"Learning from Deep Learning"

Lessons from using computer vision to identify (urban) form and function in open data satellite imagery

UCL-QML Turing workshop

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The

Geographic

Urban Grammar | The Alan Turi

https://www.turing.ac.uk/research/research-projects/urban-grammar

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Urban Grammar

Learning an urban grammar from satellite data through AI

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Project status
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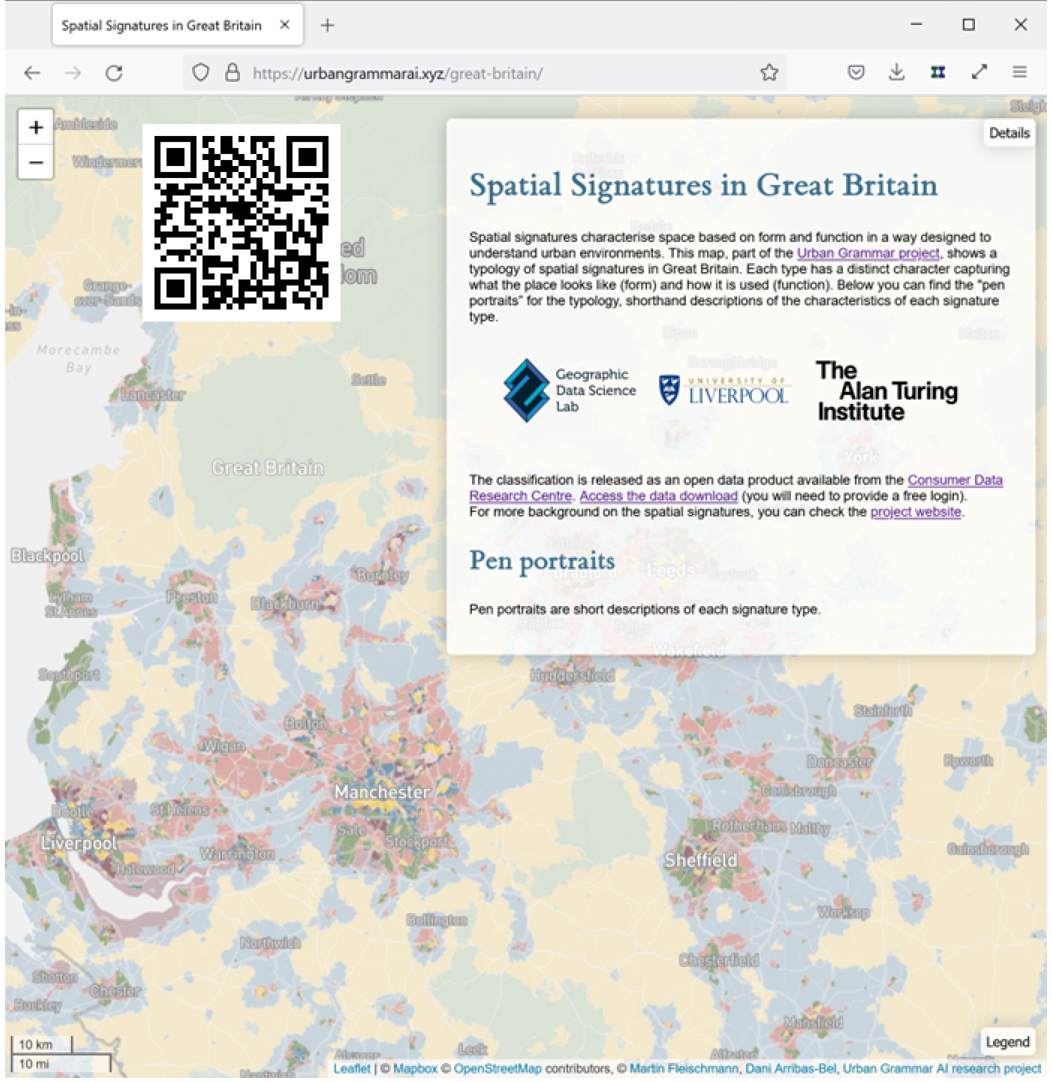
“Previous season…”



