

## Overview

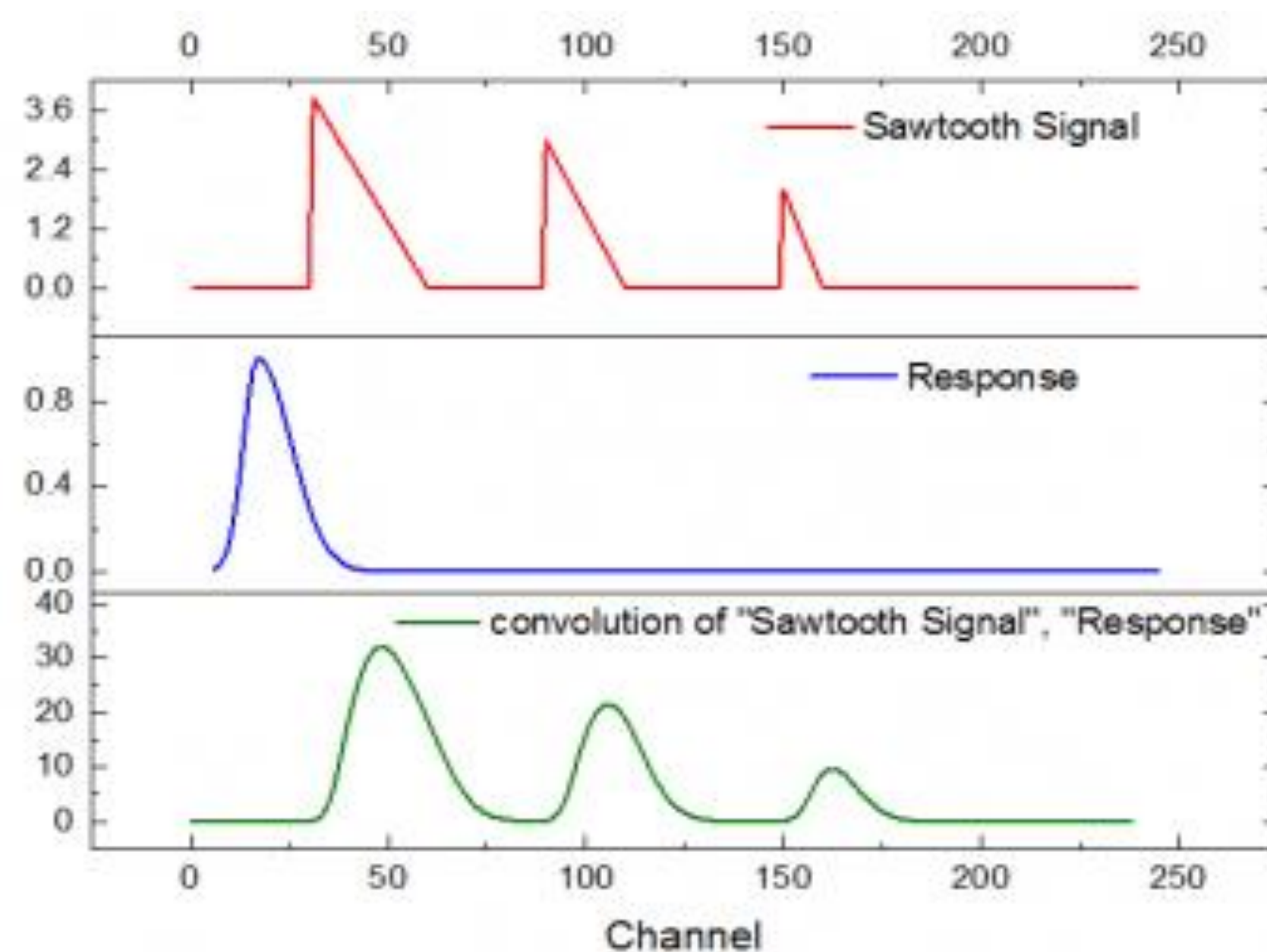
- The convolution theorem provides a method for efficiently computing convolutions using Fast Fourier Transforms (FFTs), with the caveat that the convolution is periodic. For two arrays  $F$  and  $G$  that have period  $N$  the convolution is defined as

$$(f * g)_k = \sum_{p=0}^{N-1} f_p \odot g_{k-p}$$

- Many applications such as nonlinear PDEs require a linear convolution, which can be computed using the convolution theorem, provided that the data is sufficiently padded with zeros so we can avoid aliases.
- Implicit dealiasing provides an alternative to explicit dealiasing: the FFTs are formulated to implicitly take account of the known zero values, avoiding the need for explicit zero padding.
- To maximize performance, we use hybrid padding: the padding is chosen to be fully implicit, fully explicit, or in between.

