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Escuela de Empresarios

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Machine Learning 0 - Intro

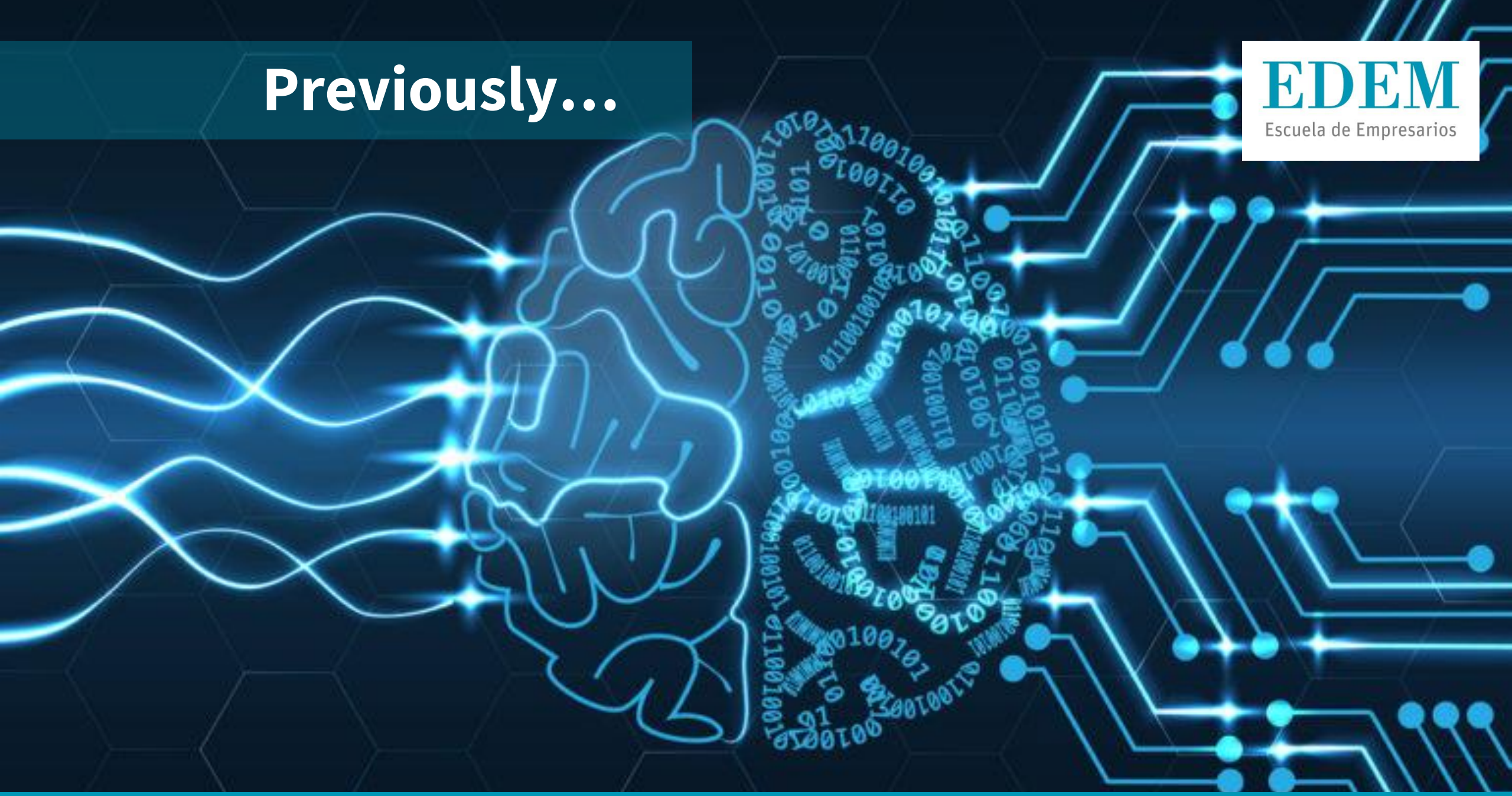
horus·ml

Jesús Prada Alonso - HORUS ML

Curso Máster en Data Analytics - Edición 4

Fecha 30/03/2023

Previously...



