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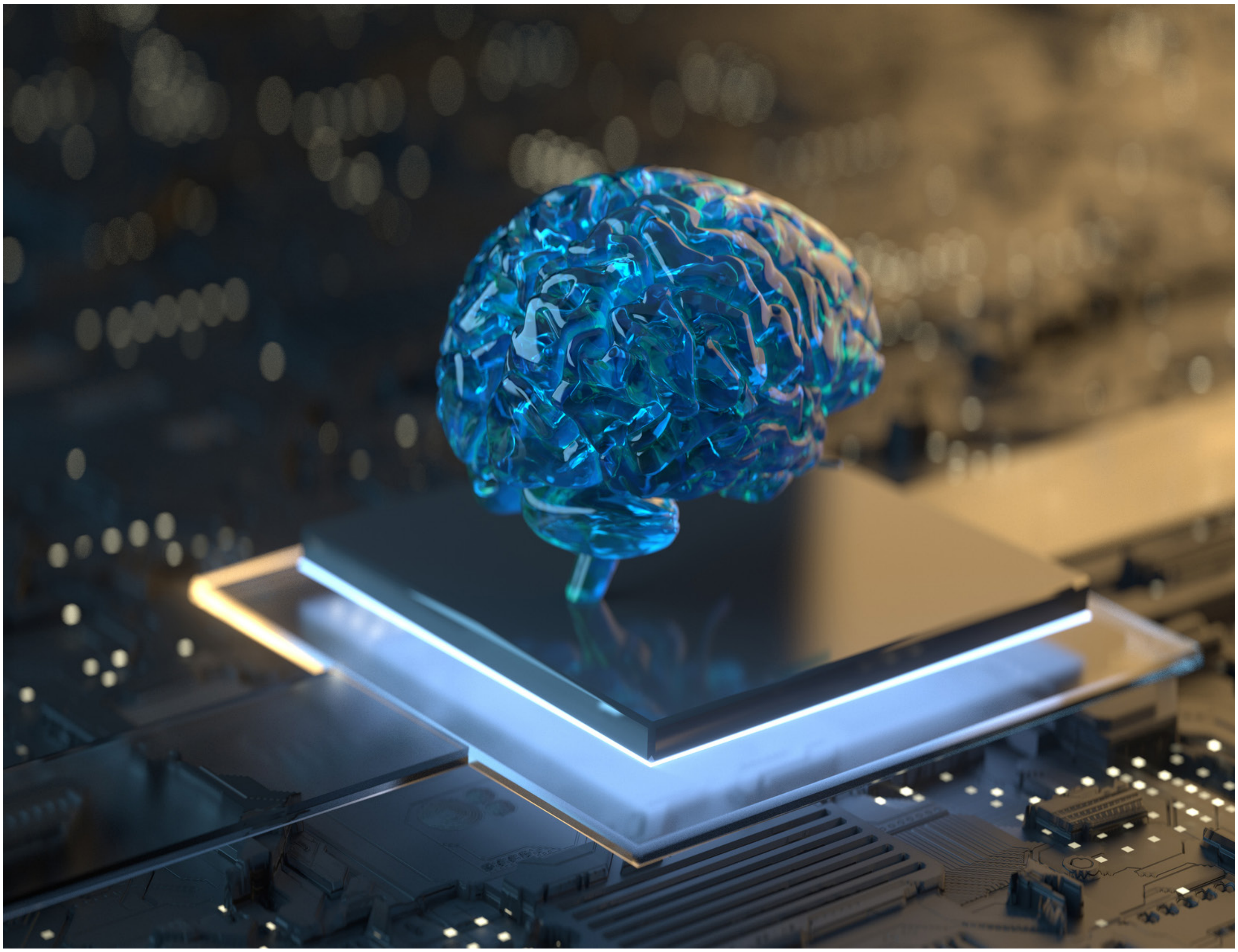


# BlackRock tests 'quantum cognition' AI for high-yield bond picks

# BlackRock tests ‘quantum cognition’ AI for high-yield bond picks

Study uses Qognitive machine learning model to find liquid substitutes for hard-to-trade securities.
By *Rob Mannix* and *Mauro Cesa*

BlackRock has teamed up with an artificial intelligence firm established by a US hedge fund to test a new way to classify corporate bonds using AI.

