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Madhavan Mukund

https://www.cmi.ac.in/~madhavan

Data Mining and Machine Learning
January–May 2022

What is this course about?

Data Mining

- Identify “hidden” patterns in data
- Also data collection, cleaning, uniformization, storage
  - Won’t emphasize these aspects

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Machine Learning

- "Learn" mathematical models of processes from data
- Supervised learning — learn from experience
- Unsupervised learning — search for structure

Supervised Learning

Extrapolate from historical data

- Predict board exam scores from model exams
- Should this loan application be granted?
- Do these symptoms indicate CoViD-19?

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"Manually" labelled historical data is available

- Past exam scores: model exams and board exam
- Customer profiles: age, income, . . . , repayment/default status
- Patient health records, diagnosis

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Historical data $\rightarrow$ model to predict outcome

Supervised learning ...

What are we trying to predict?

Numerical values

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- House price (valuation for insurance)
- Net worth of a person (for loan eligibility)

Supervised learning . . .

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Categories

- Email: is this message junk?
- Insurance claim: pay out, or check for fraud?
- Credit card approval: reject, normal, premium

} Binary

– Multi category

Supervised learning . . .

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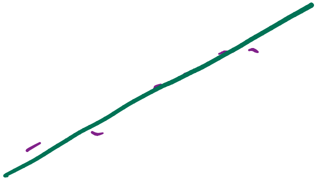
  - Different types of models
  - Parameters to be tuned
- Fit parameters based on input data
  - Different historical data produces different models
  - e.g., each user's junk mail filter fits their individual preferences



Supervised learning . . .

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- Build a mathematical model
  - Different types of models
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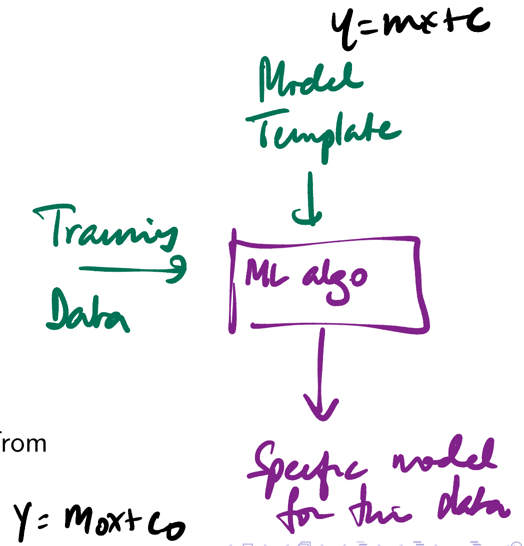
- Fit parameters based on input data
  - Different historical data produces different models
  - e.g., each user's junk mail filter fits their individual preferences
- Study different models, how they are built from historical data



Unsupervised learning

- Supervised learning builds models to reconstruct "known" patterns given by historical data
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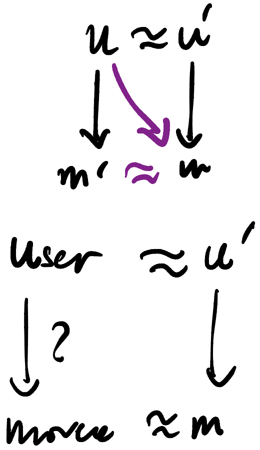
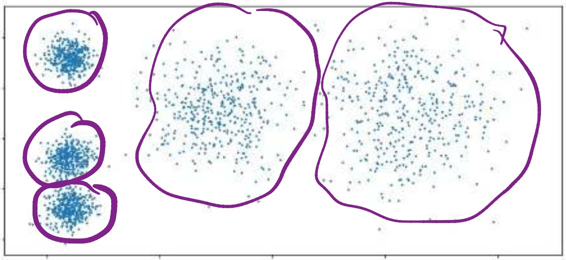
Customer segmentation

