Guided Tour of Machine Learning in Finance

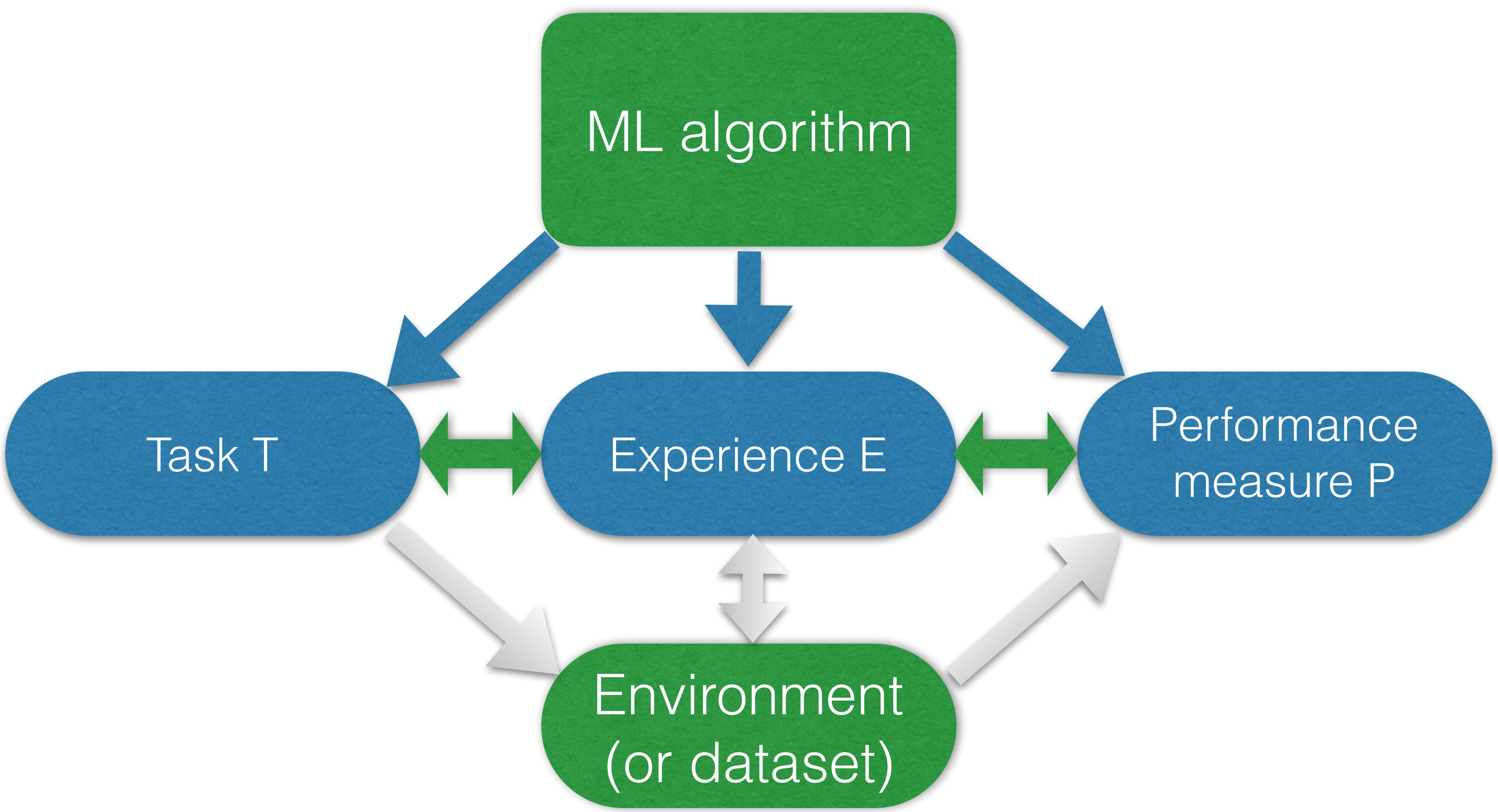
ML as a foundation of AI - part II

Igor Halperin

NYU Tandon School of Engineering, 2017

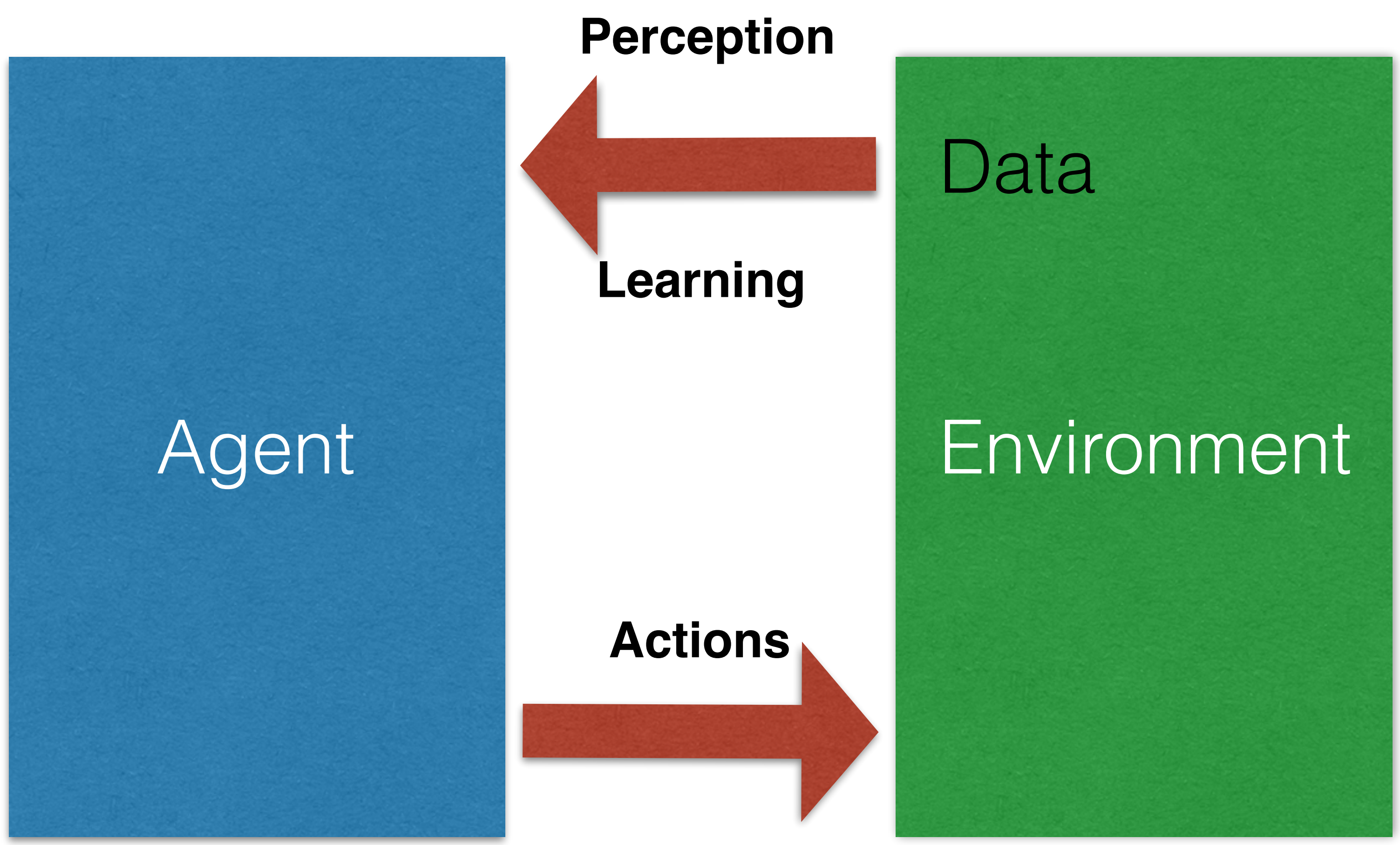
Machine Learning: core idea

“A computer program is said to learn from **experience E** with respect to some class of **tasks T** and **performance measure P**, if its performance at tasks in **T**, as measured by **P**, improves with experience **E**.” (Mitchell, 1997)



Next, we need to specify what we mean by **Tasks T**, **Performance measure P** and **Experience E**

