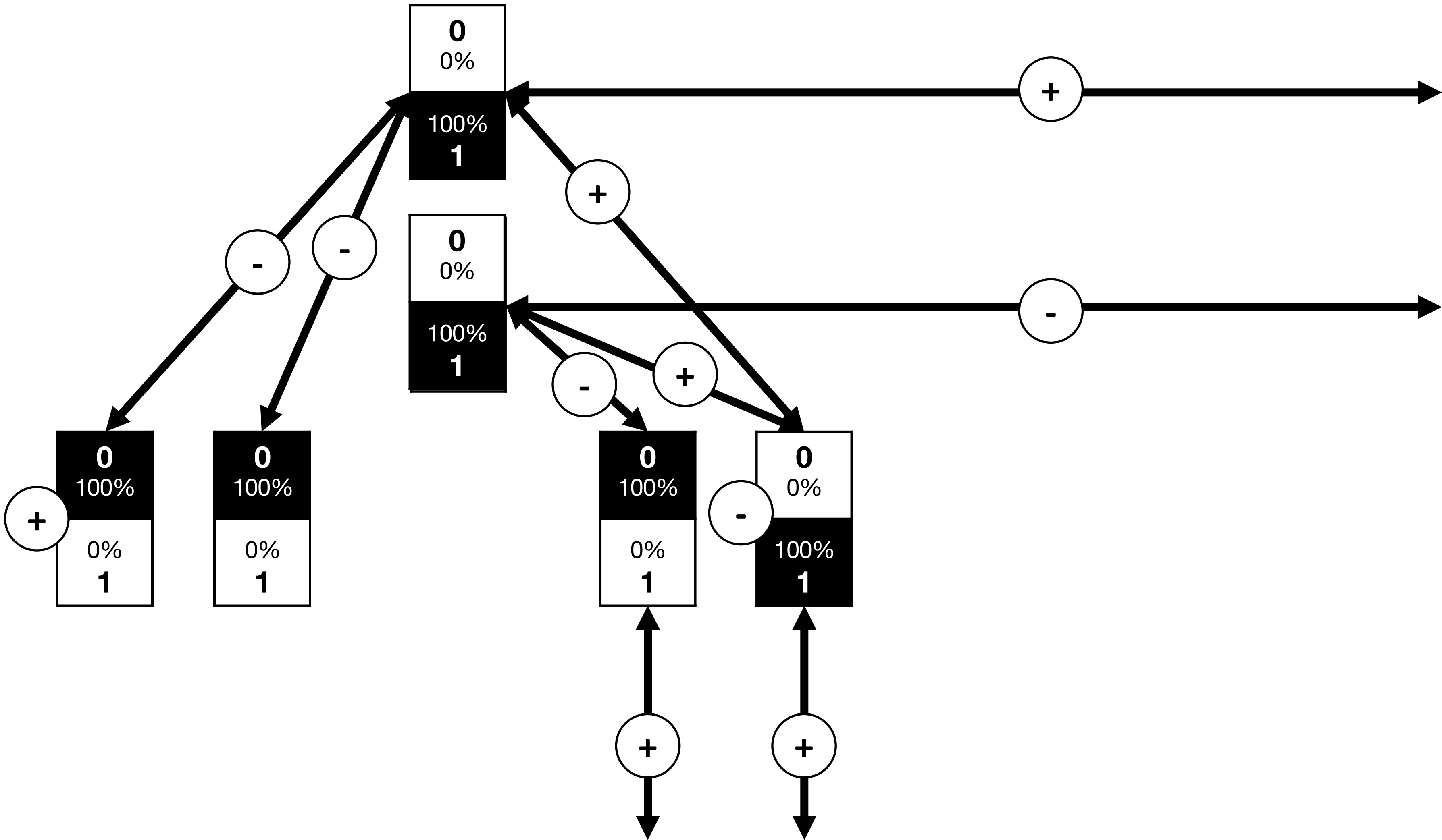


QUBO

quadratic unconstrained binary optimization

$$\underset{(q_0,\ldots,q_{n-1})\in\{0,1\}^n}{\arg\min} \sum_{i=0}^{n-1} \sum_{j=i}^{n-1} W_{i,j} \cdot q_i \cdot q_j$$

[33] QUBO

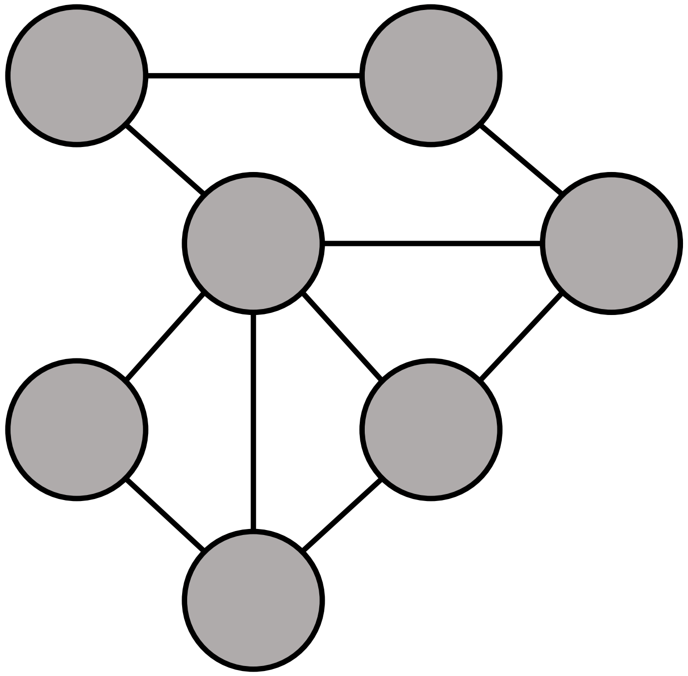
quadratic unconstrained binary optimization

NP-complete

$$\underset{(q_0,\ldots,q_{n-1})\in\{0,1\}^n}{\arg\min} \sum_{i=0}^{n-1} \sum_{j=i}^{n-1} W_{i,j} \cdot q_i \cdot q_j$$

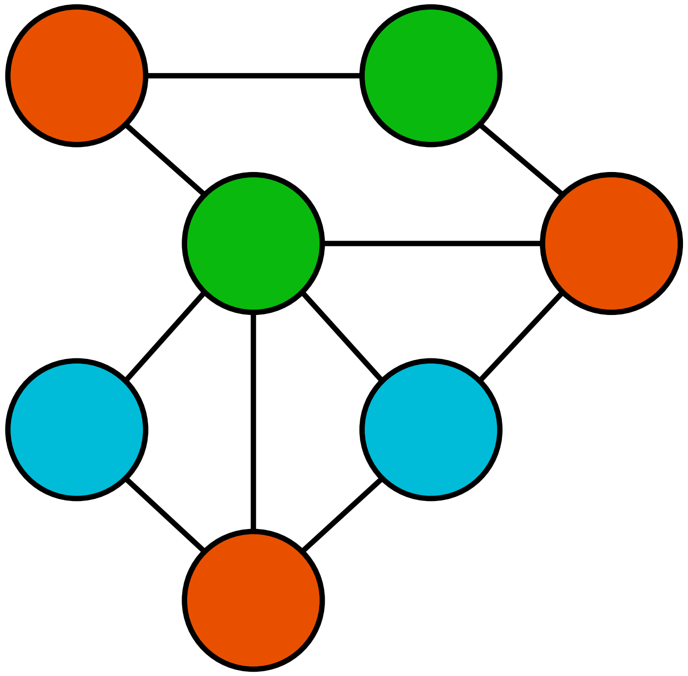
Example: Graph Coloring

Connected Graph



Set of Colors

Colored Graph



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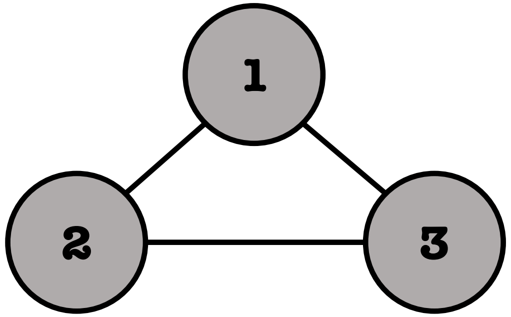

