

The Atomic Map: A Subspace Representation

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ABSTRACT

We present the Atomic Map, a continuous, data-driven geometric representation of chemical elements constructed via projection of enriched physicochemical attributes into a latent manifold. Unlike the traditional periodic table, which discretizes and symbolically organizes elements, the Atomic Map embeds each element into a continuous three-dimensional space using seven features spanning electronic, nuclear, and physical domains. We show that this representation recovers classical chemical families, identifies emergent clusters, and interprets radioactivity as a structural gradient in the latent space. A supervised classifier trained on these features achieves 97% accuracy in predicting elemental radioactivity, successfully retrodicts the radioactive character of held-out superheavy elements (Lv, Ts, Og), and extrapolates the trajectory of known heavy nuclei to hypothesize the location and behavior of a hypothetical element 119 (with a predicted radioactivity probability of ~ 0.81). Marginal radioactivity predictions for bismuth, thallium, and lead align with known isotopic decay data, suggesting that radioactivity manifests as a topological property rather than a discrete label. By reconceiving elemental identity as compositional and embedded within a latent space, the Atomic Map provides a unified and predictive framework that integrates nuclear and chemical periodicities and offers a viable, extensible alternative to the periodic table for discovery and classification in chemistry and physics.

Keywords: Periodic table, atomic map, radioactivity.

Introduction

Representation should illuminate, not obscure, the fundamental physicochemical relationships among elements. The periodic table has long served as the foundational framework for understanding chemical elements, organizing them according to empirical regularities in atomic mass and chemical reactivity. Since its formulation by Mendeleev in 1869, it has evolved to incorporate quantum theory, assigning elements into blocks and groups based on electronic configurations. Despite its historical success and continued utility, the periodic table suffers from critical limitations as a scientific model. It discretizes inherently continuous properties, conflates distinct physical and chemical dimensions, and resists predictive generalization in unexplored domains, particularly for superheavy elements, complex nuclear configurations, and borderline chemical behavior¹.

Recent critiques emphasize the lack of causal grounding in the periodic table's structure and question whether its categorical boundaries truly reflect physical law.^{2,3} Others argue that it reflects an amalgam of historical constraints rather than a coherent formalism and that it struggles to adapt to machine learning-based approaches to chemical discovery.^{4,5} Although the table remains pedagogically valuable, its tabular architecture inhibits analytical resolution and hides underlying structural continuities.

In contrast, modern approaches in data-driven chemistry seek to represent elements not by categorical labels, but as vectors in a high-dimensional feature space. This shift enables manifold learning, continuous classification, and interpolation between known points. These approaches are now routine in materials discovery and computational chemistry^{8,9}. Nevertheless, these models rarely attempt to reinterpret or replace the periodic table itself; instead, they treat elemental identity as symbolic input to a downstream prediction task.

Glushkovsky¹⁰ applies an unsupervised β -Variational Autoencoder (β -VAE) to electron configuration data (arranged as a 7×4 grid for shells and subshells) and discovers a 2D latent space that disentangles periods, blocks, and quantum-level groupings fully unsupervised. Key findings include:

- Emergent periodic patterns aligned with quantum numbers and Madelung¹¹ filling sequence.
- Outliers such as lanthanides and actinides identified as deviations corresponding to known Madelung rule violations.
- Use of a dual representation technique, where transposing input allows encoding both element identities and subshells, whose arrangement in the latent space matches quantum shell order.

Although powerful for conceptual validation, his method remains descriptive and focused on visualization without downstream tasks such as classification or extrapolation.

Kusaba et al.¹² developed a Periodic Table Generator (PTG) using Generative Topographic Mapping with latent-scale adaptation to translate physicochemical features of elements (e.g. melting point, electronegativity) into interpretable 2D or 3D tabular layouts, effectively

reconstructing periodic tables without supervision. Their algorithm autonomously produced multiple periodic layouts (square, spiral, and conical) arranging elements into biologically meaningful clusters (alkali metals, halogens, noble gases) and revealing property trends as smooth gradients across the layout surface. Notably, PTG captures key periodic phenomena: group separations, inter-block structure, and property landscape transitions that align with chemical intuition.

Antunes et al.¹³ introduce SkipAtom, a novel unsupervised embedding method, which learns vector representations of atomic species from large crystalline databases (e.g. the Materials Project). By treating atoms analogously to words in natural language processing, SkipAtom captures context-based chemical relationships, while compound representations are generated via pooling of atomic embeddings. These learned representations are applied to a variety of predictive tasks (including formation energy and band-gap estimation) showing competitive or superior performance compared to structure-based descriptors, especially when only compositional information is available.

In this work, we introduce the Atomic Map, which is a continuous, low-dimensional projection of atomic structure, derived from physical and chemical feature enrichment and nonlinear dimensionality reduction. In this manifold, stable elements cluster into attractor basins, known groups emerge organically, and radioactive transitions are revealed as coherent structural drifts.

We demonstrate that this manifold-based representation enables predictive tasks not possible with the periodic table, including:

- accurate classification and retrodiction of radioactive elements using supervised classification,
- extrapolation to undiscovered atoms, such as element 119, and
- the tracing of continuous structural trajectories that reveal transitions in stability and reactivity across element groups.

The Atomic Map thus offers not merely a visualization, but a re-foundation of periodicity: one grounded in continuous geometry, feature fusion, and projectional regularity. It proposes a unified latent structure from which both physical and chemical periodicity emerge as interpretable projections.

Methods

Definition of The Atomic Map

The projection of enriched atomic feature vectors yields a continuous, low-dimensional embedding: the Atomic Map, in which each element occupies a position derived from its high-dimensional physical, chemical, and nuclear attributes. Unlike the discrete and symbolic layout of the periodic table, this manifold arises from bottom-up relationships among features and reveals smooth structural patterns among elements.

Dataset Construction and Feature Enrichment

We constructed a dataset of the 118 known chemical elements using public data, enriching it with nuclear and thermophysical properties. Each element is represented by:

- Bulk physical attributes: atomic mass, density, melting point, boiling point, and molar heat capacity
- Electronic configuration descriptors: total electrons (Z), valence electron count, electronegativity (Pauling scale), and electron affinity
- Derived nuclear features: neutron number (N), neutron-to-proton ratio (N/Z), parity (even/odd) flags for N and Z , and indicators of proximity to nuclear magic numbers (2, 8, 20, 28, 50, 82, 126)

The selected features are given in Table 1.

Table 1. Selected Features and Their Functional Roles		
Feature	Domain	Relation to Radioactivity / Atomic Behavior
AtomicMass	Physical	Reflects nuclear binding energy trends
Density	Physical	Correlates with atomic packing and stability
TotalElectrons (Z)	Electronic	Defines periodicity and element identity
Neutron Count (N)	Nuclear	Critical for stability and decay pathways
N/Z Ratio	Nuclear	Indicates proximity to nuclear “valley”
ValenceElectrons	Electronic	Captures shell structure and reactivity
Electronegativity	Electronic	Relates to electron distribution and stability

From this enriched dataset, we selected the above seven primary features for dimension reduction and supervised classification. These features provide a balanced representation across electronic, nuclear, and bulk physical dimensions critical for radioactivity detection. Note that feature selection serves as the initial manual projection of the latent manifold with an explicit focus on predicting radioactivity; other applications could leverage different sets to tailor the Atomic Map to diverse scientific objectives.

