Uncovering Hidden Insights with Data Driven Hypothesis Testing

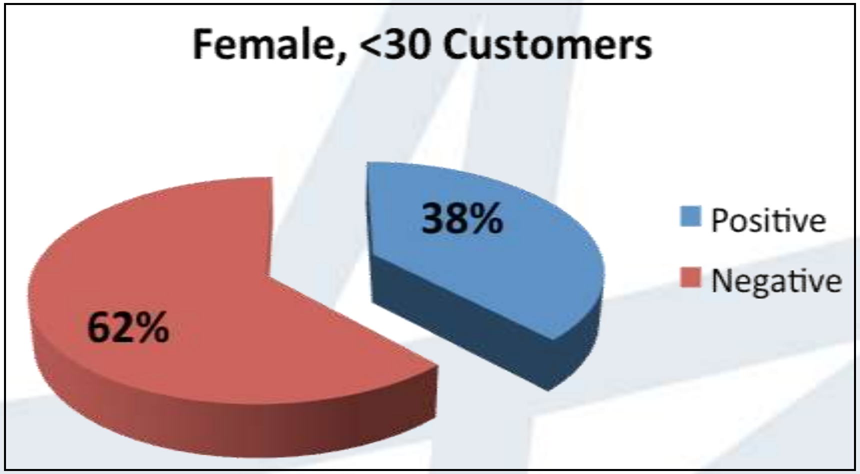
Key Features

- Represent knowledge in the form of **comparison**, i.e., hypotheses… a more nature way
- Formulation of hypotheses are automatic and **data-driven**, instead of expert-driven
- Can detect hidden phenomena, e.g., **Simpson's paradox**
- Multiple test corrections and **robust statistics** are employed to ensure the validness of findings
- Useful for a **wide range of applications**, e.g., business intelligence, census analysis, …

Knowledge Representation & Discovery via

Comparison is a natural way to represent knowledge

"Comparison"



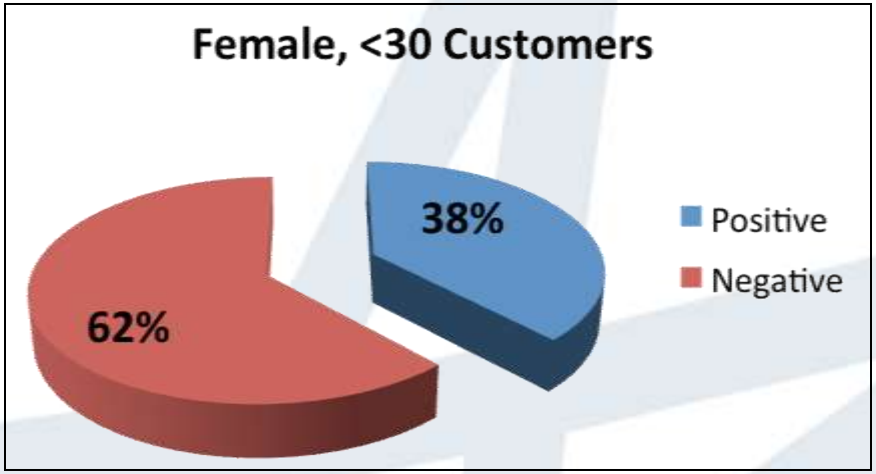
Rule-based Knowledge

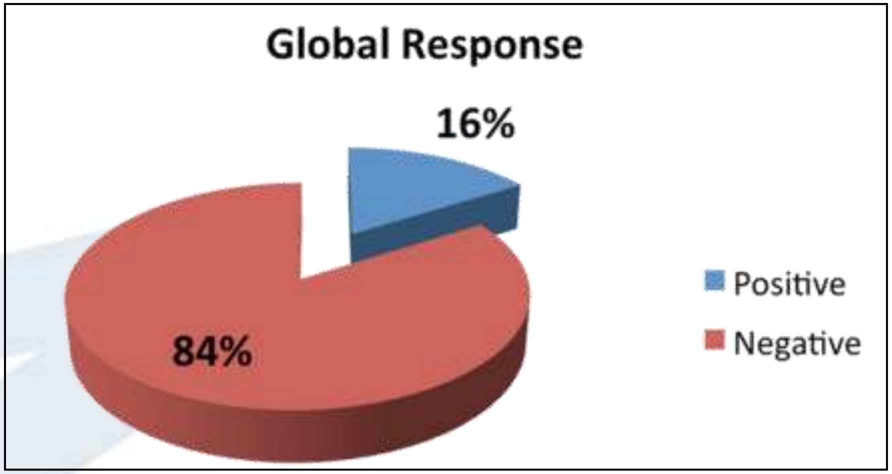
For *female, <30-year old* customers, **38%** of them respond positively to our promotion.

