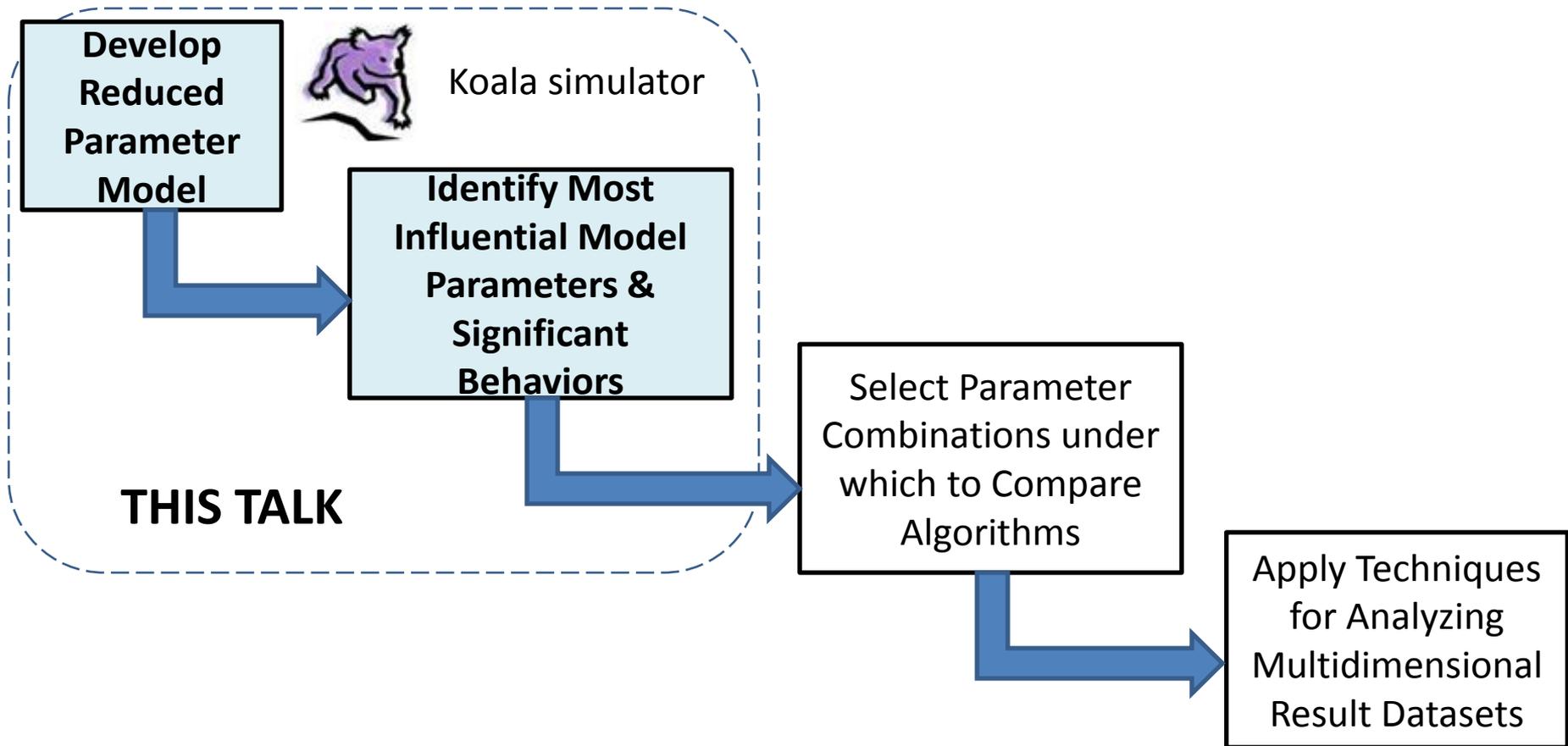


We Developed a 4-Step Method* to Compare Resource Allocation Algorithms in Large Distributed Systems



*Previously, we applied this method to compare congestion-control algorithms proposed for the Internet

Talk Synopsis

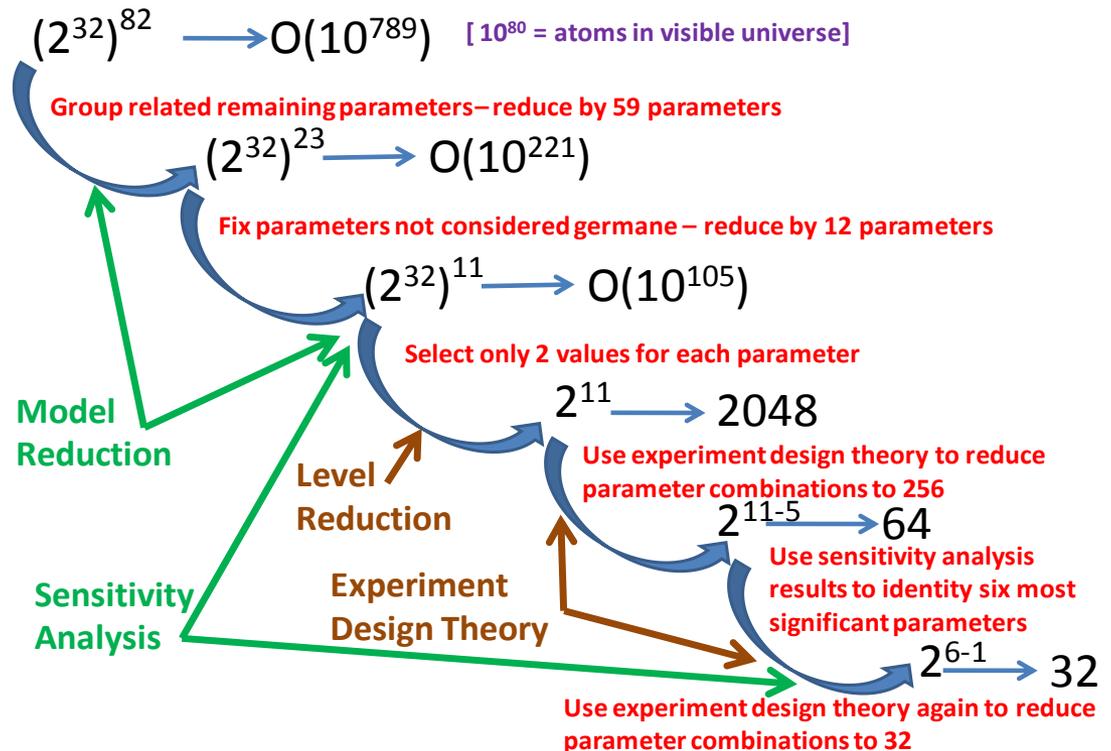
Problem: Simulations of large cloud systems typically require hundreds of parameters that can take on billions of values and that can also report hundreds of response variables.

