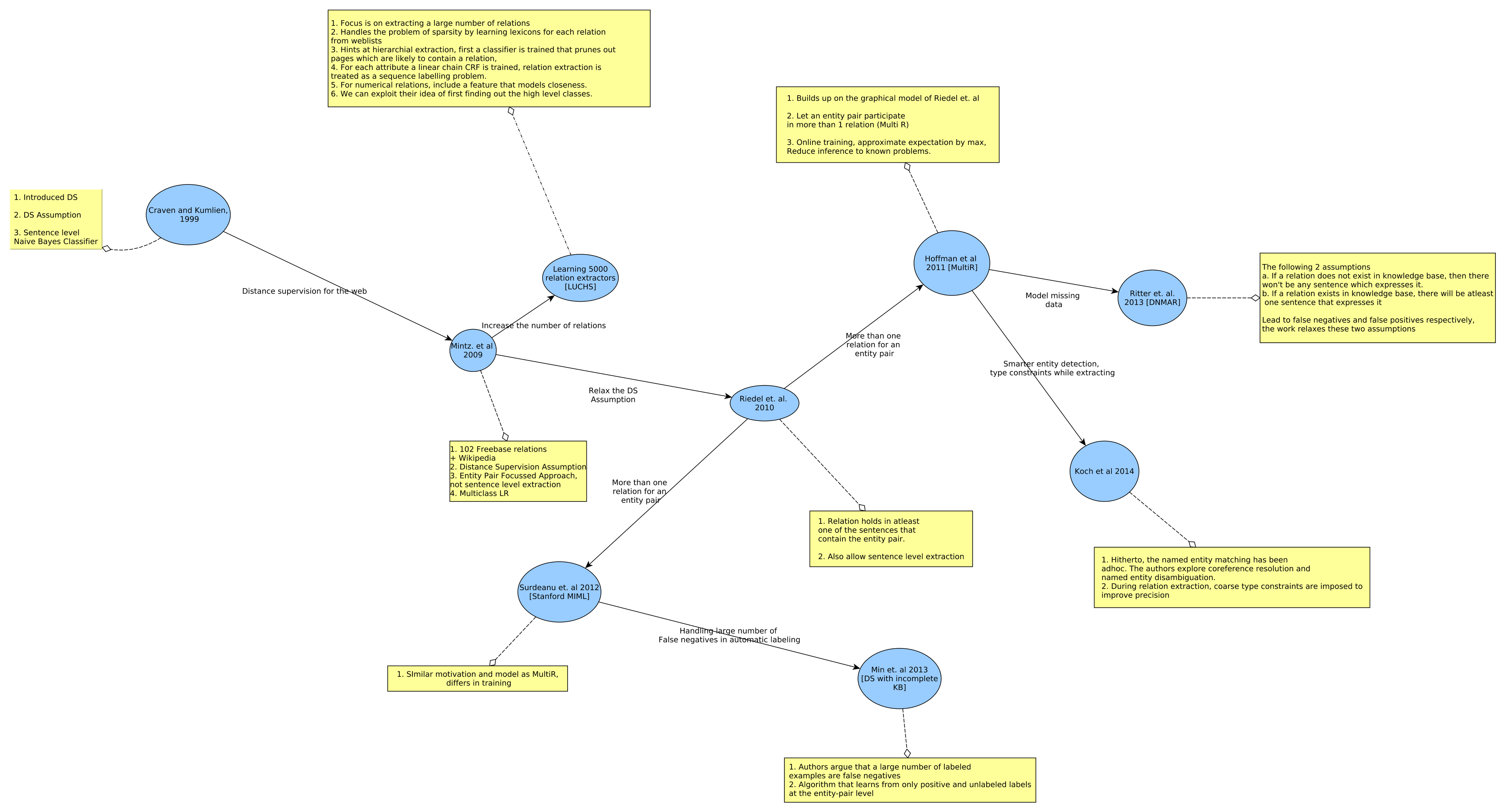
1. Focus is on extracting a large number of relations
2. Handles the problem of sparsity by learning lexicons for each relation from weblists
3. Hints at hierarchial extraction, first a classifier is trained that prunes out pages which are likely to contain a relation,
4. For each attribute a linear chain CRF is trained, relation extraction is treated as a sequence labelling problem.
5. For numerical relations, include a feature that models closeness.
6. We can exploit their idea of first finding out the high level classes.
1. Builds up on the graphical model of Riedel et. al
2. Let an entity pair participate in more than 1 relation (Multi R)
3. Online training, approximate expectation by max, Reduce inference to known problems.
1. Introduced DS
2. DS Assumption
3. Sentence level Naive Bayes Classifier
Craven and Kumlien, 1999
Learning 5000 relation extractors [LUCHS]
Hoffman et al 2011 [MultiR]
Distance supervision for the web
Increase the number of relations
Model missing data
Ritter et. al. 2013 [DNMAR]
The following 2 assumptions
a. If a relation does not exist in knowledge base, then there won't be any sentence which expresses it.
b. If a relation exists in knowledge base, there will be atleast one sentence that expresses it
Lead to false negatives and false positives respectively, the work relaxes these two assumptions
Mintz. et al 2009
More than one relation for an entity pair
Smarter entity detection, type constraints while extracting
Relax the DS Assumption
Riedel et. al. 2010
Koch et al 2014
1. 102 Freebase relations + Wikipedia
2. Distance Supervision Assumption
3. Entity Pair Focussed Approach, not sentence level extraction
4. Multiclass LR
More than one relation for an entity pair
1. Relation holds in atleast one of the sentences that contain the entity pair.
2. Also allow sentence level extraction
1. Hitherto, the named entity matching has been adhoc. The authors explore coreference resolution and named entity disambiguation.
2. During relation extraction, coarse type constraints are imposed to improve precision
Surdeanu et. al 2012 [Stanford MIML]
Handling large number of False negatives in automatic labeling
1. SImilar motivation and model as MultiR, differs in training
Min et. al 2013 [DS with incomplete KB]
1. Authors argue that a large number of labeled examples are false negatives
2. Algorithm that learns from only positive and unlabeled labels at the entity-pair level