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RESUMEN MODELOS

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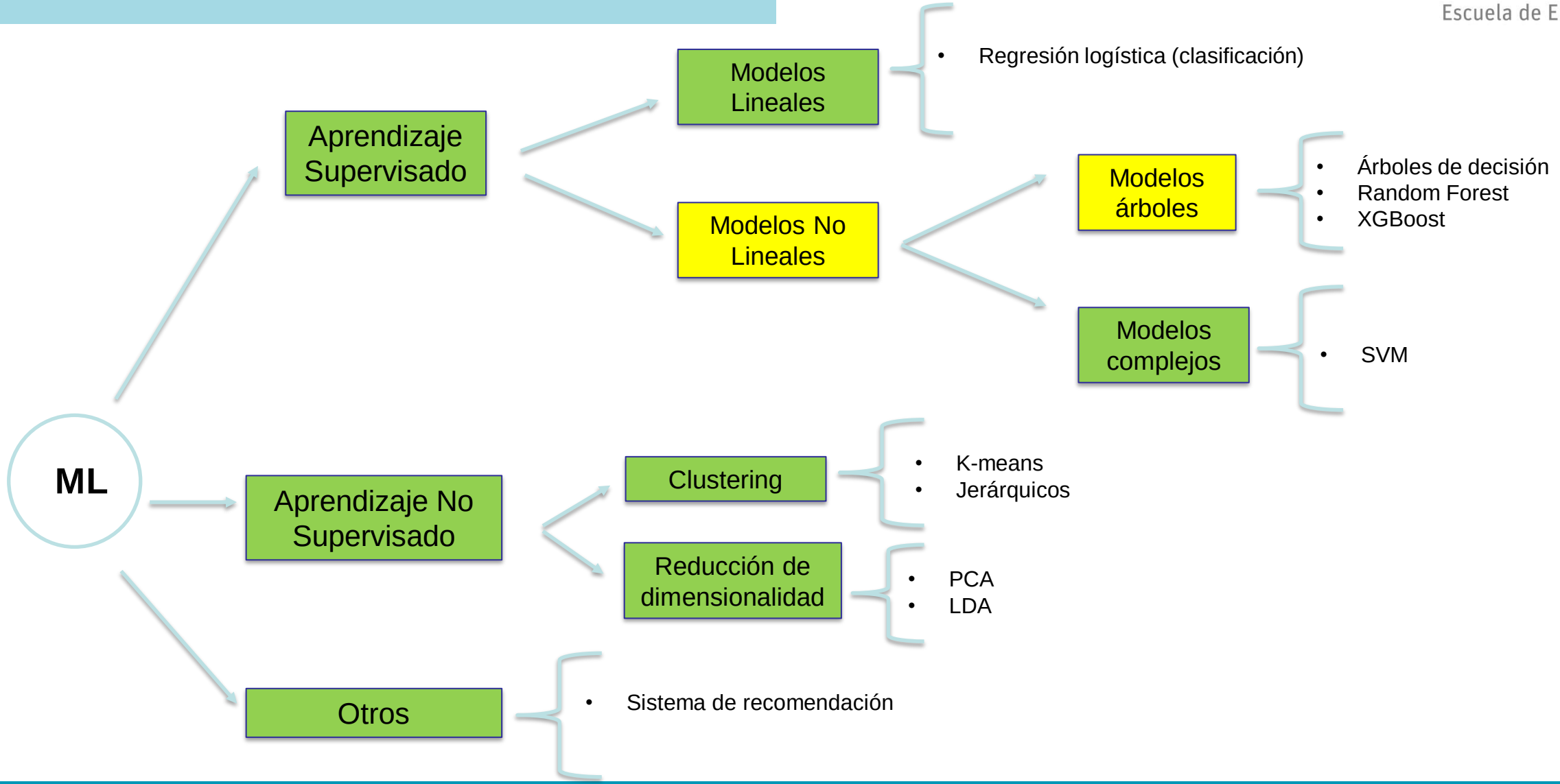

