

# xanesnet

a deep neural network for x-ray spectroscopy

\\ \\ Conor D. Rankine<sup>[1]</sup> + Thomas J. Penfold<sup>[2]</sup> // /

[1] University of York @ York, UK  
[2] Newcastle University @ Newcastle-upon-Tyne, UK



UNIVERSITY  
of York

EPSRC

LEVERHULME  
TRUST

Alan Turing  
Institute

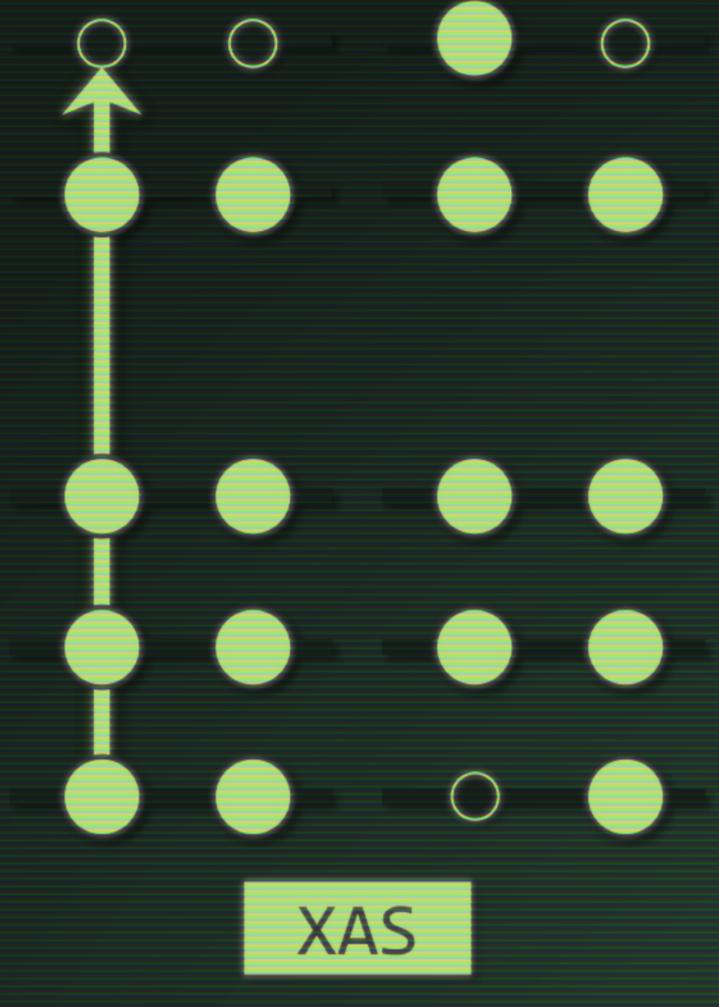
## the xanesnet project

~\$ we think that computational simulations for X-ray absorption spectroscopy (XAS) should be fast, affordable, and accessible to everyone  
~\$ the popularity of XAS is on a steep upward trajectory globally, driven by advances at, and widening access to, high-brilliance light sources such as synchrotrons and X-ray free-electron lasers (XFELs), but the high resolution of modern X-ray spectra, coupled with ever-increasing data acquisition rates, brings into focus the challenge of accurately and cost-effectively analyzing these data  
~\$ decoding modern X-ray spectra demands detailed computational calculations that are capable of capturing the complexity of the underlying physics but that are - at the same time - fast, affordable, and accessible enough to appeal to researchers  
~\$ this is a tall order - but we're using deep neural networks (DNNs) to make it possible!



