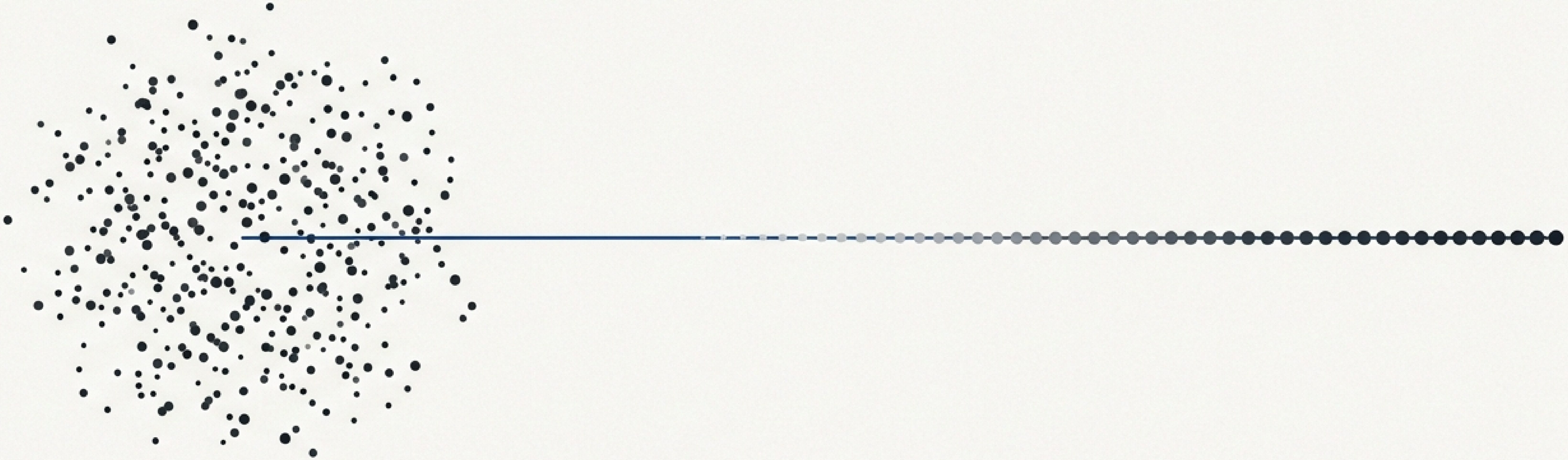
Beyond Classification: Unlocking Ordinal Severity in SEM Images

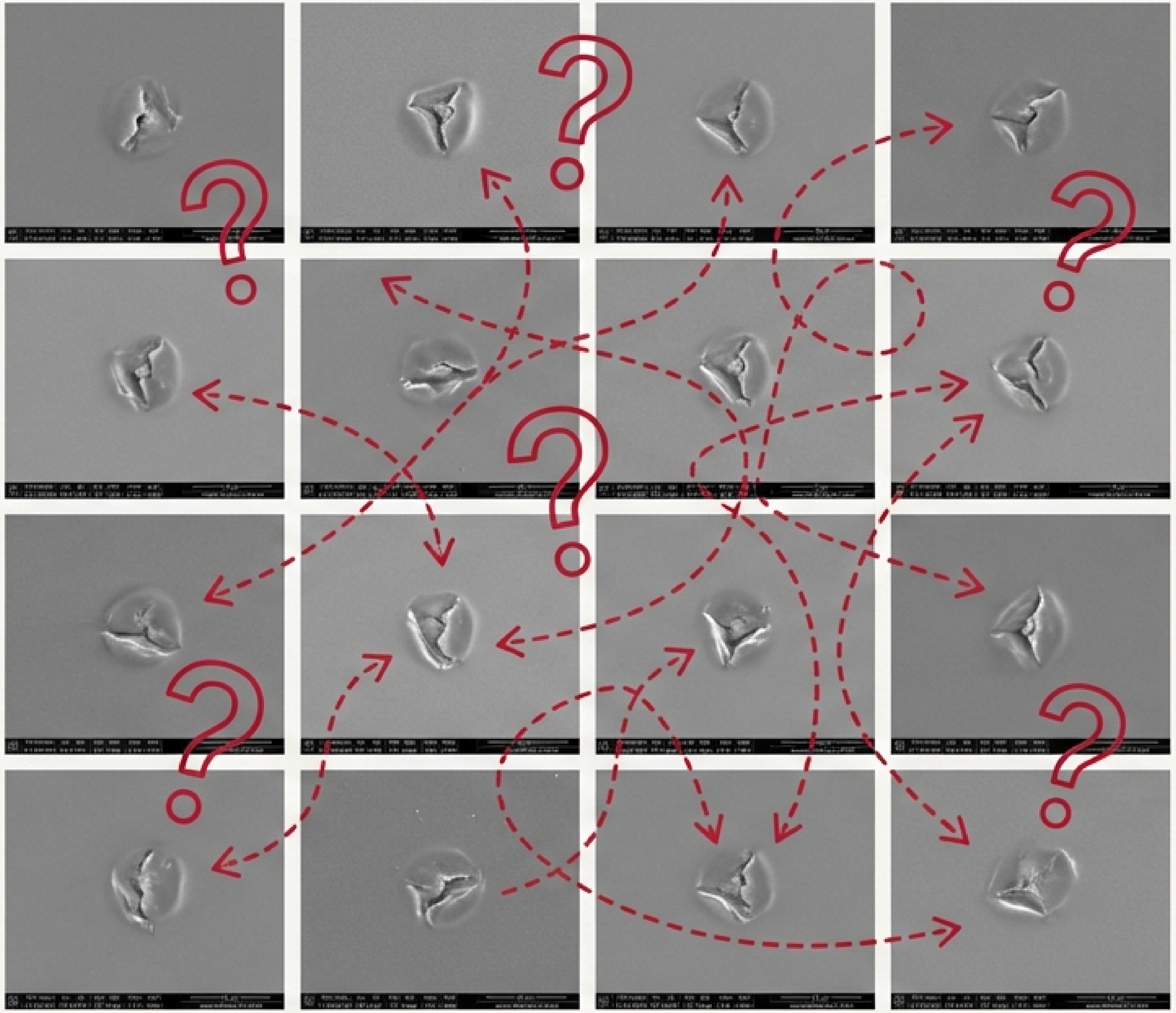
A practical guide to sorting defects using the hidden structure of visual embeddings.



