Influence Diagrams, A Universal Decision Modeling Tool

"Decision Intelligence confronts AI"

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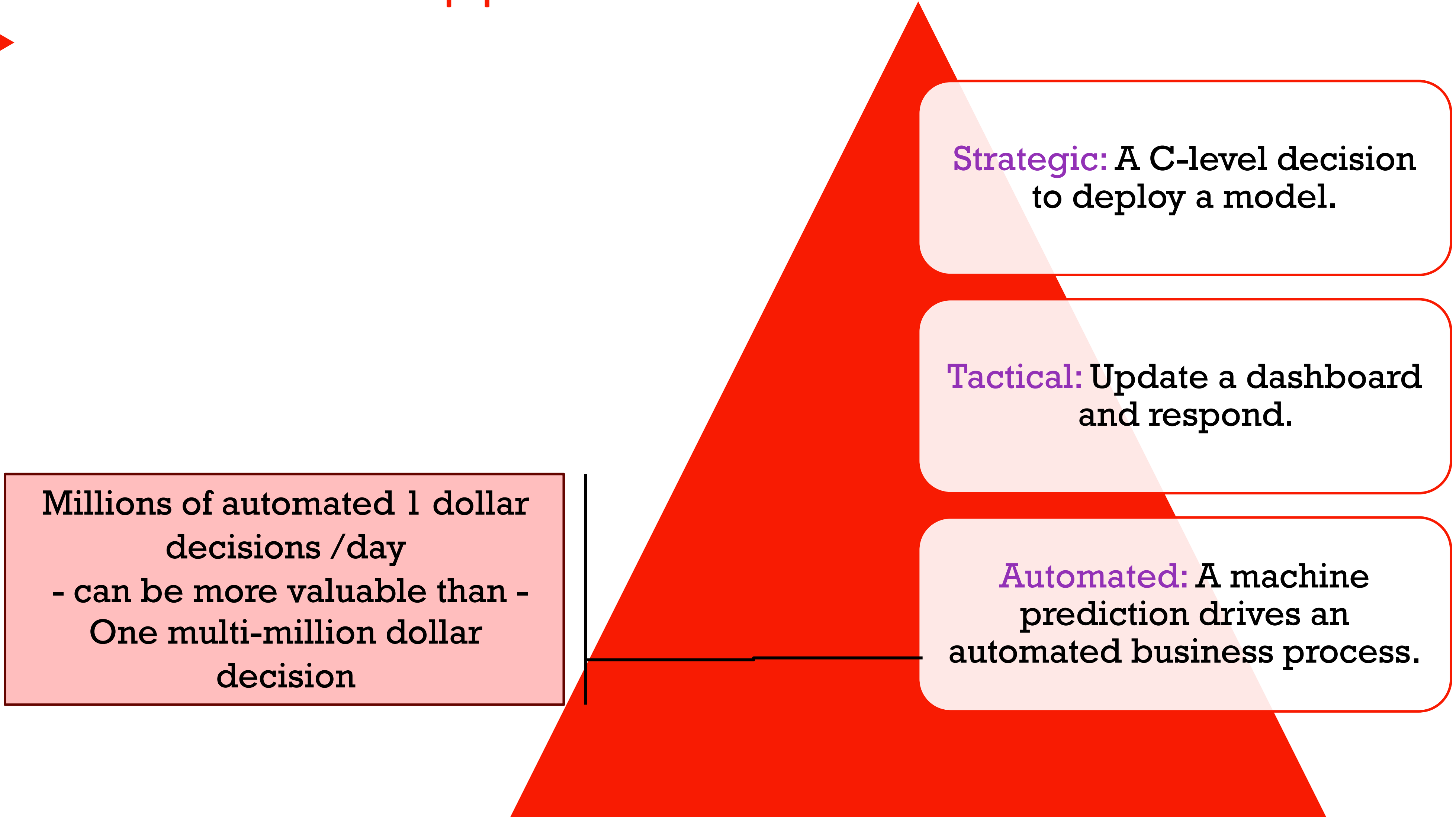
The method and An example of *why predictions go wrong*

- Modeling decisions under uncertainty
- DQ terms: "outcomes" & "rigor"
- Influence diagrams for combined predictive –value modeling
- An example: "walk-in demand"
- Demo: Solve it as an Influence diagram

Decisions happen at all Levels



Premise: "Intelligence" is Rational choice.

