



TECHNICS IN ANALYTICS: BIRD'S EYE VIEW

Analytics



Techniques

Machine Learning

Supervised

- Observations from past
 - ▣ Known outcome
- Examples
 - ▣ Age 40, high blood pressure => diabetes
 - ▣ Additional income, Earn \$ => spam

Unsupervised

- Observations from past
 - ▣ No associated outcome
- Examples
 - ▣ Power forward, 25 ppg
 - ▣ Income \$50,000, single

Classification

□ Example

- ▣ John Doe: 40 age, 180lbs, no exercise = > diabetes
- ▣ John Doe Jr.: 25 age, 150 lbs, exercise => no diabetes
- ▣ John Doe Sr.: 40 age, 210 lbs, no exercise => diabetes

□ John Doe Tiny

- ▣ 38 age, 150 lbs, exercise
- ▣ How likely to have diabetes?
- ▣ Should he be considered for treatment?

Classification

- Email
 - ▣ Email 1 => spam
 - ▣ Email 2 => no spam
 - ▣ Email 3 => spam
- Extract words from emails
 - ▣ Word 1 => spam
 - ▣ Word 2 => no spam
- New email with words
 - ▣ Spam or not spam?

Loss Functions

- X = set of historical data
 - ▣ $(x, y) \in X$
 - ▣ x = feature vector
 - ▣ y = label
- Given x , $f(x; w)$ is prediction
 - ▣ w unknown parameters
- Goal
 - ▣ $f(x; w) \approx y$
 - ▣ $l(f(x; w), y)$ = loss function
 - Penalize the discrepancy

$$\min_w \sum_{(x,y) \in X} l(f(x; w), y)$$

$$\min_w \sum_{(x,y) \in X} \hat{l}(x, y; w)$$

$$\min_w \sum_i \hat{f}_i(x_i; w)$$

$$\min_w E_{X,Y}(\hat{l}(x, y; w))$$

Linear Regression Loss Function

- $f(x; w) = w_1 x + w_0$
 - ▣ $w = (w_1, w_0)$
 - ▣ All are vectors
- $l(u, v) = (u - v)^2$
- $l(f(x; w), y) = (f - y)^2 = (w_1 x + w_0 - y)^2$
- $\hat{l}(x, y; w) = (w_1 x + w_0 - y)^2$

$$\min_{w_1, w_0} \sum_i (w_1 x_i + w_0 - y_i)^2$$

Feature Preparation

- Large/big feature values pose problems
 - ▣ Normalization
- For each feature
 - ▣ Subtract the mean and
 - ▣ Divide by standard deviation
- Standardization
 - ▣ Transform to $[0,1]$
 - ▣ Divide by the maximum value after the minimum value is translated to 0

