Approximate Scalable Bounded Space Sketch for Large Data NLP

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Abstract

We exploit sketch techniques, especially the Count-Min sketch, a memory, and time efficient framework which approximates the frequency of a word pair in the corpus without explicitly storing the word pair itself. These methods use hashing to deal with massive amounts of streaming text. We apply Count-Min sketch to approximate word pair counts and exhibit their effectiveness on three important NLP tasks. Our experiments demonstrate that on all of the three tasks, we get performance comparable to Exact word pair counts setting and state-of-the-art system. Our method scales to 49 GB of unzipped web data using bounded space of 2 billion counters (8 GB memory).

1 Introduction

There is more data available today on the web than there has ever been and it keeps increasing. Use of large data in the Natural Language Processing (NLP) community is not new. Many NLP problems (Brants et al., 2007; Turney, 2008; Ravichandran et al., 2005) have benefited from having large amounts of data. However, processing large amounts of data is still challenging.

This has motivated NLP community to use commodity clusters. For example, Brants et al. (2007) used 1500 machines for a day to compute the relative frequencies of n-grams from 1.8TB of web data. In another work, a corpus of roughly 1.6 Terawords was used by Agirre et al. (2009) to compute pairwise similarities of the words in the test sets using the MapReduce infrastructure on $2,000$ cores. However, the inaccessibility of clusters to an average user has attracted the NLP community to use streaming, randomized, and approximate algorithms to handle large amounts of data (Goyal et al., 2009; Levenberg et al., 2010; Van Durme and Lall, 2010).

Streaming approaches (Muthukrishnan, 2005) provide memory and time-efficient framework to deal with terabytes of data. However, these approaches are proposed to solve a singe problem. For example, our earlier work (Goyal et al., 2009) and Levenberg and Osborne (2009) build approximate language models and show their effectiveness in Statistical Machine Translation (SMT). Stream-based translation models (Levenberg et al., 2010) has been shown effective to handle large parallel streaming data for SMT. In Van Durme and Lall (2009b), a Talbot Osborne Morris Bloom (TOMB) Counter (Van Durme and Lall, 2009a) was used to find the top-K verbs "y" given verb "x" using the highest approximate online Pointwise Mutual Information (PMI) values.

In this paper, we explore sketch techniques, especially the Count-Min sketch (Cormode and Muthukrishnan, 2004) to build a *single* model to show its effectiveness on three important NLP tasks:

- Predicting the Semantic Orientation of words (Turney and Littman, 2003)
- Distributional Approaches for word similarity (Agirre et al., 2009)
- Unsupervised Dependency Parsing (Cohen and Smith, 2010) with a little linguistics knowledge.

In all these tasks, we need to compute association measures like Pointwise Mutual Information (PMI),

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and Log Likelihood ratio (LLR) between words. To compute association scores (AS), we need to count the number of times pair of words appear together within a certain window size. However, explicitly storing the counts of all word pairs is both computationally expensive and memory intensive (Agirre et al., 2009; Pantel et al., 2009). Moreover, the memory usage keeps increasing with increase in corpus size.

We explore Count-Min (CM) sketch to address the issue of *efficient storage* of such data. The CM sketch stores counts of all word pairs within a *bounded space*. Storage space saving is achieved by *approximating* the frequency of word pairs in the corpus without explicitly storing the word pairs themselves. Both updating (adding a new word pair or increasing the frequency of existing word pair) and querying (finding the frequency of a given word pair) are constant time operations making it efficient online storage data structure for large data. Sketches are *scalable* and can easily be implemented in distributed setting.

We use CM sketch to store counts of word pairs (except word pairs involving stop words) within a window of size[1] 7 over different size corpora. We store exact counts of words (except stop words) in hash table (since the number of unique words is not large that is quadratically less than the number of unique word pairs). The approximate PMI and LLR scores are computed using these approximate counts and are applied to solve our three NLP tasks. Our experiments demonstrate that on all of the three tasks, we get performance comparable to Exact word pair counts setting and state-of-the-art system. Our method scales to 49 GB of unzipped web data using bounded space of 2 billion counters (8 GB memory). This work expands upon our earlier workshop papers (Goyal et al., 2010a; Goyal et al., 2010b).

2 Sketch Techniques

A sketch is a compact summary data structure to store the frequencies of all items in the input stream. Sketching techniques use hashing to map items in streaming data onto a small sketch vector that can be updated and queried in constant time. These techniques generally process the input stream in one direction, say from left to right, without re-processing previous input. The main advantage of using these techniques is that they require a storage which is sub-linear in size of the input stream. The following surveys comprehensively review the streaming literature: (Rusu and Dobra, 2007; Cormode and Hadjieleftheriou, 2008).