Missing values (primarily for superheavy elements) were imputed using feature-wise mean substitution, a simple but effective baseline approach. Because very few values were missing and the primary goal was dimensionality reduction and classification. Mean imputation preserves central tendency while maintaining dataset size and is unlikely to significantly alter global manifold structure in this context.

Dimension Reduction

To embed the high-dimensional element vectors into a continuous manifold, we apply Uniform Manifold Approximation and Projection (UMAP)¹⁴, a non-linear dimensionality reduction technique that preserves local and global structure of data. UMAP operates by constructing a fuzzy topological representation of the high-dimensional feature space and optimizing a low-dimensional embedding to maintain neighborhood relationships.

We use three UMAP components to preserve curvature and spatial separability, resulting in a three-dimensional latent space (the "Atomic Map"), where each point represents an element. Hyperparameters such as number of neighbors and minimum distance are selected via qualitative inspection to balance local clustering and global continuity.

Visualization of Projected Atomic Space

Figure 1 shows the two-dimensional UMAP projection of 118 elements. Each point corresponds to an element, labeled by its atomic symbol. The relative position of points reflects overall similarity in high-dimensional feature space. Notably, element spacing is nonuniform, with some regions forming dense neighborhoods and others more dispersed.

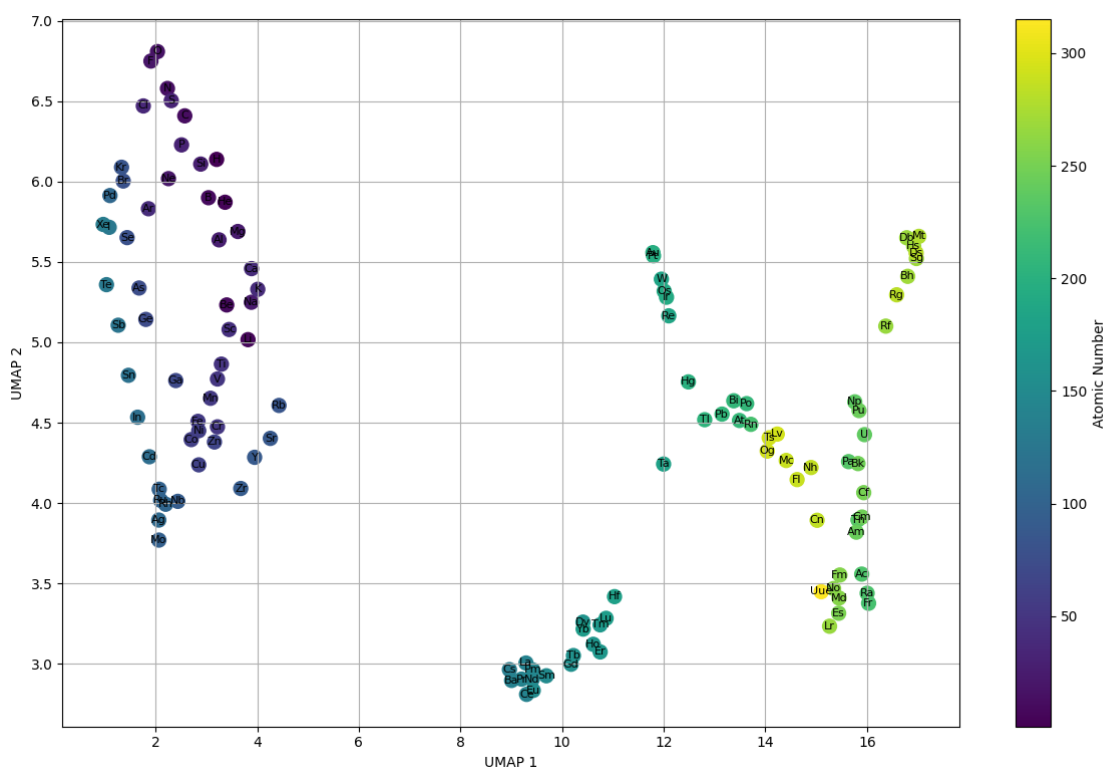


Figure 1. Two-dimensional Atomic Map. Each point represents an element and is labeled by its atomic symbol.

The three-dimensional view (Figure 2) highlights structural continuity that is compressed in 2D. Curved spatial arrangements and band-like regions become visible, offering a clearer interpretation of how atomic structure varies across the manifold.

