Competence Guided Casebase Maintenance for Compositional Adaptation Applications

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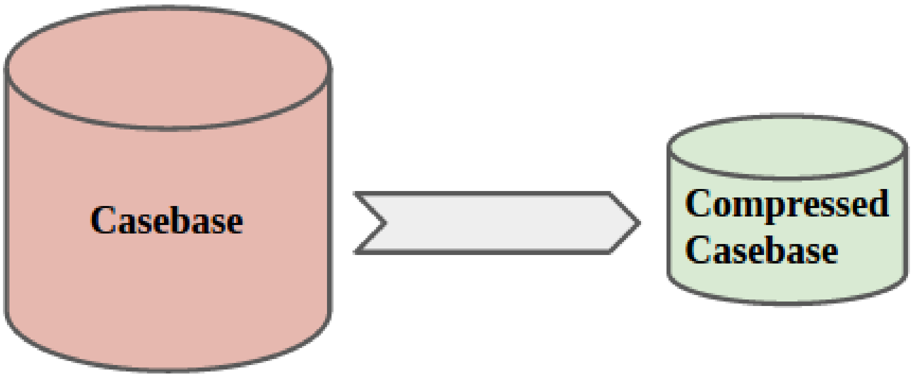
Casebase Maintenance

Goal : Maintain a compressed casebase that can solve new problems effectively



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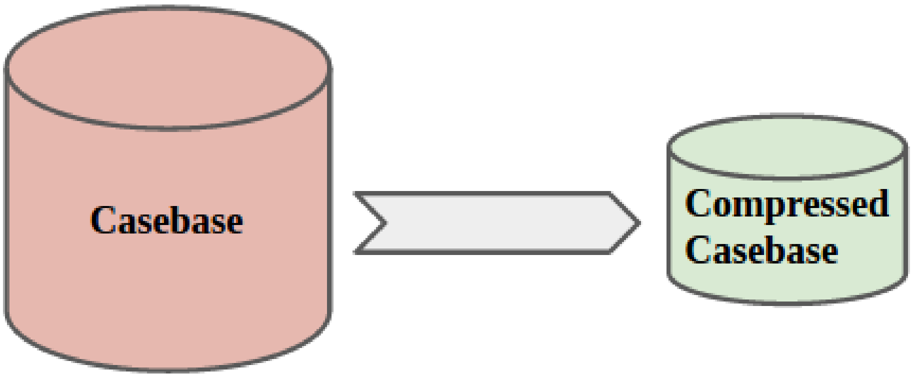

Competence Guided Casebase Maintenance

- Competence of a CBR system is the range of target problems that the given system can solve
- Competence guided casebase maintenance system retains a case in the casebase if it is useful to solve many problems
- Thus it ensures that the casebase is highly competent in the global sense

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However, Footprint based approach covers only the situation where a **single case is adapted to solve a problem**

*Smyth et al. Footprint-based Retrieval. *In Case Based Reasoning Research and Development* 1999

Motivation

Competence Guided Casebase Maintenance

Single Case Adaptation

&

Compositional Adaptation

Footprint-based Approach

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Uses **Case Competence Model**

Footprint-based Approach

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- Solves$(c, t) \Leftrightarrow c$ can be retrieved and adapted for t

Footprint-based Approach

Uses **Case Competence Model**

- $\text{Solves}(c, t) \Leftrightarrow c$ can be retrieved and adapted for t
- $\text{Coverage}(c) = \{c' \in \mathbb{C} : \text{Solves}(c, c')\}$
- $\text{Reachability}(c) = \{c' \in \mathbb{C} : \text{Solves}(c', c)\}$

Footprint-based Approach

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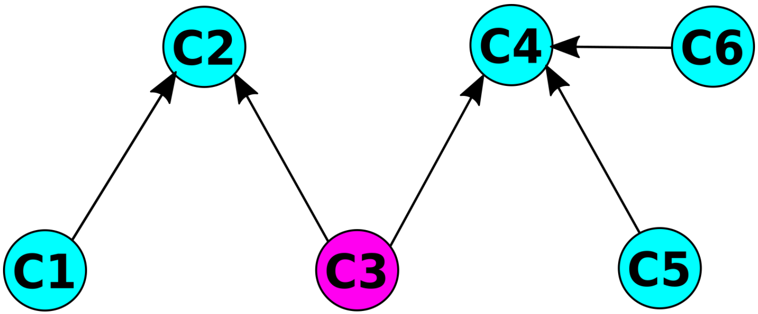
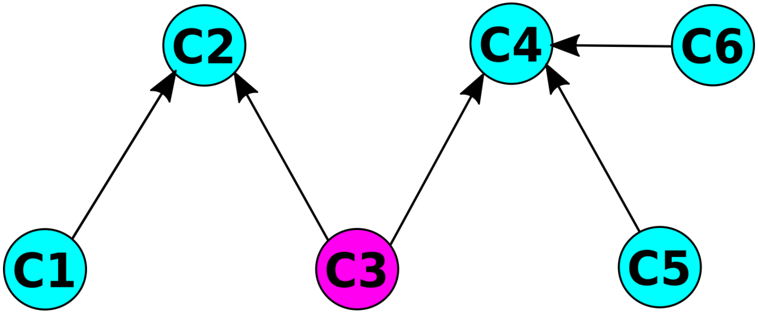


Coverage(c3) = {c2,c4}
Reachability(c2) = {c1,c3}
Reachability(c4) = {c3,c5,c6}

Footprint-based Approach

Uses **Case Competence Model**

$$\text{RelativeCoverage}(a) = \sum_{b \in \text{Coverage}(a)} \frac{1}{|\text{Reachability}(b)|}$$



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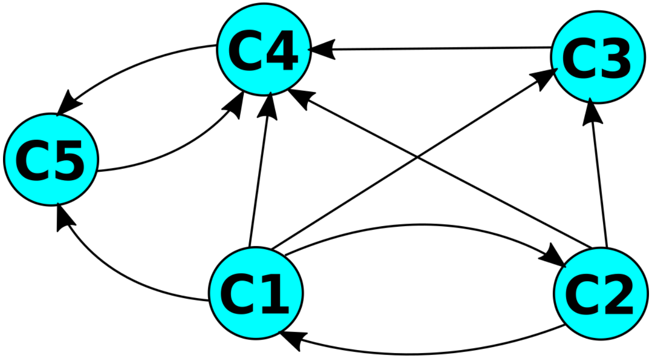
$$\text{RelativeCoverage(c3)} = \frac{1}{2} + \frac{1}{3}$$