Spatial Signatures in Great Britain
https://urbangrammarai.xyz/great-britain/
Details
Spatial Signatures in Great Britain
Spatial signatures characterise space based on form and function in a way designed to understand urban environments. This map, part of the Urban Grammar project, shows a typology of spatial signatures in Great Britain. Each type has a distinct character capturing what the place looks like (form) and how it is used (function). Below you can find the "pen portraits" for the typology, shorthand descriptions of the characteristics of each signature type.
Geographic Data Science Lab
UNIVERSITY OF LIVERPOOL
The Alan Turing Institute
The classification is released as an open data product available from the Consumer Data Research Centre. Access the data download (you will need to provide a free login). For more background on the spatial signatures, you can check the project website.
Pen portraits
Pen portraits are short descriptions of each signature type.
Great Britain
Blackpool
Preston
Blackburn
Lancaster
Manchester
Liverpool
Sheffield
Wigan
Bolton
Warrington
Huddersfield
Doncaster
Legend
10 km
10 mi
Leaflet | © Mapbox © OpenStreetMap contributors, © Martin Fleischmann, Dani Arribas-Bel, Urban Grammar AI research project

ELSEVIER
Habitat International
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Spatial Signatures - Understanding (urban) spaces through form and function
Daniel Arribas-Bel a b, Martin Fleischmann b
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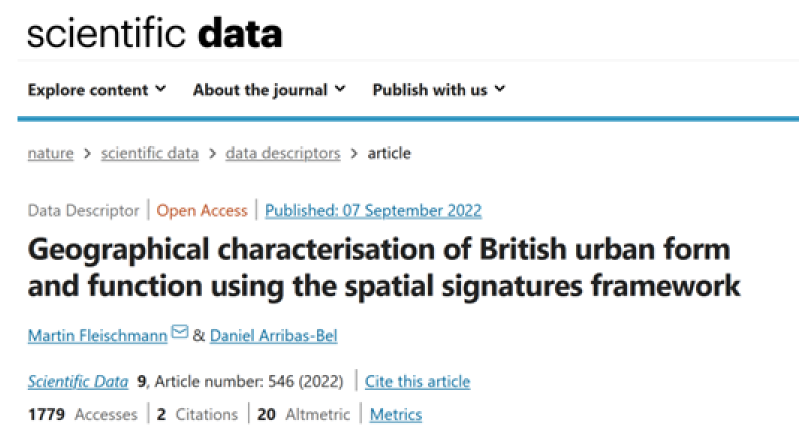

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Geographical characterisation of British urban form and function using the spatial signatures framework
Martin Fleischmann & Daniel Arribas-Bel
Scientific Data 9, Article number: 546 (2022) | Cite this article
1779 Accesses | 2 Citations | 20 Altmetric | Metrics

What

Explore the extent to which neural networks can recognise spatial signatures from satellite imagery

Why

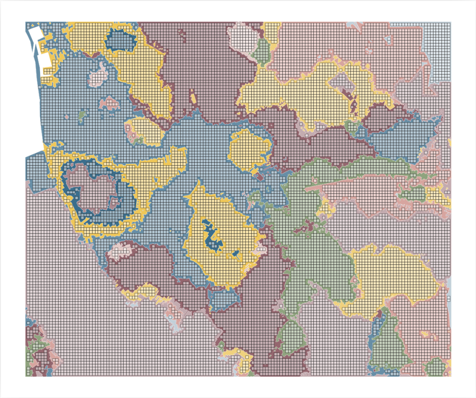
- Learn about Spatial Signatures (scale, context)
- Explore the potential of NNs for cities

Experiments setup


Atherton
Higher Folds
Manchester
Mossley
Penistone
Wombwell
Hoyland
Melling
Crosby
Eccles
Dukinfield
Stocksbridge
Wentworth
Padfield
Bootle
St Helens
Newton-le-Willows
Hyde
Glossop
Rotherham
Whiston
Sale
Liverpool
Stockport
Hoylake
Warrington
Sheffield
West Kirby
Halewood
Widnes
Hale Barns
New Mills
Thornhill

