BMAS 2003
The Glorious Future of Macromodeling (In a Nutshell)

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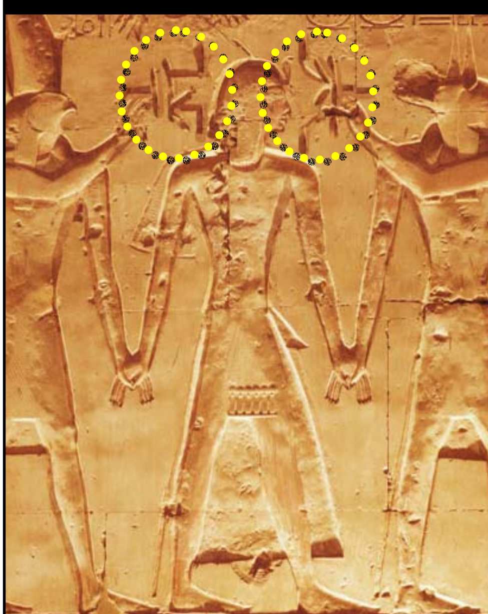
The *Past* of Macromodeling…



- Not without its own glories…
- Not always easy to decipher
- Not always easy to use…

The Questions are Ancient, and Profound …

- Archaeologists' reconstruction
- New excavation: Temple of Ductorh

Earliest known attempt at 3D full-wave model equations—sadly, incomplete

 •  = 

Remarkably ahead of its time…

The Essential Themes Recur Thru History…

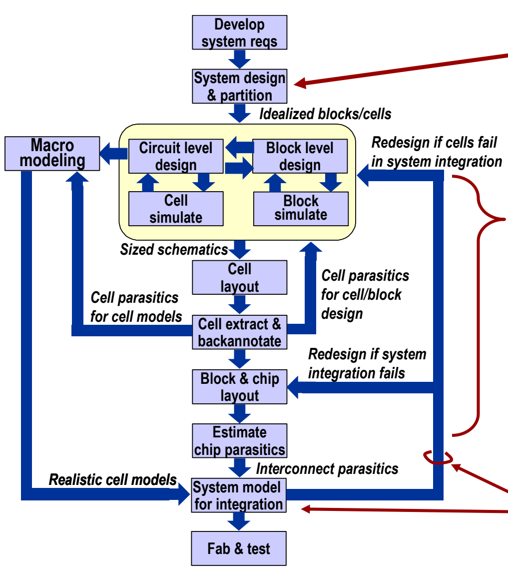
"*The Allegory of St. Darlington,*" from Pane 37, North window, Central vault, Notre Linear

So Why A “Glorious *Future*”…?

1. Exciting *new* ideas

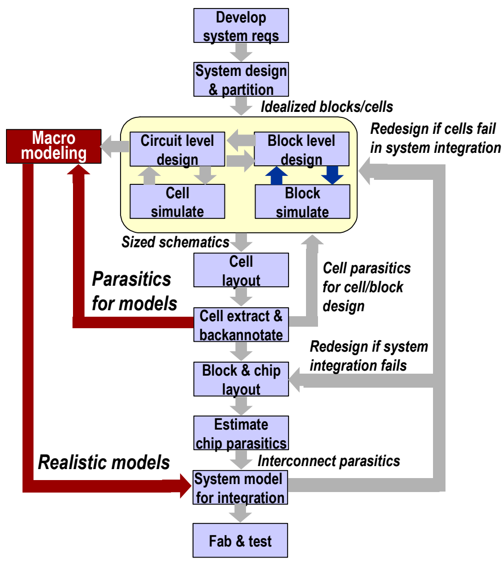
- Projection-based nonlinear MOR
- Volterra-based nonlinear MOR
- Time and frequency modeling
- Noise modeling
- Symbolic modeling
- Design space modeling
- Data mining concepts
- Synthesis applications
- Etc etc etc

No Choice…? Today, Flows Look Like This



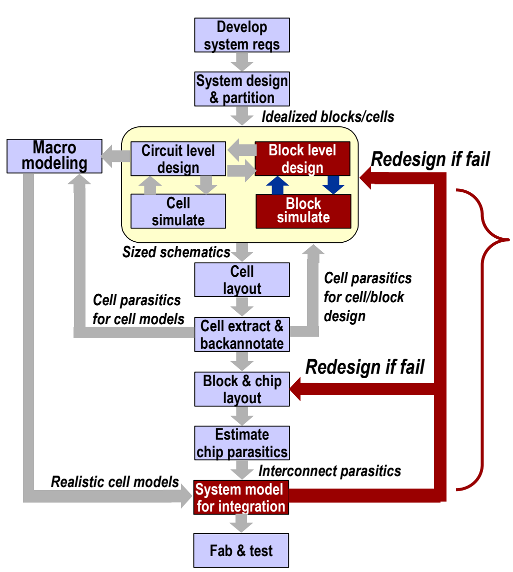
- **We design systems with ideal blocks, and simulate to verify**
- **Take each block down to a circuit**
  - Manually, or with emerging synthesis technologies
- **Replace ideal blocks with better models, integrate, and re-simulate**
  - And, often, it **doesn’t work**…

Model-Building Methods Still Weak, Limited



- Models often still done **by hand**, by experts who understand the circuits and the system

