

New mathematical tools

...to simplify sparse CO₂ monitoring with FWI

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**NSERC
CRSNG**



UNIVERSITY OF CALGARY
FACULTY OF SCIENCE
Department of Geoscience



Goal: enable FWI for low-cost seismic monitoring

...such that sparseness, targeting leveraged

Approach: engage “Projective Geometric Algebra”, PGA

....capitalize on repetitiveness from sparse acq / targeting

Requirements:

- examining basic operations in adjoint-state method
- examining operations between PGA elements
- access to PGA computation



New computational tools for new problems

- Computation via alternative hardware / physical systems
 - Quantum computers, Ising computers, analog computers
- Computation via alternative algebras
 - Quaternions, Clifford algebras, Geometric Algebra



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Geometric Algebra (GA)

- Extension of standard vector algebra
 - Standard ops, complex analysis, division, ND generalizations
- Major recent impact on theoretical science
 - Mathematics, gravity, mechanics, visualization, graphics
 - Computational packages are increasingly available



New computational tools for new problems

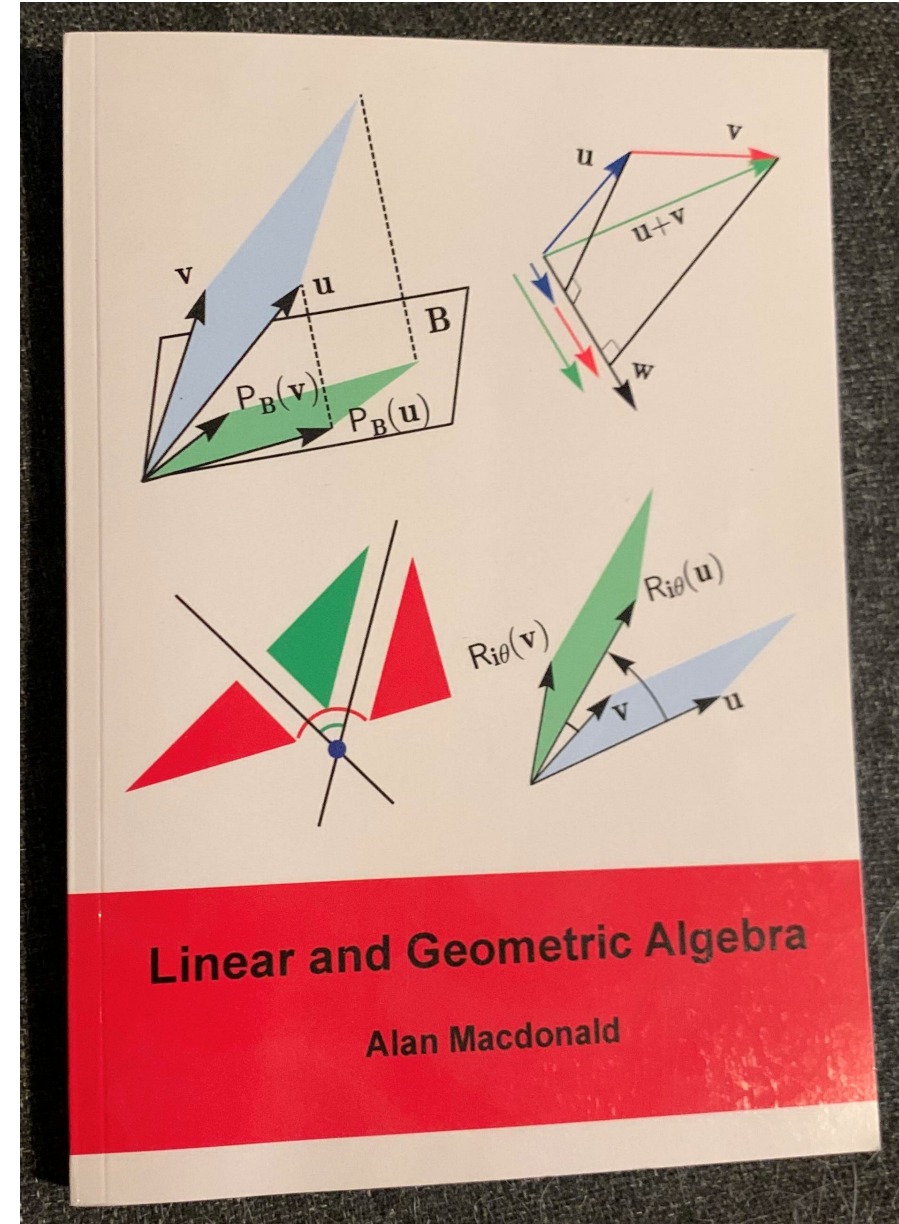
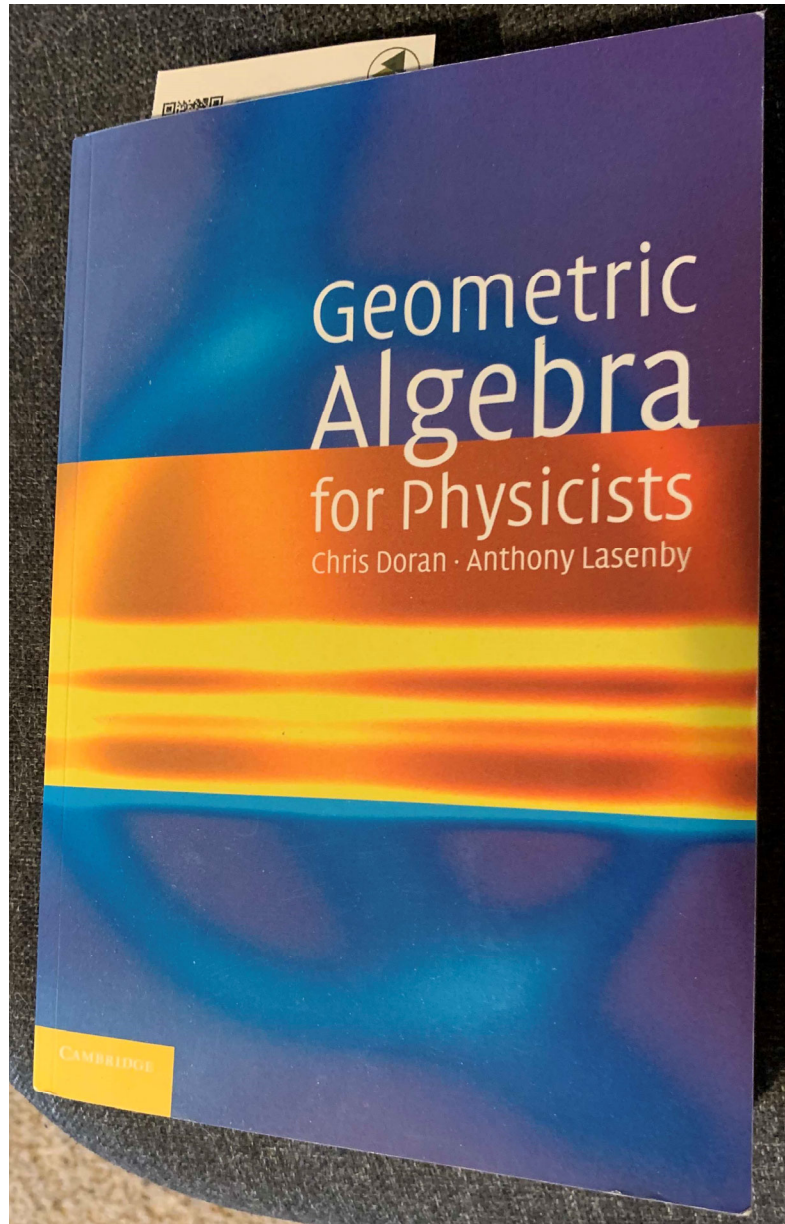
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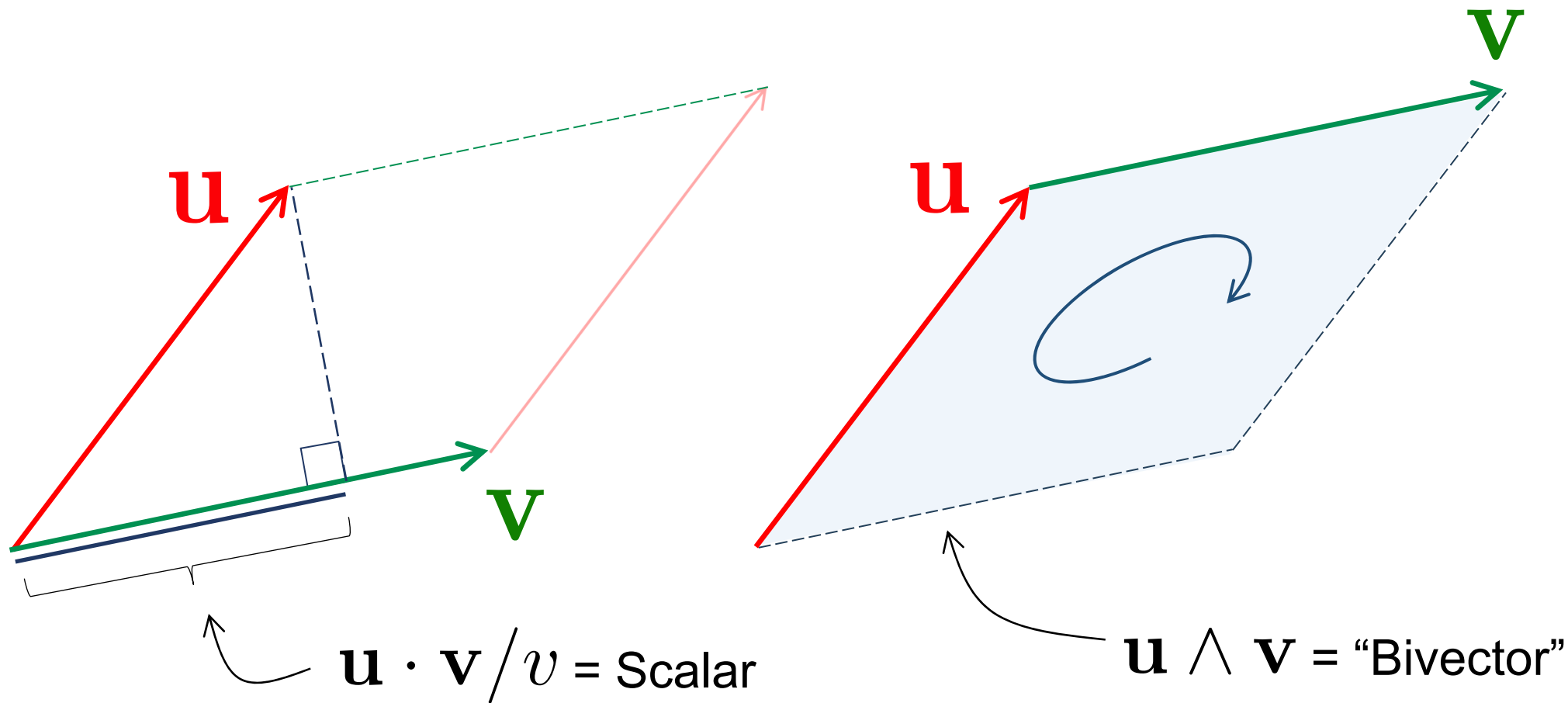
Projective Geometric Algebra (PGA)

