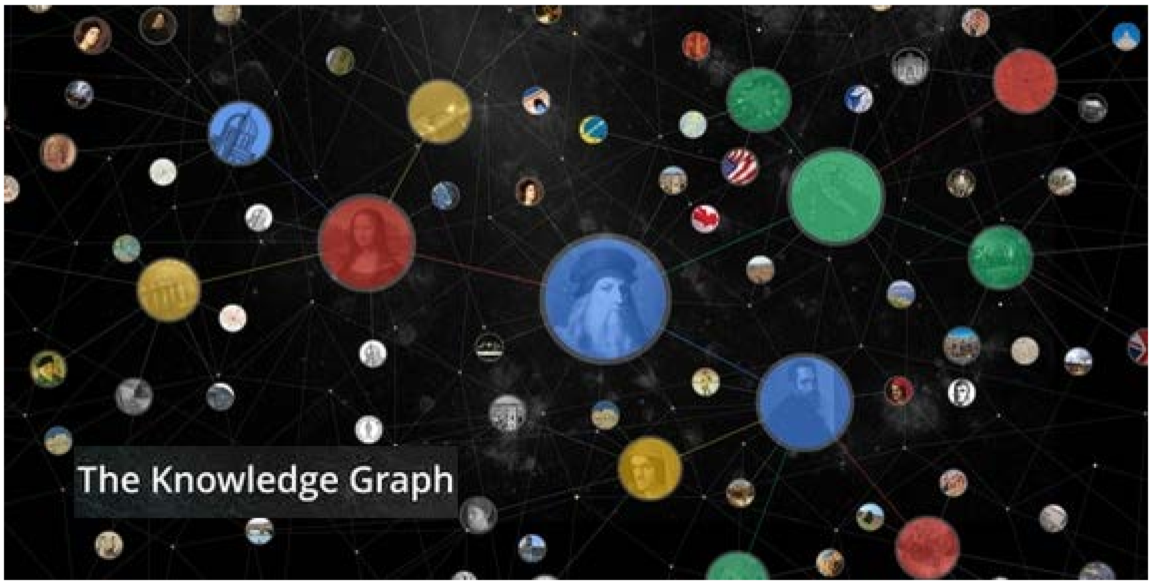
Making Product Knowledge Graph from User Reviews



"Great camera . super good pics."
"For the money this SLR is great."
"New to DSLR, this works great right out of the box."

"The D3000 has a software problem."
"I like the size and ease of use."
"This camera takes excellent photos."

By

Jatin Arora
(13CS10057)

Working with

Sumit Agarwal
(12CS30036)

Under the guidance and supervision of

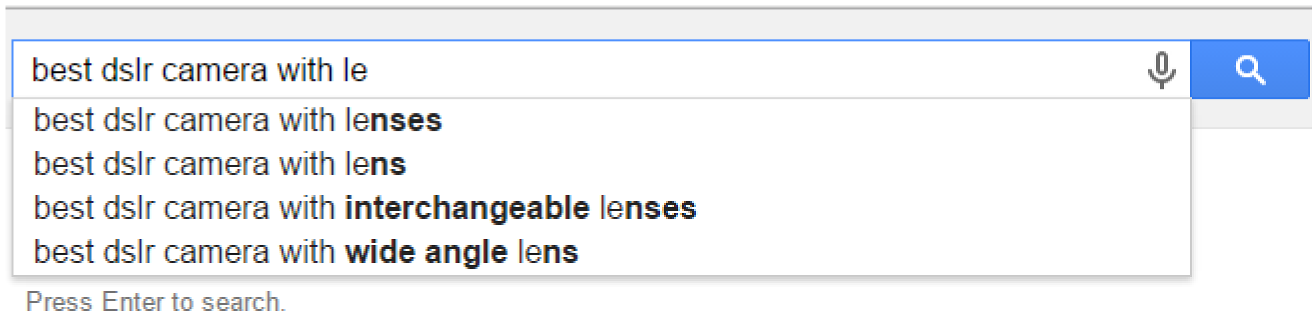
Prof. Pawan Goyal
Dr. Sayan Pathak

Department of Computer Science and Engineering
Indian Institute of Technology, Kharagpur

Motivation

User's View

- Users often search items with desired features..



- But not always is this information provided by the producer.