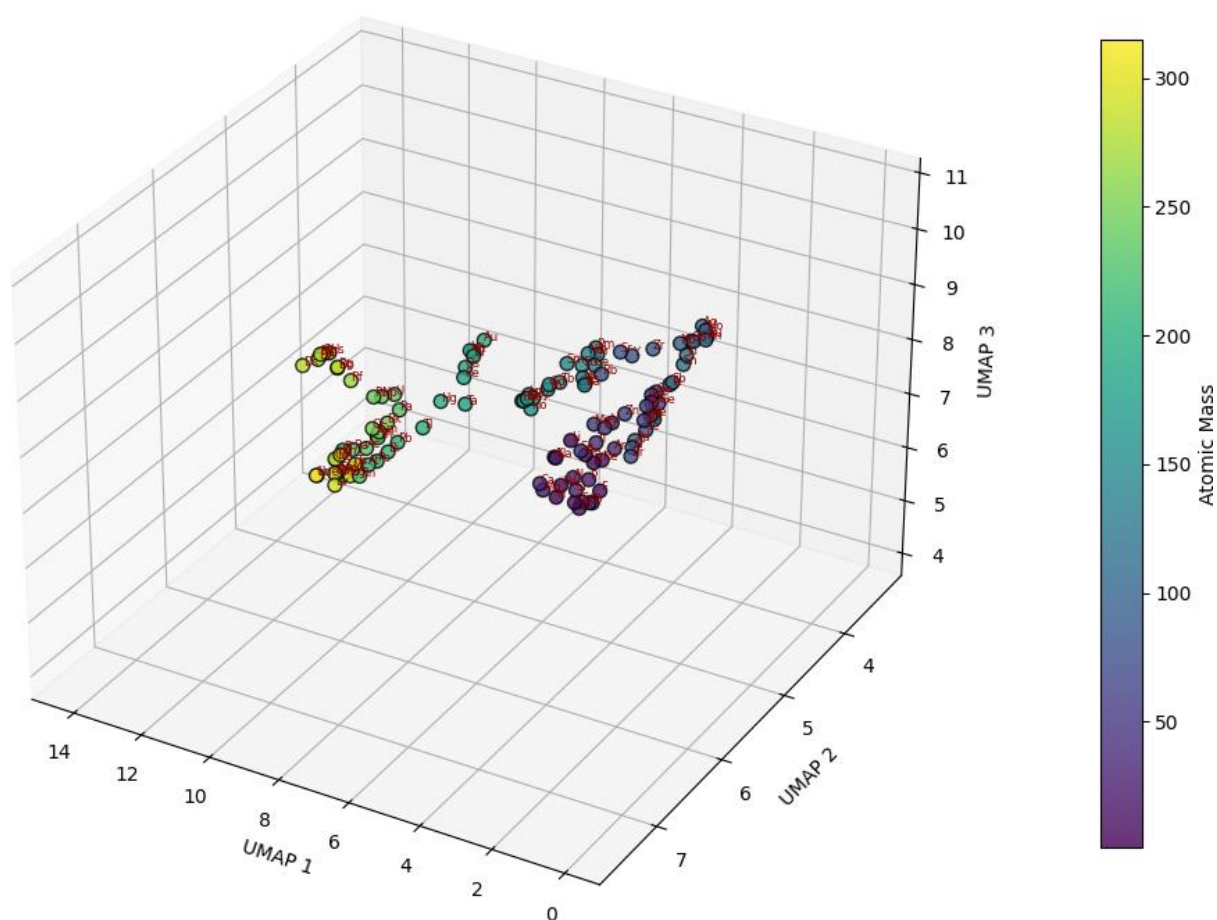


Figure 2. Three-dimensional Atomic Map. Element positions reflect similarity in high-dimensional space, colored by atomic mass.

Overlay of Physical Categories

Figure 3 overlays classical chemical categories (e.g., noble gas, transition metal, halogen) onto the 2D map. These categories were not included as features in the projection, yet appear naturally as spatially coherent regions, suggesting that their traditional definitions align with physical structure captured in the feature space.

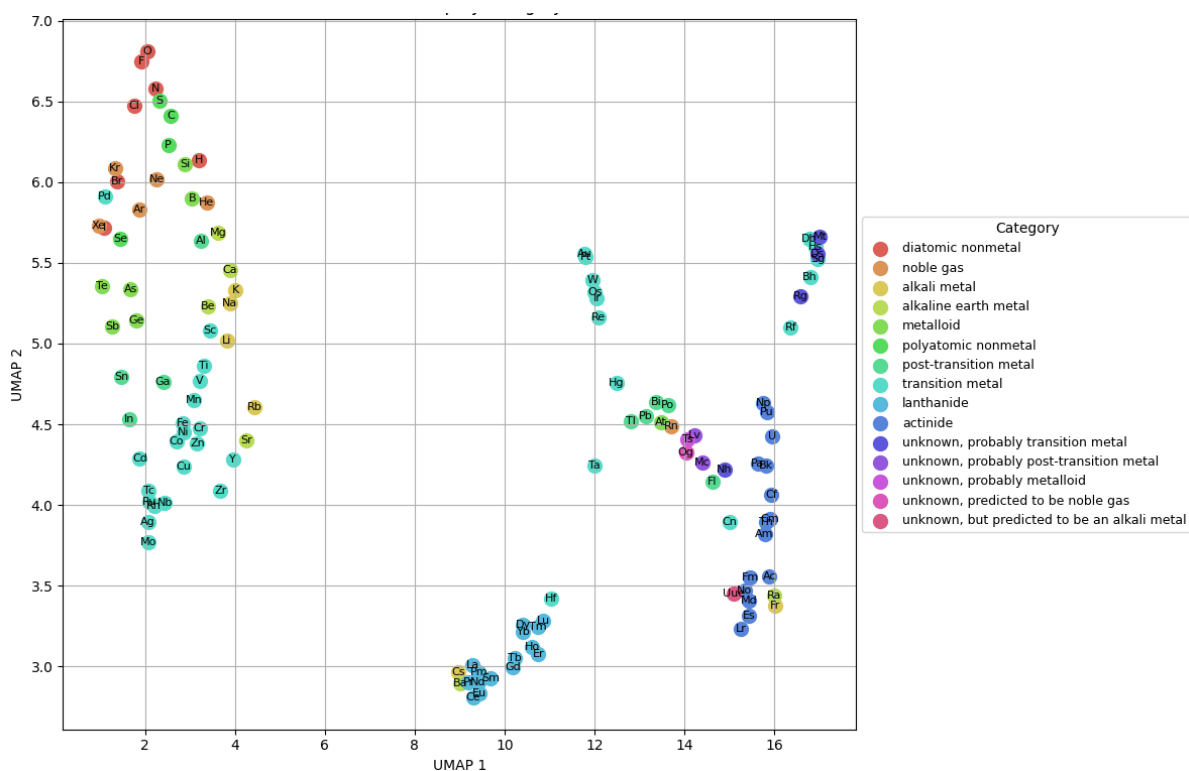


Figure 3. Atomic Map colored by chemical category. Despite no supervision, elements form spatial clusters consistent with classical groups such as noble gases, alkali metals, and halogens.

In the corresponding 3D version (Figure 4), the separations between categories are even more apparent. Categories like lanthanides and actinides form distinct lower-lying arcs in the projection, reflecting their unique high-dimensional profiles.