- A brand of GA with (possible) use for analyzing linear systems



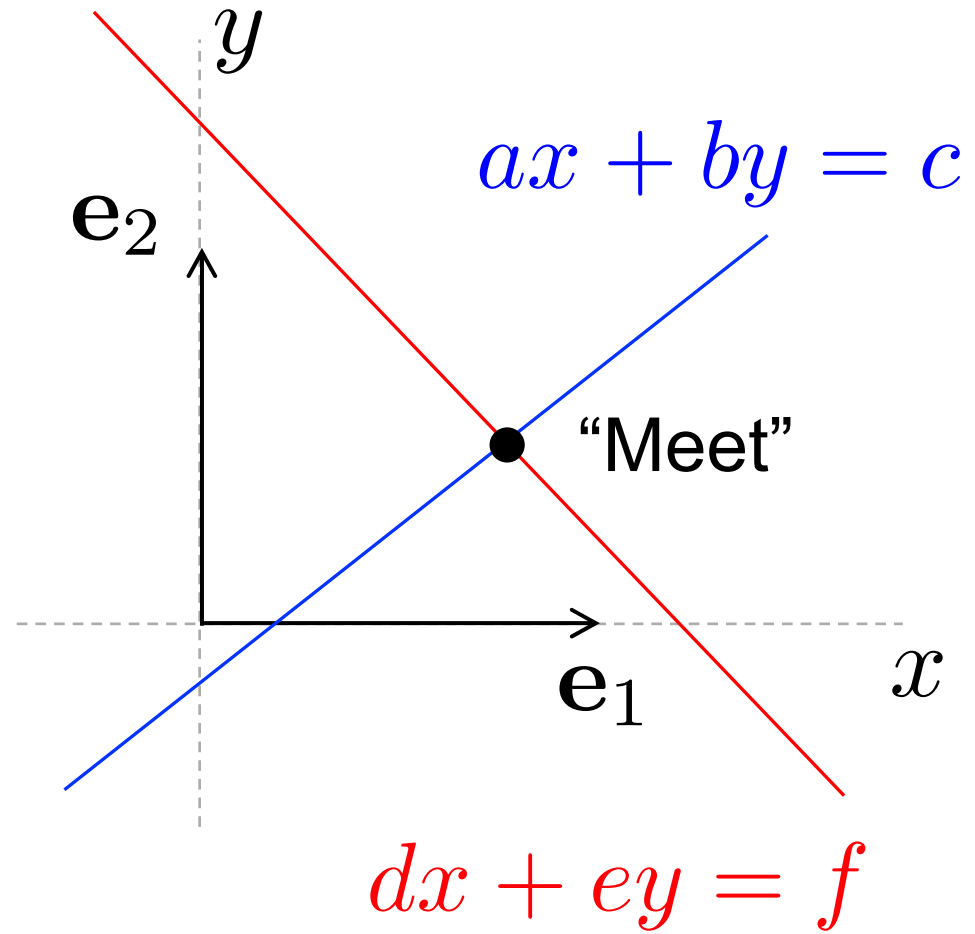


Geometric algebra – dot products, wedge products, bivectors



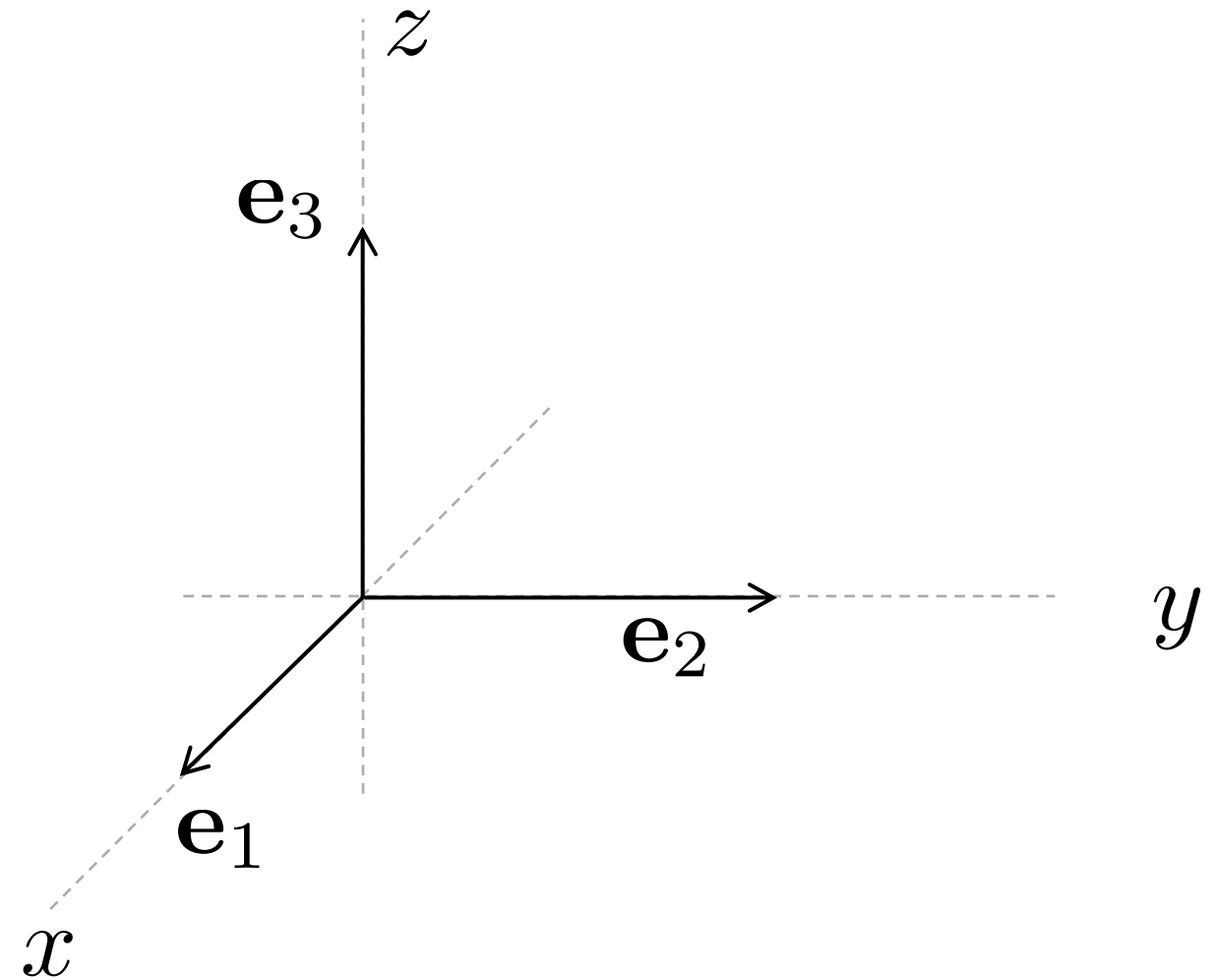
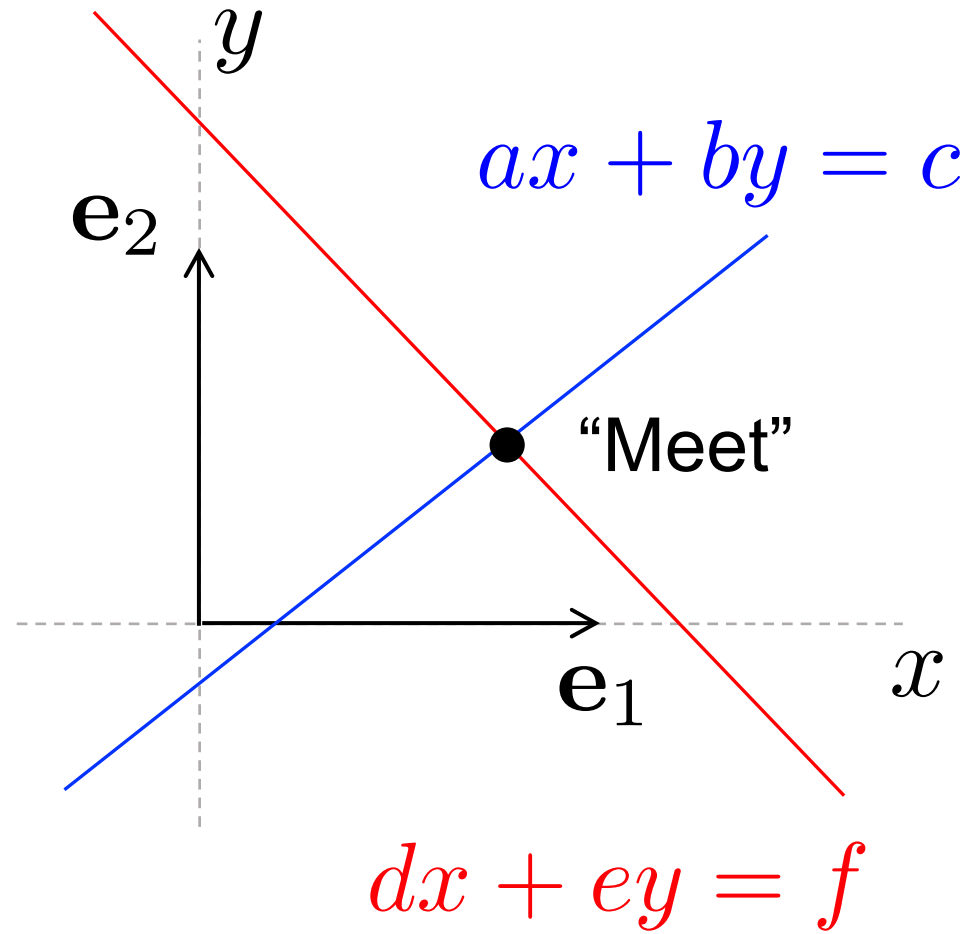


