# Bidirectional Representations Augmented Autoregressive Biological Sequence Generation: Application in De Novo Peptide Sequencing

Xiang Zhang, Jiaqi Wei, Zijie Qiu, Sheng Xu, Zhi Jin, ZhiQiang Gao, Nanqing Dong, Siqi Sun







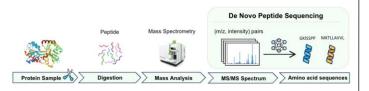




# Motivation

- Bidirectional Information: Autoregressive (AR) models, are limited in many biological by their unidirectional nature, failing to capture global bidirectional token dependencies.
- Scalable Generation: Non-Autoregressive (NAR) models offer holistic, bidirectional representations but face challenges with generative coherence and scalability.

# **De Novo Peptide Sequencing Pipeline**



# Core Design of CrossNovo

### (1) Cross-Decoder NAT Knowledge Transfer

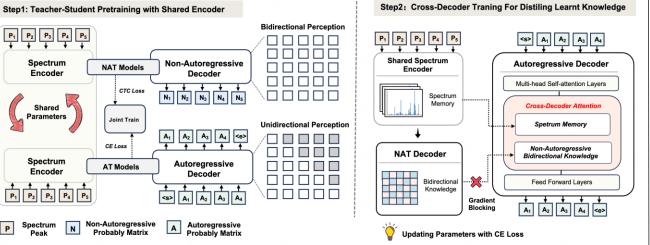
		rameters ( $\theta_{enc}$ , $\theta_{AT}$ , $\theta_{NAT}$ ) from Stage 1; Fine-turn	ing epochs
$E_{\mathrm{ft}}$ ;	Learning rate $\eta_{ft}$ ; Max NAT len	igth $T_{\rm max}$ .	
2: if E	$_{\rm ft} > 0$ then		
3: 1	Freeze parameters $\theta_{enc}$ and $\theta_{NAT}$	•	
4: <b>1</b>	for epoch $e = 1$ to $E_{\rm ft}$ do		
5:	for each $(S, A)$ in $D$ do		
6:	$\mathbf{E}^{(b)} \leftarrow \text{Encoder}(S; \theta_{enc})$	c) ▷ Use froz	en encode
7:	$V^{(L')} \leftarrow NATForward$	(PositionalEmbeddings( $T_{max}$ ), $\mathbf{E}^{(b)}$ ; $\theta_{NAT}$ )	NA
feati	ures from frozen NAT decoder		
8:	$\mathbf{V}_{\text{blocked}}^{(L')} \leftarrow \mathbb{GB}(\mathbf{V}^{(L')})$		nt blocking
9:	$\mathbf{C}_{\text{aug}} \leftarrow [\mathbf{V}_{\text{blocked}}^{(L')} \oplus \mathbf{E}^{(b)}]$	Augmented context for AT, cf. Eq. 8, 10 (v	vith distinc
posi	tional encodings)		
10:	$\mathcal{L}_{AT-ft} \leftarrow ComputeATI$	$LossAugmented(\mathbf{A}, \mathbf{C}_{aug}; \theta_{AT})$	
11:	Update $\theta_{AT}$ using $\nabla_{\theta_{AT}} \mathcal{L}$	$A_{\rm AT-ft}$ with $\eta_{\rm ft}$ .	
12: Refu	urn Fine-tuned parameters $\theta_{AT}$	(and unchanged $\theta_{}$ , $\theta_{NAT}$ ).	

### (2) Cross-Decoder Gradient Blocking for Stable Learning

 This isolation lets the AT decoder learn from the NAT branch stably, boosting model's performance.

$$\mathbf{h}_t^{\text{update}} = \text{CrossAttn}\left(\mathbf{h}_t^{\prime(l)}, \left[\mathbb{GB}\left(\mathbf{V}_{\text{p}\left\{1:T_{\max}\right\}}^{(L')}\right) \oplus \mathbf{E}_{\text{p}\left\{T_{\max}+1:T_{\max}+k\right\}}^{(b)}\right]\right)$$

## Overview of CrossNovo Framework



- Step 1 involves joint training with a shared encoder in a multitask learning framework, enabling the simultaneous training of Autoregressive and Non-Autoregressive decoders.
- Step 2 introduces a novel knowledge distillation process, transferring insights from the NAT module to the AT module through a cross-decoder attention mechanism
- Cross-decoder gradient blocking is employed throughout to optimize the training process.

