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Unravelling cell fate decisions through single cell methods and mathematical models

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**UNRAVELLING CELL FATE DECISIONS
THROUGH SINGLE CELL METHODS AND
MATHEMATICAL MODELS**

- Maria Mircea -

UNRAVELLING CELL FATE DECISIONS THROUGH SINGLE CELL METHODS AND MATHEMATICAL MODELS

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Cover (back): Molecules involved in cellular differentiation.

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The first principle is that you must not fool yourself – and you are the easiest person to fool.

Richard Feynman

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