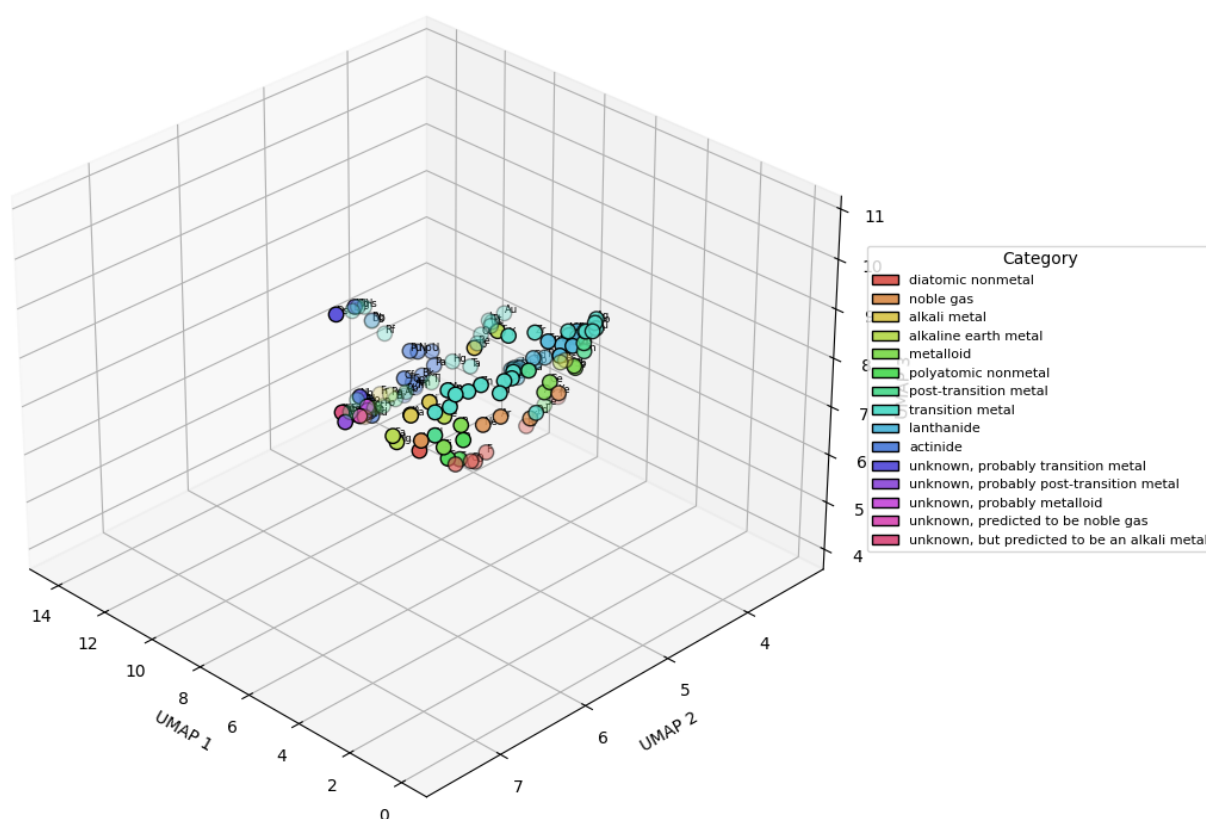


Figure 4. Three-dimensional Atomic Map colored by chemical category. Substructure within and across categories becomes more interpretable in 3D.

A focused view of lanthanides versus actinides is shown in Figures 5 and 6, isolating these two families in the 2D and 3D maps, respectively. The divergence between their respective arcs highlights that they represent distinct regions, rather than a shared linear continuation.

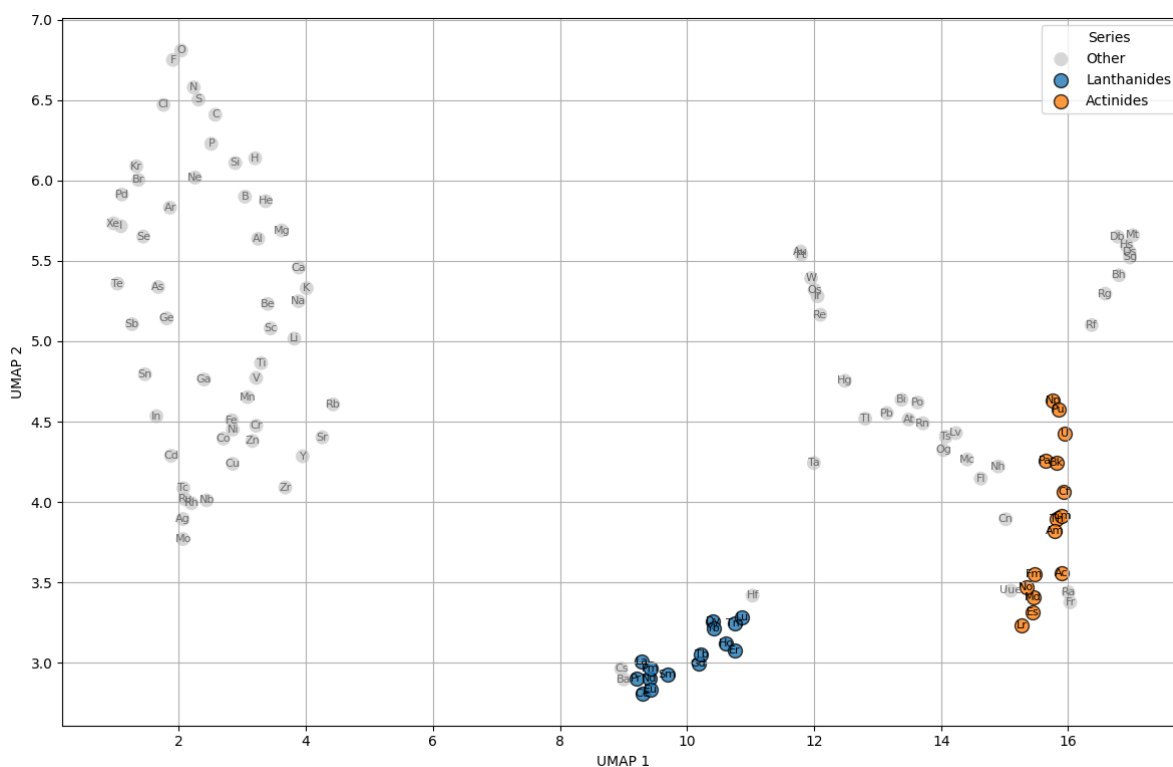


Figure 5. Lanthanides vs. actinides in 2D projection. Though adjacent in the periodic table, their positions in projected space indicate divergent structural character.