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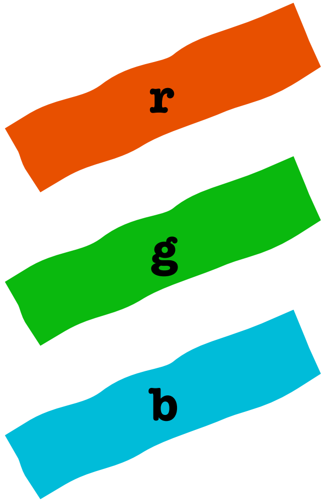
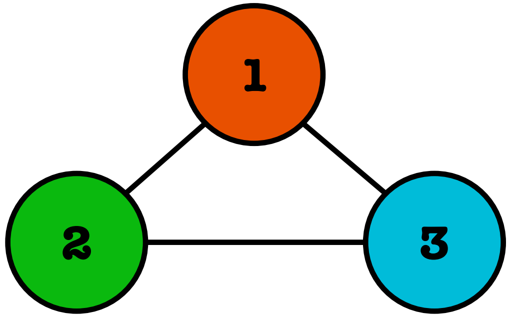


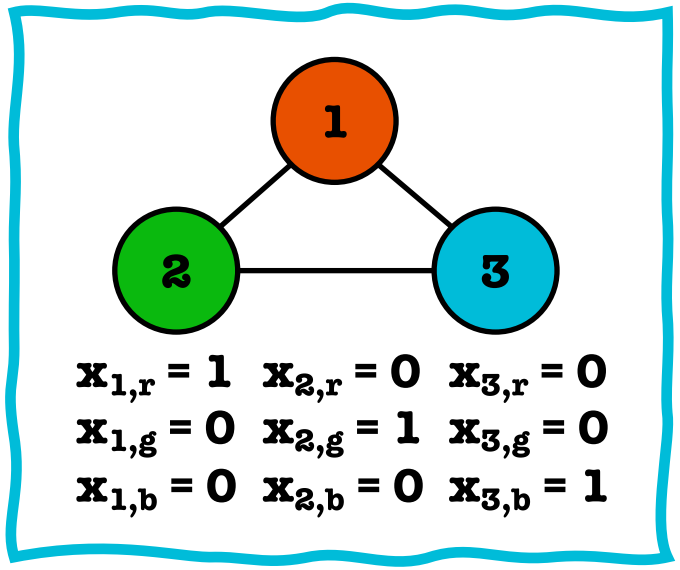
Colored Graph



$x_{1,r} = 1$ $x_{2,r} = 0$ $x_{3,r} = 0$
$x_{1,g} = 0$ $x_{2,g} = 1$ $x_{3,g} = 0$
$x_{1,b} = 0$ $x_{2,b} = 0$ $x_{3,b} = 1$

Example: Graph Coloring

$$QUBO = A \sum_{v \in V} \left(1 - \sum_{i=1}^{n} x_{v,i}\right)^2 + A \sum_{(u,v) \in E} \sum_{i=1}^{n} x_{u,i} x_{v,i}$$

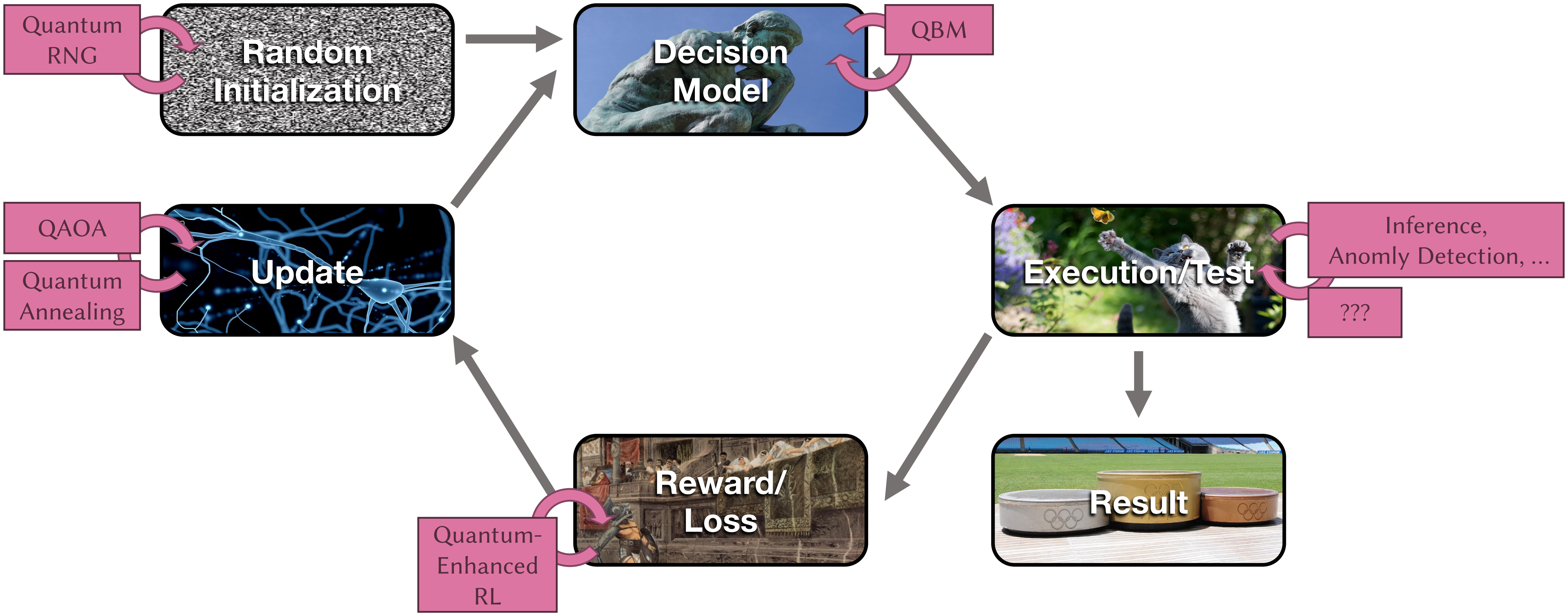


	$x_{1,r}$	$x_{1,g}$	$x_{1,b}$	$x_{2,r}$	$x_{2,g}$	$x_{2,b}$	$x_{3,r}$	$x_{3,g}$	$x_{3,b}$
$x_{1,r}$	-1	2	2	1			1		
$x_{1,g}$		-1	2		1			1	
$x_{1,b}$			-1			1			1
$x_{2,r}$				-1	2	2	1		
$x_{2,g}$					-1	2		1	
$x_{2,b}$						-1			1
$x_{3,r}$							-1	2	2
$x_{3,g}$								-1	2
$x_{3,b}$									-1

