Soongsil University 숭실대학교

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The 7th workshop on nuclear mass table with DRHBc theory

Gangneung Green City Experience Center

Jul. 1-4, 2024

Exploring New Magic Numbers

Using Separation Energy and Machine Learning

Soongsil University and OMEG institute

Jubin Park

Collaborators : Prof. Myung-Ki Cheoun, Dr. Myeong-Hwan Mun, Seonghyun Kim

LETTER

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Evidence for a new nuclear 'magic number' from the level structure of ^{54}Ca

D. Steppenbeck[1], S. Takeuchi[2], N. Aoi[3], P. Doornenbal[2], M. Matsushita[1],
J. Lee[2], K. Matsui[5], S. Michimasa[1], T. Motobayashi[2], D. Nishimura[6], T. O
T. Sumikama[8], H. Suzuki[2], R. Taniuchi[5], Y. Utsuno[9], J. J. Valiente-Dobó
A. Ozawa, T. Kobayashi, T. Suzu
[1]The Institute of Physical and Chemical Research (RIKE
[2]Department of Physics, Tohoku Ui
[3]Department of Physics, Niigata Ui
(Received 15 F

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clear breaks at $N = 16$ near the neutron drip line ($T_Z \geq 3$), which shows the creation of a new magic
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the new magic number. The origin of the new magic number is also discussed.

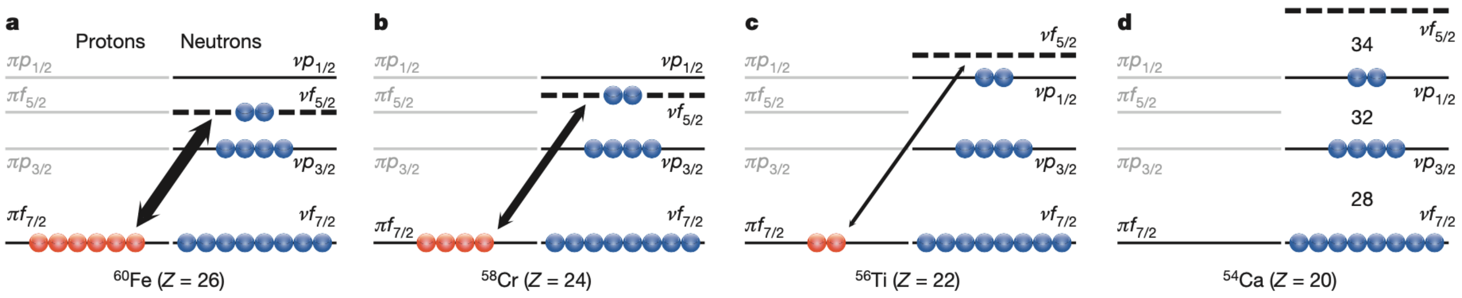
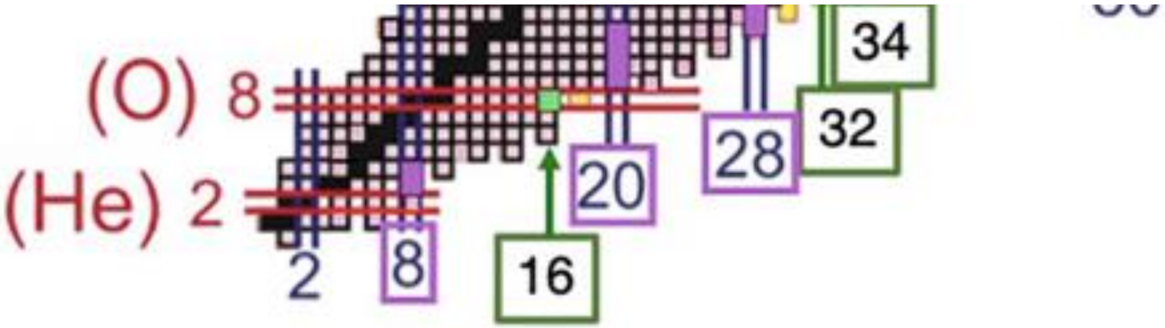
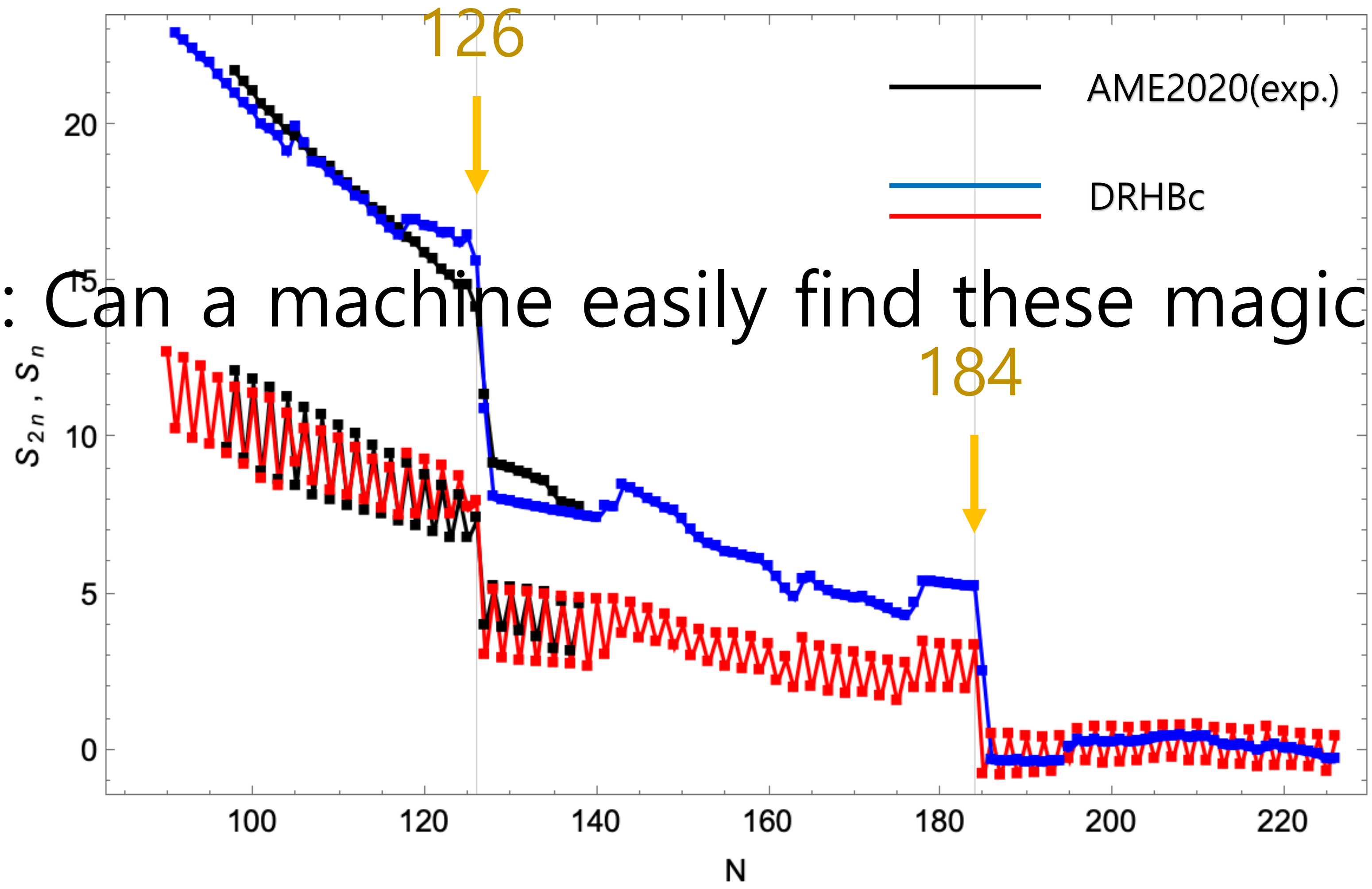


Figure 1 | Schematic illustration highlighting the attractive interaction between the proton $\pi f_{7/2}$ and neutron $\nu f_{5/2}$ single-particle orbitals for $N = 34$ isotones. **a–c**, As protons are removed from the $\pi f_{7/2}$ orbital (from ^{60}Fe (**a**) through ^{58}Cr (**b**) to ^{56}Ti (**c**)), the strength of the π–ν interaction decreases, as represented by the decreasing width of the diagonal arrows, causing the $\nu f_{5/2}$ orbital to shift up in energy relative to the $\nu p_{3/2}$–$\nu p_{1/2}$ spin–orbit partners. Consequently, a sizable subshell closure presents itself at $N = 32$ in isotopes far from stability. **d**, An additional subshell closure at $N = 34$ for ^{54}Ca is possible. The $\nu f_{5/2}$ SPO is indicated as a bold dashed line to guide the eye.



Motobayashi, T. (2023). Magic Numbers Off the Stability Line. In: Tanihata, I., Toki, H., Kajino, T. (eds) Handbook o
f Nuclear Physics . Springer, Singapore.

A well-known example: Pb(Z=82) isotopes



Motivation: Can a machine easily find these magic numbers?