There exists an extensive literature on sketch techniques (Charikar et al., 2004; Li et al., 2008; Cormode and Muthukrishnan, 2004; Rusu and Dobra, 2007) in algorithms community for solving many large scale problems. However, in practice, researchers have preferred Count-Min (CM) sketch over other sketch techniques in many application areas, such as Security (Schechter et al., 2010), Machine Learning (Shi et al., 2009; Aggarwal and Yu, 2010), and Privacy (Dwork et al., 2010). This motivated us to explore CM sketch to solve three important NLP problems.[2]

2.1 Count-Min Sketch

The Count-Min sketch (Cormode and Muthukrishnan, 2004) is a compact summary data structure used to store the frequencies of all items in the input stream. The sketch allows fundamental queries on the data stream such as point, range and inner product queries to be approximately answered very quickly. It can also be applied to solve the finding frequent items problem (Manku and Motwani, 2002) in a data stream. In this paper, we are only interested in point queries. The aim of a point query is to estimate the count of an item in the input stream. For other details, the reader is referred to (Cormode and Muthukrishnan, 2004).

Given an input stream of word pairs of length N and user chosen parameters δ and ϵ, the algorithm stores the frequencies of all the word pairs with the following guarantees:

- All reported frequencies are within the true frequencies by at most ϵN with a probability of at least 1-δ.
- The space used by the algorithm is $O(\frac{1}{\epsilon}\log\frac{1}{\delta})$.

[1] 7 is chosen from intuition and not tuned.

[2] In future, in another line of research, we will explore comparing different sketch techniques for NLP problems.

- Constant time of O($\log(\frac{1}{\delta})$) per each update and query operation.

2.1.1 CM Data Structure

A Count-Min sketch (CM) with parameters (ϵ,δ) is represented by a two-dimensional array with width w and depth d :

$$\begin{bmatrix} \text{sketch}[1,1] & \cdots & \text{sketch}[1,w] \\ \vdots & \ddots & \vdots \\ \text{sketch}[d,1] & \cdots & \text{sketch}[d,w] \end{bmatrix}$$

Among the user chosen parameters, ϵ controls the amount of tolerable error in the returned count and δ controls the probability with which the returned count is not within the accepted error. These values of ϵ and δ determine the width and depth of the two-dimensional array respectively. To achieve the guarantees mentioned in the previous section, we set w=$\frac{2}{\epsilon}$ and d=$\log(\frac{1}{\delta})$. The depth d denotes the number of pairwise-independent hash functions employed by the algorithm and there exists a one-to-one correspondence between the rows and the set of hash functions. Each of these hash functions h_k:$\{\text{x}_1 \ldots \text{x}_N\} \rightarrow \{1 \ldots w\}, 1 \leq k \leq d$, takes a word pair from the input stream and maps it into a counter indexed by the corresponding hash function. For example, $h_2(\text{x}) = 10$ indicates that the word pair "x" is mapped to the 10^{th} position in the second row of the sketch array.

Initialize the entire sketch array with zeros.

Update Procedure: When a new word pair "x" with count c arrives, one counter in each row (as decided by its corresponding hash function) is updated by c.

$$\text{sketch}[k, h_k(\text{x})] \leftarrow \text{sketch}[k, h_k(\text{x})] + c, \ \ \forall 1 \leq k \leq d$$

Query Procedure: Since multiple word pairs can get hashed to the same position, the frequency stored by each position is guaranteed to overestimate the true count. Thus, to answer the point query for a given word pair, we return minimum over all the positions indexed by the k hash functions. The answer to Query(x): $\hat{c} = \min_k \ \text{sketch}[k, h_k(\text{x})]$

Both update and query procedures involve evaluating d hash functions and reading of all the values in those indices and hence both these procedures are linear in the number of hash functions. Hence both these steps require $O(\log(\frac{1}{\delta}))$ time. In our experiments (see Section 3.1), we found that a small number of hash functions are sufficient and we use d=5. Hence, the update and query operations take only a constant time. The space used by the algorithm is the size of the array i.e. wd counters, where w is the width of each row.

2.1.2 Properties

Apart from the advantages of being space efficient, and having constant update and constant querying time, the Count-Min sketch has also other advantages that makes it an attractive choice for NLP applications.

- Linearity: Given two sketches s_1 and s_2 computed (using the same parameters w and d) over different input streams, the sketch of the combined data stream can be easily obtained by adding the individual sketches in O($\frac{1}{\epsilon} \log \frac{1}{\delta}$) time which is independent of the stream size.

- The linearity is especially attractive because it allows the individual sketches to be computed independent of each other, which means that it is easy to implement it in distributed setting, where each machine computes the sketch over a sub set of corpus.

