CS57300
PURDUE UNIVERSITY

JANUARY 22, 2019

DATA MINING

HYPOTHESIS TESTING

TYPES OF HYPOTHESES

Broad categories

- **Descriptive**: propositions that describe a characteristic of an object
- **Relational**: propositions that describe relationship between 2+ variables
- **Causal**: propositions that describe the effect of one variable on another

Specific characteristics

- **Non-directional**: an differential outcome is anticipated but the specific nature of it is not known (e.g., the tuning parameter will affect algorithm performance)
- **Directional**: a specific outcome is anticipated (e.g., the use of pruning will increase accuracy of models compared to no pruning)

Descriptive Hypothesis

Non-Directional Relational Hypothesis

Directional Relational Hypothesis

Directional Causal Hypothesis

Stronger

HYPOTHESES EXAMPLE

- The query response time is measured for a few different search engines
- Different hypotheses
  - **Descriptive:** The query response time for Google follows a normal distribution
  - **Non-directional relational:** The average response time for a new search engine, QuickSearch, is different from Google's average response time
  - **Directional relational:** The average response time of QuickSearch is shorter than that of Google's
  - **Directional causal:** The response time of QuickSearch is shorter than Google's because they cache results of more queries

HYPOTHESIS TESTING

- Statistical hypothesis test is a method used in statistics that tells you the likelihood of a specific result would happen by chance
- **Null hypothesis** (H_0):
  - Presumed true until statistical inference indicates otherwise; set up to be refuted by alternative
- **Alternative hypothesis** (H_1):
  - Rival hypothesis; that we conjecture is true
- Assuming the null hypothesis is true, what's the probability of getting a statistic that is at least as extreme as the statistic that was actually obtained through the data?

HYPOTHESIS TESTING STRATEGY

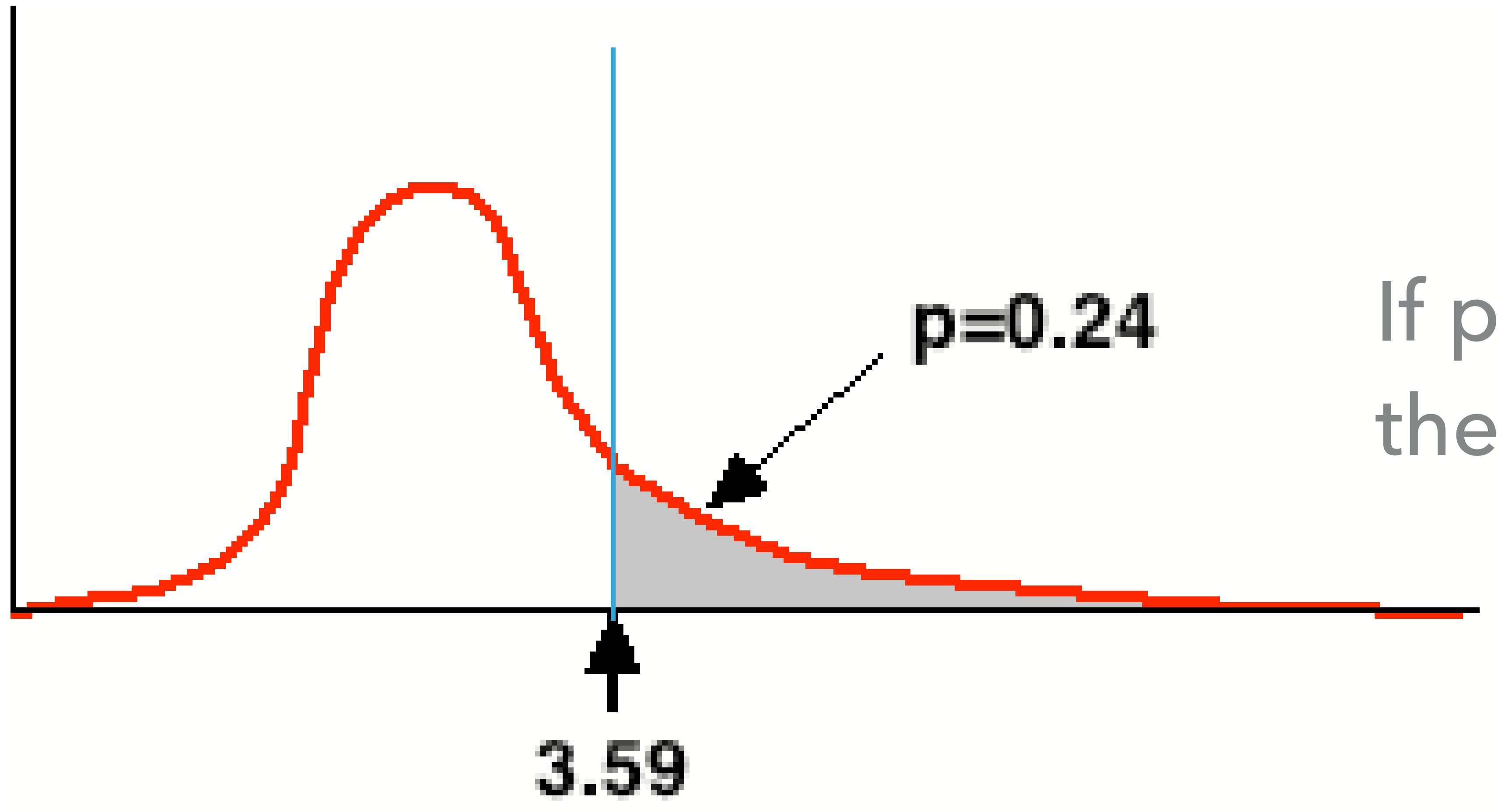
https://towardsdatascience.com/data-science-simplified-hypothesis-testing-56e180ef2f71

- Formulate null and alternative hypothesis
  - H_0: QuickSearch' mean response time = Google's mean response time
  - H_1: QuickSearch' mean response time ≠ Google's mean response time
- Gather a sample statistic (e.g., δ=difference of QuickSearch's and Google's mean response time)
- Determine the sampling distribution for the statistic under the null hypothesis
- Use the sampling distribution to calculate the probability of obtaining the observed value of δ, given H_0
  - If the probability is low, reject H_0 in favor of H_1

REJECTING THE NULL HYPOTHESIS

α = selected significance level

Sampling Distribution Under H_0

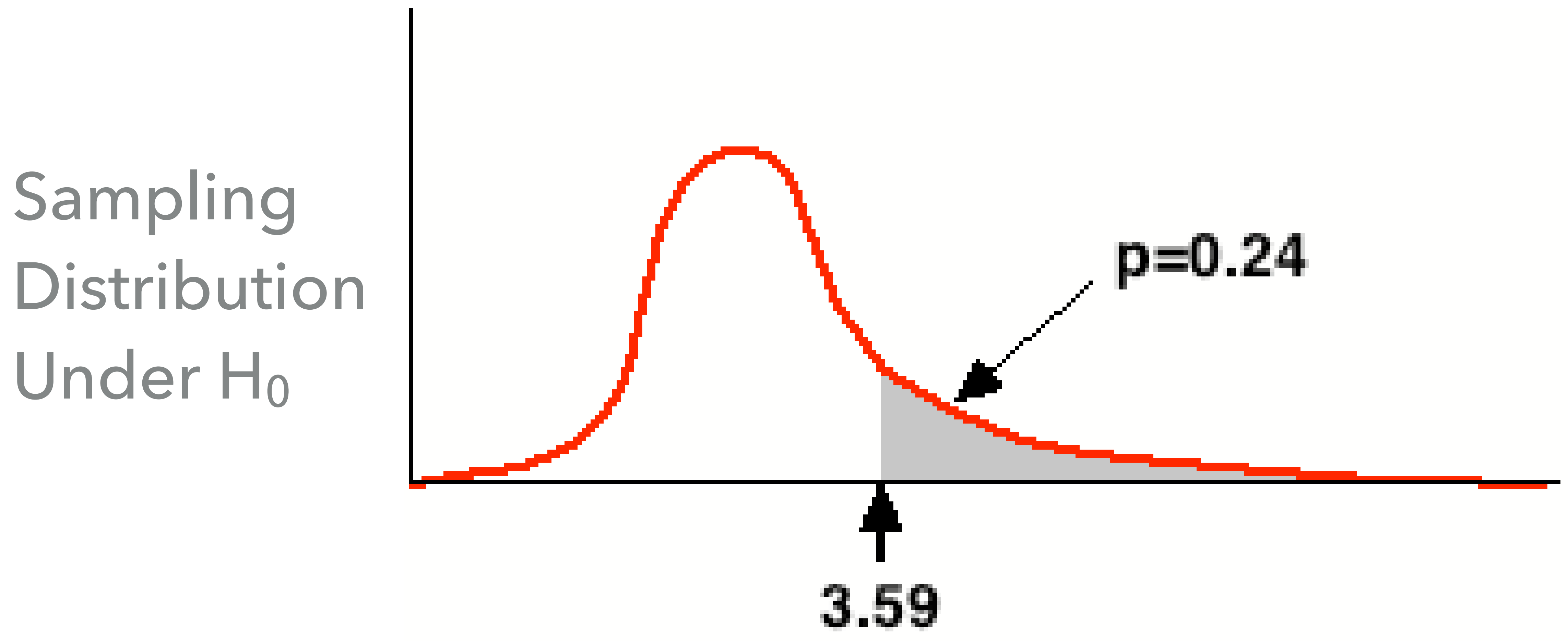


Observed value

If $p < 0.05$ then reject H_0

STATISTICAL SIGNIFICANCE

- A value of a statistic is **statistically significant** if it is unlikely to occur under the null hypothesis