Machine Learning

(In machine learning language)

“machine” = ‘model (from data)’

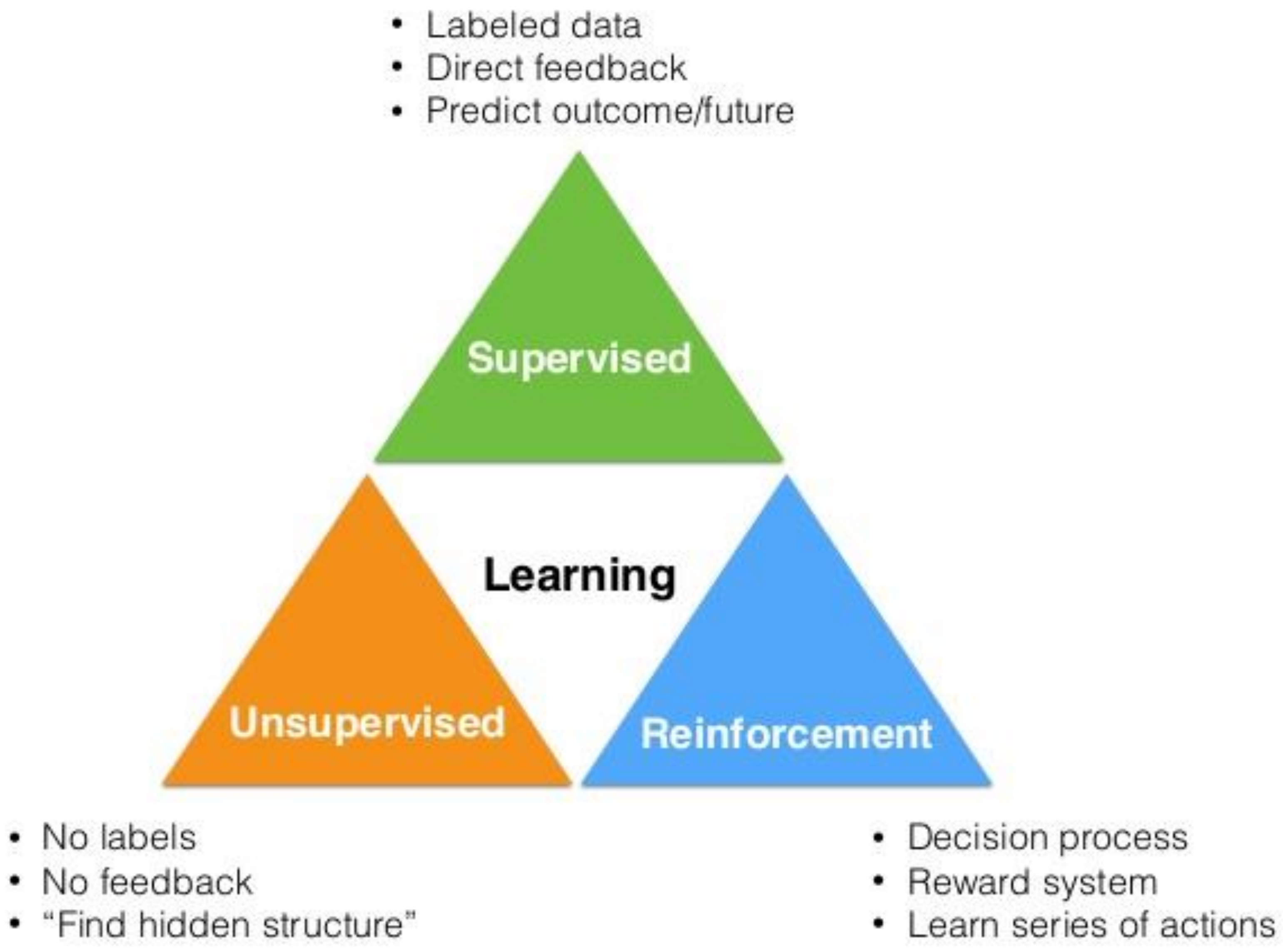
Learning = Improving performance at a task (ex) with experience

(In machine learning language)

“Learning” = Optimization of (machine’s/model’s) parameters via a proper error function which represents performance at a task.

Therefore, **“I am training a machine”**

= I am building a new model (from data)



http://solarisailab.com/archives/1785, 솔라리스의 인공지능 연구실

Machine Learning

From Wikipedia

- **Machine learning** (ML) is a field of artificial intelligence that uses statistical techniques to give computer systems the ability to "learn" (e.g., progressively improve performance on a specific task) from data, without being explicitly programmed.[2]

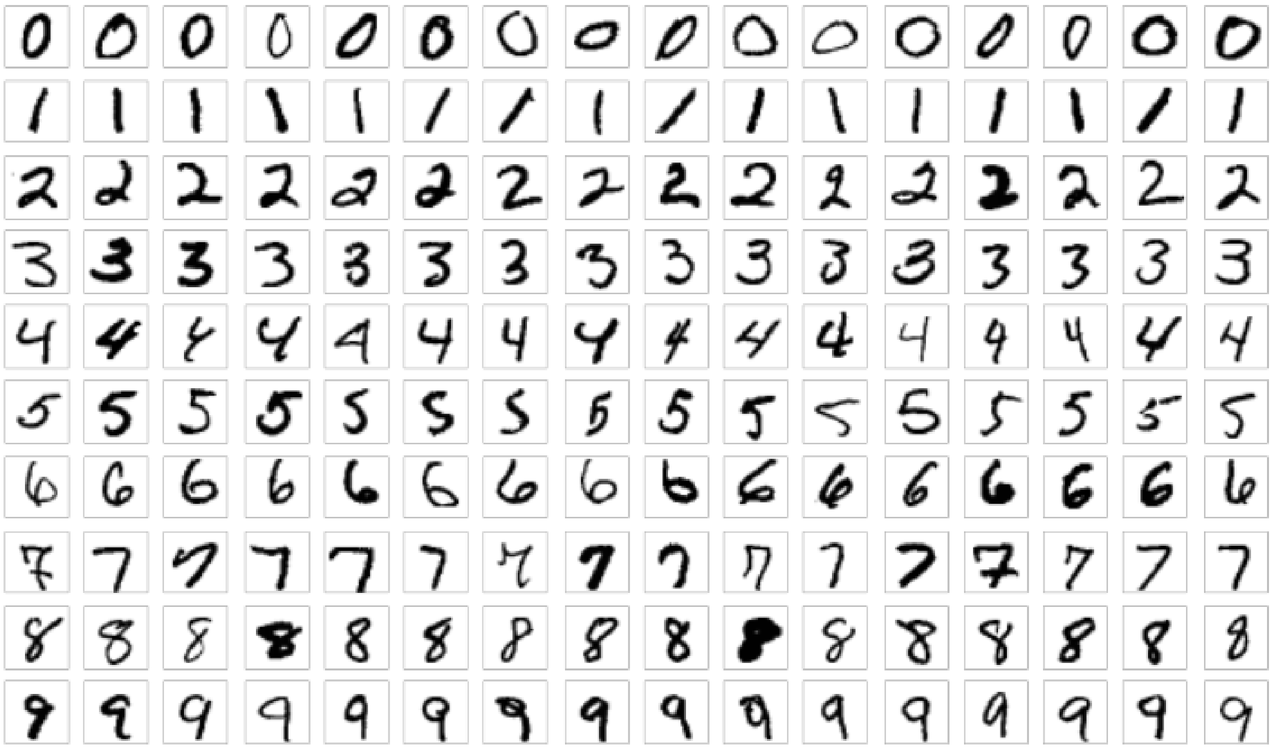
- The name *machine learning* was coined in 1959 by Arthur Samuel.[1] Machine learning explores the study and construction of algorithms that can learn from and make predictions on data[3] – such algorithms overcome following strictly static program instructions by making data-driven predictions or decisions,[4]:2 through building a model from sample inputs. Machine learning is employed in a range of computing tasks where designing and programming explicit algorithms with good performance is difficult or infeasible; example applications include email filtering, detection of network intruders, and computer vision.