2.2 Conservative Update

Estan and Varghese introduced the idea of conservative update (Estan and Varghese, 2002) in the context of computer networking. This can easily be used with CM sketch to further improve the estimate of a point query. To update a word pair "x" with frequency c, we first compute the frequency $\hat{c}$ of this word pair from the existing data structure and the counts are updated according to:

$$\hat{c} = min_k \ \text{sketch}[k, h_k(\text{x})], \ \ \forall 1 \leq k \leq d$$

$$\text{sketch}[k, h_k(\text{x})] \leftarrow \max\{\text{sketch}[k, h_k(\text{x})], \hat{c} + c\}$$

The intuition is that, since the point query returns the minimum of all the d values, we will update a counter only if it is necessary as indicated by the above equation. Though this is a heuristic, it avoids the unnecessary updates of counter values and thus reduces the error.

In our experiments, we found that employing the conservative update reduces the Average Relative

Error (ARE) of these counts approximately by a factor of 1.5. (see Section 3.1). But unfortunately, this update can only be maintained over individual sketches in distributed setting.

3 Intrinsic Evaluations

To show the effectiveness of the CM sketch and CM sketch with conservative update (CU) in the context of NLP, we perform intrinsic evaluations. First, the intrinsic evaluations are designed to measure the error in the approximate counts returned by CM sketch compared to their true counts. Second, we compare the word pairs association rankings obtained using PMI and LLR with sketch and exact counts.

It is memory and time intensive to perform many intrinsic evaluations on large data (Ravichandran et al., 2005; Brants et al., 2007; Goyal et al., 2009). Hence, we use a subset of corpus of 2 million sentences (Subset) from Gigaword (Graff, 2003) for it. We generate words and word pairs over a window of size 7. We store exact counts of words (except stop words) in a hash table and store approximate counts of word pairs (except word pairs involving stop words) in the sketch.

3.1 Evaluating approximate sketch counts

To evaluate the amount of over-estimation error (see Section 2.1) in CM and CU counts compared to the true counts, we first group all word pairs with the same true frequency into a single bucket. We then compute the average relative error in each of these buckets. Since low-frequency word pairs are more prone to errors, making this distinction based on frequency lets us understand the regions in which the algorithm is over-estimating. Moreover, to focus on errors on low frequency counts, we have only plotted word pairs with count at most 100. Average Relative error (ARE) is defined as the average of absolute difference between the predicted and the exact value divided by the exact value over all the word pairs in each bucket.

$$\text{ARE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|\text{Exact}_i - \text{Predicted}_i|}{\text{Exact}_i}$$

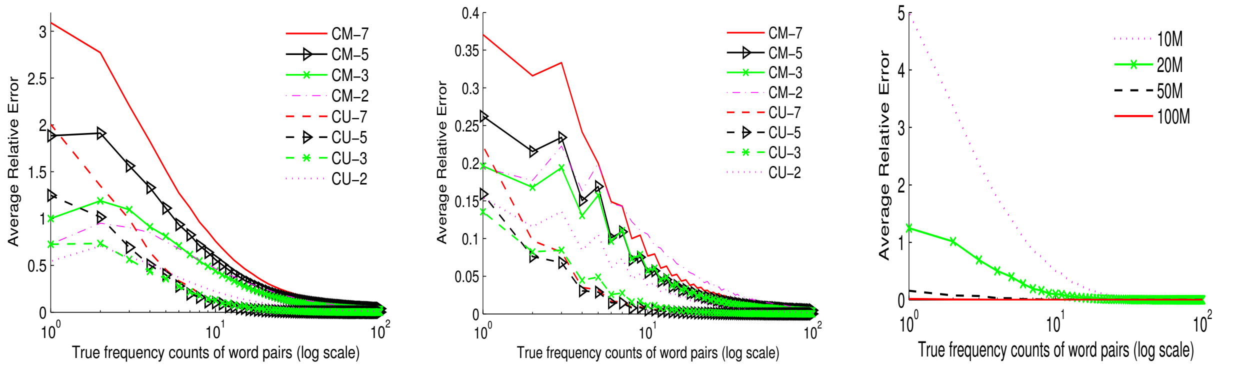
Where Exact and Predicted denotes values of exact and CM/CU counts respectively; N denotes the number of word pairs with same counts in a bucket.

