GUIDING USER GROUPINGS

LEARNING AND COMBINING CLASSIFICATION FOR ITEMSET STRUCTURING

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MUSE
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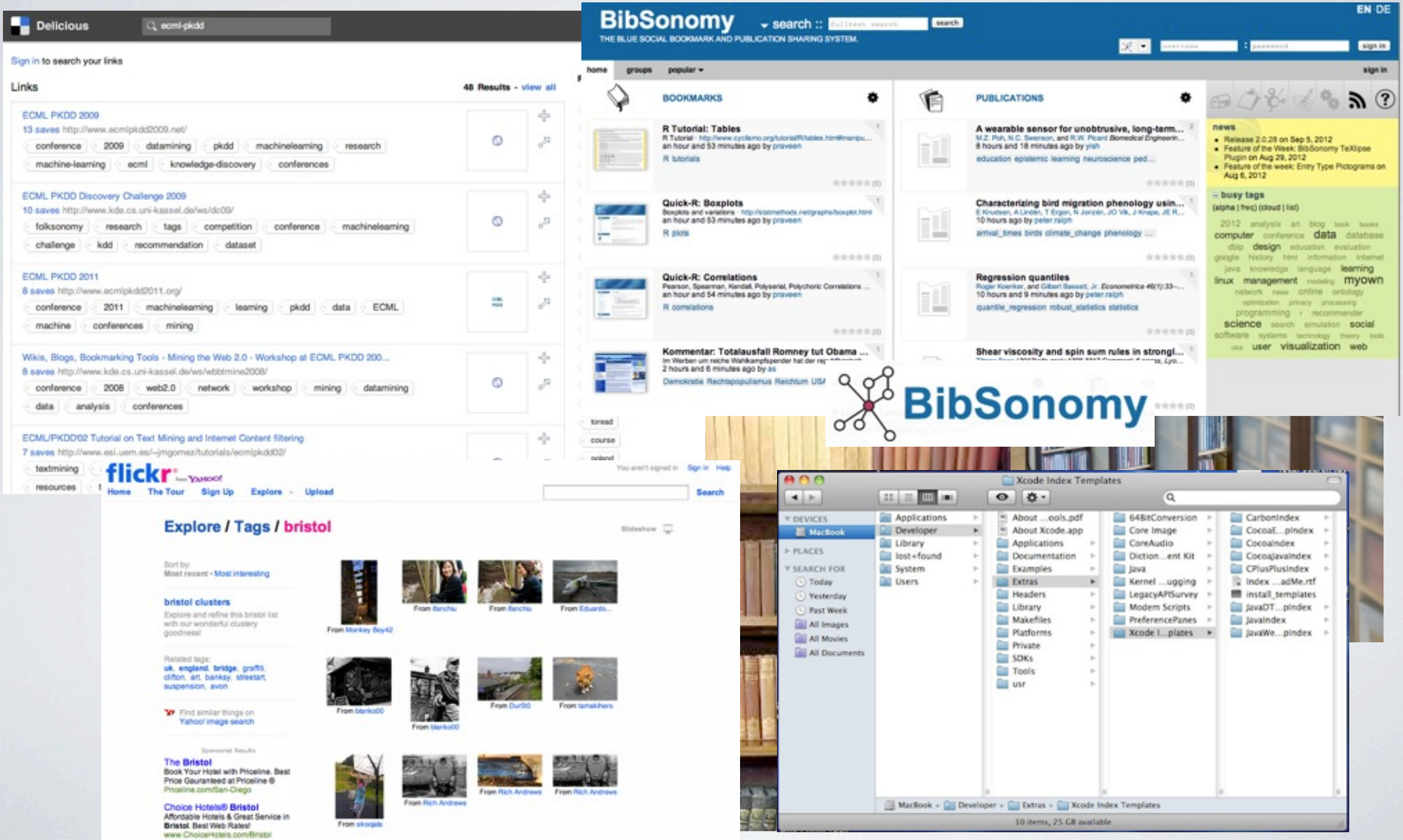
MOTIVATION

MOTIVATION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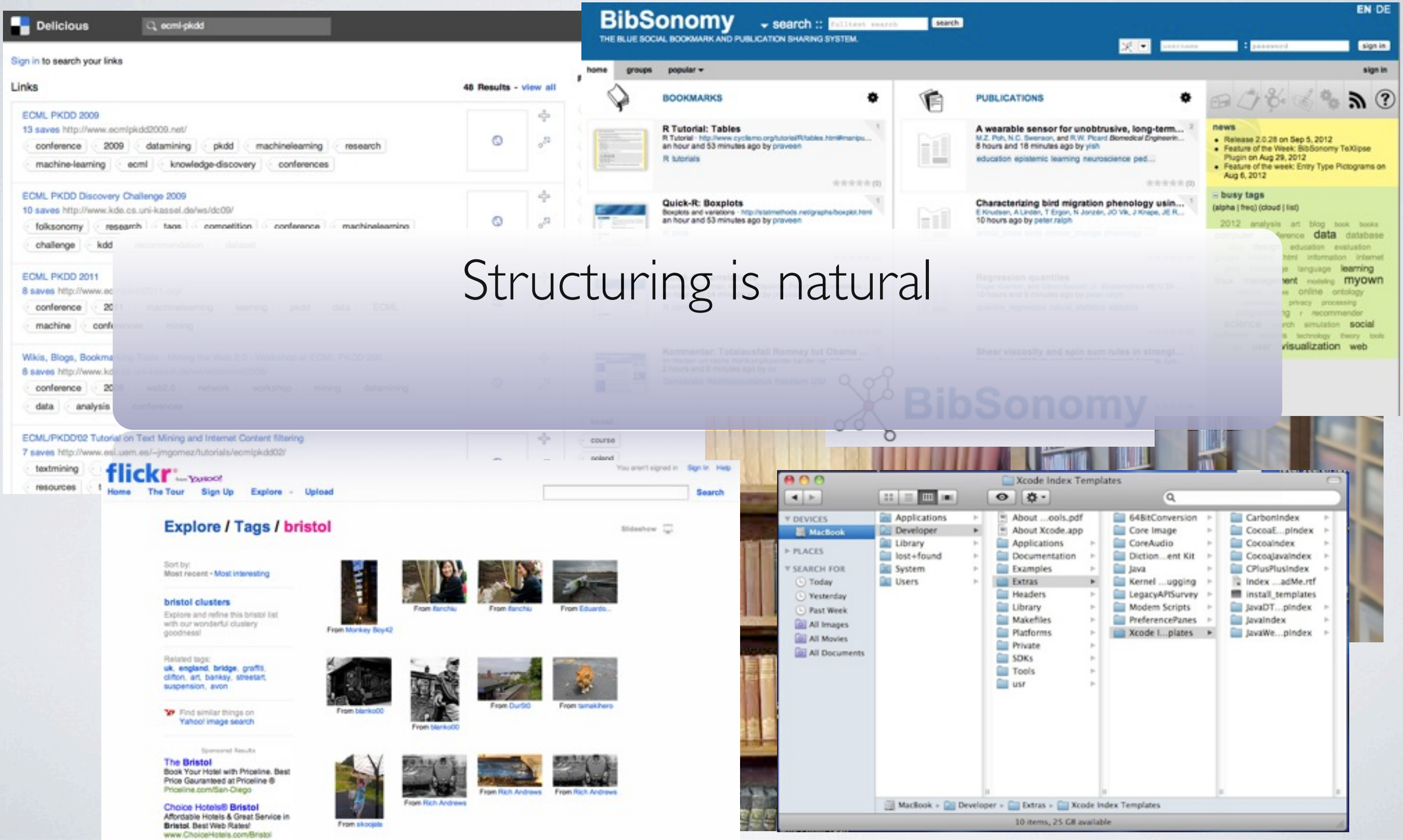
MOTIVATION

Structuring is natural



MOTIVATION

Structuring is natural

... also for digital items

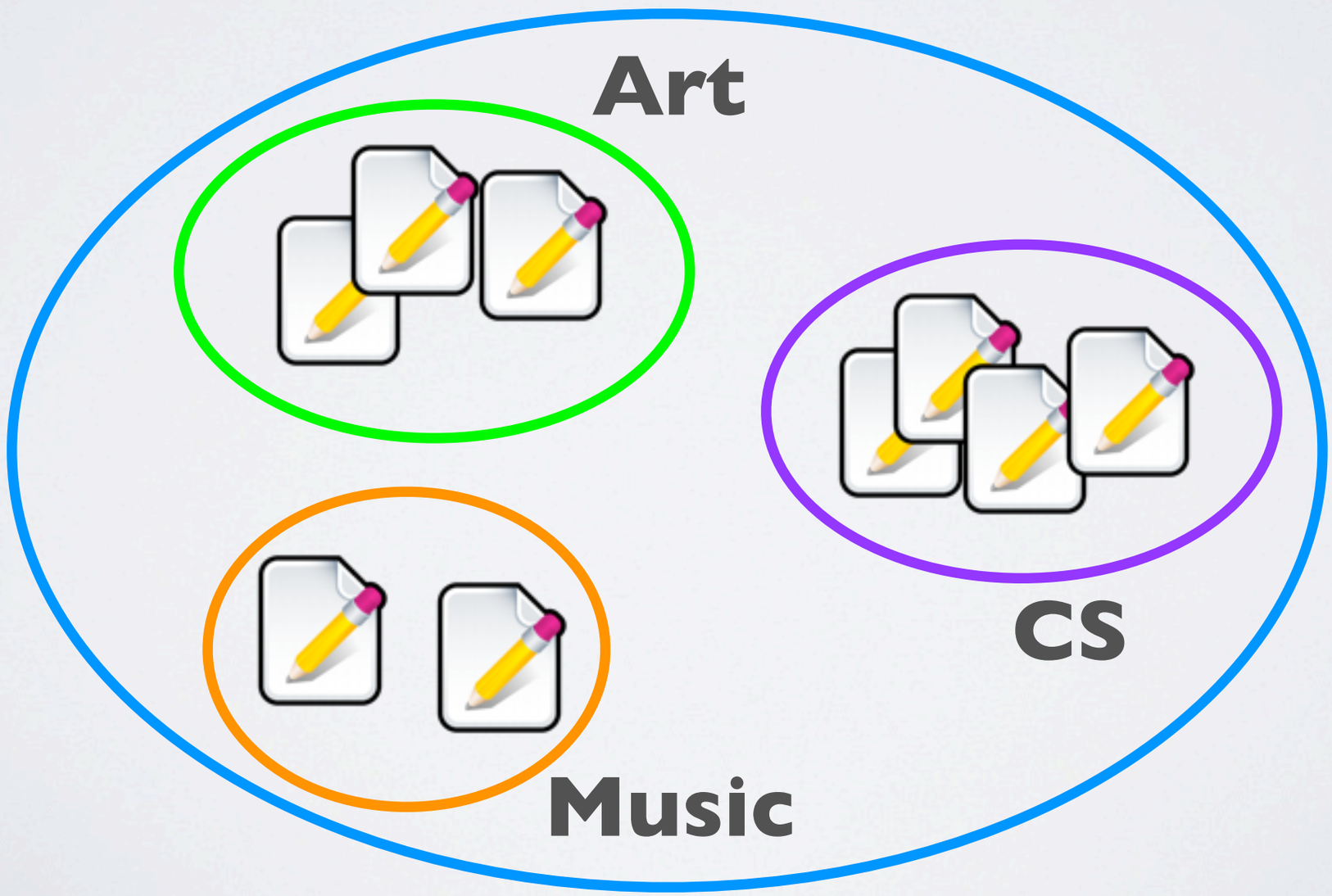
CONTRIBUTIONS

1. A new DM approach that learns an intensional model of user groupings and uses this to group new items
   → Identify structuring dynamics