$$y_1, \dots, y_z = f(x_1|_{[1, \dots, \ell]} \dots, x_p|_{[1, \dots, \ell]})$$

Response State-Space
Stimulus State-Space

How can one identify the most significant parameters to simulate and responses to analyze?

We base our study on the *Koala*  infrastructure cloud simulator



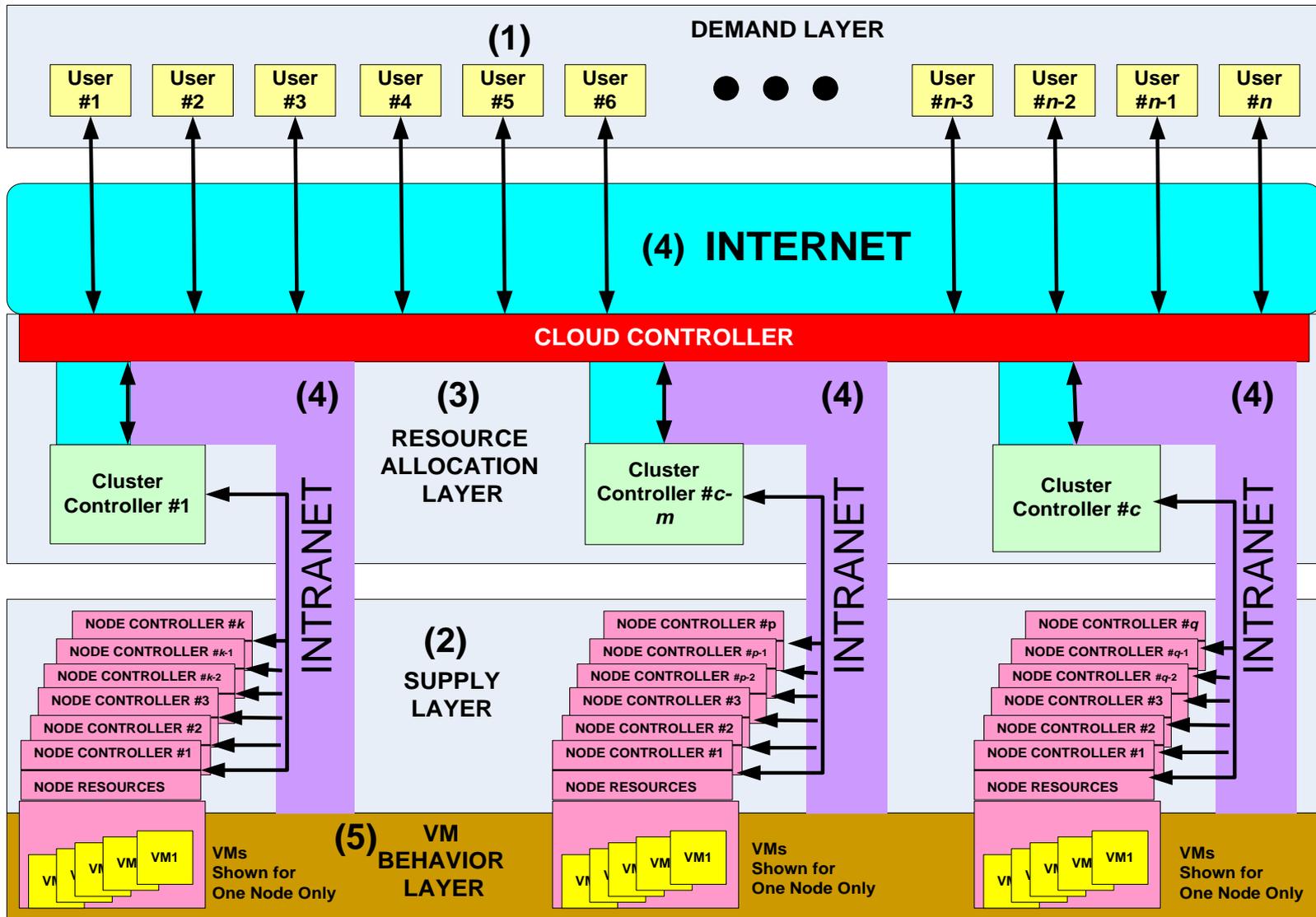
Outline

- Overview of *Koala*  Infrastructure Cloud Simulator
- Sensitivity Analysis Experiment Design
- Reduction of Response Dimensionality
- Identification of Significant Parameters
- Findings and Ongoing Work

