# Sentiment Aggregation using ConceptNet Ontology

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7th International Joint Conference on Natural Language Processing (IJCNLP 2013), Nagoya, Japan

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- Classify a review as *positive*, *negative* or *objective*

- *I bought a phone*
- *The audio quality of the phone is awesome*
- *The picture quality of its camera is bad*

- *The **audio** quality of my new phone is absolutely awesome but the **picture** taken by the camera is a bit grainy*
  - A bag-of-words model will classify it as *neutral*
  - Feature-specific SA finds polarity w.r.t **audio** as *positive* and that w.r.t **picture** as *negative*
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# Example Review

- *I bought a Canon EOS 7D (DSLR). It's very small, sturdy, and constructed well. The* ***handling*** *is quite nice with a powder-coated metal frame. It* ***powers on*** *quickly and the* ***menus*** *are fairly easy to* ***navigate****. The* ***video modes*** *are nice, too. It works great with my 8GB Eye-Fi* ***SD card****. A new camera isn't worth it if it doesn't exceed the* ***picture quality*** *of my old 5Mpixel SD400 and this one doesn't. The* ***auto white balance*** *is poor. I'd need to properly balance every picture taken so far with the ELPH 300. With 12 Mpixels, you'd expect pretty good images, but the problem is that the ELPH 300* ***compression*** *is turned up so high that the* ***sensor's acuity*** *gets lost (softened) in compression.*

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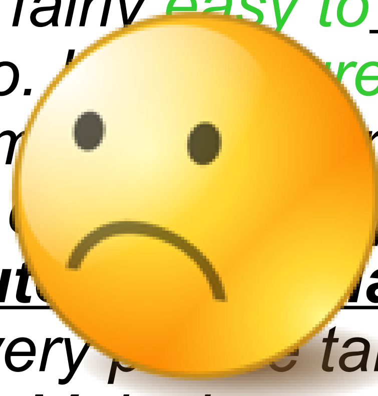

# Analyzing Reviews

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- Reviewer happy with *camera size, structure, easy use, video modes, SDHC support etc.*
- However, the *auto-white balance*, *high compression* leading to *sensor acuity* seems to disappoint him
- *Picture, video quality, resolution, color balance etc.* are of primary importance to a camera whereas *size, video mode, easy use etc.* are secondary
- Overall review polarity is negative as the reviewer shows concerns about the most important features of the camera
- Traditional works in sentiment analysis view a review as a flat structure where the association between features of a product is largely ignored
- *How to capture the association between features of a product?*

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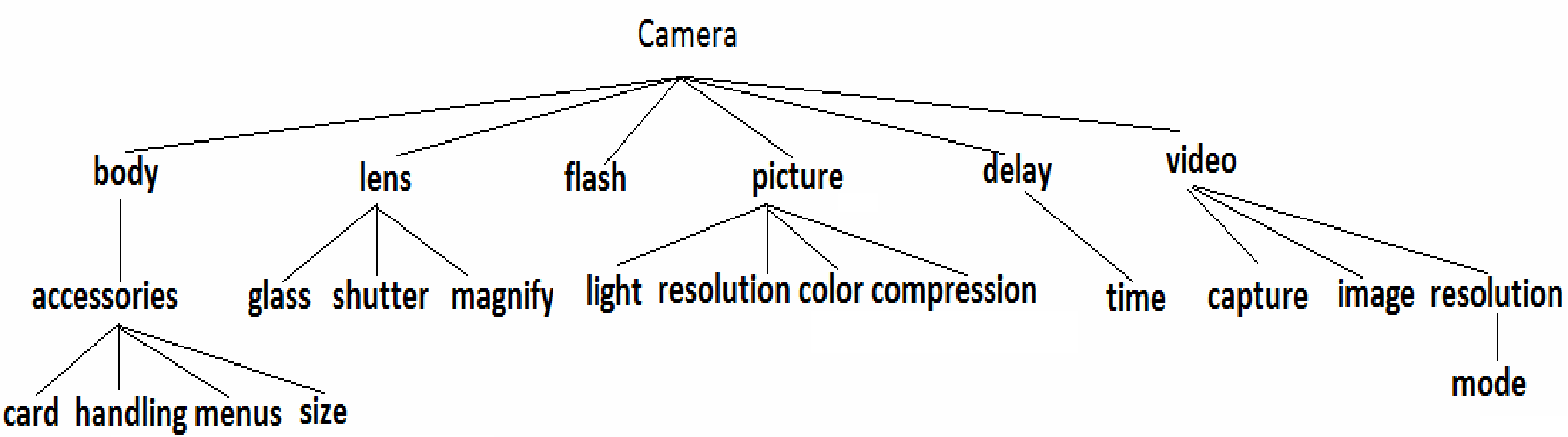
# Camera Ontology Tree Snapshot



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- Ontology is a knowledge base of structured list of concepts, relations and individuals

- *Hierarchical relationship* between the product attributes can be best captured by an *Ontology Tree*

- Ontology creation is expensive, highly domain-specific

- In this work, we use ConceptNet (Hugo *et al.*, 2004) to automatically construct a domain-specific ontology tree for product reviews

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- We categorize ConceptNet relations into 3 primary categories : *hierarchical*, *synonymous* and *functional*
- *Hierarchical* relations represent parent-child relations
  - Transitive, used to construct tree *top-down*
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# ConceptNet Relations

- Closed class of 24 primary relations expressing connections between various concepts

| |
|---|
| camera UsedFor take_picture |
| camera IsA tool_for_take_picture |
| camera AtLocation store |
| tripod UsedFor keep_camera_steady |
| camera CapableOf record_image |
| camera IsA device |
| flash PartOf camera |
| lens AtLocation camera |
| tripod AtLocation camera_shop |
| camera IsA photo_device |
| cannon ConceptuallyRelatedTo camera |
| photograph ConceptuallyRelatedTo camera |
| picture ConceptuallyRelatedTo camera |

**Table 1**. ConceptNet Relation Examples

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- Mining information from ConceptNet can be difficult due to *one-to-many relations*, *noisy data* and *redundancy*
- Relational predicates in ConceptNet have an inherent structure suitable for building ontology
- ConceptNet has a closed class of well-defined relations which can be weighed for different purposes
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- A product which takes good pictures but lacks a tripod will have a high positive polarity
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| | |
|---|---|
| Hierarchical | : LocatedNear, HasA, PartOf, MadeOf, IsA, InheritsFrom |
| Synonymous | : Synonym, ConceptuallyRelatedTo |
| Functional | : UsedFor, CapableOf, HasProperty, DefinedAs |

**Table 2**. ConceptNet Relation Type Categorization

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- One-to-many relations exist between concepts
  - E.g. *camera* and *picture* related with camera *UsedFor* take_picture, camera *HasA* picture, picture *ConceptuallyRelatedTo* camera, picture *AtLocation* camera *etc.*

- Hierarchical relations in ConceptNet
  - Definitive, less topic drift and used to ground the ontology tree
  - Preferred over other relations during a relational conflict
    - camera *HasA* picture > *picture* is *ConceptuallyRelatedTo camera*

- *hierarchical relations > synonymous relations > functional relations*

- High degree of *topic drift* during relation extraction
  - E.g. camera *HasA* lens, lens *IsA* glass and glass *HasA* water places water at a high level in the ontology tree

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4. Every relation tuple $r_{ij}(f_i, f_j) \in R$ is assigned to one of the sets $S, F$ or $H$ with ties being broken as $H > S > F$