Model-Building Methods Still Weak, Limited

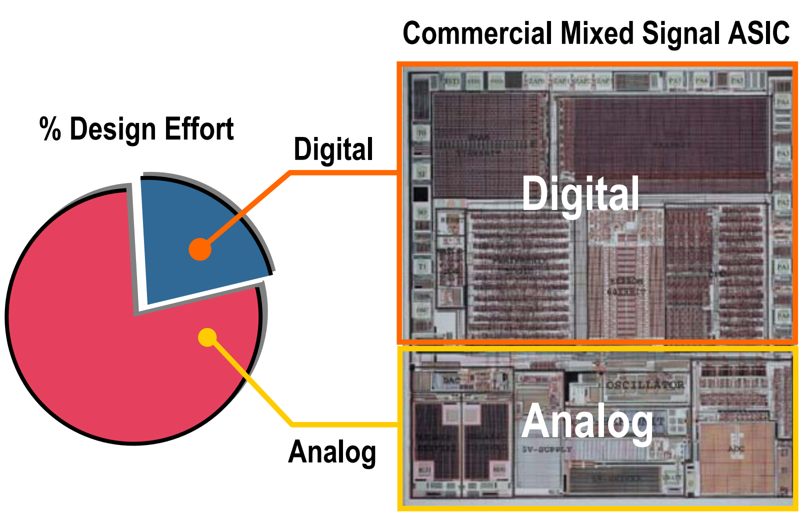


- Especially problematic as we start to rely on macromodels for full-system design **closure**

About This Talk…

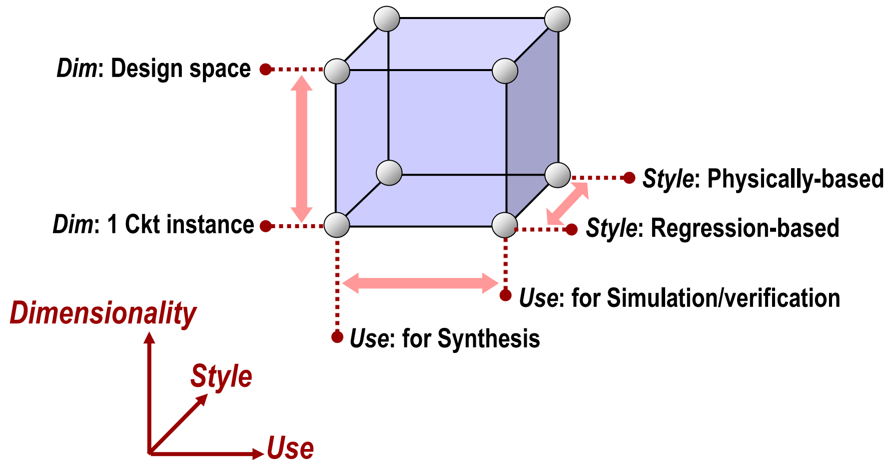
- Pieces of macromodeling puzzle
  - High-level taxonomy of approaches
- New piece of puzzle: *data mining* ideas
  - What they are, where they seem useful

Some Context: My Focus is Mixed-Signal



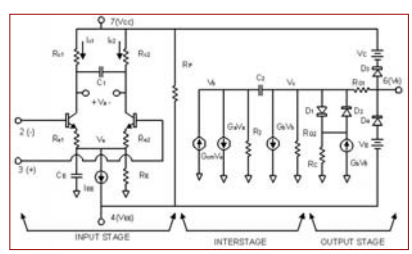
What Kind of “Macromodel” Do We Mean?

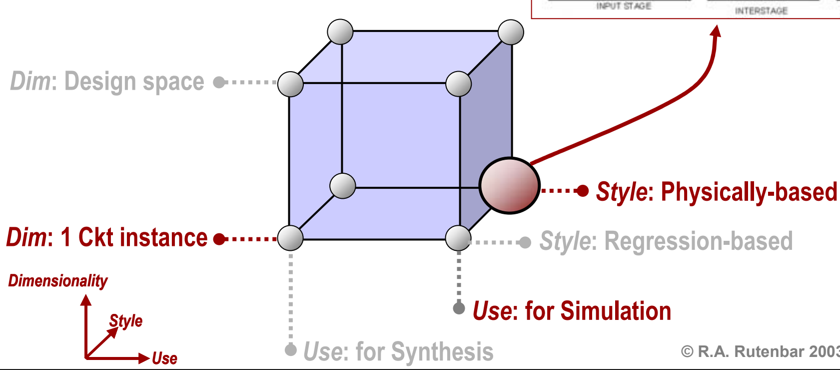
- Term “macromodel” means different things to different people…



Earliest Models: Physical, for Simulation

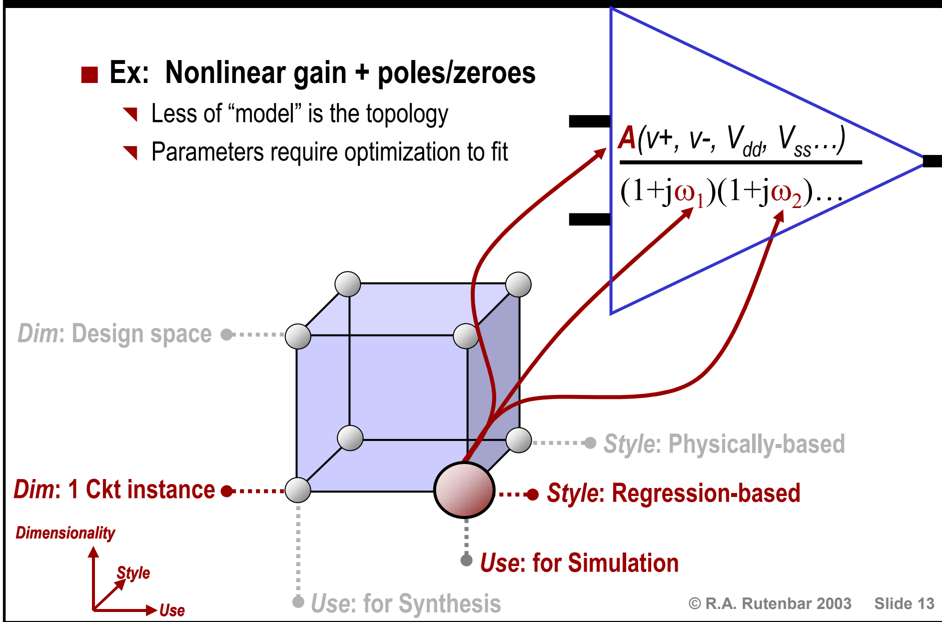
- Ex: Boyle opamp [JSSC Dec’74]
  - Most of the “model” is circuit topology
  - Parameters easy to pick off original ckt