Types of ML tasks



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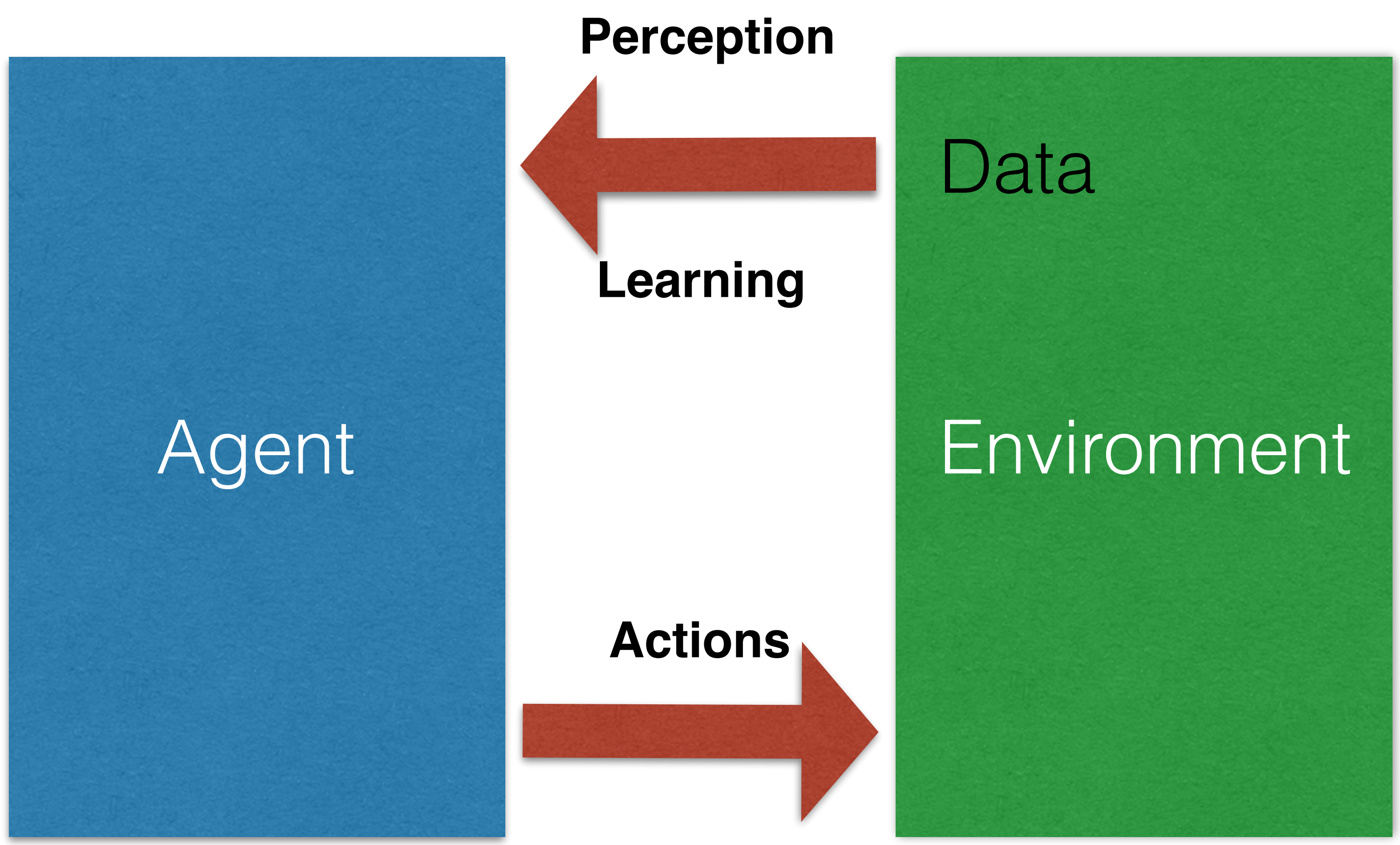

Observable/partially observable
Single agent/multi-agent
Stochastic or deterministic
Episodic or sequential
Discrete or continuous