- A *decision* makes a tangible change; an allocation that is not revocable.
- A *rational decision* aligns actions to maximize a measure over outcomes
- *Outcomes* can be assigned values by which they can be compared
- *Predictions* are uncertainties over outcomes, expressed by probability

Models

“Models to automate decisions”

Variables fall into one of three kinds

Outcome values

Conditional probabilities

Decisions, policies

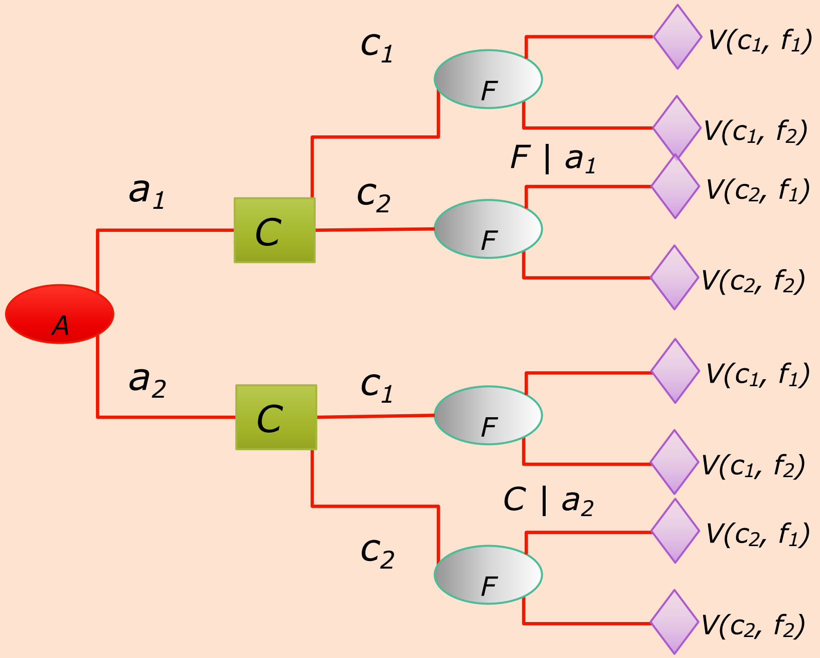
* Influence Diagrams, aka
  - Bayes Networks,
  - Probabilistic Graphical Models
  - Structural Equation Models

have three kinds of variables.

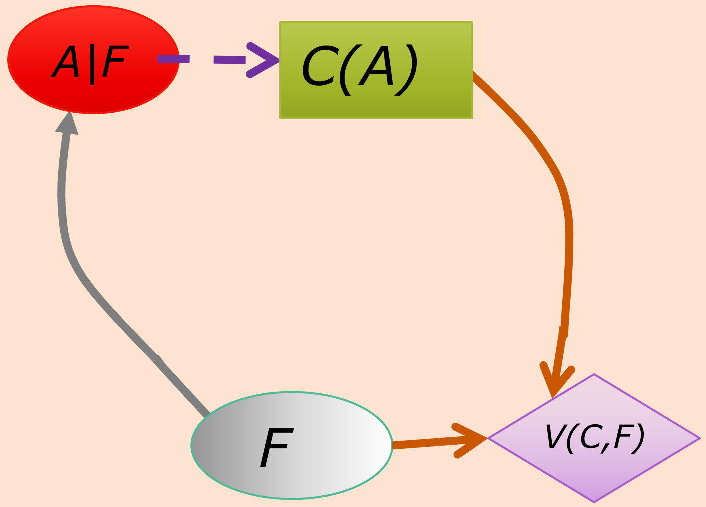
* Arcs show the influences among them

* Decision models, as one might draw out in a tree, can be formulated and solved by Influence Diagrams