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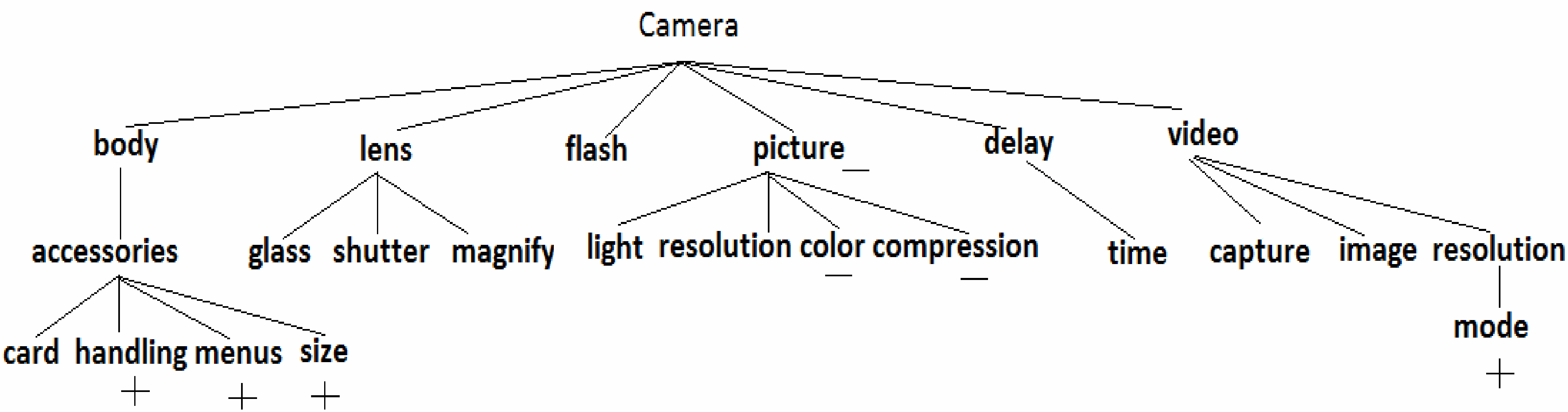
# Sentiment Annotated Ontology Tree



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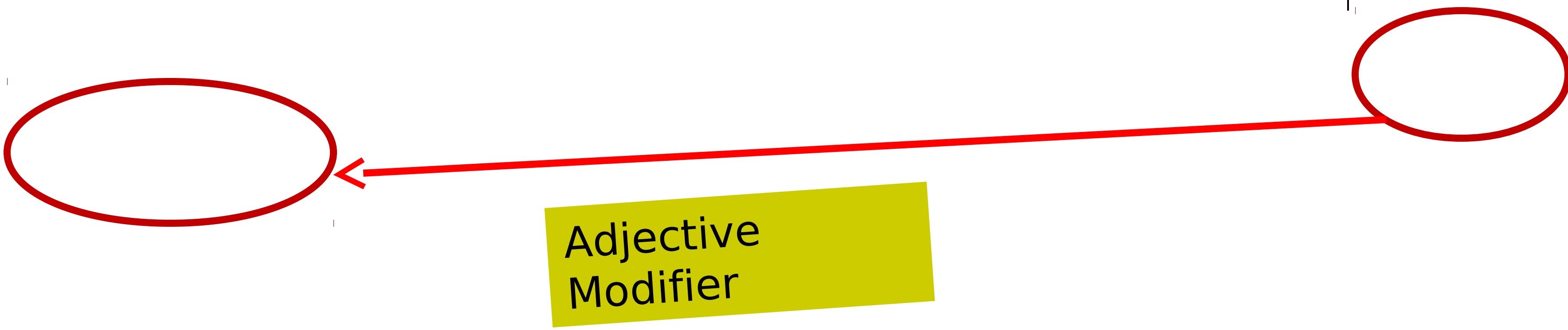

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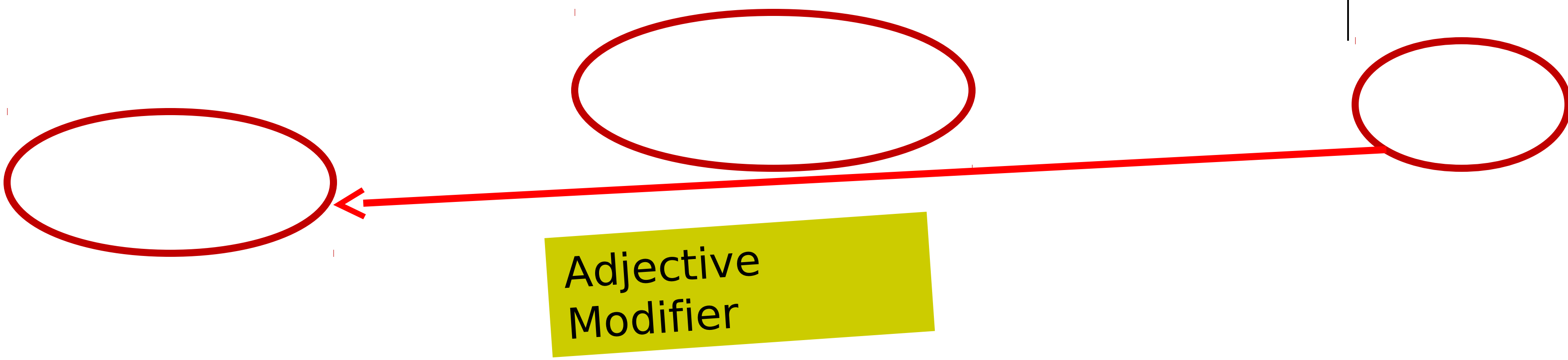

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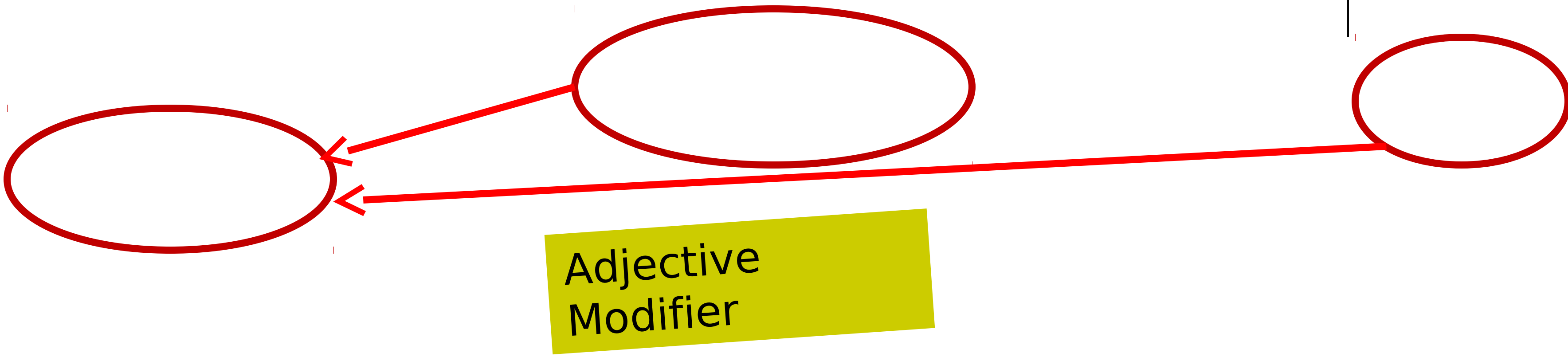

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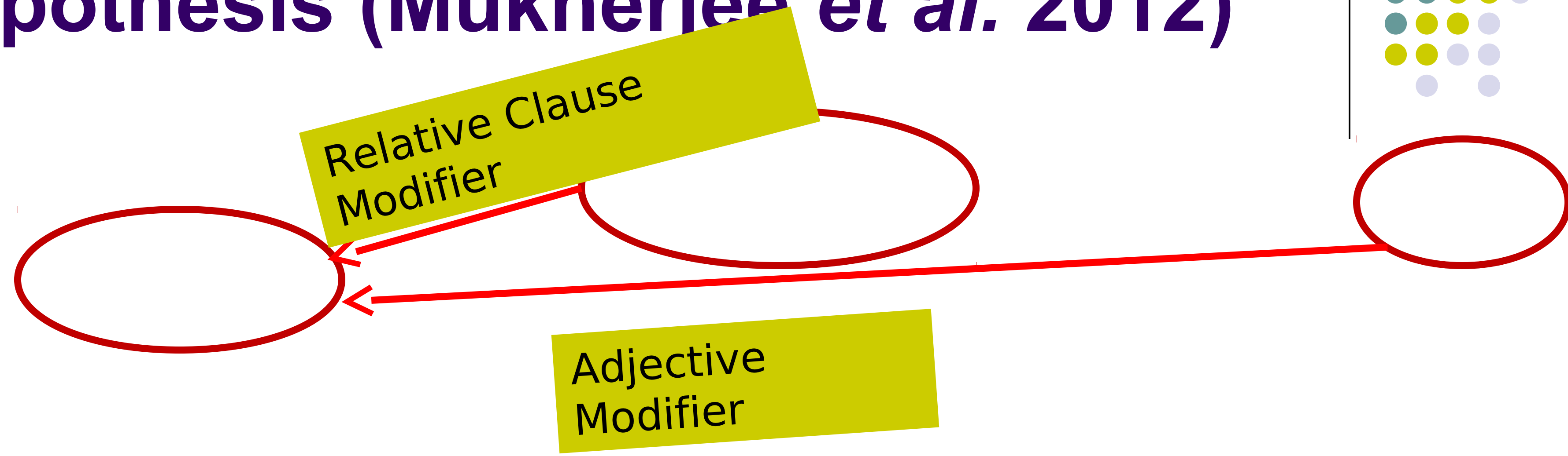