Overview of *Koala* Infrastructure Cloud Simulator



Schematic of *Koala* IaaS Cloud Computing Model



Virtual Machine (VM) Types* Simulated in *Koala*

VM Types are offered by the Cloud provider and requested by Cloud users

VM Type	Virtual Cores		Virtual Block Devices		# Virtual Network Interfaces	Memory (GB)	Instruct. Arch.
	#	Speed (GHz)	#	Size (GB) of Each			
M1 small	1	1.7	1	160	1	2	32-bit
M1 large	2	2	2	420	2	8	64-bit
M1 xlarge	4	2	4	420	2	16	64-bit
C1 medium	2	2.4	1	340	1	2	32-bit
C1 xlarge	8	2.4	4	420	2	8	64-bit
M2 xlarge	8	3	1	840	2	32	64-bit
M4 xlarge	8	3	2	850	2	64	64-bit

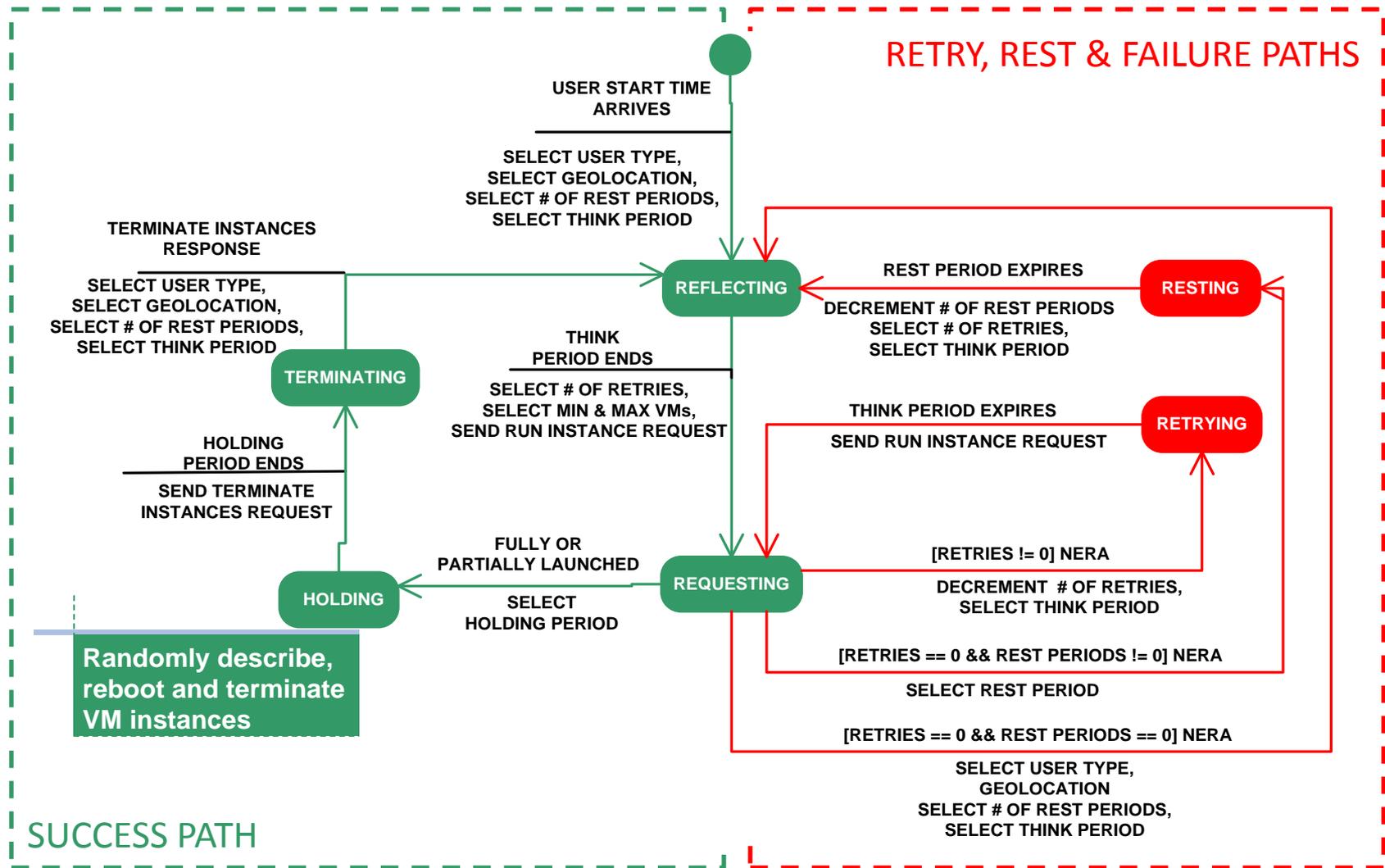
*Inspired by Amazon Elastic Compute Cloud VM Types

Description of User Types Simulated in *Koala*

We created different classes of demand, such as processing users (PU), distributed simulation users (MS), peer-to-peer users (PS), Web service users (WS) and data search users (DS)

User Type	VM Type(s)	Max-Min VMs	Max-Max VMs	User Type	VM Type(s)	Max-Min VMs	Max-Max VMs
PU1	M1 small	10	100	PS1	C1 medium	3	10
PU3		100	500	PS2		10	50
PU5		500	1000	PS3		50	100
PU2	M1 large	10	100	WS1	M1 large M2 xlarge C1 xlarge	1	3
PU4		100	500	WS2	M1 large M2 xlarge C1 xlarge	3	9
PU6		500	1000	WS3	M1 large M2 xlarge C1 xlarge	9	12
MS1		M1 xlarge	10	100	DS1	M4 xlarge	10
MS3	M1 xlarge	100	500	DS2	100		500
				DS3	500		1000