COMPARACIÓN ALGORITMOS

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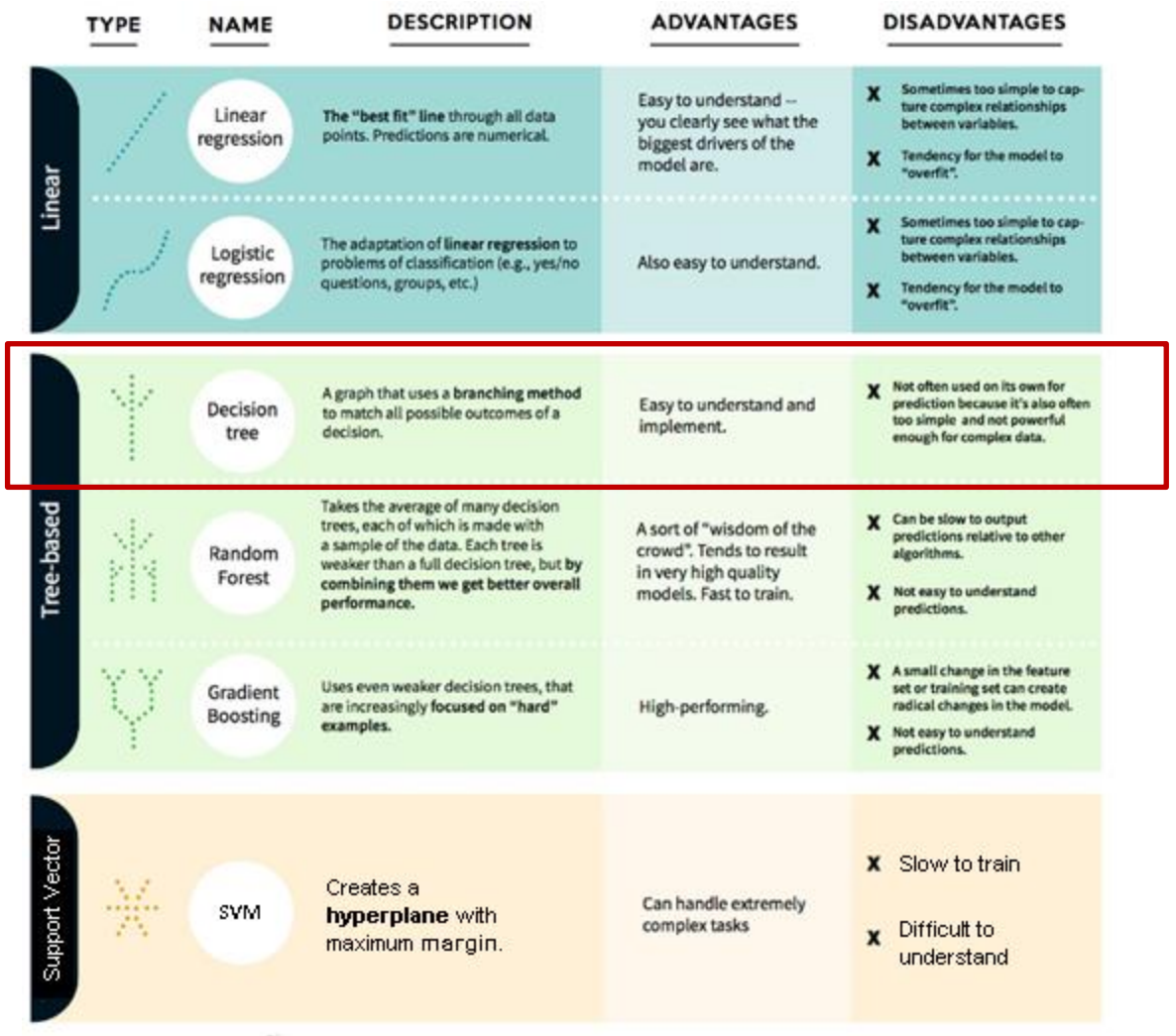

TYPE	NAME	DESCRIPTION	ADVANTAGES	DISADVANTAGES
Linear	Linear regression	**The "best fit" line** through all data points. Predictions are numerical.	Easy to understand -- you clearly see what the biggest drivers of the model are.	X Sometimes too simple to capture complex relationships between variables. X Tendency for the model to "overfit".
Linear	Logistic regression	The adaptation of **linear regression** to problems of classification (e.g., yes/no questions, groups, etc.)	Also easy to understand.	X Sometimes too simple to capture complex relationships between variables. X Tendency for the model to "overfit".
Tree-based	Decision tree	A graph that uses a **branching method** to match all possible outcomes of a decision.	Easy to understand and implement.	X Not often used on its own for prediction because it's also often too simple and not powerful enough for complex data.
Tree-based	Random Forest	Takes the average of many decision trees, each of which is made with a sample of the data. Each tree is weaker than a full decision tree, but **by combining them we get better overall performance.**	A sort of "wisdom of the crowd". Tends to result in very high quality models. Fast to train.	X Can be slow to output predictions relative to other algorithms. X Not easy to understand predictions.
Tree-based	Gradient Boosting	Uses even weaker decision trees, that are increasingly **focused on "hard" examples.**	High-performing.	X A small change in the feature set or training set can create radical changes in the model. X Not easy to understand predictions.
Support Vector	SVM	Creates a **hyperplane** with maximum margin.	Can handle extremely complex tasks	X Slow to train X Difficult to understand