In Fig. 1(a), we fixed the number of counters to 20 million ($20M$) with four bytes of memory per each counter (thus it only requires 80 MB of main memory). Keeping the total number of counters fixed, we try different values of depth (2, 3, 5 and 7) of the sketch array and in each case the width is set to $\frac{20M}{d}$. The ARE curves in each case are shown in Fig. 1(a). We can make three main observations from Figure 1(a): First it shows that most of the errors occur on low frequency word pairs. For frequent word pairs, in almost all the different runs the ARE is close to zero. Secondly, it shows that ARE is significantly lower (by a factor of 1.5) for the runs which use conservative update (CUx run) compared to the runs that use direct CM sketch (CMx run). The encouraging observation is that, this holds true for almost all different (width,depth) settings. Thirdly, in our experiments, it shows that using depth of 3 gets comparatively less ARE compared to other settings.

To be more certain about this behavior with respect to different settings of width and depth, we tried another setting by increasing the number of counters to 50 million. The curves in 1(b) follow a pattern which is similar to the previous setting. Low frequency word pairs are more prone to error compared to the frequent ones and employing conservative update reduces the ARE by a factor of 1.5. In this setting, depth 5 does slightly better than depth 3 and gets lowest ARE.

We use CU counts and depth of 5 for the rest of the paper. As 3 and 5 have lowest ARE in different settings and using 5 hash functions, we get $\delta = 0.01$ ($d = \log(\frac{1}{\delta})$ refer Section 2.1) that is probability of failure is 1 in 100, making the algorithm more robust to false positives compared with 3 hash functions, $\delta = 0.1$ with probability of failure 1 in 10.

Fig. 1(c) studies the effect of the number of counters in the sketch (the size of the two-dimensional sketch array) on the ARE with fixed depth 5. As expected, using more number of counters decreases the ARE in the counts. This is intuitive because, as the length of each row in the sketch increases, the probability of collision decreases and hence the array is more likely to contain true counts. By using 100 million counters, which is comparable to the length of the stream 88 million, we are able to achieve almost zero ARE over all the counts including the rare



(a) 20M counters (b) 50M counters (c) Different size models with depth 5

Figure 1: Compare 20 and 50 million counter models with different (width,depth) settings. The notation CMx represents the Count Min sketch with a depth of 'x' and CUx represents the CM sketch along with conservative update and depth 'x'.

ones[3]. Note that the space we *save* by not storing the exact counts is almost four times the memory that we use here because on an average each word pair is twelve characters long and requires twelve bytes (thrice the size of an integer) and 4 bytes for storing the integer count. Note, we get even bigger space savings if we work with longer phrases (phrase clustering), phrase pairs (paraphrasing/translation), and varying length n-grams (Information Extraction).

3.2 Evaluating word pairs association ranking

In this experiment, we compare the word pairs association rankings obtained using PMI and LLR with CU and exact word pair counts. We use two kinds of measures, namely recall and Spearman's correlation to measure the overlap in the rankings obtained by exact and CU counts. Intuitively, recall captures the number of word pairs that are found in both the sets and then Spearman's correlation captures if the relative order of these common word pairs is preserved in both the rankings. In our experimental setup, if the rankings match exactly, then we get a recall (R) of 100% and a correlation (ρ) of 1.

The results with respect to different sized counter (20 million ($20M$), 50 million ($50M$)) models are shown in Table 1. If we compare the second and third column of the table using PMI and LLR for $20M$ counters, we get exact rankings for LLR compared to PMI while comparing Top$K$ word pairs. The explanation for such a behavior is: since we are

[3]Even with other datasets we found that using counters linear in the size of the stream leads to ARE close to zero ∀ counts.

# Cs	**20M**				**50M**			
AS	**PMI**		**LLR**		**PMI**		**LLR**	
TopK	*R*	ρ	*R*	ρ	*R*	ρ	*R*	ρ
50	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
100	.98	.94	1.0	1.0	1.0	1.0	1.0	1.0
500	.80	.98	1.0	1.0	.98	1.0	1.0	1.0
1000	.56	.99	1.0	1.0	.96	.99	1.0	1.0
5000	.35	.90	1.0	1.0	.85	.99	1.0	1.0
10000	.38	.55	1.0	1.0	.81	.95	1.0	1.0

Table 1: Evaluating the PMI and LLR rankings obtained using CM sketch with conservative update (CU) and Exact counts

not throwing away any infrequent word pairs, PMI will rank pairs with low frequency counts higher (Church and Hanks, 1989). Hence, we are evaluating the PMI values for rare word pairs and we need counters linear in size of stream to get almost perfect ranking. This is also evident from the fourth column for $50M$ of the Table 1, where CU PMI ranking gets close to the optimal as the number of counters approaches stream size.

However, in some NLP problems, we are not interested in low-frequency items. In such cases, even using space less than linear in number of counters would suffice. In our extrinsic evaluations, we show that using space less than the length of the stream does not degrade the performance.