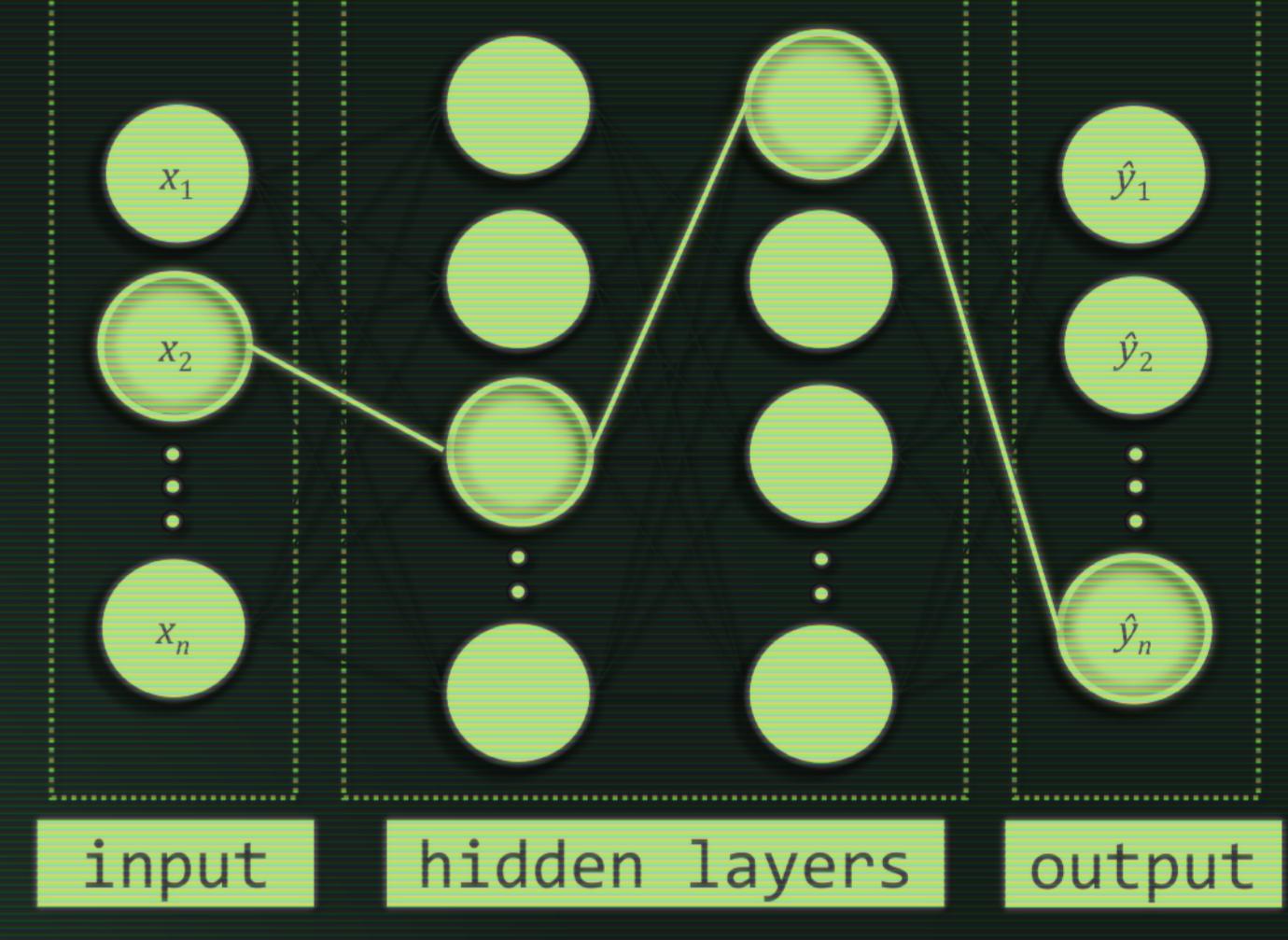
## x-ray spectroscopy

~\$ atoms are able to absorb and emit X-ray radiation  
~\$ absorption of X-ray radiation promotes electrons from core energy levels and creates high-energy, unstable core-hole states  
~\$ these states subsequently decay  
~\$ using X-ray spectroscopy, we can monitor these processes and, in some cases, what happens in between

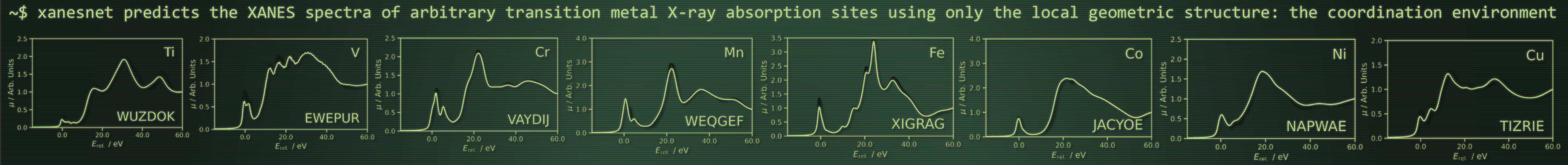


## deep neural networks

~\$ DNNs are machine-learning models based on the architecture of the human brain  
~\$ neurons are containers for numbers; these numbers are their activations  
~\$ activations in one layer influence the activations in subsequent layers  
~\$ activating the input layer by passing in data produces a particular response in the output layer that can be tuned iteratively  
~\$ DNNs can be used to produce predictions from, or to classify, input data