significance level $$\alpha = p(reject\ H_0 | H_0\ true) = p(type\ 1\ error)$$

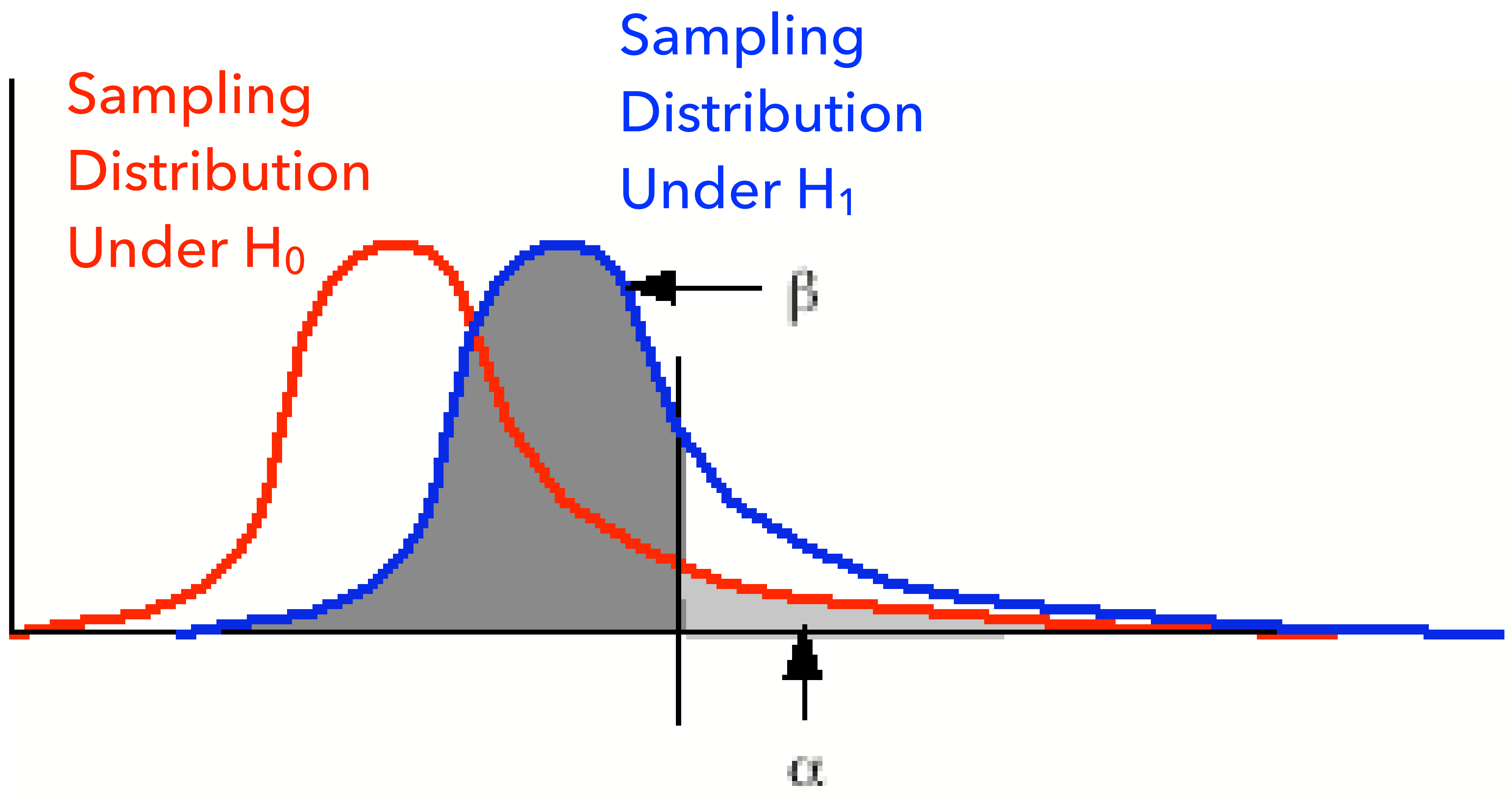
ERRORS

		Decision	
		Reject H_0	Don't reject H_0
Truth	H_0	*Type 1 error*	
	H_1		*Type 2 error*

- Type 1: null is rejected when it is true
  - E.g., conclude cancer drug increases life expectancy when in fact it doesn't
  - Generally considered to be most serious error
- Type 2: null is accepted when it is false
  - E.g., conclude that cancer drug does not increase life expectancy when in fact it does

STATISTICAL POWER

- Lack of statistical significance does not necessarily imply that H_0 is true
- Test could have low statistical power: $(1 - \beta)$ **portion of sampling distribution for alternative that is above threshold**



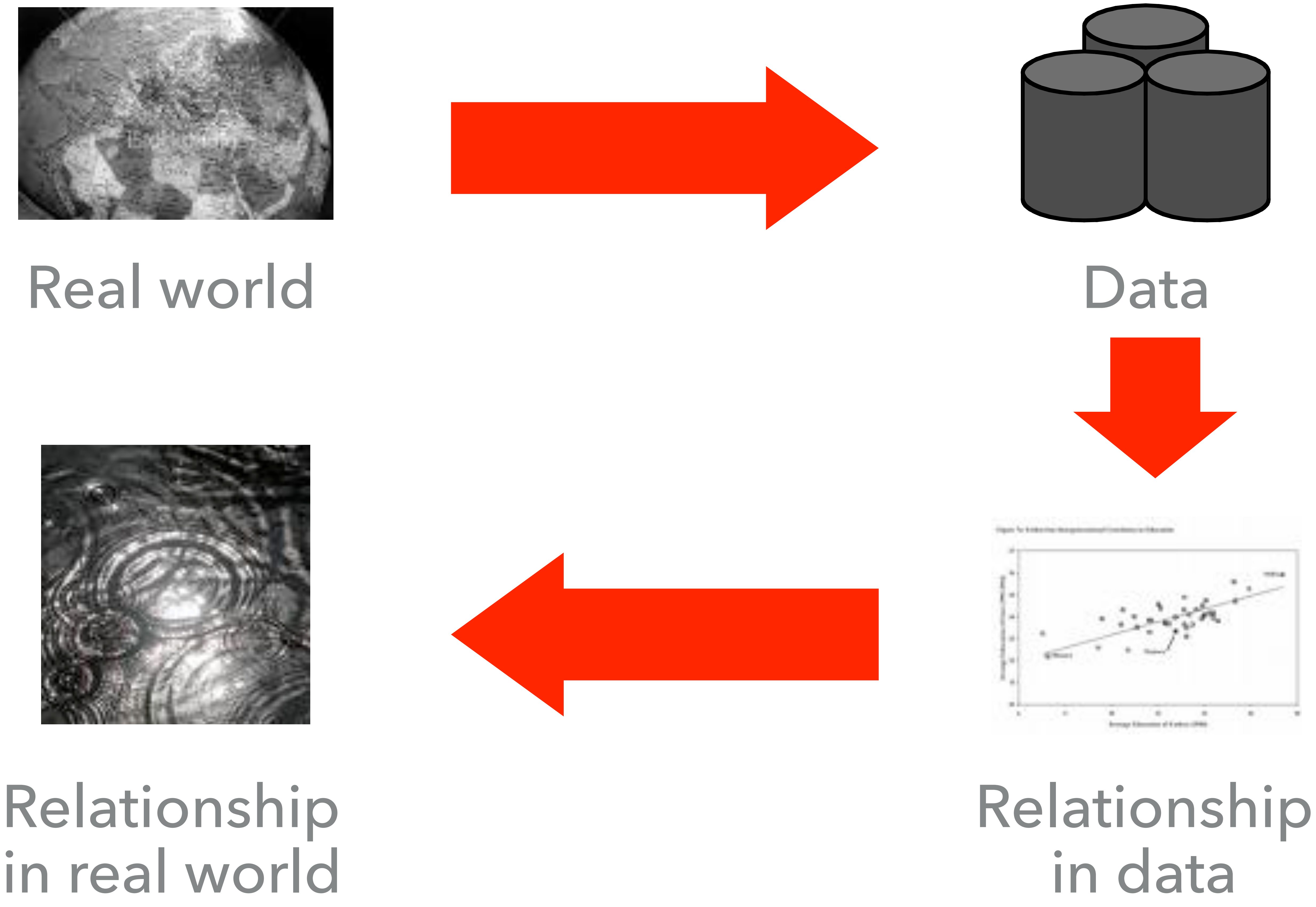
$$\beta = p(accept\ H_0 | H_0\ false) = p(type\ 2\ error)$$

HOW TO INCREASE POWER

- Increase sample size
- Decrease sample variability
  - Matching, sample selection, control for confounding variables, increase precision of measurements
- Increase effect size
  - More extreme experimental conditions, avoid ceiling/floor effects
- Increase alpha (e.g., from 0.05 to 0.10, but this increases type 1 errors)

DATA AND MEASUREMENT

REFLECTING REAL WORLD THROUGH DATA



Goal: map domain entities to symbolic representations

WHAT IS DATA?