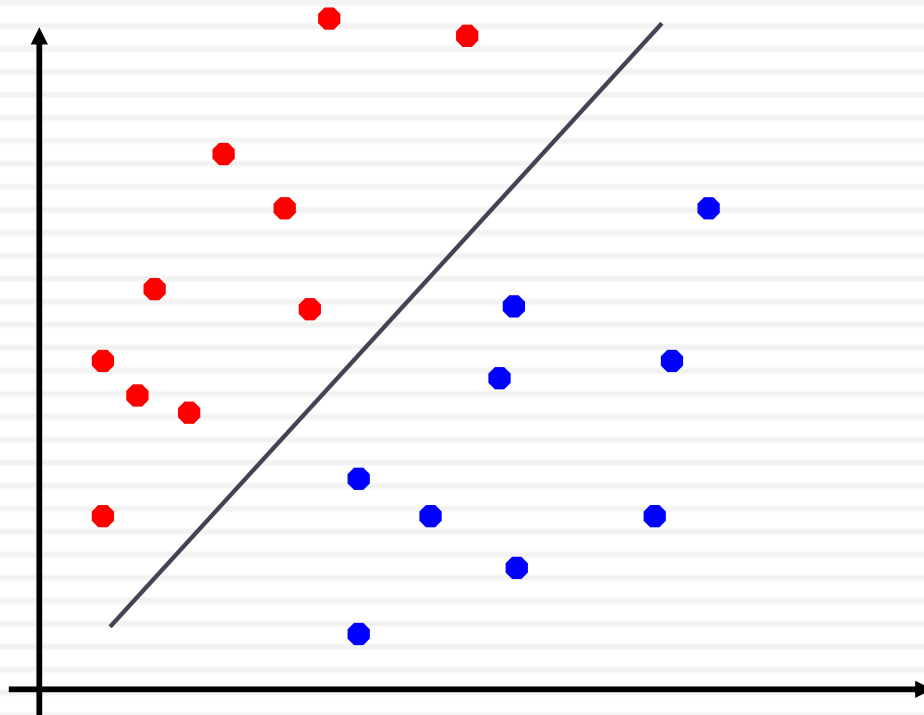
Terminology



- ML synonyms
 - ▣ Record, sample, observation, row
 - ▣ Ground truth, label
- Classes
 - ▣ Labels belong to classes
- Parametric models have loss functions
 - ▣ Non-parametric do not

Support Vector Machines

- Binary classification
- Maximize the distance from the line



Support Vector Machine Loss Function

- Margin = $\frac{2}{\|w\|}$
 - ▣ Want to maximize
- Complete separation
$$\min_{w,b} \|w\| \text{ subject to } y_i(w^T x_i + b) \geq 1 \forall i$$
- General
- $\min_{w,b} \|w\| + C \sum_i \max(0, 1 - y_i(w^T x_i + b))$
- $f(x; w, b) = \begin{cases} 1 & \text{if } w^T x + b \geq 0 \\ y_i = 1 \\ -1 & \text{else } y_i = -1 \end{cases}$
- $\hat{l}(x, y; w, b) = \frac{\|w\|}{n} + C \max(0, 1 - y(w^T x + b))$

Classification



- Training set
- Fit function
 - ▣ From training set tune parameters of function
- New entity
 - ▣ Evaluate the function
 - ▣ Classify entity

Evaluation



- Data set
 - ▣ Split to training and test
 - ▣ Calibrate model on training
 - ▣ Evaluate on test
 - How many predictions are correct on test data
- Measure is regression error
 - ▣ Is it possible to achieve zero error?

10-fold validation



- Split the data into 10 chunks
 - ▣ Train on 9
 - ▣ Validate on 1
 - ▣ Repeat for all 10 test chunks/folds
- Model selection
 - ▣ Not parameter/weight selection
 - ▣ Not one set of parameters/weights on all 10

Precision and Recall

□ Confusion matrix

		Predicted Class		
		+	-	
Actual Class	+	tp	fn	C = tp+fn
	-	fp	tn	
		A = tp+fp		T = tp+fn+fp+tn

True Positive

False Negative

False Positive

True Negative

Precision and Recall

- Accuracy

- ▣ Proportion of correctly predicted

$$\text{all correct/all} = (tp+tn)/(tp+tn+fp+fn)$$

- Recall

- ▣ Proportion of + correctly predicted

$$\text{true positive/all positive} = tp/(tp+fn)$$

- Precision

- ▣ Proportion of + among all predicted +

$$\text{true positive/ predicted positive} = tp/(tp+fp)$$

- F-measure

- ▣ Harmonic mean of precision and recall

$$2 \text{ recall} * \text{precision} / (\text{recall} + \text{precision})$$

Example

Results from Classification Algorithm

ID	Actual Class	Predicted Class
1	+	+
2	+	+
3	+	+
4	+	+
5	+	-
6	-	+
7	-	+
8	-	-

Confusion matrix

		Predicted Class		
		+	-	
Actual Class	+	4	1	C = 5
	-	2	1	
		A = 6		T = 8

- True positive = 4
- False positive = 2
- True Negative = 1
- False Negative = 1

Categorical Features



- Label encoding
 - ▣ Assign a number to each category
 - ▣ What number?
- One-hot-encoding
 - ▣ Large number of features
 - ▣ Tight models
 - Does not scale