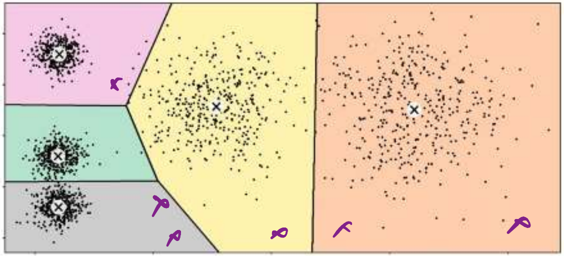
- Different types of newspaper readers
- Age vs product profile of retail shop customers
- Viewer recommendations on video platform



Clustering

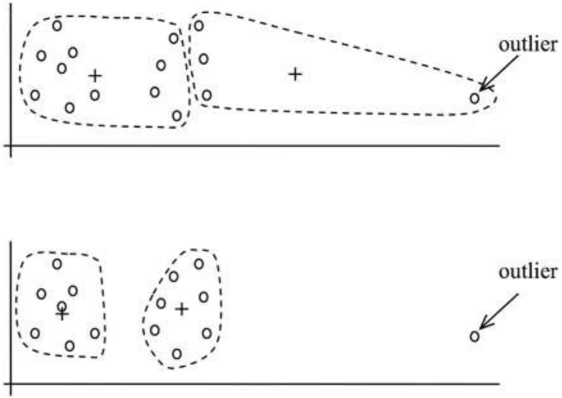
- Organize data into "similar" groups — clusters
- Define a similarity measure, or distance function
- Clusters are groups of data items that are "close together"



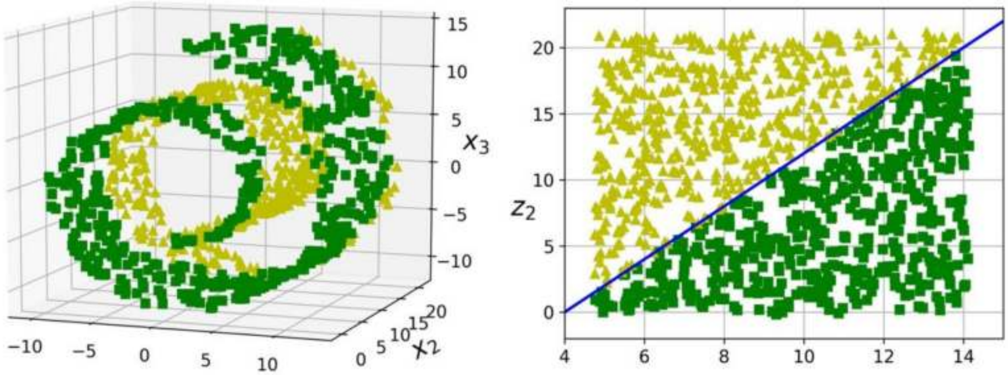


Outliers

- Outliers are anomalous values
  - Net worth of Bill Gates, Mukesh Ambani
- Outliers distort clustering and other analysis
- How can we identify outliers?

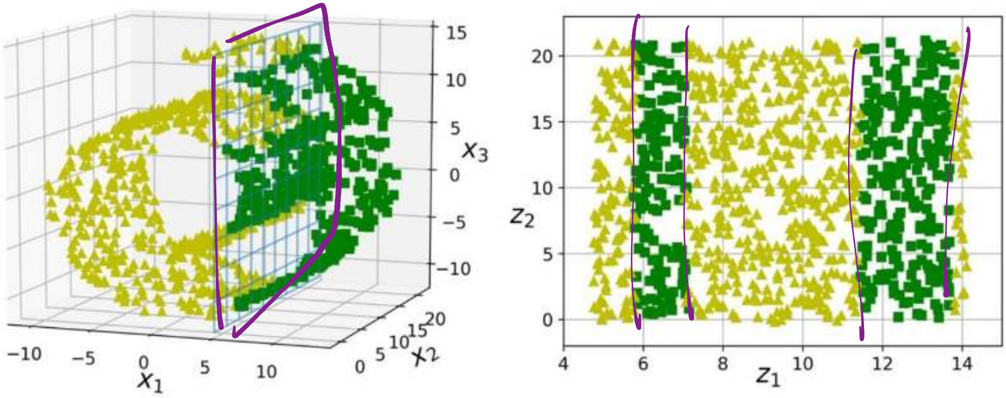


Dimensionality reduction



Preprocessing for supervised learning

Need not be a good idea — perils of working blind!