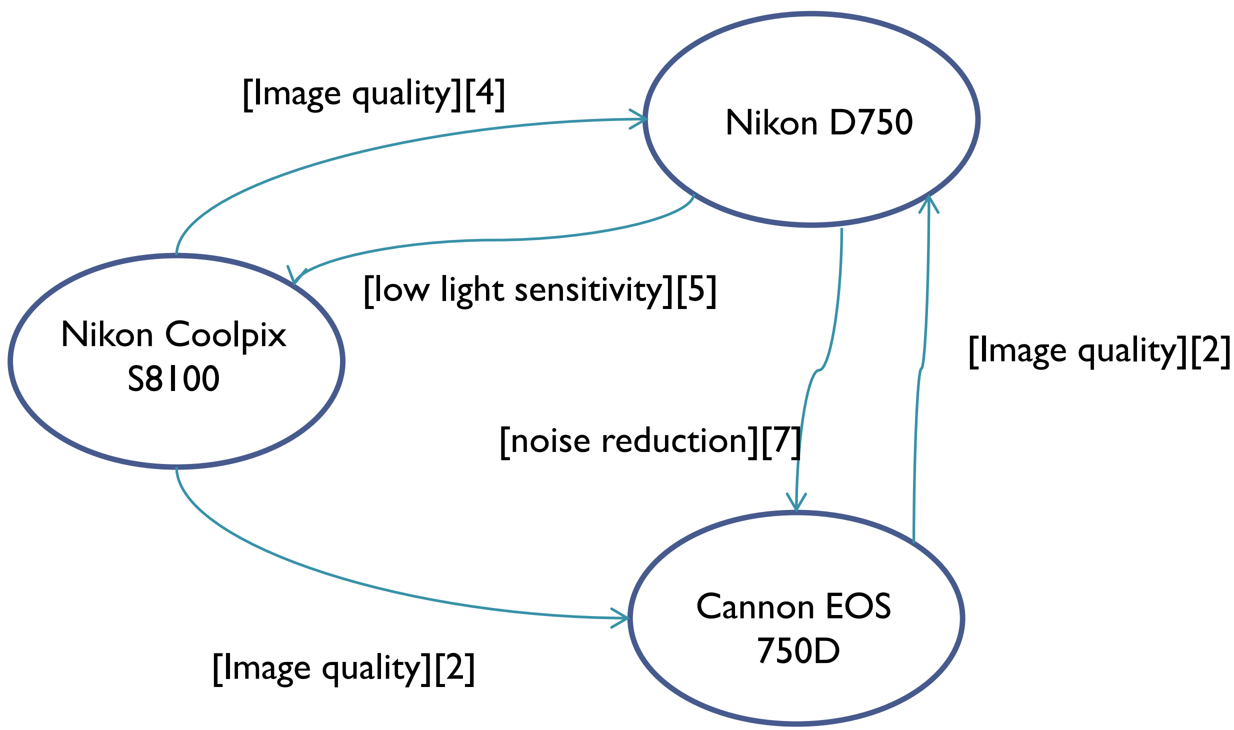
- Other users' experience with the product also matters.

Producer's View

- Producers want to bring products that have a high demand in the market.
- They can gather the information about users' wishes and demands from product reviews on e-commerce websites.
- We can design a prediction system that can predict how well the market will respond to a product based on previous trends.

Product Knowledge Graph

- Nodes: Products
- Edges: Aspects
- Weights: Strength of the Opinion
- Direction of Edge: Based on opinion direction



Approach

Getting Large No. of Reviews

Extracting Information

Building up the Graph

Step 1

Getting Large No. of Reviews

Dataset

Sites : Amazon.com and Amazon.in

Domain : Cameras and Electronic Gadgets.

Amazon.com

Total no. of products for which reviews crawled = 1260

Total no. of reviews = 1,26,410

Total no. of users providing reviews = 70,023

Amazon.in

Total no. of products for which reviews crawled = 50

Total no. of reviews = 5,532

Total no. of users providing reviews = 4,329

Step2

Extracting Information from Reviews

General Framework

Ranked Second in Best Budget Digital SLR (dSLR)

By Bestcovery.com Expert - Nov 17, 2009 - Editorial review - Bestcovery

Ideal for beginners and first-time buyers, the Nikon D3000 is a terrific entry-level DSLR that performs great for the money. This 10.2 megapixel digital SLR, which replaces the very popular and versatile D40, is the perfect

General Framework

Ranked Second in Best Budget Digital SLR (dSLR)
★★★★★ By Bestcovery.com Expert - Nov 17, 2009 - Editorial review - Bestcovery
Ideal for beginners and first-time buyers, the Nikon D3000 is a terrific entry-level DSLR that performs great for the money. This 10.2 megapixel digital SLR, which replaces the very popular and versatile D40, is the perfect

Filtering

This has better lens than Nikon CoolPix.

This is cheaper than Cannon PowerShot.

General Framework

Ranked Second in Best Budget Digital SLR (dSLR)
★★★★★ By Bestcovery.com Expert - Nov 17, 2009 - Editorial review - Bestcovery
Ideal for beginners and first-time buyers, the Nikon D3000 is a terrific entry-level DSLR that performs great for the money. This 10.2 megapixel digital SLR, which replaces the very popular and versatile D40, is the perfect

↓ Filtering

This has better lens than Nikon CoolPix.

This is cheaper than Cannon PowerShot.

↓ Extraction

This has better lens than Nikon CoolPix.

This is cheaper than Cannon PowerShot.

Pattern Matching

E.g. (Adjective Aspect) (Preposition) **model2**

(Str1) (than|as|to|over|compared|from|of) (Str2) **model2**

Canon D9 has better lens than Nikon D1.
[model1] [opinion] [aspect] [model2].

Results:

Total number of potential sentences with a relationship in training set: **2155**. Estimated Recall: ~50%

Accuracy (Precision) on training set: 68%
Accuracy (Precision) on test set: 55%

Automated Aspect Identification

- Capture context around target unigram or bigram which are either nouns or adjectives.
- Context window has 2 terms before and 2 terms after the candidate aspect.

