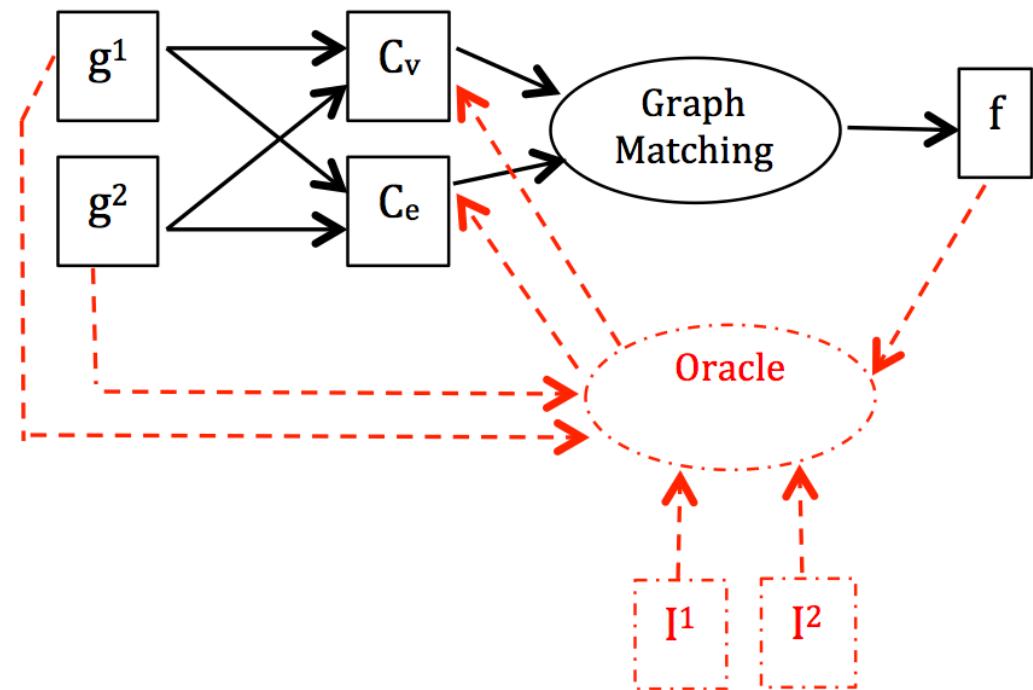
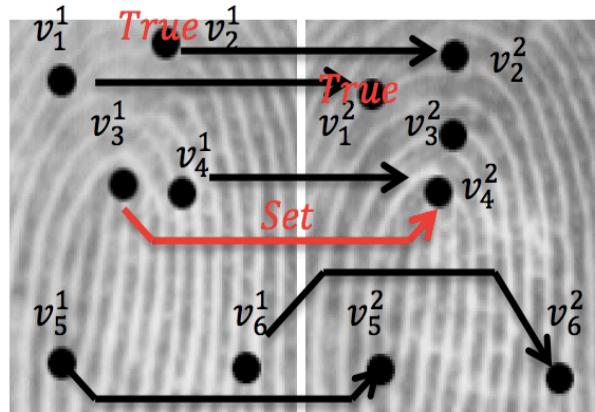


# Active & Interactive Graph Matching

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# Active & Interactive Graph Matching

**Graph matching:** The aim is to find the best labelling between nodes of two graphs such that the cost of this labelling is the minimum among all possible labellings.

**Active learning:** The aim is to achieve a greater accuracy with fewer classified training examples through choosing the data from which it learns.

