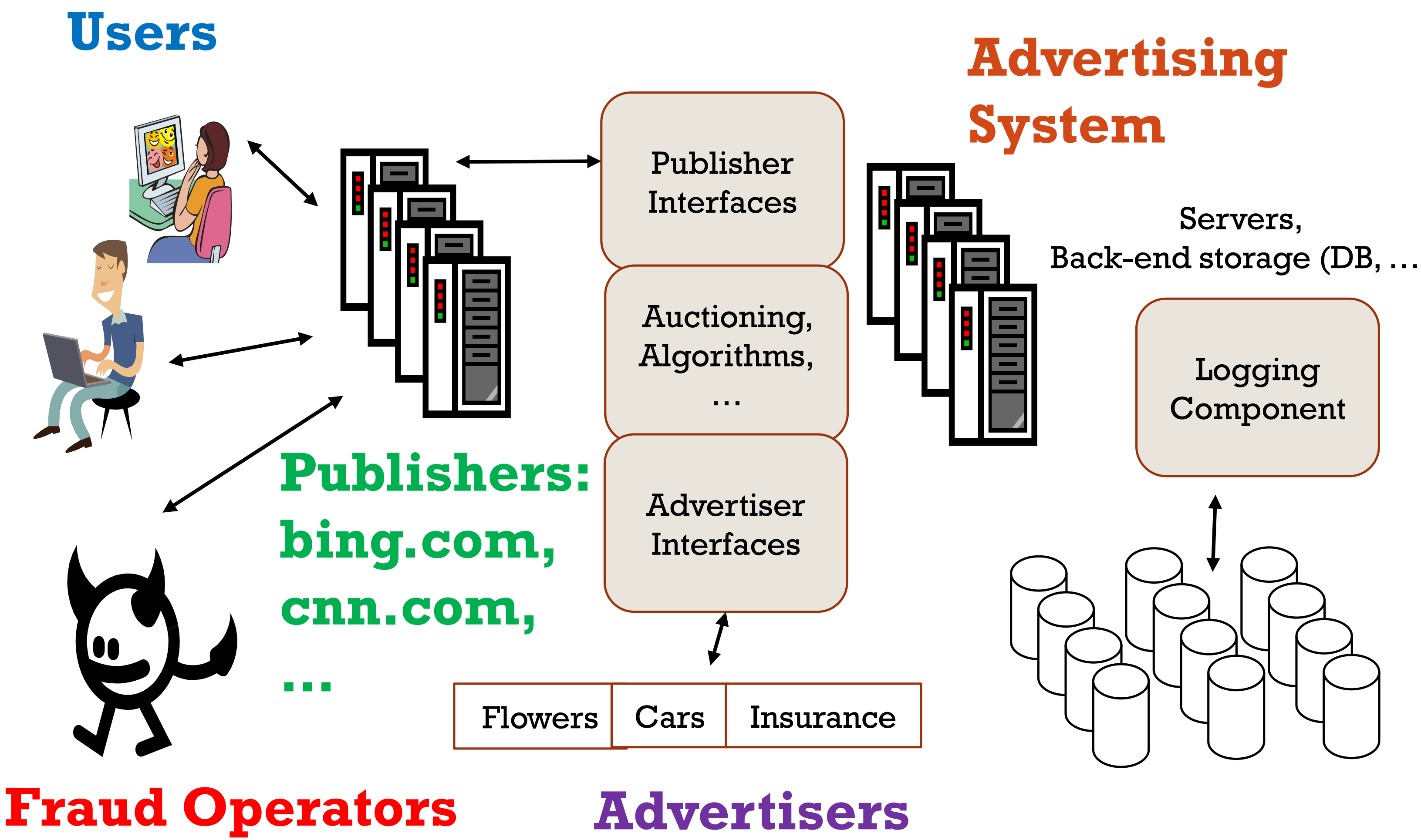
ADTRIBUTOR: REVENUE DEBUGGING IN ADVERTISING SYSTEMS

Ranjita Bhagwan, Rahul Kumar, Ram Ramjee, George Varghese
Surjyakanta Mohapatra, Hemanth Manoharan, Piyush Shah
MICROSOFT

ADVERTISING SYSTEMS ARE COMPLEX



REVENUE DEBUGGING IN ADVERTISING SYSTEMS

Why is Revenue/Revenue-per-search down *anomalously*?