You've Classified Your Defects. But How Do You Prioritize Them?

After classification, every defect type contains a spectrum of severity. Manually sorting through hundreds of SEM images to find the most critical examples is:

- **Time-Consuming:** Hours spent on subjective visual inspection.
- **Inconsistent:** Operator judgment varies, leading to unreliable data.
- **Unscalable:** Impossible to apply consistently across thousands of wafers.



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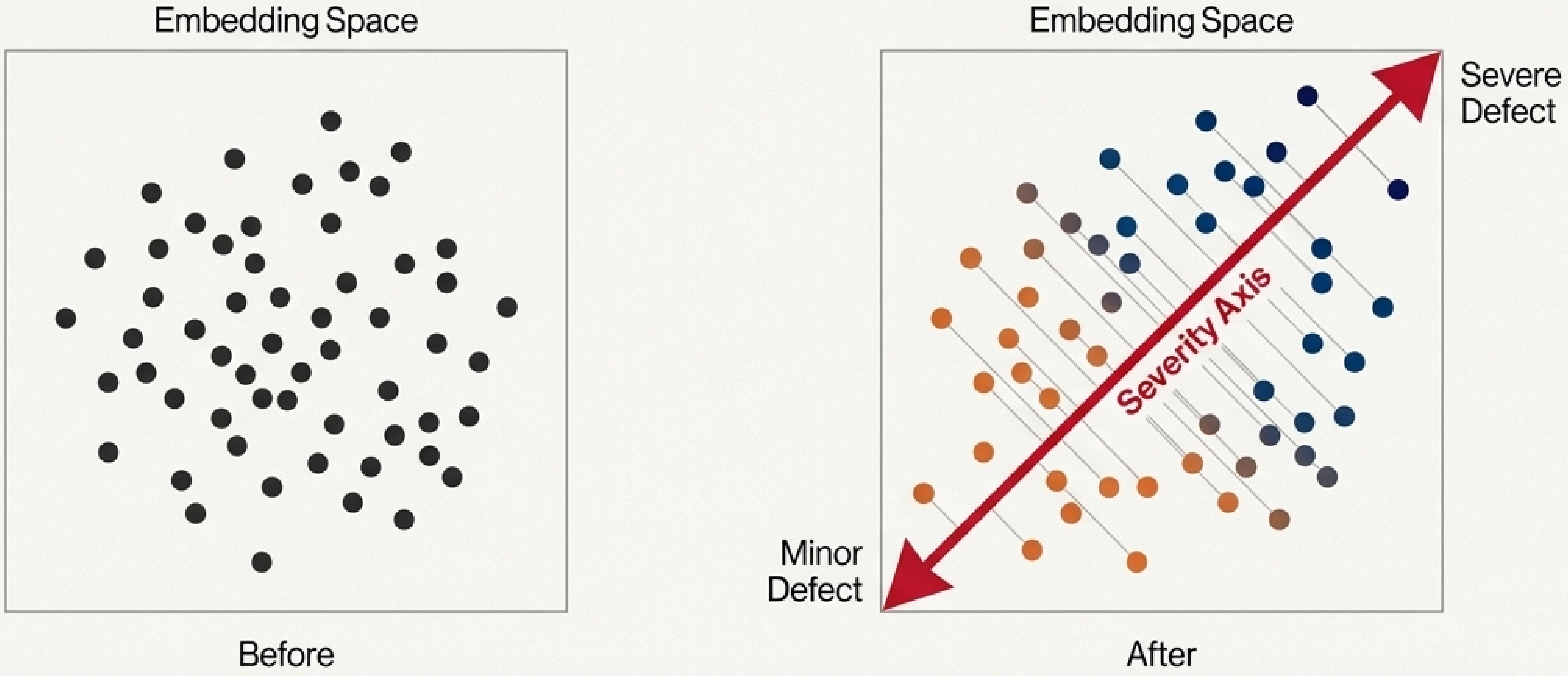
The Breakthrough Idea: A "Severity Axis" to Sort Your Images Automatically

What if the information needed to sort your defects was already hidden within your image data? Modern AI models don't just see images as pixels; they map them into a structured "embedding space." Within this space, we can find a single direction—a vector—that corresponds directly to an attribute like "defect severity."