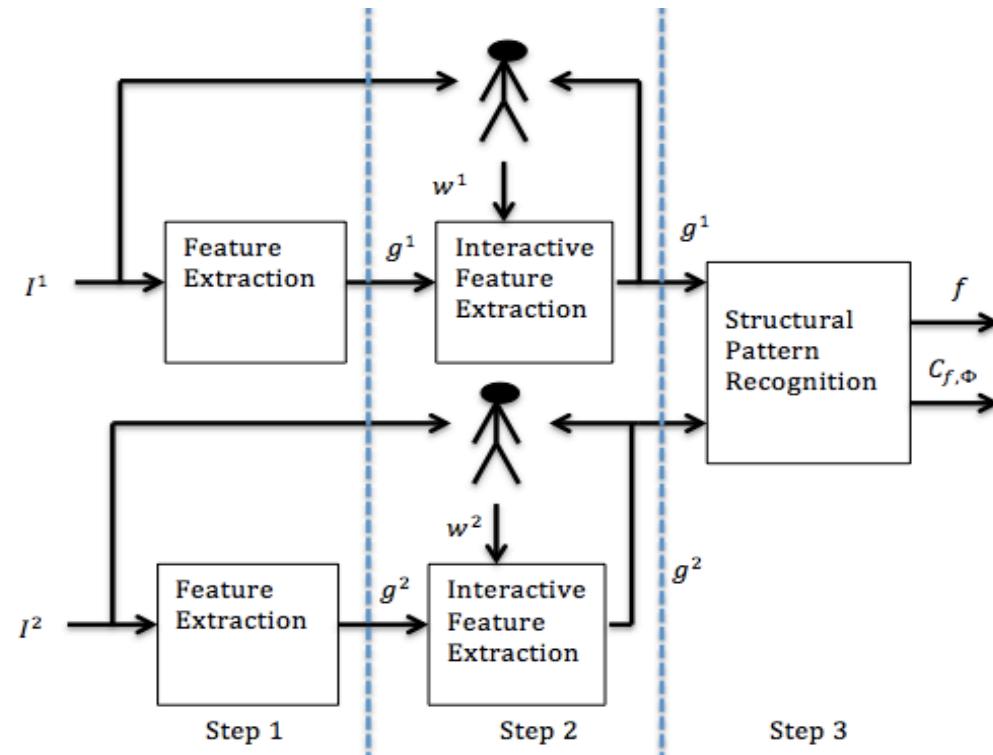
**Interactive learning:** The aim is to query some selected data and present it to an oracle (automatic system or a human annotator) for correctly classify it.

## Our model:

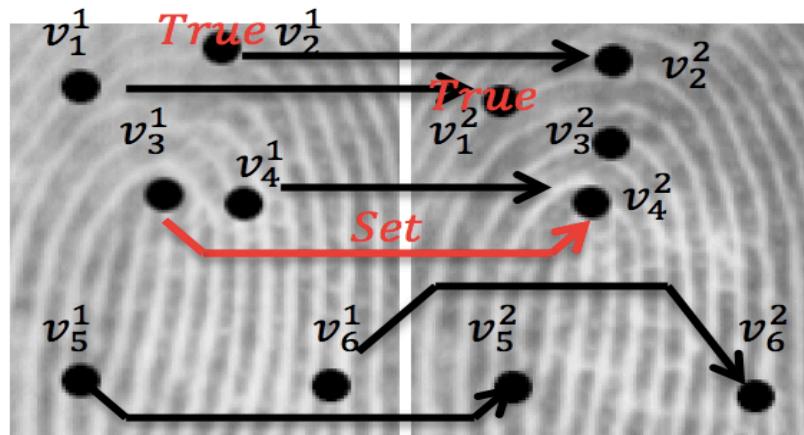
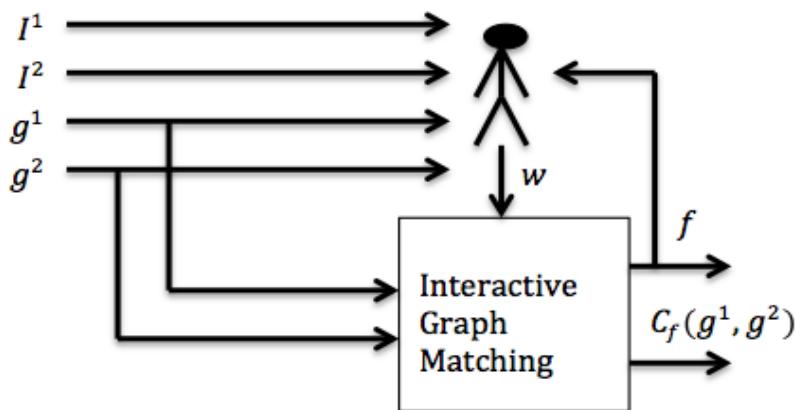
- The learner queries the graph node that it is supposed to produce a greater impact on the labelling between both graphs.
- The oracle answers which is the graph node of the second graph that it has to be matched.