Measures

Derived Measures

Anomaly Detection Problem ⇄ **Root Cause Analysis**

Dimensions

Values

- **Datacenter** in **Dublin** had latency issues that resulted in fewer ads being served

- **Buckets 18, 23, and 24** were using a new algorithm for ad relevance that wasn't working as expected.
  - Buckets: experimental trials with different algorithms

- The papal election was in progress, and users were searching for mainly non-monetizable **queries** such as **"Pope"**

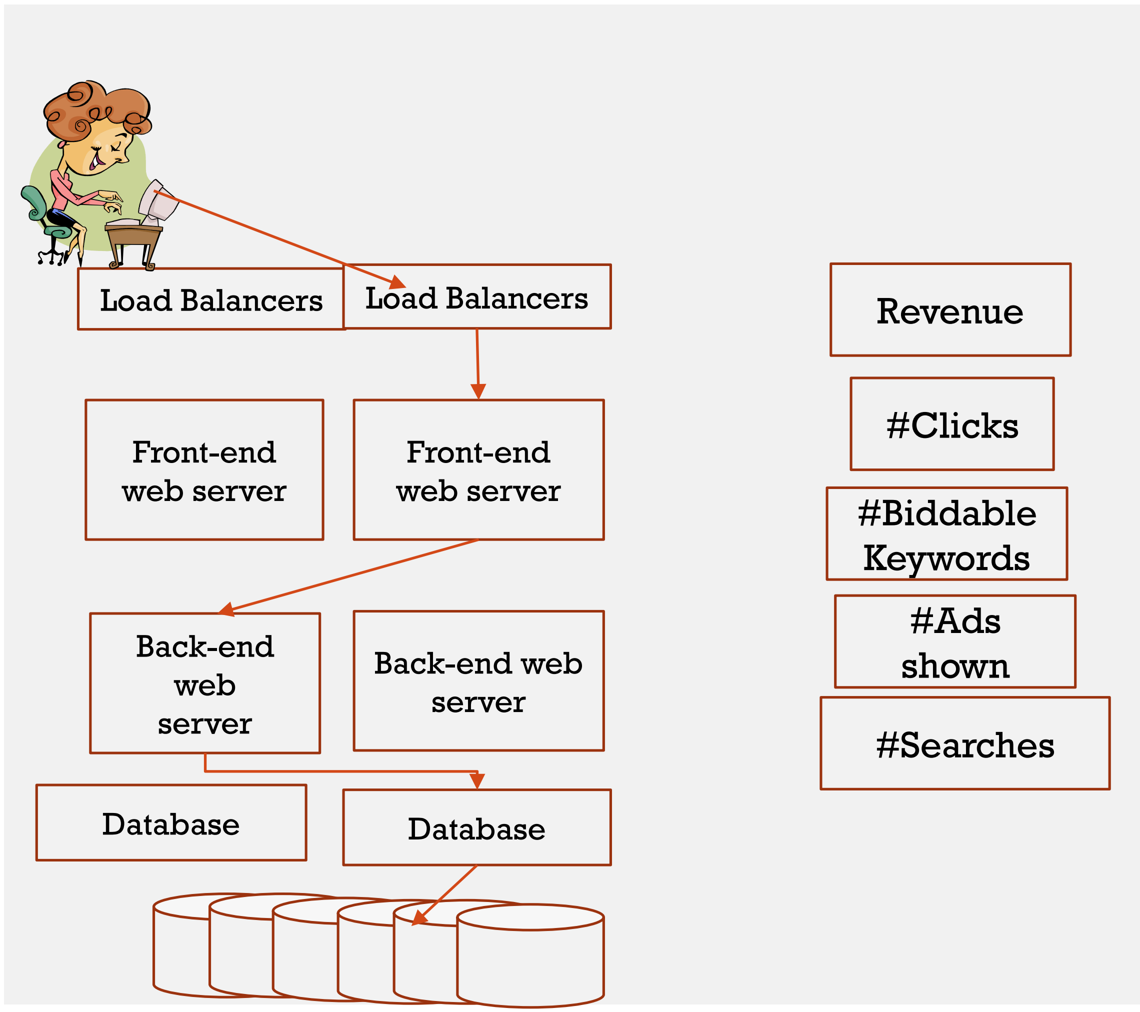
CONTRIBUTIONS

1. **Novel algorithm for root cause analysis in Ad Systems**
    - Uses explanatory power, succinctness and surprise
2. **Attribution for derived measures**
    - E.g., attribute an element's contribution to revenue-per-search (revenue/# searches)
3. **Adtributor Tool**
    - 95+% accuracy in identifying root causes in Ad Systems
    - Saves 1+ hour on average of manual troubleshooter time