- …………

Some examples on ML

MNIST

image database of 70,000 handwritten digits



Train with ML algorithm to recognize handwritten digits

ImageNET challenge

1000 object classes

Images : 1.2 M train & 100k Test

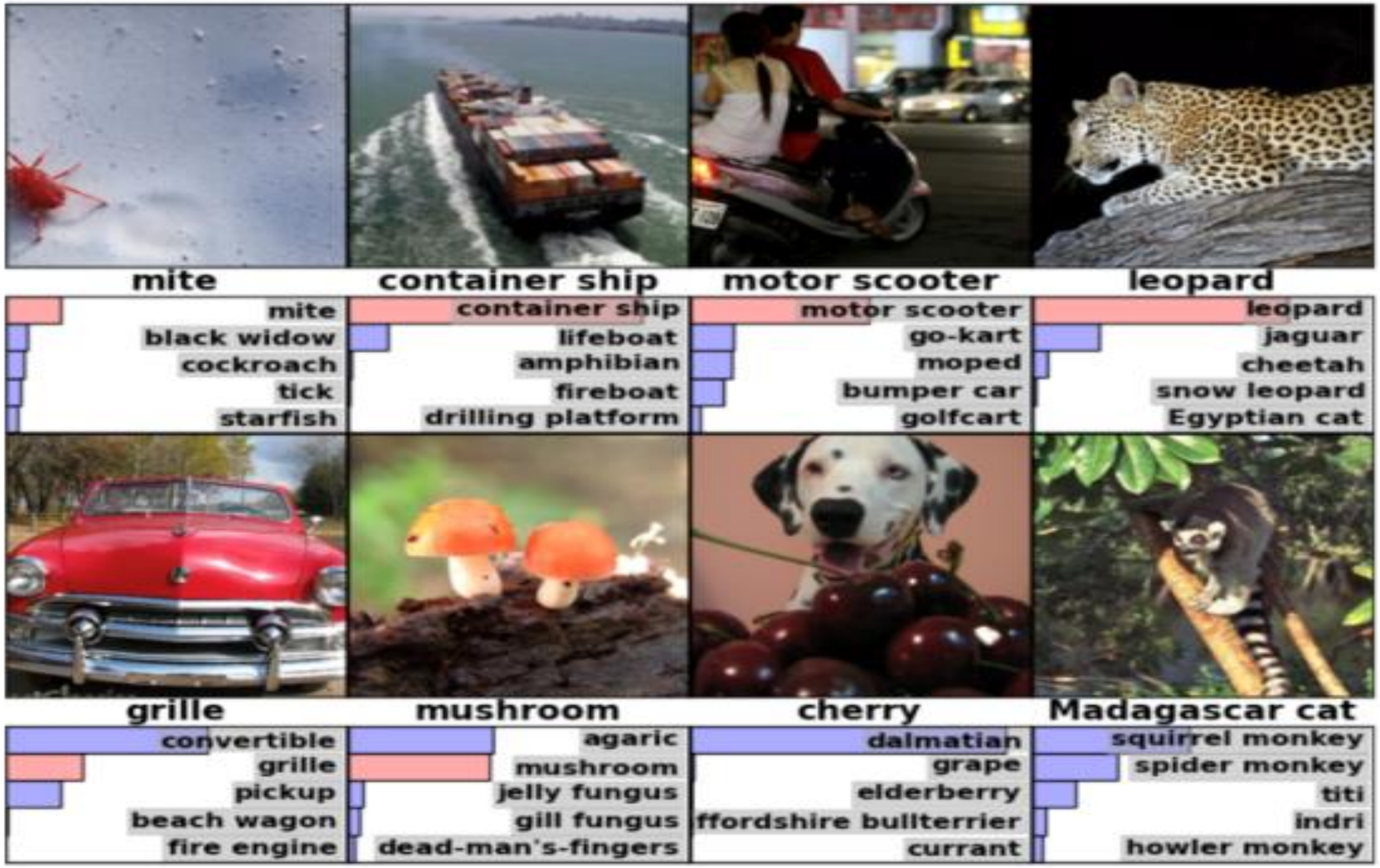
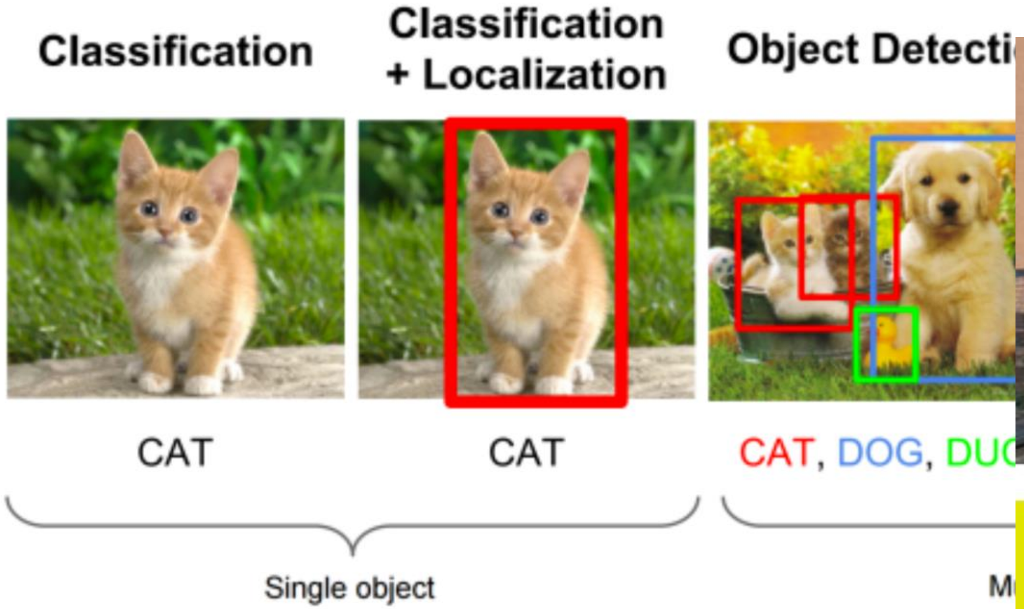
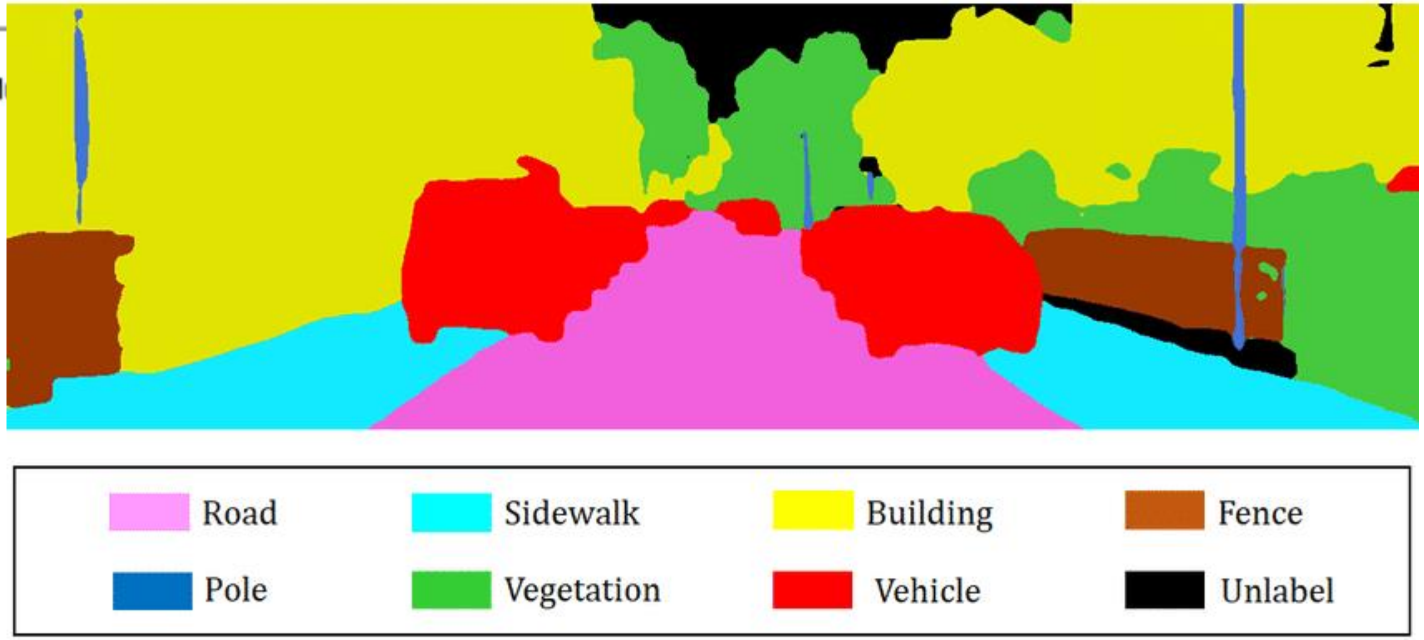


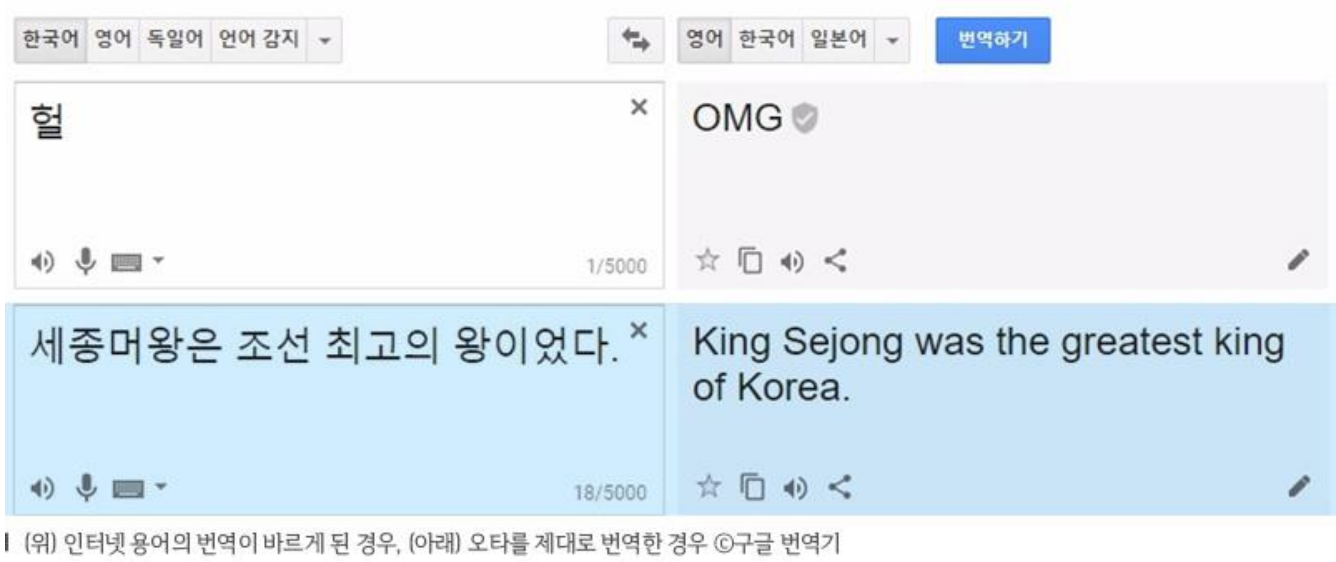
Image Segmentation beyond simple image classification....