## predictions

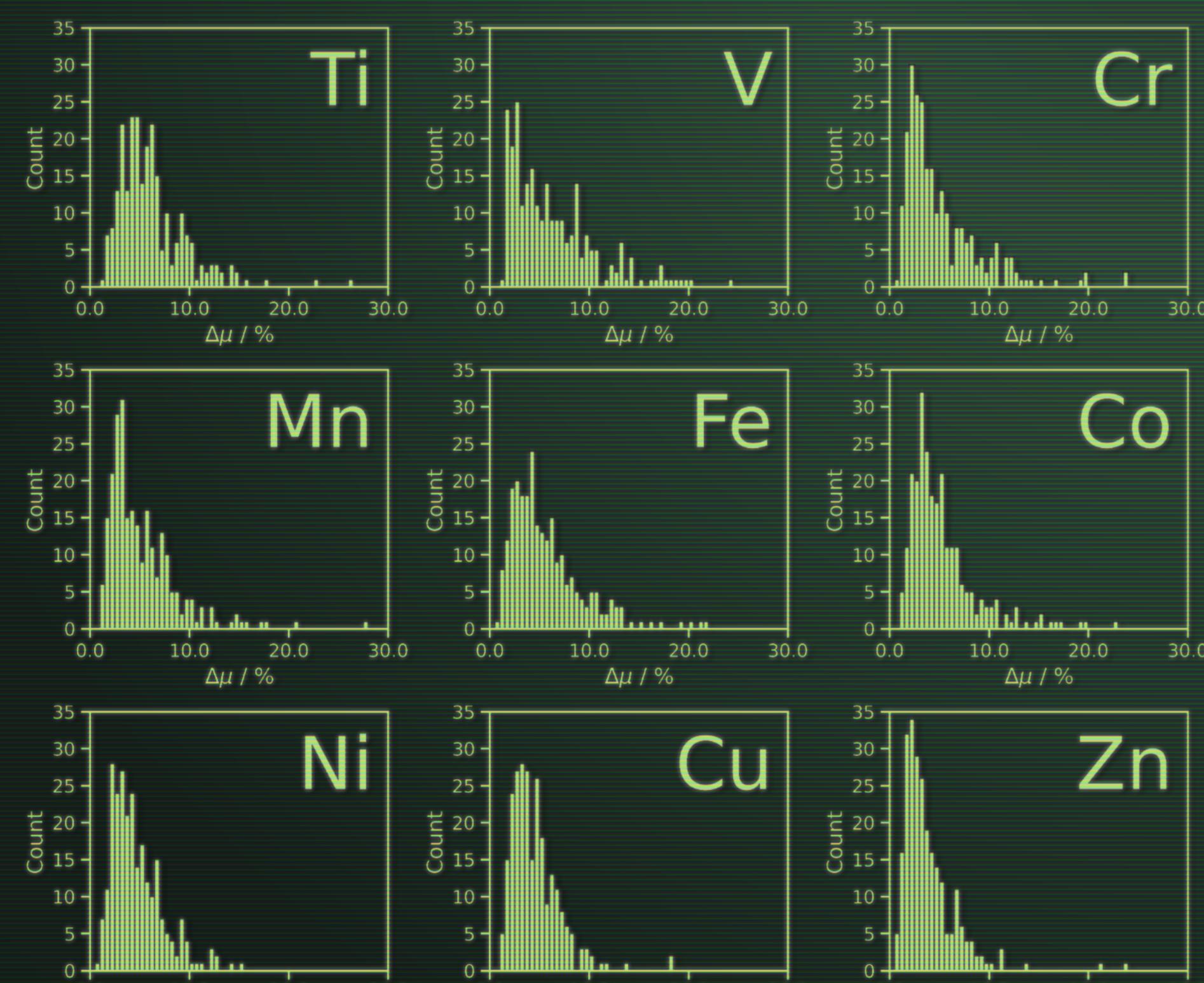


## performance

~\$ percentage differences,  $\Delta\mu$ , between predicted and target XANES spectra + skew metrics