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Relative Clause Modifier

- *"I want to use Samsung which is a great product but am not so sure about using Nokia".*

Adjective Modifier

  - *Here "great" and "product" are related by an adjective modifier relation, "product" and "Samsung" are related by a relative clause modifier relation. Thus "great" and "Samsung" are transitively related.*
  - ***Here "great" and "product" are more related to Samsung than they are to Nokia***
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> *"More closely related words come together to express an opinion about a feature"*

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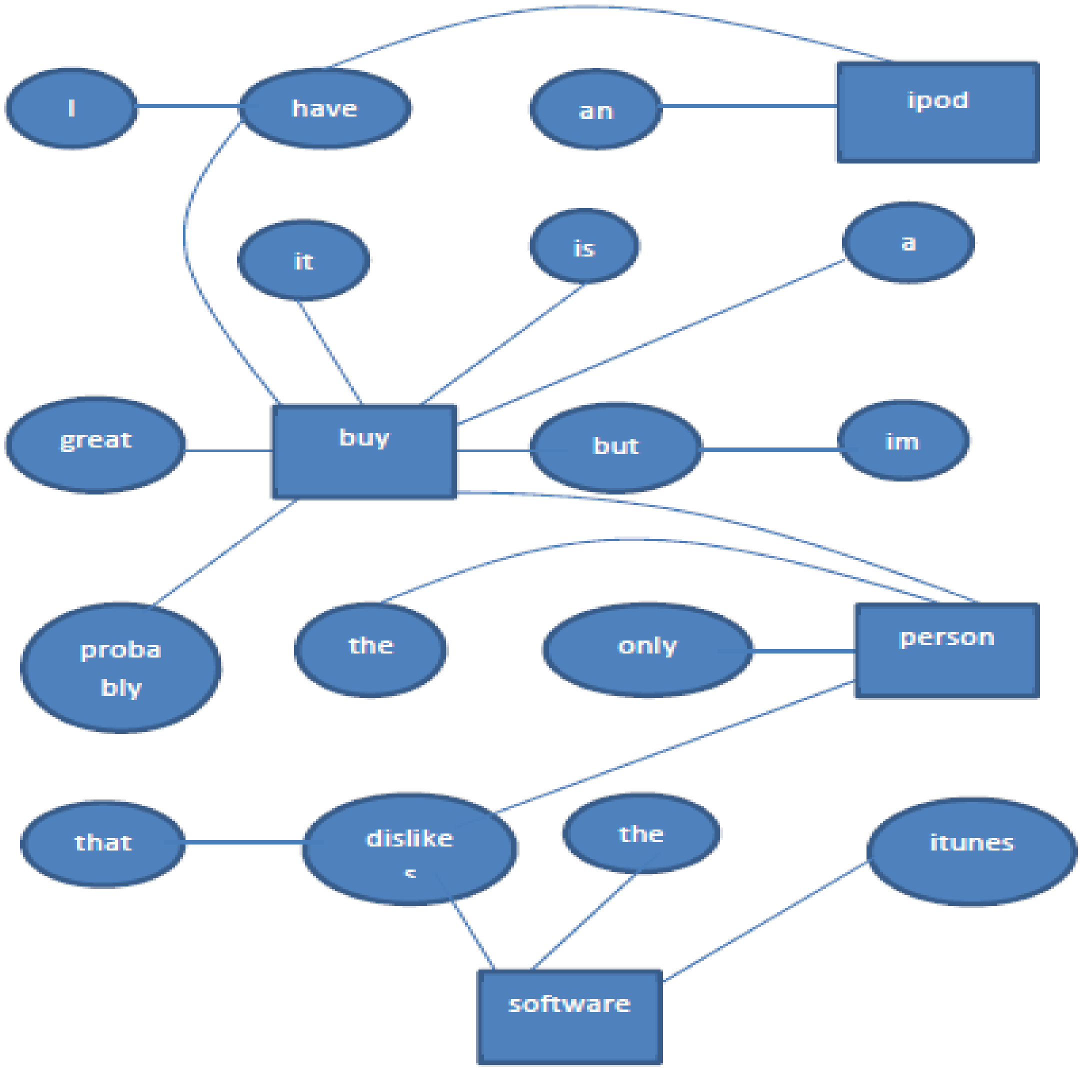
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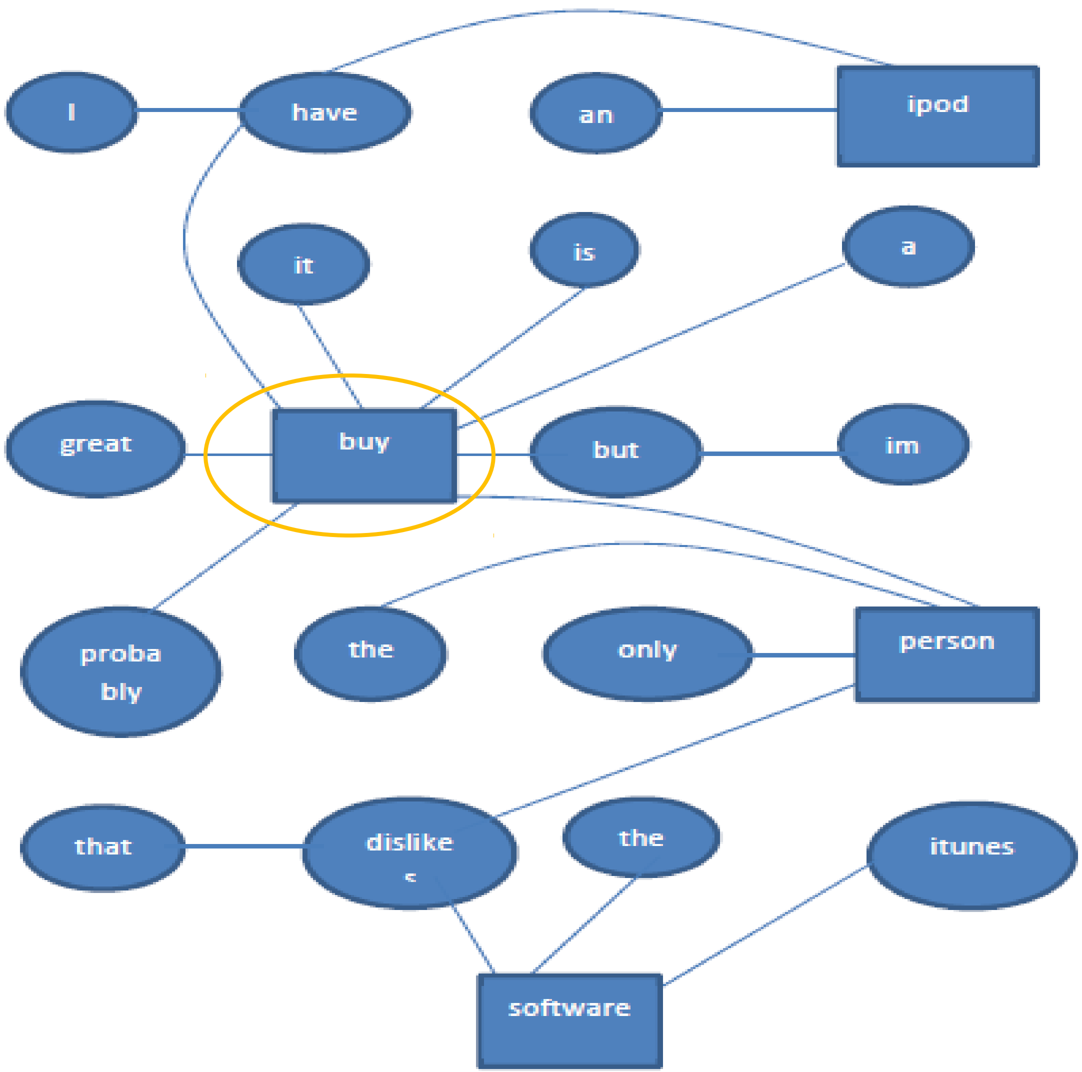
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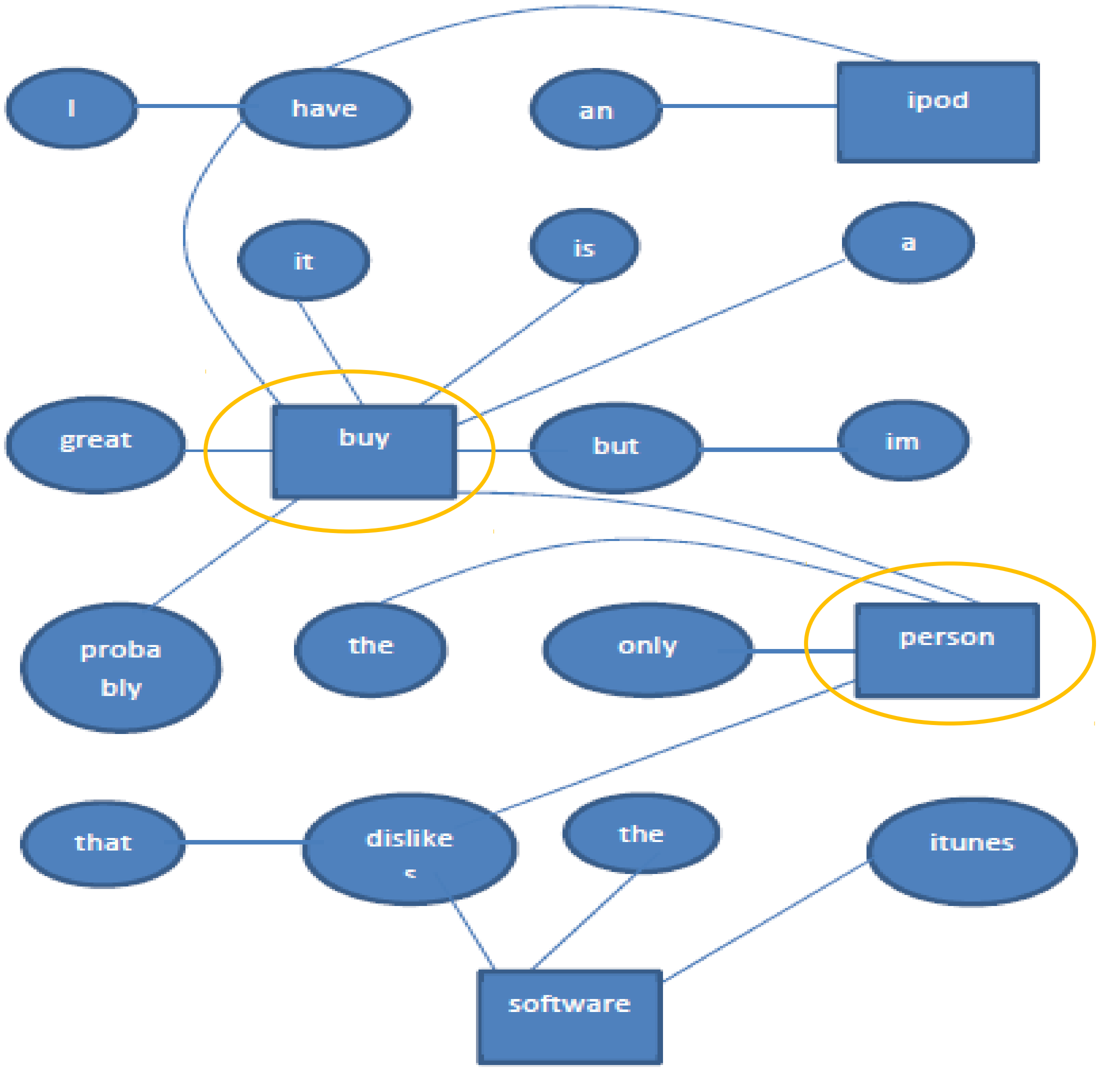