2. New divergence measure

3. A study of grouping behaviour in a social bookmarking system

STRUCTURING



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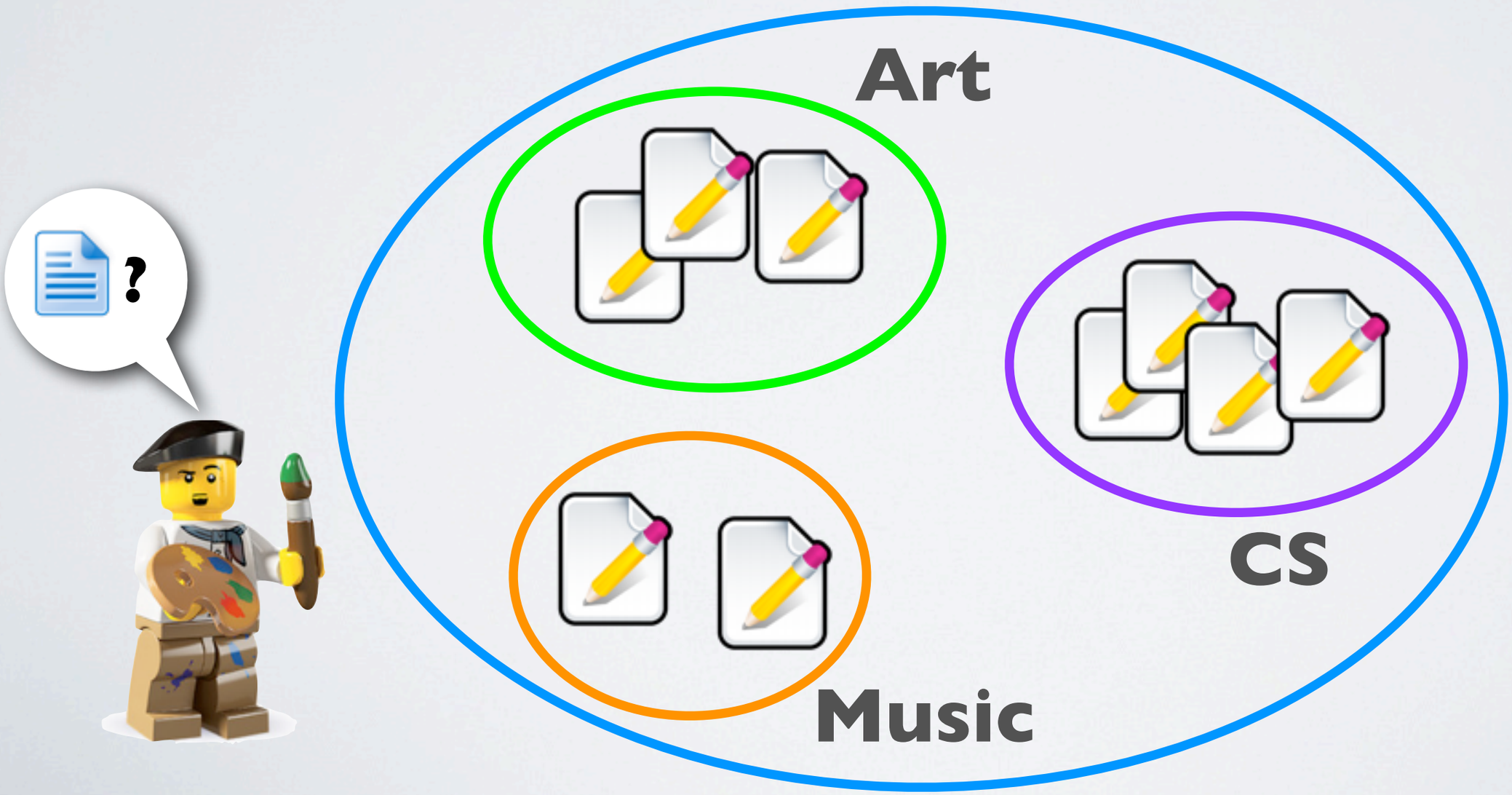

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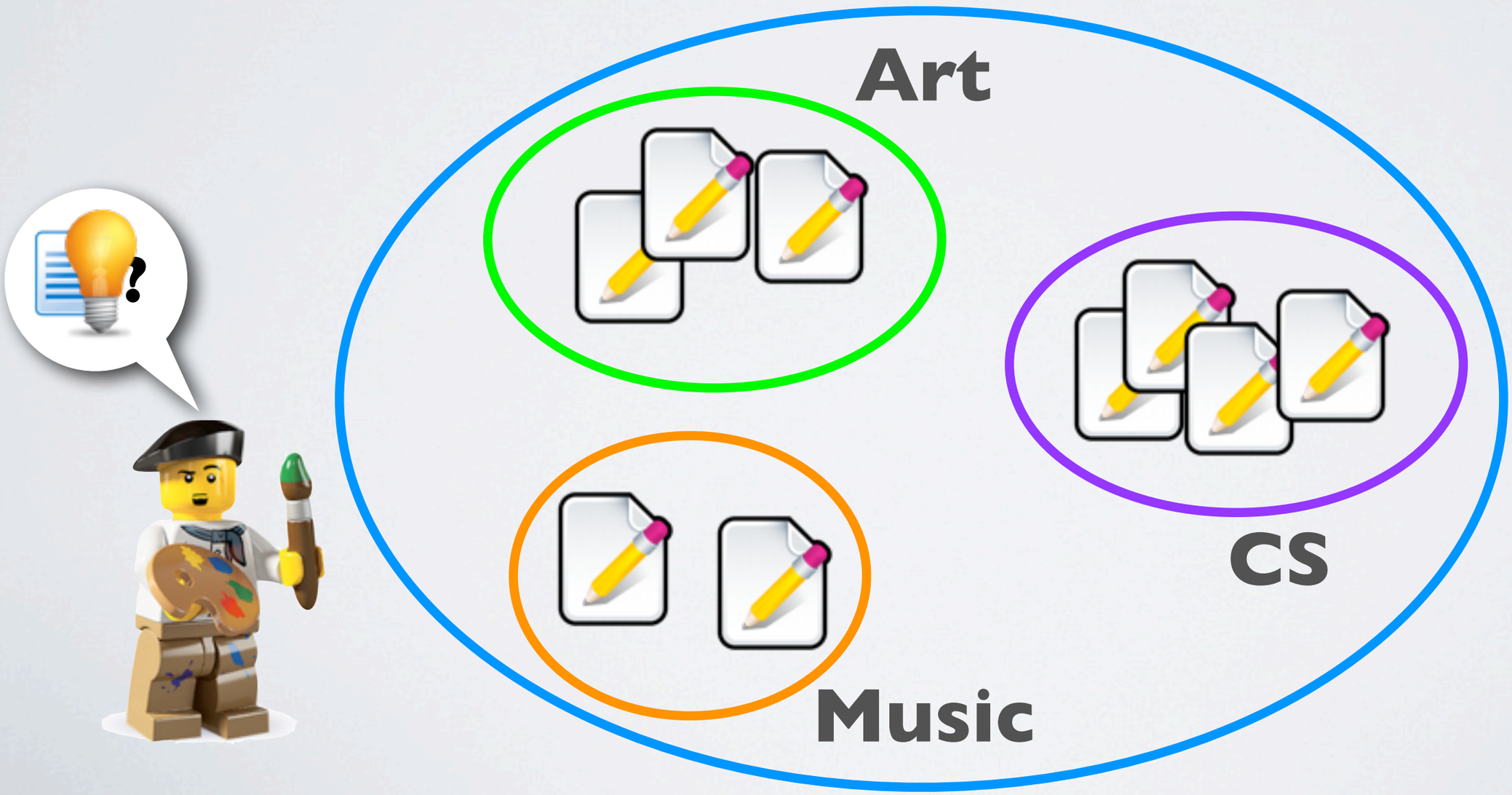

