The 'Paris-end' of town? Urban typology through machine learning.

Kerry A. Nice, Jason Thompson, Jasper S. Wijnands, Gideon D.P.A. Aschwanden, Mark Stevenson

Transport, Health, and Urban Design Hub, Faculty of Architecture, Building and Planning, University of Melbourne

AAG 2018, New Orleans, 12 April 2018





The 'Paris-end' of town? Urban typology through machine learning.

Kerry A. Nicel*, Jason Thompson¹, Jasper S. Wijnands¹, Gideon D.P.A. Aschwanden¹, Mark Stevenson¹,

1 Transport, Health, and Urban Design Hub, Faculty of Architecture, Building, and Planning, University of Melbourne, Victoria 3010, Australia

* kerry.nice@unimelb.edu.au

Abstract

The confluence of recent advances in availability of geospatial information, computing power, and artificial intelligence offers new opportunities to understand how and where concrities differ and also, how they are alike. Departing from a traditional 'top-down' analysis of urban design features, this project analyses millions of images of urban form (consisting of street view, satellite imagery, and street maps). A (novel) neural network-based framework is trained with imagery from the largest 1692 cities in the world and the resulting trained models are used to compare within-city locations from Melbourne and Sydney to determine the closest connections between these areas and their international comparators. This work demonstrates a new, consistent, and objective method for understanding the relationship between cities around the world, and the health, transport, and environmental consequences of their design. The results show specific advantages and disadvantages using each type of imagery, and we draw conclusions about the best use of each for specific analytic goals. Finally, and perhaps most importantly, this research also answers the age-old question, "Is there really a 'Paris-end' of your city?".

What makes Paris look like Paris?



Window Balustrades

Streetlamps on Pedestal

Figure 5: Books on Paris architecture are expressly written to give the reader a sample of the architectural elements that are specifically Parisian. We consulted one such volume [Loyer, 1988] and found that a number of their illustrative examples (left) were automatically discovered by our method (right).



Random Images for Paris Street-view



Extracted Visual Elements from Paris



Figure 9: Geographically-informative visual elements at the scale of city neighborhoods. Here we show a few discovered elements particular to three of the central districts of Paris: Louvre/Opera. the Marais, and the Latin Ouarter/Luxembourg.

Doersch et al. (2012)

Convolutional Neural Networks

Algorithms for understanding and categorising images Can be trained to understand edges, colours and patterns unique to individual categories of images



Using neural networks

The CNN is made up of millions and millions of individual 'neurons' that each fire in response to various combinations of RGB channel data contained within the image, itself

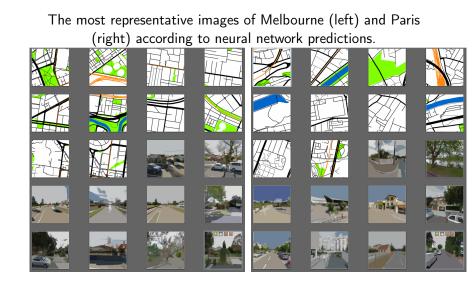
Over time, weights associated with each neuron are 'adjusted' in response to the correct or incorrect categorisation of images until the model 'converges'



Using 1.692 million images 1692 cities Cities with > 300k residents Random Sample of 1000 locations from each city 75% Training, 25% Validation Selection area scaled to reflect population size p^.85 Training takes a number of weeks Watercooled GPUs



Each model was trained until convergence for a total of 150 epochs, using the Microsoft Cognitive Toolkit (CNTK) (Yu et al., 2015).



Training data for 3 neural networks



Four sample Google Maps (GM) neural network training data images for Paris, France. Neural network was trained with 1.665 million images from 1665 cities. Reached a validation accuracy of 73.2%



Sample Google Maps Satellite (GS) neural network training data images for Adelaide, Australia and Beijing, China. Neural network trained with 1.688 million images from 1668 cities. Reached a validation accuracy of 99.4%

Training data for 3 neural networks



Sample Google Street View (GSV) neural network training data image from Sydney, Australia (Google Maps, 2017b) (A) and the processed segmented version (B). Sample Baidu Street View (BSV) neural network training data image from Beijing, China (Baidu, 2017) (C) and the processed segmented version (D). Neural network was trained with 1.074 million images from 1074 cities. Reached a validation accuracy of 43.1%