Projective Geometric Algebra and linear equations – the row picture



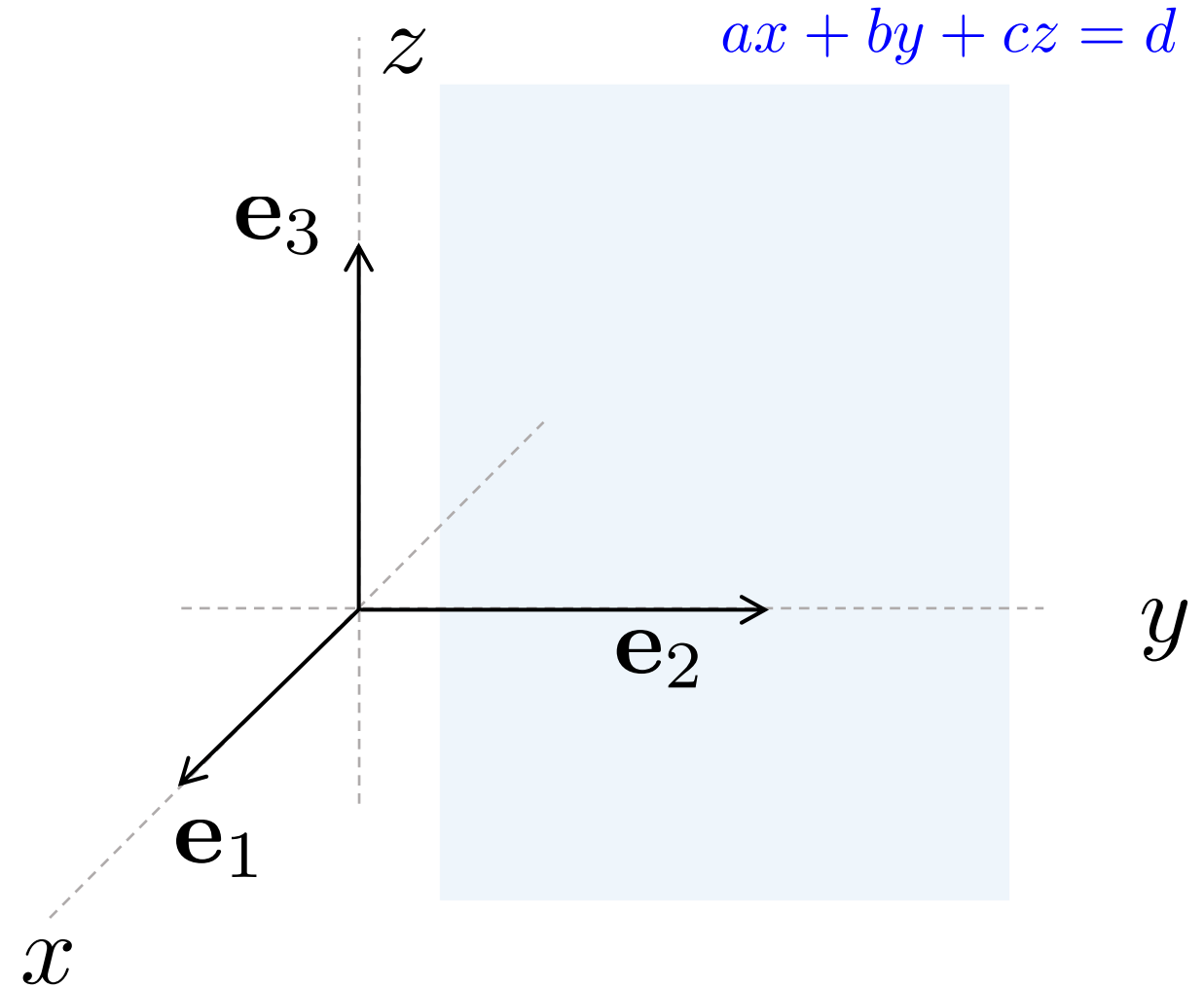
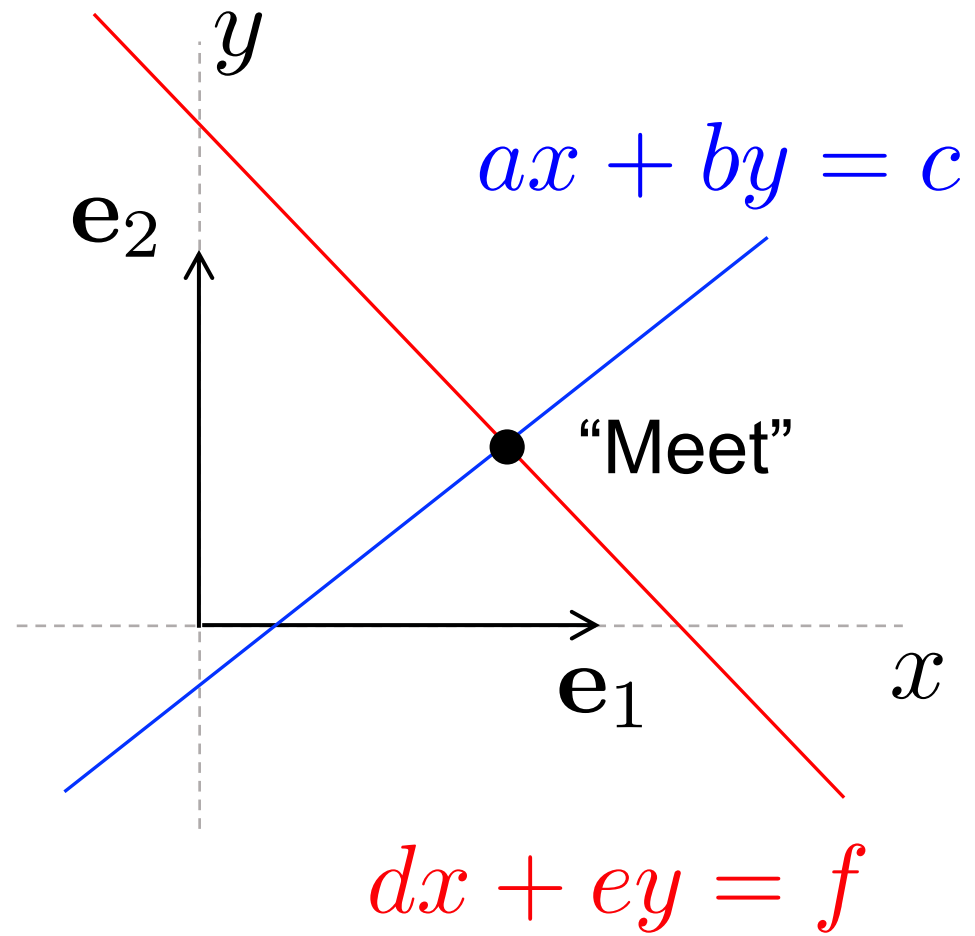


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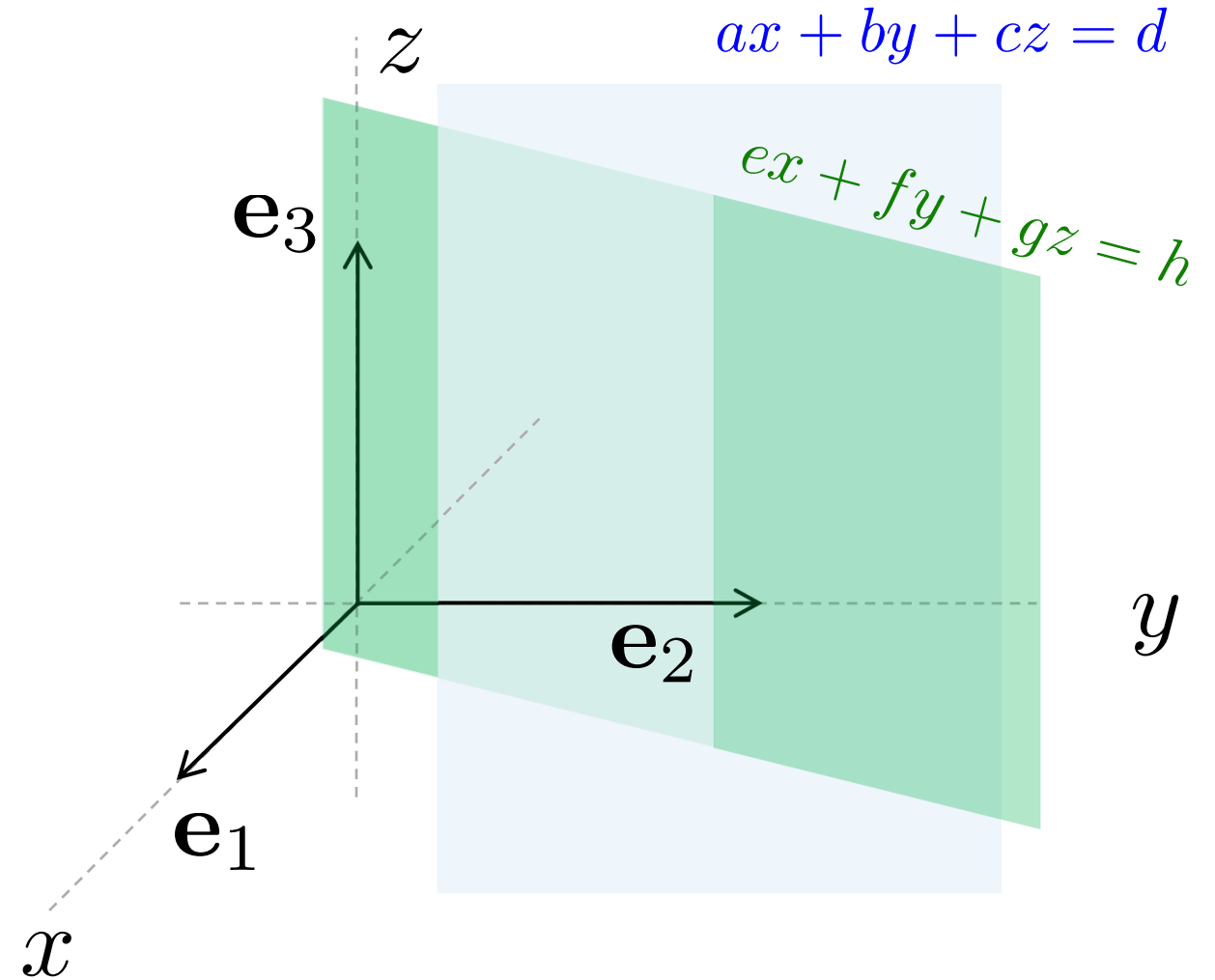
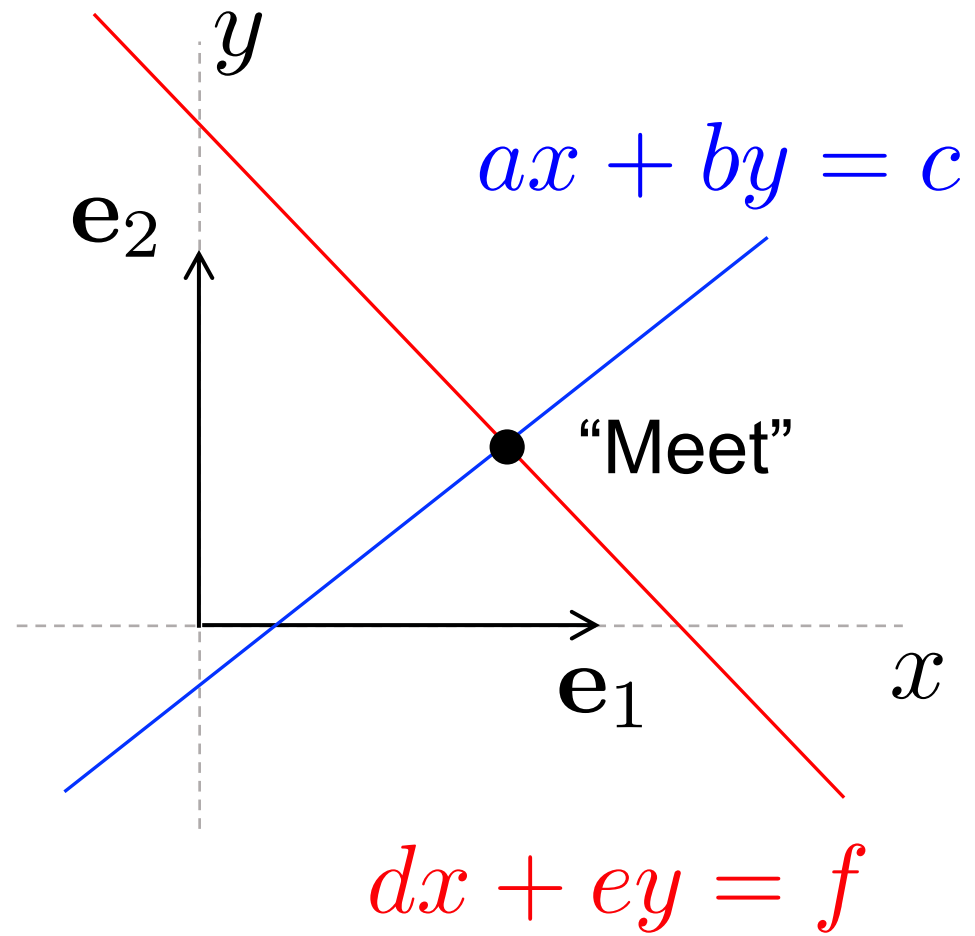