Advanced Target Encoding

- One category
 - ▣ Percentage of samples of this category in a class
- Issues
 - ▣ Data leakage
 - Get the values based on a hold-out set
 - ▣ What if only a few samples of a given category
 - Spurious correlation

Smoothed Tse Encoding

- Combine 'local' estimates with 'global' estimates
- Global ratio of two classes
- One category

$$\frac{ratio_{category} + K ratio_{global}}{n + m}$$

n = number of samples in this category

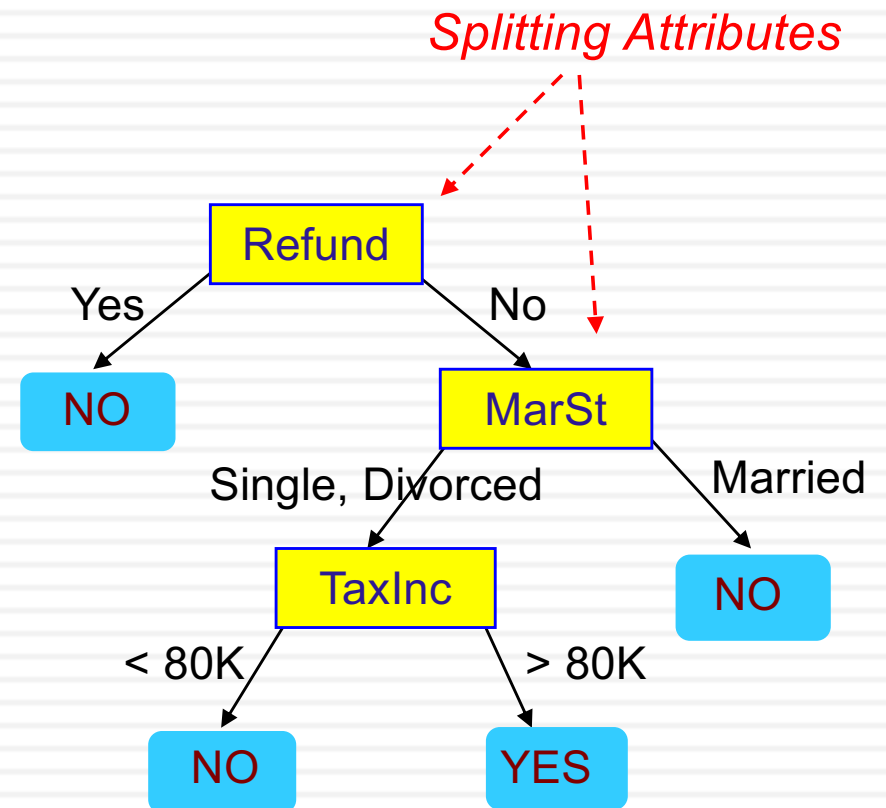
m = total number of samples

K = hyper parameter

Decision Tree

<i>Tid</i>	<i>Refund</i>	<i>Marital Status</i>	<i>Taxable Income</i>	<i>Cheat</i>
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

categorical
categorical
continuous
class



Training Data

Model: Decision Tree

Logistic Regression

- Categorical predictors
 - Predicting cancer from smoking and eating tomatoes.
 - We don't know what happens when non-smokers eat tomatoes because we have no data
- Probability of cancer?

<i>Do you smoke?</i>	<i>Do you eat tomatoes?</i>	<i>Do you have cancer?</i>
Yes	No	Yes
Yes	Yes	Yes
No	No	Yes
No	Yes	??????