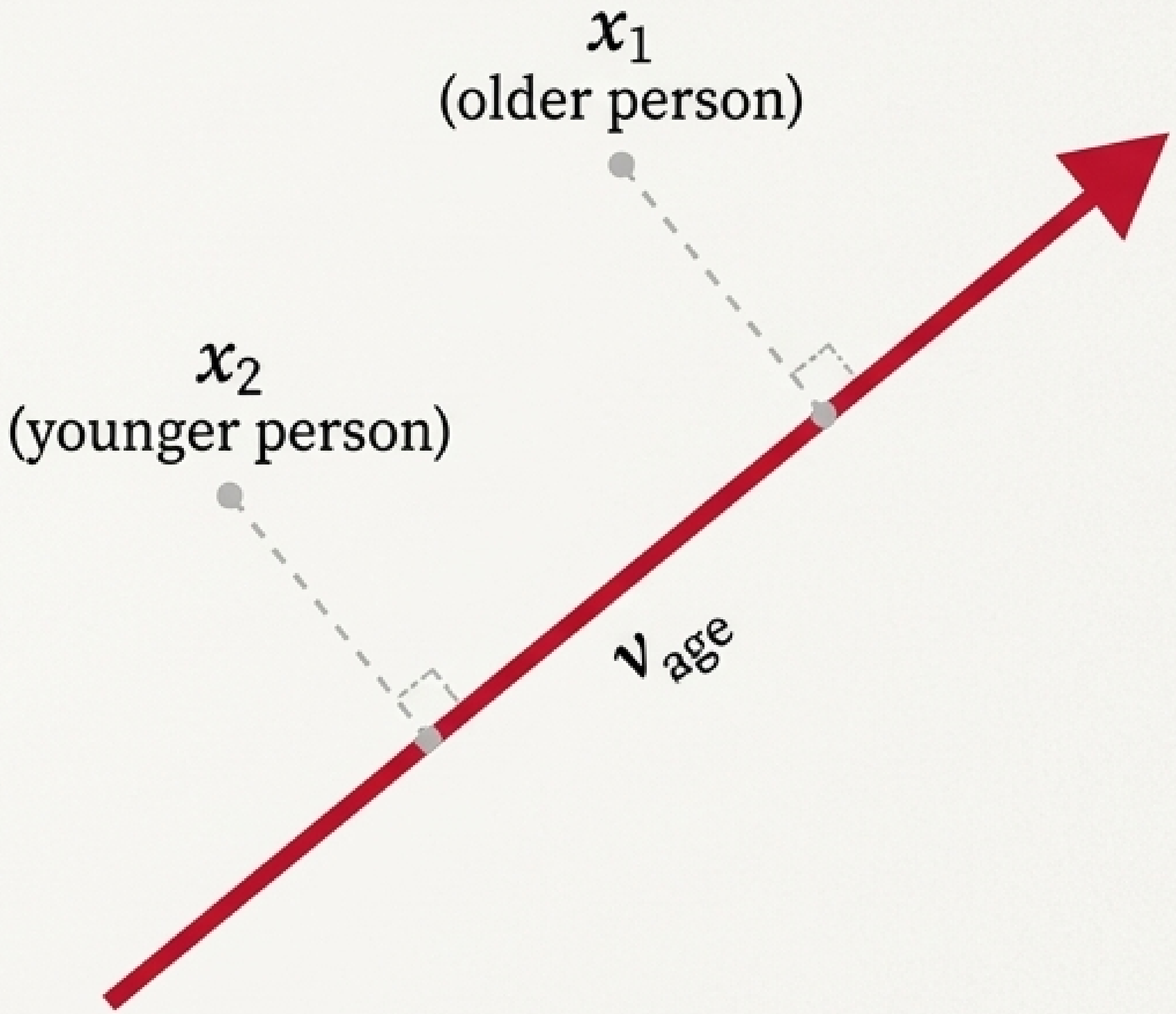


The Science Behind the Sort: Introducing Rankability

This capability relies on a property of visual embeddings called **rankability**. An embedding model is rankable for an attribute if a "rank axis" exists.

Definition from the research: "A representation f is rankable for an ordinal attribute A... if there exists a rank axis vA... such that for any images $x1$, $x2$ with $A(x1) \geq A(x2)$, it follows that the projection $vA^T f(x1) \geq vA^T f(x2)$."