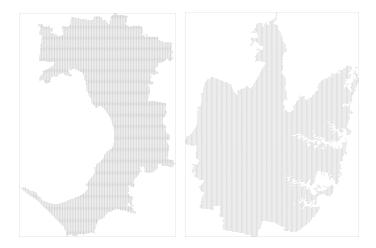
The sampling area for each city was chosen as a circular area aligned to the city's centre, where the radius r (km) of the sampling area was determined based on the population size p according to Barthelemy (2016)

$$r = \sqrt{\frac{28.27}{\pi} \left(\frac{p}{300,000}\right)^{0.85}} \tag{1}$$



Randomly generated locations to sample urban form in Hong Kong. 1000 images sampled from each city. Large water-bodies (e.g., oceans but not coastlines) were removed from the sampling area.

Evaluation locations for Melbourne and Sydney

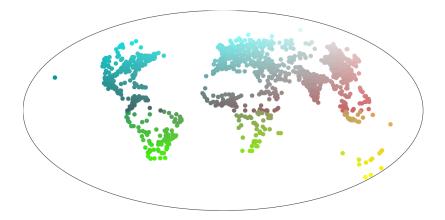


Melbourne (23,027) and Sydney (24,596) evaluation locations at 400m resolution. No training was performed using imagery from Melbourne or Sydney, so the evaluation forced the neural networks to pick the most similar city to each evaluated location.

Top 20 cities like Melbourne/Sydney using Google Maps imagery

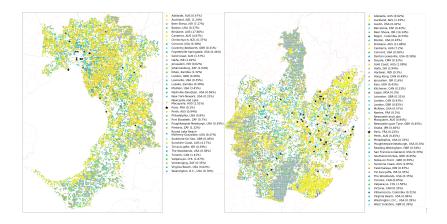
	Melbour	ne evaluation	Sydney evaluation				
Predicted city	Matches	% matching	Matches	% matching			
Brisbane, Australia	4062	17.6	2922	11.9			
Beer Sheva, Israel	1671	7.3	3479	14.1			
Canberra, Australia	1074	4.7	1770	7.2			
Sunshine Coast, Australia	960	4.2	456	1.9			
McAllen, United States of America	794	3.5	140	0.6			
Valparaíso, Chile	431	1.9	383	1.6			
Haifa, Israel	372	1.6	723	2.9			
Gold Coast, Australia	361	1.6	265	1.1			
Newcastle and Lake Macquarie, Australia	347	1.5	1214	4.9			
Toronto, Canada	325	1.4	209	0.9			
Kitwe, Zambia	303	1.3	-	-			
Pretoria, South Africa	303	1.3	-	-			
Auckland, New Zealand	285	1.2	293	1.2			
Johannesburg, South Africa	239	1.0	-	-			
Perth, Australia	216	0.9	111	0.5			
Philadelphia, United States of America	185	0.8	-	-			
Washington, D.C., United States of America	174	0.8	-	-			
Port Elizabeth, South Africa	162	0.7	-	-			
Virginia Beach, United States of America	143	0.6	235	1.0			
Jerusalem, Israel	142	0.6	393	1.6			
Tasikmalaya, Indonesia	-	-	238	1.0			
London, United Kingdom	-	-	199	0.8			
Adelaide, Australia	-	-	152	0.6			
Denton-Lewisville, United States of America	-	-	143	0.6			
Hong Kong, China, Hong Kong SAR	-	-	121	0.5			
Osaka, Japan	-	-	113	0.5			

Plotting color scheme



Latitude/longitude based color scheme for plotting cities-like for Melbourne and Sydney evaluations.

Are Melbourne/Sydney like Paris using Google Maps imagery?



Predicted similar cities using the GM neural network. Top predicted cities plotted using color scheme for Melbourne evaluation locations and Sydney. Predicted Paris locations marked with black stars.