Finite-State Machine of Simulated User Behavior in *Koala*



Description of Selected Platform Types Simulated in *Koala*

We created 22 platform classes, inspired by a visit to an Amazon EC2 data center

Platform Type	Physical Cores		Memory (GB)	# Physical Disks by Size				# Network Interfaces	Instruct. Arch.
	#	Speed (GHz)		250 GB	500 GB	750 GB	1000 GB		
C2	1	1.7	16	3	0	0	0	1	32-bit
C4	1	2	16	3	0	0	0	1	32-bit
C6	2	2.4	16	0	3	0	0	1	32-bit
C8	2	2.4	32	0	3	0	0	1	64-bit
C10	4	2.4	32	0	4	0	3	1	64-bit
C12	4	2	64	0	4	0	3	2	64-bit
C14	4	3	64	0	4	0	3	2	64-bit
C16	8	3	64	0	0	4	3	2	64-bit
C18	8	3	128	0	0	4	3	4	64-bit
C20	16	3	128	0	0	0	7	4	64-bit
C22	16	3	256	0	0	0	7	4	64-bit

Sensitivity Analysis Experiment Design

Input Parameters used for Sensitivity Analysis of *Koala*

We identified 11 parameters we expected to significantly influence *Koala* behavior

Category	ID	Parameter Name
Duration	x1	Simulation duration in hours
Demand Layer	x2	Number of users
	x3	Probability of user's type
	x4	Average (and shape of) user holding time
Supply Layer	x5	Number of clusters
	x6	Number of nodes per cluster
	x7	Probability of platform configuration type
Resource Control Layer	x8	Algorithm for selecting cluster
	x9	Algorithm for selecting node
Internet/ Intranet Layer	x10	Number of sites for cloud components
	x11	Probability range of packet losses

Response Variables used for Sensitivity Analysis of *Koala*

We selected 40 variables that we expected to represent significant *Koala* dynamics

Category	ID	Response Name (Definition)
User-Level Responses	y1	User Request Rate (Requests by All Users / # User Cycles)
	y2	NERA Rate (NERAs / Requests by All Users)
	y3	Full Grant Rate (Full Grants / (Full Grants + Partial Grants))
	y4	User Arrival Rate (# User Cycles / Simulated Hours)
	y5	User Give-up Rate (# Users that Gave Up / # User Cycles)
	y6	Grant Latency (Weighted Avg. Delay in Granting VMs to Users that Got VMs)
Cloud-Level Responses	y7	Reallocation Rate (# Times Alternate Cluster Chosen / Requests Granted)
	y8	Full Grant Proportion (Avg. Fraction Clusters Offering Full Grants)
	y9	NERA Proportion (Avg. Fraction Clusters Reporting NERA)
	y10	vCore Utilization (Avg. Fraction of Virtual Cores Used in Cloud)
	y11	Memory Utilization (Avg. Fraction of Memory in Use in Cloud)
	y12	Disk Space Utilization (Avg. Fraction of Disk Space in Use in Cloud)
	y13	pCore Load (Avg. Virtual Cores Allocated / Physical Cores in Cloud)
	y14	Disk Count Load (Avg. Virtual Disks Allocated / Physical Disks in Cloud)
Cluster-Level Responses	y15	NIC Count Load (Avg. Virtual NICs Allocated / Physical NICs in Cloud)
	y16	vCore Util. Var. (Avg. Variance in vCore Utilization across Clusters)
	y17	Memory Util. Var. (Avg. Variance in Memory Utilization across Clusters)
	y18	Disk Space Util. Var. (Avg. Variance in Disk Space Utilization across Clusters)
	y19	pCore Load Var. (Avg. Variance in pCore Load across Clusters)
	y20	Disk Count Var. (Avg. Variance in Disk Count Load across Clusters)
	y21	NIC Count Var. (Avg. Variance in NIC Count Load across Clusters)
	y22	Node Reallocation Rate (# Times Alternate Node Chosen / VMs Allocated)
	y23	Cluster NERA Rate (# NERAs / # Responses Avg. across Clusters)
	y24	Cluster Full-Grant Rate (# Full Grants / # Responses Avg. across Clusters)
VM-Level Responses	y25	Allocation Rate (Times Cluster chosen / Cluster offered Avg. across Clusters)
	y26	SD-NERA (Stand. Dev. in Avg. NERA Rate across Clusters)
	y27	SD-Full-Grant (Stand. Dev. in Avg. Full-Grant Rate across Clusters)
	y28	SD-Allocation-Rate (Stand. Dev. in Allocation Rate across Clusters)
	y29	Current Instances (Avg. # VM Instances Extant in Cloud)
	y30	M1small Instances (Fraction of Current Instances that are M1 small VMs)
	y31	M1large Instances (Fraction of Current Instances that are M1 large VMs)
	y32	M1xlarge Instances (Fraction of Current Instances that are M1 xlarge VMs)
	y33	C1medium Instances (Fraction of Current Instances that are C1 medium VMs)
	y34	C1xlarge Instances (Fraction of Current Instances that are C1 xlarge VMs)
Message-Level Responses	y35	M2xlarge Instances (Fraction of Current Instances that are M2 xlarge VMs)
	y36	M4xlarge Instances (Fraction of Current Instances that are M4 xlarge VMs)
	y37	WS Message Rate (Avg. # WS Messages Send Per Simulated Hour)
	y38	Intra-Site Messages (# WS Messages Sent with Sites / # WS Messages Sent)
Message-Level Responses	y39	Inter-Site Loss Rate (Avg. Fraction of Inter-Site WS Messages Undelivered)
	y40	Intra-Site Loss Rate (Avg. Fraction of Intra-Site WS Messages Undelivered)