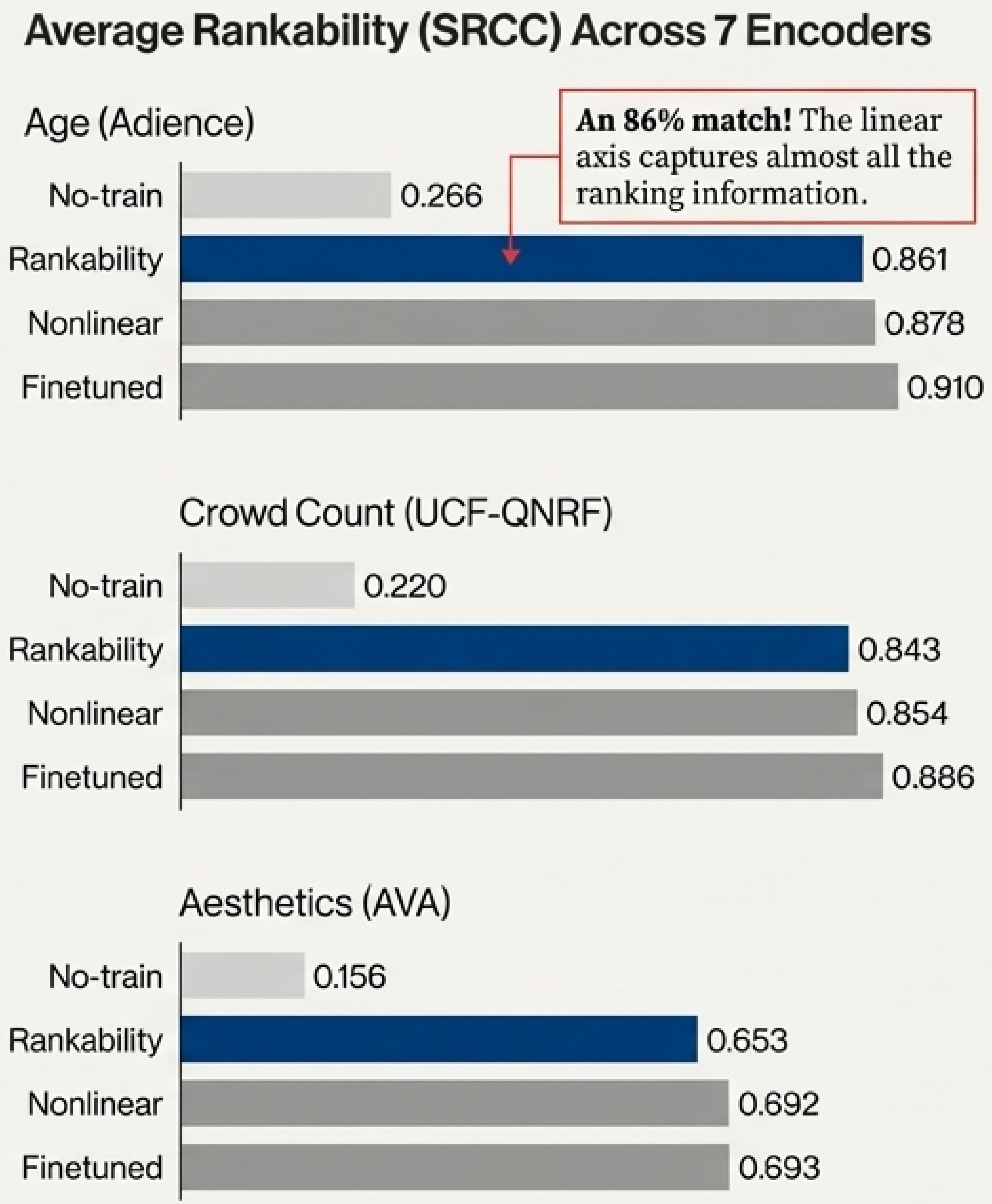
In Simple Terms: If we can find a single direction (a vector) in the embedding space, projecting our images onto that line will sort them in the correct order of the attribute (e.g., from youngest to oldest, or from minor defect to severe defect).



The Evidence: This Hidden Order is Real and Remarkably Strong

Researchers measured rankability using Spearman's Rank Correlation Coefficient (SRCC), which scores how well the model's predicted ranking matches the true ranking (from -1 to +1). The results are compelling.

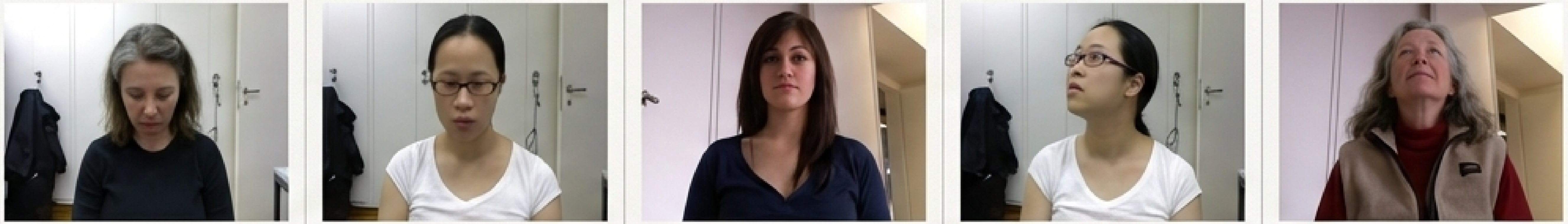
Key Finding: For most attributes, the rankability of modern visual encoders is very high, often much closer to the theoretical maximum ("Nonlinear upper bound") than to a random baseline.



Seeing is Believing: How a Single Axis Sorts Complex Images

Projecting CLIP embeddings onto a learned rank axis effectively sorts images along continuous attributes, from age and head pose to crowd density and aesthetics.

Attribute: Age
Rank Axis: `v_age`



Attribute: Crowd Density
Rank Axis: `v_crowd_count`

Attribute: Aesthetic Score
Rank Axis: `v_aesthetics`

These images were sorted using *only* the projection of their embeddings onto a single vector. No complex models were needed for the sorting itself.

