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Measuring benefit effect for customers with bayesian prediction modeling

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Strata + Hadoop World 2015, London

strataconf.com

#StrataHadoop

Kwon,JeongMin

- Data Analyst @ SK Planet
- Interests: Data Problem Solving with R, Hive, SQL, Python and others



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\$20 OFF
for you & your friends

Introduce your friends to the best in American made and give them 15% off their DODOcase purchase. For every friend that redeems your offer, you will receive a \$20 coupon back!

Offering

CREATE YOUR INVITE LIST:

From: buyer@example.com

IMPORT CONTACTS

Enter email addresses separted by commas

Congratulations! You Get 15% off at DODOcase.

Add a personal message below to go in the email with the offer details:

I'm excited to share this great DODOcase deal with you. Enjoy shopping and supporting American craftsmanship!

#StrataHadoop

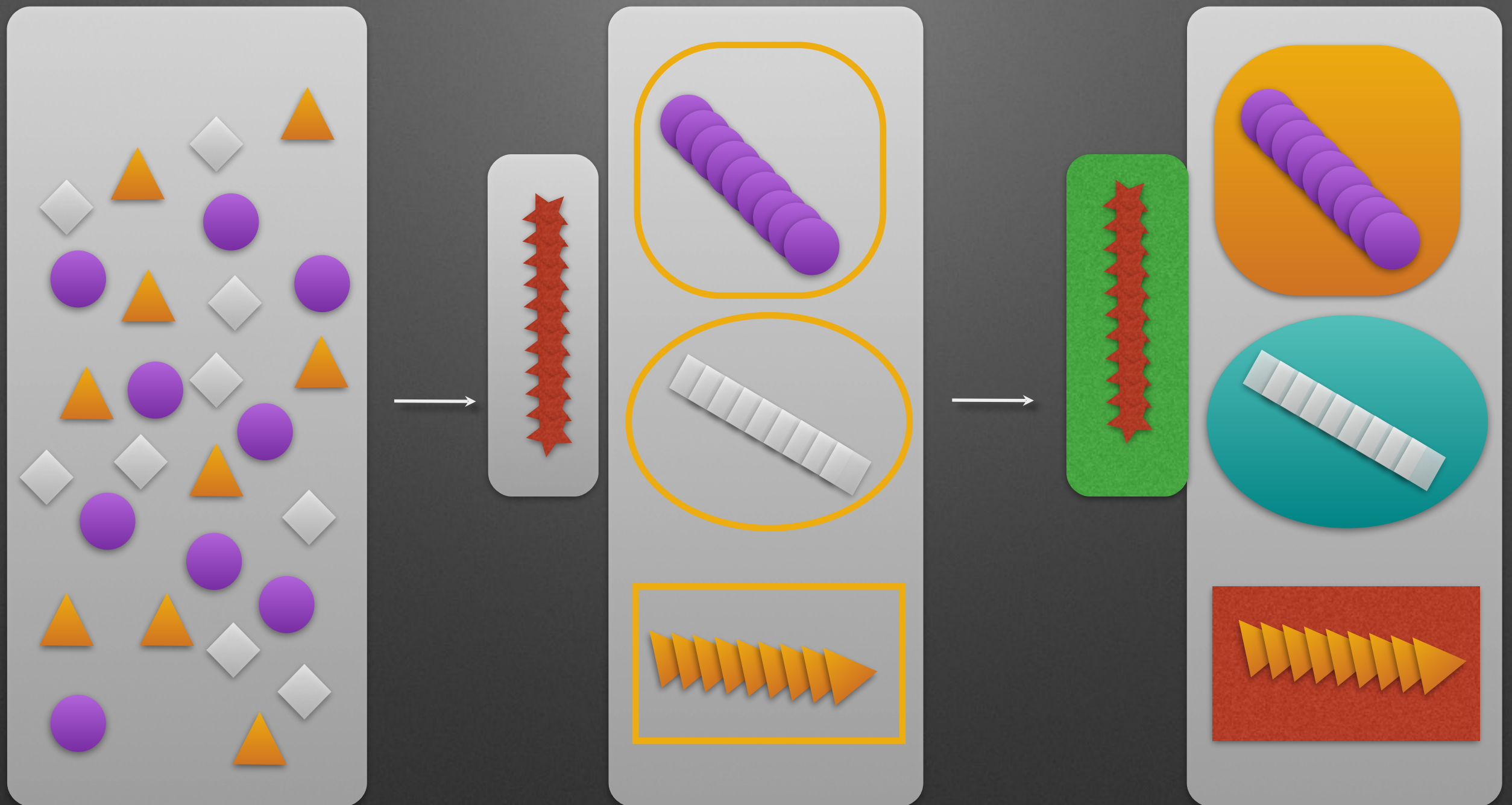
STYLISH, HANDCRAFTED CASES & SLEEVES
DESIGNED TO MEET TODAY'S MODERN NEEDS.