- **Statistically defined as Hypothesis**
- **Hypothesis vs Rule**

BUT is 38% a good or bad response rate?

"Comparison": Hypothesis vs Rule





Hypothesis-based Knowldge

The positive response rate of *female, <30-year old* customers (**38%**) is **significantly (p<0.05)** higher than the average rate **(16%)**.

NOW we can fully appreciate the meaning of 38%!

Advantages

- **Consolidates info from multiple rules**
- **Comparing groups that share similarities but have different behaviors due to one differentiating factor**

Rule-based Knowledge	Hypothesis-based Knowledge
• *Female, <30-year-old, gold-card* customers spend **$500** per month on our products. • *Female, <30-year-old, silver-card* customers spend **$300** per month on our products.	• Among *female, <30-year-old* customers, *gold-card* holders' monthly spending (**$500**) is **significantly ($p < 0.05$)** higher than *silver-card* holders (**$300**).

Advantages

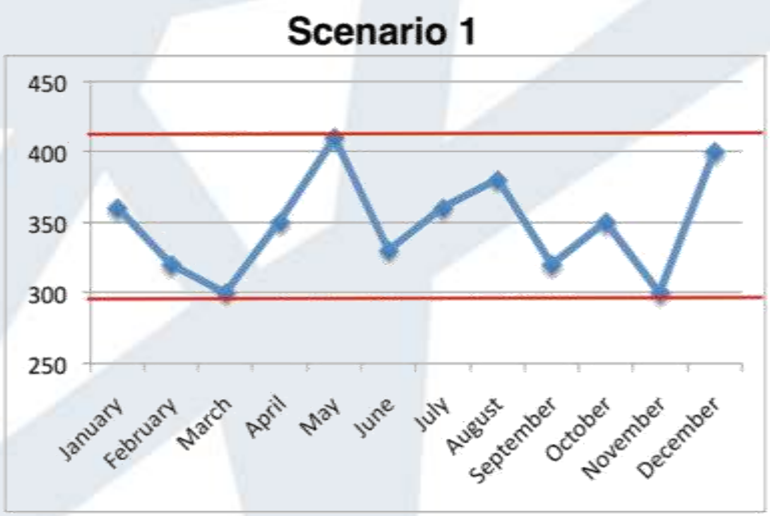
- **More reliable findings with statistical reasoning**

Observations

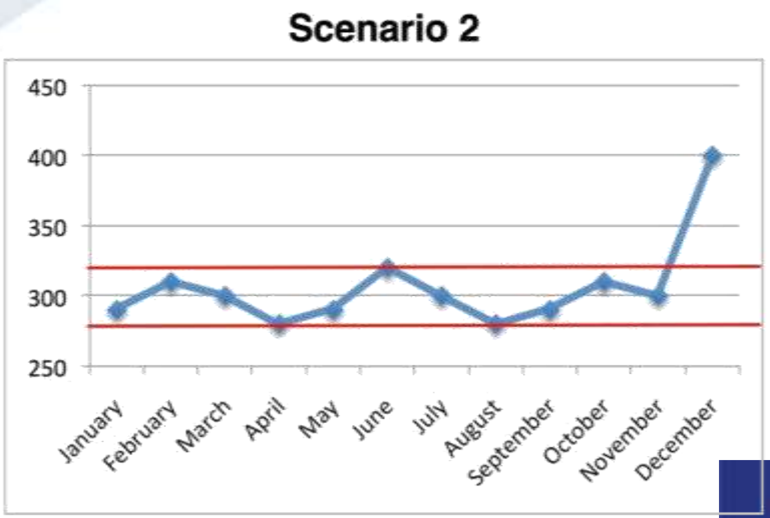
Sales on *November* is $300K; sales on *December* is $400K

Question

Is this sales increase statistically significant?