Footprint-based Approach

Estimation of compact competent subset called ***footprint set***



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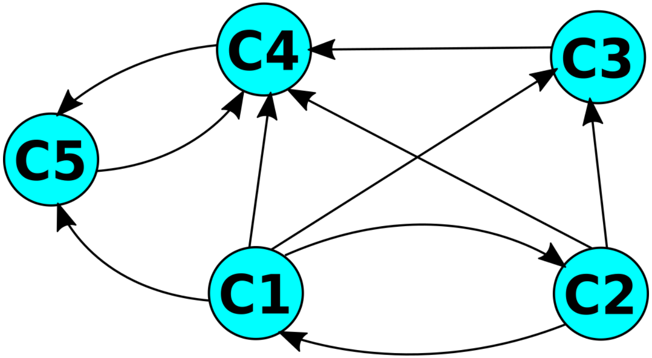

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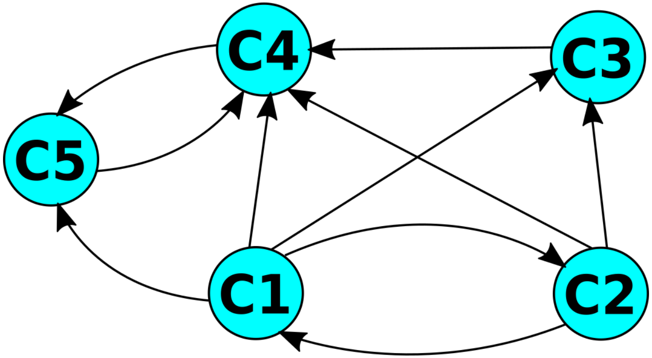

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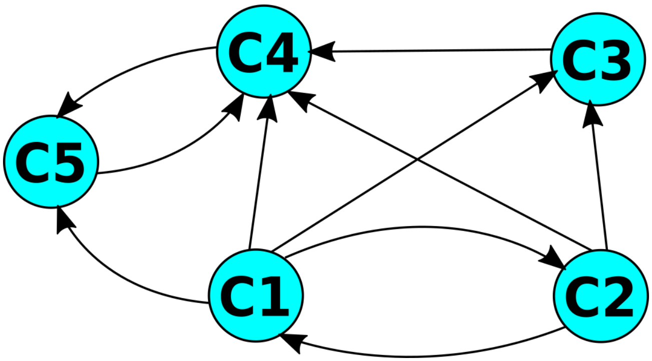

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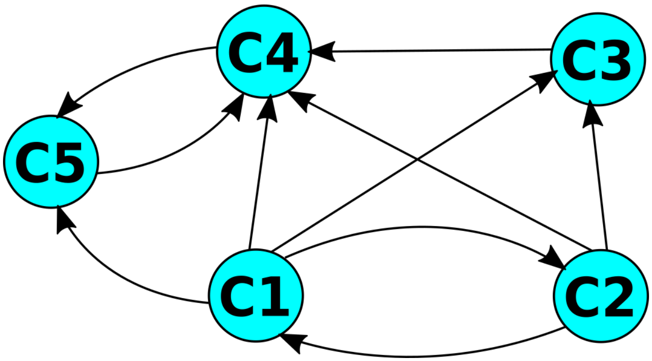

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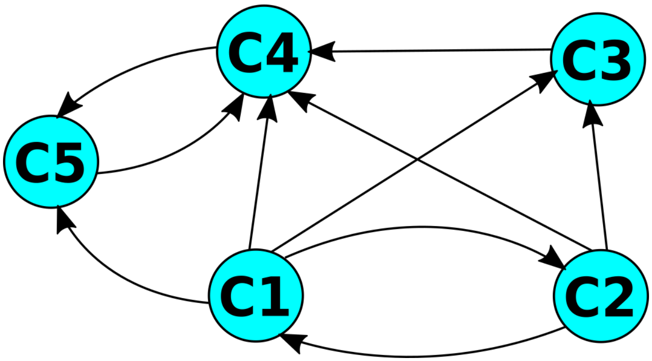

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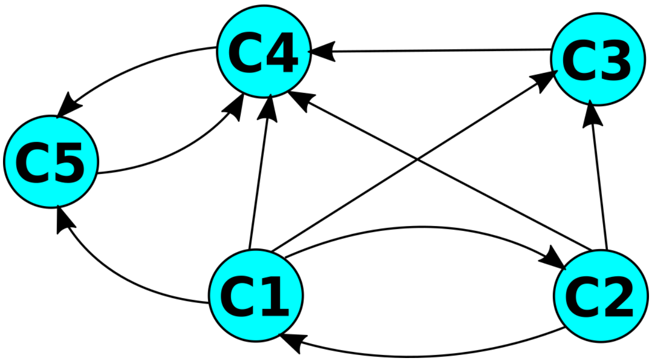

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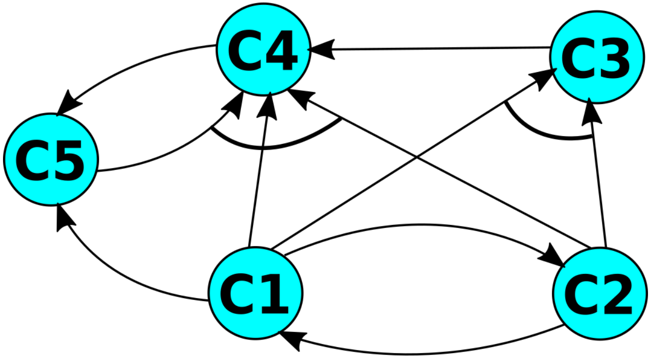
Footprint-based Approach

In **Compositional Adaptation** applications



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Footprint-based Approach - Limitations

- Covers only single case adaptation
- Transitive coverage is not considered

Proposed Case Competence Model

Proposed a case competence model which covers compositional adaptation process (of which the single case adaptation is a special case)

Proposed Case Competence Model

- We proposed a measure called retention score which quantifies the retention quality of a case in the casebase

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- **CoveredCases(c)** include all cases that c solves either on its on, or in conjuction with other cases
  - Eg: CoveredCases(c1) = {c3, c4}

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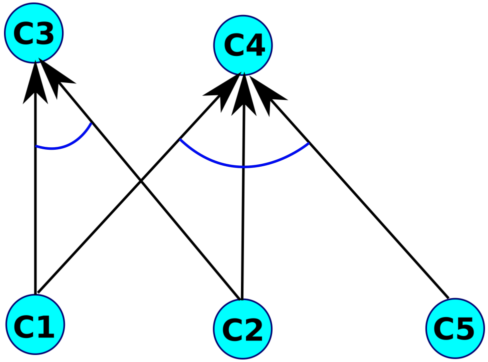
  - Eg: SupportCases(c1,c3) = {c2}



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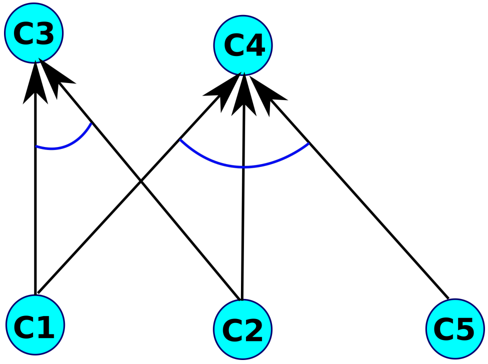