- Collection of entities and their attributes
- **Attribute**: property or characteristic of an entity (e.g., eye color, temperature)
- **Entity**: collection of attributes
  Aka: record, point, case, sample, object, or instance

Attributes

Entities

Name	Thread pitch (mm)	Minor diameter tolerance	Nominal diameter (mm)	Head shape	Price for 50 screws	Available at factory outlet?	Number in stock	Flat or Phillips head?
M4	0.7	4g	4	Pan	$10.08	Yes	276	Flat
M5	0.8	4g	5	Round	$13.89	Yes	183	Both
M6	1	5g	6	Button	$10.42	Yes	1043	Flat
M8	1.25	5g	8	Pan	$11.98	No	298	Phillips
M10	1.5	6g	10	Round	$16.74	Yes	488	Phillips
M12	1.75	7g	12	Pan	$18.26	No	998	Flat
M14	2	7g	14	Round	$21.19	No	235	Phillips
M16	2	8g	16	Button	$23.57	Yes	292	Both
M18	2.1	8g	18	Button	$25.87	No	664	Both
M20	2.4	8g	20	Pan	$29.09	Yes	486	Both
M24	2.55	9g	24	Round	$33.01	Yes	982	Phillips
M28	2.7	10g	28	Button	$35.66	No	1067	Phillips
M36	3.2	12g	36	Pan	$41.32	No	434	Both
M50	4.5	15g	50	Pan	$44.72	No	740	Flat

DISCRETE AND CONTINUOUS ATTRIBUTES

- Discrete
  - Has only a finite or countably infinite set of values
  - Examples: zip codes, set of words in a collection of documents
  - Often represented as integer variables
- Continuous
  - Has real numbers as attribute values
  - Examples: temperature, height
  - Continuous attributes are typically represented as floating-point variables

Tan, Steinbach, Kumar. Introduction to Data Mining,

TABULAR DATA

- Collection of records, each of which consists of a fixed set of attributes

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DOCUMENT DATA

- Each document is represented as a **term** vector, where each attribute records the number of times the term occurs in the document

Terms	Documents													
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14
abnormalities	0	0	0	0	0	0	0	1	0	1	0	0	0	0
age	1	0	0	0	0	0	0	0	0	0	0	1	0	0
behavior	0	0	0	0	1	1	0	0	0	0	0	0	0	0
blood	0	0	0	0	0	0	0	1	0	0	1	0	0	0
close	0	0	0	0	0	0	1	0	0	0	1	0	0	0
culture	1	1	0	0	0	0	0	1	1	0	0	0	0	0
depressed	1	0	1	1	1	0	0	0	0	0	0	0	0	0
discharge	1	1	0	0	0	1	0	0	0	0	0	0	0	0
disease	0	0	0	0	0	0	0	0	1	0	1	0	0	0
fast	0	0	0	0	0	0	0	0	0	1	0	1	1	1
generation	0	0	0	0	0	0	0	0	1	0	0	0	1	0
oestrogen	0	0	1	1	0	0	0	0	0	0	0	0	0	0
patients	1	1	0	1	0	0	0	1	0	0	0	0	0	0
pressure	0	0	0	0	0	0	0	0	0	0	1	0	0	1
rats	0	0	0	0	0	0	0	0	0	0	0	0	1	1
respect	0	0	0	0	0	0	0	1	0	0	0	1	0	0
rise	0	0	0	1	0	0	0	0	0	0	0	0	0	1
study	1	0	1	0	0	0	0	0	1	0	0	0	0	0

TRANSACTION DATA

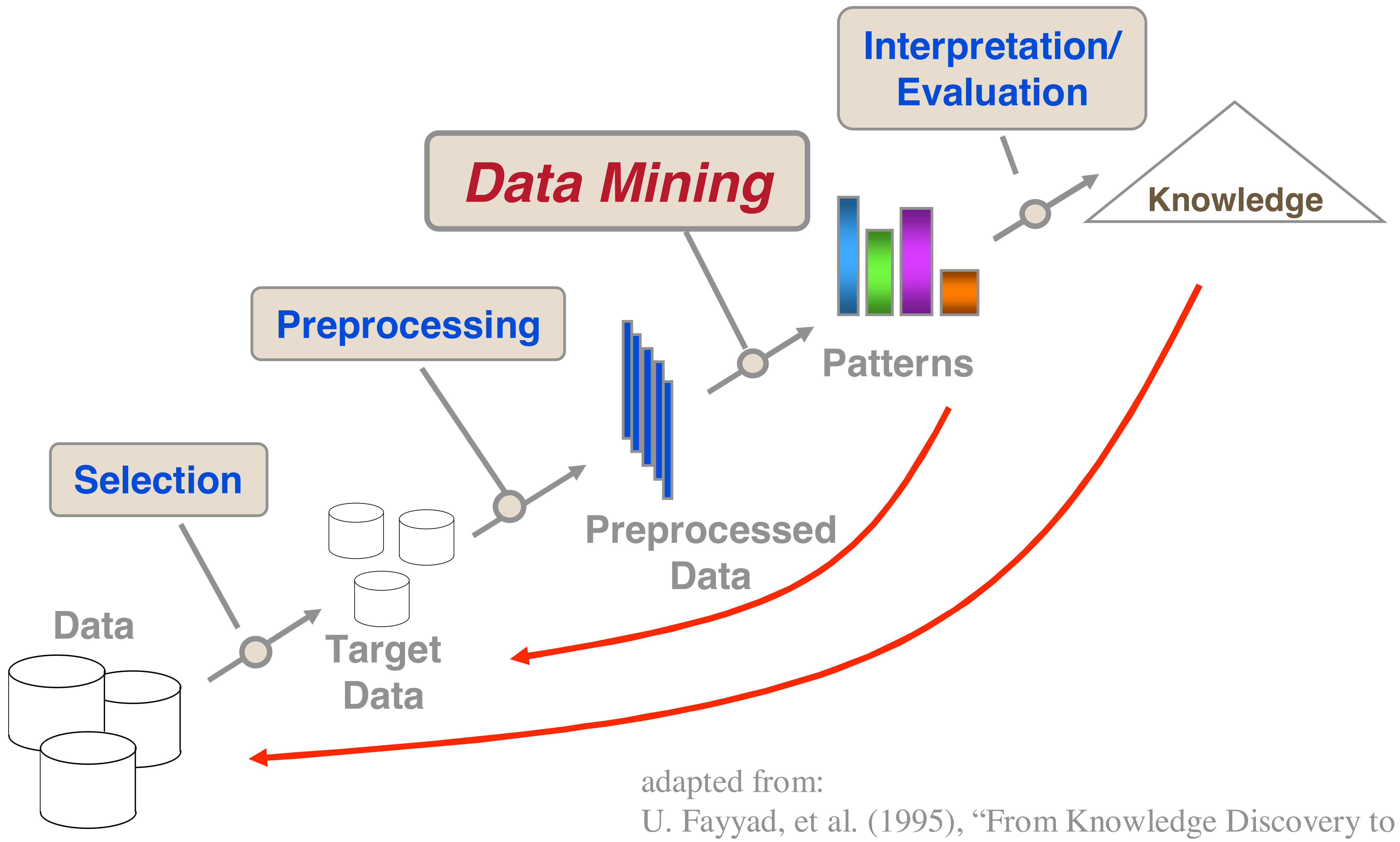
- Each record corresponds to a transaction that involves a set of items
- E.g., in a grocery store purchase, the set of products purchased by a customer constitute a transaction, while the individual products that were purchased are the items

Table 6.22. Example of market basket transactions.

Customer ID	Transaction ID	Items Bought
1	0001	$\{a, d, e\}$
1	0024	$\{a, b, c, e\}$
2	0012	$\{a, b, d, e\}$
2	0031	$\{a, c, d, e\}$
3	0015	$\{b, c, e\}$
3	0022	$\{b. d. e\}$
4	0029	$\{c, d\}$
4	0040	$\{a, b, c\}$
5	0033	$\{a, d, e\}$
5	0038	$\{a, b, e\}$

ELEMENTS OF DATA MINING ALGORITHMS

DATA MINING PROCESS



adapted from:
U. Fayyad, et al. (1995), "From Knowledge Discovery to Data Mining: An Overview," Advances in Knowledge Discovery and Data Mining, U. Fayyad et al. (Eds.), AAAI/MIT Press

OVERVIEW

- Task specification
- Knowledge representation
- Learning technique
  - Search + scoring
- Prediction and/or interpretation

OVERVIEW

- **Task specification**
- Knowledge representation
- Learning technique
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TASK SPECIFICATION

