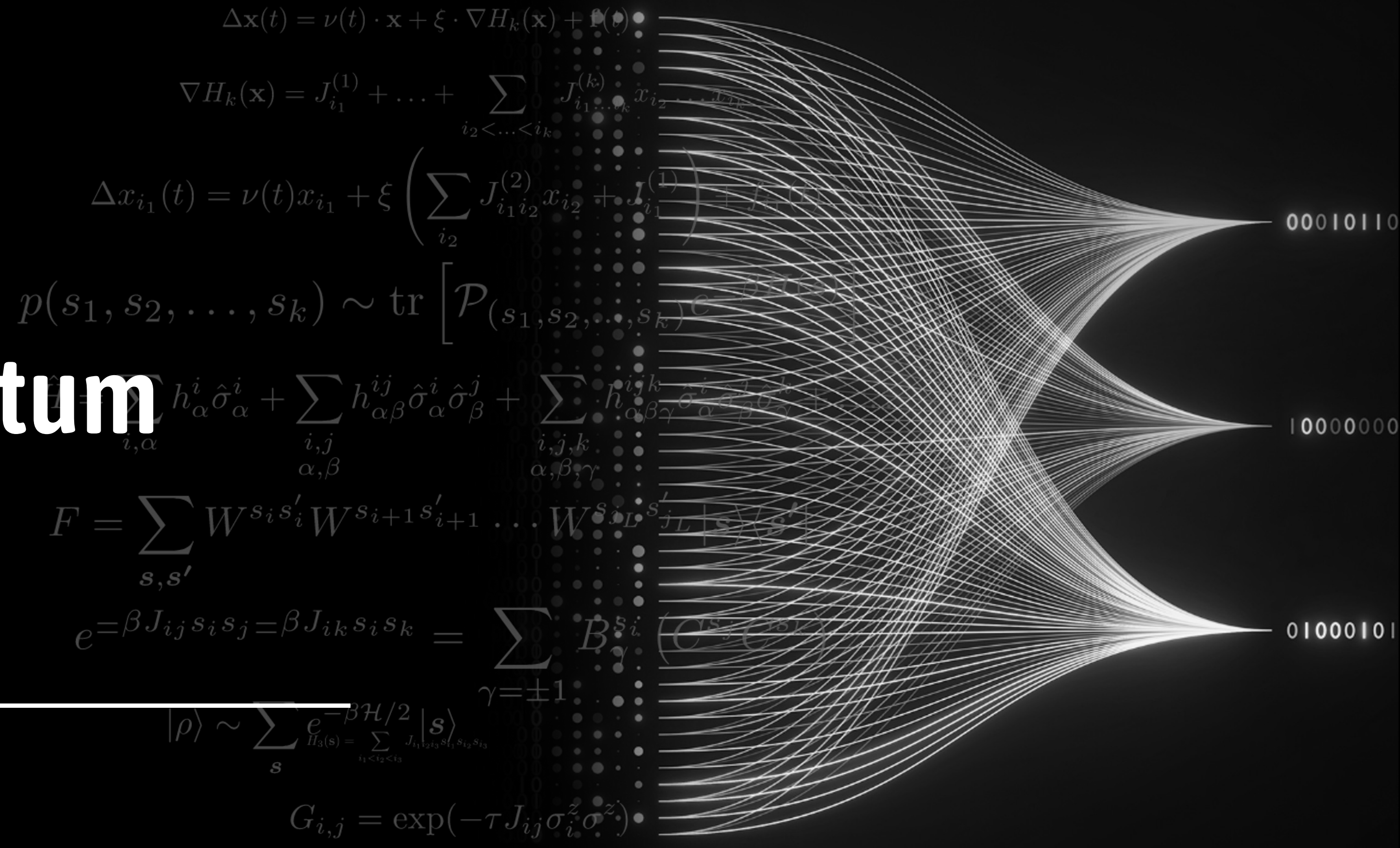
QUANTUM DATA CENTER

Ushering In the Quantum Information Age.



qdc.ai

About Me

Dominik Andrzejczuk

Founder & CEO – dom@qdc.ai

B.S. Physics – Villanova University

Dominik spent the majority of his career in Palo Alto, California,
Joined the venture capital firm Morado Ventures in 2014.
Worked directly with one of the founders of Yahoo! Jerry Yang

One of Dominik’s first investments was in Rigetti Quantum Computing

In 2018, Dominik left California to found Atmos Ventures in Warsaw, Poland.

Dominik has invested in fault tolerant quantum computing startups, Oxford Ionics and ORCA Computing.

Who are we?

Our Team has collectively published **HUNDREDS of papers in Machine Learning, HPC, Optimization, Scientific Programming, and Quantum Computing with THOUSANDS of citations.**

7 PhDs
17 FTEs

QDC takes advantage of Poland's High Quality & Capital Efficient Talent and Access to Nondilutive R&D Grants.

Investors

Jerry Yang
Founder
Yahoo!

Ash Patel
Former CPO
Yahoo!

Mike Marquez
Former EVP
Yahoo!

Itamar Arel
Serial AI
Entrepreneur

Andrew Sieja
Founder
Relativity

Marcin Wojtczak
Former CGO
Relativity

Vision

QDC is **empowering** the **future** through **physics-inspired optimization**.

Our vision is to **democratize access** to this transformative technology, unlocking efficiencies in the world's most complex challenges for the **betterment** of **humanity**.

