



# Grokking as an entanglement transition during training dynamics of MPS machine learning

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Quantum Computing @ INFN, Padova

# Outline

- ▶ Tensor Networks
  - Matrix Product State (MPS)
  - Gradient descent
- ▶ Fashion MNIST
  - Features extraction in magnetization patterns
  - Entanglement transition
- ▶ Gene communities
  - Dataset & workflow
  - MPS classification

# Outline

- ▶ **Tensor Networks**

  - Matrix Product State (MPS)
  - Gradient descent

- ▶ Fashion MNIST

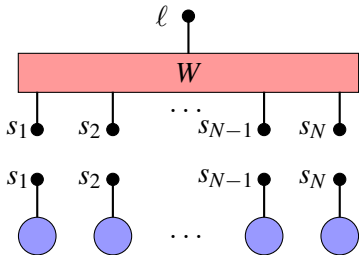
  - Features extraction in magnetization patterns
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# Matrix Product State (MPS)

**Qubits encoding:** features vector  $\mathbf{x} \in \mathbb{R}^N \mapsto |\Phi(\mathbf{x})\rangle = \bigotimes_{j=1}^N |\phi(x^{(j)})\rangle \in \mathbb{R}^{2^N}$



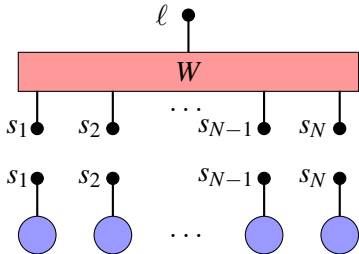
$$f_W^\ell(\mathbf{x}) = \sum_{s_1 \dots s_N} W_{s_1, \dots, s_N}^\ell |\phi(x^{(1)})^{s_1} \dots \phi(x^{(N)})^{s_N}\rangle$$

$$\mathcal{C}(W) = \frac{1}{2} \sum_{\omega=1}^{N_T} \sum_{\ell} \left( f_W^\ell(\mathbf{x}_\omega) - y_\omega^\ell \right)^2$$



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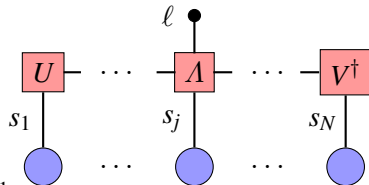


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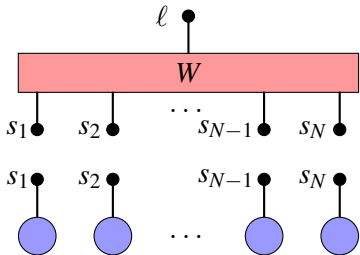
**MPS format** uses iterated SVD ( $M = U\Sigma V^\dagger$ ):

$$W_{s_1, \dots, s_N}^\ell = \sum_{a_1, \dots, a_N} U_{s_1}^{1, a_1} U_{s_2}^{a_1, a_2} \dots U_{s_{j-1}}^{a_{j-2}, a_{j-1}} \times \\ \times \Lambda_{s_j, \ell}^{a_{j-1}, a_j} V_{s_{j+1}}^{\dagger a_j, a_{j+1}} \dots V_{s_{N-1}}^{\dagger a_{N-2}, a_{N-1}} V_{s_N}^{\dagger a_{N-1}, 1}$$



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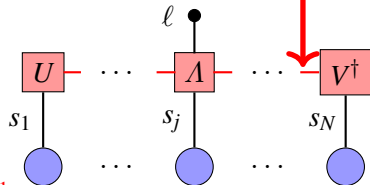
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$$\mathcal{C}(W) = \frac{1}{2} \sum_{\omega=1}^{N_T} \sum_{\ell} \left( f_W^\ell(\mathbf{x}_\omega) - y_\omega^\ell \right)^2$$

# singular values = bond dimension  $\chi$

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# Gradient descent

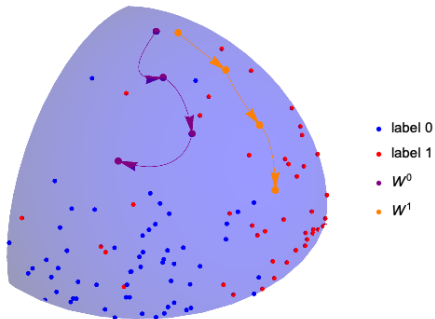
Two sites update:

$$f_W^\ell(\mathbf{x}) = \sum_{\substack{s_j, s_{j+1} \\ a_{j-1}, a_{j+1}}} B_{s_j, s_{j+1}}^{a_{j-1}, \ell, a_{j+1}} |\tilde{\Phi}(\mathbf{x})_{a_{j-1}, a_{j+1}}^{s_j, s_{j+1}}\rangle$$

$$\Delta B^\ell = - \frac{\partial \mathcal{C}}{\partial B^\ell}$$

$$= \sum_{\omega=1}^{N_T} |\tilde{\Phi}(\mathbf{x}_\omega)\rangle \otimes (y_\omega^\ell - f_W^\ell(\mathbf{x}_\omega))$$

$$\implies B'^\ell = B^\ell + \alpha \Delta B^\ell$$



Stoudenmire, Schwab, Supervised Learning with Tensor Networks, 2016

# Gradient descent

Two sites update:

$$f_W^\ell(\mathbf{x}) = \sum_{\substack{s_j, s_{j+1} \\ a_{j-1}, a_{j+1}}} B_{s_j, s_{j+1}}^{a_{j-1}, \ell, a_{j+1}} |\tilde{\Phi}(\mathbf{x})_{a_{j-1}, a_{j+1}}^{s_j, s_{j+1}}\rangle$$