Offering

- Popular way to promote products

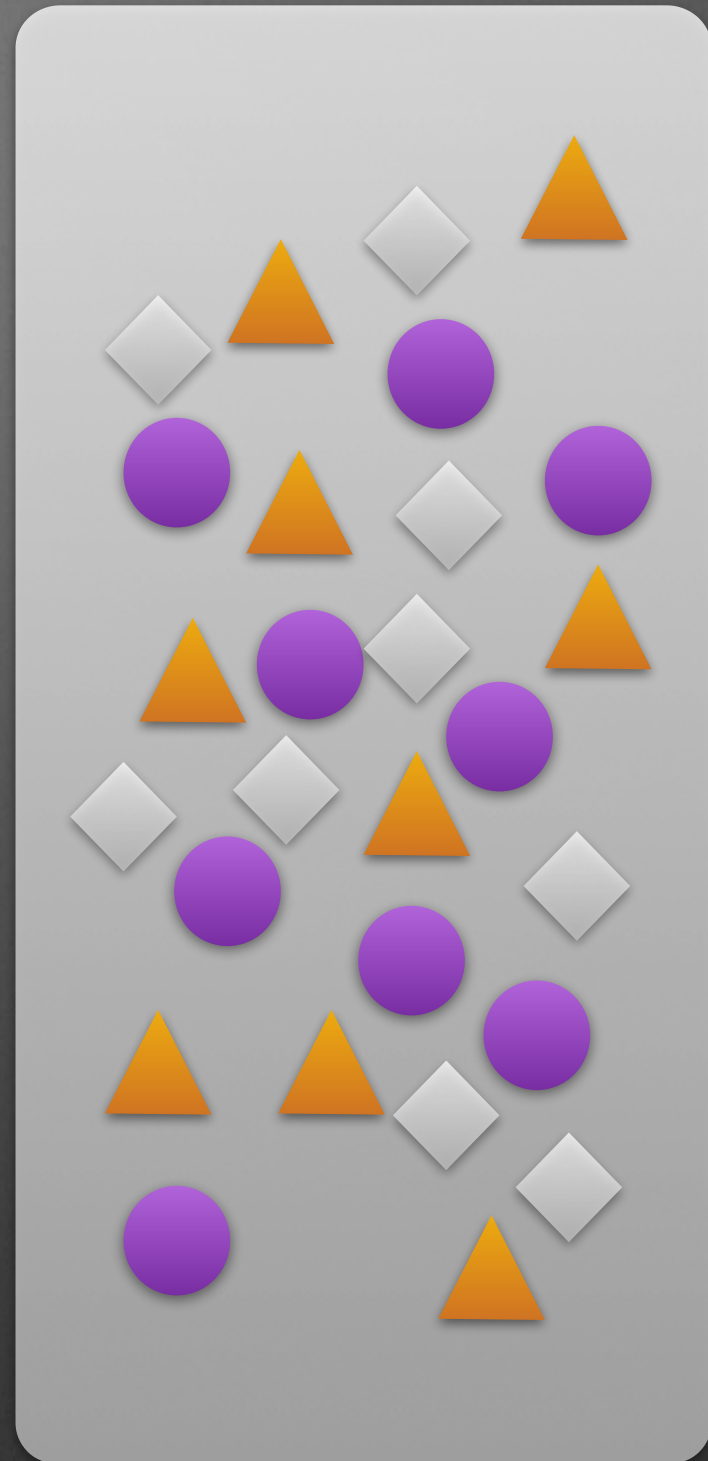


Offering Process



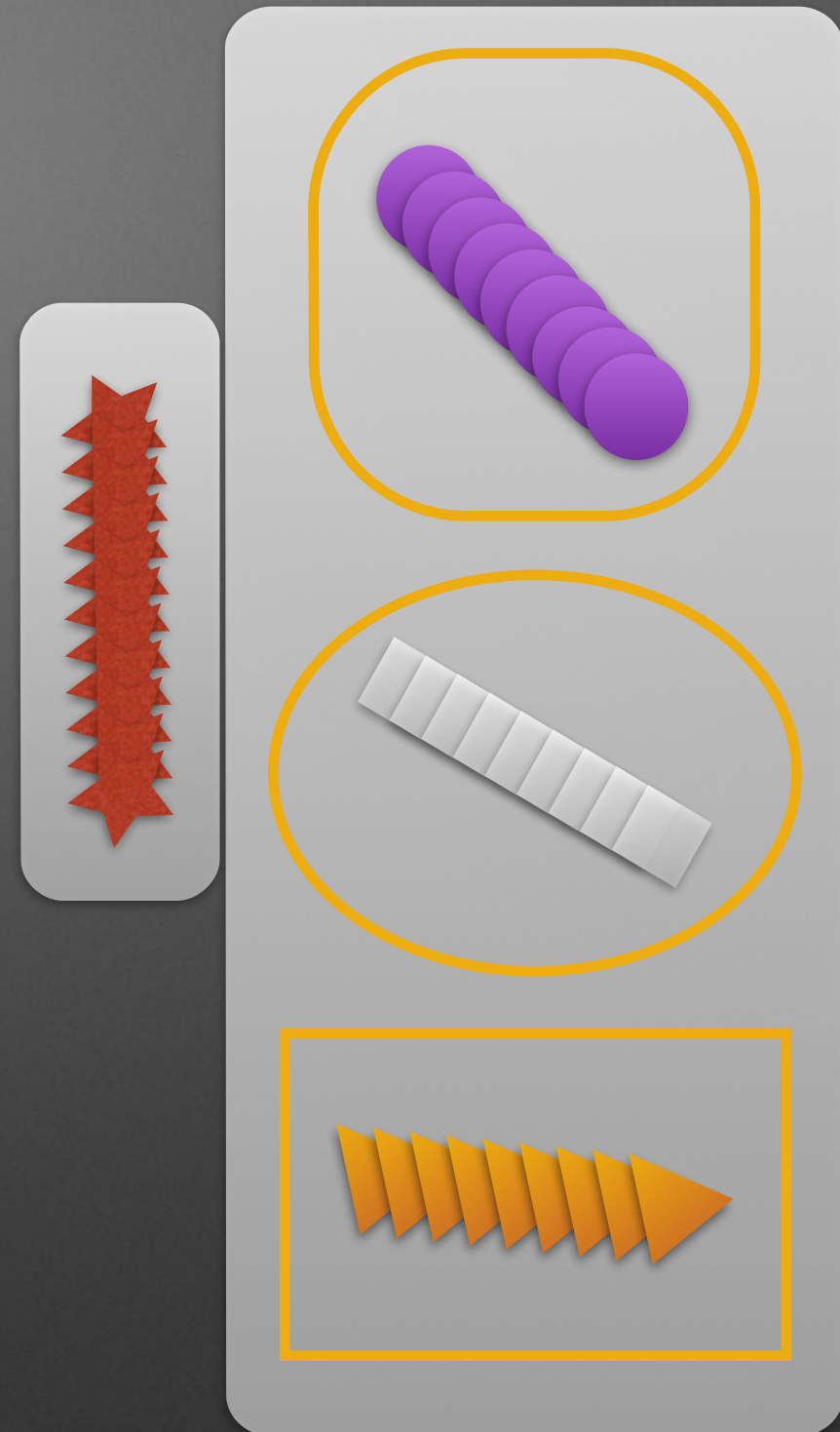
Step 1: Customer Data Management

- Monitor customers' actions
- Keeping track of customer data and information
- Defining goals



