



T-Cell Receptor-Peptide Interaction Prediction with Physical Model Augmented Pseudo-Labeling



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Main Contributions

- ✓ We propose a method that trains the deep neural network with physical modeling and data-augmented pseudo-labeling:
 1. Data-augmented pseudo-labeling of TCR-peptide pairs by a model first trained on the labeled dataset.
 2. Physical modeling between TCRs and peptides by Docking.
- ✓ We introduce a new dataset that contains over 80,000 unknown TCR-peptide pairs with docking energy scores.

Background

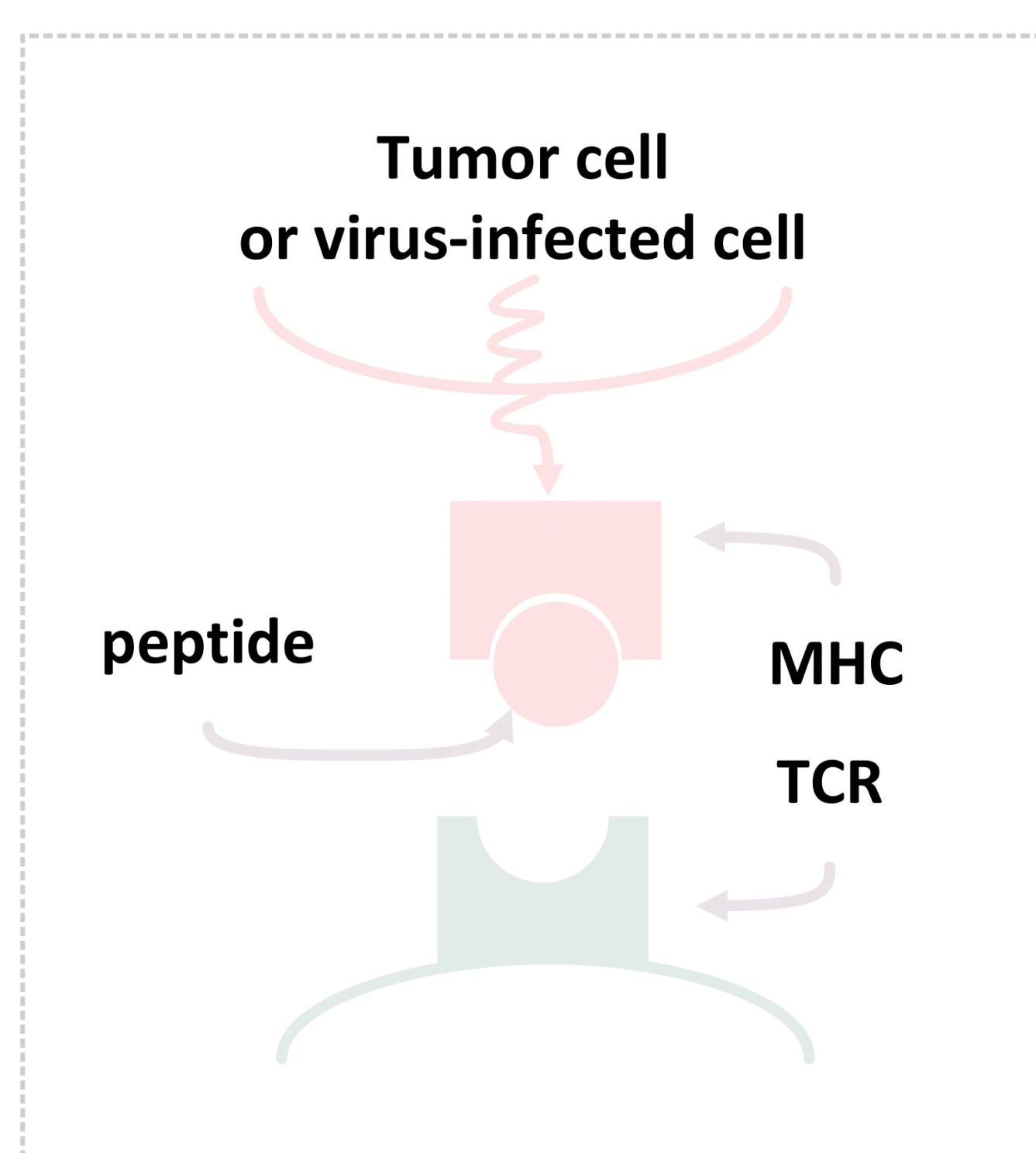


Illustration of T-cell receptors (TCR) and peptide binding: The TCR lies on the surface of the T-cell for recognition of foreign peptides. Peptides are presented by major histocompatibility complex (MHC) found on the surface of tumor cells or virus-infected cells.

Problem Statement

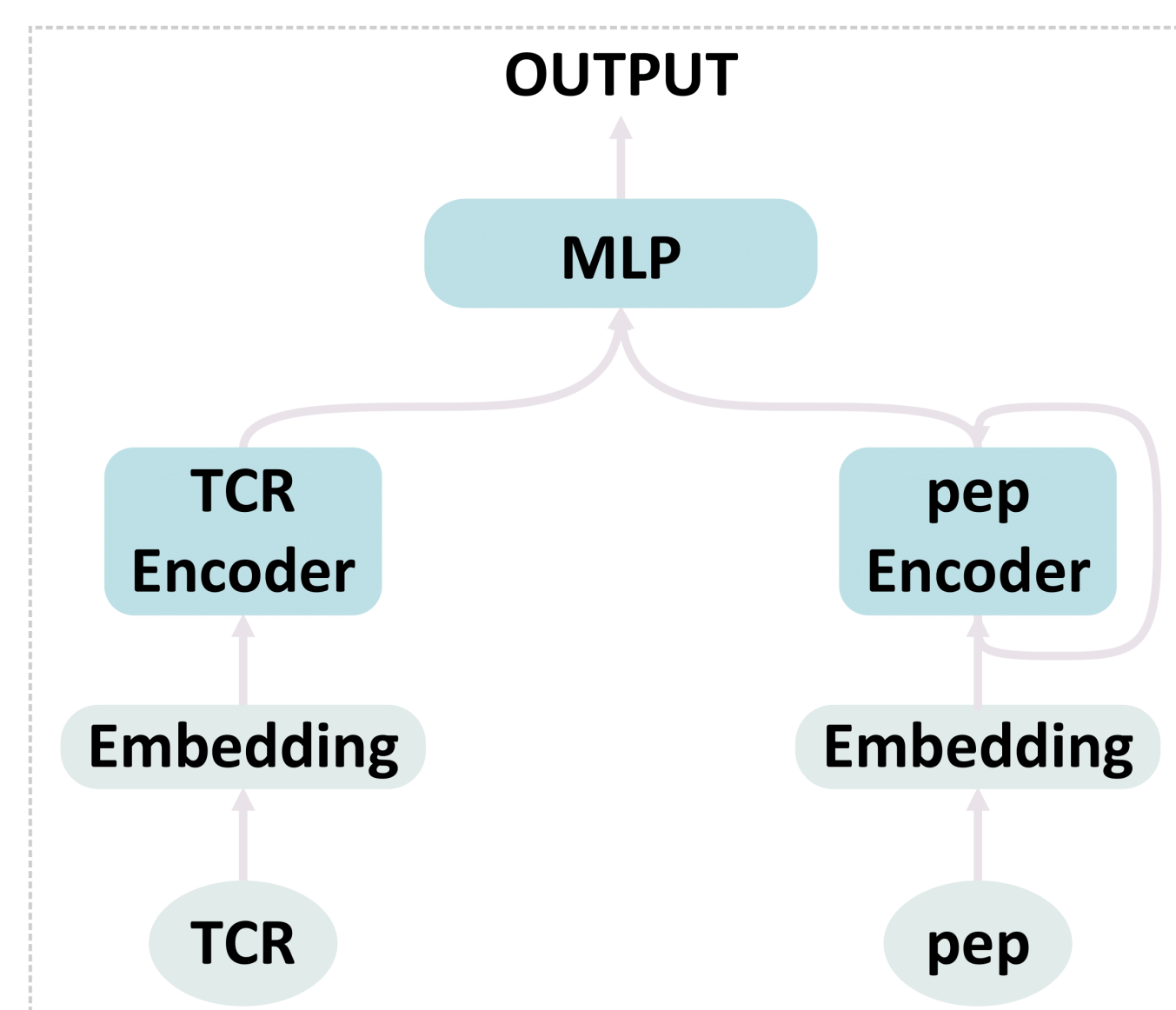
- ✓ Given a sequence of **TCR** and a sequence of **peptide**, the goal is to predict the interaction between them.