$$\Delta B^\ell = - \frac{\partial \mathcal{C}}{\partial B^\ell}$$

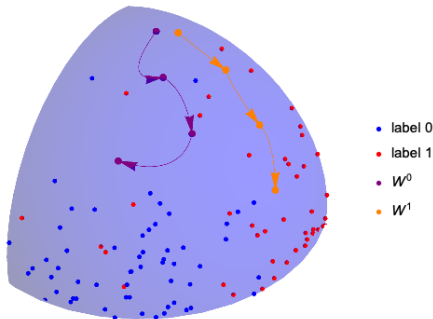
$$= \sum_{\omega=1}^{N_T} |\tilde{\Phi}(\mathbf{x}_\omega)\rangle \otimes (y_\omega^\ell - f_W^\ell(\mathbf{x}_\omega))$$

$$\Rightarrow B'^\ell = B^\ell + \alpha \Delta B^\ell$$

**SVD** → entropy  $S(j)$

$B^0$  → entropy  $S^0(j)$

$B^1$  → entropy  $S^1(j)$



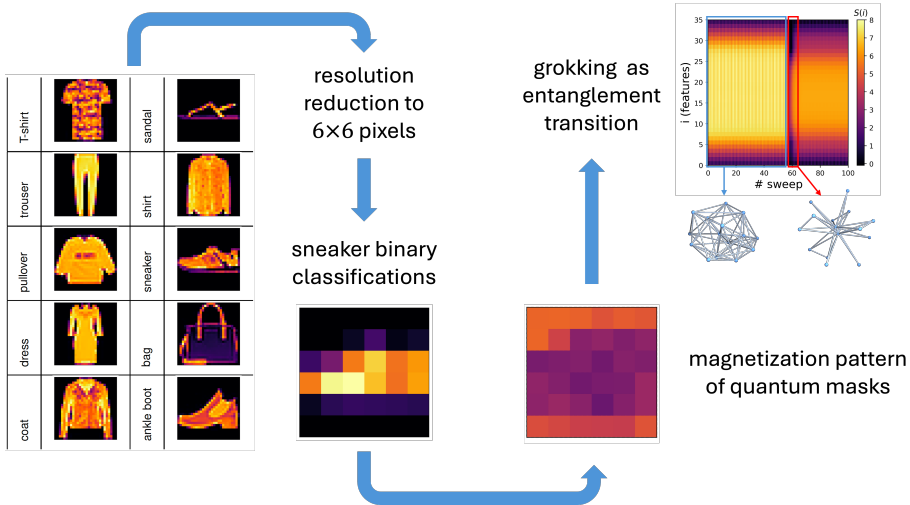
$$S(j) = -\text{Tr} \{ \varrho_j \log \varrho_j \} = - \sum_{k=1}^{\chi} \lambda_k^2 \log \lambda_k^2$$

Stoudenmire, Schwab, Supervised Learning with Tensor Networks, 2016

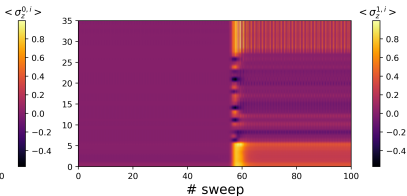
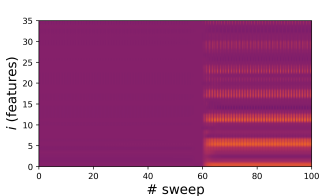
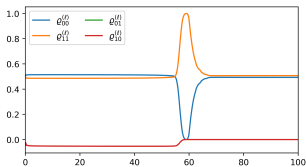
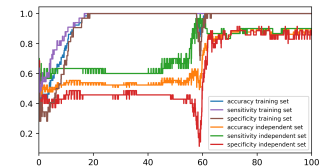
# Fashion MNIST

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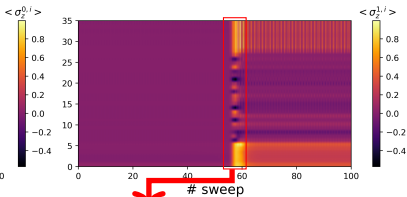
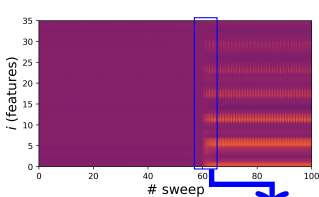
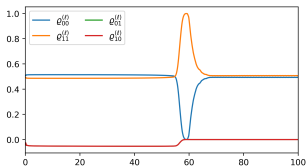
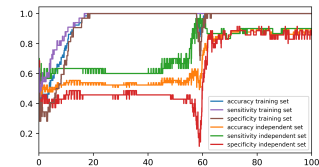
# Fashion MNIST



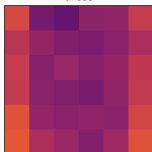
# Features extraction in magnetization patterns