ÁRBOLES DE DECISIÓN

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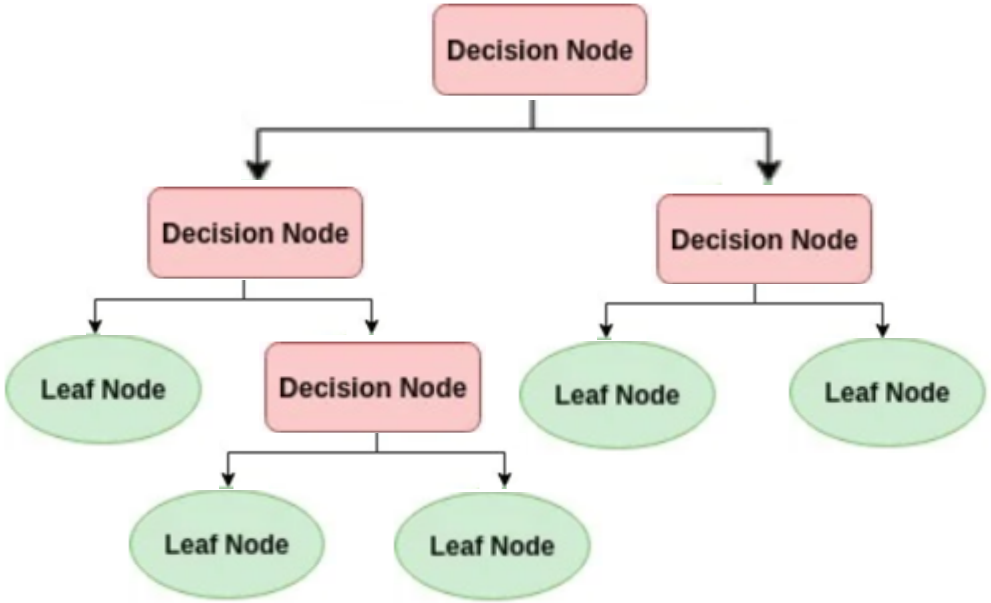
Definición (II)

- Cada nodo representa las variables de los datos, cada rama una decisión y cada nodo hoja un output.
- El nodo superior es el nodo raíz y representa la variable más importante.
- El árbol va aprendiendo de la división de los nodos recursivamente.
- Cuando un nuevo dato debe ser clasificado recorre el árbol desde el nodo raíz al nodo hoja, respondiendo a las preguntas de cada nodo en función de los atributos y el camino correcto en cada respuesta.