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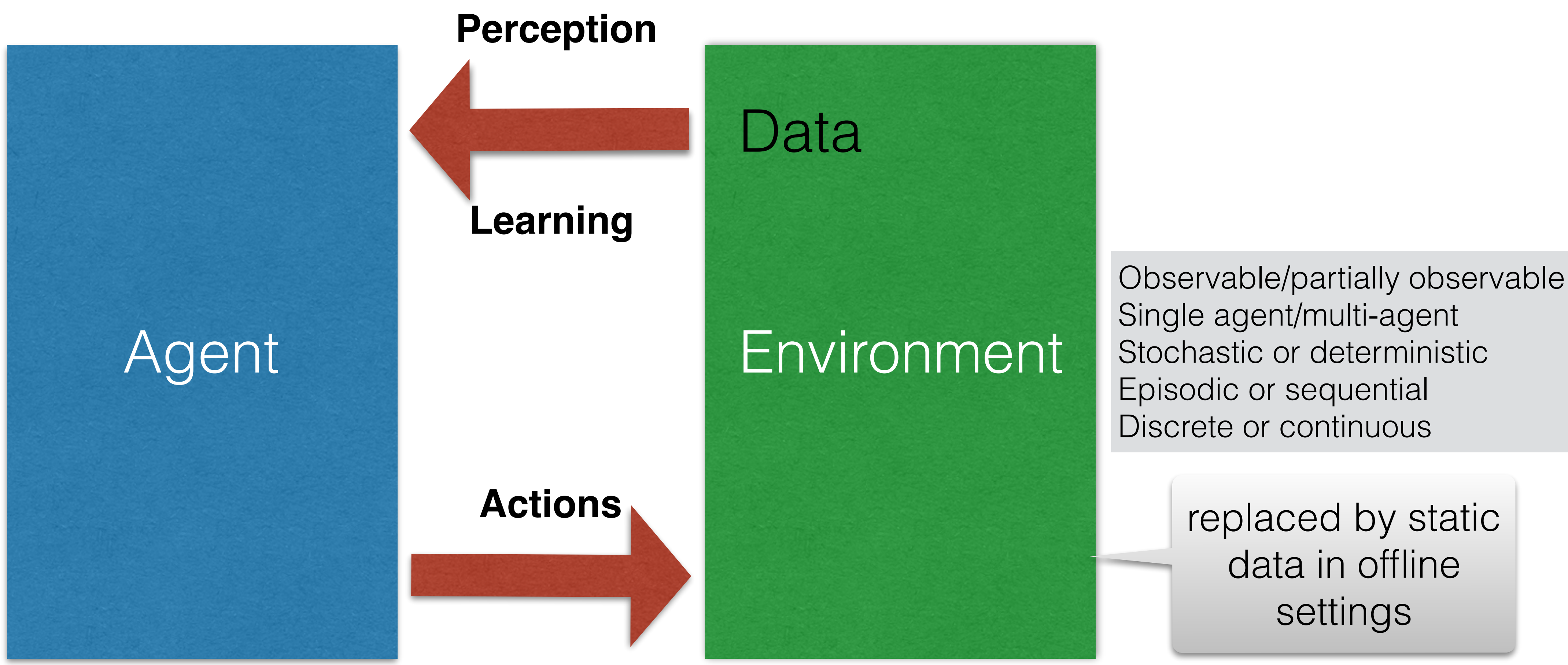