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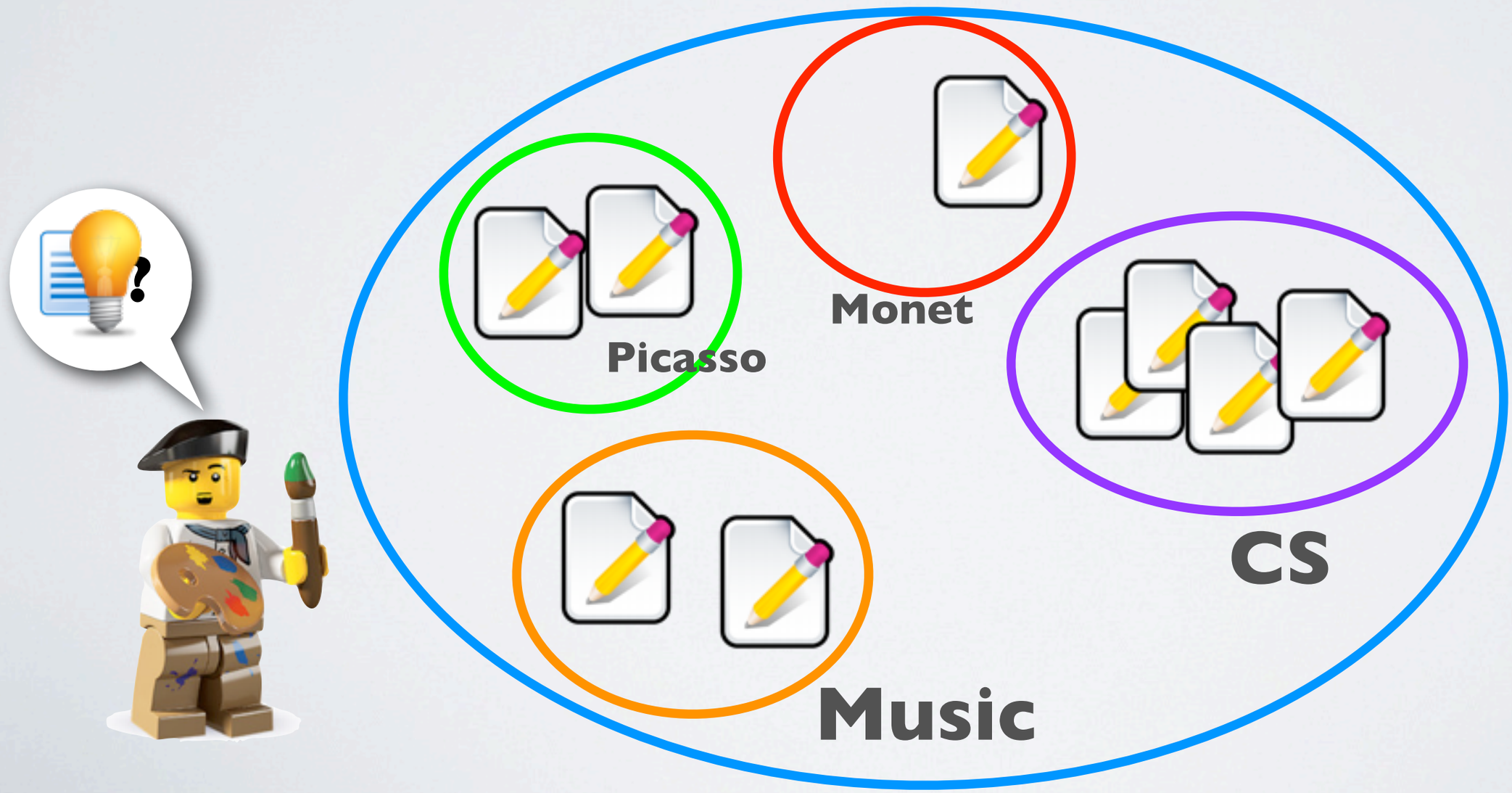

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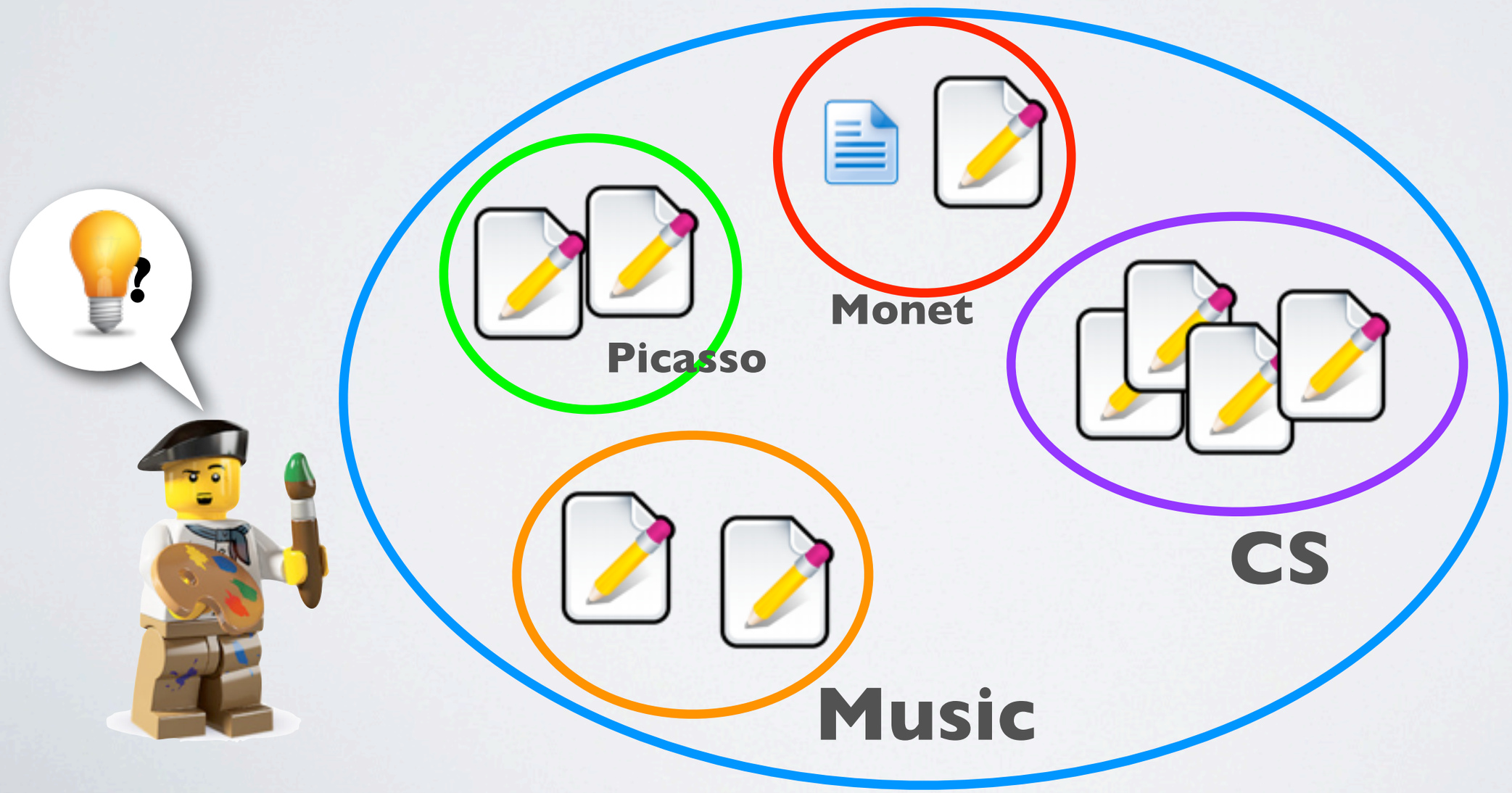

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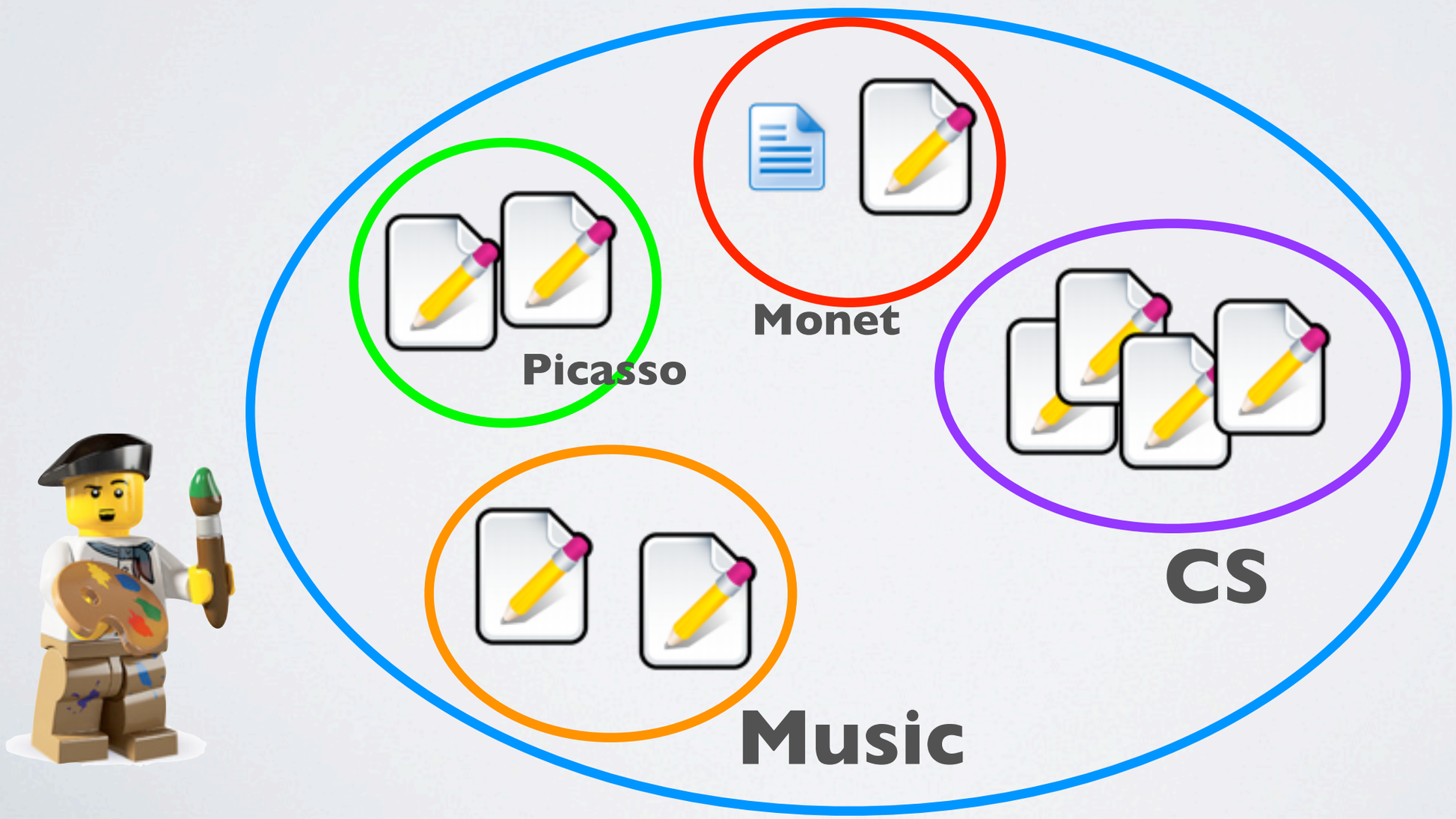