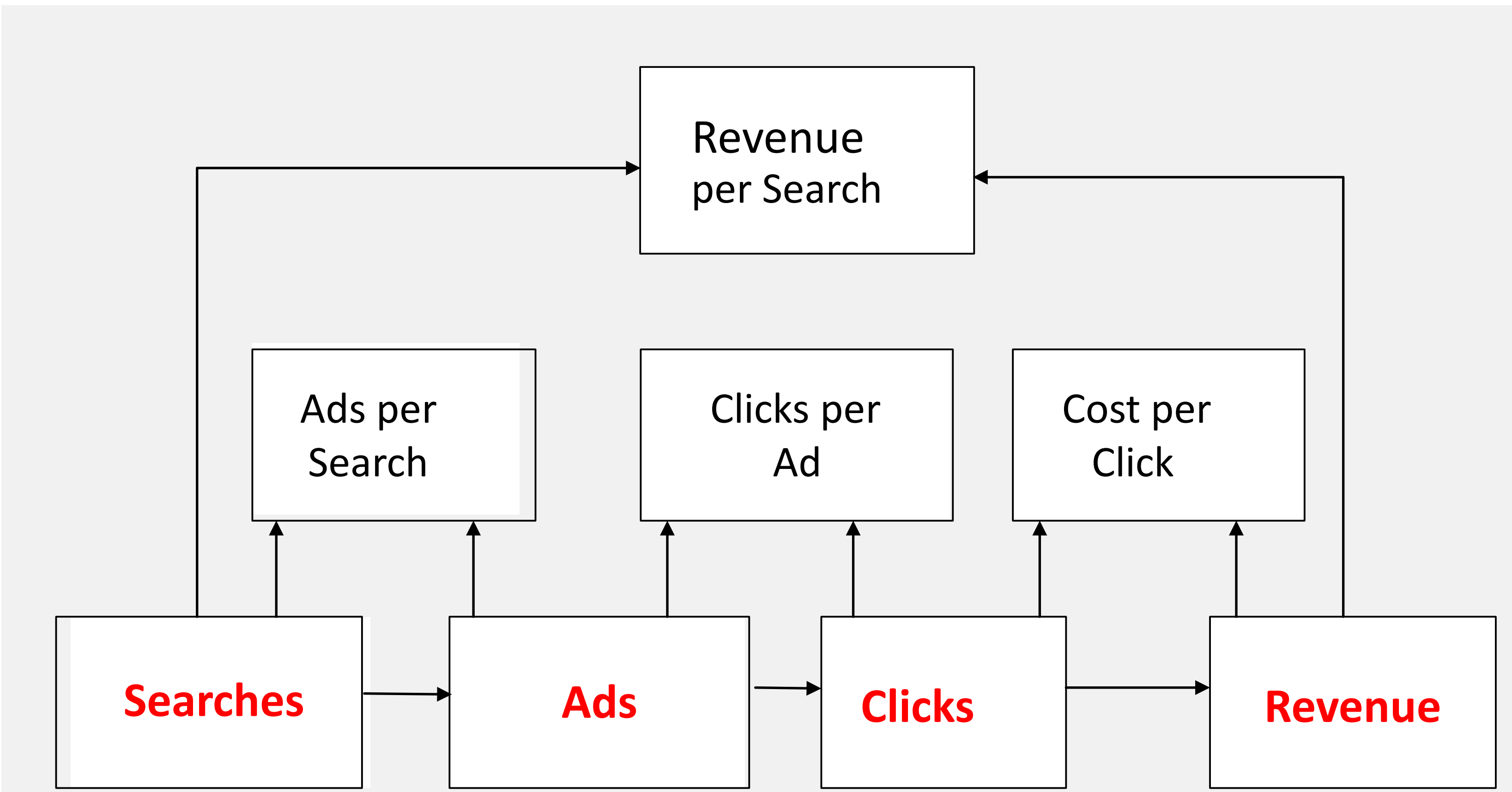
OUTLINE

- Characteristics of Ad systems
- Root cause analysis
- Attribution for derived measures
- Adtributor Demo
- Evaluation

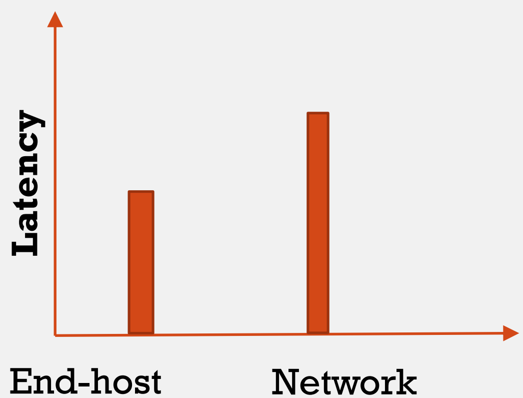
CHARACTERISTIC I: AGGREGATE ANALYSIS



CHARACTERISTIC II: FUNDAMENTAL AND DERIVED MEASURES