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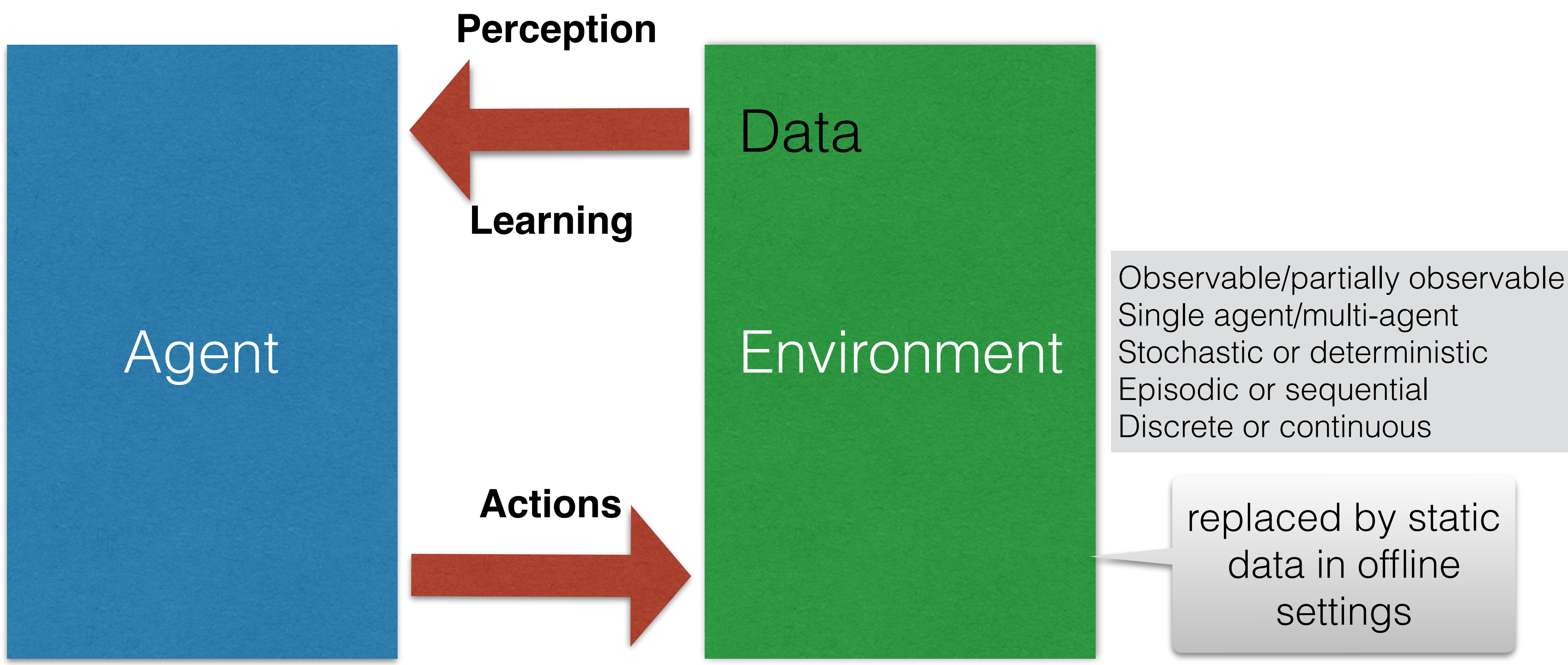

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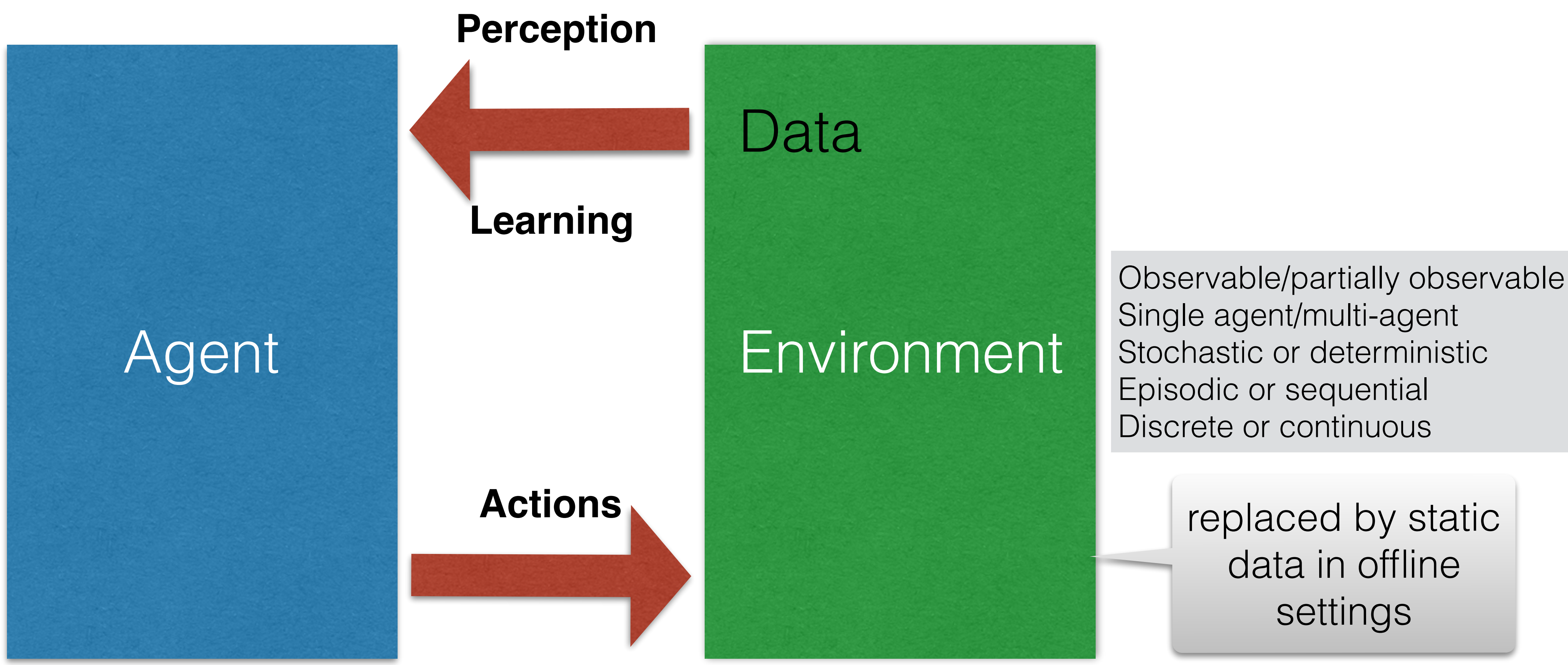

