



上海交通大学  
SHANGHAI JIAO TONG UNIVERSITY



浙江大学  
ZHEJIANG UNIVERSITY



上海人工智能实验室  
Shanghai Artificial Intelligence Laboratory



---

# Towards the Dynamics of a DNN Learning Symbolic Interactions

---

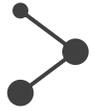
Qihan Ren<sup>\*1</sup>, Junpeng Zhang<sup>\*1</sup>, Yang Xu<sup>2</sup>, Yue Xin<sup>1</sup>, Dongrui Liu<sup>3</sup>, Quanshi Zhang<sup>†1</sup>

<sup>1</sup> Shanghai Jiao Tong University

<sup>2</sup> Zhejiang University    <sup>3</sup> Shanghai Artificial Intelligence Laboratory

\* Equal contribution

† Correspondence



# Motivation and contribution

---

Whether the inference logic of a DNN can be faithfully explained as **symbolic concepts/primitives**?

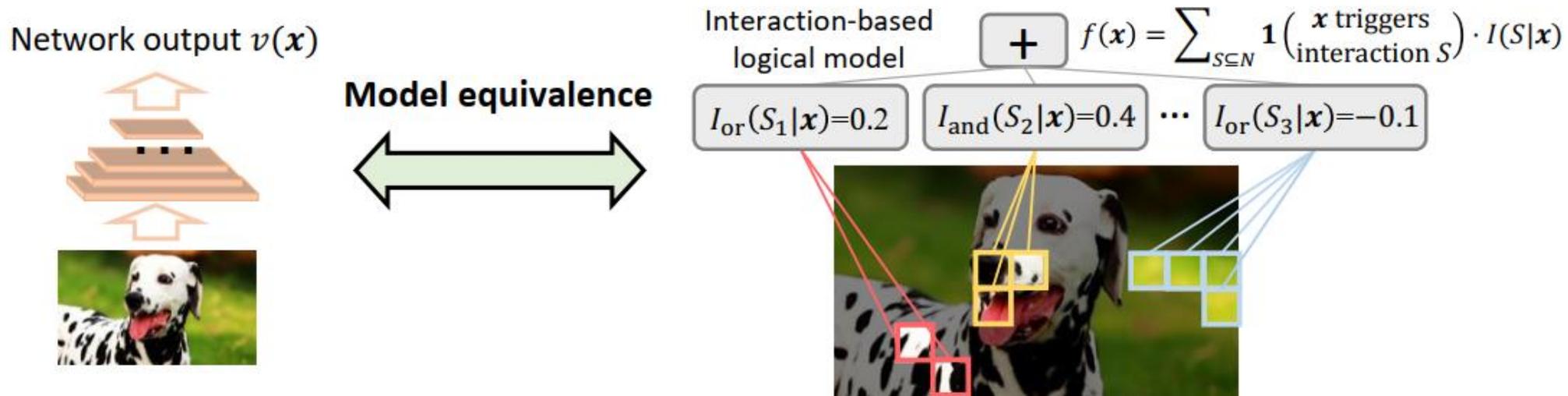
- How to define concepts encoded by a DNN: an open problem!
  - **Many previous studies**: based on intuition and empirical observation
  - **Recent studies**: mathematically formulate concepts using **interactions**, having observed<sup>[1]</sup> and proved<sup>[2]</sup> the **emergence of sparse interaction concepts**
  - Empirically observed<sup>[3]</sup> the **two-phase dynamics of interaction concepts**, which explains the change of generalizability at the concept level
- **Our main contribution**:  
**Theoretically prove** the two-phase dynamics of interaction concepts

[1] Li and Zhang. Does a Neural Network Really Encode Symbolic Concept? ICML 2023.

[2] Ren et al. Where We Have Arrived in Proving the Emergence of Sparse Symbolic Primitives in DNNs. ICLR, 2024.

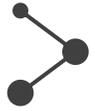
[3] Zhang et al. Two-Phase Dynamics of Interactions Explains the Starting Point of a DNN Learning Over-Fitted Features. arXiv preprint arXiv: 2405.10262v1.

# ➤ Preliminary: interactions



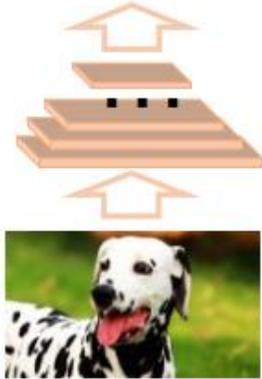
Given a DNN  $v: \mathbb{R}^n \rightarrow \mathbb{R}$  and an input sample  $\mathbf{x}$  with  $n$  input variables  $N = \{1, \dots, n\}$ , the network output  $v(\mathbf{x})$  can be **disentangled into different interaction effects**:

$$v(\mathbf{x}) = v(\mathbf{x}_\emptyset) + \sum_{\emptyset \neq S \subseteq N} I_{\text{and}}(S|\mathbf{x}) + \sum_{\emptyset \neq S \subseteq N} I_{\text{or}}(S|\mathbf{x})$$