Non-significant



Significant

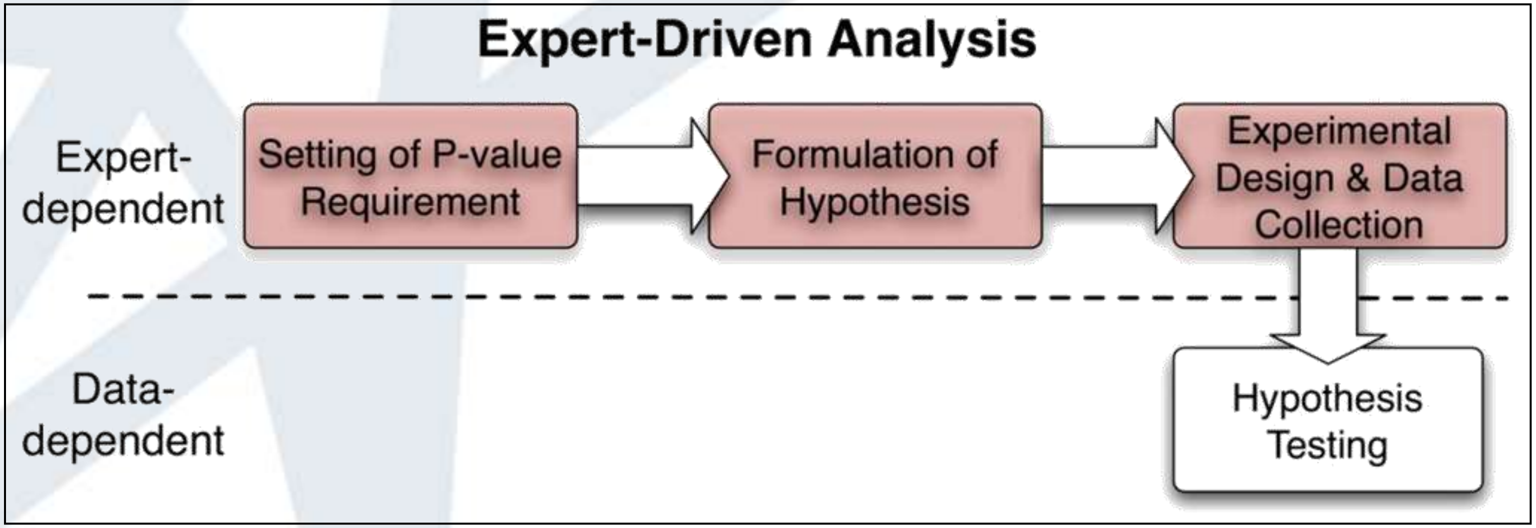
Hypothesis Testing

- **Null Hypothesis**

  Monthly spending of gold-card holders, μ_g, are the same as silver-card holders, μ_s, i.e. $\mu_g=\mu_s$
- **Alternative Hypothesis: $\mu_g \neq \mu_s$**
- **Reject the null hypothesis, if and only if**
  - $P < \alpha$
  - Significance level, α, --- the false positive rate
- **P-value**
  - The probability, assuming the null hypothesis is true, of observing a result at least as extreme as the observed statistics