The asset manager worked with Qognitive to use the firm’s quantum cognition machine learning model to pick the most similar liquid replacements for hard-to-trade high-yield bonds, a common class of problem in investing.

In tests, QCML seemed to do a better job of identifying similar bonds than random forest models, a more conventional form of machine learning.

“QCML seems to be especially appropriate for identifying similar bonds in markets like US high yield where yield and other bond features show greater variability,” says Joshua Rosaler, a data scientist at BlackRock who worked on the study.

BlackRock’s quants have discussed the potential of QCML to price thinly traded municipal bonds, match baskets of securities in ETF trading, or fill in gaps in incomplete data. The firm now plans to test the approach further using its own internal data.

“The proof of concept has gone well,” Rosaler says.

QCML’s developers claim the approach, which uses quantum mathematics but currently runs on classical computers, approximates elements of human thinking, and can achieve better results than other types of machine learning for certain problems.

QCML is the brainchild of Kharen Musaelian, co-founder of AI-driven hedge fund Duality Group. Musaelian and fellow Duality co-founder Dario Villani launched Qognitive in 2023 to develop and commercialise the technology. Duality Group has already used signals generated using QCML in trading, the firm says.

> “The proof of concept has gone well”
> Joshua Rosaler, BlackRock

### Quantum magic

In a first step in the BlackRock study, the researchers trained a quantum cognition machine learning model to predict yields and credit spreads for high-yield and investment-grade bonds.

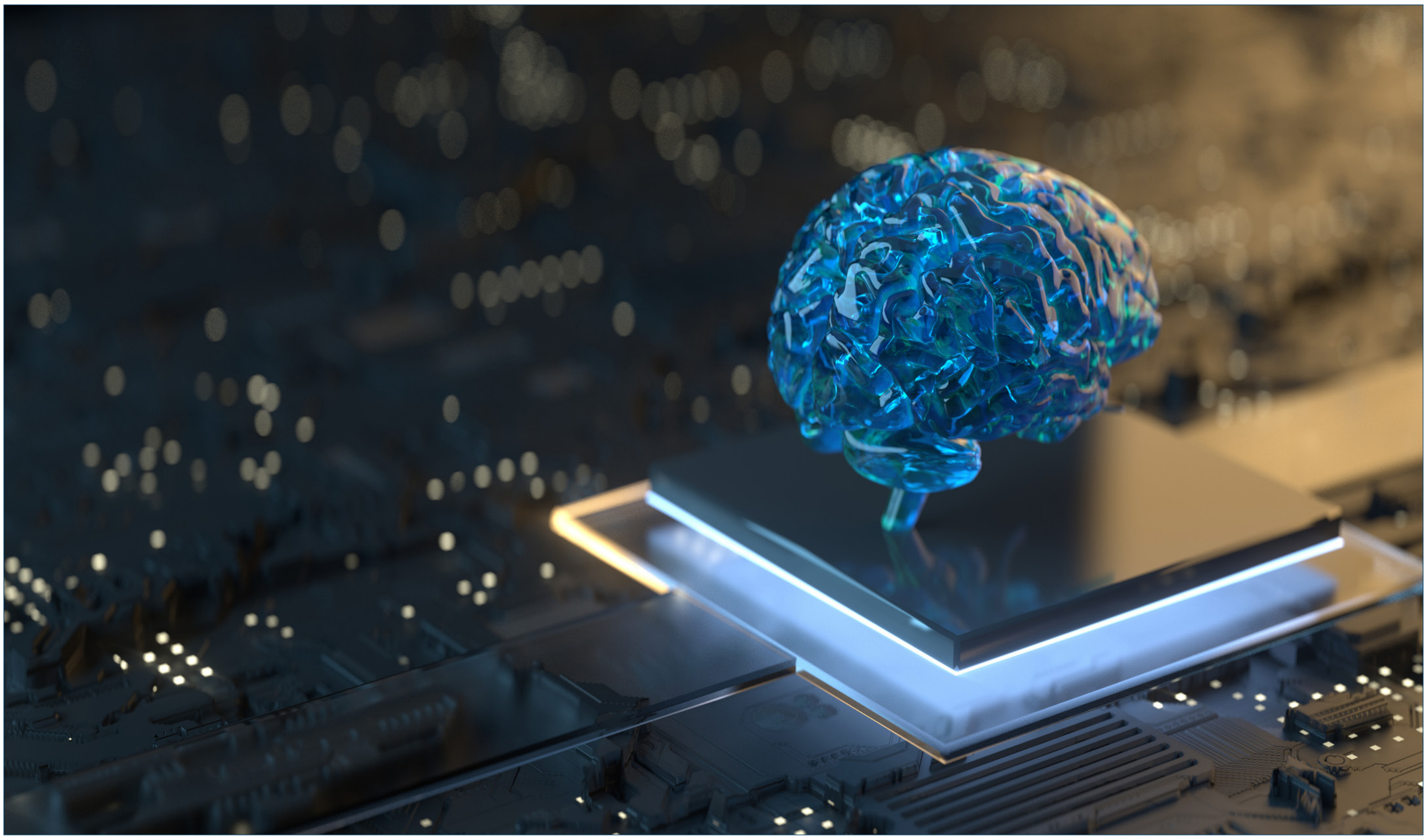
The quants then extracted from the model a metric of the similarity of individual securities. In essence, the measure equates to the proximity of bonds in the model’s representation of all bonds in quantum space.