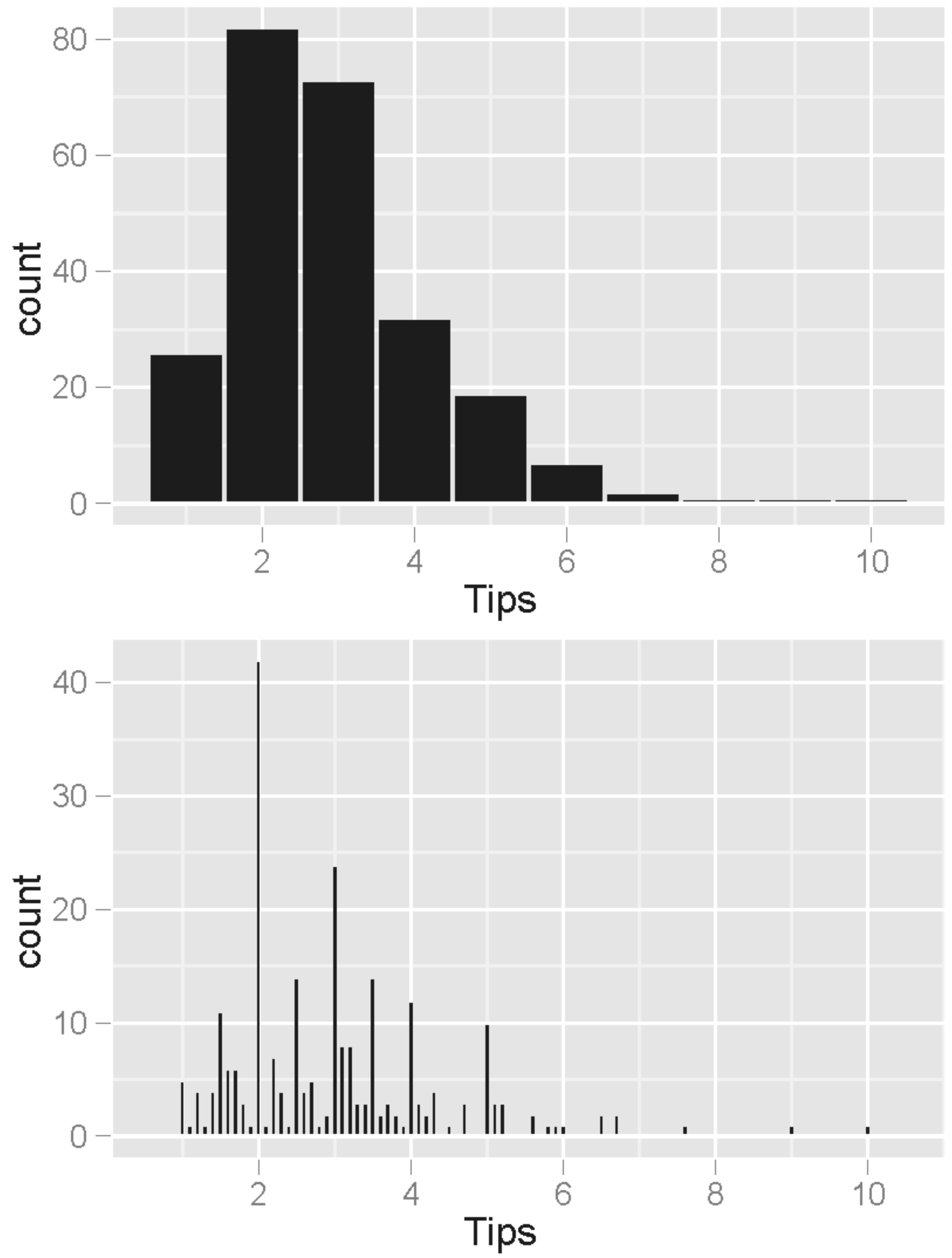
- Objective of the person who is analyzing the data
- Description of the characteristics of the analysis and desired result