2-Level OFF Experiment Designs Reduce # of Parameter Combinations, While Improving Global Coverage and Minimizing Error in Effect Estimates in comparison with comparable Factor-at-a-Time (FAT) Designs

We selected two pairs of level settings (SA1 & SA2) and two system sizes (small & large)

Adopted 2-Level (2^{11-5}) "Resolution IV" OFF experiment design, requiring 64 simulations per experiment

Instantiated 4 designs, and simulated 6 repetitions (different random number seeds) with the 2 smaller designs

Required $(6 \times 2 + 2) \times 64 = 896$ simulations

Parameter	SA1-small and SA1-large		SA2-small and SA2-large	
	Plus Level	Minus Level	Plus Level	Minus Level
x1	1200 hours	600 hours	1600 hours	200 hours
x2	500 (SA1-small) 5000 (SA1-large)	250 (SA1-small) 2500 (SA1-large)	750 (SA2-small) 7500 (SA2-large)	125 (SA2-small) 1250 (SA2-large)
x3	PU1 = 0.2 PU2 = 0.2 PU3 = 0.1 PU4 = 0.1 WS1 = 0.15 WS2 = 0.07 WS3 = 0.03 PS1 = 0.1 PS2 = 0.01 MS1 = 0.1 MS3 = 0.01 DS1 = 0.10 DS2 = 0.01	PU1 = 1/6 PU2 = 1/6, WS1 = 1/6 MS1 = 1/6 PS1 = 1/6 DS1 = 1/6	PU1 = 0.4 PU2 = 0.4 PU3 = 0.1 PU4 = 0.05 PU5 = 0.025 PU6 = 0.025	WS1 = 0.25 WS2 = 0.15 WS3 = 0.1 PS1 = 0.35 PS2 = 0.04 PS3 = 0.01 DS1 = 0.08 DS2 = 0.015 DS3 = 0.005
x4	8 hours ($\alpha = 1.2$)	4 hours ($\alpha = 1.2$)	12 hours ($\alpha = 1.2$)	2 hours ($\alpha = 1.2$)
x5	20 (SA1-small) 40 (SA1-large)	10 (SA1-small) 20 (SA1-large)	30 (SA2-small) 40 (SA2-large)	5 (SA2-small) 10 (SA2-large)
x6	200 (SA1-small) 1000 (SA1-large)	100 (SA1-small) 500 (SA1-large)	400 (SA2-small) 1500 (SA2-large)	50 (SA2-small) 250 (SA2-large)
x7	C22 = 1.0	C8 = 0.25 C14 = 0.25 C18 = 0.25 C22 = 0.25	C14 = 0.2 C16 = 0.2 C18 = 0.2 C20 = 0.2 C22 = 0.2	C2 = 0.1 C4 = 0.1 C6 = 0.1 C8 = 0.1 C10 = 0.1 C12 = 0.1 C16 = 0.1 C22 = 0.3
x8	Percent Allocated	Least-Full First	Percent Allocated	Least-Full First
x9	Next-Fit	First-Fit	Next-Fit	First-Fit
x10	4	1	8	1
x11	10^{-3} to 10^{-8}	10^{-4} to 10^{-9}	10^{-2} to 10^{-7}	10^{-5} to 10^{-10}

Reduction of Response Dimensionality

Correlation Analysis & Clustering (CAC) Reduces Dimensionality

We identified an **8-dimensional response space** within the 40 responses

Compute correlation coefficient (r) for all response pairs

Examine frequency distribution for all $|r|$ to determine threshold for correlation pairs to retain; $|r| > 0.65$, here

Create clusters of mutually correlated pairs; each cluster represents one dimension

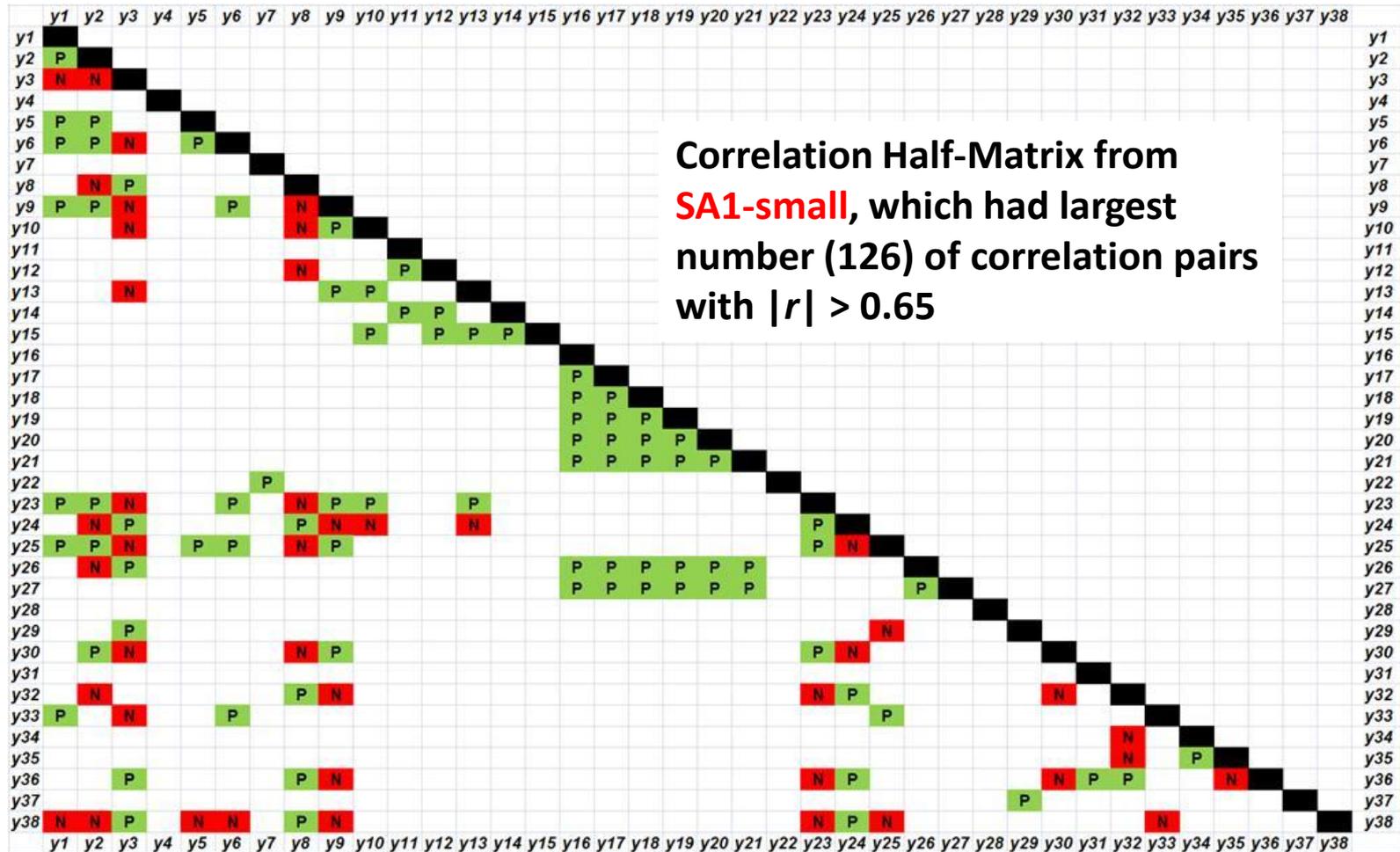
Select one response from each cluster to represent the dimension; we selected response with largest mean correlation that was not in another cluster*