Mission

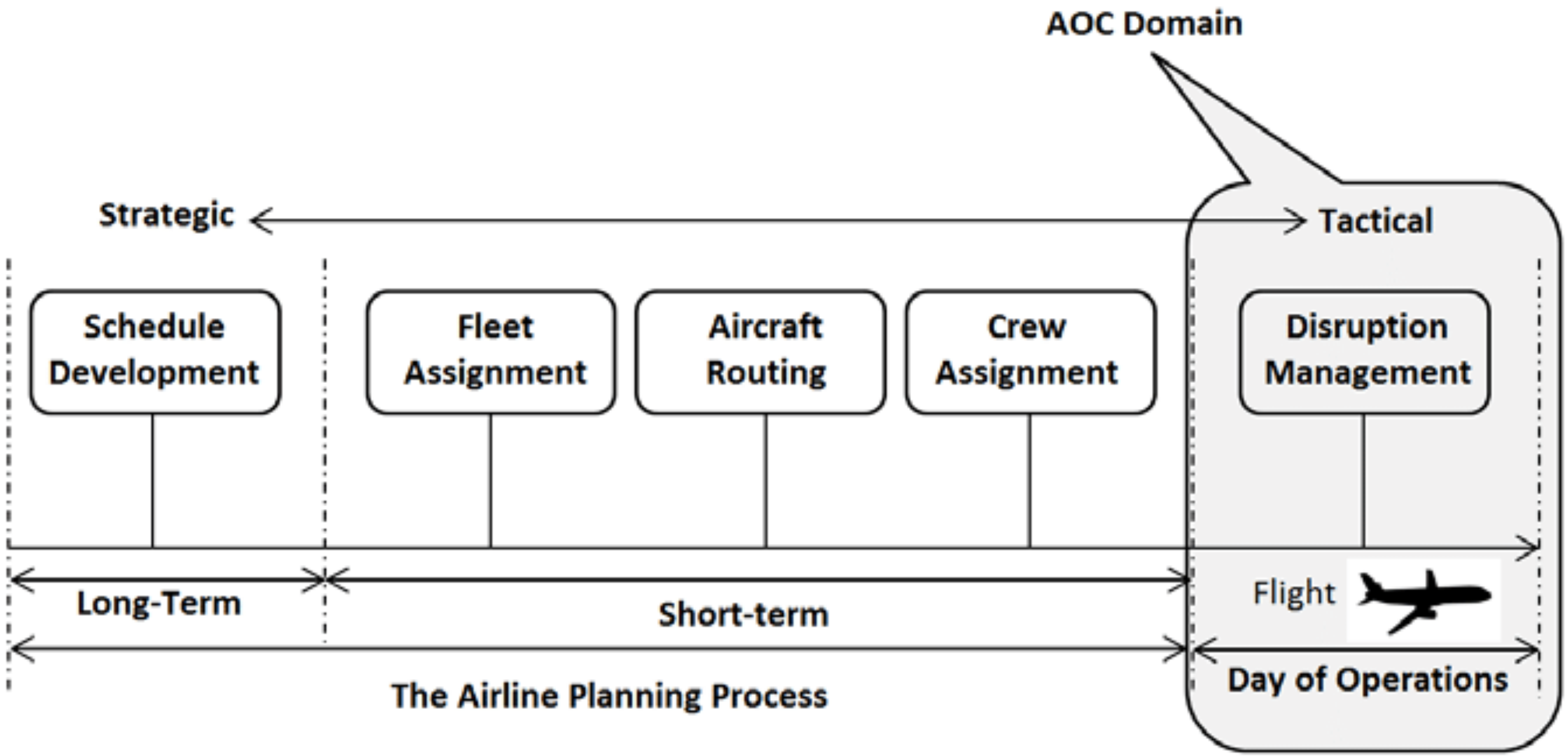
Our mission at QDC is to **bridge science** and **business**, solving optimization problems and driving value for our customers by seamlessly integrating **physics-inspired solutions** into their processes.

How do we get there?

Focus on the Business Problem First.

Airline Disruption Management

i.e. Algorithmic Decision Support in Real Time.


AOC Domain
Strategic
Tactical
Schedule Development
Fleet Assignment
Aircraft Routing
Crew Assignment
Disruption Management
Flight
Long-Term
Short-term
The Airline Planning Process
Day of Operations

“In 2007, the total delay cost in the airline industry in the United States (US) was $32.9 billion from which $8.3 billion was of additional expenses for fuel, crew, and maintenance.”

Total number of flights has ***increased by 47%*** *since then.*

Airline Disruption Management:

Aircraft Recovery

Crew Recovery

Passenger Recovery

Aircraft Recovery

The aircraft recovery problem can be formulated as follows:

given a flight schedule and a set of disruptions, determine which flights to delay or cancel, and re-assign the available aircraft to the flights such that the disruption cost is minimized.

Aircraft Recovery

Exact Optimization Methods

The time-band approximation model on flight operations recovery model considering random flight flying time in China. ***LINK***

Meta Heuristics

Dynamic aircraft recovery problem - An operational decision support framework ***LINK***

Multiple objective solution approaches for aircraft rerouting under the disruption of multi-aircraft ***LINK***

A Stochastic Programming Approach on Aircraft Recovery Problem ***LINK***

Two-Stage Heuristic Algorithm for Aircraft Recovery Problem ***LINK***

Crew Recovery

The crew recovery problem (CRP) can be formulated as follows:

given a flight schedule and a set of disruptions, re-assign to each (recovered) flight the necessary cabin and flight crew such that the disruption costs are minimized. For crew recovery, these disruption costs can include direct crew costs (e.g., remuneration or overtime compensation) and cost for deadheading crew.

Crew Recovery

Exact Optimization Methods

None

Meta Heuristics

Multiobjective Optimization of Airline Crew Roster Recovery Problems Under Disruption Conditions ***LINK***

A Solutuion Method for Airline Crew Recovery Problems ***LINK***

Passenger Recovery

Passenger recovery can be formulated as follows:

Given a recovered flight and crew schedule and a set of disrupted passenger itineraries, re-assign to each disrupted itinerary the (recovered) flights necessary (given seat availability) to accommodate passengers from their current position to their destination while minimizing cost. These passenger recovery costs can include both hard and soft costs. Hard costs are directly incurred when a passenger cannot complete its scheduled itinerary (e.g., compensation for delay and cancellation as stipulated by government regulations). Soft costs are the potential losses of future revenue as a result of passenger inconvenience, possibly causing the passenger to switch to a different airline in the future.