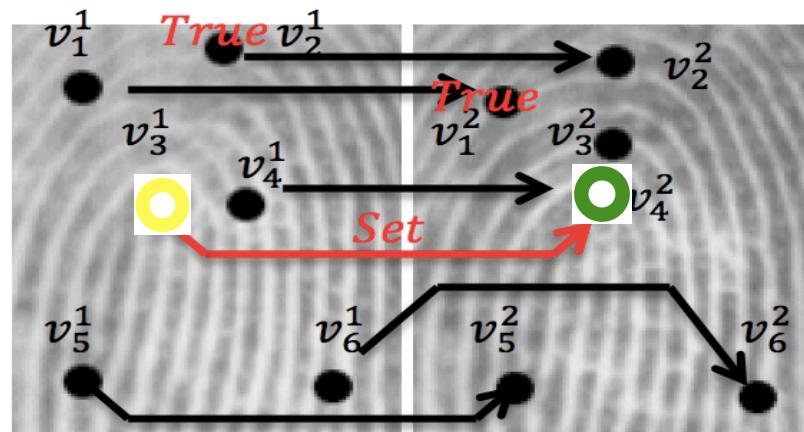
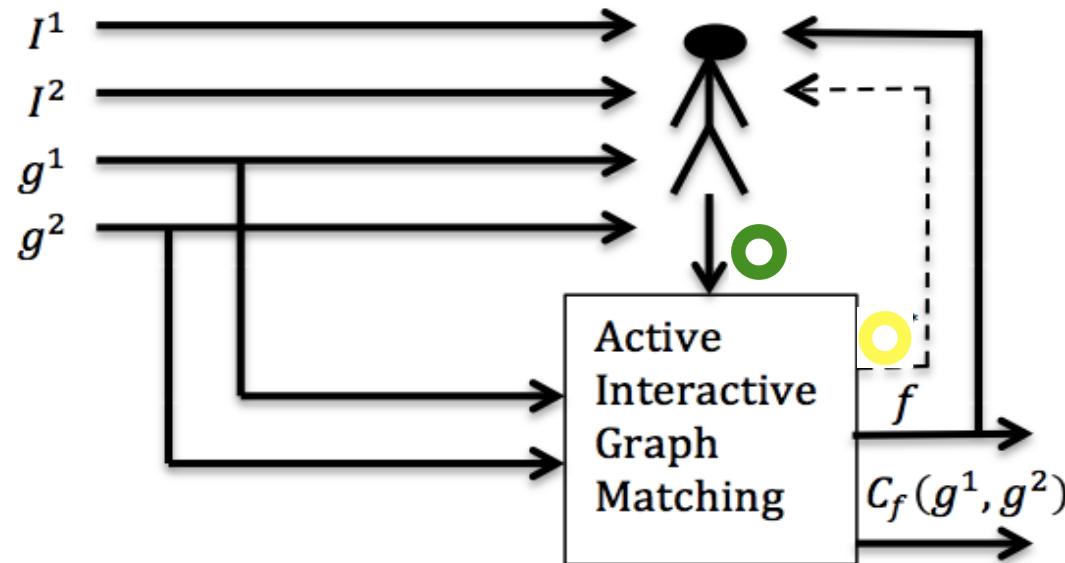
# Image Correspondence Process with human interaction



# Interactive Graph Matching

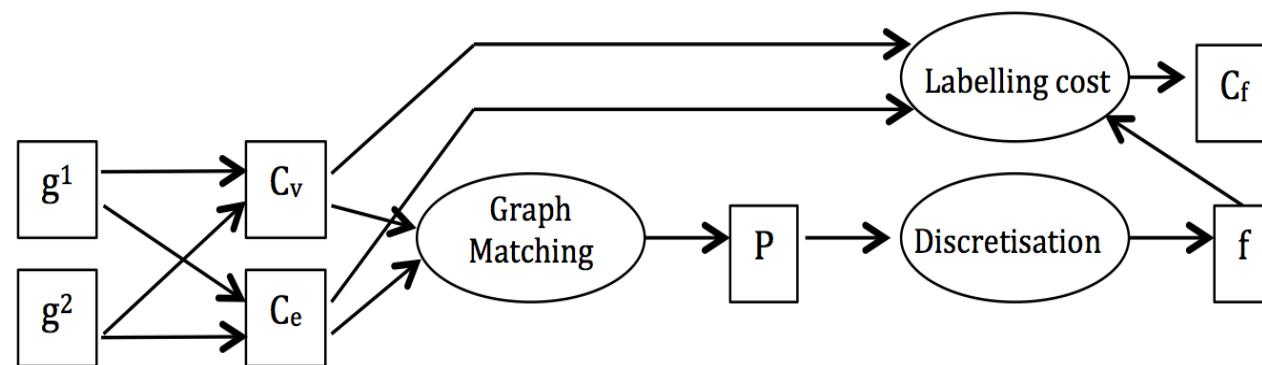


# Active & Interactive Graph Matching



# Structural Pattern Recognition based on Graphs

$$C_f(g^1, g^2) = \sum_{v_i^1 \in \Sigma_v^1} c_v(v_i^1, v_a^2) + \sum_{e_{ij}^1 \in \Sigma_e^1} c_e(e_{ij}^1, e_{ab}^2)$$