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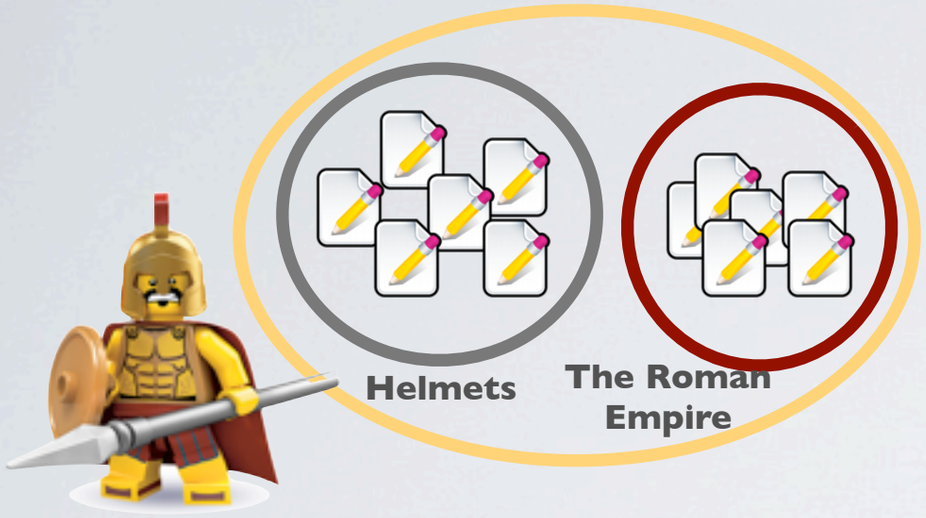

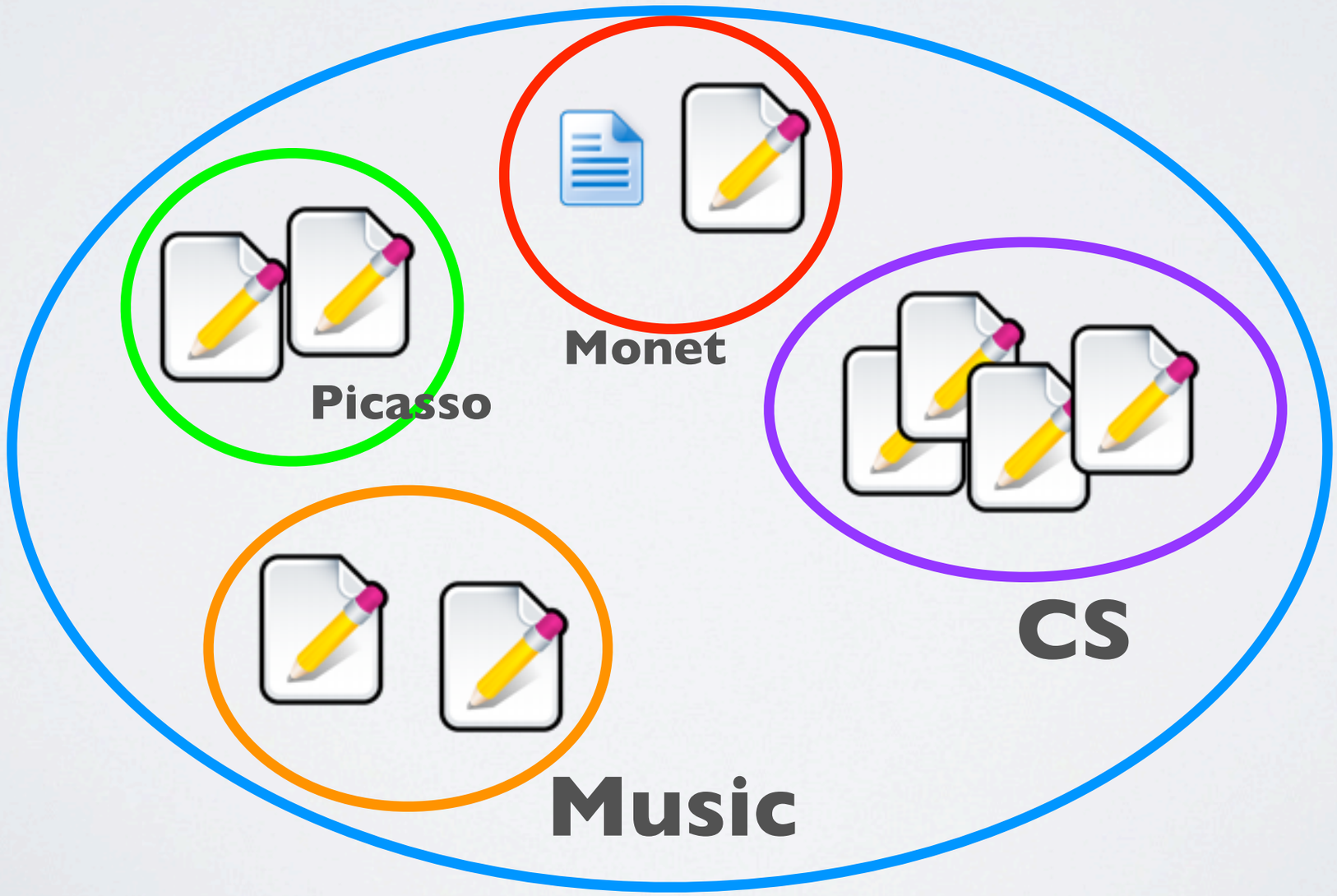

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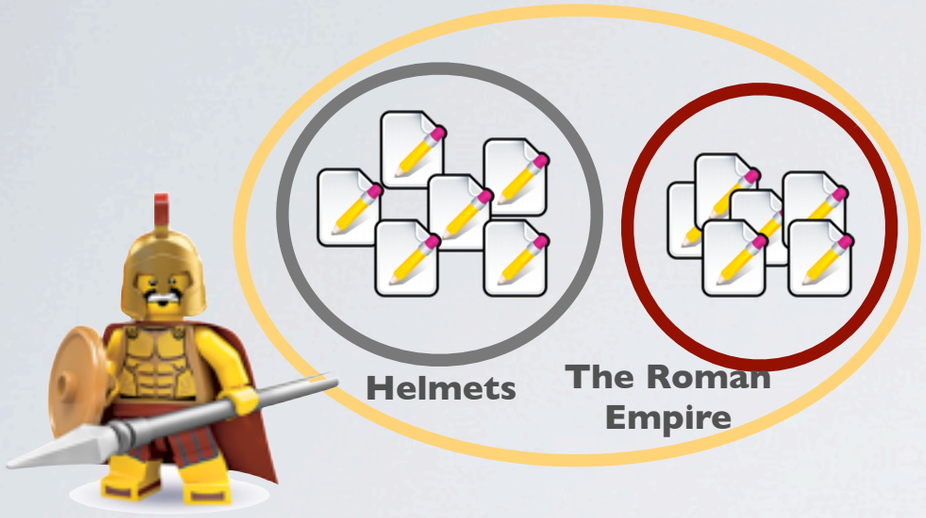