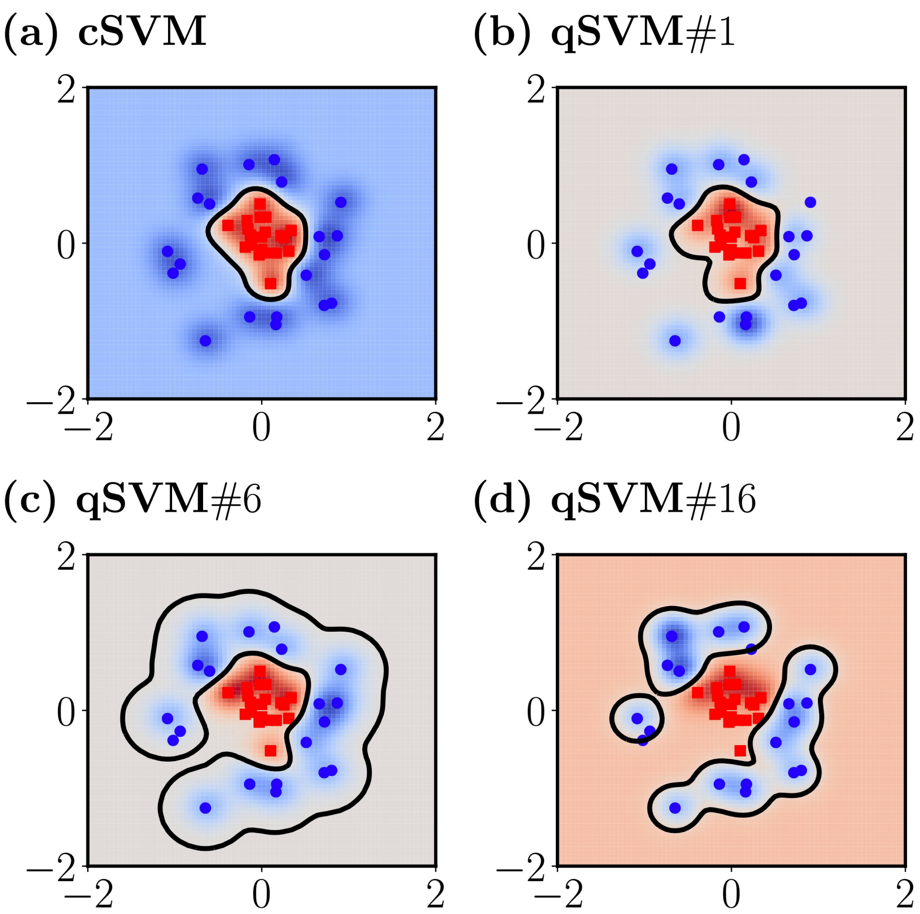
```
QUBO = {(0, 0): −1, (0, 1): 2, (0, 2): 2, (0, 3): 1,
        (0, 6): 1,
        (1, 1): −1, (1, 2): 2, (1, 4): 1, (1, 7): 1,
        (2, 2): −1, (2, 5): 1, (2, 8): 1,
        (3, 3): −1, (3, 4): 2, (3, 5): 2, (3, 6): 1,
        (4, 4): −1, (4, 5): 2, (4, 7): 1,
        (5, 5): −1, (5, 8): 1,
        (6, 6): −1, (6, 7): 2, (6, 8): 2,
        (7, 7): −1, (7, 8): 2,
        (8, 8): −1}
```

Quantum Annealing Approaches
for
Quantum AI

Quantum Machine Learning



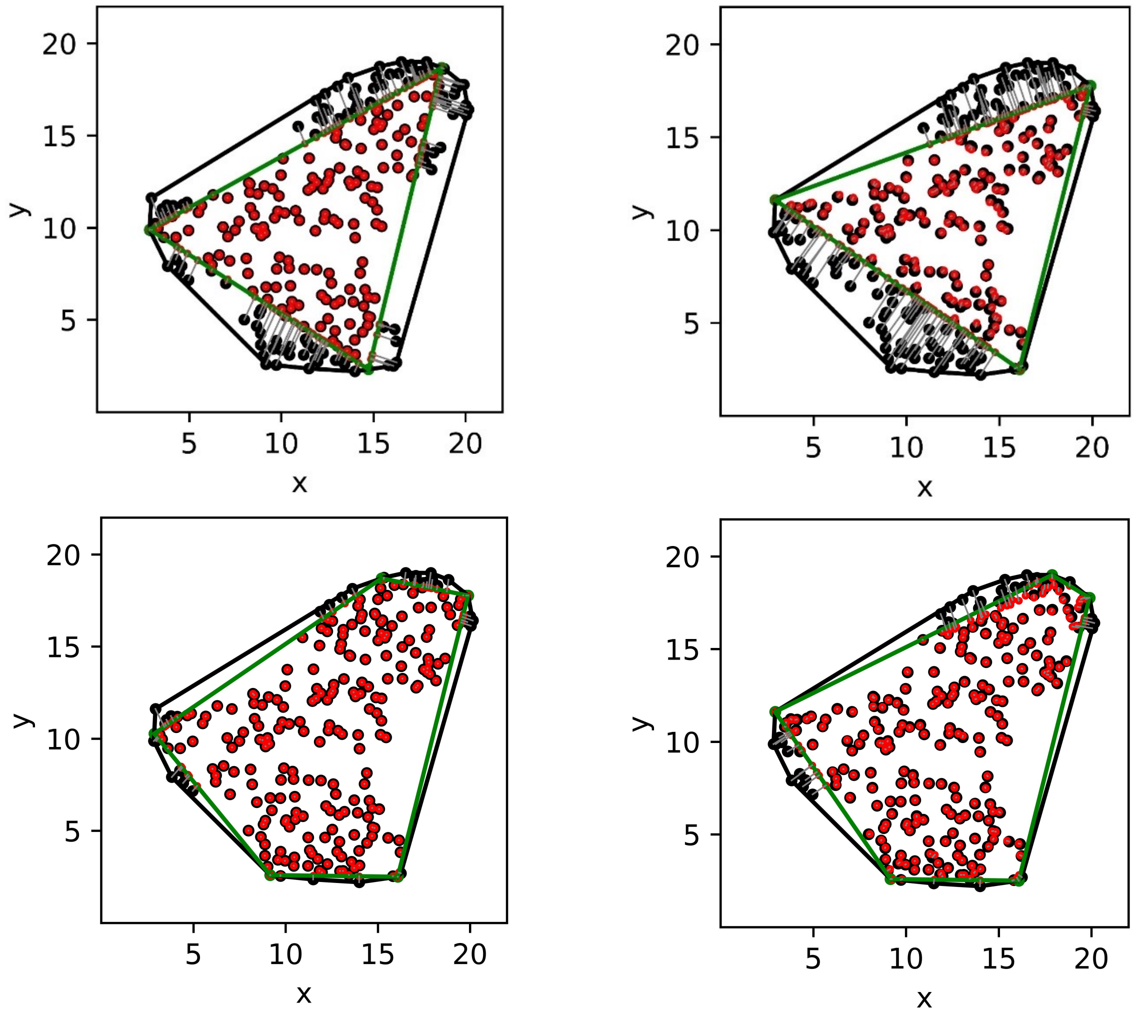
Training a Support Vector Machine



Willsch et al.
Support vector machines on the D-Wave quantum annealer.
Computer physics communications 248 (2020): 107006.

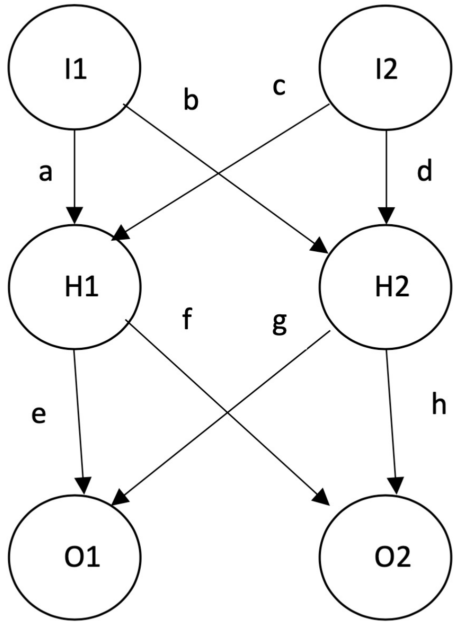
Training an Archetypes Set

R-Package “archetypes” | Our approach



Feld et al.
Approximating archetypal analysis using quantum annealing.
Proceedings of ESANN, 2020.