Challenges:

1. Though datasets like McPAS and VDJdb exists, the data scarcity issue limits the learning of potent deep neural network.
2. The labeled datasets are biased: many peptides/TCRs though different, are similar.
3. Large amount of TCR sequences (without known associated peptides) are available in database that are not being leveraged.

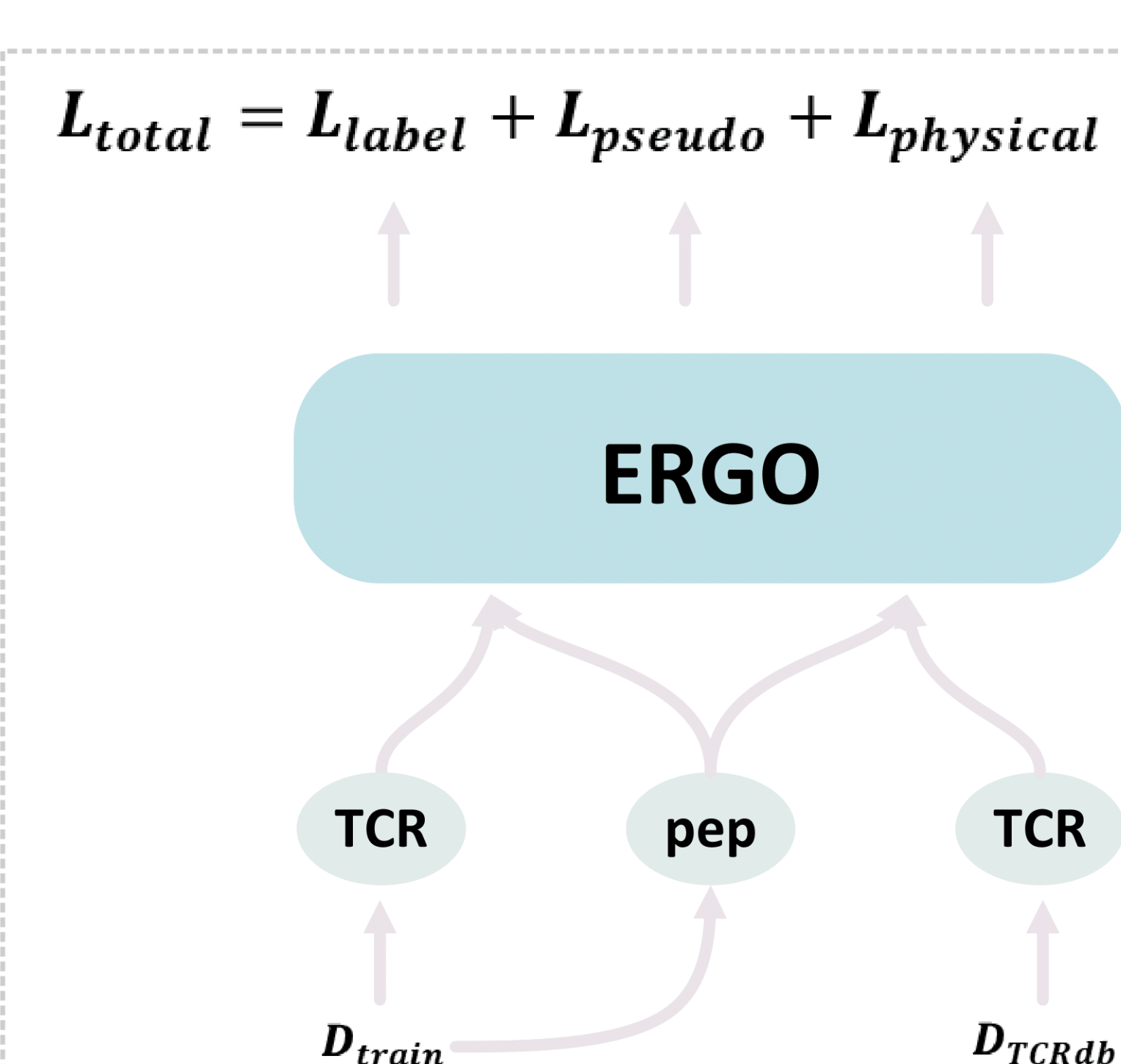
Methods

Base Model

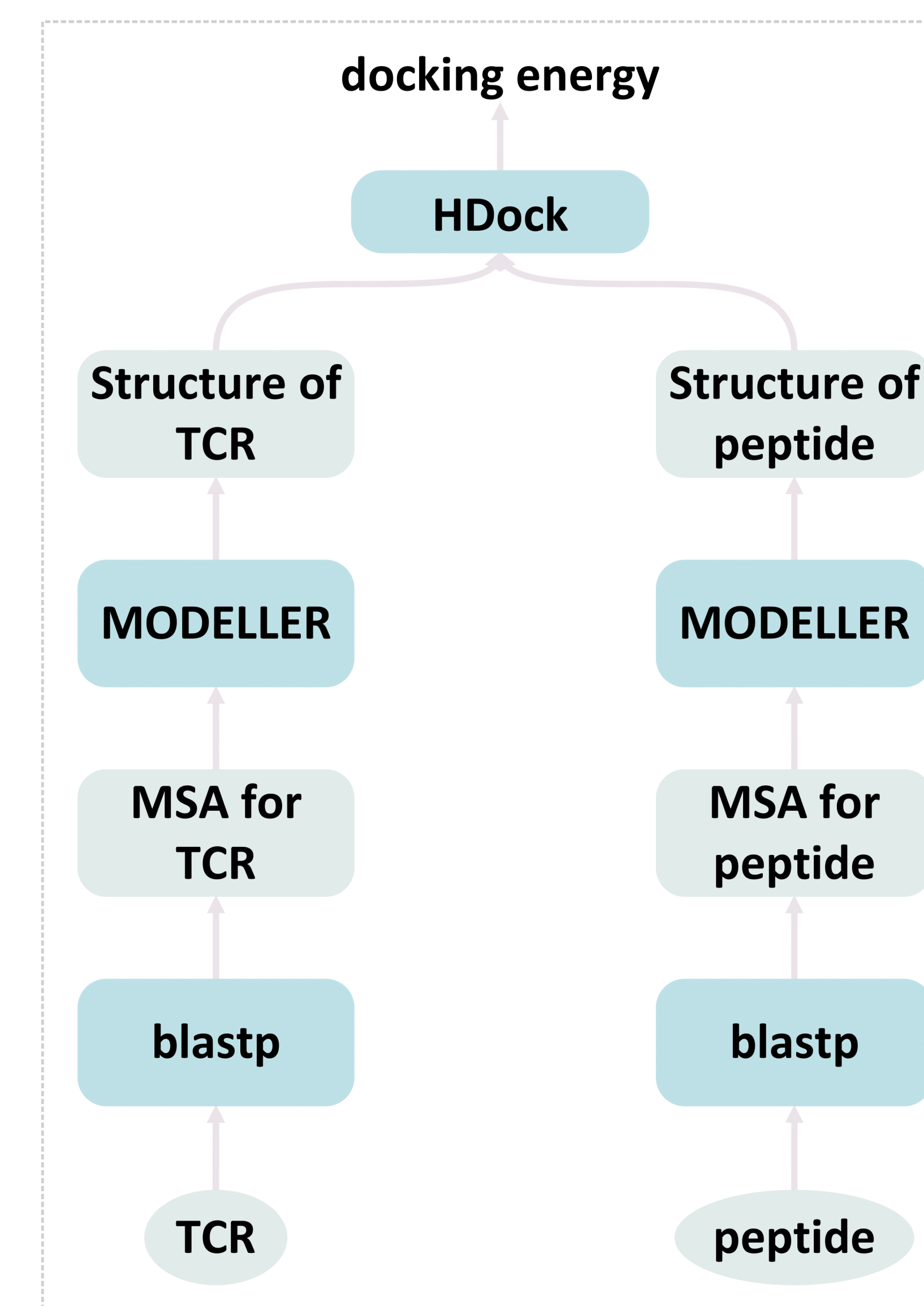


Models used in our study. The model is borrowed from ERGO for fair comparisons. The model has two separate encoders for TCR and peptide