Influence Diagrams are concise, causal, and computational



Tree, With Decision and Outcomes



Equivalent Influence Diagram

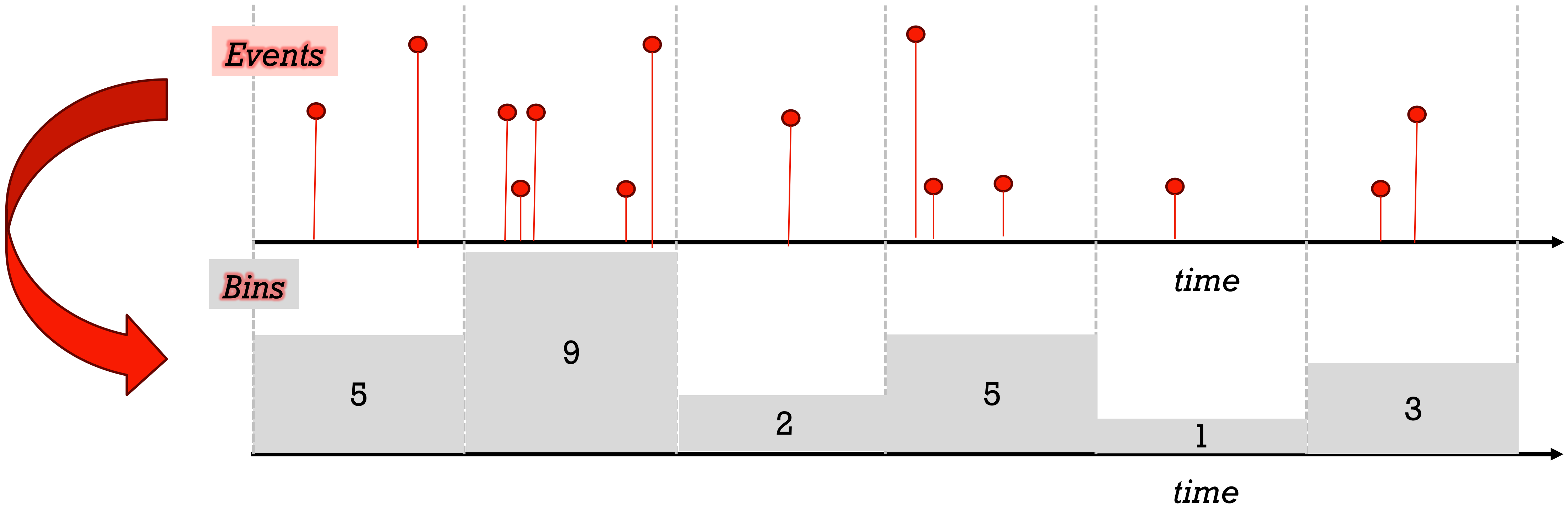
The “walk-in” (e.g. newsvendor) problem

Decision: *How much to under or over provision at any one time.*

Examples:

- How many hospital beds to have ready?
- How many perishable items to store?
- How many fast-food items to keep on hand?
- How many live CSR staff to take calls?
- How many network servers to provision?