Response Dimension	SA1-small (9 dimensions)	SA1-large (8 dimensions)	SA2-small (10 dimensions)	SA2-large (9 dimensions)
Cloud-wide Demand/Supply Ratio	y1, y2, y3 , y5, y6, y8, y9, y10, y13, y23, y24, y25, y29, y30, y32, y34, y36, y38	y1, y2, y3 , y5, y6, y7, y8, y9, y10, y13, y23, y34, y25, y29, y30, y32, y33, y34, y36, y38	y1, y2 , y3, y5, y6, y8, y9, y10, y11, y13, y14, y15, y23, y24, y25, y38	y1, y2, y3, y5, y6, y8, y9, y23 , y24, y25, y38
Cloud-wide Resource Usage	y10, y11, y12, y13, y14, y15	y10, y11, y12, y13, y14, y15	y10 , y11, y12, y13, y14, y15	y10 , y11, y12, y13, y14, y15
Variance in Cluster Load	y16, y17, y18, y19, y20, y21, y26 , y27	y16, y17, y18, y19, y20, y21, y26 , y27	y16, y18, y19, y20, y21, y26, y27	y16, y17, y18, y19 , y20, y21, y26, y27
			y17 (Mem. Util)	
Mix of VM Types	y34, y35 (WS)	y31 (MS)	y12, y14, y15, y30, y31, y33, y34, y35, y36	y14, y15, y30, y31 , y33, y34, y35
	y31 (MS)		y15, y36 (DS)	
Number of VMs	y29, y37	y37	y29, y37	y29
User Arrival Rate	y4	y4	y4	y4 , y37
Reallocation Rate	y7 , y22	y7, y22	y7 (cluster)	y7, y22
			y22 (node)	
Variance in Choice of Cluster	y28	y28	y28	y28

*Not possible for cloud-wide resource usage in SA2-small, so we selected response with highest mean correlation.