Dimensions to explore

Chip size



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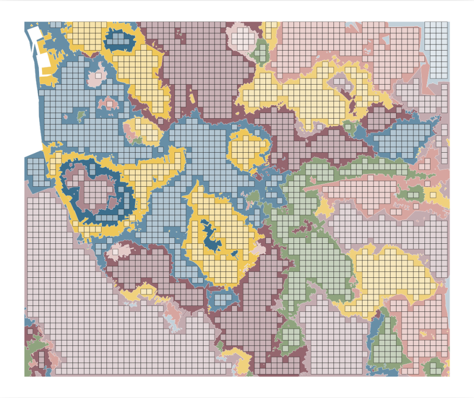

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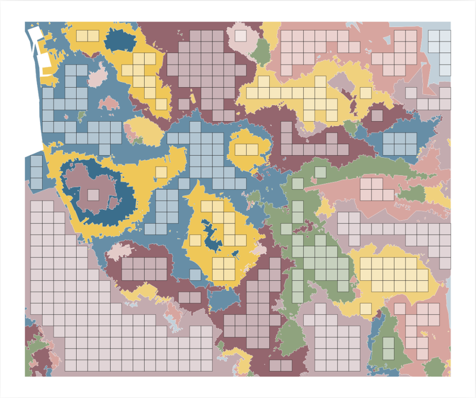

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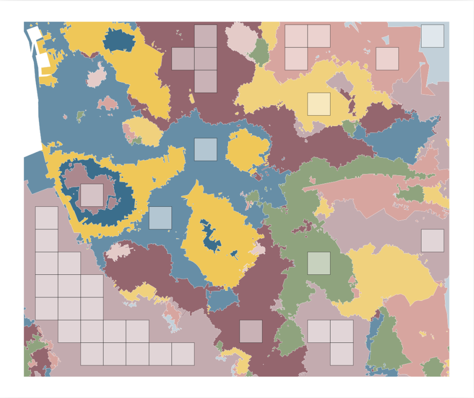

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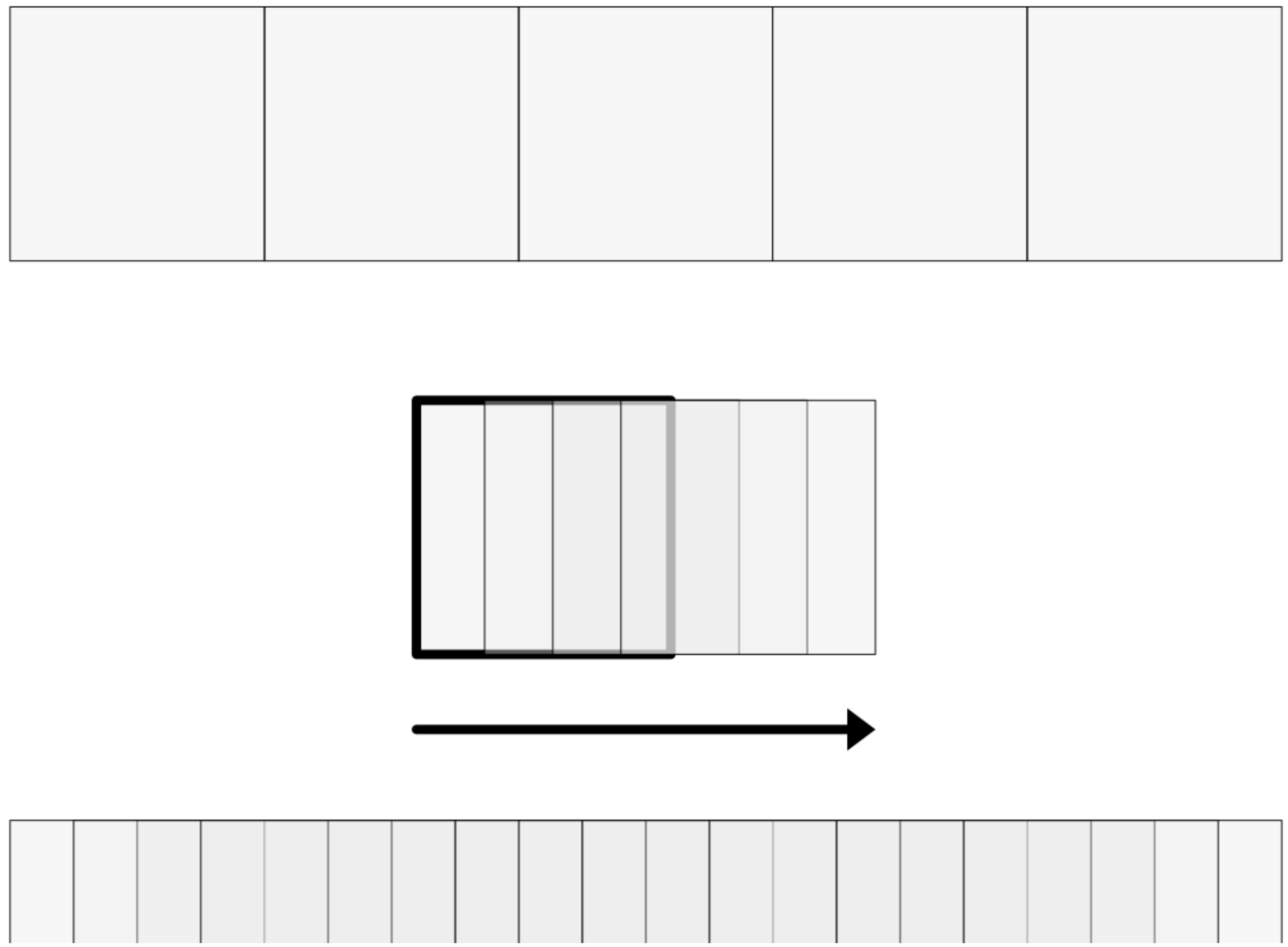


