

Compression versus Accuracy: A Hierarchy of Lifted Models

Jan Speller¹, Malte Luttermann^{2,3}, Marcel Gehrke³ and Tanya Braun¹,

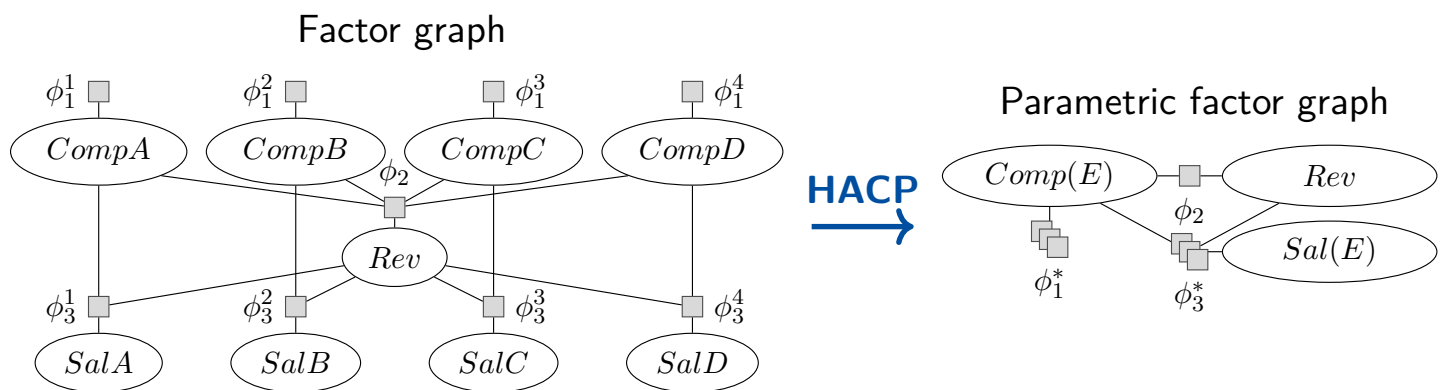
¹Data Science Group, University of Münster, Germany

²German Research Center for Artificial Intelligence (DFKI), Lübeck, Germany

³Institute for Humanities-Centered Artificial Intelligence, University of Hamburg, Germany

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Compression versus Accuracy: A Hierarchy of Lifted Models



- ▶ Introduction of **1DEED** as a practical tool for ϵ -equivalence ($\phi_3^1 =_\epsilon \phi_3^2 \rightarrow \phi_3^*$)
 - ▶ Consistency of ϵ -equivalent groupings
 - ▶ Hierarchical trade-off between compression ($\epsilon \nearrow$) and accuracy ($\epsilon \searrow$)
- ▶ Enables preanalysis of guaranteed theoretical error bounds ($p_{\max} \Delta$)
- ▶ Novel framework for hierarchical lifting

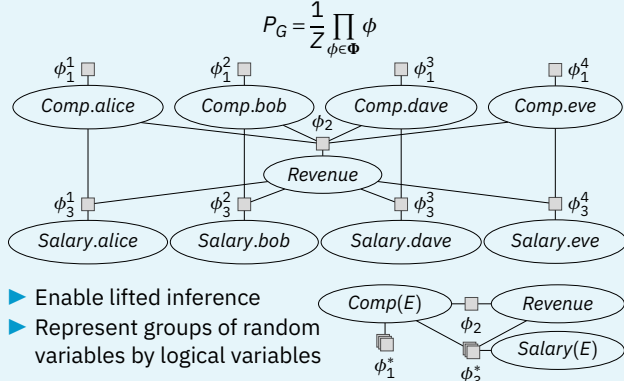


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1. Motivation and Problem Setup

- Factor graphs compactly encode a probability distribution
- Semantics of a factor graph G over a set of factors Φ :



- Enable lifted inference
- Represent groups of random variables by logical variables

Problem Setup

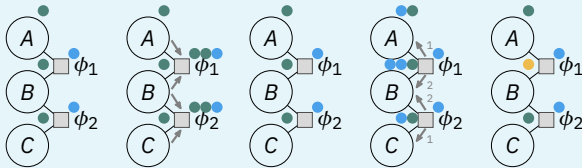
Input: A factor graph G and level(s) of compression

Output: A hierarchy of parametric factor graph(s) entailing approximately equivalent semantics to G

- With hierarchical grouping structure for different levels of compression
- With hierarchical order of error bounds
- With theoretical guarantees for query results

2. Previous Work: ε -Advanced Colour Passing (ε -ACP)

- Factors $\phi_1, \phi_2 \in \mathbb{R}_{\geq 0}^n$ are ε -equivalent $\Leftrightarrow$ for all potentials $\phi_1(k), \phi_2(k) \in \mathbb{R}_{> 0}$ in their potential tables it holds that $\phi_1(k) \in [\phi_2(k) \cdot (1 - \varepsilon), \phi_2(k) \cdot (1 + \varepsilon)]$ and $\phi_2(k) \in [\phi_1(k) \cdot (1 - \varepsilon), \phi_1(k) \cdot (1 + \varepsilon)]$
- Assign colours to random variables according to their ranges and evidence
- Assign colours to factors according to their potential tables
- Pass colours to detect ε -equivalent symmetries in the graph