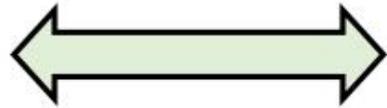


# Preliminary: interactions

Network output  $v(\mathbf{x})$



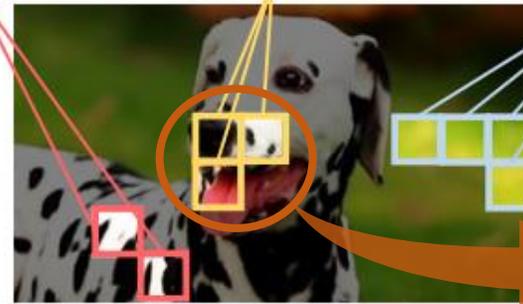
Model equivalence



Interaction-based logical model

$$f(\mathbf{x}) = \sum_{S \subseteq N} \mathbf{1}(\mathbf{x} \text{ triggers interaction } S) \cdot I(S|\mathbf{x})$$

$$I_{\text{or}}(S_1|\mathbf{x})=0.2 \quad I_{\text{and}}(S_2|\mathbf{x})=0.4 \quad \dots \quad I_{\text{or}}(S_3|\mathbf{x})=-0.1$$



AND relationship

Given a DNN  $v: \mathbb{R}^n \rightarrow \mathbb{R}$  and an input sample  $\mathbf{x}$  with  $n$  input variables  $N = \{1, \dots, n\}$ , the network output  $v(\mathbf{x})$  can be **disentangled into different interaction effects**:

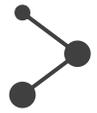
$$v(\mathbf{x}) = v(\mathbf{x}_\emptyset) + \sum_{\emptyset \neq S \subseteq N} I_{\text{and}}(S|\mathbf{x}) + \sum_{\emptyset \neq S \subseteq N} I_{\text{or}}(S|\mathbf{x})$$

AND interactions

OR interactions

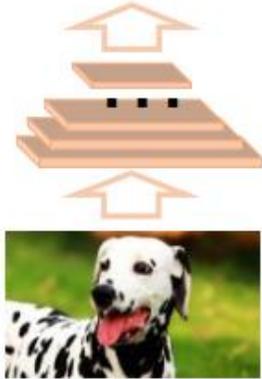
$$I_{\text{and}}(S|\mathbf{x}) \stackrel{\text{def}}{=} \sum_{T \subseteq S} (-1)^{|S|-|T|} v_{\text{and}}(\mathbf{x}_T)$$

$$I_{\text{or}}(S|\mathbf{x}) \stackrel{\text{def}}{=} - \sum_{T \subseteq S} (-1)^{|S|-|T|} v_{\text{or}}(\mathbf{x}_{N \setminus T})$$

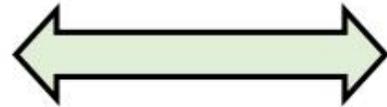


# Preliminary: interactions

Network output  $v(\mathbf{x})$

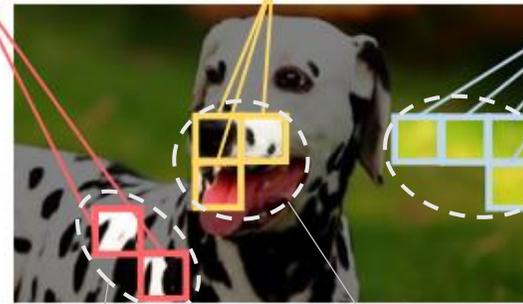
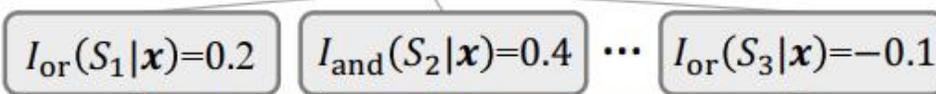


Model equivalence



Interaction-based  
logical model

$$f(\mathbf{x}) = \sum_{S \subseteq N} \mathbf{1}(\mathbf{x} \text{ triggers interaction } S) \cdot I(S|\mathbf{x})$$



2-order OR  
interaction

3-order AND  
interaction

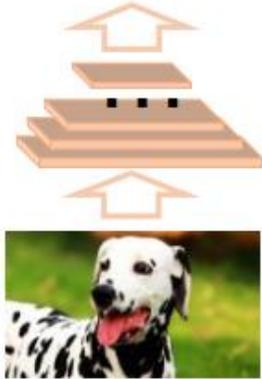
4-order OR  
interaction

- **Complexity (order) of interactions:** defined as  $|S|$

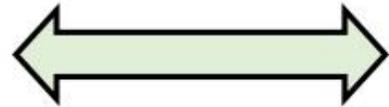


# Preliminary: interactions

Network output  $v(\mathbf{x})$

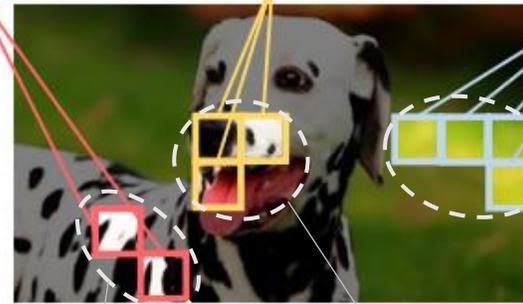


Model equivalence



Interaction-based logical model  $f(\mathbf{x}) = \sum_{S \subseteq N} \mathbf{1}(\mathbf{x} \text{ triggers interaction } S) \cdot I(S|\mathbf{x})$

$I_{\text{or}}(S_1|\mathbf{x})=0.2$   $I_{\text{and}}(S_2|\mathbf{x})=0.4$  ...  $I_{\text{or}}(S_3|\mathbf{x})=-0.1$