Training a Neural Network



	a+c+	a+c-	a-c+	a-c-	b+d+	b+d-	b-d+	b-d-	e+g+	e+g-	e-g+	e-g-	f+h+	f+h-	f-h+	f-h-	000	001	010	011	100	101	110	111	000	001	010	011	100	101	110	111
a+c+	-10																															
a+c-		-10																														
a-c+			-10																													
a-c-				-10																												
b+d+					-10																											
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b-d-								-10																								
e+g+									-10																							
e+g-										-10																						
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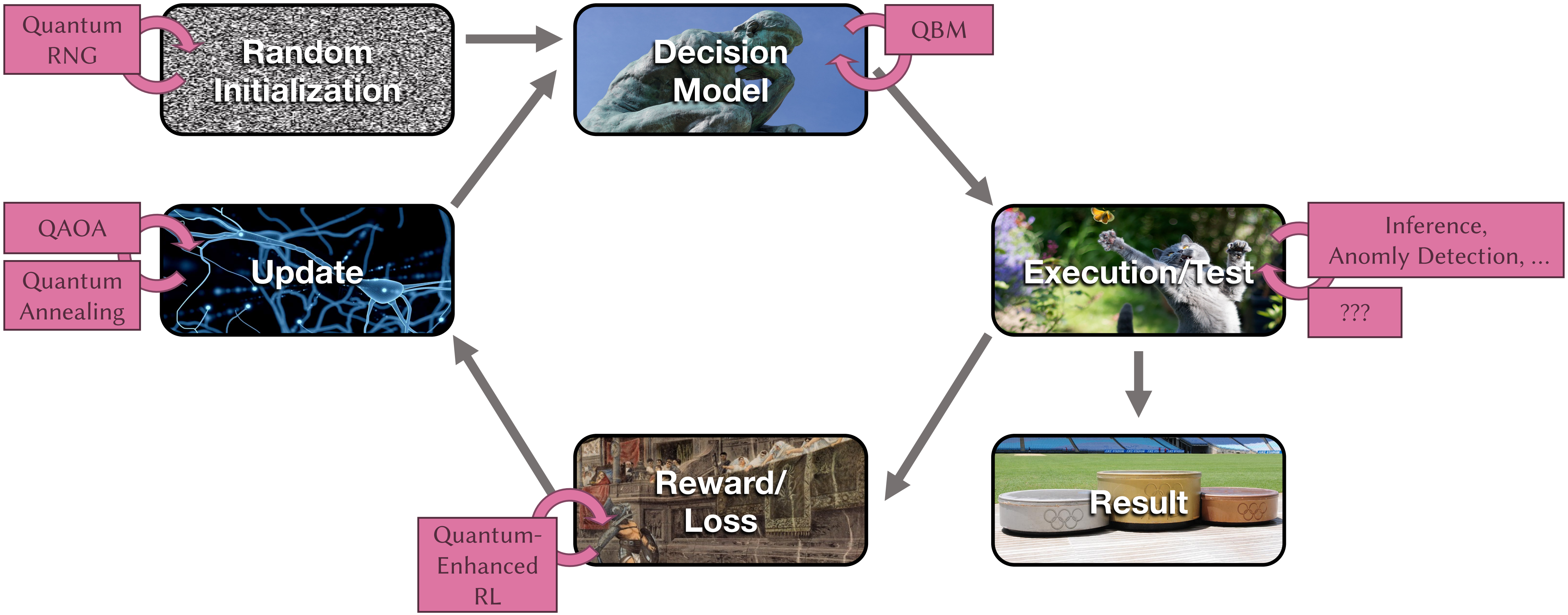
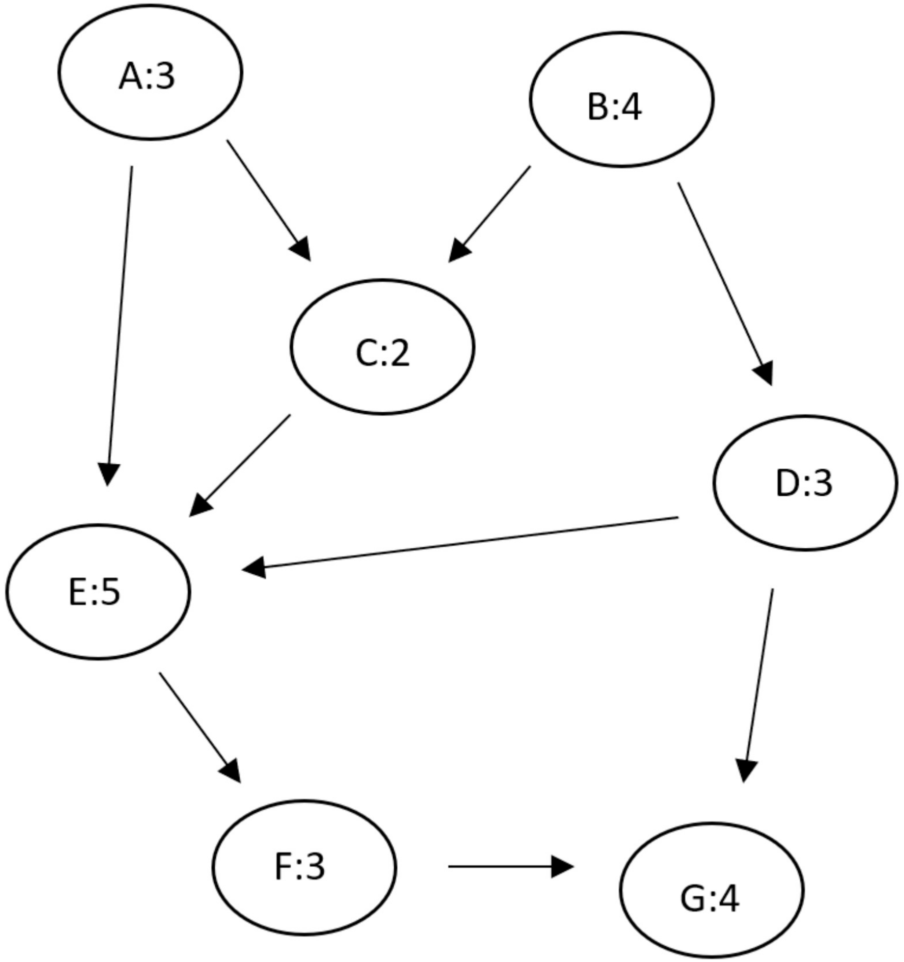
42 Quantum Machine Learning