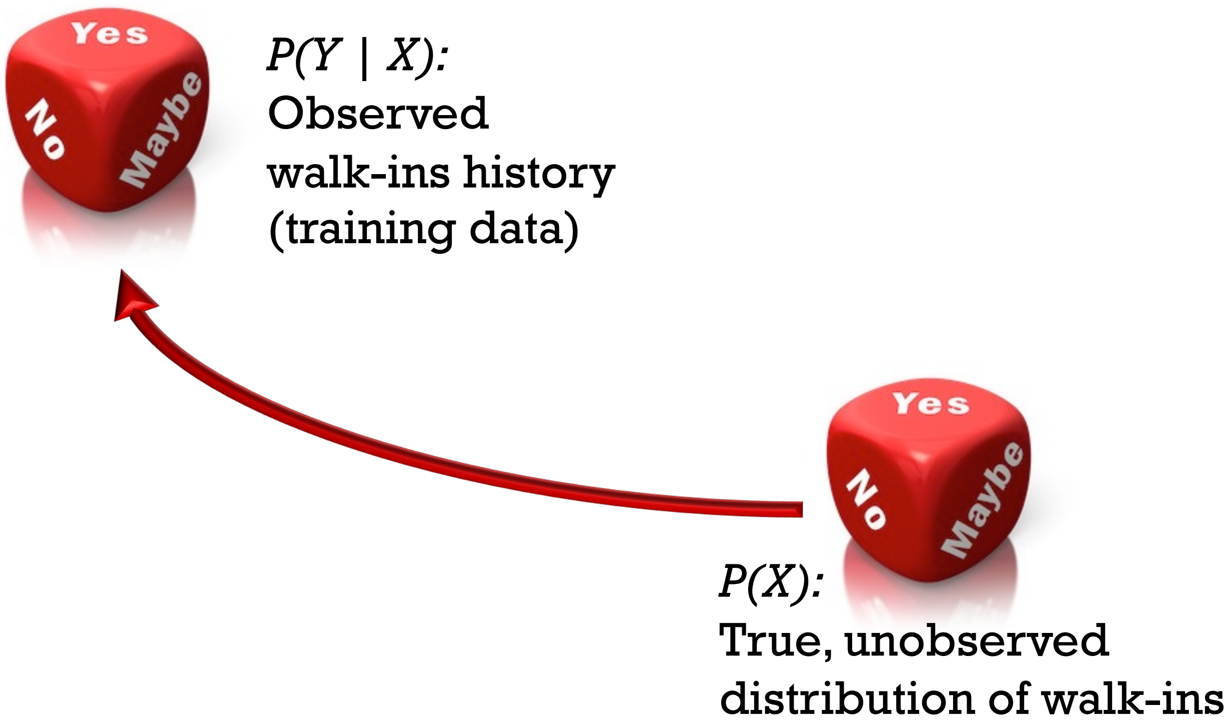
The “data”