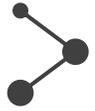


2-order OR interaction

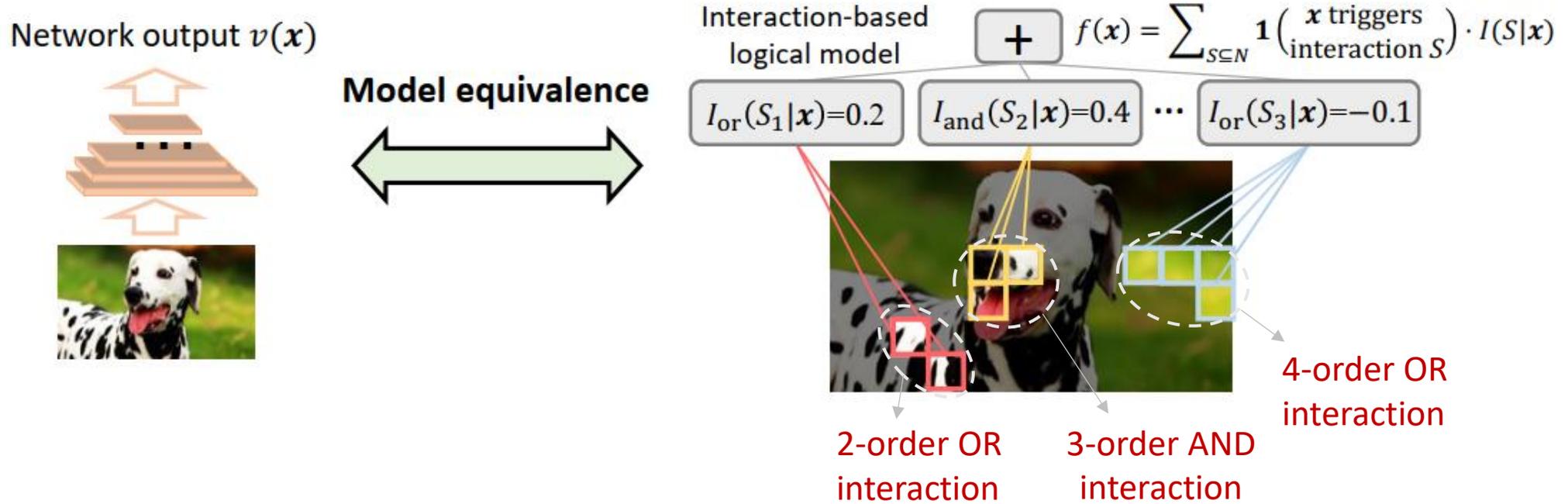
3-order AND interaction

4-order OR interaction

- **Complexity (order) of interactions:** defined as  $|S|$
- If  $|I_{\text{and}}(S|\mathbf{x})|$  or  $|I_{\text{or}}(S|\mathbf{x})|$  is large  $\Rightarrow$  **Salient interaction concept**
- If  $|I_{\text{and}}(S|\mathbf{x})|$  or  $|I_{\text{or}}(S|\mathbf{x})| \approx 0$   $\Rightarrow$  **Noisy pattern**

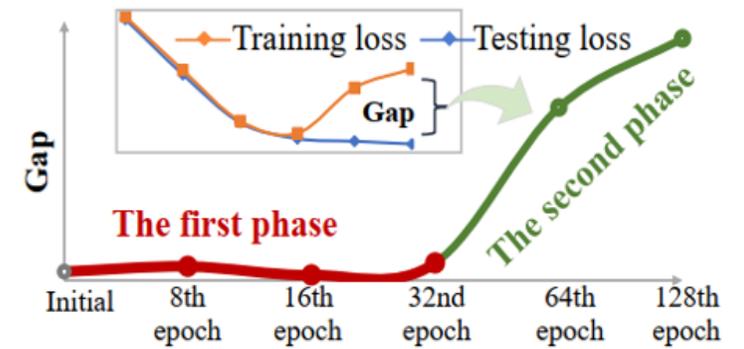
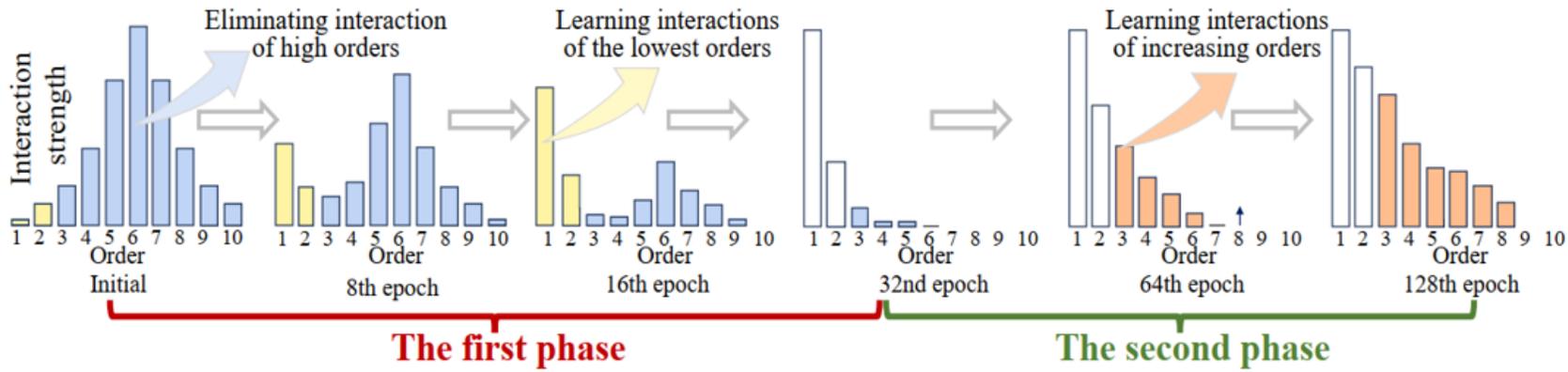


