An Active Approach to Characterizing Dynamic Dependencies for Problem Determination

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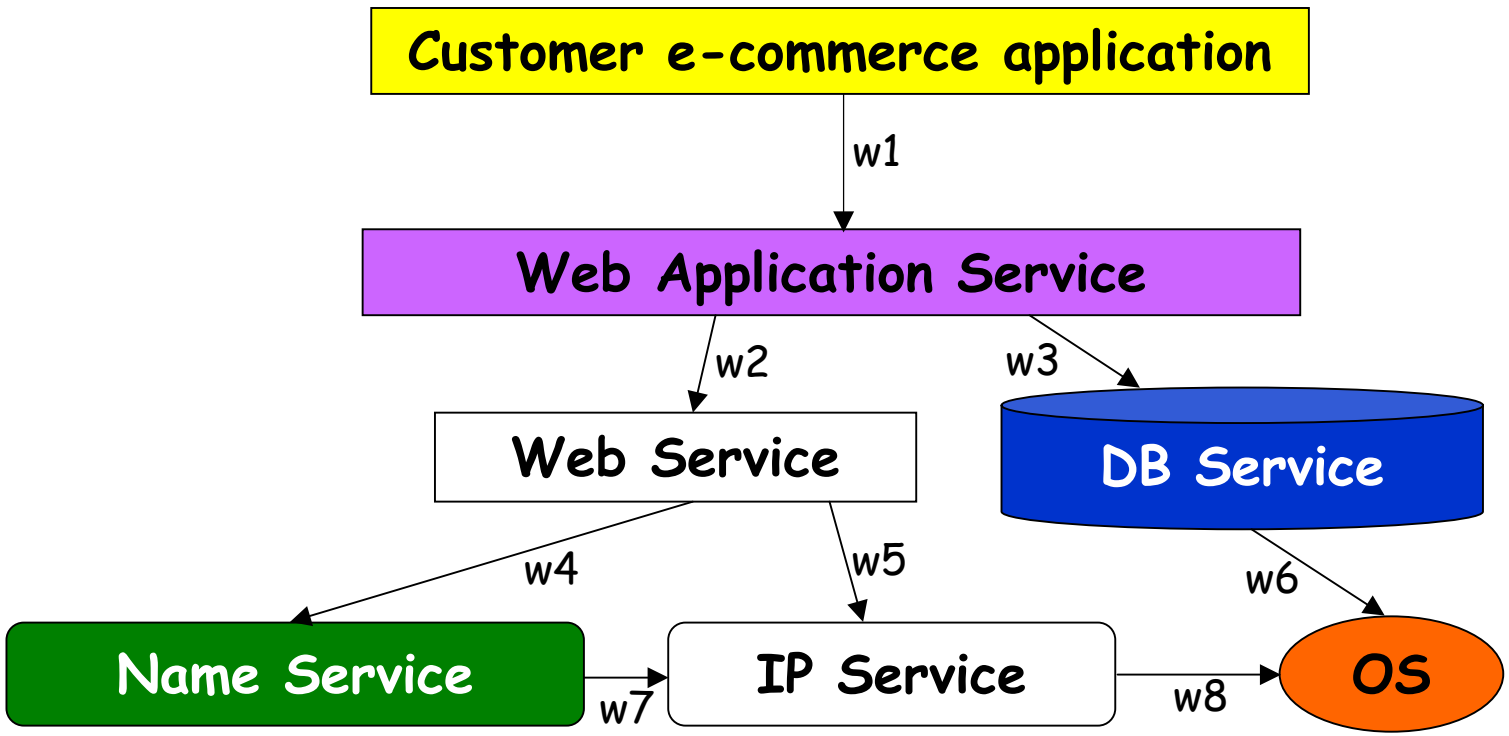
Motivation: problem diagnosis

- **Troubleshooting problems is one of the most challenging, time-consuming management tasks**
  - symptoms are typically at end-user or SLA level
  - root causes are typically much deeper in system
    - » and often confounded by system complexity
  - must map symptoms to root causes to locate problems!

- ***Dependency models* provide an invaluable aid to root-cause analysis**
  - capture connections between high- and low-level system components

Dependency models in a nutshell

- **Use a graph (DAG) structure to capture dependencies between system components**
  - if failure of **A** affects **B**, then **B** depends on **A**
  - edge weights represent dependency strengths



Constructing dependency models

- **For effective diagnosis, model must capture:**
  - static dependencies
  - dynamic runtime dependencies
    - » *e.g.*, dependencies induced by runtime queries
  - distributed dependencies
  - dependency strengths
  - all at the detailed level of individual system resources