Analysis of Correlation Directionality Aids Model Verification

We checked positive and inverse correlations for reasonableness



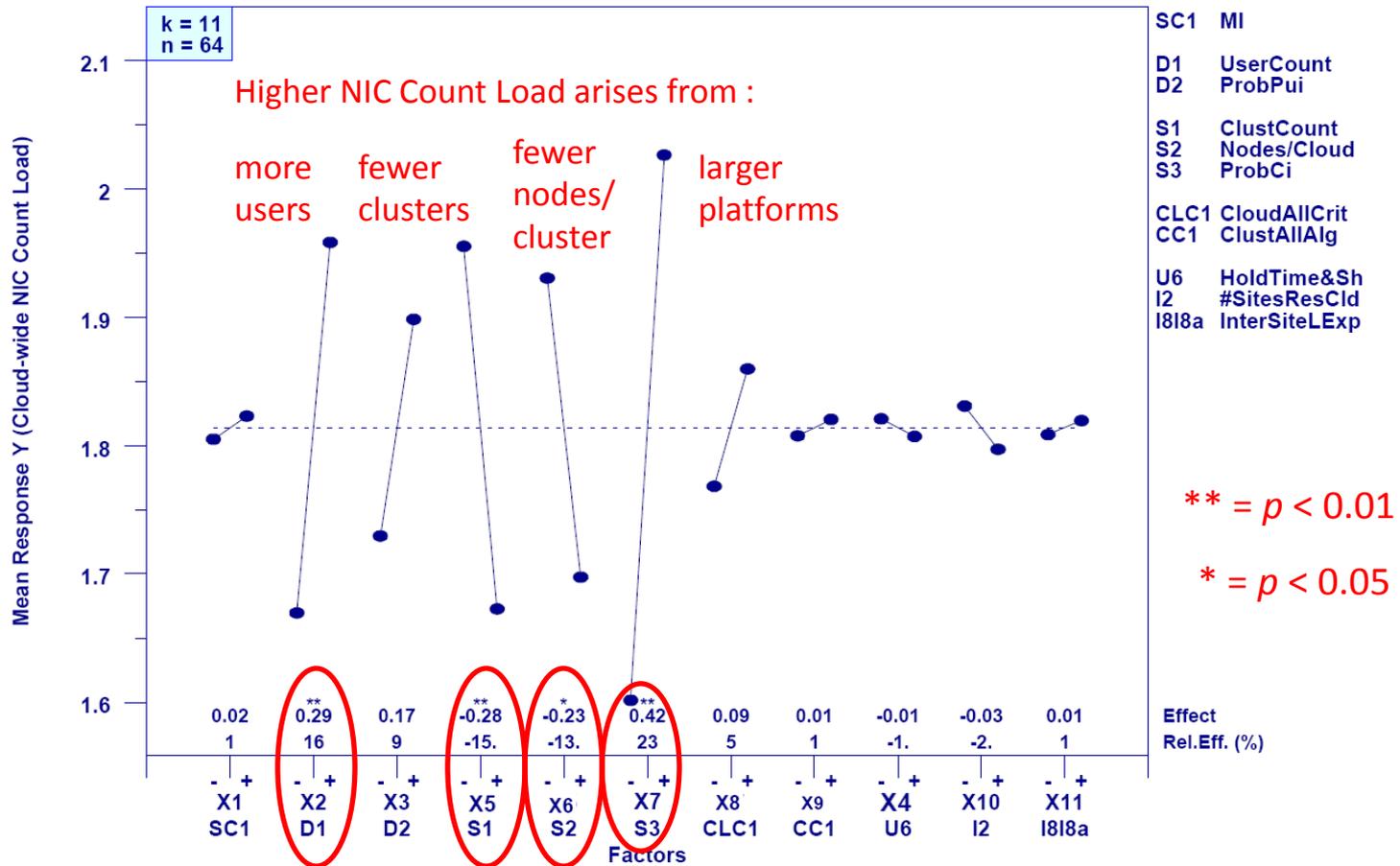
P = positive correlation

N = negative correlation

Identification of Significant Parameters

Main Effects Analysis (MEA) Identifies Significant Influence of Input Parameters on Response Variables

We applied MEA to response variables selected using CAC – this example is **y15** (NIC Count Load) for **experiment SA1-small**



Most significant parameters determined through MEA of the responses selected using CAC

We computed percent of responses influenced (Ψ) for each parameter, weighting $p < 0.05$ at $\frac{1}{2}$ and $p < 0.01$ at 1:

$$\Psi = (|\{y \mid p < 0.01\}| + \frac{1}{2} |\{y \mid p < 0.05\}|) / |\{y\}| \times 100$$

Computed average Ψ for each parameter, weighting experiment Ψ by number of repetitions

Experiment	Weight	Input Parameter										
		x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
SA1 small	6/14	1	57	22	11	44	29	30	12	0	1	0
SA1 large	1/14	0	69	13	25	44	56	31	25	0	13	0
SA2 small	6/14	2	73	38	10	45	62	10	17	1	0	0
SA2 large	1/14	0	56	50	11	39	56	6	11	0	0	0
Avg. Ψ	Est.	1	65	30	12	44	47	20	15	0	1	0

green = major influence; yellow = modest influence; orange = minor influence; gray = no influence

Most significant parameters: x2 (# users), x5 (# clusters), and x6 (# nodes/cluster)
Moderately influential parameters: x3 (user types) and x7 (platform types)
Somewhat influential parameters: x4 (user hold time) and x8 (cluster-selection algorithm)
No influence : x1 (measurement interval), x9 (node-selection algorithm),
 x10 (geo-distribution of cloud components), and x11 (packet loss prob.)

Checking Relative Effects from MEAs aids Model Verification

We averaged relative effect (Δ) over all experiment repetitions to determine how parameter increase influences direction and magnitude of effect for 8 dimensions

Dimension	Selected Response	Input Parameter										
		x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11
Cloud-wide Demand/ Supply Ratio	y3	1	-38	-21	-5	37	40	25	-2	1	5	-1
Cloud-wide Resource Usage	y15	1	23	53	1	-22	-18	19	-1	1	-1	1
Variance in Cluster Load	y26	0	-101	28	-5	96	59	66	42	0	50	0
Mix of VM Types	y31	-1	-9	43	-3	7	9	-1	8	2	-4	0
Number of VMs	y37	-5	48	11	-23	79	53	-5	8	-1	4	-2
User Arrival Rate	y4	-17	87	2	-80	29	31	15	-4	-1	-3	-5
Reallocation Rate	y7	0	0	0	0	0	0	0	0	0	0	0
Variance in Cluster Choice	y28	6	-12	-42	7	-35	32	18	97	2	4	6

green = $\Delta > 50$; yellow = $\Delta \geq 30$ & $\Delta < 50$; orange = $\Delta > 10$ & $\Delta < 30$; gray = $\Delta < 10$

Findings and Ongoing Work

Sensitivity Analysis Findings

- *Koala* cloud simulator exhibits 8 behavioral dimensions
 - 6 input parameters significantly influence *Koala* behaviors
 - Using a 2-level experiment design, comparison of resource allocation heuristics will require no more than ($2^6 =$) 64 parameter combinations, fewer (e.g., $2^{5-1} = 32$) with 2^{nd} application of 2-level OFF experiment design
-
- Analysis of direction in response correlations and of direction and magnitude in parameter effects suggests *Koala* behaviors are sensible
 - *Koala* resource requirements permit simulation of moderately-sized cloud configurations $O(10^5)$ nodes
 - *Koala* implementation and our computing infrastructure appear robust enough for maximum simulation durations lasting months

Ongoing Work

Currently conducting an experiment to compare 18 resource allocation heuristics for on-demand IaaS Clouds

Cluster Selection	Node Selection
Least Full First	First Fit
	Next Fit
Percent Allocated	Tag & Pack
	Random
Random	Least Full First
	Most Full First

$$3 \times 6 = 18$$

Experiment design is “Resolution VI” 2^{5-1} OFF, requiring simulating each of the 18 heuristics under 32 conditions (i.e., 576 total simulations)

Simulations are completed, data collected and analyzed. Paper in preparation.

