## residential r+d SCE computational design



## as we look for **opportunities** to leverage **computational design**, we consider a **"day in the life"...**



#### ... of a prototypical project





# 

## autometric

#### real-time massing metrics

Confidential Project, San Francisco



SCP

## **inform** the design process in **real-time**, from **concept** to **yield + financial impact**. evaluate, adjust, and repeat.



#### reads rhino massing w/ various user inputs



#### autometric

SCB

#### real-time yield calculation w/ linked pro forma

		Parcel No	Land Area (ac)	Land Area (sf)	RESI Area (sf)	PDR Area (sf)	Ground Floor Area (sf)	Parcel GFA (sf)	FAR	Total RESI Units	RESI Density (unit/ac)	Parking Demand	Parking Supply
output to		PARCEL_1	0.69	30,025	84,000	19,564	40,564	103,564	3.45	92	133	72	101
	outputto	PARCEL_2	0.48	21,090	58,688	9,951	24,623	68,639	3.25	64	132	46	79
	excel	PARCEL_3	0.92	40,258	129,608	40,184	72,586	169,792	4.22	143	155	122	100
	0/001	PARCEL_4	0.46	19,917	70,188	19,917	37,464	90,105	4.52	77	168	63	49
		PARCEL_5	1.85	80,567	326,333	14,389	103,710	340,722	4.23	358	194	256	270
		PARCEL_6	0.46	19,939	70,296	19,939	37,513	90,235	4.53	77	168	63	49
📕		PARCEL_7	0.46	19,881	69,964	19,881	37,372	89,845	4.52	77	169	63	49
• • • • • • • • • • • • • • • • • • •	•	PARCEL_8	0.43	18,817	22,144	7,403	12,939	29,547	1.57	24	56	17	47
		PARCEL_9	1.21	. 52,539	180,660	38,038	83,203	218,698	4.16	199	165	160	167
		PARCEL_10	0.46	20,000	70,400	20,000	37,600	90,400	4.52	77	168	63	50
		PARCEL_11	0.92	39,974	193,374	40,027	72,256	233,401	5.84	213	232	171	100
		PARCEL_12	0.92	40,068	128,936	25,148	57,382	154,084	3.85	142	154	111	137
		PARCEL_13	0.49	21,216	83,976	21,216	35,212	105,192	4.96	92	185	/3	53
	1	TOTALS	9.74	424,291	1,488,567	295,657	652,424	1,784,224	4.21	1,635	168	1,280	1,251
	real-time in rhi	displa	ay	Block of Eand Ar Block of FAR: The Lot Cove Total RES RESI Dem Parking D Parking St	Block Nor Land Area Place To Server Total RESI Dannit Parking Dee Parking Sup Block Nor Land Area Parking Sup Desk Char Block Nor Land Area Block Nor Land Area Block Coverag Total RESI Donaty Parking Deep Parking Deep Parking Deep Parking Supp Deat Coverag Total RESI Donaty Parking Supp Parking Supp Par	BLOCK 4 40, 56, 623 (1), 434, 275 (2), 510852 (2), 10852 (2), 10852 (2), 202 (2), 202 (2	CK 8 11,614 201,594 14 0,60186 3: 172 mit/ac): 645	No: BLOCK_2 ren (si): 17,217 FA (si): 132,667 r703582 Block N3 Land Are Block Gi FAR: 8, Lot Cow Total Ri RESI D Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parking Parki	Block No: Block Of FAR: 9. Lot Cever Call of Call of Call of Call of Call of Call of Call of Call of Call of C	ELOCK 3 in (st): 25,573 A (st): 232,308 004112 Error (0.503031 251 Units: 98 Error (0.107) 251 Units: 98 Error (0.107) 2421 3.710 16924 248 7/c): 219 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 370 266 27 266 370 266 27 266 27 27 266 27 266 27 266 27 266 27 27 266 27 266 27 266 27 266 27 27 27 27 27 27 27 27 27 27	SITE SUMMARY Land Area (ac) Land Area (sf) RESI Area (sf COMM Area HOTEL Area GFA (sf): 2 FAR: 7.64 Total RES RESI Der Parking	: 6.957087 : 303,052 :: 1,016,2 (sf): 761,0 (sf): 359, (sf): 359,	8 02 02 22 7 899 899 800: 129 1,589

#### autometric

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## 

## view optimization + machine learning

#### masterplan scale

Confidential Project, Oakland



## how do we know we have achieved an optimal solution within the complexity of exponential possibility?



#### maximize unobstructed residential views



#### where is the tower how tall is it? **located**?

3 variables x 18 buildings =  $1.5 \times 10^{30}$  sphere of possible solutions

#### views + machine learning



#### what is its proportion?





## through machine-learning we define the variables and objectives and let the machine run thousands of options



#### evolutionary-based solver learns as it iterates



#### views + machine learning

#### 100 best solutions of 10,000 iterations



#### views + machine learning











































#### value proposition against baseline



#### residential units with view: **48.4%** residential un



#### views + machine learning

#### residential units with view: **65.6%**



### view optimization + machine learning

#### building scale

Howard Hughes Corporation, Honolulu



through machine learning the computer can manipulate building form, within defined constraints, to maximize views for every residential unit



#### variables for the computer to manipulate



13 variables = 3.1 × 10<sup>19</sup> sphere of possible solutions

#### views + machine learning



### shift the inflection point



evolutionary-based solver learns as it iterates



#### views + machine learning

SCĘ

#### 49 best solutions of 10,000 iterations



#### views + machine learning

#### value proposition against baseline



baseline view score per unit: 23%



#### views + machine learning

#### optimized view score per unit: **47%**

## thank you.