# Features extraction in magnetization patterns

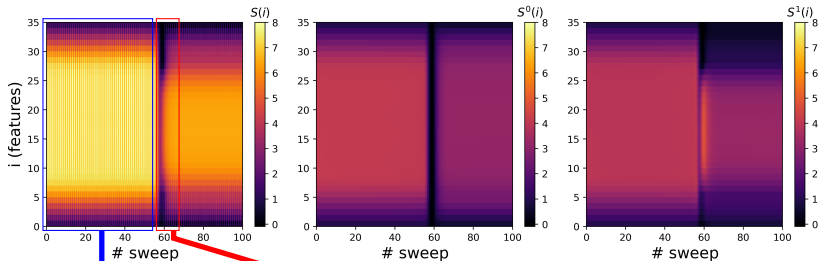


masks  
 extraction





# Entanglement transition

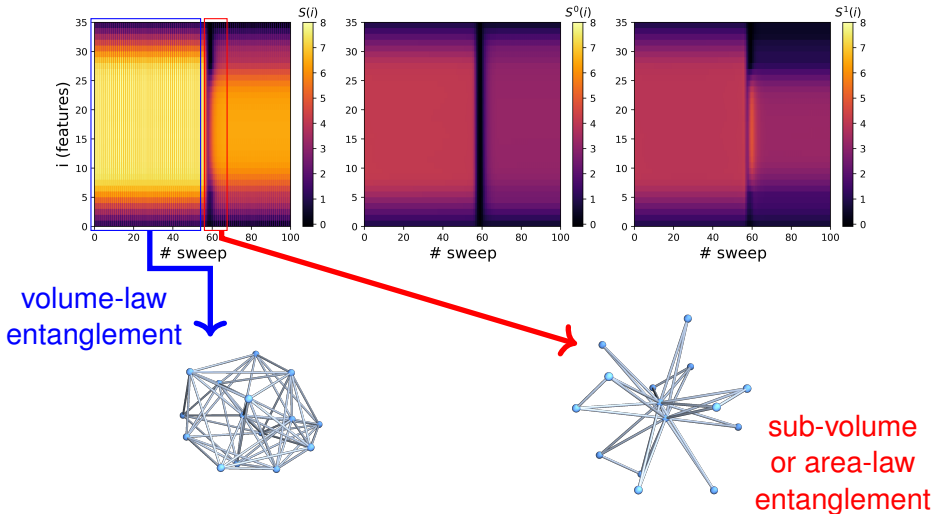


volume-law  
entanglement



sub-volume  
or area-law  
entanglement

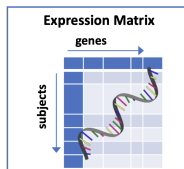
# Entanglement transition



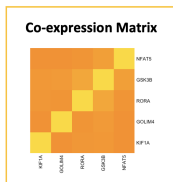
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# Hepatocellular carcinoma (HCC) classification



$$r_{ij} = \frac{\sum_{a=1}^N (i_a - \bar{i}) \sum_{b=1}^N (j_b - \bar{j})}{\sqrt{\sum_{a=1}^N (i_a - \bar{i})^2} \sqrt{\sum_{b=1}^N (j_b - \bar{j})^2}}$$



hierarchical  
clustering:  
46 stable  
communities  
C1, ..., C46

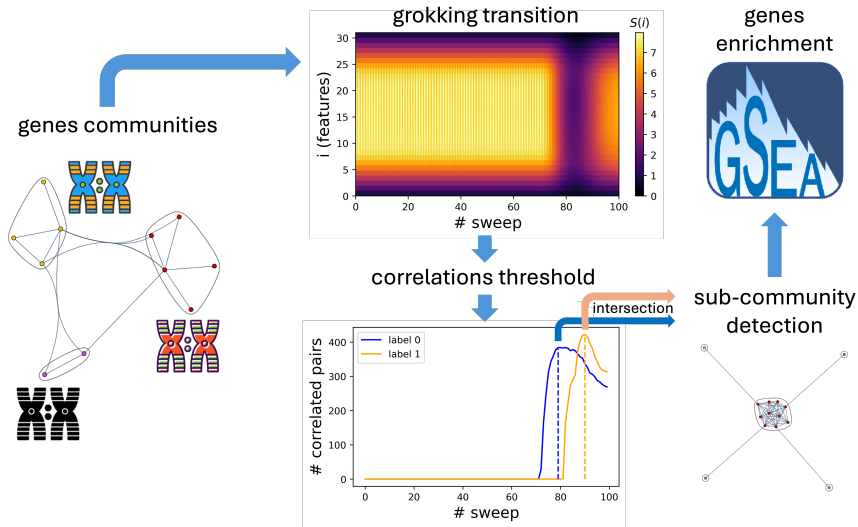
**Training set:** GSE102079 Dataset 140 samples (83 HCC)

**Independent set:** GSE54236 Dataset with 161 samples (81 HCC)

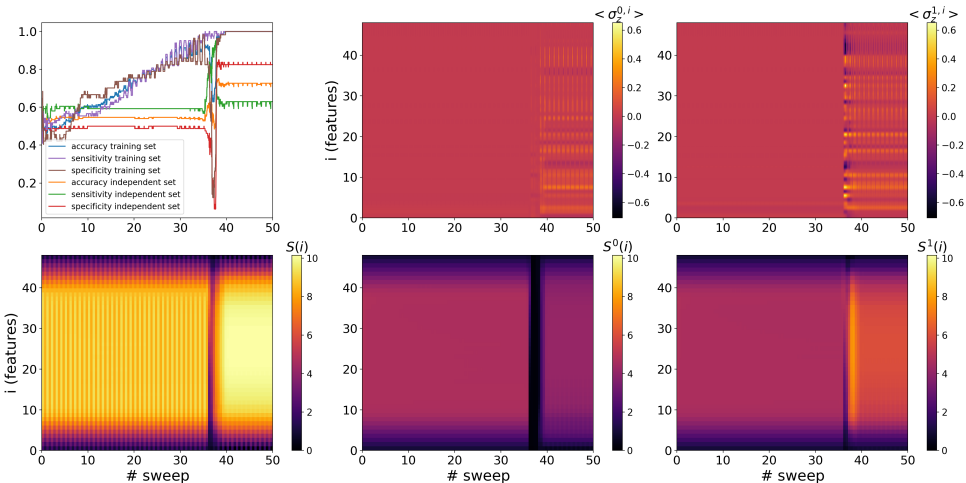
	# genes		# genes		# genes		# genes
C8	28	C17	26	C29	48	C35	31
C12	47	C23	31	C30	32	C40	29
C14	31	C24	23	C31	25	C41	48
C15	25	C27	36	C32	35	C42	33
C16	34	C28	35	C33	35	C43	32

Lacalamita *et al.*, Artificial Intelligence and Complex Network Approaches Reveal Potential Gene Biomarkers for Hepatocellular Carcinoma, Int. J. Mol. Sci. 24 (2023)