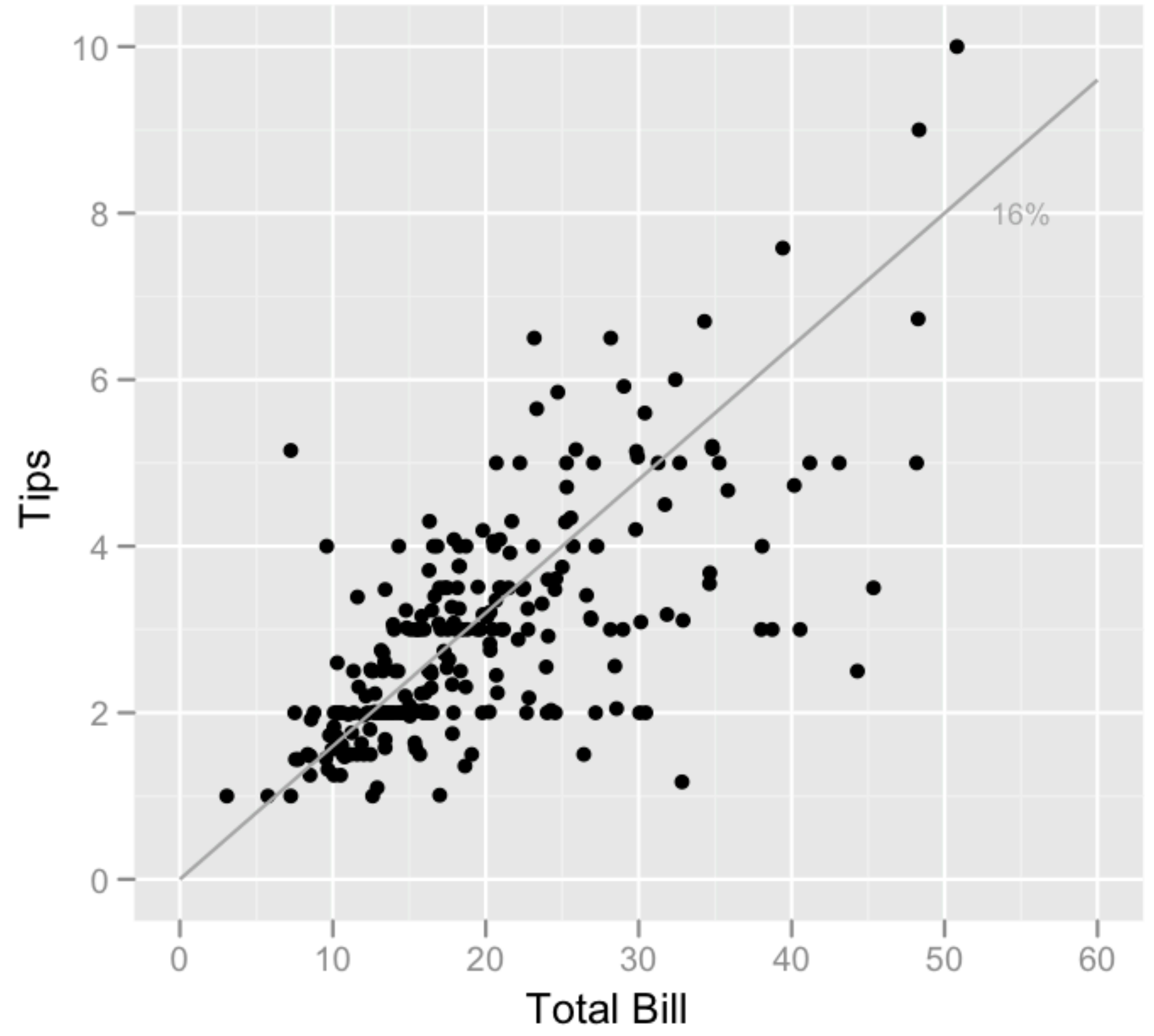
EXPLORATORY DATA ANALYSIS

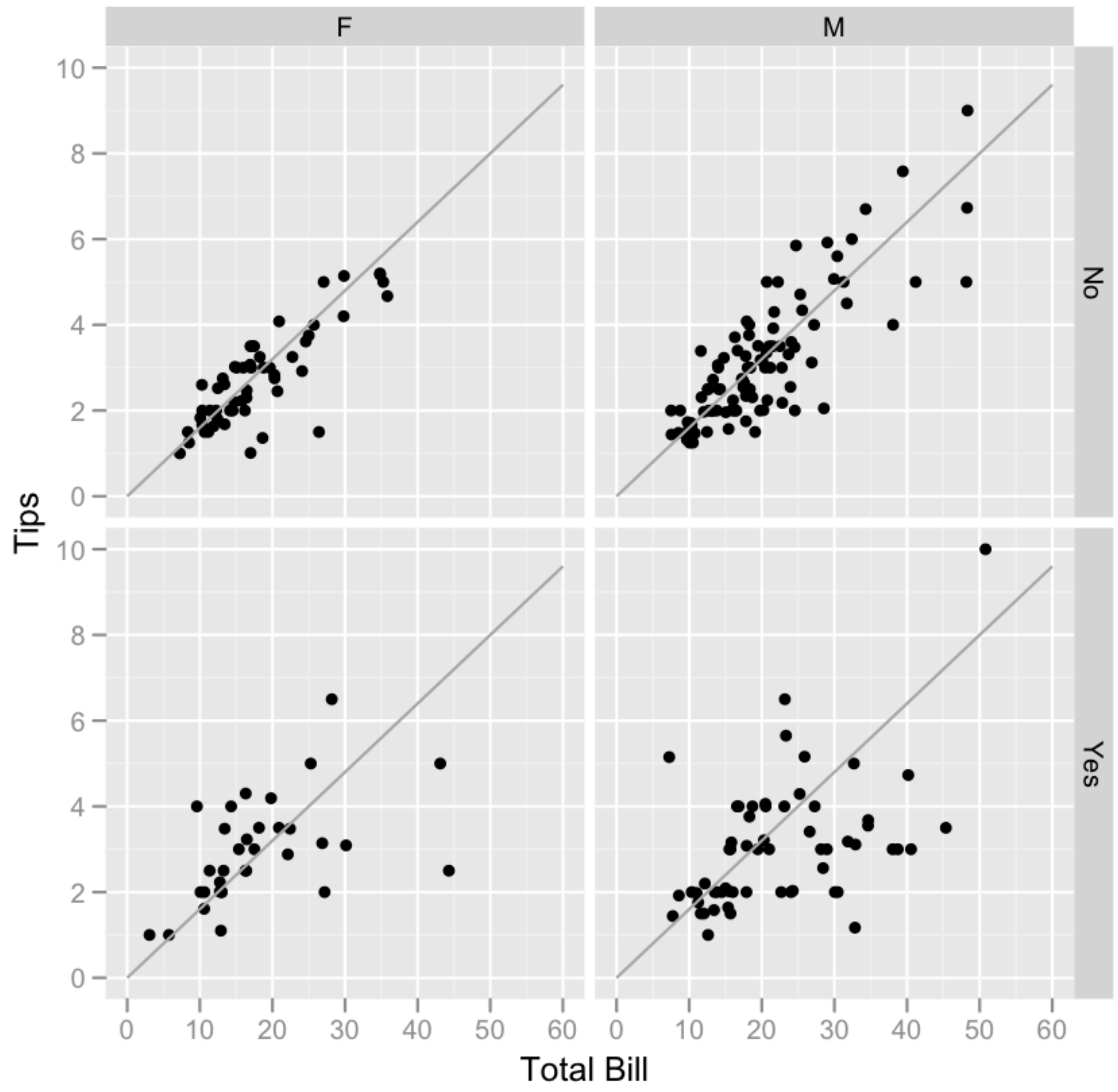
- Goal
  - Interact with data without clear objective
  - Summarize the main characteristics of the data
- Techniques
  - Mostly visualization

EXPLORATORY DATA ANALYSIS EXAMPLE

- What influences the amount of tip that a dining party will give to the waiter?







Cook, D. And Dwayne, D. F. Interactive and Dynamic Graphics for Data Analysis: With R and GGobi

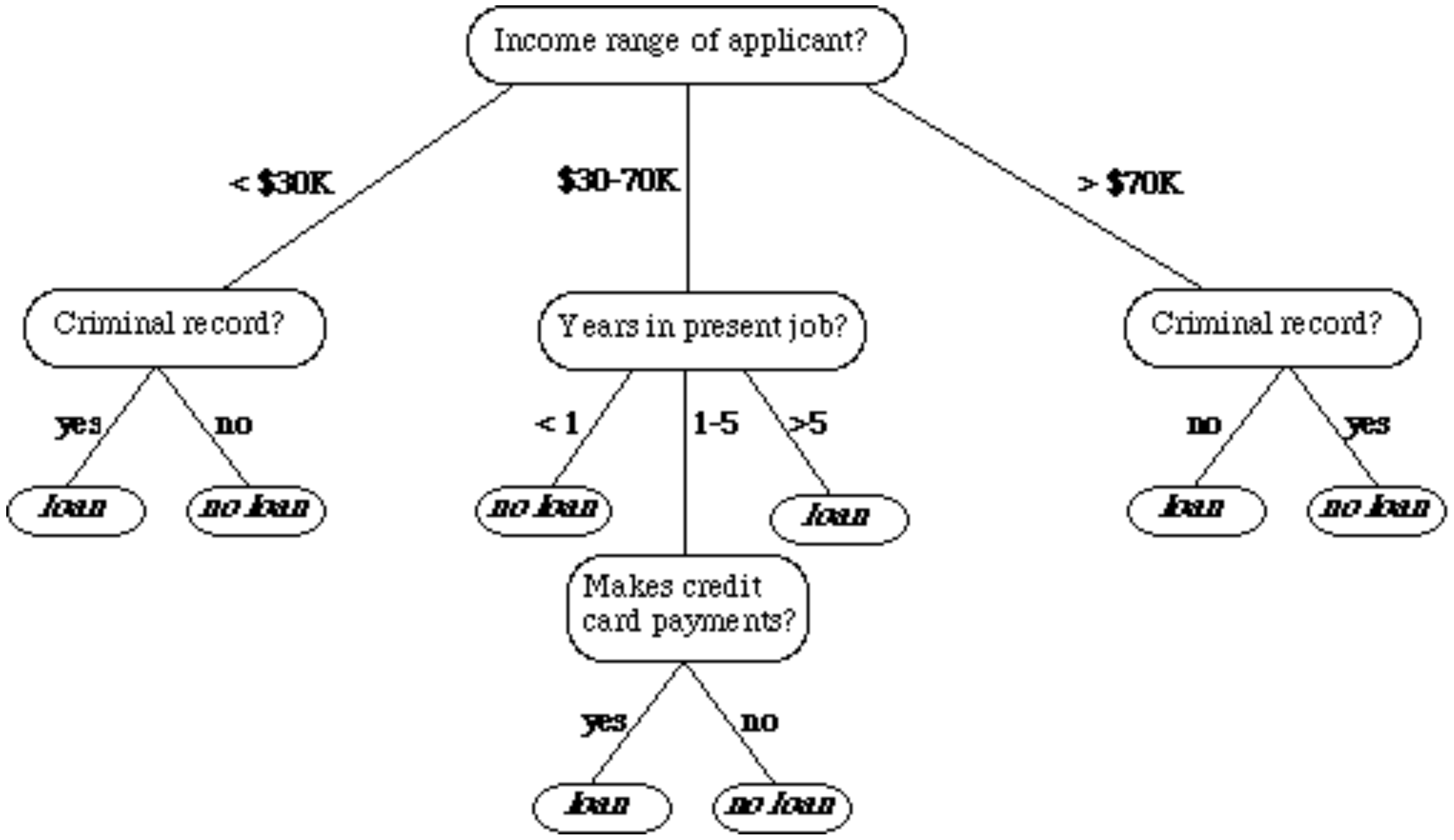
PREDICTIVE MODELING

- Goal
  - Learn model to predict the unknown value of a variable of interest given observed attribute values
- Techniques
  - Classification, regression

Also known as: **supervised** learning

PREDICTIVE MODELING EXAMPLE

- Zestimate: House sales price prediction!
- Predicting loan repayment (and thus decide whether to provide a loan)