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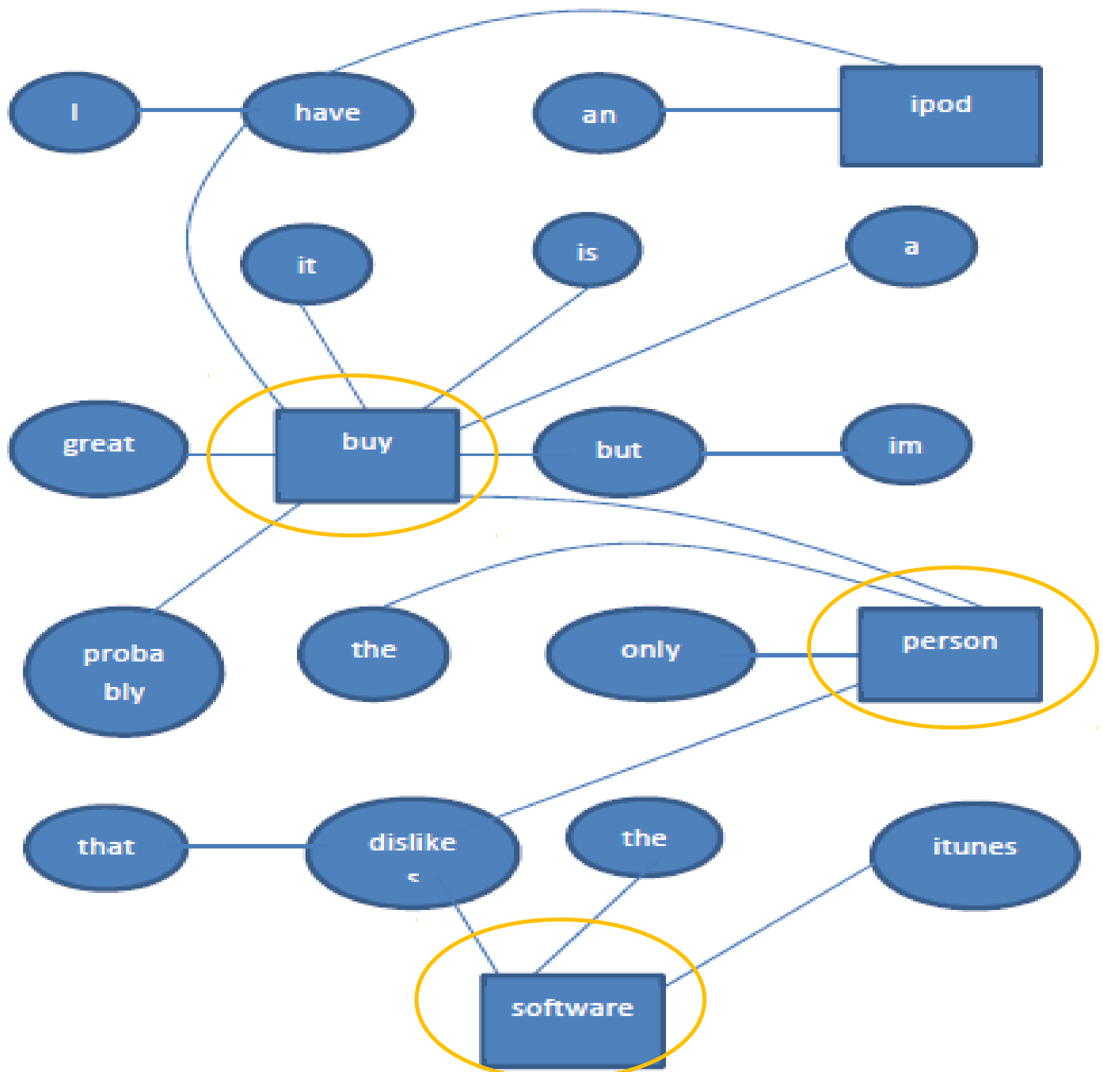