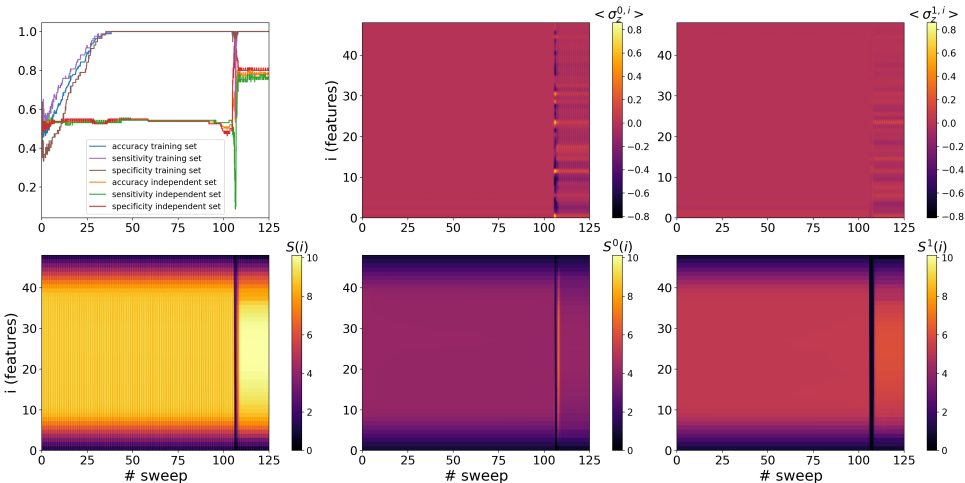
# Flowchart



# Biologically meaningful gene communities: C29



# Biologically meaningful gene communities: C41



# Volume to sub-volume law entanglement transition

Left boundary:  $\log S = q + c \log i$

Right boundary:  $\log S = q + c \log(N - i)$

	transition slope	transition $R^2$	initial slope	initial $R^2$	final slope	final $R^2$
C8	0.991	0.972	0.972	0.999	0.704	0.997
C12	0.700	0.987	0.988	1.000	0.771	0.998
C14	0.823	0.967	0.969	0.999	0.602	0.997
C15	0.656	0.992	0.971	0.999	0.640	0.998
C16	0.426	0.982	0.970	0.999	0.606	0.995
C17	0.595	0.997	0.971	0.999	0.612	0.997
C23	0.579	0.963	0.962	0.999	0.628	0.998
C24	0.611	0.943	0.890	0.989	0.570	0.999
C27	0.849	0.974	0.972	0.999	0.754	0.998
C28	0.852	0.989	0.989	1.000	0.635	0.999
C29	0.986	0.982	0.987	1.000	0.760	0.997
C30	0.538	0.980	0.972	0.999	0.564	0.996
C31	0.602	0.982	0.970	0.999	0.611	0.997
C32	0.789	0.989	0.971	0.999	0.575	0.993
C33	0.876	0.976	0.970	0.999	0.641	0.998
C35	0.708	0.994	0.970	0.999	0.618	0.998
C40	0.408	0.971	0.979	0.999	0.557	0.999
C41	0.611	0.979	0.989	1.000	0.757	0.997
C42	0.469	0.956	0.970	0.999	0.626	0.997
C43	0.492	0.944	0.971	0.999	0.634	0.998

	transition slope	transition $R^2$	initial slope	initial $R^2$	final slope	final $R^2$
C8	0.686	0.995	0.938	0.997	0.630	0.999
C12	1.004	0.972	0.974	0.999	0.761	0.996
C14	0.453	0.991	0.934	0.997	0.597	0.996
C15	0.919	0.991	0.937	0.997	0.639	0.997
C16	0.701	0.986	0.935	0.997	0.620	0.996
C17	0.835	0.977	0.937	0.997	0.626	0.998
C23	0.765	0.968	0.920	0.994	0.611	0.997
C24	0.728	0.981	0.794	0.973	0.496	0.995
C27	0.668	0.995	0.942	0.997	0.674	0.997
C28	0.670	0.987	0.972	0.999	0.669	0.998
C29	0.714	0.966	0.972	0.999	0.759	0.999
C30	0.873	0.990	0.939	0.997	0.604	0.995
C31	0.806	0.995	0.938	0.997	0.633	0.996
C32	0.654	0.962	0.934	0.997	0.566	0.998
C33	0.961	0.918	0.936	0.997	0.620	1.000
C35	0.766	0.989	0.939	0.997	0.604	0.996
C40	0.656	0.943	0.939	0.997	0.601	0.997
C41	0.726	0.965	0.973	0.999	0.769	0.993
C42	0.715	0.986	0.935	0.997	0.631	0.996
C43	0.701	0.971	0.935	0.997	0.612	0.995



## New enriched gene sub-communities

	C8	C12	C14	C15	C16	C17	C23	C24	C27	C28	C29	C30	C31	C32	C33	C35	C40	C41	C42	C43
accuracy	0.60	0.63	0.48	0.58	0.66	0.58	0.77	0.68	0.57	0.75	0.73	0.68	0.68	0.60	0.67	0.71	0.65	0.78	0.65	0.61
sensitivity	0.41	0.41	0.57	0.56	0.58	0.43	0.69	0.53	0.59	0.63	0.63	0.65	0.77	0.56	0.59	0.69	0.49	0.75	0.49	0.65
specificity	0.79	0.86	0.39	0.60	0.75	0.72	0.85	0.84	0.54	0.86	0.82	0.70	0.59	0.64	0.75	0.74	0.80	0.80	0.81	0.56

Correlation:  $C_{i,j}^k = \left( \langle \sigma_Z^{k,i} \sigma_Z^{k,j} \rangle - \langle \sigma_Z^{k,i} \rangle \langle \sigma_Z^{k,j} \rangle \right) / \varrho_{k,k}^{(\ell)}, |C_{i,j}^k| < t, t \in [0, 1], \text{ step } 0.1$

# New enriched gene sub-communities

	C8	C12	C14	C15	C16	C17	C23	C24	C27	C28	C29	C30	C31	C32	C33	C35	C40	C41	C42	C43
accuracy	0.60	0.63	0.48	0.58	0.66	0.58	0.77	0.68	0.57	0.75	0.73	0.68	0.68	0.60	0.67	0.71	0.65	0.78	0.65	0.61
sensitivity	0.41	0.41	0.57	0.56	0.58	0.43	0.69	0.53	0.59	0.63	0.63	0.65	0.77	0.56	0.59	0.69	0.49	0.75	0.49	0.65
specificity	0.79	0.86	0.39	0.60	0.75	0.72	0.85	0.84	0.54	0.86	0.82	0.70	0.59	0.64	0.75	0.74	0.80	0.80	0.81	0.56

