

# Big Data: noves eines i estratègies per a la gestió de grans volums de dades

Big data i valorització de les dades



Ajuntament de  
Barcelona



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# 1 DEFINICIÓ OFICIAL DE BIG DATA

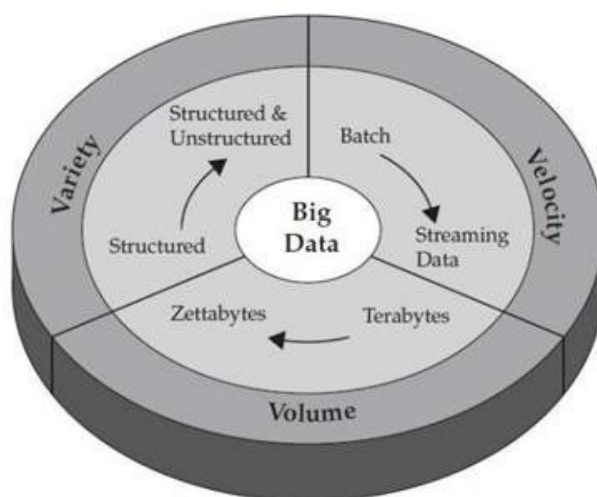
*"Big Data is high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation."*

<http://www.gartner.com/it-glossary/big-data/>

Gartner, 2012

Com podem veure Big Data és bàsicament un concepte econòmic i de gestió. De fet, Gartner ho va definir com: **el conjunt de propietats d'alt Volum, alta Velocitat i alta Varietat de les dades, que fan imprescindible la busqueda de noves formes de processament de l'informació eficients i assumibles en cost per així millorar la comprensió de les dades. la presa de decisions i el procés automàtic.**

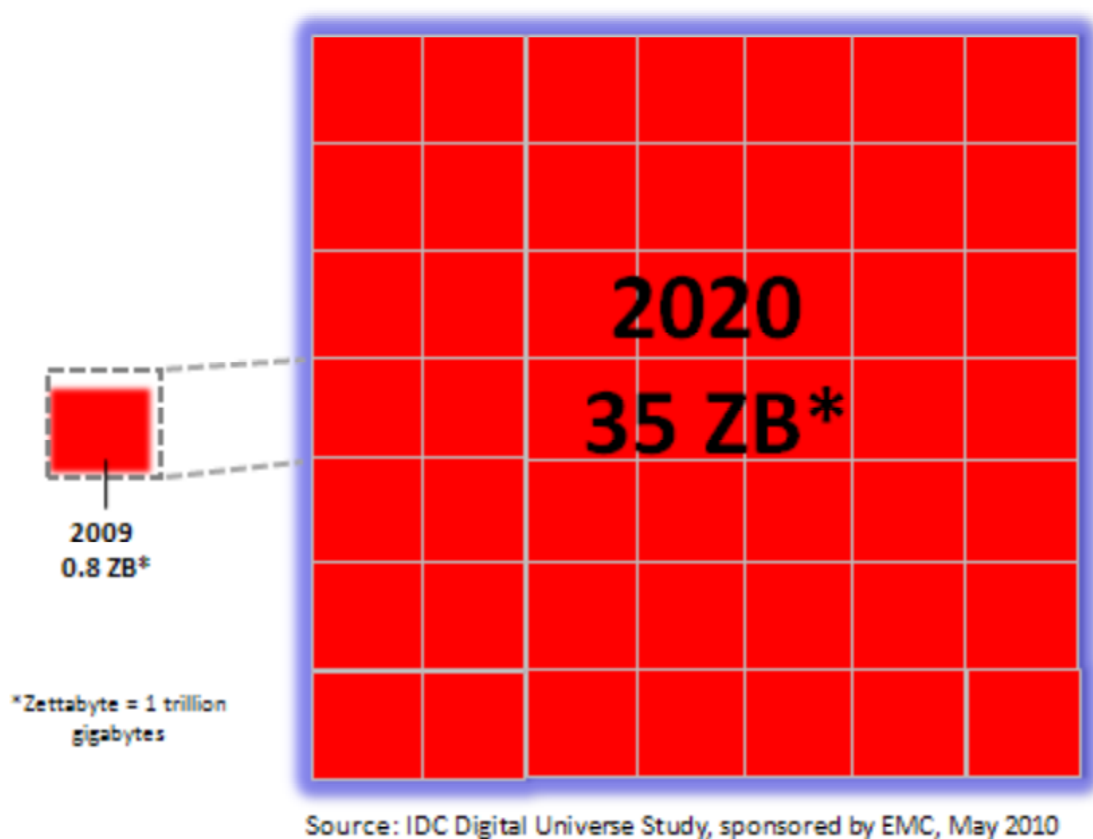
## 1.1 LES TRES "V'S"



### 1.1.1 VOLUM

Fa referència a la grandària dels datasets a manipular. Actualment és habitual haver de processar quantitats de dades en l'escala dels Gigabytes,

Terabytes o superiors de manera que les tècniques d'emmagatzematge i processat clàssiques són viables.