Standard classification models might look at the distance between data points using ordinary, Euclidean, geometry. Qognitive’s quantum system measures similarity, or proximity, by quantum fidelity: the probability that two quantum states, which represent two securities, become indistinguishable.

The researchers compared the performance of QCML, random forest and linear regression in predicting yields and credit spreads for different bonds. In the case of high-yield securities, QCML outperformed both the other methods, displaying a higher R2 — a measure of how well a model fits the data – and lower errors.

The researchers’ white paper also shows that the higher prediction performance corresponds to higher accuracy in measuring bond similarities.

The quantum encoding in QCML transforms the data in a way that makes it possible to capture greater complexity compared with classical techniques. For high-yield bonds, the



researchers mapped original data represented in 99 dimensions, for example, into a quantum representation in seven.

Whereas a conventional model would learn "smooth" activation functions – the equations that determine how neurons in the model interact – these functions in the QCML model exhibit discontinuities and jumps.

The effect is analogous to mapping the data as a cloud in a multi-dimensional space, says Luca Candelori, director of research at Qognitive and an associate professor of mathematics at Wayne State University.

But QCML is able to learn to map the data in more-compact manifolds compared with other techniques, he explains. "If there are outliers, when they get represented in quantum space by the model, they essentially get squished together."

Even outliers retain "reliable neighbours", Candelori says. "In a sense, you have brought the outliers closer to the core of the data while still maintaining relative differences in a meaningful way."

## Distant neighbours

Buyers of corporate bonds often use measures of similarity to identify tradeable alternatives to illiquid securities or to price bonds with few recent quotes or trades.

> "They're offering something new, something different, that expands the toolbox"
>
> Oleksiy Kondratyev, Imperial College London

The task for high-yield bonds can be tricky because of the high number of outliers: securities with extreme yields compared with average, for example. Sometimes a bond might have only one or two similar "neighbours", forcing investors to select an alternative based on scant data.

In the study, the performance of QCML is compared with that of a supervised random forest model that learns to group bonds through a cascade of yes-no questions, formulating so-called decision trees. Bonds that appear frequently in the same "leaf nodes" of these machine-generated trees are deemed similar.

The random forest approach performs well in tasks such as classifying investment-grade bonds, where outliers are fewer. But QCML has the capacity to perform better than other types of machine learning when datapoints are sparse or widely scattered, its creators say.

Oleksiy Kondratyev, a visiting professor at Imperial College London and Adia Lab researcher in quantum computing, welcomes the research.

"The magic happens" in models such as Qognitive's when data is mapped to a quantum state, says Kondratyev, who was among the first quants to study the applications of quantum computing in finance and continues to innovate in the field.

The ability to capture greater complexity "gives you a chance to do something special that otherwise would be hard to do", he says, though work remains to be done to develop a theoretical understanding of when and why QCML might achieve better results.

The greater the variety of models available for classification tasks of this type, the better, he adds. "They're offering something new, something different, that expands the toolbox." ■

*Editing by Kris Devasabai*