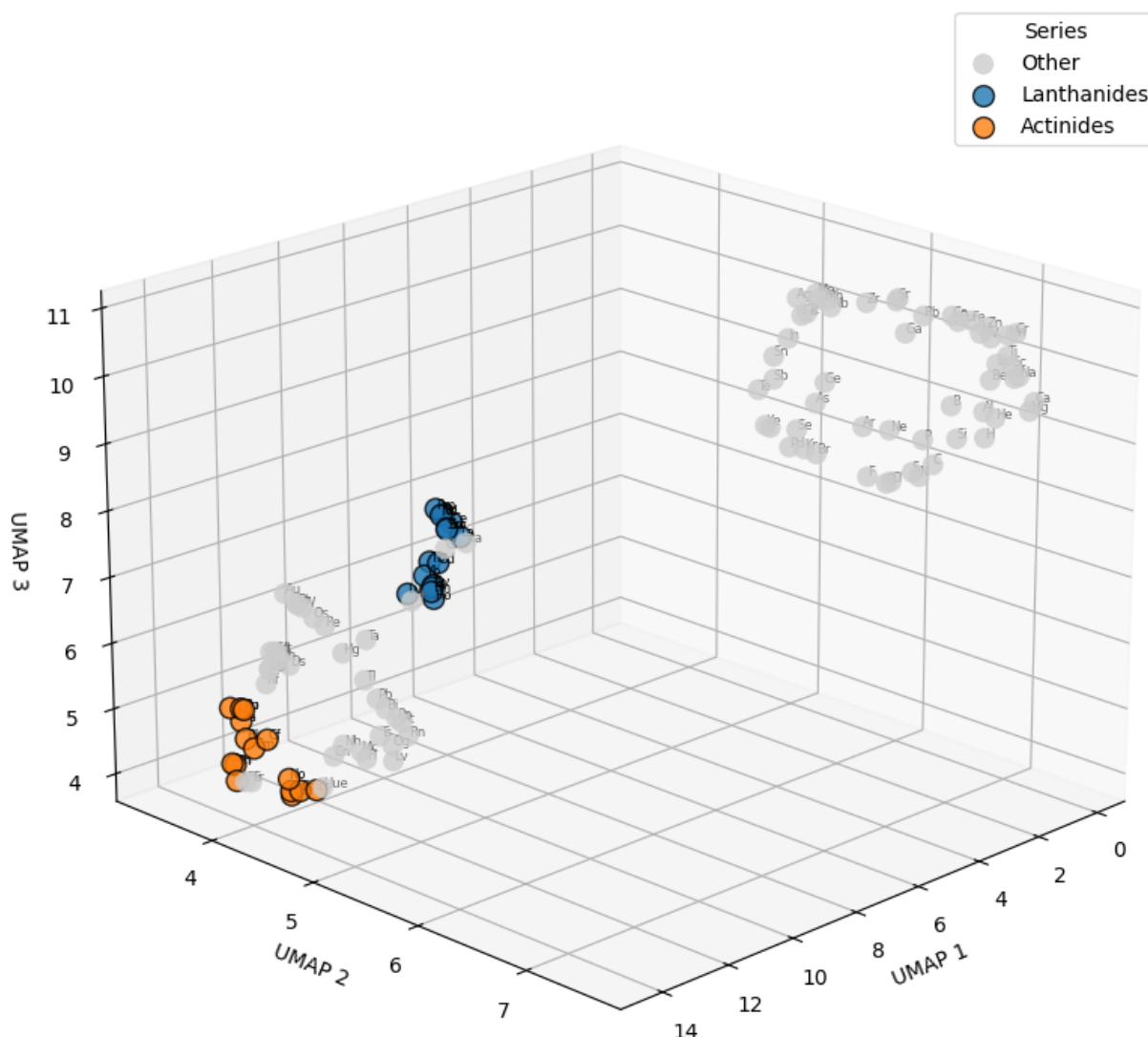


Figure 6. Lanthanides vs. actinides in 3D projection. Though adjacent in the periodic table, their positions in projected space indicate divergent structural character.

Clustering into Attractor Basins

To identify cohesive neighborhoods in the projected space, we apply DBSCAN¹⁵ clustering over the 3D coordinates. The resulting groups are shown in Figure 7. These clusters (or attractor basins) correspond to dense regions in the projection where similar elements accumulate. Unlike fixed group numbers in the periodic table, these basins emerge naturally from the geometry of the data.

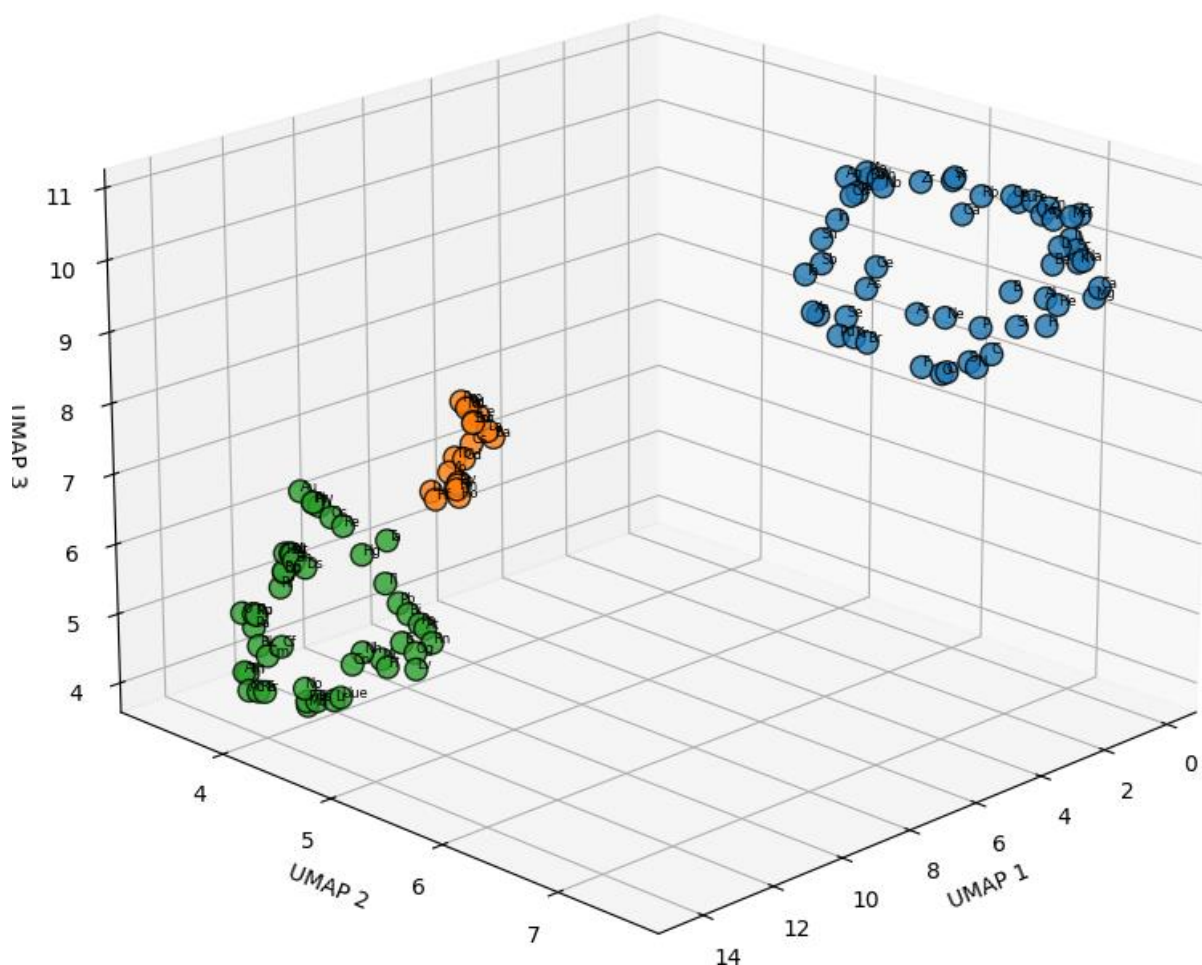


Figure 7. Attractor basins detected by DBSCAN clustering in 3D UMAP space. Each cluster corresponds to a dense region of physical and chemical similarity.

These attractor regions serve as a data-driven analogue to classical periodic groups, but without requiring categorical assumptions or tabular formatting.

Trajectories and Extrapolation

The discrete structure of the periodic table makes it challenging to analyze the continuity of elemental transformations across groups. In contrast, the Atomic Map allows us to trace continuous structural trajectories in the projected space, where paths reflect smooth transitions in high-dimensional physical and chemical attributes.

Group Trajectory

We begin by examining Group 1 elements: H, Li, Na, K, Rb, Cs, Fr. These span a wide range of atomic numbers ($Z=1$ to 87), and their progression includes both stable and radioactive species. When plotted in the Atomic Map, these elements align along a curved trajectory revealing a nonlinear transformation of structure across the group.

In the 3D projection (Figure 8), the path appears as a smooth curve embedded in the manifold's topology. This visualizes how the structural features encoded in our enriched dataset evolve

nonlinearly across the group, which lies deep within a region associated with instability and high atomic mass.