Training Losses

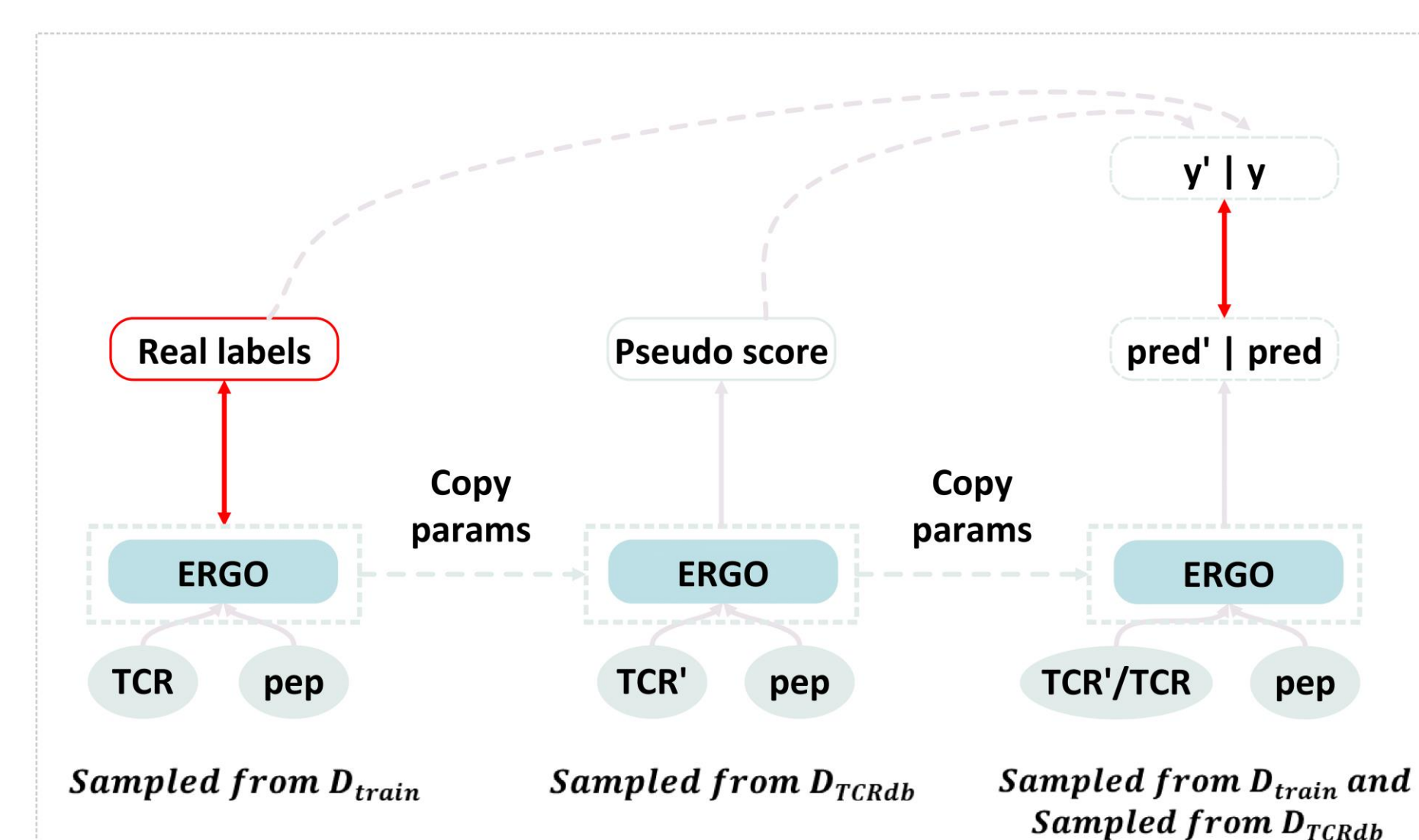


Physical Modeling: Docking by HDock



docking using HDock. For a given sequence of TCR/peptide, we first use blastp to find the multiple-sequence alignment (MSA) for the sequence. MSA and the corresponding structures from PDB are then used by MODELLER for building the structures of the TCR/peptide. Finally, we call HDock with the given structures of the TCR and peptide for computing docking energies.

Overview of Our Learning Framework



$$\mathcal{L}_{\text{labeled}} = \text{BinaryCrossEntropy}(\text{pred}, y) \quad \leftarrow \text{Supervised loss from labeled TCR-peptides}$$

$$\mathcal{L}_{\text{physical}} = \text{BinaryCrossEntropy}(\text{pred}', y') \quad \leftarrow \text{Learning from pseudo-labels by docking}$$

$$\mathcal{L}_{\text{pseudo-labeled}} = \text{KL-div}(\text{pred}', \text{prob}') \quad \leftarrow \text{Learning from pseudo-labels by a teacher}$$

$$\mathcal{L}_{\text{total}} = \alpha \mathcal{L}_{\text{labeled}} + \beta \mathcal{L}_{\text{physical}} + \gamma \mathcal{L}_{\text{pseudo-labeled}}$$

Experimental Results

Data size	6K	10K	20K
ERGO	67.6 ± 0.4	71.9 ± 0.4	76.6 ± 0.3