Later Models: More Regression, for Simulation

- **Ex: Nonlinear gain + poles/zeroes**
  - Less of "model" is the topology
  - Parameters require optimization to fit



Essential Problems in All Macromodeling

- **What do you fit *to***
  - What's the template/structure?
- **Options**
  - A simplified circuit
  - A "black box" curve fit
  - A nice mathematical form
    - Pole zero form H(s)
    - Linear ODE
    - Nonlinear ODE
    - Volterra series
    - …

- ***How* do you fit to it?**
  - What's the mathematics of "fit"?
- **Options**
  - By hand (ask someone smart)
  - Nonlinear regression
  - A nice mathematical recipe
    - Linear: **AWE, PVL, Arnoldi, PRIMA…**
    - Nonlinear: **Volterra, posynomial…**
  - Special purpose (common circuits)
    - **Opamp, VCO, mixer, PFD-CP**
    - …

Today's Spectrum of Modeling for Simulation

$$\frac{A(v+, v-, V_{dd}, V_{ss}\ldots)\,(1+j\omega_a)(1+j\omega_b)\ldots}{(1+j\omega_1)(1+j\omega_2)\,(1+j\omega_3)\ldots}$$

Nonlinear Regression Fitting

Transfer Function Projection / nonlin MOR

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Pro: handling strong nonlinearities

Con: handling dynamics, accuracy guarantees, training data

Nonlinear Regression Fitting

Transfer Function Projection / nonlin MOR

Today's Spectrum of Modeling for Simulation

$$\frac{A(v+, v-, V_{dd}, V_{ss}\ldots)(1+j\omega_a)(1+j\omega_b)\ldots}{(1+j\omega_1)(1+j\omega_2)\,(1+j\omega_3)\ldots}$$

Pro: handling dynamics, xfer functions, accuracy, less training
Con: handling wide range of strong nonlinearities

Nonlinear Regression
Fitting

Transfer Function
Projection / nonlin MOR

End-Use Diversity Complicates Problem

Intent

Accuracy
vs Speed

Domain

Time
Frequency
Statistical (noise)
…

Fitting

Regression
Projection
Nonlin MOR
…

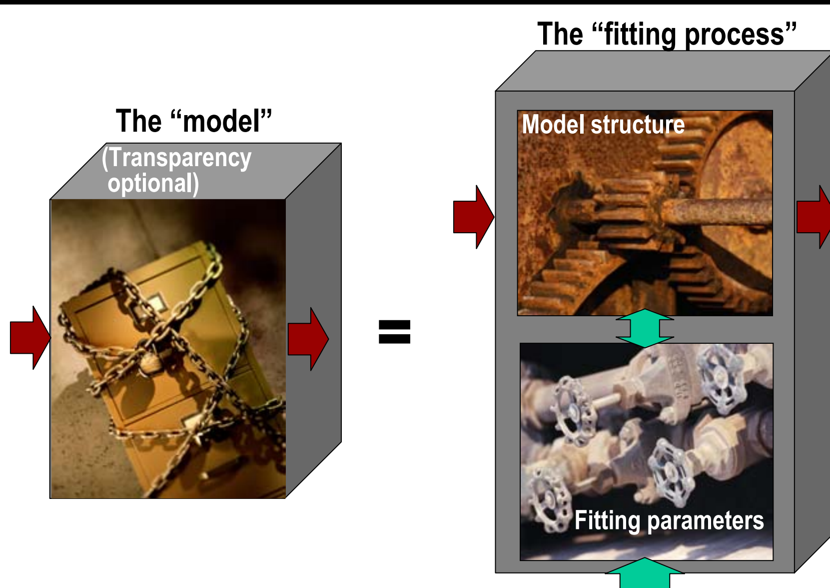
Simulation Style

Signalflow: $Y(s)=H(s)X(s)$
Dynamics: $\dot{g}(x) = f(x) + Bu$
Noise:

…As Do User Expections

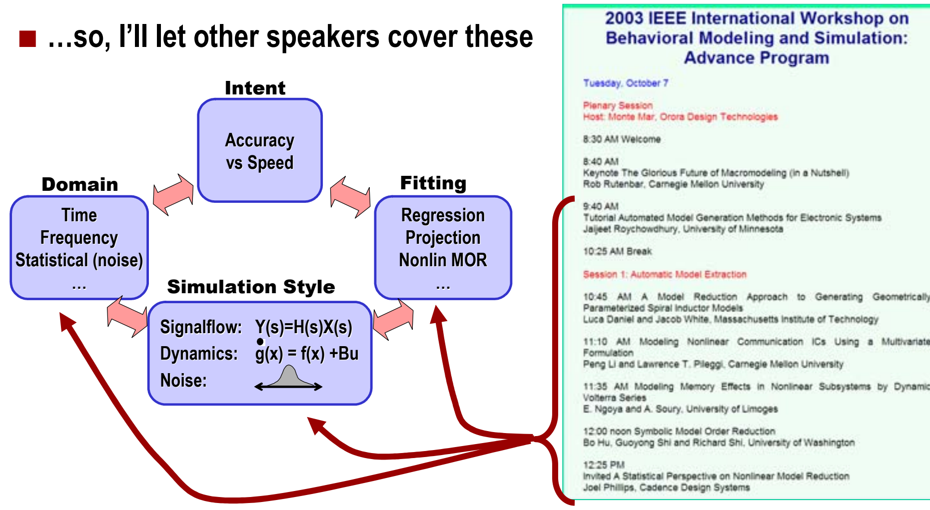
- Like simulator controls, everybody hates having to “twiddle” model details
- This is what every designer *ultimately* wants