Proposed Case Competence Model

RetentionScore Intuition

- A case has high retention score if it has
  - many covered cases
  - less number of support cases

Proposed Case Competence Model

RetentionScore Intuition (recursive formulation)

- A case has high retention score if it has
  - many covered cases with high retention score
  - less number of support cases with low retention score

Proposed Case Competence Model

For first iteration

$$\text{RetentionScore}_0(\text{c}) = \sum_{\text{c}_\text{i} \in \text{CoveredCases(c)}} \frac{1/(1 + \text{No of alternate solutions that do not contain c})}{1 + |\text{SupportCases(c,c}_\text{i}\text{)}|}$$

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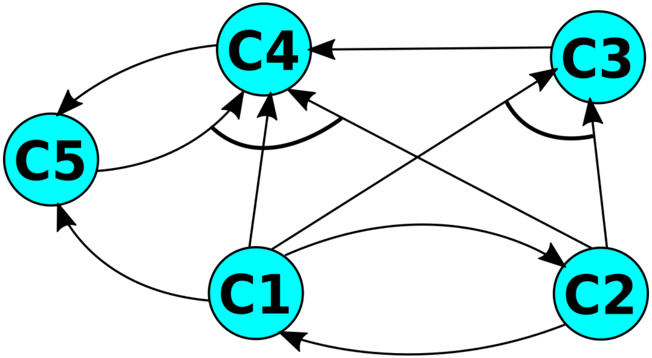

For estimating $\text{RetentionScore}_0(c1)$

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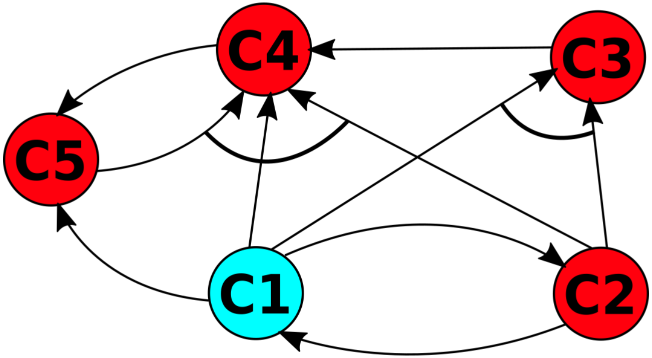

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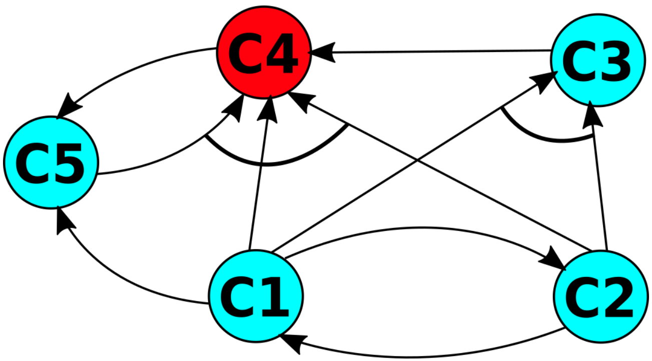

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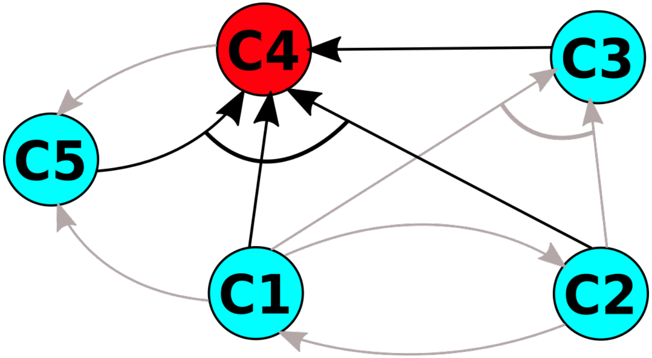

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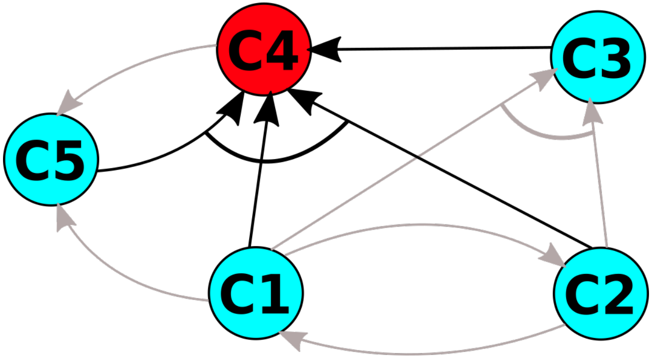

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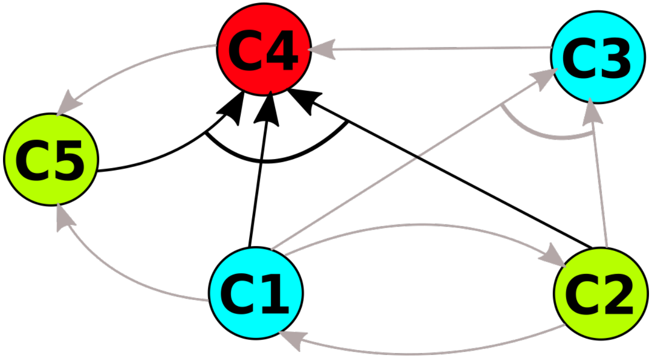

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$$\text{RetentionScore}_{\text{k}+1}(\text{c}) = \sum_{\text{c}_\text{i} \in \text{CoveredCases}(\text{c})} \frac{\text{RetentionScore}_k(\text{c}_i)}{\sum_{\text{c}_\text{j} \in \text{SupportCases}(\text{c},\text{c}_\text{i})} (\text{RetentionScore}_k(\text{c}_\text{j})) + 1}$$

Footprint$_{CA}$ Algorithm

- Modified Smyth's footprint algorithm* to obtain *footprint$_{CA}$ set*
- Modified algorithm uses retention score instead of relative coverage

*Smyth et al. Footprint-based Retrieval. *In Case Based Reasoning Research and Development* 1999

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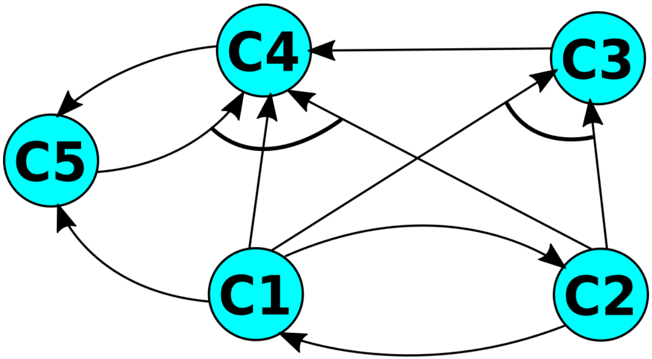

