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- fundamental importance to AI and cognitive sciences
- applications: machine learning, knowledge acquisition, decision analysis,
- knowledge discovery, expert systems, pattern recognition, inductive reasoning
- idea of rough sets can not be reduced to the idea of fuzzy sets
- rough sets are fuzzy sets but the converse is not true

Rough Sets: Key Features

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- suitable for parallel processing

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- viewed as a specific implementation of Frege's idea of vagueness
- i.e. imprecision expressed by a boundary region of a set
- and not by a partial membership, like in fuzzy set theory

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- Let X be subset of U
- characterize the set X with respect to R

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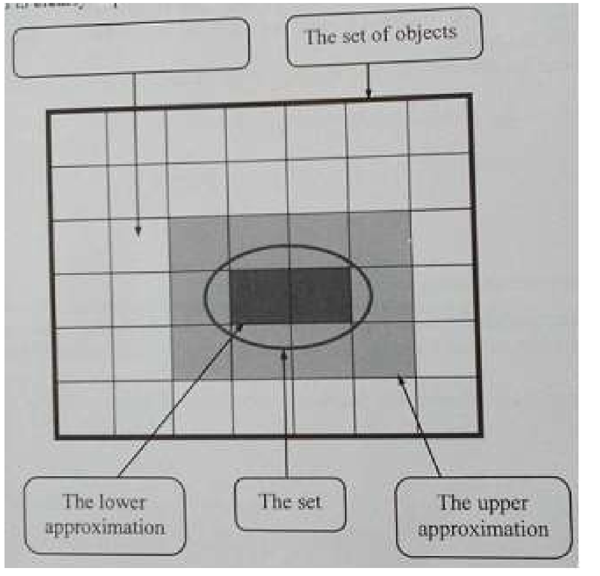
- boundary region of a set X with respect to R is the set of all objects,
- which can be classified neither as X nor as not-X with respect to R

Rough Sets



Rough Set: Topological View SRC:Pawlak's notes

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- set X is crisp - exact with respect to R
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- approximations and boundary region can be defined more precisely

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- R - boundary region of X $RN_R(X) = R^*(X) - R_*(x)$

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- $\mu_X^R : U \rightarrow < 0, 1 > \mu_X^R(x) = \frac{|X \cap R(x)|}{|R(x)|}$
- $|X|$ denotes the cardinality of X

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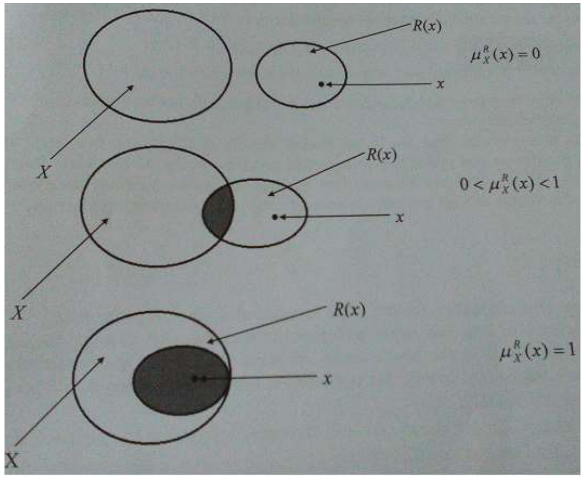

rough membership function SRC:Pawlak's notes

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  4. $\mu_{U-X}^R(x) = 1 - \mu_X^R(x)$ for any $x \in U$
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- rough membership is a generalization of fuzzy membership
- rough membership function has probabilistic flavour in contrast to fuzzy membership function

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- patients suffering from a certain disease,
- displaying the same symptoms are indiscernible and
- may be thought of as representing a granule (disease unit) of medical knowledge

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- rough set in contrast to a crisp set, has a non-empty boundary region

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- patient as object
- attributes headache, muscle-pain, temperature, flu - yes or no

Rough Sets: Example

Patient	Headache	Muscle-pain	Temperature	Flu

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p2	yes	no	high	yes
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p5	yes	no	high	no

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- i.e. flu can not be characterized in terms of these three attributes
- $p2$ and $p5$ are the boundary-line cases which can not be classified properly in the view of available knowledge

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- $p2$ and $p5$ are the boundary-line cases which can not be classified properly in the view of available knowledge
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Rough Sets

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- boundary region of the concept "not flu" is the set $\{p2, p5\}$
- indiscernibility relation is intended to express the fact that
- due to the lack of knowledge; unable to discern some objects employing the available information

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- reduction of attributes
- dropping some attributes getting the data set which is equivalent to the original one in regard to approximations and dependencies; using smaller set of attributes