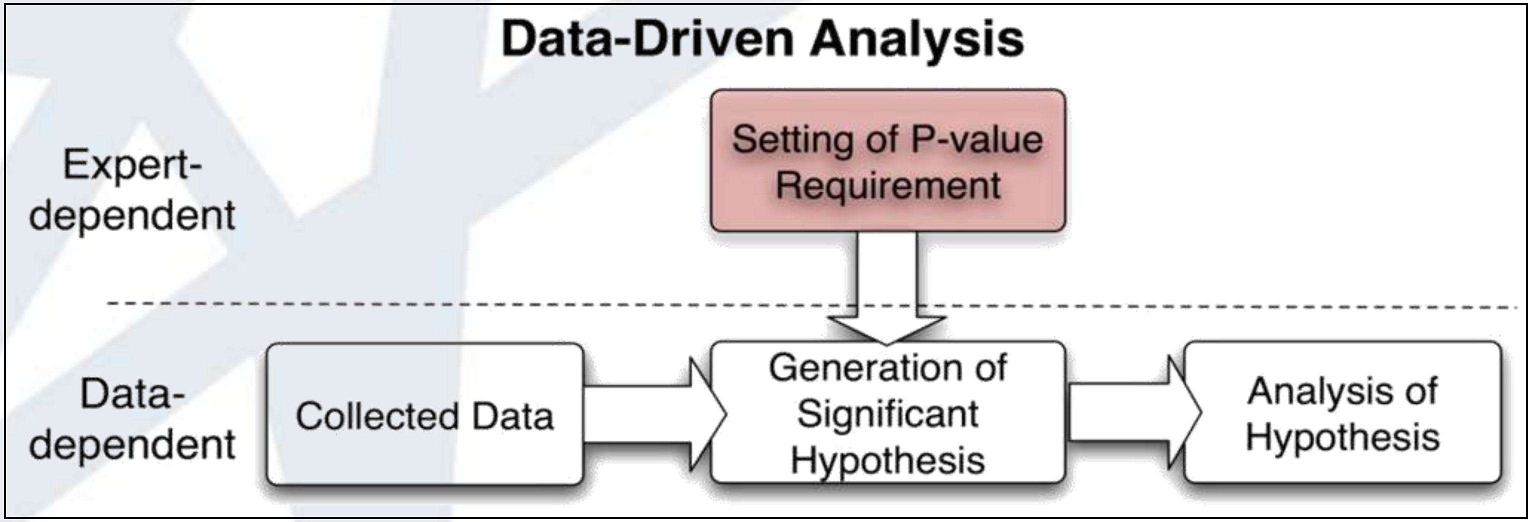
Expert-Driven Hypothesis Analysis

- **Conventional hypothesis analysis is expert-driven**
  - Expert dependent
  - Rich prior knowledge is required
  - Already have a clear question in mind
  - Often not applicable in real applications



Data-Driven Hypothesis Analysis

- **iDIG is Data-driven**
  - Minimum expert input is required
  - Suitable for analysis scenarios, where
    - **Little prior knowledge is available**
    - **Investigating question is not clear yet**
    - **Exploratory studies**



Formulation of Hypothesis

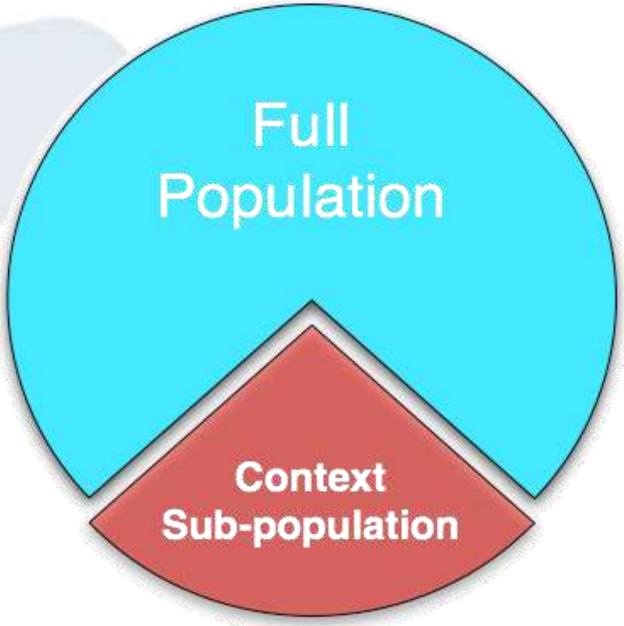
- **3 major components**
  - Target Attribute:
    - **attribute of interest**
  - Context Attributes:
    - **similarities between comparing groups**
  - Comparing Attribute:
    - **attribute that differentiate comparing groups**

Formulation of Hypothesis: Target Attribute

- **Attribute of interest/ attribute to be investigated**
- **E.g**
  - Monthly spending
  - Response rate to product/promotion
  - Performance of drugs
  - Grades of students, etc
- **Can be categorical or continuous**