# Preliminary: interactions

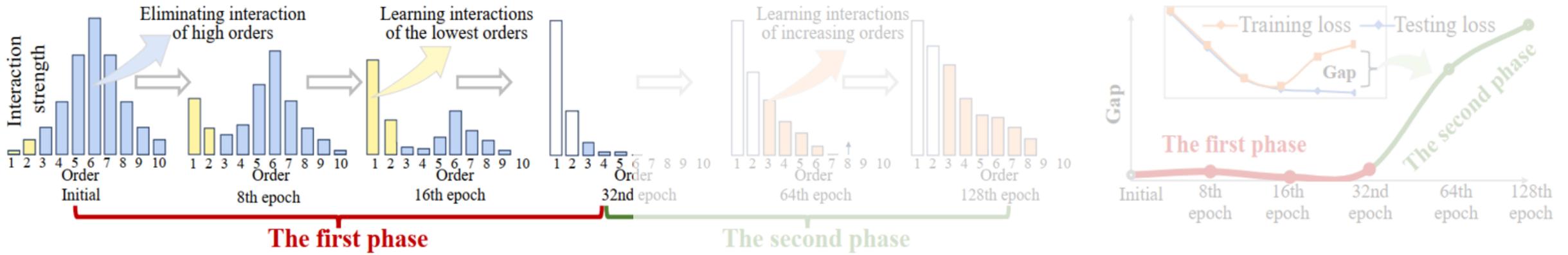


- **Complexity (order) of interactions:** defined as  $|S|$
- If  $|I_{\text{and}}(S|\mathbf{x})|$  or  $|I_{\text{or}}(S|\mathbf{x})|$  is large  $\implies$  **Salient interaction concept**
- If  $|I_{\text{and}}(S|\mathbf{x})|$  or  $|I_{\text{or}}(S|\mathbf{x})| \approx 0$   $\implies$  **Noisy pattern**
- **Desirable properties:** sparsity, universal matching, sample-wise/model-wise transferability...

# Two-phase dynamics of interaction concepts

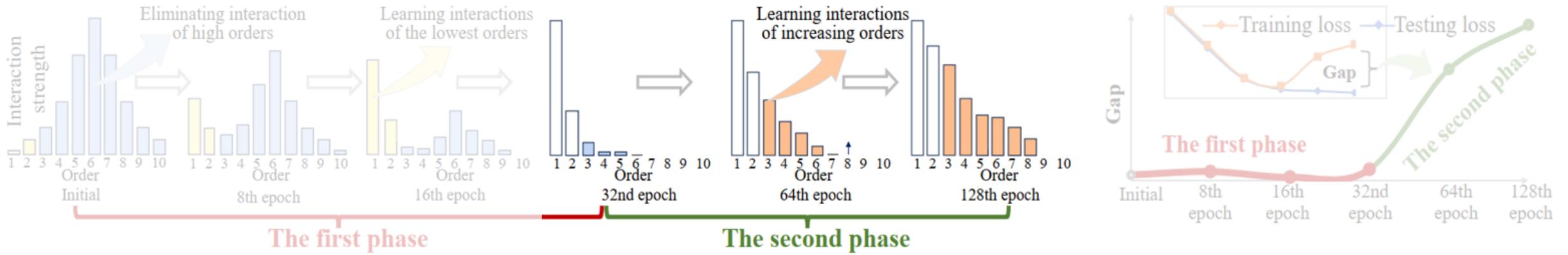


# Two-phase dynamics of interaction concepts



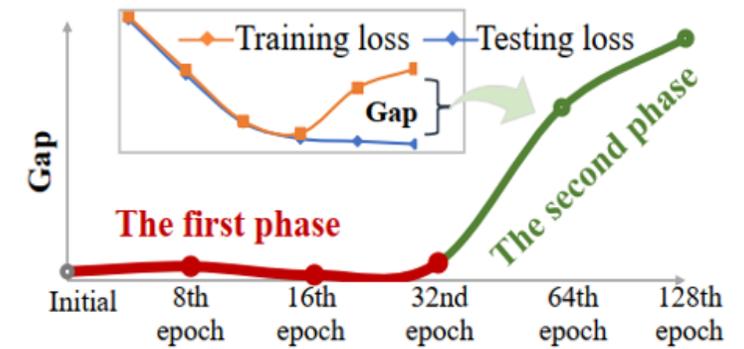
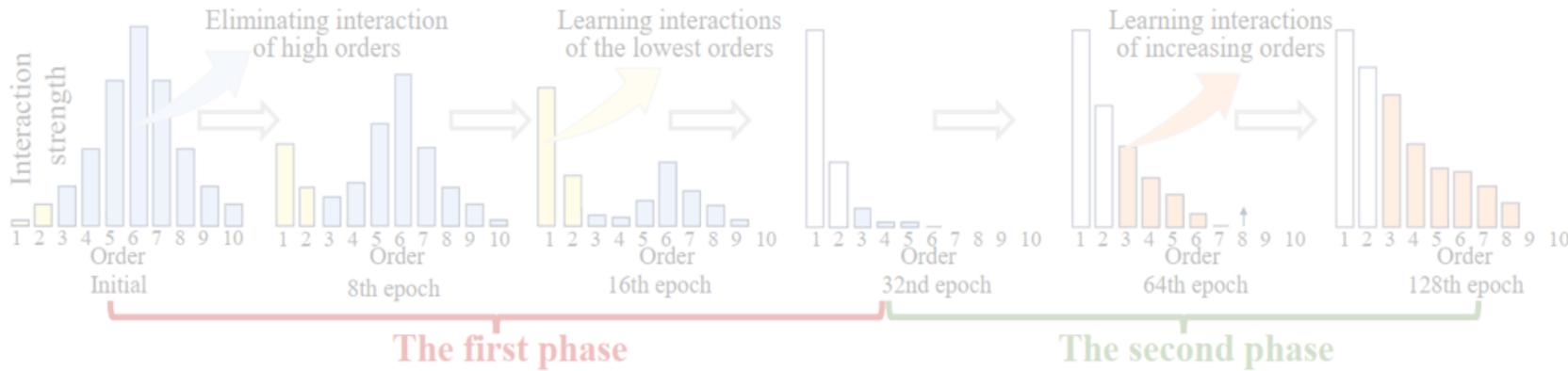
- **First phase:** random noise (spindle-shaped) → low-order (simple) interactions