# Interactive Graph Matching

## Node Costs:

If  $\text{True}(v_i^1, v_a^2)$  then

$$C_v[i, a] = 0$$

$$C_v[i, b] = \infty \quad \forall b \neq a$$

$$C_v[j, a] = \infty \quad \forall j \neq i$$

If  $\text{False}(v_i^1, v_a^2)$  then

$$C_v[i, a] = \infty$$

## Arc Costs:

If  $\text{True}(v_i^1, v_a^2) \wedge \text{True}(v_j^1, v_b^2)$  then

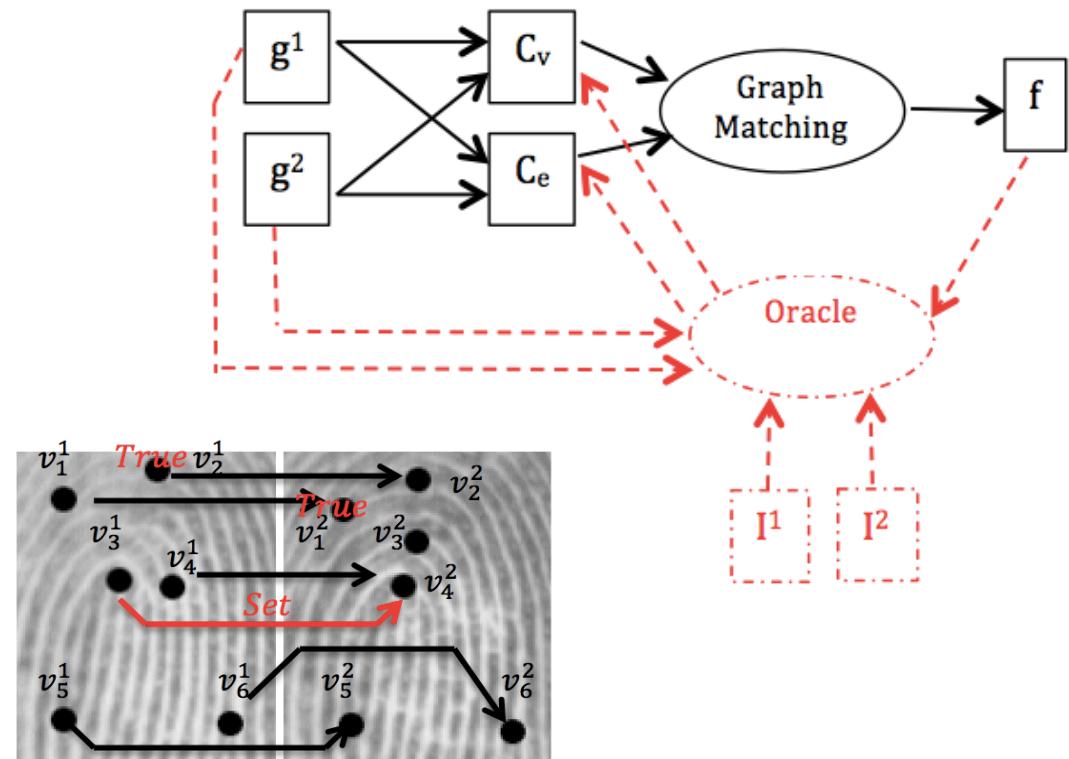
$$C_e[i, j, a, b] = 0 \wedge C_e[j, i, b, a] = 0$$

$$C_e[i, j, a', b'] = \infty \wedge C_e[j, i, a', b'] = \infty \quad \forall a \neq a' \text{ and } b \neq b'$$

$$C_e[i', j', a, b] = \infty \wedge C_e[i', j', b, a] = \infty \quad \forall i \neq i' \text{ and } j \neq j'$$