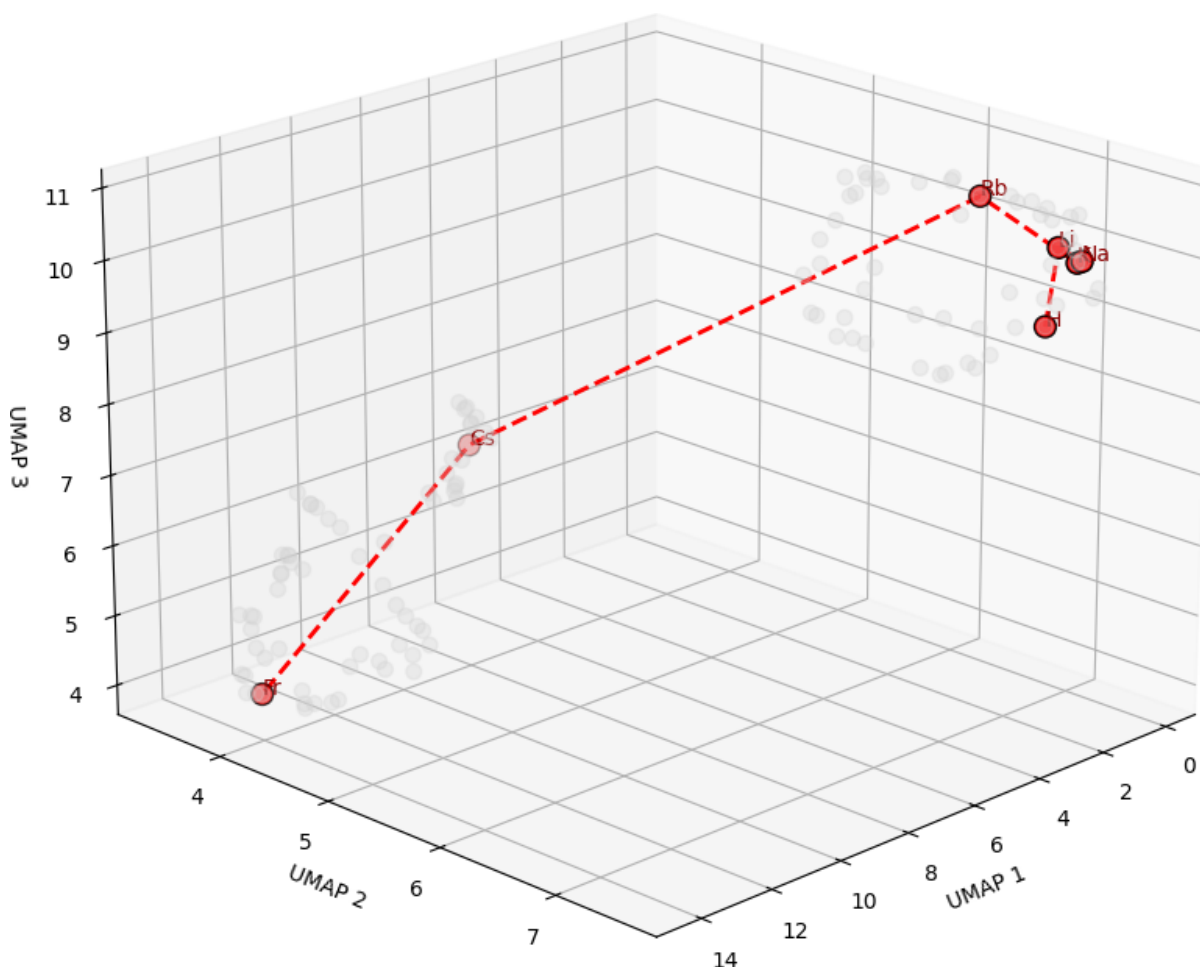


Figure 8. Group 1 trajectory in the 3D Atomic Map. The curvature becomes more apparent in three dimensions, revealing the directional drift from stable lighter elements toward heavy, radioactive ones.

Extrapolation to $Z = 119$

To assess the predictive capacity of the atomic manifold, we constructed a smooth semantic trajectory through the known superheavy elements ($Z=110$ – 118) and extrapolated this path to estimate the location of ununennium ($Z=119$). Rather than relying on a linear continuation, we fit a cubic polynomial curve to the UMAP coordinates of the sequence: Ds (110), Rg (111), Cn (112), Nh (113), Fl (114), Mc (115), Lv (116), Ts (117), Og (118).

The fitted arc captures the nonlinear curvature intrinsic to the manifold and reflects structural evolution within this heavy-element region. Extrapolation to $Z = 119$ places the new point seamlessly at the terminus of this manifold arc (Figure 9).

Visually, this extrapolated point falls within the dense cluster of superheavy elements and approaches the radioactive boundary region, highlighting a continuous drift through high-dimensional physicochemical space.

Radioactive Region in the Atomic Map

When known radioactive elements are overlaid onto the 3D Atomic Map (Figure 10), they cluster into a distinct region near the map's periphery, predominantly along the trajectory of heavy elements. Unlike in the periodic table, where radioactive elements are dispersed across several rows and groups, their latent positioning reveals a contiguous zone associated with physical instability.

