is limited to lexical entailment and they show its effectiveness for nouns. Our method on the other hand deals with inference rules between binary relations and includes inference rules between verbal relations, non-verbal relations and multi-word relations. Our definition of context and the methodology for obtaining context similarity and overlap is also much different from theirs.

3 Learning Directionality of Inference Rules

The aim of this paper is to filter out incorrect inference rules and to identify the directionality of the correct ones.

Let $p_i \Leftrightarrow p_j$ be an inference rule where each p is a binary semantic relation between two entities x and y. Let $<x, p, y>$ be an instance of relation p.

Formal problem definition: *Given the inference rule $p_i \Leftrightarrow p_j$, we want to conclude which one of the following is more appropriate:*

1. $p_i \Leftrightarrow p_j$
2. $p_i \Rightarrow p_j$
3. $p_i \Leftarrow p_j$
4. *No plausible inference*

Consider the example (1) from section 1. There, it is most plausible to conclude "*X eats Y*" ⇒ "*X likes Y*".

Our algorithm LEDIR uses selectional preferences along the lines of Resnik (1996) and Pantel et al. (2007) to determine the plausibility and directionality of inference rules.

3.1 Underlying Assumption

Many approaches to modeling lexical semantics have relied on the distributional hypothesis (Harris 1954), which states that words that appear in the same contexts tend to have similar meanings. The idea is that context is a good indicator of a word meaning. Lin and Pantel (2001) proposed an extension to the distributional hypothesis and applied it to paths in dependency trees, where if two paths tend to occur in similar contexts it is hypothesized that the meanings of the paths tend to be similar.

In this paper, we assume and propose a further extension to the distributional hypothesis and call it the "Directionality Hypothesis".

Directionality Hypothesis: *If two binary semantic relations tend to occur in similar contexts and the first one occurs in significantly more contexts than the second, then the second most likely implies the first and not vice versa.*

The intuition here is that of generality. The more general a relation, more the types (and number) of contexts in which it is likely to appear. Consider the example (1) from section 1. The fact is that there are many more things that someone might like than those that someone might eat. Hence, by applying the directionality hypothesis, one can infer that "*X eats Y*" ⇒ "*X likes Y*".

The key to applying the distributional hypothesis to the problem at hand is to model the contexts appropriately and to introduce a measure for calculating context similarity. Concepts in semantic space, due to their abstractive power, are much richer for reasoning about inferences than simple surface words. Hence, we model the context of a relation p of the form $<x, p, y>$ by using the semantic classes *C(x)* and *C(y)* of words that can be instantiated for x and y respectively. To measure context similarity of two relations, we calculate the overlap coefficient (Manning and Schütze, 1999) between their contexts.

3.2 Selectional Preferences

The selectional preferences of a predicate is the set of semantic classes that its arguments can belong to (Wilks 1975). Resnik (1996) gave an information theoretical formulation of the idea. Pantel et al. (2007) extended this idea to non-verbal relations by defining the relational selectional preferences (RSPs) of a binary relation p as the set of semantic classes $C(x)$ and $C(y)$ of words that can occur in positions x and y respectively.

The set of semantic classes $C(x)$ and $C(y)$ can be obtained either from a manually created taxonomy like WordNet as proposed in the above previous approaches or by using automatically generated classes from the output of a word clustering algorithm as proposed in Pantel et al. (2007). For example given a relation like "*X likes Y*", its RSPs from WordNet could be *{individual, social_group…}* for *X* and *{individual, food, activity…}* for *Y*.

In this paper, we deployed both the Joint Relational Model (JRM) and Independent Relational Model (IRM) proposed by Pantel et al. (2007) to obtain the selectional preferences for a relation p.