Today’s Models Don’t Always Inspire Confidence

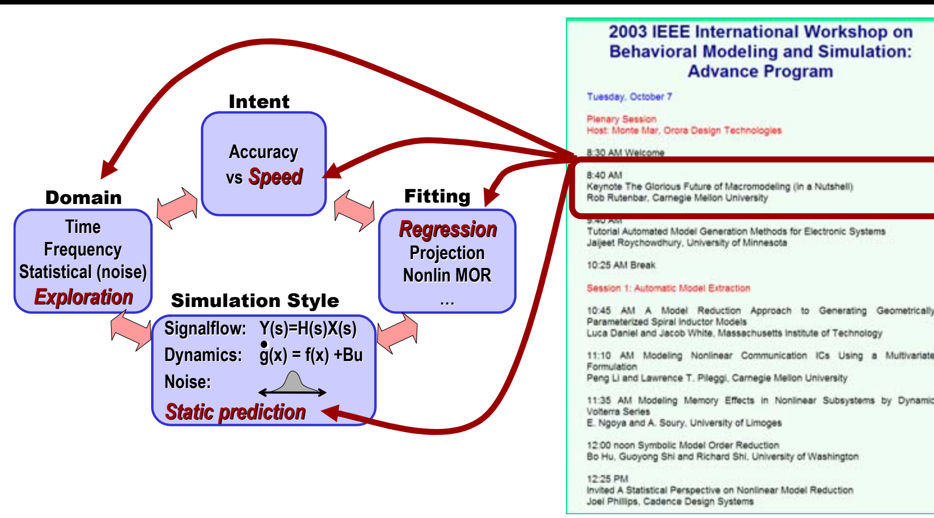


…But, Recent Ideas Offer New Hope

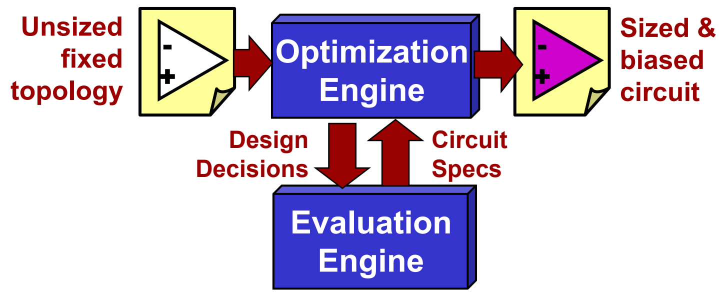
- …so, I'll let other speakers cover these



…and I'll Talk About Something *Different*…



New Motivation: *Large* Analog Design Spaces

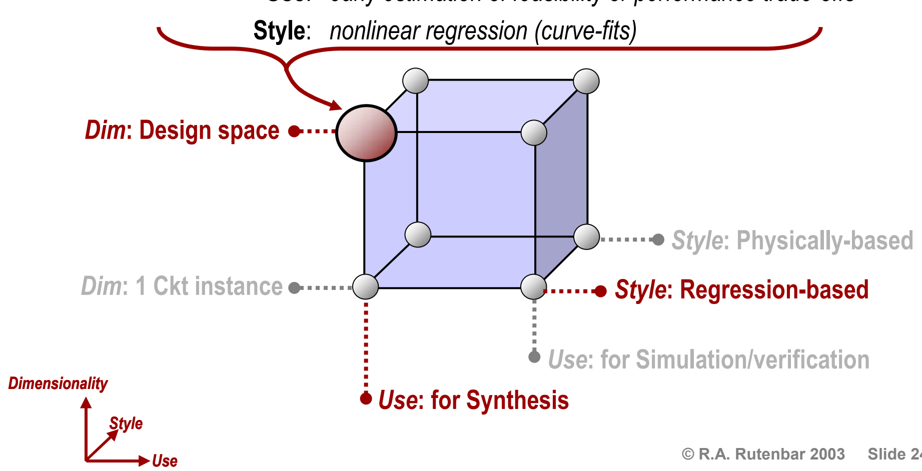


- Emerging commercial infrastructure makes it easy to sample large populations of fully qualified (*simulated*) circuit configs
  - **Optimization engine:** proposes circuit solution candidates
  - **Evaluation engine:** evaluates quality of each candidate
  - **Full SPICE evaluation:** for every spec, for every candidate

Macromodeling in this New Context

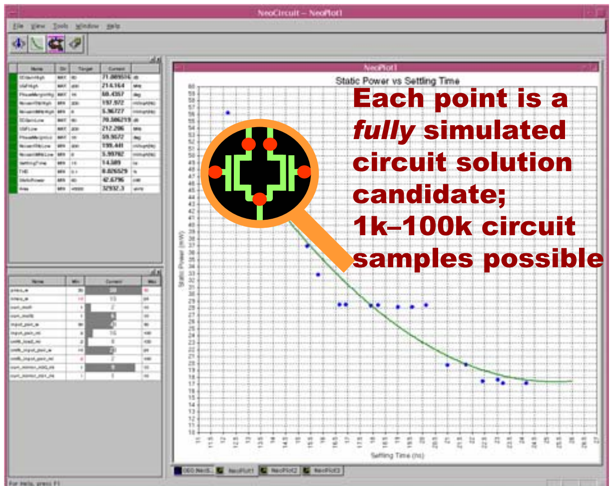
- Modeling analog **design spaces** for synthesis uses

Dimensionality: *populations of circuits, high-dimensional data*
Use: *early estimation of feasibility or performance trade-offs*
Style: *nonlinear regression (curve-fits)*



New Opportunity: *Design Space Modeling*

- Can generate 1K – 100K fully-qualified (simulated) samples of large analog design spaces – what can we do with this data?



Courtesy Neolinear, Inc.