- **Most existing techniques don't meet these challenges...**

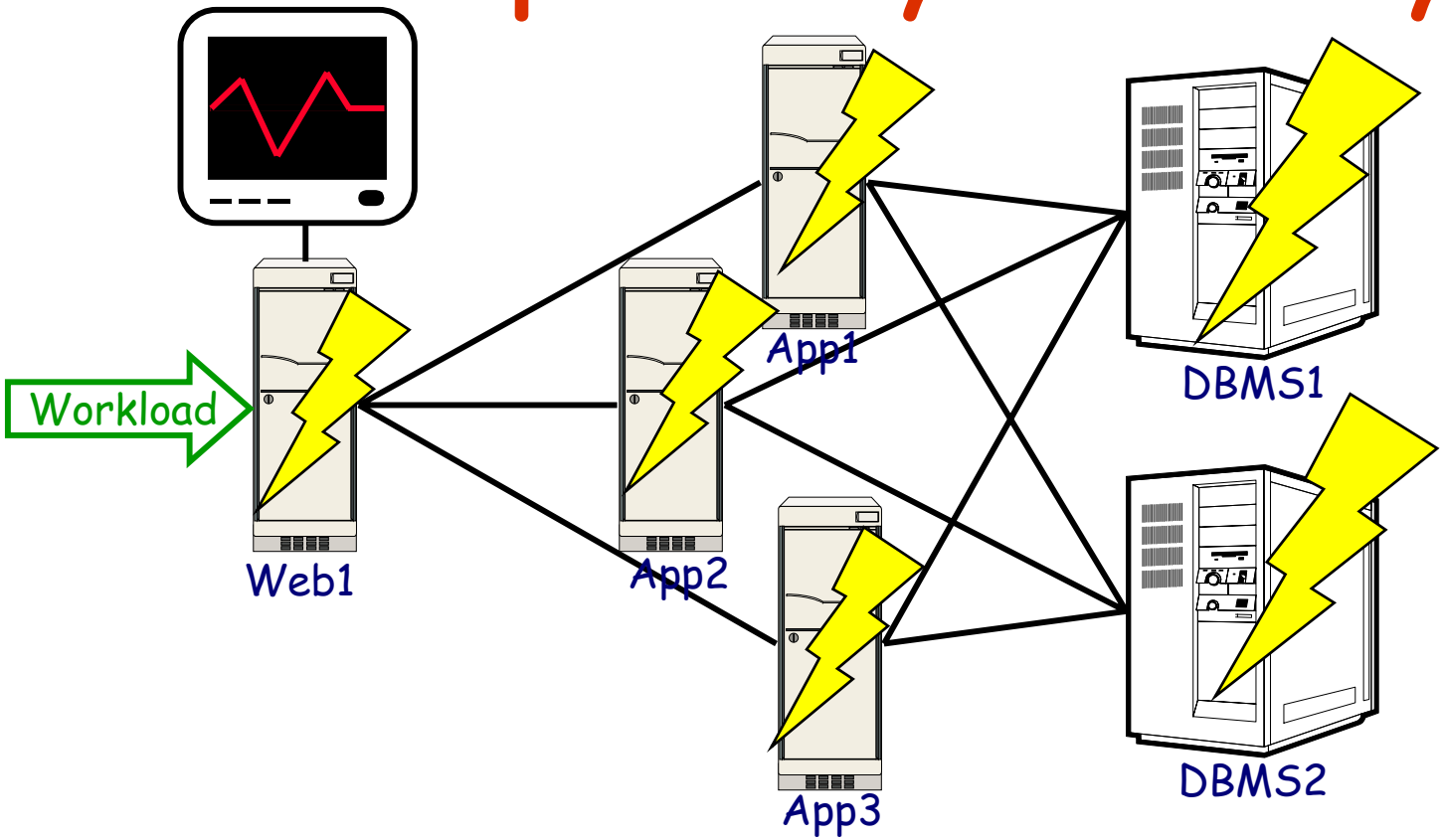
Outline

- Motivation & background
- **ADD: Active Dependency Discovery**
- Experimental validation of ADD
- Conclusions and future directions

Discovering dependencies

- **Desired properties of approach**
  - identifies dynamic, runtime dependencies
  - works on distributed systems
  - works with only black-box view of system components
  - provides direct evidence of causality
  - detects dependencies only visible in failure situations
- **These properties inspire an indirect, active approach**
  - **indirect:** no explicit modeling of system
  - **active:** perturb system to elucidate dependencies

Active Dependency Discovery (ADD)



1) Instrument the system and apply workload
2) Systematically perturb components
3) Measure change in system response
4) Construct dependency model from measurement data

Benefits of ADD

- **Coverage**
  - no need to rely on problems occurring naturally, as in passive approaches
  - can guarantee coverage by explicitly controlling perturbation
- **Causality**
  - causality easy to establish: perturbation is the cause
- **Simplicity**
  - no application modeling or modification necessary
  - existing endpoint instrumentation may be sufficient
  - no complex data mining required
  - applied *before* real problems occur

Drawbacks of ADD

- **Invasiveness**
  - can be tricky to do perturbation on production system
  - possible solutions:
    - » leverage redundancy if available (*e.g.*, cluster system)
    - » run perturbation during non-production periods (initial system setup or during scheduled downtime)
    - » develop low-grade perturbation techniques
- **Workload-specific**
  - extracted models only valid for applied workload
  - but, can model components of workload and recombine later

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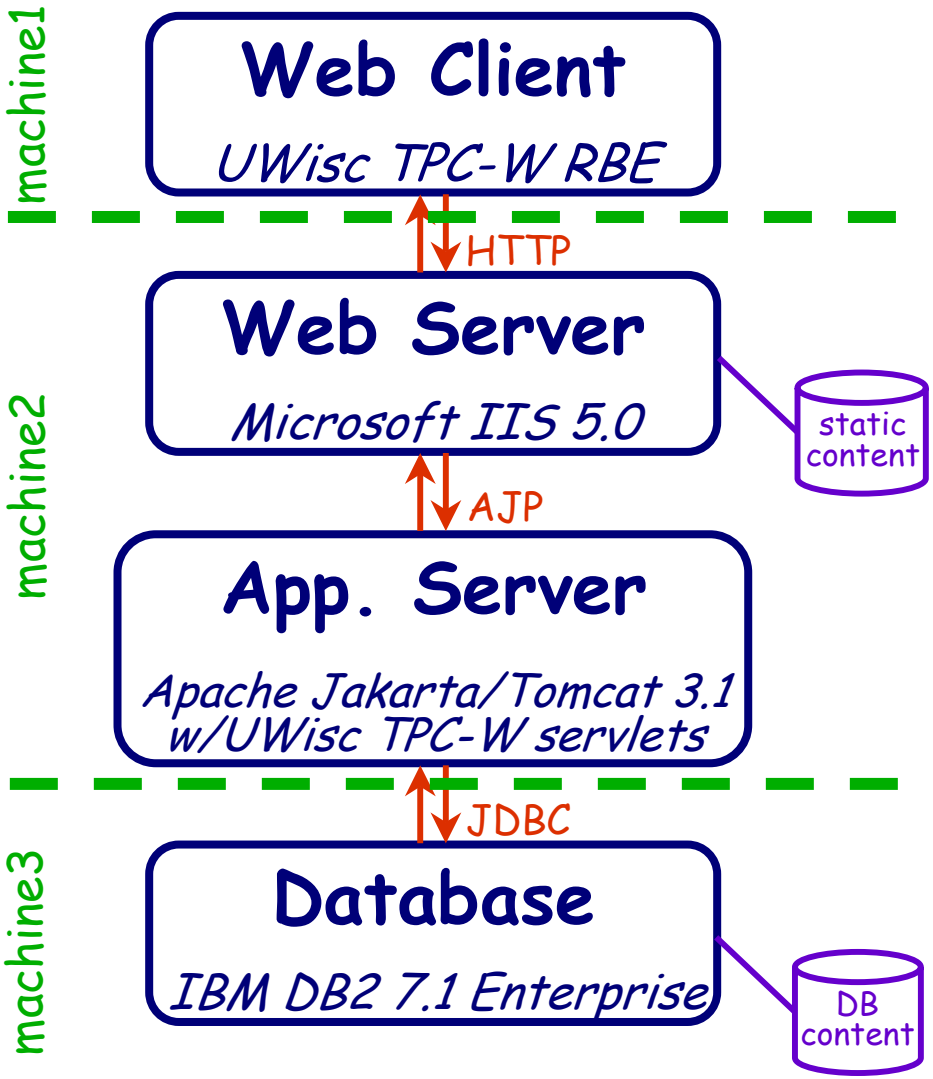
- ADD: Active Dependency Discovery
- **Experimental validation of ADD**
  - approach
  - TPC-W testbed environment
  - results
- Conclusions and future directions