The Shortcut: Finding the Severity Axis with Just Two Example Images

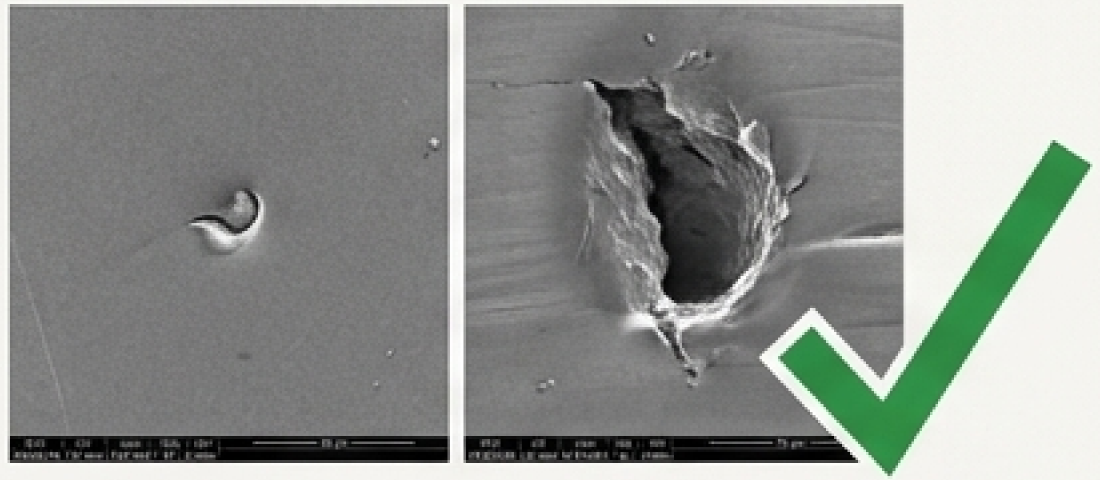
While a rank axis can be found by training a linear regressor on thousands of labeled images, research reveals a far more efficient method.

You can define a powerful rank axis—a **steering vector**—using only two examples from the extremes of your desired attribute.

For defect analysis, this means you only need:

1. One clear example of a "**minor**" or "**least severe**" defect.
2. One clear example of a "**major**" or "**most severe**" defect.

Thousands of Labels



The Recipe: How to Create Your Defect Severity Steering Vector

1. **Select Your Extremes**
   - Choose two SEM images from the *same defect class*.
   - **Image L:** A canonical example of a "low-severity" defect.
   - **Image H:** A canonical example of a "high-severity" defect.

2. **Generate Embeddings**
   - Use your pre-trained visual encoder (e.g., CLIP, ResNet, DINOv2) to get the embedding vectors for each image.
   - `vector_L = f(Image_L)`
   - `vector_H = f(Image_H)`

3. **Calculate the Steering Vector**
   - Simply subtract the "low" vector from the "high" vector. This defines the direction from minor to severe.
   - `v_severity = vector_H - vector_L`

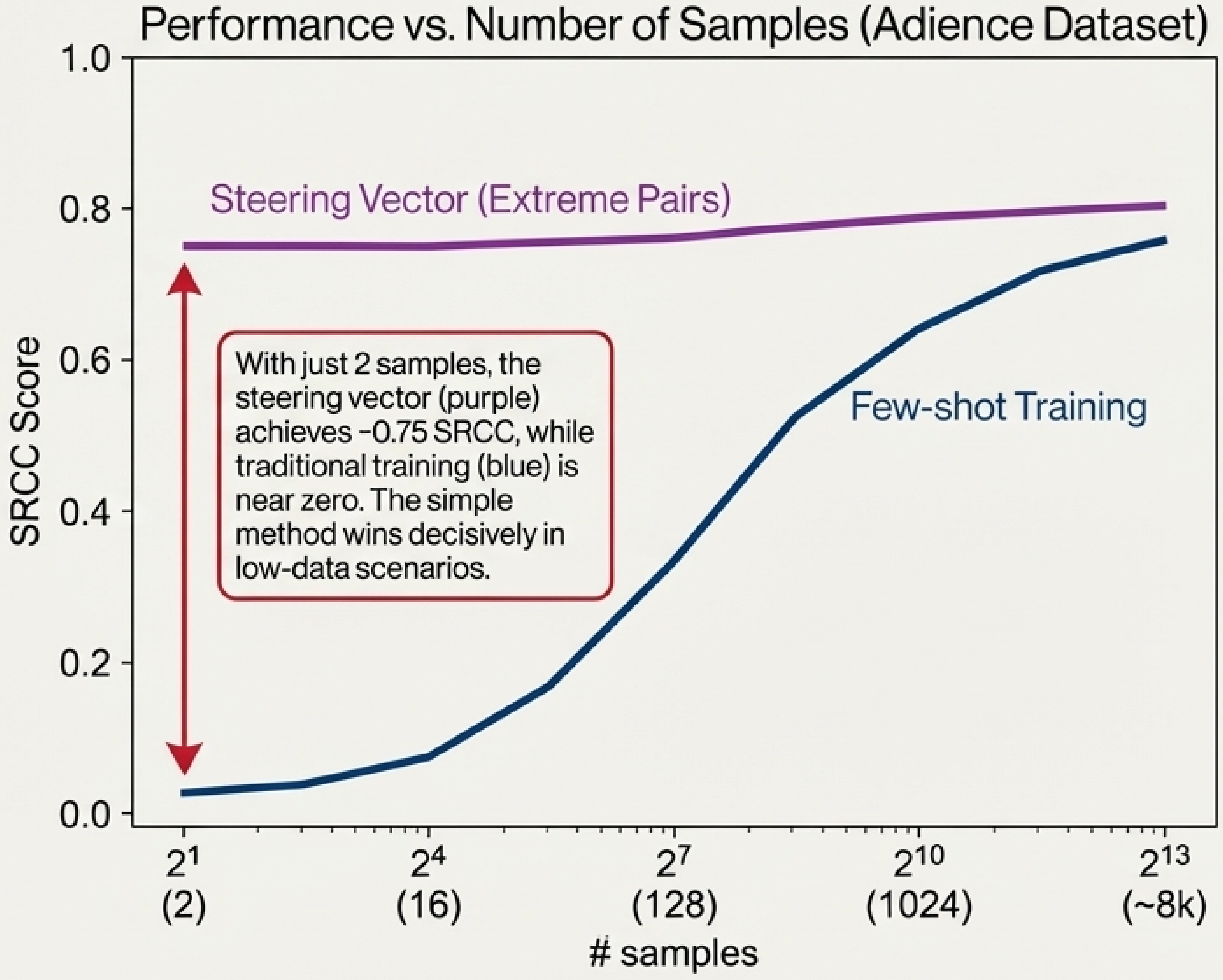
4. **(Optional but Recommended) Normalize the Vector**
   - `v_severity = v_severity / ||v_severity||`

You now have a universal "severity axis" for that defect class. To get a severity score for any new image, calculate `score = v_severity`^{T} `* f(new_image)`.