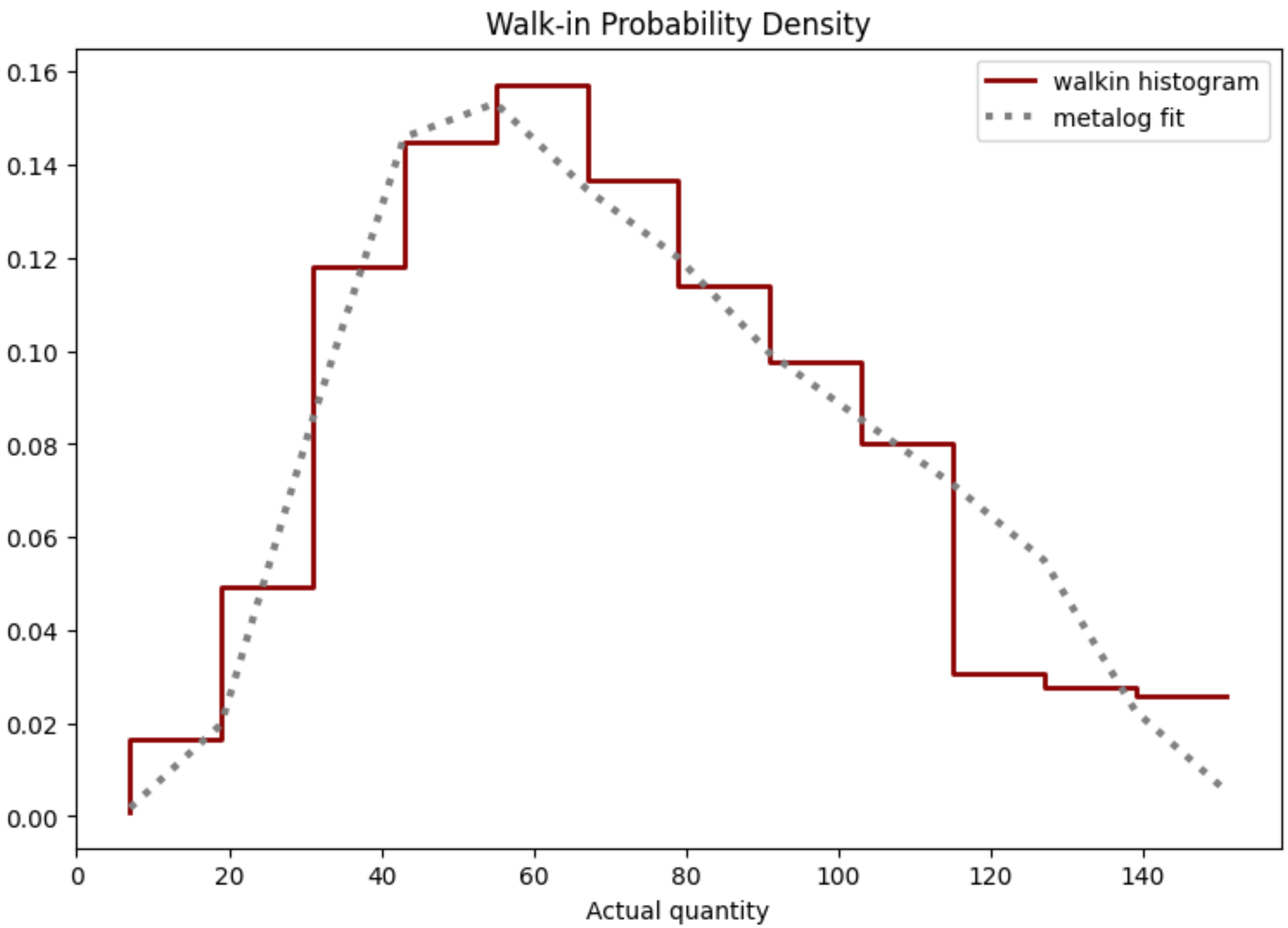


- People (walk-ins) arrive at random times.
- The number of walk-ins is binned for each time interval.
- The decision is to anticipate how many need to be served.

Probability model: *Learn predictor of X from Y*

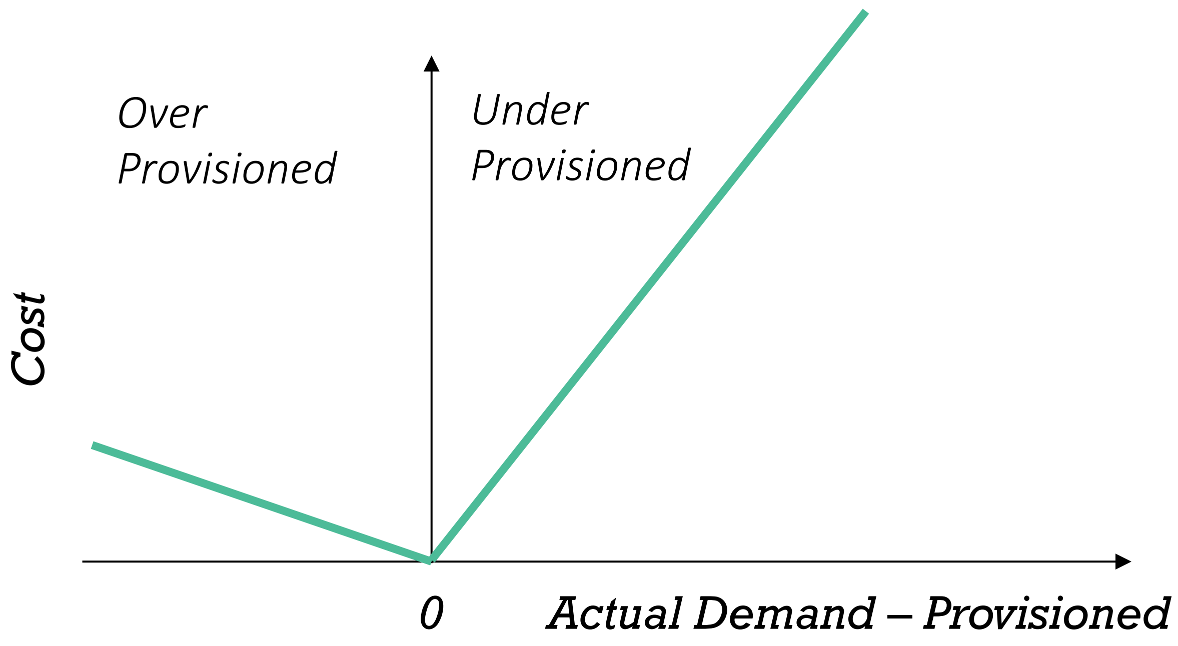
- The history of walk-ins over time is the data set from which to predict the probability distribution of walkins.
- Other predictor variables, not shown, may also condition the prediction