Validation: e-commerce case study

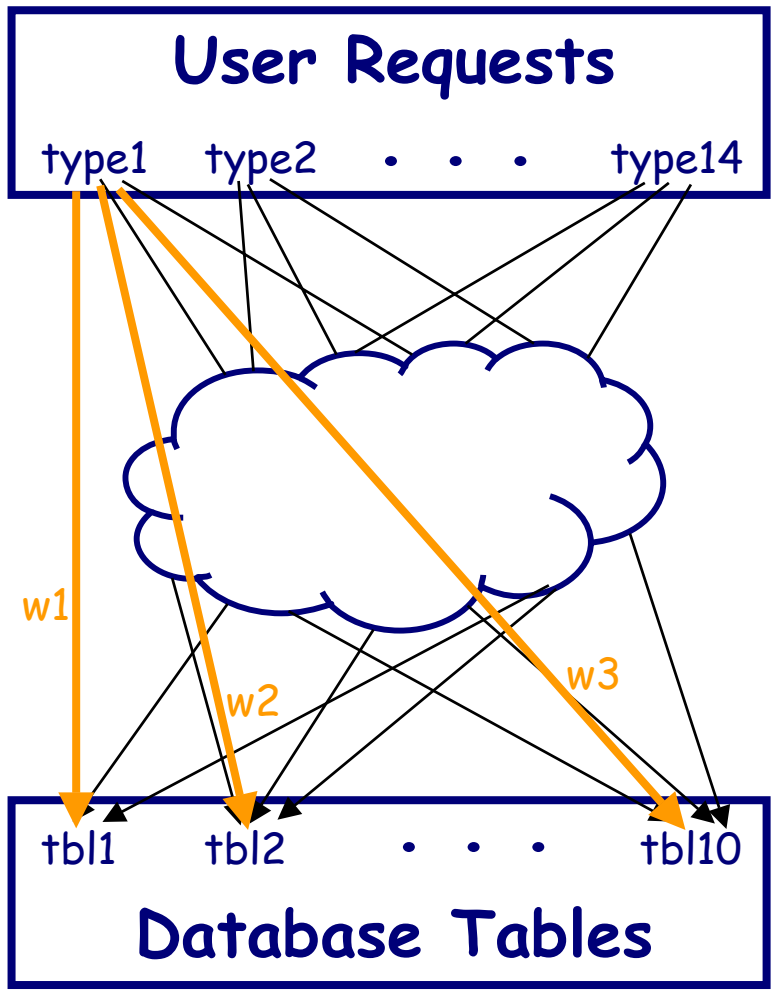
- **Goal: use ADD to discover dependencies in a multi-tier e-commerce environment**
  - using off-the-shelf black-box software
  - in a realistic environment with realistic workload
- **Task: discover dependencies of user web requests on database tables**
  - for each type of user request:
    - » extract dependencies on individual database tables
    - » characterize strengths of those dependencies
    - » hand-verify model against application source code
- **Platform: TPC-W benchmark app & workload**
  - realistic mockup of online bookseller e-commerce site