Passenger Recovery

Exact Optimization Methods

Airline delay management problem with airport capacity constraints and priority decisions. ***LINK***

Flight Network-Based Approach for Integrated Airline Recovery with Cruise Speed Control ***LINK***

Meta Heuristics

Considering Passenger Preferences in Integrated Postdisruption Recoveries of Aircraft and Passengers ***LINK***

Integrated recovery of aircraft and passengers after airline operation disruption based on a GRASP algorithm ***LINK***

A math-heuristic algorithm for the integrated air service recovery ***LINK***

Google and Lufthansa Have Validated This Approach

[AGIFORS Presentation Can Be Found HERE]

Google LUFTHANSA GROUP

Deploying an Integrated Airline Disruption Management Solver at Lufthansa Group

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danielduque@google.com

AGIFORS - Sep 2022

Google recently demonstrated a Proof of Concept (PoC) in collaboration with **Lufthansa**, focusing on the issue of network repair. In this context, network repair refers to the rapid rebooking of passengers who either missed their connections or had their flights cancelled.

+ Heuristic subsolvers	CP-SAT	+ CP-SAT
$65,678	$117,833	$34,517
$147,130	$96,968	$96,508
$283,865	$86,108	$78,677
$31,274	$98,125	$19,361
$0	-	$0
$36,419	$166,626	$28,553
$229,431	$99,279	$98,752
$367,337	$172,202	$104,383
$58,174	$186,426	$30,997
$0	-	$0

Savings per cancelled flight using Google's CP-SAT and heuristic solvers – Google OR Tools
Source: Deploying an Integrated Airline Disruption Management Solver at Lufthansa Group.
daniel.bogadoduffner@swiss.com tobyodavies@google.com danielduque@google.com - AGIFORS - Sep 2022

Integrated Recovery

*Both from a mathematical and computational perspective, the integration of all recovery stages (**aircraft, crew, and passengers**) is an extremely difficult task. The purpose of this integration is to minimize the total disruption cost. This is achieved by weighing the disruption cost related to aircraft, crew, and passengers simultaneously to find the recovery solution that overall results in the lowest cost for the airline.*

Integrated Recovery

Exact Optimization Methods

Arikan et al. (2017) developed a new flight network representation for the integrated recovery problem, based on the flow of each entity (aircraft, crew, and passenger) through the network. With the proposed flight network, the problem size is kept within limits so that real-time solutions can be provided since it does not require discretization of departure times and cruise speed decisions.

Meta Heuristics

Dynamic aircraft recovery problem - An operational decision support framework ***LINK***

Multiple objective solution approaches for aircraft rerouting under the disruption of multi-aircraft ***LINK***

Integrated recovery of aircraft and passengers after airline operation disruption based on a GRASP algorithm ***LINK***

A math-heuristic algorithm for the integrated air service recovery ***LINK***

Airlines Are Plagued By Disruption Challenges Daily

United States

United Airlines says software update prompted ground stop

By **David Shepardson**

September 5, 2023 10:33 PM GMT+1 · Updated 13 days ago

Aa

The One World trace Center and the New York skyline are seen while United Airlines planes use the tarmac at Newark Liberty International Airport in Newark, New Jersey, U.S., May 12, 2023. REUTERS/Eduardo Munoz/File Photo *Acquire Licensing Rights*

Southwest Airlines Delays and Cancels Flights for a Third Day

The headaches began with problems with a weather data supplier on Monday, then technical troubles on Tuesday, and the issues spilled over into Wednesday.

Give this article

Just as millions of people began to fly again, Southwest Airlines has had technical problems that resulted in three days of canceled or delayed flights. Mike Blake/Reuters

FlightAware, a flight tracking website, said United had canceled seven flights and delayed 364 flights, or 13% of its flights on Tuesday.

"We are not having staffing issues, but we had experienced problems connecting flight crews to their scheduled aircraft. **It is a scheduling issue, not a staffing issue,**" a SouthWest spokesperson said.

Diagnosing Infeasible Optimization Problems Using Large Language Models

Table 3: OptiChat's accuracy results.

Study group	Satisfactory answers	Troubleshooting success rate
Inexperienced	90.93%	88%
Experienced	87.20%	96.77%

