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Sequence Display-Enabled Machine Learning for Protein Evolution

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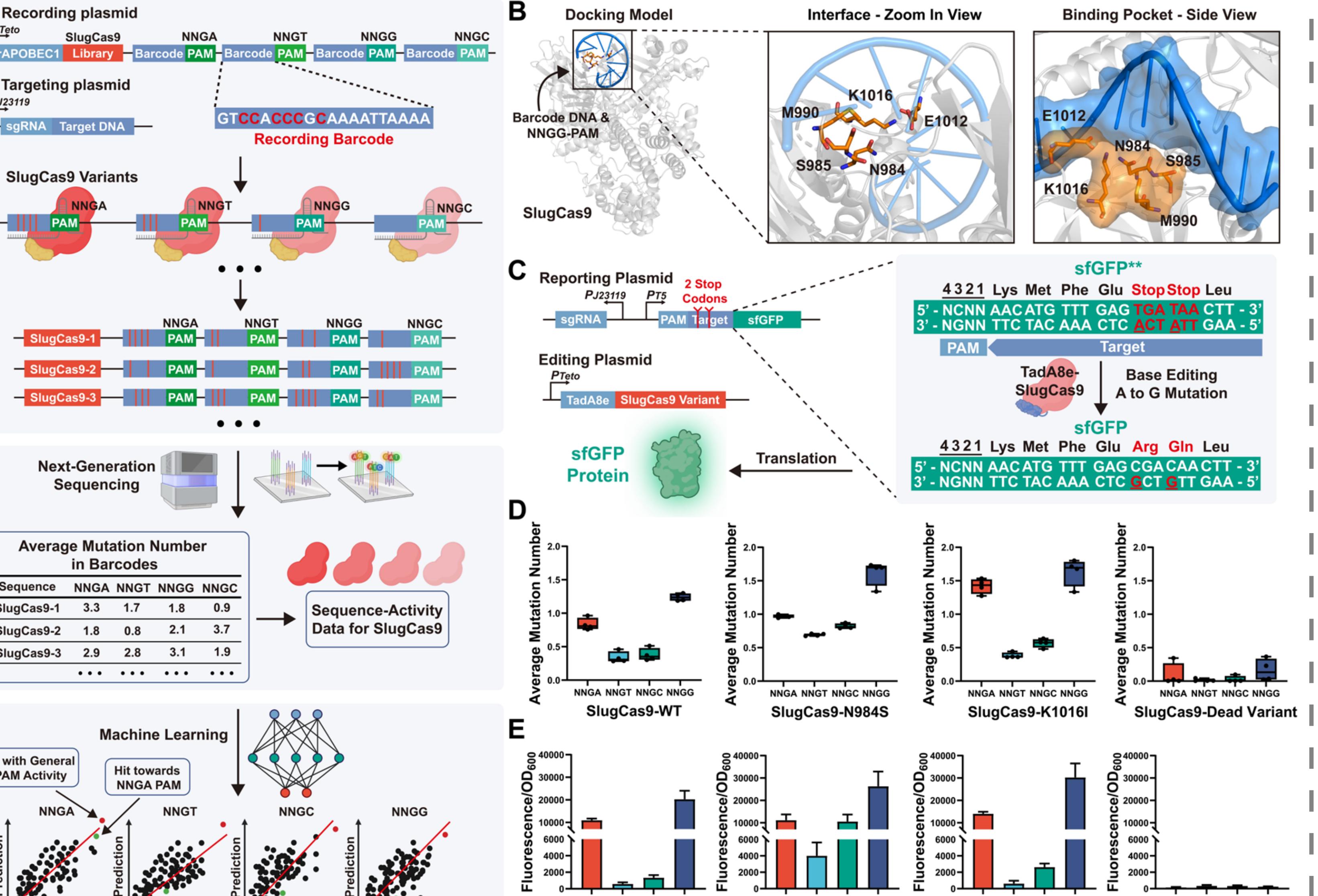
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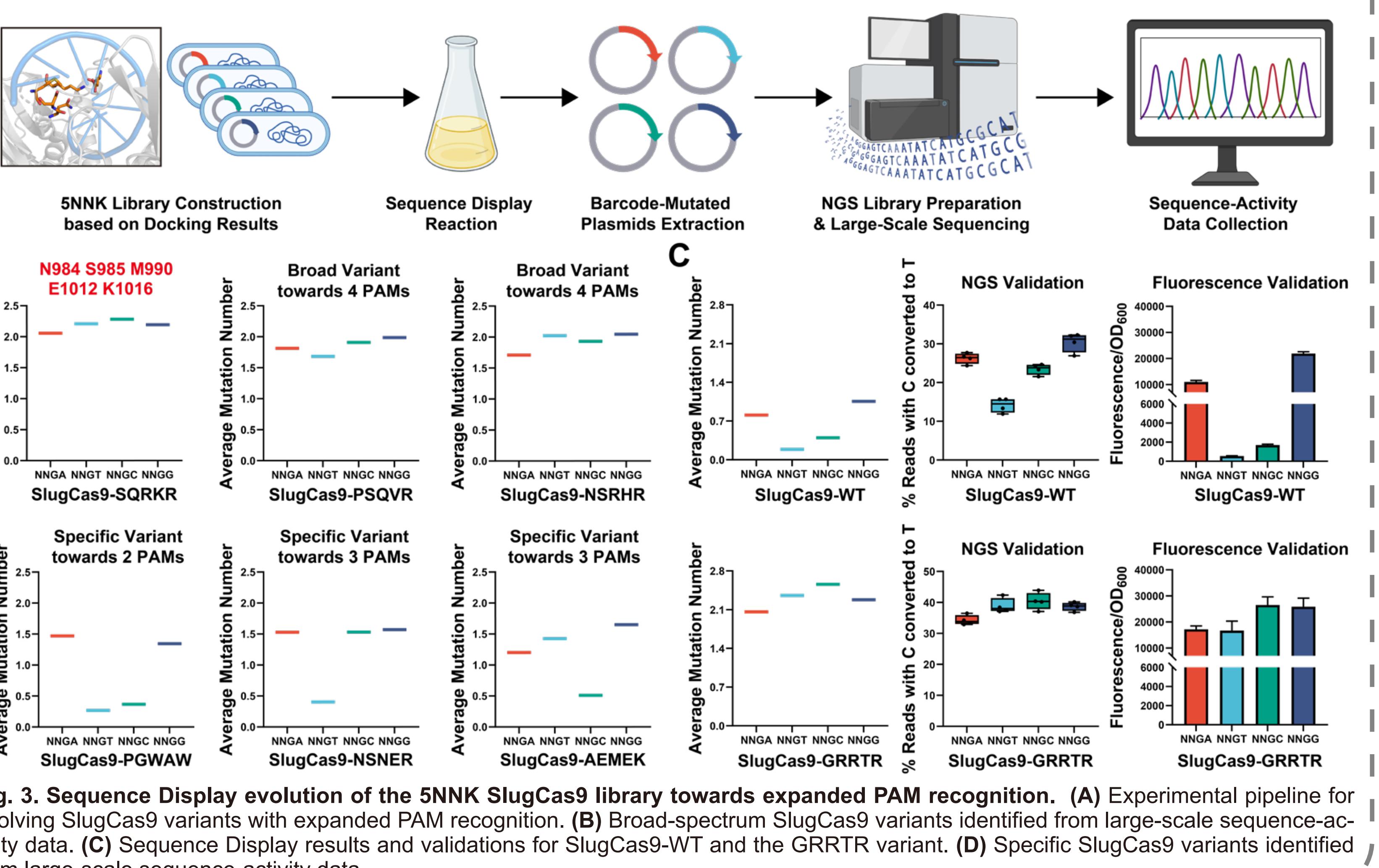