4 Extrinsic Evaluations

4.1 Data

Gigaword corpus (Graff, 2003) and a 50% portion of a copy of web crawled by (Ravichandran et al.,

2005) are used to compute counts of words and word pairs. For both the corpora, we split the text into sentences, tokenize and convert into lower-case. We generate words and word pairs over a window of size 7. We use four different sized corpora: SubSet (used for intrinsic evaluations in Section 3), Gigaword (GW), GigaWord + 20% of web data (GWB20), and GigaWord + 50% of web data (GWB50). Corpus Statistics are shown below. We store exact counts of words in a hash table and store approximate counts of word pairs in the sketch. Hence, the stream size in our case is the total number of word pairs in a corpus.

Corpus	Subset	GW	GWB20	GWB50
Unzipped Size (GB)	.32	9.8	22.8	49
# of sentences (Million)	2.00	56.78	191.28	462.60
Stream Size (Billion)	.088	2.67	6.05	13.20

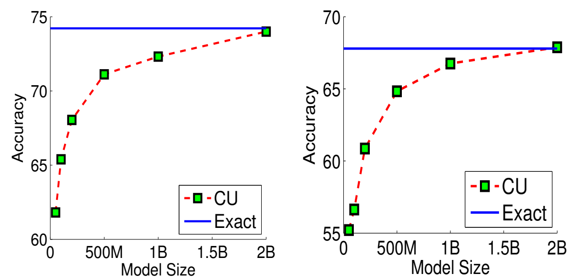
4.2 Semantic Orientation

Given a word, the task of finding the Semantic Orientation (SO) (Turney and Littman, 2003) of the word is to identify if the word is more likely to be used in positive or negative sense. We use a similar framework as used by the authors to infer the SO. We take the seven positive words (good, nice, excellent, positive, fortunate, correct, and superior) and the seven negative words (bad, nasty, poor, negative, unfortunate, wrong, and inferior) used in (Turney and Littman, 2003) work. The SO of a given word is calculated based on the strength of its association with the seven positive words, and the strength of its association with the seven negative words. We compute the SO of a word "w" as follows:

$$\text{SO-AS}(\text{W}) = \sum_{p \in Pwords} AS(p, w) - \sum_{n \in Nwords} AS(n, w)$$

Where, Pwords and Nwords denote the seven positive and negative prototype words respectively. We use PMI and LLR to compute association scores (AS). If this score is positive, we predict the word as positive. Otherwise, we predict it as negative.

We use the General Inquirer lexicon[4] (Stone et al., 1966) as a benchmark to evaluate the semantic orientation scores similar to (Turney and Littman, 2003) work. Words with multiple senses have multiple entries in the lexicon, we merge these entries for our experiment. Our test set consists of 1597 positive and 1980 negative words. Accuracy is used as an evaluation metric and is defined as the percentage of number of correctly identified SO words.



(a) SO PMI (b) SO LLR

Figure 2: Evaluating Semantic Orientation using PMI and LLR with different number of counters of CU sketch built using Gigaword.

4.2.1 Varying sketch size

We evaluate SO of words using PMI and LLR on Gigaword (9.8GB). We compare approximate SO computed using varying sizes of CU sketches: 50 million ($50M$), $100M$, $200M$, $500M$, 1 billion ($1B$) and 2 billion ($2B$) counters with Exact SO. To compute these scores, we count the number of individual words w_1 and w_2 and the pair (w_1,w_2) within a window of size 7. Note that computing the exact counts of all word pairs on these corpora is computationally expensive and memory intensive, so we consider only those pairs in which one word appears in the prototype list and the other word appears in the test set.

First, if we look at the Exact SO using PMI and LLR in Figure 2(a) and 2(b) respectively, it shows that using PMI, we get about 6 points higher accuracy than LLR on this task (The 95% statistical significance boundary for accuracy is about $\pm$ 1.5.). Second, for both PMI and LLR, having more number of counters improve performance.[5] Using $2B$ counters, we get the same accuracy as Exact.

[4]The General Inquirer lexicon is freely available at `http://www.wjh.harvard.edu/~inquirer/`

[5]We use maximum of $2B$ counters (8GB main memory), as most of the current desktop machines have at most 8GB RAM.

4.2.2 Effect of Increasing Corpus Size

We evaluate SO of words on three different sized corpora (see Section 4.1): GW (9.8GB), GWB20 (22.8GB), and GWB50 (49GB). First, since for this task using PMI performs better than LLR, so we will use PMI for this experiment. Second, we will fix number of counters to $2B$ (CU-2B) as it performs the best in Section 4.2.1. Third, we will compare the CU-2B counter model with the Exact over increasing corpus size.