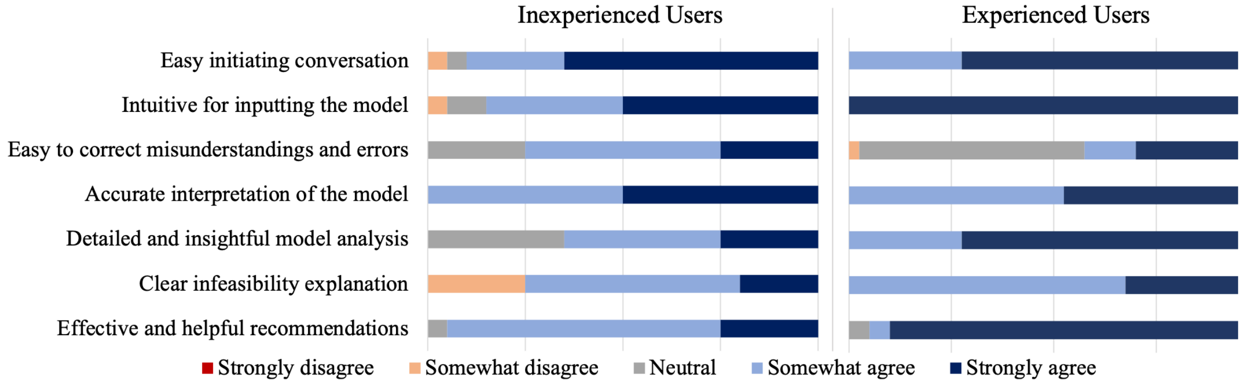
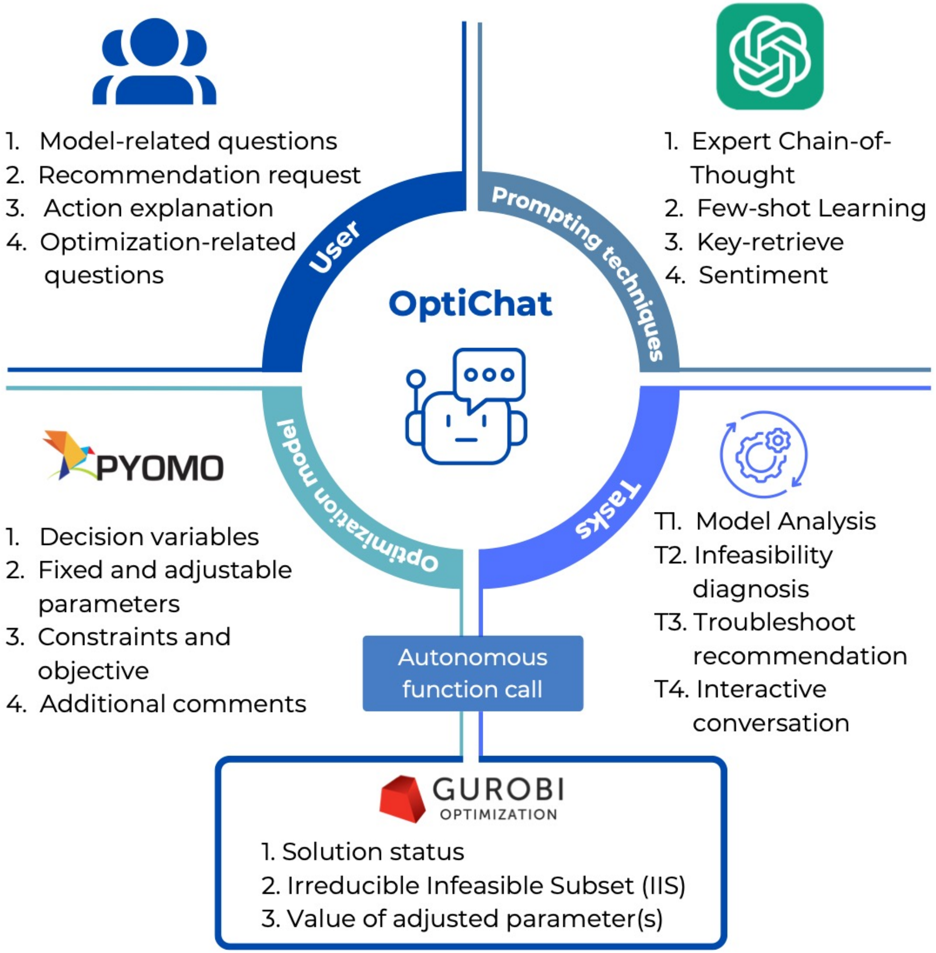


Figure 5: User study results: Likert graph of survey statements.



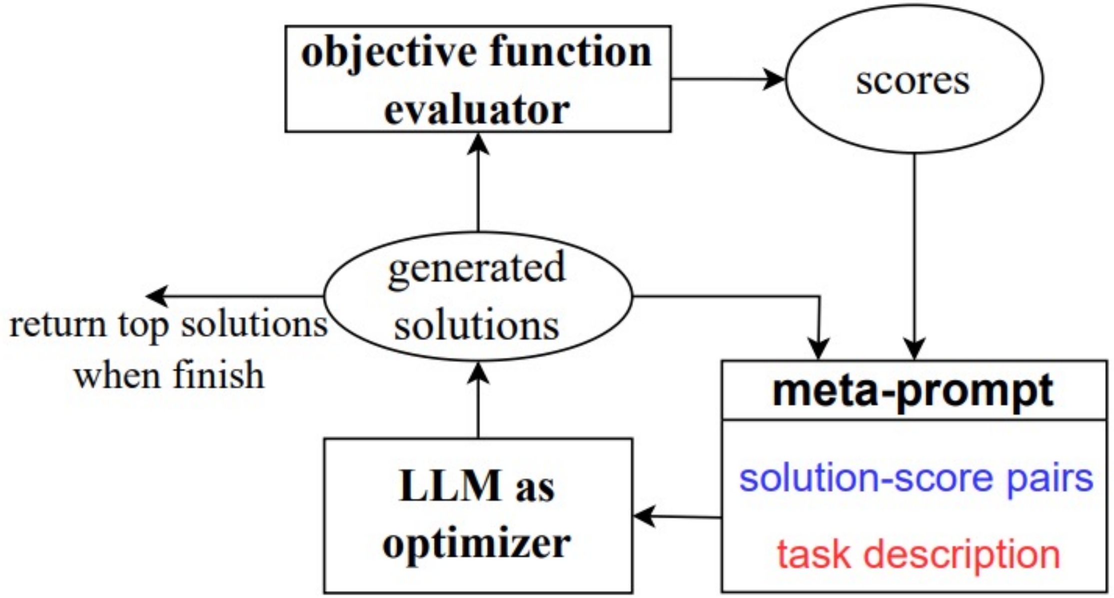
https://arxiv.org/pdf/2308.12923v1.pdf

An Irreducible Infeasible Subsystem (IIS)

Large Language Models as Optimizers – Google Deep Mind

Large Language Models as Optimizers by Yang et al. (2023) (Arxiv Link) is another fresh attempt to use LLMs for optimization tasks. Their approach is called Optimization by Prompting (OPRO).

OPRO takes the task description in natural language (meta-prompt) as a starting point, generates a solution and iterates using more LLM prompts.



Large Language Models as Optimizers – Google Deep Mind

They test the algorithm with well-known optimization tasks such as linear regression and traveling salesman problem (TSP).

