

# DREAM Challenge 2022

## Predicting Gene Expression Using a Residual CNN

*A description of team Camformers' submission (4<sup>th</sup> place) to the DREAM 2022 challenge  
"Predicting gene expression using millions of random promoter sequences".*

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DRUG DISCOVERY INSTITUTE

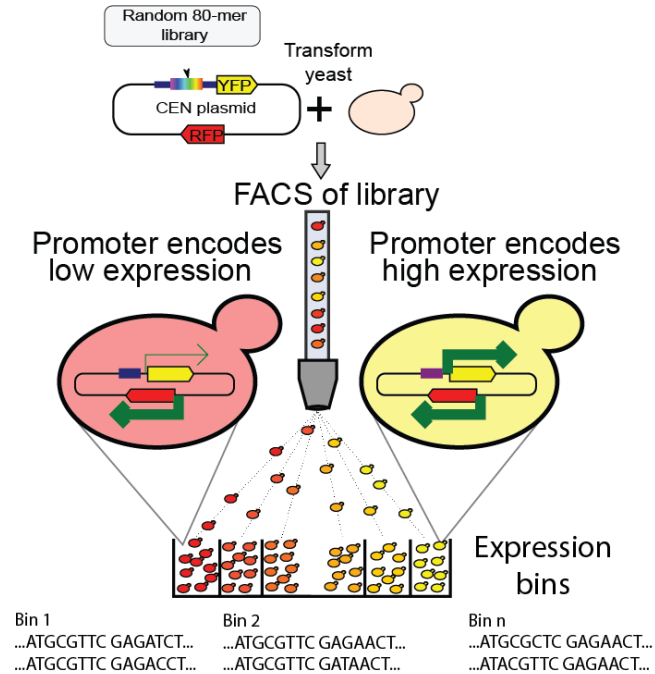


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# DREAM Challenge 2022

“Predicting gene expression using millions of random promoter sequences”



## Task

Train a sequence-to-expression model using 6.7 million random promoter sequences

## Data

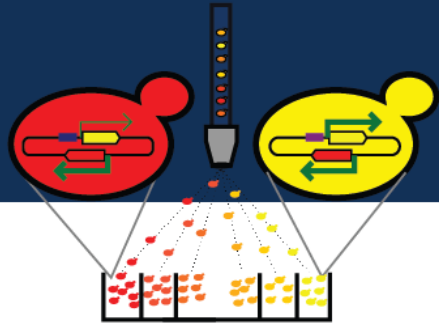
110 nt sequences + expression

## Evaluation

71,103 unseen sequences

# DREAM challenge results

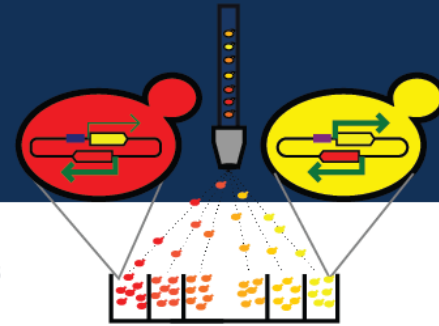
Predicting gene expression using millions of  
random promoter sequences  
DREAM Challenge 2022



IBM Research



Google Research  
TPU Research Cloud



100+ teams participating  
27 final submissions



Position	Team Name	Mean rank in competition metrics
1	autosome.org	1.01175
2	BHI - dream challenge	1.98825
3	Unlock_DNA	3.6497
4	Camformers	4.5854
5	NAD	5.81105
5	wztr	5.8152
7	High Schoolers Are All You Need	7.21835
8	BioNML	7.93655
9	BUGF	8.5263
10	mt	9.3033