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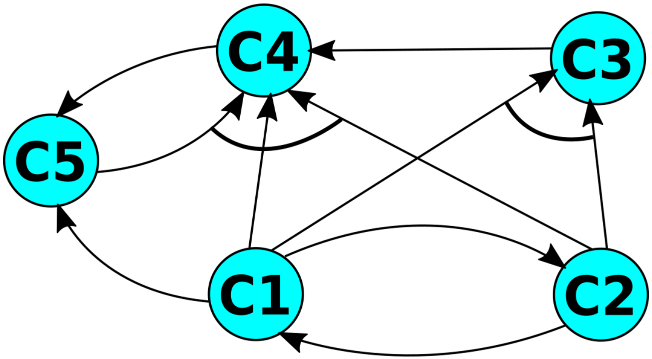

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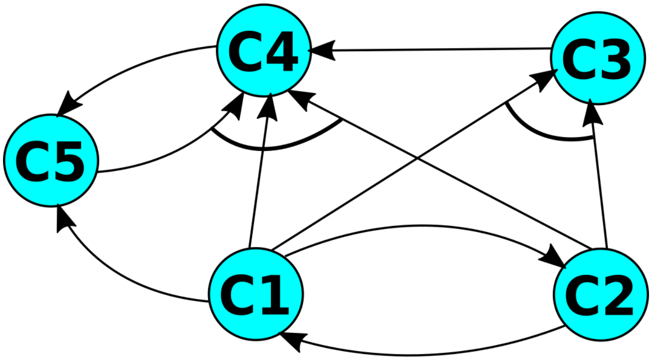

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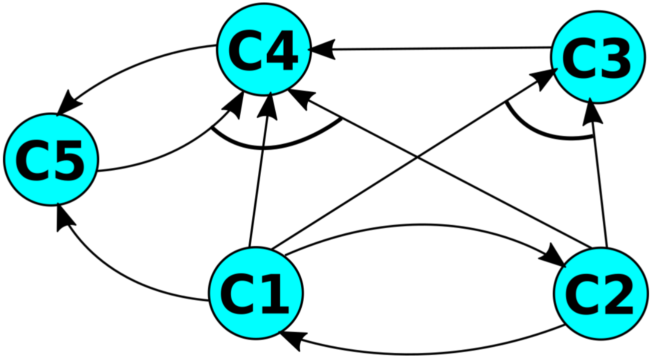

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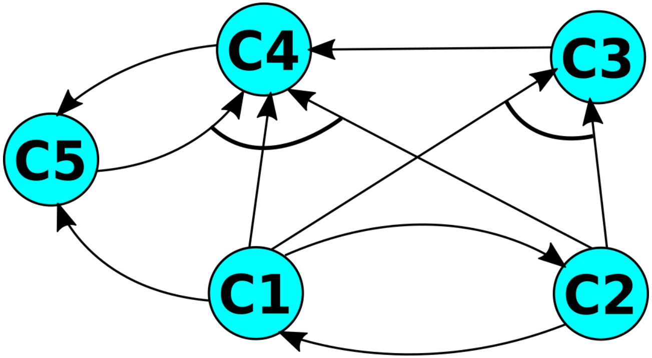

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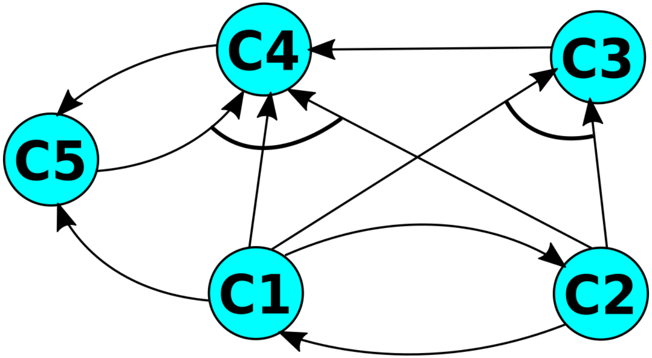

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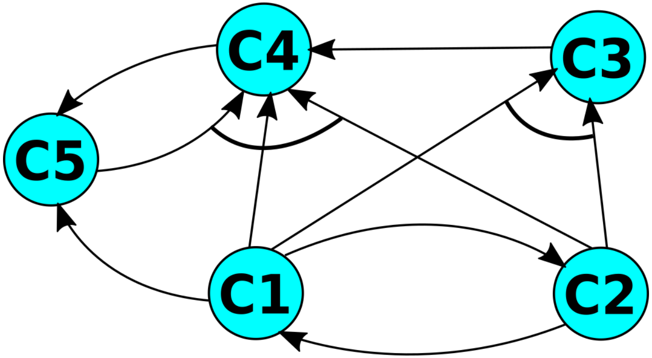

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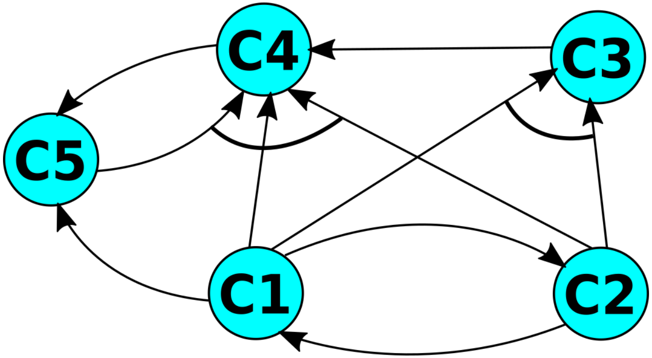

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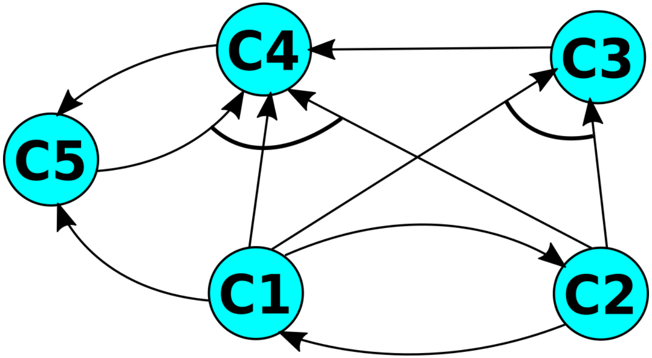

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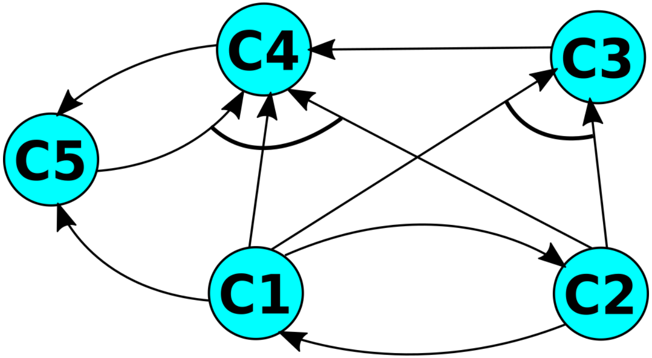