TPC-W experimental testbed

System View



Dependency View



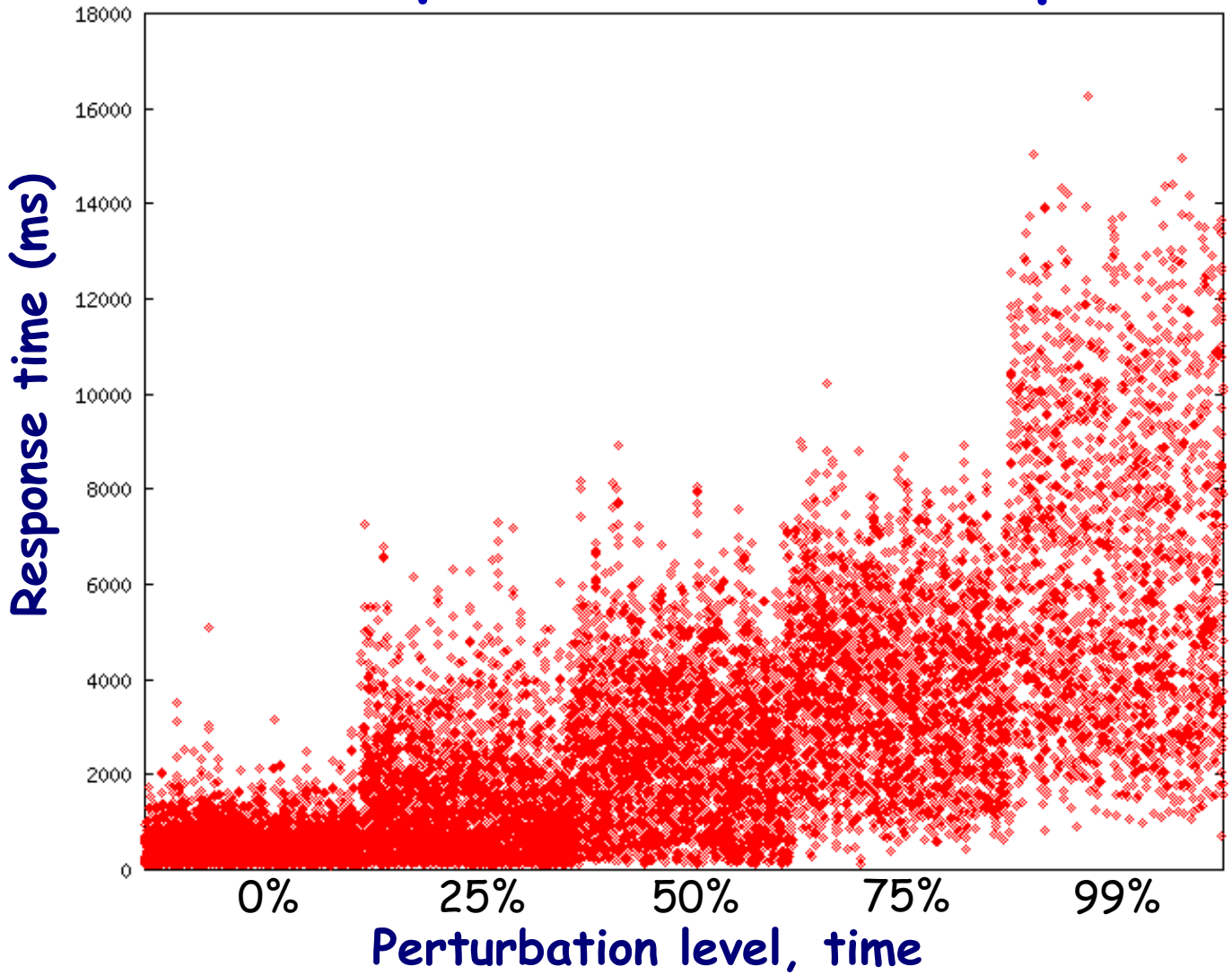
Perturbation and measurement

- **Perturbation applied to individual DB tables**
  - use DB2's lock manager to exclusive-lock a table
  - configurable "duty cycle" of lock out
    - » queries locked out for first x% of every 4 sec. interval
  - only affects one table; no impact on overall load
  - can simultaneously perturb multiple tables

- **Per-request response time measured by TPC-W front-end user emulator**
  - 14 different types/classes of requests
  - response time is end-to-end, including network delay