Y : {term-2, term-1, term+1, term+2, POS-2, POS-1, POS+1, POS+2}

Example:

Nikon CoolPix S8100 has better lens resolution than Cannon PowerShot

For [lens resolution] :

yes : { has, better, than, Cannon, VERB, ADJ, ADP , NOUN }

Results

- We used various interesting learning approaches provided by Scikit-Learn Library and also Weka.
- We have a total of 425 'yes' cases, and around 8800 'no' cases identified from the dataset.
- For various proportions of 'yes' and 'no' instances in the training set, the results were recorded.
- Results using Logistic Regression:

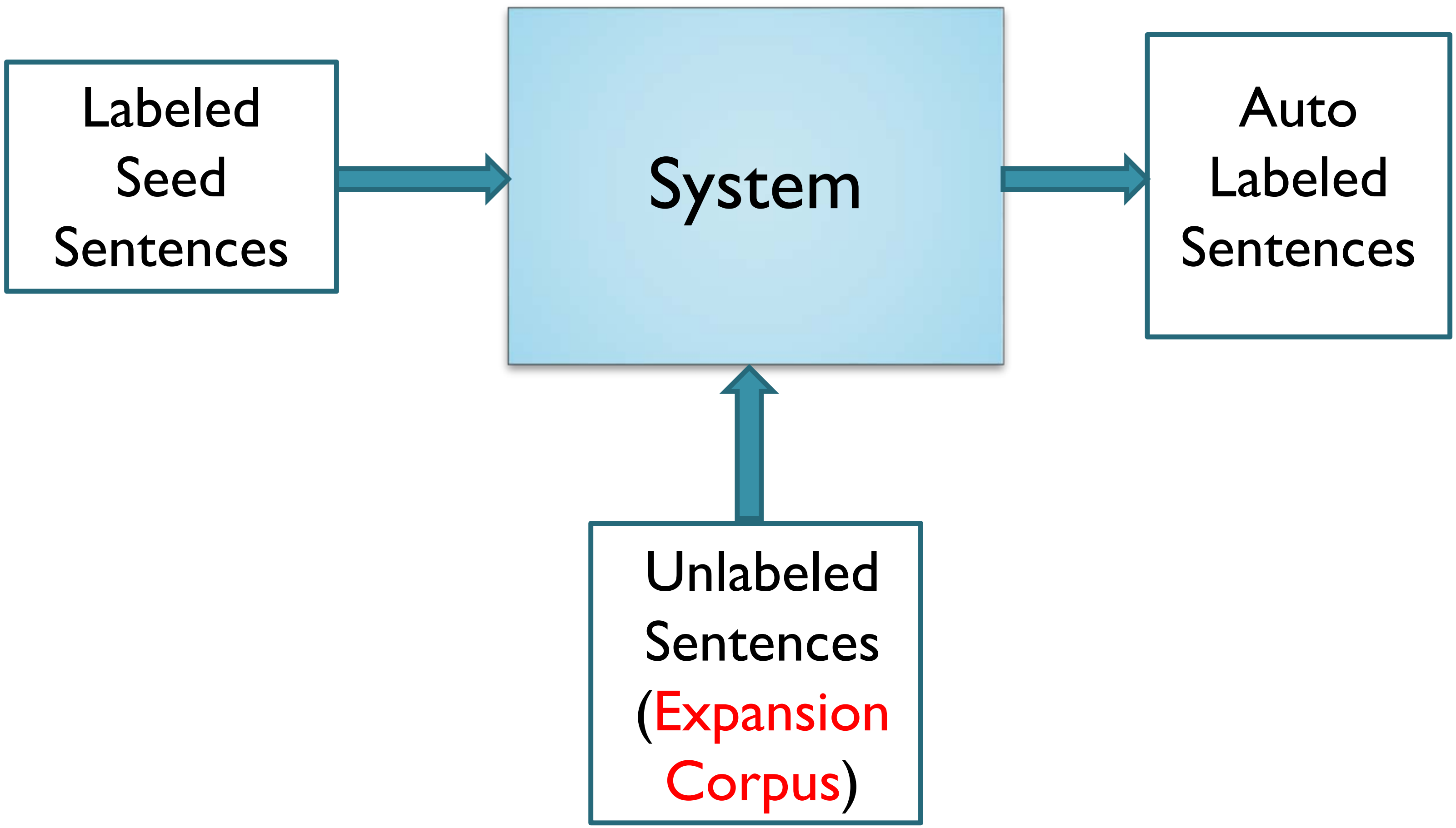
  Precision: 30%

  Recall: 55%
- Inference:

