It is well-known that fast matrix-vector multiplication algorithms for many well-studied structured matrices $A$ (e.g. those with low-displacement rank) are equivalent to small arithmetic circuit to compute $A \cdot x$. We note that the Baur-Strassen theorem a small arithmetic circuit to compute $Ax$ gives a small arithmetic circuit to compute the gradient of $A \cdot x$ wrt $A$. We implement this observation to achieve the following two empirical results:

1. Recover a number of well-known fast algorithms to compute $Ax$ given $A$. E.g. we automatically learn the FFT from the Discrete Fourier matrix for dimensions up to $N = 1024$ (by learning over a restricted class of arithmetic circuits).

2. We replace a “unconstrained” layer in neural networks with structured matrix layer and simultaneously obtain parameter savings and accuracy improvements on some classification tasks.

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