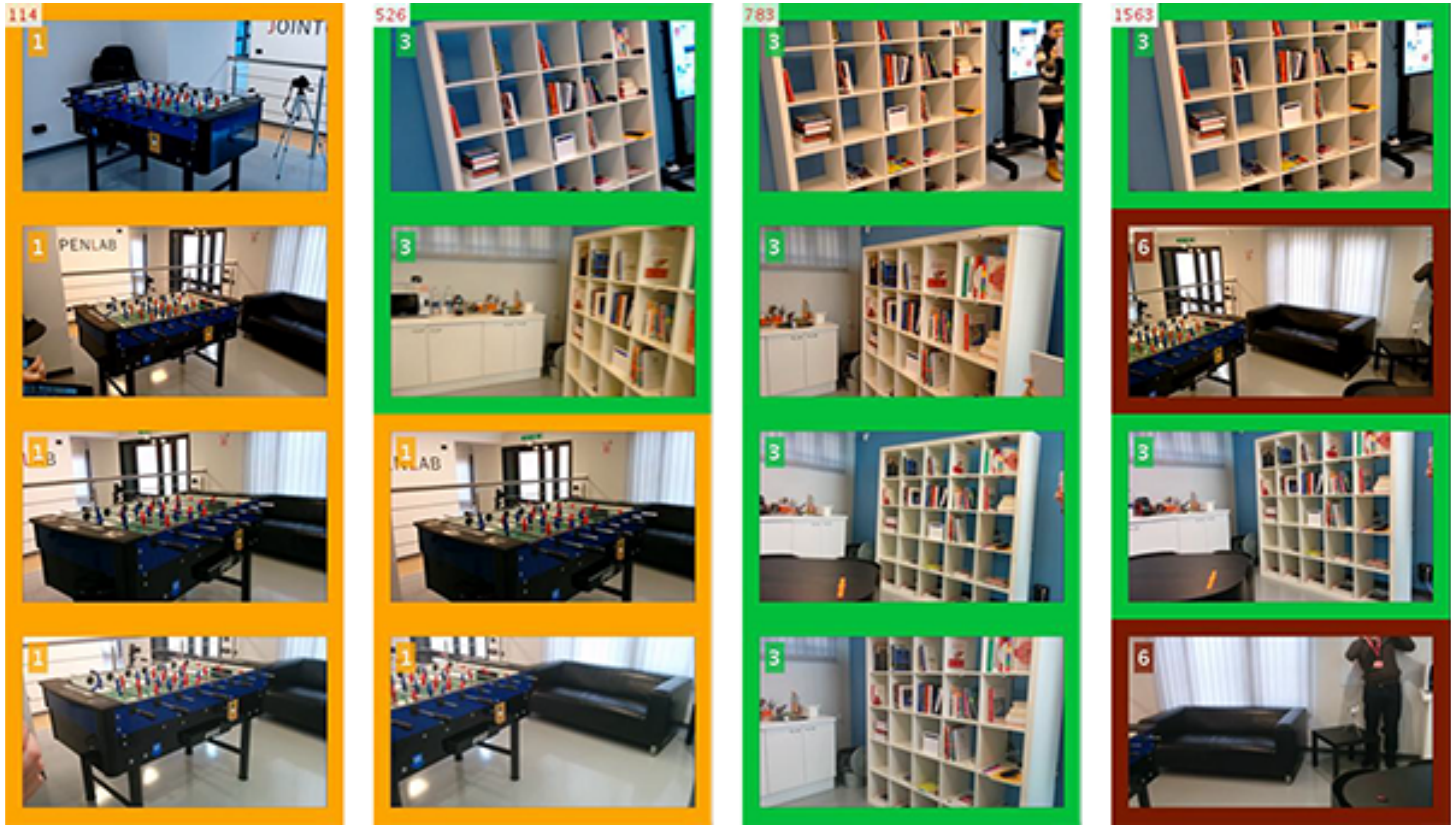
DESCRIPTIVE MODELING

- Goal
  - Summarize the data or the underlying generative process
- Techniques
  - Density estimation, cluster analysis and segmentation, probabilistic graphical model

Also known as: **unsupervised** learning

DESCRIPTIVE MODELING EXAMPLE

- Video/scene clustering



Milotta et al. RECfusion: Automatic Scene Clustering and Tracking in Videos from Multiple Sources

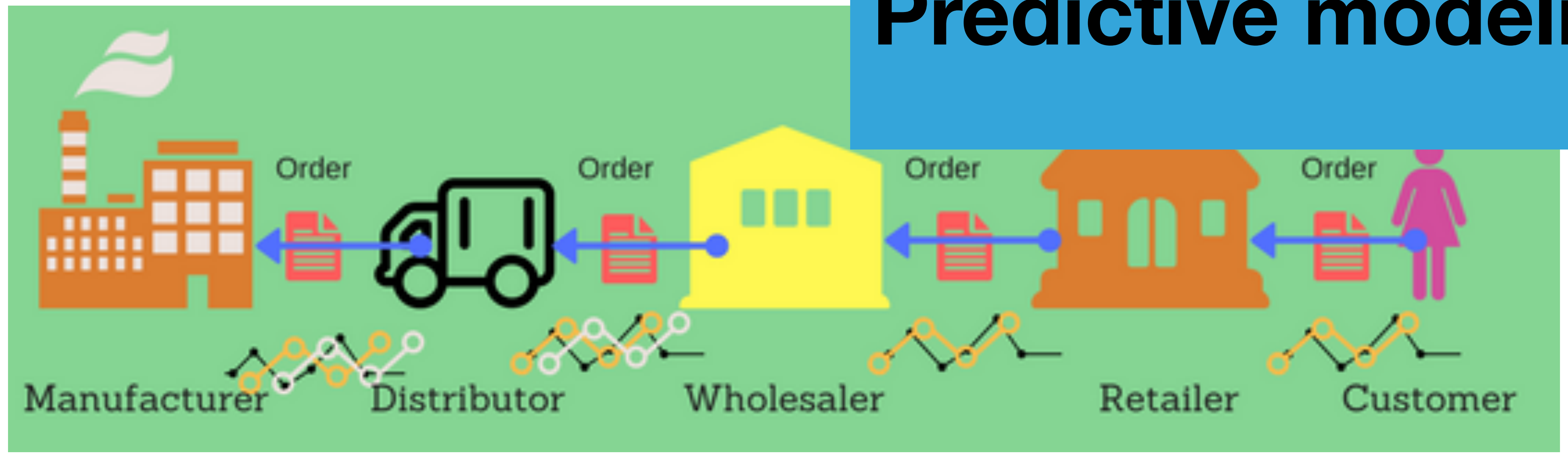
PATTERN DISCOVERY

- Goal
  - Detect patterns and rules that describe subsets of examples
- Techniques
  - Association rules, anomaly detection, etc.

Model: global summary of a data set
Pattern: local to a subset of the data

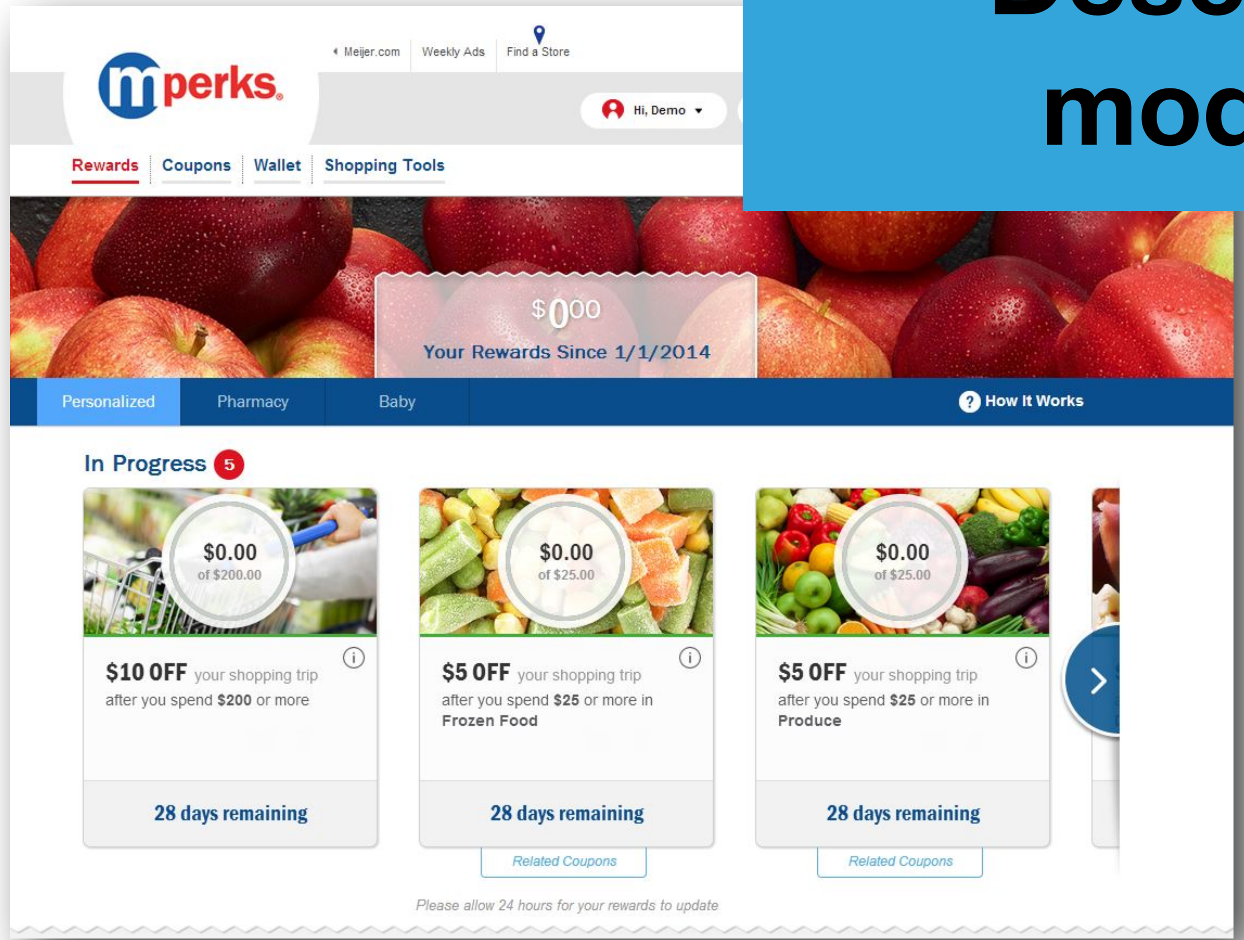
WHAT TASKS ARE THEY?