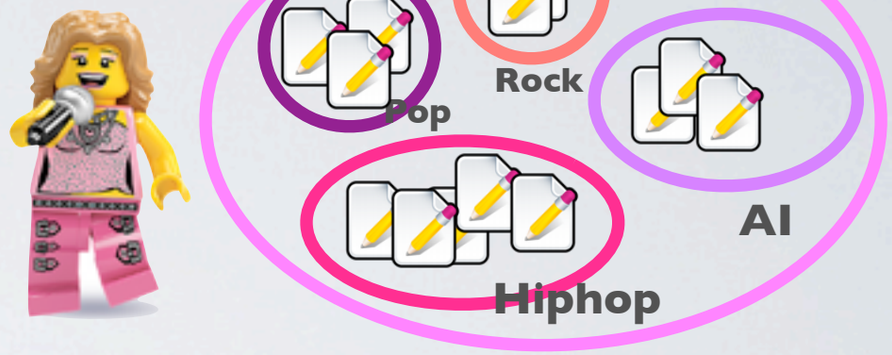

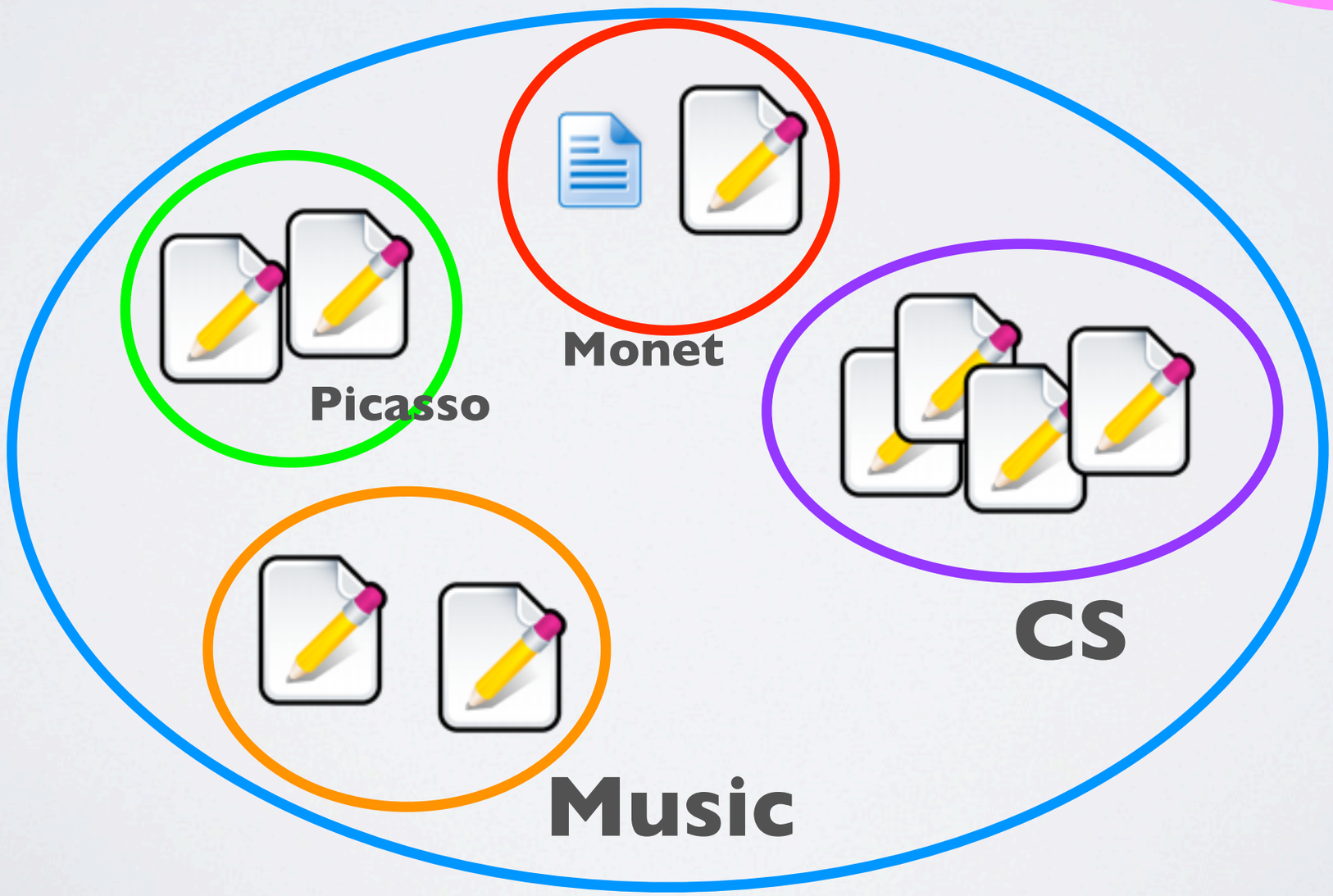

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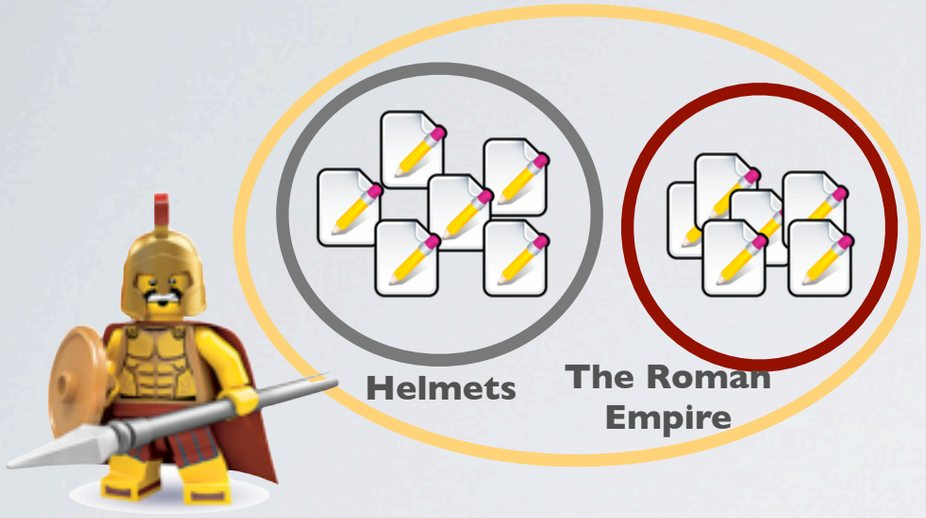

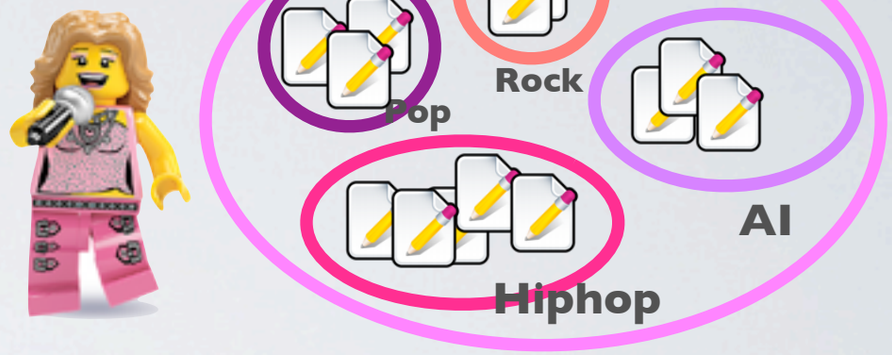

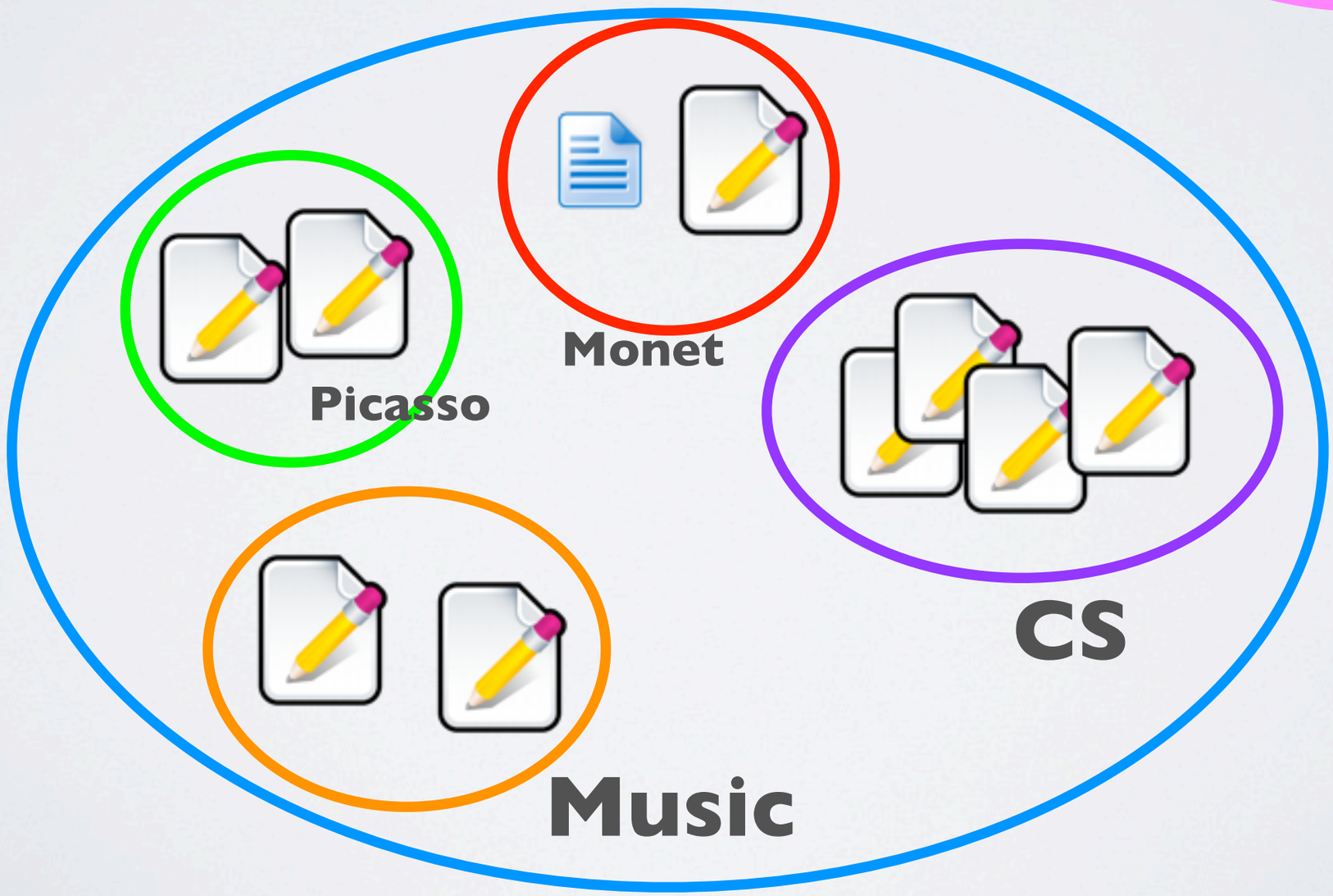

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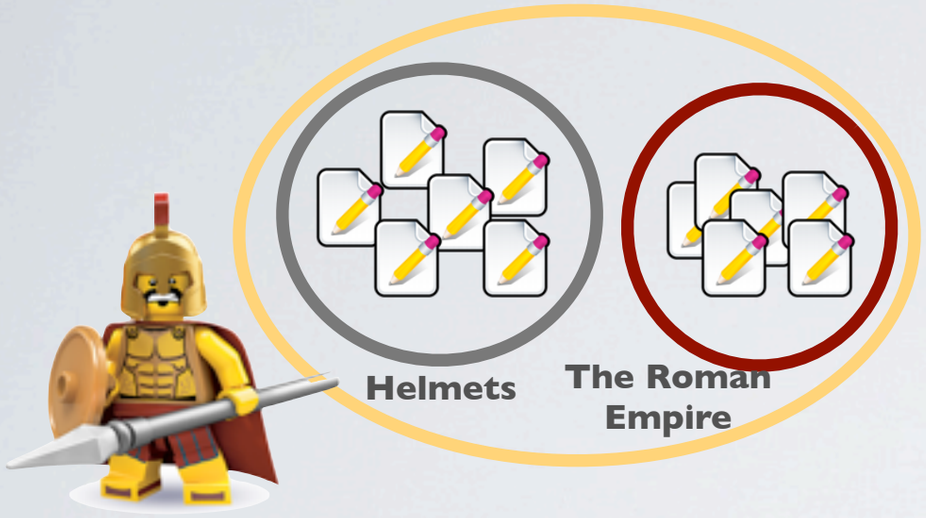