Then they use benchmark datasets GSM8K and Big-Bench Hard (BBH).

They are realistic about the current results but optimistic about the future. They have a detailed appendix section elaborating on the goods and the bads.

You are given a list of points with coordinates below: (0): (-4, 5), (1): (17, 76), (2): (-9, 0), (3): (-31, -86), (4): (53, -35), (5): (26, 91), (6): (65, -33), (7): (26, 86), (8): (-13, -70), (9): (13, 79), (10): (-73, -86), (11): (-45, 93), (12): (74, 24), (13): (67, -42), (14): (87, 51), (15): (83, 94), (16): (-7, 52), (17): (-89, 47), (18): (0, -38), (19): (61, 58).
Below are some previous traces and their lengths. The traces are arranged in descending order based on their lengths, where lower values are better.

<trace> 0,13,3,16,19,2,17,5,4,7,18,8,1,9,6,14,11,15,10,12 </trace>
length:
2254

<trace> 0,18,4,11,9,7,14,17,12,15,10,5,19,3,13,16,1,6,8,2 </trace>
length:
2017

<trace> 0,11,4,13,6,10,8,17,12,15,3,5,19,2,1,18,14,7,16,9 </trace>
length:
1953

<trace> 0,10,4,18,6,8,7,16,14,11,2,15,9,1,5,19,13,12,17,3 </trace>
length:
1840

Give me a new trace that is different from all traces above, and has a length lower than any of the above. The trace should traverse all points exactly once. The trace should start with <trace> and end with </trace>.

Figure 18: An example of the meta-prompt for Traveling Salesman Problems with problem size $n = 20$. The blue text contains solution-score pairs; the orange text are meta-instructions.

https://arxiv.org/abs/2309.03409

The Most Powerful Solver on the Planet - VeloxQ

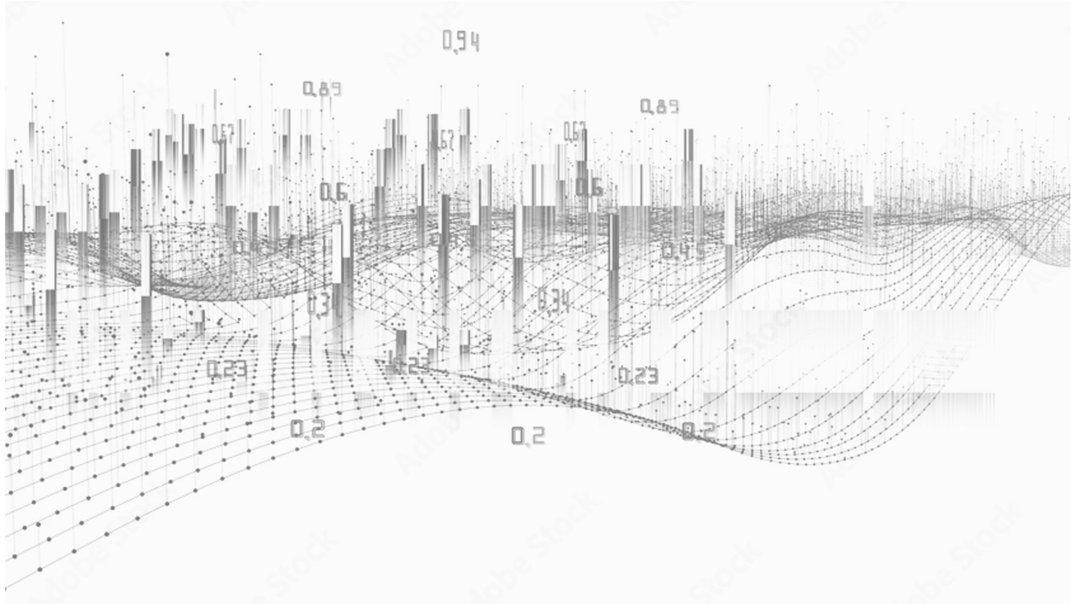
Idea

1) In nonlinear dynamical systems a small change in parameters can lead to a sudden and significant shift in the system's state.
2) We map optimization problems to such dynamical systems, and use physics-inspired algorithms to quickly navigate the solution space, exploiting these sudden shifts to converge to optimal or near-optimal solutions.
3) The approach is particularly potent for problems where traditional methods may struggle due to the vastness or complexity of the solution landscape.

Features

1) Solver for QUBO, HUBO and Ising model instances
2) GOAL: Handle up to 10^7+ variables for dense instances (fully connected graphs)
3) Delivers high accuracy results for the ground state
4) Can deliver multiple sub-optimal solutions in short time
5) Takes advantage of highly parallel computing – GPUs + FPGAs + ASICs
6) AutoTuneQ™ function to automatically adjust solver's hyper parameters
7) Quantum Ready