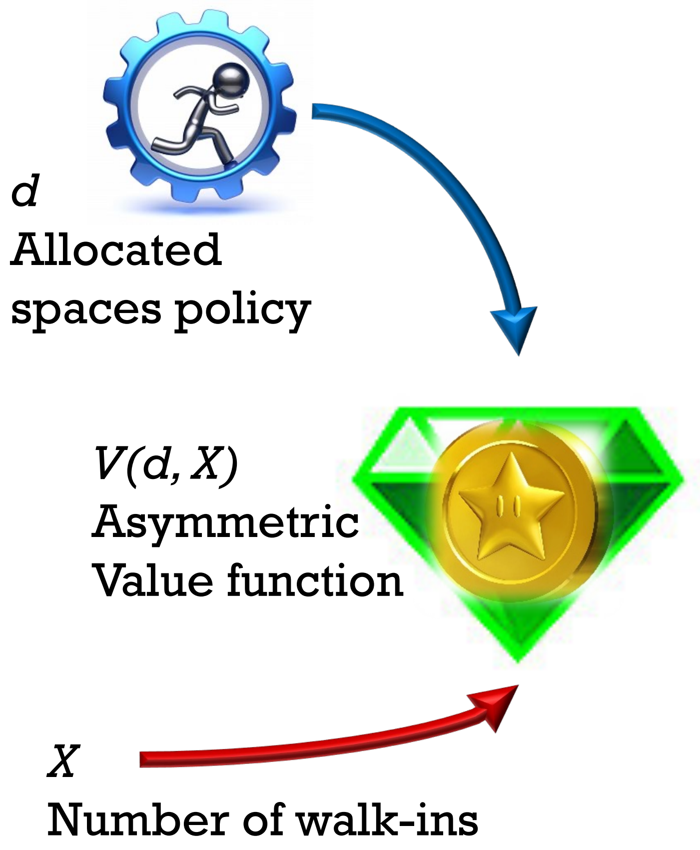



Walk-in Probability Density
walkin histogram
metalog fit
0.16
0.14
0.12
0.10
0.08
0.06
0.04
0.02
0.00
0
20
40
60
80
100
120
140
Actual quantity