Predictive modeling

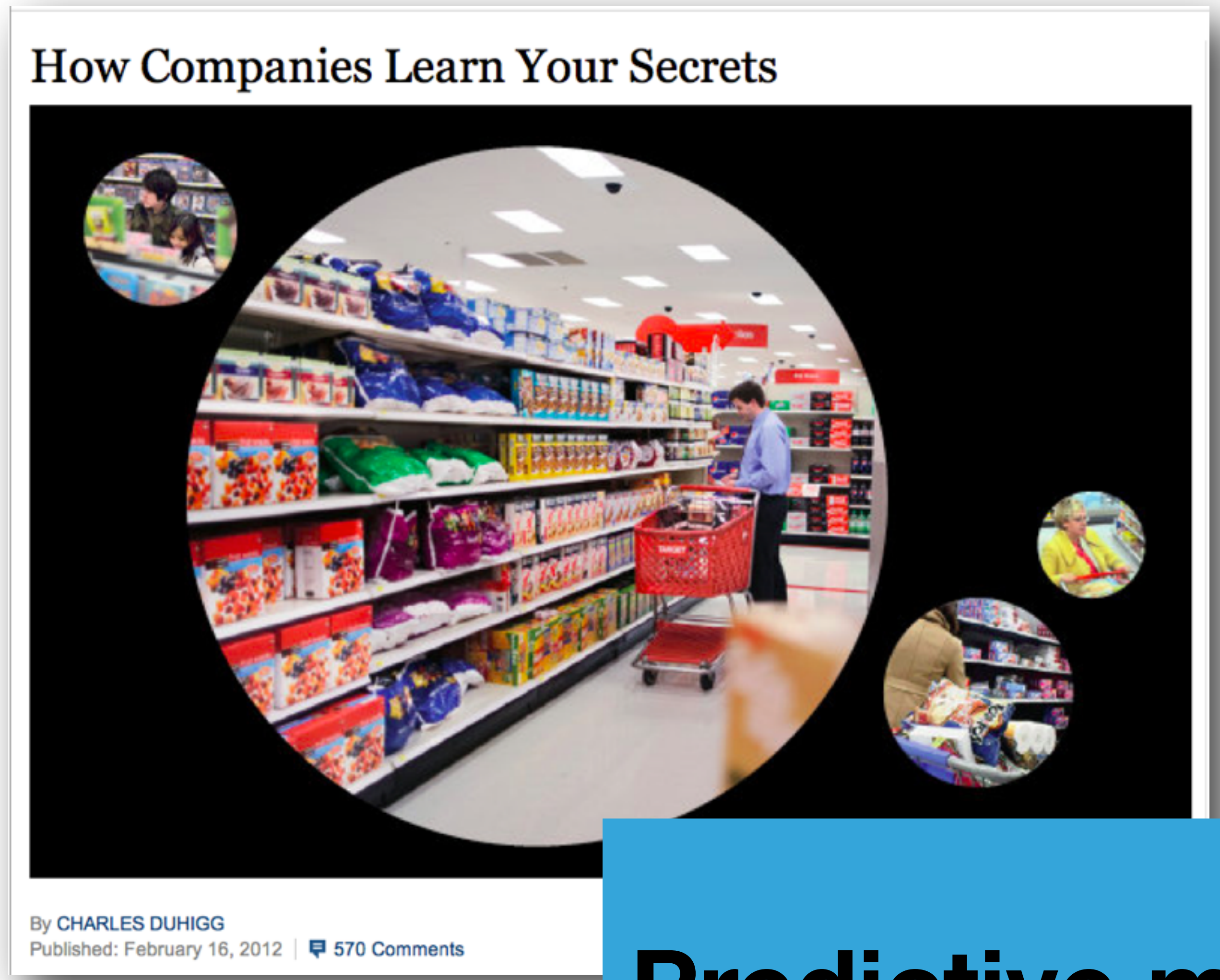


Sales and inventory forecast

Descriptive modeling



Customer segmentation


How Companies Learn Your Secrets

By CHARLES DUHIGG
Published: February 16, 2012 570 Comments

Predictive modeling

Pregnant custo

Pattern Discovery

Beer & Dia

OVERVIEW

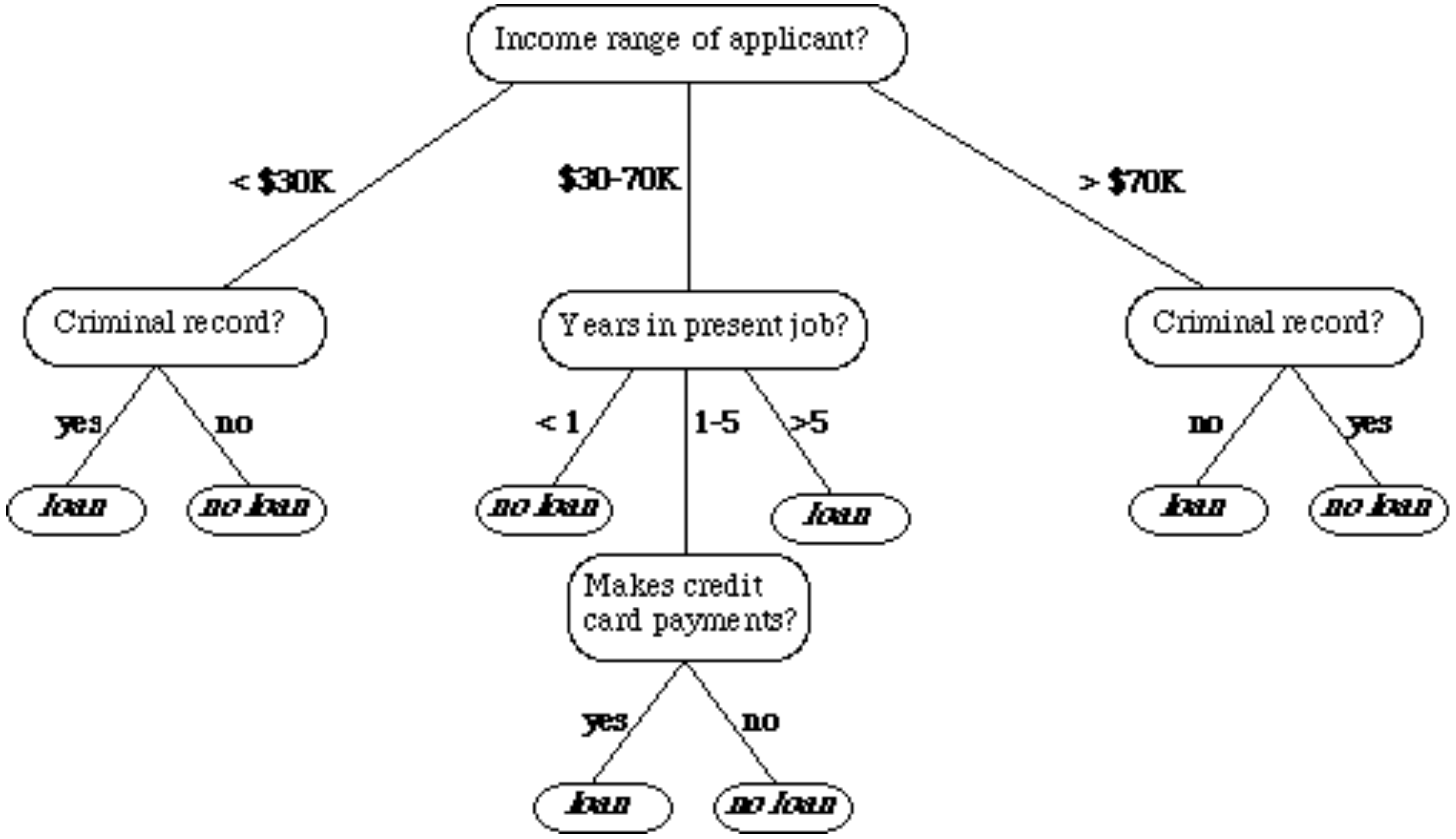
- Task specification
- **Knowledge representation**
- Learning technique
  - Search + scoring
- Prediction and/or interpretation

KNOWLEDGE REPRESENTATION

- Underlying structure of the model or patterns that we seek from the data
  - Specifies the models/patterns that could be returned as the results of the data mining algorithm
  - Defines space of possible models/patterns for algorithm to search over

KNOWLEDGE REPRESENTATION EXAMPLE: PREDICTIVE MODELING

- If-then rule
  - *If* (personal income > $70k) AND (criminal record = 'no'), *then* loan=yes
- Decision tree
  - Each node corresponds to an attribute
  - Each leaf is a class label