# Two-phase dynamics of interaction concepts



- **First phase:** random noise (spindle-shaped) → low-order (simple) interactions
- **Second phase:** low-order (simple) interactions → gradually encode high-order (complex) interactions

# Two-phase dynamics of interaction concepts

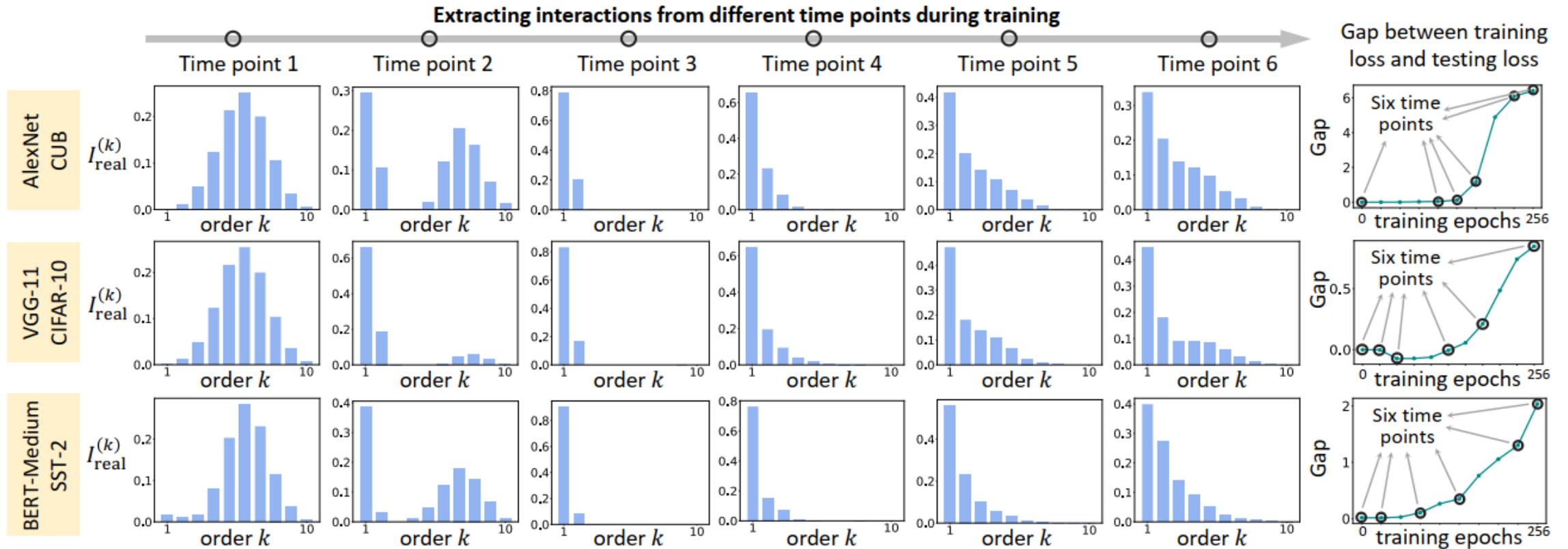


- **First phase:** random noise (spindle-shaped)  $\rightarrow$  low-order (simple) interactions
- **Second phase:** low-order (simple) interactions  $\rightarrow$  gradually encode high-order (complex) interactions
- Two phases are **temporally aligned** with loss gap
  - Complexity of interactions  $\leftrightarrow$  generalizability/overfitting level
  - High-order interactions have weaker generalization power



# Two-phase dynamics are widely observed

- The two-phase dynamics has been observed on different DNNs and datasets



# Theoretical explanation of two-phase dynamics

## Main assumptions

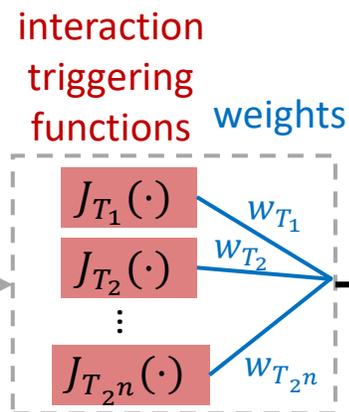
- Reformulate the inference on a sample as a **weighted sum of interaction triggering functions**