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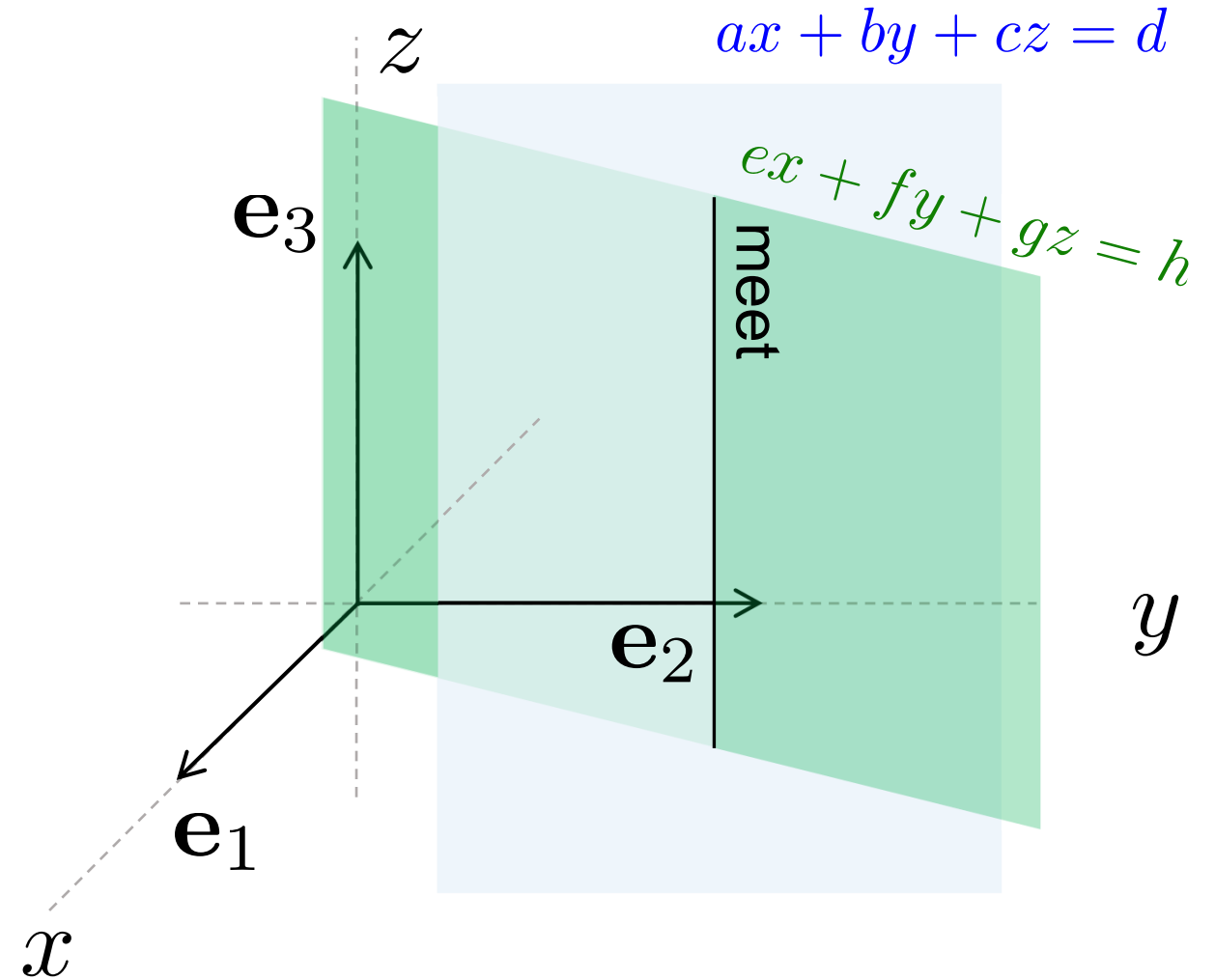
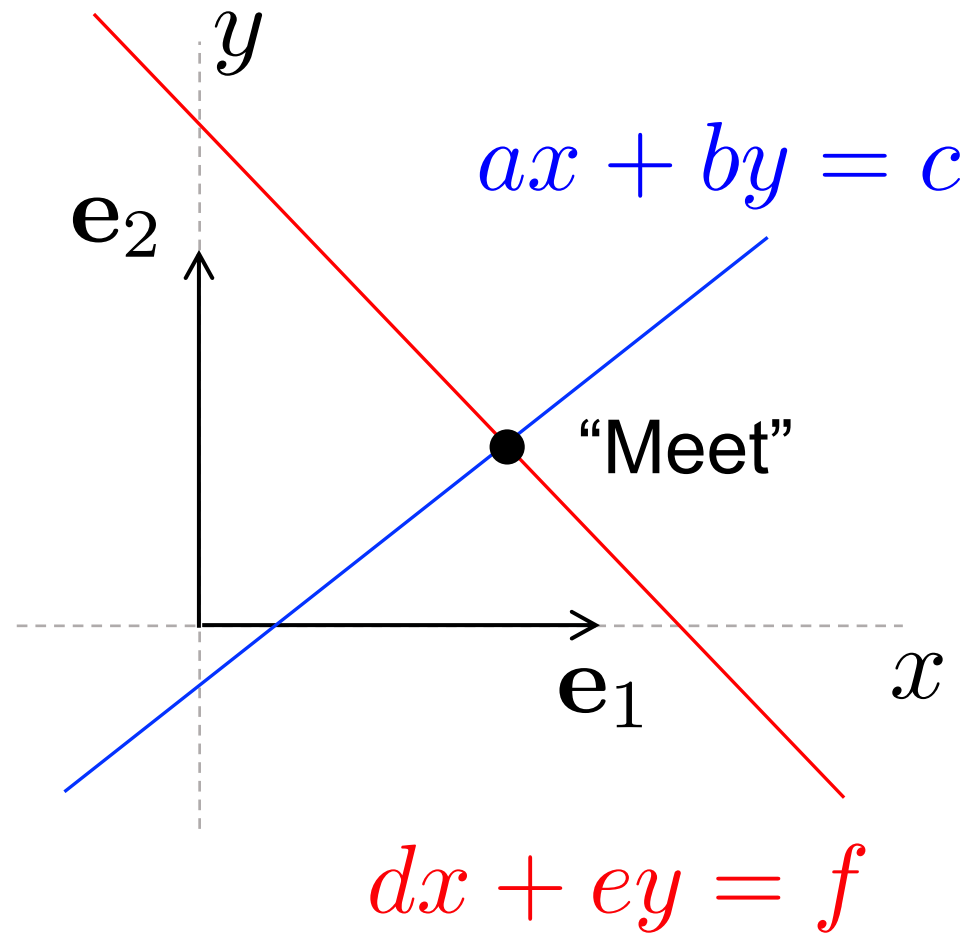


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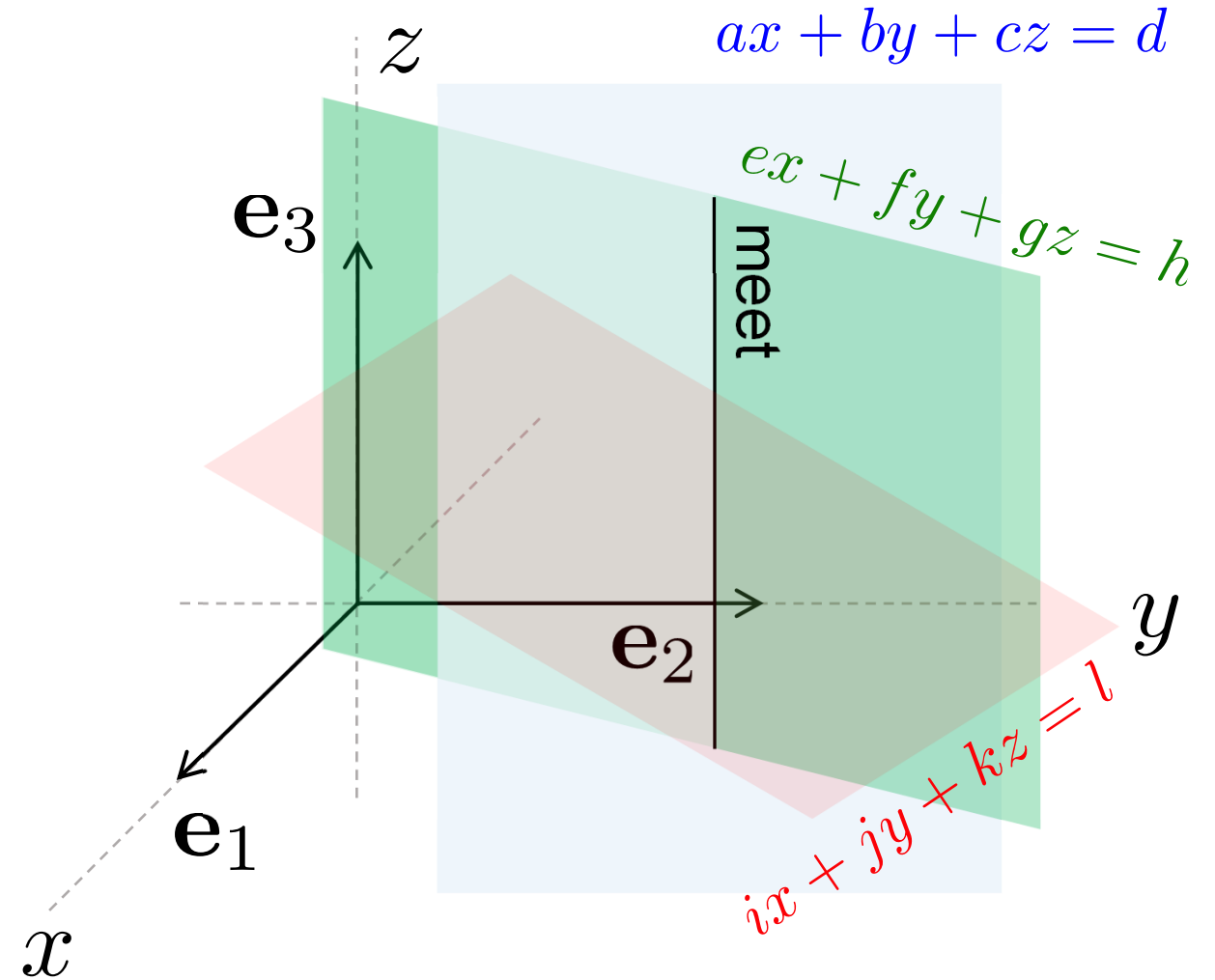
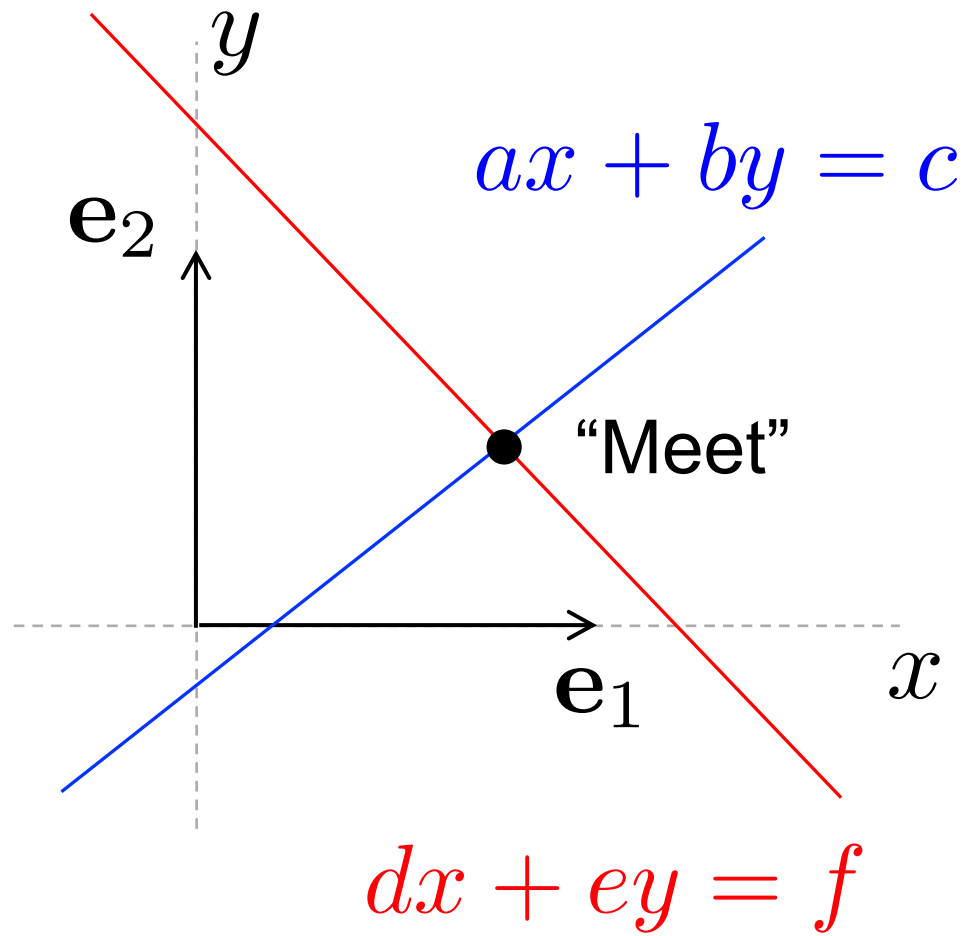