Generation of Sequence–Activity Datasets for SlugCas9 Across Diverse PAMs Using Multiplexed-Barcoded Sequence Display

Evolution of SlugCas9 toward expanded PAM recognition using the Sequence Display platform



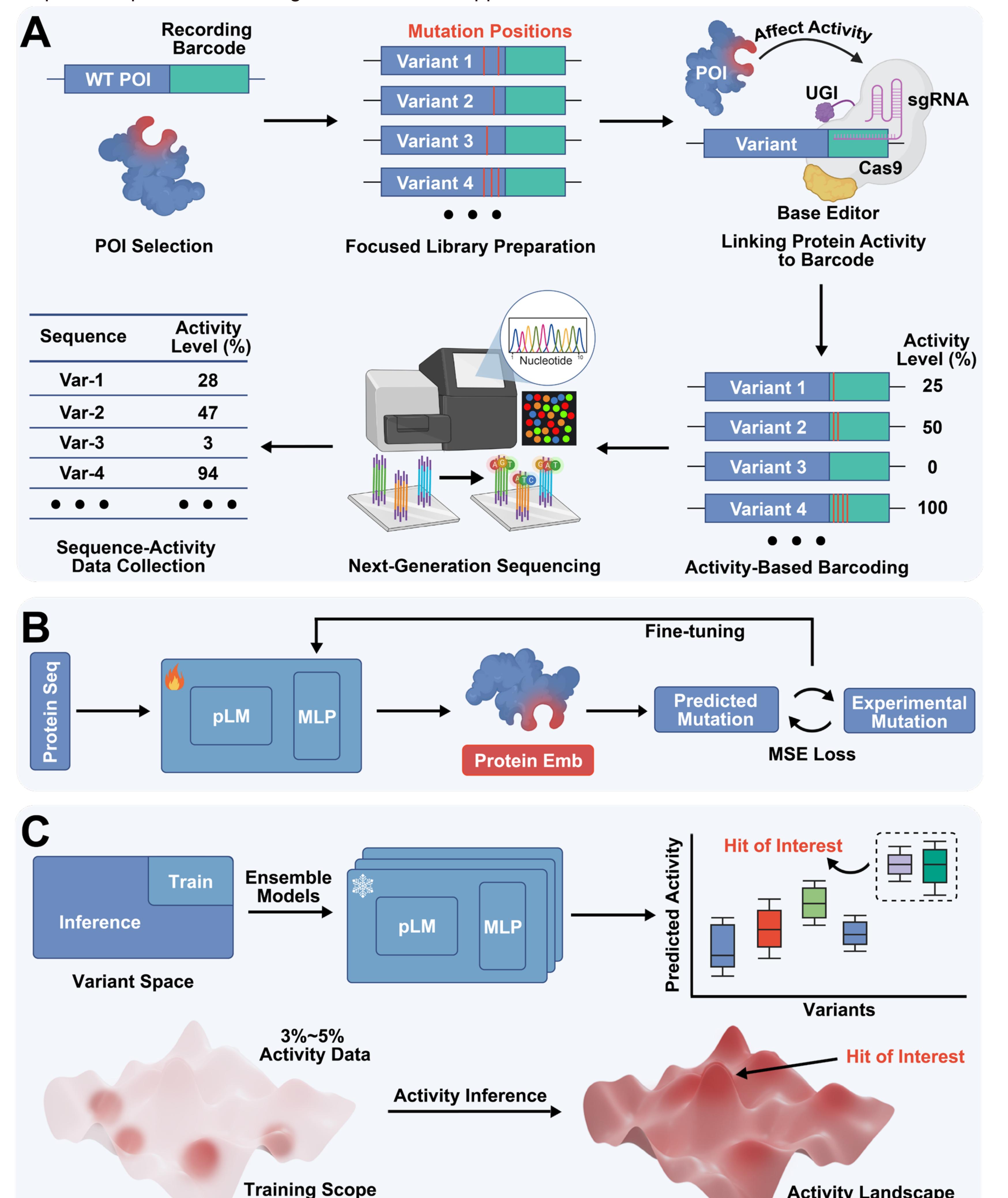
Generating Large-scale sequence-activity datasets for SlugCas9 to enable machine learning-based SlugCas9 evolution



Introduction

Sequence Display: Generation of large-scale sequence-activity datasets

Engineering proteins with desired functions remains challenging due to the labor-intensive nature of traditional methods and limited sequence–activity data for machine learning. Here, we present Sequence Display, a scalable platform that rapidly generates large-scale protein sequence–activity datasets, enabling machine learning-driven protein evolution. Sequence Display can be multiplexed to assess the specificity of individual mutants within a single experiment. By integrating these datasets with pre-trained protein language models, we construct fine-grained, variant-specific activity landscapes to identify high-performance variants. We demonstrate its broad applicability by generating datasets for cytosine deaminase, uracil glycosylase inhibitor, and a compact Cas9 nuclease. For Cas9, we produced over 32 million data points and evolved a variant with expanded PAM recognition, which outperformed a previously reported mutant from phage-assisted evolution. This study establishes Sequence Display as a powerful tool for mapping sequence–function relationships and accelerating the discovery of optimized proteins for biological and medical applications.