AI Revolution and Big Data

Language Translation

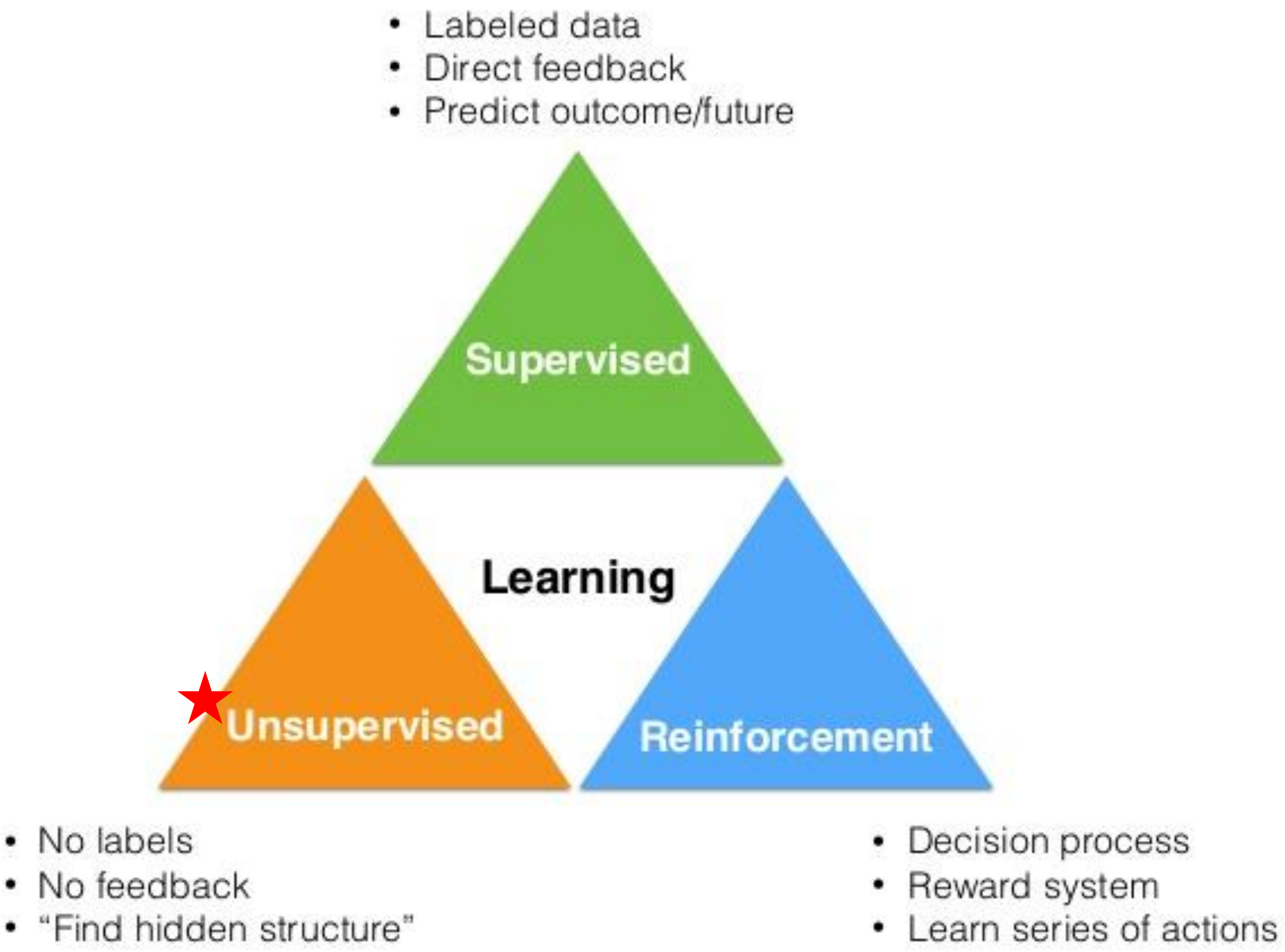


AlphaGo v.s. Master Lee

Autonomous driving

DeepFake

https://en.wikipedia.org/wiki/Deepfake



http://solarisailab.com/archives/1785, 솔라리스의 인공지능 연구실

Unsupervised Learning (UL)

Using UL and neutron separation energy (Sn) to identify magic numbers can offer a new perspective on traditional methods and theories. The use of unsupervised learning clustering techniques offers the following advantages:

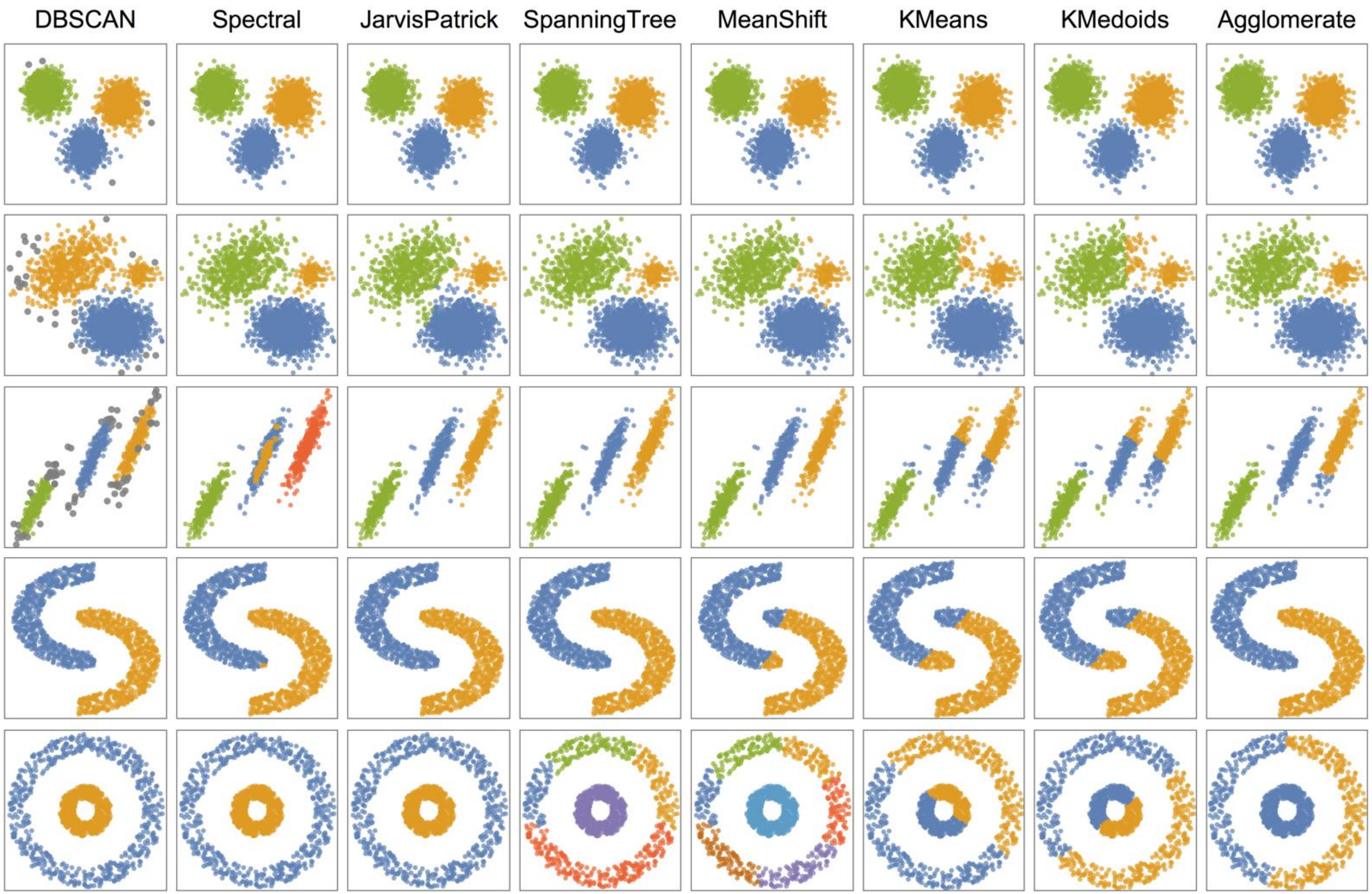
Discovery of New Patterns: Unsupervised learning is useful for discovering patterns in unlabeled data. Clustering neutron separation energy data can reveal unexpected patterns of magic numbers.

Verification of Theoretical Hypotheses: By comparing clustering results with existing theoretical predictions, new theoretical hypotheses can be verified or existing theories can be modified.

Data-Driven Approach: Machine learning can effectively handle large volumes of data, thus enabling empirical research based on more precise and extensive experimental data.

