



Universidad La Salle

Prediction of peptide MHC binding and presentation using transformers and transfer learning in cancer immunology context

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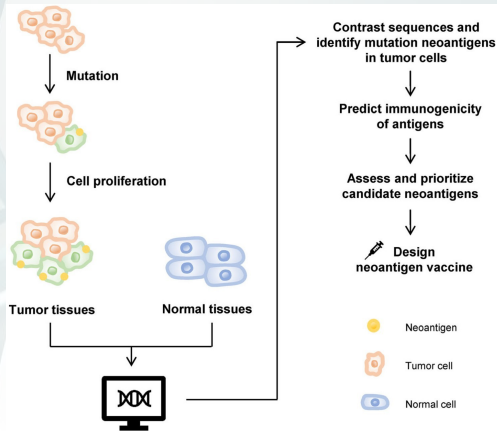


Figure: Personalized vaccines process for Cancer [1].

pMHC binding and presentation prediction

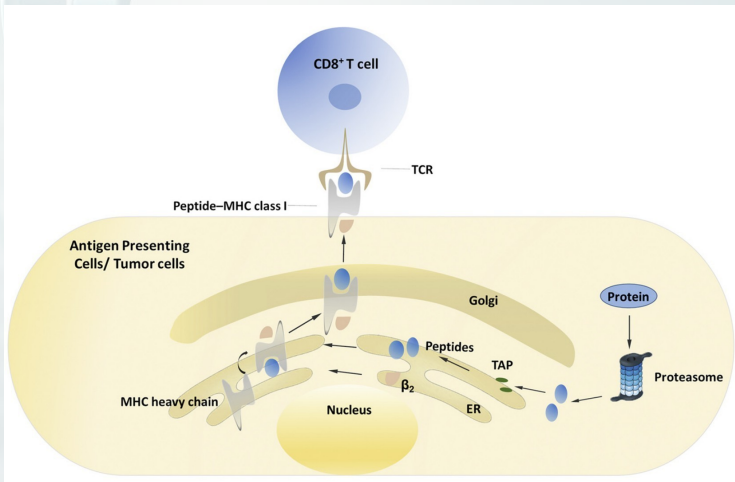


Figure: pMHC presentation process in MHC class I [2].



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Less than 5% of detected neoantigens (peptides binded to MHC) succeed in activating the immune system [3]. Moreover, recent proposals only achieve 0.6 precision and 0.4 recall [4].

This is a **binary classification problem**. A peptide could be represented like: $p = \{A, \dots, Q\}$ and a MHC like: $q = \{A, N, \dots, Q, E\}$. Finally, we need to know the probability of affinity between p and q (pMHC)

Problem

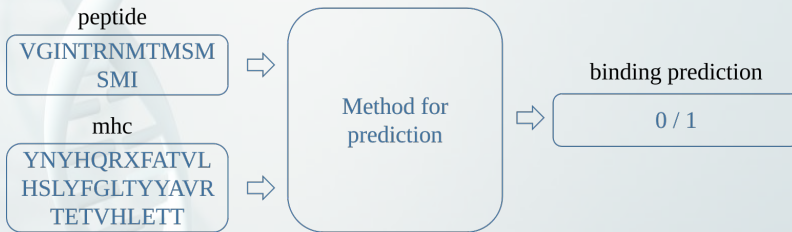


Figure: pMHC binding prediction problem.



Table: Recent works based on transformers and transfer learning.

Year	Ref.	Name	Method
2022	[5]	HLAB	Uses protBert model incascade with a RNN with attention
2022	[6]	MHCroBERTa	Five encoders with 12 multiple-head self-attention pre-trained with self-supervision
2022	[7]	TransPHLA	Based on four modules: an embedding block, an encoder block (multiple self-attention), a feature optimization block (FC layer), and a projection block (FC layer used to predict)
2021	[8]	BERTMHC	Uses TAPE model followed by a linear layer.
2021	[9]	ImmunoBERT	The same as BERTMHC focused on MHC-class I

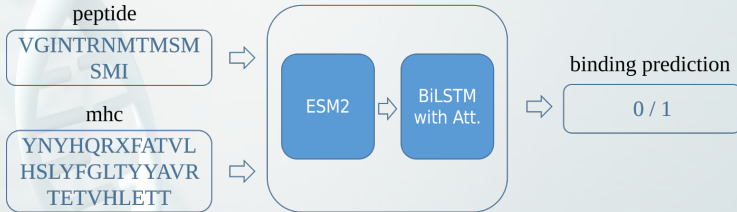


Figure: Proposal for pMHC binding and presentation prediction.