Masked sample  $x_S$



DNN

reformulated  
as



$$\sum_{T \subseteq N} w_T J_T(x_S)$$

# Theoretical explanation of two-phase dynamics

## Main assumptions

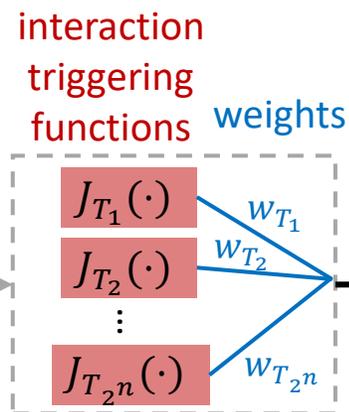
- Reformulate the inference on a sample as a **weighted sum of interaction triggering functions**
- The training of a DNN can be viewed as regressing a set of **potential ground-truth interactions**

Masked sample  $x_S$



DNN

reformulated  
as



Set of ground-truth interactions

$$y(x_S) = \sum_{T \subseteq S} w_T^*$$

$$\sum_{T \subseteq N} w_T J_T(x_S)$$

regression

# Theoretical explanation of two-phase dynamics

## Main assumptions

- Reformulate the inference on a sample as a **weighted sum of interaction triggering functions**
- The training of a DNN can be viewed as regressing a set of **potential ground-truth interactions**
- Parameters in an initialized DNN contain a large amount of noise, and we assume that this **parameter noise gradually decreases during the training process**

Masked sample  $x_S$



DNN

reformulated  
as

interaction  
triggering  
functions weights

$J_{T_1}(\cdot)$   
 $J_{T_2}(\cdot)$   
 $\vdots$   
 $J_{T_{2n}}(\cdot)$

$w_{T_1}$   
 $w_{T_2}$   
 $w_{T_{2n}}$

noise  $\epsilon$  (induced by  
parameter noise)

Set of ground-truth interactions

$$y(x_S) = \sum_{T \subseteq S} w_T^*$$

$$\sum_{T \subseteq N} w_T J_T(x_S)$$

regression

↓ as training time  $t$  ↑

# Theoretical explanation of two-phase dynamics

---

## Analytical solution

- Interactions encoded by the DNN at an intermediate point during training can be formulated as the solution to the following objective:

$$\arg \min_{\mathbf{w}} \tilde{L}(\mathbf{w}) , \quad \tilde{L}(\mathbf{w}) = \mathbb{E}_{\epsilon} \mathbb{E}_{S \subseteq N} \left[ \left( \mathbf{y}_S - \mathbf{w}^T (J(\mathbf{x}_S) + \epsilon) \right)^2 \right]$$

$\mathbf{y}_S \stackrel{\text{def}}{=} \mathbf{y}(\mathbf{x}_S) = \sum_{T \subseteq S} \mathbf{w}_T^*$ : set of ground-truth interactions to learn

$\mathbf{w} = \text{vec}(\{\mathbf{w}_T\}_{T \subseteq N})$ : weights,  $|\mathbf{w}_T| \rightarrow$  strength of interaction  $T$

$J(\mathbf{x}) = \text{vec}(\{J_T(\mathbf{x})\}_{T \subseteq N})$ : interaction triggering function,  $\forall \hat{\mathbf{x}}, J_T(\hat{\mathbf{x}}_S) = \mathbf{1}(T \subseteq S)$

$\epsilon = \text{vec}(\{\epsilon_T\}_{T \subseteq N})$ : noise on the interaction triggering function (induced by the parameter noise),  
 $\mathbb{E}[\epsilon_T] = 0, \text{Var}[\epsilon_T] = 2^{|T|} \sigma^2$ .

**As training proceeds, noise level  $\sigma^2$  gradually decreases**

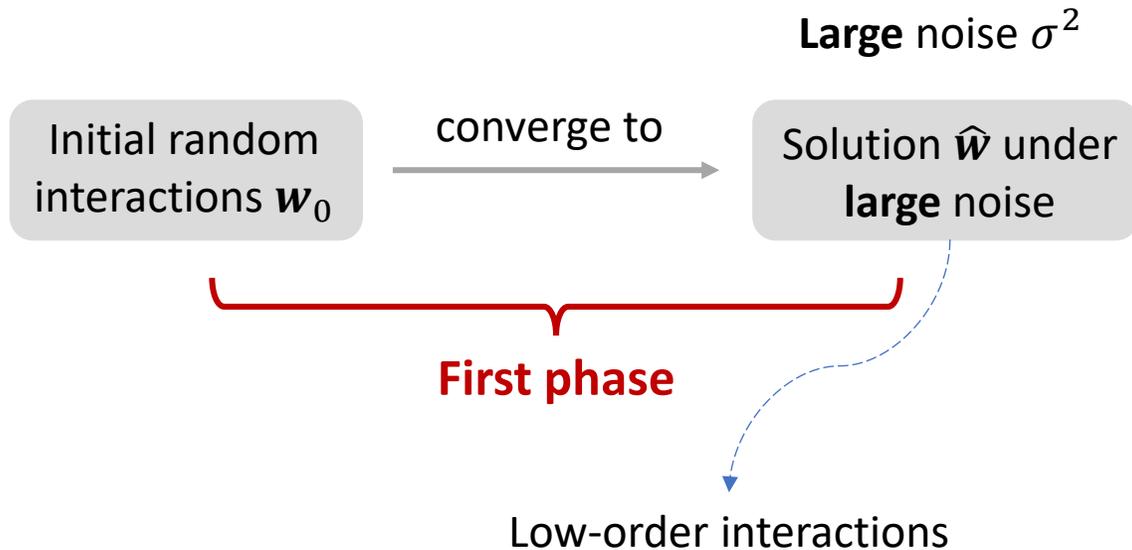
# Theoretical explanation of two-phase dynamics