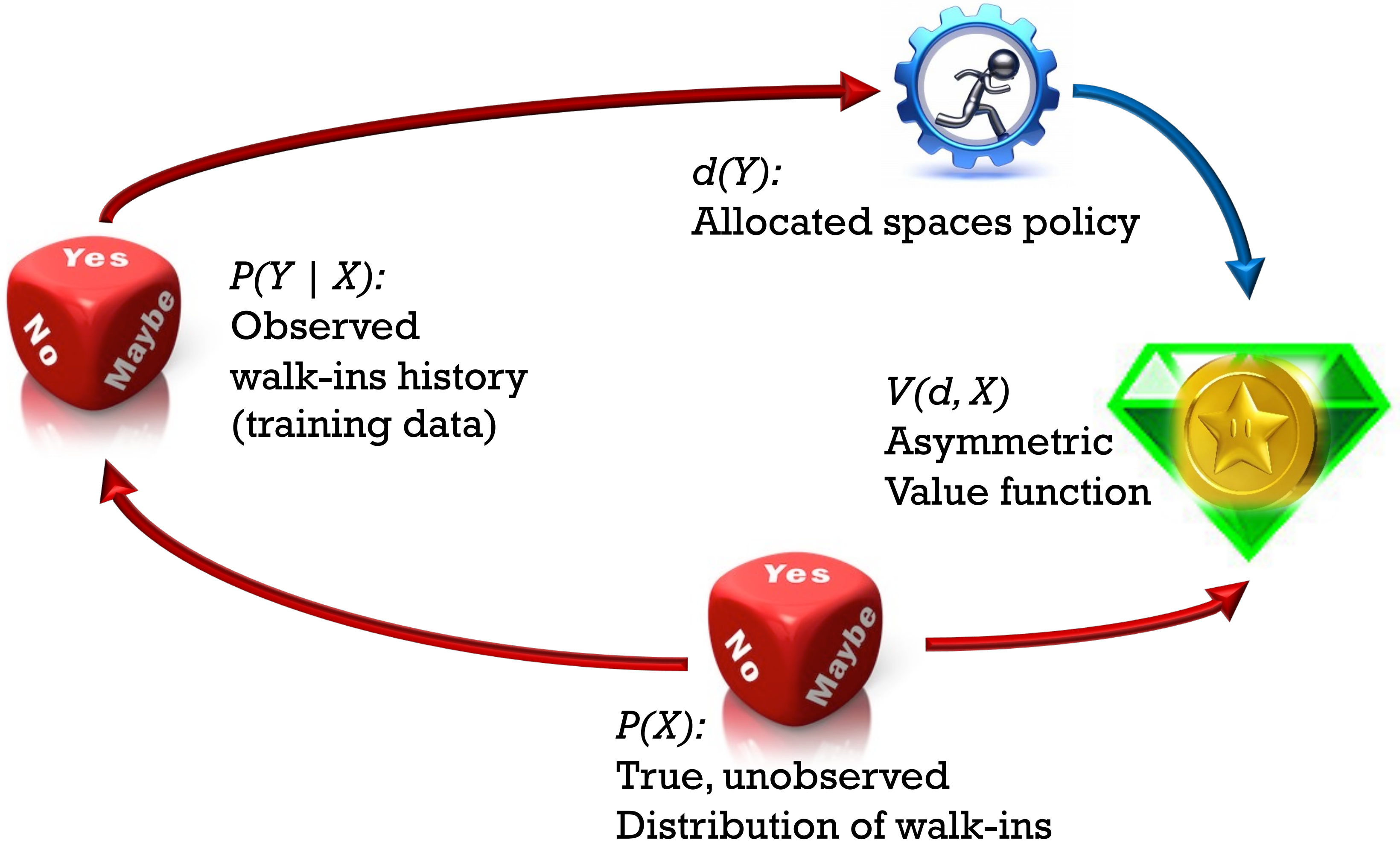
Value Model: *Elicit the tradeoff for under and over provisioning*

- The *asymmetric* value model expresses the costs of wasted space versus lost business in dollar terms.