CHARACTERISTIC III: MULTI DIMENSIONAL ANALYSIS



System Component Isolation

Publishers

Publishers, Buckets, Advertisers, System Components,…

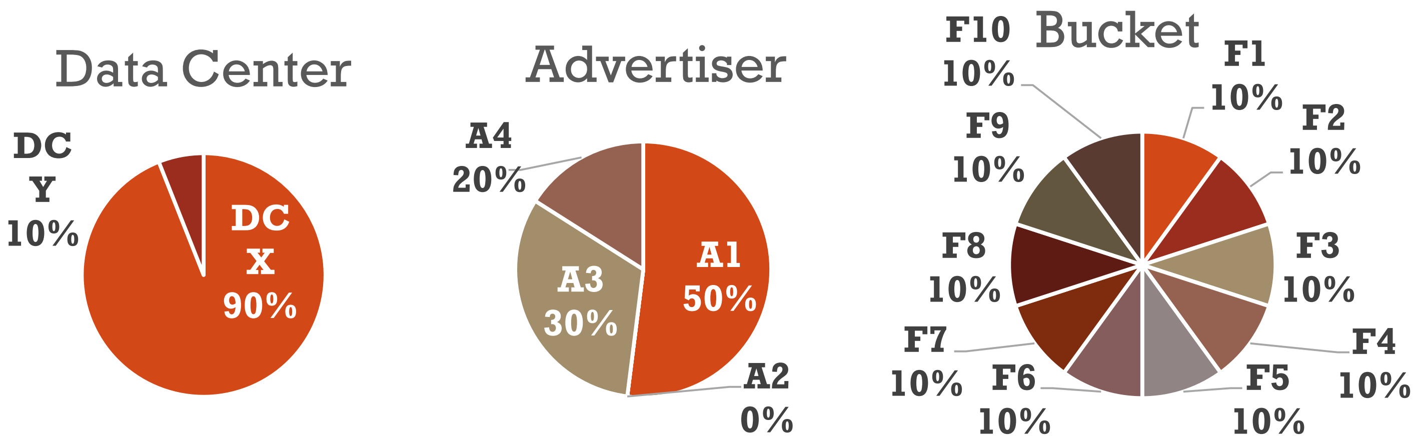
ROOT CAUSE ANALYSIS

- Example
  - Expected Revenue: $100, Actual Revenue: $80
  - Revenue down by 20% → anomaly!