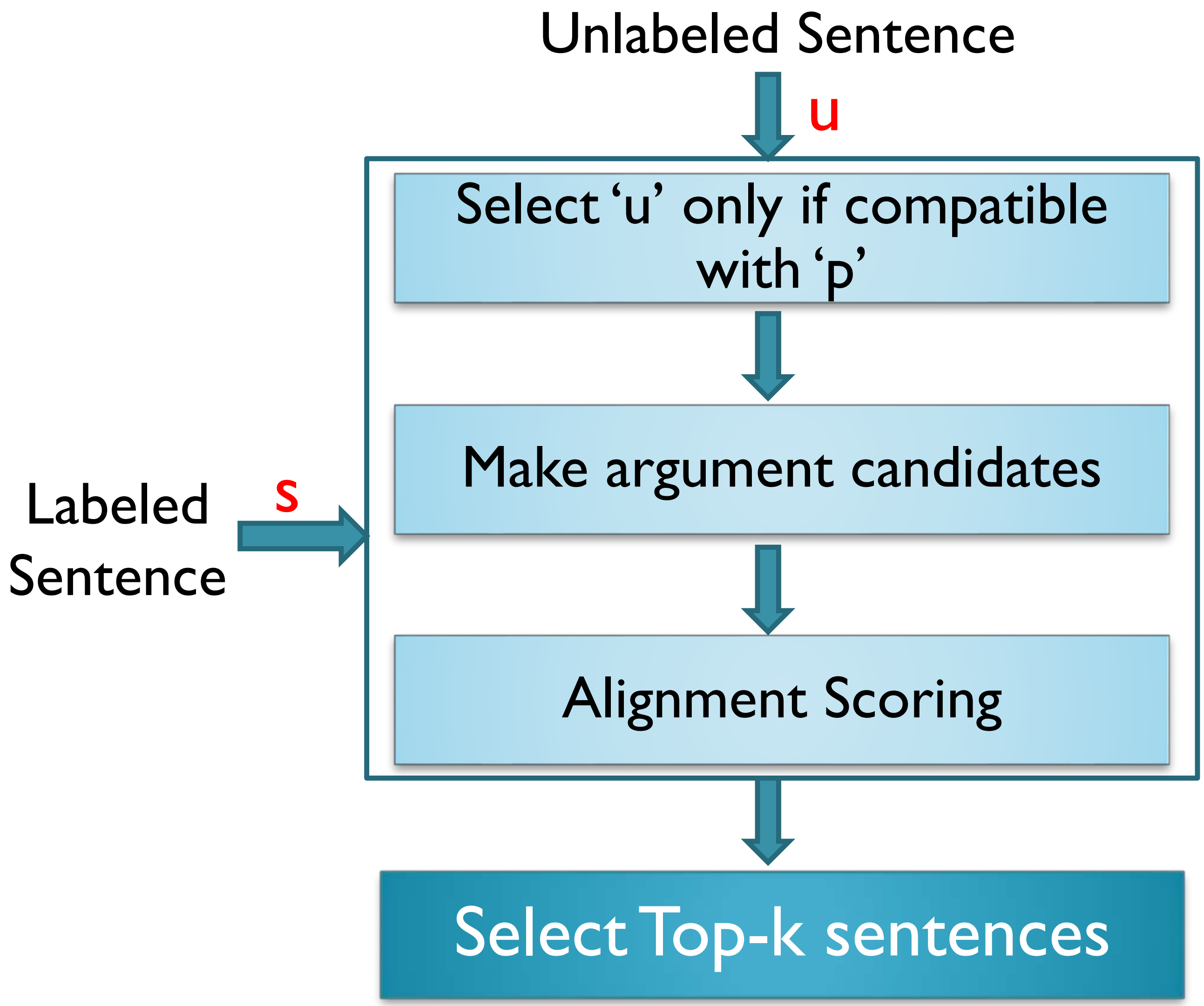
  - Not able to capture enough variety in the training set.
  - Number of labelled sentences available are less.