- Limitations: No guaranteed consistency of ε -equivalent groupings for different ε values
 - No informed choice of ε
- Solution: Hierarchical groupings for increasing ε

3. One-dimensional- ε -equivalence-distance (1DEED)

One-dimensional ε -equivalence distance (1DEED) is defined as:

$$d_{\infty}: \mathbb{R}_{> 0}^n \times \mathbb{R}_{> 0}^n \rightarrow \mathbb{R}_{\geq 0} \quad d_{\infty}(\phi_1, \phi_2) := \max_{k=1, \dots, n} \left\{ \frac{|\phi_1(k) - \phi_2(k)|}{\min\{|\phi_1(k)|, |\phi_2(k)|\}} \right\}$$

Properties:

- d_{∞} is non-negative and symmetric
- $d_{\infty}(\phi_1, \phi_2) = 0 \Leftrightarrow |\phi_1(k) - \phi_2(k)| = 0$ for $k = 1, \dots, n \Leftrightarrow \phi_1 = \phi_2$
- Triangle inequality does *not* hold in general
- Theorem:** Two vectors $\phi_1, \phi_2 \in \mathbb{R}_{> 0}^n$ are ε -equivalent if and only if $d_{\infty}(\phi_1, \phi_2) \leq \varepsilon$ holds.

4. Hierarchical Advanced Colour Passing (HACP)

Algorithm 1: Determine ordered ε -vector and nested list of factors

- Compute pairwise 1DEED for factors (upper triangular matrix)
- Run agglomerative clustering algorithm based on 1DEED with complete linkage within maximal deviation

- Choose level(s) of compression within ε -vector ($\varepsilon_i < \varepsilon_{i+1}$)

HACP: Use ε -ACP (generalisation of ACP) proceeding as follows:

- Pass groups of pairwise ε -equivalent factors based on nested list
 - Assign colours to factors according to the provided groups and run the colour passing procedure from ε -ACP
- Ensures identical potentials in resulting groups of factors
 - Goal: Apply smallest possible change to potential tables
 - Minimise sum of squared deviations between potentials:

$$\mathbf{G} = \{\phi_1, \dots, \phi_m\} \xrightarrow{\text{replaced by}} \mathbf{G}^* = \{\phi_1^*, \dots, \phi_m^*\}$$

$$\text{pairwise } \varepsilon\text{-equivalent} \quad \phi^*(r_1, \dots, r_n) = \frac{1}{m} \sum_{i=1}^m \phi_i(r_1, \dots, r_n)$$

- Corollary:** If $\varepsilon = 0$, HACP is equivalent to ACP and ε -ACP.
- HACP preserves structural consistency and comparability

5. Compression versus Accuracy

Guaranteed bounds of change in query results

- Theorem:** The maximal absolute deviation between any initial probability $p = P_M(r | \mathbf{e})$ of r given $\mathbf{e}$ in model M and the probability $p' = P_{M'}(r | \mathbf{e})$ in the modified model M' resulting from running HACP can be bounded by

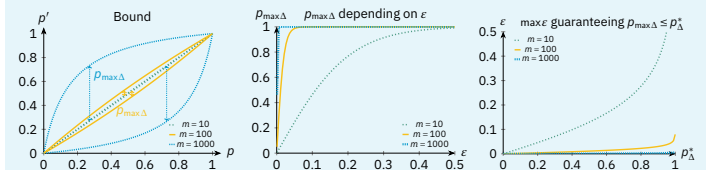
$$p_{\max \Delta} := \max_{\text{for any } r | \mathbf{e}} |p - p'| \leq \frac{\sqrt{e^d} - 1}{\sqrt{e^d} + 1} \text{ with } d = \ln \left(\frac{(1 + \frac{m-1}{m}\varepsilon)(1 + \varepsilon)}{1 + \frac{1}{m}\varepsilon} \right)^m$$

- Theorem:** For any given $p_{\Delta}^* \in (0, \frac{1}{2}]$, the output of HACP guarantees for any $\varepsilon \in (0, 1)$, which is smaller or equal to

$$\varepsilon_1 = -\frac{1 + \frac{m-1}{m} - \frac{1}{m}\sqrt{e^d}}{2 \frac{m-1}{m}} + \sqrt{\left(-\frac{1 + \frac{m-1}{m} - \frac{1}{m}\sqrt{e^d}}{2 \frac{m-1}{m}} \right)^2 - \frac{1 - \sqrt{e^d}}{\frac{m-1}{m}}}$$

$$\text{with } d = \ln \left(\frac{p_{\Delta}^* + 1}{1 - p_{\Delta}^*} \right)^2 \text{ the bound } p_{\max \Delta} \leq p_{\Delta}^*.$$

- Graphical illustration of theorems controlling the bound



- Left: $\varepsilon = 0.001$; All: Dashed (blue) line: $m = 1000$, solid (yellow) line: $m = 100$, loosely dashed (green) line: $m = 10$

- Monotonic dependency of $p_{\max \Delta}$, ε , and m
- Bounds apply to arbitrary queries and factor graphs
- Pre-specification of maximal permissible ε or $p_{\max \Delta}$ values

6. Summary

- Novel framework for hierarchical lifting and model reconciliation
- Introduction of 1DEED as a practical tool for ε -equivalence
- Hierarchical trade-off between compression and accuracy
- Enables preanalysis of theoretical error bounds