Volum, probablement la característica principal amb la que tothom associa el Big Data. D'acord amb un estudi de la universitat d'Stanford i EMC (2010), la producció de dades es dobla cada 40 mesos, això vol dir que es generen més dades en un dia que els que han existit en els últims 20 anys. Aquest estudi també calcula que a principis del 2010 portàvem acumulats 0.8ZB de dades digitals al món i aquestes en multiplicaran per 40 en 10 anys.

### 1.1.2 VELOCITAT

Es refereix no només a l'alta freqüència amb què es generen noves dades, sinó a la necessitat de donar resposta a la informació en temps real.

La velocitat en les dades diferencia principalment les tipologies d'anàlisi de dades que tenim actualment.

- El processament per lots es refereix a l'execució dels treballs sense intervenció manual. Els treballs s'estableixen de manera que puguin ser completats sense cap interacció humana sobre volums de dades

històriques emmagatzemades. Per exemple, un programa que llegeix un arxiu gran i genera automàticament un informe, això és un tipus de treball per lots.

- El processament interactiu es refereix a programari que rep la intervenció humana en la forma d'ordres o dades. La interacció pot ser directa o indirecta, a través d'una línia de comandaments de la interfície, interfície gràfica d'usuari o un sensor.
- El processament en temps real garanteix una resposta dins dels límits estrictes de temps. La latència es refereix al temps transcorregut entre una entrada rebuda i la corresponent sortida visible. En el món big data, la baixa latència es refereix al fet que el retard es redueix al mínim, i sembla i se sent instantània o temps-real.

### 1.1.3 VARIETAT

Es refereix a la naturalesa diversa de la informació a manejar. Venim d'informació estructurada que encaixava perfectament en el model relacional però ara ens trobem amb informació semi i des-estructurada (vídeo, àudio, imatges, xarxes socials, etc.) que requereix de nous mètodes de persistència i consulta.

La veritat de dades es classifica en tres tipologies:

- Dades estructurades (Structured Data): Dades que tenen ben definits la seva longitud i el seu format, com les dates, els números o les cadenes de caràcters. S'emmagatzemen en taules. Un exemple són les bases de dades relacionals i els fulls de càlcul.
- Dades no estructurades (Unstructured Data): Dades en el format tal com van ser recol·lectats, no tenen un format específic. No es poden emmagatzemar dins d'una taula ja que no es pot desgranar la seva informació a tipus bàsics de dades. Alguns exemples són els PDF, documents multimèdia, e-mails o documents de text, però també tots els documents *media*.
- Dades semiestructurades (Semistructured Data): Dades que no es limiten a camps determinats, però que conté marcadors per separar els diferents elements. És una informació poc regular com per ser gestionada d'una forma estàndard. Aquestes dades posseeixen els seus propis metadades semiestructurats<sup>16</sup> que descriuen els objectes i les relacions entre ells, i poden acabar sent acceptats per convenció. Un exemple és l'HTML, l'XML o el JSON.

## 1.2 CONCLUSIÓ BIG DATA

Un cop coneguda la definició més teòrica podem treure la conclusió que **tenim un problema de Big Data quan el volum, la velocitat i/o la varietat de les nostres dades fa impossible tractar-les amb les tecnologies informàtiques (software i hardware) habituals.**

## 1.3 PUBLICACIONS DE REFERÈNCIA DEL MÓN BIG DATA

### 1.3.1 PAPERS OF 2022

2022- [The bearable Lightness of Big Data: Towards Massive Public Datasets in Scientific Machine Learning](#)

2022- [Big Data and Education: using big data analytics in Language learning](#)

2022- [Fitting Semiparametric Cumulative Probability Models for Big Data](#)

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2021- [Toeplitz Least Squares Problems, Fast Algorithms and Big Data](#)

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2019- [Big Data in Cloud Computing Review and Opportunities](#)

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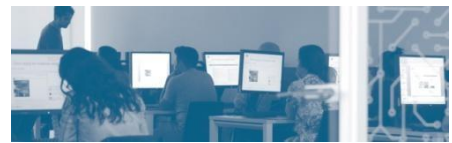
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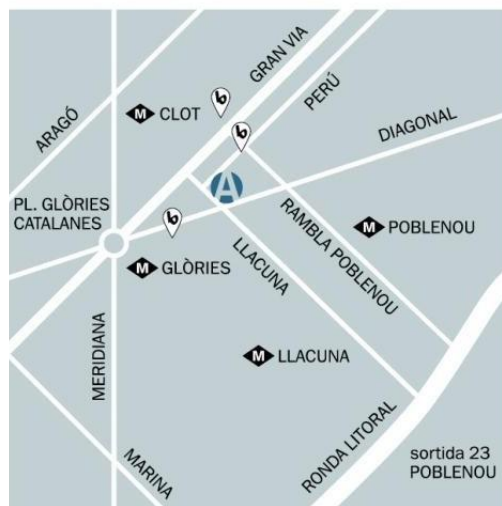
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