If  $\text{False}(v_i^1, v_a^2)$  then

$$C_e[i, j', a, b'] = \infty \wedge C_e[j', i, b', a] = \infty \wedge C_e[j', i, a, b'] = \infty \wedge C_e[j', i, a, b'] = \infty \quad \forall i \neq j' \text{ and } a \neq b'$$



# Active & Interactive Graph Matching

**Algorithm Active Graph Matching**

**Input:** Attributed Graphs  $g^1$  and  $g^2$

**Output:** Labelling  $f$  and Cost  $C_f$

$C_v^0, C_e^0 = \text{Initialise\_Cost}(g^1, g^2); C_v = C_v^0; C_e = C_e^0.$

$f = \text{Graph\_Matching}(C_v, C_e).$

**Do**

$v^{1*} = \text{Active\_Query}(P, f).$

$v^{2*} = \text{Oracle\_Feedback}(g^1, g^2, v^{1*}, f).$

$w_1 = \text{Set}(v^{1*}, v^{2*}).$

$C_v = \text{Interactive\_Node\_Costs}(w, C_v).$

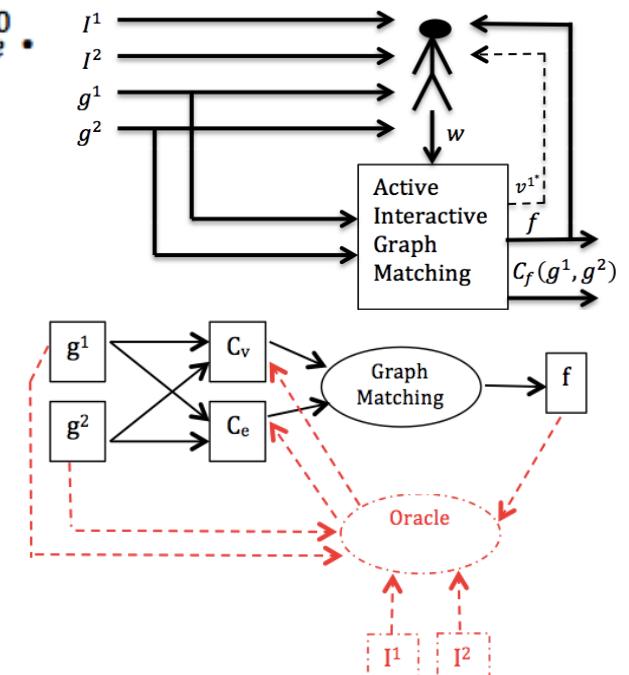
$C_e = \text{Interactive\_Edge\_Costs}(w, C_e).$

$f = \text{Graph\_Matching}(C_v, C_e).$

**Since Stop**

Compute  $C_f(C_v^0, C_e^0)$

**End Algorithm**



# Active Learning Strategies

Four strategies to select a node  $v^1*$  of  $g^1$  that have to be queried to an oracle.

The oracle feedback is the node of  $g^2$ :  $v^2* = f(v^1*)$

*Least Confident* (LC)

*Least Confident given the Current Labelling* (LCCL)

*Maximum Entropy* (ME)

*Expected Model Change* (EMC)

# *Least Confident (LC)*

**This strategy queries the node that** its highest probability of belonging to a class is the lower one between all the elements.

$$v^{2(i)} = \operatorname{argmax}_{\forall j=\{1,..,n\}} P[v_i^1, v_j^2]; \forall i = \{1,..,n\}$$

$$v_{LC}^{1*} = \operatorname{argmin}_{\forall i=\{1,..,n\} | Q(i) = False} P[v_i^1, v^{2(i)}]$$

# *Least Confident given the Current Labelling (LCCL)*

This strategy queries the node that has the minimum probability given the current labelling.

$$v_{LCCL}^{1^*} = \operatorname{argmin}_{\forall i=\{1,..,n\} | Q(i) = \text{False}} P[v_i^1, f(v_i^1)]$$

# *Maximum Entropy (ME)*

This strategy queries the node that has the maximum Shanon Entropy given the probabilities.

$$v_{ME}^{1*} = \underset{\forall i=\{1,..,n\} | Q(i) = False}{\operatorname{argmax}} - \sum_{j=1}^n P[v_i^1, v_j^2] \cdot \log(P[v_i^1, v_j^2])$$