Construction of fine-grained, variant-specific activity landscapes to identify high-performance variants

Modeling the Relationship between SlugCas9 Variants and their Activities using pLMs

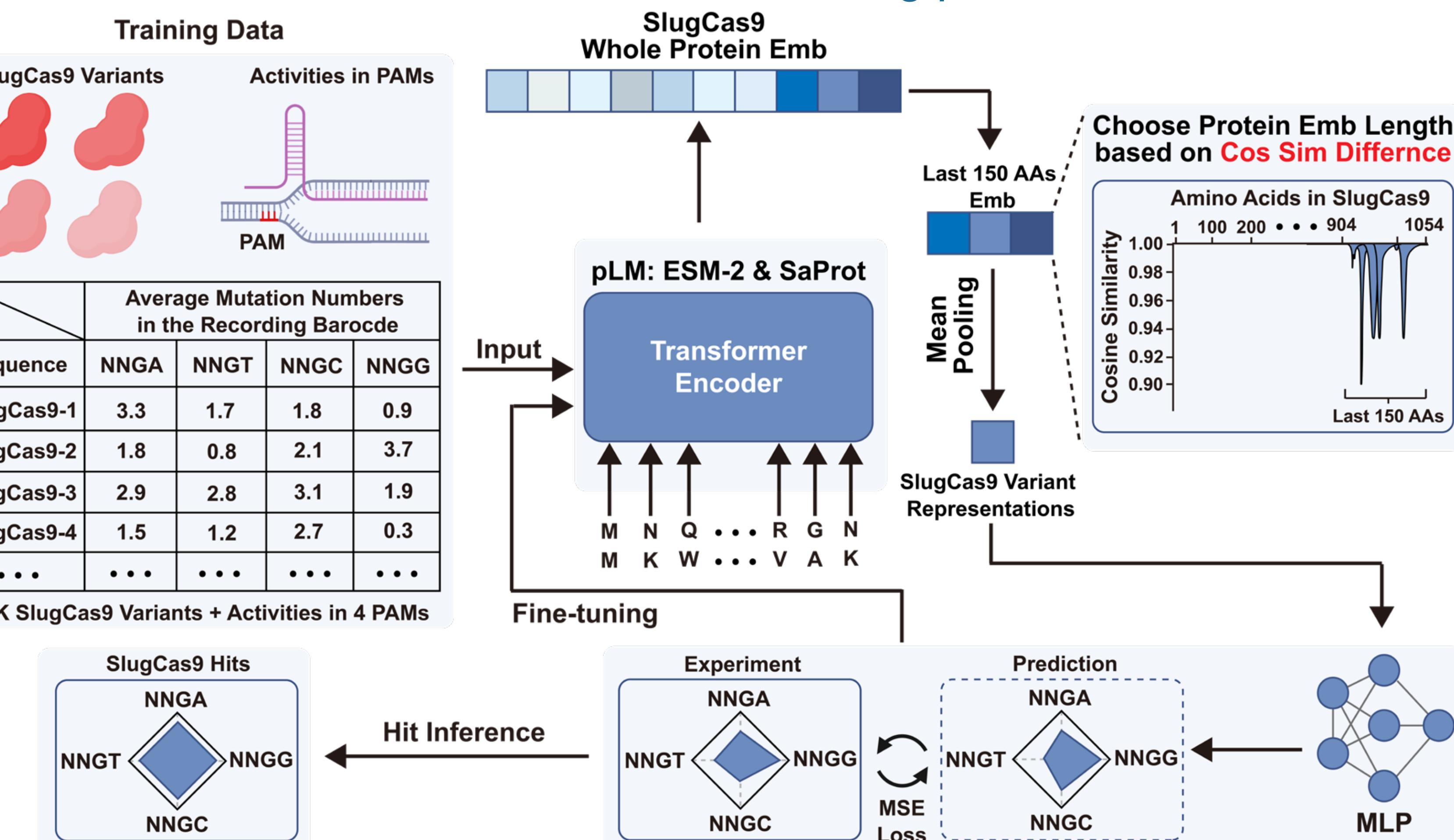


Fig. 4. Modeling the activity landscape of SlugCas9 with protein language models. Machine learning pipeline for predicting SlugCas9 activity. pLMs, including ESM-2 and SaProt, are used to extract local embeddings based on cosine similarity calculations for each amino acid in the SlugCas9 sequence.