# Sequence representation

110 nt sequences and their expression

6,739,258 sequences with known expression

71,103 sequences to predict

A T G T A C T G A

One-hot  
encoding

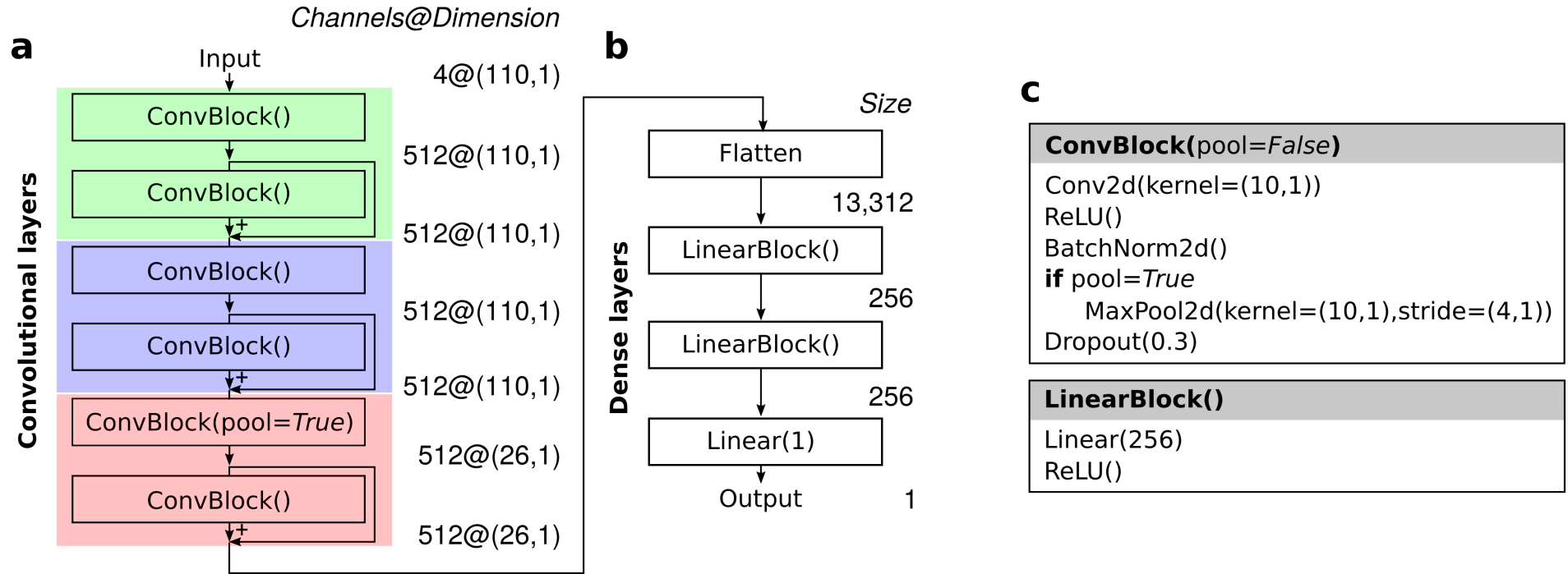
1	0	0	0
0	0	0	1
0	0	1	0
0	0	0	1
1	0	0	0
0	1	0	0
0	0	0	1
0	0	1	0
1	0	0	0

Illustration from  
Al-Ajlan & El Allali, 2019

# Data processing

- Data inclusion criteria
  - No more than three “N”
  - Length  $110 \pm 3$  nt
    - Padding with N and truncation at 110
- Data split
  - Model design and hyperparameter optimisation
    - Training set (72%), validation set (8%), test set (20%)
  - Final submission
    - Training set (90%), validation set (10%)