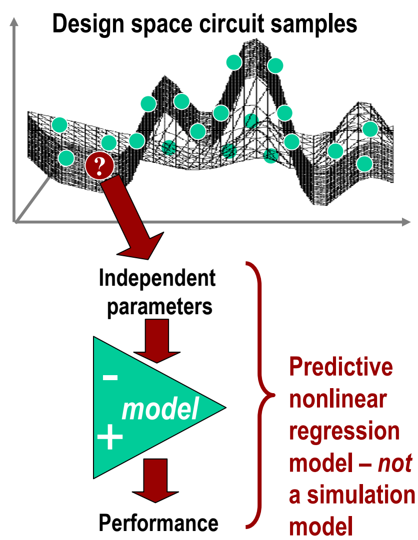
New Idea: Macromodeling as *Data Mining*

- **Problem:** Can we fit these large populations in useful ways?
  - 1K – 100K data points? Conventional, *ad hoc* curve fitting not up to the task
  - Where do we look to do better?

- **Solution:** Data mining
  - Significant breakthroughs in last 5 years in this community
  - Techniques for extracting (fitting) patterns, predictive formulas, or classifiers to large amounts of high-dimensional, possibly noisy, data

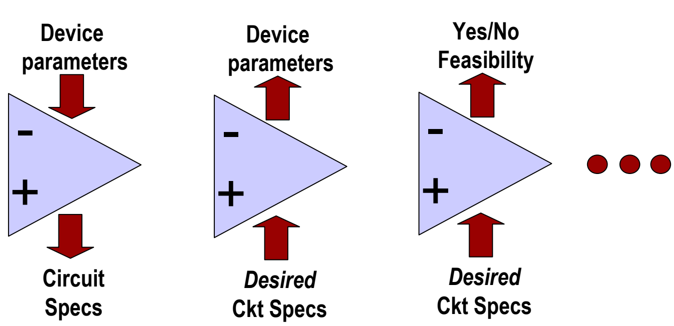
Basic Problems in Nonlinear Regression

- **Data selection**
  - Where does data come from?
  - **Focus: simulation-based search**
- **Model selection/fitting**
  - What functional form to fit populations of high-dim ckts?
  - **Focus: *boosted regressors***
- **Model validation**
  - How do you tell if you "fit well"?
  - **Focus: *rigorous model selection***



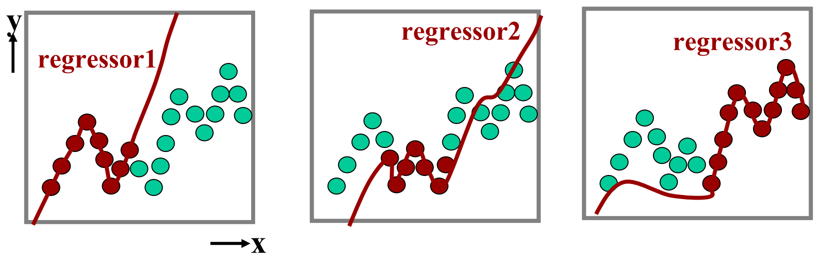
Aside: this is "Black Box" Modeling

- **We want to assume very little about base model template**
  - **Black box** = from data points alone, deduce and parameterize a model that accurately predicts basic behavior



Essential Regression Problem

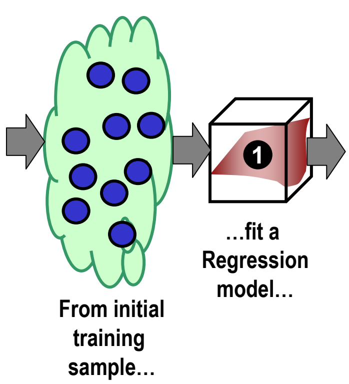
- **Very hard to find one functional form that fits everywhere**
  - Often easy to find regressors that can fit locally, but not globally
  - Problem gets worse with more data, with more dimensions



- **Could we find, then combine, a set of such regressors?**

Elegant Strategy: *Boosting* [Freund, Schapire, 97]

- **Build a *sequence* of regression models, then *combine* them**
  - Strategy for sequentially resampling/reweighting data, voting = **boosting**



Ensemble Strategy: Boosting

- Build a *sequence* of regression models, then *combine* them
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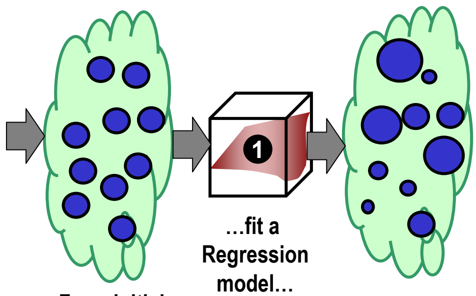

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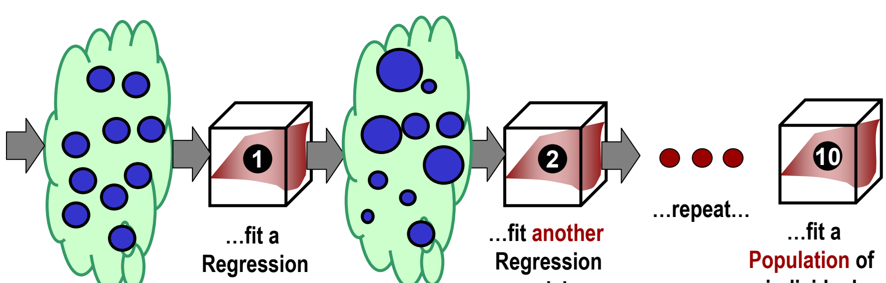

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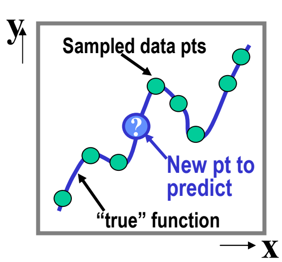
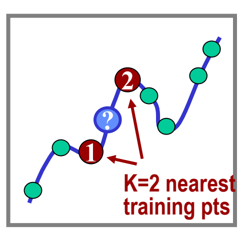
Boosting Specifics