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“**Action tasks**”: the same as perception tasks, but there are multiple possible actions. For sequential (multi-step) problems, action tasks involve planning and forecasting the future.

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L1-loss: $$L = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right|$$

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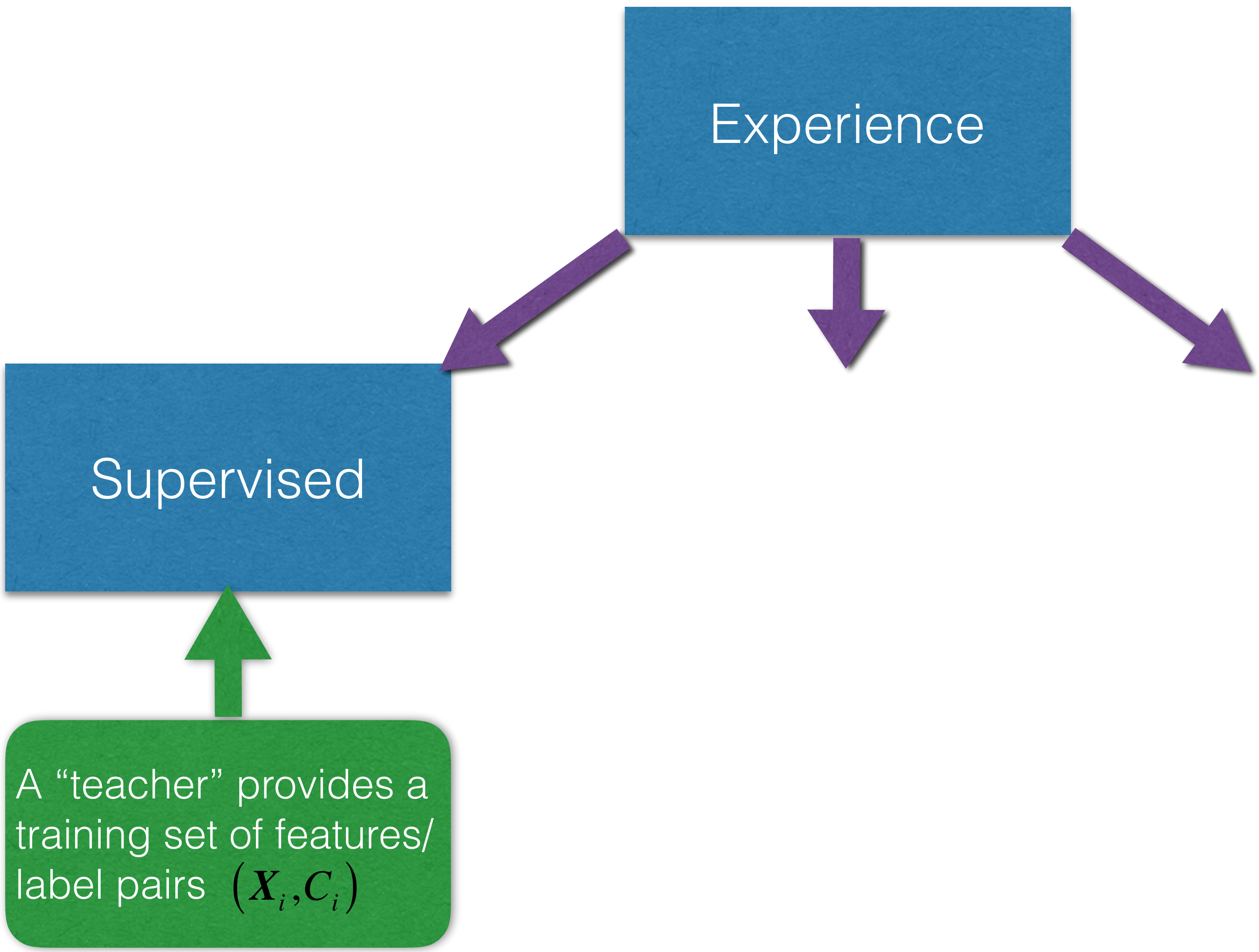