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Experiments

Synthetic Datasets

1. $y = x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9 + x_{10}$ +noise
2. $y = x_1^4 + x_2^3 + x_3^2 + x_4 + \cos^2(x_5)$ +noise
3. $y = \sin(x_1 x_2) + \sqrt{x_3 x_4} + \cos^2(x_5) + x_6 x_7 + x_8 + x_9 + x_{10}$ +noise

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- Each data instance is a case
- Each case is assumed to be solved by the combined solution of its K-nearest cases

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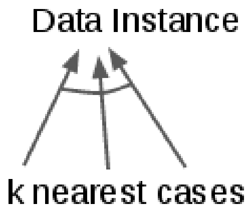
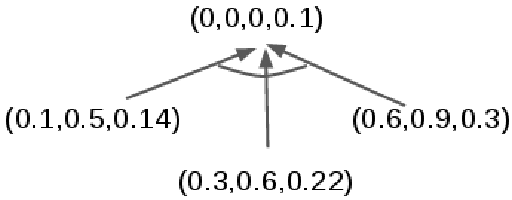
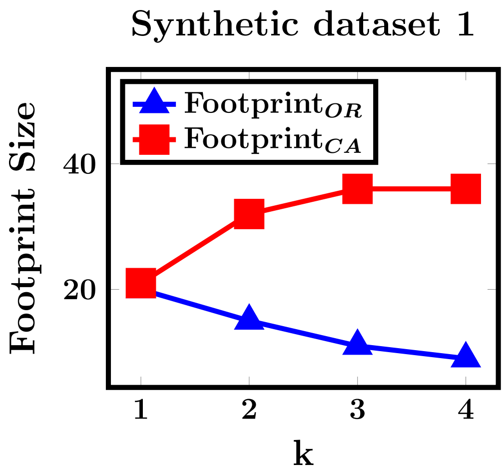




Evaluation - Footprint Size Analysis



Evaluation - Casebase Coverage Analysis

$$\text{Casebase Coverage}(fp) = \frac{|\text{Cases that are solved by } fp|}{\text{Casebase Size}}$$

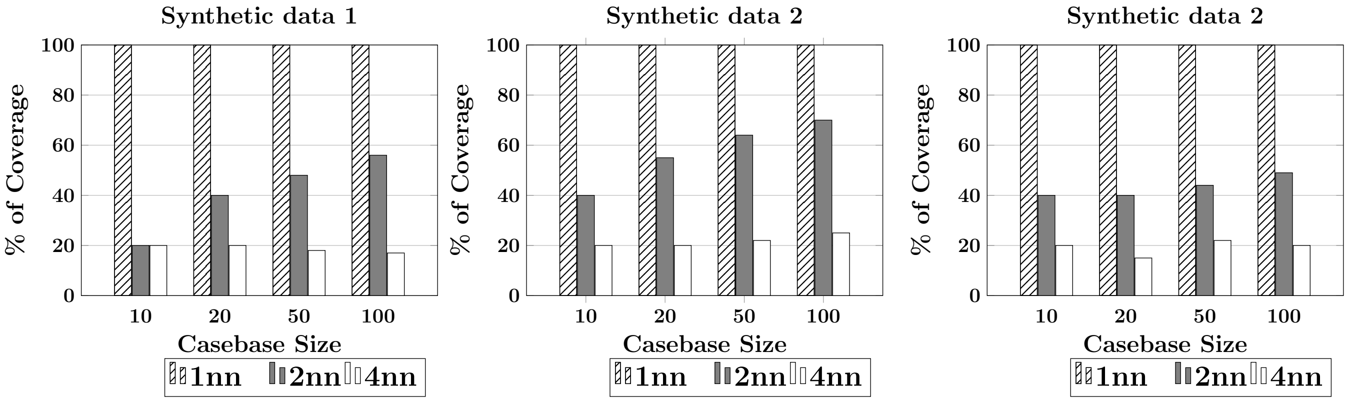


Figure: Casebase Coverage by Footprint_{OR}

Evaluation - Sanity Check

$$\text{Sanity rate} = \frac{|\text{footprint cases} \cap \text{kernel cases}|}{|\text{kernel cases}|} \times 100$$

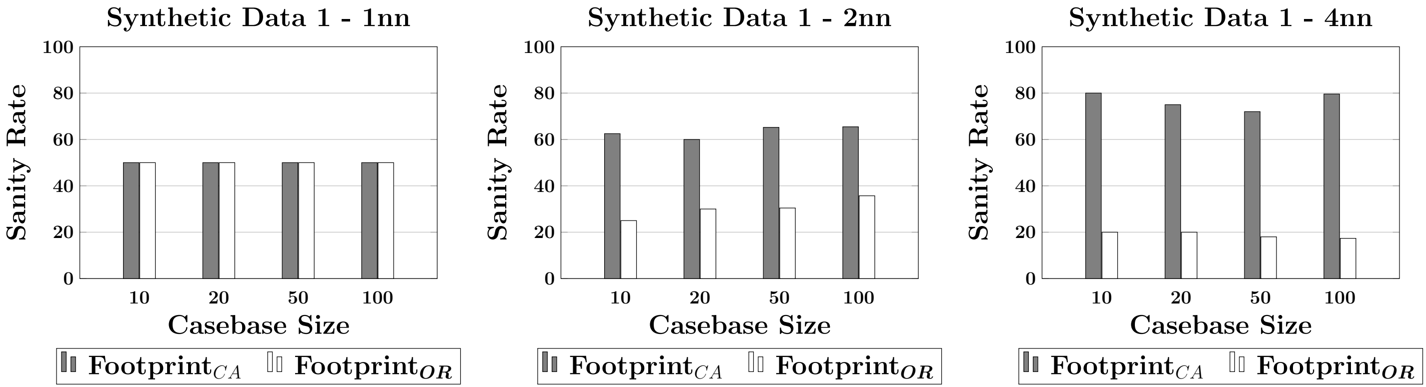
where,

- kernel cases* are obtained by repeatedly removing cases that do not solve any other cases until there are no such cases
- kernel cases cover the entire casebase

*Masse et al. How is meaning grounded in dictionary definitions? *Textgraph* 2008