+ Pseudo	69.3 ± 0.4	73.6 ± 0.3	77.6 ± 0.3
+ Docking	69.4 ± 0.4	73.3 ± 0.3	77.9 ± 0.2
ours (3 losses)	70.4 ± 0.3	73.7 ± 0.3	77.6 ± 0.2
ours + meta-update	71.5 ± 0.3	74.7 ± 0.3	78.4 ± 0.2

Experimental results on **McPAS** using base model of ERGO-LSTM. Results are collected from 5 different independent experimental runs. In these experiments, ERGO+Pseudo and ERGO+Docking perform roughly equally well.

Data size	6K	10K	20K
ERGO	68.1 ± 0.4	72.0 ± 0.3	73.6 ± 0.4
+ Pseudo	68.4 ± 0.3	72.4 ± 0.3	73.9 ± 0.3
+ Docking	69.5 ± 0.4	73.4 ± 0.3	74.6 ± 0.3
ours (3 losses)	70.4 ± 0.3	72.9 ± 0.3	74.6 ± 0.3
ours + meta-update	71.5 ± 0.3	73.8 ± 0.3	75.2 ± 0.3

Experimental results on **VDJdb** using base model of ERGO-LSTM. Results are collected from 5 different independent experimental runs. In these experiments, ERGO+Pseudo only improves over the baseline marginally, while physical modeling by docking still increase the AUC by significant margins.

rare peptides	baseline	average	ours
KRWIILGLNK	52.8	54.4	68.1
KMVAVFYTT	48.9	54.4	65.8
FPRPWLHGL	50.2	54.4	58.5

Experiments with AE-LSTM model with McPAS dataset of 6K labeled examples. "average" denotes the average AUC for all peptides in this experimental setup.