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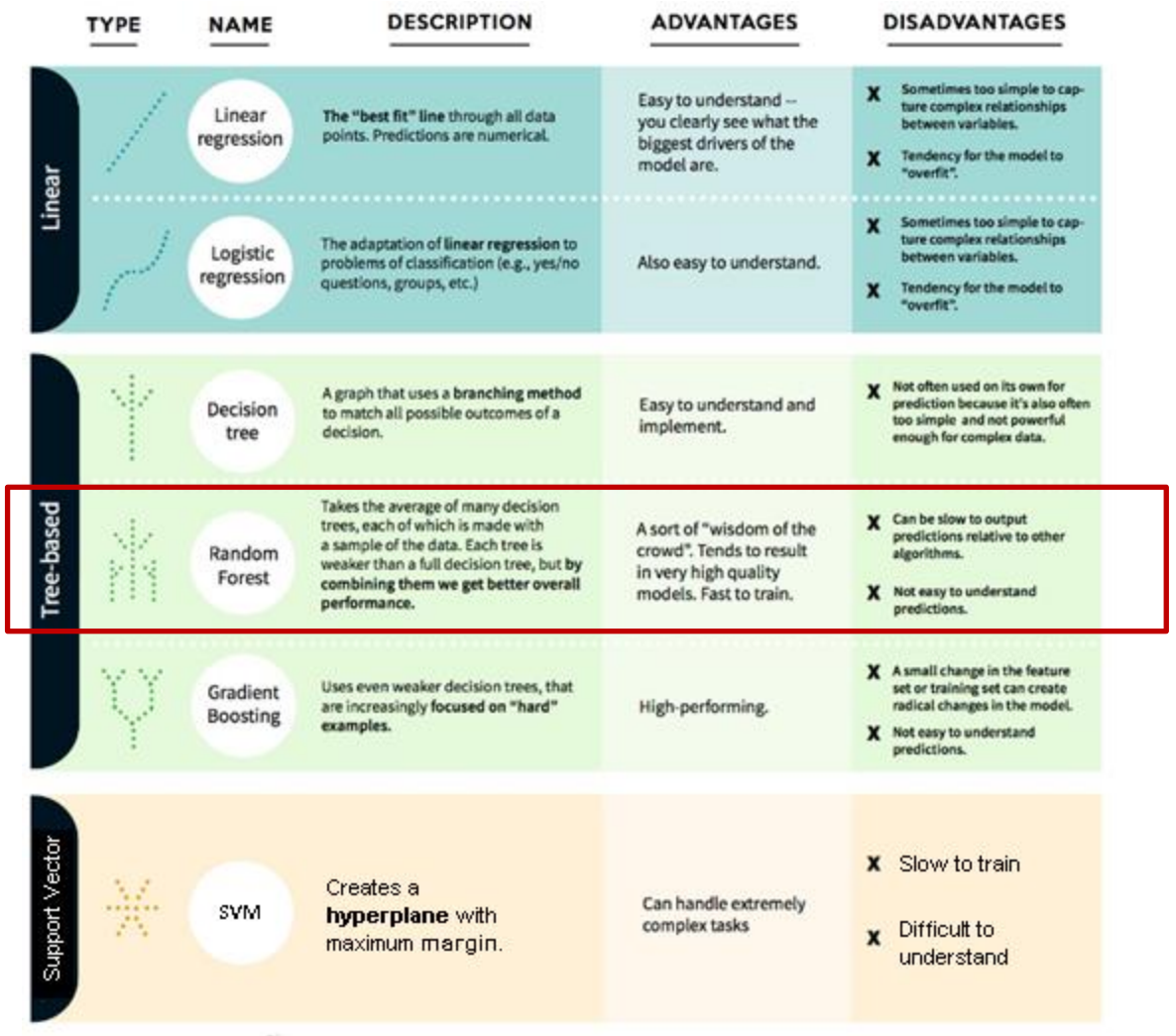

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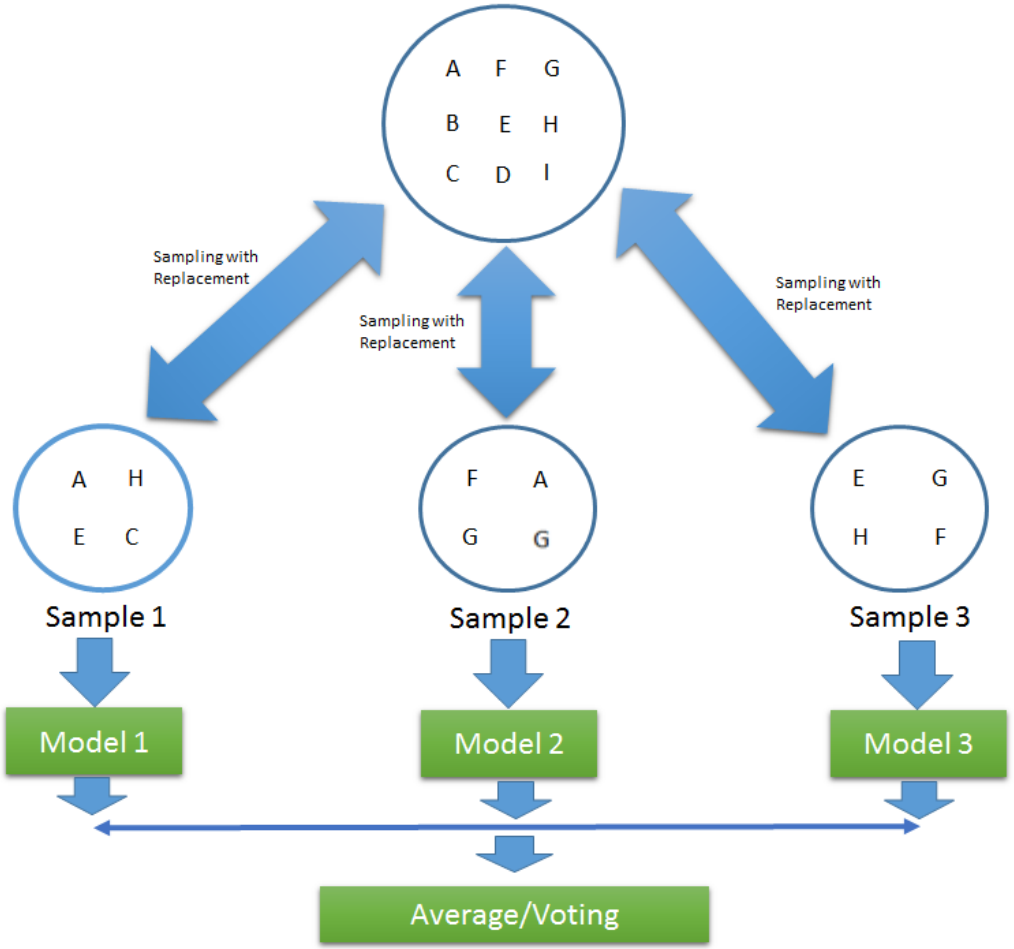
Bagging. Esquema