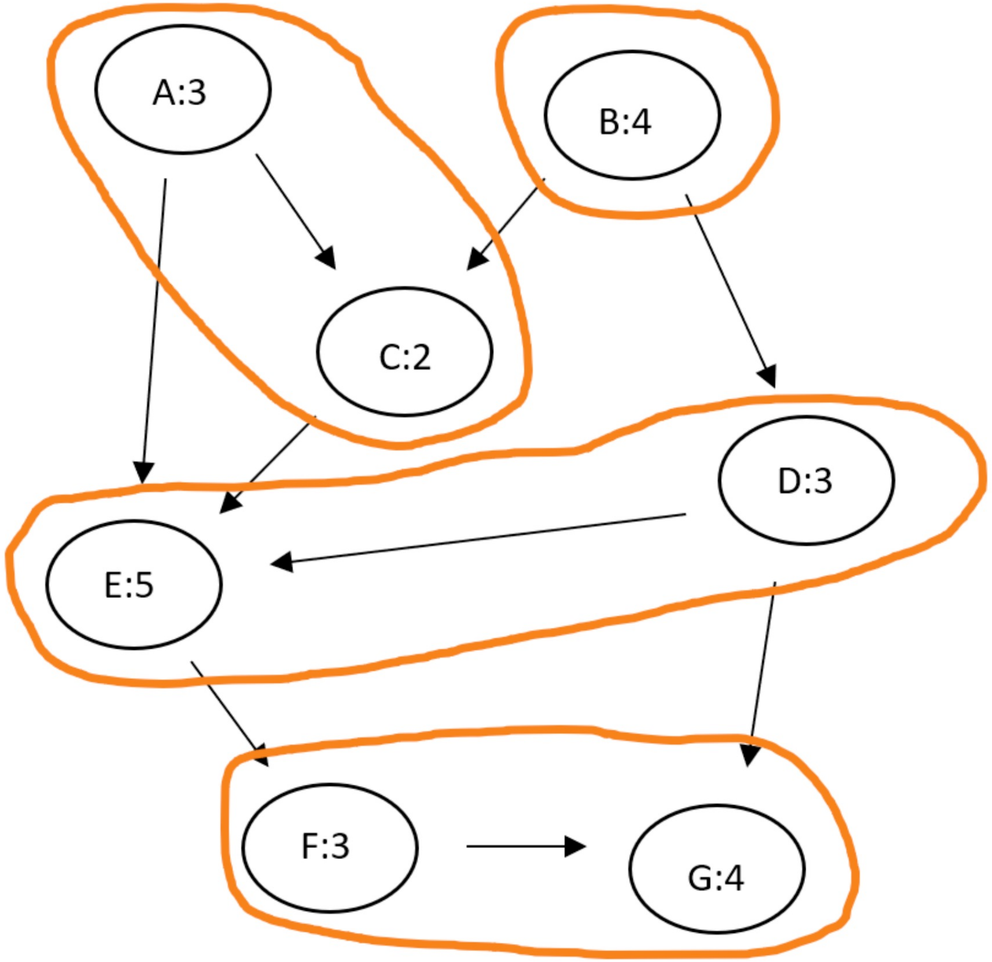


43 Inference in Bayesian Networks



	CA,B	CB,A	AB,C	CAB	D,B	DB	EA,CD	EC,AD	ED,AC	F,E	FE	G,FD	F,GD	D,GF	GFD
CA,B	-90	999	999	999	-4	-4			-6						
CB,A		-89	999	999			-3	-3	-3						
AB,C			-87	999			-2	-2	-2						
CAB				-76											
D,B					-93	999	-3	-3	-3			-3	-3	-3	-3
DB						-88									
EA,CD							-79	999	999						
EC,AD								-81	999						
ED,AC									-79					-3	
F,E										-92	999	-3	-3	-3	-3
FE											-85				
G,FD												-87	999	999	999
F,GD													-85	999	999
D,GF														-85	999
GFD															-64

44 Inference in Bayesian Networks

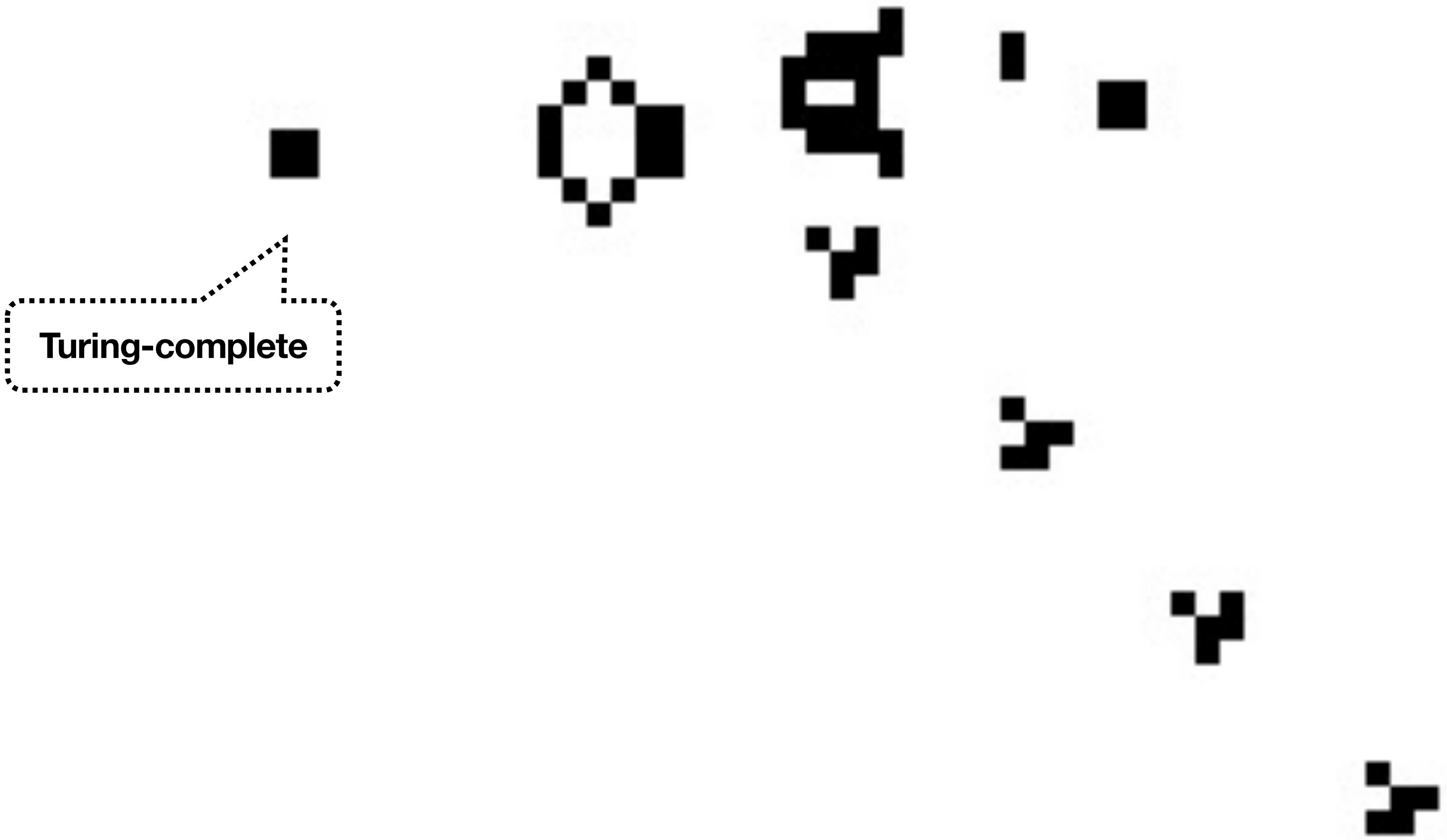


	CA,B	CB,A	AB,C	CAB	D,B	DB	EA,CD	EC,AD	ED,AC	F,E	FE	G,FD	F,GD	D,GF	GFD
CA,B	-90	999	999	999	-4	-4			-6						
CB,A		-89	999	999			-3	-3	-3						
AB,C			-87	999			-2	-2	-2						
CAB				-76											
D,B					-93	999	-3	-3	-3			-3	-3	-3	-3
DB						-88									
EA,CD							-79	999	999						
EC,AD								-81	999						
ED,AC									-79					-3	
F,E										-92	999	-3	-3	-3	-3
FE											-85				
G,FD												-87	999	999	999
F,GD													-85	999	999
D,GF														-85	999
GFD															-64