## Applications

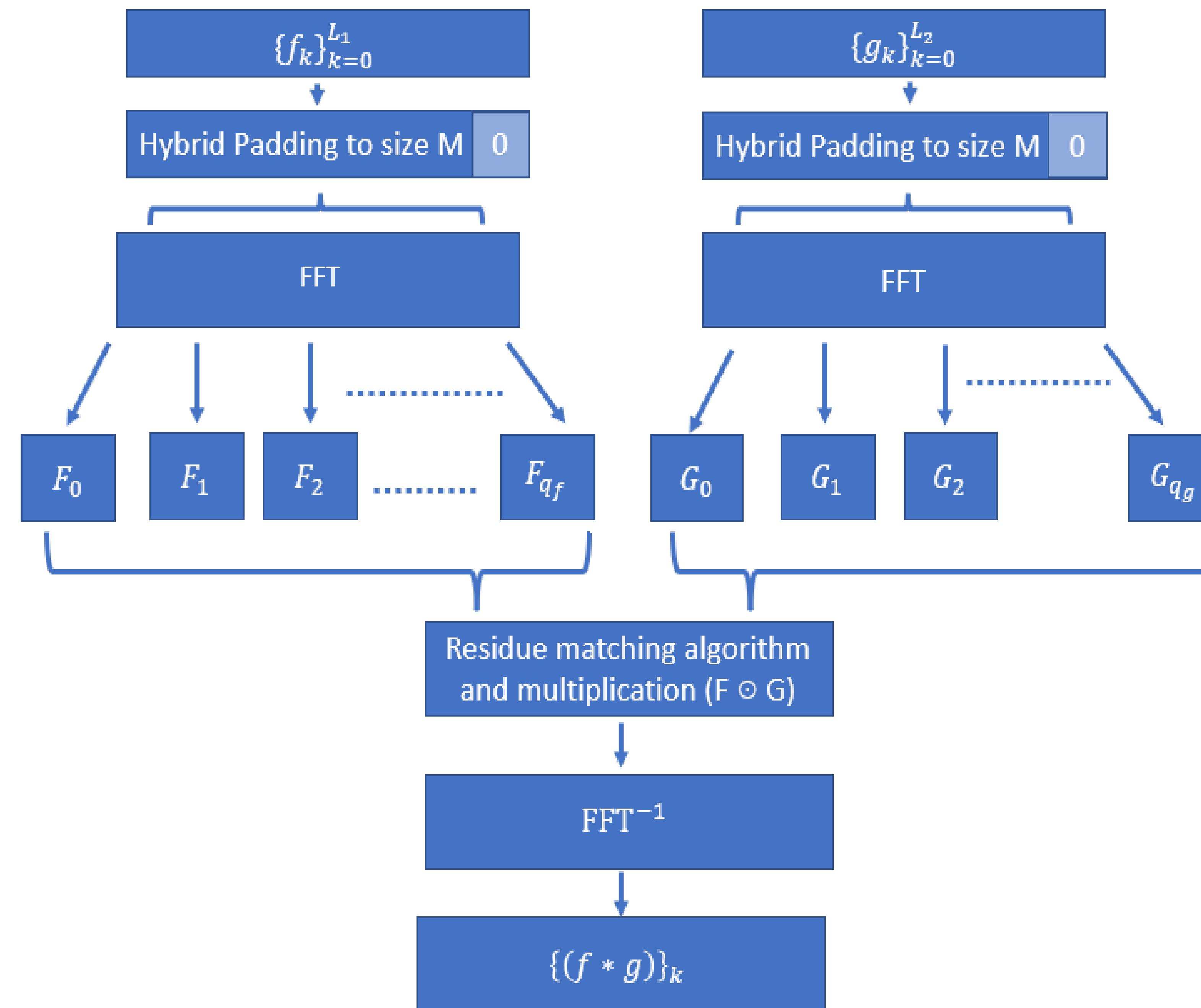
- Convolution Neural Networks, Machine Learning, turbulence simulations, Nonlinear PDEs, signal filtering, Physics, Probability Theory usually have arrays of unequal size.



## References

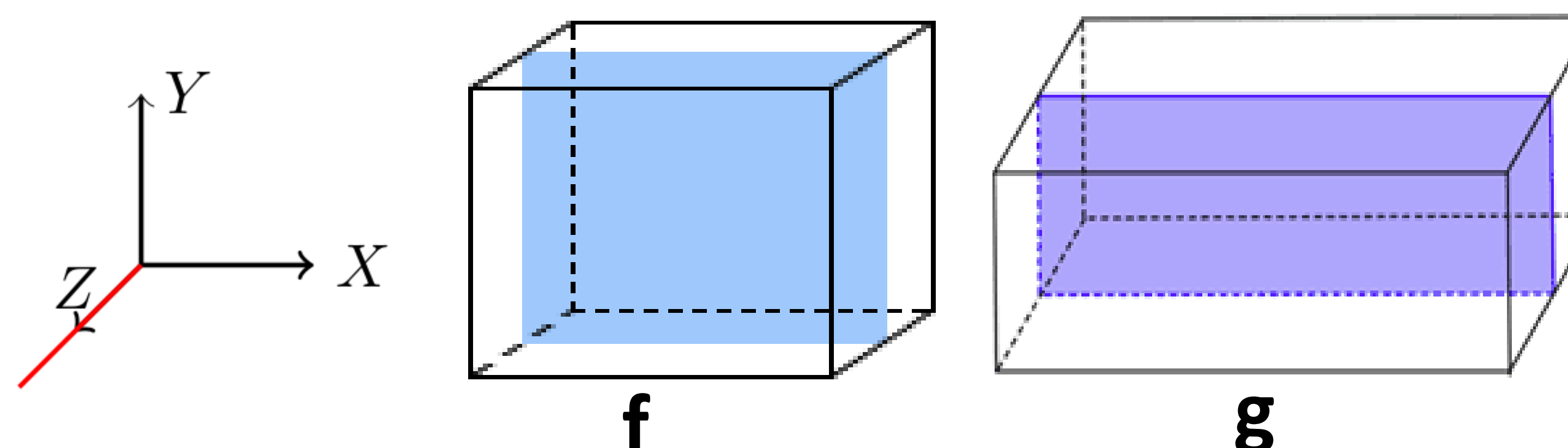
- Multithreaded Implicitly Dealiased Convolutions, M. Roberts and J. C. Bowman, Journal of Computational Physics 356, 98-114 (2018).