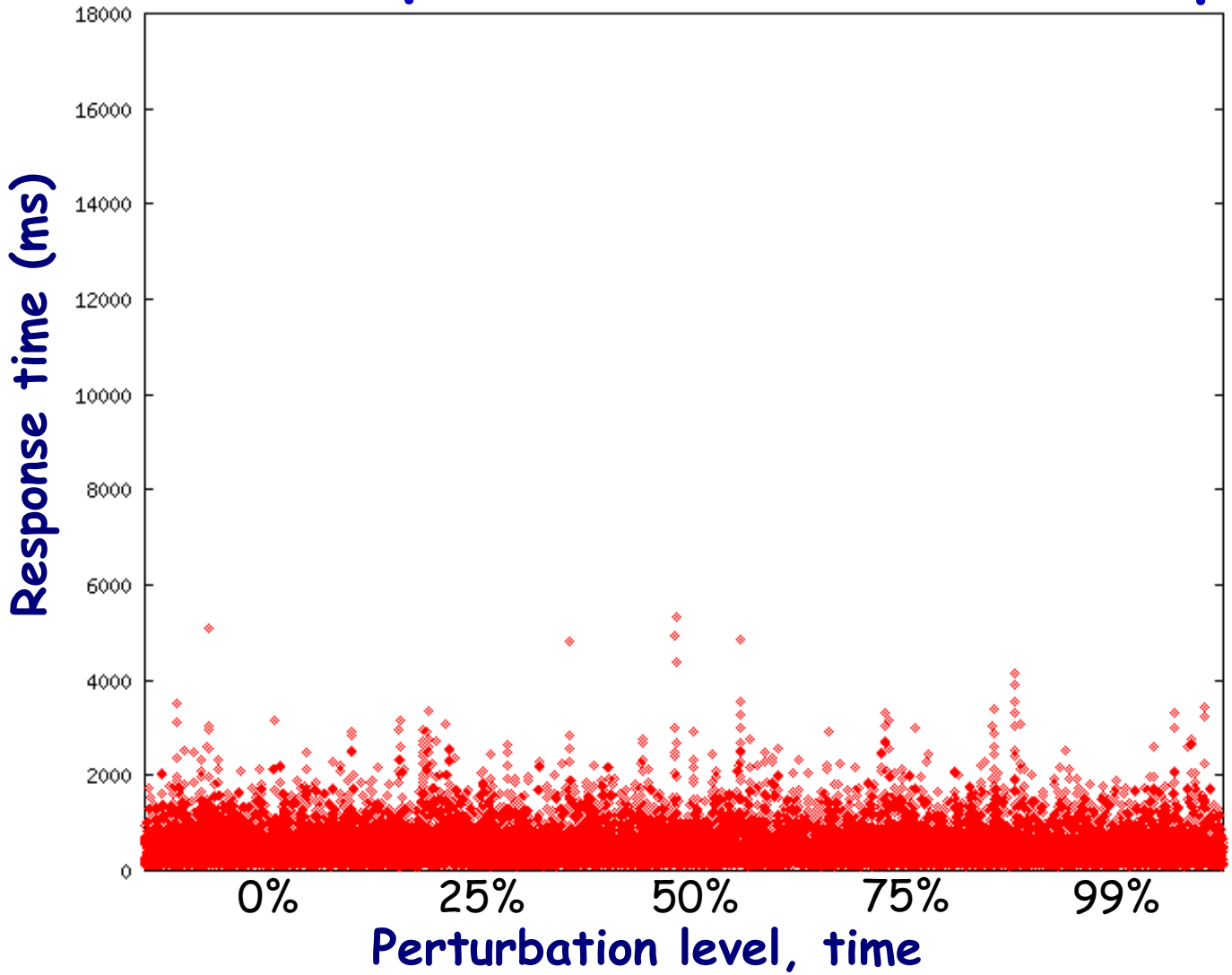
Raw perturbation results

- Ex: Search request, ITEM table perturbed



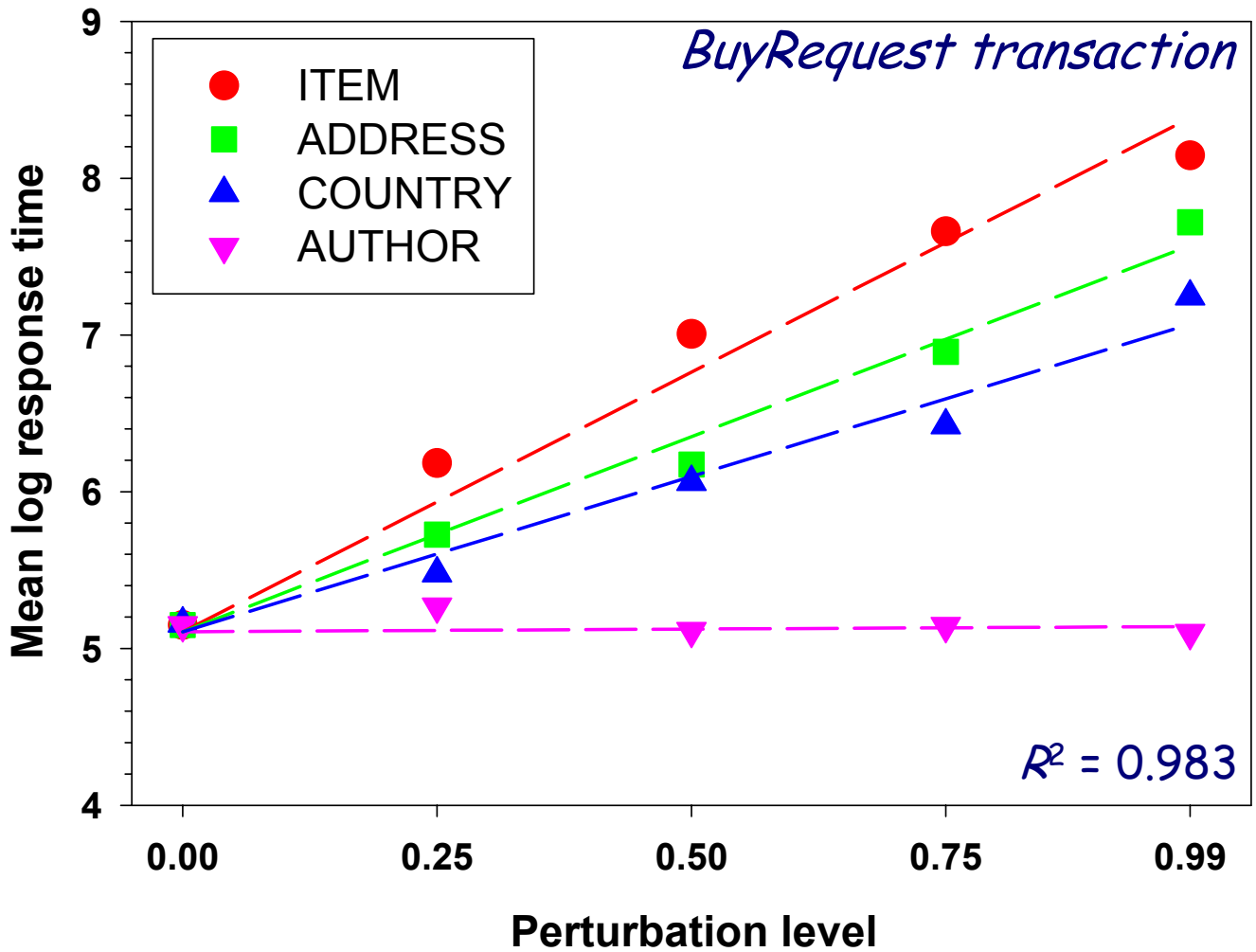
Raw perturbation results (2)

- Ex: Search request, CC_XACTS table perturbed



Applying a linear model

- **Linear regression on mean of log of data**
  - statistically positive slope gives dependency strength



Summary of results

- **Modeling correctly identified 41 of 42 true dependencies at 95% confidence level**
  - compare to 140 potential dependencies (!)
  - one false negative most likely due to insufficient data
  - caveat: some glitches due to unmodeled interactions
    - » manifested as small negative dependency strengths
    - » solution: improve model or simply discard negative strengths

Summary of results (2)

- Tabular representation of full dependency set:

Table \ Request	admcnf	admreq	bestsell	buyconf	buyreq	custreg	home	newprod	ordrdisp	ordering	proddet	srchreq	srchres	shopcart
ADDRESS				X	X				X					
AUTHOR	X	X	X					X			X		X	
CC_XACTS				X					X					
COUNTRY				X	X				X					
CUSTOMER				X	X	X			X					
ITEM	X	X	X	X	X		X	X	X		X	X	X	X
ORDER_LINE	-		X	X					X					
ORDERS	X		X	X					X					
SHOP_CART														X
SHOP_CART_L				X	X									X