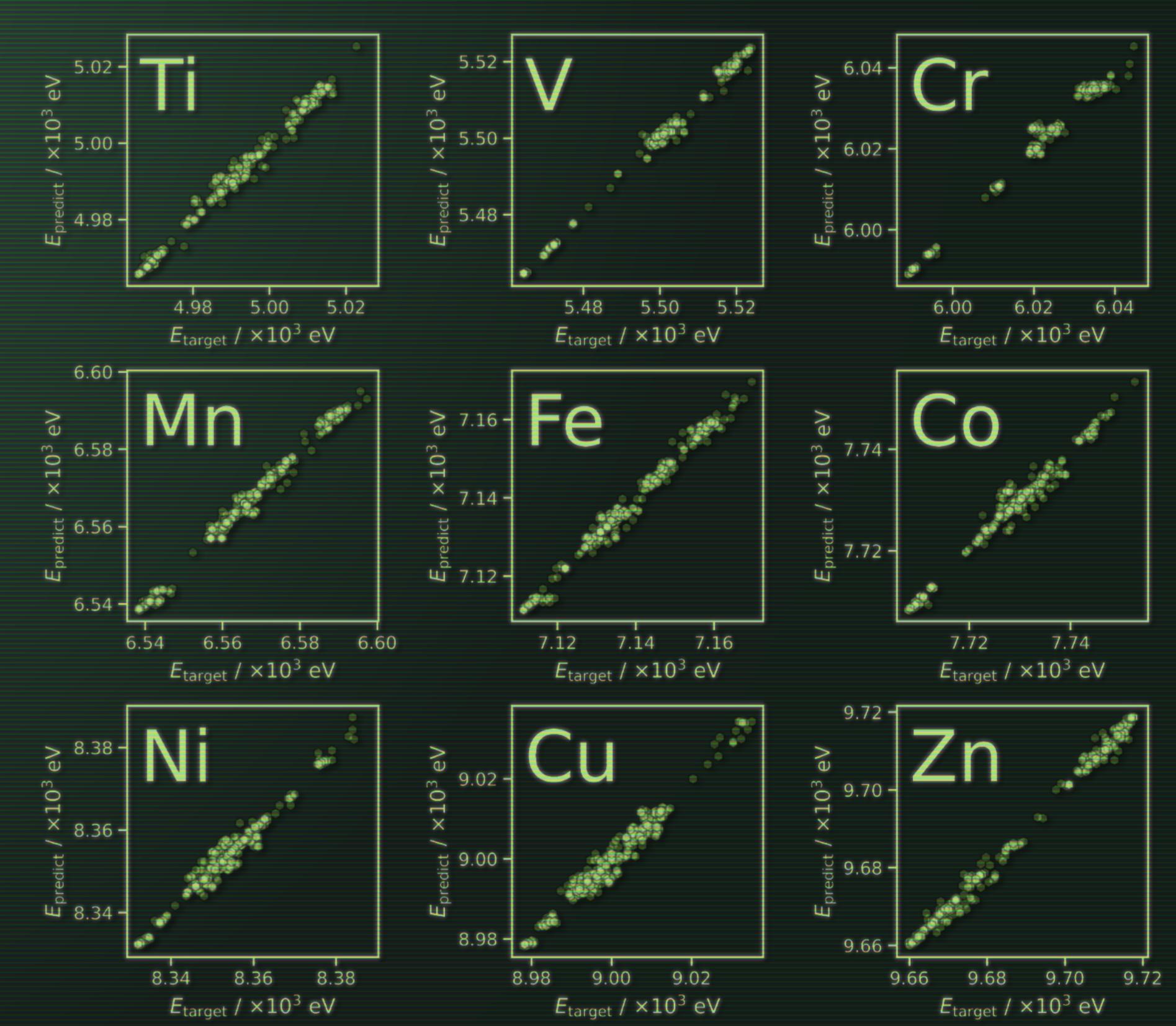
edge	$\Delta\mu_{avg.} / \%$	skew
Ti	5.5 (3.8)	1.898
V	5.2 (3.2)	1.625
Cr	3.8 (2.5)	1.926
Mn	4.3 (2.8)	2.242
Fe	4.7 (3.1)	1.607
Co	4.3 (2.8)	2.058
Ni	4.1 (2.6)	1.286
Cu	4.0 (2.7)	2.007
Zn	3.2 (2.2)	3.005