# Model architecture



16,611,073 trainable parameters

## Optimisation

AdamW, L1 loss, ReduceLROnPlateau

## Early stopping

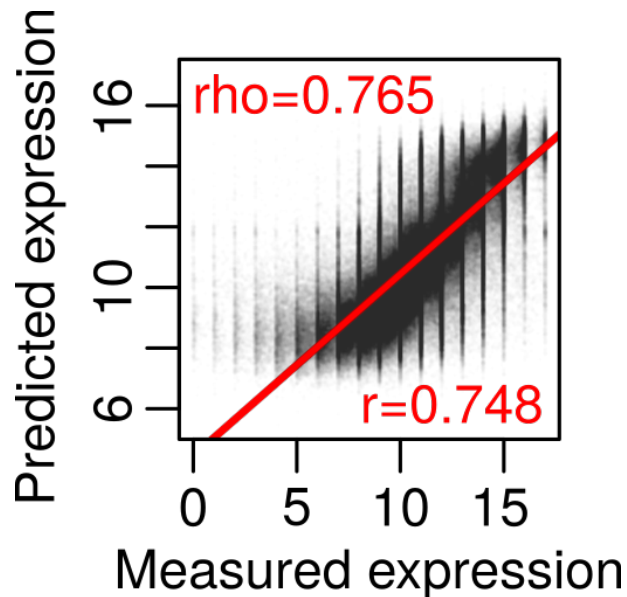
No improvement in r+p for 10 epochs

# Model training

T, training; V, validation

	T loss	V loss	T r	V r	T rho	V rho	
Epoch 1:	1.3174	1.3255	0.6716	0.7136	0.6909	0.7293	*
Epoch 2:	1.2353	1.1921	0.7153	0.7320	0.7315	0.7503	*
Epoch 3:	1.2092	1.1782	0.7267	0.7382	0.7428	0.7552	*
Epoch 4:	1.1962	1.1802	0.7318	0.7387	0.7480	0.7571	*
Epoch 5:	1.1876	1.1669	0.7350	0.7423	0.7513	0.7594	*
Epoch 6:	1.1806	1.1731	0.7376	0.7436	0.7539	0.7605	*
Epoch 7:	1.1754	1.1589	0.7396	0.7445	0.7559	0.7619	*
Epoch 8:	1.1710	1.1576	0.7412	0.7454	0.7576	0.7627	*
Epoch 9:	1.1671	1.1574	0.7427	0.7452	0.7591	0.7624	
Epoch 10:	1.1634	1.1589	0.7439	0.7455	0.7603	0.7633	*
Epoch 11:	1.1606	1.1650	0.7447	0.7463	0.7613	0.7635	*
Epoch 12:	1.1577	1.1537	0.7457	0.7467	0.7623	0.7641	*
Epoch 13:	1.1551	1.1692	0.7467	0.7463	0.7633	0.7642	
Epoch 14:	1.1528	1.1625	0.7475	0.7463	0.7640	0.7638	
Epoch 15:	1.1507	1.1561	0.7482	0.7469	0.7648	0.7648	*
Epoch 16:	1.1487	1.1576	0.7489	0.7465	0.7655	0.7642	
Epoch 17:	1.1466	1.1590	0.7495	0.7467	0.7661	0.7647	
Epoch 18:	1.1451	1.1608	0.7500	0.7475	0.7667	0.7648	*
Epoch 19:	1.1429	1.1558	0.7508	0.7463	0.7675	0.7640	
Epoch 20:	1.1411	1.1559	0.7513	0.7464	0.7681	0.7639	
Epoch 21:	1.1399	1.1576	0.7517	0.7471	0.7684	0.7647	
Epoch 22:	1.1381	1.1542	0.7524	0.7468	0.7690	0.7644	
Epoch 23:	1.1366	1.1688	0.7528	0.7457	0.7695	0.7637	
<b>Epoch 24:</b>	<b>1.1200</b>	<b>1.1509</b>	<b>0.7581</b>	<b>0.7481</b>	<b>0.7748</b>	<b>0.7655</b>	*
Epoch 25:	1.1161	1.1500	0.7594	0.7480	0.7761	0.7654	
Epoch 26:	1.1138	1.1552	0.7601	0.7479	0.7769	0.7653	
Epoch 27:	1.1123	1.1511	0.7606	0.7478	0.7774	0.7652	
Epoch 28:	1.1110	1.1509	0.7610	0.7478	0.7778	0.7653	
Epoch 29:	1.1096	1.1510	0.7614	0.7479	0.7783	0.7653	
Epoch 30:	1.1085	1.1510	0.7618	0.7479	0.7786	0.7653	
Epoch 31:	1.1074	1.1500	0.7621	0.7481	0.7790	0.7654	
Epoch 32:	1.1064	1.1534	0.7624	0.7476	0.7793	0.7651	
Epoch 33:	1.1058	1.1539	0.7626	0.7470	0.7795	0.7647	
Epoch 34:	1.1050	1.1559	0.7628	0.7474	0.7797	0.7651	

**Performance on  
validation set**  
(660,559 sequences)



# Model fine-tuning

- Optuna
  - Batch size, learning rate, weight decay,
  - Kernel size, number of layers, number of channels, dropout rates
  - Position(s) of max pooling
    - Max pooling operation at the penultimate layer improved generalisation



# Tricks that did not work (in our hands...)

- Manipulation of target values
  - Quantile normalization (**no difference**)
  - Add noise (**no difference**)
- Preprocessing
  - Extend/shorten flanking sequence length (**no difference**)
- Data augmentation
  - Upsample distribution tails (**no difference** or **reduced performance**)
  - Extend and cut sequences (**no difference**)
  - Reverse-complement sequences (**reduced performance**)

Caveat: Evaluation was done on a model that differs from the final submission.

# Performance breakdown

Category	# Sequences	PearsonR	Rank	Spearman	Rank	Weight
All	71103	0.956	6 <sup>th</sup>	0.961	5 <sup>th</sup>	1.00
High expression	968	0.557	8 <sup>th</sup>	0.575	6 <sup>th</sup>	0.30
Low expression	997	0.622	6 <sup>th</sup>	0.611	3 <sup>rd</sup>	0.30
Native	578	0.825	5 <sup>th</sup>	0.818	6 <sup>th</sup>	0.30
Random	6349	0.968	6 <sup>th</sup>	0.972	5 <sup>th</sup>	0.30
Challenging	1953	0.941	4 <sup>th</sup>	0.940	3 <sup>rd</sup>	0.50
SNVs	44340	0.821	5 <sup>th</sup>	0.674	7 <sup>th</sup>	1.25
TFBS perturbation	3287	0.975	4 <sup>th</sup>	0.959	8 <sup>th</sup>	0.30
Motif tiling	2624	0.899	16 <sup>th</sup>	0.912	9 <sup>th</sup>	0.40

Based on all data with no subsampling

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ScorePearsonR <sup>2</sup>	0.753	5 <sup>th</sup>
ScoreSpearman	0.821	4 <sup>th</sup>
<b>Overall</b>	<b>0.787</b>	<b>4<sup>th</sup></b>

# Contact

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