Discrete Choice

- Observations

- ▣ Purchase made
- ▣ AND available options

- Assumption

- ▣ Customers maximize their own utility

Choice made = the choice that maximizes utility

$$u(\text{selected}) = \max u(\text{options})$$

- ▣ Utility = linear combination of attributes

Discrete Choice

□ Travel

- ▣ Online purchasing
- ▣ Utility of flight = $\text{coeff} * \text{departure time} + \text{coeff} * \text{elapsed time} + \text{coeff} * \text{price} + \text{coeff} * \text{loyalty}$
- ▣ Coefficients fitted based on historical observations

□ Market basket

- ▣ Available goods in the store
- ▣ Utility of purchase = $\text{coeff} * \text{price} + \text{coeff} * \text{brand loyalty} + \text{coeff} * \text{home inventory}$

Discrete Choice vs Logistic Regression

- Observe actions

- ▣ Purchase, no-purchase
- ▣ Existing/left customers
- ▣ Choices not available

Logistic regression

- Observe choices

- ▣ Still capture actions
- ▣ Record all available options
- ▣ Customer select maximum utility option

Discrete choice

- Probability of selection

Applications of Cluster Analysis

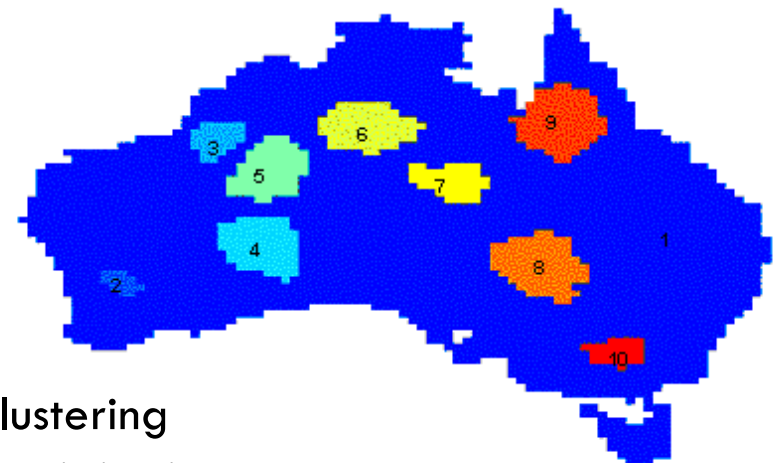
□ Understanding

- ▣ Group related documents for browsing, group genes and proteins that have similar functionality, or group stocks with similar price fluctuations

	<i>Discovered Clusters</i>	<i>Industry Group</i>
1	Applied-Matl-DOWN, Bay-Network-DOWN, 3-COM-DOWN, Cabletron-Sys-DOWN, CISCO-DOWN, HP-DOWN, DSC-Comm-DOWN, INTEL-DOWN, LSI-Logic-DOWN, Micron-Tech-DOWN, Texas-Inst-DOWN, Tellabs-Inc-DOWN, Natl-Semiconduct-DOWN, Oracl-DOWN, SGI-DOWN, Sun-DOWN	Technology1-DOWN
2	Apple-Comp-DOWN, Autodesk-DOWN, DEC-DOWN, ADV-Micro-Device-DOWN, Andrew-Corp-DOWN, Computer-Assoc-DOWN, Circuit-City-DOWN, Compaq-DOWN, EMC-Corp-DOWN, Gen-Inst-DOWN, Motorola-DOWN, Microsoft-DOWN, Scientific-Atl-DOWN	Technology2-DOWN
3	Fannie-Mac-DOWN, Fed-Home-Loan-DOWN, MBNA-Corp-DOWN, Morgan-Stanley-DOWN	Financial-DOWN
4	Baker-Hughes-UP, Dresser-Inds-UP, Halliburton-HLD-UP, Louisiana-Land-UP, Phillips-Petro-UP, Unocal-UP, Schlumberger-UP	Oil-UP