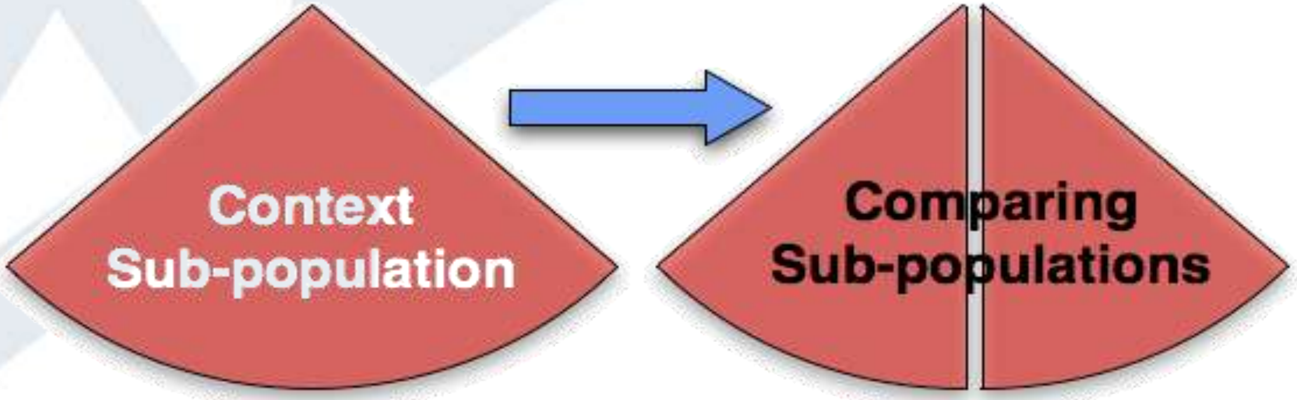
Formulation of Hypothesis: Context Attributes

- **Attributes that defines similarities among comparing groups**
- **Defines a sub-population of interest**
- **Must be categorical**
- **Example:**
  - Female, <30-year-old customers



Formulation of Hypothesis: Context Attributes

- **Attribute that differentiate the comparing groups**
- **Single attribute**
  - To avoid confusion due to confounding factors
- **Must be categorical**
- **Example**
  - Card type: gold-card vs silver-card