- Potential root causes
  - One data center had $18 less revenue than forecasted
  - Three advertisers spent $20 less than forecasted
  - 10 buckets resulted in $20 less revenue than forecasted

➢ Should we attribute root cause to dimension data center, advertiser or bucket? Which values?

EXPLANATORY POWER AND SUCCINCTNESS



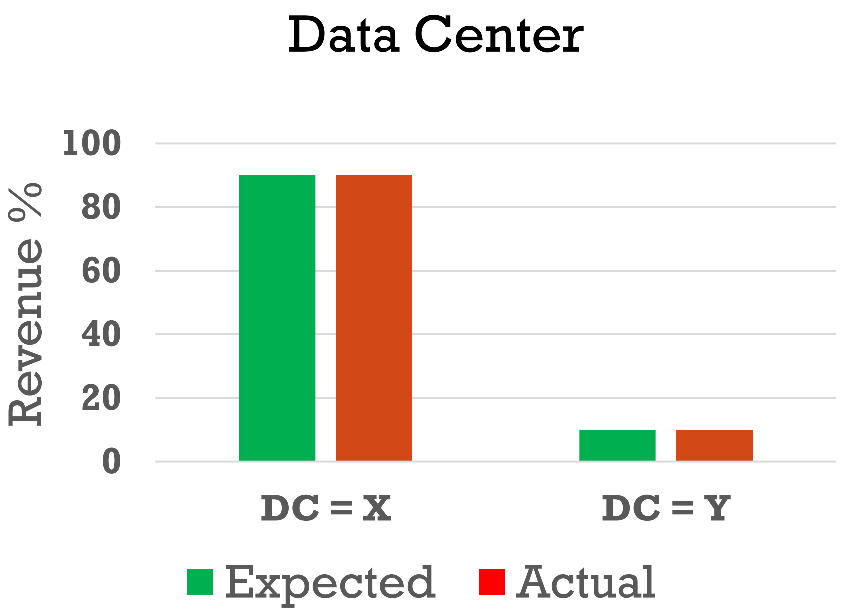
Pie charts show contribution to change by dimension-values.

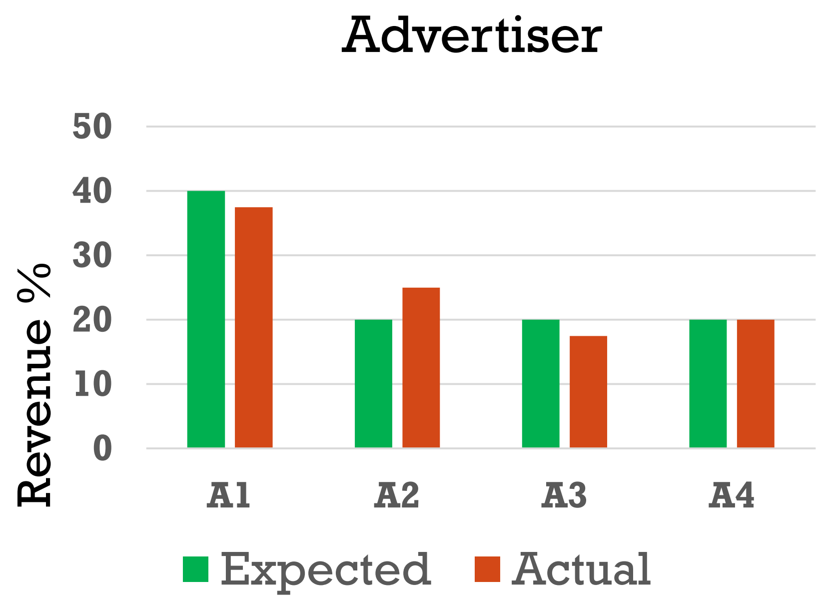
- Explanatory: root cause should explain most of change
- Succinctness: root cause likely to be few elements