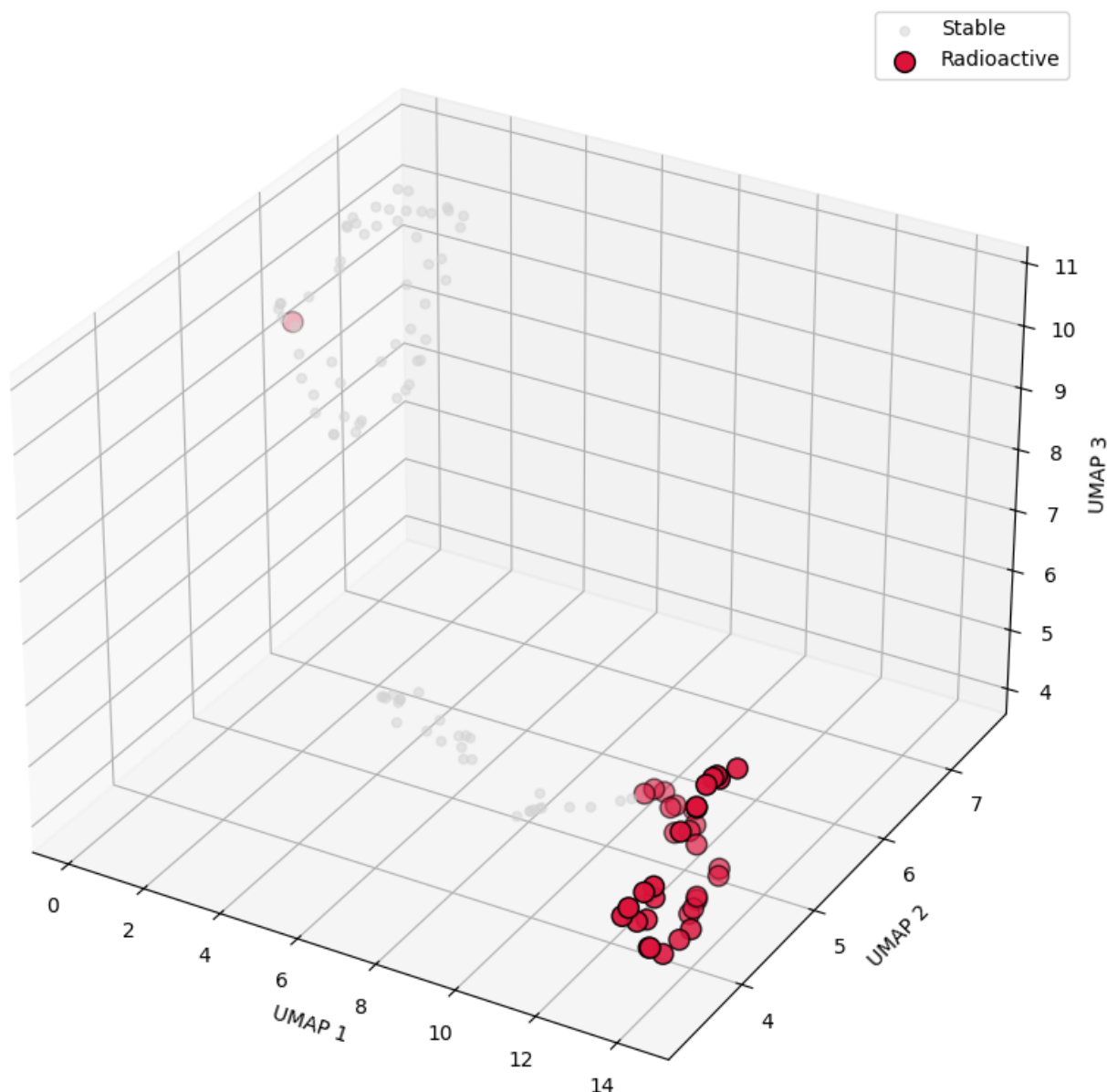


Figure 10. 3D Atomic Map with radioactive elements highlighted in crimson. The cluster indicates a structurally coherent region associated with decay-prone configurations.

This spatial coherence suggests that radioactivity is not a categorical label but a topological property: a region in the manifold shaped by a combination of atomic mass, valence structure, neutron-proton ratio, and other latent descriptors.

Classification

To quantify the relationship between high-dimensional atomic features and radioactive behavior, we trained a supervised classification model using a support vector machine (SVM) with a radial basis function (RBF) kernel. The objective was to determine whether radioactivity could be inferred directly from the enriched feature set, independent of symbolic groupings or tabular location.

The dataset was divided into training and test sets using a stratified 70/30 split to maintain class balance between radioactive and stable elements. All features were standardized using z-score normalization. The SVM model was configured with default hyperparameters ($C = 1.0$, $\gamma = \text{'scale'}$) and optimized to output probabilistic confidence scores via Platt scaling.

The resulting classifier achieved strong performance on the test set:

- Accuracy: 0.972
- ROC-AUC: 0.909

The confusion matrix is given in Table 2.

Table 2. Confusion matrix.				
	Precision	Recall	F1 Score	Support
Non-radioactive	0.96	1.0	0.98	25
Radioactive	1.00	0.91	0.95	11

These results indicate that radioactivity is a predictable property of atomic structure when embedded in an appropriate feature space. The model was able to distinguish stable and unstable elements with high precision and recall, demonstrating that radioactive character is not random or anomalous but instead follows a discernible geometric pattern in the atomic manifold.

This classifier was subsequently used to evaluate held-out radioactive elements, extrapolated candidates, and marginal cases as detailed in the following subsections.

Retrodiction of Superheavy Elements

We held out three known radioactive superheavy elements from training (livermorium (Lv), tennessine (Ts), and oganesson (Og)) and applied the trained model to their features. All three were accurately predicted as radioactive with high confidence as given in Table 3.

Table 3. Retrodiction of Lv, Ts, and Og.

Symbol	Name	Predicted Prob.	Predicted Radioactive
Lv	Livermorium	0.955	Yes
Ts	Tennessine	0.940	Yes
Og	Oganesson	0.916	Yes

Discovery Candidates

When the trained SVM was applied to all unlabeled elements, several borderline cases emerged with nonzero predicted probability of radioactivity, most notably bismuth (Bi), thallium (Tl), and lead (Pb). These elements lie near the edge of the stable region in the Atomic Map and have historically been considered “marginally stable” or “weakly radioactive” in specific isotopic forms. The predicted probabilities are given in Table 4.

Table 4. Radioactivity probability higher than 0.1 of all other elements not included in training set.		
Symbol	Name	Predicted Prob.
Bi	Bismuth	0.169
Tl	Thallium	0.158
Pb	Lead	0.129

These findings suggest that even within the traditionally stable region, there exist structural drifts that may indicate isotopic or environmental conditions favoring instability.

Prediction for Element 119

Finally, the extrapolated position of the hypothesized element 119 (ununennium), displayed in Figure 9 based on curve fitting across $Z = 110$ – 118 in the Atomic Map, is mapped back into feature space using a k-nearest neighbors approach in UMAP space. A support vector machine (SVM) classifier, which is trained on known elements, is then used to predict the radioactivity of this hypothetical atom. The model returns a probability of 0.811, indicating a strong likelihood of instability.

This result demonstrates that radioactivity is not a binary anomaly, but rather a smoothly varying function of structural position within the manifold. It occupies a geometrically bounded region of projected space, shaped by latent physical and chemical descriptors. The model is thus able to perform:

- Retrodiction of known radioactive behavior (e.g., Lv, Ts, Og),
- Inference regarding borderline cases like Bi, Tl, Pb,
- Predictive extrapolation to undiscovered elements, including $Z = 119$.

The prediction aligns with theoretical expectations that element 119 is likely to exhibit rapid α -decay and spontaneous fission, with anticipated half-lives in the microsecond range¹⁶, consistent with recognized behavior of superheavy elements. This indicates that latent manifold geometry, when combined with classical classification methods, offers a meaningful pathway for predicting nuclear behavior in new chemical space.

Discussion

The Atomic Map provides a powerful alternative to the periodic table by embedding elements in a continuous, data-driven manifold. Within this representation, physical and chemical attributes are jointly encoded in a high-dimensional space, projected into a form that reveals structural transitions, regional clustering, and topological regularities. This continuous geometry enables not only visualization but inference, opening the door to predictive and retrodictive tasks beyond the scope of symbolic classification.

Contribution to Existing Attempts

Glushkovsky¹⁰ rediscovered the structural periodic trends using a β -VAE trained solely on electron configurations, disentangling periods, blocks, and orbital anomalies in 2D latent space. However, the analysis remained strictly visual and unsupervised. By contrast, Atomic Map uses a feature-rich data vector (electronic, nuclear, physical), combined with UMAP projection, SVM-based classification of radioactivity, and trajectory-based extrapolation to hypothetical elements, which are capabilities beyond Glushkovsky’s scope.

Kusaba et al.¹² introduced a generative topographic mapping algorithm (PTG) that autonomously reconstructs periodic table layouts (e.g., grid, spiral) by compressing features like melting point and electronegativity into 2D/3D representations. Their emphasis remains on visualization of periodic order, without downstream predictive modeling. Our Atomic Map builds on this by enabling quantitative predictions, including radioactivity classification and $Z = 119$ forecast.