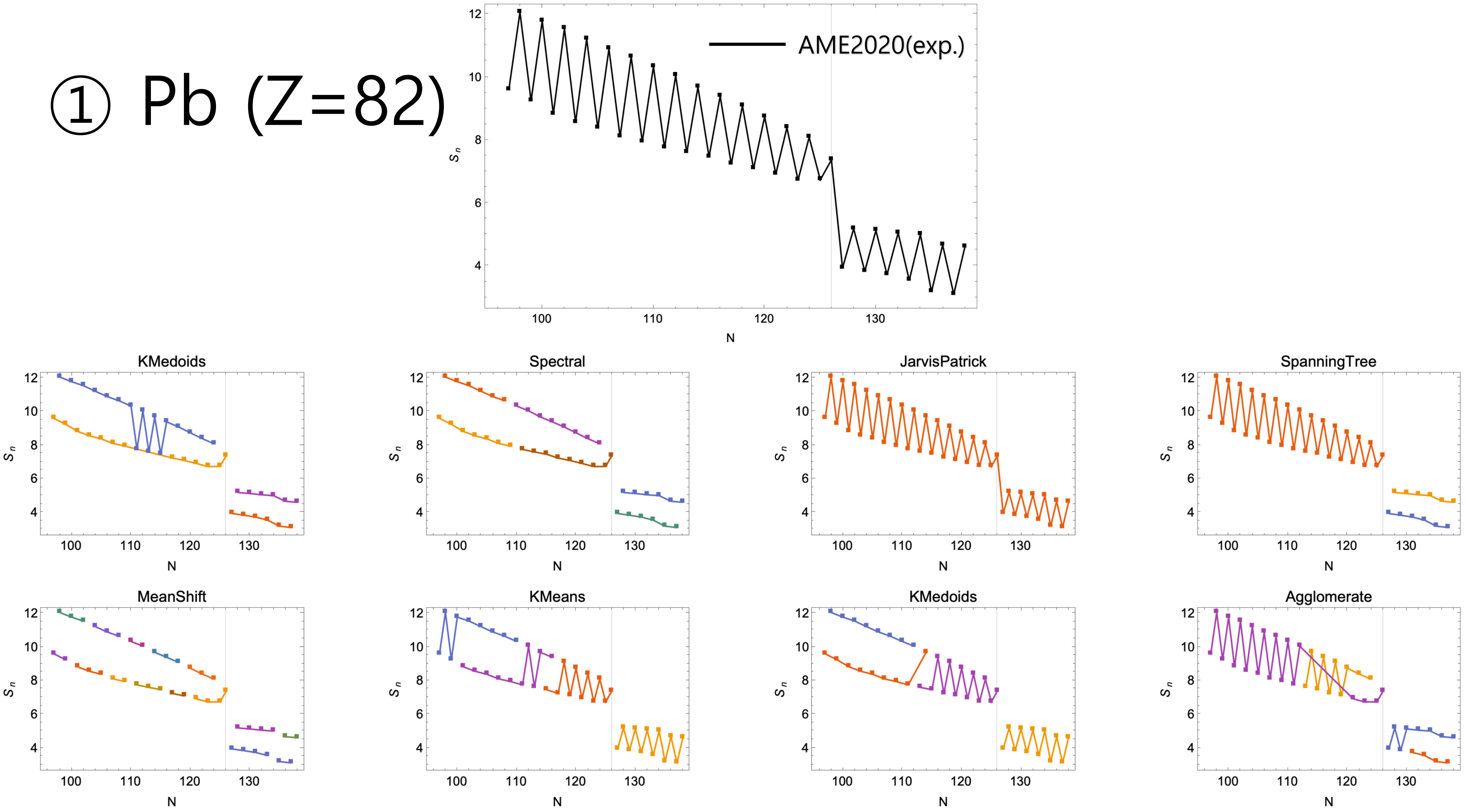
Automation and Efficiency: Techniques such as clustering in unsupervised learning can be automated, allowing for more efficient analysis of large datasets.

Clustering

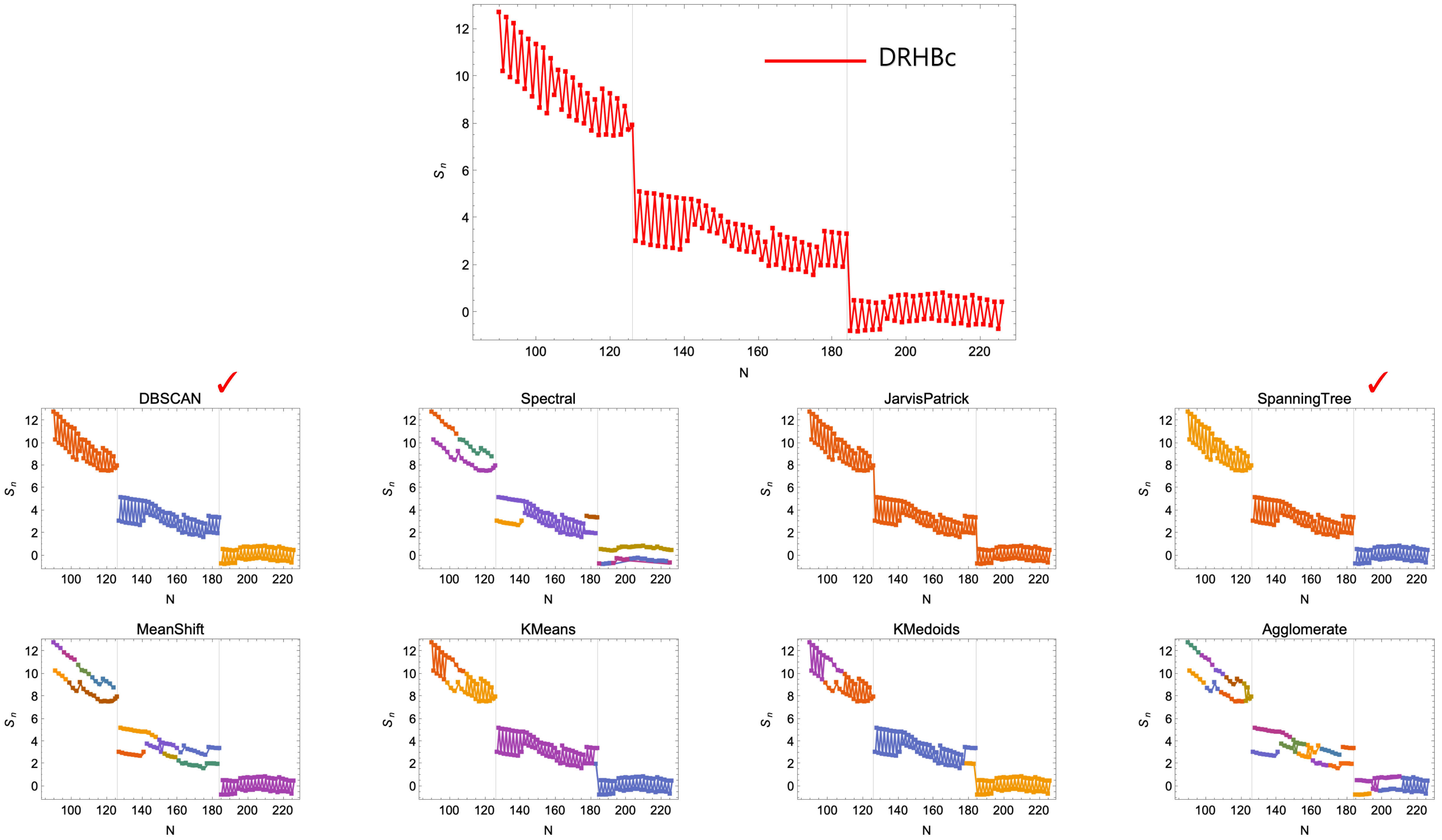

DBSCAN
Spectral
JarvisPatrick
SpanningTree
MeanShift
KMeans
KMedoids
Agglomerate

Results and Analysis

① Pb (Z=82)



AME2020(exp.)
S_n
N
KMedoids
Spectral
JarvisPatrick
SpanningTree
MeanShift
KMeans
KMedoids
Agglomerate


DRHBc
DBSCAN
Spectral
JarvisPatrick
SpanningTree
MeanShift
KMeans
KMedoids
Agglomerate
S_n
N

② Oxygen (Z=8)

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New Magic Number, $N = 16$, near the Neutron Drip Line

A. Ozawa,[1] T. Kobayashi,[2] T. Suzuki,[3] K. Yoshida,[1] and I. Tanihata[1]

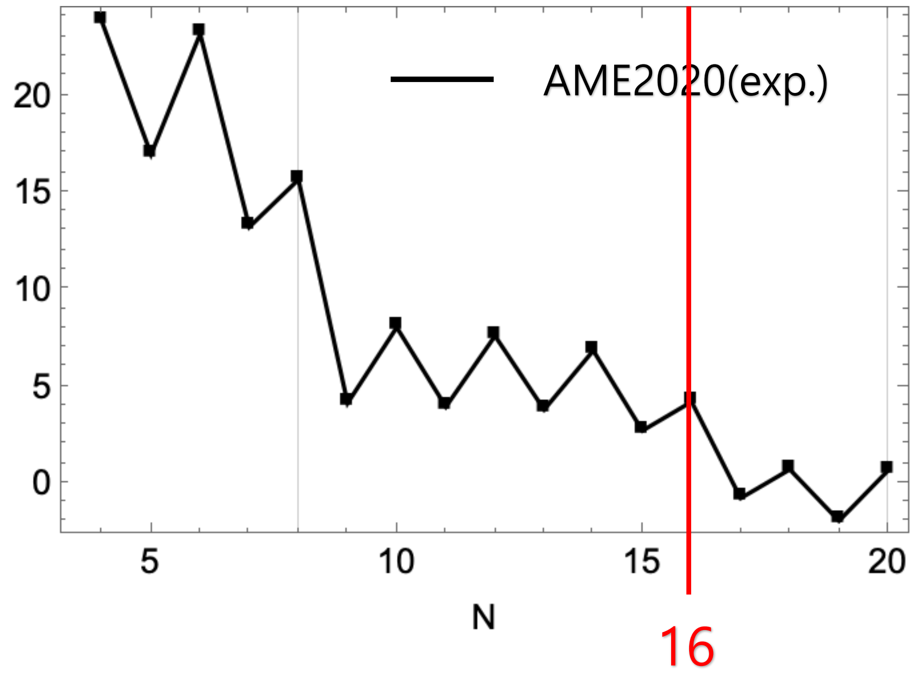
[1]*The Institute of Physical and Chemical Research (RIKEN), Hirosawa 2-1, Wako-shi, Saitama 351-0198, Japan*

