GRADUATED ASSIGNMENT FOR MULTI-GRAPH MATCHING

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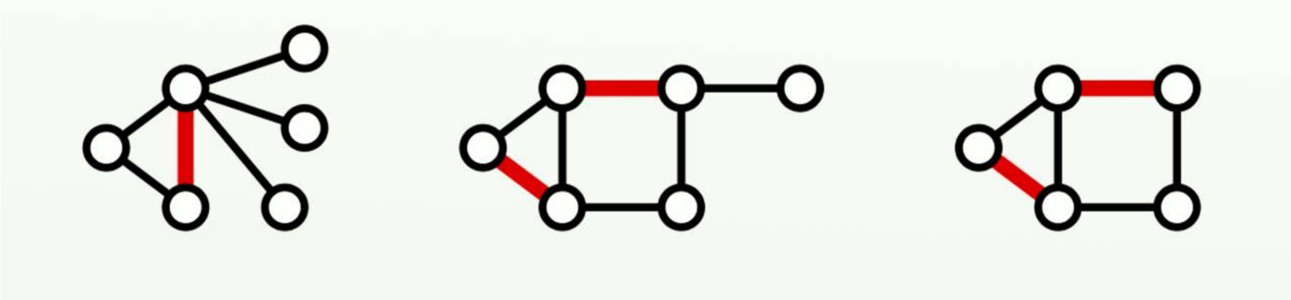
What is graph matching

Graph matching is the problem of finding a similarity between graphs

1) Continuous relaxation
2) Tree search algorithms
3) Deep graph matching

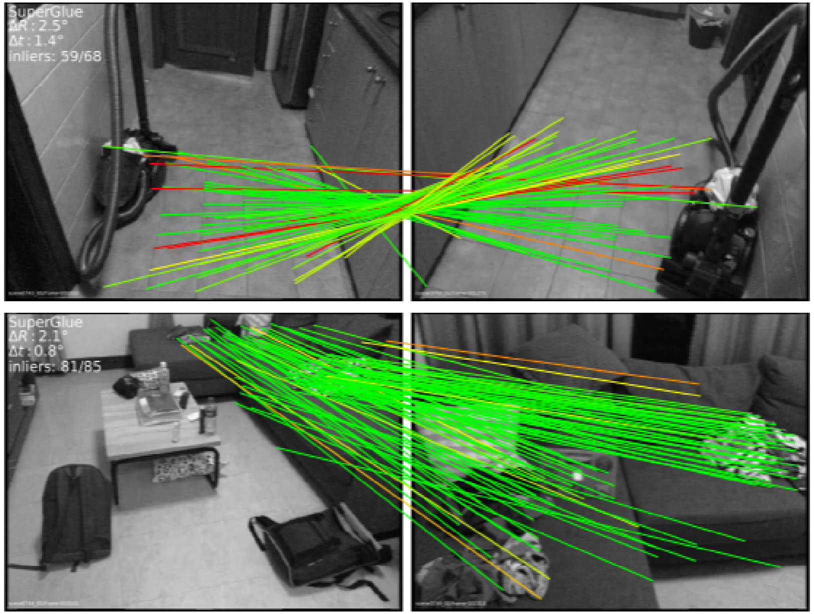


APPLICATION IN COMPUTER VISION

Graph matching algorithms can encode geometric relationships between feature points.

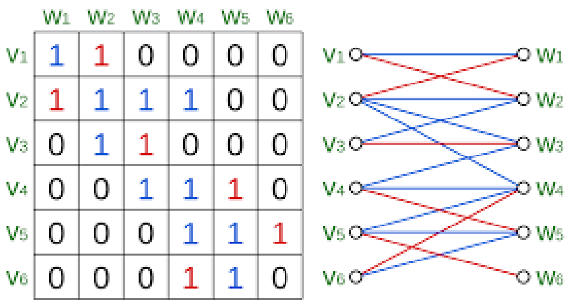
Applications

- Face recognition
- Action recognition
- Duplicate detection



Defining our problem

- Quadratic Assignment Problem (QAP) – A generalization of the ‘traveling salesman problem’
- Sinkhorn algorithm - A simple iterative method to approach the double stochastic matrix is to alternately rescale all rows and all columns of a matrix to sum to 1
- The Hungarian matching algorithm is a algorithm that can be used to find maximum-weight matchings in bipartite graphs, which is sometimes called the assignment problem



Input: Input graphs $\{\mathcal{G}_1, \mathcal{G}_2, ...\mathcal{G}_m\}$; node-wise similarity $\{\mathbf{W}_{ij}\}$; initial annealing τ_0; descent factor γ; minimum τ_{min}; clustering weight $\mathbb{B}$ (all $\mathbb{B}_{ij} = 1$ if clustering is not considered).

