# Scoreformer: A Surrogate Model For Large-Scale Prediction of Docking Scores Álvaro Ciudad, Adrián Morales-Pastor, Laura Malo, Isaac Filella-Mercè, Victor Guallar, Alexis Molina

**TLDR**: The current size of molecular databases demands faster methods to screen them. The use of **PNA** and **LRWPE** in a graph transformer allows us to capture molecular representations while **increasing inference speed**.

### Introduction

Molecular databases are growing fast due to the advances in combinatorial chemistry. This increases the need for faster tools to efficiently explore such databases to find promising drug candidates. Graph Neural Networks represent a great alternative to classical docking engines due to their ability to learn molecular patterns and their inference speed.

## Methods

**PNA** message passing layers allow **more expressive integration** of information from neighboring nodes Graph transformers account for long-range interactions, replacing the virtual node in previous SoTA models



### -Results

#### **Regression results**



Scoreformer architectures achieve state-of-the-art performance in regression and hit recovery metrics

#### Inference speed

#### Generalization

MODEL	SAMPLES/S	128M time (h)
FILMv2 ScoreFormer L-ScoreFormer	$1323.942 \\2186.828 \\2468.404$	26.850 16.259 14.404
MODEL	Speedup	# PARAMETERS
FILMv2 ScoreFormer L-ScoreFormer	$1.000 \\ 1.652 \\ 1.864$	102977 5398273 147457

CONFIGURATION	RES	$AURTC_{0.01}$	$AURTC_{0.001}$
ScoreFormer	0.458	0.344	0.359
L-ScoreFormer	0.449	0.358	0.336
FILMV2	0.431	0.333	0.314
Reference	0.746	0.653	0.735

Scoreformer also demonstrates better generalization with out-of-distribution molecules compared to previous SoTA models

Despite having more parameters, Scoreformers increase the inference speed of baseline models by 60 and 80 percent