Step 2: Targeting

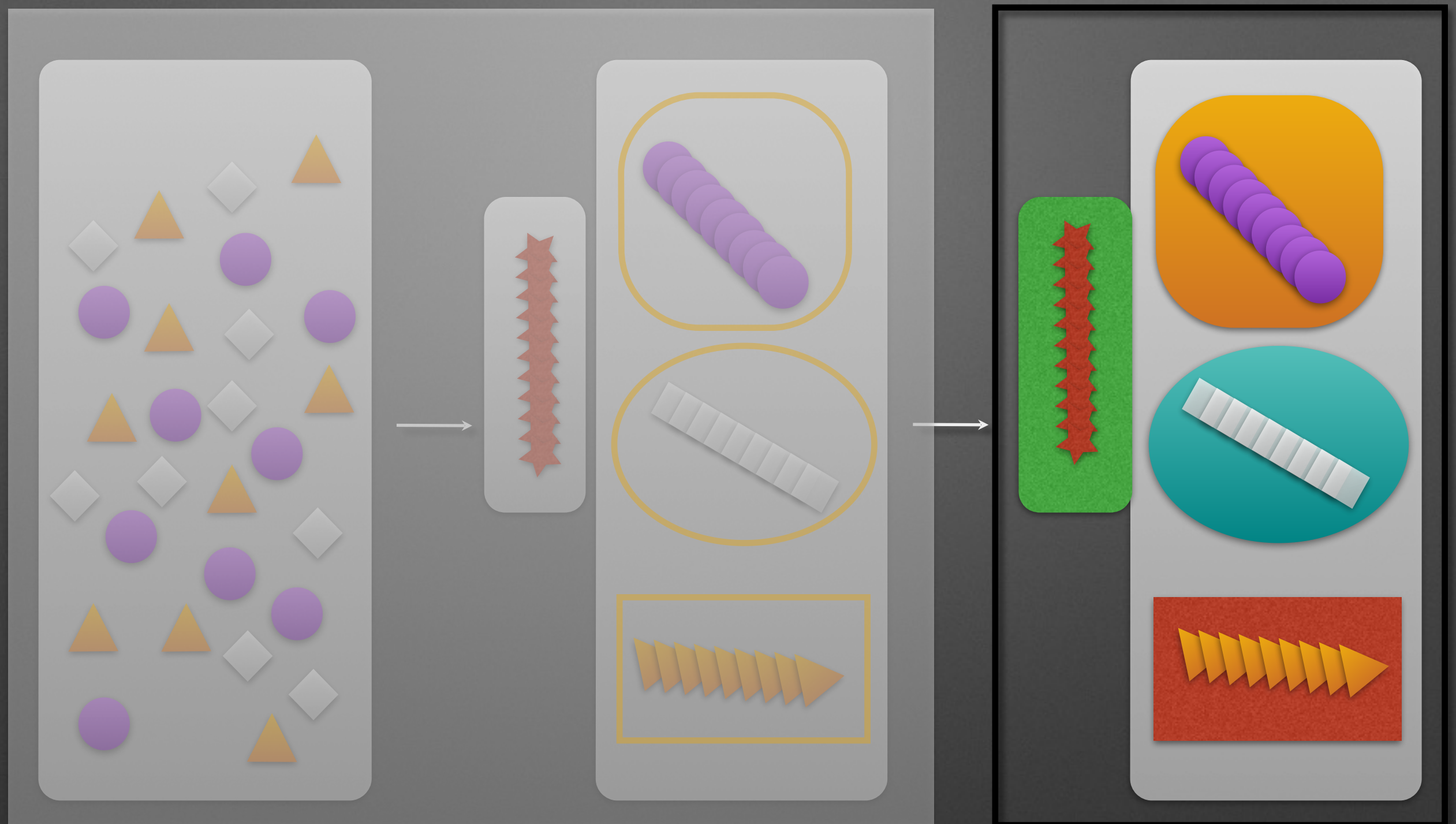
- Customer segmentation and selection with goals at step 1
- Based on demographic informations and log collections
- Statistical methods and data mining algorithms



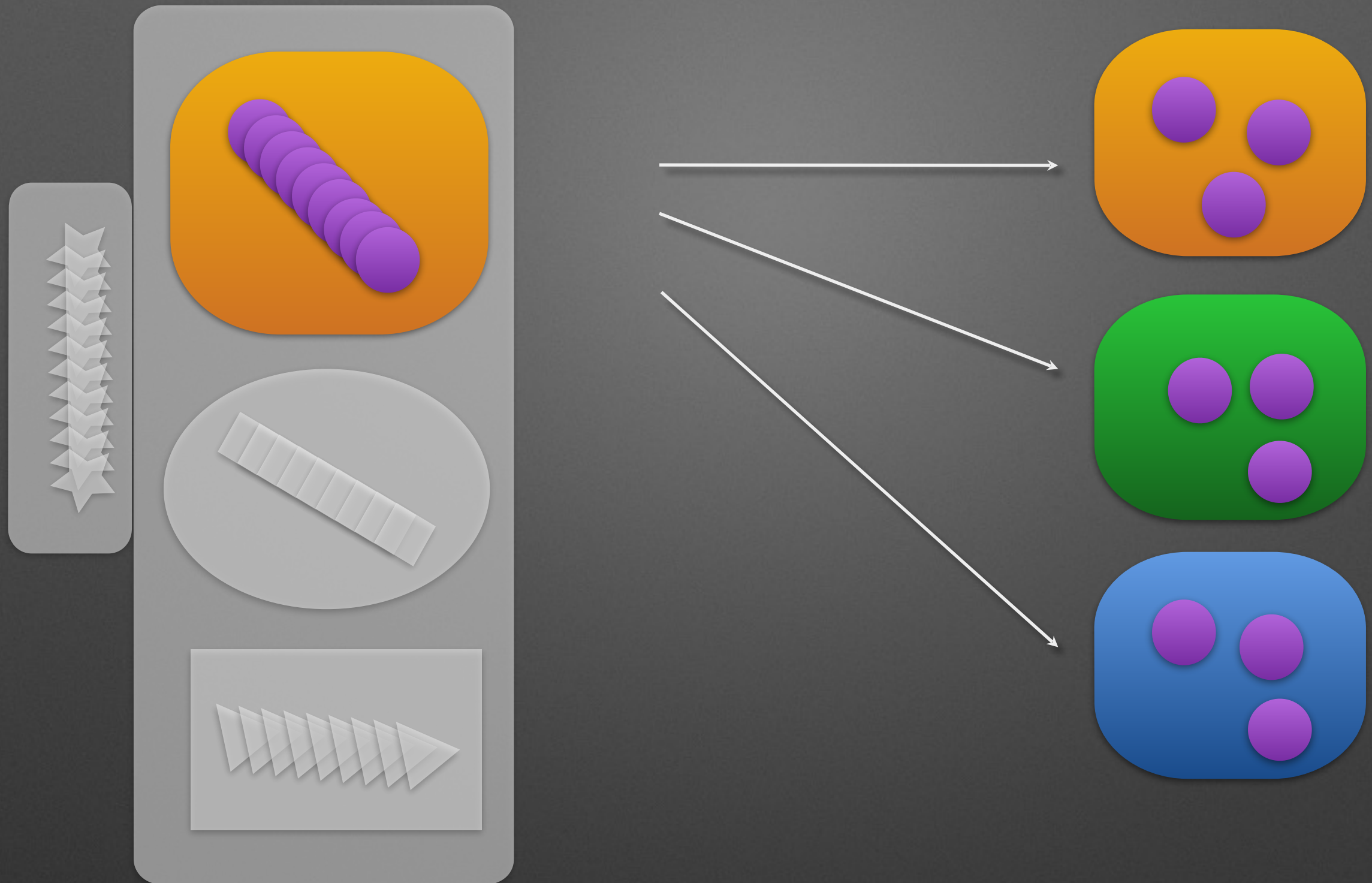
Step 3: Offering Benefit (Campaign)