Melbourne CBD GM neural network evaluation locations

		1	tinte			60			0		1	+	1	E		1=1	D	1		H			11	to'r	1-1			1	=III		201
SAcourtu	USA	GBR -	UAE Artie	Naples. ITA	GBR	Lancest	JS . Adelai er Carberr	de Adela AUS	AUS	Larse	USA Ref Pakeda	ISA USA	SAL PLAY IN	USA	Louisvil	AUS	AUS	AUS	AUS	AUS	AUS	AUS	SGP	JPN AU	JS veri	USA P	USA Inburgh	AUS	AUS	AUS	AUS a Eriber
San Mecel		USA	USA	xiliqua" MEX	AUS	CHN Shendh	AUS	Adactics	AUS	AUS	Odesa UKR	USA 9. Los	AUS	AUS	AUS	AUS	AUS	UAE	USA	AUS	AUS	AUS	AUS	GBR	AUS	vin .	GBR	AUS	GBR	GBR Condon	SGP
San Artoni	USA	USA	Adelakte	Distars	Luchari Bachari	CHN	GBR	Daycon	USA	UKR	UKR	Belfatz	Definit	AUS	UKR	Cologra	AUS	Loda	GBR In	GBR	Staffes	DEU	DEU	MEX	BRA	MEX	USA m	ninten	Eristan	Lesfon	Advisid
BRineston	1.00			jo.							1			1.		A.	1		G/	1			100		115		5	1.00	111	1	
Nativili	6-Owdetice	AUS	Carberr	USA	AUS	AUS	Carber	a Cardiff	UKR	Caperit	AElyspak lagen.	Timisos	USA	Achieve	AUS	London	GBR	Covers	geliedaver	AUT	May To	S Navark	Domm	edDortmu	ndGa (nta	S	Propidie	Cabe	FRA	London	Auth
BITELase AUS	USA	ITA	ITA	ROU	AUS	AUS AL	JS carken	GBR	BORR	BRA	CHN	AUS	MEX	Philadeter	USA	USA	IND	Frester	Singape SGP	SGP	USA	FRA	DEU	GBR	BRA	show JPN	JPN	MEX	ROU	ROU	AUS
GBR.	GBR	GBR	GBR	GBR	inter	e faristan	e Gern		an Grence GBR	FRA	Katherag	NPLS	an Lolis Por	age [ppul	Signal	USA	section	Sansag	oru	syan	reCubin	Napoja	HKG	Techeum	e Kagait		IN Talchus	g Testar	ITA	Loho	0.500
and the		1.16	Send .		12	-			10	1					11	11			in 1						11	212		CHN	100	-11	11 -
GBR /	Bashvill	lo-Duvidasi	USA	Belass	Sab	Sup	Sigap	CHN	CHN	GBR	Oute	JPN	Dinneligi Glaneligi	IND	MEX	MEX.	USA	CHL intago Me	MEX	MEX	TUR	JPN	aru -	SGP V	nico City	Tantar	N Takouri	MEX	ANaples	NEX No	MEX
S. Levis	MEX	AUS	USA	AUS	MEX BO	Rsida L	GBR	Stinger	USA	AUSCO	USA	ZAF A	JSernar	S. Lees	USA	MEX US	Arreview	IND	CHN	CHN	CHN I	MEX C	Chi M	EX Mendes	MEX	CHN	CHN **	JPN	BRA O	CHN Ca	ZAF
Andard	Entran	USA	VILLEN	EH.	and and	-	ITA	AUS	CAN	FRA	Alberto	Vercea	- 17123.1	Verona	TA US	Avore	Gastala	MEX	MEX	CHN	Non	1	MEX	CHN	CHN	CHN	BUDIO	andrest		TIRVA	Locative