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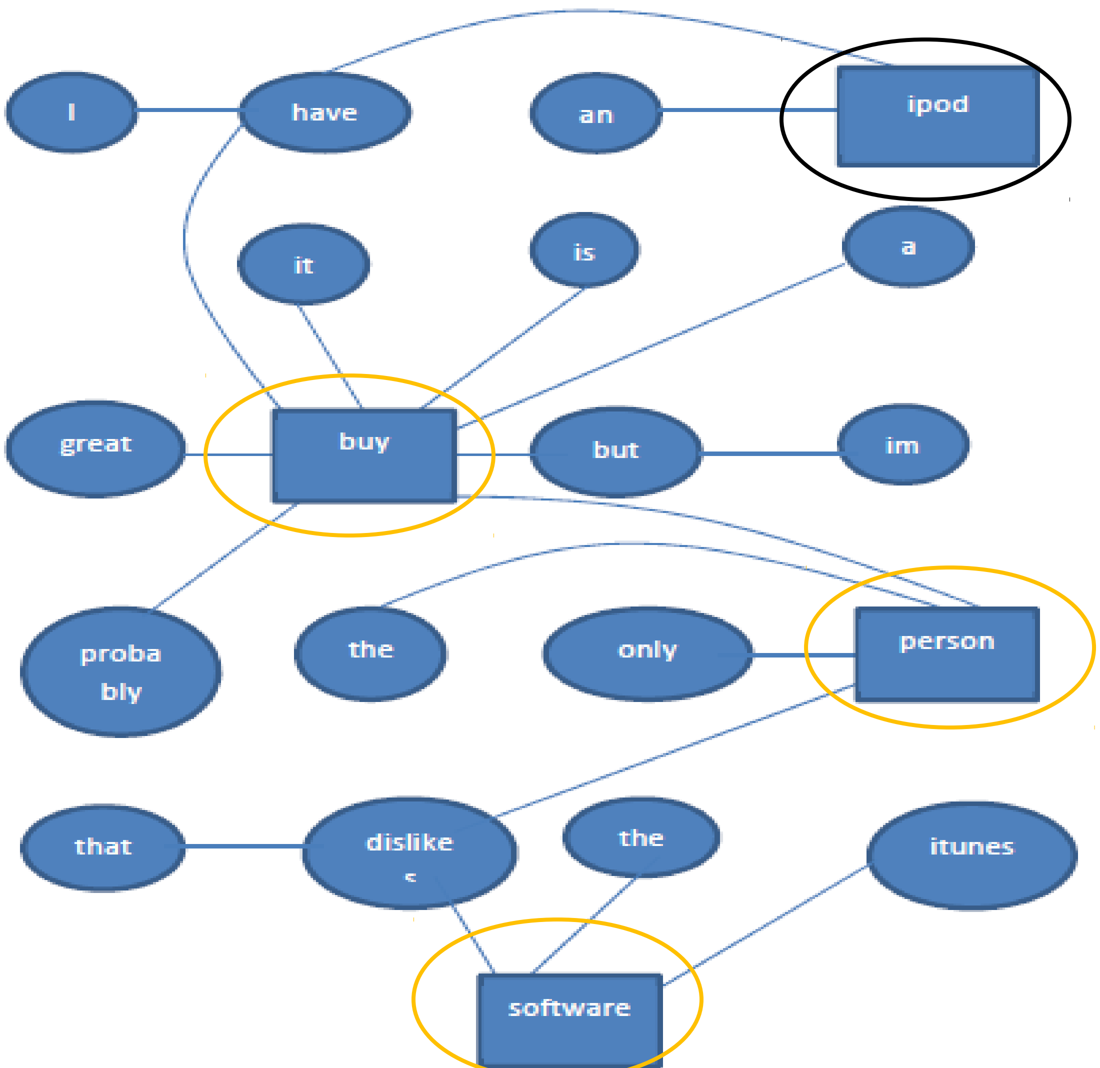
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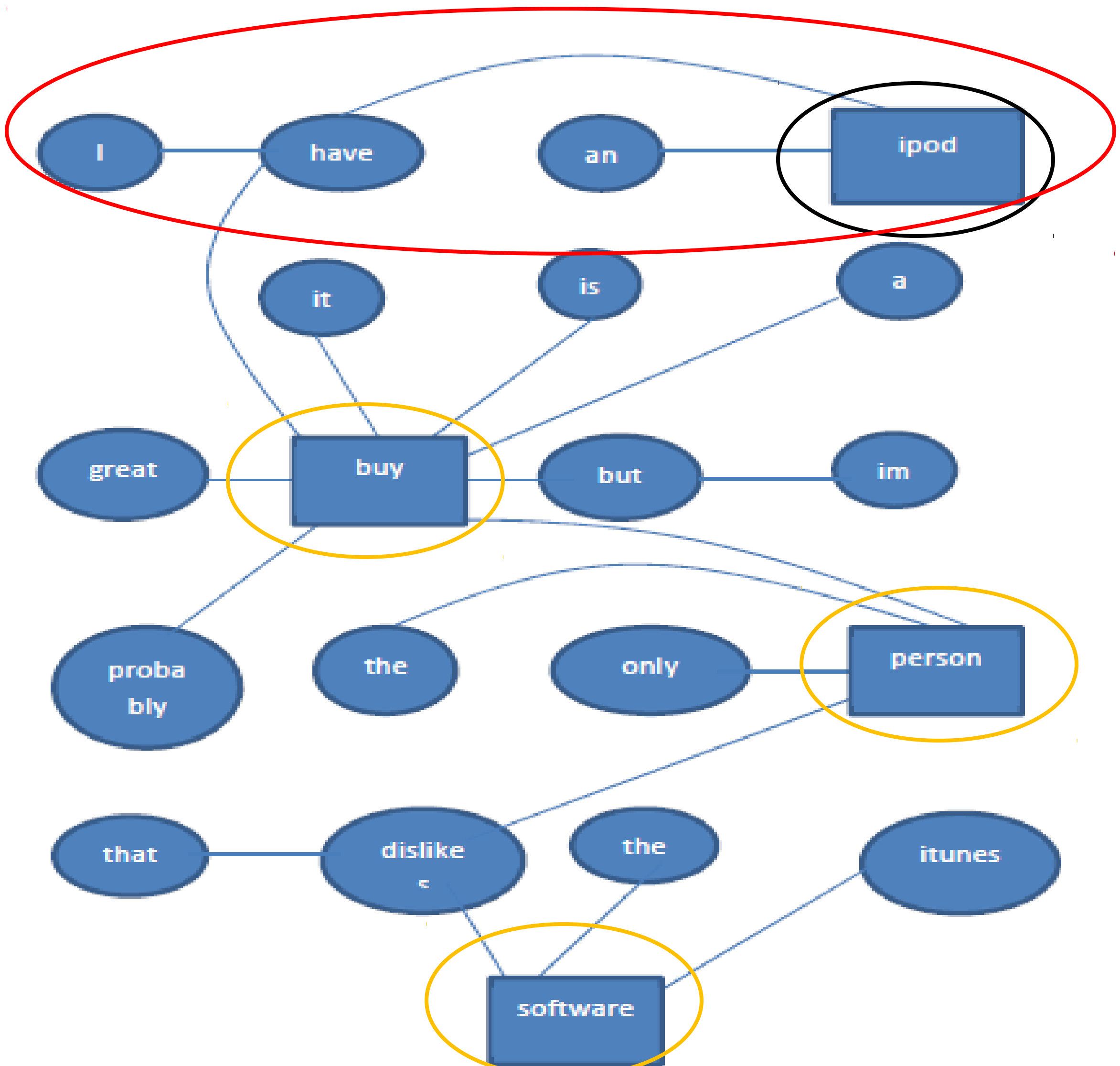