- **Individual regressors**
  - Neural networks in MATLAB. 2-hidden layers, 10 neurons/layer
  - Chosen for ease-of-use mainly
- **Boosting mechanics**
  - Fit **N** networks, in stages, with resampling/reweighting [see our **DAC02** paper]
  - Well-fit data points can **vanish** from the population, over iterations
  - Poorly fit points can **replicate** in the population, over iterations
- **To combine regressors, more data mining: *instance methods***
  - Ask the **K nearest neighbor points** from training data what they think…

Instance-Based Voting of Regressors

- **Suppose we set K=2 nearest neighbors (K is *arbitrary*)**
  - For any new data point, find **2** nearest training data points, and use the regressor that gave the most accurate prediction at that neighbor point





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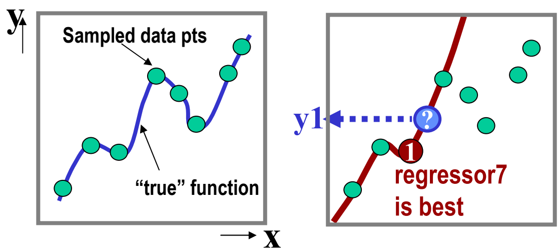

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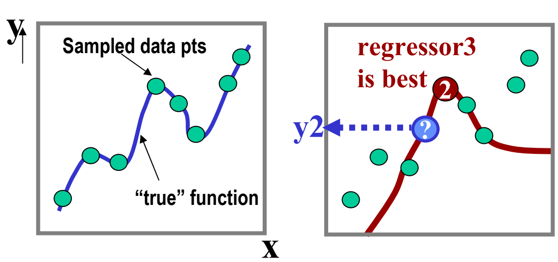


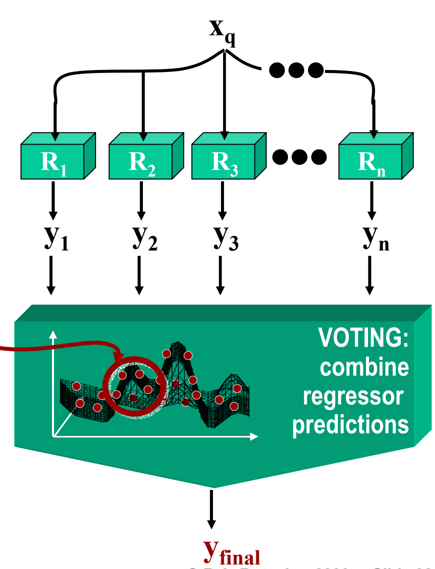
Average y1 and y2 values, weighted inversely by distance to new point

About Boosting

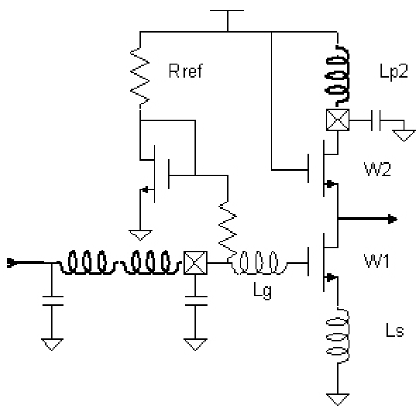
- *Independent* of the regressor (curve fitting) style
  - Use a neural net, a polynomial, posynomial, spline model, **whatever you like**
- *Many* regressors are fit; *few* are evaluated
  - Not uncommon in large problems to boost 100 rounds of regressors
  - But—our instance-based technique only evaluates the **best** regressor on each of the K neighbors **nearest** the evaluation point
- *Standard* data structures to get K nearest neighbors fast
  - High-dimensional nearest neighbor lookup is a **well studied** problem
  - Quad trees, kd-trees, R-trees, S-trees, flat vector scans, etc

What Overall "Boosted" Model Looks Like

- **Basic model setup**
  - ~10-20 boosted regressors $R_i(\,)$
  - Save training data points
- **Basic model eval**
  - Given a new "query point" x_q
  - Select a subset of stored data pts
  - Chooses *which* regressors to eval, *how* to combine (weighted vote)

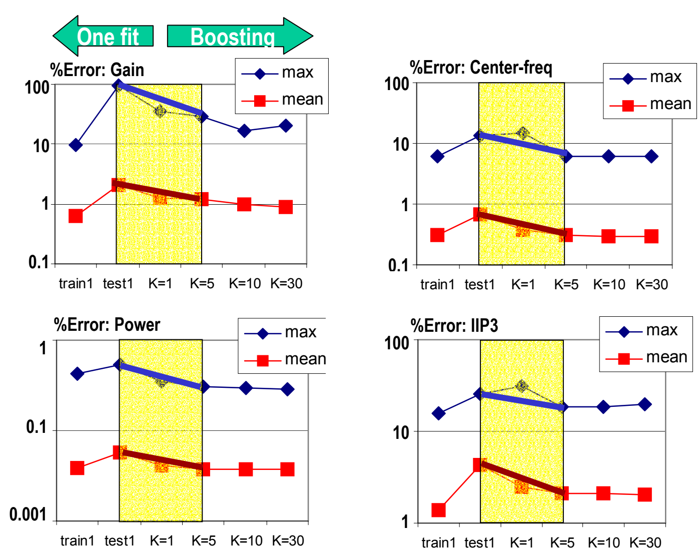


Simple RF Design Space Example

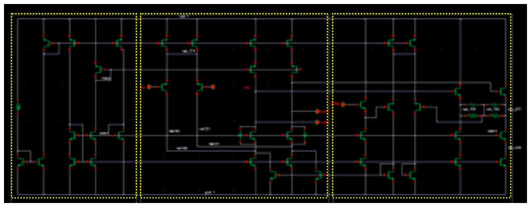


- **Simple RF LNA topology**
  - 5 independent variables
  - ~2000 HSPICE-simulated designs
  - Use half to **train** boosted predictors
  - Use other half to **test** predictors

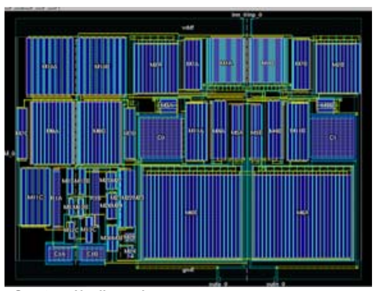
Simple RF Design Space Results



Example Synthesis Data Set



Gain: 70dB
UGF: 460Mhz
Power: 13.5mW
SlewRate: 360 V/us
SettlingTime: 4.75ns
PhaseMargin: 60°
Offset: 2.6uV



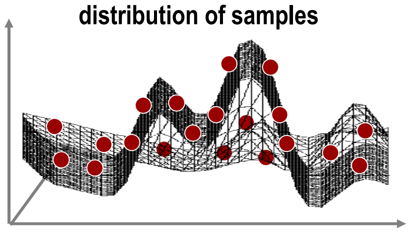
Courtesy Neolinear, Inc.