Ensemble strategy for Constructing SlugCas9 Activity Landscapes and PAM-Specific Activity Inference

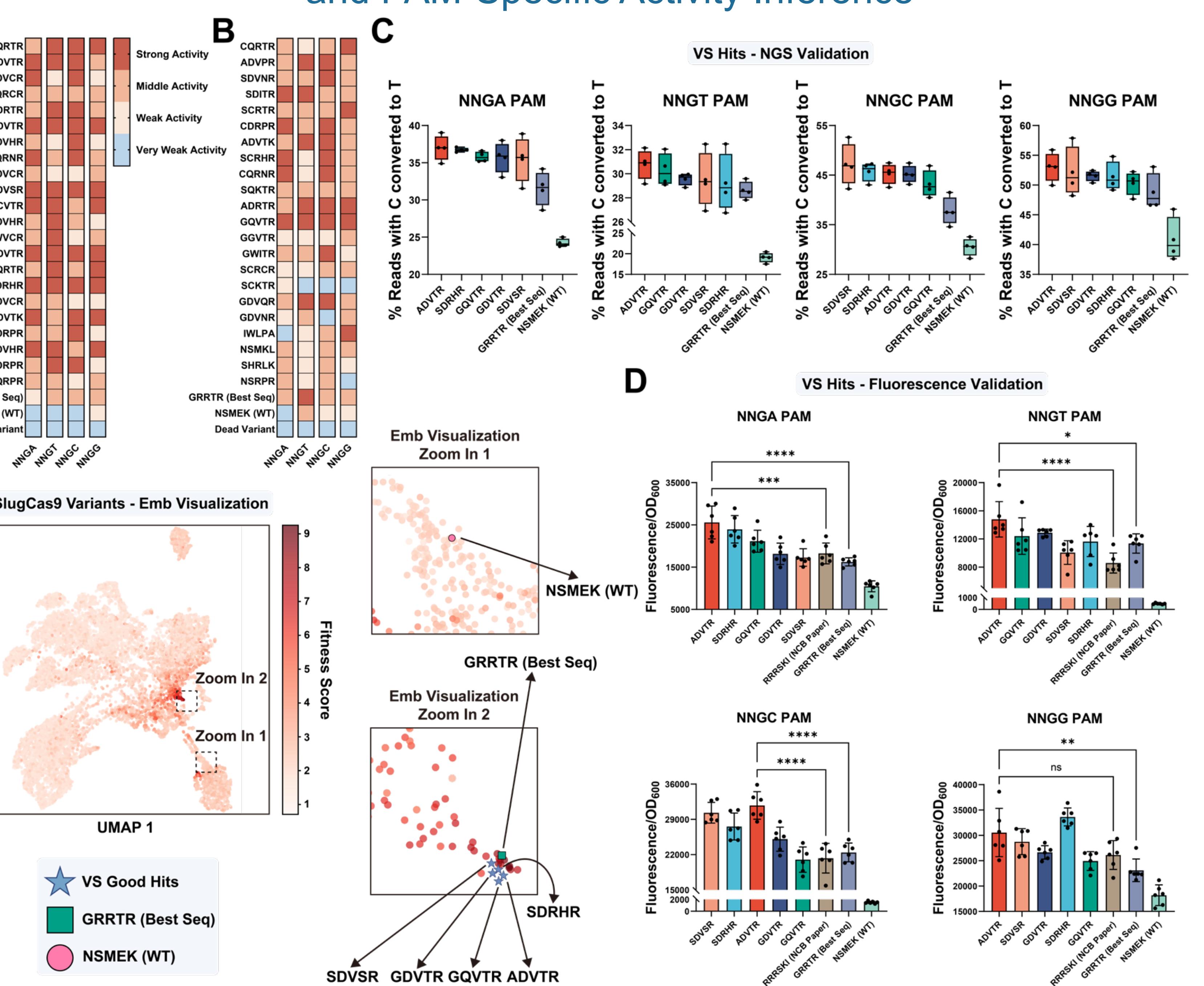


Fig. 5. Validation of ensemble models-predicted SlugCas9 hits and construction of the activity landscape. (A) High-throughput validation for top-predicted SlugCas9 variants. (B) High-throughput validation of an additional batch of top-performing variants. (C) NGS-based validation of top-performing variants. (D) Fluorescence-based validation of top-performing variants. (E) UMAP visualization of the SlugCas9 variant activity landscape.



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