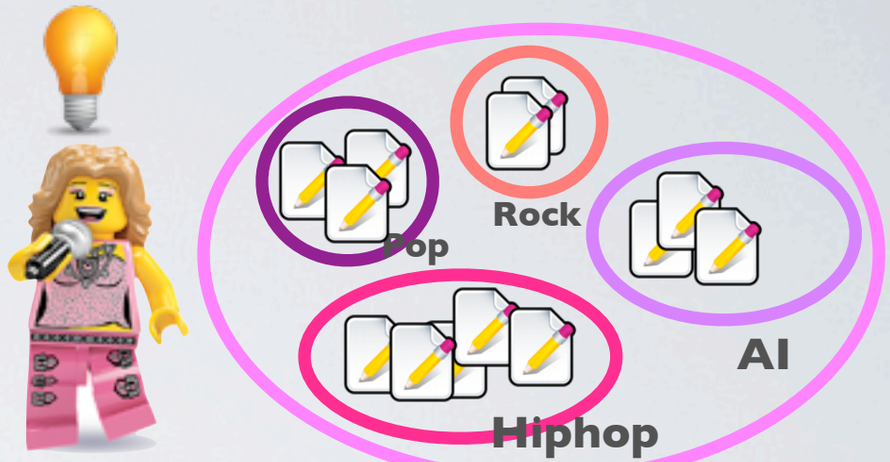

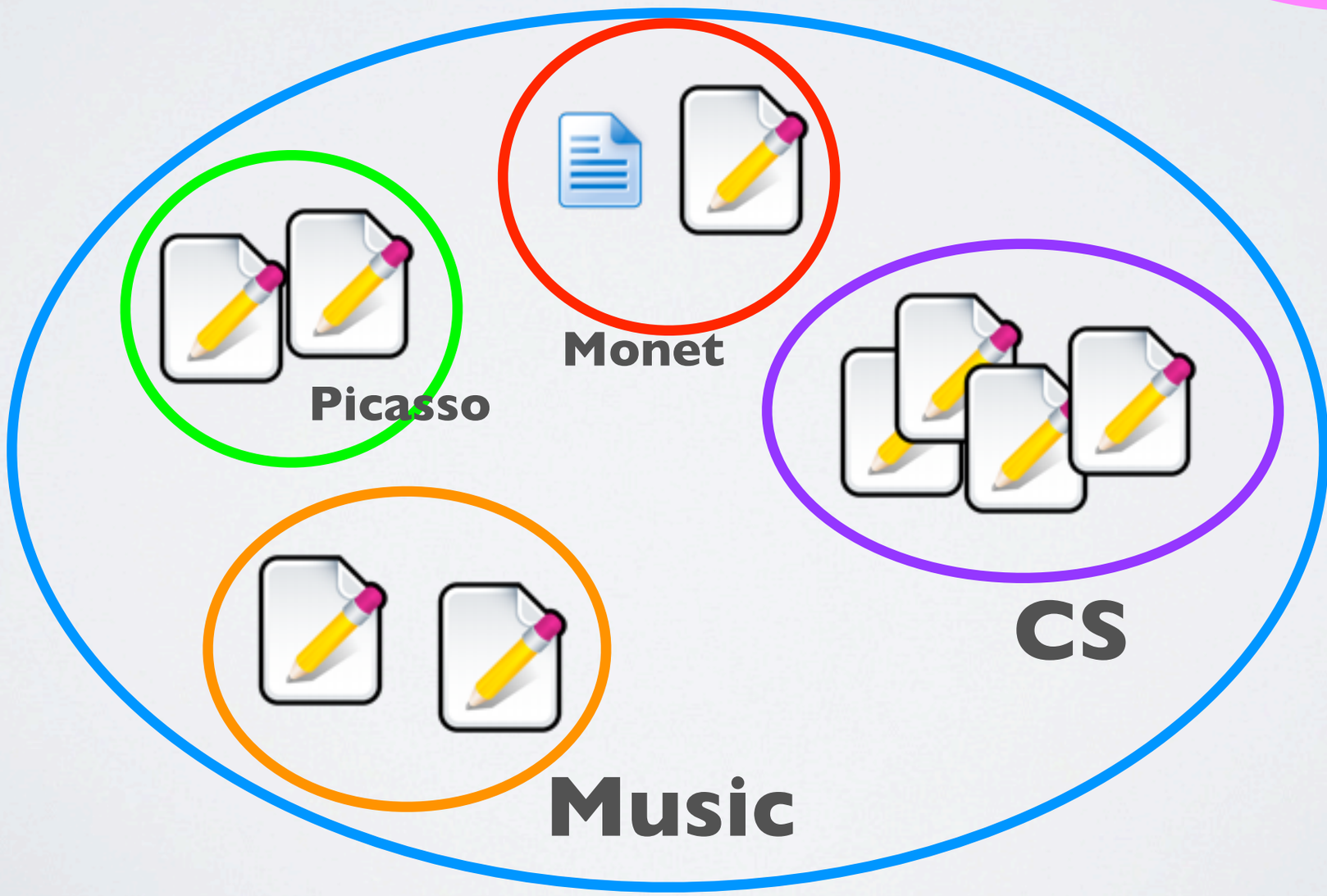

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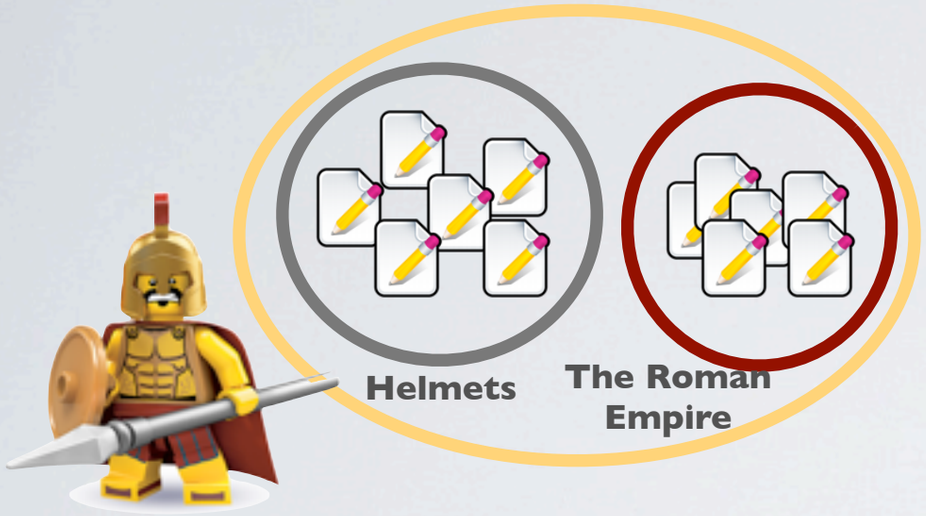

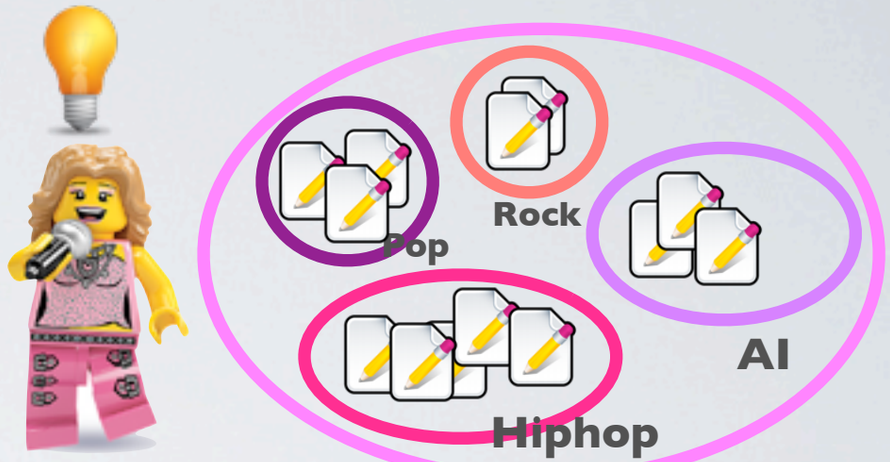

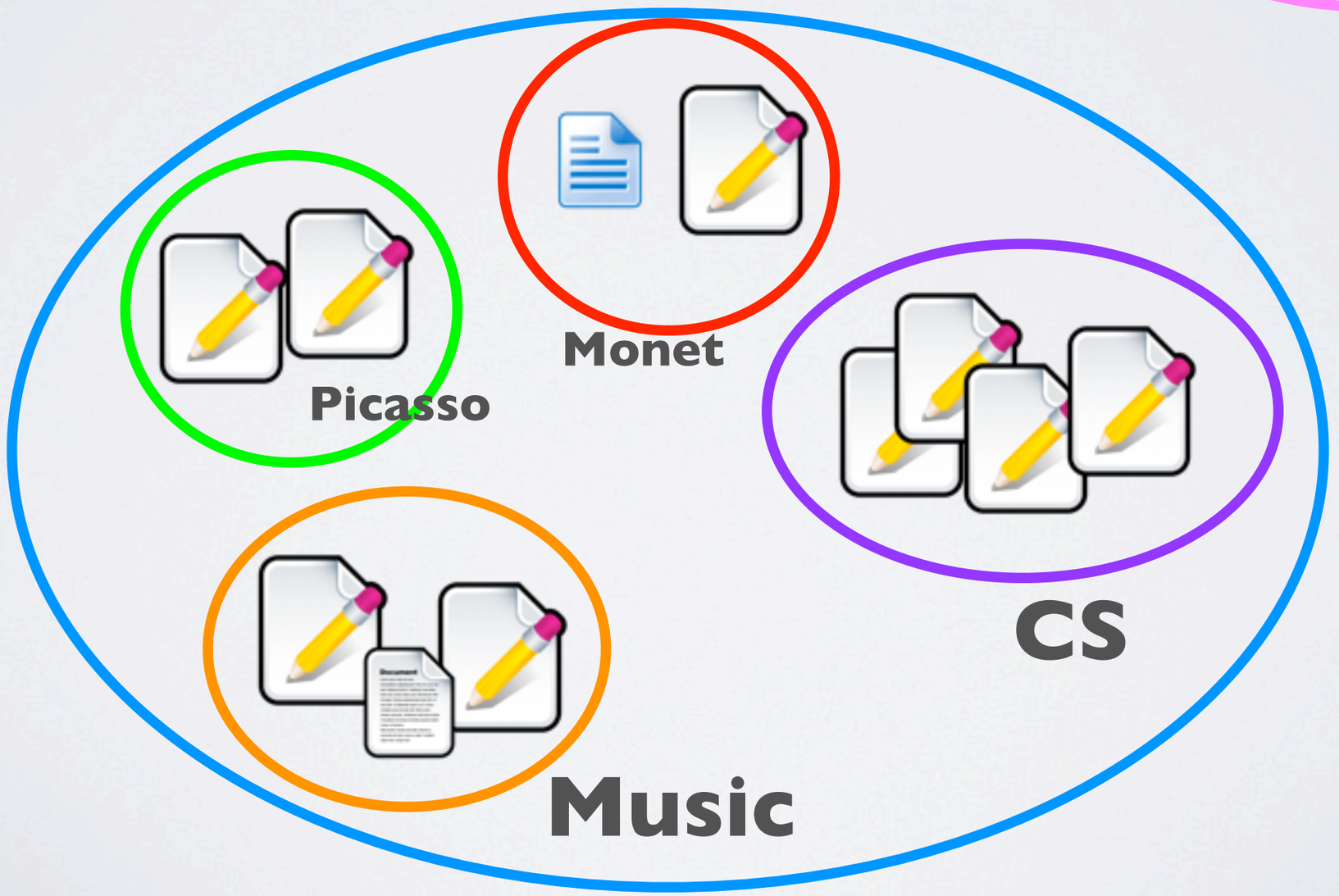

... AND ITS DYNAMICS

- Goal: insight in structuring dynamics
  → dynamic conceptual clustering that simulates the intellectual structuring process