□ Summarization

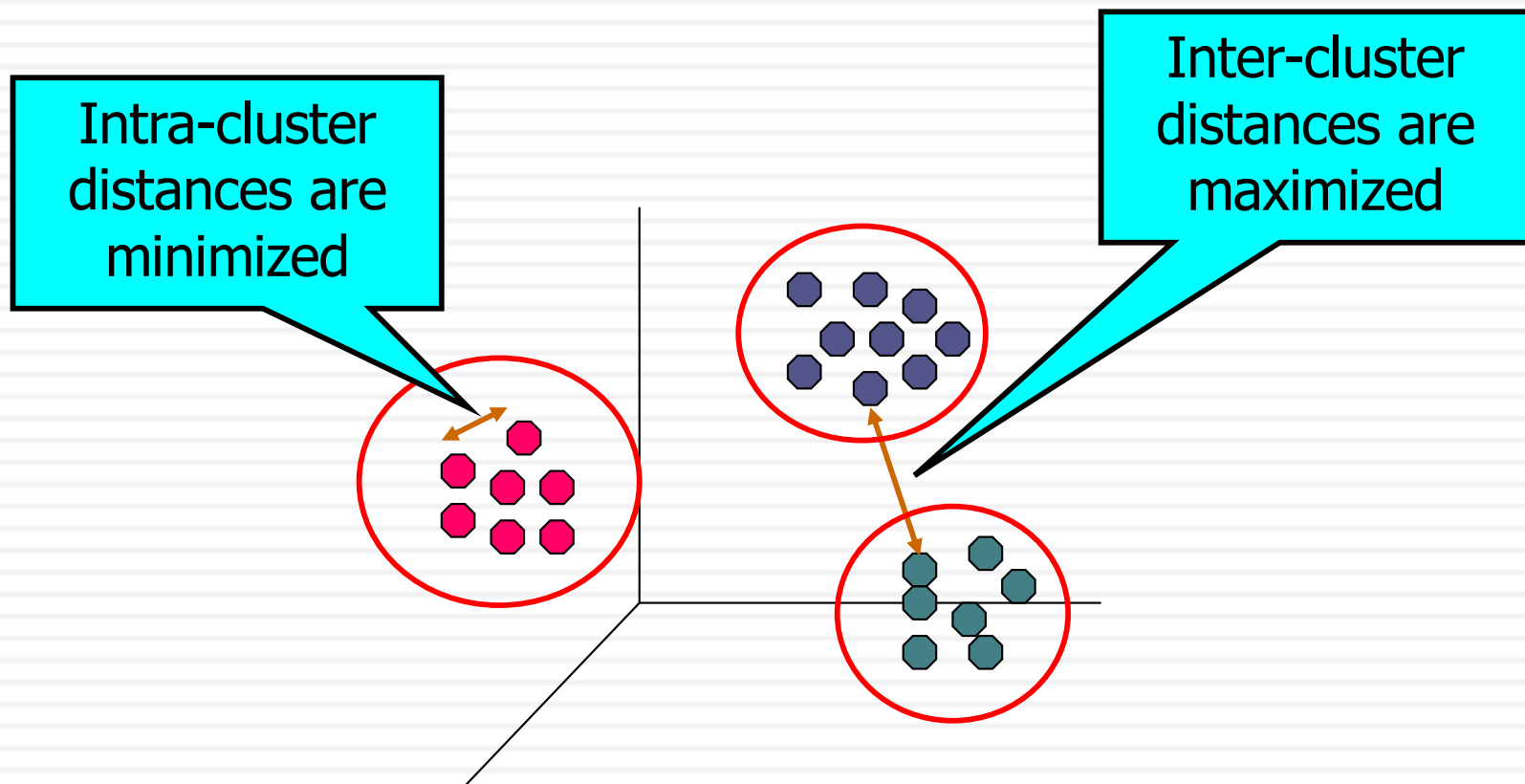
- ▣ Reduce the size of large data sets



Clustering
precipitation

What is Cluster Analysis?

- Finding groups of objects such that the objects in a group will be similar (or related) to one another and different from (or unrelated to) the objects in other groups



Association Rule Mining

- Given a set of transactions, find rules that will predict the occurrence of an item based on the occurrences of other items in the transaction

Market-Basket transactions

<i>TID</i>	<i>Items</i>
1	Bread, Milk
2	Bread, Diaper, Beer, Eggs
3	Milk, Diaper, Beer, Coke
4	Bread, Milk, Diaper, Beer
5	Bread, Milk, Diaper, Coke

Example of Association Rules

$\{\text{Diaper}\} \rightarrow \{\text{Beer}\},$
 $\{\text{Milk, Bread}\} \rightarrow \{\text{Eggs, Coke}\},$
 $\{\text{Beer, Bread}\} \rightarrow \{\text{Milk}\},$

Implication means co-occurrence, not causality!