[values in parentheses are post-broadening]



~\$ peak position errors,  $\Delta E$ , between predicted and target XANES spectra +  $R^2$  metrics

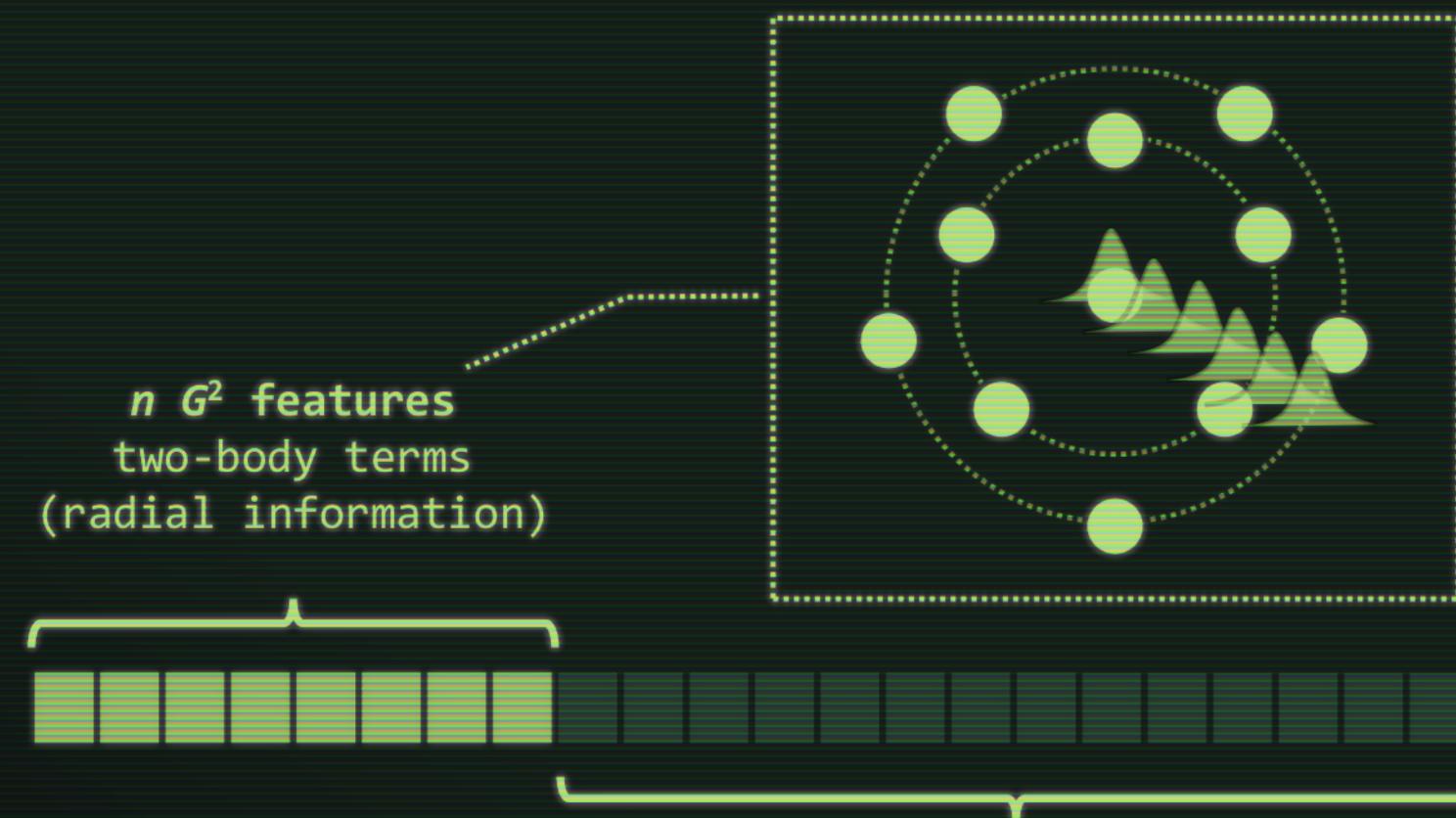
edge	$\Delta E_{avg.} / \text{eV}$	$R^2$
Ti	0.86	0.996
V	0.54	0.999
Cr	0.65	0.997
Mn	0.76	0.997
Fe	0.83	0.996
Co	0.74	0.993
Ni	0.88	0.993
Cu	0.99	0.991
Zn	0.95	0.997