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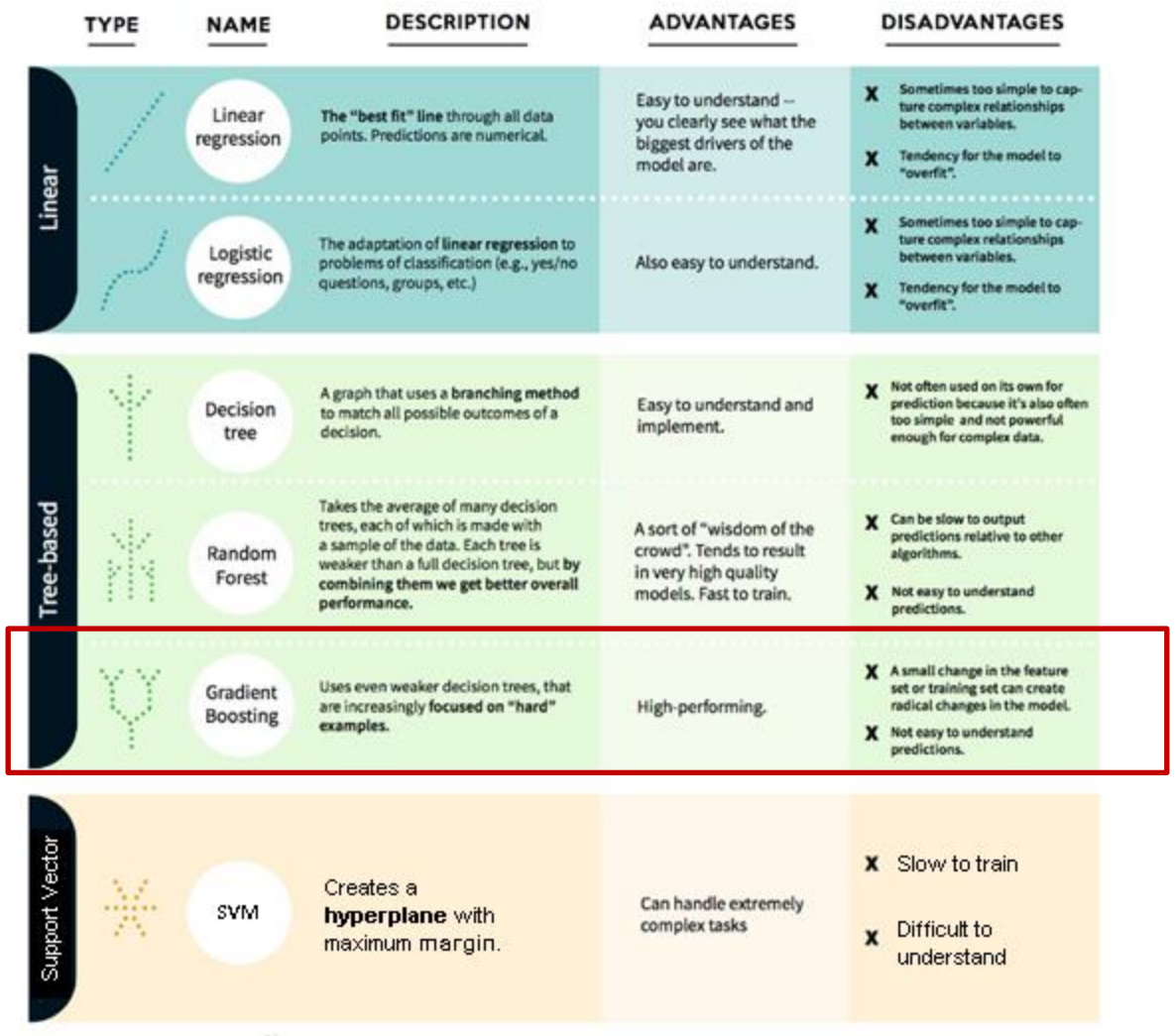