We can make several observations from the Figure 3: • It shows that increasing the amount of data improves the accuracy of identifying the SO of a word. We get an absolute increase of 5.5 points in accuracy, when we add 20% Web data to GigaWord (GW). Adding 30% more Web data (GWB50), gives a small increase of 1.3 points in accuracy which is not even statistically significant. • Second, CU-2B performs as good as exact for all corpus sizes. • Third, the number of $2B$ counters (bounded space) is less than the length of stream for GWB20 ($6.05B$), and GWB50 ($13.2B$). Hence, it shows that using counters less than the stream length does not degrade the performance. • These results are also comparable to Turney's (2003) state-of-the-art work where they report an accuracy of 82.84%. Note, they use a billion word corpus which is larger than GWB50.

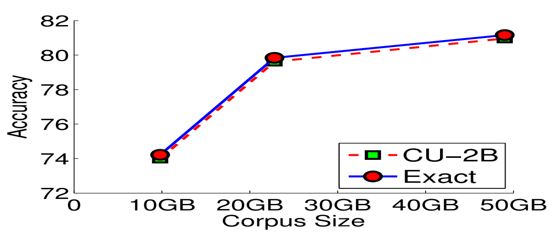


Figure 3: Evaluating Semantic Orientation of words with Exact and CU counts with increase in corpus size

4.3 Distributional Similarity

Distributional similarity is based on the distributional hypothesis that similar terms appear in similar contexts (Firth, 1968; Harris, 1954). The context vector for each term is represented by the strength of association between the term and each of the lexical, semantic, syntactic, and/or dependency units that co-occur with it[6]. We use PMI and LLR to compute association score (AS) between the term and each of the context to generate the context vector. Once, we have context vectors for each of the terms, cosine similarity measure returns distributional similarity between terms.

4.3.1 Efficient Distributional Similarity

We propose an efficient approach for computing distributional similarity between word pairs using CU sketch. In the first step, we traverse the corpus and store counts of all words (except stop words) in hash table and all word pairs (except word pairs involving stop words) in sketch. In the second step, for a target word "x", we consider all words (except infrequent contexts which appear less than or equal to 10.) as plausible context (since it is faster than traversing the whole corpus.), and query the sketch for vocabulary number of word pairs, and compute approximate AS between word-context pairs. We maintain only top K AS scores[7] contexts using priority queue for every target word "x" and save them onto the disk. In the third step, we use cosine similarity using these approximate top K context vectors to compute efficient distributional similarity.

The efficient distributional similarity using sketches has following advantages:

- It can return semantic similarity between any word pairs that are stored in the sketch.
- It can return the similarity between word pairs in time O(K).
- We do not store word pairs explicitly, and use fixed number of counters, hence the overall space required is bounded.
- The additive property of sketch (Sec. 2.1.2) enables us to parallelize most of the steps in the algorithm. Thus it can be easily extended to very large amounts of text data.

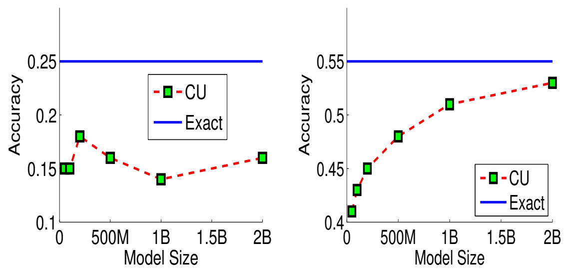
We use two test sets which consist of word pairs, and their corresponding human rankings. We generate the word pair rankings using efficient distributional similarity. We report the spearman's rank

[6]Here, the context for a target word "x" is defined as words appear within a window of size 7.

[7]For this work, we use $K = 1000$ which is not tuned.

correlation[8] coefficient (ρ) between the human and distributional similarity rankings. The two test sets are:

1. **WS-353** (Finkelstein et al., 2002) is a set of 353 word pairs.
2. **RG-65**: (Rubenstein and Goodenough, 1965) is set of 65 word pairs.



(a) Word Similarity PMI (b) Word Similarity LLR

Figure 4: Evaluating Distributional Similarity between word pairs on WS-353 test set using PMI and LLR with different number of counters of CU sketch built using Gigaword data-set.

4.3.2 Varying sketch size

We evaluate efficient distributional similarity between between word pairs on WS-353 test set using PMI and LLR association scores on Gigaword (9.8GB). We compare different sizes of CU sketch (similar to SO evaluation): 50 million ($50M$), $100M$, $200M$, $500M$, 1 billion ($1B$) and 2 billion ($2B$) counters with the Exact word pair counts. Here again, computing the exact counts of all word-context pairs on these corpora is time, and memory intensive, we generate context vectors for only those words which are present in the test set.