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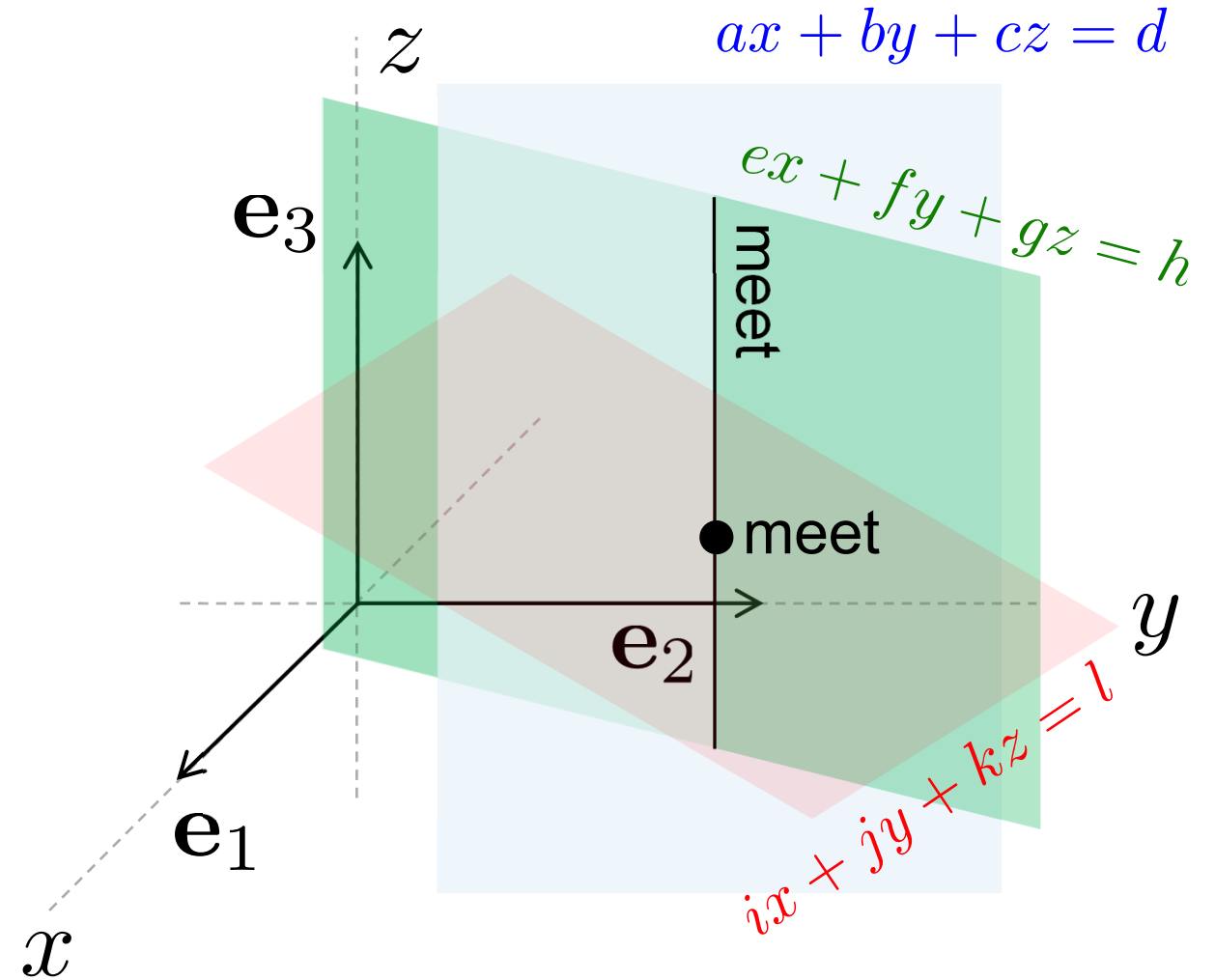
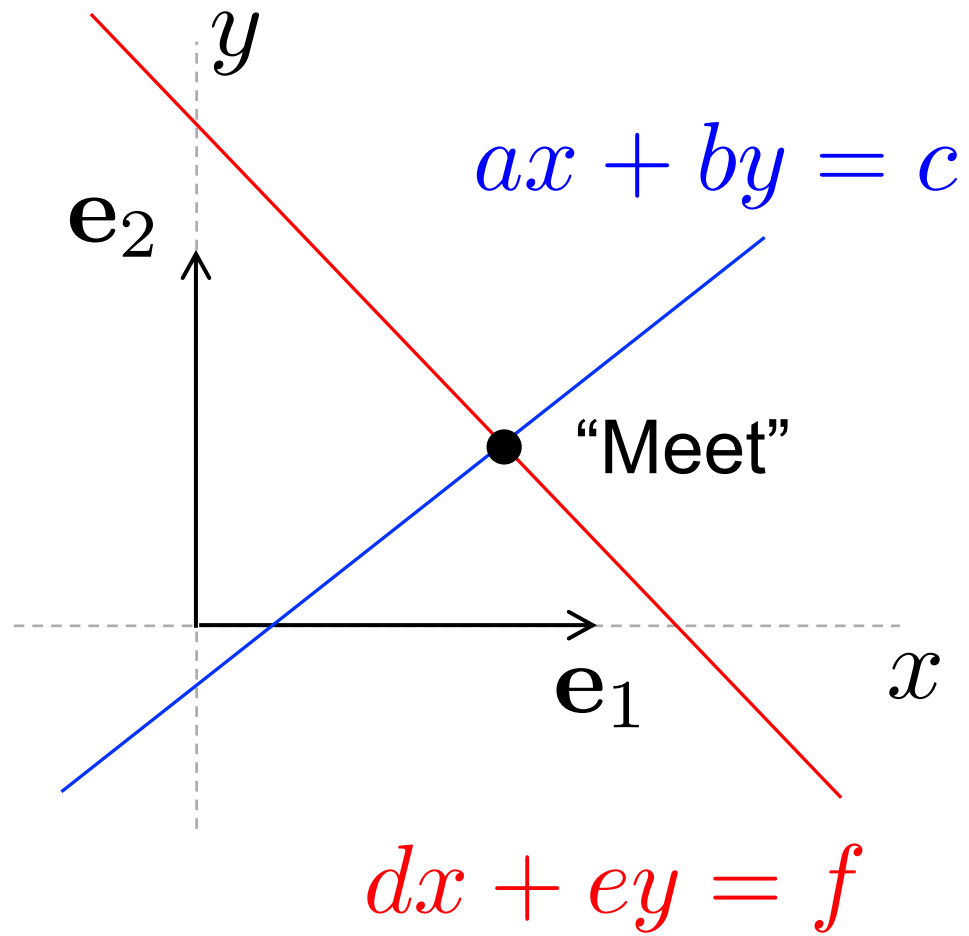


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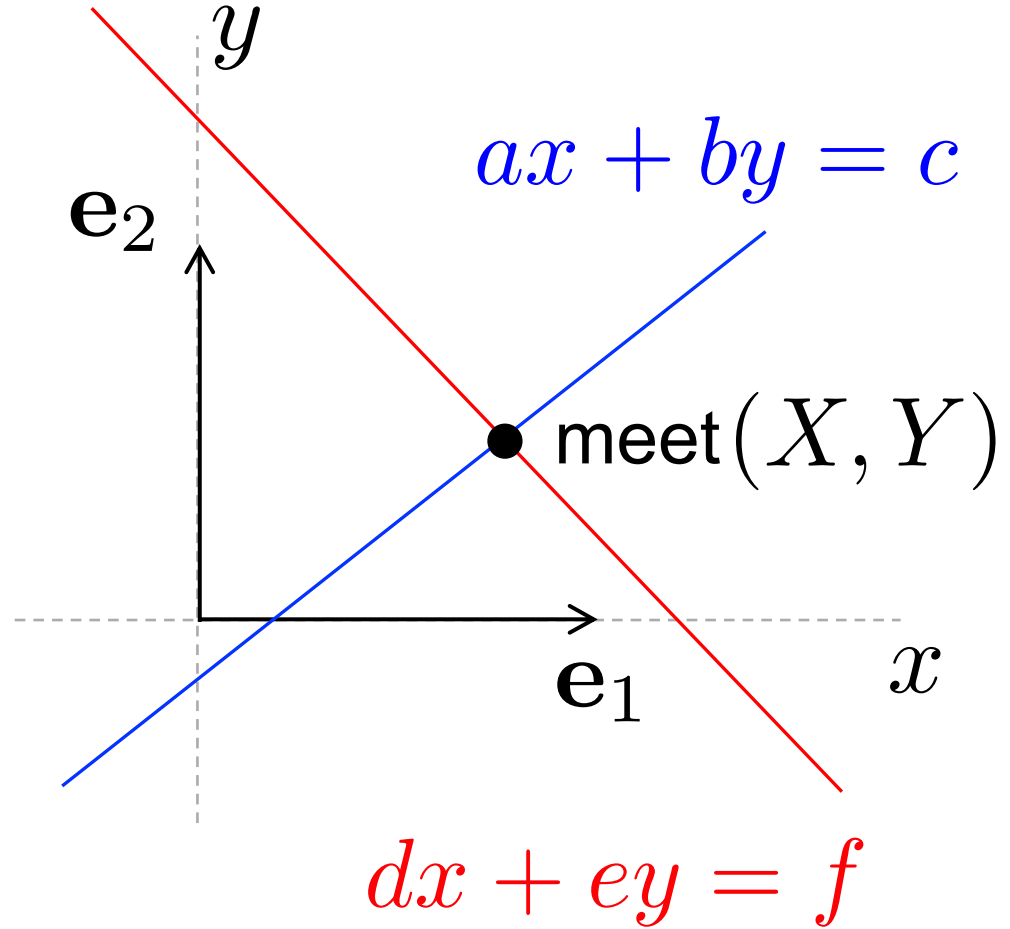