- Delivering proper benefits to targeted customer groups
- Methods: Promotion, Event, Advertisement and others
- Measurement and prediction of campaign effects





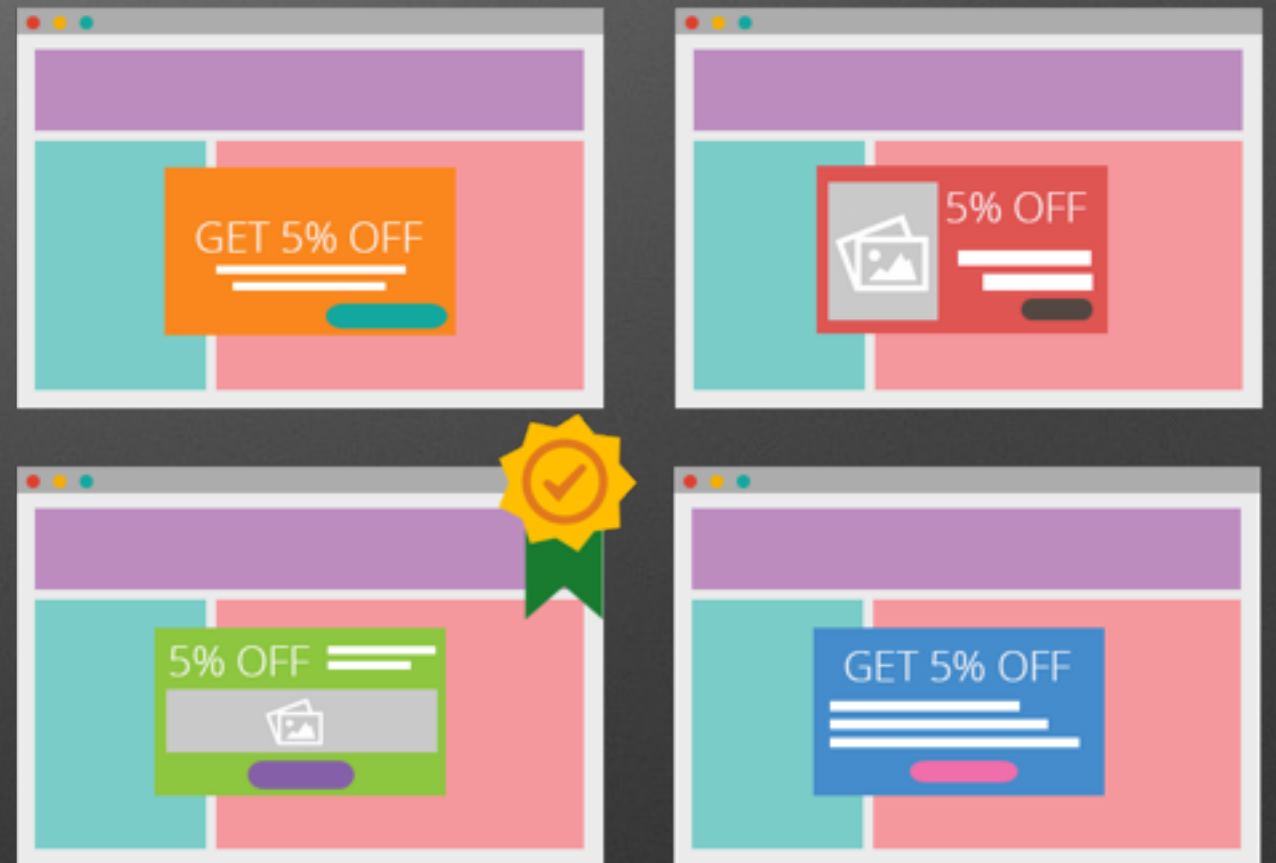
How to measure and predict



How to compare offering effects

Multivariate Testing

- Technique for testing a hypothesis with multiple variables
- Issues for offering
 - Lack of long-term prediction
 - data, benefit limitations

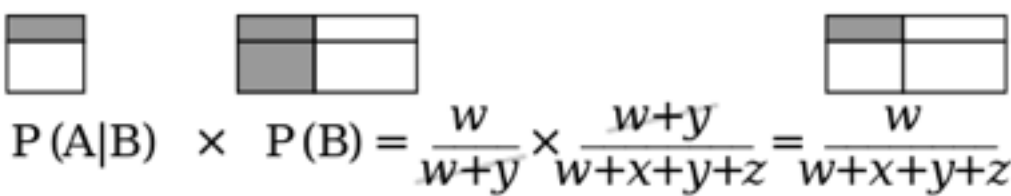


(Image from <https://www.ownedit.com/features>)

