Questions to be addressed ML overview Big Data in astronomy ML applications in astronomy ML limitations

Machine Learning in Astronomy

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credit: 365datascience.com

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• Is ML the same as Statistics?

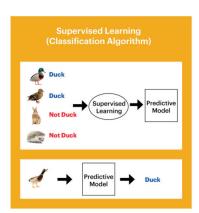
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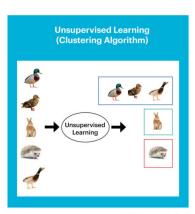
- Is ML the same as Statistics?
- How astronomy is tied to **BIG DATA**?

Questions to be addressed ML overview Big Data in astronomy ML applications in astronomy MI limitations

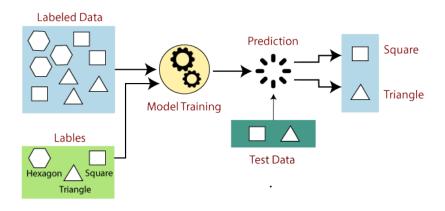
- Is ML the same as Statistics?
- How astronomy is tied to BIG DATA?
- How to implement ML in astronomy?

- Is ML the same as Statistics?
- How astronomy is tied to BIG DATA?
- How to implement ML in astronomy?
- What are the pitfalls of **ML**?





Western Digital.



credit: javatpoint.com

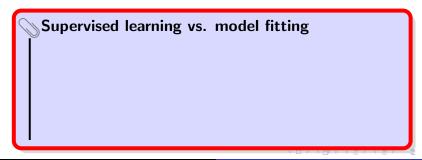
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- We need the label for each measurement.

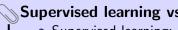
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Supervised learning vs. model fitting

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- Supervised learning:
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- Traditional model fitting:
 - Model is predefined
 - Model adaptivity is limited



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 - 2 Select the best model and use it for predictions.



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 - Spectrum: quasar, star, galaxy, supernova, ...
- Regression: continuous targets
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- OPTICS:

Deep/Shallow Artificial Neural Networks

Supervised learning Unsupervised learning

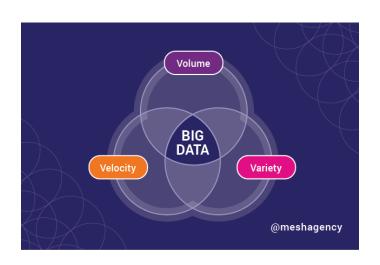
How unsupervised learning works?

• KMeans:

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- DBSCAN:

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TMT

JWST

Big telescopes Simulations Surveys

Sloan Digital Sky Server

Zwicky Transient Facility

Big telescopes Simulations Surveys

Gaia

DESI

Square Kilometer Array

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