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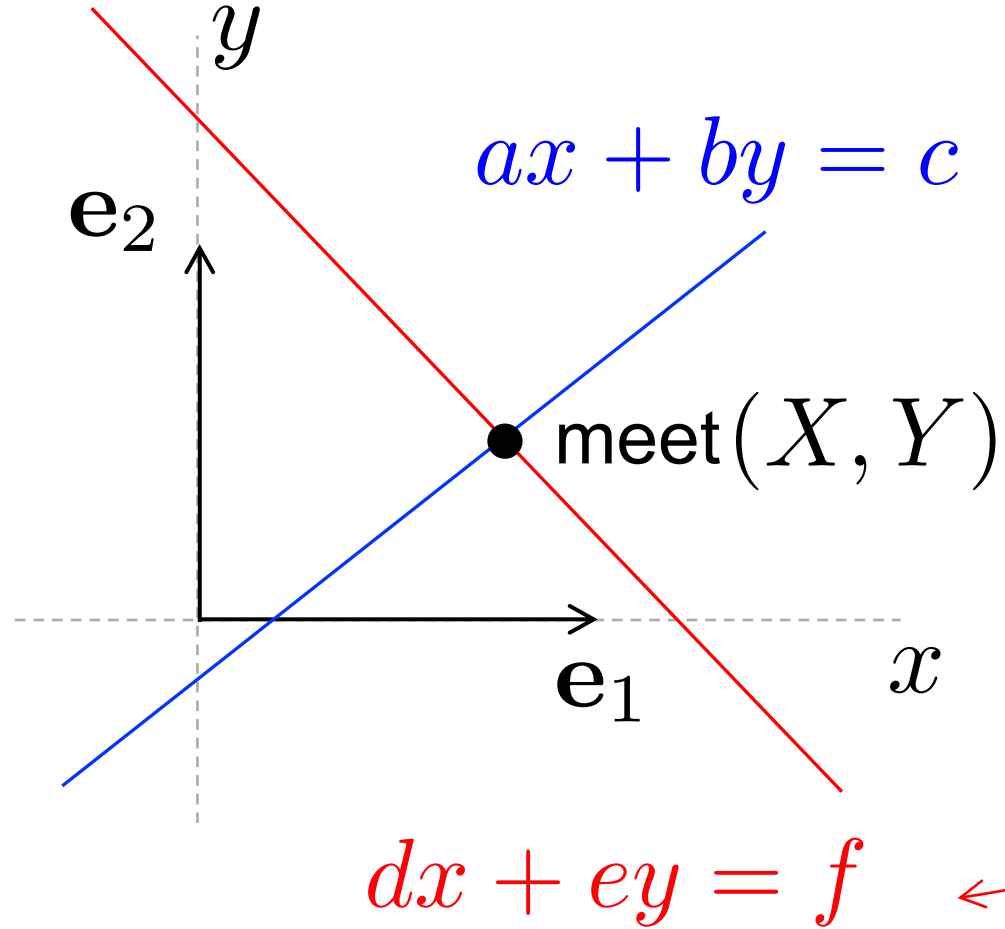


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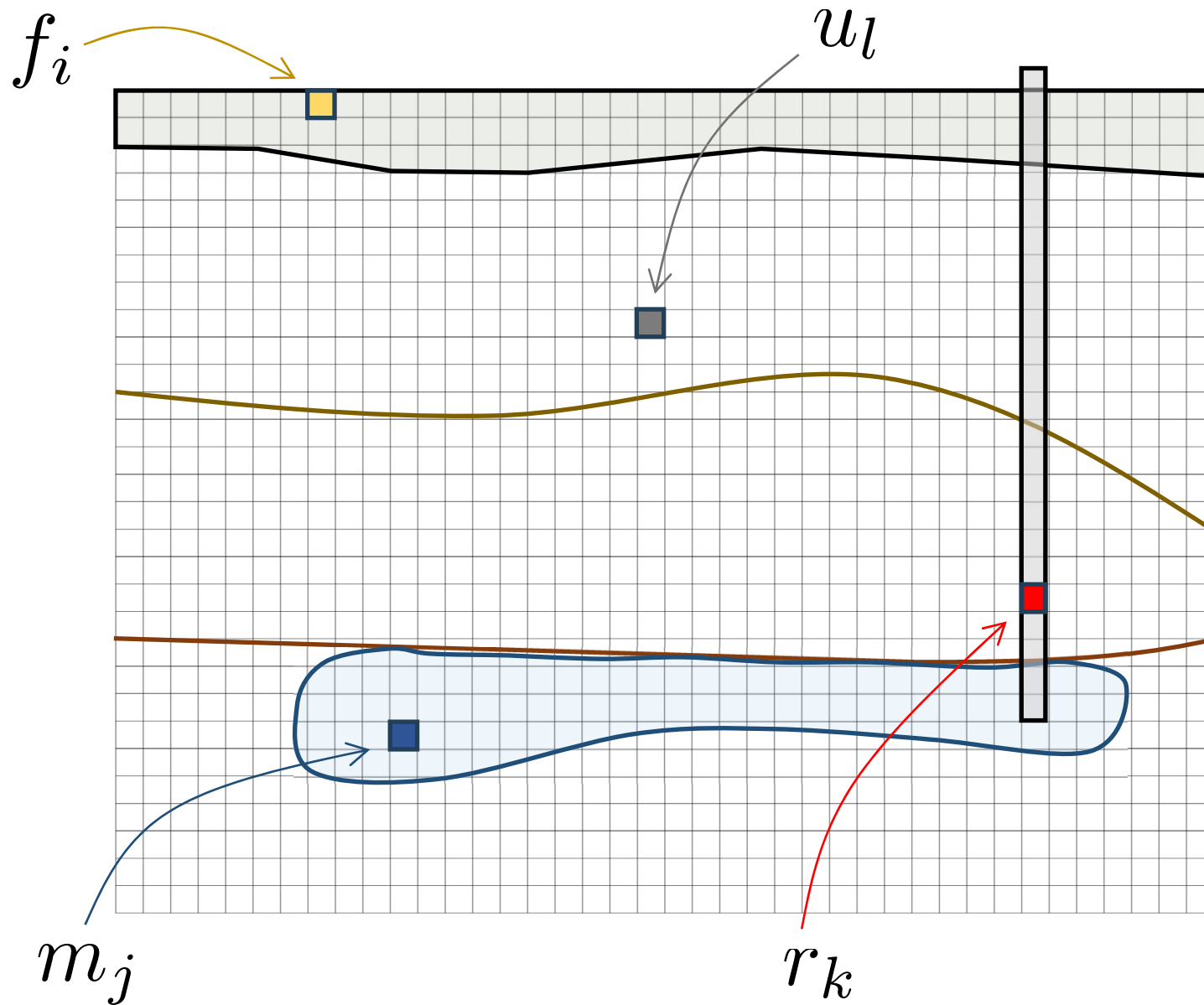
$$\mathbf{A}_1 = a\mathbf{e}_1 + b\mathbf{e}_2 - c\mathbf{e}_3$$

$$\mathbf{A}_2 = d\mathbf{e}_1 + e\mathbf{e}_2 - f\mathbf{e}_3$$

$$\mathbf{A}_1 \wedge \mathbf{A}_2 = D\mathbf{e}_{12} + X D\mathbf{e}_{23} + Y D\mathbf{e}_{13}$$



PGA encourages us to adopt Strang's “row picture” of a system of equations



$$\mathbf{S}^T \boldsymbol{\lambda} = \mathbf{r} \quad \mathbf{S} \mathbf{u} = \mathbf{f}$$

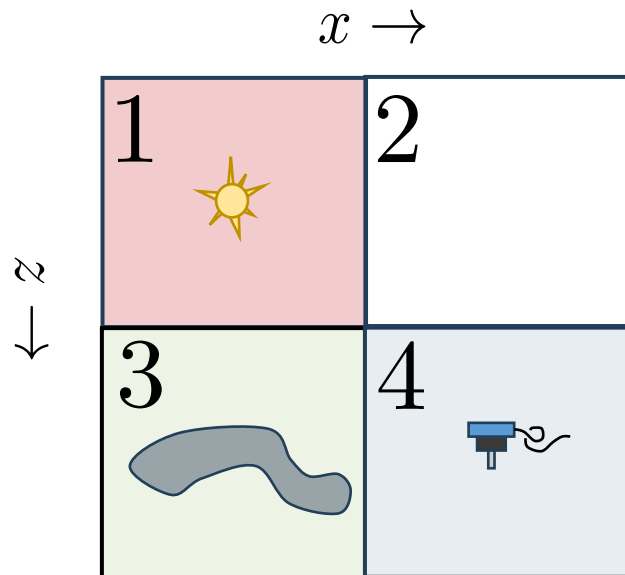
$$\boldsymbol{\lambda}^T \frac{\partial \mathbf{S}}{\partial \mathbf{m}} \mathbf{u}$$



FWI gradient via the adjoint-state method

$$\frac{d\phi}{dm_3} \propto \left\{ \left[\begin{array}{cccc} s_{11} & \text{X} & \text{X} & 0 \\ \text{X} & s_{22} & \text{X} & \text{X} \\ \text{X} & \text{X} & s_{33} & \text{X} \\ 0 & \text{X} & \text{X} & s_{44} \end{array} \right]^{-1} \left[\begin{array}{c} 0 \\ 0 \\ 0 \\ r_4 \end{array} \right] \right\}^T \left[\begin{array}{cccc} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 \end{array} \right] \left\{ \left[\begin{array}{cccc} s_{11} & \text{X} & \text{X} & 0 \\ \text{X} & s_{22} & \text{X} & \text{X} \\ \text{X} & \text{X} & s_{33} & \text{X} \\ 0 & \text{X} & \text{X} & s_{44} \end{array} \right]^{-1} \left[\begin{array}{c} f_1 \\ 0 \\ 0 \\ 0 \end{array} \right] \right\}$$

impedances
residuals
sensitivities
impedances
sources



- If certain model components are targeted...
- If source positions are sparsely occupied...
- If receiver positions are sparsely occupied...
- Then certain rows in the calculation are focused on
- Info from most rows incorporated again & again

Opportunity? Yes – but how to take advantage of it?

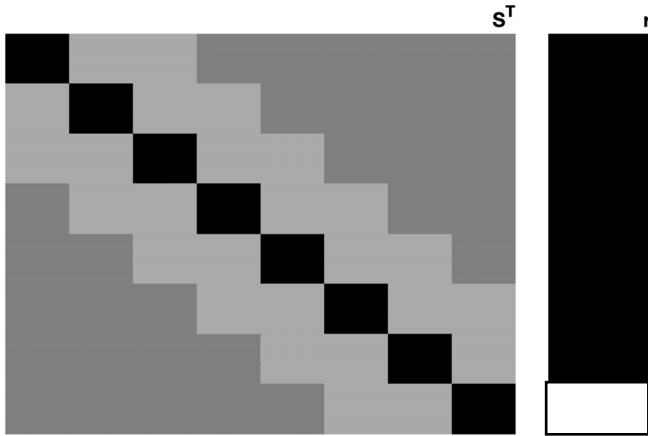


$$\mathbf{B}\boldsymbol{\lambda} = \mathbf{r} \qquad \mathbf{A}\mathbf{u} = \mathbf{f}$$

$\boldsymbol{\lambda}^T \frac{\partial \mathcal{S}}{\partial \mathbf{m}} \mathbf{u}$