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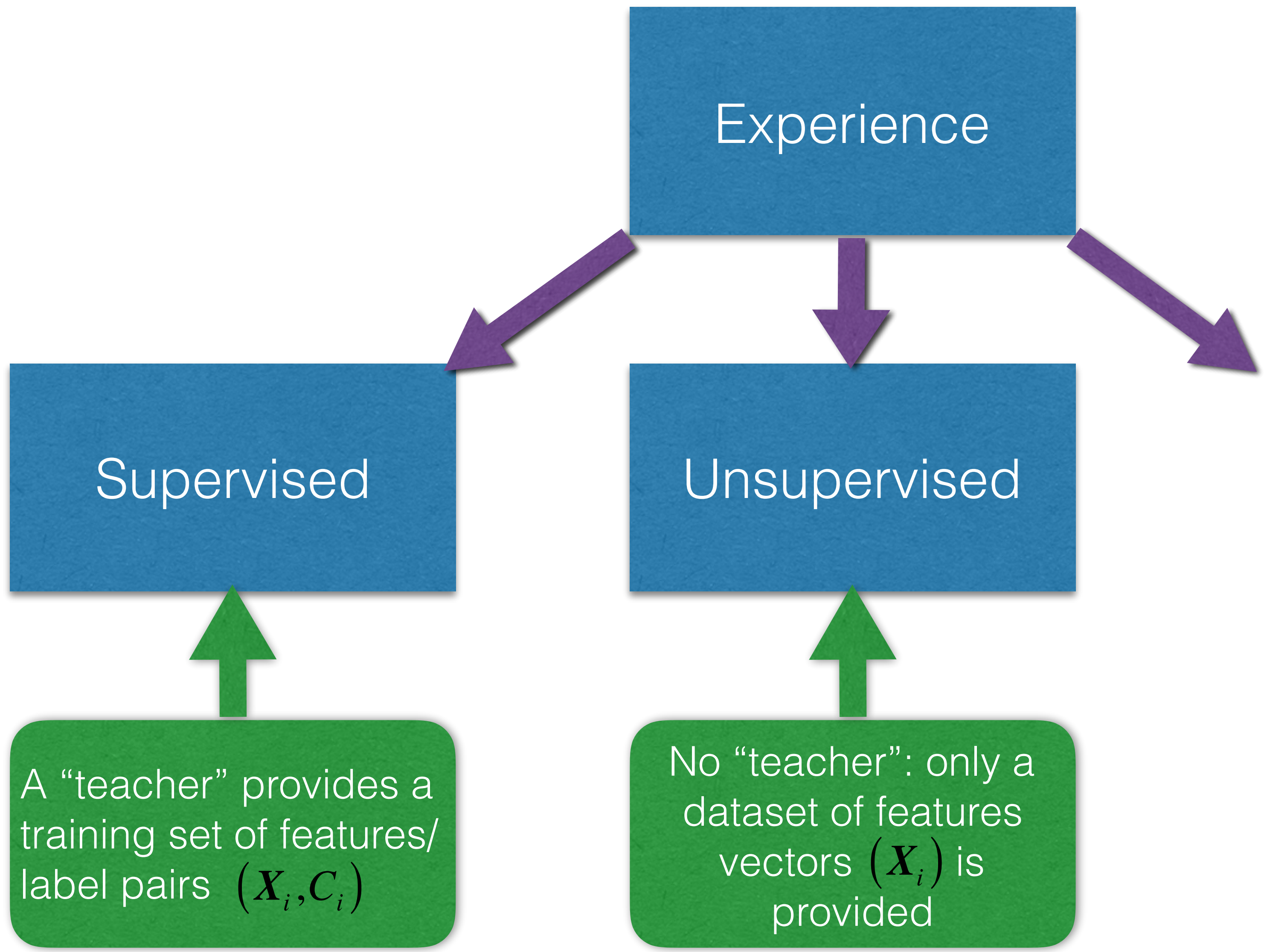

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