## Algorithm (1 Dimensional)



## Algorithm (N Dimensional)

- For each direction we would have 3 parameters namely  $\Lambda_N, m_{f_N}, M_N$  where  $N$  denotes the dimension.
- Then we call the forward transform (FFT)  $N-1$  dimension routine recursively along the  $N^{th}$  axis. We then multiply the two arrays in Fourier space using the Residue matching algorithm and then again call the backward transform  $N-1$  dimension routing recursively along the  $N^{th}$  axis.
- Finally we use the Mode selection algorithm to return how much of the convolution we want.

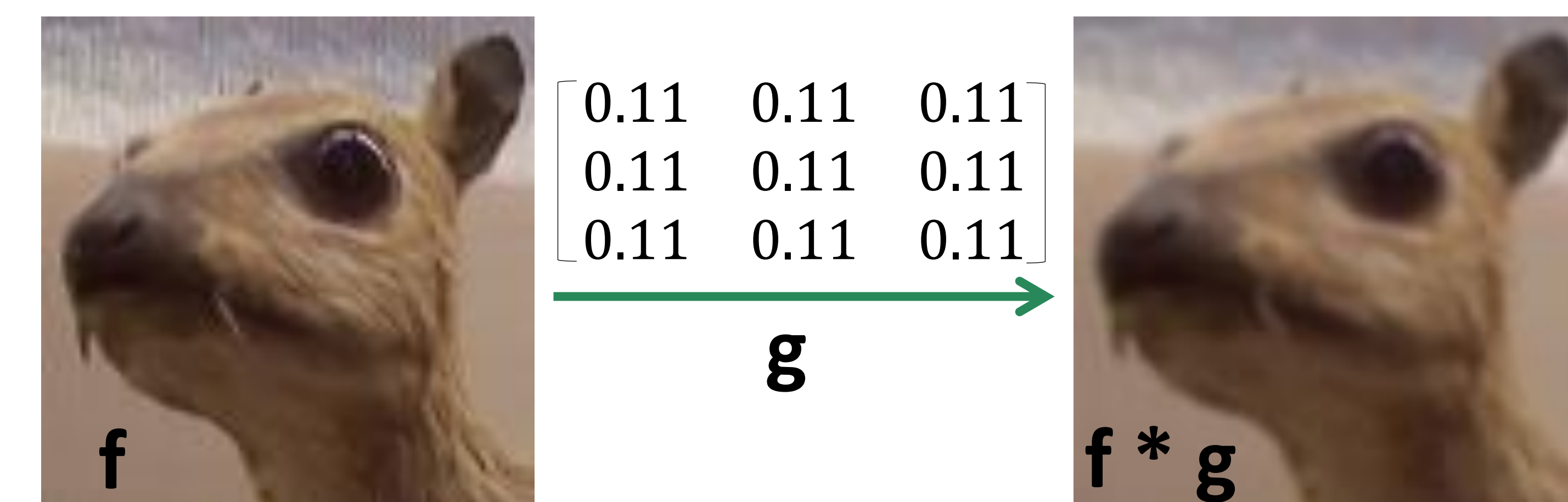


## Tuning Parameters

- To find the best  $\Lambda_N, m_{f_N}, M_N$  along the  $N^{th}$  axis dimension we use a grid search across the factors of the length of the  $f$  and  $g$  array and hence the time complexity would be  $O(n)$  where  $n = |g|$ .
- We do this independently for each dimension due to the very nature of how a multi-dimensional FFT is calculated and is optimal for any dimension.

## Results

- We offer unique solutions that expand hybrid dealiasing to issues with uneven input reducing memory and computation time.
- Expanded this to multi-convolution (both 1D/2D), applying the convolution to a sequence of data,  $N$  arrays rather than just two.
- We construct the first hybrid dealiasing solution, which is around 10 times quicker than typical explicit padding approaches.



## Future Work

- Complete 3D unequal hybrid dealiasing.
- Port to C++ and include in convolution libraries such as FFTW++; create wrappers for Python and Julia.
- Create specialized algorithms for the Hermitian and real case to save additional memory.
- Generalize if possible to  $N$  dimensions.
- Scan QR code for contact information.