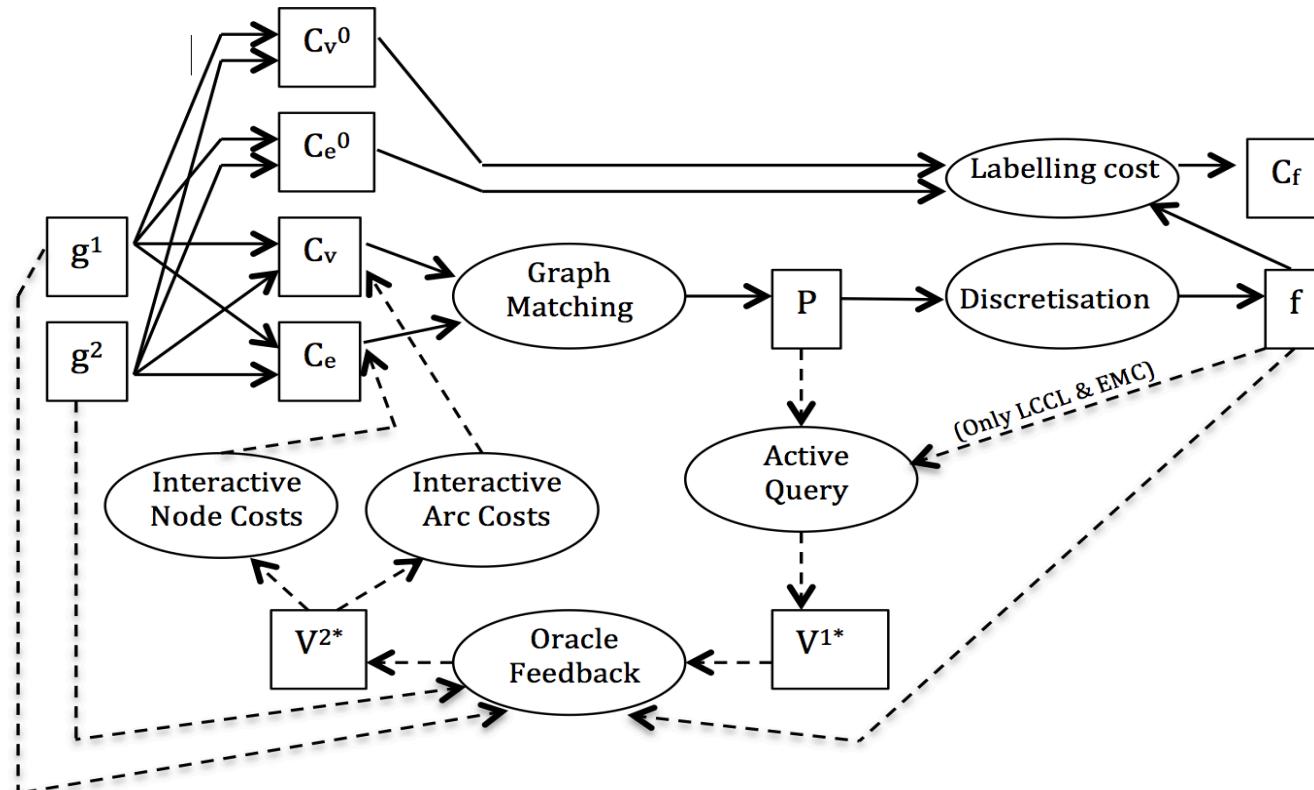
# *Expected Model Change* (EMC)

This strategy queries the node that would impart the greatest change to the current labelling if we knew its class.

$$R_i = \max_{\forall j=\{1,..,n\}} \{P[v_i^1, v_j^2]\} - P[v_i^1, f(v_i^1)]$$

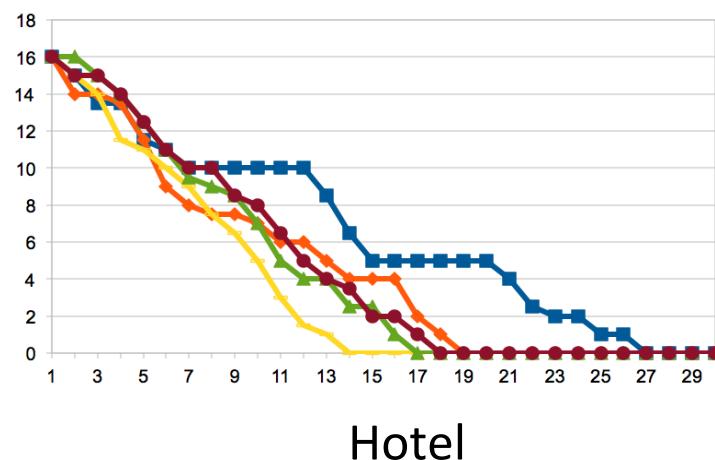
$$v_{EMC}^{1*} = \operatorname{argmax}_{\forall i=\{1,..,n\} \wedge Q(i)=\text{False}} \{R_i\}$$