Simulating the Game of Life

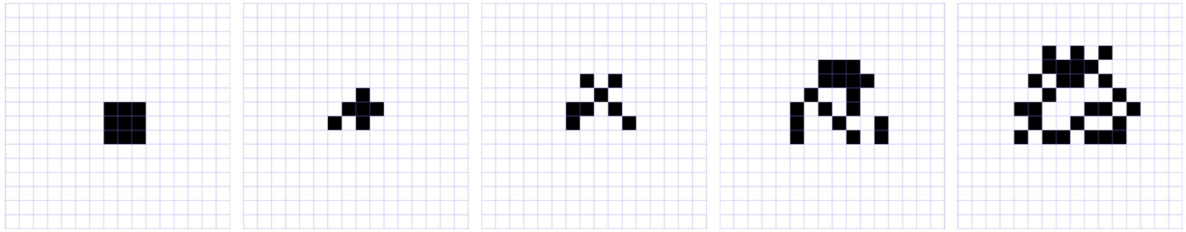
en.wikipedia.org/wiki/Conway%27s_Game_of_Life

46 Simulating the Game of Life



en.wikipedia.org/wiki/Conway%27s_Game_of_Life

47 Simulating the probabilistic Game of Life



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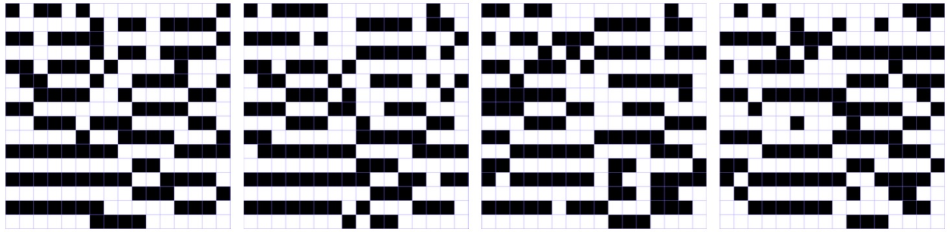
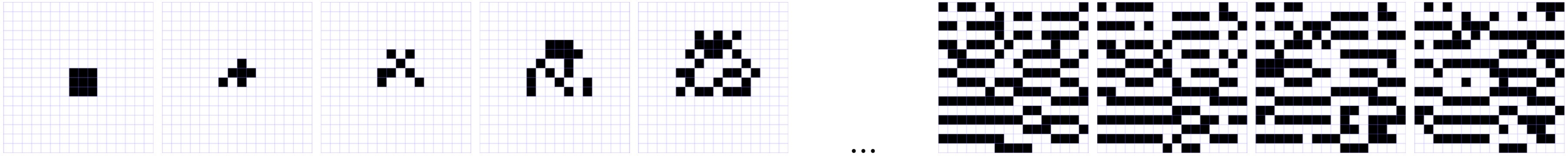
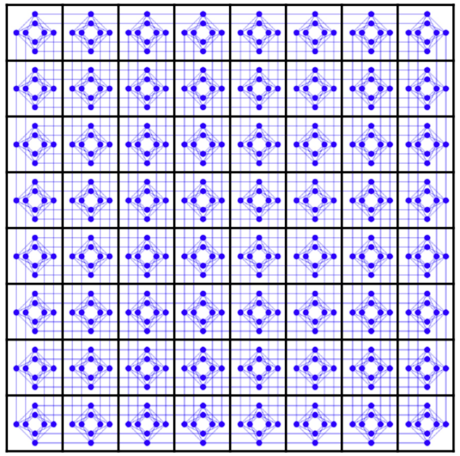


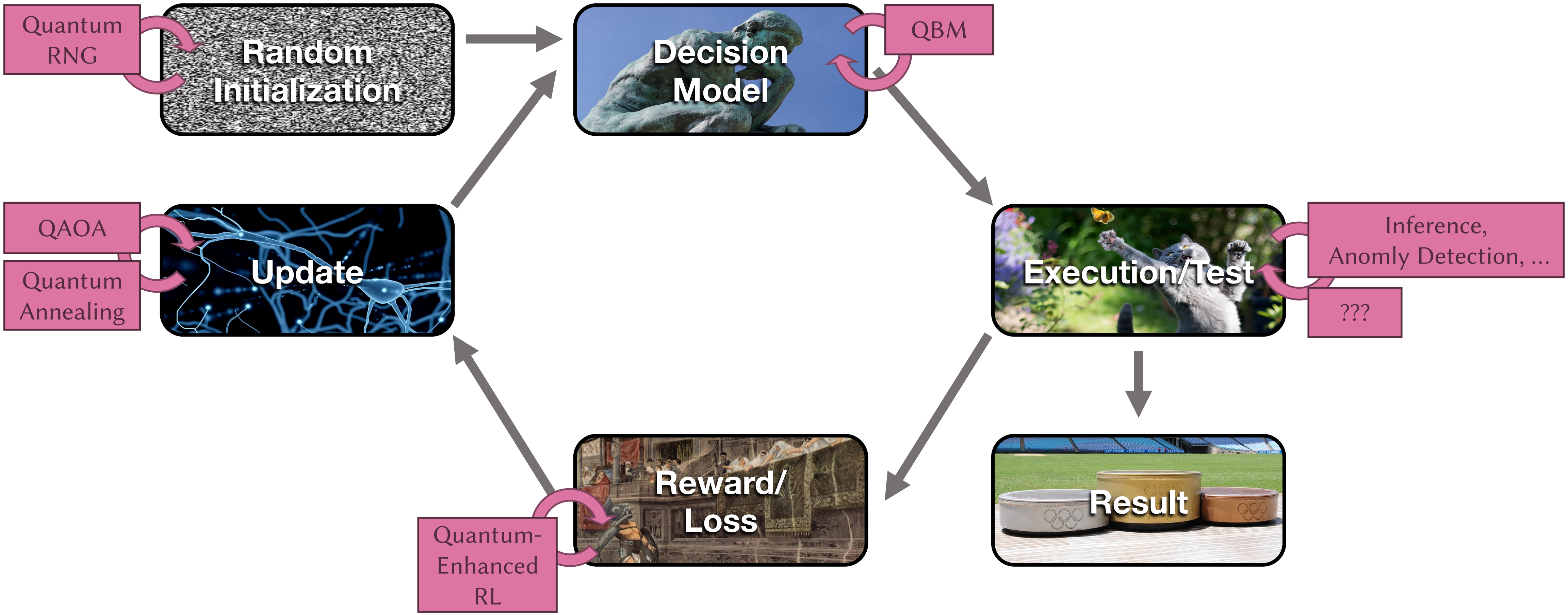
Simulating the probabilistic Game of Life