Antunes et al.¹³ learn distributed atom embeddings (SkipAtom) from materials databases and apply them to composition-based properties like band gap and formation energy. These embeddings excel at materials prediction tasks but focus on compound-level inference. In contrast, Atomic Map is focused explicitly at the elemental level, embedding each of the 118 elements using interpretable nuclear and physical descriptors, and harnessing geometric structure to perform inference on unknown or hypothetical atomic species.

In summary, existing manifold representations recover structural regularities. Our work uniquely extends this lineage by leveraging the learned geometry for quantitative prediction, enabling retrodiction, classification, and extrapolation. Thus elevating latent embeddings from descriptive artifacts to actionable models.

Predictive Evaluation of Unlabeled and Hypothetical Elements

Applying the trained SVM classifier to heavy elements not originally labeled as radioactive reveals several non-trivial candidates with low but non-negligible probabilities of instability. Notably, bismuth (Bi), thallium (Tl), and lead (Pb) are predicted to have radioactivity probabilities of approximately 0.17, 0.16, and 0.13, respectively. These elements occupy positions near the periphery of the stable region within the Atomic Map, supporting the hypothesis that radioactivity emerges through a gradual structural drift rather than a binary threshold.

This model prediction aligns with empirical evidence regarding these elements:

- Bismuth-209, the only naturally occurring isotope of Bi, was long considered stable but has been shown to undergo alpha decay with an extremely long half-life ($\sim 1.9 \times 10^{19}$ years), placing it within the radioactivity continuum despite prior assumptions¹⁷,
- Thallium has no truly stable isotopes—only observationally stable nuclides such as Tl-205 and Tl-203—and several radioisotopes with half-lives ranging from microseconds to years, including Tl-204 (3.78 years)^{18,19},
- Lead isotopic analyses also confirm the existence of trace beta decay and isomeric transitions, indicating that radioactivity extends into regions traditionally classified as “stable”.²⁰

Thus, the model captures a gradual radioactivity signature that mirrors real-world decay phenomena, even among elements generally regarded as stable.

For the hypothetical element $Z=119$, the extrapolation positioned it within the “peripheral zone of instability” in feature space. The SVM model assigns it a probability of 0.811 for being radioactive, which is consistent with theoretical expectations for superheavy elements, and providing an interpretable, geometry-based rationale for its anticipated instability.

Limitations of the Periodic Table

The periodic table, while historically foundational, imposes rigid structural assumptions that conflate different types of information (notably electronic configuration and chemical reactivity) into a fixed tabular format. It is discretized, categorical, and shaped as much by historical convention as by data. While useful pedagogically, it offers limited resolution for nuanced analysis, discovery, or predictive modeling.

In contrast, the Atomic Map captures a unified geometric structure in which chemical and physical periodicities arise as emergent properties of continuous data. Categories such as noble gases, halogens, or lanthanides appear as spatial clusters, consequences of shared high-dimensional attributes. Instabilities such as radioactivity manifest as topological gradients, enabling not just recognition but explanation.

Reframing Periodicity Beyond the Madelung Rule

The Atomic Map also offers a direct response to foundational critiques of the periodic table related to Madelung rule. For instance, Scerri²¹ challenges the pedagogical dominance and scientific legitimacy of the $(n + \ell)$ orbital-filling rule, noting its frequent empirical violations and lack of theoretical derivation. He writes, “the Madelung rule is not a law of nature, nor is it even a generally reliable guide.” This critique extends to the periodic table itself, which he views as a heuristic structure rather than a physically grounded representation. The Atomic Map addresses these concerns by forgoing prescriptive rules and instead deriving periodicity from a continuous projection of enriched physical, electronic, and nuclear features.

In this framework, exceptions to Madelung’s rule arise organically as structural drifts or bifurcations within the manifold, not as violations to be rationalized. Periodicity becomes an emergent geometric property, not an imposed taxonomy. Thus, the Atomic Map does not merely visualize chemical trends; it reframes the very notion of atomic identity in terms of topological continuity, offering an epistemically grounded alternative to the rule-based paradigm.

Toward a Unified Framework for Atomic Structure

By encoding physical and chemical properties into a shared projection, the Atomic Map unites traditionally distinct domains (nuclear physics and quantum chemistry) within a single interpretive space. This creates opportunities to analyze transitions, interpolations, and even hypothetical configurations in ways the periodic table cannot accommodate.

Importantly, the manifold framework is extensible. It can incorporate additional properties (e.g., isotopic half-lives, decay modes, orbital densities), support inverse design, and be refined as new data emerge. The ability to project structure-function relationships in a learned geometric space provides a foundation for rethinking elemental classification, prediction, and discovery from first principles.

Limitations and Future Work

While promising, this approach has limitations. The model is restricted to known elements and their empirical descriptors; extrapolations beyond the convex hull of known data carry uncertainty. Furthermore, some dimensions of nuclear complexity (such as shell closures, deformation energies, and metastable states) are only coarsely captured by the current feature set.

Future work will focus on expanding the dataset to include isotopic resolution, dynamic features, and field-based models of stability. A promising direction is the formal definition of attractor basins and local minima in the manifold, linking atomic configurations to energetic landscapes and possibly uncovering topological explanations for quantized mass and nuclear discreteness.

Conclusion

This study introduces the Atomic Map: a continuous, data-driven manifold that encodes elemental identity through projection of enriched physical, chemical, and nuclear attributes. Unlike the periodic table, which imposes a fixed symbolic classification over discrete categories, the Atomic Map arises from empirical structure and reveals regularities not apparent in traditional tabular formats.

Through the use of dimensionality reduction, classification, and trajectory extrapolation, we demonstrate that the Atomic Map preserves physically meaningful relationships among elements. Classical categories emerge as spatial clusters, while properties such as radioactivity manifest as coherent topological regions within the projection. The model successfully retrodicts the behavior of held-out superheavy elements, identifies marginally unstable candidates (e.g., Bi, Tl, Pb), and predicts the probable radioactivity of a hypothetical $Z=119$ element.

More broadly, this framework repositions the elements not as discrete, manually sorted entities, but as embedded points within a latent physical landscape, in which structure and behavior are encoded geometrically, and discovery becomes a process of exploration through that space.

While the periodic table remains an iconic scientific tool, its limitations are increasingly evident in an age of data-centric modeling. The Atomic Map offers an extensible and interpretable alternative that unifies physics and chemistry through projectional coherence and supports tasks ranging from visualization to classification to extrapolative inference.

We propose the Atomic Map not as a replacement in pedagogy, but as a new foundation for atomic representation in scientific modeling. By replacing rigid categories with geometric continuity, it opens the path toward a unified, dynamic, and predictive understanding of the elements.

Data and Software Availability

All data used in this work is publicly available on the following project repository:

<https://github.com/Bowserinator/Periodic-Table-JSON>

All simulation scripts are available on the following project repository:

<https://github.com/ersinesen/atomicmap-public>

Author Contributions

E.E. is the single author

Conflict of Interest

The author declares no competing financial interests.

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