The A”alto Dictionary of Machine Learning

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Machine Learning Concepts

máximo El máximo de un conjunto $\mathcal{A} \subseteq \mathbb{R}$ de números reales es el elemento más grande en ese conjunto, si tal elemento existe. Un conjunto $\mathcal{A}$ tiene un máximo si está acotado superiormente y alcanza su supremo (o mínimo de las cotas superiores) [2, Sec. 1.4].

mínimo Dado un conjunto de números reales, el mínimo es el menor de esos números.

supremo (o mínimo de las cotas superiores) El supremo de un conjunto de números reales es el número más pequeño que es mayor o igual que todos los elementos del conjunto. Formalmente, un número real a es el supremo de un conjunto $\mathcal{A} \subseteq \mathbb{R}$ si: 1) a es una cota superior de $\mathcal{A}$; y 2) ningún número menor que a es una cota superior de $\mathcal{A}$. Todo conjunto no vacío de números reales que esté acotado superiormente tiene un supremo,aun si no contiene su supremo como un elemento [2, Sec. 1.4].

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