Correlation:  $C_{ij}^k = \left( \langle \sigma_Z^{k,i} \sigma_Z^{k,j} \rangle - \langle \sigma_Z^{k,i} \rangle \langle \sigma_Z^{k,j} \rangle \right) / \varrho_{k,k}^{(\ell)}, |C_{ij}^k| < t, t \in [0, 1], \text{ step } 0.1$



C16	C29	C41
GOBP_NEGATIVE_REGULATION_OF_WNT_SIGNALING_PATHWAY	GOBP_AMBODDIAL_TYPE_CELL_MIGRATION	GOBP_POSITIVE_REGULATION_OF_INTRACELLULAR_SIGNAL_TRANSDUCTION
GOBP_OSSIFICATION	GOBP_EMBRYONIC_PLACENTA_MORPHOGENESIS	GOBP_CELL_CHEMOTAXIS
GOBP_HEART_MORPHOGENESIS	GOBP_MORPHOGENESIS_OF_AN_EPITHELIAL_FOLD	GOBP_NEGATIVE_REGULATION_OF_RESPONSE_TO_STIMULUS
GOBP_GLYCOSAMINOGLYCAN_BINDING	GOBP_NEURAL_TUBE_FORMATION	REACTOME_CLASS_B_2_SECRETIN_FAMILY_RECEPTORS
GOBP_CELL_CELL_SIGNALING_BY_WNT	GOBP_ODONTOGENESIS_OF_DENTIN_CONTAINING_TOOTH	REACTOME_GPCR_LIGAND_BINDING
GOBP_POSITIVE_REGULATION_OF_NERVOUS_SYSTEM_DEVELOPMENT	GOBP_NEGATIVE_REGULATION_OF KERATINOCYTE_PROLIFERATION	GOBP_SIGNALING_RECEPTOR_REGULATOR_ACTIVITY
GOBP_NEGATIVE_REGULATION_OF_CANONICAL_WNT_SIGNALING_PATHWAY	GOBP_REGULATION_OF_CANONICAL_WNT_SIGNALING_PATHWAY	GOBP_TUBE_MORPHOGENESIS
GOBP_SKELETAL_SYSTEM_DEVELOPMENT	GOBP_IN_UTERO_EMBRYONIC_DEVELOPMENT	GOBP_NEGATIVE_REGULATION_OF_MULTICELLULAR_ORGANISMAL_PROCESS
WNT_SIGNALING	GOBP_LABYRINTHINE_LAYER_MORPHOGENESIS	GOBP_NEGATIVE_REGULATION_OF_VIRAL_ENTRY_INTO_HOST_CELL
C28	WP_ANDROGENESIS	GOBP_INFLAMMATORY_RESPONSE
GOBP_COMPLEMENT_ACTIVATION_LLECTIN_PATHWAY	GOBP_METANEPHRIC_GLOMERULUS_DEVELOPMENT	GOBP_POSITIVE_REGULATION_OF_SIGNALING
KEGG_COMPLEMENT_AND_COAGULATION_CASCADES	GOBP_MESENCHYMAL_CELL_DIFFERENTIATION	GOBP_RESPONSE_TO_POTASSIUM_ION
GOBP_COMPLEMENT_ACTIVATION	KEGG_MEDICUS_REFERENCE_REGULATION_OF_Df_RTK_RAS_ERK_SIGNALING_UPQUININATION_OF_ITK_BY_CBL	GOBP_MARK_CASCADE
KEGG_POLYATE_BIOSYNTHESIS	GOBP_GLAND_DEVELOPMENT	GOBP_SKELETAL_SYSTEM_DEVELOPMENT
C30	GOBP_MALE_DENTALIA_DEVELOPMENT	REACTOME_PLATELET_ACTIVATION_SIGNALING_AND_AGGREGATION
GOCC_VACUOLE	GOBP_RESPONSE_TO_ALCOHOL	GOBP_PROTEIN_CONTAINING_COMPLEX_BINDING
GOBP_MONONUCLEAR_CELL_MIGRATION	C35	GOBP_HORMONE_BINDING
GOBP_REGULATION_OF_BLOOD_PRESSURE	GOBP_PURINERGIC_NUCLEOTIDE_RECEPTOR_SIGNALING_PATHWAY	REACTOME_HEMOSTASIS
GOBP_MACROPHAGE_CHEMOTAXIS	GOBP_MATURE_B_CELL_DIFFERENTIATION_INVOLVED_IN_IMMUNE_RESPONSE	REACTOME_ERYTHROCYTES_TAKE_UP_CARBON_DIOXIDE_AND_RELEASE_OXYGEN
GOBP_CELLULAR_RESPONSE_TO_OXYGEN_CONTAINING_COMPOUND	GOBP_POSITIVE_REGULATION_OF_MOLECULAR_FUNCTION	WP_GPCRS_CLASS_B_SECRETINLIKE
KEGG_FOSL_ADHESION	GOBP_MONODATOMIC_ION_TRANSPORT	GOCC_SECRETORY GRANULE
GOBP_MONOATOMIC_CATION_TRANSMEMBRANE_TRANSPORT	GOBP_POSITIVE_REGULATION_OF_PP1PTI1_TYROSINE_PHOSPHORYLATION	REACTOME_G_ALPHA_B_SIGNALING_EVENTS
GOBP_REGULATION_OF_CELL_CELL_ADHESION	GOBP_NEGATIVE_REGULATION_OF_LYMPHOCTE_ACTIVATION	GOBP_CELL_ACTIVATION
WP_MIRNA_TARGETS_IN_FCM_AND_MEMBRANE_RECEPTORS	C40	GOBP_RESPONSE_TO_OXYGEN_CONTAINING_COMPOUND
REACTOME_DISEASES_ASSOCIATED_WITH_GLYCOSAMINOGLYCAN_METABOLISM	GOBP_VASE_ACTIVITY	GOBP_ACTIVATION_OF_MMARF_RESPONSE
PD_FBA_PATHWAY	GOBP_GENERATION_OF_PRECURSOR_METABOLITES_AND_ENERGY	