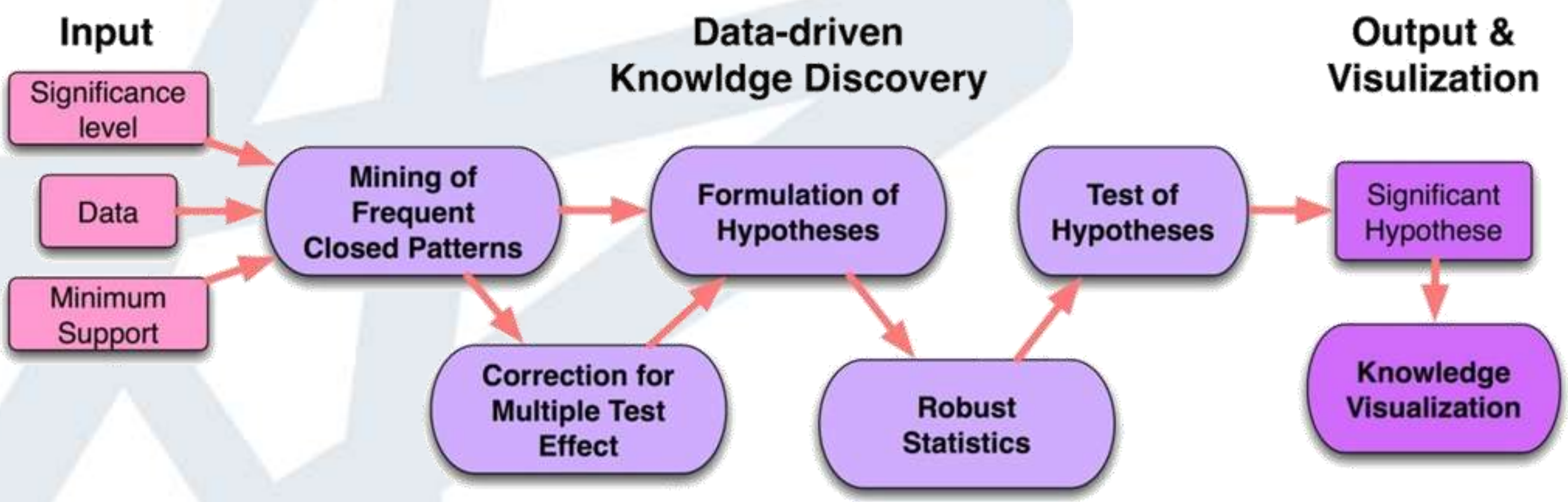
Formulation of Hypothesis

Context Attributes	Comparing Attribute: Card-type	Target Attribute: Monthly Spending
Female, <30-year-old	**Gold-card**	**$500**
	Silver-card	**$300**

Formulated Hypothesis

Among *female, <30-year-old* customers, *gold-card* holders' monthly spending **($500) is significantly** higher than *silver-card* holders' (**$300**).

Discovery of Hypothesis

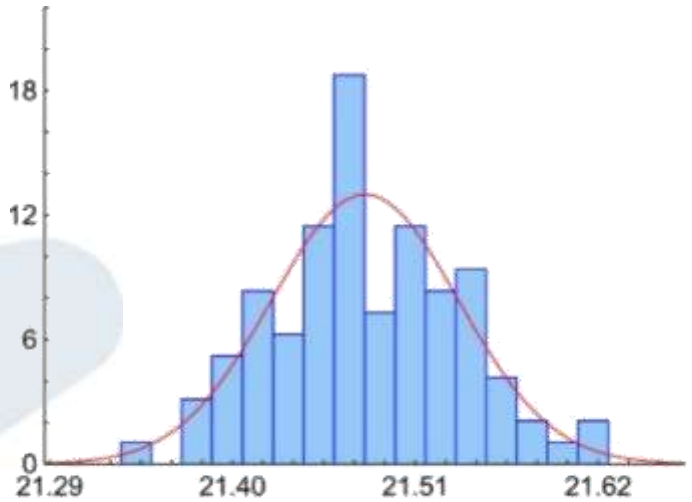


Hypothesis Testing

- **Categorical target attribute**
  - $\chi 2$ test
    - **Computational efficient**
    - **Approximation test --- tend to underestimate p-value**
    - **Some constrains on the data**
  - Fisher's exact test
    - **Exact test --- accurate p-value estimation**
    - **Computationally more expensive**
    - **Impractical for more than 2 groups of comparisons**

Hypothesis Testing

- **Continuous target attribute**
  - T-test
    - **Computational efficient**
    - **Normality is necessary**
  - Wilcoxon rank-sum test
    - **Computationally more expensive**
    - **Normality is not necessary**
    - **BUT, data's distribution must be symmetrical**
  - Permutation test
    - **Most reliable,**
    - **BUT computationally very expensive**



Important Features

- **Detection of Simpson's Paradox**
- **Correction for Multiple Test Effect**
- **Employment of Robust Statistics**
  - Protection against outliers and artifacts
- **Visualization of Knowledge**

Simpson's Paradox

- **Charing et al 1986**
  - Study of treatments for kidney stones

	Success Rate
Treatment A	273/350 (**78%**)
Treatment B	289/350 (**83%**)

  - Seems Treatment B is more effective
  - **BUT**, if we break down the patients in two groups: small stones & big stones

	Small Stone	Big Stone
Treatment A	81/87 (**93%**)	192/263 (**73%**)
Treatment B	234/270 (**87%**)	55/80 (**69%**)

  - Treatment A performs better in both subgroup
  - **A paradox!**

Multiple Test Effect

- **Occurs when one considers multiple comparison simultaneously**
  - i.e., when one tests multiple hypotheses over the same set of data
- **Example:**

> *"Suppose we consider the safety of a new drug in terms of its side effects. As more and more types of side effects are considered, sooner or later one will find at least one side effect, where the new drug is "significantly" higher than the existing one."*