Other Examples



- Market basket
 - ▣ If A, then bought B
 - ▣ How to use in promotions?
- Click sequence on the web
 - ▣ If visited X, then visited Y
 - ▣ If visited Z, then checkout
- Amazon.com
 - ▣ Recommendations

Machine Learning

Supervised learning

- ☐ Regression
- ☐ Classification
- ☐ Logistic regression
- ☐ Random forests
- ☐ Neural networks

Unsupervised learning

- ☐ Data clustering
- ☐ Principal component analysis
- ☐ Independent component analysis
- ☐ Association rules

Collaborative Filtering

- Personalized preferences
 - ▣ Amazon.com
- Market basket
 - ▣ Shopping carts
 - No order of purchases
 - ▣ Association rules
- Web click sequences
 - ▣ Order of selection
 - ▣ Aggregation trees

Collaborative Filtering

- Ratings are available
 - ▣ What people buy together
 - ▣ How they value goods
- User-user
 - ▣ Score/difference between two users
 - Recommend the choices of the 'closest' friend
 - ▣ Not many common reviews
 - ▣ Normalization
 - ▣ User rates the same item differently

Collaborative Filtering

□ Item-item

▣ Distance between two items

- Based on evaluations of users of both items

▣ Challenge

- Two users like books
- Odds of two books are low

□ Resolution

▣ Split to 'categories'