---

$$\arg \min_{\mathbf{w}} \tilde{L}(\mathbf{w}), \quad \tilde{L}(\mathbf{w}) = \mathbb{E}_{\epsilon} \mathbb{E}_{S \subseteq N} \left[ \left( y_S - \mathbf{w}^T (J(\mathbf{x}_S) + \epsilon) \right)^2 \right]$$

$$\text{Var}[\epsilon_T] = 2^{|T|} \sigma^2$$

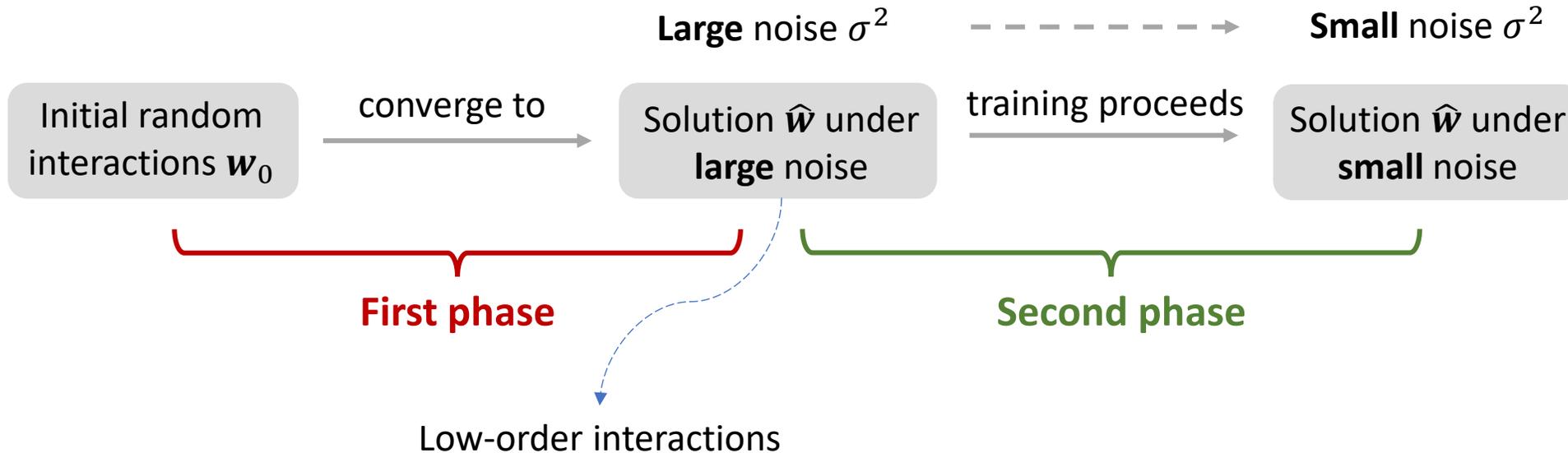
Explaining the two phases based on analytic solution



# Theoretical explanation of two-phase dynamics

$$\arg \min_{\mathbf{w}} \tilde{L}(\mathbf{w}), \quad \tilde{L}(\mathbf{w}) = \mathbb{E}_{\epsilon} \mathbb{E}_{S \subseteq N} \left[ (y_S - \mathbf{w}^T (J(\mathbf{x}_S) + \epsilon))^2 \right] \quad \text{Var}[\epsilon_T] = 2^{|T|} \sigma^2$$

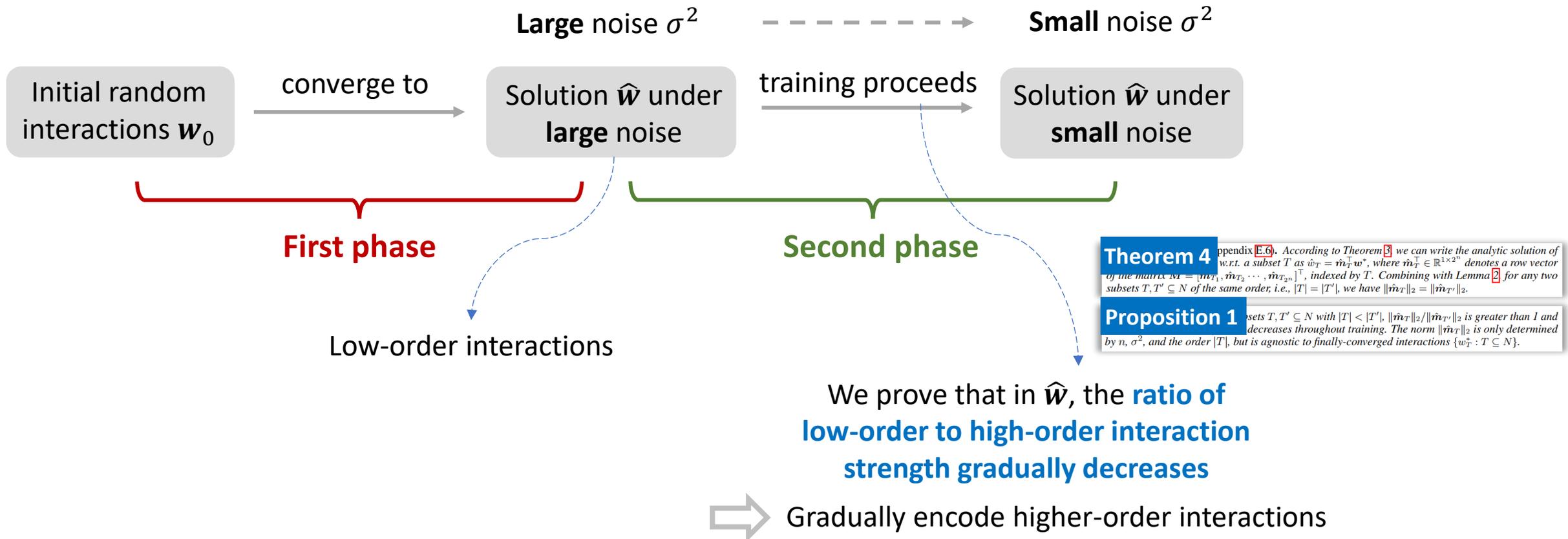
## Explaining the two phases based on analytic solution