Proof: This Two-Example Method is Surprisingly Powerful

When tested against few-shot learning (training a model on a small number of fully labeled examples), the extreme pairs steering vector method performs exceptionally well, especially with very few samples.

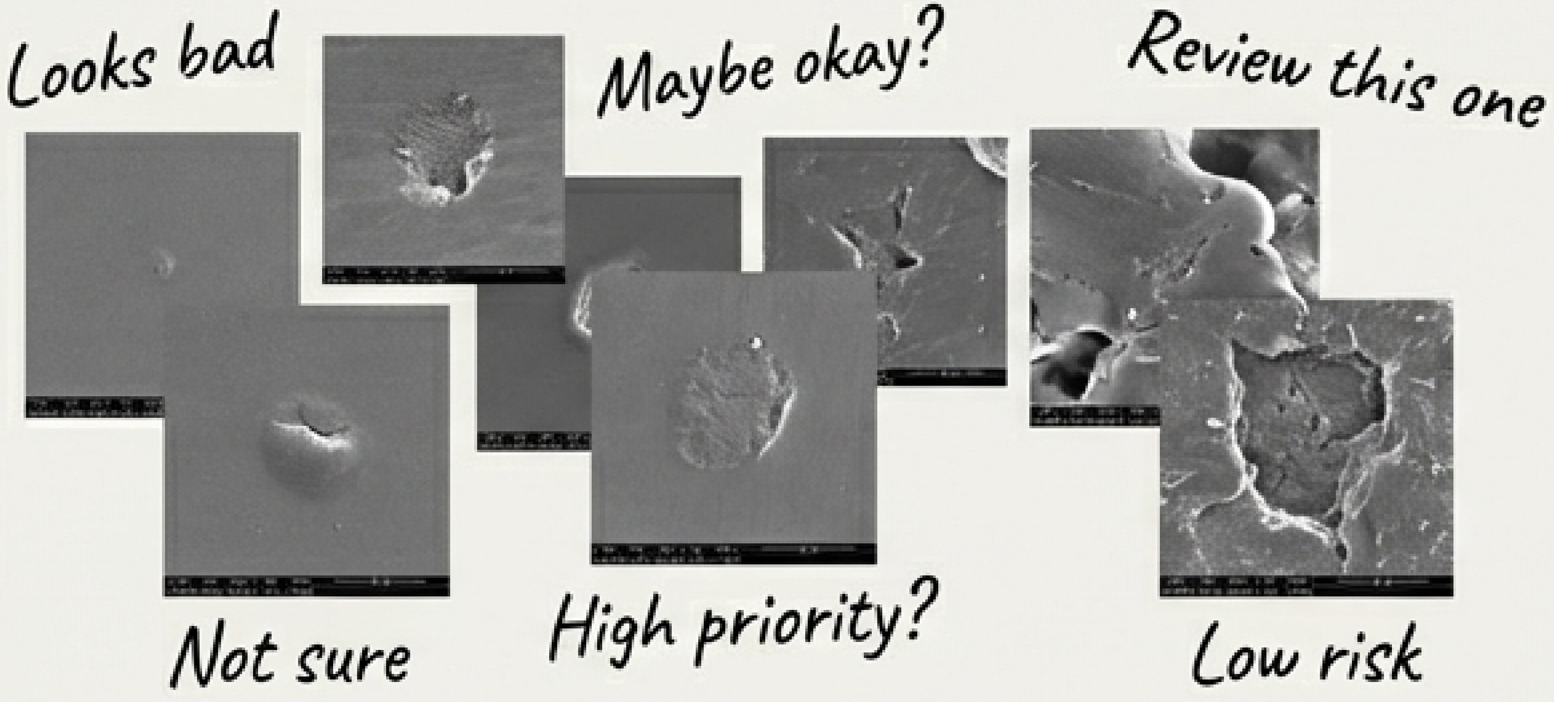
Key Insight: If you only have a handful of images to work with, using two extreme examples to define your axis is more effective than training a regressor on a few randomly labeled ones.