▣ Category-category and item-item

Survival Analysis

- Breakdowns

 - ▣ Machines

 - ▣ Computers

- What is the probability

 - ▣ Breakdown a months from now

 - Historical observations

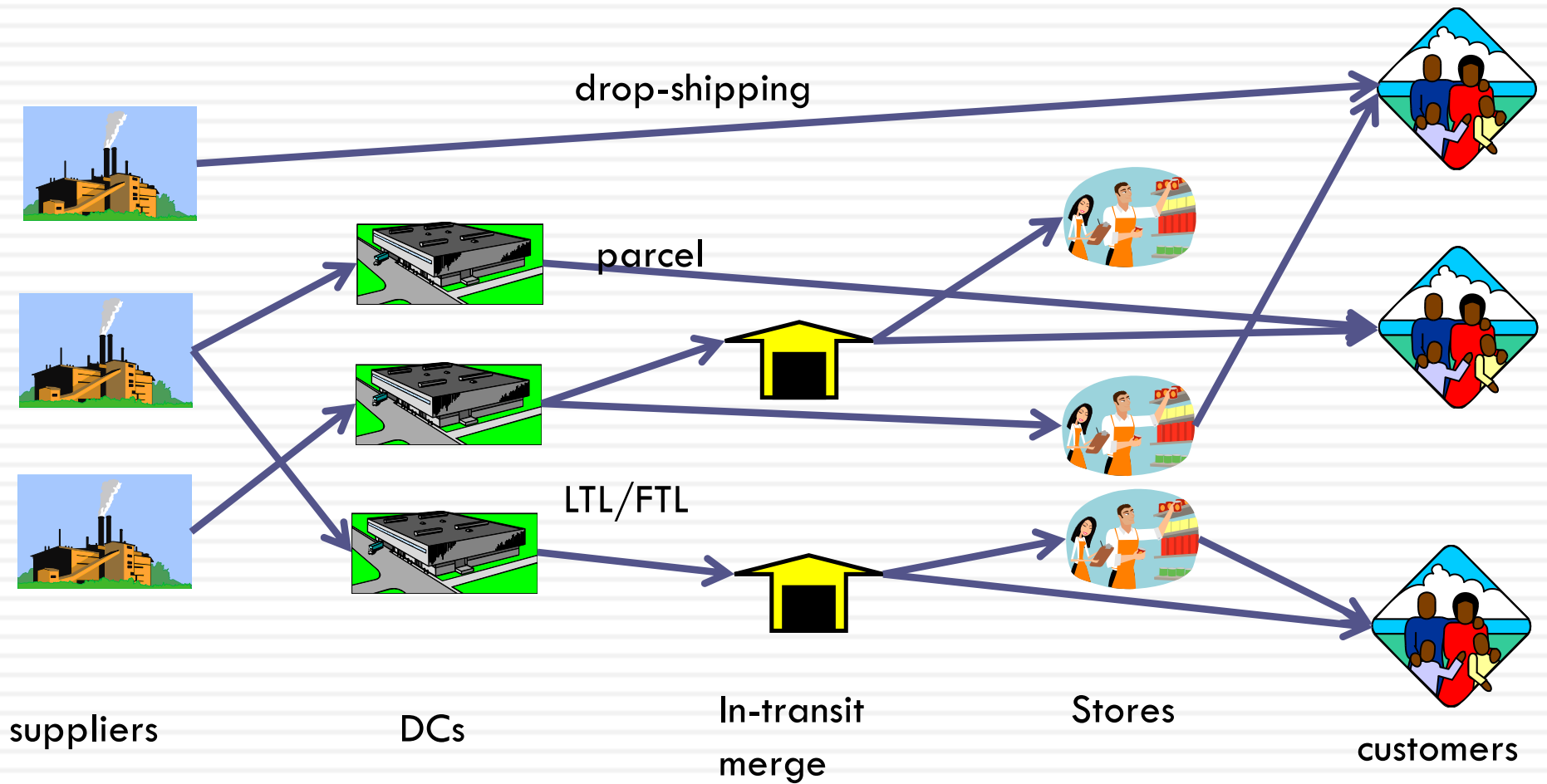
 - Breakdown 1 month ago

 - Breakdown 3 months ago

 - Distribution fitting

 - Probability[breakdown \geq 1 month]

SC Network Design





By Industry

Marketing



- Churn analysis
 - ▣ Attrition rate
 - ▣ Probability that a customer will default
 - ▣ Logistic regression
- Customer segmentation
 - ▣ By demographics
 - ▣ By spend
 - ▣ Clustering

Propensity



- What is the likelihood the customer will next buy item X
 - ▣ Historical purchases
 - ▣ Logistic regression
- Yield of campaigns
- Budget allocation

Web Analytics

- Study paths on site made by customers
 - ▣ Redesign flow on sites
 - ▣ Why customers do not buy
 - ▣ Aggregation trees
 - ▣ Markov chains
- Many steps to get to paths
 - ▣ Associating clicks to 'users'
- Digital ads placement
 - ▣ Where to place a banner ad
 - ▣ Which one
 - ▣ Optimization

Text Analytics

- Sentiment analysis
 - ▣ Tweet, blog, forum
 - ▣ Does it say something positive about a product
- List of good words
- List of bad words
- Count
 - ▣ If count of good – count of bad \leq number
 - Positive sentiment
- Many challenges

Text Analytics



- Presidential campaign
 - ▣ How many positive tweets about President Obama
- Stock predictions
 - ▣ How many tweets make positive comments about the IBM stock
- Similar documents
 - ▣ Group similar documents
 - ▣ Manually inspect the documents in one group
 - ▣ Lawyers

Social Networking Analysis



- Six (or less) degrees of separation
 - ▣ Facebook
- Recommend friends
- Placement of ads
- Improved churn analysis
 - ▣ Take friendship into account
- Challenge
 - ▣ Sheer size of data

Other industries



- Healthcare
 - ▣ Too many applications
- Telecommunication
 - ▣ Churn
 - ▣ Product bundling
 - ▣ Network design
- Finance
 - ▣ Fraud detection
 - ▣ Churn

Other industries



- Sport analytics
 - ▣ Performance measures
- Service sector
 - ▣ Sales force optimization
 - ▣ Match employees to projects
- Transportation
 - ▣ Too many
 - ▣ Airlines one of the earliest users of analytics