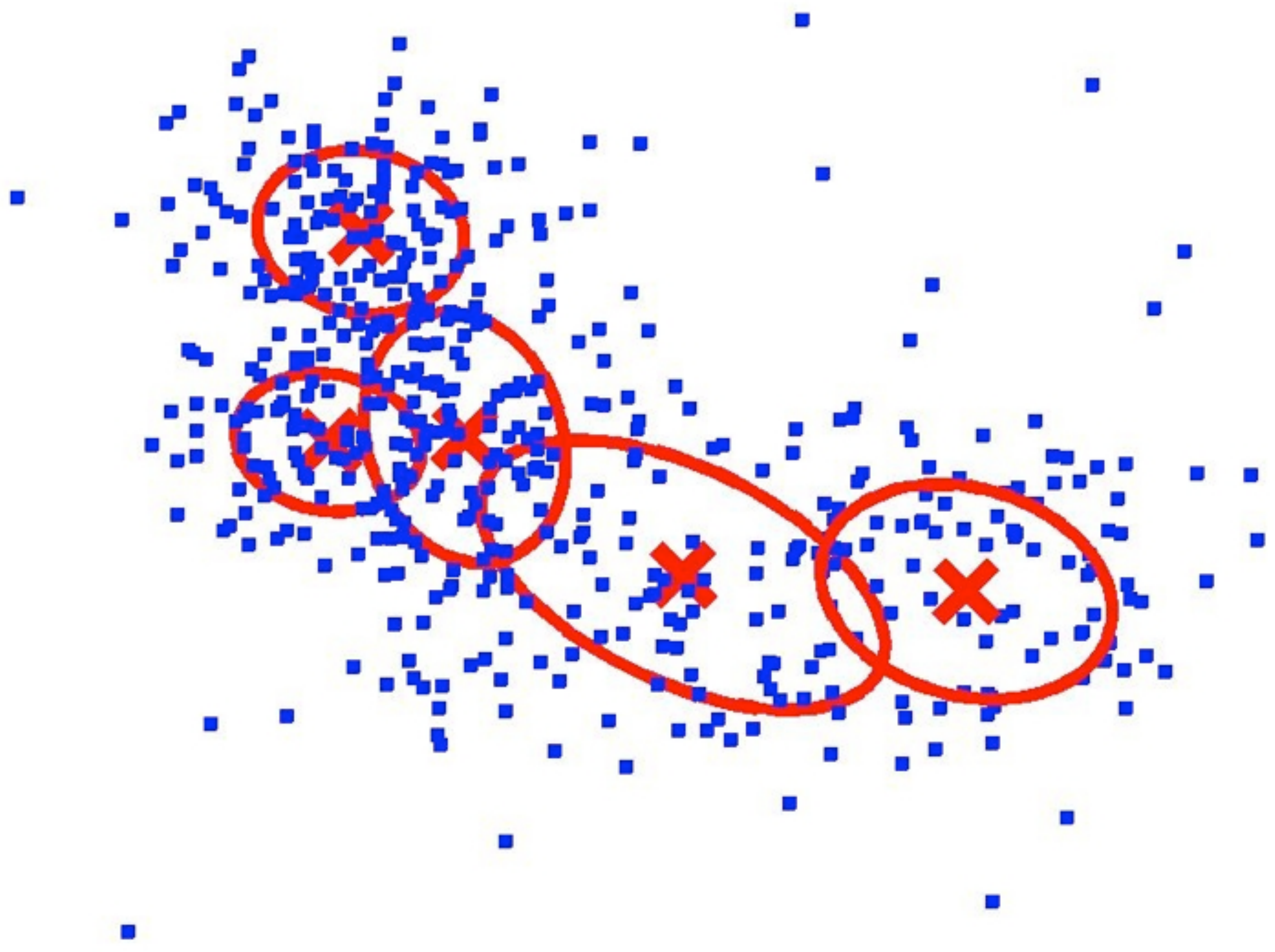


KNOWLEDGE REPRESENTATION EXAMPLE: PREDICTIVE MODELING

- Conditional probability distributions (i.e., P(Y | $\boldsymbol{X}$))
  - Logistic regression: $log \dfrac{P(Y=1|\boldsymbol{x})}{1-P(Y=1|\boldsymbol{x})} = \beta_0 + \boldsymbol{\beta x}$
  - Model the log-odds as a linear combination of predictors
- Linear regression
  - $y = \beta_1 x_1 + \beta_2 x_2 \ldots + \beta_0$
  - y is the response variable, $\boldsymbol{x}$ is the predictor variable

KNOWLEDGE REPRESENTATION EXAMPLE: DESCRIPTIVE MODELING

- Mixture model: Instances represented as a weighted combination of mixture distributions



$$f(x) = \sum_{k=1}^{K} w_k f_k(x;\theta)$$

probability of observing x

likelihood of x being generated from cluster k

likelihood of point belonging to cluster k

KNOWLEDGE REPRESENTATION EXAMPLE: PATTERN DISCOVERY

- Association rules
  - $I = \{i_1, i_2, \ldots, i_n\}$ is a set of n items
  - $T = \{t_1, t_2, \ldots, t_m\}$ is a set of m transactions
  - An association rule has the form $X \rightarrow Y$, where X and Y are subsets of I, which means if items in X appear in a transaction, then items in Y are likely to appear in that transaction
    - E.g., {beer} → {diaper}; {bread} → {milk}

Example database with 5 transactions and 5 items

transaction ID	milk	bread	butter	beer	diapers
1	1	1	0	0	0
2	0	0	1	0	0
3	0	0	0	1	1
4	1	1	1	0	0
5	0	1	0	0	0

OVERVIEW

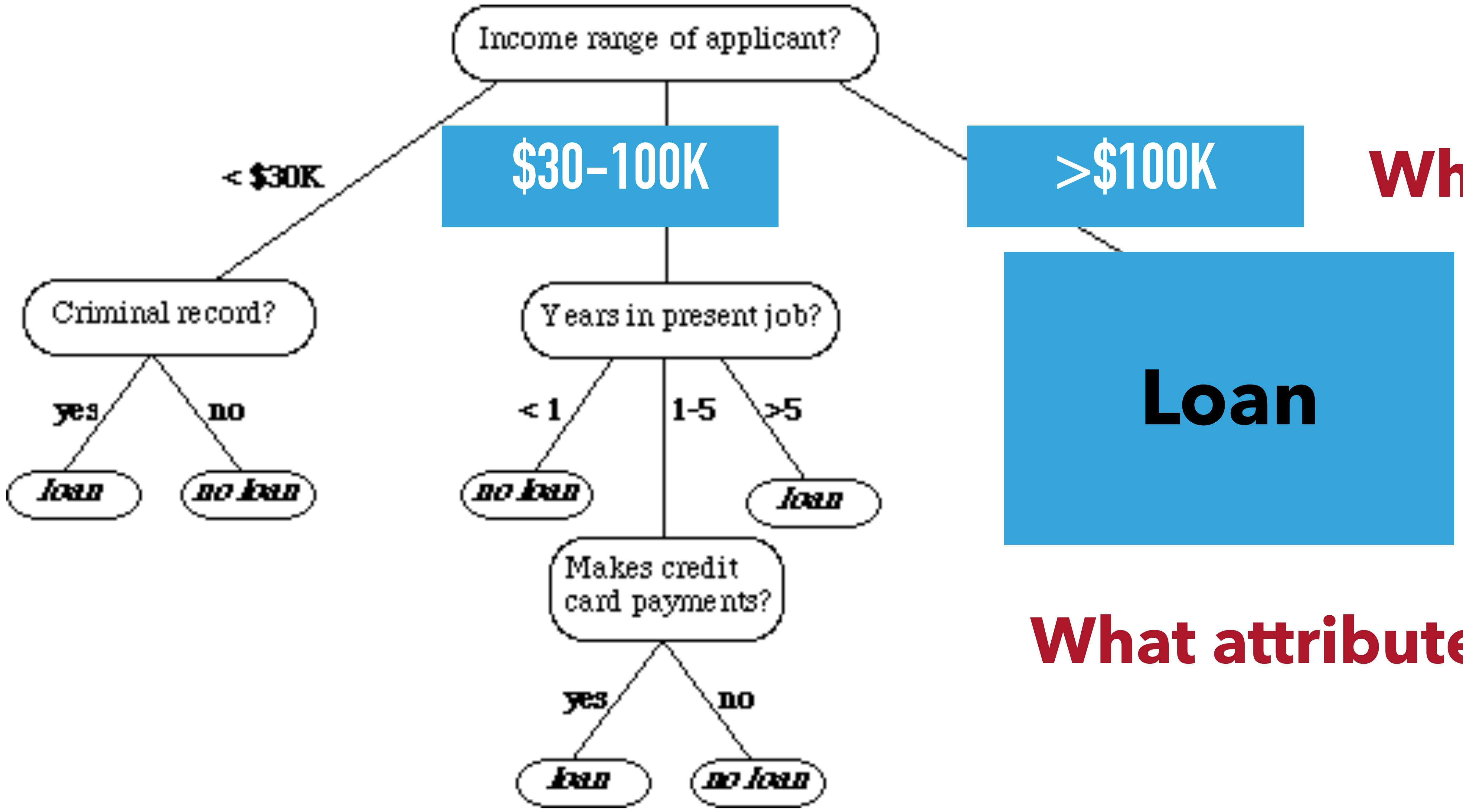
- Task specification
- Knowledge representation
- **Learning technique**
  - Search + scoring
- Prediction and/or interpretation

LEARNING TECHNIQUE

- Method to construct model or patterns from data
- **Model space**
  - Choice of knowledge representation defines a set of possible models or patterns
- **Scoring function**
  - Associates a numerical value (score) with each member of the set of models/patterns
- **Search technique**
  - Defines a method for generating members of the set of models/patterns, determining their score, and identifying the ones with the "best" score

MODEL SPACE

- Defined by the choice of knowledge representation
- Decision tree:



What values to split on?

What attributes to include?

MODEL PARAMETERS AND STRUCTURE

- Models have both **parameters** and **structure**
- **Parameters:**
  - Feature values in classification tree
  - Coefficients in regression model
  - Probability estimates in graphical model
- **Structure:**
  - Nodes in classification tree
  - Variables in regression model
  - Edges in graphical model

SCORING FUNCTION

- A numeric score assigned to each possible model in a search space, **given a reference/input dataset**
  - Used to judge the quality of a particular model for the domain
- Score function are **statistics**—estimates of a population parameter based on a sample of data
- Examples:
  - Misclassification
  - Squared error
  - Likelihood

PARAMETER ESTIMATION VS. STRUCTURE LEARNING

- **Parameters:**
  - Feature values in classification tree
  - Coefficients in regression model
  - Probability estimates in graphical model
- **Structure:**
  - Nodes in classification tree
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  - Edges in graphical model

Search: Convex/smooth optimization techniques

Search: Heuristic approaches for combinatorial optimization