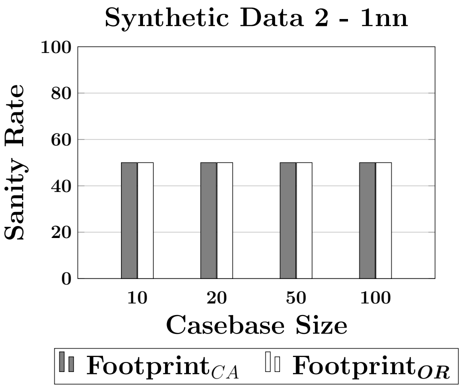
Evaluation - Sanity Check

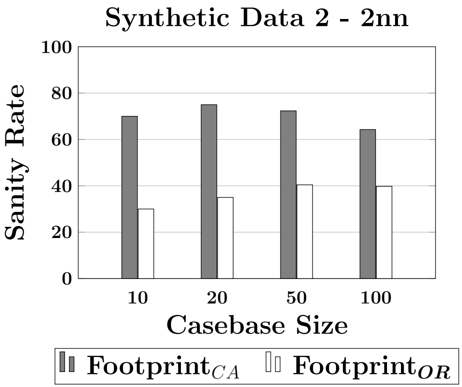
Synthetic Data 1

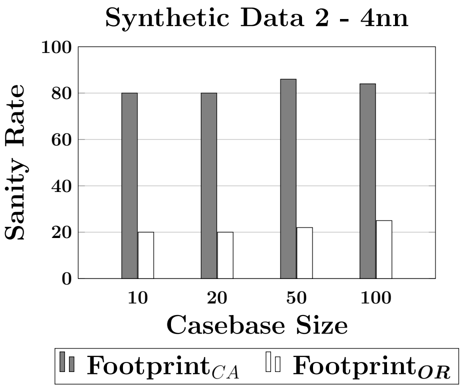


Evaluation - Sanity Check

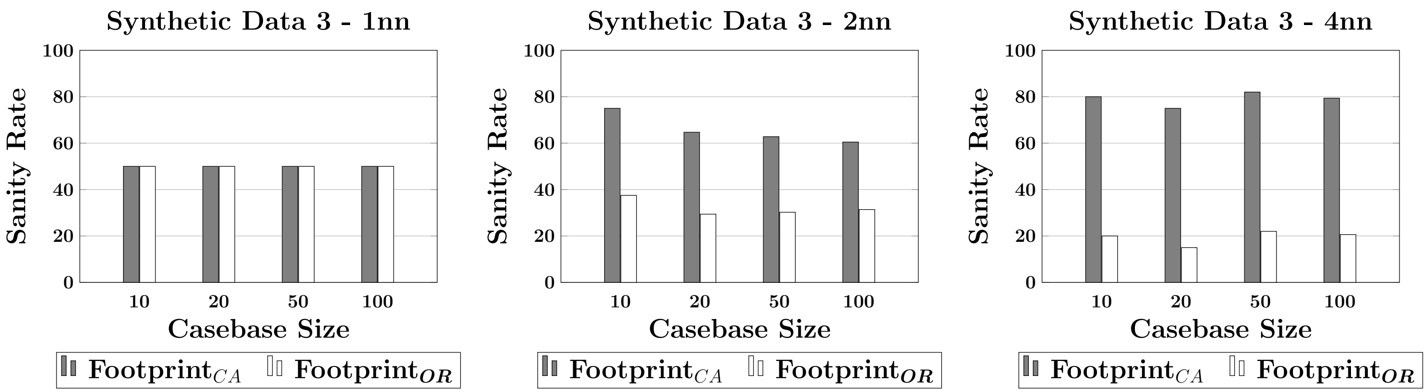
Synthetic Data 2







Synthetic Data 3



Footprint$_{CA}$ in Tutoring Application

- Encyclopedic resources like Wikipedia have less pedagogic value
- Concepts in Wikipedia (articles) are not arranged in a learning order
- An ideal textbook explains a concept before referring it which results in a sequential order for learning
- Sequencing concepts in Wikipedia may help online learners to fulfill their learning goal

For Wikipedia

Atom

From Wikipedia, the free encyclopedia
(Redirected from Atoms)

For other uses, see Atom (disambiguation).

An **atom** is the smallest constituent unit of ordinary matter that has the properties of a chemical element.[1] Every solid, liquid, gas, and plasma is composed of neutral or ionized atoms. Atoms are very small; typical sizes are around 100 pm (a ten-billionth of a meter, in the short scale).[2] However, atoms do not have well-defined boundaries, and there are different ways to define their size that give different but close values.

Atoms are small enough that attempting to predict their behavior using classical physics - as if they were billiard balls, for example - gives noticeably incorrect predictions due to quantum effects. Through the development of physics, atomic models have incorporated quantum principles to better explain and predict the behavior.

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Cases - Wikipedia articles

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Cases - Wikipedia articles

Problem Solution Pairs - (Article title A, Definition of article A)

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Cases - Wikipedia articles

Problem Solution Pairs - (Article title A, Definition of article A)

We assume the first sentence of each article as its definition

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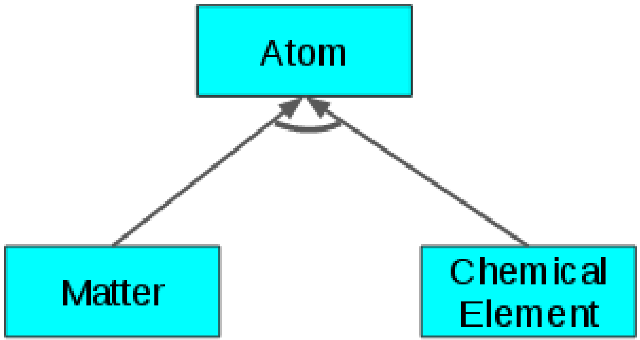
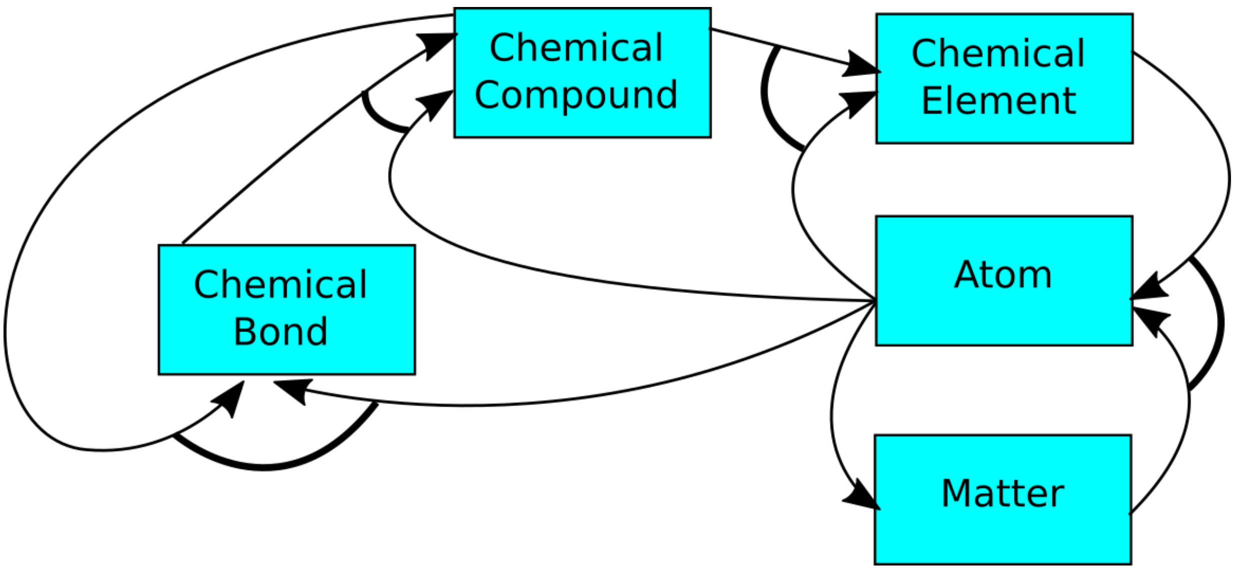