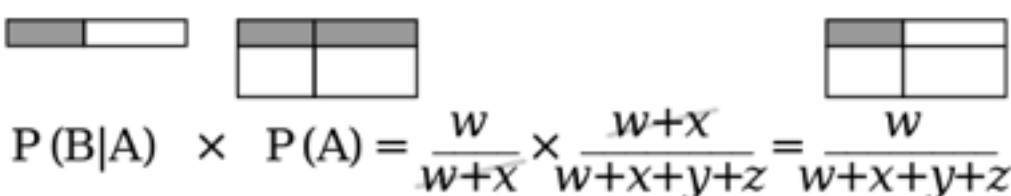
Bayesian Interpretation

- Diachronic Interpretation
 - Probability of the hypotheses changes over time
 - Prior and posterior based on background information
 - Good for simulation, decision and prediction

Relative size	Case B	Case \bar{B}	Total
Condition A	w	x	w+x
Condition \bar{A}	y	z	y+z
Total	w+y	x+z	w+x+y+z



$$P(A|B) \times P(B) = \frac{w}{w+y} \times \frac{w+y}{w+x+y+z} = \frac{w}{w+x+y+z}$$



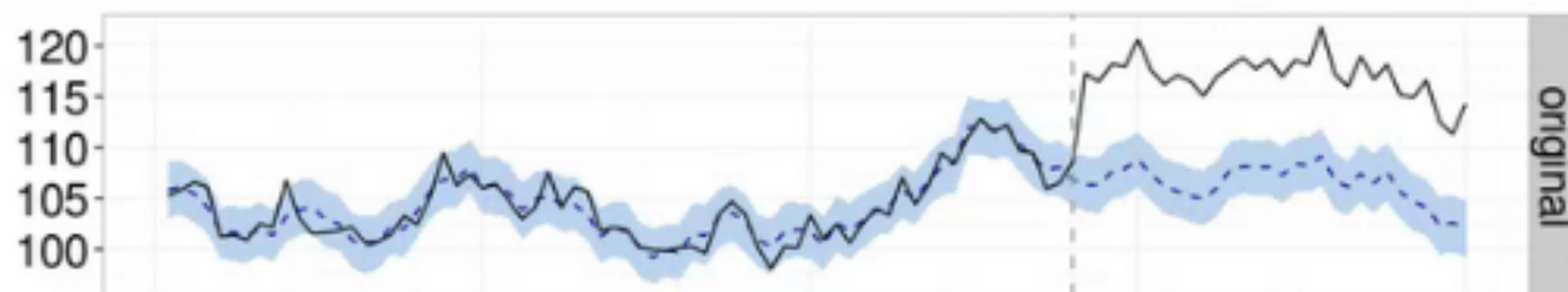
$$P(B|A) \times P(A) = \frac{w}{w+x} \times \frac{w+x}{w+x+y+z} = \frac{w}{w+x+y+z}$$

Google uses R to calculate ROI on advertising campaigns

Google has just released a new package for R: [CausalImpact](#). Amongst many other things, this package allows Google to resolve the classical conundrum: how can we assess the impact of an intervention (for example, the effect of an advertising campaign on website clicks) when we can't know what would have happened if we *hadn't* run the campaign? For a marketer, the worry is that the spike in clicks was partially or wholly the result of something unrelated (say, a general increase in web traffic) rather than your campaign.

The CausalImpact package uses [Bayesian structural time-series models](#) to resolve this question. All you need is a *second* time series to act as a "virtual" control, which is unaffected by your actions but which is still subject to the extraneous effects you're worried about. (For the marketing example, you might choose web clicks from a region where the campaign didn't run.) Then, you can model the extraneous effects and subtract them from your actual results, so see how your things would have played out had the intervention *not* occurred.

In the chart below (from the [Google Open Source blog post](#)) you can see the results of the campaign in black, with the campaign launch at the dotted line. The blue line shows the estimated results had the campaign *not* run, clearly showing that it was effective.



Google uses R and the CausalImpact package to measure the return-on-investment on advertising campaigns its customers run:

We've been testing and applying structural time-series models for some

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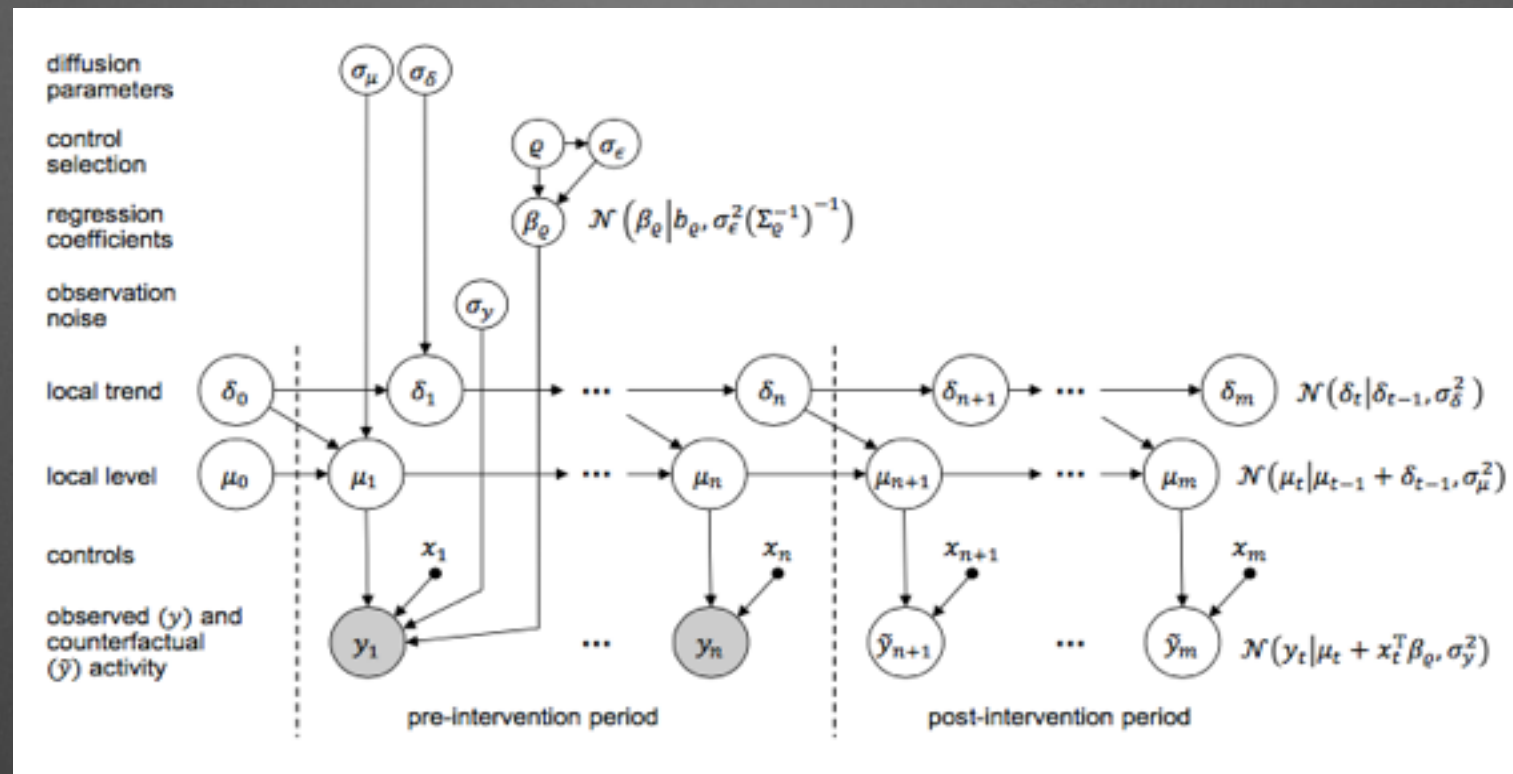