# Theoretical explanation of two-phase dynamics

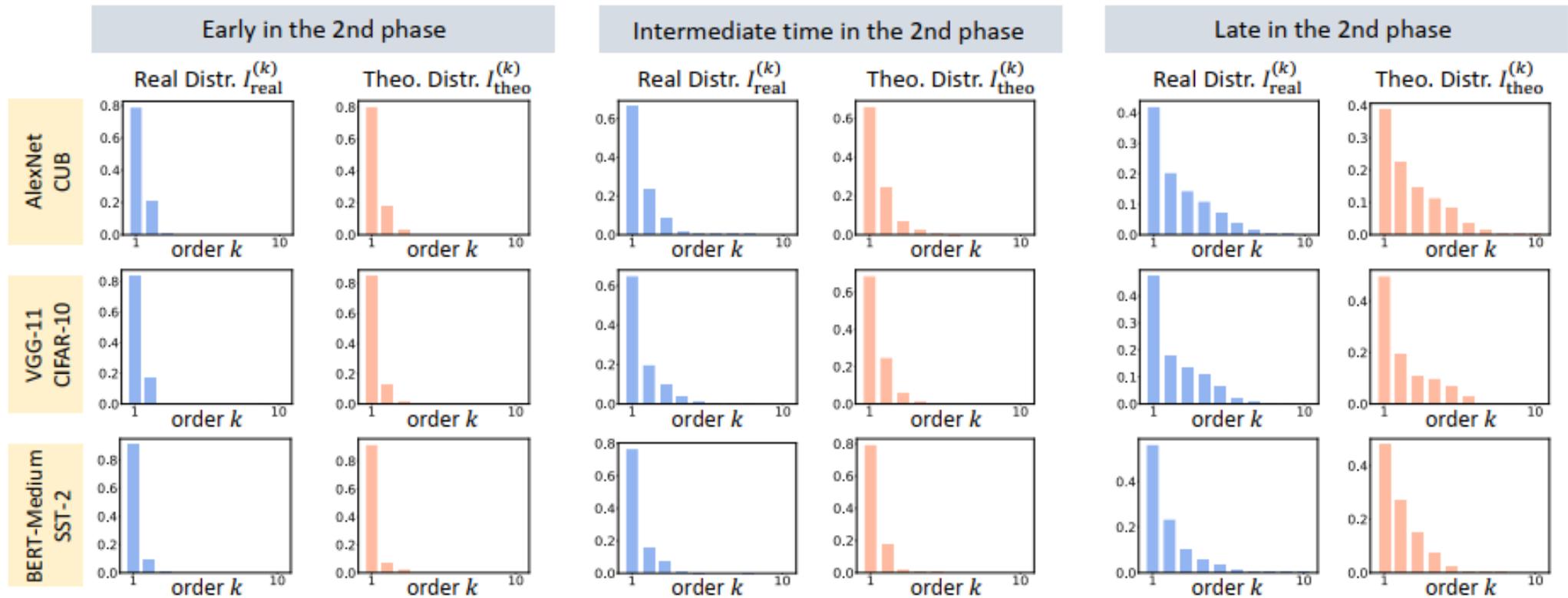
$$\arg \min_{\mathbf{w}} \tilde{L}(\mathbf{w}), \quad \tilde{L}(\mathbf{w}) = \mathbb{E}_{\epsilon} \mathbb{E}_{S \subseteq N} \left[ \left( y_S - \mathbf{w}^T (J(\mathbf{x}_S) + \epsilon) \right)^2 \right] \quad \text{Var}[\epsilon_T] = 2^{|T|} \sigma^2$$

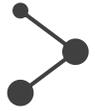
## Explaining the two phases based on analytic solution



# Theoretical vs. real interaction distribution

- Theoretical interaction distribution can well predict real interaction distribution at different time points





# Conclusion

---

In this study:

- We focus on a two-phase dynamics of interaction concepts encoded by a DNN, which is previously discovered to temporally align with the loss gap
- We theoretically prove the two-phase dynamics under certain assumptions
- Our theory can predict real dynamics of interactions quite well