An example of casebase network from Wikipedia



Footprint$_{CA}$ in Tutoring Application

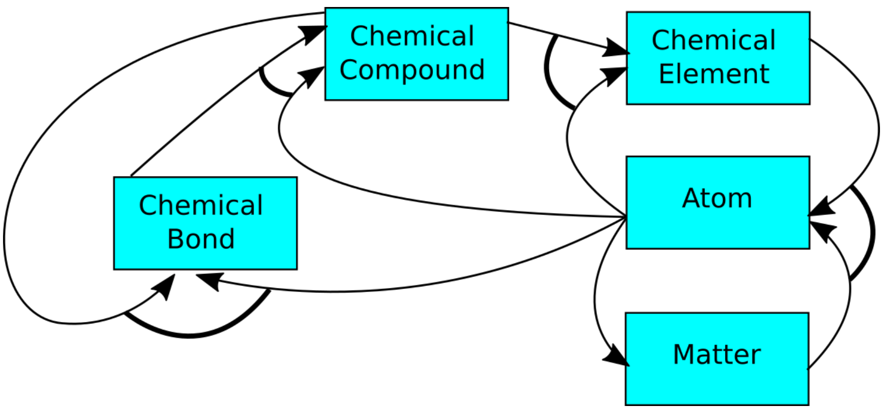
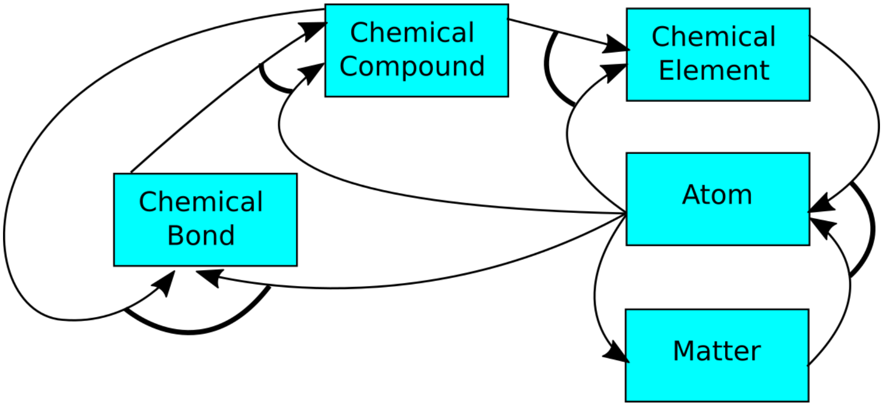


Figure: Wikipedia Concept Network Example

Concepts	RetentionScore
Atom	2.0
Matter	1.19
Chemical Element	1.18
Chemical Compound	1.12
Chemical Bond	1

Footprint$_{CA}$ in Tutoring Application

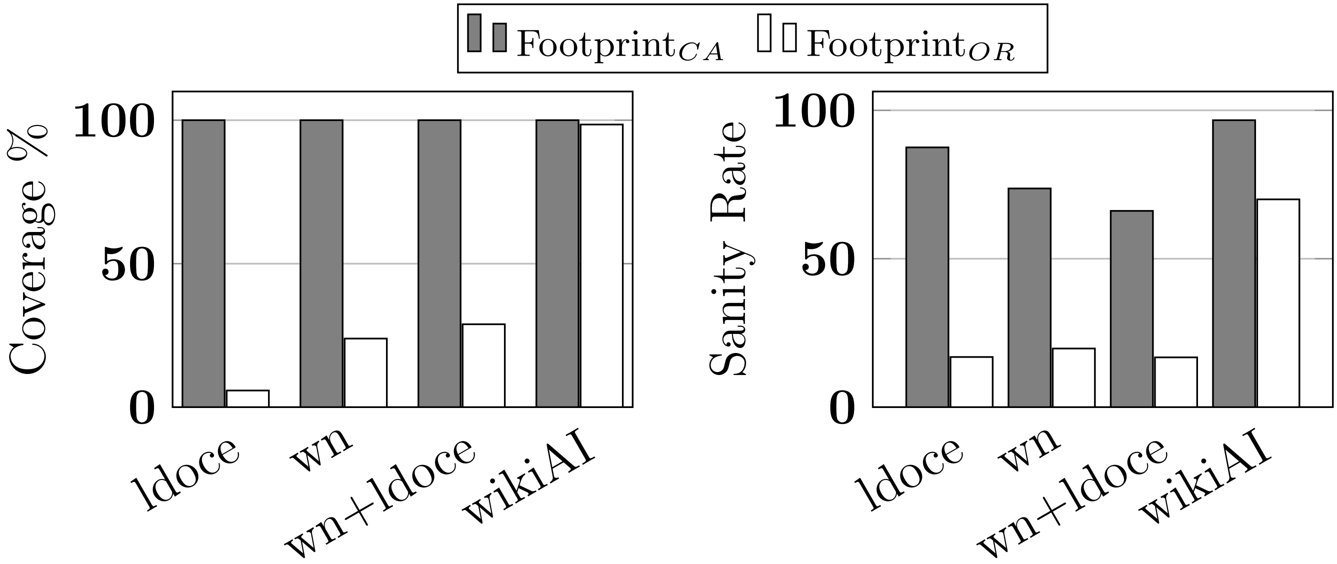


Concepts	RetentionScore
Atom	2.0
Matter	1.19
Chemical Element	1.18
Chemical Compound	1.12
Chemical Bond	1