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Categories

CausallImpact



(Image from the paper)

- Based on the paper [Inferring causal impact using Bayesian structural time-series models], Google, 2014
- CausallImpact Package in R
 - <https://github.com/google/CausallImpact>

CompareImpacts

- Integration of bayesian time series prediction model with multivariate tests
- For simple comparison of causal effects

```
CompareImpacts <- function(data = NULL,
                           pre.period = NULL,
                           post.period = NULL,
                           model.args = NULL,
                           bst.model = NULL,
                           post.period.response = NULL,
                           alpha = 0.05) {
  # by Jeongmin Kwon (cojette@gmail.com)
  # CompareImpact() performs causal inference comparison based on local functions
  # in CausalImpact package.
  #

  data.length <- dim(data)[2]
  impact.list <- list()

  # Check input
  if (data.length < 3)
  {
    assert("Nothing to compare! You should use CausalImpact. ")
  }
  else
  {
    data.list <- list()
    for (i in 1:length-1)
    {
      data.list[i] <- cbind(data[,i], data[,length])
    }

    for (i in 1:length-1)
    {
      checked <- FormatInputForCausalImpact(data, pre.period, post.period,
                                             model.args, bst.model,
                                             post.period.response, alpha)

      data <- checked$data
      pre.period <- checked$pre.period
      post.period <- checked$post.period
      model.args <- checked$model.args
      bst.model <- checked$bst.model
      post.period.response <- checked$post.period.response
      alpha <- checked$alpha

      # Depending on input, dispatch to the appropriate Run* method()
      if (!is.null(data)) {
        impact.list[i] <- RunWithData(data, pre.period, post.period, model.args, alpha)
      } else {
        impact.list[i] <- RunWithModel(bst.model, pre.period, post.period, model.args, alpha)
      }
    }
  }
}
```

Use Cases

- Same offerings in various groups



Use Cases

- Various offerings in a group



Basic Model

- CausalImpact results

```
> summary(imp1)
Posterior inference {CausalImpact}

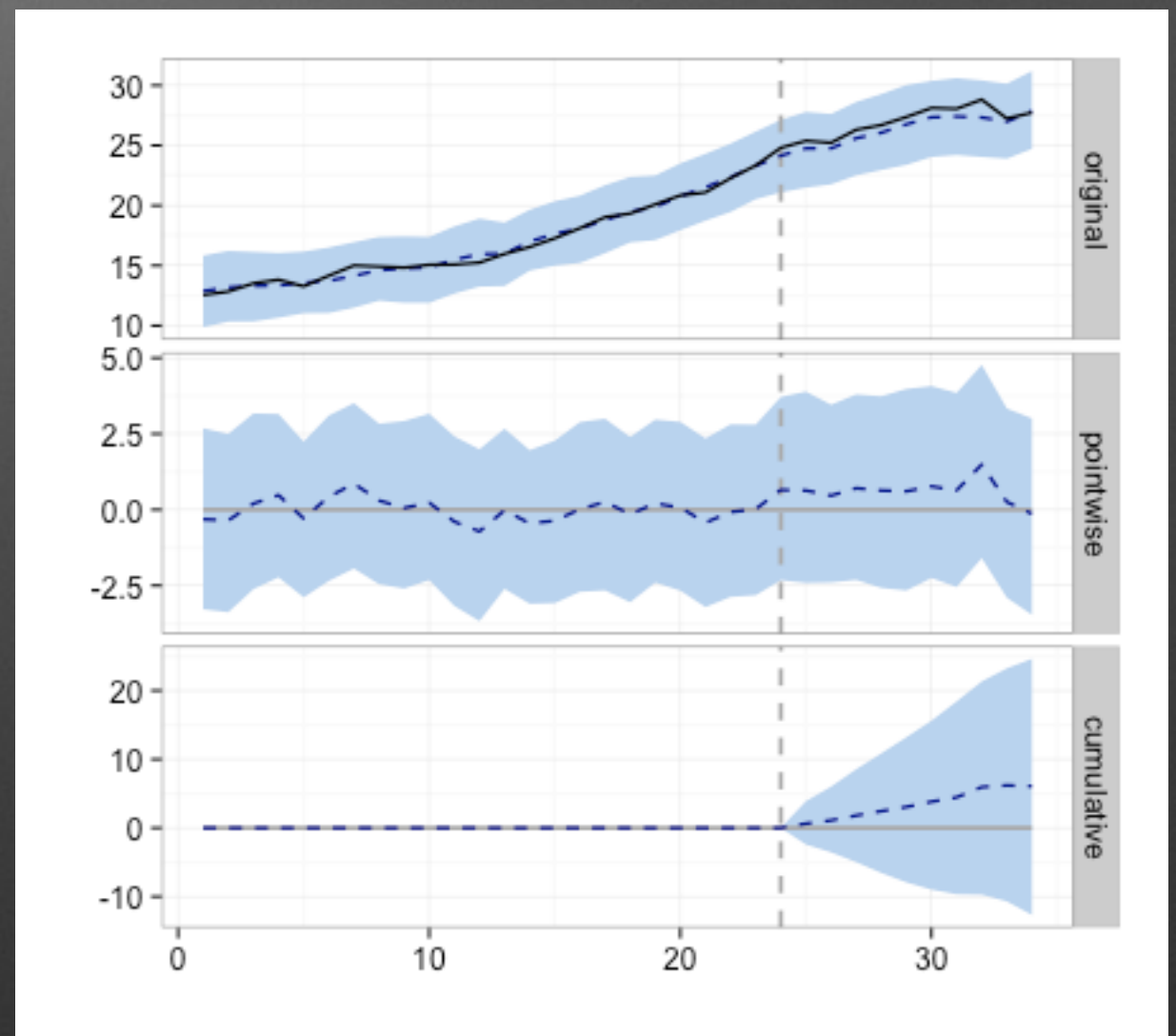