Dataset Expansion

Structural Alignment

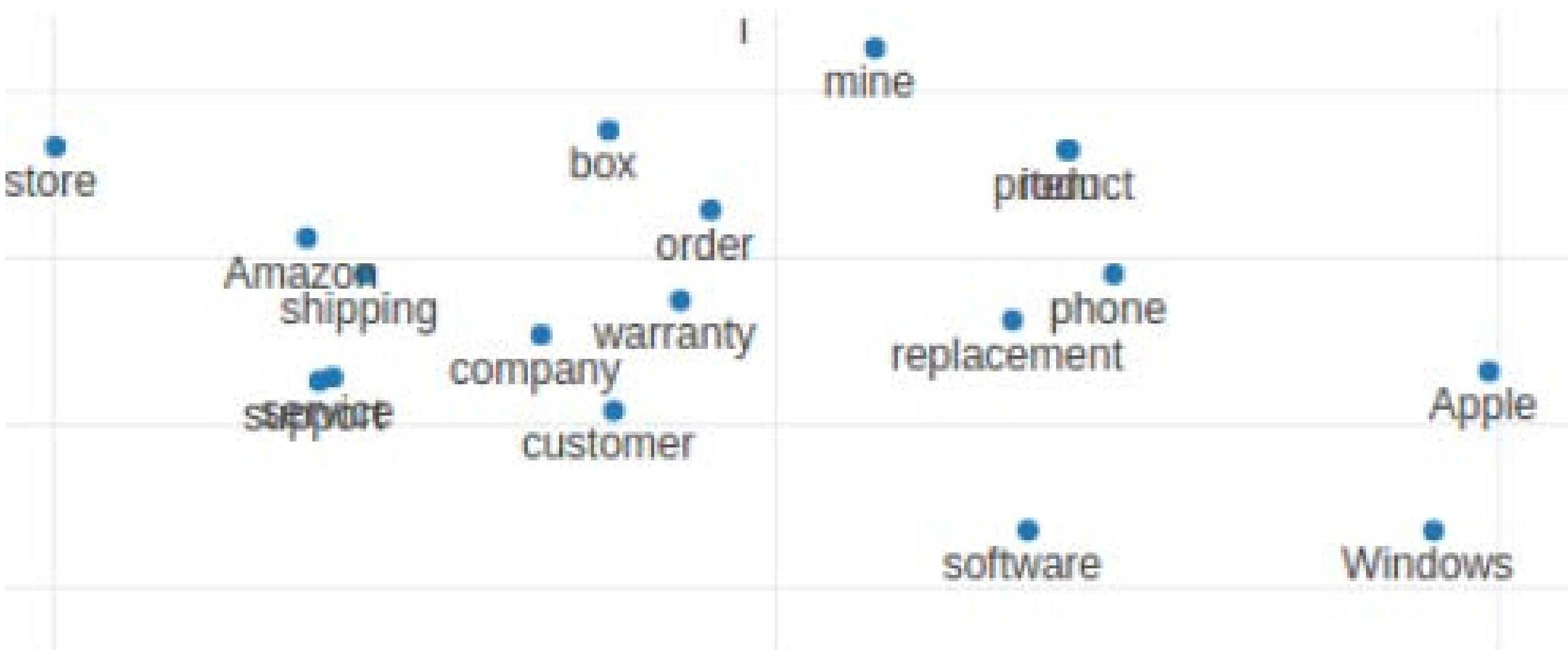


System Framework



Word Embeddings

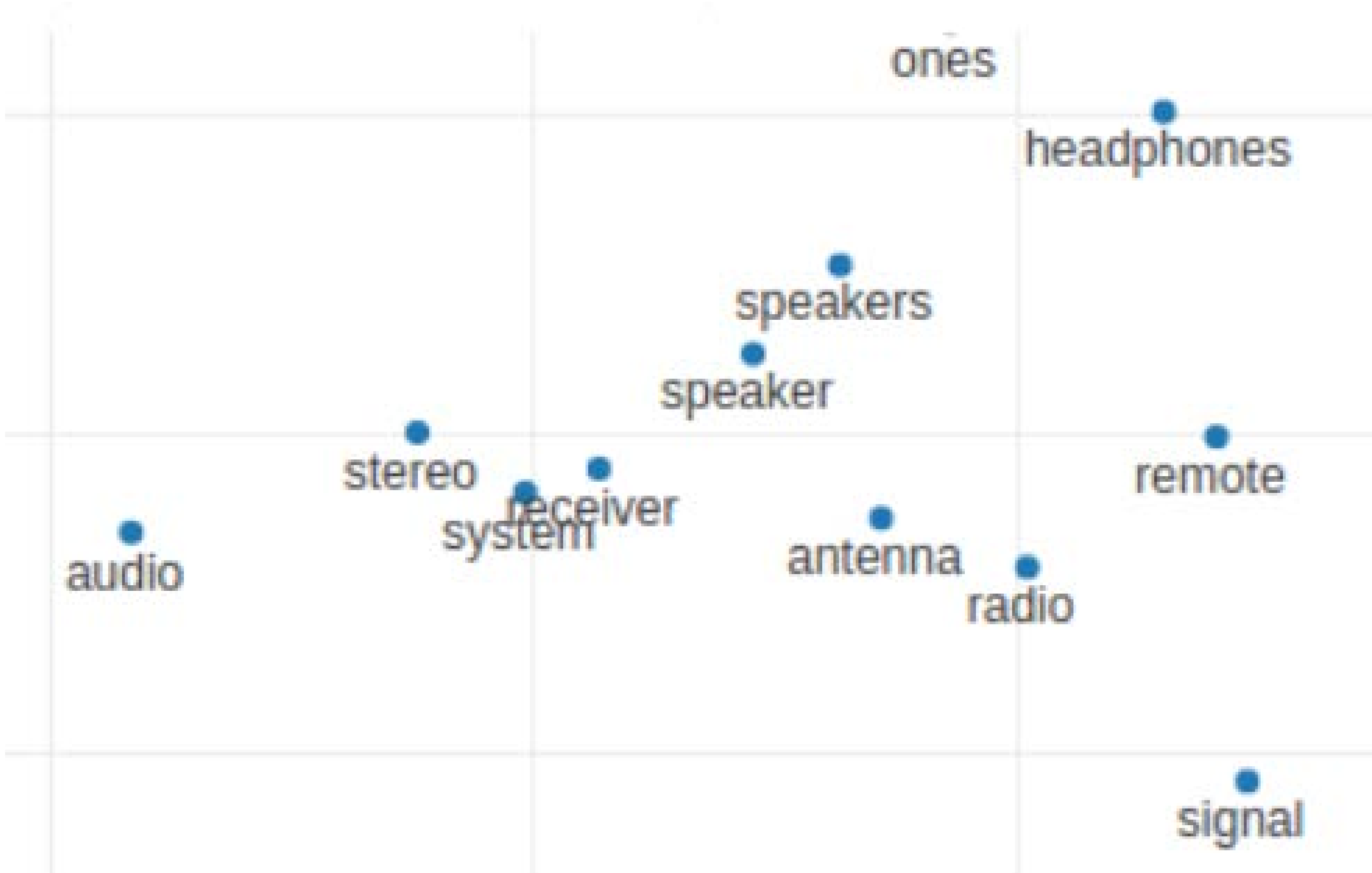
- Approaches
  - Glove
  - Word2Vec
  - Approach by University of Stuttgart
- Prepared Embeddings of sizes: 100, 1000, 2000



t-SNE projection

Word2Vec (Size : 50)