Strengths: X = (0,1] X = (1,2] X = (2,3] X = (3,4]

Using dependencies for diagnosis

- **When a problem occurs:**
  1) identify faulty request
     » from problem report, SLA violation, test requests, ...
  2) select the appropriate column in dependency table
  3) select the rows representing dependencies
     » this is the set of potential root causes
  4) investigate potential root causes, starting with those of highest weight

Using dependencies for diagnosis (2)

- **Can extend approach to multiple system levels**
  - compute one dependency matrix per level
  - iterate levels from user symptoms to culprit resource
- **This process may not uniquely identify problem**
  - but can narrow down the culprits via combinations
    - » isolating the effects of individual tables
    - » e.g., SHOP_CART_L "=" orderdisp - buyconf
  - not all tables can be uniquely isolated
    - » but could do so by adding synthetic test requests?
    - » ideal is to build a *basis* for the whole-system dependency matrix

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Conclusions and future directions

- **Dependency models help problem determination**
- **ADD effectively discovers dependency models**
  - approach is uniquely positioned in the design space
    - » active, indirect approach finds dynamic, distributed dependencies; works on black-box systems
  - initial experimental results are promising
    - » very good success on TPC-W experiments
- **Future directions**
  - techniques to integrate ADD into production systems
  - investigation of end-to-end vs. layer-by-layer tradeoffs
  - using dependency models for other management tasks
    - » impact analysis, performance optimization, ...

An Active Approach to Characterizing Dynamic Dependencies for Problem Determination

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End

Backup slides

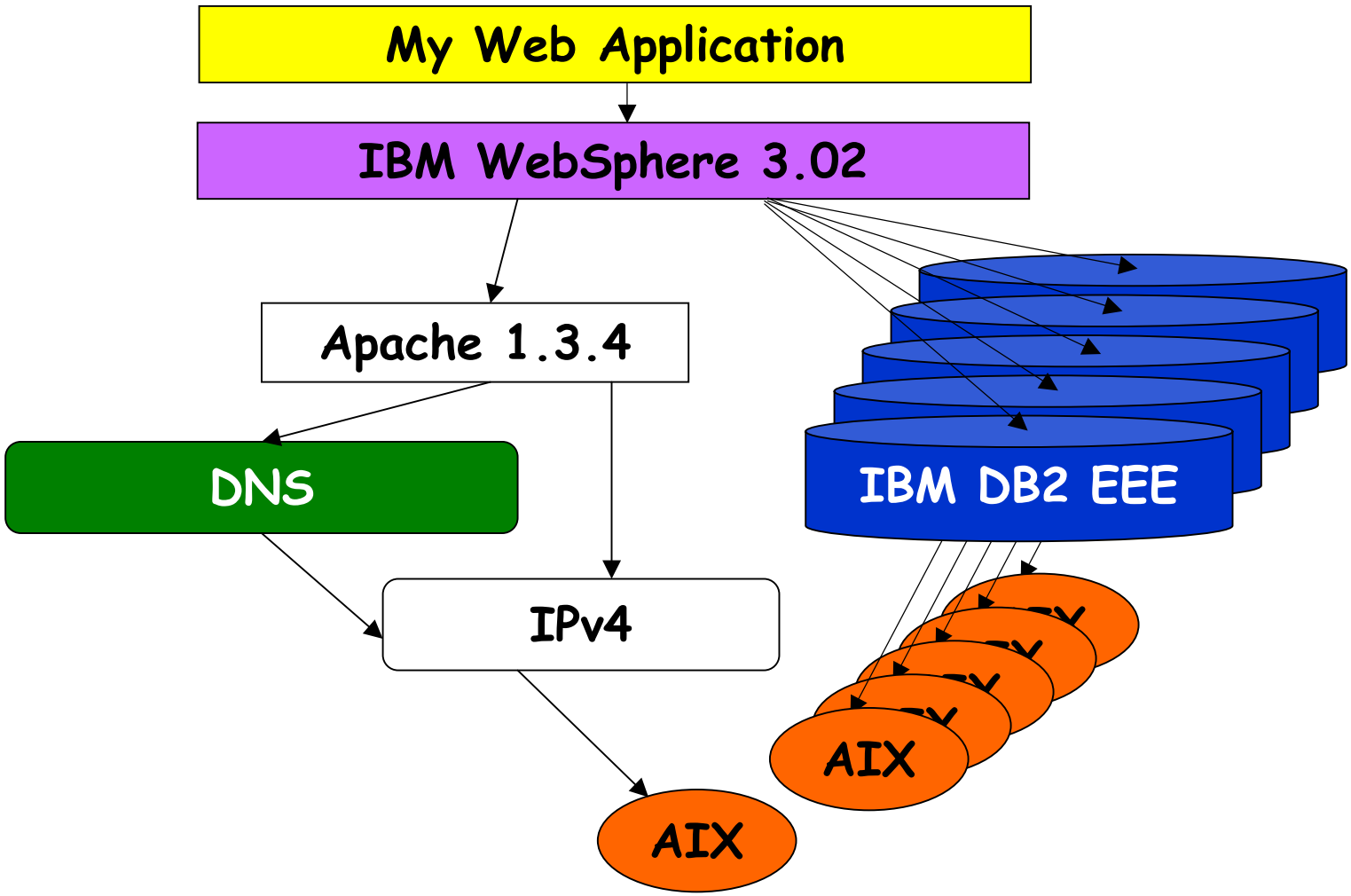
Dependencies & root-cause analysis

- **There are good algorithms for root-cause analysis using dependency data**
  - event correlation [Yemini96, Choi99, Gruschke98, ...]
  - systematic probing via graph-traversal [Kätker95]

- **But...they assume dependencies are identified manually!**
  - impractical in modern systems at any interesting level of detail
  - need automatic discovery of fine-grained dependency models to solve practical problems

A motivating example...