- Two types of *guides*:
  1. own prior structuring
  2. structuring of peers

AT A GLANCE

Combination of 2 data mining tasks:

1. Learn model of structuring (classification)
   = intension: set of conditions for an object to belong to a certain class
   (vs. extension: list of objects in class)

2. Use intension or extension to structure new items

   A. based on own structuring

   B. based on k peers

GROUPING GUIDANCE

BASIC NOTATION

- U: the set of all users (used symbols: u, v, w)
- T: the set of all time points $\{0, 1, ..., tmax\}$, where $tmax$ represents the time at which the last item arrives
- D: the set of all items (used symbol: d)

  $D_u^t \subseteq D$: the set of all $d \in D$ already considered by $u \in U$ at $t \in T$

  $d_u^t \in (D \setminus D_u^t)$: the item assigned to the structure by user u at t

GROUPING GUIDANCE

GROUPINGS AND CLASSIFIERS

- G: (machine-induced) groupings for each user's items
- C: classifiers (i.e. intensions) learned for these groupings

  - OG: Observed Grouping
  - GS: Simulated Grouping, guided by self
  - Gn: Simulated Grouping, guided by *n* peers

INITIAL CLASSIFIER LEARNING

Goal: determine intensional definitions for
the user-generated groupings

→ Each group is regarded as a class for which
a definition needs to be calculated

↓

Definitions used to assign new items to these gorups

CLASSIFIER SELECTION

= selection of peer guides

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→ Requires divergence measure between groupings of non-identical item sets

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... but existing measures require large overlap between sets

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... but existing measures require large overlap between sets

↓

Inter-guide measure of diversity:

$$udiv(u,v) = \frac{1}{2}(1/|G_u^t| \sum_{x \in G_u^t} min_{y \in G_v^t} gdiv(x,y) + 1/|G_v^t| \sum_{y \in G_v^t} min_{x \in G_u^t} gdiv(y,x))$$

CLASSIFICATION

Selected classifiers are used to classify the item under consideration

Two cases:

- Self-guided classification
- Peer-guided classification

SELF-GUIDED

U

SELF-GUIDED

U

SELF-GUIDED

U

t_u^1: item a reaches u

t_u^2: item b reaches u

OG_u^0: observed initial grouping, learned: intensional description via classifier learning from extension

apply classifier OC_u^0 to item a; learn the new classifier CS_u^1

apply classifier CS_u^1 to item b; learn the new classifier CS_u^2

OG_u^{tmax}	$G20_u^{tmax}$	$G10_u^{tmax}$	$G5_u^{tmax}$	$G1_u^{tmax}$	GS_u^0
(observed)	(simulated, 20 peers)	(simulated, 10 peers)	(simulated, 5 peers)	(simulated, 1 peer)	(simulated, self-guided)

SELF-GUIDED

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apply classifier OC_u^0 to item a; learn the new classifier CS_u^1

apply classifier CS_u^1 to item b; learn the new classifier CS_u^2

apply classifier CS_u^2 to item c; learn the new classifier CS_u^3

t_u^1: item a reaches u

t_u^2: item b reaches u

t_u^3: item c reaches u

OG_u^{tmax}	$G20_u^{tmax}$	$G10_u^{tmax}$	$G5_u^{tmax}$	$G1_u^{tmax}$	GS_u^0
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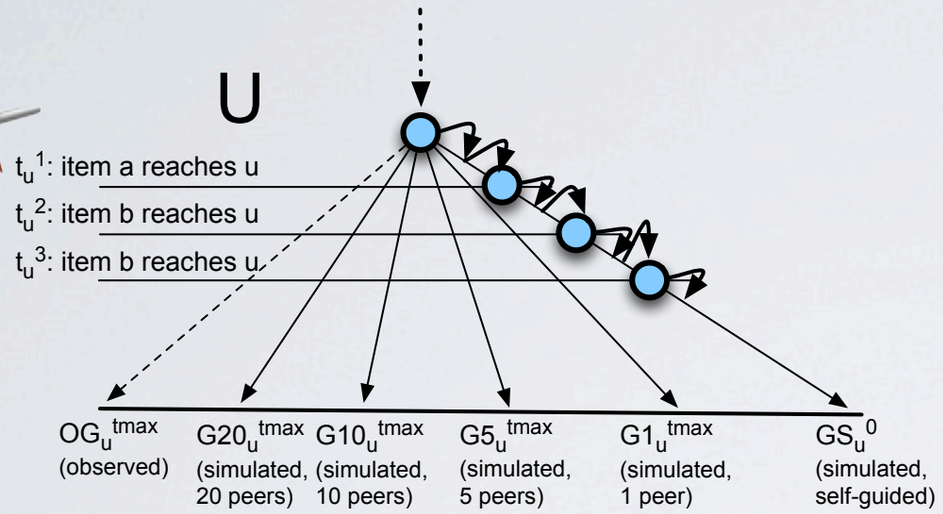
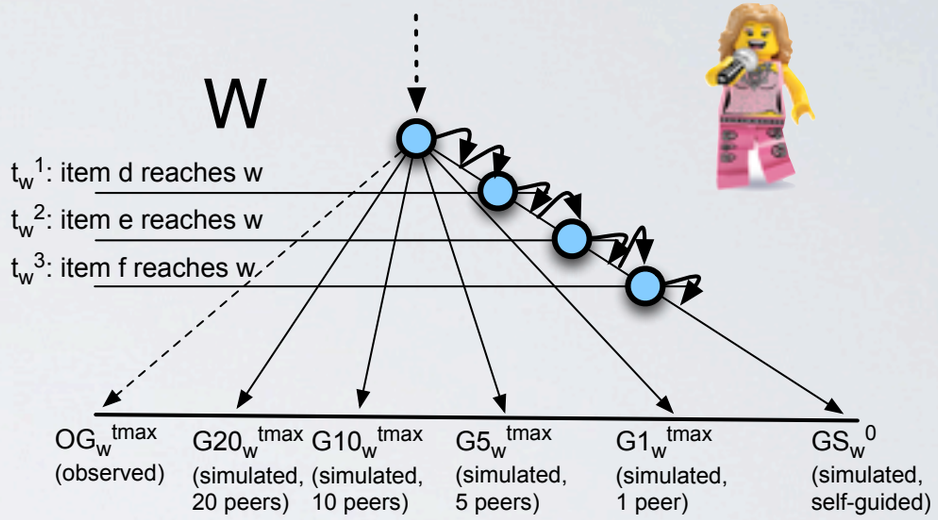
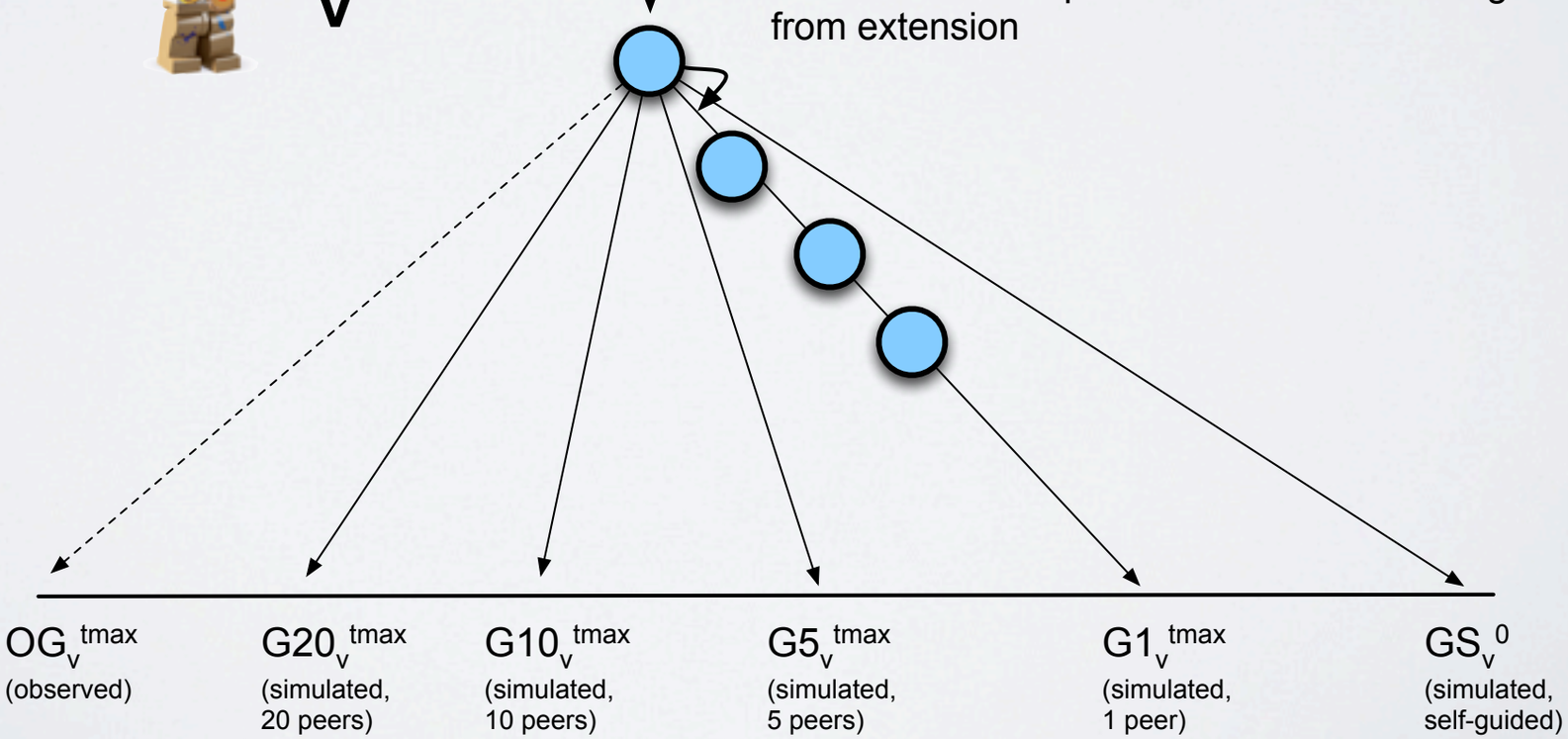
PEER-GUIDED





V

OG_v^0: observed initial grouping, learned: intensional description via classifier learning from extension



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$G5_u^{tmax}$ (simulated, 5 peers)

$G1_u^{tmax}$ (simulated, 1 peer)

GS_u^0 (simulated, self-guided)

W

t_w^1: item d reaches w

t_w^2: item e reaches w

t_w^3: item f reaches w

OG_w^{tmax} (observed)