Benefit 1: Automate and Standardize Defect Prioritization

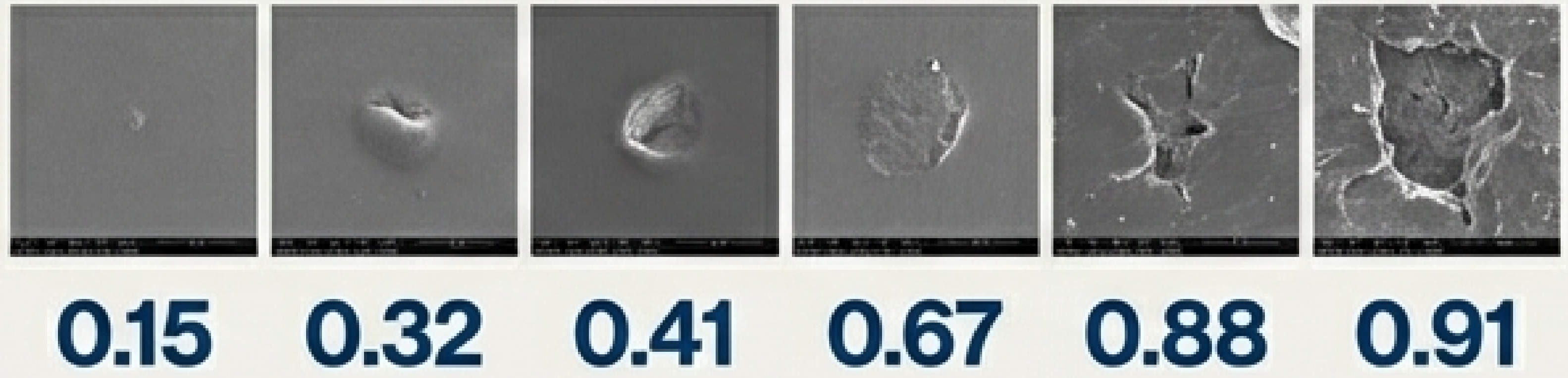
The steering vector transforms defect analysis from a subjective art into a quantitative science. Every image can now be assigned a precise, numerical severity score.

Before: Manual & Subjective



- Engineers visually compare images.
- Bins are qualitative (“low,” “medium,” “high”).
- Results are inconsistent between people and over time.

After: Automated & Quantitative

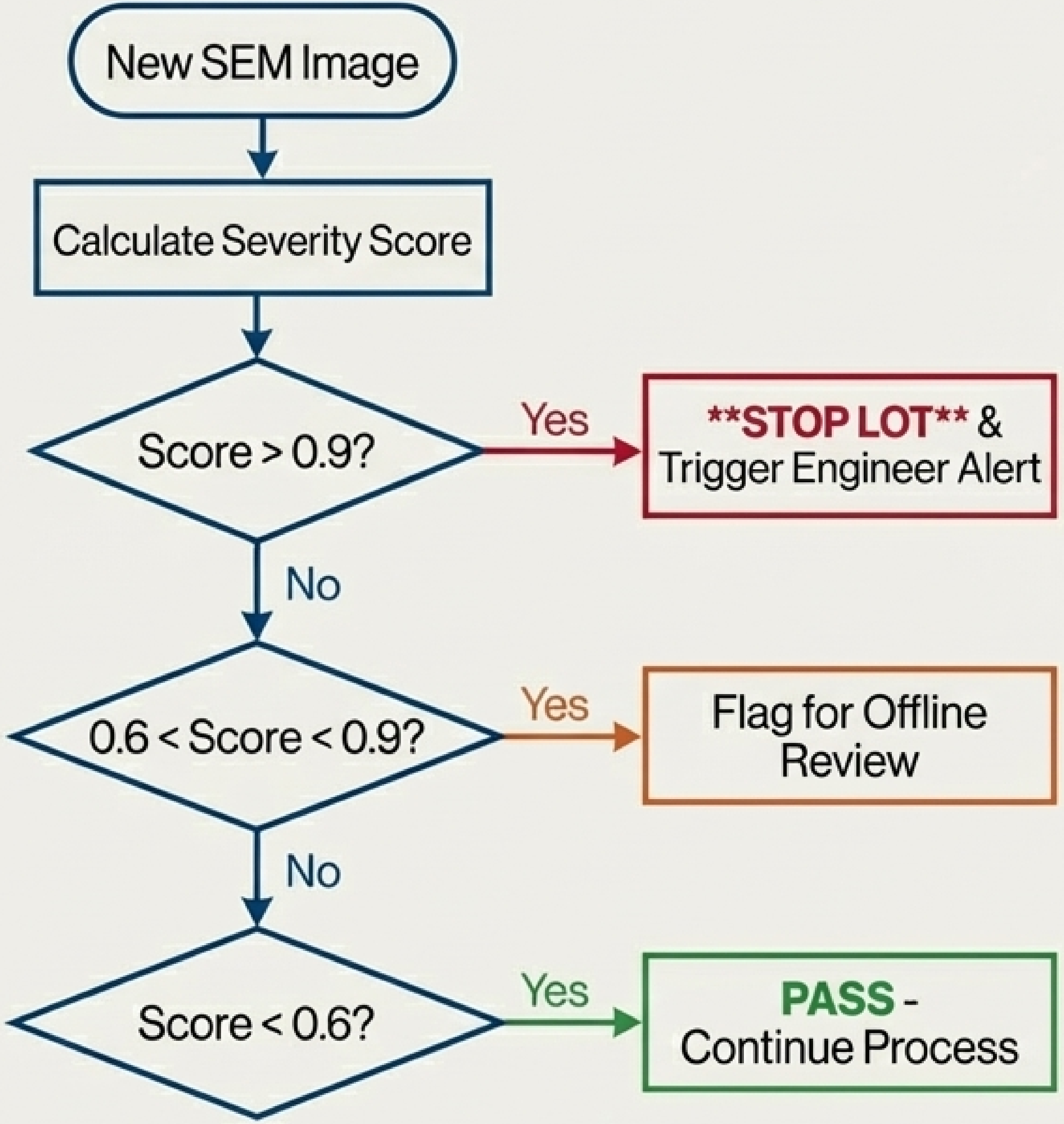


- A severity score is calculated instantly for every new image.
- Sorting is perfectly consistent and repeatable.
- You can rank thousands of defects across an entire lot in seconds.