Summary

Machine Learning

- Supervised learning
  - Build predictive models from historical data
- Unsupervised learning
  - Search for structure
  - Clustering, outlier detection, dimensionality reduction

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If intelligence were a cake, unsupervised learning would be the cake, supervised learning would be the icing on the cake, . . .

Yann Le Cun, ACM Turing Award 2018

Market-Basket Analysis

- People who buy X also tend to buy Y
- Rearrange products on display based on customer patterns

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  - The diapers and beer legend
  - The true story, `http://www.dssresources.com/newsletters/66.php`

Market-Basket Analysis

- People who buy X also tend to buy Y
- Rearrange products on display based on customer patterns
  - The diapers and beer legend
  - The true story, `http://www.dssresources.com/newsletters/66.php`
- Applies in more abstract settings
  - Items are concepts, basket is a set of concepts in which a student does badly
    - Students with difficulties in concept A also tend to do misunderstand concept B
  - Items are words, transactions are documents

Formal setting

- Set of items $I = \{i_1, i_2, \ldots, i_N\}$ N large
- A transaction is a set $t \subseteq I$ of items
- Set of transactions $T = \{t_1, t_2, \ldots, t_M\}$ M large

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- Identify association rules $X \rightarrow Y$ — Sets of items "itemsets"
  - $X, Y \subseteq I$, $X \cap Y = \emptyset$
  - If $X \subseteq t_j$ then it is "likely" that $Y \subseteq t_j$

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  - If $X \subseteq t_j$ then it is likely that $Y \subseteq t_j$
- Two thresholds
  - How frequently does $X \subseteq t_j$ imply $Y \subseteq t_j$?
  - How significant is this pattern overall?

Setting thresholds

- For $Z \subseteq I$, $Z.\text{count} = |\{t_j \mid Z \subseteq t_j\}|$

$\leq M$

M total # transaction

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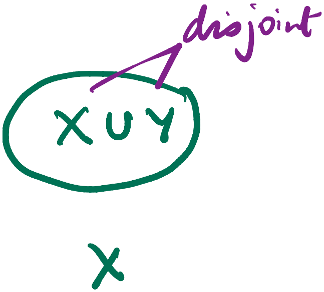
  - Fix a confidence level χ
  - Want $\dfrac{(X \cup Y).count}{X.count} \geq \chi$



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  - Fix a support level σ
  - Want $\dfrac{(X \cup Y).count}{M} \geq \sigma$

$X \rightarrow Y$

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- Given sets of items I and transactions T, with confidence χ and support σ, find all valid association rules $X \to Y$

→ Fixed set of Valid $X \to Y$

Frequent itemsets

- $X \rightarrow Y$ is interesting only if $(X \cup Y).\text{count} \geq \sigma \cdot M$
- First identify all frequent itemsets
  - $Z \subseteq I$ such that $Z.\text{count} \geq \sigma \cdot M$

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- Naïve strategy: maintain a counter for each Z
  - For each $t_j \in T$
    For each $Z \subseteq t_j$
    Increment the counter for Z
  - After scanning all transactions, keep Z with $Z.\text{count} \geq \sigma \cdot M$

$|t| \leq m$ 10–20

2^m subsets

— Decompose Z as X, Y

$X \rightarrow Y$ is valid (above confidence)

M

$M \cdot 2^m$

$Z \subseteq I$ $|I| = N$ 2^N potential subset $\sim 10^6$

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- Need to maintain $2^{|I|}$ counters
  - Infeasible amount of memory
  - Can we do better?

X Y
Rolls Royce leather seats

N – cars + accessories on sale
||
|I|

M = {t1, t2 . . . tM}

For each $t \in T$

For each ~~$Z \subseteq I$~~ $Z \subseteq t$

Check if Z.count should be incremented

For each $Z \subseteq I$

For each $t \in T$

Does t contain Z?