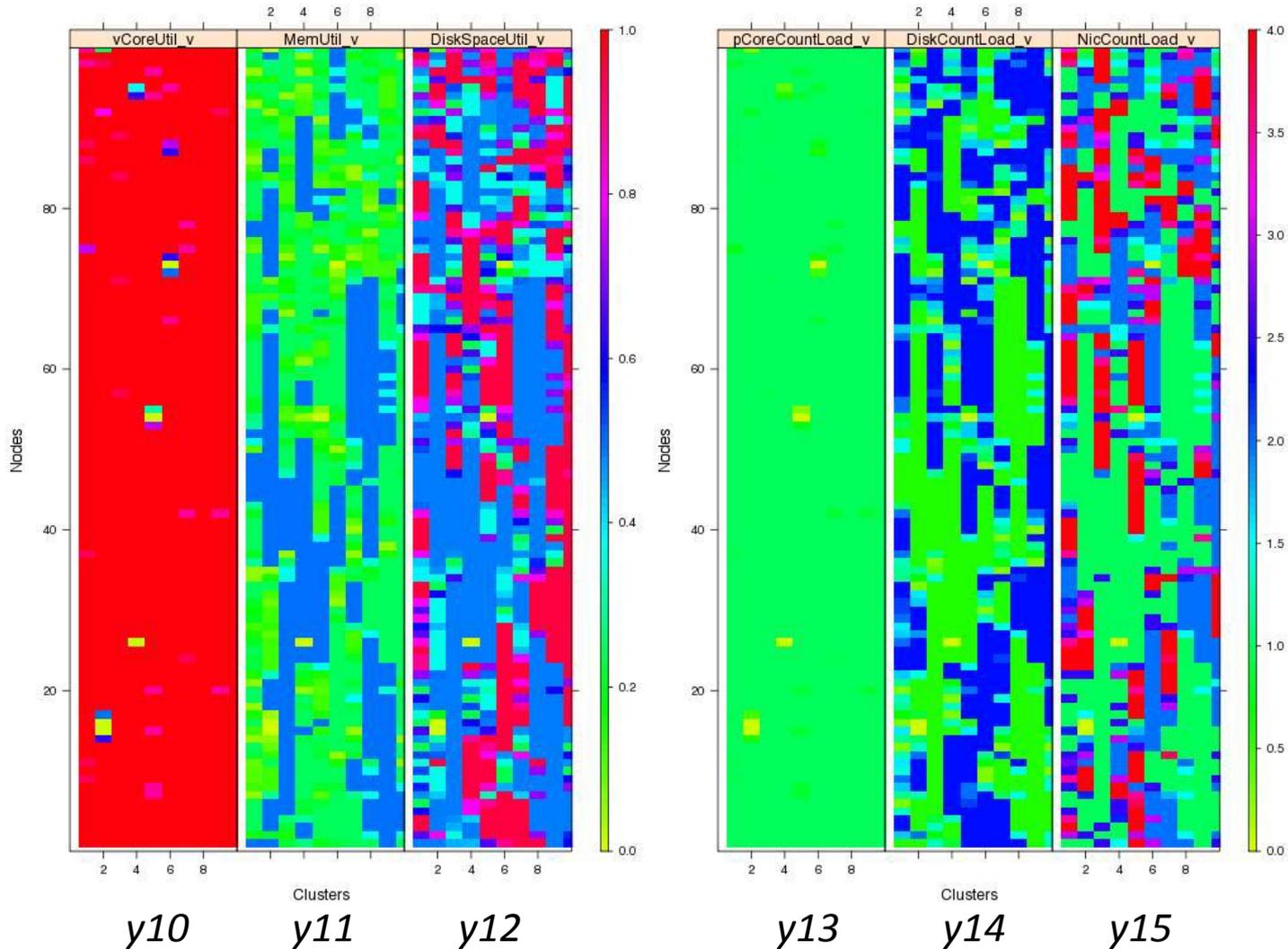
Backup Slides

Koala Information Visualizations by Sandy Ressler

(see <http://math.nist.gov/~SRessler/cloudviz.html> for animations and more)

Six Resource Allocations (Percent Allocated)

Measurement Interval: 90



Koala Performance Characteristics for Sensitivity Analysis Experiments

Resource Usage: Time & Space

Experiment	Time (minutes)				Memory (Megabytes)			
	μ	σ	min	max	μ	σ	min	max
SA1-small (avg. over 6 reps.)	17	13	2	69.3	54	12	37	73
SA2-small (avg. over 6 reps.)	56	148	<1	1019	70	44	27	187
SA1-large	2389	2723	211	12,645	266	91	134	467
SA2-large	4173	7659	29	38,057	235	179	53	764

Simulated Configurations: Time & Space

Experiment	Simulated Time (Hours)		Number of Users		Number of Nodes	
	MINUS level	PLUS level	MINUS level	PLUS level	MINUS level	PLUS level
SA1-small	600	1200	250	500	1000	4000
SA2-small	200	1600	125	750	250	12,000
SA1-large	600	1200	2500	5000	10,000	40,000
SA2-large	200	1600	1250	7500	2500	60,000