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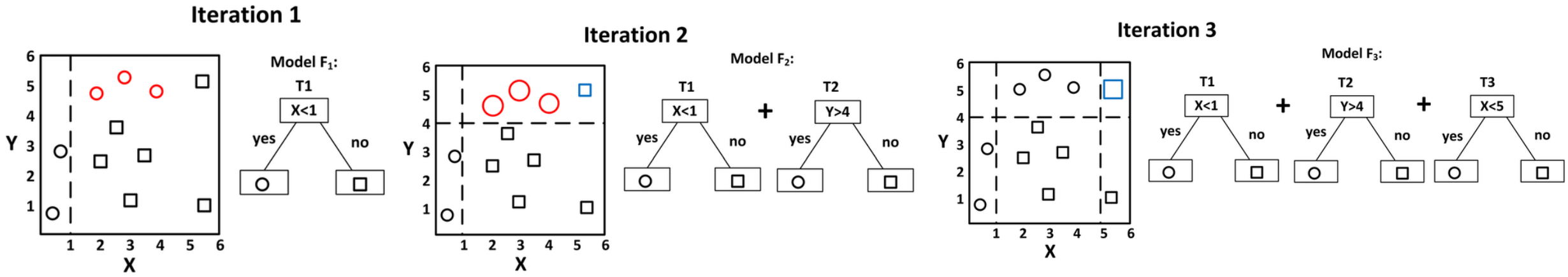
Boosting. Esquema



DEFINICIÓN (V)

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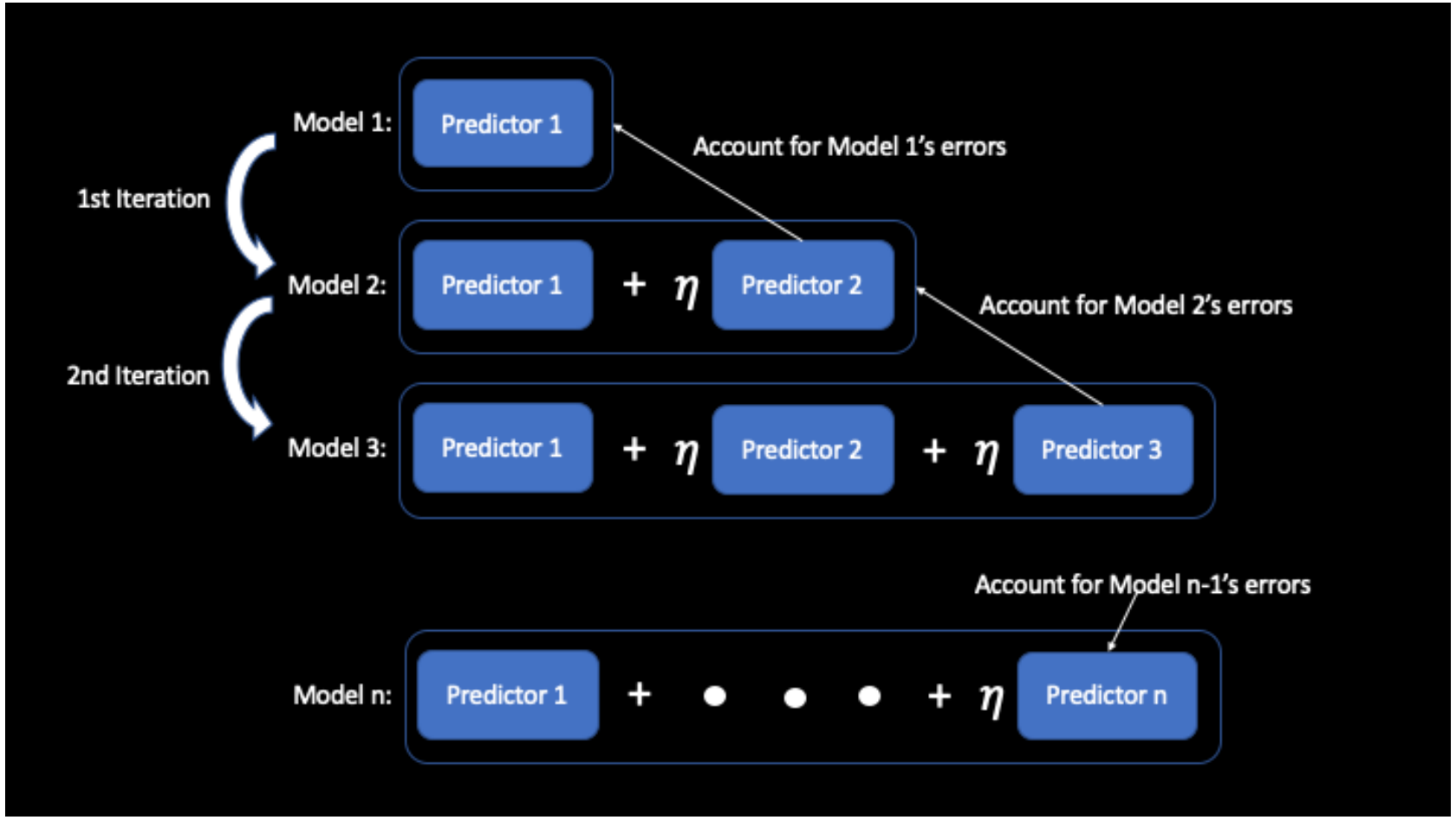
Gradient Boosting. Representación visual