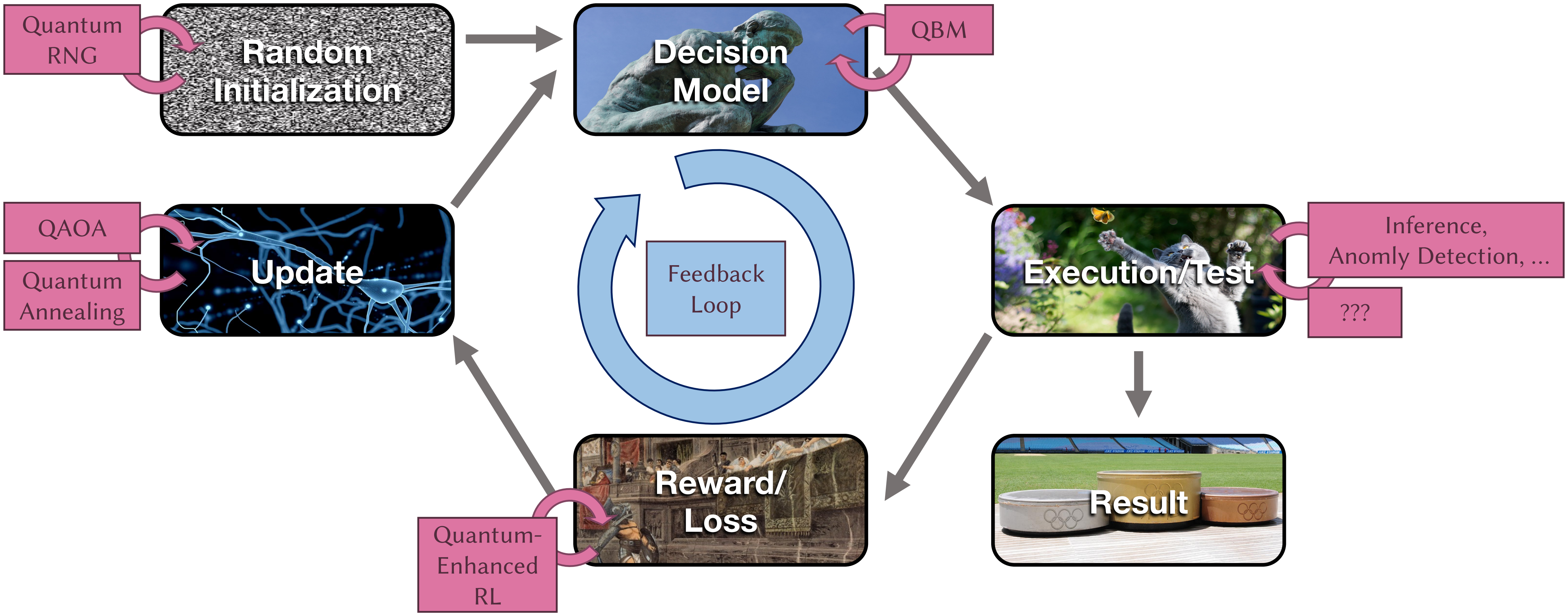


What's Next?

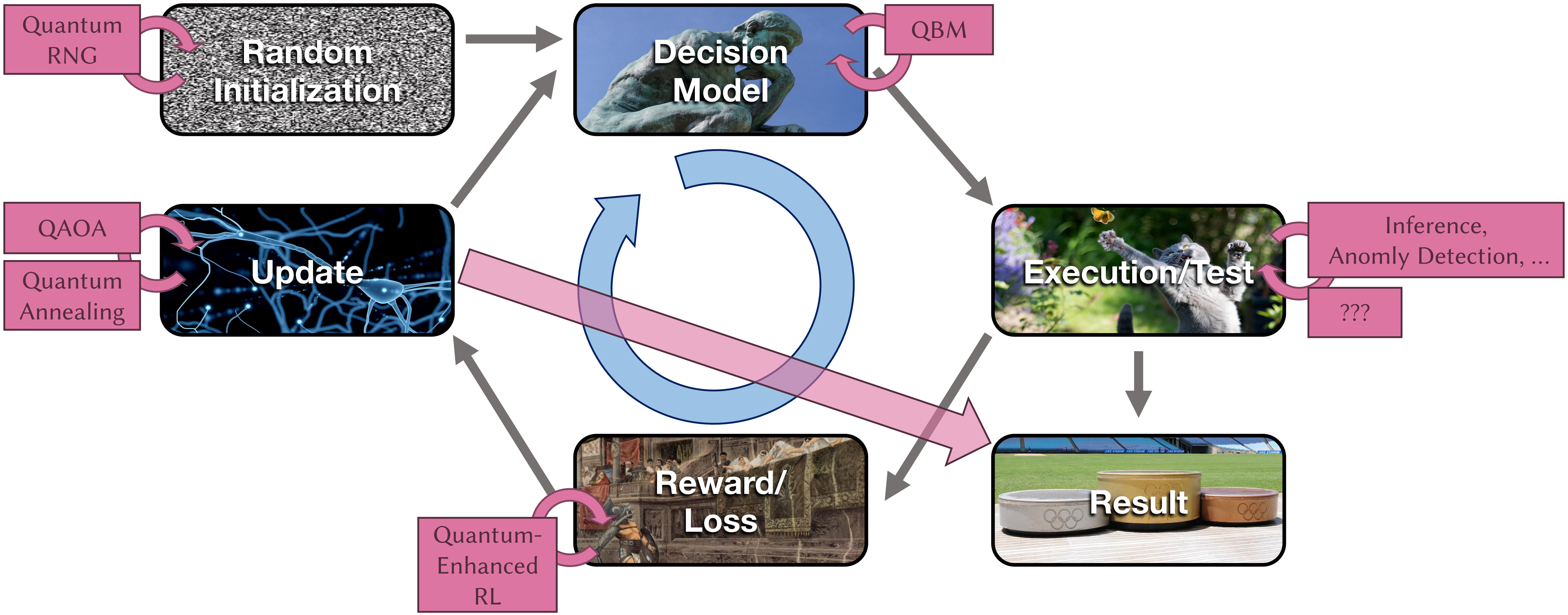
Quantum Machine Learning



51 Quantum Machine Learning



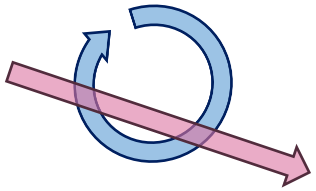
52 Quantum Machine Learning



53 Challenges for Quantum AI

The Feedback Loop

Replace the feedback loop around training entirely with a quantum algorithm.



54 The Amount of Data

	CA,B	CB,A	AB,C	CAB	D,B	DB	EA,CD	EC,AD	ED,AC	F,E	FE	G,FD	F,GD	D,GF	GFD
CA,B	-90	999	999	999	-4	-4			-6						
CB,A		-89	999	999			-3	-3	-3						
AB,C			-87	999			-2	-2	-2						
CAB				-76											
D,B					-93	999	-3	-3	-3			-3	-3	-3	-3
DB						-88									
EA,CD							-79	999	999						
EC,AD								-81							
ED,AC															
F,E															
FE															
G,FD															
F,GD															
D,GF															
GFD															

	a+c+	a+c-	a-c+	a-c-	b+d+	b+d-	b-d+	b-d-	e+g+	e+g-	e-g+	e-g-	f+h+	f+h-	f-h+	f-h-	000	001	010	011	100	101	110	111	000	001	010	011	100	101	110	111
a+c+	-10																															
a+c-		-10																														
a-c+			-10																													
a-c-				-10																												
b+d+					-10																											
b+d-						-10																										
b-d+							-10																									
b-d-								-10																								
e+g+									-10																							
e+g-										-10																						
e-g+											-10																					
e-g-												-10																				
f+h+													-10																			
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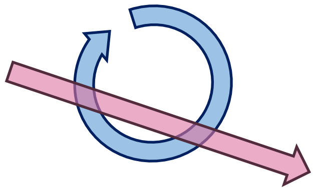
	$x_{1,r}$	$x_{1,g}$	$x_{1,b}$	$x_{2,r}$	$x_{2,g}$	$x_{2,b}$	$x_{3,r}$	$x_{3,g}$	$x_{3,b}$
$x_{1,r}$	-1	2	2	1			1		
$x_{1,g}$		-1	2		1			1	
$x_{1,b}$			-1			1			1
$x_{2,r}$				-1	2	2	1		
$x_{2,g}$					-1	2		1	
$x_{2,b}$						-1			1
$x_{3,r}$							-1	2	2
$x_{3,g}$								-1	2
$x_{3,b}$									-1

Challenges for Quantum AI

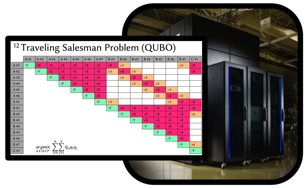
The Feedback Loop

Replace the feedback loop around training entirely with a quantum algorithm.