# Active & Interactive Graph Matching

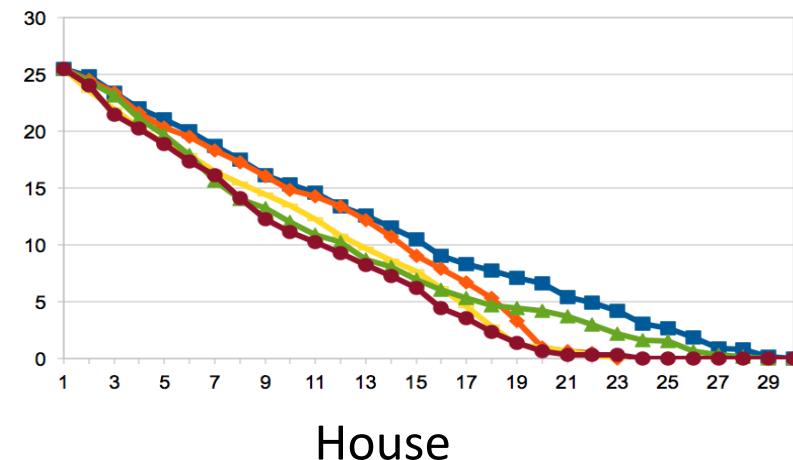


# Practical Evaluation

Hamming distance respect of the number of iterations



Hotel



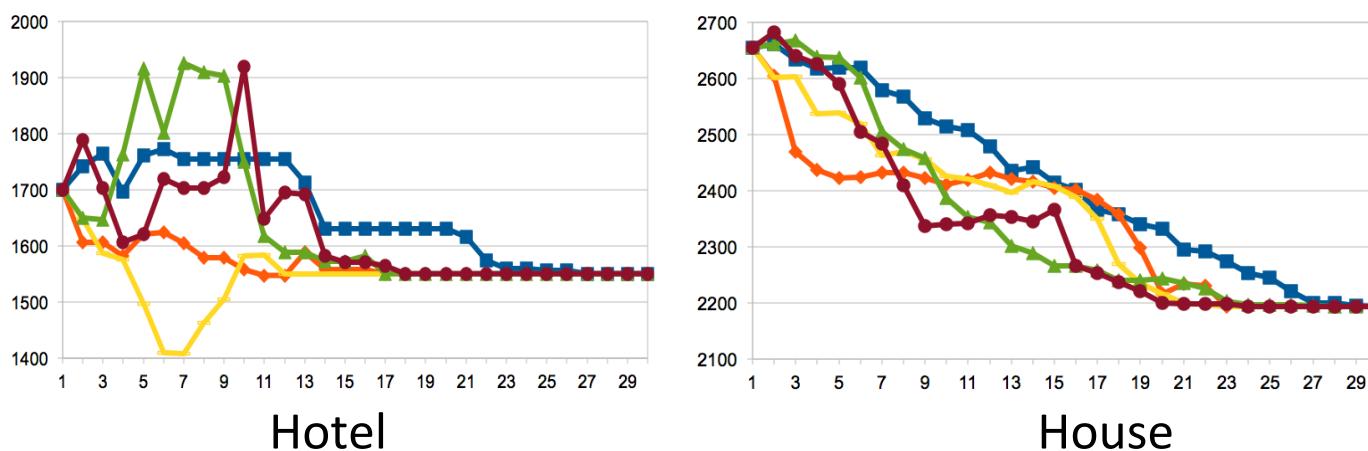
House

LCCL: —, LC: —○—, ME: —●—, EMC: —■— and Random: —▲—



# Practical Evaluation

Matching cost respect of the number of iterations



LCCL: —, LC: -·-, ME: -·-, EMC: -·- and Random: -·-·-



# Conclusions

- Four different strategies to be applied on an active graph-matching algorithm
- It is not needed to modify the code of the graph matching algorithms:
  - They read the probability matrix and
  - write the matrix costs
- Experimental validation shows that the Least Confident with Current labelling (LCCL) tends faster to find the optimal labelling