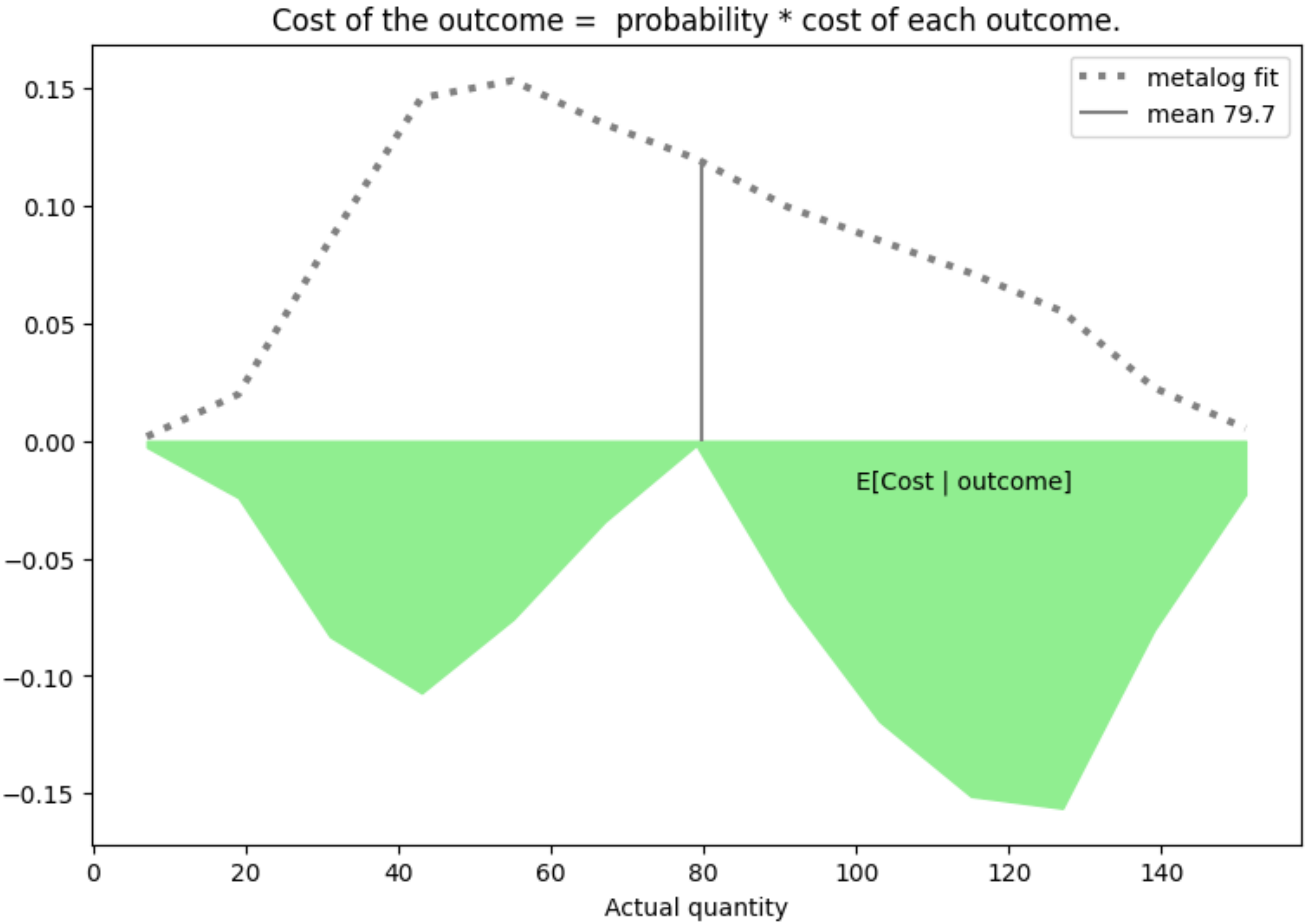




Influence Diagram: Combined walk-in model: *Solve for d(Y)*



- First, predict P(X) from the training data
- Second, optimize the value tradeoff



Cost of the outcome = probability * cost of each outcome.
metalog fit
mean 79.7
E[Cost | outcome]
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
0
20
40
60
80
100
120
140
Actual quantity

Demonstration

Takeaways

A combined predictive – value model is needed when the prediction is intrinsically uncertain.

By not weighing errors a predictive model alone gives the wrong answer.

2-level

Hierarchical regression causal model