## Conclusions

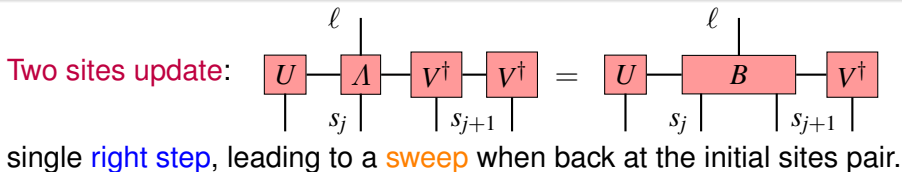
- ▶ Monitoring the **training dynamics** allows us to identify critical behaviors influencing generalization properties;
- ▶ MPS classifiers are able to manage high computational complexity and highlight **local magnetization** for each “mask” trained per class;
- ▶ **Grokking** implies an entanglement phase transition, but the viceversa does not hold true;
- ▶ **Correlations** allow us to identify gene sub-communities endowed with enriched gene sets.

## Conclusions

- ▶ Monitoring the **training dynamics** allows us to identify critical behaviors influencing generalization properties;
- ▶ MPS classifiers are able to manage high computational complexity and highlight **local magnetization** for each “mask” trained per class;
- ▶ **Grokking** implies an entanglement phase transition, but the viceversa does not hold true;
- ▶ **Correlations** allow us to identify gene sub-communities endowed with enriched gene sets.

**Thank you!**  
**Questions/Comments?**

# Gradient descent



# Gradient descent

Two sites update:

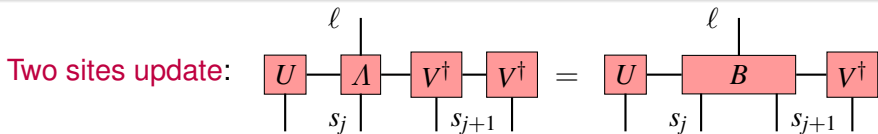
$$\begin{array}{c} \ell \\ | \\ \boxed{U} \end{array} \begin{array}{c} | \\ \boxed{\Lambda} \\ | \\ s_j \end{array} \begin{array}{c} | \\ \boxed{V^\dagger} \\ | \\ s_{j+1} \end{array} \begin{array}{c} | \\ \boxed{V^\dagger} \\ | \\ s_{j+1} \end{array} = \begin{array}{c} \ell \\ | \\ \boxed{U} \end{array} \begin{array}{c} | \\ \boxed{B} \\ | \\ s_j \end{array} \begin{array}{c} | \\ \boxed{V^\dagger} \\ | \\ s_{j+1} \end{array}$$

single **right step**, leading to a **sweep** when back at the initial sites pair.

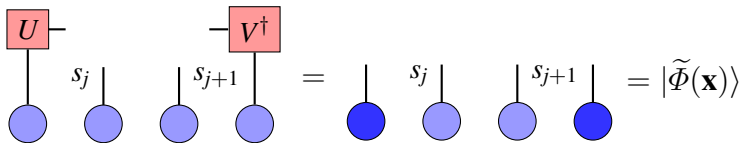
$$\begin{array}{c} \boxed{U} \\ | \\ \text{blue circle} \end{array} \begin{array}{c} | \\ s_j \\ | \\ \text{blue circle} \end{array} \begin{array}{c} | \\ \boxed{V^\dagger} \\ | \\ \text{blue circle} \end{array} \begin{array}{c} | \\ s_{j+1} \\ | \\ \text{blue circle} \end{array} = \begin{array}{c} | \\ s_j \\ | \\ \text{dark blue circle} \end{array} \begin{array}{c} | \\ \text{blue circle} \end{array} \begin{array}{c} | \\ s_{j+1} \\ | \\ \text{blue circle} \end{array} \begin{array}{c} | \\ \text{dark blue circle} \end{array} = |\tilde{\Phi}(\mathbf{x})\rangle$$

$$f_W^\ell(\mathbf{x}) = \sum_{s_j, s_{j+1}} \sum_{a_{j-1}, a_{j+1}} B_{s_j, s_{j+1}}^{a_{j-1}, \ell, a_{j+1}} |\tilde{\Phi}(\mathbf{x})_{a_{j-1}, a_{j+1}}^{s_j, s_{j+1}}\rangle$$

# Gradient descent



single **right step**, leading to a **sweep** when back at the initial sites pair.



$$f_W^\ell(\mathbf{x}) = \sum_{s_j, s_{j+1}} \sum_{a_{j-1}, a_{j+1}} B_{s_j, s_{j+1}}^{a_{j-1}, \ell, a_{j+1}} |\tilde{\Phi}(\mathbf{x})_{a_{j-1}, a_{j+1}}^{s_j, s_{j+1}}\rangle$$

$$\Delta B^\ell = -\frac{\partial \mathcal{C}}{\partial B^\ell} = \sum_{\omega=1}^{N_T} |\tilde{\Phi}(\mathbf{x}_\omega)\rangle \otimes (y_\omega^\ell - f_W^\ell(\mathbf{x}_\omega)) \implies B'^\ell = B^\ell + \alpha \Delta B^\ell$$

Stoudenmire, Schwab, Supervised Learning with Tensor Networks, 2016

## Measured observables

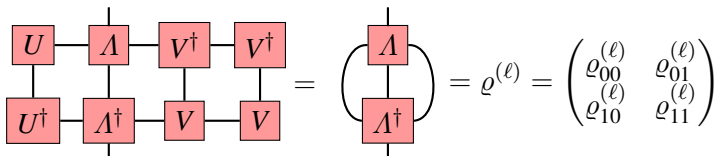
- Reduced density matrix:

$$U \Lambda V^\dagger V^\dagger = \Lambda \Lambda^\dagger = \rho^{(\ell)} = \begin{pmatrix} \rho_{00}^{(\ell)} & \rho_{01}^{(\ell)} \\ \rho_{10}^{(\ell)} & \rho_{11}^{(\ell)} \end{pmatrix}$$