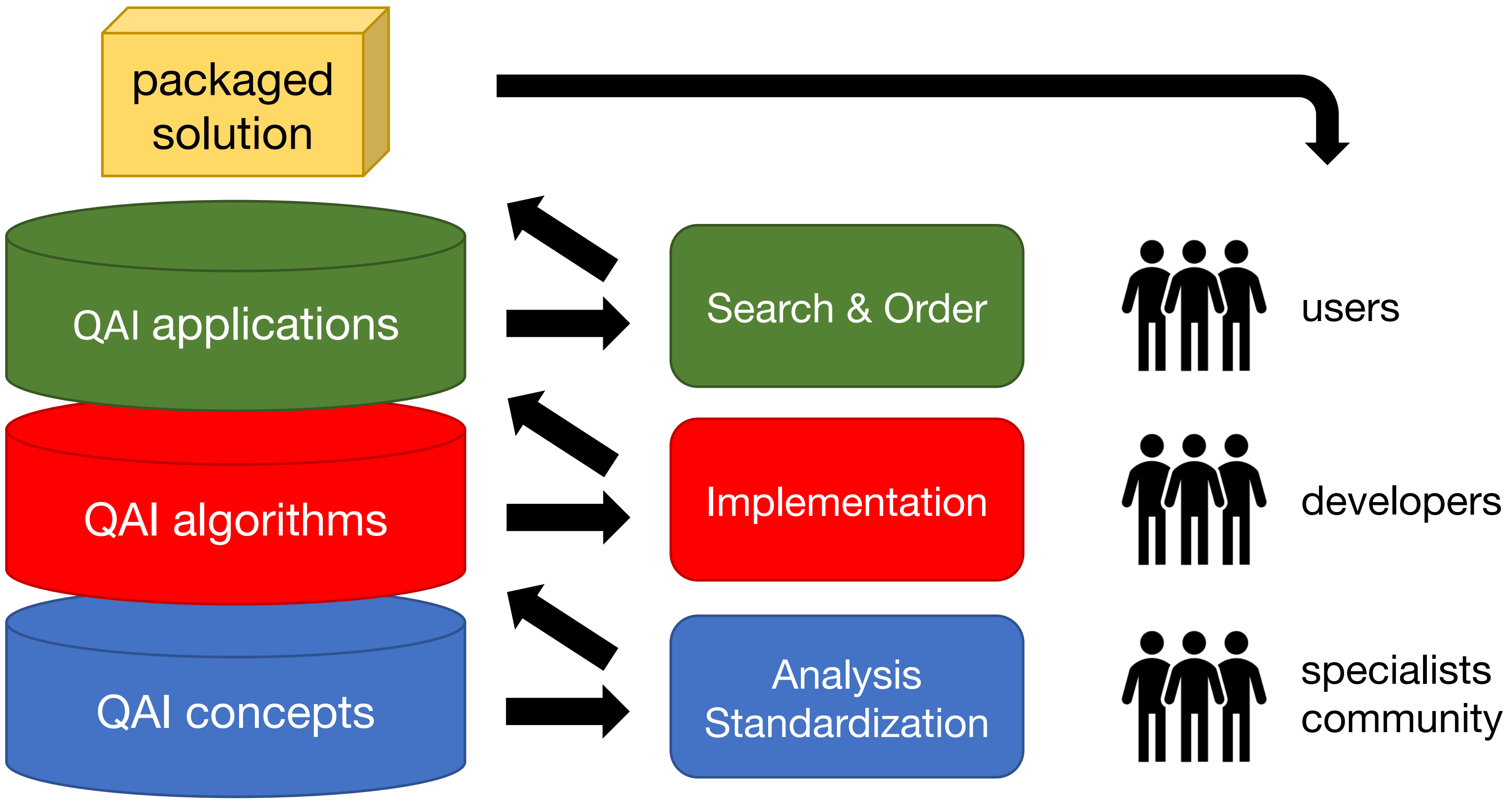
The Training Data

Provide means to process (the essence of) large amounts of data on quantum computers.



A Full Stack of Knowledge

PlanQK
www.planqk.de



Prof Dr. Dr. h.c.
Frank Leymann
Scientific Director

Challenges for Quantum AI

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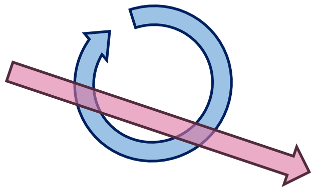

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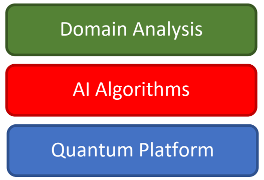
The Interfaces

Provide standardized interfaces that allow for dynamic combination of QAI components and (by extension) for experts of different fields to collaborate on QAI algorithms.



The Best Quantum Algorithm?

1. Employ a dozen algorithmically trained physicists and (physically trained??) programmers.

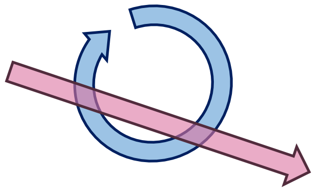
2. They will find a better algorithm than the one you wrote that one night in total desparation.

3. That algorithm may not actually need to use any quantum hardware.

Challenges for Quantum AI

The Feedback Loop

Replace the feedback loop around training entirely with a quantum algorithm.



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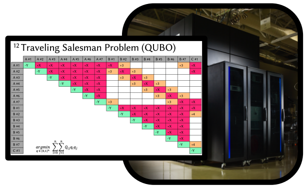

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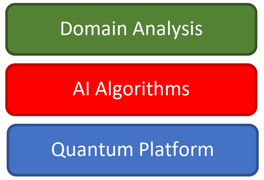
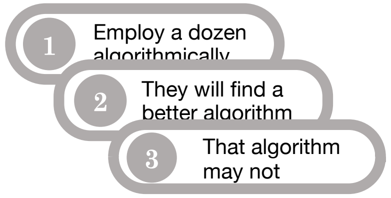


The Real Reason

Keep track of the source of observed improvements and use it wisely.



Towards Quantum Artificial Intelligence

Thomas Gabor

QAR-Lab, LMU Munich

Thank You!

QAR LAB

LMU LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN

Towards Quantum Artificial Intelligence
Thomas Gabor (QAR-Lab, LMU Munich)

Image Sources

- https://www.bostonmagazine.com/news/2015/07/30/boston-2024-winners-losers
- https://en.wikipedia.org/wiki/The_Thinker#/media/File:Le_Penseur_in_the_Jardin_du_Musée_Rodin,_Paris_14_June_2015.jpg
- https://www.boredpanda.com/jumping-cats/
- https://kinder.wdr.de/tv/wissen-macht-ah/bibliothek/kuriosah/bibliothek-daumen-hoch-100.html
- https://www.medicalnewstoday.com/articles/320289.php#carry_message
- https://www.dwavesys.com/d-wave-two™-system
- https://www.dwavesys.com/sites/default/files/styles/2014%20Finding%20graph%20minors-%20Embedding.pdf
- https://www.dwavesys.com/press-releases/d-wave-systems-announces-general-availability-1000-qubit-d-wave-2x-quantum-computer
- https://interestingengineering.com/quantum-entanglement-made-data-teleportation-possible-between-two-chips
- https://spartanideas.msu.edu/2013/11/13/smooth-and-rugged-fitness-landscapes/
- https://www.iaas.uni-stuttgart.de/institut/team/Leymann/