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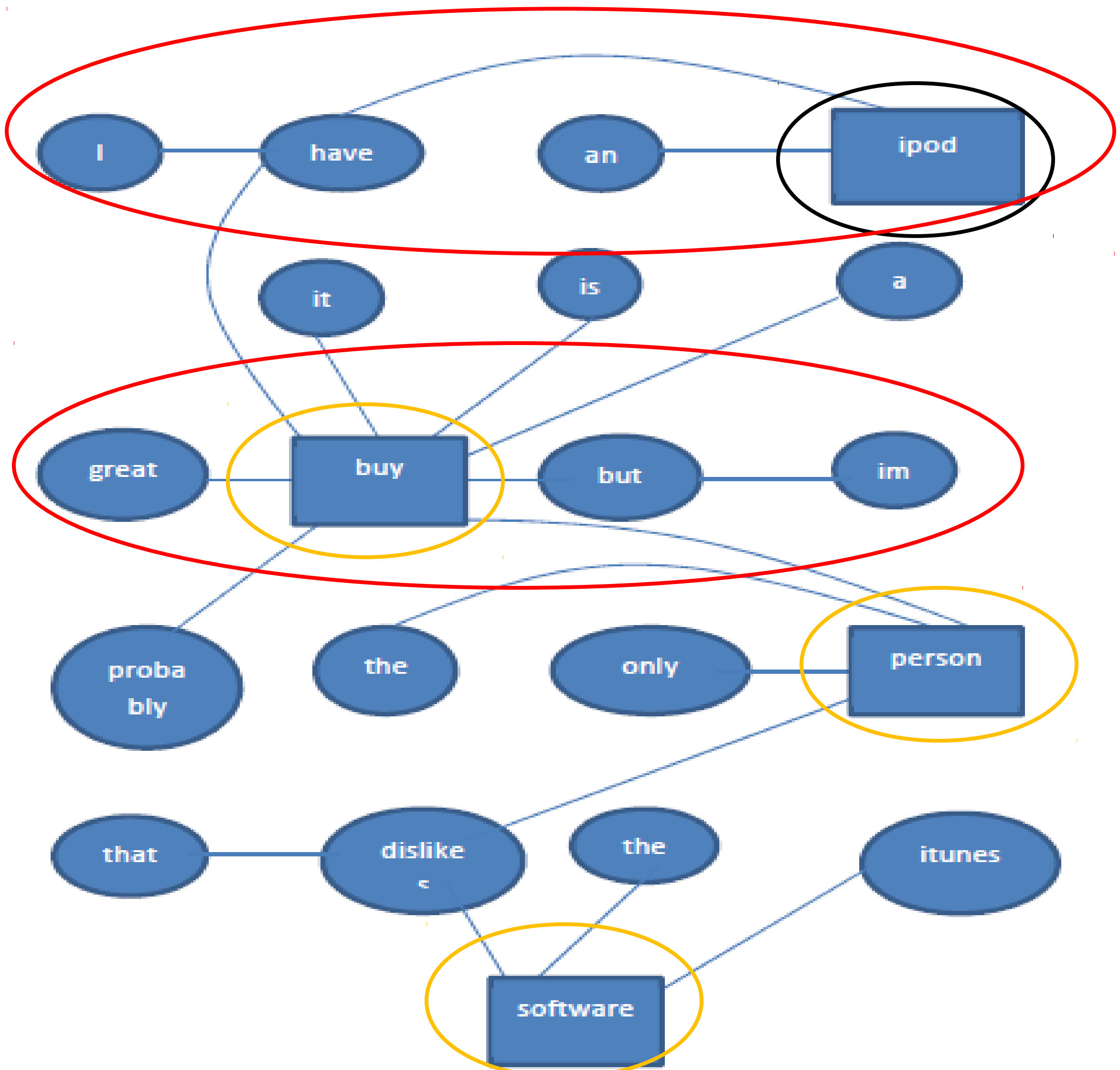
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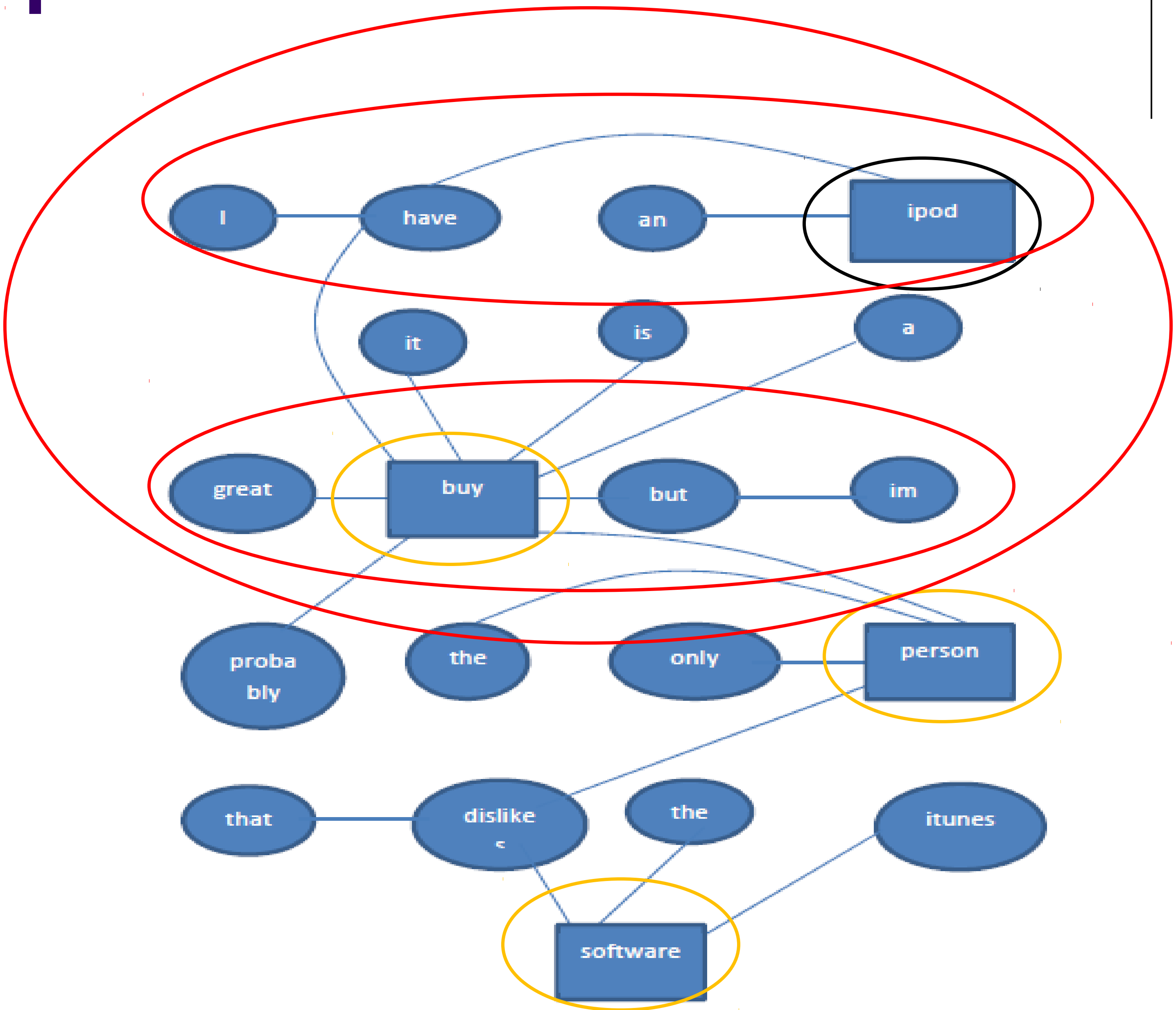
I
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is
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that
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s
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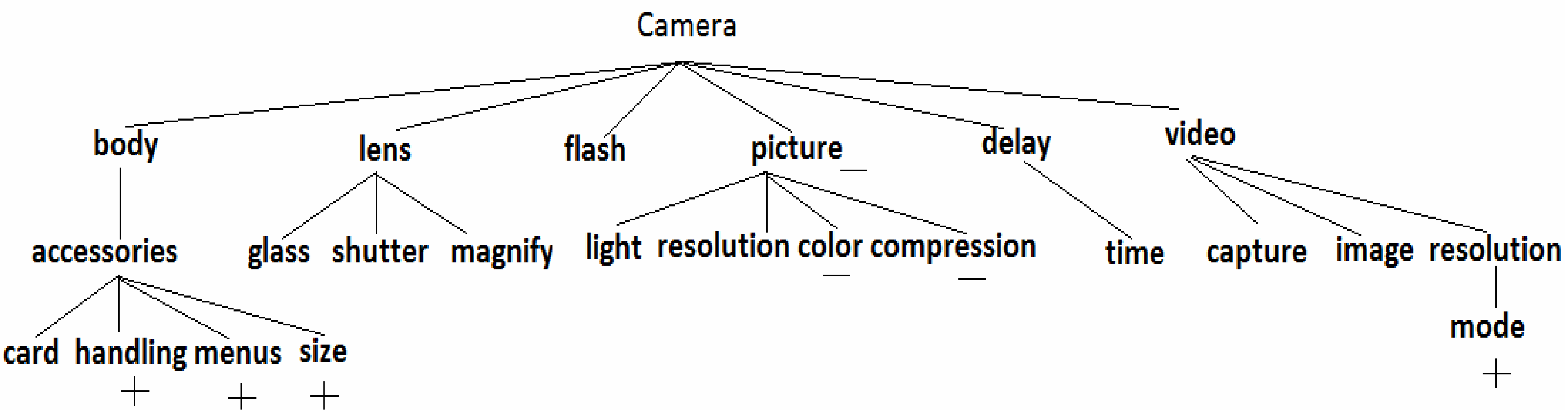
itunes
software