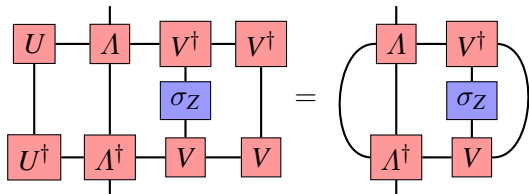


## Measured observables

- Reduced density matrix:

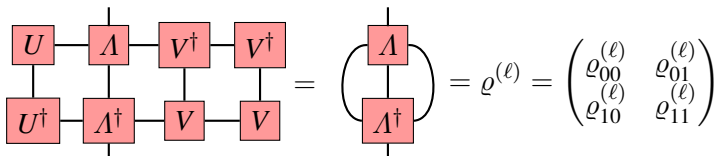


- Local magnetization  
 $\langle \sigma_Z^{k,i} \rangle, k = 0, 1:$

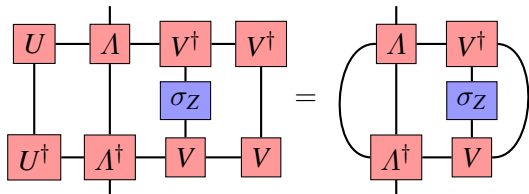


# Measured observables

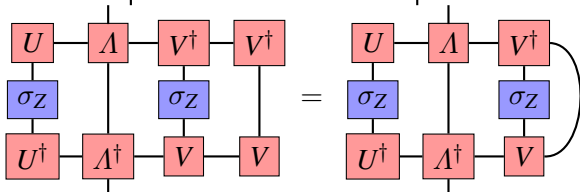
- ▶ Reduced density matrix:



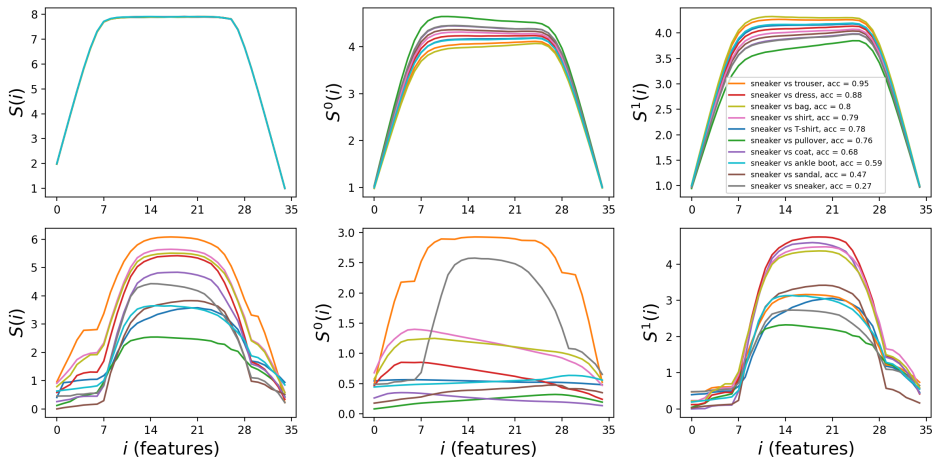
- ▶ Local magnetization  
 $\langle \sigma_Z^{k,i} \rangle, k = 0, 1:$



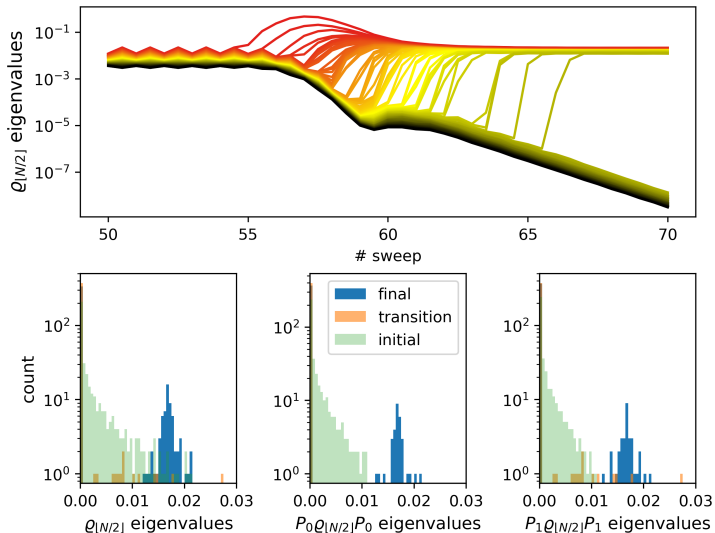
- ▶ Correlation function  
 $\langle \sigma_Z^{k,i} \sigma_Z^{k,j} \rangle, k = 0, 1:$



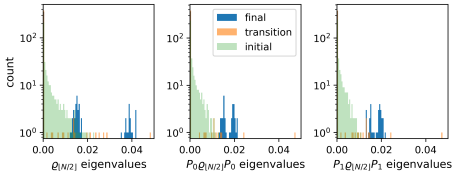
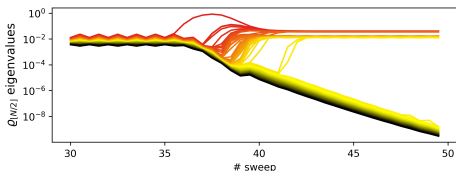
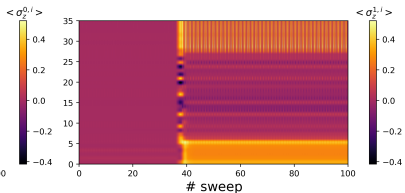
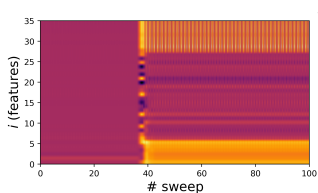
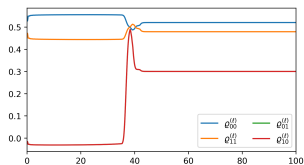
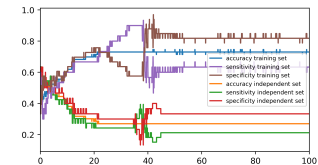
# Binary sneaker classifications entropies