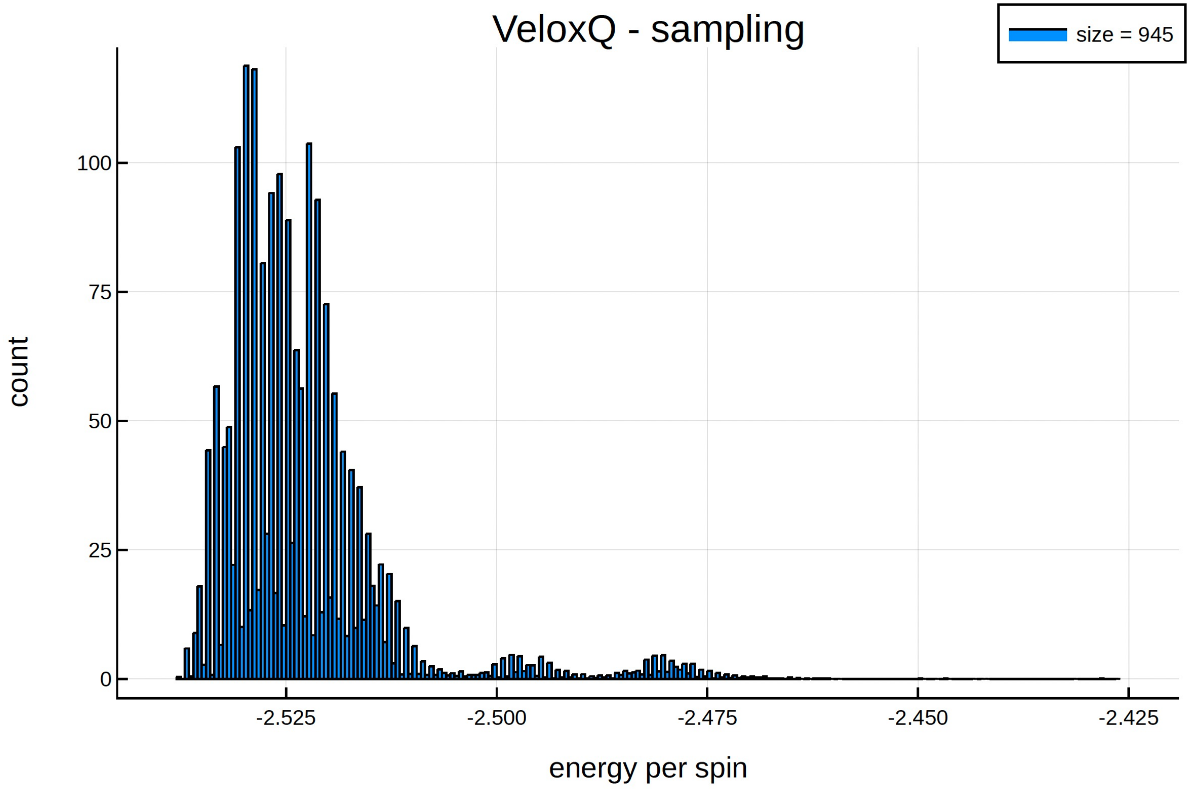
VeloxQ – QUBO & HUBO Heuristic Algorithm