AUS A	aus rea	-10000	ISA Fuel	MEX	AUS	USA	/olegies	rom	CESSING	Carrees	USA	ITA	ITA	ITA	dergrafs	Sar Art	USA	04	autend	Tel	MEX	HN M	Techone	ware to	antonj Ka	0,0363	ROU	MEX	ATIO	JPN	USA
IND A	PHL.	USA	USA	USA	AUS	AUS	AUS	AUS INT	GBR	IND	GBR	POL	ITA	Verora	ITA Seat	GBR	POL	CAMEX CADING	MEX	MEX	San Lun MEX	MEX	MEX	MEX	CHN	CHN	BGR: SoSs	UKR	SGP	USA	Locaped
PHL	Ditari	Columbi	USA	Adelarde	AUS	ITA	Perth	GEO	FRA Paris	Dortes	ritalina	Tallen	USA	FRA S	IBR US	Arresto	POL	DEU MI	Xterretor	Lacyan	Tecten	veione	BRA	CHN BE	Anny	CHN	CHN	BGR	BRA .	Tettes	BRA
		1.2		11/	1	T_{-}	11	14.	ب						1	N/A		1	af.		1	to		C.A	1	1-	t/i				-
GBR	GBR	AUS	AŬS	poeterde	Advised	Loury	e Washing	100	TUR	CHN	CHN	CHN	SARGE	a Barcelor	CHN	CAN	Hobert	GBR	SGP	HKG "	BRA	Kestow	1	BRA	Sansio	E SIN	sign	UKR	UKR	MEXI	MEX U
AUS	AUS	AUS	AUS	USA	arithan AUS	USA	USA		TUR N	MAR U	SADerrok	New Dia	USA	IR SAND Swatses	GBR	DEU	Remerch	NLD	NLD	DEU C	11 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	HN K	CHN CH	Nasha	CHN	POL	ROU IN	MEX	ROU	NONE P	GBR
Grabufe	AUS	AUS	Louina	Louiselle	. Beitur	Louisvill	e Noble	Sanjaa	ITA	TUN	TUN	USA	cetty ce O	anRUS I	aus	avon Don	Hambu	o Datan	Famerch	NLD	Horaro	HKG	HKG	HKG	-	M. Mrcela	w Outher	USA	AUS	Gerter	phivre
			11	i de la		5 .54			Cataria						17				1	no to	1	11			A	1.2	2	74	- The	ALL N	_1
AUS	AUS	AUS	BR GB	RMarthe	IN USA	CAN Best	Gatineau (Abi Dh	A Dordea	FRA	Boerstore	ZAF en blo	ZAF	TUR I	JSA vers	- ITAFS	Singapt	SGP	HKG	Ritantia	Hong Ko	HKG	Cadadia SPCroap	er MEX	MEX NOCO	USA FI	RAParts	USA	USA	FRA ?	TTA:::
Oevelans	AUS	USA	Columba	s San Die	Alls	AUS	USA U	E Sereg	Douvile	FRA	BRA US	Acien	USA	CAN IR	Nietras	Barcelos ISD	Na ESP	WHEAD	PAK	alla alla	TTRACK	la ute	SGP	Desure.	CHL	-	USA	Bardan USA US	Altreda	NLD	USA
07	-	1	Negar.		T	-			USA	20	12	1			3					\geq			1	1		100		RE		(\cdot)	NI
Children	1 51 LOLA	cirer	Gasta	ea h	2Seen	stingson	Luk so	CAN	Madeon	USA	USA	ZAF	NZL	ПАП	Aharre	Ma	nchester	Tience	BGR	teeds	Applain	ester	- Ander	Living	CHL	HKG	Batter	HALMON	Danca	GBR	Bridgan
Callenter USA	ALCOMO	Les Area	USA	MEX	Goure	es Columb	us Columb	POL	CHN pte	regen	NZL :	TA A	ickland Ce	ectent	Carloury	AUS	Abelaid	hours	Addeed	r-Cell	Peth	Parts.	Nirth	CHN To	-CHN	ISRS	IPS man	MEX	IND		USA AL

