CASE STUDY

DekaBank **improves modelling accuracy and risk management** with **NAG® DCO/C++**

DekaBank wanted better risk management, more accurate pricing and to support the bank's expanding derivatives business, all of which required a significant increase in modelling power. Replacing the legacy low factor PDE model with a sophisticated multi-factor Monte Carlo model could solve the issue, but required tens of seconds per valuation. Unfortunately the multi-factor model had over 100 inputs, and computing all those sensitivities for risk management using finite differences would lead to an unattractively expensive solution.

DekaBank turned to automatic differentiation (AD), and in particular adjoint automatic differentiation (AAD), to reduce computing costs. AAD generalises backpropagation, a major component of Machine Learning, and is one of NAG's core competencies. It is a computer science technique that computes all first or higher order sensitivities of a program dramatically faster than finite differences (bumping).

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Deka

Backpropagation in a Nutshell

Backpropagation is a method where sensitivities are propagated backwards through a code. Intuitively you "bump the output" and observe the effect on the inputs, except everything is computed analytically and results are accurate to machine precision. NAG's AAD tool provides extremely efficient backpropagation of general-purpose C++ codes. The efficiency of a backpropagation tool is measured as R = (runtime of backpropagation code) / (runtime of original code). This ratio R is known as the adjoint factor, with typical values for AAD tools ranging from 10 to 50. The lower the value, the better the tool, with any values below 10 considered very good. In DekaBank's case, an adjoint factor of 5 means backpropagation would deliver all 100 sensitivities 20x faster than finite differences.

Highly Efficient Computing and Support

DekaBank approached NAG for a deep dive into backpropagation for their specific situation, and NAG arranged an on-site visit with the NAG AD team in Germany.

"*The most important factor for us was to have a professional quality, supported product,*" says Michael Dirkmann, Head of Quantitative Analytics at DekaBank. "*We compared three tools, and NAG's AD solution, NAG® dco/c++, was the only product that fit the bill. We're a small team focused on the business's problems. Finding answers for open-source tools can be incredibly time consuming. When we have questions, we want people who can help us on demand, experts in AD and specifically in the AD tool we are using.*"

As it turned out, the team found two small bugs early on in the NAG® dco/c++ evaluation. They contacted NAG who delivered fixes very quickly.

"*How would this have played out with an open-source AD tool?*" Dirkmann asks. "*We would have needed to dive into the code ourselves or go to online forums to find help. If the community is not active, it could have taken days or weeks to receive help. We simply don't have the manpower to be our own technical support.*"

NAG® dco/c++ provides many advantages over other AD tools. Performance out of the box is strong, and NAG dco/c++ has features other tools are lacking, most notably a very flexible tape interface which allows checkpointing schemes to be implemented with ease. Such schemes are crucial to achieving good performance and low memory use. NAG® dco/c++ also supports higher order derivatives and vector tangent/adjoint modes. Finally, the design of the NAG tool is completely agnostic to the problem being tackled.

"It's difficult to imagine some of these other AD tools working well on anything other than Monte Carlo. NAG® DCO/C++ can be applied to PDEs as well as general calibration code, which is a bonus.

A 95% Reduction in Compute Requirements

The DekaBank team applied NAG® dco/c++ to their multifactor Monte Carlo model, achieving an adjoint factor of 7, meaning the backpropagation code ran 14x faster than finite differences. After this initial implementation, DekaBank arranged for NAG to access the code. "*The NAG team had lots of good advice; they were very quick at refactoring the code in our library. It's clear they can jump into an existing project and come up with helpful hints and suggestions quickly*" said Dirkmann.

NAG further improved the adjoint factor down to 5, meaning that DekaBank could get their risk 20x faster than with finite differences. This translates to a 95% reduction in compute requirements, allowing DekaBank to implement the new Monte Carlo model on existing compute resources. Once in production, this new model is expected to have a profound impact on the business.

CASE STUDY

Adjoint Automatic Differentiation Reduces Costs and Improves Risk Management

DekaBank's experience proves that AAD can provide huge computational savings whilst delivering stable and accurate 1st and 2nd order sensitivities. Although used here in a derivatives pricing context, the biggest gains from AAD frequently occur for very large risk calculations like XVA. The combination of fast and stable sensitivities for all model inputs can have a massive impact on the business. With timely access to such rich data, traders can better manage risks, especially in fast-moving markets; quants can use more powerful models with more accurate pricing, giving better value to customers; and banks can realise a step-change in risk management capability.

NAG has over a decade of experience applying AD to production codes in a range of industries. We know that even with a good AD tool, there are core computational kernels like BLAS/LAPACK, or specific mathematical operations like calibration, root-finding or nearest correlation matrix, that deserve special treatment. For these, NAG has developed highly efficient symbolic adjoints which deliver an order of magnitude or more savings in runtime and memory over straightforward backpropagation. NAG® dco/c++ users have seamless access to these through NAG's AD portfolio.

Contact us to find out how to make automatic differentiation work for you

nag.com/deka

Our AD team will be delighted to learn more about your use case and explore possibilities.
We also offer on-site AD training and workshops to get teams up to speed, and we provide support for PoCs to ensure you can rapidly quantify the impact of AD on your business.

About Deka

DekaBank is the Wertpapierhaus (securities services provider) of the German Savings Banks Finance Group. Together with its subsidiaries it forms Deka Group, which has total customer assets of around EUR 340 billion (as at 31/12/2020) and more than 5 million securities accounts, making it one of the largest securities services providers and real estate asset managers in Germany. It provides retail and institutional clients access to a wide range of investment products and services. DekaBank is firmly anchored in the Sparkassen-Finanzgruppe and designs its portfolio of products and services to meet the requirements of its shareholders and sales partners in the securities business.

About NAG

NAG provides industry-leading numerical software and technical services to banking and finance, energy, engineering, and market research, as well as academic and government institutions. World renowned for the NAG® Library - the most rigorous and robust collection of numerical algorithms available - NAG also offers Automatic Differentiation, Machine Learning, and Mathematical Optimization products, as well as world-class technical consultancy across HPC and Cloud HPC, code porting and optimisation, and other areas of numerical computing. Founded more than 50 years ago from a multi-university venture, NAG is headquartered in Oxford, UK with offices in the UK, US, EU and Asia.

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