Word Embeddings



t-SNE projection

Word2Vec (Size : 50)

Experimental Setup

- Input:
  - 360 manually labelled sentences
  - 3000 unlabelled potential comparison sentences

- Approaches:
  - Electronics Embeddings, Size: 2000, Context: 3
  - Electronics Embeddings, Size: 1000, Context: 2
  - Electronics Embeddings, Size: 100, Context: 2
  - Product Embeddings, Size: 2000, Context: 2

- Evaluation: Randomly picked 400 sentences for each variation and checked if Entity and Product identified are correct or not.
- Calculated Precison, Recall for Top-k retrieved sentences.

Results

- Best F1-score achieved by Kessler and Kuhn, 2015 : 45% with 10-fold data expansion.
- Best F1-score achieved by us: 62% with 10-fold data expansion.

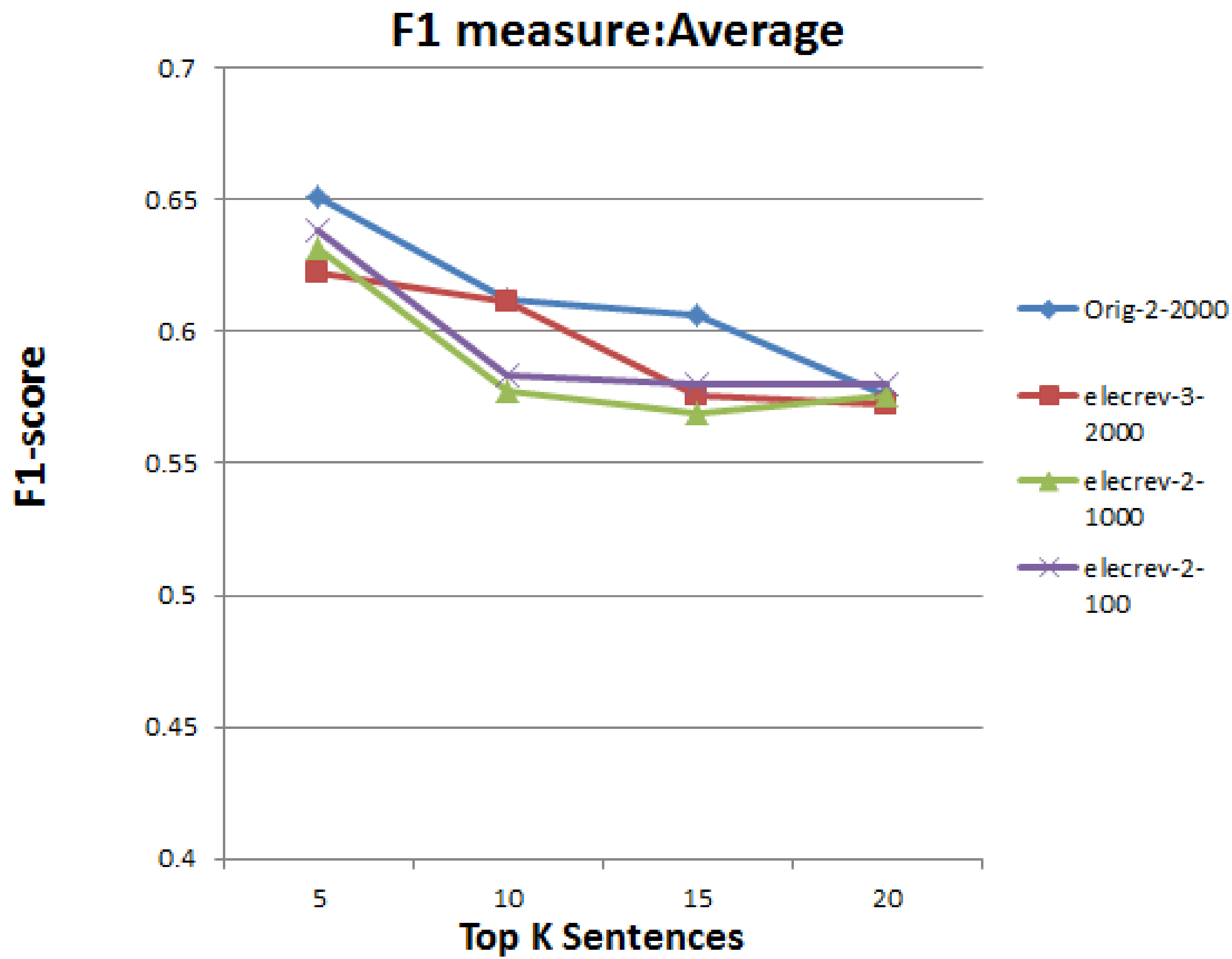
Best achieved results (Precision and Recall) for Entity and Aspect Classification and corresponding approach