Detail of Melbourne CBD, with predictions of Paris highlighted in red squares.

GM model Paris-like locations

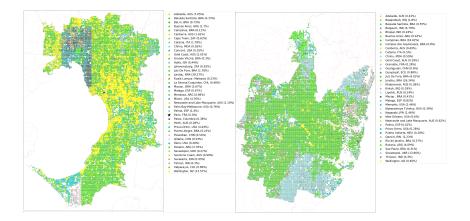


Gallery of 'Paris-like' locations in Melbourne using the GM neural network.



Gallery of 'Paris-like' locations in Sydney using the GM neural network.

Are Melbourne/Sydney like Paris using Google Satellite imagery?



Predicted similar cities using the GS neural network. Top predicted cities plotted using color scheme for

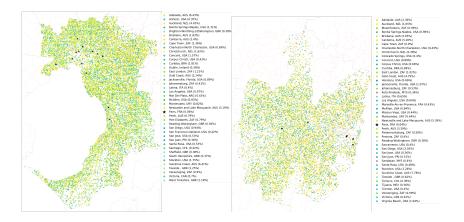
Melbourne evaluation locations and Sydney. Predicted Paris locations marked with black stars.

GS model predicted similar cities



Satellite imagery of Melbourne, Australia (A), Adelaide, Australia (B), Campinas, Brazil (C), Jundiaí, Brazil (D), Miami, USA (E), Provo, USA (F), and Wellington, NZ (G) Google Maps (2017a).

Are Melbourne/Sydney like Paris using Google/Baidu Street View imagery?



Predicted similar cities using the GSV-BSV neural network. Top predicted cities plotted using color scheme for Melbourne evaluation locations and Sydney. Predicted Paris locations marked with black

GSV-BSV model Paris-like locations



Gallery of 'Paris-like' locations in Melbourne/Sydney using the GSV-BSV neural network.

Is there a 'Paris-end' of Melbourne or Sydney?

No

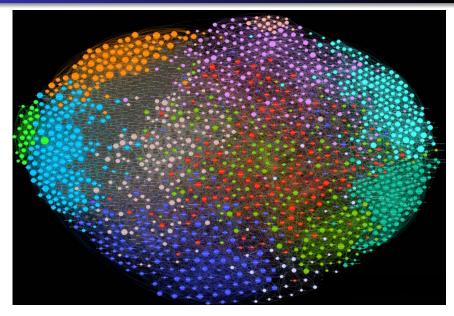
Related work - City clustering based on confusion

Most algorithms of this type are interested in accuracy - i.e., what percentage of images can the algorithm correctly classify? 80% + Instead, we were interested in what the network got wrong – when it got confused

Each instance of confusion created a link between two cities, generating city 'clusters'



Clustering of similar cities - Examine health outcomes



Thompson et al. (2018)

Summary and insights

- We have created a method for objectively and consistently defining city typologies and clusters.
- Method uses easily accessible and globally consistent imagery data.
- Can explore how urban design can impact public health and other urban issues.
- Neural networks have no preconceived notions of what they will find and use all of the data. Cherry-picking is right out.
- Sometimes the neural networks can produce mysterious or surprising results, requiring cross-disciplinary interpretation (and perhaps some reverse engineering).
- Different types of imagery can emphasise different urban characteristics.
- Sadly, neither Melbourne or Sydney can claim to have a 'Paris-end' of town.
- The trained networks are available. Contact me if you want to try it on your own town.

Bibliography

- Baidu (2017), Baidu Street View API, Available from http://api.map.baidu.com/. (accessed 15 June 2017).
- Barthelemy, M. (2016), *The Structure and Dynamics of Cities: Urban Data Analysis and Theoretical Modeling.* Cambridge University Press.
- Doersch, C., Singh, S., Gupta, A., Sivic, J. and Efros, A. (2012), What Makes Paris Look like Paris? ACM Transactions on Graphics, Association for Computing Machinery, 31(4).
- Google Maps (2017a), Google Static Maps API, Available from https://developers.google.com/maps/documentation/static-maps. (accessed 15 June 2017).
- Google Maps (2017b), Google Street View API, Available from https://developers.google.com/maps/documentation/streetview/. (accessed 15 June 2017).
- Thompson, J., Stevenson, M., Wijnands, J., Nice, K., Aschwanden, G., Silver, J. and Nieuwenhuijsen, M. (2018), Linking derived city typologies and health; A new global perspective. *In-preparation*.
- Yu, D., Eversole, A., Seltzer, M.L., Yao, K., Huang, Z., Guenter, B., Kuchaiev, O., Zhang, Y., Seide, F., Wang, H., Droppo, J., Zweig, G., Rossbach, C., Currey, J., Gao, J., May, A., Peng, B., Stolcke, A. and Slaney, M. (2015), An Introduction to Computational Networks and the Computational Network Toolkit. Microsoft Technical Report MSR-TR-2014–112. Technical report.

Transport, Health, and Urban Design (THUD) Research Group

Dr Kerry Nice (Software Engineer, Urban Climate) https://mothlight.github.io/

♥ @mothlight

Dr Jason Thompson (Clinical Psychology) Dr Jasper Wijnands (Mathematician) Dr Gideon Aschwanden (Architect, Urban Analytics) Professor Mark Stevenson (Epidemiologist) Dr Haifeng Zhao (Complex Systems Modelling)