# Entanglement transition

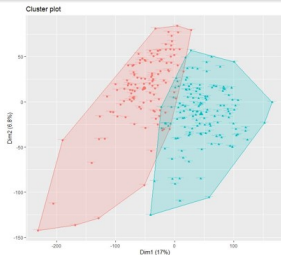


# Fake classification sneaker vs sneaker with coherence



# Hepatocellular carcinoma (HCC) classification

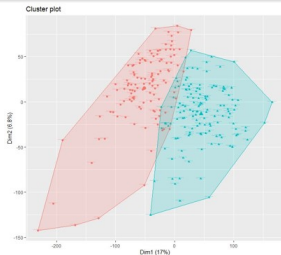
GSE102079  
Dataset  
257 samples  
(152 HCC)



	Cluster 1	Cluster 2
Normal + Peritumoral	100	5
HCC	20	132

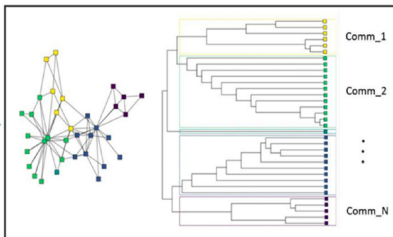
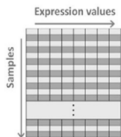
# Hepatocellular carcinoma (HCC) classification

GSE102079  
Dataset  
257 samples  
(152 HCC)

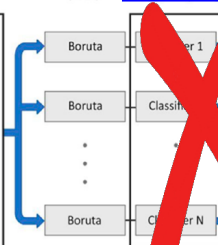


	Cluster 1	Cluster 2
Normal + Peritumoral	100	5
HCC	20	132

Step 1  
Hierarchical  
community  
detection



Step 2  
Filtering (40%)  
Classification



MPS  
classification

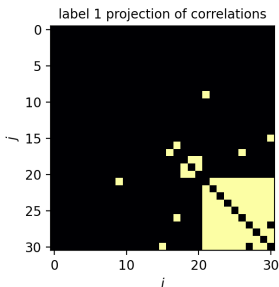
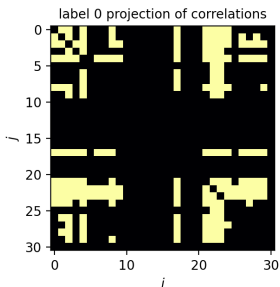
HCC vs Ctrl  
Classification

Step 3  
XGBoost analysis

# MPS correlations for gene community C23

Optimal permutation of features:

$$C_{i,j}^k = \frac{\langle \sigma_Z^{k,i} \sigma_Z^{k,j} \rangle - \langle \sigma_Z^{k,i} \rangle \langle \sigma_Z^{k,j} \rangle}{\rho_{k,k}^{(\ell)}}$$



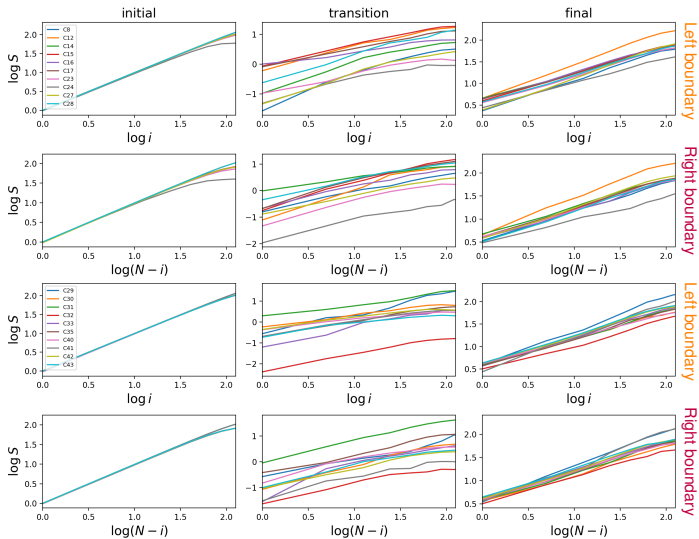
selected pairs

$$|C_{i,j}^k| > 0.5$$

Decreased bond dimension: 400  $\rightarrow$  300, still showing magnetization after  $\approx 30$  sweeps

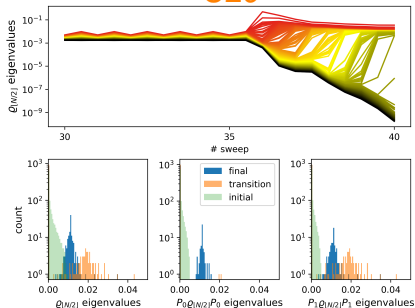


# Volume to sub-volume law entanglement transition

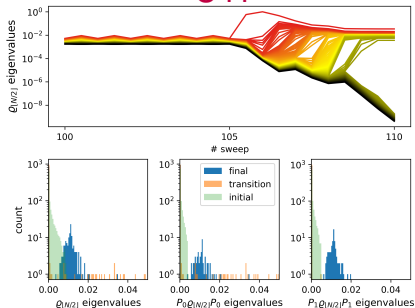


# Eigenvalues evaporation and correlations

C29

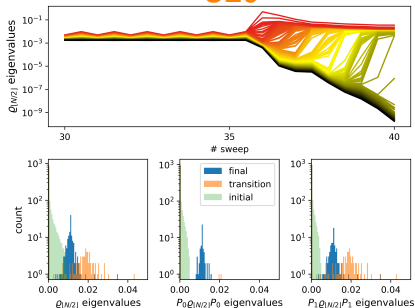


C41



# Eigenvalues evaporation and correlations

C29



C41