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We used the dataset from NetMHCIIpan3.2 [10].

Table: Samples used in training, evaluation and testing.

	Samples
Train	107424
Validation	13428
Testing	13429

Instead of ESM2 [11] model, we used TAPE [12] because it is smaller and easier to train. Moreover, the Bi-LSTM with attention layer is based on HLAB [5].

Table: Models used in experiments.

	Description
BERTMHC-LINEAR	BERT architecture followed by a linear layer
BERTMHC-RNN	BERT architecture followed by a BiLSTM layer and then a Linear layer
BERTMHC-RNN-ATT	BERT architecture followed by a BiLSTM layer with attention and then a Linear layer



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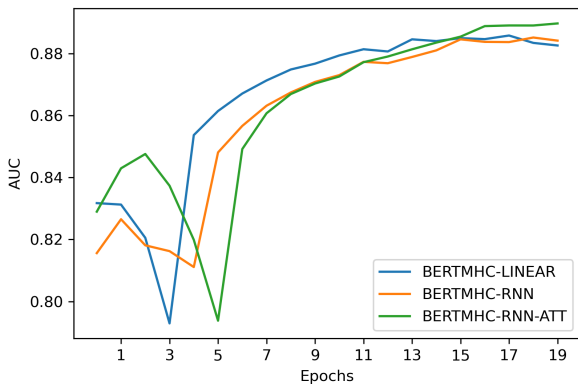


Figure: AUC per epoch of models.

Comparison

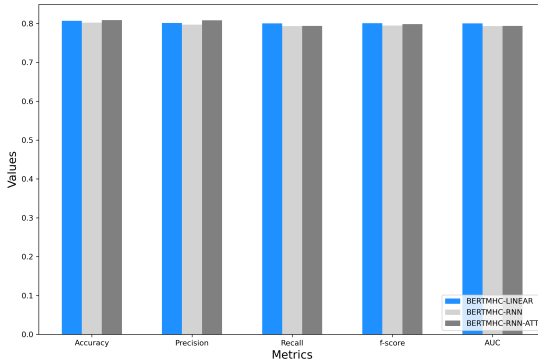


Figure: Metrics comparison.

Table: Metrics comparison of BERTMHC-LINEAR, BERTMHC-RNN and BERTMHC-RNN-ATT

Model	Acc	Precision	Recall	Fscore	AUC
LINEAR	0.8070	0.8012	0.8005	0.8009	0.8005
RNN	0.8023	0.7972	0.7932	0.7949	0.7932
RNN-ATT	0.8086	0.8082	0.7937	0.7985	0.7937

Comparison

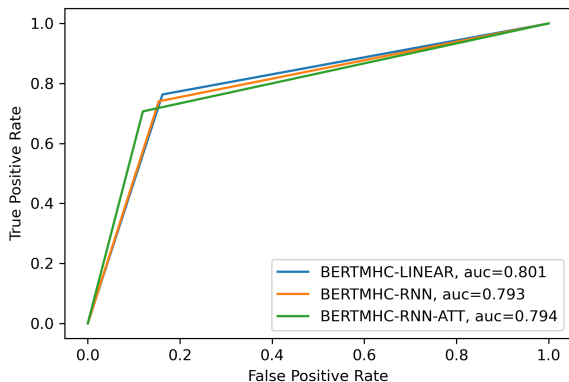


Figure: ROC curve.

Conclusions



We evaluated a BERT architecture (transformer) with transfer learning from TAPE in these preliminary results. We choose TAPE because it is smaller and easier to train. In future experiments, we will evaluate ESM2.

According to experiments, BERTMHC-LINEAR and BERTMHC-RNN-ATT got better results in netMHCIIpan3.2 dataset. It happens because we evaluated these models in a small dataset. In future experiments, we will evaluate these models in a larger dataset.



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