➢ **DataCenter == X**

➢ **Advertiser == A1 OR Advertiser == A3 OR Advertiser == A4**

SURPRISE





- Root cause likely to deviate most from expectation
  - Relative entropy of actual vs expected probability (JS-divergence)

➢ **Advertiser == A1 OR Advertiser == A3 OR Advertiser == A4**

$$D_{JS}(P,Q) = 0.5(\Sigma_i p_i \, log \frac{2p_i}{p_i + q_i} + \Sigma_i q_i \, log \frac{2q_i}{p_i + q_i})$$

ALGORITHM

- Find the dimension and smallest set of values that maximally explain the anomalous change while also maximizing surprise
- Multi-objective optimization
- Greedy algorithm
  - Smallest set → each value contributes > 10% of change
  - Maximally explains → set should explain > 2/3 of change
  - Maximize surprise

Foreach $m \in M$ // Compute surprise for all measures,
    Foreach $i \in D$ // all dimensions,
        Foreach $j \in E_i$ // all elements for a dimension
            $p = V_{ij}^{e}(m)/V^{e}(m)$ // Equation 6
            $q = V_{ij}^{a}(m)/V^{a}(m)$ // Equation 7
            $S_{ij}(m) = D_{JS}(p, q)$ // Equation 10
ExplanatorySet = {}
Foreach $i \in D$
    $SortedE$ = E_i.SortDescend($S_{ij}(m)$) //Surprise
    Candidate = {}, Explains = 0, Surprise = 0
    Foreach $j \in SortedE$
        EP = $(V_{ij}^{a}(m) - V_{ij}^{e}(m))/(V^{a}(m) - V^{e}(m))$
        if (EP $> T_{EEP}$) // Occam's razor
            Candidate.Add += E_{ij}
            Surprise += $S_{ij}(m)$, Explains += EP
        if (Explains $> T_{EP}$) // explanatory power
            Candidate.Surprise = Surprise,
            ExplanatorySet += Candidate, break
//Sort Explanatoryset by Candidate.Surprise
Final = ExplanatorySet.SortDescend(Surprise)
Return Final.Take(3) // Top 3 most surprising

ATTRIBUTION FOR DERIVED MEASURES

Explanatory Power of element j in dimension i for measure m is simply=(A_ij(m) - F_ij(m)))/(A(m) - F(m)). e.g. A1: (10-50)/(90-100)=400%

- Why derived measures?

Below 20% threshold

Adver-tisr	Estimated Revenue	Actual Revenue	% change
Overall	100	90	-10
A1	50	**10**	400
A2	**0**	0	0
A3	**40**	70	-300
A4	**10**	10	0

Below 20% threshold

Adver-tisr	Estimated Clicks	Actual Clicks	% change
Overall	500	580	16
A1	100	**20**	-100
A2	**200**	360	200
A3	**100**	100	0
A4	**100**	100	0

Above 20% threshold

Adver-tisr	Estimated CPC	Actual CPC	% change
Overall	0.2	0.155	-22.5
A1	0.5	0.5	
A2	0	0	
A3	0.4	0.7	
A4	0.1	0.1	

- How do we attribute for derived measures?