HIPERPARÁMETROS (XI)

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Resumen

Hiperparámetro	Efecto	Rango	Valor por defecto
nrounds	Número de iteraciones de boosting a realizar	[1,∞]	100
eta	Inversamente relacionado con el step size.	[0,1]	0,3
gamma	Mínima mejora en la loss function requerida.	[0,∞]	0
max_depth	Profundidad máxima de cada árbol.	[1,∞]	6
min_child_weight	Suma mínima de pesos necesaria en un nodo hijo.	[0,∞]	1
subsample	Ratio de submuestreo de las instancias de entrenamiento.	(0,1]	1
colsample_bytree	Ratio de submuestreo de las columnas del dataset.	(0,1]	1
num_parallel_tree	Número de árboles calculados en cada iteración.	[1,∞]	1
lambda	Controla la regularización L2.	[0,∞]	1
alpha	Controla la regularización L1.	[0,∞]	0
early_stopping_rounds	Numero de iteraciones sin mejora permitidas.	[1,∞]	None

RESUMEN

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Ventajas

- Una de las familias de modelos de mayor **potencial predictivo**.
- Cada **modelo individual** es muy **poco costoso** computacionalmente.
- **Poco** gasto de **memoria**.
- El elevado número de hiperparámetros permite su **ajuste a problemas muy variados**.
- La implementación oficial está **paralelizada** internamente.
- Permite reducir el preprocesado (scaling, valores no informados, variables categóricas).

Desventajas

- Modelo complejo → **Poco interpretable de forma directa**.
- **Muchos hiperparámetros** a probar, por lo que las búsquedas en rejilla pueden ser extensas y costosas.
- **Sensible** a la elección de **hiperparámetros**.

VARIACIONES DE XGBOOST

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LightGBM

- LightGBM es otro framework de **gradient boosting** que utiliza modelos basados en **árboles**.
- En **XGBoost**, los árboles crecen en **profundidad**, mientras que en **LightGBM** lo hacen en hojas (**anchura**).
- A nivel de **ajuste predictivo**, está en una escala **similar a XGBoost**.
- Ventajas:
  - **Mayor velocidad** de entrenamiento.
  - **Menor** uso de **memoria**.
- Desventajas:
  - No integrado en framework **scikit-learn**.
  - **Menos directo de** instalar y **usar.**
  - Desarrollo **menos estable.**
  - **Menos documentación.**

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CatBoost

- CatBoost también es un framework de **gradient boosting** que utiliza modelos basados en **árboles**.
- **Optimizado para** datasets con variables categóricas con **muchas categorías**.
- Su nivel de **ajuste predictivo** es **normalmente peor** que en **XGBoost salvo en el caso anterior**.
- Ventajas:
  - **Buenos resultados** empleando los **hiperparámetros por defecto**.
  - **Mejores predicciones** si tenemos **muchas categorías**.
- Desventajas:
  - Desarrollo **menos estable.**
  - **Menos documentación.**
  - **Normalmente peor**es resultados **que** en **XGBoost en muchas situaciones.**

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