[2]*Department of Physics, Tohoku University, Miyagi 980-8578, Japan*

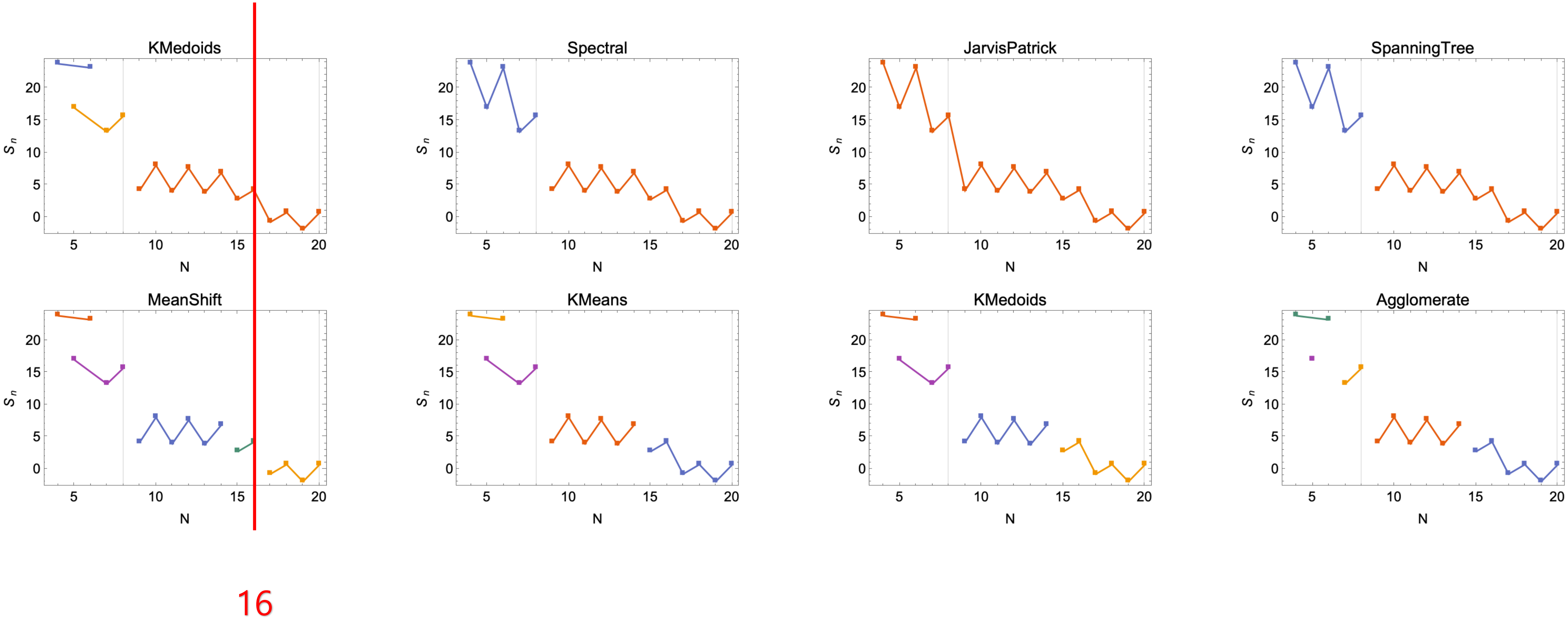
[3]*Department of Physics, Niigata University, Niigata 950-2181, Japan*

(Received 15 February 2000)

We have surveyed the neutron separation energies (S_n) and the interaction cross sections (σ_I) for the neutron-rich *p-sd* and the *sd* shell region. Very recently, both measurements reached up to the neutron drip line, or close to the drip line, for nuclei of $Z \leq 8$. A neutron-number dependence of S_n shows clear breaks at $N = 16$ near the neutron drip line ($T_Z \geq 3$), which shows the creation of a new magic number. A neutron-number dependence of σ_I shows a large increase of σ_I for $N = 15$, which supports the new magic number. The origin of the new magic number is also discussed.

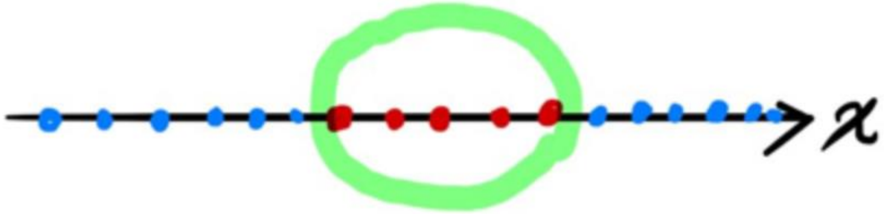


Question: Can the machine find this new magic number?

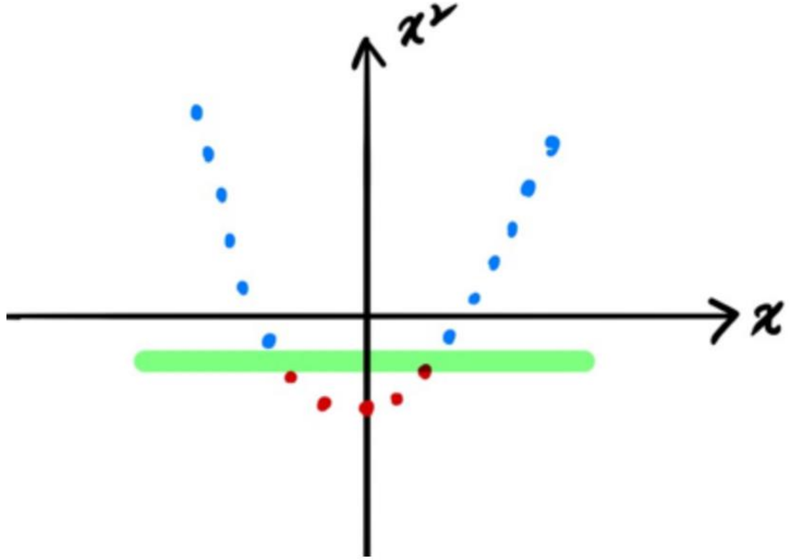


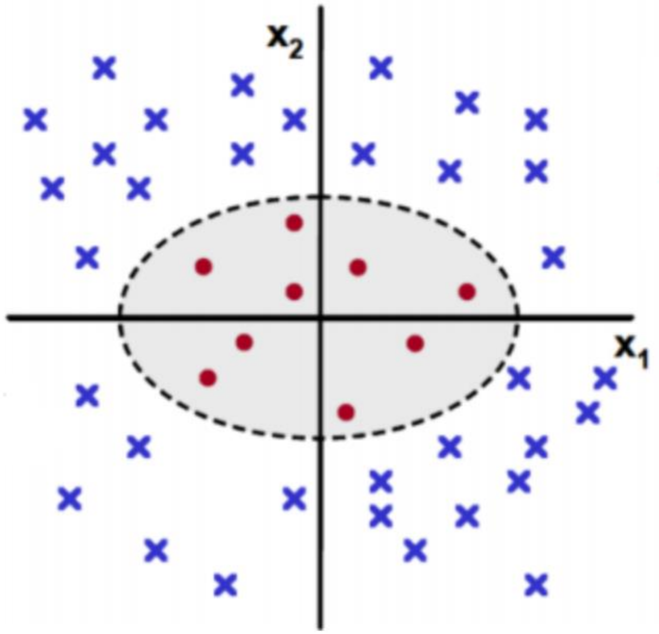
Q) How can we improve this result?