```

	Average	Cumulative
Actual	27	271
Prediction (s.d.)	26 (1)	265 (10)
95% CI	[25, 28]	[246, 284]
Absolute effect (s.d.)	0.61 (1)	6.07 (10)
95% CI	[-1.3, 2.5]	[-12.7, 24.6]
Relative effect (s.d.)	2.3% (3.8%)	2.3% (3.8%)
95% CI	[-4.8%, 9.3%]	[-4.8%, 9.3%]

```

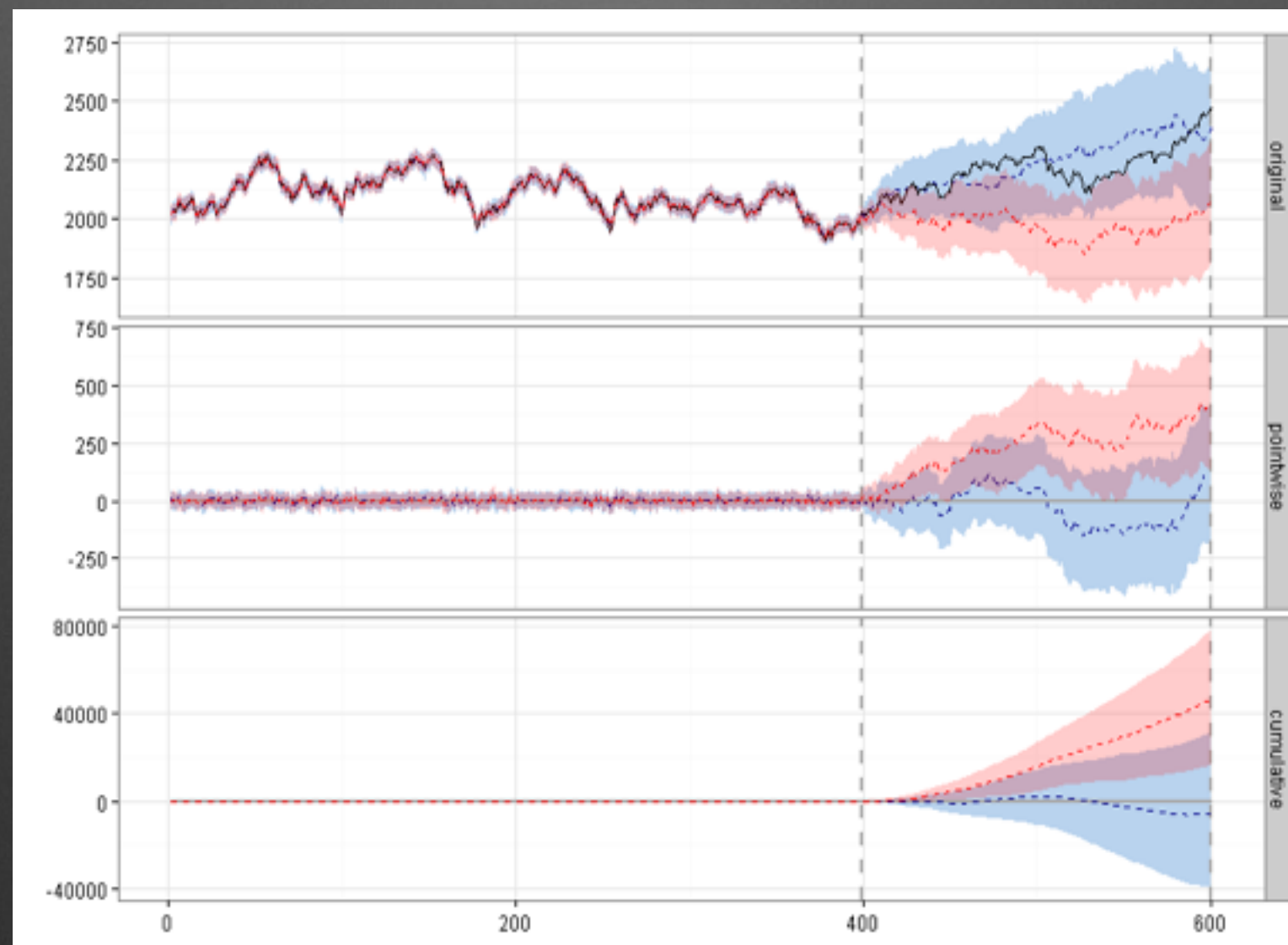
Posterior tail-area probability p: 0.25527
Posterior prob. of a causal effect: 74%