Benefit 2: Enable Sophisticated, Rule-Based Process Control

With a quantitative severity score for every defect, you can move beyond manual review and implement automated, data-driven rules in your workflow. This allows you to create systems that can:

- **Trigger Real-Time Alerts:** Instantly notify engineers when a defect exceeds a critical severity threshold.
- **Automate Disposition:** Automatically pass lots or flag them for engineering review.
- **Feed Forward Control:** Use defect severity data as an input for downstream process steps.



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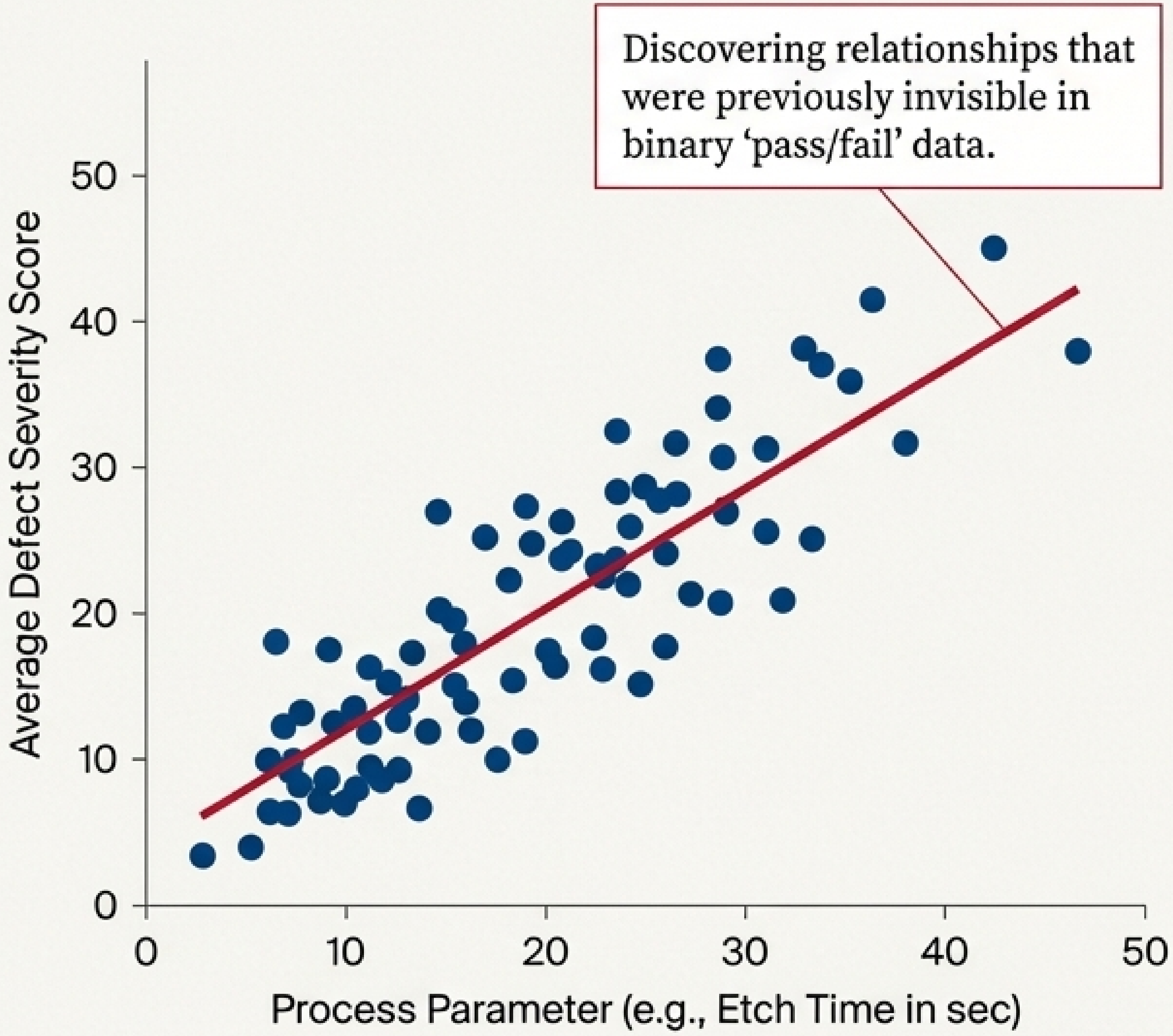
Benefit 3: Uncover Deeper Process Insights

A continuous severity score is a powerful new variable for root cause analysis. By treating severity as a metric, you can correlate it with process parameters to understand what drives the formation of critical defects.

Unlock New Analytical Questions:
- Does a specific chamber seasoning recipe correlate with higher defect severity?
- How does etch time affect the severity distribution of this defect class?
- Can we predict lot-level yield based on the average severity score of key defects?



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Your Embeddings Hold the Key to Deeper Understanding

1.

Rankability is Real

Your visual embeddings contain a hidden, linear order that corresponds to real-world attributes like defect severity.

2.

The Method is Simple

You can find this "severity axis" with a steering vector created from just two extreme example images.

3.

The Payoff is Significant

This technique unlocks automation, enables rule-based systems, and provides a new quantitative tool for process analysis and control.

Move beyond simple classification and start leveraging the rich, ordinal structure already present in your data.