K-Fold Expansion	Precision (Aspect)	Recall (Aspect)
5	0.70 / Products, 2, 2000	0.72 / Electronics, 2, 100
10	0.68 / Products, 2, 2000	0.72 / Electronics, 2, 100
15	0.67 / Products, 2, 2000	0.73 / Electronics, 2, 100
20	0.64 / Products, 2, 2000	0.75 / Electronics, 2, 100

Results

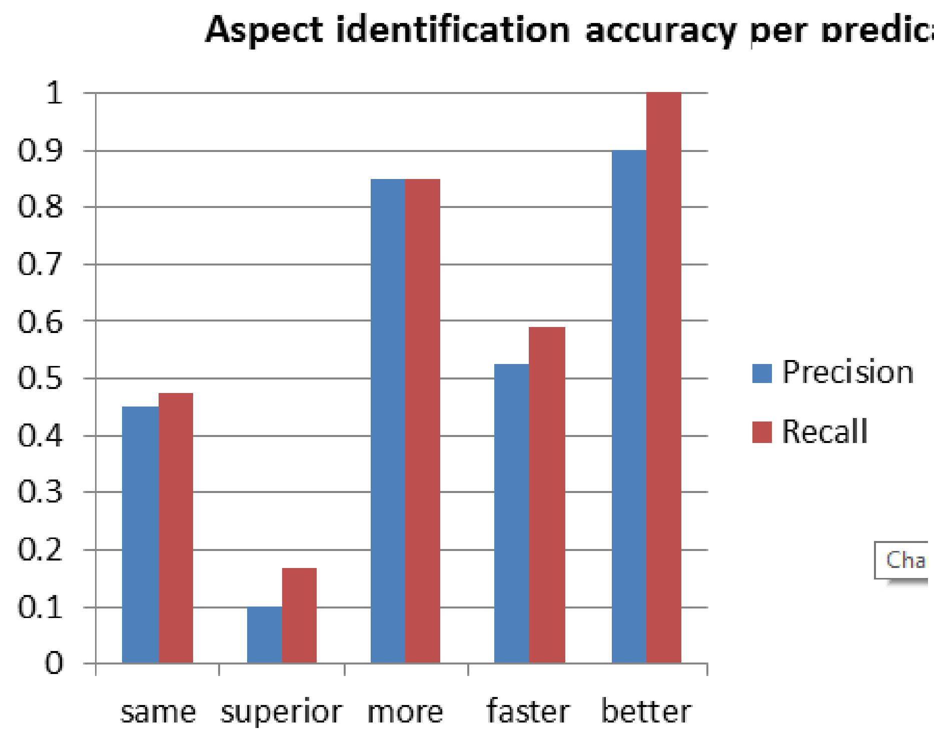
K-Fold Expansion	Precision (Entity-1)	Recall (Entity-1)
5	0.68 / Electronics, 2, 2000	0.78 / Electronics, 2, 100
10	0.59 / Electronics, 3, 2000	0.68 / Electronics, 3, 2000
15	0.58 / Products, 2, 2000	0.69 / Products, 2, 2000
20	0.53 / Electronics, 2, 2000	0.63 / Products, 2, 2000

K-Fold Expansion	Precision (Entity-2)	Recall (Entity-2)
5	0.45 / Electronics, 2, 100	0.72 / Products, 2, 2000
10	0.46 / Electronics, 3, 2000	0.63 / Electronics, 3, 2000
15	0.44 / Electronics, 2, 100	0.67 / Electronics, 3, 2000
20	0.43 / Electronics, 2, 100	0.69 / Electronics, 3, 2000


F1 measure:Average
F1-score
0.7
0.65
0.6
0.55
0.5
0.45
0.4
5
10
15
20
Top K Sentences
Orig-2-2000
elecrev-3-2000
elecrev-2-1000
elecrev-2-100

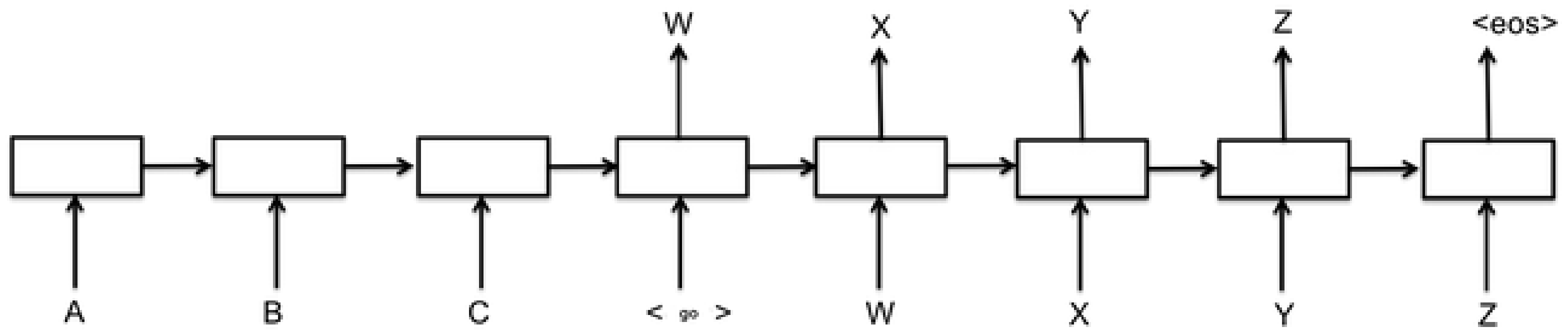
Observations

- Entity-2 identification has low precision.
- Identification of aspects and entities shows variations with predicate expanded. This is because usage of some predicates is very specific.