First, if we look at word pair ranking using exact PMI and LLR across Figures 4(a) and 4(b) respectively, it shows that using LLR, we get better ρ of .55 compared to ρ of .25 using PMI on this task (The 95% statistical significance boundary on ρ for WS-353 is about $\pm$ .08). The explanation for such a behavior is: PMI rank context pairs with low frequency counts higher (Church and Hanks, 1989) compared to frequent ones which are favored by LLR. Second, for PMI in Fig. 4(a), having more counters does not improve ρ. Third, for LLR in Fig. 4(b), having more number of counters improve performance and using $2B$ counters, we get ρ close to the Exact.

[8] To calculate the Spearman correlations values are transformed into ranks (if tied ranks exist, average of ranks is taken), and we calculate the Pearson correlation on them.

Test Set	**WS-353**			**RG-65**		
Model	GW	$GWB20$	$GWB50$	GW	$GWB20$	$GWB50$
Agirre			.64			.75
Exact	.55	.55	.62	.65	.72	.74
CU-2B	.53	.58	.62	.66	.72	.74

Table 2: Evaluating word pairs ranking with Exact and CU counts. Scores are evaluated using ρ metric.

4.3.3 Effect of Increasing Corpus Size

We evaluate efficient distributional similarity between word pairs using three different sized corpora: GW (9.8GB), GWB20 (22.8GB), and GWB50 (49GB) on two test sets: WS-353, and RG-65. First, since for this task using LLR performs better than PMI, so we will use LLR for this experiment. Second, we will fix number of counters to $2B$ (CU-2B) as it performs the best in Section 4.2.1. Third, we will compare the CU-2B counter model with the Exact over increasing corpus size. We also compare our results against the state-of-the-art results (Agirre) for distributional similarity (Agirre et al., 2009). We report their results of context window of size 7.

We can make several observations from the Table 2: • It shows that increasing the amount of data is not substantially improving the accuracy of word pair rankings over both the test sets. • Here again, CU-2B performs as good as exact for all corpus sizes. • CU-2B and Exact performs same as the state-of-the-art system. • The number of $2B$ counters (bounded space) is less than the length of stream for GWB20 ($6.05B$), and GWB50 ($13.2B$). Hence, here again it shows that using counters less than the stream length does not degrade the performance.

5 Dependency Parsing

Recently, maximum spanning tree (MST) algorithms for dependency parsing (McDonald et al., 2005) have shown great promise, primarily in supervised settings. In the MST framework, words in a sentence form nodes in a graph, and connections between nodes indicate how "related" they are. A maximum spanning tree algorithm constructs a dependency parse by linking together "most similar" words. Typically the weights on edges in the graph are parameterized as a linear function of features, with weight learned by some supervised learning algorithm. In this section, we ask the question: can word association scores be used to derive syntactic structures in an *unsupervised* manner?

A first pass answer is: clearly not. Metrics like PMI would assign high association scores to rare word pairs (mostly content words) leading to incorrect parses. Metrics like LLR would assign high association scores to frequent words, also leading to incorrect parses. However, with a *small amount* of linguistic side information (Druck et al., 2009; Naseem et al., 2010), we see that these issues can be overcome. In particular, we see that large data + a little linguistics > fancy unsupervised learning algorithms.

5.1 Graph Definition

Our approach is conceptually simple. We construct a graph over nodes in the sentence with a unique "root" node. The graph is directed and fully connected, and for any two words in positions i and j, the *weight* from word i to word j is defined as:

$$w_{ij} = \alpha^{\text{asc}}\text{asc}(w_i, w_j) - \alpha^{\text{dist}}\text{dist}(i-j) + \alpha^{\text{ling}}\text{ling}(t_i, t_j)$$

Here, $\text{asc}(w_i, w_j)$ is a association score such as PMI or LLR computed using approximate counts from the sketch. Similarly, $\text{dist}(i-j)$ is a simple parameterized model of distances that favors short dependencies. We use a simple unnormalized (log) Laplacian prior of the form $\text{dist}(i-j) = -|i-j-1|$, centered around 1 (encouraging short links to the right). It is negated because we need to convert distances to similarities.