Model architecture

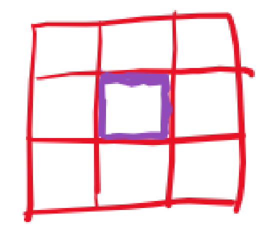
`EfficientNetB4`

- Image Classification
- Multi-Output Regression

$$S_i = f\left(\sum_K P_K + \sum_K W P_K\right)$$

$- f$

1. Argmax
2. (MN) Logit
3. Random Forest
4. Grad. Boosted Trees



$$WP_{ki} = \sum_j w_{ij} P_K$$

Evaluation

Metrics

- Standard
  κ, accuracy, F1
- Spatial

Summarisation

$$Perf_i = \alpha + \sum_m \delta_m M_i + \sum_a \gamma_a A_i + \beta_1 Chip\ Size_i + \beta_2 W_i + \epsilon_i$$

$$Perf_{i-s} = \alpha + \sum_m \delta_m M_i + \sum_a \gamma_a A_i + \beta_1 Chip\ Size_i + \beta_2 W_i + \beta_3 [\%]\, Obs_{i-s} + \sum_s \zeta_s S_{i-s} + \epsilon_{i-s}$$

Results

	κ	Global Accuracy	Macro F1 w.	Macro F1 avg.
Intercept	0.2185***	0.3236***	0.2790***	0.1798***
	(0.0209)	(0.0175)	(0.0174)	(0.0375)
(M) Logit E.	-0.0245	-0.0256*	-0.0324**	-0.0325
	(0.0168)	(0.0141)	(0.0141)	(0.0302)
(M) Max. Prob.	-0.0559**	-0.0606***	-0.0421**	-0.0296
	(0.0222)	(0.0187)	(0.0186)	(0.0399)
(A) M.O.R.	0.0227	-0.0357**	-0.0278*	0.1787***
	(0.0184)	(0.0155)	(0.0154)	(0.0331)
(A) S.I.C.	0.0232	-0.0247	-0.0171	0.1101***
	(0.0184)	(0.0155)	(0.0154)	(0.0331)
Chip Size	0.0036***	0.0043***	0.0048***	0.0014**
	(0.0004)	(0.0003)	(0.0003)	(0.0006)
W	0.0572***	0.0468***	0.0531***	0.0392
	(0.0168)	(0.0141)	(0.0141)	(0.0302)
R^2	0.7214	0.8281	0.8514	0.4191
R^2 Adj.	0.6899	0.8086	0.8346	0.3533
N.	60	60	60	60