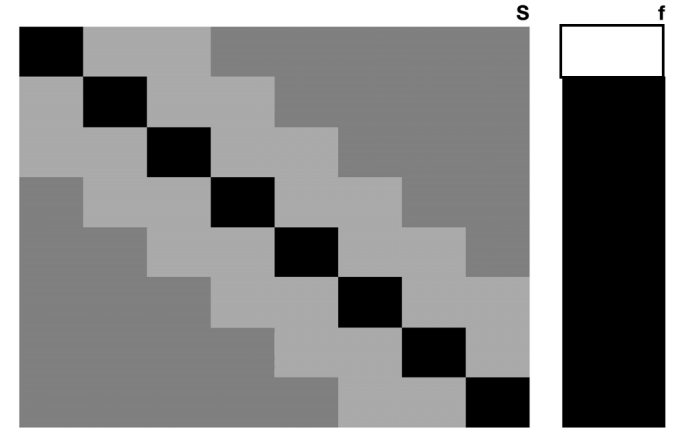
$$\mathbf{B}\lambda = \mathbf{r}$$



$$\frac{\partial \mathcal{S}}{\partial \mathbf{m}}$$

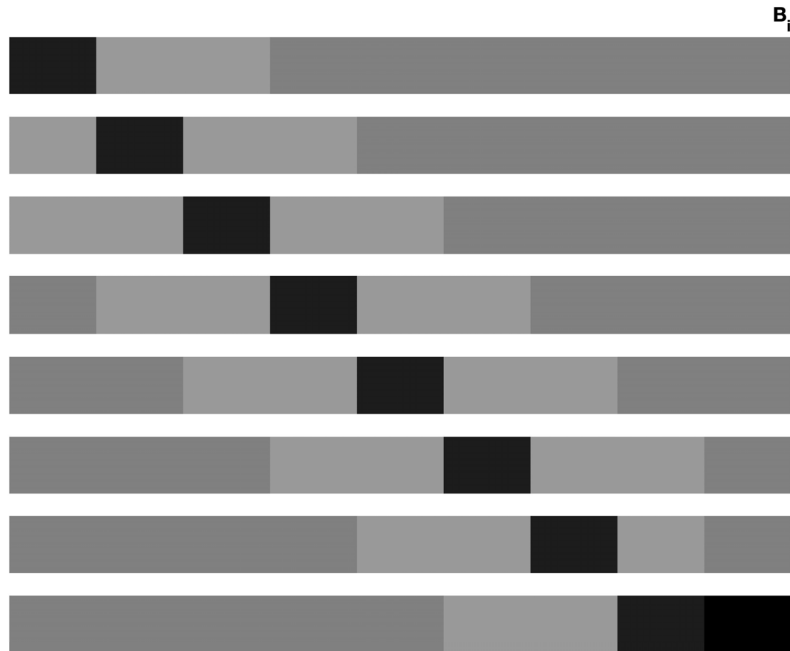


$$\mathbf{A}\mathbf{u} = \mathbf{f}$$





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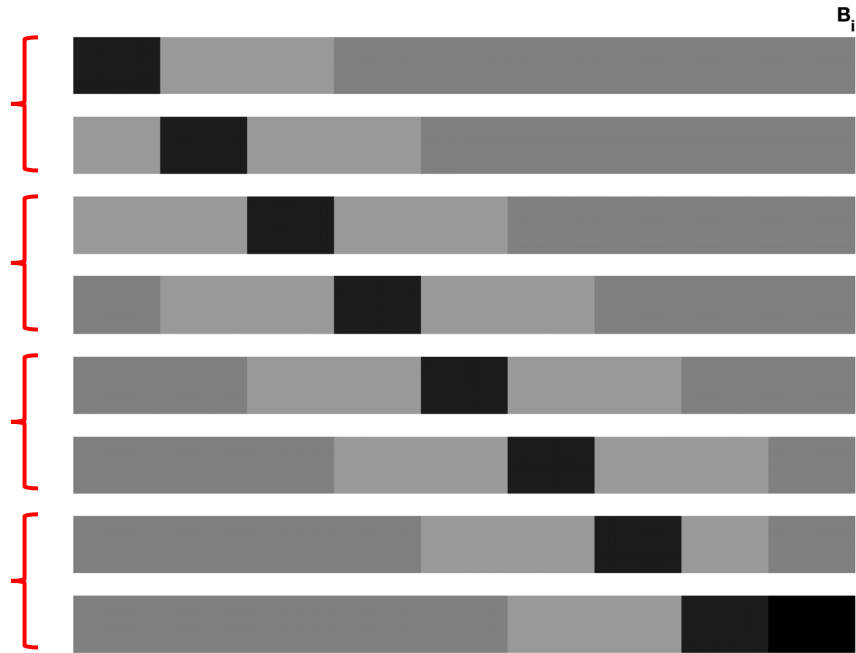


$$g(\mathbf{A}, \mathbf{B})$$





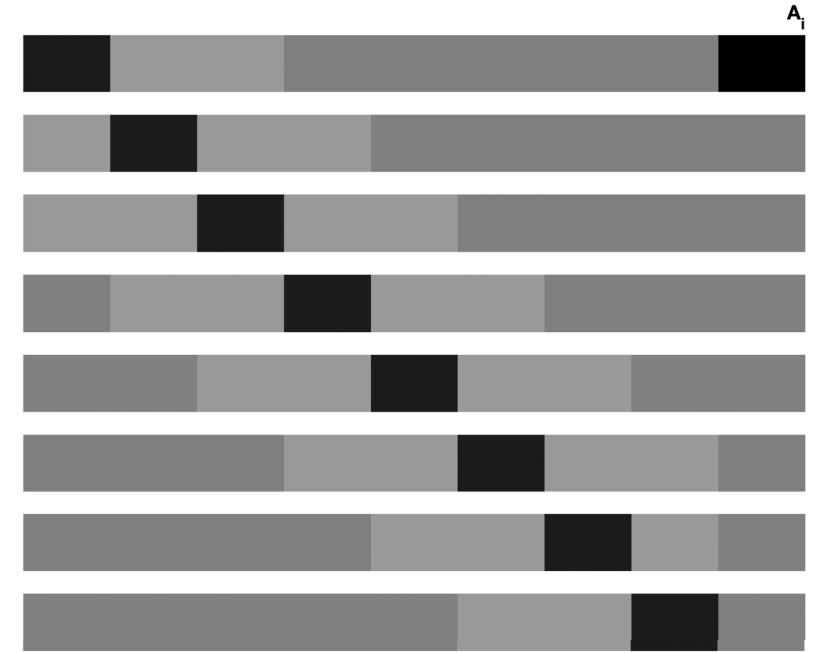
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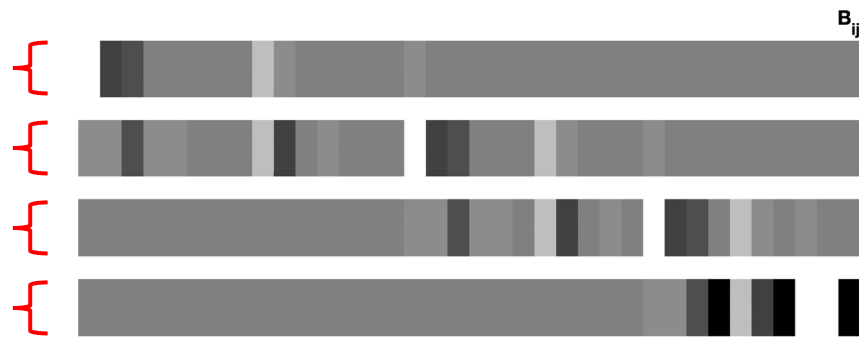


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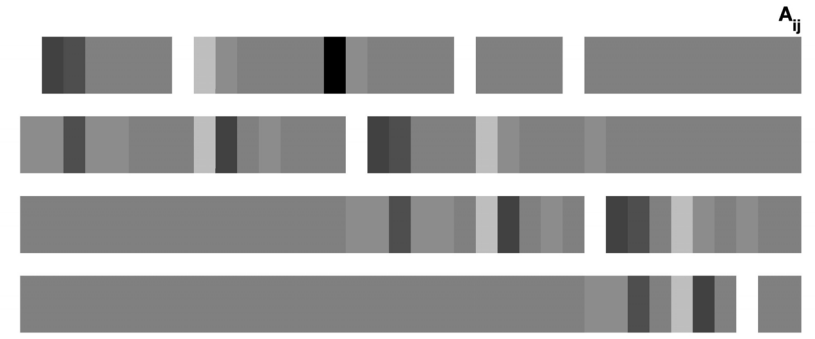
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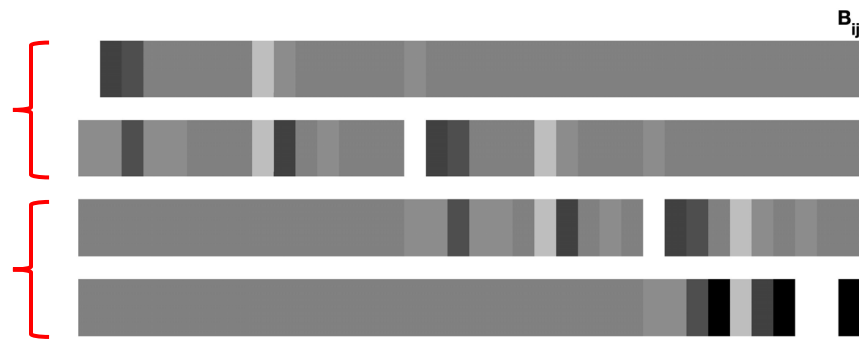


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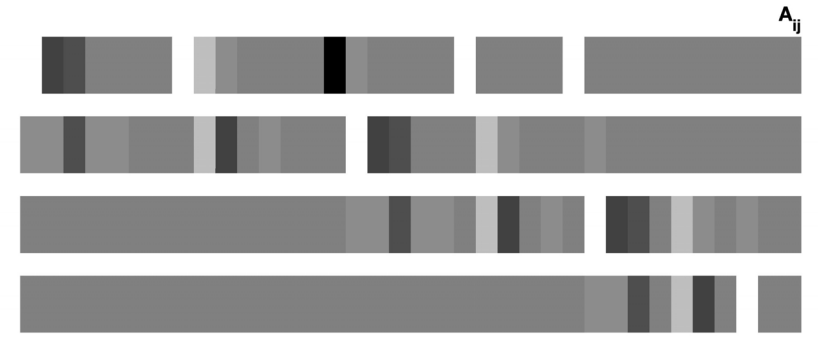
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$$\frac{\partial \mathcal{S}}{\partial \mathbf{m}}$$