Assuming only one advertiser performs the same as its actual performance, and all other advertiser perform as expected

Intuition: use expected value for all other elements and actual values for only this element

e.g. A1: (10+0+40+10)/(20+200+100+100) = 0.143 , (0.2-0.143)/0.2=-28.5%

A2: (0+50+40+10)/(360+100+100+100)=0.152, (0.2-0.152)/0.2=-24%. Below is the formula

- **Captured by Partial Derivatives in Finite Difference Calculus**

F(.)/G(.) = (Delta_F*G – Delta_G*F)/(G * (G + Delta_G))

DEMO

[Adtributor]

EVALUATION

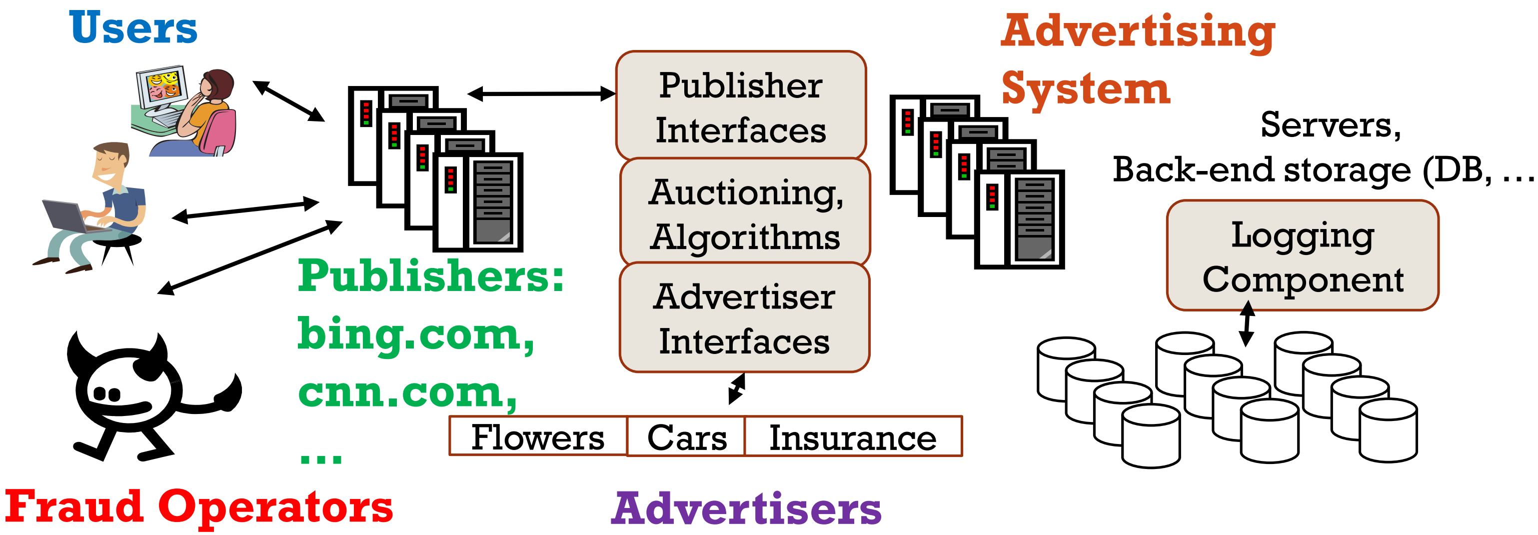
Parameter	Value
Anomalies	128
No. of matches	118
Manual errors	4
Adtributor's errors	5
Ambiguous	1
Accuracy	95.3%

- Evaluated 128 alerts generated over a 2 week period over 8 markets (US, UK, DE, FR: PC, Mobile for each)
- Compared Adtributor output with manual root-causing
- Time saved: 1+ hour on average per alert

RELATED WORK

	Root causing	Multiple Dimensions	Derived Measures
Network Component Failure Isolation (e.g., SCORE, Sherlock, etc.)	Explanatory Power, Succinctness	**Does not handle**	**Does not handle**
Network Traffic Pattern Finding (Autofocus, HHH)	Explanatory Power, Succinctness	Explores all combinations of dimensions *dynamically,* Heuristic: unexpectedness	**Does not handle**
Data mining (Summarization, Surprising Patterns)	Explanatory Power, Succinctness	Many techniques (e.g., Minimize description length)	**Does not handle**
Revenue Debugging	Explanatory Power, Succinctness	Explores single dimensions Pre-declared *statically* Surprise: JS divergence	Partial derivative, Finite differences