### Core 9-species-v1 benchmark

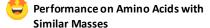
Metrics	Architect	Methods	Mouse	Human	Yeast	M.mazei	Honeybee	Tomato	Rice bean	Bacillus	C. bacteria	Average
	DB	Peaks	0.600	0.639	0.748	0.673	0.633	0.728	0.644	0.719	0.586	0.663
	NAT	Prime.	0.784	0.729	0.802	0.801	0.763	0.815	0.822	0.846	0.734	0.788
Amino		Deep.	0.623	0.610	0.750	0.694	0.630	0.731	0.679	0.742	0.602	0.673
Acid		Point.	0.626	0.606	0.779	0.712	0.644	0.733	0.730	0.768	0.589	0.687
Precision	AT	Casa.	0.689	0.586	0.684	0.679	0.629	0.721	0.668	0.749	0.603	0.667
	AI	Insta.	0.703	0.636	0.691	0.712	0.660	0.732	0.711	0.739	0.619	0.689
		Casa.V2	0.760	0.676	0.752	0.755	0.706	0.785	0.748	0.790	0.681	0.739
		Helix.	0.765	0.665	0.768	0.784	0.757	0.721	0.793	0.816	0.681	0.750
		Contra.	0.798	0.771	0.797	0.799	0.745	0.810	0.807	0.828	0.711	0.785
		Ours	0.816	0.800	0.814	0.826	0.785	0.830	0.831	0.856	0.740	0.811
	DB	Peaks	0.197	0.277	0.428	0.356	0.287	0.403	0.362	0.387	0.203	0.322
	NAT	Prime.	0.567	0.574	0.697	0.650	0.603	0.697	0.702	0.721	0.531	0.638
	AT	Deep	0.286	0.293	0.462	0.422	0.330	0.454	0.436	0.449	0.253	0.376
Peptide		Point.	0.355	0.351	0.534	0.478	0.396	0.513	0.511	0.518	0.298	0.439
Recall		Casa.	0.426	0.341	0.490	0.478	0.406	0.521	0.506	0.537	0.330	0.448
		Helix.	0.483	0.392	0.568	0.560	0.473	0.560	0.623	0.596	0.388	0.517
		Insta	0.471	0.455	0.559	0.528	0.466	0.732	0.564	0.576	0.416	0.530
		Casa.V2	0.483	0.446	0.599	0.557	0.493	0.618	0.589	0.622	0.446	0.539
		Contra.	0.567	0.622	0.674	0.630	0.576	0.672	0.677	0.688	0.486	0.621
		Ours	0.506	0.661	0.600	0.660	0.610	0.605	0.716	0.726	0.510	0.654

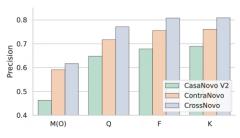
### Other benchmarks

Metrics	Architect	Methods	Mouse	Human	Yeast	M.mazei	Honeybee	Tomato	Rice bean	Bacillus	C.bacteria	Average
	NAT	Prime.	0.839	0.893	0.932	0.908	0.862	0.909	0.931	0.921	0.827	0.891
Amino Acid		Casa.V2	0.813	0.872	0.915	0.877	0.823	0.891	0.891	0.888	0.791	0.862
Precision	AT	Contra.	0.839	0.920	0.919	0.896	0.848	0.898	0.913	0.901	0.807	0.882
		Ours	0.857	0.937	0.939	0.920	0.880	0.914	0.939	0.927	0.837	0.906
	NAT	Prime.	0.627	0.795	0.884	0.812	0.742	0.824	0.837	0.849	0.626	0.777
Peptide		Casa.V2	0.555	0.712	0.837	0.754	0.669	0.783	0.772	0.793	0.558	0.714
Recall	AT	Contra.	0.616	0.820	0.854	0.780	0.711	0.794	0.799	0.815	0.575	0.752
		Ours	0.651	0.850	0.885	0.819	0.751	0.816	0.847	0.850	0.607	0.786

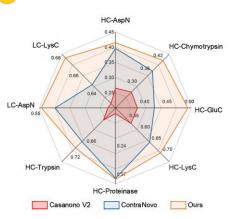
Metrics	Methods		HC							Average
		AspN	Chymo.	GluC	LysC	Proteinase	Trypsin	AspN	LysC	Average
Amino	Casa.V2	0.520	0.472	0.605	0.757	0.354	0.759	0.666	0.778	0.642
Acid	Contra.	0.580	0.565	0.642	0.790	0.348	0.787	0.702	0.793	0.676
Precision	Ours	0.613	0.617	0.694	0.814	0.367	0.803	0.719	0.807	0.702
	Casa.V2	0.265	0.274	0.399	0.569	0.206	0.595	0.325	0.625	0.446
Peptide Recall	Contra.	0.396	0.372	0.437	0.653	0.274	0.675	0.499	0.646	0.529
	Ours	0.415	0.421	0.512	0.701	0.275	0.699	0.544	0.676	0.560

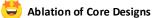
### More Analysis





### Downstream Tasks





Gradient Blocking	Cross Decoder	Shared Encoder	Amino acid Precision	Peptide Precision
	./	1	0.795 <b>X</b>	0.643 <b>X</b>
✓	/	•	0.698	0.546
✓	✓	✓	0.811	0.654