VeloxQ – Google Instances

Found the ground state

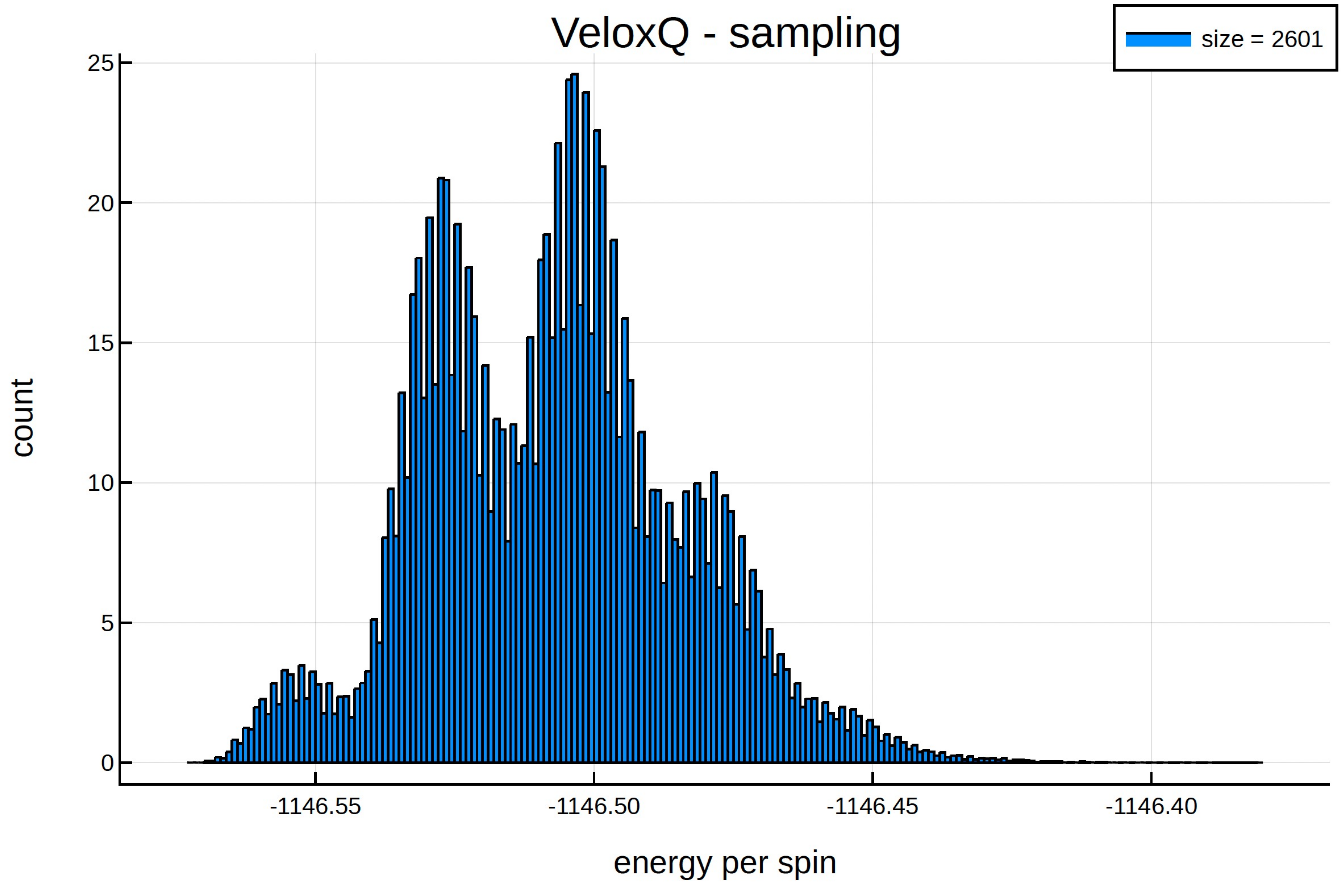
TTS ~ 25 seconds



VeloxQ – TSP-51

Within 1% of the ground state

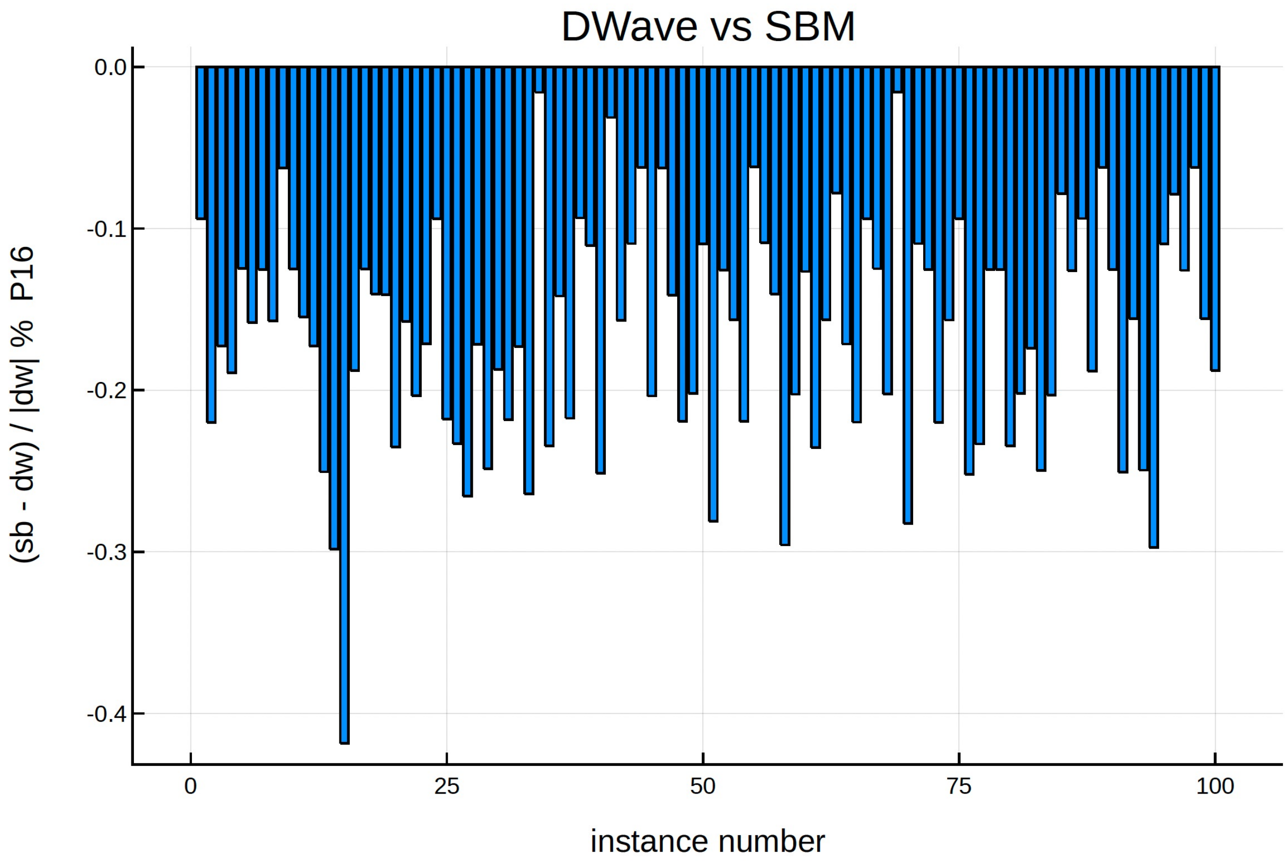
TTS ~ 60 minutes



VeloxQ – D-Wave Advantage

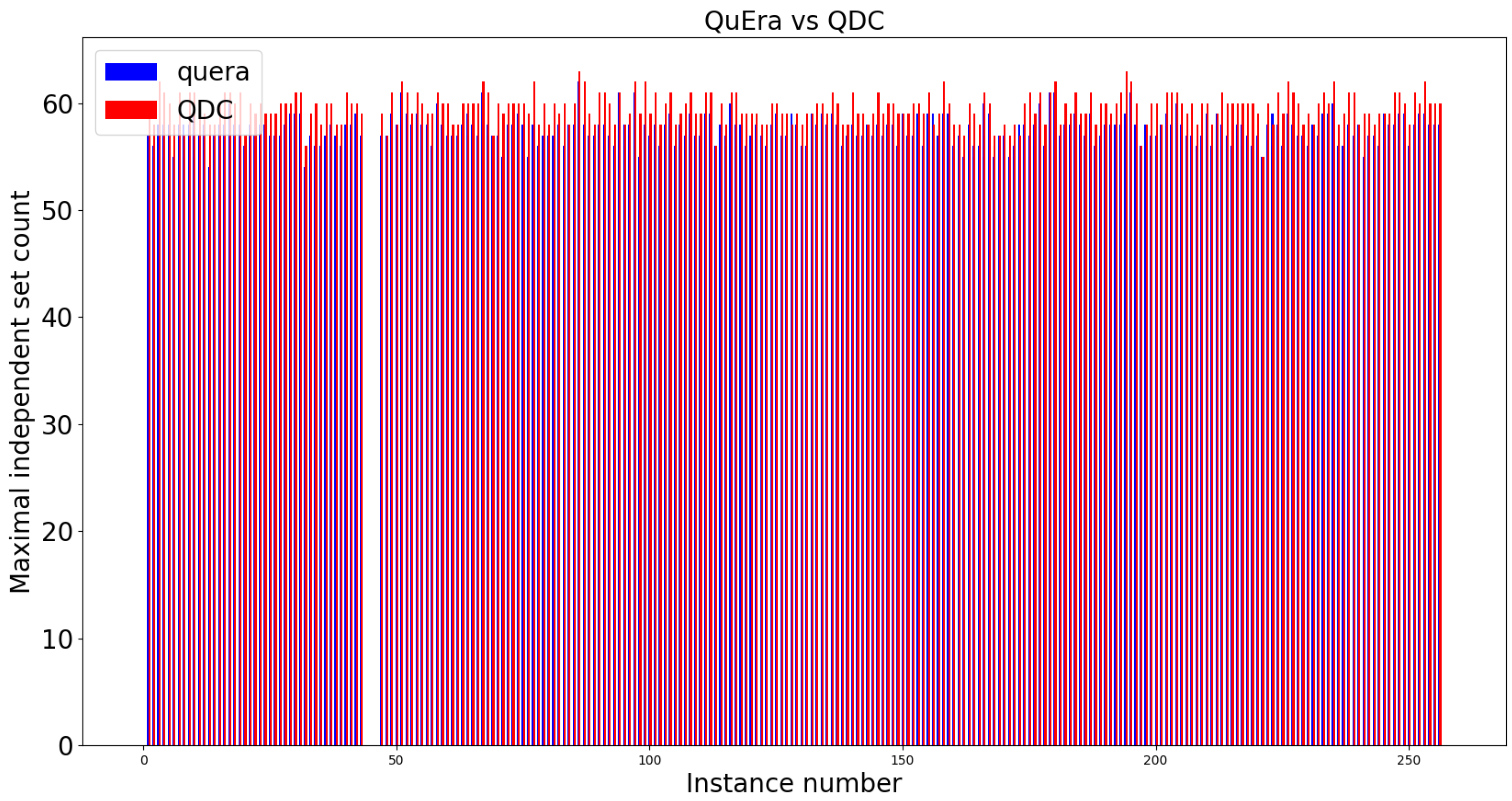
better for ALL 100 tested hard instances