Multiple Test Effect

- **Give single hypothesis significance level, α**
  - The chance of rejecting a null hypothesis when it is true is controlled to be at most α --- Type I error or false positive
  - If m independent hypotheses were tested, the experiment-wide significance level, α_w, is

$$\boxed{\alpha_w = 1-(1-\alpha_s)^m}$$

where α_s is the significance level for single hypothesis

  - i.e, if 100 hypotheses are tested on the same data, where α_s = 5%, then α_w = **99.4%**

Multiple Test Effect

- **Bonferroni correction**
  - Simple but conservative

$$\boxed{\alpha_s = \alpha_w / m}$$

where αs and αw are the corrected and targeted significance level, and m is the number of tested hypotheses

- **Sidak correction**
  - Better correction

$$\boxed{\alpha_w = 1 - (1 - \alpha_s)^m} \Rightarrow \boxed{\alpha_s = 1 - (1 - \alpha_w)^{1/m}}$$

Robust Statistics
Protection from Outliers & Artifacts

- **Effect of outliers and artifacts**

Customer	Rating for Pizza A	Rating for Pizza B	Differences
1	20.4	20.2	0.2
2	24.2	16.9	7.3
3	25.4	18.5	6.9
4	21.4	17.3	4.1
5	20.2	15.5	4.7
6	21.5	18.5	3
		Sample Mean	4.36
		Sample Variance	2.62
		Estimated test statistics	4.08
		p-value (2 tail, paired t-test)	**0.01**

(a)

Customer	Rating for Pizza A	Rating for Pizza B	Differences
1	20.4	20.2	0.2
2	24.2	16.9	7.3
3	25.4	18.5	6.9
4	21.4	17.3	4.1
5	20.2	15.5	4.7
6	**215**	18.5	**196.5**
		Sample Mean	36.62
		Sample Variance	78.4
		Estimated test statistics	1.14
		p-value (2 tail, paired t-test)	**0.3**

(b)