$$\mathbf{A}\mathbf{u} = \mathbf{f}$$





$$\mathbf{B}\lambda = \mathbf{r}$$



$$\frac{\partial S}{\partial \mathbf{m}}$$



$$\mathbf{A}\mathbf{u} = \mathbf{f}$$





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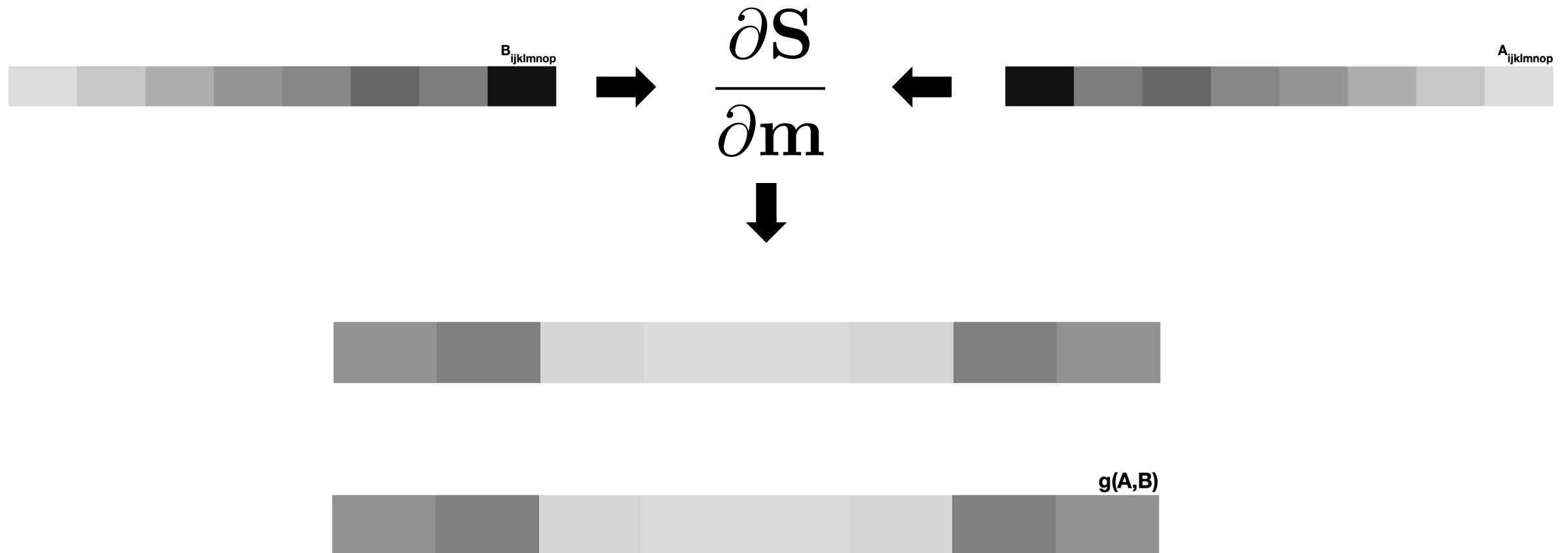
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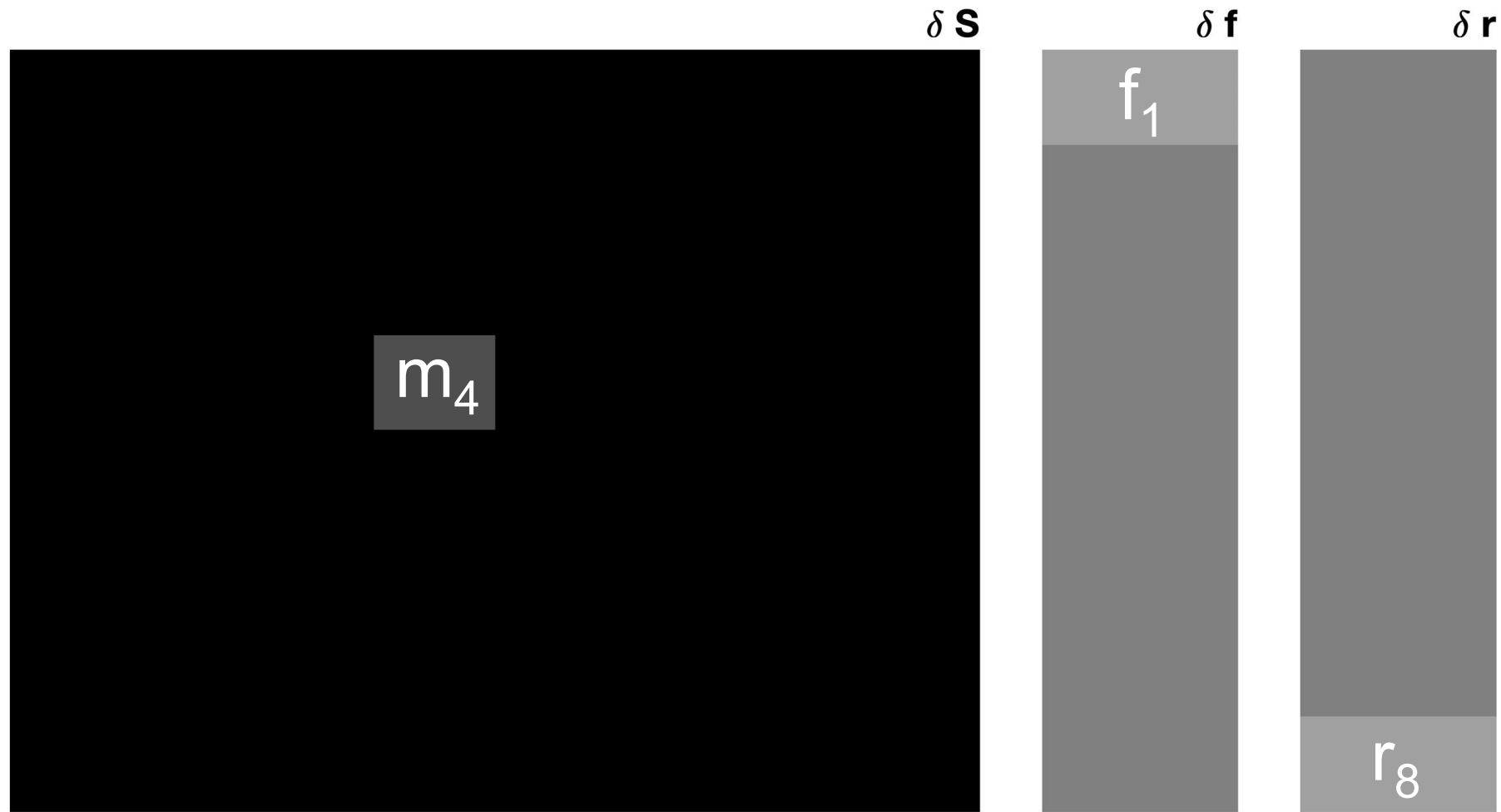
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Targeting and sparseness = low computation in PGA?

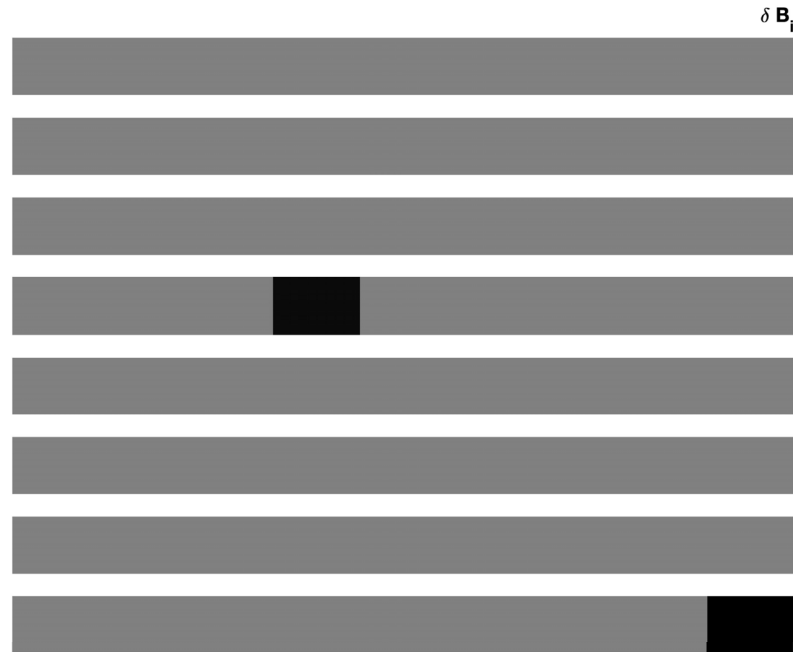


By perturbing m_i , f_j and r_k , map where computational savings reside



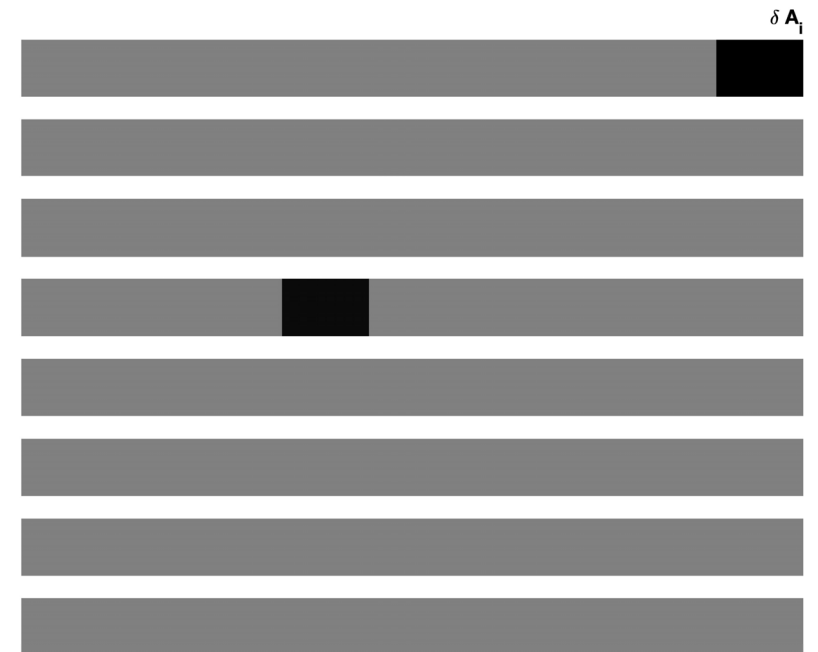
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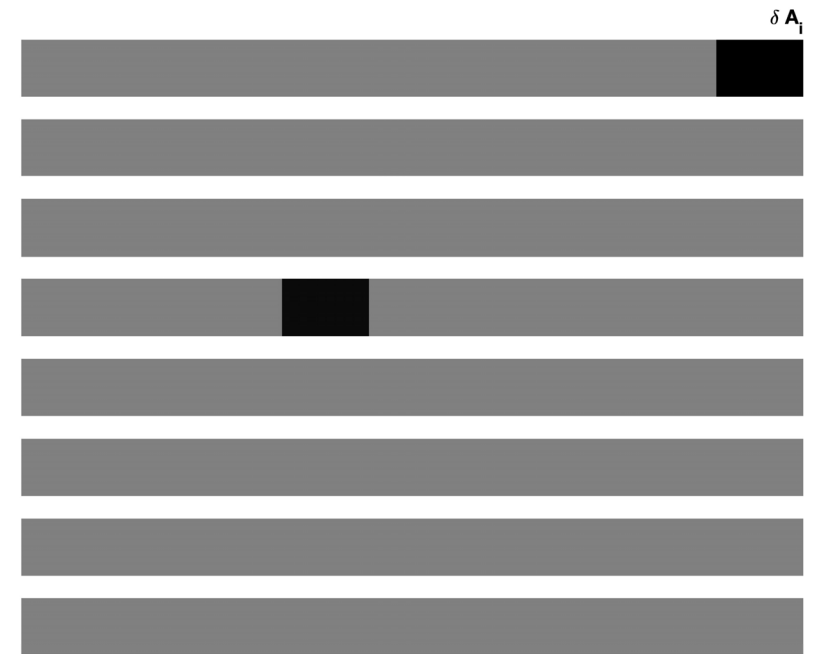
Targeting and sparseness = low computation in PGA?

$$B\lambda = r$$



$$\frac{\partial S}{\partial m}$$

$$A u = f$$





Targeting and sparseness = low computation in PGA?

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$$\frac{\partial S}{\partial \mathbf{m}}$$

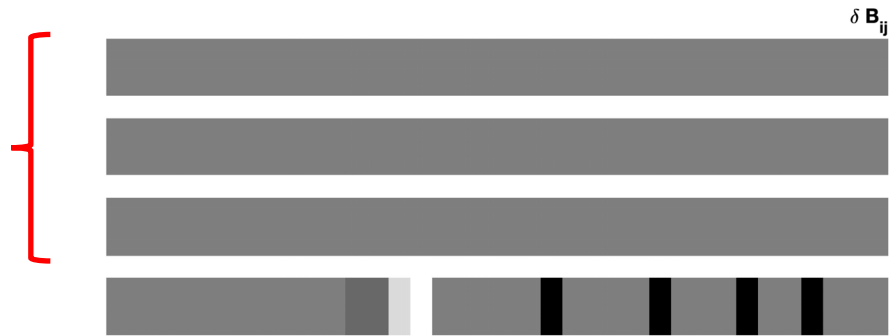
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$$\frac{\partial \mathcal{S}}{\partial \mathbf{m}}$$

$$\mathbf{A}\mathbf{u} = \mathbf{f}$$





Targeting and sparseness = low computation in PGA?

$$\mathbf{B}\lambda = \mathbf{r}$$



$$\frac{\partial S}{\partial \mathbf{m}}$$



$$\mathbf{A}\mathbf{u} = \mathbf{f}$$





PGA: geometric objects (lines, planes) ➡ algebra

...e.g., solution of $\mathbf{Ax}=\mathbf{b}$ computed in terms of “meets”

Sparse/targeted FWI invokes the same info repeatedly

....but absent “row picture” computation, hard to capitalize

Opportunities:

- Avoidance of massive duplication ($\sim \#$ targeted grid cells)
- Enable acquisition design minimizing FWI cost?

Requirements:

- Libraries for Geometric Products on significant scale