## physical insight

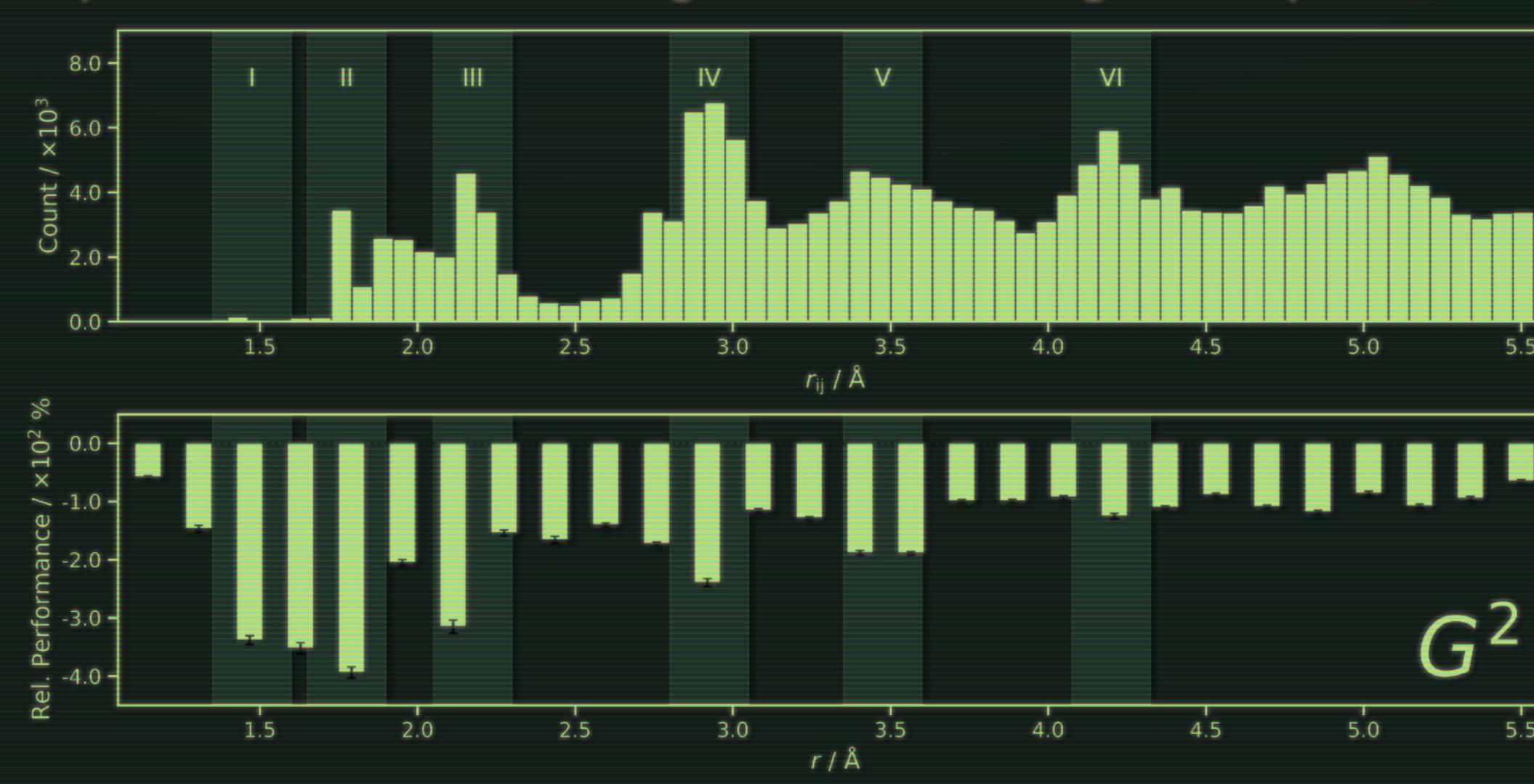
~\$ local environments around X-ray absorption sites are encoded in XANESNET as feature vectors