# Sentiment Annotated Ontology Tree




- Annotating Ontology tree with feature-specific polarities
- View sentiment aggregation as an information propagation problem

# Sentiment Aggregation

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- Product attributes at a higher level of the tree dominate those at the lower level
- Reviewer opinion about a feature at a higher level in the ontology tree (say *picture*), weighs more than the information of all its children nodes (say *light, resolution, color and compression*)
- Feature importance captured by height of a feature node in the tree
- If parent feature polarity is neutral / absent, its polarity is given by its children feature polarities
- Information at a particular node is given by its self information and the weighted information of all its children nodes
- Information propagation is done bottom-up to determine the information content of the root node, which gives the polarity of the review

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# Sentiment Aggregation Contd…

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- Consider the ontology tree $T(V,E)$
  - $V_i=\{f_i, p_i, h_i\}$ is a *product attribute set*, where $f_i$ is a product feature, $p_i$ is review *polarity score* with w.r.t. $f_i$ and $h_i$ is the height of the *product attribute* in the *ontology tree*
  - $E_{ij}$ is an *attribute relation type* connecting $V_i$ and $V_j$ and $u_{ij}$ be the *link strength* of $E_{ij}$
  - Let $V_{ij}$ be the $j^{th}$ child of $V_i$

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# Sentiment Aggregation Contd…

The *positive sentiment weight* (PSW) and *negative sentiment weight* (NSW) of a vertex $V_i$ are defined as,

$$PSW(V_i) = h_i \times p_i^+ + \sum_j PSW(V_{ij}) \times u_{ij}$$

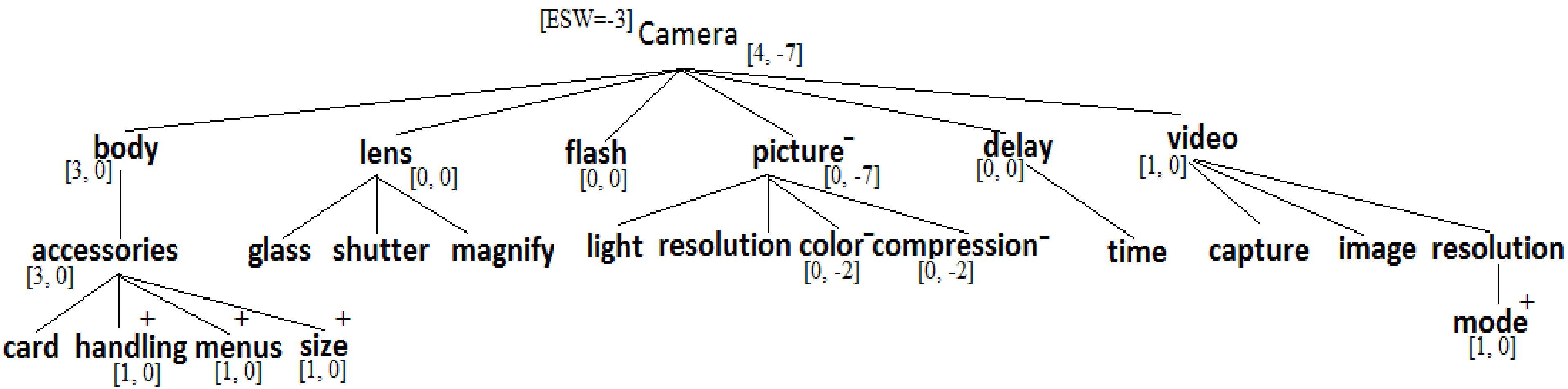
$$NSW(V_i) = h_i \times p_i^- + \sum_j NSW(V_{ij}) \times u_{ij}$$

where $p_i^+ \in [0,1]$ and $p_i^- \in [-1,0]$.

The review polarity is given by the *expected sentiment-weight* (ESW) of the tree defined as,

$$ESW(root) = PSW(root) + NSW(root)$$

# Sentiment Ontology tree (SOT)



# Feature Weight from Corpus

- *Corpus* assigns weight to each *feature* that distinguishes between attributes that are siblings

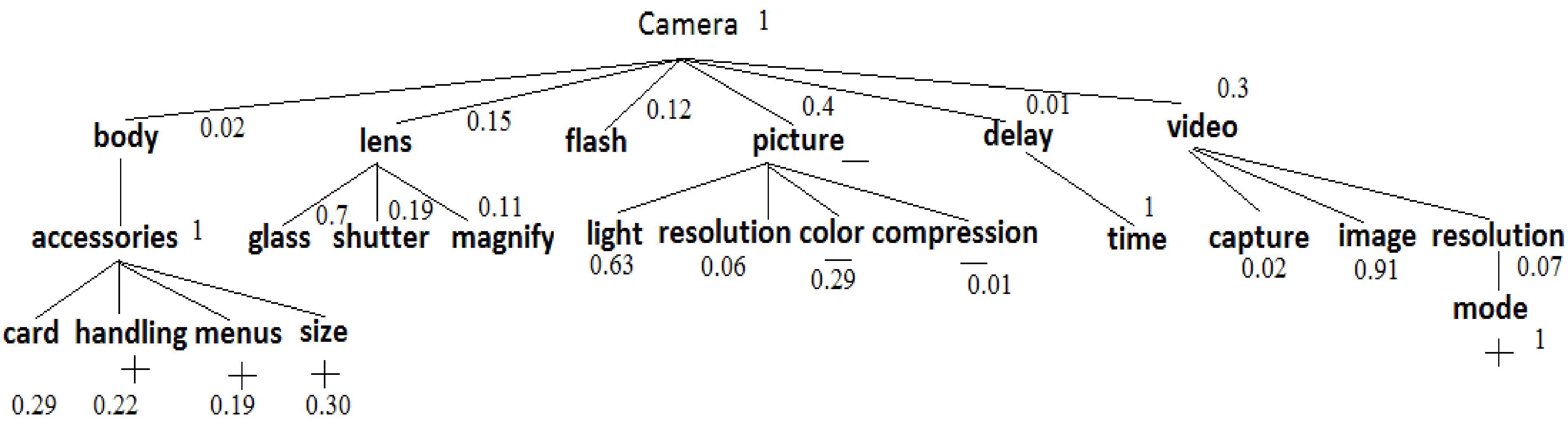
- E.g. Ontology assigns the same weight to the children of *camera i.e. body, lens, flash, picture* and *video*.
- But *picture*, in general, is more important than *body* for a *camera* which is captured from the corpus

- The feature weight $u_i$ of $f_i$ is given by

$$u_i = \frac{df_i}{\sum_{j \in Sibling(i)} df_j + df_i}$$

$$ESW(V_i) = u_i \times [\Im(p_i) \times h_i \times p_i + (1 - \Im(p_i)) \times \sum_j ESW(V_{ij})]$$