```



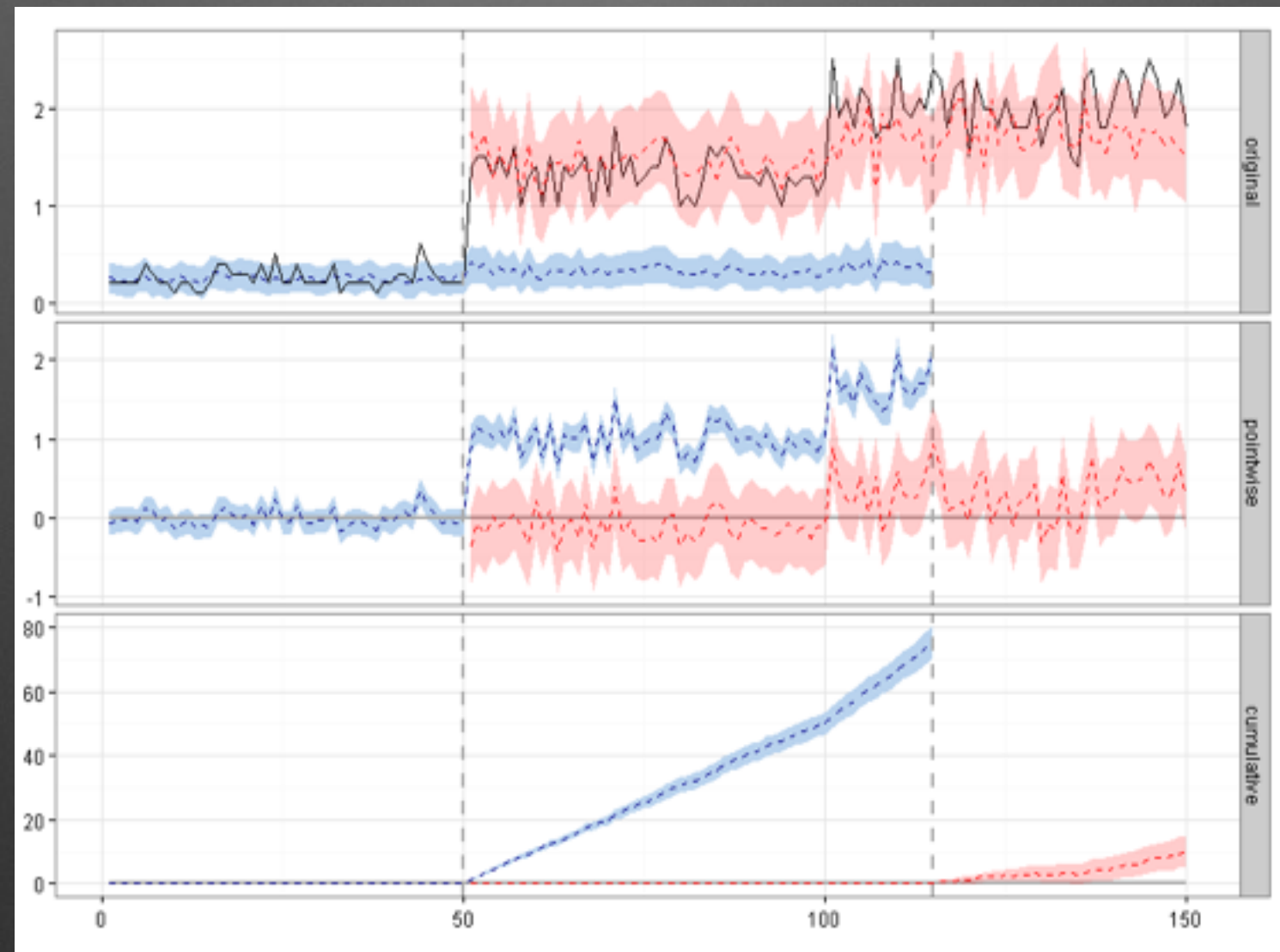
Use Case Results

- Same offerings in three groups

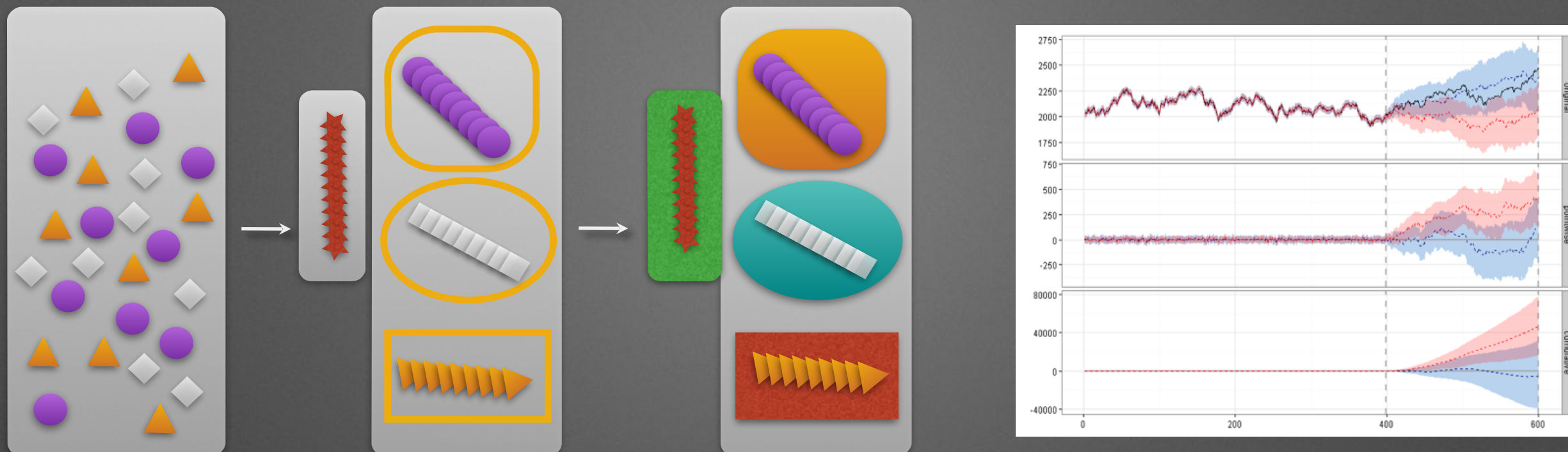


Use Case Results

- Offerings in a group with time differences



```
> CreateCompImpPlot(qq)
[1] "series 2 would generally not be considered statistically significant and plot is omitted."
```

New Tool for Offering Comparison: Multivariate Test + Bayesian Time-Series Analysis

Office Hour: 15:25~16:05, Table A
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