A) Kernel method



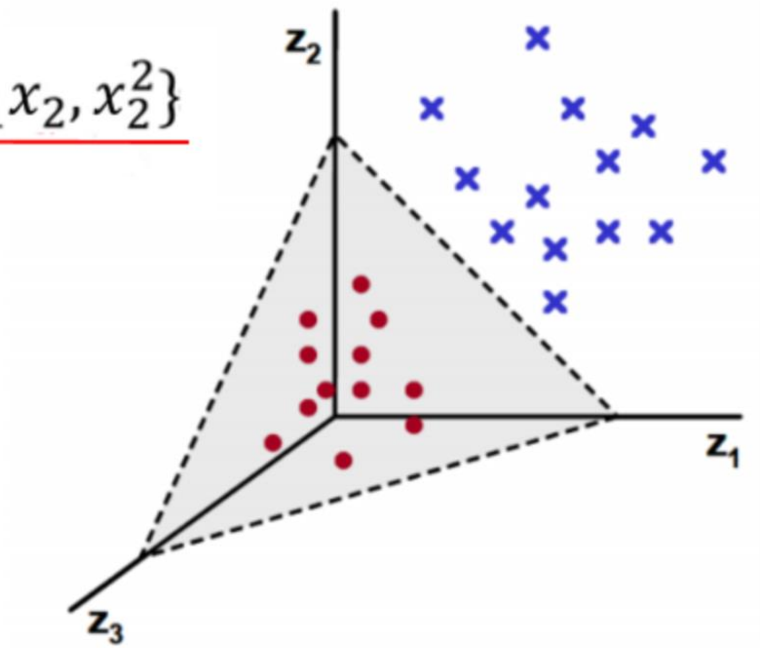
$$x \to \{x, x^2\}$$



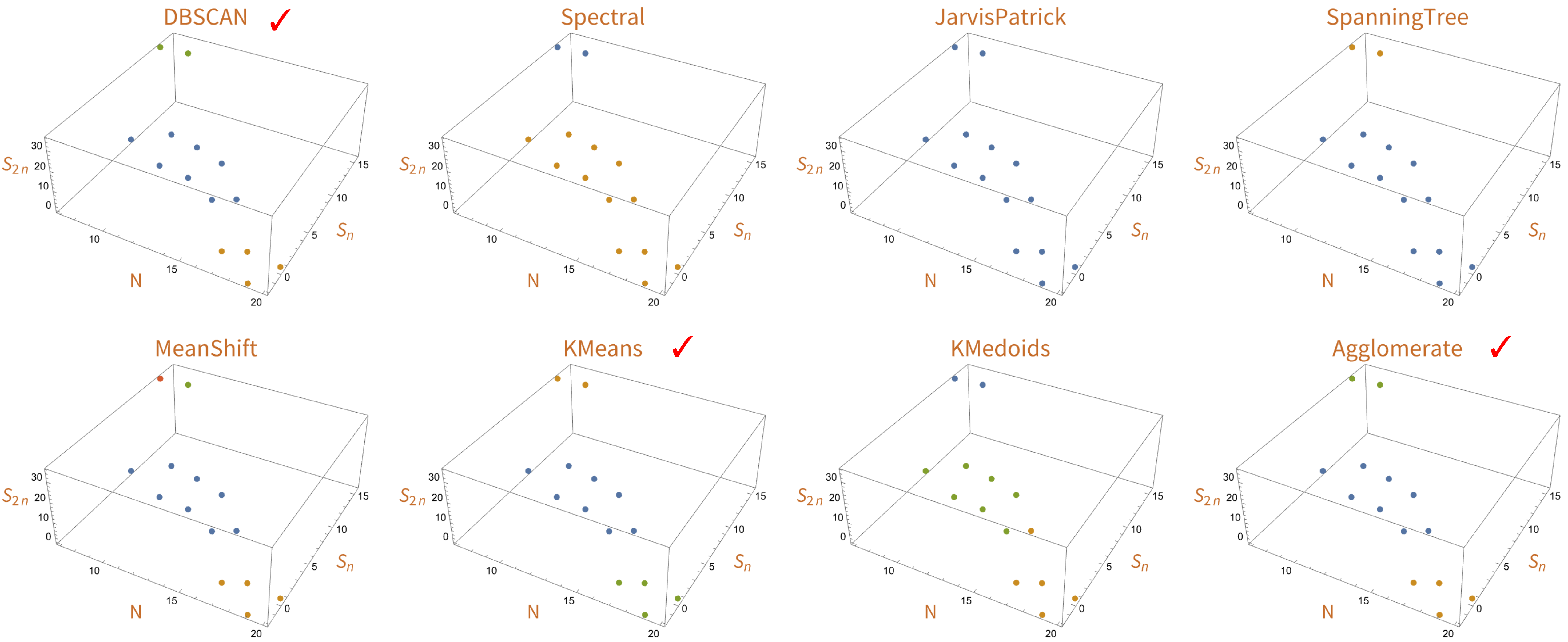


$$x = \{x_1, x_2\} \to z = \{x_1^2, \sqrt{2}x_1x_2, x_2^2\}$$

Mapping function



$$(\mathrm{N}, S_n) \to (\mathrm{N}, S_n, S_{2n})$$



③ Calcium (Z=20)

LETTER

doi:10.1038/nature12522

Evidence for a new nuclear ‘magic number’ from the level structure of ^{54}Ca

Atomic nuclei are finite quantum systems composed of two distinct types of fermion—protons and neutrons. In a manner similar to that of electrons orbiting in an atom, protons and neutrons in a nucleus form shell structures. In the case of stable, naturally occurring nuclei, large energy gaps exist between shells that fill completely when the proton or neutron number is equal to 2, 8, 20, 28, 50, 82 or 126 (ref. 1). Away from stability, however, these so-called ‘magic numbers’ are known to evolve in systems with a large imbalance of protons and neutrons. Although some of the standard shell closures can disappear, new ones are known to appear[2,3]. Studies aiming to identify and understand such behaviour are of major importance in the field of experimental and theoretical nuclear physics. Here we report a spectroscopic study of the neutron-rich nucleus ^{54}Ca (a bound system composed of 20 protons and 34 neutrons) using proton knockout reactions involving fast radioactive projectiles. The results highlight the doubly magic nature of ^{54}Ca and provide direct experimental evidence for the onset of a sizable subshell closure at neutron number 34 in isotopes far from stability.

[2], H. Baba[2], N. Fukuda[2], S. Go[1], M. Honma[4],
H. Sakurai[2,5], Y. Shiga[7], P.-A. Söderström[2],
Yoneda[2]