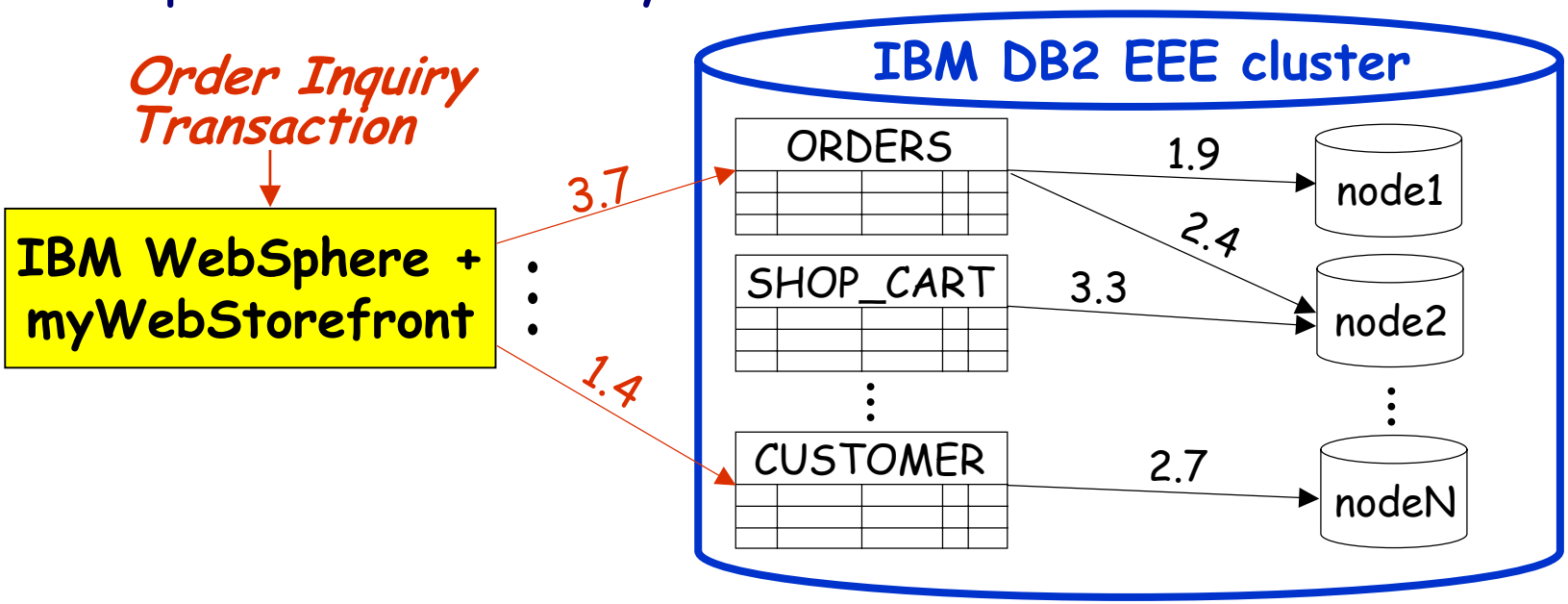
- E-commerce system with cluster database



This level of detail is called a "structural" model

What's really needed?

- **Dynamic, operational dependency graphs**
  - based on runtime behavior, not static analysis
  - computed for each type of user transaction/action
    - » each transaction's graph is a subgraph of the overall system dependency graph
  - dependencies weighted by "strength" and parameterized by workload



How is this useful?

- **Helps restrict search space for root cause of a problem**
  - presence/absence of operational dependencies tells you where you must look
  - dependency strengths may optimize search
  - in most cases, cannot completely identify root cause
- **Aids in system optimization**
  - dependency strengths reflect balance of system
- **Supports "impact analysis"**
  - strength of dependency is a direct measure of failure impact of a particular component

Dependency discovery: approaches

- **Direct**
  - relies on human to analytically compute dependencies
    - » from app-specific knowledge, configuration files, ...
  - impractical for realistic systems
- **Indirect**
  - based on instrumentation and monitoring
  - correlates observed failures/degradations across components
  - typically *passive*
    - » no perturbation to system beyond instrumentation
  - examples: data mining, event correlation, neural-net dependency discovery, MPP bottleneck detection