Table 2: Regression outputs explaining global non-spatial performance scores. Explanatory variables with a preceding (M) and (A) correspond to binary variables for the type of model (with histogram-based boosted classifier, or `HGBC`, as the baseline) and architecture (with baseline image classification, or `BIC`, as the baseline), respectively. Standard errors in parenthesis. Coefficients significant at the 1%, 5%, 10% level are noted with ***, **, and *, respectively.

	Within-Class Accuracy		
Intercept	0.1866***	-0.0237	0.0595**
	(0.0308)	(0.0311)	(0.0303)
(M) Logit E.	-0.0125	-0.0125	-0.0125
	(0.0159)	(0.0141)	(0.0146)
(M) Max. Prob.	-0.0188	-0.0188	-0.0188
	(0.0211)	(0.0186)	(0.0193)
(A) M.O.R.	0.1753***	0.2512***	0.1753***
	(0.0175)	(0.0163)	(0.0160)
(A) S.I.C.	0.1202***	-0.0783***	0.1202***
	(0.0175)	(0.0209)	(0.0160)
Chip Size	0.0014***	0.0041***	0.0014***
	(0.0003)	(0.0003)	(0.0003)
1k Obs.		0.0514***	
		(0.0036)	
% Obs.			0.0156***
			(0.0013)
W	0.0365**	0.0365***	0.0365**
	(0.0159)	(0.0141)	(0.0146)
(S)Urbanity	0.2358***	0.2022***	0.2574***
	(0.0349)	(0.0309)	(0.0320)
(S)Dense urban neighbourhoods	-0.1420***	-0.1075***	-0.0998***
	(0.0349)	(0.0309)	(0.0322)
(S)Dense residential neighbourhoods	-0.1414***	-0.0836***	-0.0983***
	(0.0349)	(0.0311)	(0.0322)
(S)Connected residential neighbourhoods	-0.1306***	-0.0726**	-0.0754**
	(0.0349)	(0.0311)	(0.0323)
(S)Gridded residential quarters	-0.0785**	-0.0127	-0.0049
	(0.0349)	(0.0312)	(0.0326)
(S)Disconnected suburbia	-0.0601*	-0.0103	-0.0019
	(0.0349)	(0.0311)	(0.0324)
(S)Open sprawl	-0.0845**	-0.0995***	-0.1143***
	(0.0349)	(0.0309)	(0.0321)
(S)Warehouse park land	-0.0857**	-0.0788**	-0.0817**
	(0.0349)	(0.0309)	(0.0320)
(S)Urban buffer	-0.0828**	-0.1382***	-0.1753***
	(0.0349)	(0.0311)	(0.0330)
(S)Countryside agriculture	0.2236***	0.1593***	0.1118***
	(0.0349)	(0.0312)	(0.0334)
(S)Wild countryside	0.3876***	0.3283***	0.2925***
	(0.0349)	(0.0311)	(0.0330)
R^2	0.4979	0.6087	0.5794
R^2 Adj.	0.4857	0.5987	0.5686
N.	720	720	720

Table 3: Regression outputs explaining within-class accuracy. Explanatory variables with a preceding (M), (A) and (S) correspond to binary variables for the type of model (with histogram-based boosted classifier, or `HGBC`, as the baseline), architecture (with baseline image classification, or `BIC`, as the baseline) and spatial signature (with Accessible suburbia as the baseline), respectively. Standard errors in parenthesis. Coefficients significant at the 1%, 5%, 10% level are noted with ***, **, and *, respectively.

