## Word2Bits - Quantized Word Vectors

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### **Problem**

Word vectors take lots of storage and memory

500 dimensions \* 4 bytes \* 4M words = 8GB

## **Approach: Word2Bits**

Extend Word2Vec to train high quality <u>quantized</u> word vectors

(e.g: each parameter is either -1 or +1)

#### **Loss Function**

$$\begin{split} J(u_o, \hat{v}_c) &= -\log(\sigma(\hat{u}_o^T \hat{v}_c)) - \sum_{i=1}^k \log(\sigma(-\hat{u}_i^T \hat{v}_c)) \\ \hat{u}_i &= Q_{bitlevel}(u_i) \\ \hat{v}_c &= \sum_{-w+o \leq i \leq w+o} Q_{bitlevel}(v_i) \end{split}$$

#### **Quantization Function**

$$Q_1(x) = \begin{cases} \frac{1}{3} & x \ge 0 \\ -\frac{1}{3} & x < 0 \end{cases}$$

$$Q_2(x) = \begin{cases} \frac{3}{4} & x > \frac{1}{2} \\ \frac{1}{4} & 0 \le x \le \frac{1}{2} \\ -\frac{1}{4} & -\frac{1}{2} \le x < 0 \\ -\frac{3}{4} & x < -\frac{1}{2} \end{cases}$$

# Intrinsic Experiments: Word Analogy and Similarity

Dataset: English Wikipedia 2017

Word Vector Type	Bits per parameter	Dimension	WordSim Similarity	WordSim Relatedness	MEN	M. Turk	Rare Words	SimLex	Google Add / Mul	MSR Add / Mul
Full Precision	32	200	.740	.567	.716	.635	.403	.317	.706/.702	.447/.447
	32	400	.735	.533	.720	.623	.408	.335	<b>.722</b> /.734	<b>.473</b> /.486
	32	800	.726	.500	.713	.615	.395	.337	.719/.735	.471/ <b>.489</b>
	32	1000	.741	.529	.745	.617	.400	.358	.664/.675	.423/.434
Thresholded	T1	200	.692	.480	.668	.575	.347	.288	.371/.369	.186/.182
	T1	400	.677	.446	.686	.581	.369	.321	.533/.540	.286/.292
	T1	800	.728	.494	.692	.576	.383	.338	.599/.609	.333/.346
	T1	1000	.689	.504	.694	.551	.358	.342	.521/.520	.303/.305
Quantized	1	800	.772	.653	.746	.612	.417	.355	.619/.660	.395/.390
	1	1000	.768	.677	.756	.638	.425	.372	.650/.660	.371/.408
	1	1200	.781	.628	.765	.643	.415	.379	.659/.692	.391/.429
	2	400	.752	.604	.741	.616	.417	.373	.666/.690	.396/.418
	2	800	.776	.634	.767	.642	.390	.403	.710/.739	.418/.460
	2	1000	.752	.594	.764	.602	.362	.387	.720/ <b>.750</b>	.436/.482

- Quantized vectors better on similarity, worse on analogy

## Intrinsic Experiments: DrQA SQuAD

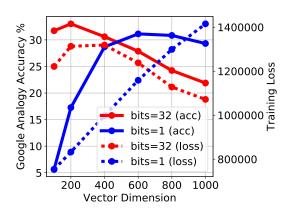
Dataset: English Wikipedia 2017

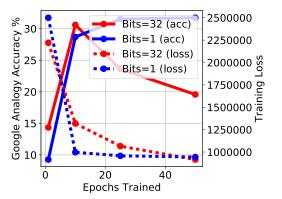
Word Vector Type	Bits per	Dimension	Bytes per word	F1
Word vector Type	parameter	Dimension	Bytes per word	
	32	200	800	75.25
Full Precision	32	400	1600	75.28
run Fiecision	32	800	3200	75.31
	32	1000	4000	9.99
	1	800	100	76.64
	1	1000	125	76.84
Quantized	1	1200	150	76.50
Quantizeu	2	400	100	77.04
	2	800	200	76.12
	2	1000	250	75.66

Quantized vectors outperform full precision vectors on DRQA
 8x-16x less storage/memory than full precision

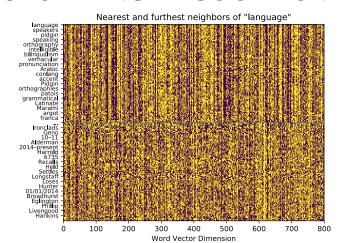
## Word2Bits & Regularization

Dataset: 100MB of Wikipedia





### **Word2Bits Visualization**



Pre-trained vectors at: https://github.com/agnusmaximus/Word2Bits/