$G20_w^{tmax}$ (simulated, 20 peers)

$G10_w^{tmax}$ (simulated, 10 peers)

$G5_w^{tmax}$ (simulated, 5 peers)

$G1_w^{tmax}$ (simulated, 1 peer)

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t_v^1: item g reaches v

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learn the new classifier $C1_v^1$

apply classifier CS_u^1 to item h;
learn the new classifier $C1_v^2$

t_v^1: item g reaches v

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learn the new classifier $C1_v^1$

apply classifier CS_u^1 to item h;
learn the new classifier $C1_v^2$

apply classifier CS_w^2 to item i;
learn the new classifier $C1_u^3$

t_v^1: item g reaches v

t_v^2: item h reaches v

t_v^3: item i reaches v

OG_v^{tmax} (observed)

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$G10_v^{tmax}$ (simulated, 10 peers)

$G5_v^{tmax}$ (simulated, 5 peers)

$G1_v^{tmax}$ (simulated, 1 peer)

GS_v^0 (simulated, self-guided)

DATASET

CiteULike dataset

→ sampled with p-core subgraphs to overcome sparsity

# users	377
# documents	11,400
# tags	12,982
timeframe	01/2009 - 02/2010

INITIAL GROUPING

Tagging as implicit structuring

- First 7 months to learn initial grouping
- Modularity clustering

INITIAL GROUPING

Tagging as implicit structuring

- First 7 months to learn initial grouping
- Modularity clustering

Initial classifier learning

- High dimensional input space (BoW of abstracts)

→ Naive bayes

SIMULATING GROUPINGS

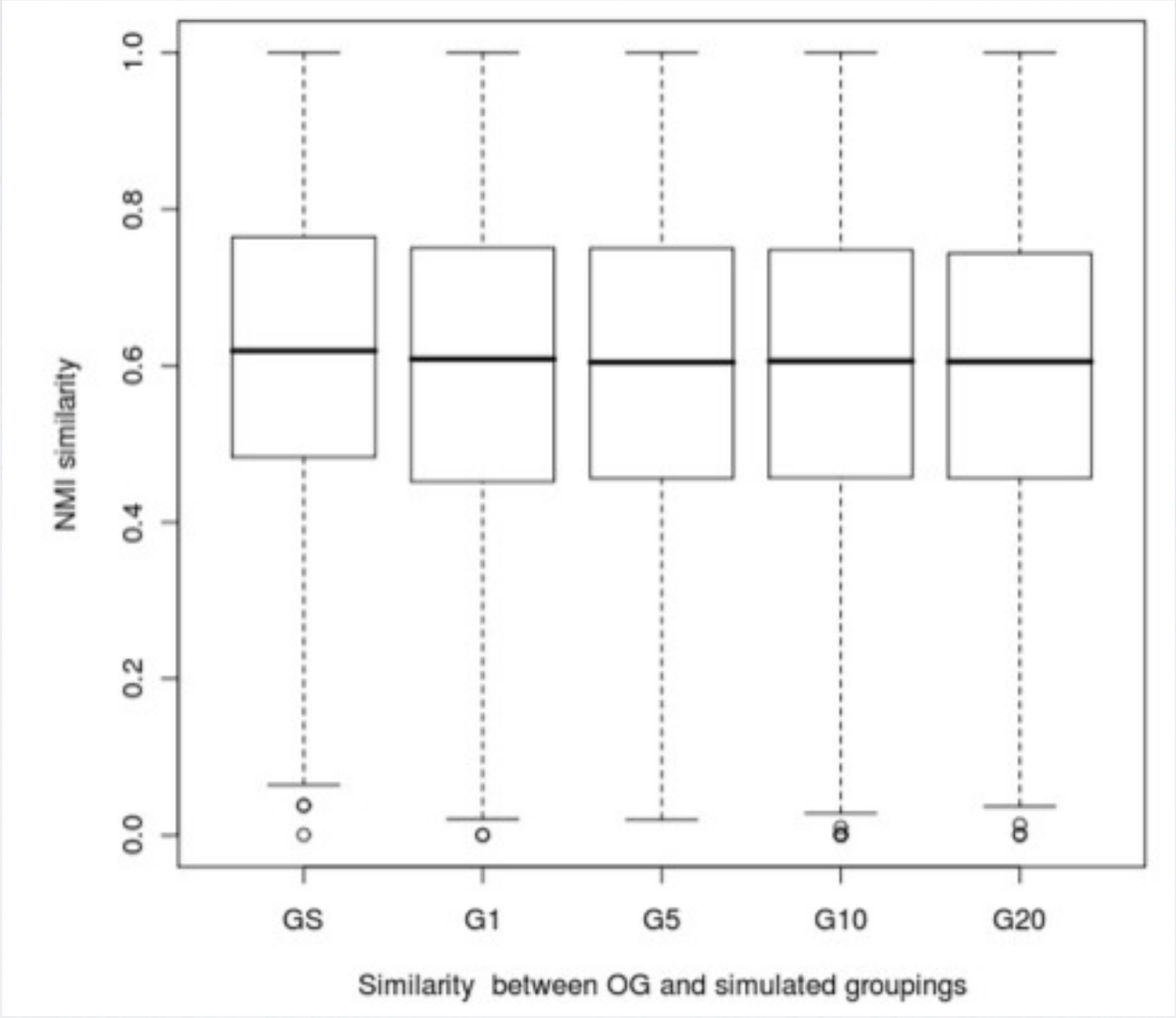
- Groups represented by language models
- Jensen-Shannon divergence as inter-group divergence

$$JS(\Theta_x, \Theta_y) = \frac{1}{2} KL(\Theta_x, \Theta_z) + \frac{1}{2} KL(\Theta_y, \Theta_z)$$

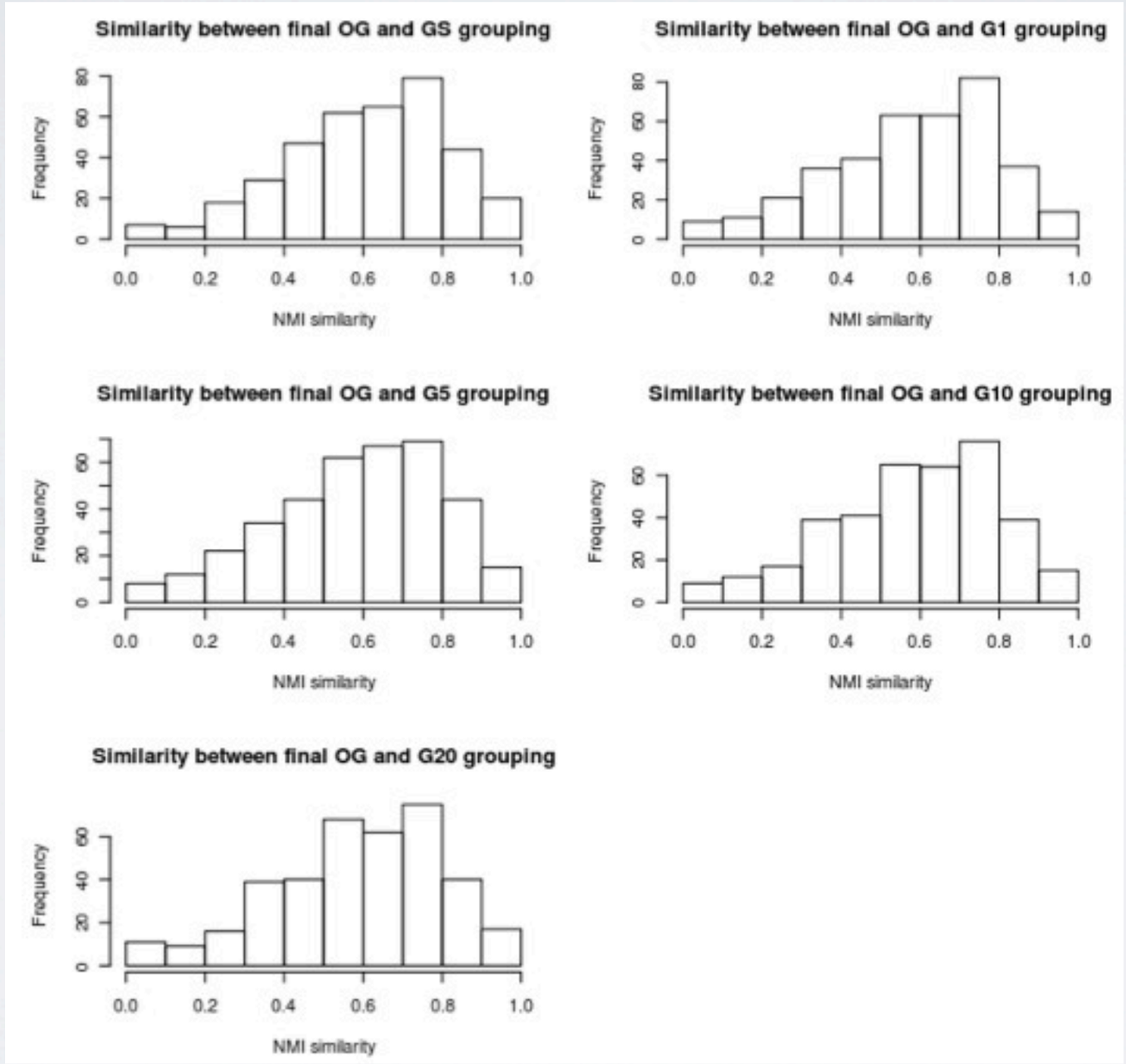
- Normalized Mutual Information to compare groupigns

$$NMI(G, G') = H(G) + H(G') - \frac{H(G, G')}{\sqrt{H(G)H(G')}}$$

RESULTS


NMI similarity
0.0
0.2
0.4
0.6
0.8
1.0
GS
G1
G5
G10
G20
Similarity between OG and simulated groupings

SIMILARITY DISTRIBUTION



CONCLUSIONS

- Investigate and simulate collaborative structuring

→ Learning and combining classifiers for itemset structuring

- New divergence measure

- Tested on social-bookmarking platform for literature management

CONCLUSIONS

LIMITATIONS

- Observed groupings based on tag assignements
- Simple classifier

... but provides initial insights into grouping behaviour and behaviour of users in social bookmarking systems

FUTURE WORK

- Applications: (tag) recommendation and social search

→ Adds new level to individual and social measures

- Regrouping based on peers

- Hybrid measure for itemset structuring

THANKS!

QUESTIONS?