~\$ feature vectors comprise informative features that XANESNET uses to predict XANES spectra



~\$ scrambling the feature vectors featurewise and assessing the performance penalty tells us about the importance of each individual feature

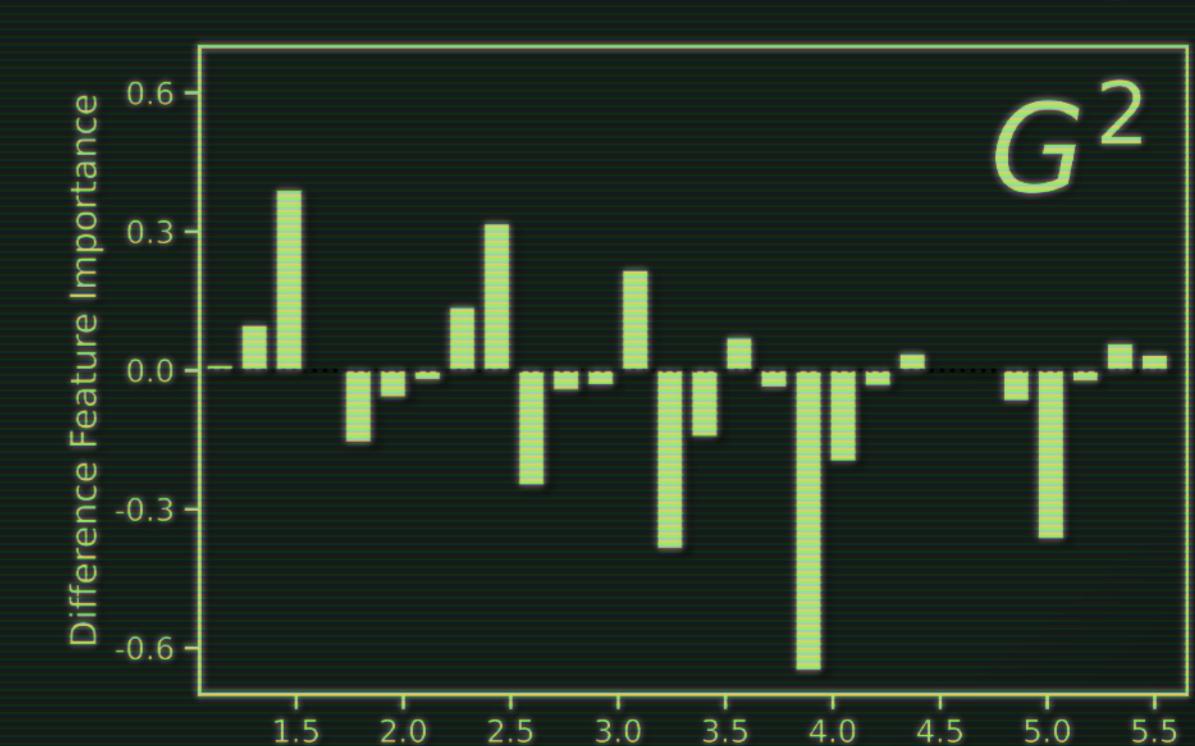
### pair-distribution histogram for Fe K-edge absorption sites



feature importance for  $G^2$  feature functions placed at a radial distance,  $r$ ; Fe K-edge

shell	label(s)
1 <sup>st</sup> coordination	I (H), II (C, N, O, ...), III (Si, P, S, ...)
2 <sup>nd</sup> coordination	IV (C, N, O, ...), V (Si, P, S, ...)
3 <sup>rd</sup> coordination	VI (...)

difference (high-energy window minus low-energy window) feature importance for  $G^2$  feature functions placed at a radial distance,  $r$ ; Fe K-edge



~\$ feature importance in the high-energy window ( $+50.0 \rightarrow +56.0$  eV) is greater close to the absorption site: single scattering

~\$ feature importance in the low-energy window ( $-3.0 \rightarrow +3.0$  eV) is greater further from the absorption site: multiple scattering