Figure: Wikipedia Concept Network Example

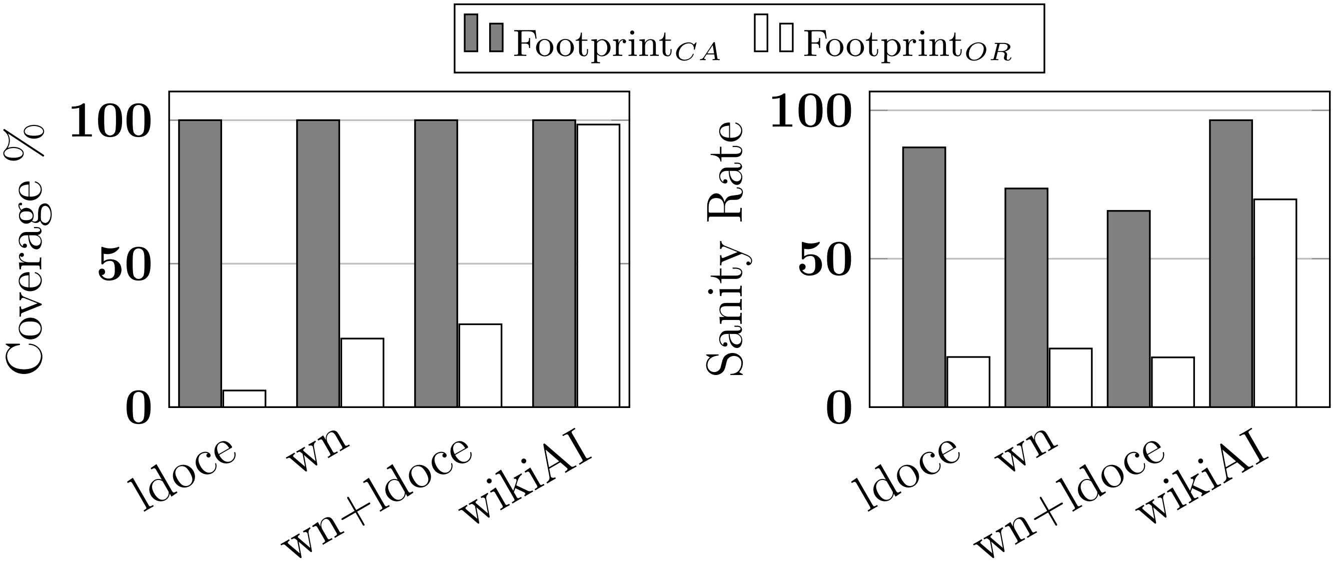
Footprint$_{CA}$ set - {Atom, Chemical Element, Chemical Compound}

Evaluation on Dictionary and Wikipedia Datasets



ldoce - Longman dictionary, wn - WordNet, wikiAI - Wikipedia(A. I. Category)

Evaluation on Dictionary and Wikipedia Datasets



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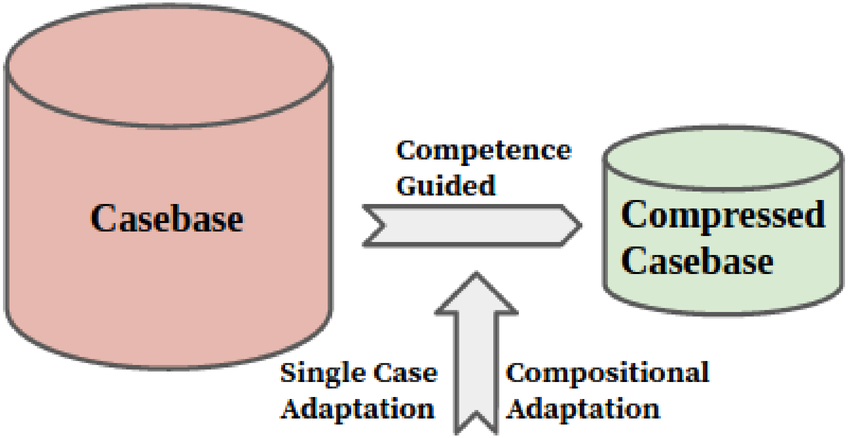
- Sanity rate $= \dfrac{|\text{footprint cases} \cap \text{kernel cases}|}{|\text{kernel cases}|} \times 100$

Conclusion



- Retention Score orders cases based on retention quality
- Modified footprint algorithm estimates competent compressed casebase using retention score ordering
- Experimented the idea in synthetic datasets and tutoring application

References

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Thank You!!

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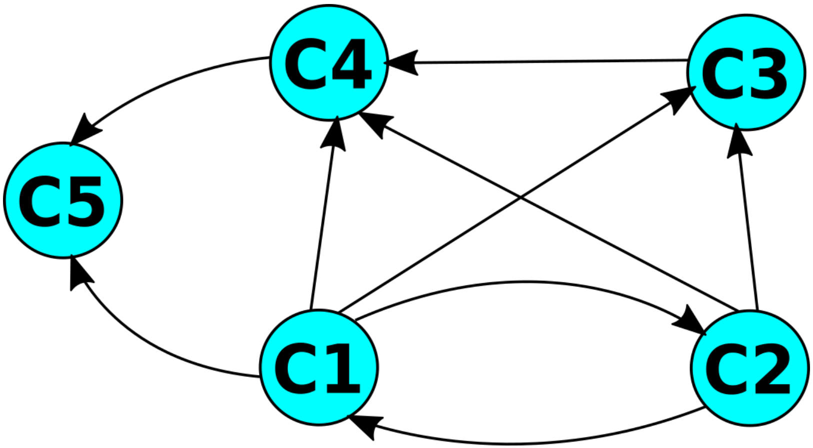
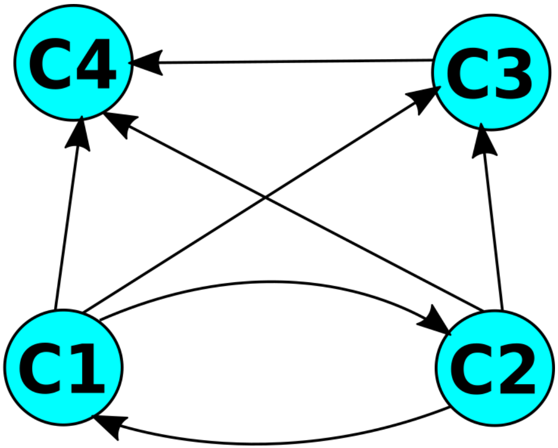
Questions??

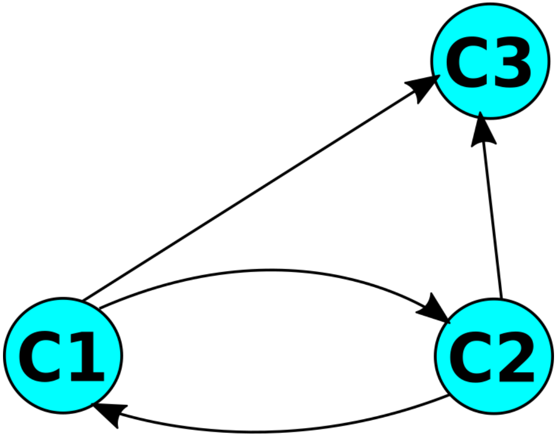
Estimating Kernel Cases



Estimating Kernel Cases



Estimating Kernel Cases



Estimating Kernel Cases