Randomly initialize joint matching $\{\mathbf{U}_i\}$; projector $\leftarrow$ Sinkhorn; $\tau \leftarrow \tau_0$;

while *True* **do**

  while $\{\mathbf{U}_i\}$ *not converged AND #iter* $\leq$ *#MGMIter* **do**

    $\forall i \in [m]$, $\mathbf{V}_i \leftarrow \mathbf{0}$;

    for $\mathcal{G}_i, \mathcal{G}_j$ *in* $\{\mathcal{G}_1, \mathcal{G}_2, ...\mathcal{G}_m\}$ **do**

      $\mathbf{V}_i \leftarrow \mathbf{V}_i + (\lambda \mathbf{A}_i \mathbf{U}_i \mathbf{U}_j{}^\top \mathbf{A}_j \mathbf{U}_j + \mathbf{W}_{ij} \mathbf{U}_j) \times \mathbb{B}_{ij}$; # update $\mathbf{V}_i$

    for $\mathcal{G}_i$ *in* $\{\mathcal{G}_1, \mathcal{G}_2, ...\mathcal{G}_m\}$ **do**

      $\mathbf{U}_i \leftarrow$ projector$(\mathbf{V}_i, \tau)$; # project $\mathbf{V}_i$ to (relaxed) feasible space of $\mathbf{U}_i$

  # graduated assignment control

  if projector == Sinkhorn *AND* $\tau \geq \tau_{min}$ **then**

    $\tau \leftarrow \tau \times \gamma$;

  else if projector == Sinkhorn *AND* $\tau < \tau_{min}$ **then**

    projector $\leftarrow$ Hungarian;

  else

    break;

Output: Joint matching matrices $\{\mathbf{U}_i\}$.

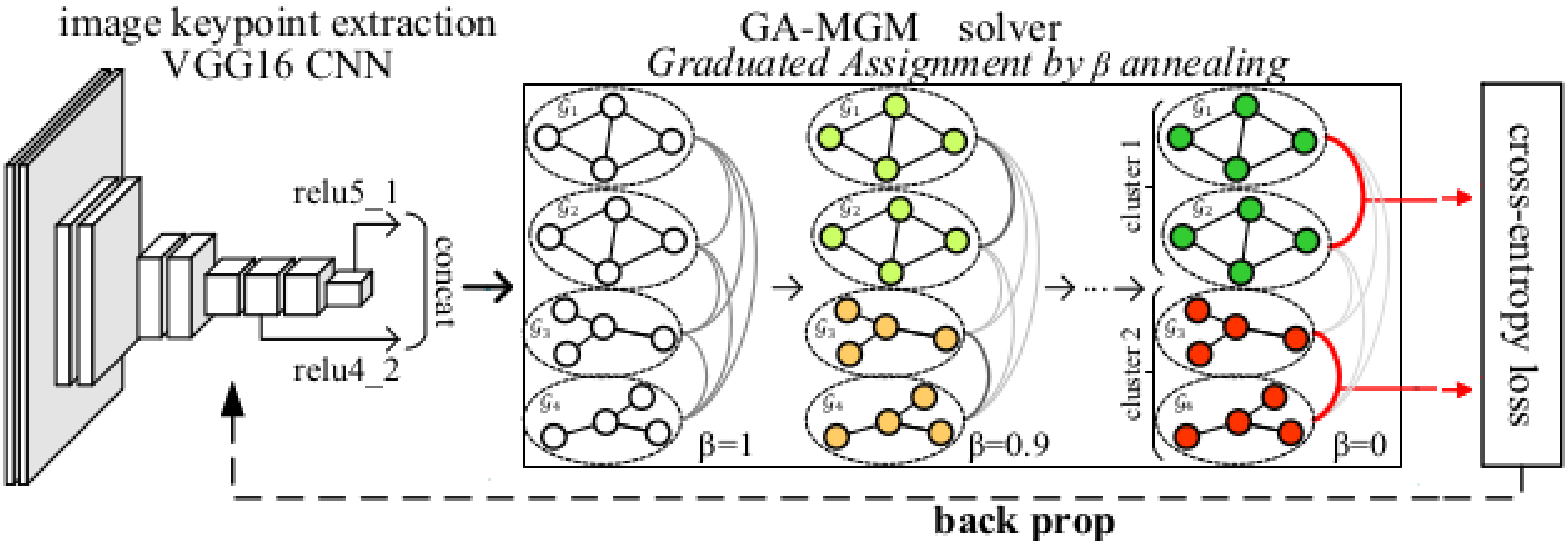


image keypoint extraction
VGG16 CNN
relu5_1
relu4_2
concat
GA-MGM solver
Graduated Assignment by β annealing
β=1
β=0.9
β=0
cluster 1
cluster 2
cross-entropy loss
back prop

APPROACH

Iteratively solving the first-order Taylor expansion of the Multi-Graph QAP.

Before iteration

- Initialize matching matrix using similarity heuristic

Each iteration

- Update matching matrix using Sinkhorn

Final iteration

- Update matching matrix using Hungarian

RESEARCH QUESTION

How robust is state of the art graph matching algorithms to sample changes?

Hypothesis

- Larger sample sizes lead to higher testing accuracy
- This will translate equally to other models

EXPERIMENTS

Experiment validation

Averages of 3 runs

Each run performed on the same machine after reset

GANN

Number of samples	F1 Score	Variance	Time (m)
20	88.87%	12.98%	1.42
30	92.85%	10.29%	1.15

GANN

Number of samples	F1 Score	Car	Wine bottle	Motorbike	Face	Duck
20	88.87%	60.67%	90.64%	94.00%	**100%**	**98.67%**
30	**92.85%**	**72.67%**	**95.08%**	**100%**	**100%**	96.50%

CIE

Number of samples	F1 Score	Variance	Time (h)
20	88.61%	15.67%	2.32
30	10.25%	10.39%	2.30

Conclusion

The experiments didn’t fully meet our expectations

Further work

Try a larger sample size

Change the size of query/target graphs