Currently Working on..

LSTM Based Sequence Tagger



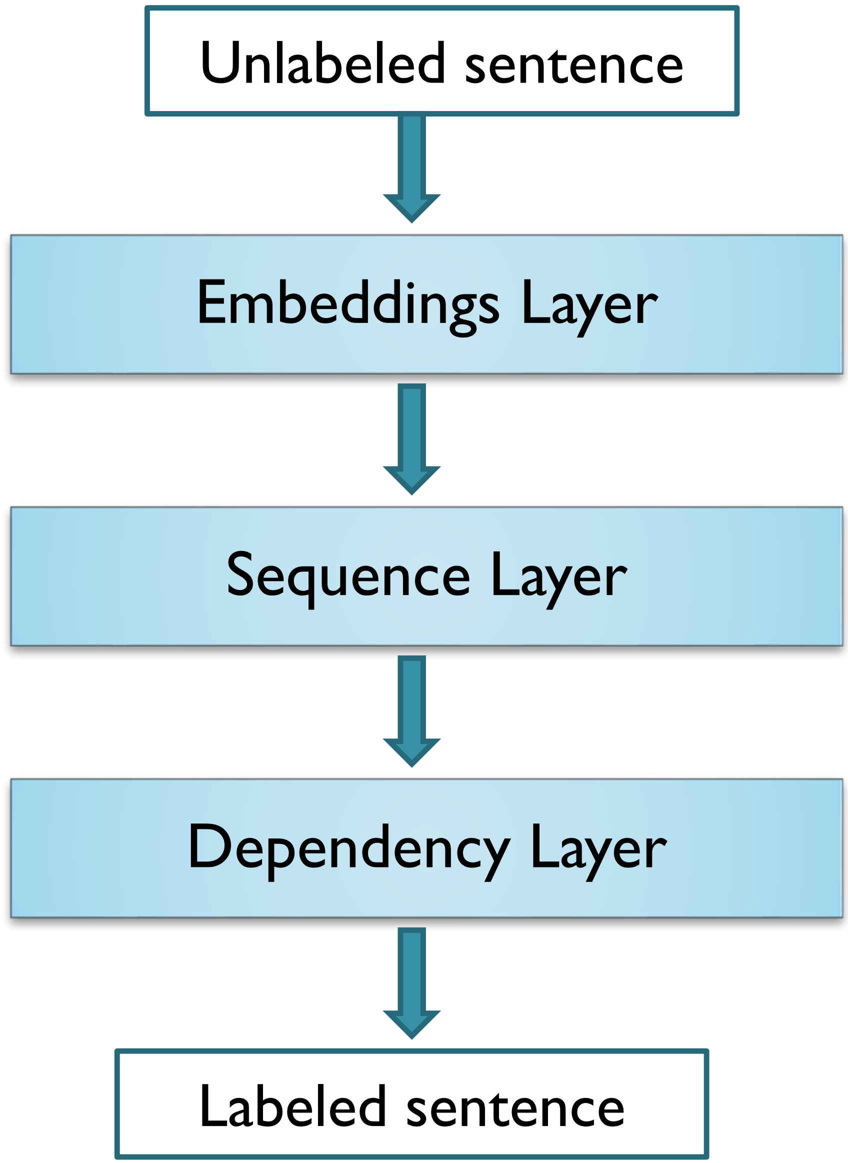
- Example:

  Sequence1: This camera is better than Nikon.

  Sequence2: {e1} {none} {none} {pred} {none} {e2}.

- Fixed input and output sentence size to 50 tokens/words
- One LSTM Unit per Word in sentence
- Fixed No. of LSTM Units to 120 per layer
- Built a 3 layer network
- Earlier trained on 360 labelled sentences.

A more complex model



References

- N. Jindal , B. Liu. 2006. Identifying comparative sentences in text documents. In *Proceedings of the 29th annual international ACM SIGIR conference on Research and development in information retrieval*, pages 244–251, Seattle, Washington, USA, August 11, 2006.

- W. Kessler and J. Kuhn. 2013. Detection of product comparisons - how far does an out-of-the-box semantic role labeling system take you? In *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, pages 1892-1897, Seattle, USA, October 2013.

- W. Kessler and J. Kuhn. 2015. Structural alignment for comparison detection. In *Proceedings of the 10th Conference on Recent Advances in Natural Language Processing*, pages 275-281, Hissar, Bulgaria, September 2015.

- M. Miwa and M. Bansal. 2016. End-to-end Relation Extraction using LSTMs on Sequences and Tree Structures. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1105-1116, 2016.

Thank You