Challenges of an indirect approach

1) Causality

- most indirect approaches identify only correlation

2) Coverage

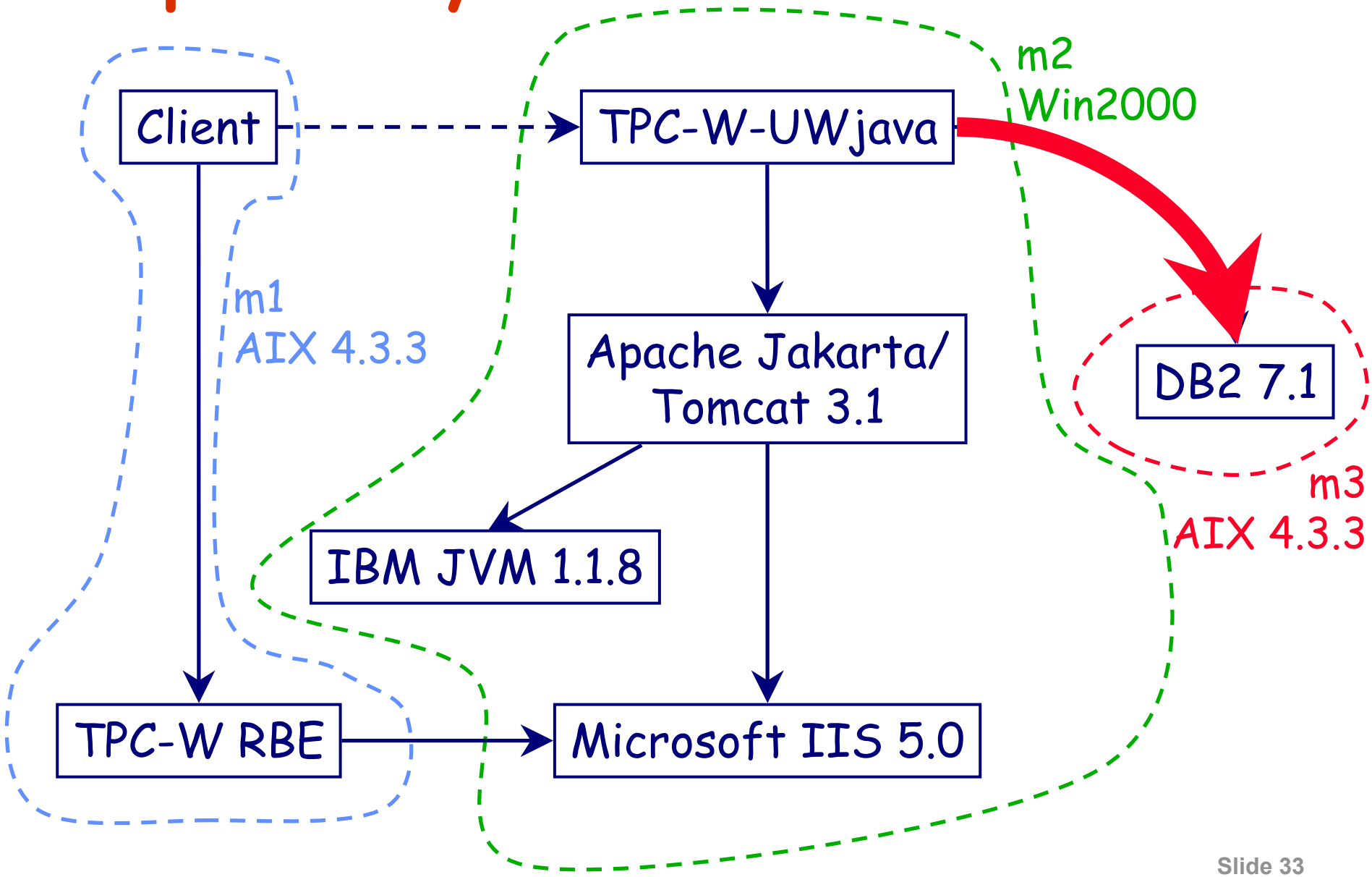
- passive approaches only find dependencies that are activated while the system is monitored
- can miss important dependencies that only appear in rare failure modes
  - » but these are often the most important dependencies!

- **Solution: an *active* indirect approach**
  - directly perturb the system, establishing causality and increasing coverage

Testbed web application

- **TPC-W web commerce application**
  - standardized TPC benchmark
  - simulates activities of a "business-oriented transactional web server"
  - implements storefront of an Internet book seller
  - includes user sessions, shopping carts, browsing, search, online ordering, "best sellers", ...
  - includes workload specification and generator
    - » fully parameterized
    - » standard mixes to simulate users that are mostly-browsing, mostly-ordering, or shopping (mix)
  - implementation in Java from University of Wisconsin

Dependency view: TPC-W testbed



Experiment details

- **Workload**
  - 90 simulated users
  - TPC-W standard "shopping" mix
  - an average of 11.8 unperturbed transactions/sec
  - servers not saturated by this workload

- **Perturbation**
  - only one table perturbed at a time
  - 0%, 25%, 50%, 75%, 99% levels for each table
  - 30 minutes of perturbation at each level

Limitations of the test case

- **Constant workload**
  - can't parameterize dependencies by workload
- **Independent table perturbation**
  - can't include interaction terms in model
- **End-to-end performance metric**
  - OK here since we're only looking at one level of system
  - assumes perturbations don't have additional effects beyond the database
  - if the dependency is not manifested in performance, it won't be detected
- ***None of these limitations are inherent***

Modeling details

- **Simple first-order linear model:**
  - assumes constant effects, independence, and linearity of perturbation (under transform of *m*)
  - let m_i be some metric for transaction type *i*
  - let μ_i be the mean non-perturbed value of m_i
  - let P_j be the level of perturbation of system element *j*
  - then:

$$r_i = \mu_i + \Sigma_j (\alpha_j P_j) + \varepsilon$$

  - the α_j's are fit to the data, and represent the effects of perturbation of the components *j*
    - » α_j characterizes the strength of m_i's dependency on *j*

Model details

- **Fit a first-order linear model:**

$$r_i = \mu_i + \Sigma_j (\alpha_j P_j) + \varepsilon$$

- **Estimated effects (α_j) for buy request txn:**

ITEM:	3.31 ± .26	SHOP_CART:	0.06 ± .26
ADDRESS:	2.49 ± .26	CC_XACTS:	0.06 ± .26
CUSTOMER:	2.41 ± .26	AUTHOR:	0.03 ± .26
SHOP_CART_LINE:	2.35 ± .26	ORDER_LINE:	0.003 ± .26
COUNTRY:	1.98 ± .26	ORDER:	-0.02 ± .26

- **Despite simplicity, models fit well**
  - R^2 ranges from .906 to .996, with mean .973
  - there are clearly higher-order effects present
    - » especially noticeable in significant *negative* effects
    - » but first-order effects dominate

Existing approaches

- **Most popular approaches are passive**
  - event collection and data mining
  - neural-network-based dependency discovery
  - performance bottleneck detection in parallel programs
  - network fault detection
  - nuclear power plant problem diagnosis
- **Passive approaches have two main weaknesses:**
  - hard to differentiate *correlation* and *causation*
  - hard to get coverage of all problem/failure cases
- **Active approaches limited to postmortems**

A less-linear result

- Not nearly as linear, but linear model still sufficient
- Example data: order confirmation transaction