Problem instance examples used in this benchmark can be found in the following arxiv: https://arxiv.org/pdf/2210.04291.pdf

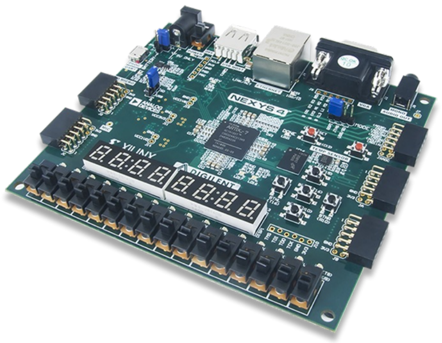


VeloxQ vs. 256 qubit QuEra Device

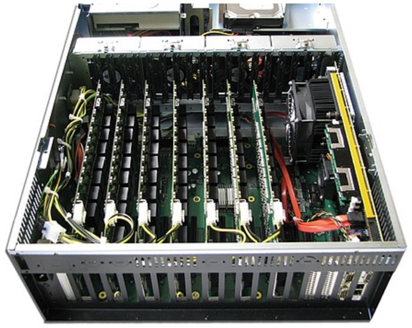
We are better than QuEra
for ALL 256 Kings graphs instances



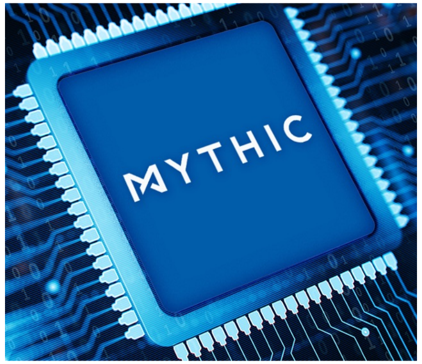
The Most Powerful Solver on the Planet - VeloxQ



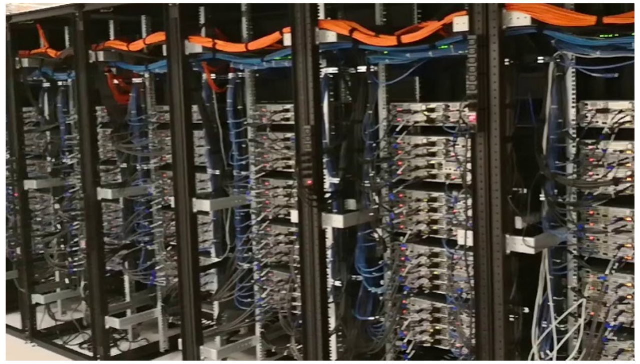
FPGA Implementation



FPGA Cluster

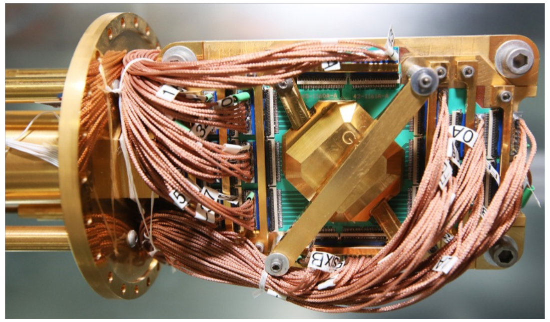


Analog Matrix Chips



Classical HPC Center with FPGAs / ASICs

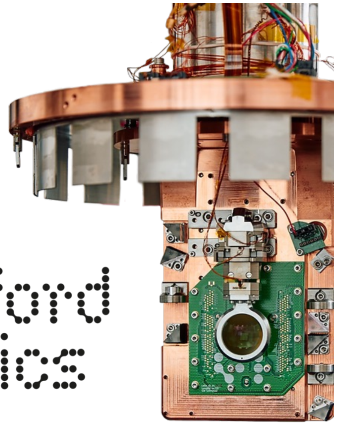
HYBRID MODULE



Quantum Computing Infrastructure

The Data Center of the Future: The Quantum Data Center

IQM



oxford ionics

QUANTUM
DATA
CENTER

Thank You

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