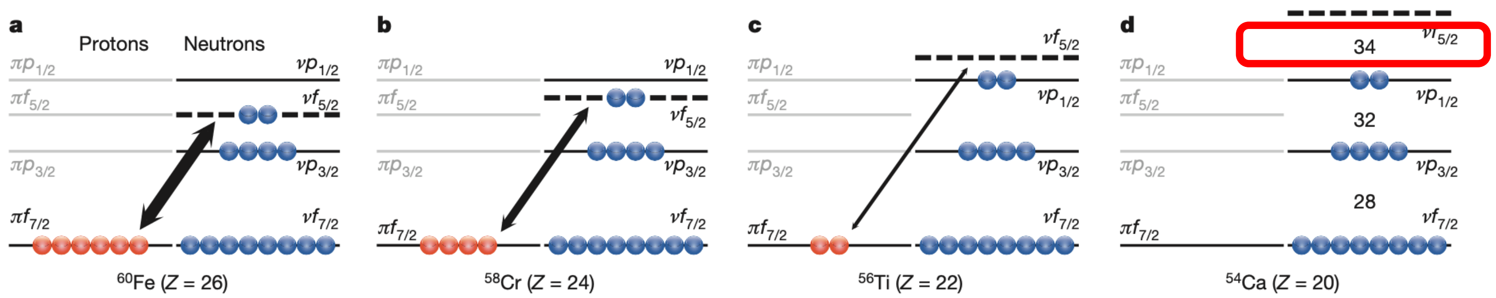
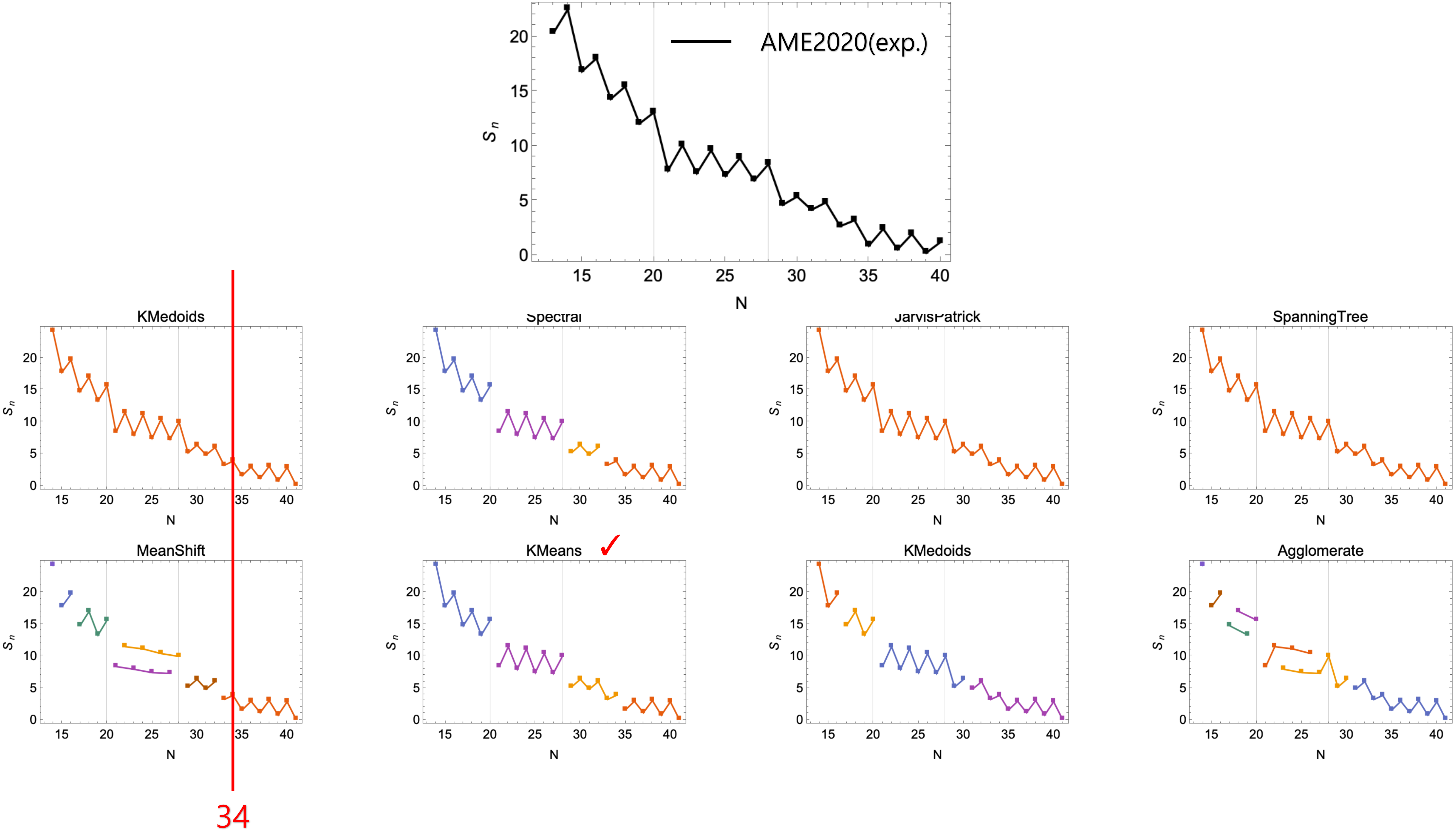
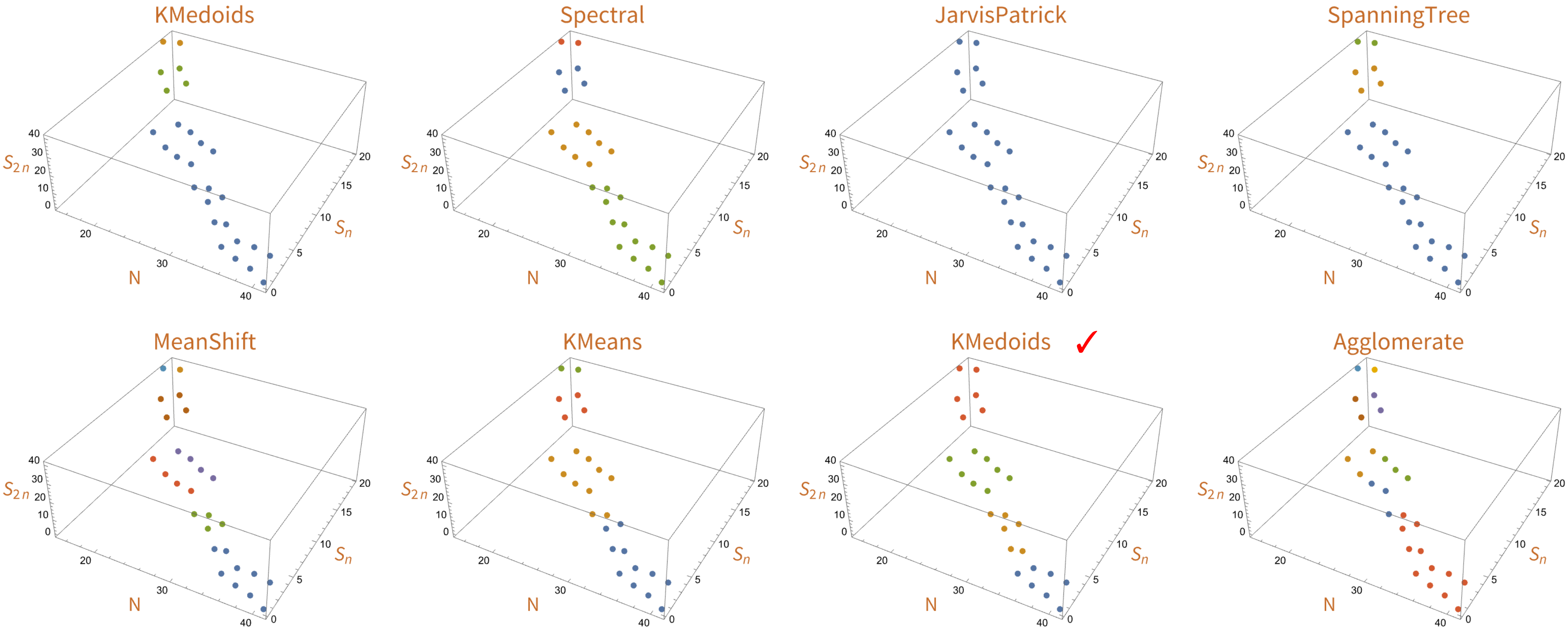


Figure 1 | Schematic illustration highlighting the attractive interaction between the proton $\pi f_{7/2}$ and neutron $\nu f_{5/2}$ single-particle orbitals for $N = 34$ isotones. **a–c**, As protons are removed from the $\pi f_{7/2}$ orbital (from ^{60}Fe (**a**) through ^{58}Cr (**b**) to ^{56}Ti (**c**)), the strength of the π–ν interaction decreases, as represented by the decreasing width of the diagonal arrows, causing the $\nu f_{5/2}$ orbital to shift up in energy relative to the $\nu p_{3/2}$–$\nu p_{1/2}$ spin–orbit partners. Consequently, a sizable subshell closure presents itself at $N = 32$ in isotopes far from stability. **d**, An additional subshell closure at $N = 34$ for ^{54}Ca is possible. The $\nu f_{5/2}$ SPO is indicated as a bold dashed line to guide the eye.


AME2020(exp.)
S_n
N
KMedoids
Spectral
JarvisPatrick
SpanningTree
MeanShift
KMeans
✓
KMedoids
Agglomerate
34


KMedoids
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KMeans
KMedoids
Agglomerate
N
S_n
S_{2n}
0
10
20
30
40
5
15
✓

Conclusion

- We investigated the possibility of using machine learning to find new (known) magic numbers.
- In particular, we tried to use unsupervised clustering methods to identify the internal structure of the data and determine the magic number.
- We first verified that our clustering method is generally able to find the well-known neutron magic numbers (126, 184) in the case of lead(Pb, Z=82).
- Additionally, for oxygen (O, Z=8), we found that the recently known new magic number N=16 can be found by increasing the dimensionality of the data (N, S_n) → (N, S_n, S_{2n}).
- For Ca (Z=20), we showed that the magic number of N=42 can be well discovered by the clustering method.

- When new physical quantities such as charge radius are included, the dimensionality of the data is expected to increase further and identification of the new magic number will become clearer.

nature physics
LETTERS
https://doi.org/10.1038/s41567-020-01136-5
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Charge radii of exotic potassium isotopes challenge nuclear theory and the magic character of $N=32$

Á. Koszorús[1,17] ✉, X. F. Yang[1,2] ✉, W. G. Jiang[3,4,5], S. J. Novario[3,4], S. W. Bai[2], J. Billowes[6], C. L. Binnersley[6], M. L. Bissell[6], T. E. Cocolios[1], B. S. Cooper[6], R. P. de Groote[7,8], A. Ekström[5], K. T. Flanagan[6,9], C. Forssén[5], S. Franchoo[10], R. F. Garcia Ruiz[11,12], F. P. Gustafsson[1], G. Hagen[4], G. R. Jansen[4], A. Kanellakopoulos[1], M. Kortelainen[7,8], W. Nazarewicz[13], G. Neyens[1,12], T. Papenbrock[3,4], P.-G. Reinhard[14], C. M. Ricketts[6], B. K. Sahoo[15], A. R. Vernon[1,6] and S. G. Wilkins[16]

Thank you for your attention !

Descriptions for the clustering algorithms:

Agglomerate (Single-Linkage Clustering Algorithm): This method incrementally forms clusters by merging similar data points. It combines clusters based on the nearest members.

DBSCAN (Density-Based Spatial Clustering of Applications with Noise): This method identifies clusters in high-density areas and excludes noise data points. It is capable of discovering clusters of arbitrary shapes, which is useful when the sizes of the clusters vary.

Gaussian Mixture (Variational Gaussian Mixture Algorithm): This algorithm assumes that the data consists of a mixture of several Gaussian distributions and forms clusters based on this assumption. It is a soft clustering method that provides the probability of each data point belonging to various clusters.

Jarvis-Patrick (Jarvis-Patrick Clustering Algorithm): Clusters are formed based on the degree to which neighbors are shared.

KMeans: This algorithm groups data points into K clusters, finding the center of each cluster. It works by minimizing the variance within each cluster.

KMedoids (Partitioning Around Medoids): Similar to KMeans, but this method uses data points as the centers of clusters, which makes it more robust to outliers.

MeanShift: This method shifts cluster centers towards the density centers of data points. It does not require specifying the number of clusters beforehand, and the clusters can vary in shape and size.

Neighborhood Contraction: Forms clusters by moving data points towards high-density areas.

Spanning Tree (Minimum Spanning Tree-Based Clustering Algorithm): Uses a minimum spanning tree to form clusters based on the connectivity structure among data points.

Spectral: Forms clusters using eigenvectors and eigenvalues based on a graph that represents the similarity among data points. This method is suitable for data with complex structures.