	JC W_thr	$\log(JC)$ W_thr	JC W_union	$\log(JC)$ W_union
Intercept	4.3454***	1.4617***	4.7103***	1.6311***
	(0.9507)	(0.1344)	(0.5763)	(0.1080)
(M) Logit E.	-0.1406	-0.0431	0.1851	0.0481
	(0.4951)	(0.0700)	(0.2995)	(0.0561)
(M) Max. Prob.	0.1128	-0.1223	0.2819	0.0223
	(0.6442)	(0.0911)	(0.3887)	(0.0728)
(A) M.O.R.	-3.1630***	-0.5744***	-2.7875***	-0.4647***
	(0.5494)	(0.0777)	(0.3301)	(0.0619)
(A) S.I.C.	0.0119	-0.2390***	-0.6666**	-0.0481
	(0.5532)	(0.0782)	(0.3329)	(0.0624)
Chip Size	0.0297***	-0.0005	-0.0061	-0.0080***
	(0.0108)	(0.0015)	(0.0065)	(0.0012)
W	-0.9325*	-0.1376**	-0.9556***	-0.1785***
	(0.4945)	(0.0699)	(0.2991)	(0.0560)
(S)Urbanity	4.6650***	0.6574***	0.1156	-0.1258
	(1.0696)	(0.1512)	(0.6460)	(0.1211)
(S)Dense urban neighbourhoods	1.7796*	0.5094***	0.7480	0.1609
	(1.0695)	(0.1512)	(0.6487)	(0.1216)
(S)Dense residential neighbourhoods	-0.8545	0.0672	-0.4636	-0.0920
	(1.0958)	(0.1550)	(0.6647)	(0.1246)
(S)Connected residential neighbourhoods	-0.3656	0.1543	-0.4388	-0.1447
	(1.1018)	(0.1558)	(0.6647)	(0.1246)
(S)Gridded residential quarters	-0.2000	0.1009	-0.6203	-0.2111*
	(1.0744)	(0.1519)	(0.6517)	(0.1221)
(S)Disconnected suburbia	-0.9752	-0.1719	-1.0303	-0.3358***
	(1.1213)	(0.1586)	(0.6684)	(0.1252)
(S)Open sprawl	1.8342*	0.1734	2.1575***	0.3576***
	(1.0604)	(0.1499)	(0.6432)	(0.1205)
(S)Warehouse park land	0.5496	0.2123	1.2245*	0.3054**
	(1.0694)	(0.1512)	(0.6487)	(0.1216)
(S)Urban buffer	-0.0558	-0.0931	2.7027***	0.5164***
	(1.0521)	(0.1488)	(0.6382)	(0.1196)
(S)Countryside agriculture	-1.3759	-0.2511*	0.6623	0.0670
	(1.0521)	(0.1488)	(0.6382)	(0.1196)
(S)Wild countryside	-2.0183*	-0.5065***	-0.5918	-0.1635
	(1.0521)	(0.1488)	(0.6382)	(0.1196)
R^2	0.1589	0.1954	0.2118	0.2660
R^2 Adj.	0.1368	0.1743	0.1913	0.2468
N.	665	665	670	670

Table 4: Regression outputs explaining (log of) differences in the spatial pattern between observed and predicted values, as measured by the Join Counts statistic. The Join Counts for each signature were computed using two types of spatial weights: one based on a distance threshold of 1Km (W_thr), and another one built as a the union of nearest neighbor and queen contiguity matrices (W_union). Explanatory variables with a preceding (M), (A) and (S) correspond to binary variables for the type of model (with histogram-based boosted classifier, or `HGBC`, as the baseline), architecture (with baseline image classification, or `BIC`, as the baseline) and spatial signature (with Accessible suburbia as the baseline), respectively. Standard errors in parenthesis. Coefficients significant at the 1%, 5%, 10% level are noted with ***, **, and *, respectively.

Summarisation summary

- Extra ML pays off
- M.O.R. worse in general, better *within* class
- Spatial context *always* improves performance
- Scale: larger is better, except for spatial patterning
- Spatial sliding rarely (within-class)

Conclusions

- Space matters for the spatial signatures
- There's value in combining NNs & other ML
- A *bit* closer to frequent Spatial Signatures

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