- **Industrial synthesis result**
  - CMOS amplifier ~50 devices
  - 27 design inputs (independent vars)
  - 12 outputs (performance specs)
- **We have…**
  - **~40,000, 27-dimensional data points**

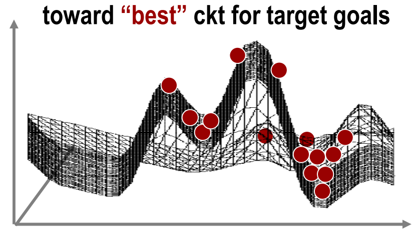
Data Points from Circuit Synthesis

- **New problems**
  - Synthesis visits many fully-qualified (simulated) samples of space…
  - …but synthesis may **not** sample in ways optimized for modeling
  - To illustrate this, we fit **first** and **last** **~20%** of time-ordered synthesis samples here; first samples have wider variance; last samples have less.

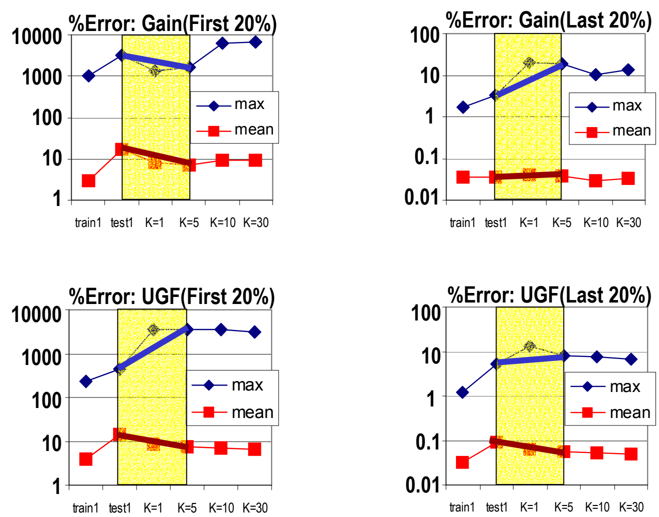
For modeling, want widest distribution of samples



Synthesis focuses sampling toward "best" ckt for target goals



Boosted Results from Synthesis



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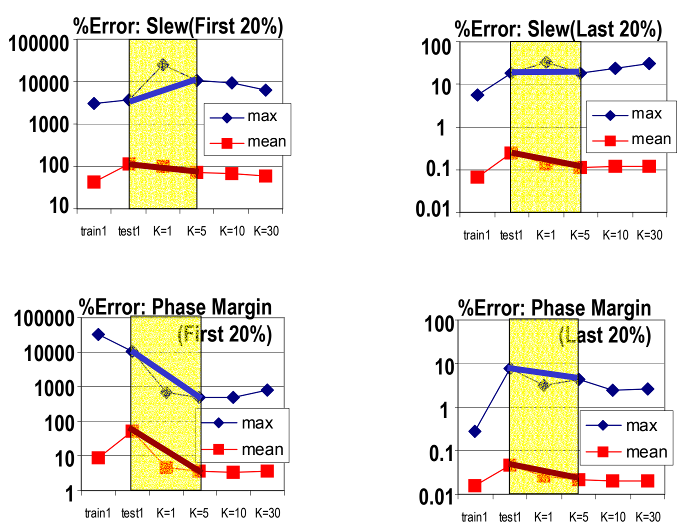
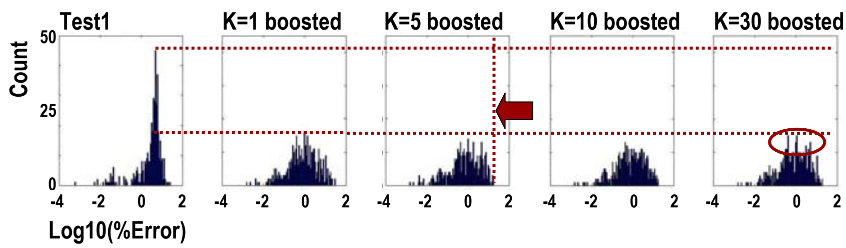


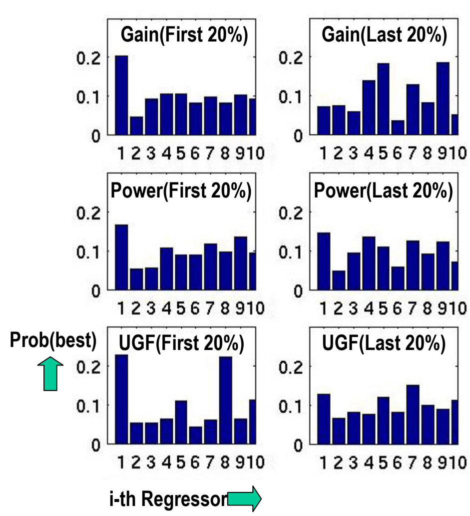
Qualitative Effects on Prediction Error

- Often, better worst-case error, and better mean error
  - Test1 is a single, conventional neural net regressor
  - K=1 to 30 show 10 boosted regressors, with up to 30 neighbors voted
  - K=small can help both max and mean; but you can also over-boost