SUMMARY



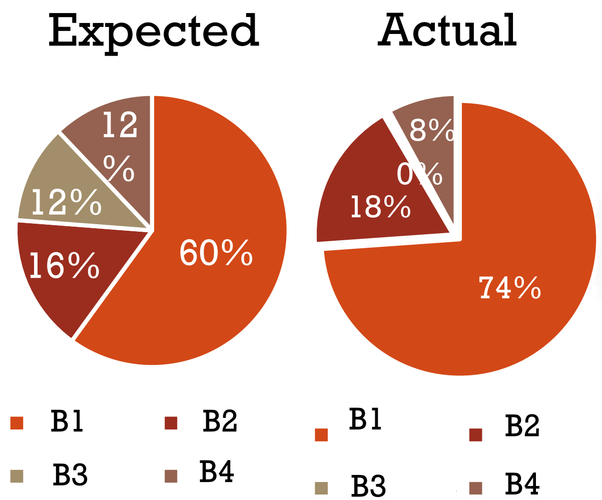
- Algorithm for Root Cause Analysis in Advertising Systems
  - Uses explanatory power, succinctness, and surprise
- Attribution for derived measures
  - Finite difference, partial derivative-based approach
- Adtributor tool
  - 95+% accuracy, saves 1+ hour of manual troubleshooting time

APPLYING OUR APPROACH MORE GENERALLY

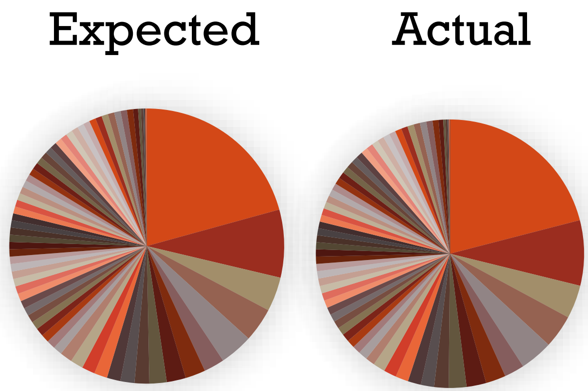
- This problem/solution is not specific to advertising
- Datacenter Diagnostics problem (Bodik et al., Eurosys 2010)
  - Problem: When there is a slowdown in the datacenter, where is the slowdown? Is it CPU, Memory or Disk that is the bottleneck?
- Derived metric attribution
  - MoS score attribution in VOIP networks: which link is responsible for drop in the Mean Opinion Score (MoS) for a given VOIP call?

CASE STUDY: ANOMALOUS REVENUE DROP

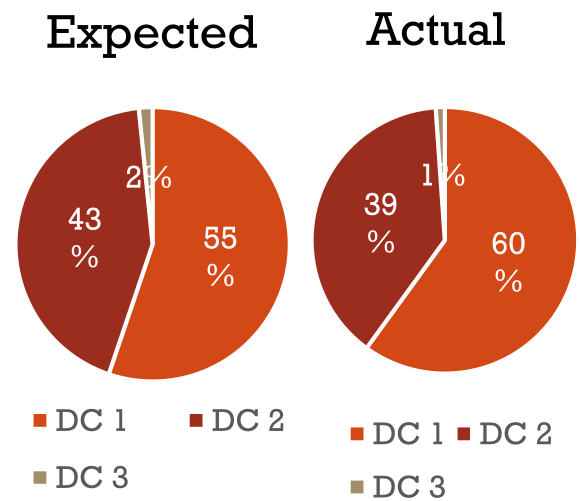
Dimension: Browser



Dimension: Bucket



Dimension: Data Center



- Maximum surprise (deviation from expected value) seen for the browser dimension
  - Configuration error caused no ads to be shown on B3 for that time