# Feature Weighted SOT



# Experimental Evaluation

- Experiments performed in 3 domains, namely *camera*, *automobile* and *software*

| Domain | Positive Reviews | Negative Reviews | Total Reviews |
|---|---|---|---|
| Automobile | 584 | 152 | 736 |
| Camera | 986 | 210 | 1196 |
| Software | 1000 | 915 | 1915 |

**Table 3**. Dataset Statistics

# Baselines

# Baselines

- 1. Lexical bag-of-words baseline
  - Majority voting
  - Sentiment Lexicons used: *SentiWordNet, Inquirer, Bing Liu*
- 2. Corpus Feature-Specific baseline
  - Feature-specific polarities extracted using dependency parsing algorithm in Mukherjee *et al.* (2012)
  - Feature-specific polarities weighed by *tf-idf* important of the feature in the corpus
- 3. ConceptNet and Corpus Feature-Specific baseline
  - ConceptNet is used to extract the feature set (**H** U **S** U **F**)
  - Aggregation done on the feature set same as Baseline 2
- All the baselines lack *hierarchical aggregation* using *ontological information*

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# Model Feature Comparison

| Models | Lexical | Corpus | ConceptNet | Sent. Aggr. |
| --- | --- | --- | --- | --- |
| Lexical Baseline | Y | | | |
| Corpus Feature Specific Baseline | Y | Y | | |
| Corpus and ConceptNet Feature Specific Baseline | Y | Y | Y | |
| Sent. Aggr. With Ontology Info. | Y | Y | Y | Y |

**Table 4**. Models and Baselines

| Domains | Corpus Frequent Features | Ontology Nodes | Ontology Edges | Leaf Nodes |
|---|---|---|---|---|
| Automobile | 268 | 203 | 202 | 76 |
| Camera | 768 | 334 | 333 | 148 |
| Software | 1020 | 764 | 763 | 208 |

**Table 5**. Ontology Tree Statistics

| Lexicons | Auto-mobile | Camera | Software |
|---|---|---|---|
| SentiWordNet 3.0 | 60.88 | 59.32 | 60.76 |
| General Inquirer | 65.70 | 68.15 | 66.14 |
| Bing Liu Lexicon | 64.43 | 63.65 | 69.38 |

**Table 6**. Lexical Baselines

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| Models | Automobile | Camera | Software |
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| Lexical Baseline (Bing Liu) | 64.43 | 63.65 | 69.38 |
| Corpus | 68.34 | 65.25 | 72.54 |
| ConceptNet + Corpus | 70.19 | 67.15 | 74.74 |
| ConceptNet + Corpus + Sent. Aggr. | **71.38** | **72.90** | **76.06** |

**Table 7**. Overall Accuracy of All Models

# Class-wise Accuracy in Each Domain

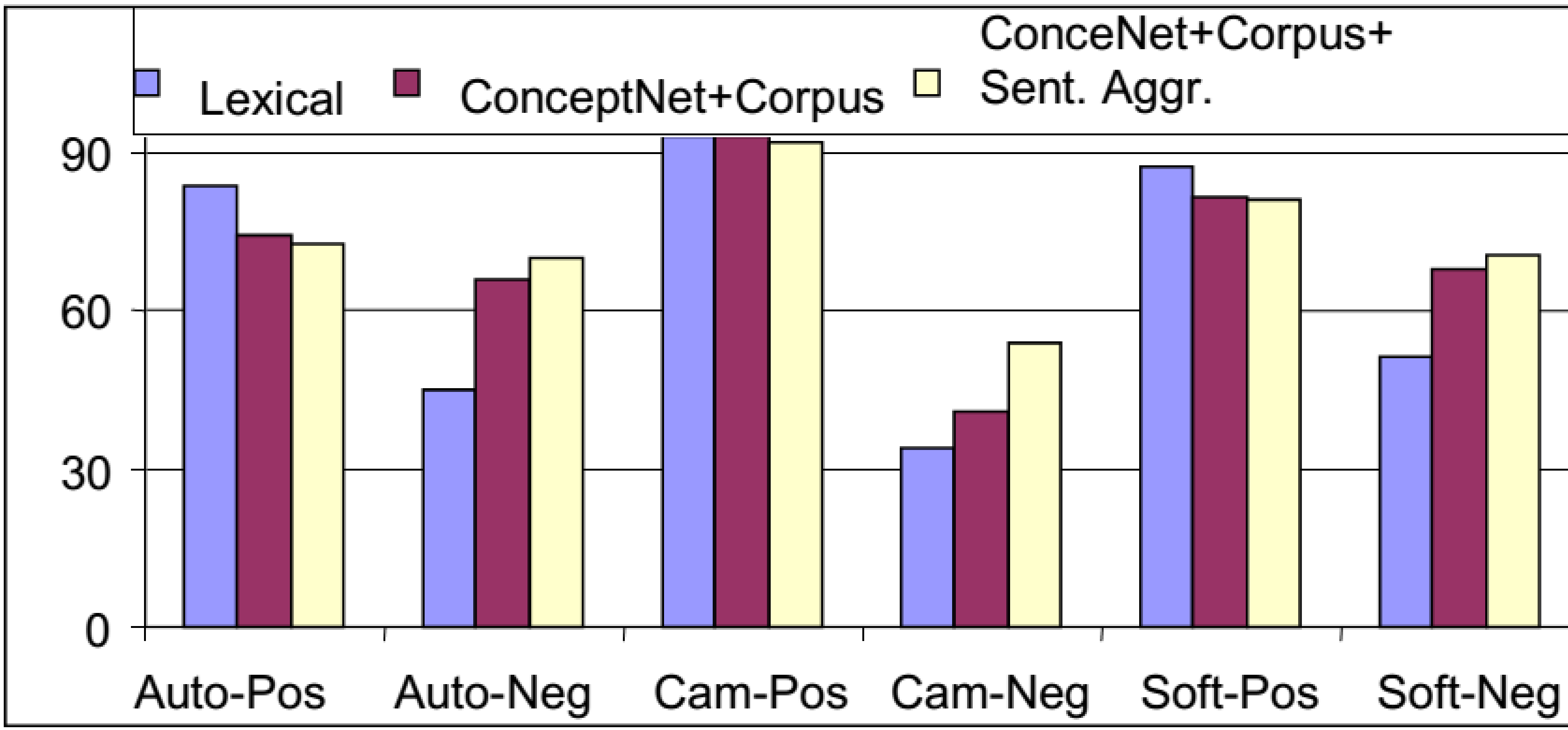


**Figure 3**. Positive and Negative Accuracy of Models in Each Domain

# Discussions

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- Difficult to evaluate purity of ontology
  - Qualitative evaluation done
  - *75.75%* of concepts in *automobile* domain, *43.49%* concepts in *camera* and *74.90%* concepts in *software* domain are mapped to respective ontology
  - In camera domain, number of ontology feature nodes << frequently occurring concepts in reviews,
  - But proposed model performs much better than the baseline, which considers all features to be equally relevant
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  - Positive bias, implicit negation, sarcasm
  - Sent. Aggr. Approach using ConceptNet captures negative sentiment very strongly

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# Ongoing Work - *Submitted*

- Automatically learning ontology from a raw corpus without *any* annotation
  - Discovering domain-specific multi-words like *Canon SX 160, Samsung Galaxy S IV etc.*
  - Discovering domain-specific relations *IS-A, Similar-To, Attributes* and *Methods*

- Uses ESG parser features, Random Indexing, HITS *etc.*

- Domain-specific ontology improves an in-house Question-Answering system (Watson) by upto **7%**
- It also improves parser performance by reducing number of incomplete or noisy parses by upto **74%**

# Ongoing Work - *Submitted*

- Learn author-specific preferences (edge weights $u_{ij}$ in ontology tree) from reviews
- Size of a camera may be of more importance to someone than a tripod
  - Different feature preference, which cannot be captured by ontology or corpus feature weight
- Generative model using HMM-LDA
  - Jointly learns product features, feature-specific sentiment, author-preference for the features, and overall ratings
  - HMM is used to capture coherence in reviews, author-writing style by capturing semantic-syntactic class transition and topic switch

- Thank you