Fraction of Points Choosing Each Regressor

- 10 regressors boosted.
- For training points, what fraction "believes" the i^{th} regressor to be best, locally?
- This is an informal measure of the utility of boosting to adapt an ensemble of models
- Note, not always true that 1st regressor dominate all others



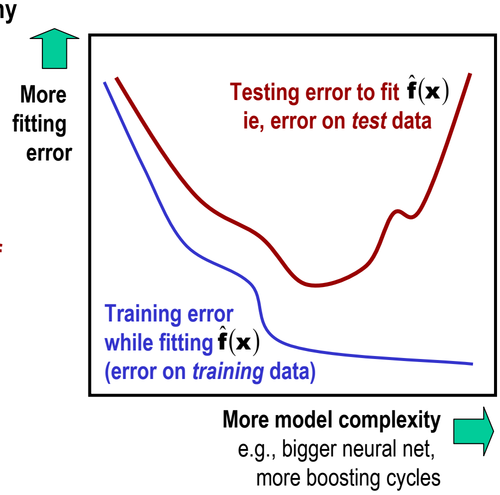
Issue: How Much "Model" is "Enough Model"?

- **Can always add complexity to any individual regression model**
- **Problem: Overfitting**
  - Easy to build more model than the data can really support
- **Classical Bias-Variance Tradeoff**
  - With more complexity…
  - Bias error **grows**:

$$\left[\mathbf{E}\left[\hat{\mathbf{f}}(\mathbf{x})\right] - \mathbf{E}\left[\mathbf{f}(\mathbf{x})\right]\right]^2$$

  - But variance error **shrinks**:

$$\mathbf{E}\left[\left(\hat{\mathbf{f}}(\mathbf{x}) - \mathbf{E}\left[\hat{\mathbf{f}}(\mathbf{x})\right]\right)^2\right]$$



Solution: Rigorous Model *Selection*

- **Generic model selection**
  - ***Divide*** the data into training set and test set.
  - ***Increase*** model complexity step by step
  - ***Fit*** each of these models
  - ***Choose*** the right model based on the test error
- **Can be applied to our macromodeling approach**
  - Base regressor selection: what is **best** single regressor ?
  - Boosting complexity selection: given right base regressor, how much boosting, etc., is **best**?

Solution: Rigorous Model *Selection*

- Generic model selection
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How Much Boosting & How Many Neighbors?

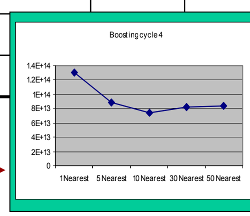
- **Experiment**
  - Run 2-16 boost cycles, and try 1-50 nearest neighbors to vote regressors
  - Pick the **best** model we see in this set of experiments

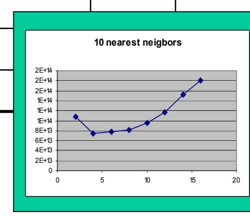
Model Selection	Boost 2 cycles	Boost 4 cycles	Boost 6 cycles	Boost 8 cycles	Boost 10 cycles	Boost 12 cycles	Boost 14 cycles	Boost 16 cycles
K=1 nearest neighbors								
K=5								
K=10								
K=30								
K=50								

Model Selection: Center Freq Model for RF LNA

- **Don't always need a lot of boosting/neighbors**
  - Mean Square Error **-18%;** Max error rate **-21%;** Mean error rate **~same**

Model Selection	Boost 2 cycles	Boost 4 cycles	Boost 6 cycles	Boost 8 cycles	Boost 10 cycles	Boost 12 cycles	Boost 14 cycles	Boost 16 cycles
K=1 nearest neighbors								
K=5		best						
K=10								
K=30								
K=50								



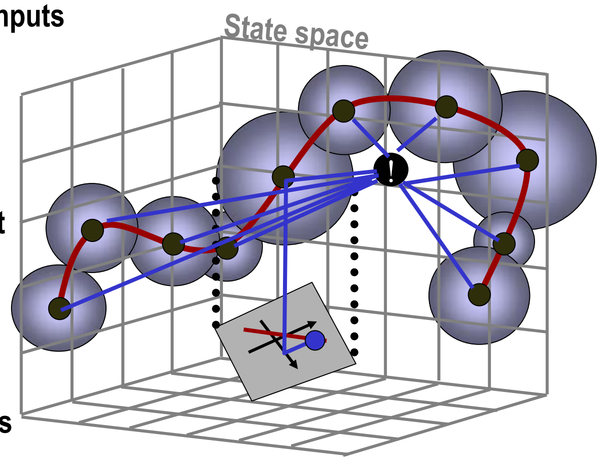


Observations

- **First rigorous application of data-mining in ckt modeling**
  - We can build usefully accurate predictive models of lots of high-dim data
  - Boosting is an elegant, robust fitting framework for exploration here
- **Rigorous model selection makes models easier to use**
  - Most users are not very familiar with regression jargon or parameters
  - Sensible application of selection / validation lets us auto-pick a 'best' model
- **Interesting connections to recent "simulation-directed" models**

Recall How Trajectory-Based Methods Work

- Simulate training inputs in state space
- Choose center pts on this trajectory
- Build simple local model near each pt projecting down to a smaller state vec
- Distance-weighted voting to compute predicted dynamics



Multiple regressors, locally weighted, with saved training data…

Summary

- **Macromodeling: Future looks pretty good (OK, *glorious*…)**
  - Because we don't have a choice, to do the systems we want to design
  - Because of many recent modeling innovations
- **Data mining: It's not just for dot-coms anymore**
  - Smart ways to handle large amounts of high-dimensional data
  - Smart ways to build and vote and validate ensembles of regressors
- **Simulation-based circuit optimization infrastructure**
  - Lots of companies making it possible to sample widely, cheaply, quickly
  - This will fundamentally change the way we get data to build macromodels