Robust Statistics
Protection from Outliers & Artifacts

- **Robust statistics**
  - Mute or down-weigh potential outliers and artifacts

Customer	Rating for Pizza A	Rating for Pizza B	Differences
1	20.4	20.2	0.2
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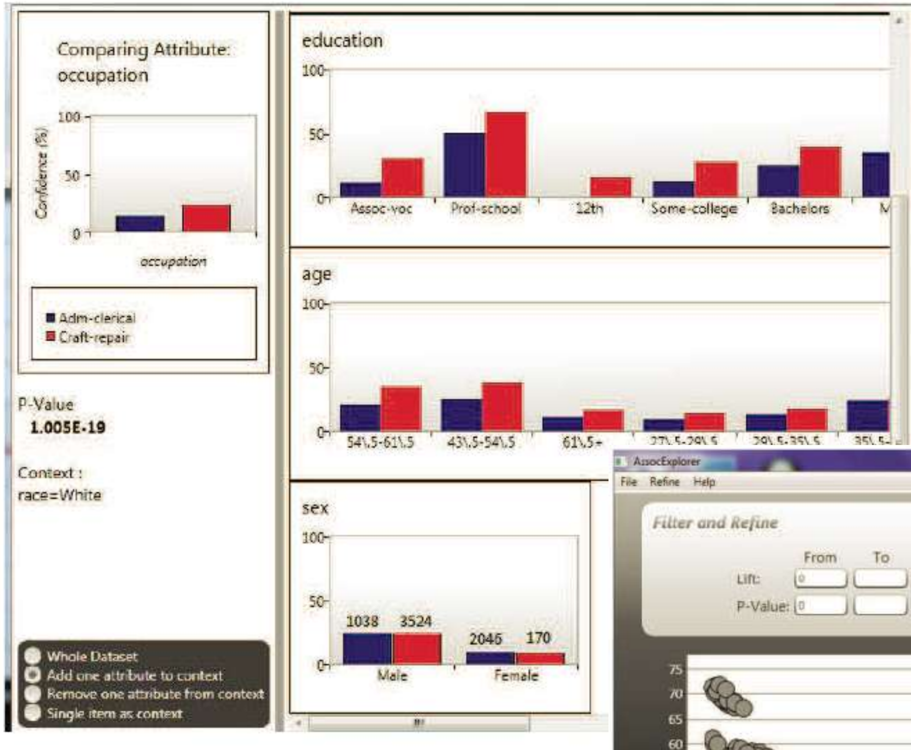
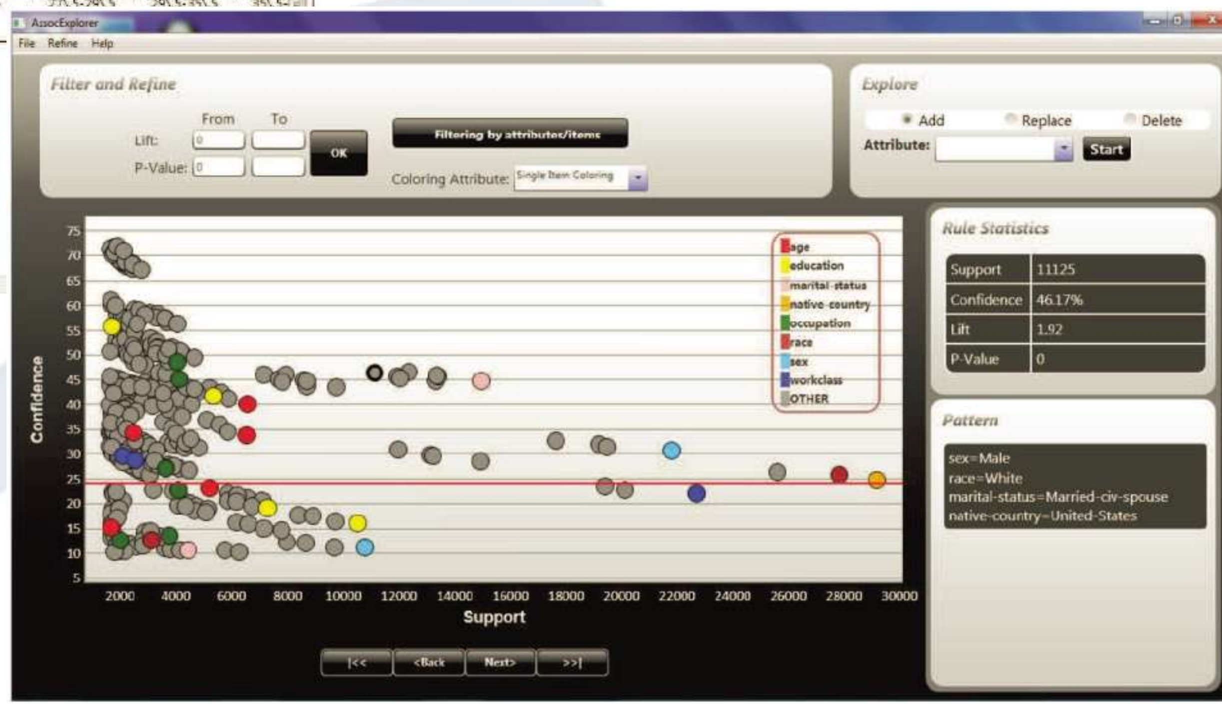
(b)

Visualization





Capabilities

- **Uncover groups that behave differently from the global norm**
- **Discover groups that share considerable similarities but have significantly different behaviors due to some differentiating factor**
- **Analyze change of behavior before and after certain events, such as promotion campaigns**
- **Detect and trace change of behavior over time**
  - Dynamic version of iDIG (under-development)

Potential Applications

- **Business Intelligence**
  - Customer segmentation/profiling
  - Customer loyalty study
  - Campaign analysis
- **Medical Studies**
  - Drug effectiveness evaluation
  - Epistasis study
  - Clinical data analysis
- **Expert Knowledge Extraction**

Features of iDIG

- **Data-driven knowledge discovery tool**
- **Represent and discovery knowledge via comparison (hypothesis analysis)**
- **Reliability of findings are ensured with statistical testing and reasoning**
- **Can be customized for a wide range of applications**

Contact

Dr Feng Mengling
mfeng@i2r.a-star.edu.sg

Dr Liu Guimei
liugm@comp.nus.edu.sg

Prof Wong Limsoon
wongls@comp.nus.edu.sg

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- **Project homepage - http://www.comp.nus.edu.sg/~wongls/projects/hypothesis/index.html**