The final term, $\text{ling}(t_i, t_j)$ asks: according to some simple linguistic knowledge, how likely is if that the (gold standard) part of speech tag associated with word i points at that associated with word j? For this, we use the same linguistic information used by (Naseem et al., 2010), which does *not* encode direction information. These rules are: `root` $\rightarrow$ { `aux, verb` }; `verb` $\rightarrow$ { `noun, pronoun, adverb, verb` }; `aux` $\rightarrow$ { `verb` }; `noun` $\rightarrow$ { `adj, art, noun, num` }; `prep` $\rightarrow$ { `noun` }; `adj` $\rightarrow$ { `adv` }. We simply give an additional weight of 1 to any edge that agrees with one of these linguistic rules.

	len ≤ 10	len ≤ 20	all
COHEN-DIRICHLET	45.9	39.4	34.9
COHEN-BEST	59.4	45.9	40.5
ORACLE	75.1	66.6	63.0
BASELINE+LING	42.4	33.8	29.7
BASELINE	33.5	30.4	28.9
CU-2B LLR OPTIMAL	62.4 ± *7.7*	51.1 ± *3.2*	41.1 ± *1.9*
CU-2B PMI OPTIMAL	63.3 ± *7.8*	52.0 ± *3.2*	41.1 ± *2.0*
CU-2B LLR BALANCED	49.1 ± *7.6*	43.6 ± *3.3*	37.2 ± *1.9*
CU-2B PMI BALANCED	**49.5** ± ***8.0***	**45.0** ± ***3.2***	**38.3** ± ***2.0***
CU-2B LLR SEMISUP	55.7 ± *0.0*	44.1 ± *0.0*	39.4 ± *0.0*
CU-2B PMI SEMISUP	**56.5** ± ***0.0***	**45.8** ± ***0.0***	**39.9** ± ***0.0***

Table 3: Comparing CU-2B build on GWB50 + a little linguistics v/s fancy unsupervised learning algorithms.

5.2 Parameter Setting

The remaining issue is setting the interpolation parameters α associated with each of these scores. This is a difficult problem in purely unsupervised learning. We report results on three settings. First, the OPTIMAL setting is based on grid search for optimal parameters. This is an oracle result based on grid search over two of the three parameters (holding the third fixed at 1). In our second approach, BALANCED, we normalize the three components to "compete" equally. In particular, we scale and translate all three components to have zero mean and unit variance, and set the αs to all be equal to one. Finally, our third approach, SEMISUP, is based on using a small amount of labeled data to set the parameters. In particular, we use 10 labeled sentences to select parameters based on the same grid search as the OPTIMAL setting. Since this relies heavily on which 10 sentences are used, we repeat this experiment 20 times and report averages.

5.3 Experiments

Our experiments are on a dependency-converted version of section 23 of the Penn Treebank using modified Collins' head finding rules. We measure accuracies as *directed*, unlabeled dependency accuracy. We separately report results of sentences of length at most 10, at most 20 and finally of all length. Note that there is no training or cross-validation: we simply run our MST parser on test data directly.

The results of the parsing experiments are shown in Table 3. We compare against the following alternative systems. The first, Cohen-Dirichlet and Cohen-Best, are previously reported state-of-the-art results for unsupervised Bayesian dependency parsing (Cohen and Smith, 2010). The first is results using a simple Dirichlet prior; the second is the best reported results for any system from that paper.

Next, we compare against an "oracle" system that uses LLR extracted from the training data for the Penn Treebank, where the LLR is based on the probability of observing an edge given two words. This is not a true oracle in the sense that we *might* be able to do better, but it is unlikely. The next two baseline system are simple right branching baseline trees. The Baseline system is a purely right-branching tree. The Baseline+Ling system is one that is right branching *except* that it can only create edges that are compatible with the linguistic rules, provided a relevant rule exists. For short sentences, this is competitive with the Dirichlet prior results.

Finally we report variants of our approach using association scores computed on the GWB50 using CU sketch with 2 billion counters. We experiment with two association scores: LLR and PMI. For each measure, we report results based on the three approaches described earlier for setting the α hyperparameters. Error bars for our approaches are 95% confidence intervals based on bootstrap resampling.

The results show that, for this task, PMI seems slightly better than LLR, across the board. The OPTIMAL performance (based on tuning two hyperparameters) is amazingly strong: clearly beating out all the baselines, and only about 15 points behind the ORACLE system. Using the BALANCED approach causes a degradation of only 3 points from the OPTIMAL on sentences of all lengths. In general, the balancing approach seems to be slightly worse than the semi-supervised approach, except on very short sentences: for those, it is substantially better. Overall, though, the results for both Balanced and Semisup are competitive with state-of-the-art unsupervised learning algorithms.

6 Discussion and Conclusion

The advantage of using sketch in addition to being memory and time efficient is that it contains counts for all word pairs and hence can be used to compute association scores like PMI and LLR between any word pairs. We show that using sketch counts in our experiments, on the three tasks, we get performance comparable to Exact word pair counts setting and state-of-the-art system. Our method scales to 49 GB of unzipped web data using bounded space of 2 billion counters (8 GB memory). Moreover, the linearity property of the sketch makes it scalable and usable in distributed setting. Association scores and counts from sketch can be used for more NLP tasks like small-space randomized language models, word sense disambiguation, spelling correction, relation learning, paraphrasing, and machine translation.

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